Forecasting Methods :
- → Mean / Median
- → Naive
- → Seasonal Naive
- → Drift

} Simple Methods

Forecasting / Smoothing Methods :

Real-world Data has:

- ↳ Noise
- ↳ one-off events
- ↳ human behaviour

> Business decisions don't care about NOISE

↓

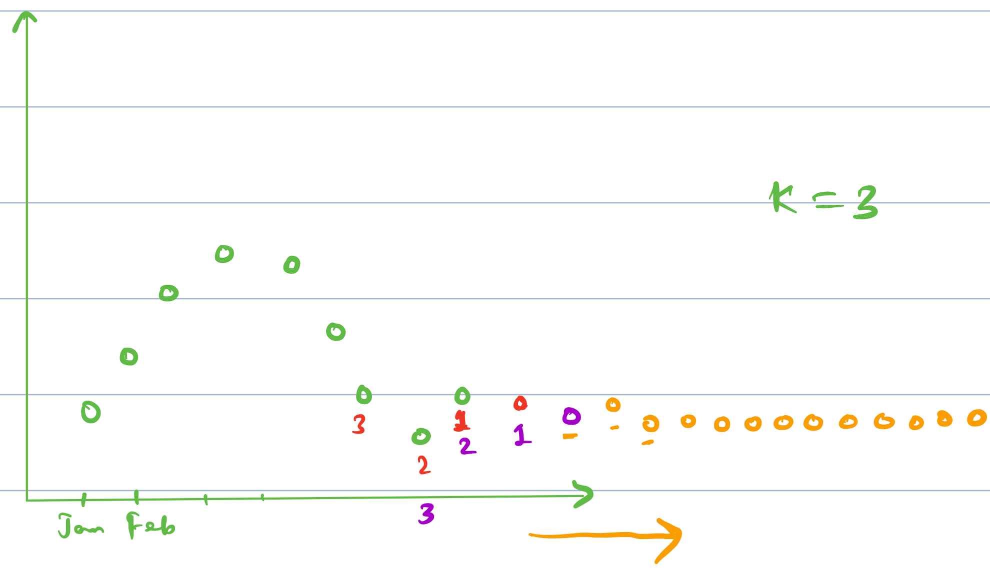
- ↳ overall trend
- ↳ direction
- ↳ pattern

1. Moving Average
2. SES - Simple Exponential Smoothing
3. DES - Double " " (Holt's Method)
4. TES - Triple " " (Holt-Winter's Method)

Smoothing techniques are methods that:

1. reduce short-term fluctuations
2. highlight long-term patterns
3. prepare data for forecasting

1. MOVING AVERAGE → rolling()



Sales

[k = 3]

Original Data

Jan 2001
Feb 2021
⋮
Jan 2019
Feb 2019 NaN
Mar 2019 NaN
Apr 2019 NaN

pred = [Nov 2018, Dec 2018, Jan 2019]

= [100, 200, 300]

↓

= $[\underbrace{100, 200, 300, 200}]$ 1st

⋮

Conclusion: Forecast is certainly better than simple methods like mean/median. However, it is not able to predict the variation and it gives a "flat line after few predictions".

MAPE : 9.4 %

② Simple Exponential Smoothing (SES) – [only level]

→ Instead of ignoring all past values → give lesser weights
recent values → give more weights

Let's consider the weight we assign to most recent value is 'α'

α → Smoothing parameter

$0 \le \alpha \le 1$

New Smoothed Value = (α * Current Value) + (1 − α) * Previous Smoothed Value

$1^{st} \longrightarrow S_t = \alpha Y_t + (1-\alpha) S_{t-1}$ → Previously smoothed value

↳ Forecasted Smoothed value at t

$$S_{t-1} = \alpha Y_{t-1} + (1-\alpha) S_{t-2}$$

Substitute S_{t-1} in 1^{st} equation.

$$S_t = \alpha \cdot Y_t + (1-\alpha) \left[\alpha Y_{t-1} + (1-\alpha) S_{t-2} \right]$$

$$\boxed{S_t = \alpha \cdot Y_t + \alpha (1-\alpha) Y_{t-1} + \alpha (1-\alpha)^2 Y_{t-2} + \ldots\ldots}$$

Weights $\rightarrow$ 1st recent $\rightarrow \alpha$

2nd $\rightarrow \alpha(1-\alpha)$

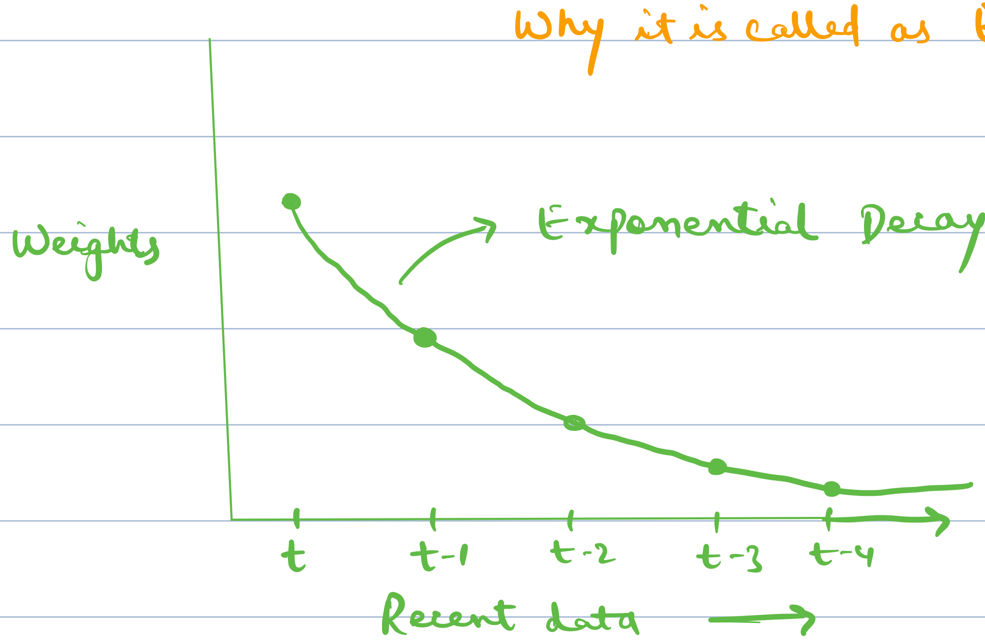
3rd $\rightarrow \alpha(1-\alpha)^2$

$\alpha = 0.8$

2nd weight $\rightarrow 0.16$

3rd weight $\rightarrow 0.032$

Why it is called as Exponential Smoothing



- Weights decrease exponentially
- Never becomes exactly zero

Sum of weights $\rightarrow \sum_{k=0}^{\infty} \alpha(1-\alpha)^k = 1$ [Proper weighted average]

Smoothing_level → α

↳ Recommended starting value is equal to

$$\frac{1}{2 * \text{Seasonality}} \quad [m = 12]$$

SES does not consider any:

① Trend

② Seasonality

SES models only level, not change.

MAPE = 11.3%

Conclusion: Looks even worse than MA forecast.

Gives a straight line.

Gives the right level ✓

③ DES → Holt's Method (level + trend)

Shortcomings of SES:

① doesn't capture trend / seasonality

② gives one unique value (flat line)

2 components:

① Level

② Trend

① Level

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

α = smoothing cons. (for level)

$0 \leq \alpha \leq 1$

② Trend

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

β = smoothing cons. (for Trend)

$0 \leq \beta \leq 1$

③ Final Equation :

$$\boxed{\hat{Y}_{t+h} = L_t + h * T_t}$$

h = horizon $\rightarrow$ 1, 2, 3, 4 . . . .

Y_t Today's sales $= 120$

Y_{t-1} Yesteraday's sales $= 110$

T_{t-1} Yesterday's trend $= 5$ $\hat{Y}_{t+1} = ?$

$\alpha = 0.5$

$\beta = 0.3$

DES = SES + trend tracking

Seasonality ✗ MAPE → 8.9%

④ TES Method (Holt - Winter's method)

(level + trend + seasonality)

TES = DES + seasonality tracking

$$\boxed{\hat{Y}_{t+h} = l_t + h \times T_t + S_{t+h-m}}$$

m → frequency of seasonality

quartely data → m = 4

monthly data → m = 12

MAPE → 5.1% (odd)

MAPE → 4.6 % (mul)

Conclusion: Perform best compared to all other methods.

Level → $l_t = \alpha(y_t - S_{t-m}) + (1-\alpha)(l_{t-1} + T_{t-1})$

Trend → $T_t = \beta(l_t - l_{t-1}) + (1-\beta) T_{t-1}$

Seasonality → $S_t = \gamma(y_t - l_{t-1} - T_{t-1}) + (1-\gamma) S_{t-m}$

γ = smoothing cons. (for seasonality)

→ Stationarity

→ ARIMA