**Chapter 14**

**Introduction and types of Machine Learning**

Dr. Arpana Chaturvedi, Associate Professor (Department of AI/ML/IT), New Delhi Institute of Management, New Delhi.

ac240871@gmail.com

**Dr. Nitish Pathak**

**Bhagwan Parshuram Institute of Technology, GGSIPU, New Delhi, India**

**Email: - nitishpathak@bpitindia.com**

**Objective:**

To provide a comprehensive understanding of the fundamental types of learning in artificial intelligence, delineating between supervised and unsupervised learning. This chapter aims to introduce the reader to the core concepts and methodologies of these learning paradigms, including classification overview, and to explain the importance of different data sets such as training, test, and validation in the development of AI models. Additionally, the chapter will address common challenges in model training, particularly overfitting and underfitting, and discuss strategies to mitigate these issues. The goal is to equip readers with the knowledge necessary to apply these concepts effectively in various applications of AI.

**Structure:**

* Types of Learning
* Supervised learning
* Unsupervised learning
* Overview of classification
* Setup, Training, Test, Validation dataset,
* Over fitting and Under Fitting

**Introduction:**

Machine learning is increasingly important because it can handle complex tasks that are too much for humans, especially when dealing with big data that we can't process manually. This technology trains computers to make our lives easier by learning from large amounts of data and making predictions. It saves us time and money.

Machine learning is a part of AI that lets machines learn from data and get better over time. It works by training on lots of data to do tasks like predicting trends or spotting patterns.

AI is everywhere now, in self-driving cars, detecting frauds, recognizing faces, and even suggesting friends on social media. It helps companies like Netflix and Amazon recommend things to customers by learning what they like.

**Types of Machine Learning:**

The four main types of machine learning are:

1. Supervised Learning
2. Unsupervised Learning
3. Semi-Supervised Learning
4. Reinforcement Learning
5. **Supervised Learning:** Supervised learning is a method where the computer is given a dataset that's already organized with correct answers. It studies this data to understand patterns, like a student learns from a textbook. The computer is shown data (like pictures or numbers) and the answers (like 'cat' or 'price'). It then learns to connect the two. After it's trained, you can give it new data it hasn't seen before, and it will use what it's learned to make good guesses.

For instance, as shown in Fig 14.1, if you show it pictures with labels, like 'spoon' or 'knife', the computer looks at the details—shape, size, sharpness—and learns to tell them apart. Later, if you show it a new picture without a label, it uses what it learned to guess if it's a spoon or a knife. It’s like pairing things up: you show it what an input (like a picture) should lead to, which is the output (like the word 'Spoon' or ‘Knife’).

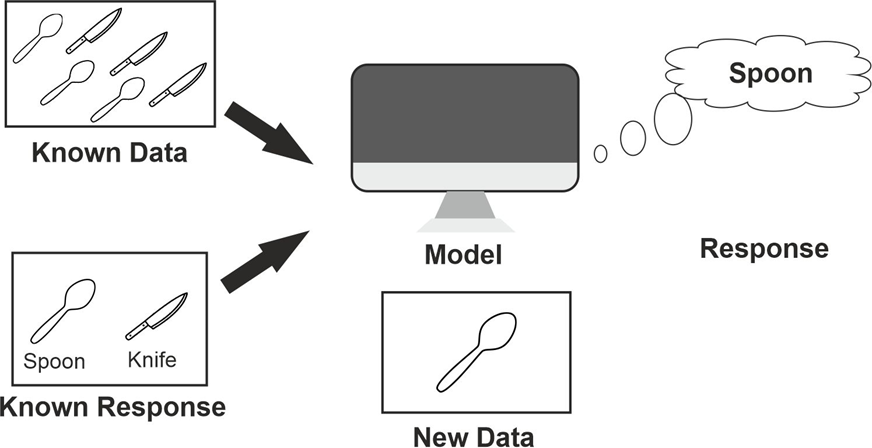


Fig. 14.1 Supervised Learning

In this algorithm the computer recognizes and understand the pattern between the input variable-x (what you show it) and the output variable -y (what it’s supposed to say). In the real world, this helps with things like figuring out if a bank transaction is suspicious or if an email is junk.

**Working of Supervised Learning**

In supervised learning, models undergo training with a labelled dataset, allowing them to recognize and learn from various data types. After training, the model's knowledge is evaluated using **test data**—a portion of the dataset originally set aside for this purpose—to ascertain its predictive capabilities. The mechanics of supervised learning are clarified further through specific examples and illustrative diagrams shown in Fig. 14.2.

Suppose there is a dataset comprising various shapes such as squares, rectangles, triangles, and polygons as shown in Fig. 14.2. The initial step involves training a model to recognize each type of shape with the following criteria:

* **Square** - A shape with four equal sides is labelled.
* **Triangle** - A shape with three sides is classified or labelled.
* **Hexagon** - A shape with six equal sides is recognized or labelled .



Fig. 14.2 Supervised Learning

After the model has been trained with these rules, it is then tested with a separate set of shapes. The model's task is to determine the type of each new shape it encounters. Having been trained on shape characteristics, the model uses the number of sides and the equality of sides to classify the shape and predict the correct label as output.

**Steps Involved in Supervised Learning:**

The process of supervised learning involves several key steps:

**1. Define the problem:**

* What kind of information do you want the computer to learn? (e.g., identifying images of animals, predicting the price of a house)
* What kind of data is needed to train the computer? (e.g., labeled images of animals, data with house characteristics and prices)

**2. Prepare the data:**

* Gather labeled data: Collect examples that are already categorized or have the correct answers.
* Split the data into three parts:
  + Training set: Used to teach the computer.
  + Test set: Used to evaluate how well the computer learned.
  + Validation set: Used to fine-tune the computer's learning process.

**3. Choose the right tool:**

* Select an algorithm: This is the recipe the computer uses to learn from the data.
* Different algorithms are better suited for different types of data and problems.

**4. Train the computer:**

* Feed the computer the training data and let it learn.
* Use the validation set to adjust the algorithm settings and improve learning.

**5. Test the computer:**

* Give the computer the test data and see how well it predicts the correct answers.
* Evaluate the accuracy of the model and identify areas for improvement.

**6. Fine-tune and improve:**

* If the model performs well, it's ready to use!
* If not, try different algorithms, adjust the data, or refine the training process.

**Types of Supervised Learning Algorithms:**

There are two types of Supervised learning algorithm. These are based on two types of problems:



Fig. 14.3 Types of Supervised Learning

There are two main kinds of supervised learning:

1. **Classification:** Classification involves creating a model that sorts information into distinct categories or classes or discrete values based on certain characteristics in the data. It assigns predefined labels to the data based on these characteristics.

The job in a classification task is to predict specific outcomes, known as class labels, by analysing different or discrete factors or features. Additionally, the task requires defining a clear separation between these categories within the data, known as a decision boundary.

For example, this algorithm can be used when we want to sort data into specific groups or categories, like sorting emails as 'spam' or 'not spam' as shown in Figure 14.4. These algorithms look at the data we give them and learn to predict the category for new data based on what they've seen.

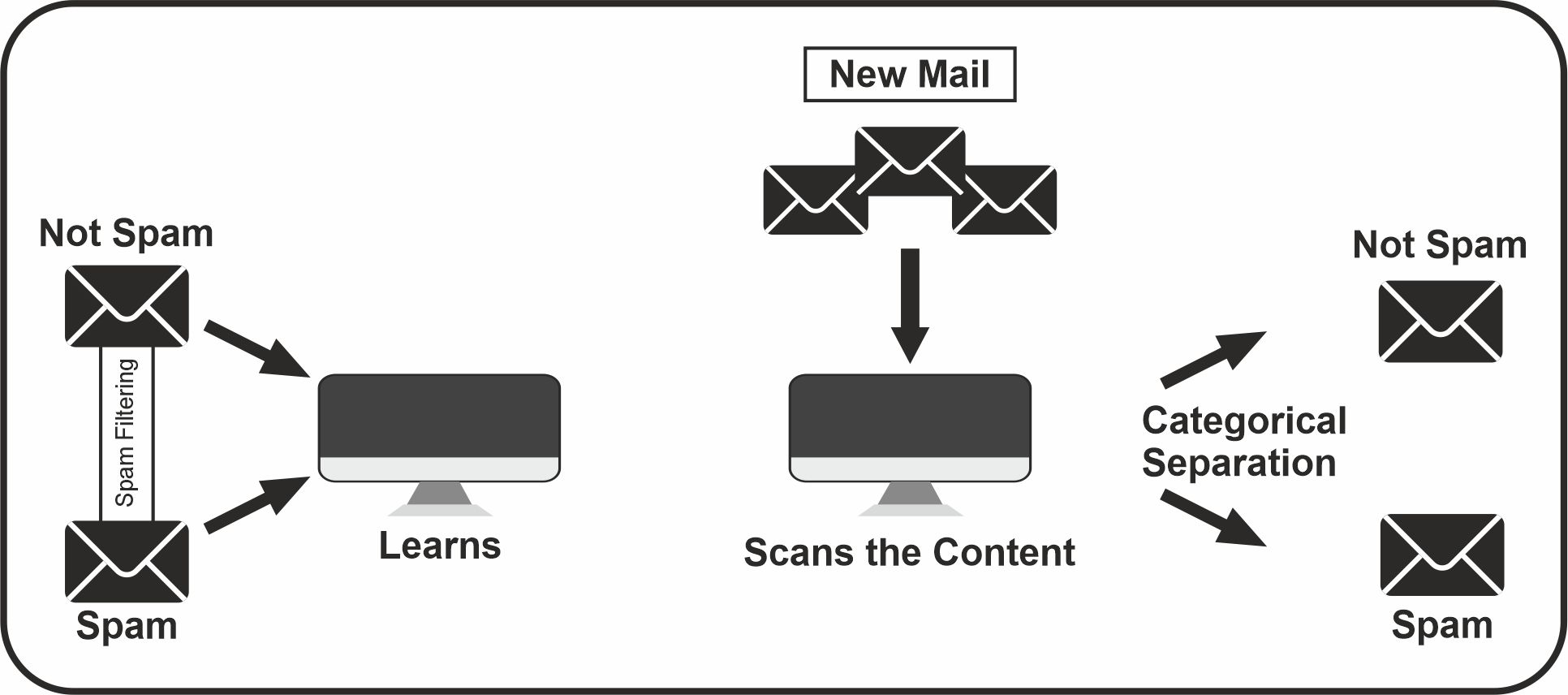


Fig. 14.4 Filtrations of Spam Emails

Another example, a shopkeeper might use a classification algorithm to predict whether a customer will return based on past shopping behaviour.

Here's what happens in classification:

* The computer is given details (features) about something, like stats from previous matches of a sports team.
* It uses those details to predict which group (class) it belongs to, like predicting if a team will win or lose.
* The goal is to find a clear line (decision boundary) that separates the different possible groups or outcomes.

In a way, the computer is making "IF-THEN" decisions. If certain conditions are met, then it predicts a certain group. For example, if Team A has won a lot of games when it's sunny, the computer might predict a win for Team A when the forecast is sunny. This process is used for decisions where there are fixed options, like a simple yes or no, win or lose.

There are various modern classification techniques or algorithms that have been created to sort data well, and they do this by using special approaches called bagging and boosting.

**1.1 Types of Classification Algorithms:**

Classification Algorithms can be further divided into the mainly two category:

* **Linear Models**
  1. Logistic Regression
  2. Support Vector Machines
* **Non-linear Models**
  1. K-Nearest Neighbours
  2. Kernel SVM
  3. Naïve Bayes
  4. Decision Tree Classification
  5. Random Forest Classification
* **Random Forest**: It's like asking a bunch of experts (trees) and combining what they all say to make a final decision.
* **Decision Trees**: This method makes decisions by going through a list of questions and following the answers until it reaches the end.
* **Logistic Regression**: It's usually used when the answer is yes or no—like if a team will win a match or not.
* **Support Vector Machines (SVM)**: This algorithm finds the best boundary that separates different categories.
* **K-Nearest Neighbours (KNN)**: It looks at the 'K' examples that are most like the one we're trying to figure out and picks the most common category among them.

Each of these algorithms has its own way of deciding where to put new data based on the examples it's learned from. They can be simple, with just two choices (binary), or they can have many options (multiclass), as shown in Figure 14.5, like sorting different types of fruits into their own baskets.



Fig. 14.5 Binary Classification and Multiclass Classification

1. **Regression:** Regression entails establishing a model or function that effectively distinguishes data into continuous real values rather than discrete categories. This process can also reveal patterns and trends within historical data. Since regression models predict quantitative values, their performance is assessed based on the error in these predictions.

The primary objective of regression is to uncover the relationship between a dependent variable, which is the quantity being predicted, and one or more independent variables, which are the factors influencing the dependent variable. By analysing the relationship between these variables, regression models can be constructed to make accurate predictions of the dependent variable.

Imagine we're looking at two things: how moist the air is (humidity) and how hot it is (temperature). In this case, the heat is the independent variable, and the moisture in the air depends on it. Usually, when it gets hotter, the air becomes less moist.

We put these two pieces of information into a computer model, and it figures out how they're connected. Once the computer has learned this, if we tell it how hot it is, it can guess how much moisture is in the air as shown in Figure 14.6.

![A diagram of a computer

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIAx4G0AMBIgACEQEDEQH/xAAcAAEAAwEAAwEAAAAAAAAAAAAABQYHBAIDCAH/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAAB1QABzZsaJTs4tMeiJ0eYMX/Nz/TC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC26DC/wB3P8MUldOiCMuOc1I+hWTaZXaAABC/uLHusNjvEcHeUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5OsZZUvoCpR2WH572KrEBz9GYFT0Kta9AUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABUsr+gcuND7sk1s5ME0ysRqEiUAAAAVqNLuZGa4AAAAVUtSpW0GTmsIWuF9V73E2AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABzdI+etxz7uiIstE1MsIoAAACn16w5/Gt41Z6cbnVrDn9aLWZyiE7Hx+hFDV/bYpkvm11JGN8KSTVa33BzYoCSqFQsp32OK1pmSXOq/o+Sa4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAVOgavicezZMb2UlxQAAAFPiLjyFhwndqQWHLNppR6YG0+8pmjxNhMY22n3IxO6+6ZK5TNU9pzY7o/tiSqGhRVVuVsFfJHJd1w2NTtHj5UAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYFvuAx27LjWykuKAAAAAAAAAAAAAAAz6as4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxrZSXFAAAAAAAAAAEd7jrAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAAAAAAAAAeHnlBTJKmj6qZ7oQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAAAAAAAAEYQuCdnCAe/wChvnKaPpBzdIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAzjR8xK946P6o8rbk3vrUmKX0tzHe01Vx5KaXT4zrO+40u5koyfkNjonXmZtmcSsKa49GUGvMevpZGcc5p7FdlPaAAAAAAAAAAAAAAAAAAAAAAAADkwHfsBjt2XGtlJcUAAAAAAAB4fP1sy0P3tOEAF43L5V2c0MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADMdOzErsjeLOQuX7VisatneoUKuGAt3qj2+dizo0Kne70nNbaleii6ti1xLlldirxpuN6ZmZosbaczNYyiycpHaFnuj1m2k5xo5KgAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxrZSXFAAAAAAAIKdxAo/wCeMgbhY/HCy54/9M/Mw91w18+aurm/D6b78l1oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQs0OLtBW7IPD98hVpGYCv2AQHnOCAlukRcRax64+UEBzWgIeYFXs3kICY94gJj3gAAAAAAAAAAAAAAAAAAAAAAAADkwHfsBjt2XGtlJcUAAAAAAB6fmH6F+dB+/g2W7fMg0iNbKMGV0AlfpX5V+oDqAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAM9NCYP6jfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWBDfWI6eT4AAAAAAAAAAAAAAAAB4nk5ukAAAAAA5MB37AY7dlxrZSXFAAAAAAAQHzp9SfMB6gLs2UYMv5j/59R5sZKD9+n/nP6WAAAAAAAAAAAAAAAAAAAAABGkTRoIS6IEuiBLogS6IEuiBLogS6IEuiBLogS6IEuiBLogS/ZXBtEth24H6AAAAAAAAAAAAAACu5Do2dgAAAAAAAAAAAADr5PWfQP7z9AAAAAAAAAAAAAAAAAyq6fPRL/RXy1pproAAAAAOTAd+wGO3Zca2UlxQAAAAAADD9wiD5s6/HmPpnCIDwPd9Q/LG3GafQPnnpjniky+61ydYAAAAAAAAAAAAAAAAAAAAAp1xphmgAAAAAD3SpCLByEU9nrAAAAAPDccO28kgAAAAAAAAAAAAAAUXO9EzsAAAAAAAAAAAAAev2es3np5ukAAAAAAAAAAAAAAAc3ThZBQwPLxG8XL5h+iCWAAAAByYDv2Ax27LjWykuKAAAAAAAAqeGfT8WfNLQqQcgPf6JC+FF3qS7AAAAAAAAAAAAAAAAAAAAAABTLnTDNAAAAAOzjsZ7q/6fA/e7gFkrvjYiugAAAA8NvxDbySAAAAAAAAAAAAAABRc70TOwAAAAAAAAAAAAB6/Z6zeenm6QAAAAAAAAoF0OsAAAAArhVMj9nrD9/ABYq6PqX25Br4AAAByYDv2Ax27LjWykuKAAAAAAAAAePkOP96x+foAAAAAAAAAAAAAADnOgAAAAAAACmXOmGaAAAAA8p+vWErwAFirthK/+eXiAAAAeG34ht5JAAAAAAAAAAAAAAAoud6JnYAAAAAAAAAAAAA9fs9ZvPTzdIABDfmHeEbowsbowsbowsbowsbowsd/p5hpF/wDnjsPoJQb1XsAAB4/O2n4iNGzn6QJGo51tx8y+M1yke+icRIb6E+ebeb2AAADkwHfsBjt2XGtlJcUAAAAAAAAAAAAAAAAAAAAenJDYWPDYWPDYWPDYWPDYWPDYcBnapGk33537j6AUS8V5gAAAAAUy50wzQAAAACx1z9H5Y4s4H71HNYPfXzmAAAAB4bfiG3kkAAAAAAAAAAAAAACi53omdgAAAAAAAAAAAAD1+z1m89PN0gAHzp4XHxioLeKgt4qC3ioLeKgt4qD3ekOvQyg6nZvbQAAGC0/u4RqWWj6mrWC9J5b3+0cZU/B5eI+mZGm3IAAA5MB37AY7dlxrZSXFAAAAAAAAAAAAAAAAAAAAc3z19C/PUAAAAAAAJPx0ckrJ4+VAAAAAKZc6YZoAAAAADykYwWyMhh7vSAAAAAHht+IbeSQAAAAAAAAAAAAAAKLneiZ2AAAAAAAAAAAAAPX7PWbz083SAAAAAAAAYXbdA95z9AAAAAfL/LZK2CQPzf1HGVW3XT50bRjJ4g3S7Qc4AAAcmA79gMduy41spLigAAAAAAAAAAAAAAAAAAAPGJmBDpgQ6YEOmBDpgQ6YEPh30Tnxn+h3f3nr9gAAAAAAKZc6aZm7RxO0cTtHE7RxO0cTtHE7RxO0cTtHE7RxO0cTtHE7RxO0R+341spJAAAAAAAAAAAAAAApFYuFiMtakTLWpDLWpDLWpDLWpDLWpDLWpDLWpDLWpDLWpDLWpDLWpDLWpDLePXq8tk6ebpAAAAAAAAAAAAAAMwyT6i+cyJ+gfn7vNHyr8H0FQ5DRTmxLcfnQ5JyE3YuYAAAOTAd+wGO3Zca2UlxQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACpW2pFhCAAAAAAAAAAAAAQ0nGSiyIAAAAAAAAAAAAAAKjYuDnJcIAAAAAAAAAAAArtiqRcegUAAAAAAAAAAAAABAzw+ZY/6ayUz97vSJmG/T3+iyauV7TwAAAA5MB37AY7dlxrZSXFAAAAAAAADhPfX8dsxq/Z867aToAAAAAAAAAAAAAAAAAAAAAAAEHOCvyla9CWxVBa1UFrVQWtVBa1UFrV4WFXhYVc5y1qoLWqgtaqC1qoLWqniey4wFjUAAAAAAAAAAAAAABVrSKT+3UUpdRSl1FKXUUpdRSfGbpxLIkS35FfpMLb0FKXUUpdRSl1FKXUUixSoAAAAAAAAAAAAAAAAA9EJYhWJaRAAAAAAHJgO/YDHbsuNbKS4oAAAAAAABnWi5ke3SKFfSoU++54bKYEb6+eR9DI6RAAAAAAAAAAAAAAAAAAAAAAAAAAAEZJ0shQAfui5zaSygAAAAAAAAAAAAAAAAAAAAAAAAAEaVLgAAC0WbOtEP0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAHJgO/YDHbsuNbKS4oAAAAAAABmWm5kSF9oV9K5nuh54bLXLHkJfrBlOrAAAAAAAAAAAAAAAAAAAAAAAAAAAA8T0Z3b4UiUsIlLCJ6uwXf9jJI/QAAAAAAAAAAAAAAAAAAAAAAAD0n7C9H4kSlhEpYRKWETNesSvnFSS+YAAAAAAAAAAAAAAAAAAAAAAAAAAAAOTAd+wGO3Zca2UlxQAAAAAAADMtNzIkL7QrGc+eaBn5suYafUSsftiFn6/T7gAAAAAAAAAAAAAAAAAAAAAAAAADwjuvwON2E43YON2Djdg4/b7x1eXP0KAAAAAAAAAAAAAAAAAAAAAAA9HvHO6Bzugc7oHO6Bzugc/l7gAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAAAAAAAAZlpuZEhjmx44bdTLnTDZcC32OMd3ON/SRePkAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHqys1l+foAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAAAAAAAAZlpuVExjmx44bdTLpQjbsP3AYM3kcHeAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAiCnZz7PXGp3v563au8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHJgO/YDHbsuNbKS4oAAAAAAAcZTs+5NQJDBdnjyaoFH1w59VwPXSfAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB+YppucFXfv5C31WxmzImWoAAAAAAAAAAAAAAAAAAAAAAAAAAAAADkwHfsBjt2XGtlJcUAAAAAAAo15z8jfb7K2X7DLDVh7vT+m1RctBGtAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+dfX7PXElvmB74BQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHJgO/YDHbsuNbKS4oAAAAAABBzgweZ5Zcydr9XKRc7FJkDbM23w/QAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAfOvr9nriS3zA98AoAAAAAAAAAAAAAAAAAAAAAAAAAAAAADkwHfsBjt2XGtlJcUAAAAAAAB4ZRrQ+dZfcOMwee2T2nN0gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB86+v2euJLfMD3wCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOTAd+wGO3Zca2UlxQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGP6rjmxHYcJ3Mf9hrjmyw1xjehFiZfCG1s/jjUWLasSbI/UbCrdkAAAAAAAAAAAAAAAAAAAAAAAAAPnX1+z1xJb5ge+AUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAQc56zJ2k5DErrPNTqvrLdGOxR4w0tQIo1RXuEt7PuU0t4UI0Bl2jnUo8Sacr1JNX9NH9x32nC9OLMrvuJxXYkvDM7eTrKrGXIAAAAAAAAAAAAAAAAAAGI7Fjtxi+0Lo/KqXolZSJKMnc3PdZo/vKnruRbVWeS8RORAzUPKFDlOj3lwnMu1GgAAAAAAAAAAAAAAAAAAAAAAAAPnX1yvhDfMS22gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOTAd+wGO3Zca2UlxQAHPjOzYzGs5JruRlp9cp21m2yY3uUYHrmW6yUD8C5Vmerp21e2VQsXn3yNZno2c7lEDBV2yVnWwZFsUZ3a6tbCN7IjpPKpW2pF/qWsZTU7Rr5wRofu9fsoAAAAAAAAAAAAAAAAACrcd1FKtfUKx5WUKrahX/2fFWs/kITrkBCdcgIOKuI9HvAAAAAAAAAAAAAAAAAAAAAAAAAcZ2Mr9ZrCKlQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADkwHfsBjt2XGtlJcUAB6qJoAUq6jMb/AN4zzQwzy6d4pda1mgHF1XCSPyk3cZloHaM80MK5VtMGdXvqGZXaXGZ9WhCswugDx4JEZjN3MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMI3f51NM7biPnf6HwfajvRMEXNTJMsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOTAd+wGO3Zca2UlxQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD51+ivnU+igYRs+MbORdQs9GJKfkLIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAcmA79gMduy41spLigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHzr9FfOp9FAwfaMY2cRUVmRvXb88XM1QAAAAAAAAAAAAAAAAAAAAAAAAAAAAHJgO/YDHbsuNbKS4oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB86/RXzqbFwxUMRmz4vtB5x3DQTYOqtWUAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxrZSXFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPnX6K+dS/w0zDEZs+L7QRtQvNdIie9EsWQAAAAAAAAAAAAAAAAAAAAAAAAAAAAHJgO/YDHbsuNbKS4oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAV85sd92okRDeVTJu6e7PzeVKuoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAByYDv2Ax27LjWykuKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYZufzsanxevQCLwH0cp5blhekFb+hvnzfT3AAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxrZSXFADPzQGH/AIbiplzAAB4HmzfSAZoaWxAbeqdsADwzo0gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD54+h8qJbL9EppUgNWo2pGYfRGJ7cAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAcmA79gMduy41spLigGcaPnBK9mZSceNisPJVLkvTX40Wm2yiEhcoHQawjZsv2qGWanllWydgrOYVquS7LGZ+uWqBqGW7ZlJfqRrGe1C6zjOoRZBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD0+4YBbNPzw7PyiesudAu2kHp7wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxrZSXFAM40eHIe4R8gMN3KKK9Q9P8SP5b3WDNdg9M2YVtENMHdlmpwZS/ZOe8p/ZpXpKBT9N7I7Md2uDqBjNGhSg6L7+wkQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHh5h4/p+gAAAHieT1+R5AAAAAAAAAAAAAAAAAAAAAAAAAAAAA5MB37AY7dlxvYiZFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPX7PWfPW64nOROzkHOFr8cn9FbCpFWNgRGWG1KvGF7oV9oRRui432Mz0zCdbqaY5xm4ZPbsmj6D/KlSa2LyxTRyyAAAAAAAAAAAAAAAAAAAAAAAA5MB3zBYmNJqEkaGKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAev2esxmWidgjFtDy7VjLbrXLIR3fKTNUCFjNWiq6Lj+70oV9oQvuMSkQGrZzayCrs1FmpZZqOVm2ZvLU4XKr2YvYoAAAAAAAAAAAAAAAAAAAAAACFx7RanF2zrbsEN+VuyUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/P0REuEb09I9EXNjx/f0Q0p7RFygOLtED7JoeP7+iF6+8cnpkRx8ssOHxkAAAAAAAAAAAAAAAAAAAAAAAAIczO15pvcdNJu35WF7hkPvjXHj5UAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB44tNQcWrQ/DzoD0Yxt3pMl1jLK7G+qVca9gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADxqZacursrEZtXl1UAAAq9oGIxX0HFRm8z1RJK/tf8AEsSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixK6LErosSuixfle/SYiOiVM87damSoW8oAD//EADUQAAEDAwMBBgcBAAICAgMAAAQAAwUBAhQGFjUVEhMzNEBQEBEgMDJgcCEiJSM2JDFBQkX/2gAIAQEAAQUC+okpgW0nUbdqenTnFeeXesh9ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8sh5ZDyyHlkPLIeWQ8rDi7EzOHNobUltUIaOXT7T7zY7cjqBxxf+Qh0XT5TqY08LYrIoGxYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVYQqwhVhCrCFWEKsIVXxgV6e0+HeitPENq+x0dyPnnmUKS0U39cnINANHGPGuxkG6ShBGBLP6YQO0TZJwN7SFIdEeiZNs+z6ZQ+wAd910siGhrWKf1CYiLDKU70UiHkbT2fi+7YwzIF3mk6ei+4s/qU7GUMaFfcEIDJsLG+GqTe05pwDJI/qmpgO7c00b3BSLeoONdW8h+PGoIJ/VCWbSGHm7xyIwnLC1W/2BdND99I/anyHRgNNGPl/CSlDGj/ALOoSHxxdPEEEMfCVkzGZCZdcZjdPFlkES8lbH2Q5F5QH821WP2CtJPrVDvbktJtdkP7WqeM0uQywuohqTutvkJB64cKDlXzi5N+4YGDlXzi5uWICMeljiqATz7bpEpJP2wMu4U7OmugjQRzpzM3M3DOsyUtZae/QkuWIvFj4KTfOfmC3in4SQJsuanCrTkTNE9Rp/M9TNd5F6fd7uVmbu3KQFvYiftap4yLjXJBbbIRLNRyJni9J8jO8TpPkdVclDWUsi5Kz/tat22jwHL6t8jpHyrVMqY//Eo1azIai4fSXm9X/npviNUDd0cyf/0WmB++P/mcpb244K7sGSXIxHGfa1Txmj/hL8nK21vjdPlNiHz0mPcDpPkdVclFcbI8zf8AhAcvq3yOkfKmW3AS9JgLuC3sgrUXD6S83q/89PFsWx+oBsiNtKvoFp0fuI3+Zl+Va8WS5GI4z7UmHQ4aJjaR3wKgLCCUVp4d1xmAGbbi4i0AiTh7TyBWu4HIgrXi60+dAYK0QqUApIMxUfSPbkI9g6xvTbFLitPtPPHjUMEiom2PdkQWj2RYBtgh11puwZihR9KUtp/My/Kt+JJcjEcZ7BIQLhBkTE2AV/mhflW/EkuRiOM/qxflW/EkuRiOM/qxflW/EkuRiOM9MYYOFYKQ0U1/Pi/Kt+JJcjEcZ6W+6llk2fWQO0zJYJn8+L8q34klyMRxnpdWynz+OlJTIZ/npflW/EkuRiOM9JqGUpHjVrWtfgy7ey7DSNkiJ+26pedaeZpJPWXvSIt0DJVOb+uauusi9LPuulT7Z1xsbRygHxnpZ0V2PrW4CRakqne9F+Vb8SS5GI4z0ciY2AKaS4YT9EUe5HljPtksftmrvH05dSkTqIhjp2lKV6hNSRY8mbJlFPln3x0WzSVkFHy5IhJZFgw1xshJEluSIgukvN6gkChjo1252POlyTCX7JUG2Kkrzgj7ibiIC8+rslKGNHvO2stPyZ0iQ91WOULJUPa1BIFDHVJkpSxo84Alq+jrXuRflW/EkuRiOM9E5fa3ZOyV0iX9WmZXCI/bNXeOLFFFMt6fMurFx7YDOouYjGbWAdV3VrIAzLgwkm/ecTMOXV07pGyndagspfE6S83qrkrbq26Y0rbSsk63Y62wMwwtUcpG8dL8nqm+tsZpFundmt0dD03fW2W1VyUNbSyL1TT5ScVxvuRflW/EkuRiOM9Fq6T+dVT/AGtwhFtn06Tk8hn9r1d4+m+I+GouYY8DVgtaqIm2GhK6gevLmRryoyCkbQHpyXbJH0l5vVXJANd/BgvXxUlJzjFwmmby366op/2cPIsPMy/JzAtSwIWQ6cRKzjN4ulgru81VyUVxuquSiuN9yL8q34klyMRxnoZo6keBddW+6lPnWDiGo9i15q5zVEQ3Uf4d3f2EM/eM+CTYYJ+1HxrB1wY1gjHwLhxiiLadm26lLqOwQN9wccMHVFxAhTjUSI00BGMAuHRQ5rw7VrDJgA5isgQbbrLLW7DQWDaBRIobr8II+8jI0UurUGC3dSlKUOihzXmGrWWTooc15hq1ln3IvyrfiSXIxHGeh1cZ38go+ttp5NL7h4oE62Wkq0tj1p+FuPvNuHFj6/DRZnyc/nJflW/EkuRiOM9A85Rpl2+rrvwg9QNOM3GDW26knLCm9Pwtx977rAAszKOyT/wi38aQ/nJflW/EkuRiOM9BP31shvp0/C3H3vusACzMo7JP/QLd3gv7TKzd1HL3n3K9q9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9dq9DnFjViZKw9v2OtaUoy+y/T7pflW/EkuRiOM9BP2Vvhvo0/C3H3vvMACzMo7JP/AEi21bF9slZdsKrkwffXqkguqSC6pILqkguqSC6pILqkguqSC6pILqkguqSC6pILqkguqSC6pILqkguqSC6pILqkguqSC6pILqkguqSC6pILqkgmJs1qsec0c16+eJqNHUp8qerDfqIZ7Hq+SUQddHmtOWut/cL8q34klyMRxnoH26PMuWVbc+Gn4W4+995gAWZlHZJ/T0E1ax3LfZ1HBt0Y+EYxkyHtkiTiBfOt13qwSahl0/2nrtWeW9Y5+I/l/YZuRtjg3L7nL1pKU7u/7hflW/EkuRiOM9Dq0PHkELRupLr44QczKOyT7Xy73/8ARkg/qjvyqzX/AO1osL5ue2apr/1vrL/xj6/MD12rPL+sc/Eby/sBL7YzEqe5IF/ClflXTcrnj/bL8q34klyMRxnoZUKyQDIZvHfXzrWnw09NNEMdm3talmW2x1HhuHFCD2Cje2aq477jbd7t8YBnOgR+SZaE46W5Zc3f9u/8Y3jvXas8v6xz8RvL+walls5/6BCHBSIw5uQE+0X5VvxJLkYjjPRTsPZItkjujPfR3rnYQIT5z0PGNRo/tuquO+2IxcSR23YU1x6+91CFOiuR9gpFK/8A39q/8Y3jvXas8v6xz8RvL+v1ZLdi36oSSuji2nLXW/sl+Vb8SS5GI4z0Z4A5zZ+mCWqvjvMV+A4ZBNY/Szl1RBWRGvbtVcd9vCapF3XVvu+gwgRwD7V/4xvHeu1Z5f1jn4jeX9DSe7k0chomz7c7I0jg77q33/XpKU7tz7JflW/EkuRiOM9LWnzVwo9ytGYs9y1Vx32qf7WWCaD+qLKGHs+1f+Mbx3rtWeX9Y5+I3l/p6oEuqBLqgS6oEuqBLqgS6oEuqBLqgS6oEuqBLqgSPupecw84xfH6hTLrb1n2Lq0ttmj6yBy01C2l22MNWWTUCwU1Wnyr8aVrSsAf1AD7BflW/EkuRiOM93Zebet9DqrjvtyQFgjP0xL4jNa/7X7N/wCMbx3rtWeX9Y5+I3l/pv8Az+8MS8LfH6hsvTd9rln1auNxwPhC0pSJn3i6TIFXahTNKUlQhHTSIyJHBGmrWbJRaYNxJP7BflW/EkuRiOM93o+6OTH6hpVNOWPWff1Vx3248Noof6KU+auIE6V9q/8AGN4712rPL+sc/Eby/wBN/wCf3xBHy74eKqD9eqiO/l/hpeZbaa+Vl6mZhkBkQZ48qJjWo0fUk78aV+VY5/JB+svyrfiSXIxHGe1PXVtZ6+auvmrr5q6+auvmrr5q6+auvmrr5q6+auvmrr5qur2rkKU8LfH6gbcVl1t9v3dVcd9w6oNQihHhfgwxe8+1W6GPId75/wC1f+Mbx3rtWeX9Y5+I3l/pu0+bW7b5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+anm6tOoYd0m+P09bam27GrPrNv7wz42uuW0CFdNIiY1qNH1JO/TpK/tQ31l+Vb8SS5GI4z2ony3oAziA7oiSqfZ9zVXHfcpX5VKNeLRctR4g86pRTrl7t/27/xjeO9dqzy/rHPxG8v6Expx+Vj9PJhltiz7JNtbCfiEK6aRExrUaPqSd+rSFtaQ/wBZflW/EkuRiOM9qJ8t98MJ8y6PgGWVSlLafc1Vx3rL/wAY3jvXas8v6xz8RvL+hbabb+5qFjuJj4BCOmkRMa1Gj6knVARFZJxqHj27JfTjDrdaVpX4QbOPE/WX5VvxJLkYjjPaq0+dOmBLpgS6YEumBLpgS6YEumBLpgS6YEumBLpgS6YEnf8AHRhnir4/T1lisstbt+9qrjvWX/jG8d67VFtb2ukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGLpBi6QYukGIuOJYHG8v63Wgfab+GnBGR4zUk78NM2W2QuopU1mUiH3Co3UVltkyoUSpsj9gvyrfiSXIxHGe7iafpVxlptmz0GqePxSFikLFIWKQsUhYpCxSFikLFIWKQsUhYpCxSFikLFIWKQsUhYpCxSFikLFIWKQsUhYpCxSFikLFIWKQnR3rW43jvXT/5+sn+JG8v60hmwhiTCcALTRhLTXw0lKWWtkBjE3HmMx4xT9xJK0zGYIn2C/Kt+JJcjEcZ+k6k8n6yY4yN4712oP8APW6gr/1TFPkx66XjWpIc0R4J/wChqUNZseecfvWnIKrdfsl+Vb8SS5GI4z9J1L5P1kxxkdx/rpgWpYEYXQsb1Z9c8/2A0Ng1mS0yQzV1q9q74gwppiiYIcD7ZflW/EkuRiOM9I862zZWejaXDksk2+5TI9SY6OJoWJ6ucvq5bZbSyz15sZdV/Lkm1nnLPOWecs85Z5yzzlnnLPOWecqyBtKdUeXVHl1R5dUeXU31nnLPOWecs85Z5yzzlnnLPOWecs85V6qYo8JoJr2J1pt2jkLHXqkDG0qwCKx90vyrfiSXIxHGejNJsDFfeMmjrdKEd26ybDGQ0hbIhe5FAvjEdabsXXhF14RdeEXXhF14RdeEXXhF14RdeEXXRF1VldVZXVWV1VlVlmKU68IuvCLrwi68IuvCLrwi68IuvCLrwi68IuquEKMj6sX+1yzvYZ+ilflVhzvWffS/Kt+JJcjEcZ6PWzlaA6JYtoGtVMWuw+iHK5Xvsg73Q30Ur8qsOd617sc73xP0w7v+e+l+Vb8SS5GI4z0euPA0XxS1DwuieQRLErUnHlljyyjqXUj/AHiVd7ZH0w7v+e6nu90N9Qzncv8A/wB++l+Vb8SS5GI4z0euPA0XxS1FwuieQV03HW3NTIDrvvJDndM1r86/SM53L/ul9/ZoU3kVwbFg2LBsWDYsGxYNiwbEzfVtu2vap72X5VvxJLkYjjPR648DRfFLUXC6J5BP6XJceB00QOb7xWvyodS4i3BvWDesG9YN6wb1g3rBvQ19W2aV+fuV9/ZVa/Ov2bbq21tupdT3ovyrfiSXIxHGej1x4Gi+KWoeF0TyCd1V3bu7lu5CO5Avut1ezS+7tV+zZf2VSvzp7hVulV3Vq7q1d1au6tXdWrurV3Vq7q1d1au6tXdWq2yltfei/Kt+JJcjEcZ6PXHgaL4qsqDSs/dS+C0TyCv09H337bjltuOTLdrLPut7dbq9yu5XcruV3K7ldyu5XcruV3KssrbX93L8q34klyMRxno9ceBoviivMyP/AKtonkEVLSNhMZKnuyP87L8q34klyMRxno9ceBoviivMyP8A6tonkFUwT55oazhFbdS6393cvtbbYmrur0r86e/l+Vb8SS5GI4z0euPA0XxRXmZL/wBW0TyCJ09IXkbckltySQDdzIP7vqg/4aZP71r38vyrfiSXIxHGej1s83dTRfFFeZkf/VtHPNtSP73KGUCEvurfeh3rx3gibCxvfi/Kt+JJcjEcZ6LUszhWxEQ/KX2Xx8EM/dS94AwCRj5uAcBppmaurf8AvU2dml/HTp+KT78X5VvxJLkYjjPQmP2iigMOS8rMn9OZjdPtWLVoYjQC0zM3P11HH9PPgzM6N/eJmwp0ToR6r/lU1ZV1zoR6jMignvpflW/EkuRiOM9DrFzsROiGadiDpnT2pJO6PFeecfvTTlzTuqraEQeh3f8AP3pz81G8j7+X5VvxJLkYjjPQ60t+cZoi6mJFyfSD5+U6mR8Z3/4+l9D2/wDl/enPzUbyPv5flW/EkuRiOM9DNC5kZpc2gclq+NrY98dNRtxpmsjaOPaTFqPF/vTn5qN5H38vyrfiSXIxHGei1TFVGfgp5u9qQ0w07WumZDtA6V/5SkwNGDwca5KGUpS2n705+ajeR9/L8q34klyMRxnor7bb7JbTN1KtFyEZdTU0h8n5OROUXpp9+ozDYzP725+ajeR9/L8q34klyMRxnpLraXUwxlZZZZT99c/NRvI+/l+Vb8SS5GI4z9OmyyW5QStai/ojn5qN5H38vyrfiSXIxHGfp0/y4flEaTYINmScm83JHxxLb7bg78oaeS/dLAKEOqcLKypY8mbLlPkTJhgQzcnIGMXlyQBARdpALsmfIEvVlwaQkhnj+5ufmo3kffy/Kt+JJcjEcZ9MyVeGDuExbhMW4TFb/tvo3XLWm4+Wocf7fP8ALh+UWrrq0GiZakexLydJFaZc+cUTOjNOyMkUcxpDwp/lwGLBw9YLS1lLY3V9P+Wnre8hXWDIohuff7MWcwY17m5+ajeR9/L8q34klyMRxn032W30fGY7mDtpfK4o6kp6jDjWoiLLxCGymCp3HOL1E52wtQ2XWO6iJ7URJWyDcvL1AJL1B8rQ9R395bdS62R1B3TjOoiLLxn2yWSpzuDytROZBklaGFXUJl1Yyf79/UZ9WLIo7AIIk6tRUPI1kLZc7AGh5GshadOVGOM1E5Qh6QtHj79RFXXRM3aW57NP8uxqAVtjcYim7OoRGn5RoRs3UVLHi73iIOEIHHMn5VgpjSHhz/L2fhrBaZ4rWCge86GLPP2lyxUU8NpJu/K9zvBL7eCWgAyrTvfy/Kt+JJcjEcZ9T/gQHLyjtWY+FcGZNmpAAwLSLte3N8q0M02LHNUfOmmrKxOk+Q1ZyOnhrGY7VY1ll4RV1umIN0ZgycPAMD0i5VTfKhwolo0oME7bbMx4bN7tHTppuy6O0vZY4fqelLYrSHhas47SHhT/AC4MKJQTVLtbpCMko4QKRcZ6gzf3jXspcIMURtwRbcEQzNo7BMIG/cLChj3oiCDevsiBGx46LaAvLhBiiKU+VJKOakECLYGPJRzUggRbAxzIsUu6zTwdtWWrGG/3UvyrfiSXIxHGfU/4EBy8m1V8CFxamHMxITcNUBys3yqhOVmeL0nyOrOR08a06Dqktt28MO67TMHi3FHtRIVkPguKb5VapcuukY0GNtCfubvkZni9K3UtkdTf84rSb9lldVFNXMaQ8Kf5ez8NVNVsPixowkOr0JR9u2ljf7UUS0Iy/qz/AJt6tu7Ucewez7+X5VvxJLkYjjPqct7TcbBvCmqRgWyXW9NOdoIVoNiQgniTFHwTwxhzNSA4WJdAK1ZyLcHYWAHp2lrlKfKkhANvuNaav7QgzYjEhBPEmKWi7JCjWmr+2Xp6tz1zfej36ac7bIVtI53TV/b25Sg0JH3x9klBvFG20+VpwjRrDmmnO1GwTYrv7XqY24ySitODssnaeCIbCfeh5SlfnT34vyrfiSXIxHGehn40kwyOauYB/gAX/Kd+GrKfKbj/APQJA9iPs3JHLckcgJcQ973ovyrfiSXIxHGfxMDnfhq3mo7j5uM6o1tGi2ioaD6aV70X5VvxJLkYjjP4mBzvw1bzUdx+oZJyMZ3WUoE++RC97L8q34klyMRxn8TA534at5qO48wNgy3oUahBWRG/ey/Kt+JJcjEcZ/EwOd+GreajuP1ZcTaN30su+llpZw6+Q96L8q34klyMRxn8TA52elLoxqCmrpMjVvNR3HlFMC29Yj0MQ0TZ72X5VvxJLkYjjP4mBzut/LaJ8/q3mo7j9RRrskxtU1QADkcF72X5VvxJLkYjjP4mBzut/LaJ8/q3mo7j5qTpGNbttW7bVDTlJIn3ovyrfiSXIxHGfxMDndb+W0T5/VvNR3HyUczIt7XAW1wFGww0e970X5VvxJLkYjjP4lMzLMbbEUvemdb+W0T5/V1t1JfT020Q378X5VvxJLkYjjP4jOSFI4KMBemDnygIBiQslppuOOfiygJYOYsn4e6Nc0zKVOH99L8q34klyMRxn8R1aTV+UH7EHp/Tsd3ikJQUBSBGWbStaVin7ZuGinb46Z99L8q34klyMRxn8RI/8s/rStcanZZYJevIf+Gib/kbqSzsTbN3aZ98L8q34klyMRxn8RlqVFndWNZURdKG3C/HRI9VKX5s1bTs2++F+Vb8SS5GI4z6dVvONJjqL9jjkiLWAlLjPrvu7NgMs+dMfDVL7rRTNJJ6y4iSDug5XOt+N93ZsBlnzpj911mDX56VkLCBZyGdj3fhFRj8i9MFNQ0VpIGpB/vpflW/EkuRiOM+nWC0vdSkZOkD2x2mKVrK6glXGHcSYq1ASr95U/I3BNNMS5bYkoYCVPXl0YCq/aTEVIuCWrfN6b4glmwhiOvuGlJo/AFYtlZCjUgfHkzrhWOFV+0lkt8WHadlJNxwiSjXwX8oT9xebseal4t+KIjNTWVsqBCHKkVCio7UYwzQgxc0aCI2EN76X5VvxJLkYjjPp1gg4wotqzT5t1YmNsj25aVHEuumzyFCcrqOPcLbZkDgEHqCneO1pcNp3mPhq3zem+ITf/kk5AxkJm7UDtUc4+6S3xmneYKfbGZc1D/smQUTfp3h/wBycstcsP0uy5V3TcjZWzTsldUHStKVHYaGa9+L8q34klyMRxn06wWluM+ErS5uWvng2xoX/JXUBZgaDmxnRZK9h8wdq5uMiH7BpEQlstlat83FTTIYR2oe8Z00Dc6Vq627vYaVDFBlCswxj/lGxD9g0jqB6hkXp+QFDbnD7TyNO8P/ADYvyrfiSXIxHGfTIR7J6CEbDZ+BoA5qGhgx774Ya4pyy1yxyBBuqJFiCXIiEDecEGaEZR8Ywc5t8JNQQNlbLbbLSGGyGqQINLy4kUlDM2jsEQgbzg4bDA1YEGt70UK6MCI2E1+2dqnwrWlFSvz+1WtKLt2qlaV97L8q34klyMRxn8Lv/Bu+5u+NLtNE1gtM8UvnSv2NXeVCjiDbXoo4a2Bl3O+Va/JU/wB+BUiQRLfClaV9yL8q34knT5SMNX5xf8Lv/AMe4oiBNqEZrBaZ4qXkXzCyIUsRjTsleVQ98gKXkyO5jYo562R1ERUeO0t3rja1d5XSPlVKN0GkjCXbI0aONkryWSokoir58N2HMqJaLDG7iQlCz44iMUAXeYD7gbX5Bs0+b07Z2JbTl/bif4Xf+GneY1MD3TxptSg9P1rSFj7nrDLzZi+yDDKYk9Wsf6cb3kAWJUcbURmSoljGj1q7yukfKqbvpfKvlWR0d1mRLukrTKOwXE//ANt921hl2eKfck6SNWtJeR9wmb+7i42zvJDVjXZM0i9/w/hd/wCGneYJZsIYLHvFI0zxRTTsTJkajpcNp8o4tTTGRGtW3OuajGp0mLYypD4au8rFStY9t/Ub19kHH3mFaqZvvDhZewFiWLcOdga0rElVqPLkF9Xi4WQpHvTEldI2aSrTD9w1W92AtMtd5J6lH76OhScWR/hjEcIw6iQRibx2Gx23Wm3rKRQNLqUpbRNxgbTjrdrrY4AwznwJFZKt6QCrIsK2tKUpSv8AtKxYVbnxB32xx2hmyQhiajjMjUejhHr8RjHFDYFr7hqMnv5HSg/YEvtpfYePUQuCMywf6pKl0CCZbvIIHatYYWpge/YijbgS277XG/6lWtKUmz84rS4Pyp8Z6Nw3oGVxLqVpWn9R1BLd6oaPuOIttpZb8X2rH2paNcAdh5i8NMPNvt/05y+1uyZmqkKNAdPeEHbFY+l1ux5uVhHB0GY+G4DPsPKy62+3+lVrS2h06Mwjj3zboqHdMqOw2M19iRhhy0bElipgh4erGoDLFZqWi3IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg63IOtyDrcg6v1LantQlXogp8mocYUWo+DYG+6THikp7TjFyv028q6dLotvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFLbxS28UtvFKmnS6qzTb6Z02zRDRgg/2P//EABQRAQAAAAAAAAAAAAAAAAAAAMD/2gAIAQMBAT8BKlf/xAAUEQEAAAAAAAAAAAAAAAAAAADA/9oACAECAQE/ASpX/8QATRAAAQMABQYJCAgFBAICAgMAAQACAwQREjOSITE0cpGhEyIyQVFxc7HRECMwQEJQYcEUIENSYHCB4SQ1YoKyBXSTolPwY6MVhMLS8f/aAAgBAQAGPwL61c8jWKqjwl/xdkXFe2PVauNSZsSvpMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvZMSvpMS4tJmxlZZA8f1NVVJhI+LF5iVrj0c/ozJM8MaOcosoY4Nv3znXtySO/UlVylsLfjlK866SQ9dSyUZn65Vo0GALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aHAFo0OALRocAWjQ4AtGhwBaNDgC0aDAFlo0f6Cpebtxn4GtVwObKNhVT2ujeOnIg2k+dj6faCtwPDh3egrfleeSzpVuZ3UOYISUiuKLo5yrMEYb8ec/mbYnYHt+KMlDrkZ9znCtwuLXBVcmYZ2+H1rbsrzyW9KL5CXyOKE1KFqbmb9380TJDUykf5L2o5WHYsuSZvKb8/qPlkNTGisp0r/7R0BCkzjzp5IPs/mnwsQ/iG/8AZNljyOamTR5nbvKKKw8VuV/WuGkHmo95/NX6VEOK/l9a4B583Lud5JJnZmCtEnjSSO2lRwt5hl+J/NV8UnJcKk6N2R7DUopecjjdajhH2hrPUEHnkxC1+vo7cDrLrQFapH0iS3Zs1b/JOyOchrXEAVD0UbqM4tcX1GoVqU0pxcQ7JWKvLPHHMQxpyCoKV8BIkFVVXWpG0l7nNDclYqTeJbkfyRzJk0tVpxObr/Ldk4zSCo9YU1HOuPn8lY+40D5qWTne6rZ6P+8Kk8NKxldmq0aulaVDiVIcwgtLzUQppWVWmtrFadHMGWQy1xR8QpZo6rTRkrTo5gyyGWuKPiEIoRHZs18YL+AidZaOM5rK8qqpnnI+rKEZoGOjo452sr3r6PSai/O13SmPhs1l1XGUjprNbXVcVcBRquEHKceZcO5r5IfjHkUkwFVs11KWaOq22rP1qRkwZU1tfFCqmaAIyQ2oKCisa3gi6quymw0lsQaH2H1DyOgorYyLdhtY/LQu543B3yUPQ7iqkn+qpQfGs7/R/wB4UnBva2xVnV9FvUkTiCWGrIqTqKTsj3hUjq+ak7I94TezHzVHDedtapDRkrkKMYHEDaqlR+s9yi7T5KfXQEmaSbLtVSnYzkh2RUj+3/IKbU+ao3U75KLrPehMBxZRvX0onjtZV/dmRldmiFf6n8tKSP8A4yoHdDwd6pXau71RtQej/vCpf9vz8lJ1yqSG57BVqY1Mc2zX0J8MMgke/wC7zKTsj3hN7MfNUXswpu1TupUfrPcou0+Sn1041ciS234hcLww1fa2KWY+26tUj+3/ACCm1PmqL1O+ShhdK0S2iLPPnT6uVHxwn0b2HPtphPKl4/h+Wk2oe5M61Su1d3qjag9HwRfYy11qWzIX26ubySSmdwtmuqz5LUT3RV8wyhPFbnPc2q07mTpRKX1ts1VLhTMWcWzVUo4q67DbNafPw7gXOtVWUQo5hOXWeaymxl5ZZdazJ7GyF9o15kBMOMMzhnCrfNI4dGZF7JTG3IA0NzZE+Aus2qsv6p72yl9oVZkGS1irKCOZMl4d5LDaGSpOdI9oaM9ZTYoq7D35OpADMPy0m1Cm9apXau71RtQe4ZJmSsDXmuoovLuElIqr6Py1m1Cm9apXau71RtQfmvNqFN61Su1d3qjag/NebUKb1qldq7vVG1B6uH0mQMBzISUd4ew84/L+bUKb1qldq7vVG1B6sXPNTQKyU6T7MZGD4KxIfMS5D8D0/l/NqFN61Su1d3qjag9W+gwHtD8vL9EmPnYxxT94fl9NqFN61Su1d3qjag9Vsxn+Ifyfh8UScpPlbJEbL2msFCQZJBke3oP4ug4KR7K2nkmpB8RpLmnnDihwklJj1iU5k18zn+8PQTuYS1wGcKUSSPeLHtOr50DReH4OwOQTUoBNa4SzltZ/qfR4AA6qsvVGc4kkxtJJ6lOYRSeDtZLJNXvubUKb1qldq7vVG1B6o6aXmzDpKfNMa3O+q2VmVuZzekJk0JrY4Vj8W0fVKirIznvUkbnNMjqrLU88wj+YU0cMxawVVCodCc+N8kcYzBpqqUPCm3SnN5+lGWN8pGvZC4CnFzmV1G1nanzP5LQrMLn18zIzUAnwU2t0UgqBca6v1U2p80GQSljbANVShkldW4trJXBUEuayuptnO5CWSSYN6bdrapgdJjbzc/Qq6Za4Wr2hUoxPb+i8Hxa25Pgp2RzkNa4gCoJ8khqa0VlcHRbTAczWZDtQkkklDem1aCNoWZmcofNBkEpY2wDVUh9DDmRNFRdXZrPWi2R7yW8pjzWmSN5LhWPec2oU3rVK7V3eqNqD1Nz3mprcpKrGSFmRg+f1+BmP8PIcJ6fxbR9UoSwsBYf6lxuDYPi5WWcZ7uU7pVI/t/xChY0VcUE9aY3mEfzUcLKJWGjPXnXDcAWZKqlRa87rIOxUh/tVgKevmqI2qbU+ab2Y+arH/hTieaMkbkWSNDmHOCvMxMYeloX9gVF7JvcqTrlAD2pACqRJ7VYapmOzFpUYHtAg7E3sx81RgPuVrrYFRezHvObUKb1qldq7vVG1B6n9BhOQXh+XkqCtuglDektP1vokx87GOKekfiyj6pUXWe/y0j+3/EKPVCjpLRkAsO+SbDSq2uZkBqrrCsUaFr2E1NB5RT2AecHGAHSniYHg356uYr6PRbTg7K51Sm1Pmm9mPmo4j7cVlVysPF4r2pzKI5/CuyV1VWU+SeWR0IFQtc5XWwKj0dhPCtjFYq6FSdcqSNnLzt609srTwbsjhzgp0VErc54qrqqqRpTxU2qpnxTezHzVF7MJvZj5qi9mPec2oU3rVK7V3eqNqD1J8vt5mD4oucaycpKqCa5zQ6kkcZ3R8AjG2RheM7QcoTqXR2hr2ZXgc48tuw6x96rJ5GTRGp7DWFHPHmeNn4ra6a3W3NUUIYq7I6fK6aXhLbs9RQaMwRDhWDzFV2HM1XKuGPjfeOU+S29hDznLTVWnsZHyxZLq8qc+G3W4VZSuEmt2qqshTImV2WioVocPHWRz5iqy17vgXINY0NaMwCHDsrIzEZ1wkQdb6SU+V/CWnGs1HyWpouP94ZCq7Dn6xVQyBcJNbtVVZCmRs5LBUFwk1u1VVkKZGzksFQ95zahTetUrtXd6o2oPUuBaeJDk/Xn8lHL+SJBXtUoiNUhabJ+KhqikY5j63OI5lSS7Nwbu7ycLOC2jD/sn8LZbAG1Wfl5ZKI45Hcdnz/LqbUKb1qldq7vVG1B6i+R2ZorT5H8pxrPlbDTX8HK3JbOZytOpEQGuF9FolfB+2/pXCz1tow/7K2+qOJgzBVnixDks8tHl+68V9X5dTahTetUrtXd6o2oPUaWR9yr6wmnrbRh/2Vt9UcTAq3cWJvIZ9WF5zuYD+KnQ0KrJnk8FXJPK46yvH7VeP2q8ftV4/arx+1Xj9qvH7VeP2q8ftV4/arx+1Xj9qvH7VeP2q8ftV4/arx+1Xj9qvH7VeP2q8ftV4/arx+1Xj9qvH7VXFO4j7rsoRyWZm8pvuSs5AiYJWSAfcdX6abUKb1qldq7vVG1B6jSwPuV/V4acFtGH/ZW31RxMCrdxYm8hn1oWHO1gHu3g2DhJ/u9HWq+FDPg1q0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AtJOwLSTsC0k7AvOFszegipWos45TTnHuB5Zke/iD12KYcx43V7k+hQu+MngmSt5OZ46QmyRmtjhWD6WbUKb1qldq7vVG1B6i+N2Z4spzHcppqPl4WcFtGH/ZW31RxMCrdxYhyGJlIpjLcjsrWHMArPBss9FSfSqG2wW5XsGary0eL7zxX1e7ZZudoydaL3mt7spPrjJm5szh0hVj1+DtPXo9Ue4i/PK7Ixqc95rc41knyfQp3cV12TzHo9LNqFN61Su1d3qjag9S4Zo83Nl/Xn8kQmu7QtdS4RxayBoyVfJVu4sQ5LEy1mrXF6Mibx5fpNvMn2s1nL5ZKY8ZG8Rnz92t+Mg+frpVGJ54293r9H1/XotUe4XzTGpjRWU6Z+QZmt6B5axnXByn+IjGX+odPpJtQpvWqV2ru9UbUHqT4XZDnaegp8Uoqe01HyVVmoeVkFIeGTsFXGPKVqoWulPotGeHyvFTiPZHkZDFnOc9ATIYhxWCr3aztR3H0tmNpc7oCezhBHZy5lLA99gsry1fFSwQccx1/DMix4qcM49IVReyb3ev0fX9ei1R7h4GE/w8ZxHp+qyaE1PamzR/3N6D6ObUKb1qldq7vVG1B6naZxaQ3M7p+BRinYWPHMfq2eEfZ6K/II6Oys855grLONIeW/p93M7Udx9IyJpALulPY0tkBCfJyS/PZyeS3C6o8/xVJfTZan1V/usmb0ZVF7Jvd6/R9f16LVHuA0Kju4xvCOb4fXD88Tsj2pr4zaY4Vg+im1Cm9apXau71RtQeqWKRHX0HnCJojhMzozOVU0T2H+oeWqCF7+oIOpz7DfuNzrg6PGGN+Hu9najuPpPpXD+d+6MqLnklx5z9WGOGKzKMpPoyqL2Te71+j6/r0WqPUp4aSytjZCA5ucZVbgeHt+HpC4XzsjAi55rccpPoPoUx4jrs9B6PRTahTetUrtXd6o2oPVsq40ER62hcWGMdTR7yZ2o7j6OpR8FLbtV/p9aX6TFbJ5OT0ZVF7Jvd6/R9f16LVH1tJjWkxrSY1pMa0mNaTGtJjWkxrSY1pMa0mNaTGqQ5hraZHEH9VbheWO6Qg2mt/vb4IPieHt6R6EucagE6T7MZGD4eT6VShXFXxWfeVlkTGt6A1OfRmNjpAy5MzlUc/wBSsZCE1zr1nFf6GbUKb1qldq7vVG1B74tRPDh8PUmdqO4+khe2W3b/AE+tJ9Mjt11VcWupH0RVF7Jvd6/R9f16LVH1j1+ntwSFhQbTG2HffGZBzHBzTzj64gYePNk/Ty0Wzm4MKW26Rpa7zdXR8FAaRe2Ba61S7ObhCmwwNrcdysWGveeU9wzqkCjVcFayVZvI1pPm5eIfl6GbUKb1qldq7vVG1B74e+F5Y6vmQbTW1f1tQfE4OaeceoM7Udx9JPJLPZcwZj9XIhEIv4n7xHoyqL2Te71+j6/r0WqPrHr9QswRl3x5grT5nFx9lvJ+vIPZi4g8oodKdZA5Djm6kHVNd0FODXB9I9lg+a4OIWpHGsn5qwzK88t/SnUShO+D5B3Dy1hQTc72Anr9BNqFN61Su1d3qjag91vcM4BKzx4VnjwrPHhWePCs8eFZ48Kzx4VnjwrPHhWePCs8eFZ48KJPP5LUEhae9BtLHBu+8MyDmEOaecemZ2o7j6WD6MDw3P8AuhwzLNebyNiaKnu6ci88wPyZx8k+Sy1to5h6Mqi9k3u9fo+v69Fqj6xu8S+yxL7LEvssS+yxL7LEvssS+yxL7LEvssS+yxL7LEnxu5TDZPksQML3fBB1MdaP3G5kGxtDWjmHoJ3/AHnk7/qVNkcB8ChFALTzuViPK88p/SnUShO+D5B3D6rB91xHoJtQpvWqV2ru9UbUHuuXVPqNcEhA+7zFcaFzCPa9k+lZ2o7j6UEZwo+HNqwqNKIbPBGuqvOmztZwTh0FF8ji5x5z6Qqi9k3u9fo+v69Fqj1KksiYXu4V2QdaDqa7+xvirELAxvQPRStOcOI+o2GBtbjuViPK88p/SnUShO+D5B3D6wJ53kj0E2oU3rVK7V3eqNqD3XLqn1CqCMn48wQdSTwr+j2VU0VD0rO1HcfXSqL2Te71+j6/r0WqPUncGwNLjWauf0lIHM42x+vlbDA2tx3KxHleeW/pTqLQnfB8g7gi55LaOzORz/BWRRYzrCtOfQhwco9nmciDkI8tGYc9is/rl9BNqFN61Su1d3qjag91kHMVo0exaNHsWjR7Fo0exaNHsWjR7Fo0exaNHsWjR7Fo0exaNHsWjR7E8DpViCMvKDqY6277gzINY0NaOYenZ2o7j66VReyb3ev0Vrc7pKgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgrsYgnSSMAaPiotUevRUto5PEd5YnxVF0jbTndKdRKE74PkHcPJR7PPWTtUkUUromMqqA51BNMKnuGVUkN6a/JFF7Ndp3V6GbUKb1qldq7vVG1B74MlMdXlrsNQZEwMb0D1FnajuKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKuJcJVxLhKJdFIB0lqovZN7vX6B249dn/AE7wotUevPilFbHiop0Mn9p6R5DFHPI2M+yHeX6FO6ya/Nk9ya6eCORwzFwRklIAHJb0qSaTlPNfk4SUeflz/AdHoZtQpvWqV2ru9UbUH4Kh7Zvz9dpGqqL2Te71+gu5hOPXZv071GP6R6/YfxZByH9CMVIZZd3/AFbMdKlDeitWppHPd0uNfkbSqa3jexGeb4n0U2oU3rVK7V3eqNqD8FQ9s35+u0jVVF7Jvd6+9jOWOM3rQd9oMjx0H1yGhR5WMNuU/L3DwdIZaG8Iuoh4aPo9pWZWOY7ocKvqCzEWM++/Ig93nZ/vHm6vRzahTetUrtXd6o2oPVbcz2sb0uNSq+lDCVao8rJB/SfecrG8scZqZIOVmd1+uR0KK9ncP0Ca1uYCr3B9JoEnAz845nKqWgWz0scv5ZJi/ZfyyTF+y/lkmL9l/LJMX7L+WSYv2X8skxfsv5ZJi/ZfyyTF+y/lkmL9lWf9NeBrfstGb/yfstGb/wAn7LRm/wDJ+y0Zv/J+y4tEDj0CT9l/LJMX7L+WSYv2X8skxfsv5ZJi/ZfyyTF+y/lkmL9l/LJMX7L+WSYv2X8skxfsv5ZJi/ZWRG2iMOdxNZVmPK48pxzn3HVLG14/qFay0Vn6ZFX9FGIrzNHiaekN9LNqFN61Su1d3qjag9Uknl5LAqsr3nksGZqrM8Qf0JpNcb+ZwzOQlGR4yPHQfebqT/ptRtcuE5iqqTBNE/oqX2mFfaYV9phX2mFfaYV9phX2mFfaYV9phX2uFXc+FXc+FXc+FXc+FVmOarVX2mFfaYV9phX2mFfaYV9phX2mFfaYV9phX2mFWaBRZHu+84VAJ1IpT+EpT856PdgYM7/q1jOmvHOPf02oU3rVK7V3eqNqD1SBgzOfWVNP7bn2P0/9PklcRxo6nNKpMfMWWv8A3b7+d952QfVBGcJrxzj3u48wyD6zoj1j39NqFN61Su1d3qjag9UousU/tT3DyUrVU/ZfMeSWzHTKrRqqDld03Y5XdN2OVHElq3wYrtZ/fNkZmfWdEese9nfeOQfXa/o9/TahTetUrtXd6o2oPVKLrFP7U9w8lK1fmp+y+Y8ha6ktrGQ5Cmxx0gF7jUBUffTn9CrOf6zH9Gf3s20SKuhcpy5TlynLlOXKcuU5cpyazPUsnvybUKb1qldq7vVG1B6pRdYp/anuHkpWr81P2XzHkkeJoanOJ51BM6aIhjw7JX75yprWmoZyuU1cpq5TVymrlNXKauU1NY/KRkWT3l8Vl9FkWT33NqFN61Su1d3qjag9UousU/tT3DyUrVU/ZfMeR7Poddk1Xn7LQ/8A7P2Whf8A2/sopqqrbQ6r3tl9H8Fk945a/SZK/fc2oU3rVK7V3eqNqD1Si6xT+1PcEQaVFWP6lSXNNYLAQVP2XzHkc9zH1uNfLV2/GVdvxlMjZyWCoe9uUuUuUuUuUuUuUuUuUuUuUuUuV+OJtQpvWqV2ru9UbUHqlF1in9qe4KXXKPYN+Sn7L5jyStFJkqDiFRmSUiQsdIAR+Xk2oU3rVK7V3eqNqD1Si6xT+1PcFLrlHsG/JT9l8x5KjSYK9cLSYMYWlQf8gQc0gg5iPxw57zU1orJRnfXwD+LZ6Aqxm/AE2oU3rVK7V3eqNqD1Si6xT+1PcFLrlHsG/JT9l8x5JXNibZLiRxwrpuMK6bjCgjfymMAP44+iRn4yeHk+iyHjs5PxH4Am1Cm9apXau71RtQeqUeJrwZGkkt6E/tT3BS65R7BvyTxK8Ntsstr5zX+PHSHlZmjpKL3mtxyk+RksZqc01pk0eZ3N0e/5tQpvWqV2ru9UbUHqf0ejH+IcMp+4EZHGzDXlkPOuBMtn2qia3FSOGYuJTKG6QEmMNcw5CjNATJR+fpam0OlurryRvPd+OzZPmmZG+P1OCkPmpNx9/wA2oU3rVK7V3eqNqD1KWd2Zja1U8mt5tPd0BQ0L/T2/xD8jAPZC4b/UPP0h2U1nIPFMkZHHHLaqbZFVfk+h0w2nVcRx5/gVXFkik4zPh8FFK7l8l3X+OeCojay/I411VBXQxDytYzlONQV0MQTW0ttUrcldddfv6bUKb1qldq7vVG1B6lZHtyAfP5Kkzc9YYFTaY/LwZss/96gmiG+kyA9CtzSOe7pca/IyRhqc01hMnqzFrx+qpUXNkcPx27r8lF7Vvf8AgCbUKb1qldq7vVG1B6lGeiUdxVIZzh9e5UuOdhcxz8tWcEJhYwtjYKm15/qNidnssZ/7sVLdzANH47d1+Si9q3v/AABNqFN61Su1d3qjag9SniHKqrb1hWZDVHLxD8DzL6bEOI68+B6fqNleP4eI1n4noUdEYckfGf1oPdypjb/Tm/HbuvyUXtW9/wCAJtQpvWqV2ru9UbUHqZpUDfMvPGq9koUX/USOgPdmPwK4SgyCOv2TlCqqiPxtIOpswq+5H4r6L/p4YZBk4uZity18CDXI48/wQAyAfjt3X5KL2re/8ATahTetUrtXd6o2oPUy14DmnIQUZP8AT8rf/EfkrAfLD/Q7NsVVcR+NlcGZZHV+wwVdyD6Z5mP7vtHwTYoWhrG8348d1+Si9q3v/AE2oU3rVK7V3eqNqD1WpwBHxWjw4AuI1reofj53X5KL2re/8ATahTetUrtXd6o2oPwfO2OkStaCMgeehQkmslg/AruvyUXtW9/4Am1Cm9apXau71RtQfg+kdY7lBqDu8j5pMzebpThRy8VezGbNX6rg6XacOdr8u9CZp82W2q1wdDtsaeS1ufag+aSZoPOX2grUgqkaajVzqWNktUTSMlkIvjlfEz2WtNSoVmWqVzTwhsjKciZDRQXTAeckqA51VNLKH57LzaBTKScgIrPwRjodtreZrMm9cJK+YDpL7QRt1CVnKq96O6/JRe1b3/gCbUKb1qldq7vVG1B9YyxVWqwMq5MOFcmHCuTDhQPqjpJDUxorJToomVRNYXWjnOUe8KR1juUGoO7yQN5i6tOj4DhC51ddqpR+Z4Msry2q1lORjiPmiaLRw9+bhOSqpIw2Cvmb81SesKkdY7lFG0ezl+JVE/u+Stc7nlUU63yVg5jaCtC0yrNIMxVmkxRTs+IqR4AWC3Ozo96O6/JRe1b3/gCbUKb1qldq7vVG1B9ap7Q4dBUnmYuSfZCgDgCKzkPUriLCEYqKxry3IXHMhw8LC34ZCmywmtpTqOYRZa6q1aR+iRt4Me0/nT/pbbLmisWfaVccUbWc1qsp3Fsyt5QTYhCH1ttV2qlG2ixh0jmgurygfBAUuNtj7zOZBzTWDlBTo6IwPqyW3Zl/EQsLfhkKbLEa2uTqOYRUHVWrSP0ZjOCH3hlKjlmZ514yR1olkcQb1FNipMbWlxqDmo0bg6+FZyq8ydKGW622aq6lFS+Crt1cWtSEx2LHxrTZQy3W6zVXUpCY7Fj41p8HAghpAtWkRRWM4Ic7udR0ikiy54HEHSiY4ow3oqJQimaI5TmqzH3PSOsdyjYY562tAzDxV3PsHimUiEHi8eo56k6Gk1hhNoOqrQFEaJI+cuyKV5j4ORzK7PwVulNrbVkNVdkpsFGrcK6y6qpUnrCpHWO5N6lRP7vkm6xVE/u+S8zVwnGs19K/jbrMWhuZP4FrTOcxayyppavNhln9fejv4WfP/wCMrRZ/+MqjOdRpgBI0klh6fwBNqFN61Su1d3qjag+vJqlUfrPcp5G5HBuRcJTOS0VtyV5U5rH1yjKzilTxc1QcqTrL6OGjg7NmrpUEbuS52VTtsiprax8FJ2R7wo+yHeVG8AW5OM4qKdgqL8jvipnV8aOtg/X/AP1cJS8zRxcleVERutTN5HFKpEXNkcFSdZR8LFbkqrcSedCSnZA3IHWqk2KjNe9regVLhWNsBz7QHQqQ5zGlwZkNSkEjWuHBnOPiEA0AC2MgVJ6wo+1HcVSesKkdY7lHw0VuQitxrQj9mNuZRx26nVVv4pzp8tCNTKw5uSqopj/vAH3M+aR8oc7oI8FeT7R4K8n2jwTImVlrBVlRdZdGT9woOsukcMxea/IXVPjJ+4VJC1nLFRdzpzoXym0KiHEJ80j5Q53QR4KpR8M54sV1WUIYi4tGXjKPhnPFiuqyhDEXFoy8ZWpI6n/ebkVZMrvgXIMiaGsHMPxtNqFN61Su1d3qjag+vJqlUfrPcp428otyKzTQ0xuFQJ5ig6SFprzNacpT5KDEWOAqNYVJ1vJRtZUnUUnZHvCj7Id5TIS4CWPJUVFDE4OsVl1SkZVxpK5AP/epFlNa0tcOKXHMUHSQtdXma05e9PkoMRZzGsKk63ksHksbkUcz7D+LW5zynOhFUZk4tQqyKk6ifWQPNHvCtNyi0Cp4nuAc6otr51HAx4c+3aNXNkVJ6wqR1juTepNk9mRvcmO4OO2G8fLzp0f0cmo1WhlB3prGCprRUB+KzLO8MYEeAo1belzl5yiir+l64Sjur6Qc4/AE2oU3rVK7V3eqNqD67m9IqUUzpYyG8w8hlhfwTjnFVYXnJ2gf0hCKEZO9SzNljAea6j5IpnSxkMNdQUsTSAXirKnSySMcCyzkUfZDvKo80L+DkLMteYoOpUoeB7LedVDMjJA/gnHOKsi87O0N/pCEUIqaN6lmbLGA811HyB1qxK3M5ednbY/pGVV0V7WMqGRyMc+W02p1S4k7bHxGVNokxtts2Scy81O2x/UMqcBLanPtHIApRI9rrZGZSzNljAdzFALgphk5iOZebnYR/UEJZn8K8ZsmQfix0TbuI2Gj486a6mN4WY5wcwR4JnASczm+C42QsdZkb0hVjN7/AJtQpvWqV2ru9UbUHqTJIGgtDKs/xKhjk5TW1H8gYa+ekD/Lyy/EN7lRq/8Axt7k11JJAcahUK1y34Fy34EY6O5xcBXlbV77m1Cm9apXau71RtQfkpB/uB/l5ZNVvcqN2Te5Rs4Xg7Br5Na0z/6/3Wmf/X+6dN9I4SttmqxV77m1Cm9apXau71RtQfkpB/uB/l5ZNVqo3ZN7lE+JjHF7quMriDejNK1rXB9ni+/JtQpvWqV2ru9UbUH5KQf7gf5eWTVb3Kjdk3uTW0mMPDcoWit2lcHR2WGV11e/JtQpvWqV2ru9UbUH5KQf7gf5eWTVaqN2Te5QfRDMDay8HWrynbXK8p21yf8AS3Uks4P7SurP77m1Cm9apXau71RtQfkpB/uB/konNjEls1ZSpI3QiOy21WDWpNVvcqN2Te5A0iRsYOataXFtVujyCRtdVY9+TahTetUrtXd6o2oPyUg/3A/yVG1yp+z+ak1W9yo3ZN7lEyFzGlrq+MryDafBGGYtLrdri+/JtQpvWqV2ru9UbUH5KQf7gf5Kja5U/Z/NP1Wqjdk3uUbzFwls1Z6loZ/5P2Whn/k/ZOhEBjqbartV++5tQpvWqV2ru9UbUH5KQf7gf5Kja5U/Z/NSare5Ubsm9yaykWqmmsWSs82JZ5sSMsHCWiLPGPvubUKb1qldq7vVG1B+Sdm8nOZnR1qjOa0nzocaubKqNrlT9n805xaQ0tFR6VFRZvNzNAa3od7/AJtQpvWqV2ru9UbUH5JGT7V2Rg+KdacauVJIUIomVyH2W8o9aa76IGRNytGY7050bRa5LmvC+jUmMNkPsOzHqQkirdR3HIedp6EYpj/ER/8AYdPv6bUKb1qldq7vVG1B+SRj9iEWf1VsjzlVo/FxX/5Gm+cnl4za+b4r+Ik4/wBwZSpp6rNt1dSBBqIT4qRyxxH/ACKZbyWX8G/u9/TahTetUrtXd6o2oPySeHe1Sav+yosddTXSZVk5LGp8shrc81ny0iPmMdew/uqTV0g7kxx52g+/ZtQpvWqV2ru9UbUH5JTnnEvCDvUdIiyhhD/0K+jGd3BVVVfD6lIpJzcgfNTcHltyWW9yAGYe/ZtQpvWqV2ru9UbUH1qLwUj2V2q7Jq6FahdSXtzVhxVcj6VHrEowz3rRWHdI+uXdArUDeRDl4g1Tn8sQjkewWPZdVzoPiNJc084cVW99IZr11b0Y5ahO3o9ofULugVqBvIhy8Qapz/jaOmMGTkP+SNApFRcBU2v2m9CL2AvoxzO6Ovy2YxVH7TzmCbRaNklc2y3/APsvpDh5uH/L39NqFN61Su1d3qjag+tRP7vkspHLKmZI9pc4VNbz1ptXM01r6PRjZdnc5cLan6bzKm0ekOMjXZic4TGQ3snP0LhmvlLTm85VWuDpbnuaDU9r8pCj+hWqjXbsivImGiV8N7NQQNMtcLWeUKvJDqfNRdZ70+KQVtcFD0iSye5WmiuRxqajLHJKW9NuyFYnc91nlMea1E6g2qnV2rIryJholfDezUE6enBxmBzHJ1J3BSSZM9l1kBASySA56nOtAqKYCq2M34ydHILTHCohW4y7ga+JIOZCL/UW/DhAM/WFajMQJ/8AG+rcrUrmHtJFwX+nMDyM2SpoRNZcTy5DmCbBCOKN/v6bUKb1qldq7vVG1B9aif3fJcJC0FtdWdZRG3rcjUbcruU5cE5nDS/d6ERRYQNVtoqjayjkgFp7PZ6QhHac0D2HtQ+lwNFf2jE8jKC1Uf8Au/xPlh1Pmous9/kbZ9qbJtVufnyBo51YolGY3oGdOfSgRKekVJvZfJUf+7/Ep0sxqYERRKM0V87udMdS2luTi8WpUf8Au/yP4zLJGhzTnBRdQ5OCP3TlC4sbJNV4+aywtZ8S8IOps1r+iPxQjgYGMHMPf82oU3rVK7V3eqNqD61E/u+S/vPln4UV+crq6QvMNdaqyMs1VKj1/eTHUcgROyV2a6igz/UBxxnrbWHKuhRlrDkqqzlMidyxFZ3KGWXkNrr2LhYayyurL5IdT5pkL45C4V5k5lGic0uFVp3MhSHjzUeb4lUd3sVEfqgyQFkgz1N5SfNZsg5go7OWuIdyhll5Da69ijmgrMQky5FI2kCy8mu3VX+iaY2kRsFQr51B/d/kfy3m1Cm9apXau71RtQfWZw9riV1VFcFDXZrry+UcOysjMRnVsRlzhmtmtGkecElq3kPOi17Q5pzgqsNe3qcrUUfH+87L5C8sc0nPZK4OAVNz5/I181utoqyFfa4lXYc/Wcg1gDWjMAjHM0OYeZV2Xn4WlHaaWhgqAZkTImElrcgrReWOaTnslGBjPNHODlrVdl4+FpMgsWGNNYsrg4i6zXXxj+Lc48mUrJ6LKVygsh99zahTetUrtXd6o2oPyMd1Jr2GpzTWCmytz5nDoKon93yTdY+TP6CDXTnQNBDchyrhDEahztNdSbRqU4uDsjXHmPkyrJ5GRF1mJswFkdflyH3lNqFN61Su0d3qjan5GO6kIWcog1bFYkyRP4rq+Yqif3fJN1ivo1GLuDtWQG+0Vw4c3i5TYOUJ0FINcjRWHdITvOyljX2wLXMppmn2eKetQcJNI5pdUQXdKNhxa95DQQppppHvFdlto1+SDXU+v5JmR5A11Y+C4ajxl8rgKgBWnvkcRVnMtaA4Sy7OCw51G6jcWZ9RyGrrXB/bW6s/PWqQ6l25HZ2i1aJRbNaac/HrDWpkheKiag5hzK1Llew2Sen3jOf6D3Jg/qCpA6TWov6axv8AyMd1Kj/3f4lfSoxxH8r4FUVj7yK0CekZKlWM/GUbqMy3KMwqrRaaJkIq5BUT5IJGsygkj4KGkDUPy+aokdfGrqP9v/oVDmzGVte/wqVFAzcHbPWVDHz1Vnr8kGup9fyUgj71SjfLlIaGho5yi2iRVajbVSaafatkZKzzKj9XzX/7H/8AJPlkNTGisqxQ4QOjJacmvp9uxXkrqz9Sl7T5e8aSf6KtuRUdv/yBRy8z21bFPD0G2PyMd1Kj/wB3+JT4pBW1wT4ZM7TtTdYoOYMgdaYekIiGJzZiM5zBOfSCDCMxs1VlTN5wLQ/RMjbncaghZ+xI2ZlDGcory9Q8sGunsEVu0a89SIiibGemutCaQHgWmsk+0VG9orDHcZOikiLgTaBahO6OxFyWKj1dB71I5w5E1qr9VS20Zjg5lRqOc/8AtSeXstNeKsmcKqOItgjNZKmHPb+XvFkXPI7cEHc0bS75IvHKiNr9FE48k8V35GiSKENeMx8gdPE17hkrXBwtss6FZlY17ehwVf0ZiqAqHka9kDQ5uUFOZIK2uyEK3BCGuzV+UCdgeBmWjt3qsUaP9cqqGQLKrX0aOvqTWSxNLG5h0KxA2y3PUq54WOPTzoiCNrK89StyUdhd0owcE3gj7ICcaPGGWs9XvEtHJi4vinzHPIah1BFrsrSKipIXeycnxCbaPnY+K781Xye3mb1psbcr3lMiZyWCryfSIx5yPP8AFqEmdhyOHSE17DW12UH80yTkAXFuWZG+KNLkGU5GeP1OEjHmH5v6T0LgZz5g8/3VWMo/NI0ajHzftuHOsuSFvLPyQa0VNGQD6jo5W2mOzhfehPJchFNW+De1CSFwcw84/M8vkcGtGclGGi1ti53c7lZZkYOU7oTYoRU0b/rFkjQ5hzgoyUauSHo52q1A+rpHMUG0kcC/p9lWmODm9I/MutxqCIh88/4ZtqrmdxeZozBB8lccHTznqQjhbZYPQlzfNS/ebzokx22feZlVcMjmdRXnLEnWKlx6Mf0ermXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcrmXcuJRiety822OP9K15+V7+socHHUz7zsgQfN56T45h6XzsLSekZCvNSyM68q4k8Z6xUryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPgryDafBXkG0+CvINp8FeQbT4K8g2nwV5BtPguPPGOrKvOzPf1CpebhbX0uy+g//EACwQAAECAwYFBAMBAAAAAAAAAAEAESFR8DFBYcHR8RBxgZGhMEBQsSBgcOH/2gAIAQEAAT8h/LDHATE8haUeJVPZ22ToxSFm68MAYCJrS9a3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3Yt2Ldi3YgOzu1YgwcCZGNcLJiiAxLP4Oqdl4LIdLfU6BBC4G88pICEdMVBIOFADVBgbxOx41QiN5c6A7KrBUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhslQ2SobJUNkqGyVDZKhskT21WCsb1LENLrtBeUHMj9aHlW51wEgj4Zqj39UP3xtbgIu9DBHgx0BRSpfhCGEkRDNtMBd/2D/TeXTFnI3IKQBEl4poOhGIuOBCsaHt7ccH5EjEPPaJkAJh4ACGvtCRGs/1EZwEZDnxxROB0MSVmY/OwYfhHBEKHSLPDIEC97knz/qZwEAwwy5yRSCfEG+YKMDCiLyvHHB+a+4OiCd0ew2XYz7f1UYmhmAXT9atV/gYP0O9nbha6lkzcE7B3AKZ4eN7h/qoLndMMU+oTcJi9AgsJyIFPujSGJHZNxfIA16em8rDgAwjNRKXqAGeKzkOFjsaEO3pOYqFgYoaSgYQNxZZpsKHJRNjwObI+k+6CAYnGCjucRGgvJ6o+JPLGFr+bs9ph0bsreSH4RbKDZif9BOiPog/0+nY1WrrucGTZKO1UIcEKIG1wQpkkHAXYnigWE+YcWhCmSQcBdieKMgEMYS7nHBM4ACKSyPLlan1klpAjXTszmYGxIKKUgghoLQQgrm/scMxOSG+LAxrkVDOwzjCBNCdsJMaJuB5RHYxC6CCmcE1xEBmhsrS4IvzUe7OA4f8AxWkFEiQ5m6jMgAGiz28C7WVZJNk5pzBy5/mcM6A8q21qfUQ8ssND7IZJt3gTqXp2NVqmM6OLvoqrQjRCmbBXkOEPwf04Q6RNB6MAnzMShWG8ooGMMd1msVEmVFiXgPpDiSAzBiCYBgBrGQHmJYLgYtwQr8HBiizKEU4PLA+GV7Dk94Zi3dWzvqIZ/wA05rvYOq/4Eb0MSFvT6xqt/A3DCd03RRTbNsIgY9k3GsXgDvb04Q6RNKzJVGK84qJMqLEvAfS7eJBxxoiYXB8aSHEGcZIXDghX4FbLkDQIAZtEmgoFv4m3w6A2yF0DN9dk3qI7kdH3/NBcdLlCTD9qgz+o51YGtB7FzYsxmfXgYalaAt54EjzORdiScdYLRjFoCOjjuNvByQidAGH2Pqgj2QQGdkWuAK8rGQMiVIyXMeDTxQpZEB1xGaBQI4saCMhEjojNOwB5InxBxAwBPBHFDZQ7MByRClBlrRTgcd7km9MgAWDehkuLkAuBg60P0Qy2AwH80oMl49UGf4J0D3gFwj9bEWAYD+a0GS8eqDP/AFh1BkvHqgz/ANYdQZLx6oM/uHHJszgSTyAiqevGH8/oMl49UGf27h7DRFwCdyRH93+lYHadsuv5+oMl49UGf27nxgREU6x4s17lS4/n1BkvHqgz+2c2gRsMsyM2SHJN/Ez1iFxTCNEF37cMwjh10cFY0OMgo+GHhCHvApuJsEhDE5+gESFiMREIFuOAIyCaDyVwjnMlCQAxmP4PBoSYkPIIuBoHJLE7wjuhh83QZLx6oM/tXHvhBf3QCdjLoBcB+U2KExfj9tqE0CwjenEhyXGBcu9uF6PHBeOUQYhwjOJkjlZjzGLXo2sUByok8kDFu8RUgHATBQ+33vCvF1C+QTEsosExOZQVrdFrYZCq/AjPSwAYuZhNHDLgnpOyhxntCe3IXIHA5Q7ADGbLEBzRgEGrw1yFc1YAYwtNJWOxoQ7J7oxE4c1HwJmgQxkDOj8RFBcVgLCJEZ6WADFzMIUAgEJNx/wEXnDM46cwrOF8oh/k6DJePVBn9o4BMZxYAjp50XKbE/nzaw0hNAuHFn7ZUJp+5IBICwsgwTAufSIzWg4bZwQC86oIRKOIwzDmX+KCp5pDmsUWm0gcu19iKZFx/geYULInuDf6mIxHBFir8CpE0vkPHcMhMR5wcMysNcIKKknwYggkc1aU2qqy8HWSXKTE5BQIjcSFtckKVx3hWT3LzjkqRNAgAAhBjHNACRej3KpMvk6DJePVBn9o5/sYRXm7hAgASTYAsLN0PytQxF2+n7ZUJqizfghUJKJ5yzHUfCMYNYsXFl6OwTBiPIgIGheAWgeVCWdwRFe3VF7oApkBFhfcq/AqRNBFjCIk4RQ4Gb42HgopgFjmIXmmLLs36plmjB5FrHlGjwRIQwAx4OkdeUuyR7guoK9kew2MyATb1T14SevG05dVSJpWZKkTSsy+ToMl49UGf2bhHZ8ZeelqNaLcXlEAByYAJ4EIgdCwU+J5gUPexsJ3Pj9/jy4xgC/EjTXj9rhOkiCVpZyHuYl+NnoLCIACWCHZwYIJQJiBwUVC4ugeU3OLLuxwNM+jFyPoBKS5pkblaQpjQQJChs4air9lhFCmdmEsdQu2irwhDjYBgEO74pgQCbEEB2zo5LtZL9uDFBmfotQyZgsD47ISCABgBcgSFDZw1FOJMXrWCBIUNnDUU4kxetYfJ0GS8eqDP7N1rwfd2DpwbGcXI22lIZBBINSoAAYub4d1Y03u7gIGHyJyGGKb2dwoGFgJjlrOBYXHUFjs3b+dUGS8eqDP7J1spz6BHgcs2J4itAMsTE3FH4FvQRlIzIhuGCEBE+ROQwxRSVrADcgAoh73WYnHicaWHUED4/nVBkvHqgz+ydaIEu+Gf5CAJ9TkMMUUlawA8ABRHFWlmJx/E9oB9R+1GTdCeMaWrnEglu9bvW71u9bvW71u9bvW71u9bvW71u9bvW71u9bvW71u9bvW71u9bvW71u9BoEvXuhVHIxGHwhmUADkmwKGgwkDe3rUGS8eqDP7J1ogC7Y5fiIEHyJyGGKMStYAeAAohiuRicfytwR9B8bERhYMKrkTgPKMO6oLJUFkqCyVBZKgslQWSoLJUFkqCyVBZKgslQWSoLJUFkqCyVBZKgslQWSoLJUFkqCyVBZKgslQWSoLJDpvoAXcJ/wARCtT8ARxwCye3w6ah7wobBoJnahEQ+DjjGI8Zk7Ec5ULyIAvHq0GS8eqDP7J1odS6hkL9iBYjiIGHyJyGGKMStYADsAFEMXyMTig1w+kpxeUSuEY0FmWPndLxEm4mAhx3BHx8aCAGAm8oDynaDHFpPvCfGPFNqIAI4MQfflDu0e9tUblNQ+Cho5rGfIIhM5aBPBkiJyKB+/VoMl49UGf2bj2Mekdh68DOsYi5oppEctrgkQ17oDE4p4Fzfk6MIIhAuT+BSaTJteIIkhAWxeCa5rH4EhwWFpNrLr8aYAFgR7e+I1uCj2e/pcPe2qpUvgRMX4TzN6oSuJAEICIIuQMWzQx9SgyXj1QZ/Zuiln0co+duOBGESwD2cQtiCWAMximjs5i2Lc07CBbi8Dz4Cr7JfEprY0Y4/NUBA/WBcojgBc7ieiATQYDnIYo82jvAmRBZ7Eu9VUGX39Lh721VKl8ASACSWAvRJJhFQS/F1DXGOBwUIEmF5fD06DJePVBn9o6F4bCUtlB/iE7vM7duBinSGZKmCZBEtPmqBUwWlYhYcXmLnkU450TZI8C9wwcHAI5IrBJY4hM4JjnE3CfUVBl9/S4e9tVSpfAWEnhlY/nExzSE+YQKrALx6VBkvHqgz+1cx02xhySp6RSxkVzfsjiKua+D3sQsts6/UbB5QKN7rR5m/wCboNsAC7gvQGBUeChI5P4mGw6EAb43v6ioMvv6XD3tqqVL2RLsk+AmcXrn0xZzF3qF6B6vnyCLsNcWk8GMvyaotclB/vn6VBkvHqgz+3cAWAESKIOQmUjDn8EgGDCA+coCxMWRR9bnaw0uf5WePcBJFrxNl3qKgy+/pcPe2qpUvyISxc5rfFvi3xb4t8W+LfFvi3xb4t8Q9goLwSQeBb1kEwfD+9HZFZWwr+iFAE5JuCe2ehv9W8IdSQwl5wV3tWgCgPENbAIzRDAIAsQbvwEykhwRchlV04z6+jQZLx6oM/zLmGuWJKw4++oOs8bMIGcFvynQqQG0+SN0Azmz01QZff0uHvbVUqX5eS9eeVWsPMXqRJWp8xcokaAVwfzMyBXYDbkOIJ2yKsAiSIa4gECDIJtgihVv6NAtxuCZwQIIJCST0UCMwI3tg78CMV3293+/RoMl49UGf5lw2cOJWxvmouuxuHUaKzo8Vx7yhZh6sBCBJld+JCYCTgrCMWtFrkv4b1FQZff0uHvbVUqX5eS9hjhFjmFPY7RM3+/zI6wB9h8k8RIzOeXpK6QuAeyNloaIYzkCByHoWCZFCgbcS09FRKUPxIAjERCf7/QHn0KDJePVBn+MdZKs7ernOc5znOc5yS0ROeE/7AWcwvXdn88worEARwfdUHQCu59uOLBEn4W1oPAO6wA0NQPMMo3/AEV9FG2A9RUGX39Lh721VKl+RAFs0sVT/Cqf4VT/AAqn+FU/wqn+FU/wqn+FU/wqn+FU/wAJj9yxY4LcOTzFnM3KZtuN1G9WQXgsB6Bz8IPzL8MEzlARftpJsCZTULcYRPRdyUo5/ic9/vvn6FBkvHqgz/GOqUvYziEUecEaX8AOwcvdUDHDEcFQh2AYM6J+I5RYmvbBMVmGiRBgVaA+I59VUGX39Lh721VKl7IoqwV76+1/70d0CgW5b0hCsfDF/wAL+BjcEzghS8xhE9F3JSjn+QnGGPBAZehQZLx6oM/xjqlL2DFzfZ5hXhG4aoZEDAABgPi6CoMvv6XD3tqqVL2R0ySOESN59QzX3Ja+34mgW43BM4IUvMQRPRdzUo5ou9GtxyIKBxe5PUplvnAnpYFCbJDEG7iUGZgWP+noUGS8eqDP8Y4Qy4GI9U5znOc5znOcAAMAYHdTyq1g5m5djSR5m0qyrQFgPjaCoMvvwtO1MSPeiCCCCCCCCCCCCCCCCCCCCCCCCCCCNrjctNpZUqXvjRCssjYe/wB8RaA17KXIKiUofhANCULy5XVS1iALmaigHgZ8etqadAIk0yATwZe/SRt06oAAMID0KDJePVBn+ZczZEgP9nRBZWwLexEkYifegEEEEEEEEEEEEEEEEEEEEEEEEEEEEDaxEgAKgy/OvGpUvfQhgCGu4Ebm6PC0daUBxZycGxF0syQiSgUmYFpXABW23PDBAOWFqNAInC+69FQZLx6oM/6W6rS98Cgy+/iEvM+9ABG8iO1GIWgHj388hYieiOIBYbgmDePxhSBhFbk9ixpuCQBJAAcm5MkxiBuMPSoMl49UGf8AS3Wq4fR71DUtUNTD7/KGtRCc82LfeFyKdYAKdx8CdD3JsJMFSM1ZDVE4AvBcRGxGCO8HqeispV3DkXenQZLx6oM/tnFYLtaE5LmBx3ZTvCXG5/JjRcDEyIo91hiQ2+8K44AiSXfx4Ks2sHIfAGghbbzq50wB+/SiiiiiiiiiIA5aTCPxPPPPPwJYCJPpooooooooooth6BoIrfibU/B4LlD9lYu5z9ShYHBM+aIvIQfv6tBkvHqgz+1cei0NM3BBAA7EQsuaL5GJI7/4mkPE1xZjBAWBjWhvk77o94itEIX60njJYNXNYNXNYNXNYNXNYNXNYNXNYNXNYNXNYNXNYdHNVXVVXVVXVVXVHYULTvWDVzWDVzWDVzWDVzWDVzWDVzWDVzWDVzWDVzWDVzRiH4Ul4XQoRGQ+MdVGjyH4mGRgLgoU7XX56gyXj1QZ/auIk3NjD/UxK+JAAeAHZ+QRAPglCXHdQLfPH4D+JGOGI4KBP11+XZEv2sfk+Us/2+eoMl49UGf2rqfIcXtXiOKBRNOyBn4muilAQjeNF/mYtXXW/wDJ85Z/t8s/AfzYtxFHlegQAIiD87QZLx6oM/tXU+Q4vQflvpxQE5HILM9kLTq3RPT5oJ+5DE3IxiORcn8j3AXZegQQCIg/KCxrgoUyyEogqIKiCogqIKiCogrAEWc2sgufOKDJePVBn9q6nyHF6TUrHFANEAgzHkj4rAiFjy+ZE9YQywzEv9AiIiIoApiEkAHJx8kIZ3AjPE59J5dieHzagyXj1QZ/aup8hxei9O0cUH2iL4XYoZOGHFLw7OH+WC4hXjZcPSMc7wQnrHyJZyI81zu653dc7uud3XO7rnd1zu653dc7uud3XO7p0F82oMl49UGf2rqfIcHou8jEGwhAhwXhxxQfYoUVp46aDDIFES8B8s4j0MqmVTKplUyqZVMqmVTKplUyqZOoQXhv3igyXj1QZ/aup8hwe02aNq2HEgEUHgGsfkjRUUzEP/PKDJePVBn9q6nyHB7TZoX46QGIKBYgw/KArK/FVLmgYmchwR+8ARHCLggSoRPZnmLepQAEBKII/QKDJePVBn9q6nyHB7TZqDjJDA7GAnmqszVWZoY4AvBeIH7w4RZmIPGbtweYJcz2en1+gUGS8eqDP7VwalyLkCBbwe02apskL44oaAh++M/E0g+g0kXnhAJMVkQRmXj5+gyXj1QZ/aOJeQTTNFozlJXtMoIAElzizYcuSsC0dSjOSaJiALJ2XIBpRd55jFc9GI82X70SACSWARzrr5z6vwsmHaPTOXz9BkvHqgz+zdbk5s5BB54vvjQJqVgCnuHaZQYEMIvGpehYmLE3fAIFi4gUJPXA/kTEM2Yv39GaOUOI6K/rb1/eTK7o8BGaobNASA2iHANzjixJYKhs1gnGM3GHz1BkvHqgz+zcUd5fKKHjERDyck2tkQudwKL00o+SotFp+keFeYcGkTmkQg7i5QgzCITzAfOB+h+9+U4UGX9AoMl49UGf2bjBxfEFPoUuR/wgH2gvwMfKEVHAtntJ8cRGxBzh8wyHOtITp+9+U4UGX9AoMl49UGf2bjBbm26gQg0sXqMuqdjLYZ0uQ1b+EMGCmy61J9lYE9g6D7Q02yhq6/vflOFBl/QKDJePVBn9o4oyOAKwVZJlvBpiiq1j603eUCwJJCigiB1OrRNhGwd0ZmiiFzN1t6ihlgBgBcP3vynCgy/oFBkvHqgz+0cNebA4IR/3ouxHNf1UD6ufsggXiJo0VY8FqdLSettUAIbMA/fPKcKDL+gUGS8eqDP7Z2BmgdEpcvVXJtDJNfv3lOFBl/QKDJePVBn/AFBzIzgYBBc6IiISTaYfovlOFBl/QKDJePVBn/UHUSRVuThYIUAtK4JoMigA46ihwo9rcRMIAbbC4I/JAINkyj5cMIqlaQj8SRbEoMeT+DAm0IDSGKgBjNDW1oDAmGJRtwCAi0wkIMmTA0DHkNyTDBkMwt+kZgp7cAmf9IPL5Zl9xCdIkmCwZH5TynCgy/oFBkvHqgz/AJuBOYwlxFb41W+NVvjVG4WkP7TlcYAUy8AjHQRPyFEkVbk4BLay6D/U2q4cOA1hooR30QLYCSE2K11w3INFWgDhhB27JulCXMz3RKlyKokiGXAAWLiJPAyEAHQnsEMXsgKdUEBS70Sj0ZoQXF9dCiLHjhwcvCNl6oN8o8pwoMv6BQZLx6oM/wCbsD6rhBmAj4JEntwDgxcAj3iuOZAC1PRa0CWl5UrBkUYswDNsJsyMG+WaJPRcmy3wEkYGuKPfaYAIerhPFBb0RvCDgRuTCJYIhS6nEkOQa1lEEDYEHovQsATCwhCK0brxgBbzQSL5NIu6bJ6GGBRTTGM2wnYhwHmYE3Ntgmxw5DeaMZBCAjGbmXRInCdnuBBQygJLi1JEEJncmA5IaQLkbveyG9eAhGdEEJjckE5Ib14CEZ1FTwG2gGWKMMlYBJOO2ATuVQM5JB2QKfi5gMS6tM4S6eB+HokiPaELNQHBulN0FzHXoivMlEyYLckCTBDFxwRWBNkuR2STXRTBeYMoTAmkELg8UQaeOWVRJF4zgdNnwMwIiYkgsm4mQAtNonOfRN2pGSBmSwRThEDiIOR+UMIGHUsq1yQ2HQQAZGz9AoMl49UGf0HVCSokyJ64uFxMAfKCLSxFqGh3RmjchExeMeScMl4IkbDl2VZgEEh4hkkXUdsFkxeEwQbIDQWMjLbw4FDYxuBiZBDGnFu9cftDYcRXhwZS47XntbftGYlAk0bYh2kmxjDyRsOSrMAg4JoSYuyZKEcGxDLQwgjiSW+kQgtJxIxQzoEjqhkUZnggORtgYC1UuR4Q6XIqiSJo4WadpuDJxUCBiMTl2Qzk3iTtjFoq4AQxBuquG8qPhjlLBIaWNxbtxTmANtW/ZEtDsXCGkyeBOlnAfSByBAdiCjEwIzfvUT6QA5wAoo5SwSGljIwBYAyxYcgWta4MkfABcQJjyWLDkC1rXBkj4ALiBMeSP3zaRx5zTdfJN4AVnXwH7tQZLx6oM/oOqElRJkExy2TIiFGKEiQIDZo9fJnLEZ7E51BkEDFrWuVZgOFZgV5DjDhjE44zEi4hRmoBOAbh9p41q8CxBHdigqHIAILbDZyLFriN7gMcgxa1VmA4ApS1bztNSTleQgMG8NYENU+AwihC5eQUaYAHNqGOoG+BcNEJixkJoHfJASViTwkI91S5FUSReMTJIFjjAckR7WAkwQFptVmFgJ5BnFM6MkALB+1314TfgJlBAGWxuT0AzTBj9p9Kw5Qhi4j9AoMl49UGf0HGFQJkI2ckuOYEcHJbczgzwRgc+pPlMgxiSbSmUwyYcccHGTDjlH2FA2AiiBMe9oOXCGwAZoOWeCj9CaYcxQAAACAATj8uVxHCSJCfHSfKtp6jElMphkw444Q5MzDuJEJgZOvCXexDA/A4SXF6h6wfiIsnh/cJwjDSgESc3ToOM7Ih2IDBYXsEeJkCODIjZwQ44gAsAAyKCC57QUwgS55QU9IbjAaeJ/bD1ktzfZLvBNR05XTa9CIfJPWwrc2CWXmoQhEcg4Pz9BkvHqgz+zcNH0yREXM0K4AYALx/gM3xXEEkC1eAyRkonJMexT7tgLey3sngxYJBR+boMl49UGf+MO6N8BCuyK/bX2sOYWJUydQxEX5iDMy+boMl49UGf+MO6HqfUq7Ii2kGHwhgqzUj6cMczACfP5ygyXj1QZ/4y7piuyIvNmCSGPRUHmicM0ESY9fnKDJePVBn/jDujorlXZETHTjuZr24ZgFiEQOszzcyfzdBkvHqgz/xZ3RE8VjDMEOLX4ogZoWxEK7IirzYjtPABeJYjB/nKDJePVBn/izuq5JVOBEsV2RFZWMmQGbAHgcNZxOMkMQJjD5ygyXj1QZ/4s7quSVTgVWkq7IjtBgxChy46aO8TcnASx+boMl49UGf+LO6rklU4ECxXZEaQbNEVsvRbL0RPSeooZ+WHzdBkvHqgz/xR0IWTgPdIjAWH3ZGTyVckqnAn61uIQXIMQNgmxDQxw+foMl49UGf+JuDZjE183II0R61G/1NcFCNinWCJY3LwE7nKhrfnizCxc2uXmp+UQhiH6hqnmYYns80/nqDJePVBn/ibhlMAAxRJ+h0QMvDAeWHTJHv6vbM0pBCwIgOAu6dUwDRhkCM2IcEWhR4xOXvT1CE7jYcCXa9PnqDJePVBn/ibgiUghPKBW4EPQP9TBAISTAIr4qQ8TxT6UQQsDwOIFGtoY7fO0GS8eqDP/E3auWFv2rzEAlW+QnS8rfA9rfgMxY2PO/Inh5OuIcDAYfO0GS8eqDP+bsSAl3SgjJYlDocdhgQwciody0gb/b8wGogyGLbRtsxfxJbjiCOikrGhxkFAEXwtH0KYKEeSYMfwAaiDIYttG2zF/7tGGZBumy7IkZAG+W9H0iCyhx5dXEALEYaDmcETGAN4F5VapwWDO4Olvb56gyXj1QZ/QcZIAjfHkooS4BK4WwtRQsF8ln2QofsBe43BXFCIXw8nfohDRIt4A9t6bxDjGHaL+aGo+SPbB1FUYHMAowP2A2Cgkb2o2F4cnV/I0Q13CvxKizIKJkOGKMjsFySXIwQotWDFP0Q16YBworoFz8Dd0UXERNbAWqCRvajYXhydHKiDbi5ZCKYPqMrDOTJ11QbRCZDeO/7kEe5K8IRMRLcUjIqOya0gFFiNW2rXTkisJRGi8U3lTEO33opzJ7C1YE16tSbSvJ+eoMl49UGf0HHFfpxERTUEz0FYyl0N0GCgwgcwtzFdVUxZeFWYFRMzBvEkmp5d3eIRbxQEMRzB1RwwVIIvDfghX4lRZuBOY2OZ1fISDZHJomzMQ+wZDxYHFjaEF4vhQvWNvfBHD5UCRLkNVErppbbCf7ogDR7BuCjtDx+tvHlMABMDImyIwfwSmaDkA9WisguB+foMl49UGf0HHa1WcTjbz01x4QQ4lYWN3ZSNZjyR4Rzmi6tQT2QTHz4jUNgAs5AQpIIhjcR8yIwA7OQzQgQggINZwr8SNW0iWtEvNDdYA4fkAREoiEa4W9la7DJB23ZG6mbZbtfVMeTMGtYQXJhNep8yIwA7OQzUH/JFlxD1NGEMYIwanVOlgVrEi6P83FBkvHqgz/m7s1Fa2ivmaO5fiOuaKYOqHYpCgOliewVGhhzvZNAjEwDgrkssLyhF6NhHDlLgTo7wYJ5J9V+0RjwsIUwoLGo5IDIwXEbwgtQYBgFab0JPiJObaoSD6sYyAEmJcsidHeDBPJWqYd2ltqbESU21T0MWrF2aJvRSdOC4x/bQUsDHnwsQHMoAOQIw9KwAc1uKsQPI/N0GS8eqDP/AA13nERmMAuKZGFk9UcDps+AIIAEjH0PIfSJTaIIijK1dv4IpwF3eMgm9+AAcgBiiAOQIw4Np3YYLNcz4EsHNisAPI/JUGS8emljeScGAfwzziMox3EQRbwnTk1mCUeB02aIwwOpjZOcESGyLZWZqOF7W42IQnaUk2JxbJAwxk4AfKJoKmZFzNO3BAxF58BOowBFY0TbzHDyH0vAfXC5dlmiG7p9DI2x72Ek7CbFOeQCApyLKBVxReiAb75X8bzasred6BOEG8EBgERYjDAhMAi0Vg4JJ0jrygEHz8i5Fx/JYxA8rCg7wCmReZ+45/wzznBBsithA6vX7RFyXU5h4PZXRRMJ1IibcgbuSBLdFvK68cm1mybGWgn8ovJTHhuSJwgeBEHkgH2xF4fCdYN31E/fDyH0vAfXAi7j6ABkhAm0oMWIgw6lzEwVsw7Y2sLF5P7cNHhEItBDYBkUTZaJgIJNFRYPkcVSqc1jE7yeKZ4fZFoQnDTEAOcD9D+Gec4IQUzHVCMsjyXFRVsU2kfKyXkUwDU4CWYmiAMmKBYTSTbjzuL/ABWIRBiYIhvA0UYjsiRuiXxvj4DcfIfSG5t4wockavQz3RyX1Sj4xxRkxYgLgRbU1A9RJ7LD2RPjGFCJjeYp9jsA9yMzcmMI0PnjFD2DmRar4kJKJnKRLmAeSOdwPI6NPkWGNpoxZQ3oDymkvkA69E8Nj9I/6x/hhAIINhTq/wBgmDhuAE4MJ3ZA4Yi7EYHCYCaV3EOOyGQgQAAYBWo0dogwKBFGcXhQpPAJs4mHm4EmBW76k7gODMhIIBAAXIAQACDAgpyuQYO1iwRi45GTQr8AkxQCI4PH2Q6eyDE80WESJYz82RKw7ZoCiwSBwx+Req4m8/8AUOiYvTDq/ZAncgTBTsl47B7IcYdRkeuv9VfCHQ5nTp9VrjM3qxUI8GV4GEUQ1QBPQZehpxmF4/qZmwA5JuR4k2DOfUpexmV+TvxIcMbES3VYoYJhMJ4TdEJFBA4Iv/qQI9CHhRggsCYnJYlCtAsLAPwCUAYivwT/AInFGJA5GGCsHKf08H4NyGAQc4mFloBNHvGIDrgvKlZTOP5DHK14R0a0G1rBPDPtY8wId3BF1uQURLCuD/SzkQFpJYBDSufhpJWfaS6SvZ08UsUK7cB9n0S4T1xDmCKkh4TreE8f3wnQUABzfeE3hjN7JC+qc1S6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6lS6kbqpzQf0XkhxAmYc8w8J+YJAHSxHiOasv6I9AMnaGvqvxPbryBOxwwAOSC87av4OhEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEnz6RIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkSJEiRIkIIhXgh0ImDhwtaJgsuN8+h//9oADAMBAAIAAwAAABAAAyef/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wDvzTMAAAQ7gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQiMAU7AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA1gDAAAAAEEAAAAEIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAvLAAAAArb08wv/wCozE6KAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE4wAAAANBNFCNOME+IA4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAFPPOHPPPKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAFPOHPKNPKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEP4BDAFMDDLADBAAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAFPBPPPCPKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMIqFwngsxq8pkIAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAFOLCFOPNKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEIEAAEEAEAEAAAAAAAAAAAAAAAAAAAAAAAAAAAKwwAAAAAAFLLHGFPHKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABDDDDDDDDDDDDCAAAAAAAAAAAAAAAAABAAAAAAAKwwAAAAAAFFPOHGPFKAAAAAAAAAAAAAAAAAAAAAJDDDDDDDDDDDDHIAAAAAAAAAAAAAAAPPPPPPPPPPPPPPLIAAAAAAAAAAAAAPPPJGPPPKAAKwwAAAAAAFOLFGAGFKAAAAAAAAAAAAAAAAAAAABPPPPPPMMPPPPPPLAAAAAAAAAAAAAAAFPPPPPPPPPPPPPPKAAAAAAAAAAAAAPPJPLPPPKAAKwwAAAAAAFPDPPNJPKAAAAAAAAAAAAAAAAAAAAFPPPPPPPDLPPPPPPAAAAAAAAAAAAAAAFPPPPPPPPPPPPPPKAAAAAAAABAAAAPPNPPLNPKAAKwwAAAAAAAAAEAIAAAAAAAAAAAAAABAAAAAAAAFPPPPPHPPOFPPPPPAAAAAAAAAAAAAAAFPPPPPPPPPPPPPPKAAH/wD/AP8A/wC+8gADyyzBDQjygACsMAAAAAAAAAAAAAAAAAAAAAQwwwww8sAAAAAABTzzzzyxTRTzzzzzwAAAAAAAAAAAAAABTzzzzzzzzzzzzzygAD//AP8A/wD/AP7YAA8UsIwEs0oAArDAAAAAAAAAAAAAAAAAAAAAX/8A/wD/AP8A/wCuAAAAABTzzzzzyyxzzzzzzwAAAAAAAAAAAAAABTzzzzzzzzzzzzzygAAAAAAAAAAAADxTiAjTzSgACsMAAAAAAAAAAAAAAAAAAAACAAAAABRgAAAAAABTDDDDDDDDDDDDDDwAAAAAAAAAAAAAADjHHHHHHHHHHHHHSgAAAAAAAAAAAADzSwzCDRygACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEEEEEEEEEEEEEHAAAAAAAAAAAAAAACwEEEEEEEEEEEEEWAAAAAAAAAAAAADzxTzjTzygACsMAAAAAAAAQyyQwwgAAAAAAAAAAAAAAAAAAAABCkEEEEEU0kEEEEXAAAAAAAAAAAAAAAACAAAAAABQgAAADAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABSzTjjCAAAAAAAAAAAAAAAAAAAAAAAAAAABAADAAAAAAAAAAAAAAAAAAAAAAAAAAASAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABTxSDzSgAAAAAAAAAAAAAAAAAAAAAAAAAADwwwyAAAAAAAAAAAAAAAAAAAAAAAAASkEEFGgAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABTxCDiygAAAAAAAAAAAAAAAAAAAAAAAAACgEEEEEAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABTxSjzygAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABTxQSwwgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABeQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABAxxDzygAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADD/sgAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAThyjjygAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD8MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABTTCiDygAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD8MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAABAAzjDCAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD8MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABgAgQwQggggAAAAAAAAAAAAAAAAAAAAAAAAD8MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAQdQAQgwgwAwBQAAQwQAAAAAAAAAAAAAAAAAAC8Tvquy64+AAAAAAAAAAAAAAAAAAAAAAAAADsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAD7ajrv85sjtytMpdi8AAAAAAAAAAAAAAAAAAABAADBCCAAAAAAAAAAAAAAAAAAAAAAAAAAQwgwwwAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAACBDCDDCADCADBAABDAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADygzDzygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADyjwCwygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADyjyjTCgAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADyhgjRygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADyiihTygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADgCQDTygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACygRjjygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMAAQQAAAAgQwAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADgTzzTygAAAAAAAAAAAAAAAAAAAAAAAAAAACsMABQ/CfvCNRA9fvwcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADzjSBzyAAAAAAAAAAAAAAAAAAAAAAAAAAAACsMABSADSRCxBxCJzAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAQgAAAAAAAAAAAAAAAAAAAAAAAAAAAACssAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQPZwAAxQsQA5CAAAAAAAAAAAAAAAAAAAAAAAACusAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABRePODsBSKOuOp8AAAAAAAAAAAAAAAAAAAAAAACdMgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACADDCCACCCDAAAAAAAAAAAAAAAAAAAAAAAAAAAcRsgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACsgBBswAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACOgAABCMvf8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/PDgAA//xAAcEQACAgIDAAAAAAAAAAAAAAABEQBgMKBwgJD/2gAIAQMBAT8Q3J1FFFFwqOhBzCgrKvRQ20202075f//EABsRAQEBAQEBAQEAAAAAAAAAABEAAWBQQJAg/9oACAECAQE/EP6IiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiIiI/JPet3rd63et3rd63et3rd63eXZmZn4d63fn3lt63et3rd63et3rd63et3rd43PA3jc8DeNzwN43PA3rd63et3rd63et3rd63et3rd63et38j//EACwQAQABAgQFAwQDAQEAAAAAAAERACExQVHwEGFxgcGRofEgQFCxMHDRYOH/2gAIAQEAAT8Q+qOGSZbps9goR0sF64JU60dkP5Cb3p1VD/hwhSsqc181u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA1u/zW7/Nbv81u/wA0tInl/rSgiGb0BYpPVpnv+xWvLI/2kO6gENTL3zjuiP48c1SYugYryL0su6hEdRgfV6VBRkSS91q9KSHZ9LshrIwAD9C4oCBjU/a0fBjl/Q+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPvzz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58+fPnz58FCDnWMQB27acORk9Sa+pRT1f8AzpW0VOR0BCyTPuUI5QXAHs97nSVzYWJqLrr/AASejtqfV9x9JbUsaRbsLTyYubURrsAuQ4ebflnUpgIInmLd/s1qnYFxa4i5iVPZi4lzZeWPWlrhLwZvmjk/upVJQ+BrZ+4zyX6bzYTodd0Fle2KUMSwBVVgbLICnUSI7RLl7Jle/wDaIxwknZadHq5Dk6LXfRHRp8Q4A2GHVezbReIMWOQMjVWAM1KdZVvZBbD9rmrUpOEmOYjWehbFf7TlwhgRDn/Z2wbReiygGAtHB/2saAFbGy8x/wBz4phuIsUleQZ6ppUCO0DUcwMXZn/atoCvWbDpzcyiWOaVbAWy/Jwh4ZqYgPUWDvUhRFDHAjqtSbJQ5t/WmOUH9qzoH1pYDmMJzKmFaWISwfRGna2aMspylJOSU0JtIzgYeqKBKJucHA9ZX+MO37gJEiAmRX+f9NQx9jgFSpIA2JZfxEeADTPiEcwpnN24XLAGfGOvnoCDEqc6sTwaUqgRG5yqE1OYQpkGS1ZhmBBCcRksF+WNYVIogAAaABr/AFuENoU5RL1Q7qRws9gqJG7OpE+npUUaQzqSPf8Aj9j0rytN81icYk9a3H5qd+xQmyOZRUISCpNQSn96kIAuq0Og0QJpELgmutP71IQBdVodIZbsoA3Bayr19XQRJIglYuReci+qwo0WiIBNkb3xtC5+IAIUlCYvKQFSFNltiRLTEogWGiGvJchIS8ii2uNRDK8rRIzGSiSYRuFWQwhZjAB7RiUCQjIxRhOSxXASc7jerCoNLryCZLOpbiVSyXlWho0oFlQEsrODCpVXokOrgWXSp4zRzGhVYb4YHCOY6zBGqCzLLCgCIQlCJen9ZgFIE5wsvPtSTYJzskPRRlmX0WVCEXK1l/pP49j0r4TjnEDr9a+BokBIFIMST9TXDhxuDXE8xvj3abAAjQbvu0xfhCwws0jgD9jr2TTQyXVr3HuElBgBIAtGkUQ+PqC0A0JjtwB9lo3TXgDLeJw5PqS81aGJ0GV7JPddKOSm5t5kl7T6h/WhukqE5qPcKYRh9GSpG1RCNT2/j2PTjbc9aT44gSsSgNbVJleMIiYXCYzlOktSbU1x5S4JwQM3ni43bXpr3P8AWtw04A/Y69k01L1JByDuiXRmJlRZFvIYeombThnMXqbFD1j7BB24A+y0BsGQj3pfakwIQ0Il8KnkrtYsGPrs1CoOxcG8ooZjD/8AdWxmdMAdID1X9aApgnQoDEX2cDG56fxhDWM3YkQprWrS4+3rM/rwdI8CSZicVIIiSNBKECC8jD0TGgUkz7gTCHBN8VeUUmNCIgzpF+dQ2iDMJTKlEJjSkIiYywpcaGAimYmk0MTS0koo3ggksVBG0AzWwhShKEMVqEWWpGmyTkpRE5I9m9BRkJPTRut0ijIFCATdkzdLm1eOmksgycnepAKxsIzIulXYQkGEYkRHMf2DS1lG4ZAV5GIYi01D7EoAzHnlFMeaCx5V5hXtRETDYAEB/Wm3a63XU4GNz0/A2MG5ShOBDeWrs8Rf0peZbSrlaLz/AFpt2ut11OBjc9P7X27XW66nAxuen9r7drrddTgY3PT7CKioqKioqKv8/QvJKjOC1LVBCSyYiMK5INRUVFRUVFR/XG3a63XU4GNz0/nPrX7ZsBJV5AV0dIjcU1V3rGVQ6ky2g5Zk8nlRct/X23a63XU4GNz0/nPrI6WF8QyDpA9hk8QlMkm45ej1Icn+vtu11uupwMbnp/OfVPdPE5CXLLV6NOjI9Km6rrxN6THA3hVj/Dt4sQxliPUxH/rmSYEZQuyJpe/IkAwwzqUjySi3OXkUdUCYCMWmAYELXExg+tlMD7MpLlAbGAliAm9QO4LiC4omI9qEEFFLqSbz9C62YkSthDbFnpnTmzwJMqt1W80oA2x3bQGI/N7drrddTgY3PT+c+mcqEBu/VPsC5VdWshYWCyAt9LpKRk3bnJMRyTSaMSoPuOiMiZJ/1u36KOALIDUXNwsSW0uALnpnULIeUTAez6VaG6UkV1OKvera0H09lq6xV7WphRSjkMWJJha6xqtNttAy9SHQjVoGOD3tzr3BZmS5zQibWiW2DmqB1p1KlqHmCWLXcXmFRZdcQpYq5dAtFey0MmKgpCso5FQTMQSc1iAqc8QEvXgM4Igx5Q5EJmmBAepEpeaQJjqj5pCEwmG0wQYpIOJwAEY0PXAcAWIk6L3oKlSQBsSyrO7KjAZGbkGbU8Mi2jJI4Y3KS8UYiMkQPU6VB0q7lYSZKIl4epTJioKQrKORRhL5GEmQ3ZyIb0Lb642MErcInIxKQBUZzAPZ/J7drrddTgY3PT+c+hEGV4ESq0rrVhcwcieRB9bAoEKWax1LHqyoAQUSJg/9Zt+ik4claorLOI0XrHIBrAZpNKiQGYAZCWC+LwBR2CIAkLc1Wm2SOUMl7x6KcDEAiVWA8VXGpsbGZUrmGSHarFhrRVLPOGgnE8zATHqvQ0q8QgZhcOynRa9l4G6YaRiMRJ5UGpfHJTDt6lA2QBSAzfuFcvDCLEEp1eLCjc9aWmOeg/bqK0IRFxGB1U9FFmRpMGSPUQe1OJF1MR+yeG5zQOGLfesqjAv19D+gpqirbv0/k9u11uupwMbnp/OfQqhMt5nQLLzgyeC4GgEq6BQ9FJsTrKR9T4uNtzt3WnSNH/rNv0fSGB37RUt0wDhkqNJCdXVUxiexsGYBbCLDN4Gh8aBgukCWbRYi9KuMxJc6iSBzSlGgMgixyLhzw0ih8QBnLDikKpAGc29l4G5776OMgntM0tMTLJxKmzgGSRcGahcrsE5iGyQjNmbVKMAGcipcYEPMaNTdAg1JE+o03yzAt8LN8Irc9aN4RDc1n1Ey50iOoCCqAWkoln0hAT08KMUKhQixMzaEMcCkSLPIB5pacN216eG7a9P5PbtdbrqcDG56fznFQGemBhjMuXI504RqEqMq96bwsASq4FARkeTS+gExJj6AepPTYGTvQn2AsteJgJlcwc+PPjGadkcIOStkpk6iWTRpEyK5y4K8xE7f9WsogrMLLNmkdTZgBSwZrxW7I3YWCWQqeCHNjAQUvfAgDiI2SmZylcdhKOhT1hJMg0F/SOCrGlJLUXTziXWn1H6ikRJLHIKeVWLm4bWMynLBGCIqWhvdVn8rxA1agwyHgaSCnJk5UQIDIvwLUebBg6AU/SZMzcQTE5MlIGEfAIbEGGpVpRYSTGDgyUJMbq/smnTJKMvMQPRkoXtg4AYAGBTlgjBEVLQ3urGfxZgQS605YIwRFS0N7qxn8WYEEuv5PbtdbrqcDG56fznFjvlg2by7e44IAGRQACVau1W6JkL1ip4GITDWwQkTitSTheDEyEd8OFy8NwLHS1dhfALMjAAoMwuAUkxhLBocLx6EuFoOsnd/XW3a63XU4GNz0/nOGpE/FkW/alwuRmiv74FmSjyHfgxA+ozZxm8UNWpXBHrQi2qEJpDb3AqxMaY3Po24T29XYXwOwcwACzYrgFOlfQ7D7jzexxXniDEpD3TQiCMj/XO3a63XU4GNz0/nOEAeJNGP2X1XKI2IFn82PYXwOiw8AAjNm0AVeEgGQfceb2PphhsBqK/v/qp4QTAmYDZjVPIzpE43l8dCbfdHHHHHHHHHHHHHHHHHHHHHHHHHMcy7xaSW6kPOgCBSdm2E+ae42cl/BqvMvAGKrgUxGIRLRUw/zbdrrddTgY3PT+c4QB4k0Y/ZfTcsDcC+Z2F8AMkPAgtmy4BTJEgLY+483sVFpy+gu2qMC0OEiP6/GxTSlgTgr3heNJGnx1k9TAvv91evXr169evXr169evXr169evXr169eFi3AzyEh6j0ppHfEBrqN4THrIffvFCVhU5HOEOcUYvfm/ePGFJyhe0940pAKEbiZ/g5bOIf7+d2Nab5qFbM2dTE5lKSUyyEj9b9W3a63XU4GNz0/nOHsymov3Tw2wyRE9Tjc/DcCx09XYXwCySPEBZsVwCmSJgWx9x5vYoFmyZddYCF4ZCcJp+uStlgiIiKHCB6KnmxIWgbTjwQgGgTAC+wWgAAsH4xlkBwCAXlInlNLjzflDKv3g8hJsEWRrmcwoQAgGCOf36XV0k7/9+9/T/dI0lVXt/BFNmUOTdncexnSZMOlTKrqvAYubZiXZuBcnNGf1v1bdrrddTgY3PT+c42zroEFkO/uOFwD1RCGLpNHCaCEoWRiuQU6R9Dsfceb2KFoENs4E+1BYmwYWCxbLCoRWS+2sFskiIDlRnCSEkhU1AeejpwgAMR1IOhHc/Gs1HNYm/YfemehSrS2aq33/ALr+/wB7+n+62HT+BlEqPoAZqoBq0iupIeA5uK5rxb2ohCjBGh4ohJcIA87hzXz+p+rbtdbrqcDG56fznFzwUsmD2Mk0WnxqTrqOYlx0eE58p0ksYMuJWsCBECNrQkxcTOLIysE5TiiluWNuWgWWSRlPTgyWSVJB6I92DOoR2yYrNc1lev5pLjrDVOxUEZQckwxIwYmXMq2pUECjCmrnQGgpcYp3YJYtOdQ8cTCuf8nsPwHj3X9/vf0/3Ww6fwBNhSpgDWkSpgxgbK5Lnc52+hvwrXgZhmiyU0wa+kZd8OZH0v1bdrrddTgY3PT+c+jCd+KA/Ro5PK1JryAYmo4I5JZ+kQ0WRXut0cGbO6W7BB7uBLQaMJBBZGhvB63/ADSWIly0AXXnbIu0MJTJiSZguDlmPMacpFUklKQZTeKlmZvrQZywFMTCPzTQ2OAVnmKDqbM2JMgsCFMlLx/H7D8B491/f739P91sOn8BYIuBdcA6p6GM36y4uhNfAcxTuZ0C+T8jEj9D9W3a63XU4GNz0/nPpnSw45OY3OmDmNYgaAuUh9QTpSkKYiV6KQ9uL9tRKi81Z3asKYjPy/SeirigkLuqXXNX82lIKzwwLC2jBdXDS1NwSUI1Vx+mG0MCUQVXtDytfL+P2H4Dx7r+/wB7+n+62HT9lGl7EBAS0ALkNsFom3YtxaYi5IfySTNVeY3ZzBexnTQaoyplV1ngIKJDOPqxI+jZ8ejJ9A/Vt2ut11OBjc9Ptmr3iEjSN3zJ7lNVaysexQEABABAfnEqnIIScposwepwsX1S9PqJVjD+QGQ7HOmJYw/i9h+A8e6/v97+n+62HT9SAAMJP/K+W/5Xy3/K+W/5Xy3/ACvlv+V8t/yvlv8AlfLf8r5b/lfLf8r5b/lYPU7HAnJGsI/kkmjknJtV0RYwvXzUYTaVHR0eTf8AhewN6ACVXSKW4utbG2YycTrGXAophJBWLaW0GKM2L2PBgV0gIoEbKzUMNYXQTOM019QEKMRPoFaRaFFxHWhGyEy6S3SL9ZMuL9W3a63XU4GNz0/MPk4JsGIMR5P3yUWt8TBAEljG/T6gcraJDUZJnAZUIIUQYHL+L2H4Dx7r+/3v6f7rYdP1bpr/ADldRGzolh1KgeSIKjuPZJ0oVbw0nJLfXMIWFhuvW9heJahJI1Ze5aXFLA2G46kSmLNCffSBDcZM4ms0HYCECAZzHeaY2M9zvkP/ADFqZZjOABJbQestYYdBDAIwtCA4WnRNbCfYgdFxfq27XW66nAxuen5jCLd6ErDAcmSsmblF88c6y6FYIHFTuZ8vvEtnhUAzXTMiwvboU4/QHashLSTcZjxIJxIsWElmF/j9h+A8e6/v97+n+62HT9W6a/YS+YxH3DY6Y6Vjy60GMUbsybdPrO6Q/mG0ZHFKDV8AUr8yotrxa0yZRdZPV/lLLmhfYRYGMN3Kk92XsrORBMvtegLBAv8AyDI8y1FiF3ey37HQ4soWIZJXI0Boj2ng/Vt2ut11OBjc9PxcC16CSRJ+q+Of7Xxz/a+Of7Xxz/a+Of7Xxz/a+Of7Xxz/AGvjn+18c/2vjn+18c/2oRJkWqzwkUUTJLRLdxUK6WiVcy/unMow8Q8moln7pKIEFBxBxoZSTIghyYStxlOkVDNszlgKSZk3G9QzEM4RT1BiKYTKvI75VaYvl9QcGRU86ZOSRfJge7my/wAfsPwHj3X9/vf0/wB1sOn6rA1Ev1pvOm86bzpvOm86bzpvOm86bzpvOm86Y/O3MkocyTgNfsSwdUsOalQz2pQeVl6COrQFgg3pA/gJqV+TEiPf6PiykA0k0ZQ6h8g180JIEhniDI8rUUhN/USHo9h9IPYW6nx+3B+rbtdbrqcDG56fi9n1/YzLBn1sbdyHnTWP3ZbRLj3Rr90ljzATJGRphxdUXJJWLSwXDKlRO4w4NiMWTjQEA7lymSC9zLIrF4A6euXL+T2H4Dx7r+/3v6f7rYdP2UdeZKjEdDm2pWyZ/q+KjBeyELq6vNv/ABMWZLIMT1PoUkme53yFGUBIYT9C8HmrUhI9pLHv2H1MwSncPVHbg/Vt2ut11OBjc9Pxez6/sIjMw/qmx0x0Kg2K8RT0x74OVFI0HA0AwPxSX2H4Dx7r+/3v6f7rYdP2QNIuiyqYrK4/yTPE0SAEcawh1HixsZ7mfIf+YtEUBIJ4oyPN6ihJv2Eoe/YUPrIBnZWwwyt4ktehPBD16ZGgLvNNax7UW5ZjoyHQoYRNeN0JkIS4HmMOD9W3a63XU4GNz0/FjkYRgiQlfGq+NV8ar41XxqvjVfGq+NV8ar41XxqvjVGgEhgAqK2EkYHVLDq1BMUMqjsdiDrRsng0nILfjEvsPwHgowrGJgBPVreXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmt5ea3l5reXmrFI+4hFhnFK2HT99KfSUXmVuRI7OMgc3ygzZYEcnOWosQu72W9kdDgoGWeBBnmQHaiJsIt1G1KmgERM0Y+ysDFAmUA7qIkOsB78K9+FtFk5XMutuoUCEAgAgDg/Vt2ut11OBjc9PzEwcwAhVM/tDrWAUlR15vNv9iTqhgEq07u8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8Vu7xW7vFbu8VOfkDGqpB+A8bDqfffbDp++HC6/RzOYwjqFIYSxYW2fJkicJyfDPnGw2nOMeJUhbIO5bkzKaymkwpBgEYxOZybVbyjsEbawUgEhYySbDkEByKQAVMAYrSMRDjV9TN52y4v1bdrrddTgY3PT/p6Hv8A+z8B4yb00M/D96jkPOjL+honYeGiD791HLDLQOqzPJSRJWJvv9x9MU3lGT3PRFLmYi3GkrTNlQAlXSpkzL+eQPoyYt7HF+rbtdbrqcDG56f8VYjEl0PvRCVjD7KKJIQn78CxY4MW+BzT1KUYGLsGzJkMSemI/eAph7pgqdbp10H8DeAd/eSHbNXFFKIfmWOsvyrEj8UdkHiFAFWwFR9gkGHUH2DSNsptn2pZeZh9L9W3a63XU4GNz0+1wFlgHdp4iWJ9CI+9RkHAVyDEeT+Tb+QTFdhzSQ60QlhzZID+zkn3gHDAvcD0JHbQoooE9Ag9j8BcsmTrwhhc7It7N6NC9HOdBX5NT5NT5NT5NT5NT5NT5NT5NT5NQcATDhmrgK+Z1+Z1+Z1+Z1nCQEy64BX5NT5NT5NT5NT5NT5NT5NT5NT5NT5NRBgGh0zIXHt1FGk5j+rXIuwZTqq/gn+i2PQNLy1uoqflSQL7ixqKBZH7U+/8u3a63XU4GNz0+0YYTIxaw81Q70m0Fu5ObAMVjm1N3yQ9NY+VMynb4t4cMCUZ3KmEkqwhMcwidYy/JwrSnoTFwQcWLIzEjQLA8eDyVT6V8Kp8Kp8Kp8Kp8Kp8Kp8Kp8Kp8Kp8YoMT7WnwWnwWnwWhrNlDAU+FU+FU+FU+FU+FU+FU+FU+FU+FU+FUPw2gK1UYjq0LYOMT42TBYgAx/F21sAyvPqwev0rOCBklxqGSAQZYE7Mn57btdbrqcDG56faL1RAyPA8pn2NKg3Uyl4OHmqehwdQzCKI6Nh00oMLMibEN7L89ZS6kLi9ie8fS+YAGSMjUdkAgywJ2ZPy9+5cjU7svf6sQ7F6YD9Pd/PbdrrddTgY3PT7dNahdiIY1e8cJgNaWpYiLRFI401quLUiiCOErzOM/mcWh4cF38Dt9WIc43RsPWHu/lre3VZcXsS+n1mOcDM3Yei05YCRME/O7drrddTgY3PT7dNaYBrU+8cJUjQtDCd9Bv4IzoCWGOv5qLW+hzLD1SkvJIxVxfqEq2oM3b2LTMgJEzPykkbvuULAZIUS4rPQraf4raf4raf4raf4raf4raf4raf4qR0MccMPa1DWkfb85t2ut11OBjc9Pt01qRxNp6hXvHCevIEwRB13povvQAUJBNvzL5oFJy3cyogw6tfAP+V8A/wCV8A/5XwD/AJXwD/lfAP8AlfAP+UpHLmjDHlB2omRME/Ja9PkaWTDP+Kc1s8jQNupmfm9u11uupwMbnp9umtEN0NXvHCydPcQExPSknBOdcIxTROnRmaEwTE4x+WWtAe9YcB2P4rVuUHGlfkX7Biv8hmZmZmZmhmOd7P5vbtdbrqcDG56fbJrS8eGBQwlNGIGR3EdEvXvHCfSQwRRW06tbC81sLzSbmcIICVxsflrJQYYJ71s+dbPnWz51s+dbPnWz51s+dbPnWz51s+dbPnV8Jci+/wD3G3a63XU4GNz0+2TWt810CHQ9aPeOENPJIAYB0FFYImTIjbT+vNu11uupwMbnp9smtb5rqIc30HXvHCb8IMUWRGxoCA9OEYExMQSuIlk5/wDcYcUDAJWmgsOZBW1qKugY0WtRCRHBH/gNu11uupwMbnp9smtb5rpKzR9q+8cJj9fTVKW5HiGDF+agAokmNz/uME+SMXH9a/8AXC/PNS/lfsNH/gNu11uupwMbnp9pAhx0QGGExg34Wt810wkqEYqsSRAtpQY1/wC8xsm+aW7F15FP5OyVGVe/CIoi5Oo6iSJotKtGJpTsvMfWzn+f27XW66nAxuen2bwlk75BOcw0L6VPkxOzdhdS62NZtTf0JFwFlJIDAsqUBmEhhE/dEooszM7YpXOFS99hEGpPQBGYY04q0xOQPnNhYzbMj/uSbAlVgCmAM2SE+oj0D6ME7tVsDkji7OX5/btdbrqcDG56fZG7NxImHqLB3oAQGxFlE4YmhJRG8K8phqNMTzXm6JpsxeHVq2aGdEDZnFGKBIEM5a3pCRBkRhGiZtDpSLzYomFxBG8TfkN1ECRPMichUwhufbexH/chDmqtUiRLg6TqcNwjwiupwC6xyAkCWxdOC4jskhES6pvFmcUnP89t2ut11OBjc9PssO688h+4UYI5yABLvPpompIMMyzmIUfsjKARbzbgm15yisbgjegLgcuDFAvzAj6lByHCLhyN2FWqSnNP+7Dt2r/wRjbtdbrqcDG56fZNqRS0E/3FHqzbkAfV1bZp2AwDAiK0mVLueAlQwLEwIvhjfiFAFWwFJDgwsVy97q/ZEqnbn/3e3av/AARjbtdbrqcDG56fZNLjFitEdUjvULJktJJTvPIOksVUZhITkALqfQUiBXYXHW8PJ1KOM1ZSQR1UV/zSkW4Jcj7gP/dm3av/AARjbtdbrqcDG56fZtQYaCN8MEuOSppUx1beR3LDFpWTG90G5bnWczlHKOyr6BiL3XB9qZA0svagQdO4qeRpg66YSzaW99C20v6VGw55jkM6SRMh0AEAGn/d7dq/8EY27XW66nAxuen2apRjkrIjiUBhyoPLVgckPNpJImJeoF7go2EEYlzsh7VodCQ6ICOTNXGuKxPSMOpvyqF+hfVXFXFW7/3m3av/AARjbtdbrqcDG56favETIj0aQIq6stOSqwfQP++27V/4Ixt2ut11OBjc9P8AjwaQTbPYQLrSvqvlEqq4v/C7dq/8EY27XW66nAxuen/JA1k97qAWA5qnTHKg18ztLXCV7l4otGiYjz64N5SZG5a0VLasyrpF50hpM4qI46oYu3A90eOftILIuoFhxjlUnm+IsCEymcNRpGYQECMmXNzqyBOQW0RhucyZYUtSRmjCoQlYJzqZ/jgMEwHnYrhEKw6glyLhKihJWTcSi4lpSSQ9BUcoqTSJwLyaOEsCYC+Jq2QichIU88acpcZAswmUwiajqflNu1f+CMbdrrddTgY3PT6h2SBoFDYT6IcOGscgqOZ9oKppQsGLBek2HlgYEBiDElbYYfkwaxRkvZixn70JmW9ogQvRCzNEeLcxwrKh5qEgM2wtKZyvaL5iwCIspNIWclBAQZ0Jgok3cI4iQaodbQoHUKzwaEgOYsAD6PrQQCdsZCz9qmTPw4IjHq0r6GZmwSwqbaFrYVK+FT5ERcbEHmKt66EqUwkWRhud4/Kbdq/8EY27XW66nAxuen1M2pFDMcm1ExCCEjLlUc/w7juNmtjeKd0xVgWVBhhMha040NRMyMZiqPp3qCgMGwsQySkpBQgolaE65V2pqDjBAt4GXpgSdNRBhFKpObGMpFSVMjQMZAPYKfrFCyEofMYbYnos68KITGiXPPOnd8QDQoLkiyBGDcJg8JEOqlh0hjXCgdfRlBIjolLAuurGIwR1BoJCpFiIKnMkj0g60D6UWCswyRslPAOlBRKMETrlUsgysGNgg5ETroYphmphDC0gLDljV/XKEVs4FBOcwC2ESgsEzjlFxkHyppIyXw1Kwe4EpnTDyxzpNnhTCPqIjSoH24lkuhGFYe8KUzph5Y51A+3Esl0IwqT84y1BSURzZVY5vqLcQJMs4u4wIpwBpBmMDFcOdpxMEk8gHrBViM6Cuib6ArOs2/EA2THLUgMTgtwKyxpBSSQYFJLYmyp5qBg0AAWLEgcWkzpkOexhQDUvOUXa6/bMSjYyztGcVabCzkEtLgJIKT1pAjlggQCEr3UC2c2QcQVJuDD+n04A9w0+hrGB42ykWDCWW2NEGmHcyXDdEIywWygUiG6/RxQJE60RAQ2QSwZKE2kmv5RCFIJcvwEDJGgkylgAXn/gNu11uupwMbnp9e/auAN3IfHWw5iHtTXBOBbRIHAUaIOMUsgkEgQkEDIx00KK4ZQgZO4+hwEN+UIwGC1LdVxWjuAbZLPcBO9NwhHBMbGGEWytQCqSJNlIf2+vBwx5lSFbmgRbCZc6THDGAAWNYgvIp81J1smDyhGkGlTBUZBIIgDcLOfOKVIfApBMFmTDmGcUtssTUn1A9PARm/u1qEAIQbRFwvMtPkyvLMwAwr0W1YzXjnORKuLQDg05JzAYMOlduBgZok7ULUqYmOYTG760JsQAEWgYfSJcCQbcB4toWQAExbGL1NcZWi6HUj2VCIajHE0ZkhyALUpmrD2QwJa1S1WtwZpA+fwwOZHjAsFOAZ8SpUm9XBYaoBPapbHhLOsAdg9ainiAFkwBJzODNcOSuNgOhBTWtumkiQhCEGAiTCoreLjDJBUlzHNQOZHjAsFOAZ0U8RCeVdW+OxugYiM6FD0lFS3Ae1dW+OxugYiM6FD0lFS3Ae1Pm+A6KxdFoOD5AvXe9BPWI4NXmua3f+227XW66nAxuen179q4A17RPxsjugViLEW1JRIEBLqYURxa0ziEbDNQwMUoHenkJiKVy25a/WII1w4QucqGqJxIQdEviTKI8tDBIWkCXU50HYuB4QoupRinAjUgUQJJu5gZ0fUqM2cgs1nMo0H5cpzFDgNsLa8RB3NJ84c1g7KUIsarJRthkhJti1Yj2YZKyEZRwahGxCJTwTnAvaplNScYgTmlPRSUFiCcUmzG7pRXHF4ICGC5eXESDth2FLddSbR2J96XdJPZCDYKKOENA2873hfATYYhxJGo8ItlguaAH/UxUVjGyvKyAumhUyeRFHWZHqooKbcgDkMH1KkWDApbL9SSOTUVFRUVH5vbtdbrqcDG56fWjIDLgKJQwnRvLSSM+Dgnpo2IJFLdxORUEdSZEZmAOt6R4+Xl+L5rBysBABUM2IRIC8EZcIZsQiQlpIzqYOlUjmxQsOZwLOuFr/Xg4JG1c6YusJiRjCZVVBXdGUt41AvrQa1AIAMAKnplPsusEZOVzSKipDYyNCwOt6WzNSpTFM1/wIAKhmxCJAXgjLgNrIsc83xJKwzaXHCmxcujDTALnehJlIFoZA4wOV1qBDIaRME2JixQSeNgBohIvc7UFONVpMiEsJaHUGgScwMGjcLzt0KmHayOyAlVwl9C9LaAsoRmQ1oYTo2l5BGVM0ikk5FXJZVEeBNbuNmpgSsQIywkfauy1r6gqhksBjEgn/UHFPuJ+CbHNZDkGtAMKYz4xESMFZHIqPSJmk8iSR0h51aJkhi7OdrmsNBeCBgjg/S/mtu11uupwMbnp9ktAeaFBC6CjntIAOZj/wB8cYKJMlJGTNuMSRd5t5RRiscVanGoZ0glwwtx11Yb4kRQbvMU/mtu11uupwMbnp/SJx2LRxgei9j54EhRVqcTCIsVYz6zNq1QXDsTIn0kZ0/mtu11uupwMbnp/SJx2LRxAYzD6eBI6wCIBKSRevgqynA74iNyzdwfzW3a63XU4GNz0/pE47Fo4yuTFr0cCSRGysCJuMuD1y8EYWAspcA9OD+a27XW66nAxuen9InHYtHEkjIH08CTnmaIsHNidaWIY9mdLSDp/tQSgpGWsYZifen81t2ut11OBjc9P6ROOxaKZ6PSbibDNQ8oEpWkIfCpHOK9h44EkC4iwBMHat//AMp+FHMABTrCevB/NbdrrddTgY3PT+kTjsWit908H2QciPRwJJNGXEiDETRPFvWkKn1EIhYZuy4P5rbtdbrqcDG56f0icdi0Vvung/GzE3PTwJIrjlPKZlNfAqfAqKiYGTiBEe6cqfzW3a63XU4GNz0/pE47ForfdPB9hHNj0cCTPIwTkReRtDxMmUqDgpgWAF5FP5rbtdbrqcDG56f0icI4FncBwTJyxel6hRXFAhGMC92t908HzUhIkRmWDDZirFEKEQE4RMWOTl9L+a27XW66nAxuen9IlSPJjQpiNC72M6ageMgXLVRActCiOGqhMWbgLm9kFkTEeSGNixoBQaMzTACqEUNHQni26Mbb0WGU1J3kmolOkmaNS8ZCh8cDoMOxz+h/NbdrrddTgY3PT+kSnPssrQHXXoCUXaZGS8rDomiMcTMHwhhLsgjG0eSy0NYLB1QUd3VGVMB5wE86FER+ELiOTUR9tw2JHnYepSmoS4N46gx2PofzW3a63XU4GNz0/pEoI+zq8rXpalckIYIPadA6Py6BbX0gpj7ETi2DkEAaHE4MEzKQH7VA2Ounu8rXvPQIeL+a27XW66nAxuen9IlRaVUmYP6FDY3NyYyPV6TWM3xXIROMoWhcLfQeiFoxDa6VR7YNiQRujA96HuDLQCDi/mtu11uupwMbnp9XayzNkyJiX1pOZOyBEkzzKHcgIHExK9i9AtgwASDIWAphiOFn6yVUAMUCaZcnRjag8xeLFi0k8UNjASxERel78iQDDDOpST9hKl5EsDnV6e9smRBkLSYXEzDiSqgBigTTLk6MbUHmLxYsWkn/ALUpDQDE1MvWVPKmD2HIziYsm3g0miaSRfTTAwPWxwJ8I5oPAPYvQqGBt96yVhzWgwYS3oWY8zkTV9D+a27XW66nAxuen1tgAEgOFUUYDaCDFdEso6UGaxnlAuoBIxgCYSTYWhXG5EXoOnwTKxM4Zjq5U4cRpeAcQQS8sxfGj4CYgjSBspbTJZoyVttEuTgtawXtQsz4MnNyqDISidRI1nmItQsjBjhRBOxFpxCNAqhgQusgBhw914AZ46iSZZDRGEdSnOI5NrB9FqAMrvWJWZgZapzoNHWKhiEHoRlTuHKOKBhVwXFR1LUkx6rhYuGLLRBOxFpxCNB/NQ3iCAAXxjAacqUi65ixBwti+7SmYFyTlKl4vEDlQ8IhGQ7SZwE/7Ep3dC7IXqPZrKSpFMHXBxMwRPiLPItX6oZ0KfaKxZ54KGMtLS3KD0NXpUc6OA3ZAHOg5eL/AMeFh9iUaWeYU/FZr/hgH0P5rbtdbrqcDG56fWyobkvgC2WcygCowy4NbGi5AWAgwPIK81xwARDIsBoJMMKXgFiJiSny1IFL634AkIAnoQjMrSJhmNrgLN04lA0AwTolPCkWSYDKUDGMlhwphYfSI0R0j6AfdeIGK2bI6CP3R5SLASYBtBmti2aCOelkESyoIFxz70wcWfEGQWiOtbvo4AhbESiSWAGauVZvXwVYUy/dTloBS9vcSJi8v/ZAlTT0CETuSNmm2ww2fRYFHw4wAHncqPa0IPWe1AhC6DyCEx0HWsm1SC6uaua3ampqamn81t2ut11OBjc9PrbY9ONqVhVBIM6WlOxmI2VYWAOqnHvkhZDIj1q21KhFssiEiLZqsWqj0wGGMSA05Y/sUbiTmBsAaYS1L/ObMGN3W1O1wpKDsF24paYAWqhYbxw91oP0sU0oiQ50ixkBCQ3F4mGbaNN8NGtDAGpKTklJoGmowBeinuaUw5FM0pIM4guIjSrq7hmFBcpYljDC8TRRXDc4Iina4UlB2C7cU96ZRBAIyJYl0a1LxI9QiUCkIul1Nu+HDLKgbFiDGy5wEkIqDy/rc27XW66nAxuen1XCGVtdNmcNNkaziIm8GhxQQPJCaQxOTJSSmsC9SyXNGKCFjhMCBXNUK7RwaI0jEqq/yRRl8QvPSssbgcG/ENGsWUh2ijBY0MqiVV5HB5RYublvZza+J0dtkincQHvUZuxz6AWCs4ipxyRLjzL1e08+Mx7qTFEETZiIc59Wp2VQhlYUDDA5FN+IaNYspDtFErVTRQiV2IFsKvaefOZ91WsikjIlBZDdZbF6Y+0SKAIWILTGs6/9aeXMAKvCLveEBNcyFKT+I0S3CUV8JqbteMDH5vbtdbrqcDG56f0ZuGlY9QDAZGptASkxB2Lick+hrMcFABT+DZNdEeikSic3SiDhm45oUIzYgpxpksZgy4VhbimTasjFSoKGIGak4IMwtJ5OKYwbaHAEQBdVsVO2vGBj8lt2ut11KRYj95vNAcyHoreP6M3DSjNSRwD+SWE5TTMQsATCjhDI8lnA4tZM4dmSkhinAbRd5Kl8CmxDBMEzDbnSiNcAgmpEvijyVbLBJcDFYSF7KhlKzkYXcNLrYxzFRYYu7VPg9oUzCYXCedAuXDoJSTjBPJ4bJrrZNNIIiSNYJF9sQFDCIB0ok3diiMwWAr2Clf0NiRNgtraAJGlQp/f3iXEJuMhHUaaedWyNhKxI2mvlv6X48znR6KJZCb6isEVBZ4CtiELYgAK4ri02gqEdmGQRYYicMqC2erCRBziDzH8iCyB7tQhxKQdRTpEAnPzi0U/PaoHsP6M3DTgDHiYKXhD2OtXzDoZCY6wD3Z0zktjjIsUap61LesRYk9qYbiHCSH31FETYAYpXKj3W4Cf3egqH7SzNqAeo/aibM4LdFjlPoGkLUEOACo1AetWH8k4lmejDtw2TXWyaeAWhvjmz7qnd0QEOQnAsq5A42ELWRZBOF4MG8BSjO6tJMBIJm1uLiycIiSwZBmuAatS4ghE1gtpaGNWoF8KCScqGBu8le5/kcmmPUYUKOSNHIX2DSwRLOt5THqcIB7fu/wBGbhpwBP0oeZmDmIJzCmZDhCDIeSQ96AJBE0aPwSHXONzs63qNR7uXiO5MpA10UWumpcEAgTLGMGsSZNqEuQOaD3UpirZtOe63pVrcBDRM6XKCYlEQggeVh1OOya6Ong02IREppanpSTmECesnKmcb67DIVzOLSc0o92gzZB8hAo66NxFAgxohnOjV5WlUrkYkkxhYylZiHISGlJvNJRFDDzITrQXRmBEnCTKAzSinpVhMkZWRm5Jk5UPFrV4mWxoEs66AAOvgID7vT8iMJERqEvuqj0kTlKQ8+1LEImMVWekJQd9elgLcvI9B/RhNSEJqVeNSWyFixgp34T5SiBJYskkr60gHBdQXFutOl6Uk2TDnzqQPOYb1intRDvgwNAMKQCII2Roy1RLFggsUjBuDJiU8R3JGUSXXQ4tHSSWImycOg8Yyc+iShOjBwDQKEIyBIjklQ25THsN/Snb1JDaRZCCMqZJbhCQCkrGBQoWBDgYEIY5TV/aJDDMSxYlx1daSk0Kd6yEvWrXXJDhGWIvIM42oMCEqCTEiuEvr+RHD95slldZULBshTWJOqHZRqUlwBCejQxKUXMv3kd5o0gAS3ge2PU/tVZ0EvIMW0LrkVFoUt0pdOhdXrRXxqCwYvNxevBJbMJfEXqpejyVhrlnEbpyYnSM2gxdVkQs/2m6Mj8ACVXIpGkndbnDWB2DnSRyKJcwd7By5jiCAKIRwaWvXsFkurlnyWyppnG153HrzMsTOROmTkDcRzP7RUCWxSMmpCzM7Tm59MUQUEtJknwEukkFyDACADQPo1NUYNTRG45NI2H1v4x6OJmEqKYAzLnr1dxnIEdlEnRzHUbn9nw4sGBzWpDTXodAxX1c4uUIcwZTzFl+hLUNCYt0Ytmt2+qK+IpB/vPEq9ywSBzDA1LmZaalV4YB6JZ64mSUwRIMTfd3WNaO0Mmk5JZ/sspHyMDVXCoMzYIk55vV1KKtln04zPNl50KKUsA6By5raThRlttiLmmKur/DcHNQza2x6kOq1dBBCgaiPUI51KXWZI6jB70CT4+4WHtSgZwBLsmPWmFq8lf08ooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooooo/D0UUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUUQLl5ooQz2SPtFT5Zg4+6oxRGRk3I2ditZJFHqLfsNLKREtt7rzl0KACCx/Iji/TLrEvenkVyS6Yven2Ayf01GLv/Q7x48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx4/wA9jx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjxwgOuqQOb++KQozES+sqffwiRdRnD0j+D/9k=)

Figure 14.6 Prediction of Moisture in Air

**2.2. Different Kinds of Regression Techniques**

In the fields of data science and machine learning, a variety of regression techniques are employed, each significant in its own right depending on the situation. Fundamentally, these methods focus on understanding how independent variables influence dependent variables. Below is a list of some key regression techniques commonly used:

Linear Regression

Decision Tree Regression

Logistic Regression

Ridge Regression

Random Forest Regression

Polynomial Regression

Support Vector Regression

Lasso Regression

The detailed explanation of few of the popular Regression Algorithm are:

* **Simple Linear Regression Algorithm:** This algorithm predicts a response using a single feature. For example, it can predict a student's test score based on the number of hours they studied.
* **Multivariate Regression Algorithm:** This algorithmuses multiple features to make a prediction. For instance, it could estimate a house’s price based on its size, age, and location.
* **Decision Tree Regression Algorithm:** This method breaks down the data into a tree of decisions. It might predict a car's resale value based on factors like its make, model, and mileage.
* **Lasso Regression:** It is used to not only make predictions but also to understand which features are most important. For example, it could analyse various factors affecting heart health to identify the most crucial ones.

**Difference between Classification and Regression Algorithm**

|  |  |  |
| --- | --- | --- |
| **Aspect** | **Classification** | **Regression** |
| **Target Variable** | Discrete (distinct categories) | Continuous (any numerical value) |
| **Problem Examples** | Spam Email Detection, Disease Diagnosis | House Price Estimation, Weather Forecasting |
| **Approach** | Finding a decision boundary to separate classes | Finding a trend line that fits the data |
| **Evaluation Metrics** | Precision, Recall, F1-Score | Mean Squared Error, R2-Score, MAPE |
| **Problem Types** | Binary or Multi-Class | Linear or Non-Linear |
| **Data Types** | Categorical outcomes based on independent variables | Continuous outcomes based on independent variables |
| **Task** | Mapping inputs to discrete output labels | Mapping inputs to continuous numerical outputs |
| **Objective** | Predicting class labels | Predicting numerical values |
| **Use Cases** | Image recognition, Sentiment analysis | Stock price prediction, Demand forecasting |
| **Algorithm Examples** | Logistic Regression, Decision Trees, SVM, K-NN | Linear Regression, Lasso Regression, Random Forest |

Table 14.1 Difference between Classification and Regression

**When to use Classification Algorithm and When to use Regression Algorithm:**

Here are some points indicating when to use classification algorithms versus regression algorithms:

* **Classification Algorithm:**
  1. When the output has distinct categories.
  2. When classifying items into groups is the goal.
  3. When each data point belongs to one of a set of categories.
  4. Use it for binary decisions (e.g., yes/no, true/false).
  5. Use it for multi-class problems like sorting animals by species.
* **Regression Algorithm:**
  1. When predicting a numerical value.
  2. When the outcome is a quantity, not a category.
  3. Use it when there's a continuous relationship between variables.
  4. Use it for estimating values, like house prices or temperatures.
  5. Use ordinal regression when dealing with ranked categories.

This should help determine which algorithm to use based on the specific needs of your data analysis or predictive modelling task. You can find below in tabular form also to choose appropriate algorithm as per the type of Problem you have to deal with.

|  |  |  |
| --- | --- | --- |
| **When to Use** | **Classification Algorithm** | **Regression Algorithm** |
| **Type of Output** | Discrete categories (e.g., Yes/No, Types of Fruit) | Continuous numerical values (e.g., Prices, Age) |
| **Nature of Response** | Categorical (e.g., Email: Spam/Not Spam) | Quantitative (e.g., Salary, Weight) |
| **Complexity of Problem** | Binary/Multi-class classification | Linear/Non-linear relationships |
| **Examples** | - Diagnosing diseases | - Predicting real estate values |
|  | -Identifying Customer Sentiment | - Estimating stock market trends |
| **Special Cases** | - Multi-label classification for overlapping classes | - Ordinal regression for ordered categories |

Table 14.2 Choosing Classification or Regression Algorithm

**Real-Life** **Applications** **of** **Supervised** **Learning**

Supervised learning has many practical uses in the real world. Here are some examples:

* **Risk Assessment:** It's used by banks and insurance companies to figure out how likely it is that something bad will happen, like a loan not being repaid. This helps them lower their chances of losing money.
* **Visual Recognition:** This is the computer's ability to recognize different things in pictures and videos, like finding out where a photo was taken or who's in it.
* **Image Segmentation**: Supervised learning techniques are employed to categorize different parts of images based on predefined categories. This method is crucial for distinguishing various elements within an image.
* **Image Recognition**: An illustrative case is the way platforms like Facebook identify people in photos by matching them to previously tagged images, a process that relies on image classification capabilities of supervised learning algorithms.
* **Diagnostic Medicine**: In healthcare, supervised learning algorithms analyze medical imagery and historical data annotated with disease markers to diagnose conditions in patients. This approach enables the accurate detection of illnesses in new patient cases.
* **Fraud Identification**: Supervised learning is leveraged to pinpoint fraudulent activities, such as irregular transactions or deceptive customers, by examining historical data to uncover patterns indicative of fraud.
* **Transaction Verification**: Supervised learning aids in determining the authenticity of credit card transactions, offering a crucial line of defense against potential financial theft.
* **Identifying Spam:** Classification algorithms play a crucial role in detecting and filtering spam. They categorize emails into spam and non-spam, directing the spam emails to a designated spam folder.
* **Voice Recognition**: In the realm of voice recognition, supervised learning algorithms are extensively utilized. These algorithms are trained using voice samples, enabling them to perform tasks like recognizing voice-activated passwords and interpreting voice commands.

**Advantages of Supervised Learning**:

1. Supervised learning algorithms operate on labelled data, providing a clear understanding of the object classes involved.
2. They are valuable for forecasting outcomes based on historical data, enhancing decision-making through past insights.

**Disadvantages of Supervised Learning**:

1. Supervised learning may struggle with intricate tasks that go beyond the scope of the training data.
2. There's a risk of inaccurate predictions if the new data varies significantly from the data used to train the algorithm.
3. The training phase for these algorithms is computationally intensive, often requiring significant time and resources.

**Unsupervised Algorithm:**

Unsupervised learning is a machine learning approach where the algorithm independently identifies patterns in data without the need for labeled training examples. The primary objective of this method is to uncover hidden structures or distributions within the data set.

Unsupervised learning, as implied by its name, is a form of machine learning where models operate without guidance from a training dataset. In this technique, the models autonomously discover hidden patterns and insights within the provided data, like how the human brain learns new concepts.

**Example:**

Consider a scenario where an unsupervised learning algorithm is presented with a dataset of various cat and dog images. This algorithm hasn't been previously trained with this specific dataset, so it lacks pre-existing knowledge about the characteristics of these images. The algorithm's challenge is to independently discern features within the images. It accomplishes this by sorting the images into clusters based on the similarities it detects among them.

**Functioning of Unsupervised Learning**

The functioning of unsupervised learning is illustrated in the Fig. 14.6 In this example, we use input data that is unlabelled, indicating that it hasn't been classified into categories, and there are no corresponding output labels provided.

A group of cats and dogs

Description automatically generated

Figure 14.6 Various Images of Cats and Dogs to identify.

Now, this unlabelled input data is fed to the machine learning model to train it. Firstly, it will interpret the raw data to find the hidden patterns from the data and then will apply suitable algorithms such as k-means clustering, Decision tree, etc.

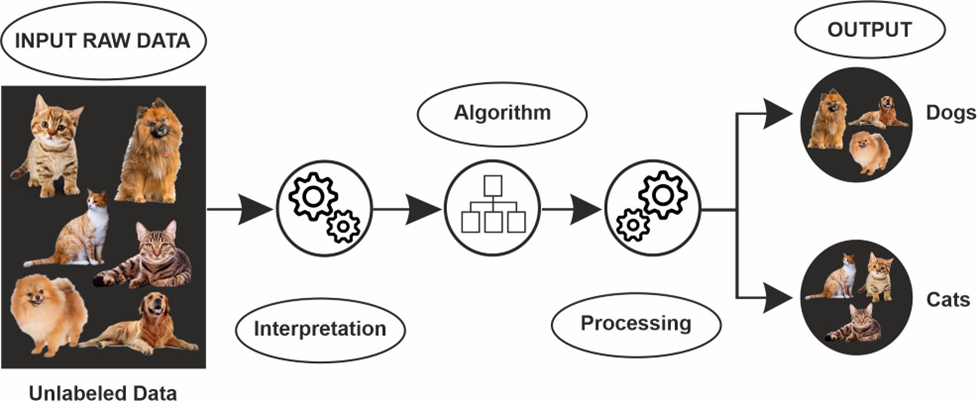


Fig. 14.7 Unsupervised Algorithm- Identifies Unlabelled Input

After implementing the appropriate algorithm, it segregates the data items or objects into clusters based on their similarities and differences.

**Types of Unsupervised Learning Algorithm:**

The unsupervised learning algorithm can be further categorized into two types of problems as shown in Fig. 14.8.:

![A diagram of a learning process

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIAdADJgMBIgACEQEDEQH/xAAcAAEAAwEBAQEBAAAAAAAAAAAABQYHBAMBAgj/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAAB1QAAAAADi7eIwqT7dijEG3qxBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xBt4xCM/oLGY13p5umgAAAAAAAAAAAHF28RlWxY7sQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAxnZsZNd6ebpAAAAAAAAAAAAHF28RlWxY7sQAq1pzUuUjW58qF7xXUiYUyKNIeFNLyzW9neqNrP2qE8SKmxBpLg4CeZpdiVV2GL2pFoO/wjPhBXinShOsyshaXPQTRlPt59jqlwk9bss1M/NCveIm5AIyjmlq/JnazWRLy4qsXZTxcGdzx6en39k0qMeX5UrOezOZEuqHmABjOzYya7083SAAAAAAAAAAAAOLt4jKtix3YgBmulZ6S8/UrIZVcaraojvOV5yRzfQ+c57hRPQgdix/TzKtHyzUykXaj3kqMDPQRc6veeQiu3itR4QOkYrXXo+d6iZN28V5ivTnNQS6cHd8KnoEXPFPs1YsxX9TyzU688R27EI3Nz/ayOxVy5xnmuVPyO7PL5SjVs30im1ouJ71hsa7k23YaXXo5+goGv5HuNYZd6VdY/HF28JKXmjXmgGM7NjJrvTzdIAAAAAAAAAAAA4u3iMq2LHdiAHL1DLfLVxCec+IDysghIK8DNbxJCu1jSRns5ZoczSZlbrHDHT6szucyKpLygVO2CClvcUecnBmdgtg56DowpV0+ihfL8Kjbg/OZ6cMx6dFEXSNLFa7JkZt1X8Q8TbgoF/CgX8V30nhQb8FAtUrHmcfj0/UWC6cvVQDGdmxk13p5ukAAAAAAAAAAAAcXbxGVbFjuxAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADGdmxk13p5ukAAAAAAAAAAAAcXbxGVbFhV4i+qEq+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL6oQvqhC+qEL7jNposbd083TQAAAAAAAAAAADy9RTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyFNXIU2p2SqRx/nbPlZZaaVcI9VyVTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyFNXIU1chTVyH4/YAAAAAAAAAAAAAAAAAAAAAAAAAAAAD8n6zfh6Th1j9fQDzyXXvhnmiZd8NSfn9AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA5T1yPmvEcV/KAAAZ5oYyDWqfTI2hzdNAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACGOjIfzqsctmKAAAAAVa0jEdf4MsjcURL0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKidmY+mwR4SZQAAAAAACKlRh2oyWQRtqqWugAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD5nB3VTr1c8/cAAAAAAAAAHP0DGLhc8mNdZ1ooAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/PnkZ2dPffj59AAAAAAAAAAAB8+jL/xqeemgfrINaPUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADk8chPW89dmAAAAAAAAAAAAAAAKXS9oq5P8ATiOvneAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABDcuZHzVuiTAAAAAAAAAAAAAAAAAIHLNxij8y+HaiWAAAAAAAAAAAAAAAAAAAAAAAAAAAAHLHVaENfqPFVjn2D19wAAAAAAAAAAAAAAAAAADhyDbecrlrxm3k1K5JYzQAAAAAAAAAAAAAAAAAAAAAAAAAPL1oxm/ERObf/Ol3NXefpQAAAAAAAAAAAAAAAAAAA8j7h03S4SEeP6L/dKutAAAAAAAAAAAAAAAAAAAAH44CSV/kLWpfiXpQRfMItkTFetlj7RZYbvrtfPoAAAAAAAAAAAAAAAAAAAfjgO+s9PGVKp6jyxR91xedNMUL1q8Kd0loQnedj59AAAAAAAAAAAACKp5ovNjMLGvwNZnyMh9GmDEOjfPcwrs2lWP+2tDKfuqjKPPWxjvLtgwbg/ohH87yuzRRRpz0gi8TuFcB/Q7HLZV3cvUAAAAAAAAAAAERUDRuXGYaNega3PkVEaPMGH9G+e5hfXtKsf9taGU/dVGUeWuDHObbBg3B/RHyP55lNliikTn6gi9TmE8R/QzHbZV2c3SAAAAAAPzVczNHoflf4y626n6VVLJ7gAAAAAAAAAABwd4pFR2Ufzxa9Po8Wee/n6dNkRMtQAAAAAAD8VPNDR6H8v8ZbbtR9Kqtk9gAAAAAAAAAAAj5AUapbMP54tul0iLVOfz7YDYkVK0AAOI9cpiJuK9p1m96+fQAAAAAAAAAAAAAAAA8aBoo/nvRbTkEbp9yjVq+gAAAHAeuURNgiuafZfagAAAAAAAAAAAAAAAAPDP9HH896RZMgjd2WalX0H4xK51GJzT/n2gAAACpQxoylTJOIqVAACu2IAAK9YQAAAAABzdIw603jC4/oRFStAAAeeIXKsRO6X8+0AAAOA73n6AAAAABx+x7AHkeqOkQAAAABy9Qwy33HDY/oVGqx7TMc/oCOoUAAA5ergKTotFvRX+eYgz7683id/tFTBAdsPLFavNclCM+/j6WKt90qQ0hB9Z6eNuphNxfPoJn+gZ3ogAAAAy3UqURek4/sAAAPyYTquK/wBDx7CgAAGbXulHfdMv0AhO2o2ol6xwzJN835pxNWzhqhY46Esp79tOmjx9PlTLZGS3EdktR/hLWr8UctsHX9BOj3o15AAAGU6tRjjQQr+25zKxowoAAADNfTRvyZjZ7T8K5VNO+GWXGxiic2h/ooEzZRnPzRxVO6dGedd3HLS7/wDCoePbyEDqdIu4AAAAoF+xAmNYp1xAAAP553XMZ2NCFAAAUHokrIZpZrFWz2pVh7CR5O6unF8uHGTNH6rgUa08PAcHfM+5VImc9YluWZgKh1i6yWz7stRR9BgLCUS+wM8AAAM80LDCfWgS2Jf0JSScmv5/2QnAAAAAAAAAAAAAAPz+gAAAAKIedK4triT/AGUAABC4r/QlFLHL4DshNAAAAAAAAAAAAAAAAAAAFBPKo8G2RJP0oCmZd/QkMVm+4l4xuqoW2v0AAAAAAAAAAAAAAAcx08lHz8tEBZdNiPmCgAAAAKRmX9CQhXr1iH4jdFStlfQAAAAAAAAAAAAAADlOrio1BLNC2XTI4JYoAAD5ULgML8N6rsV2453Uj+hWFWetOVSfOwAAAAAAAAB8iyVUqtmsV7IPeLLT75djMdGm1AAAAAAAAfKdchhXlvNciv3HOKof0Kwuz1pqqz51gAAAAAAAAPkUSyk1s1ivZB0xYqhf7sZjo0yoAAAAAAB+P2K1WdLGJQf9E/gwSY06HiuyXnHFk66FyGo+2P8AibV9xD4bd54v6Gu8uZ9RdeCF7zwibfKmR/vcZExyx6AqGmQAAAAAAAAAAAAefoKzWdMGIwn9E/iMFmNMiCvSPnHFk7KDxmpe2P8AibV9xD4bd54v6mucuadJdeCFkDmirhKmQ+u4yBjtjv6oiXAAAAAD/8QAMhAAAQQCAQEHBAEEAgMBAAAABAACAwUBBhYVERMUMDQ1QBIgUGAQISIyNiMzJCUxRf/aAAgBAQABBQLzTfRwMmIk6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2C6bYLptgum2CnZNBIN6f5Jvo9Y91/SNk92G9N8k30ese6/pGye7Dem+Sb6PWPdf0jZPdhvTfJN9HrHuv2XVm6vdVF5NEnf3cNbePMN+NO/u4au6eaZ5FhPkUOmtXWEydnsaBeyEl+dc2Dq+KnOyeN5eye7Dem+Sb6PWPdfs2/wDz1n2oz0mu+8WZzQIXX4+BY9l/vglZPEdsEcMrNld2hFRGQHXcQhTHfUw28iFJNKwKHHfjuhxsufrDKiMgs7OEDGNld9VedCdFZ2jK95ewsjZ17DBwSWmDWdhHXxiHtKCrrUcoqzsoq9vJX9tXcRHPnlZBFNsv99deRFSIzYmRyEXUZldqXq0//Ck91/g82IKHOyu+qrtIT8FkxiQSbLn6gdgjmlMnwKM3YYMwVFu8+dl7C4ojZMYfVW8Z7rY2IKOqLjMHkvIozTNiYySruozZJZGRRzbJ/ezYIMjVhzT4fs2T3Yb03yTfR6x7r9m3/wCes+1Gek133jbfQ6sHFKzaxo43a72vphJfAGOsao1tfCLFDsXvEH/Rf+733sethxlFXYMMoGqS5aYbLie2efTvH12XMVrt3/fr9aPIDeBNfVakR/XYZ8lWfcYGqda922qN+DhLkPuq2Gqlm26bOG0xdcKNbPGeXYFOdrmsCRET7EFC4DUvVp/+FJ7r/GyzZktBz6iEaCVkFrZhQmxQT1NfEfJFKZdf1p6ANhhw4sA2e776zcANkahz9Ntt3pdT9utcfVaxV40Y42O4udtly0bWAosi7SHHFjUvQ/Zsnuw3pvkm+j1j3X7NuZnMWqkMcJaTMgA1mP67XbfQ6l6Hb/8Aq1x+I6fNhV2M9tWAwDai5/e7HjOLcU0dwdnO0k++9j1wxgpV0dDEBqcWXGFswLbujqGjVRFaQVt3/frvs/8A9T/qqbjXIMk2RnpNa92s7UWB+a2qKiZ/wWW3RZ7KJtfOIQVTwkW8GJKTWC4x59iNhaBqXq0//ClzjFp30axLHnOyRZjtBWVM4wxNTMTtsz/rpRq3IVrJFLYXPs2perUHvapPddu9Lqft1j7yv/29thy4bWDYsC7QbFLjUvQ/Zsnuw3pvkm+j1j3X7CYIyYZtdIY/oJ0rquujr4rkFx8FMC4CC6rnWDKkPIIhuvQyvZrTu0EOIKG1q47BR61n6itd+uXYMdlLRBRHJutZ+sMWISCzrIT8caf21tfCBHc1brCStGyGErmp8fJUAeAHnZ3kNXSvCMsqyA/Gdaf21lLCHJPCwiKbWv7q+giHlRuuskkh11jI6aqdXzJ2O1vGpFxqRC6/JCTYAwnRO1p31VdTCDmzr4z4ma1n6zNea9xAr56ymqnV8yjopGnoCikGLua91hFTg5AGJopJjV0KTx9jOPCPHTjlvuK+CvC1RvZXfZsnuw3pvkm+j1j3X4VuO8qvoK6cGX8YcLGYO6gMifHr5Usg0DBoPs2T3Yb03yTfR6x7r+kbJ7sN6b5Jvo9Y91/SNk92G9N8k30ese6/pGye7Dem+Sb6OpLaEZySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVySFckhXJIVaFYMMG9N8mRmJI+PBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwauBQAlV10p8lnXygS04gB2OPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwa48GuPBrjwaY36GfnLu5xAqmrksJIYmQRTwxzxWtbLXS0tzgj9fu7pUtO4pMbhjf4exsjLmocHmkuu39cdnDcXdzkhUlL9f3Zx24u6XulSXOYVjOM4/WJZGRR3Fs851JS935N3S/Uqa3cHmN7ZGfqxM8Y0NlYTWc9LTtF8u6p8Eqrspa6UeaMiL9UOLiDhKJJti6iqYC3zLipYa0IsiqKDKiMh/UrKwiAizkq3Nq66ICLzrWtjPjjeVUG1x0R0P6hbWcYDIISbYwAKIKH4FgDEdDLGVUGVVnGfH+nXNu0PFeDPaECjRCw/CMFiLhODIqiaa2Ya39Mu7nEKqauSwkhiZDH8SeFk8VrWS10tLc4I/S7u6VLT5KTG4Y34z2NkZc1DhM0l12/pDs4a26uckKkpfr+VnHbi7pe6VJc5hWM4zj9ElkZFHcWrznUlL3fzbul+pU1s4N0b2yM/QiZ4xobKwms56WnaJj511T4JVXYy1sw80ZEX6AcXEFCUSTbF1FUwFn4C4qmHNDLIqigiojIfz1lYRARZyVbm1ddEBF+Cta2M+Njyqg2uPiOh/OW1pGAweAm2MACiCh/CWAMR0MsRVQZVWcZ8f5cmZo8FOX40FXNu0PFeDPaECjxiw/hixoi4TgyKommtmGtVyZ4IOCVs8P5Pay+xuuHeGKu7nEKqauQ+SGJkMf4ieFk8VrWS10tLc4IWwm+LL1Uv6ovyUj2xxmTuKKVPCPOY1uGN/FPa17LWKCAxAEZELY7D2fkdpL7sb+aayOamZy5n4iR2WsuLI1+f51cvvRPyGc9mLMrxhsEEs7hdeIkQtIHAmtw3H4pzWvaVRhzIrXiY1NDLA6pK8Gd+Ic7DcPOFYnXADU6+Bws7EJhZ2QdckhXJYkdfMJFEmqoVFfAta29AymWoLkwoeT8S52Gp5wjE64AanX4OFnYhFJsIkjSp62ZBX7YBuSQrGyDLGwh5Tb0DKZaguTCoJPmzTxQ4mvQo1NsqlvjnqSwLkWc5dlg80iZVmuTaQ/Kxr5uVjXC1xspcbJXHClnXTFmgOwnUx7U+uMYnxvYmSyRqK0NjUWwltUOyR5UFwDMmua/HzZiIYVNfBRqbZcqW+OepDy5FnOXZYNO9MqzXJtIflY183Kxrha42UuNkrjhSzrpizQnYTqY9qfXmNT43sUcskaitTo1FsRbVDskWVBbhTJrsOx8MqwFFROyYRFubOsYfK+CnOmUOty5UWuiNUdUDGo4Y4/OkFHkUtMDIpdbgyptdJap64uBRyyQuGvTIkLsQ71BPFO345ViKKidkRFsbOmtfK6CnOlUOtyZUWvCNUdUDGo4o4/OkEHkUtKDIpdbhyptdKap68uBRSyQuGvjIkLsI0igninb5rs4bg2+GhRluWSoIJSHC66Q9DUQcSiijib8cgQchE66O9FUZkCxmSGQO/JhQNqKZ8NzsNabfjwoy2LKUA8xDhddnehqIOFRxsib8cgMchE66O9FUhkCa6SCQPYCIkDaCmeXZXcAqNPIMcDVlGIOgGiTGNjb80kWAlpuuYRI0wr6+6IFQFhAa3z7G8gGRpxBjgaooxB0A0KYxrG/NJEgKwbriIHmFfX3ZAyBPgNZ9080cEVrdSlIIKc19fRjjfg5Y2SssdeWcSjTVN7iTzSJ4x4rW5lLQIM5r6+kHF/BzRMmZY68v8AlGmqb3Ev2lkxiQWR8p81PSuKUMTIY/wtgBCdHZV8wElHcZHzj+uPJNKjDgsTpTpqekcQoo2RM/C2FfCcyxAmBlo7jMOf4e7DG257jyaCp738SRDGRFbV7wJ9asv6+RI9sbLY9x5NBUfXj8QTBGTDaAPAn1qy7f42kz6IqMHxpeMdmPJtbhoknibx6rbl0hFyRILX1czyAPttbDIb/tsXHYI888Vhg0jHjEVhXjAvv2oz6WUIHjS/JLLgEbG9sjPLKJiFiikbLH/Mb2yNjNHkJ82wEYaK7Eg09cTgsO5m7+y10fuK3ySpe5G1cfErlZVkZzti9nr35i12gLlMDvy5QwzDcjVQ41mXDWSWDDL7BfjoJCBg4M2Vph5B1TLcEvHrRup2UFiaUJLsBkwYzW2Fi2vMKgs7qwyFG0O2+istCibXytrH+gjUZv7vvtZu/saAfw9Z5Ni3Npc6wRl4qIvQoXBWopjySIhYuQh/UKTEVEaeOFiG/CkfjOHYOsRgkNehzvtPCeFF7rwxN4HA4S5EJffExQg64bB4QbwHUyioRI27CHl8MrJo8njYm5AF3kMrJo/I2ofuy9Rm/o/Pa8XH0i+SezMoOpPxkNGFwhx372y0gn+san7dtntzxWmVLILiuxXXPfkbJ63Zs5xVAx23gywrYuG2jdDrlF7TsfuO2+hC9Gd/tFj/AHbMosYxtvlbXj/12r57LT7s/wDz/wCqHH0w+QbPgUTXJIIoXTxB7DYNe8GhsRRIcCAllbS1/aPZ15MVeCOG2kjbY2BokRcGskOwNrsOC5revaePexuhoh4nT0VaLDWDbLMLLm5jZJV65BF06s/2bLMWOxyQxyRUfaJavhaRtJI8coupuzkPyNtx/wCDrb8sOMj7oqrl76u8owMqtN5L2NZCXdlbFjGKeoZ3lHVm9IV2XIeMRgnNQNfRxxQd5a3G0Nc2TvYboAGxfVsKNntpL9v0UlF7TsfuO2+hD9If/tF8HK/Ldhiyyp73Ow+VtsvZBqkf1H/eRH3U9fL3wPkbNLmR3HBFaUUQ4Vae19SyMG1hthMVRJpw40hFMFOtey+Gx1t2BjJ5WQQ6zE6SLVpMRqzLwEHbkOKoJiHja3WU484uxwCCstPZ9b9orP8AZoHYD2fOcYxT58Vew/7a/wDw1H0vkbdL/ZqkX1F7QN3R2qmeZ2Y7Vn+v8Zx2rOO3+M4xn+cY7Fn+v8Z/r/GcYys4xn+OzHbcvMHk5AJ2Uo80hvlXRfjD9YG7kH79mG7k/VTO1nkNrP8A2qe3D21lV4JOovoeJTxxT2AMJ0WKSbGK8GEGOxqoTXYosyZijZDGfUxFSso8OksgcGiNEZ4BtG+LMtBA4fuMODBqHhkDVvcWdjXwns6G92BBohIWVv022cduKiv6fF9+c9mLcvxh2tDdxX2geDQ8ZkGIqz2Hj/O7MdvlbHZ/QyqCccW3GGt++3CwcHG+QUisOYcP+J2Oz7G04OTi8Y7MK/qvE4EJlDnrLGI+P8PdXWIUPBKWRWhMBH8nYKrv8BlShz1thEfH+HurrEaFHlMnrg2Aj/zc02Cl/wAos9Zftem5w7H4MkiIaO0vJCUAFMbLWgRAReXc02CFjMos9ZfMkWM4zj8GUTCLHa3cpSrwZjpa4GIGH7bCvgOZY1RAWQbEgLIN6NOsZxnHz55o4GH7FjCnmlJlraGSZQQxjx+bY1sBzbCsICyBZEhZBvRiFjPbj5888Q7D9iU0spMtZQSSqGJkEfkH0Q5CNrCg0IcQJkTY8IY8Un5ec9mCrgMdF7DPIpJJSJAaIkhAVgwXwc47cH0ME6NrSQ0IeSIhNjxlDHDE/LznGMFXIY6L2GeRPfKRIDREzoGtHCx5hlOISiteIjU0EsDhrMsdD7JJhQXwUihJgm+JNYCQqfYhWIjYiXogqchDAFEoTXMoQEcTHxTKYQlFa8TGpoZYHDWZg6H2R+FBehSKEmGb4k1iJCp9iGYiNhKepyZyMi15RKE1xChDi4+A5rXtIpQplPrblNTnRJ8b48xGExKO9OYo9knwmbLGmbCHlNvAMrFsDlYsg8rx4i8cIuoBrNmFhZuAMJ16DhP2MXCfsuFJsZWVLcnSKWeWVQjTzKChNkQ+tx4Q1YIP8t7GvaRSBTKfW3qanOiT2PjzEaTEo705ij2SbCZssabsIeU28AysWwOViyDyvHiLxwi6gGs2YWFm4AwnXoOE/YxcJ+y4UmxlZUtwdIpZpZVCLPMoKE2RD63HhDVog/yHNw7EtYFKpNfDcpNaan62ThOoTsJ1Oe1ZrTMLIRWF4UheFnXhCVgAvKxWG5TaU9yZr5uUzWplHrUOFFRAsUQQ0X4NzcOxLWBSqTXg3KTWsJ+tk4TqE7CdTntWa0zCyEVheFIXhZ14QlYALysVZuU2lPyma+blM1qVR63DhRUQLFEGND5//8QAFBEBAAAAAAAAAAAAAAAAAAAAoP/aAAgBAwEBPwE4/wD/xAAUEQEAAAAAAAAAAAAAAAAAAACg/9oACAECAQE/ATj/AP/EAEkQAAEDAQMGCQkHAgQGAwAAAAEAAgMRBCExEhMiM0FxIzJCUVJhcpGSEDA0QFBigbHBFCBgc4Kh0bLwBUPh8SRTg5OiwmN0hP/aAAgBAQAGPwLzs/Yd8lkQ5TncwWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolWolRZNlNeNhUXZHrU/5bvkm9k/gmTcPkouyPWp/wAt3yTeyfwTJuHyUXZHrU/5bvkm9k/gmTcPkouyPWp/y3fJN7J+7EGxh+XXEoTOaGkkigUj+i0lRwGFrQ6t9er1eR/RaSmwuha0EG+vmZJgMotGCex0bWZLa3HyEqKEwtAeaVr5+N7WB+UaXp0rmBlH5NB5yTcPkouyPWp/y3fJN7J+7Ztzvom9oqfsH5Kz/q/pKbI9hcCaXLOZDssmgjXC2fQ9116bJGascKhGOCPO0uyq0C07MKdTkJYTdzcyfA6J7i3aE13OKp8Lonkt2hOtDmkhtLgpZHNc3IpRu1y0rMMjtXoSwmo+SGXpSHBgV9mFO0sqE3jFpxCY18bnZQrco8zHlucKmp4qillszwJK0oeZNmZcDsKY6QF2UaABSWjNOaxtbjtTYo7PkOO25DLq6R2DQvRm07SzZbm5dgrWqdJK7JY3ErgYKt53FCKVuakOF9QfIW2aPOAcomitEUjM3IRdfUFTdj6+R25WbteXOTHcBiVdZhk9pEN0JRiwp0sxo0fuuDswp1uTY5482XXB1ahPmcCQ3YFK/NuBbg0njJ0ZgyaCuUCsy5jm3kFxNypZ4cpvScaVRZkmOUCtMapjpos4HGidJFHm2h2TRGzmN1Q/Iyq3Its0WcA5RNFmnszcpwvqCnSSHJY28lcDBVnO4oyFjhIDQsqnSMYWgGl/3ZNw+Si7I9an/Ld8k3sn7tm3O+ib2ip+wfkrP+r+kqL8z6KSeVge4HJbXYoJY2hpdUOptWSMauCrPAJC24sesm0wmPryfqFWxZObdtDqq0fp/pCj7IVo3j5Kbc35hPdM0ObGOKedSuEbWvjblAgcyki5Lm1+KkfOTm85Q06KzORRnVHgowMH1aVZ+yUJ54xI55NK7Ai2JtMzpNClsx7bfqs1HfkaAHWnQt5MR+Sj3H5JshGg5tAUI57GGjDRAIWcslM6L6VNR8FBCOKauKGebWc8Y5FVnLDosIvFKXrO8uRjQfjipZJmh2bpQHrT5msa2SO+oCm7H18jtys3a8r27IwGhCHIqKX1jxTZLMTmxJo7kBaHua1t9QaLNte2V205OUSpJLOzIjOAU/ZCyZRWNrcojnTsxE1mVjRZo8ubJ/dGAQsDKUwVn3n5KDtqT80/IK0DnkWZELC2l9Rio2jBk9P3UMQ5bqn4f7o2iRjXPLqCuxRzxNDC45LgNql/M+n3ZNw+Si7I9an/AC3fJN7J+7ZpNgJb/fcnQVGca6tOpTOeaaJA6ymO6AJ+n1UX5n0Uv5n0Vm3lPeakNc43LNzxU/8Akfd+6dLDPR2xmVWqnbfm6A/FTV25PyUcmeYG5N9TgppWcVxuU25vzCc2Y5LJBSvMVK3ONc+RuSADzqSXktbT4lPEzcpgkqRzhGfIgLKVTRZ7IWSi+uSrP2SrP+r+o+Q5IuY67raUZpLxHpnep+wfko9x+SdZ7RC+Q7RkiizkUgjBv0X/AMpossmXkyUa4bVBKOKKtKDZmRZ9uOVtRj+yh4HKYKhPbAygaA4NUsczg0SUoT1J8LXtdJJdQHBTdj6+R25Wck0GUtYzvVz296e44SAOCEubgF2kDsTYmWM5RdRpyVDDXg6ZR602WXNuk5ecOHwUrrOAIsBTcpuyFN2Pr5I//sD+ryWbtKDtqT80/IKb83yf/o/9lDKOQ6h+KNnke1rw6ortUcETg/JOU4jYpfzPp92TcPkouyPWp/y3fJN7J+66KUVa5Vs8rHDZW4rhpGby6qIYcp7uM5Mja8Mo6t6fG54fV1blEGvDMgnFZpzg7SrUIvs78zXk0qFp2kU6mrNwjeTiUHZWRKLg5cJaNH3WqsEjWR0pQhTDs/MK0Ry1uAII2LStIyOpt6EUIo35oF2hIMHhektp2URHe44uO1RubIGZIpeFHAXZRbW/4+SN7HhjgKGoxRZlZT3GpKkZ0mkJszpmuABuohnKtkGDwrrS2nZQlc7OyjA0oAnRytymOxC4G0aPM5qEk7864YClB5C+zSZuvJIuT85LlyFtG3XBPe6Rr8ptLh5CF6Qzwr0hnhUUpnach4dSiyJhhg4YhaNpFOtqy65yXpHYg2TRc3iuGxadpGT1NTPszxG0Noa3160bM54zhaGlye90jX5TaXDyNtGebQSZdKdfkimMzSGGtKKNjXhmSa3p0Tnh9X5VQnziZoDn5VKeT7Rnm0zmXSnWv+M1T9HCqcbDbA5g2Ft4UTWuy53PvJ5k80xkPyH3ZNw+Si7I9an/AC3fJN7J9TlhiplupSu9SmfJo4XUPs10MuBwPMVWGRh6waFVtErQNprlFMiiFGt+7JuHyUXZHrU/5bvkm9k/gmTcPkouyPWp/wAt3yTeyfwTJuHyUXZHrU/5bvkm9k/gmTcPkouyPWp/y3fJCZzS4UIoFqJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok71qJO9aiTvWok706ZrS0GlxUXZHrTmOwcKLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLGbxLNxGR8/NlXNWjoxDjPVH3xniv51kSGRk/NlY7ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4ljN4k1owAp7dMFlNZeU7orOSkiGt7trk2OJoawYBOjlaHMOxZyMkxV0XjYhDaTSbY7pfh90Fjd1OkH0QmtFWwbB0kGsADRgB5Sx4DmnEFGaCroP3amwWx1/JkP1/DhLjQDajBZTSHa7pJs9sbo8mM7d/wB6hwTp7IKx8pnMhBazWPkv6KqLx+GS+RwawYkrNQ1bBzbXJs9sGnyWc2/zLp7G3SxdGNu5ZqeroP3ag9hDmnAj8LmSZ2S0IMYDm66EYQmtFHT7B0fNmazACbaOkix4JirpMOxCSF2Uw/hXOTHcNpQABPQjGxZTqOnOLubd53Ljo20Dbz70WkH34yhJCajaOb8J5T73nis510nnuaFRulIeM/z9+jKOK9dFwxGxwWVHc4cZvN+Eacac4N/lE1qeU84NWREN7tp9RyJRfyXbQhfkuGDhg4LozDjM/B5iho60f0oucTk105ChFC2jR+/qZjmbUfJBwJpXQkCzctG2gbOl+DTBZDWXlP6KzktRDW921ybHE0NYMAPVXRytDmHYs5GSYq6L+ZCC1Gk2x3S/BboLG7qdIPohNaaiDYOkg1oAaMAPVy14DmnEFGaz1dB+7U2C2Ov5Mh+v4IJcaAbUYLKaQ7XdJNntjdHkxnbv9aocE6eyCsfKZzIQWs1i5L+iqi8fgUvkcGsGJKzUNWwc21ybPaxp8lnNv9ddPY26WLoxt3LNT1dB+7UHxkOacCPwGZJnZLQgxgObroRhCaejp/6fXzNZgBPtHSRY8ExV0mHYhJC7KYfwDnJjuG0oAAnoMGxZTqOnOLubd7By2UbaBt596LSD78Z2oSQmo2jm9v5T73nis510nnuaFRulIeM/2HfoyjivXRcMRscFlR3OHGbze3aDSnODf5RNanlPODVm4hvdtPsXIlF/JdtCBrkuGDhg4LozDjM9sPlfxWCqbI7j4O8hiho60f0ovcTk105ChFC2jR+/scxzNqPkg5pNK6EgWblo20D/AMvJnG8ckBqZKziuFR7UZZWnHSd9FmpDwct24owWQ1l5T+is5LUQ1vdtcmxxNDWDAD2S6OVocw7FnIyTDXRfzIQWo0m2O6SyIzwUVw6yn2VxvbpN3e03PeaNaKlSTOxcfI1tqfkt2DpdSDWgBowA9llrwC04gpzLLJls+XV5I5hyTfuQc01aRUe0m2dp0pLzu+4I2xOtMfy+KBLS08x9kktaXnojajG+N1mj5uf4/cMDjpRYbvaNTgpJdmDdypDG556gqzubEO8qrmZ13O9UaABzD2XR4DhzFVa0xO9xVgc2UdxWTNG5h6wo5OTg7d7J0iBvWlaYh+sK+0D4AlXOedzVcyY/AfyroZf2Wok716O/vT4Wskjy7i7G5Vkgnld71FktZIxvNkhXyOG9pV1pZ8bloTxO3OHsnSIG9aVph8SvtA+AJVznnc1XMmPwH8rJdZ3vbzOAVY7NLE73TcmRPje8suylqJO9XxTfssJh+lXykb2lXWlnxuWhPE7c4eu1mkYztGiue6Q+6FwNn+LnLRcxnZatO0S+JaRJK0IZHbmq6zSfEUWppvcF/lj9S48Hef4Wth7z/C1sP7rWwd5/hcaE/qP8LisP6l6P3OCvs0vwbVabHN3hcG9zdxWjaX/qv+a02xv+FFw0D29k1V04affuVWEOHOPXuGlYztFaLnSH3QuBs/xc5XOYzstWnaJfErySVoQyO3NKus0nxFFqab3Bf5Y/UuPB3n+FrYe8/wALWw/utbB3n+FxoT+pcVh/UvRz8HBX2aXwrTY5u8Lg3ubuK0bS89q9abY3/Ci4aB7eyaq6cNPv3KrSCOr1Thpmh3RF5VLNDXrf/CvmLRzMuVwc9x+KugLR79y4adjeyKrTdI/40V1mYe1euDjY3cKee4SCJ29q1OT2TRcFNI3feuCfHJ+y4SzvpzgVVYnuYfdNFpubKPeCpOx0R58QsqGRrx1H1jhZm5XRF5VLND8X/wALSmc0czLlohz3H4rUlo9+5cNO1vZFVpukf8aLRszP1Xrg42t3Dz3CQRO3tWpyT7pXBTSN33rg3xyfsuEgeBzgVCrE9zD7potMtlHvBUna6I94WVDI146j56rjQIth4Z/VgqGTIZ0WXKkMbnnqCrO9sQ5sStJrpT7xVImNYPdFPWOGhY7rpeqwPfEe8KrWiVvuK4ujePgUBPSZvXcUAx+S/oOuPqZLiABtKLYBnn/sqOkyGdFlypDG556gq2h7YhzC8rSaZT75VI2NYOZop6xw0LHddL1WCR0Z5jeFUMzrediq0ujePgUBOBM3uKpG+j+g64+bLIuFl5hgFwz9HojBVjZks6brggZyZndwWTG0NbzAevUnia/esqxyU91/8rJnjcwoNec9HzOx71WF2ltacR6gWQ8NL1YBVnfUdEYBVYzJj6brggZqzP67gsljQ1vMPXqTxNf17VlWOT9D/wCVkzxuYUGy8NHzOx71WF9+1pxH3zJM4NYNqMcFY4f3csmBled2wIOl4aXrwHsMslaHNOwovsJ/6bvouVHK34EIRW2gdsk2Hf50yTODWBFkNY4P3KpC27a44BB0nDS85wHw9hlkrA9p2FF9hP8A03fRcqOVvwIQitlGv2P2H7plmNGj91lPuYOKzmQltNWQ7BtcgyJoawbB7GpK3S2OGIVJL2HivGBQgtJrDsd0VUeaMsxu5udZclzeS3mQltVWxbG7XIMjaGtGwexqSij9jxiFkyjRPFcMCmwWo1i5LjyfKXONGi8lVwibxAhabU3Q5DDt6/ZLo5m5TCqYxO4rkLJMfyz9PMue80a0VJRdhGLmNTbTam6PIYdvX7JMUzcppWSb4zxXc6FkmP5Z+nkbZmG997ty0tUy938Kgw81mYW52fm2BZYhoObJC+zW6PNTYDZepJYTR4p81DLKavcL/vQRtZlOlNKnZ96D7G2sXLw9QdFJtwPMUWu0ZIyo5eVg7f5hllYeNpP3KrxwMd7uvq80HWh+QDcLqpr2GrXCoPnM5O7JZWlaVTZIzVjhUH7lWODhzhPs7H1mbi2h886J/wCk8xVOLJG7uKjmGJF+9Tu2B2SPgmHlSaZ81LL0GlymtkulJlUBP7+SNxcWPbym4qTbxfmhIzjNicR+6fJOQXB9MOoJkkBAcX0w6ihaDR0haKbymzvt2byxlBrQn2e2NMkY/wA2ihzrmULzmabL9qll/wASewlt+hzLOtm+ywckBM+2SfaLK40ytoT5oCMq6hWfZaBC0XNA5RVhiyxlPAzl2JUb4CA4vpgs8yf7LCeIALzvX2G3OzleK5MbCMqeS5oWd+28Ljm9izM1Gtvq2m0Dzcc45Yod4U8H6x/fd5id+zKoNyj6UmmfNGzNOhCw9/8AvROs7+PCf28mSC+TsBZEbiJOi4UWcneGtVKTU58lZyB+U1cO+hODRisk5yPrcEC01B2qkz9Loi8rJq6Mnphf8fqa9ePwUWY1WTo7kW5TpCOgEGBzmPOAeFJE99HyNOSKYqGy5fD36NDvUuY9Lvy+N/ssud4aPmqESgc5ag+Jwcw7QpInSgPjFXVGCyeFp0sm5CSJwcw4EeZZMP8AMF+8KeA9sJxO0qEDAMHmrQxuLmEBTM5QfX9v9PI187qNJonvYatdkkd6P5D/AKqT80/IKP8ANHyKjheaVY2h5lkwkTwjAY/6r7PaojDMv8P7X1CdTa4VUOYlgEWSMn+6LNzSWctx/u5CN/GYGNKs+76qw/3tUX5n0UHYb8lZeyPqrGHYAD6+SSnN/wCvm2HmkHyK3sPmWAYADzMsx5IUs1otEQmldyniqzsMjHQzcbJdWlf9b1O2LjlhARhtAzUuVe6mKbaoy1z29BysspblwsOkFm8pjARxJBRO+zV09taq02u0DLyTogoxytHUeZWiGT/IKtFttAD35V1dioMkSjiuKjjkflua4DKUUUb8hzogMpUlfEJTe55NFE+zvY6YG8sUr3sa57WXEjBRS5pmdqdPJvxVr/V8wpGTXxQji7v9Vm3saWc1FarFXg+MP73J8cnExI57k+JzG5FMKYKVuwP8zEduc+ieR/y/qFMzovIVnf7gHm3WqwNyonYtF9Oqi0rLp9tMktLc3Zm/3cpAMBk/NRM6TCFJZrbE8VdlAgJskcTmWVjuM/lFRfYnZMoY07xRBlsjlbM0UN2KitbInR2eIcZ21WSfJJYw3/sp2RZQGGlzr7Lb4ngN4rgmQ/4e2RkYNXSYJzcoupkipxN6s+76qw/3tUX5n0UHYHyVl7I+qitdlFZodnOFTMS5/DIA2pzrQKS0LiPh5uCLaXZX996kfsazzEkZ5LiFBJzsHmbPYouO81P0Wsn7x/CfNZ3SlzL6OIwQnmOrFHrPZprtlcHKCWxPcHuPFTIp8ZOq5arIPOy5WqytflwMr31Vqsktz63ddE6SQ0a0VVrmd/mmn996tFlfdK11aJ8t2Vg0HaVHM9mQXPFyifFc/NtFeZRz2hz5XyDKOkoYrOxrZK1NMaKf8tRbz81a/wBXzCmztwmFx33qpuCtdqbqxcD8lJ/fJTtyn7fmbPFtqXKZ5wDKfv8A6ITDiyj90+yvPvM+vnMPJf5L1f5Lx5blf5L/ACXhX+StFFPZauiGsYFURS5zmoprfaWZsvua0+be9urbot3IyO40pr8PMZwcSW/4p1lebxpM8ybbJNl9FmTh5C114NxUzTLnYpBewtRdY7XLZ67AhPaJX2iUYF6DJheMHDELIb/iMwi6H9lFsIvOLjiUJCTHMOW1D7XbZp2DkpscbQ1jcAFnmudDN02oOtlqltNMAUIA/NgEHCqbZZdNgbknrVLPb5o4+iP90WNe7Ok1Mrryvs8pyxkZBOFU1zLXIYmmubpcpbXna5yujk4ICUEOGDhiFkS2+Z0PQ/srNwNyW/NOtudx5GT1c6IT2ZzOZRrxaeYqcE+QcTit3LLdxpTlfDYnRcrFp61W9ksZ7issXSDjt5vX60v82bLAdM8c83Ums5AveepBrRQC4eYdHyxew9aDm1ZLGUHtucOM3mPso2SA3nWH6IN/y23vKoMPJ9os44YYjpISRGjh+60dGQcZnsh0FkNZdr+ihHGC57kI2Xu5Tuc+aNps44UcZvSQkhNDtHOqsueOMw7PZDoLG6r+U/m3IRxCrihFHjync5+4ZrPRs+0bHLlRysO4hCO26Lv+ZsKBaag7fYmXO8MajHZ6xxc+0rIhbdtdsCyY73HjO5/OGay0bNtbscrsqOVnwIQjtlGP6ewqovHsTLneGj5oxwVjh/crJiGjtccAsiLE8Z20/e4UUfseMQquGXF02rgn6HQOCDZuBf14d6qDUewMqZ7WN60W2Nlffd/CypXukeUH2uscfR5RQjhaGsGwee4QUk2PGKq9uVH024Lgn1Z0HYICXgX+9h3qow9gZU0jWN60W2Jn63fwsqRzpHlB9s4NnQ2lCOJoawbB5kuh4GTqwXCR1Z023hcBK5o5tipaov1M/hcDM0nmwPrd61ucdzMvVLOwRDnN5VZHOkeee9Ay8Cz3se5cGyr+m7H1GhwRdBwL/wDxXCx6PSbeFwEpA6OxUtUVPeZ/C4GZrjzbfW6m4LWZx3My9Us7REOfEqr3Okeee9AzcCzrx7lwTKv6bsfO1yM2/pMuVYHNlHcVSaNzD1hcHO6nM69cPA13W00Wk50Z94Lgpo37neqcJaIx1VquCbJIe4LgWsiHeVw0r37yuBhcRz4BVtUv6WfyuAiaDz7fVq5GbfzsuVYC2ZvcVSVjmHrC0J3U5nXr/iIGu62Gi0nOjPvBcFKx+53qnCWiPcDVcEySQ9wXBNZEO8rhpXv3lcDC4jnNwVbVL+ln8rgImtPPt9Ro8Bw5itXmzzsNFwE4PU8LUlw9y9Uka5p6xRcHPI39SvkD+01cJBG7dctOzvG51VeJW72rXEb2lekNXpMXiXpUHjC9Kg/7gXpUPjC9Jj716QO4q6Rx3NK0Y5j8AtCzd71oRxN/da8jsii4WR7+0argonv3NWk1sY94rh5nO6mii4OBted159byXtDhzFavNn3DRcBOD1PFFfAXD3L1R7XNPWFwc8g6spXyNf2mrhIIzuNFp2d43OqrxK3e1a6m9pXpLF6TF4l6VB4wvSoP+4F6VD4wvSY+9ekDuKukcdzStGOY/ALQs3e9aEcTfhVXzkdkUXCyPf2jVcFDI/c1aTWxj3iuHmc7qaKLg4G15zefWKOAI61pWaP4Ci0c4zc5cHaSN7VoSxHfUK5jHbnK+zn4EL0aXwq+zT+ArUS+ArUS+Er0ebwFeiz+Ar0aTuWopvcFfm273LTnYNwquEne7cKK9jn9py4OCMdeT7Do4AjrWlZo/hctHOM3OXB2k/Fq0JYjvqFcxjtzlfZz8CCvRpfCr7NP4CtRL4CtRL4SvR5vAV6LP4CvRpO5aim9wV+abvctO0MG4VXCTyO3Civjc/tOXBwRt/T5/wD/xAArEAABAgMGBgMBAQEAAAAAAAABABEhMVFBYaHR8PFxgZGxweEQMEBQIGD/2gAIAQEAAT8h+2DXRIcE3dxb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntb57W+e1vntASnhFpVP1a5V/xQ9foWrU/VrlX/FD1+hatT9WuVf8UPX6Fq1P1a5V/obOqEYDM2ac8oB5Ig0OWGrBSrUhlmI+PzkGhyw1YI8RBhGQ+kI9ycZxQb5EuPH4uADp1ngBw+8xOgiZoI3oM4ewHz9mv0LVqfq1yr/Y2NNqtbq+EIOrfhfwhoSHOg8LSbAjNZFTgdZqIeoRZZGSKIuqmV7wZ7IrInAlMqFNuzcgYuAfKYgMBIV74BIGMHQNDFaRIHlQ+OEIJC8ui6cAhYJ8GwIMyoUBnDvOtU0C6MYj7I6MEFVNKzA8QUCNRsB1nFEFSwUguYoN5d1AQWRgtbHee3VCRYIyiKOyGJDbAuTdop3xNgRl7k/JPntuVjhKD2AciaINsmZPII/k1nuVHsKJYOYBSYshB4Bc1LsR0K19z4xxay4/LmUYTzcsfqPsgJEFycQbQrqoplQJ2xHOCOxMAERfRDuu5mGKgZWBDkXyQmwzZAuUOFFZjW4I3YvpCNmMiWBcUQ4wgGhC9FRESJpsC8OKjR4MWmdOtA0MPAIRM1A2obMBxYhgw2UJPKxB5iYnjaDaFB1b8L+f86/QtWp+rXKv9jY02q1ur4Q0V5MSJguIHduagYfRoGbyjcJYDdp04uZsooENByuERHwXLkoSeL/CGoUWiUfAYQhpYgSk/QovQjeMDsn6WdcORKfxFYAFockYELDCAbwNUWbruDjEBahVU0QCAtLiCg12WVgEx0TJ2eR4KUS0a23jDkg3BhSRaXOevwMf41sDh3CBasc+ryC3lCgDM0hcAkSRiXpoDuVF6ZcgB4AHgyZ4QBBAujohR0UuQeSGgRYnDui3JMoSBs4diD1WvufGOLWXH5JkloOTnurIyG8TqVavGTeZdCyIU+FsvLovcIkPUWZFRHgnADQjK90RKMz3gokVOGmAAxRwIsgzZEXRg4IsdqLRkiIXvW9PpzEHUliHb4hlDzIMULwBMSb5NU+csH3BqKYwJeIJAcUXaKYpmZEWEDg91orn+dfoWrU/VrlX+hjBN3MAjuRSiKC2St6+EM24UTMEAiBHYv0Rory0VxaXQIbZAgHLABCEWDAI5WFwiaRzg4YtTDmJBYHb9EUwYAQvDR4TFECBBJpFODTo2gQ8fAYfkM7IEnumh0KL+JYz8EzK17z0VEJnRPL9k2BWGIc3NW5ASMRIGHMFahX4QIAEEOCnsQlEKDIq1SgbTl5PJa3V8DDsJnSHaJlNTBEENxEiB0GF7UWOfgAmI8p3/wAiWQeBRFzQI51RQjSzMBEhuDoPBXJg7oPzTKIgdMdyT0WvufGOICoEx4LZKCAWTAACh/Rg5MeyGsOIkAna6GCNgLGMDN0CEQIgC0/jymC6DA26oJ9YAyYQAQHJa9ULX3P8Say4rEO3xD1F/wA4GRINcBmSJAcE2aaYoi+KRcFIDutFc/zr9C1an6tcq/0Ntvo3XhNdGJERoB4AWs0SI2dDPwoEVkRoPYR5RWRGg1gHhOJ4Fju6fnXNGmiISJzgNEytePPdPdMS8cWpQ4xCsQ7ihCkv1BxQmGgAgm8kq4YAo6xGaYnTNiCxTSMiSZlUo6JDahoRaF3pe/R06Df/AJAhy40w6EakQM7kfPwQ6+M4yzyhHwaeG4BEGli40cIcRBhCYRgYLTLUNQpuKiY8oqOYOQBCrAMROGWLDojmE4NrwSfKmmOMnLwOFFHMSQORO9BvkCw0fi8AMt0LdCC4jQHFi6ASHinFTY873UV5QzTcgROjFTXovLCnFQezAkiczKBCkYEho4IN8gWGj8FUcOPvN8Os8AOKMTooHeCN6DMGsA8KOZgHX46xve0ya02+KxdwUdDBOZwdR0pQRYDIWByiFGPgajc/zr9C1an6tcq/IOpYAwgJ8IczSIq3+a+xMBOoi0OsN1c1fzYaeaaqNhn/AJ1+hatT9WuVf8UPX6Fq1P1a5V/xQ9foWrU/VrlX/FD1+hatT9WuVIKIWwitqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2otqLai2oh/hC0gGWrU/U8c8NqFbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MkCNXwcyGCbMRiCAuFSrs0BDIUxPbINfgwW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJbcyW3MltzJAcTIHu/uslyAxFwXo0jOPMoM0OArAQmwxJBER0wdDfemvpcoe/wDz7sm9BmREeYkH1QaqsAwA+RCzYBwQh0uXPluvXBstF2b/AJwJQJyRYAJwiVLPqiQpPiFy5AAAABgP8gIAEoEG1Ee8wM74uTpskk7hu7ISKCBwRb/zIFwvIBTKRhab8kBqmcuO9d9Mm2YGRA8Ytk3XIPs3Igf+XDMtVbghzcCIJNTUoCJMzB73/WPnjkj3UDtEMTqKFBOSJH/Kl7USDNoEcaEtIjq1C7bXFz7Rk0kLN3MgawBaRPu9PlyZMqH/AJN4tkDH0vVupQS8YKQBxBE3Cg++RQ8AYGoRQGM074J/doZnlf8A8i2bC8O+4j6I8ZQ1YheOM6bf+GFAMmbqxHIFoQYJqBhZmIu/483BQ4i+b7lMu6L5CpQnXWFU3/jcbMjaVQgnwOg393IIYTgvDL/jWWZAJXBf2T0o8eZQZoXBW/KBZlYkgCI4Ezob700xKlD3/wCLdk3oMyLDTUg+qBTRgGAH5xDzYBwQhoOXInxbr1wTLRdm/wCICECckWACeIlSj6okCT4hcuQAAAAYD9ICABKBBRHPMDO+Lk6zIJO4buyEyggcEW/8KBcL2BTaRhab8kBrmcsr979sm2YF65B0Ytk3XIPk3Igf+DHsxVwQpOBEEmpqUAEmQmPe/wDePnikj3UGPEMSqKFBeSJH/AlrESDNoEYaEtJjqZQs21xc/gjltIWbuZC1gC0jpVOlyZM6H++8WzBj6Xq0UoJeMFIC4gibhQfw5FhwBgahGAYzTvgnt2pmeV/92EYXh33ETRHLyhqxC8UZ02/+LCgGTNQiFEag4JqQF9gu/sTDyV9yKTBpIhYR6b4NSUOIvm+5TxeieQqUPV1hVN/8d8tyNpVCbOroN/dyCGElZeGXwU7DVG2LnAFGJcP+pTCujseeiEdg04ysT4TLMgErgv7J9UeNMoM0DgrfyQDMrEkIRWAmdDfemiJUoe6HFDhhK0K8wSpjr3/pvrANQBW4qagsHT45LfHXrEKmjAMAP5Y16sA4ITdp5vvW/DstgraHRB3AiC0H+l2plHM9j/goEkGYvqqjjkImDjp/JA9IgQA9SNHsIS/m5f4mXXMeWX9ERygAHJNiJE3ligyXN20yZqP5UMUzEAtXHSSFx3IDAfyzg0zA4KdS1aUOkk40H8RhirsDtIpEz8/PPkgQQCC4P8hyBakyndUiKenSQCxVXysOJS0nj7I2XSLZaoQwGWoOmapjw6P3QcHpAIDoVoVVwUlHN3LHISBcOP5ANwtSZSWGjXU9OkgFiLvlDpoYFyZAHFPFRh4D4Qv6NcA4shwQt+iVhXAF5U+4wM1oTVwUlPN3LGoynL9jOLco/gUs85ZEiA6UhmnVluPLqdoUBAdAn5URLrHqypGdCam46u1TocZCZiUFokbtkRs0ACXDISjhhU2I8T5XcO9ixfoIw5e/Cm54lQ0Xe5gm4X4LvZMAoYO8wQyabRx+4C/AUJ7Gnc2UQAjisBmnFtuPLqeoUBAdAn5WBLrGeykY0Jqbjq7VOhxkJmJQWiRu2RGzQAJcAWSlnCCpsTifK7LzPZYvEFiD4WhJ4qEj7yLBNovEGVMwpTNghc9yJOPyPAANgCEcu9tgzTwD/RaKYFIgSKYDUxdpimQ3ITvZNL/eAYLvtO9YGP8AcwUEqxpVL6J5fboHwn8hKOTyxTk1CgdQr4XkJM4oGN1CY6KN7Bc3rTfoegIGwBDi7v8AwzTyCm44Jg2JAEimUitEMM0zG5j97Ke3exgpyeDzWCHj7TGa6mASsShR6T3y2MqeSIo7sYYp0bnsAV7LyIwjmu6hMlT8qOCvGO833FIgYkksAm0kXAPPJO7iuXWa5tnm4phoo2sUzmsYXQK4VoA/Q6PdXcmnehB3sU4Aq0nPSafVK3AmxVPcqIP+kr+OJnYkYBPxAtEB52p2JJcMyqz+jNxKZ9GFZimI1bA6CCu5iA/Q7O5tdyadNLFbinYIFq56TVQGwSBX2xPdTA59Jby+uAgcHOoU/j0Qh5JgcvpK8ldrE9lDoGkyA/cysWEIjgZhEO4amSnYCZHgbVBibaDgkjkLHyvwQkghF1jknUbGBykwPL0lU9PSLZoCCkgsB+7jVAQcDNTNAsSmY3EDwNqd0zaQcMyiTDRcr/c5SpIpZXnU4KGQEyHEKaGAWj0hn/DmseC4QjATNzuzTHIO8Qjh0nI8Dj9tt9Q9gi1mTA9U+FF/Cg4xTUwCx6H8NM5UF11lc7s0K/eIRs8mEni0OH+bKSBaVAnw2YMPa9ArcZGQFI24D+NAmDWOyYNZBsG5EFkgafqiACAgxBH1MWBgAmVAn0sSTAc70BGLjIyAoLvwBgP40LkGoRFyiKaE23IockMEN3ZAuHEvgF4VxYEcCTBXNTeUMHifEV38kJQGIKdd4yvcb0SJxa68vpAQOEWBEi/BgV4lCcSbGH8kIix0vCj3jabNEjcgRdeXwZvMvjmeyZwOP05kAAAAgAPqoztTQ1NyADOfCYEumkDFxiBoIMihFCWEh5gEIgQJANaf9BdRcQBw/f8A0PnCdoI33fgAdCLoRT0zDCwi0IUBcGKBP6DREyAdeymCYvliAABhAfS+7Mw48kAgMAtB+y8zgi5JjxTBnB/xFmpDjhxNRmZhTNOLN9zQwJj0YopJ+mBTKggtAmiu7kcCDwgFxrBh9UCHglWDqcBLMMy4xGPwfssiIUQsMkkDEbYEWhj9eHBGxtEhkHPKFjaZLoOeEH5hxkRIjmyIYykyHzCANAhCNvdBve4AxpOCOgUgbiUhF0dDFLAuT5KKQJF6D1kghwSjhiQjAARmlTJ57J7GAJswApxmq4GDFA4Ibugq8Sb18K4jTyhVS3Qdr8VFwwxB0UwQIMYAOSIjxH1iD9WdOyK6MCADA/QO9u7wEB2QoGA/xlg31QWQvRs+oOSdPDVjN3t/gpJQWJER1JCHC1J0PhHADg5tNBVdvk3d01k8xaYNCEIUUHLkgqKWNsCUMoE4AuCEUEVDgcBApnjBoA8wSuUPgqXCtbsQnFSaKMYdSwR/yswOaPJMyvPCgpEY8+MzNJa1Dh58ElSHdeAK400bAupE3SOE10LkACFrNaERTD9R3wUb2v0gQOwb0KMik5AMDA+EaeCEochCOn1RwuNjIMTNxcQHl8HRNdg8dBRSz7M4IMotJD5Q4ZcgHBtABigCWlYAOBboTSaYCbE0YxCxxAgkD4H2USUMBEQL0PD2QwQihwwWolAhCA2Gj7ljPFaK8gAGAwHafFFpBMA8S7/Aia0XNr/WM2pIIACwnD/ZMRoESSJMygyMQ6fS2DPAqbB1UbZgAMF15fBDM7wQWjsh3dsRaWkiUXDr+a0Mmt7F4TiRLWoQxKUHcT4p2GkLTwoiJAYSUandQQhnwHdoXABEeHEqJ1CIGTEFwLuOoPVEoFs90z4AUYTg2Ko6J3Z0xnmhQBex2hHBPbgQB1J2N5RJZH1l5F6LPiRpPAbFwrSWwnOSwKkRumORgHci49hnwI3uIO7czYsFFEM0YASx5gJ7sGBI4Ecxd2LnA+kJsZnUslaKkEEK+wQABdyOIgcR9ZuUYBxCoQcAzIMGDsjwTYBiA1Kia7IToBAAFkCiS0Xo5KK28jkiwHMQCGRw0Alpij8ViAATOAPqCfPIcaNqAEANALXIxKBonvFkSHZUFIQZoCCn55Ld4eQnnqxIeIkO6d8qO3YCJWJ9yxnitFeWt0fBDz3OQDkBccWNl6FXNlMXpC/Cop5MR9YnWK6QyGtBjmSPf0EmjpJQhBeM4tHH6Y9QYubB1fog0HeUY0sRAVSA4o92dgOXFsORTnAkkiDDVIiia4MZcwbqDRF1MAARsJZyZMhxLD2vZLBGKgEDYwByt6IqQt+Ex8GKGvfBUI0NT1dBFtmtsPRsUcLw7EJ73SN4RiidQHeNFTczABmnA+T0CDkxRuQSTRalgVAAb4DykDEMjMoAHJNimQEaiQwArCHsWOLAO30gApiJHCA7lNQfrpDMiAE5yQPhCaKPGweev2EziD1b4AAwAi9AABgGCADACL0AGAEXqSkgeI+JoAMAAuQAGAEXoAAMAwQAGAEXoAAMAwRRwE3hSADxUkSOA9WUmPQncO9MQp0ShDd+Lov4G1mhHoAPqJYOZIJg/Q1vMuiBTdEy8nn9BCigt4IHweaFNxvBaPPM/S69lwELCL/ALgGQG0FQpszH5oaINvVcPKBCiifKgDW3uioBFVbFCseVLGCL0vamRQiaaOnLxcE47koZIGsCHg7zeIVd8SBiSUIEICIQFjOFD+JMzQW3IsJxtPAdkJnFjNOFlU1OxiFgz3Iw1gHEcNGLYLpnlEQZvd8FYedcOeSGCHBQRNpKpKmryi14V8gZXtXkw4n6AEIAESSnvQdFp+aIATawx5o2mE+sDTIWDqECEWYGoy/fZC831ghasOx5FCCCOEcxQUATAsH0AAwjSz2VSANhFiY7grbK/lCe2EGwaRRJg9KU5oQggAGAFnw8wPDs5oheGIMgoQn4bKIYi8VH8gEBlCiOCpRkTOScSSo/BG2+qI8YIViovTSVgSQUKfq2iI5hf/ICAJIZXbyOUPckyAtJKi2TWlb/ABWqJOSVnMBC2MsAOpTtwQSgTgC4P8QvvsmeAtQp+4HTYKSgnYqZtamZ5XfYfGmJWSU/COcQhthQHGp2QkUEiCLf4hRZW8+AWoC+UDHr04KCOGs9kxh5zN1Z/ptMg1SIRFSgoc6KfK1FPLkuujx6VQkESIIt/gF1aDZRJtOHLMpOwB48gEeta1IKWRT7iQ2DSbMI6oPvKIIFRienJPSuyj0qgAICUiP4F+MDnwqgCKGn2zKTmYeJ4BEHU0BjU7qXbT6AgEEEODYjkXUR8rOSIEmBoLOaxICXIopm+mbNNLntnAMf1gISAAmSnYEAa5linzWt2KWLDkSTE78I9KoADW4npy/CAgASgQUfLfsAcuVnJEiTEd5s5oxxOj0lMx5cUdWab3pW3QY/rMigEyU7CE1jJP8AW9tqWVURIror7npVCl4RDy5fa7k80hJP1E8+GK5WnkxhjuuKZBqEYumO53nDrosCJ/GSwcwCfXAWHOgTgKqbvRwTmKsbvQwRd7sgdJJpc9sYhRTN9M2S4kFiXM/lIcMZJ2i2sJJ5oR4zDFXJ/MEyA0brimYaAGLpnuV5w6wPo/jJADksE9sCKh0CchWTd6OCdRWgHehgnxdEIckwklssQqTrtWSa3MEuc/wnBpmBwn8gy7JLBDuacwxGSfXrRDDNXTKMSl/UBN0UqK48MsUKcyNw2yLB+PBUz0XYpfzwR4Ui54BA+ixWtfKIEkw5b1OeWbwtOKvUyHgDurdm9rwpDd4Jd1MgaAQm/FlOo8YhMd/vGHTKeGJ1LpjLHqj+siIswuE9EEe3tJIZzrwcOnm8xDCIq7LbRUregm6KVBceGWLDZkbhNkWH0eCpmWrsUr5jhSLngED6LFa18ogSTDlvU55ZvC05q9diEHdW7N/qUBB8Rd1JloDsRVyl6nU4MR1TKdW4B0xk/cvlMZa7PGP6LiBA6cIw2+KvPu7goroT/laBxwWGg+VMHxXYqd8sipMtVERz+MSBpE0UUi0Vyl/PYrShcfK0qOQRmP2RYB1nU2288Mp39AP1/h3HaB06TlPip3513BRchc/5WIO8Cw8Hypg9BAqd8sipMtVERz+MSBpE0UUi0VylfNYqPXPytKDkEbjfkWCZZ1MwvPDKedUA/X7/AP/aAAwDAQACAAMAAAAQAAAAAAQ7wwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwnAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAAAAoAA4gMAAIEIMAMIYoIIEYIcAMIMEMI0IEIAAUAAAAAAAAAAAAAAoAEoXK+iWrTPqWEArzbKPo6MHCT02GqIDroAUAAAAAAAAAAAAAAoAAAAAwQQQyQgQAQgQAQgAAQAgQAQQwAgngAUAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAAAArAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAXAAAAAAAAAAAAAQwwwwwwwwwwwwwwwww7A3wwwwwwwwwwwwwwwwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYoAQIIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPAAAAQ7IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEnAAAAAAQTIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEDAAAAAAAAA7IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIQgAAAAAAAAAA4IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMQgAAAAAAAAAAAAQkAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIIAAAAAAAAAAAAAAAAAkoAAAAAAAAAAAAAAAAAAAAAAAAAAAA8YoAAAAAAAAAAAAAAAAAAAkA8AAAAAAAAAAAAAAAAAAAAAAAAAQ/wDyAAAAAAAAAAAAAAAAAAABL7wAAAAAAAAAAAAAAAAAAAADCDCL0/CAAAAAAAAAAAAAAAAAAACBA8yBACAAAAAAAAAAAABB/wB8PBAAADOue8wgAAAAAAAAAAAxfMttDABCCdsfswgAAAAAAD/DAAAAAAAAAAABBBesAAAAAAABz8jAAAAAAAAAAABCDu4gAAAMiAAAAAAAAAAAAAAAACAOgAAAATPgAAAAAAAAAAAAAAAACAMQBOAAAAAwQAAAAAAAAAAAABCMAAABegAAAAAAAAAAQAQAAAAAAAsAsAAABCCTDCySCQQDggAAABQgAASsAAAASiBhCQxgBCwjyAAABQBMAAAADBCQTCjRBwyCgAAABigAADMAAAAABCQQhgw4zzDyAAAAQwCgAAAAAAAAAAAAABAAAAASOAAABQQAAAAAAAAAAAAAAAAAAACfAASswAAAAAAAAAAAAAAAQAOAAAAACT8gAAAAAAAAAAAAAAARyuAAADC9cwwAAAAAAAAAwx8/AAAAAAAAAAvswgAAAAAAAAAwi/OAAAAAAAADDTe9vM+9v98vCAAAAAAAAAAAABBDYtMfM+seuOtAAAAAAD//xAAYEQEAAwEAAAAAAAAAAAAAAAARIECAkP/aAAgBAwEBPxDuiyarJ2G0v//EABgRAQEAAwAAAAAAAAAAAAAAABEgQICQ/9oACAECAQE/EO6JRilG6v8A/8QAKxABAAEDAwIFBAMBAQAAAAAAAREAITFBUWFxgZGhsfDxEDBAwSBQYNHh/9oACAEBAAE/EPutQKIwlCw2i2UMt2vgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNPgNAqIKsgkmu1NXWV9P8AlsPYNj/FVPY9v5bD2DY/xVT2Pb+Ww9g2P8VU9j2/lsPYNj+JAdolzhBScsEgJRMtCDKEwJGPKr0dDjQKdHf8cQZQmBIx5UhiS8JHCcfZF3IuCQMnWo4IiEoEXOfohRK0OhUrVJDYshHH30ADaRCU2oINFIQnS+8fdqex7fy2HsGx/H3Tf+CxYCeDZQEZSvS6cJFIW0iLAwrDAww4EDeEegDxFCfAhxI7miYTeraox6s4KJ1sbSXosgUlQDVup8qca0bB8lokniJVhBEUCxPEKJwABySTRdlA5BZPWkhcGBRubaKbGKyAsA2DNbEnSo9Em60N5YvSDtTPFw8HCT0STjCKI0dbVoFhJuSTdYYGGCyfPJAdbPKk3QDAjiQbjDCWYdRB6CgAgxeetNtplxcNBmF3a3ZzYKxgig7aa1HLkoShDHTwSlItQBATc0LOyiOBFEieEWjJ1Gn7xkIEU1XqIdFcFDUalpuugww2RJ5Ix1/4qWbIEIu2i4EwhbEw1tnPwYANVYALqgUU/iOqmBjxangqx0KwKaCQ4mUKBkAJVYAqaqJPVxCpyx0p2RsCwMgwOSzOM6V5L9D3Db+AmbFih2A9VseFTDfrDzOpA8KEHggqaiwNsDuElOnggCWYDVf+rALSQCVhZDRggdJaub0puxgInW5vBehFLYCQFp61AC2LBgSYC5dDdgXMGawCAhMs76NqelyAjOVxdU52oJXIIwdWeCmCotKMLGXJJEM2mFEYIOUiU0LuoQkbYwDtRP5ECFEkti81JgxJWbQqcsdKP2CnAEoMCQlhNM6UimK9ge8a0b1kEd7wHzNEWBKIlfRBENhJLYl8G2gqwlb+Sp7Ht/LYewbH8fdN/wCCxYD5HWAwZCIEFaWF9ItmrBcpC4SFpJE5bbVA6fViTcjvKtA+qc5IgmjDno05/BETLEmG9gq0FAQpLpXJSO30B9+2fUHDOsYkOohqBYdYoJm7CESjIgkPWs57fFQnsWowCRybPjcPjTzSylEaCTVOato4BMBSexE17fsocNgkoomEqJ6c0zLDSXG83ryhWFshO5AeE+zVzz1MzOPMikHoNEXzvJe9e97qUHzfCdC3mOetD/5iZgGQHOXWlj7vrZlQQSEgmk0lgI7oeD6NITMclBAWIJDVaNpOiSWXQIFbWasnhIyrxJHvQmX55zSswOBtechUR7IG5gC5EicJy15L9D3Db+Al4M5WuGjeY9AoBCHbMXVLq+GkWqDVrClkVN81FMKABRFglic7ta7mAUwJshYJDXVpZ31FwwSEyQNppz5QXmtkuSQEIEvEy7UMag4ISj1aRJ16heHjT6DiGSINbddNKMErGsP917Jv+jhiQDriWFNlwdii8CXVOmkQUBHByulXiT40uUbDgSzxIeoUHlUMUFjhW52ikvgMolBLDYO8m1eZ/wAup7Ht/LYewbH8TIvhGt4UJwdjEMwNYkMYyyUA6joUQOVfCXSglS2YBd3enkdfmf0xMyu5SgwasGKU63uvMWAbxKGmtGuYiZSEHBzLFT0DmliHhTu6KZqk3k3ijtWOt/iAgsiNo8KdlWMhEBjSQP0hy+8nCEyaIROltKD8a2YKzAFZbWjLSlc+xoIPDyKyinx+1vxooLFyMTGU7LJmoA3nCF2RGQuGSvb9n0BMsCEcJUjjiW4QTq2OpU/kmGZ7fzPc+lZ73uoGsIMEEm9nINx2otMcmGJiVI1IIq2o5YbIRGRxsjs0mxC+B4keCmzrCFkjLchBjEclQTFJOsgpmNUmpObbJxtCYN6tyV+c0rEjhbWjUqMKkjEQTYiBy8NeS/Q9w2qVhBWAuy17+/dJF4QFXQJp4FqVmCU7iuyUJDGAKsC2hm+HJJRqAND2WIDW5YmcUybaoLIneBb/AMU5jgoCFZSBEQpfypBkNNyZAIFT3+jvyX6Hvm36ieyb/o48z9P1sBom0MF4knconroYobnKJI2h3o+RDQBkllvLaDt5n/Lqex7fy2HsGx/G0aQTCi4miNxpi9uBIWEnmToUojsRocEPhJUwiE8jgGhLaXN1oXM20JaWormZaAtL0SColsAtHSkTfKIgBEPSm5EVfOyRPFwwBTYgJMiGpcR1vRgqRFhiT9EBVul8eWboklYuRL0qKYduLF1YHg0LUu5oZC6stI0yzXSsyFJ4niTRHUfWGos4N1QNoYDzeOakX2Ul+X1WDsAQAVDGpguqRqK6JoktFmlLG08Dzo0o+2tYCMGx3mmwbhLiM2eKvxsOGgXs7fR0wyLicG0L4uKVlFMGwAOgHitCDKESJCfOkMSXjIZXmgfszYymBtJeHEsJLRIT3II6S9a1EWUbkyt4cq7gV595gCORGETCUUnzgB1L+BTIALaGFJWD0OGkAiCNkaDw9JY7xEcX4gtTTPXxsGSqNMHGKjgiISgzd4+iFMLS6le/P3Xvz90UniJBwGdYoE11WEEKOo6jZg1BAwluVAdBD406k5EgOSZidWV6C02GESVYkTVQSWwXKgJAbzRbXgedQiYLHRUsoh2tBV4iQZCUM30c1HBEQlBm7x9HQkRIgb050+kLVJDYkDPNIAG0iUItQQaKQDGh95pmiCwhdEz9PS7hrpzpTWex0iqYYKWTJqUzuCRpiZlg3g2pgEFwgSbaaqrdYIbdILQCfEH8qnse38th7BsfhgmrdkDl6KhDLrORLNuf60WAxi1g83eoprR50xE53It0FRFfbDBwIHjRkkLrKsyp1VVeX+VT2Pb+Ww9g2P8AFVPY9v5bD2DY/wAVU9j2/lsPYNj/ABVT2Pb+WwmB+UJDN/8AE555555555555555555555555555555555555555555555555555555555555555555555555l46IIh0dK9j2/lPoF1QwIxzD/SU6dOnTp06dOnTp06dOnTp06dOnTp06dOnTp06dOnTdMYVIN4lV0DyxaYWJBOewI01qHC1tQbOxqeElHSfKEZuTneU63Jj+jp06dOnTp06dOnTp06dOnTp06dOnTp06dOnTp06dOnPSkBLAgnw/vQL9+tHQfKdcAQyRmRdXLOVY5bVAHEdjnlcq3ajRqL4I5E0S5S+6FonSKYGmDw2CbfmRwnQ44dL2/zygKsBrXMctnd/Xw70ZMsmej1OeXTcDwgoFgAwfVuIJoWiUgKQCVdt2zsd0oMWvW2Pvtq13f8ANp0waAuquClr3DTug1PO62szjWTIdoabNWtrJNgQAQBt/EtaoEgcibVkhJs7u7vMnTGFo3jY3eeejAnTJyBwjqf5mcQqoD3pTEwkOosk0nHc3iMYKPk2Brs0a3x9goJcEtuHffVpey37LDKs3Rru7i8iQ8U0B1H/AC5r7usrQNV2K1gXiViDL4GmquxB6B779GDd+0YJiOP0znh13qbv4F0hFwamHXRDW5OidRMiaj/lcrsumxNeuDWmHrYnedYuvyCC1W6CRczYN3LwW+7ofIIEx+jI5KlM56OU2hgeZRxbKw1w6Pk5JP8AJ2qm2p9+Br6m1BQMCzI+Rvld1qFoJbPaEeM/fs6kLge04yaymosTWRbqaJc4ZoVFQP8A/YtNXDIf5B7dwbYcWOGXTVH7+A8E44H/AFqRPEl6pbbGDx/Bd3nQ9Ubm+D1hFKct9Ov1G0q54NZmET5fmMOi/wCOughGE+Ls7m0Ca8tyHyDTARi1XgLLnUJqt/1+GEy/O2mXRP8AxkqKXTYcHaGVknJSLXRgZnl37iTH+MBvnvG7oPl6sOD5IzKurlnKxy2qFuIoA/a5Vu/iwcxL4I6Jolym30LxOkUwNMHhtRVprY4ToeV0vb/FKAqwGVrFa9bO67b+Dei4pkz+2c8um4O5RALABg/HaqCaFkSm4SAlO2p2aMO6VrWPdj77eLf/ABC5MGgLqrgp+8w87oNTzutrVOtYMh2hps1a2skyBABAH5Ia1QJEciVkzBs7o67zJ0xhMV42dznnowK0y8gcI6n+FnOKqAe9NaVmEj1Fkmk47mWIwZs+dkNdpprfH5gRS6JBuDTdq0vZXdlhlWbo13dxeRJaaaA6j/gxH3dcrQNV2rVKaJWIMvgaaqQtJt8M336MG7+cOBCKP0znh13qWNoV2hFwamHXRDu5OidRMiaj/gc54umxP3g1pPymp1j1i6+QAWoFR2XM2Ddy8Fv6HRhRQJj9WRyUFnL0BubMYHmUPWysNYOj5OSf7+KoLan3dhr6m1FSMCTI+R4rutQMALYvsDxn+jg4UF4PaRpk1l9QYmsi3U0S5wzRKKAf/wCxaauGQ/vGtzE1jxY4ZdNUDPoPgn/B6S1gRiXql6GD+lR3xQ9Ubm5h6wjAKbtOucmJWPBqJrkRz6/mMOi/27+QBTDAsOVgOWoAk1gVbxS7/SNIJ0T4uzubQIWTyYruaGmAidJv0WddQmq3/X9Oay7C2mXRP/GShE4GQ4O0MqyTkpF7oxMzy79xbFSL8ESyOPSVLIYawkw8mHk/tNN5jdDCdWYcUCi+Qss2wyrqOlZHNeN3c546sNj9JTKurlnOjlqMmIoA/but3+pipiXzHRNEuUo2BGJ0imBoLPDaj7TXxsh0PK6XtQ0s4F029ywHBOtX6nSXKWuiHv2/syZLnoJXwKnDFlM6fYAdvpJfbpZLZb3ngRSjnCIBYAMH9WqRk0DIlZ5QQsnuNM37XRfpKWjR1rd5PeKxDFKBInZ/srJDWW6sdg7fwID34z4jAcWaCUAOysXZUj2X+pmjySDYUB3an2TYC5iQ4gbz/C7hnG6lPFJwP9iXa5CAF1aard1wBxJd5Wtw2j95LBy1N6LpfLUPaKzsdkHTEOo0HxYABwFj+rJbcB9YNms3FW0+XMOkVHS8F809mK2SgufJOTkpHg4RrY8FuoUTYEiMib/1HAsQPFpZAmZHgGamhT3UlT3Zx+lZ5+EedBeiH7Vqx1OjUoWxIDTI2EEqWzhaja12CvBJHEqs2x6OBDUZ3V+pUPevdgVFS7o55NACCOE/qOO6kedOICzL8AzU8K7etFTXYR+lZcuCPOnnHpSBRUzHvk3MxHEKh9ZKT1SYSBnSntscL+6Z7ouNRnfb6Oo7ub9SoO8b/RFQUi4FfJoQChHCfmWEZJcOkt6b1JHE9k9mloQ0leRRyRtHR3qQZZl67geVTujVJ7tQ19x+jKgb57tlRkE6i8hNeob+g15kP66aBdFo6FLMXjydD32A1FTXaZ6xU4h7+Sk6krEyheIafhHb1UrWQE+ktLFj0D0mlzVdde6DypfQFKdYsedMJHWR7HqrERgbdz86JyiSVegsvamAJaHiesXhNL4KVLqBRyWtHR3mpJl2fGoDyqRxapPjQZc8foSoe/e7IqMgnX0QmoDx39BrzIf100C6LR0KWYvHk6F+2O5qe7fPWKmEHfyEnUrYmUvxDTML7eqlLytmfSWoSANGem1Aarqnuo8qWTsIzrD/ANU2j9Jj3B4GsPDFTon4m6lB6sneCltoI7xL+Ck+CDhtNzutOEBMIXmtAJHSR7noo3UlWdJ/6UAtainsJ86IJg1Hq2ggNMfrD7qCIkjpUxIurXik1LK3srsPoqfIsB7wl51BhcJHsjROsmQvrKedR0Vv5UJSojtonETPLNSMvPqYA8Vb6JSXUZHh/I33gb+zIneKAt7I/m0U4tKNpgp1WkrAmUXaVoFP7U7n0UZud2hP6Ghx1OGvYD50QWHVPXaDAI09JPugCARyNTEq6q8UmpZg2z+0+ip4q4Dzwl51ClcSv2FE2zxAvHPOr+cuk7w1DNbRBHiJnlmpSxmPnijcGAukxh4fvBI2HA3VxStiiXO5eexOak7tL0WzKXdjirl4uJ1Fg6tScvPoYnmVBu76pxERwzXwjKgPyB5L0fgNnjUxRxb+zHmUdeyxnriXQak8qJSvklLA+zYDgkPcXmkuASjtdHYrx+GQQoQDdWxWBDJ53WT2EO9chSceyj4ilXxjkDyB1WpKTnwthB4qCH97yXah1Gjx7/wgPyA1mIp4MDxqdj4sfF48yjb32BdcS6DU9URKXa0JSwcsxGdBD3Jd6gf2hLsXjuP20myiu/z3gl3inTYZ8PdTyy81K5uiHsnsNCge7KDwGXuo7Va22J0gW/OtIaPAZ8hohnJPJ0Ak6I9aupOxw6hbsafWhEuHxuzJtFQR3njhqOST8Bi+pFz4cvHclLQxnw0Pqy81rli6huInsE5KFCl0tHgt+5OKL4sC9IFj87GZQQugwOzRRecy+QHkneo6CzojULDkWnGYxg/idpcRUWQp8adnJJz/ADF4Et8AMq6Bdp0HSoYDkYcO61Jcg91nBLxQMUjkHm9ZcRQAAABYD+iLDkCp2deaCzkrF4XHTxVcK/ruBr/2kluDgjYYXC28aiIIiNxPuCiG+ddAyrsUrTpUQ+LBwtutMHrj/wBxOCXigIkHPvC7su0UEEGP6LDUhR1vh5zUAw5XlV9PFSkjz/1D/pUUhjArY45suNf4RnDAXRgtV/8AWw08YlJo9+Vr6C1DA6A2e56uXTehLLEcHPLy3f6ZaYcCB+HU5W73q6enCO3qLzL0v5h+dkd/Tpa1DgYQkRwj9ry4tTlqvldbFLUrT/3otdXBAQRuPZ7u7vl0izRVihwPev8ATPbUhhxT5i3RvVwjMJg423K5yQ0yUBqXamvP0YAEFEiMifRWYUYAJV7U8iVto1F3OCDSruwgLcHymucZAAAgNP6iJrrRbI6JolTTcVGGuwNd89BvlGbhyp217jY+zhbgYBK0lbKh747j2NKkjEEW2Dtsa5bRP9QXsrrK0TRNGmbyMaDYdhaTo4au7JNugSp4L8JNj6RPhMNwPkD8qk3SH6/MD2Gi1qAQAYA+1dzIUmRiC9ws3yUfWcjYzH/q0IACTFi9NJDMM6WkQPZZBCzbC0fwYAULBYsH8grxEAwKC66Mfr+QJmkyQjunVj8AdgNnKGHp5imtX9mlQqsnYR6Vb+hrhdA5OE+xAyMidD54V6N6DAgXCPnIrwO5QIQCACAPsjpXSUBLYr3rA/Aw0j4P3MQs1kmCAujpV4iDICRhBO5/DDu65CBJsiVGlqyCC4FdMP3jRCmEo4PR3FKsH0kb5IepmrXQh4x6SMcJTM4Ay1jrJ70fUVWLw2PSA937QPWK3HB3iKCcQqlc79FOhy+kV/0TVktIbjeL70haE5tWxQ6EmJCcQ5uFCQHkQgIOVQkB5FaCHkVCtBEELoRYuwRiLVGMazRTKwWi17ZZmliOjFXQiBS0QhSancTBvtwv34aLXBVoCIXFIOpTb5WQ2FG1yyqEljNAIlBB4nabBYUIoRpMoJyw0w2ZGrHXcS1jlhkalowlltWL3ELQZcUDUCksrDyFdYwRzREagFIcathCMYTN5YSgS5JRZgUABAwMsgDVeIoRBdgM8yYv0tCdYvRnevzGXL5mJYmJY+2csHhMwQvKgqCZbXkZ+8+D7DJkezbAe9LKS0F3/n632oP7adsnxEcqQ1MZ4MoM6gPBH0hNqC3gBOSaEbs2xEoMqTYZpryQkWJQC6s2Nnauakedx+qhlz0E3QuPWnshSofcGCzdg5pgDQB03didWCioYNIXETJT/b6a7kwHVJ0qYZRdugHdKsOD6T6riviPrwUZvQVaWUnaROy0fMB6cwALJtBN5pyR7ShAkghkymagutmQeChc+ddHem8yfoqahMFlbYLr071fgUTXhTyUDZJnjR7jZMjSvXFJilcm0K3qMS2QNm8NnxULw5KRvD0RERuJ9k7a0OsRPdeFqQgu1T/zrfW6wKtBmEJbBD7QwQs3Tg8YojmTLwp8foGGUzuQuC8Qr9KeIZFSSoQSRMlBECqAH1XDgnCQSqoNeTUWpyUSJBYsHRJmn2tDQ5kEsYmZ3xNQZ5fOI9SjHCh8kkNzfmkDFLmGLkqTJEOZDsulqJCEsBF1Xzry+nyOskwIAgCj33epARjCCGesB7H0H0NKNyeZfttkLQ8Mh6eFORboi71D+cXkqMU5cpKurRZxDWwA+zbjM5ie3eQd6dJtD7N1Iii5BUuly9ViZIIDoalSJhCis5cHWjcyQbrYQSYQkWmbsIk2OiaQ3wtnIA1Ghj1JFBaQEGLX3oYYhERIyv2gaMxzlgk2aQSuUNSwSWrmqIJ3nINANFIdtZdE/wDKtWp3NldYFUgWixFiQHYdoDFCDEibZJkJRlbcKv251CBLK6QTN4mltnBxpLBMyJm0zfFHoWCDLAYoAWxMtauw6iWMjZKYXm7SAILGhKxPZTFIRLFwvBnFvoolwXYgmE2ZXcIxVu7TInBp2xUgfFdxUnVCeih0iZVl5akhHamgCsJIYRojcimtwiu5Bxae79lJhDPRb6KzwLFYPw9rGD4UW5IeP1j7bhpVokyFdncTHECuImlIXXMzW1+tSTCSVMWS8AHE7FBWsBAAwKlLw4DPnUUjSpSESkhAk1EAIAMQgSQGQue1RmyBAbIw3Ei+GtGPsAMwiQhFlE70B2kFxiaKwMKAZmBgCn/OIdpkHJRftguhIYWwwPRokOqEqZglCRYRYLRah7xbWFhUsCsTKSxF1PFVyAyOViV+jjy+nyP6az23eqGA8GYgvcchd0+llgxwSmJtq4qX1DumTtCjSPtlYSwNBhPWXhTBMg2GPI/mzmgUR6O6H6oLUhxIB2CfZfCDhjMtwpO0KJNY3QReKzeUaE4ZKkHVgan+ZKlCWCbj3HajUna8SQmFoQXCb1Zi6BaBF5EKmd6MPVTIBVgm95jSgmVtb+lZnmaJA1NEjIM9FMtAjeaIJzKCMkuKc8ZXGhuuA1aH1tOi4Nm5IOzUAjKYmBGbyM9FNhBK2ZtCRbSsaDQ1jQMQiXBZCThKUegMvCEcxMcxUuZQgLpJcmFXJpSViAkrEo3LYXRonAqYmpB9Qyg7yFYU7zq9dKtMtADKu1ORYHUufEO+jr3DavZNv2SoOzIAnfyKKKTU4lDyohZiSFgwO5Lu0UoNSs2s+AD7gY2cISd/osQNBJRoQYAgKuZqYE1qYqBJQAAACwFRdrxAx9EAiCNka4IUIKWIGgkokIMAQFLEDQSUaEGAICggJhBijQNLwJoAAABYChCJwhJ3qzp4+NciSCKNwgamjA1ds2J78UskQEBNwSQBFhZWMT9kEQASqwBUQUGyo+YXRNqttXyXuHjXoD7EbcKBYIHrQDYNKcuPo/A+y0BKvczMwToSs2+gmzikBCPZq11URWkuzGUEhNtoocEpTCXgK0JtK07AhRCuQVKOJQZib02KFYEcwo2YJGzBqCEw4iBCOyo4OgukGJcASwBF3VWoOGSgg0NY0bNi8UVBCFROYZpYHmogSKgH7eW7RcCyxMIGxKFpEYzNqEfO7gbLDdE0qM80sFAWBffSnSTYwhAJZSCXslSzmISd5STQcKVW5JEiGWLyErFWkilgXgSy1yw0xUkgiyhM3meFaLI+ORzHAzWWETDcLiI7J0hvSMTwWggbFAVcS0yGUXX9AEAFafhMcSfKzS9kTS2krQjNkQiLn2A1KoQAZVqQpjF5oe6tF9yGS4SB3JojUfDZjsyrhrT56kIXH3emlMJt905ZHtkfzwYuiJ8ftnPZy59DsZ2La2doYTScT2Dx0aOwcKACAOA+wBmhxCYXYSPWdKQ7ARC6FHiJ1KbOCn/+hZHXqJ/VHLFI9q7vgLasAwODtE8HfA7ulDdUBACwB9GOGx1xMnExuW0KSUsNkX1wxj0SoWDn2yGfGP6h+YmN3R8E5cNLOgsX4YvKvrUFcFpEDPAYDQ5Vfs4waO5GDaaanJdanPDXPU8zJeobzMpbnkDvDb+obs5bncTXlg0via25m64YN/VaCjWhGoWxoGh4/wAFxwpUI59XDrvX7LPYeI1iG0C6Uz5KA4YFAcImT+kIEMLu7BdcBRIz0qD5TJsX3dKCqULsLdb7BdqwVxP/AOQaaOWX7jrTNqjc05cOsZqwcXUDRP1qVhlIEJx18+ShOmJyBwjqf0mky5SmwXXSgBlkIDyMOHdcUMSkjIXLq7C70vQm1yE6jYNMDrK/xxztCOKfIe0N6vSu4JNI5fW2y0XFmmbvLauUNCpXtmbjR2HVoXlycg3E/oDrrSydgyvBegGrpKBzmesOjUuVSOV2wLBwFMMqALDzt634M1gt6Nd1yvLf716UUgbI+g9oq/6YIvCGX1tstIknmU+8GVyjmaBl210nGB4O9FjSUSJuP9A3NsBOgZXBLQymCyOv7vBUh3CNaWwaGwFIPaIR+p9ozRw9g8By7u63fsE2FCiRNqWG4Ymfn/kOGuYfSm6l+wUEZzK3vpjvE1OW8LydVLdl0o0Yw9I3gPywztKIA5aL04uU+T3oM3rEHUJIeD1oy6oLOwf8KcFW9wHGR4O9WGjEN+jgdBzP4IY0QJEdErJDF8ef/Jw0kmrXjlHkA0DhrKs2+Y7kPNadSW7iknZdKJGrT0d5PyxIhKIA3Wio2mc/D56Kb9jEdUh4PWjDNgo2gZexTwhL4lxo7jo03FDELeQ4HAPuIIiSORrUtlhLzCXhPNNn+408BS9oq+bLDz5Fz1KkiYEs7BOO0UCN4XPrYPiUAGFpKT2XjFBEg/sAGT8MGQC6rAVBM9DPxXyqJMYBTvQmlGLF3oIRcyPT0wdinVjD0jD2ajLOU5e4W7LrRwhcJd9M9sfiggCiEcNQWry1J5jLwHmmz5cCQdSXbsqBetlryTnqUPZmFt7BODpFAaILV1yPEocLNXE9l4pQQy+jPcGT8N2ICVWAqCZWg/ivlUcIwgneVE26xBO9DOuyJehgditHkrT7Q9pp+9p+oendRuGoYd857Jj8G0tsNuo2pThUXvmp0Z1dnjT4KcRvE06B9FRS/wD5wlCgFx53MeVEgcwL8wvOoDmL/wCLSF5j9iUgZPWQebURKOn6SrAf3dxWCXtL1gu8dEqgRL2W9GjrnoeipqbHuxVPdnU+AqTN5etT8qHJtQPIP1qdFGozug8qkx3s/uE+dTJuf+stOge6JdUIKQSK8FY7rxikl/KbpXD4FSRMAXNxnHaKLFvysUJhbqNqV2+I8cjsUqNaNR5jwKdQDEw6J6KgcGsLs0OB/CXjMeVGgS09WF50Ic/+7oOT2v7EpEyvI9WoiWdP0kVCROn1wrBL2l6wXeOiVQMl7LejR1z0PRU9N93ZVPdhU+AqVHd1L1+VCk2iB5D9am1DCid2HlUiJ9l9xPnVwrTPqi0yRDoB1hBTSWvIrHdeMVqzJB0JZJ4VAFwQB3JU7R+QjeckD2aYRckg94tLq20AB4zzpJdsH5welMMbyR8F61N9rk+Sp72R5Kz297aa82Q6YRdf+FC49txTMMcNSAmTqmUjInv5ioxNw8kvqDjPvseJUTz/AO3pEct++rAozX08XlS4j8JeMT50EEGP6J4y5IHs00iOTPe7KSVPQAHjPOklP0H5welNKWbg+b1qZ7Tf0qZ9k2Sslve2GvMAOmEHX/hQuF921Mw5w9MhOUykRGn3ZiolFueQX1Dz6u+pUTzf7OkdyF+8aQiSw+nQ8qeELjz6J8/v/wD/2Q==)

Fig. 14.8 Types of Unsupervised Learning

* **Clustering:** This technique involves grouping objects into clusters where each group contains items that are similar to each other and dissimilar to items in other groups. Through cluster analysis, similarities among data objects are identified, allowing them to be categorized based on these shared traits.
* **Association**: This method in unsupervised learning helps discover relationships among variables within a large database. It identifies sets of items that frequently occur together in the dataset. Association rules enhance marketing strategies by revealing patterns like customers who purchase one item (e.g., bread) often also buy another (e.g., butter or jam). Market Basket Analysis is a classic example of this technique.

**Unsupervised Learning algorithms:**

There are so many types of Unsupervised Algorithms. Some popular algorithms are given below:

K-means clustering

KNN (k-nearest neighbours)

Hierarchal clustering

Neural Networks

Principle Component Analysis

Anomaly detection

Independent Component Analysis

Apriori algorithm

Figure 14.10 Popular Unsupervised ALgorithm

**Dimensionality reduction:** Dimensionality reduction techniques aim to decrease the number of input variables in a dataset, preserving as much valuable information as possible. This simplification helps with data analysis and visualization by addressing the "curse of dimensionality," which is the problem of machine learning models performing worse as the feature space grows. Dimensionality reduction not only combats overfitting by simplifying the models but also improves model generalization.

Dimensionality reduction is a process that reduces the complexity of machine learning models by decreasing the number of input variables. This can lead to improved performance and better generalization to new data. There are two primary methods for reducing dimensionality:

1. **Feature Selection**: This method involves choosing a subset of the most relevant features to use in model construction.
2. **Feature Extraction**: This technique creates a new set of features from the original ones that capture the most important information in a reduced dimension.

**Components of Dimensionality Reduction**

There are two components of dimensionality reduction:

1. **Feature Selection**: This involves selecting a subset of the most relevant features from the original dataset. There are three strategies for feature selection:
   * **Filter**: This method applies a statistical measure to assign a scoring to each feature. Features are ranked by the score and either selected to be kept or removed from the dataset.
   * **Wrapper**: It uses a predictive model to evaluate a combination of features and determine the best subset. The selection process is based on the model's performance.
   * **Embedded**: This approach involves algorithms that have built-in feature selection methods during the model training process.
2. **Feature Extraction**: This technique transforms or projects data from a high-dimensional space to a lower-dimensional space. The transformation is achieved while retaining as much significant information as possible from the original dataset. Methods like PCA (Principal Component Analysis) are used to derive a set of new smaller features that capture the most important variance or structure of the original data.

**Methods of Dimensionality Reduction**

The There are various techniques for reducing dimensionality, some of which include:

* **Principal Component Analysis (PCA)**: This linear technique, introduced by Karl Pearson, projects high-dimensional data to a lower-dimensional space by maximizing the variance in the lower-dimensional representation.
* **Linear Discriminant Analysis (LDA)**: LDA aims to find a linear combination of features that best separate two or more classes of objects or events.
* **Generalized Discriminant Analysis (GDA)**: This method extends LDA for use with non-linear separations, allowing for dimensionality reduction in more complex datasets.

Dimensionality reduction can be categorized as either linear or non-linear, based on the technique employed. PCA, the most prominent linear method, reduces dimensionality under the condition that the data variance remains as high as possible in the reduced space, thus preserving essential data characteristics.

**Advantages of Dimensionality Reduction:**

* **Data Compression**: Reduces the dataset size, leading to savings in storage space.
* **Faster Computation**: Lowers the computation time required for data processing.
* **Elimination of Redundancy**: Helps in removing duplicate features, streamlining the data.
* **Improved Visualization**: Makes high-dimensional data easier to visualize in 2D or 3D.
* **Prevents Overfitting**: Reduces model complexity, which can help in avoiding overfitting.
* **Feature Extraction**: Aids in identifying significant features from complex datasets.
* **Data Preprocessing**: Serves as an initial step to simplify datasets before applying machine learning algorithms, enhancing model performance.
* **Enhanced Model Performance**: By reducing noise and irrelevant data, it improves the accuracy and efficiency of machine learning models.

**Disadvantages of Dimensionality Reduction:**

* **Potential Data Loss**: Some information may be lost when reducing dimensions.
* **Linear Correlations**: PCA may not be effective if the variables have non-linear relationships.
* **Inadequacy for Complex Data**: PCA may not work well for datasets where mean and covariance do not capture the full data structure.
* **Uncertainty in Component Selection**: Deciding the number of components to retain can be challenging and often relies on rule-of-thumb methods.
* **Interpretability Issues**: The new, reduced dimensions may be less interpretable than the original features.
* **Risk of Overfitting**: If not done correctly, dimensionality reduction can cause overfitting, especially when component numbers are chosen from the training set.
* **Outlier Sensitivity**: Some methods might be overly influenced by outliers, skewing the reduced dataset.
* **Computational Demands**: Techniques like manifold learning may require extensive computation, particularly with large datasets.

**Advantages and Disadvantages of Unsupervised Learning Algorithm**

Here are some advantages and disadvantages of Unsupervised Learning Algorithm:

**Advantages of Unsupervised Learning**:

* **Complex Task Handling**: It's adept at handling complex tasks since it doesn't require labelled data.
* **Ease of Obtaining Data**: Unlabelled data is more abundant and easier to acquire than labelled data.

**Disadvantages of Unsupervised Learning**:

* **Potential Inaccuracy**: Without labelled data, the accuracy of the outcomes may suffer.
* **Difficulty in Implementation**: Managing and interpreting unlabelled data can be challenging due to the lack of predefined output.

**Real Life Applications of Unsupervised Learning**

* **Market Basket Analysis**: Used to understand customer purchase patterns and predict future buying behaviours by analysing items frequently bought together.
* **Semantic Clustering**: Enhances search engine performance by categorizing words and phrases according to their meanings.
* **Logistics Optimization**: Assists businesses in determining demand, managing stock, and planning efficient delivery routes based on historical sales and location data.
* **Safety Enhancements**: Identifies high-risk areas for accidents from historical data, informing where safety measures should be prioritized.
* **Plagiarism Detection**: Analyses documents to uncover plagiarism in academic and scholarly articles.
* **Personalized Recommendations**: Powers recommendation engines on e-commerce and streaming platforms to suggest products or media to users.
* **Fraud Detection**: Detects unusual patterns in financial transactions that could indicate fraudulent behaviour.
* **Data Analysis**: Uses Singular Value Decomposition (SVD) for extracting and analysing specific information from large datasets.

1. **Semi-Supervised Learning**

Semi-supervised learning is a machine learning approach that incorporates elements from both supervised learning (which uses labelled data) and unsupervised learning (which uses unlabelled data). It is particularly useful when acquiring labelled data is expensive or labour-intensive but there's an abundance of unlabelled data available. In practice, semi-supervised learning algorithms work with a small amount of labelled data supplemented by a larger amount of unlabelled data. The goal is to leverage the structure and distribution of the unlabelled data to better understand the overall dataset and make more accurate predictions.

In a real-world analogy, think of semi-supervised learning as a student who has received some instruction from a teacher (supervised learning) but is also expected to study and learn on their own (unsupervised learning). The combination of these learning methods helps the student to gain a more comprehensive understanding of the subject matter. Similarly, semi-supervised learning aims to create a model that learns from both the guidance provided by the labelled data and the freedom to explore and make inferences from the unlabelled data.

**Advantages of Semi-Supervised Learning:**

* **Simplicity**: The algorithms are generally straightforward and user-friendly, making them easy to grasp.
* **Efficiency**: These algorithms can be highly efficient, as they require fewer labelled instances.
* **Problem-Solving**: They address certain limitations of both supervised and unsupervised learning by utilizing a mix of labelled and unlabelled data.

**Disadvantages of Semi-Supervised Learning:**

* **Stability**: The results across iterations can be inconsistent, leading to potential instability in the model's performance.
* **Data Limitations**: These algorithms are not well-suited for network-level data which requires different analytical approaches.
* **Lower Accuracy**: The accuracy of semi-supervised learning may not match that of fully supervised learning, especially if the labelled data is not representative of the entire dataset.

1. **Reinforcement Learning: Learning Through Interaction**

Reinforcement learning (RL) is a branch of machine learning where an AI agent learns to make decisions by executing actions and receiving feedback, optimizing for a cumulative reward. This method stands out because it does not need labelled data. Instead, the agent learns through the outcomes of its actions, akin to trial and error.

The RL process parallels human experiential learning, much like how a child learns from daily interactions. For instance, in video games, the agent learns to play better by making moves (actions) in various situations (states) and receiving scores (rewards or penalties) for those moves.

Reinforcement learning has diverse applications across fields such as game theory, operations research, and multi-agent systems. Typically, RL problems are framed as Markov Decision Processes, where the agent's interaction with its environment involves a cycle of states, actions, and feedback, leading to new states and learning opportunities.

**Types of Reinforcement Learning:**

1. **Model-Based Reinforcement Learning**: The agent builds a model of the environment to understand state transitions and rewards. Using this model, the agent plans out actions to maximize rewards. Algorithms like Value Iteration and Policy Iteration fall into this category.
2. **Model-Free Reinforcement Learning**: Here, the agent learns a policy directly from interactions with the environment without modelling it. It updates its policy based on the reward outcomes of its actions. Q-Learning, SARSA, and Deep Reinforcement Learning are key model-free algorithms.

**Categories of Reinforcement Learning**

Reinforcement learning can be divided primarily into two types based on the nature of the reinforcement provided:

1. **Positive Reinforcement Learning**: This type involves increasing the likelihood that a desired behavior will be repeated in the future by introducing a positive reward or incentive. It strengthens the behavior of the agent and has a beneficial effect on its actions.
2. **Negative Reinforcement Learning**: This category operates on the principle of increasing the probability that a particular behavior will occur again by removing or avoiding a negative condition. It's based on the concept that actions that lead to the removal of an adverse event will be reinforced and hence more likely to recur.

**Real-World Use Cases of Reinforcement Learning**

1. **Video Games**: Reinforcement learning (RL) is extensively used in video games to achieve performances beyond human capabilities. Notable examples include AlphaGO and AlphaGO Zero, where RL algorithms were crucial in mastering the game of Go.
2. **Resource Management**: Reinforcement learning has been applied to manage computing resources effectively, as demonstrated in research like "Resource Management with Deep Reinforcement Learning", which discusses using RL to schedule resources efficiently to reduce job slowdowns in computer systems.
3. **Robotics**: RL is pivotal in the field of robotics, particularly in industrial and manufacturing sectors. It's used to enhance the capabilities of robots, driving the vision of creating intelligent, autonomous machines with AI and machine learning.
4. **Text Mining**: Salesforce is one company that employs reinforcement learning in text mining, which is an important aspect of natural language processing (NLP), to improve the extraction of useful information from large volumes of text.

**Advantages of Reinforcement Learning:**

1. **Complex Problem Solving**: Reinforcement learning is adept at tackling complex, real-world problems that conventional algorithms may struggle with.
2. **Human-like Learning**: The RL model mimics human learning processes, often leading to highly accurate and efficient solutions.
3. **Long-Term Benefits**: RL is designed to maximize not just immediate rewards but also long-term gains, making it effective for strategies that unfold over time.

**Disadvantages of Reinforcement Learning:**

1. **Not Suited for Simple Tasks**: RL algorithms may be unnecessarily complex for simple problems, where simpler algorithms could suffice.
2. **Data and Computation Intensive**: These algorithms require substantial amounts of data and computational power to function effectively.
3. **Risk of State Overload**: Excessive use of reinforcement learning can result in a state space that is too large to manage effectively, potentially degrading the performance of the model.

**Importance of Data in Machine Learning: Understanding, Types, and Processing**

Data is the cornerstone of Machine Learning (ML), representing the information collected through observations or measurements used to train models. The effectiveness of an ML model is heavily dependent on the quality and volume of the data it is trained on.

Data becomes **information** once it is processed, given context, and interpreted, which can then lead to actionable insights for users. When information is further synthesized with experience and learning, it evolves into **knowledge**. (Fig. 14.13) This knowledge equips individuals or organizations with a deeper understanding and facilitates the development of new concepts or strategies.

* **Information**: This is data that has been given context and interpreted, yielding meaningful patterns or conclusions for the user.
* **Knowledge**: This represents a synthesis of information, combined with experience, learning, and insight, leading to an enhanced understanding or the formation of new concepts for an individual or organization.



Fig. 14.13. Data-Information-Knowledge

**Example:**

Consider the scenario where a Shopping Mart Owner has amassed a large volume of raw data from customer surveys. This data is made up of a series of questions and their respective answers, embodying the unrefined input that is ripe for analysis. The challenge lies in extracting actionable insights from this extensive dataset, as manually reviewing each response would be inefficient and time-consuming.

However, sifting through this extensive collection of survey responses manually is impractical and time-consuming. To address this, data manipulation tools and methods such as software applications, calculations, and graphical representations come into play. These tools process the raw data, organizing and interpreting it to produce meaningful patterns and insights – this processed output is what we call information. Hence, raw data must be transformed to yield information.

Knowledge then comes into the picture when individuals use this information. It involves understanding the context, drawing on personal experiences, and applying critical thinking to inform decisions or actions. Knowledge reflects the human capacity to interpret information and apply it effectively, which can differ markedly between individuals, even when they have the same information.

**Different Forms of Data**

Machine learning utilizes different forms of data:

* **Numeric Data**: This type of data is quantifiable and measurable, expressed in numerical terms. For example, age, salary, and temperature are numeric data.
* **Categorical Data**: Also known as nominal data, this refers to data that can be divided into specific categories or groups that do not have a numerical relationship. Examples include gender, race, or the type of browser used.
* **Ordinal Data**: These are categorical data with a clear ordering or ranking. They express attributes in a relative order, such as rankings in a race or satisfaction ratings.
* **Time-Series**: Data that is indexed in time order, often used for forecasting or understanding temporal patterns.

**Data Categories in Machine Learning**

There are two main categories of data used in machine learning:

1. **Labelled Data**: Used in supervised learning, this data includes both the input features and the corresponding labels (desired outputs).
2. **Unlabelled Data**: Used in unsupervised learning, this data consists of features without any associated labels.

**Data Preprocessing in Machine Learning**

This involves several steps to prepare the data for the model:

* **Data Cleaning**: Involves correcting or removing incorrect, corrupted, or duplicate data.
* **Normalization**: Adjusts numerical data to fall within a certain range to ensure consistency in scale.
* **Handling Missing Values**: Involves filling in or discarding data points that have missing fields.
* **Feature Selection/Engineering**: Selecting the most impactful features or creating new features from the existing data to enhance the model's learning capability.

Properly structured and pre-processed data is vital for the success of machine learning models, as it directly affects their ability to learn and make accurate predictions.

**Data Splitting in Machine Learning**

In machine learning, data is typically split into three distinct sets (Fig. 14.14):

1. **Training Data**: This is the dataset that the model is trained on. It includes both the inputs and the expected outputs (labels). The model 'learns' from this data by adjusting its parameters to map the given inputs to their corresponding outputs.
2. **Validation Data**: This dataset is used to fine-tune the model's hyperparameters, which are the configuration settings used to structure the learning process. The validation data is used frequently throughout the training phase to gauge model performance and make iterative adjustments.
3. **Testing Data**: After the model has been trained and validated, the testing data serves to assess its performance. This dataset is kept separate and unseen by the model during training. The model makes predictions based on the testing data inputs, and its performance is evaluated by comparing these predictions against the actual outputs.

![A diagram of a machine learning

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIAXEHKAMBIgACEQEDEQH/xAAcAAEBAAMBAQEBAAAAAAAAAAAABwMFBgQCAQj/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAABqgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABqTYcNqqCcN9UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTP1ULXno9Et7Y3gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPHOfRQD0fQAAADQG/Rr9LIntCBNikpnTAj2MsqNdUd25+dFla/YA5k6ZxvZAAB5pGWVzWwNqjVMNyAAASgq4DzTopwAAABozeOA78AAAAAAANBpjuAAAAAAAAfkxp+E8uwmNOAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGLLozkqTyHXgAAADlOr5Q5Cpy2ska77n/AFR2kW7rwHI2nhPWdxKa1Jq6/qOa6ElmDT2iOMocKutNLuuKNlh0OtOk1O15+Kfn5Lra8cJu0bjebflPQc7XuB748XP7ryHQbuPdFX5++33HTQmzxWO89PTxgufIdJIqqul+ecPT3Oh0ZQeB1/RHo7OH1o23MdPzBxtZk1ZHh90nPXuPNyEW3gt/o61Pc8J+x1ep1Hure+LeSA63otrICva7Fzh1Wu02wPBQ53uDccdzViOa6aT0U6QAAAAE77rR/p0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHO9FrjT9TwndgAAADlOr544esRT7j1dpoe/qPPZX4imK4SIrsmpvDVvvLs+UOO2VK3x/P1l1XnjueK7Xlq0Ot6Lwx0PM9doa9XYc10p447ZJqefXd5ro1HX6fpaktB5v1xqN15aMaDZcCKLG7ZL6r0NuUnKJJa/OToNbvvCbDk+1505vq91wMbjtp7T6+uY6fQnCVmJ5ItEg9Hd1z/AJ9N646md2CWG98f56Tx9Zpuir2SeuTsp0NucmOx5zrdHGu6PW7w5/0Zs9TO58nykfPdTOmnRigAAANB48G4N0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACX1Dkfs6sAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEx8Nc+CK2L1gAAAAc6clTuK7YAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATijjnOj4bWFMc/ujM+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5H0+R9PkfT5xmZouTOs4/396P0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGHMOS1FEE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgRPpPmlRN1IVN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTdSBN1IE3UgTf7oo5Dp/QAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaTd6M4HYbzriaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUIl0alRNVKVNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShJaDq9gb0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAADS7rTmn7DjeyAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADlPZ5fQdCAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABqfT4DT9pwvTG0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAANUcVSpp25tHx9gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA8Bp8mD8Ora3ZAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHhgf9FSY4qwS6+R9igAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEnrGkIZ0PP1uOyFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAANHvB/OX50mGKnvSgAAAAAAAAAAAAAAAADS8+d0nn4UROxRE7FETsUROxRE7FETsUROxRE7FETsUROxRE7FE0vKj4o82ylETsUROxRE7FETsUROxRE7FETsUROxRE7FETsUROxRE7FEcDuzo3z9AAAAAAAAAAAAB5eZOwT35KInYoidiiJ2KInYoidiiJ2KInYoidiiJ2KInYoidiiJ2NNWZ1lKInYoidiiJ2KInYoidiiJ2KInYoidiiJ2KInYoidiiJ2KInuxOxeP2AAAAAAAAAAAAB+c+dC4LAUROxRE7FETsUROxRE7FETsUROxRE7FETsUROxRE7FETsbnyeD4KQnYoidiiJ2KInYoidiiJ2KInYoidiiJ2KInYoidiiJ2KInnoO7aLegAA0Bn4X00c43o9iMH7mGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmGFmHi0XVCXdR1PFHauJ7YAAAAAAAAAHwJ94O+ON6veDz/WYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYYWYefW7oTvHSNeerNKqeZgAAAAAAAAAOb8fkNR0vWjw+jMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMLMMPm9447nan+Gj3s73x0wME12fWGx/QAAAA8HgwcgdskHZlI+sfyZn5hM7FlNLup9QQYDP5fTpz07DmOnD8wmcB5/QAYNQkZXdnPOVLu1O1P15PSfX54J2VQxGV5/QAAAAAcB0u3mhTgAAAAAAAAJ33fAnZbUAAADhekNscId21e0BgM6f9IbxyfWA5U6poN+AH5pzctVoDtAAAADyHrSwVNwXdn0AA0u6AAAAANfw1JnxQXg94AAAAAAAA1e0mhmouHMAAAAAeTWfXHnXIx3ZRM3hynpAYPoykmKxqfXyJ2/3gzhhyH0YjKx5ADV+Xgfwom4knyV4xGV5/QPzgdydMeU9T4+wAAAABMqb4w4ceemTWlAAAAADVbXVEqtUVtRENhqLdHM8f33DGlsEZq5KrFGLOSDeeGvEr66d0I0/nzeYw6Wl6A6fhuknZ0eguskO+3uh31aGcUecFl4HvuDPNi+/RGt0+z5k7/gLHODu+Cqc3rXd3wHWRQBQAAACa0rgju/rw+4AAAAAAAA5HYc72x6gAAAcF4u7i8XOEVDlig8nt/DXs30KuBIqvKO+j2bfgtRXSaTqeNjrNzpvmvN0mh4eO74zt+LKZr/AM5Kqtxms9B7uxnOc6HDwvSmTtY3RDotbstaRuvyS5RJd/7+TKJymy89e/NHbMSOzRqxRp9c1JR/bNKXQAADV7T8OJ7ebUkAAAAAAAATOkT0owAAAAAGPJjIPfIHeYk2fk+8Nf0vF0Qnn54faUeOW2SnXctXY6V+JWyL11GitsFizyHuvGa3V16OFuFSPteK7WOngd8gtWWZUufmu7vgOsjiN56OsNXpuh5s0Vz/AJ7/AKCPsUAAAABM30PylzOlH0AAAABqtrhI3atFvSE3LRdATT4pWgJhUfZnIlZ/FvCQV3V7oh9C2OyOC83ffJr+f7zzHPcXWuWMXBUPjopW+1G3rQyW4aA0fHU3cHkkN41xyk/sOM9kguGhNDzVY1JwO+63GbgAAAACe0KZFF9AAAAAAAAAcJ1fh1p2AAAAEUtfEHC1CXXGJPsvnVmhtUhq5Ke+4zuDQc31e1Oh4TSfJ2HB0HjDp+I32qKRxFIkZSeK6TSHk7vJOTueV8FNJpR+C784PrOb6iuj1uy15HblBNlHW+DSVklXQ+DynN3OM2gjVXlHdHDb3SbM9lMmVNoAABgz8yaGicx04AAAAAAAB8zikzIpoAAAAAGPJ+EEvnO9ERHsu00RyfR9PmJpp6L9mv4Sz640U/qmM90ZuOjOhg1554yy+t8YfHMd7xMWcVI83e+E5bV0LfnKcVYufOB33W4zi/vv9QTXrey1ZHP6A1G0MwAAAAAJq+B1Xh7GZFNa3ZAAAAAAAAAAAAAADneiE223ZgAAAAAAAAAAAAYTw8nqqgZQAAAAAAAAfktqfPHQfvAd+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAJduvedL9gAAAAAAAA4fuPk027ldLPSAAAAAAAAAAAAADHwvfCcdjtgAAAAAAAAAAAAA5jczw6V1Y/ceQTDp+o5M6xMfspacCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOmvwdrwW67c8nvAAAAAAAAAADk9HSNcerPNvgpib/pR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTgUdOBR04FHTf4KNwGDtjQ9mAAAAAAAAAAHkm1U+TS7ziNSU1Nfso6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpwKOnAo6cCjpx8FK5zlN6c9S836AAAPwNR8AAAAAAAAAAAAAAAAAAAAAAAAABtsoAAAAAAAAAAAAAAeHxAAAAAAAAAAAAAAAAAAAAAAAAAB69gAAAAAAAAAAAAAAGPUh+AAAAAAAAAAAAAAAAAAAAAAAAA+tuH0AAD//xAA0EAAABQMEAAQEBQUBAQEAAAAAAgMEBQEGFhETFTUSFDBAEDRQYCEkMjZwICIjMTMlRUb/2gAIAQEAAQUC+wlVCJEd3DTxbU29GPODjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjGjjHlyjy80zDW4KlOgsmun/AAHIvkmKKLd5Nqs2LdmX7ddtEHZHLJ1DqRcim/S/gF24I1bsGyky9LShS/b/APsSrM8W5YOiPG38ATyp3sg2RI3Q9GbcqNWHOvhSefCOuDxqfCYmXCD6JmnCr4KTj6h+dfDnXwt+RcPHE28qyZc6+DBx5pn8J92qzZ26/Xe/1OTVI3518IF6d60lHFWrDnXwh1zuY7+taZeFe/ByapG8TLu3Eh6My4Uax8BJOXjz15tyo1YW9IOHqvsVUyqpRJzRsv8Af6h6Jp2ySrh56VzdValNZE6KZ6XAxKzd264q4jXKtEG8alV7KSSNWck0Wo4beEouumkjbhaViaUpQXS43Hr2P2oW03GpPhKvSsW8RIkfiUlysHDmfSSRRuU3jQVIukHnyjRLfXtNbwu7tW8LZdLaLbvTyc4m0Vpci2sVKJvwsqRBJxcn9za5NTpnKoRz+Ek8uOhTx0+VdZY+2kwmk3TuUfUYNyT6FW2Sq+ONfJv0HrtJmgpcqnijp1Jyp8Lk6i0+x+Dx0k0RVuU/ij55JwoHtwkTULcq2sa/SfpSssWPVdXAUiMfJncsGs+isda5DeOJl03xpJ1Rm1iZMj88rKFjzqz6JGqdyn8bZcjlCUk0mBaXKr4lbhQKRg5o8aeldaPhq1V32339Nn8EVa5PDGelc3VWn2IvAWj8rdTjwM7Sbi7W4tRx4m4uzsbb6hU9EkkCmkJJ63o4ZRTjykj8Ls66zxdnY2y0SoxupAiTm2DaxYefKQVNZYn5CfuRSq8rcaVEXdu9O5jYxuvJyzBRrbhtJe7Vqi2GiVGcnDJvVY5p5Js9pq/as0G7eTSohIL18UfAdvdnXWu1TXcXM3TrH2ib8zdC1VJGKcxrVlM+W87FLVcRwuTqLT7H4XUtU76IcRrVnN+VM8iz+cifJxUc5m5Nm6b2jX8zdvzdtx6KrV4kRGKikCupBy0RUaQpvDKXN1Vo/wDe7v8Ava7RPy11tyEPaZq1j5JQzqUbM0G6E+0I0f270/pXETxxNun8UT9/XBTWItqv/k+lc3VWn2P+hcjwjl3baFUY2fceYkiRUjoaKka0hHHlpIXZ2Nt9RdDjaYNGblzTi5MOmyzVSGceZjhdnXWeLs7G3enu/wDXa3WB58pAdvdKXgkYqhncxdnYwh9uAakNISLuKYtI+2+2u5Ou7a6pTxspJJx9I58m/Sc9mJvtVOsgO3uzrrPFydRaXzdyp1JKx0XHumThGFbuGJESNBcnUWn2PwuglSycXGMHbFyhCtnC6ibOChmZZB5NR7NnG2j8xdvzdt9RJddbvcH/AERHZ3N1Vo/97u/72z1V3/8AK0vkXdKt5NM5VCXOuVWQt3p/Snq6RNs0/wDK+/pBLeY2krq19KdQUcx9IiQKKxMiYR9vG8bipyN2UO7q8+EhDuvOs6qVa3EwcunsGio3jp9m9ePYRrVowFxsVHaVuN3bSouJsq6ZW0zXaC4mDl09hUTt4y5GTh2aAbqtmAclqdtDRjtCSuNko7Rt2OXbObiYOHTuHQOjFvIJ0isjEyDw0bHPWkk+apvG5oeRaKkhpB2qzbEaN14p6Z+JWMeLSByGqxh4x4hI3E2VdMraZrtBOIqOI63GLlq5lo4sgkWNlWtWMAsorSmlBOIqOI6kRIFHFyYjo9+m+lY8kggWMlWhmUC4VWXbprNTw0g2WpDPXJLfZu2b242Ll05g0VG8c+IZRlCxrtvJm/TGxbxJ/OoKOY+22ThqrcjJw6VgkFG0fcjRd2nbjZZq1m4jztUI+XIJZlRgpb3T+ldKvgjoZLZjPv8Ab14u4PtWbbvUHSNwOkkqleTDpqjRu39KUryU3T8Kff8AcTHzTaAkPNt/tWpaV9SakKMW1tMapJfwDLx6jNeKlEnxPt+TkkmCcYyVk3P8ByUHRQyMw7Ymby7JYFVTONaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWg1oNaDWgMoQoXlmSIXm3Do0fB/30/Cn8CKpkVKvAM1Aa2aDGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjILG+KWxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyMZGMjGRjIxkYyC2zQIW+zTCKKaJf41T/d38yE/d/8AMhf3f/MlP3f/ADJ/+v8A5kN+7/5kP+7/AOZFP3d/Miv7u/mRf92/zI4/dn8IzRzkjGLaTeIcZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLhRs7LK8ZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLjjJccZLh83k2SEOcykZ9em+qtfq/tF1+6/tG5+rg+q+vTPV2t1n2i7/dX2jc3VQPU/XpfrLV637Re/ur7RuXqYDqPr0t1lqdd9ovv3T9o3J1FvdP9ddOU2pX6yS0ZayhSRqD5Bwv9npSDZUz/wDdDl+1b0JXxF+znLtFsafUIpDQSyaUM1eIujfXHrejpqctSHFtNdhh9n3Q12nYg2vmpD7PmWvm2HwhWvlY/wCu3Q12nbFvV07KWhS/Z8w182wFsNdll9oT7XyshCNfNSH16Xa+bYWm1+0pGNrzZC0IT7QuNr5hhazXaZ/Q3MmzbhS5G9BkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpRkpQncKSRclKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKCXKiG80yWFK0rT3K66SBVrgZkFblIMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKMlKK3ClVTJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSilykCNwtDhu5RcU9zX8A4mGSAPciIyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUoyUorcpa0TuJNNPJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJSjJShO5EKhtKs3H9cjIIsSeOSmatbebJhNk1TG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kwdq3OHMEzWB2cjE1iphJ77c5ikK9m1V1G8CqsZCKZIiiKVBtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mKopVC0WyWDm3zJ1azLhoqkoRVP20pLIsQVvIzAbQLNIEaN0xtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMbSY2kxtJjaTG0mNpMKM2ygdW+1VFaSULWNkkX5fjLyJWCEXFnenLShafWZiGKuIKUqtX2hzUIRyuvOO2DFFil9ZetEXiRDOIF4koVVP2k7KeUpEQ3h+tV/GktE1RNCydHyQXVKgjGoGl5H0nTtBqOXYjl2I5diKV1p/SeUZJn/ocLpNk2rxB16SypEU+XYjlmIQcIr09pcbHQRLyj5n7O4nR1l41mRi2+tvmpHjeCcHZPfZyLsrJpb7Kq6vpuXCTYnLsRy7EcuxCShVU/QWkmiKhTUMX0XL9s2U5diCSbI9afjT2sy2NHPGi5XTe6nFduObUaM/SmYysiHVvmQbR7bzjvGjBMvhIdQhPgdZNMEUIp8HNvGWc/A6qZK/7Eqz881h4ysdUf6BFUz1+FFkjG+M71Mc0866NbR9FU3MY7jHlHrMeYR1pWlaSCxm7KBcrOpgHOQlCLJHr6Zi0MWKrWOnPZOVaIN7ZRqu49CWmF2LyMdedZiVmztHkauo5Z/Bc+2hGzizp7MPDMWkJJqSBvhOSSkeIV6d+1+Nfwo3kUHDuUcmaMYWWVfuvRdKVRa5I4GSLhncSZz0rStP6KyTfznqXS30DBfzTP2U+czyUSTKkn6cux8+2rbRqUbp7zjGjBkj5ZpvpeL4HWTTBDkPQXC/cVds/lJCCq7eIk20QooRMFrQ1Ac5U6EOU9PjdXZR0JV40eQDhBO35EzZwDnIShFkj1Fyv1257c6kGcIlqU1DU9R2gVy2tdYyaqn5u6vUlett3uBKKnLK8a/kg/I5aRTGDcOivWy0W8jV6uWMiofkJT8I2OcOSrvIJwm3tp2dN7c9a0jbSMYx7rMYrtk3dyraRYqxriDdGdx9wyJ1XCFvLnQfKuiqQddYoTvU212wu4lPL2geulwefXcY2ttQjpVrIXKzWVDBsq7cNk3LGIQjHr9zKRSkcW23ajln6dz02H1K609jc6vgjINLZi/Quxv4kLScf3KHommWh38g5cIR7c1ypasZts6VefKQHbyirdFtEOGS9XblJolW5EfFcTxF4lafXSEm3YjJU9Y6Tbvhcj1IrWCeJMnazpspGRTmPWcHMUhXFxNiGbXC2VNStK0eyzdms7mWzdNC4m5z0rStBJddEEKpJVjWdRcEYRmLVdVUbvnyDJOtypasJls8UmHqTRvFrkbP2DxJ6k8nWzc5blS1aOUnaPoSiW/H2or4mXsoP8zN+qf9Eb2ImpBV26Nbi9ELfklEnNyPTtW0bEHforxj1i5rRw7iXiJ27mCjnKC86c1JZv8izcrIuFYF2snCu1Gr+RdUZs0EnMu8XjXcTSCOast8Lq7K2+oEiSiT9RZXjkIx6/cykUpHFtt2o5ZyLNZmpDRzlStx1enCFurKIoLLRj71XP5W6Yj+64/Ulett3uBL9mgXwIS8iWPSLISz+sii5QXt+mkRJdjK9bbdNZZx/whO1unrLQ/Xdvzdt0/wDJvAWn1yf90oLrpTkoLqRO9TbXbC7TU8raBaiVnaoL0pNPaMS/+hM9Xa/aPXJGjaszIO1JJu/KlaNP8Hp3dT8qyrqy9jd1f8LWmjX0HyHmWcWv5SRuVxsxtqN/G6lonkFCIxLNB1VLzTivij4Dt7p6y0P13KvVWSiohuRpcLAjNe0+uewZF3LrhU0YU3hlbkaImZ2+1SePJpEjeBtPsbrdV8UBFIma3DFopN7UdmOS6O0goxAzO4WibR9b56niRJddCdqLm6q0+wlYej5bbh2iJjlTdyzNFy3iUSOJBFikg1ShGrRacNGVQtA1fH6Faa0tD9XsVK6J2hT8PVP+iN7E36Wm75rdngWMkfNTLDz7ZRo+YnbTj1Gsc8I+bT/bs/lJ/t23yEVTWSH/ANO7K18haFKeB3ShmsB2/wALq7K2+oEmah5FRcrCOrMyDtSSbvypWjT/AAXb83bfUTMz5NQqsy/o5TOkuX8C+pcn4SjD/FdHqSvW273Al+zJ+i7kzbkPMoNGUq8M+c2+bxREl2Mr1ttdsv8A8ITtbp6y0P13b83bfUXgLT66caHaSCFxo7Ei4UdOYLqRO9TFu6MnlblLo8crybuJZ+SZPCmbSatxo7LOtSSMmWp4+HdkZPplXkYWBkk2B5uT5Clom/w+ndx/8bcvgb+xu0urSPPuMfRn2/l5OTfVeEgW/l425Hqh3jG3iHSkkiIPl/wj4Dt7p6y0P1zxallmR6KtLuUoLT65y4WlHydvN0yQtNZW4KaxFp9jcXT2n2N1ErSRgVKKRVyHoWJtIlavLo7SG6u7fm7b6gSXXQnai63BStrRRr47heqLPWtuJ+BwmUr93TVrAdvLOatGEc0UlXUtEN2MfaH/AE9BY+2jaBf7fY1prS06+Bf1T/ojexEg3UjZHI0fLwjuQdu7gUeIJRc9tpzj9B6a2m50I+4y1LLxEqi4pP8AbtvkIjsx/wDUmWtXjCIf1jnMjNldIQHb/C6uyjJsrNm6uM504GPM6dXOkZSMgZJNgebk+QpaJv8ADdxa7sHKooNrgSMnKJXCgVq6OdVclfEX1J3/ACzs5+TmqV1p6ayZVUm0U0bLBaHZrK0/CiiZFScKw8TmPbOEmbVJomrDMlVFkyqpNYto1WNTxFQiGaCztsk7SZMG7OryObPDtW6bZF6xQehm1SZpvpdrRVs1hjFuBdJd/Ep1SjQ4RI4R4NgODYBs0btaB2ybu6N4tm3O4iGa61KaUVh2Kp27dJukpDMDn8g28szjm7M/pyP564vZTiG/GWwvux3o3Q0Mugyj11nYuCKWUcNlZjaexjlurQ1VYqEbLklLlTOpHWqiokeei6vStjyrIPI97VK10zpMJGJctXBeYkCoNnDOTkEKuWTdKQYOHXmVrbtdBVJ/LR5X6CaMpGHq1k5RaNZEYtrkbrKSUSWpY26UFVXVvkMnFiQpUzBNu7TPvS1Q2iHrtVm3I0bz0St5pBWZVTdxrlsuSu+3MyfMXTVN1IxZG8jHOVmkm/StgqqDv0LiX2Iy3ENmL9kT8hc/q1/GiUMySUCyKa5OEYaopJokCsQxVM3imSBg7Zt3dGsY0aqOIlm4WKShU0YdmiqOHZbr9z5Nt5uJkV1eNj2tuJ1PK/B3GtXavBsAnDMCVKWhShSGYHP5Bt5ZnHN2Z3CCThNOGYpnctkXREodikd3GNXSqKZUUvUj/wA/cc8082wtt7vtPfyUSg+NW2ahlAIIH91JOysmlsNjV9olXhpv67InrLTBS0KX2V0NKqIRDyj1n705SnI4ttIxi21+MewRYp+7n3vlWVuNPLMhLNlIx6weJvUPrSqhEkzmVnpFMhU0/ZzTCj5tAyWn1yek9osFHeSb+zNShiqFVgpFusm4S+tPHKbRBgipMyHwUIVQjti5iV46Zbu6fWH0i3ZFrV5PLMmqTND2szEleBhMKtDoqprE+rqKESJITZljQ0R5avtXTdNyiYjyCXYSbd7T6xIy7dnRu1dTS6KREUv6H8G3c1o3mI8c+6SGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZEsceOafBlb6ZakKUhfbvGaDwisI6an5OVaily1GTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwrc1Rysm5BIZ68OxYN2RfbmpQ1H1voq1pzTAZCumMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyYZMMmGTDJhkwyByqKpzMgGECgh6Rv9/U0/0e9X+qN/9+9P+n6nT/dP9f0//8QAFBEBAAAAAAAAAAAAAAAAAAAAsP/aAAgBAwEBPwEsj//EABQRAQAAAAAAAAAAAAAAAAAAALD/2gAIAQIBAT8BLI//xABIEAABAgMDBwcHCwQCAgMBAAABAAIDETQEEjEhMpGSk6PhEBMiQVFxsTBCYXJzgcEUIzNAUFJgYnCCoQUgstFT8EOiJGODwv/aAAgBAQAGPwL8BF8Vwa0dZVyxQjEd953+lNz3QW99zivnbWJ+8qqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoaiqhqKqGoqoai+btQn7wpw4hit9Dr3iubt8EsPa3/AEg+C8Pb2j9BL8TK45re1c7aHXLOMOClAhgH73Wfw9djww709YXyixvL4PXxU29GIM5n6BPjRM1qdarV9C04fBANEgOr8QZU222LJDnlHZwTY0PrxHYf0BhWCD1HL3pkKGOi0S8k6LBMnzC+kbqhZ7dVBlsa1s/Pbh7+V8KzOAazIcnWocO0uaWPyYSy8jgIjch+6F9I3VC+kbqhRGx3AgNngr8P6Rxk1fSN1QoUb7wy9/KyJAIDi+WHoKtHyhwNy7LJLt/uiubiGkhfSN1Qi6KfnGukVFitzgMnevpG6oUKLFM3unPT5B8MPbdEQtzfTyxXNxDSQoMKK8Fjsej6PJRIsEyeJeKfDjuBaGTw9I+oOiwTJ8wowjuBDRkyfUnQ4gm1wkVEscQ9B5kPgf0Ac92DRMq0WuJj8T5N3rBRJ/8AEfEKT4bHD0hDmhKHEEwOxNvGboZuKJFdgwTUMPy3nX3+KiNZkuuvM+ChxR54ms0KHL/iHiVCmBifFZAE2CMIQ/kqyx5dOc3+/BRbOerpt5WxHw+cBddkotyFzdyXvTYRhF823pzUMsZeiuE7s81fPQBd/KU2JDM2OExyR/UPgmw+t05aFFhffbPQoMEee6ehQZ4vZe/kqz/u/wAijChM52IMcsgFlgQ5ItAuRRlLU6JFddY3EoizwOj2vKAtEGTfvMKa9hvNOUFRfanxRbZYV8DznJsK0Q+bLsgcDkT3yndE1Dgts90u65psUsL5uuymnRXsLSDIMnlKp2Xeyavw5gjI5p6kYsY5OzrK+bs7Q38xQhRmc084GeQ8sXvHionsj4jlMWO6TfFfNQGhv5ihDjs5pxwM8nIWWaHzkvOJyLpQIZHoKL4WQjOaepMY6EX3hPFQzBhziOEyCc1R7TEg3eaBwOdIIiJDMJobO8SvmIAu/nK5st5uLjLtRiuZfE5SURrIPN3RPFMa6EX3hPFQ4gYTFf5k8MvWvnLO27+UpsWEZsche6UQ4MCy2dl3smobmQ3PvYicrqZHDbt6eT3+Ts9qZkcDdn/IUKKPPaD+P7Sfyy0qf3nk+Td6wUT2R8RyWT93wUf10yAMYhy9wUa0H1B8fgoNoHqH4fFRLOcWGY7jyQ/ZDxKhd58U+I/NaJlNDsYr5lRYH3myHwUJ7sgndd3csP2o8CrX+34qH7IeJQjlgMR5OU9QUJ7Ght8ZZIDscRyR/UPgrP3/AAXY1kWX7TwXNty3AGBQIYwbBaPFWf8Ad/kUI1oi3TO9dc7OUSDDZzhLZNN2QCg+mY/hQIAwPSK+UOaHRHnE9QTXtcIJ86Tc5cyIjnic8qjgf8jvFCEyG2XXkxUdkPI1rsiiHthHwVn7z4KH7UeBUSJFbe5sCQPaudugPYRlUdvUWzXN+bCb4qG0xGc4RN8x1q9YiDDcJ5MAVAiOyuLcvJF7x4qJ7I+I5WwvNY3+SmB0RnOuE3zGVX7EQWOEzIdah85PpNuu8FzkSL0h5jjel7kYUGGS+eR92UlHH5FB9T4p0ePDa8kyE+xWlkJoY3mn5B3KDCfmuOVPg82wNu5JDBWYj70k71grR6oVn9Uo2h7A6IXSBPUFBisaAXTDpdaiDsifAKL6X3W+CEJkNsuvJipQhJjxeA7FZ/3f5HycX8sj/Kg+iY/n8f2j3eIUP0E+Pk3esFE9kfEcjWQiHMhjEdqDnYxDfUSWazoBdGC8D1gulBeR6wUJxzXdA+/kh+yHiVC7z4oQhnRTL3Ius0Muu9YMl9FE1wrtoYWuImoTznAXXd45IftR4FWv9vxUP2Q8SrP+7/Iqzdzvgv3nkj+ofBWfvPgg/wD5GzUIxMpL758VD9kPEqG/7rXn+SmtjRMsQ5XKO+50gwyc89ah9x8FZ4nVItVwZ0Nxmod9pcX9QTnwmvaAZdJRfbHx5LT6yd7L4Kz958FD9qPAq1/t+Ki948VG9T4p7jg8AjRL4KFF5uZLel0jj1owYocHDHK4qGLN9DKbffyRe8eKieyPiOW8cHNBChRbk3Sk7pHFGDGa4OGOUlPiWHMl0PeUWRXkCV49pTjDYBEJABJyq0eqFB9T4qF3nxVq9k7wVn/d/iU7uVm9cJ3rBWj1QrP6pTfWKs3eVF9p8FEmMyLP+U17DNrhMFBrDPm23T3qz/u/yPk7R3DxTfWP4/jwxiWGSjQutrp6fJuhwW3nzGRZIDh+4KRguPe4IPtpF0eY3rT+ZbN4b0R6VC+UQSId6biSOWMYEEuhF0wZhQufbdiy6Q9KY+BCL2iHKc/SVDhxm3XieT3qcKCTCYJNyhMY8SiHpO5IToDb0Rhw9Ciw7RCLYbsoyjHkYyAy+4RJy9xVo+UQ7l67L+Ux8CEXtEOU5+kqDDjNuvE5j3qB8nh37s55VcjtuuvEy5IrW4lpAUGJGglrGzmZjsUEwGX3tOHoUSLaIdzoyChvs8MvFyRy+lQoMdsnZZj3lXrL84ycxIyITfl8VzYY+868VCiOgEsa6RMxhgjCi4dR7Cp2U3vzQ3SV61G7+Z7plNgws0fyojxAN0xCZzHbyR4kOCSxxyGYTmS6XNyl7lBiRYJawYmY7ExkBl9wiTl7irR8oh3L12X8qJDgtvPMsnvUV1ohFgLZYoCd2I3NciIF6R64b8VftxutnMtnMuUhhyRIcFt55lk96yQHD9wX0UTXCgPiw3hgdl6SDSbr25rkeYvZeuG/FX7cbrcSJzcU6zkShlt3J1KcAXpYPY6SfEtsU3w03Gl0zNExoBENzZTmMihOs8IvAbLFQ4cZt14nk96tDGCbnQ3AD3KDEjQS1gnMzHYioD4kAhrXAkzCdDgtvPmMijG0Q7gIEsqgmzw74AM8qbDjNuvmcigCzw790maiNjsuOL5/wudgECN1z85c1D5yGz2mRQoZffiFt5ys/v8A8j5MM64jlZ2/lnpy/oA5jskGLk9xw/Cz41mfG5p+XoE9FBjmseR5zpzV+5M4TlJrQocJuDBLycKyszGdE/FZP0A5yGPnYX8hc3EPz8PH0jt/C2UDynRPzz8jR8UbTF+ki4T7P0C+XWDJLK4Dq4KR6Efrb/r8QdLpRTgxfLbd9H1D73D9BOesJ5uLjd6uC5r+oQXO9OB4rJGDD2PyLovae4rFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFYrFdJ7R3lZY7XHsZlXNf06C4E9eJXP/ANRdzj8bk56Vk/QW7FY17ewhdEPhn8pXRtRHexVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFGxc7++76Jqq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74qq3fFVW74rpWo+5nFdO/E9Yq7BY1jfQP02Pef8P1lPef8AD9Zff/8Ax+sv/fufrL/37n6y/wDfufrL7/8A+P1lHeP8P1lb3j/H9ZW94/x/WVneP8f0SjuhuLXAYjvXOwrY+7OWWK5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5NgujTtP3758VWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlWHbOVYds5Vh2zlzsW2Puzl0YrlAdEcXOIxP2/afVX7z+EoXe3w/CR9YKz+r9v2n1F+8/hKF3t8Pwk71grP3fH7ftPqFO9ofh+EoPe38JRO8eKs/v8ft+0+zKf7U+A/CUDvb+EovePFWf3/5H7eDoxusJlNWkwojHjm3Zpn1KIXuDRzpxPoCMKA/nCBMkYD8IFgitbEBkWuyFQP2r52MwHsGUoGRE+o/g9gjuuX8CcFGMN7XDo4GfWFBMV7WDpZxl1lPEA3gzF3V9uxILvOCcxwk5pkeTnDnxel7ur8ICO0dGLj38jAR0GdN34QiMGeOk3v5YbDnu6Tu/wC3hHaOjFx71Cgjzjl7kGtyAZB+EIjBnjpN7+TnXDpRcvu/CL5DoROm1Q2nMb0nfb8SGM8dJveotpcPyN+P4SEFg6EY3h6O1Na0SaBIfhEvaOnC6Xu606O7OinJ3fYkokZt7sblXzcGI7vyKmOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66uw7JITnnqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuunAeO4zUuduH8+RTBmPrV6NEawekroc5E7gslmdrKlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOumvNk6bcgN9Up11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11lsztZdMRIfeFOBFa/uP1rKpGNfPYzKuhAiHvMlSnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXVKddUp11SnXUjZTrprGWQhrRIC+qU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqU66pTrqlOuqY666cGI3uyqTIwDux2T++cUzecGDErofNWfQOKnHLortAXQs8IftWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6F04EJ3e0LotMJ3a0q/ZXmJB6wPiEGP+bj9nUe76uXPIDRiSuY/pjCSfPll9y5z+oRjePUDM6V0YDT6XZVkhsH7VmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QssNh9y6VnYPVyLnLBGIcMA7/a5j+psd60svFB8Nwc04EfV7ufG+6OrvV+M7moHV1DQvnA6K78xXQgQh3NWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6FmN0LMboWY3QsxuhZjdCzG6F04EI/tXzN6C70ZQpz52z6RwXQ6MQYsP9nbFdmtXyz+oEkOyhp87ggGiQHUPtoxrILkfGQ85fJbXkjtwJ6+P1UueZNGUlcxZ+jZm/8AZlXYQy9bjiftq5GbPsPWFcfN9mf/ADxTYkM3mOyg/VeZgZbQ7/1Xyi3dOKct09Xf9tZV8r/p82ublLG/BXX5I7cR2+nkfEiGTWiZT7VaR8004fDybflEQMvYKob/ACqhv8qob/KBGB/ucx8doc0yI/tvx33G4TTvk8QPu4+SMSKbrBiVUN/lVDVODEY/1T9V+W2fJEZny8U2J54yPHp+qM/p9nyknpf6Qhsx853aftx0KJgcD2FP/p9pwJ6Pfx+qPjHHBo7SnW+1dIk9Cfb2+UD47wxpMpqob/KqG/yqhv8AKa+GZtdgfImHFjBrxiEHNyg5R5K5HihjpTkqhv8AKkLTD95kpj6sy3WXI0nKOwpkaHg4KFZWYvylQ4IxAy9/k4Moty5PqmokX5QDcbeldTIAddvTy+5VI1E1vYJIX3tbPtPJ04jG95XQe13ceSLF+UAX3F0rvLJ8RjT6Tyc0H3OlOcpqKTFv35dUuWTIjHH0HluiIwu7J/2Wju+KbBDrk+uS6NpaT6WrKebijKCOtNijI7Bw7DyS56HP1lMZQo0VkrzWzE1fjvLjcPu5Jvc1o9JUmRGO7j5QtcJg5CotkdmPyD4fU4kV2DBNRrbFyunId/X5EwhChlsptJTI0gCcRyGDCYx10ZZ9qZGjNDXPyyHZyxHjFrSVCguhQwHdYXOsaHG9LKooiMa25LDlg82xrr88fcnRYjWtIfdyf2TKdAgOvlrbxcMFEjsAJbLIe9OhRIbGgMvZPJRooyljC5fQwv5X0ML+UG2mFzc/OBmECDMH+1lmY6/EcfNwHlYVsh5HNN0nwUKN94Ze/wCpwLFDOQY954JsNgk1okPKNhB9yTr05TRPykaihQpyvuDZqpGoocImdwSmrvOsvdl7l6cRje8qbHNcPQeSLZg+7Bb1Dr71A9QeCiRufDb3VdTGY3Wgcnzj2t7zJTaZjkm9zWj0lTY4OHo/sb7MfFNjCOGT6rqL4bmxQMQMhTYEQzgPMvVPJN7mtHpKkyIx3ceRkGC64HNmSMVC73ePJJ0WGD6XKbSCPR5WJBfg4KPY4mIyj4oA5sM+A/35W1ezKs/7v8TyR5OOSJ2r5W6708ovFQrPYWuc6V0ub1J0SM7mcvnjKUGiJ0pXmuaoMZ2c4Ze9WrpO+ld1+lWn2ZV2zkmLEFwehPjujCI8C84JsC8eaidXYVkMumFabxJyN+Kg3XEdD4psPnObs0LJ3lNBdOeVr2pj4hm8dElPs8JxEFmQy84oPfEbDecobJCDaXOvwujirPPs+PJaO74qH3Hw5IETzg66rSzqyFc3DhRfk4wujOU+fZf+7L4qHDvG491xzVz7HDmobOkJrm4BAfKeUyVwN520NnIDvTzab7D1viDwTInOB7SZTGSRThGdedDMp+jylltLcf8ARQIwP1K799wb8VAH3he0+RhRx5hunuUaznr6Y/7oTnuyNaJlfmjP0JvOG6wdFoC6NneR6ShDN6G84XsCo/qHwVn7z4K9bGX4c8JTUT5FC5uUr3Rkucjuut8VkgRLvbNWR8B086Y6xgontT4BSikl581uKp3y9ZEQyQ8ea5RLIb3OuAI7MeCdEjXrpZdyd4RtEVpdZz1EelObY4NyJdmTclkRc8hrRiSpQmPienAINitfC9JyhTGULmo1+9KeQJjsr3PaHBox96lFhvhjtxUxlB5LV7J3goDIjQ5pdlBVNC1UyNAyQ3GRb2FPgPM+byt7lejuxwaMSujZ3y71zYvQ4hwDutFsW9OK1wbJQo0Sd1uMu5GJBvXQbuVFjQ6K4fdwXSgPA9BmucgOvN8PI2hn5ciiQ/uP8fqdptB6pke/yzu5WX2rfHkNngE80DdAHnlXhFYYn3OKbZY7iYbuiJ+aUxkE3Xxev0Ixuea0Tl2lN+T339YfDCLYjebtDmyy9qfCimb24pkeI5phFmQXlaJOOI6/Qofsx4Jj4ZLn9QRjRY4dHOW6f9qGATce665qiRjlIwHpWV152Jc7BoXymzxb7RnSVnm44nr9HK32Y+Khd58eS0MbgHmS52Cy/GLAQPSnm032HrfEHgmROcD2kymMkinCM686GZT9Ca20OBcRPIZqz2lj28yHgyvdhQhWaHE5mXSLOtNe+K1jiJ3ZIgOysdJwGB8tDcMgiEfzkVrJ6r/+XlbV7Mqz/u/xPJafXKhtGAaAm9G/EdmtR+Tgy/8Arbk0oC2EmK5t7K6as/v8SrV7V3irV7MqF6AfBRPVKs3rL94Vp7m/FQfU+Kh+knxVk/d8FE9qfAJt/rjZdPI2XXDHiVZ+748lo7viofcfDkgN6y+atLurojxToNla0luQvcsYjWH9igN6+daP5Vp9RfsKdGiYDq7VcsjLvoY2ZTYtuc6RMgHOmrQfzDykA/nUA/8A1t8PqVnH5ioI/IPIxYP3m5O9QYjsgDpO7kWjOim6nxzhDEh3lNeY7mXRICUwgyO6A94HSJylRDZZiFPoqIe2EfBWfvPgv3hWnub8UWebCEgmOjwhEivEze6kx0HJDidXYVE9qfAJ1oiWkgEzdMIs+ZJlkuZTpVmI+9JRbSW/PNAAM/Snw47bzQyePpCiwoQkxspawUT2R8QodlbhK+70ptotDL7n4A4AL5TZ23JHpAYKJZnmd3pN7l+wJke0MER7/vdQQEESY9t6XYoE+qY/nktXsneCs3rcjvWCieyPiFzptBYQJSlMBBkQwHEYnOci+BO4182d08ic6M2ZhtcW5VBhRRNjsdCiQLPOG188s1zlqjtdC6mv6KlZLnPA/wDjGRWlvVIHyMlah6vx+pOPoVqPq/Hyzu5WX2rfFFQ+Yyxr3R719GNDUIroBvX7xyhBrTKI3K1TuRWfmZ/sLpPEVvY8IRWCXUR2FWjvHgoHqDwVo7x4KF7MeCs0/wDkHJ/+3xUPs5z4FWk9c2/FRg7AsM1Z+8+HK32Y+Khd58eS0uGHOFNfG8xoEu0q5ZGXfQxsymxbc50iZAOdNWg/mCg+p8VC7z4rmYDQ6L1k4BTh84GHrHQCiMi5Xg5UPK2R3XIeKjtPnl3+/K2r2ZVn/d/ieS0+uU3uUCLLoSu+9CDGY+bZyLetc/cuszW/996geiY/lWr2rvFWr2ZUPuPgonqlWb1l+8K09zfioPqfFQu8+Ksn7vgontT4BOcMx5vtKHPw386MbuBRjxW3b+aPQrP3fHktHd8U2MW3pTyLJZjP10Ddm7BrGpsM5+Lu9RL7crYl6R68q+ahP53sOAUAxMhEVpM+9WkATPNlNixASyUjJCPZ2uutiTM8exRBGaS18srepBkGG4QmZSSrQ3rDgfKWZnaSVDZ91oH1KC/sfJWd3aweSiSzX9MKzA/+OHI96hzzn9Mp1nDi2Ezq7Ux9oium4TusUaHCzGmQUQf/AFHwVn7z4L94Vp7m/FWifWZ/woL24FgVnh+dlcontT4BBt7I90mNOARdGiveQO4KzesrR7vEKJ7I+IVo/b/kFE9kfEJrupzAoF3zRdKiA4vIA0qNE6gyWk8F+wKzeooPqfFQu8+PJavZO8FZvW5GWcHpuN4j0KPH6pXAokG8RChmV1A2mK4u7GKJDZmCIWjumow/IVZ+8+CixWZwyBOvxcBNzjlRiNc90SYHSKtJ9A8i9/3Wkq0v9IH1IhWqEccn8eWd3Ky+1b48k2iQDr8MqfNP577vUmt55xhDK8kDBNi2R5EMZ8h/KLLbfeZ5HhM5iFdLcXkZSvnBIxHXpehRSfOkRoUCzBr+duZcmTIFaO8eChezHgrN645P/wBvinw2546Te9OvtJY7I9vWjZ7FDeXRBIkjqVn7z4crfZj4pkEwS6U8s0WwIPNk+cTNNiOB5hhmT2+hTYJ3Hhx7lEEZpLXyyt6kGQYbhCZlJKtDesOBVnd1SIUKyva/nL8hLDKVGLhkf0gmzhP50CV0YJ8SIJOebyDh15fK2SEPy+KgWvzXSJ92P8KYw8o6G/K1wkU2LBhkPbh0jyOiRIZLnGZ6R5CyI0OaeoqfMf8AsUyHEhC4zNAySRZABDSZynNOiPhm84zPSKdDfla4SKEWDDIePzFEHApsSHDIe3DpFc3HE2zninfJ2Xb2OWaDrQwuIEsZIQoIkwJnyht67hlkjDgNutJniotmtdme4NMuooRm83LGT4mHuQ5ggsYwMyYKzsdjd5HQoomx2K+iOuV9Edcr5iE1np6+T/5EIO9PWr0OCL3acqdFiQyXux6RUledAy+gkLm4LA1nYrxgAeqSE6ziE0QnYgdaL7O0tJEj0j5SFAGVsOQPifqcZoxAvD3Lm/OhGXu8lDiwmlz2GUgOpQmRIMRrCekS0jJyG02dpfezmjFCzwWxg0ZBNkpe9BpY6KSLxLWkqd1wcYWBGWclAc+DEa0E5S09ilDa5xvjIBNWjnYb2TAzhLtQiwfp2jD7wRhQocYD7vNzXym0B74r3Su4lPERjmHnDkcJdQRdAY98Oc2uZiFzL77YfnFzbqYeZiubDiZwYcoUaE3FzcivQoEURMMyadz7Hm0HEXcud2J5iQnsHNnK5susK7O7Ebla5HmmRJH7ovAoGM1/e8XQEITMpxc7tKvQ4URwujKGzVna4EENwKhGHDe8XPNbPrUJr2lrpnIR6eS0homTDdk9yD4cGO1wwIYVja9BU4rXMBxfExTIMLNb/KfaLOwxGPykDEFCzsEYNwmWy/lXAx78gN5jTJAkEX24HqQcyE+809FzWzCtEK33mvcejebJXocKIH4Ta28CnxbVeDWNm1pGPuURsWFEaHtxLT5GIPOidAJhOMQ3/qbgcjIp/wAuPl2xGQzeaZjpHkuRmNe3sKnzP/sVchMDG9g5JmAAfymSvQ4Avdpy8gFohh0sD1oRIMKTx1zJTosWGS92PSKDBmgSTYkOGQ5pmOkeTnObN+d7OKdGLC4NxAX/AMiCYbz57uj/ACopgGEIhaQJG84qGRgybjo5ecjsLnSlnL6I65U+Yn3klBrQAB1DkvGAB6pITrOITRCdiB1ovs7S0kSPSKuR2B7fSg9sHKMom4q7Hhh49KvNgAn8xmucjQ5ulLGSbDZmtEh5WJHxYyZHgE66PnGdJq5l5+chZO8fYF902RPvN61ktQ1OKD4rzGI6pSH1t8U44NHaVEtkXOfkb8T9Ucx2SzxPD7eh2aEfmoeSfiUGtyAZB9TbaYedCx7k1/8A5Bkf3/Xi14BachBU4EZzB2ETXTtOT0MRbBGU4uOJ+uFrT87E6I/2r7x85F6Xu6uQW6yfRk5R2cEIkI97ez7bc+I4NY3ElBrZts0P+B/tNYwSa0SA+qSb9MzKw/BfIrX0YjcjSfD7cNlsxnGdkJHm8VeifTvx9Ho+qEOEwVfZN1mieH+02JCdeYftsxYxkB/KNqtI+YacPhyljwC05CCvlNhJMHrHZ3oNeeai/dPX3fbPzr+n9wYr/jszT7h/soQoIyeP1bnYMm2gf+y+Tf1JrujkvdYV+E8Pb2j7YLojg1o6yuY/prXFxyX5eC5+1dK0f4/VnQozZtKLofzlmOjgULjrsT7jsftkifORfuN+KEe1Ess/VwTYcJt1jcB/aXQ/mYnow0L5lxiwx1DpfwpWiyCfvaqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgqTecFSbzgpQbKJ981INMFh9Fzir9sfzrvujBBrAGtGAH1i7HZPsPWFf8A6fHPdORUrRZ747Sz4hdKy5fX4Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBZLLvOClZrNd9IZNB/9QjyHZOZUoDMvW44n6wQ4TB6lfsruZd2dSlIxmD9/FSj2UT7y1Um84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBUm84Kk3nBSs9kE/e5SeTBhnt6PFB0f55/pw+3h+MD9t//xAAuEAABAgMHBAICAwEBAQAAAAABABEhMfBBUWGRwdHxEHGBoTCxQOEgUGBwkKD/2gAIAQEAAT8h/wAFPY8VgonhAALHtMfSEQjf9A+ymiez7VyDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3XIN1yDdcg3U+P2IMEdZ9GLJMoGBEQ3ckXJbT/gj7ZAMzq1OumWIdh1V8QCj3j/nsEKk7BRPYDNguG0Y/SxOsMRiLx/wIgLAfubAntYQDI3DheghAmABgB/oCABAODMFXNEZHd3VYoDggzIf8BMZAHn2GqbbNmOPxAxAE5DzPTYEuS4EUF70whB2a9RFODgl7W3hQm5WFljbz0ZYCAdbbZn/8wiLo/IAK8HxPodNhBmeSskPvqLG0yXQc0WBhITRfX8oLXfgDpsA0STAM4mKwRVgGT70B99Ng/oqAaRjT4Gf6AZKDrBa78AInSCwALR+IRQlhIeYBHR9EARFjX8AGIAnIeZQQySwRb+ELQ2GCN2jg360v+AThJ2gopz2Hcc1j8dNvQAABFosnMMCAlE3vIFoq9DsxAibQIj0fSm408WsU7mkvE1Yq2+oBIGOTRS3wsuNoXEoAAACwWSyjajEpIOwTubbmH0yYyMXY/UM0+eJ+AwOmfVpoMRrCX9KI2ai8T7I6OGw20jRHrizlOvKYn9sxhnNRD1HSt3kysgO5ze05Mmnf9CU4CJD7cvSfNo/LHoDogWbAnELsSpsbgJQ8yK5LuLwUKIA5EUCBCU54CYDJOQ8FD5hsLQjBZLALg4QT7A9ghYCooI3G5ALMFbewRYJpAahAm5CRg2GWE6Js7XOg/SmPJXz/AEiwZS0CTCMYAJtwRnlRJUt1Yw12HWi3P4Q2GFAATK4IkruOk+k+c7RRnTpZ6qELtehOzBAnCC2mlIUosNaKD5l1O/FCIAR3AeyOYMbmVjMn7BzEOUkVnhDHOBwKb7wRWmjECERYXT7hnBrIZNSRZQQi8IWK40EJvcHF4wKBwkdzPZNgURIuDBz/AEjsgDBEVxRxQzpdmIafGScChRegSB2Fx/vyCLfabVCvf1A0+Om3/wAIZ+g+k/CfzH2ykbH9okbH9ofrSzz99YdFvI8DFmwCuKO2B3Pp00AAEuAf2ZGhLjYMUC/afj+UM4cFc5OwWYZItYO0Gcgz9oh6Q7716Vu8mDjPsoYMCHZA+yKXWAvJjqpSJfBDTogRREByPCZRPZIB5sMYowwkJs50Q4IZ4d9g1ToMQAOxCHtDnF3vYLRHFDEEyAjJ7BVqJGhIhmUFZsZAk7zeonQtFgmjlZkJRL3SGHwM5A54+kfg2YAxYlm9ogsRyH9qKcAAMQcn6yQ4MchSXTErJJ8gakBaIcD0fKKNACvIgT66UW5/CG7GGLUWMhmbwKXXSsRwBitAI7zIlMCxLO50xCMQG7jA6YZISgGpFFnIHI/tV+JFhPGLgBh3QN9YCwmTo5hALOACdFHpIAEOaBCJNH3QVNvVQvVQvR5xII7F3l1C3+DQM2qIGRGQbXcxY2AsUNssRAk7yjBptkiIIGXv5EBF2kPINUR9M/e/35AhcagEYsft8dNv6QyQBJLAIysQnAlNsghuMf4SH0/lR+f10/boAXhGANVCIIxJqnwMTw/s3WHRbydi1rWInTNDnRMQGFUBqgBoyCQXCf4/rRsfP84Zw0GJtUulbvKiXkzIgF2Ih9MjnF8+36dIbAhyw9lHeA8mnJ9GUVYe+yQwd2sQgnNhRmQDEveYgvqggwYA7lwauTkSGLEAWp8KewTZ7D1BrMAvdrRL3WGdFuKvwdIw4PmDoIXmvTev4AA/ZPLui3lFbG3pRbn8IZeCLHaGiLAzwMrO1CwcCwIP2TyIjkXhCeMbXQTcNo2ov7on9x5KMW8OgDlusq/EqDeVVv8ARD3nR1NvVQvVQvVNvVLuCosCeecjbxEPSAzbBaEJoASDESdPkQAWbj0RAe8vv/fmFHCdzQQTh+nD9H4z0zGYQLUac1gDVMYVSmhHzHefyKIb+N2sgis0xSgI329X4gDAnFp+EXCMQQ+SHSIYAI4hxRWhjyL2kwTkzT2kzpk73pDif03R1voYQIu+ICGYwGJAAhYbdOhqQQwIEMTuolLVILtFLuEOkQwARxDiiRIuF2cyjGUAhAGdr08rHggwhd0EI48vLJwoSQRNbej5i4YQIhj2COSZHkF3MZdvaHFD4AGiNvdNk4CcvPSKKAzSG5z0QQPcnTsHbyUcKICcBdPFBfiiCd8EQmBY9tiCRqnDXThrAA7IXmKZlaSiBgrYor+jrNMyh3QyxT70CIfE2BFijUghgQIYndRKWqQXaKXcIrQxoFrCZQHEgXLi4o9p+x6OCb9zAQPYIVE+0qIkgCAAAYAWdCtDGgWsI05rAGqoDVB4HJkTDNTgSadsOyCbQmBA9ggKNvtaobogyG7IZjiFF7LhFyYwkyAeQCLU2bh0wZ4N5TqA4gAxc3lFaGPIvaWIQRCSZRYhwjOYvQkjEyCpOxoQzR6ZjMIFqL9BiIF44Iv0GIAGjij0xGcQbUQARDCA0r0V+wASDBlyaBOGCQN0FJi5sIHI/SihD7HJIhkhZz44NxgQ2AjsiFwxj0Y/8AmeDLpmQwz/AMsdoNey1wEKB7AGZGKHHjM35Bnij/OC+/H4zlDncGZ+m8IAAAwEAP8AgBQvniAJ2o1QRwIzvFu/yxJyjiPkNWGsF+iA+WsYX/P/AAKNQSvvaW9ghowAIpnje/0B44AQzE4m4KLUvc+QAJL/AIGegiMxiOF5DLYt8KBxkx+ZIQ4/BKwmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmawmaDuJwAhJ8wPpX/gR6ZBHMYTiGK1AAAAAIAD/AIKXmC9BGyfEvIujTCO7qnXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuolKYkdiwfVOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ66h11DrqHXUOuoddQ5iB2UIAv7mR6ZYHoa/8AIDiCb3f9l/b/ANln7/8AZf2j/suT2f8AwTOIWmgPiMZiILUDjCKDGCrjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40RwxSGwkL0lXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxoq40VcaKuNFXGirjRVxon5jESMVGmFI5MT/f0GKkUy/5LhuKtM/38feKdVAf8k4rt6i7/wC39/GurV3+SUC7/JjR9r7f7+Klh/k+FJu/yVFuKL++IS/INwDiphgQbRA1yI0FQ5DL7tv8gayI20RZHREHQYOpUQi29AUlwBtB3/x7Lc5tMLHsTixRCBQjMmCkdW2AAzjYL/72VY2DcbDmn+QAuI6NI2LQ9+f8hLYsn9N76RnsgFmbf5BnT5K3iPPVjjA8z9MPH99J4vAZ6e08TLK60ckJRmwLB/kG9ODwt5eeji0Pky1P+Rkq9xMZpjz5EP2w/v24ODwqbyvYxno9/wCShXO0WDoim8xAuA/yMdSG+jXwmAfQf2/r+kOkkGN9SRDyTNyq2yqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyfJfMFolzZiqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsiDB8LYiYidg/aXtDYRJEGf5Xhy0/ZGyHN7Y9sn8YMRGiqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyqWyOlIDYgLPZgqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsnUAMBOiJAY06PSZ47Zw7j8ogBJAAWlGCAGw+8kOYThblUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtlUtkSEgYEH9EFEwCQDwqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqlsqtsi2fBsRYE7H+/50cCFwxT2J1oHNM0Fi0oP6hH2hrYw181wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdCWAYpAie3FkUVCqIDim0JmYvpzWn44WquQwAUgjphdlncq3VhzwSDB3pxQ1h2ALg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDrg64OuDoKwTEUIL1eL/SnE8Ux8ApSaFlxwY/aAuNyIH8cARlwN7LEbDtiB9Fruc0NBvEwMghTdpVwdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdcHXB1wdBW76LoESWIeg7pgGPfdSPTZzojteP4PYNDaxwT3WWpiN2BBKDMAMB/dAAgIoQ2FOwMFCFth/FB2CuJAKJUxyTJqGCnD/7rJW3WM28FR4s8JBeLguQ+YDC38WK7Cc2boRAcnj914/3QAgAEGBBUfKXRjsRswP2lzo5EYie2Q1k3dot/al8VrhRgxaf2uH2Lh9i4fYhHDgcH+RiJGhgROz+LYjsS9EgKMgBg/xAcxJLFw+xA5b1nZEYaJsFv5OAQCYn5ysfMB+nvCORhCln7fiOohobSZakycZ/7ygX5hZEInjMXSGHD8Q0SQ7gkE9kVN5a2fIzyJK+guH2Lh9i4fYgZRnBaPgBBAILgqd5kBgjOMwS8fECTtAMlw+xR4lCKIAICDIj+QIMi/4A/ZaSuOxVrZmuNoQzqTti0CQz+kypFHeU/jgAv8Z2xwRFikkXbyihk50OzEdFVt1Ex2nIuBqRoOpo0xm4YQhxOEeglCzxZy9/UeKEgMIEACC4KO1CY9YIZBoIQmfHHoSAJJYBHwQmBnrhngJP8PR/RGCpAS90gg+whRqhoEiTcBqELYSNYT38qSI3A3GoCKCSIQAiKsDqQb15SSFnTHTDSdTLhn5BKA2DaEYAvxszyh5/Dm408WU38FxRLL7+FiYzw5B/bp9nMBWEHoJ+ge+aP0yes4GS6mAgQEHAIjZyC44gSoF1Nli6aE4hHF3263jPjg37IokTJZA6/wACBCAATJROhDEIDA2zUBS6REBqiiBOe8wNfiGCAEDIsHVVuVduRWgwQx3CE2AcEWj+MS3AZmQZnx8pRhWCzLPRBBX+C17f8OIkRqPGpNOmFgPkIITG5cEaqUTD0dNw7DDs5ZVbdYJtGdArBcA/U0xm4YWOmHukFoBJjAMXlVu4gTFMGe0AL8FGuab2HRmi8mkCQCSILjpjxppYjkJx/CkXoHYGQ9zMWvQz6uBAwFqLJYgNpIjz0x0w0nUy4Z6ebW3GZ7ERJiXJ+z0wAUALExRP8tmhnuNhUB85FcQWD6QzMB93yqzd1QIrEhbuQBPZxhgLAhg7acLSMSUTg6QpNaWUJTAm0KBTLFhXIH2EIICAtV9GSQWIi+ETxXUvERH0poDyfFiZo/SAIeYMO4Q2TFOB7qGKTC6DIFdLWlC1EZjbStmoQclnBT1Jm/NbkyP0VsmvHwwQ8sOSLdzYm6bimImI2zRCCJL4nu6ej+nUYu0HwIfROPKR947BCVAsOCCvLaoRgDXiM93BBExXMIln8IW2xIQJjchh6jiQI5ACdHBJgnc6b40TUcLyhCiAdMRGDLOZZB/fyF5He1QpYHH4RjAY+M4ILNF37bfCxuPkUvf2mCEmiUJC4GuAQAIztsR0RaGKATksJAIXvoEIIxdrYudVu8qJeUi3i9dkCxkEi+baotFcYWkrgFByrwHy/aaSBGQxY6Q2kRnAnZfgvtRiZWZyJi14vVkoekaZ+SjPiDXLuaIYdwS9JkEO6GzEbBOEPpBei5DABEbRsxM4o1BPMBCRQQOCLVZc02Ip3wouAEOMCGjEWsh3QmUAOCLelVvpnQQBwYIEx8YBR8u0L2wbCBRNhGHL1mf2hIwGSP2QhIheIhCHADFSwlF4t+wo6rJYczBTHxNYuwOqh3nNge6N7uB2IcekDYSuI+EJUOSZ7hEewjHDaDsG4P4Yz2O2OYen+b3iqt3oP5c3gR8qBAXgLdkJ4NmexHaxkbyQQ2YCbXGIUfFYhGxTfjzVkbk7d8wTDFBBxFBwLiTqH7EETEBoIeBiQMBG57VAlI4MSXJDCHlAlU5w+KMhDQjqBcs7XhCQYtfFJGoKWKUMExXIwIhiLQh4WJBxOtIvSi3ukEmHrA6jDxEwTfGiajheUIUQDpiIwZZzLIP7TXzYkgfFB8CUiBaLBsEXM4wTk7oRZRibky3dE4B10EGKn8ozs3K/2r7CMZB8tZu/gg4Y+AEAYBFjExu5KEAkpYAeW6GLRMQHIn4KMMbjVVb6rNyAUbSMyiGaAqzAqTVPoxX4kIHFrObqcO/TUWfoAWYo90ez+3T0f06jDOYwBgB+wpLshxQ815oHtACCzekkA3oogsz0K9gpFMk/rZhMrAjcC4whiT+kTMkwi1wgEa5EHr5AXgEPSMamSen4RrsSeghCJAPr4RGmjB1lg5siWgqgxQKcswA9pn6bymf1Q8PmgEBkCXmxWmTSz2DkIScC+YCduZCUS8pNU+jD84QWJDk1cgeInF4rAEP8ik4RnbCPSG2ZnClcC8IQRlwgDMfs1RrYe4Nqili61ANs8lFpFRAIRYs7pgwBB36EN/BEpyD0+SDieH1xamk2wswwdu7KAAYtloZtmplM0Li7icAgIeEyhwHQJyCBl7RGNyHhBAeulVvqswPQQcH70ZbeCJhSIE0DyEQrO0wPiITUqNpsQRofIIMW/QT/AABY7WioiOCBEgkM4fsmP8JEHxLxQUJkYsstcyUVS5ln8ICFIwREWdi/CEFTBFCvUHzPeKq3UZBxMAo3YwBc0fJUBqinKOrR3vTcJ7hliCix/FuWQEVAREUc4buy+AqJcVbuKiXOggh5HffQQaEiDEwujAaeEkxT2MqJe60i9KLe6T0TJvinqmbk2GZG4FxhDEn9ImZJhFrhAI1yIPSr8Sot5O4uANtbGvT9pGEMYGBKI07g3dz3QsTMBvlhv9BbPoHz8us3fwQd6xXuF9znrsnw4IEGIvfNPITXjEZ36kBrYJ4JVW+qzd0GqFyrMCpNU+jFfiVFvdThgWIPD7uR4KeQIoABJhGCJiYewEobIr2f26ej+iIHEAYWmE/P8TNEfTiGyFWoTWJRxeplMy1gCIeCh3mkIMgmJdAaIYgxkThYZF8E8Chq5DoEEGgkDkYd0ATcE5IP6iglo2uJMvAj7QzuwA7fIIWnJ23T9TyUfhF5TA7IAW1+vihk3tp+3RBCWn7bZ9BM8G9zL0yHOEAgZyHc5pkuEIGex4usSpjoQEkAJRLyk1T6MDQDADEEEW1ynpGkZDHhcIAa5dIZ7EATEElgisgEs297QADjRhhcf8KGhDIkSo9iUXCiwXEFH3YD3lh+gUMVv9wEfZTKZr0Cr8Sot7pVb6rMD0CYIdwD9/RRRggAl7xP0M1A4JAwJEyb4p82RLQAwe1Xu3GAiDJkPpUS8gVOIYJJZ/ad/BmW8JqWIQN4AQC/Afs/CIlLIQiizEPw+4/CEckQyuCybuIP383vFVbvRxqCGBDuMpIwyCuR97k5Wb5DA7TKfsoBCSLpJIM5wwJ7EJ3dwxDAgi4mMCUwwAfSGIwDGBo+wUEUAARCKJaqJc/iI4jNeE3hZ5DjysLWIBGoijGKeYGHZUS91pF6G75kxsy9yF+CaNDsGQMZ1BAxIE9hBPARqgCbgnJB/UUEtG1xJl4EfaGd2AHZQjifYuEe1J0AxE8USkCAt4ZB1i2Aia+5SW9WacYYIMuAA+W1BmnztQEcMwSB6IQiOQcEfIBV2E7OCnajOJJhr8ej00w05zQAAEgpxPguCgPHO0P7VpoJbkUXOyOLyiWR5pxJc2oCrsJ2cFBBIQCSTQZCGKMvByc1TorZgIR8IikJsRubumlhhBweERS9YEvOKixiwmx2eXYItJ1gkYsBb2RYSSDANxiQpXtqgj9o6DYG6JMMIoeBAiSDY8dejAgMDsq81Qfqc02H6BAReZ9AAExKQPIih5vyKW9nRNYOQA/tNAPANFGIgOJbD4BVv87X2iIkMwEyBUmaSkGM1Ms2AEdj8hzqvC4fH4ZBx/vT6dDcGJ8kRrl8TtnR0SX7HtDCzYAWo9kAwYQCEPQE4BAZwLUxCDkAucIIeiYMObHRuZHBMsDN3TzmAMBEgN6x0VqlSBdd5JgmCdDA7oU7SZkHCCb7IwGgxiWlYi3iZwTIg/z0nutEEXpjccGSRjBz4R0xHKABiR4RGgDg6T2ItAQlZI+igGtNakLQYIl6icA6Bcg7BG44FMnJi8IeAgGzwGyJg/ECKiJi50CFraCBiEC3GEkZFchUs6yM3Q5QKAByS5G8m7gHpEBptyXZMfSjEoNECZmVpKJtED2iFqYYCbwO8ftQdVwDmsOBQQQxAMXCSKgvnaQwI/wbMRC5wigLWMPpOpqahK4Db3UOL4MHFH4QhC3sJ+nRARjC8wHoD8M5gaOEXzABAZFAshzSiC4t6GpIsXVve0P7QWFbFkYhjJHh8vPUQQG0pFLc+nbYoDyFY0EZgzKnIkMYXoW7MIwT00w8xz6eblbO96GVmDiMSybBaEAD3A/aKL+IwR5OiH9AJuEH2R1GgTFBCHhV5qmXA8MyJULGwAwCIcMYhERIZgJkCpM0lIMZqZZsAI7FFRtiyRmPEDHNXY1tDsZhCAgk4ORLJ3Js4HAOyCKQ2CXYfKTFFlWMB+xFEe8teMkKXPQnxLL+gBoHbWC1OYgYqLSpwXo/lsFtHoIUc5KSG2P2fR/DIcMZI9iS9jzA+DDNCMv71xAZwVYISjNgWD8MBhlNnj8H7R3ESb7eZ/nDWrYBCIiVd49hQ/hRPtEx4t/MBQoTgi1DwYyWFhr56BsZ0KRGYOKrFG6SNM7j/djbA9gQAbe9nchphgFg/EgsFAYo5AhJlr48f7zxwNRs7k9Cgvh/iApAmINoTDLCvudiCWBcEf3djpQtK4JmRDWS0h1/fUAt7AIR13WGXBaMUIBesO5/cmjRsRT8WeUAgCsKPCYEjEkzK8/jBSwk7MBxxTIczIzrxj9oLKtq/wDcTg/FYKwkUiPZqhgaNEB3G4/jexhxiMU+kfF5u/2IdX5C8L/7ljOxJLusQOQsQhcOqAgAYH8Y2ZaMXfYoDIIrM0R4Qg0DD7H/ALUqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqj7pf1AR7dQxmUCyZpgOxMz6QWoMAwH5DZbZMOwUXnuDuKEUwW4aCDgHsb/aKqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqiJb4uQy4G2M8mCNAvjLsJBQCDvXm/ICUCYkHBRBaG3vCkElWEFQovB/taqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqqMQFCTK9lAg5CJEym7AYfFvlAABhAfAZFT/8kJ/8moz/ALOUpf8AL//aAAwDAQACAAMAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYAwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwgUMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAkAAAAEMIAAMIEAEAAAMIIAAAEAIAAAAEAAAAAAAAMAAAAAAAAUIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAUoPea0kfoQ8GIWzfCMQzqEgsAEAoQnEOIY4IQs8cAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUgAAAAQr0rTUAAfA/sgcvgrzGYQwUQLMArEDOLgosmaY+TAAAAAUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAkwAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAsIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEAYgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgwwwwwwwwwwwwwwwwwwwwwwbwwwwwwwwwwwwwwwwwwwwwwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwawwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA0vAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEnAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQXgAAAAAAAAAAAAAAAAAAEMMMMMMMMMMMMsMMMMMMMMMMMMIIAAAAAAAAAAAAMMMMMMMMMMMMMMcMMMMMMMMMMMMAIAAAAAAAAAAAAEMMMMMMMMMMMMMcMMMMMMMMMMMMAIAAAAQgAAAAAAAAAAAAAAAAAAAAAAAAAwkAAAAAAAAAAAEgAAAAAAAAAAAAAAAAAAAAAAAAAAAQsAAAAAAAAAAYQgAAAAAAAAAAAAAAAAAAAAAAAAAAwoAAgAAAAQ4kIAAAAgAAAA4IEMAEIAAAAAsAAAAAAAAAAgAAAEEIAAIEAAEMAAAAEMEAAIAAAAAgAAAAAAAAAUIAAAAAQwsAEEkoAEIA0MEIIEIAAAAAEwgAAAAAAAX+/bT/3TjHo8AL7z8PAAAAAUoAAAAAAAAYAAAAfCUMvAXQqjMQcUQU6fogPCIAAAAIAAAAAAAAUAAAAAAUvXajHnYnaPADQ0PbD+AAAAAAwsAAAAAAAYkcg4wYcc/owow04w8AAAAAAAAAAAAAAAkAAAAUu/K/bTfHy3yqGoQv6jWvjoAAAQgAAAAAAAAwAAAAAAQgE0UkwsAIXAAs48YkAAAAAAAA0AAAAAAAAAAAAAAAQAAAAAAAAAAAAAEcAAAAAAAAA0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQgAAAAAAAAAEAAAAAAAAAAAAAAwQAAAAAAAAAAAAAIMAAMMMMMMMMMMMMMMMMMMMMMMMMMMMI8gAAAAAAAAAAAEEMMMMMMMMMMMMMMMMMMMMMMMMMAcgAAAAAAAAAAgAMMMMMMMMMMMMMMMMMMMMMMMMMMIYYAAAAc8888888888888888888888888gAAAAAAAAAAAAAA88888888888888888888888888gAAAAAAAAAAAAAAg8888888888888888888888888cAAA/8QAFhEAAwAAAAAAAAAAAAAAAAAAAYCw/9oACAEDAQE/EIcZeX//xAAXEQEAAwAAAAAAAAAAAAAAAAABMICw/9oACAECAQE/EMOMkbs//8QALBABAAIBAgQGAQUBAQEAAAAAAQARITFBUWHw8RBxgZGhwbEgMEBQYHDR4f/aAAgBAQABPxD/AAQ/Hs0PfflLh6UgnI+R8k4YRDAcEfghl4a/YR/mnLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuXLly5cuPRo/mizjoEArgH8Eshe2j9cej6TSbnaL4JqPJz/AMEZZgVrlOAb7ObQkmdxQTdOrsv5qoSYyvfxz6FHL/PPqCVX6ByfjjD8xwL5BxyNV6I0qAZheJucff8A4FkhuDXSDmtEoB3ISnPBgbWrfFUPP40BgAND/QGUFQLE4MuVXfFOWehycYhbKNttDV8vkR3/AOA3k8cyUWrydfXglKiOIt1zW15v7RMdYzVDhnWX1BYc4G+wMNIleJdLFo5GjcC0ESxsfBiZlje1bws8yjNRWsE3hm0KeAPnhQCnCdZfU6y+pVmN1NJqHBjy+eoOonmeqTrL6jZ06dAYfQPiJAeRWgp5ieUCGcsZ0fqSMWyXSUx5k6y+of7wZoEoxukXHCosEErekPpOsvqYpwFDRYMaD9gqB5OhYLrh4pGLZLpKY8yAjvQkAZCzIftCB7LIIYcaLFoDzQgbDgv4BMdYzVDhgV5apVDofwnQmfuj884jMTHDWw8jat04f8ASqlzgCvwQ760rnKU8gry/cWXa1ULgVIEMI64SXcNvrW0V7ZE9G0QEdWQHsgRozGXWCwc1o9ZqIMDALb51UWqEqgKKtnIPNSr8ahuw+Bs9Jfr7GXa1UKg8AZQWT6uuLAmeWsTTF7FPncx7IQZxqfIHzUfH4Bc4BOQ39XikUJJoucR4z1nPUo7HoGl/eBjQiINake+UUPpD0FetZoPOrLKCRyYXELHks84J0AeLHibJomyeKx71gDhT4CXloubVtPdekVAAM3CgfUsIYQRPAXuR6+ALFDteZlKGLCgvWxIMtgyG+9v4lOG4zZWisFLwJZM5r/UHkZV0AyuCMSykB59r3YKOlILnrvHrAb3XsTRIYZUroFo3aMrk6jmuanlATfRK4AS7NA265rWXFvr1RGvWopXgNjpAcKgYkImLetHvlHLHW0VMACy1+Wic43J/TUYAhjwr21HZ35IkaAylvYju/BqoRLRFqxGzig+ZeQXlMJQU7DY8bQ/WGcWcAEW/Qd3D6CtAsqpDkyOLgHlmY0Ya9aCoKdtTmRQFWggkQ1X8cIKOdnKzMAu6E/u3+JRx6pubrTUaad6dxJQBWNrCqR4TPO+srQEZUF1ihHeVijLokIs5DV15QZguzooCyqgBFEAuQS4ph5LYrtKa5rgGzWk03aaaYtAWtV2jExoDIqVgOEUZECxIVkeMC6TTQC04uyAX5awJcnIBcc2Lyx6RrlkJSXSGyIj5RMTqQoY5gxeVzQ00XN3Y30JCwxmJEKKbu7Ew+4YjprLcNHN6/t2V7oglp6J8ZTkUU3Ap6Nn+/Qqn2QOBRMveNfvuxw3TOGER4Vzjp8GekfsupznrH7rqcpfghu9QPIL+i4DcnhmAr8EtDU2tVU8jB5QMGJTDLVcgvSIg0R/9gHq/UcM4pSSCSZs0ylrLvoSudbAGyDdALyjW+zFn5LxWIc1XtE+oyiJNhDb5YAiHLjK1zuvpK0se8PCQN1DWiXbbEr1pp0dYJD2KIltBTTg2iR+zv2hHZ0sdQnon14QQYlqZhbS0SmuOED/QFYxZKAZ3anCBAEQaSgbXb5qFVTi6tao6EDQxZVMnn5aQrrlgXYB5XR5TXXT5rfEG4VfYPK0Rug6vFt6hKR9PpcNNTBrlCm5N50n5y+XwGhPWCfRENRpIWrqEoNMS7wbd2AIUUQNnCfq9ZzVP6gzi+2mbdRfh9GHyyvDzd2WoNMXvBoZLr9GhCrAaN74x10WtotGRQuzjG0NqkToEXM1d8dSFB9OAc0rqLKoMwA6786T8p8rCrys7hbbFqddgrVj0TKQV3HmwSkLcF0vUspjOYvqgQEsAwjUTykfQFfC+FnT+KdP4IM4LVIbtFVnWgl9x/kLGhhaQuunCIKuXugpXvb6zITxYCo8jA+ax/MmlipVMrz8jErZupkeQF2rYB+4C4y+XKI+FCR2oeQh8J/v9Yw9AM/iaiCXnZ9n7tjgywLVaAl1l6WUbtEAL4jHF1Q6jD0UgtV55Obf35cKidhuWtmtb4s29aJvU7/LumIF5Fnp+hwGwIggo4196vJQ8OL4Bpam3DwIkNRYgUuxTUZx4YM7h5p+oOGcA9U4x0Ph+isB4j23Fe/h74rhSzC3y4Fg9Q8HDkJQtFTXxM7u5sEg2tKDQxisS3J0FXYwxYqVq0guCvODV+FhwRRsAA9Re0yNUfINU4Np6oqF0EAM5bWh2mBtK10KrLwnDWdJ4vETq/F+kG4YN8LALW1q2AvlSoYlnoAFaNWOFQJd2KQGrS3SbQfRmC6zfnKc8f1BnChMeMYLL438iFZig6CrhhbmuCbRRBhXKwbLdU1W5KuUVr0ad4WL4ETU+ldRQ23sufmx1RYEqizRhagjkhQB5Lv8ABPlYEKTW3xlAPUOE6nx8LOn8U6fweNgn5OdvwksVWvWj6w6kFbELGZKEiZgXyEcmz9wHSYfWJn5jK0M8sPp/39BB5xufkEsSDJyh+fe/bK8PYIWW1CNXopXq9Jy4ywpjxzWF1AFyh00g4hd8SAsKUgwDmgLr0h5BdZSw0lwr18VE1ElaQQ4V0bSpt5C0KVimUvXeULwQRVKB0HvFtnGIFDIpokp8aIG6JCZa9ENha4NNQWYwB6eD2UFInltBj3DMh8zoQpGwnhp3ghCK2g1HvP8A3/pqOnySheCCKpQOg95jmKRULIpoj6wj2zsirqODHue4CxRtJs+DVzRasYHux5fMsWPATqD1jwD6TKXIMPvTB7jvgKLNUUg3uiEgRkMUHW+wZSimQ94VkKoS7DYtMZTpeISjzirlIKWWXyZX8gJsBMsCa1j7bSqqac7KcxTeZ8sAWtgQZxZhzg3RInM0QcbCiPKBzmTlXFfbQwE1YtGWw1lp4V188AULpDtGfpGxa3S9NYrC9WAgYE6pKd4IQitoNR7z/wB/6ajp8kW2cYkEcqGgzWKFZFWTYl3COWM6luqOYl8RF7DcxKlPVBmDcgDrtFIHdtc7OQr6gKAaAeC2zjEgjlQ0GNXopXq9PCRGDPaA5UHcvidLkplG6ovyHaEzgvNyFPcloRuCm9EKF7try4GDqBCoFhoWBPIjtmyajJoCVqZM1bEEDZGlllSGi+msrFK/WCATWWEaxQrIqwbMW2cYgUMimiRkxRIUgW4ypMQ3SlCwJ1Q9YTdhBxaiVKkgDlotCvD2CFltQlrHaEEpky1jtCIQyI14ewBsNikMl20hKajgxaw76UbydxlKj26JpaaAwO5Q1VxuAu4TKWud6W7xRNGSiEN1cTlbcWAggjTzwf2wF+q69vue+XEkE6imj/wDqKhXAWz0bPL/ACzTqG1pwRgW0dM1rM9fEj0i3t9wuFQQI6WugVVas1cQsKIpQZXNbfX9t0V+mBv2QPNzQQggBQBt/wAAfqQRxQ8UqnqbweiU1ksBxdDmzuf5bmAIF/cIWI1TxI4fJo4zQ5g1Nu3N0+QcX/gWe0Rs7TuWeBbtptzLZXVHRy1N+L/n8kbPKj8g67XFgIIdFHkB+edrAAAAGAP+BIJTklxRArXrZ/4eUOs4gYTcdDnjzZewdSv6mXosMr2iR8M7OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OnZ07OjEM1RPllff0a54XYPVIzw0MX4gvzVfMhVFtSDxb/kY5piCEYAoA2D/guvwI3tMTus6lvJ9hUSPAgP3D/W99999999999999999999999999999999999999999999vS1rBf/wAV/Wu+++++++++++++++++++++++++++++++++++++++++++yB4aBe6vxCyHlyPyK91hsO2xXi1q83/m2I8fyP+y4Fx/J/7Lj1OX/ZcH5/+ysPT/7KwPVh/wBlxXj+H/2XBuP4H/ZcV4/h/wDZcOb+D/2XBuP/ABIIy+b14gyNXKMDG4asA/n/ACVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSCqbcot8pWsNP8lSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUkoHVsFqw1jHGJKWu6UVcrVf35svP8I7LgX+SYcz/JEWvBvljt8x/fwo8z5IrPgf+ScW4/5IC14NCscn+/zS5nxFY8B/yVgvH/JM23B/hHZ5f9+ijzPnHZcB/wAl4px/yQNpwWTtcj/fA3l5awphaDTmq4xFab4AMTVwkLmssbHdgsA2qrjLR/yBEBGLqaaqTiIgYprHG84vIC+8/E2fOtXl0Nk3/wAeEmsSvRaGFm80Szlw8+IY02rAPWYnPE1bMjVsXgrJnP8Ae0ZiEGnn0gPpHxOPqik9zw1gzWZDYPz/AJAwfaMYBB97OaeDPxsphUpeaHlf+Qwx7SzWtHkg0x4b0cJTSNPM/vgxpaYYGHuLc2KMlANrPpBYFEXQgKA9P8hwD+s50DyXBw06zT8VZksD6voJ/keTJBgt8VscEmTP5zF408n3H9+XnyhnQPMuCjQJpvJPwvyf5K1IojCl+J1wqAUCXQFB7H+Rz0BrMtPwBHADnEyKh72cw/pGF8DeLwS1vOoyAzdN+VG/FXlntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7ZntmdMXvhaTzqZ2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zIPjxW9mCptjfukS67GQcRNf5V7J0SXINV5EEsGny9r4gFzc5+U7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7ZlX+5N4oc9J2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zL/ADY+kxcq6iP1a/EZkhYB+QPU/lCUK1KA4s1/VO+D7RWbMfwcdsz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9sz2zPbM9syGB0CiOoyU0TNAoPSTtme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zntme2Z7Zk3/ayACHer92MfxAW7gNBfJYIgjY/qHtArR5v2PlxEurJWU7mo8QxexANbUVvJPl6IToexfUi33gZQZ0bToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OhPqK1DpEj2lorLncV5VHPrcqN1b+SuJEFAUZjzN+bPC/wCO5thQLVV0lj4J82q6Oway1/qo+VoPIE5wWH6jdeOsPQIOGNinwToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqcoKLPxDJRztxut+stunAd8tT5nrCLWNlB0EGOQzGcT4gdbfx6+GtSFtHYctXyzEopoVTavPKkAZWqreVWOSsMhTg33qdWfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9ToD6nQH1OgPqdAfU6A+p0B9RYz1nKNbNvReTVkS5dLb+bX7CDLDpLGcxy8yi+MrCUgvOXyHqH6DBHqnHPlPlxxTIUqqDb4AVZwNR7wEANADQ/um2frHM2fl0XXjE9gC+JG7KfOuI3/EaDVGhFqs0byNKH116csOHQKgtzdjgGD+6MNmcT2C8tHcYKWmkcwbwF7vKkLzPRA9abfxUEw1gytGt3sertbCUW9W5yey4N7dP7kQjIFiOokX5ZYjXXl8eG64ShuVWDSo4cTZ5J4cco6UGhxXQOLEjDW5YyXIzxXmAAAAGAP2uYWk0tg6U9/0dOnSvMHGCWP6nOqK9yDGxH9OMC6KlrowPBg9MRJS1ahwf2isjRKCw2zqnh0GC9ayJ7xvJWL5gyev6kgDAC6+X75xtEIoJRW5V8qdmOJscUmocBSedbfxMXoN7ZbkYXpwYEywqU0ZfLYNj1/vMPdsSwe6Pks3l9CFXFHkKTnXF/iEKPZf/ADG7yGYsHDebR4DjgR4H7htUAqLFDA7L2/R06dDrNMQ4mf2CZAsRsSI/8FakE0K0SFnFHcLH2f2kwgFRsoOB4Ph0FDpo+6CDga0WJxH9VrRRppunh/AzgjNm3aDbvGzelkezEubdJOYiekTjcdKqrnZ8zCpoB88/fTkH7fG11vs6q/OOo1F4S1d60mI4qj2DZd4a7zv2UfswiroC4/VKKvktzBAIiORIFedEvyxYKbi/D4EFjp5el66ur8crRlV8hYZYFiNiQeVYUYJVWcZXb4Fy+Zd/h4GWBarQEytGVTzB8FAVaCbQX+PRv9LjFhHiWOlnDjErsAC+ovxAuRl44sdEpKTkkuUBSxSocmwchFAqgGVZn/NXFvhVwwIWix8mAKMitGlgkFreRwbCwMaB4clBA+6znIc/sP7icmhWIUjySXcURa49Yp838NoDGXWCwOa49ZqH1TljhSA5L9lOMeqtTdNYA9JesbvDghfEp9fC+Xa7gYFIUL1XAURYqLIsrqF+p46GpYFRB9osJ0cTEtraDF7OsBlhOELVNd4tdr4vrGOVUnH7QWDO+wXsrnP2/QOBrRQHFYeRrrw44NdmObNRz02t7rOigsOb2JWyuM/b9rWZ2eOBrbE7jAtzR5wTgQLM8gQ5l+UNER+xCxHc/SwmMkJQ7V5FFt61+7fxjSpn2IS+fBKYxEDQMH0A/hsAAa5ChUb4H1gLBJ7BR+5r7wpVWqznvlLuF1L5olxUDWh7VvV3U79lC1mzRTeramfuVVbeV34hXnRL8s5KCB9x8GENU7BTcTLGDl4LDjyEnTWVv0R1ikCVgF16eA6B1rzytg5esZPJPAa4tVD7rAijof3j9O67KKLs6qcOETqZrSyqWYXgb4DBDhZu95AVSaZvbM5KCB91nOQ5/YfCwf4NPKjYxdlPOMmRKtq+C3PNWx6LCLhgIPc/dC0t4r3g5iD6Re1tXZt8vRmw745owfl7/u9L4/EGlb8WFFqjKFaKNvgqadAUxne0avAMQveCGkyF1TTFb6huaCRC3Vbc43aCzUGtTJtkEye89NS9Ro4ZMbQu4ABAeZHDKANI3it1O9iE3iwWXS72jdaUWgLWUytwv4llpXESJbLSNa3nQlHatodOGaBOL6Z4o4hJR7eRKM7SqL1qMspq0YrNwJIsBbTnmDW+5mcYxcOlLmq3O2K1S4o4xahsNFi8KNCVEYWBavIa+IRUnMUOQOwU60kT+7EtfEcdb4vBXmFPG2+T7sUhYpwVX3+CLtoJmAvDXg0FXi4j0SyuJ8waA+rXq00FI2bCaMBqQVINwCnCasSNCEKVeQXeLYJs5rXSwBTkhEAFLjstA1xYEA4YIjL1iYUxbwcjtLiiRtwbNVGl7gb2/uDZVNTFkK/H0j92BOIln8KpsurWlr8T1hDpd91VfhHp+y6qvQ81PkKnS/A+ZXx/BhD0z2Cr7EwYMaaF6+Qv0JT+aY6A2tAcjeogNgo/YH8w8OiIo0BcLtYW0FrXisBiAZfOcabY2cxTRjKFdhzVe6G7YxKGgMr9CtAsFmLoP5iLdcJ7Do2tHOjWF8HD1Tz3MLQHm5zQzS6jiK8q+5gS97KrAoPJxZYXDnw2LRkW1rY4QVFWncBizFKHVZ+StjaxV12ghmDaJth4qrlHJkLBaquhC37rB5RyexEqjRSLzyHnVcUgvbJ2B0RNSLSowSjRmzhEkJGU5EtYJjLyrMqvyXOepSHkMFaRawORHc8VFRjRg2wjrGoQ8U9zMWC3Z4DYc2NRaTXNDyABWl/sB+G0uViWWC34MqBZnJHJs5Y+gP5hPaFCuUFL5NPC4OTrdFCZbKzICHpZCCizdILAfR1EYtxQi8oVoE2u59BIVN/KvZ+0FcpxUOqMjk9ESxH9mooe5f4yXDluQRD3Pr/D3Of8X0t+91Dh4qMbc8m2zTUcA00dY8NrgCdxxegXvvLoPRdkC5E+QpVZtY7e8PMm4leoXWcjqcQKoyosq74qxaUmjtORPJhwjq5AT1MYBrK1DV8rqAN0fZQKUFwkRPGmlzIAUc4Vb0IA5cRZVKq5usXm4+rc5SGt6lirRKuvCHago4GsxN9dQRWaLEb1wmiwyoCNGUHlbbyGDIBWZGwaFtAPi0xMoZt410z5zZd4qxq3sQjy/wBW4MXASArNQPIx6QJIp6yLLaWF2l5CIAKXHZaBriwIBwwRGXrEwpi3g5HaXFEjbg2aqNL3A3tlZJWwsKUG4xs3zKCtKZtvmUV9dtqXNAVjRvOhDZoCW5YKyniU1H0FtdYFbiaLkw4YIBERyJ+7rXENkRPkzf6wNv8AwP7vS+PxB6nxmlEGgAAPaO2xTAUVa2CzzXzQwHcqvBvpzpF4iJdoBsmuAUlJtuBwWPh8FHS+OHbbyc1fhYQQImjvn4CdD4T1TjHysCQp5kaPwEBaotrfgcaTtR4XZy+fChzAvIfgP0OHHW+Lwbo4tFIvv70Lehc0Fk9BPeMKDeAdCTRwruON42M09hxYejcT9aEcXR4tYRdCGpLQc19i3aOjXPN4AgZ1oSpF3LRNjIUPDygE1QvMV/k/cUvQHktfwTWHR5v8IAXUXmf+jNENHkE/ZGWzIWBn0gvSWgUDvC85CtO5LH6Eamt8qgyg2tOVY8iPRMEcMGtaLVuLb2OEG6QqVeX0gGmPONEV5xqCryU6XnSLqpfq3wB9D4T1TjDvbc/FDzyoeiV5I0aLGYKGl1W86UWElezFFraiDz2wRwEBdPFzSqAAo6Gsu7izBTDlR5rzj8IhjwZ/ClW0tQhVlTja3lcIOCQNodFEgvWkC2rlyvg4LS2sUJUbkWpzW0qb+exKDsTS27VQZtyuxuTUGxEKKKeWUGg71qNeUJerwYVsQBfkBY0DbyCqiAj1txIAYNeQwUPOth4MegD0/SoEYkFQKaOH3AFVkS8KU/l94xFhrKGshaq53gR0uqqyuaLsVW1SyoFqjYsu9BLu90WKtCXnW4RC58WkAZMmQmD6Q37ZNNCvKHmlB6DSlRrijKQadpBM6AC9LcG0BbMzYETfz8fsk7YqOTLSWvVCfv8AhaQLPMGcwXlGf73UOHgoZukh4NTFcB2UNnB7+DIl0ATDKaOLhLwt6/UrghxnZCUiY2xXzKPJSEYtLItb1Vbmr5S5sl8EC23KRHFiYNP0A1gPpfDDuvAcwp8ngAQAKAbSgyYVvVR1whABZDeaFPlZQbmDSzH4/WD3BlBEwHAGX61cyji7AA819i3aOjXPN4AgZ1oSpF3LRNjIUPDygE1QvMV/knyvgBrEXrXWFCLSnUATXQI7hojdaHMWCVGd5uW2ud4uiivMP3dnRk81Pyx6yBDvpfB+70vj8Qep8Z1DhBHS0HQEB8xa80JJMqlKNirNcKDJKu3Wbcth0NrIaAOao0ENd0j/ABT6+CjpfHOt8U69xeAnQ+E9U4x8r+gDM40lkzC5HZTThTvGg6mjmtIQ6omLxcqovn0FuOpdju3pp+hw4RS9u2wu6eME21Ah7jiqz3xLloN3d5NgAdJN05IsOQBzVe8r1Sgbpcwp9Y1Z+nxICU3wZ5RJeAiRmzaKWGiWq+DnMYUYUmEFLyHpcr4UXAdQnAl1wWukTShQwkIpatvitG8azj8JioWaAtyjSFXUfkA/P9wiNsDkAflFKUiOCJ9fwjMWIuV6WEu+5NbPe/2gJj/q38ePComwQDKtesP7zF6dKm6oeYR6Mq/UuDFRqYAOMXvEvaMARdnsOwfctHvk3FBYvG7mmqjyH4A+h8J6pxgWQTJVgxx3PSGUEqbrCx5jY8yPYHZZSxXNPAcUqyu5wBi6curnkTbraVl5M0I0lQ+oFPklJtmRwGfg/Q4BcP4tNqwJ+H1JZYReysU+ZT5JC62sZBsQQa+6APEYb8r+oDKBDh1BtO0ptaK4wQ2bdUg/T4UySc4U1LdsvQCt7AKQOw2bBfMBLqt7zRjO+KzKB6ZfFfgDD5bgsGK41lW9QrzY9xaAKbvGj4iJqfGTkAbC5vSKRoLyf/E/ZZ+lDwEfqKQypzDf4RqApeTHx6z5vkh/e6hw8VFPg1YcBz3D6SIZGMQhXXO8uV8t5VZoGg71jQKb1dmZrwqZWRSahRKx6CSFHqHNpNHRL1qirj8kMhWqomzF5z5ZsG5T0iwNls+SSyyu5ifYekCl9gQYNmmlMefgD6XwzqfHxZs3jK1OF6KWQrm1AsjSDWRFNasIZo4RGIKq2FaAt8v0A9ypPBw26LcYyoWtk1AA8FXyhPxUxK0b5C+BwslKgSFoHtcqrwBdomlChhIRS1bfFaN41nH4TFQs0BblGkKuo/IB+cNa6Q7Er5/MvEimpiShw5Ym1wAbgs8kT0mHqDLFLL4w4WcN4pxZWCnTLgSnhFMGuG8Jf7r2Kckuv4MS1kwake8e6BfKQsRyJ+4v8U0gUlmSYnMFSxYUOF4J4ocCatFCCHQAeUIQNG+gZWNkoaX8tnLSCGMq1jULmGK0QqQgFLNaEE3rhtEooZWL/FNIFJZkhCGCICnCppCntBXViUy2NrkGq0aOsP5bMaXTaHdgroGJLVqa1ZgOmzWWqRuxOxJ1ilZVdVn/ALT8SC4PaBcFobS6CGHulVWkQWUm5cpFrI9uSrs4WPzDw+MFkiuEYWY4YgGkupWm8zDwSCcNJBHUyZDwhACuDo5IdORkQcF2vV8C0LV6TgMU5XUvKkX5mjag8wuAjEdVQXRTaA8QQVa1xd2LM2lk8gHoEBFC0qFdVUrdbx0zWg/QB6BKtemaSEUNkQyt4mfiisgcol2a668f3NmqvJTfivzfw1SNjNbVq5oHrMo6k3tX90ftEFhdb7oy0HulbzpwZzADRDnUAgAKAKAmkSebm4BAwW3fHGNwM0ZRTUNrbNCHQ+M2bwZROWsOzWwLVZm6PnGrQYxPKlGZoB3kAs0F1F0cLwhtVC9SVuVFAXXm6BWlxlHiPnapDmq1Bxw0wde2e1KShwANL20gC4qRTukMWOeUwEiQl2A2BwaN7B0D2/PFB5WvchspFSNpDd2TLrGCGKqnNnYsLiUsNV6rBBCwyO02nh5UyoxiOhpBlxUS3VoZoccojY1RYhnyAuuA7Uh6lTwPRQEPNBl0G7DWuAvQuitF6RzSMMQZa2DQNji2upbecLssKicGkI4I5IhsYCWgocxS8KhWxY508EkZ6QIANVdpTg4SnEYeuvDDfcLmsu5z3V1eRjKRwBQdYZ5pc/GkTDYTt2HIdbL1eV0QgrKuqSJ53F7OTfQKAcQvDi6LqEV2o66Q5Euo1ubWrgShMmznOSXcUmMjBg0a7LR1hgpbVd0sFDQ05MYGUdS/OHCCKtReSrmpZ6j7BUrR9nP9m0KQr1MvTUepKERZ4U91Hr/D0YiNA4HoEPT94Q7BHyim9ctIlNHIeDomuiB4nB5k4PXcznf6FF8WtXnAIAopHeOna1K90+EdxcU5GiDQeYeCgMJY+VYQ5XUMvcL4BGrAwppvFO2IkUAYKGAi0B7S0SgvygeKPAGjTR8O+asrDXaBc5CABbPBSOaz1xBpm2ihHAvSLAXxUABWhav3RHTz8A/C8RLFBOioUg3fCERHWz8YD6kHk1KBwAwEBgEKRLEjpmtB+gD0CVa9M0kIobIhlbxM/FFZA5RLs1114xmiYejxHUcuSmXWCoOGjTR9bgU+toRXVCk8kj4eujPUe4gYpo+yVhBvCuUdsSgty0Y/d81bA+V49DLR3pDNDD52xxCGrpALnR/MeXF/QOGEKiwaDYpxw6F1A+ZCD+Ur/OXcNi3VrgtcT+WwqsPe+Dd5DOOZiw29QBf5P4YIAopHeMgqo9Fr35cjiiAKEcib/wB6tJXLlCPwg40cYFEXQgKA9P4dr1WaybPkeSdpWVJvQGzgMPNNv5ypnhWopEiXMUFyg2V52x7BS5pr1cfZiQNS6yaW7BnBRn+YfcMRy58Q0c04QTcgEyJk9F/+HhiOi3DkejwcYgbRgpz/ANDuf3aJkNUDrbeMQK1bjlbYaDb0WaWsDAKD+IrC8Ri3dPCh5IPGa2JmqYyaDQ4mNQv+7NDNrjgUriVxB41Kg6W7uhfl5+R/EeYs+xCkTgkJt6ssXWt5uHc80nCbSbiJsmibf3Z3BUfly3X/AOuCLVCEzrOKC7W9+gAACg28E8rCtGok1L6rXrv/ALkb05XX+hptzcPk0+ev9yyUq3nC8jnQiV7xcvOXGLbQviucUlW37br8aGP4zNasYM04I29DiqtKAD0Nq+0LY0l0hHk1o8nP9wRTLNL1Zec+ceVrnm04bxGLV9q6t+66G16/xgzGyaLsmw4xyw+Bp2CegMPPJCyOZADvwHmeof3IDKwC29jy5eUWGuIo2yzju79aoqiYvAfburlf03h31Ovxwe6PWbN0Bp4Hwz1mxqG1+wgxzlGktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaSu260H4cHHLjQHHUHksVum5V5jpZuVm7HDwAwfyLdMfgMyeWjuTgTF3jZP56OU23C2Dy+iwW2GtvwVKS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpKBRnpZ8ATNfTKvNj+pBS5v0uB9tfKICgr3M4ORRy/kJwwKA6iOpGNq5Bd5fTZwItsZQuDhWJ7R8HGEPgeAWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJaS0lpLSWktJXglvlXAWvsI2REgM4PsCMfrkFl+/3E5EBCAUAUB+x8b+0BqT4n87T8v7TV8v53xJr+f9n86fFP1f/9k=)

Fig. 14.14 Splitting of Data

In machine learning projects, datasets are crucial and typically divided into two parts: a training set and a test set. The training set is used to teach the machine learning model, and the test set helps evaluate how well the model performs. This split helps determine the model's ability to handle new, unseen data. It's important to make sure these datasets accurately reflect the problem being addressed and are split correctly to prevent bias or overfitting.

![A diagram of a training process

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIBfkGowMBIgACEQEDEQH/xAAcAAEAAgMBAQEAAAAAAAAAAAAABgcEBQgDAgH/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAABtQAAAFWxGTQuM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIzmCM5gjOYIt15KmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD1PJZsgKSWxW5rwDaGrWRW4AAWLETUAAAANpNCtwGZaBUa3McqtuNOAAEm0hiAAAPuyysV26cqp7+AAMsxEljQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABbAqbAAAAqWFzSFwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAtKrb7NDWeboSw5dSHRJzxvfC8SoNfYsNPeE3dVB7bOza7NFrr5qIzY7bFcmP52bjEZilm/pU0nwrCI1GJtJCs7Qq+0CkQbK8aOu4p3fQMX9Ql+U0eElk0YNXqbyqgtmqrYrmoHLPiTxoYpZYqsErsOpLyKKsfbxMwIb6zo1X7MvMqazsTcHpVNxVIa4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFsCpsAAACpYXNIXAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAC+qFs4iMfuaszU9DwGQFVXfQl8HPm90O+LQg05rEnVS3tVBZFf2zUxYdc2NXJYMDnkBPSdQWdFU2bpNubT2rmxqqu0KvtCKRBsrupG8TnxJ9yWBTFxUkTaRyChy9qTuOnS4qVuqnD9sfF1ZL9Tpd3VRCPXOk8xIVO6nnpjbfWelbLzjejiw4tqdqbOsLTq8+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPv4Fib+nBaFeYQyLFrINlrRYNf/m1JDs5rEK31cWtR8TKLaoTuN6gbmRQQbKzKhFi+1aDZS+vgBl2RVgtPGrUbLXfgsrYVKLEienFhZ9XDfWHTwsL4gAA+7ErgXHrqtGV94Qtj0qMbX704uGt9MAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAALYFTYAAAFSwuaQuAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMzY6IZOMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFsCpsAAACpYXNIXAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFsCpsAAACpYXdOqiq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qCq1qa8rtJJgVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQVWtQeiQK2wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEaksbK0u+j7wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEckcdKwvGjbyAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEekMfKsvOjLzAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGg3+gKqvSir1AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGh32iKmvaiL3AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGj3mkKivihr5AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEZk0UNzj0XkRm3tzv8ARcubSV/V7AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAfn6KG1Vo1dA+ifWdrNnQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHhQPQtYEAlUVuWJSKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAI/rSZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJlrNAK5vetdzEyQ1UyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMmtwCQoaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJk1g2YAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAW/FZVFSFAAAAAAAAAAAAAAAAAAAAAAAAAAAAtgVNgAAAVLC5pC4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAt+KyqKkKAAAAAAAAAAAAAAAAAAAAAAAAAAABbAqbAAAAqWFzSFwAAAAAAAAAAAAAAABnek+kRT69tCU54SiLgADLxJ8QjwlcUAH38Zx9a+3aiAAAAAHv+3kVNgWXvyg00hYANuar5tmpgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAC34rKoqQoAAAAAAAlxEU5EGTmMGtAAAPs+Gw14Ab2Vlbp5CTxAANka0AAAAAAFsCpsAAACpYXNIXAAAAAAAAAAAAAAAADfaHfFs0Re9EE4kmu2x+Q+P7MspX1gVVEp8d3EX2Hztj23UdhpJ4XdlLll1XedHlqecs59Lop62YOYlm+NfEv/YZaNUQI2l3c+z41eDb2bVN6aVZ8SDJ08Sr8mm6rKLdqadU0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAW/FZVFSFAAAAAAATWFC1pPVNj1E4jq7GiE41xZhRX7tbBK6xrV3RRFnRO2ivYLelJmNk42QX1WlnQ+szAjccjE98y4ymdfc+jIhaUenFc+fMviEAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAN9od8WzRF70QWX5+nmVxc1M3caHZ4m/qA7rV7SNLttTtjWxiTxgualbqpUuqj7wo8vTn/oDn8uCHzCHk/q/dTwqa29fsKogRupDEbxKBmkr3B4RzwjRY0fl+lrS6SVQ6LFpq/KjI+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAC34rKoqQoAAAAAAAEnseuLHKR6A5/vwgkhhXqbXc13siwYxppzVQWViZcaWDTmDA3h5zjb04XzHIVadQmSRjfxHrIp7aGltCr7QKRAAAAAABbAqbAAAAqWFzSFwAAAAAAAAAAAAAAAA9PMZ+AGV+YwZGON9qccZbEHv8AeKMjy+BsML4GwwfkbDXhmePiJZ8eFhFf2Vi18RwD38BIcTUgDYZ2hH1+fg3uuwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABb8VlUVIUAAAAAAACQzuowmkLF5fNHjayuvxeCjxvt5BRetL4QfXyLYktBC+q0iAzLgpMXjEK9GfdtBiZQ0AAAAAALYFTYAAAFSwuaQuAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAALfisqipCgAAAAAAAAAAAAAAAAAAAAAAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAW/FZVFSFAAAAAAAAAAAAAAAAAAAAAAAAAAAAtgVNgAAAVRDeiRzs6JRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzt+dFRopj73V3nOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JHOzokc7OiRzs6JEQi1sK52dEo52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRI52dEjnZ0SOdnRIhaaKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAARuSRwrK8KOvEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAR2RR4q+8aNvIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAR6Qx8qy86LvQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaDf6Eqi9aJvYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaLe6MqS96IvcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGGZmj3mkKivihr5D4xjMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgM+xylNlGseMmTRAZ131fcNAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAVfAb6oePk3BaMl/P2gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFO3FGilrTrS/49xQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABH9aTJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkN2hvms0BMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEy/IcPGcQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJDRMkNEyQ0TJrsAkCGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZIaJkhomSGiZNYNmAAACpYXNIXAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACSxraEkg++0IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABPNJ+YJrQAAAAAAAAAAAAAAAAAAAAAAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJVFc8mNf7fUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFiaHBxDCAAAAAAAAAAAAAAAAAAAAAAAAAAABbAqbAAAAqWFzSFwAAAAy8SfETW1Iig8e4IaQcAAHv6SDZkBAA2OuuMp389vEAAAAA+95ZfiVpp7yjJWQAH163EUsAAAAAAAABL4hlE9rjPwAAAAAASEjzf6AP2bkHevkAEkwTUpFiGoAe8rIaAAbI1pJSNNnrAAAAAAyJuQBY8SNKAAZBjsrFAAAAAALMjul8DGAAAAAAAJcRFORBk5jBrQAAD7PhsNeAG9lZW6eQk8QADZGtAAAAAABbAqbAAAAqWFzSFwAAAABkdDc89DHOMkjcwJXt/Wnay7MqrbxYNbTTwIvs/LdEXlmhlR76qr+iK5yuOn+gYoG2qnvgiMgqmYEQx5plm51ujiBa1M9Hc4gHRFW41i1Um1t+v4ra1YjYR9wqOXdVc2ZQ13lewEgAAAAAAABM4Z6lk1jkY4AAAAAl8Q9S6qQ6Fos2NqxjEK72Ng55VGJfdSE5jckjZh4U30pBs+VTwqG5dPuKoP297rinNbbWxKdvGvrOrneV50hiutRMPwjXpcuKUt+2TCzWe97xcrDF6Eo41gLX/AD53lQuyK3jca7x/bWK5wrd2RRl011cBTceuSmwAAAAAC1IzGfg8gAAAAAAJrCha0nqmx6icR1djRCca4swor92tgldY1q7ooizonbRXsFvSkzGycbIL6rSzofWZgRuORie+ZcZTOvufRkQtKPTiufPmXxCAAAAAALYFTYAAAFSwuaQuAAAAAMjobnnoY5xmEPmBMKfuCnyy9rhbGtf+bfXke3Wl3UaXdaXdFWdHc49HHOvQHP8A0AUHfFD3wUXO4JOz0zsGNGwh96aQl/OPR3OIzMP6LHre78crC8tDhVErCpi7IhjK3NVVddD3/HPCXREAAAAAAAATiDi1qpAAAAAAC2dPpbcrypW26QjdTKXVeWnW8mjNSSNySNxvtLutKTKuLDgZq7lqG3ihJth2Ea2U0ldtUPelF3pHP9uVHbhE5/AJ0Vro5Joi/aQuuki5aDveiC667sOvCMA9ZxJ69LH3nPl61Tl7U5cEVjNK02h+TmprZKv0O+0IAAAAABbkWhgAAAAAAAAk9j1xY5SPQHP9+EEkMK9Ta7mu9kWDGNNOaqCysTLjSwacwYG8POcbenC+Y5CrTqEySMb+I9ZFPbQ0toVfaBSIAAAAAALYFTYAAAFSwuaQuAAAAAP3Y60PbxGZhh6bvQDI9sEe/piD39MQNlrR+7DXD9z9ePr3xhlbmObY3Wgs7IN7z3MYcAfe70I3el/AysUSHSeIbfUDZa0AAAAAAAAE6gv2WtU3p5gAAAAAH1dtICbwgLX29Ii44jChZWiiQsbUw8SS0qJFsbClxtbjocW9sKRGReNDCwM2shKMePi7/wBo8TKP60XHTgWzB48AJZZ1Ci/I/UY+5/XovHypMZdkVYLppYAAAAAALfisP+T4AAAAAAABIZ3UYTSFi8vmjxtZXX4vBR4328govWl8IPr5FsSWghfVaRAZlwUmLxiFejPu2gxMoaAAAAAAFsCpsAAACpYXNIXAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACbQnILKq3MwwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAC14xG/I8AAAAAAAAAAAAAAAAAAAAAAAAAAAAWwKmwAAAKlhc0hcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJjDs0nta7PWAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFnxzT4xiAAAAAAAAAAAAAAAAAAAAAAAAAAAAtgVNgAAAVRDuiBzu6IRzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7oiuyu05s853dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53ktxqrCDdEDnd0Qjnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3RA53dEDnd0QOd3teJRDogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IFaaS5lc7uiEc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiI2U23N3nO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogc7uiBzu6IHO7ogQtNFAAAAAAAAAAAAAAAAAAAK7sSuzEs+r7QAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOfLyo68Y2IoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABG5JGytLvo+8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAABXdiV2YdoVfaAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABz7eFH3hGyFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAI3JI2VneFH3gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAK8sOvDCtCrrRAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOfbwpC742QoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABG5JHCsrwo+8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAABXlh14YNo1daIAeFZlpqsFpqstE+gAAFZWQeoACN4pLgAAAAAAAAAAAAAAAAAAAAAAc/XdSN3RsxQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACOSOOFY3jR14gAAAAAAAAAAAAAAAAAAAAAAAAAAAAACvbCr0wLRq20gDzjknFP8Atme8SDN3VE1bfrU8+N/ooJKyUbbny/SCzygL7NZ70pLyTSik5kb7H1GuLC8ovACz9rDoDHQeFlUPVn7qGQ2Loz64segAAAAAAAAAAAAAAAAAOfrupK7Y2YoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABHJHHCsbxo68QAAAAAAAAAAAAAAAAAAAAAAAAAAAAABXthV6a+0qttIAArH38PeLHom9qJq2N7p/0ikd095xQF+0Pe5RN90JfZRF30heZBPj7+DN12x1xtdFvdKWnzj0dziXtT92UQdB1tMKyrf2PXFjgAAAAAAAAAAAAAAAAAHP92UndkbQUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAjsijpWF40beQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAr6wa+NdaVWWmAAQz1lwVlZo12b6Cpfi3RV8+2Qqq0PUVZZeQIj8zARfEmYjWumwVHbg+ItKqNN547GMxLbGi8ooAAAAAAAAAAAAAAAAADn+7KUuuNoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAR2RR0q+8qNvIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAV9YNfGttOrLTAAAAAAAAAAAAAGJliM5+3AAAAAAAAAAAAAAAAAAAFAXVSt1RtRQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACOyKPFXXlRt5AAAAAAAAAAAAAAAAAAAAAAAAAAAAAACv7Ar81lp1XagAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQN00tdMbUUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAj0hjxVt50ZeYAAAAAAAAAAAAAAAAAAAAAAAMAz0Z1JPFYa0uFR2CX9jc/fsXvj0zkFseVZepYsR1f0ek7gH4WH61p5Fre9O45eeVzz5HRrn3Oq9FN7EtNX+1JW1ezP0AAAAAAAAAAAAAAAAAAAAAAAAAAFA3RS90RthQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACPSGPFW3nRl5gAAAAAAAAAAAAAAAAAAB8R4kisowXTHqi3sSHRbzfFVfF57IpHbWyqudlNBG8/ajHyAAAAAAAePsNbgSEQ7XWEKq1N1jn3y6HwYp/eyjRG0kNVx86FUJJqtVE5MewAAAAAAAAAAAAAAAAAAAAAAKCuemLmjbigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEfkEfKsvOi70AAAAAAAAAAAAAAAABhmZ+V5By14bHpnEBzbg2xWcnkqvL1AAAAAAAAAAAAAAAAAAB8/Q0MYsUUjpuh8GKtmOFDS6vTnyaVZ7V7QAAAAAAAAAAAAAAAAAAAAoK5qZuaNuKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAR+QR8qu9KLvQAAAAAAAAAAAAAAGOZGvgUHJlDJpYMVpOpEr8/QAAAAAAAAAAAAAAAAAAAAAAAAA1EGtAc9SW14JEp3fPknLca7Y0AAAAAAAAAAAAAAAAABQdy01ckbgUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAj8g0BVV6UXegAAAAAAAAAAAAAedYEnqz9taITZmyUAAAAAAAAAAAAAAAAAAAAAAAAAAAAABjV1Zw57saS1NF4/tMW3WYAAAAAAAAAAAAAAAACg7kpu5I3AoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABoN/oCqb1oq9QAAAAAAAAAAABjftLnr6bC1YxssoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB5+gq2LX3AYlO1oC662gAAAAAAAAAAAAAAAKEuOnLijcigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGg3+gKpvWir1AAAAAAAAAAAH5+wUi2Rprvj0/SgENmVcGhtOjLNiU1TMatLRmta2NXohHiT1hZoRfUk+0GfpDTWJTkrJwjMmKrsWKS8y0Z9iQIFMzKfkRJeg8zPUGqgczqsvIAwDPQHfEgNWbRAM8mD8jhJEY/STIrlEgQOaEcwt1jkmazDN+gm6JCao2qBbwkLTbkAAr6EXxUcWpkVTa1AAAAAAAAAAAAAAAUJcVO3FG5FAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAANDvtCVRetE3sAAAAAAAAAAAeFCWXD4snfFAAK4seuDQZOzh8SLB1sxPiQx6V1FPLUYsbqWwzZEcm2HYdVDM5XFCq7Qhtwxzzf1EXaU3cNPXCVFI45a5X2bto+SKKZWrJHheGAXYK0NV2pVcXkK/KJuugotSvt/pi2oJIdZWyrvN08W/W1h14flgfsqqg5pC7pisN76YRsddsdcbWBT3RkhqzofnE6KoS6qXLIgt315XhZVa2UAAMTLHPl1wzHi0xQAAAAAAAAAAAAAFC3DT1wRuhQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADQ77QlT3tRN7AAAAAAAAAAAFPyiAWzG+FAAK4seNEdj9hecV7Kttk1F8KYZxEvnXSCI3KPOb1T9jRjVRjTbLyara4IZMygLth05KTuGLTMpi2Y5LyJx+d641WDZldkkw43Pzbg0NRXXBTdNKJnS1wfJkRfUbgmNCdFQckFSSDdxsa9s3SVsZPqtqUHdUQm5CMKWeBq9dLsY1+lmuCSznHo6tSw6Gv7QGJX8mwoybKrayaAAA0dP3zztHRjy9aAAAAAAAAAAAAAAoW4KfuCN0KAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaHfaIqa9qJvYAAAAAAAAAAAoO5KosiJOKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/KLvX5Kh1Fx5ZpJIAAADnW/qCi/8r8/aAAAAAAAAAAAAAAoa3qht6N2KAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaLe6Iqa9qIvcAAAAAAAAAAAq/2ldPxf7z9KAAAAAAAAAA1EJx4ZHQv3EpbUdxtbrizjRm8aX0Ns+fk9EZ2BtjCM1rcA1u51uxMzyquVksie/q8u5ovU3BqzaNdqySvCPEoY+QAAAAAAAAAARCB+ktidCgAAAAAAAAAAAAAKGt6ordjdigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGi3uiKlveiL3AAAAAAAAAAAFL3RqSI2Jz3cpvwAAAAAAAAPH2hZWNjwCcRHLl5zvsieu2OuJDXEi25q4J0VzyX9TNo1FUujV4xE+tDqdtELmH1ZhUchj0sK22/1NTNpe6KtJVAehKNLjpy1Krrb6u0IpEb2mykhBrdpK7aAAAAAAAAARfdUcft8xmVgAAAAAAAAAAAAAAFD25UduRvBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADR7zRlSXvQ98AAAAAAAAAAAAEPq/oCCkj2/P1xG/AAAAAAAApS46qM3Zzn0KY38thMbTXSXDrB1ln1oTaj7BgsXpR19xapNBY1nRl+1gRatXY8PmBUcswd8V/NMSFxZtX2vDKsqjbyrIl9V29BiXxObaA1cjw9wVTd1a2UAAAAAAAAMXwps+pRjWnH6KAAAAAAAAAAAAAAAoe3KktuN4KAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaPeaMqO+KHvgAAAAAAAAAAAAAh9V9CaYjk7ovNi6Gr2lAAAAAAAAAAQ+DXToCMQ2z9+ZQAAAAAAAAAAAAAAAAABimVF4jFY/J3vZTX5+gAAAAAAAAAAAAAAABRFtVLbUb0UAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA0e80hUV8UPfAAAAAAAAAAAAAAB515Y456m88riLOy+epvVnNdsQAAAAAAAAAAAAAAAAAAAAAAAAAAYxk+UDgJYFebqy4glm5agAAAAAAAAAAAAAAAAAKItqprZjeigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGk3ekKivihr5AAAAAAAAAAAAAAAANVALUHPMktiGRspRR+vOg1Uy2pS8vUAAAAAAAAAAAAAAAAAAAAHyfSPRMsyP1L+RJYhPpuVfYMgUAAAAAAAAAAAAAAAAAAABRNsVPbEb4UAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA0m70hUN80NfIAAAAAAAAAAAAAAAAAA1G3FcxS8RzxIrXjUYMig8dL2++dt3V3Ks3ROUd2xmAAAAAAAAAAAAMfVG9QrTFnflL6Mu2O11IYRqyJMU1LLOVH9/+gAAAAAAAAAAAAAAAAAAAAACibYqi143woAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABpd1pSoL5oa+QAAAAAAAAAAAAAAAAAAAAADE0UoFeaW3RRer6I/I562Vy60r3OkmCY2XgYhJPeFeBYfrWHmWt+1JjFy/NLZ5a/nV/oWNjwfIJPiazLPPA3+cQLXW9sSh9ne30U9ubIVEd7sQAAAAAAAAAAAAAAAAAAAAAAAAABRVrVTa0b8UAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA0u60pT99ULfQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhE3hBGbdqK3QAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACirWqq1IkAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABpd1pSn76oW+gAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCJvCSMW7UVugAAAAAAAAABp9ITNDBM0MEzQwTNDBM0MEzQz8JohYmiFiaIWJohYmiFiaIWJohYmiFiaIWJohQmqFCaoUJqhQmqFCaoUJqhQmqFCAWpUVuxIBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADTbnTFPX1Ql9gAAAAAAAAAAAAAAAAAAAAAAAAAAAAACEzaEkYt2obeAAAAAAAAAAK+gs610YC4VU8uEU8uEU8uEU8uEU9+3AKfXAKfXAKfXAKfXAKfXAKfXAKfXAKfXAKfXAKgW+KgW+KgW+KgW+KgW+KgW+KgW+Kg/beFQ2RtgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA0250xTt90JfcBQAAAAAAAAAAAAAAAAAAAAAAAAAAAACEzaFEWt6obeAAAAAAAAAAK+12x10WkKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAafcacpy+6EvuAoAAAAAAAAAAAAAAAAAAAAAAAAAAABEJfXRN4xU/rEqtfnz5LdktN3dQAAAAAAAAFfa3Za2LTFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAANPuNOU3flB35AUAAAAAAAAAAAAAAAAAAAAAAAAAAAAw8wc7eU2hMDOLPmPx90AAAAAAAPw/Wj3hX2t2Wti0zT1uHl6gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADT7jTlN35Qd+QFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAaSjOjqTiO2RXd+maKAAAAAAAAqOO2/SEbTz142uXH7dJiKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAajb6gpq/KCv2AoAAAAAAAAAAAAAAAAAAAAAAAAAAA+MYzGs8TcxDZ+ZBLbhW4N603qbRhZB6gAAAAAAUfeEMKkEZ9+V7YtAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAANRt9QUzftBX7AUAAAAAAAAAAAAAAAAAAAAAYcbJgq7QF26mj8yLN1Ue2xj66WbErPCunNKB9ehPQ5+9r7FEfV6qor5vcUL5X+jnjx6N+DnvMu7CKt2E01xr9rp9UWJt6N1h0WonfVbCESQ2YHn6Dn7GsLWxZuaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA1G31JTF+0FfsBQAAAAAAAAAAAAAAAAABiwon+lqTDicxXfysp+QXH6lc7+TqxMsAAAAAAAAAAAAHj7CPaCwBT0c6E+Sh5VMIpEokVD+ReGDEpxWxAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA1O21JS9/UDf0BQAAAAAAAAAAAAAAAB5V4TmvoVMYhsls7Z1FpP8AQAAAAAAAAAAAAAAAAAAAAaHfCqod0NilWWJEoDHQip7MrMAAAAAAAAAAANcbFGxJEbkB6I7IgAAAA1o2QDB1JJEbzzagAAAMeKkya3ZAAAAAAAAAAAAAAAA0RvUbEkRuRn6AA8fU/WtGyAAAAAPE9n5+gADU7bUlL39QN/QFAAAAAAAAAAAAAAANHqqsMzZy6bxq9oUAAAgU95xLR9MfVFj59EXqfTxwzZPnHMprNmDFMqISCoC4Y3s9MSzLw8wNZ7mZje9Mlt+Op2hq5TEZQez4+w8fU/WPhG1AAAAxMsVXEego3GNLaAm9WQAAAAAAAAABX1g18Qjf/lkRXFn/ABlVVtq0Re4URvC21A3EbxDa+LzUPaZHRFjioNXthRyPqMdA1eSCYVhJKlajPovFqoeWKpD8JTpdF9xc+00tZ1cykdgW8+KaLoUZMCw1E7gt5QckLYUJaRKUUrcvNQ9mEsQqHFzKQzi4SsCz1H/RdzHrQtNR2zLefn6KNvKjYzM3d7ohVr6Pc16qV+C7VPTMrW9Od7AiQNaqfK+jhcii9mXCpUXU+abLmUl+l2UPZVQx0R6VnK6kKjP0vJod8NVtdUUtf1A39AUAAAAAAAAAAAAAAh25pM+rkb4AAAAAc49Hc4xf+orL2rTXbqNuUrked/RFqzlenPnfoSXTSlh6c84j0LRhatV2pVZbMLmlKVINbd3wROtL7pyPWde/hUK2+os6ITPqQn5Xd0wTZEG2+LLDVWnzt0RX6AAAADApi9sEgVl0DZ8S8UAAAAAAAAr6wa+IDtdvacVfZnp51z30Rzv0RHOPQvPXRxVW51G2JNHottyPSTDzACxxUGrGzo5Ee+76Vpaqu+jYm+qyss1X1KYseNoQKwarHNws2PfRbnVlpU3clP1M62sauYsqSa7a1zr0Rzv0dFKT2B2GaPGy8IncbjuTWp3H7+RsdHvNcWRzz0RzqdAUdd9Il+x+Q6CvqnLeqGLcq6wMc32/12xpRt5UbGZmzWSVWs8zvEoOdbfSRuZlz5eNUV0Jz30JFeA+Pn6+yR1daNal2879E87nQEa2NPVPq1uGo4vzn/oDn86EqG3qeqQfmNtYjluxSV01W11RSt/0Bf8AAUAAAAAAAAAAAAANUVZJ69v6PUUAAAAA5x6Oo2LqyPH2pptzqynb2qC3yucCxqjiyddA5xX3F7Vp2LoobbfpYtV21XlWFTV1aIkGqrX0iy62taD1KPCvrJIFcFZWaUxqLThkWLH5zj1U9hVtjxN5vX9g0AAAAABGamv+k4uf1h0xofh+o1Aiz4LANxFybAoAAABX1girLTB5+g536IDnHo4Ks209FUaq68Mp3f2gK4WOAINHLcACDTkUd5XZ9EejVnCvrBCsc2wRhUzef4VDg29nHnR17DTbX0HOPRwUrYcnFfYVnCsY9d+CVFs7YEC11nDz516OCnrhFN6y6csxKluj8Ke1lzZp45AKNvIc/wDpfiKDuLdKorcW3glNXb7fRQkzsH5ICscVr92OI3Wt3Bzv0QNTSvQHgVRG779zW0tffgV9u5JklF/t1/kRSaFNVtdUUrf9AX/AUAAAAAAAAAAAAAhE3r80Fv1XagAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAruxIOaWzKplpiQP60sAJHHM8tNAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTxAxPEDE8QMTzBiI1F/1FbtAAAAAAAAAAAAAAIbMsEqi5eeL8jLFAAAAAAAAPL11pqtpQswi3dHvKDq2ZHQF/g+T6APk+NFsKVL8AfP0eeg29GF/gAAAAAAAAAVrZNEkqs2MScRuSCnop0ZrYoOUbqHF+vD3oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACpvax6Mi/0MmdAAAAAAAANbstaUjl4u+izaeknyRO/6AuMgun8L1KQt+F4xIKy2NhEB1Fw08XrTU6g55Sff1CX3Rl30gX+KAAAAAAAAGiNJBNdc8bz9KAAePsMXKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABot6OfLN3dOxfqrLNr2AAAAAAA1uy1xSk8hFsRSlu1RehSFw1HfJR15U/4klwozcJVNh41bFv05vtMWHCLgpYsTDimQWfSF50jV9AAAAAAAAPyAG/p75tePOYlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMTLFP6O/IpHxLaIyC8ESldfQAAAAAAAAGNkj5+geHuPz9B+foxcoAAAAAAABHiQ6Cu9DGy+ZtOTVbcoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD5hs0FF49+R2I5Mq6iR0Ko+V1YrR7s/QAAAAAAAAAAAAAAADVG1QKKluQ+spNGvw7RlRAZ17qAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAeXqIpFbVFB4/Qmsir9/n6Elm6pzTnRDn3a1dqptiWQg2aSxHso27X+xlPD6PV5/J7MXyM9qcY36K4RN1da4tZS2qL20tL7WJvofvfFeeV07kqOVTNWNkgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/P0azVSgQTXWYKkwroFGYt+jnvy6JRzl+dG4xz3+9AZZzv69Cigcm9VUpm28Kw2E/ET2u3Hx9gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB//xAAxEAABAwMDAgQGAwADAQEAAAAEAAMFAQIGExY1FBUQNFBgERIwM0BwICEyIiMkJTH/2gAIAQEAAQUC+hk77rch1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkLqyF1ZC6shdWQurIXVkKGcvvjfoZXyX7Lg+L+hlfJfsuD4v6GV8l+y4Pi/oZXyX7Lg+L+hlfJeyG7Lnbwsdspb2YBFY8NfaaI6G94xjFpJ0pCjDAfxiYYYqPlh7BZD6EYxaSdKQowwHgG3R0vbwa28GncbHrSRAeAc/jGxD5qLboyV/Ky2t9wOPN0s7MB8DMeYvtfavYd/gMO6S5JxlQBvZMHxf0Mr5L2RiwdLWJ6UqFS40q66DmHLn5gOhgVltb73ocxloWCKIZtFKGkT25egiBiyjaP4+W3YNFlk2FDuDPR7ctUOQo/QwWLLKZbjinCq44V8pI7ozqFhDCLa44V8CxHxL4Llp/iPCN5Eu6tgndzlGzz1HjhrSxbra23BAkGXUxwpGQ5YtggzpboVlzQcpGFWvUpW6rEAY5bfjpdKEMODu+GM2UvlJx94eP60r5oaXscGyZwd59DQRj1pECYzbX+q40E+PfkIT5jRLF4z3siD4v6GV8l7IjLPkjpy+t8qqV+FbK/NbWzTmLraX2vzwrJAb/U5HP8RFDdWcW+2CHbkZGqNe26zknL47w+RcxjXEzElSOug5e8x7KmqXARFR7TpCcZaYjJ194vIGrXIqC5af4jwjeRO8j4AXfMDM2/LKASEcMHfkZOoC/1YfUdrmBXNYaWmbr1j7ojBMpO2tKEmHTCMsatqH4RxVQzGHmyGiYgJ9F45dSjrd7TmLBWuXzktUGsJMXGOZUHbaoCRqXSZkKx7Z5NTC/ZEHxf0Mr5L2RGX6kdPN1blVZbW++2ny2/PqS793yMqC5af4jE+Ryvjljda9pyTl8d4fIuYxriclr8ZbGeVyXiQhXDCB4ARq1l6NHdm+KguWn+I8I3kTvI+ANtbApm755SOx+l7fTxYKHdbfZmeUjeOkuRi49w95qEAYsEIBo7lXG+Fll96tqWDcPkRNijJJk+mWD26WM0/wDlHRYhRAcWEIRkFbL4nEfNZd9j2TB8X9DK+S9kYsbSrU3F9fZfFm23QkNey7Nm0DCD82V5VQXLT/EQRNBpKVE60KyINueCHoKLknL47w+RcxjXE5Jy+M8rkvE4j8utlNj14sAC66dN8VBctP8AEeEbyJVlXBexnqPx93WkS7QhRa0uNfpdVigxF78cxUYGZ5SN46TacpIYn8vQZY29V7GAnaEZVxnhihNGyZuP68a6LNtux6MdEuyx62g2KP0uEycFzqIuKdOulImse3iXmsssuuGutusr7Ig+L+hlfJeyLLq2XBZFWlKTwPwJyNqlCiXSnWL9N97IWL2lHP0FNkpxkoJR084O2/klPkgnXH47I+Xi5tkQGUJtLOippoMKVKtMNiS7QjJWaaMCALcCJayAO60/IfjR/IBnmI5+gpslOMlBeArlGStyDrcg6dyW34GmvmuKOyCyjRGQi2WiZF8tsqS2WZDzbbA0lNBvBxMjfHvUnwq2kZFWpEnNDmB+Ft1bLgsj+FvfgfgTkbNLSX3CXgyXBHx8iGvteyESy2RNdOfizaglUnwa2y5LZZ3siD4v6GV8l7SiyaCH3NDls7aa+f8A6I4Mx6pJXvSD4v6GV8l7TYJeYXdjvg8+6/X3rB8X9DK+S/ZcHxf0Mr5L9lwfF/Qyvkv2XB8X9DK+S/ZcHxf0JKIaPf22OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622Oj4UYMUJgIorbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OttjrbY622OhArBh/duRcPBct+08i4eC5b9p5Dw8Hyv7TyDh4Tlf2nkHEQvK/tOf4iF5T9pz3Ew3KftOd4mH5T9pznExHJ/tOc4qI5P8Aac3xUTyf7TmuKiuS/aJsrQEsc4YhTPFxfJXXUtoVNBjqMJvMH/Z2Ri9QAtZ35La1tuvcvcqMzcQQ03a01+zq0+NJMbpDfHFBfmd/aGVC/Ox4Up8axo3SBftB9q15khq5h9Y4L1Eh+0srF+V1Y6L08f8AtKRGoWFHC1JPp/VPdp8qOC9uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDQ0mAwduINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINBGWGMnSrATu4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINDGtksfQyvkv0ji/F5ZyPrEHxf0Mr5L9I4vxeWcj6xB8X9DK+S/SOL8XlnI+sQfF/Qyvkv0ji/F5ZyPrEHxf0Mr5L0FsQhyzoS10Ja6EtOtOM3fyaHeeo6y4zX+FtK3XXBlW2/Uaaceuthj7qEAkj0/l8K+yMX4vLOR9Yg+L+hlfJegw0oGPGsSoT7rrlrLXe49ZCUyWb/LHZAYQbISmSyv4BX2tmmy4LgX02G7nnhBmY8W/IQ7bgzGDWskj7RXf4RQtph02M0LC+x8X4vLOR+uJBPkj7bJW2yVtslHiXBEfzttrdcWI6JXxj4wg5W41/RGOPW0dbvac/jYE/cL9aD4v6GV8l6FBctL8YscBHMtrBDdbMhhNR0FFUNVRYwVORYBLckJcEXjseMWNkIrIhWOgDGNOwLFTBxY2+2eiG2GArLXDTYgFsIa2l5JUIJ040bHhWkxIRFhg9wpMNG3Hu0AjxWiIYMqkjEhMg+EXfRuQLYoSMVBGM1DKJi3pCXfOYGYvJfEhhBW+ijS7ZmLuAvx0JjoyWGyWshFZEK9jYvxeWcj9cOevGGjJu4wyQI6QPct6kS6mktBku2utONXeFoJd9HWHWfDE2rdDLKVqb4DN6xFdMQR3IibroWW6+7Khrbhk0047c4GS3aoZqjklO0/+RWlafWg+L+hlfJehQXLS/GLEP8ZGbeIK4YQ6yDKmD2Xx0ie/CAuAD5b57EvKZb57EfsZa/dbZDX3NycpT5o2N5GS44Pzbt+m065c85jbl18XlFPhKY83RuKyMi56Rx8m5iRl+M8Yue0WxzxSE6029ZPRVoaxFmlb8n6lyyLZNGOmWaPRmN8vkvE+x8X4vLOR/Axvl5/iFjkZZe3ITA4brd4sqJKB1CMxsBuwUmfGYeFJHkhpQS0CTCMZMsNkRg3CbqXkJhzRfZcbJYKx1hyr0KcLV116qjhLjS//ACxYYM0MW9kcZZRrGjWLByXrB2chNZNv+rB8X9DK+S9CguWl+MWIf4zDwgArBgpGf0H4Ax81vLfPYl5TLfPYj9jLvNRXJSXHRvIyXHB+bO8isX4vKeTgrqXRM63VuVhW6uSkvxnhEh2nFSkJaIEscMIodO/CsTiFf+qXlKx1+5k7keo1jfL5LxPsfF+LyzkfwMb5ef4hA20sCIgCniIOOej65fYscLsdALiRCrn8ecstIZcYdxLymW+e8QJEgKo+SNVQho5ayQGx0XELKak4A6fY3jxVjhNmqPBctP8AEfWg+L+hlfJehQXLS/GLEP8AGYeEGTaTHGwDZBQNgwqy5uvUYl5TLfPYj9jLvNRXJSXHRvIyXHB+bO8isX4vKeTxyRtHuPjxz6DshRN8vxngGRcKSKSyaw7j4d94EeOCslkbL7IQ2gRpwjMkNHwTYpGSPjNMQLlrUrIC0NEmI/t7vsbF+LyzkfwMb5ef4hRzlHQDpCQHLFfmC7JJw6qFhDb6UlzwnYaT7hTLrLfhiXlMt894Q1rN8jIxTLoN9t1l0Ay65JS19LIzEXKUfyN4kdlqTkXXXr5tm2C5af4j60Hxf0Mr5L0Ky+5u68wm+1MvvMp5917wZecYvvlzr7W3nWr3SHnqNEPM0deceq0Q8zR1516tt1bLrjCrrba1tuuMKutpWtK1NKuomin2rXXb3bo+GuOFNFOi7YVh0iSnnKNxXi064zdbMn20fkS36eAxhAyclz3KVrWtU1LHNWkEvE3exsX4vLOR/AgXbGZOZOFdjFAy1BE7YAfRwwGPZkjLjioKYsZbdZjza6wEc1MH1PJxk5oe4poIhGUsoWqV+FYydZdsuqKQryhBrJyW61CEXikCyYZrTQ8eHdPTFjzQL3TF0fFLZyFkRn60Hxf0Mr5L1mIk74+9ueBvTk8DbSXlL5C72pi/F5ZyPrEHxf0Mr5L9I4vxeWcj6xB8X9DK+S/SOL8XlnI+sQfF/Qyvkv0ji/F5ZyPrEHxf0Mr5L9I4vxeWcj6xB8X9DKrbqyOnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071Wy6ipT4rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWM/8AGMymlbpDTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWneoSlaRnu3IuHgeW/aeRcPBct+08h4eD5b9p5Dw8Jyv7TyDiITlf2nP8RC8r+057iIblP2nO8TD8p+053iYfk/2nOcTEcn+05vionk/2nNcVFcl+0epZ11NcXF8krrrbLRiGiafs7KhfmZHlDB0/OEPjDu1YfdyAy9OvvlXx49BQ/wBnENWvsvtXMPeONC65/wC0MrF+R7xx8Xpo79oSQ3VhVp8KqKG6s79pZIL056xUX5B/2lPi9THsNXPvMNWss/tOMi+nl/dx8qwC9uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINR8owc4eY2CzuINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINAltmsHyrAL24g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINbiDW4g1uINCmtksfQyvkvY0Gc2A/NyzBwnsmGl2Ag5s1s4v1iD4v6GV8l7GACdOcOiyAmvZIUSQYycG6E76xB8X9DK+S9jY+YyGRPyQxgfsmDlBRAZ8towz1iD4v6GV8l7GEEeLvLjihG/ZIsaWU0WK8I56xB8X9DK+S+k0O89ToS10Ja6EtPMPM/zaZceq6O8zT+NAiq0r/Vfp221uubiD3KPRhjNP5UpWv4mNksjE5GcMSD7Jx88YcDIiGiTvWIPi/oZXyX0sdkBhBrZkC6q73HrIzhzLf5Y8UyIVkUgMWN/EeZAtYdr8zv04WPsDGJnQ2HAJMc6uSx1ml/BmzUe7ewFH/hsMOkXPiEMWfUjYtw9uSi3gLVT+67cJTtvyOeMdEunsSIV4D8bFOntyQN4Dvgw3V59+AIZY/iME+RYo6IeOYkA7wX/psMuPusY27dS/Gv6kI4gGv8WGXH3CWbh3/qshkP2PsuMX/XEgnyR9tkrbZK22SjxLgiP5221uuLEdEr4x8YQcrca/ojHHraOt3tOfxsCfuF+tB8X9DK+S+mx9/wgRmijiYEa+5yOBtYigO4FUAjhLOijirZyN6B7HhWSysijxhBseFZLKLgWHHRhIy2svCs3DoeGAuYdp8rokODeKHECCN3R4BDUwD0BUaHecSxFAitkxYBzbcIDp+LLlrrRuPkN3N9TGkkzpJDFKVurGwLTdlBox6s3DUFsxkNgi2+2l9mRR4wg34WMPNslZMSw8B9TGSNGQnR+ojFAD9RJypHSgKwEq+jw7zPhifHZZyMTKXgtSxtxzyaEJdtBsvblJLjk21e7d28xXW1tqJZ85JdtLQK0rRRcteENKF3Gkplh15OiEM08PlqmWHX08O8x/DFR7bA5mZvDIFyJ6jjzdhLDzdWnlaCVfa5Zc3d/wDqx9u2yLnLa91+rjhLDUdkzrbx/wBcOevGGjJu4wyQI6QPct6kS6mktBku2utONXeFoJd9HWHWfDE2rdDLKVqb4DN6xFdMQR3IibroWW6+7Khrbhk0047c4GS3aoZqjklO0/8AkVpWn1oPi/oZXyX02Pv+GLcnKk1EArIF1tBkCAk+xJSrkFFvgu5b5TEvPZb5TEvPZK/czGt33NuK6nwuF8q/98HyM0/c/JYjfdVvL6f1ibVKCZYRdV8Am4Qr+ERMXhUGlQyFWlt9s7Dt0ZxtmjspPVfpHtiGt32/94o9vySB3kfw7G73K3suN0+o1fVtxhy19iQY6Y3Ex/lYy0j+8aAstHMnBhnwyWTxpwW0SQxPjss5HEvKZb57G460i6QkGALRTA5W+S44NipJX/mjA2MgFdemg2ygsaNYGo5fRtvIJEcwfFeNynk4CMoZeaaNGtATAxrmQRNlGorki2LSh7poES7/AKih5EfpTvDFSrbhpCLHORGOPWoihwla1rWuPxljTBc6KO+60NKBhfCMmhnrCGZOUFbs+rYy7fS+y5uv4GN8vP8AELHIyy9uQmBw3W7xZUSUDqEZjYDdgpM+Mw8KSPJDSgloEmEYyZYbIjBuE3UvITDmi+y42SwVjrDlXoU4Wrrr1VHCXGl/+WLDBmhi3sjjLKNY0axYOS9YOzkJrJt/1YPi/oZXyX02Pv8Ahi3J5RxaxYKzSl5mgLkHJkHm5b5TEvPZb5TEvPZb5Twv/wBi+Vf++D5EzzeHrL/8YpdSsfldlaHtWVdd8RGqPlPY7ZYOo0wgYi+lK24rdSklKm9ANuZbmTbmtKHeR/DxS6lpeVX23R31cWI1AssG+DwDHShSZHVHRwJRdzON0QIbITWWcjifHZZyOJeUy3z2PW0tiMhvrfLRN9W5OS45CwRbzY+PitVK8qH5s7yKxXjcp5OCbo3FTzlzkq3fVu/+nWo2nyysld8kese4fI+X8G3LmrxcjdtoNNBP1fZbIZJG6eQrT/htwlQoToI2V2fLIQHETvLfVxm+2kZlVaXSP4GN8vP8QgbaWBEQBTxEHHPR9cvsWOF2OgFxIhVz+POWWkMuMO4l5TLfPeIEiQFUfJGqoQ0ctZIDY6LiFlNScAdPsbx4qxwmzVHguWn+I+tB8X9DK+S+mx9/wxbk8o4tYqTbcNKw9h7seKLGVytut0fiXnst8piXnst8p4X/AOxfKv8A3wfImebw9Zf/AIgj6BFFDDyA9gYEPTxpWtKxMi2cwXCiEuBRAojk/I2DDhEVFK/88kE1jjVr8w8MKMxf8j99LX2JaIpHjeg46RoSZDFhFs4R00aoxq1kCUky7ysWsuoDlnI4nx2WcjiXlMt89jjlL4rJGatycIxc/JyXHY01a5KThTggNrxJpJXlQ/NneRWK8blPJ487R2KyIe5mSFYuJIectHHjK/GUl+MWO8PknL+EUGE6DNhXCGUpWtYlpxmOnXKd6+OozfKSDd7Ds0QzIXlXOwHETvLfn43y8/xCjnKOgHSEgOWK/MF2STh1ULCG30pLnhOw0n3CmXWW/DEvKZb57whrWb5GRimXQb7brLoBl1ySlr6WRmIuUo/kbxI7LUnIuuvXzbNsFy0/xH1oPi/oZXyX06f1Xri/Bp29q50p921WXXWXd4P+SrztXbyyXLGnnGaukPPUaecZq6Q89RdcX4UNKpSv91oaVbSta1qy+6ynn3nlFRlZCwqOOjWmW3ziCXNEfxturbc3LnN0dlTXVX+/Bgh0e6syfW1xy929DSJY1pRxJVPwsS85lnHfVpWttR5US9jJjbCXFBSrV4xTEddcPNCXv5M4w+9jRY7AOSvtPnYyWwOLkr7RBcLI9A9deEey8eDGWnyAl4MaVUIxskQ1hx+MiqWSYbw/2XxTRi2cgHCZExwwdgDInm35CHkbo96hIEi03SPj6Tkv1ijbrbD5M8RyPUGcMzFzztj0n4Qkr0NWzBCbKdIwpKcZZbuurddBTFjTTo8eZcVJhgslP3kkY5IM9HIsAX2/Vxfi8r5H8CBdsZk5k4V2MUDLUETtgB9HDAY9mSMuOKgpixlt1mPNrrARzUwfU8nGTmh7imgiEZSyhapX4VjJ1l2y6opCvKEGsnJbrUIReKQLJhmtNDx4d09MWPNAvdMXR8UtnIWRGfrQfF/QyvkvQo01wAhnIA76XzgFKTEzUyz0C26tquvuu9lUvutpddW71mD4v6GV8l7GxZuxwvKGWm4/2TjTLV8blFljch6xB8X9DK+S9jNPOM1dJfet9ktFPtWuuuPXesQfF/QyvkvY2NDtEFZIGOOD7Jx4IZ+PyRhoc71iD4v6GV8l7GGJeFuJOJJs9kjnlDNkkOk3+sQfF/Qymy66R071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWneoIVh4icBDZE071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071CghOhTgrLJenetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9ad6071p3rTvWnetO9QlK0jPR8v/AM4j5j2KX5qO4/2bkXDwXLeu5f8A5xHzHsUvzUdx/s3IuHguW9dy/wDziPmPYpfm47j/AGbkXDwXLeu5f/jEfMexS/NxvHezci4eC5b13L/8Yj5n2KZ5uN472bkXDwXLeu5f/jEfM+xTPNxvHezci4eD5b13L/8AGI+Z9imecjeO9m5Dw8Hy3ruX/bxHzPsU3zkZx3s3IeHg+W9dy/7eI+a8X79NjchC3IQtyELchCtr8bf5PZC/Y63d8zf8Js+8BqElHJBz043zkZx3s3IeHg+V9dy/7eI+a8b7aX2djAWQhMBu46CwauxgK+SDZvLkxRbQZAc1FmjiU3AF8Q5AYuqdag9Sz4fJfKhWXlnDiWtzoN91taXUlrQrm4myPtvJJZFsHNHITs6C3cGeOZ4FEsi2Unwa3OHDNtClsFejG+cjOO9m5Dw8HyvruX/bxLzX8cu+/h/hL8mIAXJKABcBYeCPKN201p3fOKSzfqNFeaY+wd54CIvkbJiO7e9ib9bx8u8riP38t8jHtvkukY5baOI9cOTddS204pw4ofG7asyAzwLuH+jG+djON9m5Dw8JyvruX/axLzX8cu+/h/hL8nBWUsikfkXy31kJM1O23WuB+UK80x9g7zwFvyg5gsQ/3l3lcR+/lvkcTt/93hI8TFUpWSWX0/vD/RjvOxfG+zcg4eE5X13L/tYl5v8Ajl338P8ACX5OG4uYrdSMj9LrXHGh2SXNYkPyZXmmPsHeeD8pmCxD/eXeVxH7+W+RxLzfg63rCW/OKUPJCPMz51ppWH+jHedi+N9m5Bw8JyvruX/axLzf8Z6NfOcgI54DwPgynzI9m4cK+2l9hsAS24NBGPXF487rxzbjIT8AXe81T5WyYEtwkeyrbE/HPHqBjngLp0F05mBjXwXJ0J04aCjHwX1t4xW/1bLQ9ht1mOFVunQGgGsQp/Xop3nYvjfZuQcRCcr67l32sS83+XdT5rSLjAnx8jrYzJnuSD2PCXCgein+ei+N9m5BxEJyvruXfaxLzf5hA7JFtYMCqGjhBrvRj/PRfG+zcg4iE5X13Lvs4l5z2Kf56K432bkHEQvK+u5d9nEvOexT/PRXG+zZ/iIXlfXcu+ziXnPYsh5+K432bP8AEQvK+r3EM2q48SirKg0VZkCi74Au+grIJAc1uAMaCI78Cu+AKk1H1VJYGqtkA6q0li5UrSvr8h5+K432bP8AEQvK+numDNJycBsTmSMUTmSuq+fNuV8sderiyb1W6tyttuuVBSLlSPMqqRR1V2c9dkkF2SQXY5BdkkF2Y9ViTqKscZRVDJtVzd9qp/StJfsVkobYrJ461N5I/RN5K2m54G9NSAjqpX4+ryHn4njPZs/xELynpTxDLCfngm09ktyemznE6Q88m2XXU3EHOJvHS7k3jSsx0SishQLVZHh2q1lq369zdlyuAEuV8MBcr8eDuTmNWJzHCaJyFOsToz7SbdcbqzMHNJnJHqJnIRL0waM/6nIefieM9mz/ABELyno111LaEzQTCIyS+qIlDH1bbe7cxDHOpnGr0zj4ViaAFa/PdEHeT0EC4nsaT8Ea0nWXWasHlDofIyLUNPBupp2x2306R5CJ4z2bP8RDcp6HWvwoXNBjorISHE+Q8/UaNLIQ+N31Q8IEym7LG7fRq0pdQiJCfRGN0RMQawrL3GbxZ4tlCz4rybvtct9LkeQieM9mz3EQ3KegkksjWGZHSiKNIKqJHlFIXG6IaPFG9PIFYJoVjjNyLiDBkw+6PcHkTlqDPGLp6TI8hEcZ7NnuIhuU/PLMYEtOyF1xVq4Q6FAEvIOHEG9VLjhS0ZjrlidadHcBnSR0DJjGekSXIxHGezZ7iYblPzX3m2G5HILrl/2kOgY85ehA2BLfWH2W37DsdpVPsPDOR86+OgzGDLPRZLkYjjPZs9xMNyn5kpMtCIsp4tyOg3iUGEwHZ64+w2Q3I4/darLnRnouetcVP7p6HJcjEcZ7NnuJhuU/Kvvtbslpy55BiPGOxkOyH7BkI5g62SjXwboqXdCqKQ0U16FJcjD8Z7NnuJh+U/JIebHalpRw++JiXDqjDtDNewr7bb7ZiEqygDXQno85o5n0GT5GH4v2bO8TD8p+Q+7Yw1KyN570HD9SraUtt9izkNqIMl0N+PMbOH9Ak+Rh+L9mzvEw/KfkTsl1j0DF9VdT+v45Ee+Eu+nKOf6kE57pw++nLHj3zbvoTZLgoEHKFFneMhMmMnAOXPBfSlHrxwIyYMfP/CyAx4JjHpAg1362QxXz0jTbwSWHbH2fz5PkYfi/Zs7xMPyn4+TH6TUSDccU3Za3Z/HMFa38WMUe+cPKnvkAq38GMQ/3fdbZY/kQ1lbMkZrUUloppGzQot9uStfEMtkxvJuKxu62yRfyIey6PmRjL0WbFWEi3WXjEzQo75UsMMzbkjPzDPtktIueFYvZyMe65pyx2zwneJhOV8TC2Q27slZ+YCVGNqjjmArLsla+Is+K7ei5gYUgqZHYYjJdo9x6cEadOlhg6N5IzW5h5t9qWeEZbiSAX7zzWgWxZUUix3I2Lbo+WHNuR57ANlMkZ+a+XEtFAkWTq/yyGO6V7Gj9F/8APk+Rh+L9mzvEw/KfjPOWstFPXFEwwXRBfyzBRTWtH4u9pyOVPfOdJNaUViH+54YkseKgfip6KHFGxO+tDsiLuFBho/ryTYAeo8KwcObk3FBMXFFVx8PSvpcw+PfqsS/JxXGzfKwkRYWzkEY2EsSdrr5QXVkaCjKHXzUK0yLi5dbCvCd4mE5XxkSrzjRsfGtYkRbo86LJ6sGXjDyTGIAS1mWFtEOgL6uRORcxFxjsioSMuj7pLkYiHsJYn46wFzEXK/DLvK4j9/LfIxYtxpJGPi1HZcqy9ddS2wp9wwoXHxrWZgGseRiH+/5FMWEjvtXjERJfWA/nSfJQ3F+zZ3iYjk/xsqI0w8eG6iR/nmCxG35k3WoUkXfU2TyyylrWIf7l5G2Pauk5Ey8oAxtnFeSy/wD1iHw+TwybisYp/wDUR3no3jpfk4rjZvlYWnwist8jifI5ZyEcWcwy8bKvNRg5Dcj4TvEwnK+BflGq3Wu9ymEZ1xjuMWONgy07c09bWUkEYK4I7jfEZFzGNU+ESpLkYz+o7L/tYj9/LvK4j9/LfI4lT/3eB3Fx3ILL/h8mIf7/AJ5YN8L8UI+Qn86U5KG4v2bO8TEcn+Nk7upJ4oz8oX88wWHrI2tKVx9rVlcv+1iH+8s+br8WJHbYySRZdYxXk8pHq6Hjx1gZJckMOPHyMg8Vk3FYvyiO89G8dL8nFcbN8rDcXlvkcT5HLR61pjUg0OpOWZEZipm84nwneJjXrRztwBLcASDMZkGnbLwzBZMV9knIqNkhP3EiXfGlzUgH00uVQw/G+JyLmMb4hSXIxvHZf9rEfv5d5XEfv5b5HEvN+Hy0vZIacDLGnRHGJuQ68nEP9/zm2daMjXdA/wDOlOShuL9mznExHJ/jS93zScHb8kT/ADmYysioaMrHKYiu4Xw8T292YjqyFsPGVjqyYDZ7N2OF/MPj7Vg8fB3hl1pStDcdpdfZjhVbouLaApKCdaJFQ1QSk/jtzr4zeiMZAXEFCNaAx0DUksJnphZcCsgxERFQCXW7XWy8cu+ZrHCa3RwDQDXgeP1Qm2rltq5bauUPH1j2pSKaPV2Ol0qDjtLL1KwVCXWccIreVjzV9kQFcAxIwdTDIwXow0Tj1zxIzeiNMR1ZC2Hiqx98xH1kGoeKrH3y4FZBiHiax7y21cqf1aeALJUtxr/lkIjIQuIU/v8Anfb81n/5Vq752/zZTkobi/Zs5xMRyf40lyMP/cX7BkwXAiBZ4lhgwsiRfggqhBfQv/u8b+hvzZTkoXi/Zs5xMRyf407ZpyuOOfPFewbqUupWPErVlhln6JbmkK3bqOUp8KfmyvJQvFezZziojk/xstZ+BGJP/C78aUMoCJTJb/jbdS61TMhdHtQ0pdIOfUl5i8EqJMqcKWWyI3HF0NHkH6ihx05eUZ+dk7+lHQDOtKfnSvJQvFezZzionk/xpsXqo4Eiopbd9rln4uVE/OVc3dbZjROvHrLvK4j99FSoY1wkmIVdfIiWX0r8aX32t23zgNtRJEUqqIKYGVDhqsDzAT7koxGuEx/SDh5C82/IQBwzEdO8TAcuTKhjXiSQpdyckBGr3zB2GW5sG++91uxvvoHzMPNvt/i5AX1R+Ki/IN+dK8lC8V7Nm+KieT/HnwukNxc/40/Edco005deWXPA0tiMdJ6eRWXeVxH7+RG3CiRYF8g8dAXDsuX1cvY8vMSFxxAeO1vZk492Oex+QqYxl/8Asex8lRUOQxJZVyUE1rwMkHUEmOhbzRp3iWKuUesxr/qdsvFJBdq+HN8rGxbsnZMR/b3wGSJK6WheiGxh+5uR/Enz+jFBGuLKabtab/OleShOK9mzfFRPJ/jyYdpwt1HBSIiQtPH/AA8oJ0go19sYx3IR3W/j8Kx5HVB5d5XEfv5bX/1YlSnSIilLXzbq2w0XbS+RWUW0rGYvd8JTL/8AeIWUq4sq5LFuMyjlMZ4qd4mDp80spvlYLiZvlYH+onL/APeIU/vIuHgOX/DMJbEHNJcMJgI/ox/z5bk4TivZs3xUTyf5E/F9W2KQ6IRGnNnMfhT5PUyUbBWkh7bZU1GdvriZKy7yuI/fy1itbcZObHvkJJgRitfjW5rXj2rrhShn2yGcpMs08THrV/L/APeH+GVcli3GZRymM1/+VO8TAcupvlYLiZvlYLicv/3h6yLh4Dl/wiX2xmZWQvPfx2L+avoEtycJxXs2b4qJ5P8AJnYjXQxDoj8XJtH2fgEamhbj5lb7LaWWKYD60ICHOFLnwnTWYCOfBdeaseaJxx628LHbvnIpShDP9My8NaZd2qRZuDgCXbxmGxmcgj3zrsfj3gfCciyDDIQVwMLIItwu+yKkVIsuER0VDlDHqShiyDoxm4cCShiyDoxm4cDII9867H494FS495UfFQ5Qx/4JpjQbMlIOnuwUPr19BluThOK9mzfFRPJ/lTMPaWq0dFfip2138jJLH+lBmCR3n8kppxwt5pno8rMNBIkh0t6Gg/Q5bk4TivZs3xUVyX5cjHsnWSEc+DfGS74SBOYNs/GfiAnq0ggaVHYaHs9FIIaGbk55x5CjPFuxUQ0F6JLcnB8V7NmuKiuS/MvstcsksfX/AGjPR+Q3WoYhomz1py+1uyQyGy1PvvFOxsC68hh2hm/RJfk4PivZs1xUVyX5xgTBlh8A+ym3HR3QcivtQhg5dPVn32mLDcitoii3yrwIYkpR8WOF6PL8nB8T7NmuKiuS9AMAHMobjzzavscYcDnS2EJOiPq26l9vqJcuGMjMhfcV97j7gUEU+gYkUT0mX5OD4n2bNcVFcl6E+w0RYXjrVyLiyxkOQ8PcNkT9iGnA3k3fY5b6VWtKUJmAmETkl9UUcSUhQSSkJjiFCHFp6VL8nBcT7NmuLiuS9FKjhSUTjaJijB0244zcPOGtJjJLKpiXCeVt1t9PQq/0n5INlP5GxaiMgLcT5Dz9RgCiUNjjlULEBj+nTHKQXE+zZri4vkvSHxGCERjwt6fx0mxPx5bCsvvbqzLnNJrJH6JrIx6puZBcTZLDn5LjzTaclgW07kQtqdyVyqemznE6+68mRCH0xj5jiYxxi1Dx4o/qMxykFxPs2Z4uL5L0x4Zl5PQQLidxq1O48ZanIs1tXt3tpt51tWShtisnjrVZkhKtyZW5IyqZEHVUnwaqk4AqTIC7sCu6gruoK7sCqzACrNx6rPA0VchDorskYV2TK7JH1fPm3K+WOvV5L7ittrdVuOMcTUAbemsaqmYAKxMhDM+qzHKQXE+zZni4vkvUnAxnFfDAXq/Hg6q7GmldjV6uxwpXQBtFWDPoqw59F2s1dtNT4r7FrLLj9/bTV2s1UiDqqkIfVUgDqq3HC6q3GnVbjVisx0SishALU2AI2raUtp6zMcpA8T7NmeLi+S9dyzyGK8n7FmeUgeJ9mzPFxfJeu5Z5DFeT9izPKQPE+zZni4zkvXcs4/FuT9izPKQPEezZni4zkvXcs4/FuT/FkD2gLdxBrcQa3EGtxBrcQa3EGtxBrcQa3EGtxBrcQa3EGtxBrcQa3EGtxBrcQa3EGtxBrcQa3EGtxhrcYi3GItxiLcYi3GItxiLcYi3GItxiLcYi3GItxiLcYi3GItxiLcYi3GItxiLcYi3GItxiLcYi3GItxiLcYikHrSDIHiPZsxxcZyPruWcfi3J/i5f9oEJ02/sBq7AauwGrsBq7AauwGrsBq7AauwGrsBq7AauwGrsBq7AauwGrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+atvmrb5q2+aoti8YD2bMcXGcj67lnH4tyf4uX/axLzfv2Y4uM5H13LOPxbk/xcv8AtYl5v37McXGcj67lnHYtyf4uXfaxLzfv2Y4uN5H1us1YOUwWOQss47FuTddbaoXPCsoa5y9j8LLvtYl5v37L8ZG8j63lYv8ASudcutsvusrWtbqwYvVSH4eXfaxLzfv2X4yN5H1stihIzllW3PHGBdEL8PLvtYl5v37L8ZG8j65lAukX4BD1KLstpZZ+CNJjP3LLvtYl5tFyQoibu+dv31L8ZG8j65Mi9WB4YmL+Hk4uiawaSwizyDLQzHg7n5At9QYvVSHvuX4yN5H12eF6WQstrfeExQUX8KcF6qP/AIYyLog++5fjI7kPXclF1wcYF1jfxJoXpJDwBHqUXZbSy333LcZHch6xW6lqqSxRVPEoqyYVF3YFXSsfdbGFRwI/dgVSUCqqSAdVQseqtvtu/AycXVD8MUF/r35LcZHch6hddS2jsmE0ncgDtTmS0V+RlVV82fcr5Ey5XPu3+FG76qgpFVQAuq7aYu2Grthq7aaqgGUVRCaKrLlPC11y1Wnl2qyZPsVmQmWpvJapvIhLk1LAuJtyxyn877aX2GMVGKbsq5eGxQYX35LcZHch6Y+Uwwn8gDbT+SPVT0sc6r77r6tBEupqCOvTeNPVTeNs0VkADarIkG1WhjWK2y236dbaXK4Ue5XRYVyvggblfjY9U5jV6cgDbE7HFtL/AJWXMyRjKZyIm1MZENchzxSP45YKsXF1TPfstxkfyHpJUmIMickREqYQrLL3bmIQ11MY0mYMFtNDss/luNNuUehwXU/jbdU/AGtp5h1io55Q6GyN21CzIRCpX40NHoULDidGD79luMj/AD/oz77Q9hmRt2ouSLKQ4r5NRscfvQ8GEym7LG7fQq0pWhEQE+icbuoio8oVDGEC1EyOqENHLp79luMj/P8AohZbAlh2QuXq+9whwOCKfQkGIwraUtp6SXEiEozHn21fY4w4DPEMIGSGNp77leNj/P8AoTjlrVkjkCrV0h0DH3XEGCOJT04gdoiw7HU8y6M7HTzrKFJaKb/HLMYDp3uPXe49d7j1bfS6yk0BWv0TDRw0GaOZ4llMiWd7j13uPTEgI/d9B95thu7IQ6XAmNGt+gPSoTDve49d7j13uPVP7/i65Y1ZT+0YaOGgzRzPqOuWNWU/v+crxsf5/wBBkpJkCw8982+MhnzEECOFb9DcjK3IyrckHQZbJjf0jZxoUkN+hQxc60MSK9Qgf+D77Y7YhFhQ8gXaENHTLZpH4BI7RLclAONId90V6JmWy/x8v+1HAuHubcLW3C003WwazHS7b/o5gsP8ct8iAG4c/XHC0UM6I9jZ1xQ388vvqoKMbPUcE2Cz6BN8qHCkFjbcLW3C1bT4W/wkS3in7P8AE9HOyCgY52P+pIlvFP2f4/lK8bH+f9Ampi0Rf9pT8VB2MfUbx1m5uSgbh2Iom4Q2taUpRyy6rhwrblK0uo+Q0xRo4V27wffaYowYO/dP8vBcSbDjEFBtWsDJw8Rq5gph9VrSlMicq5KY+5ZSJkhrCxYyLYEJucstrbdS6iq63StK/GjzzbNrcgI5d9OUiWTqFiuhvQs3+Nl/2sYebZK64RNljuX3/wCGji9RNSBVrr18lL1tvICfhzOuCyCTuDtZGOkE5aZHOQJ1xwuYLD/HLfI4rySy12y5/EaV6idk+hsbaNk77XzYx+NMtOFygh5l7uhPRQ9Hryi+q+InWfAN2rMUfLkmOVi5C22Lmnh77bqXWyhhNkjISLpixajlR2ZEmx53ucsmCCAXnzzpW95soB6APuNGn5GoTLTJ0lV1oyPvx+QvNZyh51kcKWKbaMCkKWQso8wSpuZcq63HHk2ByJYDw7tr7M1MuXu2xx97cVMvDO0/unhN8rDSgY8b3uPTUsE867fa02XIlyBF0TIN0iZh4Z7Iup0K/H4wfX9flT7rKxV915ZS+8zeNJmVHNENHQU4QOwQJJENxUm6I/WtKUkZUgx+sTIUtjZV8R3Iep6evx+MH1/XzMhQBinWyjvxOi3YeQoeN4SvGgee/PnpTpLB2XS34uNaAb+ow83oS0iOyIO3V5+Z4sZ+8Z7oirmiHqREOOwTKFyMM+GzjclfffIlUDD+L55d+PlNNvu3vOwXEzfKw3F5HJX6sfCvmNGiPxpAz7ktCFj3ikRsUS/TJuKxflMsG/vEiES7Rgdiy800x+yPBp1MoYbBEDMY5JX2PfTNEaMZkgHAHsflvhX8TL/tCCPF39kkFDRZg8lf/hr7vgM3RkfLKU63EvKGsB3U71HiNy8nWRrh6zBYf45b5Fp1xq7rS7kOCUTfEg0AFnXKuSsTJACgZEaGYPiTvwIy77+KjWuv/Jb8+XffxD7WWPVtExVi1wxZIxaxJ4y7VyMl+Txwa1qO+S2xtNWUaayHmMYbpZGZfT/hiFf+0wcRylJeOCbl5XuFuI/fy7yuKNUvPepS5qlfhU1yrIYLdHjf/wARcQKUSRZYBFBaXV97j1L3suyEE5qxXhN8qHCkFjbcLQMESwYc3V4Jh1wQgfJEF2gxylPhR37tn+MwWHrL/wDeI2Uq7kXDw7dHZNOU+DlnwcYI7UC8/kjdE7fqOMfYd+7Z/jJnK3ykFIAiATx4RgOLOVskvCV40Dz350obaCJ/2FEREfYAx9WkWbWlkMfcoaHoFdM8WA3R41ZddXUhZJuPtJyBh4eOv0z8tr/48SspUtTVlG5SC4mb5WG4sm75yR7KNsPjsvppptqmRcxjvD5NxWL8pIj9WFGv9IflRPyCYoN8z2XXV6eFPbAdrkbFaN31bc+oYM2WwcK4GTj0h1bH4eX/AGsS834X/wCGvu+OW+bxHyuSE3OyEPCsvi5KMOK3h6zBYf45b5HFeS8Zu2tkrHwghQTkCA2o6KGDey77+IfaWXffxD7WXN/EfEnbbSVk7lrkni7dbI2X5OG4u/8Ax4ZFzGN8Rl/2sR+/lBN15sJDNFDZEIMIJiP38u8riP37/wDCkLKuAx7lGjkbKjBkFPtnRATdjpe3BF2KP+cEWwMfwm+Vx3h/B1yxqwhuKkXyMbvTzbgz8Y9c+A792z/GYLD1l/8AvD1kXDwHLp37pj9RokNmppo8GE0ivl6lj7Dv3bP8ZJZW2WiIcU0FyABboBDijkeErxoHnvzp8zqjsXB+Wz6zH2PCZ4uI5NZc3VY00KQiAo4dkW6GedyputwGLv2tH1r8KSb1CD4LiZvlYbiz2qsmx79CApiUpHqJku40yLmMd4fJuKxflFkI3TyJhN5V0QN0sfljdbg8csHdKdjwGm2b4R276s8D1ggJFwhTd9rjf8SzhxKGZFfcgLHLBPpZf9rEvN+F/wDhr7vjlvm8R8rkwV9hQMuSEyY2YSziTtLSMwWH+OW+RxXkvHIoy8lAyRICMLIkn4GPqEPl338Q+0su+/iH2jB7ChihCo0i7IDatxsc/IPNN2tNy/Jw3F3/AOPDIuYxviMv+1iP38oCv14+VIBsKtNOZxV2lh2XeVxH79/+PCbirxXR50xlltomTLDGtFFmIxwN5qeNsaEFIkiR2rWGfCb5Vsshuzri11xaaaoZEFCkRpO4TPlGGJkimGrWGZFi4Y2HmCCDMwWHrL/94esi4eA5dO/deY6qMuteCJul5A2hY94r8c7R8GRYuGNh5gggzII6prQZpMc4dIEyN2OxtwtnhK8aB5782Uf6YAVmpBLdlrbf1e0nJmnwZ8JSy52PjY0xs9GjWFjERhoTrncTFBRFRbnmrXmj4gkRxpuVOobCkNPRDd7MdLRxbsjF2XNR85E9Ym7ZEG5sA852ODsCFySOevKDukW1PMuER2PgkjyCyIK4sSMiCanIhmx9k2ILEdcukibYOGvZd+tPDdNI4u/qx/ibMiDI2dKfVa1rWHZ15L8egg9LvqOjsvJplpr6FafGnRjUu+p0g3z/AELhBrrrbaW08KhjVutpS2n0K0pWnRC/GlKW0TrTbtGmGmvpOstvUaabap4OtNu0aYaa8HWWnU0wy1/CV40Dz35uWX/AHF2/nk/Xsub/AOGJX/At12xqw3IWW0ZIlF/wgimRDO/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/grv4K7+Cu/go6aDeDA89+bl32cS8569lvkcV5KUhaGXGRpQn8QxHjHOxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ67GeuxnrsZ6Ehjmyvzcpb+eOxt3TlPxHb7Wm++AII5g3wKlBBXm5oJy/+bt9rTbUyE65/C+6lljc0E5f+Llzv/LEW/wDu8DYYQlGwRTCrSttVjbunK/ow1jqRLa3sPCv2kj/hyXHU/tYu9pyKkHeoOB894VrSn8K1pRSXHRvI+FK0r4GeUB89+JX+qSpPVnY6P08b/AsIcuhuOXUVW3wSGHLXmf0ZkwWiVjJ+k5+HJccD53yErJPaEfGNal4PnlLzTrrrUUcQ2MaXGvglWGDT0nUJtlkqQevqfGNRvIvO2stHSJMg89GGitwMvfc6Z5QHz34mSn6LMQHU02n9U/k63Y7YOzYO3+jCx7ChzBnAyIGVoVZ+FJccB57JmtOTkzNSAg2v/lA+em3asxcOzaRJLLWbfkxF2urkV9b5bHGqNxcy1R2MjeRypytsdAvjjG1m4+tK3fI8Rd84APnvw5aQsAYuq6URDgUBF/S0tH2HsOtuikQ0zaR+FJcdG8jlrXxZrddWyNa0seB89Ot1dioV21mUWWu26WItf92RWVslsdco5FTDlGoyN5HK7K3R8GKyYXt8JNxMU4iLaNgA+e/ClZRoCx950t+Ciukt/TEnHNHtGiPBvRU7cymnLHm/ryPHxzd/cJ1nWi22HL7yLPkABbv62v8AdJaHdGcYnDWWmmS5QmPEsCFyCNqY2IWTHu/+6arHN39wKYtJHKFJjSXpsx5iEinCHjPKAt39b+BWvwpKz1tistdKfh4iwOn6aJHaKalIV0VBGvh3x84wT+Pcw1dWlKUp4XtNuKn9eNafGlGGaV/CkJUYJSMoQbWOjHzro8BkFv8ATsjCsFI0AgK4GUJDQU6M+qVpWnppsuKKjpwklDDPFOR2PttqlKW0/T91KXUOgGHkZGFCIQ0gSomRoU4Yr0kghke0vImbEZKFloUN8qoOO2Wplptmz9SGQ4hKLx4htOsusXjSxg6HySiHlQn1Svxp6CRICDojI2bUTNmvr/m84LBFvISCEYVttLafqhyyxy0mCDeRGOkWJ8IkdMkPMJieNbTOS2pqcBcTRTDv5LrzTSdmQW09kjVE/kJd6fMJfTAzz6Hx8txDY8K2mGGmLf1e+AK+n8dFvT2OP2p2IOaTjd7dWyX2k3Mn2JvIi6KzJaq3JBlbPg1VsyBcqSQVVQ0WqoQzVara+exfPatSxVfZoqmDUVZEOiulwLVdPA0V2Ri0V+S0V+Rk1Tk2fenDCXVbbdfVqMNdTOOlXJnHGLUxFhMqn9fretPjRwAR1OQQNyvxtiqvxq9X46ZRXQZ9FdFnWqoJdFUd6irZfT+NLLqqjDtVQIqqtjDblbCn3K3HjaqzGnVZjTSbgAbU3Ghtq222yn7HuVqp+rP/xAAUEQEAAAAAAAAAAAAAAAAAAADQ/9oACAEDAQE/ASCD/8QAFBEBAAAAAAAAAAAAAAAAAAAA0P/aAAgBAgEBPwEgg//EAEoQAAEDAQMFCwoGAgEEAwACAwEAAgMRBBIyITEzkZITIkFRcXJzobHB0RAjMEBQUmBhgYIUIDRCYnBDsqJTk+HwBSTxY6MVgIP/2gAIAQEABj8C9AwRyvaNzGQOpwlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2ytPLtlaeXbK08u2Vp5dsrTy7ZWnl2yoS57icuUn5+hZ0Q7T/ZkP17T6FnRDtP9mQ/XtPoWdEO0/wBmQ/XtPoWdEO0/2ZD9e0+hZ0Q7T8EhkYLnHMAg61vJd7rcy/TjaKP4cuidrCMcwy8B4D+SKGSt1xy0Us0ZkvNzVP5oppDJfdXMfmpYY63G0z8noYoZK3XHLRSzRmS83NU+WGN2F7w061im2lim2l5uWVp+eVXZcrTmcMx/MHHzcPvHh5FNG3Mx5aNf5w1oq45AEHWxxc/3WnIF+nG0UTZnGN/EcoTo5W3Xtzj8u5wML3KJ0j70jzlAzD4Kh+vafQs6Idp+CTanDfvyN+QQigpuzstfdCvG0S155TbPanXg7I15z1T20843fM5U1rc5NAnSSRgNaKnfBCTeRg5g5MhZQWn9tCpDaneZ/dlHkvRtAZ7zsgV5u5yfJpyouijyA3TU0yoxTCjwmGyOpBlu5Rxp4teWfJe1ISwxgsP8gnWdsdZGYuILSQ14qlbnOwtd5A662Np98rJJCfqVdnYW8XzVn5e5WjkHb5bL0re1TObkcGEjUv1DtQTW2wh0Z/dSlE+F/DmPEUWuzjIqQMqBnPAFllh60XuaHsGcsNVucAq6lc6gjfiaxoOpWq0Fg3K+51bwzVQDRUngVXXI/k45VVr4nfKqMczC144PK29+1pITn2fFXKeIK9+Imvc8qltma2RppV3CFFLZ5GPJFHXfJecGxD+edXmhko/gcqyp8sraMkYLuVQiztvFpy5aJ0Uwo9uf4Jh+vafQs6Idp+CbM0f9MK0V4DTyAjOEDxq4MzZ6f8ldcKjiRio91DQuAyJsvA55pyUVo5B2qOI4c7uROkI3rBQNHYqujj3P3QmyxYZN8peQdis/3f7FWj7f9Qo+U9quWeNpmk3zqowztaH0qC3hTZKb5js/yTH2t1I25c1cqBsjmyyHqUcU7WXXmlWjKpqjK3fBWfl7laOQdvlsvSt7VaOjd2eWzuOcxtPUrSP51TY45hvW5chylVZHEGcRCjmpS+MytDo2BwBLQ2qilpS+0OorTZNxFKll6vzTpbW+64DeZKprbEWSE5S48C3Gdra0qC1Ry037X0+nljmGUDOPkhJE4OYVUwhruNmRE2WW9/F/iiyRpa8ZwU+1SCtw0ZypsULQ6UiuXgRhna0SUqC3hTLVGKVN163Axhu5MGWudRubGH3jTOnzlt29TJ9PgmH69p9Czoh2n4Jszh/0wp68JveRrW5yaBAcSvjM6ev/ACUjhnDSfJZ+XuVo5B2p/RHtCZ0o7D5Iq8Z7VLyDsVn+7/Yq0fb/AKhR8p7VJ8gOxN5pUnKO1Niiznh4lWYulPzNAmxwGESON0XBUq081Wfl7laOQdvlsvSt7VaOjd2eWztOcRtHUrSf50TZLY5wr+wLfthaf5mpTZITVhzK089WXom9itXSu7VdZvWNxO4lelBfT9z3LcLIYr54Iwm9IO/y7xrncgQcN1gLvpVeeYyUaijcq17c7SorQBvgbh+aZzijLPI4PPE4Js0cjrzeNwU2+aSKEZfmp+YrPzj8FQ/XtPoWdEO0/BJsjzvhlZ8wg+M0nbm+Y4ldNmk+gqhaLXQObhYnUPnX71nioOeO1Tcw+Sz8vcrRyDtUbnmjHb0p8QyOzt5Vue4OHzObWo4W5boUvIOxWf7v9irR9v8AqFHyntUvIOxN5pUnKO1Wj3qCij3IOMYO/AUcpYREw1LirTzVZ+XuVo5B2+Wy9K3tUzG4nMIC0Q2wmvthaGDLdGWqfK7P+0cZURlzGQXtakEeO6bvKtz3KQy1yiihhOdoyq089WXom9itVWO0jjm4KqSmLdMuoKJwDjBdpyFG0yMLWBtG14UOkHf5ZIXf5Bk5QgGUErMra9iumzSfQVT5rRvXuF0NUUP7nOvfRSQ/uY6v0K/ExtLmOG+pwJ1axxj95bwoPdM11TQCmVT8xQlrSQHZVR4IPEfgmH69p9Czoh2n4JDmEhwzEK7bI7382eCxPH2r/wCtE5zuN+QIyTuvO7FG85muBT2CGTfAjg8kUzgSGnMFLC2KQF3CfII52bq0ZjXKjuEBvcbymyzEue5xynlU307FHA+OQltco5VJOwEB1Mh5E2F8b3EE5QnzMBaDTIUJntLgARQJ0LI3tJIylCWPkI4wqvvsPFSqu2JpH83J8boZaPbQ5lFM4Ehp4FLC2KQF3CfLDKcoY8OWhl6loZepeZs5r/Iq9O6vEOAeQMtgdeH7xlqvMh8juSgTvxTHOcXVF3gCdNE1zbwygpsFpDt7mcFLEy+4vbQb1EgXo3YmqtZB8rqj3FhbCDvq53BPh3KQE5j5Q5pIcMoIQbbIyT77PBY37K/+vE57v5ZAnSzOq8oSwmjh1rz7Xxu1hebEkh5KLdJclMjWjgQlAvNpRw+SrV4+V1PmiBDXUz/BMP17T6FnRDtPwnFM7CDlVbrHseMVF+ofd4qIAm5FGOFSzH95r8aw/XtPoWdEO0/CnmZXs5Cv1L1WaR7z/I/G0P17T6FnRDtP9mQ/XtPoWdEO0/2ZD9e0+hZ0Q7T/AGZD9e0+hZ0Q7T/ZkP17T6ESySPaQ27kWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6lppepaaXqWml6k+d0kzg3gFEyFv4gF3CaLTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUtNL1LTS9S00vUmxNc4hvH8XT/b2hWfl7v7Un+3/YKz8vd/alo+n+wVn539qWj6doVm539qWj6doVm539qWjkHarNzv7UtHIO1Wbn/2paOTvVm5/wDalo5O9Wbnj+1LRzVZueP7UtPNVm6Qf2paearL0g/tLc7RGdzcKte1eZmYTxVyq081WXpG9qq4gD5rSbo7iZlW7PYGNcd6Pl/Z5e0b+LffTh8hZuj7p4LyBaSCOELfuc7lKjiZneaJsbMLRQf2fQqSLgB3vJ+SS0uGRu9by/2iy0tGVm9dyeWgzqKLhAy8v9ovjfhcKFPifiYaeQOI3kW+PLwf2my0tGR+9dy+RriN/Lvj3f2nJDwkZOVRwEcO+5Fk+LhHMJLxF7ehYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlWi0BstZf45uNYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlYZtlbrC112tMqEczZLxF7IFhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2Vhm2U2WO9ddx+hZ0Q7T/SX3lM6Idp9sw/XtPoWdEO0/wBJfeUzoh2n2zD9e0+hZ0Q7T/SX3lM6Idp9sw/XtPoWdEO0/wBJfeUzoh2n2zD9e0+hZ0Q7T7CDo4JXNPC1hK/Sz/8AbK/Sz/8AbK/Sz/8AbKuyxuY7PRwp+esMMjx/FtVSaN7DxOFPyhrQS45AAi51mmDRlJLD6W7Exz3cTRVVFnP1cAqzQvaOOmT85yZvgj7ymdEO0+2Yfr2n0LOiHafYUMU0117a1F08abHFNV7swulOkkNGNFSV+o/4O8Ex9nfeaI6ZqcJ/PI20SXCXVGQlRvs777Qyman5YHvNGtkaTrU7GT1c6NwG9PF6RkbMTzQK62jWtFXO4/mqASu+Yai6F1RmIPAmzQikcmccR/LHC8kNOeieyBgaKj65fgj7ymdEO0+oMmZJGGuFctVpYetaWHrWlh60YZCC4CuT0Aa0Ek8ATBOLrnC9T8lYwGx++7Mt9asvyYqwTNk+RF1FkjS14zg/mfaLlIW/uPD6eH69p9Czoh2n2HZ+XuVp5h8k/wCIjv3aUykJrgykAbhqd8VLJ+HjaWje3RTKjLPUQg0oP3INkjszOkp3qrYmUOZ0eROhJqM4PGFI60R3yHUGUhRss7LjSyueqmNojvlpFMpCDgNzsrWZRezlFkMdmkpxUcUbRZRdAxNUDHirXSNB1qd7IKObG4jfHiUTXZi4AqT8PBSWm935zpotLonTH/qHuVNxaw8Do8ikhfnaUam7C3Ee5b+KEN96TL2pstjLBvst11WuU8kcNHtbUG8fLZ3vyNDwpIXGgeKVW8aJW8bU6kdHOFC2QFblKyINrXegpkUQq5yrMBK4Z3PzI7nHA6nDFTJqQc0l0Dsx4vkoLVc8/vt9U8ZCMc7bzDwVUbLOy40srnr8D/eUzoh2n1COEQNdcFK3kyEwhta5aqSYNvXeBfpm7SMxbdqKUV6OCVzeMNVJWOYeJwp5ats0xHMK87E9nOFPJLIWb+9StFFQHR9/liizX3BqNG0jiZWg4gvNsjY3WnRytDZQK5MxTbQBv2Gh5PJdiY57uJoqr0lnla3jLfJAHsvMrwhTgDgHaso9ND9e0+hZ0Q7T7Ds/L3K08w+S08re9MEJuvkOfiC3KWZ72VrvjVNhgoWjM26nTSRXS8/uyUTmSyB1TWg4FF0feVNz+5RdH3q0c4KGFpoHVLlZ7pzuulWqv/Td2Ky9K3tVq6J3YoOeO1Pf7oqnSSGrnZSUy8a3SWhH5sCipndVxT2V3ke9A7VG0HeSG64K08w/kbFawXNGQPGdeamYTxZirsrGvbxEITWeu4k0I91TzHOKNCihs8cr2HK642qhkFnnAvUdvDmVobxNvD6KLkPYpOUdvwR95TOiHafUYuQ9itHIO3yfirQ29XAD2rc3Xnv4Q3gVaX4zwHOCnRHK3O08YTbS8AyvzfIJ0YbI8tNCQiWb5mZzXBBo0WR45EXwEkA0zIMncQ4iuZSubmLiR5I5BnY4OTXso6N4RMEjovlnCvw7/wCcZyoslkkPGHFMhbkrnPEFWgjjbrK3IX2OOG9wo2qBt0jGB2pllc47s5xoKJ0spoxudQmBxN0GuT00P17T6FnRDtPsOz8vcrTzD5LTyt71ZPu7vJHJd87ILxKfDZ4gSw0LnKZ89MjqCgUXR96m5/couj71aOcFBzFZekCtXRO7FZelb2q1dE7sUHPHarR0buzyfeV9gVnpxU61PXhN5WcN4HXtStPMPl3J0m572uatUZonve5py14vJHBec6J1d6eBWivF3q0j5hRjcN0DxnvUX6T/APs/8J7PwuIU0n/hRch7FJyjt+CPvKZ0Q7T6jFyHsVo5B2+SBozBgUkhli37ieFS7q9jg+mFWaThyhMhqN1jyEIufHdec7mZEfwloPNdkTo5mlrxnBU3P7lF0ff+TzLt7wsOZUtELmnjblXmJQ48XCnWhopLHn+YVpfwgAf+6lE2J7WhpJN5NcJoqtNeFSx+80hWfl7laOQdvp4fr2n0LOiHafYdn5e5WnmHyWnlb3qyfd3eSKh30YuOCdK2Yx3jUi7VfhLO7fN3xHD9VBJwFt1Tc/uUXR96tHOCg5isvSBWrondisvSt7Vauid2KDnjtVo6N3Z5PvK+wI2ec0jcatdxFN3UGozObnTGN00puiuVx/8ACtPMPljmZnaVeiIc05weDlVRujPk0o7g3fHO451+Egdey78jsQc/RP3rvFBrjkzte1CZ8plLcIu0RhbHEbQ/+I3oUBfmOTqT4S67Xh4lGwPv3m1rSnwP95TOiHafUYuQ9itHIO3yWd44WBSxGdwuu4uBOfZ5Hva3Icyay33+MXgmSscyOu+BveCdFK4SXDQh4UgMdxzPnkVmf+7KFNz+5RdH3+WJloaHMdky8akZZoY2SZ2kCiLXgtcM4KidFW6w1c75K0l3/TI1qePhc0HV/wDqilszy1taOomxxzuLnGgzIukMlBlJFCrPy9ytHIO308P17T6FnRDtPsMOY4tcOEFFr7RM5pzgvPkO4yyR1z3XUQ3aV8lM151fJfhe5juMK6bQ6nyACLo5HsceFpoqTTSPH8nVVIZpGD+LqKs0j3njcao7jLJHX3XUQM0j3ke8aoOaSHDMQi11pmLTkILyg5pIcMoIRa60zFpyEF5QINCEQ60zEHgvnyXYp5WN4muIV6V7nu43Gq3aOZoy0oQm+efubv8ApuNFC+jiGuvOcVP8xd/Jeie5juNpoqC0H6tBVJJ3kHgzeXzEz2Di4FQ2h32gBVOU+S6y0Op8wD2oGeRzyOP4H+8pnRDtPqMb5XBrQDlPIp2RzxucQKAH5+TcbRXcSch91Bz9xlpw3ldD2NA/YzOnSuyDM0cQQs9qNGDC/iV9+4yH3g5ENdFGOJucq8ARG3I0KWGdwYH5Wk5k19o3J13MS5TCOhZfN2nF5KjOgy1u3OX3uAqrtwk1FZZYmAcAPctyhqIBly/uTJo8TVRzmAnPHIt1YIYz7xcjZ7KatOJ6im911SiBJHJG4ZRVQCx7nw3g019ND9e0+hZ0Q7T7aIpfidnat897Oc3wW9e5/Nb4oClyFuZvwr95TOiHafbMP17T6FnRDtP9JfeUzoh2n2zD9e0+hZ0Q7T/SX3lM6Idp9sw/XtPoWdEO0/0l95TOiHafbMP17T6FnRDtP9JfeUzoh2n2zD9e0+hZQE+bHaVhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWVpWRYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalR2Q3znTC0VG5jNylYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqWF2pYXalhdqUNRx9p+Lp/t7QrPy939qT/b/sFZ+Xu/tS0fb/sFZ+d/alo+naFZud/alo+naFZud/alo5B2qzc7+1LRyDtVm5/9qWjk71Zuf/alo5O9Wbnj+1LRzVZueP7UtPNVm6Qf2paearL0g/tIw3wJR+0+S081WXpG9vkvPIaBwlOMLrzQaV/s9lpbnZvXcioyd1OJ2VPhlZHRwpUKOUCpY68t7ucfI1DdZHyOOYEqKEftGXl/s98T8LhRPifiaafk3QjeRb768H9ostLRkfvXcv5GVG/k35/tGSLhI3vKqHP5I4/253cn9pl7RvJd99eHyPtDhlkyDk/tN1Bv49+EyJmJxomRswtFP7UtEhHm2aP6/F4jmEl4i9vQsM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4pzIQ8ForvghJMHXSbu9WGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHit1ivXa03yEcwkvEXt6Fhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vhm2R4rDNsjxTZYw667j9Czoh2n4HkfMHkObTepsUTZA4Pvb4fBW5StlLrxO9ATZYg4NDLu+9sw/XtPoWdEO0/A7mQ3agVylCSa5dJu5D8FbrDcu1plKEc1LxF7J7Zh+vafQs6Idp+B5HTkgFtMybHA4lwfXN8j8FbnM4h14nMmyQGrQymb5n2zD9e0+hZ0Q7T8DltnZfcBU5aIPtEV1pNK3gfgrdIIrzM1bwQZaGXXEVpWvtmH69p9Czoh2n0dYYZHj+Lar9LP/2yv0s//bK/Sz/9sobtFJHXNebT89IY3vPE0VVZoZGD+TafmqLNORzCsvpAGgkngCqLO76kBVks76fLL2fnyZfVJXTvDAWUTGQSh7t0Bp9D8FXJpgx14miY+B4e3cwK/U+2Yfr2n0LOiHafRyNtElwl1RkJQAnyn+DvDyfqP+DvBQfh5L92tchH55H2h9xpZTNVRts8l8h1TkI/NG10+UNAwOTyMxPpGuLfPuFXHuRZv5CPcCIhJD/ddnRtcQo8Y/n8/wArGZrzgFaBC3fbm6rznOT1QiGNzyOJXpoXsbmqR6VzopIxdNCHJjpHNcHZN75KBaWHrTmVDrppUfkMsb2NAdd3yEUjmuJbe3qc+N7Ghppvk2ORzXEiu98scTc73BqkldLFRjS7h/M98bPNsFS45vJusb42itN8tykc1xpXJ6QRxNLnngCrNO1nyaKreWnL82LzzasOZ7c35gyFhe48ATopKXm56emvwwve3jAV2ZjmOz0PqDJmSRhrhXLVaWHrWlh61pYetGGQguArk9AGtBJPAEwTi65wvU/JWMBsfvuzLfWrL8mKsEzZPkRdRZI0teM4P5n2i5SFv7jw+nh+vafQs6Idp9JHzh5dznbeZdJpWiiELNzbe35vE5EQ6zx3GjPTLrRAqyFuVx7kN0jhA45f/K3kUDhxx/8AhN3MkxPzV4FIy0MvtDK56KN1njuEuocpKkZaGX2hlc9FCIG7lHl3Q1JK3KJtne/iNHFPlsrbkjRWgzHyRudBlLQcbk8DMCoXugq5zATvihJ/8g5l88DnUaFkghunM5gp2K4DWNwq0lCJmQZ3O4gt9Ex1M7pMqcbG6Jsg4Yzk+qbfg31Mu/d+RkjMLhUImzUlZxZimSmJzHtzXxkKfE9kN14oaA+KAGUlB1rG6S+7wBbk2OyudxNpVGezVMX7mn9qkkmZeexwumpTmOytcKFRus8dwl1DlJ9TlMsjGC5+404UxsU0b3boMjXA8B9LuZO9lFPqpR+5u/H08kXus35+imk/dSjeXyVbZpSOYV52KRnObTySdKewKPoh2lPYyHdLxrnTXvj3OjaU8l6KCVzeMNVmbI1zXbq3IRThVq6J3Z5KRMc88TRVfpZtgqjgQeIqIEVaXgFTtY0ACN1AORZQUYmwXxerWq3VzLhpSnk8zE9/NFVWWCRo4y3y5ivMxPfzRVeeieznCn5HT/veaV+S3CBjS4DK5yH4ljHR8N3OnMfvo3hPjdnY4t8l5tmmI5hV2Rpa7iIWRRENAc7F88qtGQ5+7012WeJjr5yOcAmOie17dzGVprwn1COEQNdcFK3kyEwhta5aqSYNvXeBfpm7SMxbdqKUV6OCVzeMNVJWOYeJwp5ats0xHMK87E9nOFPJLIWb+9StFFQHR9/liizX3BqNG0jiZWg4gvNsjY3WnRytDZQK5MxTbQBv2Gh5PJdiY57uJoqr0lnla3jLfJAHsvMrwhTgDgHaso9ND9e0+hZ0Q7T6SPnDy/YVLK3EMg5U9rrRIWvFCCaoiBwAdnqE2R8ByCg/aOtPkme3fNpdaoef3KXo+9Q8/uUvR963hoXuufRNew0c01HkIUPMCk5xVn6NvYp7xqGuLByBWlhO9aWkdasp53cpZOFz6av/ANUdnB3gbePKmSsOY5fmPy7lKC+Drat7M0HifkVHAOaU60WVt0tyuYMyaTmjBenNszXue83d4Kmia9lmtAcMoO5lAStpfZvm8qjYc7ZQOtWjo3dnqlGNc7kCq+N7R8x6Vr24mmoTJG4XtqpouBrsnIpZzncboUNnHPd3IWqRoMj8Nf2hOiuve5uQ3VfjysO9IcE5kYoxwvAKTpT2BR9EO0qbn9yi6PvRtE4rGw0a3jKG61qczW500XSJYzfaHZ1auid2KOEZL5oq4Im6ygwtkZeNASpCR5xjatcnxyuIdI4Xcic92FoqVG2BxJDq5k7pD3L7AjLNoWcHvFNDsnusYFuYvMkPA7hRtNmbdIxtHarL0gToXkhrs9EIIWOLG5KsGRcEkTxrU0IzNOTk8rrOTv2Go+YV6QFsnvNVYJWSfI5CgyYzR8W+yIkmpKZaJm1mdlbX9oRio95GQlqBxMdhdwhD8SaCImp+ibLEasdmVos7nndbpbh+Xpqsje4fIKj2lp+Y9Ri5D2K0cg7fJ+KtDb1cAPatzdee/hDeBVpfjPAc4KdEcrc7TxhNtLwDK/N8gnRhsjy00JCJZvmZnNcEGjRZHjkRfASQDTMgydxDiK5lK5uYuJHkjkGdjg5Neyjo3hEwSOi+WcK/Dv8A5xnKiyWSQ8YcUyFuSuc8QVaCONusrchfY44b3CjaoG3SMYHamWVzjuznGgonSymjG51CYHE3Qa5PTQ/XtPoWdEO0+kj5w8v2FfePIbU8VfWjfktyZHfkpXLmCe2W6IwytGjhqFDz+5S9H3qHn9yl6PvUPP7vK7lUPMCk5xVn6NvYp+ee1Wv7e9Wbld3J44RJ3BMfwOYmRtxONB+SKIuu33XaqRzJXvlDatFM/kj3FzqF1LnAUQ7DwpwPDGR1hCXc9031KVov0n/9n/hfpP8A+z/wmyUu35r1OLKrR0buz1SapA3nemUcD50dh9M6E54j1FRTtGLeHlUUXuty8qml4CcnIj+GyAZ31oFW0Wgk8N0K5ADQ5TU51H0Q7SpOlPYFH0Q7Spuf3KLo+9QU4anrU1f20aNSsxb74GtWrondnkG7ybkz3TlOpB0rnyEfQKbmFQc8dqtHRu7PI7pD3L7AoKcIvKe9+03QmvYaOaahb4ZHDKFZ28UoHWrS7h3M9nks/wB3+xUvIOzyh8bi1wzEKlpiEn8m5CqboYzxPFEY5WhzHJ1ndwOp9EQygNMi00XWnRSva6rqi6mOH7mKz8h7VaOXu9NlcBvymUNfNDtPqMXIexWjkHb5IGjMGBSSGWLfuJ4VLur2OD6YVZpOHKEyGo3WPIQi58d15zuZkR/CWg812ROjmaWvGcFTc/uUXR9/5PMu3vCw5lS0QuaeNuVeYlDjxcKdaGiksef5hWl/CAB/7qUTYntaGkk3k1wmiq014VLH7zSFZ+XuVo5B2+nh+vafQs6Idp9JHzh5fsK+8eR1nJ37TUD5ISiQxvpQ5K1TYQ+s8vHnKY4fsflUvR96h5/cpej71Dz+7yu5VDzApOcVZ+jb2KfnntVr+3vVm5Xdy85oX5HfL5oCSj2Z2uaUbQ8ku4C81P0/ICM4QygTAb5qLyHMcc9wq+wOc8Zi85k6FhrO8U5oUczf2lHLfieNSDnzOfGDgu06050kcTpDgaQDVRvP7XAoitWPbnHEmy7rulX3c1PYTAcMm8KaJBhcHj6KUjE7eD6+SBjfcBUrN0dGxri263InvfXfvqK8Kj6IdpUnSnsCj6IdpU3P7lF0feowM7CWlPfTeyUIUF3Mx18/RWrondiBd+xpcEZIcdaV4lHG+WSQudmJU3MKg547VaOjd2eR3SHuX2BRcbN6U937JN8CmRRjfOKc92FjaqzE/wDUCtPMPks/3f7FS8g7PLDKLPGSW5aiuXhTzd8y81aeDkVAKlQRzYwMqkc3LdI7FWN2Ju9Kcx87w4GhFFusLnuZ9EBbb26AfuVn5D2q0cvd7Ai5D2K0cg7fJZ3jhYFLEZ3C67i4E59nke9rchzJrLff4xeCZKxzI674G94J0UrhJcNCHhSAx3HM+eRWZ/7soU3P7lF0ff5YmWhocx2TLxqRlmhjZJnaQKIteC1wzgqJ0VbrDVzvkrSXf9MjWp4+FzQdX/6opbM8tbWjqJscc7i5xoMyLpDJQZSRQqz8vcrRyDt9PD9e0+hZ0Q7T6TIv1U//AHD5L0T3MdxtNFdlnle3ic4nyBzCWuGYhXfxBpyBbruj9096uVFslolc08BeVWGR7DxtNFSaaR4/k6qrDI9h42mipNNI8fydXyfqp/8AuHyUFpnA55WVANtMwA4L5RJNSUdxlfHXPddRDdpZJKZrzqqUtlDHMpkIW6RzG5w7k4hBu/keTnOVSyH9rSfyAtJBHCFktDvrlW+tD/pk7Fl8lYZHMPyKp+IOyFekc57uMnyXYZ3BvFnVJ5XOGenB6nNzO9M6Udh9MCM4THPnja4jK2uZRRwPD2NFSRx+RkE7wyVguiuYhbvaBDX3ic6fHeEcTBvXHJVQywSsfkumhT2zTMY7dCaE/IJjoXte3cwKjlKlE0rGEv4So3Qva8BlMnKjeywvxDvW+dFKz5nMtysQjL3HLdzDlKtDW2iMuMbgBX5Jk1KgZCPksj43sdnaU50LY9191mU/+EL88bb7cra5lvSDcdkIQLJGZRlaTlCb+F3ISX8oBy0RbNMxjr5NCVfheHtuDKEcl6J2JquudG8e67IQi5hhi+dcq3Gz1EHCfeVnc80aHgkq0MZaIy4sNAD5IWSzxteK1BPzKkfE4OaQMo5PKY5QXQO4v2rezROB4Ce5XhuEfzyBFtlcJZeMZgi5xqTlJQs9rNAML+5bo8QyH3g5Ua5jiMMcafNJicULPK9rHszXjnClll3HdS0i8Xem+8pnRDtPqMb5XBrQDlPIp2RzxucQKAH5+TcbRXcSch91Bz9xlpw3ldD2NA/YzOnSuyDM0cQQs9qNGDC/iV9+4yH3g5ENdFGOJucq8ARG3I0KWGdwYH5Wk5k19o3J13MS5TCOhZfN2nF5KjOgy1u3OX3uAqrtwk1FZZYmAcAPctyhqIBly/uTJo8TVRzmAnPHIt1YIYz7xcjZ7KatOJ6im911SiBJHJG4ZRVQCx7nw3g019ND9e0+hZ0Q7T7D3SPKDkc3jW/vxn5iqySl3IwrcYWlkPDXOfYO9JHIt84nlPwVvXEfVb4k8vtmH69p9Czoh2n4HlEjGuFzhFeFMMcbGndBmHyPwVV8bHG+cpamCNrWjcxmHzPtmH69p9Czoh2n4HrDI9h/iaK7LNI9uejnV+CrsU8rG8TXEK9K9z3ZquNfbMP17T6FnRDtPwPKJo2vAZwpjoYWMdugFQPkfgq/NCx7rxykJjYWBjdzBoOU+2Yfr2n0LOiHafgcugeWE5FcnlL21rT4KuQylrc9FfnffdSlfbMP17T6FlGk+bHaVgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqUgtrd5dyXjdTXWJo3S/TevLsmVYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHaletbRut453kJrbEzzdyu9N7LlWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalgdqWB2pYHalDUHh7T7Isv3dytHNHwNNzyrN0Tez4On+3tCs/L3e3rL93crRzR8DTc89qs3RN7Pg6f7f9grPy93t6y/d3Kfmj4Gm557VZeib2fB0/2/7BWfl7vb1l5Xdyn5vwNNzz2qy9E3s+Dp/t/2Cs/L3e3rLyu7lPzfgabnntVl6JvZ8HWj7f8AYKz8vd7es3K7uU/N+Bp+ee1WXom9nwdaPt/2Cs/L7es3K7uU/M+Bp+ee1WXom9nwdaPt/wBgrPy+3rNyu7lPzPgafnntVl6JvZ8HWj7f9grPzvb1m5XKfmfkkeM7WkrQxda0MXWtDF1rQxdaB/O9ghj3pI4U13GK/ljfG1rrxplUjZGMbdFcns+fnntVl6JvZ8HWj6f7BWfne3rNylT8z8jmuzEUK0R2yoRZ23Q4ZctVaPxDb127TLTjWiO2UY3ztDm5CE0yPyuFQBnojuDqkZwQvPyBvy4V/k2VSCUF3unIfI++/fVy5XJt3DTIi107Q4GhQM8gFcw4VQvcz5uagWmoPCEz8eaNrkzqT/8Ax5q6m+ylB07wxpNE/cZWuuZXfJUvufzQjuElSODMfJfnkDAqXngcd1MlfM3c3ZnJ34eQPu5/Y0/SO7VZeib2fB1o+naFZud7es3KVPzPzWfmlWv7e/yWnnlOkbQgZLzipzMzzpOavAFWaGQOkdiIyBad9/jpkRANJI3UqOMJj/eAKm55UfNCtHSO7V+Ktkzt/mpnTQHXo34SpoTmjNR9VBz1aOaFF0ncvw0DqCTF9ETFM4ygcOYqOVmdpqi45hlTpHVy5Gt4lWeZwkPA3gRs0jqsxDiPzVr+3v8AY0/SO7VZejb2fB1o+naFZud7es3KVPzO/wDNZ+aVa/t7/JaeeVZ6cIr5CyxsDqfvcqRukI4ompzZMYNDyqDmDsU3PKj5oVo6R3arOOKNvYrJ93crTyN71Bz1aOaFF0ncpTxR948to6I9iswP/UHksp4d93K1/b3+xrR0ju1WXo29nwdaPp2hWbne3rNylTczv/NZ+aVa/t7/ACWnnlWbmK03c9xQ/iKbley1V97msjClk99xcoOYOxTc8qPmhWjpHdqg5g7FZPu7laeRveoOerRzQouk7lNzO/yuiP72XUCRSSJ+b5hCQTMbxhxoQhuWijFAeNWv7e/2NaOkd2qy9G3s+DrR9O0Kzc729ZuUqbmd/wCaJ0JZvRQ3ip92LN/Sl08vkmlYYrr3VFSoYn0vNbQ0TmuFWkUIR/DUlj4MtCEN380wcZqj+FczcuC8cqijmpfYLuRSOBioXE501p4BRSvaYqOcSMqjYc7WgKDcSzeVrePIpjMWb+lLpUbYbtWurvlK6Ys3woLpTGQ3ah1d8pHzFlHNpvT5MUO0gFusbtzm4TwOW+khDeOpVlZHlcb15x4cytR5vf7GtHSO7VZejb2fB1o+naFZud7es3KVNzO/1wjjTonTTNLeJxyoNmgvvAxXs6DnNugZGtC84KPkN4ji9jWjpHdqsvRt7Pg60fTtCs3O9vWblKm5nf67SeNrx8wtCdoq9FA0O4zlPse0dI7tVl6NvZ8HWj6doVm53t6z8pU3M7/ga0dI7tVl6MfB1o+naFZud7es/OKm5nf8DWnpHdqsvRj4OtH07QrNzvb1n5xU3M7/AIGtPSO7VZejHwdaPp2qzc72xvpYxyuWW0w7YX6li/UDZK0x2CtI7ZKhEBJLSa1CkfOSAW0yBY3bK0p2Cv1H/Er9SxZLVDtLezRHkcFkNfb9p6R3arN0Y+DrR9O1Wbne0POTxt+5aUu5rV5uGR3LkXm7OwcpqshjbyNWW0P+mRb60SnleVlJK3rSeRb2CU/YV+lm2F+mev051hfp/wDm3xWg/wCYWh/5haD/AJtX6c7QX6Z6/TS7Ky2eYfYVvmOHKFkW8mlbyOKyWmT65Vle13K1echjPJULzlneOaarK57Oc1by0RbSye17T0ju1Wbox8HWjkHarNzvZfnpWM5St658h/iF5mzgfNxqtLcH8QvOyyP5XLzcb380VWSzuHOyLfvib9V5y06mrfPld9Voa8rislmi2VvY2Dkb6ffMaeULfWaHYC/TgchIWQyt5HLzdpcOVtVvJYndS0N7mkLzsMjeVqrG9zOaaLJOXD+WVeehY7mmi84JI+UVXmp43Hirl9p2npHdqs3Rj4OtHIO1Wbnex6uIA4ytJuh4mZV/9eFrfm/Kt/O6nE3IqMa57vllWhuD+eReetDR8miq39+TlcvN2eMfO76/52GN3K1ZGOj5rl5m0fRwWRjZB/Aqksb2c4UXmp3gcVahefjZIPlkK35dEf5BXonteONpr7PtPSu7VZujHwdaOQdqs3O9iVKpf3R3EzKqQMbEOPOVWaRz+UrzcDqcZyBVtEwb8mCq0e6HjeaqkbWtHEBT2PQioW+ga08bMi/+vP8AR4WWEvHGzKqsc5jhxZFSS7M3+WdUlrC755lejcHN4wfZlp6V3arNzB8HWjkHarNzvYV6eRrB81SyR1/k/wAF5+VzhxcC8zE677xyBVtU32s8V5qFoPGcp9n+fiY/lCrZpHRnidlCq6O+33mZVehkcw/Iqlrjvj3m5CvMyAn3Tn9lWrpXdqs3MHwdaOQdqs3P9gVnkDflwlFtkbubfeOdZS+SQ/UlAz0hb88pVRHuj/efl9q+diF73hkKJsj90HuuyFUka6N440Gy+eZ/LPrVI30f7js/si1dK7tVm5g+DrRyDtVm5/rxfM8MaOEossQuj3znX75JHfUlB1rdubfdGdUgjDfnw+2bkzGvb80XWN9P4O8VdmY5jkG2jz0f/IK9A+vGOEexrV0ru1WbmD4OtHIO1Wbn+ulkXnZuLgHKr87y48A4kHz+Zi6yqQMA4zwn27cmYHt+aL7Ebw9w51VpdHI36FCO20Y73+ArJ7EtXSu7VZuYPg60cnerNz/Wy55DWjOSjFYyWx8L+Eq5A2p4TwBB7/OTe8eDk+AfOto/geM634vR8DxmQY7zkHu8XIhJC680+w7V0ru1WbmD4OtHJ3qzc/1p0kzrrAqYYBmb4q++rIPe4+RCOFoa34DLXgOac4KM1jBdHws4Qr8J5W8BV+LP+5vF7CtXSu7VZuYPg60cnerNz/WXSSm6xucquGIYWoT2kUh4G+8gGigHB8DOtFkbv87mDhQkiNHDOONCSPP+5vEfYNq6V3arNzPg60cnerNz/WdzjPmGZv5fNbvOPMNzD3lk/LZ/w7gL96uSvEtI3ZChlOdzcvKppeFrajlWkbshT/iHA3aUyehdLCaPqFuczgW3Sc35Jo43tutdQb1QSPxOYCfRzSxZHtGRQxSPaWOOXe+pxOgIBc6hyKYTuBDRkyendarM3fZ3tHD80JGZW/ubxhNkjNWOyj2Bauld2qzcz4OtHJ3qzc8esfhozv34vkEGZmDK8/JNYwUa3IB+ayfd3J8nukDXVSRcMbuopsfDI7qCZJ7zi3VTxVp5G96LnkBozkqkTHyfPMt/BIB8jVbpA683s8hZlkeM4ZwLfQPA+Rqr8D68Y4Qnc4K88hrQw1JVIo3yfPMtzyxyHMHcPkkbNZ70gO+O5hRuhFIy3ej5J8Um6Xm56BRvcSTI0OawZ6LfQSBvGChJC68w+QtjvTEe7mVJY3x/POg+Nwc05iPLaOTvVm535L877o4OMrewPpyq6wlsnuu8gM7s+Zozlb2zvI+ZQbIHRE8Ls3kdDLul9uegUb984yC81vyRjbG9jwK/JPjdul5hunept8lz3Ct1udb+GRo4xlTZInXmHMUw22O+0nJvaqQWKLcyBl3tE1816hNMile1xa2MVcXCipHE9448yuNqyT3XcPkrM7KczRnKywSXeOqbPeLmE3cgygp4gvb3PUfn3aIeZf8A8Svw0h83Jh+R9gWrpXdqs3M+DrRyd6s3PHq75H4WipT5X4nlNaR5x2+f+eyfd3L/AOSbwhjXasq3PgkbT6pkQ/xt6z/6F/8AGjhcHu10Vp5G96ZFZqXa1dlpVOd/8g0jiYChLZ6tNaXSVIz9rmVVIzR8hu14kWuJEbcriE78MHNlAyZa1UcjbPKGZnVFMidzgmQMNC9XRfv+/VFtd+x1KhRv95oKtPPKsvRhWnnL8Ray5zTka2vFkUckFdzdkIPAVPFXIW3k2BmeXPyJ75q7kzi4SjPZai5ibWuRfhnHeSZuXy2jk71Zud+Rz84rRg+SAnvPlOcg5kYw45N8xyilOI5HcqkluB7f20dmCAlDnycJqnxRuqzOFAXZxVvWrR9v+oTnX7rG5LxyqYvcHF1ACOJWrpXdqFpthc8vzCqjdDXc38B4FaIuAUcFBz1aOaFF0nchAHFrDlciIbwlpkcSmSMxNNUXnCBVOkdlc85B3IfiLz5OE1pRXA4uidlaVaeRvf8AnfDJhcE+N2R7Co5P35ncvr9q6R3arNzPg60cnerNzx6uyEZ5Dl5Aml2CPfn0Fk+7uVrrxNHah/8AxSZfoU8t/wAklG9ysdMzajsVp5G96BpekdharsTn82II2i1AgfydUp3RnuVl+7uVp46t7/K7nBDmnyWjpHdqsvRN7FaeeVZejCtPOVm5qi6TuUnRHtCj6IdpRbY2OLL1TSOuVOjfHJdcKHzSs7jBKBfFd6fLaOTvVm53lm5h7EwsxA5Fo3/9lCSeGUuApo09srHNO6ZLwpwBOhsgG9yF57lvTO9upq3Oal+lcii5T2q0fb/qEz5k+S1dK7tVl6JvYrNylWjmhQc9WjmhRdJ3KU//AMff5bR0LuxWWv8A1W9vks3HV3crTyN7/QR2lvDvHKSA5nio5R6/aukd2qzcz4OtHJ3qzc8erlvBG0DvUkvC93UPQWT7u5Wv7e9SHgeA5Q8Td8VZuUq08je9R1w7nk1qWOR7WSl1d9kqELPA8PNauIzI9GUyVoqYjl5CnCY0jkFK8RTpBNG803rWurVRQsncbx4QCnc4L7D5LR0ju1WXom9itPPKsvRhWnnKzcxRdJ3KToj2hQ2gDNvHdyfBO641xvNccyrE9ksvA0Fbl+HpkqXB2by2jk71DLJW605aL/Lsr/LsqTcr13CaotOOJyEm7MbxhxpRObDEJIhmdWlUyYx7mXioFao3sXCmvbNG1lM1c30UkrMGZqi5T2q0fb/qFFynt8lq6V3arL0TexWblKtHNCg56tHNCi6TuU3M7/LdOYtonMOR8bs6DpX7m/hbRAsBETMjaq08je/0E44QLw+igk4nivr9q6R3arNzfg60cis3PHq9pP8AMhWcfKvoIaS3LleCqmrLfv04KKNwkEZaKZq1T3mQSFwpmoowJLlz5VUpMt+/Tgorr964YXcS3skJHHUqQSPvzOFA6mRqjmFoBu8F3OqHKCi6ySBv8HLfPiA5SiQb8pzvKMIfcqa1ot2MwfkpS7TySSfiALzi7Aooq1uNDaqWX8QBfdWl1RRVrcaG1Uk34gNvmtLqihreuClUyMSXLrr2aqdKZg+rbtLtE6OQXmOyEImyytu+69eckia35ZVdiyk4nHOfLJDeu3+FfqRsL9SNhfqRsJ7DJfvGuaivE3JR+4LevhI5Sg+1vD6fsbm8hmszwx7s7TmK89LG1vyylRCzv3O6MpIreTonS7oCajJSiknE4bepku/JMhLr1K5aeSWX8QBfcXUuqKKtbjQ2qjAkuXPlVSOMt+8KZqJjBJcumuaqkcZb94UzUTIxJcuuvZqp7zKH3m0w08n6kbCHyQJcL4zPYVvrVvfkxWWKEUymp4SrUeb3+gLTmIp5GO4xX161dI7tVm5vwdaORWbnj1e1dK7tVm5g+AnNc07nXeu402O6x93IC7Oml++dma1oVJNK83nfL0LuVRc0evWrpHdqs3N+DrRzVZuePV7QOM1UY9wlvwFRwqFls0OwF5mJjOa2noZpPdaSmsGdxoqevWrpCrNzfg60c1Wbnj1eGYZnC6VNZzw78ermWlTWgHGhWztpyoOblByjyRvawPvGmVSNdGGXRXIfSiJsTXb2tSVurmhpvUoFfnfd+XCVuzW3RUgBSTAXi0ZlHCYWtDuGvr+5/ulNPoouJm/P09ftXSFWbm/B1p5qs3PHq8jQN+3fNUczf2nqTXsNWuFR6syAZoxU8pTHOG9fhPGgwnfxb36cHkg56tHNHkuyS7/iblV2KUX/AHTkRa60MDgaEVVRmRc9wa0cJVN1LuRpVIZQXcRyHyDd5WsrmqnTCZm5NzuQjZLRxyCopVVtsl2W771MicbM8bgCSXVV+F4e26BUJrJZmMdU5CrRyd6s/KexXJJau4m5VdhlF73TkPkLJJ2NcM4KbLLK0MdlHzV3dac4LdHvaGe8TkVN1PLdKD4Xh7eMerENPm496E+0OGWTIOT1+1dIVZub8HWnmqzc8esEtHmpN83wX4SQ5Rlj8PVXyPwtFSi798r+1RXM9n7OFNacEu8Pd5IOerRzQgyM0klyV4gixhutbidxIzWWVznMy04fonPeaucakqPmhGhO4twN70HWmUscf2gZk2rrzTheMiLJT56Ph4wrNyO7k2zQ1dlvXVE60MG5t31Qa5U3ox3qaIGl8uFVuLnBxpWoQmbK1oJpQhWjk703ca7ocgp81v7RSX5DInMOSSN2cKGU53NBKtPOQmnlLY2i43kCa29eY4VBTLKJDuUeXLmat2jlLwMQIW5fslByeq3WHz0mQfL5pkLOHOeIJsbBRrRQev2rpCrNzfg6081WbpB6w6J2LO08RVDVksZ1KuaVuNvqghGKU9SZNK0uDctBxpzH2eS64UOVVCim94ZeVQc9WjmhQD+Hepjw3+7ySNGYOIUpGfce5WYHNug8lTna8EID3mEKzcju5Wl/CAB/7q8jejHevvK+wJvOKtHJ3qz8vktPOVn5O9WnnKz8nerNyO7lajze9Wj7f9grP9ez1R0spyDrTpZM54OJbpIPPSZ/kOL2BaekKs3N+DrTzVZukHrO7Qjz7f8AkEJIjR7VfjyOGJvF6nJQ7yPeBMmlke0vy0C08mpRlji9j+E8alszue3vUHPVo5oUM4zDelSQzOutflBPGi6+1z6b1oOdVOdbl78d3qTXU38T83ImyROvNKbZWOq6t59OBS2g4Wi6OVWbkd3K1/b3+RvRjvX3lfYE35OKtHJ3qz8p7PJaecrPyd6tPOVn5O9Wbkd3K1/b3q0fb/sFZ+U9nqbpZnXWhXjkjGFvEm2u0DJ/jae32DaekKs3N+DrTzVZukHrRtFlHnf3N95CSI3XhZN7MM7PUZNxpulN7XjQvXKVym8msaKNaKDyOjbS/nbVRTDc96cu+4FE2ClWurlKlM92jhkoU6OUVY7IQv8A60jXs/lkKDrY8XfdZwqUDMHFM5oW6wkMm4eJyIZE/lY7Oh+IpCzlqU2KIUY1Q7hd3ta1Kn3e7v7tKHl8gkhu3btMpW5TUvXicibNZ6F4F0t40WtheAc++oFJE2m6OCilkuXG56H5eSaWO5dcclXKGKSl5oy0U0sdy645KuUMUlLzRloodwu72talT7vd392lDyqWGKl91KV5VFLJcuNz0Py9S3SZ3IOEq8/IwYWcSFotQ81+1vvewrT0hVm5vwdaearN0g9bMsFGz9TllvRysP1CEVsox/v8B9YZNZ3PG5nfXTwIGR75mcLXOR3CA3+NxzJkYFRWrz8vZBYzzk/u8XKr8zi55Qmto5I/H2HaeeVZub8HWnmqzdIPXKSCjxmeM4XnBVnA8Zigw+ch908HIqwvy8LTnHq9XQAH+ORaNx+4q7BG1g+Xsa/O8Mb80Y7JWOP3v3FXIWlzuxB7/OT8fFyexLTzyrNzfg6081WXpB66WvaHNOcFF9h/7Z7l++OVv0IQZbG3h77c6vwSB4+XtsukcGtHCUWWNt8++7Mr0z3Peg+1Vij939xW5wMDW+xbTzyrPzfg6081WXpB6/dnYDxHhCLrN55nF+5VY50bx9EG2xl8e+3OqwSNd8uH2veme1jfmi2xsvH33ZlenkLuxBxG5R+87wVWNvSe+7P7HtPPKs/J8HWnmqy9IPYPnowT7wzousrt1b7pyFUcHRvH0KpIRM3+WfWqPJhd/LNrVWkEcY9pUMl93usyqlnaIhx5yqvc6R548qBl8yz+WfUgWsvye8/2TaeeVZ+T4OtPNVl6Qew7s0bXj5hVsshjPuuyhb+IlvvNyhVhkczkKpOxso4xkK3zzEf5hXo3NcOMH2XUmgWWW+eJmVUs0Ib835V56ZzhxcC8xE5w4+BVtcv2s8V5iJrfnw+y7TzyrPyd/wAHWnmqy9IO32N52Ft73hkKrZpvo/xW+hcRxtyqsbnMd8jRZXiQfzC8/A5vzYarJO1p/nkVWEEfL2HlW/tDOQZV5mJ7+XIvN3Ih8hVVmle/lK81C8jjzBVtMwb8m5Vkivu435fZ1p55Vn5O/wCDrTzVZekb2+yfPQsf8yF5pz4jrC809kg1Fecs8g+dKqrHOafkaLJOXc7KvOwxv5Mi85FI3kyrT3ecCF5uaN3I71nzkjG851FltDTzcq3jJX/Si81Z2t5xqtLcH8QvOyPfzjVeahkd8wF5y5EPmarz0r38mReagYDx5z7RtPPKs/J3/B1p5qsvSN7fZvnYmP5WrIxzOa5eatBHOat4Y38hW+s0n25exb9jm8oXm5Ht5HUWS0yfXKsr2O5WrfRRHkqt9ZdT1voJByFZWTD6DxWJ4+1ab/gV+oGyV+oav1LF+pYv1LF+oGorT/8AArG4/asMx+1b2GU8tFvbLrf/AOFvIYhy1KyGNvI1ZbQ76ZF5yaR3K4regk/Jb2zS/UUW+DGc53gvO2j6Nat8Hyc53gvNQRt+dPatp56s/J3/AAdaearL0je32nv7PEftC0AHISFkMreRy3loeOUVW9tLTytW9khP1KzRn7loa/eF+ndrC/TSL9NLsq9NC9gzVcFdhY57uIBfppdlfppNS/Tu6loP+QWFg+5ZXwj6nwW+tDByBb+0uPI2i3z5nfVaGvK4re2aLZVGgAe2rTz1Z+Tv+DrTzFZekb2+3ouk7ij0Z7vga089Wfk7/g608xWXpG9vt6LpO4o9Gfga089WfkPb8HWnmKy9I3t9vR9J3FHoz8DWnnqz8h7fg608xWXpG9vt6Ppe4o9GfVmGYPN7NdCwzbI8Vhm2R4rDNsjxWGbZHisM2yPFYZtkeKwzbI8Vgm2R4rBNsjxWCbZHisE2yPFYJtkeKwTah4rBNqHisE2oeKwTah4rBPqHisE+oeKwT6h4rBPqHisE+oeKwT6h4rBPqHisE+oeKwT6h4rBPqHisE+oeKwT6h4rBPqHisE+oeKwT6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4rRz6h4qWVlQ15qKqz8h7fg608xWXpW9vt6Ppe4o8w+rWblKc2ClWiuUrNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtLNHtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/HtL/FtL/FtL/FtL/FtL/FtL/FtL/FtL/FtKKGSl9uenL8HWnmKy9K3t9vR9KOwr7D6tZuUqbmd/x9aeYrL0re329H0o7CvsPq1m5SpuZ3/H1p5hVl6Vvb7ej6UdhX2H1azcpU3M7/AI+tPMKsvSt7fbklntjCwtONuUFeZmY/kKj6UdhX2FVle1g/kaKkVZnfLMmOmAa8ipA4PU7NylTczv8Aj608wqy9K3t9uR2pozbx3d5LrnuLeIlVY4tPyKqTUpgI3jN+71SzcpU3M7/j608wqy9K3t9uSQuzPFE5j8jmmh/Jurhvpcv09Us3KVNzO/4+tPMKsvSt7fbonaN7Ln5fLHC39xQa0UaBQepFl/c5RkLH5D5LNylTczv8nnZRe91uUpri0tqK0PB8d2nmFWXpW9vt2RgxjfN5fLJanD+De/1Pdmjey5fqvNTPaOKuRNbaH3rubInOs7rpcKZqrzk8hHFWiYCN4zfu+PLTzCrL0re328+g3j9+1Na0Vc40Cjhb+0epyNA37d838u6uG/ly/T48tPMKsvSt7fb26tG/iy/ThRmcN7F2+qyNA3jt83yxwj9x6kGtFAMg+PLTzCrL0re32zviAss0Q+4L9VDthfqY9a/UsRa6dpB+RW5NtLTvia0K/UNX6mPWv1UO2FkniP3hb1zTyH1ATNG+i7PLJanD+De/49tPMKs3St7faNXEAfNb60x/Q1W93R/I1ebs2ty3kcTfotNd5GhZbTL9HUW+leeV3kyMcfoskEp+wr9LPsFfppdlfppNS/TSal+ml2V+lm2CstnmH2FZY3j6eTevcOQrJaZtsrT15QFvmxO+i85ZtTlv2ys+lVktDRzsirG9rh8jX0DmOFWuFCpIXftKaxoq5xoFHC3M0U+PbT0ZVm6Vvb7N89KxnKV5u/KfkKLzMLGc7Kss7hzciq9xcfmV5uCQ/assbWc5y85PG3kFV5yeQ8gosrXu5XLJZmfXKt7Z4R9gW9aByD0eUArfQRHlYFls0f0yLJG5vI4reSyt5aFebtDTytot6GP5rvFb+zyfQVXC0reWh/1yrzrI5BqK86ySM6wvNTsJ4q0P5Y7U0fwd3IzOG9i7fj609GVZukb2+yvOTC97rcpVLND9X+C387gOJuRUY1z3fIVWjEY/mV5+0fRgWWMvP8ivNRMZyN9bpIxrx/IVWhDT/E0XmJ3N5wqt4GSD+JVJo3s5wXmp3gcWcKloia8cbcipum5u4n5FUKSF37gmRuxnfO5fj609GVZukb2+x700jWD5qlljLz7zsgXnJTd91uQKkETn8gVbRI2McQylZWGQ/wAyrsbWtHEB7DoRULLCGHjZkVbNMD8nrz0LgPezheYlc35cCpa4q/yZ4LzEod8uH4+tPRlWbpG9vsW9PIG/LhKLbI24PednVXudI8/VVk8yz+WfUquburuN/gqNFB8vZW+iuu95mRVszxKOI5CqPa6N448hQbP55nzzrzT9/wC47P8AHlp6MqzdI3t9hl8jg1o4Siywj/8A6HuWW9JI76koOtTtyb7ozqkEYB97h9n3Z42vHzRdY3/Y/wAVdla6N4QZavOx8f7gr8Dw4dnrDTaH3L2bISv1H/B3gv1H/B3gv1H/AAd4IPB3pFVQT/8AB3h6Jv4mS5ezZCU78NJfu58hHlD7Q+40mmaq/Uf8HeC/Uf8AB3grsU7C7i9CZJXBrBwlUAmd8w1F8BNAaGo9gujlmo9ucXSv1H/B3gv1H/B3gv1H/B3h+YvkcGtHCfI38TJcvZshKd+Gkv3c+Qj0hfI4NaOE+gtXRlWbpG9vsLf76Q5mBVmdveBozBB7/NQ8ZznkVIWZeFxzn0Ogk1rQSa1vopRqV+B97j+Xo3wuieS3hCZM0EB3AU+F0TyWGlQo5gKB4rT8pfM8Mb802aOtx1aV5UZntLgDSgW4sie00rU+o3J2B7fmi+yVkZ7vCFficWPCEc1I5+p3q9m5SnMhLAWiu+Wkg1nwWkg1nwTIznDLqad0gyHjPh6Kyfd3K1/b3+WLpO5blEWh1K75Y4NZ8Fuczbrk6OU1ki4eMegszK5MpopTK9waymFGKIuILr2+9g2nnJk0b4g13vE+C0kGs+C0kGs+CA/K4zPqAcg4Am8ig3FzBcrW99FPuzmG/Sl36+kcZn1AOQcATeT89q6MqzdI3t9gmKCjp/8AVfuklefqUJLVR8vu8DfSNdu0mUVTpoZN0DcpBGWijeDva0d8wqnIFQPaTyq5JaI2v4i5VBqFWaRjOcVdjtEZdxXvLWaRjOcVdhmY93ECrRyjsVn5O9SSvtJa5xyjIo42OvNaKA+S6+0Rg8V5eZmY/kKqTQKUX7zG0u5c2QKAF7a5clf5FGKV9xtc63SK0X3UpTIqOe0HlVWkEfLyUL215VUK9NI1g/kaKjbRFXnekLhvJveHDyrc5m3TwfNCC2u5sh7/AFazcpUpmkYwXP3Gi/VQf9wINjnic48DXgo8ib/9qfP/ANQ+RhdaZy0HKL5TnwsfuHA0Gg/8ogOfFI05QmyOxjeu5U2KDTPy14gi9okl+bneKAdukLs4oUd10rDQnjVk+7uVr+3v8sXSdyd0Z7vJBG0gvYDeVoPBdCDIqGd/HwDjTi2/MRnJORXSXsI/Y7MUJW5DmcOIqDcZZI6tOF1FuG6yXi+peXZacSIhfIN65xun5Jv4zdq8G617078H+Ipw7lXuUclrLgWsq+/nV2Mujj4GMzlbruD+OtcqDbQ4yQ/POEHNNQcoKtDWWiZrQ80AeU1pc7c2gC7XP8yrQ8vdcG9aKpjn2idzQ4Ei+cqMjGP3HgaDQf8Albxzo3NOVq3OyMc1tMoae0rzl+KTPkKcJdLHkJ401sWmfm+QTi3dJqZyXIX90hJzUcntm0kfDxqEwyPYS79popWNdJLNJQMLjeurd7UyQjjLqqOOR5dC40oeDyOgsjrjW5HPGcrdmxPeD+4lULnEDI6N/wD7kTJY8LhUJ0NkdcjbkLhnK3dsMhGetcvigy0uL4eGudqqPLaecoYpprr21qLp41+o/wCDvBNjjmq9xoBdKdI/C0VKuxl4aTRsbFum4O+jhVNbO9z4DnvZaKL8Hu169l3KvcsudM/Efityocd6is24yvjrerddTiVp3aV8lLtLzq8as+4yyR1BrddRfhoXSSTvdiJqafJCW1NeK/uLqp8bvOn9hdwI2idkjm58p7k0OeXQE75pRJzBFsTnNirRrW8K3TcHcecVTbz3Pi4Wk1UX4Pdq3su5V7llzpn4j8VuVDjvUQIFZX4QjS/M7lyBAEviPFXIVeNBK3I8eW1dGVZukb2+wNxgPn3f8UGRgukcsm+lOJ/pY/OMwjhUrRI18jgWhrTVRxjO51FaeYhLFkeK01LdtwkLDlvUUYAG6AXRzkaG885XOdwLdbzZGDPTgX4Wd17JvCexSTHKRmHzXDJM8rdI5GOkGWg7kXymrznVn5O9WnnKzcxGywOutGMjh+S3W82NhzV4UA40Odr2lSx5PxA3p+fzToZaX256KG0Mubnern4inc4L7CorS3mO7lLZjz296kldmYKprf3yvylF9MjBRrexUrfldqCMoc2QNyupwJtlmdWN2Rlf2n0hjmbUcB4Qrj8rThdxptltLsmZjj2eq2blKLbOy+QKnLRfp/8Am3xUMs0N1ja1N4cSdyJnL5Y42igaKKI8JZ3qbn9yMlsZFznIRWZr3NGa6MnWmeaDAytMtSrX9verJ93crX9vf5Yuk7leie5juNpoqfiZz95VI4nmv7iMi3OtXnK4qevAboUUbpqPpV29OdR7hJfla73SMini4C29q/8A1WfmlSzPFdzpdrxlX7ov5qqz80q08oUUQ/e7L9FJK7/GMnKfIbmQSNvoNP8AjcWq088pklPOSZSU+40N4cnkaxuFooFaPp2BBwzvcSVZjw1KtI+QW6WtkdAMTluVla5za5mjxTWbkGNaa56lWjmhQc9PeRgZkTwcxCqFPIM7WEhQRnM54B8hmlDrxz0KmFnBaGMNMqi/EaK9vl+o/wCDvBSyWY1jdlzUyqAnOBd1eW085MmjfEGu94nwWkg1nwUMr3w3WOqaE+CnjbicwgISM3sjDwhUtEH1Ye5Exxs3VxqWyDKqDMn8qbyKyfd3K1/b3qzcju5Wl/7mgAf+/RT/AG9oVna7KL1fI4DjQDgC1zcoKa97Y2zNygNz6l5iBzvm40T30peNcij5oT+VN5E5vBG0DvQbLLdlJJdvSrsUt6UGrd6Vc4HsPltXRlWfpG9vr7pDlfmaOMrhfLIdZVM8rsTvTAizvotARykLdpiHTcFMzVaeYoIzmc8A+SzN4KEqW/G5zn0zKSPcH79pCs7h74UI/n3KZ5ztZk8loDc16qs/J3q085WbmKVxzlxKjY3M1oCbu0TJLua8KqkTGsH8RRWj7f8AUKz/AHf7FO5wX2FSw8JGTlUUhyXXUdycKZAM8hqeQKS0OGRm9byqBvAXVUj5Iy8uFBREGCSia8Z2mvpXRSjIepOikzjMeMLcpT56PrHqlm5SpuZ3+V3Imcv5IeZ3qfnp0VfNxZAEye0Fzr2ZoyKzss8YYTVWv7e9WT7u5Wv7e/yxdJ3J3Rnu/JaAfeqopt0mq4ZaEZ9SG6Tytrmq9o7lu0EkjjSmUgqz80q08o8ln5pVp5QoJPdcRr//ABTRnO9tR9PJRv7GBp/9+qvH97ye5WnnlWbmJ3J5bR9v+oUXKe1WblKtHNC3Cu8jGb5oT2hziCcjQoWwRhji/Pwq0c0KDnq0c0J3J5LQxucsKge7MHivk3Ka9epWoCtLrOS4XTwKKOUkMc6hIWkn1jwRb+JkvDOL7fBCKIuLc++8tp5ys/3f7Hyl8rgxo4SUGX2md3DHnX/15wfk8UTmO3sjDwKCR+Ityp/Km8isn3dytf296s3I7uVr+3vVo+3/AGCs/KezyP5U6VuIRinKmRF2WQ5XFCrDIeN5UtzDfNKKPmhP5U3kUhP7gCNSbK+SW/UhwaR4Ksk8rR83gdyZPDLI5zf5Ajy2royrP0je319wafNx71q/FyDKcjPH08fNHltPMVm548lnl4MrVNHaI2OfnbVOllgjDG/JNbC2PdK5BdITXj9j8qLHmm6NoOVVOZTytwl2RWfk71aecrNzFPGeB5UMg4W5eVRgMD3O4K0yKTzJjufOqtH2/wCoVn+7/Yp3OC+w+R5A3km/HemOf+xgZqUUZxUq7lUUg/Y7KnxWljXFw3t5Oe+zxhrRU5EGtbHePAWH0xLR56PK35/JMmZ+05RxhNew1a4VH5vPygH3eFXbJHd/k7OoxO4ulIq4nj9HZuUqbmd/ldyJnL+SHmd6n56NpaCYn5/kVuUdxzOC8MyNutIN2t3Lk/8AQp4uFzQdX/6rJ93crX9vf5Yuk7k7oz3fkFos4rI0Uc3jCcyOl3hY8cKbf3zszWMCJl00mf5fJWfmlWnlHks/NKtPKE+GTM7qQcatod7IMyu+bB967lV43hHWrpCmxsFGtFArTzyrNzE7k8to+3/UKLlParNylWjmhfimNqwijvkiyK65nE8Zk+2z6Nmbg1J8Z/e3IoOerRzQncnldLC0mznLk/ahHvH0yAuGVEgF8jjvncATIG5mjWnOY0mznM7i+SuVY7+ThlRpU1NXyHgTImYWinltPOQbHPK1o4GvIX6qf/uFfqp/+4VFHMSd0hbU/TOheq0g714zFUpFXjuokVcXHfPOYJkTMLBRSxvFMuT5hQWeW5dpStMpyKyfd3K1/b3qzcju5Wv7e9Wj7f8AYKz8p7PI/lRh96NZb0czCtwiAvOyebGVOhlxt4lBIOFoUsbxTLk+YUFnluXaUrTKcibJDpmcHGE4Mye8x4TBJmGZjAnTTikr8gHEPLaujKs/SN7fXppRnAycqjibne6iaxgo1ooPTfpnpgOeg8s7IxVxbkCge+BwaHgk+R8MmY8PEqsY80zSRoMeLRJ8qLd7TTdab1vup0cgq1woVvGOkj4HNCENZtz4b+QK7Z43yMoN9xlQMkbdeBlCnfHA5zCchUDJBRwblC3aCgnHB7yIY2ePkGRXnMkqf3yZE2JmXhJ4yvxEEZe1w313OCmxwttFy9W6AU5kLS59RkCvzQuY26cp8jTE29LGcg4wovxELmxA1JPkfFIKscKFVja6RgzPYtyf+IkbxUKFotYo4YWd/p5A3A/fhbmc8Rp9PyEB26v4mIiM7iz+OfWqnKVAw5q1P09YvCCIO47g9L52KN/ObVeajYzminoKHMr34eG9x3B6W9+Hhvcdwehq6zwk8ZYFRoAHEPLeNnhJ47gVGig9DQioVfw0NeYFQCg8lJWNeOJwqvNRMZzW09FSWNjx/IVVIo2MH8RTy0lY144nCq81ExnNbTyedjY/nCq81FGzmtp+S1dGVZ+kb2+vRs956ve4wnu9v2eT5lqmZxsrq/8A1XpXtY3jJRFlaZXcZyBedkN33W5B+Qyz1pcoKBYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KxP2VifsrE/ZWJ+ysT9lYn7KnjY595zCBvVZ+kb2+vWfnFTczv8Ab8XSdxTujPcjIyZ7X8TjULzse895uUflLIG3nAVz0WhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthaEbYWhG2FoRthQvdFvWvBO+HH68He48FMB/eC31V0j8LRUrSnYKd+Hfeu58lPIYppKPHBQprGym840G9PoHSPwtFSmxskN5xoN6fyuc7MBUprGym840G9Pq1ni5XFWiXiaG/wDuryk3Nzf7zETF55n8c+pUcKHyMHvgt/o2WE/ubRAjI9jutRzMzOFfVLV0TuxZFufBI2n18k8gy1cacis/SN7fLlP5MpVq6J3YrL0re3y5D5J+YexWfpG9vquVSy/tzN5EwnFJvz+Xz8QcePhRdZJL38X50wyMcx7TUVTJGYXCo/o38Qweblz/ACcvwsp3jzvfkfVLV0TuxWfpG9q6KXqqp5QczcitDuCOB7upWfpG9vkdFZHXIhkvDO5bqIjQ5d8aEq5Vwu5435k2aPMeDiKEcOnf/wAQjcDpX8JJT4ZgdxkaW0JqFZelb2p8kho1oqVcbeDCaNjat2dGWgcLTmTbNanXr2B5z14lPzD2Kz9I3t9V/DRnzkmL5BNZ+wZX8iyfnuyNa5vEQtziFGcA4v6NfDJhd1J0UmccPGhBOfPjMfe9TtXRO7FZ+kb2ou4JGh3crI2u+fkP2r/5KXjYWjUrP0je1TuGel3XkUEb8rSan6ZfJDP+6twqeHgIvKav7aAalGRnfVxVoDuBt4fRWXpW9qDR+94BRltJoA3e5K5UQZCQf4FXojkDqtUruOMnqVn6Rvb6pXPKcLVU1fLIdau/5XZXn+l6ZpW4XK68FkjChDaSGzcB4HepWrondisvSt7VBN7puoNJ3ozBfN0bna1Z+kb2q0AZwL2pWd78grTWKeSCH91bynl4A26pq/uoRqUQ4WVaVaS7hYW68isvSt7Uxw/bJlRitF7DUUK/y7S83Pe5JApGDM2MjqVn6Rvb6nTFMczPFF8hL5HLdpx588Hu/wBM0fvZBhfxK5M2nEeAoRWyr4+B/CEHxODmnhHqFq6J3YrLvXaVvB81OBnAvD6JrQx1SaZlIxuYRkDUrPvHaRvB81Qpz4Gl8Hy/arl5rqZi4ZUXZZHHO85gmxMy8JPGU2WHTM4PeCdudWn9zHBVk3sLMtQN6rLvXaVvB80+GTC8UQJqLp3sgzFGIuaARQkDKU2WZhbA3Ll/cpuYexWfeO0jeD5+o1OZGOxb53/U4ByKjb0krzrQklo+f/X+mzHMwOai+GssPWFegfTjbwFBs3mZfnmPq9XRMJ4y1UGQeXfsa7lCyeXKqiKMHju+pkOdfk9xqo43Ivcat4LsXC8qkQ33C85z/TxfH5qXjGYrzzN77wzKjH3o/cdmQEvmX/yza1UGo9nEF99/usyotjO4x8Tc+tXYGF7kH2w7o73BmVGigH9QEOAIPAUXWc7i/i4F52OrPeblC8xK5o4uBUtcX3M8F5mVrjxcPsms8jWcpVLMwyHjOQKkklGe63IFSCJzvnwIOtj7x9xuZXImBjeIf1KSY9zf7zMirA5sreLMVSVjmO+YW9mLm8T8qpaYPqwreztB4nZFUewvOzsB4galUs8Tn/N2RZH7k3iZkX7nvP1Kq8CFv8s+pVkrM7+WbUqNAAHAP6puyNDm8RCqxpid/ErzEjJB88hXnoHtHHTIvMyvZzSt85sg/kF56zkfNpWWQsP8mrzU0buR3rPnZGM5xotNeP8AEVXmYHu5xovNiOPkFV52aRw4q5F5mJ7+QLztyIfM1KrM58p1BUhjawfIf1h52CMnjpQrzTpI+sLzUsb+XIstnceblVJGOafmKLzc0jeRy05PKAVvmRO+i39m1PW+ilHJQrK57eVq/UD6tK/UxbSyWmE/eFkmj2ljbrWJutYhrWNutZZY9pZbRCPvC/Uw7Sy2hv0BWR7ncjVvY5j9At5Ztb1vIom6ytNd5GhecnlP3KjQXH5Le2eT7snavOPjj6156Z7+TIt5Z2V43ZVk/rfKt/Z4j9qyRuZyOW8mkHLlW8tLTytosjoXfVaGvI4LLZn/AEWWzTbBWWKQfasrXavy5GlZInn7Vks0x+wrJZpPqFoKcrgsu5N5XLf2hg5BVb+0PPIKLK17+Vy3tmj+oqqNAA+X/wDrt//EAC0QAAECAwcEAQUBAQEAAAAAAAEAESEx8EFRYaHB0fFxgZGxECBAUGBw4TCQ/9oACAEBAAE/If8Ag9k86BFOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qqc1VOaqnNVTmqpzVU5qjBnGQTP/wC00A6AdAOgHQD3TaYKPD0X2DvagMNQ9UVLGgn3RzTDeYEm8fQSwGzjGRRNMYLMiYF31BT4psCBC7BFTOCe5iB1/wCJLAbOMZFE0xgsyJgXfLm8DJsQC4xsuMbLwbUdEEBFDlv1Nyes8i1FKJMhmwZ9ZLxoAmSjgJGEwCbVLUPVWILF/wBUU4QxPpASDYLMTcgrCguBn/HDoDvIhKbCfk+lBmTij2L11S+Qn5XsBYBvdRuAEjRwd0NJxgYlPTTDzDyn4CXNLkdhBN8ouwuRMZEBj9oux+Mct7nS0omKzbPYJ4eWwkAmGKApauAXnFG1kgN2nni6PqxEcGw0sGRQSEAkEliiwHdMkC4EqJI+AcWNovBt+JzSAtE9poZxy5jRDZ4ZpjoKzP2VEufNVuo07lLiCVMaIpbWLRY4WIegh9AUJxjuGKIi5xh3EUIA3PsV3hhnaaZFfMICHdBMYdXEACh92MhBBHKFMADklDzeaYAp9juEDmFMxIXyWgfvKWqFuYQCHxqvWZxBy0sM2N1RNJXzs0n8nwhEsJobIkgZHgB7RiALCZCEBIAIIgQUFudEwvahJSJcFjFAqtmAvMPr/GzoAL4PchyjFdfQBvgx0xHBUF2YCyAWwPshoEeZSKNYJozD5imfJMS4gGTKiXEOf57CJ2TYcaCPYAQol3RAXbq80FMMRAMT1xVFufQggNP8qkFjm8wUHdHN0MpO3AxJj0gqrfIDYlUEfB7AF2xG1GP4uABMrUZBFstxfZ1mfsqJc+ardVQvfJJ0Z4JnLS8o6qa5wNFqMxNGm4EDDDEug2lJuGRQCGZ4AAlFNOYccOhxwhbmEzdkNaxPOIzMKim2iiBGDqjEeRhiJWFMKTHEDsPkSDlr4pq39qPRRUlK09ZLDTIRp2RFwsBEIQEGI+R7Q8p0laZR3Vg2ZBga9MqFCLTYcvSbgAgLoIJ3QzCxkMUcqXZgGn8bOgCuAnqAxQDsQG8EfA8nGBeSmzsMmXcvdyJJSOwU1mfsqJcQAviTCDIbtc+AiyAI6OVFufQggMQA2NKbd8DCDtiUgvKbyEScqG6AswB4JvI1VZiFmfsqJc+ardVQvfM8tHYEyFheENEYgi4hkDE6Iy5+CLlWoD2aUFmCqt1VW+iI0wcPyV6kGQHhggdqHkIYiCpF3yKscueVi5Tg+MzTWLSFvVDJBcQz3e8Xo4UD1uEEjw2aADC0p8oZiACAhDsinzzPhEEXYoGiAJgLIPaqF38cOgNaDl49Qa90IMCsRlfE5wN7DyIIZkQedjeVKkSC3Hs2VbuKo3fGZ+yolxRMAPcD/rJ+QgmMmKJhdjDFDfMae8zJ8qi3PoQQGotxU274GFydOcvoj2QZyJOE0xs/DAkSAviomKOsz9lRLnzVbqFC4GxIVeap4Bw6dhNwRKwwMTshEUcyWEyNCxgK5kEXvOIJ3xRUQZdfMqB68jdqkEc2YcumIg9EDtkT0EDYJEQ6XyZHRMYsSN2Col3yJUA0X+DwT4RiQibAb/TwnqJ6DyIISQiJdg4LnwE+ESm4ARrkjpMlFFrokRehh3i/BmTzB9oe4JOhWdsECWWe0XYNwDs4WGaxj/GzoBbquQxBQ2QQuHPVCnEy4mjsdBBqckZqSAuC4CxCAiSEDAoLiQhN4dfh2E4zDBAbOAGGEQUA8kzebBYI1TceRCAHYTRhIptIkb4QHKoilzDRI6qApdMgA0RtNEFolAK2FrAMra1QYo2miC0CmhyREyukF3vL3BdfqGPYJxeF0cdU7CcRMYIDZwAwwiD8jBJCAmWLqq3Kq3J5BFgtjwFKFSYdEfDI9s35Beim5YzRKjPZAgXCF2AQMwG2Q94QjvDEIh56wwA2O6aG1nG7jFPwZfj2TOZzAwmCgP8AkzQIPX5NbVwYgphA3EeqA7mDc9FQsqYTUooCdN2AUm4GMguKEL0sP9kSXBAY8lQUAFgCnuIT1nR8Dr8eyA6iSxgG0/kp0AAhJQbcQx9o/I9sAGBuKmJmxduv+JxRZA6J3JQQWJWXCwf1I6A5x+YOAeyloHbZC46k6W/90zoB0A6AdAOAQgxrTJ1VBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsVBsTMOniIkC7FFWOkAjRB7lQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbFQbE+vZix4knX9viz/ANv6qxmft/VZKbA/1TKLVmB/qmSWqcP6pRLqyX+qUy4sk/qmX+iyL+qZX6f1X1NiFTr/AOqUmIVFv/qlTiqTf/UhVtkY6ghDw6sDwMVnvxITjqZJghRAp6Mk5aiO5ZaT1f8Ap8dCH9Gvb4AgBiYvMeyKkZwRiCngcvMVKCvRihKMELAf08BAODAgot/wryl9EoR7yeXv+ozwPuJZ+/kgAOUAAhXjDvKJ/qIE3L7yCpEn8RHqY6x7f1PR8BLL18QMvBWPHv8AqZlNFHcEkfEB4wmgAADAQA/bihAMAQzkX4LhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuoX6MGey0xXCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1wjdcI3XCN1O40EAuO6h9hNEM5F+C4RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEbrhG64RuuEboUQPMxjAtp/G4FT0/qrA6BU9P6qwOgVPT+qsDoFT0/ZWB0CRn4QPdlXuir3RV7ohgrBhZNfH6z0DFiTgPCFTGHBZEd/pLiRgck3IKLGCAF8v+uMeASgwKJymNbjeQh9YICBETG79Iqen7KwOgW6BTZzNgxTrTMxv5ClyIDsPgBhJhl0TlvX64G9yUYXBR+AC6Jzf9L65mzsABKbXM23JICz/AKSXj3kxF4OBZMkbjYszHyQmk1BmPUE5bxAZYeB0P0uBVJTQDqJd+08Q2/pFT0+xYMWZATvS5LYuS2LktiBRw6WP/A2NmAHJQJrGfEDH6IdwWMDsvQ2+oe0VkQvTVEXC0wPqeWBcwJmhf+bOgZn7fLjW8KyjvcUVMvvopm5kzIomFJ66AlOKdMxkAlshDhCEwo1jDszQTaK6sUTe5KMLio/AAdE5vTRcUkhgUx0wiIl8vEyDMrTHIB3iUWIWI7hrwm1zN2cEAU+uZvsQRFqFE44vBKOEApvMHuKDmxyRgHoViKQLCAh8QKjdtnvFh8JxpizM4MU+g+YRmRoAA1oPEQkWuT9GXGx8/JeIgNyJAgJYiA3rY+DFHeFAVs2ggAJC8AvG8m9PREwwxKbvp5V2k3VNcFASAUEZKx5leQokbRg7STvTAlwS6KPwAHROb/0ep6fYsBMCIMfJC74kx8g9yOHCEFxZ4garneyEzMDBeSCCxIkg91ir8ln8CJYTQyYJGYjTdbfb4CCpY4gGknbGAYlL4ihMlzlk5XkwA6PTZ0EEu5dHY3WyIY4AGvL/AH38YiOJZI+AEyWHwDcSMOAwKwFAAGBTAHUfmjoGZ+30OYJVKBswTbJHxCBswMT1RDnyFM42RRbroSbcDGLIkzbutBipm1qK/AqLEqhci3WaFrM2qOZgziAwKGBevDlVbqqt9Vu4ngDu+IR6JzhOPOQbkEoWk+kd8yiTsAitPpoFovKPkw1Nx8/S44HmwQxFqaX1IzkGKMDBegrcRGLtkASD3UT6CB1IPgG4Fu6ZZ840TMXgiIAcnWi0VFvfpI1T0+yYUW8qJc+BwVy7QtBM+HsPkjFmEIW0RRNjM1pLbsnFqkzGNZijVQCQzi6KGIDW2HUIiMRtLOlknHbjkIplXqAZgorXTgn4MBOADoXUUpcbRcUYsG2P9kaSAmx4QPhQcIxWfQowDIrsmUXWAU3UoNDYyGwwM0CsXDMCNSCAEnDeeyK8iCAe1kG0iOITb80dAzP2+pzBsVNy5sYgeEcktMwcTgN0VtoAtAQiqLEq/AqLEqhcsw9qs3qq31Vbqqt9Vu4qhe+JFMlJqmjBYIuxIR2YDeCHQtJJdIvocVToJsDQq5D8olAdnVvhglwJHDQS4uQWDae7EE20HyOyigIRaxZI/FPK118UwlFvfpI1T0+yYUW8qJc+BqsDyT43ETaPRBGCQOgQ94xQYAtZ8EaprE7aSHgQjzC3IcdFCPGJnu42RGRoV+BUWL6JiTLxJ9k03jLfENUALWDmUOxQ04TkM/oiLL/oSdiDusSMTBpd0NdAAg2OyCUD56FmfsqJc/NnQMz9vqcwbcTW0AgMPKCur7hmxdDSIRxTxW4kBar3Avqq/AqLEqhcsw9qs3qq31Vbqqt9Vu4qhe+JFMlJqmh7XoSxsCjsJObMu6IsZIZDiDl9B1oXmvFo8JiVmnsAI2bzY2zBQR7JJchcmwJh0ISSWgdEbEGCZtBbobQo7goCDfMupyIDEvMCipMYvxJAZo8aCQIdwLyQDDGCmPd+j1PT7JhRbyolz4OjDyAGOaddwBB0GVyOQByGPdEDIHCAekMFAHd8ChrsR5ZzUONgkhxO/iShAH98Qruq/AqLF8vJzbgQzTEWsEiRY+KK9FgGIKFkFwQud5ImjA92DDMor2ZPcUH5xtgZs3o+UJT4TRE9kKRHAIDssz9lRLn5s6BKrc2I7oFEGIgc/gKAS0neF1OVM6P8CoItWTVbFHkB0MOTE0j3CHQMXAOA8o9Ixcg4HwhURhgWQHdCwJEQZ3hCAowJ2eUaGjkMQUFFjhAi6aLiRwYg3oKLHCBF00ZkQ4ImEKpTEjAjz8ROA7EyUDnM5LNCJK85VsUCmrYcMCmuvPRAbFEIliIMXP0Yx4BJ6AKJwiSboCw9h8weYGF/CSZLDEfICMikkSTb8DbBlpIqUGR0v0ep6fZMHJvJ2Eyjp3FJg+AZnAGLreyPqwgAOBc4L9lYFW2S7DVAr/wIivrDP0FDwbsH8gq3DpM5OgiUy4zubXnEowEAbZ1oq5C2vIw1RnRXRuIoN8EEQgC4IsQnA4Eh38ExGZkSlnWfT0TgDIuMBLZEJiuxkbwmP0ZprAox7Ajo5guwPsRcE6wJAgC0W5JpgAljEWKERZMrGe2/9ROgFFOnmY3hDnwEu5OYvcXYgDeHcdzef1Wp6f1VgdAqen9VYHQKnp/VWB0Cp6f1VgdAqen6GwOKgyyCOSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSIA4IvIRCYCTcFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyRckXJFyREHmyILkd01ODo5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSLki5IuSIJEBvj9us4lm/t/VSMz9v6rBVYH+qjVmB/qmSWocP6pQLv9VGqXFkn9Uy/0WVf1TI/T+quosQqdf/VKzEKi3/1SpxVZv/qQc7YsCXuv7fSuhxMkRgFFLdEQJwv/AKe3eN3Es/aFAoOFzR3t0EQfaESAADIsULI6x45uh8QGcI4BMoPEX2s/6eAxyzQjWLP6GN0Ghn2/qMlj7CWXr6HA1msh4/qI4XGFcEkQwCALEH4f8O/tJ7d0ICH9SgqQVHfv8TtLt/8AfX9Tf72UzHhCMgx7oDzBj2/qlct+g4/bzxQMAQzkX4fo5gwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMOIaWBDyjxAIMcuxOn6UYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYaGDkBjBHigQYIZyL8PzJgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwCJcZkYFtP1CA3VRaCXfEhCV4IiAZiLCb/ANKm+gkCPUoSPDBALuTYTf8Awk6BNhbCgpbYo5didP0q24pMuFKbk9wzkafwk6Aw/eYjFwgm+mCYgxr+lSh6AZgiWxpksi5r/CToEDYQyDuVACZmHY4fpUwKkEe5UApliDt0/TToB6BixJwHhV7oq90Ve6IKQS0nefrNRGHJZAdkOkYsCcD5+oOLAcERskBIAIIgQf8ApAzsAOSmSwxnMo2YEzDGb6yLCSuH2jLMgm0uEFDSABl/p+lTfrAMoIeAkBf/AKfpp0CBvclGFwTtcjD5AAreFZR2vH1w+AC6JxcoG9yUY3j6mHJwLRuiGVuSR5/6CNF0REPYThDDEgIfqSEKLA5EzEYLmhosH2+mNc03OUIuMUTGW/aDDM5AuwQUcixkH/6zVrA/WVMjOvLnQOL1D4AgA5MAEDgODB9im9CwFrR9B5dGOd2BuxQ5RHOZnI0TnqMOuwCZpTlzTa3p8lAAECZAksigBgAXEAPd9RmjmHAwfufgrDJtc9mGKhGG97R/6SFaoCSqjkovsoXtBBAQxDkbvqkJKApeyDjiT/8AaPDWig6Dj0GBYt9gxZkBO9Lkti5LYuS2IFHDpY/8DY2YAclAmsZ8QMfoh3BYwOy9Db6h7RWRC9NURcLTA+p5YFzAmaF/4Q6BUL/m+7oRQuTVscIgskHN6BzkE2AeSPLwCJAs6kXpOeBcoDpl+AM0AY498QmFD4ADonFyib3JRjeVD4ADonFyZpBIBgQYBycUxLpkzblYMHsicLD8OOTg2jdUMLYkDyneQSeSOqKAlh0ZxKCiYKBZkiutjGuKKZdBThYkv3RgFLEEOXYAhgvtPtLbfoIw4feRHJkOZ8qOkjCiw7oN24nSDLJDAC0p78B4u3iiIITh/iKKWAbUcQNyd8mYmtsKHy4AvBUTe5KMbz9ma8mAjAll6ETxnY2B/wBZYvGojUd0xYcPd/w/wwCH2dmybUt5RAb/AADnWRDBQdxt5A+iHDBxCLcGgnXqdO8SdfjHRTI8oK9Oukqqt/4xpaSyREHSG47mBinLREax0Po0GwEVikg6hDxGKMF2GCkt2M8vguQxzdYsazsDz8AOWE0QhyIdEeIY5usTRE5Ou+higJ+AFnl8kcAkMqHuAQbLDEBADyg1Bj7XhTnodQW+BQgxBERFoOmyIQBJgJOCHvckmiTpo0sJsWwf9o/AHJZehE8JmD4H2AmBEGPkhd8SY+Qe5HDhCC4s8QNVzvZCZmBgvJBBYkSQe6xV+Sz+BEsJoZMEjMRputvt8BBUscQDSTtjAMSl8RQmS5yycryYAdHps6CCXcujsbrZEMcADXl/vv4xEcSyR8AJksPgG4kYcBgVgKAAMCmAOo/BnQKhf8zapKW3DqiyIow2xB9IIehwCXQY0BcEC8OTSHOxi8yfPlCHbd5UWBV+JUWBEwOLIicBJ9I6QAQX/DASBZVG5VC9VC4iQcGbARoI4QgC4mL0EK+OCbT9D/SKJDCvInbNEuBhvkH0jblOAMjZAg+7Z+aOJgAQ4KCOEtQLSBYgKuxMRAZkIZEJOAieXRu6LSdhBPhBYEiQZkQizoDslQvfaGBaIkGKjVBnOB/1L+wBsQo7wAjqJI7TEewZMmj5JE8zknTcoGWpG4IYTsFoYp9DHQDA3RRUInGTjcQm9SXYGzyD8w4dfgVFiQdLwJYmAT/il6TZF0JwDAxdwVVb6M66KuFp8Iu2AWwRdSU0tgGG7xghj3jaIaLdCgviwBHBElYg2ATv/wCcxBlSLkk1TQnS83odEHeOSO3SQCELMBjwKFPiQoEXLlWb02aO8YEHRSYFk3pGKDYs9ohwCE8ravRGR+QdAYK8/wBRhhAwMx73p/CLneCskdEd0LsjMiHJMyh5RcoNinGNZQwPmKPoARwhi4JgmCQB3cwD3cIryIIhrWUkZRzOb3f/ALYj5OQodcdmj9jRbyolz4HBXLtC0Ez4ew+SMWYQhbRFE2MzWktuycWqTMY1mKNVAJDOLooYgNbYdQiIxG0s6WScduOQimVeoBmCitdOCfgwE4AOhdRSlxtFxRiwbY/2RpICbHhA+FBwjFZ9CjAMiuyZRdYBTdSg0NjIbDAzQKxcMwI1IIAScN57IryIIB7WQbSI4hNvwZ0CoX/M2qSmUz+CR96+JBb12QLPYSa46p22YNPYvVfiVFgVfiVFgVfi+c8VRuVQvVQuKt3vk2BHMU46oK6XAOIJfTyhwuGLE/Q2ngguzorjQAAFd8AI4Anu6ZMmPSQIdcpzAzq5oiAWyByTgxkbs/mqYFoEV4nsqhe+0NQi+WsIAmrAv/2H82Xze3VgZgixKsECRkXsObphS7fpQGSMwE5iMESQbog3mdkUCiOOEvohw4dfgVFiTALR5J3BZguDNXR5GJ7UmPtVW+gCSAA5KYxPFw6RRwOMT6o5qo3Kt3FUL3xSLkk1TQlAO+xJLp1EGC4AUe6YoAS4hMxyOEJ3EAogkAyRf8I3EKrd+TWnchiEJYyMqXpBDhl7SWaEoSWoRyYkDE3lI+CjCUhdFyJy5KeuxWypZCAv6IIFLfqCR6ZUS8sj9P8As1jUgnoiiILAv9iUW8qJc+BqsDyT43ETaPRBGCQOgQ94xQYAtZ8EaprE7aSHgQjzC3IcdFCPGJnu42RGRoV+BUWL6JiTLxJ9k03jLfENUALWDmUOxQ04TkM/oiLL/oSdiDusSMTBpd0NdAAg2OyCUD56FmfsqJc/CHQKhf8AM2qSmUz+A1AffC/1RaLEMOjhDI2uyxgLAgJOAnoII9sqLAq/EqLAq/F854qjcqheqhcVbvfJsHQMswLViPhC4mIKDxoLR0QDR+gzbEcG5dxZt7xgi1fcmnN7EFD1vZOyxBHwILS09pIX7l4i8WjwnDAGYsYloQn0YJg4F2iHWZiYV7XIEpEexUWYg5MhYhgMoSVAm83fgnKN5QyzZPjB1YTp9TD7v+H+AGhnDWkhyfKHscB5AWiZlRLhyWAAD+X8fRDhw6/AqLEs9wR39EI/CAy74AHMIQAWBbhFsO6qt9NqlpG+A1TfIIXg8dqFoAASRO6SqNyrdxVC98Ui5JNU0EQZnWB2IRng/wCuzTkxl0vKgfHRG4I04E58/Q5Ci3PkW7z5ZCbF0HhggYWtCEyiQAEyniZcbIwHYMrMy9wDqz6N1RAo1FRAQPhCJvJAIa/Yo/cqAMQFRLyyP0/AUW8qJc+Dow8gBjmnXcAQdBlcjkAchj3RAyBwgHpDBQB3fAoa7EeWc1DjYJIcTv4koQB/fEK7qvwKixfLyc24EM0xFrBIkWPiivRYBiChZBcELneSJowPdgwzKK9mT3FB+cbYGbN6PlCU+E0RPZCkRwCA7LM/ZUS5+EOgEQEiCIghV7r8QOczkslE4DsTP4K1ByGIQB7NeWdOkR7x4uqnhOOA9nRqYwxLIjsh0DFwDgPKNTGGJZEdkOgYuAcB5+K91RiXM0HBgMAIWaIkJEkxJKFUpgAgB5RmRDkmZXU5U7qyCgEtJnlFRiES7vb2RXHzOIYnBBlDRMWYkoZUw8SPoiZ2BGITEP6R7hAiBgcOkiJEkSTafg0P04T9U9LGAT5ZGB5m6Pw345GAI6AyUQN3Dug+zocH/dgctiOCgrvkzXWhFuWMuHWeBn8O2tBsFKN6ldbsR7RQthCXdIssR0K8bzMXHsor5CMiyAP0YVw6HJ7AGnDBPm2ibsXI44loxMGwEFghi0TUE0CWI+JoIF/YRkkkM3dkU0UAKRIfuCjEBiBH8HixGkxEo3CITlwrEECxmihErsQEJjTOxmAe82Uj5IizBQIKOuHiigSh9QYoVJ+OOhj4TrgEYpD2mEIFyQP+UFqbiQDoYJyIk/Ei4lSFMTeTuJPkhoB7xXhNyyaP5ITRa4s2wwETHe3sjKC3EyUdbD2QF7dCN2Ij1IMUxOLEA+pI6s8WkLgnjTMg8Xh5UENQIRaHf/tQ9PsuDk3k7CZR07ikwfAMzgDF1vZH1YQAHAucF+ysCrbJdhqgV/4ERX1hn6Ch4N2D+QVbh0mcnQRKZcZ3NrziUYCANs60VchbXkYaozoro3EUG+CCIQBcEWITgcCQ7+CYjMyJSzrPp6JwBkXGAlsiExXYyN4TH6M01gUY9gR0cwXYH2IuCdYEgQBaLck0wASxiLFCIsmVjPbf+aOgMiAjiQoEfbobJOotdqAEXkAuRcI/AknKYmQJgVzn6U3A1wYiTlLyf+EnQBCE8AVgmRqnGD+lEFejImxOjVM0P4SHQDcxBiTkR2QgHiwsH7/pUThOxMkMB4RMm7/wk6A9GYALsXCMWRDIt+lEIk0UWgjF8QFg/wDCQ6AMmTiGiEFh1kgJ0f0qOP4AE0HlBZK6j+hHGAVZB0c4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4UFKe9ifqE5JgJwgsOcFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhc4XOFzhSc4jLdHCiCAE4EVqOC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucLnC5wucINAGyR+IswihX/AKMRoZqi3P08LP8A2/PZ5FCv/R2q7c/T6M/9vz2eRTr/ANGqt5Vm7+nkZn7fn4Mn9/o1XvKg3f08jM/b8+Bkfv8ARqfeVBu/p6GZ+359jI/f6NW7yqN39PQzv0fz7GTe/wBGqd5Vm5+n4Z36P58jJPf6NQ7ypNz9PgosD+eomCyD39BgIEBBwCqtyqtyqtyqtyxAD/WVxAQm4eqMagRfSLxXQfcgSUQRx/H0+8qRc/T5KbA/nqbgsg9/QNJzgYFV5qjJSJcVrFR42KbHil0CrzVHkK4BhknlYQ9yvIC/DcoCEJE+ZTF2CME7b+StdCwfAfggwo+OeKbup2Ig8QGMCOyPhRcMS7IbeUJDJBKBOCOCgPjuEWwTXJAmId00HAJeaDkEByQDujEWEy+ELZTxhjsfi5KrzPQWp4r+m26FwlYUQfCscKEGDy9fhq5eVYufp41Jgfz1PuCyz39VQv8AoN0hYwoQEh2UiowDnBDy5U7MhPnuCkpewi6f6gezdwIrBs1CqN6qFyqF5NRbEIhfgMEZlYSScJgo1Lg4IdDyM1mHpVC9UWJHBjc3WtFOWvMI6GCKkQPBaLR4RC2E44J4kSYWLAEIBE7IbDijCnIfQgsO34c6peVSufp41Zgfz1DuCyz6lQv+g3AK8+5JRIAJJYBAFMTWZ6BEidC0A3cRzQPCD3S5iiq3cVRvVQuVQvJr7Bk+TYzD0qheqLEnr6DzsfJMwoNxw7n8Ch4gNO/4c6BeVCufp81Zgfz1DuH10qF/0G7IEVrYO1uSwuLrvgj8B5yHZDBggMhxLqp3FUb1ULlULyrdz5NjMPSqF6osSr8HyGHAR3UMiZ2BJXiC12cPgSE7d4BTWn1+HOkXlQrn6dlFqzA/nqHcFV4PqC6A7gLeiiCXol0Y/DnEHl28KAG1gQ8xIi0FGQCjYAYuhiy1DJsAP8VmJEXE0bL1Nn09wwlkyZ70Odp6Is+BLwo630bsS9yYNeLXgKAJcifRgjygAHBk+GKO+Lg5rEV0A3A29EVcX9zBmI1R2VpcMX6fHONkLhMBk3xIYfqboFFsgJkyeNe5rbRrkSP4ZWLyoVz9Oyy1Jgfz1buCr8H3gCMgZH6tBkAsIwR7DUxvWYIb4OZNuUJEzpJhYKv/AA1Evfp8mWWoMPz1buCr8H3oULpRm6Ik7HTfQYFJPC6Ey/D0S9+n6ZJahw/PVe4Krwfo1evKl3fp2SWqcPz1VuCq8H6NWrypN36dlkqnD89XLgqnB+jUK8qzd+nZb0/mJJADksFkCgXp2RTnsuVNuwXREMidNlFbHbxQNibpHxIuEP8AXoHsuuyrAd9tSruOF7UCFmypDXEGB/P0K8q7d+nZT0/kRmPXEH8KVk3EWeNG9E5n7FXb9XUmXb6BZ5YRpzGJdZIR1lzEUt7hBSDusEDV2aBEGEpxWBpxRBU9ohoc1MOwxU/7ZFZ1m0s3ECIk5EHBZciUynXqWVP6MqJ53ROUuxZ5ro6YHRNhAHwUAASBBtH5etXlRbv06gXfxijn6Fgp1FS5sjXFUzBk6sFwMZzWfJFGGOYvopcGIe6jgHqJ9INr013U9vEQPSvXvM1XteJ9rLfB/wB8vsKnIxRMSKyKyqQ+wisg9QWaw5elddeVq6ko3mCeTryowYEEe8U2gPeQ9U1Ajewy2TG8MHwn+Tr95UW79Ool1ZL+HJxXMjAJwELY+0s09AJeO8BOTMsDknyBYBIphIK8IZJoxjjLzFkwsN0hkya3IXBPkoAAMID754d7wP5Tg+Xm1dCianaNk5EYt0SxT4bio0NbgDBMIvRwskwjtu8hYGBAfj6LeVVu/TqJcWW/hAEIABMlOAN6Rkna9dxZJx/6zJjL3Z5xTZ1dHkpiJMPCSWCq0H4c4CJMEOnQ0EwgjnJhc+zGydSI1xNXhHESCZiYA3kE1OTr8hqg0nSdA/jK7eVWu/TqpcWW/grhEOiegtT0/drsj+xBYO0kykouQKEZxg6tk3kdssw/j25ikQd5p5oirfacCQ4PdX/XhP1TaJUgkcl4F0Ht+KrN9U679OqlxZJ+AwviboBeYCT0GafhltdBwRdno7pjYFIS/KvBeudTctAGRyUxeIGPZOBbvQ0vQkdln+u34ig3/wBPdXLiyT760SUK5BW4ugsWLbFDybmfeQzWLPTl1P5kvuYF1GGX8O25NOOIf2Co4r0nMt7po9uD1B+GoN/9P9TLiyT72DoMGHytF4+AdAUeBIxHiFndPStrHqH86aH2wE/rPfg6G1O4d0Fc2IHMu9dEQASBBiCPwlVv/p/sm9FkH3Yh4uQwCs7HI6NwzTgtseQlQ8XZDoa/oMqiLi3CmuTBxdbinMbQjGqxBL+UDcfwdZv/AKe7J/RZV90NpMkpi3M6+OJDrDMbWHchM3dbib/0MbUGAcFWtAndG8IGhTOk4oRMwwLM/wAFSb36eTL/AEWVfchKgORPU5fTxOKI6pso/wCUEIEwAMAP0YIsW8ox9qSWBJBcUcNpCTuvwNJvLIv07L/RZF9wSACSWARp6u5SCb4giW9kAAAAAJAfTiYSEkHv42dkCJD2HN1Ll054Z/Gw6AjCETfb/iDEATkPMoRh6AIj9Ato8BAwRQ3OTNEj/mYgACRD2hNKggAFn2Zw7HAMGQQySwRb/wBwwE6IYqNEQVNj65+ApF5ZV+nZf6fcka2wXMeHugNeDNm4obMZhYPrMouR6jBPqZkUXgpjTBg+T2yPYoLsL4MDWq5DABFLH6J8xyXXkgbEPgyDeVxHwOBONIFiUb1cDsTdQjA6gVNvR2aOQwAR6JjpnpagEOKY/AH5UODnqmpPFhmsQQcnbRI9odeCZ0ibkc26AJ8IPe2CzAqSGFMjqIWBj0x1tQDzuQ4PzkfoqzA/QxUSSfQCAYXfIA+EO9O8npf8MJTJH7CA6iBCucmB80IhxJS9BMiIBvxQ9hnmBxG5QihJizr3Qf3liBwWvTBEBFIb7kxb8gyITcVwKC50WNLIZMITa8KQW9rxZBQeYQOj0OWiHp/tl9a/4BCrLuiChXAE+EFOG6DsQo2Fpgp8fXKOWIHh6FWxiamP4CsXllX6dkfp9wY5bF9pRZnLXXBCtAzG7t/wO5wDYjoTyRi2YIj0U/iEfyekdqYfKMm+GH4cBLzJCsFFzgsJjiSFC2UnLjB4oOzMhiCG9lOmMwJhaavTUb2hgAjU8pxhhKKwBl8nOfnsqben9EYm4TPpEm1Ziv0koIhVwIKkvZOIf4dWblWYBAcKGY4tD2ZsFBGK9P0EI9NG4gtqiys88XbO+6NgBgGgN0gazxWDeDo/cCJG4Q/rT5yP0VZgfkkAEmQUZZMFsBNUhJQWH+qViQIFrD12R5bOwgUHpQsAYMptRTapTYjgAmsUzhch7CjwODsAgMvhBjAb31cAsE/pFZKq31Hpzd7yZotMXEd4a3ujzDKFxLg6LMPSqF6osSiVwxcLW75oBw00ucQjxMGPZFoZwOCedZbgWAgc5iAYFgmZBeejiNf+DAlHZdLipTZuPYTkmDxqfv8Af1K8sk/Tsj9PuPPjm6F7Jujh7lmfr/iYLUCQOqFUku3iEREGfxTtkZBaFjGDbPhixt7jdScEfORubeI5od0EB3l1SL0OFYyLjmOlD8029AJzYcfFQvKq3fh1ZuVZgEAAY1RYviGZbeCI2huLCFrdEW+OEGwPZC2x8RAAljZ85H6KswPyZBRAj3kENxSLO5eEFQtkLY2yCEHJuxQjmIgSBDsqTO8bWaoM5HaC96CY+DDCdnVFvfCAyRM8+W0+KrfQwV5kVLuCqF6zD0qheqLEgm1hmTb5hqI026aL4uOQ6UH/ABYZtrLNfCfXXjt6+/oV5ZJ+nZH6fceijmE/6QjAk6MSf+RnYgE+GOYKiwO72hDNlS7h8MA5c4Mx9FFSRkIAW4R8owxibcALHRNi+wKPWHMegmjnFdJE4RKjgCAEdkkxBUGSWmIuVNvUimXxULyqt34dWblWYBZAqLF8Q3CQeS63Ugo68gMxBNkgnaIQHXqS0kBNxnaA6N85H6Kbk7DlYVHVYVHVG4GZNphQ9oU9C4KBwtnHl5o4zWcleUblBkWFCLewmKbo0F80AcCOQSPXBG+F7XwhRb3xVb6qt1Uu4KoXrMPSqF6osSr8HzjfnQhWAaeh1TUPEYjHBpoAoBiY3mrv+LAG9+7olFJh2gwOX39CvLLf07K/Y+4851niFtE2Vp+RJ1/4QAX+M7Y4KAC7wmfHFPfmJ4Sy3qoJ5bQg7m3ohvXiYxnQyDQQhM+OKGzmLCHJbIAhYEgaJ2McwbwE9XReGwhr0ZhADEG1DTJvWHQoEFvyCH0jZgWAaFwFgRRYQHHSQaCPatO/xKBIsOXvT9OwwzsGQQgknWzTuvwAzsEDYFoWzRSj0mZ0IBODEgRqg4E7F4DfghcwHFqi5knQR3E11VoiXhgjQRi6S3yQO4DQu0VVt1Vt1Vt0BRPxCghYIGYCdxcRajkWKLGinY1aupQAAAAYBEMc4sa9xJBV5y/0BRkuDxxHNB0dFhH0h0WdezAL8EUSmZNY7l/gShZ4s5e9P07DDOwZDevExjOhMWzBCzQFE/MaCExbMELNCATgxIEaqQNSIEevxVt0LQmRMEEwAlrjeFDxugJzUamOSMERKNdWD/gBOiJEFi0FYCeT7+TLf07K/Y+4cLANJIgxuv0GafzGDDrejZDBkMGMUBnBMOgTcWYGQVf/AMTcCRIoWJmPX+26LRYj7h12gB7gFX3EPL+iP0IpAJMEOE9nSHWJzYd4/wCL2baEeTCPdAAEhD76l3/p402IVOv+3Zlmwc5IJbIPSdPt2zmx5Zx/x1ba4sbsjOANwWj4MToImaCHLhTD/wDUCVIPAmTso/qPHkmsgsm6ATjJzAuWCCPcnGcUX/JDDLQJ0+/CwMD2onTypdfaGbff0m/9PmkxCq1/28aLyws8Or/SIvtDwgEABBaD9s9us3ZvKNlACcAWOYUUYrqO3b4zD0qhf8EY5CYiQ6tJAb8kFx6PNF3aIkIQhEcg4KjVoJWAUrhaYF1P5eAz+DgkbbNEkisIwBuThBsHc6oAEYAAlaf6gNNHIANsUVxBhBCrkzkZrI/RUS8jgEMwFnhPQLqcyfwYzbERCCAZ2bcBag518iUDyjMBh9QRBER0SIEtp9tHa7ubT59KdBdn/vr7+s3qpx/TqzEKrX/cQLnbgG1AFnghtFurz9qbBi+kEwJ4QPaUAm4uEB2mUMzFPhbyH+od/jMPSqF6OqOIAYgmRkg0RnKHwd0ACjzDQWkLU5QS+EzRAEJYD1JiwZrDqxQQhvHdxVog7eHop/8AMP4R6/DDSwEwCAdmc9gmalMEEJDyQeypF6FEhgSscBEjFGDTROKHAyWR+ieGBr+8GqEY4gvxOqPDCHJEWhZ7vDRVZgEIGSG5IGYXAbooCPkGOIQpIRtgalDdxgMU7QhgSWA2HAcHI+ftQFhos2LUn6H7Apg0gsB9/Wb1Q4/p1ZiFVb/uGKAjCzyJIIUJoLUGB+0fPaumJzZPqfDwES4KEyRQIZSCC4IgUAZPspDmsw9KoXo10BFBm8TSegb/ABBdAPKebkQSKWTo7/BWLYDVEGSJe9PhghAG+cC+z4pF6TapKZTNU29ZH6IYJvnwCfiswCzP2VZgEADF45vhgV6DfigbMX+37RtNKFpXBFHjwCQWAKWITu7W78BRb1QY/p1ZiFRb/ubAXEDxdUZYYxBtvBQcSSLM9vs5oMhnm6gy2CErFxpDDNEMSBRSqG0ZrMPSqF6De7uG8RqgtjxBgMXXROX+bCW2KMYjkXJQCEWmrnQ9zABJwiUkBMG8LMDijgbowEgffZA482KPr39DB0i9JtUlMpmhFgibwWR+iol74rMAsz9lWYBZn7fQwaFEvfZgAWu/AKJmFu1/VSQcbRi0/A0W9UmJ/TqTEKi3/ddXMOYY+0bnAkG3AhNFgkY5i8fYyDFxIXE5EStApvkABYB8Eh9IPI4/x0DibC1aHhB6eChWIczSIq1CeiOEaGwgNjRQ8OLznATYhJgAgBc6EhmY9CPz3azLjiiGA8GDeBR4iMYC9ANUwbjAaoogwRgptsoXYhSi9/A+2xlYud1j44cNBD3d6LMsbyUdYjCBOsVDXMRMHcIN70mJMw+BlR+AMlHzYOOJlDKj8AZKPmwccTKKIMEYKbbKF2IUovavLAGEBOiDe9JiTMPsjZkLGbcE8WzBhuOKISQMS5zh7QAAYQH4Gq3qsxP6dQYqi3/dh707OrjimoHTBE9WREvXuOSEQ4l9u+HmiwXWwuZS85LHwSigAkIQWJrUcAXALR/EAmNwMOtojWEQC7ABMHHz+9iEJfgqteqzE/p1Biq7f95D6FQiME0n01SBXdD0epYmZiNy6w+3JTPaZyiCfhwBVe6MCz9b/wAMYiy210vVwhGgyffUSbMRKGM7yIVW/hKteqTE/p1Tiqzf96IMDAOCpyxJfbdERDrihcZbWYWrq0VEdRZ+bm5OKwC6CSMHQWp4RQD+gFeLFCCAwFYLet/4WnXqmxP6dU4qs3/fvQokw6BTyvCDtb2Uha4FwwXgBHuEjknSy2UO0/y+IuDZ148Z7BP0nkuwGToFGzbGJ6WkCF6YnZd+Idnfs/p80m/8DhWMIe6aBoGwqZ3cQQJkENlTy6YizZU8shQ9yI4P5Elg5knQEeK8yTnf+41L6pyJFMqBraXllAUMY9rB+K9nfs/p40u/8HhzN5uifagAzGacyN01ndOr/aPUJvpwrMkzAlsgeRBBBLvQ/FmQQJkpxAQ1zLNPABfO8BOHWlvAQRAdGW8jBHg0rm2TSIWzl3n+M9mft+6qs7kwuUCHFncPRsnIjeHyTBOtMSZwL2O5him4VAMWTFhjdgsc1k4/BkAJIAC0p3jRavyT+Dd7B1TkO4TyU6k45ZMj6tjMME2gd27zymciBj/EskAAGEB+ONmft+8LoKjHUeZp3N1AfdHNPhu9UM06NAsMeQsdtmJMjNcI94ppYMZPVTX+gdFLgK7RFl75+5yXxPec9VAjHQHteao/oycw24GM5ow5zFRubTaW8pgPdNkm0nbhbqmIgFsZh/JEz/2/Ts9/HSeT4RKcHW82ro1zhz2YUhPonNT8dCjTGbjBZo8k/nXrWRD6MgPXmqNZHH/FF5AFZ4Sk4640TMx12UTLvbKB9s7KpKoSiH/RBT7e0gr3TZUq6I1LuhDdB+kNUK26pH5o2FTD9XUv/SPULPnyY1ygdWTDayzTF5c1KEIxSiTomV66GhNboLl/P5XOln/t+nZ6qFc/JEAhiHCmV3l5Tgysisns1CMyB2IfOEaoLNgaKTdDvUqHo3VMO0TVEewiqBxXLCQHUKUPFFkCb5AqEi75DVXU676nHXivYfIZnCUNkDqKm4dIHpXz3maqQU3tJWDAAG/NZ0s39v07PFQrn57LUUS/9GZgs29v07NFQrn57LUUS8fo2aKuXv07NFUrn57K0VC8fo2aKqXv07MFUrn57KkVC8fbDjBkMDLv+QMGLFixYsSJEiRImTJkyJUqVKhRo0aNGjRo0aJEiRIs3bt27du3bt278F5gk6ql79OzpVi5+ey5FSvH21LuCB0bxAh9r3ve97nOc5xjGEIQhGCrBVgqwVYKsFWDV0WDV0WDV0WDV0VH/Co/4VH/AAqP+FV/wqv+FV/wqv8AhVf8Kp/hVP8ACqf4VT/Cqf4VT/Cqf4VT/ChukhxxMf07OlSLn5/lNqiPtqXcFV4P37OlSbn5/nNql9tS7gqvB+/kpNz8/Tm1S+2rdwVXg/fzVm5+caJmEAWFpiHVCAXqyJ4n8Q6fosR2gQcfDfkdFjHTEs+zrdwVXg/f/Vm7+cfjj/S95fACLy4NIfooHUZ2inwrwl1G+8QLPLfaVu4Kvwfv/qrd/OTvS642HyhbOAriPocWh/DLU/aVu4Kvwfv/AKg3fzsti8P+Nn83UmTcLT4TE4gCwD7EyhNFoJEhDdcfit3BV+D4EFyPE2d0YgArVgP746g3fzrGnD2W8R3+YFQxes/s2FgN3TPQoSAPWPVJCtiZMEekCi6CyDugBBxMGPAUb7xAs8t++uoN388y2s8mPLpvMALyVJsbJvNp8/ZxMvPCzw/0vTQvhlqf3ynXKs3fz09Ba3g9lKA3HXLX7WEN4M2di4+bjXJutHwmLjABYB++Va5Vm5+ZzpCyz/FT/wAspp23oh/0QwNMRMHhFJYSZiMLLmQPtnZSLuMUk7oFlfbi9up9hO03PXPTP5amj/V6z/fatcqLc/I4maJlaEqwWj+9srUHFvJlKy6ifaloBdtF7fnos6sKmVl9Esv5EiosEC775P4i3imnZVnsbCzuDRDGKzn0LL8SKWGFx2ilh4mPRViDi3kyhBToDIplfur3WLghf8D/ACAF4Kn6Ng3iw+ExSAF5KvdWvNp8/vtVuVFufjQPZhg+E4DsmzTiBV5E9E+ttzfVYnEcKlb3gm8qRheDR1mCW1ZMNuWcX6MpmO72WXYj0Rn/ADFecDrPfClY6NCrh2LqqwdAg81tRXqnNCkTAtZeQsAexCZoMWG3NN46IO1kmUX4HNkmB7cAY/TEqGL3kpHnDrlrl+/UW5Ve5+KcwaFEJd0ePd+jdPQI8Pkn+5YYk3kmLWMpoED1tSdkws605yEFl3Q+7wE4FHQm+jZZJ2OBC9GTye6nwWT8LihNrStnIMEyXsL68JgB5Z+0s0ABAQZEKVY2DcbD5RhxvMtoD9+otyr1z8PjjE2fonGukEzknQDlwAn3XWIoA6mSaKOaxNBE7XMhBBALuQ/BmQRJgp8JjTEk8Bt2x8jZOBAbHsCfAe4XLtJDM0d/yThJWyh2/fqLcq1c/CsBdnoBeUPvGQzWNRZJFNowaj/TJrL64NCCRAyAMB+KcyI+J2KdKhuwqdxbAQLyQzD3t7oQDdqB/vt++V25UK5+DjUuJGAR5JYz6bp9mexQ8qwHoFeM4ol3/H4GhCXS5e5r1uU7EA8O4TeDKqRQbbW0+oWfcNwxETTwPoAAAcpMJwQs5JLD/kL0jbjM8hiFckbMd2mMD8wfAC6Lt8gAAJOk5iegP/GYbVDOJdGzLovTKAx/AvhYzm3gfQAAAQAESP0zWfFYIgAIkVekbcZnkMQrkjZju0xgf+k1nxWCIACJH66zcqFc/BR4ZR0T1uClOLsiIAll4GqbKBi1d7/jxpcaRJ8M7VMxAJJHqH/Mr3wCQMYOh3XcTBFPqeCBijsmgUx9Iq1tJDRcQDGBDRCAEtEUDuAcBofYkl1ljobE8uaJ5V6k54diFgaA9G329LuCdsovIGQPzu3GIDYiJOzIxWAH/tjOixI4DxvIgN2BvQIcGwChocOIjMXhEltA+ZJPjD/hBNr4oAaqCtgBrknqERywiUXYDT8DWYBPxrYAGBI9PnducCYDfSXESA4dALLFiw9InYYG5YsPSZWnAv8A+hcRIDh0Ass+us3KhXPwIEsmZmOvHBAQvdhELHmhNvH/AKHUIikCZduDAtFFPAhHezREUAmShwqWACjISTAh1uQyESIILgoGDTJkOg4jQDDn5Dw0yZDrAxhfwqJcWZ+ydBKdgXVOWfgwDs2CQiLGxEgZI7IyCBaSnSABCITTd0J4twOh6DAZbOqDzHrp0LBgBALEgBP8EAMJgigAICDIhYmHAgYeOQYH/wCgAhZiyLUaFBiQkF4KM+Gelu+2pdwRpCYCMDEXqvdVIz8YHs6gKJuRAyQEfL1+ABolycP1QiRzCc8hymZvDeRaihQBiESZQRqgAOn/ANky2gxhH6kilYMT4gUWmQWhgP0mdFiVIv8AgXEayx2YZIoGUR6kw9FQfg4sVIIERiQh5ghdqxccXSTYhDnjogsCEEGdHBF66KODADAboFErIeIEtBmywp3xsExwDeo4l8O83i6LSwWM8hESoCrSAyu6O/8AAz44NvRC9BsLQhSQAIDNNVBS0ARvCjR7RJMCA5byFKmiGAymonBkgC33I7kSw7Gk9xCbW4Q5z6EEgJIZvcIzIJhchkcj4TOcVxjjIJbiwgepLIazMU7uCoxDTtZpl3giEUgk7oYIi3DBaOwNsQjmbZGMdncICfxleODi74KfKM4LWNgQlEEAwT0cunTPcy3SMyLw4yC3SrTbWNgTygDWn4gO5EW8tNxAZ9kQARwYgj5rMArdAps5mwY/AEuTA3PhFMY42AUZRTe2miEgtFzPAF0QKjOOxg6J3zgGa1IyOKLrr/sLCcFictOxssTlpmF0NQkSnSuR44mDBsk7vFRVQwEj6gonMCLcnjeEzR0YnAzjwh64AlwBeLkdsADko2POdj1NMm5Oh0xvB3USltLmFxRmWPvBmtSMjii66/7CwnBBZQx5Yk4JtlOEQaARmccRNIpjEFPsYH5rNyrVz8BBgRRN2/qilkck5klSjCiDIXD/AKgudA3IbO5BOQznBBLJChxKzBGAYAVzkHzTffaS+P8AqM2AjsJRJ9lCAsccAqxXqCwnsuTx7nT0JoJBg18UkQwJaQqwIdmBZBfFf4RrzIERGAbRZn7KswCyBHHkGZEtCHSmbGcTXK3lOo9DegrcAPwEQI7lIkERxEPqgjuhFHaelTb1IpkmhkDuaslFNqbQp+Z606V/IC5PtDuLe/GQJhIr7J0AQmtMPBC/EIjyPC6A6H/pcVgm3hX1UMQHdGjJwbFp9rS7goW5hkHc/AFugU2cxYcVniy338sxnAIYUWnyRlmyJG6gBi2D0dBzM2MXpxIY4mA7bfUZnRYlATzOSbsjEHFj2qAyQokDuJQIAH484YI6kWaLgAyB8EwfinYvIMYgvMXsjRRn5mSoXoVNoACESOWawZSYtc6qF6pdxREGeOIf6IQwASNpstMj8EEGAgLCSQfT90dkkhXunr8ObzitIs8B4RCARcgDOb/gc4AAhcEADCw4g+HQtogQ8AX8LqA+ZRiTZNgMOqZwhGSfqhwzWiXCqF6zD0gTjbBIks/h0EtzQReGRhQCC4WeTo0FHB6QPFAAAAGAsRB0QAMAtaiviYxYnriUQFIAQLg8OnwgGGaHgpEZ4o82ryEDID5rMAn41sADAkenxuPlACdJnxrMo9rQkWEEIsHd+ubo3I9GAmJgYeEAAAAgAFnvtZZ9BmweIDjYF39EILlkCh5grgNrB9FNAhQAgEAtgEUCCJJ/RWEkD0ap+Bu5Dk6IUAitkDlVC5Z77WWI73YY6jcgLBaftYRAuZFjSxM4GJFyKHQQjER3+aTcq9c+/aCImf7GkQTBHaQw/wCx+Ig4MERDYwLVQw+wZDFZggmuLMHihAMJKOMLLGCHxciMSHKIe1Ei0I5czP8AR4o4sZf4LdAwlO4/58QjvYD6rM/ZVmAWQI8zO7lAMYQ7BFSjCwH4RUTLA+nyghTb1IpkhkPThEZor7BgN6CPFpB3bwpXg5inl7QFvJdh/qEsjCwjHRH4iDEOFKNI9QUCCARI/wDR9tKNpXhBTtLCyIRSuRTPn+0pdwVfg+c8WW+/or8SyD0jeKBYHZyVH3klsAdo2oumDJESQGmTH6jM6LEqRf8AQtRPCY6o4ongQkPkrlKihDApHDjHoMFUL1S7j8VC9Uu4og8QI4MQhTCYlD8PmfvJyUO7CekNB+HZAs8+hCi3lS7gqhemnJsbhMO/ghE2CBbShErH5yEALzG0KoXrMPSqF6zz4lEeOrIiwB8jYHj8ABxIYwBPZMFzziID2oXv05D/AButSTRYdkHlZIEgTHp81mA+hCahpsFGYpjMUL5GVqCc3H7AbKQWcUjgVEaHdeZOs99rLPqM2DQol74z32va0gwGZR5INmDeT1TuH7zkIJxuBC5GeCqFyz32ssUp7p5g0QBmEABB0MgcjFgXoo52VniAIsGPzSblXrn35n0fxjafPpBLPbtgt/7qhd85h8ubCld6zGqMBW1ta3TyhM8clHDfNR+4UtwR6CG9sgrAjVwuNUAxAAiSbFesJeBAelmfsqzALIEBFoTo8MkbMFiCy0PKIvDkyl5PAAMclok9sPlBCm3qRTL4h5eUO72ppofG97TEGPukf87IJDhnACP8Ce25xhMDt6RL1CWAE6/rAA58IBgAJD/qF1gH3EmyewAmlgGvB+p6WGCJdk/BD1/CXtOocbas7S/50u4KvwfOeLLff0V+JZB6Qf6h4umiocAXAx7GIR4gwAhJYwpFGFJPcfpGdFiVIv8AoCITAnfDEJ/BOmAHsEztixA6BDWEIjNoklQvVLuPxUL1S7ipalMTKwoCBnp130TBwjN3GyUdJvLextKYNMK4D4dkCzz6EKLeVLuCqF6ZjhbInFpwb0nboXBhBYMQhUmEHBjE2LsUclvOIj6dZh6VQvWefJPKyPE4YoSCIHGQHYpzcogbqXBRrWhJtWlHWs4o9a5BZlgMHvuyKAnbCF4nZB9YYPmswCkZ+EB2dV7qq91UYgjiXYe54o0A8ssHRAcfxT+2Q0HiN5NlKMI9keSwyZtDAqNRkQsYIh/H1GbBoUS98Z77QyBYiAJsLQzQKx1DDHEJl2Bzrh1eCByAw8wiHRybVgRA5o8lhkzaGBUajIhYwRD+EGh5OSU/ebEfETCaCcjDPe1pTGfOZ75+aXcq9c++f4zXrQHtSJg+7FNrAFcB/wBqAIgowCI7fJZp8AtKM/8AA0B8S0eATKwpuzOdPqIUPaJEbK68gRxF7098YCPS858e4EkYp5CM9025pi1WWRFFLEgSyJTuaYGjBFmjwSwozWQYlADunB/MFdoU/wBJj4eTojJOEm2MmBMgAcCEujJoSIEzTRwqN3EGNjQJ/EXMIJkgR6PZEGAvLIt3+IDIhOh44rkdhEFDYb5jdf8AUIZbZyDe/wC4Rhsxnm6KQr+aRGvyYTUFVxvJkmNjWVPDIyKSRJNqGOOPbRafbkAgghwVhf255/6kHO4HsgLDbg+n/ABgAlMFBkC6l6QDBhAf9O8mc8t/xx1mB9IXHcgMPiatsy570gkAEgAw/wCJ0ESYIWZuN6QwECwBvjBf5DNZGZ6f8gQJWB9lg9IIZfOC/wAhmsjM9PgKw/B9lksnp9FLuVeuffFGWb9AD/iC6Ep6w1fnxkMRBHseij2HnSGwguQVIom8o6Q+8Tb3+gyoPRCJI0f7oYxjGMYxjGMYxjGMYxjGMfI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjXI1yNcjRyh8imQqdc++Ev2aARhq3a/PkGbWoEwqilhRJXbuT6SkKmzv9IAzpBCDv1VY6qsdVWOqrHVVjqqx1VY6qsdVWOqrHVVjqqx1VY6qsdVWOqrHVVjqqx1VY6qsdVWOqrHVVjqqx1VY6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUjqqR1VI6qkdVSOqpHVUzqqZ1VM6qmdVTOqpnVUzqqZ1VM6qmdVTOqpnVUzqqZ1VM6qmdVTOqpnVUzqqZ1VM6qmdVTOqpnVUzqqZ1VM6qmdUAmCNLA6vvjhxOOhcahDOGGujMfalMY81wAcqvNFEpBjJj9enwUAICQMz9ESkAFbHt/wKYx5rgA5RLIcU4ksLPpOkxxMAiUgArY9vtgkUxAC6wHoopYQ8wX+UxXg+RJMqAraXh0cmAgQQxHwA0WGQv7H8NBaCDA2Zp85+jYBXqIw2j7Sq30BIAHJkAnwjFdiOh+Dw0OZclkFULnyUYAOJ+iQA6qq31VbvyUYBOB+K3eVQufakCEgAIklM4Yz2Et0UJY/YMsm+lk2ElDumMg6XlL0hFXtZsc0UJw+9/DTCiChjPygnYOjPh7/aVW+onqATm1A8wagggAEr8TAZkJ2Nxxqqhc+DiS4vuPYE8tgiHyUWE+NplnUK4lCU7QIzgYcE+RW7nl3UlX2P0IIgbCqrdT3RiJ9F5j63lTb7IJPiU1yQeQL1W7yqFz7UJYaiFcUQYM6pbJAAAGAgAPrKj1N0EOlCJLrxXfw0WLgnaVhCEWx4BILCE0BDEs7/AGdVvqKkgTbjMHBWvHqyHNlLjnt4yfYVQuIq7G02LcglgqA2sLMvhtgA8S8M418oI4wIjoWPsIRSB0zDqUH4Pk3xYZAIXAL+EYtFVbqkP9EAE+wE6nME+I12DobcGIMTJAOVFHQwTSSWKhc+0dhhevicEceRJFAxMYBvu6D+Luq0Zd4HBHXTcIxBQ2VGTsn7Kq31VbqbQTT7h9EUYSk3Dz9KDGZewkZMqhcQS4HyAnIIyEWZNjmr4joCZmLgza5IhawAnqX0RCCHUgzUFDIQ4ALIv6IRamADrA9qq3VIIEeggjZHkAPgzkEaJq2jovavJ01qvcEqFz7MwgGhGWNwIxQWhkAEMAhHC53/AIzKAYAjuCKnyxk3goVZBM694zUuLxHH2AkiAcn20IYiAtV1EGnlq8/p0w0IIrUAEg10QAhALxcQAgHBgQUdH4iY4DugARQZzDvug4Bqy9Y2dFHTCT6xQeQRt6HX/U+2TgB6hO6GZJiBwvKEMRAWq6rSQMLig4Hc900UKHA4KuRnxSW6RggcYnrkAQgF4ufYgMQAIkmxADxJNAeqZh1QST6ZE7OjHH+NnBK+YxFyvfFwPONU8wBmR6gUKVwfiO/2+B9wSgIIBID5OAnxIjKAAAAAFg+QEAAg2FYb5A/2YBmcQ97kVXcld70OGJQcO16iznUPX8eh5PFnyBNw9yMfdN7axey5PbwyjpehIIkQRb+OhY+M7mQUaAtYuuxleCxpDqbE0hNsPW9DIgTAAMB/IIJRiBwU7BcIn2s7J5JQVFndOy0E5dihwa0zboAOvLeBj+JZV+8egTpX/W+k4EmrLe6xumQOpkvABPcZ+kFhWxb+SxMCkJJzpJxhmmh9YYJrAphc4o9iBe+yO6ZHli80ABAQZEfgnRmf4AJ8J7xqeAElj7TQEIOvkTeWbTo7smwINtTy6B4ZgBgP5SVE6boJ8vGheCnw3C4WafmJieQgjD9RQmMUbiGRDDrTyO6andYYeoLxaiJ+5CuEwUe3G4NmkncYiDenMAb3GeydX1a9UkTbqGQmklTADdMFwROUI5rs66f+YOZKrGYEU4Erc/ujmnYjMJPVPDTeY9Vg4YyZxMFIRbtMUlvqB9qzZx/yRleOqzknRSIHQ6KW95iymt5TY9BQJI/b808Rz8ZSRdQWd5vKf9oSvaIegs7Z1WeKDVW7OLWiz4gT2pAAXCaKXLcTbwnCTYDlNjYG0FMJFXOSy3TYSdwgdUwuAsH5oAAAAAWD+bgYAEXFThL2A+QpmGPq6y742IfOPUVkMGPYUrAac16Qn9KUuq5ZzhKSLqhDT+iYHoFkZEspraWiN9q7jB6qcuoaBG537EJlfuVDX0ZZ/dasMNA39HMvnl/ln//aAAwDAQACAAMAAAAQAAAAnPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPAAAAAX/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/AAAAAX/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD77/73/wD/AP8A/wD/APP/AH/3/wD9/wD/AP8A9/8A/v8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8AAAAAAX//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP67+gz193y535x6/wCv+utdzf8A/wC74+80/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8AwAAAAF//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A7Xa7fHbXrXrzsr/v/Ti737w/XPIfHX//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A8AAAABf/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wA+9+8/Df8A/wD33z/3/wC8/wDPP/8A77/3/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD8AAAABf8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8AP/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wAAAAABf/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AMAAAABPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQ9cwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB/uAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAS8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwxyYwwwwwwwwwwwwwwwwwwwwwQwwwwwwwwwwwwwwwwwwwwwwwwwwwwAAAABf/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD6/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8AwAAAAF//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/r//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A8AAAABf/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wBPf/8A/v3/AK3/AP8A/wD/AOf/AP8A/wBf/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AK//AP8A/wD/AP8A7zz/AP8A/vf/AD7/AP8A/wD/AP8A/wD/APwAAAAF/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wBfNuB8MOf+7Mcj/wD8XcHH/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AOv/AP8A/wD/AP8A76Hx7/176xG78yN//wD/AP8A/wAAAAABf/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/ANdftB8MP/8AXrbI/nrH4Tb/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A+v8A/wD/AP8A/wD/AOu/d8B9fssDKev/AP8A/wD/AP8AwAAAAF//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AN//APP/AHzz/wD/ALv/ALz/AP8APv8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD+v/8A/wD/AP8A/wDz/wA9+9++/wDfPPP/AP8A/wD/AP8A8AAAABf/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wCv/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/APwAAAAF/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A6/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AAAAAAEM888888888888888888888888888888888888888888888888528888888888888888888880M888888888888888888888888888wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEB32AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAG+yAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABKwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCAAAAAAAAAAAAAEAAAAAAAAAAAAAAAAAAAAAADAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAF/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD+vf8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/ANP/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wAAAAABf/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8ArX//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A8f8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AMAAAABf/wD/AP7+7/8A/wDn/wD69/8A/wD/APyx/wD+f/8A/wD/AP8A/wD/AOtf/wD/AP8A/wD/AP8A/wDz3/7/AP8A/wD/AP8A/wD/AP8APP8A/wD/AP8A/wD/AP8A/D//AP8A/wD/AP8AvPP/AP8A+9/8+/8A/wD/AP8A/wD/AP8A8AAAABf/AP8A/wD8OuCvpdOyMNvM/f8AETvow/8A/wD/AP8A/wD/AP8A9/8A/wD/AP8A9/If9cuNzstD/deO/P8Ak3DPjX//AP8A/wD/AG//AP8A/wD/AP8AvofHv/XvrEbvzI3/AP8A/wD/APwAAAAF/wD/AP8A/wAOv/BhdesMP9N9f8MAvwP/AP8A/wD/AP8A/wD/APf/AP8A/wD/APwB63F649/yK/0sz9z/APcBaOP/AP8A/wD/AP8Az/8A/wD/AP8A/wD/AK793wH1+ywMp6//AP8A/wD/AP8AAAAAAX//AP8A/wD/AP8A9/8Avv8Az/33+9/z/wD8+/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8AvfP/ALz7z37z3/8A/wD/AD/z73z/AN//AP8A/wD/APj/AP8A/wD/AP8A/wDP/Pfvfvv/AHzzz/8A/wD/AP8A/wDAAAAAX/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A61//AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wDwAAAAF/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A+v8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8Av/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD8AAAACAMMMMMMMMMMMMMMMsMMMMMMMMMMMMMMMMMNCAMMMMMMMMMMMMMMcMMMMMMMMMMMMMMMMMMMMOAMMMMMMMMMMMMMMMMMsMMMMMMMMMPAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAQwgAAAQAAgAAAAAAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgCCcDwQDRSigyZS4gAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAABcBA+ddOuu9cdigAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAABDBDACACCADSugAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAADAAAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAAAAAAAAAAAAAAQABM989udOcQQwgAAAAAAAAAAAAAAAAAAAAAAAAAADsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAAAAAgT+M8DCAAAAAAABBCBCfvMwAAAAAAAAAAAAAAAAAAAAAAAAcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAQBMsCAAAAAAAAAAAAAAAAAAABCcsAAAAAAAAAAAAAAAAAAAAADsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAj9CAAAAAAAAAAAAAAAAAAAAAAAAACDuogAAAAAAAAAAAAAAAAAAcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAjPAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABBcwAAAAAAAAAAAAAAAADsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAAhOAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABBOQAAAAAAAAAAAAAAAAcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAABA8AATP+QwghQQgwAgwABwAAwQgwQgxgQgAAAADOgAAAAAAAAAAAAAADsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAACcAABSctCscBQMcO/998D8D/vC8PiuOuvffAAAAAcAAAAAAAAAAAAAAAcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAB8AABDahB/RvQhwCjwiwCjBxxwOQjQCjxADcgAABMAAAAAAAAAAAAAACsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAACsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACCiAAAAuAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAC8AAAAAAAAAABuigAggAAwRzwAAgwgAAAAAAAAACMAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAABSQAAAAAAAABC8eu/cxAOsdftfzNcAAAAAAAAAAQAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAASgAAAAAAABDjeAgszuyBAPhDCTCAAAAAAAAAy8AAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAACT8AAAAAAAAAADSQAAAAAAAAAAAAAAAAAAAKiAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAADDswgAAAAAAAAAAAAAAAAAAAAAAAAAABAvAAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAACDv8wgAAAAAAAAAAAAAAAAAAAAQzfvAAAAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSAAAAAAAAAAAAAAAAAABCAvcgggAAAAAAAAAAAAAwhM+BAAAAAAAAAAAAAAAAAAAAAACMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCbMMNsttedtNueMDAAAAAAAAAAAAAAAAAAAAAAAAAAB8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCAAAAAAAAAAAwwAAAAQwwwwAAAAAwwwwgAADMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQgAAAAAAAAABMDDDDCAAAADDDDDAAAABDDCBAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSMAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQd/gAAAAAAAABcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAASsAAAAAAAAAAAAAAAAAAAAAAAAAAAAABf8AAAAAAAAQhcAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABSMAAAAAAAAAAAAAAAAAAAAAAAAAAAAABeMAAAAAAAADf8AbAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAALAAAAAAAAAAAAAAAAAAAAAAAAAAAAMEAsAEAAAAAAAA/gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUrAAAAAAAAAAAAAAAAAAAAAAAAzrfjDjAQDnfTjXMMAQ/gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQDAAAAAAAAAAAAAAAAAAAMf36QgAAAAAAAAAAAAAQEvnQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAErAAAAAAAAAAAAAAAAAAn4gAAAAAAAAAAAAAAAAAAAAAQHAAAAAAAAAAAAEMIAAAAAMAEMAAAAMIAAAAAAAAAAAAAAAEMIAAIMAAAAAEAAAUjAAAAAAAAAAAAAAAAMbAAAAUsMMMIEEcAAY8EIAMAAAAQyEAAAAAAAAAAA3wAIEMI/ArjEEEMvIAMMIIEIIEIEEEIAW3oMETAEAAIEDkEAADAAAAAAAAAAAAAAAYwAAAAAXkgf/bbH/QML8T+PjoAAAAAEuAAAAAAAAAAr0Drf2//AAK8Eoy4A/xK9OwwwK+75xI8yFuBFwF/x34zF6+K4AKwAAAAAAAAAAAAAAJwAAAAAF4AAG0Dj8AGzNAA8C0AAAAAAM6BBJwAAAAAIEAIMOMMAIAAPIAAAFAEIAANAIMEMFKAEE4HMDMEMAAMJCMoFKwAAAAAAAAAAAAAECAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEDN//wA888888888889//wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8APPPPPPPPPPPPPOAAAAAAAAAAAAAABQoAAAAAAAAAQ9QAAAQwAiAAAAAAAAAABAhDbMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACMgAAAAAAABSNsNt8v8ATPDAAAAAAAAAArAAAQgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQ7AAAAAAAAQ3XDDff7PnIAAAAAAAAEPAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATzEAAAAAAAAAQgQAAgAAAAAAAADTgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQTTEAAAAAAAAAAAAAAAAAAILfgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQgT7/ABAACCDADDDADF5+wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEI27wwMEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAP/EAB8RAQEBAQABBQEBAAAAAAAAABEAAWAQIDBAgJBQoP/aAAgBAwEBPxD/AEI7+m+dXns5/Y36tMzMzMzMzMzMzMzMzMzMzMzMzMzMzMzMzPlmZmZmZmZmZmZmfDMzMzMzMzMzMzMzMzMz+KG/pXvV769tt9Gfx8+Tv1aZmZmZmZmZ8szMzMzMzMzMz5ZmZmZmZmZ8MzMzMzMzMzMzMz4ZmZmZmZmZmfLMzMzMz+HWfZs9g/dLPodvV71e9XvV71e/JfdeF3q96ver3q96ver3q96vfms+WeJ3q96ver34+fxdt+Dvqz38856d6vf0LZmZ5X//xAAgEQEBAQABBAMBAQAAAAAAAAARAAFgECBAgDBQkHCw/9oACAECAQE/EP8AFI3le/Dv3GerRERERERERERERERERERERERERERERERER1IiIiIiIiIiIiIjoREREREREREREREREREfihn6V5yvO/LLOzfp98nPVoiIiIiIiIjqRERERERERERHUiIiIiIiIjoRERERERERERERHQiIiIiIiIiI6kRERERHtFn8Tzt32aZ72f5lnK8/LXfeTOV5yvOV55J8pwXOV5yvOV5yvOV5yvOV5yvPNIiIjhOcrzleca3wc8ffpcs8HO7e7fh34M5Xn6FERERxX//EAC0QAQABAgQFAwQDAQEBAAAAAAERACExQVHwYXGBocEQkfEgUGCxMEBw0eGQ/9oACAEBAAE/EP4EJJKowzA42Pb/AAdw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4/BXDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhxdreMQJKs4H/wBpi6xdYusXWLiZOVKOVA6YXLVjPRHXGoui4s+7OsZCmeSnc9jRVzJFciuZ3MEH6E0QYoBLKOmlDmrLgZIDJc/qsag7BeBWQzq4qDC68oGay/hTRBigEso6aUOasuBkgMlz9VcKI4CiHWH1hw0M5wYXoC71fs3OdUlLDMe5f6s8RTJGxNjjlUWz6ZKCxnB9Y84hlTABmrQu5F00EriIY440Dg0Rne99YuuOvwZt5y8mkjHyh4OCJcSyM/Tc8xDYTEmAvi2obIw2SUC3V8bcs/8AHFi4LwkYqEcQTkNWsOU7BIgyspGJtbDCptc5AHRDbpS3yzLrFGBWFuKXjA0kYZAGHhgTk5FBWWRiUgJ5tJ4odAYsEmkuQE7CyiQeN+FB3IB5dMi2LTjFSsMKUWrXZMPQS9sDkdDzASo5ZlG6Ah5TPCj4GqLSRBEkoOxI0gAXFMEqzogQtBdzKRTcCRqLORTCGCKqGyjjSGkBG8EjLk4y5UtJiYlPAWM9qJXkBthQLCzc09I6ylhNQiOoU2DLykcnPRInmUFwLP7M/qcA1CoQ9xQD7lBs1garyTNgUQRmRMXNGIkeYlLB5PuSZ02FlWIGE96RWELOGVaeBLwoypsQ8dagW6VAdVBAzYin9mzGESygzKIGWyMIJLNxpipJMZarpwS0UVDDpCwAYtA0YIhgmkTko02FDEzlCe6VhDMOJqJZOJJ6hdY5uEQPSXWKEwEsTTJMMYJyupaa8nHfvtUd6wGxItRceQt1qAU+FyLhmxcqBAFTAGdDVaUQc4nKDRyglcByE8iWlCMgQiZJRwIC4KCwyW1omktCCAxE1b8AUkAuKNh/jaxctABUZhT3Wm2lENBD9d/R+QBMkZGuI4qYkmKgrlQEWgP1Ry7gshomZwpK3nQFmJCBkUMrTUvhkEMbDyegHK7NYYswTlMXcaBBChktomRwJcqcuzATPJ+4kcKFFJEIQJhkgHlGX0BgQd71Vg6pbE2QIpYEkByolQagASUlvDImQ9XyYAFwU5Ey6UHIkBiwoFiWdM1W/iwGEo2WQFs72hHrwWimYJMTbPG0UQYWcSIpzQ6/wuAai03aojmrP7oIpFh1i6BOmcDDsSmexpUm7p70QCXiAWwqCUzO5IhxJHpTAYUixAYcAChJsoZGcJziagUtbYMYGeSaJQgirl8MIAE6qlE2MHKAJHAt8CMZsnyK4qJBUwW5GGc09gCc6snunvr6uVYBiSAcYZOIUTLLLMMXDJJuNysS0jl7P2KDPGUI/AFl5g41bE6IlACQTIRHmhBzOIVc6QdaoWElIuNgzmpmQHIzFJYBeZhBwi60CvEDix6whaSxuhVi8i2E0oQcXaBmwzjV46aCzDBxdf8AG1i72SMFoe4NBjbTInsydPRC5yZiA92gUKCVzgisO8DaQP3XdxSRP1SqVVW6vq4BoIKhJgx26LRkkA8RP+w9AdLKpqv2v0BgQd71VgmBcoPl9LN70UPVyEHjwieqhnQA3ywYzEEOao79iEEAN1zfxCOAai0TiHaQiJt0oIdFj1v0tt6WhhPN3QEazIX87mC15Fk5FG9EwsomwQS45fQ1QoLyYggswBaVDBJg0yCgW9cwgOc0FmiHkCVSl1Z+jdx3WH2KiwSbeEYgAuYiVAcXFOc6Bq6QCiYkLCbZPDCoDVQXlBzKgOQtNWZ+goeHdEACBTVkXeplZAZLOoz5AFkngHRTrWyaa2/R/jixcAZTxC58RmGicmkhftsyZMrqjxZxkVhrHlJ3VZVlQ9fLSZBN72iKVBCi2KRyAzOsM/RZuGv6HAMFgV2DAq5AEug1eTOB2BPBFJymaOPDhAzcicpnKavnXRidYGUpev0BgQd71eoaze9FZVZYPmaytkkciIYjNgKVLJlW4JGKyYwMchCIK325PqcA1BBGgQlIEuF30hTIbJ6GZC2oiuVpkehZn0PQm7oC00t4olQn7TVzX4RIpTleKBTgKr11OGqts6JUUeCagakreihCMl+lElCRW1Kh8kNkIFjEIzxolwSwzHYXes1D9yvlZIYKorjDGDS7IJExKHIDfVIm8BVBQd4esC9ZZpLOaKIjK7BSEcphTqMppEEsT+1O6oxg0E6EGJWxleaNaTUryQnFs5qCvMQ4lkcBLma0tMDZ2YgwWJqM4kuDJuBIQSyYrDbqVgXvcRVi5BnfM1pkEkrR00QrlKyRMaw0xLgVYCCMN7iPJ/xtYuHBrQK4iYNH+yIRziCeInKj/GyO0nem7cgiZrAvI91HR65bIYAcDVcWsTUsCAoe1PwqiAoS9XosU0RcRabZ0sJ0bS8hnKkSBYJsZU7ciOVgMiAyweLTC+AJLrc7iuDhhoWyAiALERlQhMXucvmrrlpmh4lnAVgOemEvMWxVMmspNImLOdBrMQQhUxbKkSBIJIjNiiTWUigXBnKoVwVIREv2Hgg1aot3A6EknFindspHQJuGuOrq2GGgLImVBBTgmli2ioFFptnSwnRtLyGcvXCZ2eGgnO1fI0fI0GU3BQ5gznmUReZx4TiZGBdlYJWPSJ1BhCWmaTUkzwpnel646j2GnlpSUoQRZsje6ze9QDXbLGCFsh1TUiOY9WqE0kTAk2ixEqyKaQS6QsMNhoUBC5GGyZCXgi8E4lzX6L3ViMlNOuDC3RZYuElB4BK4YixgsnJfU4wUgTIiYI0QnkIy5xAdUehUwall7W70z6CQnZMC8i3Om4LKWBkGQZFArloJZiWY/wDEhBojh376J2R1acIzis8bh0GpU60CzBqua48gB2gSSNDZyRB6RnQGP5lQ9l7qE5RBKimBe7/JVi5ZjASzmDNCUcKCJgkIRMEjxxGiaseOjr4nj7KJOOkiXYNVLBitKAJWzM4nAg6f6ksXfgClJOIYetKZIiYn73UZBoUC0JbHA/8AumsXWLrF1i6wSGF+CRcb3V8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XR8XQtASgqEiaEFOBQK4OCvi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6Pi6M04FEpMGv5cHRaTj/VBRSFH+qcCeVUcc9/qkZpJR/qhBNMOOQ/b/VDNSqN9Z/1QzVajaY/6oJpVx/qhma4cbi/+qCeWqUf6o4zRFG0s/1QTzH6U43dv+pYi8zowTzExHBLU2YOP9O7KM765SjcWVhACQOa0AssBgu/OeFR3LGsCwEqMAWDGf8AT7ngYS7D9HZ9I+ZGJaMoSjjkcBYIlxriDsPutGxaLEwW64BK8q4QvQCD9f6eWg6BIjiNRybycVfnAw8R+i6lIUyJZxIHX/qN7qUBi1zyUetvTQCVXAKHoQxcU8bqHAP9Ri+MM4EScTEqK9oCw4nBxOD6WbkTFmUDZj/1O00Q4YFe8wnpvrO8XGf9HNf6mYkqrin7gPBadh0hIb0ujAnNKEIIAQAZH5cR9IygC6LyvyYWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixaRln8f0Q6PtgsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYvkGRATaWtQmNuOAvG8r7yLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLFixYsWLF2pMJ3BSC5r/Gy+But/qomsXwN1v8AVRNYvgbrf6qJrF8Ddb8lE1i82XrQSjAQwidPoiRIgcspElIAGJEng/XNsdzMYUMNXnKooiQBJI3+kzI0iTAAuq2inMTCyJUsAC8/yiUckijWAw40XCWSnsLT3FsoHObu+s21CRIFgnS9vwjA3W/JRNYvwO2JFdRsGzUw+LoIXEQsOLU0cpyBiwCvQ9NMMdm4oII4D3+vOUrNCmWMRqMW9vpcQRwT6byzFSQQSsA4Vh7MXIJSEqY/yGEMjYSgl4XpJCKYkSn35FinstAJxid2omTrgSYJkmdxvezQxyBwS9mQShkwQQH0WmfZsWBNiYiYaPk5QvQvjLi/hGBut/RE7CDTglLwjL6GbNm0HE7YJMQf4A4OUIcAC60RMd4WoWYNm2Wf0CswAqOZAVciDNKlCTxLLq39qPkkzU4DIeqVG/UUJvP6h4dWFIAONziWNfvixdxuenpCnM7QJ4U4GNQcuRauIRBgCSpxqBKIhMKsMQUZsNCyMogQUnISS5zBg00bmLZXuLVzvWMpghMpxWGYlQqwRoyDGTZHiNZSlZpUQRitRi3v9DmWuAVMIF2hSlqetX6BLA5KoXWeWaDCDEZuF7D3q7PkQpC/cukl8ZIiryzFQQSQki4Vj7MXIIWMIY1dV/iQIkl8GhwAQjIWUjmNFPgnjR0Xai8atGGKnkh3A0hBYkgYEOaHrSu32aRwlzQ3wDmDYpAlp4zwuhFArGwihnTeWUHC8mDfPsFmFj1PUfMm8AsS8CZpn3HdXkxnDDFBq1wdnGKXAnnQDIX5AEgVJCTxaDcNhkAuKIWVWWbzgMVMgJV0KPWtKtXYbDqc6R+SVAzErs446UwoIOos2mJRtMNiKgmkHEHtIDDvWPFACqS6HHjUYt7/AEOZa4B+D4G639ETgfkMVyzGDGlSeHolwQ0ooziIljPQgnO8uSETMFdjrjVCGizaSKByB6BAFTAGdGDKRgHBi9GlDYvnKBNAqAStArkYetgtwlZjGlQ0JKNKKRESyPohhRb0cu9WhqjuJQasDji1Pbjb3lYC8gqYm4bdgwKoilpZnhQrCuQz4nWIRzelpoTZDWAtCgiRPMYg9GePwxICYJIWajt4wzBbAqNveEhP3tYu43PT03TShRvuGEyZKonnU8Op3AhiMXWmMNKR3wVqpUQEyrjUIvGwZBEggCGAKhfXGXAYYLMGRhQLQkC1dlo7HXt+qkfFZEYC5xKowsaU5RODZcDrZ9wqWqCx1Qdw+hQoWBChImJkfFNaahdXxwouQaEsWQ6TBwCpAJ5yv+gUMgKnUQ7DpS2Ma7QDBqyJ0CoqtSLjJFqIvopnW56fQAFEOgsDRYZjNsGo+9hIq5WuysUHQudDnxogwlNJ7kLdcJfBzZKCotOhLaa06UnrggwOF0To5FTUE4wAZQiGb4IOVMyPCXLeNFkdX0Db3o/CMDdb+qJhgYMtQ8kUOcZEBsQt5EhVMSIncEpeIYOsULFbHwMOBJcc7NQKABXlSeJCuKqPCw7JBwKJXGENZITszMhEybjeI0mmmmjJcYvGiIpxkYYRclk16zUUapDnU/sW6QHBNGoVgVrJJkNRpIlbJEpS3J9DvJpmkDtSNQQARCEMNRNRKnjM2W6EoDq0uAWtyaSkeEqGOIFsBwUxGkOuY047mZHFKIcUDCcmavuAszV0hNAKRis8hW1GP1DLsQDAKTGIziMygARISTBGCoeRiBAgWLt0p+xbGqRjjg/e1i7jc9PTdNPUzgU4pFt6AiTNmcoQxhebICJQRJhhhTvQ2MaBm4mK12OvstHY69v1Vsmutr0/wKFChZaY2PWrOycOIH9UU1oSgCs5SnMaSgrHS5X2jrW56eqBlC5krBJFlZolK8gLkUBMiz4T0qcNBZBJciXizOExRnCAJ0IdwoIN+nBE/amG7FIIDC9iPX0UykvKxITGPHD0Db3o/CMDdb+qJhgYFg6CJtl5repkutwSMe+jEu3LMGDKg2IXHgid/dRYCIsSSLMhh0TiVPzRVTipdLiqTU2t7hZGJtrdLjHEqCqi4eYlkdSzXZaOx/Rp44YVtr3WbFxG1FxSBIrrKQUfsaSLqkMSxMRQN4FQyAmpFx0EpXFxIzV70HhwBGAiDhr1qQqnCKETpqNgg4mZTz9+cA1i7jc9PTdNPUwgiZeKhNADOGJk0wcUNNpUCJbwjd6VPZn58omCJQWtaLBFJktp08Mfauy0djr2/VWya62vT/AoUKFlpjY9azg3SCQEWUBfATioN47bJvciOa4xlEsmHlgKAwABuoAxmgVuenrewutgaycFJ1q1/shkL5VxIwcpL0+zk2ryGHKaWINqfLsAnICYJwKGyYToykUsswukBjIMCkmBZkSBjI9lzprTZYNMbgmZg8wRsY2jJliDLC9QFkAS2VMSlgzhXIoSrOmA7oAogzfIADcThETnUk2sKiIJNojN/B8Ddb+qJhgZVkNjIAdAnSmrRVOZSWhQnOo7AQ4aYLJYixOJrRaa+Bwoi9J5jZAQQQowlTlXoZGJDC1FWltPFVyJBWi/OihBkYuMj2V91dlo7H66mHlkJLK8B1oCjCqqZxmyS7BJpTs6NgsRHCozGpJCZTqMHHQagGIPEl7FK+JTxYCHd0piTrIITZGAgnUcKLYUykQXYHNwpMHQDBKrOwffXANYuxMZYfhYXKXbYt7iIwT0UUIi38JkTEvvWbuZrxNxiYJjQ9DRNElJo6nBqz7In2Hu6kDWE2oooKSD0qbY7mYSCYam2O5mEoiWrzlUUTApglbU4WgTowURNTtMNRoKYKO9puNgiXHjTmJpZEKGCJaKMyNIEyBLiN5pzE0siFDBEtFCmo/CFxEwacjh3AhEbhMvS5N13LiwgmrWxW5mBKWKY41czRkbyI4Z0c5yDSMm0N7a30aKJaYBzd5qQGNGrGM3RCHSXo/QJByCKNJHDhQsMzQ91a7T+PzCJwj1Oujio6zmXSuMPvYSe9KdGTlWq+jVQAGQMhRHWj6kjmC4wYHT8HwN1v6QmDNiAJAl5pRECAoCsHIfRl7N0mzBdWNrjNmasXczxJABfFm4UfJLMU5mLrDi1MFgKyHhLW6rquGFTMkJwDLGXicG8TDATUQRhdJkIl60TsqD8ckTKXCpDHO2SvFYsTGABLEtpCSAiI4EkIsF18KghBiAG8SCS2DJRvzgFluFoiMLehX1IQowRoXUkC54s9Rg0bwBEohcRwWeNP8AWUvS49CoqmhQ8wpkJsdXICkEVgOCcEUedO5C1E6mR5dQwqGn0gWuMuUtFrUkRgEIJm/dJLvCCRo8WHQlgHGTUfnzbrJIVzBKelcEkZ97wJcrZ/iKxdqC8SQRPkxZMEDQSYliZF5YFNoMwt7B3p67V/RxPgsTBlLjM/iuBut/qomsXwN1v9VE1i+But/qomsXwN1v9VE1i+But+Bia0BmUuk07I8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8VsjxWyPFbI8UnI8UhQVpwCVrZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHihAJGSUcDQIsxAHDkrZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeK2R4rZHitkeKCRLhBPy4PQolH+qDmeG0HH+qcGago5r/VITyKzjmf9UBNcKNzF/qhmtVHJ/p/1QTRbjaY/6oZoVR/qlia4Ubi/+qGeSqUf6o4TRHG8s/1QzuYKUbu3/UlA+U8cSM8HVp6Cef8A2U42FnoRmpLJqrYqV/aYKCickly18f8AT8JlKF5rnkorbAcQmaF6HKKWxMn5zxHapT1ryAgxlao4dwhHVjtRCcqBJgMAxyKkaFizLv3PSP8AT+LyYgkScTE4lcOgxUYk4OJz+iyUSksuw95/1FsLSEMCueYj6OrMguA7ULar/qLXLtOKc5XIeC01pQEImI+jr/Qt/wB1uYUAAAFgMv8AUrCDYyxOB7x6Nkqapgt05z9v+p6VRS6DvStqFTktERUS8DF5VEmY5wIl4uL/AKmgiJI5VYCuJLMFtuX8vG4kZQBdF5X4PgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYME36KZcFoV5aN5sDIBZS0L8KwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYIboyQmwtr60nxYlAF0XlfecGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGDBgwYMGCxYJMuFILms/xAvBxKCIW+AtUOKeEOBVMnLX8KOYNhmEXFm2lJqnQQcgCIGev+ErF9AM23Bazm1Ys2QmAtBaF+FcS0SwTaHWrBm4jAXgvK/wAJWLztz7rKwOA0egObFDKaj8KJ27r5RFw4UyiGTigh4D/CVi+VDCaQTJGKVB024TFCGcF7fhWKqchsSAc9KgSbcZqDLTFe34asXm2O5mMKGH6IkSIooUVv4xAmJPf67zlUURKBglL1NsdzMYEEv1HdElgcEcRShGQIRMk/kYIUoRoBdrhD72kTR2ZyIJqqAfXbNqwSwEv9SBo51JKLDkNBG0kQgtwzHv8AhQe6qRlY2HSiDiSgFEuGQ9/w1YvnKVmhTLGI1CQAoJVgPVpKnMbQI4U4OH1zi3v9LiCuA1lKVmhTJGKfVdyTRAAkmuppA6IkUj/IOC8uhTwAsMYpOkHNuNkYkA8ySurVNOEKOOS1ApCcDos0KS5jLh9JrMIEmwJjrQeWCTUGQ4EFv6ksaH1JEvVo9F0aIUJ1gfb+VvyLREkliIbnVRJqjoIGIDEmOb0VAoBirlTkokqscKicC798ly8MW+hpUlChIsrQaIXJRBQLheXU5cAFWDJJa9SazwgSgwL3es2nTYEFjKWplGmgkE44PqwddUEwHQyJeRf0QaVYyBTZEWUBUZGoJguDNv5EHdBr8VyAzWxTAmDMZwVRPKSnEnJaCnmW+zUuikIybkEbNkJhifqzaxExq5BxbVdxYIBRCc8f5r1CTsDEmjwFRolBjSR9v6FhBpwSl4Rl9DNmzaDidsEmIP8AAHByhDgAXWiJjvC1CzBs2yz+gVmAFRzICrkQZpUoSeJZdW/tR8kmanAZD1So36ihN5/UPDqwpABxucSxr9kWL79o9WPC1IwZQ5udIiYKBVpgWF4td4I2XtEgqovtOdIOljRrEtpQkui3iK8kB+zieUUZH3Q480v1oBpJIYiVMcRH/ks4t7fQ5ljgtZylZpUQxiFTi3t9DmWOC1CLxUVnILmwLrNhipy71C6iDViCpp8J2MkSyBiIJsl5Ks5JolBWDXUUgdMwCAqxrV+BVgiXcqauRGBNhKRZqpeAtKwHTJXEinDWnax4WJDBaROpDaYoc0MiQGLGbgBmpgSkFLOOXi/UCgYNILyC0B4AnGIoKBmEDElbXP0ClcA5CSmrdYUOMIgdJGWMCmvCQMIoygi4NIDaCgcxUT0oiZDpUYANaDuUmpeRvM1toZo2LwKDGcOr1GQQLbEM7M3LMpMYqOqMHAA3DEav40dIEJJcs5VnKVmlRDGIf073N9UECiWllYSIGqJYlL8T+W+xFiwYy8cCvkDOGOLD19JE1NjAh3M9am2FMMOOHJegaBUAlaOtkwg1GL1LGLCJyUh+hw4leFOQgRYdKH4MQ4Li4egWxYMvIENTqW2HUEH1UZ2j7IBabqDgj7BSeBhAOY1dBARFER6UPJgIMAFijxNbShUmNDgKCIF8qAHtarE3lDX0fA+TEFqUl+JL1EeiACqwBdp8KYqwKWk+bEFqWGexnIpf6FBaMXfANJkdeSpR7kKCQQTZGVzwtQpQj7sUlDGMQTqVN+AiGUSJqWR1Bp9BQTCUu56HSaSAalr9KxNltzw3owgYAlo2qNiQRWLBYojpMgoj+YGYZrlsYQxSy8JEHRUkwluJ/QgfkMVyzGDGlSeHolwQ0ooziIljPQgnO8uSETMFdjrjVCGizaSKByB6BAFTAGdGDKRgHBi9GlDYvnKBNAqAStArkYetgtwlZjGlQ0JKNKKRESyPohhRb0cu9WhqjuJQasDji1Pbjb3lYC8gqYm4bdgwKoilpZnhQrCuQz4nWIRzelpoTZDWAtCgiRPMYg9GePwxICYJIWajt4wzBbAqNveEhP2NYvv2j12PWsU16SQEGMLTN9KWCs0FCAyWaRReizVhBdJzwmnoIMXigkZmZJnkUojeqCBEASALTxUxwQQMXB/4Fdzr7rR3Ot8QrxIIPG14NM6YqEDJSCIgjZGinisTwa3DTW/avS1LiEd0AHGF5rTOCK2CIc6lZf0SPxUXS8PCp3oCsYcgQJ1gs5qgl8FgdJdRO8OX0zFURLzLfZFlkl7yXmJvspumAXktE0mzH4jZKTc4uz5sC6FoGIS5uZgYWE6K6UIf3WYlAUEkfKgwbFEGRKS0xhFYnG5EpervHMYR/X9W0QMpAhqgUEe4Gp0lMbPt/KmM8MkEfcqEFaGYJJcSYaRqBJ4qu+6kAsNnEvo4IFQsqUjaWQ5xPqVOO4XASDgkb4xERLM5S4Q+MkSmD+6PuASQCb4bI4pDTlHKveCOBA4Qerhx2WjsdcG9MiMFRmCWwV4Io5NZlDOFAySvKYosjs1nBrJISTfTP0URzQUZzoM4C9KYwyG8mxxVn+gtaGyzqwMU5NagZ3l0W7wIjjNCKWCqmJC10pggYEoCrGdiosxuJlMU1fTdsetU8jxKWZuMhC53DWBBgIeQbpZIcWOE0MZjHCOICixkw6TWA+X2fLMZhZL2Rna9NRzArMIGk2TxpU75TMbg3zLnjLM0oY+CRblnB7iZJToK6qWAndYJ9UKNHNyprEp5lH8EWyTAEQX0niUESbim4GI80oSMEbGFoKQLYNKmo/KN1VxaBt6JIxKGsuuJIEXlBTWwbEFEjOLcaRN/JCSm4iQja16k4C3AFBeJHJoeRqBIJWblxoOSxVl4LIyfzXwNF6tJCgjvAxjWHKz/AFAwMGWoeSKHOMiA2IW8iQqmJETuCUvEMHWKFitj4GHAkuOdmoFAArypPEhXFVHhYdkg4FErjCGskJ2ZmQiZNxvEaTTTTRkuMXjREU4yMMIuSya9ZqKNUhzqf2LdIDgmjUKwK1kkyGo0kStkiUpbk+h3k0zSB2pGoIAIhCGGomolTxmbLdCUB1aXALW5NJSPCVDHEC2A4KYjSHXMacdzMjilEOKBhOTNX3AWZq6QmgFIxWeQrajH6hl2IBgFJjEZxGZQAIkJJgjBUPIxAgQLF26U/YtjVIxxwfsaxfftHrsevrYXHbzBCTxKk5YMWpu6VJ3BhKi8ERJfEAsjK4gDKqs5o7V3WjudfdaO51919TcNa3DTW/avotLG3TSghJvMCA9n2o8m0KCGE5wKo7EiM0A/f0a+LplBaSboY50ZGAiSSEKzCBJdPSYKaEANGWbOJNAcDGFReeEUwkCuvgFT9wWt0XagIj1KohoSIAdyCYmJg/q2mJqAkHmUU5JBqOH/ADXTba8Qc/0xSNyPmFx8VFK2hhHNpXeUlSsKqpHCcrB5rRAOK26SXWHAFvxpaWwxTnfZ50kfNdERLNiwWAPocOHHZaOx12REt1W/7AdKM2TkzAluaXWmKJ8MSAvZeihmSIAJVo5gUiFrKEDdsoktilAlIKxwobhr+lZa3bHrUThCmZSeiHSnREU6Q4g5s8ypvgj4okfcpj4x0ZzR7NOole6ArNbDwSB909EqSsC9BBwCVePqzdaGRzKHUBDIOLBTypPkwXJ0qetIcRFXysmSZJSgQiQoGDVB61H0lIQsRZoWpEiMqqrWVRE5AQSwzpHMVvWSdjp/QBuCc88MfdRz8EkJ4f8AUDAwLB0ETbLzW9TJdbgkY99GJduWYMGVBsQuPBE7+6iwERYkkWZDDonEqfmiqnFS6XFUmptb3CyMTbW6XGOJUFVFw8xLI6lmuy0dj+jTxwwrbXus2LiNqLikCRXWUgo/Y0kXVIYliYigbwKhkBNSLjoJSuLiRmr3oPDgCMBEHDXrUhVOEUInTUbBBxMynn7M4BrF9+0eux6+th7bkcsqaxKeZRimDQTDIJMTOEWqUmkYUWAYILxc2xSVoCYEg9w613OvutHc6+6+puGtbhprftX0WljbppQnIzhYptZxKPBcUCgUQiarCHJ+xojEjAYuMFTExaboT9DoTDYoZGmACBmILJZvG2Ew1HuwktigBeAVgbWR8QADxidKd2WfKC+kqsxvOBUMD5MTkTcUnWjCmEFow6qGNdSsGayBMAK2sBjCMaYX9uGQkMGK4ZYpQsSEBkDh0rBHZWBSsMGzRG4TRhM5nt5fYrIqekPXEdWr/wC8E4RPBJHgtWjY64McQvp6H6FDAd1CWlenIiiwhGJZYuwBapu8iC3EONg+g4cOOy0djrbohsylNLHzlUQTOsjHE4U3FA1hxJ5oHEeiglCzUlCDUv6TlQdg+LElg2WwXtejJn0K3JKAXcgCtw1/Sstbtj1rMyc+kgPc9asiyrBYAzqBtomtNUJMEgzOASvApnhMIJLBOrAHFpipeOKWtz0+oENELCZxajJS2KWcLngUpGgOdKusDVHAAxagwMESlSvMHSlqgW0YV0ROlYLCCkhcg6jRwDIUGEeamLkEyGGIFJzDJ0pXaEeyzkFvsoNwGBlWQ2MgB0CdKatFU5lJaFCc6jsBDhpgsliLE4mtFpr4HCiL0nmNkBBBCjCVOVehkYkMLUVaW08VXIkFaL86KEGRi4yPZX3V2WjsfrqYeWQksrwHWgKMKqpnGbJLsEmlOzo2CxEcKjMakkJlOowcdBqAYg8SXsUr4lPFgId3SmJOsghNkYCCdRwothTKRBdgc3CkwdAMEqs7B9mcA1i6hGEIRMx9Yl7Yrc3ElDFWJuu5MGEk+k5ux36iXGoZsolXea0AGYXB1E5KJJARbM3UG4VecqiiYVEkhaptjuZhIJhq85VFEwqJJC1TbHczCQTD6xEoiplXOjuiCwGAGApQjKEqua0ZHBuBAAWAZUqaj8o3VXFrJ3Ml5i4TEsTq0ooVF/4xJiYPamZRGEGDBtdGDT2CMcLMCBkiZxSmNBKELdEwGMtBxmx1RO/0MEKUI1EuVFOxF/8AdmiqxCXp0UUoUqSr6WuxJgNBgnOoFcYn2gn1msfeLP1b+gkWQEczYpdpFDy+JxjLwBN3LP8AqeD+ZNiJhsRGRoFrck4WHRkqSTRYaLuHoRzgDFIYrAAEWWJJlibuAhkMJADyuK2NKJMGm2URAgFhjE2IoA2IyMg8HtcaHBZNEYxpI+1AgMmAdJ1hPeoI4PKCk60Usg8SMPGEqGHaKi9wSiZjwKsVegE1hhfZvRUfphkwylYFiUl8KNUbpEgDVWnCIRtyQDiYnEKg23PA0vhOXEpmKiZGpvESnJiKE32KEuM5kpTcMGUW0EyYmhSthEhc76kxDlJRpfd7U9lQHAL8qYuwFRCMaWaN5HOhkT1KhugJhIwy4TyS1rJAxllOCQBynoaew3oaMKqJMDTCpSD40kZJMi3BusLERSvvDgQVXSgIYUVFgPS1JWUhiTkj1oGbEgQDfmPqZdbxYVDMTE4CZjhIqmK+cLjqUyOFGWcyKPTTfVqwcBIc0zSl1GUMquq1cmExclDcBwwRZgJqKLzFCYQWAi80AygRGA4Dxeg4UBBUUocAnIADgVBy2QKIksKKIxgONAmVmCGKFhFoYWx/MbN1v6SmDNiAJAl5pRECAoCsHIfRl7N0mzBdWNrjNmasXczxJABfFm4UfJLMU5mLrDi1MFgKyHhLW6rquGFTMkJwDLGXicG8TDATUQRhdJkIl60TsqD8ckTKXCpDHO2SvFYsTGABLEtpCSAiI4EkIsF18KghBiAG8SCS2DJRvzgFluFoiMLehX1IQowRoXUkC54s9Rg0bwBEohcRwWeNP9ZS9Lj0KiqaFDzCmQmx1cgKQRWA4JwRR507kLUTqZHl1DCoafSBa4y5S0WtSRGAQgmb90ku8IJGjxYdCWAcZNR+fNuskhXMEp6VwSRn3vAlytn96WLnJBDiTMTkmI5cRRb2BYoPBmp0OVL9Mtew70CNGCtkEGJIYvcL/YVykQqJOlCy9kQJ1v8AhV6TzKHsUDIyBCjS/wDhKxeHxgYOICUyCseieJDCx7fhQ/BpDZJSnQlhmY5gMbHt/hKxe9JdVEwqJKHlkJgIIJJhb8X8KvbFdy4sIJoOeQRBUBSxK24v+ErF7T4HUFJ0akmHQEqcpD2/CgVhPIFhNSHLoCFecB7f4SsXgHPdMkxccwo/ggQCINgyXv8AhV095KSxbjpRPZAghVCwZr3/AAJYryKXE8GtneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneKMGWUVsskjE2puK9oLN0RJdH7rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3itneK2d4rZ3ihx+SaxFlrG8VOwvayTcwYLJ/dbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xWzvFbO8Vs7xQr3cgT7QNI1NPlVrIr/wBP4NA5edx1f+HZZXWknEfvy7Pp+D8d61fh5Luvv4Kbfp/iykZg777+OGw6f6q/6GOHG8af6qPqeAHG6af6qXSOALW/af6qDuWoDW7aU23T/irwl2VDvX363rSuyafowNSwKiD7V8jR8jR8jR8jQzQCSDifW/CqJIhL0UDIjBgKD9KOb2kBKSEpjQ5eSpeV0/Ppnbsqnfvv1seldu0/QlYZGJCEnk+kImktKIAxMV/2vwmE+hCnrsrWWij6212MI5Dxibxg0UDYe7g3s9Foa5zfLqEscYihRJKI2883al4ESgDNAJDUn0ElaiKJslsZoguQC5CMeFJpks6ITqKhkMRLqAWOLBxqcIAIJvGUc2Ch74EAcESyUZI0tm42vDWkgUCQ5Me+cKhEK9DBYsOQ0VZtwxN1ARZ9qUPpFZeCwPMkqKGJeBrYU4knpL0WJVXQJVyK40wTtnspSplFpiCG9cAtJjZgxl7fmrBt21bun3+S7lp+rb9Hq2561LiSZ0gEQ4QwILUaUjGyQZi7sTwjMsIAW0mQDKcCmEcFevM8cPdSlxx8RJOpVrcGaQPmtw11v2j0tZpzEh2EpFiwMIwpPgK4MggWkkua0leU7qQ4SvNVsmutv1V2Ot1q5G+ZS8Ets2OFKuQQlLwC8srteysEDkKR4NH5XyYCV9qx+lo34FrrGKrnQCoKSkxLMjUjzURB3TCiBoBE1hcB/NmoXuwrd8+/xXetH1bfo9W3PWgfCVDNc/cdKJkCVWAKuOcBddNFNFelSGcIPhTh1oD6FiAiTmzPos3DXW/aPS0S4SUCJi5Ho26a02TXW36q7HWTqSIRzE7X9WQoYeixrARIc4Cdz0OQSl1BYd3v+bMgOdrW7z9/Cva/0+rb9Hq256+jZH79GSt3GiyuyniOXUiZtEzapQUyQJkAxXIMcqAMvxAeDHOnKlys3DXW/aPotLG3TWmya62/VXY6+y+o8AuaMd0mtCASwsPUpmIKmM0M4zcs5TRKjDUTMiNwsCdJz/zZpEisIp7d9ROw5BlCRC0rjefRxpkafQTwsEE2kHemoSklSaKFD3cyQkI8xpT5kGQgEDGEjfGCpouhA805J5tFqCGDAAlCGQuWMRapH40dbEVBwStjNAFGY2ESeuobLaYSAaDKLjyInXDTHpNUkEY4SVxvPp4UQtdWyWYMpzI0U21zqIYWganYcgyJZka0Q17LkJA3kVDcSqWW8i0HrDWOQVHAqzgxEQEES4haGVkbRKXF2Y4Qz1Sk7SGAxZbISwZS4qtFeWgzmX/s/wA1daGUkjsX9wlFkONEirv5DRCm6DxlRfDu+giBULaUnFsYVM4/reZVcxjIwLawwHnCAGMmCUysy+zito0fh7Le8X3/AEdg/uksELBc7E6UxE3KF3oop5mDqlVyj7Ru3DR+H8tpxff7HYfwcLbDp/DzHbP2/wAG4CZt70/h9zsH7f4NEcDbXp/D7vYv0/d3QgxVgqTtmPlmpe6MlPYaxSc/6BrEltLV3yjjUeCcv+VTldIiICJ5VNZuo7rA4DScS5/86xzfGFMEDkf3XBZy/uKwc7+6VA3zaDXEwhJ2/AP2/afw972r9P29sS4VOAXH9+T2qeC+Z90DvUkRmEM+zSR4T4ukncdBj30mL5o/XVORTkB7LXGDTLvS8M8X9KjLjuAqGi7q4Vhg5P2NYWHM/wB1zIcwoNkU3U6ereVHHX5J+q40eb9DWLfeWGpi16X90mLVtEoYBZqGomyYeNajrNo/rag7boZ9tIaDzkr7tI/ir+1KQU45IiqCYbMXsParndhJH7we2TT+H9ez/p+1qbFmHXIWXpUEAtChPOL2muBFrl0Ie9QRN/70PdSDGuRfstZaUj9IaiV1nHdEPagDMYTuhDvQ4Wax+7xqDcyHsYn3qObT/wANZ2qHuTBb9w1B23DxRQQQYfzS99x8oVNyziAfcJqbWmcF0AVLTeUR3KkXQTvB+ipxPMm7uO9T6sdS9PBU+jsR/ukVmo2Qe4lQwVjPOo/aoI1Z5hXh+qnTOMF6taRjCQj3Mdn3TVumj8Py7do/ZyNDIAOK1Db45+2rJ3A1ONgHq1Ds7si0SMnOanguZZciWpUbpXmn9K4mRKOpD2qQDsf1R/aptg8u5j3oEAFgCA/vXojP+xJUuS5J2i7VdGaS+9TQgQv7DoVf6MBIcpL1FMHGg97spkTYst1J7FSyW0ST4TEcWKCpv/SB+4Ets0fh4PftH7IGNpRAGq1L3aRgnjM7l4U40MA76Q93Or7NknHIYHSp2uFbGpCPSag5sVHItA9GtTDBLojtoQV4CHQI+zlW6Bg8xqWBazHWILqNbZ8FumrYRB4ws6hU67RLbS0NRFmyWzhFfijTWG62/wAP3ArA2W3KJb7aS3/R+Hw9u0fsXwzMJdchqc/CLfMDL1TlTZeZD0Yx1RNaDKf6YektSHPFhHseHOiMKK89bydI+3qLRgJ0jZ0akcdwOiNhzWmsyxY1QIHFCrtIxA4BgnBqGy2SB4v6FBVsy96bvMk4/nUA4XunH7BdMyZ+ibvPDVpYV7RBuBfuOJVuw0pbQxXlQt1KCU5WDqHhUFFxYc6kIdCeNAAAQGAfdDG2UQOsMeslRC245yT9ik95QEKM1nzKeCsogDhieh6UflS8fTMOo9PtJjd9Pw9XunH+9i1ChE6Ga8C9LvXkZ5nbmZeBS3fNzd1oWQrzhON3ccCpuNIi6tu8pj7y+F5WDqOI8S9HZnSnkxjlLnU6b2MTGQsnEaah6DBHB9l3EqyRiS70S5zwcl+z+Nh0/D9ey8f7uP6lefAz4L6xSq7RgE5FY/bnNHPiAWvi4OPsalXBHuk36YaH33WkZodRxHiQ0CUpRgPa5GHitWTrMSnMT9jTsgwNDcOfjQMRhCRHBH7Ko3jT8qXtSKQoEzVpi4K9H3d5wwo/Ypsh9kd3IaCIKHFfY5r8sPwFUWIMGmL2HpGNImxTHAB2HotMS1yQzU4djwmasGsUtmgxE0fsljaNPykPsSuzmnIDNcgphd0LfTFjwYGWasNcAYWIOOmQ4tqyR4i71MVxfwNXdiwdEcaMMM3odc/AxOOWFUBs6IfpxKtcajyzqOTg85D7Ea2LT8oir0t44NDVWwZrTZWRPYd59sDisLmVPEune5WvQ58GgLABgfgwQDkSDWeWs6L4o9bcLi55j2xLlR3K8TnlqaOZ1D/CGUysybAlVgCnyx5G0NlcMTgvnTuZFsI8uXNzbawJQgBABkfTzgQzji2Kt5eKZMkRgjgmVllQ7Y5gYQXmgreXilyxWyqeBfB/CTHWMxA2aVe5j4RFw4/QghnMBtdL0VEigEC2MP4z+jAApYNmy1IxFmSTiFsP6bywidEs6CvLRKocD+eIgKNhzLRmZ44zKuMCZBJc5mI5PCSg3Ah00dEZEyT8w7LKblr/AGFve5Xweq7oOtWFq1qwPYOrk0HbIsAEB9bT8o2GALnqTrVwqBaBJs41CFAE43O3Om2seRqTvlW6a0VM0oFiq0F+wROS8goSSrFXs0Zf2xbMIuPPnh6KV4AIMRUJNCYzoqZ+Vez5UqYwISdEuYPBy9LDBl2CiVXApXZxccVKV1CsBXIUPQmF4MLl6NLusHbsmXnUO6PM4IQsWyrCIbMkDZ5qA91lQiBYF83JiYq/mshuaP3Vu9BIKMQbiaNKBVALq0yUkhhdJ48wTjTPqiCcVCPYNWGNDDn/AAOBJRYgSToF39GcVcB+X3JJ3p2qFDI92YpmYGYJj0etPwL4xo4sHGmplBP7A/ulUwAQF1LbmgapSAQUSJnQ3ZG7CwwyFH94GCpiVgKJmulmldBcLFBszkYhjVtktmSUOSSiIGmICRmh1M6DR5zYmhxbO01cRWO+ojcRsjco2zCcQlhbWoQJimCwSN70dKtvdxuSWgaN1I4CQiFlthypQfJHOILsc4eFTbOUAICVYpAG1mzaL+gjwLYPoZHFQ40+5H/w0d6tHp5ZCSRLH/JKPwjE86Iu6vrM5zwrJd4LiaXMinzCWrafLDzjV/MG2eGwa/15/PDgJtxqeBSK8MB4BAcqDcEZiZblFucuf8DQiLAaWYo5yOtShhPI3b2HrQACSE4XHZSKBJURMu4DpW6a0LBrw8EU2SVWXEogEHGRgVlteAEwZpGgt0sN8wMZ4LTmJfNM6BdavJuyIMk6xBwuyqIh8ZOWJVhb30GlUMnACYGccJIhjHCgi3NEhLDMSDjzelhi5O3BJEzgTGcUZFoG06nI4R1zo5ObCLNI8ymVuu6SzZwvW561ten0ER7shzJiQWBEHRQa3LWISKbog44JxsykGNYBJMiQzrBpT773rkQ9RDkDOni+Vkr3ZAQudyNRRCBFIQpcJMt4geqaUlbXgaSEdU+s4EZkAlXIpiMSw4sEauLxWoU4rLBcJZDWU42wpRKTqVs2MAic5UDQNAwlUjIUkNEqC+v1kRhwtdDNU0eG3bLyAAcJmk2FSABKhmM9IpXQYuiHQB09AbprBKQETDAjMgSlBcFSJFkcFUtfB6KJtVSRbYxRYsDYjHKJBSTF2DEiCJvZvUotndQOse2tk11t+qux13PS5Y6YuA0eaklaUI+BhQ4WCmkJUYupjlQi0NKCV9qYq+HMzHCBB3xaMYOxRLhIkNWZ4YUIlW2FhSEsyYxhklK3TX60pNGxd4hxGE5VPC40S4yJokI8SiFkIjK0vCSOQfYLmy8fw9xvGv8AXSC4wOkp1XtaPHWgshA+4eS/haGHikF39VlNqLwA6g+9GIUhGcVGWW/4H2/at01o7p9siCJWQk4qxqgVY2ahrMo8Wii6ZUqC0r7x6bkZ1jhxX/goyy6V17IbcfosJy/PEB+l+i0o3PWtr0+gkykIu1VX912P03CGqCBNhZf0e1J6FBtglzIs48aaSklIQkllEqOHEIrAAV+twIy6hEyaGAmZbQjVeLZ18mqUmRPCAg1Kkno1FYAhaRvSn68IcgwIG0pm9ohcG2ZXtJaIzdSkSgUtNsvUMCO8cT2f6D1UCOUN1xbz6Cdv1Vsmutv1V2OtBLLJlC7+nqlIojCVBBCck4R6Rltkrr2S24Vumv8AAGCy9DKK+aQ6KTBFK84OaXo+wGN04/h7jeNf67DyDmUEntOlQpo11CD+Is0dAIw1/YVPdL4aaXv9IndNaGsytMnur9lQssbA4BYyHHNrUUeJRGILKqNpiNaACghOLP4pWCQBKEC6PRlyqfqBCjF6QTlI4TU9A4QGwE2mJcAp+QbipiyjAFxy+qxi0o3PWtr0+ojex+m4XtCAmCyOhMZ1TWiExZgRagEC2s3wpAA5ZCblWRMascainRoBGKs6hjn9DgiFlIISx1r4nT4nR2VUDboXcmghhFCBQgaJCcGoFapWzERbiWaATBiALizaZi2F6VQpY5TIwWSHDBKMIhDWXnjNDUuAXDnCYQHKjzLsMKQSmUsscaAQijeDN5+sEMoUCdv1Vsmutv1V2OvsvqWHmFmcB/dOuzBGMMnwSBzqLUtvs0wgcs9SkCPtkjKmUwEaDjW6a/wLrQ6hkeYJ1pBIAXG/afsGjZtX8PtbRr/XVpLT0YCJX+DGtrpfZ0R+9aWul93TP61KID3QjkRD3VB6F+qgmU9lSPt1LINSMKjt8C3fEmf0p9pp5IuJmoJJJguRUjSZCcScPKawXUkRhIlZi64YRegSYCUkRM8mcMQpVpBpA2RMymJ/MKfgyxwR51Nj1lRwIz7lQsuah3IJxV1sVa4BpJTESfuhYqVVgvMtPQnnMabqE44mnBUcYHlGUxMUTXQ2psxMZpzhsMEQmLxhUfrJpWhExnDShJhIwRziWKcsDwUESUnXhRCZ0y4Y40umODh3jUqhJgDoE+4PNBDNnTeB3KW1RAyGExYEsB3ZX0JkSVHAOEk4a189r89r89qpvAYQhESzXKMG4LKF9RNcqnJG62OJh92gsygCJxYU4Ac8qJkCACAKVxB0JxIKm62ZWbZlGYS7kIdZ6UExSPtREEh9lyIinoRcciAXW1j71auaQ8wwmbsM6sZVAycEuuvoQWOnd4TjiYmnBUcYHlGUxMVI+3Usg1IwoL2YmwrOKcaU3osYQiJIoL2YmwrOKcacsDwUESUHm3kwDMy09PntRNIEXDAxo97XsLMLk3wlhJZEkDbkK0lYd6uAhmSCpniWICbBS41svVleO5/Be35AJDTNWjWySpl/6QfP97aNVb9q/h5rc9f6744k96lDAdQEP6/AUAiCNkaRgcxK/A4BZMbaIop/wSGAgDBAWG11pIZE/uXQpVerbgUWJBFHAEpjAS8Vj/COCgclp8FEzy/3tw1V2f8Ab+Hdqq3fX+u6hC1rOd19qGennOMfgSHL0DJzGkjaxQJ9igAP5LQJ/hNlEM8VTvRyrAmqA/dE7BgNA/vbDrrtf7fw7t39iOW8pY15J5lUZGIup3Yfa/10Tb1BWE8AulW9oNeLxJjFBhKlZCROnogAbSISm1Fg3KXFIucP5Z+TckgiAo1OpQEAvLzp222xjoF39GcUdJcKQgWLC4xeNWhdyLgkDE50v4Q4hhE/vlUcQTeQfsKKdkVtMS9/9/ueuuxft/Duyf2L5oG0YSpsjioc0qRZRHnW6ySsJ4xwJH2f6yzfFhxAYTha5qSClMAkXJCsHe5bzuuUSPTsmutv1ejHJh1cyCFwUacExCz1gNWE1FPswuhHiI0F4IGCODRknhptVbFPy5I+7CA9JrgLuVyAeifQDUqYIkTHKT3q4URCAPEtyxdmkcgipGAERLkMUSvYhRBg4tEbiJlBctAKHDzSpEyd6R0WjgbH1cA3sHD69FEDwWatruZC5APZPpaLEKmjQ3Vy1ICJS2I2M6IC1Cv9kHWKFvxgIODkvlrTGKMR8Se1YPA5ROjo8G/9YIoqw2Bt87JzBSRdL0uKynOXs/v7Xrrtn7fh3bKtv0f2FlFIDFdpZOCVCXkRxOlccOA/qzVM2gK/qnwnm6yo6EgcKwfwkkQ3WQ8Gnh03Gw7rnZ1PTZNdbfqqJuBQYmGDcDxXKjkBdANgFpUMEmDe1XKDpxcoYIkIlyZgUuNFi5VbVWgRIFWAI0uKWQiC0Gq/IYoNuSNTyZu6gW1aP8IYpgkSVCzi4kOMWBVNi2LwIj0c63TWj7O1FmTNrQS4SxjeBsWARGsJcDN6bihnxIhSnWgBqeBErQ8qIbCSEomR9HBVPvUMLRyWyeNEWYKDoV0RxtypY60ld2SzkI8qNsIoIJizhM+gkX+0t6DY1F5cEy029qGkMIakl+NS/Mc0m7BEiwC5sQTUEhcESgQylCOONPtySsfzsB/VCNBNXw+BGBxeDQNJgyQrryPdgzouAZ5BB/f3vXW04vw7tNW2aP7GacoYZZ5Nx4LR15VYSkR7jglOUeEc8i+Bk4v9O13FIsinuQ8SaRsqcFgiZyJnmFYxzoII56NTAfNAmCRg08pEiZFn2NbJrrb9VMY2oaKp/RQFEbWCA7vekERJGhIh7oDClRAQVCTGTlM0U8o1ILHK3pNwRNFldlUuNg9CP2FbprRbqBFxWmzD13bHp9FixxhDnWidz1EUz+kCCSAxjVd7tbprRji0Dwbv0egKLUMfRF/qRTDAt3gWa/8AXAqQJCZI/ZHdlxaZYbAL43Mz4oMvsGya63vF+Hibpo/sgxyxWB+jJzw0hUiAmDk8xzPJQZAC0+YsnPnIf0uEITa9n1d2kUHhlGCaK+oT1K3z4pM0AQ5S2okcmo8Q215Ad8U2TXW36qZit4TmLwkHNNaVnB8OQiwIRdt1Ug2CDi7TExLFfuCkvJIzXFqI454hHpNLyYyWNbzEaFNYKuswyGCVG6YFIB5pWzEhrToCVZIFHIHtrdNfoNu2PT0sHSkBHFM36I9f4HAMRwI43TX+sYEGdApVisgzXIpLK7KtqNVm9MqaE3CMeRaHub4BP2DdNX4hJJsmj+0YMAQsG5t+2LAPQLCb54tc/SUdSVXzm/8AoZ5T/QtSGdoEQl0GHpUC3ooAt2Iu4tHiwRwIA5B6RVHogNhOUodaSuABelsLNJS8NozDC1qEMus5Es240+F9kk5lxzEuJTGK3DgmBXO3Kok7ibxBCGsS6JjWGyZwDAKMeAE0YUAlLC2iBhfAsHlnRSK9BB1I50AIReB4hDmraNEHzAK5pzVutK+5stRi18VWJf3XLWw+j/Ka9graOCnIjUeEL9GoNADsFUm0lyUyohWQiI4gPehZhcjgRl6NCvYGIggjVPRUbKQQLkcKPAEVwWs8mlRspBAuRwo8ARXBazyaV9zZajFr4qsS/uuWthoE1bsQOXkqFewMRBBGqf0iwNJeaBz54GdXsi3o9XUz/QtSSUDYVkG/JiSEAgAgD7Dtmr8PE3vBWyaf7YSmJPsNHyaimYTMjMfOCUfYTih28bswpAIKJEz/AK7FDNlolSuIToK4TUC3qgRzlIj/AM5NFUCyRaA9klEyylYNlnVJDVSgAgID7OlxyMVahhyX5Y0uVYRYTY2BwP3TBskH+w766UAAACwGX2Lb9Vd8/Dra8Fb9p/uYPeHOQ/sdIb1hX0JeEvYekl6cShbBOxDJyxqAIJ/8hOJJx/rIIiSNS/CW9HOQ7KOD9GOyNKGVkGSIlYri3+zZ0wi60GK4AtFkfKWB4Rh5X4mFBFhoxzVg51Zw84y0D+1+WH2X7un4dbzgra9P92KZYwNEau6/+yv692VR0cUN2Si2igAD2+Yh4ND81246JdcEPvZ5wk3nFocK+LPZDzMHOpxFuZiXAWDgFPsXAhZ5OHnfhnV+z0N1qm64v2Y7v34dd8/Str0/34Gwj2TbnLDUphELxIPZ3uFTTdJZWaP2NQ6BaALjZ6HQ0JgqZOrcDnEfd3RdgHkBivAvRamBChxxXXoagRzLo5LY6FYKGZgGuNzMHGofsYPwDyvqv2fc9fw813L9lb3p+wviMx7Cm7yZOFQ5W4oJwf8AhyqT/oDLqYPWsBpsAnAXniKEW0E8XAWjjQM75DBwSz9xBEAEq5Vw6yJtEMOrNS0GxEhzSHs86m02CGyDF6FYy5QyjgLnVTPilonUfoJ4/ado1/D7Xev2VsOn7GgyVBzFiPEp1u3JeWYDnTovRmrFxyFXY7KIdgepUVZx9zsK9lYfzW0utDmlYLAhN1LfaxaRKwA4rWhXxJ4Qs6isr7HXFoHq0sGLMf07sqZksTh84u6nRIxQl5Ifrqo/HcQdU56Jj7XvGv4e47v+yth0fZs72Av6sC9ZpM3xOezTols2uJDmFKXlCY8JEa0Q8yjYStSS2CAvHAe7UERZSzqD2NEE7A6dT7GNRpUgKhWaoc6JNOtQQvBV9buxUG34Nl4ynsFXKJIEcg2OlS3DL9Nu6s3jquWqAeRTXt6uayseQokIBABAH23YNfw/h3f9lbho+0thIRBjywujUigwgnShBFMErdGaJJiFD/dO9QWLKDqXqHFcZR1D3VFjmKk94dqjxtnGdZXaooS6I6sO9Qs04CfsP9ktRTGxe6VPyBkJOpSp/JNEerLtUwaV2CP2qAEv/dh7quW6ZhPdqdYbfoqD3q+AYlh4Ez3SopvdI/BxeyU/gfQ7309/uO5a/h5TftSto0fbSkfckuSklSZ3iJ2gPauCEEn1D9VOuRhfaId6mrDmP7msk6yXuVD2XC1ezUVZNP8AS1GWzQzVAhXAr3UGDWIXZf7qM3x4xURI8UdlUFuZlNbtzwdYCeQ/dcE640F/6f8AFJf9P+KxToD8ViZ5n9UwlvSj2n/iFTnSL+zU11h+lUCRmkDseVTPBfENJ6/aDHvpOXfZFUzDOID3an+mYXsVHTMBLdYFWd7jDD2UVxMk9hRZFsZB7CkowKDe9L3/AMEHF27U+56HQksiSNSqizb3RNSi6zhuhDtUyqZSDu1O8H8Y0kOHeFVTaLxL96l+nR+hWyKcTWMDbWpj7ci/poGPTTUtg4FBYFzgfakAG26JEsGVysE6wVh/Xh+6w5bS9MWJ1PWL6xP1NRSJoo7eVQnFvKpUVxXzlEQ5gHsk+9Q6o/8Aw0DtUJEsF7oi0KCsBD2P8J2H2TU/1XRPHN37pw/wY5vC7pw/D1ey8P8ABrl+runD/JRbbzdLPpMoECzI19cGB+2sDBgwYECBAgRcuXLlaNGjRgyZMmTPnz58+379+/OVKlSpUqVKlSoVD9SAI6gpPX/Joe2xdaJw58O3R+2vhn/K+Ef8r4R/yvhH/K+Ef8r4R/yvjn/K+Of8r45/yvjn/K+Of8re/wDlb3/yt7/5W9/8rY/+Vsf/ACtj/wCVsf8Aytj/AOVsv/K2X/lbL/ytl/5Wy/8AK3H/AJ9MUUUXDrcP36cP36cP36cH36cH36cH36cH36cH36bTpvOm86bzpvOnH92nG92nG92nGBmQCHkn+Sr7Abont3+fA+Sjc9f68T278+Ny0/ACQjYdf6+R278+Ng0++2nJ9BVbrmEMFHYF0WPN2dT0cYuy9FOgVPdaVQdgMbxL9GgIHMYdxfeQQXUf6kjs358bxp99Ma2QBkyp1hPGgwyY0DIBAgQRMTC+9Om9JjDiSZU1VsVJ6tXWJdLKkLmhyX+ro7F+fG8affVEcBMBOd0APSlgrnmIT3PowfHSXJA9XoJ/V0di/PjaNPv3i19gxYEH3k4p6plhAWXfpBelCowJQIA6H9GQkDCwsTTxFxxLCFZJHBaLknpo7F6BXngTOkPAU95hBcJsZmfH873HT78Y0W8rxqByeohxFcTkh2T/AE2XQ4WIA9TqLWBnpj7s9lMIYZYoDMCcCpljPjE2AmJWYHYXnAdqvsS6WVIXNDlP55u+n38xoaALAn2II0ilbALiiA92oR0xOf1EvX+nZgtsumyOcHNPptgGZLkgevsJ/nZ2DGQVpdUA6R1FX1L2LMh7CXBD+rfQ9osO2bAPWc8QFlX6QWhNYKIEAdD/ADb4EdIep/tUrbNN+2syugjs1iR5H6UpfoD8Upmb0EIR5KehpyZwlwEcxrAOuNMAexjTdhsLtdx6fqkdeND9H+hf6tUuwnsZcD1Y6VwmVkOsJ4fnrb9X3Lk9IcSA6tOIwYk06TqXAmSAfeu1Fk04/YX7phMjKN1YdqkhRkfdT3qRhziCdxTCtu6WlZFVdaj75rv0V3WJ+iv2yP8AdArdYqHw6qKQx6NcQ6aV+0Y/RXZk9Ox5v2UiARMmkRTMLB7NRMQMAHsqVBAbU/Vl3qMM4TnYO1Fg15/cX7qNzcUjrJ2pINsjD1IVwC8z3H+A8SC4AhPZqb9cw4/UQ9aS8I+KID3aiyRIEZ3US9fz3bNX24k2XQmYOWJ6FOCBg9xi+w1LiLHMq0D2ahD/ACYepH3akz+abq0OL/Av3iO9QC6+HS7VEcct3vSEn8/N0g7LoJqhbRr/AHmoiRMzPvFdv4/T+OIE6F+1Bt52CVP37X/cVJzjmj9qFKs6wPZO9TLpx3w/RU9DmjL2ULXHpoe4UMoW8pZ+yo5lSPdJlMhzFEOotE+KxADqRRBMFHI9rs+mHEVwOanZNL40mZZlPYS4P583TV9rlOY72KaJKXRSIM089p0qKbRsU5rSxzTMLyJaLyIv2pHtQJR4N7NSefAnBe1ABB5t+4f28pAQD2RqfMaY6H9KFR8Q68JsezQAivbIbUE1dpkEC8lIelRbCqGe92U9gGWc1GR6UU3KW6oMbSiRNRqJ4QrLv0gPSjIz4b8CeA6H59smr7RuSZLh5AxXgTSRgsT80NjnRXO6rej5Cp5+YUdYs6tTFC6XScBzFrh69na9w1goCEXQI+xi0iBiJxGtfGqZxhd1GtOgdoSL0VpB8/tg6w0UEmWaOLle1Rc4CkcykPROVDI3mTq3D1iPz7ZNf2Y9KYCWZ5Dd9qj3e0Q3Eu6nsqW7oFm0MXoUNeokyzgLnVQM53YZeAwc550OnYEBoBh9pQSG5R2mZy6oEnMaJM97AHCXuHKpfughMkwepUeALTEuHiLxKABHMAuRhzJ/PN+1/ZPxSTh4ObTmJXV+8V/fsq374mU0MV5UPJsNs3F/6uoUHUiAde79MOH29ix4S3iWK4iNDCY4/oeIdaknuAqtghicRpMiQJ2ObbrvxpsXtJCaJdc/7Ex9jcCJxoxMfo000i/PDSWSMN8KgusEErh/E+TjDKIzNa+DjDKZyNPXPBt9BYgrgPrpo6Y4ef0gL0/hBv0usaBmrkF2nM0xA81nsqGUqdwDF7NkwX7DnmOyRMSo45P0aaaKXICPD6S/PJodWlLkBHhXycYZRGZrXwcYZTORp/IX55NDq0pcgI8Pr2vX9jHZwcC5y7j0GpfRZl8mZvFloQ9yLd7pxQaThVs9HuJo4EHD+HfPmt8+aLBs4mE9lJF+CirRLmDwcp/jLsoHILJ50opbAwIvHKor4A7A2nnRc6siDkx9ONFONLoGK8C9E+gXQTMZSp5NI9xKClGdIwc9IQtbn/RVgcAutQuuIlAHmcDuw+zwaLKOAtMN1WTglQsXaWG43B4ui/2BMuWqoJC2Iv6lSqTrIMgUlpiTSmB0ITQM/wA1m7HWyyDCJBJRNmVJUZqb70BmZaJMwxiMN+GpS5mJZlpLMSFztN5f4A2xxziJjyGHNoF5lQmGVQADS85RcWUhFrIAYDL7EJb690ysgjFZ+pUq0cRqOB9NnjkTFNCeOLm1uGlc2euwuYZmMq5M9djcgxE5/wAlnjkTFNCeOLm1uGn17Xr+xBgONGc89WnJi6MaHGTG+QGlGG8Y8cf3YGU4/wAi84wRig6UmNc+RcEYYLpBYccKG2oWyACZxicQowISiA5tYddHj0Gk6ZBhel3dFEO+DA1ExrMouHkFl6U56YYPoDd6euLFZ0ELfpT4cJnI5uaOPqDcQXSQxwEXvlSNhGIxM7W9HIdEgNEJjrSQFQcNUMlYrKBAdWobEBDKDISlYzo72TBXQWmlOLYQipDJR1vLCzEubKkYdisOi1cTUQB7no6PIAI8SaLG0okTUaAorAUXQlu0kdAVCciYl5fyHQZkiyMhxxO1XKJFOUzR3M4aBKBhzDRd9daESRkf6wkvv3qTQKJfSJNl60EKwEsAvSmpECCZWoX0KKCQ9FsOrNBSGDJrRteomDJQajeGYjCoXSAUH2AkYyJqVlAtpAyaSKjKYypF6WAp4EG0kQ0h4UPDuHOAAFJwMJpzULiDOSkNS/GhPQBAFJhLC3ELSSRMH0M3Y/X3BlAbkzs63MaI500TGWUl7KFGWopwUjNUQYSK4QywMBJcAWDOA9qPD6XE8SlCYmMI1e8ibKWJOYiI6JnNGdoToEKImkT2P/HVZJIxjMYKI4VOYSEGMs9a49nHl8yJ0rtfNN44mMTQbA2oTGFxWIxVKkj/AMEljGDOBbhnUnwlzC2MbvSaStoqS6i44psWiiSNRkQkR0ih63W8bAEAqTdzKwYi4iy4e6yGmdPEDYYwf+UlixOCLBgyCXpicAki0FwLjdeS2APPVNGGFdnrzL3oa067AurASkBQTGacpS1ETiOjecGjkLAiMrhYbDHFnSdm2QCxi2WUAbYuUKpWQY0gIMOBgUTsnGCMDChi03zNaX8eTFykhaChjhTvMmonZUSUm2xPC+xlWCIteYBDYbOFzQgwxAKRh1+8A7cDEmETafS0guEdhjA5l2LMYg9iNniMJGYlKJVQrG4LuIdRLUt99OIOTojZNSkQgag1uILEXYmYYo3hGgYxNwYQXyoYGJrf8QDNTYtFDgMISI4J9AnA7YkV1GwbPppHHK+xgSkOrVs3PTAKvsUMniCSaWFxdWxfAqK6V4R3ZMulBLeajbTrwdETaaTTaa89xmROtcTLXnOeNfvorO7jRFdH8L2XCYlidWur+F7rjEwTGhSihRb7GZExL70+MUBVMZGCche2JLXzlMSChHHGM6Q4t+yV5N4sBbQGGEwblbBMkoI0hS2oMtMM8yMbYxDwRixjYAlalGcoOYHGsNBYDNdWYvlOMwu9JqXChUCd2eBws50ziYu+w8yJ1riZa85zxr99FZ3caIp+WOEo5qEljFQ1SF+E8DysodrFpio4WnAudhTvfGKYNQTsLhNewxoiXiX02vX9hzCkwI3nzceRli5S/wDWgsXnJjNWjQBRdHaRnnlH8hCJAR0nGjoRFCoA2F1mMIL0eIUYrBPn0aFlPSZxLiCTiFQhZwILe3FHGyONQ7HXYFYZDzsJvQHfWN9iuReAHIinzTAdksCrVBI54Vf8h2TCVcyCScITCAOqEjPQHhLLwGonalebBkBLoA1ALuO4uShMgilr2xiQuNYE/Q4EaNySCLBuyBjqqOF5nhwUegdyk5WvSH44MAONhBmYnJGkNaBjJBGEByxHKgTFuwBMPIUtQBYoqWRqvWxhQWGc1JT2jPCkOOwBeQfvHOsVyxwFjmsHWnGpAjDsMl0qJkmWIDgTDkDQfEN3A7rpw3dbo56MExAli8tmLxjCkIuByFeRGSkYv8gIEvYahyeznNJRv4J4gzMuJDUxqBS7ybTVlhhEf1ROTpSaQTJGKemnA7YkVlW4LFbhpW76PUdAOcAx4zd40boCMziH905bYQcUT+ij6zFCLxgubBNXWznBVVwxLk0gn6U8QSwEWWjr9TM3Y63bYm5rElDFi3CjI+onO6UmZaCV7tl5qHQhlo4jgFjq50nYNmRQOsvWoaiE6aZJFiYm9gpVKExxiQjBbTVUcJsI+5Oytv0UtknQCSE5h09FBQlLb446kSFuFbfo9BLPwaMmMe76FRY0hMhPYB19DkgaghBzXzKnQAClsD0LTlW561ia08yCcYgMarQNDIwhdBm6+gz1ggAg/VGxAlwarPdoKrOy2JyMnF1pbBB+BGnYqCLmk6f9akN6qJ1icIStpxaZAULvMrIKcpyi1L3E9RCYwAQ4XwL1t+qtk10gJRckdA5Nnq0K9vsEQntSXQyRMJhTBolGhvdFG+DxzZh7TRlhQAgDQoUM94yBQTMQY5FAQR1JlmUuZTPV9SllECoxERn6CHAIBJDCBvJwxa/VcX6FAS317plZBGKz9Cq8OxWDeBBPWocYpbC2A9Yp70xilCg4KJjfKjhCjAfakqwhSSYEVdbJDkFBrUAgAwArd9Vbhp6s26a0fOTBcVwoUwKknJi/S1kXylKi6mikAiCNkaKKHEzALFGoWAuChsiMUbQ8OAwtkssQDDOKDkKhzQiR5WpG1ooRGDhet+0Vu+qtw0pQZBsLCTfCpkpjMyuEbFZz50FKXq44BIk2nIoxLSIwF6AOr673r+wdiQuOcUtPAxeBqlLNesUN8AqBpQMxf1O+PA/lFMIGIbjjQUMsI84syoLKYVRSGSSotMECnH0aAN4s2Ye00AAAEAZUySLlWUifY7tPKWiABgvxVRLeC8UBYeNJhc5xEHUU60Ec/wCYD9qlMAZyjl54Or6DcJbCISfdfQ4EbrdtTdV/dBABZkAH6pIRgcWpgdYe1QUckwxhYH0gg2MDYTlNsU+wnhNWpGIiWBNQVjUKILbHvhJ7pHNV9CTMIZRxIFTc2+4wn70uCgQTdKdY9lIn0iNGyY1aX5ahP1TNSEjqfyQ0/I8m2Sf9GzV5YQyEd12RMqjDGKXwjjSw9HP+qJ7L6m4aVu+j6O60bJpocMB25hZrLHIKcrWoohIubLZMakez6IJIVdtLr9TM3Y/p9wqouLYiDtQs8AlAogpgCXaWLrbkTEJupzDm6QZs3szrb9HqJ2/R6CVgqwaBoDqVrmMhxifR9IwktMCbPYUZcdNz9lW56+jdw0+oEMJ2/VR8NEVLiDNAGl9WgC0qMJTFOI2IyvlTM7LJbZFFE2MMOFbfqrZNdbfqrcNPQfJD9ZYPesM45kOXQn0hWRWZQDDM4sMEpnzOq2UAAvSlzCwEyBFELpiehUUa44HAw3Bue9NemIVS3AR0+sQGCjUEcsF3VtUNYhxIlUCwamFKm03dB1p9lStyhuhcQ6I0i6kYiG7qSetbvqrcNPVm3TX6TAg931U70CNJgVxwBp6ZU/CWTdQOOLQNyeQF6SOY0mU6AATwAtERhW/aK3fVW4aUYkWUxH7LpkiCJxACnG8c6j3utQLAuKBtwasYs2krMLgs8fXc9f2DtKgYBsD3xE6CpxMaHD5iyHAdf59+0fQ3c9fRZSs3RR7ge2pSr4yrwHJlTHmsduwAZqoBTogFIzchAm040f68CXS9w61OZc2CQJ4kDVgzoraqEAMVcinzlXCQnUD1+hwI1iLIHNpXVD1pm6cqYgG5Bqce6zFa6HFsWydKOFogSCwwwxWzNfqBAsYsCGyWEs9i8hQu3gmUDFxVXWuvaHjh5W5BT4rCaFL1DrQ81xpJ+oVPJ0uXT4BLR45X2jACwleNEYgIDQ/lkRgQuPIFuIcaleZUkSWXmT1hoSA55CR9n6kcLyjpjfrhxplp2BG4hsebQsPJI4iMglAILfyCey+puGlbvo+jutGyaaXWCOQwjQICLmppV8/JeVllYKrDN6ktEsDls7BYnNzXaaGJzzgJzxdH6Wbsf0+5gsd9hc1JG2KJGAMyXalgSwIloSeZViWKG5dxFWCVVsZFB2IG4lcLLdVM2LwNbfo9RO36PQSCaRzCDI8RB7VGzmbLkmAYxV+EUqk9xdd1OkBEkk3tiY7OsOPEuZp5CCtz19G7hp9QIYTt+qhIuGZHBoKBOTdiUnE+ojFkCdJjhdpwsHNCDDuFJ7mKLwnJuLId3pWya62/VW4aerEHlnmypGAywRA3xFZ8MIgJCY1RaOXCCOwLCACxoQDhRY2wMS6HFVjpUPYewD7obC2SLzISsPSAyuBJqiuc09J2IplGC3sLuVXCxvFAxeLi8X6BJsvXglWAAlV6+sSINpmG/vDiIScyh+nPZBkcCbXV9SiqhIn1cF7pTKiY+Lqi06DkEUZKTDigiXi41BCnFlE9RO8mI0K6d2hwpSVGAY+rNumv0mBB7vqowuFeEKeABoNMLpChsMk6ialEZsgzrMpQvdIjUo7EKaSAQxezQWENFmFD0CdKghTiyieoneTEaFdO7Q4UpKjAMaGmNJAnuzcxuc0zqdlAJyGGAnJGpy9hxu2IuQSsXiJZwnJkypvogKZAZyHpsOv++WWUNbMUboh6UyCZ6QW/QS9KBkOeQgPY/m2v/VNGTDJAJ64pBzkyKtuvEA3W/oHSaIO48R97mdXhGlsa53nHNpSsZZ9yWwTxahw1IiFIQWUWtYFuza9f14kTJydHJq8I5YjLGI1w0aRkcCbjk8t3CrxihAIGJNiZg0zcaxi0xqb9JWA9GQQJL1ikHODJqdEj2AwJwBgLZwUghaU79XWwpbEmkcV7UmWYhoHlUibK5FxhlgAZAY1Yk9XGCi6IuBiGYtQBVFuApMEDFyQbznRX00UoSW9D4uDkogs+iCrIFhFOxUJ1VoJaxZgOS+kieMxwTRGEdQpcULiEyLaGuGjUriF6IYNl4c+apqNsLIlGJCYL3ZYSP57DWmFgbA5AcoqVaJll/wCwnkeqAqALq5VLDYWyPsuivCsBAppZxV6FezJyrVatNB3BBY8Gzr/XJkCESRKuPiYT2if5SgZgvnsadsuI19h/AUNIBInEo6OMhEOs3UBAAQAQB/GgiJI0ACBdS64k0AEBAfwfLu3GVYPPDDkHogEQRsjV0G3LLWbqHL0DByD+G12gZHmNcW059rNMKthgcg9C4YySlyDWf1uwfxYVEDp0DTphZXroD1LhjJKXINZ/W7B6FgjAP7GmVUcb/wCw+jYdf98srsSOJaPd9lEpUmdXgf3+AI76iHsdypR27NUQ/asTcZuVLnwqCUWJydQ8BzoVLhRwR5H6A9xdnpPJT5lXzKvmVfMq+ZV8yr5lXzKvmVfMq+ZV8yr5lXzKvmVfMq+ZV8yr5lXzKvmVfMq+ZV8yr5l+KkEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEMMMMMMMMMMMMMMMMMMMMMMMMMMMAyFRCgJcsf79aIMAvOx+mgKxzORL+z7+BmNDkTfspC4BXl8VN0soD4BZPJThT3LM7VS/QPpQ2uKhQWUZj3/AC8QIECBAgQIECBAgQIECBAgQIECBAgRw48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48ePHjx48cOHDhw4cOHDhw4cOHDhw4cOHDhw4cOHDhnn/KgFYJNj+9MWVGhL3okcIrqkXUTr/VQ2VwsokF2w+kIbLOUuRgJxekQOhKElwmCNJcyAygBLZd/gQ2VwsokF2w0pvXDCBLAun0pWGQmAlY5FJcyAygBLZd/rdIMwRSsywLqzP09z0QREkagzFLE33XsPGsSCoYBxV3qo0j5MjRHD0kNPPFgOonX/DYpCYuEMroB6UbQ4gvNQ8kpuSOCZyk4iI8v6qhSigBKuhVjI+a2b7D19EdngZm0uhX4fRaCImAAv0GiW4Sj6VChICYgMf2FloQjKEAGK1KMwdyt8kx1LUoMCcQAPsXV+lpGkCdOYekxWZmxjlBu6nNRf99QRJDgLYklSvmHATDx/wANgC4CWAv7DqpdZo1kt0WdTj/VUECBEkaCSJ9bPaPOjIBy2jpEYFTWssXvPp6WlAVYClCsUKPEYpMIul1vBHmkODUGN8liZIoIgbyw0lmGSDLEpcUnwRYvE7iOdTBLKG7FriqITay5QixUvGM5uDOCdYofAWA74ShSsWmLmfoozuyowGRm5Bm1e5RjE2ABjcbaBQYIc6m3jmYZxT9byZGRdWS3m15t/WWWs9mZdcTnh5TqVOscXItydVA5zlQhBAEAGR9eBPdm6NK0MDEkpKWJVjj/AIbZJnDiOKGGltS1pm1o9mTEoD8OnDMeUxM8dY/pqAiBVMCqbAk2UBR2vWoPmQ1uAo85aW9QKL2Yc+16WkNAKoSBI6gnpR6QCkMoNG15+lm4QLspuSUIBW+2GQOfaKWK2Wg/YTrR9R0zT9juKl2nnEaU7OS+ihfI4pxHYtUCDIQMJIMYPWmwkewJCJkoKhS8QkfOxRgoDHBb5/q2kTvibF2DnrgUp+VCUoAPYDAKsP7nkbF4kHVz/wAXkqIwsXcWemPMthERkFwGWYlE/UPjQcODg5af1FCieqVppEnkv3pVMibOFnOFSRQ76+gC1ImAWm3dRQlxwCgC8JPoYBOjcUF5qjmpfscmCkg5R9yoZBOjED9DpSW+coGB6jrRYuJs4Dr6FA0rwmk3ujrSfcGDlBccy9GkSoBdU0iJE5L5WgOJ71jmjUskJ6H9S0RWedAN/wCjlmgU+gEt2BsDICrjJNccwOPNywM5/wAYg0KX5NH9HtFMlvt57hfszimSPBbDa0ccKMQ8nJ/7wy/oM2AAEq0N3AVIDkVAmCCTIKDVA60F4tMQoDLjTRoUGSgdqPlEVIDkUOAyBIjiNJ0FYp9HFDLRjDVo7ylMLEn3USKwKDwCAGAORTDYhwVCUywAMgC+NNhDeC7N2hlLxfUVIymdyGA8ImpD7tEOV8CBwTw8WByllu4CpAcii9VqESsQnMQTiFRpOW8BMA6q+pDe+CUrCGWYJ4CicDzoXAccEuESF8ECKhAzoPlEVIDkf0StqoQAxVq+miyeQcXFbSaBtot1zFV7rYrCTILm4mvV0Gc/41erGFi6mK4lJjBKkDwsQ0dQqX5J3WakOjR71QYk7PKHBaEQREbif1s/idxEowIQCA5HriV6BOUlDUaAIA9QztCEj0q+0Jh/cH9PJApwXjw676DV5AShOGeL520CokpBCOoM/A6pVrUhFee5HBbrf/HnSSivf9/Eh1mnADY9vcjwYeFc+gBHVPQhwaPVazIThgOgoX1yYg1Ex+3DDW0oDp+wZ4UWBaSIvcok9zKOJmlhxWkTfAkH4se04NFIwOAYAGB/kA9whANEcSptneCd3dSDSmuWR+ql+gUJlqVeumOsTSxhYLydU/XRU+ZJnD9rs+02YbJAdwehRWEw99DFyShmPzg2jFxzNQ+AwJ1LA5TNTj40qHCyunU1gDJKOdsXi3/yRBESRpbFBINdWEvaeNKHq4nsKW0VMp0im2ZOPMrpGJ2k2DklTAegO3HuoEZvbNphF5LRY2lEicH7FAMQIl772qNA2Cc0CV6xXHPhvfPsSoMyYAr3WsbqGVDgLzwoxzewC8BaOCoR0IQDQCx/lOCShm6Nqk4l814zEcCKjPGEzdGexU4xEb7l3VLZTKCvMGHrUIctAjHVe81x4Qc+gUjX/oEA91Dkm/8ADBk/srAbP9olQgdrfoP2qaKwBHO0v1QGROG9WlDBjgw9mOysQvhSHNCDrU8gxLRwlPcUyQ8ZDQWBpCH1ku9f8wcxICp7XdUkJwBDoKIw1gIulnepYFwkPRr2rJjUs9kqPjzAP9hqICOqOrLvQIZwV7qQ7UKDWoHZf7qJnuAD3FRvWZ5VGT2xk1ER+V+8V3MDTuQnzQsjcE80Ng3If9pHEeYrBhz/AO1dmF+a7AVpiG3VlqckRtUoJ6J/0KmhjUF73tQpNKB2D/dEoQ5kOw7VOCP/ANYp71OCr5kitRiA3QrR2EH7oqfA4ovoIo8BMULni7lTLAxU2szjpQ1GgCAP83bPeISPSpxYYlroD3qfXGf6qFMLp5B+xSR4WfoKJBMynuzTLDs/1kNTkuND9zUjFasPvTsbf9ld0EPFIoCPE9QVgJa7kK0xHOj4ruIGkVBnZspAvTOA6X9qiev6PcqB415OkXxnz7SNtesTVFqEwCjrNoiPZcex/o+NWasn+Wn/2Q==)

Fig. 14.15 Splitting of Data

**Overfitting and Underfitting in Machine Learning**

In machine learning, two common issues that can affect a model's performance are overfitting and underfitting. The main aim for any machine learning model is to be able to generalize well. Generalization refers to the model's ability to accurately respond to new, unseen input after being trained on a dataset. Therefore, to ensure a model performs effectively, it's important to check for overfitting and underfitting, which indicate whether the model is generalizing correctly.

Before diving into overfitting and underfitting, let's clarify some basic concepts that are key to understanding these issues:

* **Signal:** This is the real pattern in the data that a machine learning model uses to learn.
* **Noise:** This refers to unnecessary or irrelevant information in the data that can lower the model's performance.
* **Bias:** This is an error in predictions caused by oversimplifying the algorithms in machine learning. It's essentially the gap between what the model predicts and the actual results.
* **Variance:** This happens when a machine learning model works well with its training data but fails to perform effectively with new, unseen data (the test dataset).

**Overfitting**

Overfitting happens when a machine learning model learns too much from the training data, including its errors and irrelevant details (noise). This makes the model less effective and accurate because it's too focused on the specific data it was trained on, rather than being adaptable to new data. An overfitted model usually has low bias but high variance. The risk of overfitting grows the more we train the model, as it starts to reflect the training data too closely.

Overfitting is a major issue encountered in Supervised Learning.

**Example:** The concept of the overfitting can be understood by the below graph of the linear regression output:

![A line graph with a line going up

Description automatically generated with medium confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIA64HcgMBIgACEQEDEQH/xAAcAAEBAQADAQEBAAAAAAAAAAAABgcDBAUCAQj/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAAB1QAAELz9fnLQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhOfg54tBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhOfg54tBQAAABNyxprp9wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHhHX58Q+o/ot0e9QAAAAAAAAAACNsvgzxoQx/ko+ePPaEqUr/AI+wAADBPM0qAi60nwfeoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB53o/h/PfHc1se32IS7oAAAAAAAAAAAACE5+Dni0FAAAAfGHbHiEf0A4+SgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD4+wAAAAAAAAABO0Wanu1vFyme1XrZaao4+QAAAAAAAAAAAAhOfg54tBQAAAE/B1vEe37MbZAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADFdo/ns/Nqw7W4sxQAAAAAAAAHzmtPxFUB5npjN9Ii+6U4AAAAAAAAAAAITn4OeLQUAAABA18JpJnGkZppYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAyu+mia1jzfDLYAAAAAAAAA+DN9IzbTAABmGn9Y+e3l2ogAAAAAAAAAAEJz8HPFoKAAAAzXSs10ozTS88uzsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHRILRYHRBmGnw5cPI9cAAAAAAAAS9RmZS0/z9AAAE55dvnRoryfWAAAAAAAAAAITn4OeLQUAAAPwzbSs10olO33pguQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAM5vs9L7uA6/YGb6RmekHIAAAAAAADjzig5ykAAAA+PsZXqPmSBooAAAAAAAEVajNWlDGfuo548lpSo6xAAB0u74ZO30hXn5m2lZoaWAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAfBCVULpwABPdGvzA08AAAAAAA4jN9LzjSQAAAABEW4nKPLtHO0AAAAAAAACE5+Dni0FAAAJSrhT2/f8/wBAZppcEXro94AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIfOjfUdYgAAAAAAACLs8vLT3QAAQN90zi9HO9EAAAAAAEjXZkVlD+foAAAAAB1M70+YKdF2gAAAAAAABCc/BzxaCgAAGb6RmppH0CbpOoeHT5/oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABjUttWbR6Guwt1QAAAAAAAEt+y2oH6AAADMdMmRUAAAAAA4c99f0z3gAAAAAAAZv3+DMY3n1cG3mgAAAAAAITn4OeLQUAAAzXSs1NKABmml5ppYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAPwz+zz7TzNbju5eaq+PsAAAAAAeD72YHt2nx9gAAAHzmenZ2aI6fcAAAAB1zOdNzrRgAAAAAAACWx7+iuMyXXgAAAAAAAhOfg54tBQAADNdBhjQgAZto8XQnqgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATtFmZ71d8fY8n1hnOjRnaKkAAAAAHly3S0M5wAAAAPO9EQF/mGngAAACLtMxLP2wAAAAAAAAAAAAAAAAAhOfg54tBQAAHj+J3OQowAeF51RAGigAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA4M99P3D2gAMy03hOt38r1I+gAAAOn3M7PzRel3QAAAAACQ73vZsaYAAADqwvd989gAAAAAAAAAAAAAAACVquoR6sGY8nq80fasV49P1e0AARNFHaAcoAGaaXmhpYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB5RC6fCXYAAB40rocQW6apQAADhzrv0x6wAAAAAAGb6R5B3+xDXIAAOmZ7p2e6EAAAAAAAAAAAAAAAAAAQnPwc8WgoAADNdKzXSgABnOjSBVcvh+4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHW8k98AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADOtDzQ0PtAAAABmGhcuaGpvz9AHz9Rp4Wnz9AAAAAAAAAZhp8T7h7QAELdZiXPqgAAAAAAAAAAAAAAAAABCc/BzxaCgAAM10rNdKAAHk+t8kZa5tpIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABhvh0M9GrXGN6fXqgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAl/wBmNMPoAAAADw/cGf6BCeyUQPzL6rjKsAAAAAAAAHDnmk5oaW4uUA6MbyVR6QAAAAAAAAAAAAAAAAAAITn4OeLQUAA4uXyyN0aItwAADNNLzTSwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACZ6PmaCfeeaMIu0mJc091+wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOp24M62i+Z6YAAAAAB+ZfqPVPzt5Z7p4unxVsAAAAAAAAAPB94RtlmGng88gdOgb4AAAAAAAAAAAAAAAAAAAhOfg54tBQACco407dP4/sAAAGfW3hcpRgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHTM+03PtBAHS7oyy192CL5A3p+gAAAAAAAAAAAAAAAAAAAAAAAAAAAAZhaeMWgAAAAAAAMdk7mGi/0/O9EoAAAAAAAAACDqezCGiwF/mJfegAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAZ7oWamg9kAAAOhJXmaGlgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAARtlmZY+3+foAAB4MVqfXOLu5jTlOAAAAAAAAAAAAAAAAAAA647AAAAAAABxmdaHnWlgAAAAAAAH553pAAAAAAAAAAABmWmyh60zF6me4AAAAAAAAAAAAAAAAAB1+xJFEix8801yRqKLVb9iVqgBmulZqaUAAABmml5oaW/P0AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/M0s/ELQAAAACLtBnNP5OTRv8A3/593+vsAAAAAAAAAAAAAAADod/yTEPrrfMf0F3PK9WgAAAAAEhX5gV9AAAAAAAAAAAAAAAAAAAAADKNXhTK6qY0aNFFAAAAAAAAAAAAAAAAAAAQnPwc8WgoABmukZyaQAAABC3U8eh6MrVAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEBYwGmgAAAAAE7iv8ARnnmJb3mGogAAAAAAAAAAAAAAADpd3Njq1Pv9sy7T/KiDTn5+gAAAAHQjvyzO8AAAAAAAAAAAAAAAAAAAAAD5+gAAAAAAAAAAAAAAAAAAAAhOfg54tBQAHnynudMqwAAAOt2RnuhZppYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA4uWYJ7SJmmAAAAAAAIj3+9CmiAAAAAAAAAAAAAAAA86N62iHYA8X2hmel+FKmkAAAAfn7Oklp8jXAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAkfSnbE7oAAAAM00vN9FPsAAAAAAAAAAAAAAAAAAAAAAAAAAAAADNtJzI0nkAAAAAAABmOnRRavF9oAAAAAAAAAAAAAAeV6uYnoX3FygACdohneiTPimgAAAZnouemjfYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQnPwc8WgoADNdJzbSgAAAACM9v58gsQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAdCQ7HvnrgAAAAAAAdbsjOdGzHTgAAAAAAAAAAAAADxfA8jTT7AAAAlKsQl3IdctwARPuRWngAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAzXSs10oAAAAA4880fNDSwAAAAAAAAAAAAAAAAAAAAAAAAAAAAD8M00zM9MAAAAAAAAAI31vVz80cAAAAAAAAAAAACfoMtPetPn6AAAAAEXaCMs4ftFd5Xq50dq76vaAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABFFqzUd/njfuNjZqrSkdYj8/emQOlQF+AAAAAM00vOzRHBzgAAAAAAAAAAAAAAAAAAAAAAAAAAADwvdz09Kw6vaAAAAAAAAAGY6dHlf++D7wAAAAAAAAAAAPwmuvN6ifoAAAAAAEDfTpGefLI/o55PrUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCgHie3KnFXz9AAAAAAJOs8w6fvw9wAAAAAAAAAAAAAAAAAAAAAAAAAAAAMy0aANGAAAAAAAAAA4eYZvpGZaYfoAAAAAAAAAAEnV5cVVQAAAAAAADh5hjnNro+PsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAITn4OeLQUAhbrNy39H4+wAAAAB+fozXSs00sAAAAAAAAAAAAAAAAAAAAAAAAAAAAlOzL6OfYAAAAAAAAAAJHve3nZpIAAAAAAAAAB8Eh6EhqIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCgGa6VmppQAAAAAAM00uBsTugAAAAAAAAAAAAAAAAAAAAAAAAAAHmELpsLdAAAAAAAAAAADMtNkyr/AGdogAAAAAAAABEWWaln7gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQnPwc8WgoBmulZqaUAAAAAACa/PajC/AAAAAAAAAAAAAAAAAAAAAAAAAAAhbrMi69MAAAAAAAAAAAHHyDNdKzPSj6AAAAAAAAOAiaaJ00AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhOfg54tBQHXhKzwyzAAAAAAAzTS80NLAAAAAAAAAAAAAAAAAAAAAAAAAAB8ZxU9QrAAAAAAAAAAAAASvLRZuaWAAAAAAAfh+59TSBcekAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAlipQw+eeX5I1hDKuUzTEz9ebQnqgAAAAAAZrpUQW375fqAAAAABHZwbwjrEAAAAAAAAAARVrjx4Wk5NWxsIoAAAAADOr3OtNAAAAAAAAAAAAAGZ6ZMFL9TFOAAAAAAMu1DFCd0HPruNTFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAOn3B5z0RnXNyc8Ub0VdTthnV/nelAAAAAAADwfe4CZrc60UAAAAPnPidltL6ceZsWV3lewAAAAAAAAAdE+M7/dPM76WrdUdrK9POUAAAADq9qQPL0PwfeAAAAAAAAAAAAAHx9jNNLzTSD7AAAAA4ernRy1nqegTdByAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACE5+Dni0FAZrpWa6UAAAAAAAAZppeaaWAAAPO8PwTrXfp8wB85np34eJ7ma1RQAAAAAAAHVPnNmmn1zAB50BqHiHtfub6QAAAAM00vMzSvoAAAAAAAAAAAAAAJrjp81NMAAAAn/K6p5+lcn6AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQnPwc8WgocZnOlZzowAAAAAAABnGhSnqntgHkHpZ11dCPCrwAAA/M50cTdJnntlQAAAAAcJ85k0k+u0AAAEz5F7GFmj7AAAA8jwOCtPQAAAAAAAAAAAAAAAzXSpw9/klKsAHVOxnPUuzzKsAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAITn4OeLQU8z0508q3l6gAAAAAAAA8jwrHMjUHVzk9npe/Snx9gAAAAAgb4SVbC9ksQAAD4PzL/rQT674AAAAAQHt0mamlPG9kAHGZtpubaSAAAAAAAAAAAAAAAPn6GZabm2iHKSx6UF29GODtAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCkbZZ8VHs9XtAAAAAAAAGdZtfQMeztOWa/QAAAAAAACKtRE20d1i6APw/Mx+rc+/UAAAAAAB8/Qy3Qu3l5qrrdkTVLnB79Rw8wAAAAAAAAAAAAAAABJS/nS8aV3pfXqAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHAc7qiO5+nzRdOqrkyrzZ6P6H58P3CgAAAAAAAOObqBwc4AAAAAAAAAJKtEBfyObm65rIaqdr2wAAAAAAAAdTtjK9Q6EGafmVxKGgAAAAAAAAAAAAAAAAAgc5/oQRdoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACRrhnzQRj3JRc8dJoKv576uzRETH9DStVQAAAAAAAAAAAAAAAAAAAHiYZ/R0IZZuc/dgAAAAAAAAACEu4cyqinPSjfBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAfn6Jb2PRAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhOfg54tBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJz8HPFoKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAhOfg54tBQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACKtRmrShjP3Uc8eS0pUdYgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAITn4OeLQUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAITn4OeLQUAAAAIIvQAAAACCL0AAAAAnygeF7oAAAAAQV6AAAAAEFegAAAAB4H6e8AAAAAQRegAAAAEEXoAAAAB4J7zwPfAAAAACCvQAAAAAgr0AAAAAPD4ihAAAAAIIvQAAAACCL0AAAAA8Q9tO0QAAAAAQV6AAAAAEFegAAAAB4vWKMAAAAAAAEJz8HPFoKAAAAZrpWamlAAAAAZrpWamlAAAAATFPMHJRzlGAAAAAZrpWa6UAAAAAZrpWa6UAAAAATQKUAAAADNdKzU0oAAAADNdKzU0oAAAACbpJs+aaZpgAAAADNdKzXSgAAAADNdKzXSgAAAACd4ebhKgAAAADNdKzU0oAAAADNdKzU0oAAAACeoZ469TLVIAAAABmulZrpQAAAABmulZrpQAAAAB4HT7nTKsAAAAGdcVR8E0pRNKUZ99+nyx+qVU0pRNKUTSlE0pRNTmkRMeipVTSlE0pRNKUTSlE1OaREx6KlVNKUTSlE0pRNKUTXmXHhx4vo9v2iaUqppSiaUomlKJpSjN6PzraJpSqmlKJpSiaUomlKM3o/OtomlKqaUomlKJpSiaUoiHuI6qlVNKUTSlE0pRNKUTU5pETHoqVU0pRNKUTSlE0pRNTmkRMeipVTSlE0pRNKUTSlE151t4seF6XZ9wmlKqaUomlKJpSiaUozej862iaUqppSiaUomlKJpSjN6PzraJpSqmlKJpSiaUomlKIn59/jjrqVU0pRNKUTSlE0pRNTmkRMeipVTSlE0pRNKUTSlE1OaREx6KlVNKUTSlE0pRNKUTXn2vjk96nP70TSlVNKUTSlE0pRNKUZvR+dbRNKVU0pRNKUTSlE0pRm9H51tE0pVTSlE0pRNKUTSlEXw0fXjhUqppSiaUomlKPGUA94AAEJz8HPFoKAAAAZrpWamlAAAAAZrpWamlAAAAATFPMHJRzlGAAAAAZrpWa6UAAAAAZrpWa6UAAAAATQKUAAAADNdKzU0oAAAADNdKzU0oAAAACbpJs+aaZpgAAAADNdKzXSgAAAADNdKzXSgAAAACd4ebhKgAAAADNdKzU0oAAAADNdKzU0oAAAACeoZ469TLVIAAAABmulZrpQAAAABmulZrpQAAAAB4HT7nTKsAAAAAAAEJz8HPFoKAAAAS1SAAAAAEtUgAAAAB5PrDy/UAAAAACWqQAAAAAlqkAAAAAPKeqAAAAAEtUgAAAABLVIAAAAAeX6g8r1QAAAAAlqkAAAAAJapAAAAADzPj1gAAAAAlqkAAAAAJapAAAAADzPTHkeuAAAAAEtUgAAAABLVIAAAAAebw+wAAAAAAAAITn4OeLQUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABCc/BzxaCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAP//EADIQAAAFAgMHAwUBAQEBAQEAAAIDBAUGAAEVFjASExQgNDVAEVBwECMkJWAiITYxMyb/2gAIAQEAAQUC5pb0kU7d82y3pIp275tlvSRTt3zbLekinbvm2W9JFO3fNst6SKdu+bZb0kU7d82y3pIp275tlvSRTt3ygseUiUaF1SrBeXLekinbtJ1dikFFyUzbSKC1RHyE9niTttBFcIkJtz0fjuT3wSvM1Zmp3dsQJaXjgE2ZqzNTW88cp53MYhuFREYtr5CcE3Fo1BI05pYdowgsJRHj3Da9bAa2A1LA2skiobXbtgNbAasG1tB9ZzDTk6cw89nQWQJvkK//ACzSGzi9OzaBWkji+4reVLekinbtIV9kLSbsOvyG/KOHbI0n3LdUhRCKMa1oVyXyZb0kU7dpOAthBYFwEAFtg+K7CsLx5GO6lwLBYsuhWsIJlhsToWMJgPIlvSRTt2k/C2GkZP8A/MMxm9a/ip3cjFh5JphI2ZbxyPxL3tazHa615+rikAtSsKsaRT5Et6SKdu0pQLZbAk7UWipm03fFN7etjyhEHVFiRFoPEkCjcNkbT7lt5JE378picONTePLekinbtKXC/HTF/gxQWwd8VOVsTfXdss2iIGEwjxJCK6tzAGwAcroQNqXpTwKSPGlvSRTt2lKv9qqRfjyn4pdFXBoosl2SXdNxTfFlO8R+GIVghYA3WO3MpJAoIbzhs7j40t6SKdu0nb7sjp4/HkPxS/GCXORJYSiqD+skfhyJRuG2Op9w2c7238cmjjhvQeLLekinbtL/APWW1Lgf5Tj3pHxOtUWSpYwnuYZ9JUm20rUp4tB4T9e6x3DawQ6EgRiTnNiwK5L4kt6SKdu0mj7sjqTF7bUwmbxq+J5KeI49IQFMm+h5QTiY0aJOr8EYrABHQ3VOWiMNhh/2xOgBWGHw5b0kU7dpRT/amnIveoImZ6o/iY80JBMeKErX8j6G6J2AKwweBJFG5bY+n4ds0nJGFclj6wSc7wHO7txfq/16v9Ot3LdNV3Th/V/r1f6aruvFcywWwjiIfx/pGfsuPxNKVN9htTWSIuR9TcS3RlTvkHgPV+OerW9Lacjb96BkcOOTeFLekinbtF7FsNUXDstf0D+PK/iUYrAA0hu5PPMj/WSDXNHYsuNgupXariSNncUxwFBHgy3pIp27RkwtlqYQ7DT9JD9h3+JZOr3SRlScIg5pUn+23qOKR60mUbluYk/DtmqqIApIazxtTh4Mt6SKdu0ZaL8NvDsIPpLS/VMhM3qL4PkDqNLfjVW2wOgllvCT/tn7nVk2UposdcA9Z3/Pfdd9b+NTR1w35XgS3pIp27Rlt9owNtkP0kJe8aY4ZttXwfJACC61FgCE5eDIlfDII8k4ZBoO1sOfLX9bahxliioyXc9X4D8kGkU2kafZQriFodaW9JFO3aL591++qsvepYiZ6k/B78QQY3pGo5Shix5N0/gn/tn7RkSbiG6OqeIbtSTqN03sifhm3wJaeIJVNZ4k6/WlvSRTt2ib92W8jF+O+fB8qPvekRFkyR6SDQKkCsC1NrvSvhEEYSblHo3t62ar4c+ajn+wf/Bf0AlqYYRAEwtph6nWlvSRTt2i3fdk/If+PK/g9B+ykFGACYWC5jE5gFYYdZ1FdyeQhsAOlKSLgGkPspTaSg2xJEXKuaf4QgBF4Et6SKdu0Yz9xw5JTbdLLX9bfBr8p4ZtjSbct/0c0YFyVhWjTH6rkqsjRRZLexem4J+KRxVR9vSlKjdoWZPwzd7FLekinbtBQLYTxAP2uSVl7SBqM3rd8GvwrrXUAbAB9ZC3cQWwuPGkakgNEscCCgkk6iz9ZINJf+wkXsct6SKdu0HcWw2RUPo28j4XvGqLmbbZ8GHGBJJjZYlC3ld0o21YhVAWJtJYeFMmjJAjj9WTJt8gYlPEt2gpNsQnixVxj9jlvSRTt2hJBbLTHg7LRyGg3hUSH6X+DJSp3aNoTcK38pxYTiiBmMbmG9hW0ZOoEaaiIClS6ow2GBiFdE7aEqUbtG0p+Gb/AGBe9FI1OZE9ZkT09Opa8hmdykCXMiesyJ6bngpco5ZYL0QNYdhu5Wz8eS/Bhn7OR87qhCuSx9cIk3QOMCSUwliWuWvJShEKyDQnk86r9hI/YTExBguDS1waWpQQUUljCck1v4NLXBpaLTkli5ZeL/hQdgvlcvx5N8FuajhUMVT7KfQkTfvQMbhxyfnlKrZKa0vBotd1TcWgiqnbS8ys6ydLFSb39llvSRTt2hIvuO/NLQegih7wr4KlB1zTkxNk6fRdE42pcjUAVJ+UV7BC2Wu5vXgi/WSPmlajYStifhUHskt6SKdu0Fn3ZVzSgvbbGQzeNX8GeeUnAU7oTR/wl72tZntdwe9I8oB5KQwxkcrX9bckmV7lExpOEQeDKU28Rs6nim/lO/YyX2WW9JFO3aCT7sq5nYvetsUM2kH8G8qhKl1RZUI1P/ByJTuG6PJuHbdN3QhXpo8vEEXIV+3f/COLCaVHDBJl3ItP4ZJFCP8AHsst6SKdu0I99x45hW2rRa+7V/wb2jGlW0jEtaaQLyVxf8E7XxB8tb0tqSJvuKzK4WXJvpIFfDII4k4dB4cgBdG5ljsYX9ZWfsp24jhUXsst6SKdu5zRbBcRDoJvx5V/ByIyxbVHkJQUIw2GFezmpjGp7Af/AAKo6ydPFybmG6ziQNncEp4FJFK/2z9/88R7TcU3RhTvUP1v+xkvs0t6SKdu53QWw3RMPog53z8d9/g5UZcw4kuxRP0dWgpbSRxUtZpBxZ5fv0qUbJDan4VDrKSAKCEJ42VwWvybh4ul3aXxU/6yRfRwP4ZFFCPQn2aW9JFO3c8hFstEbDstPPLi/spTN6m/gifzZRyK0xSoo5MsZDWxzJXB99J/ZyPwJKoua41FFIrH+LKk+0Q2qOKRVKz/ALSAjhkfs0t6SKdu55UL0bWgOw2c8kL22qPmbxp/gVZu4SxMr/HL/wDac2T/AE2Pf+rf997eFPCt8WTbpF4EmRDApqLohgv4qomyhPGDrlHUD9jJfZ5b0kU7dzy8X2kwdhPzry96iiRnql/gZSdu29lJ3DZzubYSuCSpWMhqRSUrK95khl1K4kuxRXgXt62shS2H47za6B5cFNiG+KJ9lP7PLekinbueT/ccNGO/Ydv4F9/LedE8ks8tW3KWs1qdylvs5xxRNijizra4xWABgDdY6e1SUsA2xQ4iObGYZAm/2QZxQL8SRXEkVKjSzEsXNLA38SRXEkUA4sd+Rx+7J9G/48r/AIFk/MfNN1ZAH0geDUxhzuhKulVkKw+xL1HCpDzjFBqY8xMckOsoTa0mU7lAxJuGbfapUcIS2o2cItz9kcGUC1VloqstFU8tQG8lnaAL0uWiqy0VTazgQqOQr7st0ZL9ly/gHg7cNsVJ2EGpKrF2Q0kUDSqAC2g+wupF1Lfe17XprL3TfrLv2Ug9rkbaNTVw3sKONphZvs8t6SKdu52P7r9oywv1Rtxm9Qe/yw77SInh0mo+pBLEF7XtdAlGsVBtsh9hWKApUzO3WcriYke4QKzmdUG9hB1Fx9kqSKkX2fbPS3r7RLekinbuYV9kMSttGaL+XvGmNGbbV7+p/Nk+seiTHiUBs1yH2KQniVrEpAUyenJCWuIbVprUptf1tpyo+96REWTJP5WW9JFO3czgLYQxIP4eioL3qeImf49+NHYsuLguap15Un3iNpUcS3+wOCkKRJGU1zB/V0QFryGpeY3H6aD9lIP5aW9JFO3cz8LYaYyHZatJm/HkHv0jO3LXHSdy166kqx6eKm3AP2B8NEvcSCgkE8js3AXktDiNGdovynhm2NJty3/y0t6SKdu5pQLZa2QOw1aSz8eU+/ScdzlhYLFl+Au/XyLz3NVZGjjCW+zzPDaBeUzOQyDNB+Fda6gDYAP5aW9JFO3c0uF+MiDsI9KVhuBQAW0H31H+bJvBlKfeIWdRxLd5zuMTk7FACUXzvLYFcWyOYgj5jjLEkxsu6hb/AC8t6SKdu5pX/tTpyovabmczetnvi47h0cTJ9CPBUFWPIixtyzvNd1fBIowk2CdF7a7LQMbpe4uWUqd2jaE3Ct/8vLekinbuZ3+7I9N5L3rXFjNpt98lR2whaSeHbvCcf18h81wFd2eQBsAGk+NXFhY3Xe8pn7OR/wAxLekinbub/wDWW6ZgdsETFsm++PH5j94coT71AyqOJbfLe1nBoYyj3KXUfGriKY3XibfRzUcKhiqfZT/zEt6SKdu5mn7sk1EH48o97vf0swW4t38M8uxxMXMuSo8tTe7w92ta1tV8armXY3WysNSg65pyYmydP/MS3pIp27miv+1Wo7fjyL3t7O3DZFyd23eI6fgP/lP6zhEMbR8Oj131sv65jUbpvWAMef5ZzE7WV7b/AFtv9OonK5TUJzsn23+tt/pqE6XVfRYLYSREP4+pLgf8IHvSfepYb62SlbhN4knT71vZFHENvk3/AHL54EgEILT9GkQhNv8AMS3pIp27lehbDVFg7LZqSYvba2IzeNXvQ/zZR4pxdjSoyZchX5EiWcMij6PhUPgHFhOKWsaokxvYlBxgQ2CH+YlvSRTt3LJhbLUwh2GnUcy963xMzaRe8nmWJJipdxmeM7/gPvj3v6WJ/cvf9bLekinbuWWi/Dbg7CDUv/20Y+yv95kp26bGAnctfjSZPvW5iUcQ2eNJVm4SMaPg0P8AWy3pIp27llt/UYbbIdUv8eV+8yQV1DiENgh8Y0FjC40O6dd4ohWCFCG7u9f10t6SKdu5X37r7rSD7Dz7y2/myPyHm3Avdr+tvEk6zdp2dHwSH+ulvSRTt3Kd92Wa0uL9U6Izeo/d3I7h0ETJ2UnkSVPvm5gUcQ2eGYMJZbUATo7/ANfLekinbuVv+7KNaRF7xpjhm8afd5YdspGwnh0HkGAsYXHB3TOHhydXewGtJZEi/r5b0kU7dyxn7jlrLC96kiJnqR7u5/myLyny3BPNr2vbwTjAklMhYnBz/sJb0kU7dyKBbBEQD9vXYfsPXuwr2CGOWupcvKkiffNsfUb9s8GTKriu3JbI0n9hLekinbuR3FsNkVD6N2ud+PK/dn47ctcZJ3TZ5Qw2GCPCukc9e9/SxrojLDHyRLF39jLekinbuSRi2WmPB2WjXlFt0utf1t7JIHQSSuNU7cfdBK9eVmXGMguxJHlv1ro3YN7CDrShaO6ioqsFY3+uXvRKNTmRPWZE9PbqUvIZXcpAlzInrMiem94JXKKlYvRvag7DbrysvaQtZm9btN+dLorYis22F0ut8eTliC6VGSxCdNYP5so8yRJ9+2x1Rv2zWfjCjXOoqlEJT/XGJSDBcElrgktShOSSljKcg1BwSWuCS0WmIKFUvF/woOwVrvpe8aowZttenJe7VGQCE6eKuVloiEyU97U5avtmFnMK1MeWpJ1FRu4TxMr180QbCCwCujddQ0wBRaxeodjm9oTpScEQbYABLB/Yy3pIp27kkX3HbwDgbwmJD9NIV7Bs4vQzRpY9tE5aN21aFQzGtq8peT4axUWkITEnviwsASwUpILUkkjOYlxYwmA05Odu25jJ3DZ5sgDdI6AFYYdJarKRk/lvyhEkKRk/2kt6SKdu5Fv3ZV4LV+PJNBasJRlDMWvprc3koQfS9rCs4oDWw9rcS15XgqlBaUgos9+WlFgJL+q9IWtTt6o1oV2v620pBfina1vS3myFPv2yOKN+26Lq5lIAIkCh1OKLCUX/AGst6SKdu5Ev3ZX4Lh+PJ+d1eS0lImo9eaUWAoHJf/tnRuMQHNLkWvK11J5aYm1j35aQUAgrldUAF6dmXjRnaTR+Y/8AnCtYVmK90TxoO7zYi7UzXEP+3lvSRTt3JH/uPPgywOyMsW2XyGDCUBa7HrjWpmLS6Ls2DSms7mBeXqnmgIKFc9+WpiC0xPO9NllxTC532tB2O4duipOwi8+RBulcQCsMHKK9g2cXU1Ya0NAEVv7iW9JFO3fUwWwXEQ+FKS9ttZTN61/VwcCUJYQLX01EjJRFaTw1CKMZnUK4GmaYAks0w9+WpE5aUjRfmvibMTpxQeeWHeidATw6Lz39PxDZG1G+beRQeWnKPUKnw9uQEoSv7mW9JFO3fVzFsN0TD6IfBdy962RUzab/AKOj2Eq7ezDPMCGwQ6jy0isNldgrA6JgwlgUnHvixGlLSEab62iCNmcgryeZb+bJfYL29bMt+Bevq4ryUJRJCp8PTEFpiv7qW9JFO3fWQC2WiNh2WnwRWsIMaPAmPPPKIKVL1Tsa1tJKG2u9NNxiZXayrQGKwArFJz0rQpC0RGq7oRoFDYuAvT8hgrABGA3PW+wyQF0y8sdjC6d3ctFZuajVpoQ2CH+7lvSRTt31lQvRtZw7DX4MoXDBem4rjVSVOUlK8F6ad/TK7b/mFewbL1Zruqb0RaEjWva17LkxrMsRKi1if6yE7ctccJ3TX7DJrlYa2vvCpl75vbNDNYm/97LekinbvrLhfaTB2E3gytMKyio0mEa4eG9NNlVMrtcYvre/pZyWmuihtQloSPANLCaWMJzCvTnAUE/SUjuaoKBYor2GSGCG61Fhejn/AH0t6SKdu+hpoCQP60hYpJNLOB4JgAmAuxIbjJKLIL8R6aQrAszsKw/o6rzHA9rby0BHhKk5akgg05iXAGEwFJ/zZP7FIWsZ47JzrjjzYJJb+7EaWG+/Jrfk1KjADSRc0sDfvya35NPS4SxZTOtEjV+0v7eUoTiclgiuPVbljRFJkniOCMtanbVZjSqWrCk5ETJ+18QODKBaqy0XWWi6eGoLeS0NAV6bLRdZaLpSTchRRBVzjvaXoAjGv6MoBFtfiyzdcLTKvGjVfEct6SKdu+ju0gXVl9btNDQBDf2pdHizTEMeLKM8aVJxGpabk4lSz4jlvSRTt38Pf/tjmJEYNGjIRh+I5b0kU7d82y3pIp275tlvSRTt3zbLekinbvm2W9JFO3fNst6SKdu+bZb0kU7d82y3pIp275tlvSRTt3zU5mOoVe9fq3r9TqNxEU1jcwp96/VvX6moboJV81S3pIp275tlvSRTt3zbLekinbvm2W9JFO3fNst6SKdu+bZb0kU7d82y3pIp275tlvSRTt3zbLekinbtNgVHnrtN6VHku+m+mjJbGQwZzXpsKo85w03tUeS6ab6aMlsYzRnNmmxqjznPTfVR5LlpvhoyWtiNGc2abKqPOddN+VHkL9N7MGS2MJozm3TZlR5rxpyBUeQt03owZLYwmmHtum0KjzXrTkKo8hVpvJgym1gOMPbteW9JFO3acZ7jpv8A3zTknaI92fTjfdNOQ9505H2iO9n0473fTkfdtORdnjnaNOP9605L3PTkPZ432nTYe+6cn7hpv/aI12nTY/8A0GnKet037tMZ7Vry3pIp27TjPcdN/wC+ack7RHuz6cb7ppyHvOnI+0R3s+nHe76cj7tpyLs8c7Rpx/vWnJe56ch7PG+06bD33Tk/cNN/7RGu06bH/wCg05T1um/dpjPatE2RiLNzKKsyirMoqzKKsyip1druBTW8XQJ8yirMoqzKKsyirMoqzKKsyirMoqzKKsyirMoqbXK6JRmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFS9yurW5lFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRU4vd1iRvfLo0mZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVNzldEpzKKsyirMoqzKKsyirMoqzKKsyirMoqzKKsyipwcrrFmZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVOD5dYkb3y6NJmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFTe5XRq8yirMoqzKKsyirMoqzKKsyirMoqzKKsyirMoqcHK6xVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFTg+XWJG57ujSZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRUgcrpFmZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVOLldapzKKsyirMoqzKKsyirMoqzKKsyirMoqzKKsyipe+XVpG57uiSZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRUhcrpF2ZRVmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVOTldcfmUVZlFWZRVmUVZlFWZRVmUVZlFWZRVmUVZlFS99urSNz3dElzKKsyirMoqzKKsyirMoqzKKsyirMoqzKKsyipE5XSr8yirMoqzKKsyirMoqzKKsyirMoqzKKsyirMoqc3K647MoqzKKsyirMoqzKKsyirMoqzKKsyirMoqzKKlz7dUlbXq6JLmUVZlFWZRVmUVZlFWZRVmUVZlFVn+97CZkIhYI31gjfWCN9YI31gjfUhb0yNPH25KrRYI31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfTGiIVLMEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvp3REJ3TBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6emtImbmZrRqG3BG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6ZERClfgjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9PCIhO5YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfT01pEzczNaNS24I31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfTMiIUuOCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI309IiEzhgjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9PLWjTNrK1pFLdgjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9M6IhQ54I31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfT2iITLsEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvp4akaduZGtIpbsEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvppREKHXBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6fURCVXgjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9O7UjTtzI2JFLfgjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfWCN9NSIg93wRvrBG+sEb6wRvrBG+sEb6wRvrBG+sEb6wRvrBG+n5EQlU4I31gjfWCN9YI31gjfWCN9YI31gjfWCN9YI31gjfTs1I07cxtiRU34I31gjfWCN9YI31gjfWCN9YI31gjfVmhFbnlvSRTt2nGe46b/3zTknaI92fTjfdNOQ9505H2iO9n0473fTkfdtORdnjnaNOP8AetOS9z05D2eN9p02HvunJ+4ab/2iNdp02P8A9BpynrdN+7TGe1a8t6SKdu04z3HTf++ack7RHuz6cb7ppyHvOnI+0R3s+nHe76cj7tpyLs8c7Rpx/vWnJe56ch7PG+06bD33Tk/cNN/7RGu06bH/AOg05T1um/dpjPateW9JFO3abU2CRKdNxbBK1+m6JbrETamukRabW2CRq9NybBK12m5prrETYmujRabY2CRrdNzbBLFmm5prrETYlujRaba2CSLtN0bBLVWm5Jrq0TWlujR6bc2CSuGm7NglqnTcU91aJrS3RI9NvbBJXLTd2wS4/TcU91SNqSXRI9eW9JFO3fNst6SKdu+bZb0kU7d82y3pIp275tlvSRTt3zP/AP/EABQRAQAAAAAAAAAAAAAAAAAAAMD/2gAIAQMBAT8BXUf/xAAUEQEAAAAAAAAAAAAAAAAAAADA/9oACAECAQE/AV1H/8QARxAAAQICAgwKCQMEAQUBAAAAAQIDABEEIRIwMTM0QVFxkqKxwRMgIjJAUmFyc4EQFEJQYHCRoeEjYrIFgtHwJBVjk6PxU//aAAgBAQAGPwLjM9/dC/EOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfNEoKlLWLoQLkWLailfVVV0xnv7oX4p2C12EuEePs5I/UYTY/tMB1kzSfmG6tFSrgPoCkmRFwwy6bqkgnpCmeAs5Y7OUYJ/7PxGCf8As/EIRwPB2JnzpwWuAs5qsp2UowT/ANn4jBP/AGfiOB4CwqnOynaKQV3bM+ikI9mo/MNxm5ZCo9sKbdTYrEJSVBIJlM4obbRzUpkOkVgRzR9I5o+kMyA5+6FzAvh2COaPpHNH0ioC0GkUUWRVzkQGWkzcOKLEmbiq1H5h1w/SXBZNprkfoIsW0pS4itEtkep0ip1HNns6Wz390L8U7BayckUdZxrl9fmI7LnL5AgLPOdNl5egU+jVKSeXLbAcFSxUoZD0pnv7oX4p2C10hWRtWyG6QP8A9CPpKEqFwifysqIPR6PQ2/8ASYShPNSJD0EKEwYskzNGc2QlaDNKqweks9/dC/FOwWukZpfeG15HbLdFGV+2X0q+VaglRDAPJTlgLaWUKGMQHFXwclXRSTcEP0tVxNY87n24iml/2nIYV/T6VVXyew9JZ7+6F+KdgtcussCLD/tWe+CnqLPyqIhbTgkpJl6FLVVwipjN0VyXOc5AhKjzneVxfWGR+s3dljEWKz+ujndvb0hnv7oX4p2C10dOVRMNNG5wYT9opTKrtR+VYYbuJ5KlD7wy4glxsmuyhtbfMUJjotHoaMV3OYCU3AJDjJplFH6SjWN0IdaPJV0dnv7oX4p2C10Rr/a/Q8jrlX3r+VTjvtXE54XSl85yoZodbHO5yc8KZPOaNWbohUq4K4pFMXiuef4462nRNKoVRaQf0Vm7v6Oz390L8U7Ba6KjJYbZ+ijPYlWJP1l8qmaC1cSa88IbRUlIkPRK407sP56IsDnOciEE85zlm0cm/IrT/iPVX763zZ4x0Znv7oX4p2C19iTsT6KM6MRKYbc6yQflQ48r2RD1NdrUTIb/AEofTdbNeaGnPalJWfobFDTcTUfP8QALgtKf6hRaiDy5ZcsJdTzrihkPRWe/uhfinYLXSl5LPb6FHqKCt2+GOwWPyoZoLNZnM58UNsouJEvStpfNWJQ/Qnbs5jOOhKUrmpEzFIpi8VzObUUqE0moiMZozmz/ACICkmaTWD0Rnv7oX4p2C10p3N9/RSEZUGHW+qufynW6vmpEzD1OexGrPxWKY3cVWc4/EJUmtJEx0FSRznTYw3PnL5ZtamlVKupOQwr+n0qog8ieXJ0FXqU+Bqlzd8Y/oiMf0RCP+ocydXNu+UH1C9WVfNu+cY/oiMf0RH/OvMv23fLjvqyIJ+0Pqyql6aXR/wDaj8p26I3zl1ndDbWMDlZ+K4Bz0ctMcGec0ZeWLoLFETzU1Hf9okLls9aYvrd2WMRyr8ipX+ehs9/dC/FOwWqkn9son1lk+kjEs7R8pipRkkCZhyluDkIMxu46mbjTlQ87nQFLVzUiZikUxz/SbcmlUYforNzdCHWjNKuhM9/dC/FOwWpQ6ygIo47J/f00WkZvsflMGEnlu3c0IQRy1cpWfjtUpHOQbEw091hXnt9gOc6bHyhoHnL5Z87ctp0clUKodKP6SjUd/Qme/uhfinYLUynKuf2ijpyNp2elhzqql9f/AJDC+sgH5IBij1OETUrJFl6w7Zd8wpp+/JE59YdDLprYbr8hctDjKrixKH6G5UoGyA229mijmoqO09AskD9dHN7eyPV3j+s3cnjHQWe/uhfinYLVRWx27oAGL0vZUyVDf7SU/JBwquLAI+noshzUpM+hFKTy3eSN8BShy3eUd1papSeYus74mLltW4rmpEzFIpjl255noKf6hRaq+V2GEzadspVyibCqxdSbot7Pf3QvxTsFqojfd/lxHm+sgiKQ3kUFf79Pkg4t8VtiaSMsLpDfs3E9aFMpSEvCs/u6EGxWw3sF21KI57XLG+Eg89rkHdbeDHOdMvKGknnK5R8+gssjmrmT6GVp60jmt7Pf3QvxTsFqSOqR/GfFpTGLlAeR+SDNERzlGyI2Q0yPZEJp9EqE+V2GEut+YyHoC1A8tXJTBeUOW7stUjch2iq5i6hutrVHFaEVHaehAtX1usDLBSsFKhiMIecSQyg2Uz7VvZ7+6F+KdgtVIV1bL/HFQrEsj7iXyQXSDW23WN3oUhYmlVREWKpmjObP8wFJM0msG3t0RB5CDI74CUiQFQtbFMbqUk2JOyG3k+2J2tbqriBOKRS3Lpq87p6Hykg5x0Bnv7oX4p2C1Ut3s2ni0V8f7IwCLh+RzkucvkCOEPOdNl5YvSW1VKupVkMH+n0uqRkmeI5Lc47jA5OeHKW5znKhbHWesKs8O0VfOQbIWsNC66fsIZR7RFkc59xs9/dC/FOwWl1XVSTFJVlIHFQvqrijq/YB8jmKGi4m7nP4hKU1JAkOJ6wyP1kXZYxFg4f10Xe3ttrNBZxGvPCG0c1IkLal6405WfO7a22LrbdR2n3Iz390L8U7BaaSf2EQo9Zw8WkDImy+kWPUURv+Rq3F81ImYpFNcu4s54yadRKkE1jIf8Ql5u4boyG1uPLuJEPU56tRMhnx27hBzmjPyxw2Tz0cg2lx1VxAnFIpa7p5M/ufcjPf3QvxTsFpd/cQPvDHbM/firQfaEopLR7D8jUsjnOmvMIabPOlZKz8ZTbgmhQkRBbcmaMvH2ZYBBmDamaE1WomZ3Q2yn2RblJVWkiRh+huXFVDOPxaUMi64fsIZb9qUzn9wqZW2tRGMReXftF5d+0IQ2haSlU64U042tRK7KqLy79ovLv2jgkNrSZTr4zacrm6KMP+2ONSGsS7Ib/kaE3Wmtg/NoKDUsVoVkMGgUqpQMkT2Wlbi+akTMPU53Eas/QGKa1dnI5xCHUc1YnaEtXW2jI+V33FZOMtqVlKQYwZnQEYMzoCGi00hBs/ZTKFl1ptZ4Q1qTPEIwZnQEYMzoCLJtltBypTLjUVHeOyEJyCXGYc69j/AI+RjruMCrPDlIVdcMhmtPrTF+RdljESXf0c7t7bQiio5zlZzQ217V1WfoDrftSmnPC2Fc5s1ZuO66fYTOH6Uu6o2IO33Kz390L8U7BaaI1m+549GeF2sQhYuKE/kWxQ26yTM58UNtJuIErUmmUW9E1jJ2Ql1q4ftxipVQFcOUpd7brG7oU7jTuw/njtsC64ZnMIZaxgV5/crPf3QvxTsFpaT1SnZPj2XUWDuijnImx+lXwJZvLShPbFil8T7QR8Ckm4IepauaisbrWpp0TQqowph6ujrx74mLnF4FJ5btXlCAR+orlK6El4c5o15oacPO5qs/GCLrbRl9Pz7mZ7+6F+KdgtLquqVbJcekJ/YTC0dRfwI4SeSk2KR2ehxlZnwUpZvgRSRzneQN8IJ5znLNssbjia0GPUaVUtNSJ7OLZ3WGtg6GttfNUJGH6E55ZxxXXj7KYepKrqjYjf7mZ7+6F+KdgtNLdz/dXHINwxSmDd/wAH4EWZfprNkk+hNI4L9Fy6D/tUWTKuVjSbo+A2qKnmIqO+JC5bfXKPU6jnS2xyr8ipQ3+lQSf1HOSN8Bahy3eV5YuiMU1vHdziErTzVCY4jVHTdWZmGWsaRXn9zM9/dC/FOwWhSsgnFKX3RttDicSyfuJ/Ajk5TVyROG3nGkl1XKmRcgpWAUm6DHrP9MKgRXYC6M0BqlybeuTxH4BcdVcQJw/THKyTIHbb00qjD9FRuboS60ZpV6Esi8t1eWPoriRzk8pMFo85oy8uJlbaOz8+52e/uhfinYLRST/2zDisrm60UV/EbEn6/AlGoqLpr3CENpuJEvSVp/Tf62XPHq9PSpTeI5M2WA4yoKQcY9/t0dN1wzOaGmsYFee3qadE0qhVGpJ/QVj3w6KMpRdlJNUKpCuc7czdGLdxp2ryNz0uvdVNWeHaQq6s2I9zs9/dC/FOwWh/tkPvDX7iT97RR3MhKf8AfpDTnWSD8BqVdQ0dn54vBvpshsgvUZRco+P8xyeS7jQffxXdaa2D89BLfstVD0LoxPIIsh2HozdJTdbMjmhp3GRXn9DNHTdWbIw0z1U15/c7Pf3QvxTsFoSOs4Iow/YDaHD1CFQzlTNPwE671Ekw/SFXVGx41ccP/T+Q4K7AVfSOA/qHIcFVmavrFXvt1Y5x5Kc8F4850/boJpKRNtd3sPoVSnBIEWKP89GcaVcWJQ/Q3KiDMZ8fondbaOz8+6Ge/uhfinYLRRk5STDSeqkC0PoyoMPN9Vc/r/8APgINi64qXlDCcZFkfO0crku4liA1SU8JR8X4jhGFWQ2e+qPQm/POYQ2jmpEh0GRiyFGasu70hmlo5q6zvh19J9nk7ocfN1ZkMw90M9/dC/FOwWiiNdm02ql0fP8AY/AVHoouCQPn+LUW3khSDiMes0BSlN4xkz5YCFfpv9XLm9zzecQjvGUTacQsftM+gKWqpKRMw/TXMVzOfx7rUVEBSDNM4YohHMNZy5IaTR1WQQJHP7lktxCTkJi/N6Qi/N6QhmwWlXLxHshYW4hJ4Q3T2CL83pCL83pCJIcQo9h4tHT1bH/Nq7FnaP8APwFSKUbiZkbB9rYXaLJt67LEY9W/qYUCKrM3RniSnwT+2uJ0dwL9xuvXbEQXHlFSzAcZVYqENvD2xO38GOc6ZeUNg85fLPutLXsITPz9CEDmuTB9yqeU6pJOICMIX9Iwhf0hC0uKXZKlWIU6p1SSFWMgIwhf0jCF/SOFS6pRlKRHFUeqT9kytVEpH+1H4BfXjsZDzhTmNxX2H+m2pUpALhVJKsnoQ62a0/eAoXDX7ieaTziKokaj6KOgEHk3Rb0MXWm6j5XfdiaQwLJaRJScoiRBnkj1p9JTVyAbuf3Qz390L8U7BaKW53j97U051Vy+sUdeVA+AGGBdUbKGmuqmVtKW74k2QGWJESMJaRjunIIAFwe4nHl3EiH6TS5yUapZYUhKCFH251iDRaZecRydogFJmDjtrrx9kVZ4epS+co2IO33bPH7pZ7+6F+Kdg45JxRSnD2b7U/2cqEDqKKfgBCLqGyB9K7fZPMoUrLKG1IFiyvYavcbVAYrrrzwhlHNSJeiwXUoc1WSPU6desRyfiJi5bGaIjnKNkRshpkeyPhZnv7oX4p2Dj0hWRtWyHlZVy+1qdb6ySIpDWQhXv9S1XEiZik0pd259a+gIeF1s/Ywy57UpHP7hceViuDKYcpz1alGSd54liqpwc1WSPUqfUgXCfZ/FsXSDW23WN3wuz390L8U7Bx6QeyX3hJ6yibXSWcRsgPr7/WMbhsIbyr5fQHGlXFplFIoi7o5UvsfcLVBYuJNef8QhpvmpEhxeq6nmqj1Kn8mVSVH2fxanJc5fIEcIec6bLyxfC7Pf3QvxTsHHl1lgRRh+2draX1yn71e/6NRUXd5hKE3EiQ6Ch6425WfOo+4Fu+1cTnhdMdrWupM/uePVyX081W6PUqfySmpKji7LSxQ0XE3c5/EJSmpIEh8Ls9/dC/FOwcdhOVU4YTkQB9rXRXxdufSAoXDX7+ccuobmfpUOhJdF1o/Ywyv2pWJzjp7dDaPIQZE7YShAklIkLRZIkH03Dl7I9Sp00uDkpKth463F81ImYpFNcu4s5+GGe/uhfinYOPRWs/3tiVdRcUZX7JfSr36871U1Z4eePtGx6E40q4sSikURy6K5fY9OW57Z5KM8KpTnPcuZrVwjVVITrR6pTKnRUknH2HjJZHOdNeYQ02edKyVn+GGe/uhfinYOPRUZLDbbKSn9s/pXBT1Fke/UNY3FfYf6IYRjsZnz6G3SLiHKzsPTkUZs/pN1T2mAlIkkVAWvhmKqQNaPVqXU+KgT7X54oTdaa2D8/DLPf3QvxTsHH7EnYm2KSbhEopTKrtR9+sUb2UyB2nogdF1o/aGVe0BYny6YopP6iuSmC+sct25mtvrFGqpAuge1+Y9XpNVIGt+fS67jAqzw5SFXXDIZvhlnv7oX4p2Dj0peSz2ytrzfXsv8+/JmKTSjcEyPPoi21XFiUUihuXbvmLvTA0m8N7McAC4Ld61RKnxWQMf5jgX6qQNb0MUNuskzOfFDbSbiBL4ZZ7+6F+Kdg49Ld/2s22jO4lWJOz34+rGRYjzizxuKn0VqkjmLrOw9LISf1HOSmOFWP1Ha/LF0A02h8lxPKUBthIDTdnjUccJpNNN3JcB+F1epA8DVKpMXD9ERcP0RCP8AqA5E6qhd8oPqA/Ssq6hd84uH6Ii4foiP+cDwUsibvpeVkQT9opCsqgLbRnRimIbc6yQffdHo6bpNlLZDTQ9hIHReEHOaM/KGlHnJ5B8ulZaO3s/PQX7HsH39NGK7tgPhlnv7oX4p2DjUk/tlE+ssm2qPUUFbt8MHILH6e+wLqGj/AB/PRltq5qhIxSKG5du+Y6TwaT+o7V5Y4ClD9R3lHd0FTbgmlQkYPBJ4VvERANJTwTWOd0wEpEgKh8Ms9/dC/FOwcZY6ygIo+Yn722kI/YYcR1V++luKuIE4pNJXdPJn9z0dmlDmrrOw9ImbkFZwdvZ8XM9/dC/FOwcZlOVc/tFHTkbGy3Uujn/ZH30pONw2MM5V8s+fR7Mc5oz8oaJ5yOQfLo/AoP6juyEhQ/UXylfFzPf3QvxTsHGoqB27oAyW5QxLO0e+qNRE/wCzgJFwVdHUhXNUJGKRQ3Lu8dGKlGQFZhVIWP0W65bB8Xs9/dC/FOwcaiN93+Vvor+Ko/Q++nn7qUTI2DpLNLTzVVnYYmOiijN8927mhCDfDyl5/i9nv7oX4p2DjIHVI/jO3sOdVVj9f/kMudZAPvh93GE1Z4deN1apfTpJWOc0bKG585HIPRFLWZJSJmHKW6P00GYGwfGDPf3QvxTsHGpCuqVf4t7uVMlQ1+2affDbQurVPyEMN4wmvP0lSFc1QkYpFDX/AKR0RFEa57lapZIQ17V1Wf4wZ7+6F+Kdg41Ld7Npt7zfWQRD7eRQV9f/AJ74ZYupRIHaelsUtNxVZ8rv2gEXD0JbizJKRMw7TnhyUmrPi+MWe/uhfinYOK4rqpJikqykDoFKYxVj6H3uVG4IpNLV/s+lqUOc1yobnzm+QehN0JmtSjNUvsIbZF0XTlPxiz390L8U7BxaSf2EQo9Zw9AQcSyPuJe93squQPOArG4bLpakquESMUihrx3M46BM3IWeHbUUi4Ddh2nv4jVn+Mme/uhfinYOK72yH3hntmfv0CiUgf7I/mJj3KGaPfVCZVkEWXrDtllszBYpF9SJhWUW+jUZN08qX2G+G2xcQkDpjFMRcNZ8vxAULht/qqTJCRNXafQqiq5hFknsPxeWVtuFQyReXftF5d+0NobQtJSqfKhTTiFqJXZVReXftF5d+0cE22tJlOv0Npyuboow/wC2OgNr6q4o6v2C2BpiXDKE59URZesuz70Fp+XDJE59YdHKjcWkEehKhcQkk28m6ho/x/PTVkc5vlwgHnN8g29xbCrIGUz2+hVII5CBIHKfi+ycYaWrKpIMYMx/4xGDMf8AjENFpptBs/ZTKFqdZbWeENakzxCMGY/8YjBmP/GIsmmW0KypSB6KMjvHZCE5BLoFIGQWX0gJ6iiN++2LrnUPQki4lJJ6MXXTmGWFUikkoZFQlsEYTye5AWia6Ov7/mEutGaFW1x0+wkmKRSFXSbGe3ppSq4aopFDXjueX4tpW4oJQLpMerUFJDWM5c/ZBStIdWocoqEWXA+VkYCUJCUi4B8ZM9/dC/FOwcWiNZvuegrR1kkRSWjikbUSoyAxx6v/AE0FSjVZjdClUxxXDKyYv8xhCLHLKE0miLK2/a/PZFkipY5ycnRC68ah944akTTR0/7IQEIASkVAD0KadE0qjg3Zqoy/v254C0GySawbZYC64qUMDGRZHz6dR6YjHdziApNwiYtfCPKlkGMx/wDnRknyH+THBspkMZxn41Z7+6F+Kdg4rKeqU/56FSGsSrIDbabN9UsgxmLBscHRh9PPLEmxNeNZun0kETBj1ygT4PGOr+ImnkuDnI6Ep14ySPvHCOTRRkfbszwlttNihNwcQtO+RyGDRKZeSajk7YmLlro1FGKQ+sSFzpzkuc3yxCUnnN8i1S5zxuIj1qnqIaxDLm7ICG0hKRcA+Nme/uhfinYOK4rqlWyXQmHOvY/4tBbZk4/9kx6z/UlKsT7OM/4gIbSEpFwDi1x65/T5hIrKR7P4jqvDnJ6Ap15UkCJmaKKj7fmEttJsUJuDjWJqcHNVkj1GncmRkknF+LW/SfZTMjYOnkG4Yfoiriqh5XPtaSxROW/cn1Y9Z/qPKcNdgd/xwz390L8U7BxaW73vuroVFeF2sQlYuKE+KVuKCUi6THq39NSqR9rGf8QHH5OP/ZNp9c/p80yrKRiiRkl8XU5c1uU46qxQm6YkJooqPt+YS0ymSBaLJFT6bhy9kep0up1NSSdlpfcx2MhnhbuNxX2H+n3BR6YjzziErTzVCY4xKjIDHHqv9NBM6ioXTAcdkt/L1c3xyz390L8U7BxFKyCcUpfdG3oVl1FgxRz+2x+lXEm6ZqxIF0xZL/TowPl+YsGUyynGbX65/T5pUKylO0RYOSTSBdGW2KccVYoTdMcG1NFGR9u3PCWmRJI+9q9Yo4/5CcntRwD5/wCQnWtDLI9pVl9IZa6qa8/uByXORyxASec0bHilx5QSkRwNHBRRxd/MWLYms85Zun46Z7+6F+Kdg4lJP/bMOKyubuhUlP7J/SFI6i/TwND/AFHrlliH+Y9Y/qZJUa7A74ASAAMQtvrdA5LgrKU7RHBPcmkDWtRWshKRWSY4GjzTR0/7MwGmRVttnrtDqcTWoDbElVPp5w38dtq6luQ+lZ9wyNyH6IrmqqG77cSydM1HmoF0xwr5sKOLn4gNspsUj47Z7+6F+Kdg4j/bIfeGz1iT9+hEG4YpLTziUzuTMrkF11YSjLBo9BSUtYz/AJiyP6j/AFsmboHrVC5LwrKRj7R2xwFI5NIGtaCpRkkXSYFGotTAx7zAaaGc5bcKdQakgzUB7P4izTUsc5OTiqWq4kTMUmlLu7z7io9Mb/0iErTzVCY9BQ3Jb+TJnj1r+pFUjWEm6YCUgADEPjxnv7oX4p2DiAdZwRRh+yfQk0VsyBE1y2ehmjOuqDdcuyA2wgJT0L1iicl8VkD2vzHq9L5L4qBPtfnjEqMgIFEod5xnL2nsjg27vtKy28giYMClUS8HFuMB1o1Yxk4jmVfIhBxuGz9xFLipLnNGeG2XGSsJ9oKhLX9OCitftSrGaA/TOW/dlk+Pme/uhfinYOJR05STDSeqkDoSKQByFCxPYfQHZchqsnt6Jw1H5NIGtHqtN5LwqCjj7D28SZuR6nQb3jPW/EWCK1HnKy9BUhwWSFVERZImujL+/wCYS60ZoV6aNRUXbv1qEIQm4kSHuJxJuIAA+nolK6g+Xx+z390L8U7B6St1QQkYzDHBLsm03TKAtpYWnKOhFK0hSTdBifBnNZGAhpAQkYh0XhWZJpA1o9Up80uCoKVsPp9SoFaTdI9r8RYprcPOVl6Gpp0TSYLT01UZf+zgKQZpNYPoWu6ho7KvcfrNGFkuUlJyxYhpyyyWMKefEnVCQTkHx5JTiAe0xfW9KL63pQzYLSrl4j2QsLWlJ4Q3T2CL63pRfW9KFV/pIMkDf6Emf6SjJY91LfmEOtidllhLfrC7FOQyhTRfcKFXQTOELbNmtwTK+ilpzyOQwaHTL1Oo5O3NDii4izCZpE7sPvm6o2PyhU8XlJJxSjCFaMYQrRhC0uldkqVYhTqnSiSrGUowhWjGEK0YcaVdQZehDabqjL3VSEou2M/TR0ru2M+jNWSf1SrknJl9CRP9FZkpO/5SM9/dC/FOwemzSbB7LliX6cstlHCLPCPZcQ91ldGXwU/ZIqgLpLnCy9kCro7bqRPgjXmPobbQMdfYPlIz390L8U7B8EVxZWKkdiTEmEWM7pxn5SM9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfOtQoaTwNUqhHNOimOadFMI9fEkTqqF2D6gJtWVdQuxzTopjmnRTH/OBDUsgu/Otnv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2D53M9/dC/FOwfO5nv7oX4p2C2UlLrqlpTcBz2yittuqShVjMDvWxxbSilYlWM8MrdUVLM5k5zbKSh11SkpnIHPbKK206pKFSmBntjq2lFKxKsZ4ZW6oqWZ1nPbKUh11SkJnIHPbKMhp1SUqlMDPbHltKKViUiM4hpbqipZnWc9spTbrqlITOQOe2UZDTqkpVdAz2x5bSilYlIjPDa3VFSyTWc9spTbjqlITZSB71soyWXVISq6Bntjy21FKxKRGeELdUVKmazbKU046pTabKST3rZRksuqQFXZZ7Y+ttRSsCojPCVuqK1TNZ6Az390L8U7BbKXm32yh5k/ytjucbYo/n/I2yl5jttlDzJ/lbHv7dsMf3bTbKZmP8rZQ8w22x/wDt/kIZ89tspmZX8rZRM2+2Ujy2iGs522ymZlfytlEzb7ZSPLbDec7bZTf7/wCQtlEzb7ZSMw2wjvHoDPf3QvxTsFspebfbKHmT/K2O5xtij+f8jbKXmO22UPMn+Vse/t2wx/dtNspmY/ytlDzDbbH/AO3+Qhnz22ymZlfytlEzb7ZSPLaIaznbbKZmV/K2UTNvtlI8tsN5zttlN/v/AJC2UTNvtlIzDbCO8bUtHqw5Jlz4wUacYKNOMFGnGCjTjBRpwhBasLEz504LQZC5qsp2UowUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpw66G7OzxTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnDNI4Ox4OVU7tcYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04UwWAieOyhDHABVjOuy7YwUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpw68G7PhMU4wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpw0/wdjwcqp9sYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04WxwATZSrsoQxwAVYzrsowUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpw6/wdlwmKfbGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOGnuDseDxTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnC2OACbKVdl2whgMBVjOuyjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnDz/B2XCTqn2xgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjThp0t2HB4pxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjThbHABNljsoSyGAuWOyjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnD1I4Oy4SdU7lc4wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpw04W7CwxTnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOHGOACbLHZQlkMBcsdlGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOHqTwdlwk+TO5MzjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnDThbsLDtnGCjTjBRpxgo04wUacYKNOMFGnGCjTjBRpxgo04wUacYKNOHGeACbLHZQGQwFyM52UYKNOMFGnGCjTjBRpxgo04wUacYKNOMFGnAPq40oKlM1mvnGLxrmLxrmLxrmLxrmLxrmG1UduxJVI1kwpykN2SrOXOIxCLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmKQh9FklNyvti8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5ijMtIk2uxmJ9sXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMOOstWKxKuyOWGXXmrJapzNkcsXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMUht5FkhFwT7YvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYozTKLFC5TE+2LxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmHXWWrFYlI2Ryw0681ZLM5myOWLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmLxrmKS08iyQichPti8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5i8a5ijtsosULlMT7YvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYddZasVplI2Ryw2681ZLM67I5YvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYpLTyLJtE5CfbF41zF41zF41zF41zF41zF41zF41zF41zF41zF41zF41zFHbZRYpVdr7YvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYedZasVplI2Rywh15qyWSa7I5YvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYvGuYpLLqJtospCfbF41zF41zF41zF41zF41zF41zF41zF41zF41zF41zF41zFHQwixSq7X2xeNcxeNcxeNcxeNcxeNcxeNcxeNcxeNcxeNcxeNcxeNcw8601JaZSNkcsIceaslkmuyMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMUlh1E20WUhP90XjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMUdLCLFKrtcXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMPOtNSWkVGyOWEuPtWS5muyMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXjXMXnWPHZ7+6F+KdgtlLzb7ZQ8yf5Wx3ONsUfz/kbZS8x22yh5k/ytj39u2GP7tptlMzH+VsoeYbbY/8A2/yEM+e22UzMr+VsombfbKR5bRDWc7bZTMyv5WyiZt9spHlthvOdtspv9/8AIWyiZt9spGYbYR3j0Bnv7oX4p2C2UvNvtlDzJ/lbHc42xR/P+RtlLzHbbKHmT/K2Pf27YY/u2m2UzMf5Wyh5httj/wDb/IQz57bZTMyv5WyiZt9spHltENZzttlMzK/lbKJm32ykeW2G8522ym/3/wAhbKJm32ykZhthHePQGe/uhfinYLY86pwKC8lsYpCXAkNyq87YtlKgkmVZhthSgopnWM9seeU4FBeIZ7Yy+lwJDcqjnti2EqCSqVZzw2wpQUUzrGe2PPKcCg5OoZ7Yy8lwJDeI57Y4wlQSVSrOeEMqUFFM6xbH31OBQcnV52xl1LgSEYjntjjCVWJVKvzhLKlBRE6xbH6QpwKDk6vOdsZcS4E2GW2OMpNiVY4SypQUQTWLY/SS4CHJ1ZzO2MrS4E2GW2OMg2JVjgMqUFEEmY6Az390L8U7B87me/uhfinYPncz390L8U7B87me/uhfinYPncz390L8U7B86P/EACwQAAECAwUHBQEBAAAAAAAAAAEAESFh8DAxQVHRQHGBkaGxwRAgUHDhYPH/2gAIAQEAAT8h9xENlv2REvl/u6K+b7v4V833fwr5vu/hXzfd/Cvm+7+FfN938K+b7v4V832lwg1kcua5Ovm4bjuw2yvmtODA6A7CzMyUID+cBHNdXagcj9hldJQBMHLP6GwFOC8FdV3ho7QG4aDOB7mTEGITZnfQ3BYlLuIBrjkmIMQm5yrhYOPQ8cGLAel8UO7Ma4fYYDZduAIjqi1iWIKAKhFdTK6QRpAbQScozHqpTFCUTI0FHGHqKUScIyFhejxdF8wnOAIcWuvRUIezu3CQ+wyBCTAXlBYuAC4jBPDsozzMGD6kVmLkYxAv3hV21181pwGXuB0YwuCPJ5+xHgTdRv6OmkMR2Brx9HxRhyDhrTblBmG1V81pwz6Yb3LJ9O8CHdCuGg4/VnSoL7ObaIZ954HdClYAUh6BCBMQcQg0eDZ5N4QGYzDEbTXzWnB9ZhzAE+GIldKOlYgMNTd9Vt7SAMAzOauWVFZEDACsjPPZTNsByUBO+cwMAdXsghEx5MVkg7+RuOH7tNfNacK00T4VyMXUrnmIHAsdfqp7MQyfoMXoFEwCcgZ++ytQm6lf0dMQYj92HSPH2lusQXtcINwlpOG0K+a04M/hQfqCBN6dCNdpA3Eg9x9VjDwIdRhEuFyhSEAxEW4pqFiEYBtlIXgEmgGQJmGBkB7mfkgg4lIp/oB9xyOz181pwNsvY9QHhAMGFyyyBOT6qidLjOZ3a8EQFczpyGJ4nsm4OI4Cm4p2fcP6+yGcYbjkEACDy7A3OTveykbHVYc6YRlr/Nnr5rThKzR5vRkByczp9VEJgBvLzwHlARZhSHpFXnw/Hs2R5TFZuN/TumKMXmXdGsBQYvnPPiRCmIE2IDDeNmr5rThWKX9M2CB5EdimW1kP9UXVrwGZwHNRMyOcSYlU/VjV23n63NPGX5EgdeOxlVuGMDET0IIbCYDIWLtAw5FEUzANlMr5rThKTw5R6UWRQ93iYuBI7N9URmEAjNAPPFZyHZnE8/W+cJ8VCEcBwD07bEftiCZAIPeLc0R3sg3hXGIVdjUooN4VhiNkr5rPgSwJNwQP17dQnx6YmFlvaCey/lCPw/U5iWLUB53OPoO49o8ogYxgEcfJHzYiZg7C9JgB3XnTioBN1a7o1m3AhjtBwZGphsIOGbi+0c3rnJsbnxgIBHxIBgjeub1zki9i3jcZvf8A5zxJnLvIP30IcEG4oicwB5tefqcJ+JwMZPBxPZBW0YWZX+1vD8wF/R1F9+ev9DhsJiB2WMCYl0ckIQGAMBaECIgT4wMd4QmTF055bGr5rPhNDqFvKrBQHj1y8dxj9/qYE4kQ4AI0yGjgbh4X8PfG8TKaLrhsBf2KNIId0XLbxzyHe2xZkwjPT+JlI3GmxV81nwrYi/hTULmI+sNQDGaciPqa+yeAb+eqgdc7YcID3mMEdIyNx590IZfwVw9bdwM3kB04pqDA8Lo1s/0A26YTOiQQcNw7FXzWfBn/AAotVJoHk9ZyPKTGkkt7R+kCNjFA3ITQGzPIYaggw/TYiWDmAQ38LMsBxMedhf2F2RwPNRcSIwIgHbrbkSF2muby7IAAAAMBbhuEvIxQt1iK9rjYa+az4HvJHzZ4QbhA3rCGAcDo6a+Jjm/Y/SA3i48mDuD6FAjFu+AFZbFAc4UMXKHFQmOFDBy72JAJjwuQ8o8UARHIOCLW85e6AUaQiQMxzU9hwQct5m44/qvbAQgwMoxR+5uA3At6+az4SvCeJez/AGyQv9FgN9IDZnEGIwDiWRNgxEMxZeyMceeOfC7YseCxyxHEw5IQDC6xZe/IPx2Tr35B+O1q0GbkSJ8c00xgcf8ADDYSCkEm2Zh19CCkQCzIsRb181nwz2Og9pkAuwOj/SASNZDHAOb8lho4JzOJ5rGp4C7QKhVPDHxhsEL7nZx4Byr4ZcSG7XlZAMByDEFGKmPG5nyhxtcSmKnhw2IRjmOSG8dAoLECBiEJY5gzhcBb181nwzu/p9rLVIJ/R5hesZFwhDX6DTjOMQiPMbPNuVegWhWFxFub1HQzvPxwQrAYAMBZwMQAwIiXforqwLMjiOdnea0+CjfGaZvw57GSBJi4ubBXzWfDfUo8Xx7SXvAbreUI4cDj6OcBN1m/o6agt4x5Hj6sjgSnlDdaAHD9tjDaEDMrk4ATE5yeJ4ntaAOX8FeHVGMEYJyuI597Nz11PMPVk4gbqE/OHwdfNZcP85QJn8LA6+1orx8iD+LEcuN4ge30cWuIAzCITwQObEDID2EudwXtYIFyHh0jakedrj6DuUBNg+FawvE8KDrjZwREDKYf4/CV81lwntzkPKnyOgHtzL6g/hMNN1fRpwmL4SGi7iC4h5Dv7hWREV2IN6sESXmGIDZ4rDbM4DmooAFOJRLxztoPvz1/g8E/h+Yi7o1jf/Hfko/J2Zifw+Er5rLgyv8ACHwps7p7RXaKfEIkLkFnmD4+jXt0FzZNUY+IR/OHuDLeAiJ81YN4Y/4glgnBGIsoAZDGJMAqSuRWicziedsPNyBmCj5RC5jEB4+Fi4q/nmd2TkBubon4EGWwYLRDqq1Kq1J7SiW5IxADmtcB4VVqVVqUQa3taHuzUFyBLeuniH92UCCHT0H0bmBscsXn3WDGVIGCcjNZA1hYlLY40ghowNxdB42CEowTiDp2V0YR42GXgymi6ofBEZOvLFU3hVN4R/EYSB0DkgBSJgTTFU3hVN4UPIsxL3QBiUJK/IPdksEZO+Pt9GR/ZrvoBN6vicn72sStZAXG8LHeEF2DDBYBC8kzYmgOJ7IDOGBzM79gaEPyBEaJyV63n6/P33aZN44BX7Hkxx8Pha+ay4ZvcD0fHvJCoReRHlAuAR4j6LgXoLMoB35q6ju/OyH+0kliUii7OO7EsQfcVABOJwCG0XmjyHzw2KCvPh+PZ73E0Q4tyTwBnu+ifha+ay4Zm7T3tSn/AEs6+oaP4ScWDvQYLK5pPEj+FM2wHJOCAC5i9OA8u1m2prCKiS9xsNaAAgJRBHtamUVIb9OagLc3OHAbEzPuH9ZOwcRwFPx90xM3Rnw+Gr5rLhnTtPeYhlhvEfCcQxLyIH7/AAhfT/BAD59C9iJ05nhwb+Ee6xuB+O6aG3LDd072hTDuROW4ozePOJhfp9sQWIGWFzOxgYcvdFGfYkk9RzHb2ixZETOHVGvd9Hn1Ny+Gr5rLhntwfU8e8MVAYo91wB5g8/wh3G/wcYtw9AJzZDG8YPmV1Q/g8mNnIGuZ8uyAIDAGAFqBDMTjkDuFXKIgG8X69YWnBxi5d1AgjpYHnjsgJb4M2oEbdwDSPsfBd4ZC7r2UNW5mievw1fNY8Jj/ACBQiYmwGTaUz/hGZkUMnifx0WZpB8QeDcuqDRRgHBWOCI/QJIhgmKBfB/gby870lG1YzEmJdra9Yk7YRmcsvxM/E+6R9CJC53NkvcTDkgAAADAYbIyZxcYfjhP7fnmI8+yFGjVc/h6+ax4blUcQyzSMOACwyA4NzD0b+EiGXXMk6iuFOO4BvUGxyAhVigcczCGZYFcOU+fDl90xku69kNrv++ibdjYmOqJIJ3hhIfP4gDFOHgPmm8RmkH9fps0VxTMrzkMPUONE7A6sj4mgchf17fD181jwmzsCdX+kHiwcB1wOn+3aP4PNIHtHtF4ODmWYKKQBwQaXymObQio8Mx89mBOMsHnFsOB6G+IcmsvQsokjyL6lsxwW+YzXde6G/wB33UD6HETaAyEB17IIq8Q7nV/h6+ax4S5HQlT25yPmwzMAc28qMTeHAlujfwQzOA72gj3oCJMonuPcQAIBwbwUUP3kRemw3IobkyAvSYb0QAEnBuI+be0wuIp+CYLgN2A6vsJ27N43Ud/ocW1hxGPRs15Xd2ajXoLIIB25ekTjbhVz+Ir5rHgz+FgNV/jqCwxvIo3tBSuOV/BHUQXAifCdkNxpF5sHOLQgo8cwilCHFBsz8INBxcyyI+aJy5BB6DkO6Bwwe6GwgIAEG8FN7bzt2gLUaFiRAeXdBQFnlmT+k1+91GPb4ivmseG8oQ4HiyjCAYBy/J/gjJ8+5BJz2IAAACAFjeOUQXhmYQyDAg7HMGFWHw4UCm4hdzTVyxD2bAflwJkAg8QMl2Fxy+LBT5MV5y5OjQM5uC516IKsLhkYnG/4WSbSD6nHBI+HEDOJO8hMMeocdieBhk+3Ob+k2SHN3PfwOuvWIDy36i0I4tAgXwVhsiP0CaE5HT1hHjWvAgRvBj8GA6L2Bmbh1V+NUlH2dVIyQ3WAWZHEW8Z25aifA4pizc5P43xbzyxATY9vQzpYD4Ejt8KGLoDA3Bl/g1/g0U+QIA0EUElgOAPlf4Nf4NRb1aBf7c9iyAgyDAc3vKBcOP4Bmi3MoPKdkRTcjvagUe4y+T29DRga7JiCgXcQHwWL+wzILgdEZhICxBw9BNiiXHBJjC3gyJ4UWn4wUTZJfmBMSns4RUMJIBNFo+Ir5rHhIwa4jZZ1coH4FGhy73tH+AavlkBKA79FnOIt+PW1CI4Usw5FGZQCxBvCGvm5wUGAwMPgsYhNmcAnmZsRnvEpj4YERIgFEmXvNBJBCBOALgi1zyObAOaOibocy5ty+NwATfE181hwDcIHKLexh5kvFkxAIiA4EeHWdPUn8/wGeyN0brC3mI5HzQZjaAuERyMfg4lgDx9Au9amZ9DfHQ7z0RA4HZu+JkABASiCMbQJGshjgHN+Sw0cE5nE8/5avmsOE3gOZN/40Gtl/tGhlE2ADe4PYfP3j33QCvnt6ZO7DnsDCrueR3ZOQX5OgfgWUC3tATtpQhxJ/wAOfshgjc9oi1wxlgFw4usjC9YyLhCGv+Xr5rDhNQOYAqyIt4s8hMjc4dPn2SLCBxiegKdZDHJcbugGwX7w3ZqCSdmQj8PgT1OxPDOeDyhUMN7RjFgvzMlG0B9pHsNk4CbrN/R01BbxjyPH+Xr5rDg6UInwp6dQk+bPJw6R8/MtFFpjDt1QBGE3Q2GD4kZTf6PgDvZgZOJ3KOckkvM/UPb3ulgG8mko7iu8ksjYlriAMwiE8EDmxAyA/l6+aw4M5t5B+qmeCzuFQLt4EdygXdQHz2aSDd5EdialjeQerJyS4dCfvHb7lNhni4XJk8gpCwhubd8yisHEqLveeJi+Eh4u4guIeQ7/AMxXzWHAiKvbqAeEAAABcLNiREJ4EEaLESCpu+djqxOex1TXojAyH+9NivqKfFQNjNyEfhtwwhwibS9HGMMzfPxPayZsBIG5mR1Qccn3WfI9z26C5smqMfEI/nD+Yr5rDhKbR5zaSgrOCcm/gBY+T863BxfM7o+4bmUR77HAUUON/rtx6jxIJf5IM4EAYAWYCDAuEG5b5oxgxwrwYH2swNjli8+7+Zr5rDgaxSbQN+0XFFukgbiQfHzsNxZW/wAGyNAvvFA+E4JfiuDQ8dsg2c9z4LPk3YYed/K1bEd9gIEbCXEEwh9Uf2a76ATer4nJ+9v5mvmsOEgGQ5LVkoGHOH5wBCMBElGA+QCcOj7Je/0+Kg2CWiY3hy2wjxMMkZL3Ew5ITIAGAGFsZBOFctxCAZALubnvl6QL0FmUA781dR3fn/M183v4EsHNyB8vYdQ+LXKrk4u6fOMoW4+g1UXiK4RAdjsuChxU5R4oRu2qCVwzM1mrnDO7heeOwBSDq7YZoibyGekcAZkEoHXhcGHAfy4TIbeEWjfH1qqeYGPDcQHkLkBbg0etVTOEfvBJd6/4/wASZ/Cg/bUogBIp5EdighLuch/myxQUfR3FDuhyEbK1CfmSB8ck9xwcX8NtTmh2bT5IBgwu2AhvcgjZEAfVxp950/ma+b38J4dYt5VKSA8W0vEbomLiI+bl0N17Zl5y90VCkcQExjUtpfmT4yxPHFQ4mpIwVnsLtxgSTmb2b4hEMALucIBC8BgAwH8zXze/hShF/CbWfMEbWAzkmG8BwnHve4EDQ/NXp1PgFHaMzMT+GzgYJaapu7oEEAiIOzgIQAIklCQsmKxubcOJjz/rq+b38Gf8uLVZvOd7LUAQGIKI3oA8Xn5psDD8N57dUziGF4HRtnehPzNA+DwT0HBxbnRtnbMIlsMfO7moYHDchw1/rq+b38D32jbewIYe4ALbLh3f7/NEVyfebdghOsNgls4f3LFIoul4kbxj07bMJwG4cAiCnwBZD/bn/X183v4SnCeJW8FwYbq9G+aiCLK3f7bSYUZlqUDk3NAARwYg7KQ0xm3j9nyhAHdGHC7+vr5vfwzqOgtyY7yHSNTklvb5iLDF8SA6lMwuTd+idpYY4AbrjrwThJ+j3dG2R5IhMgFeFEM/Ff8A2FfN7+Gce1tzhAig56EpgYmTnoR8w769KMyFB1gjvInqdpBC5ApFE/iXbe+R22R4okAL0UBxPZQhY/M79OH9hXze/hvCUeL4t4XORW9l/g8G+YQLFBVYbWQXumMTAHQjNuBwdif7MZXvJhhkcB4/sa+b3cP8fAJn8JPrsEfwJrodH+XKiwHJkhi5tInoNrYw5G7rj0jwUaH6Fd0bYnugwMVD8kxSQPnF5/sa+b3cKShh5U/x0A2DJNYJ/LvwFh+R0dOmI/guHbrtYYnOBmCjx4hNqh9gAQgARJKeBAY8yBB8d3j6Dx/ZV83u4NvE+kPhT73zYCXwA8yAARwYj4V3wGMG6n6Lg7wHCDfTt4pZnTFC7DDwG2DcuWMTAR0IqLicHMW7i4YIxoxkzehA3I6oKy/rwLlBdrRD5ql1Kl1JxHCWZIlGjmszAZyVLqVLqUYS3taHH0zwFyBLem8w+wNDe3wIP4sQyRHeAx7Wl7MAo/ovO63K5DrsAYfps4FS8O4N49BIl4d4bzb/AJwttGlOVm4X9H5Jwjl5F3RrYwDlN5cALmBoZ3D0JUBmcPz+vJzheac1XHhVx4RDaYSJ0DkhsOBiTTFXHhVx4UIGM5OnpB2JQl78g2CBkeqP4tQvAYrAJwxuh6PH8NWbuRs0ukO88gnkJUDiVlPW7on8GL4cjkGH+pgnHB8G1BczkIRAiwh6u4baJxxuGYRiIPDsTc5utQLhciARqd5DMywkTBGz48gMAgDibh3QgwMAwH9lXze7hn9x2vjYRm7uchke5yQRzB8WQSgTkiwCceuAcnc8oF8DD3fPMrhxK/L9QRgABEXSDMnj4zMT02RrzdAXlkEVPOwAubuZlB9ngAHowTzGUwit53cYMkmI/EF2GwxFpH6C4RE9hzTqhu+nZtuEhgM2oGRDnGJmDZlzJgXuQCnFgAmaC9zJ/ta+b3cMwdoNi5CKJxb0FjAVYN7IIpdaOTexSUXsFQgJeoywTEG4hP4AC447hzSFwO+umJbF18PLITRo6TMLgyZ5j+IZIBgYewIl8R35wT724LsEigAICUQRjZmO4OJE49AEAQGAMBtzkB+gX9HTzHK7dh07WToMJCPU5BBREkEcgwpNAnGwEB/bV83u4Zy7TYjLAIid8fawysJu5omMEQFAHggPnYBgPaAIABBgQU7IrSIpgoH9RLYAABYnOQUbK8nkkHsAwPcWNxue0R68GYfLwNnHEXVRht4S3AxGaKPeOYmIuqxbhNEMQXkqJA1pXjnpV39vXze7hn6BbEHuyibmI8od1AHH2jsG5DALCCBGAPCaz9LQnOwvvV7s9/iUlBmusktg9AHIou15M5kgABYDOZsGuAPdcyJdkzHS2KdiyRYC3iA7p9BgeR3+ADvvbe1R2R+XAJmD7glAnJFgAvzGpOQmn4HwUY/3NfN7eDx3G5E85jE6vGxMOPgBceQpT1HD2RtUVC6aASXdk3Zpq/jXvVNnEwePCi5AjQyJxpaDJAOTBCjhO5uDN2D9XVwkszOyuFAcjAHlXWg3nDnvsH5RMW7/AF0UOGIR3OvwEIn6Nf0dPWcg91404e3G+sewRaW165sz8KtIAlL+6r5vbwzRDO9lPaHINdixBLg3xeE9xiXkQDr6nTJriJZZk/LsRE0wQMzMAMBakACXdxJ7kkBEAG4TicrILs8AAQU87km5qGCa8jeTeWZtIwzMd3fKhAF3snvzcibv8HwIDAcgxCMUM65i0S6ufsoQQZTQ+efcu3DiZ/4g38EMZn+7r5vbwnzqAVbEQ8bFdjjFDqbHCAkiPKCSuI37s1uS/iRmWAkhhvEMf4bAUAJV2voTQwFEACYD9ysA3xXIgAhYktyVxqgFPpHvPM2z8GcE1IcZgM9p7SsMYSQQRoocVz26/BCmi4feOOY7I37gGkfRxJjdn0JyRglvchJAwMwAwA/vK+b28JPjoT4U8g5o+diMTebEMPQZ+Mw73HYZOyCAWV5OZOOxPiLJBvBHwNki3D7gSgTkm4BDxLTkKBULlEl524mwDEG4hPWErHAPFkVHHIEvPI+xtgs2HG/oCn6DGF2HQD4JiIohxIX9CVcjHfGfJvKONaYleMAzmmQjFhlweZzP99Xze3g3+dgNV/naDYibCKTI/O3o9M0ZgGA2QYRiIIEB+5oIISLtfQn7AEIAESShl4vy94yIfxUcRPTYQZQHGKFHj5MjIgyxHB9Yph3Jlqc1dhfdAfBFRLZ5Bh8+jgwWjtJ/f183s4X1GisEJ2iQ+F5j2RWVuK42IE42AcFQJxlaV2GoGykQAF9wlM5oAITu4k9yfoSwc3IaeOZYhAjc9psbCd8QcxNPFI7jEZJ5j8QhorC4j0zyBG6F1j8GPXEO9lxCclXYzrU7EKf95L+QQV/lF/lEOCAuAOJPEZMEI/yi/wAomhjgl3+vR/1lhWz3j4p1JOQIwKIIIGERxIiUThbNcTeYoXQHnpCWygVY3jvzk7aDkX4JqxQ+Mk0XJoMEYRMECZRPccvqEYZQGPuDL/Lar/Lao9ygWGgj8YrD8AfK/wAtqv8ALaq+zu/P0F+448figiE3QSIJ7eoTCLociSR0OzEDSWmWoPQ1zIJV0e76kr5vZwLhvhoYDPVflV2dMzlDQcnX4uMlHLzgyUZIOGnFns5azhowYj0HoW4XEnkXn6kr5v4ngAIABBgQUTA/iWY5ItH3hvD9SV833fwr5vu/hXzfd/Cvm+7+FfN938K+b7v4V833fwr5vu/hXzfdnAlo1x+LRv8AWmkVHxMNySGZXEB7gz4etNLIdO8cl33XXzfd/Cvm+7+FfN938K+b7v4V833fwr5vu/hXzfd/Cvm+7+FfNa8BDgLi60ABM7QLkLQ+9G3lxZ4xaNpAdM4QFpEQR+gYxaE+o2+EKjdU3xjtBJEdIC0gXM4QNpzMqUISJnR98YrQRBH6AhFoI0wcQNozTi0IU73RvL1oBcTtAMAtABAiL7QEcuJCBHDsZvL7QRoHyAYALQTAoCvtAGwsQIEY2RYl+wV81rw6laarmtKLk2mSmoZrTq+z8NFEGR13ftKpktOhWsak5rSq5doB03ZtRuk2hApmRUnPYK+a14dStNVzWlFybTJTUM1p1fZ+GiiDI67v2lUyWnQrWNSc1pVcu0A6bs2o3SbQgUzIqTnZPEHX4mO5VLRVLRVLRVLRVLRCK32IkNye8I5kAZSVS0VS0VS0VS0VS0VS0VS0VS0VS0VS0VS0QFLLOa0XyVS0VS0VS0VS0VS0VS0VS0VS0VS0VS0VS0RACYBfwOvZVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRB0BgtezF8kGwuVu5HKaqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiAZICHNaL5KpaKpaKpaKpaKpaKpaKpaKpaKpaKpaKpaIgxMAv3Z2SqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiNgHM2Yg5SQrC5W7knKaqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiqWiEITAi7Z3ZKpaKpaKpaKpaKpaKpaKpaKpaKpaKpaKpaIzxMAL12L5KpaKpaKpaKpaKpaKpaKpaKpaKpaKpaKpaIlhc7ZgOUkHA5G7l8lUtFUtFUtFUtFUtFUtFUtFUtFUtFUtFUtEJomAXbO7JVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRCGkADHvF8lUtFUtFUtFUtFUtFUtFUtFUtFUtFUtFUtEfwrcdmIOUkCYGS9t5fJVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRCCJgF3FiNJVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRVLRCOssyNF8lUtFUtFUtFUtFUtFUtFUtFUtFUtFUtFUtESArcdmIOUkKoES9l53KpaKpaKpaKpaKpaKpaKpaKpaKpaKpaKpaIQRLJYC80lUtFUtFUtFUtFUtFUtFUtFUtFUtFUtFUtEJCyzCNF8lUtFUtFUtFUtFUtFUtFUtFUtFUtFUtFUtEfoogX7RfJB2BHGX8FUtFUtFUtFUtFUtFUtFUtFUtFf0A9WR/JOSOPzU5TNTlM1OUzU5TNTlM1GueXRplNqcxNwkGanKZqcpmpymanKZqcpmpymanKZqcpmpymanKZqcpmmrrLXhrmBU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM01TkVLuYN5yU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM09iTHF4ZlYKFQdjGBkpymanKZqcpmpymanKZqcpmpymanKZqcpmpymanKZpjeDGhrmBU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM011UdLu3EqcpmpymanKZqcpmpymanKZqcpmpymanKZqcpmpymadoOMLwGJWGIcLiGBU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM01BUVDXcCpymanKZqcpmpymanKZqcpmpymanKZqcpmpymanKZpieIqXuYlTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzWOJUGcRiZpy03sLiGBU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM0x1EdDMIwKnKZqcpmpymanKZqcpmpymanKZqcpmpymanKZqcpmmtbDXl7mJU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1jMUFnAYlMakFhcWRU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM01b0VDMIEQclOUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNMXXC8vxFTlM1OUzU5TNTlM1OUzU5TNTlM1OUzU5TNTlM1OUzTRPRG0AxKb7ALC4yKnKZqcpmpymanKZqcpmpymanKZqcpmpymanKZqcpmmPOj4ZgAiDkpymanKZqcpmpymanKZqcpmpymanKZqcpmpymanKZprvYXl4zKnKZqcpmpymanKZqcpmpymanKZqcpmpymanKZqcpmm4eFzaDMpwICLDGRU5TNTlM1OUzU5TNTlM1OUzU5TNTlM0AAEArv99fNa8OpWmq5rSi5NpkpqGa06vs/DRRBkdd37SqZLToVrGpOa0quXaAdN2bUbpNoQKZkVJz2CvmteHUrTVc1pRcm0yU1DNadX2fhoogyOu79pVMlp0K1jUnNaVXLtAOm7NqN0m0IFMyKk57BXzWvAXjWABmi9oKhQkxEsRtCZBJh7i6unAiBcj5tAaJIAGa9aC0QBBEs60u5AC5gPhXNARAuR82gJkAAXO60FMgAgd2daXFARAMB8I2wIBryTaA6QAARDutBXNAIHe9aCcQIhAMB8InwSYa8vaAyUIERDhaAZsWIB3i9oMaCGLBiD4R6iDDXm0BC5oiIZ8LQEbFiAd4vaAfggAsIgpiSgGv2Cvm+7+FfN938K+b7v4V833fwr5vunh//aAAwDAQACAAMAAAAQAAAMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAjAAAAAAAAAAAAEAjAoAAA3AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAALoAAAAAAAAAAAAA+AAAAA/IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAAAAUoAAAAAAAAAAAAAA+AAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE/AAAAAAAAAAsAAsAAAAAAAAAAAA+AAAAAMgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQcAAAAAAAAAEoAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEIAAAAAAAAAAUgAAAEIAAAAAAAAAA+AAAAEIgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAcgQsAAAAAAAA8AAAAAIAAAAAAAAQwfwAAAUokAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAwAAwAAAAAAAEwAAAAAAMAAAAAAAAA+AAAAAAUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMIAAAAAAAAMAAAEIAAAAAAQoAAAAAAEIAAAAAAAA+AAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATgAAAAAAAAMAAAA8AAAAAAcAAAAAAAAnoAAAAAAA+AAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEIcAAAAAAAUoAAAAkAAAAAAwAAAAAAAAgAAAAAAAA+AAAAMAAYAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUgQAAAAAAAAAAAAAQgAAAAUgAAAAAAAAAAAAAAAAA+AAAAwAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA8AAQAAAAAAAAAAAAAwAAAAsAAAAAAAAAAAAAAAAAwPwAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEIAAAkAAAAMAAAAAAAUoAAEAAAAAAAAAAAAAAAAAAA+AAAAAAAEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIgAAAAYAAEIAAAAAAAAMAAQgAAAAAAAAAAAAAAAAAA+AAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMAAAAAAMA8AAAAAAAAAEIAAAAAAAAAAAAAAAAAAAAA+AAAUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA4AEIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUgAAAAAAksAAAAAAAAAAQgAIAAAAAAAAAAAAAAAAAAA+AAAAAAAAwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEgAA0IAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAA3gAAAAAAAAAAAQgAAAAAAAAAAAAAAAAAAA+AAAQgAAAUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUIAAA0AAAAAAAAAAAAAAAAAAAAEAAAAAAAEAAAAAAAAAAAAAAAAAAAAAEsAAAAAAAAAAAAAAAAAAAMPMgAAAAAAEIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAsAAAAAAXIAAAAAAAAAAAAAAAAAHoAAAAAAUAAAAAAAAAAAAAAAAAAAAAEjAAAAAAAAAAAAAAAAAAAA+AAAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYAAAAAAggAAAAAAAAAAAAAAAAEYoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAA+AAAwAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAAAAAA4AAAAAAAAAAAAAAAA8AAwAAAAUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAMAAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAUIAAAAAAAAAAAAAAAAAAAEAAAcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAgAAAAAkAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYAAAAAAAAQoAAAAAAAAAAAAAAAAAAAQAAAwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAAAUAAAAAAAAAAAAAUoAAAAAQgQoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAM3MAUoAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQgAAAAAAAAAQgAAAAAAAAAAAE0AAAAAAAUvAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAkAAAAAAAAAAAQgAAAAAAAAwgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAEAAAAAAAAAAE4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAEgAAAAAAAAAAAUAAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAEAAAAAAAAAAAAAAAAAAAAAAAAAAAUAAAAAAAAAAAAAkAAAAAAAAE4AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAsAAAAAAAAAAAAA0AAAAAAAAEAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAzAAMAAAAAAAUAAAAAAMIAAAAAAAAAAUrAAAAAAAYAAAAAAAAAAAAAQIAAAAAAIrAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAw+wAwAAAAAAAEoAAAAE/AAAAAAAAAAAcgkAAAAAQoAAAAAAAAAAAAAQAAAAAAUowAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAIAAAcYAwkAAAAAAAEUAAEAAAAAAgAAAAAAAAAAAAAAQAAAAIIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAwAA0gAAAwoAAAAAAogAAAUAAAAkAAAAAAAAAAAAAAAAgAEUgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAYMogAAAAAAoAAAAQgAAAAAQIAAoAAAAAAAAAAAAAAAQkA8AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AUoAAAAAAAA3wAAAAAAAAAoAAAAAAAAAAQ0IQoAAAAAAAAAAAAAAAAfoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEM2MPIAAAAAAAAQAAAAAAAAAAQosgAAAAAAAAAYcAAAAAAAAAAAAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAw/wfgAAAAAAAAAAAAAAAAAAAA0wAAAAAAAAAAUPAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAwfwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAEAAAAAEAAAAAAIAAAAAIAAAAAIAAAAAIAAAAAEAAAAAEAAAAAEAAAAAAIAAAAAIAAAAAEAAAAAEAAAAAAAAAAAAIAAAAAIAAAAAIAAAAAIAAAAAAAA+AAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAsMMTMMMMMLMMMMMLMMMMMbuMMMMMHMMMMMHMMMMM3MMMMMLMMMMMLMMMMMLPMMMMMHMMMMMHMMMMMnMMMMMLMMMMMLMMMMMcnMMMMMHMMMMMHMMMMMbMMMMwAAA+AAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAUAAAAAUAAAAAUAAAAAAoAAAAAoAAAAAUAAAAAAAA+AAAAAAAAAAAAAAAAAQgAAAAAAAAAAAAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQAAAAAAAAAAAAAAAAAAwAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA+AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/8QAFBEBAAAAAAAAAAAAAAAAAAAAwP/aAAgBAwEBPxBdR//EABQRAQAAAAAAAAAAAAAAAAAAAMD/2gAIAQIBAT8QXUf/xAAsEAEAAQIDBwMFAQEBAAAAAAABEQAhMUFRMGFxgZGh8SBAsRBQcMHwYOHR/9oACAEBAAE/EPUqMpYMUIiLHWfzd90/N5n7p+bzP3T83mfun5vM/dPzeZ+6fm8z90/N5n7p+UjO5BYRNopJbhUooSpD5Mq4DPvO6bQzslAGOTCExORCu7GpKu3BLWZD2rBVWEgWIZJ/WfyHa/kQskHJBY3xSyy40Dr7MAZEdZowwGggmLN0z7hnvW4gzOutb5XvlYBLm9CItY0La0z5snWznW+V75WUZ824tEdddggylTIXkADl9LxoxMpR3Ph+Qyt3IwYK7oE7pr4O3mRzEuNTYGigUFRkY06c46JADzifcLEbMVrxavFqZXVCgUQOlSC1+LV4tWTkpAdgBqwaWd57M5mM3Jmy7TAkYLJUCAelGAxjpCDjDjiq2mD8hCEEqMAGdRi+xTADaxXjRrNBjrFFogcEHKgkTgNmWdHDT3bum0M+In3wCajWPNK/n+RLMrNaZ9hdX53ZLws8IH6FiPi3BsHQ5HWrUJHcAy3sTpiPuu6bQzxOwl0DvFPsirZCtzn0paJcNwk+fxWoCrAUQpowpQ6e3mAJZwDBPAHgq3DSwAA6H0fYo+RCETMSkUS4pv349k1I1aOplWRCR9z3TaGe4cJe/wDVLWLoPeKdzoq6ElXelfiqsEuFMk02AMb843wwM1ZpEorg6m5tSMlgQJBgaIjxky9qaFxmABK0r1ffw5QdB6IFRWko4HwmYtSKoTuy3i81avuXdNoZ8ZxzmCnmkxDVEfisGRpoA938VCVIMkykplAbTRxNyQjo/Qr45ESAcz0A+1v0ou3ifx9RV39Zy87HhA9ITYT7AV7dQ3SaVElCJxwB44O/ie47ptDPe3KeXWzUD7oqlugtwf6Rl+K4fXAJE1OeITmb6RuMCiYDjIT0aPIFgAoQgwgtGXtX8w4mZJXgrm0as5MhAdD1TuDgs++7UpozGBVtp4cc7eDI+37ptDOjK5wpIEEAgNK3BwygCdj8VDcBnNw4outyp+y19c4bnt1rS59vjgcSaL38kLdVTpBwT2gYWV4ASvSmyz640BwB09csHTzNBojCOpTOoilprHoJbRFBEkue27ptDPr1RbpnZ+lnXW4BD0HX8VT20EuBympf503PUQCDn9Lpw0yDW4ARw9ot5tG3xOWCclXRUmLxA5Yrm7BImFwe+ukLaMb6TORLbMueDw4Ptu6bQzl3PoP+D6PEION5QDjCGxuP2/FEGSlLE9ucg51NSde6vlhPB9Vxt+YzhPLuKGV3ecceMcg9m6tTWmckF1o15ZsAIDpsYIVoZ1o6OA372oKVYtzLnBxHR4+17ptDPq1FboPZ+kYEpnc7UlWRBpGdn4oTvL+xvjgKuByqEyFYjOTepef1JidwoIk3mNIdGgwmhOIHh7KaVhMhK9ClV3OWYbHBTk2Sc4gyMQjyr/ou98jzHKhc4oyMSJy9p3TZmcnEBK6FIMuJd/0TG5ZPdT3BUvJgtw47/ielkMM4CYN7gb2rOBJXIcDc8f8Ah6UShDZYblIFAKhLgCR6PscENE3zvCCjNC9XD8fds4qRclzLPBwTR4VJStLOvPTEt+89idHJrFjIzTjW7/purd/03UTg5MYnHhONqDTnx5jB8HvW7/purd/03VHzpbxGRvbvXeOL3xH6q1+f8/6SMCEI5lIGiKHNP7/xOoN1vUwh5vLrRpWKb8+tjcHpsPm0XhYHFDilZyyy3ZlexDdkT2RNwHUoLxQCADA2gZyDbdgxxeHAoIMJg91NGL6M7vZ902ZnvLHw6qAjHPYPq9/Hfwf8/ibBUKUCVeRSuGSb4CMGY19SCIkjSc2u5qQ4Qnx9huNUwCvYqSwQbgOg4EcNqSSG5SOJAFmbvoJfRFIcOvmarRGRNT2XdNmZ7hxz2KdooX9/6h+upiWrM9h+JrVkCDdQ9SDeUsUa6XALuDoPrGlAxIaZt0jjVbSJEybPQ8tvbPcA3hd7FF81NaYMt4Ty211p5MXloIwlRrHks+x7iB0YnB9l3TZme9+n4StoYeMLnefrHpK66Ev6VKbIjePyn8ICDM0E+ANpYy4EayY6tM07TEbsKZlxoBICoWApMWZN/sgZACVWAKQChClzR3EaOwRmgRfwAHlUpmJER3wo25njprCbDgQ40JsCACANuyFKYxxl44m/i0xYR7AFrzwHdDr7HumzM9wlkeqg+VYRlPAI+tkJXcIZ7qT6y6cGOx+EJeihghPQX0l3GyMHELfm9legbC3h+RzCsKxyl1P/AEcVsUtAGLL3yjioV4pCRHBNq/8ACtvC/FH/AChYM7OBBw9imVYGbKxM3sDVoJlIGxVxIRO4pT4xvW10byTft+6bMz2FchtFD2j0WZlCN6h3anRwg4y+H4QIIeAUgk0gJ+waRdSSiArqQM0SlwxWcTBfvSMCzm+ySuUnMTT2M6NAAAAgDLY3rRYLoIHUvEVeFFxuglcJBzbW3OUTG2vWNOaavjQ7zoPYxf0tjDJqSmNQ+klcNOFI5PWHLb902ZntLAnXd59N52YNUX8ICbkjHLusXQqJ622C35yXnRnKA+7xU36JqupTjEMxkGL8jmI+wtQew3CbPIBrVgQEpeUdTO8bIV5oCRHEaaUg6s/OU8W1NXQXMILnGOoUAABAYB7E9zQMRiN1uHCM6cPEvZojcoqrBElMnEkFcIIz2/dNmZ9EFjuR+/ptvD5k3/yfwegKgC6uVFKKc+GDblTnH6Ni6LZCEpQHsk37Di3MzgoS8UZUSI6Rt1bHYMdzA5t6sMsUQEAcA2chmIER3wJpEaNBwOQE5bNFM78QLHFwoApl5isnH9ns8FvQI4T7DumzM+v/AEwI7XoTUDWPMCaiSfg6ze7beSy5FcYrHxBJcNj6nFWAFxLPBwTR1ipHWKZl58xau5tmCuk3I773dw0Q10nUyn3Mf97Q7SZNybvQcqWlSxIbZboPHZ7dZwm9r4Hm1mzrl8QO8E+xndNkZ72xc9JX9VYHAXifTh9Ji6GPcpP7IxqPzL8HM/UO6w3qAetEVCXAEB0PQbWT8A72jjGaSaVCfHJY4Yfje4m1igrBchxd1/8A8Kgu8M4ES73F2pbNePCaB4SjvKEQRkdlkEbzSyb1nlPsndNkZ7yx2HVJRcF3Hzh9MOEwG6B9lUrssPoMft/BswgtuC232qJMNMJ7PIOHq2mzFfYgb3gyWpYBMIyLqjuQ57OBZcZRlcRQc6mEB9iYfAQcRltpmzbBdiBQsPm+3hJPFLiuxjQmw5gk5mDnU57rs1L/AHN+yd02RngthD6jsqvAiV5x9o9Mcl/NEH5qesaeSfg0rN9iG8gvX5a00ab44eBHqEyKzQfh0cmkW2NkkkCcoZk71BWA/IhIjmRspB0LYr5avFVC0nIRn8xLz2wFUlwBCdGkSjjZcblIuxW04aOku7pat/wFL4I8Jjl9hbnSSaAYs515GjyNE+0AwSRBC60ADk8Axrpe6vI0eRoxb0K1C1l19UFsLO/9ilWthBNEV3X1fDAJT8GhbvGSRPIkToNhcXFBkYO9g9cQqYTwdybp0cejM2PCgyBLG+pr7hbgMAbrfP2AlowGE0rxCcKsZO4UEw7zDYW9ZBvM/GfT9iANgLELEqT9YUJpu00MJQSUGViGSYkLF22/6woVxCrBHEkBj1K3FROg+WgMwL5B+vV8RZk9r8GBICm/+JUeA07E5+J7s72zw7EYMVluAI/904BUMYWHjgE356O5NgcoV3YYLc/1rBgXbxxRgbg9gMvu94YcY5FpcPXuM6xy7D1xRIMcg7jBzpmXngKRua9L9l7psjPY1kNvX9HrueltKNF2s1AT5/BdjVlcT85clYFhGIkF1vWXnssGGZZuC0pTR0grF+ssB1Q/+4PqeyNaACVeVLTBMsJ1YEt+97K2cdcg1+AE8PWyBcm4YeKXNVo1T/thU5fZe6bIz8krp/2euUJdJ0GfkalhmS3SfAf4R2dsWktAxXcXpiZR0YI6tCIIyP8AhDQuOQAJVpwohGDJnArx2YZCKdNTRGEckoQ8G25sGamANHGCi1qISI4I+m9I2BvCXztvDorU+sXAIXIOM6+yvfwUF1QekvBa1Ofb4avEj1FhWjMM93KeY+zd02Rn/wCPT/t9cPEhGox7irvkQaOHf/CErpm4IkNYS8dx9GxoPlw09Eo3IZf4TLxQbjJXCCclXwXeLwQegeK2kJppejdO4h5OVSLYFgzG8hdyTI9CgKsBnQQs65dLbz5jRdPZxvG24R53qFUscF0h1eB9MWFpuGCeaDnSRXNWQub5XMvs3dNkZ7mslt4fBesKZAtRIaTa5R1Z+P8AhIFXQXClPVMRpDn9BBxrQSwRe4pOM4OFWoBGMNvMzeW+P8G05ZrBbTeAONCvFAQAYBtY4FFZdgxo9DmGocDtuA0hyZNPrjYGJuh2LJyRV7ZE5eD4F9ovFCA2IYjuhOTW9p+QCPR9CoDmMwxG9DUYULZn+5P2bumxM4vYN8x/VO3tBep+TYXVjbRtPgf4QlFeCCSpOYENHWbRaF7C0pKJsUUC4iONTtgpu8l3svGYoGgO4uhnpNlw0/wMfU1JiQW4lg51LcIjFfOHN2yARBGyNL0kAWZvvwJ0RS0PNOKzDJGR+ihGnVpZ7RaGWFACANPaaXfd41g3vUVhRgFuyryYcA9G5tOZPfiL6fZ3dNiZ7lwimio7pU2kCN/7FdhY3NBOH+ErnIn/AFiOuu1G+B8fWzX5L60BjwXN8RVmeDuSmA3OJhaIoiOyiTg5iZjc+/uEcaCrZG9jWFIApn+5U4BtyVx9mOQckYR1KDxUBIGxtLQDTOjRW3XLXIYSt9KISXo4pTvJwPbOkk4WxyZaD9UUg5PNWeqgKrm0b6neo+z+6bEz2AxD85+01YmFf+GQ2EdsUeEPlV/5X3eK/P8Ag9NG5gEY6Hn6VU+6bc4h/m1TQjFloA4OQe0xQq561dV94uZh9+uvjekiO5LNF9i6kBuMQdUhyfRhDwZEBDQRvwe2UMYSkW6d1tYWkAmXSbi8E+iJOY82GN6edSMBAMFXfNL7P3TYmeCG6JuPnBVtY7D2FHxJZyrs6x4cAftH+CO6WQ5hQ5sHOlGOIGYT83oeoygoBImjSBeDaRec70aRggMGbTgjO9GsY0JQQokTU+967M98ETeE0WX5bS5L1JeEexG90fMYcAAI6yaTUffBwsjBpYGsu722LqRiZJbiGHlV/dlcT8Zc3011AzJ4OS54faHdNiZ7k5TwNbExY9IT9bCFSDfF+UVKbKQaEPyv8FZ0eGt26h51ZIHXktd4A5bBVY9auge03Mkpo1iMtRODmvtM0om2BbnEP8W+9QxlhgOEurwdQ5G24A+PYhjaASJolBiZgbbqWs+4ZqAHQOcY8VVrqDbQxGpIeFIvXyxzE4pPtDumxM+q9iCpJDhWSQNqwOyf4JgUPGRLyD5UTYCAMA2IEdgEnEzEyS5VyWJmauA3uJjaJqwX4by1TjxXN8T9nwaHGcEiabWRJg4qY9gaFBchK9CnUonqADgJzPtcP9FDhp1VWbjShYWZ7JxFuIclChqAsMzLipd82+ypyiFHp3LX9p+6/tP3SV6oEMRBp1rA1TFhcLNf2n7r+0/dW4/gq1gfTpwNNyfvstHP2H83f4FQKgC6tBMMuslwfxhtFLC7yabdYsuOtTBgBm6h2svGZpUkBgEHUU5TNAJs+4NA5n2MLaZeCoLuUFMYCV4bgyDILFKPmZGxzDNZlS+NZzMdhk5bfJyGG5EtC2HsO8Ig8AOI/a3sUobKq9AOTr9NGi7sNRqOLRdfsrQw5QgxPCv5P91/J/upxYggSZtwosu8AhOl/kV/J/uv5P8AdYbmAIheTh6bgxZusu8bIJtk5M/0ZoAQRJEz/wABd0U+eFThdyqz8ktbDajCgcQUQExEhDa85fQWzVDB1EJapPbkaJJ9iNGSSohucQc6VaYaFFkTJ+g0V4V0JGJK326V8DHhiTorPKUAABAfa4hazkioGaK2xRIwpARyIA6RjNHHszwiFDcJIDdldJ+z902JnuW5M0hHadlHRKW6JnvVKsmPdB3D/gHdLiWQYOa6CUBDucbucnntd+mtgR41I3hSrrDohiI4NJOu0hpLwnmoZ0EkAWgEH2JOxaJw4Yb1Q50hZUp7sLcSAYXdKXZnPZgksRqQScogTXMgrbWeeRnMRPJqdASImJtYzpUHBLc5BUpjWOIPUIc321YJhYhfr9p7psDPjCXhBNXg3J1UPhsr5G7yc0Soyo7PY/4C2eBCBN4z27Whxp8Rd51JFmHB0PIYcPsbFyQjZCw7mV4ulArAwxCsU3qq8foKJMAn9lZmfEEObGaRNs2edoznJRe1EJA4I5m0mZIxy55xLkqJ622C35yXn/lu6bAz3lh4wsd4qxOFPjNlJUEve9/amXUXjc+/iX+GbRC9ih9lYrN8PD2Avpy0NJdnW1f/AILN8UeMTz+wyNEaOLbnOO6WoplXuiesw9BVGiMl0HVZnPEoBpj0icL5vEcuEwAIKJEwTZICoAurlRSinPhg25U5x/y/dNgZ7hQn/wBGdWFjnsbN3r2cD9L1+/8ARaCr4BzrmxF5R7BY8JEuZIORh5VLq67MQ9fn9hiYsC8hc3S0hU2s4DF3uK6vpvmowYPefbEzFZfuGLJs1bIJMsC5JsbN7tt5LLkVxisfEElw2P8ALnumwM94Y57FOwMbNysG/N0S3qP3+TdExeRz8JUijONAA7Hsc5hOSSXgzzn2BfVyFRwLruGoYXEZXOJYne19dxcpywx3q1ybmY4zs7C8n5ORlEbBn6h3WG9QD1oioS4AgOh/l+6bAz3Jy/l1sPFv4BswR5SP8oypPJaNRJPv153EZQjHMeyXTwqDS/h1rHbtW+IXewe/H9Sb4GN+AhvHWjyFnkEGwjjdpY1HTRyd00eTAbSLDOerPDSfVNILbgtt9qizDTCezyDh/mPdNgZ3NuYN9NJuAgNDZ44knRB3aXRkKdW53++iikps4QeaCnRp5YwypxfZWKCdGEEniY8quoe5xcPH9X3wmgZGZMPATyRnTnlW+gN+QngHPZPtFWFna6cjbDFxesFr2XAXHDHH02b7EN5Bevy1po03xw8CP8wd02Bn10gt0ns7S2kqE3oonxZhoA9+h99srAhrcd1LIiRzLU8GHL2eeqcwDuPmlFyT3qCmHaCnsA1g1rCVLQCAOAbOWCZLAYJyOXI5IuU28MBmwEc+OPot3jJInkSJ0H+Z7psDPamIOVz4bTsXNBH5qx5wE/M+j768Uwq8Sl7elBBBh7O6edsXt9yfJrVnRvnHeh7wFcQmNxF+VLxjWkhYiBc/2cxtSRCS8DgTQRZzw0qwDUexitkIuZ46x9BICm/+JUeA07E5+J7s729P+Z7psDPrtS3ROztdBbGUELsffC0DUYAYtNWbozgPIn2hzTuvAk8b0ts2vKBG9PeDi2WrTkbrEGgpWDQAsAbZUol4N1vARz44woTS2BiDIZ8xaQqxqyuJ+cuSsCwjESC63rLz/wAz3T1mcESAStMauNdqGzLncE+0Ov3znwAyTjeCuVSkY8uOFdU5+1KaWOYQ2OPcogChG4mfusaDRNwnbGJ1FQcBJJf9xLyNPYI4ompYjoiJTPHHFhy/YdRuJdvpSkl0wmOiyFneEHVoRBGR/wAsfQTQljEc01/Tfqv6b9UdBJ5yOLCcallWWZS4nDgr+m/Vf036q9QecUGIzr9bxxe+I/VWpznju1yHg5q0CImExoH7fe5ozyxU+Z6NQVXIZoC82Xn7WymUzGyPWdOfS7gC72Tn7lQFUAurTAzmjFfPHmQ7qAAAEAYB7BGwi4jrYKcH6sAglxIELmA/5nunrM9wYk6aqRjHO4Nq49JeoLRO0ijSE7B9700azAJDuvOftj/kW3CPzS/wosLbOJDw9yykg28fwIObKswhMvH2RnivY75RrIi2jvoVdqaRMiWZ4SUMR0BBoJidWI34VhJmiAgDgH+Z7p6zPceOdxXmchZ3w3ZNrHEGurO4FTmlJNIbv96OtYcIx2q1ASMx/Hf7cFlzRjFg4seNGZASIyJ7ctSqEAGK0t5gBct7fMjR0f67unrM97b80A/WpDID6h3naiGCRHMpSkTI5q/v+9WdgUY3dKIUuxBvpT7d2ZyKY4D3oc01KwS3s/P29rYGZc8f8WdFYWWnLpOytxf9c7p6zPfLZvyvgNYafeARtrrxO62PxPvTOlIQyLdwB50AIkWQIDp7fffggEezUEyAuE6Dip4e2JialABKu4Ka4AWwj1EWbtX+v7p6zPY9wC0ZnaNvmsK6rfIPvWaQRcQHZ7PctYXFYsRcXzULQMAyI4PtWW4BhLhyI4Azog5dM4DsRyLn/r+6esz2/gXrO87eHC6TupJeka3jPefvEYQI9P0JVkALuZYnIcvc4eaovleEJRZ5TcvMfl9pEU0+AJXoUoKNeAFuQJRmb/8AYd09Zn3oGeT99vfA5CEaEoM8vGn3gWbFnqGHUcqlGAnT9ie53wywBE6NRM1u4LBjirwHtHeugGA44fxowFiD/wBALDcP9h3T1mfV+3oYYgC3mHeKnZww+8BkoUXEP+Ll7t4ou7hzi6mjQmGwRJH2XDJCATbfkGtSgJGvKWd0Tx/2LunqM9wYu+kj+qkcwd4G/H2GWALqj8i+7mafdkCVp3Ck5Zq24Ic/d2b1jLxs8JNEflTdvh+fofZZ27rJY5zg3aqscjW9daxuD/Y909RnuLEy+GqYy4DuPnD7CzcDGt9837vZ+PeSj5fKrNSecYMXCJe7E3eTIQnRpDN8zMMJxVyPYBjRQgAzWrPJEICZCyuFQAt5wQy3OBx0f7LunqM8GsDes7KpikIvOPsHsAZbUTUDQnAxDMfstwxGCUoQbShxwOJG91OI+cN1WAEYISCAtCTDE4M7aSFomaUIs5i1AJ7e8UyLrDOaQ60Zss2CEj0287XIRAAagkGruPpco0sQiDckvHef9ekvEU0AxDnXjaPG0RxEhFJEELe9ADhHEo1xe6vG0eNowQKO1C1k5/SKGF01Re6VYiGSaIru+wjZJk6DPcpPrIfX5AtpPKjWCRBjBSMTYi5creHmP2dm6KhvRpBICwWApMWZws+30JiRAM6rqfTSqJEITqOm31QLqAQPC15+9s9pGXwOWS5KuypM3iDyzHJ2yEQAJVyolJJMIYskXMJnj9E7NIgskNYlPE/15cCBEgQShfry5NNulxNCgkoWZUWCxIWJW2/68uV/zLMHEkDH0uZKqcAHy1EZB08P17CG5CG6B9lU+MsLoKbQdIzAMQkOjIsbzX6AXIAwlBP8I9tasFw3UP3kXqfXxOGgtoMcx3tsPi8ZW6RbzqCp7WAXY7XCs+igH6wBzDJGybWH+xXNRDmwc6n0eLFf3PR96GFleCEJ0pKs+uNUcRdNrbF6IH9lnSJChr8//wB0c5UCP9igGqzObi5Rci3uPPh8MKgmeODQCx/su6eoz2lYKN6/o9jA/MZ0T9qIkK7k/wDh2ROuBQDFVwKvsgtRmfu741qLWLGGZlM7zLG7ZreH3PzRTcQLJpFimDkxmCmDBCU/cWT8MntMLZOG5Zr/ANbFI9JbYYt8reAoj5woBkfQx8IZrJMkbjVnzALYMOVgzOqivzXkTBNpOwI0Y411CnN0OVQnghy989+HEzII8UcmhtnDgCR6OzKddL7qE9jOKCU8TPx2OROQ3HfabrqE9jKP9r3T1GfkFdP+72XwkghsQagaS80GdxwM0pwWJ143QRYthjWHVxx3H6HOW/1Ylg8UWRHEordmKBxDN7dGpDBJJL7i15PsiCgwL5As1p+qQOFk1G9LaHRREsl2H7d+b6IKpYG6fuMySsYBLjKtr5xkzmIlrUQkDgjps0zNo5QrkyitBAwAwPfXxWa0T+dcirpbyt4XfCQc2yWpLLoaL/0cs0u8Gv5T3Fi5StLGj1A/23dPUZ9Hv4fj7LoX8ibdFsLdjcWW3zF3L6pRePq+bBHbL8MaskaGHpEIyBIjklG3EurqQzczLhhECPX/ADrqYOS7eUwpMVkGa4BTu1G1xsjIWLlwgf3iIAua4q4vqgQJhX0HVZnPEq4+bMbBuaxwCdG2yz3zV8bff09+BFx2ASEpmo2+hzCXM2MiBRk5aA7eA4zhQ3Gw7K8ji9BnoAAAALAf7funqM912IHeD8D7KzXK6FfLp2eTgJ8+mGNwwN7TI+cHVke6h4YVbeLFJbdcd5yDP1oBAI2RqbUkLfWebvOQnKwIvmnsO9qMTou1/WKhBquAZtA7sb3GzZCwMuErCYUGKzTNcV2El3Z7GJJpo5O5aCOta8Ffy5OeGMTsLqCvMuxwQ8qt/KFqEO77AjZrcMwWeKHBVu3MIBHo+pemDQGKrgVCJNDjUH11HIxgiKbZmxJZ64tIvP8AuO6ekzjihnIv6p1dqDqeyIULvdAXvVK7KS5n0F6Jlo8vLeW4tqfvhAeGbcVYvhhRg1hv21zOGBkbNMeCsXMTLXji1qaCUDYTH9+ThtGBZbgH/u7OgClYNBvVfQ6qEKa63zDZr+tslVhVmcJG7FnPDSBEEYWYceDmc9Y9bWOxMYIB4tQWM03iX1P2CNWX1fy9tY56BvneEPpDRHfGXIMVdCiDCU4ErExdD3iaspQgEv60Du3/AN13T0meK2A1vMO6VI5CBvP2V7KGCw2tj3FXyCQ0Id/qL5iQTloB0S063Ki0wGunPI3eDGFEFIYAYAGBtcIJXAvZw1Zsr2bw7xgDEMtXMWkNi08aUAxWhOgtsMG+W/kax9l47tmvbAsbRYGHPSXs5mTPHWZblI7Bwh0czJ5T6rTs/wAkEnmv2EVppBIjiU2RE9im7iuh6LJoZBJ+tSsb21JG6QwSbs5j/RTD4fiLNMVdX/d909JnkowJ74b2mrFQr+yAGpeWokNP3+bhAFYl+FAxWcJLAhicgu0uGWk3G7btjhfCiOQZNqBk34u4t7CdcIZBexhmj5YmaOAsMYMtebEzD1pyjEBEqulQluogjfcH8OFuwWDfU+DIttrcaAsmLGckJlOja3E86Xd6q8P7H07n0qAq9CpZ0gW9zFwIfYkIhgzBNJxI4U34q4AR6P0wiySmfBDPqdxUr6CcDKHTEPAxIGYwBgAYH+87p6TPBTeD3H6SrAx7J8F/TULKSaWV1k3/AESPbkMExWFmRyau9CcXNBb32V9gzV8vJlvZ8b1fcMReLQZbmfG3qTph+AEqrgUcLJWQBu2QyM2M0C3+wUa90NDI5rtnRUPlBCJmVdSe1RWXeORGoLNoula4lqdyHP0Xajvc5FXozBV+Qc/sTlOJJUwGkBcCTdUZ4pCXyE4MDGDAo65kMnNOkZTiYzIvdeTv4DhLf/fd09JnvflvCVtbFn0hP17ISSXJEMTpKtxfQ1gwCygLreeBv9obw5Cwwly05sHJI1xhkFrmGSflj9Q1qoQAYq0br4gog3bLvW3FGkRoB+iMjLir7Fq8R5A/2NW0rQtunElnPgoRYUPLUTJGyZP1T+TM5k+CgK4JtwDsfYpfQbgiXmp6fSSb9gVCpHLCOf8Av+6egz4RelDdLnupM6QHEbBBbDArCLWvAtg7vZQpsGBojTSbMoHznvWSeJjjvd7f2toU7ADBMtHI2iMJoDAtd6M2d7tAiACVcChpmvQIxvkcVz4YkoGFl9A0GRzx9mSqKcskmQyatZmlbADyNj/ooj305VcR+l/cA0ApxjzfY24kMFuZMWTGAirossX+kRNDAv0FnFlqQtkG9D/dogO6Qclr+z/df2f7pE9VWhiWaZwAKUxYXdX9n+6/s/3Raq4VwMO8wmdIMvobpADc2Ld5I8TP7VLRVRYpt4ujjleo4P8AdDKy0LrhUvUSU6CQDmCDnUVSsRBJM4GmK46HtMmkdOSH7Myr1YmlRWXPMMmWyBBqSXOJklljCiFcSZAk5v4hjkw5wQYl3fV48nBKFIkzZdKjKXUUJ0qeH1ePAxRIpEBtwJCcfo3YahmongY0EEfabDIGIhI5L63sQMQEnke2JGQBhEniGRGrOVKuNONoiRIIGQs7wj8Sd09BnHLn2JgHG2Qub7QjDOUXeeP0VKyQGAuIW8uCsrQXn7SkkOFAZTQnXGYiN1zSC1AaRSnTCaqN1jWS1BBBY9sRphiUEuEZuM/SIYSFlC3A7wZ/iTun+JM4hGQJEckp24riXchjgQVbfyVeML8sN34k7p+bzP3T83mfun5vM/dPzeZ+6fm8z90/N5n7p+bzP3T83mfun5sM5UlFCsYr8Zr+e/Vfz36o9Vm5WTjwnGm2xlmMvfhwV/Pfqv579VetPOIDFfr+a+6fm8z90/N5n7p+bzP3T83mfun5vM/dPzeZ+6fm8z90/N5n7ptTOraqaMO3LaKOmhJQk3gG0LBk+BIPZav5QCYAJ5ActorzKehARyttFQXwErJOFtoIbRsSCxyUpC2yswCTyA5bRSUctCAjlbaOI7jpUM8rbS8OkYkRDwU50ZTJswETyA2jiL5CEkG4Y2jks4qWN+Vtof0JCJBY5Kc6DxguUAHY2jov5SEoNwptDcRYowr8to18JESGxyUpzfhygYdto6jWQtsNwptHdVY4tF+W0VgiqEQtyWkL1nlBYew7p9mM+AMN2W0n8zT7kgz7naL+To2n9DXtO/8AsoOpquw9zt3XtXx2t3+3q9xM7h8Pe65e6fZjPgDDdltJ/M0+5IM+52i/k6Np/Q17Tv8A7KDqarsPc7d17V8drd/t6vcTO4fD2+uUhHu0XBMcNec185r5zXzmvnNTx99MQRENaIaTohMCJedec185r5zXzmvnNfOa+c185r5zXzmvnNXazJF/OlOlec185r5zXzmvnNfOa+c185r5zXzmvnNRbyijKykTMYV5zXzmvnNfOa+c185r5zXzmvnNfOa+c1mUig4OCGmtWJyknkGcZMcq85r5zXzmvnNfOa+c185r5zXzmvnNfOauRgMM8+U6V5zXzmvnNfOa+c185r5zXzmvnNfOa+c1EXgCMzHCJmMK85r5zXzmvnNfOa+c185r5zXzmvnNfOasbVITyJDcxpUyISeRZRFmOVec185r5zXzmvnNfOa+c185r5zXzmvnNVV4kjExynCMK85r5zXzmvnNfOa+c185r5zXzmvnNfOamrxFGbjhGMYV5zXzmvnNfOa+c185r5zXzmvnNfOa+c1v7kBPIMZmzHOlYopJycEtYxrzmvnNfOa+c185r5zXzmvnNfOa+c185qqeQ0Y2OUxEYV5zXzmvnNfOa+c185r5zXzmvnNfOa+c1NLAZbzoRpXnNfOa+c185r5zXzmvnNfOa+c185r5zU9ylCeRYzkxzqcKKDZMEtda85r5zXzmvnNfOa+c185r5zXzmvnNfOaqHlNGHmJizCvOa+c185r5zXzmvnNfOa+c185r5zXzmrBcgji0IrzmvnNfOa+c185r5zXzmvnNfOa+c185qHMShPIkZyY1MgHlsjhLXWvOa+c185r5zXzmvnNfOa+c185r5zXzmpu/CkdSExZhnXnNfOa+c185r5zXzmvnNfOa+c185r5zVXPEZgsUIwrzmvnNfOa+c185r5zXzmvnNfOa+c185qncQE4DBGcNamYAq2UxEvmvOa+c185r5zXzmvnNfOa+c1i5xQnaSsXVJcplYNb6qdOnTpubdZMlYhDEpKA8wigQBiuu0p06dOnTp06dOmtRsMtqAttdpTp06dOnTp06dNfTq+91IlgWdpTp06dOnTp06dNrIdo4BshguVKk0Q4rAFhltKdOnTp06dOnTprIZ3GIrgttdpTp06dOnTp06dN8Cq+yK6JYiztKdOnTp06dOnTppnCWPLWQwXKmDrxHhrAYBltKdOnTp06dOnTprSR3mALgtnN2lOnTp06dOnTp03+KrzLV0S2jtKdOnTp06dOnTpqO1Q4rINkYU+EBe8JYDAMtpTp06dOnTp06dN5iO+4FwWyl3aU6dOnTp06dOnTfc/WWZroltNpTp06dOnTp06dNKgs5TWQbLlSCblXAFgMAy2lOnTp06dOnTp03qMr720FhJd2lOnTp06dOnTp014Fqy1mKJbTaU6dOnTp06dOnTXUwxidZBsuVOmNieKFgMN20p06dOnTp06dOm9p5pLYLCS7tKdOnTp06dOnTpr8TUlomKJZy2lOnTp06dOnTp00EXiiQbINlxKeYdk8IFgNjTp06dOnTppWAAMj1+6fZjPgDDdltJ/M0+5IM+52i/k6Np/Q17Tv/ALKDqarsPc7d17V8drd/t6vcTO4fD3uuXun2Yz4Aw3ZbSfzNPuSDPudov5Ojaf0Ne07/AOyg6mq7D3O3de1fHa3f7er3EzuHw97rl7ptTOtOSVTxp2ixYBsuwmoxtBHuGAhwHCr+BzDAEeTaPz0Cp4i7R9vBWVtTjG0V06GJkAowJksMgXk2jz+CjEvXhG0f3yFTLU4xtLIhjHIE5KYOwsDkjx2j1aTkPevCNo8OQKjgJtAgeFnEEOSnfvGBlwPHaPxkGQ5K6BG0HbZKtNG0KbaNTEgUcWZQGRweO0Gf6mQhK2sQ2i/fJVasjhtBv3GpC8DhT7giAynB9h3T83mfun5vM/dPzeZ+6fm8z90/NJn/AP/Z)

Fig. 14.16 Concept of Overfitting

From the graph shown in Figure 14.6, it's evident that the model attempts to include every data point in the scatter plot. While this might seem effective at first glance, it isn’t ideal. The objective of a regression model is to discover the best fit line, but in this case, no such line is found. As a result, this leads to errors in predictions.

**Strategies to avoid the Overfitting in Model**

To prevent overfitting in a machine learning model, which can lead to poor performance, there are several strategies you can use:

1. **Cross-Validation**: Use different parts of your data for training and testing to ensure the model works well with unseen data.
2. **Training with More Data:** More data can help the model learn patterns better and not just focus on specific details of a smaller dataset.
3. **Removing Features:** Simplify your model by removing unnecessary features that might be causing it to learn noise.
4. **Early Stopping:** Stop training the model before it begins to learn the noise and inaccuracies in the data.
5. **Regularization:** Apply techniques that penalize the model for being too complex, encouraging simplicity.
6. **Ensembling:** Combine the predictions from multiple models to balance out individual errors and biases.

**Underfitting**

Underfitting happens when a machine learning model fails to capture the main trends in the data. This can occur if training is stopped too soon, leading the model to learn too little from the training data. Consequently, the model struggles to identify the most important patterns or trends. In underfitting, the model's learning is inadequate, which reduces its accuracy and leads to unreliable predictions. Typically, an underfitted model will have high bias but low variance.

**Example:** We can understand the underfitting using below output of the linear regression model:

A graph with dots and lines

Description automatically generated

Fig. 14.17. Concept of Underfitting

Looking at Figure 14.17, it's clear that the model fails to accurately represent the data points in the plot.

To avoid underfitting, you can:

1. Extend the training duration of the model.
2. Add more features to the model for a better understanding of the data.

**Goodness of Fit**

"Goodness of fit," a term from statistics, is a goal for machine learning models. It measures how closely a model's predictions match the actual values in the dataset. A well-fitted model falls between being underfitted and overfitted. Ideally, it should predict with zero errors, but achieving this is challenging in practice.

When training a model, errors in the training data typically decrease, and this trend is often mirrored in the test data. However, training for too long can lead to overfitting, where the model starts learning the noise in the data instead of just the relevant patterns. This causes errors in the test data to start increasing. The ideal point to stop training is just before these errors begin to rise, to ensure a good fit.

Two other methods to find this optimal point are using resampling techniques to estimate model accuracy and employing a validation dataset.

**Bias and Variance in Machine Learning**

Machine learning, a part of Artificial Intelligence, enables machines to analyze data and make predictions. However, these models can sometimes be inaccurate, leading to prediction errors often referred to as Bias and Variance. It's common to have some level of error in machine learning since there's usually a small difference between what the model predicts and the actual outcomes. The primary goal of machine learning and data science professionals is to minimize these errors to achieve more accurate results.

A diagram of a model complex

Description automatically generated

Fig. 14.17: Bias, Variance, Errors

**Errors in Machine Learning**

In machine learning, errors are used to gauge how well an algorithm predicts outcomes for new, unseen data. The choice of a machine learning model often depends on its error rate. There are two main types of errors:

* **Reducible Errors:** These are the errors you can decrease to improve the model's accuracy. They are further divided into two categories: bias and variance.
* ![A diagram of machine learning error

  Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEBLAEsAAD/4RD+RXhpZgAATU0AKgAAAAgABAE7AAIAAAARAAAISodpAAQAAAABAAAIXJydAAEAAAAiAAAQ1OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNhbmplZXZhbmltYXRpb24AAAAFkAMAAgAAABQAABCqkAQAAgAAABQAABC+kpEAAgAAAAM4NQAAkpIAAgAAAAM4NQAA6hwABwAACAwAAAieAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAMjAyMzoxMToxNyAxNjo0MDowMQAyMDIzOjExOjE3IDE2OjQwOjAxAAAAUwBhAG4AagBlAGUAdgBhAG4AaQBtAGEAdABpAG8AbgAAAP/hCyNodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvADw/eHBhY2tldCBiZWdpbj0n77u/JyBpZD0nVzVNME1wQ2VoaUh6cmVTek5UY3prYzlkJz8+DQo8eDp4bXBtZXRhIHhtbG5zOng9ImFkb2JlOm5zOm1ldGEvIj48cmRmOlJERiB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIi8+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczp4bXA9Imh0dHA6Ly9ucy5hZG9iZS5jb20veGFwLzEuMC8iPjx4bXA6Q3JlYXRlRGF0ZT4yMDIzLTExLTE3VDE2OjQwOjAxLjg0NjwveG1wOkNyZWF0ZURhdGU+PC9yZGY6RGVzY3JpcHRpb24+PHJkZjpEZXNjcmlwdGlvbiByZGY6YWJvdXQ9InV1aWQ6ZmFmNWJkZDUtYmEzZC0xMWRhLWFkMzEtZDMzZDc1MTgyZjFiIiB4bWxuczpkYz0iaHR0cDovL3B1cmwub3JnL2RjL2VsZW1lbnRzLzEuMS8iPjxkYzpjcmVhdG9yPjxyZGY6U2VxIHhtbG5zOnJkZj0iaHR0cDovL3d3dy53My5vcmcvMTk5OS8wMi8yMi1yZGYtc3ludGF4LW5zIyI+PHJkZjpsaT5TYW5qZWV2YW5pbWF0aW9uPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgPD94cGFja2V0IGVuZD0ndyc/Pv/bAEMABgQFBgUEBgYFBgcHBggKEAoKCQkKFA4PDBAXFBgYFxQWFhodJR8aGyMcFhYgLCAjJicpKikZHy0wLSgwJSgpKP/bAEMBBwcHCggKEwoKEygaFhooKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKCgoKP/CABEIBCoGZwMBIgACEQEDEQH/xAAcAAEBAQEBAAMBAAAAAAAAAAAABwYFBAECAwj/xAAVAQEBAAAAAAAAAAAAAAAAAAAAAf/aAAwDAQACEAMQAAABqgAAAAAAAAAAAAAAAAAAAAAAAAAPrOuj2TI/NKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1UoTVShNVKE1/Gofgfj7ZnTAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAJp1TbGQNemNKP0AAAAYLWHRAcXjGzAAAAAMObhx+wAAAAAAAACcFHfh+4AAAAATb8inJj+5RwAAAAAAAAAATWlTWlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1pQAB/O/Q5/ei1RGoS84X9B/z/AP0AfnwcBpq1vW/n66nozuC6ZuOxC6kTOizr3xuNHHu1W05X55Mqnn4ksK77MbgI/ob8viM1ROzg8nF3eD30jVljRutXlNWDOHs8Ux7kVT7S3c18eCf9mKP9pBQq6XNjmgis/GUn9VbpYnBx/QmC3cCq88/1Q8tnJyHGi2fbAe6un+0l0Mbrrfzt/Q1foD+fKZM9bGr/AEzHWNrzvtCatHRkW0NPzI5oYsfP5kvqnaKfZKLpx+n/ADzVw90f2BpOfNdXFA9Ehr1AATWlTWlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1pQAB/O9An9kie9fAWAk9+glsM5ls9eyBW6NWchn9Efz9cj3fbD9apnTZlUI5GY0+YNZk9ZkzY4fcYosEAv8ALHErnEja5ezZsbTwe+kassaN1q8FpDszLa5Uy3W/TdRF7rmeeeDhdTaExp0xpxMLnEbdWKzOmzcVn+d/6I/nc/oCEXeEFzh9wh5aMlr8hXi83p/aOjtpds6in9Dfzr/RUfoK/nymTOtx9PZ+yv3htyiUX7M6fMVN7fFbUSzr+bxxUYlaITVYil7gkf0L4+jyqi3U2/Qjnbj+dP6Hr9AATWlTWlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1pQABI6t+wj9U9gk1S/cSXz2IS3ddgZXAWkSKqekTXbdQZvi74Z/g74cLN0EJTVh48xsxFenVx+f6AndEEfWASaoekSLx2kZXp9cRXt08SnfdgTWlBm+PvAkdcH5S6rDzzOqDx5/WDFa30Ysz/ALOBoInv9DQ26gVJvwsAj6wDxzWrBxO2JvSA/CX1cRXZ7cI/YB9Py9AkngtQn9AAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtJPkAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD4+Rn/NqR5vSAAAAAAAAAAAAAAE1pU1pQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABlvw2GMNmmnyUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSkh6hSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FK5eJ/c+tF/P9AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qa0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAB8Hy+nwfo/H6noeb6nreL4Pc5/1Ok5n1Oq5P1Ow4vwdtwvqd9n/qaJm/g0rMfU1L8v1AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGB300PuownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMJyownKjCcqMIro6N9ibKUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmqlCaqUJqpQmvzSROPmjCd/NDE++2/GB+28GF+dyMR9tqMX9tkMf868ZL51gyv21AzH20ozmVpuINL0uZ0wAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABNaVNSlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAYnbYo0PU5XVAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1KUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABi9pjDu9bj9gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATWlTUpQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAGO2OPOv2eL2gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABNaVNSlAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAZDX5E6fb4fcAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1KUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAD4yf1nBWe5C6iaQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAB+cC/oGcGOu+C3wAAAAAAAAAAAAAAAAAAfGYNQxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNrNerkSxsUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxQ2rFDasUNqxXZO4AAAAAAAAAAAAAAAAAAAAAA+M0aZihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG18WXGs9OKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobVihtWKG1YobViusd8E10ebpZynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcrNboY7YzSlgAAAAAAAAAAAAAAAAAAAAE57mepZynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcp1RynVHKdUcrPbYYlxx+lKmtKAAAGc0eUJw/ayRGd36pWX0zNaZM9gdwzho8H4ecabaz7vmicXonpYrahnMsUz8c5pSNWPDbcjVt/nenRuk+31YP3cLom9fhgiiMBuz9AY6fbXgxyFqVmdd9M4aZjvxNuyH5G0ZTrnUTb3m6fXhneZDnFAcfGFLYHdn3AAAAABNaVNaUAAAAAAAAAAAAAAAAAAAAATWlTWlAAAABDacaQAAAAABLO0bkAAAB5I0XB44Qf0GASYrLFbUAAE+KC/nn1RfEDpta8AAAAAAAAAAAAEwB+tKmtKAAAGU1eUJRoudQonejyFpPvGadLisSfTcgr8Kq84KdNbfNK9Xi9vijo6jL6ioxbInVolNandmI7U/f56gl7gl7j+erBJ/6FI9ov24R6Ojzuicn15r1nS9XH95TxWCnNG4Mchalc+fVeUHLoXg3REfb4qTHzKLRFSpZKsZeuD8Z/QRj6JxqZUS1/pnEbbVx2tVowAAAAATWlTWlAAAAAAAAAAAAAAAAAAAAAE1pU1pQAAABDadMadGc8+c051uFv4UbTX8n31yc35rJGd1sAslZrN8a6RHdljdkfr0Mh2q1OF2MiLtPtFLT06zaTyKHN6BEKucFvUBjafnSZ0U6Xdbkmk7/AAMdX6+rW8KN/wCicUek+oM+ObU/559UXxA7NWb5vPR1vz2UhNP3eTrq8OC4dyid0ue/nXf4jgR1tH05IdHpd34Nn+3O6NAAAATAH60qa0oAAAZTV8wlFqyOuJrnLThzTxu28M/XHejUnZhH9A54/Ka6fvnI/DWdAmXb8nfiW2zNbWoFW/rl4zla5mlr+f73j9qfzrXfy+sZbSfTe1M+j2/QYT20DBn79Ljbw9AMFjarnADv4Td+c5m54/YIjSvJoD2QW+8s5GS9/vjyfWi8OsnSs/oCU6nsYo5nZ++7P2AAAAABNaVNaUAAAAAAAAAAAAAAAAAAAAATWlTWlAAAAENp0xp0TGpyyqHe/nf+iP53P6AzGn89RPR53exxNVia4Ry2QGgHI7k9oRxez4+AUuR6TNlIx9PiJffPisBVvhtrikXOE3aBH9E4HzZQ0Xm12RNJP6Bwzn+j7fkaPc5TV0n1BnxzanB+/FZSbYVjNNmdPG1hN2hNVz9Pp1yEXmFbGOvi/Juzjff6fco+Z00Tr0Z6hZiKBqsZs6AAAAmAP1pU1pQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABNaVNaUAAAAAAAAAAAAAAAAAAAAATWlTWlAAAAHC6npHC6voDO6IfX7ByuDsx4PeHN4mtHK/f3D88nsBy/L3g5nTGM0XRH04WgH04neHA/PRhyesPF6vuMn+unHx8g53RGbaQZvp9Ecj1e0OD3h+H7h+GW2A4PeDmfPSDy+oY726QAAAAATAH1qPAx5T01FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk18pVE1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FK889/M/SleP2AAAAAAAAAAAAAAAAAAAAAEuqHFxZT01FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUpNRSk1FKTUUr8p1+R9m+HvAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAOcezk4bSnSc8dBzx0HPHQc8dBzx0HPHQc8dBzx0HPHQc8dBzx0HPHQc8dBzx0HPHQc8dBzx0HPHQc8dBzx0HPHQc8dDoZ/kFEY3ZAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAnNGmpQ/3AAAAAAAAAAAAAAAAAAAAAAACZ0ya0oAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAATWlTUpQAAAAAAAAABkzWOP2BNaVNSlAAAAAAAA5sbsMUj1fe38iuDuYBfyI2jC7w/Rl8qVJhN2GUzJUWL2gAAAAAAABNaVNaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJTVpWat+/wAnm+PX8nj+Pb8ngdAc746fycv46vycj47I43x2/k4Tu/JwPjQjPZmkYgnuk5W7jt53f4CqUAAAAAAADlQq6xKO74K/5TGVL+ervUKvcEvMTzWz74OBbYlbCH1jiYc2dEiVlrogAAAAAAAmtKmtKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1pU1KUAAAAAAAAABxuyPp9wTWlTUpQAAAAAAAOVDr7jzz+bo/YmN78fWP58tvA2R/P1c8vjic2fxdmpTQv1y0ZOo+LY0AAAAAAABNaVNaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAACa0qelCeL2gAAAAAAAAAAAAAAAAAAAAAAE1pUxpwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAPL6hLPbRvyMA3wwLfDAt8MC3wwLfDAt8MC3wwLfDAt8MC3wwLfDAt8MC3wwLfDAt8MC3wwLfDAt8MC3wwLfDAt8MC3wwPipf6mc0gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACa0qalKAAAAAAAAAAAAPMen85h7Sgp+KAn4oCfigJ+KAn4oCfigJ+KAn4oCfigJ+KAn4oCfigJ+KAn4oCfigJ+KAn4oCfigJ+KAn4oCfigJ+KB+k78ZUWb0gAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAmtKmpSgAAAAAAAAAAAJ7Qpqb32gAAAAAAAAAAAAAAAAAAAAAABMadNaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJrSpqUoAAAAAAAAAAz5oHn9AmtKmpSgAAAMLuseffWxK2nimvczsVz58GXrbsvqA4P0NDLNpwDbej8fEdNiOoaM4B33G4htH4fuGd5htXl9QZzwGyfl+oAAABNaVNaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAJhT8idxmPk0rNjR/Ge+TQfHA+Tu/HEHb+ON8nXcj5Or8cwdP453ydD48Hye3G6bKmO2mH2EUTF67I1SgAAAPy/Ufz1dZt744G+lF+Jb3PjKHOrEdrROPn4pB55df4AXOW1LD17Zx2OBFzj9Zkx3vFReEczRZD2Gd1n676pBtdVMjP6LN9SPmtQS90AAABNaVNaUAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAM1pR4fcCa0qalKAAAABmI3/AETMI/OqcXt1/Ol5yPCjlUviaKpjSuHqzqwC/wA0NnEb/PDdxLRdaNVJ61lK1Wf1XNMP3PTsCU0TD82PR2u136l+8xHPjXbLPaGgAAAJrSprSgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABNaVOSjPw/cAAAAAAAAAAAAAAAAAAAAAAAmtKmdMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAHO6Ilel1MuNUxg2bGDZsYNmxg2bGDZsYNmxg2bGDZsYNmxg2bGDZsYNmxg2bGDZsYNmxg2bGDZsYNmxg2bGDZsYNmxg2fI4lBOXsgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA/8QAMxAAAQMDAwIEBgIBBQEBAAAABAADBQECFQYTFjU2ERQ0cBASMDNAYCBQIyEiJCUyMUL/2gAIAQEAAQUC/tK1pbQqXJMfpDSLiwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwRqwZ1F5uSirxCWy2P2zVJNWhIcK0IP8AXX2rH2oStwMx+2ar9T+vv92/tmqvVfxv1G5bfFTVTS1My9QHuSuJu75m/oSM5eKZHv1KD+EsZUEWImLzivpyk1eEZFF1NE/CI1C40+xfuM/Td1E5Y7yVxclcQ+oXHX/xn+7f2zVXqv4u/dEvqHJKZcqTLXU+W5j7BJLI1lZ4HxEkBS6q+62y1ycBsuFkhCrlP9XjCGRoW2cAuusutvtk7BnBotiNbJeebYsYMHIvfmAmbw5AYv4OuWNWXToFLhS2CqfHUvVtM9K+JciKJVqaBcupXxoipMQa6k6DWrDzb9jztjLbJoz9900Da44Uw2ywWwQnpoFu4Q4cv4PjQ1XmaW0avkRLLyTBxrG5sG+6laXURMsGPeJJCl1ukg7bviV6oOFDdDwIKbhAm3L7qWWNyAjt5EuEw7QseozJoz91ZsGjll1L7SjhhFbOgVq07Y9YqSQd1S5QQRwUpkpsqTEGutnQK1Zebfs/i/3b+2aq9V/F37s81tmiF0rDwrdSJZ37rH2D2TizrdNW7bzd4hQbu8JqA+4kuP0/V4eTBvjyYIq8sCf6vFxjsk3MxVY+mkiLtzVPTNK9S1N0oLeq9XTX+Cy68d9m/cZmj7jShtOVvHdsfjDgSKFifDUvVtM9K+E6bUIKMBckSJSCqKPpg66x+XvfsBj4l8siRgaDi6dfuak9RdHacvbrhDvk1PZRqJBo+647pvwYGeuHfpXxod64P0kl1ECLelKTEdWPd0m/dczqQ24YaKj75B0+CuGZvurffZ/4+BXqh9QOMsclcUXNXmmSXTmnLmnG4c1xiTY8tppq++1UgzfCZMxwAAj0kU/pvwajzHY8pu+jjdl1bLmIw01ulHIrTsWFkCitOfK1BWmDm/xf7t/bNVeq/i793VDP/FZM+WB0k14vv08H2PsSE/Yy5dLyJVX6OUdjP9Iqz/c4vCnip/q8Bb8sRqzp2lepap6ZpXqWpulaZt8ZVHeuYr8sI1d8jnJXFJm1PI0pd4x3w1L1bTPSvhq6v+WKlLo+17ULjrIF3yHEvtjMk6jdrV4qRMahOq6i6PC2UclFqzp2lKeMknfusfYO9cH6SS6jF08I3V/2tI/f1ZX/ALDSdP8Agf8A1X0+W+z/AMfAr1QcKG6HgQUJFCivSXThrNwlak6RBWUvllq26vnNJW08qp+2lsvp+6t0QhrKNjyYvnAn2HhXWJg1lRk9aQ5/F/u39s1V6r+Lv3Zprdh1phrbjCvVEXXWRItLKk02mGZB6hB0V0wpmo5IJNhY03L3hkQprpzE/wBXguk6s6dpXqWqemaV6lqbpWl+qI71wVvzxX+4Ykfy5DRMuCOSE62+P8NS9WgDhmI7KBKkkHdXVrNat6Wea+c5wcMcKVCKf1ddds6WbYvKniW2I6E6rqLo8B1das6dpPqKd+6x9g71wfpJLqMb07V/2tI/f1axXx0ye2xWSkmRB1Z/4+BXqgJESwHKBLKBKS6cD65ak6Rp3rC1axWtNLGWtOOuWNNnv+cOjWPLAqz/AMShvkGAJhqQfKhgXLf/ANWePyfwf7t/bNVeq/i5Am1vrZ8zPHzUG1sCvwRl71lv+GQgX23GIc99Gaedo5EtOsAzMTacsVIs3CQBTt47Ng7MrDlEnxjNw4E8G6aJBxZAZk2K4YFBxZAZk0M4WDCRRIZqKgzHCQ26tCTMN5y/FyLaB0++5fZZa3Z8JmJJLP4+auPmpiCMseIZsIZMgCmr8VIvXQ0TQBSYVpwt8Oe04FAvPXjQpzBEuPeVHxUOUMep4N00SBiyAi05Am1vap8rRUGY4SPbWwcyDLdLDbq0JPgvHWQEc+C6QzYQyTp1+28DT1aOOfct/wDPwfgjL3uPmrj5q4+ajG6uiCwZjZKmB7ygIiHKFkE+1Y+0bp99u7FyLiiISg164+arf9LX2bH2TNPkt342SvpEQdWXf4v92/tmqvVf32pbH9gCZJHdI1J4txIlxZv5r/dv7Zqr1X9+9Dgu1pBAUTDDTFn5r/dv7Zqz/Qj9fd/3at/bNQh1KCgJKwhj9dkDWgmdOsOPlftslB2EX+WnGltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8nypZgnbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bc8tueW3PLbnltzy255bM9VDQLjjtllrdns5Ndxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxe5k13F7mTXcXuZNdxf1fzUXz2rcsW82t9leZYXmh15sZedFXnhF58NZANZINZMJZQJZUFZYFZcBZgBZqPWbj1nAFnAFWeBTV9HW/0UrUOwTyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJlyZcmXJkbJeZkOTVXJL1yN1chfWfKWeMWcOWbkFmZJZeUWVllk5dZGYXn5ledml5ubXmZxeYnVvTy3J9fNPr/AL9fLPrbnlszq8vOrys4vJza8jNLHzKxswsXLrEyyw8osNJLCSCwRqwJa4+SuOvrjjq41euM1XGVxlcZouNWrjTa400uNMrjbC42OuNjLjgq44IuOhrjoa48GuPhLABLAArAgrBALBgLCR6wketRADCCRvTv0WL7l8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi8KLwovCi+Wn6Hqz0EZ079Fiu5fYXVnT4vpv6LF9y+wurOnRXTf0WL7l9hdV9NiemfosX3N7C6q6bEdM/RYvub2F1V0yH6X+ixfc3sLqnpkN0v8ARYvub2F1R0yF6V+ixnc3sLqjpcJ0r9FjO5vYXU/S4PpPj/r+iRnc3sJqNq/yz8kUQxZJl2DwLFWQf0SM7m9hHLKOWGMVFKixvNnfosZ3N7C6rFWlBflZ/RYzub2FMYtJGHatYY/pK18KETgTN3IxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxEHItMzHIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEXIxFyMRcjEQcoIXX+tJmwmLuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYi5GIuRiLkYiElhCrlLkPSB4kKIxZjw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jw1jg1JwTd1mnpC4pr+rnCnSjAoQVizHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHhrHBqRgmXW9On3vU0r/ALy/08T/ABaq/q9Pf5Jj9Pv/AMGqtI/c+hPPODx2WOWWOVkwfaoWY85f/PUxb412miniW/oPV8GR5Q24h6vgy3Km1c+OpTCBntNkvEj/AMtSEvDD5Y5ZY5ZY5abIdJE/NZ7t/q9NdS/Tyu6dI/c+hqbpWn6Uul9ltTgY98fHXVtPUlMMBXU1Lf4x0kwfRScsyDW3Ut3zahLaMt0h9qTlLI++MPtkGyXaMDsagaefUlLsBV5Lf4xs0wZffX5bGpwW9x/7DX3TdQtNXjajsuvsupfbq77+kfSvO2MNkakpS8bUbd11l9rlnw1d6XSttLpDZbWy2rbbbVJy7YD7s6zYHGTlSyjZxoUk2ebZah5bIOHHMBNualr8wmomXLra0upKSVkerZ1iogmoavEyMgyBZdqW/wARtRt3XW3Uvt+oz3b/AFemupfRm+q6d6P9TVvq9Jeh+gXStRQgirTDPSC+q+OrOo6T6d/LV/2mmXHq+RLXkS1plpxkD8orunSP3Poam6UIReKRyA1GSRRlsBFOVfkiPKggD1OOchQrmLauAHOEW2hU3CymIUNtmaC8iZpD7Wrvv6R9LK9Njeonv+VDFavOOpDA0achDbCf8nkRfVP/AGEBCjNDz8dYE7pMmtzWrvv6R9Lqoqt5On4pl4bUUY0O3pMqtfjq70o5Do1+WOWWOUQ5e9Has6jER10g7GQ9oBU/1eHiKn2RcfbGWGkXnGAwgrLOoIuwRaVMuqtYKMDuOJCg7BDZ6+6+VimolweQ0/W96IGdDE+oz3b/AFemupfRm+q6d6PIzhIxp0+78mnjyTa8hK3pGefuegi3zBJOf23LZ0+l0PMWm1UrO1adbnjrb5k6w+/SXoZyUeAfgznDxz3rhwwZ0l8xSc/tuZw/5omd33X76tsDagKdIM9IxdS183UD994moCW7x3rCGdWdR0n06ROaAYfnzb7hNQkWXDvWEM/DV/2tJer+M1Lvglvagc8nBSZhRh06SwZIT7q08cSbSWl2wauTp91RNRPW3MO2PtTsk8BdTULnkouXOeOmJmgV104fWomoX7L2nLXW/old06R+59DU3SoNqx6UkIMd5kd94ImNNsOG1N0oDzPmP+8TkbIOXvW32acheqrV/wBzSH2tXff0j6aV6bG9R1H0jTfhl/g/9gX1T/2BvDzC1b6LSXj57V339I+ln+riZbyz7MwQ3AAlDSPw1d6XSttLpDZbWy2qUpSmrOo6Sp/w1P8AV9O0/wCnk+mx3UFqTpOm/HL6wWkKf5VNw9THCASR0MaQNWFkfPsfUZ7t/q9NdS+jN9V070eb6rAxLJAoITQVjv3YyEGuCkaWxkJBi2lyDw7TrF/zCGnk/JEx4/mjW2Gm2Z4S0SQ0l6HVvq9JehmelxHU51+o8ZCi0LkKst1arpxzeIpWgAPrjPSWW1vvCEaDY1OHYw7pJ6tbNWdR0n07Ub9XpPTwljAGqhG7bNJP1+Or/tNMuPV8iWvIlqKtusjtVdS0/Gtm1Djhw3ZfqcHEMPiMsMxYdNwwsMVoRnU4Fllukya0e1f/AO4IC04oaLFGJlfmpJR80FRl+LDkXwBbQx/old06R+59DU3StO9YWp4/wrCHeSMkx/NgR5FQTqzIOy1qAy915veH/wAgZbE0G4zMm+eL0h9rVzdfHTZ7Ql83LM3ixvUT2PNBjOXhG2zINWipEh81q1yyNF9U/wDYUbNjuj6gkbTXdKDVsY1d9/SPpdVDVsL0/Kssjyk7a2oOQIP+OrvSwxtoBXJGVyRlRclZILVnUdJehU/1fTvR7raXWlsOBFgzYrzOoJSwtaVDrRawWkP/AGpWSkBzI+aGdH1ESIQ5pFq6lv1Ge7f6vTXUvozfVdO9Hm+qwXSU790f7GqKf9WAHea/xwtccLUo1c1pzT9fCXWra087pL0OrfV6S9HM9LiOp6op4xelq+Emt5r5zPRg+uM9IJdS0taur/x9I0/5GrOo6T6dMU8JQeCJfY44WoSJIBL+Gr/taS9X8dVdS0n05S/U4bpctT5o2KrS2SWp60pF6YtrWU1f/wC9H/CUiGjqkQRrSutdGd0+dcaL9ErunSP3PoSAlpowMI0IUnLLXLK6bY8RGfLjyUMwZdxq/wAY2IYBqpOKZPVmmq/ORCjuDxcdZH2lDtlMuaar8wEKwLRjT7TL6kohg2vGr/GOhmA777fmsb06zY5fb81jGn2WXz4Bp+8TTlll9tKW0k4uyQvjALY9t9lshp/TdK3MabpS5hlthr4SYFsg3xtlcbZXG2VFxtkepOIbPfjAbQGUbBtFEgjUEFRwLBtjmmq/MJp1lu6lKW0lI2yQUXGWR9UeAwdZfpq7xH03ZS5puxlv6jPdv9XprqX0ZvqunejzfVYLpKd+6x9g8ehYbDjsebfqRrZAMkSCX2qPDutvAmN6ka2TnXiXdJeh1azWqhJOkfdJyt0i3EdTOHoUJZc9Hm8kZ2rLHpA1xqjMaD64z0jdlzl4OoKNsyx90gRp0O4UPVnUdJ9O1QFda/DzVBGJObcfc0/cW6P8NX/ajjnAHORlrkZagpB0+zVXUtJ9OUv1OG6XWnjSTCvAKD1HZRmXkrpBzTgFwrGr/wD3o/4TDZIxQmom6MzUjSQd0wLcwJ9ErunSP3P09nu3+r011L6L0UE+6Oy2Oy9FBPusNWMNKsKBWttPlojABzFTTofzCCMCWIwJgy1qACbvJjxSaCCsiWOWWuWX6eCuuGAGGaaiQmXUYCOZTjofzCBsCW320vsshwbL77aX2NRITLpsSKXcHDCC3ouOFLcEFZEbutpda9AhOVGgwmbviWGwZTCR6wkesJHoQNgOhUcKU4IKyI2nYkJ51luxlpPNNv2OaeCuqJFCC3IsEcxBhDh/Ahhohu/Twd1RoUJi76RXdOkfufp7Pdv9XprqX6eV3SBfi5v9OfdsYagLbi5X+ravxWoP/v6c65a03EeJ85KxrZ7dmZj1kphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphWzUlc7kphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWRmF5CSk7xB2xWP6uUj2z2rLJiOWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkphZKYWSmFkZheTlJO4IVsNj+hju5/cyO7n9zI/uj3Mj+6PcyP7o9zI/uj3Mj+6PcyP7o9zI/uj3MA7o9zAO6PcwDuj3MA7o9zAO6PcwDuj3MA7p9zAe6fcwHun3MB7p9zAe6fcwHun3MB7p9zAe6fynHLG7ayoNFlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgVlgUwUwR7Bhd0/knlWhiihkzV9NPhUpgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAlgAkZp/bpAyVxPsEF3T+Tq2+tast2stf15tPLan9gQu6fydVeq/sJjuP2BC7p/J1V6r8CSuusAyRqyRqtlTrVCTNSnERImWkM18WfyJjuP2BC7q/FkpO+PLDkRS/jqr1X4Er00H1vyWqUGZdBA8fPJ3UDVjllfmsk5hkK+upH/ELULbrik5pkO/kj3jHzzRDn4Mx3H7A2kNi6jzoCzwKzwKzwKz4Kz4Kz4Sz4S5AEuQBLkAS5CEuQhrkIa5EGuRBrkQa5GIuRiLkYi5GIpyTYPZQcyWMo6ZYMu1V6r8CV6a3fVtzOnIuTLKs0wyNV9FeqY+w7p8hwi6PjmWTLW7Co++t0bZdS4gZuIIse045Uge26xj8CY7j9gW2GydS4YBYYBYcBYcBYgBYgFYkFYkFYoFYoFYoFYsJYsJYwJYwJY0JY0NY4NY4NY8NY8NaoaHYaFDfKuC05bRDjtD2aq9V+BK9NDpS4vHBp+ICdsvpcOQC9UgMr1TVaWjSE0SQ41CnkoxioxMV02Ugb7nSBHx0HIlCVAKtME/AmO4/YEPur8V+OYIJttpbb8NVeq/Alemj37T/ACWxPakrWxuxwh8VqjA5Xqn7KuRQzmyTfOBWsku1fIjvmuh6yx7ZDc2De3LvskHaeZuZi/wJjuP2BD7q/J1V6r8Ahqj7HGxlxsZU04Kgo8YP4OaeHvcst+WyQgWSXBtON23mQgxLgItAxpGKHOrXTNfEKAHYv/BmO4/YEPur8nVXqv7CY7j9gQ+6vydWtV+QN+0ob+vcu8/qb2BD7q/JJZsIY2z4V2mpv9OTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1Fyai5NRcmouTUXJqLk1E7JnSSho2gDXsCH3V+XWyyq27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2LbsW3Ytuxbdi27Ft2Lbs9hA+6vcwTur3ME7q9zBO6vcwTuv3ME7r9zBO6/cwTuv3MF7r9zBe6/cwXuv3MF7r9zBe6/cwXuv3MF7r9zBu6/cwbuz3MG7s9zBu7Pcwbuz3MG7s/LrfbRbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWLcsW5Ytyxbli3LFuWewg3dn5JL1g7G6fNO00z/AKcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaLjNFxmi4zRcZouM0XGaJ2MOjVDSVD2vYEfuz8nVrtfkDYtFG/r3LfIam9gR+7PydVeq/sJjuP2BH7s/J1V6r6M3JlAEwMnef8DX6DCtTxzrv8yZ4tske+rjH5Mx3H7Aj92filybQhTLzb1nw1V6r6Opx92PgSPLya1W/wDILpgfdPLLZEsu1GL4izgb96Ilgx3i5cUZqOlWDr33YTeZ+XaNOHDtrqMXxDmBCr0/LhsPEyQw7FmohK3Mu2Pto2YEEus1EJWoxDRLaNmBBL2tQiX3N32uWfRmO4/YFtyxvVXnhF58RefEXnw1kA1kA1kQ1kQ1kglkglkwlkwllAllAllQVlQVlgVlgVlwVlwVlwFqQsUtpl5xi8PUTtiDkBi1qr1X0XbKOtPN3MPgP+ZD1CRvyemh9mOmQpAk1jTo+zKieSMgnbnoqf6vHxxEkoGNcBR3rg/SHx8iSZZpwXbOY8oZGuVeAm+qxMT59qdi7QFpJ6u7qE2ogcPH1kCD9PtWDQPmhztQmVECho7IPysE2yLpky5ov6Mx3H7AlwTJJPGxlxsZccFXHBVxwRccEXHBFxwNcdDXHQ1x0NceDXHg1x4JcfCXHwlx8JYAJYAFYAFYEFagAGCZssuvuC0+Q6gosURaq9V9LVI+2bp47Zjx27iirLaWWSs75d3zsoai2Hh3dN9In+r6ct8IhHeuD9JI6grY55iUORDTjD0N0ub6rCU8IrVvodJ9R1dX/NpGn/H+GrvvRsgQHY5NHuNhW32GfRmO4/Zc+LocUMKwLb8NVeq+lqIffjaXVpTSg/zl1/8Al3j8zBA3lJkm0uQ030if6vp3o6O9d/uxDFbaP+ZHsYkX6EnQ3S5vqsN0vVvodJ9R1YxW4fTJtgz55rQo0dLSDxWrGK3MaYNbYckT2gx4+coYR9GY7j9m9Veq+ldSl1LtNvfNEBeREUrBVeeZ0+XfcVp2lbYYN0EeSg3ijYsa4QFEaffdIYs22JHT99XR9PFX3F6d+a6KGcEDkIJ4kwFmo4c0DeePCxLoBTllrlhmnXKX2QBt1YmKbAo63a62Zp12l7enzbqxUY3H2/RmO4/ZvVXqv7CY7j9m9W2VpVly15r+vNr5nU/s3IC2mCimEwrlNQBVpnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwlnwkZqDcpAxtw3s67ZY5YQy1R3abW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptbTa2m1tNrabW02tptRLLVjH7D//EABQRAQAAAAAAAAAAAAAAAAAAAMD/2gAIAQMBAT8BV6//xAAUEQEAAAAAAAAAAAAAAAAAAADA/9oACAECAQE/AVev/8QARxAAAQMABQYJCQYGAgMBAQAAAQACAwQRNJGSEiExMjNxEyJBUXKTsdHhEFJhcHOCo7LBFCMwQEJgIENQYoGhovAFJFNj8f/aAAgBAQAGPwL+qEk1ALgP/FtNXncp7llS0vP0yVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVaxeVxaYK+kUBSwZYfSa/8AabLCa2n/AF+7WQt0ynPuCa2r7x2d59P7edHKMpjtIU1CceK7R9P9fu2i7j+4Gbx8v7tou7+Ij7OzMedCF8bWVjNUfIyNkYeS3KNZVnZiTXc4r/BkhELXBvLWo5iMkuGjy8K1occqqooxOia3i11g/iOhbC1wAGetCZzQ0kkVD8nJHwDTkuI0qN/nNB/EezgGcU1aVZ2YlZ2YlHHwDRlOA0/l2bx8v7tou7+J+9RudmyH593klyc/GyB2IjmUfRCyp5GsHpWu7CqoJQXc2g+Que4NaNJKq4Uu3NWTDMMvzTmPkpG8dio755AxtXKquFI9JaUHMIc06CFVTXZMVfPVnVdCkypcnzq8yy5nBjecrJhma91VdQWSZco/2itVQSgu83QfIXyODWjlKq4Qn05JVdHla/0cv8Em4dib0j/BVNKA7zRnKq4XJ6QqVYzjyZMswyuYZ1tHD3SsuF7Xt5wi+VwawaSVkRTMc7mCyOG/yBmTZXytEbtDudHgZWvq01LJ4XK6IrX3EgcRycvkkMkwy8o5XH5UwR6lWbci11IYHA1EVoOmla0HR6VVwpbvaqwawfJkPlrdzNzrJhlGV5pzFFrqRGCMxz/wTdMqCR7XZTmBx43oWq/Emva12U01jjIucamgVkoMjnY5x0ALg3y8YaahXUvtHCt4HzlkxTMcaq8yyOG/zkmpBzDW05wQvv5WtPNyqrhCN7SsuJ7Xt5wfIAKRHWfSsiWTj8wFdSy4HhzVkyzDK5hnW0cPdKy4Xte3nH8TN4+X920Xd/E/emu5JI2u+ibSXfpjrO8KHKz1Oyz/AIT96j6IRfJBKC41NrbmAXGpB4T0NzJzK6nxu0hQynS9gJTomn7mM1Ac5502SkSFmUKw0BBpdWDna4Jplr4RvFJ5/SqRvHYg+WUthZxW+Ca9r8uNxq3KWjk8WrLHoXvhO9mfondILgqManyjI/ws0/327Mg5vFkYUx/nAFOqP3LDUwfVB08pZIf0gaFUHZMjNBHKo5h+oaPT5ZNw7E3pHy1x7V/Fb6PSnDKqAzvec6M0MheG6wIX2WQ1xv1fQU/7K1zpTmGTyItla+Fozlzmp80MpdkCsghRtB4snFIVI935gjwZILhk5k13BjPyV5woGN1WvAFxRo1GNRmzHciY5y6UclWYpkses01oFUj2ju1QdAdipXtXdq+00qUtaczfSmjKy2P1SpoXaGZ2/wCU2OI1SS8vMEWtOSxus5cPRZXOLM5Gg7wi52dxNZTd3lm6ZUcQgachobXWrOzEmwuha0EHPWqV7J3Yg+M1OGgrhmx5jnArzlcFytDa99acIya3jJNXKmExipxz59CAizPPEZ6EWh2fS57l9zPXJzOGlV56q6ns5017DW1wrCDhpGdGkNbXlZ63HWRqGTO7T6K/BGMyZGbKJ01ouo8xc8fpcNKY5sE3BOzP4pqq/iZvHy/u2i7v4n71RJPN4hu8FNR6+MZABu/6FPL5rcn/ALcpB/cVH0QjHRmcI4fqOhZMRI9ETU4T5XCcuVpVHP8A+Q7EAeU+SurP5KRvHYqP/k/7UftR2FO9mfovfCd7M/RO6QTDzNJ8lI9o7tUZGkUcfKmPqryTXUrOzEhK5gYQ3JzJw82Q+WTcOxN6R8tGHJUVIGxNfl85T4zR2VOBbpVHdzSDtTpZjU0L/wBaJrRzvzlOLjK6Kqs1CptSo3SVI935gqOD51fkj9qOwp3ojPaPI/eo+iFSPaO7VB0B2Kle1d2qi+zb2KjbyqR0QoxycF9SpTy8J9B5HDmKbu8s3TKgke12U5gceN6FqvxISwtdlj0qleyd2KJh0OcB5Jd47VRweeu4eSFnIGV/78FM7lL6v9eSkAeg/wClBXyVj/fkjYNDWgKSGuonRvWTKx0b1mmLhzPzpsVJaI3nQ4aD/EzePl/dtF3fxP3qTna3Ku8gd/8ARxd9FN0ypHM1hDmuUQm2eUMrcqxkRxAbgppW6rnZlRvZhSRHSx1SZKw6Rn9BTIqNkOcBx686dJMxrajUMnlVI3jsVH3fVR+1HYU72Z+i98J3sz9E7pBe4fJSPaO7VAw6HQtH+lxxxo3ZxuTZImxuY70J0Rhysn9TWhNlgbksd6KvLJuHYmslmYx1ZzFWmO9ACkR1n0qCYaG1tKlglDcp2dtadLLGyoclWlNiZA4PdorYFR2/pLiSpOFDS8DiAqVrnDLkGS1qo3SVI935gqPvPZ5I/ajsKk9ke0eR+9R9EKke0d2qDoDsVK9q7tVF9k3sVG3lUjohQ0gDNqFPgmcGh5raTorTiHtdKRxWg+Ru7yzdMqjtdSGBwjaCK/QrTHerTHeqV7J3YqP7Rvb5Jd47VR/e+U+SGcaBxSn0eQ1Zedu9F8jg1o0kqWUDXOYKGI6WjPv8jdyEvBmQV1ZuRcBPCxjXDNlGutOcWcF/c01VLi5+ZNytNWf+Fm8fL+7aLu/icfu8585ZDtBFRX8vEoovMaApHDg6i4nWTWO82oomijhIuQV5wgyQGOMee7R/hD7KQ5lX6jyqOKerLZmzLhIyGTi4o5ET97HL7+qJnLWaymxRCpjVLLHkZDtFZ9ChikqymjPUmRw1ZQflZz6CjJNk5OTVmK4KGrKygc6Mk2Tk5NWYoxQ1ZVY0rhZsjJySMx8kr28HU5xI4ygjdrMYGm5cNAQ2blB0ORa2J4r81yBpX3UfNXWSgxgqaMwHldLFkZJA0lfy8S/l4lG48HUHA6ydFKK2OR4CqZm+ooZUT973IySHLmIq9ARicajpa7mKzRE1aHMKy6e4tHNXWSo5QI+I4HWUsMVWW6qqveopZMjIbpqPo8jI4asoPys59BT5JsnJLMnMfSPI4/d5z5yYDpAUr28HU5xI4yjY7S1oCnkbkZL3lw43pUEbtZjA03KEQZPFJrrKlM+TU4ZqinRSjKY7Sv8A15GPZ/dmKDqY9uSP0N5U6rnQ8sjhwdRcTrL+XiX8vEv5eJTxt1nsLRconu4OprgTxvI+KKrLNWneoppcjIbXXUfR5HRytymO0hE0U8KzmOYoNMT6h5ztCE1JIdKNDRoHk/l4kE6KUZTHaQj9nqlZvqKyTFIRzFybNSyK252sH8TN4+X920Xd/X45qO57eDrysg8irle+aPRkuciIISHnlcdCjYBxAa3n0fnmbx8v7tou79gVmAA/2mpbNx94rIhY1jfR+eZvHy/u2iu5M/7gbVyEfL+7a4xXJHxh6U2CR1U7BVn/AFD9vF8pz/pbylS0+blryd/7uMtGdwUun0FZLJC4dMHtWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNWscTVrHE1axxNTIJJSJX1VDMtY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiatY4mrWOJq1jiaqss4mrhf/IzZfoBrr/yg1gAaNAHqdofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN6zaH7nzes2h+583rNofufN/TNIWsL1rtvW0ZetrHiW2jxLbxYwrRDjCtMOMK1QdYFaoMYVqhxq0xYlaYr1aY71aWK0NVobcVaBcVaP+JW3/4O7ltv+BW1OAraOwlNezVcKx+xpYvs1eQ4try/BWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBWX4ngrL8TwVl+J4Ky/E8FZfieCsvxPBQ0rgsng6uLlaajWrKMfgrKMSsovVkH+1ZB/tWQXFWQYSrGMDlYx1blYx1TlY/hOVjPUuVkPVFWU9UVZz1a2B6tbI4AtmcAWocLVoNzVy3MXL/wXLexaxxNWucTVtDjC2xxrbnrFaD1itR60q1nrSrYeucrZ8Vytg6xytgxuVsGJytYvKtYvKtY/wBq1C4q1DCrUMCtQweKtfw/FWr4firUcHirS7ArQ7CrQ+5beS5beT/S20v+ltZv9LazXjuW0nvHctee8dy1psS0y4l/MxLRJiWq/EtR2JbN2IrZHGVsP+ZVn/5u71G+jxZDi+rSeZUX2Tez9jUre/tWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWhaFoWgfsOL2n0Kovsm9n7GpW9/b6ho/ajsKovs29n7GpW9/b6ho/ajsKovsx+xqVvf2+oZntB2FUb2Y/Y1K3v7fUM32g7CqN0B+xqVvf2+oYe0H1VG6H7GpW9/b6hvfCo3Q/Y1K3v7fUN74VG6P7GpW9/b6hvfCo3R/Y1K3v7fUMekFR9yq5f2LSt7+31CtpMDnNki5WnkXAzSZbPSE2GOYtjboqQfJWZZeO4n9i0re/t9QrmOFbXCoqSF36Soov011u3fsak739vqGjpTR/Y76J9JdpfxW7v2NSd7+31DSQu0OCZEzVYKv6LWdCqynSH+wLZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvU1Kc1/BvyqgNOdbOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rJjkqf5rsx/p2TlmQ/2CtbOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHetnPcO9bOe4d62c9w71s57h3rZz3DvWznuHeslkmS/wA12byfYKKeIDU70lDLZwr+Vz1ZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwoyUIZEoz5PIU6Gc/fR8vOP6YP/H0Xc70ocI3hpOUu7lZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwKyw4FZYcCssOBWWHArLDgVlhwouog4OUcnIU6i0ivhY9BPMqVK7Wq7f2hI1uhxd2V/0ylyO1s/b+0Dkcuf/AIqlbm/X8Fz4XFr6xnCtL1aXq0E7wFwM4DZuQjQ78Cj8BIWZVddSnM8hfURVX+C8jTUVGDSH1FwTyNNRTQaQ/T/BCIJSwEGupSmd5eQ7l/jiMDywl3IrS9Wl6tL1I6d5e4Pqz7vzzt5+X+mUvd9f2h/3zFStzfr+C7pBQAiscb5Stmy5TPMbWvYMoOAqVHLdPCN7fJkbSXzRyLPRm1dJfdnJkGlh0+TI2kvmhcejDJ9DlRZIXV5nVjlGhUneExr43OyhXmT3sYW5JqzqSUisMFajiELwXuDfJkH7yXzW8m9WZtXSXBkGKXkB5U4nkCa0UUgk1cik6JTN6LKOzhav1V1BVUiHIHnNNaDmkFpzghUfolT9NGSVwawaSVVBBlN53GpVUiEsHnNNaDmEFpzgjywdNSZQB+6OneFs2XLZsuXFAG5CJ8bnEtysybMGHLeTUytNgdBUXcrSnwuieS3lCj4NmXI9odk16qcww5BaK6wcyyp3adDRpK+7o4q/ucg2kRmL+6usIFprB5VHlsc7Lr0J85Y4VHJDeUpkbqPrmoZLkDLWXHQ0aVxaM2r0uVVIhMY84GtBzSC05wR+K7efl/plL3fX8Kk9JUf3vmP4sPQ+ql9p9PwZgBWSwqAuo0wAeM+QedT9A9ih6Y/gj9kO0qT2p7B/HRt5VUMb3n+0Vqyz9WVZZ+rKe2WNzHcITU4Vcg/N/wDfMVK3N+v4LukE2aKrLborX8vCsiWTieaBUm0mkMLGMztB0kqablAzb0yNzjxzW5y4MRZP9w0rNtInp1IGdoZli5acqWV3+1kPi4Q8rishlfBuGU1UneFR+iVP01SvZlUX2re1SzeaM29MYXcaR2dyyOBr/urzpwgYS1ruK/KAX31XCcHxquepQ9MKTonyN4eMSSkcYlMfDXwT+TmKlo7v0cZqo/RKn6abRgeKwVnevtFJbl5R4o5E2kUcZLa6nNUlGccw47fr5YOmsuB5Y6qqsK0vVpeoHyOynkZyo/ZDtKcMrJjZpKdKJMsFtQrGhUjeOxOlkeWRg1CrlU5L8rKz11cgTpDWS41NHN6EOGjEsv6iU2ajiqImot5in0V5rAGUxUT3vohE05I0k8yjnEpcG8hHKp8rkNQTB92ZauNwhz1oGg5LWHSHHQhDO9r6jmq5PxXbz8v9Mpe76/hUnpKj+98xUsLGQlrTUKwe9Rto2S12QC91XLzBSifJc1g1qqjWsnIgqyqtB70RQyGRjlqrLk6SkZOtUCOVGOhgGrMXn6Ksyg+gtC4KUBk/+neQxUMNJbmLz9FW57XjmLQoZGgtIZU4KX2n0UbIWxkObXxgnvmDAQ6riqWVlWUxtYrUMT2Q5L3VGoHv8hjobQ6rMXnR/hV8MN2QEIaUGtedVw0FSPGlrSVExzIanOA0HvU/QPYo3O0BwKIotUbOQ1VlD7RVKzlzVFNliOUx2hR+yHaVJ7U9gWXLnJzNaOVfdlsQ5g2vtQ+0hsrOWrMU2WI5THaPLRt5U3Q+v8AiibEW5NfGBUeQGfaHV5VQzNQilLXsqJJqqIU0TGQ5LHVCsHvTWUQtbmGU+qvP6FL9oyS1lXGqqXBtHCTc3Ms0jWehrQqqUwPZztzFNkidlMdoKhELYzl115QTnObH9oLqmgaAOdRROc14eeVugLgoWh83LXoas0wb6AwIfaWtkZy1CopskZra4Vg/hf8AfMVK3N+v4LukFCyVocw11g7ij9mYIpRoq0FZcfFkbmIPYhK3MdDm8xT+kF/6eVwtXIv53+k574Hlzs5KLJBU9sNRCo3S8lG3FUneFR+iVP01SvZlUX2re1Tf47VFXzHs8snRKh6YUnRKir0ZQ8kXtPopebg/qFR+iVP01SN47Ez7NwvA/pqqWRM2VzOY1IPlhc1mSQT5YOmpMoA/dHTvC2bLls2XKoCoKP2Q7Spj/f8ATyUjeOxQe92lUqr/AObuxUX2re3yS7x2qKrmNdyonvfRUk+geTh6OQJeUH9S++he0c9Wa9fczOb6ORHKFUrNar8V28/L/TKXu+v4VJ6So/vfMVSekuHpTcrKPFFdSe2Cupxrzp+9MfSWl0jxlaaqk+OCsfpH+Uxkmdg4xCML2NMeipOyDxon5juKkpDDpjrad6ih5HHPuXBMY0R6MmpFsYqY4ZQHMpfafRQ9D6qX2n0VJ6Co3TCmc3WPFH+VHG/UHGcuDLG8HoyasycWztayvi8pqUgccpwjNZ58yo/tG9qn6B7E1rdJNSEcTd551HNE3JEmsBorU8J0CpwUfsh2lSe1PYE9v6Y+KFHLkjhZBlFyjpLAA4uyXVcqmgJza4+v08tG3lVQxvef7RWrLP1ZVln6sqjteC1wbnBTfZj6qSSkVmNuarnKe+BpGUKqq61SemUJ6U0uy9UV1VBTGIHIFchrQrNckr9O9COFoHOedNpMLQ3PU8DtUlHJ4pGUN6o2530REtfBMFZq5UJoGFrgKqq61SsrTwhTY3N4CoVaMy4ajztA/U2OrShCxznNHnfhf98xUrc36/gu6QVH975T5PtcQzHNJ3oFx+6fmf3qWIaXDi70yUg8U1OauE4av+2rOg1sUTso1AVZ0+N/625JqWfNLE5Zb5eDPK0rLaCI28VqpO8KjycmdqljnOS19VTk6j0V3CPkzVjkVF9q3tUsPnDNvTHlvHjdnaVl8NV/aRnT5IJJWBx4rWuWTM4uk4PjE86h6YUnRPkaKS8RyjTXy+lMZDsmcvOVJO4VcJmbuVH6JU/TTaQBxJBUd6FHpLsjJ1Xcia2glr3fqJGZSGWNjWNzVt5/LB006V7S4FmTmWwkvWwkvUmQxzcirSo/ZDtKl9p9PJSN47FR/e+YotOg5k6M5nMNYP1Q4aQRS/qBTYaOa4gay7nKfSnjSMlionvfRUnc36+SSIy5IBzVNGcJvDyCOUDjVqP7KGlwryngVKeU6pqaPxXbz8v9Mpe76/hUnpKj+98xVJ6So+76+R+9R9EL3wuCiLQ6qvjLaQXnuW0gvPcjE6ouYxgNXoIVHr9PYfJEOUR/VS+0+ih6H1Uw/wD0+ipPQVG6YW54W9h8hbwjMoaRWp+gexUf2je1T9A9ihcdAeD/AL8kA5cpTn+1R+yHaVJ7U9gVJ6aZKySHJeKxWT3LaQXnuRllfEWlmTxSfLRt5U3Q+v8AA32Y+qk9qeweSk9MqjdBUkDzCqMT/wDQeQ18rghVyMJVG3O+ipfu/XycJXwc3nc64rWyj+0rjB8Ug/wU4S55IzUTz/hf98xUrc36/gmF7i0E11hMnbK9xbyHyOY8VtIqIW2kTIssvycwJXCAmKXnHKrS2rorLH3kvnHk3eTKPEl88Lj0ni+hqjhYTG1hrzcqkDHudl86MUwraV93SBk+lqJJMktVWUeRRyiZ5LHB3ky9nL5zeXerS2rooSEmWUcp5E5vOKk1/DScU1pzecVKOUTPJY4ORfR38ETpFVYQdSZeEHmgVIBoqA5Exz5HNyRVmT2MeXZRrzoxzNDmHkVcE9Q5nBVzz1jmaE2OFuSwcnlYx7y3JNeZbeS5beS5beS5SZD3Oy6tKEr5HNIbk5k6Njy4E15/I+Z0rwXcgTIGkuDeU+TJnbnGhw0hfd0gVf3NQdSJDL/bVUEA0VAcijy3ubkV6FIWPc7L5/JkzDONDhpC4lJFXpaq55y4czRUmxxtDWN0Afiu3n5f6ZS931/CpPSVH975iqT0lR9318j96j6IUsJ/UM29B2TVJGc7SuJDJwvMdCbFFSH1u589SfE/Q5uSVU7iyRmsL7yF/C+jQvtMzahJq/4UvtPooJwOKOKU9sjS6N/NpC+z0SJ+Sc7q9OZUbphSwn9Q/wBoGrJlidoK2MnCc3Jes2eWR1ZT4m6GREf6VH9o3tU/QPYgxgrcdAQjpcby9uatvKsojJY3M1qLpBVJLnq5go/ZDtKk9qewL7UwcR2Z3oK4GdjnMGqW6U37IXwsb6c5Rlpchc12oCP9+WjbynPhDCXCrjLZwXHvWzguPepTM1gySKslN9mPqpPansHkpPTKo3QRB0FFpryNLHc6ApUby8crOVNqbkxt1WoyyiqWTk5gqNud9FS/d+vkfHLJK5hztLnE1hNFJjkyxyt5UwsZktYOXSnSSCoynMPR+F/3zFStzfr+0Hbz8v8ATKXu+v4TpJYa3u0nKKbFC3JY3QE6SWGt7tJyimxxCpjdA8lZg/5u70ANA8n38dZH6tBVeVNuyh3LJo8Ybz+nyVTsrq0HlCyjwj/Q45kwTRAhmZtRIqRZR2ZDSa9NaLJGhzTpBVY4Vo5g5OjijADhU7nKbJHDU9prByj5Pv4w4jQeVV5U27KHcqqPGG855Si12giopr2wVOaaxxii12giopskcNT2msHKKy3tLX+czMg8NL3jQX5/IH0iLKcBVrEIso7MlpNemtFrgCDyFVgPj6BQOQ6Qjzz/AANFIZl5OjOQrP8A83d6s/8Azd3qz/8AN3enCjsyMrTnJXCTxZT6qq8ohFlHZktJr01+R0kkNb3GsnKKbHGKmNzAeTIlYHt5is3Cs9DXLKjjrf5zs/kb9ojy8nRnITvs0eRlac5PkyJ2B7fSsxlb6A5B3Bl7hyvNf4f/AHzFStzfr+0Hbz8v9Mpe76/tD/vmKWGbixvzV9n7PdJKamN0qemuFTc95/pknC5opOX0H9nufIclrc5KlpdXEb//AALPxZW6rlwbWmWMaM2V4qyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqirIeqKsh6oqyHqijE2FpkGloYa1ZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UUDTXcHF6e5NihFTR/TMl3FeNV3MsiMGWIaKuMO9WQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RVkPVFWQ9UVZD1RQ+1ngovTm/0hFCM3Pz/ANCpG93rNpG93rNpG93rNpG93rNpG93rNpG93rNpG93rNpG93rNpG93rNpG93rNn3u9Zs+93rNn3u9Zs+93rNn3u9Zs+93rNn3u9Zs+93rNn3u9Zs+93rNn3u9Zs+93rNm3u/N5Ujmtbzk1K0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWlitLFaWK0sVpYrSxWli+5lY/0A+oObe7806Z/JoHOV9opUhbDyeC/mH3lokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEtEmJaJMS0SYlokxLRJiWiTEuEoEjstufJJ7CjR6Tt2cvP6gpt7vzVGiGg1lMjZqtFQ/qEDmZuELa/8AOb1BTb3fmqLu/qND9z5vUFNvd+aou78jSHMNTgwkFWmW9WmW9ZqS/wDznXAUmrhP0uHL5JQKTJUHHlTCdNQ/M0P3Pm9QU2935Zokjy4HisEaQvupBleacx8tF3fkaV7Mqj+0b2rVCm4RjczSQeZUfI1uEbVf5Ht+y11GrSmu5xWuDDTJLzDkWaCOpBlIj4Kv9VdY8nBtbwsvKAcwWwjqQjmZwTjoNdY/JUP3Pm9QU8sxqZWVtHYSto7CVruwrXfhWs/CtZ+FaZMK0yYV/Mwr+ZhX83Cv5uFaJcK0TYVqzYVqzYR3rUmuHetSe4d62c9w71s57h3rZz3DvUYiZIHNd+ryAZfCs5noR5LmSnk0qi7vyNK9mU17dZprC2jcIWRLLxOYCpcI+UGkDVj5vJN0yo+iFlvnjcHOrceVVSRQtbzu71K2B2VEHcU+hUdxzu4MdiDp6y0urfz+lZMTYD6P1d6fwMjGw/pr0qNkjsp7RUXc/wCRofufN6gp45m5TKzmVn/5FWcYirOLyrOLyrO28qztvKs7VZmKzMVmYrMxWaNWaO5WaO5WaK5WaLCrNFhVmiwqyw4VZYcAVlhwBQshhjY9xr4ralVBG53p5EHUuSv+1nesmCNrB6FRd35GlezKga4VgvFd6ssOFEcC1h52Zqk4A8aN2kehQynS5oJU3TKYToDURA4xRcgbpKy5Bk18sjs6khJyiw1Vqi+zCdLQ6qjn4M/RffQvZ6SMyHBSHJ812cJkzRVlaRzfkaH7nzeoKbe78tw1IHCECoNOgKpoAA5B5aLu/I0r2ZUclVeS4OVmdiRENHqdzucg1vGkeVHEP0NqU3TKexms6GoXKKQivIcHVLLEhcfMAzqSV2l5rUPBOqfwVQPpX30rq2O4zKgFlGXJ/tLSnyUZuTHuqrUeXmLuNV+RofufN6gpt7vzVF3fkZInVgPFWZbWb/S2s3+lnlmvHcvuI+N5xznyOcZZa3GvkQbzCpGSJ5icdOasKueYyDzQKkHVujqbk1M0IQsc5zRorWU+tknnNWalZuh4oPlcZnDnzD8lQ/c+b1BTb3fmqLu/qND9z5vUFNvd2fmqPMNDSWlRzM0OH9Qj4POyIjPu9QUu93Z+afFKK2OTjCOFo59FY8Fnoufp+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+Cspx+C4KhwljTpLe9Eu40ztY/T1BS73dn5zO1ty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRty1G3LUbctRt3qEl3u7PWbLvd2es2Xe7s9Zsu93Z6zZd7uz1my73dnrNl3u7PWbLvd2es2Xe7s9Zsu93Z6zZd7uz1mybz2es2Teez1mybz2es2Teez1mybz2es2Teez1mybz2es2Teez1mybz2es2Teez85ncL1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b1rtvWu29a7b/AFCSbz2fmnSympjU4QngqOPTUPFZ6Vn6HirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHirUcHiuFocxe0aQ3uRDuLM3WH19QUm89n5qjwjQ4lxUcLNDR/UI+DzMlIzb/UE/efl/NUXd/UaH7nzeoJ+8/L+aou78JrYxHwbm1isKVswaHtz8Xm8ksx/Q2tMjY2HKcahxfwJWNEVTXEDMo3nS5oP5qh+583qCfvPy/luCpLXNaRW1+kLKie17ecHy0Xd+Fwg1ojX/AIUROq/iH/PkjhH8w1ncFwh1YhX/AJWVO8NHJ6VmjmP+Ag3KdG4+ePI6KWQh7dPFKjeSXcIMprWjPUiyLLDwK6nBScKz7zKOVmdpTOD1Ks25VzvqJ0DlKzRTf6QY1xY86A8VeR0ckhD26eKUyWR+aQZTQNJVRZK0c9SEkTg5h5R5Cxzi940tZnVTmTN9NS4SB4e3yFjnF7xpDFU4SM9JCD43BzToI/CofufN6gpHSOaxtZzuNXIrVB1gVqg6wK1QYwrVBjCtUOMK1Q41aocStMWJWmLErTFerTHerTHerTHerTGrSxWlitLFaWK0NVobcVaG3FQmCUPe083IsqF7mO5wUBSmcIPObmK+5lGV5pzFUXd+E5jtVwqKfGdZjqlFN5zc+9SVasfECDjrSnKUknAuLNDKiNCHDvkMnLklOhBym6QVA55rdo/2qRvHYi5rgGt4uU7sUxmyctxqFXMqR7R3aoOgOxOkkhPGdmzjMFU+SUv5wVJDXXkHSqO92dxYK1SekhPSpH5Gq0DmCY+FzjG7Nn5Cp4a+LVl1KqM1SSZh6Ai2vJjbncU59GdJltFdTs9aYRDLwT+K/imresmM1SS8UegcqcC7JjZrEJ01Fc/iZy13Mvs7j93J/o/hUP3Pm9QT5nSyAu0gLazf6W1m/wBLazXjuW0nvHctpPeO5bSe8dy2k947lrz3juWvNiHctabEO5a02JaZcS0y4l/NxL+biX8zEv5mJaJMS0PxLVfiWq/EouABD3O5TyINY0uceQIGkEQtvKBZHlP892cqi7vw2zDRKP8AYVKa/wDlDLb/AN/7pTI/1SO0prW5gBUE6GitDntzFx0BERulcP8A8xV2LJpAqk06a1FvPaqRvHYoTzkn/fkpHtHdqg6A7E6Ohtaav1lcR0zh/YKgnRzCqQaVRugqT0lRuiovafRSeyPaFRx6CqQeXKHlo/RKeKOxpyjnrbWnMdEypwq1CoHZLszwdHp/CofufN6mGvnkPBMFQY1VQRtZ5aLu/DeRrR8dEA6cxT5zojFQ3lZkcrTypr4nxthAzZ6qlJJHqaAot57VSN47FR/e+Y+Ske0d2ria3AZsKjMmplDK3LhOFjEVWY1qaYaHHMqN0FSekqN0FF7T6KT2R7Qopx+g1H/KkjmcGtk0E86dI57a6uKK9JUUOWH5Tqs7eRRTj9BqP+VJDM4ND87SedF5Ic79La9KbD9nc1zuY11fhUP3Pm9TlF3fhkHQUcmaOrkrXBEgvrrcR5HTURzQXGsscvvMiNvPXWohRngEDjF/KnRSva4ZVYqUszZYwHchUcDyCW15xv8AJJIJY6nOJ5VGw/paAi+hluSf0HNUvviyNu+spv2V7WtDajlcpTYZXNdknMQpZmyxgPNdRUUTiCWCrMmRxua0h1edOlkkY4FmTmRY8VtOYhE0R7SzzXaQs4jbvci6vLmP6k5kgra4VEImiva5nM7SuMI2b3IkHLldpd+FQ/c+b1OUXd/UaH7nzepyjSjQKwmSM1XCsf1CBrM/Bltf+M/qcdC/l0HmK+z0qMuh5PBfzB7q0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhWmTCtMmFaZMK0yYVpkwrTJhXB0CN2W7NlEdgRpFJ27+Tm9TpbI1rm8xFadVGy5ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWo25ajblqNuWzbcg5kbGu5w39xf/8QALhAAAQIDBgYBBQEBAQAAAAAAAQARITFRQWGRofDxEHGBscHRcCAwQFBg4cCA/9oACAEBAAE/If2gywTkmQCMbqR1IwBA2QOwlfzhZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZc1QIKf4RZ4zlO/NZ0UFQ/1pqWI8DEhMCNC2Gjp/PBKgMRFqExDqgOX9aiGZeQf0ELH9as+7j6nZjgnT9cyTjkWYPwkNKA0Ydit0JygxF9kX/IDjDwB8oI9yYZR4w/UeNNASoJ4MiPf3DxEHEJhOeUA8vww2GeXxYsiHQxYaOPuD4YFc+wrdC3Qi2GeXwct8CVZ93H1Z73RNYMHgOXAD2QfL2T52mWoUVPcWjyEygWA94NXpug4B4DbA5DAIkgFpiEMGSkAk5PPholCfVS1UTIWqeaoSC1ByHBUsQl+gRAI4BAKw/xGIJLWCPBo4WxHzdm8zrJEyAokhkHhMJ8VgF0ExpH7AmEA5gx+kbTa/RdDkyBJBkcZOhjJAEUEiCLeBe0ZjJjm0k3DeSoPqwurjYqFihxp3LEfk5oE04kyc94wdFHhPC7kgiMnxN4MZIWbcJQ6HgFkMgODOiiWOAg+SCLu0RIQgvle2eQTQbGJEwGKGRgHBBcHgbBhgQFvNk9QpO5NGcmwZCgXAIkeOo1R4NnCmQK3qmxcRkwg7jRFgCMZtiIlFLgjOgJBAZDRHIbcBWVRuTmLNJiQfotgELvGOARTjX9khUoydDgeuIwFpc4ccXMml0WLQIN4RMNGYyY5tJMg30+JCpJtX/s6s+7j6s97pmPQfRHMd29AxzCjiiHF3ZZ73WsUUR3OoqAeSobTmOSe/ZhClIhGziEQiaQUIYAmSIlZygLH9JrJpc/ooIblwOnAtEoVmC+cm6jmrU+kMSbdOEGG8zHuFJ1TWkVTTap+McrQiIJ7Joo7HDtfSvVFgOFkIYsMMdDoBFhAYH/SEBN4kc9URvG8kHpDPaMaJCMfoG02vEoIxXMyA71iHclRBTsxAqE7a4L+c3IqxXOOaihRDdQPIA2qrpgwtijco1VCGfBBwQZWiDYg8mjDsxLSEGNg9cFQ8AjtBGJomsCdzbi5H+ZkvuQhkiHWoVLW6FqtasCyg5AQhQKD6iWGMJg4hHSc4uonGWaO1eBkwz1zQbIzlDtQAVR9EPAw1oKIu7kSpKyzjqNUFxCCOLBluhHiIMIyC1WtGyyxYgNyBwIFVkzNbqABObomGMqYCRDJMxAAwSRNpCAxw2bgn09IoA2uLCpqU6kwhYR6Jj2i54uqa2AaoKgGnAc0wJkWEErnR5cnMRMhhGwiIorMUAMQ4wB07wIeBedJ/wBnVn3cfVnvdMW3MOHcotGAocT3Yp8RIDqXQxiYBmtQoh6oUmnuqjRyX3yVP8ecvRMUwRAephAlAAAASCJgICEi3DRKEIAWjELhD1iqSdU1pFU02qAcsrBvPDUKkeBiASDhi5axW6EOTBhO8SXzRTdgHJgff0DabXiakHzHpEbBAksSQxAsjtDIoAkOcibI+N9wR2NLACWaBPpYuGWsuPBAB7jsB/HGG6arI88M97rUKLUKlrdC1WtNwVsQK0ugWoVRoqACyBhrEY0c0QAIIcFDCyIFlnHUao8GzhTIFb1QWABAJMzWq1oUyn6lCAYSWi0IT4IBx1IR24HEWfzJeiHHE4Nwg7ngIlg/UIko6PJiLgTcAKsAdAmoYnM2BEJjKSeGBt6JrAXYd5ioUEyY1Lv7OrPu4+rPe6b4kBzHJ+Doz6BsWo1TgIMJCwqTxjHG00clbyJwwApwpPJYgcJl409+CHVFhQzZYbiAp8CBAYKCB54oX3dnWIzWiULM+7hD0iqSdU1pFU02qkaZcNQqQ58J1FAAgJi20lJMrA4IFGnPMSodHwxQBjWfQMKuTORnwUeuIwFpDCidTEdigYSpxETaOysKgAXKgRDTWBWwoQbOAAN3KYfaYnmRfJACCbQXgVrLjwQ0Sr6YcPPe61Ci1Cpa3QtVrWq0rS6BahVRSGO0tHlPPmU1gQclPigok15cMs46jVF3aCQgOKlarWtQo4aLRxQHe7x6WjygzxMHMBYbrDBAHG5EAjFbqzSGQCP59aJzPDLE6hx9zdSKIcFidIhQoMOWbokiJCMTEBNcoXV/ZVZ93H1BaGEKDN6zMrlVXivNooNbEcxTYEGAVkk59i4GXJeafoKcDkQFtW5bNSD2DkRwQ8EyggzmTf7RDgHgwjgULEXUQCcgPKb8xgEG96DAmQKPmwccTKgMyUKDHlD7fOdi49K/xwwaKH2+c7Fx6UV5NEwgUEgqhMeAXorrBKa5gZUAEIh+1C1OwNMwxwKarBMAwUAhGR2Fg4hnZAgmAVyq5UGtyOQpuzGIRAFzBgALwfCAYY0GDDEoUBdhEmg9prBmEQ3jpQFva3pVo2BFMDeNiqlADCAHwg3vSYkzDhAZkoUGPKBy8hHi544BaGEKFkIg4IL0V1glT1KNUBC5jMsEimuYGVABDKcZBTZDmaRFWoEsBgRRQDmPCLGRHX6ihAHICZCQMzAHENbEcxVyq5Vcqa5iZUkEF6C6wDwj/kg5hACgGVAmJDzwCcAYiHAsiAPgqLfIYbEVHepjO88LlQsTMBkLWAyCJS4A83RHDSQTZlFrTOLsak/2dWfdx+/Fd8B6C5owo2aA2ydmAUIP4wxhrURCQLIA03wXVn3cfvzEMZIzOVpsogjjm4lVw2BZ/guqKrGQhAuHEv5+FRxH9bjeFgTC0aogOmCLBIi/+eA1hgmKhPzheKZFwl/XDqGLhbVuQCYqR/0P12OOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOMyfjN3LCPP9djjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjMgg2+pCRBWmlzF4QhqsAwA+HdXf8Ak3V3/k3V3/k3V3/k3V3/AJN1d/5N1d/5N1d/5N1d/wCTdXf+TdXf+TdXf+TdXf8Ak3V3/k3V3/k3V3/k3V3/AJN1d/5N1d/5N1d/5N1d/wCTdXf/AFbgWpn3Jtbb6Z9VbQTHpphBqDymJ6a9NaHNHUXdH/ILZ3EqNSVt59LVHha/8K4a7uBF703LXvhAsxeSi3OGa4h/4YjCswuxZHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KHUodSh1KCdcEvBlRRPyxPpOyxvpPyxEekg5JS9JS5LQXp2WovT8tTenpa/NPy1F6fRvoH1X0HlTilxA4rdsRjS/ag+hfVOKXPRTijnup1A6rdnqLk5Mddycnq7k9PVXJyaJ2at+al2aDk9Renp4z2nJ6HPi0DK+AlrntbX9rYK2Iq2CgtNLkqmN6KvxRuibI9LZXpav+OGdzrd/CrXPlXzTfwADAcZeg6pWg0/wwguhG6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YK6YKK8Tkm/gstRpFHya3w0Kj5N4Q6TT5N4kaLT/0zR48RolEyr5MAlaoFZZ8mAa/n8mzBM0zWsvPyXA4dnjw/q7ymOcGRb5KwdmeLAvnm2aNYsBgPC9AyIwCAcZo9pFxcxll3+SsHKQAqCp8rYNRYcEVoi6BNAAAABgPktjWTV3yTHInQTz7fJjFi63obDipbhH9KAhAAiSbEUCKnGGJYfoN27du3bt27du3bt27du3bt27du3bt27du3btxM0jAJnP8AXbt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bty4Jdkgucq/rSWDmSKGbOExl/Hbt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27du3bt27duFHxILj44DDRwPAE3uCHgb4ZSW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FslE8SqcGhRghDNO+vH6wu5iXQZptyAmmc+QuibQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQW0FtBbQWyVPmwCenciikKoIQIN4QiMGo8xJ7fyAiD3gc/J+sCawBjmf5CTuAOIc3nP7UAwqF1FoAtAEVcXIrwpZ4+EGr9gPDwvkkbFiUJ/ZIaMBgeiMOCiIRDohowGB6I0kCAMvoIqmC1FCX3ANgN9Zl9wTaDLQBaALQBMzQjQz+KRz7+QzuQ+0g02qCKJIQ6NkplJVROLEQxvAcDIQRzKw5jYpqKAb9kcgwD5kKjg/gLLvs3M2JtmMZoyTfpEJtghaXQo0rMDxBDhbgHNFTETAtZCtSCSIOW4E7lWzLEZe4PfsgIsTbjkKGFOCEiqBfGBaBytQooXKe6eZyYlgaoYOLcHRAtq4OCFqFVkHbh21BYUC/uiGzlQRzCENVwgRxzDsgcNcYHTslbJQVhtxkBzpxipHhFOwBweFpNgUbXGesweIRXvgEgYwdE19EmACHD33IhOmuIJMTVOSE7c9inJPEiDMVaEEoE4AwIVJ7PEGb2i0F9kOt2TUcBM4Q55I9F59/ilk5nwh8wUUcw3tCtq4OCP3KOffa6y4feQ195aK59kiIBAEzBEiVkhABly1upajX7kOHpdAjUBByDkMFr3wte+EcVhCyaZH8udyH2kGm1UyQQHEQ3lXqovxF2wH2j2gY2sBagmm4a36oDMp7oJMFpk80TBk0DFpq9qdZsUObFj0KjJrfCJAADALm0ih8Qojy5N1OiCYhRBYKLS6FahVZB2Ws0Wq0ocGd93QM2RAhjqJqT3UI8ExdbqkbYCwzTkTQlZLRajVahRTQ0eZIg0CbRPhxdqx0ThwQ5BmMe61CqyDsoFLDqf8AndCgjwHMAEHPV06jm6QeRCiWAZpH2GfHMOyMSA5Q0FoAtAEUsSJLYnhDOxsBbcxkBmjGWjYMUey0ShQiII5L0mwsrEwv9K5FBisQAmAo3oAgp5yxek1yMzYKyoz78DZ7gJ4diGTcyxgZ3TxCWroME38sWMVGfwjHDouxXTR6AQx2Ckb3/co599rrLhwQdNjHyHlTAt0YBIDYEeEEgiHKFhRARiGJZOhT7sG7xGxCQgZjSJ8/OZh7nlMAd1ZB1B5UADgeuB1iMrh6B5V0u+GTJ52Q2F62rRXE/RxeJncQmLr4EgMwNpNUI4iASoeUAZ1wO2ZzN1y3mhPAcj2TlatBkoRYmjSAvKAQKs9IeYlk1upGcY4NzoPo5iAXGCZi+sA8mggSwHLjDhxhEWgaIi7YBZnILWoB16IEsBy46XQLX3PoNTQvILuaEUUPd8RGHIECZp9ujCAKNeyPlEGdIa8ANOGRDrFLIgA4SclJxXjYcx8J1ibizdCdowGfByQewDgQ0CBOjJqEVUkEZMAIoppP0gAqM1yhXB8A5lP8BcOYQYtSafCF5bBaPtTuQ+0g02qobFoxkawE5l0CE8gmEBiQQnaoVpNVCW1fa3hD8+cNEo7t4ljJsTVuDL30rS6FahVSdzstZotVpT4Fe2rAPB5u46hRajVahRMX1Y8NNeUit35wPK1CqyDstEpV2ygmjg3F0CSkQccw7IHDXGB07JWyUJBAsA4QxVhbk4aJQhAgtJFT6jzE2NLw+DY1zgVy8E7y3AwVAHmeEEHNLskXqntkX2BBCxFCt8BgnKM4AJC8iP3KOffa6y4cENZcE/oJA/BhB4XuhZA9udoSWe90IauayZCCISBnyYxRL1iUCpmaoCzFkXGBJlyogDR+Lz/BQ2mgLC0A5p6y0moicggIECgTChhqoEYgrRXFr7y0VxZhwcQlgg2Ds6BS7wKgWYsntbJCDkjnR5YCB0Oqa9iZZ1plqFC1upS2sHMoZwACXE6lD5ugAzFvXwj1Oe4vA9hxhw3RQQLvmnYDoCLWAdF0kLpJB5wR0sABpZxNLoEagIOQchgte+Fr3whsQgFiFpFUGETAiW0eUdcicYHJ47cHHIJGKABZ4KDAIJzKWSaTQAlUkGCASInUo3wLYYF5IScW3QIHHxwYkKAkzrBqiOkTGhG2NvtDEsTGjwyZFntCEeMeUXl4TB6rkVzhILHD8vtTuQ+0g02vFChwALDZ4LtQVTo9qA0veREdlFgqQLSI5oYgCC0joyN3YrTSDuoOw7zAREIjLGoPZDogRDlwbqp2EJg0r1Wl0KaIGeNDAjzgosOmIAiuKmwNDAPJK1WlDgztu6hmyLkFiFxCccYYkN6KLN2ghIBggoJk4eSK1Gq1CiAJIADkoAF2s7oosJL8QZ61E/OBy0Lcey1CqyDsoOAEu/42CilAvCIGLFHXnOULKIDBpPB6ImnHMOyPp0znB8LbS20qz2eIu/rhD0VzholHBATrjJC5Ps3ixYCIIgKN6goKecsGpNcoGwjVotOTY/QbET5k6ZF2QhbIAsCagqoMS0mF6CMRzwQ79x+5Rz77XWXDghrLghAbDR93DPe6AAYgPEjEiLCnNRtdeZAhyHHduLMTKTYIR1Q8IoczBxLRXFr7yIVgdkRgPVcHEIQIEnNBZMxxkfHAGBemZuOi0OpahQtbqUJUuwcAR0RluiKbOBGJ/wA4w4ZATUUPZBE64NxXAGGGYNou46XQLX3Po0iqTtvE3CA1QizY/gEUVh5eAyJiOL7fCM0hrt54MTFbw2uNhmBxzBHSa5jYFAk2Q4Ir0eEBKAZHv9qdyH2kAgBLRBPuzYAYuCPPABA8RaE6MMUYI50cWOLWIvIExuOYIT94e/dArlHyLOEaSMMAz5i1NjWPOaL+86ImbSeiAGSBLRBln2cDUJ1zSGaOmJMmDxYEK1IBAixfgTk9GyLUZe8PfupeABsOQJyCwMglGIGMLE5BYGQQiACBFi6dqZ4p5URKIIww8yglAmACACNKzA0RQ4W4IyU46pItJv8At1HpBpN336n0hNRWAcRwtgRmttLbS20qz2aIM/tAc6YIqT5UXVvyt44Fe+CQBhBk97Nphck+eA24mRuQU7ctijNNMCLMVVDKBMADABUns0RdvSY5oAtEGf3wES7ions6vugoJX91QyQNYP3KOffa6y4cENZcFmfdwz3utQojhAThsmBxROwfmQnYwSDDTzd8kb9NEsALTFFyJOJbETURQUlWkRcmIwaIa883fJGRhJFDQMOS0VxDnJw9LR5TYvibYEcjBPtcIughwcZsCGCbLBxRizJokR3RjhD2xHpRGAF6JYHmeQUrmvRNQoWt1I7s9gWlB5XDCSoJEUGNVchU3p9lAZBjYA548YcMTNIwUWEBiOyCnzlky5io+tUFvZMnJaAW9uOl0CdsotJGRHHduI8xGSJvUlaRX6EN2QIQw4GIQpnDcXtADk0Ii+XIZC4lvHJJtN6K6Yxz9/0MGcixCBB24bFs88SGRrJwC0dHuDiSmRzP2p3If3qBHPvtXwsdjfAqOgUQlnL280+Fjsb4FM9czhLY8DZySXKAQtgMOAsNSwFjqEA4cVMIVAJmmeY8B8c5GHUTYQzHjgEJSrAEOhFFF8ADouqD4NgHBTx+S2YJThsw8G8zU+TA2OPAUEoGAdQgCJjkEPnrecwoEznAqCm+QElkdUCZzgVBU+TA2OKPy3MjjzsRIeOXB0lwgJMmQnYb1ESZDopW8kDEzEDghHbrLtBzdETEwL2QYKXFuGImSYH6AAAG4YgZpiUPsqgHQqIkyHRSt5cJcmBucUyjkQ7DgclWxdOMw0DZgofaUiuHKwcDRvHWI/IqiRtxnaZvPAqpaEuVE/RdE2YKEiROyS+3O5D+9QM59/IZ3IIONGw5AEufj+PC9EciieAQZA6D9YAOLm4COD0MMUCABBcG3+OBFCcWIDsw8Q94Yw7IadSORuQBk0Yz0sfoG2222222222222222222222222222223EHOoOj/rW222222222222222222222222222222222222222222230YK2IuzA3IbeazUrJqf1geWxoj/AIQWzgDCsfxzbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbbfZd6Eu0IchmeabsDElMqn9Fptf+AEbWMYhCnPe9a0MYxjoNPk3SafJum0/LIw1NkRRj0XK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hWkK0hU+7m8PgPXKflR9ZMACLXKZoyGwXoYBeqf8AH67Oc5znOc5znOc5znOc5znOc5znOc5znOc5znOcmZuEiuhJD5SmDEb7x8Ba5T8o1kx5wA8oZTB9L9gOayAXn/AWuU/KzruP2Od73wFrlPys67j8ErUXEwW41qZcnm8kKjExYhdIrwEGggBLFGJHIxPT8nO974C0Sn4w17kLGExfZigoD7ttvTjnXcfg6zRRPaAWwqNtbViYDgutYBnAnSI7mxY8k3gYAYoajcmYc5UkNBJUeEMBxFOBGcCwOaaoy1ycp992iE+Pws73vgIvMQyQHmONS271vFbl+gfcXqtX/S1P9K4wva217W3Pa2B7+uxMaLL1B3Y5wDMRGR5IQME+rG/wM1VMyGHqPLLOu4/B1miJKwBrxw2KziUxgPNlGEBwNzXnlLhqNVrFEWTCkIjFgyZRIaWcSHQIMF0iRB+ZQm4yQTB8yD3eGdDMj3NM0kRgm+M1AW/g53vfATseOXEWXK7ab1pHytfeVo7ytUeVpjyt/PtaQ+1qCtSVsK2z6UeLTZy2+tk8ZBCOMkQEwF3NX2bIHMyUQLyh1TkaFPmbVnXcfg6zRDYBYG0MWyU8+BCMRsuaBCiU0IFm4ratRqjhsKSaBk69jQgrz6RgBakESgM3AAZ1rNEdUyuIxBvSRItA3CSdBjbZNnRQhhMmEx+Dne98BahT8YHNAFYXK3qhaHYAYDjnXcfg6zROsw0VYutt+k/ChB43RkBo4+SivuAPqwmtRqp2gBUqNjBSpi6fiIgTFSiDkxJgWPYmOIwFhwGe0PAiIHDGILBRM7RdBgIoAEgAqLSyCgksvWAyy/Bzve+AtQp+VnXcfgnoJTMwdbl6LcvRWo8gI+kAMMTOdeAdkgmNrogCpCQh53GJNWsQcNb35l1BOwGhB0Rppkk1w5dMi6mPOqkBzKiYIADJ/Czve+AtQp+VnXcfsc73vhzAkHECjsR2KLQC6IobR+wHRYZNGTjD4cYZyFj7T8BTmY5i0hTXJ+ukkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkkh5hRiD1lCPgJNkBR8PMFHKN6baW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2ltpbaW2lthAABgGH/AAUbHHHEAAAEEGDbbbfccYYYZZgzemyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIWyFshbIQIIcFx8Ohs7C59J2ApjIczaXgb9dFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFBzGrAFr5Sg4CTZEUfDkYJOAFWYDuUGgBgTU2n9gGiwyaEjGPw51nXcfsc73vhzrOu4+0amfJyXtE9OgTFYMYEtZ8GCIgA2mwYo0EHGTPVB2DxP1x1vo3YFqpg14tUj8rO974YaCxFCxOdoQEeKrjnXcfag0+KoHweicAxPCzbg+aOkLyME/jfFkB5wQuepJnkCCIDKseU4kjANA9RDhKRIcvoiE8MQKoyQMHZslXELUAIDOYkURnseFBAQcox6CCiAq3sq+GGdZcDLwYHPCgySGcJDy9oLKlsC2BUu2vAkEyDhzMkFghtAQM0AkG0Wc6cJIDk7czJCo+bORkXQdBuQ4P2s73vgICcuCAOdal8rSvlaS8rUXngJtBbJW31sb6an8jfFuK1JWgK2w+ls59LTHhao8IhI4IBCIf4EKXUJND6REjkg4caaFnXcfaDO5YrijMkHPlEGaCOZxFmLN0xCfIp5umfs48pD31RUizGTDKD9eqGCQiIAAN0EE8gAKmxqjAAAvNrEBky0ShQKLcmwQDoyjNAENwy3E5LUKlrdCkucTwehIyQgsFEQRuDIthSKhMItZJCNpaa1lwRoTIORMCdIMnTHLJ+ZqSFJiCFBBY9xghV83rbQjLFEEYbOdwCmC3QBvSafjnFhLOj2hxwiQGNoGWKIQggZiMgM0ZQIOgL2iEFkGWM3rLD7Wd73wEbkrsG7LcvRbv6fZkcK25IUkGNkelt70tleleYHpan+Fo/4Vzxs33Gt6ovFtNMAj3ClMoC5KuFCYvSxM5B0lnRZ13H22c23AOTIJJOEbQbMWR2xIoPMYlDzZgUATwOWuUAtT1zjENh1Rw8weC5FaLUtEoQhEzWMeOGoVLW6EIgmxjgm4eUJ8+5BgrEBbvOKyBay4IIgv4l1or3CGaiB8wgQkQjhxMs2AuYQMyAkTsTwhDaQeqav5cfazve+GANloQ1JOpJs8tIETzMzxzruPtt6is5CeTo2gAWKh37gJmtGaIPinOtWIzI6OaboWxpQApcjxEwnNoFq0GpaJRxQ1CpAg73siFC4kCrooj2nAAzXIKJE+pIKJqhay4LIFor3CGFVwblsjiM0CI4dMAG6L8SmKyZQWeJuFowax0NVwTlyZjNMpHgQZYTqSsd9YzQpWqCAVMvtZ3vfDmddx9sJbgYioVrFtHbBMZSOUE7Nwl0BIHtIKDQVsJ7AI9NQeR1UYpm+DzCI2cEOOIAKIpdIiR88BiYaDI5eiIRAkiRcE6Pbv4BogmqzkgFCeyJJqI3YJEyJf2mGTDjhD2FIyFPoRy+hHlFECY95g+EA2O4tCOFRgVupam6Jr6EZDaxYwAoAgRXwWhFRiR2DrI5JggKudk3ATHDQoKD7Wd73w5nXcfsc73vhwVkx5wI8o5Dh9b9gOSyIXn/AA5B1mwQoscp2nM7Rchgl6h/1+uznOc5znOc5znOc5znOc5znOc5znOc5znOc5znMZuEiuhMofKUCiRNbz8OnYqxAgkEHkBW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdbXW11tdD/ACaKVsCICev9F//aAAwDAQACAAMAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAEwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAAEEAAAAAMAAAAAAAEIAAAAAAAAEIAAAAAIEAAAAAAAAAAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAADaXUggMv8IsOAiAUoAig607wiIEes20AD2MAPcicM6IAAoAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAoAATfTzfTIvTrrDTGoUoYTqH/AKFw61yBwHwB8K4AG0P/ADsQACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAACBDDBCAAAAAABCAABDDCAAAAAAAAStoAAABABDACCAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACwAAAAAAAAAAAAAAAAAAAAAAAAAAAAABBCAAAAAAAAAAAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAgAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAAAAAQgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAgQQgwQAgQQggAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABTDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDAzCDDDDCDDBDCDDADCBDBCBBCCBCCBBCDBCgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAACgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAADQwAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABRgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAAAAAAAAAwAAAAAAAAAAAAAAAAAAAAAAgAAAAAAAAAAAAAAAAAAABCAAAAAAAAAAAAAAAAAQDjDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDBCgAAAAAAAAAAAAAAAAAAAADjDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDBAygAABTf8AAMAckAAAEEHI0EEA78gIEMEAAAEAAAAAAoAAAAAAAAAAAAAAAAAAAAAoAAAAMAAAAAAMAAAAMAAEAAAAHMAAAAAAAAAAAAA8oAAAULPfL/QDg7SEXLnXXHAr8cA/HE/YDMAAAAAAoAAAAAAAAAAAAAAAAAAAAAoAAAA/LLUvAb38gQ+wDffQ3IAnI3jcf8nrDgAAAA8oAAAUIUkwg8UKwbwQnYYEIAk8QgwwGwIEAAAAAAAoAAAAAAAAAAAAAAAAAAAAAoAAAA//AA2M/q3+45yKxxtw16ALzEwJL3xwO6AAAAPKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAKAAAAAAAAAAAAAAAAAAAAAKAAAAIMAAMAAAEEEMAEAAEAIEMMAEIEIMEMAAAAAPDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDGAAAAAAAAAAAAAAAAAAAAAAKDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDDAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAABMMMMMMMMMMMMMMMMMMMMMMICAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAFIAAAAAAAAAAAAAAAAAAAAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAABCFAAAAAAAAJ3KLBCAAAAAAAAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAELECJECNELNHH3AAAAAAAAF8qF8631AAAAAAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAEIFAAAAAAAAHGACA1DoAAAAAAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAFCAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAENDDDDDDDDDDDDDDDDDDDDDDHIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAACDDDDDDDDDDDDDDDDDDDDDDHCAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAAAAFIAAAAAAAAAAAAAAAAAAAAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAAAAAABCFAAAAFAHjCBHBBAAADADCAAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAELJGDNGLNGDME1AAAAAE7+46wwJ1/uwMF6AAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEIFAAAAAB6B5NBJL9GOO6P6AAAAKAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFCAAAAAAAAAAAAAAAAAAAAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEDDDDDDDDDDDDDDDDDDDDDDBIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAP/xAAZEQEAAgMAAAAAAAAAAAAAAAABALAwcID/2gAIAQMBAT8Q5dMpCFPQ6cLwX//EABoRAQACAwEAAAAAAAAAAAAAAAFgsBAwgKD/2gAIAQIBAT8Q5ddrhp6CAMcfV2UJX//EAC8QAQABAgUDBAICAwEBAQEBAAERACExQVHB8GFx8RCBkdFwoWCxIDBQ4UCAwJD/2gAIAQEAAT8Q/wCoxKD8AJVciKvyZIqRZHyLfC5hQi5dHuixHxP8c/8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wD/AP8A/wBLad92BohaEif0nR8M6gIOEbAxLJP/AHB/lquZtG7Evu9gJRWJZlwTdpKA7ub/AB5JMSMTU0TEcmtZmyO2synuafy3MzAfyCuViyfE/mdY5AkcaGNKmh56hTYmhe3pcvaSFQLGf9Fc82piBEDKQY/0j+EOJYQKK7k3JBGL29Sr1KAgN5O1T8m5JBEJ/sAYkvGBwDrU5YJASiZf/jBlPZIeWHShBtAZEDH7/wBhKU6JZCcOlc82rnm1IynlkHLDr+CoK3L6qmUMoLpTot+fRWGHW0YHRC+9IoFVpnDFc9ooUpzcmHGCfYGkgc0N+SaSFYs5RjAi9yfSHxY5dVbFBFyR+XEB7k1Y4IkkTABg0n1BxrMpXeEEq6AtAEFQAfOLd2o3djh1Es0XLf14DCT3plexCiTD1KE1ongLgUyr0xQoL2lPmiBrggrsPgNA2KRCZoAp1JPQdXSb7xpATjD/AGgH9VD0MsQ6wgdU/wAOb0f42dXyIu4Pyije3wvfkId1KK6IlIHBHP0LXtrFpAy6MVHnasfoWn6NjAnRzHo1AXKREiCfdD3q+097YYtPCmgfewv3JKWOQusEA9h+Kiua5+s1LhUI32BL2Wmc8lhJqgMdcPRQzgmChGV5q8wupkCU52iop9mF0I9RGo4xJUdrjKLlwzqXMULf4Qd2KKVwcBwRMT0ZXcvGYiECaLNWG3MpuwD4TSZi3IDCPZKJxISOp68hrp1l6IXEGV19PAaVxYEEt3KaeZkBpV6ANXixCpoUq96PUwihEmYSlSgdCSgVsZuM2hpv3pqhiV0JKaBcJx6AudS3WiodSlRIjpFGAjJBLmTEw6xFEQywf1AatbDGZzJM+noRFhrksAVhiYvQElliyWb3wpPKRBgphAR7lM5OFC0AZd4qBK1Y/RadMkQQOjo9G/8AOYK3L6qjBAa1hiv3P3oHj6gIPdfmsZCN1CV7ge9cvqpQt7YXbRidgFEDhAJJRiVW61DAVcRPcZT3J6YUxk1GUrspsneg8AmMAKx7rSMqqCkAwbiGh3aErQqqum5pey2s2Ic8FLA6TYeujnUsQVxABDWUS6j6A7SRDDLoKAFvdLON6UTHHH8DDDIKbYYUm/8Aa2QIe/6u9cHp691jeJplwAuRbLoNAlSYSPuIMvlGVTQ6iYuudbkJnUCYUmYA3VPDCxAsrVuZyIKhBtia4DUlhIRFyXGksDyMskeqMR6jRSrVMxPwgnrzej/CzCyDhwLB0MOqZUrA0Gok9bicXJZoS7QjNWLIZkYSzQAMBcwihoA21CMWUqHJE7gheQEIwUqcVDYlggJV74EM5C5HiuQ4gNoLxGVEEDJMXFRqAvopn6AlOmxikd4jsxSgoCxKzGWYSmmNdE8OBn6KbLkSMizAkrGIRfBlqCBvMl17r/SGR4GIZrokj0awA0Oyf4WliiF/gRyWYGkGKosZoDmw3EIGpiGM5UxWdjgsHSZd1TzgR4gLHJVCdNVDyVihnAJUOYQN8Bs40oK5QxhMY2szAsNSUCRK26tchp68hrorPcSDkkZxXPNqQxJeEjgnT0USynzCRJOsOND7lrAvBPvDd0woEhCZ5pUvhIzJCYvdBBiSZ1AQjIYFxgTLCxQbgrJjAxcQRHVlakLQXLtdMUcCb9hS8NqIvQR/ad6x0iiADARwN4cR6KI0BzyEj8NKeIlJgMn7Kj1aT3Msl75sHWkCz6ybLuA96iMiuyAgUlbpm2N6d1MjETAMHSR9saJCnHacagTKGcSZv85grcvqpbfBMZwcDOpXabFw2ukk/esPZO6zI7A+ad8ViYSIrntFOtxjZGQLmc5C1pxp20LybtGB9mgYJlOshNzee9LEIFPQVLQuldluzreiZAIAyKxsUAU7PqDuATzGKvePb1cLuD09e6yAiZoTf9Vl62mpkVohSp8LJkERh7xXPNqkTJcISC54Pal/U6RX959XN6P8LHtbEOqD/SkJh8QBAsdX5pFUxJAytF8aZcWrS4e5agWzyxVkGatgqUZUGWNZAXSjsxGOAzIgkTZX1EBO8Ntwlj+x6uAfiS7Z+icvqrntH+FpYoCNQ2JF0P79BPH6qatQLQs7+j4ooCXuoOf2+aMsCEcEpgVArjAxXIaevIa6dZeiFxBldfTw/mg2BDZ6PooKqTh0Ef7oAAAIAy9Ax42QJJG9kPoPjcmUI/qgjIXOoEfPzehKEcGonuq02oBrMP4EHt6DeFRoBULx2HIJOjEPRaBIWWGUZlYdUlaVeIPBg0rcR4pwQ3m4XS+X85grcvqqO114ws/oPf0j1nwvBAdr33rkNdOFiPAJE6mPtQDFwoDOMuYr0YLlavxkgjrU+y6pClhJlIDFAIFAjnbUfNhWQf2EPvTNOIt4rDJGe5elEQNhKYQjAk0FHYIIBAVCbSmeun+INw43cHp/l3WMWrfnYoT/AHQES5G4ropSLoLM6iRZMEbjUAtraa5dMGz1GkoKiHBkwdsfXm9FI6LRwNj6EIiw1yWAKb0tQTFq9Cx7lLmo1ohBXOJB0aXIjJz2AIx/olqPdzGQKZRIBZiiDZkm0R+tcCXumZiNke4v1onAWTPAaAyvbNP9AgINw45fVXPaP8rSxQoE8fqp8SWQxS+2zy0O9keISDYkILayYpS4cBjJZBgMVdIJbenIaevIa6gr34TSPUR/0kIotBgUMwe1Xe2GdY1pNfByElPUWdxilWFPKBTg8ZFKIHGuA1oOwLAZBEz3PTkNKifMAlIoqGC0YYprTniQ87jgJRYteI0oayVQQvKpIdqheOYBushjegSjlHRf9/ziCtC7xnKq6UE0rLUZKQUm6+NYLyCYIAvdlq+xZxYRJt1qPnEN1YJ1KHm0AFjAizCSV0KWNAkrWgVmFyDqUKcR89+AMME7xQG4FvyVPZj2qwcufRESRMhOkNoVAXIo95I71cGMAXUN+496I9qec1XNVVdWlXsDEESRqNHgCK4LWezQFu2hii+sij+Q17JS0dVGRWg8JX9yj+Q17JS0dVCIzOGSN6GkGZqEWjp6YMtwMlJI0agrTKknEOZI0YIgsYLDIKQtODBhjWHTU8fWw+9IKxJxaFwOqyaUQrYsBEAer6ztfBG0a1wv1XC/VW2LObALFulAu1PGYjkjCOSFOhMn1CAF7mcYMsMMUE/JHaoINj1TLdW0qMLBeY0GXSAS5mIonXoVeCQoXUZB7g0uiHAHZXEwM1ytjR8toQgCmGYR70Dqt2MPL2VCvYGIggjVPQC3bQxRfWRQFt9DMFowhekLvGcqrpUedlmSQDWDLcDJSSNGodLjpIIx7lJX2lGMSRZhKgrTKknEOZI0/plEQCLdGhDLrORLNutSgTH5EckQRySl1EqUNNhsruJOhTzGJbsOEGoTOpRKAWDAJYom4CTRj1vsWcWESbda4X6rhfquF+qkrTKgjEuRKViy3AwVgjQ9B2eBuIX7DQZ9+wR4I1HokY+cHRxExEuJNKnrIraMx3BJ0qdasIiwtYPam5fdVdSh0LQdWErhfqlwUV3CpkJ58iOSII5IVNhmTBNAge430MKgW8Aj+ko4HIJG5glHAJJhnL8ZQVjz0BNIHIsvZdgWdyGuW8XEske9zrTcgh4bkAyO5UfJYXaWXViHV7/kqCsBAFEI51iwOBfIfpUbdox+kaJBbKWTVcV6t/wXAEKmP7t/soAQUSJn/H0XoBDpJ+D+WzmvhTBgusQ9bM6M15CIkagBCY2nO38dXgSOgMDTVwKdhKhIG+0LO6Zfy6TGZjmcF3N5J7TejVreDu9XPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN655vXPN6sApQpdoISEu1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzeueb1zzekGCRgx7qaWj0ejVfB09iUAdsULAD/+GZJJJJJJJJJJJJJJJJJJJJJJcYDu04oO4pxQ9xSeId/spxw9/upDEu/304gu/wBtOMPv9lJ4l3rOCfes4o6AMfaeg8fZXekcfbbekcfYDSePty2pDH2FbUhj7a0Sx9pqJY+w1UMfbWqevtQRwftTSwbtQSuFhwXW5SXFOIUgYysn8GJ3WpNKJRMYT/A++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++1OX36chEzGDFOSu7p9z1fvXp9q21fU72r7lK+93evtcp9ytPvcrln2oZIdqWSPnm1kh4ZtZQfdu1lD9m9ZY+GdZIeGdZAeedZA+eZWSH2tqj/3is0ft71mh45NZoeGVZw+GVZw+OVZ4fZtWaPlkVmD55FZgeeRW4FLcqj9r1fuXp9y21fa/tX2KV/7P3r7XKfarT7nNTMDs6DzB2rM9u1Zmv2FDPTsKmY3agZz9vuozE7VmYe31Vm12hQzV2GpnHsNDMaqFi3esBi/emHineiDiPuaB4t3X1QOKd6AsV7/fQGLd/uoDF+9ALFO9MH7UDFCHJkxCGIU5f+DQDgmCnRXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dXh1eHV4dUGRImE0AwA7fwI3K9z/BtuM0fgYXKNz/BqOd0/gYz0Kpzy7f4NxOn8DCejXueZZ/BuB0/gYz0KRTwbfwbkdP4GE9GuU/wY+V0/gYT061TxLv8ABuN0/gYz2/0UU9l/b/Bud0fgYT06Cn+DE5nR+BZGBAFJuHBoT0v7mlPd1CgYBSuDMMez8fwXkdH4FPcPudwEl2JO1HQrFHPBYC+9OqwX4q4TMudS3dQUFqt8jfNfwXgdH4FC8o+AIT4anqXMIz/cQ+9MVMpMr3ZIQdUomQIAIA/gvK6PwNa6wh3U/SeyrXc6TB7jvZ/BvK6PwNE2KKJzvYA+1GPFgLsF16rd6v8AxS1qoQAxVpY8xYz0RPZf+AVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVQpwjMCSIO9/wDmlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSoyCHVqk+/TSSsugv/ADQRABKuAUFksCIe5F7L/DSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVKlSpUqVEcKq7lcTc0HE9Bn0c9BJFwbPjzRxtUNG2EF6YR8vVrmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12rmu1c12pQRu6HtR1UglgvEmdKGOhiHYQ6tieogXOTOf8AmRngwqckk6zqnSrNcIKzzMAO8vWua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXaua7VzXalCOP2owRlTJqHHoltTOmnicblwzINUei0K1lnj/AGhP8QE20LDF/p/zBKTGchS/Env/ABCB4wDBb53U1ymv+kV9NFIMEvXF+lcX6UJEDKJel6XcJWkC7IqAviiDhEf6EZxmF4xmTq0zk8hYkog6H+lowYZIkaXerrEImFNGDDJEjQcTzMKdP8IlmwXABuVGNQyYLFj/ADjGoZMli5XF+lcX6VxfpT4sQ0kmLGq//dxur+ehecpr/qWXq2DB6DXPtqUJsIcBIXHCHXWKb4BCaIJ7inoM2pE0GPLoC9CSgy0yXyl/VW5EnAYWLSZmpIT6SRyxIUs3rtIXOIrGRYlFqTBelvarfZDxI6E/I5L6CXoKACDF570dD5BUkyRTCP7hAmCe1R4Yq0QW+F/SDCEpMRJJaVrXbjEVcAzxJ8vpWE+cX6W5eiHSa6S3kAsUtkW3wA/uue1UhCAFVysp5aEtE6RT1saSU/ponHrWDHZXpQ5khEiRExK4/RXCaaA5cqgMg6q2AutN/KCY7SMHdnoU5Jo/UCIdpelAGbJFYI+vCa6GLQBA40Nc+2rn21M2xlBC62oJUUgBhXzv+aG1hxBwmm5bBV7MZLLpTFIFoMZ9qLsoHILJ70mosEKBg3DMMr5kzz6JMSEMgje2ODV1Ioco/R1YOtRARbIQ1QgfLSpdwhPWwD2aDpg0oJETEro++M3M6x+KB3GanK0YAbuXdBvLXwcBIgcb3KkDpZvVugdT7TSHpOZfoVCao9+ICHaXSjjBCJEiJiJ/t43V/BAhAf2tH7P/AE4vqvlFgAYtCZz3BFVsAz9FnIaf9rhwJi2+6mEoGD1iRG9ZESOABiRJ6P8A9nnKa/6liJi/YguTsq4X7oYgGSGZJgm6IFcBxqS0TweIriWLihFqRSI0EkxKZkE9JqTq7NkM5xUOObVkA7rqB+Dals0lLEwOxJ2asjSB0k97fNJMAl5FLoS+xUFioCNdg+0/ZvQxHK5UUW5oj7J6CeP0VwmmuL1+ihRyaGBVl7oU+fjgS/VoCihzNYyh6LjnBbpUzXjpQjcDJbAxGKEUrSJ0DpM1yGmue1UCgBVsBR45IKoucwBhOLj0DVAB1omS6IyTLZq43Ytx32gD3dcforhNNOLCG4GSezI7qUaNNIKAxUCGxGuDtwGlYLKwuQmFyIvKD8uMsAHSUjVWfrwmun1+iJWil+o+K4v0ri/SsYtMai/oPRwyw8rhMLCWFOUVeHBqEKUYcENsX0B4Ct0sExNgSE3m5aKL2SnKggktxlTG3YDcHPm7BHJVc6F5NSoWMqANYl/VTcJAmEpMsocWzGsCmV0xGQ7diHoYcsK4OBQzVQDrSAmwshCBhLrEYhdq0eEcBiD5XutXV/cWNgQRM6acpNvE4qEiOGUdQpaJw0mG8CxJhn/t43V/2AhAZsBgWQN0BnpQbCKxmgARRmWbWiVKkoVEYGxEJYMqn5UMUsTNuFO1OuEWVFBZETq3gOKWZsgVSYxYkjBtapD2ByjGBuDms5CQ03m+YP8AQ/agt+jSYSs7iXZLYmW8U70iwBZkEw5pMYM6LyJLEGglfunDqvd+2yL2f0V+zrlyFQjItgrU5UbEXRxEqhf8QrTUEY96Hh2KRbwqJ9vQE6kjAYQEh1MOQl6DJMzP7D90RWKaRwQsnJGFYgoky5MpRJjK1Edj1AUkq8PostZBKYAVg6FRxGDqOLcJ0hjVogSwQUnFAs0S+pjUIEx+ETJERMk9XDgRheLtdAzcuqg47cgg0Qk9QKa6YBQwkRdabQTqVCBMfhEyRETJP8BP6X/AR6HlECSKLMqxGAYPEIlgN1AyvaGLJoEDCGIXM6Xh2KwbSgJ9qgQQBkhBIAySiuWEskgLmukYugMgxNaQS0xwbg62cL9pGuuvC/Sv3T6kwP1ET7HyrXG8nUTERkRuIjVl2mVKEdU1oDCwLCiKlZUCSY6MjwXDslaIyBbzhTEnCtuEyC6DMSQJ2pk6ZoPkf3S0MxikxIZdkJ1KNkbPA/Xb/X5ymv8AqWWC5RMBJ9wfapFNJChjmAdSEb3wbkbmBhuWUlzpk0RI3FEMTqOI6OslStTF2vbJW/Ktp6dO3bpTFb0NBFyUAh9imJIEC+so/fpeiMfrEx39BPH6KReEipXi9foozpF+NM39Uxig5nsvafXntVchprntVJCEVkSRGfSOTMaRP9geEpx+iuE01O9M5tJGZGiSmJvjNDXQrRTBtTTebIJJMHUPXhNdDFoAgcaGufbVz7asFlAgPY9HABmNPQg/t9QZIQ9YMX9BU8qP0736msq4icI9DIk47XK9poJFavpQyFlpPRl/o9FKaZ4iQAwARchguRdGPstj+T9q6lrl7zL4o5406KV1gMNsk6n+3jdX/ZCEBEWg8ojSShVAxiDrZauynqBBxgi0zi1y+qnd8LYMgIvCTM3mp5gYvvYRYIJoaV0DY9LLoqXSagRnAgcmGIyTCm2dXqgXvQ0ZoC4AuyWpmIBYgGHrJVsf0CzqOM5rjRSj3WCQdLDQQr9nX+1o/Z+m3k9aWCcDCKkjqSHaosOkIhydjA9FpC83uERFkVCm0yyJcLCM6H+LUYsbjEssS+tpYUQibmkH7agnQQa9c10wCxYqG8uQRIDJCzGpxWmVhJ6g9rnz6uHCcaRmwhLjWSexpRwuAgNZmRZ3V6VbPs0EmBomTiiaFITyHdXxX4f8BMW33UwlAwesSIx+4r9Ebj6bmoqLLEspDARgnwpqelYRVlK6SZXBXJ61e4oHBiBVRziIoB0JjENjpACgvZ5DaE9ifYKHawhWl1zX/wALVc6qmQsBYZEdZKmmBzZhB2I15TWjiQc4IxLkN2aDhhLAU3VICWYhWoyIRs02+2UOlNYrg5iLCvuDrVuh83RZk3MkkXxxWm7D4pEoQLTL7v8Ar85TX/YsBzjnQQQ9bLrDm0i0QlkJ/YZ7OqpLyCmyhf0UHZp5dQiRjCck4OYVi84GR1Bbvh1iojijKVAAmZeMsqHosqFBSdJtRsjOAwThylQPUak8VQZ4ge1P02oz4Yt2Sq0Ur2DT0EzWo5FYHuUXFaZMkRDAQXwIvUVkihekkvQATizFhpQo4NTAC69gqzWjYtK9JFPejxa6QGkRl6knWhojLBAlUKgSXlXGr+8zCmic4WJ6VyGmue1UzZEAEq0GE8dmCLCL4w3GcS9TdtDLJIG8AQTDdqPkaEXMjopKcforhNNKORPkMQ9zDu0qWvUkpKQmEVu2h+T7pgTCwwllmS1u9RlyCm7wEwhN8zX14TXQg4LAizr5X/Nc53rnO9dX3xk4jSfz6OP2f+GDBJMyWaIT4qJ+EKL095B2ZMqF5MCiGMKEdJk/dTcJAiEAMMJcS7Gkp6LgjMHtyA+huU19A5VIYXBJLazDiJlQ+zsgiGJEOMTJ+6GplRSeIgmQs5TZuwsQluEwvbE6v+3jdX/ZCEBEJCEsBF1X9+nL6qJ0AQCAI0CEjjQs/tKTj8ggQISM30yfUqVX0kKqCooMRoMKWyBkdUj9p6SAABpMP9Nfs6/2tDiOIdmH+mkFAQSuagVyetS2kLQs/tKXvHUNn+heiDMIT8TDKRhKYoMj65aWMsKVyBH+vQrxBsyF7+z5ozt/nWU/t6uHBAwsbo3P0lC6oBAkwwiff0KoqZSAisJHd/gJ/S/4m4FgSJfQ5PWgEASQGaq1LRkmcinwVGQQVykB/foawV6pYfCfamGSEcyC73FcprQFgQCPojbxtWMC1KYSIxrAUAArB7MpgZ6E0d+w3WMEzuUMsy2TKxrYOsT/AK/OU1/0ke4hESnOrCCIpFmOkvQAcmyIQjSUcqieDSYqKQMBHgYtYt2CsBwfr1ty9RFzmrAGeBPh9qYIggYuIYMxN5W7ePQQjaQwyModx6xV6UNxgtLwP3UbiGhsFWLZ/RABSMU4FhLR3on9zZgWCZJrtUmnWw8Xcg/qg2rB2As7DfFV7VHhirRAbYW9HzYQkbCCTIReRsXirAmeIPh9qww5YvU5h6qplFE4ICYkkUHMuo1Qw26UTggJiSRUbPa9EBtgxU5zkzDmJH2yaBSRBBZ7JFU6Ed6Dpg0AIADAo6Cggkzee1HQ+QFBEEUYg4/VRLiZJcp5dwk/dE8TRy7jJ+6Y4mv7UFlVbq4q3fV6HyCpIhmuc7Vznauc7V0ffGTiNZ/FBKisCEq+d/xT4NsARhC3obsoHALJ7VZwhASLMdYejeZN27+joiYWtUwU2yANFIPwUxfcJT0uUe5RUMGgLABgV1ffGbmdI/NOJygMhEei85cq7xhwR0RPegJathAHcU/qmv0L7SWrHYHrUQJFQDd6t3/bxur/ALYQgIjjl9Vc9opADDgiRXQB7UvhwSyQiRki3NRMqvdN57yZA7J6VPDyeV3QIAZdgxKgFKEyHROdRKHiWSnVKBqyV3vtCgHujrTlEyEtFLiSCc2c5r9nWtABZjUl6O3WlEEKN2JBQZGEkwKVeiKXKQKBBWcg78nrUsBhpCv7QGkI2oWckdUNzEkOddzrdkumOvxpG5SDdSmMF8BFTeLG4opL1Yn1tLMz8qtI61e/+Y4BaGRxl0qcZ0qVG6ZqCYsQF4lVPCsIR1l1GVmI+rhwShTJjCOgATr1FO/uQhWVoCSqM2mL5Q+alJFFykgixLiukN/AQ0zMgFFATkTmf4CYctUQSNsRb1KlT1KQyBM9B/huccnr6NHMwjBGyVLV3JSyXMmCYzfBFBZZlEGBIOcSdsKX/SaokVmwAyvq0R9UDALgmSWUygMZrlNfUyMjmjbXVlJh69Ek0zSzgRIkHMvSpvNiqFWLBYgvnrQPQYhhZjKVO0Of+vzlNf4g43V/1gs8x2SImBDDIrqpsaFdK3TdrPMdkiJgQwyKnHxZRK4pW64vpJdZIJXGkFACmYAgPR5GoaFpmF2zJ0odIc/ELBj3q8U8VV1JXFzgy9Cl4jGdoLx0bdKIgzAYX0YnRWlLFWiiQCRZ8Vng2+gEy1wCmAIiw0SrjGmK9s/uKcIhqUEJLZdsIE2io45W2MGFj7noLsIUl0IGOjJ0o4pGZ+wtL90nCMXe4ZU6TBV9XyJAhJL4NXsaPyJGGLczq+r5EgQkl8Go45W2MGFj7lYGs96sIp6pNQSxBTmRAEjJiT0grbaoqCCMV81KW29zBMtcB8UwkxhDERxKevIgy9jA6EUmQLDj1JPcaAAAAWA9Yj7G4MThTgY/4aaaRH2NwJjGjFwqFnBwIqEAZuVSltvcwTLXAfHpPHK+xiwEPYqMY8pAylVfd9MW/JROpOD1L11loX7T91ON8tu1Dc6gPpG3IdohOFOBjXk4wyiMjX0fBmc81WK6iNJtbg/bfuomxNguthL2/wBnmF4T/EHM6v54FfHQf6UtsgLpDLRXRoRJGR/hz1V/1RquAZtMJNTySBc7s9zX/mWwGj/o3CT0oZYUgZE1P4cneqcAKtOj3Vf1vaWvcgyg085e43MxO2VMWdljox2rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9RWxQN4yJEVwfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71wfeuD71gg1zwflqCzJzEYw7uFQ0Ji3Vima8t/zEZS2eRxEzVpKw8kLg6MHpYrg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3rg+9cH3qewPX/wB6MDhCPkDqQ70nTMo/Fs1j2IP+Fzuj8m8Tqfk3kdT8m8rqfk3hdT8m8bqfk3mdT8m8T0/JvA9PybyPT8m8p0/JvGdPybxnT8m8x0/JvEafk3hNPybymn5N5TT8m8Zp+TeI0/8A8gsACMJKzB7tqSoJqD5CK8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9a8R9aZQ2SgSauI+Pw7UfkSHYWwN3IFyqW8twkG6bBgqb6swEJsTi/AK8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q8++q576pBYw4SdBLSfkpVEUkI2GGtjrjk/hzqAYxMmSPaflQEzAGQj5/6AM5JBLfLder/APnpKt+SrK+8OBJEda8zrzOpj7pD4CUulSCSEuAICyWYiC005DnMAYBSaEwxVEv4x/R38yWUi9aF2XVXaFzOktw/+StxeuiAAiSOdHhNRsl2UYGIudkkbNZu/YWPRC8vGkJ+FHBFGiQYp2JgbOuF+FGYBtjEkqTlBN+ZP6qxu0DV6wR1uawX9MNe4M0hfYD1SruKeJ2O87UlMC/lgLApcMTqfhT85gWrmAsXp4N/VPEv6p5P/VOqUOq0P/sqf/UfdPN708rvTq/HR0vho6lUactU3V6bq1Bq46rWazuTQXKrzJfR+yAkZk+FJBSJcTKsuIXmHwvlOlJjBzXdCw6j/wCJW4vXRBEwJBBGM7lcy2pYZDCZ0BToqUHHIZiuJW0UwYCrlFchrqVmJtT21k1C/wAjkC3YFMqISzHE1VJn3onSEQZSE5xhOcU3CiLdgXe9PIMW7mjqJ96tTqHa+Hu/dKEhQ+AkQhZkGbga0OInhIkYs2J/Cf4cS2TUkXQ+n8KslRw6UFRCvAdaC+yoPi/ugPo+1H/pvuj/ANb90BWKGD9CgPrUU0Dzf1QHH/VA8D9UBxv1S2B72NCiYU/HSo9QYE9ywO0zUyeOu9lCX2DvR7M4jerEXVX/AOKtxeuhoO3IgImiVyParOehTskiz2RKcbcmBoDS5NAeCQgmYOkzXIa6B+32AFWl3NaQAjeXRATF4mrXBMxR1EHZCraUACgbHvXF6aW6qdRdkwLkpGugYkRJl2N3s1abG8Q0k/0PWryqCylRJncs5kP4p/d2inmFLgxKq3GFrUCxoQDQCx/8lbi9dCwJhYQUJ9vRAbBwhL1iJ+agVzM10q/tXIlrBcd4kA+5l965DXQ1KTMyAe+HvTJD8YicPeKvzdBvUkB3mNJo3WH6kmHYt7Uj1WgOIo4gLlBbHAOURZiPeiq2lhSuQh7FoNAhBCMFhL7sS3azJocT8JA+/wCPv2daBOf0AhSbT6s2Z56V9kq4ohQsyWBYsQehBwqAKVj30iqgFxQIpaLilq6JClxhjpSwwmy9EhjtD1qPoKcSUMKvCHsVa0LiERYCJV96groE4CYBSB++tTOPWkkKMaUHgmaVXsqdP/z3+TrfgnpQgzSPDKjBhA996jJ7f9BJZIriVmaXhzk1/DlVlHOWTMDkjCOpV+lYIWpXhtODa7UB1TC/dPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08Np4bTw2nhtPDaeG08FpdOtjG4iAPsPWhpyQNUS5Ti5vY/DxCtyxQV/Vc62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1c62rnW1cO2okILAEB/8AwUZHGCBNJKOOINVTSWVRdfaacmxAErk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29cm3rk29EhJcRkfw6ndVz4rkAzVgDVphrWCFoV4YtgWsY0SFJY4P7p4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNPCaeE08Jp4TTwmnhNLXwsYmKij7r0o6eki6sS5TiZPc/Dmb0oQOKB4ZUYMYDvnVZff/oFBJFYCsTS8GUGn/5zIrfiKxFERYFJgYWcMlMcOayQbK3E/T0kdZAIY9xB70DC3YVAPm0QTALoRL2/zTKbnyInXBRHgNEEFY6S/jL9QP4YYDZAXBHAbQ2msrtyI6MYPR/21jKOoQltj/ZS5yHagfpft6OrDY+hZ7opeNCeV8fifcUtcYQVaBK4k5GdBw7GMdQy02xIQzSZHunop2wEgoC5BslST4sPwYiHeJhiYaTYqC2oIRhIxRvhScIDmmbEWxnCiZhOYSIM18IxoFYSN64F46sHWnAGwRz7VQt0CJ6AWWhM+kMbXIMTiQcaTWNJhQmMIcYGVKj6Id1Ir8TRw8l8jqdEzG56JR6A0zEIgTMmTSnINHcwxP4GrHmJbrQN10QfRg4QO3oiB1Jk0pceYA95v0qIhgwOifgz8CkWQKJKQxpHGoIVBOvJVJPhfunmv90lw/3Tzz+6aoS+nSf0qQotGR+79Uh976pH7PpTxW1IUJGrJ1hKiJUnNEpZQz+ahCfNNNGMTo1HtrJAdX+hQ4al7B7se5J/rrdadGAj+mn8IhKsIfElMIgBSAsfYCokRkGs/wC8exUjq0mJheyFDU3iTIkCQt0Jj2USFay4uBUxq4xhlUBsGZFODMZOsTnSwh+MO8LPQDVGNoiwABWOgAlYzwfxTBQSYIQf7+lpYk65QMG5AI/brUC6o71SKDoq3xqSVxOzAJ0YT3rEjntGFd0X39BCfgDg2NwwbAE2cM0kDqiYkIBIkxaTVTCFROAMHUk7Kk6+dgBPXXE5XZUcNYYiWJWbDfAB6C986IEShARGGU2gxpwkwIjYRiCTM6Qzp4cSYA6qSROV2VF264XddWFi5whpUpzSWIAhCVLyGWc40R2xCg0gK1ej8GfsCZeJgLT0daM2pmbRzPpRn1YzPRBU12uegYQa5QKFlKzXKJQw8bQ03UcLtRr3u+q8m+qKINfoPzosrkD1pTIkOs6BdqTV3wl2Me5k0pi7CQg6mXsH+ytawlLpH9j80FVWVgIT7fdQmPTEo3HsSvagKjLgCA+CjdMKqFhJCjBZAcmhJZ7AVAg7tKSTBIShUW9tfUMDKkLK4uyH+FpZfb0sDGOLGpZ0iFt7XEtpwjB3ad6glLEFyKNkz9WiYDb8qL9tfo/TcMU2oaLJ/RRQiYM0Lf7fn1c9tA6sn9FJp81CEBKIxattLqYEY7Gj5eNMwTT8Rfhz5NhFlHCWCAwFyphQRJd9/Y/7q0DCZ+gh+S9igFPEwRIPSR3CrjMxdUSPQB7KyBa3YTSOtt6pees0cskgGMRmMEbzRskHoSxZospN4SmIiKG9P8YGDaC4GX0nWKsa/CYBCM7TTKMEVasAx0AvlTKipxRBHRgLUxKEgt7+ojf0fpuH5wZytF0AKrfJuz4FbAiu5hrQKQ4hQWDO8S5EtENUQLiTDAFrZppcFzCCT0IO4pdYsQQRyEkRNsGKUrXFkHOUTBmsWpP8NiwVRLINM4/GP6sBdx+CEI1nG1jGWmITFKU62yLETewHefR/hFEngQ4t0c1hwKnjDIDpiPdKRvQyXSAAhmR2xZaX0lgoASQzJ92hhOjaXkEZViOemUPE3wHoIvWJBQOq9YeJ4FAU6WqZ1DlG3iKHQMR1onOtqQew+Uo4aUsKstCLiWsEWtUg12wwhkLi+yKhmxCJAXgjKpg6VSGZNBIVaSWhA3oLDmcCzrha/wCaXRseRCEanPgWJoAQdWPfGhGfZ0+AtXFse85vmCxLixlhSPOYImPmkLMq3TwHufCg0wknHwVpzpFrsUeoC3lQnAD/APOX6t+kEMzIkD3j4UBdwDkJ+f8AoIjmkEt8Nx6n4cXy0GJSwP6TMUzqectggW6bJiqL6MykLi4VPhFeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdeffdIlhjkL1HQn4aERVCZNLLWx0wzfw6INJXD2SKBN1AYfquObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzauObVxzapJxPapeYgu0QT/Iv/9k=)

**Fig.** 14.18

* **Irreducible Errors:** These errors are inherent in the model and will always exist, no matter which algorithm is used. They are caused by unknown factors that cannot be accounted for or reduced.

**Bias in Machine Learning:**

In machine learning, a model looks at data, identifies patterns, and makes predictions. During training, it learns these patterns and then uses them to make predictions on test data. Sometimes, there's a difference between the model's predictions and the actual or expected values. This difference is known as bias error, or simply bias. Bias happens when a machine learning algorithm, like Linear Regression, can't fully understand the true relationship between data points. This is often due to the assumptions the model makes to simplify the learning process. Models can have:

1. Low Bias: These models make fewer assumptions about the target function's form, trying to be as flexible as possible to fit the data.
2. High Bias: These models make more assumptions, which might cause them to miss important features in the dataset. They might not perform well with new data. Linear algorithms usually have high bias because they are simpler and learn faster.

For example, Decision Trees, k-Nearest Neighbours, and Support Vector Machines are algorithms with low bias. On the other hand, Linear Regression, Linear Discriminant Analysis, and Logistic Regression typically exhibit high bias.

**Ways to reduce High Bias:**

High bias often results from using a model that is too simple. Here are some methods to reduce high bias:

1. Add more input features, especially if the model is underfitting.
2. Reduce the regularization term.
3. Switch to more complex models, like those including polynomial features.

**Variance Error**

Variance in machine learning refers to how much a model's predictions would change if it were trained on different datasets. In other words, it measures how a model's predictions vary from its expected value. Ideally, a model should show consistent performance across different training sets, indicating it understands the relationship between inputs and outputs well. Variance errors can be low or high:

* Low Variance: This means there's little change in the model's predictions when the training data changes.
* High Variance: This indicates significant changes in predictions with different training data.

A model with high variance learns in detail from the training data but struggles to perform well with new, unseen data. It performs well on the training data but often has high error rates on test data, leading to overfitting. High variance models are usually more complex.

Nonlinear algorithms, which are highly flexible in fitting models, tend to have high variance.

A diagram of a optimal balance

Description automatically generated

Fig. 14.19: Underfitting, Optimal Balance and Overfitting

Examples of machine learning algorithms that typically have low variance include Linear Regression, Logistic Regression, and Linear Discriminant Analysis. On the other hand, algorithms like Decision Trees, Support Vector Machines, and K-Nearest Neighbour’s often exhibit high variance.

**Ways to Reduce High Variance:**

To reduce high variance in a model, you can:

1. Decrease the number of input features or parameters, especially if the model is overfitting.
2. Avoid using overly complex models.
3. Increase the amount of training data.
4. Raise the regularization term to prevent the model from fitting too closely to the training data.

**Different Combinations of Bias-Variance**

There are four possible combinations of bias and variances, which are represented by the below diagram:

A diagram of different types of objects

Description automatically generated

Fig. 14.20 Combination of Bias and Variance

1. **Low-Bias, Low-Variance:** This combination represents an ideal machine learning model, but achieving it in practice is challenging.
2. **Low-Bias, High-Variance:** In this scenario, the model's predictions are accurate on average but inconsistent. This often happens when the model is trained with many parameters, leading to overfitting.
3. **High-Bias, Low-Variance:** Here, predictions are consistent but generally inaccurate. This situation usually arises when the model doesn't learn effectively from the training data or uses too few parameters, resulting in underfitting.
4. **High-Bias, High-Variance:** This combination leads to predictions that are both inconsistent and inaccurate on average.

**Identification of High variance or High Bias**

High variance can be identified if the model has:

A diagram of a test error

Description automatically generated

Fig. 14.21Identification of High Variance and High Bias

* Low training error and high-test error.

High Bias can be identified if the model has:

* High training error and the test error is almost similar to training error.

**Bias-Variance Trade-Off**

While building the machine learning model, it is really important to take care of bias and variance in order to avoid overfitting and underfitting in the model. If the model is very simple with fewer parameters, it may have low variance and high bias. Whereas, if the model has a large number of parameters, it will have high variance and low bias. So, it is required to make a balance between bias and variance errors, and this balance between the bias error and variance error is known as **the Bias-Variance trade-off.**

A diagram of a model complex

Description automatically generated

Fig. 14.22 Bias Variance Trade Off

For a machine learning model to make accurate predictions, it ideally needs both low variance and low bias. However, achieving both simultaneously is challenging because bias and variance are interconnected:

* Decreasing variance often leads to an increase in bias.
* Decreasing bias tends to increase variance.

This interplay is at the heart of the Bias-Variance trade-off, a key concept in supervised learning. The goal is to create a model that not only learns effectively from the training data but also generalizes well to new, unseen data. However, this is difficult to achieve perfectly. A model with high variance might perform well on training data but could overfit, especially to noisy data. On the other hand, a model with high bias might be too simple, failing to capture important patterns in the data.

Therefore, the Bias-Variance trade-off involves finding the optimal balance between bias and variance errors, essentially hitting the 'sweet spot' for the best possible model performance.

**Conclusion:**

In conclusion, we have established a fundamental understanding of machine learning's core aspects. We explored the crucial types of learning—supervised and unsupervised—and acknowledged their roles in propelling the field of artificial intelligence forward. With a focus on classification, we've seen how algorithms can be adeptly trained to categorize and analyse data.

The vital importance of various datasets, such as training, validation, and testing sets, has been underscored, highlighting their roles in creating strong AI models. We've tackled the challenges of overfitting and underfitting, gaining insight into their effects on model efficacy and examining ways to mitigate these issues.

As we conclude, machine learning is an ever-evolving field, characterized by constant learning and adaptation. The concepts and strategies discussed here are essential, practical tools for solving real-world problems through AI. This knowledge is meant to empower readers to apply machine learning principles effectively, thereby fostering innovation and contributing to advancements in the broad and dynamic domain of artificial intelligence.

**Let’s Practice**

**Case Study: Email Filtering with Supervised Learning**

**Background:** An email service provider aims to improve user experience by automatically filtering out unwanted spam emails. To achieve this, they decide to implement a machine learning-based spam filter.

**Challenge:** Spam emails are not only a nuisance but can also be dangerous, potentially containing phishing links or malware. The service provider must accurately distinguish between spam and legitimate emails (often referred to as 'ham') to protect users while ensuring important emails are not incorrectly classified as spam.

**Approach:** A supervised learning model is selected for this task. The model is trained on a labelled dataset where emails are pre-classified as spam or not spam. Features such as the frequency of certain words, the sender's email address, the presence of attachments, and the use of certain phrases that are commonly found in spam emails are used to train the model.

**Implementation:** The service provider compiles a large dataset of labelled emails. A variety of models, including Naive Bayes, Support Vector Machines (SVM), and neural networks, are trained and validated against a validation dataset. The best-performing model on the validation set is then tested using a separate test dataset to ensure that it can generalize to new, unseen emails.

**Outcome:** The chosen model demonstrates high accuracy in classifying spam and not spam emails. It is deployed as a part of the email service's pipeline. Regular updates and retraining sessions are scheduled to adapt to evolving spam tactics.

**Questions for Discussion:**

1. What features were most indicative of spam in the emails, and how were they selected?
2. How was the training data collected and labelled, and how did you ensure it was representative of actual email traffic?
3. Which supervised learning model performed the best during validation, and what were the performance metrics?
4. How did the model handle edge cases, such as marketing emails or newsletters that users might have subscribed to?
5. What measures were taken to update the model over time, and how often was retraining required to maintain high accuracy?
6. How can a supervised learning model be used to classify emails into 'spam' and 'not spam'?

**Case Study: Customer Segmentation Using Unsupervised Learning**

**Background:** A retail company seeks to better understand its customer base to tailor marketing strategies and improve customer service. The company has collected a variety of data on customer purchase history, demographic details, and browsing behavior.

**Challenge:** The company's diverse range of products and customers makes it difficult to manually segment the market. They require an automated method to divide customers into distinct groups based on similarities in their shopping patterns and preferences.

**Approach:** Unsupervised learning, specifically clustering algorithms, are chosen to tackle this problem. The aim is to segment customers into clusters that exhibit similar characteristics without prior labelling.

**Implementation:** The company compiles a comprehensive dataset, including variables like age, gender, purchase frequency, average spending, and product categories purchased. Clustering algorithms such as K-Means, Hierarchical Clustering, and DBSCAN are applied to this dataset. The number of clusters is determined using methods such as the elbow method for K-Means and silhouette analysis.

**Outcome:** The unsupervised learning model successfully segments the customer base into distinct groups. These segments reveal insightful patterns, such as a group of high-value customers who purchase frequently and another group of occasional shoppers who buy only sale items. The marketing team uses these insights to craft targeted campaigns, while the product team adjusts inventory based on the preferences of each segment.

**Questions for Discussion:**

1. What pre-processing steps were taken to prepare the data for clustering algorithms?
2. How did you determine the optimal number of customer segments?
3. Which clustering algorithm yielded the most meaningful segmentation, and why was it chosen over others?
4. How did the company ensure that the clusters were actionable and relevant to their marketing strategies?
5. What were some of the key characteristics that differentiated the customer segments?
6. How does the company plan to use these customer segments to influence business decisions going forward?

**Case Study: Implementing Predictive Maintenance with Supervised Learning**

**Background:** An industrial equipment manufacturer aims to integrate a predictive maintenance system into their machinery. The goal is to predict potential equipment failures before they occur, thus minimizing downtime and maintenance costs.

**Challenge:** Predicting equipment failure is complex, as it must account for various factors that could contribute to a machine's malfunction. The manufacturer needs to determine the types of data required for accurate predictions and develop a model that can process this data to predict failures effectively.

**Approach:** The company decides to use supervised learning, where a model is trained on historical data that includes instances of equipment failures and normal operations. The data collected comprises machine operational parameters, usage patterns, maintenance records, and failure histories.

**Implementation:** The team collects a dataset of sensor readings from machinery during operation, maintenance logs, and records of past failures. Features such as temperature, vibration, operating hours, and error codes are included. A variety of machine learning models, including Random Forest, Gradient Boosting Machines, and Neural Networks, are trained on this data. The models are then validated using a cross-validation approach to ensure they can predict failures reliably.

**Outcome:** The supervised learning model that best predicts upcoming failures is deployed within the machinery's operating system. The system provides real-time alerts to the maintenance team, allowing for proactive repairs. This results in a marked reduction in unplanned downtime and more efficient maintenance scheduling.

**Questions for Discussion:**

1. What specific types of sensor data were most indicative of impending equipment failure?
2. How was the historical data labelled to distinguish between normal operation and failure events?
3. Which supervised learning model provided the highest accuracy and reliability in predicting equipment failures?
4. What challenges were encountered when collecting and preprocessing the data for training the models?
5. How were the models tested to ensure they could generalize well to new, unseen data?
6. What procedures were established for updating the model as new failure data becomes available?

**Case Study: Community Detection in Social Networks Using Unsupervised Learning**

**Background:** A social media platform is interested in understanding the natural groupings or communities within its user base to enhance content relevance and advertising targeting. The platform has access to vast amounts of user interaction data but lacks explicit labels for community membership.

**Challenge:** Identifying communities within a social network is complex due to the vastness of data and the dynamic nature of social interactions. The platform needs a method to discern these communities based on patterns of interactions without predefined labels.

**Approach:** The company employs unsupervised learning, specifically clustering algorithms that can detect communities based on user interactions such as likes, comments, shares, and messaging patterns. Algorithms considered for this task include K-Means, Hierarchical Clustering, and DBSCAN.

**Implementation:** The team compiles a dataset consisting of anonymized user interaction data. Features such as frequency of interactions, strength of connections (e.g., number of mutual friends), and similarity in content engagement are extracted. The clustering algorithms are applied to this data to identify distinct user communities.

**Outcome:** The unsupervised learning approach effectively reveals distinct communities within the social network. These communities show high internal interaction rates and are characterized by shared interests or demographics. The insights gained are used to improve the user experience by personalizing content and optimizing ad targeting.

**Questions for Discussion:**

1. What methods were used to ensure user privacy while conducting the analysis?
2. How did the platform determine the number of communities, and what validation methods were used to assess the quality of the clustering?
3. Which clustering algorithm was most effective in identifying meaningful communities, and what were its key parameters?
4. How did the characteristics of identified communities align with known user demographics and behavior patterns?
5. How will the social media platform utilize these insights to enhance user engagement and business outcomes?
6. What steps will be taken to update and maintain the community detection system over time, considering the evolving nature of social networks?

**Practical Exercises:**

**1. Building a Classifier (Supervised Learning)**

* **Exercise**: Use a dataset like the Iris dataset to train a classifier to predict the species of an iris plant. Split the data into training and test sets, train a model, and evaluate its performance.
* **Questions**:
  + How did you preprocess the data?
  + Which classifier did you choose and why?
  + How did you evaluate the model's performance?

**2. Market Basket Analysis (Unsupervised Learning)**

* **Exercise**: Perform a market basket analysis on a dataset from a grocery store. Identify frequently purchased items and itemsets.
* **Questions**:
  + What patterns did you find in the data?
  + How can these patterns be used to make business decisions?
  + What rules did you derive from the analysis, and what are their confidence and support?

For each case study and practical exercise, the learner is encouraged to consider the full pipeline of machine learning, from data preprocessing, choosing the right model, training the model, and evaluating its performance using appropriate metrics. Additionally, for unsupervised learning tasks, the focus should be on interpreting the results and understanding the actionable insights that can be derived from the models.

References:

[1]. Liu, H., Estiri, H., Wiens, J., Goldenberg, A., Saria, S., & Shah, N. (2019). AI model development and validation. *Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril*, 119.

[2] Ayodele, T. O. (2010). Types of machine learning algorithms. *New advances in machine learning*, *3*, 19-48.

[3]. Ghori, K. M., Abbasi, R. A., Awais, M., Imran, M., Ullah, A., & Szathmary, L. (2019). Performance analysis of different types of machine learning classifiers for non-technical loss detection. *IEEE Access*, *8*, 16033-16048.

[4]. Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN computer science*, *2*(3), 160.

[5]. Cunningham, P., Cord, M., & Delany, S. J. (2008). Supervised learning. In *Machine learning techniques for multimedia: case studies on organization and retrieval* (pp. 21-49). Berlin, Heidelberg: Springer Berlin Heidelberg.

[6]. Hastie, T., Tibshirani, R., Friedman, J., Hastie, T., Tibshirani, R., & Friedman, J. (2009). Overview of supervised learning. *The elements of statistical learning: Data mining, inference, and prediction*, 9-41.

[7]. Liu, B., & Liu, B. (2011). Supervised learning. *Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data*, 63-132.

[8]. Niculescu-Mizil, A., & Caruana, R. (2005, August). Predicting good probabilities with supervised learning. In *Proceedings of the 22nd international conference on Machine learning* (pp. 625-632).

[9]. Barlow, H. B. (1989). Unsupervised learning. *Neural computation*, *1*(3), 295-311.

[10]. Ghahramani, Z. (2003). Unsupervised learning. In *Summer school on machine learning* (pp. 72-112). Berlin, Heidelberg: Springer Berlin Heidelberg.

[11]. Celebi, M. E., & Aydin, K. (Eds.). (2016). *Unsupervised learning algorithms* (Vol. 9, p. 103). Cham: Springer.

[12]. James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). Unsupervised learning. In *An Introduction to Statistical Learning: with Applications in Python* (pp. 503-556). Cham: Springer International Publishing.

[13]. Golbraikh, A., Shen, M., Xiao, Z., Xiao, Y. D., Lee, K. H., & Tropsha, A. (2003). Rational selection of training and test sets for the development of validated QSAR models. *Journal of computer-aided molecular design*, *17*, 241-253.

[14]. Bennin, K. E., Keung, J., Monden, A., Kamei, Y., & Ubayashi, N. (2016, June). Investigating the effects of balanced training and testing datasets on effort-aware fault prediction models. In *2016 IEEE 40th annual Computer software and applications conference (COMPSAC)* (Vol. 1, pp. 154-163). IEEE.