Final

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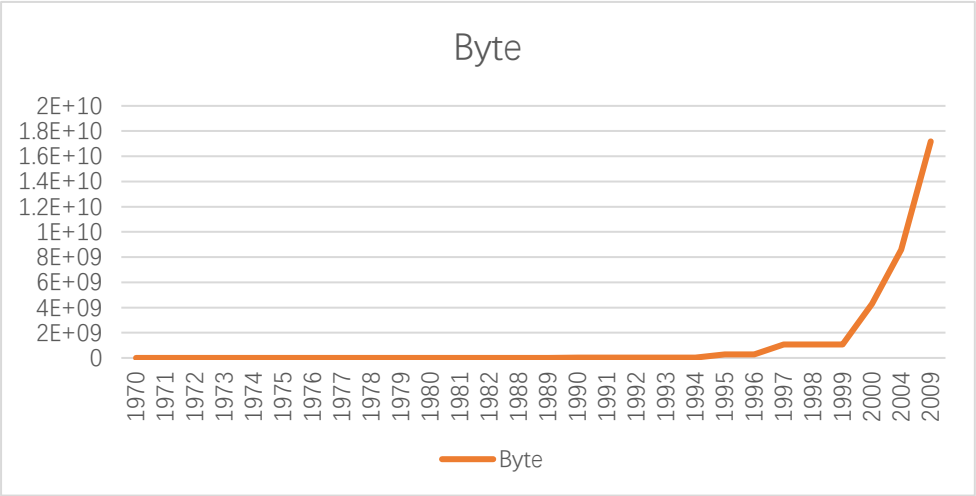
HW Unit 1

Q1. Calculate the i**ncrea**se of memory of PCs over the last 30 years and check whether the FMRI analysis could have been done 20 years ago.

| year | Byte |
|---|---|
| 1970 | 262144 |
| 1971 | 262144 |
| 1972 | 262144 |
| 1973 | 262144 |
| 1974 | 262144 |
| 1975 | 262144 |
| 1976 | 262144 |
| 1977 | 262144 |
| 1978 | 262144 |
| 1979 | 262144 |
| 1980 | 262144 |
| 1981 | 262144 |
| 1982 | 262144 |
| 1988 | 2097152 |
| 1989 | 2097152 |
| 1990 | 2097152 |
| 1991 | 16777216 |
| 1992 | 16777216 |
| 1993 | 16777216 |
| 1994 | 16777216 |
| 1995 | 16777216 |
| 1996 | 2.68E+08 |
| 1997 | 2.68E+08 |
| 1998 | 1.07E+09 |
| 1999 | 1.07E+09 |
| 2000 | 1.07E+09 |
| 2004 | 4.29E+09 |
| 2009 | 8.59E+09 |
| 2014 | 1.72E+10 |




2. prepare 2-5 slides explaining logistic regression

# Logistic regression

Logistic regression is a regression model where the dependent variable (DV) is categorical, where a categorical variable is a variable that can take on one of a limited, and usually fixed, number of possible values,

# Logistic regression VS multiple linear regression

- There are many similarities between logistic regression and multiple linear regression, the biggest difference is that their dependent variables are different, and the others are almost the same.
- If the dependent variable is continuous, that is, multiple linear regression, if it is the two distribution, that is the logistic regression.


3. I have done that and my account is Bingren Sun026.

HW Unit 2

1. memory.df = read.csv("byte.csv",header = TRUE)

plot(memory.df$Byte~memory.df$year,type="o",main="The development of internal memory")

2. splines.reg.l1 = smooth.spline(x = memory.df$year, y = memory.df$Byte, spar = 0.2)

splines.reg.l2 = smooth.spline(x = memory.df$year, y = memory.df$Byte, spar = 1)

splines.reg.l3= smooth.spline(x = memory.df$year, y = memory.df$Byte, spar = 2)

lines(splines.reg.l1, col = "green", lwd = 2)

lines(splines.reg.l2, col = "pink", lwd = 2)

lines(splines.reg.l3, col = "blue", lwd = 2)

3. lambda=4

x=6

dpois(x,lambda)

lambda=5

x=0

dpois(x,lambda)

HW Unit 3

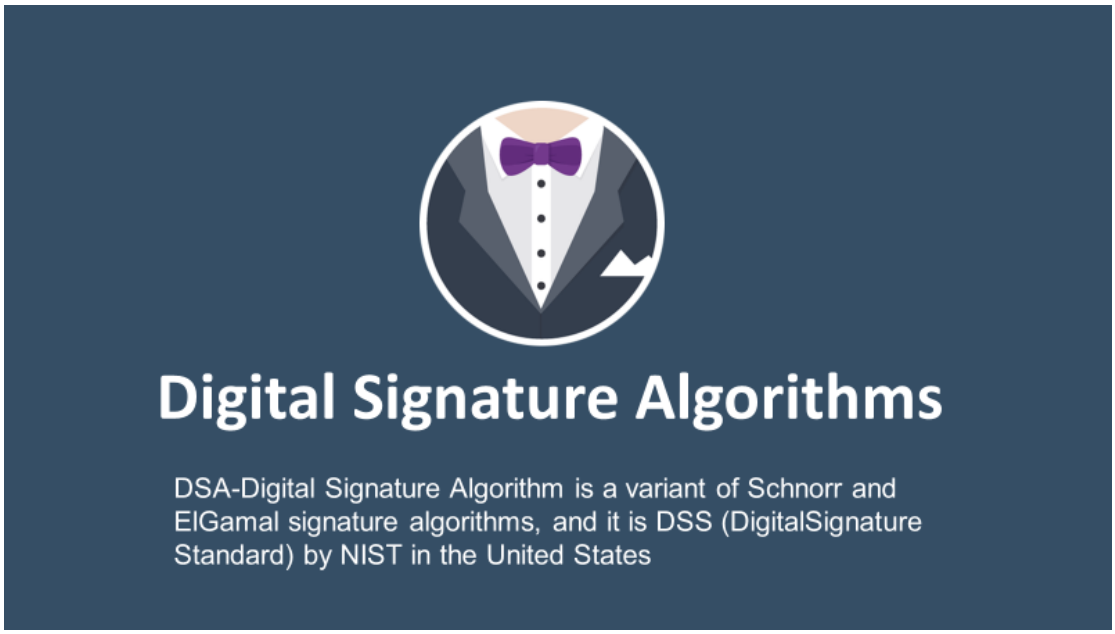
1. #install.packages("digest",repos='http://cran.us.r-project.org')

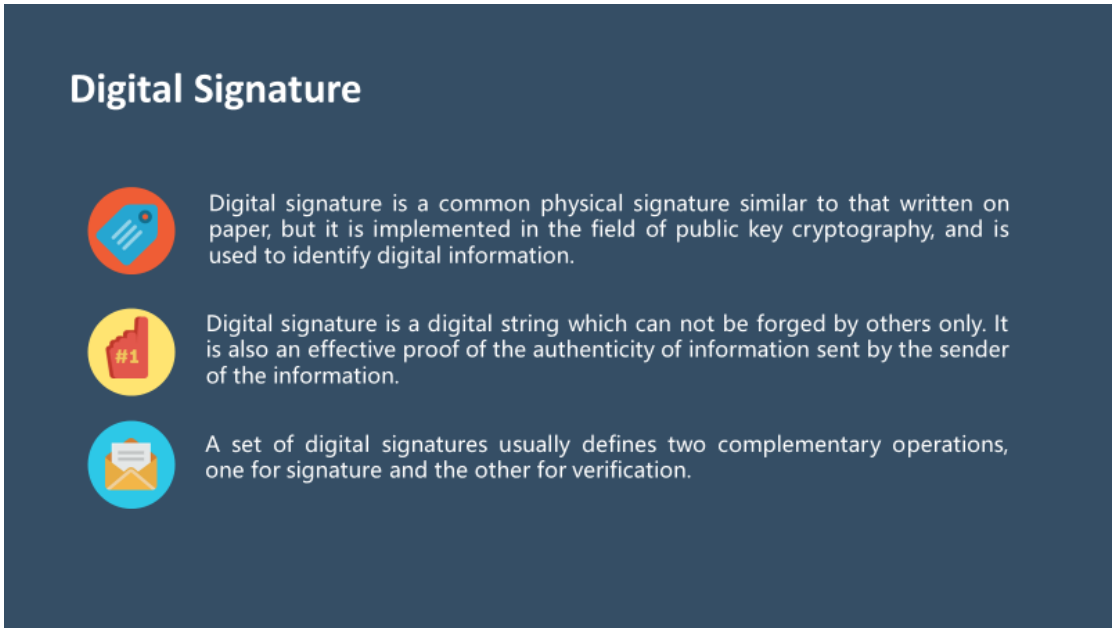
library(digest)

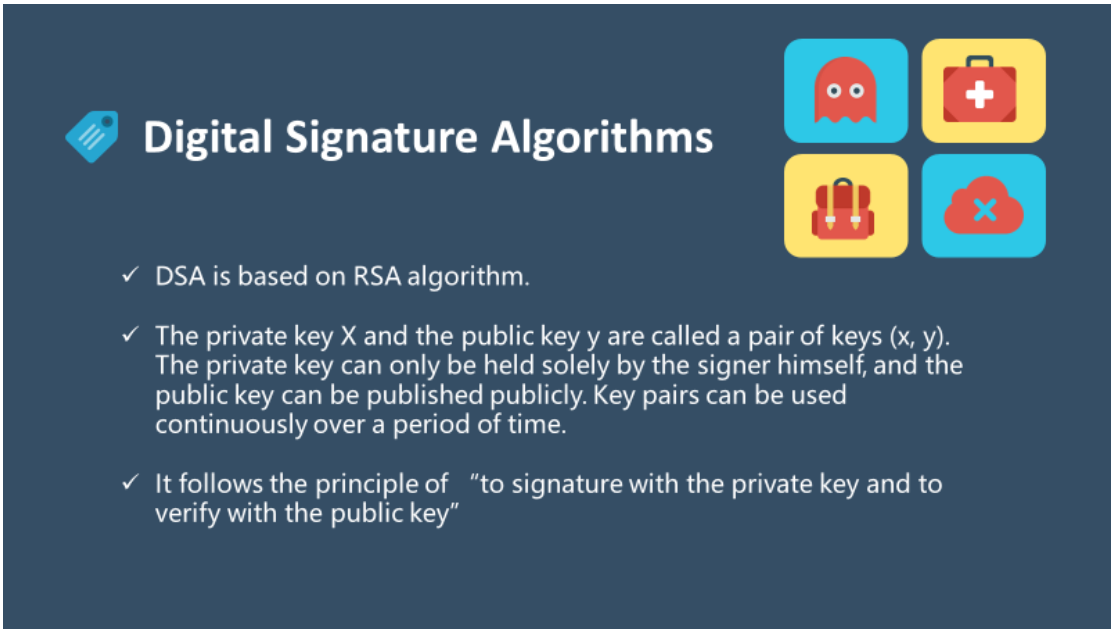
digest("I learn a lot from this class when I am proper listening to the professor","sha256")

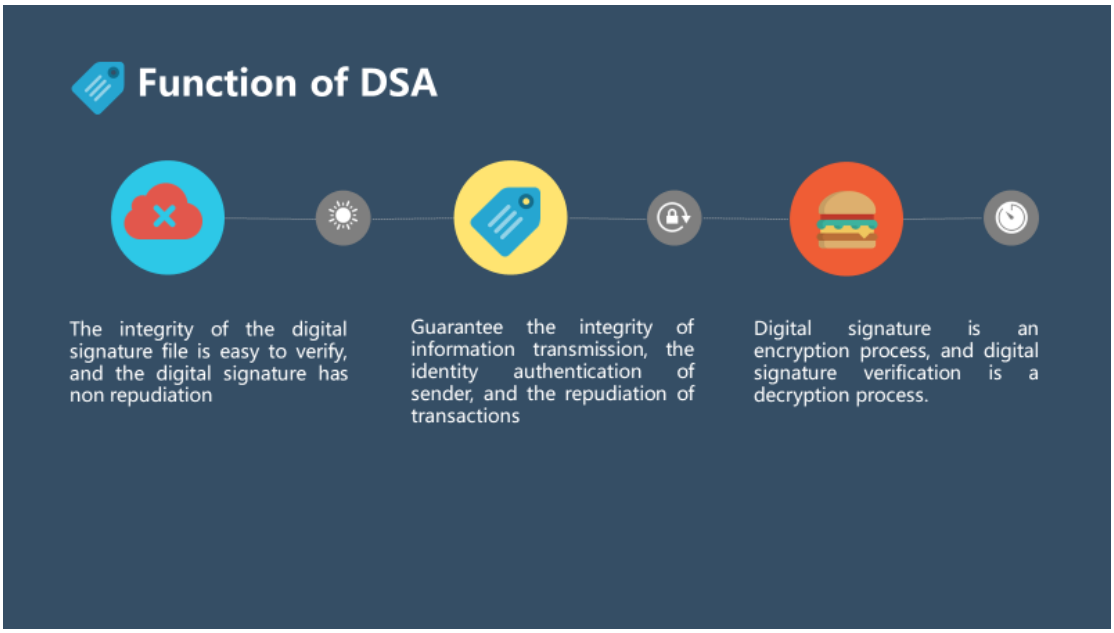
digest("I do not learn a lot from this class when I am absent and playing on my Iphone","sha256")

2. Make 3-5 slides (in PPTX) on the DSA (Digital Signature Algorithms)






3. library(rjson)

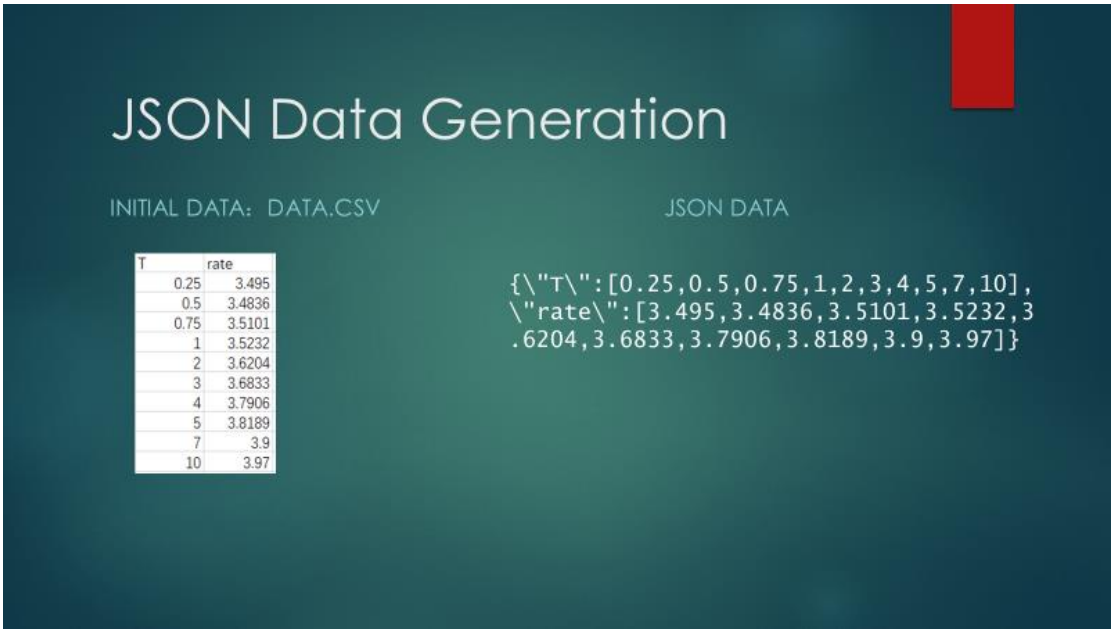
   library(readr)

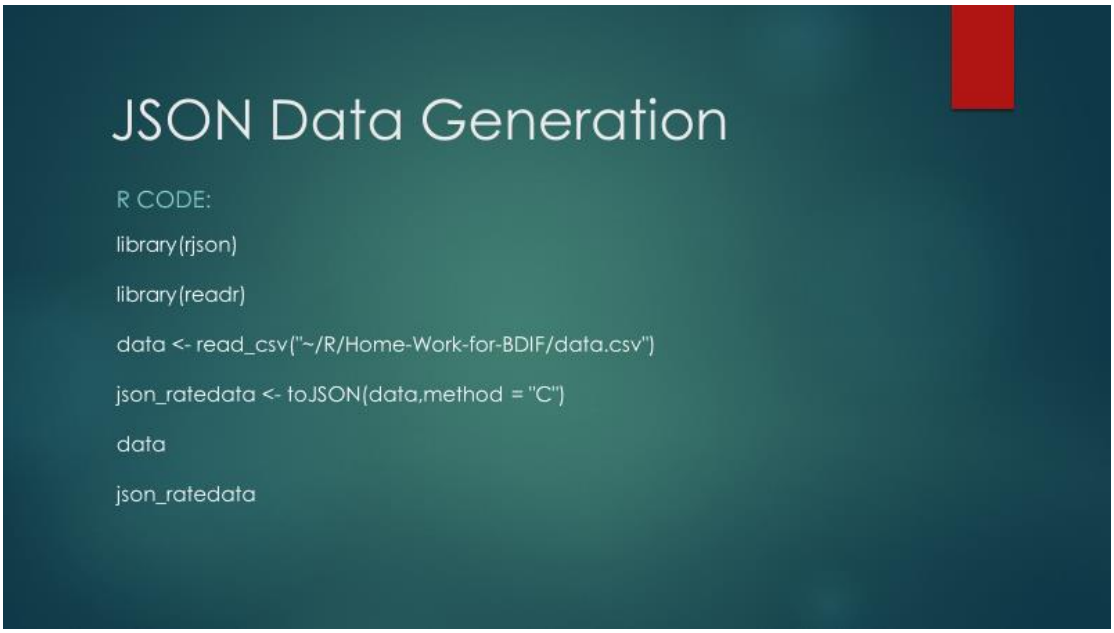
   data <- read_csv("~/R/Home-Work-for-BDIF/data.csv")

   json_ratedata <- toJSON(data,method = "C")

   data

   json_ratedata




4. #install.packages("rjson", repos="http://cran.us.r-project.org")

   library(rjson)

   json_file = "http://crix.hu-berlin.de/data/crix.json"

   json_data = fromJSON(file=json_file)

   crix <- Reduce(rbind,json_data)

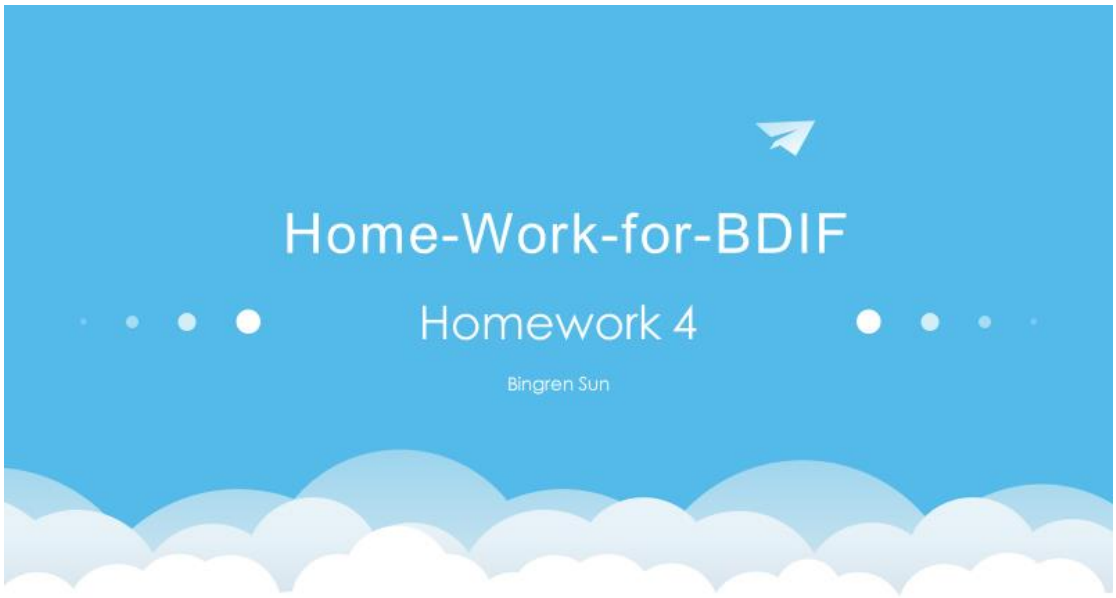
   crix_data_frame <- as.data.frame(crix)

   lst <- lapply(json_data,function(x){

   df<-data.frame(date=x$date,price=x$price)

```
return(df)
        })
 crix_data_frame <- Reduce(rbind,lst)
 plot(crix_data_frame$date,crix_data_frame$price)
 #library(forecast)
 #library(tseries)
 plot(crix_data_frame)
```

HW Unit 4




# Q1-Figures

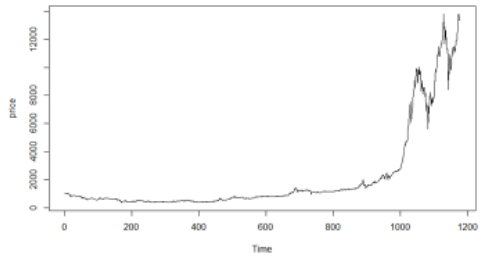



Figure 3

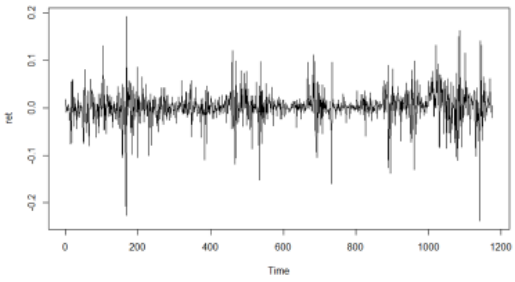
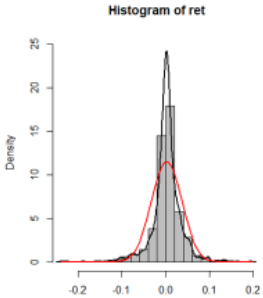



Figure 4

# Q1-Figures



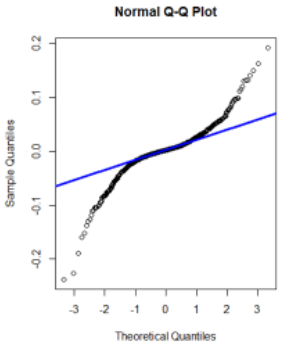




Figure 5

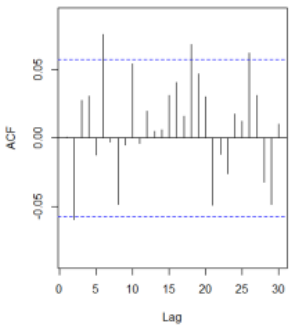



Figure 6

# Q2

```
# install and load packages
libraries = c("zoo", "tseries")
lapply(libraries, function(x) if (!(x %in%
installed.packages())) {
  install.packages(x)
})
lapply(libraries, library, quietly = TRUE,
character.only = TRUE)
# d order
Box.test(ret, type = "Ljung-Box", lag = 20)
# stationary test
adf.test(ret, alternative = "stationary")
kpss.test(ret, null = "Trend")
par(mfrow = c(1, 2))
```

```
# acf plot
autocorr = acf(ret, lag.max = 20, ylab = "Sample
Autocorrelation", main = NA,
          lwd = 2, ylim = c(-0.3, 1))
# LB test of linear dependence
print(cbind(autocorr$lag, autocorr$acf))
Box.test(ret, type = "Ljung-Box", lag = 1, fitdf = 0)
Box.test(autocorr$acf, type = "Ljung-Box")
# plot of pacf
autopcorr = pacf(ret, lag.max = 20, ylab = "Sample
Partial Autocorrelation",
           main = NA, ylim = c(-0.3, 0.3), lwd = 2)
print(cbind(autopcorr$lag, autopcorr$acf))
```

# Q2

```
# arima model
par(mfrow = c(1, 1))
auto.arima(ret)
fit1 = arima(ret, order = c(1, 0, 1))
tsdiag(fit1)
Box.test(fit1$residuals, lag = 1)
# aic
aic = matrix(NA, 6, 6)
for (p in 0:4) {
  for (q in 0:3) {
    a.p.q = arima(ret, order = c(p, 0, q))
    aic.p.q = a.p.q$aic
    aic[p + 1, q + 1] = aic.p.q
  }
}
aic
```

```
# bic
bic = matrix(NA, 6, 6)
for (p in 0:4) {
  for (q in 0:3) {
    b.p.q = arima(ret, order = c(p, 0, q))
    bic.p.q = AIC(b.p.q, k = log(length(ret)))
    bic[p + 1, q + 1] = bic.p.q
  }
}
bic
# select p and q order of ARIMA model
fit4 = arima(ret, order = c(2, 0, 3))
tsdiag(fit4)
Box.test(fit4$residuals, lag = 1)

fitr4 = arima(ret, order = c(2, 1, 3))
tsdiag(fitr4)
Box.test(fitr4$residuals, lag = 1)
```

# Q2

```
# to conclude, 202 is better than 213
fit202 = arima(ret, order = c(2, 0, 2))
tsdiag(fit202)
tsdiag(fit4)
tsdiag(fitr4)

AIC(fit202, k = log(length(ret)))
AIC(fit4, k = log(length(ret)))
AIC(fitr4, k = log(length(ret)))
fit202$aic
fit4$aic
fitr4$aic
```

```
# arima202 predict
fit202 = arima(ret, order = c(2, 0, 2))
crpre = predict(fit202, n.ahead = 30)

dates = seq(as.Date("02/08/2014", format =
"%d/%m/%Y"), by = "days", length = length(ret))

plot(ret, type = "l", xlim = c(0, 1200), ylab = "log return",
xlab = "days",
    lwd = 1.5)
lines(crpre$pred, col = "red", lwd = 3)
lines(crpre$pred + 2 * crpre$se, col = "red", lty = 3, lwd
= 3)
lines(crpre$pred - 2 * crpre$se, col = "red", lty = 3, lwd =
3)
```

## Q2-figure

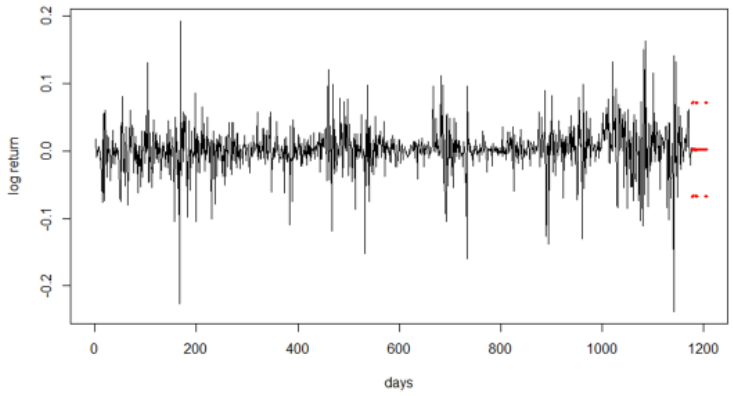
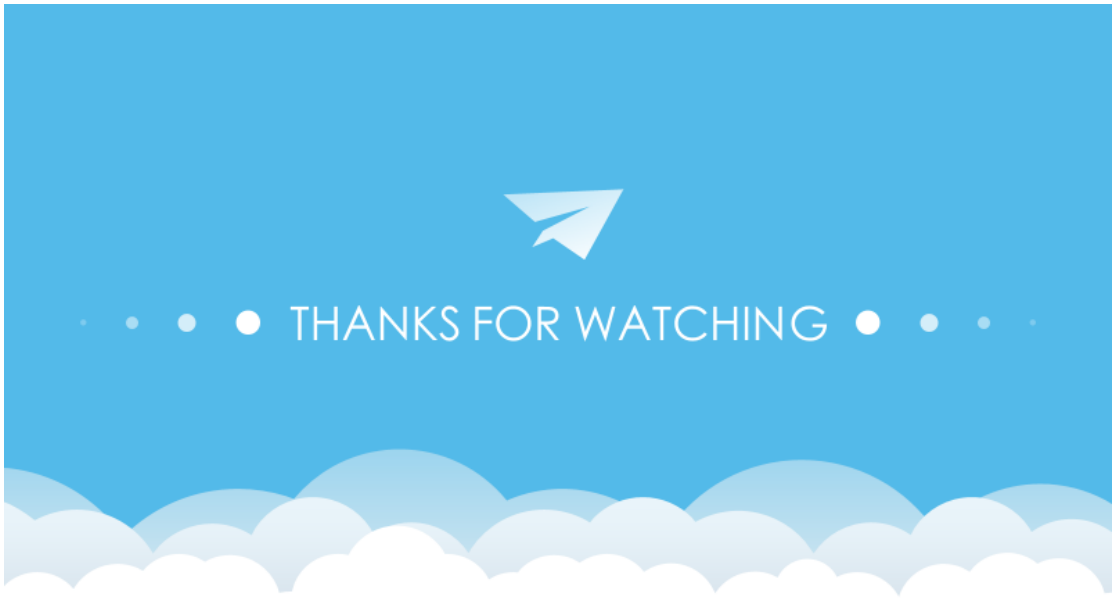



Figure 7




Question1

```
library(rjson)
json_file = "http://crix.hu-berlin.de/data/crix.json"
json_data = fromJSON(file=json_file)
crix_data_frame <- as.data.frame(json_data)
w=crix_data_frame
dim(w)
n=dim(w)
a=seq(1,n[2],2)
b=seq(2,n[2],2)
data=t(w[1,a])
price=t(w[1,b])
#figure3
ts.plot(price)
#figure4
ret=diff(log(price))
ts.plot(ret)
#figure5
hist(ret, col = "grey", breaks = 40, freq = FALSE)
```

```
lines(density(ret), lwd = 2)
par(mfrow = c(1, 2))
# histogram of returns
hist(ret, col = "grey", breaks = 20, freq = FALSE, ylim = c(0, 25), xlab = NA)
lines(density(ret), lwd = 2)
mu = mean(ret)
sigma = sd(ret)
x = seq(-4, 4, length = 100)
curve(dnorm(x, mean = mean(ret), sd = sd(ret)), add = TRUE, col = "red",
      lwd = 2)
      # qq-plot
      qqnorm(ret)
      qqline(ret, col = "blue", lwd = 3)
      #figure6
      library(forecast)
      library(tseries)
      Acf(ret)

      Question2
      #rm(list = ls(all = TRUE))
      #graphics.off()
      # install and load packages
      libraries = c("zoo", "tseries")
      lapply(libraries, function(x) if (!(x %in% installed.packages())) {
         install.packages(x)
      })
      lapply(libraries, library, quietly = TRUE, character.only = TRUE)
      # d order
      Box.test(ret, type = "Ljung-Box", lag = 20)
      # stationary test
```

```
adf.test(ret, alternative = "stationary")
kpss.test(ret, null = "Trend")
par(mfrow = c(1, 2))
# acf plot
 autocorr = acf(ret, lag.max = 20, ylab = "Sample Autocorrelation", main = NA, lwd = 2,
 ylim = c(-0.3, 1))
# LB test of linear dependence
print(cbind(autocorr$lag, autocorr$acf))
Box.test(ret, type = "Ljung-Box", lag = 1, fitdf = 0)
Box.test(autocorr$acf, type = "Ljung-Box")
# plot of pacf
 autopcorr = pacf(ret, lag.max = 20, ylab = "Sample Partial Autocorrelation", main = NA,
 ylim = c(-0.3, 0.3), lwd = 2)
print(cbind(autopcorr$lag, autopcorr$acf))
# arima model
par(mfrow = c(1, 1))
auto.arima(ret)
fit1 = arima(ret, order = c(1, 0, 1))
tsdiag(fit1)
Box.test(fit1$residuals, lag = 1)
# aic
aic = matrix(NA, 6, 6)
for (p in 0:4) {
   for (q in 0:3) {
   a.p.q = arima(ret, order = c(p, 0, q))
   aic.p.q = a.p.q$aic
     aic[p + 1, q + 1] = aic.p.q
   }
}
aic
```

```
# bic
bic = matrix(NA, 6, 6)
for (p in 0:4) {
   for (q in 0:3) {
      b.p.q = arima(ret, order = c(p, 0, q))
      bic.p.q = AIC(b.p.q, k = log(length(ret)))
      bic[p + 1, q + 1] = bic.p.q
   }
}
bic
# select p and q order of ARIMA model
fit4 = arima(ret, order = c(2, 0, 3))
tsdiag(fit4)
Box.test(fit4$residuals, lag = 1)

fitr4 = arima(ret, order = c(2, 1, 3))
tsdiag(fitr4)
Box.test(fitr4$residuals, lag = 1)
# to conclude, 202 is better than 213
fit202 = arima(ret, order = c(2, 0, 2))
tsdiag(fit202)
tsdiag(fit4)
tsdiag(fitr4)

AIC(fit202, k = log(length(ret)))
AIC(fit4, k = log(length(ret)))
AIC(fitr4, k = log(length(ret)))
fit202$aic
fit4$aic
fitr4$aic
```

```
# arima202 predict
fit202 = arima(ret, order = c(2, 0, 2))
crpre = predict(fit202, n.ahead = 30)

dates = seq(as.Date("02/08/2014", format = "%d/%m/%Y"), by = "days", length =
length(ret))

plot(ret, type = "l", xlim = c(0, 1200), ylab = "log return", xlab = "days",
        lwd = 1.5)
lines(crpre$pred, col = "red", lwd = 3)
lines(crpre$pred + 2 * crpre$se, col = "red", lty = 3, lwd = 3)
lines(crpre$pred - 2 * crpre$se, col = "red", lty = 3, lwd = 3)
```