**Name:** Alireza Mahin parvar

**Class:** ISE-201

**Date:** Dec 6th ,2021

**Project Proposal for Diabetes Dataset**

**Background:**

During this project I’m going to look over the “Diabetes Dataset” that I found over Kaggle website. To look closely to this data set you can use the following link [Pima Indians Diabetes Database | Kaggle](https://www.kaggle.com/uciml/pima-indians-diabetes-database). This dataset is originally coming from the National Institute of Diabetes and Digestive and Kidney Diseases. The original owner of this data set is UCI Machine learning, and it is public dataset, and it was created on 2016-10-06. The goal of the dataset is to demonstratively anticipate whether a patient has diabetes, considering certain indicative estimations remembered for the dataset. A few limitations were set on the choice of these occasions from a bigger information base. Specifically, all patients here are females somewhere around 21 years of age of Pima Indian heritage. The reason why this dataset collected was because the data set has large range of numbers that gives us the chance to have great valuable analysis over the dataset.

**Description of data:**

The datasets consist of several medical predictor variables and one target variable, Outcome Predictor variables includes:

1. 1-Pregnancies (Number of times pregnant)
2. 2-Glucose (Plasma glucose concentration 2 hours in an oral glucose tolerance test)
3. 3-BloodPressure (Diastolic blood pressure (mm Hg))
4. 4-SkinThickness (Triceps skin fold thickness (mm))
5. 5-Insulin (2-Hour serum insulin (mu U/ml))
6. 6-BMI (Body mass index (weight in kg / (height in m) ^2))
7. 7-DiabetesPedigree (Diabetes pedigree function)
8. 8-Age (years)
9. 9-Outcome (Class variable (0 or 1) 268 of 768 are 1, the others are 0)

In total in this dataset, we have 769 rows and 9 columns of data so we can say it is matrix of 769\*9. And the data in each column are double or integer. 7 columns have included integer data type and 2 columns include double datatype. As now we call Integer values and decimal values which are doubles are numeric.

**Goal:**

in this project I want to go deeply

1. analyze the factor that increases the diabetes in females and to see how many number of factors affect the diabetes or if having specific range of factors like Diabetes pedigree function and age make someone have diabetes.
2. I would love to see some statistical result of BMI of people and make connection with that with their factors and
3. I would like to see the outcome of having Diabetes regarding of the age of people and their insulin
4. Using Hypothesis testing to analyze different columns of data and to conclude the strength of evidence from sample
5. Using linear regression to predict if person has diabetes or not by giving different factors
6. Using principal components to see if factors have linear relationship or not with each other

In this section I just detects if there are any missing values in data set data set detect the outlier of each column in data set and to cleaning up some variables, I needed to remove outliers for blood pressure, skin thickness and BMI. Removing outlier values allow us to have better analysis during this report. We can have better linear regression, logistical regression and Principal components

library(ggplot2)  
library(dplyr)

##   
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':  
##   
## filter, lag

## The following objects are masked from 'package:base':  
##   
## intersect, setdiff, setequal, union

library(explore)  
library(tidyverse)

## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v tibble 3.1.3 v purrr 0.3.4  
## v tidyr 1.1.3 v stringr 1.4.0  
## v readr 2.0.1 v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse\_conflicts() --  
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag() masks stats::lag()

library(ggrepel)  
library(ggbiplot)

## Loading required package: plyr

## ------------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.  
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:  
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------------

##   
## Attaching package: 'plyr'

## The following object is masked from 'package:purrr':  
##   
## compact

## The following objects are masked from 'package:dplyr':  
##   
## arrange, count, desc, failwith, id, mutate, rename, summarise,  
## summarize

## Loading required package: scales

##   
## Attaching package: 'scales'

## The following object is masked from 'package:purrr':  
##   
## discard

## The following object is masked from 'package:readr':  
##   
## col\_factor

## Loading required package: grid

library(factoextra)

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

mydata<-read.csv(file.choose())  
mydata=as\_tibble(mydata)  
summary(mydata)

## Pregnancies Glucose BloodPressure SkinThickness   
## Min. : 0.000 Min. : 0.0 Min. : 0.00 Min. : 0.00   
## 1st Qu.: 1.000 1st Qu.: 99.0 1st Qu.: 62.00 1st Qu.: 0.00   
## Median : 3.000 Median :117.0 Median : 72.00 Median :23.00   
## Mean : 3.845 Mean :120.9 Mean : 69.11 Mean :20.54   
## 3rd Qu.: 6.000 3rd Qu.:140.2 3rd Qu.: 80.00 3rd Qu.:32.00   
## Max. :17.000 Max. :199.0 Max. :122.00 Max. :99.00   
## Insulin BMI DiabetesPedigreeFunction Age   
## Min. : 0.0 Min. : 0.00 Min. :0.0780 Min. :21.00   
## 1st Qu.: 0.0 1st Qu.:27.30 1st Qu.:0.2437 1st Qu.:24.00   
## Median : 30.5 Median :32.00 Median :0.3725 Median :29.00   
## Mean : 79.8 Mean :31.99 Mean :0.4719 Mean :33.24   
## 3rd Qu.:127.2 3rd Qu.:36.60 3rd Qu.:0.6262 3rd Qu.:41.00   
## Max. :846.0 Max. :67.10 Max. :2.4200 Max. :81.00   
## Outcome   
## Min. :0.000   
## 1st Qu.:0.000   
## Median :0.000   
## Mean :0.349   
## 3rd Qu.:1.000   
## Max. :1.000

#view(mydata)  
#is.na(mydata)  
outlier\_Pregnancies=boxplot(mydata$Pregnancies,plot=FALSE)$out  
outlier\_Glucose=boxplot(mydata$Glucose,plot=FALSE)$out  
outlier\_BloodPressure=boxplot(mydata$BloodPressure,plot=FALSE)$out  
outlier\_SkinThickness=boxplot(mydata$SkinThickness,plot=FALSE)$out  
outlier\_Insulin=boxplot(mydata$Insulin,plot=FALSE)$out  
outlier\_BMI=boxplot(mydata$BMI,plot=FALSE)$out  
outlier\_DiabetesPedigreeFunction=boxplot(mydata$DiabetesPedigreeFunction,plot=FALSE)$out  
outlier\_Age=boxplot(mydata$Age,plot=FALSE)$out  
outlier\_Outcome=boxplot(mydata$Outcome,plot=FALSE)$out  
mydata<-mydata[-which(mydata$Insulin %in% outlier\_Insulin),]  
mydata<-mydata[-which(mydata$BloodPressure %in% outlier\_BloodPressure),]  
mydata<-mydata[-which(mydata$SkinThickness %in% outlier\_SkinThickness),]  
  
  
mydata<-mydata[-which(mydata$BMI %in% outlier\_BMI),]  
view(mydata)  
mean(mydata$BMI)

## [1] 32.06456

var(mydata$Pregnancies)

## [1] 11.32855

g0<-ggplot(data=mydata[mydata$Age<60,],aes(x=Age,y=Pregnancies,colour=Outcome))  
g0+geom\_point(alpha=0.5)+geom\_smooth()

## `geom\_smooth()` using method = 'loess' and formula 'y ~ x'

**Summary of analysis:**

To have better understanding we just looked at the minimum, maximum and standard deviations of values in each column and it goes at follows:

* For number of pregnancies, we see that the highest data collected was 17 and the lowest was 0 with mean 3.85 and standard deviation of 3.37.
* For Glucose the min is 0, max is 199, mean 121 and standard deviation 32.
* For blood pressure min 0, max 122, mean 69.1with standard deviation 19.3.
* For Skin Thickness min 0, max 99, mean 20.5 with standard deviation 15.9.
* For Insulin min 0, max 846, mean 79.8 with standard deviation 115.
* For BMI min 0, max 67.1, mean 32 with standard deviation 7.88.
* For diabetes Pedigree function min 0.08, max 2.42, mean 0.47 with standard deviation 0.33.
* For age min 21, max 81, mean 33.2 with standard deviation 11.8.
* Finally for outcome min 0, max 1, mean 0.35 with standard deviation 0.48.

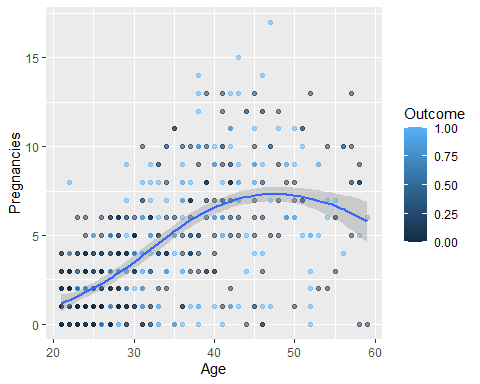


Figure1

Based on the graphs that we see above we can conclude that as the ages goes from 20 to 40 and pregnancies increases the chance of have diabetes also increases. If we look closely to the plot above the slope is positive from age 20 to 45 but in this data set, we see people from age 45-50 we see that the slope is kind of 0 and after that the slope becomes negative. Another thing we can conclude from plot is that by looking at data we see women with age 45 and above have more outcome 1 which means they have diabetes and the women with higher rate of pregnancies have some situation also. Based on this we can totally conclude that the risk of diabetes increases with ages and pregnancies.

BMI\_<-mydata$BMI  
hist(BMI\_)

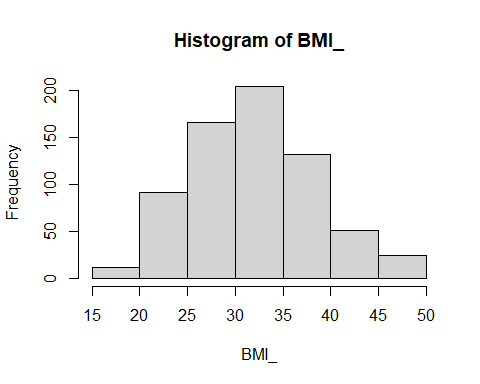


Figure 2

ggplot(data=mydata)+geom\_point(mapping=aes(x=Age,y=DiabetesPedigreeFunction, color=factor(Outcome)))

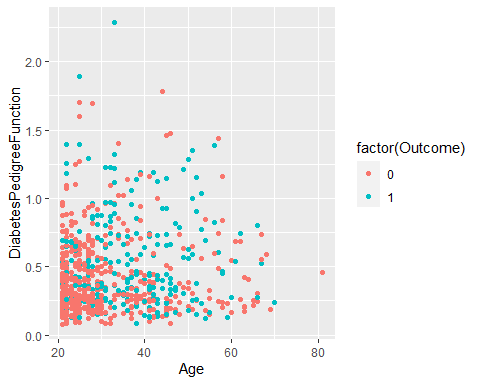


Figure3

By looking at Figure 2 we can conclude that most people in this analysis have BMI between 25 and 40 which is high, and this shows that most people in this dataset are overweight, and they have obesity. Based on data summary that we have above we see the mean for BMI is 36 and the first Qu is on 27.3. As we all know having BMI above 25 increase your risk to have diabetes so we can conclude most people in this dataset are at major risk of diabetes and the reason for having outcome 1 among them a lot is because of this factor. BMI and outcome have linear relationship. As we all know, diabetes pedigree function shows the likelihood of having diabetes so, by looking at figure 3 we find out that most people in this dataset with positive outcome, which is diabetes, they had diabetes pedigree function between 0 and 1and majority of people between age 20 to 30 with pedigree function between 0 and 1 had outcome zero.

mydata.pca <- prcomp(mydata[,c(2:6)], center = TRUE,scale. = TRUE)  
summary(mydata.pca)

## Importance of components:  
## PC1 PC2 PC3 PC4 PC5  
## Standard deviation 1.3559 1.1217 0.9660 0.7660 0.61937  
## Proportion of Variance 0.3677 0.2516 0.1866 0.1173 0.07672  
## Cumulative Proportion 0.3677 0.6193 0.8059 0.9233 1.00000

str(mydata.pca)

## List of 5  
## $ sdev : num [1:5] 1.356 1.122 0.966 0.766 0.619  
## $ rotation: num [1:5, 1:5] -0.329 -0.261 -0.538 -0.503 -0.531 ...  
## ..- attr(\*, "dimnames")=List of 2  
## .. ..$ : chr [1:5] "Glucose" "BloodPressure" "SkinThickness" "Insulin" ...  
## .. ..$ : chr [1:5] "PC1" "PC2" "PC3" "PC4" ...  
## $ center : Named num [1:5] 118.9 72.1 20.7 65.8 32.1  
## ..- attr(\*, "names")= chr [1:5] "Glucose" "BloodPressure" "SkinThickness" "Insulin" ...  
## $ scale : Named num [1:5] 31.32 11.38 15.3 79.87 6.43  
## ..- attr(\*, "names")= chr [1:5] "Glucose" "BloodPressure" "SkinThickness" "Insulin" ...  
## $ x : num [1:680, 1:5] -0.518 1.069 1.379 0.523 -1.51 ...  
## ..- attr(\*, "dimnames")=List of 2  
## .. ..$ : NULL  
## .. ..$ : chr [1:5] "PC1" "PC2" "PC3" "PC4" ...  
## - attr(\*, "class")= chr "prcomp"

ggbiplot(mydata.pca)

Chart, scatter chart

Description automatically generated

Figure 4

Chart

Description automatically generated

Figure 5

fviz\_eig(mydata.pca, addlabels = TRUE, ylim = c(0, 30))

As we all know PCA is the techniques for reducing the dimensional of such data set increasing interpretability but at the same time minimizing information loss. In this PCA we created sample of our large dataset that has all the features of original data set. Before we talk about our PCA we should talk about our scree plot. Our scree plot shows completely hos much variation each principal component captures from the data and Based on the Scree plot (correlation scree plot) that we see about more than 90% of variances by choosing 4 factors and we see by only taking two factors we can have about 50% of variances. This scree shows us having two principal component is sufficient for us. By taking all data into PCA you see plot gives us the idea that on factor 7 and 8 our plot is flatten out and so it Based on our pca we see that their groupings happening in our plot so in figures above we showed the relationship between blood pressure and BMI. We concluded that in certain range of glucose we see certain range of blood pressure too and these two factors are linear to each other we can see same things on our PCA also when the direction of Blood Pressure and glucose are kind of same. Another group we see are insulin, Skin thickness and diabete pedigree function. If we look at whole pca of out dataset we see that it seems like Age and skin thickness directions are perpendicular to each other and same kind of things happens for pregnancies and insulin. By looking at this PCA we see that correlation is kind of negative and it is in middle toward down (4th quarter)

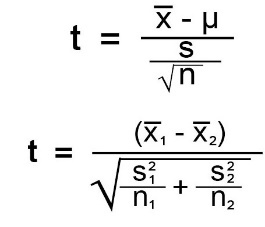
mydata1.df <- as.data.frame(mydata$BloodPressure)  
mydata2.df <- as.data.frame(mydata$SkinThickness)  
sample1<-sample\_n(mydata1.df, 100)  
sample2<-sample\_n(mydata2.df, 100)  
t.test(sample1,sample2)

##   
## Welch Two Sample t-test  
##   
## data: sample1 and sample2  
## t = 28.315, df = 187.46, p-value < 2.2e-16  
## alternative hypothesis: true difference in means is not equal to 0  
## 95 percent confidence interval:  
## 46.20021 53.11979  
## sample estimates:  
## mean of x mean of y   
## 71.65 21.99

x<-as.matrix(sample1)  
y<-as.matrix(sample2)  
cor.test(x, y)

##   
## Pearson’s product-moment correlation  
##   
## data: x and y  
## t = 0.90164, df = 98, p-value = 0.3695  
## alternative hypothesis: true correlation is not equal to 0  
## 95 percent confidence interval:  
## -0.1076312 0.2820967  
## sample estimates:  
## cor   
## 0.09070444

One of the great things from hypothesis testing is that we can use this technique in order evaluate the strength of evidence from the sample and provides a framework for making determinations related to the population. Here in this project, we decided to get certain sample of data which is 100 from both Blood Pressure and skin thickness column. We see that by this testing about 95% of confidence interval happens at 46 on Blood Pressure and 95% of confidence interval happens at 53. In a two-sample t-test, you compare the means of two groups of data and test whether they are the same. We can specify two-sample t-tests in one of two ways. data we want to compare are in individual vectors (not together in a dataframe), we use the vector notation. The formula for t-test is like the picture below and you can see how it was calculated



As we know in cor.test(with formula = ~ x + y) , we are accessing the relationship between two variables on a ratio or interval scale and here we chose Blood Pressure and skin thickness. The test statistic in a correlation test is called a correlation coefficient and is represented by the letter r. This test r has 3 ranges, -1 which shows that two variable data have strongly negative relationship, 1 which shows two variables have strongly positive relationship and 0 which shows they have 0 relationship. By taking correlation hypothesis testing interesting things came in the detail and we found out that about 95% of the confidence interval for blood pressure sample happens at -0.1076312 and for skin thickness it was 0.2820967. The r value here is around 0.1 which shows these two-sample data have very little positive relationship with each other. The final we got from our hypothesis testing on blood pressure and skin thickness sample is that the mean values for these sample are not qual and even for their correlations also the t is so low for correlation testing that we had rather than t for samples which shows the differences between correlation of two samples were not that much but the differences between two samples as regular was more

![Text, letter

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4THeRXhpZgAATU0AKgAAAAgACAALAAIAAAAmAAAIegESAAMAAAABAAEAAAExAAIAAAAmAAAIoAEyAAIAAAAUAAAIxgE7AAIAAAAHAAAI2odpAAQAAAABAAAI4pydAAEAAAAOAAARZuocAAcAAAgMAAAAbgAAEXQc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFdpbmRvd3MgUGhvdG8gRWRpdG9yIDEwLjAuMTAwMTEuMTYzODQAV2luZG93cyBQaG90byBFZGl0b3IgMTAuMC4xMDAxMS4xNjM4NAAyMDIxOjEyOjA2IDIwOjI3OjA4AEFwdXJ2YQAAAAaQAwACAAAAFAAAETyQBAACAAAAFAAAEVCSkQACAAAAAzE4AACSkgACAAAAAzE4AACgAQADAAAAAQABAADqHAAHAAAIDAAACTAAAAAAHOoAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAyMDIwOjExOjI4IDIxOjQ2OjMwADIwMjA6MTE6MjggMjE6NDY6MzAAAABBAHAAdQByAHYAYQAAAAAGAQMAAwAAAAEABgAAARoABQAAAAEAABHCARsABQAAAAEAABHKASgAAwAAAAEAAgAAAgEABAAAAAEAABHSAgIABAAAAAEAACAEAAAAAAAAAGAAAAABAAAAYAAAAAH/2P/bAEMACAYGBwYFCAcHBwkJCAoMFA0MCwsMGRITDxQdGh8eHRocHCAkLicgIiwjHBwoNyksMDE0NDQfJzk9ODI8LjM0Mv/bAEMBCQkJDAsMGA0NGDIhHCEyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMjIyMv/AABEIAKIBAAMBIQACEQEDEQH/xAAfAAABBQEBAQEBAQAAAAAAAAAAAQIDBAUGBwgJCgv/xAC1EAACAQMDAgQDBQUEBAAAAX0BAgMABBEFEiExQQYTUWEHInEUMoGRoQgjQrHBFVLR8CQzYnKCCQoWFxgZGiUmJygpKjQ1Njc4OTpDREVGR0hJSlNUVVZXWFlaY2RlZmdoaWpzdHV2d3h5eoOEhYaHiImKkpOUlZaXmJmaoqOkpaanqKmqsrO0tba3uLm6wsPExcbHyMnK0tPU1dbX2Nna4eLj5OXm5+jp6vHy8/T19vf4+fr/xAAfAQADAQEBAQEBAQEBAAAAAAAAAQIDBAUGBwgJCgv/xAC1EQACAQIEBAMEBwUEBAABAncAAQIDEQQFITEGEkFRB2FxEyIygQgUQpGhscEJIzNS8BVictEKFiQ04SXxFxgZGiYnKCkqNTY3ODk6Q0RFRkdISUpTVFVWV1hZWmNkZWZnaGlqc3R1dnd4eXqCg4SFhoeIiYqSk5SVlpeYmZqio6Slpqeoqaqys7S1tre4ubrCw8TFxsfIycrS09TV1tfY2dri4+Tl5ufo6ery8/T19vf4+fr/2gAMAwEAAhEDEQA/APf6KACigAooAKKAILySeGzmltoPPnSNmjiL7d7AcLntk8ZrmPD3ivU/E2lNeafp1ijxyNDPbXN5IkkEi9UceUcEUAM1bxN4j0FoJ9Q8O2z6aZFW5u7S/Mn2ZCQC7I0akgDk4zwK6y4uIrW2kuJ5FjhiUu7scBVAyTQBX0m+fUtNhvWgaBZxvjRz82wn5SR2JXBx2zjtV2gAooAKq32pWGmRLLf3ttaRs21WnlWME9cAk9aAKb69aXGnXVzo81vqslsoZobW4RifbIJGSAcA4yR261c06/t9U0+3v7STzLe4jEkbYxkH27H2oArx6qs+uzaZBGZDbRCS4kzhYy33F9yRk+wAz1FaVABRQAVDdXdtY27XF3cRW8CfeklcKq/UnigClBrunaiJY9J1GwvblIy4iiuVb6Z25IGcc4qTR9Uh1nTY7yFXj3EpJFIMPFIpKujf7SsCDjjjjNAF+igAooAKKACigAooAKKADtXB6tp1zoHj7T9Y0VUcaxILXUrEMF8wAZFwvug+96jA6mgDuZI45Y2jlRXRgVZWGQQeoIrlviOxXwPdRDhJpYIZP9x5kVh9MEj8aANTXJZI44lXUUsIcO8rgr5rKqlsIGBHuTjoPxHOeCr/AF6fT7DWde1q0NrdaYJ3t3RY2VtwIkzxhdhXP+0x6DAoA7KwuXu9PhuXWJWlXeBDL5iEHoQ2BnIwf8aq3Oo38Nw8cWiXVwi9JUlhAb6BnB/MUASWV9eXMxS40m5tFC5EkskTAn0+ViaxvGd/LYaZdXI1KOzitbKa62oVM0rIBgAMCNuSM9ySo47gC+FRq4aQ6tqNrPJLa2832aNAskDsG35A/hJGF/3TUfgBiulapbLjybbWLyKEAcBPNZsfgWI/CgCDwk91PbeKpoDH9ufWLpUMv3QUCom7HYBV6VjQeKNXbw3HJFemaXUtfGn6dcPGpYwiTa7EAAdI5SOOBigD0SG5SaWaJVkDQsEYtGygkgHgkYYYPUZGcjsagvry7tXQW+mT3isMkxSRrt9vmYUAQwalqEs6RyaHdwoxwZHmhIX3wHJ/IVleP9RvdI8KXmoWlwIBbxs7sAC7HBCKuQRy5XJPbPc0AQadqOqP4xstHnliP2XR1uNRMUYw87sFUDuB8shxUvhUmPxN4vtUH7hNQjkX03PBGzj8+fxoA6uigAooAq6hqFtplm91dyFIUxkqhckk4ACqCSSTgADNZ+l+LND1q8Fpp2oxXEzQC4UIDh4843K2MNg8HBODwcUAaVxf2doyrc3cELMMgSSBc/nUS6xpbsFXUrNmJwAJ1yf1oAu0UAFFAEN1P9mtZpxFJL5aF/LiXcz4HQDuTXEaTrd3HeS6jqPhnXm1CcbfltlKQR5yI0+bp3Jxljz0AAAJNV8Ua/qDR6bo/hjV7Z7mRYn1C5RES2RiA0gG4kkDJAI610+u6THreg3mlyOUFxEUEnUo38LfUEA/hQBQ/sO18RWljN4h01TfWqujLuIXJG18YPzRsB0PUHBAORSzeF7W20O8s9JUQXElsIYJZnaXytoPlgFiSFU8gDgHmgDS0eyOm6PaWJ2AW8QiVU6Ko4UD1wMDPfGavUAFY+reFtF1y5FxqVilxIITASzEBoyQSpAOCMgHnuAaAHfY4tC065k060mubhsEIZWd5WwFUF3JOBx1OAM0eG9JbRNDhs5ZBLcFnmuJB0eWRi7n6bmOPagClb6ffaTqus/YokeHUc3cLN92O42BWV++G2qQR6NntnA8O+Dboaxpup6haCxGnRystuk5ZXuZfvyKm5ljTlsAHJLEnGMEA6DwhbX9rp90l/FcRu11I6CeXeQpPygcngAD6nJ6HnoqACue8Y2d9qGjJaWljDfQSzoLy2kOGkg6sEJZQHzjBJGOtAFXwx4fl0L+19WvfMkvb9xK0SyNO0caLhIwzEl2x19zgcYq/wCGNLn0+0u7m9ULfajdPdzoG3CMtgKmR12oqrnuQTQBuUUAFFAGH4vt7q48LaiLC1+036wP9lTjIlKlVIz0IzmpdC8P2Wi6dYwxW8P2i1s47TzxGA7Io6Z64zk49TQBLqNleXTobaeziCjBFxaGYn6HeuKqJpOqpIjNeaWVDAkLphBI9j5vFAG4RlccjPpXOnwZZk5/tXX/APwb3H/xdACf8IZZjrq2v/8Ag4uP/i6xtRstG0y9NpJfeMJ5QgdvslzfXAUHOASmQDx060AVc6J/f8ff98al/hRnRP7/AI+/741L/CgAzon9/wAff98al/hRnRP+enj7/vjUv8KADOif3/H3/fGpf4UZ0T/np4+/741L/CgAzon/AD08ff8AfGpf4UZ0T/np4+/741L/AAoAM6J/z08ff98al/hRnRP+enj7/vjUv8KADOif3/H3/fGpf4UZ0T/np4+/741L/CgAzon9/wAff98al/hRnRP7/j7/AL41L/CgAzon9/x9/wB8al/hRnRP+enj7/vjUv8ACgAzon/PTx9/3xqX+FGdE/56ePv++NS/woAM6J/f8ff98al/hRnRP7/j7/vjUv8ACgAzon/PTx9/3xqX+FGdE/56ePv++NS/woAM6J/z08ff98al/hXYeHILeLSxJayao8Url/8AiZvMZV7YxL8yjjp7570Aa9FABRQAUUAHauc03V9Os7F9T1G/tbRdRuHliaeVYw6DCpjJGfkVT+NAFr/hLvDf/Qw6V/4GR/41asNb0rVXdNO1Kzu2QAuLedZCoPrg8UAW5po7eF5ppEjiRSzu7YCgdST2FSA5FABRQAUUAFMM0YmEJdfNKlgmfmIHU49OR+dAHN+IfFF3oRuLj+zTJYWvkebKWKmTzZNmI+MMVOCRnnOOOM9DdXdvY273F1PHBAgy8srhVX6k8CgDM/4S7w3/ANDDpX/gZH/jUlt4l0K9uktrTWtOuLhzhIorpGZsDJwAcngGgDV7VHDNFcJvhkSRMldyMCMg4I49CCKAJKKACigAqMTRmYw718wLu2Z+bGcZx6UAc9rnia70ed3/ALMZ7OGeCF3ZirSeawUGPjDbSRkcHr+PS0AFFABRQAVXuL62tZbeK4njikuJPLhV2AMjYJwPU4BP4UAUvEE0q6NNDBuE90VtoypwVMhC7v8AgIJb/gJqn4k8J2fiHwz/AGSWNs0AVrOePhraRPuOv0x+VAFLwT4hk1qyuNN1eCOHXtMfyL+ADhj2kX1VhyK04vCumWniFdbsbeO0umjaK4MKBRcKcEbsdwQCD16jvQBS12f7Z4u0HQzkwOJb6dezCLaEB9t7K3/ARVjWPF9joryGeC5lhhkjimmhVWWOR8bEIzuJO5egP3hmgC1pXiGz1XT3vAstqkdw1s63QCESK+wjOcH5uAQTmtagBu9f7w/Ol3Ajgg0AcTr2vNBqKeTqOrw28tyLGM2ttbvG9xtJ2AupYnggt90EEEjBqLWtVS7+H1p4rtGufO04rdRy3EYjkdVbbKGUcYZN/A45BHQUAausaVrWp6raXNrc6d9hg2yJDcwO7B+7ghgM4OBxx1+nQXlnb39nNaXUSy280bRyRsMhlIwQaAOD8JXM3hXXm8D6tJ5kJUy6LdSYzNCOsRPd0/l6YrptY8J6VrE1vdvaxRahaypNbXaRgSRspBHIwSpxgjPINAEXjXUJtP8ADTrbSmK4u7iCyjkU4ZDNKsZZfcBiR7ilv9d0vwnBZ2Jt5RCvlQqsCAiJWcRpnnPLHGBk8E44NAGhaa1aXus6hpcO8z2Ai884+UGQFlAPrgZP1FaNADd6/wB4fnSgg9CDQBx0mtLqfiuTS7PXdQtW8qSRRHBA0JEbBJMMylshsjnjIOOlVNW1iKbwTpfi+0lnc2ckUyzTRhJJYGcJJlV4wyndj1CnHFAGrq+ja7qGtw3Nve6elnBtMKSwM8kbfxSA7tu/BIBIOB9Tnpx0oAWigAooAK4P4paWP+EfXxJbwNLqGhzw30WGP3I3y4HoCpbPrgegoA6HzotW1vT2ixJb20H2wOD0eQFI/rlTL+laOoX8Gm2Ul1cMQi4ACjLOxOFVR3YkgADqTQBmaPpBXUJ9d1CCJNWuoxGdgB8mEHKx7u57k9z04AFWpNcsk12DRkfzb2WNpmjQg+VGv8TegJIA9c+xoAydYg+yeO9A1Vjthkin0+RjwAz7XTP1KED3IHeqOvaH4k1XVYWZ7KbTbPUYb23gLGNnVF+4xwf4juz/ALIFAE+r3WrWc2hw3VzEzXN6TOiwB1CglwoJGSQAFBABJO7tiuudFkjZHUMjDDKRkEUAZH/CI+HP+gDpn/gJH/hWhaWFpp9uLeytobaEEkRwoEUE9eBQBx11ovim78Q2OpXZsLmLTbu4ltYVkaLckibY9xweVGcnnO89Mc2fGEd03gKTSbidZ9R1PZYgooUM8hw20eiruPrtXJoA66NBHGqD+EAU5mCKWYgKBkk9BQBzcFtF4n1K21W6gU2Fk5k09XUZkfGPO9QMZCj33H+HGlq+uWWiQRNcyL5s8qQQQhhvlkYhVVR9T+A5NAGX48tGn8Mi6SMu+n3dtf4HXbFKrvj32BuKz/Gk1veXvh2OK6ty8Fz/AGoIZXKRyxRKfmMgBC4LqwJ4OKAMbQrm8tND/tS8s3EviTV/OYLctC0cRZQmCBuwIkL9vlU5xmvT+CpB5BoAx/8AhEvDn/QB0z/wET/CtCx06y0yAw2NpBbRE7ikMYRSfXA70AeZ+Lb+6XVPEV7oxiu7y4tYtEhQsySwzHcxCDaQ/wDrVY4IxtOelb3ijSo7TwBY+FbUsXuTbadD6lQVLt+CI7H6UAduOlFABRQAUUAFQXtpDf2FxZ3Cb4LiJopF9VYYI/I0Act8N9G1DR/CsMWrA/bh+5JPURR/JGP++Rn/AIEa3tX0HTtdiii1GBpkibegErpg4Iz8pHYkfiaAMhvh14Vddr6YWX0a4lI/9Cq3oPgzw74Ynmn0bSoLOWZQjumSWXOccmgDYurWG9t2guI1kjbGQfUHII9CCAQexGamoAKKACigAqCSzglvIrp4w00KssbH+ENjOPc4HNAE9Vr+xg1KxmsrpC9vOhSVNxXcp6jIINAGB/wrzwuRg6cxB6/6TL/8VRYfDrwlpmpxalZ6Jbx3sTbkmJZipxjPJPNAHTkZGKoNoelPDbQy6dayx2rbrdZIg4hP+xn7vtjpQBLeabaagYjdW6S+S++PcPunBB/MEg+oJFWhQAtFAFVdNsU1B9QWytheuux7gRL5jL6FsZI9qe1nbvex3bxI1xGjJHIRkopxkD0zgZ9cCgCeigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKAMbU/EdrpFw0V1DcADyirqgKvvZlOOedgUu3ouDz0qva+L9Pm1WaylLWypGJElm+VX+aZTz0AxAzAk8g57GgC8PEGlFQftYBIdipRgyhQCxZcZXhl6gfeX+8M3ba6hvIFmgfdGSRnBBBBIIIPIIIIIPIIoAmooAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKKAM/UNE07VZ4pr2382SKKWJCXYYWQbXGAccgYz1HbFQv4Z0iRCj2m5TAluQ0jHMaK6qp57CR/c556CgBF8L6Ilk9mmnQrbPG0bRqCAytjOfc7V568VYsNKttNlf7IHigMaxpbqcRR4Zmyq9iS5ye+B6UAX6KACigAooAKKACigAooAKKACigAooAKKACigAooAKKACigAqC8vIbC0kubhisUYyxClj6cAck/SgAs7yC+tluLd90bZAJUgggkEEHkEEEEHkEYqegAqre6hb6fEslwzDc21VRGd3OM4VVBJOATwOACegNAFlWDKGByCM0tAFWDULW5sLe+imU21wqPE7fLuD429ecnIwOvNTQzpOheM5AZkPBHKkg9fcGgBl3dw2Vu1xO+yNcZOCTknAAA5JJIAA5JIAp1vcR3UKzRElGGRuUqR7EHkEdweRQBWu9WtLKVYp5CsjAEARs3Vgo6A9WYAfWpzdxCBZtx2MwUHac5LbRx9TQBNnimxTRzIXjdXUMykqcjIJBH1BBB9xQA+igAooAKKACigAooAKKACigAooAzV0eIeI5tZYo0slrHbKDGNyBWkYkN7+YOP9nv2rzeGbD+yLnTrOMWkdwVLmLOcgg+uQeOx4oAoXfgyJ9RiurOaGBY4HiXzIWkdWKuN4beASTIWberbj6E5qGLwNHHpc1u8ljLcPGqI8lm3lx4meU4USBtpL4xv/hGc9KAEl8CLPM5nvYZY2aFiWs18x9ksUjK7A4ZT5IUAKAoY9cCtT+wri1sLeLTb2K3uLYusTS2/mRhGbOwoGU4A24wwxtHbIIBRbwWkt/cT3F1FJHJKJBGLYAuDMsrCU7j5mCu1TgbVJGDmll8GRG8sriGS3UwXTXEge3b5i0okypV12vwBuO4EAZGOKAKcXgDYqLJe20whs4baESWWRmPyiC43/OuYQdvBw7Dd0xZ/wCEKP23zvt0ZQvLI2bb94peWWQBH3fKv73DDB3Ads0AXf8AhGETT7q2tp0hL3UV1Bth+SF41jwCoIypaPcQCCdx5B+aqd54Ol1G6knu9SXdNCySSQ2+yVXMTRny3LHZHhi2zBO7nd1oAbF4FtTFALn7E8kWzPlWhVMLOJSAHdyAcEEZ7k+1WP8AhEz9uM/2qFkMkcuXtsyqySrJtV93yoduNuOpJz2oAowfD+FLBrWW6hkASVI5Ps7bvmQKsj7nIaUYyXG3PHAwK6HSNJXSY7qJDEY5rqS4XZFsI3tuIY5+Y5JwcDjAxxkgGlRQAUUAFFABRQAUUAFFABRQAUUAFFABRQAUUAFFABRQAUUAFFABRQBj6x4m07Q7iCG7aTdKyKxjXIiDtsVm9AWOBjJ68YBxZtdYs7zVr7TIHL3NisZnG3hd4JUZ9cDP4igC/RQAUUAFFABRQAUUAFFABRQB578QriAGO2t9QuodYuJ7O3tgsjIsG+Y5kXoCSAwPXgKOM86NjcWGhaVcRWmsTSfab9lhkuIXnWJi6IY1xglQxC5z1JyTzQB2NFABUYmjZnVWDMjbXCnO04BwfQ4IP40AMjvLaVIHjuInW4GYWVwRIMZ+X14547VPQAUUAMilSaJZYnV43AZXU5DA9CD6U+gAooAKKAOL8bmOTVvD0SNDLNDd/bpLMsqPNHErfMGbCjYzBvmIFYvh6/uYtHbVLq2nS48TauZY3gcKyRblSNQxHP7tS/TG0Ocg4BAPTRS0AFQm7t1gknaaMQxbt8hcbV253ZPQYwc+mKAFFxCZlh81PNdS6puG5lGMkDuBuHPuKloAKiuLiG0t5Li4lSGGJS8kkjBVRRySSeAB60AS0UAFFABRQBXmsLK4dnntIJXZPLZnjDErnO05HTPOKo6roMOpRWEaStbJZXAnjWFQBwrKBjtjdkehAPagCxLp3m6jFefa7tPLGPJSUiNuvVe/X9BWfDpGqefrPnam4hvV22oR2LWn3hkZ65yG7YPy8gCgDG1Hw94su/JMGsRwMbeXzmS6lUCV45htC4wVV5IyrcECPoeMW77w/rbahG1hqAjtRepO+66lD+WogBXuHB8uQEH++DnqCAUdP8I63a6ZbwNfRo9tAIoljupGGRC6F1ZlzGWLAYUYULkZJwNcaVrA03S4hcP9oguvNnL6g7ApubKlhGDKADwpC9Bk8cgGfbeHPERt7kXeqkSsshiEV7MVWQqgU84IXKsdp3Y3Yy3UrHoevrqyxm/l+ypIrrM13I2E+0Svs2fxkxlIyW6A5BOMUARReGfEFvbNAl87hbeKOLZqbwrlfLyNoibaPkbkHkMQQM5HaRqyxqHYMwADEAgE/mf50APooAKKAKN/o+nao0bX9lBcmMEL5qBsA4yPpwOPak1DR7LVEt0u4RIlvJ5sY3FQG2le3UbWIx0waAJPsP8AxMBefabgEJs8kSHy/rt9fesaz03WRo13FJfSfaxPm0Z5T/q4mHlhyM53hMsRyQ54oApTeG9flucDWJBAscCbhdyq0m2SFpCQPusRHKMg8iTGBgkt1Lwvrd5FJbR6gi27R3YANxJ8xlM21XXBDACROeqlD97IKgEbeFtcYi4F4scyxOiRpfSkqC8B2iYqWAPksTxxvxgitSXSta8rS1gu8S29s8c0k927qXKAAsqqnmnI+9lCMk4zxQBnw+GtfMMfn6tKrLLG21L+ZsJ5waRd2F3ZTcoJA6jpjihdeF/EWoWWo6bJeny3tDbrNNeSuJCbby8FORje24sfmyvQ5zQB1Gj6dqNnqWpTXdzJJDNJugDXZlAG5z9woPLwGAwGYHA6YraoAKKACigCveX9np0Hn311BbQ5C+ZPIEXJ6DJ4qOx1fTdTMgsNQtbvy8b/ACJlk25zjODx0P5UAXKKACigAooAKMUAFFABRQAUUAVr29isIBLLHO6ltuIIHlb8lBOOOtR2GqQaj5nkxXaeXjP2i1khznPTeoz07UAXaMUAFFABRQAUUAFFABRQAUUAYfiS4a3gV21FbK2jilnmKFfOkCLnam4EY6knrwB3rJ8Evrlzb2N7rGrQTNd6ZFO9mqBXR2Od3H8O3aP97d7AAHZUUAFFACZFLQAUUAFFABSZFAC0UAcX8R0um0qzW1vZraa4u4bOLy3KhXlkUCQkf3VD4HTLfSp9AvJ9V8deJZ/OdrGxEFhCofKeYAXlOOm7LqD9MUAdbRQAUZxQAUmRQAtFABRQAUmRQAtFAGVq/hvSdemtpdTs1uGtg6x7mIG1wA6kA8ggDIPFO07RLLR43FlE+5kVC8krSPtUfKu5iSFGTgdBk+poApmPxDHo8iCQPfNcRBWEqSbYi6hz/q4xkLvOMH+lZszeNkj8qBIpmYpmVzGhT/XbsYyP4YCeD998Y/hALkbeJ59QmjljFtasyhZVaNyoBIJVccZ4I3buvblalmk8QvFpu2LZIbcPdCMRkedlPkO48Jy+SuTxwegYAgt9P1nTdG2WJQ3kl1O8zyohJ3l9jnbtBwTGx77QR1wKzNXh8Y3N1JLbWag2k0k1izTRnLfZ7qNcjjjcYODn75567QDUebxVLq0PlWkUViJsuZXTOzcAQQM5JXcVwRg9c/dMN4PFJ8NQvBCW1mIznaZk2swhlEZONqlS5j+UjjPPTdQBdvf+Eht9GnWxK3WoRzfuWnVAJE6/MAVHGSBjHIGeM0/VJdehuB/Z9us8JgLclAyyKrEKckA7yYxxwNrcjIoAzLJfFtwANRQxLHJEQqSR/OBdNuJZcE4hCHACg5Ix1WqBj8Zz3i3slk8U0KXHkKJIXHzJCyo/I+Xerg4yQB948NQBo6Lb+JLPUIoHgjj00TXEsheRSW3zzsMAAnODEeoABIwT93raAMHxJo9/qz2Ytprc20bP9otLmPdFcAjC7uDkKeccZOORUOjeGP8AhGfDcun6Sy/aZJGneUbYg8rEFiBtYKMcAbTgAD3oAgnj8XfaoIo5tsO1VkkUxORlZiWyVXJDLAo+UcO3B6hPO8ZNJdO1pAsZRVijSZA24tHypKkKADKTu3ZIXAH8QBd0U+IXdZ9WAj3IitbqEKqfJjLNkZJPmeYvXGMfU5rWfiPUrzTV1BWW1S6jnuU/dFRhJsqByWQOICMjdk5zkfKAXL5/E269jtodyo2LaRHjQyBvmySwbbtxs+6d27PHUVIF8UWruYrMf6RdRSSHehCKZYhL1bP+r8zGM9PXGQCXTn8XmK0l1KCMM0y+fDBLHlVO3dyVxtU7vlHzY/jJHzWJU8QrqrG3JWz89WIJVt6l4ww+Y5ACeacDHIH0IBZgu9Rl8S3lkxQWcMQlV1Az84AVfqCkpPsye9Z3neMMWLG0iLtMn2pUkQIiDy1fGclgf3rjkEDbnkbSAVJP+E0h0mOWG3M+qSWNuZA00aos4ErSLj7uNxjXgAkY+bjIht9K8R28LxpAzgalc3aJK8e0BrmR49pU7sFWBIbkZAHcAA6fQP7Y+wsNZWNZ9/yBXDHZtH3iAATu3dAOMdTknVoAKKACigAooAKKACigAooAKKACigAooAKKACigAooAKRvun6UAIKdQAUUAFFAH/9n/4TNhaHR0cDovL25zLmFkb2JlLmNvbS94YXAvMS4wLwA8P3hwYWNrZXQgYmVnaW49J++7vycgaWQ9J1c1TTBNcENlaGlIenJlU3pOVGN6a2M5ZCc/Pg0KPHg6eG1wbWV0YSB4bWxuczp4PSJhZG9iZTpuczptZXRhLyI+PHJkZjpSREYgeG1sbnM6cmRmPSJodHRwOi8vd3d3LnczLm9yZy8xOTk5LzAyLzIyLXJkZi1zeW50YXgtbnMjIj48cmRmOkRlc2NyaXB0aW9uIHJkZjphYm91dD0idXVpZDpmYWY1YmRkNS1iYTNkLTExZGEtYWQzMS1kMzNkNzUxODJmMWIiIHhtbG5zOmRjPSJodHRwOi8vcHVybC5vcmcvZGMvZWxlbWVudHMvMS4xLyIvPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6eG1wPSJodHRwOi8vbnMuYWRvYmUuY29tL3hhcC8xLjAvIj48eG1wOkNyZWF0ZURhdGU+MjAyMC0xMS0yOFQyMTo0NjozMC4xODI8L3htcDpDcmVhdGVEYXRlPjx4bXA6Q3JlYXRvclRvb2w+V2luZG93cyBQaG90byBFZGl0b3IgMTAuMC4xMDAxMS4xNjM4NDwveG1wOkNyZWF0b3JUb29sPjwvcmRmOkRlc2NyaXB0aW9uPjxyZGY6RGVzY3JpcHRpb24gcmRmOmFib3V0PSJ1dWlkOmZhZjViZGQ1LWJhM2QtMTFkYS1hZDMxLWQzM2Q3NTE4MmYxYiIgeG1sbnM6ZGM9Imh0dHA6Ly9wdXJsLm9yZy9kYy9lbGVtZW50cy8xLjEvIj48ZGM6Y3JlYXRvcj48cmRmOlNlcSB4bWxuczpyZGY9Imh0dHA6Ly93d3cudzMub3JnLzE5OTkvMDIvMjItcmRmLXN5bnRheC1ucyMiPjxyZGY6bGk+QXB1cnZhPC9yZGY6bGk+PC9yZGY6U2VxPg0KCQkJPC9kYzpjcmVhdG9yPjwvcmRmOkRlc2NyaXB0aW9uPjwvcmRmOlJERj48L3g6eG1wbWV0YT4NCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIAogICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgCiAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAKICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgICAgIDw/eHBhY2tldCBlbmQ9J3cnPz7/2wBDAAMCAgMCAgMDAwMEAwMEBQgFBQQEBQoHBwYIDAoMDAsKCwsNDhIQDQ4RDgsLEBYQERMUFRUVDA8XGBYUGBIUFRT/2wBDAQMEBAUEBQkFBQkUDQsNFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBQUFBT/wAARCAEwAeIDASIAAhEBAxEB/8QAHwAAAQUBAQEBAQEAAAAAAAAAAAECAwQFBgcICQoL/8QAtRAAAgEDAwIEAwUFBAQAAAF9AQIDAAQRBRIhMUEGE1FhByJxFDKBkaEII0KxwRVS0fAkM2JyggkKFhcYGRolJicoKSo0NTY3ODk6Q0RFRkdISUpTVFVWV1hZWmNkZWZnaGlqc3R1dnd4eXqDhIWGh4iJipKTlJWWl5iZmqKjpKWmp6ipqrKztLW2t7i5usLDxMXGx8jJytLT1NXW19jZ2uHi4+Tl5ufo6erx8vP09fb3+Pn6/8QAHwEAAwEBAQEBAQEBAQAAAAAAAAECAwQFBgcICQoL/8QAtREAAgECBAQDBAcFBAQAAQJ3AAECAxEEBSExBhJBUQdhcRMiMoEIFEKRobHBCSMzUvAVYnLRChYkNOEl8RcYGRomJygpKjU2Nzg5OkNERUZHSElKU1RVVldYWVpjZGVmZ2hpanN0dXZ3eHl6goOEhYaHiImKkpOUlZaXmJmaoqOkpaanqKmqsrO0tba3uLm6wsPExcbHyMnK0tPU1dbX2Nna4uPk5ebn6Onq8vP09fb3+Pn6/9oADAMBAAIRAxEAPwD9U6KKKACiiigAooooAKKKKACiiigAooooAKKKKACkOe3WlooAy9d8Qad4X0m41LV9Qh07T7cKZbq5cRogJwCzHgZJArkE/aC+HEi7l8caHIp5DJeIQBjPr6V0/jTwbpHxA8J6r4c12yj1DSNSt3trm2kGQ6sMH6HuD2Ir8uvhnbQ/8E/f2qH+Gnj/AE3Tda+FHiubfo2vanYRSPaljiNvMK5wrERuueM7gMUAfodeftRfCXTuLn4h+H4D/wBNL1BVM/tdfBdTg/FDwup9H1KIH68muuk+FPgXUI183wd4duI3XI3aXA4Yf988jkVz3if9lr4P+MLF7XVfhl4VuI2BG5dIhjkXjqHRQw/AigDd8A/GLwV8UpruHwh4r0rxJLZLG1yun3KTGNXztLAHjOD+VdrXwV4H/ZNtv2Kf2ovDni/wFLqN58P/ABlLJoOp6SyGf+zGdTLBLvHJi3xbQzZI38nmvvINu5zwRkcUAI0oWMuWAUDdluBj3Paszw94m07xVpcGpaPfQanp0zOsd1buHR9jFGwRwcMrDI4yK+bv2u/H+reKPF3gr4C+Er2Sw13xszSarqFu5WXTtKj5ndSOjMNyg9e4r6O8KeFdH8E+G9M0PQdPg03SNNt0trS1gQIkUaLhQPw/maANqimbjzz+fFLuoAdRRRQAUUUUAFFFFABRRXhvj/43fEnwv4uv9L0L4J6r4p0u3ZVh1aHV4IEuMqCdqMhIxnHJ7UAe4noaybnxRpVnr1pok+o28Or3kbTW1i8gEsyL95lU/eA6nFeLeGfj98Uta8R6Zp+ofAXV9HsLq6iguNSk1qCRLWNnCtKyhMsFBLYHXFXv2rvgnJ8Vvh1LqOhTvpPj3w4G1Hw/rFt8ssE6fMI8jqj42spyCD0oA9uV92Of0/Snt909/pXj37J/xwi/aG+BfhnxjtEWpzRfZ9UgUYMN5EfLmUj0LKWH+ywr2GgDM1zxBp/hnSbrVdVv4bDTrVDLPc3LBI0UdyT+Q7mrtvcJcwxyRSLIkih1ZTkMp7/jXyf4j1Sf9pX9rQ+Ag5Pw5+G6Q6nrMKnjUdUcZt7d/wDYjAMhU8EjkGvrIKq/KB93oAOlAEtFMD5HXkdaXPSgB1FFFABRRRQAUUUjHapP86AFpG4U/wBa4b4seOPE3gXQoLzwv4JuvHV7JOInsbW7S2ZF/v7nBBFeT/8ADRnxhbOP2ctYI748QW2fyKUAe+eIfE2m+FNLk1PWNQt9L06J445Lm6cJGhdwi5PbLMBzxzV9ZjJsKnKtzu6gjjv+P41xVjpw+MHwpNj468KDTBrVk8OpeHryVbgw7sgpvHBOOQRyDjHSvFv2QPG+qeG/F3jn4F+JdRudU1XwLKjaTfXwJuLvSZP9S7tn5iuduTk+poA+paKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKAEb7p/rXh/7XX7Muk/tSfB/UfCt6VtNVizd6TqTLlrW6VSF567GHyt7H1xXuDfdOM9O1c3498eaJ8M/B+qeJ/EeoxaZo2l27T3FzMcAAdh3ZieFUcsSAOtAHxn/AME7f2pNY1K4vvgR8UC2n/Ebwoz2tqLr5XvYYuGXJ+86DB/2l+btX3geeK+XfgD8Hz8RfibcftCeNfD0Wj+JtTi8nQNKK7ZdNsMbUef+9cSJyxOcKQowOK+ojwDQAgjUZ4o28HrURlYd8c5OR2zj8P8A61SnODQB8TfCW4XxZ/wU4+L+oXKiQaB4Zs7K1btESyBgPQnLfnX1L8W/Hl38Ovh7q/iDTtDvvEupW0W200vToTJJczMwVF4zhdxGSegr5d+DenyeE/8Agph8Z7O5/dJrnhyz1C15/wBaA6biPcEtnHpXvH7T3x9i/Zx+GEviz+wb3xJePcRWNpp1ihMks0hwgY44GcD1OeOaAPmr9pL4k/Gb9lvwX4H8faj46h8SeKdZ1iDTr3wc1rHBpf72KV2jhbDSgowRd5c5wDg5IPXfDvxN8e9D/ak8NeGNei1TxD4Q1HSW1DWdalt0i061maKRhDbKEDAI/kp88jMck4rx/wDaI+I1n+0J+1R+zZ4ZvozpWkWVwNR1tHIMVtqbwpNHZySjKmZVjUeXncN/Ir7O0n4zN4n+ON14H8O2EeqaVpVg1zruuRy5htLlm2w2aMuQ0xAd3XOVVOeSBQB1PjD4reGfAGueF9J1/VBYX/ia+/s7SYfIllN1ORuCgopCjH8TEAetde3CmvmbQ/2i9X8TftB+EPCN74KtV0/Wbe+1GxmlYnUtOghJRbmeNl2wrMcKqhixHavpqgCjq2sWWhWM19qV7b6fYwDdLc3UixxxjOMs5OAOe9cv/wALu+Hf/Q/eF/8Awc2//wAXXSa94d0zxRpNxperWMOo6dcDbNa3C7o3Gc8g9eRXD/8ADNnws/6ELQv/AADWgDT/AOF3fDv/AKH7wx/4OLf/AOLroPD3irRvFts9zoes2GtWyNsabT7lJ0VuuCyEjOMVxv8Awzb8Lf8AoQtC/wDANa6rwj4B8O+AbGaz8OaNZ6LazSea8NnEI0Z8AZwO/AoA2L66Wxsbi5dJJEhjaRkhQu7AAkhVAJY8cADJr498ceJviv4k+EfjX4v3Xi3UvhdYaXZXN7oHhQafD5rxwxvsa/aXLMZHydi7Nq7eeTX1n4q1+Pwr4Z1bWp4ZriHT7SW6eG3GZHVELEL7kDivzY/ay/bEuPjZ+wtqZi8NXnhrVvE2pGGDR2O+4OkQSRu98ygDbCXCRliNoLYBPWgDrz8eP2jfE3wt+GPxP8P6Jea1f+JLmGD/AIRvSkRdOt7fO0XF0xVpT5pGSVKInqelfoOmZFUSIAxXLrxwen5dfyr560/4naf8JPB/wf8Ahz4Ngs/EviHWIrS1trKGbKQWaqrXV45TJVETfgkAMxVcjNfQ69icb/5n/CgD4t/4J83k2h/Ez9pDwWoWPT9M8cXOoW0CgDyluCcKB2XCL9MV9quwjVmYhVUZJPQV8VfsA2susfF79pnxWoV7K88bz6bFOvPmfZywyD6YcfnX2rJGssbI43KwII9QaAPiL/gmTfT+LbL4z+Nr35rvXvF0rPJ1ysWVUf8Aj1ezfHTxf4tvPFVh4P8AD19d+EtIGlz61rfjKKzEq2kMYISGAuPL812GfmzhecV4z/wS/tbjw1ofxf8AB94vk3eg+MLhJIx/D5mSB+SivTv+Chusa5of7IXxBl0COV7qSy8ibyR8yW7nbK2R0ATJPtQBnfsJ/HnxR8Yv2dbvxl4yDTx2uo3sdlqTKFkvrOE5WVlGAGBDxnGBmM1D+wb8dvF/7RXhfx/4z8Qz276M/iWay0S3hh8sQ20caEDPVgd6sWOedw6DA8n8afGTwf8As/8A/BMrwpa6Hr1lBqmteFLe00qOF8vcXM0a/aSFGTw7zFsjAOQcE169+y1D4f8A2bf2Nvh7b+KdSt/DSyacbmS4uzsYTSh7gk56lYyT04VDmgD6fVi3/wBcU49D2rz34GaDPoPw50+Obxxc/EYXTveReILorunjkbco+QkbVHAx6V6HQByWsfFjwX4d1KXT9V8X6Dpl/ER5lpe6nBDMmQCMqzgjII7d6q/8Lu+Hf/Q/eGP/AAc2/wD8XR4h+CXgLxZrFxqus+EtK1PUrjaJbq5t1eR9qhRkn0AFZv8Awzb8Lf8AoQtC/wDANaANrTPi54H1jUILDT/Gfh+/vZ22Q29vqkEksjZ6Kqtkn6V12eM1wmkfAf4eaBqltqWm+DdIsb+2k82G4gtlV429QR0ruivykD0+tAHyf+058VPGlnN44Glaxf8AgPwf4I0ZdRv9eisR5+p3ciB4re2eVDGyKGjDsM5LlflKk1t/AP4/eINX/Yj0v4qeNPLh1uLRLq/meVRsnMbyLC5VcYEgVOBjlq4n/gqxd38H7Ks9rZLIlrfazZW99LGSdluWYsxAByCQAc1xH7dHxP8ADPgT9i/wz8LPC2safd654ms9O0fTrCymV3a3xGWlwpyFO1RuPUvjrQB79+wz8R/Gfxg/Z50nxp47nguNT1q6uLm3+zxCNEtvMKxqB3wFbnrxXlPxIu/+ED/4KhfDK8QiGHxV4bubC5PTzDGH8sH6NtxX1B8D/AcPwx+D/g7wtap5cWl6ZBBsxjD7QW/8eLV8v/FKxHjf/gp58JLFAZIvDfh28v7nBGYwwYxE/V9ooA+3KKKKACiiigAooooAKKKKACiiigBKZ5hzx9CPSnSfcbp0/i6V8z/tU3HiDWLqe2bUtc8MfD7w1od5r+t61pF21nJcTRofItVmUhhhgJGCkZHGaAPpfzM8j5h6jkUiscjv9P6+lfmP8MYf2ivjX+xvpnj9PE2seJfEzSfZPD+i2l9Jpm+FZ3Rry5kiZHuHG0gJuCFFBKkkk/oP8HbPxRY/Cvwnb+Nrtb7xYmmwDU5woUNcbAX49Qc8+1AHa0Vz/jSbxJFoMj+FItOuNX3LsTVC4hK55zsOc4rzr+0vjz/0CfA//f65/wDiqAPZaK8ZbUvj1tONJ8DZ7Zmuf/iq6/4e3fj65mvv+E0ttCt4cIbP+x3kYt97dv3k9tuMetAHb0UV578VPj78PvghDp8njvxZYeGkviy2zXpYCUr1xgGgD0Kivnz/AIeAfs8f9FX0H/vqT/4mj/h4B+zx/wBFX0H/AL6k/wDiaAPoOivnz/h4B+zx/wBFX0H/AL6k/wDiaP8Ah4B+zx/0VfQf++pP/iaAPoOkbIUkcmvn3/h4B+zx/wBFX0H/AL6k/wDiaP8Ah4B+zx/0VfQf++5P/iaAPd9S1K30nT7i+vLiK1tLaNpJZ53CRoqjLMxPQCvjC0+KXgb9pz4kQeJvF3i/RrD4XeG7wt4f8P3t4iNq93GcfbrhSeYlI/dIfTcRnmu+8X/tofsw+PPDd/oGvfEvQNQ0e+Tyrm1aaZBKmclSVAOD3GeenSvGTN/wT0PfwLnjn9/njigD7E0/47fDi+Ura+NtBlCD7sd/HgAfjWF4u/ay+D3gi1ebWviN4etAAT5X26NpGwOgUHJPtXyv5n/BPP8A6kX8p6fHd/8ABPaH7jeBV+gnoAu+Cf2n7H9tj9rDwx4c8FC9X4c+Coptf1C7kV4hqN4D5UCkD+BS5dc4yQfQV95bQq8DHFfHnwt/aB/Y0+Ck2oS+BvFPhHw1LqCxpdPZiUGUJnYCSp4G4/nXoX/DwD9nj/oq+g/99Sf/ABNAHKftceFtW8C/Ef4ffHvw/YT37eD3ktfEVnbDMsukTKRK6rj5mjJLY5OBx0r6IuLPw18UPCccd3Bp3ijw3qkSyhZEW4trmN13KSDkFSMYPvivH2/b8/Z2ZSrfFbQWXGCC0hznr/DWR4T/AGzv2XvAuiQaNoHxG8OaVpVuzNDZ27SCKLcxYhF24VckkKMAdgKAPZv+FIfD3/hD/wDhEz4J0E+GPN87+xzp0RtPM27d3lbduccZxW94W8G6F4F0aPSvDukWeiabESyWlhCsMYJ6naoAz7+wrxX/AIeAfs8f9FX0H/vqT/4mj/h4B+zweD8V9BI/3pP/AImgDjtB+HPj7Tf2vvHPi+XRw51h9PsNP14lWtrTR4lDzoqtkiZ3Gw9uc19ZDP16fj718+f8N/fs7/8ARV9B/wC+5P8A4mnf8PAP2eP+ir6D/wB9Sf8AxNAH0HRXz5/w8A/Z4/6KvoP/AH1J/wDE0f8ADwD9nj/oq+g/99Sf/E0AfQdFfPn/AA8A/Z4/6KvoP/fUn/xNH/DwD9nj/oq+g/8AfUn/AMTQB9AyRrLGyOodGG1lYZBB7Vx/hv4N+BPB/wDa39heD9F0f+1gw1D7DYxw/awwwwk2gb8jrmvLv+HgH7PH/RV9B/76k/8AiaP+HgH7PH/RV9B/76k/+JoA9V8G/CTwR8N5LqXwr4S0Xw69zzO2mWMduZMc4baBkZ5x681xv7TfxkT4O/DG+urSJ9Q8U6nnTtA0u3G6a9vZBtREHJOMhicYAHNc5/w8A/Z4/wCir6D/AN9Sf/E1g337Y37LWpeLNN8T3fxF8OXGvabBJb2d9K8rPbo/3wny4BPQnGccZxQB3/7JvwP/AOGe/gd4f8KXEq3OtYe91e7Uk+feysXmbJ6gM20H0UV7C33TXz4v7f37O68D4r6CB2G+T/4ml/4eAfs8f9FX0H/vuT/4mgDjZNLf9m79sC88SyQvH4A+KUUVte3T/csdZQnyTJ6CYEoP9ogVZ/bW+MHxC+Gt54CsvCqaPY+HNXvZItd1nX0R7KC3VQSshOQoYZwcc9AO9aXij9tT9l/xtoN5ouu/EbwzqmlXaFJrW48xkYdc/d4IPIYcg8gg1oQ/t6fs5wW4gX4q6F5QXbtaSRsjGOSV54HegD5y8ZfB/wAF/tYfEzw/4d+EvgXS9B+GWm6jFqXifxtY6VHZJqckWTHa2rhAZflY5ccAOete3/tzQQeEvg5FeaLE6+KtRT/hCfD8BlIgjfUGiid9hONyxQvhuoBYA/Mc9Gv7fn7OyKAvxW0EAcDDyfl92sXxZ+2V+y3460f+y9f+IfhnVdP8xJVguPMKq6nKuvy/KwPQjB60Aek/s1r4b0/4T6P4f8KNNLo/h0f2P9oaMqk8sIHmSRt0dC5b5hweRXq1fNWhftvfsyeF9KtNM0j4j+GNM020Ty4LS0Ro4olyThVCYHJJ+taX/DwD9nj/AKKvoP8A31J/8TQB9B0V8+f8PAP2eP8Aoq+g/wDfUn/xNH/DwD9nj/oq+g/99Sf/ABNAH0HSNnacde1fPv8Aw8A/Z4/6KvoP/fUn/wATR/w8A/Z4/wCir6D/AN9Sf/E0AedftT/HfxX8Pv2jPAfhPVF0LTPgtq1i8viDUvENsJbWbDyB4SxGFbAjAU9d1ea6P+z74a/ab/aC8KeIPBngWz8DfBfwdcNqJvodKWwfxJqRYEGMAAtGhiT5yMfK3qK+jG/b6/Z1kGG+KugkZzjfJ19fu+1O/wCG/v2d+cfFfQR9Hk/+JoA9x1zWbHw3ot5qup3UVjptlE09zdTOESGJQWLE9gAK+Yf2RvCd58Q/ih4//aC1azuLSLxaUsfDcN5GUmXSojhJGQ8p5hUMB1wea1/FX7an7MPjbQ7jRtd+JHh3U9LuCvnWs7SFJArhwGG3kZUZHQjg5BIrUj/b7/Z1hVUj+KugIijCqrOAABjGNtAH0NRXz5/w8A/Z4/6KvoP/AH1J/wDE0f8ADwD9nj/oq+g/99Sf/E0AfQdFfPn/AA8A/Z4/6KvoP/fUn/xNH/DwD9nj/oq+g/8AfUn/AMTQB9B0V8+f8PAP2eP+ir6D/wB9Sf8AxNH/AA8A/Z4/6KvoP/fUn/xNAH0HRXz5/wAPAP2ef+ir6D/31J/8TXsvgnxxofxG8M6f4i8NanDrGiX6eZbXtvnZKucZGQD1oA3qKKKACvkP/gqH40ufC/7J+u6bYB31DxHc2+kIsalnKySAuoABJLLlce9fXlU9Q0ix1aOOO+tIbyOORZkWeMOFdTlWAPQg9DQBxnwJ+G8Hwk+DngzwfCMjSNKt7SRtuDJIsah3I9S2TXe7B2AHal2gUtAHK/EDRdc8SeHZNN8O+JB4V1Z2Rk1L7GtyVUN8y+UzLnI75ry3/hSvxj/6Lw3/AIS0P/x+ve8Y6UtAHgf/AApb4xDk/Hhsf9itD/8AHq7f4WeCfGvg+61F/Ffj4+NY7hYlgQ6Sll9mK7txBV23bty9f7tei0m0DOBQAdeKxvEHgvw/4tSFNc0PTdaSFi0S6haRziMkYJUODj8K2qKAOM/4Ur8Pf+hD8M/+Ce3/APiKP+FK/D3/AKEPwz/4J7f/AOIrs6KAOM/4Ur8Pf+hD8M/+Ce3/APiKRvgr8PQpI8B+Gc4/6A9v/wDEV2Z6HnHvXmv7Q3jS98C/B3xJqGmSBNcuIP7O0nfwDfXDCC2X8ZZEFAHLSa1+zZDI0cl78K45EOHV5dNBU+hGaT+3v2af+gj8KP8Av/pn+NZfhr9g34E6doOm2t18M/D2pXMFvHHNeT2mZJ5AoDSMSc5br+Naf/DCv7P/AP0SXwz/AOAY/wAaAHf29+zT/wBBH4Uf9/8ATP8AGj+3v2af+gl8Kf8Av/pv+NN/4YV/Z/8A+iS+Gf8AwDH+NH/DCv7P/wD0SXwz/wCAY/xoAd/b37NP/QS+FP8A3/03/Gj+3v2af+gl8Kf+/wDpv+NN/wCGFf2f/wDokvhn/wAAx/jR/wAMK/s//wDRJfDP/gGP8aAHf29+zT/0EvhT/wB/9M/xpP7d/Zp/6CPwo/7/AOmf40n/AAwr+z//ANEl8M/+AY/xo/4YV/Z//wCiS+Gf/AMf40AL/b37NP8A0EfhR/3/ANM/xpf7e/Zp/wCgj8KP+/8Apn+NN/4YV/Z//wCiS+Gf/AMf40f8MK/s/wD/AESXwz/4Bj/GgBf7d/Zp/wCgj8KP+/8Apn+NH9u/s0/9BH4Uf9/9M/xpP+GFf2f/APokvhn/AMAx/jR/wwr+z/8A9El8M/8AgGP8aAF/t39mn/oI/Cj/AL/6Z/jR/bv7NP8A0EfhR/3/ANM/xpP+GFf2f/8Aokvhn/wDH+NH/DCv7P8A/wBEl8M/+AY/xoAX+3f2af8AoI/Cj/v/AKZ/jR/bv7NP/QR+FH/f/TP8aT/hhX9n/wD6JL4Z/wDAMf40f8MK/s//APRJfDP/AIBj/GgBf7d/Zp/6CPwo/wC/+mf40f27+zT/ANBH4Uf9/wDTP8aT/hhX9n//AKJL4Z/8Ax/jR/wwr+z/AP8ARJfDP/gGP8aAF/t39mn/AKCPwo/7/wCmf40f27+zT/0EfhR/3/0z/Gk/4YV/Z/8A+iS+Gf8AwDH+NH/DCv7P/wD0SXwz/wCAY/xoAX+3v2af+gj8KP8Av/pn+NL/AG9+zT/0EfhR/wB/9M/xpv8Awwr+z/8A9El8M/8AgGP8aP8AhhX9n/8A6JL4Z/8AAMf40AL/AG7+zT/0EfhR/wB/9M/xo/t39mn/AKCPwo/7/wCmf40n/DCv7P8A/wBEl8M/+AY/xo/4YV/Z/wD+iS+Gf/AMf40AL/b37NP/AEEfhR/3/wBM/wAaX+3v2af+gj8KP+/+mf403/hhX9n/AP6JL4Z/8Ax/jR/wwr+z/wD9El8M/wDgGP8AGgBf7e/Zp/6CPwo/7/6Z/jS/29+zT/0EfhR/3/0z/Gm/8MK/s/8A/RJfDP8A4Bj/ABo/4YV/Z/8A+iS+Gf8AwDH+NADv7e/Zp/6CPwo/7/6Z/jSf27+zT/0EfhR/3/0z/Gk/4YV/Z/8A+iS+Gf8AwDH+NH/DCv7P/wD0SXwz/wCAY/xoAX+3f2af+gj8KP8Av/pn+NH9u/s0/wDQR+FH/f8A0z/Gk/4YV/Z//wCiS+Gf/AMf40f8MK/s/wD/AESXwz/4Bj/GgBf7d/Zp/wCgj8KP+/8Apn+NH9u/s0/9BH4Uf9/9M/xpP+GFf2f/APokvhn/AMAx/jR/wwr+z/8A9El8M/8AgGP8aAF/t39mn/oI/Cj/AL/6Z/jR/b37NP8A0EfhR/3/ANM/xpP+GFf2f/8Aokvhn/wDH+NH/DCv7P8A/wBEl8M/+AY/xoAd/b37NP8A0EfhR/3/ANM/xo/t79mn/oI/Cj/v/pn+NN/4YV/Z/wD+iS+Gf/AMf40f8MK/s/8A/RJfDP8A4Bj/ABoAX+3f2af+gj8KP+/+mf40f27+zT/0EfhR/wB/9M/xpP8AhhX9n/8A6JL4Z/8AAMf40f8ADCv7P/8A0SXwz/4Bj/GgBf7d/Zp/6CPwo/7/AOmf40f27+zT/wBBH4Uf9/8ATP8AGk/4YV/Z/wD+iS+Gf/AMf40f8MK/s/8A/RJfDP8A4Bj/ABoAX+3f2af+gj8KP+/+mf40f27+zT/0EfhR/wB/9M/xpP8AhhX9n/8A6JL4Z/8AAMf40f8ADCv7P/8A0SXwz/4Bj/GgCW31X9m+8uIoLa8+Fc9zK4SKKKXTWd2JwAADkkntXsOk6XY6Lp9vZaZaW9hYwrsit7WNY4o1zkBVXAAPtXkOn/sSfAfS762vbT4V+G7e7tpFmhmSzAZHUgqw56ggGvbEjWNQqqFUDAUdAPSgB1FFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFACV4R8XLj/hNPj18LvAyfvLWwmm8V6kvUCO2XZb7h/18SRMO/yV7xXz/wDs/E+Pfil8UfiM432098nhzSpG/wCfa04kZcfwySNn/gNAHvitu9R+v60/n1r4J/4KYeFfip4R0yx+Kfw98Y+I7XSNN2R63oGn6hNFEYgf9cojIIGM7j2612n7Pvw98HftGfC/SPGnhv4nfEo2t4mJ7ZvFU/mWk4GJInGf4WB+owehoA+wufWkLV8/3n7IFpPblI/il8TrWT/npH4nmY/gGBFeB/G79h/432Gi3GofCz9oPxtqV3EGb+yfEOqsDKACdqSx4G7sAyj3NAH32rZOD19BzTq8P/Y5+KGo/FX4C+Hb3XjOvirTFbSddguv9el7A3ly7x2JK7voeK9wZtqkk4AGc0AR+YdwG764/wD1etSV83eBfHGsftFfHTWbnSr67074YeAbptOV7Scx/wBt6sAfN3lcEwQo2zbnDOxyCBX0jtHHtQAtFFFABRRRQAUUUUAFFFIaAForH8UeK9K8E+H73Wtcvo9P0uyjMtxdS52RqBkk456V5L/w258Dv+ij6V/3zL/8RQB7i33Timb/AJSd2Pw6VyXw9+KnhP4w6Jd6j4Q1yDXdNhma1kuLQsu2TarFRkAg4dea8U+HXxM174T/ALRV38GvG2pS6zpmvQy6z4M1u6fdMY1I87T5WPLvH/rFYktsbBJwKAOw/ak+O0/wP8IaJPZjy7/XdYttFhvHtXuY7PzWG+ZkQZJVN20dC5UHivNZP2hPHnwT/aY8GfDPx/e2Xivw/wCNov8AiU67bWgtZ7e43bRDIigKVJ74zyOa+nPEWtaT4d0G71PWbmG10uzj+0TT3JGyNVGQ3P047k9K+a/Dvw1uPjF+0Bovxn8ZLNa6dpCNaeC/DO0LOsZ5a+uRnhmzuVOqqATngUAfVp6Go1k3Ywcjpng/j/OnM2FJyF4z83avh3/gpd4T+KWjeF9P+J3w28V+ILK10EBNc0HT76WCKe1DZ84CMg5UkhiOdrAj7poA+5OfWjn1r4x/Zt8G+Df2lvhbpfjHQfiZ8SofPzFe2D+LJ/Ms7hcbo2/Hoe6nIr068/ZBs5rcqnxS+J1s/wDz0j8UTE/+PAigD38scHHWm7myAeD/APX9a+C/jZ+w38Z7fRbm8+F37Q3jm8vVBZdL8Qaq2JRj7qzx7QD2GV/GvfP2K/idrnxJ+BemDxaJYfG+g3Mui69DdEeatzEeN2O7RtE3PXdQB723Q03ccjvTj0r5o8O+Oda/aK/aA1G10PVLrTvhj4Buvs17LYyGNtb1VSCYiw/5YRdWAPzH5TkEigD6X5/xpaQDFLQAUUUUAFFFFABRRRQAUUlec/Eb9ob4efCHVbbTfGPiuz0O+uohPBBcByzx5I3fKp7qw/CgD0eoVkLbcEY659j0rxFv23vgftOPiJpucd4Z/wD4itb4/aP4x1LwVbeJfhvqrw+KdBkGpWVhJMRZ6tGBl7WdOhEiblVsblJyCDzQB662dpwQDjqelfLA+MHxE+MfiL4o2XgHXLXwreeBb1rJNL1HSfP+3MIwwZ5GPRmDgeWRgbc5r2r4I/GDSfjp8L9B8baIGSy1SASNbyY8y2kHEkT4/iVgVP4VyHx38Y6tcW918Pfh+1onjnW4cTXUyKYNJt3BV7qcfxHAIVOrEjtQAz9kH9oa5/aT+EEPibUdLXRdbtL6bSdTs4zlEuoSvmbMknbhl7969wrxn9lr4e+EPhL8Nn8EeD9QOqL4f1CSz1e7lP7yXUDGkszPjjcRLGeOMEDtXs1ABRRRQAUUUUAFFFFABRRRQAUUUUAFIc4OOtLSHoaAMfxN4r0rwXod3q+uajDpmmWi757q5YKqA9Mn69q01k3KCGBBGQe3/wCrmvgv/gp98LfiB8Q/hP4p11NVFh4T8KRW99ZaXZtlr9gc3E9x/soCAi+q5NfSv7IPxNT4wfs1/D3xQH8ye50uK3ujuyfPhBhlJ998bH8aAOn+OXjyT4b/AAj8UeILcj7fb2TR2Kt/FdykRW6H6yvGPxpfgd8P4vhf8KPDHhpAQ9lZoJ2Yks0zfNISTycsx5rjvjeo8bfEz4YeAVHmQTahJ4k1Neo+y2Sjy1b/AHrme2x/un0r2tV2+59TQBX1TS7TWNNurC+gS5s7qJoZoZBlXRgQVIPUEE8V+XWn/wBpf8Ev/wBrB7J5Lh/gT45m8yOVk3JZOWHHHRoi23J5ZCpOdpr9TzwDXzP+3noPgzxl8EZPCfiTTpNX1zW7hbXw3ptgAb6W/wD4DFnoq5Jdz8oTIPUUAfRmm6lBq1jbXtpMlzZ3MayxTRnKSKwBDA+hBq5tGMY4rxz9kv4Oa58BfgX4b8G+Itdl8QatZIzTTsxKQ7ufJjJ5KJ0Geepr2SgDI0XwnpHhy81S70zT4bO41Sf7VePECPPlxjew6Z964/8AaL8fH4X/AAJ8deKVJD6XpM8yMOobYQpH4kV6NXz7+3xptxqn7HnxSt7XeZBpDOFUZLKrqxX8hQBS/wCCevhtfDv7IPw98xP9NvrebUrqUjLyyzTyOXb1YqQM9eK7r4j/ABnvfD/jDTPBHhDRYvFnje9ha9ksZbwWtvY2akKbi4l2sVBdkRUVWY7s42qxGb+x3fw6t+yz8Mbi3QCF9DgXC4IyF2nr6kGpoviZ8JNH+Nev6TFf6bD8SpdND6mPKf7Q1rboXG9tvKorE4B/WgDyR/28r1b/AMVeGj4Ba38c+E0mudftLnVdmladaRqWN096ICTGcAACHfzyvevYv2af2hNM/aT+FVl410u1ewhmuZ7V4JCzKrRSMm5XZELKwCkHaD83IBDKPlj/AIJxaTZfEaz+Nnxf8SwQG18Zazco32xlaP7GpYyK5IAxnr2wK+ovCvxW+GvhP4J6N4n8NRrY+BGCx6ZHpumyBpssVUQwBd7lsHBUHIO7JXJoA9ajuBISAfukK2SMg8HB54JBFSt90143+zPZ+A5PC+ua/wCANTv9Xs/EWuXmoahPqE8k0kd5vCTRDf8AcVCm0IOABxnk17JQAxZN2CDntx0p/NeU/Er4O+IPHXiBNR034meJfCdusYX7BpLoIif7xyK5X/hmnxh/0XXxv/33F/8AE0Ae/wDNJuz0/LHNeEWH7OPi2y1C0uX+NvjO7jhlSR7edozHKoIJRuOhxg+xr3XbtGMkjj730xj86APOfjh8VtA+F3hOKXWNP/t+91W6TTdK8PRiMzapdyHCQoHO3B6l2+VVyWIAr578VftGaX8K/iRpvgLx58E9ItvFOvWYuPD9p4dkg1Bb6UtsEDu0EXkvkdSCv+0RzXvHxS8d/CrwD4z8FXHjq/0nTvEclw1t4fm1Hh0lkxG3lkjC53bS3YH0r5b0t4/jh/wVS1Sdyt9pPw10JbeAHP7u5cZJ6DG2R355OQOccUAe3/sy/tF6N8UvGnjzwNZ+HNJ0LVPCk8a6gmgTST2nmu0iNGztbQjzUaEqwAIJB2syrk+d/wDBTCKPwf4L+GfxRthIureC/F9nMksR+Y2su4Tx59H2oD9K+hfhvqnw8/4TjxxpXg+0sbfXbO8ifxBLY2hjVrmVS6K8oUK77TkrklS4B614F/wVekj/AOGP9VtRGXnvtVsLaAKOd5l3DH4A0Ae4/Gb4I+Hv2lPAum6N4gv9Ys9JeWO+ZNHvPszTMoyoc4OQCQQPUVwfwz/YR8BfCvxzpnivSvEHjS71OwYmJdT1+SeGTJ5DIR8w46GvevCcbR+FtHjf7y2UAPbnYM1sbRQAVBe6fbalaz2t1AlxbzxtFLHIuVdGBBUjuCCR+JqxSHoc9KAPys1a01P/AIJe/tVW+sWwun+BfjafyLiBW3LZuTnp/fiBLDHVAwr9RdJ1S31rT7a/srmO6srpFmhmibcsiMu4FWHBGCORXgv7cVj4J1/4D6p4b8X6dNq93rbrZaDpNgoa9uNSP+pFuOzBsFm6Bd2eM1q/sc/BDX/2e/gXoPhDxH4gk13VIMySAuWitA3It4c/wJ09OuKAPc9oznHNYujeC9D8O6zrOrabpsNlqGsyJNqE8IKm5kRdqu4zgtt4z1IAznArbpD0OODQBxnxl8bH4c/CPxp4qBw2i6Nd6guQDlooWZRg+pArxP8A4Jx+Hv7G/ZG8H3czGS71czavczPy0kk8hk3Me55HNdp+2lpNzrP7J/xXt7UsJR4evJsIMllSNnYD6hSKofsK3kN9+yH8KGiAURaDbQvtP8SoFJ+uQaAKXxy/ayk+FsvipNC8MjxOng6wj1HxLcTXwtIbJZBuS3jOxzLcspV/L+VQrId/NdnF+0N4df8AZ3X4vkzDw8dIGrGNhtkwR/q+e+/5cmvlv/gpn9m8M/D/AMNeAPDWnRafefE7xPGNUntcK8+wRK5OeuQYx7BABxVv/gpVcR/Dn9kbwv8AC/QGEc2vajp/h21hUYLwRjk+/wAyxZ93oA+qP2fvi8Pjt8I/DnjtNKm0WDWoTcRWc7h2VAxUHI9cZr0avJNP8P698I/2eNN0X4e6Haav4h0fSYINP026n8iGaUBQwaTsMlm/DFemaLNfzaRZPqcMVtqTQobmGF98aSEfMqt3AOaALzHAJpm45Az/AEJp0i7o2UEgkYyvUV4Lffs3+Lbm+nmj+N/jS3SWVpFhjeMKgJ+6Bt6CgD3smm7j68Z9K8B/4Zp8Yf8ARdPG/wD33F/8TXW/DH4Q6/4D16XUNS+JXiPxfbyRbBY6uUKIT/EMAUAepnODjrXyB8fv2u/Dvgdtd19vh9a+L/CnhnUotC1XxDfSRoTdN8zQ2imOQzGPLeZnYoOQpJBFfX7Y2nPIxzmvz7/bZ8B6T4k+L3wC+BWjWEOkaD4h1+88R6tDar8ssinzHcqepYmck/7RoA+h/jl8RPh38EfgHqHxRv8AwZpd/p8Fnb3MNjFZQJJO07IsSZZeMmRc8cAE44r1n4e+Jm8aeBtC11rBtLOo2cVz9idg5h3KDsyOOBXxP/wU3un8UN8EfgjpUXlx+KvEcDTQwt921gxGV28HYBNuz0/d+1fd+nWC6bp9raR8JbwrEoHAwoA6fhQB8b/sI6nH4P8AjX+0P8K4d/2HRfE0mq6fEzHbDBcMfkUem4E/jXYeLP8Agnr8O/HHjDW/Euo+I/HCaprFw1zd/ZdfeBCScqoRV4VVwoB6CvP/ANl9Tqn/AAUP/aT1GFdlrBDaWb7R8rSLgH8eCfxr7l2jpjigDz74K/BfQ/gH4MTwx4dm1C6077Q9y02p3JuLh5HwCWfGTwqjnoBXoVJtGc96WgAooooAKKKKACiiigAooooAKKKKACkpaKAMLxv4Vs/Gvg7W9AvohNZ6lZy2ssbcgh0K/wBa+Ff+CSXia68O6H8Ufg/qzn+0vB2vyFFbjETs0bAD2khY/wDbSv0GPIIr8vvix4qT9j//AIKSa54jWPydG8feHnmjUcRm8ZSik+p8+D/yLQB9o/B9h44+NnxN8bMN1pZS2/hbTnzwUgXzp3X2Z5kB94h6V7geleZ/s5+C5vAfwd8NaddjZqc0LX99ySTczsZZRk+jPt+iivS2YKpJIAA79KAOV+JnxL0T4T+C9Q8TeILk2+n2qZCqMyTSHhIo16s7NgBRySa8t+B/wp1vVvFdx8W/iTAqeN9Sh8jS9EYhovDthklbZO3msCDK46njooAzP2kv2V/Ev7QHi7w9q1r8S73wjaaAfP0+0sbCOXbck/69i5ILjA2ED5SARgjNcZ/wxf8AF7gf8NP+MgvXH2aHGfXHr70AfYLKOuMntWD438d6H8OvDV/r/iLVLfSdJso2lmuLltqqqgk49TgdBXypefsP/FfUF2zftQ+OdvpHHHH/AOgkV5z4x/4JK33xCZW8U/Hfxh4kZTuX+1mNzt+m9zigD6j/AGVfjLrXx98Fan46vLcWPhzU9TnTw/bNHtmFlG5RZJePvORuHoK9X8XeG7fxd4V1jRLpVa31G0ltXDDIw6Fc4/Gs34XfD7TvhT8PPDvg/Stx07RbKKygZvvMqKFBPvx1611J6UAfLn/BP7UpfD/wl1H4VarJs8SfDjVLjRbuF8BngaQzWs4H9x45MKf9hvStvxR+xh4b8RfFfW/HFtrF/o02vxLbaza2MEKtfQ4UNGbjb5sauq7WCMuR1zXf6p8H7Kb4taX8QtJu5NG19IPsOqrCqmPVLTkok6Y5dGOVcEEZYcjivScetAHzHov7DeheG7PV/D+heMvEOifD3V7t7y88H2MqR20u/wC/H5oHnLGwyCiuFOeldH+1Q2mfC/8AZ91XxFpugR3l94Vsj/YdvFF8trMyCBHCjgBQ/XHAFe8bRUV3ZW9/bS29zBHc28qlZIZkDI4PUEHgj60AeDfsY6Tp/gz4S2ngfS7aaWDwyIra71o48nU7+WJbi6kjbq4V5ipc9TkdVNfQFVdP0uz0izitLG1hs7WIYjggQIijOeFHHXJ/E1aoATaBRS0UAFNZcg96dSUAeJfHj9lvQvjn4o8JeKJ9QuNF8R+GJHk0/UILeG4KhiD/AKuVWTIYBg23II4Nctp/7E2k+D/EF3r/AIG8aa/4N8RapY/Ytb1a0aO4m1XLlzPIZlfEpZm+dcMOMHgV9LYo29KAOJ+E/wAJ9C+DfhUaJocUrCS4lvLy9unMtze3MrbpJpZGJLOx6knsB0Ar5u/a0R/jp+0H8IfgnYSJJZWd8PGXiLBDGG1tcCBW/uiR3ZexOBX2JKreU/l7VkwdpIJGe2QMZrzT4S/A/S/hjqXiDXJ521zxd4huWuNU126UCaZcgRRKP4I0UABVwMjOCTmgD0qNREsaDgLwoHsKlpMUtACHoa5j4i/ETRvhb4P1LxL4gufs2m2Me5to3SSseEjRf4nY8BRySRXTk4BNfOv7TH7MfiH9obWvDU9j8SL3wfYaC/2u3s7Oyim3XYyFmfdxuXjbx8pBI5ANAFn4H/D3xB408WP8XfiTbfZvEFzC0OgaBI25NCsnOcnt9okH336gHaCBkV7/AMYG0Dj2r4/P7GPxfY8/tQeMj/27Q1Xu/wBiH4r3wCzftQ+OMf8ATOKOP/0EigD6x8VeLtI8FaLdatrmoW+madaxtLNcXDhAABk4z14FeS/sr/GvV/2gtJ8VeNdqw+DLjWJLPw1E0QWWS0hUI9wxxz5ku/HoFxXzL4w/4JOal8QlVfFPx68ZeJI0bcserOblVPqA7kD8BX2x8G/hfpfwZ+GfhvwVpAJsdFtFtY5D1dslpH9tzlmPuaAOo1zR7bX9F1DS7xPMtL63ktpk/vI6lWH5E18v/sA3Nx4H8B+Ivg9rEq/8JF4C1a4siuMNNZu5kgmA67SpxnoSMV9Wt905OBivN/Enwds9W+KGh+P9LvJNB8SWA+y3stsilNVsjwbadSOQp+ZHGCpHpxQB8/8A7Smr/Db9oL4/+HfgTrula6fEulw/23aeJdJl8pdJlKB1JIHQqF5PGeOteKyfBe4+Nn7dHg7Sf+Ew1n4laR8OIRfa/r2plBBHcBg1vaRJHiISKQhZgNx5yflGPurx1+z14G+I2uSa1rGmXUWrzQLa3F7pOqXenS3MKklY5mtpYzKgJOFfIFdF4A+Gfhf4W+HY9D8KaHZ6FpiMX8izj273P3ndvvO57sxJPc0AfK/7YEPie1+JXgmw0vxTeQa94q8Qabpnh+z06SRRp1vDKLjULySMELJIUjVMkHEZZRhWYH7Espkmt4pIplnRgMSKch+Ou4dfrXkHxj/Zxg+LnjLw34oj8R6l4c1fSLO705biwEchNvcgLOIxKrLG5VSokUBgHODXqnhvQbLwxoen6TpsKW9hYwpBBEvO1FGB06n1oA1qTaKWigBKMUtFADWO1Sfavi3xxrPgT9qr9prUPBlrF4h8M+NPherXVn42sHWJIZXCCSIhhhsbh97g8+tfadeUeLv2Xfhv431fVtR1TRbtbjWHV9TjsNXvbKHUGVVUG4igmRJeFA+dT0oA+LP2e/hbqXxb/b7v/Ho8U6z468KeAbWSyHibWdhjvtQZXjZLdYwI1jUSs2EAAZBX6L+IPEFh4W0LUNY1a7isNN0+CS6ubqY7UijQEszH0ABpnhfwjovgnQ7TRvD+l2uj6VaLsgs7OIRxoPYDv79a4z40fBuy+OOk6ZoGu6jcR+FEvEudT022Yx/2kifdgkkByIy+NyrgsMjPNAHif/BPPwtqF94J8X/FXWrVrTU/iVrtxr8ccgw0dqzEQL9NoDf8Cr62qvY2FtplnBaWdvHa2sCCOKCFAiRqBgKqjgADsKsUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFACH3r5n/am/ZWH7QnxM+EGvAWqW/hXVXudSMx+aW3IVlQev7xBx7mvpjrxSGNWwSOhzQA1FCBRnoMDjFSUlLQA3YuQccjoe9LS0UAFJtHpS0UAJS0UUANCKvAAA64p1FFABRRRQAUUUUAFFFFABRRRQAUUUUAJ14PIoChenHalooAKKKKACm7R1/rTqKAEpaKKAEwPSgKB0FLRQAU1UVcADAHYcU6igAooooAb5a+n0pdo696WigAooooAKKKKACkpaKACmrGq9Bz655/H1p1FABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUVleIPEmm+E9HudX1rUbTSNLtVMlxeahOsEMKDqzux2qB1ySB60288UaVpuraXpd5qtja6lqpkXT7O4uESa7Mab5PKQkNJtXLHaDgcnjmgDXorkNe+KnhbwrqEVjqWvWq3kmo2mlfZYszTR3N0222jkSMMybznDMAuBkkAE119ABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAc98QPBen/ELwL4i8L6mudP1vTp9NufXy5Y2Qke4DEg18DP4q1Px9o3hv4rai851f4F6bpttqiQyBv9N+2tb6+hAPBFnbBue0ozwTX6NVz9r8PfC1jY65ZW3hrSLez16SWbVreKxiWPUZJV2yvcKFxKzrwxfJYcHNAHxz4ms7vxJ8M7Dxva3a22o+OPjHpmo2N7KonEdpFfxWdg4QkBlMFtFKF3f8tSc4yK6jx38ZviJ8J9B+Kuiprt34svNH1nw/puma9e2lit9aw6m0MUjuqrbWrvG7uYi4jTLxiUlQ1fUS+BfDcejaVpC6Bpg0nSXhk0+w+xx+RZtDgwmGPG2Mx4GzaBtxxipLzwdoGoR60l1omnXSa3D9m1RZrWNxfxbCnlz5H71djMu1sjaSOlAHyt4q+JHxt8A/C34hXt2uuaSLW70NfD2ueNIdFnv2kuL6KC8glh02TyGhVChVisbnz3G7Kqw2viZ4v+InhXx/4M+GukeIPGviSW50a81q613Q7bw9Hqt80c8cYiAvVhtUhQS5by4nkOYuQA5f3HQfgf8ADnwtpN7pei+AfDGkaZeyRS3VnYaNbwQzvE4eJ3RUAZkcBlJGVIBGDWl42+G3hL4lafBYeL/C+jeKrGCXz4rbW9PivI0kwV3hZVYBsMRn3NAHMfB/xpr9x4K8I2PxJFnoHxE1G3uDJo8lxbi4uRBJtaZY4pHByjQyOI2ZUMwBI4r0uuD0f4Q+F9D8Y6Trmm6dDYHRdKfR9J0yzjihstOhkkWScwQoo2PIY4FY9NsSBQMvu7ygAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKRuFOP1qIyMBn2zyP8PwoAmpOvBqETHIJ4DHgNgH09fU/qKnoAbtHpmnUUUAFFFIeATQAtFR+Y20YGcnscj+VIkhY8Hjt7/j3oAlooooAKKa7bUY+gz0J/TvWbpfiDTtakvl0/U7W+NjcNZ3a20ySG3mUAtFJtPyOAykq2CAw45oA1KKhMjAA45/u46dPzpyud3XIz/n/AD7UASUUUjfdODg470ALRVdZz8vYkZIbAIHYnOO//wCoUvnMXUZ4zggDJ/H0oAnopGztOOD2rn/Fvj7w74B0c6v4n1/S/DWlB0jN9rF7HaQKzZ2qXkIAJwcAnPHSgDoaK5q1+Inhm+8XXXhe38SaTceJLW3F3c6LFfRNewQEIfNeAHekf7yM7mGPnX1FdFuPHGD/AJ4oAfRUSybmHOD1Kn3/AF7VJQAtFQrIflHU56njj/HpU1ABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQByPxg8XXvgD4S+NvFGnRQz6homiX2pW0VyrNE8sMDyIrhSGKkqMgEHHQiqPwh1fxbrfguy1fxjd6LLe6nHHeQW2h2k0cVpDIissLSSSOZ2GT+9CxBs8RrjnqfE3hvTvGXhvVtA1i3+16TqtpNY3lvvZPNhlQpIm5SGXKsRlSCM8EVY0vSbTRdNtLCzhENnaRLBBFksERVCqoJOeAMUAfP3gH4v8AjbXPGek2Go+IftdlPNslh/4Ux4k0cOu0nH2y5uWhh5A+aRcdsc1kftaaXpesfFv4JW2r+BB8SLE3WsM/h14LKbz8WWQ+y9lihwhw3zODx8oNfUHlrjHP5nNYmreB9E1zxJoGv3tl5uraC076dcCV08gzR+XKdqsFbchx8wOOoweaAPlbTvFnjH9mzwT4P8Grpy6NqHijWNXv9MsU0W+8Rx+GdLRhNFY/ZrBvMnkQSpHhJFijy+12SNVk7CH9orxbN8MtMu9Rit/Cnii71e602KS+8IaxdyahDAWZbu10aMLeMkiBGIaQCEMSXfA3e2ePPhf4c+JMFimu2lw82nzG4sr7T764sLy0kZWRmhubeRJYtyMyNscblYqcg4rC1X9nvwZrmi6Fp19Hrtw2h3Etzp2qN4m1MapbvKrLIFvxcfaSjKxBQylSAox8q4APF/Cv7THxD+JHh/4UxaBaeH9M1zxVqGuaZqN1q2mXnk2x06SWMzpamWOVfM8hj5MsilS4QvlCW7az+LnjHT/jmPC3iu80vwxos12lnpKTeG7x11/Np5heDUxc/ZreUypP/okiPKEgJBYOGHc+F/gF4C8F/wDCNjRtBFkPDtzfXmlAXc7/AGaW8Lm5YbnO7f5j8NkLn5QMDFiT4L+FrjxxB4suo9W1DV7e5N5bR6hrt/c2VtOY2j82Gzkma3icI7gMkYI3tjGTQB4t4b/aI8f33hH4bfEe9j8Oy+CfHGtWOnQeH7aymXU7C3vZWjtZmvPtDRTSLmFpIhboAHkw/wC7Baton7RXxLurKx8WXsHhUeE5PiFJ4IfSrezuvt0sLaq+nxXguWmCRurGPdD5LhhGzCRDII4vXdB/Zs+HnhrXrXVtP0W4iezvJdRstPk1W8l02yupDIXnt7F5jbQSZmlIaONSPMfBG451ofgn4Lt9BTRY9F2aYmujxKsAupuNRF4L3zt2/d/x8ASbM7OMbdvFAHnv7Slx/bOvfCjwdfTPbeEvFXiWTTNdVJGjF3CunXc8VlIwI/dzSRIrRn765UghipPGWmaF+zjo1mvwz8KaF4d1jxfrdjocNvDCbfSre4cSYupLWIopZU35KbJJdsKNIAqFPWfG3w/8PfEbw7caF4i0yPUtMnKuY2do3jdSGSSORCHikVgGV0KsrAMCCM1yX/DNvw/k0HVdJvNLv9Wi1N7eS4vNX1u+vr/dAxe3Md5NO9xF5Ts7p5ci7GkdlwzsSAeS+OP2j/iB8LtO+J2k6rF4Z8Q+KPC1po2qaff2VrPY2V1Bf3TWxhmgM00kUqPDMQwkYFXQ7flIbo/Efj74uaT8SPAXw+g1XwS2s69pOq6nqGsyaJeGG0+zSWgjWG1F3ulyLgqd0qZz5ny7PKk7y1/Z18A2/hfXNAfSLq/stclgm1OfUtWvLy8vGhKmESXc0rTsqbF2qX2gZAGGIPVX3gTQtR8ZaV4ruLHzNf0u0uLG0u/NceXDO0TSpsDbW3GGI5YEjbwRk5APmvWv2rvGkvjTxANA8P3Oq6RofiL+wW0Gz8GazeXV+kcyQ3NwuqRL9kgKlpGWNkcFYhmRTJhGeEviFP8ADjTvjLd2uo2OmX1/8ULixtpb3TbvU3Z3sbRgsNjajzruXCE+UjJ8geQsBGc+6XHwH8IS+LLjxJbxa1pOpXN0l9dJo3iLUdPtbq4UIPNmtredIZXKxorF0YuFAbI4pmsfs9+AtctNQgudGmja+1k+IZLqz1K6trqO/MSwmeKeKVZISYlEeI2UbSy4wzAgHzdffGz4kfFTwX4Ru9I1vT/Derad8S/+Eav7iTw7qFsmoheYpGs5bqKaBDG6iS3lZizdHQDnodc+KFz8LfiZ8W7q00bR7vxXMng/Sl1T/SILe9vr2Sa0iknV5nVIImbftjwxXILscMPZl/Zq+Hcfgy68LJot1HpVzqq67LImr3q3h1BSjfaxdibz1mLRqzSCQMxLFiS7E39S+AvgXWrLxNa6loZ1KPxLYWmmas15eXE0l1DahxbkyPIWWRN7MJlIk3YfduUEAHjvxD/aC+IfwfsPiXpuvHw3r2vaD4Ll8X6TqWn6bcWdqwR3ja3uLVrmV+HVSHWYBgxAUFcnuPAfxH8dxfF6Hwb41XQbmLV/DbeIrCbQ7aeD7E0c6RTWkjSyP9ox58JWYJCTtfMS5AXdg/Zv+H8fh3xRotxpV9q1r4ms/wCz9WuNZ1m+1C8urbDAQm6nmeZYxvchVcBS7EAFiT1y+BdDj8W2niZbLGuWunSaVFdedJxbSPFI6Fd20ktDGdxBb5cA4JBAPEb/AMNaL8Y/2mvGfhzx5plj4j0LwzoOk3Wj+G9WgWeyaS5e8E981u4ZHkzEsIcglAGA2+a2/UuNS13w74+0z4QfDL+w/DFnpOhLrcl74gtbjVI4IJLiWGC0trdbqFgo8qUj97siREjVMEBPQvHfwX8JfEbUtP1PWLK8h1ewjeG21TR9Uu9LvY4n+/F9otZYpDGSATGWKkgHGQDWTqH7N/w/vrXRYY9KvtKl0e3ltLS+0XWr7Tb3ypZBJMsl1bzJNMJJQJX8x23yfO2XO6gDxD/hsDxPr2j+A9Os7C20TxHq0Osy6vqFv4b1PxNaxf2beiwlFvaWO2ZllmYSCR3VY0G1i7OtZWseK/H/AMUvHX7NusT29l4O1CfVdYSXTtd8N3YYXNvZ3kbXQilngkVJoVLRxsoePzFZmcDB+jNV/Z78BapoXhzSV0WXSbbw4rppM2g6jdaXdWaOu2SNLi1ljlCPgF037XZVZgWVSNW0+E3hq1n8K3D217fXfhd55NKvNS1S6vLiFpo3ikLyzSs8uUkdf3hbAPGMDAB8awtr+kfC74z6h4nfw74ptY/itp8Rs4dLurPddDUtLhE4kjvS21EMZSLPytENzSLlK+jvCPxA8f8AxE8deI59DPhqy8I+HfELaBc6bfW80l/eCNYzcXC3McuyAjzPkiaBy/lDLoJAy9lefBDwVf6FrejT6Lv03WtYj1+/h+1Tjzr6OaGZJdwfK4kt4m2KQvy424JBiu/gT4LvfG0niuTTbpdWmuYb24ih1S7isrm5iC+VPPZrKLeaVPLiKySRswMURBzGhAB8x+Bfj1e+Afhl8NPDXhXRLPQJvEF54kuBPZeHdW8QwWNvZalJG5WytpDcySSvcRZZpURMvwPkjPc6Z+0F8TfE8fwy0e10PTfDfiHxRfaxp15deItIvreMLZKzR3tvZyNHOI5kXzVhlZWAfaZPl3P6zdfs6+ALjw3o+hx6Pc2Fno91c3mnT6bqt5Z3lpJcPI9wYrqGVZ0WRpX3KH2kEAjAAGtp3wh8MabceGLjyNQv7zw0bltMvNV1e8v7iL7QrLNvlnld5cqxAEhbaAoXG0YAPnDxV8Tvif4y0PwB9h13RPC2u2PxIufDGpyQ6ZczW2otC1wkcwiW8RkhYIWeB3cszr842fP9cWP2pbSBbuWKa5VFEskMZjR2x8zKpZio64BJx6nrXE6x8B/BGuaDd6RcaVPFa3Osv4haSz1K6tbmPUHcs1xFPFKssLklv9WyjDMuMEg9zZWcen2cFtEZGjhRY0aaVpXIAwCzuSzH1JJJ7mgCeiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAopGztOOtfLPj79vDSfAOow6lP4YuLn4eHWv7Ak8Vfa1Qm737XEVvsJkRCDl965AyoagD6noryb9pP9ojRP2avhnL4v1m2n1EG4js7WwtSBJcTSNhVBPQcE5r0rR9RbVtKsb4xPb/aYUmMMg+aPcobafcZIoAv0UUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFAHC/Gf4gah8M/hrq/iDSdEuPEWrw+TbWGl26kvcXU80cEKnHRN8qlz2UMe1fKf7QHx4+Nf7K8ngDWNX17SfHd34o1D+y5vCkVlFawQzNGSphmVRIVDYBLsck19PfHz4t/wDCi/hNrPjZdEvPEzae9qiaXYcT3TT3MVuqrwckGUHGMnFfGnxc8Yad8ev+CiPwR8NtcrFo/hmN9VmR2DIb9E88QFvutIjIqkLnGT0NAHrPwe+Lnxmh/aovPhn4vtrnXtBttKW8vNfGnxW1pHO0StstyiAtGHJTLszEjPFfSWv/ABH8N+FfE3h3w7rGt2un654geWPS7GZ8S3jRgM4QY5IVlJ+tcj4a+N1r4q+KviDwhommNqOj+HLNH1PxFHOHt47phuFogVT5kgT5nORtztIzXAeDP2gIPiP+0F4f8M6p8O4YLiTR7jXdH1aeRZb2wtjKYVeaMxg25nEeVCuxxgNigD6VooooAKKKKACiikPQ9qAForJ0HxJpvijSrXVNG1K01fS7oFoL2xmSaGUZx8rqSG6Hp6Gqdz470e08Z6Z4VmvfL1/ULGfUray8pz5lvC8SSvvAKDa08XBYE7uMgE0AdFRXPal440fRvFWheHL298nWNcFw2n23ku3niBFeb5gpVdqsp+YgnPGa6GgAooooAKKKKACis/xDr1j4W0DU9a1Sf7Lpmm20t5dT7Gfy4o0Lu21QScKCcAEnHAo0XWrXxFpFjqmnzefYXsEdzbybCpeNwGVsEAjIPcA0AaFFFFABRRRQAUUUUAFFFFABRRRQAjAMpB6Y5r87fjh4N0DxR+2V8BPgDoWmxaZ4L8K7vEVxpoJeIsgaUKckk7ghUkk/eNfokxwpP86+H93gb9qn9qPUfEXw48R6t4O+JPw5WSyutck0xLiwu4mJjKMjSKX6sD049OtAGL+3wYfiz+0v8Avg06s9nPfjW9R8s8i3DFAD/wB+2/P3r7A+IninxT4a/wCEfTwp4S/4Sl7rUYrW/wAXiWy2FoQS9zhvvgYA2r16V8P/ALF/w9u/in+2D8QvjBNr934z8P6Kp0bSfEF5EY4r24KhJpIIxlRErK+3bjAYHk816i2teOm/bS8HeG/+EmuGu47XVNe8SWMMwk0+HSmlFvp1uFYfLKRH5pPXc74+U5oA+x1ZjjIx+Ofwp9RKfUbeemMe1S0AFFFFABRRUN5dw6fZz3VzPHa28MbSSTzMFSNQMlmJIAAAyST2oAmorP0nWrPXtLtNS028t9R068hS4truzlWWKaJ1DI6OpIZWUhgw4IOazovHWjy+NZfCK3mfEMOnR6rJZ+TINts8jxLJvK7eXjcbd27jOMUAdDRXO/8ACdaPH42s/CUl5s8Q3mnTatBZeS53WsUscUknmBdgw88QwWyd2QCATXRUAFFFFABRRSE4GT0oAWiuf8ceONG+GvhHVfFHiS9Gm6HpVu11e3XlPL5USjLNtQFjx2AJ9BW1HIXVSeOmR+H/ANfvigCaiiigAooooAKKKKACiiigAooooAKKKKAMXxd4N0Xx54dvNB8QadDquj3gUXFnPkpJtcOM4PZlU/hXJ3n7Onw0v/Ctp4bn8GaXJotpK08Ft5RHlyNnc4YHdk5OTnmvRqKAMLwr4J0PwLoMekeH9KttM0+LJS3gXALE5JJOSST3OTXzL8M/BfjrQ/2pviZ4nvtAlF1rurwQx61Koayh0G3tU8pIWJ/10krvuHAzGx7ivrYjcCKNo446dKAPNfjVN4m/sGxHho+Mvtf2r97/AMISNFF1s2t/rP7W/deXnb/q/n3Y7Zp/wTbxN/YN/wD8JMfGf2v7V+6HjX+xPtWzav8Aq/7K/deXnP3/AJ87u22vRvLX096NoHQY70AfK3wp+NPjLxF+0HefD3VfFNvc6DoVzqs9rrq2aRyeJ/LeJDZAmJYg1ibjZM0BBd1iPybZ0PS/HP44a98CvHs95cyHVvDWseGrn+xdLaGNW/ty2cFLdXG12N0kwABLYNsxGAWz7LafDvwrp9vo0Fr4a0i2h0WZ7nTI4bGJFspXDB5IQF/dswd8lcE7jnrVrXfCOheKP7O/tnRtP1b+zr2PUrL7dapN9luo8+XPFuB2SLk7XXDDJwaAPkv45/GL4g/Dnwjrlrp/izxFrHi3wH4QttW12fRtL0WKx+2PHMyyag146O8MzWz7YrFFkRQ/zOzxBfQ/BfjDxp8Rv2gvEGnf8JfcaN4Y0PQdA1j+x9PsrVxcTXf2syJJLLE0nlEQDKptfhSsich/W/FXwj8DeOtUttT8S+DfD/iHUraFreC81bTILqaKJgQ0avIpYKQzZUHB3H1rasPDOj6VqFxf2WlWVnfXMMNvPc29uiSSxQ7vJjZgMsqeY+1Twu9sYyaAPjvwF8UtcuPgr8LPD+iX+uaZ4hv9L1HU5NN8A6RodtP9nt7ryvMzfFLKGBDKu+NI/MkZ42VlVJd+V4J8beIvjd8Rv2dNavfGLeDvEHiP4f6xJc6jpdtavcXTrcWLNHbJOksSufK8xj5cgCLKFVch0+uNV+Cvw913S9J0zUvAnhrUNM0iRpdOsrrSLeWGydjlmhRkKxknklQMnmjVvgp8PNf0u20zVPAnhrUtNtYGtYLO80i3lhhhaRJWjRGQhVMkcbkAYLIpPKg0AfMPgv4ia9408bfA3WtZmj8R6tp0/jXTo9TtYkiXWEtH8iK4RV+QGZIlYlMJuLbQFIVdf9m/4pfGT4kXHw78W3dl4h1Pwx4otJLzWm1EaDDo2nxyQmWJtP8As07Xx2ShYdlzvYqxLiNhx9RWngvw/p/9im10LTbY6JAbXS/JtI0+wQlFQxwYH7pCqqu1cDCgdhWNpHwX+H/h/wAXTeK9L8DeG9O8UTySzS63a6TbxXskkpJldp1QOWcsxYk5O45zk0AeZ/tIeLPGXgbUtP8AEq6t4g0T4YaZp80+tXvhKHTJry3lEkZ865S/jctbJEJDi1BmJz8rZXHnXx2/aG8VeGfEmt6t4S1fxDdab4b1/SdGvbeLT9Jg0OJriS0823uzcyf2hLOyXRYSWwSNd8KlcxzO30r4i+EPgXxhr+n67r3gzw/rmuads+x6nqWlwXF1bbXLr5crqWTDksMEcnPWmav8G/AHiDxKfEWqeB/Dep+ICqodWvNJt5rrauNq+ayFsDAwM8YFAHzV4++JnxSt4/jb4j0nx+2mW/gfxVZafpGjPo1pNaXETwac80V0SomkU+fJt8qSGRS7Eu4KLHd+J/xO+IXwf0f446UPHFz4hvNB8A2/ivSdY1CwsluLO6lkvomjVYoUieIG0RlDozAsQxYYA+nJ/Avhu6t9Wt5tA0yaDVpVuNRjktI2W+lVUVZJwR+9YLFGAzZICKOwrl/jJ8HrD4sfD/xroUZtdH1bxNob6HLrq2iyTpCRIEVjlWdEaWRghYDLtjG4mgD5/wDiB428UaXb674fuvH6/ETQvFnww1zxBIVtLSFNNkijhEUtq1vGp+yzi7dUWZpm/dIRK3zbspfiV8TNSvNG8F+DYvFFqmheAtG1C2XwtDoZN3dXEUih7o6pKpNujW6oFtwr5aXfICYhX1J4X+EvgnwvaavHpnhDQLB9bULrMlnpcEX9pkhwWuNq/vc+ZL94t/rW/vGneKvgr8PfHVrpdr4k8CeGvENtpcXkWEOq6Rb3SWkZCgpEJEIjXCIMLj7i+goA8U8V+Pvif4Z1bwh4m8cvrnhHwjNp2jx6nb+E10u8gsdWmnEVzBfi4jkneBpJoIkayJIAkJK8OPpsMeOfqO4/zxXISfBf4fTeJNO8QyeBPDUmv6akUdlqr6Rbm6tUjGI1il2bkCDhQpGB0rsVQL09MdaAHUUUUAFFFFABRRRQAUUUUAIehrwbXv2NfAeu3mrt9o8QaVpWs3D3ep6DpesTW2nXsrEFmkhTAOT24r3qkChegx9KAMXwr4R0bwL4ds9C8P6Xa6RpFjGI7aztY1jjjUDHAA4rxTxF+ymniD40a74zl8RXKaXr76a+p6YIQZJVsg3lW6S8NHCzFZGAIyyDtX0KVB6ikEagYx/nrQB538ZB4iXwnZf8IwPFwvvtab/+EJ/sf7X5flvneNV/ceXu2Z2HzM7cfLvo8D2/inUPhbc2l9qHijSfElxFcRQah4qi0mXULaRgRHKUsAbVgpIZVxkgfMDXom0dcYNIygLwMY6cdKAPmz4C/G/xV8Y/GGgabLdiwfwxoEsfjiySGMg64bhrVbfftygRrS8lwmMrJAeVYbo/jV8bPGPwr8ceLvDsN5HdXfijRbZ/AMc1ugEOqNcR2M0JwmZUSS6srht24hXl/hAC+qfCn4V23w1uPGF4btNT1bxR4guNbvbpLUQffCRxRAbjxHDHGuc/OQ74G8iuw1bwloevajpmoano2n6jf6XI01hdXdqksto7LtZomYEoxUkZXBwcUAfJX7QXx+8YfD+TxNd+GvEfiHVG8Cy6TaapJb6fo0WjGeZrdmivzcOLuSSVZhzZCNU86NQGdHrubPxB4z8WfFb45w3XjGeHwv4PmitrDw7Dplk8M6zaLbzuLl5ImkkQSSl1VGQ53hy6FUT2LxB8HPAPi7xCuva74I8Oa1riwm3XU9R0mC4uREVKlBI6FgpVmGM4wx9a3YfDGj28+rTQ6VZRTauwfUZI7dFa9YRrEGmIH7wiNFTLZ+VQOgxQB8Y3vxm8RW/7P/w7s/Des69p3iG0+F1j4pvLfwfpWh28FjGbUBLi5GoFIVtd8cgWG0jVlET5KqYxVzw7rmu/F74/+GdXi8cP8O9V134RaTrVw2j21rLM5e5uJGSP7YkqiJWk3MPLL42/OvO/6j1X4L/D7XY9Bj1LwL4b1CPQESLSFutIt5BpyIFCLbgp+6ChEACYxsXHQVDr3wL+G/iqys7PWvh94W1i0s4IbW2t7/RraeOGGEOIYkVkIVIxLIFUcL5jYAyaAPk/wz8aPEepa94T+J15Zwar4it/gv4i1UR28Rig1CWG+sWjZBnIE3lqwUHADjBFem/s8+MPi74i8R+G7/WbfxFqvg7WtEN7fal4g/sCO3guWWJ4H05dOneUwSB5gVnMjBViPmZ3b/oiPwzo8Op22pR6VZR6ja2rWMF4lugmht2ZGaFHAysZaOMlAcEopxwKwPDPwY+H3gnXrnXPDvgXw3oOtXSyJPqWl6Rb21zKHYM4aREDMGYAnJ5IBNAHl3xi8Y+MfAvxKsNd1PV/EGl/Ctf7OthP4Xg0yZY7uW7MLrqCXUT3JikaW2jU2Y3L+9LY+VxwPjb9oTxVp/xX0K98Par4i1DwvJ4/t/Bd0s1hpMOgSs0hgnhTLnUjcRMXPmjETPA2F8tga+ldS+EvgfWPGFt4tv8AwboF94qtSpg1y40yGS9iKjClJyu9SO2DxUEnwX+H03i2bxTJ4F8NyeJ5pI5pdafSLc3rvGyMjGYpvJVo4yDngopHQUAfMV98SfixcaTrHie1+IzWawfFA+CrPR5NEs3sxZS6qtkskx2CaSWMThlaOVFIiQMrEuxv/En4vePvhT4H+NFp/wAJ4b+78J6j4fbTvEeu6fZ+bbwXstqs6XKQxwxOigykMI42CSH5sqHH1IvgXw3HayWy+H9LFu+oDV2h+xx7GvRKJhdEbcGbzVEnmfe3ANnPNch8YPg7YfE7wbrOjWslvod9q13p1zd6pBZq8032W6hnQSbSpbIhKAk/KG6cYoA+Zv2lfEPijQ/hz8c/AeqeMbjx5pf/AArz+3Vvr60tYbmxlkkli8otaxRRtFIqGRNybxsf5mGMdN8SPil8Y/EXxW+J+i/D6x8RTXPg37HBpNjo8ehHT7yeSzjugdSa+nW68qR5PK/0URkJGxDM+VX6I0X4M+AfD/hvUvD+l+BvDWm+H9WydR0uz0e3htLwkAHzYQm18gAfMDxipPG3wX+HvxKv7e+8X+BPDXiq9t4/Jhuda0i3vJI48ltitIjELkk4HGSaAOn066uLiztXu7b7HdSRI8tv5gcROR8yBgPm2nPPfirlNCKOgp1ABRRRQAUUUUAFFFFABRRRQAUUUUAFFJXkvxU+J3xH8H65BaeEPhRJ460+SHzHv112GxCN02bHjY/jQB63RXzvp/x0+NlzqFpDdfs+SWdtNMiS3P8AwlcDrDGWAZ8CHLYGTjjOK+g1LbV3HHTPT/PtQBLRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABSFQaWigBu0Zz3/wA/4U6iigAooooAKKKKACiiigAooooAKKKKACikbO04649M15H8bNI8barf6V/wi3xXtPhvBteOSG4021umu5MggqZ1OMDjC0Aeu0V82SfCP4/LCZf+GilWPbu3t4U07bt5+Yny+nSvf/Dkkx0PTVuNRj1a5FtGst9Eqqtw4UB5AF+UbiCcDgdqANSiiigBvlruzjmnUUUAFFFFABRRRQAUUUUAFFFFABTRGoXAGB6dhTqKAECgZwMZ60tFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFACN90180TSfEH42a14y1eTxDr3wr8E6E81no6WkEUN5qTxA+ZezNMCFgLDCJhS6gnctfS7Y2nIyMema/Pn4p/t1H4qfsv8Axgl0/wAKaroVyry6BossybpNRd8xyPEnVjGcs2BgDrg8UAch4J+PX7Q3xq/Zej+JWj/2nqGs2d+mh6bpfhtY7d791LGW/uWkR90YJSPykAOUYlgK/RfwPLqtx4P0KbXovK1t7GBrxQc7Zii7x/31mvkz4F/E7R/2c/2J/hDpmgxWviLxbr1hANG8O2twvnXtzcu00hO0khIzJIzv0UKQTnFfY2my3E1jbPdxLb3bRq00MbbgjkZZc9+aALlFFFABRRRQAUUUUAFFJXJ+P/idoPwy0uy1DXrm4iivLqOytYbOwuL24up3VmWKKC3SSWRtqO2EQ4VGJwASADraKrW919qjikQuI3AbEkZV8HkZBAKn1BGR3xVhs7TgZNAC0Vz19440fS/GGieF7q9Meua1BdXVja+S582K28rz23BSq7TPFwxBO4Yzg10NABRRSHoaAForKsPEmmapq2oaZZ6pZXmoacUW+tLedHltS674xIgYsm5SCNw5BBHFatABRRRQAUUUh4BoAWisrSfEmma9JfppupWeoPYXLWV2trOkpt7hQrNDJtJ2uAykqeQGHrVLxJ460fwjeaDa6te/Y59d1FdK09PJd/PuTDLME+VTt+SGQ7mwvy4zkgEA6KisDxV450XwRFpkut3v2KPUtRt9JtW8p5PMup3CQx/IDt3MQNzYA7kVv0AFFFFACN908Z49K/N3/goB4V1Twr8O/F/iDxM9vrXjrxhr0Gh+Dre1leRdKskbcgiUqPLmdQzOyjIJHzV+kTfdNfHn7cnw+8Ua546+CfjbSPDt94u0Dwf4gjv9W0rTVEtysQZW81IyQXIC8qBk4xx1oAp/tveLtV+DX7BVvoN3eyTeKdR06w8ONPG+2SSdo0SRxjHPynOPWvof9nPwj/wg3wI8AaE/mNNZaNarL5jMzCQxhmySck7mNfBf7UXxUi/ay/ai+Bnwws/DmvaRosGpHVbmbXLGSxluACVLCB8SKgEJwXVSd3THNfpwihQoQAKBgLjHHAoAlooooAKKKKACiiigAoqvf31vpljcXl3cRWlrbxtLNcTuEjjRQSzMxIAAAJJJwAK534d/EXSPil4bt/EGgHUG0q5w0Emo6Xdae0qlVYOiXEUbshDAhwCpzwTg0AdVRRXP+OfHGj/DfwnqfiXxFef2fommxeddXflvJ5SZAzsQFj1HQE+1AHQUVDHIWwSceo9Pb/OKmoAKKKyr/wATaZpN9ptjfalZ2d7qczQWNrcTpHLdSKrOyRKzZdlRWYhcnCk9BQBq0UUUAFFFFABRSHoeM1mXfiLTbHVtO0y51SzttR1AyfY7OadFlufLUNJ5aE5fapBO3oCCaANSimTTJbwySyNtjjUszegAyTWF4K8baT8Q/CmkeJfD959v0PVraO8srryni86J13I2xwrLkEHDAH2oA6Ciue8EeOdG+Inh2117w/e/2hpF0ZFhuPJeLeUkeN/ldVYYdGHI5xxmuhoAKKKKACiiigBOvFcXpHwV8B6B4su/FGm+EdIsvEN2XM+pQ2iLPJuBDZbGeQSD7Gu1ooA4Xwl8C/h94B1q41jw34N0bRdWmUq95Z2iRykE5IDAcZPXHWtfxvPdR+GNVTT5NRXUpLaQWq6M1p9uMm3K/Z/tZ8jf6eaNmcZ4ro6aUDYzzjn9MUAeG/BuTx6PFrL4lb4o/YDavj/hMh4V+xb8rgj+y/8ASN+N23I2YDbudtcp8VvFnxA1f4xfEfw7oHj+88G6V4f8D2mvWcdjpljcStfPJfLlnuIpAYcQJvjC7iVUrJHhxJ9O7BnOO+azZPCuizX9/fSaRYyXuoWyWV5cvbIZbm3TeUikYjLovmSYVsgb245NAHzV4V+K3xB0PV/AWrav4gfxRD4z8Gaj4jn8Prp8FvBY3NvBaTxx2ZRPPCEXLIVneZvukMOc53wI+Knxb8QSeEPFutx69d+CNa0i41PXdQ1pdBTTNNzB50L6etlO100auDGUuPMfY6szKytn6kt/COh2s2lSw6PYxS6TbNZ6e6WyA2cDBA0UJx+7QiOMFVwDsX0FYWg/Bf4feFvFE/iXRfA3hvSPEdwZGm1iw0mCC8kLnLlpkQOdxPOTz3oA+ZfAf7QPjm88f6Ej6p4hv/D3i7wfqniOxn8QWGjwQt5KW8kE+nxWcj3EcDC4P7q+LSAeWNzsshre+CvxB+I0k3wB1fxF43m8TQfEXQJLnVNMuNNtLe3s5hYR3cUlsYYVkDDDJIJJHVjISipgKvvXh74JfDvwjeTXeheA/DOi3UyyrLNp2j29u8iyACUMUQEh9q7geuBnpW5Z+DdA0+PREtdE0+2j0OLydKSG1RV0+Py/K2QAD90vl/JhMDbx0oA8q+I/ibxH4g+OGgfDjTPFdz4GsbjQ7nXH1HT7e0lvb+SOZIfs0X2uGWIIiuZJMIX5iwVXIfwO61rxb8Xpv2fr+/8AGuqWt5a+Ote0Nda0O1sVh1AWdvqsMeoKs1vInmzRwEED91+8lKxr8hT7F8bfDPwh8SrG3svF/hbRfFVnbyebDb61YRXkcT4I3KsisA2CRkc4OKuR+DPD8MeiRpoemomh4/spVtIwNPxEYR5HH7rETNH8mPlYr0OKAPO/jl4+1f4X6p4D8TDUI7fwX/bK6T4jhkSPYkV0PJtrjzGG5fLuTCp2kArM+QSFx5avxg8Z+IPBfgcHV/E8fiPxzLqOv6Zo/hHT9JGpw6Orq1spl1IpbIqQTW/m71aVpJsIQqNX054g8M6P4s0S60bXNLs9a0m6j8q4sdSgW4hmTIO10cEMMgHkdqy/GHwv8G/ELS7PTfFPhLQ/EunWbB7az1fTobqGBgu0FEkUhTjjgdKAPkv4V/EzXPiz4k/Zx8XalMl54hvPB/i4SXNrFGvnyxTafEswVCyZcxgkKdm5jt+Wu3+G/wAevEPiHQv2WvtXiO2vtV8b6fNda3DGluJL8xaTLNIyoF+QLcCPJTYAcKeuK+iLDwN4b0u4064svD+l2lxpqTx2UsFnGj2qzsrTrEQuUEjIpYLjcVBOcCsvQfg74B8K6xPq2i+CPDmkarPcfa5b6x0mCGeSYrIplaRUDF9s0w3E5xK/945APm39nn4tfGf4n3HgDxjLpXiS98PeIZZX121vjoMei6dbMkpQ2TQTG/MsMyQxMtwGJBm3LG4UJ3/7PHjLxl/wleqeE/iVqniGbx5Hp66k9ndW+mjRZYfPkiabTZbWITCLcFAS8YTBShK53mvTbf4H/Dm18WS+KYfAPhiPxPK0rya0ujW4vXaVWSVmn2byXV3ViT8wYg5yaueCPhP4J+Ga3i+D/B+g+FFvdn2oaJpkNn9o2AhPM8tV343NjOcbj60AfM/xU+JXibwTrHx7vvC95pujaxY654OtbW/fSYHO26ls4ZftOArzgpK6gO+5VOEZMAj1X4T654r0P4zeOvAXiHxXeeM9P03SdK1ix1LU7S0gu4zcyXcUsLm2ihjZQbRWX93keYwLNxj0++8A+GdTbUGvPDulXbahLbz3jXFlG5uZYCrQSSEr87RlFKM2SpUEYwKvQ+H9Mt9audYi061j1e5gjtp79IVE8sUbO0cbSY3MqmSQhScAu3qaAPmTxx8aPGOgftMWvw1tvFNuvhrWtQsJ5dfNmhn0F2ilkGkA+SYXe7+zAxvK3mIssvVjb59O+OHj7Wvhhq/gLxGL9YPBv9rrpPiSF4k2LHdgQ21yXKlk8u5MK8OAVnbIJC47y5+HfhW9tdQtrjw1o9xb6jeLqN7DNYROlzdKYys8gK4eQGGIhzlh5ac/KMXPEPhXRfF2jXOka5pNjrOk3SeXPYahbpPbyrkHa8bgqwyAcEdQD2oA+X1+MfjPxN4R8Fsut+KIte8Zf2l4lsdG8IabpC6jBpAlj+yq02plLZI44Z4fMDK00kkqlGVEdTkfDj4xfEf40f8ACiLIeOZPC6eJ/Cmsanrl5pGn2UlxcS2k9pHFLCZ45YomYyMT8jx7WcKCTHJH9R+LPhX4K8e2FhY+JvCGheIrLT23Wdtq2mw3UdscBcxrIpCHAA+XHAq7p/gbw5pE+nTWGgaXZTadFNBZSW9nHG1rHM6vMkZA+RXZEZguAxVSckCgD5it/ibe6DY/EmxtLm50zV9S+J8+habD4V0nT11K8kNhBOyRtcBLbzdqSSNcXe/KIycsYwPOtW+JXib4i+Efhvb694ln0TWdH+Nc/hqPW9Wg09r+FV0+/WNZlgY2bXambylKAx+YqFo3O5G+1tY+FngvxDpGpaVqvhHQ9U0vU7r7dfWV7psM0N3cYUedKjKQ8nyJ87An5V54FVf+FM+AP+Edj8P/APCD+HDoMbmRNL/smD7KrmA25YRbNuTCTFnGdhK/dOKAPlrxt4s1++1L/hE9b8Qy+LovCvxY8K2lnrlzBbw3Mwla2uHimECRxM0ZmIyiJ8rJkE5J1NF+LXxo8c+Ntd1Tw1pXiS+tNH8bT6C+kxLoKaCNPt7sQTmZ5J/7RFwYA9wrLtXc0SiN05f6c0n4X+DdB0HTtD03wnomn6Lp10t7Zaba6dDHbW1wrmRZo4wu1JA5LB1AO45zmqerfBb4feIPFsHinVPAvhrU/E9vJFNDrV5pFvNexSRY8p1mZC6sm1dpByNox0oA69S24E5A6Y4/z7VJTdoHanUAIxIUkDJxXxx4g+EPxV8IftbeJPivp+laj4+06401bDRdIg1i3s7a23JhvtCzOOAc4KIfoelfZFN2DIOOf8/40AfN/wACf2atW0f4ra98ZfiVeW2rfEnWk8iG2sSxs9GswAFt4S3LHjlu5z616V8apPEn/CM2J8Mv4vF6bxfN/wCEKGjfavL2Py/9q5h8vO3Oz95uKY43Z9H2g9aQqG60AfLHirxh8TfCvgfw7EmseMtD1nWvGmm6MLvxxZ6BcTrbT7lkESab+529CC537h/d4rmvFXjz4p+DdE+NWpr8Ub7Uo/hfqVsbCC60fTlfWIns7S9kiv3SBQyFZzEhtRbuo3Mxcldn19qnh/S9c+yjUdOtdQ+yXKXlv9qhWXyZ0JKSpuB2uuThhyM8VVvPBPh7UIdahutB0y5h1og6pHNZxut+RGsYM4I/e4jRE+bPyqB0AoA+XfiZ8VPjFr3xS+J+i+ALDxLNc+DvscOlWOjxaF/Z97PJZx3IOotfTJc+VI8hi/0XYVWNyGLnatP9pj9orxh4L/4S3V/C994hSfwTHpsmq6dp9ro/9jWtxOYpPsd/LduLuZpEdQHslUBZowCXDY+lfG3wX+H3xKvoL3xd4E8NeKry3i8iG41rSLe8kjjyW2K0iMQuSTgcZNL4l+DHw/8AGmuLrPiHwN4b17V1tzaC/wBT0mC5nEJDKYvMdC2zEjjbnGHYY5NAHzx8UviJ8SodS/aK1nRvHs2i6d8NrKLU9I0eHS7SWK6K6VHdyRXMksLO0TMrACNkcea/zkbAnrXx8+KmreAfgjL4m0ma10++uZNNtvt93F50Gmpd3MMD3ci5AKwrM0nJ2ny8HAya9EuPBHh28TXUn0HTZl15PK1YSWkbf2gnleVtuMj96PL+TD5+XjpVzUNC03VtJuNKvbC2vNLuIGtp7G4iV4JYWUq0bRkbWQqSCpGCD0oA+RfjZq3jLRdJ+MHw8uPiHrPiTTf+FbXniQatcWunR6hYSp5iG2ZoLVIjDcIrgEw+YPLl2yA7Svs3hHwv4qh/ZotNK0TxZey+L5vDq/2ZruoW1o729y0AaDMawpE0cbFQMoSVBySea7Xw78IfAnhHQ9T0XQvBfh7RdG1QML/TtP0uCC3uwy7GEsaIFcFflO4HI4rqLWzgsbWG2toY4LeFFjihiUKkagYCqo4AA4wKAPlXSP2qr7xf4e13x4NT/wCEW8IeG/B0E+qRyWC3Zj1y5+doCmVdmtVRUKCVAzXYDfdyPLPip8SPGmqfDP8AaG8DeKJPElzBpXhbTtSth4tTSDqcLTzzpIjHSSYDERBGyhwJMl85UrX3JY/D/wAL6bpms6bZ+HNJtNP1qae41S0gsokiv5ZhiZ50C4laQcMzAlu+ayNJ+B/w60HS7zTNM8A+GNO028gW1ubO00e3ihnhV2dY3RUCsgaSRgpGAXY9WOQDxT4ifG/xD4Q0f9qa4PiC209/BmkRXfhxp0tx9keXSfMhI3L+833YYL5m/cwKDI+UYnj74rfFfxJ8SNc8L+D18TpLoXhywv7Y+G4dBZL26uo5WEt7/aUqN5AaIKFtgh4mJcEoF+jvEvwh8CeM9ci1rxB4K8Pa5rEVs1nHqGpaVBcXCwEODEJHQsEIllG3OP3jcfMaZ4y+DfgD4jCxHizwP4c8UfYVZLT+2tJgvPs6tjcI/MRtgO1cgYztFAHjGv8Ajv4keGfGnhPXfHs2ueEvCF/DottJZeFxpl5Z22qXDmOe21AzxPdFGnkghjktDjDEsY8bq6/42axPpvxW+BcMUNs6Xnia6gke4sop5UT+yb5/3TyIWicsgBaMqxXIJKlge4Pwa8AHxXaeKP8AhB/Dn/CTWaoltrX9kwfbIVVNiBJtm9Qq/KADwOBxXQah4d0rVbzT7u9020vLvT5zc2c88Ku9tKUaMyRsRlGKOy7hg7WI6GgD5P8Ah78TviXceG/ht431Tx1LqsOv+Nrnw5d6AdNs47I2X2m9gjdXSETmdTDE+8SBCqEGPOWPsHx0+JGpfB/xD4H8U3mqLZ/Ds3sumeJRJEhS1E8f+iXbOV3KFuI1iIBAxdEkEquPQ4fA3hqx0uz0+Dw/pdvp1hcm+tbSKziSK3uN7SeciBdqvvd23DB3MTnJJrmvjh8K4vjZ8Pbrwbe3kdppeoXdo2oCS1E/nWsVzHNLAAWXaZFjMe/5tu/cBkCgDC+F934+8efs+rqeo6zJo/jLxJZXWpWFw1nDnSFuTJJZQ+WU2uYI3hVt6sWKNuyTXlfhj9qTW/Fnh298W3Gow+F9E8I+CJL7xR51gt7FFrryPGYWVGV3Fs1ncFo43jL+fGCyn7v1dGgjRUAAUfL2/kKydP8AAvhvSoNZgsvD+l2cOtTy3WqR29lGi380i7ZJJwF/eu6jDM2SRwaAPjXXP2gPiX4L0n416ZLqnie2vdB8AjxPpN14yttDfUbS4L3CBsadmBoj5aEJLHvBVsjBFep63caz4N+KvwVTxF4iHia5vH1m7vdS1PSrGJ7UDTlkaG1ZIQ9vErKTje0jKdskkgHHrmjfA34ceHdKvtM0nwB4X0vTb+BrW7s7LRraGG4hb70ciKgDocnKkEHNdLP4a0m6vtOvptMs5rzTd/2G4kgVpLXemx/KYjKbl+U7cZHFAHyV8Mvjx4w8Q/FTwdZ3GreINV8J+N/Dmp6vBNr1jpNpayiJIJIp9NitJHuoYGEzDy71mkCtGCzOrk87+y/4q8S+DfhP+zDdaf4/PiTS/FqroVx4W+xWv2a1hisbiRpbdoUNwJIHtVSYyyupZ5MrD8qJ9ceHPgz4A8H6lNqOg+BvDeiajMXaW807Sbe3mcv98s6ICc9+eaXwv8G/APgjW21nw54H8OaBq7Wy2Rv9L0m3tpzbqEVYjIiBtgEcYC5wAi8cCgD44+GPxI8Z6Z8Pvg74G8KQ+IbeHV7XxHq1xdeEV0htQlNtqfliGM6o62wjH2kyOVDyHagUBd7V9bfA3VPG+qfDXSJPiHpjaT4qRpoLmKV7dpJUSZ0hmf7O7xLJJEqSOqNtVnYDAGBpa18HvAXiTwzbeHNX8E+HdV8PWs5uoNJvdKgmtIpjvzIsLIUVz5knzAZ+dvU1ueHPC+j+D9FtdH0DSbLQ9ItV22+n6bbpb28K5JwkaAKoySeB3oA06KKKACiiigD/2Q==)

p <- ggplot(mydata, aes(x=Glucose,y=BloodPressure))  
p +geom\_point()

Chart, scatter chart

Description automatically generated

Figure 6

Above figure gives us an idea of the relationship between glucose and Blood pressure in this dataset. As we see majority of data came in between range 100 to 175 of glucose and it happens in range 60 to 90 in blood pressure. Based on data with see people with high glucose in blood have higher blood pressure and this is also lead them to have diabetes. This is one of the relationships that BloodPressure has with other factors that we see in this data set. We will also test other types of relationship with linear regression

mydata\_lr<-as.data.frame(mydata)  
SAMPLE\_X <-  
slm <- lm(mydata\_lr$BloodPressure~mydata\_lr$Glucose, data = mydata)  
summary(slm)

##   
## Call:  
## lm(formula = mydata\_lr$BloodPressure ~ mydata\_lr$Glucose, data = mydata)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -33.683 -7.601 -0.203 7.709 38.310   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 61.78495 1.66518 37.104 < 2e-16 \*\*\*  
## mydata\_lr$Glucose 0.08685 0.01355 6.411 2.71e-10 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 11.06 on 678 degrees of freedom  
## Multiple R-squared: 0.05716, Adjusted R-squared: 0.05577   
## F-statistic: 41.1 on 1 and 678 DF, p-value: 2.706e-10

plot(x =mydata\_lr$Glucose , y =mydata\_lr$BloodPressure, main = "Linear regression of DiabetesPdigreeFunction over Blood pressure", xlab = "Blood Pressure",  
 ylab = "Diabetes pedigree function", col = "blue")  
abline(slm, col = "red")

Chart, scatter chart

Description automatically generated

Figure 7

plot(slm,1)

Chart, scatter chart

Description automatically generated

Figure 8

plot(slm,2)

Chart, line chart

Description automatically generated

Figure 9

As we all know Linear regression attempts to model the relationship

between two variables by fitting a linear equation to observed data. In our situation we have right now If we look closely to our first plot (Figure 7), we will see that almost all of our variables are near the line that we have, and we see also outliers above the line that we have. If we look closely to our second plot (Figure 8), we will understand that: Here we see that linearity seems to hold reasonably well, as the red line is close to the dashed line and as we go to the end the spread of the residuals seems to be consistent and it keeps straight with little bit damping. Last plot also shows us that most of variables happens in range [-3,4] as we see in linear line. After 2 we see that values are getting away from the line we have, and they go increase exponentially In overall we see couple of data that they are far away from the line one is. The R squared number and adjusted R squared number shows that all data did not fit into this model perfectly that much, but it also shows that Glocose and blood pressure are in a same way and by increasing glucose the blood pressure is increasing also this shows how accurate our principle component was because we had same data in our PCA and we were getting kind of same results over there too.

mydata1<-transform(mydata,Insulin=as.numeric(Insulin))  
mydata1<-transform(mydata,BloodPressure=as.numeric(BloodPressure))  
mydata1<-transform(mydata,Outcome=as.numeric(Outcome))  
x1=mydata1$Insulin  
x2=mydata1$BloodPressure  
y=mydata1$Outcome  
glm.fit1<-glm(y~x1,mydata1,family='binomial')  
glm.fit2<-glm(y~x2,mydata1,family='binomial')  
glm.fit3<-glm(y~x1+x2,mydata1,family='binomial')  
summa=summary(glm.fit3)  
summa

##   
## Call:  
## glm(formula = y ~ x1 + x2, family = "binomial", data = mydata1)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.3674 -0.9026 -0.7565 1.2890 1.9241   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -3.550241 0.574568 -6.179 6.45e-10 \*\*\*  
## x1 0.003115 0.001021 3.051 0.00228 \*\*   
## x2 0.035964 0.007584 4.742 2.11e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 860.49 on 679 degrees of freedom  
## Residual deviance: 829.31 on 677 degrees of freedom  
## AIC: 835.31  
##   
## Number of Fisher Scoring iterations: 4

tabel=as.table(c(glm.fit1$deviance,glm.fit2$deviance,glm.fit3$deviance))

table

## A B C

##852.9303 838.6008 829.3103

beta=glm.fit3$coefficients  
beta=as.vector(beta)  
beta

## [1] -3.550241218 0.003114627 0.035963933

glm.fit4=glm(y~x1+x2+x1\*x2,family=binomial(link=logit),mydata)  
Sum1=summary(glm.fit4)   
Sum1

##   
## Call:  
## glm(formula = y ~ x1 + x2 + x1 \* x2, family = binomial(link = logit),   
## data = mydata)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.3613 -0.9026 -0.7556 1.2897 1.9279   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -3.579e+00 7.621e-01 -4.696 2.65e-06 \*\*\*  
## x1 3.519e-03 7.130e-03 0.494 0.621610   
## x2 3.635e-02 1.010e-02 3.600 0.000319 \*\*\*  
## x1:x2 -5.475e-06 9.548e-05 -0.057 0.954273   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 860.49 on 679 degrees of freedom  
## Residual deviance: 829.31 on 676 degrees of freedom  
## AIC: 837.31  
##   
## Number of Fisher Scoring iterations: 4

In above we did some logistical regression that gives us interesting results also. In this regression we used insulin, blood pressure and output to see some results. Based on the model above we got beta for Insulin and Blood pressure which shows that Insulin has beta 0.003114627 and Blood pressure has 0.035963933. this shows that blood pressure has more impact on Output rather than insulin. based on the results we see above we can say that our model c which include both Blood pressure and insulin has lowest deviance. So, our model fitted in section is adequate and So last model will be using for the rest of the analysis. By adding interaction term to this model, we see that the residential deviance and AIC did not change that much, and we got same kind of result which is interesting to us and it shows that adding interaction term does not worth that much because the results wont change for us that much after adding it.

**Conclusion**

Based on the values we have we see there is no missing data or any mismatch data in any columns and that gives us opportunity to have better analysis because we don’t need to remove any rows for missing values or mismatches. Based on our analysis on plot diagram of Age vs Diabetes Pedigree function we can say people with age between 20 to 32 with diabetes pedigree between 0 to 0.75 did not have diabetes because the outcome shows 0. By looking at plot diagram of Age with pregnancies also we see people with age 20 to 30 had mostly 0 to 5 times pregnancies. In other plot diagram we see most people with glucose 75 to 120 have blood pressure between 50 to 90. in these discussions 1- we worked on the relationship between sample of blood Pressure and skin thickness. 2- It was great idea to use and calculate PCA on covariance and correlation matrices of this dataset for next stage it is important to apply more hypothesis testing and statistical plots along with linear aggression so major question can be answered for this project. During this project we analyzed the major factors that can lead women to have diabetes. We saw that factors like Pedigree function in low percentage had higher diabetes rate or we saw that by increasing glucose the blood pressure can increase and this highly increases the chances to get diabetes. Having high BMI and being obesity and overweight are also another factors that causes diabetes. Finally in this data set people by increasing their number of pregnancies increased the chance of having diabetes but after some age we saw that there is some damping rate.

**References:**

<https://www.kaggle.com/uciml/pima-indians-diabetes-database>