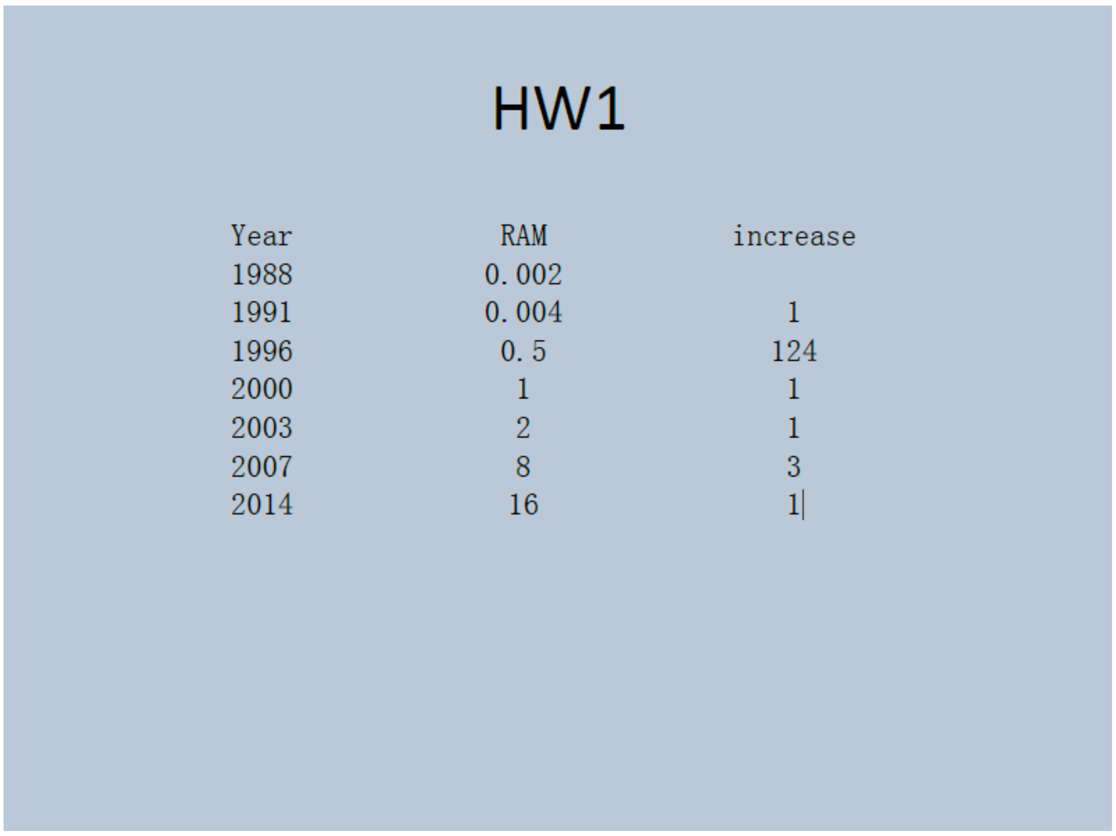
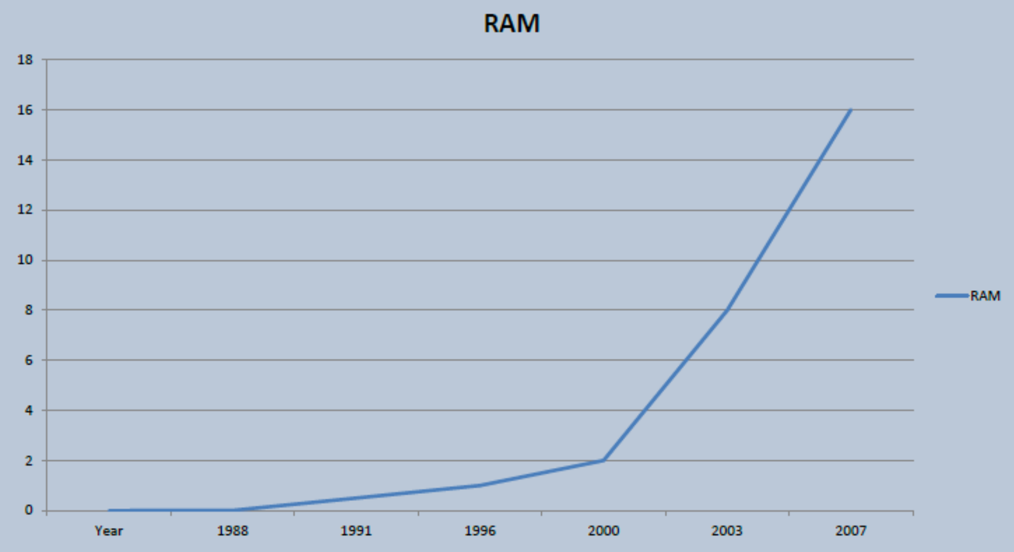


HW1

Year	RAM	increase
1988	0.002	
1991	0.004	1
1996	0.5	124
2000	1	1
2003	2	1
2007	8	3
2014	16	1



logistic regression

In statistics, logistic regression, or logit regression, is a mathematical model used in statistics to estimate the probability of an event occuring having been given some previous data. Logistic Regression works with binary data, where either the event happens (1) or the event does not happen (0). So given some feature x it tries to find out whether some event y happens or not.

For example, if y represents whether a sports team wins a match, then y will be 1 if they win the match or y will be 0 if they do not. This is known as Binomial Logistic Regression. There is also another form of Logistic Regression which uses multiple values for the variable y. This form of Logistic Regression is known as Multinomial

Logistic Regression. Logistic regression does not look at the relationship between the two variables as a straight line. Instead,

Logistic regression uses the natural logarithm function to find the relationship between the variables and uses test data to find the coefficients. The function can then predict the future results using these coefficients in the logistic equation.

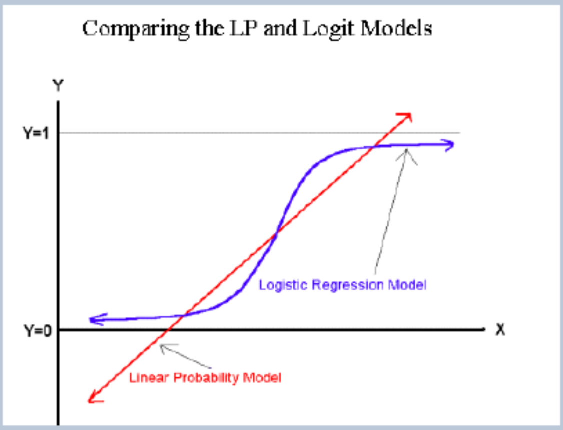
The model logistic regression model is that

$$p = \frac{\exp\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p\right)}{1 + \exp\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p\right)}$$

Because logistic regression predicts probabilities, rather than just classes, we can fit it using likelihood.

$$L(\beta_0, \beta_1) = \prod_{i=1}^{n} p(x_i)^{y_i} \left(1 - p(x_i)\right)^{1-y_i}$$

The null hypothesis underlying the overall model states that all βs equal zero.



HW2

```
#Question 1
setwd("C:/Users/xiumei/Desktop/big data")
read.csv("hw unit2.csv")
plot(year,RAM,type ="o",col="red",main = "RAM of computer")

#Question 3
x = 6
n = 1000
lambda = 2
p = lambda / n
dbinom (x,2*n,p) # binomial probability mass function
dpois (x, 2*lambda ) # Poisson probability mass function
dpois (0, 5 )

#Question 2
f<-read.csv("hw unit2.csv")
year<-f$Year;RAM<-f$RAM
plot(year,RAM,type ="o",col="black",main = "RAM of computer")
# load necessary packages
require(datasets)
require(class)
require(grDevices)
require(lattice)
# define log-returns for the DAX and FTS
x= year
y = RAM
# estimated log-returns for the DAX index for different bandwidths
splines.reg.l1 = smooth.spline(x,y, spar = 0.2) # lambda = 0.2
splines.reg.l2 = smooth.spline(x,y, spar = 1) # lambda = 1
splines.reg.l3 = smooth.spline(x,y, spar = 2) # lambda = 2
# plot for the regression results
lines(splines.reg.l1, col = "red", lwd = 2) # regression line with lambda = 0.2
lines(splines.reg.l2, col = "green", lwd = 2) # regression line with lambda = 1
lines(splines.reg.l3, col = "blue", lwd = 2) # regression line with lambda = 2
```

HW3

What Is DSA (Digital Signature Algorithm)?

Digital signatures are essential to **verify the sender of a document's identity.** The signature is computer using a set of rules and algorithm such that the identity of the person can be verified.

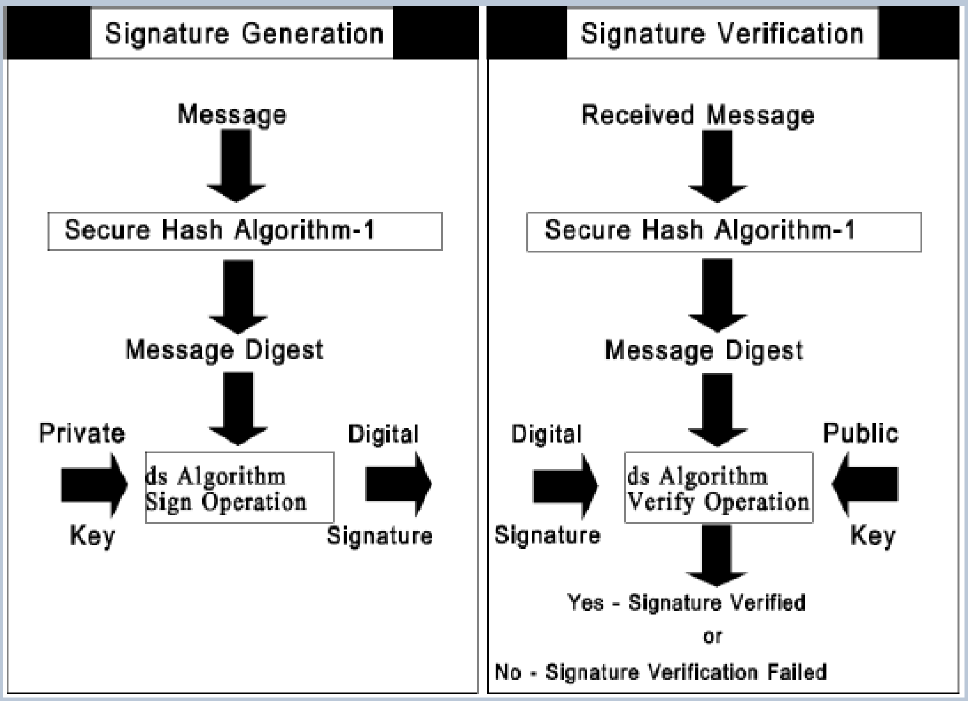
The signature is generated by the use of **a private key** that known only to **the user.** The signature is verified when a public key is corresponds to the private key. With every user having a public/private key pair, this is an example of public-key cryptography.

Public keys, which are known by everyone, can be used to verify the signature of a user**. The private key**, which is never shared, is used in signature generation, which can only be done by the user.

What can DSA do?

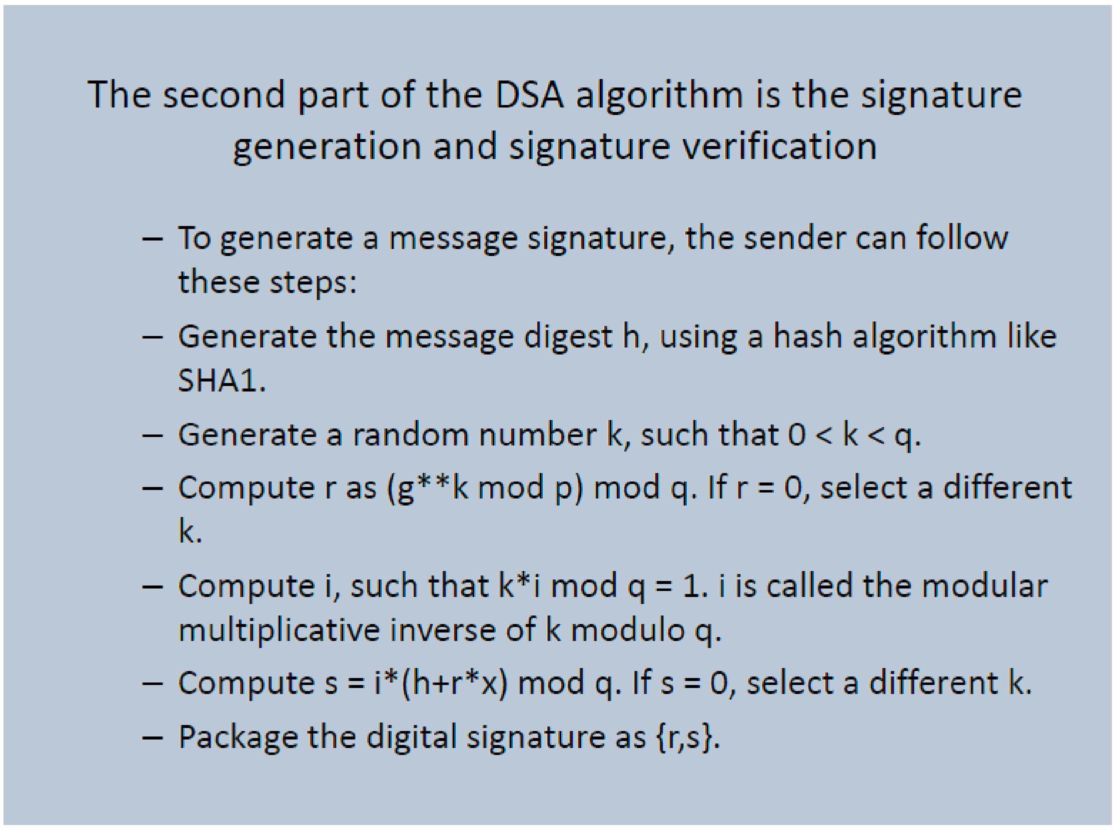
Digital signatures are used to detect unauthorized modifications to data. Also, the recipient of a digitally signed document in proving to a third party that the document was indeed signed by the person who it is claimed to be signed by. This is known as nonrepudiation, because the person who signed the document cannot repudiate the signature at a later time.

Digital signature algorithms can be used in e-mails, electronic funds transfer, electronic data interchange, software distribution, data storage, and just about any application that would need to assure the integrity and originality of data.



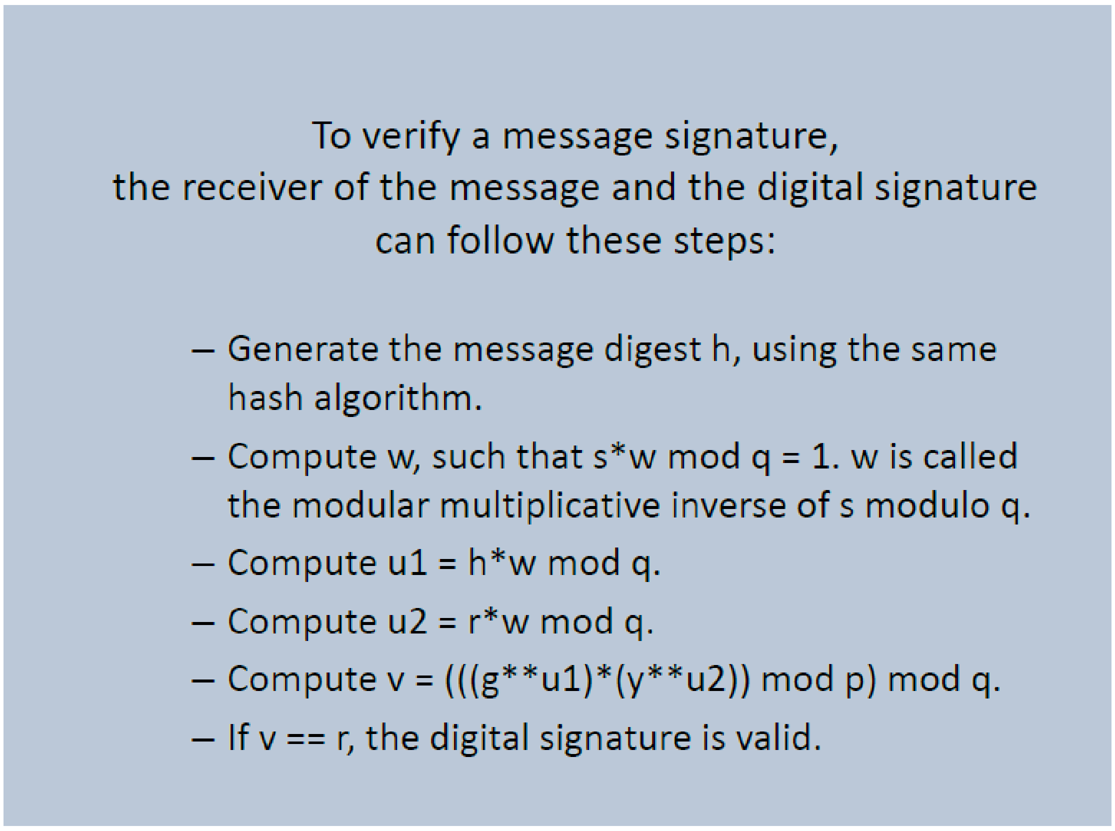
The first part of the DSA algorithm is the public key and private key generation

- Choose a prime number q, which is called the prime divisor.
- Choose another primer number p, such that p-1 mod q = 0. p is called the prime modulus.
- Choose an integer g, such that 1 < g < p, g**q mod p = 1 and g = h**((p–1)/q) mod p. q is also called g's multiplicative order modulo p.
- Choose an integer, such that 0 < x < q.
- Compute y as g**x mod p.
- Package the public key as {p,q,g,y}.
- Package the private key as {p,q,g,x}.



The second part of the DSA algorithm is the signature generation and signature verification

- To generate a message signature, the sender can follow these steps:
- Generate the message digest h, using a hash algorithm like SHA1.
- Generate a random number k, such that 0 < k < q.
- Compute r as (g**k mod p) mod q. If r = 0, select a different k.
- Compute i, such that k*i mod q = 1. i is called the modular multiplicative inverse of k modulo q.
- Compute s = i*(h+r*x) mod q. If s = 0, select a different k.
- Package the digital signature as {r,s}.

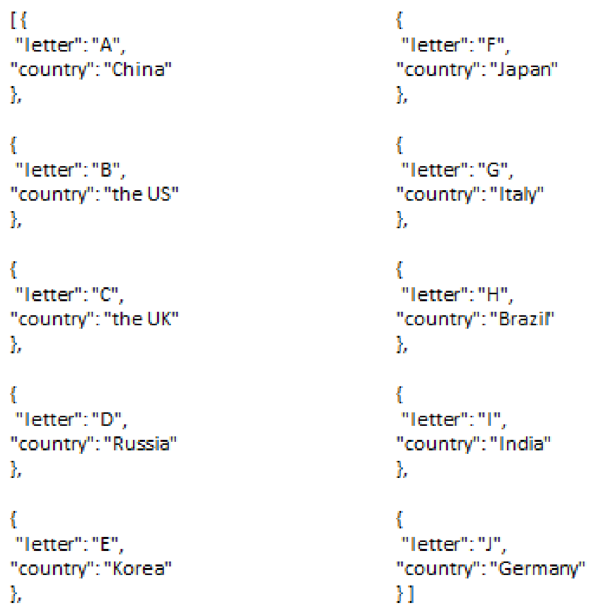


To verify a message signature, the receiver of the message and the digital signature can follow these steps:

- Generate the message digest h, using the same hash algorithm.
- Compute w, such that s*w mod q = 1. w is called the modular multiplicative inverse of s modulo q.
- Compute u1 = h*w mod q.
- Compute u2 = r*w mod q.
- Compute v = (((g**u1)*(y**u2)) mod p) mod q.
- If v == r, the digital signature is valid.

R-code:

```
>library(RJSONIO)
> letter<-LETTERS[1:10]
>country<-c("China","the US","the UK","Russia",
                         "Korea","Japan","Italy","Brazil","India","Germany")
> data<-data.frame(letter,country)
> da<-as.matrix(data)
>cat(toJSON(da))
```



```
[{
 "letter": "A",
"country": "China"
},

{
 "letter": "B",
"country": "the US"
},

{
 "letter": "C",
"country": "the UK"
},

{
 "letter": "D",
"country": "Russia"
},

{
 "letter": "E",
"country": "Korea"
},

{
 "letter": "F",
"country": "Japan"
},

{
 "letter": "G",
"country": "Italy"
},

{
 "letter": "H",
"country": "Brazil"
},

{
 "letter": "I",
"country": "India"
},

{
 "letter": "J",
"country": "Germany"
}]
```

HW3 Unit3

Answer 1

```
install.packages("digest")
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")
```

Answer 4

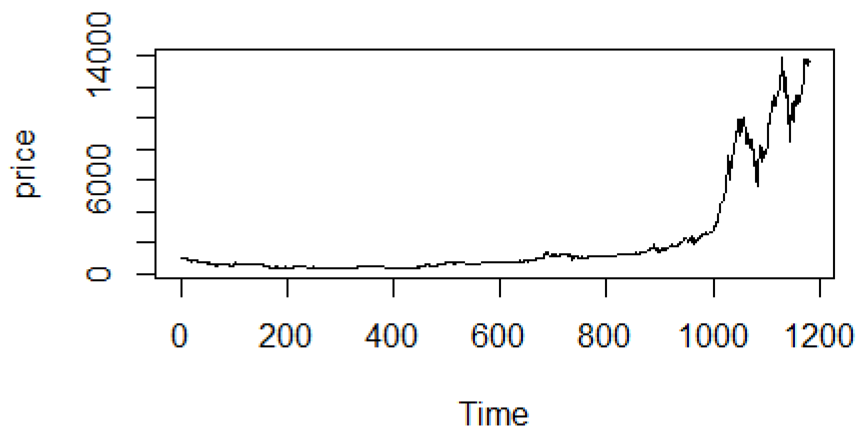
```
rm(list = ls(all = TRUE))
graphics.off()
# install and load packages #
libraries = c("zoo", "tseries")
lapply(libraries, function(x) if (!(x %in% installed.packages())) {install.packages(x)})
lapply(libraries, library, quietly = TRUE, character.only = TRUE)
# load dataset #
load(file = "C:/Users/xiumei/Desktop/big data/crix.RData")
ret = diff(log(crix))
# 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)
```

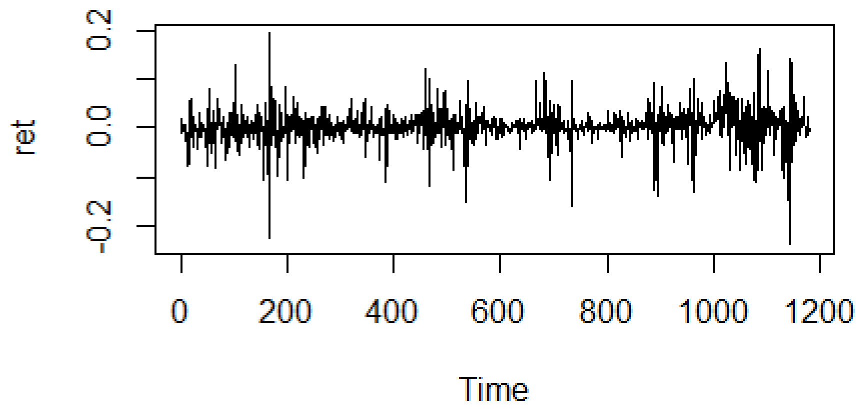
HW4

Q1

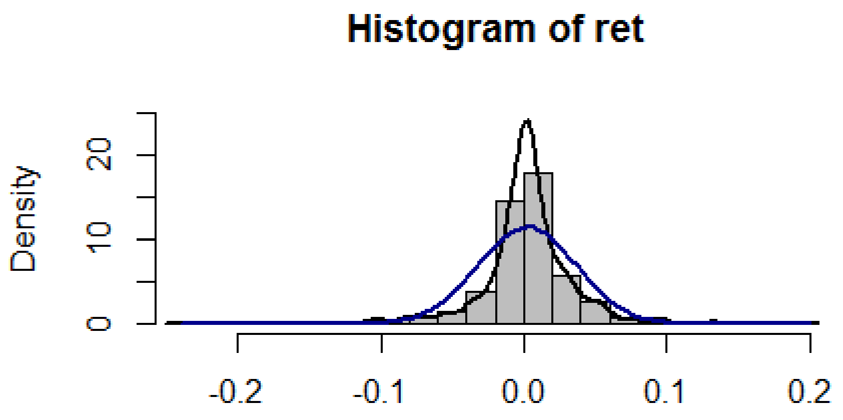
```
#20171017 JSON input from CRIX , trial done in XMN

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_data_frame = as.data.frame(json_data)
x = crix_data_frame
n = dim(x)
a = seq(1,n[2],2)
b = seq(2,n[2],2)

#figure 3 :    The daily value of CRIX
date = t(x[1,a])
price = t(x[1,b])
plot(price)
```



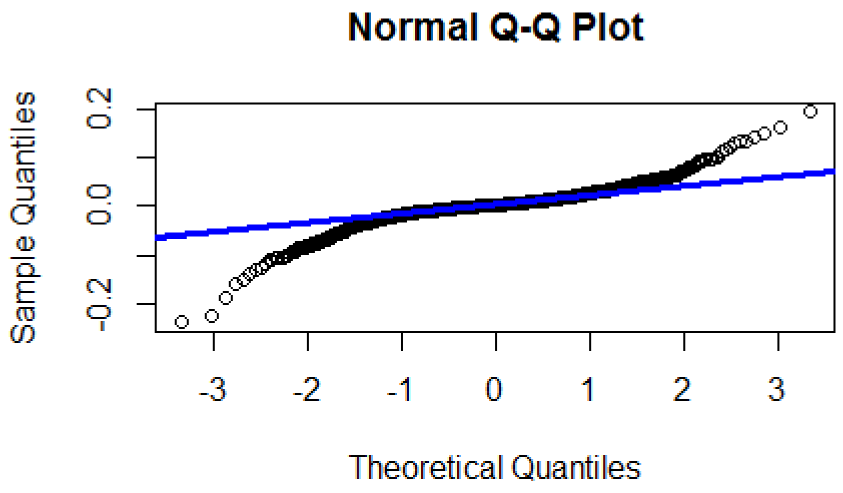
```
#figure 4 : The log returns of CRIX index
dim(price)
ts.plot(price)
ret = diff( log(price) )
ts.plot( ret )
```



```
#figure 5 : Histogram
hist(ret, col = "grey", breaks = 20, freq = FALSE, ylim = c(0, 25), xlab = NA)
lines(density(ret), lwd = 2)
mu = mean(ret)l,
sigma = sd(ret)
x = seq(-4, 4, length = 100)
curve(dnorm(x, mean = mean(ret), sd = sd(ret)), add = TRUE, col = "darkblue",    lwd = 2)
```



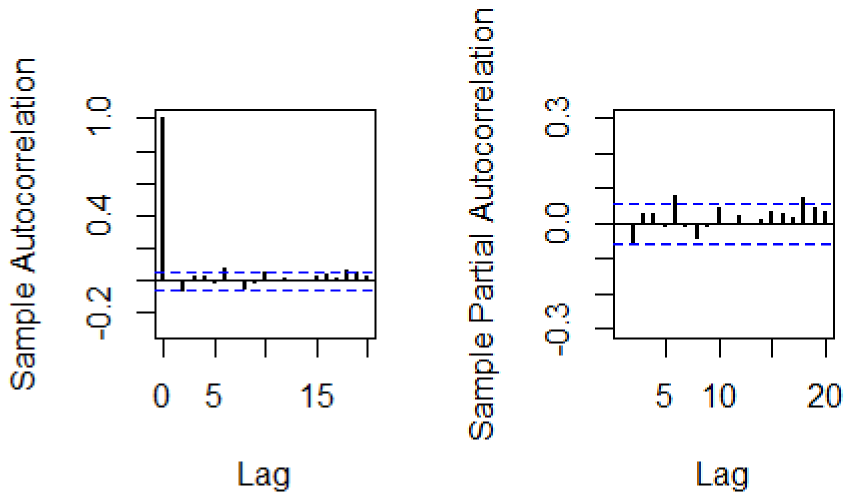
```
#figure 6 : QQ plot
qqnorm(ret)
qqline(ret, col = "blue", lwd = 3)
```



Q2

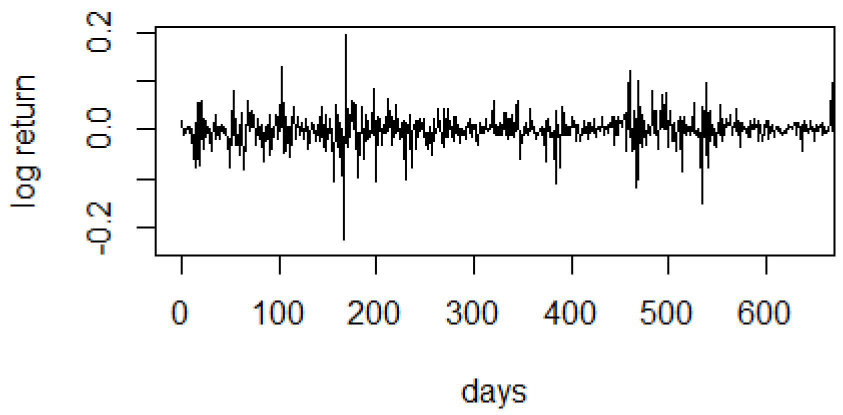
```
rm(list = ls(all = TRUE))
graphics.off()

# 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)

#RET
("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_data_frame = as.data.frame(json_data)
x = crix_data_frame
n = dim(x)
a = seq(1,n[2],2)
b = seq(2,n[2],2)
date = t(x[1,a])
price = t(x[1,b])
dim(price)
ret = diff( log(price) )

# 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))
```



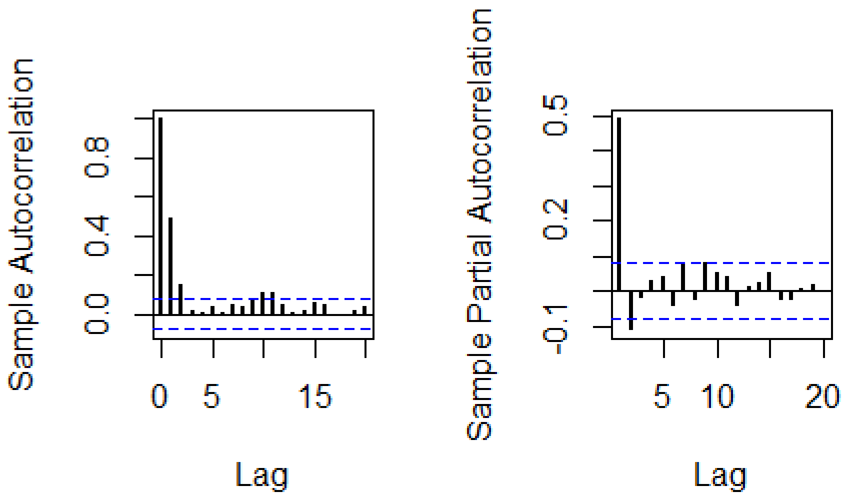
```
# arima model
par(mfrow = c(1, 1))
auto.arima(ret)
fit1 = arima(ret, order = c(1, 0, 1))
tsdiag(fit1)
Box.test(fit1$residuals, lag = 1)

# 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, 644), 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)
```



Q3

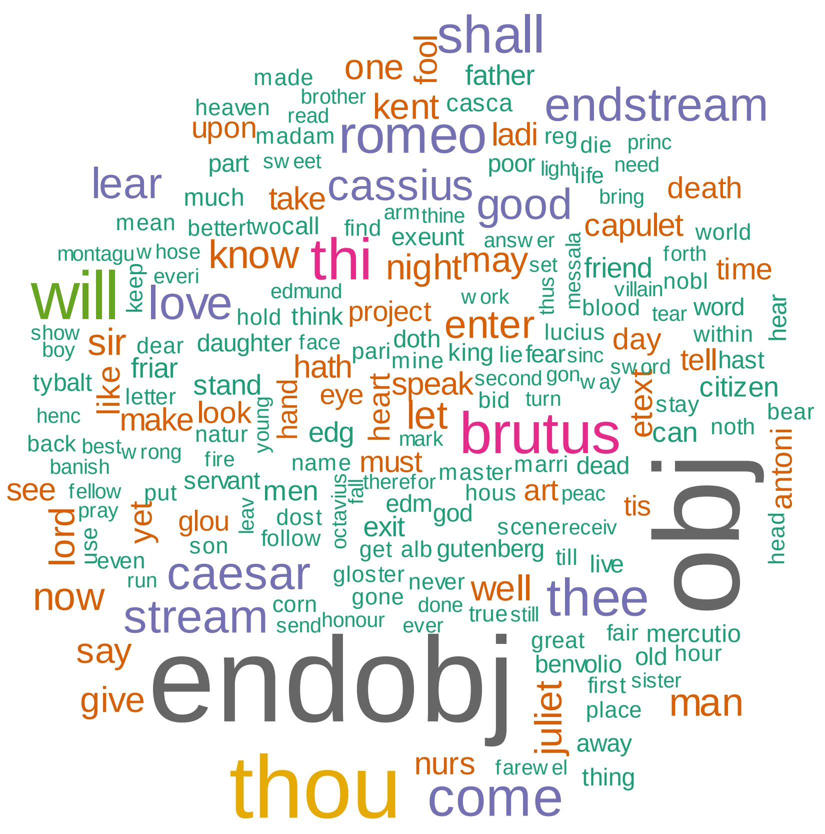
```
rm(list = ls(all = TRUE))
graphics.off()

# install and load packages
libraries = c("FinTS", "tseries")
lapply(libraries, function(x) if (!(x %in% installed.packages())) {
   install.packages(x)
})
lapply(libraries, library, quietly = TRUE, character.only = TRUE)


# plot of crix return
ret = diff(log(crx$Pr))
Dare = factor(date1[-1])
retts = data.frame(Dare, ret)

# comparison of different crix returns
par(mfrow = c(2, 2))
plot(crx$Da, crx$Pr, type = "o")
lines(crx$Pr)
plot(crx$Da, log(crx$Pr), type = "o")
lines(log(crx$Pr))
plot(retts$Dare, diff(crx$Pr), type = "o")
lines(diff(crx$Pr))
plot(retts$Dare, retts$ret, type = "o")
lines(retts$ret)

# ARIMAfit <- auto.arima(ret, approximation=FALSE,trace=FALSE)
# summary(ARIMAfit)
# arima202 predict
fit202 = arima(ret, order = c(2, 0, 2))

# vola cluster
par(mfrow = c(1, 1))
res = fit202$residuals
res2 = fit202$residuals^2
tsres202 = data.frame(Dare, res2)
plot(tsres202$Dare, tsres202$res2, type = "o", ylab = NA)
lines(tsres202$res2)

par(mfrow = c(1, 2))
# plot(res2, ylab='Squared residuals', main=NA)
acfres2 = acf(res2, main = NA, lag.max = 20, ylab = "Sample Autocorrelation",
                    lwd = 2)
pacfres2 = pacf(res2, lag.max = 20, ylab = "Sample Partial Autocorrelation",
                       lwd = 2, main = NA)

# arch effect
res = fit202$residuals
ArchTest(res)    #library FinTS
Box.test(res2, type = "Ljung-Box")
```

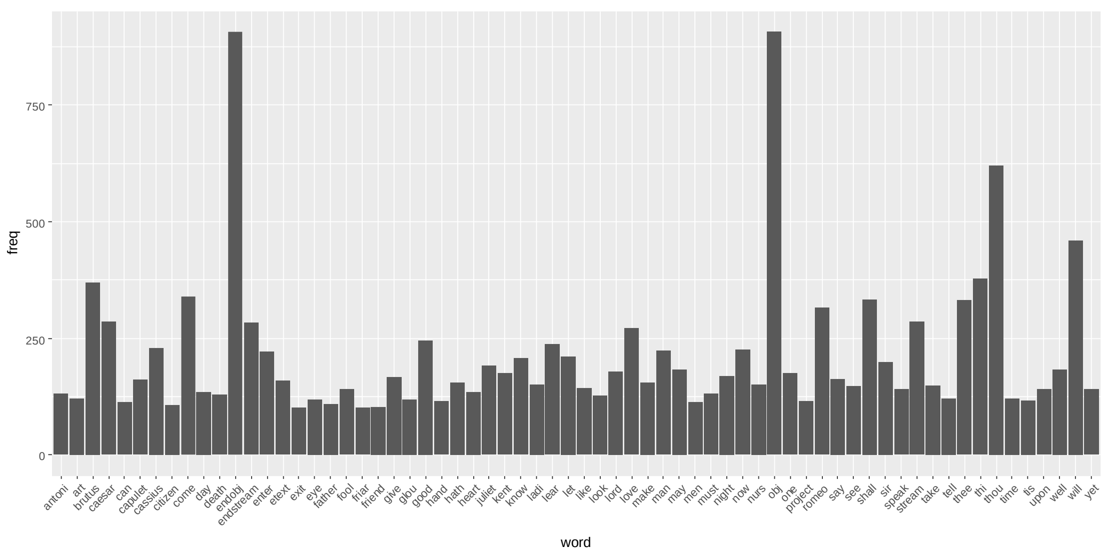


HW 5

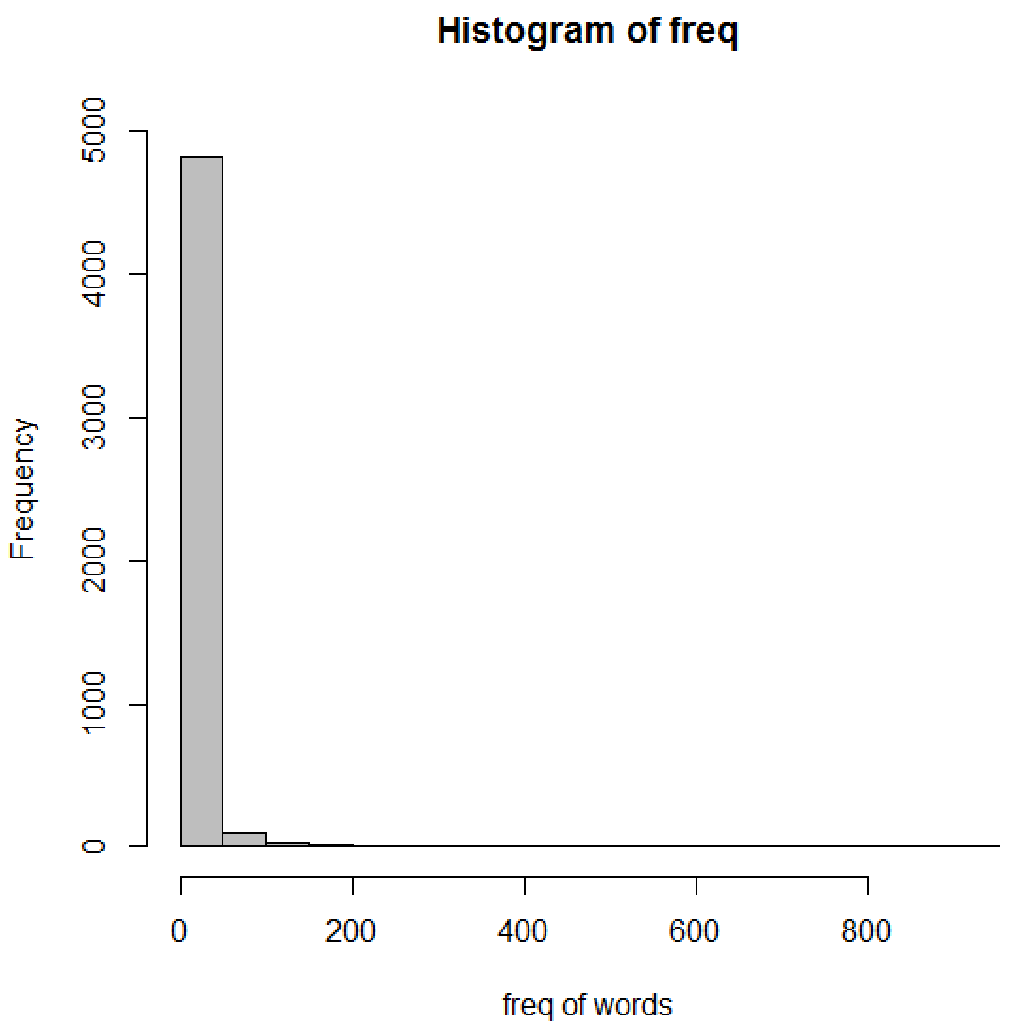
Q1&Q2

```
rm(list = ls())
library(RCurl)
library(XML)
library(bitops)
library(stringr)
url=paste(c("http://publicliterature.org/pdf/2ws1610.pdf","http://publicliterature.org/pdf/2ws2
410.pdf","http://publicliterature.org/pdf/2ws3310.pdf") )
abs=lapply(url, FUN = function(x) htmlParse(x, encoding = "Latin-1"))
clean_txt = function(x) {
   cleantxt = xpathApply(x, "//body//text()
                                          [not(ancestor :: script)][ not(ancestor :: style)]
                                          [not(ancestor :: noscript)] " ,xmlValue)
   cleantxt = paste(cleantxt, collapse="\n")
   cleantxt = str_replace_all(cleantxt, "\n", " ")
   cleantxt = str_replace_all(cleantxt, "\r", "")
   cleantxt = str_replace_all(cleantxt, "\t", "")
   cleantxt = str_replace_all(cleantxt, "<br>", "")
   return(cleantxt)
}
cleantxt = lapply(abs,clean_txt)
vec_abs = unlist(cleantxt)
vec_abs
library(tm)
library(SnowballC)
abs           = Corpus(VectorSource(vec_abs))
abs_dtm     = DocumentTermMatrix(abs, control = list(
   stemming = TRUE, stopwords = TRUE, minWordLength = 3,
   removeNumbers = TRUE, removePunctuation = TRUE))
dim(abs_dtm)
inspect(abs_dtm)
#Find the words that occur more than 5 times
findFreqTerms(abs_dtm, 5)
#Remove sparse terms
removeSparseTerms(abs_dtm, 0.5)
inspect(removeSparseTerms(abs_dtm, 0.5))
library(ggplot2)
library(wordcloud)
freq = colSums(as.matrix(abs_dtm))
wf      = data.frame(word=names(freq), freq=freq)
plot = ggplot(subset(wf, freq>100), aes(word, freq))
plot = plot + geom_bar(stat="identity")
plot = plot + theme(axis.text.x=element_text(angle=45, hjust=1))
plot
freq     = colSums(as.matrix(abs_dtm))
dark2 = brewer.pal(8, "Dark2")
wordcloud(names(freq), freq, max.words=200, rot.per=0.1, colors=dark2)
dev.off()
```





```
hist(freq, col = "grey", breaks = 20,ylim = c(0, 5000), xlab = "freq of words")
```


Histogram of freq
Frequency
0
1000
2000
3000
4000
5000
0
200
400
600
800
freq of words