Time Series Forecasting

Saturday, 2 August 2025 19:15

Time Related

Numerical

Weeks	No of visitors
1	2882
2	3105
3	2791
4	4725
5	6720
6	4850
7	3990
⋮	⋮
40	5185

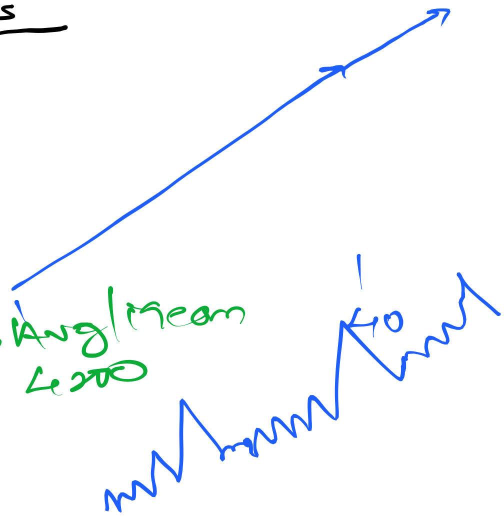
Startup

Beauty

Sequential

Avg/mean

4200



41	?	5185	4200
42	?	5185	4200
43	?	5185	4200
44	?	5185	4200
45	?	5185	4200

Regression

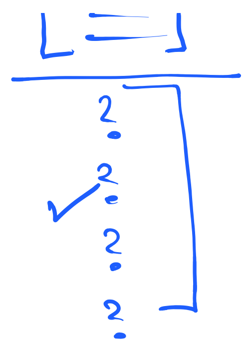
$C_1 \quad C_2 \quad C_3 \quad C_4 \; \cdots \; C_{50}$ → output

Inp

Auto regression

No of visitors

Inp



Methods of Time Series Forecasting →

Quantitative

→ Data available

→ Historical patterns repeat & we can track them

→ We can easily capture complex patterns through available data.

Exp

Qualitative

- No data available

- We can't track historical patterns

→ We can't capture / identify the complex patterns present in the data.

3 components of Time Series Forecasting →

1. Time Series Data -
2. Time Series Analysis.
3. Time Series Forecasting.

Profit

$1M

$2M

Steps in Forecasting →

→ Define the problem statement.

→ Goal, strategy, Forecasting expect.

→ Collect the data.

→ Analyze the data.

→ Build and evaluate the forecasting models.

Some caveats associated with Time-Series Forecasting →

→ Day
→ week
→ Month

① The granularity rule → The more aggregated your forecasts are, the more accurate they will be.

July 25
Aug 25

October

② The frequency rule → Keep updating your forecasts regularly to capture any new trend that comes up.

③ The Horizon Rule → When you have forecasted for some future weeks/months, your forecasts are more likely to be very accurate in the earlier weeks/months as compared to later ones.

Jan 24
⋮
Jan 25
→ Feb 25
→ Mar 25
→ April 25
→ May
→ June

→ July |

→ Three important charateristics of a time series data →

1. Relevant : Data should be relevant to our goal or objective.

2. Accurate : Data should be accurate in terms of capturing the timestamps & the related observations.

3. Long Enough : Data should be long enough to forecast accurately. This is imp. to identify all the patterns of the past.

Basic Approaches for Time Series Forecasting →

1. Naive Approach →

Forecasted value = Last observed value

2. Simple Average Approach
3. Moving Average Approach
4. weighted Moving Average approach.

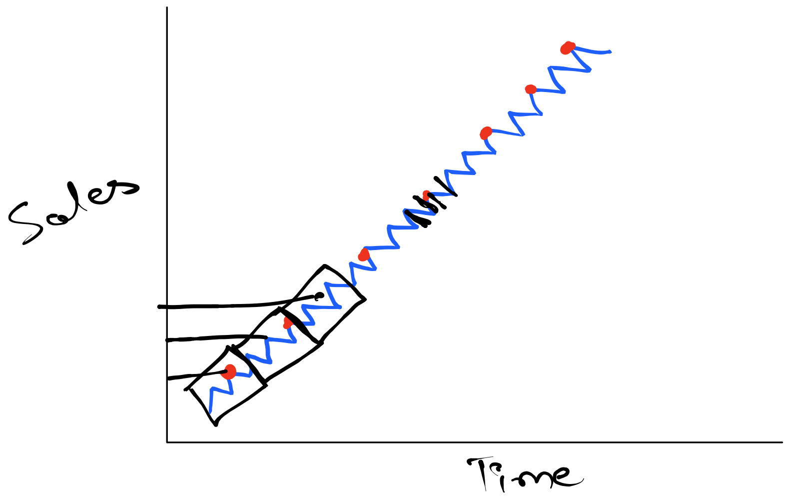
$x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5$

2000 2100 1980 3150 2950

$$\text{Avg} = \frac{(x_1 + x_2 + x_3 + x_4 + x_5)}{5}$$

$$\text{weighted avg} = \frac{(\omega_1 x_1 + \omega_2 x_2 + \omega_3 x_3 + \omega_4 x_4 + \omega_5 x_5)}{\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5}$$

Some examples of Time Series Data

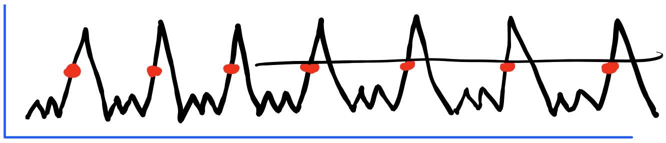


Upward Trend
+
Seasonality

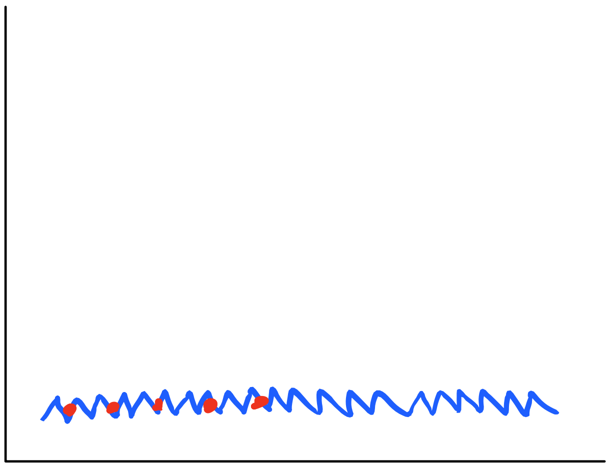
Oct - Nov

Varying Mean
&
Constant variance → Non-stationary Data

No Trend = Constant Mean
+
Seasonality



Constant mean
&
varying variance → Non-stationary Data.



No-Trend
+
Seasonality

Constant mean
&
Constant variance → Stationary Data ✓

Every time series data that we give to the algorithms, has to be 'Stationary'.

If the data is Non-stationary, then we need to do the necessary transformations to make it 'stationary'.

→ Mean
→ variance

Time Series Transformations →

① Differencing : To be used when your data has varying mean but constant variance.

$$\left[\begin{array}{l}\text{varying Mean} \\ \quad + \\ \text{Constant variance}\end{array}\right] \xrightarrow{\text{Diff}} \begin{array}{c}\text{Constant Mean} \\ + \\ \text{Constant variance}\end{array}$$

② Box-Cox Transformation :

$$\begin{array}{c}\text{Constant mean} \\ + \\ \text{varying variance}\end{array} \xrightarrow{\text{BCT}} \begin{array}{c}\text{Constant mean} \\ + \\ \text{Constant variance}\end{array}$$

③ Differencing + Box cox Transformation →

$$\begin{array}{c}\text{varying Mean} \\ + \\ \text{varying variance}\end{array} \longrightarrow \begin{array}{c}\text{Constant Mean} \\ + \\ \text{Constant variance}\end{array}$$

Box-Cox Transformation →

λ = lambda

Sales

$$y^{\lambda} = \begin{cases} \left[\dfrac{y^{\lambda}-1}{\lambda}\right], & \text{if } \lambda \neq 0 \\ \log(y), & \text{if } \lambda = 0 \end{cases}$$

$\boxed{\lambda = 0 \rightarrow \text{log transformation}}$

$\lambda = 1 \rightarrow$ No transformation

$\Rightarrow \lambda = 0.5 \rightarrow$ Square root transformation

$\lambda = 2 \rightarrow$ Square of the data.

$\lambda = -1 \rightarrow$ Reciprocal of the data.

Time Series Algorithms →

1. Auto-Regressive (AR)
2. ARIMA (Auto regressive integrated moving average)
3. SARIMA (Seasonal ARIMA)

ACF & PACF Plots

ACF (Auto Correlation Function)

column	Lagged value
S_t	S_{t-1}
S_t	S_{t-2}
S_t	S_{t-3}

$$S_t \longrightarrow S_{t-3}$$

PACF

S_t S_{t-1} S_{t-2} S_{t-3}

df_boxcox_diff

train test

(OD) (sales)(K)

t	1	2	3	4	...	16	17	18	19	20
Y	25	7	19	31	...	51	38	15	46	50
Y boxcox	3.22	1.95	2.94	3.43	...	3.93	3.64			
Y boxcox diff	NaN	-1.27	1.00	0.49	...	0.19	-0.29			
Y pred								0.03	0.25	0.18
Appended Series	-	-1.27	1.00	0.49	...	0.19	-0.29	0.03	0.25	0.18
Cumulative Series	-	-1.27	-0.27	0.22	...	0.71	0.42	0.45	0.70	0.88
Initial Value Adjustment	-	1.95	2.94	3.44	...	3.93	3.64	3.67	3.92	4.10
Exponential	-	7	19	31	...	51	38	38.98	49.83	59.73

AR

reversal

reversal of differencing

y_{20}

df_boxcox_diff + preds

BCT → diff

$e^{1.95} = 7.$

exponential

$\log(7) = 1.95$

$7 = e^{1.95}$