Predicting Fraud and FICO Score

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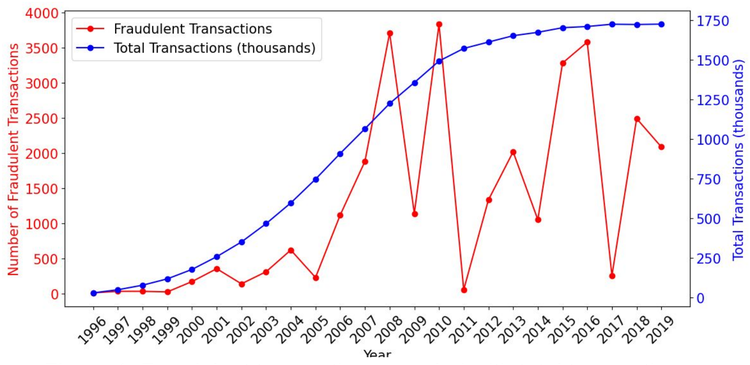
INTRODUCTION

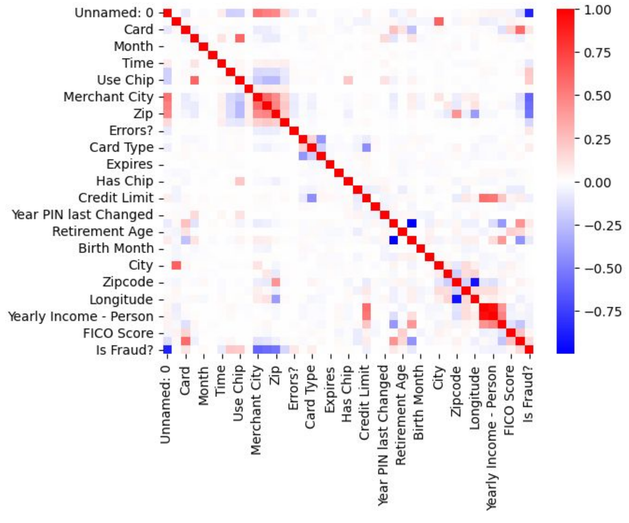
According to the Federal Trade Commision, fraud losses have increased by 14% between 2022 and 2023 and is projected to grow even further. Fraud detection and credit scoring are critical in financial services to mitigate risks and improve decision-making. This project explores predictive modeling for detecting fraudulent transactions and estimating FICO scores.

DATA

- Sourced from Kaggle
- Created by a multi-agent virtual world simulation performed by IBM
- 24 million credit card transactions ranging from 2009-2022
- The dataset is split into 3 main files
  1. **Transactions** - 24 million transactions
  2. **Credit cards** - Credit cards used to make purchases
  3. **Users** - Contains information on a total of ‘x’ users made purchases recorded in transactions.csv



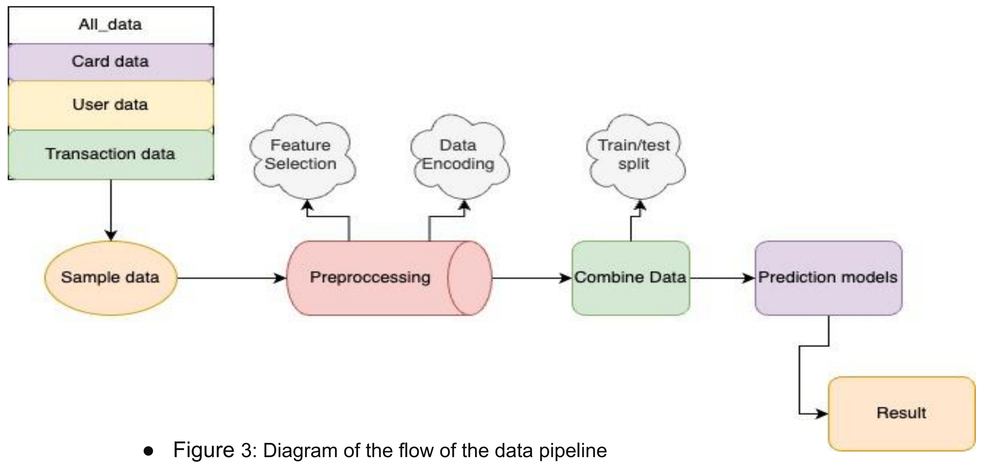
- Figure 1: Fraudulent transactions coupled with total transactions



- Figure 2: Correlation map of all features. Note features related to is_fraud?

METHODOLOGY

- Sampled data to get 50% fraudulent transactions and 50% legitimate transactions
- Categorized raw FICO score into 4 classes (Very Low,Low,Medium,High) based on industry standards
- Selected relevant features for each model
- Encoded categorical features to numerical values



- Figure 3: Diagram of the flow of the data pipeline

- Fraudulent Detection features:

  In US, in state, ZIP code, online transaction, swipe transaction, is suspicious amount, amount, number of credit cards

- FICO Prediction features:

  Current Age, Birth Year, Gender, Yearly Income - Person, Total Debt, Number of Credit Cards

RESULTS

Target Variable	Model	K	Accuracy	Precision	Recall	F1
FICO	NN (cosine)	25	38.50%	43.22%	81.70%	56.38%
	NN (euclid)	25	39.25%	43.40%	81.66%	56.67%
	NB	-	42.25%	42.25%	100.00%	59.40%
	Random	-	42.25%	41.18%	28.99%	34.00%
	Majority	-	42.25%	42.25%	100.00%	59.40%
Fraud	NN (cosine)	101	75.85%	86.85%	69.37%	70.35%
	NN (euclid)	5	75.6%	87.1%	64.1%	72.4%
	NB	-	36.95%	24.64%	16.50%	19.77%
	Random	-	49.90%	49.84%	37.29%	41.55%
	Majority	-	36.95%	24.64%	16.50%	19.77%

- Figure 4: Performance Metrics for Fraud Detection and FICO score prediction models

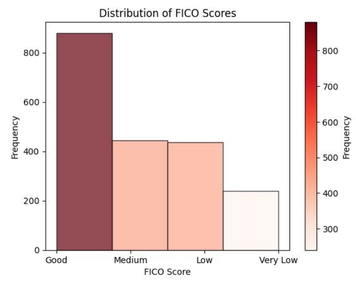
- Fraud detection best model: Cosine and Euclidean Performed 30% better than baseline random model for the F1 metric.

Measure / model	K	Accuracy	Precision	Recall	F1
Cosine	1	70.7%	81.1%	64.2%	60.4%
Cosine	50	74.00%	84.6%	67.9%	67.3%
Cosine	101	75%	85.9%	68.9%	69.2%
Euclidean	1	74.7%	83.1%	66%	67.6%
Euclidean	3	76.3%	86.8%	66.6%	72.6%
Euclidean	5	75.1%	87.1%	64.1%	72.4%

- Euclidean 3 KNN yielded the best performance metrics for fraud detection.
- FICO score prediction best model: Naive Bayes. Performed 22.38% better than baseline random model for the F1 metric.
- 25 KNN yielded the best performance metrics for FICO score prediction.

ERROR ANALYSIS

- One fraudulent charge for every ~800 legitimate charges.
- Skewed dataset- Large majority of FICO scores fell into the “good” category. This caused errors for Naive Bayes and large KNN.



- Figure 5: Uneven distribution of FICO scores

- Majority classes heavily favored in both models

DISCUSSION

- Challenges: Large data size, encoding nominal features, skewed data.
- Our classification of the FICO scores into four categories may have oversimplified the variability of credit score.
- Further work on this subject could benefit from additional data such as regional economic data.

https://colab.research.google.com/drive/1f0ZdyU4-x5zj-0CD3qSza46WXbIhPvIV?usp=sharing