Time Series

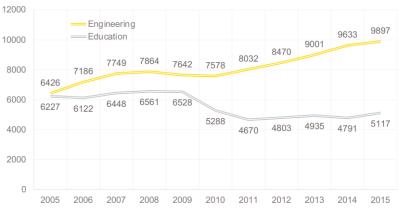
Cross Sectional Data: Multiple objects observed at a particular point of time

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- Examples: customers' behavioral data at today's update,companies' account balances at the end of the last year,patients' medical records at the end of the current month.

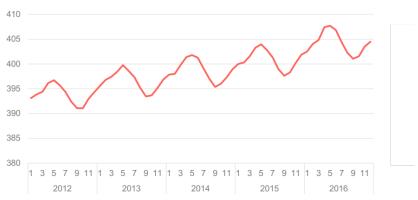
► Time Series Data: One single object (product, country, sensor, ..) observed over multiple equally-spaced time periods

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- ➤ Examples: quarterly Italian GDP of the last 10 years, weekly supermarket sales of the previous year, yesterday's hourly temperature measurements.

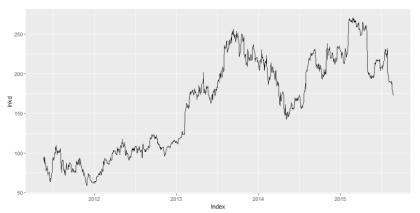
Numbers of Doctorates Awarded in US, annual data – Engineering Vs. Education



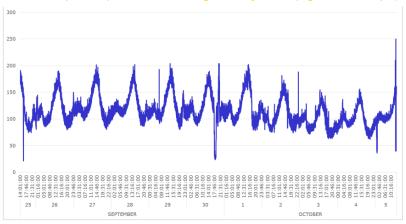




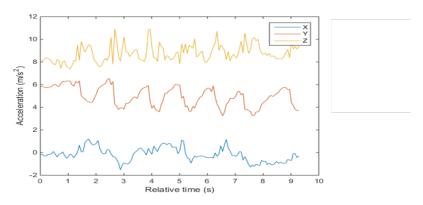
LinkedIn daily stock market closing price

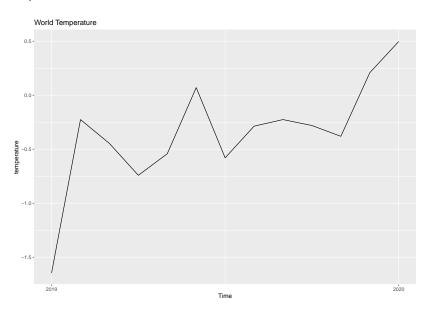


Number of photos uploaded on the Instagram every minute (regional sub-sample)



Acceleration detected by a smartphone sensors during a workout session (10 seconds)





What to do with time series?

- ▶ Understanding of specific series features or pattern
- Forecasting

Smoothing

Smoothing

Smoothing is usually done to reveal the series patterns and trends.

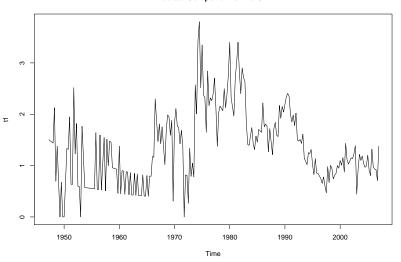
Simple Moving Average Smoothing

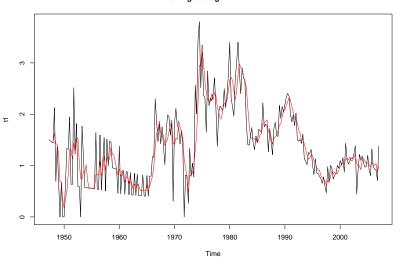
- Moving Average (MA) creates a new series by averaging the most recent observations from the original series.
- \blacktriangleright MA(k) creates s_t as follows.

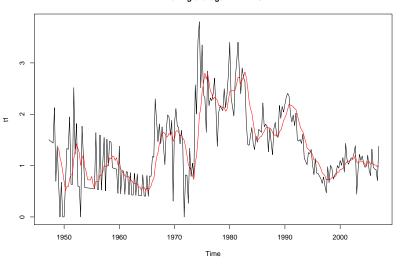
$$s_t = \frac{y_t + y_{t-1} + \ldots + y_{t-k+1}}{k}$$

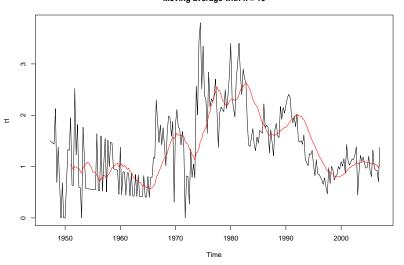
ightharpoonup Larger k will smooth the series more strongly

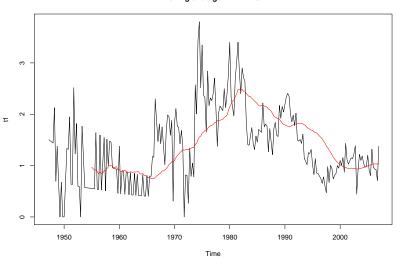
Medical Component of the CPI



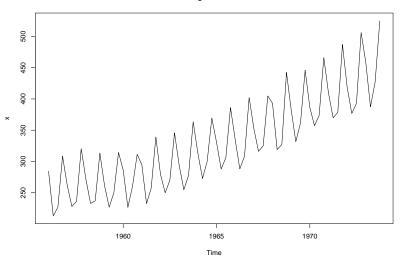


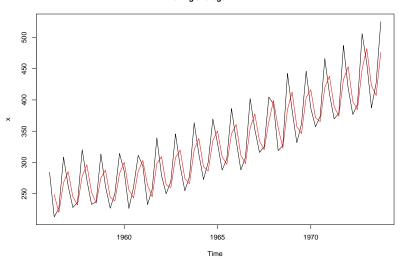


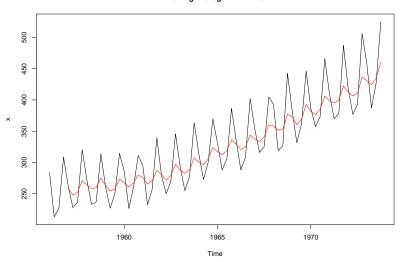


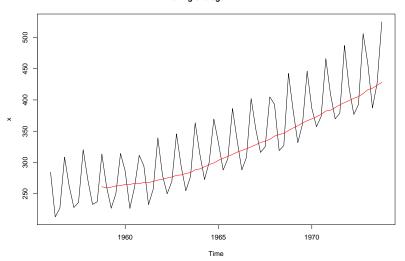


Original Series









Forecasting

- ▶ We can use MA smoothing for forecasting
- ► We have

$$\begin{split} s_t &= \frac{y_t + y_{t-1} + \ldots + y_{t-k+1}}{k} \\ &= \frac{y_t + y_{t-1} + \ldots + y_{t-k+1} + y_{t-k} - y_{t-k}}{k} \\ &= \frac{y_t + \left(y_{t-1} + \ldots + y_{t-k+1} + y_{t-k}\right) - y_{t-k}}{k} \\ &= \frac{y_t + ks_{t-1} - y_{t-k}}{k} \\ &= s_{t-1} + \frac{y_t - y_{t-k}}{k} \end{split}$$

Forecasting

- \blacktriangleright If there is no trend in y_t the second term $(y_t-y_{t-k})/k$ can be ignored
- Forecasting l lead time into future by (\hat{y}_{T+l}) is a forecast of y_{T+l})

$$\hat{y}_{T+l} = s_T$$

If there is a linear trend in a series, we can use the double moving average to estimate the trend (slope)

Double MA

Double MA

Linear trend time series:

$$y_t = \beta_0 + \beta_1 t + \epsilon_t$$

▶ Step 1: MA Smooth the series

$$s_t^{(1)} = \frac{y_t + y_{t-1} + \dots + y_{t-k+1}}{k}$$

▶ Step 2: MA Smooth the smoothed series

$$s_t^{(2)} = \frac{s_t^{(1)} + s_{t-1}^{(1)} + \dots + s_{t-k+1}^{(1)}}{k}$$

► Step 3: Calculate the linear trend/slope

$$b_1 = \hat{\beta}_1 = \frac{2}{k-1} \bigg(s_T^{(1)} - s_T^{(2)} \bigg)$$

Forecasting

 \triangleright Forecasting l lead time into future by

$$\hat{y}_{T+l} = s_T^{(1)} + b_1 \cdot l$$

You are given the following time series

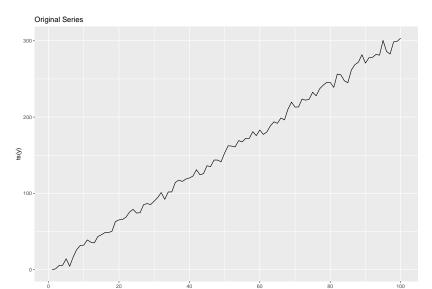
\overline{t}	1	2	3	4	5
y_t	1	3	5	8	13

- \blacktriangleright Forecasting y_6 using simple moving average with k=2
- \blacktriangleright Forecasting y_6 using double moving average with k=2

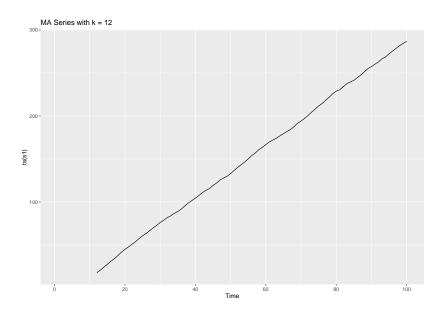
 \blacktriangleright We simulate 100 data points (T=100) of

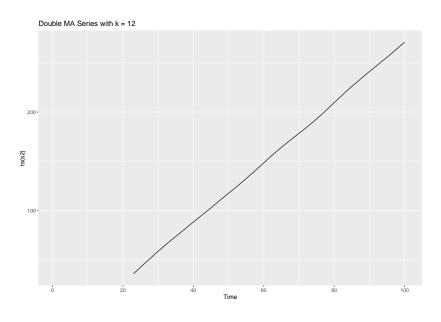
$$y_t = 1 + 3t + \epsilon,$$

where, $\epsilon \sim N(0, 5^2)$.



Time





- lacksquare Using the above steps, the estimated trend is $b_1=2.92$
- lacksquare The forecast for the next points from y_{100} is

$$\hat{y}_{100+l} = s_{100} + b_1 \cdot l = s_{100} + 2.92 \cdot l$$