Final Exam

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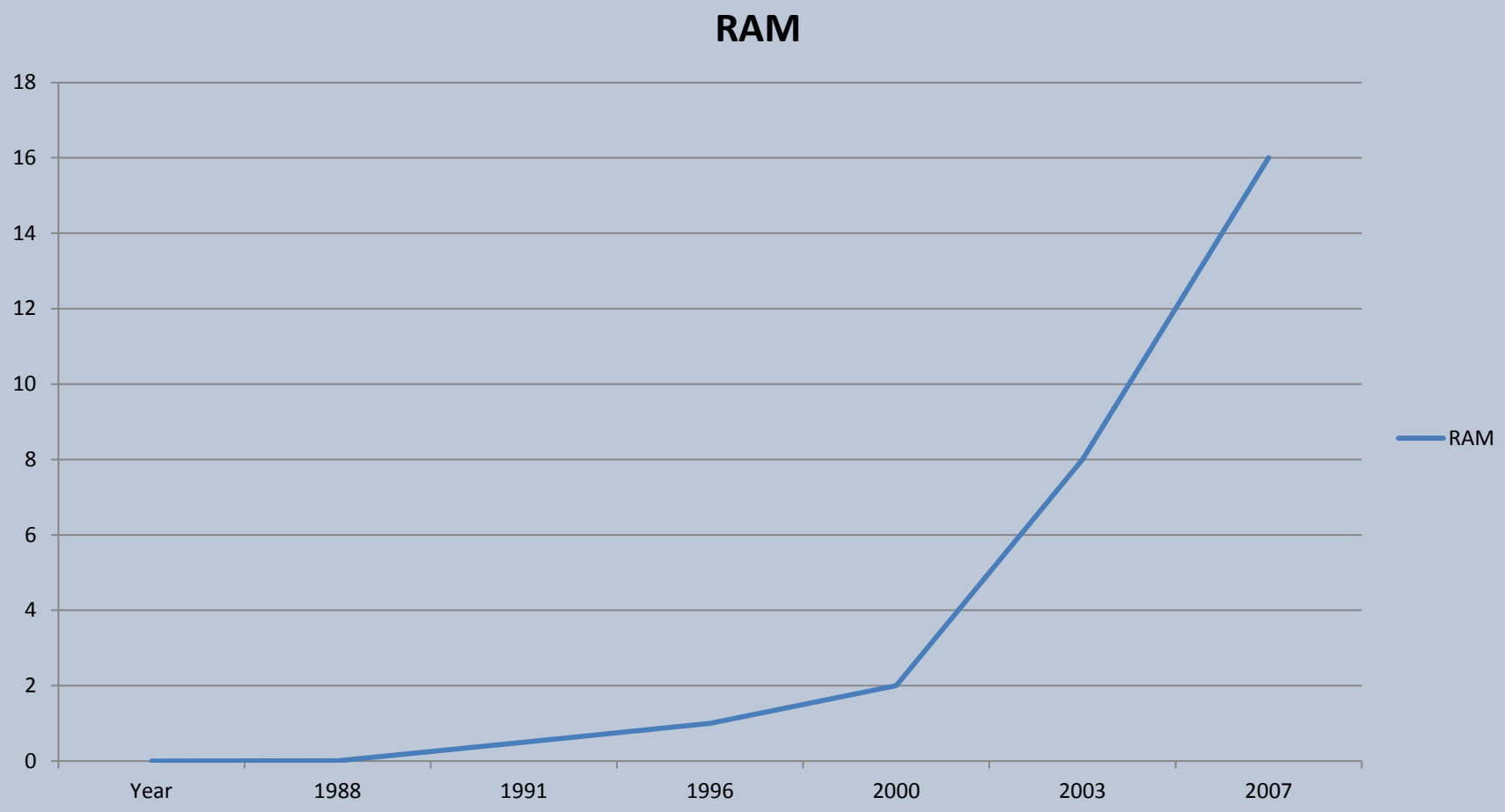
HW1

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


RAM
18
16
14
12
10
8
6
4
2
0
Year
1988
1991
1996
2000
2003
2007
RAM

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.

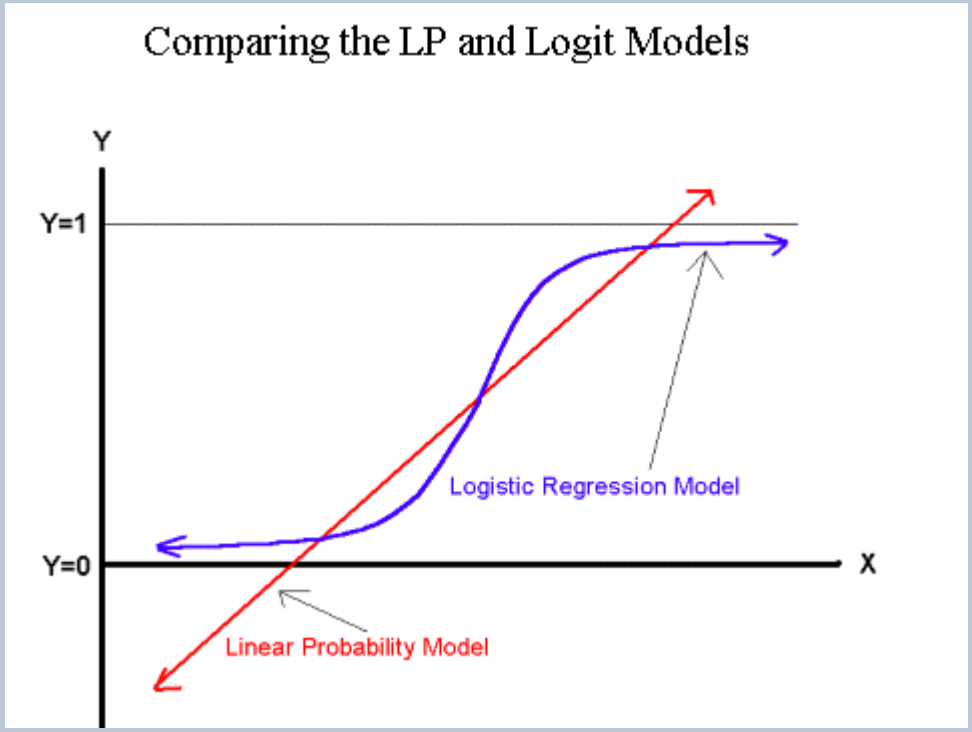
The model logistic regression model is that

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

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

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

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.

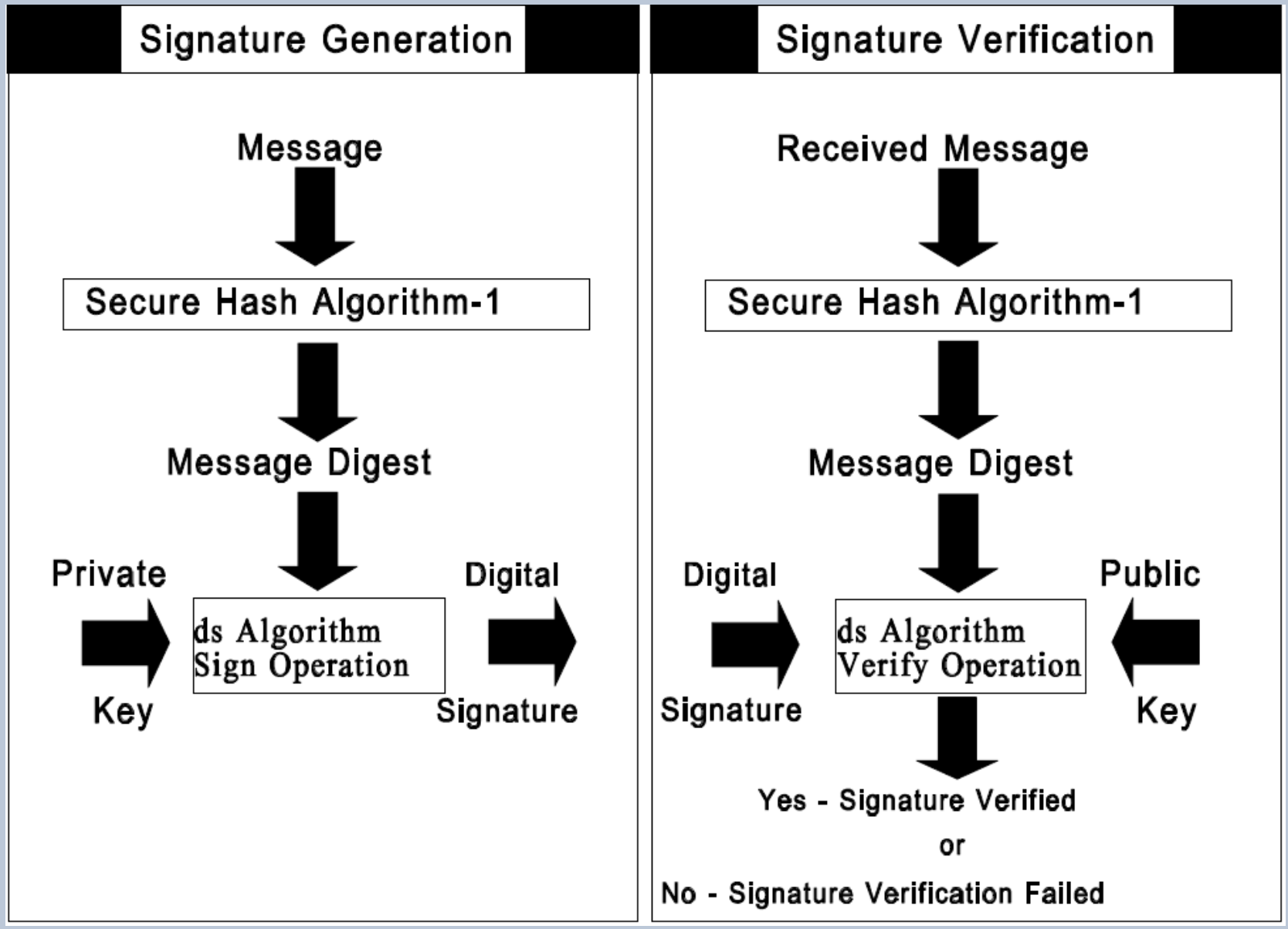
The signature is generated by the use of **a private key** that known only to **the user.** The signature is verified when a public key is corresponds to the private key. With every user having a public/private key pair, this is an example of public-key cryptography.

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.


Signature Generation
Message
Secure Hash Algorithm-1
Message Digest
Private
Key
ds Algorithm
Sign Operation
Digital
Signature
Signature Verification
Received Message
Secure Hash Algorithm-1
Message Digest
Digital
Signature
ds Algorithm
Verify Operation
Public
Key
Yes - Signature Verified
or
No - Signature Verification Failed

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)

```
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)

# Produces GARCH estimation results using ARIMA model residuals
rm(list = ls(all = TRUE))
graphics.off()

# install and load packages
libraries = c("FinTS", "tseries", "forecast", "fGarch")
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(crix1))
```

```
# vol cluster
fit202 = arima(ret, order = c(2, 0, 2))
par(mfrow = c(1, 1))
res = fit202$residuals
res2 = fit202$residuals^2

# different garch model
fg11 = garchFit(data = res, data ~ garch(1, 1))
summary(fg11)
fg12 = garchFit(data = res, data ~ garch(1, 2))
summary(fg12)
fg21 = garchFit(data = res, data ~ garch(2, 1))
summary(fg21)
fg22 = garchFit(data = res, data ~ garch(2, 2))
summary(fg22)

# residual plot
reszo = zoo(fg11@residuals, order.by = index(crix1))
plot(reszo, ylab = NA, lwd = 2)
```

HW4

Q1. Improve the R quantlets on GH (from CRIX directory on quantlet.de) and make excellent graphics that follow Fig 3,4,5,6 of the ”Econometrics of CRIX“ paper.

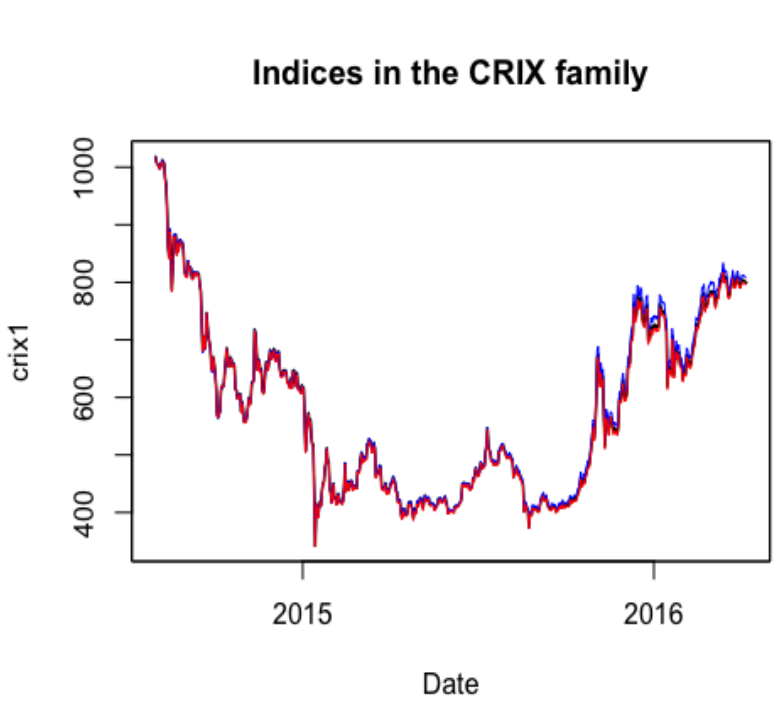


Figure 3: The daily value of indices in the CRIX family

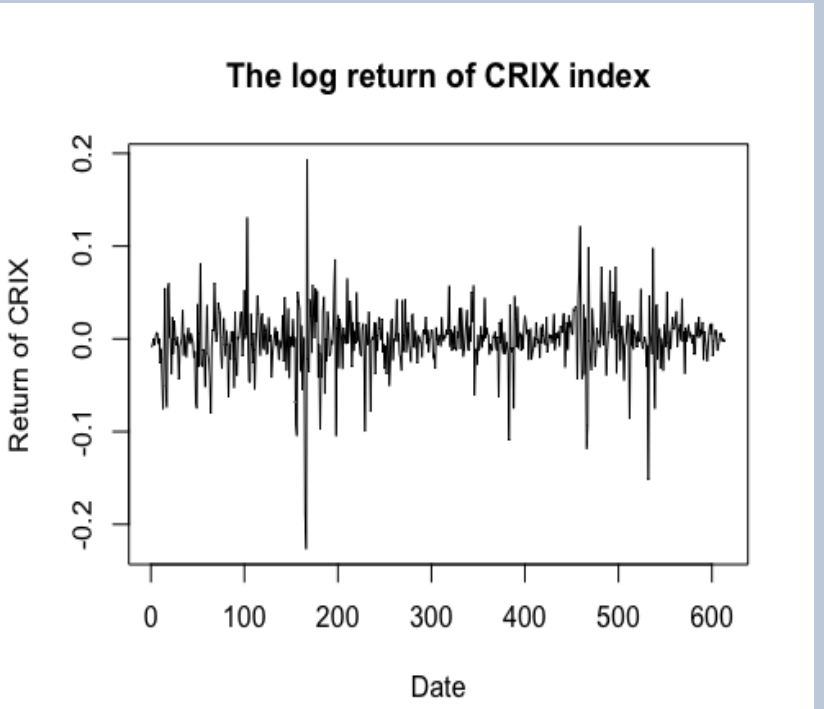


Figure 4: The log returns of CRIX index

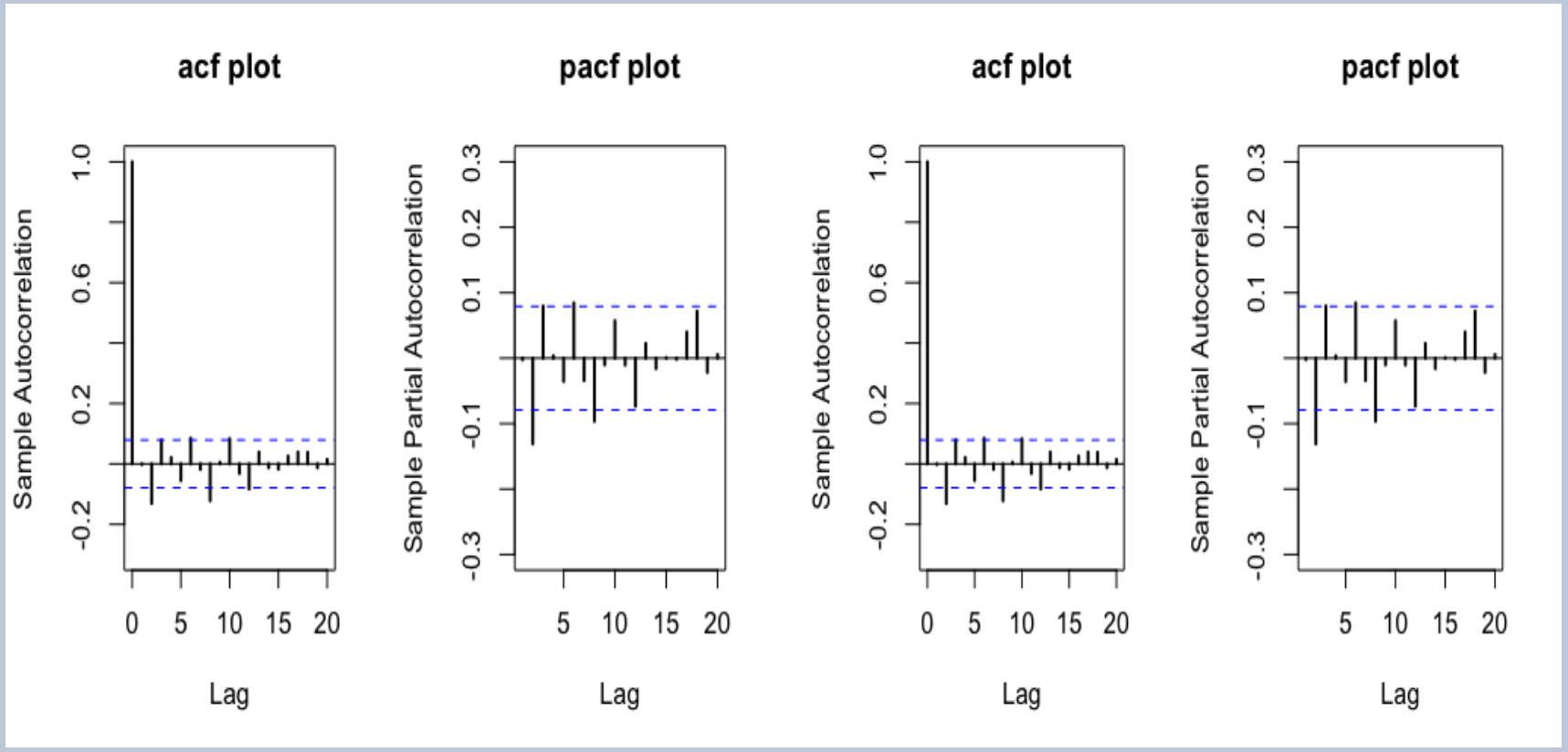


Figure 5: Histogram and QQ plot of CRIX returns

Figure 6: The sample ACF and PACF of CRIX retur

```
rm(list = ls(all = TRUE))
graphics.off()
# install and load packages
libraries = c("zoo", "tseries", "xts","ccgarch")
lapply(libraries, function(x) if (!(x %in% installed.packages())) { install.packages(x)}
```

```
lapply(libraries, library, quietly = TRUE, character.only = TRUE)

# load dataset
load(file.choose())
load(file.choose())
load(file.choose())

# three indices return
ecrix1 = zoo(ecrix, order.by = index(crix1))
efcrix1 = zoo(efcrix, order.by = index(crix1))

# plot with different x-axis scales with zoo
my.panel <- function(x, ...) {
  lines(x, ...)
  lines(ecrix1, col = "blue")
  lines(efcrix1, col = "red")
}
plot.zoo(crix1, plot.type = "multiple", type = "l", lwd = 1.5, panel = my.panel ,
main = "Indices in the CRIX family", xlab = "Date")
```

```
# plot of crix
# plot(as.xts(crix), type="l", auto.grid=FALSE, main = NA)
plot(crix1, ylab = "Price of CRIX", xlab = "Date")

# plot of crix return
ret   = diff(log(crix1))
# plot(as.xts(ret), type="l", auto.grid=FALSE, main = NA)
plot(ret, ylab = "Return of CRIX", xlab = "Date")

# stationary test
adf.test(ret, alternative = "stationary")
kpss.test(ret, null = "Trend")

par(mfrow = c(1, 2))
# histogram of returns
hist(ret, col = "grey", breaks = 20, freq = FALSE, ylim = c(0, 25),  xlab = "Return of CRIX")
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)

# acf plot
autocorr = acf(ret, lag.max = 20, ylab = "Sample Autocorrelation", main = "acf plot",
lwd = 2, ylim = c(-0.3, 1))

# pacf plot
autopcorr = pacf(ret, lag.max = 20, ylab = "Sample Partial Autocorrelation",  main =
"pacf plot", ylim = c(-0.3, 0.3), lwd = 2)
```

Q2. Make your R code perfect as in the R examples on quantlet.de i.e. make sure that the
code is ”time independent“ by using actual dimensions of the data that you are collecting
from crix.hu-berlin.de Recreate Fig 7 from ”Econometrics of CRIX“.

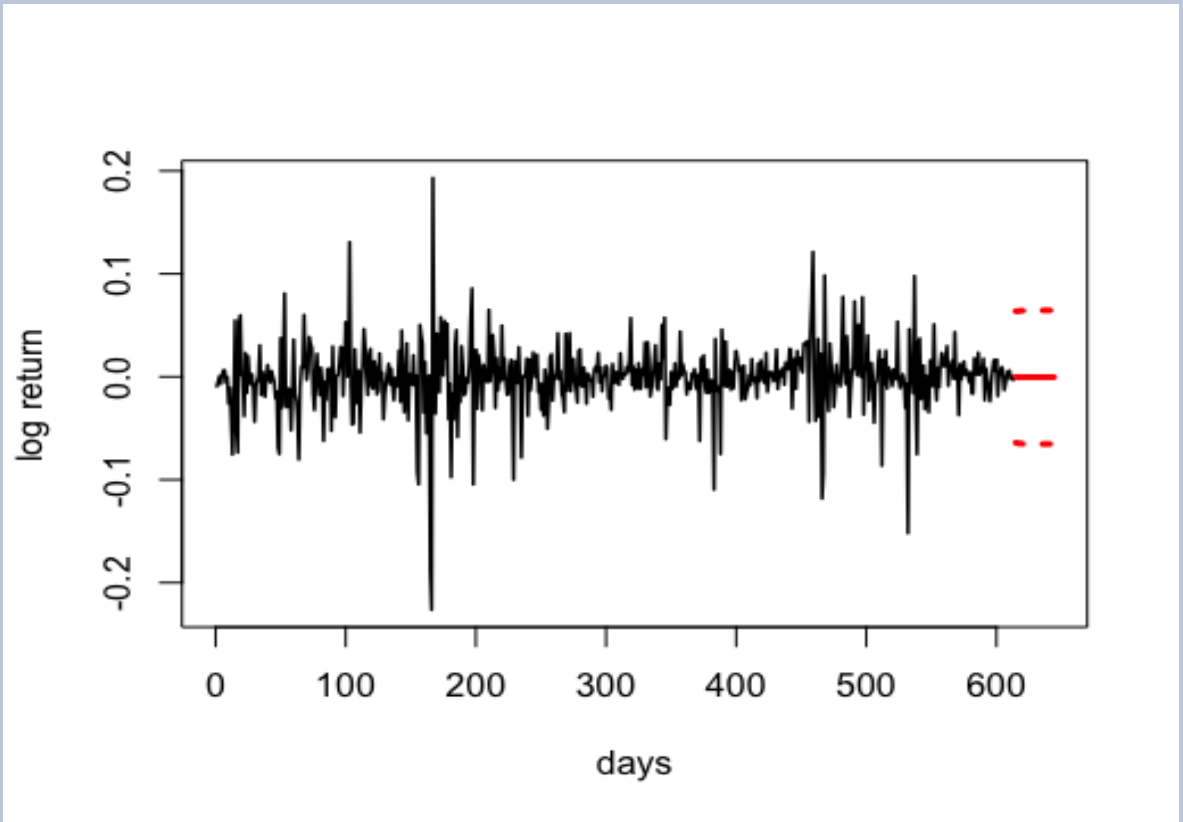


Figure 7: CRIX returns and predicted values.

Codes:

```
# arima model
par(mfrow = c(1, 1))
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
  }
}
```

```
# 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
  }
}

# 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))

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

dates = seq(as.Date("02/08/2014", format = "%d/%m/%Y"), by = "days", length = length(ret))
plot(ret, type = "l", xlim = c(0, length(ret)+predict_num), ylab = "log return", xlab = "days",
    lwd = 1.5, col = "black")
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. Redo as many figures as you can.

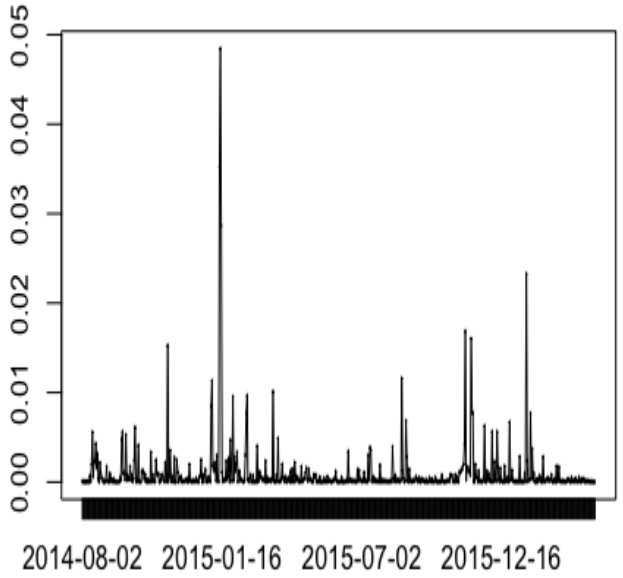


Figure 8: The squared ARIMA(2,0,2) residuals of CRIX returns.

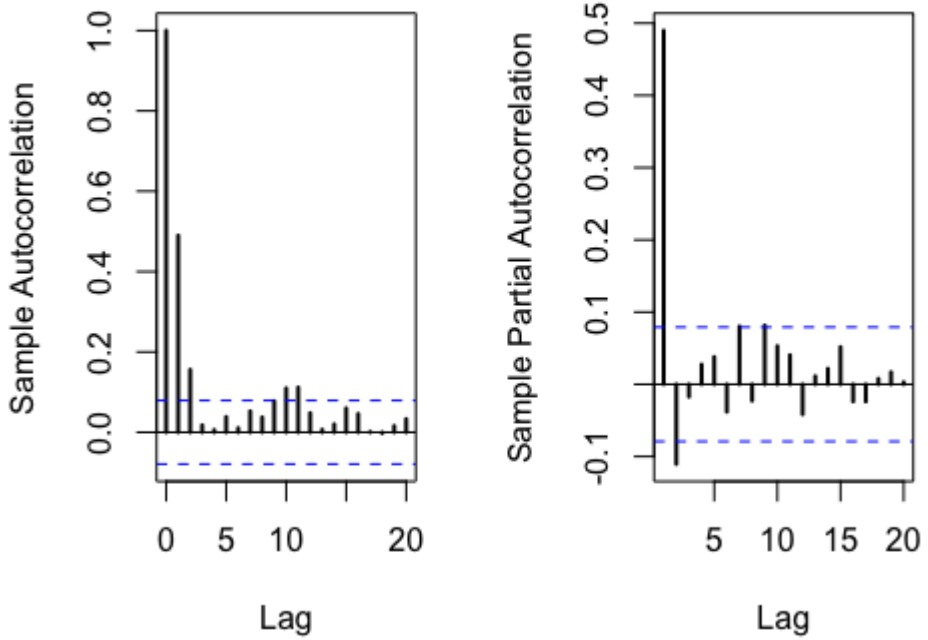


Figure 9: The ACF and PACF of squared ARIMA(2,0,2) residuals

Codes:

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

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

# please change your working directory
setwd()
load(file.choose())
Pr = as.numeric(crix)
Da = factor(date1)
crx = data.frame(Da, Pr)
# plot of crix return
ret = diff(log(crx$Pr))
Dare = factor(date1[-1])
retts = data.frame(Dare, ret)
# arima202 predict
fit202 = arima(ret, order = c(2, 0, 2))
# vola cluster
par(mfrow = c(1, 1))
res = fit202$residuals
res2 = fit202$residuals^2
tsres202 = data.frame(Dare,
res2)
plot(tsres202$Dare,
tsres202$res2, type = "o",
ylab = NA)
lines(tsres202$res2)

# plot(res2, ylab='Squared
residuals', main=NA)
par(mfrow = c(1, 2))
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)
```

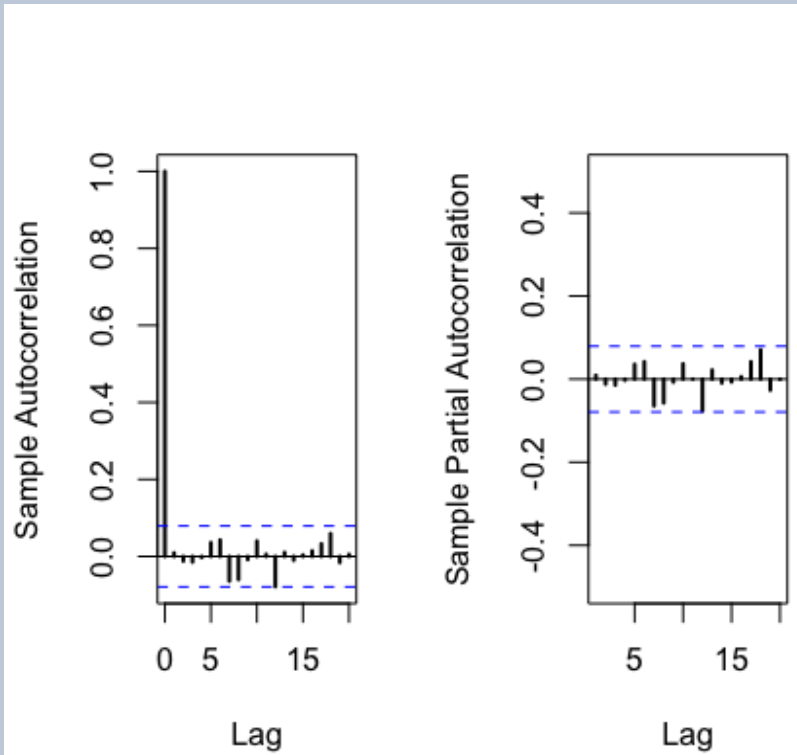


Figure 10: The ACF and PACF of squared ARIMA(2,0,2) residuals

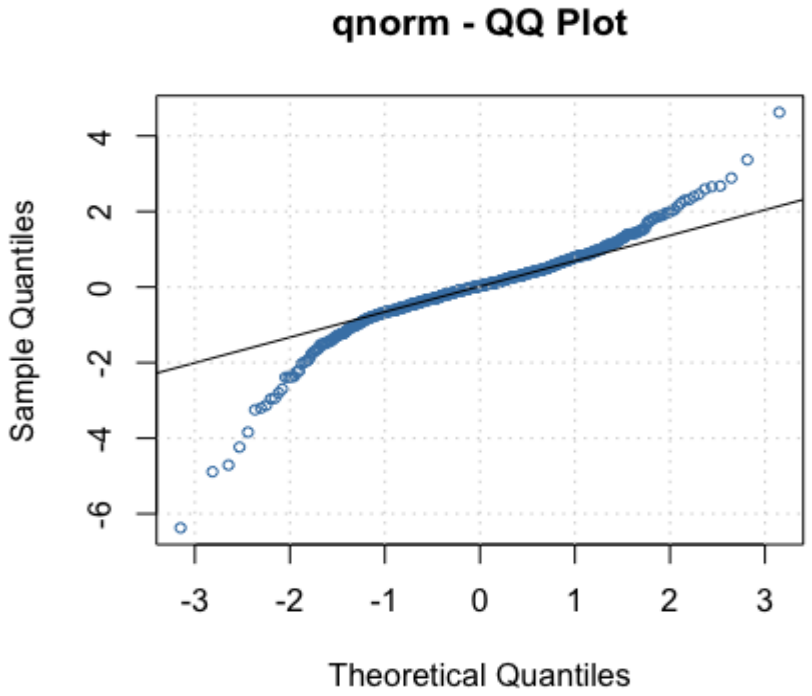


Figure 11: The QQ plots of model residuals of ARIMA-GARCH process.

Codes:

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

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

# load dataset
load(file.choose())
ret = diff(log(crix1))

# vol cluster
fit202 = arima(ret, order = c(2, 0, 2))
par(mfrow = c(1, 1))
res = fit202$residuals
res2 = fit202$residuals^2

# different garch model
fg11 = garchFit(data = res, data ~
garch(1, 1))
summary(fg11)
fg12 = garchFit(data = res, data ~
garch(1, 2))
summary(fg12)
fg21 = garchFit(data = res, data ~
garch(2, 1))
summary(fg21)
fg22 = garchFit(data = res, data ~
garch(2, 2))
summary(fg22)

# residual plot
reszo = zoo(fg11@residuals,
order.by = index(crix1))
plot(reszo, ylab = NA, lwd = 2)
```

```
par(mfrow = c(1, 2))
fg11res2 = fg11@residuals
acfres2  = acf(fg11res2, lag.max = 20, ylab = "Sample Autocorrelation",
           main = NA, lwd = 2)
pacfres2 = pacf(fg11res2, lag.max = 20, ylab = "Sample Partial Autocorrelation",
           main = NA, lwd = 2, ylim = c(-0.5, 0.5))

fg12res2 = fg12@residuals
acfres2  = acf(fg12res2, lag.max = 20, ylab = "Sample Autocorrelation",
           main = NA, lwd = 2)
pacfres2 = pacf(fg12res2, lag.max = 20, ylab = "Sample Partial Autocorrelation",
           main = NA, lwd = 2, ylim = c(-0.5, 0.5))

# qq plot
par(mfrow = c(1, 1))
plot(fg11, which = 13)  #9,10,11,13
```

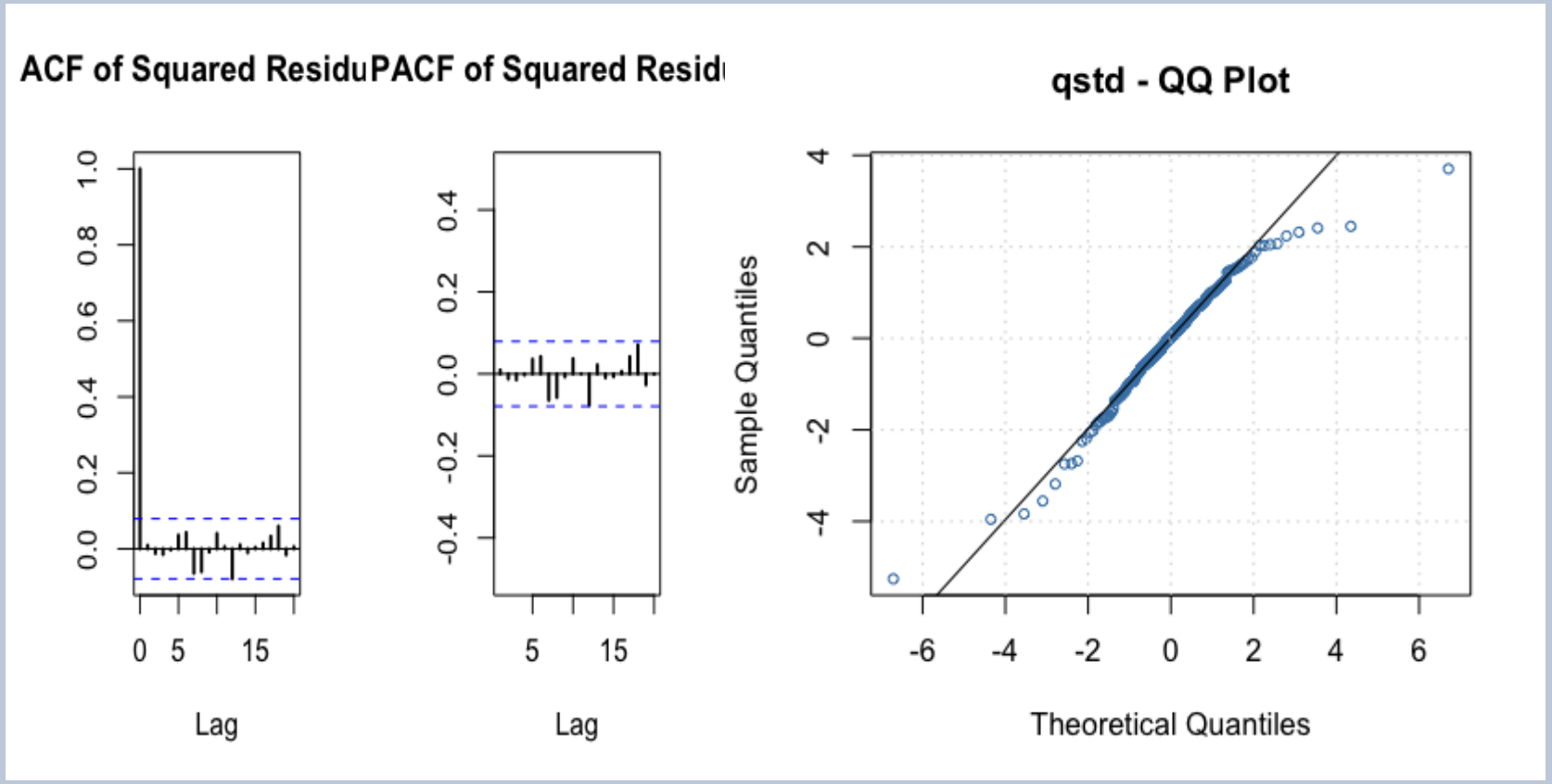


Figure 12: The ACF and PACF plots for model residuals of ARIMA(2,0,2)- t-GARCH(1,1) process.

Figure 13: The QQ plots of model residuals of ARIMA-t-GARCH process.

Codes:

```
fg11stu = garchFit(data = res, data ~ garch(1, 1), cond.dist = "std")

# different forecast with t-garch
# fg11stufore = predict(fg11stu, n.ahead = 30, plot=TRUE, mse='uncond', auto.grid=FALSE)
fg11stufore = predict(fg11stu, n.ahead = 30, plot = TRUE, cond.dist = "QMLE",
                      auto.grid = FALSE)

par(mfrow = c(1, 2))
stu.fg11res2 = fg11stu@residuals

# acf and pacf for t-garch
stu.acfres2 = acf(stu.fg11res2, ylab = NA, lag.max = 20, main = "ACF of Squared Residuals",
                  lwd = 2)
stu.pacfres2 = pacf(stu.fg11res2, lag.max = 20, main = "PACF of Squared Residuals",
                    lwd = 2, ylab = NA, ylim = c(-0.5, 0.5))

# ARIMA-t-GARCH qq plot
par(mfrow = c(1, 1))
plot(fg11stu, which = 13)
```