

# Hi all welcome to the series

# Time Series Data ?

↳ is a collection of observations collected or recorded over a sequence of time interval

Ex → Price of a stock collected daily

AAPL → 01-01-2024  
02-01-2024  
03-01-2024  
⋮  
20-12-2024

Temperature → 01-01-2024 - 00:00 -  $T_0$   
00:01 →  $T_1$   
00:02 -  $T_2$

Why time series data is treated differently ?

# Key characteristics :-

→ chronological order —  
↳ ordering of time →

→ Sequential dependence ←

→ Temporal component → - Trend ✓  
- Seasonality ✓  
... ..

→ P →

- seasonality ✓
- cyclic patterns ✓
- Noise ✓

→ constant frequency →

01-01-2027 ←  
02-01-2027  
03-01-2027  
04-01-2027  
04-01-2027 00:01  
00:02

→ Dynamic nature → external factors

Time series Analysis →

understand the past → patterns

forecast the future

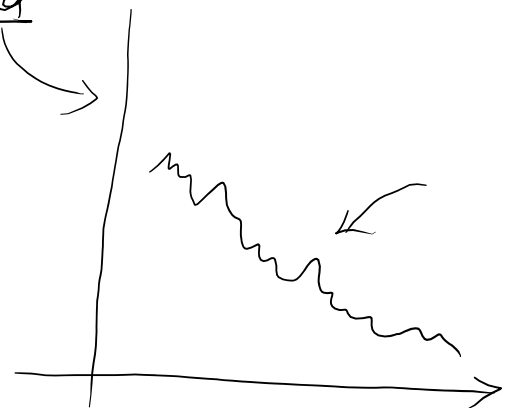
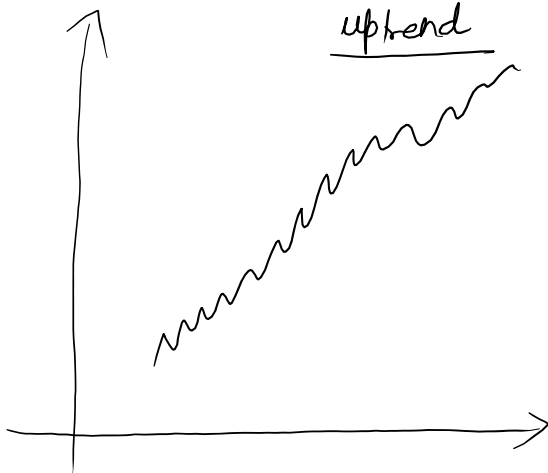
components of Time series :

→ Level → the average of your entire data

→ Trend → The long-term direction of data

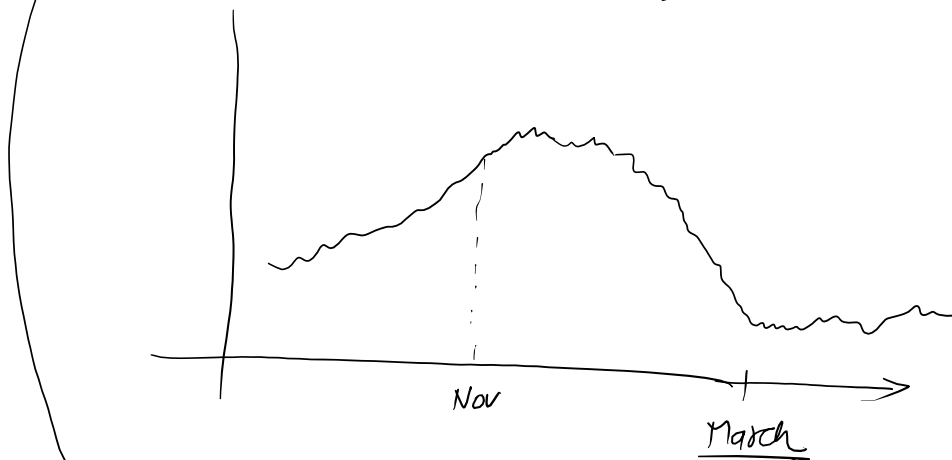
uptrend

Downtrend



# seasonality → September

→ Blankets → Sales of Blanket



→ in a calendar year → daily patterns,

→ weekly patterns →

→ monthly →

→ Quarterly patterns →

→ yearly →

Ⓝ 5-yearly pattern is not considered seasonal

→ regular or predictable patterns over a fixed period of interval like daily, monthly, etc -- generally falling in a calendar year

cyclic patterns → (i) repeating pattern over a longer duration

(ii) There is no strict criteria of repetition over a fixed duration



## Recession

→ 2009-10

Big Short  
↑

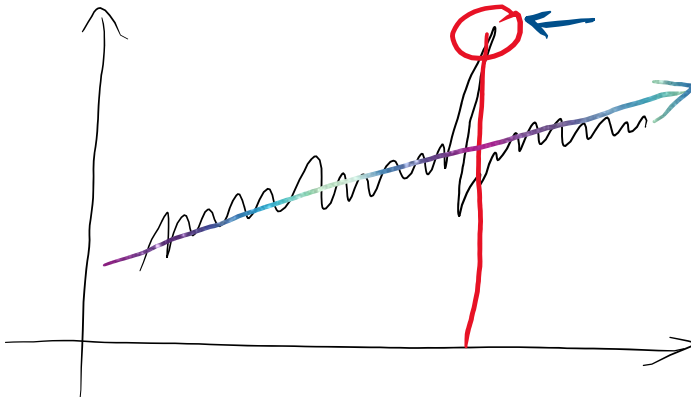
→ covid

→ Two types of cycle :

(i) Economic cycle

(ii) Business cycle →

→ Noise or Residual → Random fluctuations in the data which does not have any explanation



## # Decomposition Method

→ Additive model ✓✓

$$y_t = T_t + S_t + R_t$$

The equation is shown inside a rectangular box. Arrows point from the terms  $T_t$ ,  $S_t$ , and  $R_t$  to their respective parts in the equation. An arrow also points from the entire equation to a circled  $y_t$  on the left.

Multiplicative model ✓

$$y_t = T_t * S_t * R_t$$

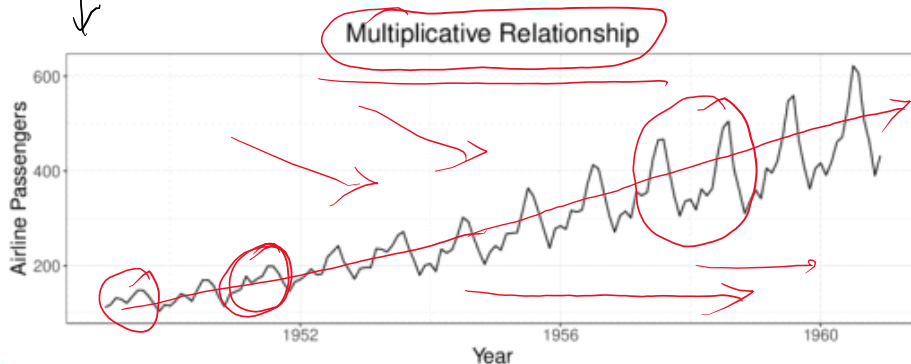
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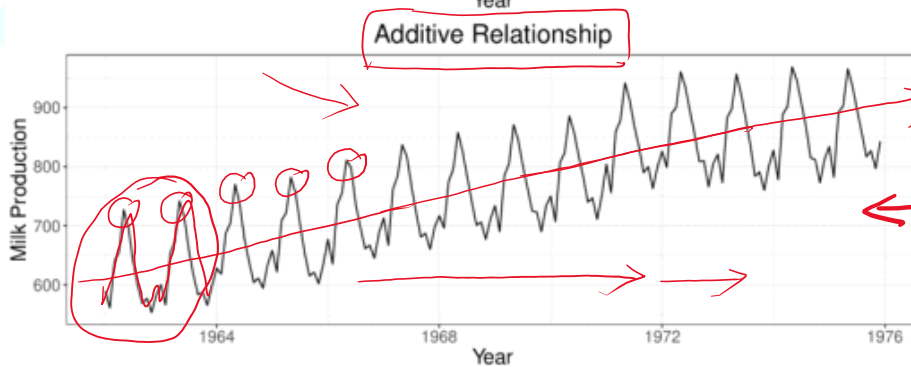
$$\underline{\underline{y_t = T + S + I}}$$

classical decomposition

and  $\underline{\underline{y_t \approx \hat{y_t}}}$



$$\underline{\underline{T_t * S_t}}$$



→ STL decomposition → Seasonal and Trend decomposition

↓  
LOESS

locally estimated scatterplot smoothing

→ only supports additive decomposition

→ classical method assumes fixed seasonality

↳ fails to learn the variations in seasonality

→ fails to learn the variations in seasonality

on the contrary, STL method can learn the variations in seasonality.

# stationary data :-

statistical prop → mean  
Variance  
Auto-correlation

→ mean → constant  
Variance and

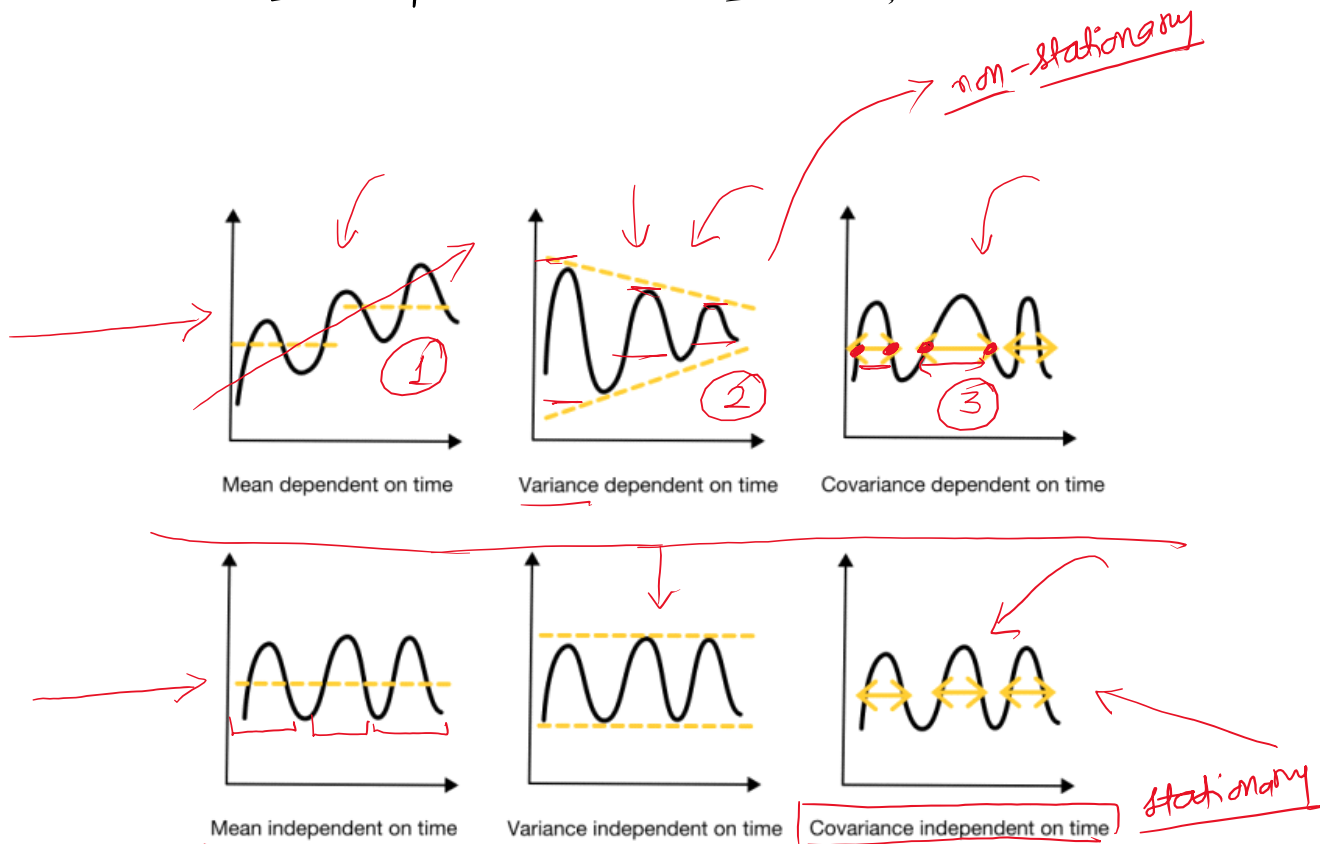
auto-correlation → constant over time

then time series data is considered stationary

# why is it important?

(i) majority of models for time series forecasting assumes the data to be stationary

(ii) help us make better prediction

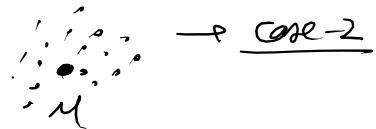
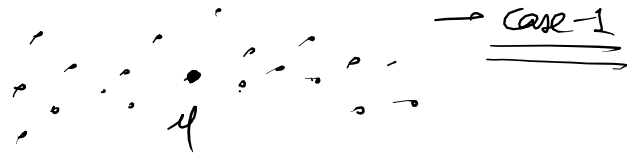


stationary

When you want to understand how does the value of Var1 changes or varies when there is a variation or change in Var2

correlation  $\rightarrow$  -1 to 1.

Variance  $\rightarrow$  understand the average of the spread of the data around mean



## Savings and expenses

①

if you inc exp by 3 times,  
results in dec. savings by  
3 times.

salary and YOE  $\rightarrow$  +1

### How to check for stationarity

stationary  $\rightarrow$  weak stationarity  
stationary  $\rightarrow$  strict stationarity

Weak Stationary  $\rightarrow$

mean

## Variance and auto-correlation

stationary over time

strict stationarity  $\Rightarrow$  exhibit all the properties of weak stationarity  
 joint distribution of different samples from

strict stationarity  $\Rightarrow$  exhibit all the properties of weak stationarity

- joint distribution of different samples from the same time series should be same.

$$\left( \underline{y_{t_1}, y_{t_2}, y_{t_3}, y_{t_4}, y_{t_5}} \right) \left( \underline{y_{t_{21}}, y_{t_{22}}, y_{t_{23}}, y_{t_{24}}, y_{t_{25}}} \right)$$

Presence of non stationary trend

# ADF test  $\rightarrow$  checks for the presence of unit root in the data

unit root  $\rightarrow$  non-stationary

Null Hypo: ( $H_0$ )  $\rightarrow$  has a unit root  $\rightarrow$  (non-stationary)

Alternate Hypo ( $H_A$ )  $\rightarrow$  does not have a unit root

stationary



p-value  $\rightarrow$

p-value  $< 0.05 \rightarrow$  we reject null



1 - rule

$p\text{-value} < 0.05 \rightarrow$  we reject null  
 $> 0.05 \rightarrow$  we fail to reject the null Hypo

$\rightarrow$  (#) KPSS test  $\Rightarrow$

$H_0$  : - the data is stationary

$H_A$  : - non-stationary

both the above tests are for weak stationarity

strict stationarity  $\rightarrow$

KS test

$p\text{-value} > 0.05$   $\rightarrow$  no difference in the dist.  
 $\hookrightarrow$  stationary

null Hypo  $\rightarrow$  stationary

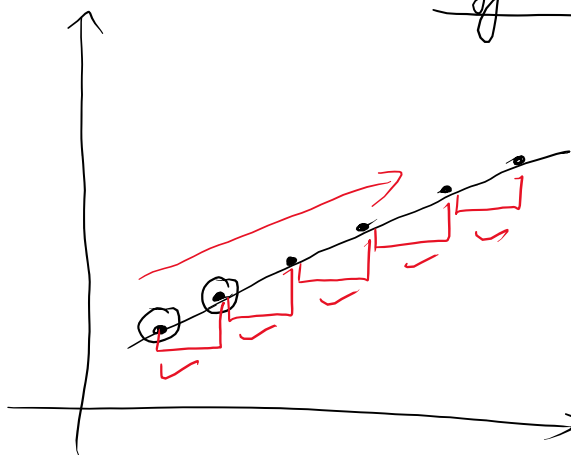
Alt Hypo  $\rightarrow$  non-stationary

smoothing techniques

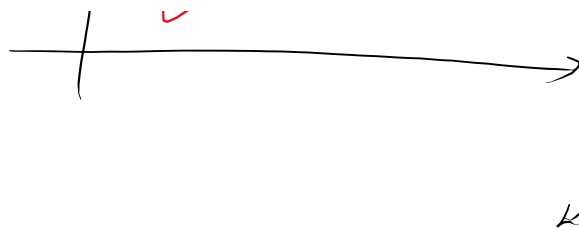
$\rightarrow$  differencing  $\rightarrow$

remove trend and seasonality

de-trending



$$\begin{cases} y'_t = y_t - y_{t-1} \\ y'_{t+1} = y_{t+1} - y_t \end{cases}$$



$$u_{t+1} = y_{t+1} - y_t$$

First order differencing

→ second order differencing

→ FOD

$$\begin{array}{ccccccc}
 y_1, y_2, y_3, y_4 & \cdots & y_t \\
 \hline
 y'_1 & y'_2, y'_3 & \cdots & y'_{t-1} \\
 \hline
 \end{array}$$

SOD

$$y''_1, y''_2, \dots$$

$$y''_t = y'_t - y'_{t-1}$$

second order  
differencing