

ST565: Time Series HW5

Amirhosein “Emerson” Azarbakht azarbaka@oregonstate.edu

Required reading 5.4 & 5.5 in Chatfield

Question 1

Fit a seasonal ARIMA model to the Johnson and Johnson quarterly returns data in the package `astsa` and forecast the next 12 quarters (including prediction intervals).

```
# install.packages("astsa")
library(forecast)
```

```
## Loading required package: zoo
```

```
##
```

```
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      as.Date, as.Date.numeric
```

```
## Loading required package: timeDate
```

```
## This is forecast 6.2
```

```
library(astsa)
```

```
##
```

```
## Attaching package: 'astsa'
```

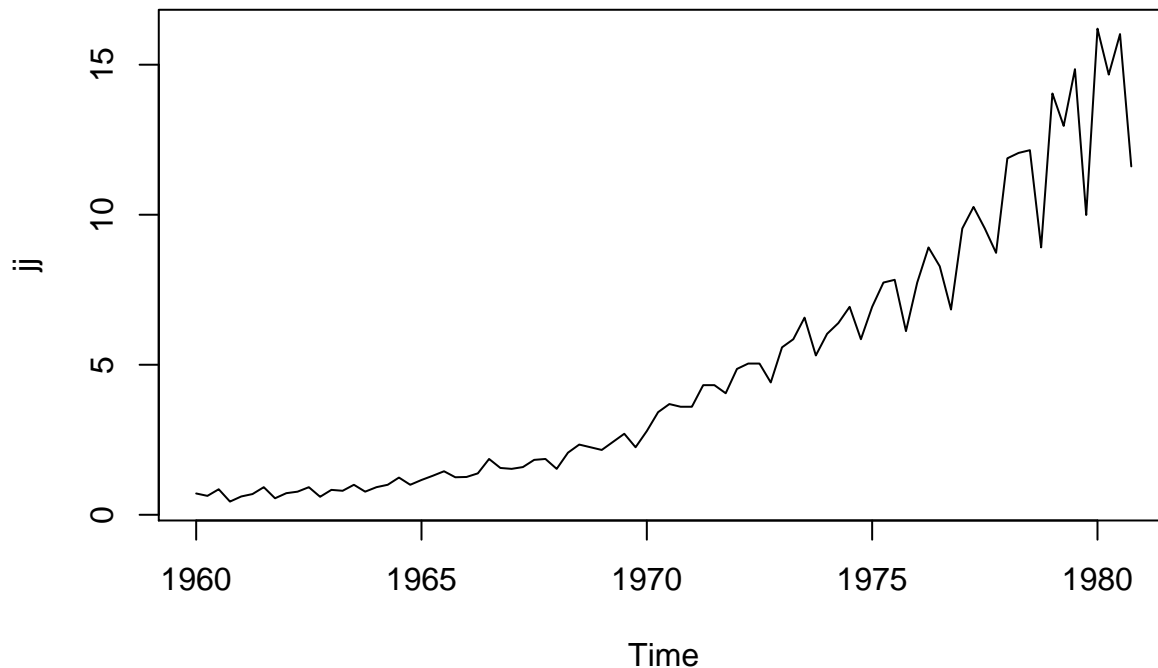
```
## The following object is masked from 'package:forecast':
```

```
##
```

```
##      gas
```

```
data(jj)
```

```
ts.plot(jj)
```



```
get.best.arima <- function(x.ts, maxord = c(1,1,1,1,1,1)) {
  best.aic <- 1e8
  n <- length(x.ts)
  for (p in 0:maxord[1]) for(d in 1:maxord[2]) for(q in 0:maxord[3])
    for (P in 0:maxord[4]) for(D in 1:maxord[5]) for(Q in 0:maxord[6])
    {
      fit <- arima(x.ts, order = c(p,d,q), seas = list(order = c(P,D,Q), frequency(x.ts)), method = "CS")
      fit.aic <- -2 * fit$loglik + (log(n) + 1) * length(fit$coef)
      if (fit.aic < best.aic)
      {
        best.aic <- fit.aic
        best.fit <- fit
        best.model <- c(p,d,q,P,D,Q)
      }
    }
  list(best.aic, best.fit, best.model)
}

best.arima <- get.best.arima(jj, maxord = c(2,2,2,2,2,2))
```

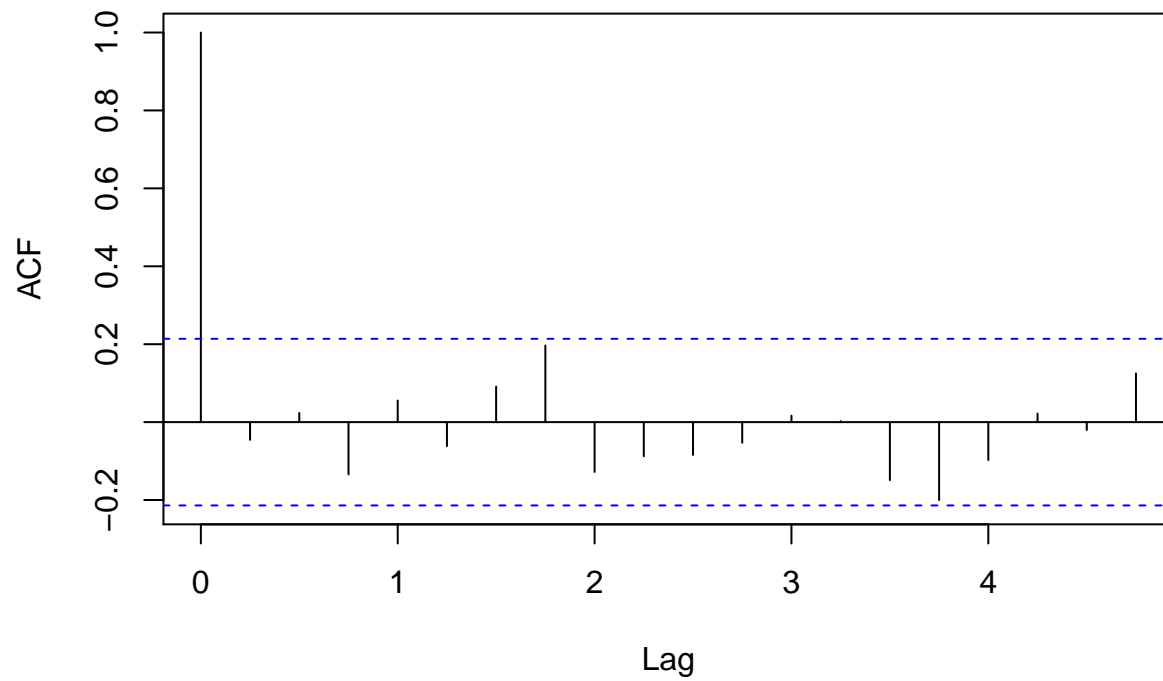
```
## Warning in arima(x.ts, order = c(p, d, q), seas = list(order = c(P, D,
## Q), : possible convergence problem: optim gave code = 1
```

```
## Warning in arima(x.ts, order = c(p, d, q), seas = list(order = c(P, D,
## Q), : possible convergence problem: optim gave code = 1
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```
## Warning in arima(x.ts, order = c(p, d, q), seas = list(order = c(P, D,
## Q), : possible convergence problem: optim gave code = 1
```

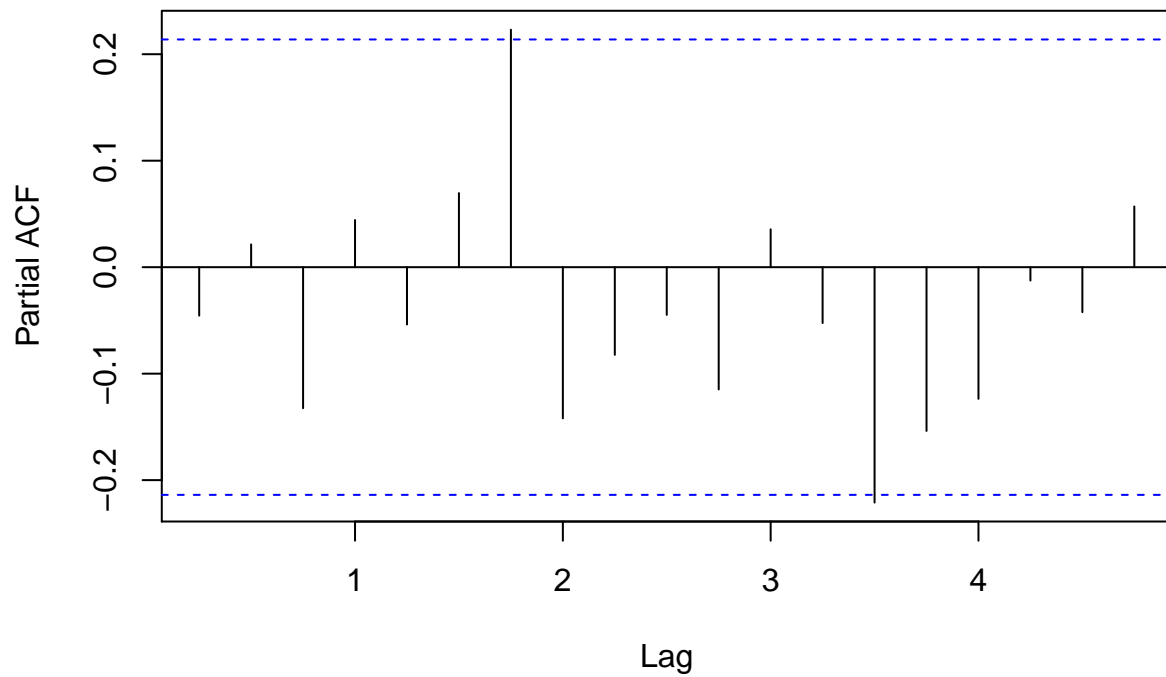
```
best.fit <- best.arima[[2]]  
  
acf(best.fit$residuals)
```

Series best.fit\$residuals



```
pacf(best.fit$residuals)
```

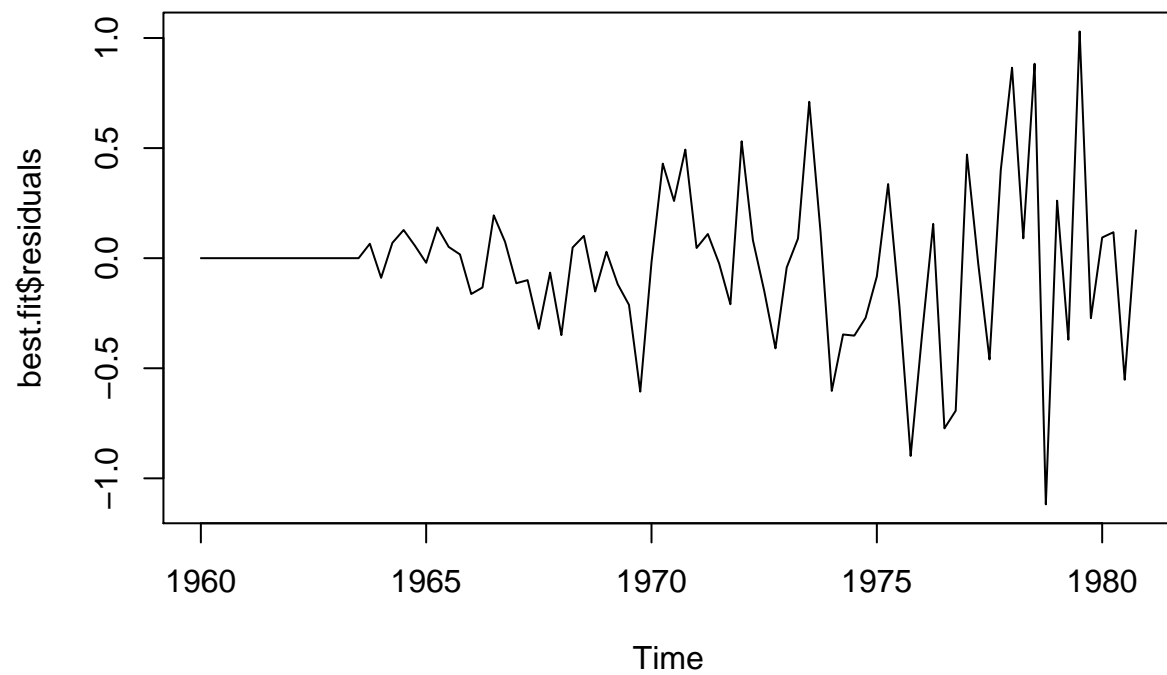
Series best.fit\$residuals



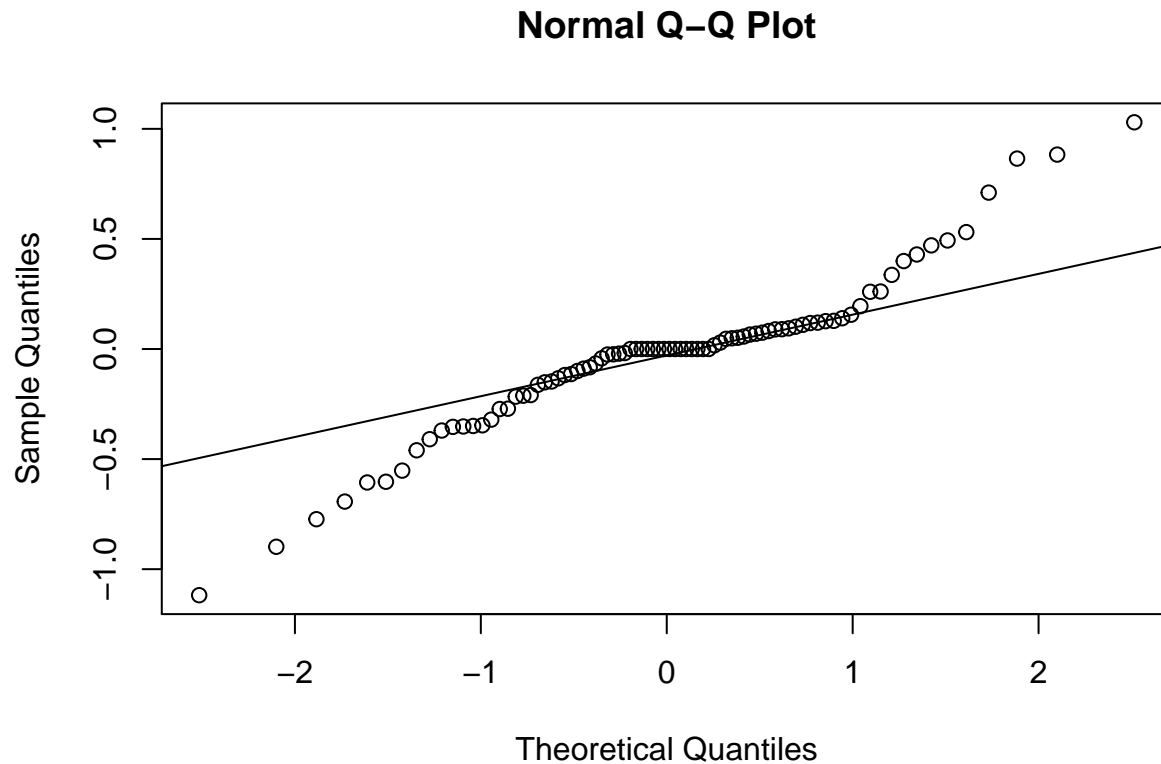
```
best.arima [[3]]
```

```
## [1] 2 1 1 1 2 1
```

```
plot(best.fit$residuals)
```



```
qqnorm(best.fit$residuals)
qqline(best.fit$residuals)
```



```
prediction <- predict(best.fit, 12)
```

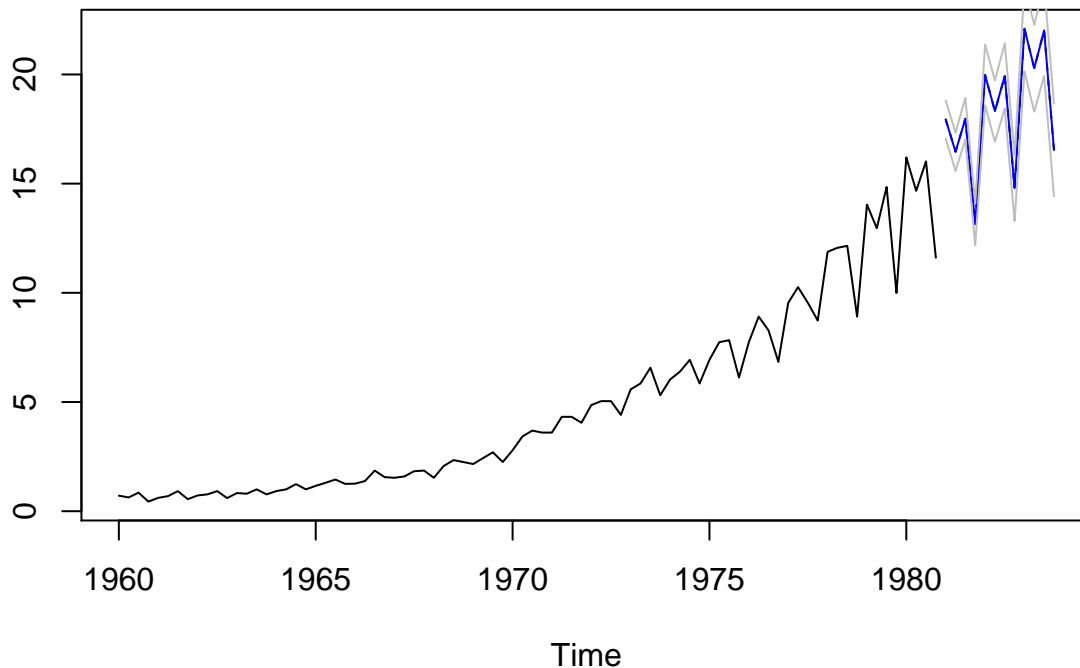
```
## Warning in predict.Arima(best.fit, 12): MA part of model is not invertible
```

```
prediction
```

```
## $pred
##           Qtr1      Qtr2      Qtr3      Qtr4
## 1981 17.93643 16.45906 17.97239 13.13971
## 1982 19.97997 18.32015 19.93535 14.79452
## 1983 22.09596 20.28372 22.01715 16.54413
##
## $se
##           Qtr1      Qtr2      Qtr3      Qtr4
## 1981 0.4364227 0.4394069 0.4734084 0.4777317
## 1982 0.6944537 0.7038458 0.7439318 0.7547596
## 1983 0.9765810 0.9937175 1.0456149 1.0642018
```

```
ts.plot(cbind(window(jj,start = 1960), prediction$pred), lty = 1:2)
```

```
lines(prediction$pred, lty = 1:2, col = "blue")
lines(prediction$pred - (2 * prediction$se), lty = 1:2, col = "grey")
lines(prediction$pred + (2 * prediction$se), lty = 1:2, col = "grey")
```



Question 2: The Holt Winters Method

What decisions need to be made to use a Holt Winters forecasting approach? What starting values do you need to specify? What parameters need estimating?

- If data contains trend and seasonality, we can use Holt Winters method, rather than Simple Exponential Smoothing method.
- Plot the data, examine whether the variance is constant or varying through time. If former case, choose an additive method, if latter case, choose a multiplicative method.
- We need to specify starting values for L_1, T_1 , and $I_{1...s}$ for the first year, using the first few observations in the time series. For example, we can use $L_1 = \sum x_i / s$.
- Values for α, γ, δ need to be estimated by minimizing the square one-step prediction error $\sum e_t^2$.
- Decide whether to normalize the seasonal indices at regular intervals by making them sum to zero for the additive case, and sum to 1 for the multiplicative case.
- Choose an automatic approach or non-automatic.

Investigate the R function `HoltWinters`. How do you specify the decisions from above? How does the function choose starting values and estimate parameters?

Using the function options, e.g. `seasonal = c("additive", "multiplicative")`, etc.

```
# HoltWinters(x, alpha = NULL, beta = NULL, gamma = NULL, seasonal = c("additive", "multiplicative"), s
```

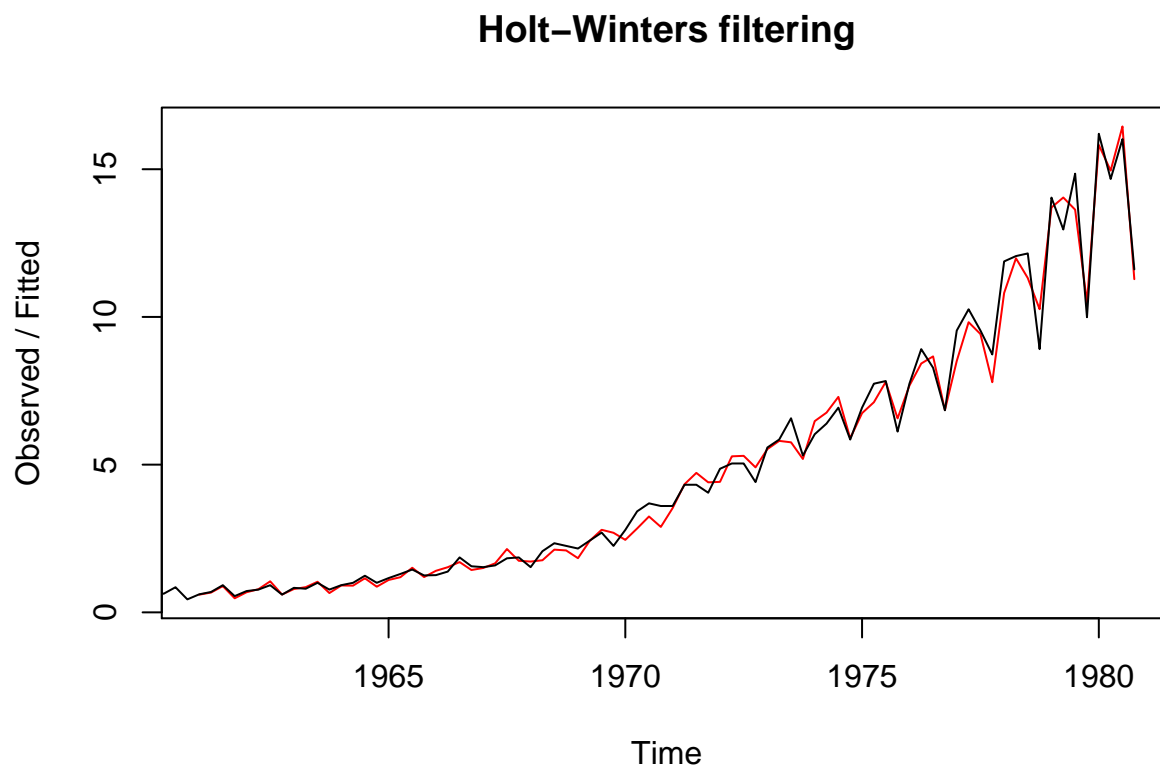
According to R documentation: “For seasonal models, start values for a , b and s are inferred by performing a simple decomposition in trend and seasonal component using moving averages (see function `decompose`) on the start.periods first periods (a simple linear regression on the trend component is used for starting level and trend). For level/trend-models (no seasonal component), start values for a and b are $x[2]$ and $x[2] - x[1]$, respectively. For level-only models (ordinary exponential smoothing), the start value for a is $x[1]$.”

Use the function to produce forecasts (along with prediction intervals) for Johnson and Johnson returns in question 1.

```
hwt <- HoltWinters(jj, seasonal = "multiplicative", start.periods = 2)
hwt$SSE
```

```
## [1] 14.35317
```

```
plot(hwt)
```



```
predictHW <- predict(hwt, n.ahead = 12, prediction.interval = TRUE, level = 0.95)
hwtfit <- hw(jj, seasonal="multiplicative")
plot(hwtfit)
```

Forecasts from Holt–Winters' multiplicative method

