# Future stock trends- Analysis and Forecast

5th April, 2023

## 1 Abstract

The data set I plan to use for my project displays date, open, high, low, close, volume, and name of JPM stock throughout 5 years. The main objective of my project is to perform time series forecasting of JPM stock data by using the last 5 years of stock data to make informed estimates that will provide predictive direction of the future stock trends for JPM stock. This is important because it would allow consumers and the company to understand the future of their stock price which is relevant to a multitude of financial decisions that will be made.

For analysis and forecast, the data has been divided into two sections; namely 'training data' and 'test data'. This helps the model to make accurate predictions. After the analysis, the creation of the time series plot shows an obvious trend in which there is a seasonal component and the variance varied. In the next step, the model has been made approximately normal. The Arima model has been selected as the best model for forecast of future closing stock trends.

## 2 Introduction

Stock price, opening and closing rates fluctuates throughout the year. Buyers and sellers of financial assets such as bonds, currencies, and equities trade in the stock market. Shares are one of the most popular assets. They are units of ownership in a company that investors purchase in order to receive dividends or profit from future price increases. Companies can also raise capital by selling their shares.

A company cannot trade on the stock exchange unless it has a certain amount of capital, shareholders, and other requirements. Brokers are essential players in the stock market. They are qualified professionals who connect buyers and sellers and execute trades for a commission. Companies and individuals interested in investing in the stock market should use a broker. The price of shares changes based on supply and demand and in that aspect it's similar to any other product. In addition, there are several other factors such as information, the economy, a company's financial health and some external events such as the impression about the company's performance etc. So, my analysis is basically based on showing the futuristic trends of the stock closing price so that buyers and sellers can look at those trends and decide whether to sell or keep the shares. After running the time series analysis, the model with the lowest AIC has been selection and the predictive analysis has been run. The forecasted points that lie within the 95% confidence interval have been carefully examined. The results depict that the model is accurate enough to predict future stock closing price values.

# 3 Time series analysis:

Time series is a series of data points in which each data point is associated with a timestamp. The analysis has been carried out in the following sections.

## 3.1 Original dataset plots

I started by plotting a time series plot with the original data. However, I have modeled the data by only having closing prices and also by excluding the dates. The reason of cutting off those dates is to plot the daily JPM closing stock price with ease and smoothness. Including the dates would skew the results, and would cause inconsistency with the rest of the data.

First of all, the data has been imported into R studio and the table below shows the overview of the imported dataset. The dataset has 1259 observations and 7 columns.

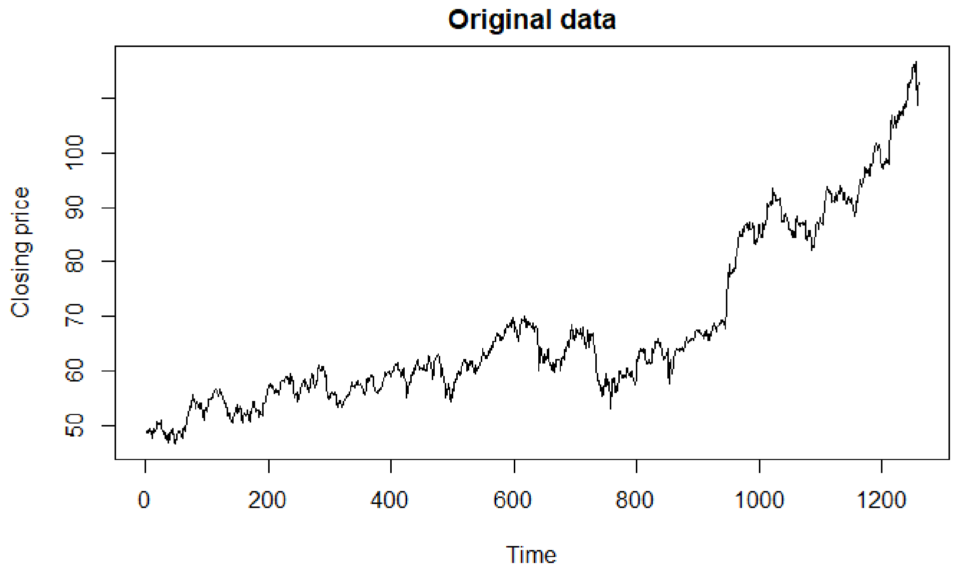
| | date | open | high | low | close | volume | Name |
|---|---|---|---|---|---|---|---|
| 1 | 2013-02-08 | 48.3300 | 48.6900 | 48.2600 | 48.63 | 15217458 | JPM |
| 2 | 2013-02-11 | 48.5100 | 48.9000 | 48.3800 | 48.66 | 13934328 | JPM |
| 3 | 2013-02-12 | 48.8000 | 49.3100 | 48.6000 | 49.14 | 16387566 | JPM |
| 4 | 2013-02-13 | 49.3500 | 49.4500 | 48.5000 | 48.68 | 21635732 | JPM |
| 5 | 2013-02-14 | 48.4000 | 49.2899 | 48.3700 | 49.22 | 18017634 | JPM |
| 6 | 2013-02-15 | 49.3500 | 49.4600 | 48.5700 | 48.88 | 20015681 | JPM |
| 7 | 2013-02-19 | 49.1200 | 49.6800 | 49.1200 | 49.45 | 20445200 | JPM |
| 8 | 2013-02-20 | 49.3500 | 49.5400 | 48.3600 | 48.61 | 24787660 | JPM |
| 9 | 2013-02-21 | 48.4100 | 48.4500 | 47.8300 | 48.25 | 24436578 | JPM |
| 10 | 2013-02-22 | 48.6300 | 48.9100 | 48.4100 | 48.91 | 23583917 | JPM |
| 11 | 2013-02-25 | 49.1000 | 49.2000 | 47.6500 | 47.70 | 32749013 | JPM |

Showing 1 to 12 of 1,259 entries, 7 total columns

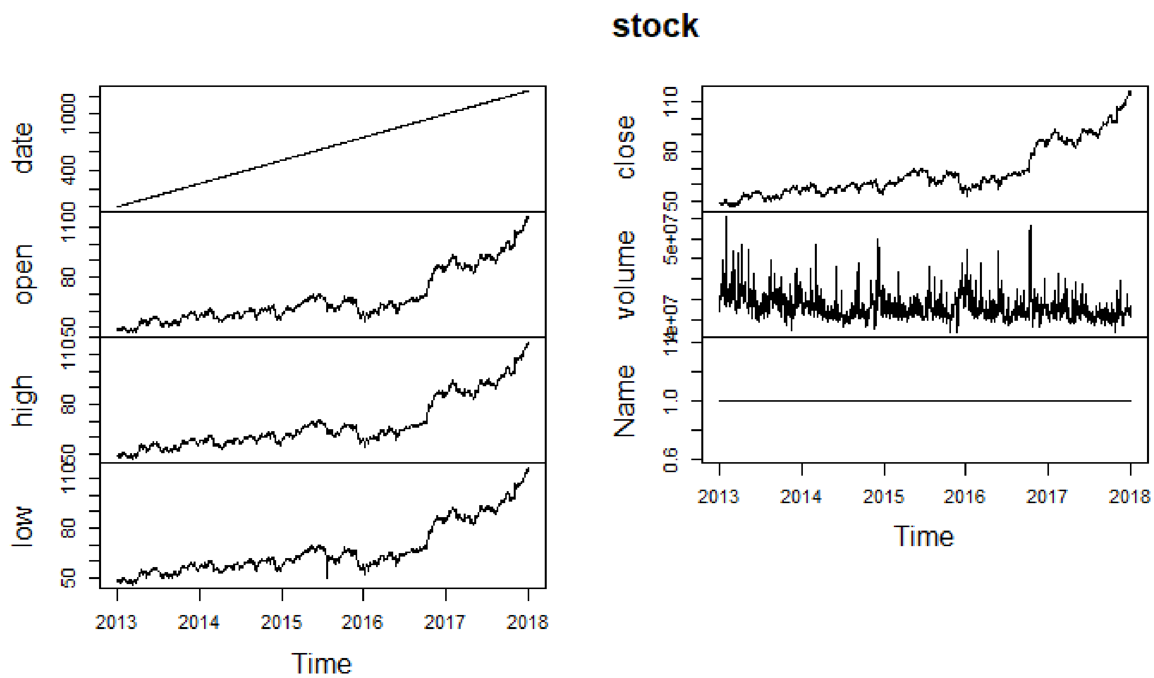
The null values have been removed by using na.omit function in the pre-processing step and the dataset has been divided into training data and test data. The training dataset has 1247 observations while the test dataset has 12 observations.

The time series has been plotted with a frequency of 251 to generate 1261 observations.

The original dataset and the time series plots are shown below:

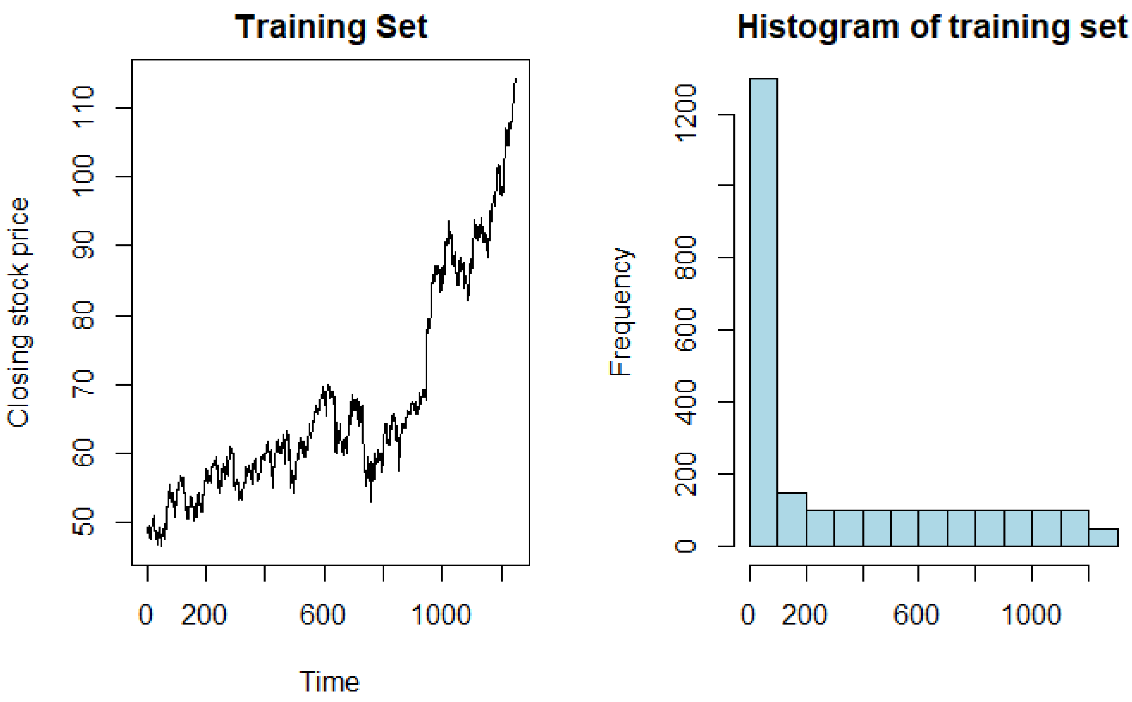



I started by plotting a time series plot with the original data. However, I have modeled the data by only having stock closing price and also by excluding the dates between the years 2013 and 2018. Instead of these years, the time series has been created of 1261 observations. rest of the data.

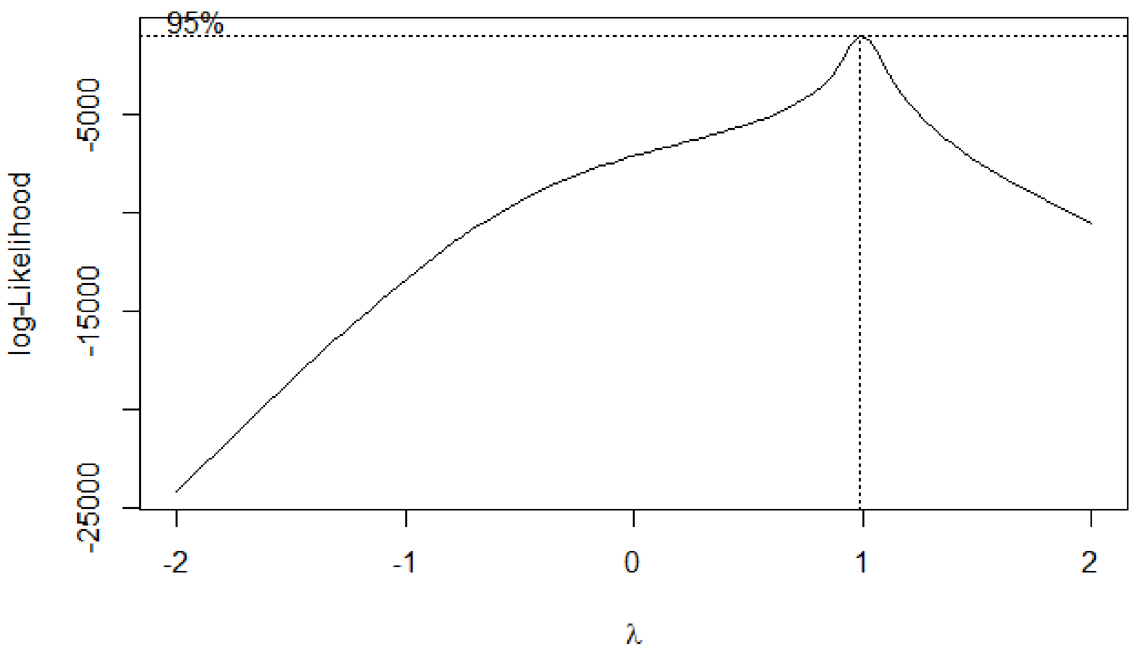



## 3.2 Plotting the training dataset

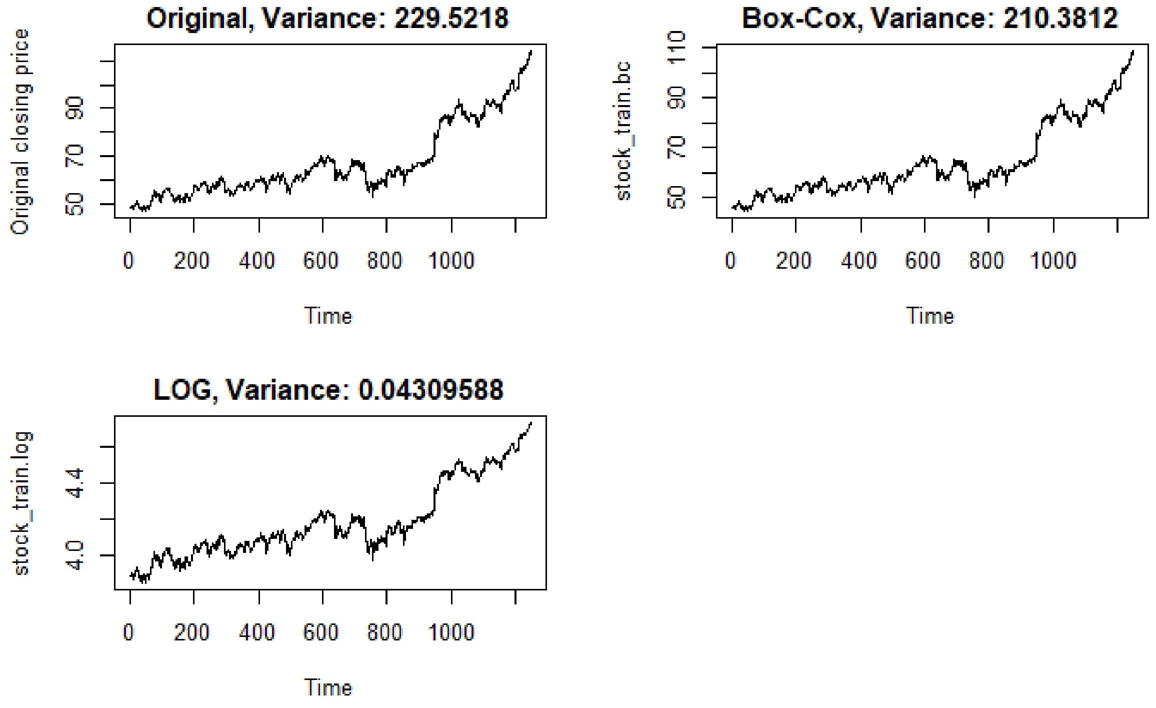
In order to make sure our model was relatively accurate; the data has been sectioned into training dataset and test dataset. I removed the last 12 observations, in order to compare the forecasted values with the original data values later in the analysis.




After observing the time series plot, it can be said that the trend is generally increasing and decreasing but the overall trend is increasing especially at the end of the interval, the value of closing stock price reaches the highest value. There is also a seasonal component. The histogram is right skewed and the variance is non-constant. Based on these observations, I would say it would be best to perform a Box-Cox transformation.



In the next step, the variance of the original stock_train dataset, the boxcox stock_train dataset and the log transformed stock_train dataset has been compared after the transformation process.




> var(stock_train[,2]) has the higest variance

[1] Variance= 229.5218

> var(stock_train.bc)

[2] Variance= 210.3812

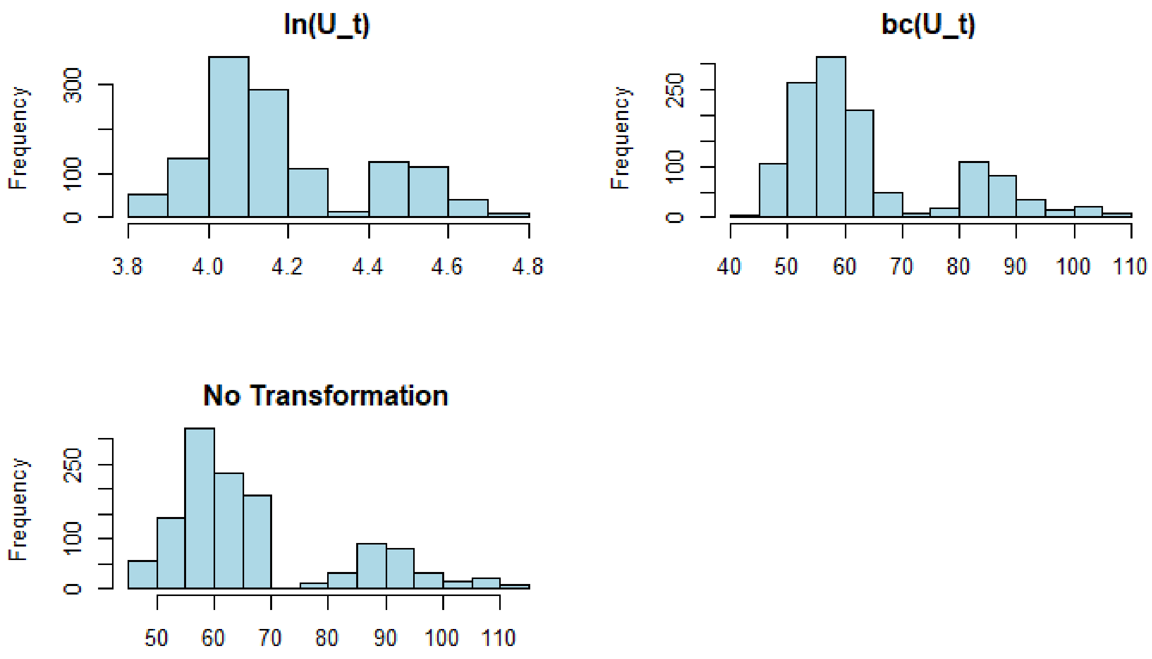
> var(stock_train.log) has the lowest variance. So, we will choose the logarithmically transformed dataset for further analysis.

[3] Variance= 0.04309588

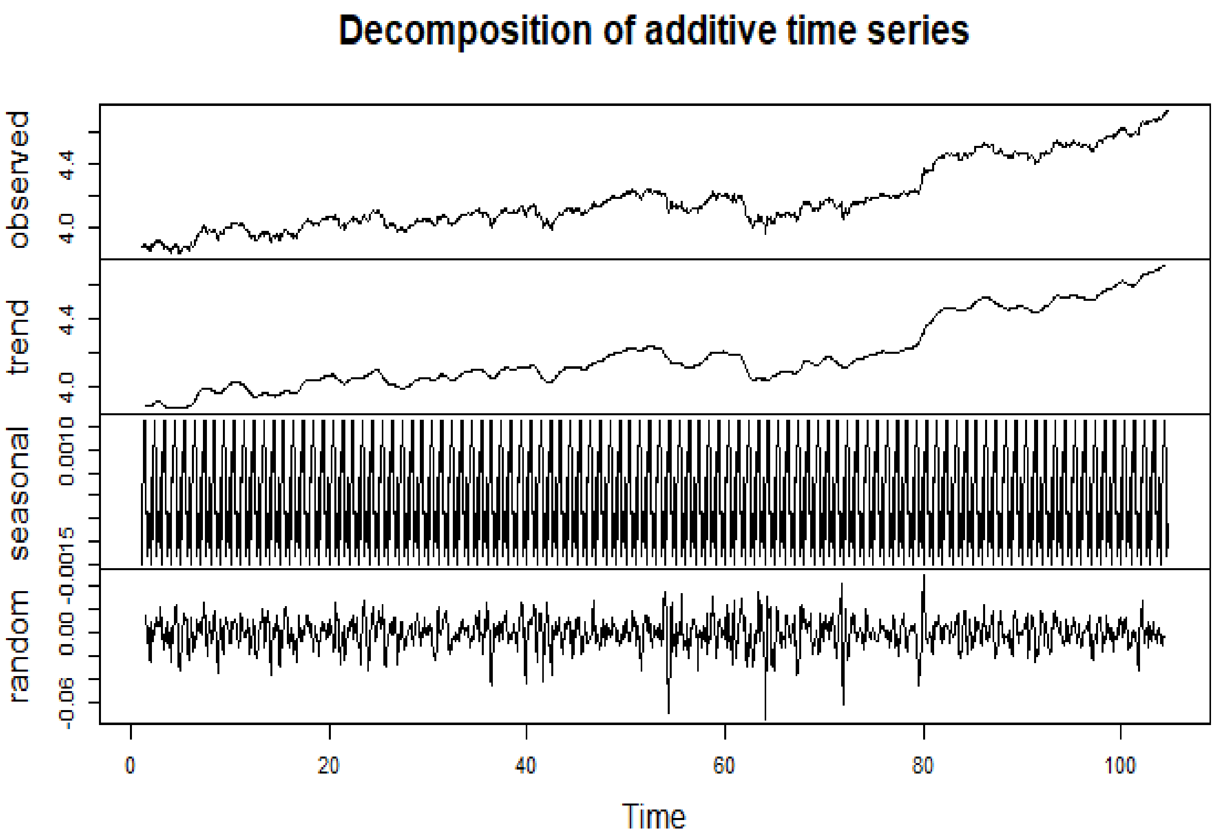
Looking at the 95% confidence interval for the true lambda and by looking at all the plots, we could see that either no transformation or logarithmic transformation is suggested. Looking at the plots we could see that the LOG plot actually didn't have as sharp dips and tips. This was most prominent around time 200, 400 and 600. Also, when looking at the variances, we could see the Box-Cox transformation slightly decreases the variance whereas the log transform drastically decreases the variance.

The histograms showing the trends of the various transformations are shown below:

The histogram that least resembles the normal distribution is that of the logarithmic transformation. Hence, based on the variances, histograms and the plots, the logarithmic transformation has been selected for further analysis.



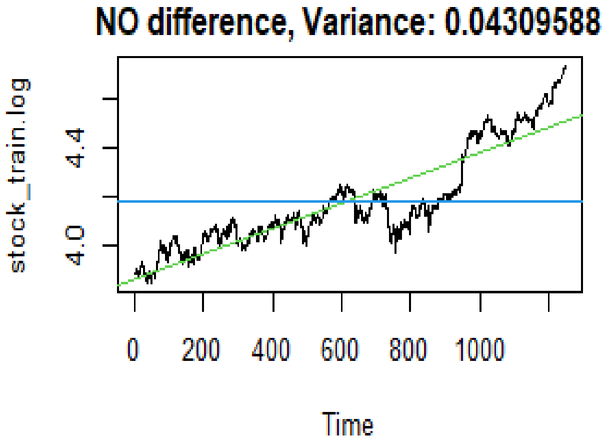

## 3.3 Decomposition of log transformed training dataset

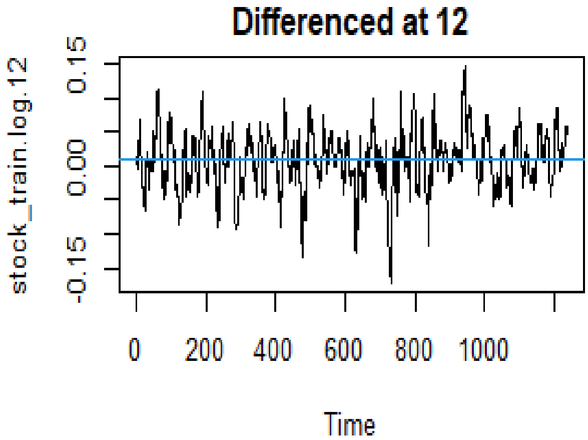


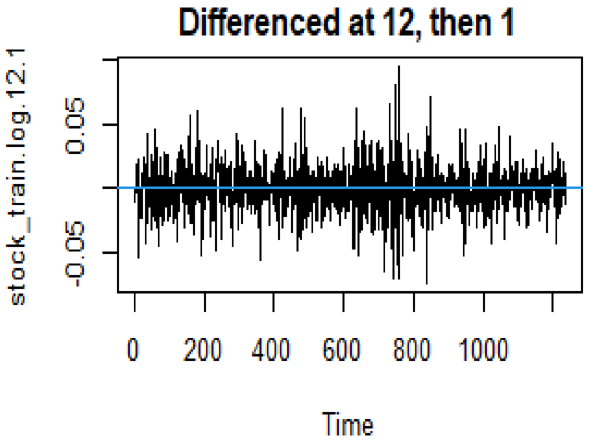

In the aforementioned graph, there is clear trend and a jumbled up seasonal component. To correct this, differencing has been performed which will be explained in the following steps.

## 3.4 Differencing

The differencing has been done two times. The plot of no difference and differenced at 12 and at 12, then 1 are shown below:



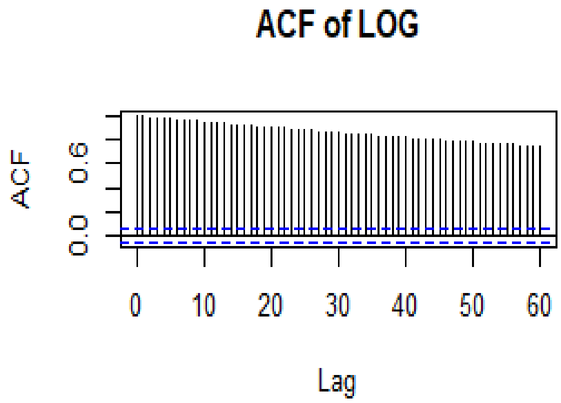



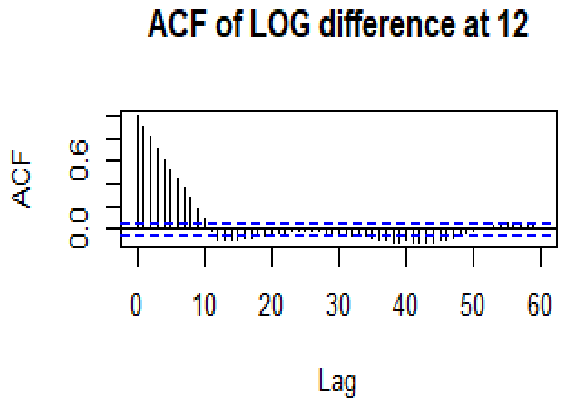



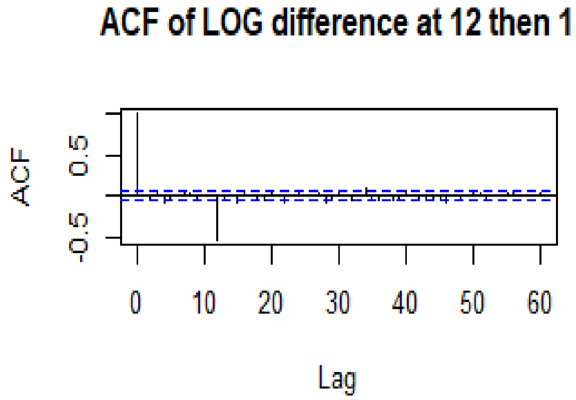

The green line is the fitted line whereas the blue line shows the mean value. By looking at the three plots mentioned above, it can be clearly seen that the plot 'Differenced at lag 12, then 1' had the least common or apparent trend and the least apparent seasonality. The variance of the plot differenced at 12, then 1 is lower (approx. 0.0003) than the variance of the plot differenced at 12 (0.00177) but the visual depiction of the data is clearer for the plot differenced at 12. The mean of the plot 'Differenced at 12, then 1' is closest to 0 which is 0.00003495.

## 3.5 Plots of ACF differences

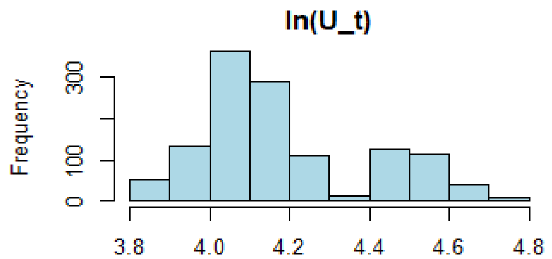
The ACF plots of no difference, differenced at 12 and differenced at 12, then 1 are shown below:

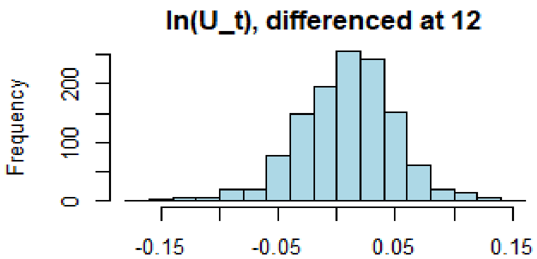


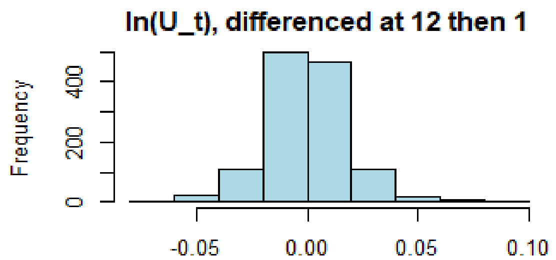




Comparing the ACF's of the three graphs, the non-differenced and differenced at 12 still contains some seasonality, and the ACF has decayed slowly which indicated non-stationarity. The ACF of the log plot differenced at 12, then 1 had no apparent seasonality and the decay corresponded to a stationary process. The histograms of the three processes are as follows:

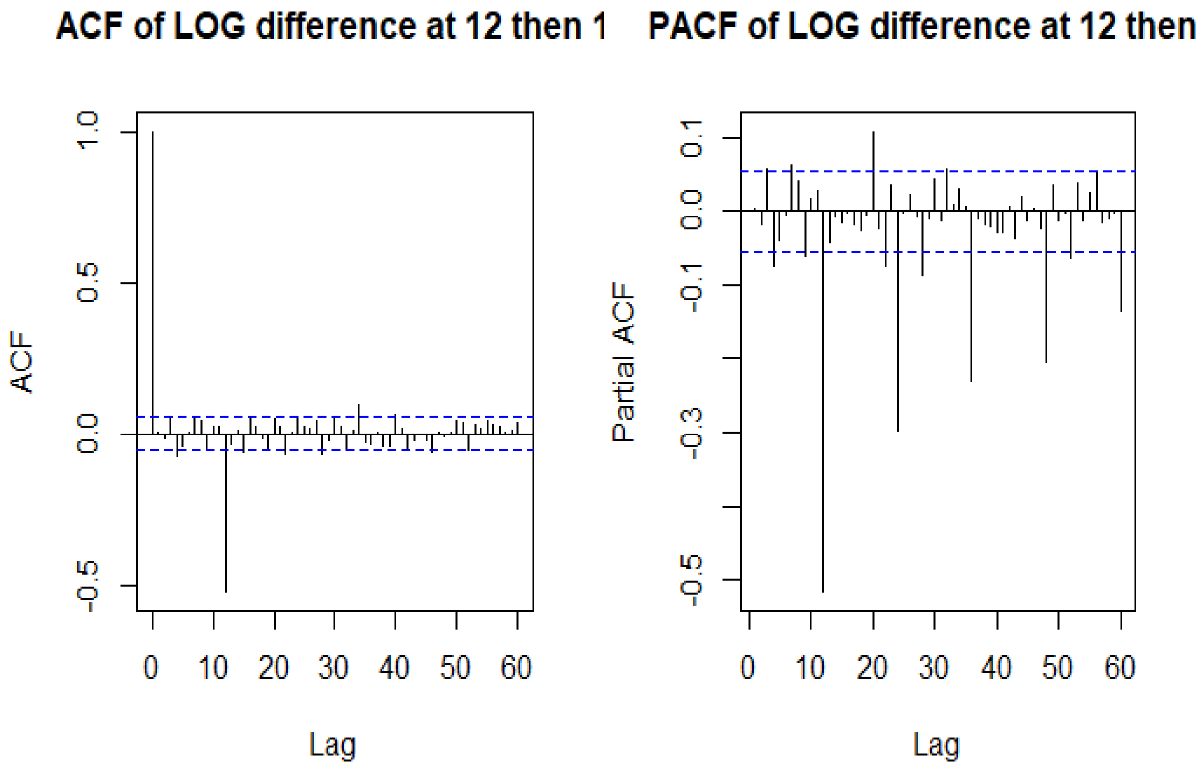


After analyzing the histograms, it is clear that the histogram of log differenced at 12, then 1 has the most normal like distribution so it has been chosen for further analysis.

## 3.6 ACF and PACF of log differenced at 12, then 1




Looking at the ACF and PACF plots, I have made the following deductions:

ACF outside confidence intervals: 1 and 12

PACF chosen outside confidence intervals: 2 and 12

SARIMA for log: s=12, D=1, d=1, Q=0 or 1, q=0, P=0 or 1, p=0.

## 3.7 Trying models:

| | p <int> | q <int> | P <int> | Q <int> | AICc <dbl> |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | -6374.694 |
| 2 | 1 | 0 | 0 | 0 | -6372.712 |
| 3 | 0 | 1 | 0 | 0 | -6372.712 |
| 4 | 1 | 1 | 0 | 0 | -6370.702 |
| 5 | 0 | 0 | 1 | 0 | -6771.910 |
| 6 | 1 | 0 | 1 | 0 | -6769.902 |
| 7 | 0 | 1 | 1 | 0 | -6769.902 |
| 8 | 1 | 1 | 1 | 0 | -6767.889 |
| 9 | 0 | 0 | 0 | 1 | -7200.961 |
| 10 | 1 | 0 | 0 | 1 | -7199.006 |

1-10 of 16 rows Previous 1 2 Next

| | p <int> | q <int> | P <int> | Q <int> | AICc <dbl> |
|---|---|---|---|---|---|
| 11 | 0 | 1 | 0 | 1 | -7199.008 |
| 12 | 1 | 1 | 0 | 1 | -7196.994 |
| 13 | 0 | 0 | 1 | 1 | -7199.601 |
| 14 | 1 | 0 | 1 | 1 | -7197.647 |
| 15 | 0 | 1 | 1 | 1 | -7197.649 |
| 16 | 1 | 1 | 1 | 1 | -7195.635 |

The best model with the lowest AICc is when p=0, q=0, P=0 and Q=1. The AICc in this case is -7200.961 and the second lowest is -7199.601 when p=0, q=0, P=1 and Q=1.The second one will be taken as an alternative model.

## 3.8 Models

The first model is:

```
fit4.1

##
## Call:
## arima(x = stock_train.log, order = c(0, 1, 0), seasonal = list(order =
c(0,
##     1, 1), period = 12), method = "ML")
##
## Coefficients:
##           sma1
##        -1.0000
## s.e.    0.0161
##
## sigma^2 estimated as 0.000163:  log likelihood = 3602.49,  aic = -7200.
97
```

The second model is:

```
fit4
```

```
##
## Call:
## arima(x = stock_train.log, order = c(0, 1, 0), seasonal = list(order =
c(1,
##     1, 1), period = 12), method = "ML")
##
## Coefficients:
##           sar1     sma1
##        -0.0232  -1.0000
## s.e.    0.0287   0.0182
##
## sigma^2 estimated as 0.0001628:  log likelihood = 3602.81,  aic = -7199
.62
```

## 3.9 Diagnostic checking 1st model:

```
## Shapiro-Wilk normality test
##
## data:  res
## W = 0.96574, p-value < 2.2e-16
```

```
# p-value is less than 0.05 so it does not pass the shapiro.test
Box.test(res, lag = 9, type = c("Box-Pierce"), fitdf = 3)
```

```
##
##  Box-Pierce test
##
## data:  res
## X-squared = 10.845, df = 6, p-value = 0.0933
```

```
Box.test(res, lag = 9, type = c("Ljung-Box"), fitdf = 3)
```

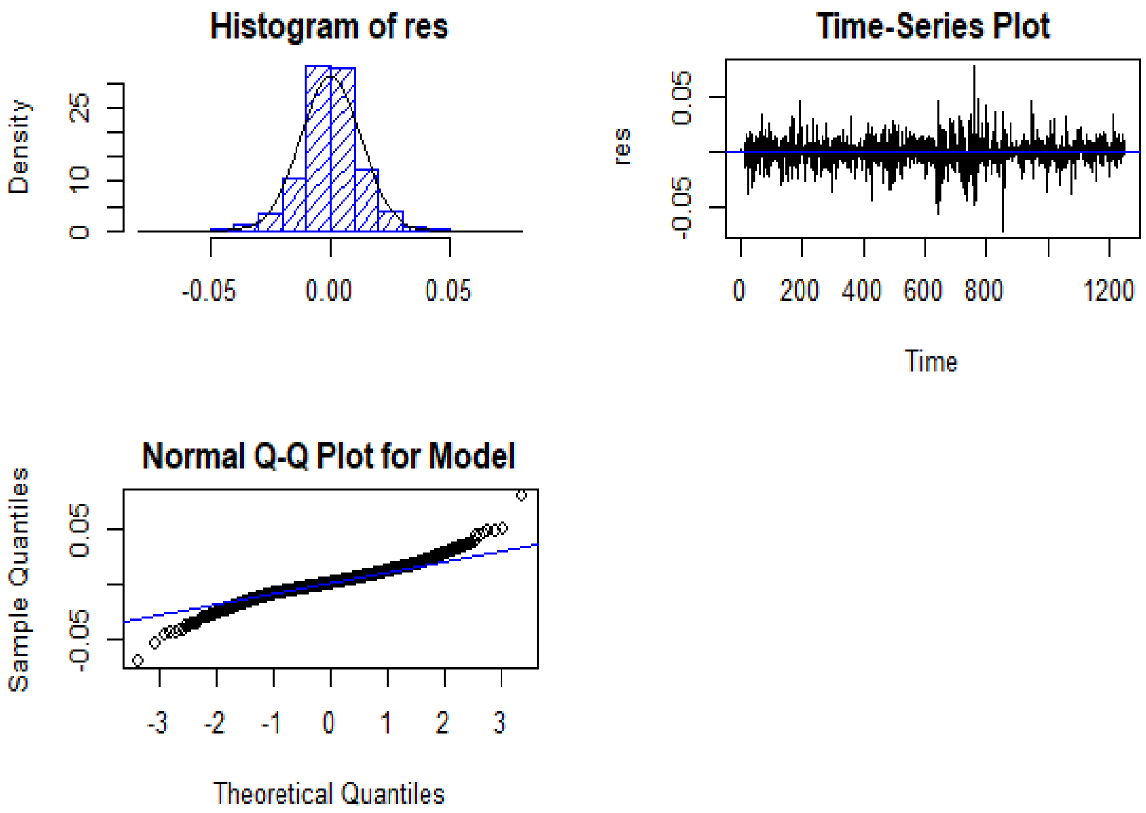
```
##
##  Box-Ljung test
##
## data:  res
## X-squared = 10.916, df = 6, p-value = 0.091
```

```
Box.test(res^2, lag = 9, type = c("Ljung-Box"), fitdf = 0)
```

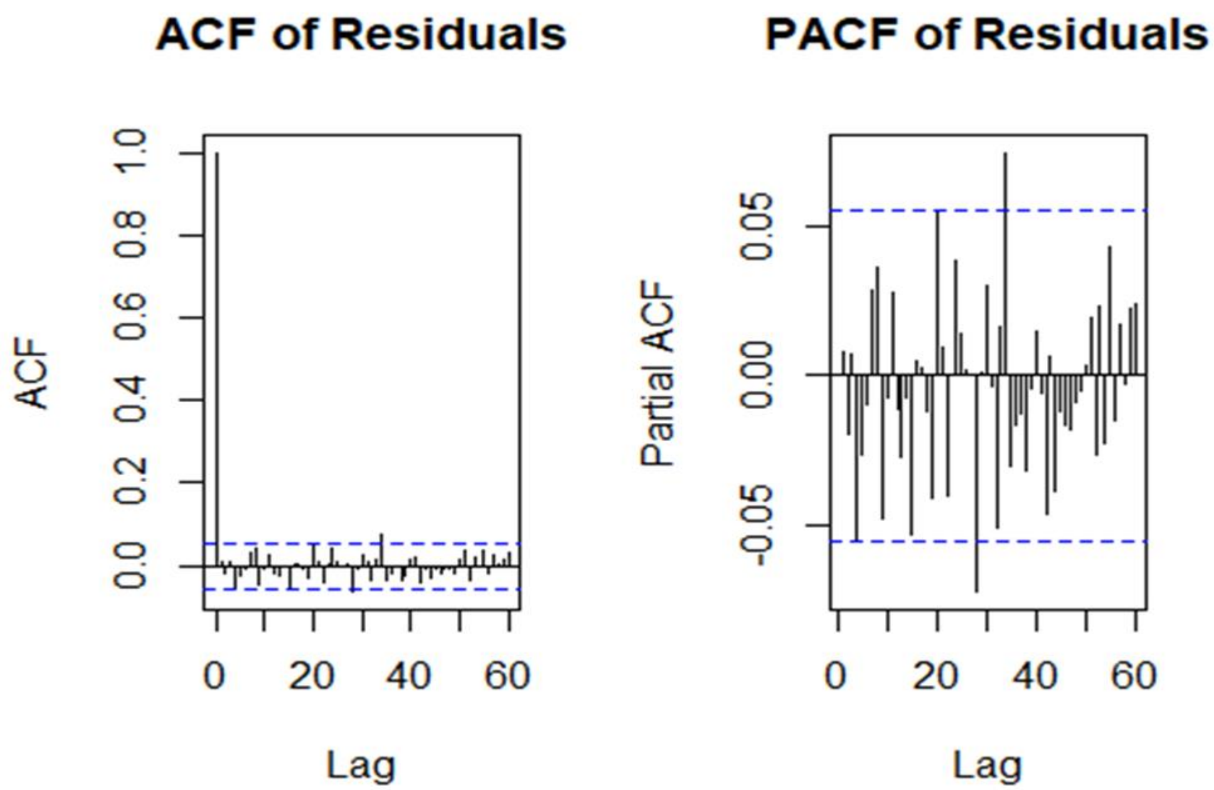
```
##
##  Box-Ljung test
##
## data:  res^2
## X-squared = 98.369, df = 9, p-value < 2.2e-16
```

**Passes the Box_Pierce and Ljung-Box tests, since p-values of these two are larger than 0.05.**

The histogram of residual, time series plot and normal Q-Q plot for model 1 has been plotted below:




The new ACF and PACF are:



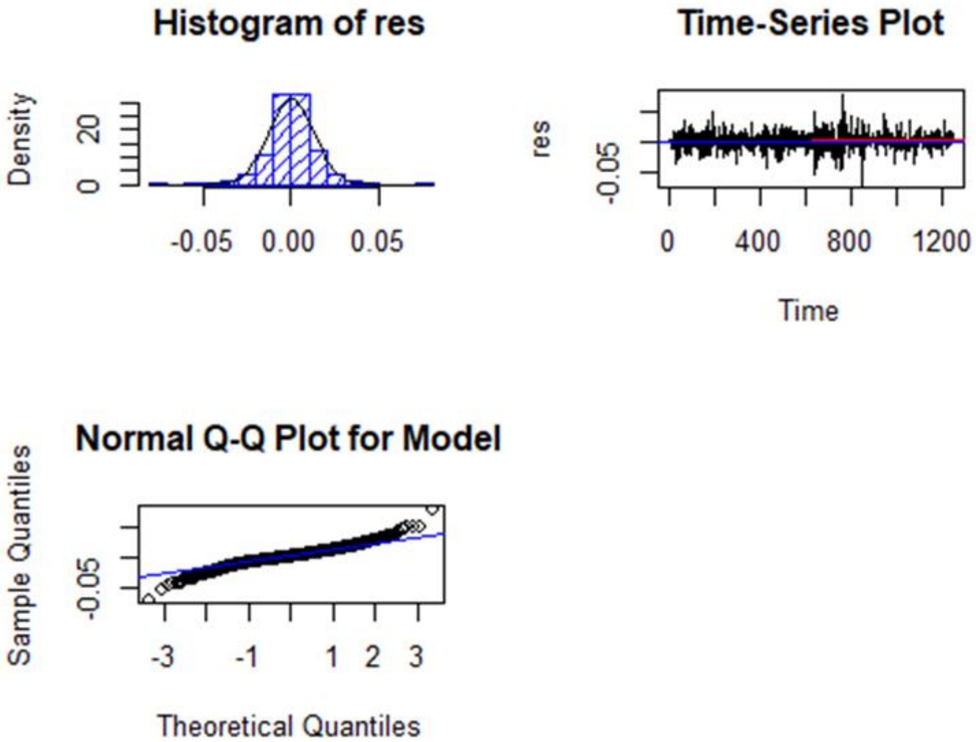
```
Call:
## ar(x = res, aic = TRUE, order.max = NULL, method = c("yule-walker"))
##
##
## Order selected 0  sigma^2 estimated as  0.0001616
```

## 3.10 Diagnostic checking of Model 2:

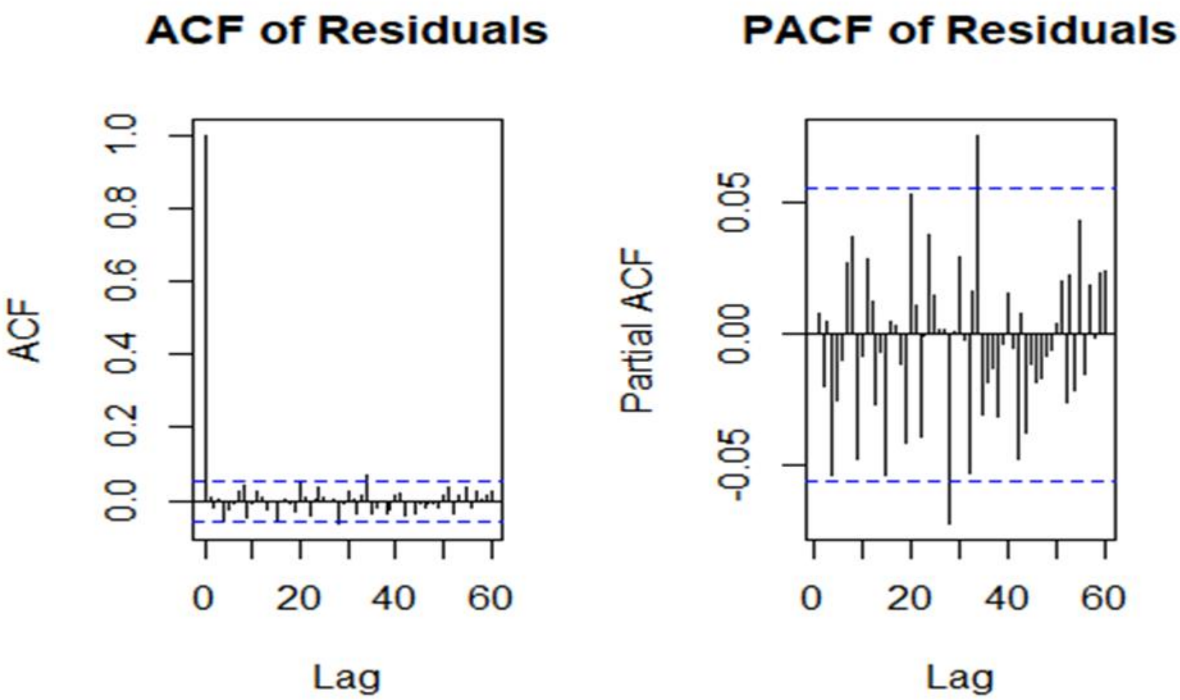
```
## Shapiro-Wilk normality test
##
## data:  res
## W = 0.96591, p-value < 2.2e-16

# p-value is less than 0.05 so it does not pass the Shapiro test
Box.test(res, lag = 9, type = c("Box-Pierce"), fitdf = 2)

##
##  Box-Pierce test
##
## data:  res
## X-squared = 10.538, df = 7, p-value = 0.1601

Box.test(res, lag = 9, type = c("Ljung-Box"), fitdf = 2)

##
##  Box-Ljung test
##
## data:  res
## X-squared = 10.608, df = 7, p-value = 0.1567

Box.test(res^2, lag = 9, type = c("Ljung-Box"), fitdf = 0)

##
##  Box-Ljung test
##
## data:  res^2
## X-squared = 98.234, df = 9, p-value < 2.2e-16
```

`It passes the first and second Box test i.e., Box-Pierce and Ljung-Box test because the p-values for these tests are larger than 0.05.`

The histogram of residual, time series plot and normal Q-Q plot for model 1 has been plotted below:




The ACF and PACF plots are:




```
## Call:
## ar(x = res, aic = TRUE, order.max = NULL, method = c("yule-
walker"))
```

```
##
## Order selected 0  sigma^2 estimated as  0.0001614
```

When performing the different types of tests on the two models, we saw that the models passed two of the Box Cox tests because it's p-values were greater than the significance level of 0.05. Moreover, both the models failed the Shapiro test and residual squared Ljung-Box test. Looking at the time series plot, we saw that there were no trends, no change in variances nor seasonal components. After carefully analyzing the Q-Q plots and histograms, we could see that they were approximately normally distributed. In the final ACF and PACF there were minor lags outside the confidence intervals. Based on all the evidence, I have decided to go with the model with the least AICc which is the first model, although the second model could have also been chosen since both the models almost resemble the normal distribution. Another benefit of the first model is that it had one less coefficient as shown in the analysis of the first model. Hence the first model is best for forecast.

## 3.11 Forecast

According to the forecast function, the forecasted dataset is as follows:

| | Point Forecast <dbl> | Lo 80 <dbl> | Hi 80 <dbl> | Lo 95 <dbl> | Hi 95 <dbl> |
|---|---|---|---|---|---|
| 1248 | 4.741280 | 4.724839 | 4.757721 | 4.716135 | 4.766424 |
| 1249 | 4.740064 | 4.716813 | 4.763316 | 4.704505 | 4.775624 |
| 1250 | 4.741786 | 4.713310 | 4.770263 | 4.698235 | 4.785337 |
| 1251 | 4.743925 | 4.711043 | 4.776806 | 4.693637 | 4.794213 |
| 1252 | 4.744116 | 4.707353 | 4.780879 | 4.687893 | 4.800339 |
| 1253 | 4.746000 | 4.705729 | 4.786272 | 4.684411 | 4.807590 |
| 1254 | 4.746738 | 4.703240 | 4.790236 | 4.680214 | 4.813262 |
| 1255 | 4.746158 | 4.699657 | 4.792659 | 4.675041 | 4.817275 |
| 1256 | 4.745083 | 4.695762 | 4.794405 | 4.669652 | 4.820515 |
| 1257 | 4.746689 | 4.694699 | 4.798678 | 4.667177 | 4.826200 |

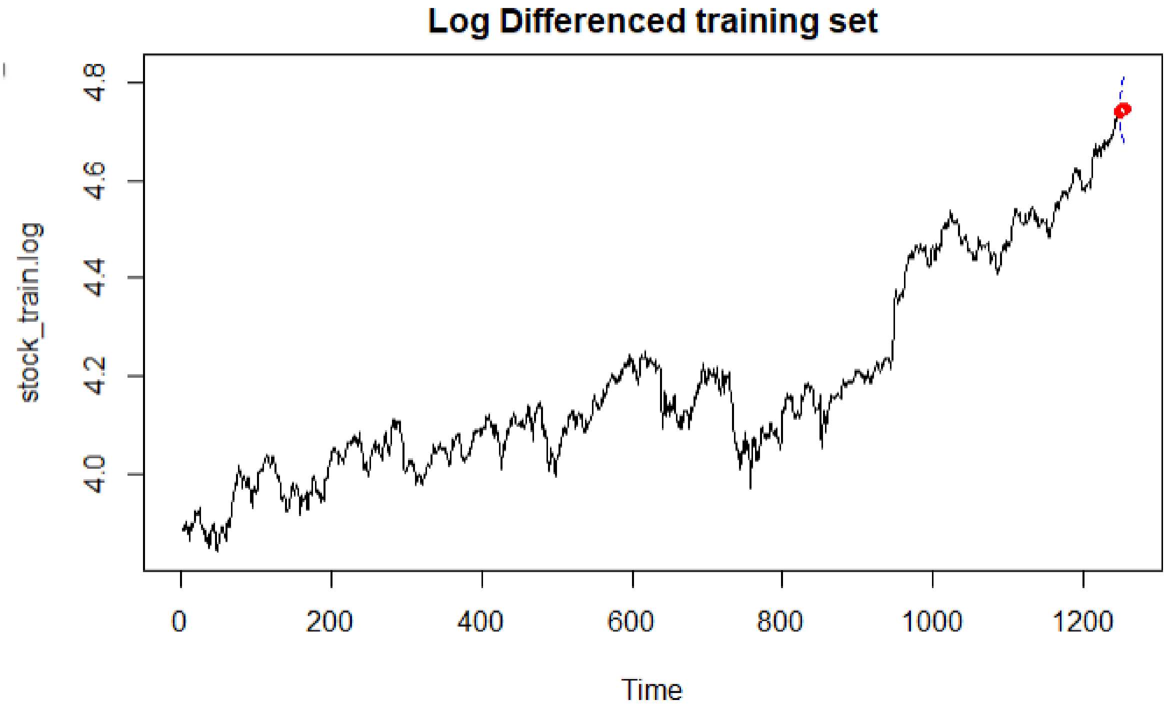
1-10 of 24 rows Previous 1 2 3 Next

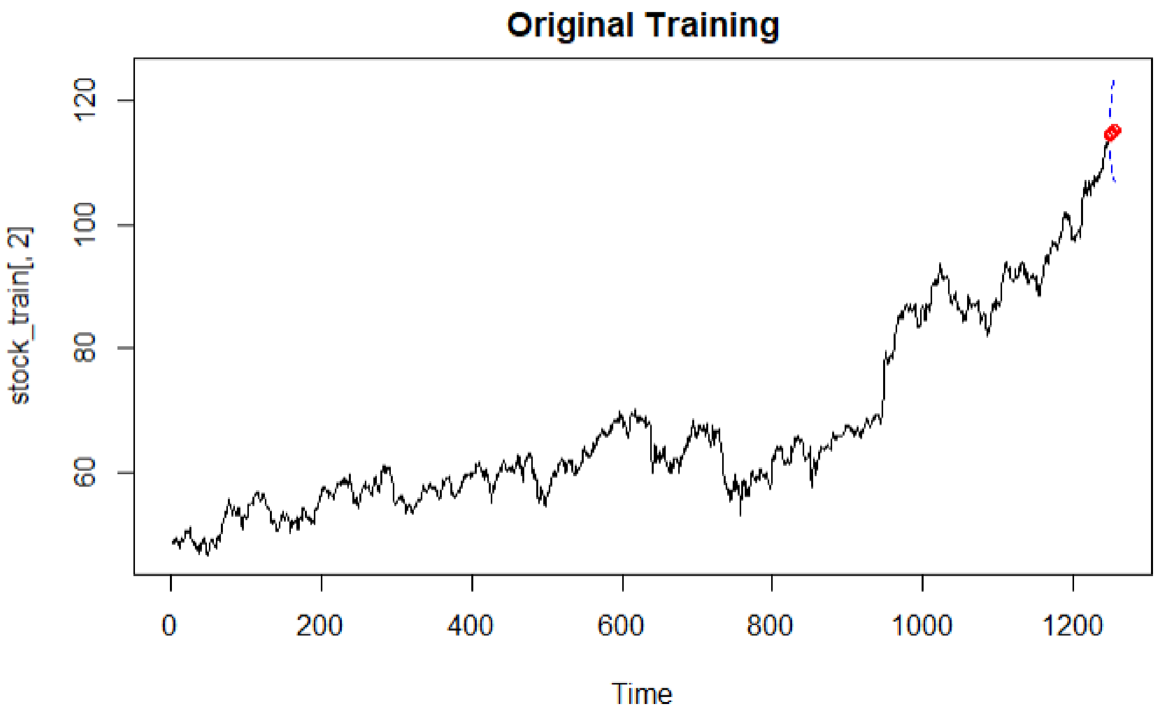
| | Point Forecast <dbl> | Lo 80 <dbl> | Hi 80 <dbl> | Lo 95 <dbl> | Hi 95 <dbl> |
|---|---|---|---|---|---|
| 1258 | 4.746808 | 4.692281 | 4.801335 | 4.663416 | 4.830200 |
| 1259 | 4.747321 | 4.690370 | 4.804273 | 4.660221 | 4.834422 |
| 1260 | 4.749512 | 4.690191 | 4.808833 | 4.658788 | 4.840236 |
| 1261 | 4.748297 | 4.686697 | 4.809897 | 4.654088 | 4.842505 |
| 1262 | 4.750019 | 4.686222 | 4.813815 | 4.652451 | 4.847586 |
| 1263 | 4.752157 | 4.686238 | 4.818077 | 4.651342 | 4.852973 |
| 1264 | 4.752348 | 4.684372 | 4.820325 | 4.648387 | 4.856310 |
| 1265 | 4.754233 | 4.684260 | 4.824206 | 4.647218 | 4.861248 |
| 1266 | 4.754970 | 4.683056 | 4.826885 | 4.644987 | 4.864954 |
| 1267 | 4.754390 | 4.680586 | 4.828195 | 4.641516 | 4.867265 |

11-20 of 24 rows Previous 1 2 3 Next

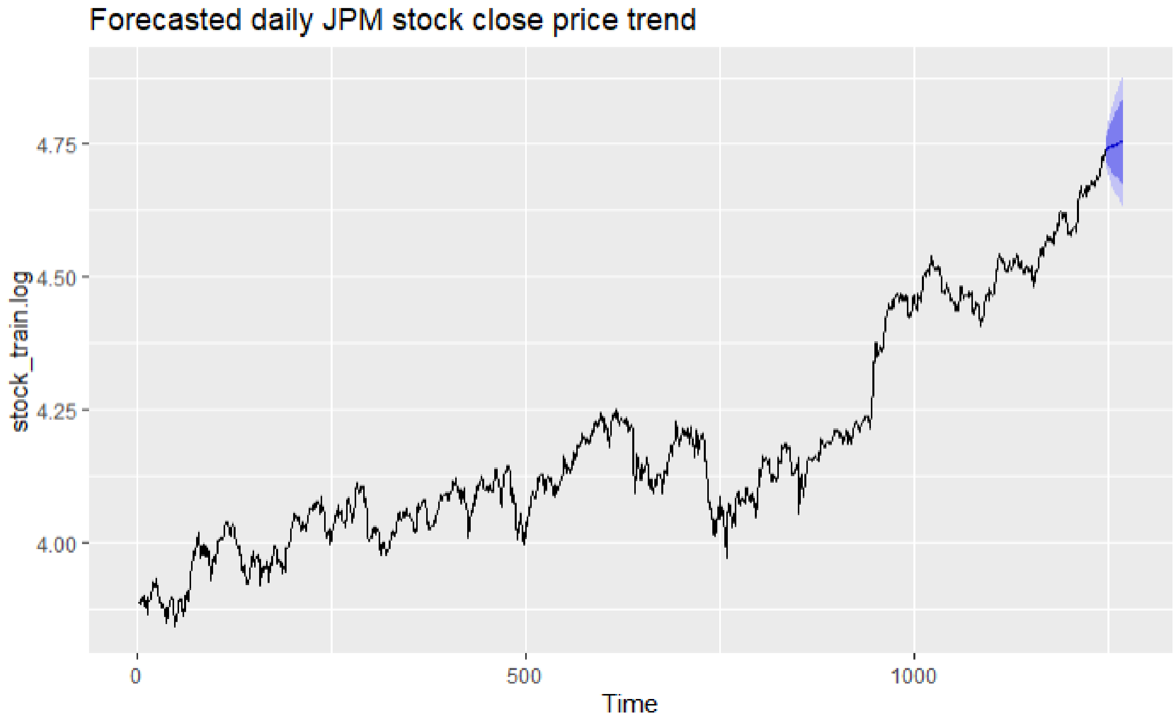
| | Point Forecast <dbl> | Lo 80 <dbl> | Hi 80 <dbl> | Lo 95 <dbl> | Hi 95 <dbl> |
|---|---|---|---|---|---|
| 1268 | 4.753316 | 4.677668 | 4.828964 | 4.637623 | 4.869009 |
| 1269 | 4.754921 | 4.677474 | 4.832368 | 4.636477 | 4.873366 |
| 1270 | 4.755041 | 4.675836 | 4.834246 | 4.633907 | 4.876174 |
| 1271 | 4.755554 | 4.674629 | 4.836479 | 4.631790 | 4.879318 |

The 12 points have been forecasted for the daily closing price of stocks. The plots of the tlog differenced and original training datasets are as follows:




The plot of original data points along with the forecasted data is as follows:




# 4 Conclusion

To conclude, the forecasted daily closing stock price has been evaluated. The goal has been achieved by using the first model instead of the second one. In the evaluation process, firstly, the dataset was divided into two parts; training data and test data. Then it was log transformed and then differenced at 12 and differenced at 12, then 1. After that, diagnostic checking has been done and after confirmation, the model has been used to predict the future closing price values which are close to the original data. With this analysis the customers can make informed decisions about the stocks they are interested in.

# 5 References

Data source: [Kaggle.com]

# Appendix:

```
#reading the data

library(tidyverse)

library(dplyr)

stock.csv <- read.csv(file = "JPM_data.csv")

#Time series

stock=ts(stock.csv,c(2013,1),c(2018,1),252)

ts.plot(stock.csv$close,main = "Original data", ylab ="Closing price")

plot.ts(stock)

nt=length(stock)

abline(h = mean(stock), col="4")

legend("bottomright", legend = c("Fitted Line", "Mean"), pch = rep(15, 4), col = 3:4)

#Training and test dataset

stock_train <- stock[c(1:1247),c(1,5)]

stock_train.csv<-stock[c(1:1247)]

stock_test <- stock[c(1247:1261),c(1,5)]

#Plotting the training dataset

par(mfrow=c(1,2))

ts.plot(stock_train[,2], main = "Training Set", ylab = "Closing stock price")

#fit <- lm(stock_train ~ as.numeric(1:length(stock_train[,2])));abline(fit, col="3")

#legend("bottomright", legend = c("Fitted Line"),pch , col = 3)

hist(stock_train, col = "light blue", xlab = "", main = "Histogram of training set")

## Transformations:

library(MASS)

bcTransform <- boxcox(stock_train~ as.numeric(1:length(stock_train.csv)))

lambda=bcTransform$x[which(bcTransform$y == max(bcTransform$y))]

stock_train.bc = (1/lambda)*(stock_train[,2]^lambda-1)

stock_train.log <- log(stock_train[,2])

par(mfrow=c(2,2))

plot.ts(stock_train[,2],ylab="Original closing price", main = "Original, Variance: 229.5218")

plot.ts(stock_train.bc, main = "Box-Cox, Variance: 210.3812")

plot.ts(stock_train.log, main = "LOG, Variance: 0.04309588")

var(stock_train[,2])# higest variance
```

```
var(stock_train.bc)
var(stock_train.log) # lowest variance
par(mfrow=c(2,2))
hist(stock_train.log, col="light blue", xlab="", main="ln(U_t)") # Has the lowest variance
hist(stock_train.bc, col="light blue", xlab="", main="bc(U_t)") #looks the most symmetric and normally distri
hist(stock_train[,2], col = "light blue", xlab = "", main = "No Transformation")
## Decomposition of LOG transformed training set:
y <- ts(as.ts(stock_train.log), frequency = 12)
decomposition <- decompose(y)
plot(decomposition)
## Differencing:
par(mfrow=c(2,2))
plot.ts(stock_train.log, main = "NO difference, Variance: 0.04309588") #0.04309588
fit1 <- lm(stock_train.log ~ as.numeric(1:length(stock_train.log)));abline(fit1, col=3)
abline(h=mean(stock_train.log), col=4)
stock_train.log.12 <- diff(stock_train.log, lag =12)
plot.ts(stock_train.log.12, main = "Differenced at 12")
fit2 <- lm(stock_train.log.12 ~ as.numeric(1:length(stock_train.log.12)));abline(fit1, col=3)
abline(h=mean(stock_train.log.12), col=4)
stock_train.log.12.1 <- diff(stock_train.log.12, lag =1)
plot.ts(stock_train.log.12.1, main = "Differenced at 12, then 1")
fit3 <- lm(stock_train.log.12.1 ~ as.numeric(1:length(stock_train.log.12.1)));abline(fit1, col=3)
abline(h=mean(stock_train.log.12.1), col=4)
var(stock_train.log)
mean(stock_train.log)
var(stock_train.log.12)
mean(stock_train.log.12) #-0.003156617
var(stock_train.log.12.1) #variance went higher, 0.04487819 went higher
mean(stock_train.log.12.1) #0.008926943 went lower
#ACF differencing plots
par(mfrow=c(2,2))
acf(stock_train.log, lag.max = 60, main = "ACF of LOG")
acf(stock_train.log.12, lag.max = 60, main = "ACF of LOG difference at 12")
```

```
acf(stock_train.log.12.1, lag.max = 60, main = "ACF of LOG difference at 12 then 1") #ACF decays corresponding
## Comparing the histograms at different differences:
par(mfrow=c(2,2))
hist(stock_train.log, col="light blue", xlab="", main="ln(U_t)")
hist(stock_train.log.12, col="light blue", xlab="", main="ln(U_t), differenced at 12")
hist(stock_train.log.12.1, col="light blue", xlab="", main="ln(U_t), differenced at 12 then 1")
## ACF and PACF of log then differenced at 12 then 1:
par(mfrow=c(1,2))
acf(stock_train.log.12.1, lag.max = 60, main = "ACF of LOG difference at 12 then 1")
#ACF outside confidence intervals: 1,12
pacf(stock_train.log.12.1, lag.max = 60, main = "PACF of LOG difference at 12 then 1")
#PACF outside the confidence intervals: 1,12?
#List of candidate models to try:
#SARIMA for log: s=12, D=1, d=1, Q=0 or 1, q=0, P=0 or 1, p=0.
## Trying models now:
df <- expand.grid(p=0:1, q=0:1, P=0:1, Q=0:1)
df <- cbind(df, AICc=NA)
# Compute AICc:
library(MASS)
library(MuMIn)
for (i in 1:nrow(df)) {
sarima.obj <- NULL
try(arima.obj <- arima(stock_train.log, order=c(df$p[i], 1, df$q[i]),
seasonal=list(order=c(df$P[i], 1, df$Q[i]), period=12),
method="ML"))
if (!is.null(arima.obj)) { df$AICc[i] <- AICc(arima.obj) }
# print(df[i, ])
}
#df[which.min(df$AICc), ]
df[(df$AICc),] # second lowest AIC -45.75403 when p=1, q=1, P=0, Q=1
# when p=0, q=1, P=0, Q=1 we get the lowest AIC -47.91584
final <- which.min(df$AICc)
fit4.1 <- arima(stock_train.log, order=c(0, 1, 0),
```

```
seasonal=list(order=c(0, 1, 1), period=12),

method="ML")

fit4.1

fit4 <- arima(stock_train.log, order=c(0,1,0),

seasonal=list(order=c(1,1,1), period=12),

method="ML")

fit4

## Diagnostic Checking 1st model:

res <- residuals(fit4.1)

shapiro.test(res)

# p-value is less than 0.05 so it does not pass the shapiro.test

Box.test(res, lag = 9, type = c("Box-Pierce"), fitdf = 3)

Box.test(res, lag = 9, type = c("Ljung-Box"), fitdf = 3)

Box.test(res^2, lag = 9, type = c("Ljung-Box"), fitdf = 0)

#passes the Box_Pierce and Ljung-Box tests, since p-values are larger than 0.05

par(mfrow=c(2,2))

hist(res,density=20,breaks=20, col="blue", xlab="", prob=TRUE)

# Approximately normal and almost symmetric.

m <- mean(res)

std <- sqrt(var(res))

curve( dnorm(x,m,std), add=TRUE )

plot.ts(res,main = "Time-Series Plot")

fitt <- lm(res ~ as.numeric(1:length(res))); abline(fitt, col="red")

abline(h=mean(res), col="blue")

qqnorm(res,main= "Normal Q-Q Plot for Model")

qqline(res,col="blue")

# Looks approximately normal

par(mfrow=c(1,2))

acf(res, lag.max=60, main = "ACF of Residuals")

pacf(res, lag.max=60, main = "PACF of Residuals")

# All ACF and PACF are within confidence intervals and can be counted as zero.

#acf(resˆ2, lag.max=60, main = "ACF of Residualsˆ2")

ar(res, aic = TRUE, order.max = NULL, method = c("yule-walker"))
```

```
#2 diagnostic checking

res <- residuals(fit4)

shapiro.test(res)

# p-value is less than 0.05 so it does not pass the Shapiro test

Box.test(res, lag = 9, type = c("Box-Pierce"), fitdf = 2)

Box.test(res, lag = 9, type = c("Ljung-Box"), fitdf = 2)

Box.test(res^2, lag = 9, type = c("Ljung-Box"), fitdf = 0)

#passes the first and second Box test i.e Box-Pierce and Ljung-Box test because the p-values for these test are larger than 0.05.

par(mfrow=c(2,2))

hist(res,density=20,breaks=20, col="blue", xlab="", prob=TRUE)

# Approximately normal and almost symmetric.

m <- mean(res)

std <- sqrt(var(res))

curve( dnorm(x,m,std), add=TRUE )

plot.ts(res,main = "Time-Series Plot")

fitt <- lm(res ~ as.numeric(1:length(res))); abline(fitt, col="red")

abline(h=mean(res), col="blue")

qqnorm(res,main= "Normal Q-Q Plot for Model")

qqline(res,col="blue")

# Looks approximately normal

par(mfrow=c(1,2))

acf(res, lag.max=60, main = "ACF of Residuals")

pacf(res, lag.max=60, main = "PACF of Residuals")

# All ACF and PACF are within confidence intervals and can be counted as zero.

#acf(resˆ2, lag.max=60, main = "ACF of Residualsˆ2")

ar(res, aic = TRUE, order.max = NULL, method = c("yule-walker"))

##Forecast

library(forecast)

library(dplyr)

library(ggplot2)

fit4.1

forecast(fit4.1)
```

```
#par(mfrow=c(1,2))

pred.tr <- predict(fit4.1, n.ahead = 8)

U.tr = pred.tr$pred + 2*pred.tr$se #upper bound

L.tr = pred.tr$pred - 2*pred.tr$se #lower bound

ts.plot(stock_train.log, xlim=c(1,length(stock_train.log)+8), ylim = c(min(stock_train.log),max(U.tr)), main = "Log Differenced training set")

lines(U.tr, col="blue", lty="dashed")

lines(L.tr, col="blue", lty="dashed")

points((length(stock_train.log)+1):(length(stock_train.log)+8), pred.tr$pred, col="red")

pred.orig <- exp(pred.tr$pred)

U = exp(U.tr)

L = exp(L.tr)

ts.plot(stock_train[,2], xlim=c(1, length(stock_train[,2])+8), ylim = c(min(stock_train[,2]), max(U)), main = "Original Training")

lines(U, col="blue", lty="dashed")

lines(L, col="blue", lty="dashed")

points((length(stock_train[,2])+1):(length(stock_train[,2])+8), pred.orig, col="red")

forecast.plot<-forecast(fit4.1) %>% autoplot(main="Forecasted daily JPM stock close price trend")

forecast.plot
```