HW1

1. Calculate the increase 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	268435456
1997	268435456
1998	1073741824
1999	1073741824
2000	1073741824
2004	4294967296
2009	8589934592
2014	17179869184

For 20 years ago, it's impossible for us to perform FMRI analysis as the memory of computer is not large enough for us to handle the huge amount of data.

Logistic Regression

Reporter： Aiqing Jiang

What is logistic regression?

- In statistics, logistic regression, or logit regression, or logit model is a regression model where the dependent variable (DV) is categorical.

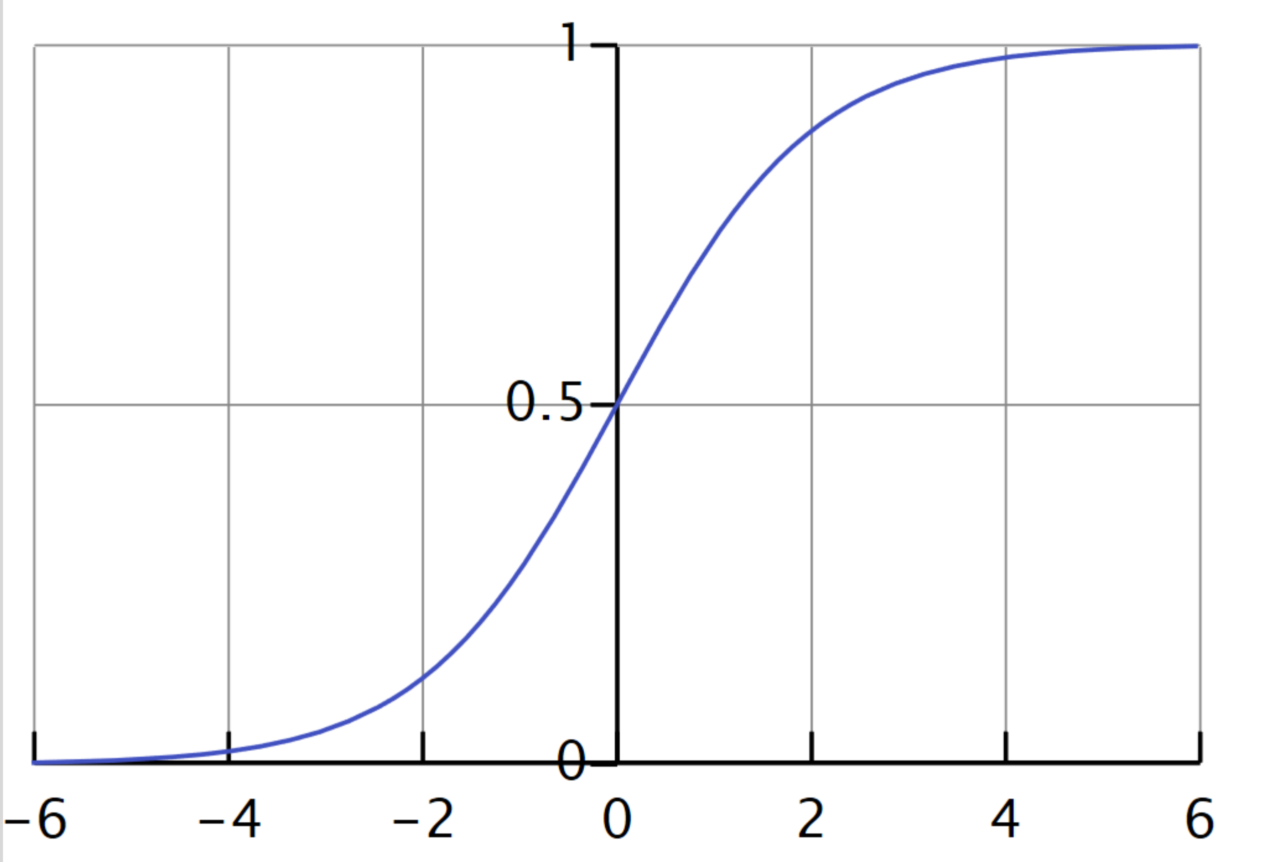
Which means the dependent variable can be binary—where the output can take only two values, "0" and "1", represents outcomes such as pass/fail, win/lose, alive/dead or healthy/sick. Cases where the dependent variable has more than two outcome categories may be analysis in multinomial logistic regression, or, if the multiple categories are ordered, in ordinal logistic regression.

- The logistic function is useful because it can take any real input t whereas the output always takes values between zero and one and hence is interpretable as a probability.

Definition of Logistic Regression

- The logistic function $\sigma(t)$ is defined as follows:

$$\sigma(t) = \frac{e^t}{e^t+1} = \frac{1}{1+e^{-t}}$$



Logistic Function on the *t*-interval (-6,6)

Definition of Logistic Regression

- Let us assume that t is a linear function of a single explanatory variable x, which means $t = \beta_0 + \beta_1 x$

- And the logistic function can now be written as:

$$F(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}}$$

Note that F (x)is interpreted as the probability of the dependent variable equaling a "success" or "case" rather than a failure or non-case.

Applications

- Logistic regression is used in various fields, including machine learning, most medical fields, and social sciences.
- Logistic regression may be used to predict whether a patient has a given disease (e.g. diabetes; coronary heart disease), based on observed characteristics of the patient (age, sex, body mass index, results of various blood tests, etc.).
- Another example might be to predict whether an American voter will vote Democratic or Republican, based on age, income, sex, race, state of residence, votes in previous elections, etc.
- It is also used in marketing applications such as prediction of a customer's propensity to purchase a product or halt a subscription, etc. In economics it can be used to predict the likelihood of a person's choosing to be in the labor force, and a business application would be to predict the likelihood of a homeowner defaulting on a mortgage.

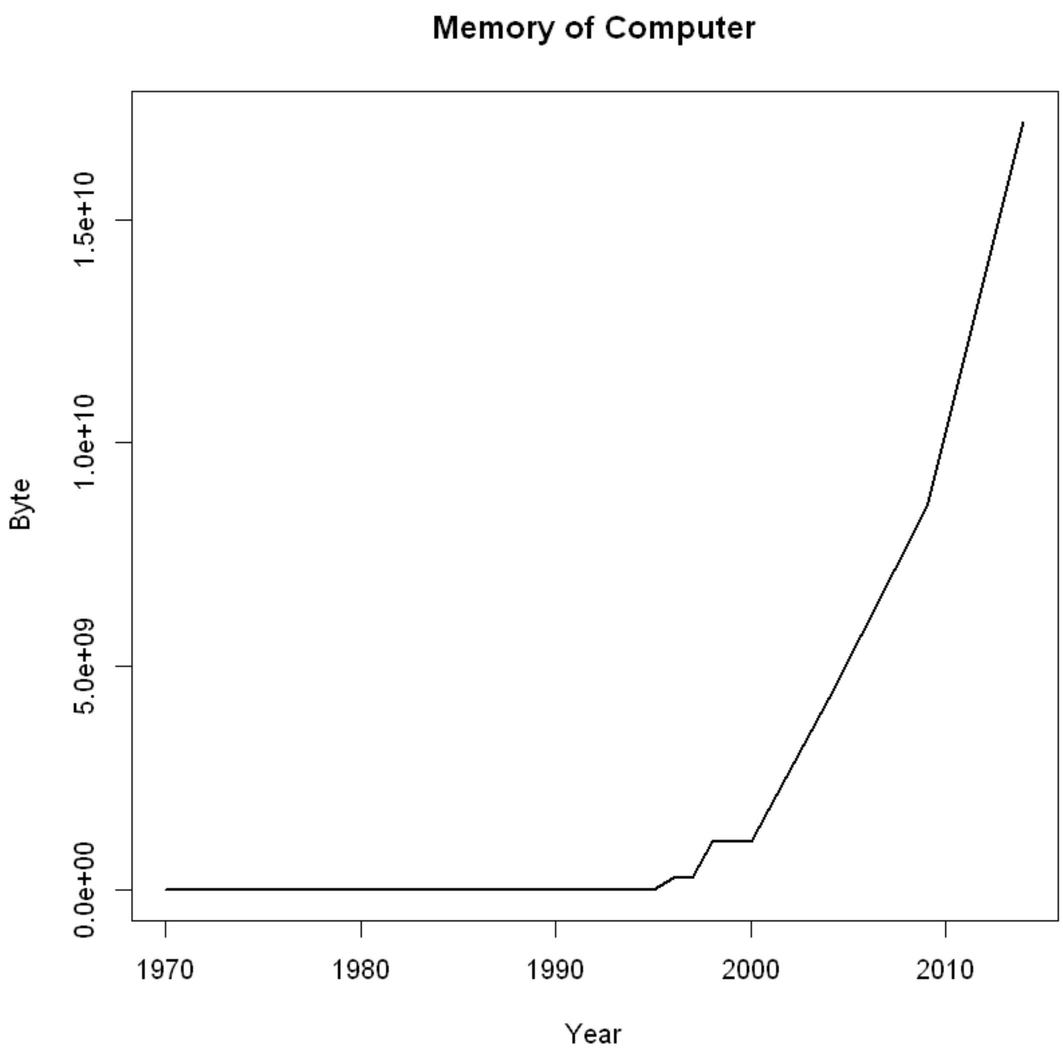
HW2

October 21, 2017

0.1 HW 2.1

0.1.1 Make an R quantlet to solve HW #1 from unit 1 with R and show it on Github (GH)

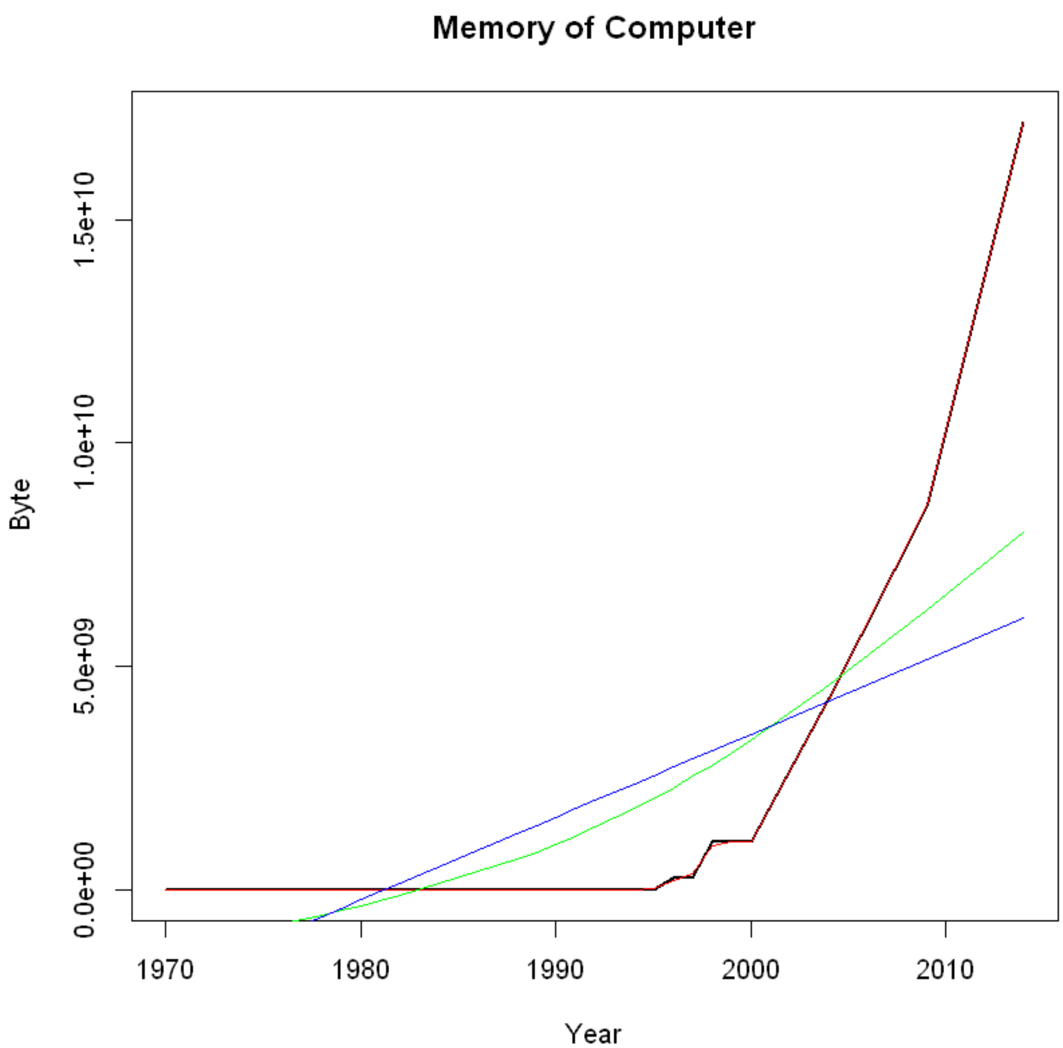
```
In [1]: library(readr)

Warning message:
"package 'readr' was built under R version 3.3.3"

In [2]: cpum <- read_csv("cpum.csv",col_names = TRUE)

Parsed with column specification:
cols(
  Year = col_integer(),
  Byte = col_character()
)


In [3]: par(mfrow = c(1, 1))
        plot(cpum,type="l",xlab = "Year",ylab = "Byte",lwd=2,main = "Memory of Computer")
```



0.2 HW 2.2

0.2.1 Use R with B-spline code to solve HW#1, any comments?

In [4]:
```
plot(cpum,type="l",xlab = "Year",ylab = "Byte",lwd=2,main = "Memory of Computer")
splines.reg.l1 = smooth.spline(x = cpum$Year, y = cpum$Byte, spar =0.2) # lambda = 0.2
splines.reg.l2 = smooth.spline(x = cpum$Year, y = cpum$Byte, spar =1) # lambda = 1
splines.reg.l3 = smooth.spline(x = cpum$Year, y = cpum$Byte, spar =2) # lambda = 2
lines(splines.reg.l1, col = "red", lwd = 1) # regression line with lambda = 0.2
lines(splines.reg.l2, col = "green", lwd = 1) # regression line with lambda = 1
lines(splines.reg.l3, col = "blue", lwd = 1) # regression line with lambda = 2
```



0.3 HW 2.3

0.3.1 Suppose you observe that in n=1000 mails (in 1 week) you have about 2 scams. Use theLvB /Poisson cdf to calculate that you have 6 scam emails in 2 weeks. In Scammyland you have 5 scams on average, what is the probability to have no scam mail

In [5]:
```
lambda=4
x=6
P1=exp(-lambda)*lambda^x/factorial(x)
P1
```

0.104195634567021

In [6]:
```
lambda=5
x=0
P2=exp(-lambda)*lambda^x/factorial(x)
P2
```

0.00673794699908547

HW 3

October 21, 2017

0.1 HW 3.1

```
In [1]: library("digest")
```

```
In [2]: digest("I learn a lot from this class when I am proper listening to the professor", "sl
```

'c16700de5a5c1961e279135f2be7dcf9c187cb6b21ac8032308c715e1ce9964c'

```
In [3]: digest("I do not learn a lot from this class when I am absent and playing on my Iphone'
```

'2533d529768409d1c09d50451d9125fdbaa6e5fd4efdeb45c04e3c68bcb3a63e'
For the first sentence,the hash number is "c16700de5a5c1961e279135f2be7dcf9c187cb6b21ac8032308c715e1ce99
For the second sentence, the hash number is "2533d529768409d1c09d50451d9125fdbaa6e5fd4efdeb45c04e3c68b

0.2 HW 3.3

```
In [4]: library(jsonlite)
```

```
In [5]: json <-
        '[
          {"Name" : "Mario", "Age" : 32, "Occupation" : "Plumber"},
          {"Name" : "Peach", "Age" : 21, "Occupation" : "Princess"},
          {},
          {"Name" : "Bowser", "Occupation" : "Koopa"}
        ]'
```

```
In [6]: data_frame <- fromJSON(json)
        data_frame
```

Name	Age	Occupation
Mario	32	Plumber
Peach	21	Princess
NA	NA	NA
Bowser	NA	Koopa

```
In [7]: data_frame$Ranking <- c(3, 1, 2, 4)
        data_frame
```

Name	Age	Occupation	Ranking
Mario	32	Plumber	3
Peach	21	Princess	1
NA	NA	NA	2
Bowser	NA	Koopa	4

In [8]:
```
toJSON(data_frame, pretty=TRUE)
```


```
[
  {
    "Name": "Mario",
    "Age": 32,
    "Occupation": "Plumber",
    "Ranking": 3
  },
  {
    "Name": "Peach",
    "Age": 21,
    "Occupation": "Princess",
    "Ranking": 1
  },
  {
    "Ranking": 2
  },
  {
    "Name": "Bowser",
    "Occupation": "Koopa",
    "Ranking": 4
  }
]
```


In [9]:
```
write_json(json,path="C:/Users/Aiqing-Jiang/1.json")
```

In [10]:
```
read_json(path="C:/Users/Aiqing-Jiang/1.json",simplifyVector = FALSE)
```

1. '[{"Name" : "Mario", "Age" : 32, "Occupation" : "Plumber"}, {"Name" : "Peach", "Age" : 21, "Occupation" : "Princess"}, {}, {"Name" : "Bowser", "Occupation" : "Koopa"}]'

0.3 HW 3.4

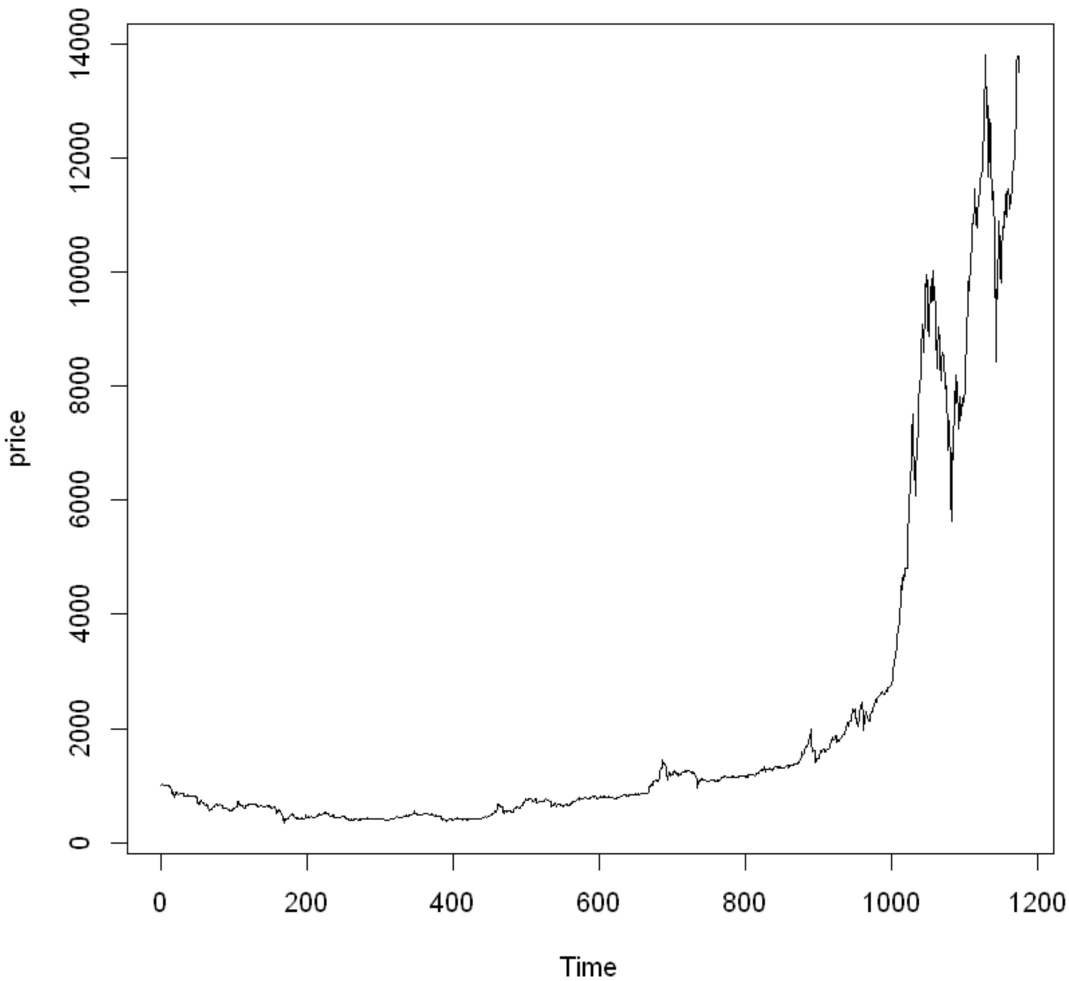
In [12]:
```
library(rjson)
```

In [13]:
```
json_file = "http://crix.hu-berlin.de/data/crix.json"
json_data = fromJSON(file=json_file)
```

In [14]:
```
crix_data_frame = as.data.frame(json_data)
```

In [15]:
```
a <- 1:1175
n <- 2*a
m <- n-1
```

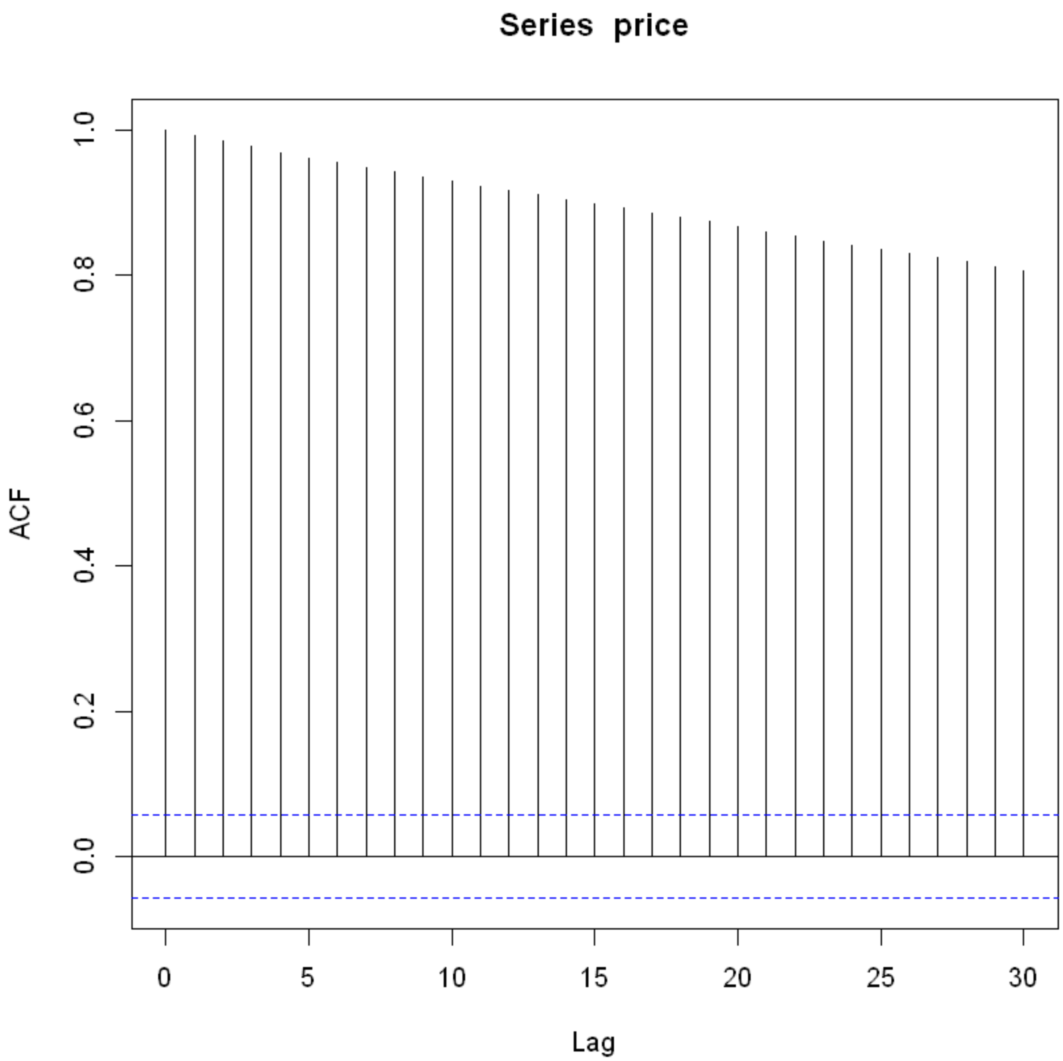
```
In [16]: date <- t(crix_data_frame[m])
         price <- t(crix_data_frame[n])
         crix_data <- cbind(date,price)

In [17]: ts.plot(price)
```



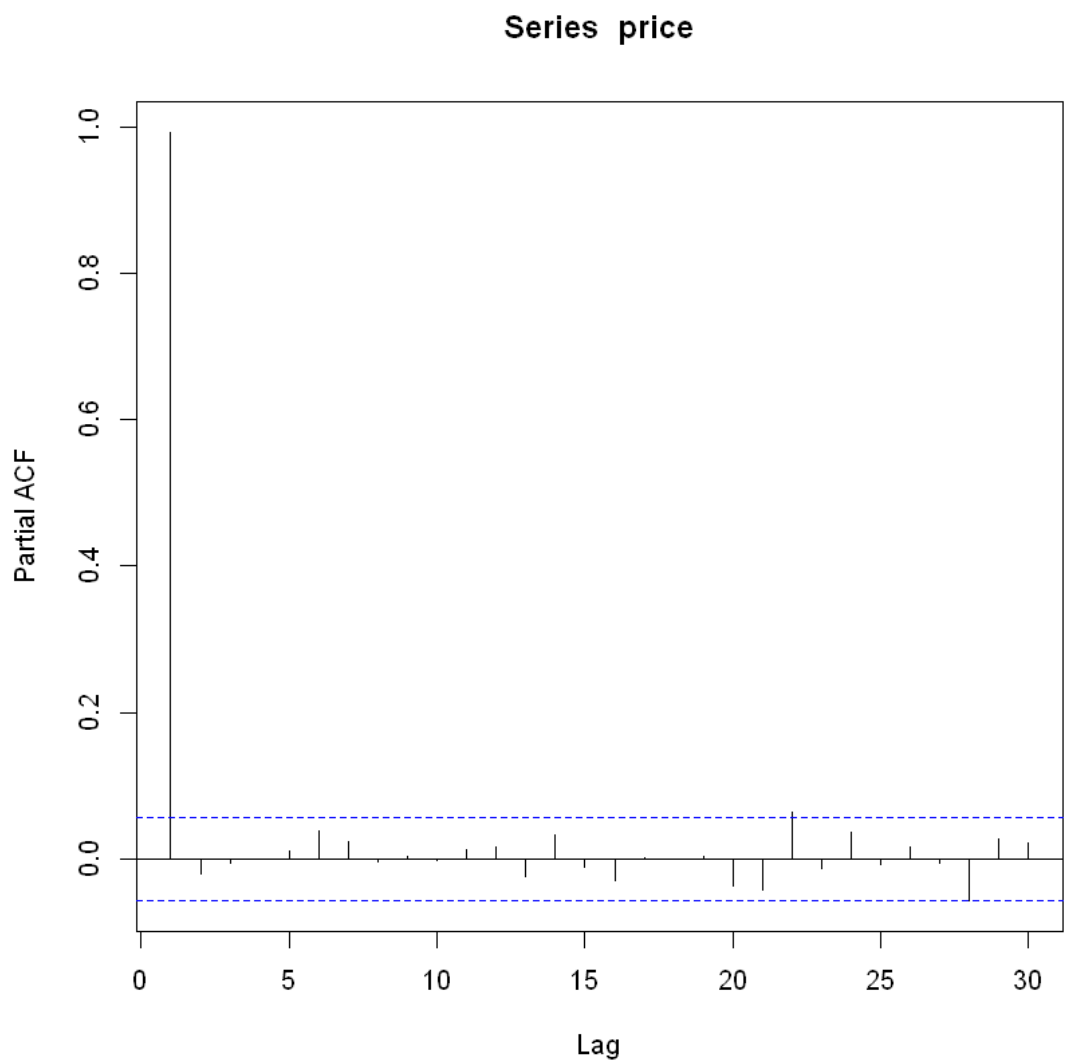

```
In [20]: library(tseries)

In [21]: adf.test(price)

Warning message in adf.test(price):
"p-value greater than printed p-value"
```

```
Augmented Dickey-Fuller Test

data:  price
Dickey-Fuller = 0.47023, Lag order = 10, p-value = 0.99
alternative hypothesis: stationary
```

In [22]: `acf(price)`



In [23]: `pacf(price)`




```
In [25]: library(forecast)

In [26]: auto.arima(price)# ARIMA(5,2,0)

Series: price
ARIMA(5,2,0)

Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -0.8808  -0.7101  -0.5786  -0.4783  -0.2543
s.e.   0.0284   0.0359   0.0380   0.0362   0.0286

sigma^2 estimated as 32821:  log likelihood=-7761.48
```

```
AIC=15534.95   AICc=15535.02   BIC=15565.36
```

Digital Signature Algorithm

Jiang Aiqing

2017.10.19

What is digital signature ?

- A **digital signature** is a mathematical scheme for demonstrating the authenticity of digital messages or documents.
- A valid digital signature gives a recipient reason to believe that the message was created by a known sender, that the sender cannot deny having sent the message, and that the message was not altered in transit (integrity).
- **Applications**: software distribution, financial transactions, data storage etc.

Digital Signature Algorithm

- The **Digital Signature Algorithm (DSA)** is a Federal Information Processing Standard for digital signatures. In August 1991 the National Institute of Standards and Technology (NIST) proposed DSA for use in their **Digital Signature Standard (DSS)** and adopted it as FIPS 186 in 1993.

Steps of Digital Signature Algorithm

- Key generation

  Key generation has two phases. The first phase is a choice of *algorithm parameters* which may be shared between different users of the system, while the second phase computes public and private keys for a single user.

- Signing
- Verifying

HW 4

October 21, 2017

```
In [1]: library('rjson')
```

```
In [2]: json_file = "http://crix.hu-berlin.de/data/crix.json"
        json_data = fromJSON(file=json_file)
        crix_data_frame=as.data.frame(json_data)
```

```
In [3]: x=crix_data_frame
        dim(x)
```

1. 1 2. 2356

```
In [4]: n=dim(x)
        a=seq(1,n[2],2)
        b=seq(2,n[2],2)
```

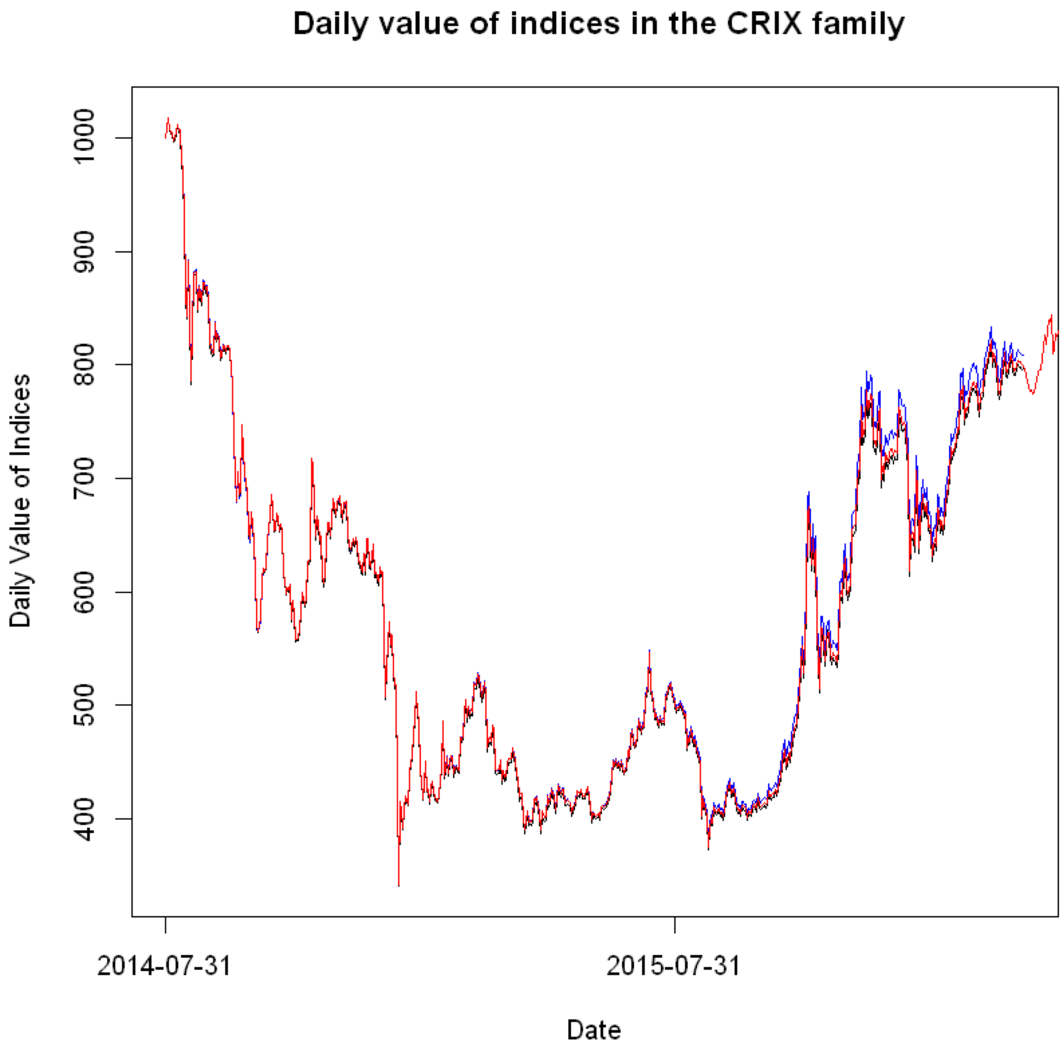
```
In [5]: date=t(x[1,a])
        price=t(x[1,b])
```

```
In [6]: crix=data.frame(date,price)
```

```
In [7]: load("ecrix.RData")
        load("efcrix.RData")
```

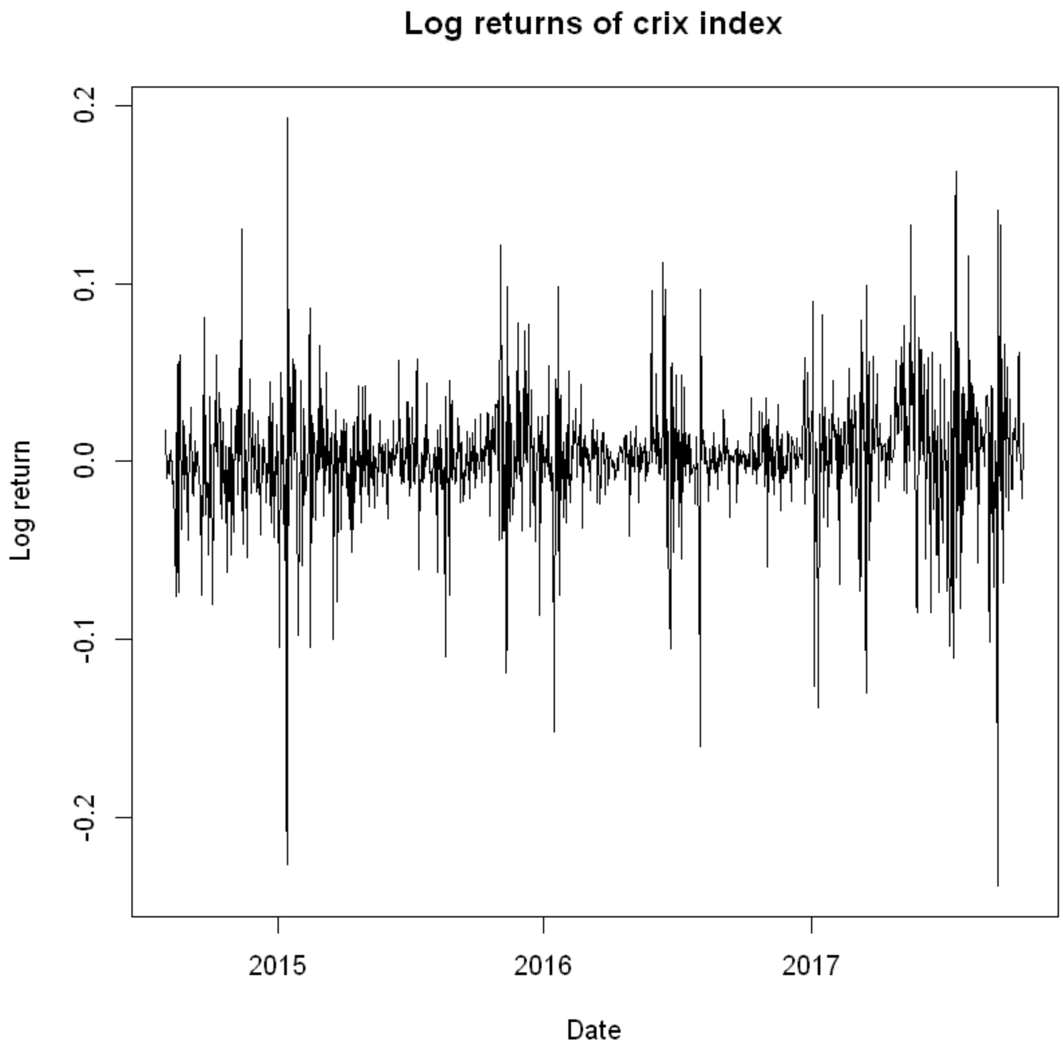
0.1 Figure3: Daily value of indices in the CRIX family

```
In [8]: plot(ecrix, type = "l", col = "blue", xaxt = "n",main = " Daily value of indices in the
        lines(efcrix, col = "black")
        lines(price, col = "red")
        lab=seq(1,n[2],365)
        axis(1, at = lab, label = names(ecrix)[lab])
```



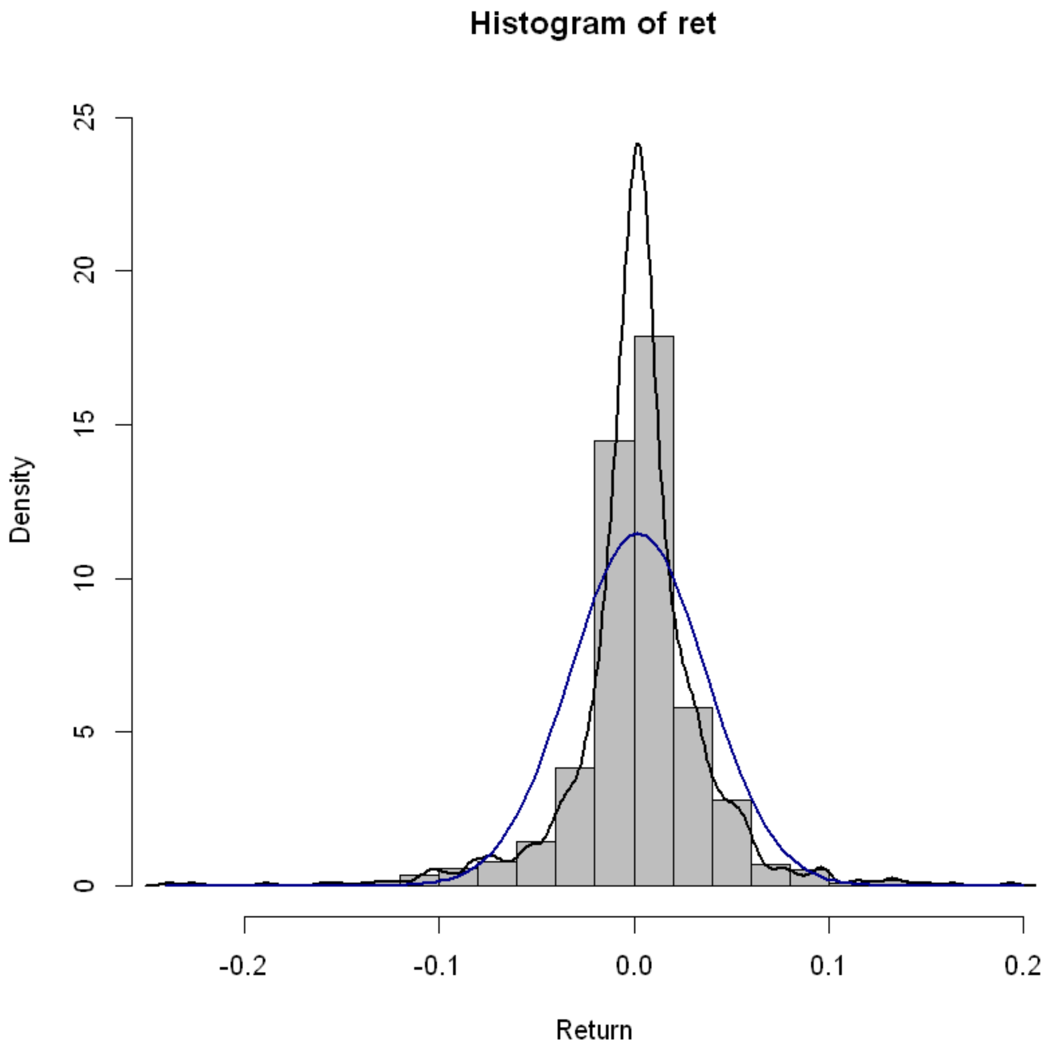
0.2 Figure 4: The log returns of CRIX index

In [9]:
```
ret=diff(log(price))
plot(ret~as.Date(date[-1]), type="l", col="black", xlab="Date", ylab="Log return", mai
```

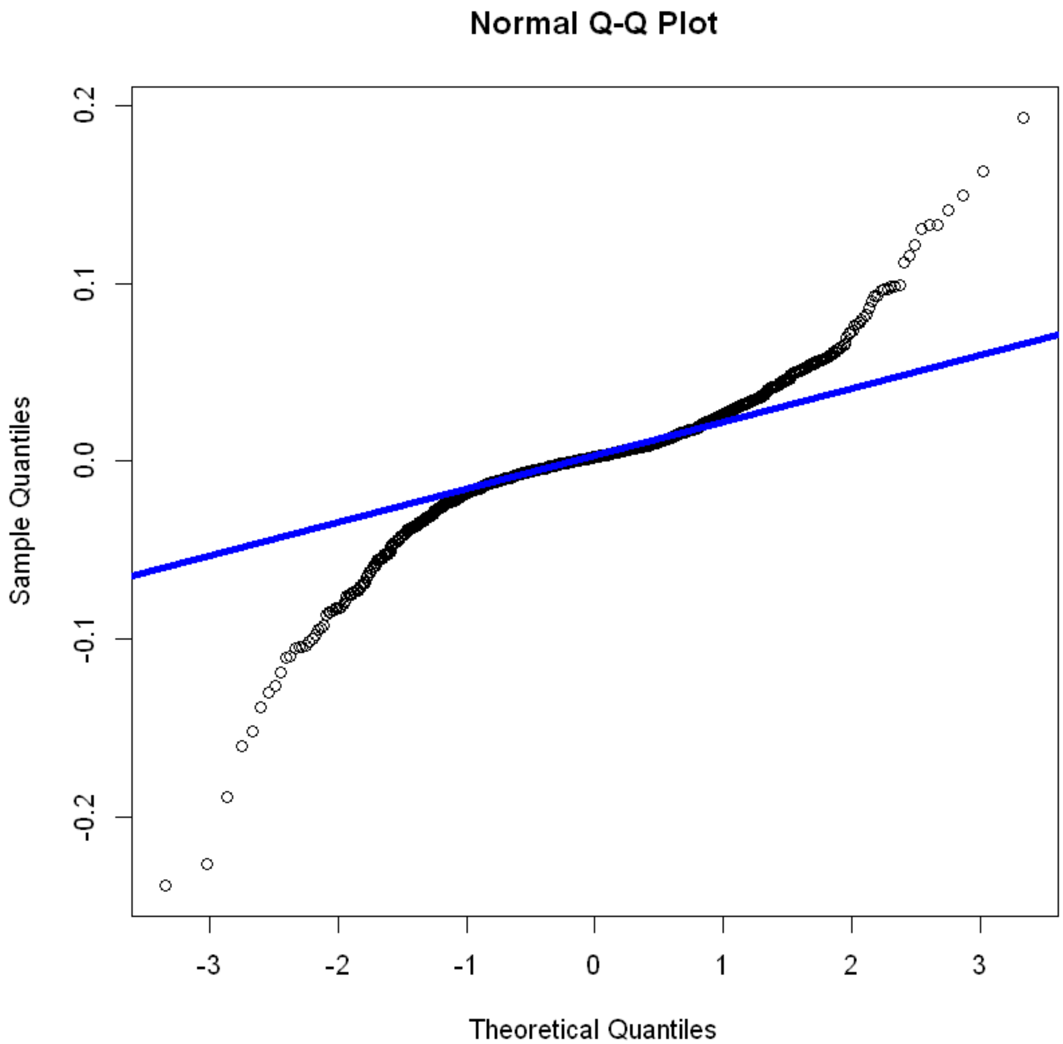


0.3 Figure 5: Histogram and QQ plot of CRIX returns

In [10]:
```
hist(ret, col = "grey", breaks = 20, freq = FALSE, ylim = c(0, 25), xlab = "Return")
lines(density(ret), lwd = 2)
x = seq(-4, 4, length = 100)
curve(dnorm(x, mean = mean(ret), sd = sd(ret)), add=TRUE, col = "darkblue", lwd = 2)
```

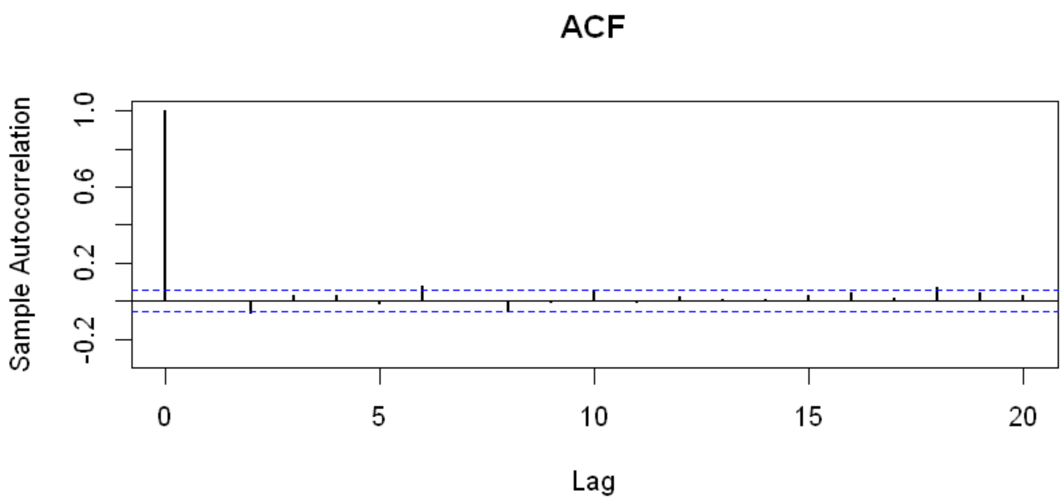


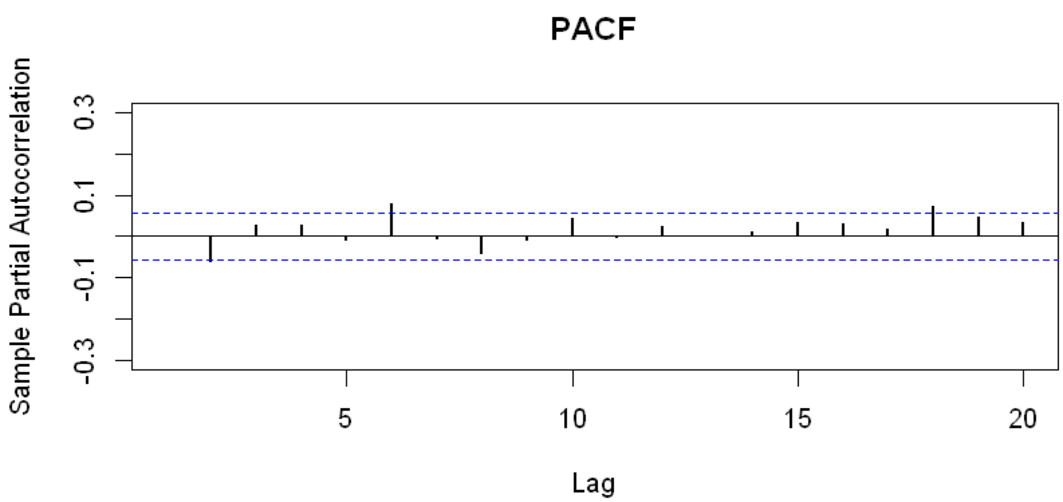

```
In [11]: qqnorm(ret)
         qqline(ret, col = "blue", lwd = 4)
```



0.4 Figure 6: The sample ACF and PACF of CRIX returns

In [13]:
```
par(mfrow = c(2, 1))
libraries = c("zoo", "tseries")
autocorr = acf(ret, lag.max = 20, ylab = "Sample Autocorrelation",
               main = "ACF" ,
               lwd = 2, ylim = c(-0.3, 1))
autopcorr = pacf(ret, lag.max = 20, ylab = "Sample Partial Autocorrelation",
                 main = "PACF" ,
                 ylim = c(-0.3, 0.3), lwd = 2)
```



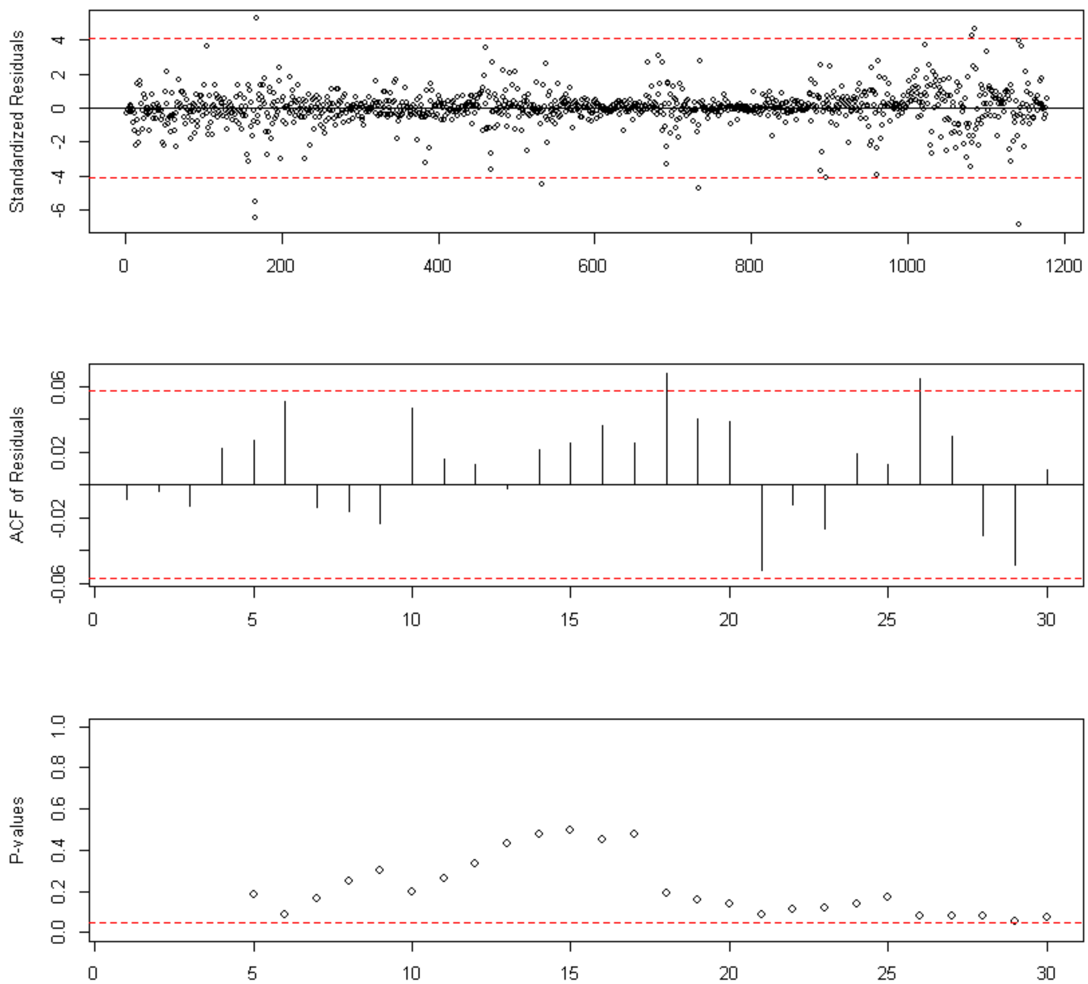


0.5 Figure 7:Diagnostic Checking

```
In [15]: library(TTR)
         library(TSA)
         library(caschrono)
         library(forecast)

In [16]: auto.arima(ret)

Series: ret
ARIMA(1,1,0) with drift

Coefficients:
```

```
          ar1   drift
      -0.4695   0e+00
s.e.   0.0257   9e-04

sigma^2 estimated as 0.001881:  log likelihood=2022.35
AIC=-4038.7   AICc=-4038.68   BIC=-4023.49
```

```
In [17]: fit = arima(ret, order = c(2, 0, 2))
         tsdiag(fit)
```




```
In [18]: par(mfrow = c(2, 1))
         crix_pre = predict(fit, n.ahead = 30)
```

```r
#dates = seq(as.Date("31/07/2014", format = "%d/%m/%Y"), by = "days", length = length
plot(ret, type = "l", ylab = "Log return", xlab = "Date",
     lwd = 1, main = "CRIX returns and predicted values")
lines(crix_pre$pred, col = "red", lwd = 1)
lines(crix_pre$pred + 2 * crix_pre$se, col = "red", lty = 3, lwd = 1)
lines(crix_pre$pred - 2 * crix_pre$se, col = "red", lty = 3, lwd = 1)
```