Linear Regression Method :

$y = a + bt$

Given

y_t	t	$y_t \cdot t$	t^2
26	1	26	1
28	2	56	4
29	3		

$\Sigma y_t = na + b\Sigma t$

$\Sigma y_t \cdot t = a\Sigma t + b\Sigma t^2$

find out a and b

and calculate nth day by $y = a + bt$

→ can handle trend data

→ Moving Avg only for applied in constant data.

* Exponential Smoothing

model where the prediction is weighted sum of past observations

→ Use exponentially ↓ weights for past obser-

3 type

① Single Exponential Smoothing (ETS)

- without trends or seasonality.
- smothing factor (α) → control the rate at which the influence of the observation at prior time steps decay exponentially

Large (α) → model pay attension mainly to most recent observation → Fast Comp

Small (α) → more of history taken into account → Slow Computation

Date:
Page:

Given

t	A_t	F_t
1	39	
2	44	-
3	40	
4	45	
5	38	
6	43	
7	39	

$$\boxed{\begin{gathered} F_{t+1} = F_t + \alpha(A_t - F_t) \\ \text{or} \\ F_{t+1} = \alpha A_t + (1-\alpha) F_t \end{gathered}}$$

- Let $\alpha = 0.2$

$F_{t+1} = 0.2 A_t + 0.8 F_t$

- Let $F_1 = A_1$

$F_8 = 0.2 A_7 + 0.8 F_7$

2) Double Exponential Smoothing

or

Holt's method → Charles holt

→ extension of simple exponential smoothing that explicity adds support for trends.

(α, β)
- ↳ smoothing factor for slop (handle trend)
- ↳ smoothing factor for level

$F_{t+1} = a_t + b_t$

$a_t = \alpha D_t + (1-\alpha) F_t$

$b_t = \beta(a_t - a_{t-1}) + (1-\beta) b_{t-1}$

Let $\alpha = 0.2$ $\beta = 0.3$

$a_1 = D_1 = 26$; $b_1 = \frac{D_6 - D_1}{5} = \frac{35-26}{5}$

series = 26, 28, 29, 31, 32, 35