NUS Fintech Society

Machine Learning Department

Training Wing

Session 3: Time Series (19/9/2020)

Content

- Intro to time series forecasting
- Decomposition
- Simple Moving Average
- ACF and PACF
- Autoregressive Model (AR)
- ARMA Model
- ARIMA Model
- Stock forecasting with GARCH
- Release of Project 1
- Activity

1. Intro to Time Series forecasting

Let’s start with some basics

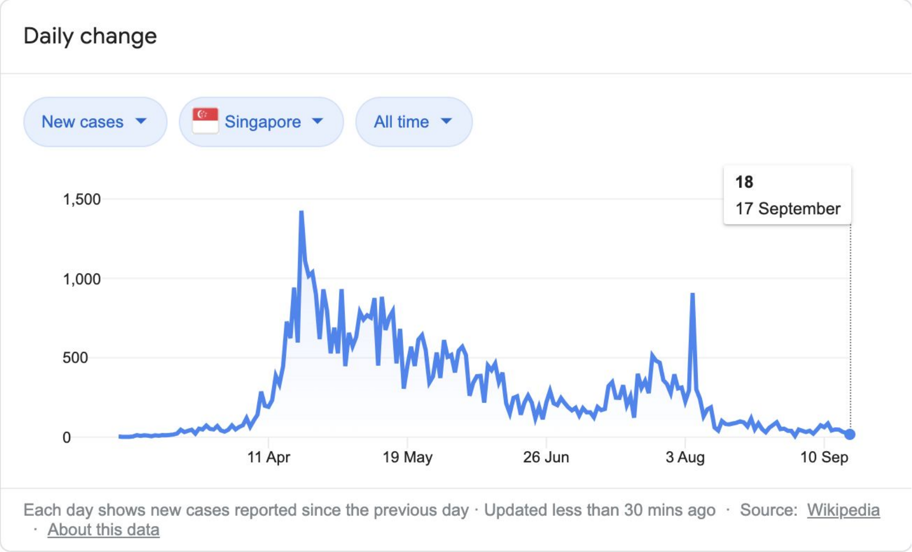
1. Intro to Time Series forecasting

A **time series** is a series of data points indexed (or listed or graphed) in time order.

Most commonly, a time series is a sequence taken at successive equally spaced points in time.

Time series forecasting is the use of a model to predict future values based on previously observed values.

Examples of Time Series



2. Decomposition

The classical way

Time Series Components

Trend	Reflects the long-term progression of the series
Cyclical	Reflects repeated but non-periodic fluctuations
Seasonal	Seasonal pattern exists when a time series is influenced by seasonal factors. Seasonality occurs over a fixed and known period (e.g., the quarter of the year, the month, or day of the week).
Noise	Represents the residuals or remainder of the time series after the other components have been removed.

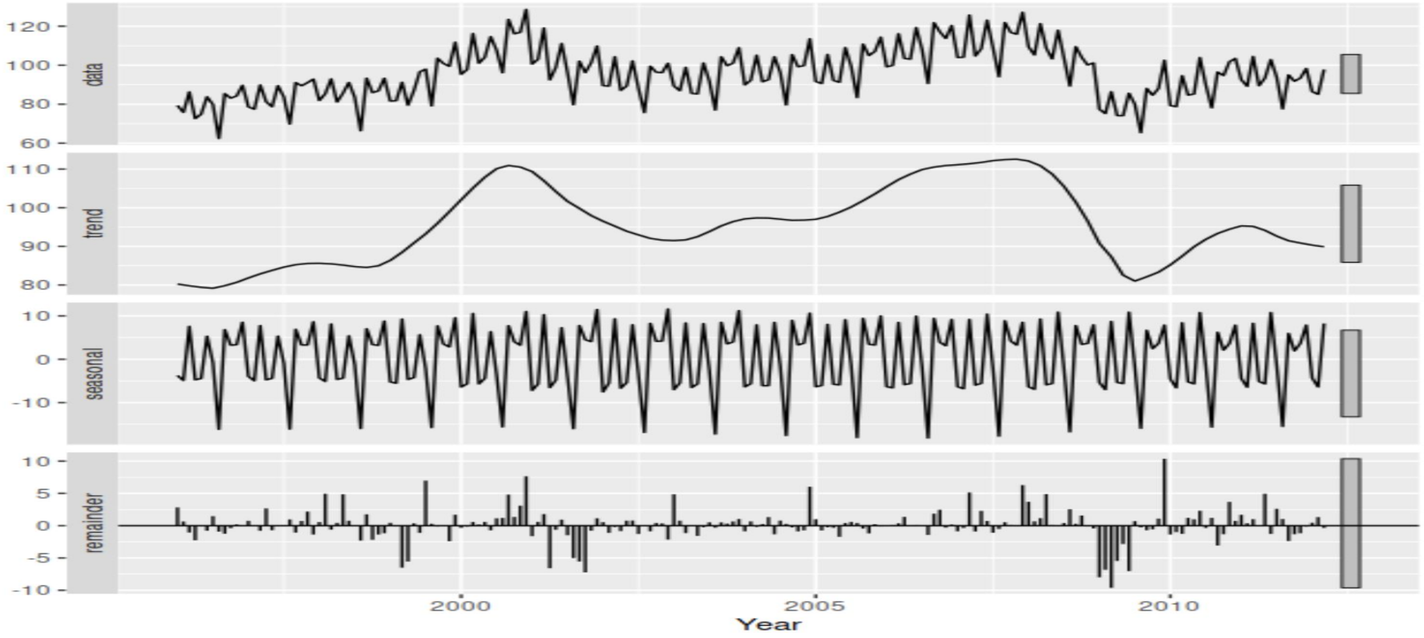
Classical decomposition include additive and multiplicative decomposition

statsmodels.tsa.seasonal.seasonal_decompose

Time Series Components

Additive: y(t) = Trend-Cycle + Seasonality + Noise

Multiplicative: y(t) = Trend-Cycle * Seasonality * Noise



3. Simple Moving Average

It is really very simple

3. Simple Moving Average

A simple moving average (SMA) is an arithmetic moving average calculated by adding recent values and then dividing that by the number of time periods in the calculation average.

Formula

Simple Moving Average

$$\bar{p}_{\text{SM}} = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i}.$$

Weighted Moving Average

$$\text{WMA}_M = \frac{np_M + (n-1)p_{M-1} + \cdots + 2p_{(M-n+2)} + p_{(M-n+1)}}{n + (n-1) + \cdots + 2 + 1}$$

Cumulative Moving Average

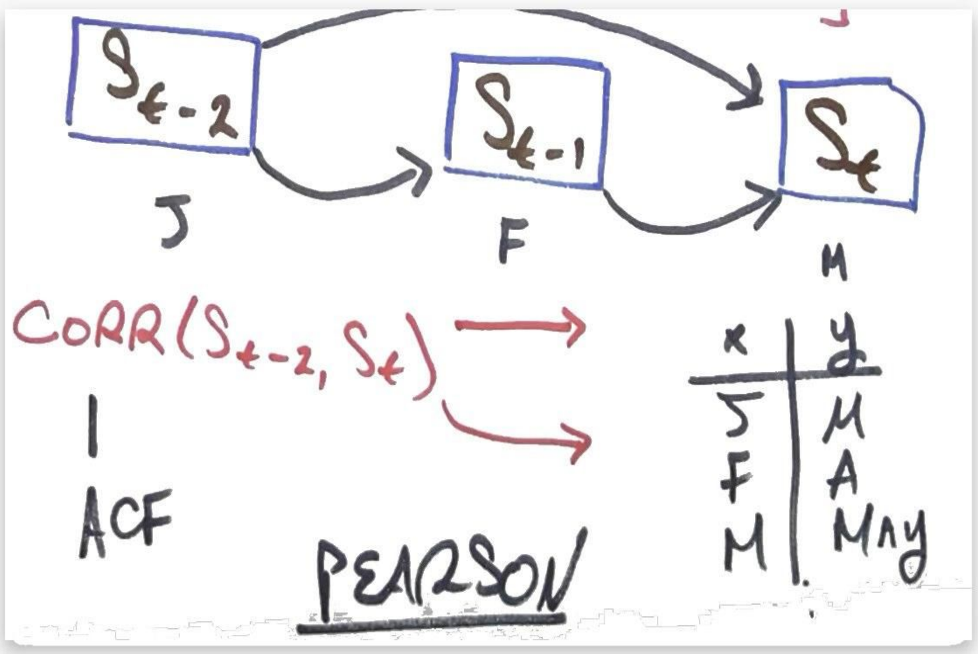
$$CMA_n = \frac{x_1 + \cdots + x_n}{n}.$$

Exponential Moving Average

$$EMA_{\text{Today}} = \left(\text{Value}_{\text{Today}} * \left(\frac{\text{Smoothing}}{1 + \text{Days}}\right)\right) + EMA_{\text{Yesterday}} * \left(1 - \left(\frac{\text{Smoothing}}{1 + \text{Days}}\right)\right)$$

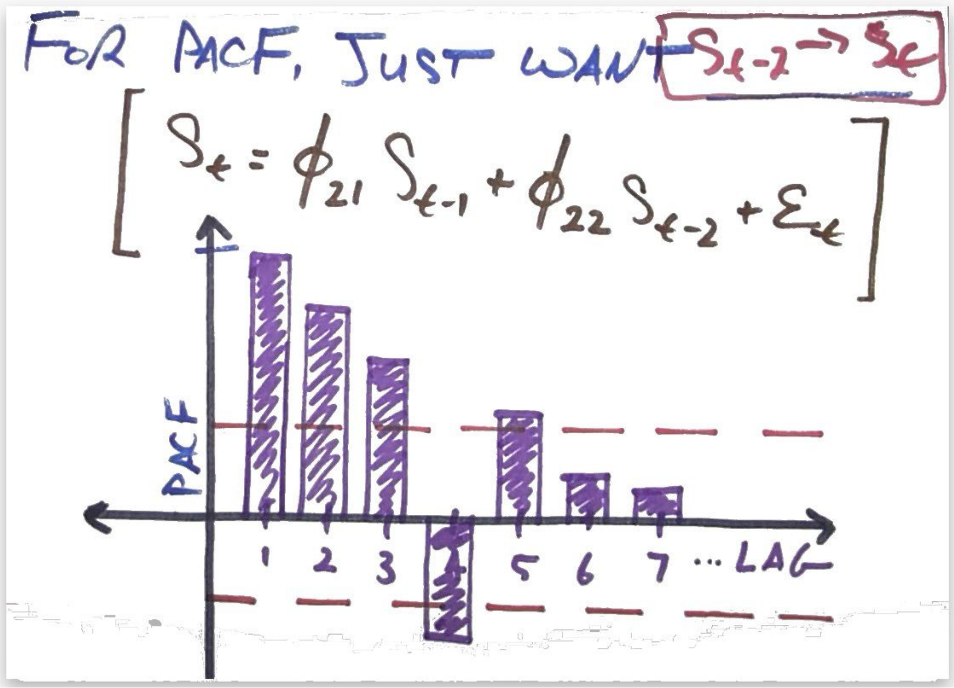
4. Autocorrelation (ACF) and Partial autocorrelation (PACF)

Autocorrelation Function



Measures both direct and indirect effect

Partial Autocorrelation Function



Measures only the direct effect

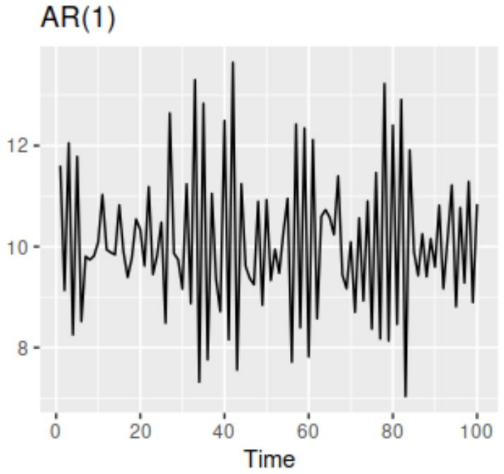
$\tilde{y}_t = \phi_{21}\tilde{y}_{t-1} + \phi_{22}\tilde{y}_{t-2} + e_t$

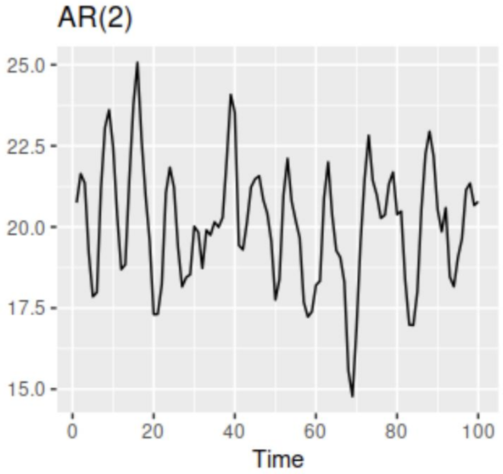
5. Autoregressive model

Autoregressive model (AR)

In an autoregression model, we forecast the variable of interest using a linear combination of past values of the variable.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$





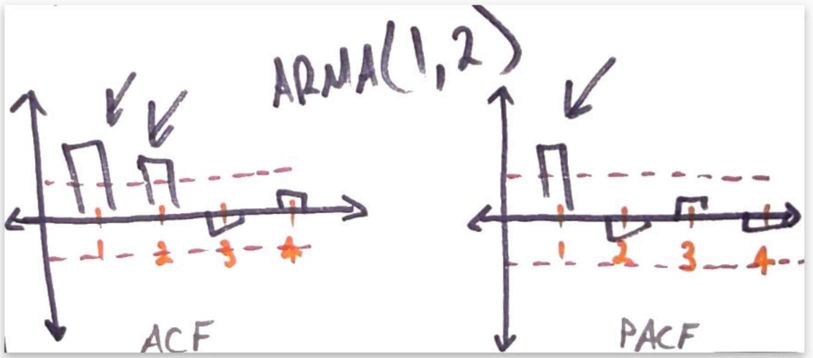
6. ARMA model

ARMA model

- Autoregressive Moving Average(ARMA)
- ARMA(1,1), Blue -> AR, Orange-> MA
- $\Lambda_t = \beta_0 + \beta_1\Lambda_{t-1} + \Phi_1\varepsilon_{t-1} + \varepsilon_t$
- Λ_t(Predicted) $= \beta_0 + \beta_1\Lambda_{t-1} + \Phi_1\varepsilon_{t-1}$
- ACF(Average Cost Function) determines MA(Moving Average) value
- PACF(Partial Average cost function) determines AR(Autoregressive) value

Λ_t -> number of light bulbs in month t

ε_t -> error in predicting light bulbs in month t

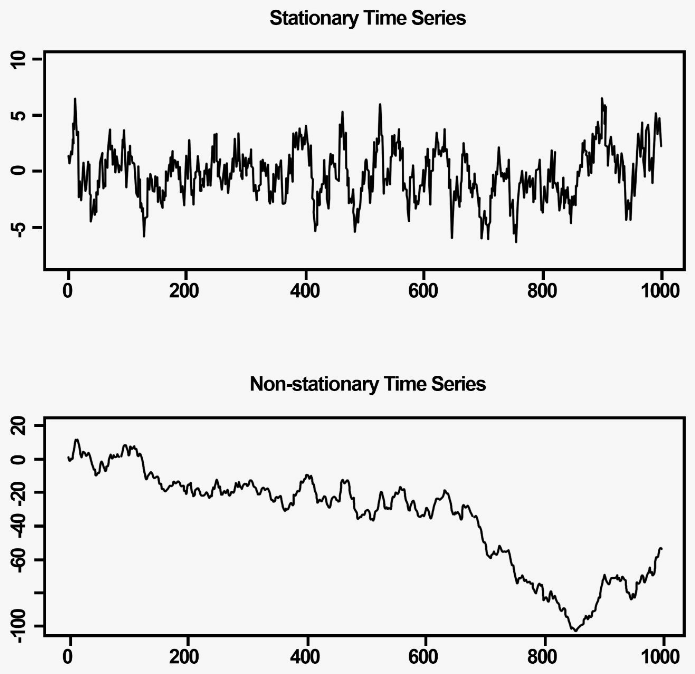


7. Stationarity

Stationarity

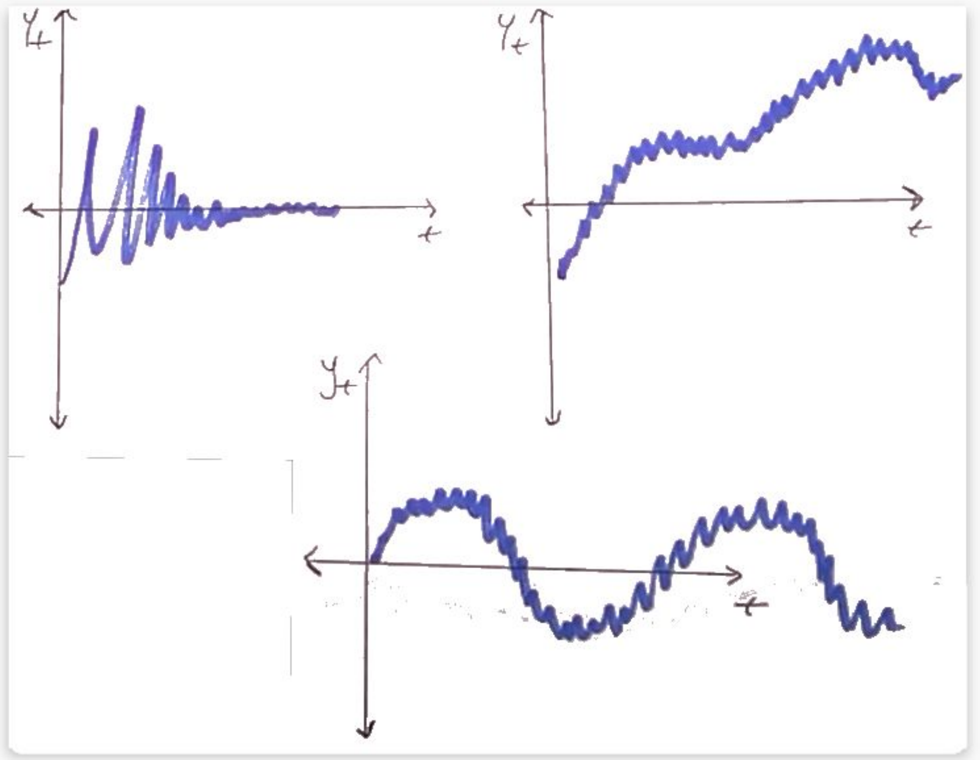
- To achieve stationarity, we need 3 parts:

1. Constant mean
2. Constant standard deviation
3. No seasonality



Stationarity

Not constant standard deviation > not stationary!



Not constant mean-> not stationary!

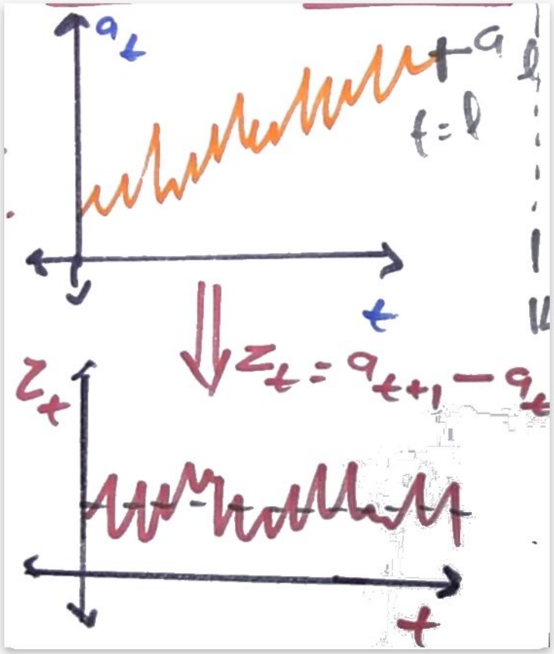
Seasonality -> not stationary!

8. ARIMA model

ARIMA model

- Autoregressive Integrated Moving Average(ARIMA)
- ARIMA(1,1,1) -> P,D,Q:
- $Z_t = \Phi_1 Z_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$

- A_t -> number of anchors in month t

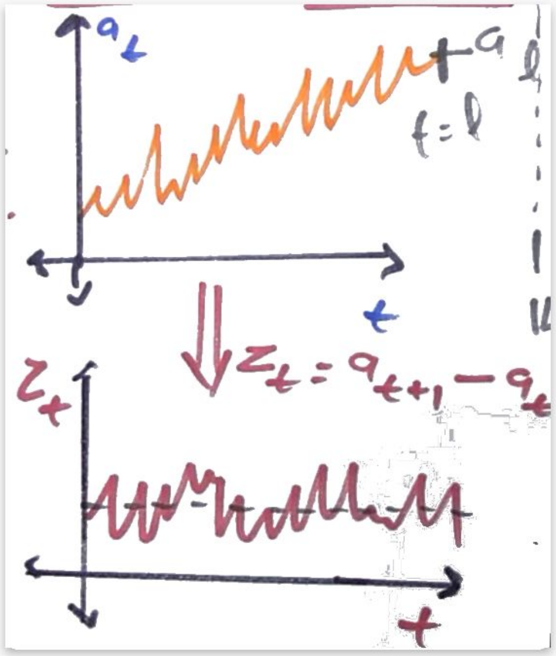


ARIMA model (Optional)

- How to recover a_k?
- Suppose we have a_0, a_1,...,a_L, (K>L)
- We want $a_k = z_{k-1} + a_{k-1} = z_{k-1} + z_{k-2} + a_{k-2}$.
- = ...=

$$\sum_{i=1}^{K-L} z_{k-i} + a_L$$

- A_t -> number of anchors in month t



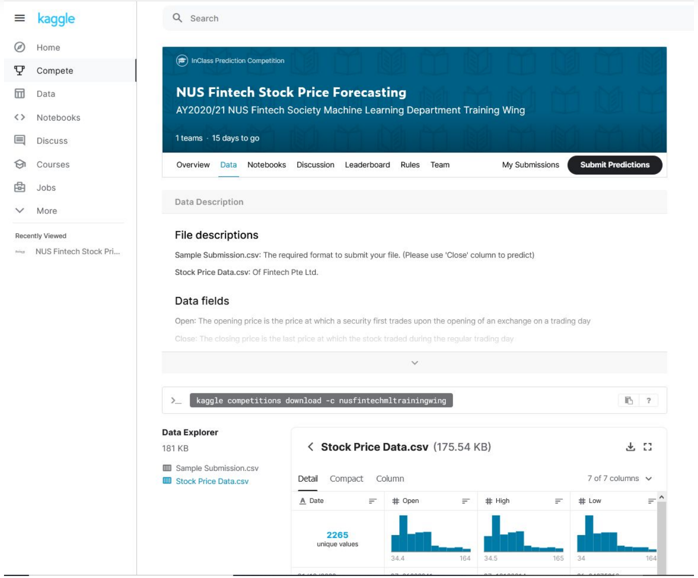
9. Stock forecasting with GARCH

8. Stock forecasting with GARCH

- We will exploring what we have learnt in this lesson so far with the GARCH model.
- Download the Jupyter Notebook here:
- https://github.com/NUS-FinTech-ML-Training-Wing/ML_TrainingWing_Materials/blob/master/Session%203/Fintech%20ML%20Training%20Wing%20Session%203%20Notebook-Time%20Series.ipynb

9. Release of Project 1

9. Project 1



- And... We hope that you are ready for your very first project at Fintech Society Training Wing!

9. Project 1

- Join Kaggle Competition: https://www.kaggle.com/t/a22be594f7964a11a05a7e178894b922

- Deadline: 3/10/2020 (Sat) 11:59pm
- Compulsory
- Push your code to Github & submit your answers to Kaggle
- We will be monitoring your progress!

9. Project 1

- Rubrics used to assess project performance

Component	Descriptors
Algorithms	• Use at least three difference machine learning algorithms
Prediction	• Root-mean squared error of stock prices prediction
Github	• Utilising Github for project management
Code quality	• Organised code into logical components, easy to understand code

10. Activity Time!

10. Activity Time!

- You will now be split into breakout rooms of 4-5 people! This discussion session will last for about 10 minutes.
- Look at project 1 and discuss among yourselves the following questions.
- Each group will send a representative to answer these questions:

1. What are the time series forecasting models that you know?
2. Which of these models will be relevant to this project and why?
3. Plans for recess week :D

THANKS!

Any questions?

- Credits to **Ritvimath**
- https://www.youtube.com/channel/UCUcpVoi5KkJmnE3bvEhHR0Q
- https://machinelearningmastery.com/decompose-time-series-data-trend-seasonality/
- https://otexts.com/fpp2/classical-decomposition.html
- https://en.wikipedia.org/wiki/Moving_average
- https://machinelearningmastery.com/gentle-introduction-autocorrelation-partial-autocorrelation/