Imputation Methods Data Mining & Neural Networks

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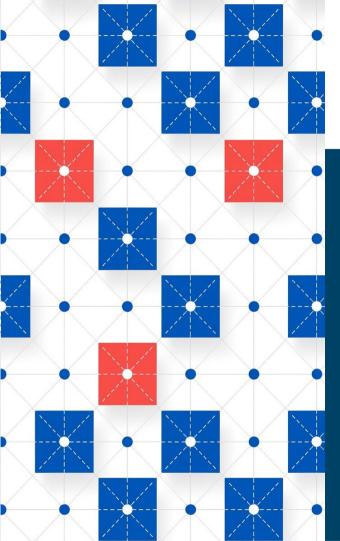




Imputation Methods for Missing Data

- In data mining and neural networks, handling missing data is crucial for building robust and accurate models.
- This session will explore various imputation techniques, their advantages, limitations, and practical applications.



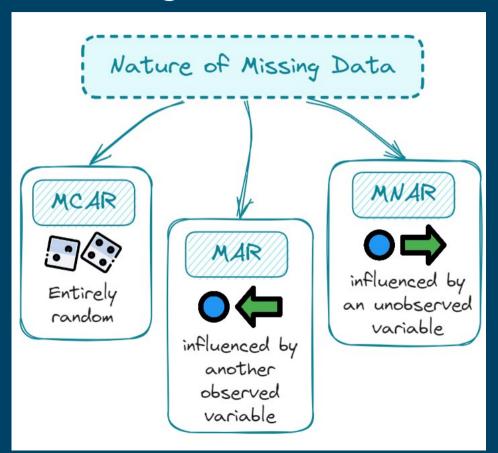


Introduction to Missing Data

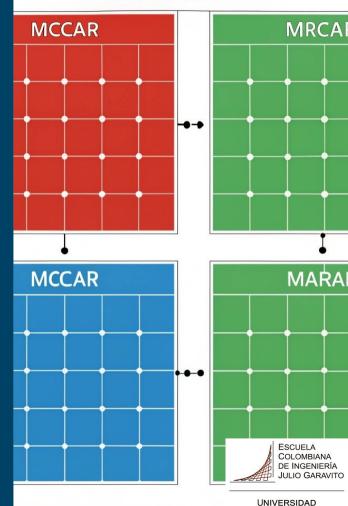
- Missing data occurs when no value is stored for a variable in an observation.
- It can arise from data entry errors, equipment malfunctions,
 or non-responses in surveys.
- Ignoring missing data can lead to biased results and reduced model performance.



Types of Missing Data



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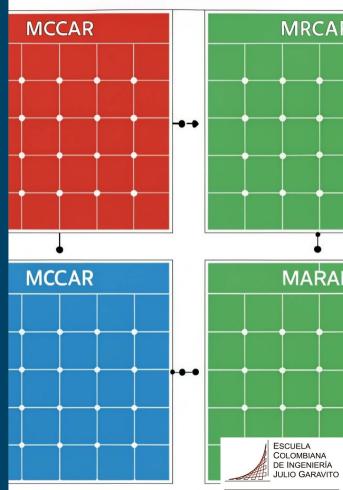


Types of Missing Data (1)

- 1: MCAR (Missing Completely at Random):
 - The missingness occurs entirely at random and is unrelated to any values in the dataset.
 - The missingness does not depend on any variable, neither the ones measured nor the ones missing.

 Example: Imagine a survey where some questionnaires were lost in the mail randomly, with no connection to the respondents' answers or characteristics.

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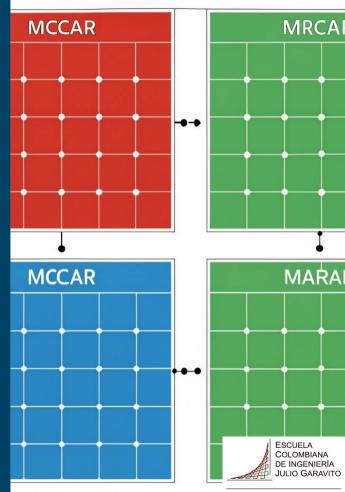


Types of Missing Data (2)

- 2: MAR (Missing at Random):
 - The missingness is related to observed data.
 - The probability of a value being missing depends only on observed data.
 - The missingness can be related to other variables that are observed in the dataset.

- Example: In a medical study, older patients may be less likely to answer income questions.
 - Here, missing income data depend on age (observed), but not on the income values themselves.

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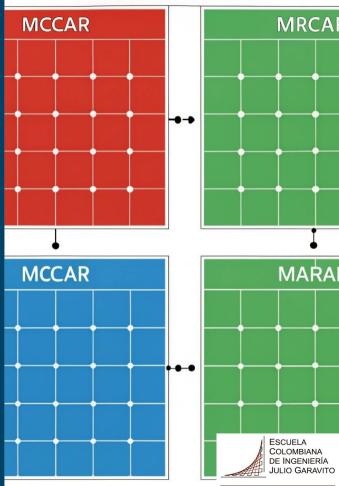


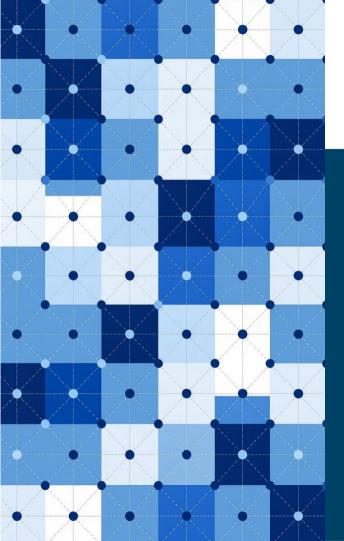
Types of Missing Data (3)

- 3: MNAR (Missing Not at Random):
 - The missingness is related to unobserved data.
 - Missingness is related to the value of the missing data.

- Example: In a survey about income, people with very high or very low incomes may choose not to report their income
 - The missingness depends on the income value itself.

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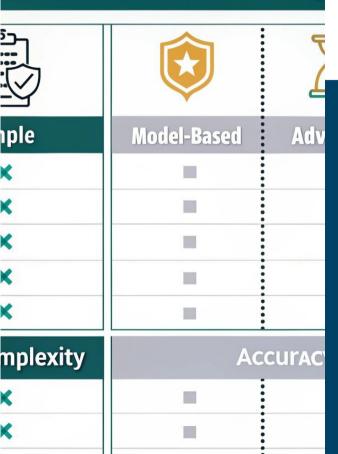


Why Imputation Matters

 Imputation allows us to retain all observations by filling in missing values, preserving statistical power, and reducing bias.



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Overview of Imputation Techniques

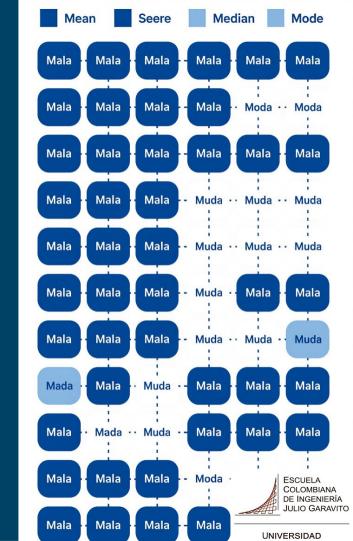
- Imputation methods can be broadly categorized into:
 - **Simple Imputation** (mean, median, mode)
 - **Model-based Imputation** (regression, k-NN, MICE)
 - Advanced Techniques (deep learning, GANs) Each method has trade-offs in terms of complexity, accuracy, and computational cost.



Mean/Median/Mode Imputation

This is the simplest method where missing values are replaced with the **mean (for continuous)**, **median (for skewed)**, or **mode (for categorical)** of the variable.

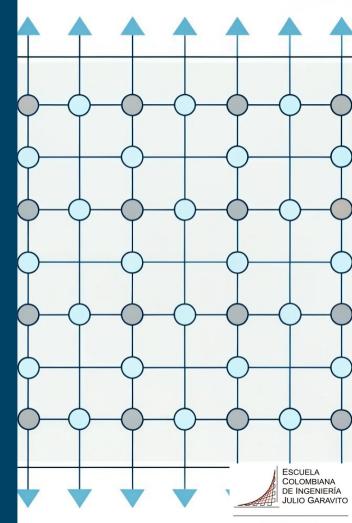
- Pros: Easy to implement, fast.
- **Cons**: Ignores feature relationships, underestimates variance.
- Example: Replacing missing age values with the average age.

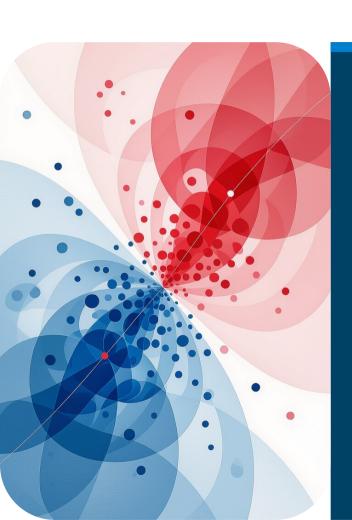


Constant Value Imputation

A fixed value (e.g., -999 or "Unknown") is used to fill missing entries.

- Pros: Useful for flagging missingness explicitly.
- Cons: Can introduce bias or mislead models if not handled properly. Often used in tree-based models that can treat such values separately.



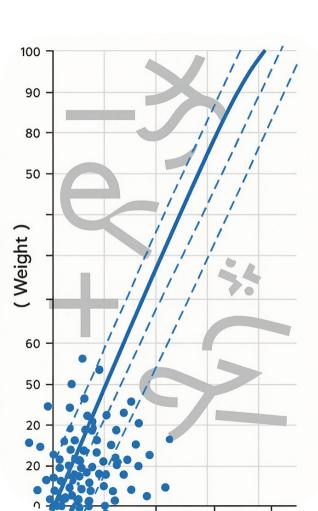


k-Nearest Neighbors (k-NN) Imputation

Imputes missing values using the average of the k most similar instances:

- Pros: Captures local structure and relationships.
- Cons: Computationally expensive, sensitive to distance metric.
- Example: Filling missing income based on similar individuals' profiles.





Regression Imputation

Predicts missing values using a regression model trained on observed data:

- **Pros**: Utilizes relationships between variables.
- Cons: Can lead to overfitting, underestimates variability.
- **Example**: Predicting missing weight using height and age.

Multiple Imputation by Chained Equations (MICE)

Each variable with missing values is imputed using a model based on other variables:

- Pros: Accounts for uncertainty, flexible with variable types.
- Cons: Computationally intensive, requires careful tuning.
 Widely used in medical and social sciences.

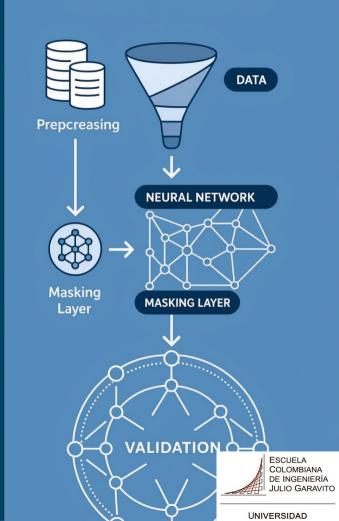


Imputation in Neural Networks

Neural networks require complete data. Imputation can be done:

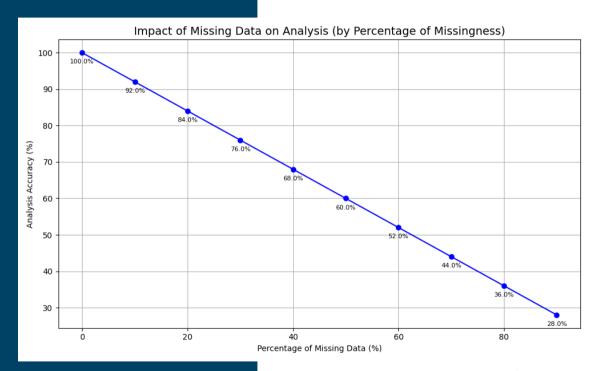
- Preprocessing step (before training)
- Within the model (e.g., masking layers)
- Best Practices: Normalize after imputation, avoid data leakage, validate with cross-validation.

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Impact of Missing Data:

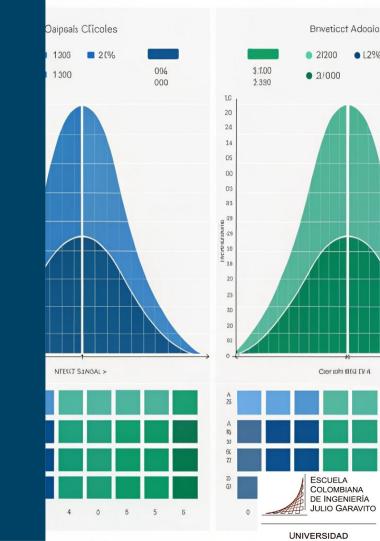
- 0-5%: minimal impact.
- 5-15%: Impact becomes noticeable; imputation methods are recommended to reduce bias and loss of power.
- 15-30%: Missing data can seriously affect results; advanced imputation or modeling techniques should be applied.
- >30%: High risk of bias and unreliable conclusions.



Evaluation of Imputation Methods

Evaluate imputation using:

- RMSE/MAE for numerical data
- Classification accuracy for categorical data
- Visual inspection (e.g., distribution plots) Use simulated missingness to benchmark methods.





Tools and Libraries

Popular Python libraries for imputation:

- pandas: fillna()
- scikit-learn: SimpleImputer, KNNImputer
- fancyimpute: MICE, SoftImpute
- PyTorch/TensorFlow: For deep learning-based imputation Choose tools based on data size, type, and model requirements.





Common Pitfalls

- Imputing test data with training statistics
- Ignoring the mechanism of missingness
- Overfitting with complex imputation models
- Not validating imputation impact on model performance Always document and justify your imputation strategy.

Summary

- Missing data is a critical issue in data mining and neural networks.
- Imputation methods range from simple to advanced.
- Choice depends on data type, missingness mechanism, and model goals.
- Evaluate and validate imputation strategies rigorously.

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