

Time Series Analysis final Project - Competitive

MATH 1318 Time Series Analysis Final Project

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1 Introduction

Bitcoin or BTC is a digital currency, otherwise known as a cryptocurrency. it was introduced to markets in 2009 by ‘Satoshi Nakamoto.’ The most notable aspect of BTC is that no banks or financial institutions are needed to facilitate trades. Additionally, it runs as a virtually anonymous financial system whereby buyers and sellers do not need to input their names, addresses or any other personally identifiable information to transfer BTC.

Rahul Made these changes

2 Model Diagnosis

```
# Import Libraries
```

```
library(TSA)
library(fUnitRoots)
library(forecast)
library(CombMSC)
library(lmtest)
library(fGarch)
library(rugarch)
library(zoo)
library(ggplot2)
```

```
residual.analysis <- function(model, std = TRUE){
```

```
  library(TSA)
  library(FitAR)
  if (std == TRUE){
    res.model = rstandard(model)
  }else{
    res.model = residuals(model)
  }
  par(mfrow=c(3,2))
  plot(res.model,type='o',ylab='Standardised residuals', main="Time series plot of standardised residuals")
  abline(h=0)
  hist(res.model,main="Histogram of standardised residuals")
  qqnorm(res.model,main="QQ plot of standardised residuals")
  qqline(res.model, col = 2)
  acf(res.model,main="ACF of standardised residuals")
  print(shapiro.test(res.model))
  k=0
  LBQPlot(res.model, lag.max = length(model$residuals)-1 , StartLag = k + 1, k = 0, SquaredQ = FALSE)
  par(mfrow=c(1,1))
}
```

```
Bitcoin <- read.csv("../data/Bitcoin_Historical_Price.csv", header=TRUE)
```

```
Bitcoin$Date = as.Date(Bitcoin$Date,'%Y-%m-%d')
```

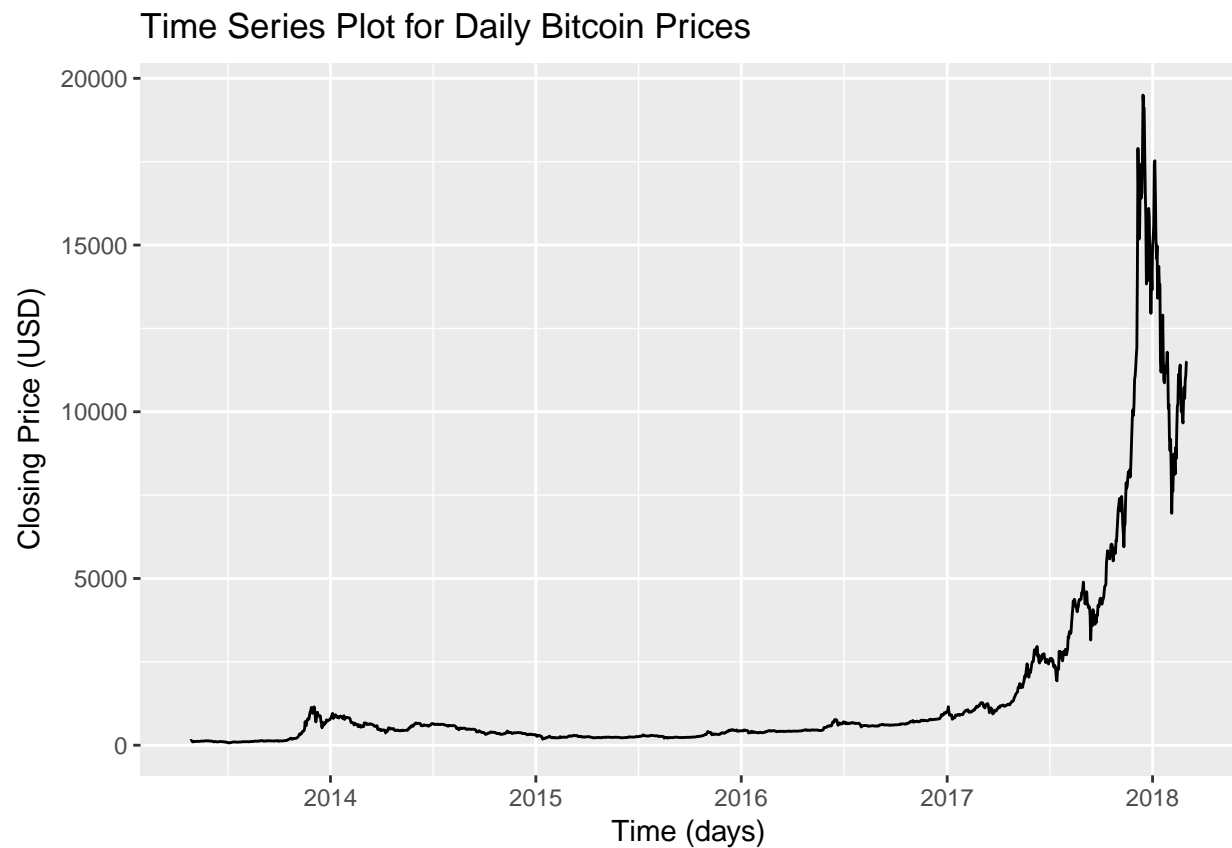
```
Bitcoin.zoo <- zoo(Bitcoin$Close, Bitcoin$Date)
```

```
class(Bitcoin.zoo)
```

```
## [1] "zoo"
```

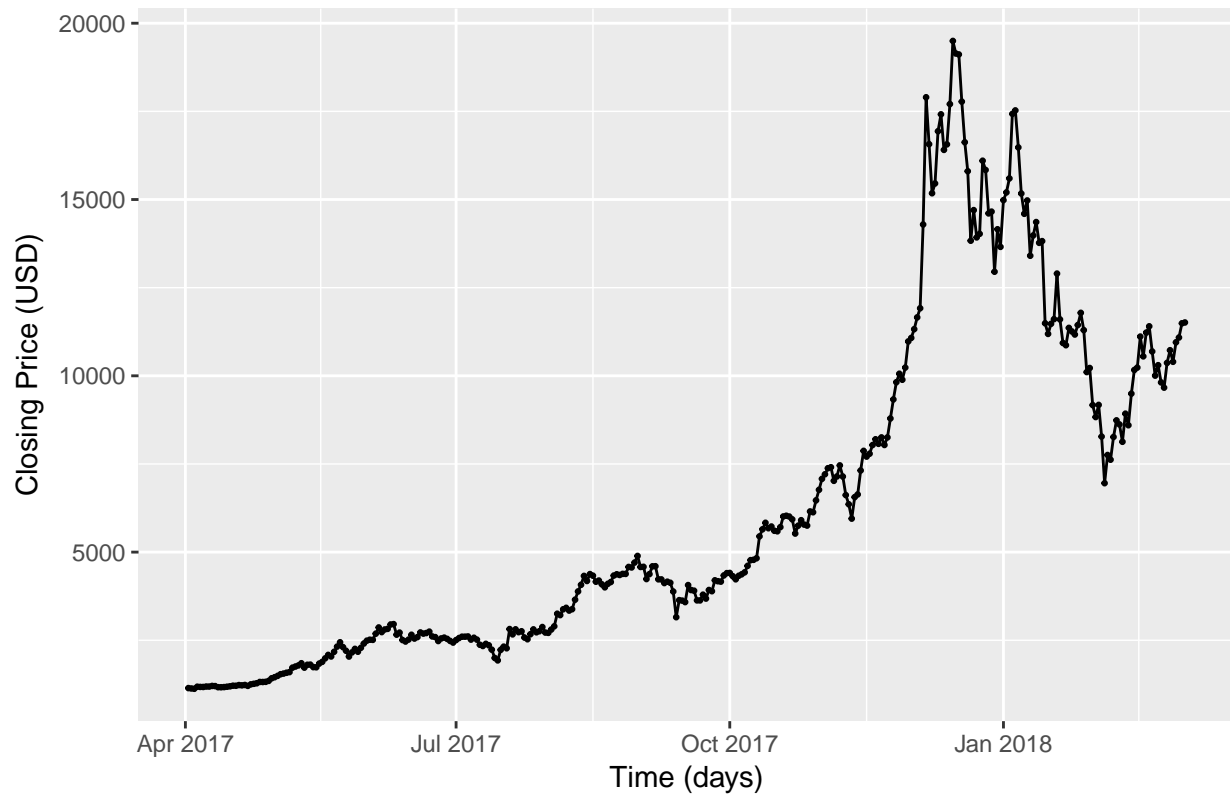
```
Bitcoin.raw = Bitcoin.zoo
```

```
autoplot.zoo(Bitcoin.zoo) +
  ylab('Closing Price (USD)') +
  xlab('Time (days)') +
  ggtitle("Time Series Plot for Daily Bitcoin Prices")
```



```
Bitcoin.2017 = Bitcoin[Bitcoin$Date > as.Date("2017-04-01"),]
Bitcoin.2017.zoo = zoo(Bitcoin.2017$Close, Bitcoin.2017$Date)
autoplot(Bitcoin.2017.zoo) +
  geom_point(size=.5) +
  ylab('Closing Price (USD)') +
  xlab('Time (days)') +
  ggtitle("Time Series Plot for Daily Bitcoin Prices (2017-2018)")
```

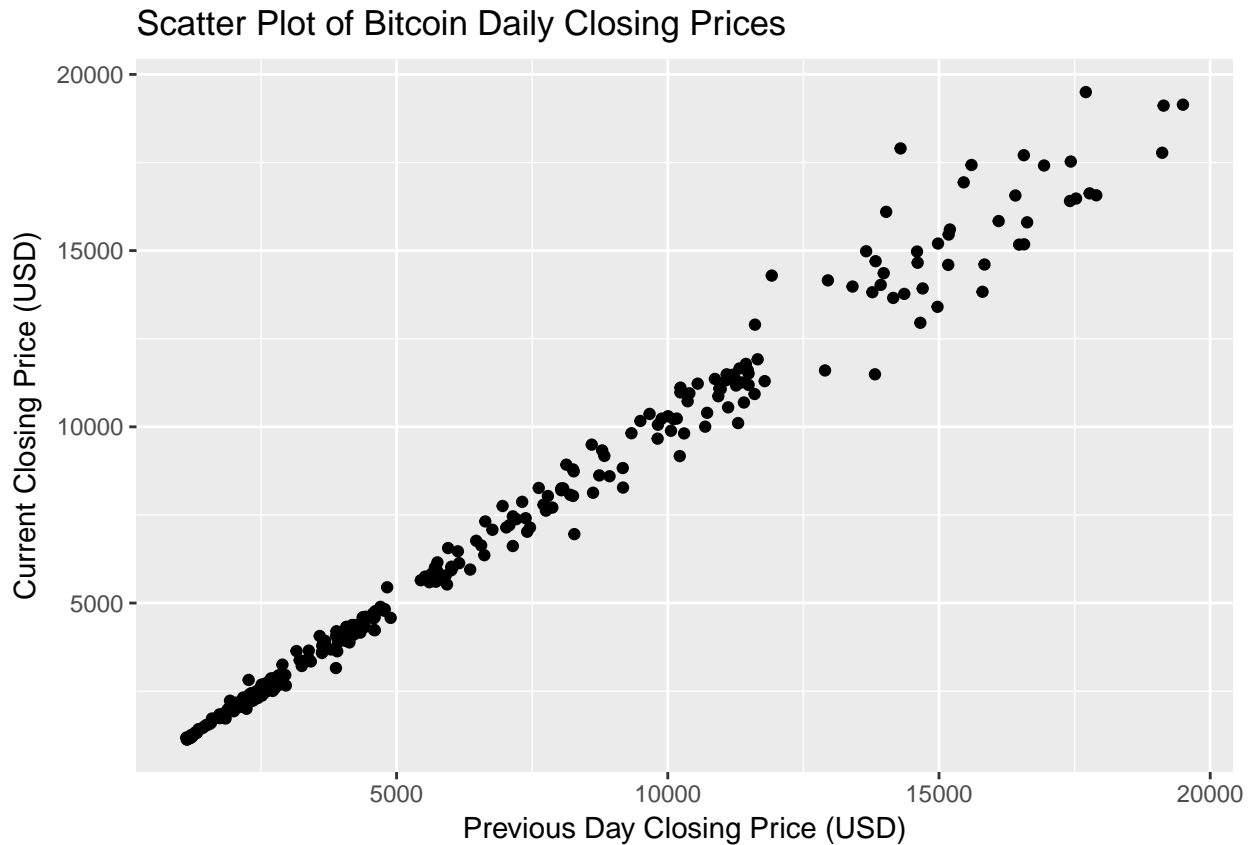
Time Series Plot for Daily Bitcoin Prices (2017–2018)



2.1 Scatter Plot and correlation

```
ggplot(Bitcoin.2017,aes(zlag(Close), Close)) + geom_point() +  
  ylab('Current Closing Price (USD)') +  
  xlab('Previous Day Closing Price (USD)') +  
  ggtitle("Scatter Plot of Bitcoin Daily Closing Prices")
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



```
y = as.vector(Bitcoin.2017.zoo)
x = zlag(Bitcoin.2017.zoo)
index = 2:length(x)
cor(y[index],x[index])
```

```
## [1] 0.9935557
```

2.2 Linear Model

```
model.ln = lm(Bitcoin.2017.zoo~time(Bitcoin.2017.zoo)) # label the linear trend model as model.ln
summary(model.ln)
```

```
##
## Call:
## lm(formula = Bitcoin.2017.zoo ~ time(Bitcoin.2017.zoo))
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-4954.5	-1579.6	-668.9	881.2	9660.6

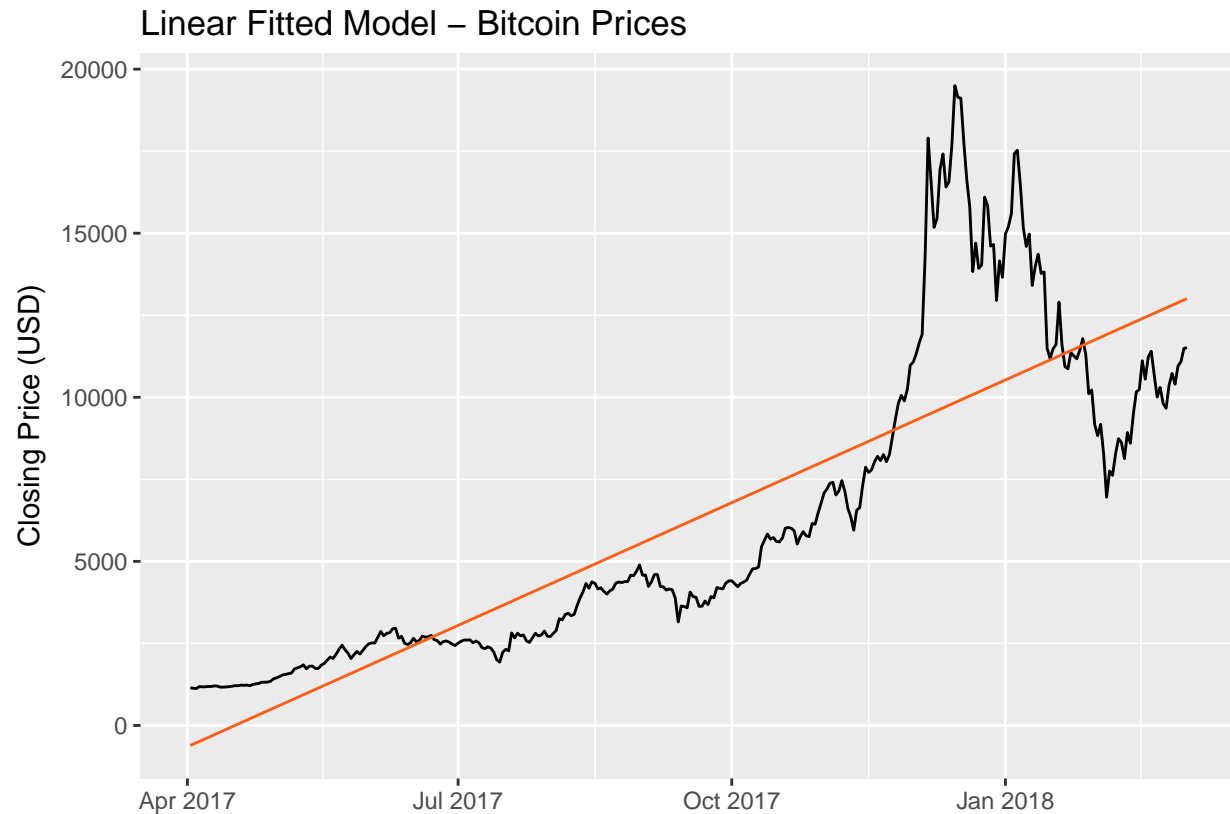
```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-7.021e+05	2.461e+04	-28.53	<2e-16 ***
time(Bitcoin.2017.zoo)	4.065e+01	1.412e+00	28.79	<2e-16 ***

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2511 on 334 degrees of freedom
## Multiple R-squared:  0.7127, Adjusted R-squared:  0.7119
## F-statistic: 828.6 on 1 and 334 DF,  p-value: < 2.2e-16
```

```
ggplot(Bitcoin.2017,aes(Date,Close))+
  geom_line() +
  ylab('Closing Price (USD)') +
  xlab('') +
  ggtitle('Linear Fitted Model - Bitcoin Prices') +
  geom_line(aes(y=fitted(model.ln)),color='#fc5e13')
```



2.3 Residual Analysis - Linear Model

Below are the findings of residuals from linear model

```
residual_analysis_qq <- function(myresiduals, title = 'QQ Plot of Residuals') {
  data=as.data.frame(qqnorm( myresiduals , plot=F))
  ggplot(data,aes(x,y)) +
    geom_point() +
    geom_smooth(method="lm", se=FALSE, color='#e36209', size=.4)+
    xlab('Theoretical') +
    ylab('Sample') +
    ggtitle(title)
}

checkresiduals(model.ln)
```

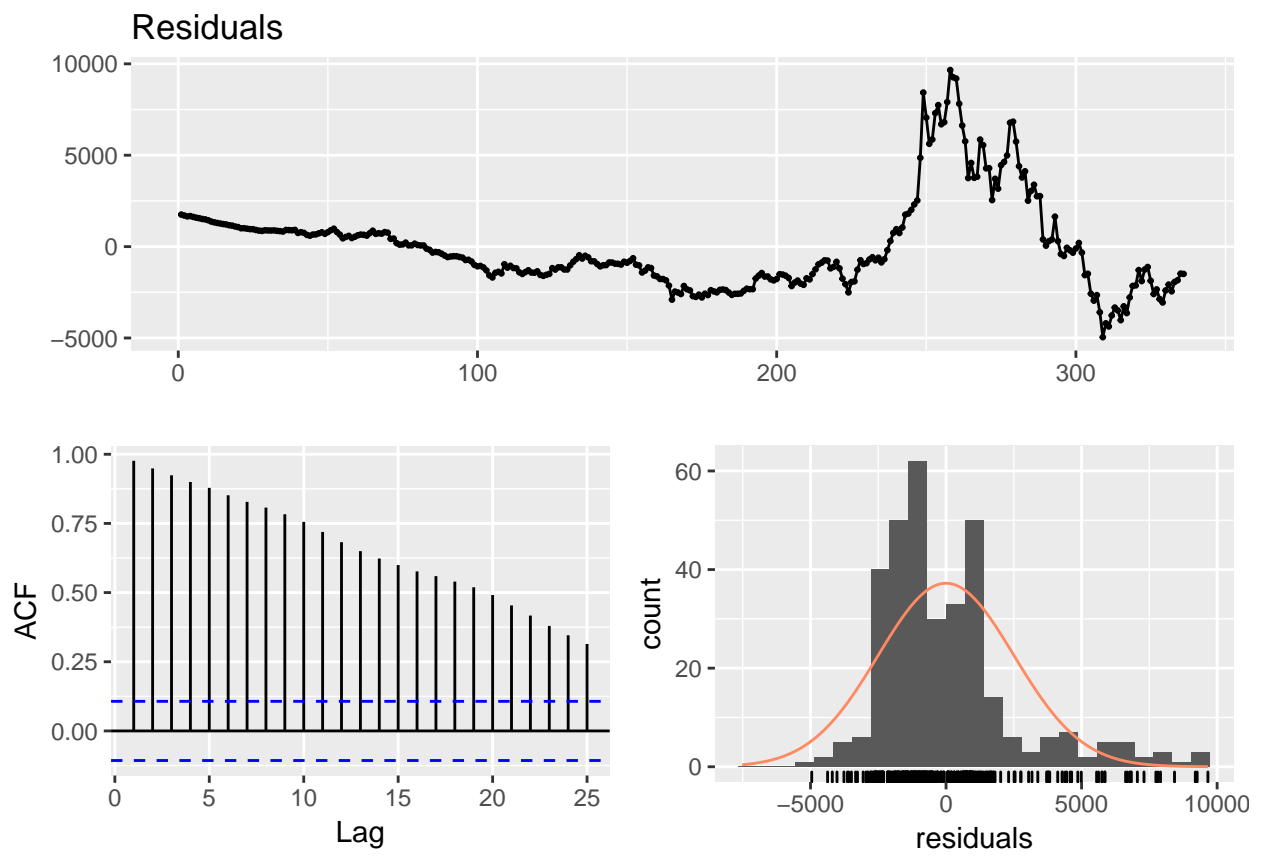


Figure 1: Residual Analysis Linear fitted Model

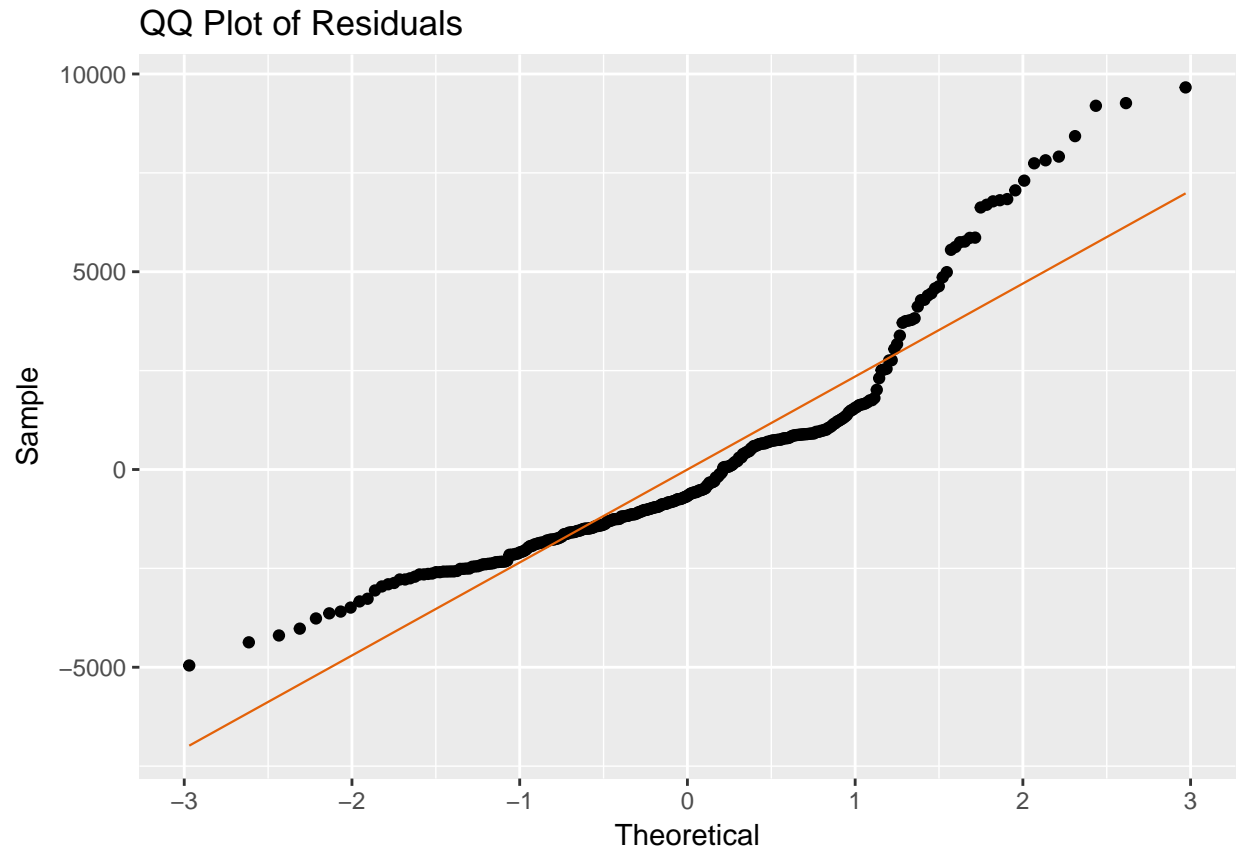


Figure 2: Residual Analysis Linear fitted Model

```
##
## Breusch-Godfrey test for serial correlation of order up to 10
##
## data: Residuals
## LM test = 321.71, df = 10, p-value < 2.2e-16
```

```
residual_analysis_qq(residuals(model.ln))
```

```
shapiro.test(as.vector(residuals(model.ln)))
```

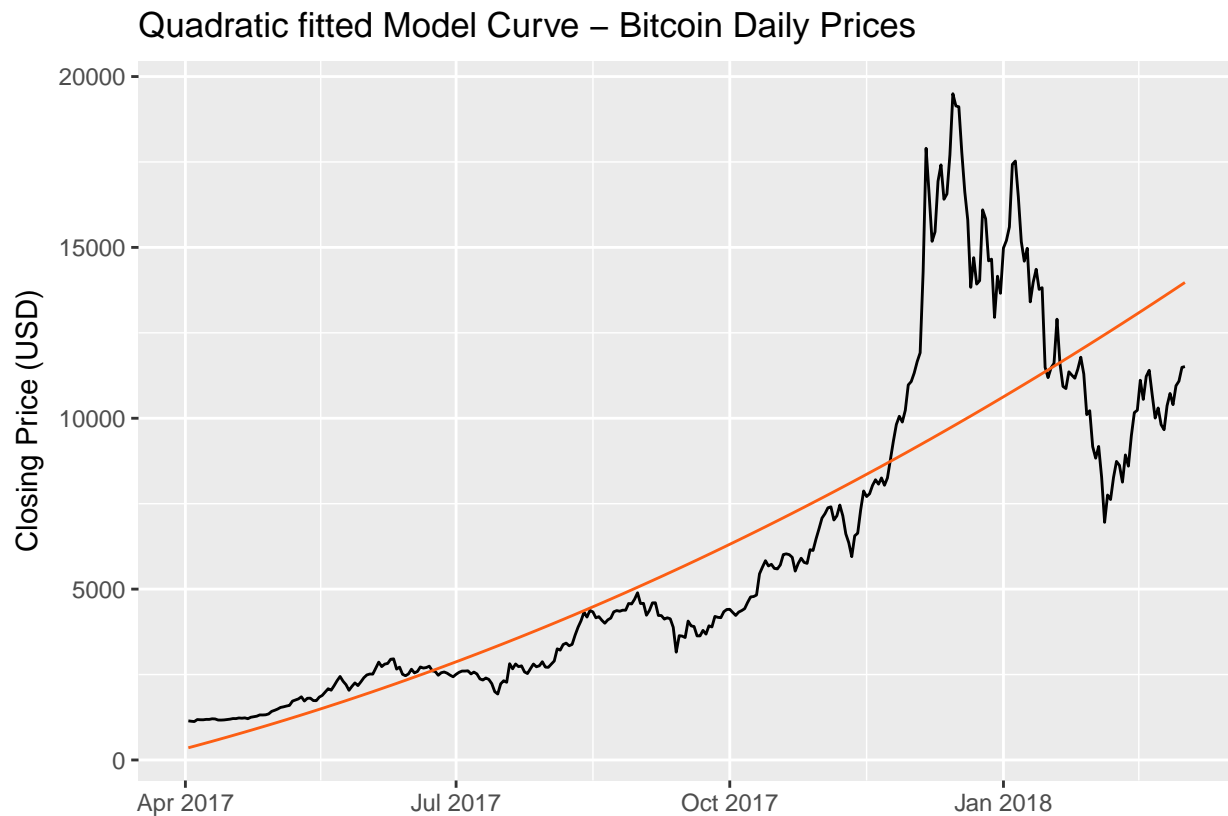
```
##
## Shapiro-Wilk normality test
##
## data: as.vector(residuals(model.ln))
## W = 0.87841, p-value = 1.204e-15
```

2.4 Quadratic Model

```
t = as.vector(time(Bitcoin.2017.zoo))
t2 = t^2
model.qa = lm(Bitcoin.2017.zoo ~ t + t2) # label the quadratic trend model as model.qa
summary(model.qa)
```

```
##
## Call:
## lm(formula = Bitcoin.2017.zoo ~ t + t2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5490.1 -1286.7  -408.4   497.0  9733.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.504e+07  4.874e+06   3.085  0.00221 **
## t           -1.766e+03  5.594e+02  -3.156  0.00174 **
## t2            5.183e-02  1.605e-02   3.229  0.00137 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2476 on 333 degrees of freedom
## Multiple R-squared:  0.7214, Adjusted R-squared:  0.7198
## F-statistic: 431.2 on 2 and 333 DF,  p-value: < 2.2e-16

ggplot(Bitcoin.2017,aes(Date,Close))+
  geom_line() +
  ylab('Closing Price (USD)') +
  xlab('') +
  ggtitle('Quadratic fitted Model Curve - Bitcoin Daily Prices') +
  geom_line(aes(y=fitted(model.qa)),color='#fc5e13')
```



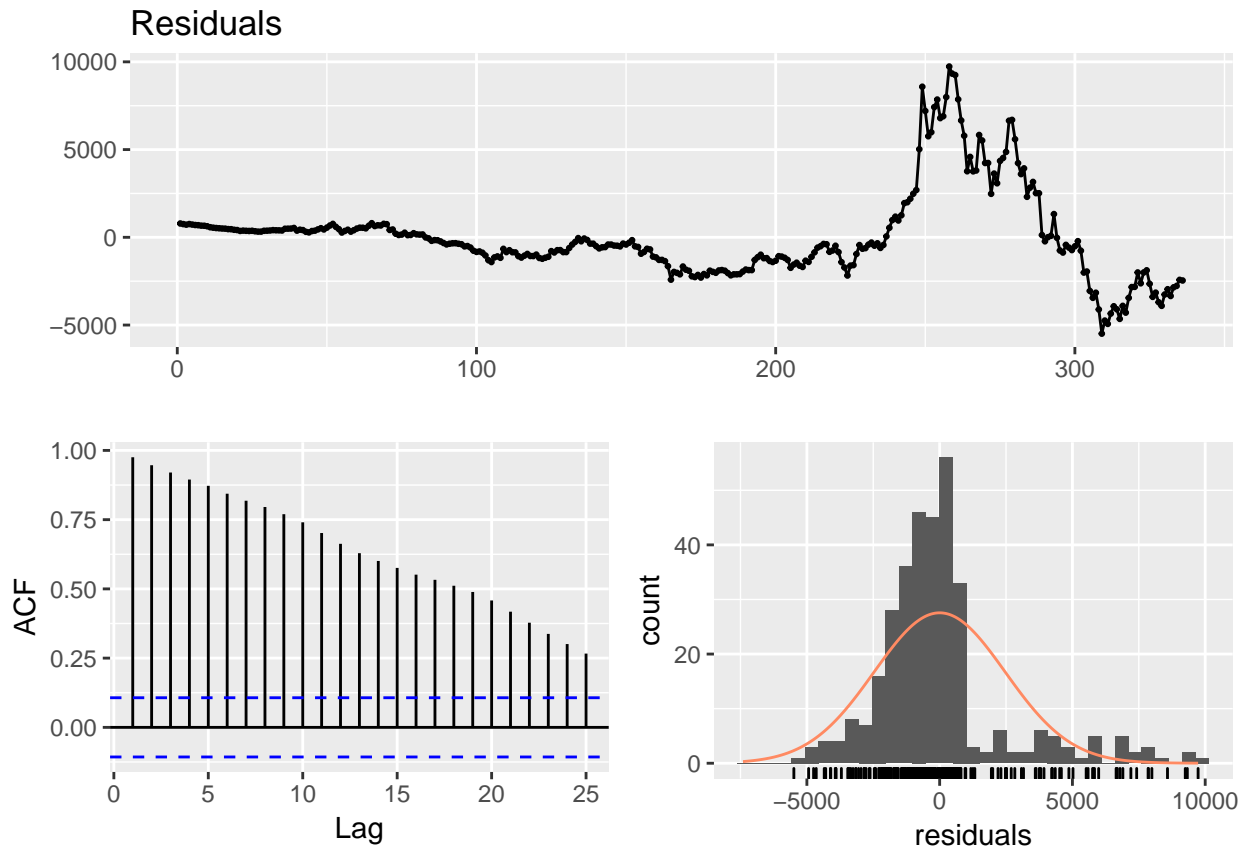


Figure 3: Residual Analysis Quadratic fitted Model

2.5 Residual Analysis - Linear Model

Below are the findings of residuals from linear model

```
checkresiduals(model.qa)
```

```
##
## Breusch-Godfrey test for serial correlation of order up to 10
##
## data: Residuals
## LM test = 321.7, df = 10, p-value < 2.2e-16
```

```
residual_analysis_qq(residuals(model.qa))
```

```
shapiro.test(as.vector(residuals(model.qa)))
```

```
##
## Shapiro-Wilk normality test
##
## data: as.vector(residuals(model.qa))
## W = 0.86085, p-value < 2.2e-16
```

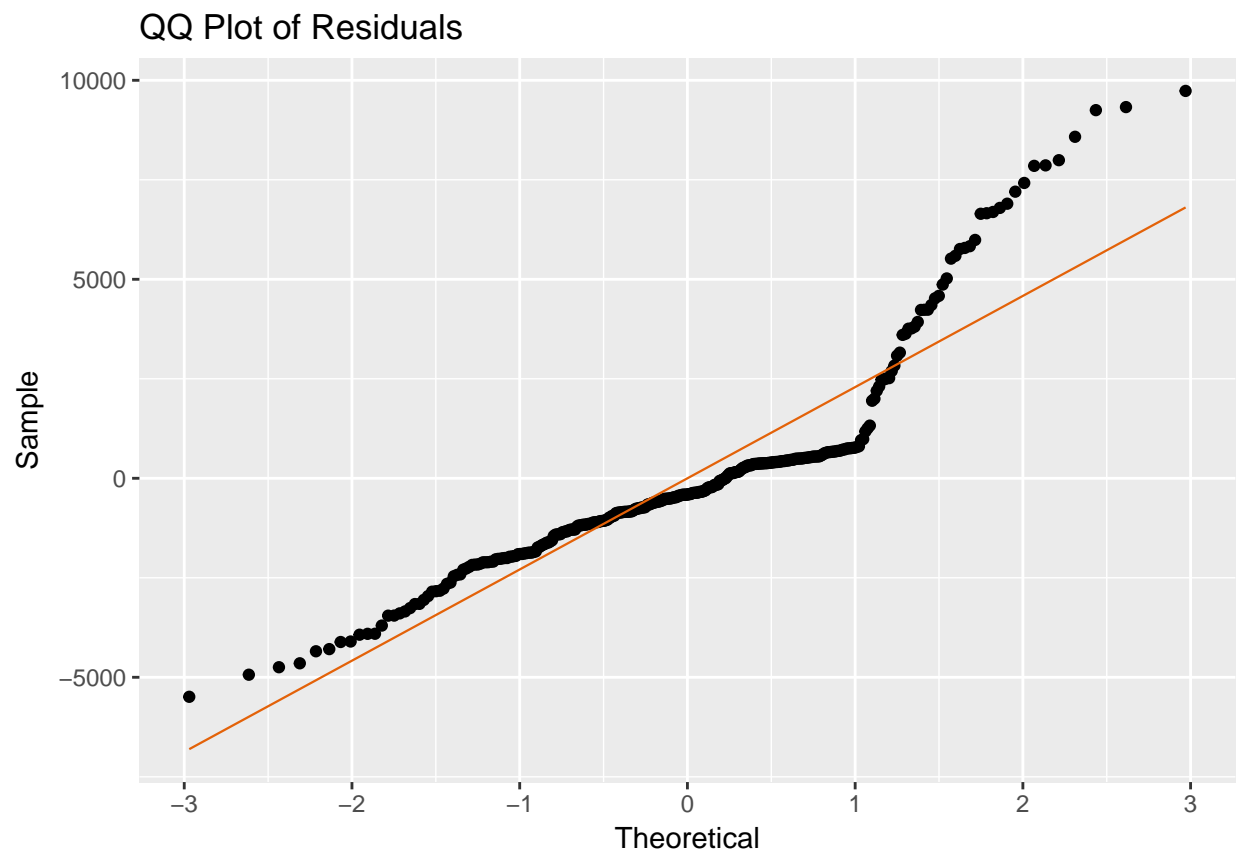
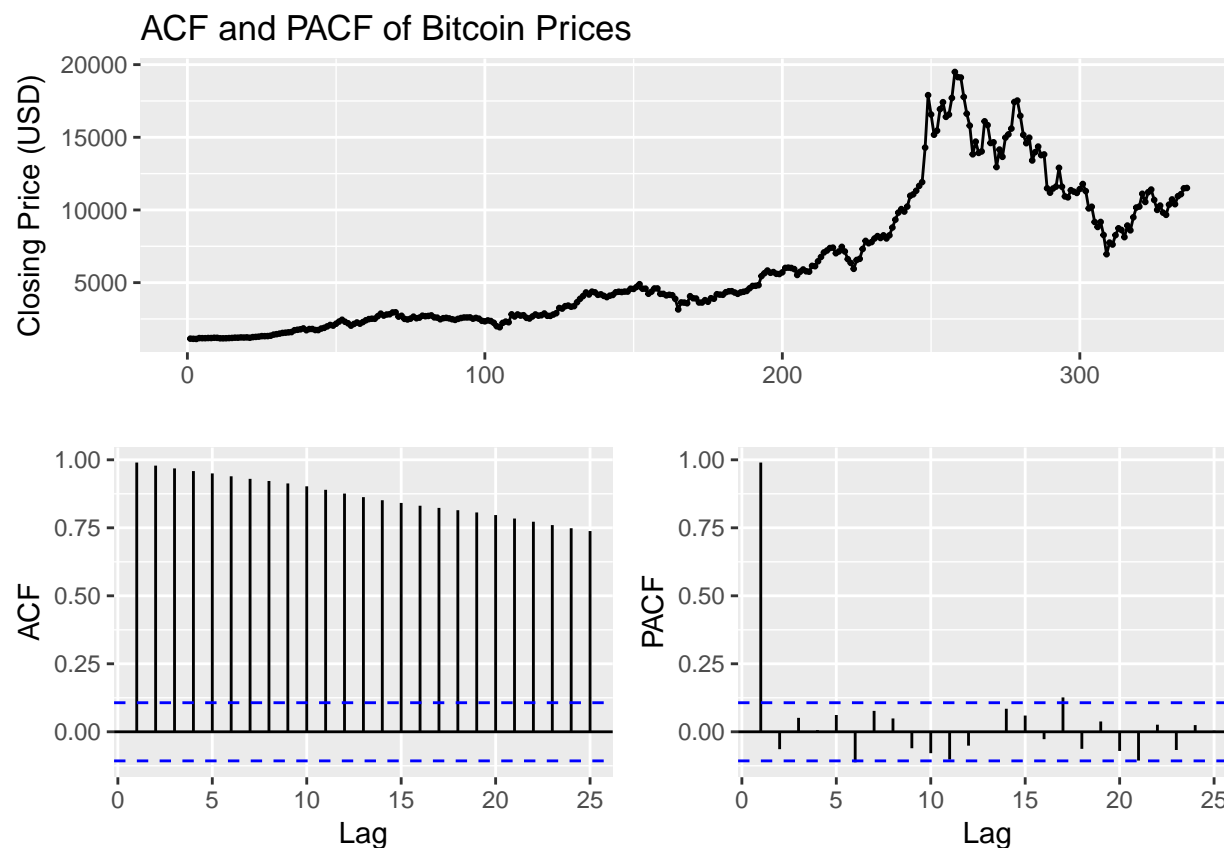


Figure 4: Residual Analysis Linear fitted Model

3 Models for Nonstationary Time Series

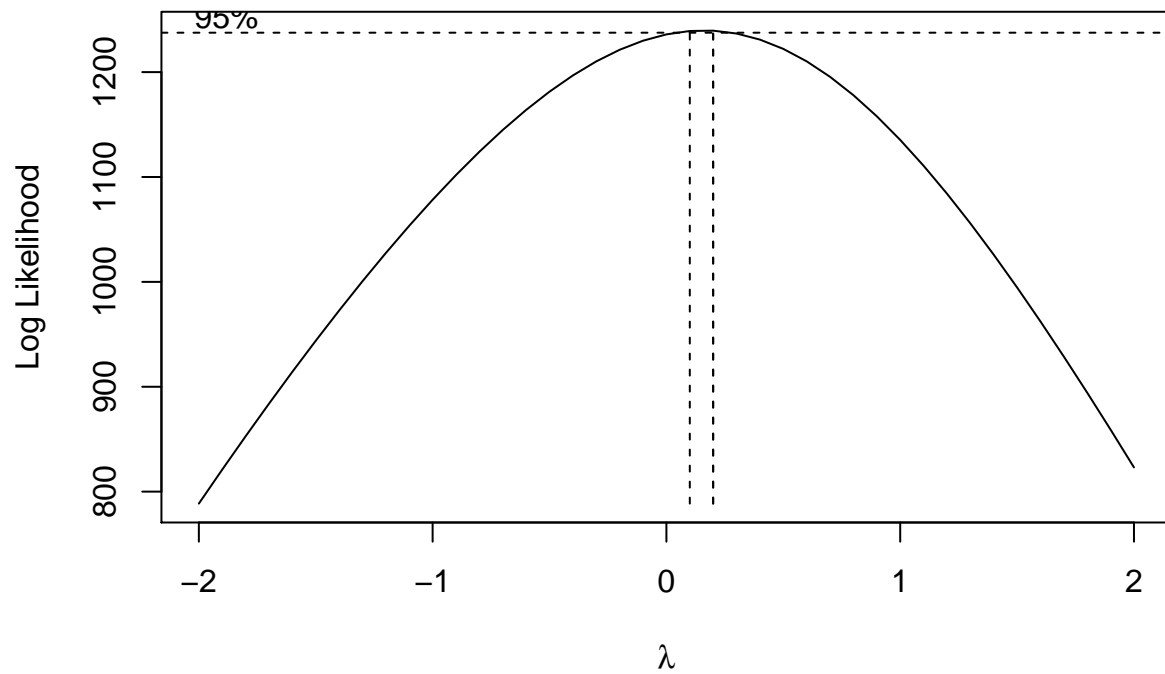
Auto regressive behaviour and non stationarity is the first thing we need to check.

```
ggtsdisplay(Bitcoin.2017.zoo,  
            main = 'ACF and PACF of Bitcoin Prices',  
            ylab='Closing Price (USD)')
```

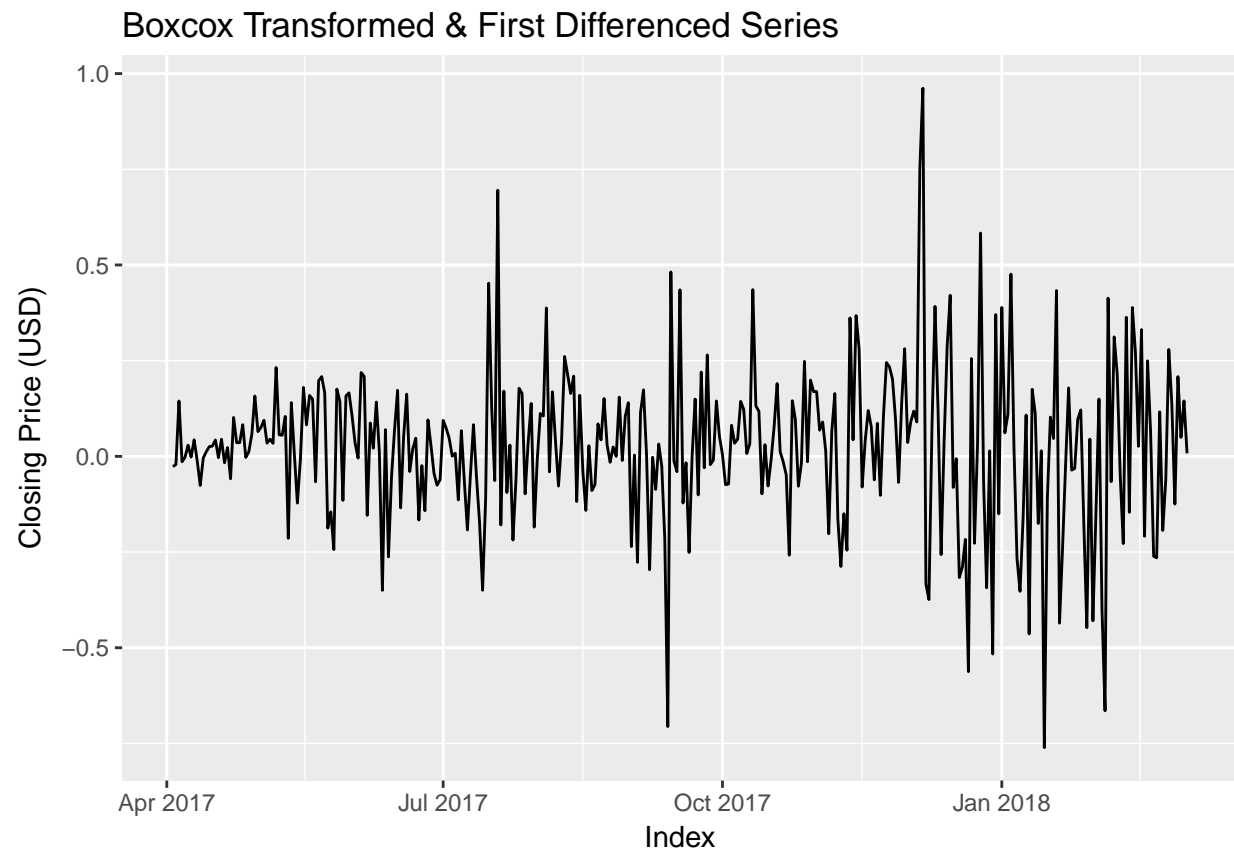


strategy to make stationay is transfromation.

```
Bitcoin.transform = BoxCox.ar(Bitcoin.2017.zoo, method = 'yule-walker')
```

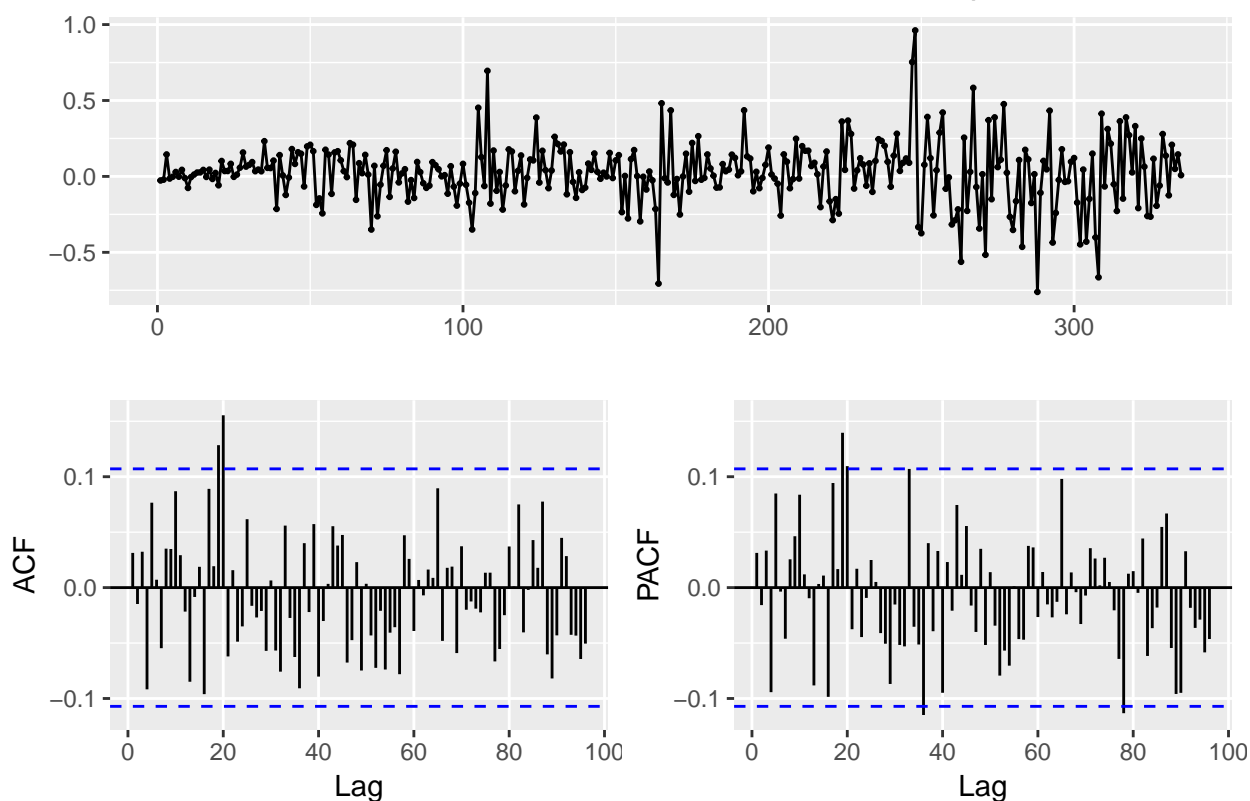


```
lambda = sum(Bitcoin.transform$ci)/length(Bitcoin.transform$ci)
Bitcoin.boxcox = (Bitcoin.2017.zoo^lambda - 1) / lambda
Bitcoin.diff = base::diff(Bitcoin.boxcox, differences = 1)
autoplot(Bitcoin.diff) +
  ylab('Closing Price (USD)') +
  ggtitle('Boxcox Transformed & First Differenced Series')
```



```
ggtsdisplay(Bitcoin.diff, lag.max = 96, ci.type='ma',  
            main = 'Boxcox Transformed & First Differenced ACF and PACF plots',  
            ylab='')
```

Boxcox Transformed & First Differenced ACF and PACF plots



```
adf.test(Bitcoin.diff)
```

```
## Warning in adf.test(Bitcoin.diff): p-value smaller than printed p-value
```

```
##
```

```
## Augmented Dickey-Fuller Test
```

```
##
```

```
## data: Bitcoin.diff
```

```
## Dickey-Fuller = -6.968, Lag order = 6, p-value = 0.01
```

```
## alternative hypothesis: stationary
```

```
eacf(Bitcoin.diff)
```

```
## 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 o
```

```
## 1 x o o o o o o o o o o o o o
```

```
## 2 x o o o o o o o o o o o o o
```

```
## 3 x o x o o o o o o o o o o o
```

```
## 4 x x x o o o o o o o o o o o
```

```
## 5 o x o x o o o o o o o o o o
```

```
## 6 o x o o o o o o o o o o o o
```

```
## 7 x x x o x x o o o o o o o o
```

```
# ARIMA(0,1,0),ARIMA(1,1,1),ARIMA(2,1,2),ARIMA(4,1,3)
```

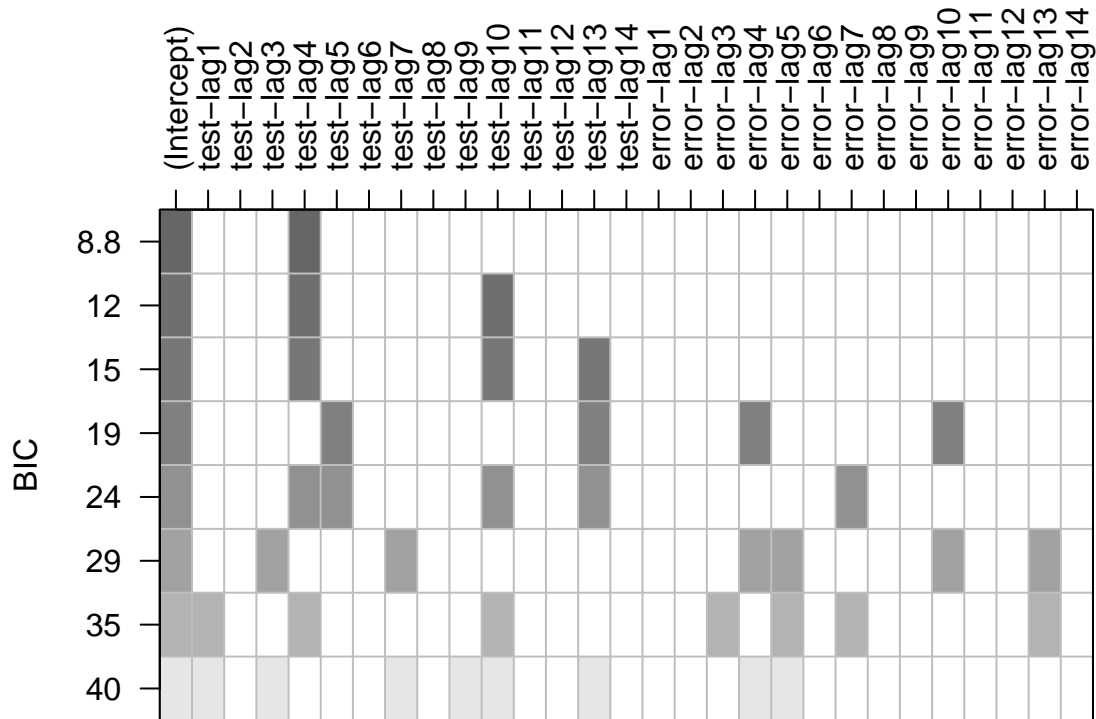
```
res1 = armasubsets(y=Bitcoin.diff,nar=14,nma=14,y.name='test',ar.method='mle')
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 14 linear dependencies found
```



```
plot(res1)
```



```
#ARIMA(4,1,4),ARIMA(5,1,4)
```

```
#The final set of possible models is
```

```
# ARIMA(0,1,0),ARIMA(1,1,1),ARIMA(2,1,2),ARIMA(4,1,3)
```

```
# ARIMA(4,1,4),ARIMA(5,1,4)
```

```
# ARIMA(0,1,0)
```

```
model_111_css = arima(Bitcoin.boxcox, order=c(1,1,1),method='CSS')
```

```
coeftest(model_111_css)
```

```
## Warning in sqrt(diag(se)): NaNs produced
```

```
##
```

```
## z test of coefficients:
```

```
##
```

```
##      Estimate Std. Error z value Pr(>|z|)
```

```
## ar1 0.021830      NA      NA      NA
```

```
## ma1 0.022332      NA      NA      NA
```

```
model_111_ml = arima(Bitcoin.boxcox, order=c(1,1,1),method='ML')
```

```
coeftest(model_111_ml)
```

```
## Warning in sqrt(diag(se)): NaNs produced
```

```
##
```

```
## z test of coefficients:
```

```
##
```

```
##      Estimate Std. Error z value Pr(>|z|)
```

```
## ar1 0.020106      NA      NA      NA
```

```
## ma1 0.024617      NA      NA      NA
```

```
# ARIMA(2,1,2)
model_212_css = arima(Bitcoin.boxcox,order=c(2,1,2),method='CSS')
coeftest(model_212_css)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error  z value Pr(>|z|)
## ar1 -0.028530   0.079410  -0.3593   0.7194
## ar2  0.906936   0.075863  11.9549 <2e-16 ***
## ma1  0.085848   0.084591   1.0149   0.3102
## ma2 -0.913597   0.083838 -10.8972 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_212_ml = arima(Bitcoin.boxcox,order=c(2,1,2),method='ML')
coeftest(model_212_ml)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error  z value Pr(>|z|)
## ar1 -0.0021222  0.0653257  -0.0325   0.9741
## ar2  0.9248274  0.0619597  14.9263 <2e-16 ***
## ma1  0.0590080  0.0774408   0.7620   0.4461
## ma2 -0.9409861  0.0773613 -12.1635 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# ARIMA(2,1,2)
model_313_css = arima(Bitcoin.boxcox,order=c(3,1,3),method='CSS')
coeftest(model_313_css)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error  z value  Pr(>|z|)
## ar1 -0.571168   0.021168 -26.983 < 2.2e-16 ***
## ar2  0.736466   0.038762  19.000 < 2.2e-16 ***
## ar3  0.842896   0.020398  41.324 < 2.2e-16 ***
## ma1  0.578964   0.046389  12.481 < 2.2e-16 ***
## ma2 -0.812537   0.031263 -25.991 < 2.2e-16 ***
## ma3 -0.837218   0.036048 -23.225 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_313_ml = arima(Bitcoin.boxcox,order=c(3,1,3),method='ML')
coeftest(model_313_ml)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error  z value  Pr(>|z|)
## ar1 -0.704438   0.087921 -8.0122 1.127e-15 ***
## ar2  0.657008   0.107606  6.1057 1.024e-09 ***
## ar3  0.890417   0.080571  11.0514 < 2.2e-16 ***
```

```
## ma1 0.750869 0.098881 7.5937 3.109e-14 ***
## ma2 -0.648222 0.131848 -4.9164 8.813e-07 ***
## ma3 -0.864195 0.095694 -9.0308 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# ARIMA(4,1,3)
```

```
model_413_css = arima(Bitcoin.boxcox,order=c(4,1,3),method='CSS')
coeftest(model_413_css)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1 -0.606687 0.103204 -5.8786 4.139e-09 ***
## ar2 0.724842 0.045366 15.9775 < 2.2e-16 ***
## ar3 0.868001 0.088273 9.8332 < 2.2e-16 ***
## ar4 -0.034735 0.061179 -0.5678 0.5702
## ma1 0.633092 0.085276 7.4240 1.136e-13 ***
## ma2 -0.780848 0.042049 -18.5698 < 2.2e-16 ***
## ma3 -0.899628 0.092503 -9.7254 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_413_ml = arima(Bitcoin.boxcox,order=c(4,1,3),method='ML')
coeftest(model_413_ml)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1 -0.681608 0.122969 -5.5429 2.975e-08 ***
## ar2 0.673771 0.133685 5.0400 4.656e-07 ***
## ar3 0.882439 0.082700 10.6704 < 2.2e-16 ***
## ar4 -0.020472 0.061829 -0.3311 0.7406
## ma1 0.743163 0.110054 6.7527 1.451e-11 ***
## ma2 -0.652845 0.146801 -4.4471 8.702e-06 ***
## ma3 -0.869292 0.099522 -8.7346 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# ARIMA(4,1,4)
```

```
model_414_css = arima(Bitcoin.boxcox,order=c(4,1,4),method='CSS')
coeftest(model_414_css)
```

```
## Warning in sqrt(diag(se)): NaNs produced
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1 -0.551983      NA      NA      NA
## ar2 0.172921 0.038259 4.5198 6.190e-06 ***
## ar3 0.915619 0.060298 15.1850 < 2.2e-16 ***
## ar4 0.435558      NA      NA      NA
## ma1 0.580501      NA      NA      NA
## ma2 -0.196556 0.043484 -4.5202 6.178e-06 ***
```

```
## ma3 -0.920758    0.052864 -17.4176 < 2.2e-16 ***
## ma4 -0.551651          NA          NA          NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_414_ml = arima(Bitcoin.boxcox,order=c(4,1,4),method='ML')
coeftest(model_414_ml)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1 -0.858500    0.281071 -3.0544 0.0022552 **
## ar2  0.075681    0.128007  0.5912 0.5543661
## ar3  1.122140    0.098181 11.4293 < 2.2e-16 ***
## ar4  0.639474    0.253747  2.5201 0.0117314 *
## ma1  0.923109    0.264539  3.4895 0.0004839 ***
## ma2 -0.032671    0.177524 -0.1840 0.8539858
## ma3 -1.117752    0.155372 -7.1940 6.29e-13 ***
## ma4 -0.719323    0.226069 -3.1819 0.0014633 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# ARIMA(5,1,4)
```

```
model_514_css = arima(Bitcoin.boxcox,order=c(5,1,4),method='CSS')
coeftest(model_514_css)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1  9.9074e-02  1.9514e-04 507.703 < 2.2e-16 ***
## ar2  1.3895e-01  3.0111e-04 461.475 < 2.2e-16 ***
## ar3  5.0499e-01  7.2128e-05 7001.257 < 2.2e-16 ***
## ar4  1.6450e-01  1.5559e-04 1057.251 < 2.2e-16 ***
## ar5  9.0947e-02  3.6146e-04 251.613 < 2.2e-16 ***
## ma1 -8.1368e-02  5.7083e-03 -14.254 < 2.2e-16 ***
## ma2 -1.9260e-01  1.6938e-02 -11.371 < 2.2e-16 ***
## ma3 -5.1953e-01  1.7609e-02 -29.504 < 2.2e-16 ***
## ma4 -3.1371e-01  6.3856e-03 -49.127 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_514_ml = arima(Bitcoin.boxcox,order=c(5,1,4),method='ML')
```

```
## Warning in stats::arima(x = x, order = order, seasonal = seasonal, xreg =
## xreg, : possible convergence problem: optim gave code = 1
```

```
coeftest(model_514_ml)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1  0.216613    0.581949  0.3722  0.7097
## ar2  0.125243    0.255393  0.4904  0.6239
## ar3  0.472679    0.519846  0.9093  0.3632
```

```
## ar4 -0.054074    0.426025 -0.1269    0.8990
## ar5  0.109269    0.078398  1.3938    0.1634
## ma1 -0.166104    0.585508 -0.2837    0.7766
## ma2 -0.144679    0.251819 -0.5745    0.5656
## ma3 -0.438182    0.523533 -0.8370    0.4026
## ma4 -0.056614    0.413995 -0.1368    0.8912

sort.score(stats::AIC(model_111_ml,model_212_ml,model_313_ml,model_413_ml,model_414_ml,model_514_ml), s

##           df      AIC
## model_212_ml  5 -102.65580
## model_313_ml  7 -102.11673
## model_414_ml  9 -101.78404
## model_111_ml  3 -100.97940
## model_413_ml  8 -100.23246
## model_514_ml 10  -95.11157

sort.score(stats::BIC(model_111_ml,model_212_ml,model_313_ml,model_413_ml,model_414_ml,model_514_ml), s

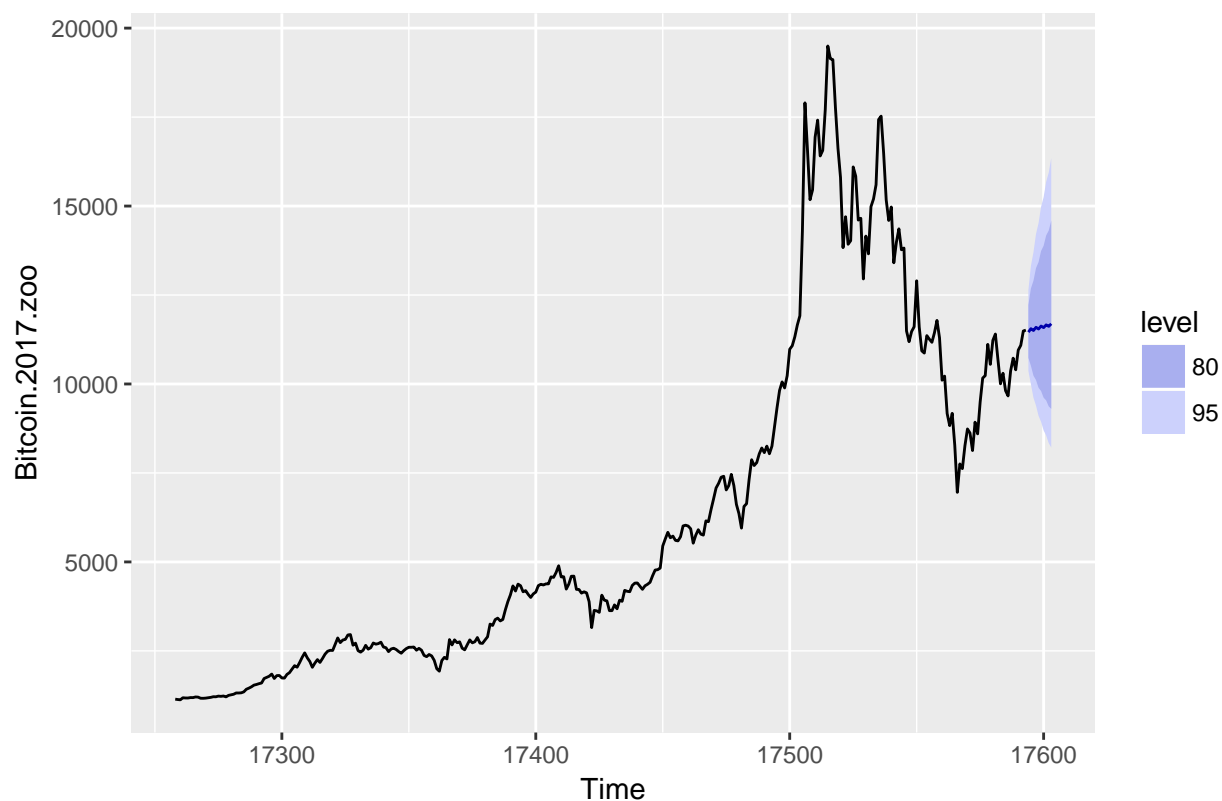
##           df      BIC
## model_111_ml  3 -89.53701
## model_212_ml  5 -83.58515
## model_313_ml  7 -75.41781
## model_413_ml  8 -69.71941
## model_414_ml  9 -67.45687
## model_514_ml 10 -56.97026

fit <- Arima(Bitcoin.2017.zoo, order=c(2,1,2), lambda = lambda)
summary(fit)

## Series: Bitcoin.2017.zoo
## ARIMA(2,1,2)
## Box Cox transformation: lambda= 0.15
##
## Coefficients:
##           ar1      ar2      ma1      ma2
##          -0.0041  0.9230  0.0612 -0.9387
## s.e.      0.0657  0.0623  0.0771  0.0770
##
## sigma^2 estimated as 0.04208:  log likelihood=56.33
## AIC=-102.66  AICc=-102.47  BIC=-83.59
##
## Training set error measures:
##           ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 16.4692 525.3894 292.1485 0.3296403 3.946196 0.996653
##           ACF1
## Training set 0.05351391

autoplot(forecast(fit,h=10))
```

Forecasts from ARIMA(2,1,2)



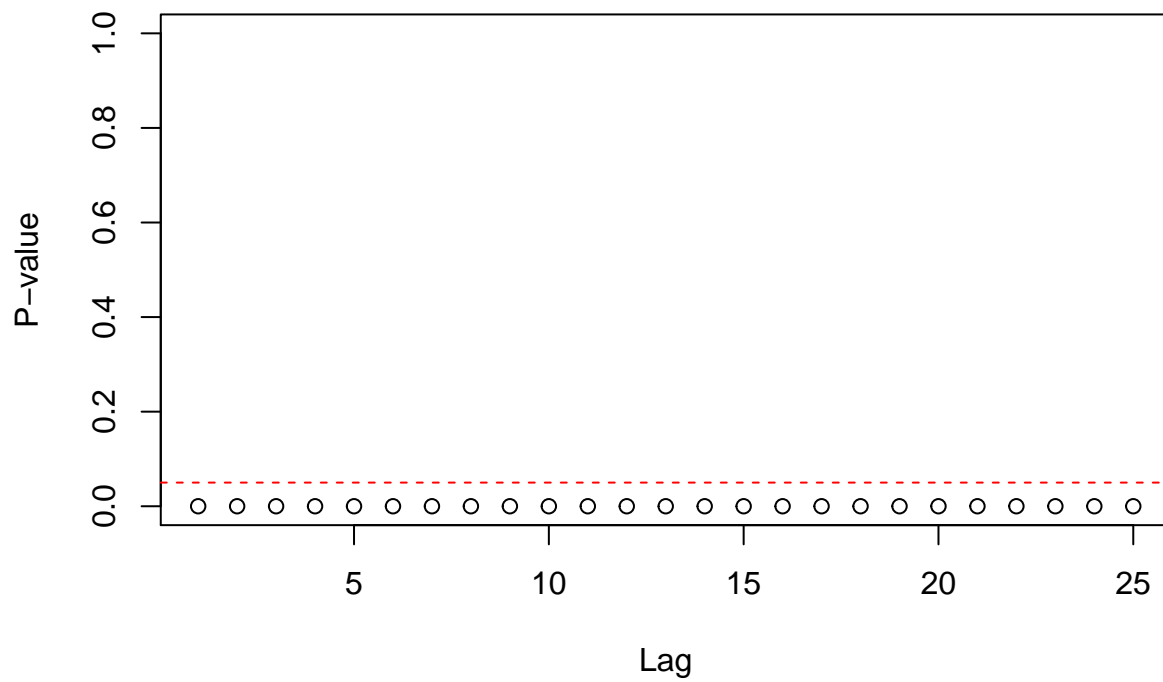
```
Bitcoin.forecast <- read.csv("../data/Bitcoin_Prices_Forecasts.csv", header=TRUE)
Bitcoin.forecast$Date = as.Date(Bitcoin.forecast$Date, '%d/%m/%y')

source('MASE.r')
MASE(Bitcoin.forecast$Closing.price, as.vector(tail(fitted(forecast(fit,h=10)),10)))

## $MASE
##      MASE
## 1 3.174453

McLeod.Li.test(y=Bitcoin.2017.zoo,main="McLeod-Li Test Statistics for Bitcoin")
```

McLeod-Li Test Statistics for Bitcoin



```
residual_analysis_qq(Bitcoin.2017.zoo, 'QQ Plot')
```

