DSCI445 Term Project - Bank Account Fraud Detection

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0.1 Introduction

0.1.1 Motivation

One important use of statistical models is protecting customer and business interests by identifying potential fraudulent applications. In these models, there must be a balance between correctly identifying the fraud (high recall) and reducing false positives.

False positives are when legitimate applications are incorrectly flagged as fraudulent. The cost of undetected fraud has a high monetary cost to the organization. A high false positive rate can create a negative customer experience while putting additional work on support teams that must handle these verifications.

With these consequences in mind, fraud detection models must be able to detect the difference while also minimizing the negative impacts accurately.

Our goal in this project is to work with various machine learning methods to find the best model based on the following metrics:

- **Precision**: Correctly identified fraudulent cases across all *classified* fraudulent cases
- **Recall**: Correctly identified fraudulent cases across all *truly* fraudulent cases
- **F1-Score**: A metric providing a balanced measure of the harmonic mean of precision and recall
- **ROC-AUC**: Model's ability to distinguish between classes, where a higher score indicates better classification performance

We are not including accuracy as part of the metrics as while it's important to see if models can correctly identify non-fraudulent data, it does not correctly reflect the project's goals.

Reference for Text: https://seon.io/resources/dictionary/false-positives/

0.2 Dataset overview

For our modeling, we will be using the Bank Account Fraud NeurIPS 2022 datasets (called BAF for short), which are a suite of synthetic datasets meant to evaluate machine learning methods. The dataset has 1 million bank account instances with 31 features and the fraud_bool response for each instance.

Variable Type	Feature Name	Description	Values/Range
Categorical	`payment_type`	Credit payment plan type	AA to AE (5 types)
	`employment_status`	Employment status	CA to CG (7 types)

Variable Type	Feature Name	Description	Values/Range
	`housing_status`	Residential status	BA to BG (7 types)
	`source`	Application source	INTERNET, TELEAPP
	`device_os`	Device operating system	Windows, macOS, Linux, X11, other
Numeric	`income`	Annual income in quantiles	0.1 to 0.9
	`name_email_similarity`	Email and name similarity	0 to 1
	`prev_address_months_count`*	Months at previous address	0 to 380, -1 = missing
	`current_address_months_count`*	Months at current address	0 to 429, -1 = missing
	`customer_age`	Age in years (rounded to decade)	10 to 90
	`days_since_request`	Days since request	0 to 79
	`intended_balcon_amount`*	Initial amount transferred	0 to 114, -1 to -16 = missing
	`zip_count_4w`	Applications in same zip (last 4 weeks)	1 to 6830
	`velocity_6h`	Apps per hour (last 6 hrs)	-175 to 16818
	`velocity_24h`	Apps per hour (last 24 hrs)	1297 to 9586
	`velocity_4w`	Apps per hour (last 4 weeks)	2825 to 7020
	`bank_branch_count_8w`	Branch apps (last 8 weeks)	0 to 2404
	`date_of_birth_distinct_emails_4w`	Distinct emails with same DOB (last 4 weeks)	0 to 39
	`credit_risk_score`	Internal risk score	-191 to 389
	`bank_months_count`*	Months of previous account	0 to 32, -1 = missing
	`proposed_credit_limit`	Proposed credit limit	200 to 2000
	`session_length_in_minutes`*	Session length on website	0 to 107, -1 = missing
	`device_distinct_emails_8w`*	Distinct emails for device (last 8 weeks)	0 to 2, -1 = missing
	`device_fraud_count`	Fraud count for device	All values = 0
	`month`	Application month	0 to 7
Binary	`email_is_free`	Free email domain	0 or 1
	`phone_home_valid`	Home phone validity	0 or 1
	`phone_mobile_valid`	Mobile phone validity	0 or 1
	`has_other_cards`	Other cards with bank	0 or 1
	`foreign_request`	Request from foreign country	0 or 1
	`keep_alive_session`	“Remember me” enabled	0 or 1

* Negative values indicate missing data for these variables.

0.3 Methodolgy

0.3.1 Data Preprocessing

Our first step was the data-cleaning process. At first glance, no columns had missing data. However, a unique attribute of the BAF is that certain numeric columns had negative values that signify missing values. Inspection of those columns was required to determine their data quality.

After that inspection, a decision had to be made about dealing with the missing data: either removing the column entirely from the model or imputing the data.

The decision on what columns had to be removed was determined by calculating the percentage of each feature with missing values and removing the columns over a threshold of 50%. As shown by the table below. Imputing data over that threshold can add bias to our model.

Imputation was applied to the columns below the threshold. Imputation is the process of filling the missing values with reasonable values. In this data set, the median value was used. For our model to know the difference between values that were imputed or not, we created an additional column __is__imputed so our model can determine if they were imputed or not.

During the initial process, we found that device__fraud__count has only 0 in its column, which did not provide any meaning, so we dropped that column from the dataset.

Reference to Text: https://scikit-learn.org/1.5/modules/impute.html

[9]:

	Percentage Missing
intended_balcon_amount	74.2523
prev_address_months_count	71.2920
bank_months_count	25.3635
current_address_months_count	0.4254
session_length_in_minutes	0.2015
device_distinct_emails_8w	0.0359

0.3.2 Exploratory Data Analysis

Since the data cleaning process was completed, we looked at the remaining columns to see if there were any clues or indicators of what could determine fraudulent applications. Before, we looked at the categorical, numeric, and binary Predictors separately. We first looked at how many fraud cases we had in the data set and what percentage, as shown below. With the number of fraud cases being so imbalanced, we will need to understand the effect of the imbalance and how to address it.

[11]:

	Fraudulent Status	Count	Percentage
0	Non-Fraudulent	988971	98.8971
1	Fraudulent	11029	1.1029

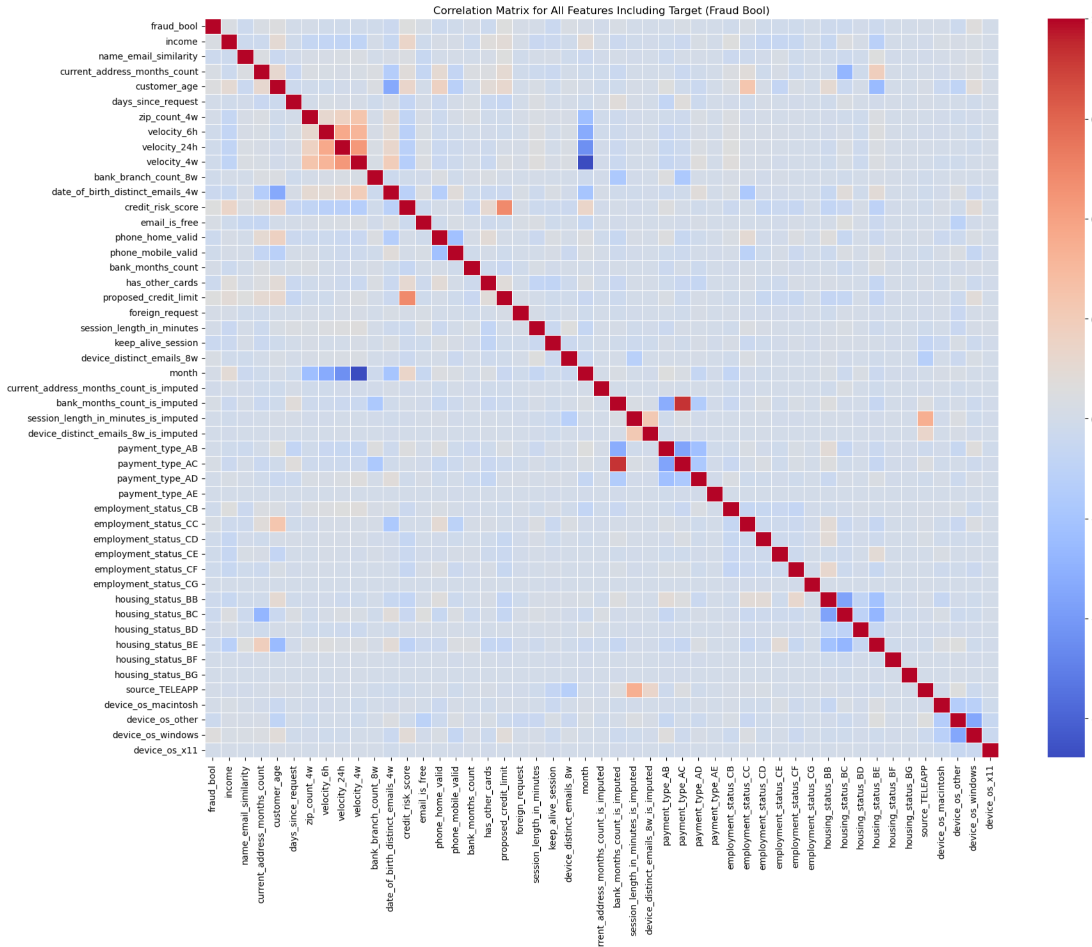
Our exploratory data analysis and correlation matrix showed insights into key predictors that can determine fraud. Those insights allowed us to perform feature engineering before model selection to help our model accurately classify our objective. When we performed a summary of statistics on numeric features for fraud and non-fraud cases (See Table #1), it showed us higher fraud rates for income, proposed__credit__limit, and customer age. When we performed a Fraud Rate by numeric features binned (See Table #2), it confirmed those claims with 13% fraud rates for people requesting credit limits above $1500 and 4.2% for people over 60. When completing a Fraud

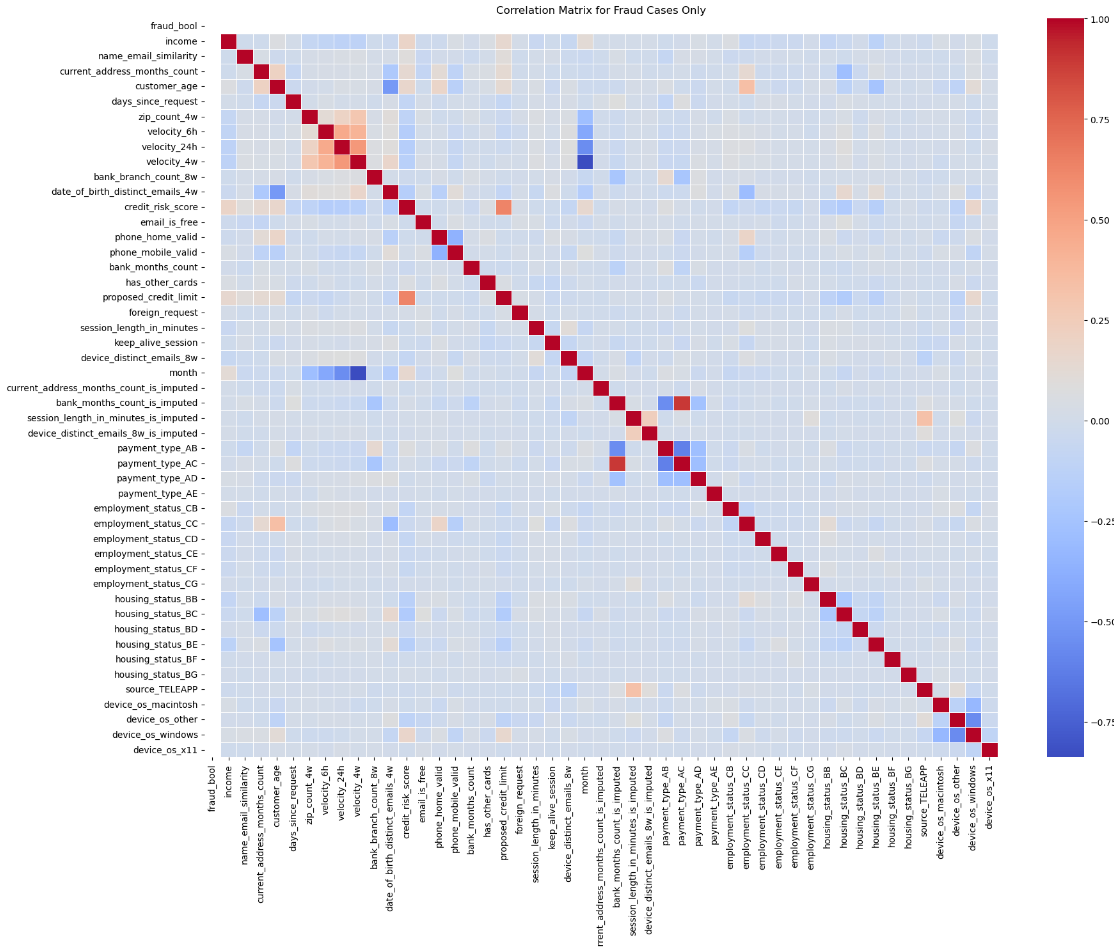
Analysis by Categorical Features (See Table #3), payment types like AC (1.75%) and BA (3.75%) were indicators of fraudulent activity. Our Analysis for Binary Features (See table #4) showed us that identity and foreign_request (2.2%) were also fraud indicators. The correlation matrix (See Table #5) confirmed our finding when looking at the predictors separately. Still, there is high collinearity due to the time series' relation to each other, and some, like days_since_request, showed weaker correlations for limited predictive potential. Initially, we created feature engineering to create high-risk flags and risk categories based on this known information, but they failed to improve model performance which will be discussed further in the analysis.

-Free email domains, invalid phone numbers, and foreign requests show significantly higher fraud rates -applicants without other cards and non-remembered sessions are correlated with increased fraud

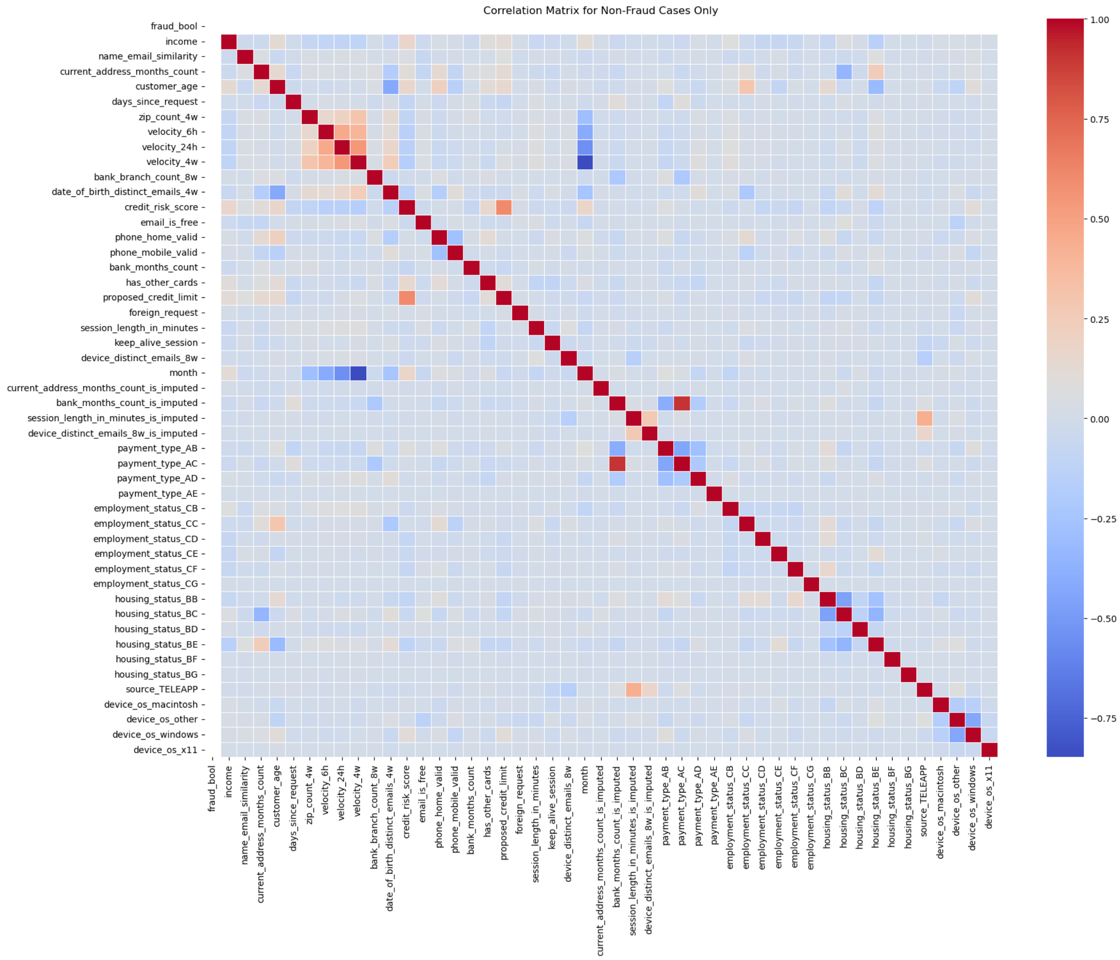
[ ]:

	Feature	Count_True	Fraud_Percentage_True	Count_False	Fraud_Percentage_False
0	email_is_free	529886	1.375956	470114	0.795126
1	phone_home_valid	417077	0.669181	582923	1.413223
2	phone_mobile_valid	889676	1.054429	110324	1.493782
3	has_other_cards	222988	0.417511	777012	1.299594
4	foreign_request	25242	2.198716	974758	1.074523
5	keep_alive_session	576947	0.653093	423053	1.716333


Correlation Matrix for All Features Including Target (Fraud Bool)
fraud_bool
income
name_email_similarity
current_address_months_count
customer_age
days_since_request
zip_count_4w
velocity_6h
velocity_24h
velocity_4w
bank_branch_count_8w
date_of_birth_distinct_emails_4w
credit_risk_score
email_is_free
phone_home_valid
phone_mobile_valid
bank_months_count
has_other_cards
proposed_credit_limit
foreign_request
session_length_in_minutes
keep_alive_session
device_distinct_emails_8w
month
current_address_months_count_is_imputed
bank_months_count_is_imputed
session_length_in_minutes_is_imputed
device_distinct_emails_8w_is_imputed
payment_type_AB
payment_type_AC
payment_type_AD
payment_type_AE
employment_status_CB
employment_status_CC
employment_status_CD
employment_status_CE
employment_status_CF
employment_status_CG
housing_status_BB
housing_status_BC
housing_status_BD
housing_status_BE
housing_status_BF
housing_status_BG
source_TELEAPP
device_os_macintosh
device_os_other
device_os_windows
device_os_x11
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



Correlation Matrix for Fraud Cases Only
fraud_bool
income
name_email_similarity
current_address_months_count
customer_age
days_since_request
zip_count_4w
velocity_6h
velocity_24h
velocity_4w
bank_branch_count_8w
date_of_birth_distinct_emails_4w
credit_risk_score
email_is_free
phone_home_valid
phone_mobile_valid
bank_months_count
has_other_cards
proposed_credit_limit
foreign_request
session_length_in_minutes
keep_alive_session
device_distinct_emails_8w
month
current_address_months_count_is_imputed
bank_months_count_is_imputed
session_length_in_minutes_is_imputed
device_distinct_emails_8w_is_imputed
payment_type_AB
payment_type_AC
payment_type_AD
payment_type_AE
employment_status_CB
employment_status_CC
employment_status_CD
employment_status_CE
employment_status_CF
employment_status_CG
housing_status_BB
housing_status_BC
housing_status_BD
housing_status_BE
housing_status_BF
housing_status_BG
source_TELEAPP
device_os_macintosh
device_os_other
device_os_windows
device_os_x11
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



0.4 Naive Approach

{talk about the naive approach to the problem: using the dataset as is into some models, the results, why it performed horribly}

After cleaning up our dataset and doing EDA to check if there were any correlations or predictors that may stand out to help us work with our models, ultimately nothing of much use came out from it, so we decided to jump straight to model creating. The first idea we decided to check out was our "control" models: if we did nothing to handle the imbalanced data and instead throw it into some models, how would those models perform? This is the naive approach that we took a look at.

We selected 4 models for our control group: logistic regression, K-nearest neighbors, decision tree, and a random forest of 100 trees. We looked into doing more complex models such as support vector machines or possibly any unsupervised models, but with our million row and 30-something feature dataset, these models would take a long time to calculate, so we decided to have the random forest be our most complex model for our control group.

Below is the results of the naive approach alongside an interpolated recall score if the model had a

5% false positive rate (FPR).

Model

Precision

Recall

F1-Score

ROC-AUC

FPR

Recall @5% FPR

LogisticRegression

0.447368

0.007665

0.015071

0.872193

0.000106

0.504959

KNeighborsClassifier

0.150000

0.001353

0.002681

0.660778

0.000086

0.294612

DecisionTreeClassifier

0.083089

0.102344

0.091717

0.544839

0.012665

0.136288

RandomForestClassifier

0.428571

0.001353

0.002697

0.819742

0.000020

0.439317

As expected, these models did not have good recall rates, but the false positive rates were pretty low for all of them–some of them could even be considered 0%. The only useful thing to take away from this is that last column: a higher FPR somehow results in a higher recall rate, and seeing this trend later on has caused us some trouble with our original 5% FPR restriction, leading us to scrap it. We had to deal with this recall rate / false positive rate balance throughout our project to ensure that our model was predicting fraud data as best as it could while also not incorrectly predicting fraud data frequently, which was a pain to deal with for hyperparameter tuning.

The reason behind the recall rate and false positive rate having some kind of influence on each other is simple: because our data is imbalanced, we're trying to make our models have a better chance of predicting a fraudulent transaction–which'll increase recall–but in turn, it'll increase the chance the model incorrectly predicts a non-fraudulent transaction as fraudulent, increasing the false positive rate. If we fix the FPR, the model will be more conservative and predict less fraudulent transactions, resulting in the possibility of fraudulent transactions being predicted as non-fraudulent, which is very bad.

Having a high FPR may seem scary, but in the case of fraud detection, it's actually better to have that than a lower recall rate. If a fraud detector predicts that a legitimate transaction was fraudulent (a false positive), the worst case scenario is the company loses a customer. If a fraud detector predicts that a fraudulent transaction was legitimate (a false negative), the worst case scenario is the person lost money and has to file a dispute to try and get their money back. So in our project, which deals with fraud detection, we decided that it was better risking our models having a high recall rate and FPR than trying to stay below our 5% FPR restriction and having a low recall rate because of it.

0.5 Imbalanced Data Handling

0.5.1 Sampling Techniques

{talk about each of the four methods we tried: SMOTE, ADASYN, Under-sampling, SMOTE + Tomek's Links; how each of these could help improve performance for imbalanced data, and the results we got using those techniques for each model(?)}

0.5.2 Imbalanced Models

{talk about the two imbalanced models we tried: Balanced Forest and XGBoost, how each of these could help improve performance for imbalanced data, and the results we got using those models on the various techniques(?)}

0.6 Conclusion

{talk about what we got out of the results, why the recall-FPR tradeoff is important in fraud detection, what we tried and failed, and what we could've done differently}