

Time Series Analysis & Forecasting

Class 4

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auto.arima: Hyndman-Kkandakar Algorithm

Refer to <https://otexts.com/fpp2/arma-r.html>

Time Series with Drift

```
set.seed(1)      # so you can reproduce the results
v = rnorm(100,1,1) # v contains 100 iid N(1,1) variates
x = cumsum(v)     # x is a random walk with drift = 1
plot(x)
model1 <- arima(x, order = c(1,1,0))
plot(forecast(model1, h=12))
kpss.test(x) # not stationary due to drift
kpss.test(x, null = "Trend") # cannot detect drift, only deterministic trend

# same effect as it does not consider drift term
model2 <- Arima(x, order = c(1,1,0))
plot(forecast(model2, h=12))

# correct results with drift included
model3 <- Arima(x, order = c(1,1,0), include.drift = T)
plot(forecast(model3, h=12))
# Refer to https://www.stat.pitt.edu/stoffer/tsa4/Rissues.htm
```

Model Estimation

- TS $\{y_t\}$
- Maximum Likelihood (ML) is estimating the unknown parameters such that the probability of observing the given $\{y_t\}$ is as high as possible
- Use differential calculus to solve for the parameters and get the maximum value
- t-value given by

$$t = \frac{\hat{\beta} - \beta}{std_error(\beta)} = \frac{\hat{\beta} - \beta}{\frac{\hat{\sigma}}{\sqrt{\sum x_i^2}}}$$

- ARIMA models include any parameter whose $|t\text{-value}| > 2$

Model Diagnostic – Residual Analysis

- Define residual = actual – estimate
- Autocorrelation – use Durbin Watson

$$d = 2(1 - r)$$

$r \Rightarrow$ 1st lag sample autocorrelation of the residual

$d = 2 \Rightarrow$ no autocorrelation

- Normality – QQ plot
- Normality – Shapiro-Wilk test where the null hypothesis is that the dataset is normally distributed. If p -value is lower than threshold, then reject

Ljung-Box Test

- Let sample autocorrelation function of the residuals be denoted as \widehat{r}_k

- Box-Pierce statistic

$$Q = n \sum_k \widehat{r}_k^2$$

- For ARMA(p,q) for large n, Q has approximate χ^2 (chi-squared) distribution
- Ljung-Box noted that even with large n, n=100, the approximation to χ^2 distribution is not satisfactory
- Ljung-Box modified Q

$$Q = n(n+2) \sum_k \widehat{r}_k^2$$

Trend and Seasonal Decompositions

- Trend adjustments
 - Fit a regression model and subtract from TS to get residuals with no trend
 - Assumes constant trend historically and continuing into (immediate) future
 - Difference the TS
 - No parameter estimation (simpler)
- Seasonal adjustments
 - To eliminate seasonality say with lag = D
$$\nabla^D Y_t = (1 - B^D)Y_t = Y_t - Y_{t-D}$$
- Most TS require a combination of trend and seasonal adjustments

R code – Trends and Drift

- `ts.plot(cumsum(rnorm(1000, mean = 2, sd=sqrt(9))), col="purple", ylab="yt", ylim=range(-10:2000)) # RW + stochastic trend with beta = 2 and white noise variance = 9`
- `x <- 1:1000`
- `yt <- 2*x + rnorm(1000, sd = sqrt(9)) # RW + deterministic trend with beta = 2`
- `lines(x, yt, col="blue")`
- `lines(cumsum(rnorm(1000)), col="green") # RW with no trend`
- `legend(1,1999, legend=c("drift/stochastic trend", "deterministic trend", "no trend"), col=c("purple", "blue", "green"), lty=1:3, cex=0.8)`

Seasonal ARIMA

- Mathematically using the backward shift operator

$$B^s z^t = z_{t-s}, s \Rightarrow \text{seasonal period}$$

- TS represented as

$$\Phi(B^s)Y_t = \Theta(B^s)e_t$$

- Also, since errors are autocorrelated as in regular ARIMA, we also have

$$\Phi(B)Y_t = \Theta(B)e_t$$

- So multiplicative seasonal ARIMA is represented as

$$\Phi(B)\Phi(B^s)\nabla^d\nabla_s^D Y_t = \Theta(B)\Theta(B^s)e^t$$

R code – seasonal and trend difference

```
ts.plot(AirPassengers)
```

```
auto.arima(AirPassengers) # model_1 with d = 1 (ie trend diff) and D = 1 (ie seasonal diff)
```

```
# try to do both the diff manually
```

```
# trend diff
```

```
trendDiff <- diff(AirPassengers)
```

```
ts.plot(trendDiff) # the plot has seasonality
```

```
# seasonal diff
```

```
seasonalDiff <- diff(AirPassengers, 12)
```

```
ts.plot(seasonalDiff) # the plot has trend
```

```
# both trend and seasonal diff – order does not matter
```

```
comboDiff <- diff(seasonalDiff)
```

```
ts.plot(comboDiff)
```

```
auto.arima(comboDiff) # the model should be identical to mode_1
```

Textbook Chapters

- Materials covered available in books:
 - FPP: Chapter 8, MJK: Chapter 5, TSA: Chapters 7, 8, 10