Title: ***Modeling Tesla Stock Closing Prices***

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Download the closing prices from a stock of interest to you from https://finance.yahoo.com/ and propose an appropriate time series model for the time series.

```
library(TSA)
```

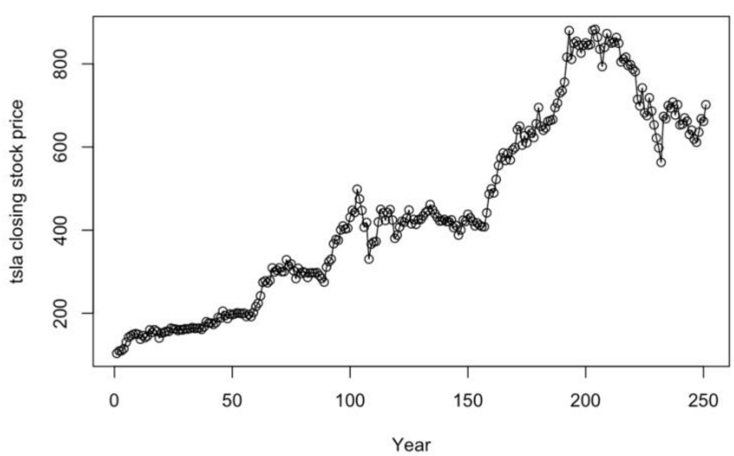
```
## Warning: package 'TSA' was built under R version 3.6.2
##
## Attaching package: 'TSA'
## The following objects are masked from 'package:stats':
##
##     acf, arima
## The following object is masked from 'package:utils':
##
##     tar
```

```r
library(tseries)
```

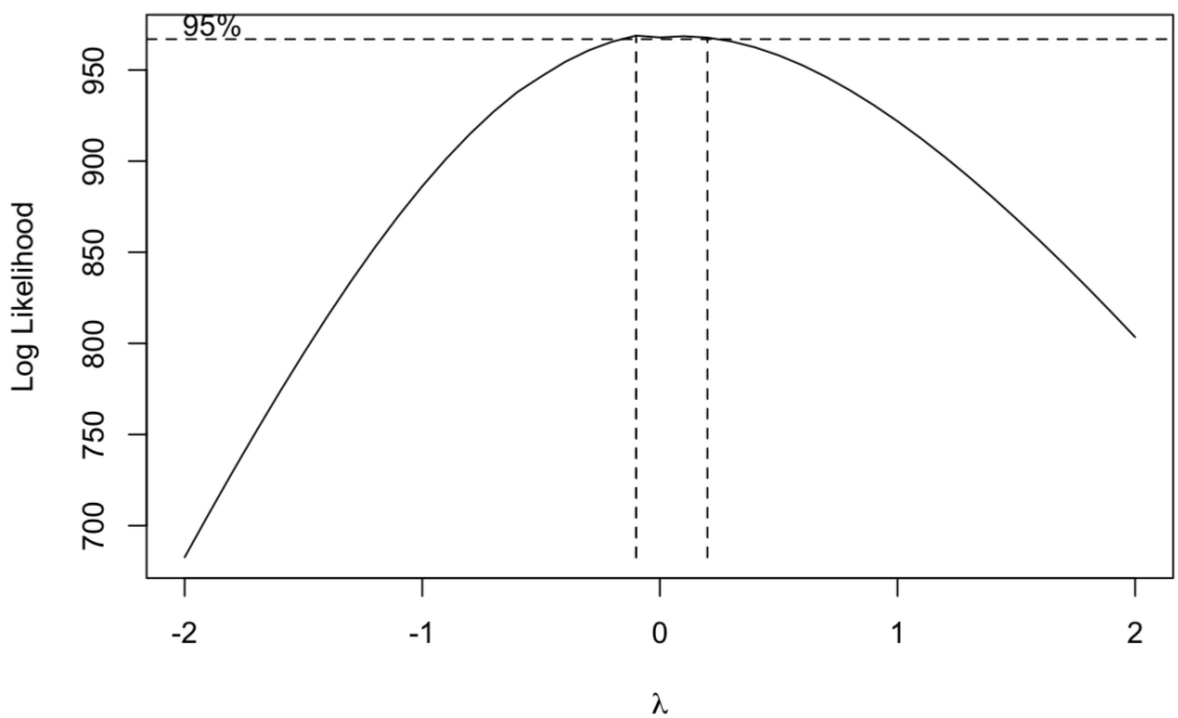
```
## Warning: package 'tseries' was built under R version 3.6.2

## Registered S3 method overwritten by 'quantmod':

##   method            from

##   as.zoo.data.frame zoo
```

Load and plot the tesla data

```r
rm(list = ls())

tsla <- ts(read.table("~/Documents/BGSU/time_series_analysis /bonus assignmen
t/tsla.txt", sep=""))

plot(tsla,ylab="tsla closing stock price",xlab="Year",type="o")
```



```r
#boxcox transformation
BoxCox.ar(tsla, method= "burg")
```

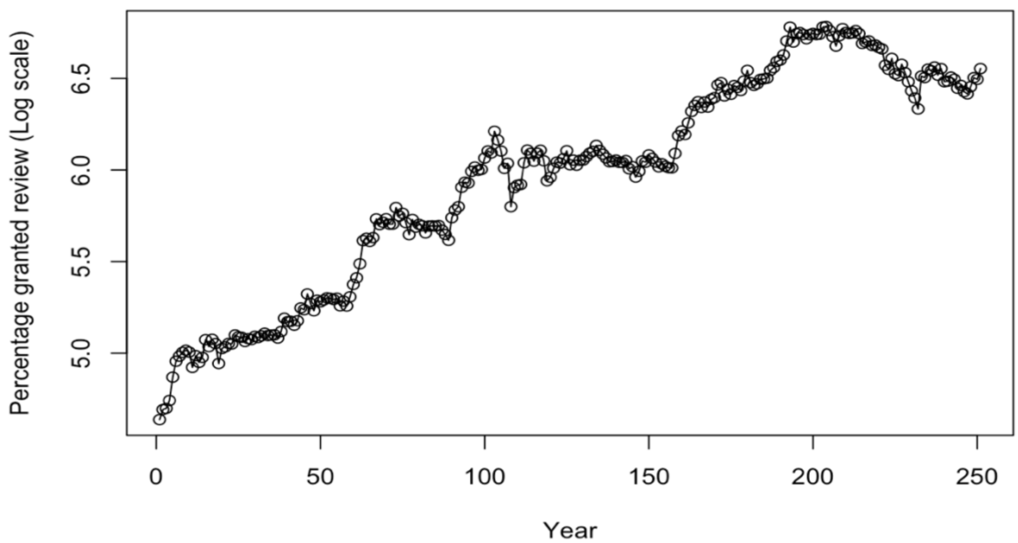


From the plot we can see a clear trend hence the data is not stationary

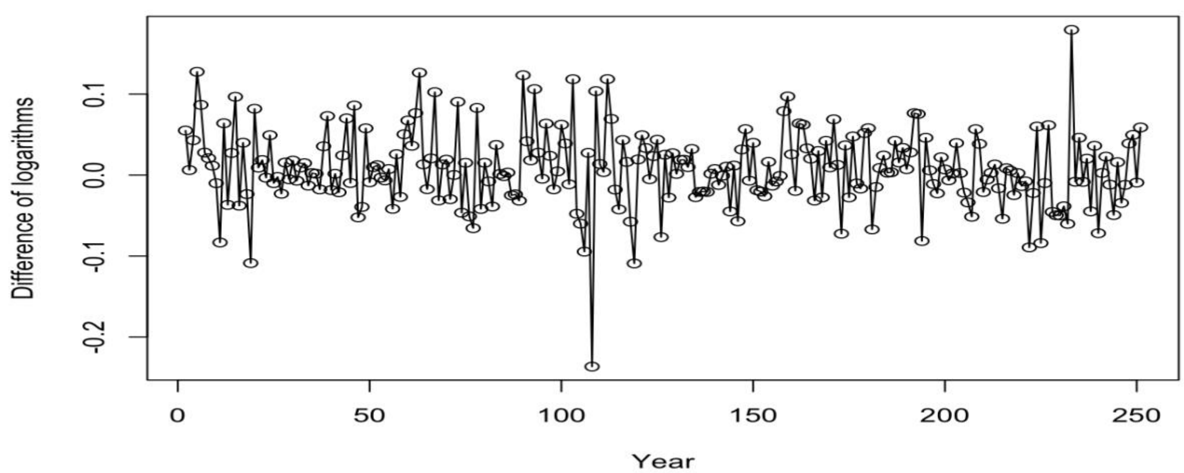
For the Box-Cox transformation, The (lamda) λ value is 0 so we can do a log transformation.

log transformation and difference process

```
plot(log(tsla),ylab="Percentage granted review (Log scale)",xlab="Year",type=
"o")
```




```
plot(diff(log(tsla)),ylab="Difference of logarithms",xlab="Year",type="o")
```



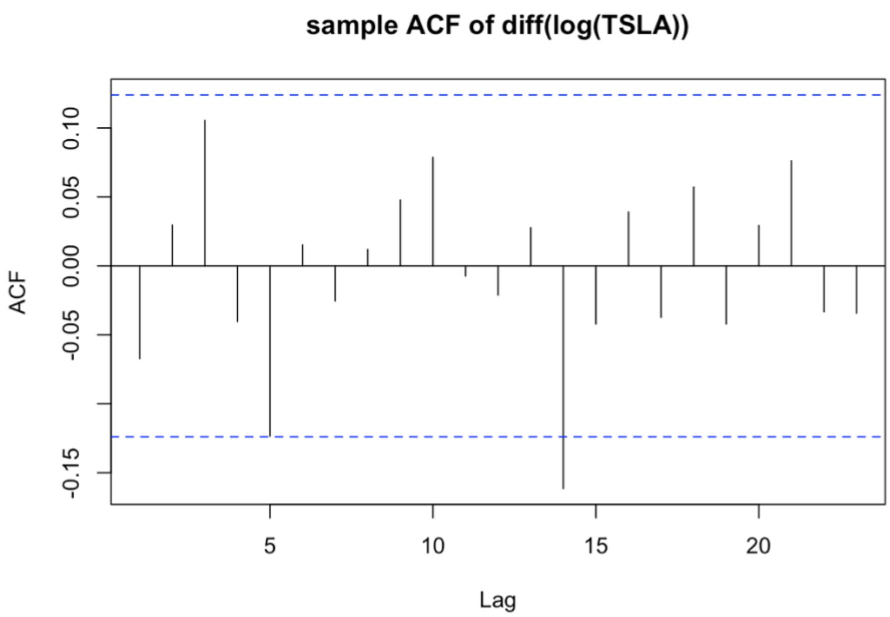
The log-transformed series still displays the linear trend, as expected. However, the variance in the {logYt} process is more constant than in the original series. It looks like the log-transformation has "worked". We are going to take a difference of the log transformed series to make it stationary # The first differences of the log-transformed process appear to be stationary.

```
# ADF test
adf.test(diff(log(tsla)))
## Warning in adf.test(diff(log(tsla))): p-value smaller than printed p-value
##
##  Augmented Dickey-Fuller Test
##
## data:  diff(log(tsla))
## Dickey-Fuller = -6.7886, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
```

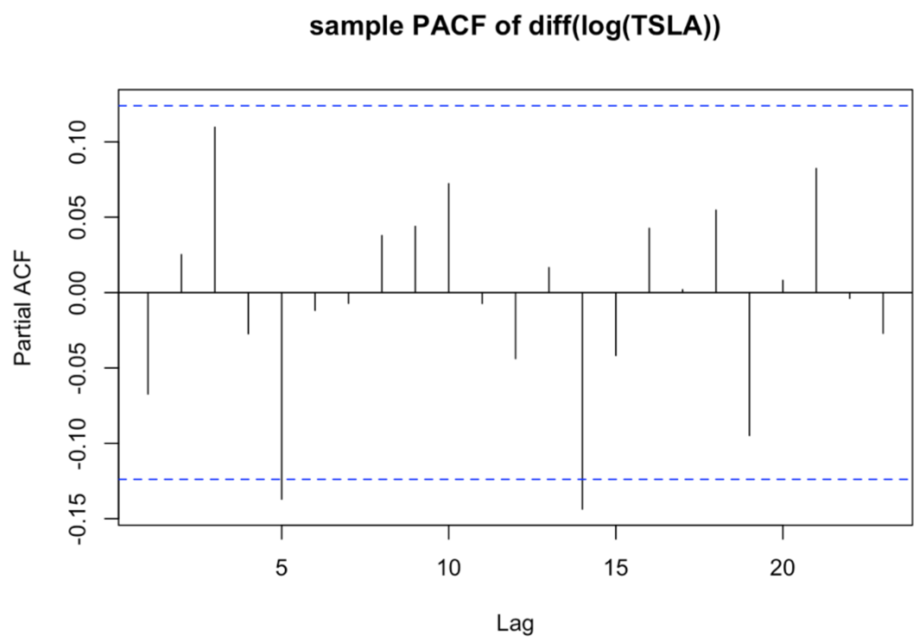
The stationarity of the process is confirmed by the ADF test. The small p-value here (p = 0.01) indicates marginally strong evidence against the null hypothesis. There is relatively sufficient evidence to conclude that the difference of the log transformed tsla process is stationary.

First difference sample ACF/PACF/EACF

```
acf(diff(log(tsla),),main="sample ACF of diff(log(TSLA))")
```




```
pacf(diff(log(tsla)),main="sample PACF of diff(log(TSLA))")
```



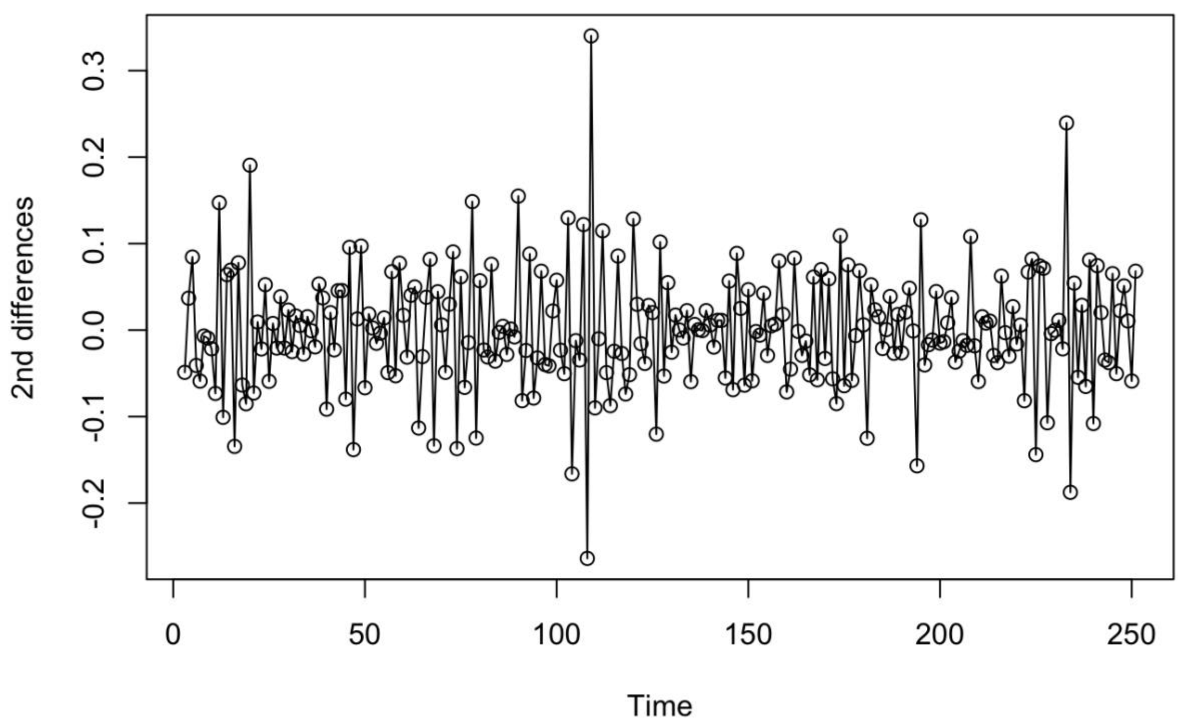

```
eacf(diff(log(tsla)))
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o o o o o o o o o o  o  o  x
## 1 x o o o x o o o o o o  o  o  x
## 2 x x o o x o o o o o o  o  o  x
## 3 x x x o x o o o o o o  o  o  x
## 4 x x o o x o o o o o o  o  o  o
## 5 o o x x x o o o o o o  o  o  o
## 6 x o x o x o o o o o o  o  o  o
## 7 x x o o x o o o o o o  o  o  o
```

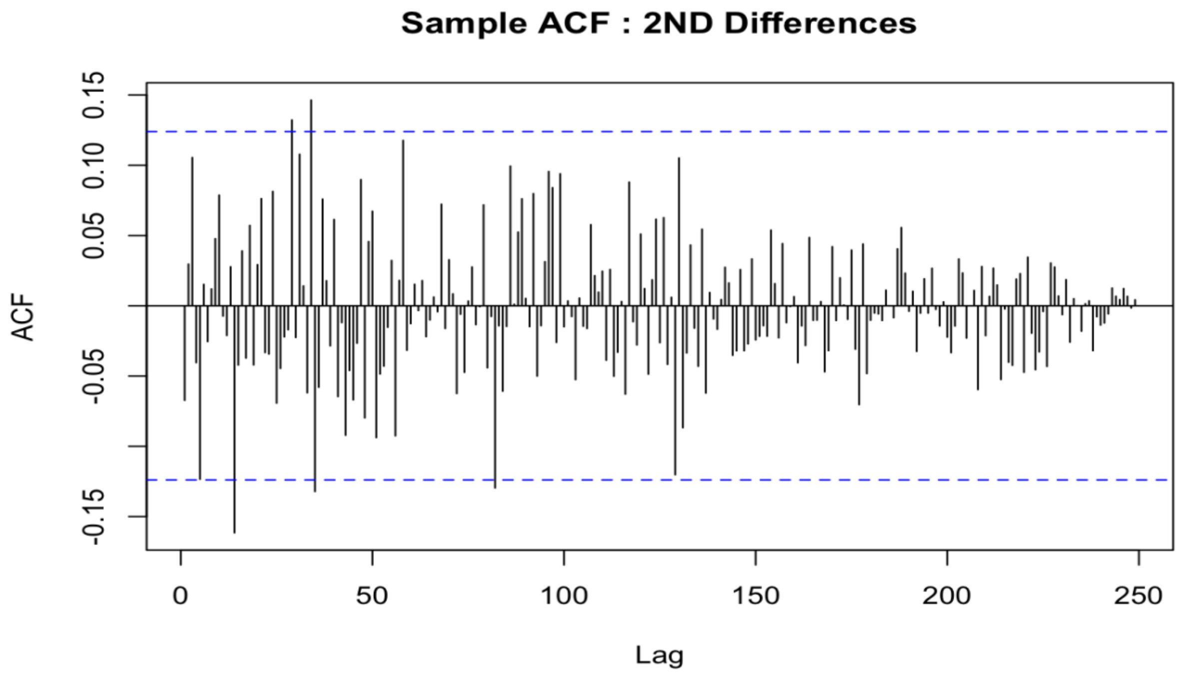
From the sample acf, eacf and pacf, we can’t see a candidate model hence we take the second difference

taking the second difference plot, sample acf, pacf and eacf

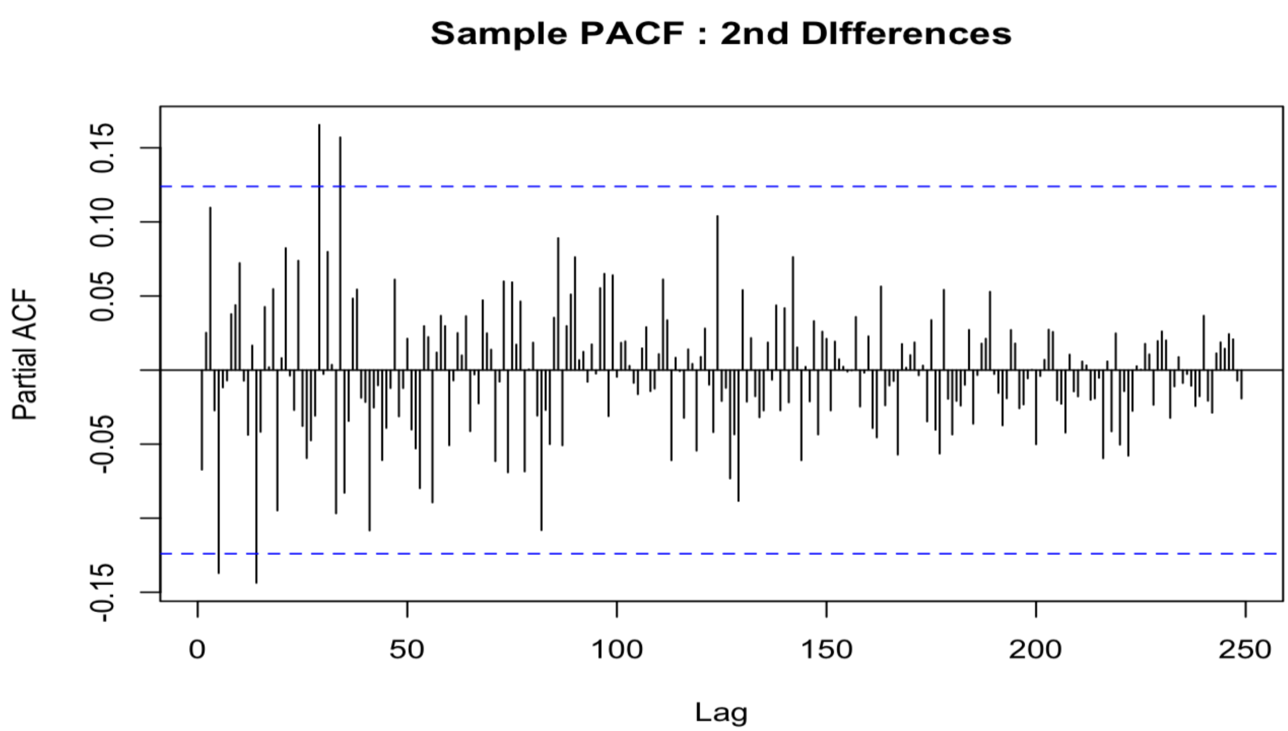
```
plot(diff(diff(log(tsla))),ylab="2nd differences",xlab="Time",type="o")
```




```
acf(diff(log(tsla)), main = "Sample ACF : 2ND Differences", diff(2))
```




```
pacf(diff(log(tsla)), main = "Sample PACF : 2nd DIfferences", diff(2))
```



```
eacf(diff(diff(log(tsla))))
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 x o o o o o o o o o o  o  o  x
## 1 x o x o x o o o o o o  o  o  x
## 2 x o x o x o o o o o o  o  o  x
## 3 x o x x x o o o o o o  o  o  o
## 4 x x x x o o o o o o o  o  o  o
## 5 x x x o o x o o o o o  o  o  o
## 6 x x o o o o o o o o o  o  o  o
## 7 x x o o x o x o o o o  o  o  o
```

from the second difference of the sample eacf, pacf and acf, we can't see still see a clear standout candidate model this means our data is similar to a white noise process.