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# Time Series and Prediction

Practice Homework
| *17 January 2019*

Loading the data into R workspace and constructing log return from the adjusted price series of the AAPL ticker over the entire sample. AAPL <- read.csv2("AAPL.csv",

```
                sep=",") dates
<- as.character(AAPL$timestamp)
AAPL <- as.data.frame(
  lapply(AAPL, as.numeric) ) log.returns <- log(AAPL$adjusted_close[-
1]/AAPL$adjusted_close[-nrow(AAPL)])

(ADF <-
adf.test(log.returns,
               k=21)
               )

Warning in adf.test(log.returns, k = 21): p-value smaller than
printed p- value Augmented Dickey-Fuller Test

data: log.returns Dickey-Fuller = -17.415, Lag
order = 21, p-value = 0.01 alternative
hypothesis: stationary
```

**Question 1**

ADF test stat: -17.415

**Question 2**

The P-value is less than to the alpha level of 0.05 which it is, then we can reject the Null Hypothesis. So our Null in this case is rejected. Yes, we reject the null of nonstationarity.

**Question 3**

```
cat("Mean:",
mean(log.returns))

Mean: -
0.001290663
```

**Question 4**

```
cat("Variance:",
var(log.returns))

Variance:
0.02253269
```

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**Question 5**
```
cat("Skewness:",
skewness(log.returns))

Skewness: -
0.1459896
```

**Question 6**
```
cat("Kurtosis:",
kurtosis(log.returns))
```



```
Kurtosis:
75.04732
```

**Question 7**
```
hist(log.retur
ns,
     main="Distribution of Log
     Returns", xlab="log returns")
```

## Distribution of Log Returns

0 052y cneuqerF0log returns 0051005–2 –1 0 1 2

From the skewness we can see that the emphirical distribution of returns is **negatively skewed**.

**Question 8**

Inspection of the kurtosis revelas that the emphirical distribution of return is **thin tailed**.

**Question 9**
```
cat("Max:
",
    max(log.return
    s), "Min:",
    min(log.return
    s))

Max: 1.637481 Min: -
2.397895
```

**Question 10**
```
cat(sum(abs(log.returns)>0.05)/length(log.retur
ns)*100,
```

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```
"% of days with a return larger than 5% in absolute
value")

20.35214 % of days with a return larger than 5% in
absolute value
```

**Question 11**

2

```
(JB <-
jarque.bera.test(log.returns))


    Jarque Bera
    Test

data: log.returns X-squared = 1240500,
df = 2, p-value < 2.2e-16 cat("JB
stat:", JB$statistic)

JB stat:
1240527
```

**Question 12** `cat("JB p-value:", JB$p.value)`

```
JB p-value:
0
```

**Question 13**

The P-value is less than to the alpha level of `0.05` which it is, then we can reject the Null Hypothesis. So our Null in this case is rejected. Yes, we reject the null of normality.

**Question 14** `sd(log.returns) * sqrt(250) * 100`

```
[1]
237.3431
```

**Question 15** `index <- unname(sapply(dates, get.year.index, year="2007"))`

```
sd(log.returns[index]) * sqrt(250) * 100

[1]
79.12173
```

**Question 16** `index <- unname(sapply(dates, get.year.index, year="2009"))`

```
sd(log.returns[index]) * sqrt(250) * 100
```

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```
[1]
241.5642
```

**Question 17** `index <- unname(sapply(dates, get.year.index, year="2014"))`

```
sd(log.returns[index]) * sqrt(250) * 100
```

```
[1]
272.5155
```

**Question 18** `ACF <- acf(log.returns, lag.max=126, plot=TRUE)`

3

**Series log.returns**

0 .18.06.0F C A 4.02.02.0 –0 20 40 60 80 100 120

Lag

```
acf(log.returns, lag.max=5,
plot=FALSE)
```

```
Autocorrelations of series log.returns ,
by lag

   0 1 2 3 4 5 1.000 -0.231 0.004 -
 0.063 0.003 0.006
```

**Question 19**

```
sum(abs(ACF$acf)<0.0
01)
```

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```
[1]
4
```

**Question 20**

```
sum(abs(ACF$acf)>0.
05)

[1]
```

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