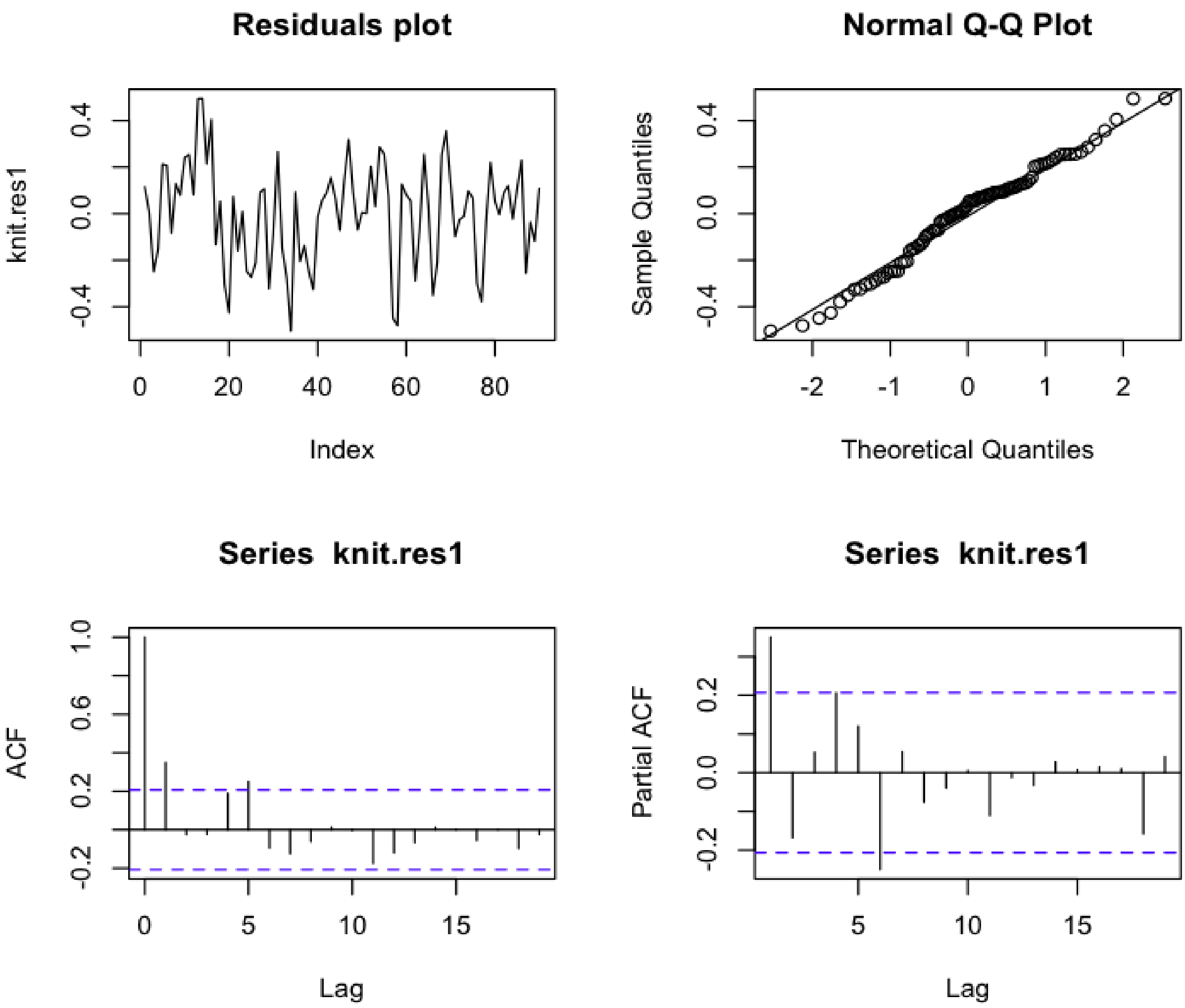
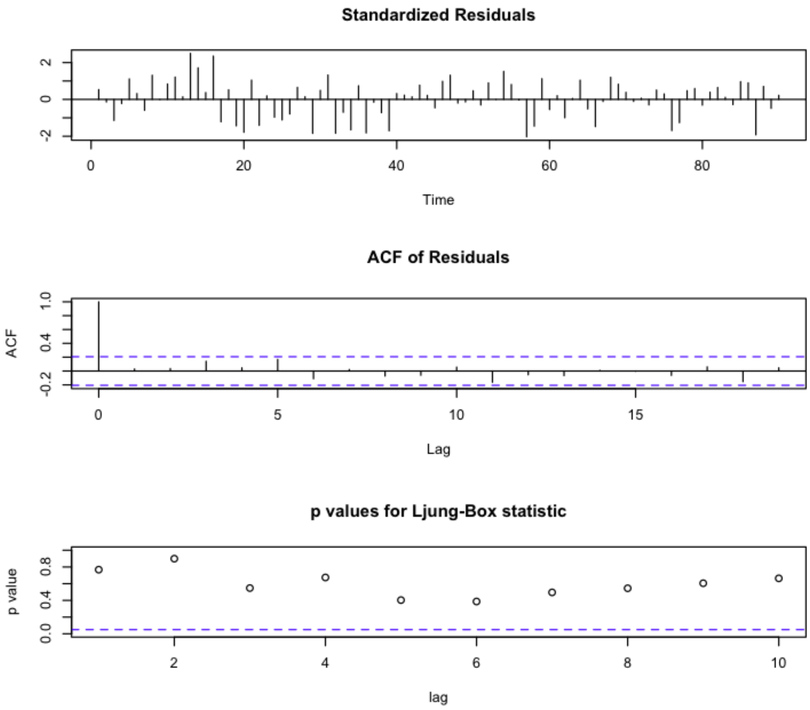
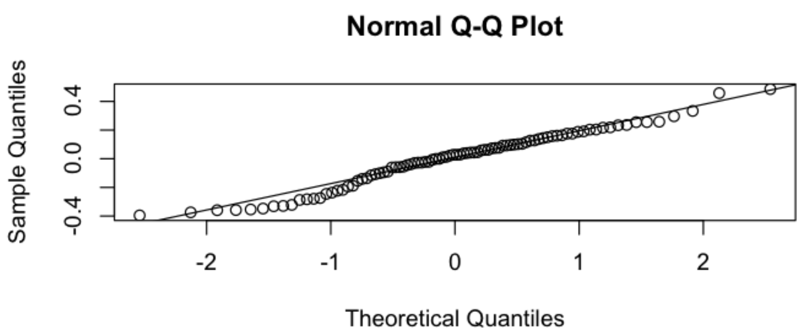
Assignment 5
Question 3
Part a:
By using simple exponential smoothing and continuous updating we find optimal α_o:
0.1605292
0.1616113
0.1660129
0.1332740
0.1571405
Hence, the corresponding forecasts for the next 5 weeks are:
4.010899
3.971307
3.960845
4.025984
4.100335
Afterwards, we find the SOS value which is 0.5017395.
Part b:
We fit the constant mean model and plot the residuals:



- From residuals plot we do not see any obvious deviations from stationarity like changing mean or variance.
- Each of the sample ACF and PACF plots contain 2 spikes. The pattern of these graphs suggests that we should fit ARMA (2,2) model to residuals.
- We fit the ARMA (2,2) model and then test for the white noise assumption:





- From residuals plot we do not see any evidences against stationarity.
- From Q-Q plot we see that it fits the line in the middle, hence, no evidences against normality.
- All autocorrelations and partial autocorrelations are within the blue lines, hence, no evidences against white noise.
- Finally, Ljung-Box test supports that residuals are white noise.

  Hence, after fitting ARMA (2,2) model to the residuals of the constant mean model and using continuous updating we obtain the corresponding forecasts for the next 5 weeks:

  4.032419

  3.877656

  4.014773

  4.220822

  4.097400

  And the SOS value is: 0.3316289

  If we compare SOS values from Part a and Part b, we see that SOS for Part b is less than SOS for Part a. Hence, Part b constant mean model with ARMA (2,2) residuals performs best.

```
## Question 3
mypath = "/Users/safurasuleymanovs/Desktop/4B/Stat/A5/"
data.set ="knit_y.txt"
linear.y = scan(paste(mypath,data.set,sep=""))
linear.ts = ts(scan(paste(mypath,data.set,sep="")))
knit.future = linear.ts[91:95]
## Part a - Slowly drifting mean model
knit.train1 = linear.ts[1:90]
knit.s1 = HoltWinters(knit.train1,beta=FALSE,gamma=FALSE)
alpha1 = knit.s1$alpha
pred.s1 = predict(knit.s1,1,prediction.interval = FALSE)

knit.train2 = linear.ts[1:91]
knit.s2 = HoltWinters(knit.train2,beta=FALSE,gamma=FALSE)
alpha2 = knit.s2$alpha
pred.s2 = predict(knit.s2,1,prediction.interval = FALSE)

knit.train3 = linear.ts[1:92]
knit.s3 = HoltWinters(knit.train3,beta=FALSE,gamma=FALSE)
alpha3 = knit.s3$alpha
pred.s3 = predict(knit.s3,1,prediction.interval = FALSE)

knit.train4 = linear.ts[1:93]
knit.s4 = HoltWinters(knit.train4,beta=FALSE,gamma=FALSE)
alpha4 = knit.s4$alpha
pred.s4 = predict(knit.s4,1,prediction.interval = FALSE)

knit.train5 = linear.ts[1:94]
knit.s5 = HoltWinters(knit.train5,beta=FALSE,gamma=FALSE)
alpha5 = knit.s5$alpha
pred.s5 = predict(knit.s5,1,prediction.interval = FALSE)

pred.s <- c(pred.s1,pred.s2,pred.s3,pred.s4,pred.s5)
alpha <- c(alpha1,alpha2,alpha3,alpha4,alpha5)
SOS.s <- sum((knit.future-pred.s)^2)
```

```
## Part b - Constant mean with ARMA (p,q) residuals
knit.mean1 <- mean(knit.train1)
knit.res1 <- knit.train1 - knit.mean1
plot(knit.res1,type="l", main = "Residuals plot")
qqnorm(knit.res1)
qqline(knit.res1)
acf(knit.res1)
pacf(knit.res1)

knit.arma1 <- arima(knit.train1,order=c(2,0,2),method="ML")
#tsdiag(knit.arma1)
pacf(knit.arma1$resid)
qqnorm(knit.arma1$resid)
qqline(knit.arma1$resid)
pred.arma1 <- predict(knit.arma1,n.ahead=1,se.fit=FALSE)

knit.arma2 <- arima(knit.train2,order=c(2,0,2),method="ML")
pred.arma2 <- predict(knit.arma2,n.ahead=1,se.fit=FALSE)
knit.arma3 <- arima(knit.train3,order=c(2,0,2),method="ML")
pred.arma3 <- predict(knit.arma3,n.ahead=1,se.fit=FALSE)
knit.arma4 <- arima(knit.train4,order=c(2,0,2),method="ML")
pred.arma4 <- predict(knit.arma4,n.ahead=1,se.fit=FALSE)
knit.arma5 <- arima(knit.train5,order=c(2,0,2),method="ML")
pred.arma5 <- predict(knit.arma5,n.ahead=1,se.fit=FALSE)

pred.arma <- c(pred.arma1,pred.arma2,pred.arma3,pred.arma4,pred.arma5)
SOS.arma <- sum((knit.future - pred.arma)^2)
```