

# Chapter 09

# Time Series Analysis

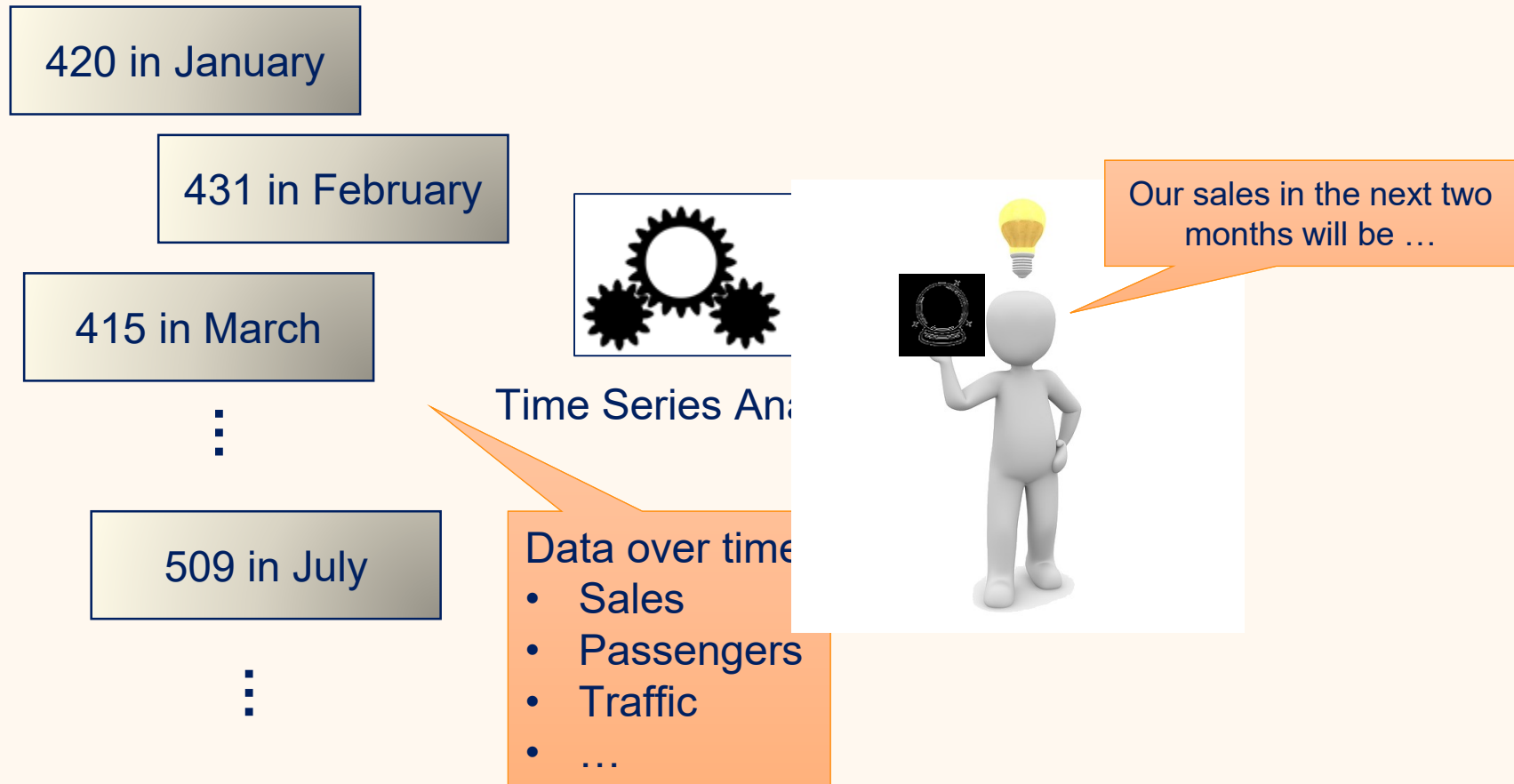
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# Outline

- Overview
- Methods for Time Series Analysis
- Summary

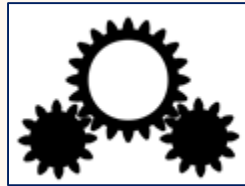
# Example of Time Series Analysis



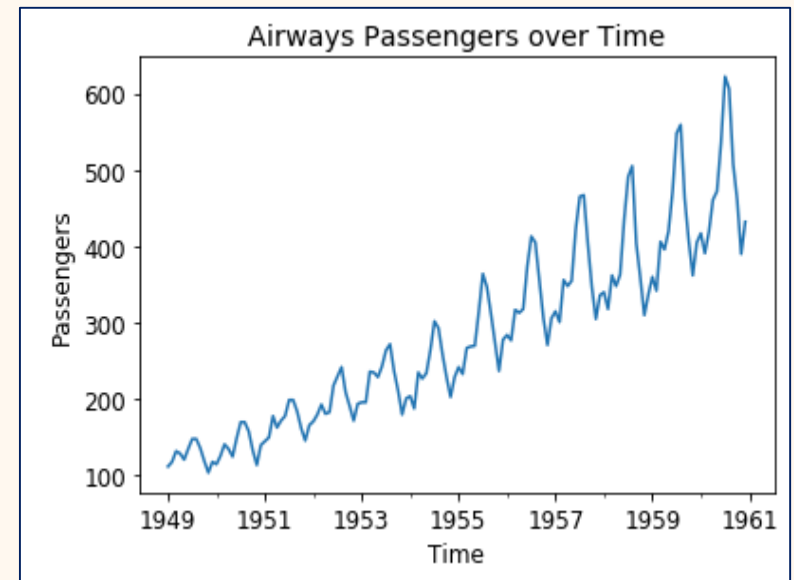
# The General Problem

## Data over time

- Value at time point 1
- Value at time point 2
- Value at time point 3
- Value at time point 4
- Value at time point 5
- Value at time point 6
- Value at time point 7
- Value at time point 8
- Value at time point 9
- ...



## Time Series Analysis



# The Formal Problem

- Discrete values over time
  - $\{x_1, \dots, x_T\} = \{x_t\}_{t=1}^T$  with  $x_t \in \mathbb{R}$
  - Can be seen as a series of random variables or a stochastic process
  - Time between  $t$  and  $t + 1$  must be equal for all  $t = 1, \dots, T - 1$ 
    - Minutes, hours, days, weeks, months, ...
- Components of a time series
  - General trend of the time series  $T_t$
  - Seasonal effects on the time series  $S_t$
  - Autocorrelation between observations  $R_t$
  - $x_t = T_t + S_t + R_t$

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- **Methods for Time Series Analysis**
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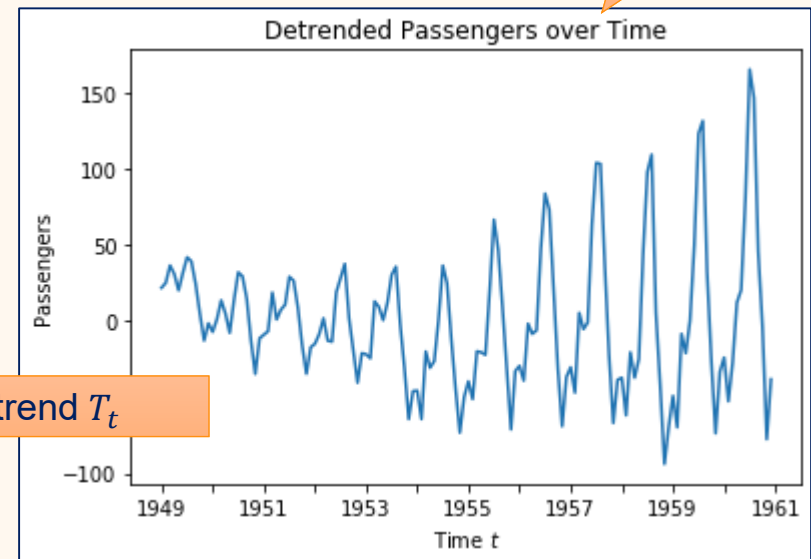
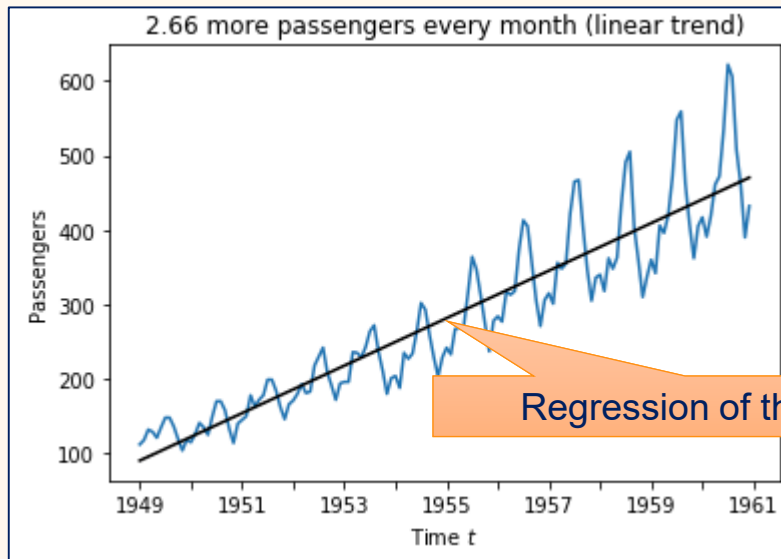
# Time Series Analysis with Box-Jenkins

- For stationary data
  - Stationary means constant mean value and variance  
→ Requires de-trending and seasonal adjustment
- Models autocorrelation as a stochastic process
  - Observations depend on past observation and a random component
- Tries to model time series with only few parameters
  - Goal are simple models

# Detrending Through Regression

Detrended series

$$x_t - T_t$$

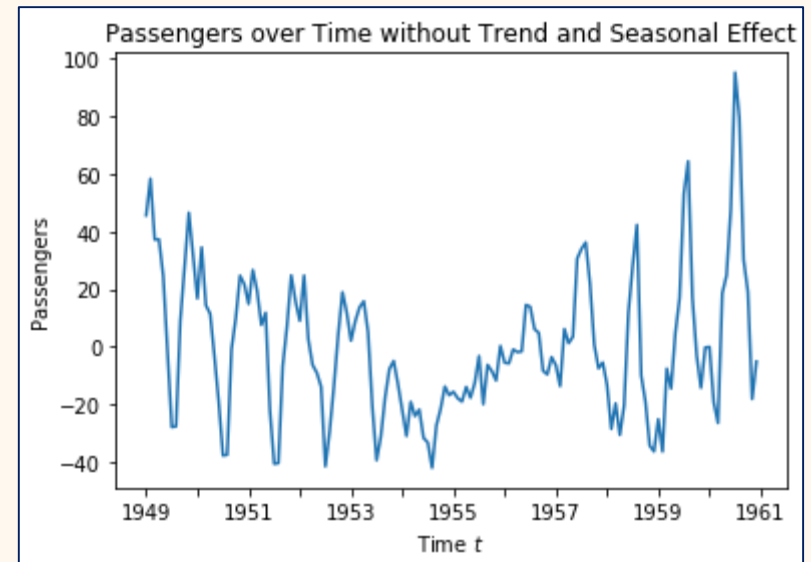
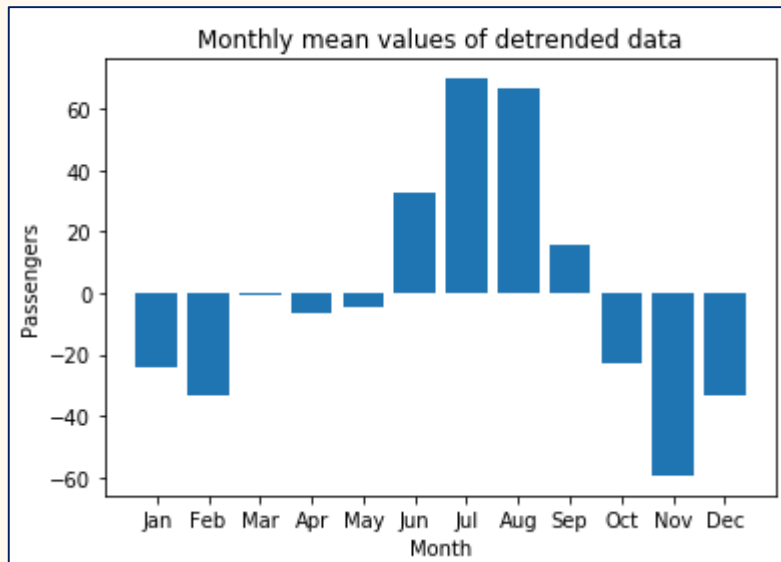


- Non-linear regression for non-linear trends



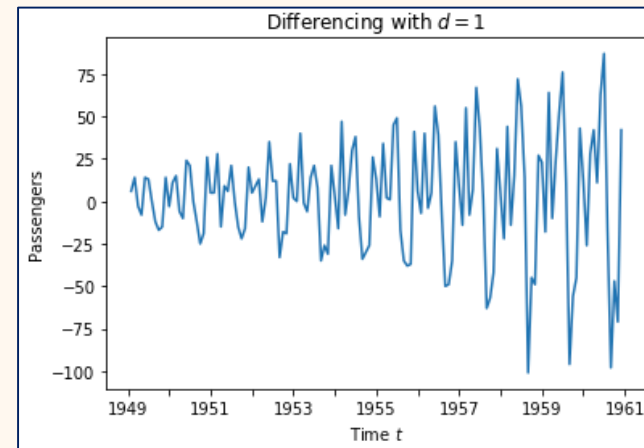
# Seasonal Adjustment through the Mean

- Seasonal effect:
  - A regularly repeating pattern
  - Monthly, weekly, ...
- Seasonal adjustment through the seasonal mean value



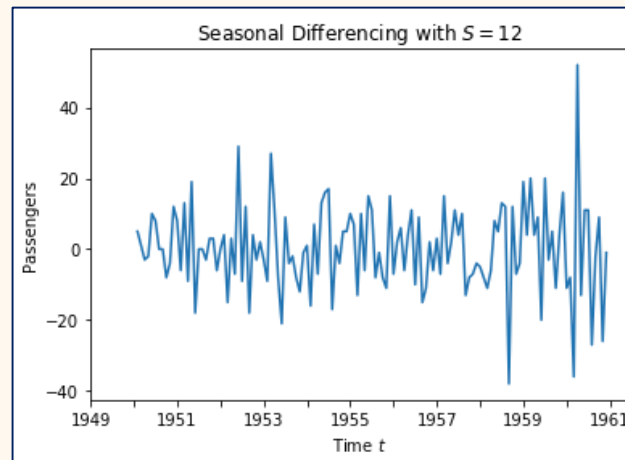
# Differencing for Detrending

- Instead of regression / removal of mean seasonal effects
- Differencing for detrending of order  $d$ 
  - First difference for moving mean values ( $d = 1$ )
    - Similar to linear trends
    - $\Delta^1 x_t = x_t - x_{t-1}$
  - Second difference for moving mean and the change in the movement ( $d = 2$ )
    - Similar to quadratic trends
    - $\Delta^2 x_t = \Delta^1 x_t - \Delta^1 x_{t-1} = x_t - 2x_{t-1} + x_{t-2}$

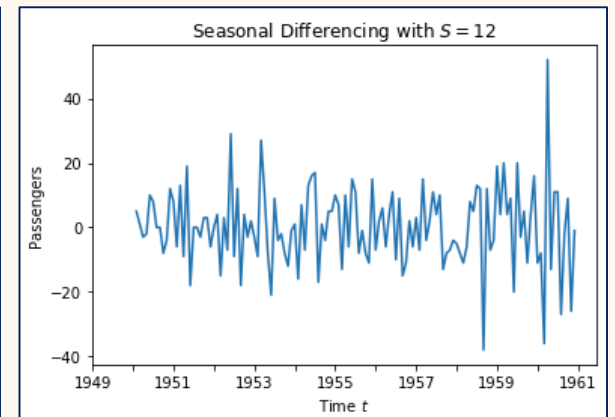
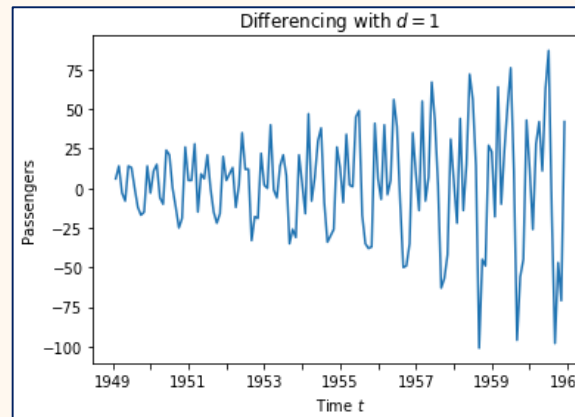
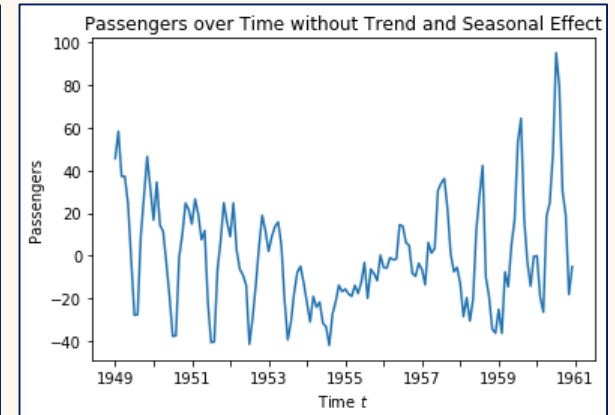
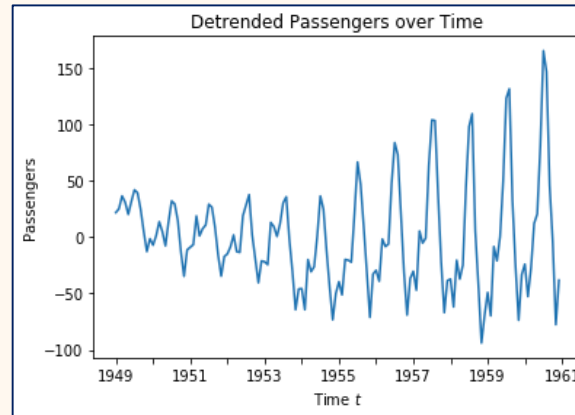
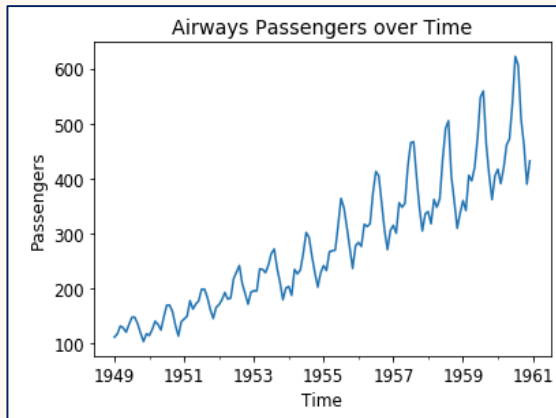


# Differencing for Seasonal Adjustment

- Seasonal differencing for seasons of periodicity  $S$ 
  - $\Delta_S x_t = x_t - x_{t-S}$
  - $\Delta_S^{12} x_t = x_t - x_{t-12}$  would be seasonal differencing for monthly data

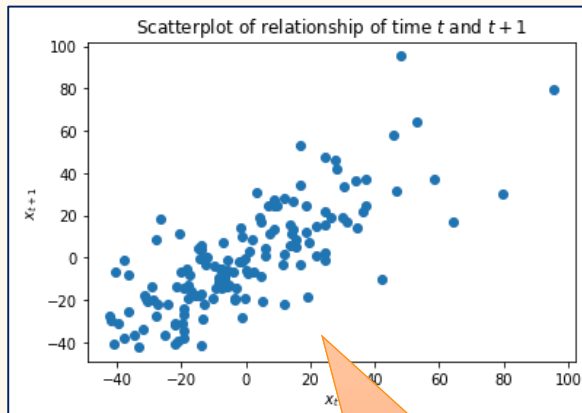


# Comparison of Adjustments

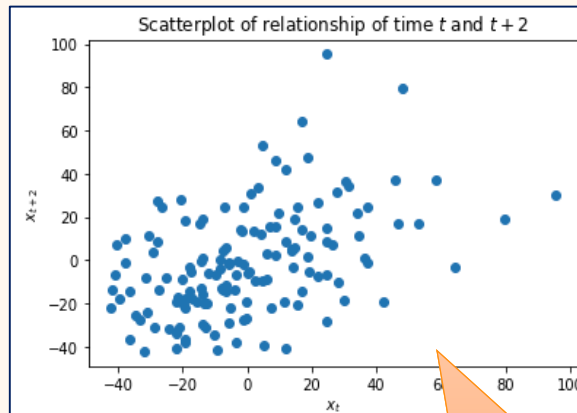


# Autocorrelation

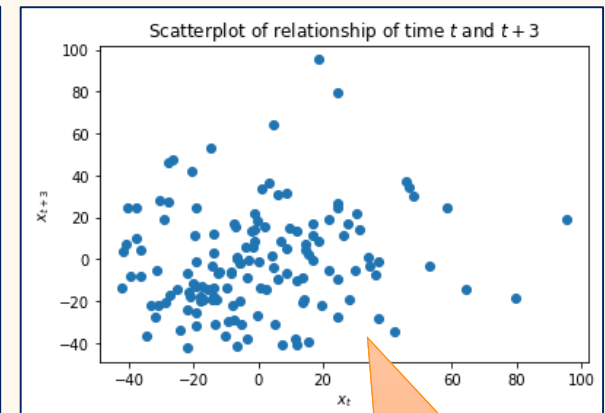
- Relationship between time series values with other time series values



Fairly linear relationship

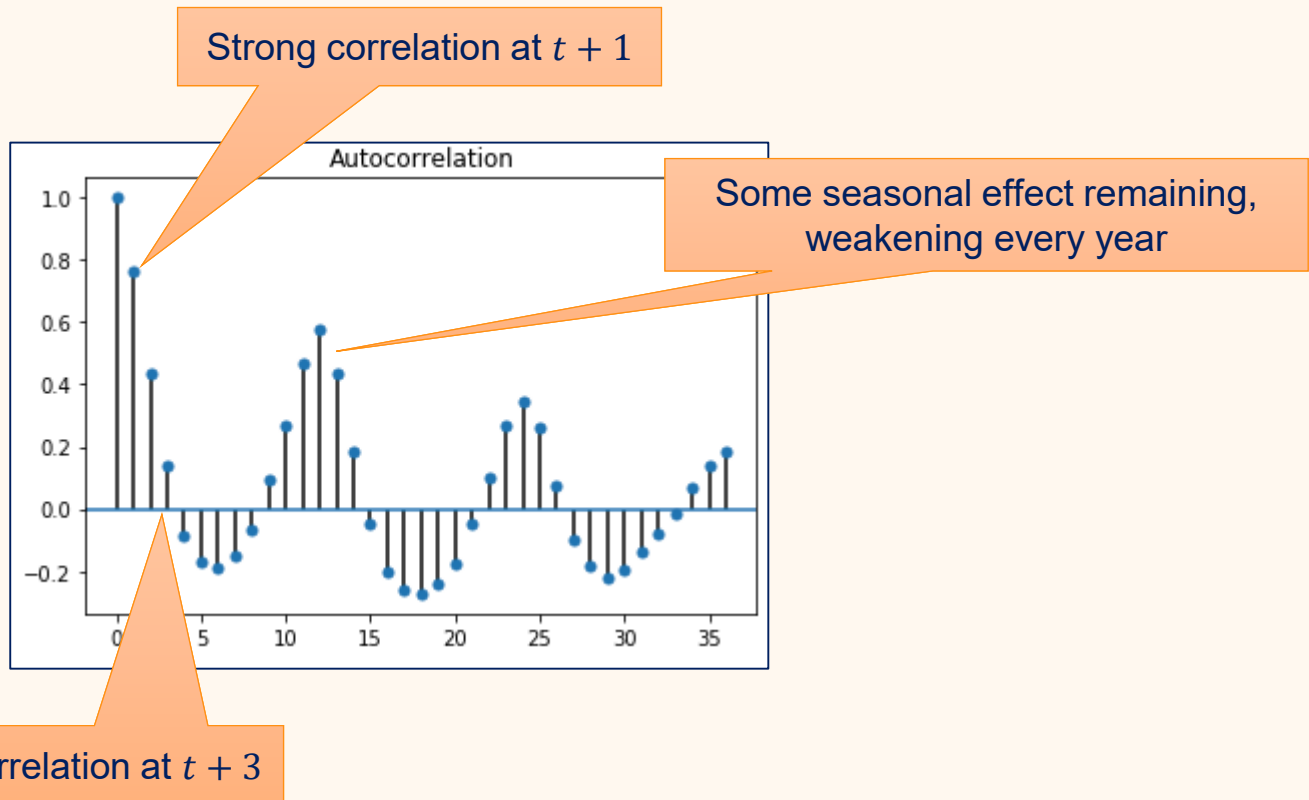


Spread increasing



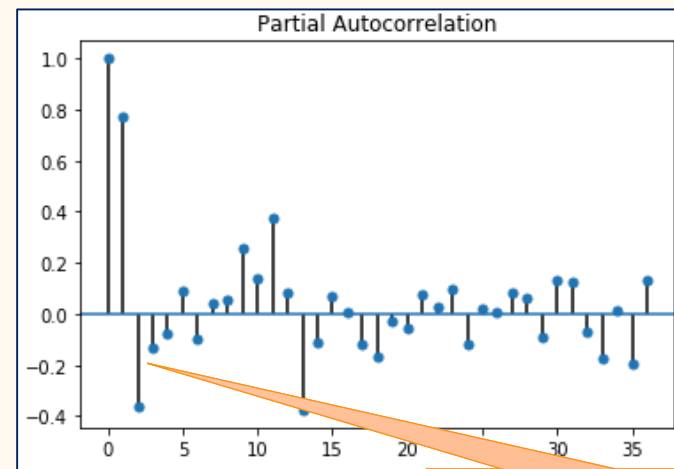
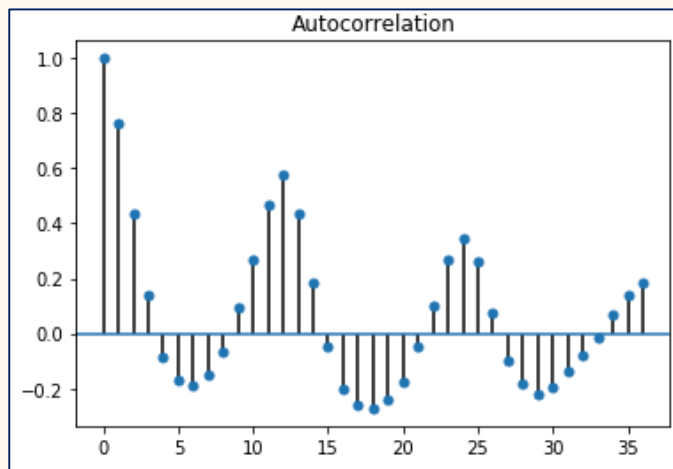
More or less random

# Autocorrelation over Time



# Partial Autocorrelation

- Autocorrelation that is not explained by „carrying over“
  - $x_t$  and  $x_{t+1}$  are correlated
  - $x_{t+1}$  and  $x_{t+2}$  are correlated
  - How much of the correlation between  $x_t$  and  $x_{t+2}$  is not explained by the above correlations?
  - In other words, how much of the correlation between  $x_t$  and  $x_{t+2}$  is independent of the correlation between  $x_t / x_{t+1}$  and  $x_{t+1} / x_{t+2}$ ?



Correlation at  $t + 2$   
explained by auto  
correlation at  $t + 1$

# ARMA Time Series Models

- Requires detrended and seasonally adjusted data
- Model for the autocorrelation part  $R_T$  of a time series

$$x_t = a_0 + \underbrace{\sum_{i=1}^p a_i x_{t-i}}_{\text{Autoregressive (AR)}} + \underbrace{\epsilon_t + \sum_{j=1}^q b_j \epsilon_{t-j}}_{\text{Moving Average (MA)}}$$

$\epsilon_i$  is a random variable with an expected value of 0  
→ white noise

Autoregressive (AR)   Moving Average (MA)

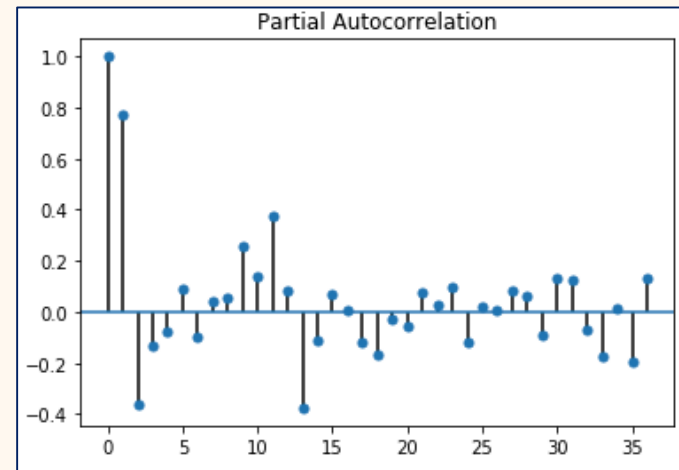
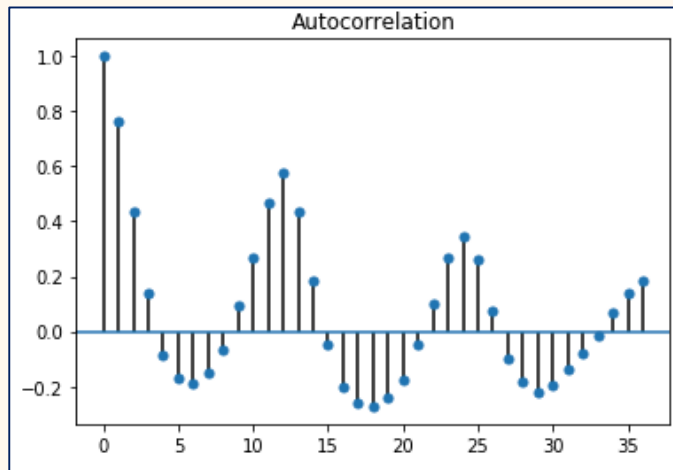
Constant plus linear combination of the  $p$  past values

Noise term + linear combination of last  $q$  noise values



# Picking $p$ and $q$

- Analyze (partial) autocorrelation function
  - $p = 1$  would model everything except the missing seasonal effect
  - $p = 12$  would capture missing seasonal effect at the cost of a more complex model
  - $q = 0$  or  $q = 1$  to account for low random fluctuations



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# Summary

- Time series analysis considers data over time
  - Equal intervals
- More than just regression
  - Seasonal effects
  - Autocorrelation
- Complex topic with many options for modelling
  - Trend detection
  - Seasonal adjustment
  - Autocorrelation modelling
  - Completely different approaches, e.g., based on neural networks