

# Time Series Analysis

## Basics of Time Series Analysis

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Decomposition: Trend Estimation

# About This Lesson



# Time Series: Basics

**Data:**  $Y_t$ , where  $t$  indexes time, e.g. minute, hour, day, month

**Model:**  $Y_t = m_t + s_t + X_t$

- $m_t$  is a trend component;
- $s_t$  is a seasonality component with known periodicity  $d$  ( $s_t = s_{t+d}$ ) such that  $\sum_{j=1}^d s_j = 0$
- $X_t$  is a stationary component, i.e. its probability distribution does not change when shifted in time

**Approach:**  $m_t$  and  $s_t$  are first estimated and subtracted from  $Y_t$  to have left the stationary process  $X_t$  to be model using time series modeling approaches.

# Exploratory Analysis

## # Load BTC data

```
databtc = read.csv('BTC-USD.csv',header = TRUE)
pricebtc = databtc[,c(5)]
mydates=as.Date(databtc[, 1], "%m/%d/%Y")
tsbtc=xts(pricebtc,mydates)
dlbtc=diff(log(tsbtc))[-c(1),]
```

## # Display BTC data

```
plot(tsbtc,main='BTC-USD')
acf(tsbtc,main='ACF of BTC')
```

## # Display BTC log differenced data

```
plot(dlbtc,main='Diff_log_BTC')
acf(dlbtc[-1],main='ACF of Diff_log_BTC')
```

# Trend: Moving Average

Estimate the trend for  $t$  with a width of the moving window  $d$ :

If the width is  $d = 2q$ , use

$$\hat{m}_t = \frac{1}{d} \left[ \frac{x_{t-q}}{2} + x_{t-q+1} + x_{t-q+2} + \dots + x_{t+q-1} + \frac{x_{t+q}}{2} \right]$$

If the width is  $d = 2q + 1$ , use

$$\hat{m}_t = \frac{1}{d} \sum_{j=-q}^q x_{t+j}$$

The width selection reflects the bias-variance trade-off:

- If width large, then the trend is smooth (i.e. low variability)
- If width small, then the trend is not smooth (i.e. low bias)

# Trend: Parametric Regression

Estimate the trend  $m_t$  assuming a polynomial in  $t$ :

$$m_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \dots + \beta_p t^p$$

- Commonly use small order polynomial ( $p=1$  or  $2$ )
- Estimation approach: Fit a linear regression model where the predicting variables are  $(t, t^2, \dots, t^p)$
- Which terms to keep? Use model selection to select among the predicting variables. **Cautious!** Strong correlation among the predicting variables.

# Trend: Non- Parametric Regression

Estimate the trend  $m_t$  with  $t$  in  $\{t_1, t_2, \dots, t_n\}$ :

## 1. Kernel Regression

$m_t = m(t) = \sum_{i=1}^n l_i(t)X_{t_i}$  where  $l_i(t)$  a weight function depending on a kernel function.

## 2. Local Polynomial Regression

- An extension of the kernel regression and the polynomial regression: fit a local polynomial within a width of a data point

## 3. Other Approaches

- Splines regression
- Wavelets
- Orthogonal basis function decomposition

# Trend: Non- Parametric Regression

## **Which one to choose?**

- Local polynomial regression is preferred over kernel regression since it overcomes boundary problems and its performance is not dependent on the design of the time points
- Other methods are to be selected depending on the level of smoothness of the function to be estimated
- For estimating the trend in time series, local polynomial or splines regression will perform well in most cases



# Summary

