



# CIS 678 Machine Learning

Time series data modeling



# Outline

- How are the time series problems different than non time series problems
- Stationary vs non-stationary signals
- Signal decomposition
- AR(I)MA: Autoregressive Integrated Moving Average
  - From non no-stationary to stationary
  - Auto Regression
  - Moving Average



# How are the time-series problems different?

- The models (Regression and Classification), we have learned so far are of the form:

$$f(y|X)$$

- For certain data, especially the time series, we can take advantage of the form:

$$f(y_t|X, y_{t-1}, y_{t-2}, \dots, y_0); \text{ essentially, here the input features are } X \text{ plus the lagged instances of the target } y.$$

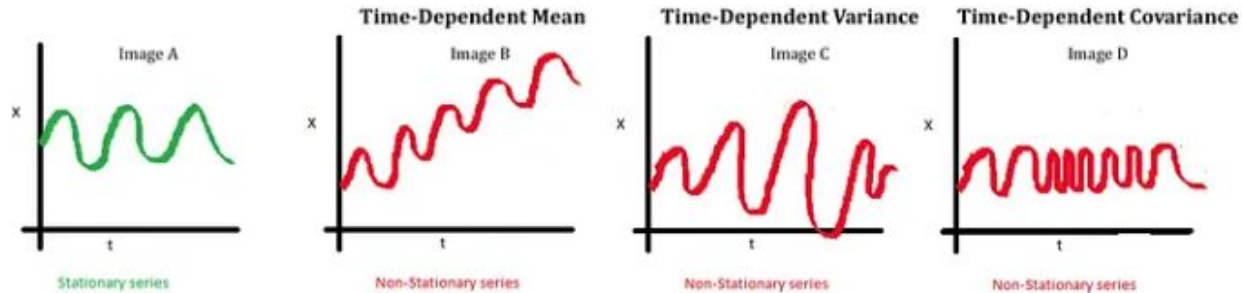
- Purely time series models are of form :

$$f(y_t|y_{t-1}, y_{t-2}, \dots, y_0), \text{ where there is no explicit, } X.$$

# Stationarity vs non-stationary signals

- A time-series is said to be stationary if it does not display any trends or seasonality.
- One more way of defining stationarity is that it is when data does not have any time-dependent mean, variance or covariance.

## The Principles of Stationarity



[ref](#)



# Non stationary to stationary

- If signal is non-stationary, we can convert them into stationary signal by differencing

$$T_t = S_t - S_{t-1},$$



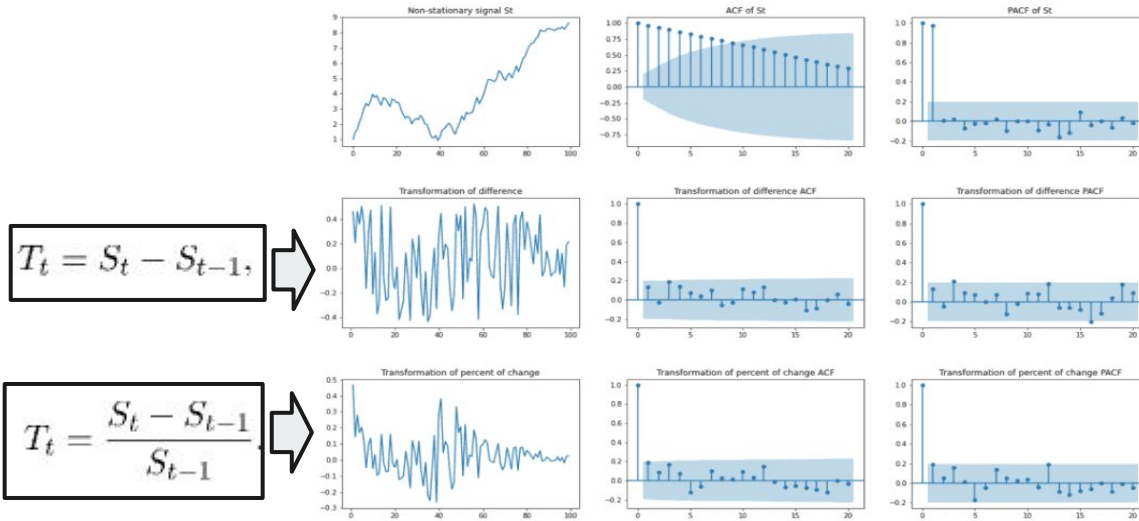
## Non stationary to stationary

- If signal is non-stationary, we can convert them into stationary signal by differencing
- or calculating percent of change

$$T_t = S_t - S_{t-1},$$

$$T_t = \frac{S_t - S_{t-1}}{S_{t-1}}.$$

# Non stationary to stationary





# Statistical time series models

- Moving Average (MA)
- Autoregressive Models (AR)
- Autoregressive Moving Average (ARMA)
- Autoregressive Moving Integrated Average (ARIMA)

$$f(y_t | y_{t-1}, y_{t-2}, \dots, y_0)$$





# AR(I)MA

- AutoRegressive Integrated Moving Average (ARIMA) is a statistical model for forecasting time series data.

A combined model with **AR**, **MA**, but first transforming the signal to stationary.

- **AR (Autoregression):** This emphasizes the dependent relationship between an observation and its preceding or 'lagged' observations.
- **I (Integrated):** To achieve a stationary time series, one that doesn't exhibit trend or seasonality, differencing is applied. It typically involves subtracting an observation from its preceding observation.
- **MA (Moving Average):** This component zeroes in on the relationship between an observation and the residual error from a moving average model based on lagged observations.



# AR(I)MA

The parameters of the ARIMA(p,d,q) model are defined as follows:

- **p**: The lag order, representing the number of lag observations incorporated in the model.
- **d**: Degree of differencing, denoting the number of times raw observations undergo differencing.
- **q**: Order of moving average, indicating the size of the moving average window.

A combined model with **AR**, **MA**, but first transforming the signal to stationary.

[ref](#)



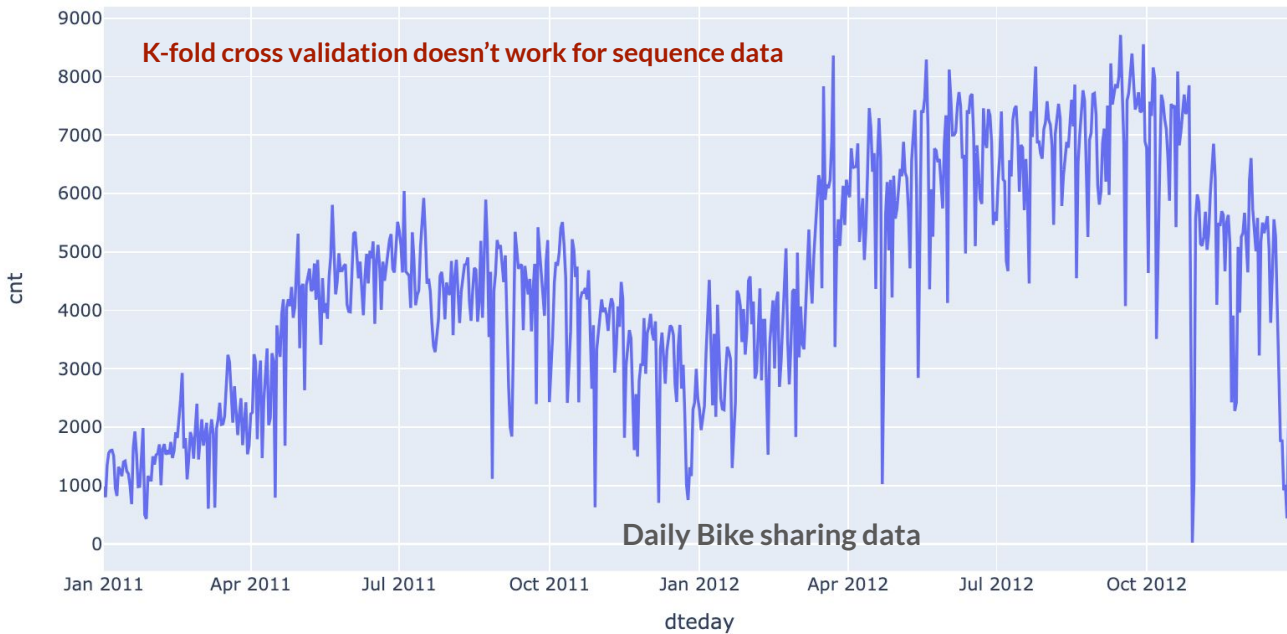
# Notebook presentation

Notebook



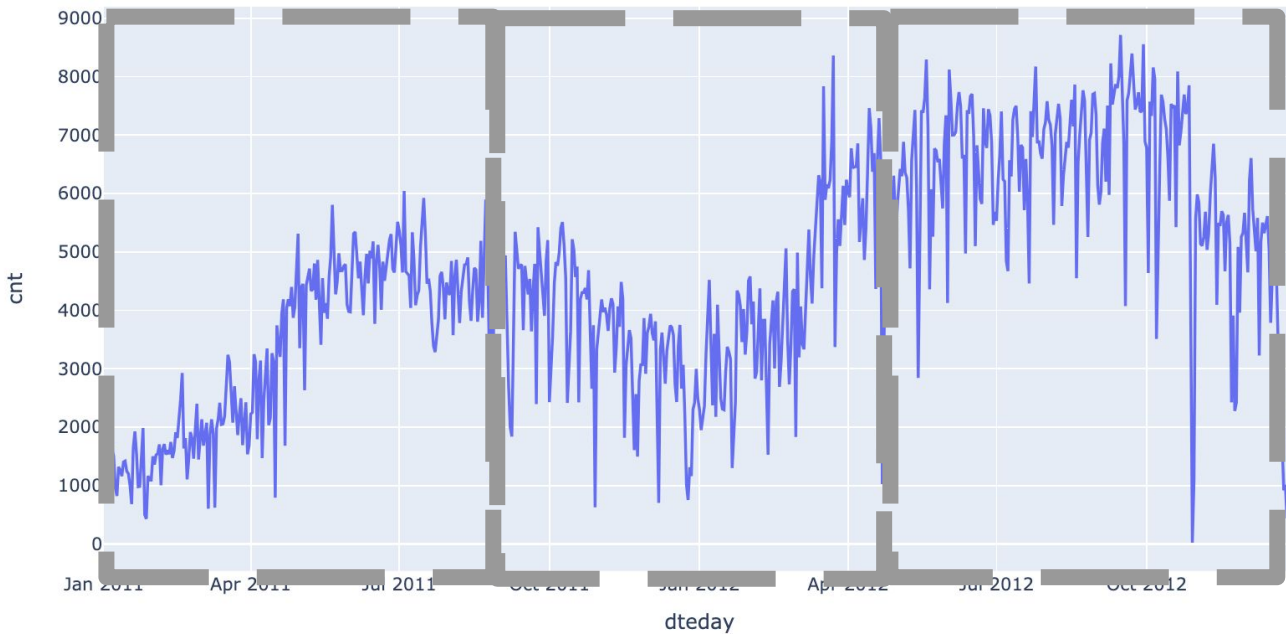
# Sequential cross validation

# Sequential cross validation





## Sequential cross validation



# Sequential cross validation



Valid configuration:

Training on **first**  
**two folds**, and test  
on the **last fold**

# Sequential cross validation



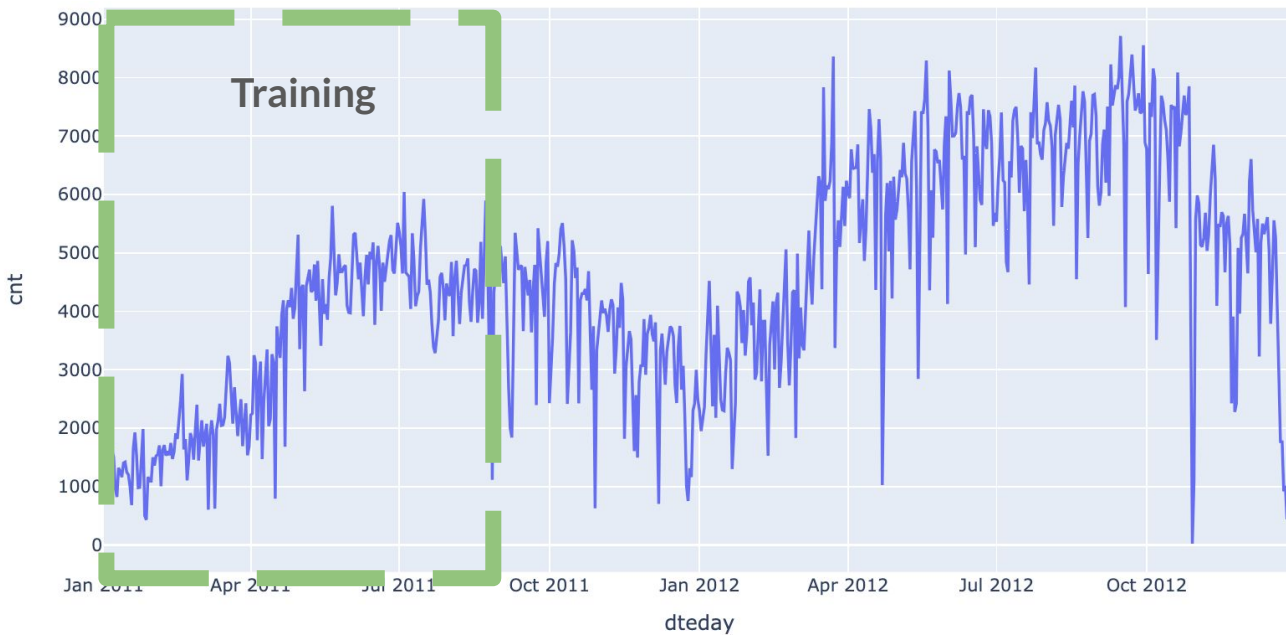
*Invalid  
configuration:  
Training on **first  
fold**, and test on the  
last two.*





# Sequential cross validation

# Sequential cross validation



*Always follow!*

# Sequential cross validation



*Always follow!*

# Sequential cross validation



*Always follow!*

# Sequential cross validation



*Always follow!*



**QA**