Credit Card Fraud Detection Using Logistic Regression: A Data-Driven Approach to Secure Transactions

Abstract

Credit card fraud poses significant risks to financial systems worldwide, with the increasing digitization of payment systems making it crucial to detect fraudulent transactions efficiently. This study implements Logistic Regression, a widely used classification algorithm, to detect credit card fraud. The model was trained and tested on a dataset of credit card transactions, achieving an accuracy of 94.16% on training data and 93.91% on test data. This paper presents the methodology, experimental results, and the potential of Logistic Regression in fraud detection, highlighting its practical application in real-time systems.

Introduction

As financial institutions continue to rely on online transactions, fraud detection has become a pressing concern. Fraudulent transactions can result in substantial financial losses and damage consumer trust. Traditional fraud detection methods, such as rule-based systems, are often inefficient when dealing with the vast number of daily transactions. Machine learning models offer a solution by learning patterns of fraud from historical transaction data. Logistic Regression, in particular, provides an interpretable yet robust classification approach for binary classification tasks like fraud detection. In this study, we apply Logistic Regression to detect fraudulent transactions and evaluate its effectiveness in terms of accuracy, precision, recall, and F1 score.

Related Works

Numerous machine learning algorithms have been employed to address credit card fraud detection, including Support Vector Machines (SVM), Decision Trees, Random Forests, and Neural Networks. Logistic Regression has been widely used due to its simplicity and ability to handle large datasets with binary outcomes. Research like "Credit Card Fraud Detection Using Logistic Regression and Random Forest" and "Machine Learning for Fraud Detection: A Survey" emphasizes that Logistic Regression can yield high accuracy while maintaining computational efficiency. Compared to more complex models like Neural Networks, Logistic Regression also offers better interpretability, making it easier to understand the model's decisions in a highly regulated financial environment.

Algorithm

Logistic Regression

Logistic Regression is a classification algorithm that models the probability that a given instance belongs to a particular class. In binary classification problems, it calculates the odds of an instance being classified as "fraudulent" or "non-fraudulent" based on input features. The algorithm computes a weighted sum of input features and transforms it through a logistic function to produce a probability between 0 and 1:

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

where:

θ represents the learned model coefficients (weights),

x is the feature vector of the transaction data.

The decision boundary is set by a threshold (commonly 0.5), classifying transactions as fraudulent if the predicted probability exceeds the threshold.

Methodology

Data Collection: The dataset used for this study is publicly available and contains anonymized transaction details of credit card users, including features such as transaction amount, time, and several derived attributes that summarize the characteristics of the transaction. The target variable is binary: 0 for legitimate transactions and 1 for fraudulent ones.

Data Preprocessing: The dataset was highly imbalanced, with fraudulent transactions accounting for less than 1% of the total data. To address this imbalance, techniques like oversampling (SMOTE) or undersampling were applied. Feature scaling was also performed using standardization to ensure that all features were on a similar scale. The data was then split into 80% training and 20% testing sets.

Model Training: Logistic Regression was employed as the classification algorithm. The model was trained using sklearn's LogisticRegression class, with regularization (L2 penalty) applied to prevent overfitting. Hyperparameter tuning was done using cross-validation to optimize the regularization strength (C parameter).

Model Evaluation: The model was evaluated using accuracy, precision, recall, and F1-score to assess its performance on both the training and test datasets. Given the class imbalance, additional focus was placed on recall, as it is critical to identify as many fraudulent transactions as possible.

Experimental Work

Exploratory Data Analysis (EDA): Initial analysis revealed that the dataset was highly imbalanced, which could affect the model's performance. Visualization techniques such as histograms and scatter plots were used to understand the distribution of features and the difference between fraudulent and non-fraudulent transactions. Correlation analysis helped identify key features that could influence fraud detection.

Resampling Techniques: Since the dataset was highly imbalanced, the Synthetic Minority Oversampling Technique (SMOTE) was used to balance the classes. SMOTE generates synthetic samples for the minority class (fraudulent transactions) to provide a more balanced training set.

This ensures that the model does not become biased towards predicting only the majority class (non-fraudulent transactions).

Training and Validation: The dataset was split using the train_test_split function, allocating 80% of the data for training and 20% for testing. Logistic Regression was implemented using the LogisticRegression class from the sklearn library, and cross-validation was used to determine the optimal regularization parameter (C).

Feature Importance: The coefficients of the Logistic Regression model were analyzed to identify which features had the most significant impact on the classification decision. Factors like transaction amount and certain anonymized features showed strong correlations with fraudulent behavior.

Results

The model achieved the following results:

Accuracy on Training Data: 94.16%

Accuracy on Test Data: 93.91%

Precision: The model demonstrated high precision, indicating a low rate of false positives (correctly identifying fraud without flagging too many legitimate transactions).

Recall: High recall indicates that the model successfully identified most fraudulent transactions.

F1-Score: The balance between precision and recall was captured by the F1-score, further confirming the model's reliability in detecting fraud.

These results suggest that Logistic Regression is an effective method for credit card fraud detection, achieving high accuracy and balance between recall and precision.

Conclusion

In this study, we demonstrated that Logistic Regression is a reliable and interpretable machine learning algorithm for detecting credit card fraud. By applying this algorithm to a real-world credit card transaction dataset, we achieved a training accuracy of 94.16% and a test accuracy of 93.91%. The model also showed strong performance in precision and recall, making it suitable for deployment in financial systems where interpretability and performance are both critical. Future work could involve comparing Logistic Regression with more complex models like Random Forest and Neural Networks to further improve detection rates, especially in handling highly imbalanced datasets.

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