

ARIMA Model GBP And USD

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Forecasting Exchange Rate Using ARIMA Model for British Pound And US Dollar

Reading GBP and USD Currency into r

```
library(readr)
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
```

```
GBPUSDARIMA <- read.csv ("GBPUSD_Candlestick_1_D_BID_01.01.2000-31.12.2020.csv")%>%
  select('GMT.TIME', CLOSE)%>%
  rename(Date = ('GMT.TIME'), RateGBPUSD = ("CLOSE"))

head(GBPUSDARIMA)
```

```
##           Date RateGBPUSD
## 1 2000-01-03      1.6355
## 2 2000-01-04      1.6357
## 3 2000-01-05      1.6423
## 4 2000-01-06      1.6469
## 5 2000-01-07      1.6391
## 6 2000-01-10      1.6369
```

Conversion of Gmt time to date format

```
library(dplyr)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

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

```
GBPUSDARIMA$Date <- lubridate::ymd(GBPUSDARIMA$Date)
head(GBPUSDARIMA)
```

```
##      Date RateGBPUSD
## 1 2000-01-03    1.6355
## 2 2000-01-04    1.6357
## 3 2000-01-05    1.6423
## 4 2000-01-06    1.6469
## 5 2000-01-07    1.6391
## 6 2000-01-10    1.6369
```

```
##Checking for obvious errors or missingg value
```

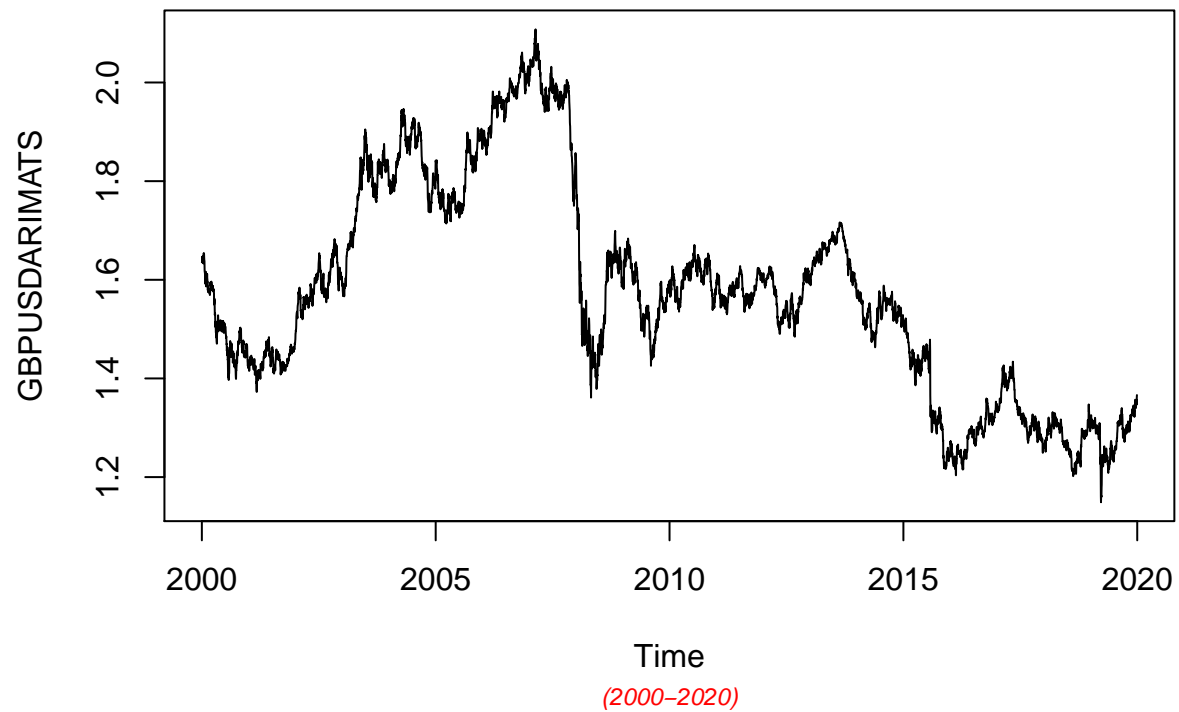
```
#Checking for obvious errors
which(is.na(GBPUSDARIMA))
```

```
## integer(0)
```

```
##Converting the data set into time series object
```

```
#Converting the data set into time series object
GBPUSDARIMATS<- ts(as.vector(GBPUSDARIMA$Rate), frequency = 320
                  , start= c(2000,01,03))
plot.ts(GBPUSDARIMATS)
title("Time Series plot of GBPUSDTimeseries ", sub = "(2000-2020)",
      cex.main = 1.5, font.main= 4, col.main= "blue",
      cex.sub = 0.75, font.sub = 3, col.sub = "red")
```

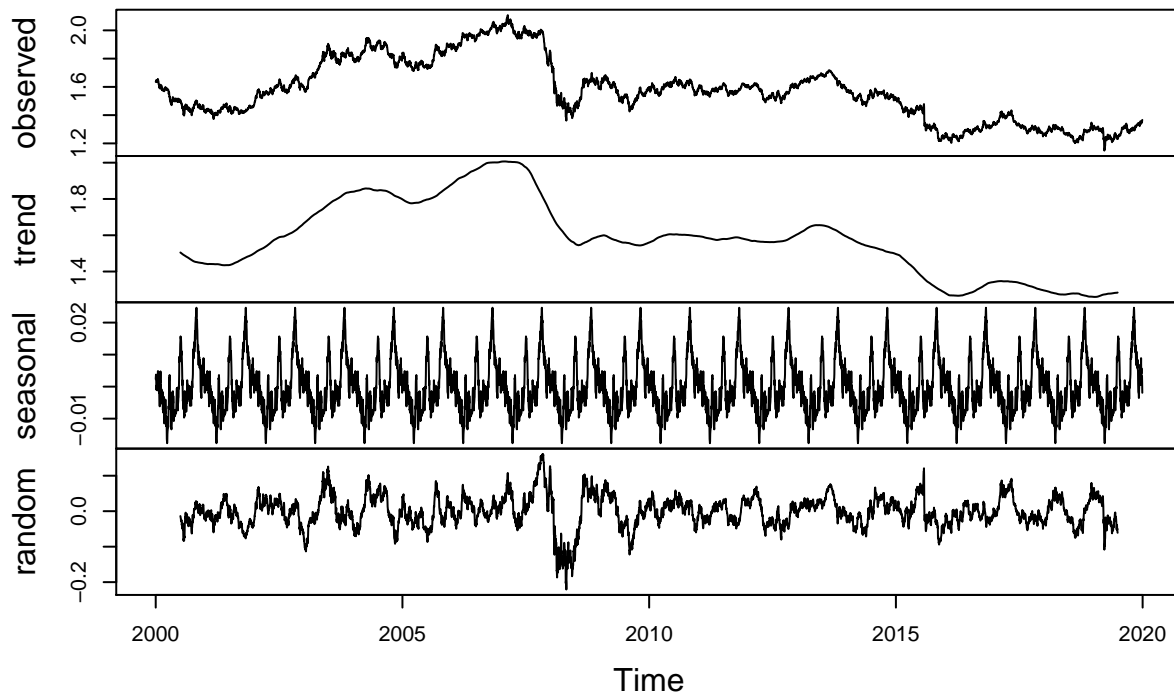
Time Series plot of GBPUSDTimeseries



Finding the component of the Time Series

```
ComponentGBPUSD <- decompose(GBPUSDARIMATS)
plot(ComponentGBPUSD)
```

Decomposition of additive time series



To To achieve stationarity by differencing the data – compute the differences between consecutive observations

```
library("fUnitRoots")
```

```
## Warning: package 'fUnitRoots' was built under R version 4.0.5
```

```
## Loading required package: timeDate
```

```
## Warning: package 'timeDate' was built under R version 4.0.4
```

```
## Loading required package: timeSeries
```

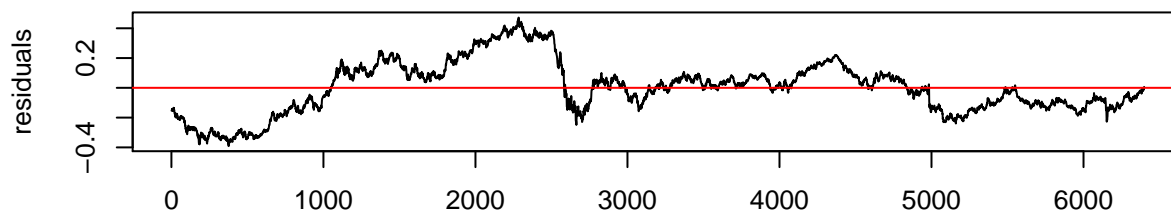
```
## Warning: package 'timeSeries' was built under R version 4.0.5
```

```
## Loading required package: fBasics
```

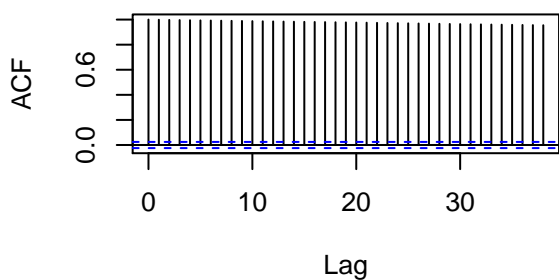
```
## Warning: package 'fBasics' was built under R version 4.0.5
```

```
urkpssTest(GBPUSDARIMATS, type = c("tau"), lags = c("short"), use.lag = NULL, doplot = TRUE)
```

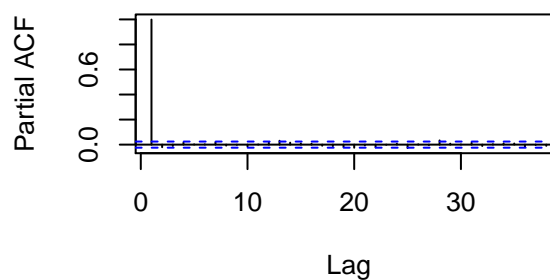
Residuals from test regression of type: tau with 11 lags



Autocorrelations of Residuals

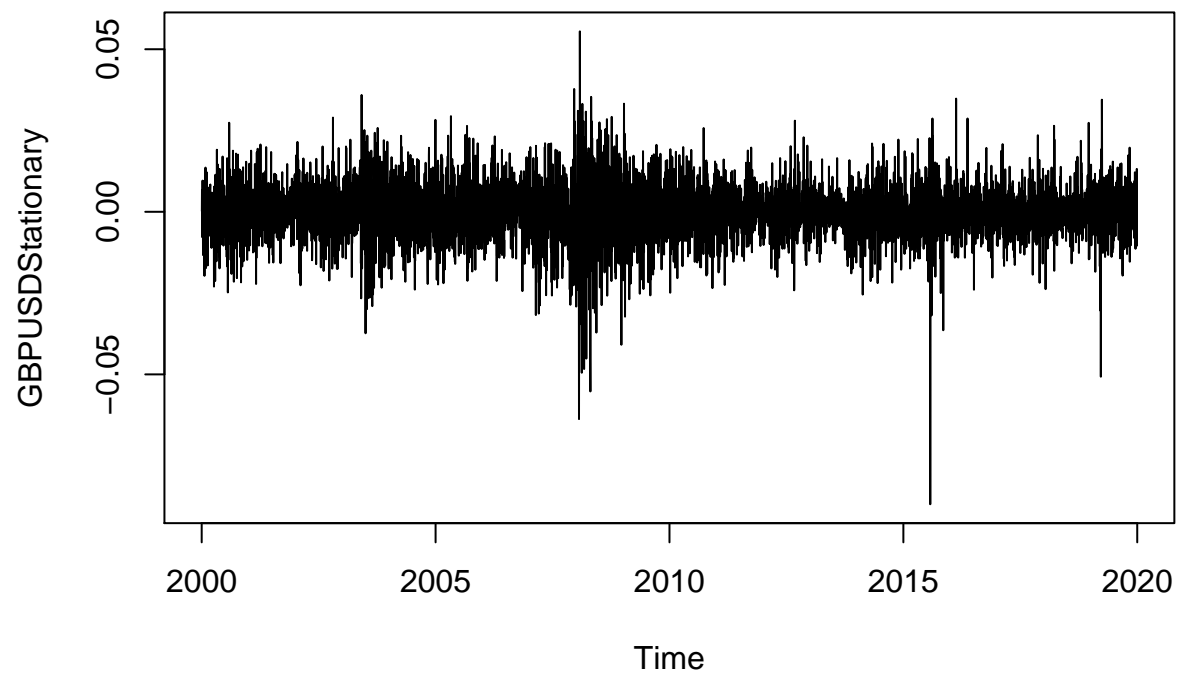


Partial Autocorrelations of Residuals



```
##
## Title:
## KPSS Unit Root Test
##
## Test Results:
## NA
##
## Description:
## Tue May 04 00:29:15 2021 by user: janeo
```

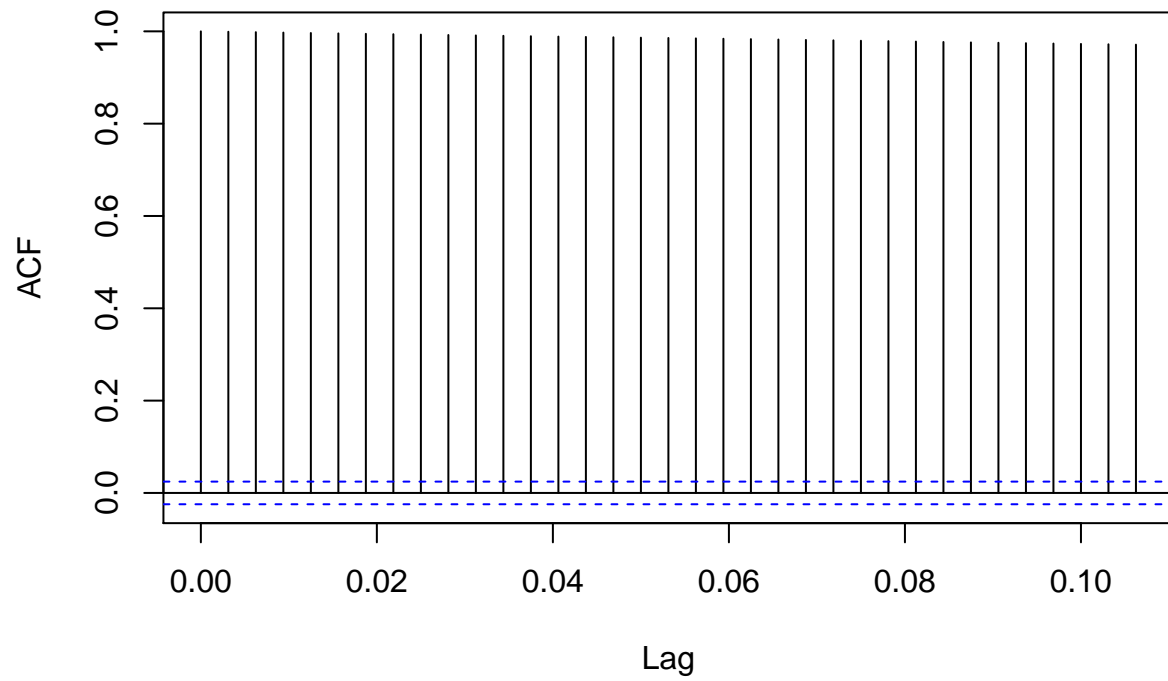
```
GBPUSDStationary= diff(GBPUSDARIMATS, differences=1)
plot(GBPUSDStationary)
```



Calculating Autocorrelation function and partial autocorrelation function

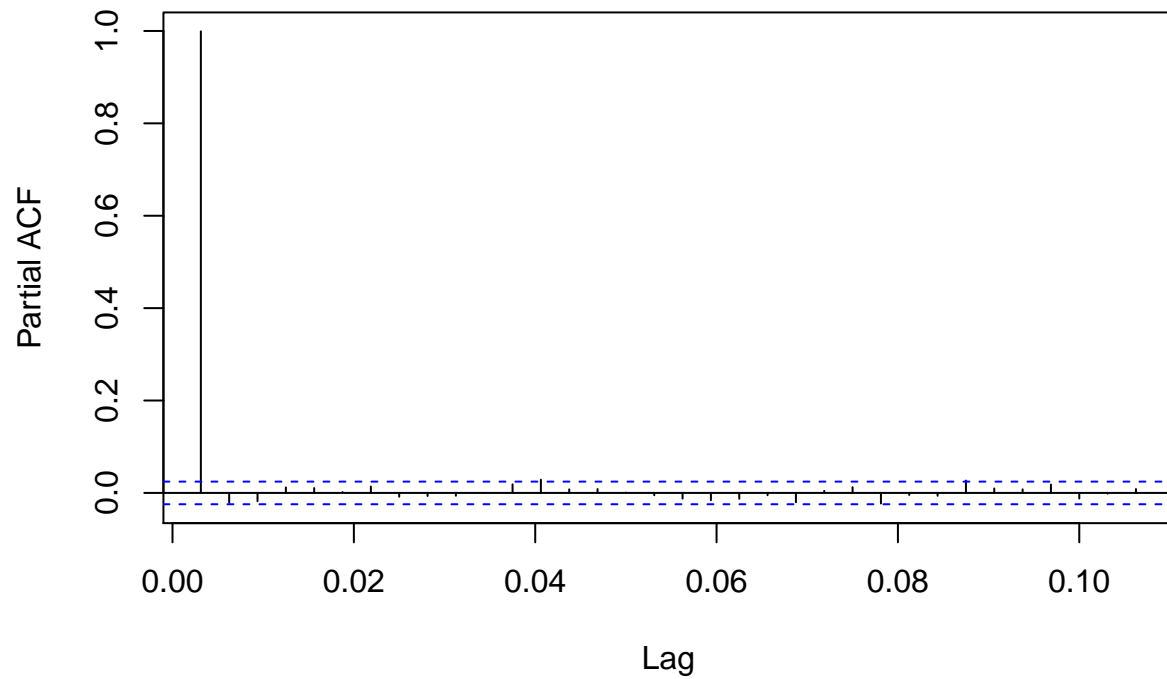
```
acf(GBPUSDARIMATS, lag.max=34)
```

Series GBPUSDARIMATS



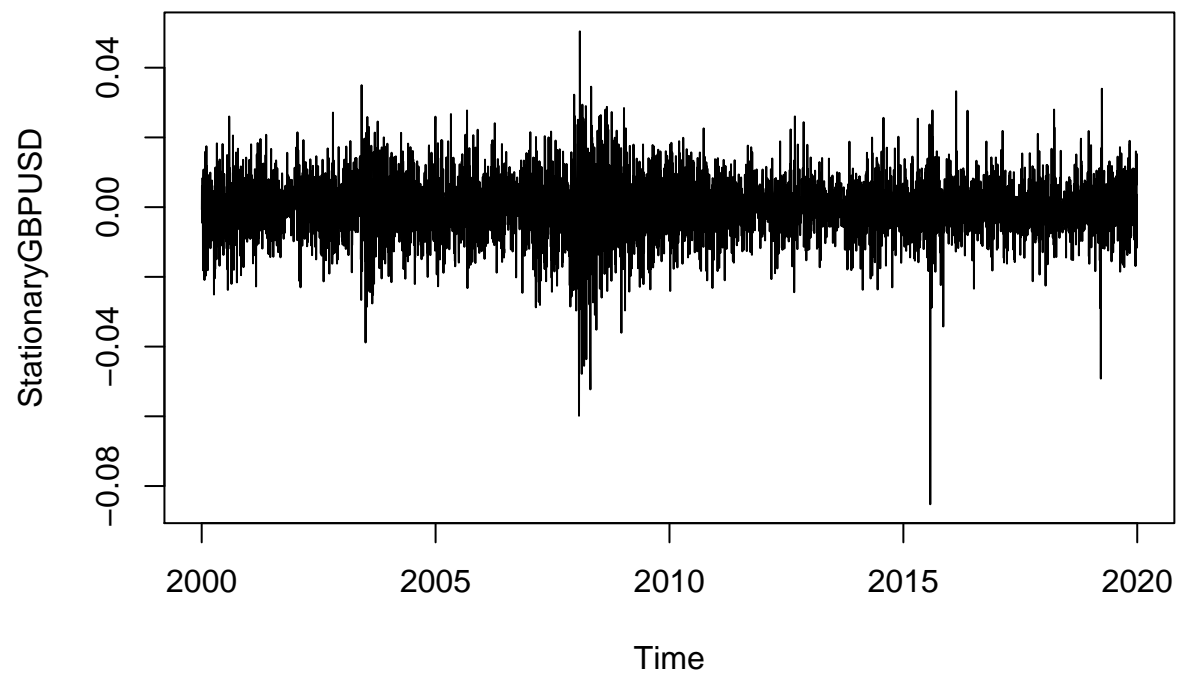
```
pacf(GBPUSDARIMATS, lag.max = 34)
```

Series GBPUSDARIMATS



Adjusting and ensuring there are no seasonality

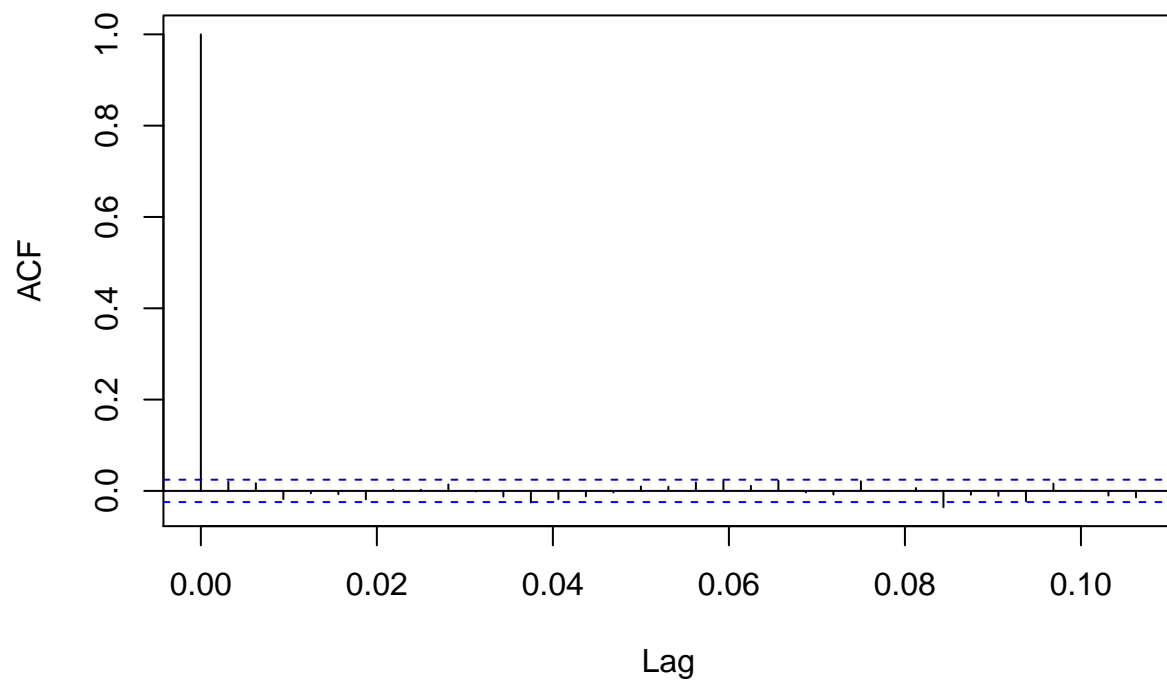
```
TSseasonallyadjustedGBPUSD <- GBPUSDARIMATS - ComponentGBPUSD$seasonal  
StationaryGBPUSD <- diff(TSseasonallyadjustedGBPUSD, differences=1)  
plot(StationaryGBPUSD)
```

Calculating again for ACF and PACF after finding stationality

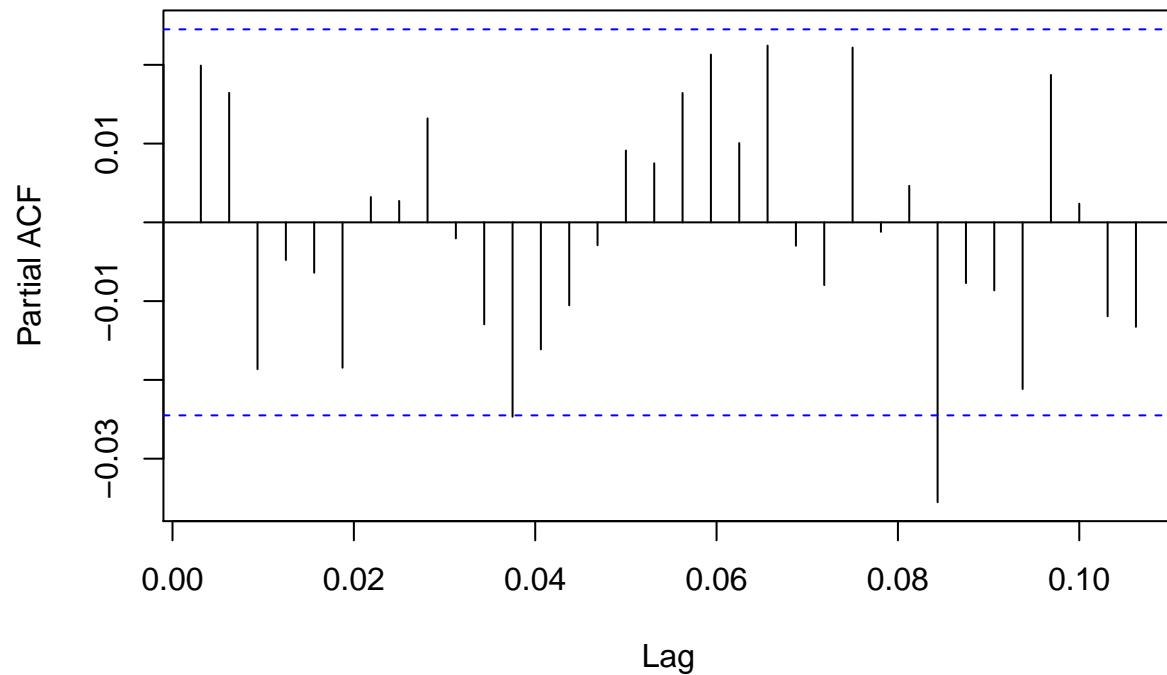
```
acf(StationaryGBPUSD, lag.max=34)
```

Series StationaryGBPUSD



```
pacf(StationaryGBPUSD, lag.max=34)
```

Series StationaryGBPUSD



Fitting The ARIMA Model

ARIMA fitting (1,1,0)

```
fitArima1GBPUSD <- arima(GBPUSDARIMATS, order = c(1,0,0), include.mean = TRUE)
fitArima1GBPUSD
```

```
##
## Call:
## arima(x = GBPUSDARIMATS, order = c(1, 0, 0), include.mean = TRUE)
##
## Coefficients:
##          ar1  intercept
##      0.9993      1.5746
## s.e.  0.0005      0.1255
##
## sigma^2 estimated as 7.073e-05:  log likelihood = 21493.5,  aic = -42981
```

```
##Arima Fitting (0,1,0)
```

```
fitArima2GBPUSD <- arima(GBPUSDARIMATS, order = c(0,1,0), include.mean = TRUE)
fitArima2GBPUSD
```

```
##
## Call:
## arima(x = GBPUSDARIMATS, order = c(0, 1, 0), include.mean = TRUE)
##
##
## sigma^2 estimated as 7.076e-05: log likelihood = 21491.94, aic = -42981.88
```

Arima Fitting (2,1,1)

```
fitArima3GBPUSD <- arima(GBPUSDARIMATS, order = c(2,1,1), include.mean = TRUE)
fitArima3GBPUSD
```

```
##
## Call:
## arima(x = GBPUSDARIMATS, order = c(2, 1, 1), include.mean = TRUE)
##
## Coefficients:
##          ar1      ar2      ma1
##          0.0103  0.0128  0.0109
## s.e.      1.3905  0.0521  1.3902
##
## sigma^2 estimated as 7.072e-05: log likelihood = 21493.89, aic = -42979.79
```

##Fitting Arima (0,1,3)

```
fitArima4GBPUSD <- arima(GBPUSDARIMATS, order = c(3,1,0), include.mean = TRUE)
fitArima4GBPUSD
```

```
##
## Call:
## arima(x = GBPUSDARIMATS, order = c(3, 1, 0), include.mean = TRUE)
##
## Coefficients:
##          ar1      ar2      ar3
##          0.0212  0.0127 -0.0155
## s.e.      0.0125  0.0125   0.0125
##
## sigma^2 estimated as 7.07e-05: log likelihood = 21494.65, aic = -42981.3
```

##Best possible model is selected by AIC scores of the models

```
library(dLagM)
```

```
## Warning: package 'dLagM' was built under R version 4.0.5
```

```
## Loading required package: nardl
```

```
## Warning: package 'nardl' was built under R version 4.0.5
```

```

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

## Loading required package: dynlm

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following object is masked from 'package:timeSeries':
##
##   time<-

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

ARIMAModelSelectionGBPUSD = AIC(fitArima1GBPUSD,fitArima2GBPUSD,fitArima3GBPUSD,fitArima4GBPUSD)

## Warning in AIC.default(fitArima1GBPUSD, fitArima2GBPUSD, fitArima3GBPUSD, :
## models are not all fitted to the same number of observations

sortScore(ARIMAModelSelectionGBPUSD, score ="aic")

##           df      AIC
## fitArima2GBPUSD  1 -42981.88
## fitArima4GBPUSD  4 -42981.30
## fitArima1GBPUSD  3 -42981.00
## fitArima3GBPUSD  4 -42979.79

```

Base on the above the fitArima1CanJap is selected

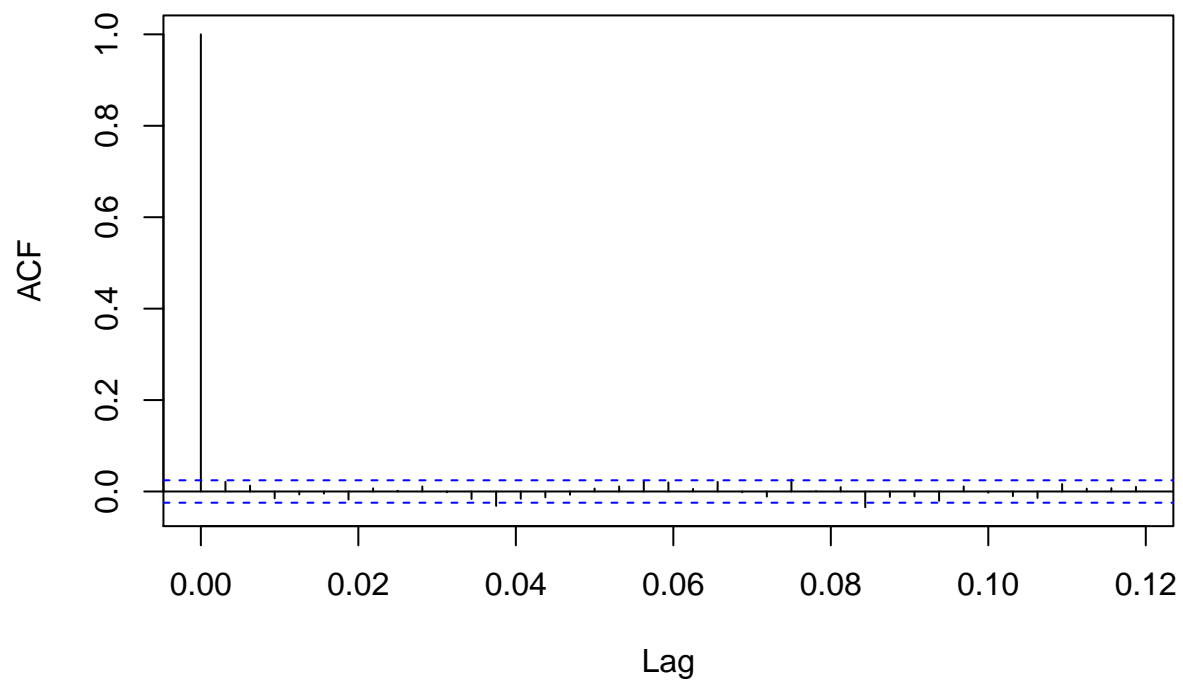
```
confint(fitArima2GBPUSD)
```

```
##      2.5 % 97.5 %
```

Runing code to obtain Box Test Rest

```
acf(fitArima2GBPUSD$residuals)
```

Series fitArima2GBPUSD\$residuals



```
library(FitAR)
```

```
## Warning: package 'FitAR' was built under R version 4.0.5
```

```
## Loading required package: lattice
```

```
## Loading required package: leaps
```

```
## Loading required package: ltsa
```

```
## Loading required package: bestglm
```

```
## Warning: package 'bestglm' was built under R version 4.0.5
```

```
library(bestglm)
```

```
Box.test(resid(fitArima2GBPUSD),type="Ljung",lag=20,fitdf=1)
```

```
##
```

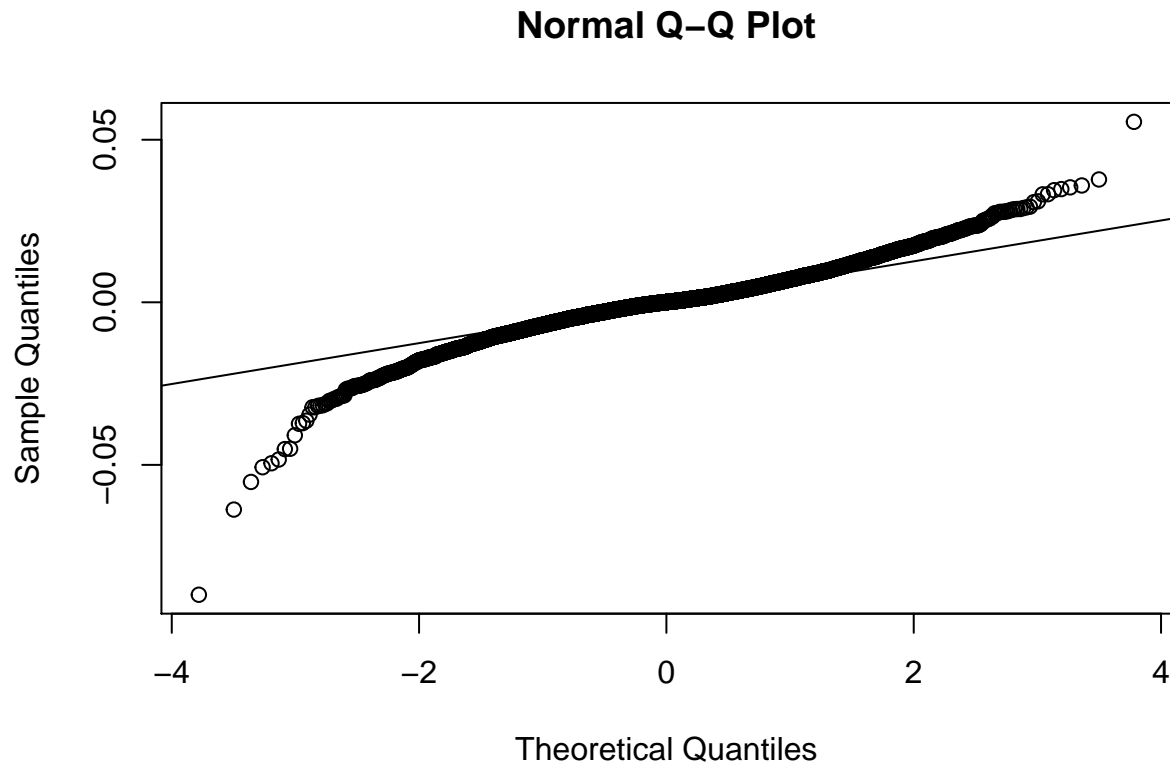
```
## Box-Ljung test
```

```
##
```

```
## data: resid(fitArima2GBPUSD)
```

```
## X-squared = 26.938, df = 19, p-value = 0.1061
```

```
qqnorm(fitArima2GBPUSD$residuals)
qqline(fitArima2GBPUSD$residuals)
```



Using Auto.arima to find the best model fit

```
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.0.5
```

```
##
```

```
## Attaching package: 'forecast'
```

```
## The following object is masked from 'package:FitAR':
```

```
##
```

```
##     BoxCox
```

```
## The following object is masked from 'package:dLagM':
```

```
##
```

```
##     forecast
```

```
auto.arima(GBPUSDARIMATS, trace=TRUE)
```

```
##
## Fitting models using approximations to speed things up...
##
## ARIMA(2,1,2)(1,0,1)[320] with drift : Inf
## ARIMA(0,1,0) with drift : -42970.48
## ARIMA(1,1,0)(1,0,0)[320] with drift : Inf
## ARIMA(0,1,1)(0,0,1)[320] with drift : -42969.78
## ARIMA(0,1,0) : -42972.32
## ARIMA(0,1,0)(1,0,0)[320] with drift : Inf
## ARIMA(0,1,0)(0,0,1)[320] with drift : Inf
## ARIMA(0,1,0)(1,0,1)[320] with drift : Inf
## ARIMA(1,1,0) with drift : -42970.38
## ARIMA(0,1,1) with drift : -42971.3
## ARIMA(1,1,1) with drift : -42968.34
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(0,1,0) : -42981.88
##
## Best model: ARIMA(0,1,0)

## Series: GBPUSDARIMATS
## ARIMA(0,1,0)
##
## sigma^2 estimated as 7.076e-05: log likelihood=21491.94
## AIC=-42981.88 AICc=-42981.88 BIC=-42975.11
```

forecasting using Best model: ARIMA(0,1,0)

```
forecastarimaGBPUSD<- predict(fitArima2GBPUSD,n.ahead = 100)
forecastarimaGBPUSD
```

```
## $pred
## Time Series:
## Start = c(2019, 320)
## End = c(2020, 99)
## Frequency = 320
## [1] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [11] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [21] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [31] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [41] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [51] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [61] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [71] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [81] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
## [91] 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663 1.3663
##
## $se
```



```
## Time Series:
## Start = c(2019, 320)
## End = c(2020, 99)
## Frequency = 320
## [1] 0.008411936 0.011896274 0.014569900 0.016823872 0.018809660 0.020604951
## [7] 0.022255890 0.023792548 0.025235808 0.026600877 0.027899235 0.029139801
## [13] 0.030329666 0.031474582 0.032579287 0.033647743 0.034683300 0.035688821
## [19] 0.036666778 0.037619321 0.038548333 0.039455476 0.040342227 0.041209901
## [25] 0.042059679 0.042892625 0.043709701 0.044511781 0.045299661 0.046074070
## [31] 0.046835677 0.047585095 0.048322892 0.049049593 0.049765684 0.050471615
## [37] 0.051167808 0.051854655 0.052532523 0.053201754 0.053862670 0.054515575
## [43] 0.055160752 0.055798470 0.056428981 0.057052525 0.057669327 0.058279601
## [49] 0.058883551 0.059481369 0.060073238 0.060659332 0.061239817 0.061814852
## [55] 0.062384586 0.062949164 0.063508723 0.064063395 0.064613305 0.065158575
## [61] 0.065699319 0.066235649 0.066767671 0.067295487 0.067819195 0.068338890
## [67] 0.068854662 0.069366600 0.069874787 0.070379305 0.070880231 0.071377643
## [73] 0.071871611 0.072362208 0.072849501 0.073333557 0.073814438 0.074292206
## [79] 0.074766921 0.075238642 0.075707423 0.076173319 0.076636383 0.077096666
## [85] 0.077554217 0.078009084 0.078461314 0.078910953 0.079358044 0.079802630
## [91] 0.080244754 0.080684454 0.081121772 0.081556744 0.081989409 0.082419802
## [97] 0.082847960 0.083273916 0.083697705 0.084119358
```

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