

## Topics Covered

1. Decomposition From Scratch
2. Simple Forecasting Methods
3. Accuracy/Performance Measurement
4. Simple Forecasting Methods
5. Single Exponential Smoothing Method (Will again cover in next Class)

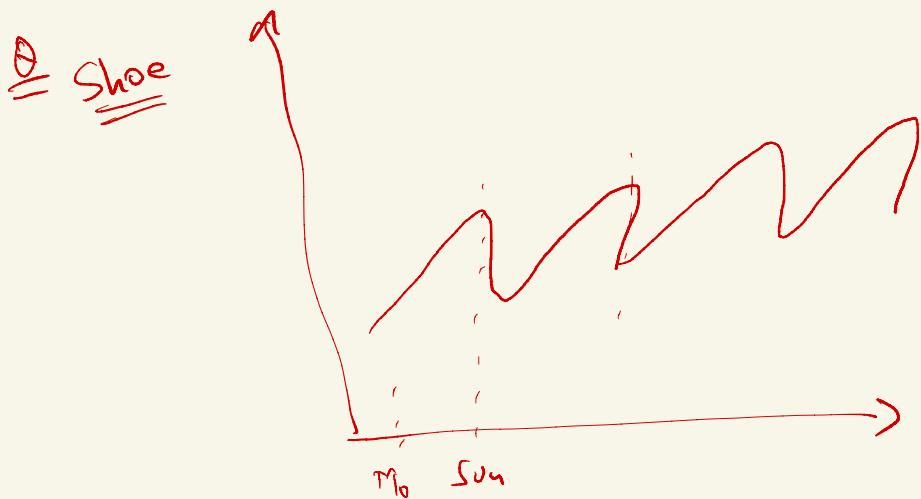
- $\Rightarrow$  ① Decomposition from Scratch  $\rightarrow$
- ② Simple method of forecasting  $\nearrow$
- ③ Smoothing method

| Start at 9:05

Recap  $\rightarrow$  What is TS data

- $\hookrightarrow$  ① forward moving data
- ② No repetition Jan 2017  $\leftarrow$  Jan 2016
- ③ Imputation  $\rightarrow$  Linear Interpolation
- ④ Anomaly/outliers  $\rightarrow$  Quantile

$\hookrightarrow$  Trend, Seasonality & Error



Trend  $\rightarrow$  MA  
 $\hookrightarrow$  Ideal value

for  $m = 1$  Seasonal Period.

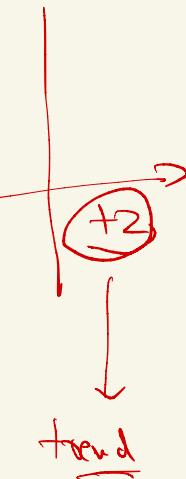
$$\Rightarrow y(t) = b(t) + \underline{s(t)} + \underline{e(t)}$$

\* ignore

Monday  $\rightarrow -20$  from Sunday  $\curvearrowright$  Seasonality

Mond	10
:	12
:	15
Sun	30

Week 4

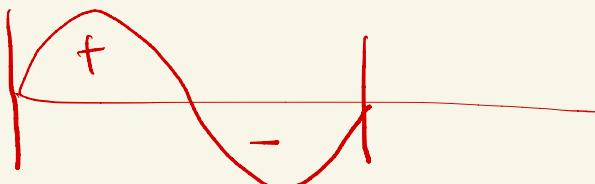


12  
.  
.  
32

Week 2

$$\boxed{y(t) - s(t) = b(t)}$$

Seasonality



Cancel out in 1 Time period

MA at this  
Time frame

effect of seasonality

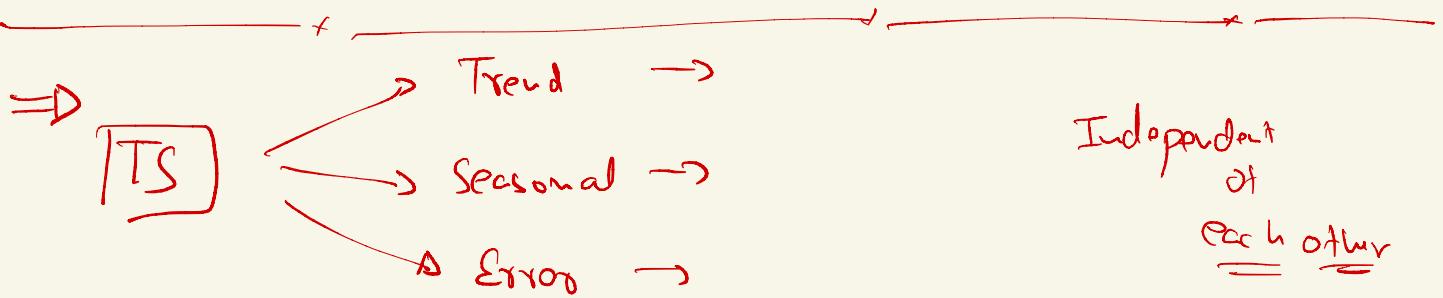
~0

Thus  $\rightarrow$  Trend is left.

$\Rightarrow$  If you use  $\circledast$  MA for approx Seasonality Timeframe

$\downarrow$   
Approx Trend  $\rightarrow b^*(t)$

$\Rightarrow$  If I remove  $\rightarrow y(t) - b^*(t)$



Approp  $b^*(t)$

Trend  $\rightarrow$  MA of 12 months  $\rightarrow (y(t) \rightarrow \text{seasonal component})$

$\downarrow$   $y(t) - b^*(t) \rightarrow \text{detrend } S^*(t)$

Corresponding mean  $\rightarrow \underline{\underline{S(t)}}$

To get a better trend -

$\underline{\underline{y(t) - S(t)}} \Rightarrow \underline{\underline{\text{Better Trend}}}$

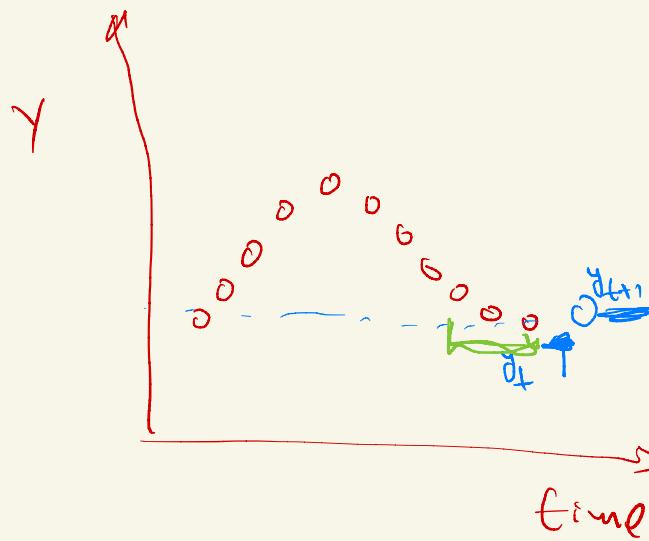
$\Rightarrow y(t) \rightarrow \text{MA} \rightarrow \underline{\underline{b^*(t)}}$

$\underbrace{y(t) - b^*(t)}_{\hookrightarrow \text{Aug}} \rightarrow \text{detrend} \rightarrow \underline{\underline{S(t)}}$

$y(t) - s(t) \rightarrow \underline{\underline{b(t)}} \rightarrow \underline{\underline{\text{MA}}}$

## Forecasting →

→ Analysis  
→ Forecast / Error



→ Simple Forecasting →

① Naive Approach →

$$\hat{y}_{t+1} = y_t$$

Trend X  
Season X

② Mean Approach →

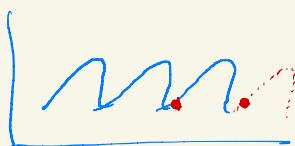
$$\hat{y}_{t+1} = \frac{y_1 + \dots + y_t}{t}$$

T  $\times$   
S  $\times$

③ Seasonal Naive Approach

$$\hat{y}_{t+1} = y_t \quad \text{xxx}$$

Trend X  
Season ✓



↳ last timesteps pending Seasonal value.

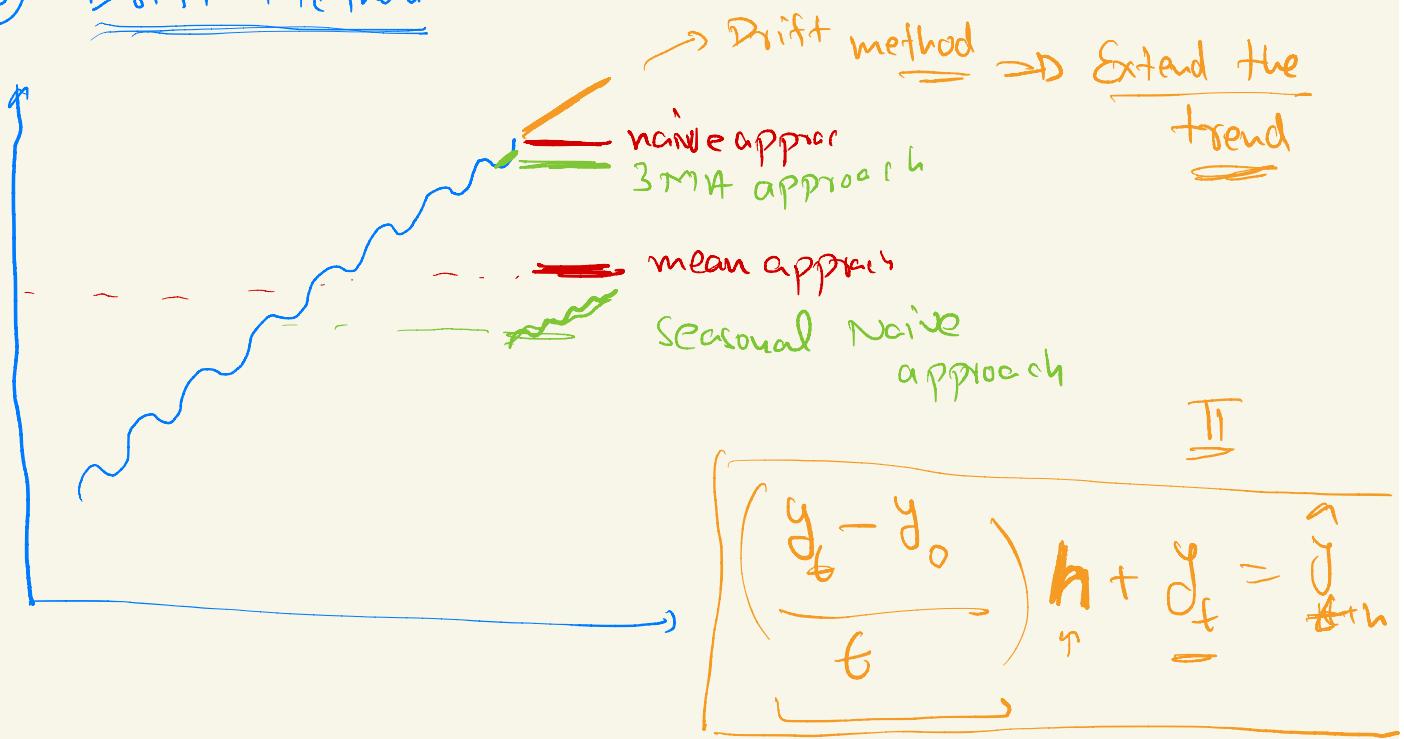
④ Moving Average →

$$\rightarrow \hat{y}_{t+1} = \frac{y_t + y_{t-1} + \dots + y_{t-m}}{m}$$

Trend X  
Season X

$$\rightarrow \hat{y}_{t+2} = \frac{\hat{y}_{t+1} + y_t + \dots + y_{t-m+1}}{m}$$

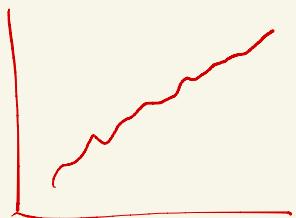
## ⑤ Drift Method



$$\hat{y}_{t+h} = \hat{y}_t + h * \text{Slope}$$

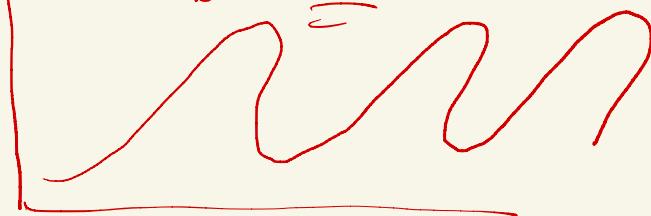
Aug slope of Naive

① Increasing trend  $\rightarrow$

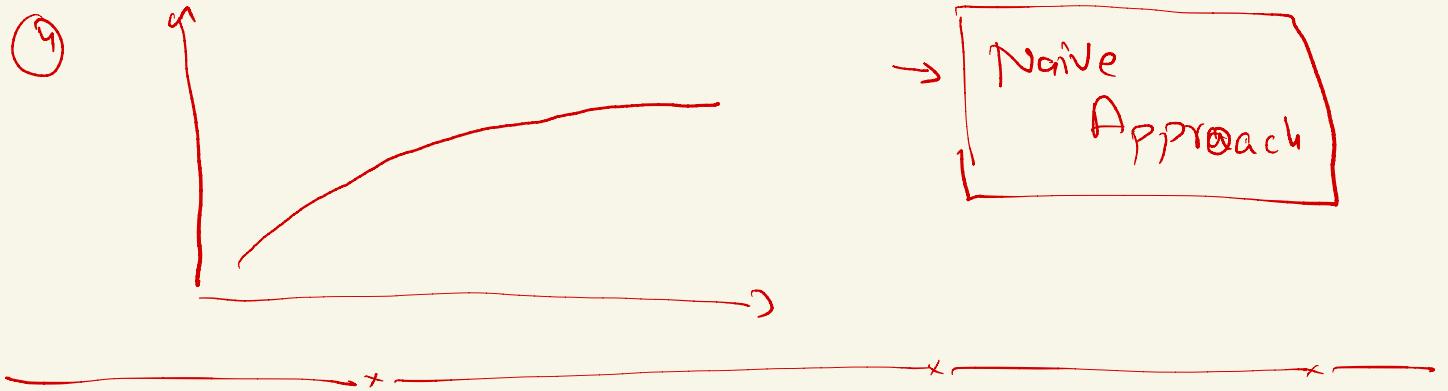
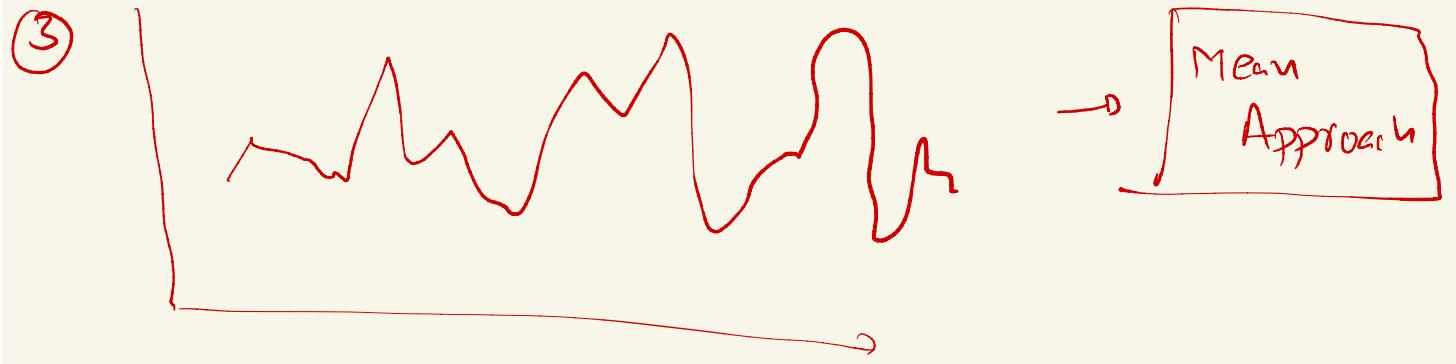


Drift Approach

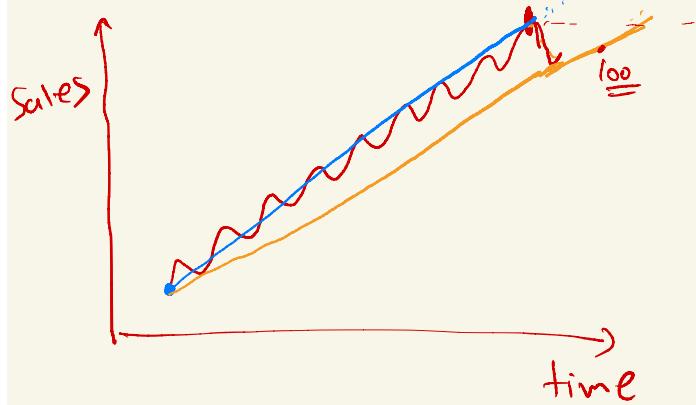
② Seasonal data



Seasonal naive



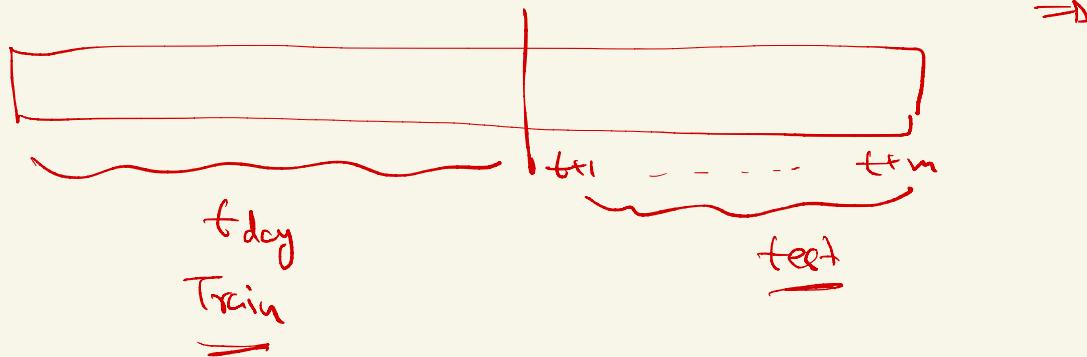
⇒ Drift Sensitivity → Predict next Quarter values



$$\frac{y_t - y_0}{t} = \underline{\text{Slope}}$$

Based on the time prediction  
all future values can  
change significantly.

$\Rightarrow$  Train-Test Split  $\rightarrow$



$\Rightarrow$  Accuracy

$$MAE \Rightarrow \frac{\sum_{t=1}^n |\hat{y}_t - y_t|}{n} \quad RMSE \Rightarrow \sqrt{\frac{\sum_{t=1}^n (\hat{y}_t - y_t)^2}{n}}$$

MAPE  $\rightarrow$  Mean Absolut Percentage Error

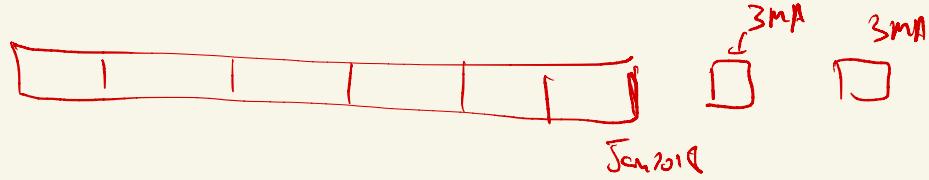
$$\Rightarrow \frac{\sum_{t=1}^n |\hat{y}_t - y_t|}{n} \times \frac{1}{y_t} \times 100$$

$\rightarrow$  Splitting  $\rightarrow$  Train  $\rightarrow$  Jan 2001  $\rightarrow$  Jan 2018  
 $\rightarrow$  Test  $\rightarrow$  Feb 2018  $\rightarrow$  Jan 2019

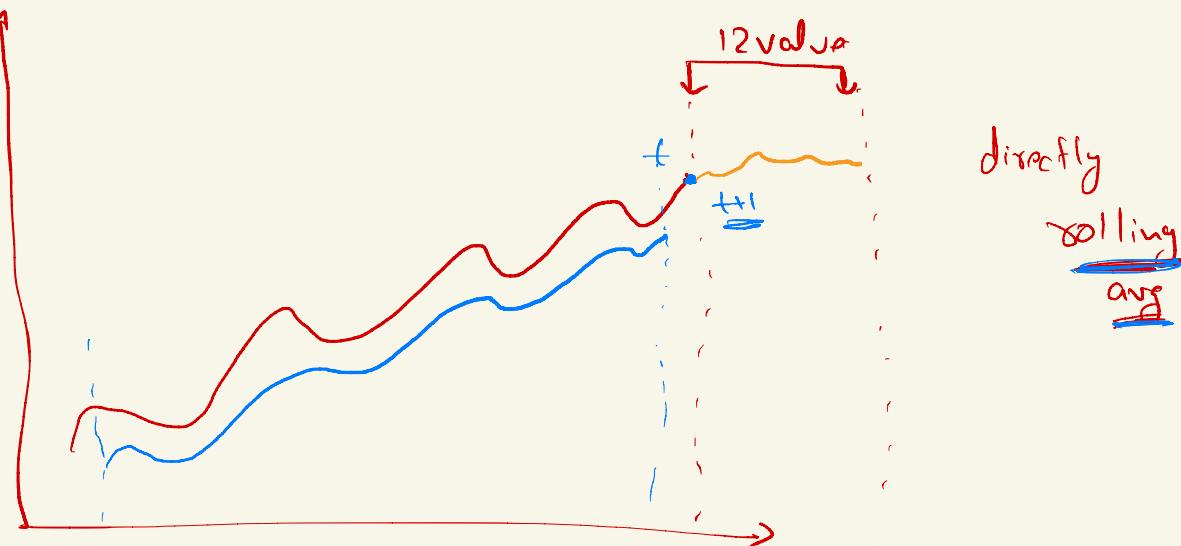
$\rightarrow$  How to get last 3 day MA for Feb 2018

Nov 17 Dec 17 Jan 2018

New  
Data  
Point



⇒



$$\frac{(P_t + P_{t-1} + P_{t-2})}{3}$$

Last 12 value

↓  
Push them as  $\hat{y}_{pred}$

⇒ Smoothing

## ① SES → Single Exponential Smoothing

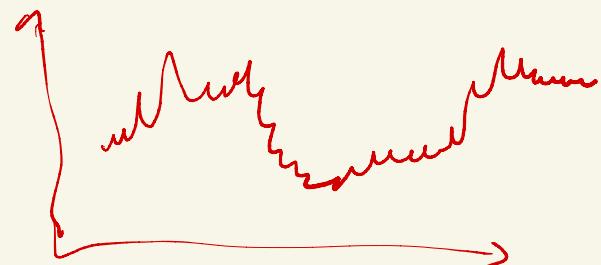
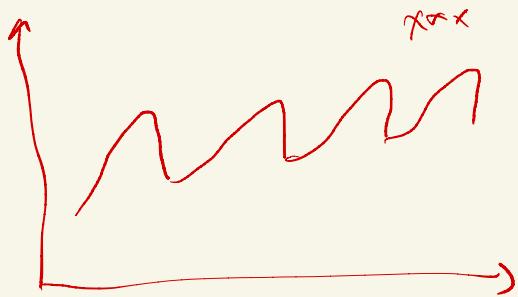
→ naive approach = give weightage to last value

→ mean approach = give weightage to all historical value

⇒ Give higher weightage to the recent value

but give at least some weight to other value

$\Rightarrow$  only work on non-seasonal data



$$\hat{y}_{t+1} = y_t$$

$$\hat{y}_{t+1} = \underbrace{y_t + y_{t-1} + \dots + y_0}_t$$

SES  $\hat{y}_{t+1} = \alpha_t y_t + \alpha_{t-1} y_{t-1} + \dots + \alpha_0 y_0$

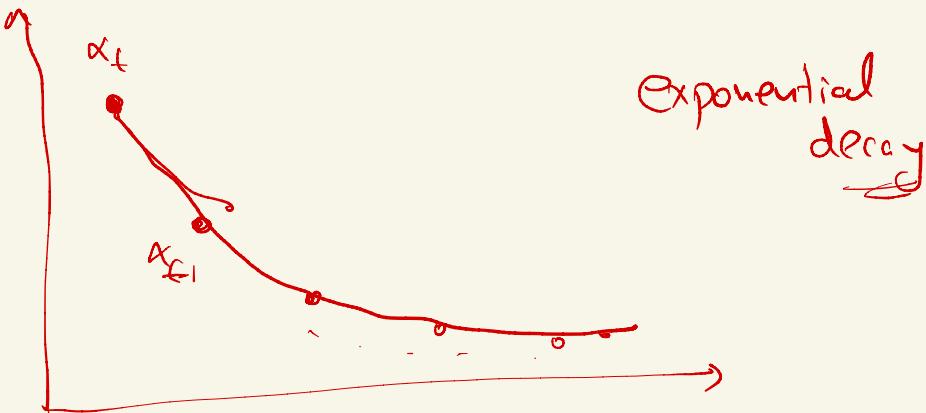
$\Rightarrow \alpha_t \rightarrow$  should be high  
 $\alpha_0 \rightarrow$  should be low

S values  $\begin{matrix} t & t-1 & \dots \\ 0.3 & \underbrace{0.2}_{\text{}} & \underbrace{0.1}_{\text{}} \end{matrix} = [1]$

$$\hookrightarrow \frac{1}{3} \quad 0 \quad 0 \quad 0 \quad 0 \quad \Rightarrow \text{naive approach}$$

$$\hookrightarrow 0.1 \quad 0.1 \quad 0.1 \dots \quad \Rightarrow \text{mean approach}$$

$\Rightarrow$  Exponential decay



$$\Rightarrow \hat{y}_{t+1} = \underbrace{\alpha y_t}_{\text{Gr-P}} + \underbrace{\alpha(1-\alpha) y_{t-1}}_{\text{Exponential decay}} + \underbrace{\alpha(1-\alpha)^2 y_{t-2}}_{\dots} + \dots$$

Gr-P  $\alpha, \alpha(1-\alpha), \alpha(1-\alpha)^2, \dots$

Exponential decay