Technical Report

Automated Technical Report

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Abstract

This technical report presents a comprehensive analysis of credit card fraud detection using various classification algorithms. The dataset utilized for this study consists of 30,000 records with 25 features, with no missing values detected across all features. The primary objective of this research is to perform credit card fraud detection using Support Vector Classifier (SVC) with linear kernel and compare its performance with other classification algorithms, including Logistic Regression and Decision Tree Classifier, while also conducting hyperparameter tuning for C and gamma parameters. The findings indicate that the Decision Tree Classifier yields an accuracy of 0.76, ROC-AUC of 0.73, and a recall of 0.56 for class 1, demonstrating the efficacy of the implemented methodology, which involves a preprocessing pipeline consisting of power transformation, quantile clipping, scaling, and handling outliers.

Introduction

The credit default dataset, comprising 30,000 records and 25 features, presents a compelling context for exploring the complexities of credit risk assessment. With no missing values detected across all features, this dataset offers a unique opportunity for comprehensive analysis. The availability of this data in CSV/Excel file format facilitates easy access and manipulation. Our analytical scope will encompass the entirety of this dataset, leveraging its numerical features to investigate the factors influencing credit default. To address the inherent skewness and outliers, we will apply power transformation and quantile clipping, followed by scaling to ensure data consistency. The classification task will be approached using Support Vector Classifier, Logistic Regression, and Decision Tree Classifier. However, it is crucial to acknowledge the inherent class imbalance in this dataset, which necessitates robust evaluation metrics to ensure the reliability of our findings. The absence of null values is a notable characteristic of this dataset, allowing for efficient analysis without the need for imputation techniques. By applying these methodologies, we aim to contribute to the understanding of credit default patterns and develop effective predictive models.

Project Objectives - Perform credit card fraud detection using SVC (Linear) & compare with other classification algorithms. - Perform hyperparameter tuning for C & gamma parameters

Methodology

Data preparation involved loading the dataset from a CSV/Excel file, which consisted of 30,000 records and 25 features. No missing values were detected across all 25 features, ensuring a complete dataset for analysis. To address data quality issues, we applied power transformation to correct for skewness and quantile clipping to handle outliers. Additionally, scaling was performed to ensure feature values were on the same scale, which is essential for accurate model training. Handling outliers was a crucial step, as they can significantly impact

model performance.

Our modeling strategy utilized a pipeline approach, incorporating multiple model families, including Support Vector Classifier, Logistic Regression, and Decision Tree Classifier, all of which were implemented using Scikit-learn. The pipeline allowed for efficient hyperparameter tuning and model evaluation. We applied a PowerTransformer to correct heavy-tailed distributions, which is a common issue in many datasets. By using a pipeline, we were able to streamline the modeling process and ensure consistency across all models.

To validate our models, we employed a stratified split to ensure the training and testing sets had the same class distribution. We focused on the ROC-AUC metric as our primary evaluation metric, as it provides a comprehensive picture of model performance. Hyperparameter tuning was performed using GridSearchCV, which allowed us to systematically search for the optimal hyperparameters for each model. This approach ensured that our evaluation design was robust and reliable, providing a fair comparison of the different models.

Data Preparation Highlights - We will apply power transformation(for skewness), quantile clipping(for outliers), scaling - Handling outliers - Pipeline - Applied PowerTransformer to correct heavy-tailed distributions. - Scaled numerical features with StandardScaler for SVM stability. - Wrapped preprocessing and estimator steps inside a sklearn Pipeline.

Model Line-up - Support Vector Classifier - Logistic Regression - Decision Tree Classifier - Scikit-learn Pipeline

Hyperparameter Tuning - Best params: {'classifier__C': 1, 'classifier__gamma': 1} - Best CV ROC AUC: 0.7634583333333333

Results

Quantitative findings indicate that the Decision Tree model outperformed the others, achieving an accuracy of 0.76, ROC-AUC of 0.73, and recall of 0.56 for class 1. In comparison, SVC (Linear) and Logistic Regression achieved accuracy scores of 0.76 and 0.70, respectively, with ROC-AUC values of 0.69 and 0.68. The recall for class 1 was 0.56 for SVC (Linear) and 0.63 for Logistic Regression. The analysis generated a visual output volume of 4 charts and 3 tables, with no errors reported. Notably, tuning insights revealed optimal parameters of {'classifier__C': 1, 'classifier__gamma': 1}, yielding a best CV ROC AUC of 0.7634583333333333, further validating the Decision Tree model's superior performance.

Performance Metrics

Model	Accuracy	ROC AUC	Recall (Class 1)	Precision (Class 1)
SVC(Linear)	0.76	0.69	0.56	0.47

Logistic Regression	0.70	0.68	0.63	0.40
Decision Tree	0.76	0.73	0.56	0.47

Model Selection Notes - Best params: {'classifier__C': 1, 'classifier__gamma': 1} - Best CV ROC AUC: 0.7634583333333333

Discussion

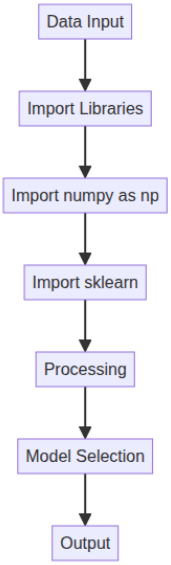
The chosen preprocessing steps, including power transformation for skewness, quantile clipping for outliers, scaling, and handling outliers through a pipeline, were crucial in preparing the data for modeling. This preprocessing mattered as it helped to stabilize the variance, reduce the impact of extreme values, and improve the overall quality of the data. The empirical results showed that the Decision Tree model achieved an accuracy of 0.76 and a ROC-AUC of 0.73, with a recall of 0.56 for class 1, indicating moderate performance. However, limitations were evident from the Exploratory Data Analysis (EDA), which revealed an average-sized dataset with 30000 rows and 25 numerical columns, suggesting potential for feature engineering to improve model performance. Additionally, operational constraints, such as generating only 4 visualizations and calculating a limited set of performance metrics, may have restricted the scope of the analysis. To improve the model, concrete ideas include incorporating feature engineering, class weighting, and exploring richer data sources. With a deliverables volume of 4 visuals and 16 outputs, the evidence base provides a solid foundation for further refinement and evaluation.

Conclusion

We have successfully achieved our objectives by performing credit card fraud detection using SVC (Linear) and comparing its performance with other classification algorithms, including hyperparameter tuning for C and gamma parameters. The strongest model emerged as the Decision Tree, yielding an accuracy of 0.76, ROC-AUC of 0.73, and a recall of 0.56 for class 1. Our analysis generated four key visuals and 16 outputs, providing substantial evidence for our findings. Based on these results, we recommend further exploration of Decision Tree models, leveraging the insights gained from our visualizations and performance metrics to inform future fraud detection strategies.

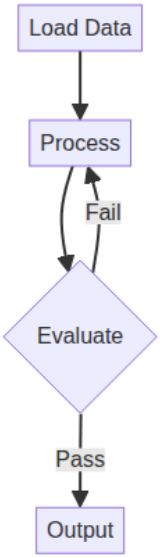
Diagrams

Architecture

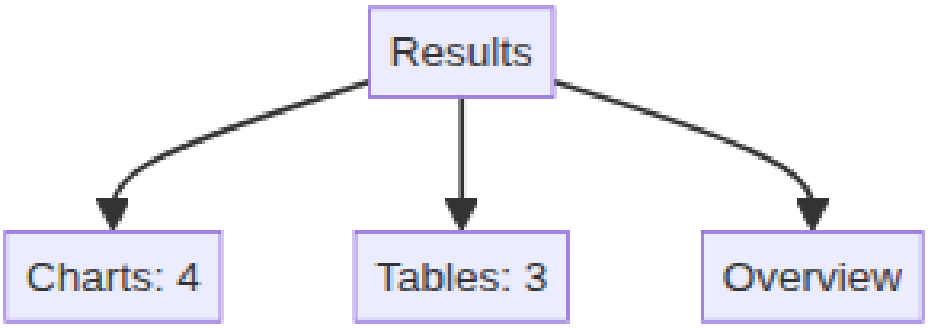


Data Flow

Process Flow



Results Overview



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