

"TIME-SERIES ANALYSIS"

→ Data is recorded at regular time intervals → Time Series
(order / sequence matters)

"Stock Chart"

* Daily life examples of Time-Series Data:

- ① Weather Forecasting
- ② Stock Market Charts
- ③ Retail Sales Forecasting
- ④ Fit tracking → Steps, Weight, Sleep hours
- ⑤ Social Media and Internet Activity
- ⑥ Healthcare Monitoring

TIME SERIES:

↳ is just a story told over time.

- Objective :
- ① Finding patterns
 - ② Forecasting

- MOBIPPLUS → Mobile Manufacturing Company

* Sales ✓

* Defects

* Demand ✓

→ Forecast no. of phones to be manufactured.

Over-forecasting

→ Stores will be filled

→ Mobiles will be wasted

→ Money gets locked



Under-forecasting

→ Demand not full-filled

→ Loss on potential revenue

→ Brand trust suffers

Timestamp

Value (Stock price, Quantity,

(hourly, daily, weekly, quarterly, yearly) Sales, Revenue, Profit)

[Forecasting is not about perfection, it's about making better decisions]

Sample Data

DATE	SALES
2001-01-01	6519
2001-02-01	6654
2001-03-01	7332
2001-04-01	7332

- What makes Time-Series data different from ML Regression?

Regression:

Future Sales \leftarrow Orders + Price + Quantity etc.

Time-Series:

Future Sales \leftarrow Past Sales ✓

- ↳ X and Y variables are not required
- ↳ Time is itself 'X' \rightarrow input

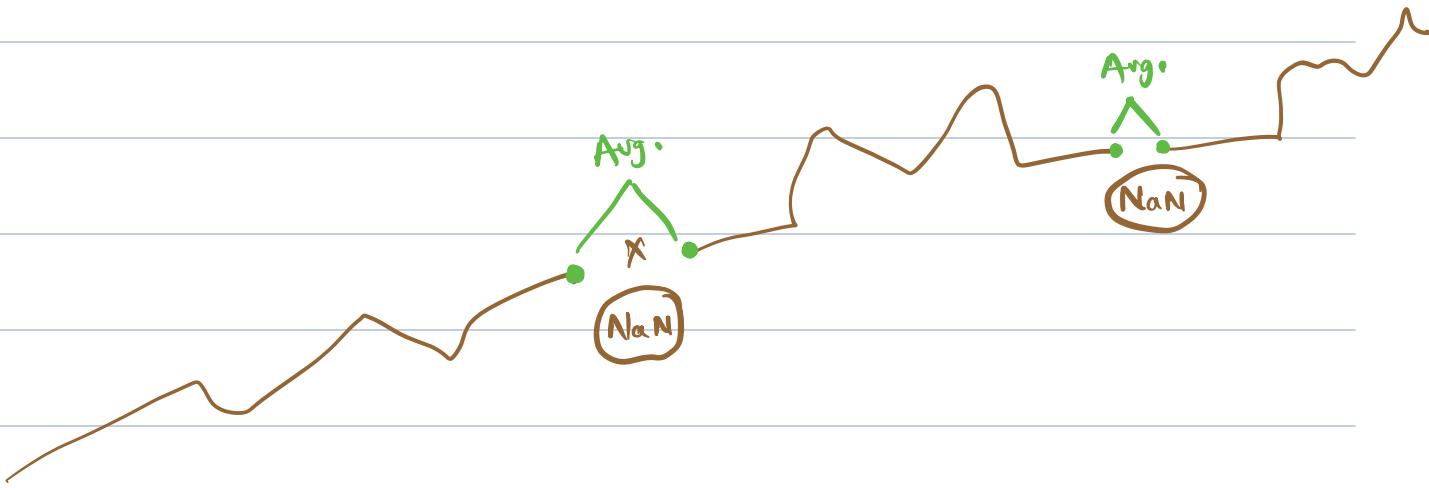
MObIPLUS Dataset (Colab)

- ↳ 217 months with sales
- 19 sale values are missing.

• Handling missing values

- ① Imputing by mean } Inaccurate results
- ② Imputing by 0 }
- ③ Linear Interpolation

↳ Average of first before value and
first after value of a missing value,



Representation of Time Series Data:

Time Series $\rightarrow [y_1 \quad y_2 \quad y_3 \quad \dots \quad \dots \quad y_{t-1} \quad y_t]$

$t \rightarrow$ Current Time
Latest Time

Forecasting $\rightarrow [y_{t+1} \quad y_{t+2} \quad \dots \quad \dots \quad \dots]$

Missing Value $\rightarrow x_t$

$$\text{Impute} \longrightarrow x_t = \frac{x_{t-1} + x_{t+1}}{2}$$

2 important components
of Time-Series

TREND

SEASONALITY

[long period duration]

[short period duration]

Q1: Does our data has a trend?

Yes → increasing

Q2: Are there any repeating patterns?

Yes

What these repeating - patterns indicate?

↳ This is domain-specific

↳ In February → sales go down

In Oct - Nov → sales go up

Good Forecaster → Should be aware of trends in their domain.

Bangalore weather :

* Moving Averages :

Calculating averages of moving points as a sliding window is called as Moving Average

↳ important for Forecasting

Take last 'n' values → average → move forward

What does Moving Average do?

- ① Reduces noise
- ② Reveals underlying structure / information
- ③ Introduces "lag"

points → [100 200 300 400]
↓ ↑ ↑
 $300 + 200 + 100 / 3$

$K=3$ → Moving average at every point

$$400 + 300 + 200 / 3$$

MA → [NaN NaN 200 300]

Think of MA as :

↳ a noise reducer

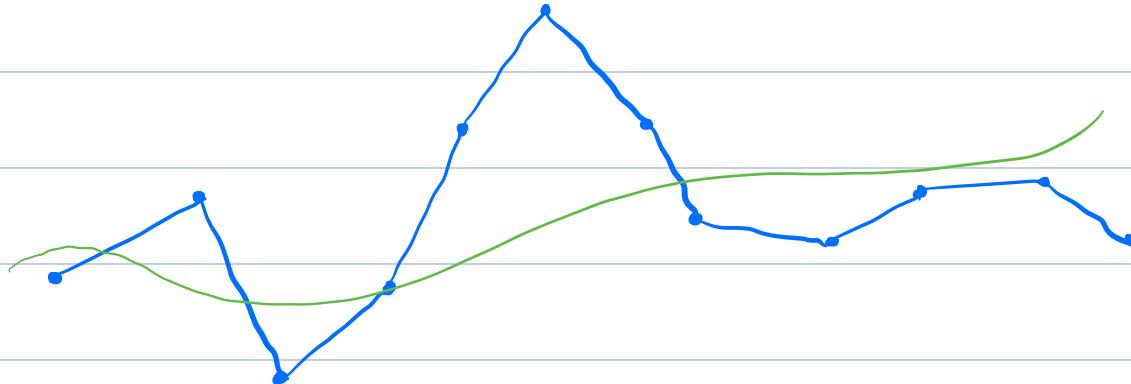
↳ a smoother

↳ a way to see the real direction of the data (trend)

Mobile Sales :

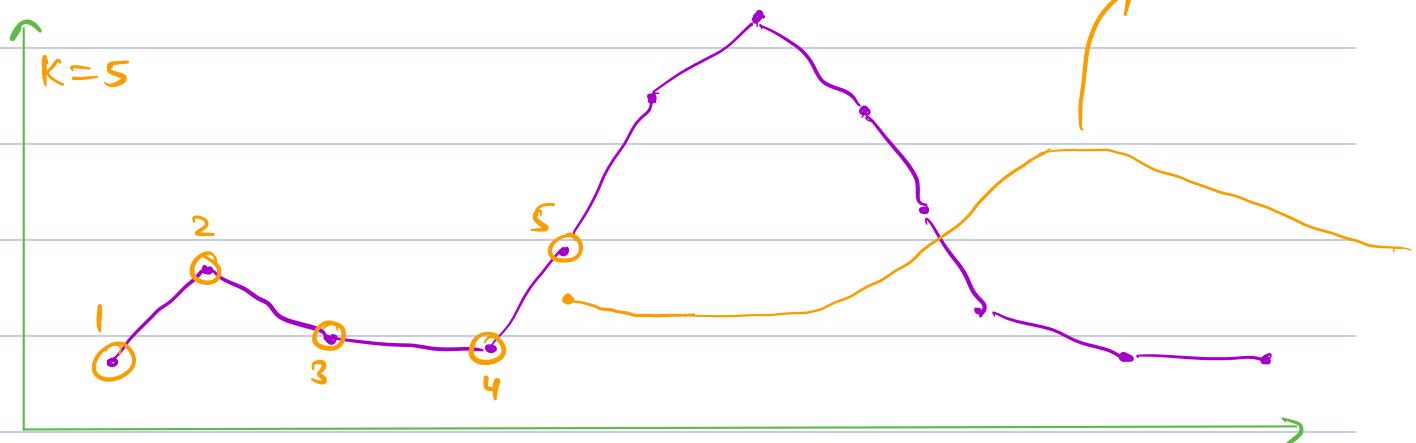
↳ Daily sales fluctuate a lot due to:

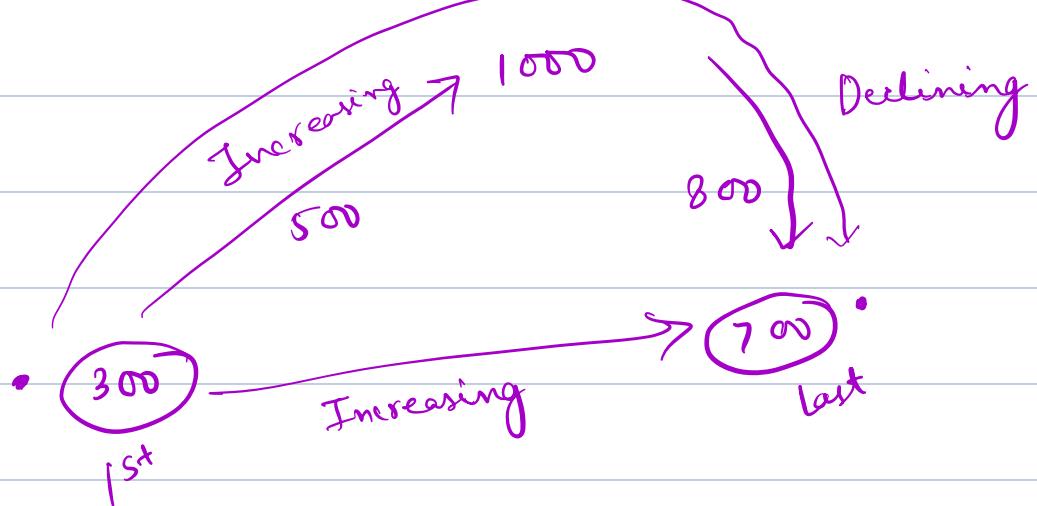
- offers
- weekends
- stock availability
- customer needs / demands.



Business leaders focus on:

- ↳ are sales growing overall? }
↳ are sales declining }
Moving
average





$K=3$ (Small Window)

(Large Window) $K=12$

- | | |
|--|---|
| <ul style="list-style-type: none"> ① Smooth but noisy (ups & downs) ② Short-term behaviour ③ Reacts quickly | <ul style="list-style-type: none"> ① Very smooth ② Long-term behaviour ③ Reacts slowly |
|--|---|

→ Moving averages "LAGS":

- It only takes past values.
- So, when something suddenly changes:
 - Sudden spike.
 - Demand drop.

→ Moving average reacts late.

- ↳ Peaks appear later
- ↳ Dips appear later.

Mathematical representation of M.A:

Notations:

y → Actual / Current value

\hat{y} → Forecasted value (using M.A)

m → No. of observations

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

$$\hat{y}_t = \frac{1}{m} \sum_{j=t-m}^{t-1} y_j$$

• Weighted Moving Average:

→ In weighted MA, we provide more weights to recent data and less weights to past data.

$$\hat{y}_t = \frac{a_1 * y_{t-1} + a_2 * y_{t-2} + \dots + a_m * y_{t-m}}{a_1 + a_2 + a_3 + \dots + a_m}$$

Normalizing

Relation $\rightarrow a_1 > a_2 > a_3 \dots \dots > a_m$

Centered M.A
(center = True)

Imp'

Non-centered M.A
(center = False)

- Analysis / finding patterns
 - Uses past + future
 - Not realistic for prediction
 - Visualization
- Forecasting / Predicting
 - Uses past values
 - Realistic

" TIME - SERIES DECOMPOSITION "

↳ TREND

↳ SEASONALITY

↳ ERROR / RESIDUAL

① TREND :

↳ can be thought of as - linear increasing / decreasing behaviour of the series over a long - period of time.

increasing /
uptrend

decreasing /
down-trend

changing

→ 'Trend-line' is a "smooth predictable function" that traces the trend of a time-series and can help predict time series indefinitely in future.

② SEASONALITY :

↳ Refers to patterns that occur at a regular interval repeatedly.

FIRE CRACKERS → DIWALI / FESTIVALS (every year)

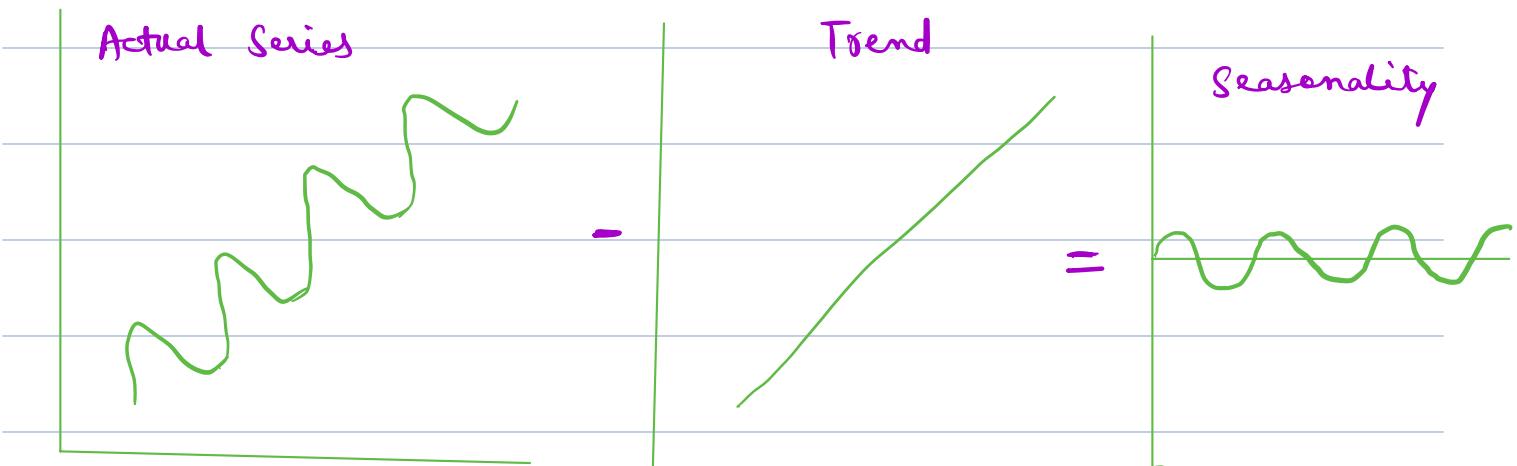
FLIPKART - Big Billion Days → October (every year)

Sunglasses Company → Summer Season

Quick Commerce → Weekends vs Weekdays

→ It is called as simple repeating wave.

→ It is always for a "fixed and known period."



Time Series Decomposition:

→ Additive
Seasonality

$$y(t) = b(t) + s(t) + e(t)$$

$y(t)$ → Actual Series Amplitude is const.

$b(t)$ → Trend

$s(t)$ → Seasonality

$e(t)$ → Error / Resi

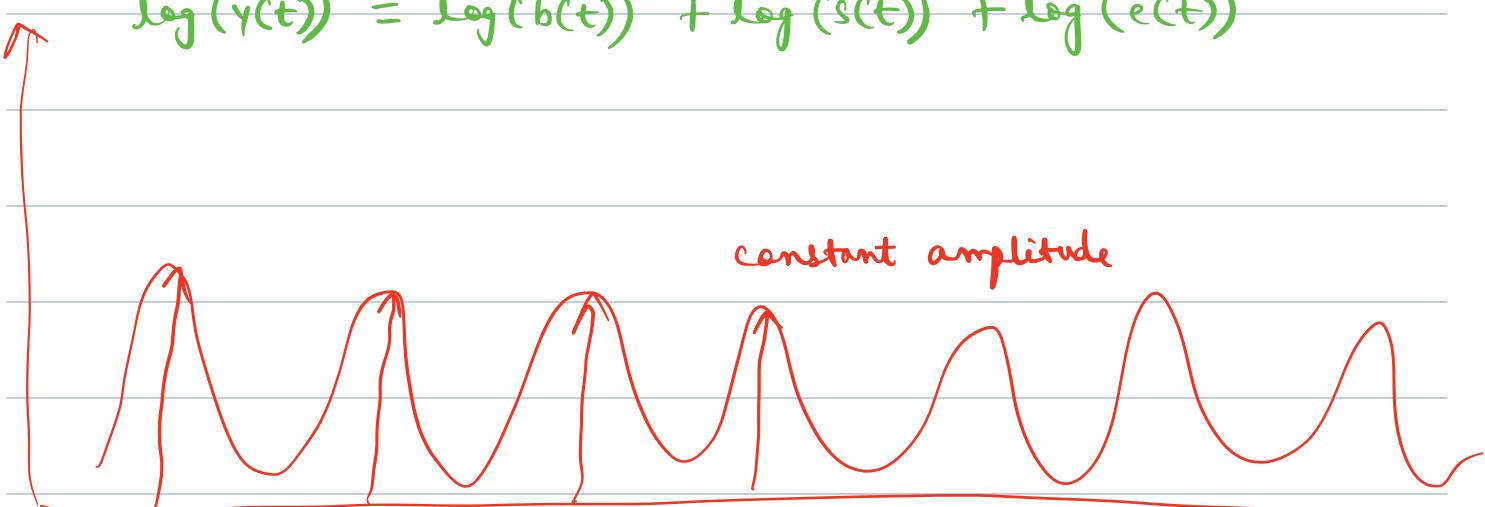
• Multiplicative Seasonality:

$$y(t) = b(t) * s(t) * e(t)$$

LOG
Transformation
↓

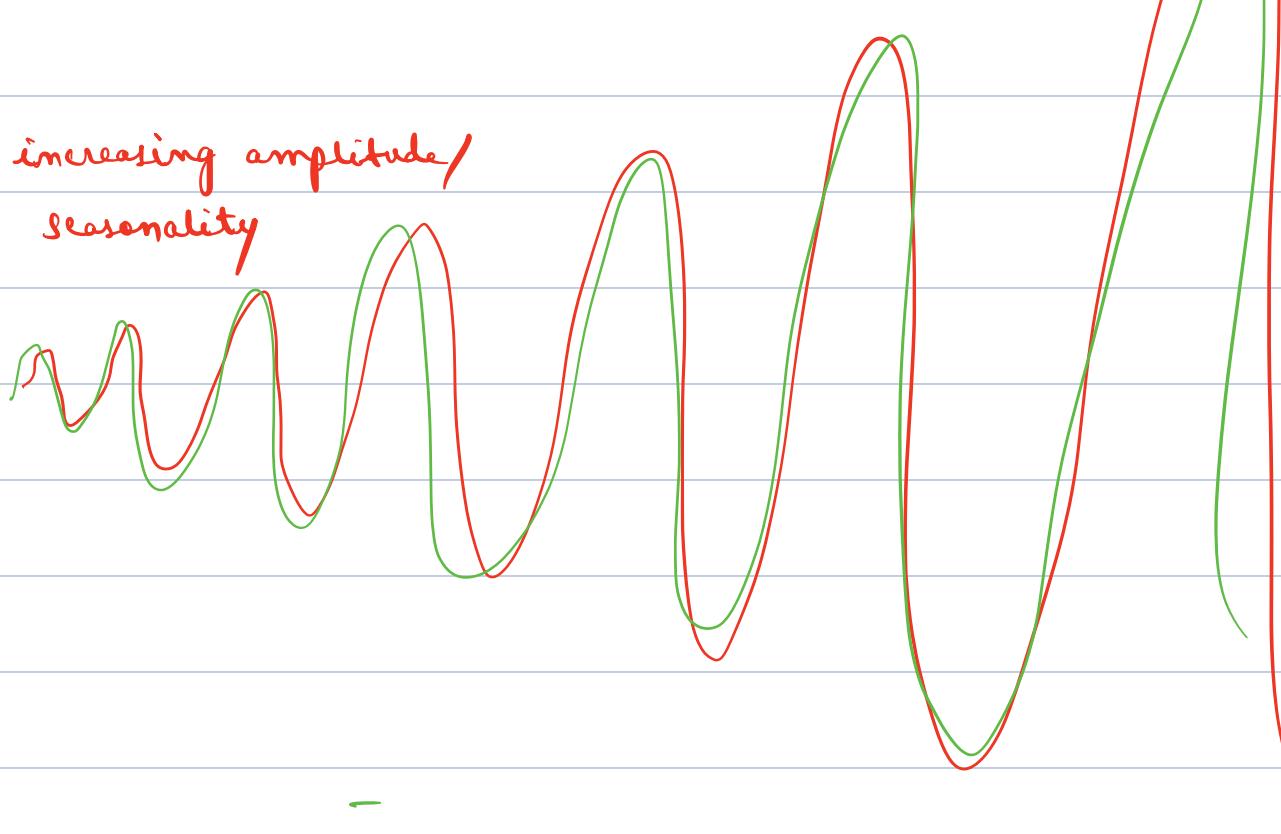
↳ Amplitude will change as
per seasonality

$$\log(y(t)) = \log(b(t)) + \log(s(t)) + \log(e(t))$$



constant amplitude

increasing amplitude/
seasonality



Centered MA $\rightarrow k$ is even.

