

# Adjustment and diagnosis

Xiaodong Lin

# Box-cox transformation

- Variation changes with the level of the series.
- Box-cox transformation:

$$w_t = \begin{cases} \log(y_t) & \text{if } \lambda = 0; \\ (y_t^\lambda - 1)/\lambda & \text{otherwise.} \end{cases}$$

- The logarithm is natural log.
- Chose the proper  $\lambda$

```
#BoxCox.lambda() choose a value of lambda for you.  
lambda <- BoxCox.lambda(elec) # = 0.27  
plot(BoxCox(elec,lambda))
```

# Box-cox transformation

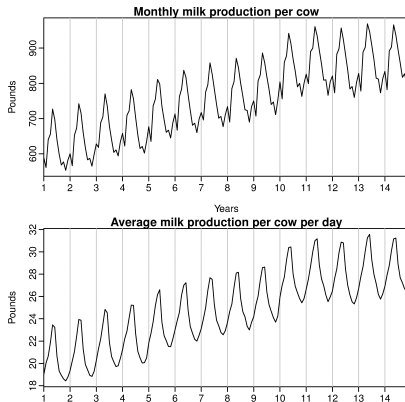
- Once a transformation is chosen, we need to forecast the transformed data

$$y_t = \begin{cases} \exp(w_t) & \text{if } \lambda = 0; \\ (\lambda w_t + 1)^{1/\lambda} & \text{otherwise.} \end{cases}$$

- If some  $y_t \leq 0$ , no power transformation is possible unless all observations are adjusted by adding a constant to all values.
- Choose a simple value of  $\lambda$ .
- Transformations sometimes make little difference to the forecasts but have a large effect on prediction intervals.

# Calendar adjustments

- Some variation seen in seasonal data may be due to simple calendar effects
- Calendar variation between the months due to different numbers of days in each month



# Calendar adjustments

- Seasonal pattern becomes much cleaner after adjustment.
- Similar adjustments can be done on number of trading days/month ect.
- Population adjustments
- Inflation adjustments: consumer price index(CPI).  
 $x_t = y_t / z_t \times z_{2000}$  gives the adjusted price at year 2000 dollar.

## R code

```
plot(log(elec), ylab="Transformed electricity demand",  
      xlab="Year", main="Transformed monthly electricity demand")  
title(main="Log",line=-1)
```

```
# The BoxCox.lambda() function chooses a value of lambda.  
lambda <- BoxCox.lambda(elec) # = 0.27  
plot(BoxCox(elec,lambda))
```

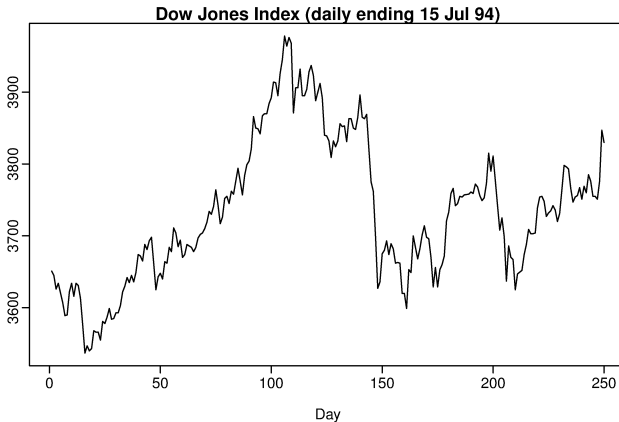
```
monthdays <- rep(c(31,28,31,30,31,30,31,31,30,31,30,31),14)  
monthdays[26 + (4*12)*(0:2)] <- 29  
par(mfrow=c(2,1))  
plot(milk, main="Monthly milk production per cow",  
      ylab="Pounds",xlab="Years")  
plot(milk/monthdays,  
      main="Average milk production per cow per day",  
      ylab="Pounds", xlab="Years")
```

# Residual diagnostics

- A residual in forecasting is  $\epsilon_t = y_t - \hat{y}_t$ .
- The residuals are uncorrelated.
- The residuals have zero mean.
- We also need to examine the variance and distribution of the residuals

# DJ index example

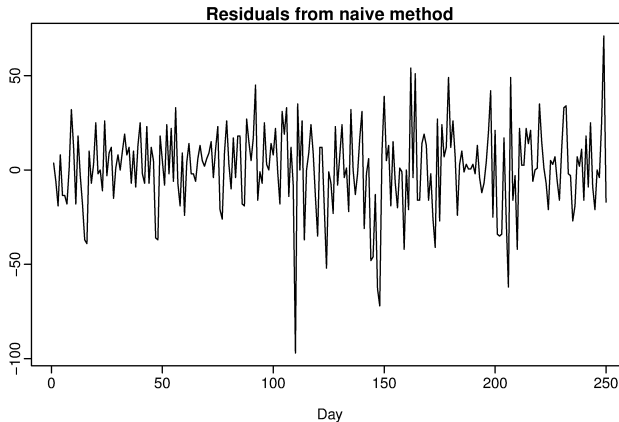
The daily DJ index for 250 days.





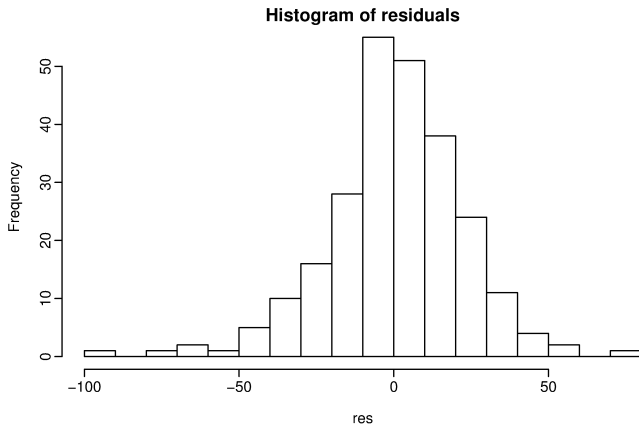
# DJ index example

Residuals computed from the naive method



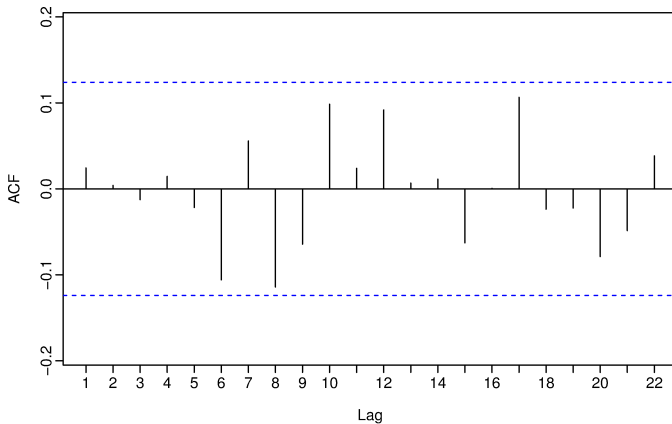
# DJ index example

## Histogram of the residuals



# DJ index example

The ACF plot



## R code

```
dj2 <- window(dj, end=250)
plot(dj2, main="Dow Jones Index (daily ending 15 Jul 94)",
     ylab="", xlab="Day")
res <- residuals(naive(dj2))
plot(res, main="Residuals from naive method",
     ylab="", xlab="Day")
Acf(res, main="ACF of residuals")
hist(res, nclass="FD", main="Histogram of residuals")

# lag=h and fitdf=K
> Box.test(res, lag=10, fitdf=0)
      Box-Pierce test
X-squared = 10.6425, df = 10, p-value = 0.385

> Box.test(res, lag=10, fitdf=0, type="Lj")
      Box-Ljung test
X-squared = 11.0729, df = 10, p-value = 0.3507
```