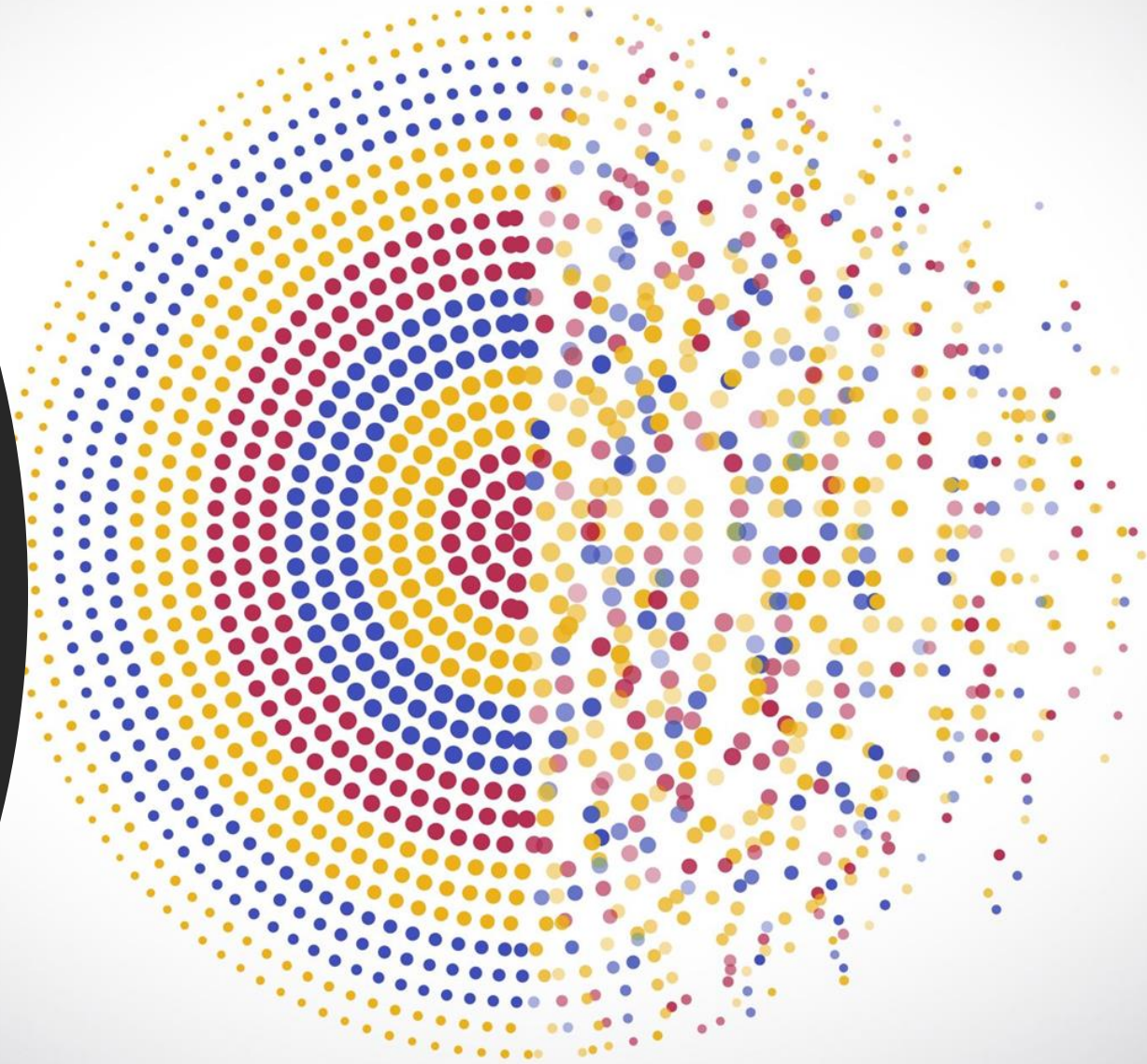
Data Preprocessing

Dr. Mohamed AlHajri



Data Preprocessing

- Aggregation
- Sampling
- Normalization
- Encoding
- Discretization

Aggregation

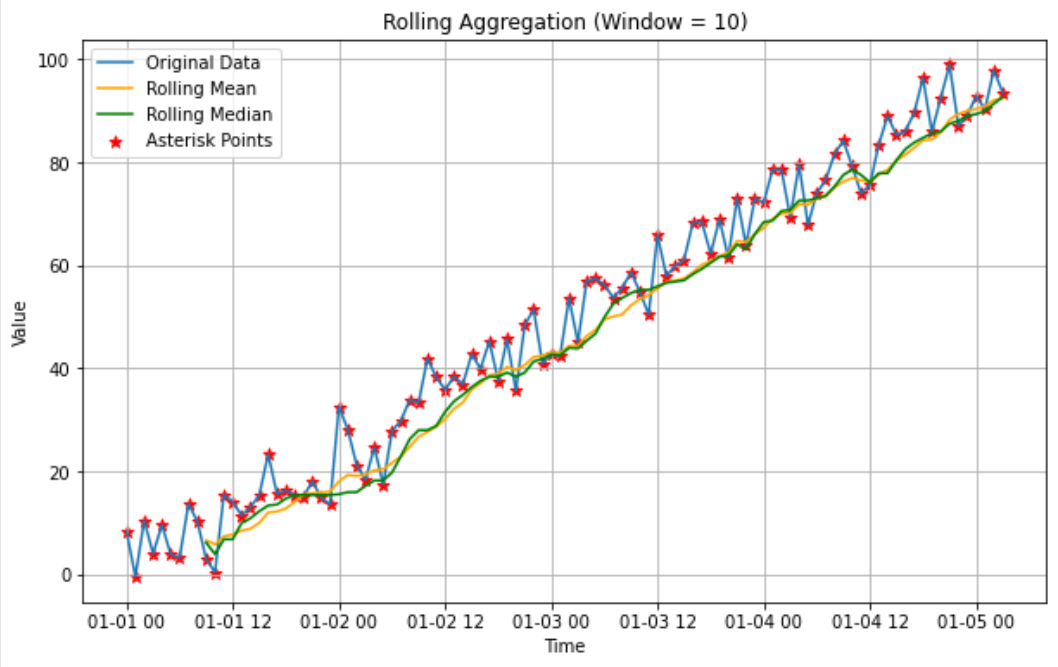
- Aggregation involves summarizing or combining data points to reduce the dataset's size and complexity. This is particularly useful when handling large time-series data, or data that needs to be summarized at different levels of granularity. Aggregation can be used to calculate various metrics such as sums, averages, or maximum values across groups or time windows.

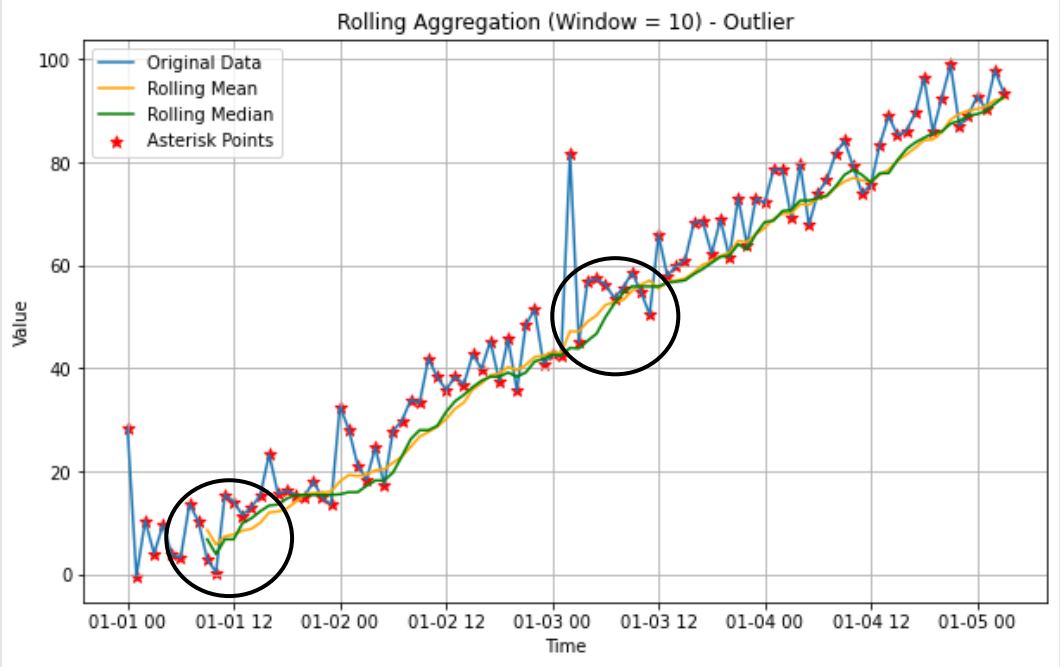
- Common Aggregation Techniques:
  - Sum Aggregation: Sums values within a group.
  - Mean Aggregation: Averages values in a group (e.g., mean temperature over a day).
  - Median Aggregation: Finds the median, which is less sensitive to outliers than the mean.
  - Windowed Aggregation: Aggregates values within a specific time or data window, often used in time-series data.
  - Spatial Aggregation: Combining geographically close data points (e.g., population density by region).

Aggregation

Aggregation Technique	Advantages	Disadvantages	When to Use
Mean Aggregation	Simple, works well for normally distributed data.	Sensitive to outliers.	Use when data is symmetric or without significant outliers.
Median Aggregation	Robust to outliers.	Does not capture fine-grained variations like the mean.	Use when data contains outliers or is skewed.
Windowed Aggregation	Helps track trends over time windows.	Can introduce lag in real-time applications.	Use for time-series data to smooth and detect trends.

Aggregation





Sampling

- Sampling is the process of selecting a subset of data from a larger population. It is used to reduce the amount of data for processing while maintaining a representative sample. Sampling is critical when working with large datasets or imbalanced data.

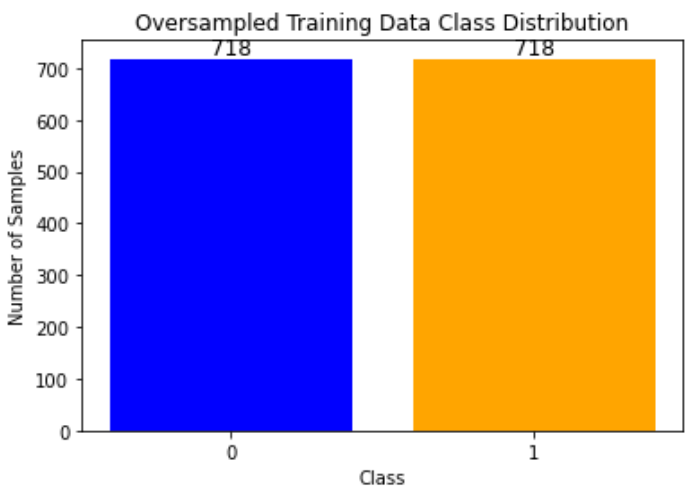
- Common Sampling Techniques:
  - Random Sampling: Selecting random instances from the dataset.
  - Stratified Sampling: Ensures each class or group is represented proportionally in the sample.
  - Oversampling/Undersampling: Used in cases of imbalanced classes, where the minority class is oversampled, or the majority class is undersampled.
  - Systematic Sampling: Data points are selected at regular intervals.

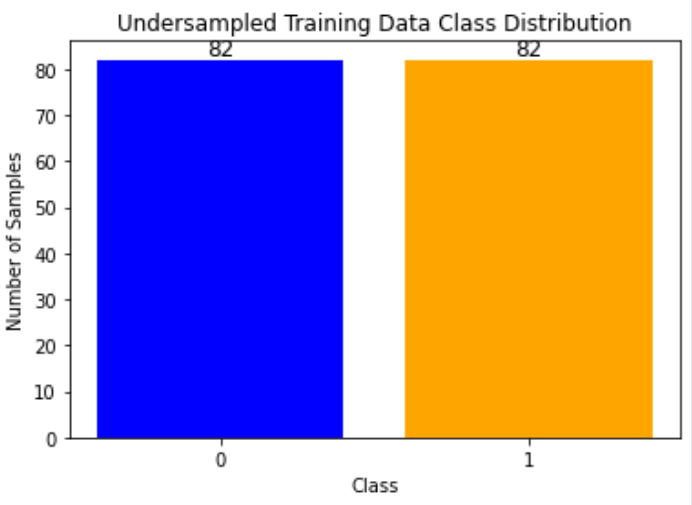
Sampling

Sampling Technique	Advantages	Disadvantages	When to Use
Random Sampling	Simple, effective for large, homogeneous datasets.	May not represent all classes proportionally (in imbalanced datasets).	Use for large datasets without inherent bias.
Stratified Sampling	Ensures proportional representation of all groups/classes.	Requires knowledge of class labels.	Use for imbalanced datasets with categorical data.
Oversampling	Effective for balancing minority classes.	May introduce overfitting if the minority class is repeated too often.	Use when dealing with imbalanced classification problems.

Sampling


Original Training Data Class Distribution
718
82
Number of Samples
Class
0
1
0
100
200
300
400
500
600
700


Oversampled Training Data Class Distribution
718
718
Number of Samples
Class
0
1
0
100
200
300
400
500
600
700


Undersampled Training Data Class Distribution
82
82
Number of Samples
Class
0
1
0
10
20
30
40
50
60
70
80

Normalization

- Normalization is the process of scaling numeric data so that it fits within a specific range, often to improve model performance. Normalization is essential when features have different scales (e.g., age vs income). Different types of normalization handle different data characteristics.

- Common Normalization Techniques:
  - Min-Max Normalization: Scales features to a range between 0 and 1.

$$\frac{X - X_{min}}{X_{max} - X_{min}}$$

  - Z-Score Normalization: Centers data with mean 0 and variance 1.

$$\frac{X - \mu_X}{\sigma_X}$$

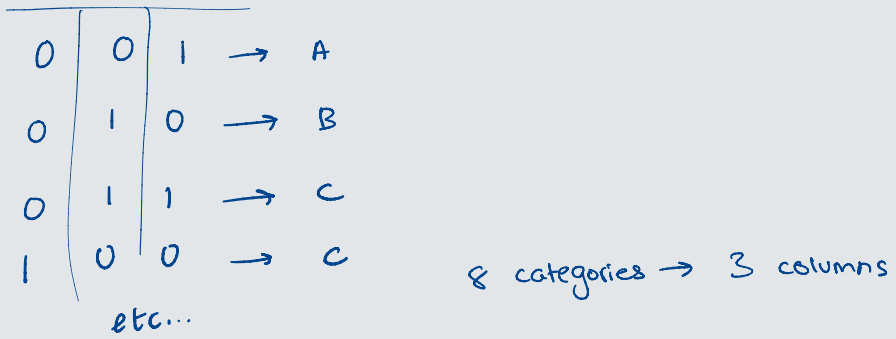
Normalization

Normalization Technique	Advantages	Disadvantages	When to Use
Min-Max Normalization	Simple, ensures all data is in [0, 1] range.	Sensitive to outliers; compresses the range of large values.	Use when data is bounded and doesn't have outliers.
Z-Score Normalization	Handles both positive and negative values well.	Less intuitive interpretation of scaled data.	Use when data is normally distributed.

Encoding

- Encoding is essential when dealing with categorical data. Since most machine learning algorithms require numerical input, categorical features must be converted into a numerical format. Different encoding techniques handle different data types (nominal vs ordinal) and cardinality.

- Common Encoding Techniques:
  - Label Encoding: Converts each category to a unique integer label.
  - One-Hot Encoding: Creates a binary column for each category. 8 categories → 8 colums
  - Frequency Encoding: Replaces categories with their frequency in the dataset. label encoding but w/ freq.
  - Binary Encoding: Converts categories to binary codes.



Encoding

Encoding Technique	Advantages	Disadvantages	When to Use
Label Encoding	Simple and memory-efficient.	Introduces an ordinal relationship that may not exist.	Use for ordinal categorical data (where order matters).
One-Hot Encoding	Avoids introducing ordinal relationships.	Can lead to high-dimensional data if categories are numerous.	Use for nominal categorical data with few categories.
Binary Encoding	Reduces dimensionality for high-cardinality categories.	May be less interpretable.	Use when the dataset contains high-cardinality categorical variables.

Encoding

Category	LabelEncoded	Category_A	Category_B	Category_C	Binary_0	Binary_1
A	0	1	0	0	0	0
B	1	0	1	0	0	1
C	2	0	0	1	1	0
A	0	1	0	0	0	0
B	1	0	1	0	0	1
C	2	0	0	1	1	0

Discretization

- Discretization is the process of converting continuous features into discrete bins or categories. This is useful when you want to apply models that assume categorical inputs or to reduce the granularity of features.

- Common Discretization Techniques:
  - Equal-width Binning: Divides the range of data into equal-width bins.
  - Equal-frequency Binning: Ensures each bin has approximately the same number of data points.
  - K-means Binning: Uses clustering algorithms (like K-means) to form bins based on cluster centers.

Discretization