Tesla, Inc. Stocks Research

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Task description

Nowadays it is a quite popular thought that any person can make money on the stock exchange - all you need is some starter money and a bit of knowledge. We decided to check if it is possible to get big revenue from some big companies without much effort.

Data description

For our research, we first wanted to use the **New York Stock Exchange dataset** that consists of the historical data on New York Stock Exchange from 2012 until 2016 parsed from Yahoo! Finance. But since the data are quite outdated and we do not need the data on all the companies, we decided to get similar data.
For our final dataset, we downloaded the historical data on **Tesla, Inc.** stocks from Yahoo! Finance from January 5, 2015 until January 4, 2020.
You can find the .csv file created **here**.
We're going to load the data and see what we have.

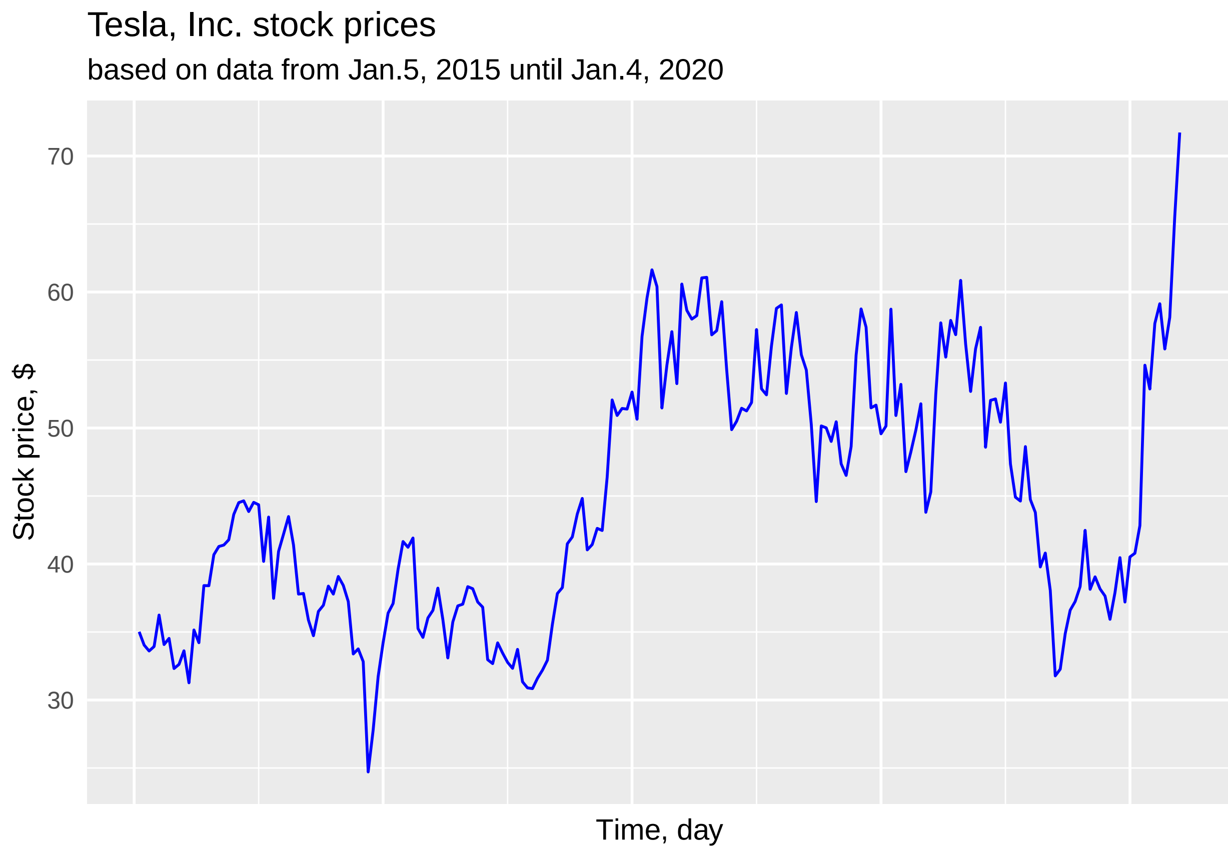
```
tsla.data <- read.csv("TSLA-5.csv")
head(tsla.data)
```

```
##         Date   Open   High    Low  Close Adj.Close  Volume
## 1 2015-01-05 214.55 216.50 207.16 210.09    210.09 5368500
## 2 2015-01-06 210.06 214.20 204.21 211.28    211.28 6261900
## 3 2015-01-07 213.35 214.78 209.78 210.95    210.95 2968400
## 4 2015-01-08 212.81 213.80 210.01 210.62    210.62 3442500
## 5 2015-01-09 208.92 209.98 204.96 206.66    206.66 4668300
## 6 2015-01-12 203.05 204.47 199.25 202.21    202.21 5950300
```

Here we have a data frame consisting of **7 different columns** and **1259** rows. What do these data mean? Each row in the data frame represent a day, the stock was out on the market. The date of the day can be found in the **date** column, consisting of data objects.
All the following columns, except for the last one, tell us about the **price** of the stock. The **open** and **close** columns tell the price of the stock when the market opened and closed on that day. The **low** and **high** columns consist of the lowest and the highest values the stock price reached during the day. **Adj.Close** column consists of the close price adjusted for both dividends and splits, although it almost always is the same as the close one.
The last column - **volume** - consists of integer values referring to the numbers of shares that have been bought and sold for the day.

Data analysis

Let's first check how Tesla stock prices behaved themselves during the last five years.
For a better look of the plot we're going to plot every 6^{th} day data, we'll show later why it doesn't change much.



As we can see here, the stock prices have significantly increased during the last months. Let's then check if we can make some good money here :)

Daily return

Since we wanted to check if we can make easy money on Tesla, we'll test one of the easiest ways - buying the shares one day and selling them the next day. Even easier way that does not involve any tracking - buying and selling at the same time.
For our case let's take the buying and selling time to be just before the market closes.
For this we'll need a **daily return** notion - the amount of stock price daily growth. A simple intuitive formula calculates the Daily return

$$R_t = \frac{C_t - C_{t-1}}{C_{t-1}} = \frac{C_t}{C_{t-1}} - 1$$

```
tsla.data$PrevClose <- tsla.data$Close
# since there is no previous day for the first day, we'll get NA value
# in order not to get NA in further calculations we'll get rid of the first day
tsla.data <- na.omit(transform(tsla.data, PrevClose = c(NA, PrevClose[-nrow(tsla.data)])))
tsla.data$DailyRet <- with(tsla.data, Close / PrevClose - 1)

head(tsla.data)
```

```
##         Date   Open   High    Low  Close Adj.Close  Volume PrevClose
## 2 2015-01-06 210.06 214.20 204.21 211.28    211.28 6261900    210.09
## 3 2015-01-07 213.35 214.78 209.78 210.95    210.95 2968400    211.28
## 4 2015-01-08 212.81 213.80 210.01 210.62    210.62 3442500    210.95
## 5 2015-01-09 208.92 209.98 204.96 206.66    206.66 4668300    210.62
```

```
## 6 2015-01-12 203.05 204.47 199.25 202.21    202.21 5950300    206.66
## 7 2015-01-13 203.32 207.61 200.91 204.25    204.25 4477300    202.21
##       DailyRet
## 2  0.005664254
## 3 -0.001561918
## 4 -0.001564361
## 5 -0.018801591
## 6 -0.021532938
## 7  0.010088487
```

Now we'll see what we can say on the daily return values we got.
We can start with some simple numeric characterics.

```r
cat("mean value: ", mean(tsla.data$DailyRet), "  ")
```

```
## mean value:  0.000991882
```

```r
cat("max value: ", max(tsla.data$DailyRet), "  ")
```

```
## max value:  0.1766923
```

```r
cat("min value: ", min(tsla.data$DailyRet), "\n")
```

```
## min value:  -0.1390154
```

```r
cat("standart deviation: ", sd(tsla.data$DailyRet))
```

```
## standart deviation:  0.02829682
```

Looking at these numbers we already can say that day-to-day changes in the stock prices are not that significant. Small standard deviation tells us that a variety of all the values is quite small meaning that day-to-day buying-selling is not a risky strategy.
It drives us to a conclusion that the strategy of selling the shares just the next day is **not the best strategy for a good money income, although it's a safe one** - you will not lose much if something goes wrong.

Annual return

Still, a daily return can give even more information on some company stock prices - daily return can be used to derive **annual return**.
An annual return is the approximation of finance return in a year. It can be calculated with a single daily return value by the following formula

$$Y_t = (R_t + 1)^{365} - 1$$

We're now going to add one more column with calculated annual return.

```r
tsla.data$YearRet <- with(tsla.data, power(DailyRet + 1, 365) - 1)
head(tsla.data)
```

```
##         Date   Open   High    Low  Close Adj.Close  Volume PrevClose
## 2 2015-01-06 210.06 214.20 204.21 211.28    211.28 6261900    210.09
## 3 2015-01-07 213.35 214.78 209.78 210.95    210.95 2968400    211.28
## 4 2015-01-08 212.81 213.80 210.01 210.62    210.62 3442500    210.95
## 5 2015-01-09 208.92 209.98 204.96 206.66    206.66 4668300    210.62
## 6 2015-01-12 203.05 204.47 199.25 202.21    202.21 5950300    206.66
## 7 2015-01-13 203.32 207.61 200.91 204.25    204.25 4477300    202.21
##       DailyRet    YearRet
## 2  0.005664254  6.8586848
## 3 -0.001561918 -0.4347831
## 4 -0.001564361 -0.4352877
## 5 -0.018801591 -0.9990200
```

```
## 6 -0.021532938 -0.9996457
## 7  0.010088487 38.0111416
```

Now we can analyze what data we get.
Again we'll start with some simple characteristics.

```
## [1] -1
```

```
cat("mean value: ", mean(tsla.data$YearRet), "  ")
```

```
## mean value:  6.782408e+22
```

```
cat("max value: ", max(tsla.data$YearRet), "  ")
```

```
## max value:  6.193926e+25
```

```
cat("min value: ", min(tsla.data$YearRet))
```

```
## min value:  -1
```

The data we got seem quite interesting and not that self-explanatory.

```
cat("standart deviation: ", sd(tsla.data$YearRet))
```

```
## standart deviation:  1.860227e+24
```

Standart deviation here is not that small which tells us that there is a variety in the annual return values.

```
cat("skewness: ", skewness(tsla.data$YearRet), " ")
```

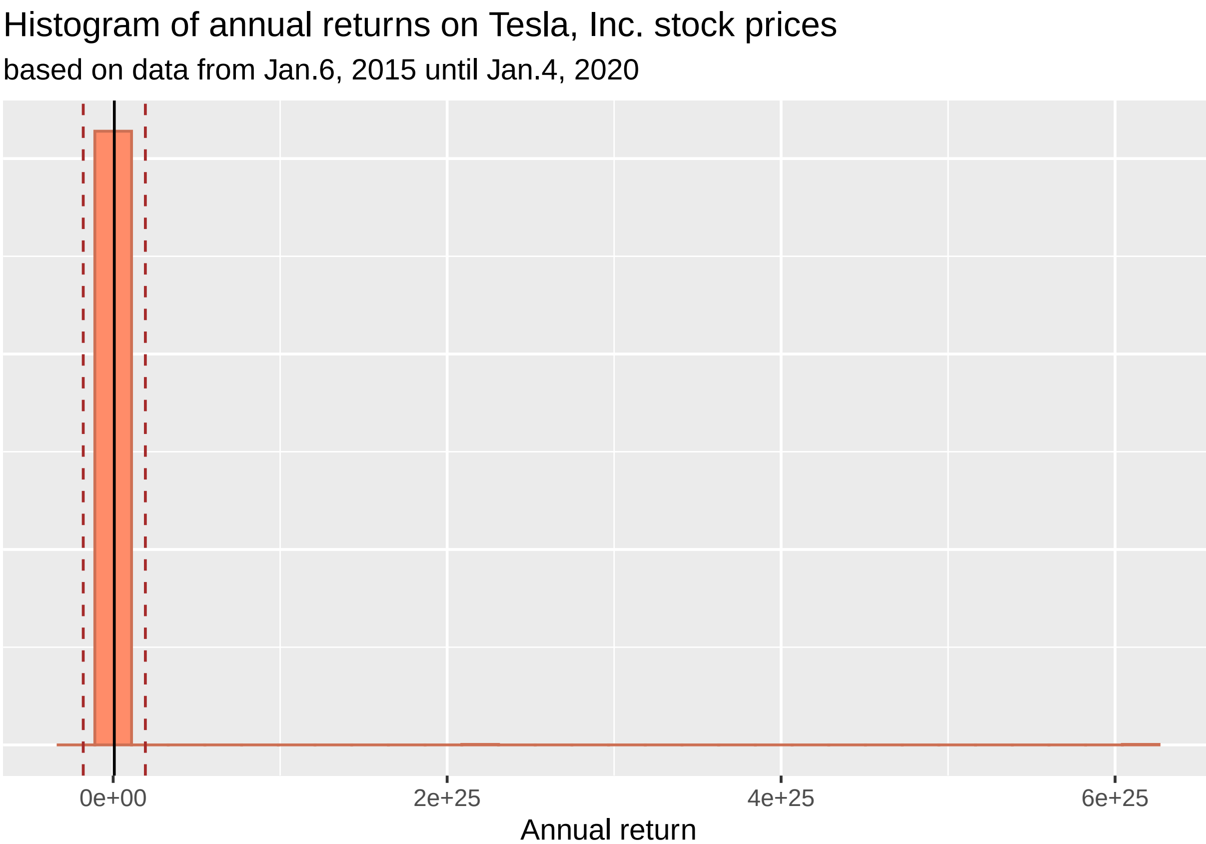
```
## skewness:  30.73026
```

```
cat("kurtosis: ", kurtosis(tsla.data$YearRet))
```

```
## kurtosis:  992.0115
```

Positive skewness tells us that the distribution of annual return has a heavy right-tail. In terms of return itself it means that values are mostly concentrated around expected value, although there is a small probability to get values much bigger than the expected one.
Positive kurtosis means that the distribution has so-called thick tails. The high value of kurtosis tells about frequent extreme values in the distribution. In terms of data, the fact that we got it one more time means that there are a lot of extreme values for an annual return.

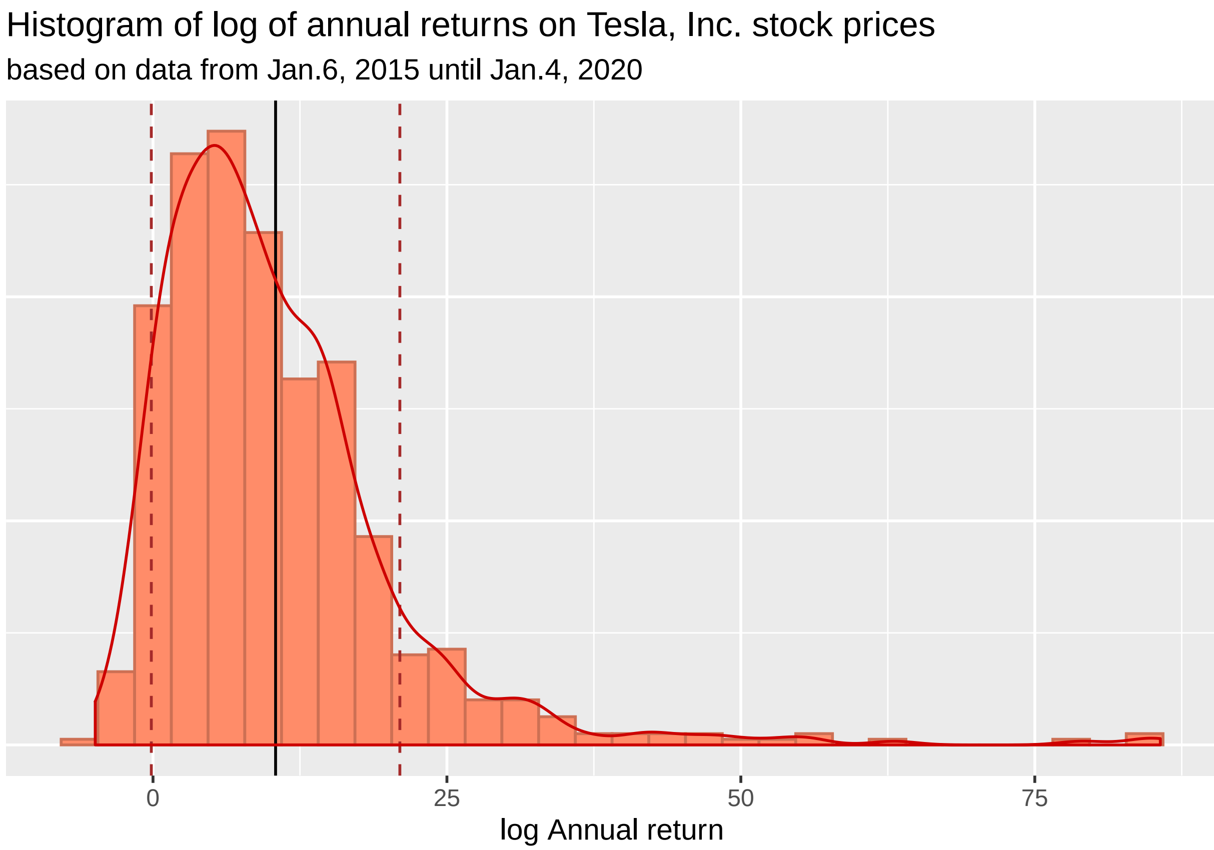
For further analysis we'll visualize all the data we got on annual return.



As we can see the data turned to have some quite extreme values and the plot does not help much. In order to fix this we're going to take the logarithm of the annual return, since we're working with ratios, and plot the data we got.

```
log.ret <- with(tsla.data, log2(YearRet))
log.ret <- log.ret[!is.nan(log.ret) & !is.infinite(log.ret)]
head(log.ret)
```

```
## [1]  2.777932  5.248350  3.126778 12.578770 13.357224 13.583587
```



It would be expected to suggest that annual return follows a lognormal distribution, but since it assumes both positive and negative values lognormal distribution is not suitable here.
Our next suggestion here is **logistic distribution**. By its shape it may resemble a normal distribution although it has a heavier tail - meaning higher kurtosis.
To check it, we're going to run **Kolmogorov-Smirnov test for goodness-of-fit**.

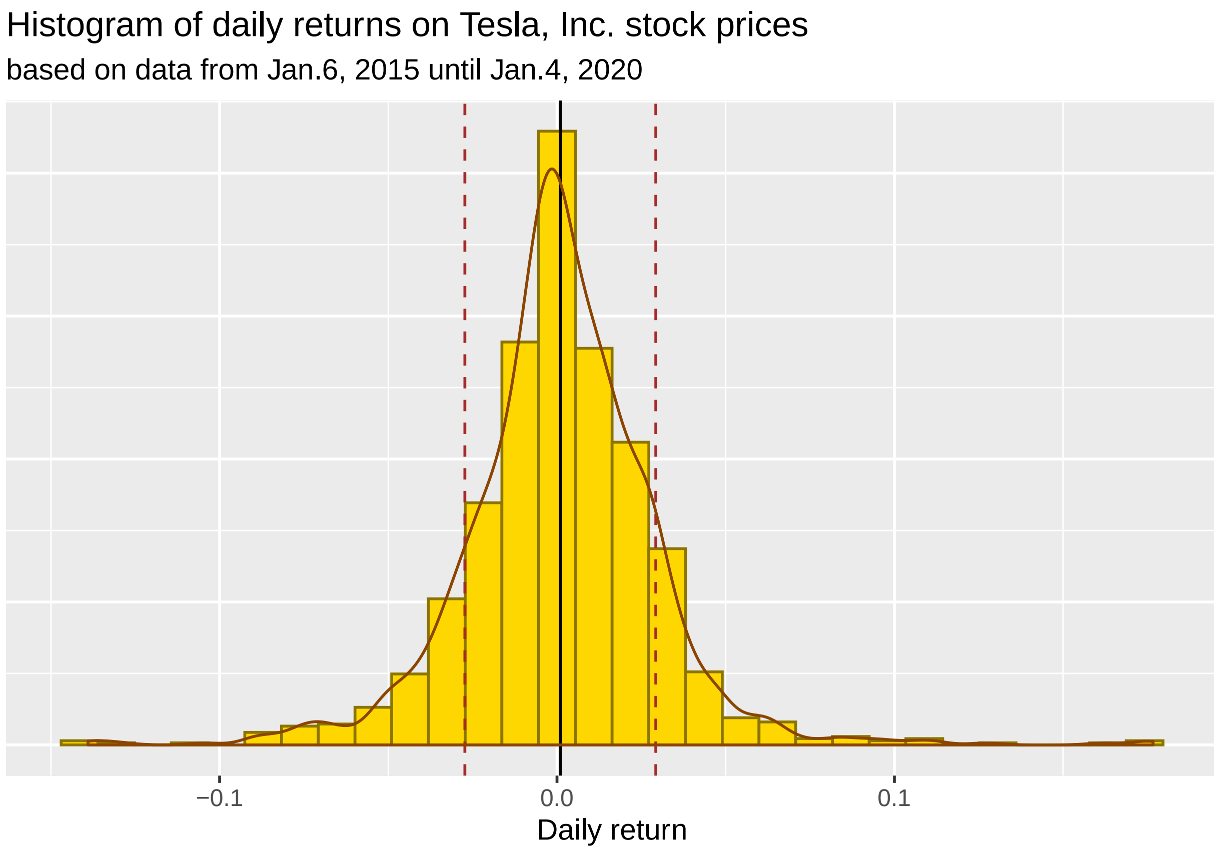
H_0 : annual returns follow distribution F, being s logistic distribution with parameters $\mu = \hat{m}_1$ and $s = \frac{\sqrt{3}\hat{sd}}{\pi}$
H_1 : annual return does not follow distribution F

```
ks.test(tsla.data$YearRet, "plogis", location=mean(tsla.data$YearRet), scale=sqrt(3) * sd(tsla.data$Yea
```

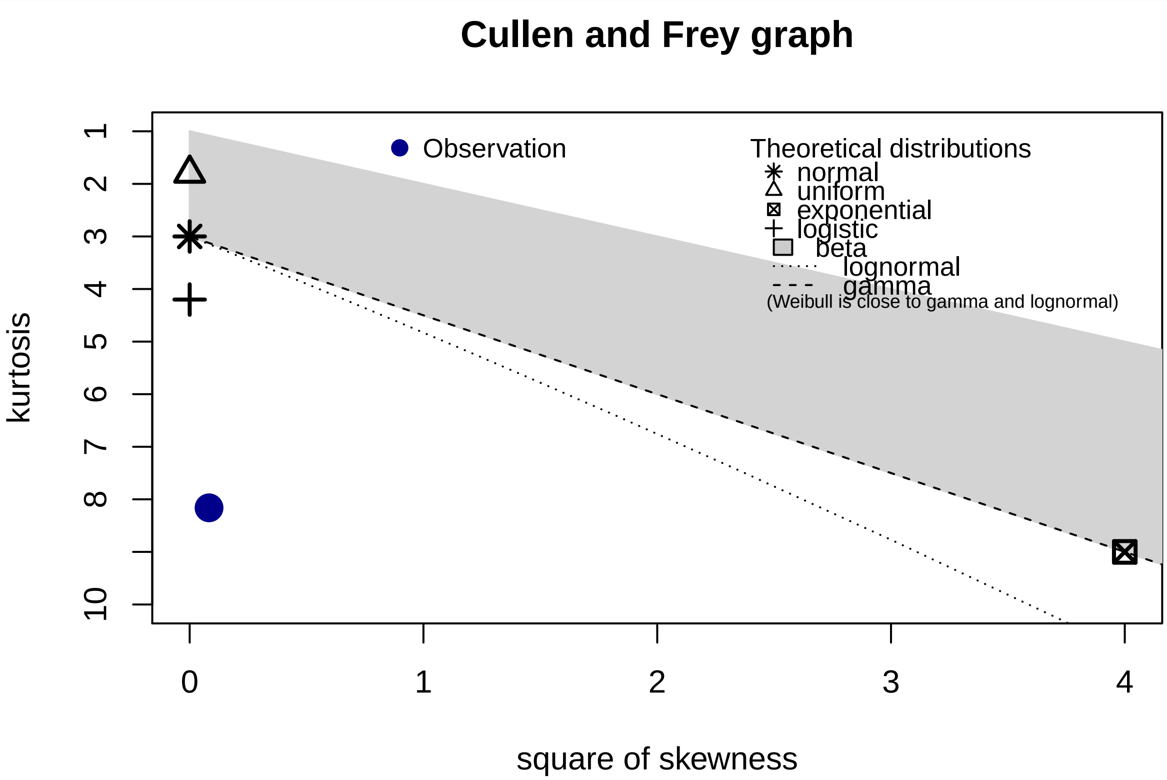
```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  tsla.data$YearRet
## D = 0.51414, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

p-value of the test is almost zero which means that our guess was wrong and we **reject** H_0.

To understand the annual return distribution we'll go back to how we calculated it.
We used a formula $Y_t = (R_t + 1)^{365} - 1$, where R_t was the value of a daily return.
We'll plot daily return data and try to fit them to some distribution in order to get some idea of how annual return is distributed.




```
descdist(tsla.data$DailyRet)
```

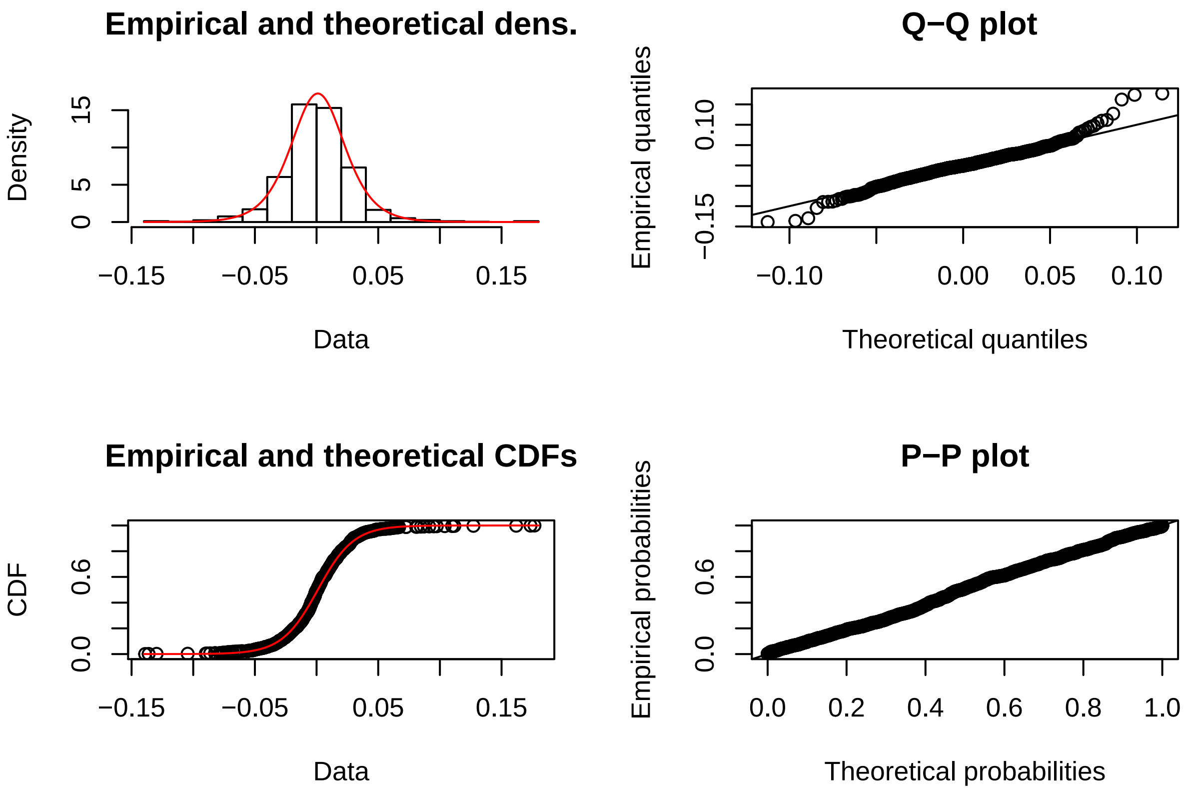



```
## summary statistics
```

```
## ------
## min:  -0.1390154   max:  0.1766923
## median:  0.0004990788
## mean:  0.000991882
## estimated sd:  0.02829682
## estimated skewness:  0.2877739
## estimated kurtosis:  8.161372
```

It seems like daily returns might follow a logistic distribution.

```r
fit.logis <- fitdist(tsla.data$DailyRet, "logis")
plot(fit.logis)
```




```r
fit.logis
```

```
## Fitting of the distribution ' logis ' by maximum likelihood
## Parameters:
##             estimate   Std. Error
## location 0.00102485 0.0006989643
## scale    0.01450561 0.0003408756
```

Now we'll run a test.

H_0 : daily returns follow a distribution $F = logis(0.001, 0.01)$
H_1 : daily returns do not follow distribution F

```r
ks.test(tsla.data$DailyRet, "plogis", location=fit.logis$estimate[1], scale=fit.logis$estimate[2])
```

```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  tsla.data$DailyRet
```

```
## D = 0.032773, p-value = 0.1341
## alternative hypothesis: two-sided
```

p-value of the test is not that big, so in most cases we need to reject H_0. Still the plots of fitting empirical data to theoretical ones look quite good, but following Cullen and Fray graph our data are not that close to actual theoretical logisitic distribution.
Still, there are no better estimates for the distribution, so we stick to **logistic distribution**.

To calculate annual return we raised daily return + 1 to the power of 365, basically we did multiply.
Product of two and more i.i.d. r.v.s never has the same distribution. In fact, it has a **product distribution** except for some cases like lognormal distribution.
So, based on the way we calculated annual return, we make a conclusion that our data on annual returns follow a **product distrubution**.

Conclusions As we mentioned above, the idea of making money on stocks in concise periods is not the best one, since the spread statistics of daily return got minimal values. It's just impossible to get a high income, only unless you buy all the shares open on the market.
A similar thing happens when trying more extended periods like year. Year return showed to have some extreme values with a low probability of their occurrence and very high probability of getting values close to the expected value.
In other words, we can say that making good money on stocks without any good knowledge involves only a great amount of luck and affecting circumstances. And if you're not lucky or if you simply know something about statistical analysis and probability, you need to use them :)

Dependences

Now we're going to check on some dependencies between the data we have.

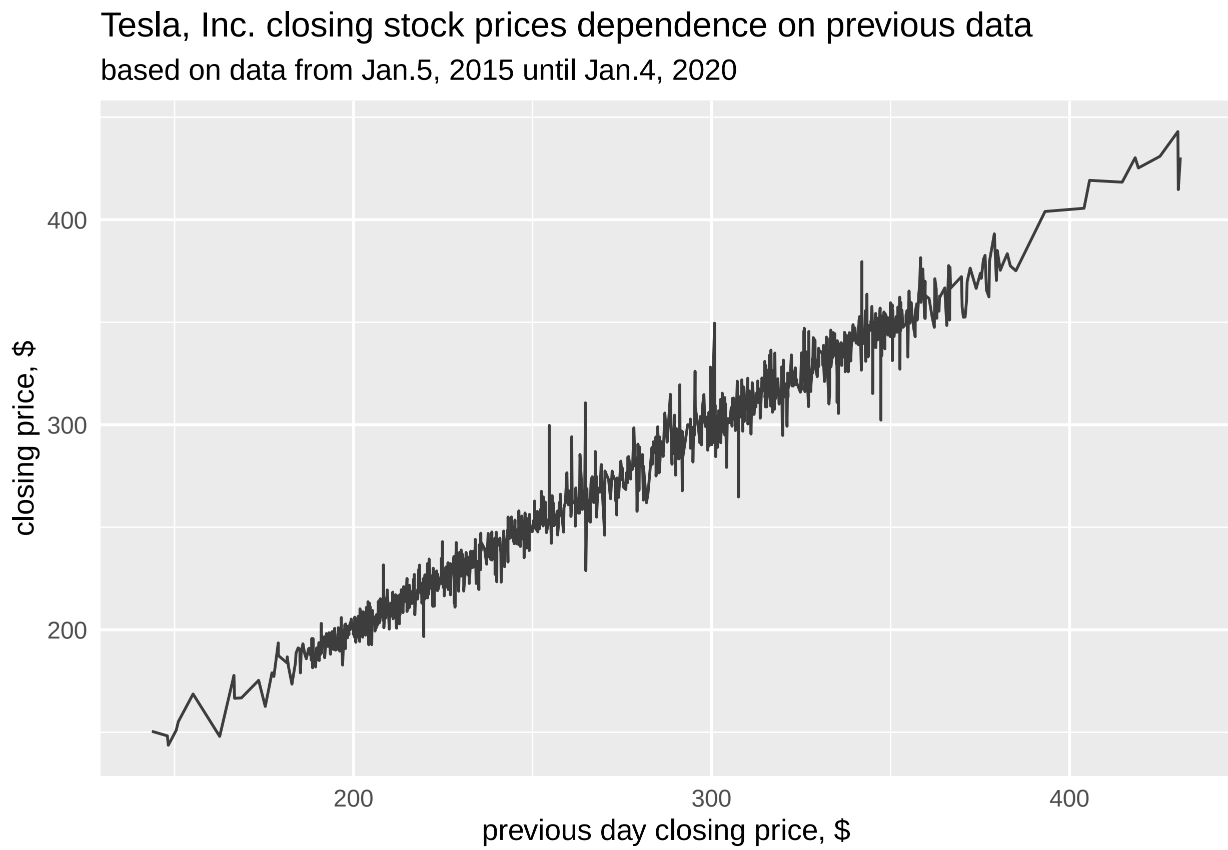
```r
drops <- c("Date")
no.date <- tsla.data[ , !(names(tsla.data) %in% drops)]

dependence <- cor(no.date)
dependence
```

```
##                    Open       High        Low      Close  Adj.Close
## Open       1.0000000000 0.99724191 0.99725593 0.99372905 0.99372905
## High       0.9972419059 1.00000000 0.99681462 0.99761669 0.99761669
## Low        0.9972559295 0.99681462 1.00000000 0.99720342 0.99720342
## Close      0.9937290466 0.99761669 0.99720342 1.00000000 1.00000000
## Adj.Close  0.9937290466 0.99761669 0.99720342 1.00000000 1.00000000
## Volume     0.2377591753 0.26338293 0.21426069 0.24185432 0.24185432
## PrevClose  0.9963232739 0.99426028 0.99366462 0.99036152 0.99036152
## DailyRet  -0.0005577134 0.04162793 0.04185908 0.08487536 0.08487536
## YearRet    0.0203243315 0.02126841 0.01843548 0.02176967 0.02176967
##                 Volume    PrevClose      DailyRet      YearRet
## Open       0.237759175  0.996323274 -0.0005577134  0.020324332
## High       0.263382927  0.994260277  0.0416279272  0.021268407
## Low        0.214260688  0.993664618  0.0418590828  0.018435482
## Close      0.241854316  0.990361518  0.0848753640  0.021769665
## Adj.Close  0.241854316  0.990361518  0.0848753640  0.021769665
## Volume     1.000000000  0.243700266 -0.0048235550  0.183205248
## PrevClose  0.243700266  1.000000000 -0.0513504764 -0.007377567
## DailyRet  -0.004823555 -0.051350476  1.0000000000  0.225323307
## YearRet    0.183205248 -0.007377567  0.2253233069  1.000000000
```

As we can see from the output the greatest correlation here can be seen between the values of low, high, close,

open etc. columns. It was quite obvious to get such a result, since they all denote different values of the same, so to say, stock price function, that as we showed before do not change extremely in a short period. Still, we can make some use of these correlations. We can suggest a linear relation between close and previous close price values to build a model for price predictions.
We're going to plot the data in order to see the actual dependency between them.

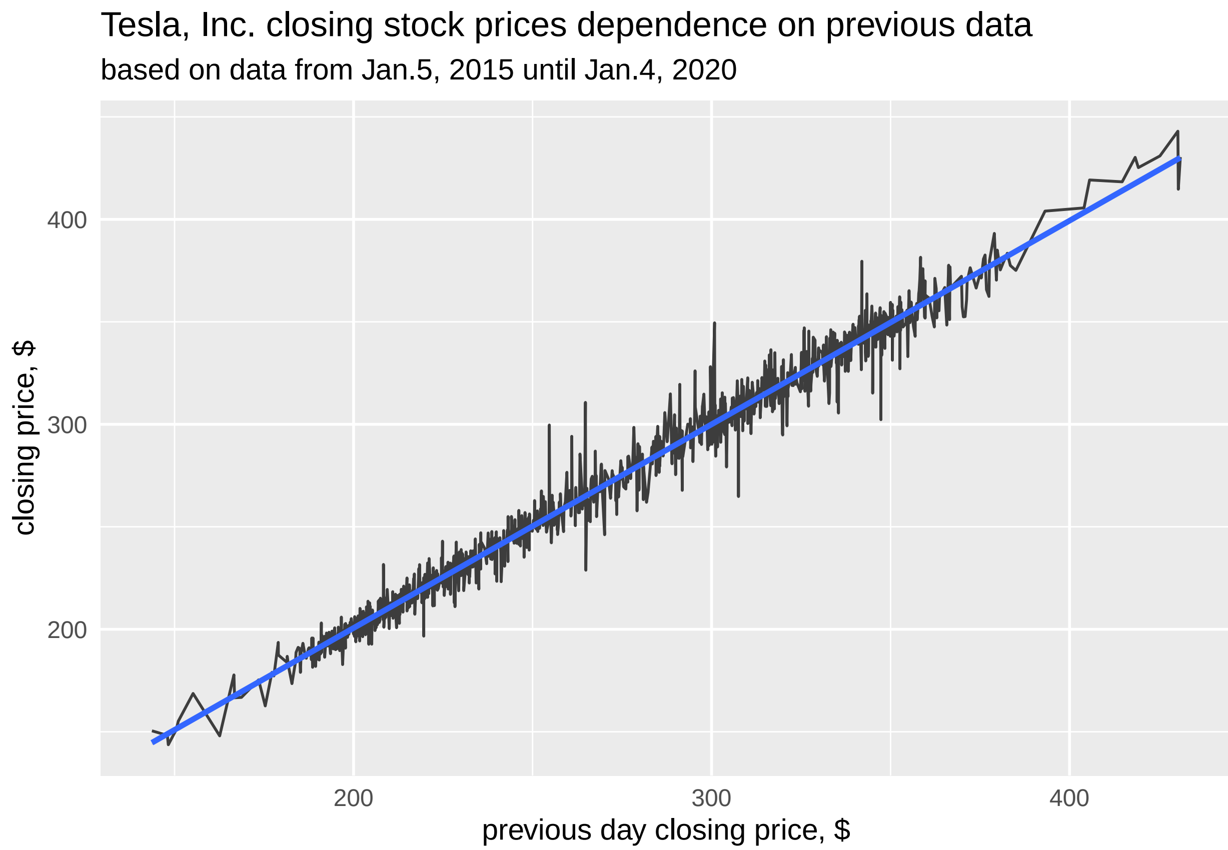


It seems like there actually might be some linear relations between the values of close and previous close prices.
A **linear regression** seems a quite too simple model for such a case with stock prices, although we'll try it.

H_0 : there is no linear regression pattern in the stock prices behaviour
H_1 : stock prices depend on the prices of the previous days and they follow a linnear regression model

```
price.lm <- lm(tsla.data$Close~tsla.data$PrevClose)
```

We'll also plot the regression line and check the regression summary.




```
summary(price.lm)
```

```
##
## Call:
## lm(formula = tsla.data$Close ~ tsla.data$PrevClose)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -44.741  -3.548  -0.219   4.019  48.716
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1.886647   1.077996    1.75   0.0803 .
## tsla.data$PrevClose 0.993677   0.003921  253.41   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.828 on 1256 degrees of freedom
## Multiple R-squared:  0.9808, Adjusted R-squared:  0.9808
## F-statistic: 6.422e+04 on 1 and 1256 DF,  p-value: < 2.2e-16
```

p-value of the F-test is almost 0 which means that we **reject** H_0 **and there is linear relation**. Although residual standard error is quite large, as well as values of residuals statistics, to tell that model is good-fitted, as mentioned above - simple linear regression is still too simple model for this case.

Conclusions

To sum up, we can say that there are not many obvious correlations between the current stock price and previously closed one, which makes stock prices prediction not a simple task to complete.
Still, during last months Tesla, Inc. stock prices are growing quite extremely, which created a good setting for a linear regression model testing.
We tested linear dependence between close and previous day close prices value and it turned out to be quite good but still not the best model since the values of residuals were quite big. We believe that it is possible to improve model results by exploring other dependencies, although in the data we got there were no more important factors that could significantly increase the model performance. Overall, using our results and having an interest in new Tesla projects (e.g. new Cyber Track and Tesla Model 3) one may consider investing in Tesla stocks.