FRAUD DETECTION IN THE FINANCIAL INDUSTRY

THINKFUL SUPERVISED LEARNING CAPSTONE

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BACKGROUND

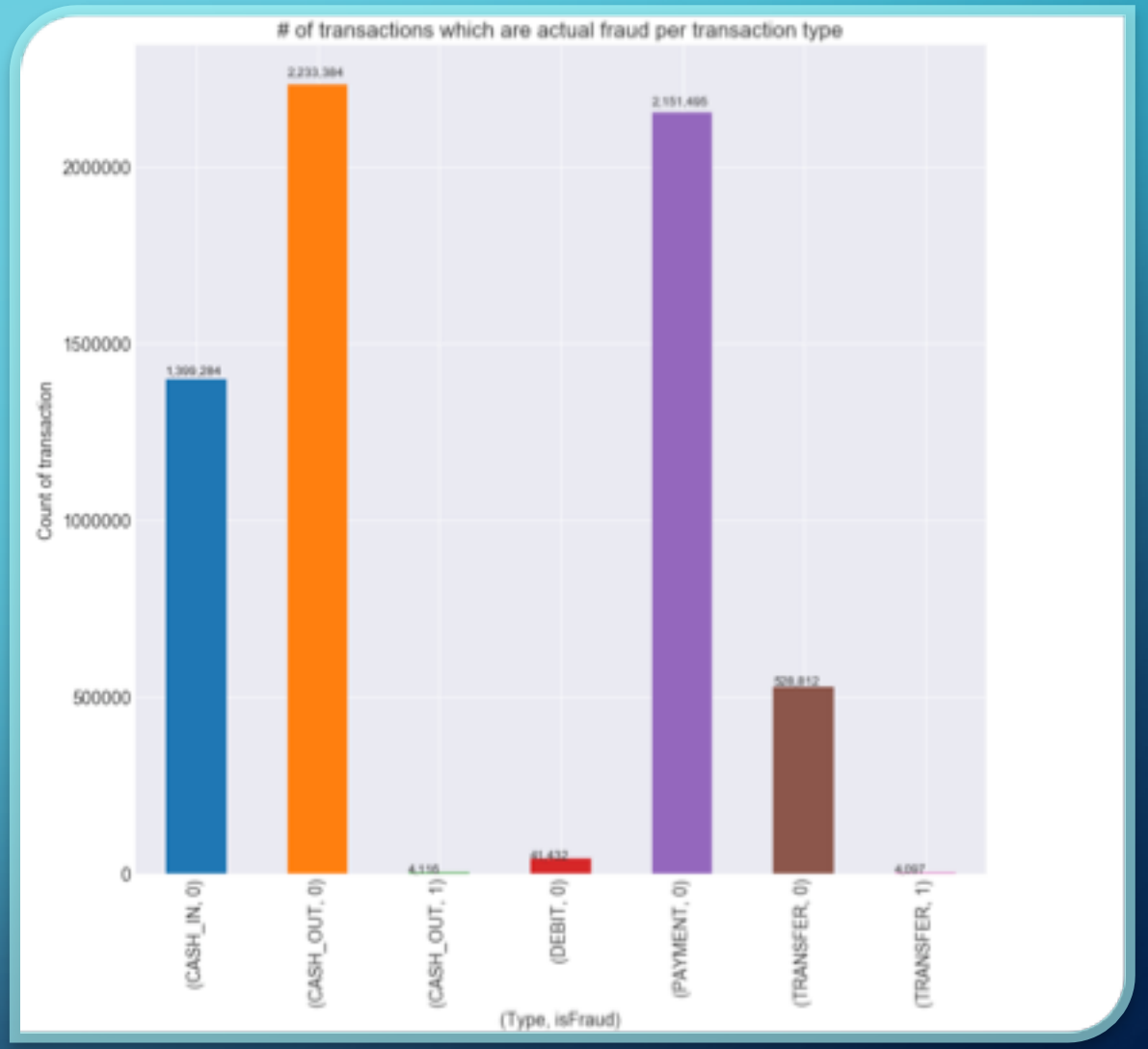
- Found on Kaggle: https://www.kaggle.com/ntnu-testimon/paysim1
- Synthetic financial dataset created for fraud detection generated by Paysim.
- Fraud- fraudulent mobile money transactions where an agent attempts to gain access to a customer's account and empty the funds by transferring to another account and cashing it out of the system.

WHY CARE ABOUT FRAUD DETECTION?

- Mobile money transactions are prevalent in today's society, it might even become the economic standard.
  - Ex: Venmo, Zelle, Apple Pay, Samsung Pay, Google Wallet, Ali Pay, Wechat Pay
  - Making it safer to use and more secure could increase usage and acceptance of these mobile products.
- Creating an accurate classifier will help boost the trust in these products and attract more users.

WHY CARE PART 2

- We see that no matter how intricate the scam may be, the ultimate goal is to TRANSFER and then CASH OUT.
- If I can create a classifier that can accurately and quickly deduce whether a transaction is fraudulent or not, there can be an implementation where the money is frozen so that the fraud doesn't occur.



GOAL

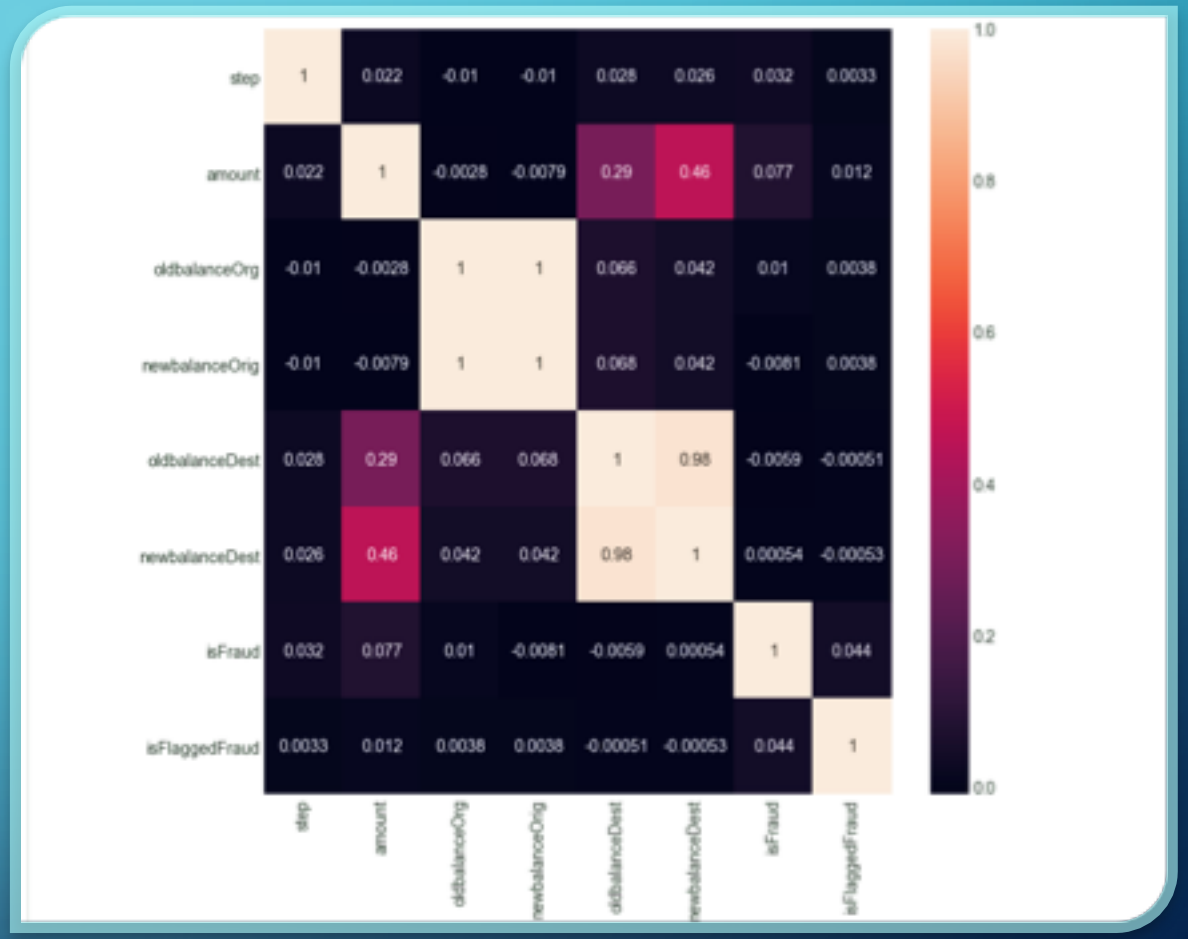
- Two type of models:
  - I want to testify, I need to CLASSIFY
- Find the best model to accurately label data as fraud.
  - BEST – Not only fast, but accurate too.

DATA EXPLORATION

- 11 features in the dataset:
  - Categorical: Type, nameOrig (customer who started the transaction), nameDest (recipient of the transaction), Fraud, Flagged as Fraud (isFlaggedFraud)
  - Continuous: Step, Old/ New Balance Owner, amount, Old/New Balance Destination
- What to do with the categorical data?
  - Get dummies for the type column.
  - Drop the names.

DATA EXPLORATION CONT'D

- Created a heat map to see if any of the variables had any sort of unexpected multicollinearity.
- Dataset had 6,362,620 rows originally.
- There weren't any missing values.
- Suffering from class imbalance:
  - Only 8213 out of the 6,362,620 were fraud.



CLASS IMBALANCE

- Class Imbalance, so what?
  - Most of the data is non-fraudulent, not balancing the data will skew any model and make it 99% accurate even though it isn't.
  - Resample: 100,000 cases of true and false.

BUT WAIT… THERE'S MORE

- Feature Selection Method
  - SelectKBest vs Principal Component Analysis
    - SKB removes all but the highest scoring features.
    - Scoring in this case is determined by the f_classifier aka using the f-test to determine if there is any statistical significance in the sample variance of the dataset for the features.
    - Principal component analysis transforms all the features in the dataset and gives entirely new features that are independent from each other.
    - I chose to use 4 Principal Components.
  - *SPOILER ALERT*
    - The feature selection method I liked the most was PCA. I'll talk about it as we move through the models.

PERFORMANCE RUBRIC

- Best Parameters – parameters that allow for the best classifying score using Grid Search CV
- Average 5 Fold Cross Validation Score – resampling the dataset into 5 equal sized samples and running through the model again.
- Classification Report (Average scores between the fraud and non fraud cases)
  - Precision – (TP/(TP+FP)) Ability of the classifier not to label as positive a sample that is negative.
  - Recall – (TP/(TP+FN)) Ability to find all positive samples.
  - F1 - a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0.
- AUC – A high Area Under the Curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall).

MODEL 1: GAUSSIAN NAÏVE BAYES

- Why Gaussian?
  - Because there were initially more continuous variables before I got dummies for the categorical type data and that's the only way I can incorporate them unlike Bernoulli and Multinomial NB.
- SKB Results:
  - Best Parameter: 3 Features
  - Avg. CV: 77.90%|| Avg. Precision: 85% || Avg. Recall: 78%
  - Avg. F1: 77%||AUC: 15.44% ||Runtime: Fast
- PCA Results:
  - Avg. CV: 83.43%|| Avg. Precision: 83% || Avg. Recall: 83%
  - Avg. F1: 83%||AUC: 37.62%||Runtime: Fast

MODEL 2: KNN

- Had to prep this when using SKB by normalizing distance in features.
- SKB Results:
  - Best Parameters: 8 features, 2 neighbors
  - Avg. CV: 99.37%| | Avg. Precision 99% | |Avg. Recall 99%
  - Avg. F1: 99%| |AUC: 0.51% | |Runtime: Slow, 4.1 hours
- PCA Results:
  - Best Parameter: 2 neighbors
  - Avg. CV : 98.84%| |Avg. Precision: 83% | |Avg. Recall 81%
  - Avg. F1: 81%| |AUC: 37.67%| |Runtime: Fast 13.7 seconds

- Overall: Both models overfitted. I managed to reduce a little bit of overfitting by using PCA, but this model still isn't quite there.

MODEL 3: DECISION TREE

- SKB Results:
  - Best Parameters: 10 features, max depth of 8
  - Avg. CV : 98.76%|| Avg. Precision 99%||Avg. Recall 99%
  - Avg. F1: 99%||AUC: 48.95% ||Runtime: Fast, 30 seconds
- PCA Results:
  - Best Parameter: max depth of 8
  - Avg. CV : 93.13%|| Avg. Precision: 87%||Avg. Recall 84%
  - Avg. F1: 85%||AUC: 41.22%||Runtime: Faster 1.5 seconds
- Overall: Although SKB looks superior, the possibility of the model overfitting is quite high so I would rather go with the PCA model here.

MODEL 4: RANDOM FOREST

- SKB Results:
  - Best Parameters: 9 features, 75 trees, max depth of 6
  - Avg. CV : 97.46%| | Avg. Precision: 98%| |Avg. Recall: 98%
  - Avg. F1: 98%| |AUC: 48.25% | |Runtime: Slow, ~2.5 hrs
- PCA Results:
  - Best Parameters: 100 trees, max depth of 8
  - Avg. CV : 93.27%| |Avg. Precision: 89%| |Avg. Recall: 87%
  - Avg. F1: 87%| |AUC: 42.30%| |Runtime: Moderate, 18 minutes
- Overall: Both used maximum depth allotted in GridSearchCV. PCA model needed 25 more trees. PCA model less likely to have overfitted. This is just a bunch of decision trees so results being similar to DTC is no surprise. A con to this model is that it's a black box model where you can't see the calculation/voting process.

MODEL 5: LOGISTIC REGRESSION

- Used the Ridge Regularization due to the amount of rows. Had to prevent the overfitting of the coefficients.
- SKB Results:
  - Best Parameters: 8 features, C (inverse of regularization strength): 1e-05
  - Avg. CV : 90.73%| | Avg. Precision: 91%| |Avg. Recall: 91%
  - Avg. F1: 91%| |AUC: 43.22% | |Runtime: Fast, 2 mins
- PCA Results:
  - Best Parameter: C = 1e-05
  - Avg. CV : 83%| |Avg. Precision: 84%| |Avg. Recall: 84%
  - Avg. F1: 84%| | AUC: 37.85%| |Runtime: Faster, 9.2s
- Overall: SKB definitely is the superior model this time. The time difference is negligible. Performs slightly weaker than the other models but definitely the penalty has stopped this model from overfitting.

MODEL 6: GRADIENT BOOSTED MODEL

- SKB Results:
  - Best Parameters: 12 features, 1000 estimators, max depth of 6
  - Avg. CV : 99.85%| |Avg. Precision: 100%| |Avg. Recall: 100%
  - Avg. F1: 100%| |AUC: 0.12% | |Runtime: LONG, 8 hours
- PCA Results:
  - Best Parameters: 1000 estimators, 0.3 learning rate, max depth of 8
  - Avg. CV : 99.33%| |Avg. Precision: 66%| |Avg. Recall: 65%
  - Avg. F1: 64%| | AUC: 22.84%| |Runtime: Faster, 5 hours
- Overall: GB is a greedy learning model. Used the maximum amount of parameters to achieve the best score. Tried using a learning rate to inhibit overfitting but it wasn't effective. It would be a great model for prediction, but classifying limits its inherent strength.

WHERE IS SUPPORT VECTOR MACHINE?

- It took too long to run.
- Even tried to use a linear kernel but to no avail.

CONCLUSION

- In production, if only one model is allowed to be used to classify whether an activity is fraudulent or not:
  - PCA Random Forest is the way to go. Superior accuracy with a moderate calculation time.
  - Runner up: SKB Logistic Regression given its superior run time and moderate accuracy.

QUESTIONS?

Find the notebook at: https://github.com/lamka/Thinkful-Unit-3-Capstone/blob/master/Unit%203%20Capstone%20Project.ipynb