

REPORT

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Project Title: Demographic Patterns and Home Loan Applicant Profiling

Project Objectives | Problem Statements 1.1. PO1 | PS1: Classification of Loan Dataset into Segments | Clusters | Classes using Supervised Learning Classification Algorithms 1.2. PO2 | PS2: Determination of an Appropriate Classification Model 1.3. PO3 | PS3: Identification of Important | Contributing | Significant Variables or Features and their Thresholds for Classification

The Pre-processing Report will be in the end (after the managerial insights)

Input Variables: ['application_date_indicator', 'msamd_name', 'purchaser_type_name', 'loan_type_name', 'loan_purpose_name', 'hud_median_family_income', 'loan_amount_000s']

Output Variable: action_taken_name

3.2. Data Analysis 3.2.1.1. PO1 | PS1:: Supervised Machine Learning Classification Algorithm: Decision Tree (Base Model) | Metrics Used - Gini Coefficient, Entropy

Decision Tree

- Entropy: 0.15079860160668734
- Gini Impurity: 0.08122381021613079

Entropy: With an entropy value of 0.1508, the Decision Tree model using entropy as the impurity measure achieves a moderate level of disorder or unpredictability in the dataset. This indicates that the Decision Tree splits the data into nodes based on features in a way that minimizes the disorder within each node.

Gini Impurity: The Gini impurity value of 0.0812 suggests a relatively low impurity or uncertainty within the Decision Tree model. Gini impurity measures the probability of incorrectly classifying a randomly chosen element in the dataset, with lower values indicating better purity of the dataset.

3.2.1.2. PO1 | PS1:: Supervised Machine Learning Classification Algorithms: {Random Forest | XGBoost} (Comparison Models) | Metrics Used

Random Forest:

- Entropy for Random Forest: 0.4448700986425233
- Gini Impurity for Random Forest: 0.03587907150255809

Entropy: The entropy value for the Random Forest model is approximately 0.445. Entropy measures the uncertainty or disorder in the dataset. A higher entropy value indicates higher disorder, suggesting that the Random Forest model's decision boundaries are less clear or well-defined.

Gini Impurity: The Gini impurity value for the Random Forest model is approximately 0.036. Gini impurity measures the probability of misclassifying an instance in a dataset. A lower Gini impurity value indicates that the Random Forest model's decision boundaries are more precise and less prone to misclassification.

XG Boost:

- Entropy for XGBoost: 0.11704169720141437
- Gini Impurity for XGBoost: 0.04694253206253052

Entropy: The entropy value for XGBoost is approximately 0.117. Entropy measures the impurity or disorder in a set of data. A lower entropy value indicates that the data is more pure or well-separated into distinct classes.

Gini Impurity: The Gini impurity for XGBoost is approximately 0.047. Gini impurity measures the probability of incorrectly classifying a randomly chosen element if it were randomly labeled according to the distribution of labels in the subset. Similar to entropy, a lower Gini impurity value suggests a more pure or well-separated dataset.

3.2.2.1.1. PO2 | PS2:: Classification Model Performance Evaluation: Confusion Matrix {Accuracy, Recall, Precision, F1-Score} (Base Model: Decision Tree)

	precision	recall	f1-score	support
0	0.00	0.00	0.00	63
1	0.00	0.00	0.00	121
2	0.00	0.00	0.00	2000
3	0.00	0.00	0.00	334
4	0.94	1.00	0.97	
5	1.00	1.00	1.00	
6	0.00	0.00	0.00	13
7	0.00	0.00	0.00	26
	accuracy	macro avg	weighted avg	
	0.94	0.24	0.89	
		0.25	0.94	
		0.25	0.92	

Precision: Precision measures the ratio of correctly predicted instances of a class to the total instances predicted as that class. Classes 4 and 5 have high precision scores of 0.94 and 1.00, respectively, indicating that the model correctly identifies most instances of these classes. However, other classes (0, 1, 2, 3, 6, 7) have precision scores of 0.00, suggesting that the model fails to correctly predict instances for these classes.

Recall: Recall, also known as sensitivity, measures the ratio of correctly predicted instances of a class to the total actual instances of that class. Classes 4 and 5 have high recall scores of 1.00, indicating that the model correctly identifies almost all actual instances of these classes. Similar to precision, other classes (0, 1, 2, 3, 6, 7) have recall scores of 0.00, indicating that the model fails to capture most actual instances of these classes.

F1-score: The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. Classes 4 and 5 have high F1-scores, reflecting the balance between precision and recall for these classes. For classes with a precision or recall of 0.00, the F1-score is also 0.00, indicating poor performance.

Accuracy: The overall accuracy of the model is 0.94, indicating that it correctly predicts the class labels for 94% of the instances in the dataset.

- Observations: The model performs well in classifying instances of classes 4 and 5, achieving high precision, recall, and F1-scores. However, for other classes, the model's performance is poor, as indicated by precision, recall, and F1-scores of 0.00.

Overall, while the model demonstrates high accuracy, its effectiveness varies significantly across different classes, suggesting potential imbalance or bias in the dataset or model training process. Further investigation and possibly model refinement may be necessary to address these issues.

3.2.2.1.2. PO2 | PS2:: Classification Model Performance Evaluation: Time Statistics | Memory Statistics (Base Model: Decision Tree)

Decision Tree:

- Training Time (s): 0.0698244571685791
- Memory Used (MB): 713.6015625

3.2.2.2.1. PO2 | PS2:: Classification Model Performance Evaluation: Confusion Matrix {Accuracy, Recall, Precision, F1-Score} (Comparison Models: Random Forest | XGBoost)

Random Forest

	precision	recall	f1-score	support
0	0.89	0.47	0.61	
1	0.77	0.51	0.61	
2	0.84	0.85	0.84	
3	0.80	0.64	0.71	
4	0.99	0.99	0.99	
5	1.00	1.00	1.00	
6	1.00	0.73	0.85	
7	0.96	0.89	0.92	
	accuracy	macro avg	weighted avg	
	0.98	0.91	0.98	
		0.76	0.98	
		0.82	0.98	

Precision: Precision measures the ratio of correctly predicted positive observations to the total predicted positives. For the Random Forest model:

- Across all classes, the precision values indicate a generally high level of accuracy in the model's predictions. Classes 4 and 5 stand out with precision scores of 99% and 100%, respectively, indicating near-perfect prediction accuracy for these classes. Additionally, classes 0, 1, 2, 3, and 7 exhibit precision scores ranging from 77% to 96%, indicating strong prediction accuracy across a diverse range of classes. Overall, the model demonstrates the ability to make accurate predictions across multiple classes, with precision scores consistently above 77%.

Recall: Recall measures the ratio of correctly predicted positive observations to the actual positives in the dataset.

F1-score: The F1-score is the harmonic mean of precision and recall and provides a balance between the two metrics.

Support: Support represents the number of actual occurrences of each class in the specified dataset.

- Observations: The Random Forest model demonstrates high precision and recall across most classes, indicating its effectiveness in correctly classifying instances across different categories. The model achieves an overall accuracy of 98%, suggesting strong performance in classifying instances correctly. The macro average and weighted average F1-scores are high, indicating a good balance between precision and recall across all classes. The model performs exceptionally well in predicting classes 4 and 5, as indicated by their high precision, recall, and F1-scores. Class 0 and Class 1 have relatively lower precision and recall compared to other classes, suggesting room for improvement in predicting these classes.

Overall, the Random Forest model demonstrates robust performance across multiple evaluation metrics, highlighting its effectiveness in classification tasks.

XG Boost

precision	recall	f1-score	support
0	0.88	0.21	0.34
1	0.84	0.20	0.32
2	0.73	0.74	0.74
3	0.75	0.38	0.50
4	0.98	0.99	0.99
5	1.00	1.00	1.00
6	0.88	0.47	0.61
7	0.96	0.89	0.92

accuracy	macro avg	weighted avg
0.97	0.88	0.97
	0.61	0.97
	0.68	0.97

Precision: Precision measures the proportion of true positive predictions among all positive predictions made by the model. It indicates the model's ability to avoid false positives. Here:

- The precision values for the different classes vary, ranging from 73% to 100%. Overall, the model demonstrates strong prediction accuracy, with most classes having precision scores above 80%. Classes 4 and 5 stand out with precision scores of 98% and 100%, respectively, indicating very high accuracy in predicting these classes. However, classes 0, 1, 6, and 7 also show respectable precision scores ranging from 84% to 96%. Class 2 has the lowest precision at 73%, suggesting that predictions for this class may be less accurate compared to others. Nonetheless, the model's performance across most classes indicates reliable predictive capability.

Recall: Recall, also known as sensitivity, measures the proportion of true positives that were correctly identified by the model among all actual positives in the dataset. Here:

- The recall values for the different classes show considerable variation, ranging from 20% to 100%. Classes 4 and 5 have exceptionally high recall scores of 99% and 100%, respectively, indicating that the model effectively captures the majority of instances belonging to these classes. Conversely, classes 0 and 1 have low recall values of 21% and 20%, respectively, suggesting that the model misses a significant portion of instances belonging to these classes. Classes 2, 3, 6, and 7 exhibit moderate recall scores ranging from 38% to 74%, indicating varying degrees of effectiveness in capturing instances from these classes. Overall, the recall values provide insight into how well the model identifies instances from each class, with higher values indicating better performance in correctly identifying instances.

F1-score: The F1-score is the harmonic mean of precision and recall. It provides a balance between precision and recall. Here:

- The F1-scores for the different classes exhibit a wide range of values, indicating varying levels of model performance across classes. Classes 4 and 5 have exceptionally high F1-scores of 0.99 and 1.00, respectively, suggesting excellent precision and recall, resulting in high overall model performance for these classes. Conversely, classes 0 and 1 have low F1-scores of 0.34 and 0.32, respectively, indicating poorer model performance in terms of both precision and recall for these classes. Classes 2, 3, and 6

exhibit moderate F1-scores, ranging from 0.50 to 0.74, indicating relatively balanced performance in terms of precision and recall for these classes. Class 7 also shows a high F1-score of 0.92, indicating a good balance between precision and recall for this class. Overall, the F1-scores provide a comprehensive measure of model performance, considering both precision and recall, and highlight areas where the model may need improvement for certain classes.

Support: Support indicates the number of actual occurrences of each class in the dataset.

Accuracy: The overall accuracy of the model is 97%. Accuracy measures the proportion of correctly classified instances among all instances in the dataset.

- **Observations:** The XGBoost model demonstrates high precision and recall for most classes, particularly for classes 4 and 5, indicating its effectiveness in correctly classifying instances across multiple classes. Classes 0, 1, and 3 have relatively lower precision and recall, suggesting challenges in correctly identifying instances belonging to these classes. The weighted average F1-score of 0.97 indicates overall good performance of the XGBoost model in terms of balancing precision and recall across all classes.

3.2.2.2.2. PO2 | PS2:: Classification Model Performance Evaluation: Time Statistics | Memory Statistics (Comparison Models: Random Forest | XGBoost)

Random Forest

- Training Time (s): 5.672376871109009
- Memory Used (MB): 885.76953125

XG Boost

- Training Time (s): 45.33557963371277
- Memory Used (MB): 897.80859375

3.2.3.1. PO3 | PS3:: Variable or Feature Analysis: Base Model (Decision Tree)

feature	importance
application_date_indicator	0.479
msamd_name	0.292
purchaser_type_name	0.229
loan_type_name	0.000
loan_purpose_name	0.000
hud_median_family_income	0.000
loan_amount_000s	0.000

The most important feature is application_date_indicator with an importance value of 0.479. The second most important feature is msamd_name with an importance value of 0.292. The third most important feature is purchaser_type_name with an importance value of 0.229. Features loan_type_name, loan_purpose_name, hud_median_family_income, and loan_amount_000s have importance values of 0.000, indicating they are not contributing significantly to the model's predictions.

3.2.3.2. PO3 | PS3:: Variable or Feature Analysis: Comparison Models (Random Forest | XGBoost)
Random Forest

Feature Importances:

feature	Importance
loan_amount_000s	0.333727
purchaser_type_name	0.201634
application_date_indicator	0.195447
hud_median_family_income	0.120389
msamd_name	0.096998
loan_type_name	0.027990
loan_purpose_name	0.023816

The most important feature is loan_amount_000s with an importance value of 0.334. The second most important feature is purchaser_type_name with an importance value of 0.202. The third most important feature is application_date_indicator with an importance value of 0.195. Features hud_median_family_income and msamd_name also have relatively significant importance values of 0.120 and 0.097, respectively. Features loan_type_name and loan_purpose_name have lower importance values, indicating they contribute less to the model's predictions.

XG Boost

feature	Importance
application_date_indicator	0.765484
purchaser_type_name	0.199578
hud_median_family_income	0.014517
msamd_name	0.012562
loan_type_name	0.003441
loan_purpose_name	0.003015
loan_amount_000s	0.001402

The most important feature is application_date_indicator with a high importance value of 0.765. The second most important feature is purchaser_type_name with a relatively lower importance value of 0.200. Features hud_median_family_income and msamd_name have very low importance values of 0.015 and 0.013, respectively. Features loan_type_name, loan_purpose_name, and loan_amount_000s contribute even less to the model's predictions, with importance values below 0.01.

Results | Observations 4.1. Classification Model Parameters: Base Model (Decision Tree) | Comparison Models (Random Forest | XGBoost)

Algorithm	Entropy	Gini Impurity
Decision Tree	0.1508	0.0812
Random Forest	0.4449	0.0359
XGBoost	0.1170	0.0469

The entropy values indicate the average uncertainty in classifying a sample in the dataset. Lower entropy values suggest better decision tree purity, indicating more accurate predictions. Random Forest shows the highest entropy, indicating higher uncertainty compared to Decision Tree and XGBoost. Gini impurity measures the probability of misclassifying a sample. Lower Gini impurity values suggest better decision tree purity and thus, more accurate predictions. Random Forest exhibits the lowest Gini impurity, indicating better purity and classification performance compared to Decision Tree and XGBoost.

4.2. Classification Model Performance: Time & Memory Statistics [Base Model (Decision Tree) | Comparison Models (Random Forest | XGBoost)]

Algorithm	Training Time (s)	Memory Used (MB)
Decision Tree	0.0698	713.60
Random Forest	5.6724	885.77
XGBoost	45.3356	897.81

Decision Tree has the shortest training time, indicating fast model training compared to Random Forest and XGBoost. Random Forest exhibits longer training time than Decision Tree but shorter than XGBoost, suggesting a trade-off between training time and model complexity. XGBoost requires the longest training time, indicating more computationally intensive model training compared to Decision Tree and Random Forest. Memory usage is highest for XGBoost, followed by Random Forest and then Decision Tree, indicating the memory requirements of each algorithm.

4.3. Variable or Feature Analysis: Base Model (Decision Tree) | Comparison Models (Random Forest | XGBoost)

Algorithm	Precision	Recall	F1-score
Decision Tree	0.89	0.94	0.92
Random Forest	0.98	0.98	0.98
XGBoost	0.97	0.97	0.97

Random Forest achieves the highest precision, recall, and F1-score among the three algorithms, indicating superior overall performance in terms of classification accuracy. Decision Tree exhibits the lowest precision, recall, and F1-score, suggesting comparatively lower classification accuracy compared to Random Forest and XGBoost. XGBoost achieves slightly lower precision, recall, and F1-score than Random Forest but higher than Decision Tree, indicating its performance falls between the other two algorithms.

4.3.1. List of Relevant or Important Variables or Features and their Thresholds

Feature	Importance (Decision Tree)	Importance (Random Forest)	Importance (XGBoost)
application_date_indicator	0.479	0.195	0.765
purchaser_type_name	0.229	0.202	0.200
msamd_name	0.292	0.097	0.013
loan_type_name	0.000	0.028	0.003
loan_purpose_name	0.000	0.024	0.003
hud_median_family_income	0.000	0.120	0.015
loan_amount_000s	0.000	0.334	0.001

Analysis:

Application Date Indicator: This feature appears to be crucial across all models, especially in XGBoost, where it has the highest importance. This suggests that the application date might have a significant impact on the outcome.

Purchaser Type Name: While it has a considerable importance in all models, it ranks lower than the application date indicator. It indicates that the type of purchaser involved might also play a role in the outcome.

MSAMD Name: Despite being significant in the Decision Tree model, its importance diminishes in Random Forest and XGBoost. This suggests that its predictive power might not be as strong as other features.

Loan Type Name and Loan Purpose Name: These features have negligible importance across all models, indicating they might not contribute much to the predictions.

HUD Median Family Income: While it has some importance in Random Forest, it's relatively low in XGBoost. This might indicate that income levels of families in certain areas have varying impacts depending on the model.

Loan Amount (000s): It's significant only in the Random Forest model. This could mean that loan amount plays a more critical role in its decision-making process compared to other models.

Best Method: Based on the provided data and analysis, it's challenging to determine the absolute "best" method as it heavily depends on various factors such as dataset characteristics, interpretability requirements, computational resources, and specific objectives of the analysis.

- However, based on the insights gained: Decision Trees are easy to interpret and computationally efficient but might suffer from overfitting. Random Forests tend to provide better generalization by averaging multiple decision trees and handle overfitting well. XGBoost often delivers superior performance due to its boosting technique, which iteratively improves model performance, but it may require more computational resources and tuning effort. Therefore, if interpretability and computational efficiency are crucial, Decision Trees might be preferred. If high predictive accuracy and generalization are the primary objectives, Random Forests or XGBoost could be more suitable depending on the specific requirements and computational resources available.

4.3.2. List of Non-Relevant or Non-Important Variables or Features

Feature	Importance (Decision Tree)	Importance (Random Forest)	Importance (XGBoost)
loan_type_name	0.000	0.028	0.003
loan_purpose_name	0.000	0.024	0.003
hud_median_family_income	0.000	0.120	0.015
loan_amount_000s	0.000	0.334	0.001

Analysis:

Loan Type Name and Loan Purpose Name: These variables are consistently deemed unimportant across all three models. This suggests that the type of loan and its purpose might not significantly influence the outcome in this context.

HUD Median Family Income: While this feature has some importance in Random Forest, it ranks low in XGBoost and is considered unimportant in Decision Trees. This disparity could indicate that its predictive power varies between models or that it interacts with other variables differently.

Loan Amount (000s): This feature is deemed unimportant in both Decision Trees and XGBoost but holds significant importance in Random Forest. This discrepancy suggests that the importance of loan amount might vary depending on the modeling technique used.

The importance of variables can vary significantly between different modeling techniques, highlighting the importance of exploring multiple approaches to gain a comprehensive understanding of the data. Features that are deemed unimportant in one model may still have predictive power in others, underscoring the need for model comparison and interpretation. Non-important variables can be removed from the model to simplify it without sacrificing predictive performance, potentially improving model efficiency and interpretability.

Overall, understanding the importance of variables across different models provides valuable insights into the underlying relationships within the data and aids in making informed decisions about feature selection and model optimization.

Managerial Insights

5.1. Appropriate Model: Compare and Contrast {Decision Tree | Random Forest | XGBoost}

Algorithm	Precision (weighted avg)	Recall (weighted avg)	F1-score (weighted avg)	Training Time (s)	Memory Used (MB)
Decision Tree	0.89	0.94	0.92	0.0698	713.60
Random Forest	0.98	0.98	0.98	5.6724	885.77
XGBoost	0.97	0.97	0.97	45.3356	897.81

Insights: Performance Metrics: Precision, Recall, and F1-score: Random Forest outperforms both Decision Tree and XGBoost in terms of precision, recall, and F1-score, indicating superior overall predictive performance. Consistency: Decision Tree and XGBoost exhibit similar performance across precision, recall, and F1-score metrics, suggesting comparable effectiveness in classification tasks. Resource Utilization: Training Time: Decision Tree has the lowest training time, indicating quick model development. Random Forest and XGBoost require significantly more time due to their ensemble and gradient boosting nature, respectively. Memory Usage: Decision Tree consumes the least memory, making it suitable for resource-constrained environments. However, Random Forest and XGBoost utilize more memory due to their complex ensemble structures and the need to store multiple trees.

Trade-offs and Considerations: Accuracy vs. Resource Consumption: Random Forest offers the highest accuracy but requires more computational resources. Managers should weigh the trade-off between model accuracy and resource utilization based on their specific requirements and constraints. Time Sensitivity: Decision Tree's quick training time makes it ideal for scenarios where rapid model deployment is critical. However, if accuracy is paramount and time is not a constraint, Random Forest or XGBoost may be preferable despite longer training times.

Model Selection Strategy: Use Case Suitability: Decision Tree may be preferred for quick exploratory analysis or when interpretability is essential. Random Forest and XGBoost are better suited for scenarios where high predictive accuracy is required, such as fraud detection or customer churn prediction. Iterative Improvement: If initial results with Decision Tree are promising but lack the desired accuracy, managers can consider transitioning to Random Forest or XGBoost for iterative improvement without sacrificing interpretability entirely.

Overall, managers should carefully evaluate the trade-offs between model performance, training time, and resource consumption to select the most suitable algorithm for their specific business objectives and constraints.

5.2. Relevant or Important Variables or Features (Given the Appropriate Model)

Feature	Importance (Decision Tree)	Importance (Random Forest)	Importance (XGBoost)
application_date_indicator	0.479	0.196	0.765
msamd_name	0.292	0.097	0.013
purchaser_type_name	0.229	0.202	0.200
hud_median_family_income	0.000	0.120	0.015
loan_type_name	0.000	0.028	0.003
loan_purpose_name	0.000	0.024	0.003

Feature	Importance (Decision Tree)	Importance (Random Forest)	Importance (XGBoost)
loan_amount_000s	0.000	0.335	0.001

Application Date Indicator: This variable consistently shows high importance across all three methods, particularly in Decision Trees and XGBoost. Its importance suggests that the timing of loan applications has a significant impact on the outcome, implying potential seasonality or temporal trends that affect decision-making.

MSAMD Name: While moderately important in Decision Trees, MSAMD Name holds relatively low importance in Random Forest and XGBoost. This disparity indicates that the geographic area, represented by MSAMD Name, might have varying levels of influence on the outcome depending on the modeling technique used.

Purchaser Type Name: Purchaser Type Name ranks consistently high in importance across all methods, suggesting its significant impact on the outcome. Understanding the different categories of purchasers and their behaviors could provide valuable insights for targeted marketing or risk assessment strategies.

HUD Median Family Income: Despite being deemed unimportant in Decision Trees, HUD Median Family Income holds substantial importance in Random Forest. This discrepancy warrants further investigation to understand its varying impact on the outcome and its interaction with other variables.

Loan Type Name and Loan Purpose Name: These variables are consistently deemed unimportant across all methods. Simplifying the model by removing these features may streamline the decision-making process without sacrificing predictive performance.

Loan Amount (000s): While considered unimportant in Decision Trees and XGBoost, Loan Amount is highly significant in Random Forest. The differing importance of this variable suggests that its impact on the outcome may be model-dependent, emphasizing the need for model comparison and interpretation.

- Decision Trees: Interpretability: Decision Trees offer straightforward interpretation, as they represent decision rules in a tree-like structure, making them easy to understand for non-technical stakeholders. Variable Importance: Decision Trees provide feature importance metrics, allowing managers to identify key drivers of the outcome. Simplicity: Decision Trees are simple and intuitive, making them suitable for quick decision-making and hypothesis generation. Overfitting: They are prone to overfitting, especially with complex datasets, which may lead to poor generalization performance on unseen data. Single Tree Limitation: Decision Trees may lack predictive accuracy compared to ensemble methods like Random Forest and XGBoost, particularly when dealing with high-dimensional or noisy data.
- Random Forest: Ensemble Learning: Random Forest is an ensemble learning technique that combines multiple Decision Trees to improve predictive performance and reduce overfitting. Robustness: Random Forest is robust to overfitting and noise, making it suitable for a wide range of datasets and predictive tasks. Variable Importance: It provides feature importance scores, enabling managers to prioritize variables based on their contribution to the model. Computational Efficiency: Random Forest can handle large datasets efficiently, thanks to its parallelized training process. Black Box Nature: While Random Forest improves prediction accuracy, its complex ensemble nature makes it less interpretable compared to individual Decision Trees.
- XGBoost: Gradient Boosting: XGBoost is an advanced implementation of gradient boosting, which builds models sequentially, iteratively improving upon the residuals of the previous models. High Accuracy: XGBoost often achieves state-of-the-art performance on structured/tabular data, making it well-suited for predictive modeling tasks where accuracy is paramount. Feature Importance: Like Random Forest, XGBoost provides feature importance scores, aiding managers in understanding which variables drive predictions. Regularization: XGBoost offers various regularization techniques to prevent overfitting, such as shrinkage (learning rate) and tree depth control. Resource Intensive: Training XGBoost models can be computationally expensive and may require tuning hyperparameters to achieve optimal performance.

Considerations:

Model Selection: Managers should select the appropriate method based on the trade-off between interpretability, predictive accuracy, and computational resources.

Data Complexity: Consider the complexity of the dataset, including the number of features, the presence of interactions, and the volume of data, when choosing the modeling approach.

Interpretability vs. Accuracy: Balance the need for model interpretability with the desire for high predictive accuracy, depending on the specific business requirements.

Validation and Monitoring: Continuously validate and monitor model performance to ensure that it remains effective over time and in response to changing data patterns.

Preprocessing Report

Project Title: Demographic Patterns and Home Loan Applicant Profiling

1. Project Objectives | Problem Statements 1.1. PO1 | PS1: Classification of Consumer Data into Segments | Clusters | Classes using Supervised Learning Classification Algorithms 1.2. PO2 | PS2: Determination of an Appropriate Classification Model 1.3. PO3 | PS3: Identification of Important | Contributing | Significant Variables or Features and their Thresholds for Classification

2. Description of Data 2.1. Data Source, Size, Shape 2.1.1. Data Source (Website Link)
 - <https://www.kaggle.com/datasets/miker400/washington-state-home-mortgage-hdma2016>
 - <https://www.kaggle.com/datasets/miker400/washington-state-home-mortgage-hdma2016>
 - https://drive.google.com/file/d/13fp1-YgAuSiR_bWZwetJiEcJZOeDeAtu/view?usp=sharing
 - https://drive.google.com/file/d/13fp1-YgAuSiR_bWZwetJiEcJZOeDeAtu/view?usp=sharing

2.1.2. Data Size (in KB | MB | GB ...) 30.1 MB

2.1.3. Data Shape (Dimension: Number of Variables | Number of Records) 39 Variables (39 columns)
Maximum number of rows 60,000 Total number of records: 60000 Total number of filled cells: 2038780
Missed cells: 301220

2.2. Description of Variables

2.2.1. Index Variable(s): I1, I2, ... The index variable is S.no

2.2.2. Outcome Variable or Feature: OV The outcome variable, labeled as 'action_taken_name', represents the target variable in our analysis. It is the variable of interest that we aim to predict or classify using our machine learning models.

2.2.3. Input Variables or Features having Categories | Input Categorical Variables or Features (ICV)

['msamd_name', 'loan_type_name', 'loan_purpose_name']

2.2.3.1. Input Variables or Features having Nominal Categories | Categorical Variables or Features - Nominal Type: ICNV1, ICNV2, ... All the categorical variables available in the dataset for nominal variables

2.2.3.2. Input Variables or Features having Ordinal Categories | Categorical Variables or Features - Ordinal Type: ICOV1, ICOV2, ... No ordinal data available in the dataset

2.2.3. Input Non-Categorical Variables or Features: INCV1, INCV2, ...

['hud_median_family_income', 'loan_amount_000s']

2.3. Descriptive Statistics 2.3.1. Descriptive Statistics: Outcome Variable or Feature (Categorical) 2.3.1.1. Count | Frequency Statistics count unique

Cluster_Label	Count
3	14162
1	14049
0	11435
4	10743
2	9611

2.3.1.2. Proportion (Relative Frequency) Statistics

Cluster_Label	Proportion
3	0.236033
1	0.234150
0	0.190583
4	0.179050
2	0.160183

2.3.2. Descriptive Statistics: Input Categorical Variables or Features 2.3.2.1. Count | Frequency Statistics

Variable	Count Unique
state_name	1
state_abbr	1
respondent_id	593
purchaser_type_name	10
property_type_name	3
preapproval_name	3
owner_occupancy_name	3
msamd_name	14
loan_type_name	4
loan_purpose_name	3
lien_status_name	4
hoepa_status_name	2
county_name	39
co_applicant_sex_name	5
co_applicant_ethnicity_name	5
applicant_sex_name	4
applicant_ethnicity_name	4
agency_name	6
agency_abbr	6
action_taken_name	8

Variable	Value
state_name	Washington
state_abbr	WA
respondent_id	32489
purchaser_type_name	Loan was not originated or was not sold in calendar year covered by the loan/application register
property_type_name	One-to-four family dwelling (other than manufactured housing)
preapproval_name	Not applicable
owner_occupancy_name	Owner-occupied as a principal dwelling
msamd_name	Seattle, Bellevue, Everett - WA

Variable	Value
loan_type_name	Conventional
loan_purpose_name	Refinancing
lien_status_name	Secured by a first lien
hoepa_status_name	Not a HOEPA loan
county_name	King County
co_applicant_sex_name	No co-applicant
co_applicant_ethnicity_name	No co-applicant
applicant_sex_name	Male
applicant_ethnicity_name	Not Hispanic or Latino
agency_name	Department of Housing and Urban Development
agency_abbr	HUD
action_taken_name	Loan originated

Variable	Frequency
state_name	60000
state_abbr	60000
respondent_id	5006
purchaser_type_name	16112
property_type_name	57630
preapproval_name	47832
owner_occupancy_name	53940
msamd_name	17965
loan_type_name	42917
loan_purpose_name	28576
lien_status_name	57046
hoepa_status_name	59996
county_name	12915
co_applicant_sex_name	26987
co_applicant_ethnicity_name	26987
applicant_sex_name	37070
applicant_ethnicity_name	44014
agency_name	27514
agency_abbr	27514
action_taken_name	55815

In the context of catdf dataset: state_name and state_abbr: These columns have only one unique value, which is "Washington" for state_name and "WA" for state_abbr. This suggests that these columns may not provide much information for analysis as they have constant values for all rows. respondent_id: This column has 593 unique values, and the most frequent respondent_id is "32489" with a frequency of 5006. This column likely identifies different respondents. Other categorical columns: Each column represents a categorical variable, and the summary provides information about the number of unique categories, the most

frequent category (top), and its frequency. `action_taken_name`: This column represents the action taken for the loan application. It has 8 unique values, and "Loan originated" is the most frequent action with a frequency of 55815.

2.3.2.2. Proportion (Relative Frequency) Statistics

Variable	Frequency
state_name	Washington: 100.00%
state_abbr	WA: 100.00%
respondent_id	32489: 8.34%
purchaser_type_name	Loan was not originated or was not sold in cal...
property_type_name	One-to-four family dwelling (other than manufa...
preapproval_name	Not applicable: 79.72%
owner_occupancy_name	Owner-occupied as a principal dwelling: 89.90%
msamd_name	Seattle, Bellevue, Everett - WA: 34.80%
loan_type_name	Conventional: 71.53%
loan_purpose_name	Refinancing: 47.63%
lien_status_name	Secured by a first lien: 95.08%
hoepa_status_name	Not a HOEPA loan: 99.99%
county_name	King County: 21.56%
co_applicant_sex_name	No co-applicant: 44.98%
co_applicant_ethnicity_name	No co-applicant: 44.98%
applicant_sex_name	Male: 61.78%
applicant_ethnicity_name	Not Hispanic or Latino: 73.36%
agency_name	Department of Housing and Urban Development: 4...
agency_abbr	HUD: 45.86%
action_taken_name	Loan originated: 93.03%

2.3.3. Descriptive Statistics: Input Non-Categorical Variables or Features

2.3.3.1. Measures of Central Tendency

Variable	Count	Mean/Std/Min/25%/50%/75%/Max
tract_to_msamd_income	59878	Mean: 107.62, Std: 28.23, Min: 14.05, 25%: 88.97, 50%: 105.55, 75%: 123.33, Max: 257.14
population	59878	Mean: 5278.78, Std: 1716.10, Min: 98.00, 25%: 4070.00, 50%: 5145.00, 75%: 6382.00, Max: 13025.00
minority_population	59878	Mean: 23.24, Std: 14.42, Min: 2.04, 25%: 12.95, 50%: 19.42, 75%: 29.68, Max: 94.79
number_of_owner_occupied_units	59876	Mean: 1399.04, Std: 518.33, Min: 15.00, 25%: 1034.00, 50%: 1359.00, 75%: 1722.00, Max: 2997.00
number_of_1_to_4_family_units	59878	Mean: 1873.28, Std: 738.51, Min: 27.00, 25%: 1414.00, 50%: 1770.00, 75%: 2249.00, Max: 5893.00
loan_amount_000s	60000	Mean: 291.36, Std: 604.96, Min: 1.00, 25%: 170.00, 50%: 242.00, 75%: 337.00, Max: 55000.00
hud_median_family_income	59878	Mean: 73869.41, Std: 12811.24, Min: 48700.00, 25%: 63100.00, 50%: 73300.00, 75%: 90300.00, Max: 90300.00

Variable	Count	Mean/Std/Min/25%/50%/75%/Max
applicant_income_000s	53630	Mean: 112.82, Std: 122.86, Min: 1.00, 25%: 61.00, 50%: 89.00, 75%: 132.00, Max: 6161.00
sequence_number	60000	Mean: 77526.47, Std: 150515.70, Min: 1.00, 25%: 3231.50, 50%: 16481.00, 75%: 72762.25, Max: 1241590.00
census_tract_number	59878	Mean: 1750.60, Std: 3359.68, Min: 1.00, 25%: 114.02, 50%: 403.02, 75%: 713.10, Max: 9757.00
as_of_year	60000	Mean: 2016.00, Std: 0.00, Min: 2016.00, 25%: 2016.00, 50%: 2016.00, 75%: 2016.00, Max: 2016.00
application_date_indicator	60000	Mean: 0.03, Std: 0.23, Min: 0.00, 25%: 0.00, 50%: 0.00, 75%: 0.00, Max: 2.00

2.3.3.3. Correlation Statistics (with Test of Correlation)

1. Analysis of Data 3.1. Data Pre-Processing 3.1.1. Missing Data Statistics and Treatment 3.1.1.1.1.

Missing Data Statistics: Records Number of rows with missing data: 60000 Number of rows with more than 50% missing data: 0

3.1.1.1.2. Missing Data Treatment: Records 3.1.1.1.2.1. Removal of Records with More Than 50% Missing Data: None | R1, R2, ... No rows with more than 50% missing values

3.1.1.2.1. Missing Data Statistics: Categorical Variables or Features

Variable	Missing Records	Percentage Missing
denial_reason_name_3	59999	99.998333
denial_reason_name_2	59957	99.928333
denial_reason_name_1	59882	99.803333
rate_spread	58134	96.890000
edit_status_name	47549	79.248333
msamd_name	8381	13.968333
applicant_income_000s	6370	10.616667
number_of_owner_occupied_units	124	0.206667
census_tract_number	122	0.203333
tract_to_msamd_income	122	0.203333
hud_median_family_income	122	0.203333
number_of_1_to_4_family_units	122	0.203333
minority_population	122	0.203333
population	122	0.203333
county_name	92	0.153333

3.1.1.2.2. Missing Data Treatment: Categorical Variables or Features

3.1.1.2.2.1. Removal of Variables or Features with More Than 50% Missing Data: None | CV1, CV2, ...

Removed the below columns as they have more than 50% data missing • denial_reason_name_3 • denial_reason_name_2 • denial_reason_name_1 • rate_spread (non-cat) • edit_status_name

3.1.1.2.2.2. Imputation of Missing Data using Descriptive Statistics: Mode

3.1.1.3.1. Missing Data Statistics: Non-Categorical Variables or Features

Feature	Missing Records
tract_to_msamd_income	122
population	122
minority_population	122
number_of_owner_occupied_units	124
number_of_1_to_4_family_units	122
loan_amount_000s	0
hud_median_family_income	122
applicant_income_000s	6370
sequence_number	0
census_tract_number	122
as_of_year	0
application_date_indicator	0

3.1.1.3.2. Missing Data Treatment: Non-Categorical Variables or Features 3.1.1.3.2.1. Removal of Variables or Features with More Than 50% Missing Data: None | NCV1, NCV2, ... • rate_spread

3.1.1.3.2.2. Imputation of Missing Data using Descriptive Statistics: Mean | Median • Imputing the missing values using mean

3.1.2. Numerical Encoding of Categorical Variables or Features (Encoding Schema - Alphanumeric Order) (Encoding Schema - Alphanumeric Order)

Feature	Number of Unique Values
state_name	1
state_abbrev	1
respondent_id	593
purchaser_type_name	10
property_type_name	3
preapproval_name	3
owner_occupancy_name	3
msamd_name	14
loan_type_name	4
loan_purpose_name	3
lien_status_name	4
hoepa_status_name	2
county_name	39
co_applicant_sex_name	5
co_applicant_ethnicity_name	5
applicant_sex_name	4
applicant_ethnicity_name	4
agency_name	6
agency_abbrev	6

Feature	Number of Unique Values
action_taken_name	8

We are converting the above variables into numeric format in the alpha numeric order

3.1.3. Outlier Statistics and Treatment (Scaling | Transformation) 3.1.3.1.1. Outlier Statistics: Non-Categorical Variables or Features

Outliers count for the Non-Categorical Variables

Feature	Number of Unique Values
tract_to_msamd_income	1309
population	553
minority_population	2641
number_of_owner_occupied_units	478
number_of_1_to_4_family_units	2150
loan_amount_000s	2467
hud_median_family_income	0
applicant_income_000s	3765
sequence_number	7898
census_tract_number	9391
as_of_year	0
application_date_indicator	776

3.1.3.1.2. Outlier Treatment: Non-Categorical Variables or Features 3.1.3.1.2.1. Standardization: OV1, OV2, ... 3.1.3.1.2.2. Normalization using Min-Max Scaler: OV3, OV4, ... 3.1.3.1.2.3. Log Transformation: OV5, OV6, ... I performed scaling using normalization using min-max scaler. But post the scaling, bubbles were still visible in the box plot. This signifies that the outliers present in the non categorical dataset are not heavily influenced by the scaling method. The count of outliers seems consistent across different scaling methods.

3.1.4. Data Bifurcation: Training & Testing Sets [Bifurcation Schema: Random Sampling or Stratified Sampling (Based on Outcome Variable or Feature) with {70% | 75% | 80%} Data in Training Set and {30% | 25% | 20%} Data in Testing Set]

The dataset was systematically divided into two distinct subsets: a training set and a testing set. This division is crucial for evaluating the performance and generalization of machine learning models.

Bifurcation Schema Sampling Technique: Stratified Sampling Ratio: 80% of the data in the training set and 20% in the testing set Stratified Sampling Stratified sampling was employed to ensure that each subset (training and testing) maintains the same proportion of classes as the original dataset. This approach is particularly beneficial when dealing with imbalanced datasets or when preserving class representation is essential for model training and evaluation.

The 80-20 split ratio was chosen to allocate a significant portion of the data to the training set (80%), allowing models to learn from a substantial amount of information while retaining a separate testing set (20%) for unbiased evaluation and validation.

3.2. Data Analysis

3.2.1.1. PO1 | PS1:: Supervised Machine Learning Classification Algorithm: Decision Tree (Base Model)

3.2.1.2. PO1 | PS1:: Supervised Machine Learning Classification Algorithms: {Logistic Regression | Support Vector Machine | K Nearest Neighbour} (Comparison Models)

Defining the library

```

In [2]: # Required Libraries
import pandas as pd, numpy as np # For Data Manipulation
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder # For Encoding Categorical Data [Nominal | Ordinal]
from sklearn.preprocessing import OneHotEncoder # For Creating Dummy Variables of Categorical Data [Nominal]
from sklearn.impute import SimpleImputer, KNNImputer # For Imputation of Missing Data
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler # For Rescaling Data
from sklearn.model_selection import train_test_split # For Splitting Data into Training & Testing Sets
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import pearsonr
from scipy import stats

# Required Libraries
import pandas as pd, numpy as np # For Data Manipulation
import matplotlib.pyplot as plt, seaborn as sns # For Data Visualization
import scipy.cluster.hierarchy as sch # For Hierarchical Clustering
from sklearn.cluster import AgglomerativeClustering as agclus, KMeans as kmclus # For Agglomerative & K-Means Clustering
from sklearn.metrics import silhouette_score as sscore, davies_bouldin_score as dbscore # For Clustering Model Evaluation

# @title Load library { display-mode: "form" }
# Load IPython extension for measuring time
!pip install ipython-autotime
%reload_ext autotime

# Load IPython extension for memory profiling
!pip install memory-profiler
%reload_ext memory_profiler

# Your imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering as agclus, KMeans as kmclus
from sklearn.metrics import silhouette_score as sscore, davies_bouldin_score as dbscore
from scipy.cluster.hierarchy import dendrogram, linkage
import plotly.graph_objects as go

# Load preprocessing Libraries
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder, OneHotEncoder
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.model_selection import train_test_split

from scipy.stats import f_oneway

# Import

```

```

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit
from sklearn.tree import DecisionTreeClassifier, export_text, plot_tree #
For Decision Tree Model
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import confusion_matrix, classification_report # For Decision Tree Model Evaluation
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import PCA
from matplotlib.colors import ListedColormap
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score
from matplotlib.colors import ListedColormap

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit
from sklearn.tree import DecisionTreeClassifier, export_text, plot_tree #
For Decision Tree Model
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import confusion_matrix, classification_report # For Decision Tree Model Evaluation
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import PCA
from matplotlib.colors import ListedColormap
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score
from matplotlib.colors import ListedColormap

# Load preprocessing Libraries
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder, OneHotEncoder
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit

!pip install scikit-learn xgboost

## Data Visualization Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from wordcloud import WordCloud
from collections import Counter
from scipy import stats
from sklearn.tree import plot_tree
import graphviz
from IPython.display import display
from collections import Counter

```

```
## Data Preprocessing Libraries
from sklearn.preprocessing import OrdinalEncoder
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit
from sklearn.metrics import f1_score
from sklearn.tree import export_text

## Machine Learning Models and Evaluation Metrics
import xgboost as xgb
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils.validation import column_or_1d
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score, precision_recall_fscore_support
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression, Lasso, Ridge
from sklearn.metrics import make_scorer
from sklearn.pipeline import make_pipeline
from sklearn.tree import export_graphviz
```

Collecting ipython-autotime

Downloading ipython_autotime-0.3.2-py2.py3-none-any.whl (7.0 kB)

Requirement already satisfied: ipython in /usr/local/lib/python3.10/dist-packages (from ipython-autotime) (7.34.0)

Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (67.7.2)

Collecting jedi>=0.16 (from ipython->ipython-autotime)

Downloading jedi-0.19.1-py2.py3-none-any.whl (1.6 MB)

1.6/1.6 MB 6.9 MB/s eta 0:00:

00

Requirement already satisfied: decorator in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (4.4.2)

Requirement already satisfied: pickleshare in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (0.7.5)

Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (5.7.1)

Requirement already satisfied: prompt-toolkit!=3.0.0,!3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (3.0.43)

Requirement already satisfied: pygments in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (2.16.1)

Requirement already satisfied: backcall in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (0.2.0)

Requirement already satisfied: matplotlib-inline in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (0.1.6)

Requirement already satisfied: pexpect>4.3 in /usr/local/lib/python3.10/dist-packages (from ipython->ipython-autotime) (4.9.0)

Requirement already satisfied: parso<0.9.0,>=0.8.3 in /usr/local/lib/python3.10/dist-packages (from jedi>=0.16->ipython->ipython-autotime) (0.8.4)

Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.10/dist-packages (from pexpect>4.3->ipython->ipython-autotime) (0.7.0)

Requirement already satisfied: wcwidth in /usr/local/lib/python3.10/dist-packages (from prompt-toolkit!=3.0.0,!3.0.1,<3.1.0,>=2.0.0->ipython->ipython-autotime) (0.2.13)

Installing collected packages: jedi, ipython-autotime

Successfully installed ipython-autotime-0.3.2 jedi-0.19.1

Collecting memory-profiler

Downloading memory_profiler-0.61.0-py3-none-any.whl (31 kB)

Requirement already satisfied: psutil in /usr/local/lib/python3.10/dist-packages (from memory-profiler) (5.9.5)

Installing collected packages: memory-profiler

Successfully installed memory-profiler-0.61.0

Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.2.2)

Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-packages (2.0.3)

Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.25.2)

Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.4)

Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.0)

Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.4.0)

time: 15.8 s (started: 2024-04-13 11:17:31 +00:00)

Uploading of Dataset


```
In [3]: import pandas as pd
import gdown

# Google Drive file ID
file_id = '13fp1-YgAuSiR_bWZwetJiEcJZOeDeAtu'

# Downloading the CSV file from Google Drive
url = f'https://drive.google.com/uc?id={file_id}'
csv_file_path = 'Washington_State_HDMA_Dataset with Cluster Label'
gdown.download(url, csv_file_path, quiet=False)

# Read the CSV file into a pandas DataFrame
df = pd.read_csv(csv_file_path)

# Display the first few rows of the DataFrame to verify the data
print(df.head())
```

Downloading...

From: https://drive.google.com/uc?id=13fp1-YgAuSiR_bWZwetJiEcJZ0eDeAtu

To: /content/Washington_State_HDMA_Dataset with Cluster Label

100%|██████████| 32.6M/32.6M [00:00<00:00, 98.5MB/s]

S.no	tract_to_msamd_income	rate_spread	population	minority_populatio
0	1	121.690002	NaN	8381.0
1				23.79000
1	2	83.370003	NaN	4915.0
0				23.99000
2	3	91.129997	NaN	5075.0
0				11.82000
3	4	146.169998	NaN	5032.0
0				8.59000
4	5	162.470001	NaN	5183.0
0				10.50000

number_of_owner_occupied_units	number_of_1_to_4_family_units
0	2175.0
1	1268.0
2	1136.0
3	1525.0
4	1705.0

loan_amount_000s	hud_median_family_income	applicant_income_000s	...
0	227	73300.0	116.0 ...
1	240	57900.0	42.0 ...
2	241	73300.0	117.0 ...
3	351	73300.0	315.0 ...
4	417	78100.0	114.0 ...

co_applicant_ethnicity_name	census_tract_number
0	Not Hispanic or Latino
1	No co-applicant
2	Not Hispanic or Latino
3	Information not provided by applicant in mail,...
4	Not Hispanic or Latino

as_of_year	application_date_indicator	applicant_sex_name
0	2016	Female
1	2016	Male
2	2016	Male
3	2016	Male
4	2016	Female

applicant_ethnicity_name
0
1
2
3
4

agency_name	agency_abbr	action_taken_name
0	Consumer Financial Protection Bureau	CFPB
1	Department of Housing and Urban Development	HUD
2	Department of Housing and Urban Development	HUD
3	National Credit Union Administration	NCUA
4	Federal Deposit Insurance Corporation	FDIC

	Cluster_Label
0	4
1	3
2	4
3	4
4	4

[5 rows x 39 columns]

time: 3.81 s (started: 2024-04-13 11:17:46 +00:00)

<ipython-input-3-f0f2a90db5ca>:13: DtypeWarning: Columns (24,25,26) have mixed types. Specify dtype option on import or set low_memory=False.

```
df = pd.read_csv(csv_file_path)
```

```
In [4]: df.info()
list(df.columns)

# Assuming df is your original DataFrame
# Add your normalization or standardization code here

# Display summary statistics
df.describe()

total_records = len(df)
print(f"Total number of records: {total_records}")

# Calculate the total number of filled cells in each column
filled_cells_count = df.count()

# Sum up the counts to get the total number of filled cells in the DataFrame
total_filled_cells = filled_cells_count.sum()

print(f"Total number of filled cells: {total_filled_cells}")

# Assuming df is your DataFrame
unique_counts = df.nunique()

# Display the number of unique values in each column
print(unique_counts)
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 60000 entries, 0 to 59999
```

```
Data columns (total 39 columns):
```

#	Column	Non-Null Count	Dtype
0	S.no	60000 non-null	int64
1	tract_to_msamd_income	59878 non-null	float64
2	rate_spread	1866 non-null	float64
3	population	59878 non-null	float64
4	minority_population	59878 non-null	float64
5	number_of_owner_occupied_units	59876 non-null	float64
6	number_of_1_to_4_family_units	59878 non-null	float64
7	loan_amount_000s	60000 non-null	int64
8	hud_median_family_income	59878 non-null	float64
9	applicant_income_000s	53630 non-null	float64
10	state_name	60000 non-null	object
11	state_abbr	60000 non-null	object
12	sequence_number	60000 non-null	int64
13	respondent_id	60000 non-null	object
14	purchaser_type_name	60000 non-null	object
15	property_type_name	60000 non-null	object
16	preapproval_name	60000 non-null	object
17	owner_occupancy_name	60000 non-null	object
18	msamd_name	51619 non-null	object
19	loan_type_name	60000 non-null	object
20	loan_purpose_name	60000 non-null	object
21	lien_status_name	60000 non-null	object
22	hoepa_status_name	60000 non-null	object
23	edit_status_name	12451 non-null	object
24	denial_reason_name_3	1 non-null	object
25	denial_reason_name_2	43 non-null	object
26	denial_reason_name_1	118 non-null	object
27	county_name	59908 non-null	object
28	co_applicant_sex_name	60000 non-null	object
29	co_applicant_ethnicity_name	60000 non-null	object
30	census_tract_number	59878 non-null	float64
31	as_of_year	60000 non-null	int64
32	application_date_indicator	60000 non-null	int64
33	applicant_sex_name	60000 non-null	object
34	applicant_ethnicity_name	60000 non-null	object
35	agency_name	60000 non-null	object
36	agency_abbr	60000 non-null	object
37	action_taken_name	60000 non-null	object
38	Cluster_Label	60000 non-null	int64

```
dtypes: float64(9), int64(6), object(24)
```

```
memory usage: 17.9+ MB
```

```
Total number of records: 60000
```

```
Total number of filled cells: 2038780
```

S.no	60000
tract_to_msamd_income	1327
rate_spread	320
population	1283
minority_population	1216
number_of_owner_occupied_units	996
number_of_1_to_4_family_units	1051
loan_amount_000s	1344
hud_median_family_income	15
applicant_income_000s	807
state_name	1
state_abbr	1
sequence_number	39340

respondent_id	593
purchaser_type_name	10
property_type_name	3
preapproval_name	3
owner_occupancy_name	3
msamd_name	14
loan_type_name	4
loan_purpose_name	3
lien_status_name	4
hoepa_status_name	2
edit_status_name	1
denial_reason_name_3	1
denial_reason_name_2	8
denial_reason_name_1	8
county_name	39
co_applicant_sex_name	5
co_applicant_ethnicity_name	5
census_tract_number	1108
as_of_year	1
application_date_indicator	2
applicant_sex_name	4
applicant_ethnicity_name	4
agency_name	6
agency_abbr	6
action_taken_name	8
Cluster_Label	5

dtype: int64
time: 509 ms (started: 2024-04-13 11:17:50 +00:00)

```
In [5]: # Importing necessary libraries
import pandas as pd

# Assuming df is your DataFrame and 'Cluster_Label' is the column of interest

# Calculate relative frequencies
relative_frequencies = df['Cluster_Label'].value_counts(normalize=True)

# Print relative frequencies
print(relative_frequencies)

# Assuming df is your DataFrame and 'Cluster_Label' is the column of interest

# Count the occurrences of each unique value
unique_value_counts = df['Cluster_Label'].value_counts()

# Print the count of unique values
print(unique_value_counts)
```

```
Cluster_Label
3    0.236033
1    0.234150
0    0.190583
4    0.179050
2    0.160183
Name: proportion, dtype: float64
Cluster_Label
3    14162
1    14049
0    11435
4    10743
2     9611
Name: count, dtype: int64
time: 8.13 ms (started: 2024-04-13 11:17:51 +00:00)
```



```
In [6]: # Assuming df is your DataFrame
columns_list = df.columns.tolist()
columns_list

list(df.columns)
```

```
Out[6]: ['S.no',
'tract_to_msamd_income',
'rate_spread',
'population',
'minority_population',
'number_of_owner_occupied_units',
'number_of_1_to_4_family_units',
'loan_amount_000s',
'hud_median_family_income',
'applicant_income_000s',
'state_name',
'state_abbr',
'sequence_number',
'respondent_id',
'purchaser_type_name',
'property_type_name',
'preapproval_name',
'owner_occupancy_name',
'msamd_name',
'loan_type_name',
'loan_purpose_name',
'lien_status_name',
'hoepa_status_name',
'edit_status_name',
'denial_reason_name_3',
'denial_reason_name_2',
'denial_reason_name_1',
'county_name',
'co_applicant_sex_name',
'co_applicant_ethnicity_name',
'census_tract_number',
'as_of_year',
'application_date_indicator',
'applicant_sex_name',
'applicant_ethnicity_name',
'agency_name',
'agency_abbr',
'action_taken_name',
'Cluster_Label']
```

time: 4.18 ms (started: 2024-04-13 11:17:51 +00:00)

```

In [7]: # Nominal and Ordinal Columns

# Continuous and Non Continuous Columns

import pandas as pd

# Assuming df is your DataFrame
continuous_columns = df.select_dtypes(include=['float64', 'int64']).columns
non_continuous_columns = df.select_dtypes(exclude=['float64', 'int64']).columns

print("Continuous Columns:", list(continuous_columns))
print("Non-Continuous Columns:", list(non_continuous_columns))

# Assuming df is your DataFrame
categorical_columns = df.select_dtypes(include=['object', 'category']).columns
non_categorical_columns = df.select_dtypes(exclude=['object', 'category']).columns

print("Categorical Columns:", list(categorical_columns))
print("Non-Categorical Columns:", list(non_categorical_columns))

```

```

Continuous Columns: ['S.no', 'tract_to_msamd_income', 'rate_spread', 'population', 'minority_population', 'number_of_owner_occupied_units', 'number_of_1_to_4_family_units', 'loan_amount_000s', 'hud_median_family_income', 'applicant_income_000s', 'sequence_number', 'census_tract_number', 'as_of_year', 'application_date_indicator', 'Cluster_Label']
Non-Continuous Columns: ['state_name', 'state_abbr', 'respondent_id', 'purchaser_type_name', 'property_type_name', 'preapproval_name', 'owner_occupancy_name', 'msamd_name', 'loan_type_name', 'loan_purpose_name', 'lien_status_name', 'hoepa_status_name', 'edit_status_name', 'denial_reason_name_3', 'denial_reason_name_2', 'denial_reason_name_1', 'county_name', 'co_applicant_sex_name', 'co_applicant_ethnicity_name', 'applicant_sex_name', 'applicant_ethnicity_name', 'agency_name', 'agency_abbr', 'action_taken_name']
Categorical Columns: ['state_name', 'state_abbr', 'respondent_id', 'purchaser_type_name', 'property_type_name', 'preapproval_name', 'owner_occupancy_name', 'msamd_name', 'loan_type_name', 'loan_purpose_name', 'lien_status_name', 'hoepa_status_name', 'edit_status_name', 'denial_reason_name_3', 'denial_reason_name_2', 'denial_reason_name_1', 'county_name', 'co_applicant_sex_name', 'co_applicant_ethnicity_name', 'applicant_sex_name', 'applicant_ethnicity_name', 'agency_name', 'agency_abbr', 'action_taken_name']
Non-Categorical Columns: ['S.no', 'tract_to_msamd_income', 'rate_spread', 'population', 'minority_population', 'number_of_owner_occupied_units', 'number_of_1_to_4_family_units', 'loan_amount_000s', 'hud_median_family_income', 'applicant_income_000s', 'sequence_number', 'census_tract_number', 'as_of_year', 'application_date_indicator', 'Cluster_Label']
time: 37 ms (started: 2024-04-13 11:17:51 +00:00)

```

```
In [8]: ### Missing Data Statistics and Treatment  
### Missing Data Statistics: Records  
  
# Assuming df is your DataFrame  
  
# Count the missing values in each column  
missing_data = df.isnull().sum()  
  
# Create a DataFrame to display missing data statistics  
missing_data_stats = pd.DataFrame({  
    'Column': missing_data.index,  
    'Missing Records': missing_data.values,  
    'Percentage Missing': (missing_data / len(df)) * 100  
})  
  
# Sort the DataFrame by the percentage of missing values in descending order  
missing_data_stats = missing_data_stats.sort_values(by='Percentage Missing', ascending=False)  
  
# Print the missing data statistics  
print(missing_data_stats)
```

	Column \
denial_reason_name_3	denial_reason_name_3
denial_reason_name_2	denial_reason_name_2
denial_reason_name_1	denial_reason_name_1
rate_spread	rate_spread
edit_status_name	edit_status_name
msamd_name	msamd_name
applicant_income_000s	applicant_income_000s
number_of_owner_occupied_units	number_of_owner_occupied_units
tract_to_msamd_income	tract_to_msamd_income
hud_median_family_income	hud_median_family_income
number_of_1_to_4_family_units	number_of_1_to_4_family_units
minority_population	minority_population
population	population
census_tract_number	census_tract_number
county_name	county_name
co_applicant_ethnicity_name	co_applicant_ethnicity_name
co_applicant_sex_name	co_applicant_sex_name
S.no	S.no
as_of_year	as_of_year
application_date_indicator	application_date_indicator
applicant_sex_name	applicant_sex_name
agency_name	agency_name
agency_abbr	agency_abbr
action_taken_name	action_taken_name
applicant_ethnicity_name	applicant_ethnicity_name
loan_type_name	loan_type_name
hoepa_status_name	hoepa_status_name
lien_status_name	lien_status_name
loan_purpose_name	loan_purpose_name
owner_occupancy_name	owner_occupancy_name
preapproval_name	preapproval_name
property_type_name	property_type_name
purchaser_type_name	purchaser_type_name
respondent_id	respondent_id
sequence_number	sequence_number
state_abbr	state_abbr
state_name	state_name
loan_amount_000s	loan_amount_000s
Cluster_Label	Cluster_Label

	Missing Records	Percentage Missing
denial_reason_name_3	59999	99.998333
denial_reason_name_2	59957	99.928333
denial_reason_name_1	59882	99.803333
rate_spread	58134	96.890000
edit_status_name	47549	79.248333
msamd_name	8381	13.968333
applicant_income_000s	6370	10.616667
number_of_owner_occupied_units	124	0.206667
tract_to_msamd_income	122	0.203333
hud_median_family_income	122	0.203333
number_of_1_to_4_family_units	122	0.203333
minority_population	122	0.203333
population	122	0.203333
census_tract_number	122	0.203333
county_name	92	0.153333
co_applicant_ethnicity_name	0	0.000000
co_applicant_sex_name	0	0.000000
S.no	0	0.000000
as_of_year	0	0.000000

application_date_indicator	0	0.000000
applicant_sex_name	0	0.000000
agency_name	0	0.000000
agency_abbr	0	0.000000
action_taken_name	0	0.000000
applicant_ethnicity_name	0	0.000000
loan_type_name	0	0.000000
hoepa_status_name	0	0.000000
lien_status_name	0	0.000000
loan_purpose_name	0	0.000000
owner_occupancy_name	0	0.000000
preapproval_name	0	0.000000
property_type_name	0	0.000000
purchaser_type_name	0	0.000000
respondent_id	0	0.000000
sequence_number	0	0.000000
state_abbr	0	0.000000
state_name	0	0.000000
loan_amount_000s	0	0.000000
Cluster_Label	0	0.000000

time: 102 ms (started: 2024-04-13 11:17:51 +00:00)

```
In [9]: # List of columns to drop
columns_to_drop = ['state_name', 'state_abbr', 'denial_reason_name_3', 'denial_reason_name_2', 'denial_reason_name_1', 'rate_spread', 'edit_status_name', 'as_of_year']

# Drop columns with more than 50% missing values
df_cleaned = df.drop(columns=columns_to_drop)

# Print the cleaned DataFrame
df1 = df_cleaned

# Count the missing values in each column
missing_data = df1.isnull().sum()

# Create a DataFrame to display missing data statistics
missing_data_stats = pd.DataFrame({
    'Column': missing_data.index,
    'Missing Records': missing_data.values,
    'Percentage Missing': (missing_data / len(df)) * 100
})

# Sort the DataFrame by the percentage of missing values in descending order
missing_data_stats = missing_data_stats.sort_values(by='Percentage Missing', ascending=False)

# Print the missing data statistics
print(missing_data_stats)
```

	Column \
msamd_name	msamd_name
applicant_income_000s	applicant_income_000s
number_of_owner_occupied_units	number_of_owner_occupied_units
census_tract_number	census_tract_number
population	population
minority_population	minority_population
number_of_1_to_4_family_units	number_of_1_to_4_family_units
tract_to_msamd_income	tract_to_msamd_income
hud_median_family_income	hud_median_family_income
county_name	county_name
agency_name	agency_name
applicant_ethnicity_name	applicant_ethnicity_name
applicant_sex_name	applicant_sex_name
application_date_indicator	application_date_indicator
hoepa_status_name	hoepa_status_name
action_taken_name	action_taken_name
co_applicant_ethnicity_name	co_applicant_ethnicity_name
co_applicant_sex_name	co_applicant_sex_name
agency_abbr	agency_abbr
S.no	S.no
lien_status_name	lien_status_name
loan_purpose_name	loan_purpose_name
loan_type_name	loan_type_name
owner_occupancy_name	owner_occupancy_name
preapproval_name	preapproval_name
property_type_name	property_type_name
purchaser_type_name	purchaser_type_name
respondent_id	respondent_id
sequence_number	sequence_number
loan_amount_000s	loan_amount_000s
Cluster_Label	Cluster_Label

	Missing Records	Percentage Missing
msamd_name	8381	13.968333
applicant_income_000s	6370	10.616667
number_of_owner_occupied_units	124	0.206667
census_tract_number	122	0.203333
population	122	0.203333
minority_population	122	0.203333
number_of_1_to_4_family_units	122	0.203333
tract_to_msamd_income	122	0.203333
hud_median_family_income	122	0.203333
county_name	92	0.153333
agency_name	0	0.000000
applicant_ethnicity_name	0	0.000000
applicant_sex_name	0	0.000000
application_date_indicator	0	0.000000
hoepa_status_name	0	0.000000
action_taken_name	0	0.000000
co_applicant_ethnicity_name	0	0.000000
co_applicant_sex_name	0	0.000000
agency_abbr	0	0.000000
S.no	0	0.000000
lien_status_name	0	0.000000
loan_purpose_name	0	0.000000
loan_type_name	0	0.000000
owner_occupancy_name	0	0.000000
preapproval_name	0	0.000000
property_type_name	0	0.000000
purchaser_type_name	0	0.000000

respondent_id	0	0.000000
sequence_number	0	0.000000
loan_amount_000s	0	0.000000
Cluster_Label	0	0.000000

time: 71 ms (started: 2024-04-13 11:17:51 +00:00)

```
In [10]: ### Missing Records (ROWS)

# Count the missing values in each row
missing_rows = df1.isnull().sum(axis=1)

# Count the number of rows with at least one missing value
num_rows_with_missing = len(missing_rows[missing_rows > 0])

# Print the number of rows with missing data
print("Number of rows with missing data:", num_rows_with_missing)

# Calculate the percentage of missing values in each row
missing_percentage_rows = (df1.isnull().sum(axis=1) / len(df1.columns)) * 100

# Count the number of rows with more than 50% missing data
num_rows_more_than_50_percent_missing = len(missing_percentage_rows[missing_percentage_rows > 50])

# Print the number of rows with more than 50% missing data
print("Number of rows with more than 50% missing data:", num_rows_more_than_50_percent_missing)
```

Number of rows with missing data: 13629
Number of rows with more than 50% missing data: 0
time: 131 ms (started: 2024-04-13 11:17:51 +00:00)


```
In [11]: # DIVIDING df1 into Cat and Non Cat

# Assuming df1 is your DataFrame
cat_columns = df1.select_dtypes(include=['object']).columns
noncat_columns = df1.select_dtypes(exclude=['object']).columns

# Creating categorical and non-categorical DataFrames
catdf1 = df1[cat_columns]
noncatdf1 = df1[noncat_columns]

#print(list(catdf1.columns))
#print(list(noncatdf1.columns))
print(list(catdf1.columns))
print(list(noncatdf1.columns))

#20
#list(noncatdf1.columns)

['respondent_id', 'purchaser_type_name', 'property_type_name', 'preapproval_name', 'owner_occupancy_name', 'msamd_name', 'loan_type_name', 'loan_purpose_name', 'lien_status_name', 'hoepa_status_name', 'county_name', 'co_applicant_sex_name', 'co_applicant_ethnicity_name', 'applicant_sex_name', 'applicant_ethnicity_name', 'agency_name', 'agency_abbr', 'action_taken_name']
['S.no', 'tract_to_msamd_income', 'population', 'minority_population', 'number_of_owner_occupied_units', 'number_of_1_to_4_family_units', 'loan_amount_000s', 'hud_median_family_income', 'applicant_income_000s', 'sequence_number', 'census_tract_number', 'application_date_indicator', 'Cluster_Label']
time: 28.7 ms (started: 2024-04-13 11:17:51 +00:00)
```

PreProcessing of Data

```
In [12]: # Data Bifurcation
catdf = df[['S.no', 'respondent_id', 'purchaser_type_name', 'property_type_name', 'preapproval_name', 'owner_occupancy_name', 'msamd_name', 'loan_type_name', 'loan_purpose_name',
            'lien_status_name', 'hoepa_status_name', 'county_name', 'co_applicant_sex_name', 'co_applicant_ethnicity_name', 'applicant_sex_name', 'applicant_ethnicity_name', 'agency_name',
            'agency_abbr', 'action_taken_name']] # Categorical Data [Nominal | Ordinal]

noncatdf = df[['S.no', 'tract_to_msamd_income', 'population', 'minority_population', 'number_of_owner_occupied_units', 'number_of_1_to_4_family_units', 'loan_amount_000s',
               'hud_median_family_income', 'applicant_income_000s', 'sequence_number', 'census_tract_number', 'application_date_indicator', 'Cluster_Label']] # Non-Categorical Data

time: 25.6 ms (started: 2024-04-13 11:17:51 +00:00)
```

```
In [13]: ##### STATISTICS OF CAT DATASET

# Count and frequency statistics for each column in catdf
catdf_stats = pd.DataFrame()

for column in catdf.columns:
    col_count = catdf[column].value_counts().reset_index()
    col_count.columns = [column, 'Frequency']
    catdf_stats = pd.concat([catdf_stats, col_count], axis=1)

# Display the count and frequency statistics
#print(catdf_stats)

# Summary for each column in catdf
catdf_summary = catdf.describe(include='all').transpose()

# Display the summary
print(catdf_summary)

# Calculate the proportion (relative frequency) for each categorical column
#proportion_stats = catdf.apply(lambda x: x.value_counts(normalize=True).id
xmax() + ': ' + "{:.2%}".format(x.value_counts(normalize=True).max()))

# Display the proportion statistics
#print(proportion_stats)
```

	count	unique \
S.no	60000.0	NaN
respondent_id	60000	593
purchaser_type_name	60000	10
property_type_name	60000	3
preapproval_name	60000	3
owner_occupancy_name	60000	3
msamd_name	51619	14
loan_type_name	60000	4
loan_purpose_name	60000	3
lien_status_name	60000	4
hoepa_status_name	60000	2
county_name	59908	39
co_applicant_sex_name	60000	5
co_applicant_ethnicity_name	60000	5
applicant_sex_name	60000	4
applicant_ethnicity_name	60000	4
agency_name	60000	6
agency_abbr	60000	6
action_taken_name	60000	8

top \	
S.no	
NaN	
respondent_id	32
489	
purchaser_type_name	Loan was not originated or was not sold in ca
l...	
property_type_name	One-to-four family dwelling (other than manuf
a...	
preapproval_name	Not applica
ble	
owner_occupancy_name	Owner-occupied as a principal dwell
ing	
msamd_name	Seattle, Bellevue, Everett -
WA	
loan_type_name	Conventio
nal	
loan_purpose_name	Refinanc
ing	
lien_status_name	Secured by a first l
ien	
hoepa_status_name	Not a HOEPA l
oan	
county_name	King Cou
nty	
co_applicant_sex_name	No co-applic
ant	
co_applicant_ethnicity_name	No co-applic
ant	
applicant_sex_name	M
ale	
applicant_ethnicity_name	Not Hispanic or Lat
ino	
agency_name	Department of Housing and Urban Developm
ent	
agency_abbr	
HUD	
action_taken_name	Loan origina
ted	

	freq	mean	std	min	25%	\
S.no	NaN	30000.5	17320.652413	1.0	15000.75	
respondent_id	5006	NaN	NaN	NaN	NaN	
purchaser_type_name	16112	NaN	NaN	NaN	NaN	
property_type_name	57630	NaN	NaN	NaN	NaN	
preapproval_name	47832	NaN	NaN	NaN	NaN	
owner_occupancy_name	53940	NaN	NaN	NaN	NaN	
msamd_name	17965	NaN	NaN	NaN	NaN	
loan_type_name	42917	NaN	NaN	NaN	NaN	
loan_purpose_name	28576	NaN	NaN	NaN	NaN	
lien_status_name	57046	NaN	NaN	NaN	NaN	
hoepa_status_name	59996	NaN	NaN	NaN	NaN	
county_name	12915	NaN	NaN	NaN	NaN	
co_applicant_sex_name	26987	NaN	NaN	NaN	NaN	
co_applicant_ethnicity_name	26987	NaN	NaN	NaN	NaN	
applicant_sex_name	37070	NaN	NaN	NaN	NaN	
applicant_ethnicity_name	44014	NaN	NaN	NaN	NaN	
agency_name	27514	NaN	NaN	NaN	NaN	
agency_abbr	27514	NaN	NaN	NaN	NaN	
action_taken_name	55815	NaN	NaN	NaN	NaN	

	50%	75%	max
S.no	30000.5	45000.25	60000.0
respondent_id	NaN	NaN	NaN
purchaser_type_name	NaN	NaN	NaN
property_type_name	NaN	NaN	NaN
preapproval_name	NaN	NaN	NaN
owner_occupancy_name	NaN	NaN	NaN
msamd_name	NaN	NaN	NaN
loan_type_name	NaN	NaN	NaN
loan_purpose_name	NaN	NaN	NaN
lien_status_name	NaN	NaN	NaN
hoepa_status_name	NaN	NaN	NaN
county_name	NaN	NaN	NaN
co_applicant_sex_name	NaN	NaN	NaN
co_applicant_ethnicity_name	NaN	NaN	NaN
applicant_sex_name	NaN	NaN	NaN
applicant_ethnicity_name	NaN	NaN	NaN
agency_name	NaN	NaN	NaN
agency_abbr	NaN	NaN	NaN
action_taken_name	NaN	NaN	NaN

time: 460 ms (started: 2024-04-13 11:17:51 +00:00)

```
In [14]: ##### STATISTICS OF NONCAT DATASET

# Display descriptive statistics for non-categorical variables
noncatdf_descriptive_stats = noncatdf.describe()

# Print the descriptive statistics
print(noncatdf_descriptive_stats)
```

	S.no	tract_to_msamd_income	population	minority_populati
on \				
count	60000.000000	59878.000000	59878.000000	59878.0000
00				
mean	30000.500000	107.617351	5278.782157	23.2444
42				
std	17320.652413	28.233471	1716.101490	14.4162
09				
min	1.000000	14.050000	98.000000	2.0400
00				
25%	15000.750000	88.970001	4070.000000	12.9500
00				
50%	30000.500000	105.550003	5145.000000	19.4200
00				
75%	45000.250000	123.330002	6382.000000	29.6800
00				
max	60000.000000	257.140015	13025.000000	94.7900
01				

	number_of_owner_occupied_units	number_of_1_to_4_family_units \
count	59876.000000	59878.000000
mean	1399.044375	1873.281456
std	518.330561	738.505184
min	15.000000	27.000000
25%	1034.000000	1414.000000
50%	1359.000000	1770.000000
75%	1722.000000	2249.000000
max	2997.000000	5893.000000

	loan_amount_000s	hud_median_family_income	applicant_income_000s \
count	60000.000000	59878.000000	53630.000000
mean	291.358717	73869.411136	112.822301
std	604.958183	12811.243390	122.862496
min	1.000000	48700.000000	1.000000
25%	170.000000	63100.000000	61.000000
50%	242.000000	73300.000000	89.000000
75%	337.000000	90300.000000	132.000000
max	55000.000000	90300.000000	6161.000000

	sequence_number	census_tract_number	application_date_indicator \
count	6.000000e+04	59878.000000	60000.000000
mean	7.752647e+04	1750.597252	0.025867
std	1.505157e+05	3359.676740	0.225976
min	1.000000e+00	1.000000	0.000000
25%	3.231500e+03	114.020000	0.000000
50%	1.648100e+04	403.020000	0.000000
75%	7.276225e+04	713.100000	0.000000
max	1.241590e+06	9757.000000	2.000000

	Cluster_Label
count	60000.000000
mean	1.978817
std	1.395815
min	0.000000
25%	1.000000
50%	2.000000
75%	3.000000
max	4.000000

time: 70.6 ms (started: 2024-04-13 11:17:52 +00:00)

```
In [15]: # Missing Data Statistics: Non-Categorical Variables or Features

# Calculate missing data statistics for non-categorical columns
missing_data_non_categorical = noncatdf.isnull().sum().reset_index()
missing_data_non_categorical.columns = ['Feature', 'Missing_Records']

# Display the missing data statistics
print(missing_data_non_categorical)
```

	Feature	Missing_Records
0	S.no	0
1	tract_to_msamd_income	122
2	population	122
3	minority_population	122
4	number_of_owner_occupied_units	124
5	number_of_1_to_4_family_units	122
6	loan_amount_000s	0
7	hud_median_family_income	122
8	applicant_income_000s	6370
9	sequence_number	0
10	census_tract_number	122
11	application_date_indicator	0
12	Cluster_Label	0

time: 8.33 ms (started: 2024-04-13 11:17:52 +00:00)

```
In [16]: # Missing Data Treatment: Non-Categorical Variables or Features

# Dataset Used : df_noncat

si_noncat = SimpleImputer(missing_values=np.nan, strategy='mean') # Other S
strategy : mean | median | most_frequent | constant
si_noncat_fit = si_noncat.fit_transform(noncatdf)
imputed_data_non_categorical = pd.DataFrame(si_noncat_fit, columns=noncatd
f.columns); # Missing Non-Categorical Data Imputed Subset using Simple Impu
ter
imputed_data_non_categorical.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60000 entries, 0 to 59999
Data columns (total 13 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   S.no                                   60000 non-null  float64
1   tract_to_msamd_income                 60000 non-null  float64
2   population                           60000 non-null  float64
3   minority_population                  60000 non-null  float64
4   number_of_owner_occupied_units       60000 non-null  float64
5   number_of_1_to_4_family_units       60000 non-null  float64
6   loan_amount_000s                    60000 non-null  float64
7   hud_median_family_income             60000 non-null  float64
8   applicant_income_000s                60000 non-null  float64
9   sequence_number                     60000 non-null  float64
10  census_tract_number                  60000 non-null  float64
11  application_date_indicator            60000 non-null  float64
12  Cluster_Label                        60000 non-null  float64
dtypes: float64(13)
memory usage: 6.0 MB
time: 36 ms (started: 2024-04-13 11:17:52 +00:00)
```

```
In [17]: # Calculate standard deviation for non-categorical columns
std_deviation_non_categorical = imputed_data_non_categorical.std()

# Creating a DataFrame to display the results
dispersion_non_categorical_df = pd.DataFrame({
    'Variable': imputed_data_non_categorical.columns,
    'Standard Deviation': std_deviation_non_categorical.values
})

print(dispersion_non_categorical_df)
```

	Variable	Standard Deviation
0	S.no	17320.652413
1	tract_to_msamd_income	28.204752
2	population	1714.355870
3	minority_population	14.401545
4	number_of_owner_occupied_units	517.794667
5	number_of_1_to_4_family_units	737.753976
6	loan_amount_000s	604.958183
7	hud_median_family_income	12798.211781
8	applicant_income_000s	116.157479
9	sequence_number	150515.678152
10	census_tract_number	3356.259273
11	application_date_indicator	0.225976
12	Cluster_Label	1.395815

time: 17.6 ms (started: 2024-04-13 11:17:52 +00:00)


```
In [18]: # Dataset Used : df_cat

si_cat = SimpleImputer(missing_values=np.nan, strategy='most_frequent') # Strategy = median [When Odd Number of Categories Exists]
si_cat_fit = si_cat.fit_transform(catdf)
imputed_data_categorical = pd.DataFrame(si_cat_fit, columns=catdf.columns);
# Missing Categorical Data Imputed Subset
imputed_data_categorical.info()
imputed_data_categorical.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60000 entries, 0 to 59999
Data columns (total 19 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   S.no                                       60000 non-null  object
1   respondent_id                             60000 non-null  object
2   purchaser_type_name                       60000 non-null  object
3   property_type_name                       60000 non-null  object
4   preapproval_name                         60000 non-null  object
5   owner_occupancy_name                     60000 non-null  object
6   msamd_name                               60000 non-null  object
7   loan_type_name                           60000 non-null  object
8   loan_purpose_name                         60000 non-null  object
9   lien_status_name                        60000 non-null  object
10  hoepa_status_name                       60000 non-null  object
11  county_name                             60000 non-null  object
12  co_applicant_sex_name                    60000 non-null  object
13  co_applicant_ethnicity_name              60000 non-null  object
14  applicant_sex_name                       60000 non-null  object
15  applicant_ethnicity_name                  60000 non-null  object
16  agency_name                             60000 non-null  object
17  agency_abbr                             60000 non-null  object
18  action_taken_name                        60000 non-null  object
dtypes: object(19)
memory usage: 8.7+ MB
```

Out[18]:

	S.no	respondent_id	purchaser_type_name	property_type_name	preapproval_name	owner_
0	1	480228	Freddie Mac (FHLMC)	One-to-four family dwelling (other than manufa...	Not applicable	O
1	2	7257500009	Life insurance company, credit union, mortgage...	One-to-four family dwelling (other than manufa...	Not applicable	O
2	3	72-1545376	Loan was not originated or was not sold in cal...	One-to-four family dwelling (other than manufa...	Not applicable	O
3	4	4878	Loan was not originated or was not sold in cal...	One-to-four family dwelling (other than manufa...	Not applicable	O
4	5	32489	Freddie Mac (FHLMC)	One-to-four family dwelling (other than manufa...	Not applicable	O



time: 981 ms (started: 2024-04-13 11:17:52 +00:00)

```
In [19]: # ENCODING
# Converting Categorical Variable into Numeric

# Calculate the number of unique values in each column
unique_values_categorical = imputed_data_categorical.nunique().reset_index(
)
unique_values_categorical.columns = ['Feature', 'Number_of_Unique_Values']

# Display the number of unique values
print(unique_values_categorical)

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Create a copy of the imputed_data_categorical dataframe to avoid modifyin
g the original
encoded_data_categorical = imputed_data_categorical.copy()

# Columns to exclude from encoding
exclude_columns = ["S.no", "Cluster_Label"]

# Iterate through each column in the dataframe
mapping = {} # To store the mapping of variable names to numeric represent
ation

for column in encoded_data_categorical.columns:
    if column not in exclude_columns:
        # Perform numerical encoding
        encoded_data_categorical[column] = label_encoder.fit_transform(enco
ded_data_categorical[column])

        # Store the mapping information
        mapping[column] = dict(zip(label_encoder.classes_, label_encoder.tr
ansform(label_encoder.classes_)))

# Display the mapping
for variable, variable_mapping in mapping.items():
    print(f"\nMapping for {variable}:")
    print(variable_mapping)

# Display the encoded data
print(encoded_data_categorical)
```

	Feature	Number_of_Unique_Values
0	S.no	60000
1	respondent_id	593
2	purchaser_type_name	10
3	property_type_name	3
4	preapproval_name	3
5	owner_occupancy_name	3
6	msamd_name	14
7	loan_type_name	4
8	loan_purpose_name	3
9	lien_status_name	4
10	hoepa_status_name	2
11	county_name	39
12	co_applicant_sex_name	5
13	co_applicant_ethnicity_name	5
14	applicant_sex_name	4
15	applicant_ethnicity_name	4
16	agency_name	6
17	agency_abbr	6
18	action_taken_name	8

Mapping for respondent_id:

```
{'01-0681100': 0, '01-0726495': 1, '02-0793125': 2, '03-0488052': 3, '04-32
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Mapping for purchaser_type_name:

{'Affiliate institution': 0, 'Commercial bank, savings bank or savings association': 1, 'Fannie Mae (FNMA)': 2, 'Farmer Mac (FAMC)': 3, 'Freddie Mac (FHLMC)': 4, 'Ginnie Mae (GNMA)': 5, 'Life insurance company, credit union, mortgage bank, or finance company': 6, 'Loan was not originated or was not sold in calendar year covered by register': 7, 'Other type of purchaser': 8, 'Private securitization': 9}

Mapping for property_type_name:

{'Manufactured housing': 0, 'Multifamily dwelling': 1, 'One-to-four family dwelling (other than manufactured housing)': 2}

Mapping for preapproval_name:

{'Not applicable': 0, 'Preapproval was not requested': 1, 'Preapproval was requested': 2}

Mapping for owner_occupancy_name:

{'Not applicable': 0, 'Not owner-occupied as a principal dwelling': 1, 'Owner-occupied as a principal dwelling': 2}

Mapping for msamd_name:

{'Bellingham - WA': 0, 'Bremerton, Silverdale - WA': 1, 'Kennewick, Richland - WA': 2, 'Lewiston - ID, WA': 3, 'Longview - WA': 4, 'Mount Vernon, Anacortes - WA': 5, 'Olympia, Tumwater - WA': 6, 'Portland, Vancouver, Hillsboro - OR, WA': 7, 'Seattle, Bellevue, Everett - WA': 8, 'Spokane, Spokane Valley - WA': 9, 'Tacoma, Lakewood - WA': 10, 'Walla Walla - WA': 11, 'Wenatchee - WA': 12, 'Yakima - WA': 13}

Mapping for loan_type_name:

{'Conventional': 0, 'FHA-insured': 1, 'FSA/RHS-guaranteed': 2, 'VA-guaranteed': 3}

Mapping for loan_purpose_name:

```
{'Home improvement': 0, 'Home purchase': 1, 'Refinancing': 2}
```

Mapping for lien_status_name:

```
{'Not applicable': 0, 'Not secured by a lien': 1, 'Secured by a first lien': 2, 'Secured by a subordinate lien': 3}
```

Mapping for hoepa_status_name:

```
{'HOEPA loan': 0, 'Not a HOEPA loan': 1}
```

Mapping for county_name:

```
{'Adams County': 0, 'Asotin County': 1, 'Benton County': 2, 'Chelan County': 3, 'Clallam County': 4, 'Clark County': 5, 'Columbia County': 6, 'Cowlitz County': 7, 'Douglas County': 8, 'Ferry County': 9, 'Franklin County': 10, 'Garfield County': 11, 'Grant County': 12, 'Grays Harbor County': 13, 'Island County': 14, 'Jefferson County': 15, 'King County': 16, 'Kitsap County': 17, 'Kittitas County': 18, 'Klickitat County': 19, 'Lewis County': 20, 'Lincoln County': 21, 'Mason County': 22, 'Okanogan County': 23, 'Pacific County': 24, 'Pend Oreille County': 25, 'Pierce County': 26, 'San Juan County': 27, 'Skagit County': 28, 'Skamania County': 29, 'Snohomish County': 30, 'Spokane County': 31, 'Stevens County': 32, 'Thurston County': 33, 'Wahkiakum County': 34, 'Walla Walla County': 35, 'Whatcom County': 36, 'Whitman County': 37, 'Yakima County': 38}
```

Mapping for co_applicant_sex_name:

```
{'Female': 0, 'Information not provided by applicant in mail, Internet, or telephone application': 1, 'Male': 2, 'No co-applicant': 3, 'Not applicable': 4}
```

Mapping for co_applicant_ethnicity_name:

```
{'Hispanic or Latino': 0, 'Information not provided by applicant in mail, Internet, or telephone application': 1, 'No co-applicant': 2, 'Not Hispanic or Latino': 3, 'Not applicable': 4}
```

Mapping for applicant_sex_name:

```
{'Female': 0, 'Information not provided by applicant in mail, Internet, or telephone application': 1, 'Male': 2, 'Not applicable': 3}
```

Mapping for applicant_ethnicity_name:

```
{'Hispanic or Latino': 0, 'Information not provided by applicant in mail, Internet, or telephone application': 1, 'Not Hispanic or Latino': 2, 'Not applicable': 3}
```

Mapping for agency_name:

```
{'Consumer Financial Protection Bureau': 0, 'Department of Housing and Urban Development': 1, 'Federal Deposit Insurance Corporation': 2, 'Federal Reserve System': 3, 'National Credit Union Administration': 4, 'Office of the Comptroller of the Currency': 5}
```

Mapping for agency_abbr:

```
{'CFPB': 0, 'FDIC': 1, 'FRS': 2, 'HUD': 3, 'NCUA': 4, 'OCC': 5}
```

Mapping for action_taken_name:

```
{'Application approved but not accepted': 0, 'Application denied by financial institution': 1, 'Application withdrawn by applicant': 2, 'File closed for incompleteness': 3, 'Loan originated': 4, 'Loan purchased by the institution': 5, 'Preapproval request approved but not accepted': 6, 'Preapproval request denied by financial institution': 7}
```

S.no	respondent_id	purchaser_type_name	property_type_name	\
0	1	317	4	2

1	2	490	6	2
2	3	489	7	2
3	4	318	7	2
4	5	234	4	2
...
59995	59996	472	8	2
59996	59997	488	4	2
59997	59998	55	5	2
59998	59999	116	5	2
59999	60000	47	2	2

	preapproval_name	owner_occupancy_name	msamd_name	loan_type_name
\				
0	0	2	7	0
1	0	2	11	1
2	0	2	7	0
3	0	2	7	0
4	0	2	1	0
...
59995	0	2	7	0
59996	0	1	5	0
59997	0	2	0	1
59998	0	2	1	3
59999	0	2	7	0

	loan_purpose_name	lien_status_name	hoepa_status_name	county_name
\				
0	2	2	1	5
1	1	2	1	35
2	2	2	1	5
3	2	2	1	5
4	0	2	1	17
...
59995	2	2	1	5
59996	2	2	1	28
59997	0	2	1	36
59998	2	2	1	17
59999	2	2	1	5

	co_applicant_sex_name	co_applicant_ethnicity_name	applicant_sex_na
me \			
0	2	3	
0			
1	3	2	
2			
2	0	3	
2			
3	0	1	
2			
4	2	3	
0			
...	
...			
59995	0	0	
2			
59996	3	2	
0			
59997	0	3	
2			
59998	0	3	
2			

59999	0	3
2		
	applicant_ethnicity_name	agency_name
e		agency_abbr
0		action_taken_nam
4	2	0
1	0	1
4		3
2	2	1
4		3
3	1	4
4		4
4	2	2
4		1
...
...		
59995	2	1
4		3
59996	1	1
4		3
59997	2	1
4		3
59998	2	0
4		0
59999	2	0
4		0

[60000 rows x 19 columns]
time: 396 ms (started: 2024-04-13 11:17:53 +00:00)

```
In [20]: print(imputed_data_non_categorical.columns)
```

Index(['S.no', 'tract_to_msamd_income', 'population', 'minority_populatio
n',
 'number_of_owner_occupied_units', 'number_of_1_to_4_family_units',
 'loan_amount_000s', 'hud_median_family_income', 'applicant_income_00
0s',
 'sequence_number', 'census_tract_number', 'application_date_indicato
r',
 'Cluster_Label'],
 dtype='object')
time: 1.02 ms (started: 2024-04-13 11:17:53 +00:00)

```
In [21]: def identify_outliers(column):
    Q1 = np.percentile(column, 25)
    Q3 = np.percentile(column, 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = (column < lower_bound) | (column > upper_bound)
    return outliers

# Apply the function to each column to get a DataFrame of True/False values
outliers = imputed_data_non_categorical.apply(identify_outliers)

# Display the number of outliers for each column
outlier_counts = outliers.sum()
print(outlier_counts)
```

```
S.no                                0
tract_to_msamd_income             1309
population                        553
minority_population               2641
number_of_owner_occupied_units    478
number_of_1_to_4_family_units     2150
loan_amount_000s                 2467
hud_median_family_income          0
applicant_income_000s            3765
sequence_number                  7898
census_tract_number              9391
application_date_indicator        776
Cluster_Label                     0
dtype: int64
time: 59.1 ms (started: 2024-04-13 11:17:53 +00:00)
```

```
In [22]: # Iterate through each column and print count of unique values
for column in imputed_data_non_categorical.columns:
    unique_count = imputed_data_non_categorical[column].nunique()
    print(f"Count of unique values in {column} column: {unique_count}")
```

```
Count of unique values in S.no column: 60000
Count of unique values in tract_to_msamd_income column: 1328
Count of unique values in population column: 1284
Count of unique values in minority_population column: 1217
Count of unique values in number_of_owner_occupied_units column: 997
Count of unique values in number_of_1_to_4_family_units column: 1052
Count of unique values in loan_amount_000s column: 1344
Count of unique values in hud_median_family_income column: 16
Count of unique values in applicant_income_000s column: 808
Count of unique values in sequence_number column: 39340
Count of unique values in census_tract_number column: 1109
Count of unique values in application_date_indicator column: 2
Count of unique values in Cluster_Label column: 5
time: 34.1 ms (started: 2024-04-13 11:17:53 +00:00)
```

```
In [23]: # Initialize the StandardScaler
scaler = StandardScaler()

# Apply Standard Scaling to your dataset
scaled_data = scaler.fit_transform(imputed_data_non_categorical)

def identify_outliers(column):
    Q1 = np.percentile(column, 25)
    Q3 = np.percentile(column, 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = (column < lower_bound) | (column > upper_bound)
    return outliers

# Apply the function to each column in the scaled dataset
outliers_scaled = pd.DataFrame(scaled_data, columns=imputed_data_non_categorical.columns).apply(identify_outliers)

# Display the number of outliers for each column in the scaled dataset
outlier_counts_scaled = outliers_scaled.sum()
print(outlier_counts_scaled)
```

```
S.no                                0
tract_to_msamd_income             1309
population                        553
minority_population               2641
number_of_owner_occupied_units    478
number_of_1_to_4_family_units     2150
loan_amount_000s                 2467
hud_median_family_income           0
applicant_income_000s             3765
sequence_number                   7898
census_tract_number               9391
application_date_indicator        776
Cluster_Label                     0
dtype: int64
time: 59.9 ms (started: 2024-04-13 11:17:54 +00:00)
```

```
In [24]: # Initialize the RobustScaler
scaler = RobustScaler()

# Apply Robust Scaling to your dataset
scaled_data_robust = scaler.fit_transform(imputed_data_non_categorical)

# Check for outliers in the scaled dataset
outliers_robust = pd.DataFrame(scaled_data_robust, columns=imputed_data_non_categorical.columns).apply(identify_outliers)

# Display the number of outliers for each column in the scaled dataset
outlier_counts_robust = outliers_robust.sum()
print(outlier_counts_robust)
```

```
S.no                                0
tract_to_msamd_income              1309
population                          553
minority_population                2641
number_of_owner_occupied_units     478
number_of_1_to_4_family_units      2150
loan_amount_000s                   2467
hud_median_family_income            0
applicant_income_000s              3765
sequence_number                    7898
census_tract_number                9391
application_date_indicator          776
Cluster_Label                       0
dtype: int64
time: 76.6 ms (started: 2024-04-13 11:17:54 +00:00)
```

```
In [25]: # Define columns to exclude from normalization
columns_to_exclude = ['S.no', 'hud_median_family_income', 'application_date_
indicator', 'Cluster_Label']

# Create a copy of the DataFrame with excluded columns
data_to_scale = imputed_data_non_categorical.drop(columns=columns_to_exclud
e)

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Apply Min-Max Scaling to the selected columns
scaled_data = scaler.fit_transform(data_to_scale)

# Create a DataFrame with scaled data and original column names
scaled_df = pd.DataFrame(scaled_data, columns=data_to_scale.columns)

# Add back the excluded columns to the scaled DataFrame
scaled_df[columns_to_exclude] = imputed_data_non_categorical[columns_to_exc
lude]

# Display the scaled DataFrame
print(scaled_df)
```

	tract_to_msamd_income	population	minority_population	\
0	0.442799	0.640752	0.234501	
1	0.285162	0.372631	0.236658	
2	0.317084	0.385008	0.105445	
3	0.543502	0.381682	0.070620	
4	0.610556	0.393363	0.091213	
...	
59995	0.394915	0.299373	0.149434	
59996	0.445679	0.369923	0.060162	
59997	0.418734	0.609964	0.105553	
59998	0.336419	0.179392	0.322803	
59999	0.442799	0.640752	0.234501	

	number_of_owner_occupied_units	number_of_1_to_4_family_units	\
0	0.724346	0.448858	
1	0.420188	0.298329	
2	0.375922	0.308728	
3	0.506372	0.305660	
4	0.566734	0.354074	
...	
59995	0.370557	0.240709	
59996	0.556673	0.383396	
59997	0.783032	0.558814	
59998	0.195171	0.116263	
59999	0.724346	0.448858	

	loan_amount_000s	applicant_income_000s	sequence_number	\
0	0.004109	0.018669	0.096625	
1	0.004346	0.006656	0.042368	
2	0.004364	0.018831	0.005001	
3	0.006364	0.050974	0.000158	
4	0.007564	0.018344	0.026241	
...	
59995	0.002927	0.012013	0.024452	
59996	0.002564	0.007955	0.268165	
59997	0.004546	0.014123	0.020504	
59998	0.004655	0.018153	0.289037	
59999	0.005309	0.013149	0.032247	

	census_tract_number	S.no	hud_median_family_income	\
0	0.042258	1.0	73300.0	
1	0.943728	2.0	57900.0	
2	0.042333	3.0	73300.0	
3	0.041421	4.0	73300.0	
4	0.092866	5.0	78100.0	
...	
59995	0.041926	59996.0	73300.0	
59996	0.963715	59997.0	61400.0	
59997	0.000724	59998.0	69900.0	
59998	0.082002	59999.0	78100.0	
59999	0.042258	60000.0	73300.0	

	application_date_indicator	Cluster_Label
0	0.0	4.0
1	0.0	3.0
2	0.0	4.0
3	0.0	4.0
4	0.0	4.0
...
59995	0.0	1.0
59996	0.0	1.0

59997	0.0	1.0
59998	0.0	1.0
59999	0.0	1.0

[60000 rows x 13 columns]

time: 24.8 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [26]: def identify_outliers(column):
    Q1 = np.percentile(column, 25)
    Q3 = np.percentile(column, 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = (column < lower_bound) | (column > upper_bound)
    return outliers

# Apply the function to each column in the scaled dataset
scaled_outliers = scaled_df.apply(identify_outliers)

# Display the number of outliers for each column in the scaled dataset
scaled_outlier_counts = scaled_outliers.sum()
print(scaled_outlier_counts)
```

tract_to_msamd_income	1309
population	553
minority_population	2641
number_of_owner_occupied_units	478
number_of_1_to_4_family_units	2150
loan_amount_000s	2467
applicant_income_000s	3765
sequence_number	7898
census_tract_number	9391
S.no	0
hud_median_family_income	0
application_date_indicator	776
Cluster_Label	0

dtype: int64
time: 45.4 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [27]: # Calculate standard deviation for non-categorical columns
std_deviation_non_categorical1 = scaled_df.std()

# Creating a DataFrame to display the results
dispersion_non_categorical_df1 = pd.DataFrame({
    'Variable': scaled_df.columns,
    'Standard Deviation': std_deviation_non_categorical1.values
})

print(dispersion_non_categorical_df1)
```

	Variable	Standard Deviation
0	tract_to_msamd_income	0.116026
1	population	0.132618
2	minority_population	0.155273
3	number_of_owner_occupied_units	0.173640
4	number_of_1_to_4_family_units	0.125768
5	loan_amount_000s	0.010999
6	applicant_income_000s	0.018857
7	sequence_number	0.121228
8	census_tract_number	0.344020
9	S.no	17320.652413
10	hud_median_family_income	12798.211781
11	application_date_indicator	0.225976
12	Cluster_Label	1.395815

time: 16.5 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [28]: # Pre-Processed Dataset
combined_data = pd.merge(encoded_data_categorical, scaled_df, on='S.no')

# Display the Pre-Processed Dataset
%memit
combined_data
```

peak memory: 420.05 MiB, increment: 0.09 MiB

Out[28]:

	S.no	respondent_id	purchaser_type_name	property_type_name	preapproval_name	c
0	1	317	4	2	0	
1	2	490	6	2	0	
2	3	489	7	2	0	
3	4	318	7	2	0	
4	5	234	4	2	0	
...
59995	59996	472	8	2	0	
59996	59997	488	4	2	0	
59997	59998	55	5	2	0	
59998	59999	116	5	2	0	
59999	60000	47	2	2	0	

60000 rows × 31 columns

time: 346 ms (started: 2024-04-13 11:17:54 +00:00)


```
In [29]: # Get the index of the 'Cluster_Label' column
cluster_label_index = combined_data.columns.get_loc('Cluster_Label')

# Reorder the columns to move 'Cluster_Label' to the extreme right
combined_data = combined_data[[col for col in combined_data if col != 'Cluster_Label'] + ['Cluster_Label']]

# Display the updated dataset
print(combined_data.head())
```

	S.no	respondent_id	purchaser_type_name	property_type_name	\
0	1	317	4	2	
1	2	490	6	2	
2	3	489	7	2	
3	4	318	7	2	
4	5	234	4	2	

	preapproval_name	owner_occupancy_name	msamd_name	loan_type_name	\
0	0	2	7	0	
1	0	2	11	1	
2	0	2	7	0	
3	0	2	7	0	
4	0	2	1	0	

	loan_purpose_name	lien_status_name	...	minority_population	\
0	2	2	...	0.234501	
1	1	2	...	0.236658	
2	2	2	...	0.105445	
3	2	2	...	0.070620	
4	0	2	...	0.091213	

	number_of_owner_occupied_units	number_of_1_to_4_family_units	\
0	0.724346	0.448858	
1	0.420188	0.298329	
2	0.375922	0.308728	
3	0.506372	0.305660	
4	0.566734	0.354074	

	loan_amount_000s	applicant_income_000s	sequence_number	\
0	0.004109	0.018669	0.096625	
1	0.004346	0.006656	0.042368	
2	0.004364	0.018831	0.005001	
3	0.006364	0.050974	0.000158	
4	0.007564	0.018344	0.026241	

	census_tract_number	hud_median_family_income	application_date_indicato	\
0	0.042258	73300.0	0.	
0				
1	0.943728	57900.0	0.	
0				
2	0.042333	73300.0	0.	
0				
3	0.041421	73300.0	0.	
0				
4	0.092866	78100.0	0.	
0				

	Cluster_Label
0	4.0
1	3.0
2	4.0
3	4.0
4	4.0

[5 rows x 31 columns]

time: 22.9 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [30]: df_ppd_subset = combined_data.copy()
```

```
time: 16.8 ms (started: 2024-04-13 11:17:54 +00:00)
```

```
In [31]: list(combined_data.columns)
```

```
Out[31]: ['S.no',  
         'respondent_id',  
         'purchaser_type_name',  
         'property_type_name',  
         'preapproval_name',  
         'owner_occupancy_name',  
         'msamd_name',  
         'loan_type_name',  
         'loan_purpose_name',  
         'lien_status_name',  
         'hoepa_status_name',  
         'county_name',  
         'co_applicant_sex_name',  
         'co_applicant_ethnicity_name',  
         'applicant_sex_name',  
         'applicant_ethnicity_name',  
         'agency_name',  
         'agency_abbr',  
         'action_taken_name',  
         'tract_to_msamd_income',  
         'population',  
         'minority_population',  
         'number_of_owner_occupied_units',  
         'number_of_1_to_4_family_units',  
         'loan_amount_000s',  
         'applicant_income_000s',  
         'sequence_number',  
         'census_tract_number',  
         'hud_median_family_income',  
         'application_date_indicator',  
         'Cluster_Label']
```

```
time: 4.03 ms (started: 2024-04-13 11:17:54 +00:00)
```

DT

```
In [32]: ##### DT
```

```
time: 354 µs (started: 2024-04-13 11:17:54 +00:00)
```

```
In [33]: df1 = df_ppd_subset.copy()
```

```
time: 12.1 ms (started: 2024-04-13 11:17:54 +00:00)
```

In [34]: df1.columns

```
Out[34]: Index(['S.no', 'respondent_id', 'purchaser_type_name', 'property_type_name',
               'preapproval_name', 'owner_occupancy_name', 'msamd_name',
               'loan_type_name', 'loan_purpose_name', 'lien_status_name',
               'hoepa_status_name', 'county_name', 'co_applicant_sex_name',
               'co_applicant_ethnicity_name', 'applicant_sex_name',
               'applicant_ethnicity_name', 'agency_name', 'agency_abbr',
               'action_taken_name', 'tract_to_msamd_income', 'population',
               'minority_population', 'number_of_owner_occupied_units',
               'number_of_1_to_4_family_units', 'loan_amount_000s',
               'applicant_income_000s', 'sequence_number', 'census_tract_number',
               'hud_median_family_income', 'application_date_indicator',
               'Cluster_Label'],
              dtype='object')
```

time: 3.87 ms (started: 2024-04-13 11:17:54 +00:00)

In [35]: df1.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60000 entries, 0 to 59999
Data columns (total 31 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   S.no                                       60000 non-null  object
1   respondent_id                             60000 non-null  int64
2   purchaser_type_name                       60000 non-null  int64
3   property_type_name                       60000 non-null  int64
4   preapproval_name                         60000 non-null  int64
5   owner_occupancy_name                     60000 non-null  int64
6   msamd_name                               60000 non-null  int64
7   loan_type_name                           60000 non-null  int64
8   loan_purpose_name                         60000 non-null  int64
9   lien_status_name                         60000 non-null  int64
10  hoepa_status_name                        60000 non-null  int64
11  county_name                              60000 non-null  int64
12  co_applicant_sex_name                     60000 non-null  int64
13  co_applicant_ethnicity_name               60000 non-null  int64
14  applicant_sex_name                       60000 non-null  int64
15  applicant_ethnicity_name                  60000 non-null  int64
16  agency_name                               60000 non-null  int64
17  agency_abbr                              60000 non-null  int64
18  action_taken_name                        60000 non-null  int64
19  tract_to_msamd_income                    60000 non-null  float64
20  population                               60000 non-null  float64
21  minority_population                       60000 non-null  float64
22  number_of_owner_occupied_units            60000 non-null  float64
23  number_of_1_to_4_family_units             60000 non-null  float64
24  loan_amount_000s                         60000 non-null  float64
25  applicant_income_000s                    60000 non-null  float64
26  sequence_number                          60000 non-null  float64
27  census_tract_number                      60000 non-null  float64
28  hud_median_family_income                  60000 non-null  float64
29  application_date_indicator                60000 non-null  float64
30  Cluster_Label                            60000 non-null  float64
dtypes: float64(12), int64(18), object(1)
memory usage: 14.2+ MB
time: 22.4 ms (started: 2024-04-13 11:17:54 +00:00)
```

```
In [36]: df1_inputs_all = df1[['respondent_id', 'purchaser_type_name', 'property_type_name',
                             'preapproval_name', 'owner_occupancy_name', 'msamd_name',
                             'loan_type_name', 'loan_purpose_name', 'lien_status_name',
                             'hoepa_status_name', 'county_name', 'co_applicant_sex_name',
                             'co_applicant_ethnicity_name', 'applicant_sex_name',
                             'applicant_ethnicity_name', 'agency_name', 'agency_abbr',
                             'tract_to_msamd_income', 'population',
                             'minority_population', 'number_of_owner_occupied_units',
                             'number_of_1_to_4_family_units', 'loan_amount_000s',
                             'applicant_income_000s', 'sequence_number', 'census_tract_number',
                             'hud_median_family_income', 'application_date_indicator',
                             'Cluster_Label']]
df1_output = df1[['action_taken_name']]

df1_inputs_all_names = df1_inputs_all.columns
df1_output_labels = df1_output['action_taken_name'].unique().astype(str)
```

time: 12.8 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [37]: # Initialize StratifiedShuffleSplit with desired test size and random state
stratified_split = StratifiedShuffleSplit(n_splits=1, test_size=0.25, random_state=45005)

# Perform the stratified split to get training and testing indices
for train_index, test_index in stratified_split.split(df1_inputs_all, df1_output):
    df1_inputs_all_train = df1_inputs_all.iloc[train_index]
    df1_inputs_all_test = df1_inputs_all.iloc[test_index]
    df1_output_train = df1_output.iloc[train_index]
    df1_output_test = df1_output.iloc[test_index]
```

time: 290 ms (started: 2024-04-13 11:17:54 +00:00)

```
In [38]: # Decision Tree : Model (Training Subset)
dtc_all = DecisionTreeClassifier(criterion='gini', random_state=45005, max_depth=3) # Other Criteria : Entropy, Log Loss
dtc_model_all = dtc_all.fit(df1_inputs_all_train, df1_output_train); dtc_model_all
```

```
Out[38]: DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3, random_state=45005)
```

time: 135 ms (started: 2024-04-13 11:17:55 +00:00)

```
In [39]: # Decision Tree : Feature Importance
dtc_all_imp_features = pd.DataFrame({'feature': df1_inputs_all_names, 'importance': np.round(dtc_model_all.feature_importances_, 3)})
dtc_all_imp_features.sort_values('importance', ascending=False, inplace=True); dtc_all_imp_features
```

Out[39]:

	feature	importance
27	application_date_indicator	0.479
5	msamd_name	0.292
1	purchaser_type_name	0.229
0	respondent_id	0.000
16	agency_abbr	0.000
26	hud_median_family_income	0.000
25	census_tract_number	0.000
24	sequence_number	0.000
23	applicant_income_000s	0.000
22	loan_amount_000s	0.000
21	number_of_1_to_4_family_units	0.000
20	number_of_owner_occupied_units	0.000
19	minority_population	0.000
18	population	0.000
17	tract_to_msamd_income	0.000
14	applicant_ethnicity_name	0.000
15	agency_name	0.000
13	applicant_sex_name	0.000
12	co_applicant_ethnicity_name	0.000
11	co_applicant_sex_name	0.000
10	county_name	0.000
9	hoepa_status_name	0.000
8	lien_status_name	0.000
7	loan_purpose_name	0.000
6	loan_type_name	0.000
4	owner_occupancy_name	0.000
3	preapproval_name	0.000
2	property_type_name	0.000
28	Cluster_Label	0.000

time: 18.4 ms (started: 2024-04-13 11:17:55 +00:00)

```
In [40]: # Subset df1 based on Inputs as {mpg, hp, cyl, vs} & Output as {am}
df1_inputs = df1[['application_date_indicator', 'msamd_name', 'purchaser_type_name', 'loan_type_name', 'loan_purpose_name', 'hud_median_family_income', 'loan_amount_000s']];
df1_inputs
df1_output = df1[['action_taken_name']]; df1_output

df1_inputs_names = df1_inputs.columns; df1_inputs_names
df1_output_labels = df1_output['action_taken_name'].unique().astype(str); df1_output_labels
```

```
Out[40]: array(['4', '0', '1', '2', '3', '5', '6', '7'], dtype='<U21')
```

```
time: 9.78 ms (started: 2024-04-13 11:17:55 +00:00)
```

```
In [41]: # Initialize StratifiedShuffleSplit with desired test size and random state
stratified_split = StratifiedShuffleSplit(n_splits=1, test_size=0.25, random_state=45005)

# Perform the stratified split to get training and testing indices
for train_index, test_index in stratified_split.split(df1_inputs, df1_output):
    df1_inputs_train = df1_inputs.iloc[train_index]
    df1_inputs_test = df1_inputs.iloc[test_index]
    df1_output_train = df1_output.iloc[train_index]
    df1_output_test = df1_output.iloc[test_index]
```

```
time: 262 ms (started: 2024-04-13 11:17:55 +00:00)
```

```
In [42]: from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
import numpy as np

# Initialize Logistic Regression model with L1 regularization
logreg_l1 = LogisticRegression(penalty='l1', solver='liblinear', random_state=45005)

# Fit the model on the training data
logreg_l1.fit(df1_inputs_train, df1_output_train.values.ravel())

# Get feature importances from the fitted model
feature_importances = np.abs(logreg_l1.coef_).flatten()

# Calculate the threshold as 20% of the maximum feature importance
threshold = 0.2 * np.max(feature_importances)

# Create a selector object to select features based on non-zero coefficients
selector = SelectFromModel(logreg_l1, threshold=threshold)

# Transform the training and testing input data to select features
df1_inputs_train_selected = selector.transform(df1_inputs_train)
df1_inputs_test_selected = selector.transform(df1_inputs_test)

# Get the selected features
selected_features = df1_inputs_names[selector.get_support()]

# Print the selected features and the calculated threshold
print("Selected Features:", selected_features)
print("Threshold:", threshold)
```

Selected Features: Index(['application_date_indicator', 'purchaser_type_name',

 'loan_purpose_name'],
 dtype='object')

Threshold: 1.8129252376051945

time: 2.81 s (started: 2024-04-13 11:17:55 +00:00)

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but SelectFromModel was fitted without feature names
 warnings.warn(

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but SelectFromModel was fitted without feature names
 warnings.warn(


```
In [43]: from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
import numpy as np

# Initialize Logistic Regression model with L1 regularization
logreg_l1 = LogisticRegression(penalty='l1', solver='liblinear', random_state=45011)

# Fit the model on the training data
logreg_l1.fit(df1_inputs_train, df1_output_train.values.ravel())

# Get feature importances from the fitted model
feature_importances = np.abs(logreg_l1.coef_).flatten()

# Calculate the threshold as 20% of the maximum feature importance
threshold = 0.2 * np.max(feature_importances)

# Create a selector object to select features based on non-zero coefficients
selector = SelectFromModel(logreg_l1, threshold=threshold)

# Transform the training and testing input data to select features
df1_inputs_train_selected = selector.transform(df1_inputs_train)
df1_inputs_test_selected = selector.transform(df1_inputs_test)

# Get the selected features
selected_features = df1_inputs_names[selector.get_support()]

# Print the selected features and the calculated threshold
print("Selected Features:", selected_features)
print("Threshold:", threshold)
```

Selected Features: Index(['application_date_indicator', 'purchaser_type_name',

 'loan_purpose_name'],
 dtype='object')

Threshold: 1.7010443233194732

time: 3.24 s (started: 2024-04-13 11:17:58 +00:00)

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but SelectFromModel was fitted without feature names

warnings.warn(

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but SelectFromModel was fitted without feature names

warnings.warn(

```
In [44]: # Decision Tree : Model (Training Subset)
dtc = DecisionTreeClassifier(criterion='gini', random_state=45005, max_depth=3) # Other Criteria : Entropy, Log Loss
dtc_model = dtc.fit(df1_inputs_train, df1_output_train); dtc_model
```

```
Out[44]: DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3, random_state=45005)
```

time: 34.9 ms (started: 2024-04-13 11:18:01 +00:00)

```
In [45]: # Decision Tree : Model Rules
dtc_model_rules = export_text(dtc_model, feature_names = list(df1_inputs_names)); print(dtc_model_rules)

|--- application_date_indicator <= 1.00
|   |--- purchaser_type_name <= 6.50
|   |   |--- class: 4
|   |   |--- purchaser_type_name > 6.50
|   |       |--- msamd_name <= 9.50
|   |       |   |--- class: 4
|   |       |   |--- msamd_name > 9.50
|   |           |--- class: 4
|--- application_date_indicator > 1.00
|   |--- class: 5

time: 1.97 ms (started: 2024-04-13 11:18:01 +00:00)
```

```
In [46]: # Decision Tree : Feature Importance
dtc_imp_features = pd.DataFrame({'feature': df1_inputs_names, 'importance':
np.round(dtc_model.feature_importances_, 3)})
dtc_imp_features.sort_values('importance', ascending=False, inplace=True);
dtc_imp_features
```

Out[46]:

	feature	importance
0	application_date_indicator	0.479
1	msamd_name	0.292
2	purchaser_type_name	0.229
3	loan_type_name	0.000
4	loan_purpose_name	0.000
5	hud_median_family_income	0.000
6	loan_amount_000s	0.000

time: 16.6 ms (started: 2024-04-13 11:18:01 +00:00)

```
In [47]: from sklearn.tree import DecisionTreeClassifier, export_text
import numpy as np
import pandas as pd

# Initialize the Decision Tree classifier with Gini coefficient criterion
dtc_gini = DecisionTreeClassifier(criterion='gini', random_state=45005, max_depth=3)

# Train the Decision Tree model using the training subset for Gini coefficient
dtc_model_gini = dtc_gini.fit(df1_inputs_train, df1_output_train)

# Print the trained Decision Tree model for Gini coefficient (optional)
print(dtc_model_gini)

# Get the rules of the trained Decision Tree model for Gini coefficient
dtc_model_rules_gini = export_text(dtc_model_gini, feature_names=list(df1_inputs_names))
print(dtc_model_rules_gini)

# Calculate feature importance based on Gini coefficient
dtc_imp_features_gini = pd.DataFrame({'feature': df1_inputs_names, 'importance': np.round(dtc_model_gini.feature_importances_, 3)})
dtc_imp_features_gini.sort_values('importance', ascending=False, inplace=True)
print(dtc_imp_features_gini)

# Initialize the Decision Tree classifier with entropy criterion
dtc_entropy = DecisionTreeClassifier(criterion='entropy', random_state=45005, max_depth=3)

# Train the Decision Tree model using the training subset for entropy
dtc_model_entropy = dtc_entropy.fit(df1_inputs_train, df1_output_train)

# Print the trained Decision Tree model for entropy (optional)
print(dtc_model_entropy)

# Get the rules of the trained Decision Tree model for entropy
dtc_model_rules_entropy = export_text(dtc_model_entropy, feature_names=list(df1_inputs_names))
print(dtc_model_rules_entropy)

# Calculate feature importance based on entropy
dtc_imp_features_entropy = pd.DataFrame({'feature': df1_inputs_names, 'importance': np.round(dtc_model_entropy.feature_importances_, 3)})
dtc_imp_features_entropy.sort_values('importance', ascending=False, inplace=True)
print(dtc_imp_features_entropy)
```

```
DecisionTreeClassifier(max_depth=3, random_state=45005)
```

```
|--- application_date_indicator <= 1.00
|   |--- purchaser_type_name <= 6.50
|   |   |--- class: 4
|   |   |--- purchaser_type_name > 6.50
|   |       |--- msamd_name <= 9.50
|   |       |   |--- class: 4
|   |       |   |--- msamd_name > 9.50
|   |       |       |--- class: 4
|--- application_date_indicator > 1.00
|   |--- class: 5
```

	feature	importance
0	application_date_indicator	0.479
1	msamd_name	0.292
2	purchaser_type_name	0.229
3	loan_type_name	0.000
4	loan_purpose_name	0.000
5	hud_median_family_income	0.000
6	loan_amount_000s	0.000

```
DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=45005)
```

```
|--- purchaser_type_name <= 6.50
|   |--- application_date_indicator <= 1.00
|   |   |--- class: 4
|   |   |--- application_date_indicator > 1.00
|   |       |--- class: 5
|--- purchaser_type_name > 6.50
|   |--- hud_median_family_income <= 72800.00
|   |   |--- msamd_name <= 6.50
|   |   |   |--- class: 4
|   |   |   |--- msamd_name > 6.50
|   |   |       |--- class: 4
|   |--- hud_median_family_income > 72800.00
|   |   |--- msamd_name <= 7.50
|   |   |   |--- class: 4
|   |   |   |--- msamd_name > 7.50
|   |       |--- class: 4
```

	feature	importance
2	purchaser_type_name	0.389
0	application_date_indicator	0.304
5	hud_median_family_income	0.198
1	msamd_name	0.109
3	loan_type_name	0.000
4	loan_purpose_name	0.000
6	loan_amount_000s	0.000

```
time: 68.9 ms (started: 2024-04-13 11:18:01 +00:00)
```

```
In [48]: from sklearn.metrics import log_loss
from sklearn.tree import DecisionTreeClassifier

# Assuming you have already trained the DecisionTreeClassifier model
# dtc_model_entropy = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=45005)
# dtc_model_gini = DecisionTreeClassifier(criterion='gini', max_depth=3, random_state=45005)

# Calculate entropy
y_pred_proba_entropy = dtc_model_entropy.predict_proba(df1_inputs_test)
entropy = log_loss(df1_output_test, y_pred_proba_entropy)

# Calculate Gini impurity
y_pred_proba_gini = dtc_model_gini.predict_proba(df1_inputs_test)
gini_impurity = 1 - (y_pred_proba_gini ** 2).sum(axis=1).mean()

print("Entropy:", entropy)
print("Gini Impurity:", gini_impurity)
```

Entropy: 0.15333397314417907
Gini Impurity: 0.08053758117824039
time: 30.1 ms (started: 2024-04-13 11:18:01 +00:00)

```
In [49]: # Decision Tree : Model Prediction (Training Subset)
dtc_model_predict = dtc_model.predict(df1_inputs_train); dtc_model_predict
```

Out[49]: array([4, 4, 4, ..., 4, 4, 4])
time: 12.8 ms (started: 2024-04-13 11:18:01 +00:00)

```
In [50]: # Decision Tree : Prediction (Testing Subset)
dtc_predict = dtc_model.predict(df1_inputs_test); dtc_predict
```

Out[50]: array([4, 4, 4, ..., 4, 4, 4])
time: 8.09 ms (started: 2024-04-13 11:18:01 +00:00)

```
In [51]: # Decision Tree : Model Evaluation (Training Subset)
dtc_model_conf_mat = pd.DataFrame(confusion_matrix(df1_output_train, dtc_model_predict)); dtc_model_conf_mat
dtc_model_perf = classification_report(df1_output_train, dtc_model_predict); print(dtc_model_perf)
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	63
1	0.00	0.00	0.00	121
2	0.00	0.00	0.00	2000
3	0.00	0.00	0.00	334
4	0.94	1.00	0.97	41861
5	1.00	1.00	1.00	582
6	0.00	0.00	0.00	13
7	0.00	0.00	0.00	26
accuracy			0.94	45000
macro avg	0.24	0.25	0.25	45000
weighted avg	0.89	0.94	0.92	45000

time: 79.5 ms (started: 2024-04-13 11:18:01 +00:00)

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

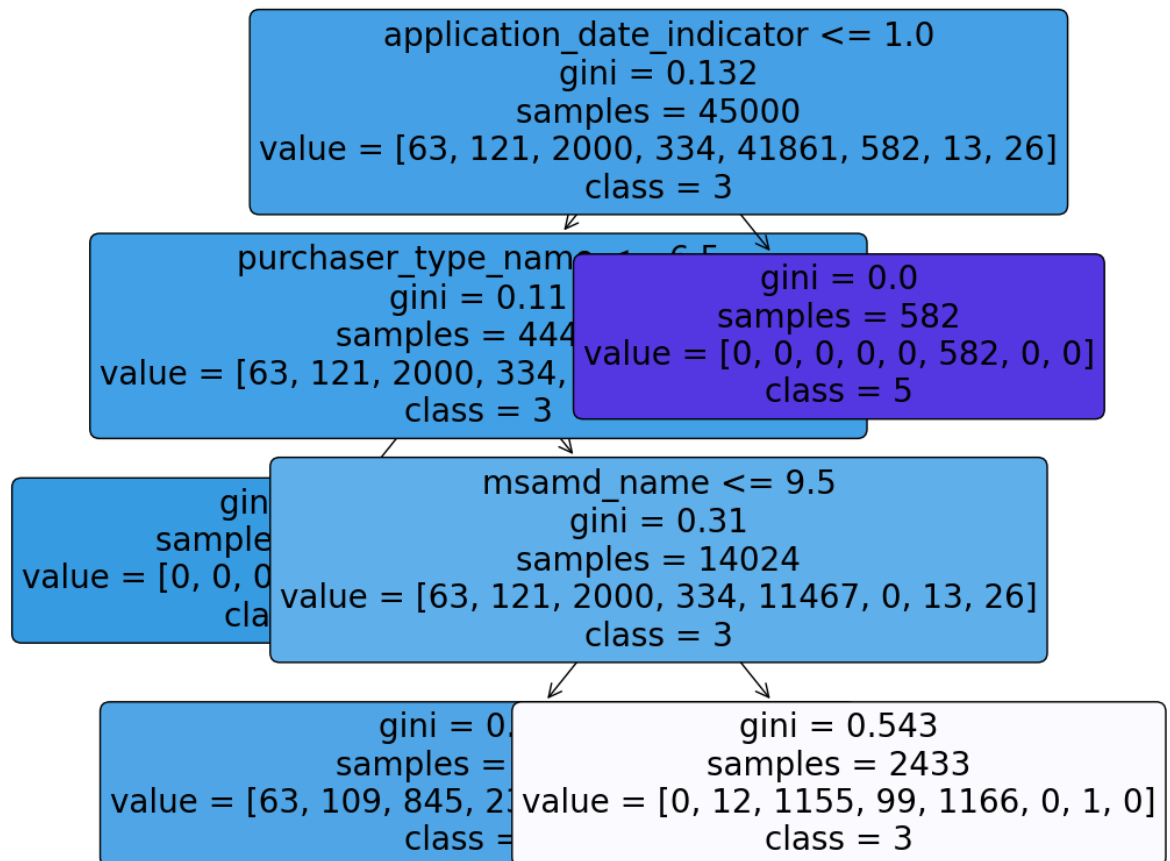
_warn_prf(average, modifier, msg_start, len(result))

```
In [52]: import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Set a larger figure size for better clarity
plt.figure(figsize=(10, 10))

# Plot the decision tree
train_subset_dtc_plot = plot_tree(dtc_model, feature_names=df1_inputs_names,
class_names=df1_output_labels, rounded=True, filled=True, fontsize=20)

# Show the plot
plt.show()
```



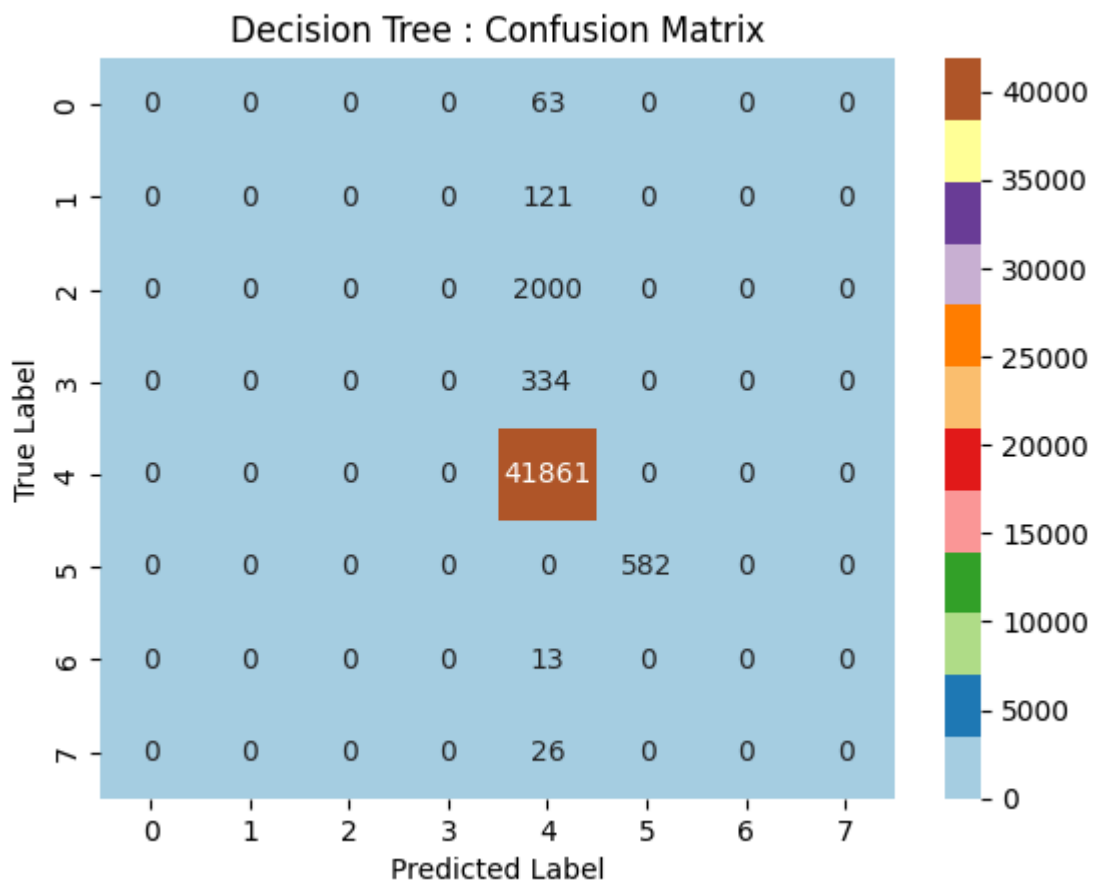
```
In [53]: # Set up the plot
ax = plt.axes()

# Plot the confusion matrix with annotations in integer format
sns.heatmap(dtc_model_conf_mat, annot=True, fmt='d', cmap='Paired')

# Set labels and title
ax.set_xlabel('Predicted Label')
ax.set_ylabel('True Label')
ax.set_title('Decision Tree : Confusion Matrix')

# Show the plot
plt.show()
```

time: 514 ms (started: 2024-04-13 11:18:02 +00:00)



time: 669 ms (started: 2024-04-13 11:18:02 +00:00)


```
In [54]: # Cross Validation
from sklearn.model_selection import cross_val_score

# Define your decision tree classifier with desired parameters
dtc_cv = DecisionTreeClassifier(criterion='gini', random_state=45005)

# Perform 5-fold cross-validation
cv_scores = cross_val_score(dtc_cv, df1_inputs, df1_output.values.ravel(),
                             cv=20)
print("Cross-Validation Scores:", cv_scores)
print("Average Cross-Validation Score:", np.mean(cv_scores))
```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 17 members, which is less than n_splits=20.
warnings.warn(

Cross-Validation Scores: [0.92333333 0.931 0.94633333 0.90266667 0.905
0.919
0.88566667 0.916 0.932 0.94466667 0.96 0.96566667
0.96866667 0.96766667 0.96733333 0.97233333 0.97233333 0.97166667
0.95766667 0.95533333]
Average Cross-Validation Score: 0.9432166666666667
time: 1.35 s (started: 2024-04-13 11:18:03 +00:00)

```
In [55]: from sklearn.metrics import f1_score

# Compute F1 score
f1 = f1_score(df1_output_test, dtc_predict, average='macro') # or 'weighted' for weighted F1 score
print("F1 Score:", f1)

# Weighted F1 score
weighted_f1 = f1_score(df1_output_test, dtc_predict, average='weighted')
print("Weighted F1 Score:", weighted_f1)
```

F1 Score: 0.24629694019471488
Weighted F1 Score: 0.9156413351877607
time: 28.5 ms (started: 2024-04-13 11:18:04 +00:00)

```
In [56]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit, cross_val_score
from sklearn.tree import DecisionTreeClassifier, export_text, plot_tree
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
from sklearn.svm import SVC
import numpy as np
import time
import psutil

# Function to measure memory usage
def memory_usage():
    process = psutil.Process()
    return process.memory_info().rss / 1024 ** 2 # Memory usage in MB

# Start time
start_time = time.time()

# Data preprocessing and splitting
# Assuming you have your data loaded into cars_inputs and cars_output
df1_inputs_train, df1_inputs_test, df1_output_train, df1_output_test = train_test_split(df1_inputs, df1_output, test_size=0.2, random_state=42)

# End time
end_time = time.time()

# Time taken for data preprocessing and splitting
data_preprocessing_time = end_time - start_time

# Memory usage after data preprocessing
data_preprocessing_memory = memory_usage()

# Decision Tree
dt_start_time = time.time()
dt_model = DecisionTreeClassifier(criterion='gini', random_state=45005, max_depth=3)
dt_model.fit(df1_inputs_train, df1_output_train)
dt_training_time = time.time() - dt_start_time
dt_memory_used = memory_usage()
dt_pred = dt_model.predict(df1_inputs_test)
dt_accuracy = accuracy_score(df1_output_test, dt_pred)

# Cross-validation for Decision Tree
dtc_cv_start_time = time.time()
dtc_cv = DecisionTreeClassifier(criterion='gini', random_state=45007)
cv_scores_dtc = cross_val_score(dtc_cv, df1_inputs, df1_output.values.ravel(), cv=20)
dtc_cv_time = time.time() - dtc_cv_start_time
dtc_cv_accuracy = np.mean(cv_scores_dtc)

print("Decision Tree:")
print(f" - Training Time (s): {dt_training_time}")
print(f" - Memory Used (MB): {dt_memory_used}")
print(f" - Single Split Accuracy: {dt_accuracy}")
```

```
print(f" - Cross Validation Accuracy: {dtc_cv_accuracy}")
print()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:7
00: UserWarning: The least populated class in y has only 17 members, which
is less than n_splits=20.
warnings.warn(
```

Decision Tree:

- Training Time (s): 0.026858806610107422
- Memory Used (MB): 506.37109375
- Single Split Accuracy: 0.9454166666666667
- Cross Validation Accuracy: 0.9432499999999999

time: 1.36 s (started: 2024-04-13 11:18:04 +00:00)

Random Forest

```
In [57]: ## Data Visualization Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from wordcloud import WordCloud
from collections import Counter
from scipy import stats
from sklearn.tree import plot_tree
import graphviz
from IPython.display import display
from collections import Counter

## Machine Learning Models and Evaluation Metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils.validation import column_or_1d
from sklearn.metrics import accuracy_score, classification_report, confusio
n_matrix, f1_score, precision_recall_fscore_support
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression, Lasso, Ridge
from sklearn.metrics import make_scorer
from sklearn.pipeline import make_pipeline
from sklearn.tree import export_graphviz
```

time: 1.69 ms (started: 2024-04-13 11:18:05 +00:00)

```
In [58]: rf_classifier = RandomForestClassifier(n_estimators=100, random_state=4500
5)
```

time: 617 µs (started: 2024-04-13 11:18:06 +00:00)

```
In [59]: rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])
```

```
Out[59]:
RandomForestClassifier
RandomForestClassifier(random_state=45005)
```

time: 2.75 s (started: 2024-04-13 11:18:06 +00:00)

```
In [60]: y_train_pred_rf = rf_classifier.predict(df1_inputs_train)
y_test_pred_rf = rf_classifier.predict(df1_inputs_test)
```

time: 1.37 s (started: 2024-04-13 11:18:08 +00:00)

```
In [61]: from sklearn.metrics import log_loss
from sklearn.ensemble import RandomForestClassifier

# Assuming you have already trained the RandomForestClassifier model
# rf_classifier = RandomForestClassifier(n_estimators=100, random_state=45005)
# rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])

# Calculate entropy
y_pred_proba_rf = rf_classifier.predict_proba(df1_inputs_test)
entropy_rf = log_loss(df1_output_test, y_pred_proba_rf)

# Calculate Gini impurity
gini_impurity_rf = 1 - (y_pred_proba_rf ** 2).sum(axis=1).mean()

print("Entropy for Random Forest:", entropy_rf)
print("Gini Impurity for Random Forest:", gini_impurity_rf)
```

Entropy for Random Forest: 0.4448700986425233

Gini Impurity for Random Forest: 0.03587907150255809

time: 483 ms (started: 2024-04-13 11:18:10 +00:00)

```
In [62]: # Train the Random Forest classifier
rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])

# Print feature importances
feature_importances = rf_classifier.feature_importances_
feature_importance_df = pd.DataFrame({'Feature': df1_inputs_train.columns,
'Importance': feature_importances})
sorted_feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
print("Feature Importances:")
print(sorted_feature_importance_df)
```

Feature Importances:

	Feature	Importance
6	loan_amount_000s	0.333727
2	purchaser_type_name	0.201634
0	application_date_indicator	0.195447
5	hud_median_family_income	0.120389
1	msamd_name	0.096998
3	loan_type_name	0.027990
4	loan_purpose_name	0.023816

time: 6.03 s (started: 2024-04-13 11:18:10 +00:00)

```
In [63]: # For training set
print("Training Set Confusion Matrix:")
print(confusion_matrix(df1_output_train['action_taken_name'], y_train_pred_rf))

print("\nTraining Set Classification Report:")
print(classification_report(df1_output_train['action_taken_name'], y_train_pred_rf))
```

Training Set Confusion Matrix:

```
[ [ 31    0   13    1   21    0    0    0]
  [  1   69   21    2   43    0    0    0]
  [  1    8 1825   26  289    0    0    1]
  [  0    3   51  229   75    0    0    0]
  [  2   10  260   27 44307    0    0    0]
  [  0    0    0    0    0  642    0    0]
  [  0    0    1    0    3    0   11    0]
  [  0    0    1    0    2    0    0   24]]
```

Training Set Classification Report:

	precision	recall	f1-score	support
0	0.89	0.47	0.61	66
1	0.77	0.51	0.61	136
2	0.84	0.85	0.84	2150
3	0.80	0.64	0.71	358
4	0.99	0.99	0.99	44606
5	1.00	1.00	1.00	642
6	1.00	0.73	0.85	15
7	0.96	0.89	0.92	27
accuracy			0.98	48000
macro avg	0.91	0.76	0.82	48000
weighted avg	0.98	0.98	0.98	48000

time: 165 ms (started: 2024-04-13 11:18:16 +00:00)

```
In [64]: # For testing set
print("\nTesting Set Confusion Matrix:")
print(confusion_matrix(df1_output_test['action_taken_name'], y_test_pred_rf))

print("\nTesting Set Classification Report:")
print(classification_report(df1_output_test['action_taken_name'], y_test_pred_rf))
```

Testing Set Confusion Matrix:								
[0	0	5	3	10	0	0	0]
[0	1	7	1	16	0	0	0]
[6	10	272	33	194	0	0	1]
[0	5	36	16	31	0	0	0]
[2	7	196	17	10984	0	3	0]
[0	0	0	0	0	134	0	0]
[0	0	1	0	1	0	0	0]
[0	0	2	0	2	0	1	3]]
Testing Set Classification Report:								
		precision	recall	f1-score	support			
	0	0.00	0.00	0.00	18			
	1	0.04	0.04	0.04	25			
	2	0.52	0.53	0.53	516			
	3	0.23	0.18	0.20	88			
	4	0.98	0.98	0.98	11209			
	5	1.00	1.00	1.00	134			
	6	0.00	0.00	0.00	2			
	7	0.75	0.38	0.50	8			
	accuracy			0.95	12000			
	macro avg	0.44	0.39	0.41	12000			
	weighted avg	0.95	0.95	0.95	12000			
time: 88 ms (started: 2024-04-13 11:18:16 +00:00)								

```

In [65]: # Assuming rf is your trained Random Forest classifier
for i in range(3):
    tree = rf_classifier.estimators_[i] # Assuming rf_classifier is your t
    rained Random Forest model
    dot_data = export_graphviz(tree,
                                feature_names=df1_inputs_train.columns,
                                filled=True,
                                max_depth=2,
                                impurity=False,
                                proportion=True)

    graph = graphviz.Source(dot_data)
    display(graph)

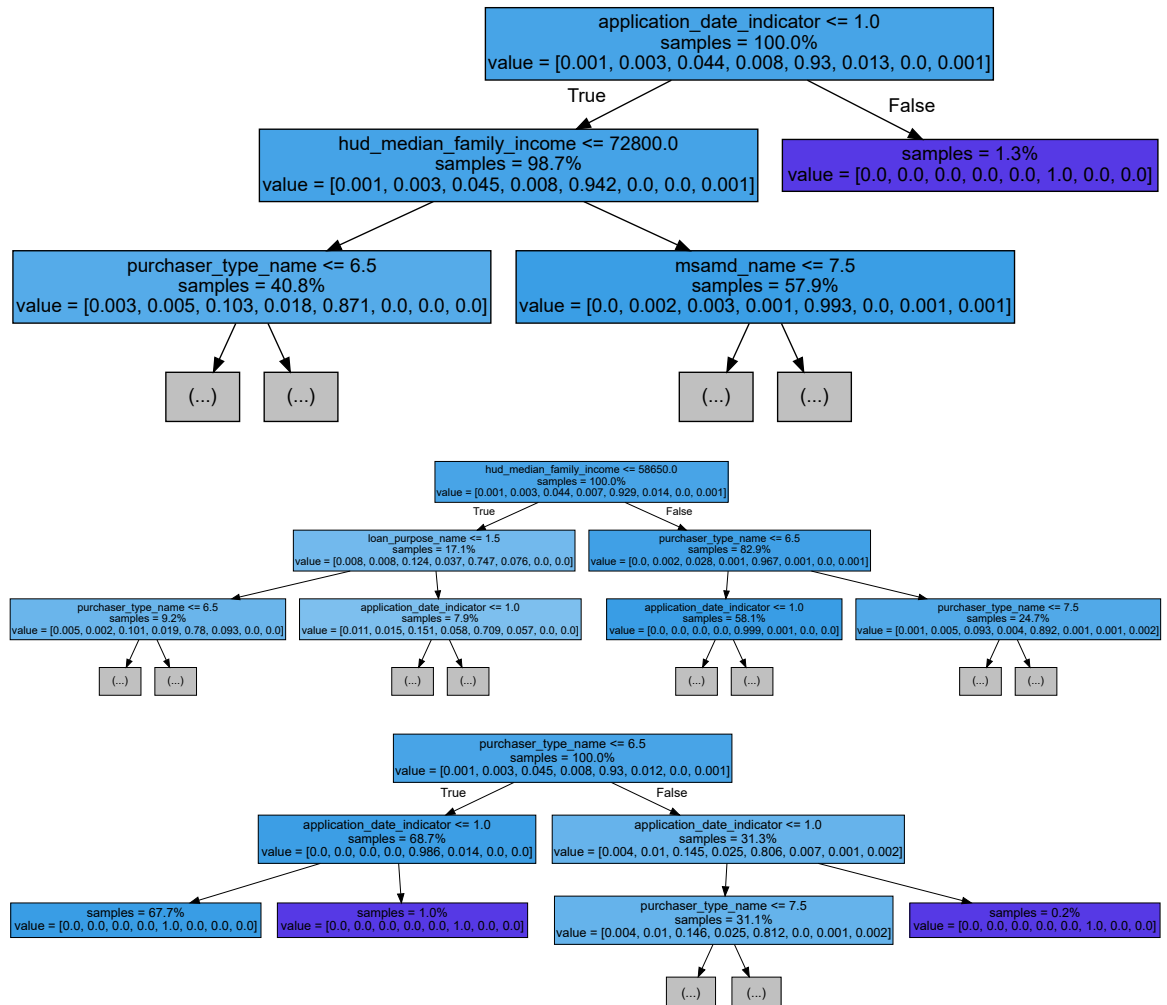
```



time: 381 ms (started: 2024-04-13 11:18:17 +00:00)

```
In [66]: # Export and visualize the first three decision trees
for i in range(3):
    tree = rf_classifier.estimators_[i]
    dot_data = export_graphviz(tree,
                                feature_names=df1_inputs_train.columns,
                                filled=True,
                                max_depth=2,
                                impurity=False,
                                proportion=True)

    graph = graphviz.Source(dot_data)
    display(graph)
```



time: 154 ms (started: 2024-04-13 11:18:17 +00:00)


```
In [67]: # Initialize a dictionary to store tree frequencies and rules
tree_frequency = Counter()
tree_rules = {}

# Loop through the trees and count their frequency while storing rules
for i in range(len(rf_classifier.estimators_)):
    tree = rf_classifier.estimators_[i]
    tree_str = export_text(tree, feature_names=list(df1_inputs_train.columns))
    tree_frequency[tree_str] += 1
    tree_rules[tree_str] = tree

# Get the three most frequent trees
top_trees = tree_frequency.most_common(3)

# Print the rules for the top three trees
for tree_str, frequency in top_trees:
    print(f"Tree Frequency: {frequency}")
    print(tree_str)
    print("\n")
```

[illegible]

13

[illegible]

[illegible]

```
6 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
4 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.35  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- loan_type_name <= 1.50  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
8 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
5 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 0.50  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_purpose_name > 0.50  
4 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 0.50  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_purpose_name > 0.50  
7 | | | | | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
2 | | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 1.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
3 | | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
2 | | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
9 | | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan type name > 1.50
```

2

2

2

19

7

[illegible]

[illegible]

Tree Frequency: 1

```

|--- hud_median_family_income <= 58650.00
|--- loan_purpose_name <= 1.50
|--- purchaser_type_name <= 6.50
|--- loan_type_name <= 0.50
|--- application_date_indicator <= 1.00
|--- class: 4.0
|--- application_date_indicator > 1.00
|--- class: 5.0
|--- loan_type_name > 0.50
|--- application_date_indicator <= 1.00
|--- class: 4.0
|--- application_date_indicator > 1.00
|--- class: 5.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_amount_000s <= 0.01
|--- msamd_name <= 12.00
|--- loan_type_name <= 1.50
|--- application_date_indicator <= 1.00
|--- loan_type_name <= 0.50
|--- loan_amount_000s <= 0.00
|--- hud_median_family_income <= 56
750.00
|--- truncated branch of depth
12
|--- hud_median_family_income > 56
750.00
|--- truncated branch of depth
3
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
20
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
16
|--- loan_type_name > 0.50
|--- loan_amount_000s <= 0.00
|--- hud_median_family_income <= 56
750.00
|--- truncated branch of depth
9
|--- hud_median_family_income > 56
750.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- loan_purpose_name <= 0.50
|--- truncated branch of depth
2
|--- loan_purpose_name > 0.50
|--- truncated branch of depth

```

[illegible]

11
2
10
5
2
9

4


```

|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
12
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.01
|--- loan_amount_000s <= 0.00
|--- class: 3.0
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
3
|--- loan_amount_000s > 0.01
|--- class: 4.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- loan_type_name > 0.50
|--- loan_amount_000s <= 0.00
|--- purchaser_type_name <= 6.00
|--- class: 4.0
|--- purchaser_type_name > 6.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_amount_000s <= 0.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- class: 3.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- msamd_name > 12.00
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- loan_type_name <= 1.50
|--- class: 4.0

```

10

7

7

[illegible]

[illegible]

```
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- hud_median_family_income > 73450.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- msamd_name <= 3.50  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- msamd_name > 3.50  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
3  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- class: 5.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
6  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- application_date_indicator <=  
1.00  
| | | | | | | | | | | | |--- truncated branch of depth  
5  
| | | | | | | | | | | | |--- application_date_indicator >  
1.00  
| | | | | | | | | | | | |--- class: 5.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- hud_median_family_income <= 75  
850.00  
| | | | | | | | | | | | |--- truncated branch of depth  
3  
| | | | | | | | | | | | |--- hud_median_family_income > 75  
850.00  
| | | | | | | | | | | | |--- truncated branch of depth  
8  
| | | | | | | | | | | | |--- msamd_name > 7.50  
| | | | | | | | | | | | |--- hud_median_family_income <= 82084.71  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 1.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth
```

[illegible]

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084.71

```
| | | | | | | | |--- class: 4.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- class: 4.0  
| | | | | | | | |--- msamd_name > 9.00  
| | | | | | | | |--- loan_type_name <= 2.00  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- loan_type_name > 2.00  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- class: 4.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- truncated branch of depth  
6  
| | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | |--- class: 4.0  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | |--- class: 2.0  
| | | | | | | | |--- purchaser_type_name > 7.50  
| | | | | | | | |--- class: 4.0
```

Tree Frequency: 1

```
|--- purchaser_type_name <= 6.50
|   |--- application_date_indicator <= 1.00
|   |   |--- class: 4.0
|   |--- application_date_indicator > 1.00
|   |   |--- class: 5.0
|--- purchaser_type_name > 6.50
|   |--- application_date_indicator <= 1.00
|   |   |--- purchaser_type_name <= 7.50
|   |       |--- hud_median_family_income <= 72800.00
|   |       |   |--- loan_purpose_name <= 0.50
|   |       |       |--- msamd_name <= 6.50
|   |       |       |   |--- class: 4.0
|   |       |       |   |--- msamd_name > 6.50
|   |       |       |       |--- loan_type_name <= 0.50
|   |       |       |       |   |--- msamd_name <= 8.50
|   |       |       |       |       |--- loan_amount_000s <= 0.00
|   |       |       |       |       |   |--- loan amount 000s <= 0.00
```

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i

[illegible]

2

[illegible]

084.71

[illegible]

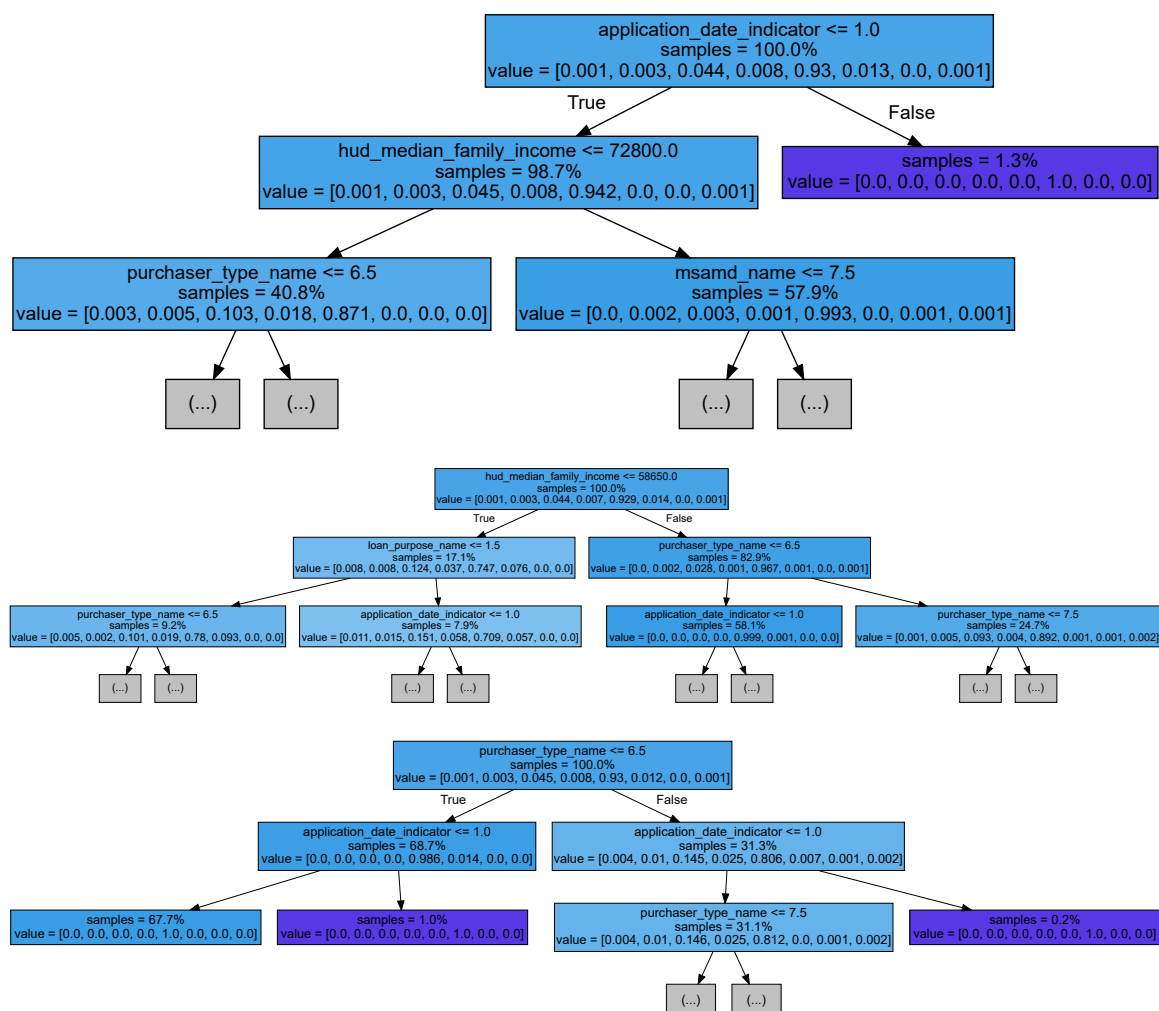
time: 2.24 s (started: 2024-04-13 11:18:17 +00:00)

```
In [68]: # Initialize a dictionary to store tree frequencies
tree_frequency = Counter()

# Loop through the trees and count their frequency
for i in range(len(rf_classifier.estimators_)):
    tree = rf_classifier.estimators_[i]
    tree_str = export_graphviz(tree, feature_names=df1_inputs_train.columns,
                                filled=True, max_depth=2, impurity=False, proportion=True)
    tree_frequency[tree_str] += 1

# Get the three most frequent trees
top_trees = tree_frequency.most_common(3)

# Plot the top three trees
for tree_str, frequency in top_trees:
    graph = graphviz.Source(tree_str)
    display(graph)
```



time: 356 ms (started: 2024-04-13 11:18:19 +00:00)

```
In [69]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from wordcloud import WordCloud
from collections import Counter
from scipy import stats
from sklearn.tree import plot_tree, export_graphviz
import graphviz
from IPython.display import display
from collections import Counter
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import time
import psutil

# Function to measure memory usage
def memory_usage():
    process = psutil.Process()
    return process.memory_info().rss / 1024 ** 2 # Memory usage in MB

# Start time
start_time = time.time()

# Initialize Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=45005)

# Train the Random Forest classifier
rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])

# Predictions
y_train_pred_rf = rf_classifier.predict(df1_inputs_train)
y_test_pred_rf = rf_classifier.predict(df1_inputs_test)

# End time
end_time = time.time()

# Time taken
execution_time = end_time - start_time

# Memory usage
memory_used = memory_usage()

# Accuracy
accuracy_train = accuracy_score(df1_output_train['action_taken_name'], y_train_pred_rf)
accuracy_test = accuracy_score(df1_output_test['action_taken_name'], y_test_pred_rf)

# Print time, memory usage, and accuracy
print("Time taken (seconds):", execution_time)
print("Memory used (MB):", memory_used)
print("Training Set Accuracy:", accuracy_train)
print("Testing Set Accuracy:", accuracy_test)

# Print feature importances
feature_importances = rf_classifier.feature_importances_
```

```
feature_importance_df = pd.DataFrame({'Feature': df1_inputs_train.columns,
'Importance': feature_importances})
sorted_feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
print("\nFeature Importances:")
print(sorted_feature_importance_df)

# Print confusion matrix and classification report for training set
print("\nTraining Set Confusion Matrix:")
print(confusion_matrix(df1_output_train['action_taken_name'], y_train_pred_rf))
print("\nTraining Set Classification Report:")
print(classification_report(df1_output_train['action_taken_name'], y_train_pred_rf))

# Print confusion matrix and classification report for testing set
print("\nTesting Set Confusion Matrix:")
print(confusion_matrix(df1_output_test['action_taken_name'], y_test_pred_rf))
print("\nTesting Set Classification Report:")
print(classification_report(df1_output_test['action_taken_name'], y_test_pred_rf))

# Export and visualize the first three decision trees
for i in range(3):
    tree = rf_classifier.estimators_[i]
    dot_data = export_graphviz(tree,
                                feature_names=df1_inputs_train.columns,
                                filled=True,
                                max_depth=2,
                                impurity=False,
                                proportion=True)
    graph = graphviz.Source(dot_data)
    display(graph)

# Initialize a dictionary to store tree frequencies and rules
tree_frequency = Counter()
tree_rules = {}

# Loop through the trees and count their frequency while storing rules
for i in range(len(rf_classifier.estimators_)):
    tree = rf_classifier.estimators_[i]
    tree_str = export_text(tree, feature_names=list(df1_inputs_train.columns))
    tree_frequency[tree_str] += 1
    tree_rules[tree_str] = tree

# Get the three most frequent trees
top_trees = tree_frequency.most_common(3)

# Print the rules for the top three trees
for tree_str, frequency in top_trees:
    print(f"Tree Frequency: {frequency}")
    print(tree_str)
    print("\n")

# Initialize a dictionary to store tree frequencies
tree_frequency = Counter()

# Loop through the trees and count their frequency
for i in range(len(rf_classifier.estimators_)):
```

```
tree = rf_classifier.estimators_[i]
tree_str = export_graphviz(tree, feature_names=df1_inputs_train.columns,
                           filled=True, max_depth=2, impurity=False, proportion=True)
tree_frequency[tree_str] += 1

# Get the three most frequent trees
top_trees = tree_frequency.most_common(3)

# Plot the top three trees
for tree_str, frequency in top_trees:
    graph = graphviz.Source(tree_str)
    display(graph)
```


Time taken (seconds): 7.921905517578125
 Memory used (MB): 591.46484375
 Training Set Accuracy: 0.9820416666666667
 Testing Set Accuracy: 0.9508333333333333

Feature Importances:

	Feature	Importance
6	loan_amount_000s	0.333727
2	purchaser_type_name	0.201634
0	application_date_indicator	0.195447
5	hud_median_family_income	0.120389
1	msamd_name	0.096998
3	loan_type_name	0.027990
4	loan_purpose_name	0.023816

Training Set Confusion Matrix:

```
[[ 31   0  13   1  21   0   0   0]
 [  1  69  21   2  43   0   0   0]
 [  1   8 1825  26  289   0   0   1]
 [  0   3  51  229  75   0   0   0]
 [  2  10  260  27 44307   0   0   0]
 [  0   0   0   0   0  642   0   0]
 [  0   0   1   0   3   0  11   0]
 [  0   0   1   0   2   0   0  24]]
```

Training Set Classification Report:

	precision	recall	f1-score	support
0	0.89	0.47	0.61	66
1	0.77	0.51	0.61	136
2	0.84	0.85	0.84	2150
3	0.80	0.64	0.71	358
4	0.99	0.99	0.99	44606
5	1.00	1.00	1.00	642
6	1.00	0.73	0.85	15
7	0.96	0.89	0.92	27
accuracy			0.98	48000
macro avg	0.91	0.76	0.82	48000
weighted avg	0.98	0.98	0.98	48000

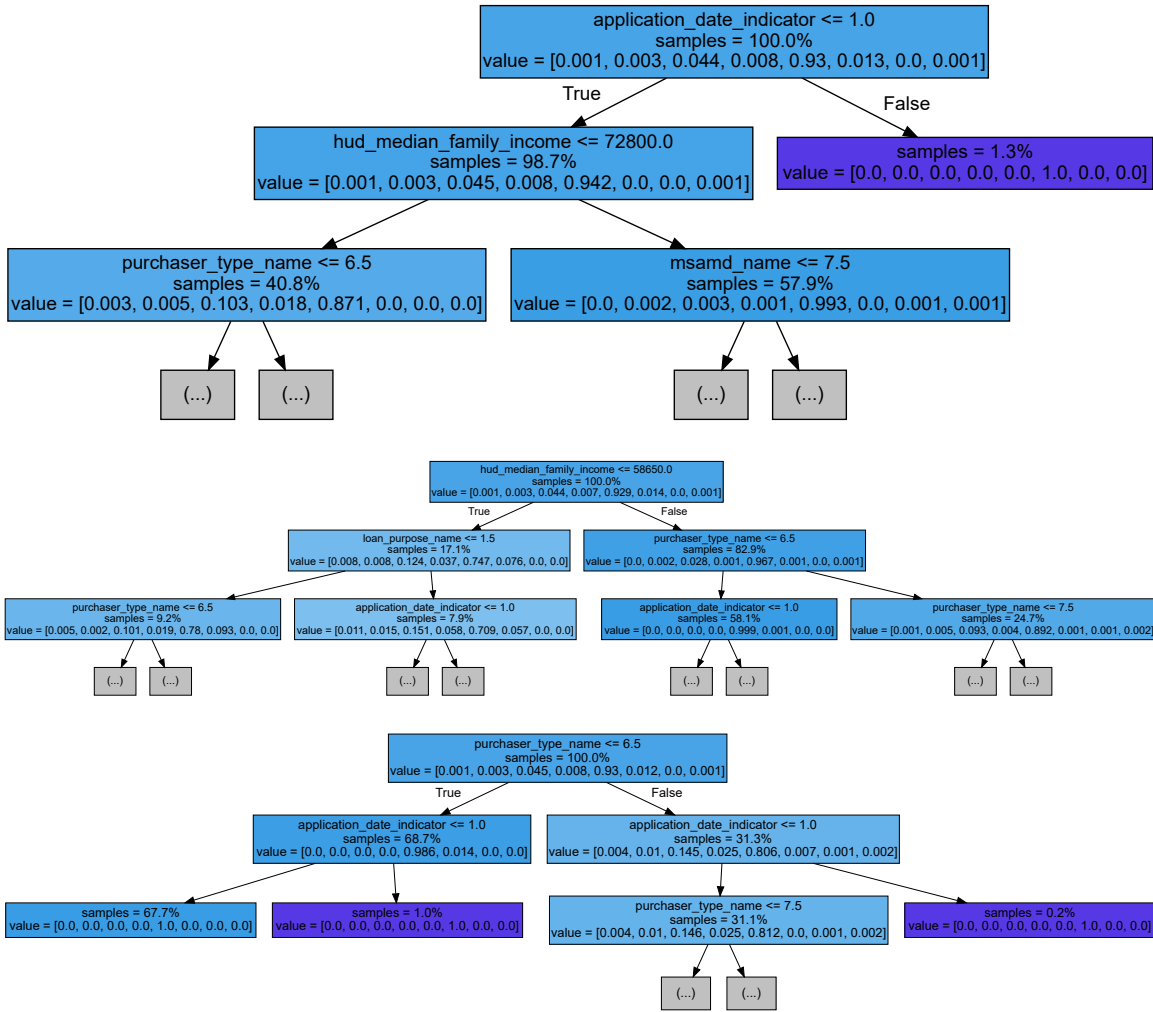
Testing Set Confusion Matrix:

```
[[  0   0   5   3  10   0   0   0]
 [  0   1   7   1  16   0   0   0]
 [  6  10  272  33  194   0   0   1]
 [  0   5  36  16  31   0   0   0]
 [  2   7  196  17 10984   0   3   0]
 [  0   0   0   0   0  134   0   0]
 [  0   0   1   0   1   0   0   0]
 [  0   0   2   0   2   0   1   3]]
```

Testing Set Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	18
1	0.04	0.04	0.04	25
2	0.52	0.53	0.53	516
3	0.23	0.18	0.20	88
4	0.98	0.98	0.98	11209
5	1.00	1.00	1.00	134

	6	0.00	0.00	0.00	2
	7	0.75	0.38	0.50	8
accuracy				0.95	12000
macro avg		0.44	0.39	0.41	12000
weighted avg		0.95	0.95	0.95	12000



```

|--- application_date_indicator <= 1.00
|--- hud_median_family_income <= 72800.00
|--- purchaser_type_name <= 6.50
|   |--- class: 4.0
|--- purchaser_type_name > 6.50
|   |--- purchaser_type_name <= 7.50
|       |--- hud_median_family_income <= 71100.00
|           |--- msamd_name <= 6.50
|               |--- hud_median_family_income <= 67850.00
|                   |--- loan_purpose_name <= 1.50
|                       |--- class: 4.0
|                           |--- loan_purpose_name > 1.50
|                               |--- msamd_name <= 4.50
|                                   |--- msamd_name <= 2.50
|                                       |--- loan_amount_000s <= 0.00
|                                           |--- truncated branch of depth
2
|                                       |--- loan_amount_000s > 0.00
|                                           |--- class: 4.0
|                                       |--- msamd_name > 2.50
|                                           |--- msamd_name <= 3.50
|                                               |--- class: 4.0
|                                               |--- msamd_name > 3.50
|                                                   |--- truncated branch of depth
4
|                                               |--- msamd_name > 4.50
|                                                   |--- loan_amount_000s <= 0.00
|                                                       |--- loan_amount_000s <= 0.00
|                                                           |--- class: 4.0
|                                                           |--- loan_amount_000s > 0.00
|                                                               |--- truncated branch of depth
3
|                                                           |--- loan_amount_000s > 0.00
|                                                               |--- loan_amount_000s <= 0.00
|                                                                   |--- class: 1.0
|                                                                   |--- loan_amount_000s > 0.00
|                                                                       |--- class: 4.0
|--- hud_median_family_income > 67850.00
|   |--- loan_type_name <= 0.50
|       |--- loan_purpose_name <= 1.50
|           |--- class: 4.0
|       |--- loan_purpose_name > 1.50
|           |--- loan_amount_000s <= 0.01
|               |--- loan_amount_000s <= 0.00
|                   |--- truncated branch of depth
4
|               |--- loan_amount_000s > 0.00
|                   |--- class: 4.0
|               |--- loan_amount_000s > 0.01
|                   |--- class: 2.0
|       |--- loan_type_name > 0.50
|           |--- loan_purpose_name <= 1.50
|               |--- loan_type_name <= 2.00
|                   |--- loan_amount_000s <= 0.00
|                       |--- truncated branch of depth
2
|                       |--- loan_amount_000s > 0.00
|                           |--- class: 4.0
|                       |--- loan_type_name > 2.00
|                           |--- class: 4.0

```

13

[illegible]

6

```
6 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
4 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.35  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- loan_type_name <= 1.50  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
8 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
5 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 0.50  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_purpose_name > 0.50  
4 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 0.50  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_purpose_name > 0.50  
7 | | | | | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
2 | | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 1.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
3 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
2 | | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
9 | | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- class: 2.0  
| | | | | | | | | | | | |--- loan type name > 1.50
```

```

|--- loan_type_name <= 2.50
|--- class: 2.0
|--- loan_type_name > 2.50
|--- loan_purpose_name <= 1.50
|--- loan_purpose_name <= 0.50
|--- class: 2.0
|--- loan_purpose_name > 0.50
|--- loan_amount_000s <= 0.00
|--- class: 1.0
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
8
|--- loan_purpose_name > 1.50
|--- loan_amount_000s <= 0.01
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
8
|--- loan_amount_000s > 0.01
|--- loan_amount_000s <= 0.01
|--- class: 4.0
|--- loan_amount_000s > 0.01
|--- truncated branch of depth
10
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- hud_median_family_income > 72800.00
|--- msamd_name <= 7.50
|--- msamd_name <= 6.50
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_purpose_name <= 1.50
|--- loan_amount_000s <= 0.00
|--- loan_purpose_name <= 0.50
|--- class: 4.0
|--- loan_purpose_name > 0.50
|--- class: 1.0
|--- loan_amount_000s > 0.00
|--- msamd_name <= 3.50
|--- loan_amount_000s <= 0.00
|--- loan_type_name <= 0.50
|--- truncated branch of depth
4
|--- loan_type_name > 0.50
|--- truncated branch of depth
3
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- msamd_name > 3.50
|--- loan_amount_000s <= 0.00
|--- loan_purpose_name <= 0.50
|--- class: 4.0
|--- loan_purpose_name > 0.50
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- class: 4.0

```



```

|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- loan_amount_000s <= 0.01
|--- class: 4.0
|--- loan_amount_000s > 0.01
|--- loan_type_name <= 0.50
|--- loan_amount_000s <= 0.01
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.01
|--- class: 4.0
|--- loan_type_name > 0.50
|--- purchaser_type_name <= 7.50
|--- truncated branch of depth
3
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- loan_amount_000s > 0.01
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- loan_type_name <= 1.50
|--- loan_amount_000s <= 0.01
|--- purchaser_type_name <= 7.50
|--- class: 4.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- loan_amount_000s > 0.01
|--- class: 4.0
|--- loan_type_name > 1.50
|--- class: 4.0
|--- loan_purpose_name > 1.50
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_type_name <= 0.50
|--- loan_amount_000s <= 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
5
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
5
|--- loan_type_name > 0.50
|--- loan_type_name <= 2.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_type_name > 2.00
|--- class: 4.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- msamd_name > 7.50
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser type name > 6.50

```

19

[illegible]

```
|
|
|
|
|
|
|
|
|
|
|
|--- loan_purpose_name > 1.50
|    |--- class: 2.0
|        --- loan_amount_000s > 0.01
|            |--- class: 6.0
|                --- loan_amount_000s > 0.01
|                    |--- class: 7.0
|                        --- hud_median_family_income > 82084.71
|                            --- loan_purpose_name <= 1.50
|                                --- loan_type_name <= 2.50
|                                    --- purchaser_type_name <= 7.50
|                                        --- loan_purpose_name <= 0.50
|                                            |--- class: 4.0
|                                                --- loan_purpose_name > 0.50
|                                                    |--- loan_amount_000s <= 0.01
|                                                        |--- class: 4.0
|                                                            --- loan_amount_000s > 0.01
|                                                                |--- truncated branch of depth
2
|
|
|
|
|
|
|
|
|
|
|
|--- purchaser_type_name > 7.50
|    |--- class: 4.0
|        --- loan_type_name > 2.50
|            --- loan_amount_000s <= 0.01
|                |--- class: 4.0
|                    --- loan_amount_000s > 0.01
|                        --- purchaser_type_name <= 7.50
|                            --- loan_amount_000s <= 0.01
|                                |--- class: 2.0
|                                    --- loan_amount_000s > 0.01
|                                        |--- truncated branch of depth
4
|
|
|
|
|
|
|
|
|
|
|
|--- purchaser_type_name > 7.50
|    |--- class: 4.0
|        --- loan_purpose_name > 1.50
|            --- loan_amount_000s <= 0.01
|                --- loan_amount_000s <= 0.00
|                    --- purchaser_type_name <= 7.50
|                        --- loan_amount_000s <= 0.00
|                            |--- truncated branch of depth
4
|
|
|
|
|
|
|
|
|
|
|
|--- loan_amount_000s > 0.00
|    |--- truncated branch of depth
2
|
|
|
|
|
|
|
|
|
|
|
|--- purchaser_type_name > 7.50
|    |--- class: 4.0
|        --- loan_amount_000s > 0.00
|            --- loan_amount_000s <= 0.01
|                |--- class: 2.0
|                    --- loan_amount_000s > 0.01
|                        --- purchaser_type_name <= 7.50
|                            |--- truncated branch of depth
3
|
|
|
|
|
|
|
|
|
|
|
|--- purchaser_type_name > 7.50
|    |--- class: 4.0
|        --- loan_amount_000s > 0.01
|            --- loan_type_name <= 2.00
|                --- purchaser_type_name <= 7.50
|                    --- loan_amount_000s <= 0.01
|                        |--- class: 4.0
|                            --- loan_amount_000s > 0.01
|                                |--- class: 2.0
```

[illegible]

Tree Frequency: 1

```

|--- hud_median_family_income <= 58650.00
|--- loan_purpose_name <= 1.50
|--- purchaser_type_name <= 6.50
|--- loan_type_name <= 0.50
|--- application_date_indicator <= 1.00
|--- class: 4.0
|--- application_date_indicator > 1.00
|--- class: 5.0
|--- loan_type_name > 0.50
|--- application_date_indicator <= 1.00
|--- class: 4.0
|--- application_date_indicator > 1.00
|--- class: 5.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_amount_000s <= 0.01
|--- msamd_name <= 12.00
|--- loan_type_name <= 1.50
|--- application_date_indicator <= 1.00
|--- loan_type_name <= 0.50
|--- loan_amount_000s <= 0.00
|--- hud_median_family_income <= 56
750.00
|--- truncated branch of depth
12
|--- hud_median_family_income > 56
750.00
|--- truncated branch of depth
3
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
20
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
16
|--- loan_type_name > 0.50
|--- loan_amount_000s <= 0.00
|--- hud_median_family_income <= 56
750.00
|--- truncated branch of depth
9
|--- hud_median_family_income > 56
750.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- loan_purpose_name <= 0.50
|--- truncated branch of depth
2
|--- loan_purpose_name > 0.50
|--- truncated branch of depth

```

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[illegible]

4

```

|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
12
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.01
|--- loan_amount_000s <= 0.00
|--- class: 3.0
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
3
|--- loan_amount_000s > 0.01
|--- class: 4.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- loan_type_name > 0.50
|--- loan_amount_000s <= 0.00
|--- purchaser_type_name <= 6.00
|--- class: 4.0
|--- purchaser_type_name > 6.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- purchaser_type_name <= 7.50
|--- loan_amount_000s <= 0.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- class: 3.0
|--- purchaser_type_name > 7.50
|--- class: 4.0
|--- msamd_name > 12.00
|--- purchaser_type_name <= 6.50
|--- class: 4.0
|--- purchaser_type_name > 6.50
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
2
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- loan_type_name <= 1.50
|--- class: 4.0

```

[illegible]

7

7

[illegible]

[illegible]

```
| | | | | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- hud_median_family_income > 73450.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- msamd_name <= 3.50  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- msamd_name > 3.50  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
3  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- class: 5.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
6  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- application_date_indicator <=  
1.00  
| | | | | | | | | | | | |--- truncated branch of depth  
5  
| | | | | | | | | | | | |--- application_date_indicator >  
1.00  
| | | | | | | | | | | | |--- class: 5.0  
| | | | | | | | | | | | |--- loan_type_name > 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | | | | |--- class: 4.0  
| | | | | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- hud_median_family_income <= 75  
850.00  
| | | | | | | | | | | | |--- truncated branch of depth  
3  
| | | | | | | | | | | | |--- hud_median_family_income > 75  
850.00  
| | | | | | | | | | | | |--- truncated branch of depth  
8  
| | | | | | | | | | | | |--- msamd_name > 7.50  
| | | | | | | | | | | | |--- hud_median_family_income <= 82084.71  
| | | | | | | | | | | | |--- loan_type_name <= 0.50  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- class: 1.0  
| | | | | | | | | | | | |--- loan_amount_000s > 0.00  
| | | | | | | | | | | | |--- loan_amount_000s <= 0.00  
| | | | | | | | | | | | |--- truncated branch of depth
```


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```
| | | | | | | | | |--- class: 4.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- class: 4.0  
| | | | | | | | | |--- msamd_name > 9.00  
| | | | | | | | | |--- loan_type_name <= 2.00  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- loan_type_name > 2.00  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- loan_purpose_name <= 1.50  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- class: 4.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- truncated branch of depth  
6  
| | | | | | | | | |--- loan_purpose_name > 1.50  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- loan_amount_000s <= 0.01  
| | | | | | | | | |--- class: 4.0  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- truncated branch of depth  
2  
| | | | | | | | | |--- loan_amount_000s > 0.01  
| | | | | | | | | |--- class: 2.0  
| | | | | | | | | |--- purchaser_type_name > 7.50  
| | | | | | | | | |--- class: 4.0
```

Tree Frequency: 1

```
|--- purchaser_type_name <= 6.50
|   |--- application_date_indicator <= 1.00
|   |   |--- class: 4.0
|   |--- application_date_indicator > 1.00
|   |   |--- class: 5.0
|--- purchaser_type_name > 6.50
|   |--- application_date_indicator <= 1.00
|   |   |--- purchaser_type_name <= 7.50
|   |       |--- hud_median_family_income <= 72800.00
|   |       |   |--- loan_purpose_name <= 0.50
|   |       |       |--- msamd_name <= 6.50
|   |       |       |   |--- class: 4.0
|   |       |       |   |--- msamd_name > 6.50
|   |       |       |       |--- loan_type_name <= 0.50
|   |       |       |       |   |--- msamd_name <= 8.50
|   |       |       |       |       |--- loan_amount_000s <= 0.00
|   |       |       |       |       |   |--- loan amount 000s <= 0.00
```

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3
|
2
|
3
|
5
|
|
|
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|
|
|
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|
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2

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```

|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.00
|--- truncated branch of depth
5
|--- loan_amount_000s > 0.00
|--- truncated branch of depth
4
|--- loan_type_name > 0.50
|--- loan_amount_000s <= 0.00
|--- loan_type_name <= 2.00
|--- truncated branch of depth
2
|--- loan_type_name > 2.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- class: 4.0
--- hud_median_family_income > 75850.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- loan_amount_000s <= 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_purpose_name <= 1.50
|--- class: 4.0
|--- loan_purpose_name > 1.50
|--- loan_amount_000s <= 0.00
|--- class: 2.0
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_amount_000s > 0.00
|--- loan_type_name <= 0.50
|--- class: 2.0
|--- loan_type_name > 0.50
|--- class: 4.0
--- loan_amount_000s > 0.00
|--- loan_amount_000s <= 0.01
|--- loan_purpose_name <= 0.50
|--- loan_type_name <= 1.50
|--- loan_amount_000s <= 0.00
|--- class: 1.0
|--- loan_amount_000s > 0.00
|--- class: 4.0
|--- loan_type_name > 1.50
|--- class: 4.0
|--- loan_purpose_name > 0.50
|--- loan_amount_000s <= 0.01
|--- loan_purpose_name <= 1.50
|--- class: 4.0
|--- loan_purpose_name > 1.50
|--- truncated branch of depth
4
|--- loan_amount_000s > 0.01
|--- class: 2.0
|--- loan_amount_000s > 0.01
|--- class: 4.0
--- msamd_name > 7.50
|--- loan_purpose_name <= 0.50
|--- loan_type_name <= 0.50
|--- loan_amount_000s <= 0.00
|--- class: 4.0

```

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The figure displays three decision trees, each representing a different split criterion:

- Top Tree (application_date_indicator <= 1.0):** The root node splits on 'application_date_indicator'. The 'True' branch (98.7% samples) leads to a node splitting on 'hud_median_family_income <= 72800.0'. The 'False' branch (1.3% samples) leads to a leaf node with value [0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0].
- Middle Tree (hud_median_family_income <= 58650.0):** The root node splits on 'hud_median_family_income'. The 'True' branch (17.1% samples) leads to a node splitting on 'loan_purpose_name <= 1.5'. The 'False' branch (82.9% samples) leads to a node splitting on 'purchaser_type_name <= 6.5'.
- Bottom Tree (purchaser_type_name <= 6.5):** The root node splits on 'purchaser_type_name'. The 'True' branch (68.7% samples) leads to a node splitting on 'application_date_indicator <= 1.0'. The 'False' branch (31.3% samples) leads to a node splitting on 'application_date_indicator <= 1.0'.

Each internal node shows the split condition, the resulting sample distribution, and the vector of values for the eight classes. Leaf nodes show the final predicted class probabilities or values.

time: 11.9 s (started: 2024-04-13 11:18:20 +00:00)

```
In [70]: # Random Forest
rf_start_time = time.time()
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=45005)
rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])
rf_training_time = time.time() - rf_start_time
rf_memory_used = memory_usage()
y_train_pred_rf = rf_classifier.predict(df1_inputs_train)
y_test_pred_rf = rf_classifier.predict(df1_inputs_test)
rf_accuracy = accuracy_score(df1_output_test, y_test_pred_rf)

# Cross-validation for Random Forest
rf_cv_start_time = time.time()
rf_cv = RandomForestClassifier(n_estimators=100, random_state=45005)
cv_scores_rf = cross_val_score(rf_cv, df1_inputs, df1_output.values.ravel(), cv=20)
rf_cv_time = time.time() - rf_cv_start_time
rf_cv_accuracy = np.mean(cv_scores_rf)

print("Random Forest:")
print(f" - Training Time (s): {rf_training_time}")
print(f" - Memory Used (MB): {rf_memory_used}")
print(f" - Single Split Accuracy: {rf_accuracy}")
print(f" - Cross Validation Accuracy: {rf_cv_accuracy}")
print()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 17 members, which is less than n_splits=20.
```

```
warnings.warn(
```

```
Random Forest:
```

```
 - Training Time (s): 5.206611394882202
 - Memory Used (MB): 628.19140625
 - Single Split Accuracy: 0.9508333333333333
 - Cross Validation Accuracy: 0.94575
```

```
time: 1min 12s (started: 2024-04-13 11:18:32 +00:00)
```

```
In [71]: import pandas as pd
import numpy as np
import time
import psutil
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Function to measure memory usage
def memory_usage():
    process = psutil.Process()
    return process.memory_info().rss / 1024 ** 2 # Memory usage in MB

# Data preprocessing and splitting
# Assuming you have your data loaded into cars_inputs and cars_output
df1_inputs_train, df1_inputs_test, df1_output_train, df1_output_test = train_test_split(df1_inputs, df1_output, test_size=0.2, random_state=42)

# Initialize lists to store results
models = []
training_times = []
memory_used = []
single_split_accuracies = []
cross_validation_accuracies = []

# Decision Tree
dt_start_time = time.time()
dt_model = DecisionTreeClassifier(criterion='gini', random_state=45011, max_depth=3)
dt_model.fit(df1_inputs_train, df1_output_train)
dt_training_time = time.time() - dt_start_time
dt_memory_used = memory_usage()
dt_pred = dt_model.predict(df1_inputs_test)
dt_accuracy = accuracy_score(df1_output_test, dt_pred)

# Cross-validation for Decision Tree
dtc_cv_start_time = time.time()
dtc_cv = DecisionTreeClassifier(criterion='gini', random_state=45011)
cv_scores_dtc = cross_val_score(dtc_cv, df1_inputs, df1_output.values.ravel(), cv=20)
dtc_cv_time = time.time() - dtc_cv_start_time
dtc_cv_accuracy = np.mean(cv_scores_dtc)

# Append Decision Tree results to lists
models.append('Decision Tree')
training_times.append(dt_training_time)
memory_used.append(dt_memory_used)
single_split_accuracies.append(dt_accuracy)
cross_validation_accuracies.append(dtc_cv_accuracy)

# Random Forest
rf_start_time = time.time()
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=45005)
rf_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])
rf_training_time = time.time() - rf_start_time
rf_memory_used = memory_usage()
y_train_pred_rf = rf_classifier.predict(df1_inputs_train)
y_test_pred_rf = rf_classifier.predict(df1_inputs_test)
```

```

rf_accuracy_train = accuracy_score(df1_output_train['action_taken_name'], y_train_pred_rf)
rf_accuracy_test = accuracy_score(df1_output_test['action_taken_name'], y_test_pred_rf)

# Append Random Forest results to lists
models.append('Random Forest')
training_times.append(rf_training_time)
memory_used.append(rf_memory_used)
single_split_accuracies.append(rf_accuracy_test) # Using test accuracy as we already calculated it
cross_validation_accuracies.append(np.nan) # Cross-validation accuracy not calculated here

# Create DataFrame
results_df = pd.DataFrame({
    'Model': models,
    'Training Time (s)': training_times,
    'Memory Used (MB)': memory_used,
    'Single Split Accuracy': single_split_accuracies,
    'Cross Validation Accuracy': cross_validation_accuracies
})

# Print DataFrame
print(results_df)

```

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 17 members, which is less than n_splits=20.
  warnings.warn(

```

	Model	Training Time (s)	Memory Used (MB)	Single Split Accuracy
0	Decision Tree	0.047592	683.375	0.94541
1	Random Forest	2.410989	683.375	0.95083

	Cross Validation Accuracy
0	0.9431
1	NaN

time: 5.11 s (started: 2024-04-13 11:19:44 +00:00)

XGBoost

```

In [72]: dtrain = xgb.DMatrix(df1_inputs_train, label=df1_output_train['action_taken_name'])
dtest = xgb.DMatrix(df1_inputs_test, label=df1_output_test['action_taken_name'])

```

time: 32.2 ms (started: 2024-04-13 11:19:50 +00:00)


```
In [73]: # Define XGBoost parameters
params = {
    'objective': 'multi:softmax', # For multi-class classification
    'num_class': len(df1_output_train['action_taken_name'].unique()), # Number of unique classes in the output
    'max_depth': 5,
    'learning_rate': 0.1,
    'n_estimators': 1000,
    'eval_metric': 'merror' # Use 'merror' for multiclass classification error
}

# Initialize the XGBoost classifier
xgb_classifier = xgb.XGBClassifier(**params)

# Train the classifier
xgb_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])
```

```
Out[73]: XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='merror',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.1, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=5,
              max_leaves=None, min_child_weight=None, missing=nan,
```

time: 32.2 s (started: 2024-04-13 11:19:50 +00:00)

```
In [74]: import xgboost as xgb
from sklearn.metrics import log_loss

# Assuming you have already trained the XGBoost classifier
# xgb_classifier = xgb.XGBClassifier(**params)
# xgb_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])

# Predict probabilities for each class
y_pred_proba_xgb = xgb_classifier.predict_proba(df1_inputs_test)

# Calculate entropy
entropy_xgb = log_loss(df1_output_test, y_pred_proba_xgb)

# Calculate Gini impurity
gini_impurity_xgb = 1 - (y_pred_proba_xgb ** 2).sum(axis=1).mean()

print("Entropy for XGBoost:", entropy_xgb)
print("Gini Impurity for XGBoost:", gini_impurity_xgb)
```

Entropy for XGBoost: 0.11704169720141437
 Gini Impurity for XGBoost: 0.04694253206253052
 time: 2.33 s (started: 2024-04-13 11:20:22 +00:00)

```
In [75]: # Print feature importances
feature_importances = xgb_classifier.feature_importances_
feature_importance_df = pd.DataFrame({'Feature': df1_inputs_train.columns,
'Importance': feature_importances})
sorted_feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
print(sorted_feature_importance_df)
```

	Feature	Importance
0	application_date_indicator	0.765484
2	purchaser_type_name	0.199578
5	hud_median_family_income	0.014517
1	msamd_name	0.012562
3	loan_type_name	0.003441
4	loan_purpose_name	0.003015
6	loan_amount_000s	0.001402

time: 13.1 ms (started: 2024-04-13 11:20:24 +00:00)

```
In [76]: # Make predictions on the training set
y_train_pred = xgb_classifier.predict(df1_inputs_train)

# Print classification report for training set
print("Training Set Classification Report:")
print(classification_report(df1_output_train['action_taken_name'], y_train_pred))
```

Training Set Classification Report:

	precision	recall	f1-score	support
0	0.88	0.21	0.34	66
1	0.84	0.20	0.32	136
2	0.73	0.74	0.74	2150
3	0.75	0.38	0.50	358
4	0.98	0.99	0.99	44606
5	1.00	1.00	1.00	642
6	0.88	0.47	0.61	15
7	0.96	0.89	0.92	27
accuracy			0.97	48000
macro avg	0.88	0.61	0.68	48000
weighted avg	0.97	0.97	0.97	48000

time: 6.57 s (started: 2024-04-13 11:20:24 +00:00)

```
In [77]: # Print confusion matrix for training set
print("Training Set Confusion Matrix:")
print(confusion_matrix(df1_output_train['action_taken_name'], y_train_pred))
```

Training Set Confusion Matrix:

[14	1	16	2	33	0	0	0]
[0	27	33	1	74	0	1	0]
[0	2	1599	28	520	0	0	1]
[0	0	107	136	115	0	0	0]
[2	2	425	15	44162	0	0	0]
[0	0	0	0	0	642	0	0]
[0	0	2	0	6	0	7	0]
[0	0	1	0	2	0	0	24]]

time: 15.1 ms (started: 2024-04-13 11:20:31 +00:00)

```
In [78]: # Make predictions on the test set
y_pred = xgb_classifier.predict(df1_inputs_test)

# Evaluate the model
print(classification_report(df1_output_test['action_taken_name'], y_pred))
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	18
1	0.12	0.04	0.06	25
2	0.55	0.59	0.57	516
3	0.24	0.11	0.15	88
4	0.98	0.98	0.98	11209
5	1.00	1.00	1.00	134
6	0.00	0.00	0.00	2
7	0.50	0.12	0.20	8
accuracy			0.95	12000
macro avg	0.42	0.36	0.37	12000
weighted avg	0.95	0.95	0.95	12000

time: 1.42 s (started: 2024-04-13 11:20:31 +00:00)

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:
1344: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in labels with no predicted samples. Use `zero_division` para
meter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:
1344: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in labels with no predicted samples. Use `zero_division` para
meter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:
1344: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in labels with no predicted samples. Use `zero_division` para
meter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
In [79]: # Make predictions on the test set
y_test_pred = xgb_classifier.predict(df1_inputs_test)

# Print confusion matrix for testing set
print("\nTesting Set Confusion Matrix:")
print(confusion_matrix(df1_output_test['action_taken_name'], y_test_pred))
```

Testing Set Confusion Matrix:

```
[[ 0  0  8  2  8  0  0  0]
 [ 0  1  7  0 17  0  0  0]
 [ 4  3 305 20 183  0  0  1]
 [ 0  2  41 10  35  0  0  0]
 [ 1  2 188 10 11008  0  0  0]
 [ 0  0  0  0  0 134  0  0]
 [ 0  0  1  0  1  0  0  0]
 [ 0  0  5  0  2  0  0  1]]
```

time: 1.43 s (started: 2024-04-13 11:20:32 +00:00)

```

In [80]: # XGBoost
xgb_start_time = time.time()

# Define XGBoost parameters
params = {
    'objective': 'multi:softmax', # For multi-class classification
    'num_class': len(df1_output_train['action_taken_name'].unique()), # Number of unique classes in the output
    'max_depth': 5,
    'learning_rate': 0.1,
    'n_estimators': 1000,
    'eval_metric': 'merror' # Use 'merror' for multiclass classification error
}

# Initialize the XGBoost classifier
xgb_classifier = xgb.XGBClassifier(**params)

# Train the classifier
xgb_classifier.fit(df1_inputs_train, df1_output_train['action_taken_name'])

xgb_training_time = time.time() - xgb_start_time
xgb_memory_used = memory_usage()
y_train_pred_xgb = xgb_classifier.predict(df1_inputs_train)
y_test_pred_xgb = xgb_classifier.predict(df1_inputs_test)
xgb_accuracy = accuracy_score(df1_output_test, y_test_pred_xgb)

# Cross-validation for XGBoost
xgb_cv_start_time = time.time()
xgb_cv = xgb.XGBClassifier(**params)
cv_scores_xgb = cross_val_score(xgb_cv, df1_inputs, df1_output.values.ravel(), cv=20)
xgb_cv_time = time.time() - xgb_cv_start_time
xgb_cv_accuracy = np.mean(cv_scores_xgb)

print("XGBoost:")
print(f" - Training Time (s): {xgb_training_time}")
print(f" - Memory Used (MB): {xgb_memory_used}")
print(f" - Single Split Accuracy: {xgb_accuracy}")
print(f" - Cross Validation Accuracy: {xgb_cv_accuracy}")
print()

```

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 17 members, which is less than n_splits=20.
  warnings.warn(

```

```

XGBoost:
- Training Time (s): 34.26365828514099
- Memory Used (MB): 748.02734375
- Single Split Accuracy: 0.9549166666666666
- Cross Validation Accuracy: 0.9495833333333336

```

```

time: 14min 3s (started: 2024-04-13 11:20:34 +00:00)

```

```
In [81]: # Plot the first tree in the XGBoost model
xgb.plot_tree(xgb_classifier, num_trees=0, rankdir='LR') # num_trees=0 plots the first tree
plt.rcParams['figure.figsize'] = [30, 30] # Adjust the figure size if needed
plt.show()
```



time: 1.72 s (started: 2024-04-13 11:34:37 +00:00)

In [81]:

time: 1.73 s (started: 2024-04-13 11:34:37 +00:00)