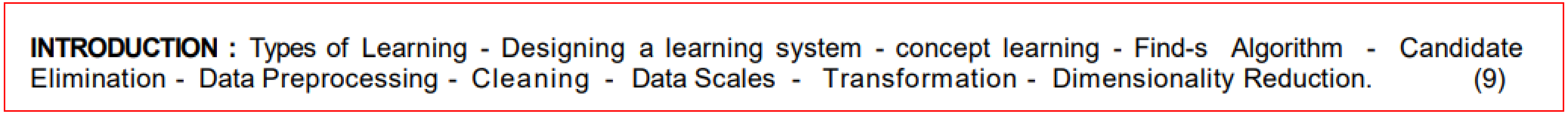
19Z601- MACHINE LEARNING

UNIT- 1 INTRODUCTION



INTRODUCTION : Types of Learning - Designing a learning system - concept learning - Find-s Algorithm - Candidate Elimination - Data Preprocessing - Cleaning - Data Scales - Transformation - Dimensionality Reduction. (9)

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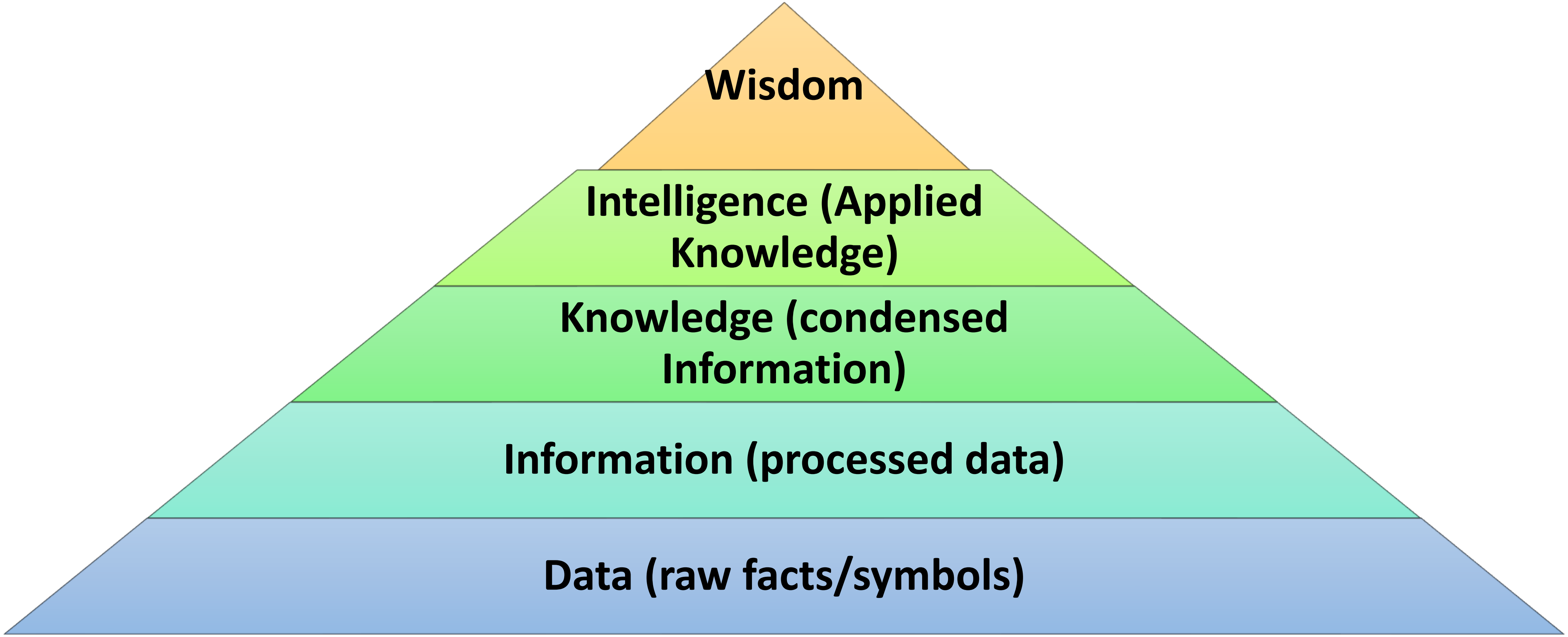
CSE

Data

What is Data? Why it has to be processed?



Wisdom

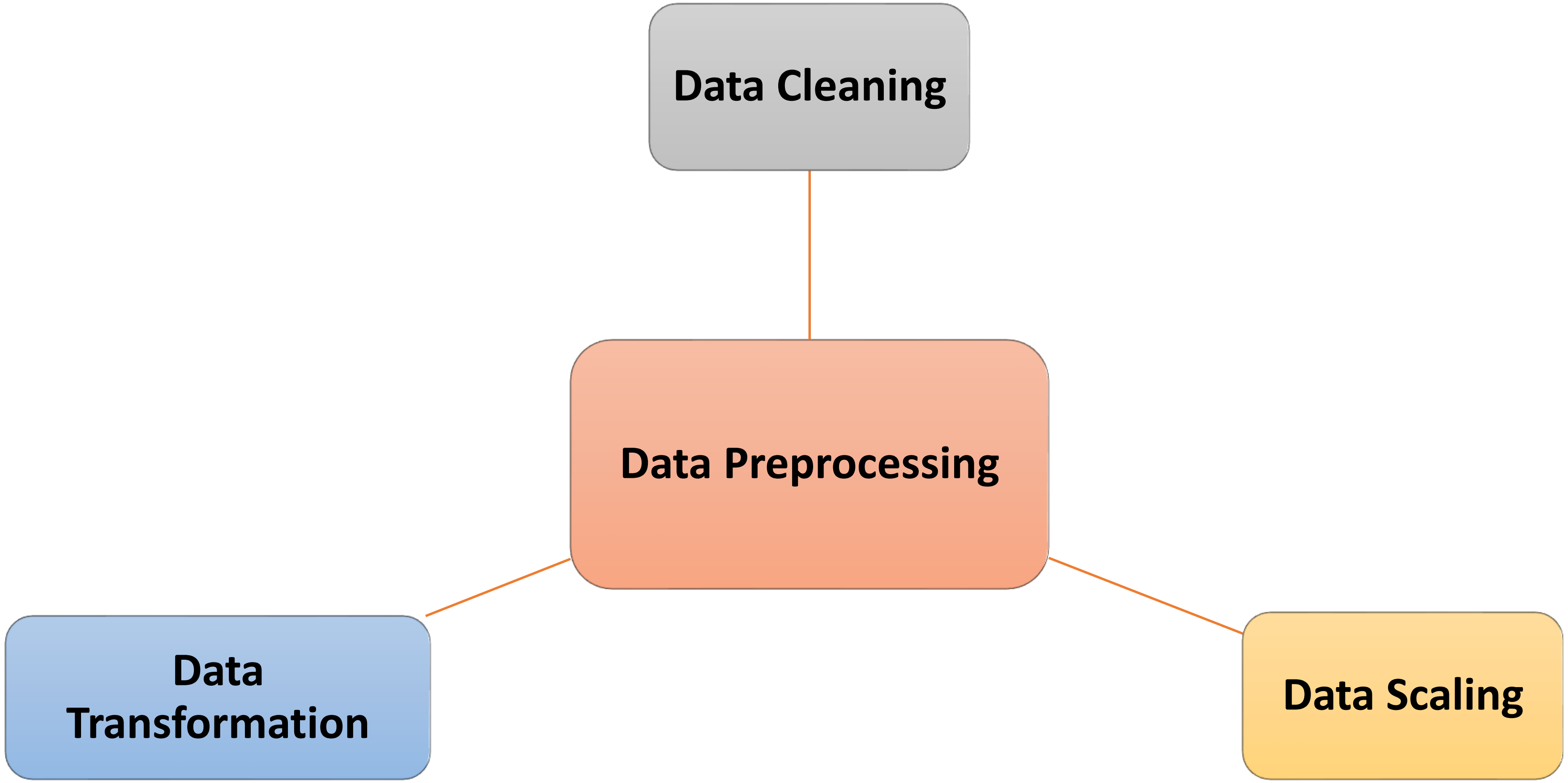
Intelligence (Applied Knowledge)

Knowledge (condensed Information)

Information (processed data)

Data (raw facts/symbols)

Data Preprocessing



Data Cleaning

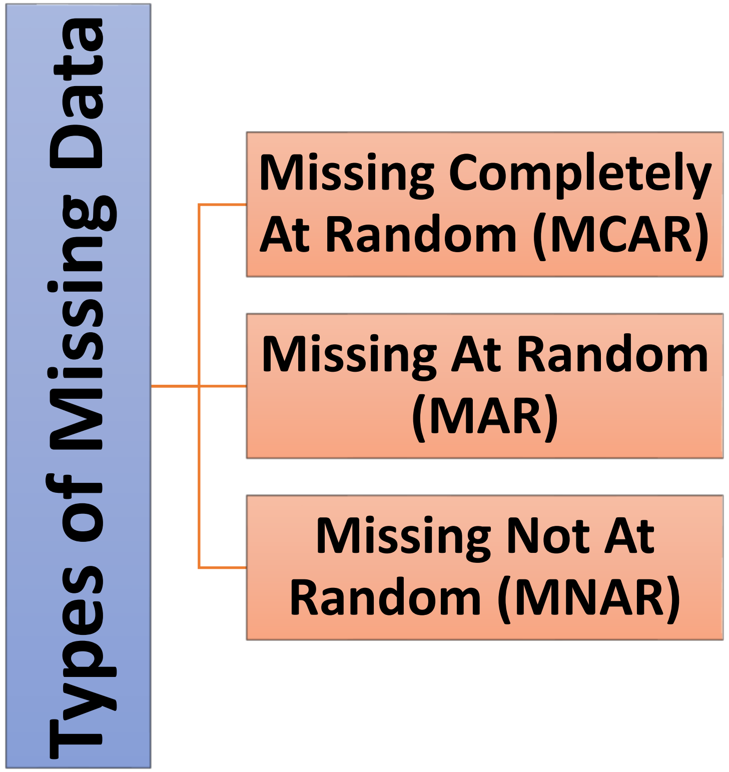
Data Preprocessing

Data Transformation

Data Scaling

Data Cleaning – Handling Missing Data

- **Removing** the **examples with missing features** from the dataset.
- Using a **learning algorithm** that can deal with missing feature values.
- Using a **data imputation** technique.



Types of Missing Data

Missing Completely At Random (MCAR)

Missing At Random (MAR)

Missing Not At Random (MNAR)

Types of Missing Data

➢Missing Completely At Random (MCAR)

- In this type, the **probability of data being missing** is unrelated to both **observed and unobserved data.**
- In other words, **missingness is purely random and occurs by chance.**
- MCAR implies that the **missing data is not systematically related to any variables in the dataset.**
- For example, a sensor failure that results in sporadic missing temperature readings can be considered MCAR.

Types of Missing Data

➢Missing At Random (MAR)

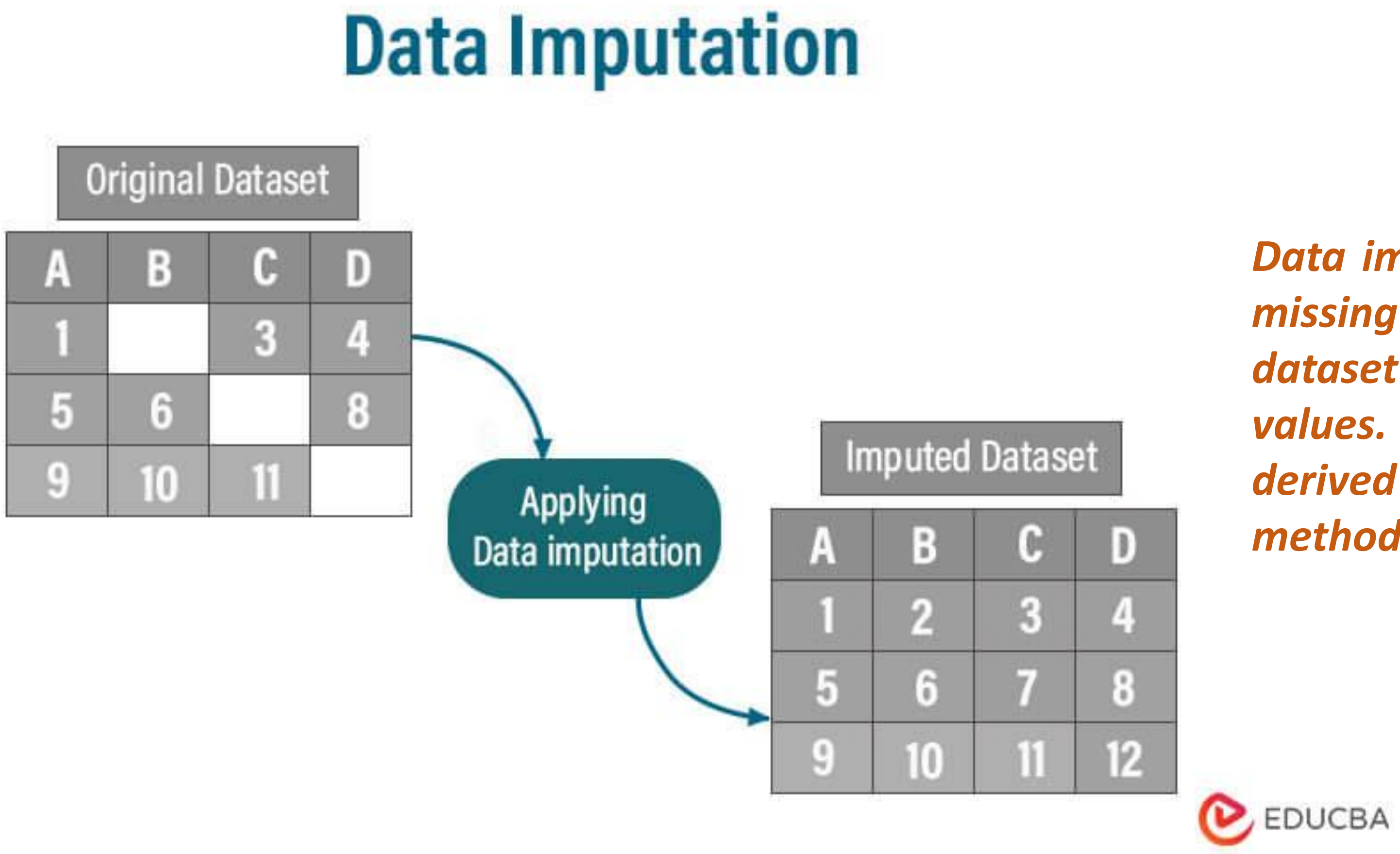
- Missing data is considered MAR **when the probability of data being missing is related to observed data but not directly to unobserved data.**
- In other words, **missingness is dependent on some observed variables.**
- For instance, in a medical study, men might be less likely to report certain health conditions than women, creating missing data related to the gender variable. MAR is a more general and common type of missing data than MCAR.

Types of Missing Data

➢ Missing Not at Random (MNAR)

- MNAR occurs when the **probability of data** being missing is related to **unobserved data or the missing values themselves.**
- This type of missing data can introduce bias into analyses because the missingness is related to the missing values.
- An example of MNAR could be patients with severe symptoms avoiding follow-up appointments, resulting in missing data related to the severity of their condition.

Data Cleaning – Handling Missing Values – Data Imputation Technique



Original Dataset

A	B	C	D
1		3	4
5	6		8
9	10	11	

Imputed Dataset

A	B	C	D
1	2	3	4
5	6	7	8
9	10	11	12

Data imputation is the process of replacing missing or incomplete data points in a dataset with estimated or substituted values. These estimated values are typically derived from the available data, statistical methods, or machine learning algorithms.

Data Cleaning – Handling Missing Values – Data Imputation Technique

- **Mean Imputation:** Replace missing values in numerical variables with the average of the observed values for that variable.
- **Median Imputation:** Replace missing values in numerical variables with the middle value of the observed values for that variable.
- **Mode Imputation:** Replace missing values in categorical variables with the most frequent category among the observed values for that variable.

Example

Bumrah – Cricket Player – Number of Wickets Taken by Last seven games

2	3	1	4	5		2

Mean = sum of all data points / Number of data points
Mean = 17/7 = 2.4 = 2 (Need Discrete value)

2	3	1	4	5	2	2

Median = n is odd , $((n+1)/2)^{th}$ observation

n is even, $$\frac{(n/2)^{th} + ((n/2) +1))^{th}}{2}$$

Median = 4

2	3	1	4	5	4	2

Mode = The data point that appears the most.

2	3	1	4	5	2	2

Applicability of Data Imputation Technique

- Use **mean imputation** for numerical variables when missing data is missing completely at random (MCAR) and the variable has a relatively normal distribution.
- Use **median imputation** when the data is skewed or contains outliers, as it is less sensitive to extreme values.
- Use **mode imputation** for categorical variables when you have missing values that can be reasonably replaced with the most frequent category.

Data Transformation - Binning

- Consider the following set : S = {12,14,19,22,24,26,28,31,32}

- By **equal-frequency bin method**, the data should be distributed across bins. Assume the bins of size 3, then the above data is distributed across the bins as follows:

Bin 1 = 12, 14,19

Bin 2 = 22,24,26

Bin 3 = 28, 31, 32

Data Transformation - Binning

- Consider the following set : S = {12,14,19,22,24,26,28,31,32}

- By **smoothing bins method**, the bins are replaced by the mean of the bin.

Bin 1 = 15,15,15
Bin 2 = 24,24,24
Bin 3 = 30.3,30.3,30.3

Data Transformation - Binning

- Consider the following set : S = {12,14,19,22,24,26,28,31,32}

- By **smoothing by bin boundaries method**, the bins values are replaced by:

Bin 1 = 12,12,19

Bin 2 = 22,22,26

Bin 3 = 28,32,32