Final Exam

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Practical Problems

```
library("forecast")
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

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

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

```
## This is forecast 7.3
```

```
library("fBasics")
```

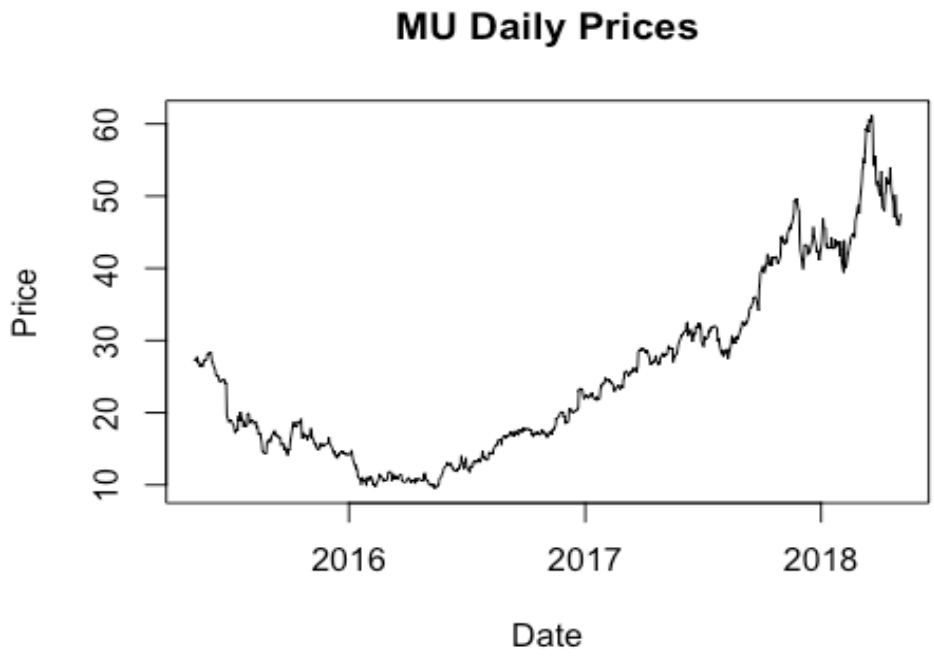
```
## Loading required package: timeSeries
```

```
##
## Attaching package: 'timeSeries'
```

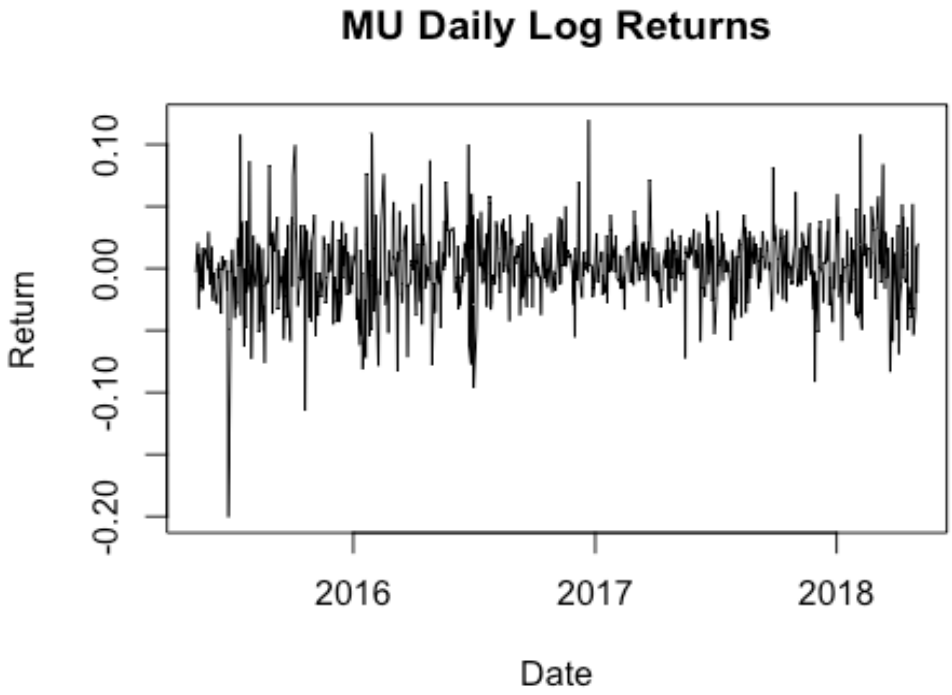
```
## The following object is masked from 'package:zoo':
##
##     time<-
```

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

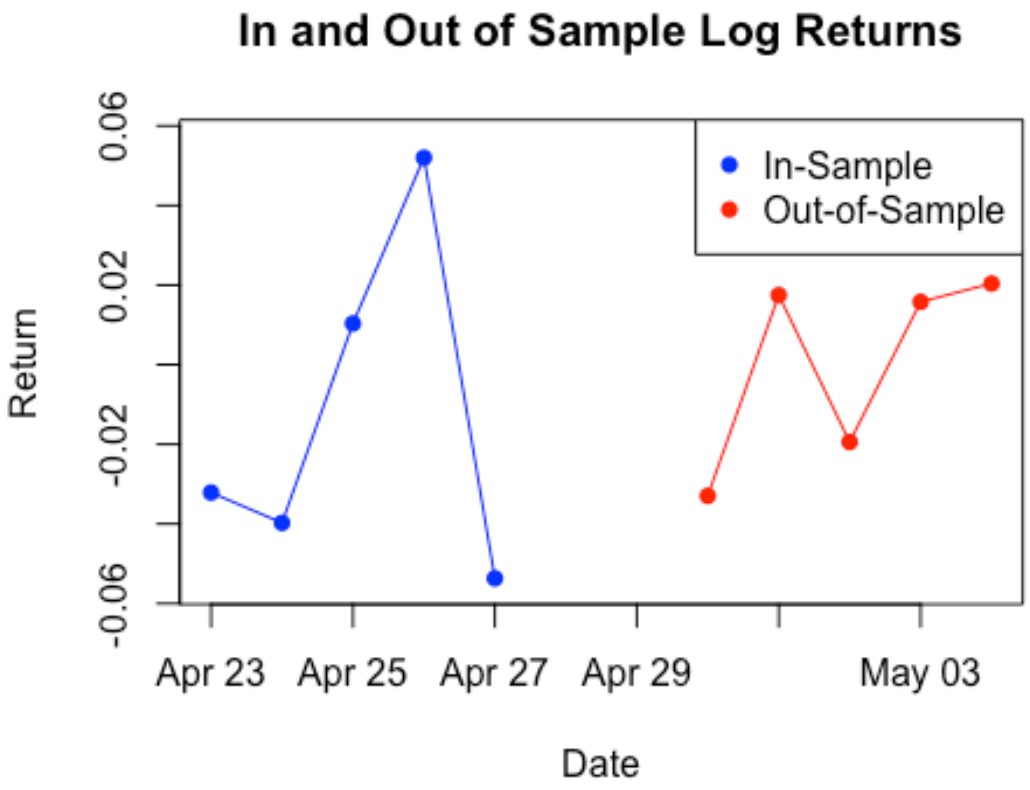
```
#Part A
MU <- read.csv("MU.csv", header=T)
MU$Date <- as.Date(MU$Date, format="%Y-%m-%d")


prices <- data.frame(MU$Date, MU$Adj.Close)
colnames(prices) <- c("Date", "Price")
plot(prices, main="MU Daily Prices", type="l")
```



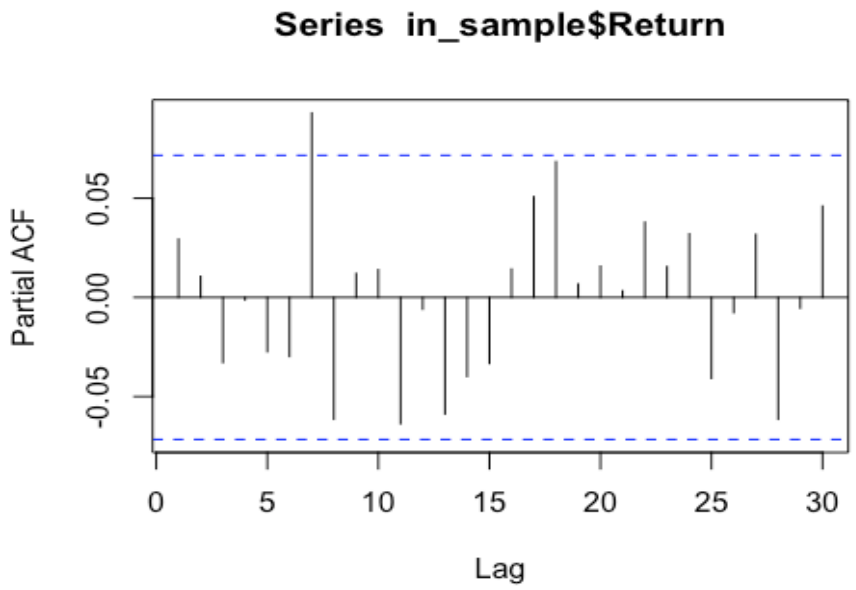

```r
returns <- data.frame(MU$Date[2:755], diff(log(prices$Price), lag=1))
colnames(returns) <- c("Date", "Return")
plot(returns, main="MU Daily Log Returns", type="l")
```



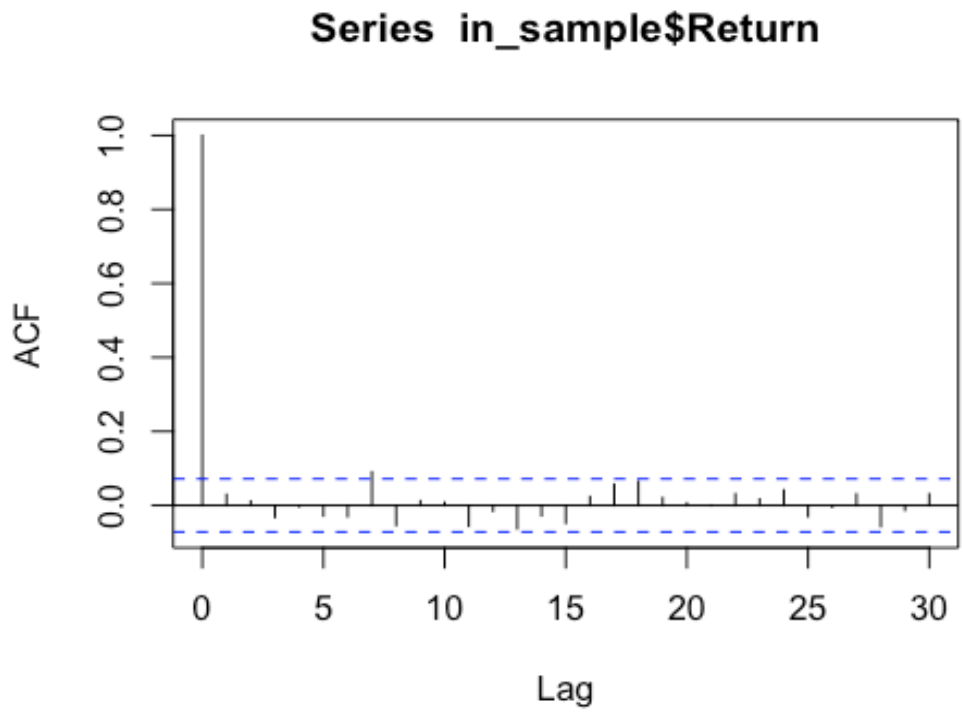
```r
#Part B
in_sample <- data.frame(returns$Date[1:749], returns$Return[1:749])
colnames(in_sample) <- c("Date", "Return")

out_sample <- data.frame(returns$Date[750:754], returns$Return[750:754])
colnames(out_sample) <- c("Date", "Return")

in_sample_last5 <- data.frame(in_sample$Date[745:749], in_sample$Return[745:749])
colnames(in_sample_last5) <- c("Date", "Return")

plot(in_sample_last5, main="In and Out of Sample Log Returns", col="blue", xlim=as.Date(c("2018-04-23","2018-05-04")), ylim=c(min(out_sample$Return, in_sample_last5$Return)-.002, max(out_sample$Return, in_sample_last5$Return)+.005), type="o", pch=16)
lines(out_sample, col="red", type="o", pch=16)
legend("topright", c("In-Sample", "Out-of-Sample"), col=c("blue", "red"), pch=16)
```



```r
#Part C
pacf(in_sample$Return, lag.max=30) #The PACF is used to give a recommended orde
r for the AR model. In this case it is order 7.
```




```r
acf(in_sample$Return,lag.max=30) #The ACF is used to give a recommended order f
or the MA model. In this case it is order 7.
```



```
adfTest(in_sample$Return, lags=7)   #one test we learned in class was the Augme
nted Dickey-Fuller Test (ADF). If the p-value is small, it is likely that there
are no unit roots. Since the p-value is significant here, we can conclude no un
it-root.
```

```
## Warning in adfTest(in_sample$Return, lags = 7): p-value smaller than
## printed p-value
```

```
##
## Title:
##  Augmented Dickey-Fuller Test
##
## Test Results:
##   PARAMETER:
##     Lag Order: 7
##   STATISTIC:
##     Dickey-Fuller: -9.7529
##   P VALUE:
##     0.01
##
## Description:
##  Fri May 11 17:12:05 2018 by user:
```

```
Box.test(in_sample$Return, type="Ljung") #When no lag, this gives us a pretty h
igh p-value, so we accept H0 that all correlations are 0.
```

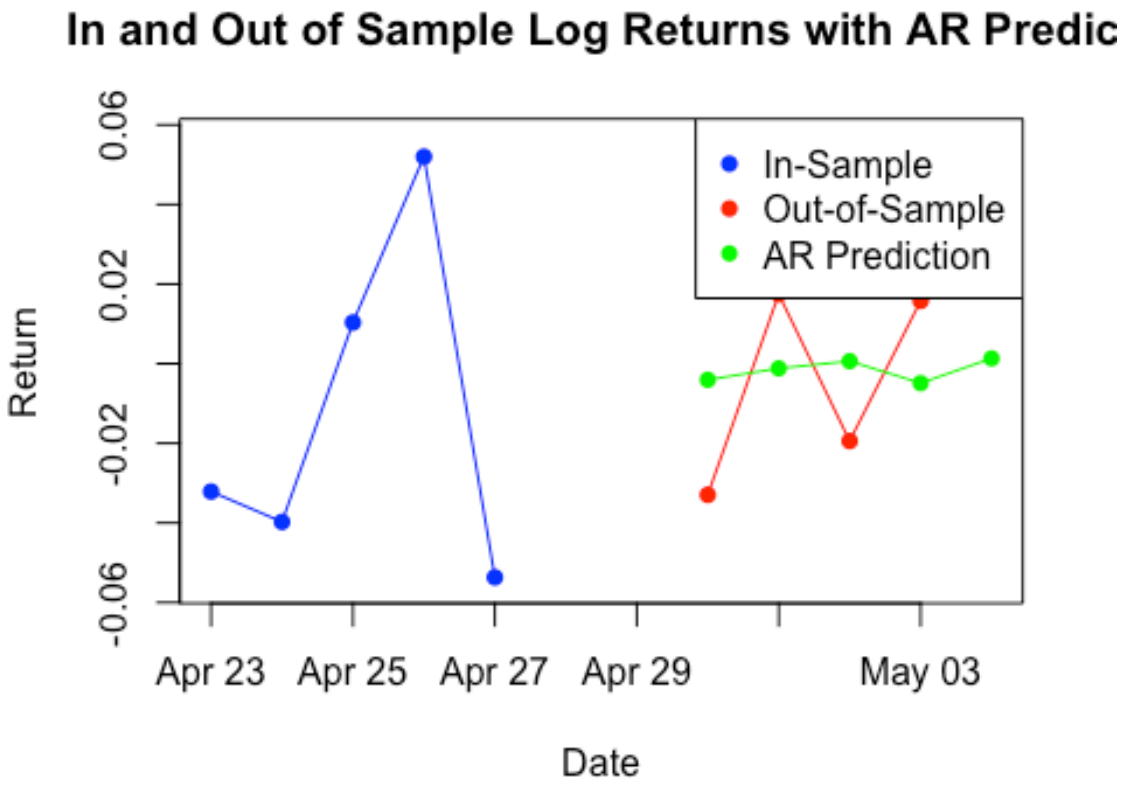
```
##
##  Box-Ljung test
##
## data:  in_sample$Return
## X-squared = 0.64955, df = 1, p-value = 0.4203
```

```
Box.test(in_sample$Return, lag=7, type="Ljung") #When we run the test again at
lag 7, we still accept H0, since the p-value is greater than 0.05. However, we
saw improvement from no lag. This could potentially mean this lag isn't the bes
t fit for our model.
```

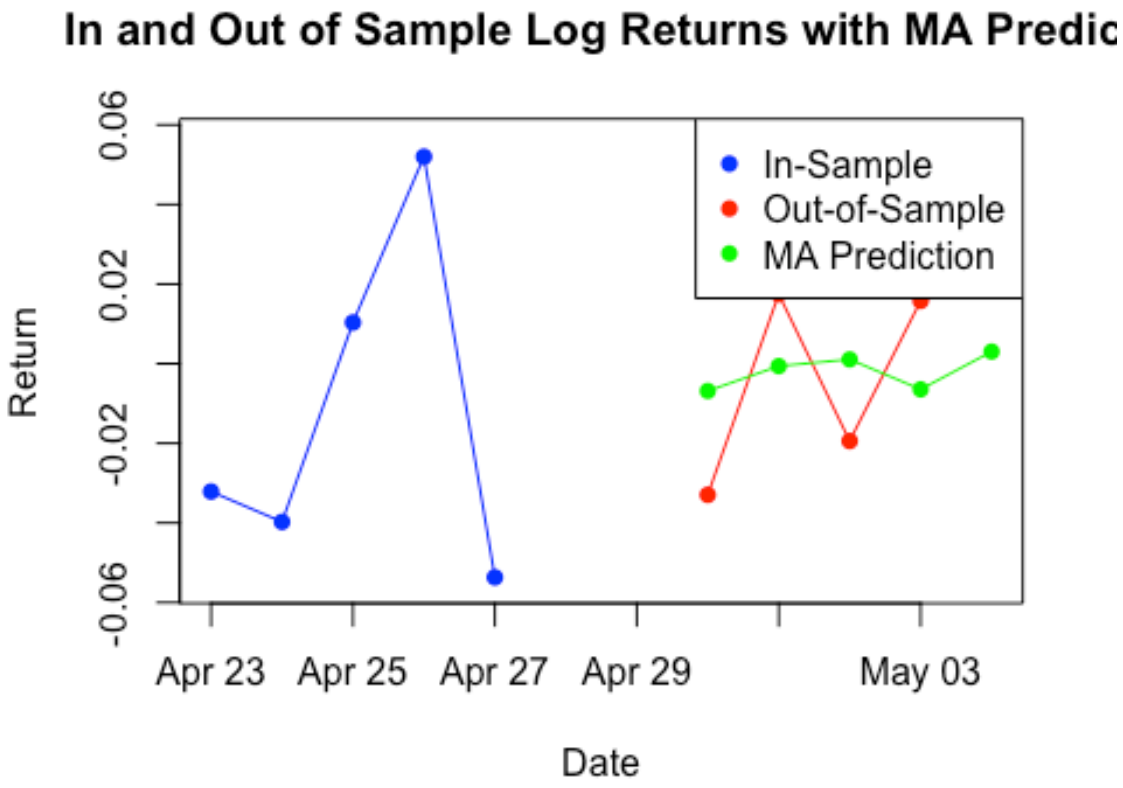
```
##
##  Box-Ljung test
##
## data:  in_sample$Return
## X-squared = 9.033, df = 7, p-value = 0.2503
```

```r
max.p=7
max.q=7
model.aic <- matrix(NA,nrow=max.p+1,ncol=max.q+1)
for (p in 0:max.p){
  for (q in 0:max.q){
    model.aic[p+1,q+1] = arima(in_sample$Return, order=c(p,0,q), method="ML")$a
ic
  }
}

min(model.aic)

## [1] -3111.207

which(model.aic == min(model.aic), arr.ind = TRUE)

##      row col
## [1,]   3   3

#This means that our recommended p=2 and recommonded q=2 for our ARMA model.


#Now we build our models with this information
AR <- arima(in_sample$Return, order=c(7,0,0)) #We build our AR(p) model with p=
7, since we found that lag to be significant with our PACF.
MA <- arima(in_sample$Return, order=c(0,0,7)) #We build our MA(q) model with q=
7, since we found that lag to be significant with our ACF.
ARMA <- arima(in_sample$Return, order=c(2,0,2)) #Above, we tested various value
s for p and q for our ARMA(p,q) model to find the one with the lowest AIC value
. After checking multiple values, I found that the best model to be p=2 and q=2
.




#Part D
predictAR <- data.frame(out_sample$Date,predict(AR, 5))
predictMA <- data.frame(out_sample$Date,predict(MA, 5))
predictARMA <- data.frame(out_sample$Date,predict(ARMA, 5))
colnames(predictAR) <- c("Date", "Return")
colnames(predictMA) <- c("Date", "Return")
colnames(predictARMA) <- c("Date", "Return")
```

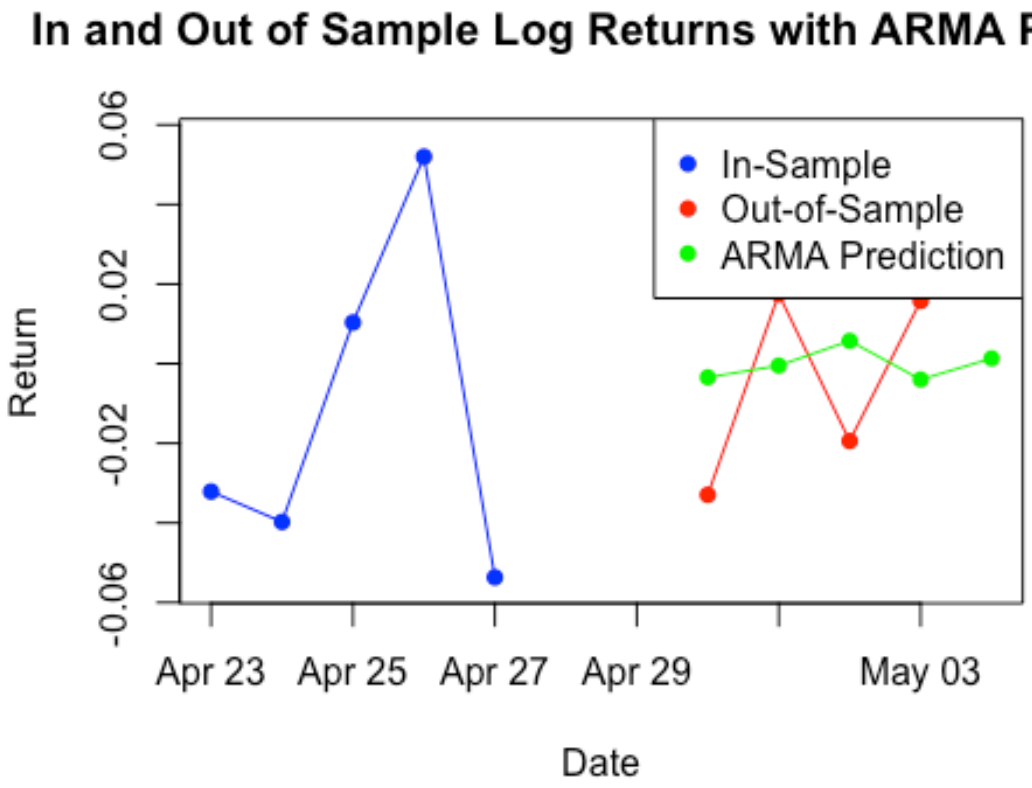
```r
#plotting AR prediction over actual
plot(in_sample_last5, main="In and Out of Sample Log Returns with AR Predict",
col="blue", xlim=as.Date(c("2018-04-23","2018-05-04")), ylim=c(min(out_sample$R
eturn, in_sample_last5$Return, predictAR$Return)-.002, max(out_sample$Return, i
n_sample_last5$Return, predictAR$Return)+.005), type="o", pch=16)
lines(out_sample, col="red", type="o", pch=16)
lines(predictAR, col="green", type="o", pch=16)
legend("topright", c("In-Sample", "Out-of-Sample","AR Prediction"), col=c("blue
", "red", "green"), pch=16)
```



```r
#plotting MA prediction over actual
plot(in_sample_last5, main="In and Out of Sample Log Returns with MA Predict",
col="blue", xlim=as.Date(c("2018-04-23","2018-05-04")), ylim=c(min(out_sample$R
eturn, in_sample_last5$Return, predictMA$Return)-.002, max(out_sample$Return, i
n_sample_last5$Return, predictMA$Return)+.005), type="o", pch=16)
lines(out_sample, col="red", type="o", pch=16)
lines(predictMA, col="green", type="o", pch=16)
legend("topright", c("In-Sample", "Out-of-Sample","MA Prediction"), col=c("blue
", "red", "green"), pch=16)
```



```r
#plotting ARMA prediction over actual
plot(in_sample_last5, main="In and Out of Sample Log Returns with ARMA Predict"
, col="blue", xlim=as.Date(c("2018-04-23","2018-05-04")), ylim=c(min(out_sample
$Return, in_sample_last5$Return, predictARMA$Return)-.002, max(out_sample$Retur
n, in_sample_last5$Return, predictARMA$Return)+.005), type="o", pch=16)
lines(out_sample, col="red", type="o", pch=16)
lines(predictARMA, col="green", type="o", pch=16)
legend("topright", c("In-Sample", "Out-of-Sample","ARMA Prediction"), col=c("bl
ue", "red","green"), pch=16)
```



```r
#Part E
sseAR <- sum((out_sample$Return-predictAR$Return)^2)
sseAR
```

```
## [1] 0.002374043
```

```r
sseMA <- sum((out_sample$Return-predictMA$Return)^2)
sseMA
```

```
## [1] 0.002222692
```

```r
sseARMA <- sum((out_sample$Return-predictARMA$Return)^2)
sseARMA
```

```
## [1] 0.002580017
```

```r
#Here we computed the sum of squared errors between each predicted model and th
e out of sample data. AR gave a value of 0.002374043, MA gave a value of 0.0022
22692, and ARMA gave a value of 0.002580017. You will notice that all of these
models gave low values, however, the best choice of a model would be the one wi
th the lowest sum of squared errors, which is the MA model in this case.
```

Interview Problem

```
x <- read.csv("qf-202-final-data-xxx.csv", header=T)
y <- read.csv("qf-202-final-data-yyy.csv", header=T)
z <- read.csv("qf-202-final-data-zzz.csv", header=T)

estimateParameters <- function(data, fileName){
  model <- arima(data, order=c(3,2,6))
  mu <- model$coef[9]
  mu <- c(mu, NA,NA,NA,NA,NA)
  phi <- model$model$phi
  phi <- c(phi,NA,NA,NA)
  theta <- model$model$theta
  sigma <- sqrt(model$sigma2)
  sigma <- c(sigma, NA,NA,NA,NA,NA)
  result <- data.frame(mu, phi, theta, sigma)
  write.csv(result, file=fileName)
}

estimateParameters(x$x, "xxx-result.csv")
estimateParameters(y$x, "yyy-result.csv")
estimateParameters(z$x, "zzz-result.csv")



#The approach I took to this problem is as follows. First, I read each csv file
, saving it with its corresponding letter. I made sure to indicate header=T, si
nce there are headers to our data. The next step I took was to create a functio
n that would estimate the parameters for the data, no matter the data length. T
he function, estimateParameters, takes in 2 parameters, the first being the dat
a and the second being the name of the file you want the result to output to. T
he function creates an ARIMA(3,2,6) model using the data it was called with. Fr
om there, I was able to access each component of the result. First, I found the
mean (mu), which is the last coefficient for the model. Next, I found all the p
hi and theta parameters, referencing them from our created model. Lastly, I too
k the variance of the model and took the square root, so that I can get the sta
ndard deviation. Since there were a different number of parameters for each of
the values we were seeking (mu, phi, theta, sigma), I padded my results with 'N
A' to fill in empty spots, so that I could return a data frame that was nicely
formatted.
```

Below are screenshots from the outputted csv files from the Interview Type Problem

xxx-result.csv

	A	B	C	D	E
1		mu	phi	theta	sigma
2	1	0.43290739	0.76351488	0.24787526	0.42651013
3	2	NA	-0.2389413	0.66746293	NA
4	3	NA	0.34461485	0.33150744	NA
5	4	NA	NA	0.78818715	NA
6	5	NA	NA	0.19731868	NA
7	6	NA	NA	0.43290739	NA

yyy-result.csv

	A	B	C	D	E
1		mu	phi	theta	sigma
2	1	-0.510384	0.24270746	-0.4176316	0.44600512
3	2	NA	0.56179668	0.24321747	NA
4	3	NA	-0.4292908	-0.2056018	NA
5	4	NA	NA	0.11126603	NA
6	5	NA	NA	0.26901919	NA
7	6	NA	NA	-0.510384	NA

zzz-result.csv

	A	B	C	D	E
1		mu	phi	theta	sigma
2	1	0.78405266	-0.4310662	0.20879335	0.99126864
3	2	NA	0.64169784	-0.5550526	NA
4	3	NA	0.22216389	0.43734038	NA
5	4	NA	NA	-0.3296473	NA
6	5	NA	NA	0.11334138	NA
7	6	NA	NA	0.78405266	NA