

Credit Card Fraud Detection

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Agenda

- i. Background
- ii. Objective
- iii. Key Insights
- iv. Cost Benefit Analysis
- v. Data Attributes
- vi. Data Methodology
- vii. Recommendations



Background

- Finex is a leading financial service provider based out of Florida, US.
- It offers a wide range of products and business services to customers through different channels, ranging from in-person banking and ATMs to online banking.
- Over the last few years, Finex has observed that a significantly large number of unauthorized transactions are being made, due to which the bank has been facing a huge revenue and profitability crisis.
- Many customers have been complaining about unauthorized transactions being made through their credit/debit cards.
- It has been reported that fraudsters use stolen/lost cards and hack private systems to access the personal and sensitive data of many cardholders.
- They also indulge in ATM skimming at various POS terminals such as gas stations, shopping malls, and ATMs that do not send alerts or do not have OTP systems through banks.
- Such fraudulent activities have been reported to happen during nonpeak and odd hours of the day leaving no room for suspicion.

Objective

- Building a fraud detection system using different machine learning techniques to identify fraudulent activities at the right time and prevent them from happening.
- To build a fraud detection model to help banks identify credit card frauds and be vigilant enough to reduce losses incurred due to such unauthorized transactions by the fraudsters.

Key Insights

- The category of grocery_pos and shopping_net showed the most number of fraud.
- Both male and female category revealed equal number of Credit Card Frauds.
- The most number of credit card frauds are reported in States OH,TX & LA.
- Most number of frauds occured in jobs of quantity surveyor then followed by naval architect and material engineer.
- The most number of frauds are reported in the cities of Dallas, Houston and Birmingham.

Key Insights

- Average number of transactions per month = 77183
- Average number of fraudulent transactions per month=402
- Average amount per fraudulent transaction = 530.66
- Cost incurred per month before the model was deployed= \$ 213,392
- Cost incurred per month after the model is built and deployed= \$ 271,9139
- Total cost of providing customer support per month for fraudulent transactions detected by the model = \$ 13106.75
- Cost incurred due to these fraudulent transactions left undetected by the model =\$ 14084.64
- The cost incurred per month after the model is built and deployed= \$ 27191.39
- Final savings = \$186200.83

Data Attributes

Columns (total 23 columns):
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Data Methodology

- Dataset Loading
- ▶ EDA
- splitted the data set into training data and testing data in order to check the performance of your models with unseen data.
- Built Random Forest Model
- Adjusted Class Imbalance using ADASYN of Sampling Method
- Done with Hyperparameter Tuning because of extensive computational times.
- Model Evaluation

Recommendations

- The banking segments and local department needs to find out ways to curb these frauds in the state of OH,TX & LA as these states have shown highest number of credit card frauds.
- Based on the Analysis, it can be seen that the frauds are not biased towards any specific gender. Hence, security should not be gender specific.
- The Banking sector should moniter the online credit card transactions in the cities of Dallas, Houston & Birmingham as they show the highest number of frauds.
- Reconcilement of Baking accounts and transactions on daily basis.

Files Attached

1. Model Evaluation:

Credit_Card_Fraud_Detection (1).ipynb

2. Cost Benefit Analysis:

Cost Benefit Analysis (2).xlsx

THANK YOU

