732A62 Lab 3

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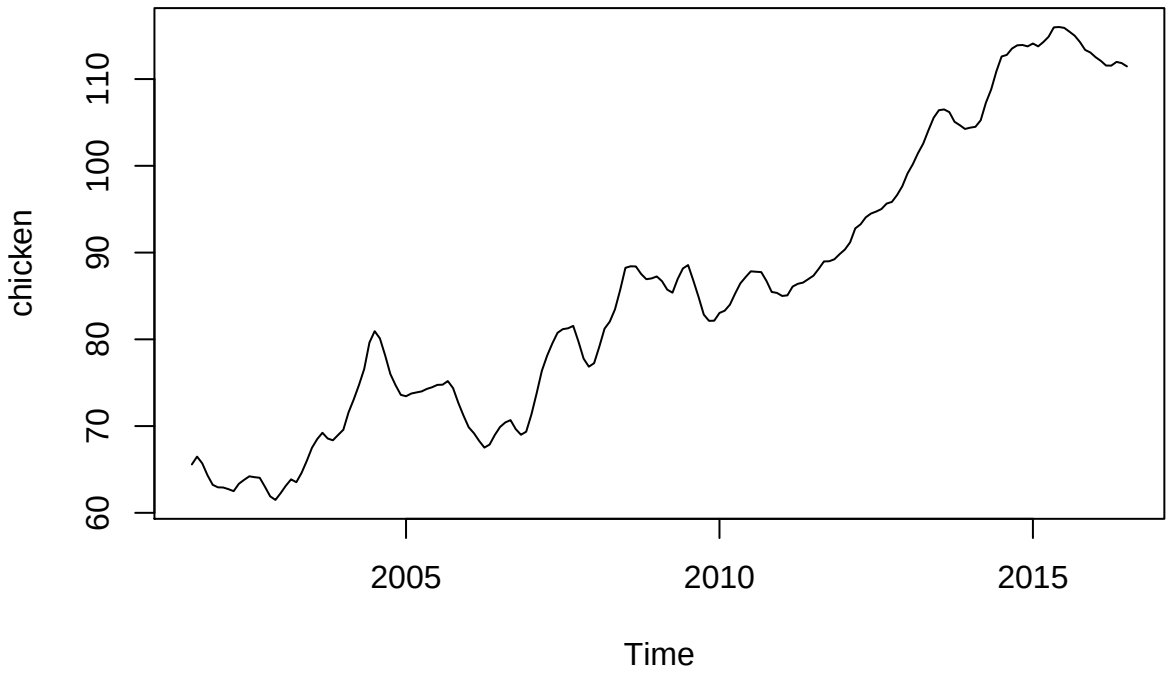
Assignment 1

1)

```
library(astsa)
library(TSA)
library(forecast)
library(fGarch)

plot(chicken)
```

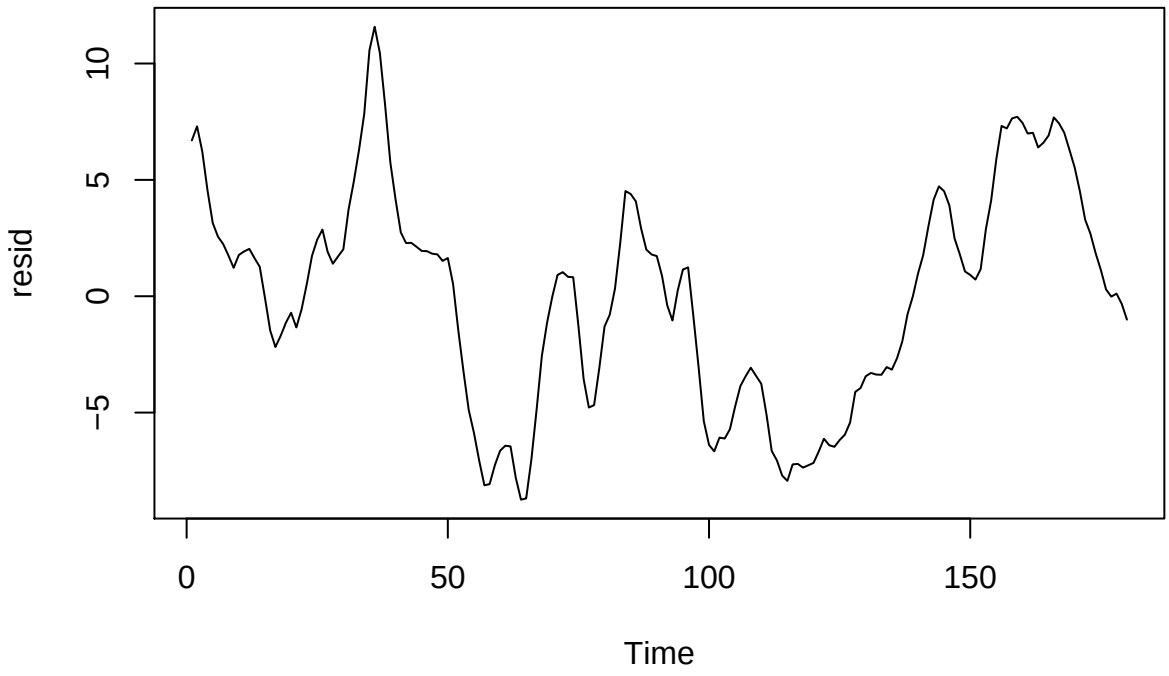


It looks like a linear, potentially quadratic, trend.

2)

```
lm_data <- data.frame(chicken=chicken, time=1:length(chicken))
lm_fit <- lm(chicken ~ time, lm_data)
```

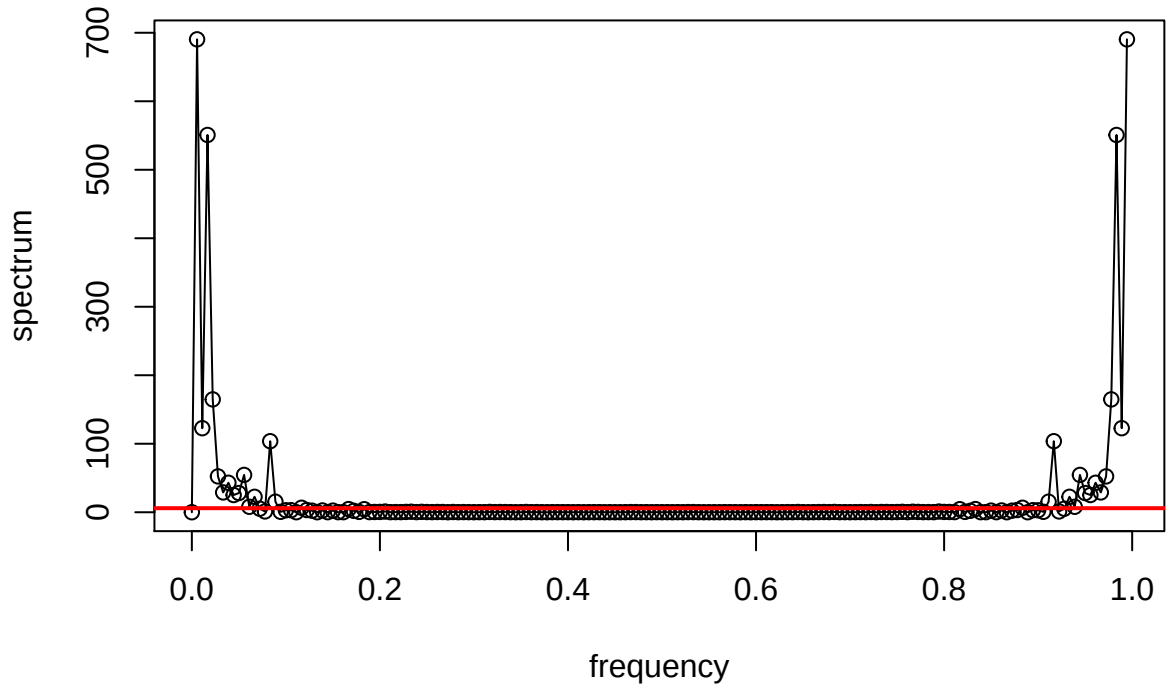
```
z <- resid(lm_fit)
plot(z, type="l", ylab="resid", xlab="Time")
```



The residuals do not look stationary.

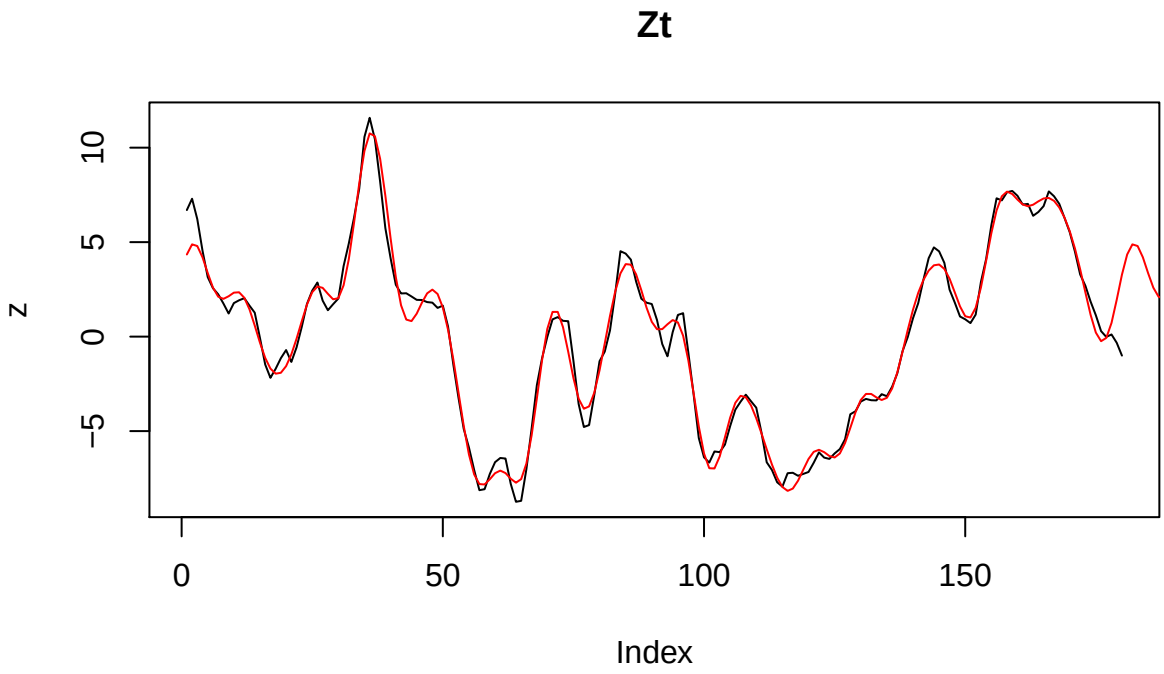
3)

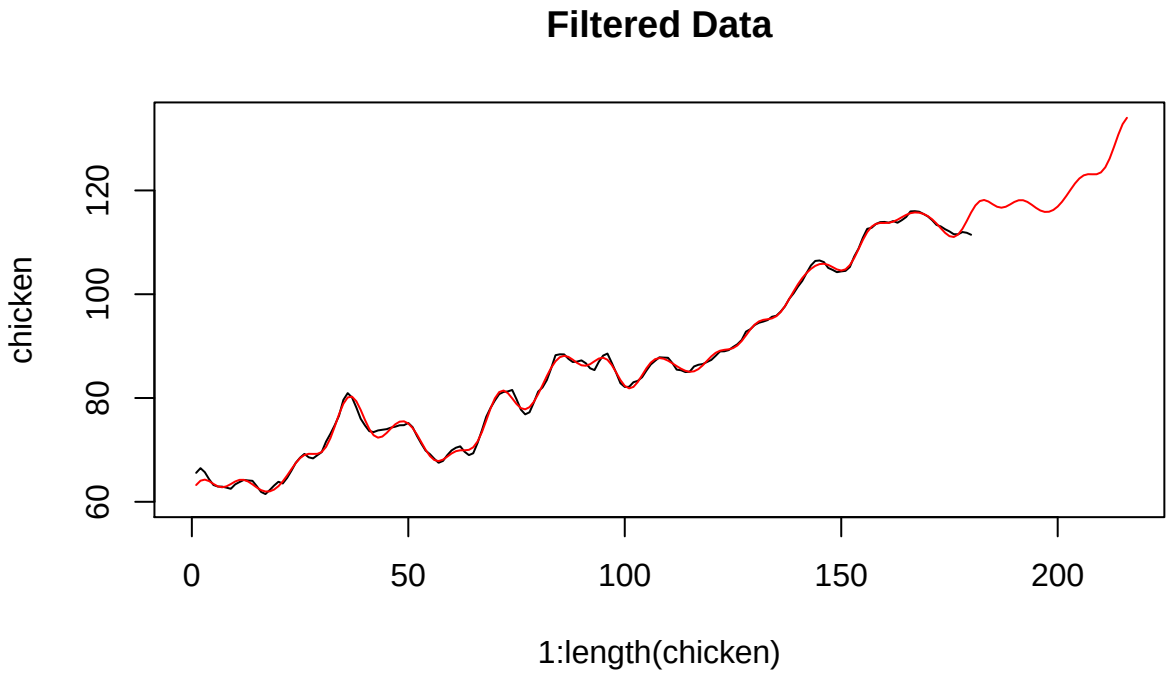
```
denom <- sqrt(length(z)) *
    exp(complex(imaginary=2 * pi * 0:(length(z) - 1) / length(z)))
density <- fft(z) / denom
periodigram <- abs(density)^2

upper <- 2 * mean(periodigram) / qchisq(0.025, 2)
lower <- 2 * mean(periodigram) / qchisq(0.975, 2)

plot(0:(length(chicken) - 1) / length(chicken), periodigram, type="o",
     xlab="frequency", ylab="spectrum")
abline(h=lower, col="red", lwd=2)
```



4)

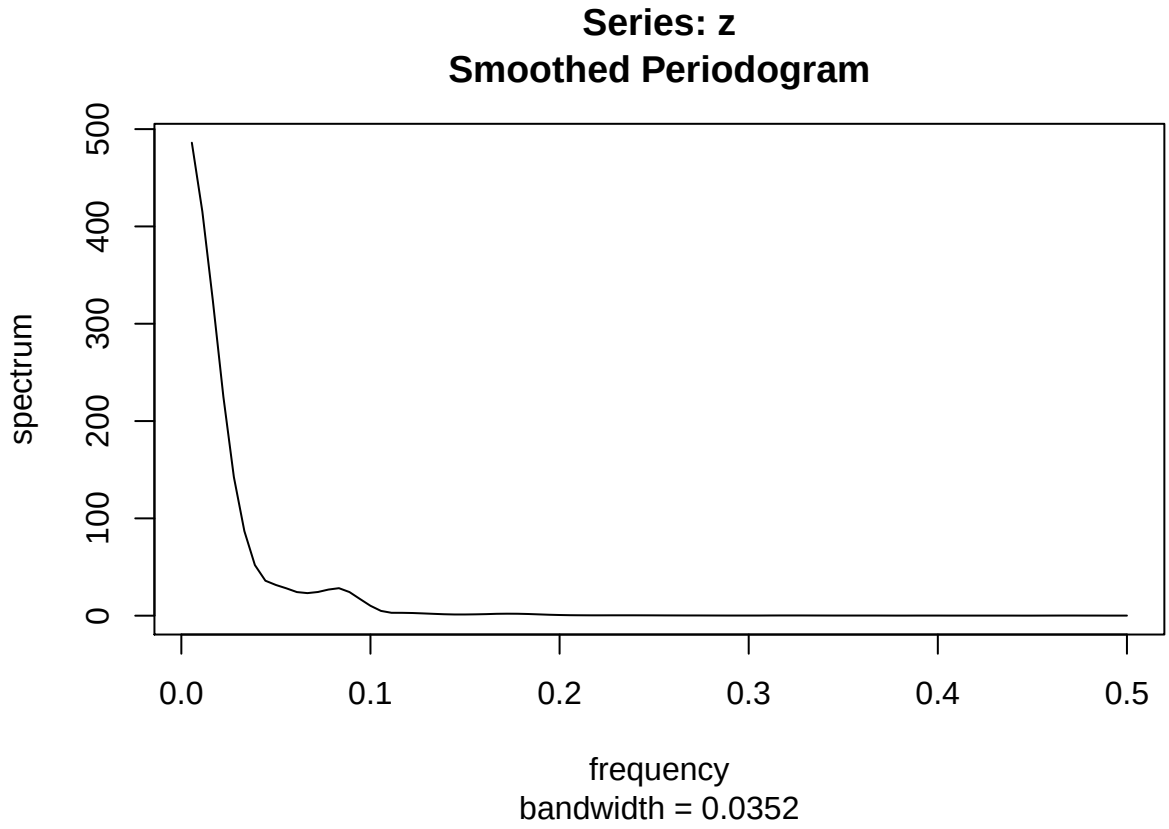
```
freq_density <- density
freq_density[periodigram < lower] <- 0

n <- length(z)
ts <- 1:(n + 36)

xs <- rep(0, n + 36)

for (t in ts) {
    xs[t] <- sum(freq_density * exp(complex(imaginary=2 * pi * (0:(n - 1)) / n * t))) / sqrt(n)
}

filtered_data <- predict(lm_fit, data.frame(time=1:length(xs))) + Re(xs)
```


Zt
z
10
5
0
−5
0
50
100
150
Index


Filtered Data
chicken
120
100
80
60
0
50
100
150
200
1:length(chicken)

5)

```
k <- kernel("modified.daniell", c(2,2))
md_dan <- mvspec(z, kernel=k, log="no")
```



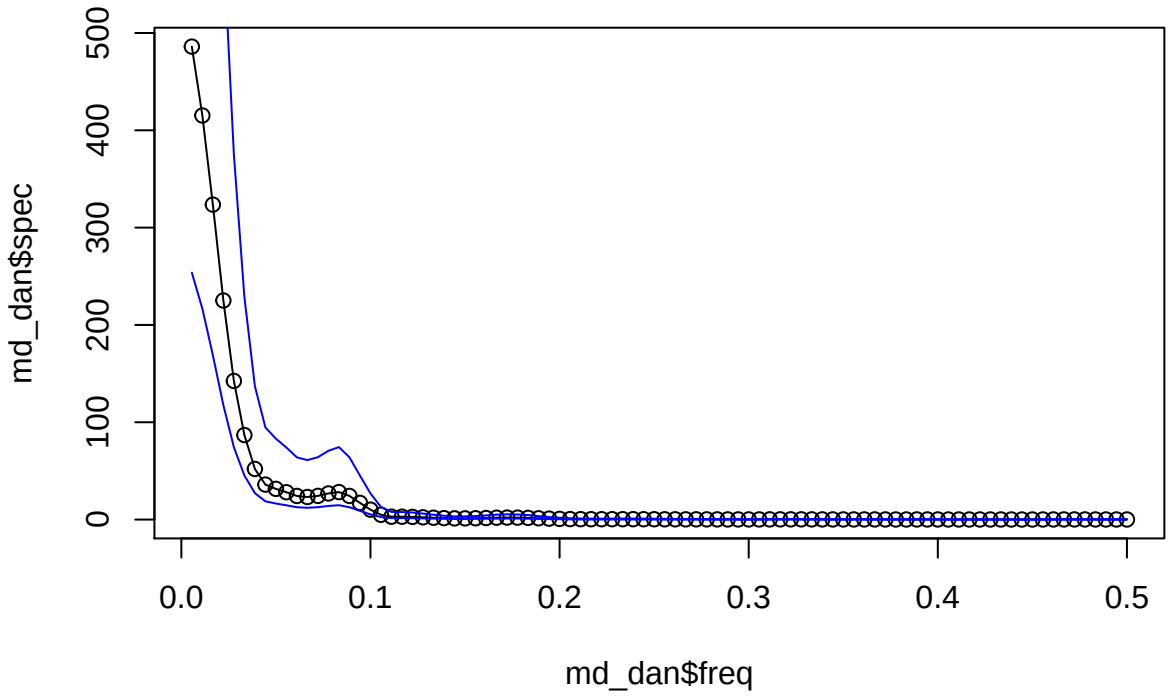

```
Lh <- md_dan$Lh

lower1 <- 2 * Lh * md_dan$spec / qchisq(0.975,2*Lh)
upper1 <- 2 * Lh * md_dan$spec / qchisq(0.025,2*Lh)

# Comparing frequencies

freq_4 <- 0:179/180

freq_4[periodigram > lower]
```

```
##  [1] 0.005555556 0.011111111 0.016666667 0.022222222 0.027777778
##  [6] 0.033333333 0.038888889 0.044444444 0.050000000 0.055555556
## [11] 0.061111111 0.066666667 0.083333333 0.088888889 0.116666667
## [16] 0.883333333 0.911111111 0.916666667 0.933333333 0.938888889
## [21] 0.944444444 0.950000000 0.955555556 0.961111111 0.966666667
## [26] 0.972222222 0.977777778 0.983333333 0.988888889 0.994444444
```

```
md_dan$freq[md_dan$freq < 0.1]
```

```
##  [1] 0.005555556 0.011111111 0.016666667 0.022222222 0.027777778
##  [6] 0.033333333 0.038888889 0.044444444 0.050000000 0.055555556
```

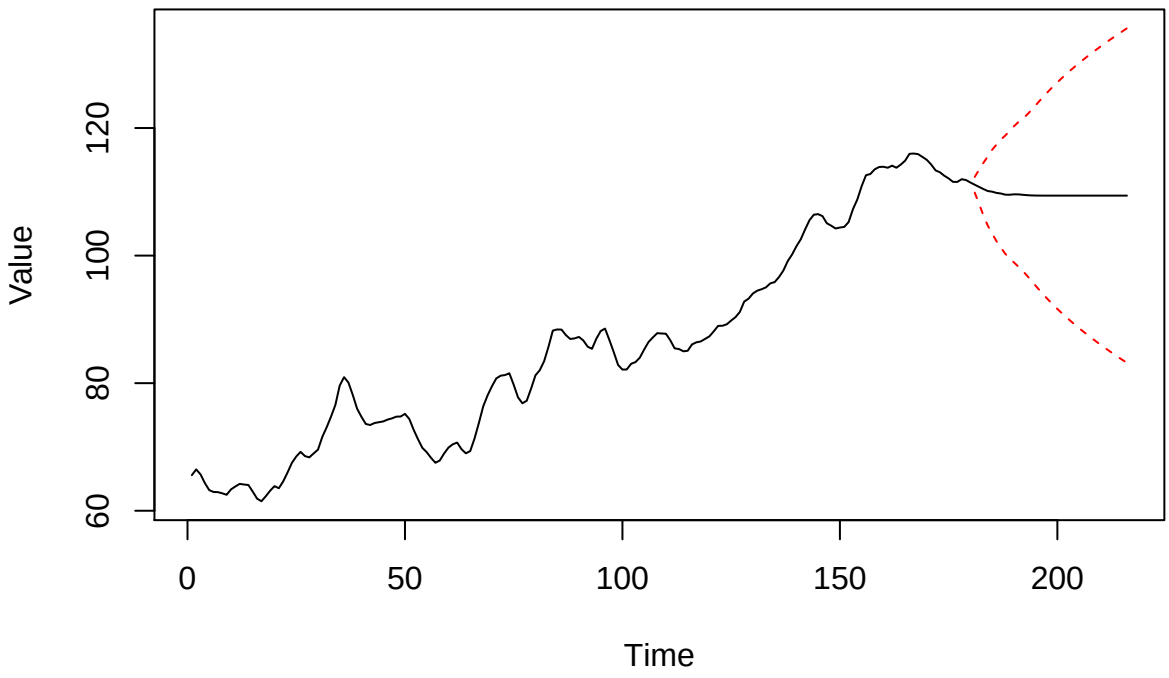
```
## [11] 0.061111111 0.066666667 0.072222222 0.077777778 0.083333333
## [16] 0.088888889 0.094444444 0.100000000
```



6)

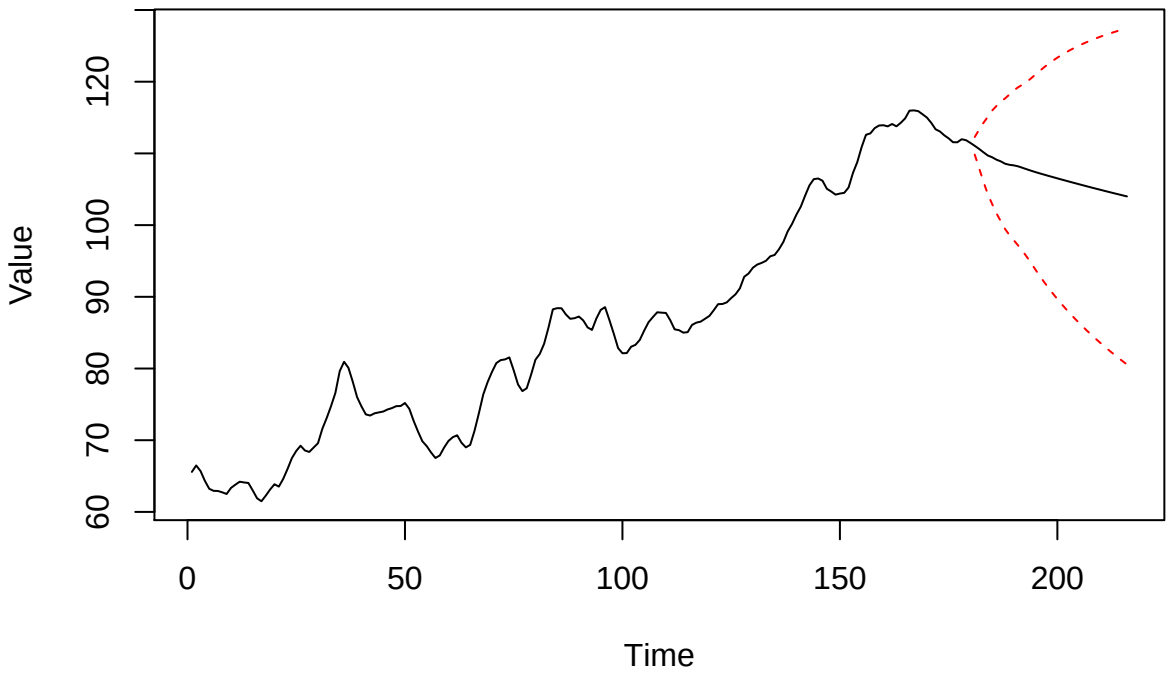
```
fit_plot <- function(model, data) {
    nahead <- 36
    pred <- predict(model, n.ahead=nahead, se.fit=TRUE)
    upper_band <- pred$pred + 1.96 * pred$se
    lower_band <- pred$pred - 1.96 * pred$se

    n <- length(data)

    plot(c(data, pred$pred), type="l",
         ylim=c(min(data), max(upper_band)), ylab="Value", xlab="Time")
    lines(n + 1:nahead, upper_band, lty=2, col="red")
    lines(n + 1:nahead, lower_band, lty=2, col="red")
}
```

```
fit <- arima(chicken, order=c(2, 1, 0), seasonal=list(order=c(0, 0, 1), period=12))
fit_plot(fit, chicken)
```



7)

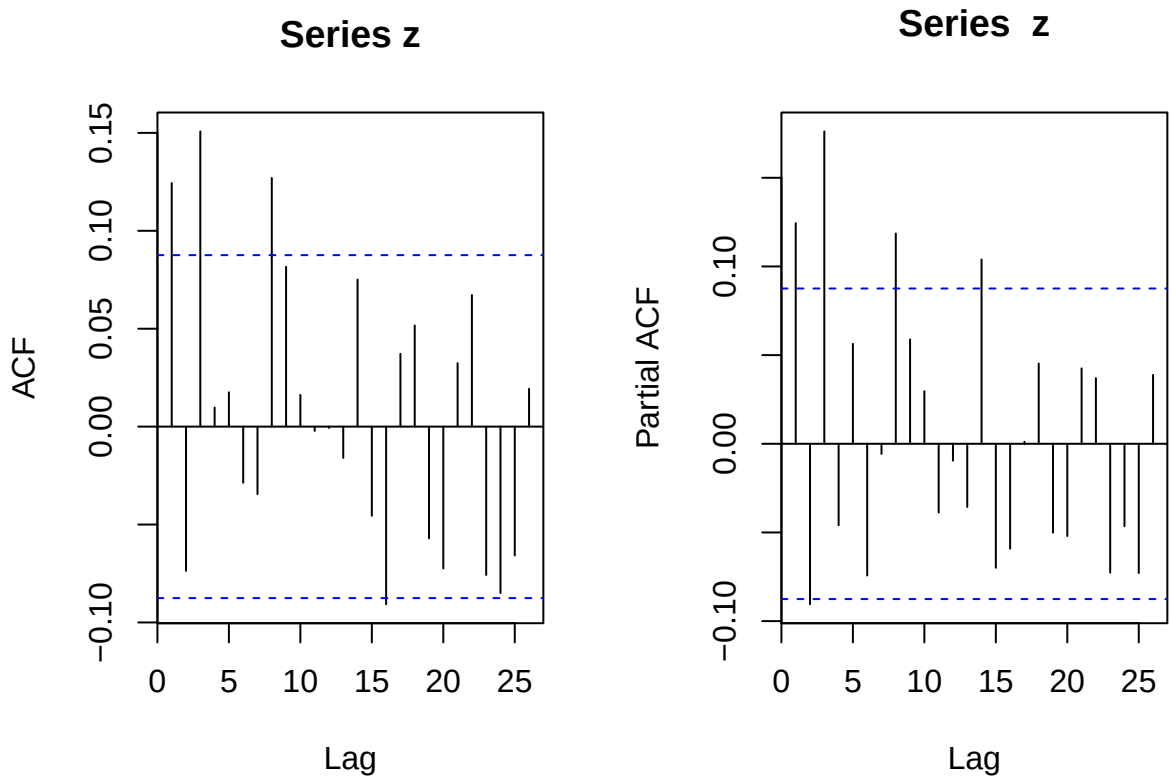
```
fit <- arima(chicken, order=c(3, 0, 0), seasonal=list(order=c(0, 0, 1), period=12))
fit_plot(fit, chicken)
```


Value
60
70
80
90
100
120
0
50
100
150
200
Time

Assignment 2

1)

```
ld_oil <-diff(log(oil))

z <-ld_oil[1:(52*9 + 33)]

old <- par(mfrow = c(1,2))
acf(z)
pacf(z)
```




```
par(old)

suggested_model <- Arima(z, order = c(3,0,0))

summary(suggested_model)
```

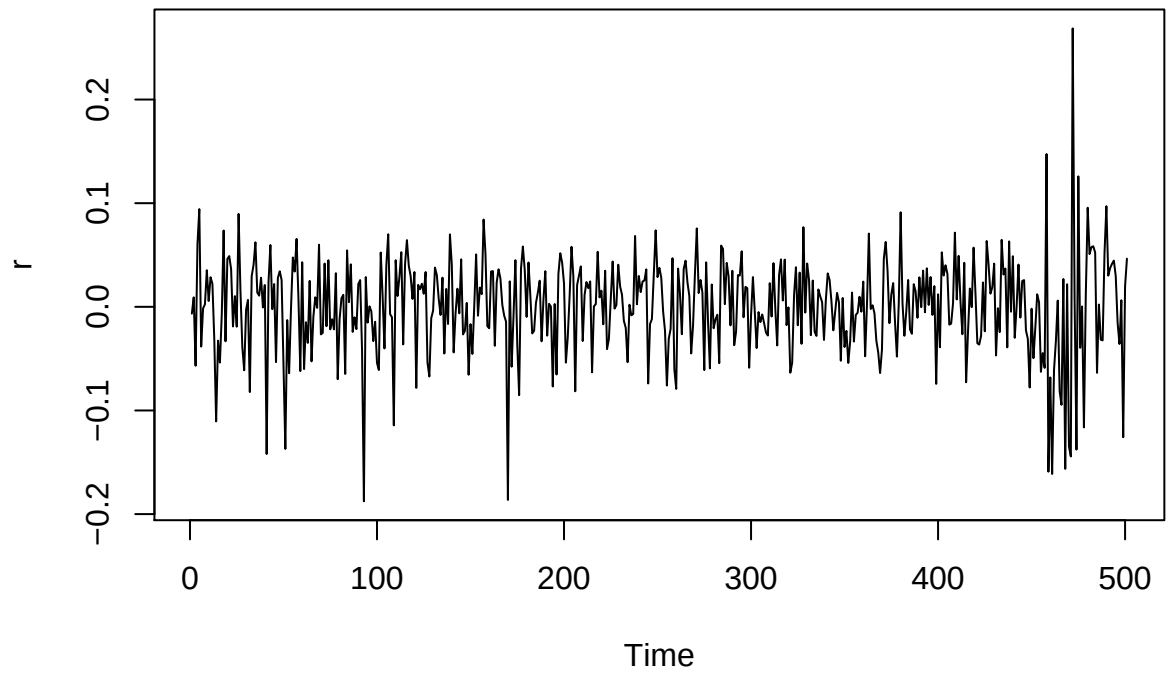
```
## Series: z
## ARIMA(3,0,0) with non-zero mean
##
## Coefficients:
##          ar1      ar2     ar3    mean
##       0.151  -0.1147  0.1777  0.0018
## s.e.  0.044   0.0442  0.0442  0.0026
##
```

```
## sigma^2 estimated as 0.002171:  log likelihood=827.28
## AIC=-1644.55   AICc=-1644.43   BIC=-1623.47
##
## Training set error measures:
##                        ME       RMSE        MAE  MPE MAPE      MASE
## Training set 2.381642e-05 0.04640656 0.03454024 -Inf  Inf 0.7492286
##                     ACF1
## Training set 0.008324494
```

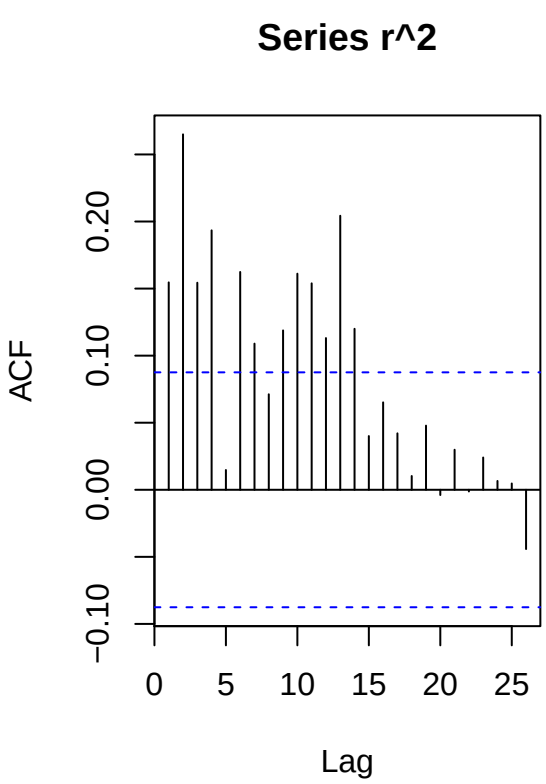
```
r <- resid(suggested_model)
```

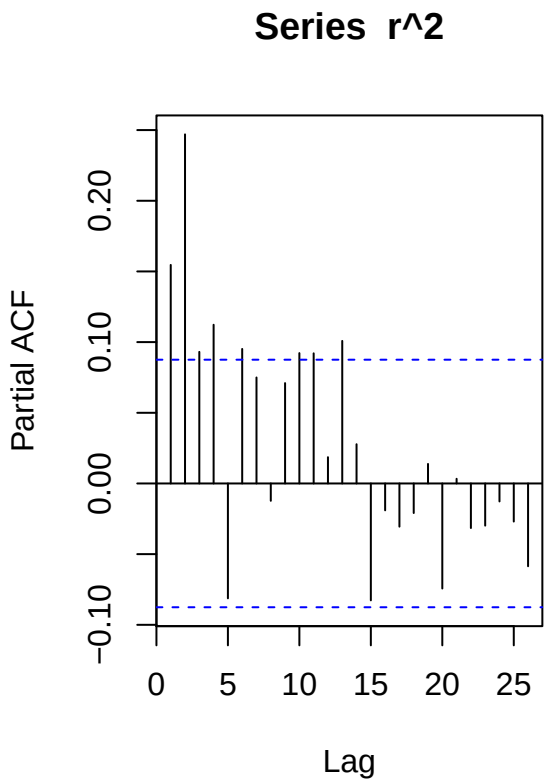
2)

```
plot(r)
```




```
old <- par(mfrow = c(1,2))
acf(r^2)
pacf(r^2)
```






```
par(old)


fit1<- garchFit(~ arma(3,0) + garch(1,0) , data = ld_oil, trace = FALSE)
fit1
```

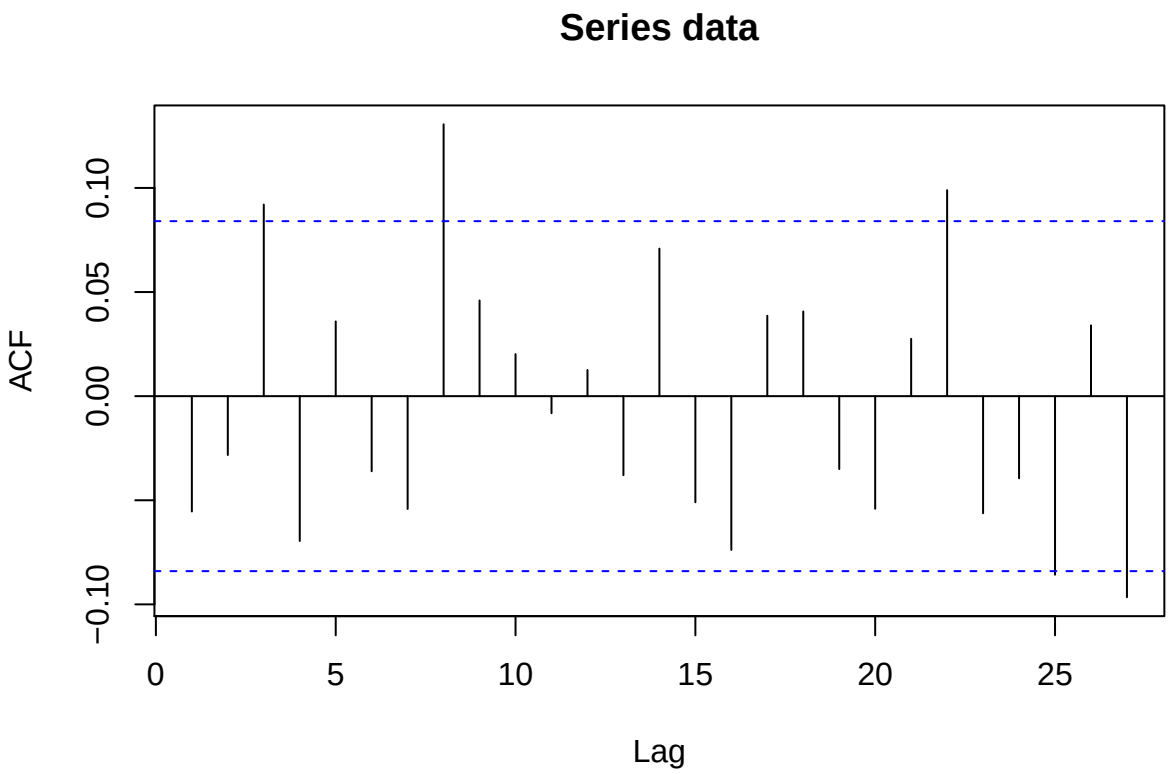
```
##
## Title:
##  GARCH Modelling
##
## Call:
##  garchFit(formula = ~arma(3, 0) + garch(1, 0), data = ld_oil,
##     trace = FALSE)
##
## Mean and Variance Equation:
##  data ~ arma(3, 0) + garch(1, 0)
## <environment: 0xc260e40>
##  [data = ld_oil]
##
## Conditional Distribution:
##  norm
##
## Coefficient(s):
##         mu         ar1         ar2         ar3       omega      alpha1
##  0.0017864   0.2225996  -0.1021282   0.0944799   0.0016814   0.1863076
##
## Std. Errors:
```

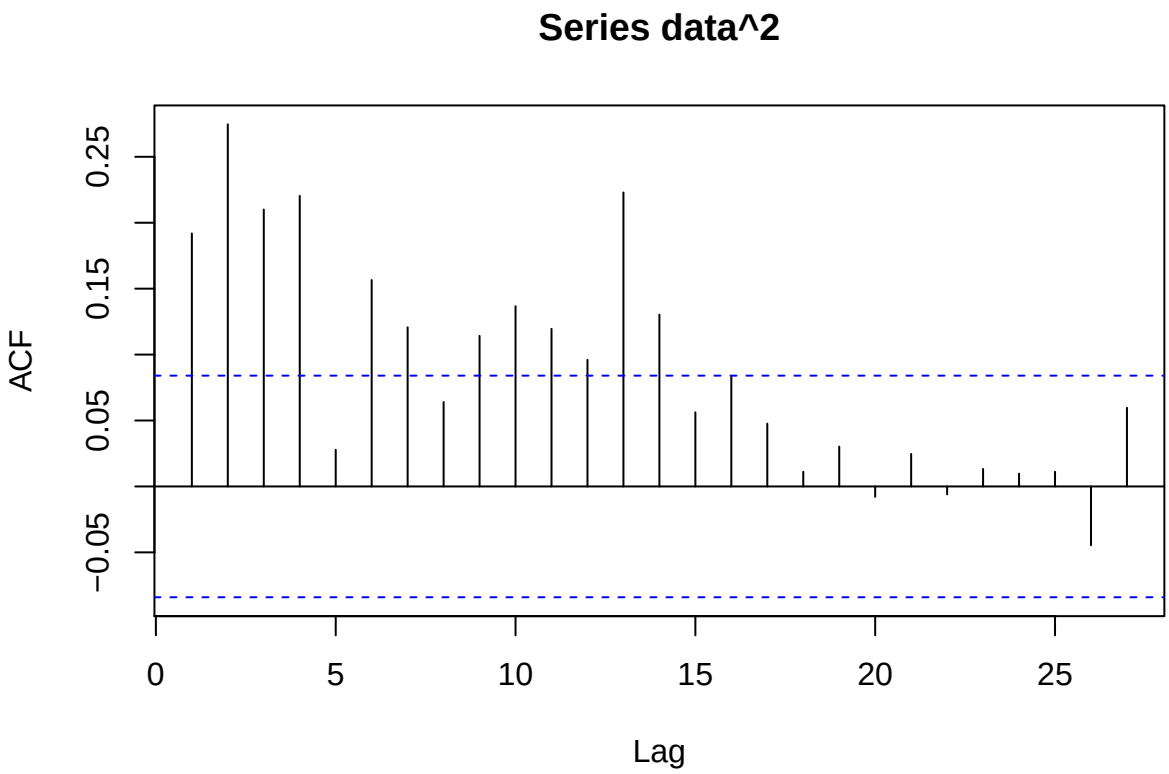
```
##  based on Hessian
##
## Error Analysis:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.0017864   0.0018866    0.947 0.343685
## ar1     0.2225996   0.0647442    3.438 0.000586 ***
## ar2    -0.1021282   0.0414650   -2.463 0.013778 *
## ar3     0.0944799   0.0442595    2.135 0.032787 *
## omega   0.0016814   0.0001308   12.856  < 2e-16 ***
## alpha1  0.1863076   0.0599895    3.106 0.001898 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
##  920.699    normalized:  1.692461
##
## Description:
##  Wed Oct 11 13:53:29 2017 by user: r
```

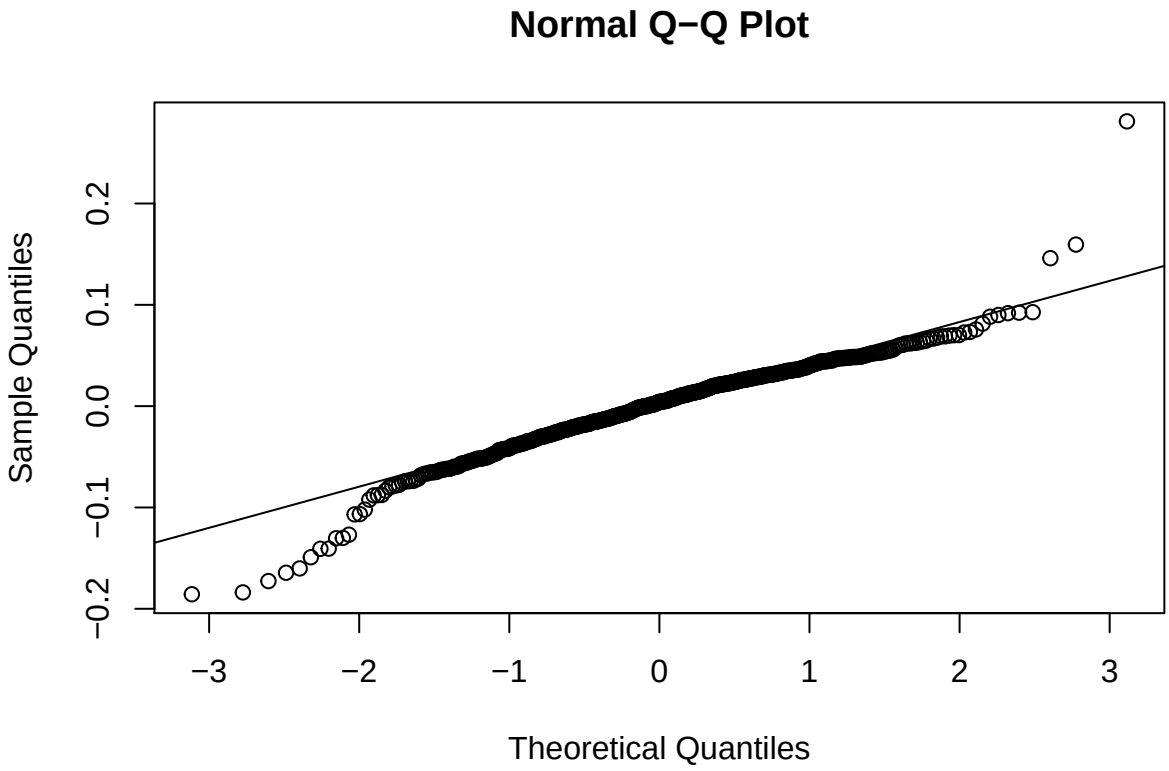
The time series of the residuals seem to have an increasing variance in the end of the residuals.

The ACF of the squared residuals trails of and in the PACF they cuts of after 2 lags. Indicating a GARCH(p,q) An p = 2, q = 0 maybe? ## 3)

```
helper <- function(data){
acf(data)
acf(data^2)
qqnorm(data)
qqline(data)

}


helper(fit1@residuals)
```


Series data
ACF
0.10
0.05
0.00
−0.10
0
5
10
15
20
25
Lag


Series data^2
ACF
0.25
0.15
0.05
−0.05
0
5
10
15
20
25
Lag




```
fit1@fit$objective
```

```
## [1] 742.6219
```

4)

5)

6)