Welcome to the CoGrammar Data Preprocessing

The session will start shortly...

Questions? Drop them in the chat. We'll have dedicated moderators answering questions.



Data Science Session Housekeeping

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly.
 (Fundamental British Values: Mutual Respect and Tolerance)
- No question is daft or silly ask them!
- There are Q&A sessions midway and at the end of the session, should you
 wish to ask any follow-up questions. Moderators are going to be
 answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Academic Sessions. You can submit these questions here: <u>Questions</u>



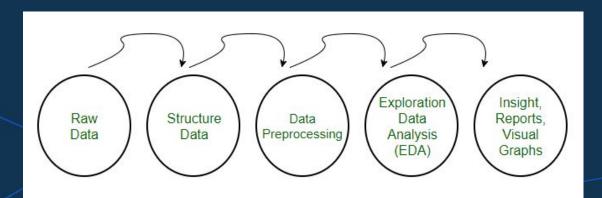
Data Science Session Housekeeping cont.

- For all non-academic questions, please submit a query:
 www.hyperiondev.com/support
- Report a safeguarding incident:
 www.hyperiondev.com/safeguardreporting
- We would love your feedback on lectures: Feedback on Lectures



Data Preprocessing

Data preprocessing is a crucial step in the data science pipeline, going beyond basic cleaning to ensure data quality and suitability for machine learning.



Source: GeeksForGeeks





Overview

- Feature scaling: Standardization, min-max scaling, robust scaling
- Encoding categorical variables: One-hot, label, ordinal encoding
- Feature engineering: Creating new features from existing data
- Handling imbalanced data: Oversampling, undersampling, class weights



Learning objectives

- Understand the importance and purpose of data preprocessing in data science projects
- Learn and apply advanced data preprocessing techniques beyond basic data cleaning
- Gain hands-on experience using Python libraries for preprocessing real-world datasets
- Integrate preprocessing techniques into machine learning workflows



Recap of Data Cleaning





Data Cleaning Recap

- Data cleaning addresses fundamental data quality issues:
 - > Handling missing values: Deletion or imputation
 - > Dealing with outliers: Removal, transformation, or winsorization
 - > Resolving inconsistencies: Standardizing formats and conventions
 - > Removing duplicates: Eliminating redundancy







Importance

- Improved data quality: Addresses complex issues beyond basic cleaning
- Enhanced model performance: Optimizes data for learning algorithms
- Reduced computational complexity: Reduces dimensionality and creates efficient representations





Feature Scaling

- Purpose: Ensure fair comparison and contribution of features
- Techniques:
 - Standardization (Z-score normalization): Transforms features to have zero mean and unit variation $X' = \frac{X \mu}{X}$
 - ➤ Min-max scaling: Scales features to a specific range, typically 0 to 1

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

- Robust scaling: Uses robust statistics (median and interquartile range) to scale features
 - (X-median)/IQR

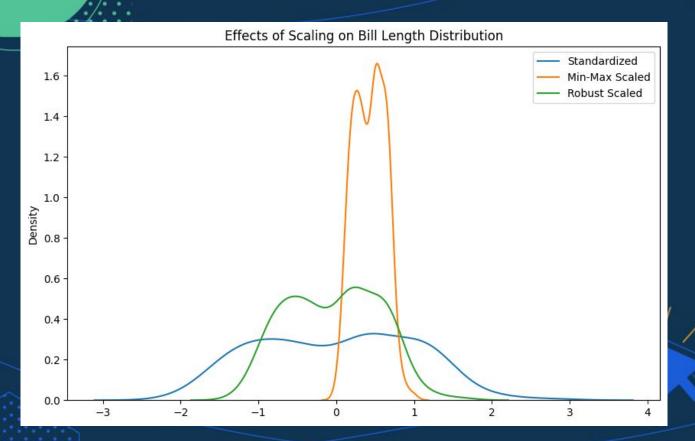


Considerations

- Standardization: Good default, assumes Gaussian distribution
- Min-max scaling: Suitable for bounded features or non-Gaussian data
- Robust scaling: Recommended when outliers are present









What is the purpose of feature scaling?

- A. To convert categorical variables into numerical representations
- B. To create new features from existing data
- C. To ensure fair comparison and contribution of features in machine learning
- D. To handle imbalanced class distributions



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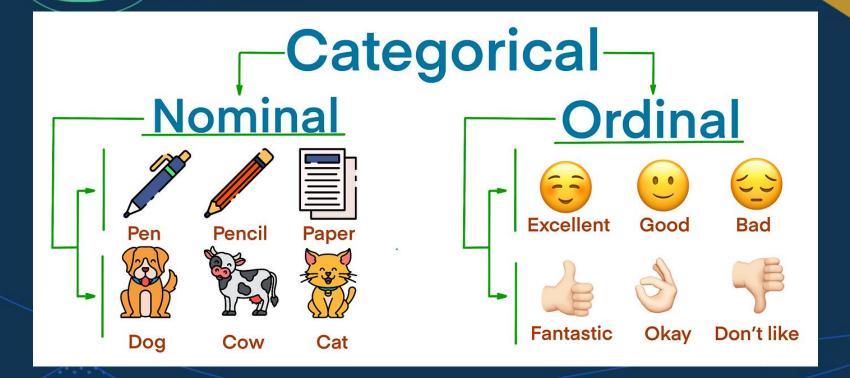


Nominal vs. Ordinal

- Nominal: Categories without inherent order (e.g., color)
- Ordinal: Categories with meaningful order (e.g., size)







Encoding Nominal variables

- One-hot encoding: Creates binary dummy variables for each category
 - Increases dimensionality, which may impact model performance

Index	Animal		Index	Dog	Cat	Sheep	Lion	Horse
0	Dog	One-Hot code	0	1	0	0	0	0
1	Cat		1	0	1	0	0	0
2	Choon							
2	Sheep		2	0	0	1	0	0
3	Horse		3	0	0	0	0	1
4	Lion		4	0	0	0	1	0





Encoding Nominal variables

- Binary encoding: Assigns unique binary codes to categories
 - > Useful when the number of categories is large, and one-hot encoding leads to high dimensionality

	City
0	Delhi
1	Mumbai
2	Hyderabad
3	Chennai
4	Bangalore
5	Delhi
6	Hyderabad
7	Mumbai
8	Agra

	City_0	City_1	City_2	City_3
0	0	0	0	1
1	0	0	1	0
2	0	0	1	1
3	0	1	0	0
4	0	1	0	1
5	0	0	0	1
6	0	0	1	1
7	0	0	1	0
8	0	1	1	0





Encoding Ordinal variables

- Label encoding: Assigns numerical labels based on order
 - Maintains ordinal information but implies linear relationships between categories
 - May not be appropriate if the ordinal relationship is not linear

De	egree
0	1
1	4
2	2
3	3
4	3
5	4
6	5
7	1
8	1

Source: AnalyticsVidhya





Encoding Ordinal variables

- Ordinal encoding: Assigns numerical labels based on order
 - > Preserves ordinal information without implying linear relationships
 - > Suitable when the ordinal relationship between categories is meaningful

De	egree
0	1
1	4
2	2
3	3
4	3
5	4
6	5
7	1
8	1

Source: AnalyticsVidhya





What is the main difference between nominal and ordinal variables?

- A. Nominal variables have categories with an inherent order, while ordinal variables do not
- B. Ordinal variables have categories with a meaningful order, while nominal variables do not
- C. Nominal and ordinal variables are the same
- D. Nominal variables are always encoded using one-hot encoding, while ordinal variables use label encoding



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Handling High-Cardinality



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Handling High-Cardinality

The Curse of Dimensionality:

As the number of features grows, the amount of data we need to accurately be able to distinguish between these features (in order to give us a prediction) and generalize our model (learned function) grows EXPONENTIALLY.

Source: AnalyticsVidhya



Frequency-based Encoding

- Replaces categories with occurrence count
- Useful when the frequency of categories is informative





Target Encoding

- Replaces categories with mean/median of target variable
- Captures the relationship between categories and the target variable

	class	Marks
0	Α,	50
1	В	30
2	C	70
3	В	80
4	C	45
5	Α	97
6	Α	80
7	A	68

	class
0	65.000000
1	57.689414
2	59.517061
3	57.689414
4	59.517061
5	79.679951
6	79.679951
7	79.679951

Source: Analytics Vidhya





Hashing

- Applies hash function to reduce dimensionality
- Useful when the number of categories is extremely large

	Month
0	January
1	April
2	March
3	April
4	Februay
5	June
6	July
7	June
8	September

	col_0	col_1	col_2	col_3	col_4	col_5
0	0	0	0	0	1	0
1	0	0	0	1	0	0
2	0	0	0	0	1	0
3	0	0	0	1	0	0
4	0	0	0	1	0	0
5	0	1	0	0	0	0
6	1	0	0	0	0	0
7	0	1	0	0	0	0
8	0	0	0	0	1	0

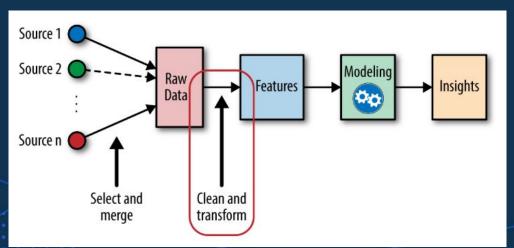
Source: AnalyticsVidhya





Feature Engineering

 Create informative features that improve model performance and interpretability



Source: AnalyticsVidhya



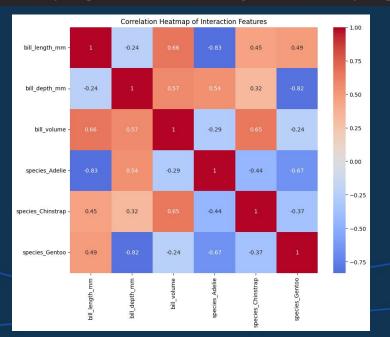
Techniques

- Interaction features: Combine existing features to capture interactions
- Polynomial features: Generate higher-order terms to capture non-linear relationships
- Domain-specific features: Apply domain knowledge to create meaningful features



Interaction Features

Interaction features
penguins['bill_volume'] = penguins['bill_length_mm'] * penguins['bill_depth_mm']







Polynomial Features

				Co	rrelatio	on Hea	tmap	of Poly	nomia	l Featu	res				
bill_length_mm	1	-0.24				0.66	0.95		-0.23	0.19	0.49				
bill_depth_mm	-0.24	1	-0.58	-0.47	-0.22	0.57	-0.4	-0.43	1	0.81	0.19		-0.52	-0.48	
flipper_length_mm	0.66	-0.58	1	0.87	0.65	0.083	0.86	0.88	-0.57	0.0056		1	0.93	0.87	
body_mass_g	0.6	-0.47	0.87			0.11		0.94	-0.46	0.043		0.87	0.99		
bill_length_mm^2	1	-0.22	0.65		1	0.67	0.95		-0.21	0.2	0.49			0.58	
bill_length_mm bill_depth_mm	0.66		0.083	0.11		1	0.48	0.34			0.53	0.08	0.099	0.099	
bill_length_mm flipper_length_mm	0.95	-0.4	0.86		0.95	0.48			-0.39	0.13		0.86			
bill_length_mm body_mass_g	0.82	-0.43	0.88	0.94		0.34			-0.42	0.1			0.95	0.94	
bill_depth_mm^2	-0.23	1	-0.57	-0.46	-0.21		-0.39	-0.42	1	0.81	0.2	-0.57	-0.51	-0.47	
bill_depth_mm flipper_length_mm	0.19	0.81	0.0056	0.043	0.2	0.77	0.13	0.1	0.81	1		0.002	0.028	0.034	
bill_depth_mm body_mass_g	0.49	0.19			0.49	0.53			0.2	0.62		0.55			
flipper_length_mm^2	0.65		1			0.08			-0.57	0.002		1			
flipper_length_mm body_mass_g	0.63	-0.52	0.93	0.99		0.099		0.95	-0.51	0.028		0.93		0.99	
body_mass_g^2	0.59	-0.48	0.87			0.099		0.94	-0.47	0.034			0.99		
	bill_length_mm -	bill_depth_mm -	flipper_length_mm -	body_mass_g -	bill_length_mm^2 -	bill_length_mm bill_depth_mm -	ill_length_mm flipper_length_mm -	bill_length_mm body_mass_g -	bill_depth_mm^2 -	oill_depth_mm flipper_length_mm -	bill_depth_mm body_mass_g -	flipper_length_mm^2 -	flipper_length_mm body_mass_g -	body_mass_g^2 -	







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Challenge

Skewed class distribution leads to biased models and poor minority class performance

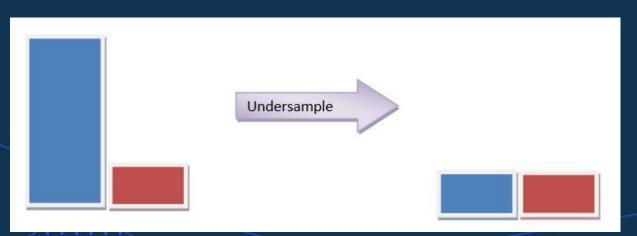


Source: AnalyticsVidhya



Techniques

- Undersampling: Reduce majority class instances
 - > Random undersampling: Remove majority instances

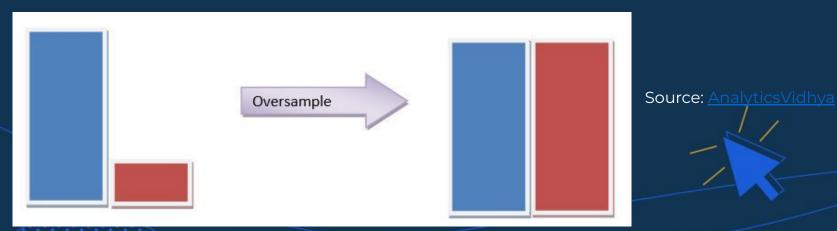


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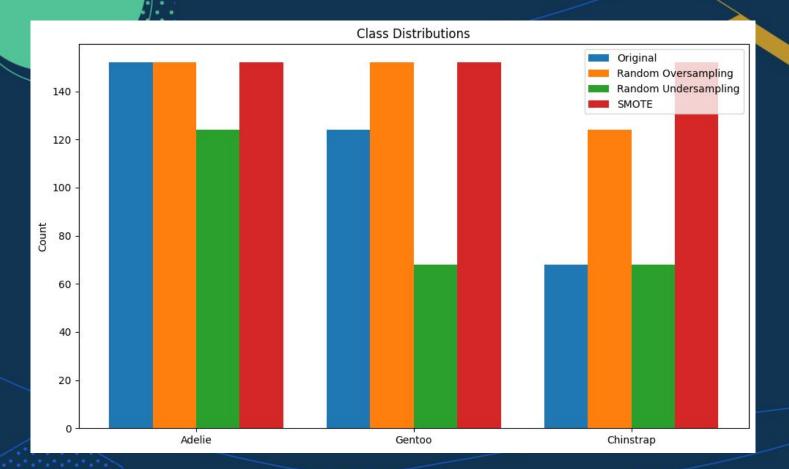


Techniques

- Oversampling: Increase minority class instances
 - > Random oversampling: Duplicate minority instances
 - > **SMOTE:** Generate synthetic minority instances









Considerations

- Oversampling may lead to overfitting, especially with random oversampling
- Undersampling may discard potentially useful data





What is the purpose of oversampling in handling imbalanced data?

- A. To reduce the number of instances in the majority class
- B. To remove majority instances that are close to minority instances
- C. To increase the number of instances in the minority class
- D. To generate synthetic minority instances by interpolating between existing instances



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Questions and Answers





Thank you for attending







