



CREDIT CARD FRAUD DETECTION

SUBMITTED BY

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AGENDA

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- ❖ Objective
- ❖ Solution Approach
- ❖ Key Insights
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BACKGROUND

- ❖ Fraud transactions has increased drastically around the globe
- ❖ Retaining high profitable customers is the most important business goal
- ❖ Rise in digital payment channels is directly proportional to the number of fraudulent transactions
- ❖ The Federal Trade Commission (US) has estimated that around 10 million people become victims of credit card theft each year
- ❖ Credit card companies lose close to \$50 billion per year to fraud
- ❖ Fraud detection using Machine Learning algorithm is a “MUST”

OBJECTIVE

- ❖ To develop a machine learning model to detect fraudulent transactions based on the historical transactional data of customers with a pool of merchants
- ❖ Data set captures the data from Jan 1st 2019 – Dec 31st 2020
- ❖ ~1000 customers, ~800 merchants
- ❖ ~9651 out of 18,52,394 (0.52%) are fraud transactions
- ❖ Perform cost-benefit analysis

SOLUTION APPROACH

❖ Data Understanding, Data Preparation and EDA :

- ❖ Firstly , we checked the shape and datatype of the dataset and then assigned correct datatype and deleted unwanted columns. Thereafter, we checked for null values and outliers and no outlier or null values were found.
- ❖ Further, we checked for data Imbalance and skewness and binary mapped categorical columns with two values and created dummy variables for rest of categorical columns

❖ Train/Test Data Splitting :

- ❖ We split train and test dataset into X and y

SOLUTION APPROACH

❖ Model Building or Hyperparameter Tuning:

- ❖ We used ADASYN to oversample the dataset
- ❖ We used Random Forest model for model building

❖ Model Evaluation:

- ❖ We evaluate the model performance using appropriate evaluation metric such as Precision, Recall and F-1 Score

❖ Cost-Benefit Analysis :

- ❖ We checked for cost implications before the model was built and after the model was built

The background is a blue gradient with faint concentric circles. In the corners, there are white line art designs resembling circuit boards or neural networks, with lines and small circles connecting them.

KEY INSIGHTS

KEY VARIABLES

- ❖ Transaction amount, category and gender are the most important variables
- ❖ Gas and transport, kids_pet and home are the top three categories
- ❖ Transaction month, longitude and miscellaneous category are the least important variables

| | Varname | Imp |
|----|-------------------------|----------|
| 0 | amt | 0.877397 |
| 13 | category_kids_pets | 0.028940 |
| 8 | category_gas_transport | 0.023524 |
| 12 | category_home | 0.013879 |
| 18 | category_shopping_pos | 0.010981 |
| 19 | category_travel | 0.010898 |
| 10 | category_grocery_pos | 0.010155 |
| 15 | category_misc_pos | 0.008859 |
| 7 | category_food_dining | 0.004213 |
| 17 | category_shopping_net | 0.003882 |
| 1 | gender | 0.003158 |
| 3 | age_at_trans | 0.001953 |
| 2 | city_pop | 0.001433 |
| 11 | category_health_fitness | 0.000412 |
| 9 | category_grocery_net | 0.000195 |
| 4 | lat_dist | 0.000097 |
| 6 | trans_month | 0.000015 |
| 5 | long_dist | 0.000008 |
| 14 | category_misc_net | 0.000000 |

FINANCIAL IMPLICATIONS BEFORE MODEL

- ❖ Average 77,183 credit card transactions per month
- ❖ Average 402 fraudulent transactions per month
- ❖ Average \$ 531 amount per fraud transaction
- ❖ Total costs incurred per month from fraud transactions before the model was deployed is \$ 213,392

FINANCIAL IMPLICATIONS AFTER MODEL

- ❖ 8,745 fraudulent transactions detected by the model
- ❖ \$ 1.5 cost to provide customer support to these transactions that is \$ 13,117 in total
- ❖ 27 fraudulent transactions not detected by model which amounts to \$ 14,284 loss
- ❖ Total cost incurred after new model deployment is \$ 27,401
- ❖ Final savings after new model deployment is \$185,992 that is reduction in losses by ~87%

APPENDIX: DATA ATTRIBUTES

| | |
|-----------------------|--|
| index | - Unique Identifier for each row |
| trans_date_trans_time | - Transaction DateTime |
| cc_num | - Credit Card Number of Customer |
| merchant | - Merchant Name |
| category | - Category of Merchant |
| amt | - Amount of Transaction |
| first | - First Name of Credit Card Holder |
| last | - Last Name of Credit Card Holder |
| gender | - Gender of Credit Card Holder |
| street | - Street Address of Credit Card Holder |
| city | - City of Credit Card Holder |
| state | - State of Credit Card Holder |
| zip | - Zip of Credit Card Holder |
| lat | - Latitude Location of Credit Card Holder |
| long | - Longitude Location of Credit Card Holder |
| city_pop | - Credit Card Holder's City Population |
| job | - Job of Credit Card Holder |
| dob | - Date of Birth of Credit Card Holder |
| trans_num | - Transaction Number |
| unix_time | - UNIX Time of transaction |
| merch_lat | - Latitude Location of Merchant |
| merch_long | - Longitude Location of Merchant |
| is_fraud | - Fraud Flag <--- Target Class |

APPENDIX: ATTACHED FILE

❖ Cost Benefit Analysis

❖ Cost+Benefit+Analysis.xlsx

❖ Random Forest Machine Learning Model

❖ Capstone Project I.ipynb

❖ Presentation File

❖ Capstone_Project_CC_Fraud_Detection.pptx

❖ Video explanation

The background is a blue gradient with faint concentric circles. White circuit-like lines with circular nodes are positioned in the corners: top-left, top-right, bottom-left, and bottom-right.

THANK YOU !!!