Time Series Analytics & Forecasting

Things to be followed while working on TS Aff

1. Every Data should be numeric in nature, not in category.
2. Data type < datetime column, target variable } Index, Numeric
3. Data should be in a sequential order (Timeseries always in an ascending order)

** (4) There should not be any missing data in TSF. if yes, first impute the missing data and then try TSF.

⇨ NO missing data is allowed in TSF as data is for order.

⇨ It is simply not possible to shift the series to fill in the gaps.

(5) Before building TSF, we have to check data

component — Trend | Seasonality | error (Irregular)

↪ Decomposition — Vizualization

Process :- TSF - Life cycle

1. Understand the Problem Statement | Define Goal
2. Gather Data - Data Acquisition - Web Scraping . NLP
3. Explore - 5 points - pre-requisite rule
   &
   Visualization Series - Decomposition
4. Pre-process Data
5. Partition TSeries < Train = Model Building > Evaluating
   Test = Prediction

Supervise ML (Reg / Classification) — Split - Yes

Train 75% — Test 25%

Split = Randomly

TSF = Seqn. order

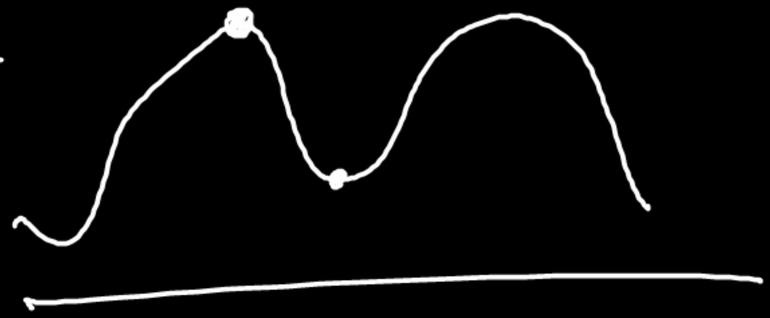
1
2
3
4
5
6
7
8
9
10

Train	Test
1	2
3	5
4	6
7	10
8	
9	

Train				Test	
1	2	3	4	7	11
2	3	4	5	8	12
3	4	5	6	9	13
4	5	6	7	10	14
5	6	7	8		
6	7	8	9		

(6) Apply Forecasting method

- → Level → The avg value
- → Trend → Systematic part
- → Seasonal Data
- → Noise - non-systematic part



DNN

Date	Temp
T1	10
T2	15
T3	20
T4	30
T5	35
1	
1	
Tn	

EWMA - Exponentially Weighted Moving Avg

$$E_t = \beta * E_{t-1} + (1-\beta)\theta_t$$

θ_t → Temp.

$1-0.9=0.1$

Hyperparameter

Avg days - 10 days

$\frac{1}{1-\beta} = \frac{1}{1-0.9} = \frac{1}{0.1} = 10$ days

more steps ↓

$\beta = 0.9$ = 10 days Avg

$0 < \beta < 1$

$t=0$ $E_t = 0$

$t=1$ $E_1 = 0.9 * 0 + 0.1 * 10$

$E_1 = 1$

$\beta = 0.5$

$\frac{1}{1-0.5} = \frac{1}{0.5} = 2$ days

$t=2$

$E_2 = 0.9 * E_1 + 0.1 * 15$

$= 0.9 * 1 + 0.1 * 15$

$= 0.9 + 1.5 = 2.4$

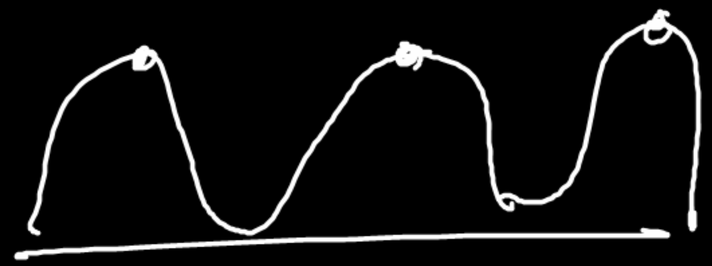
$t=3$

$E_3 = 0.9 * E_2 + 0.1 * 20$

$= 0.9 * 2.4 + 2.0$

$= 2.16 + 2.0 = 4.16$

→ Level



Trend ⇒

Noise - No Pattern

⑦ Evaluate & Compare Performance

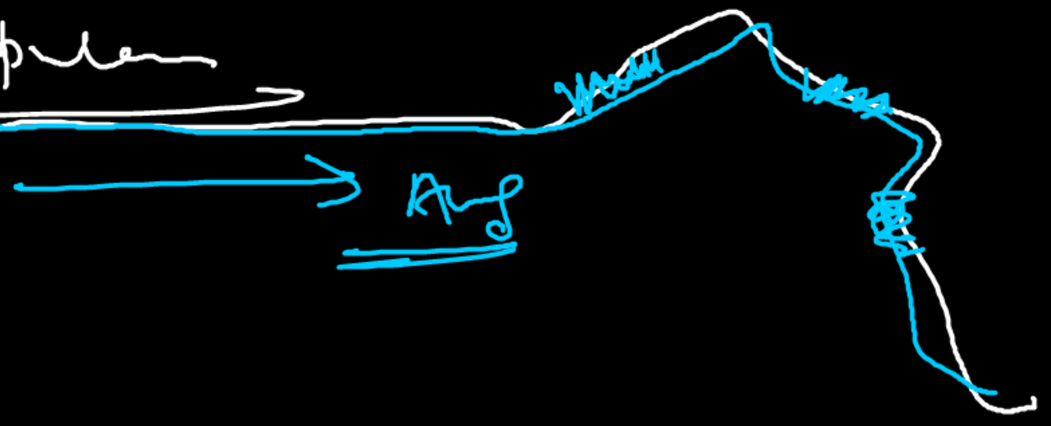
⑧ Implement the forecasting System

* Models for forecasting

↳ Linear Regression → $Y = mx + c$ / $Y = C + m_1x_1 + m_2x_2$

→ Smoothing / Neural Net / Naive forecast

Smoothing data :- Simple & Popular



The idea :-

1. A long time series
2. A series with no Trend (incr—
3. A series with no Seasonality

→ Moving Avg method

Simple exponential smoothing only (Algorithm)

- No trend & no seasonality
- only - level & Noise

Q	Sales	SES fun
Q1	17cr	
Q2	22cr	
Q3	25cr	
Q4	21cr	

Winter's method

Holt's

$$F_{t+1} = L_{t-1} + \alpha (Y_t - L_{t-1})$$

$$L_t = \beta Y_{t-1} + (1-\beta) F_t$$

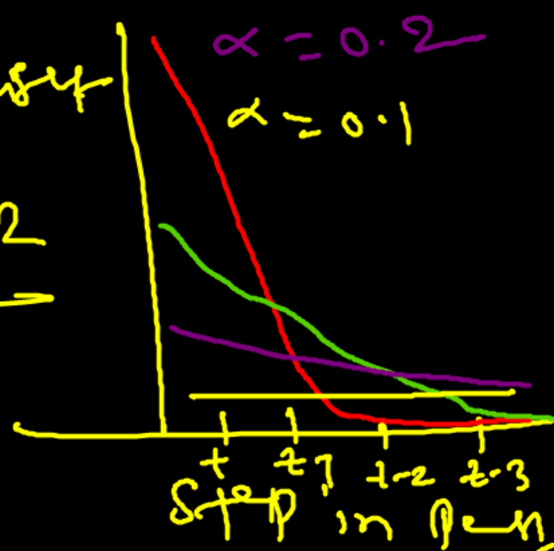
level $\beta = 0.9$

$\alpha \alpha \leq 1 \rightarrow 0.2$

Rule :- α determines how much weight is given to the past

$\alpha = 1$; past observation have small influence over forcasting (under - smoothing)

$\alpha = 0$; over smoothing



Selecting α :- typically, value = 0.1 or 0.2

RMSE / MAPE

(2) Holt's model (double exponential Smoothing model)

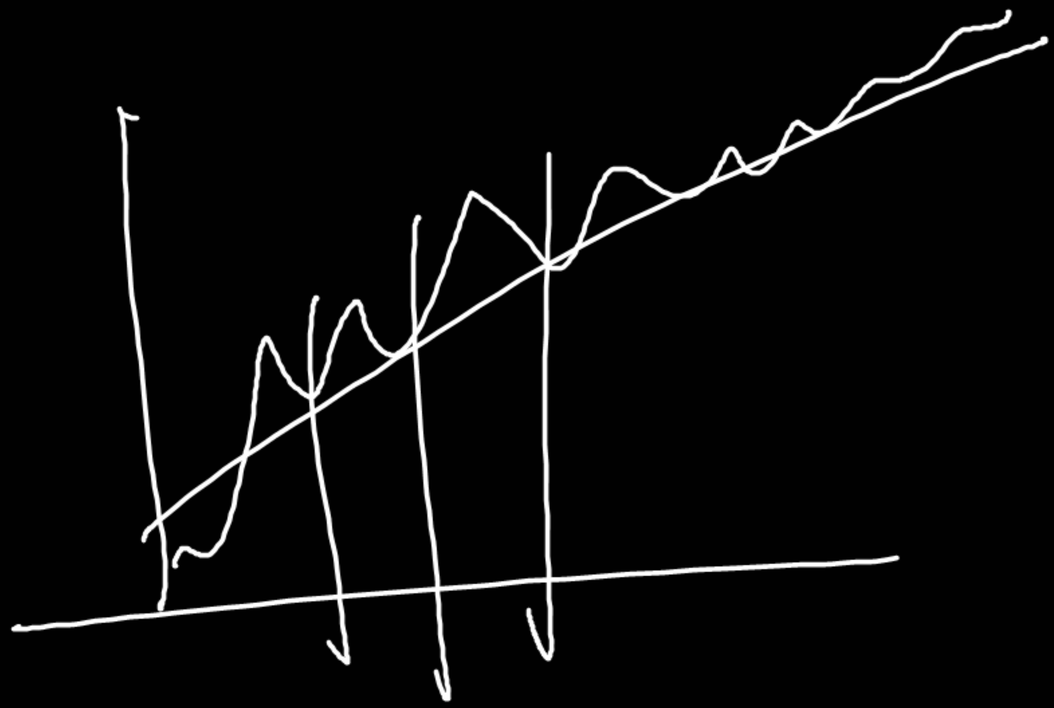
↓

Have Trend but no seasonality

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta) T_{t-1}$$

$$F_t = L_t + K \alpha T_t$$



TSF - Algorithms

(1) Winter's model | 1960 | Single exponential Smoothing → α parameter
→ No Trend & No seasonality

(2) Holt's model | double exponential Smoothing → α & β
→ Have Trend but no seasonality

(3) Winter & Holt's model | multiple exponential Smoothing → α, β, γ
↳ Have Trend & seasonality

4. AR - Auto Regressive
5. MA - Moving Avg
6. ARMA
7. ARIMA = Auto Regressive Integrated Moving Avg
8. ARIMAX - with external factor
9. SARIMA
10. SARIMAX

11. VAR
12. VARMA
13. VARIMA

and so on —

* Extra model - Automation

⇒ Facebook Prophet ✓

⇒ Darts - DL

⇒ PyCaret - Hyperform

⇒ Algorithm Trading