CREDITCARD FRAUD DETECTION

CAPSTONE PROJECT CONTRIBUTED BY

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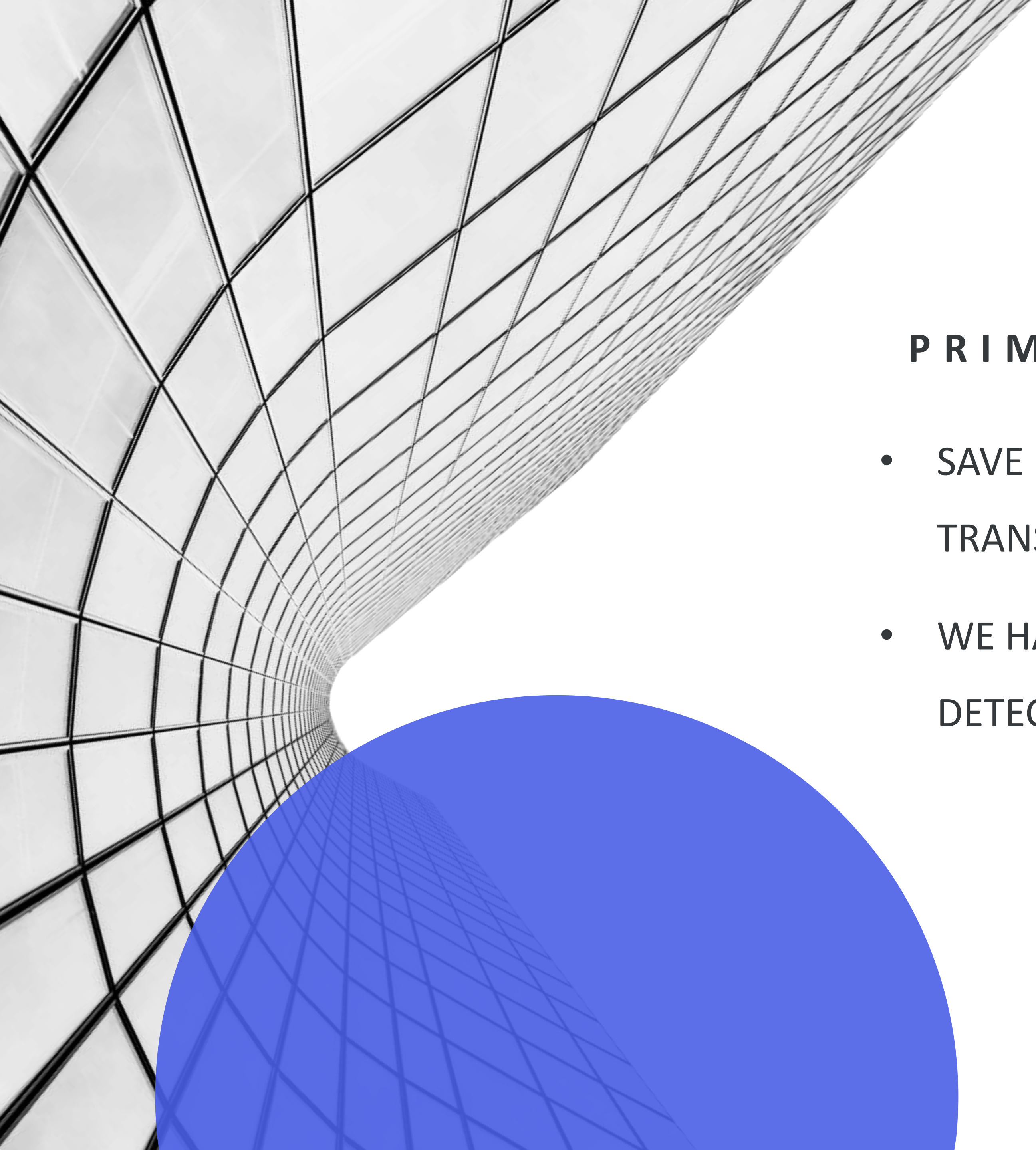
PROBLEM STATEMENT

Fraudulent activities have increased severalfold, with around 52,304 cases of credit/debit card fraud reported in FY'19 alone. Due to this steep increase in banking frauds, it is the need of the hour to detect these fraudulent transactions in time in order to help consumers as well as banks, who are losing their credit worth each day.

Every fraudulent credit card transaction that occur is a direct financial loss to the bank as the bank is responsible for the fraud transactions as well it also affects the overall customer satisfaction adversely.

The aim of this project is to identify and predict fraudulent credit card transactions using machine learning models.



PRIMARY GOALS

- SAVE BANKS FROM HIGH-VALUE FRAUDULENT TRANSACTIONS.
- WE HAVE TO FOCUS ON A HIGH RECALL IN ORDER TO DETECT ACTUAL FRAUDULENT TRANSACTIONS.

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APPROACH

The approach to the problem can be divided into below parts:

1. Data Understanding, Data Preparation and EDA

Class	0	1
Count	284315	492

First look at the data used here from the Kaggle dataset suggests that it is highly imbalanced in nature. The positive class (frauds) account for only 0.172% of all transactions:

Class is the target variable which we have to predict where 0 is normal transaction and 1 is fraudulent transaction.

Features V1, V2, … V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for exampledependant cost-senstive learning.

Since the PCA transformed variable are already Gausian, there is no need for normalisation.

We can start with the basic EDA like correlation, boxplots etc for outliers.

MODEL SELECTION AND MODEL BUILDING

We will start building the model with the train-test split. (At least 100 class 1 rows should be there in the test split), use the stratified split here. (80-20 ratio can be used) We need to find which ML model works good with the imbalance data and have better results on the test data.

- Logistic regression works best when the data is linearly separable and needs to be interpretable.

- KNN is also highly interpretable, but not preferred when we have a huge amount of data as it will consume a lot of computation.

- The decision tree model is the first choice when we want the output to be intuitive, but they tend to overfit if left unchecked.

- KNN is a simple, supervised machine learning algorithm used for both classification and regression tasks. The k value in KNN should be an odd number because you have to take the majority vote from the nearest neighbours by breaking the ties.

- In Gradient Boosted machines/trees. newly added trees are trained to reduce the errors (loss function) of earlier models.

- XGBoost is an extended version of gradient boosting, with additional features like regularization and parallel tree learning algorithm for finding the best split.

We will start with the Logistic regression model with the different value of regularisation and hyper param tuning, then go to the decision tree and so on etc. We will also try ensemble models and use votingclassifier, Bagging, Boosting etc on the best performing individual models to find the best model.

Hyperparameter Tuning:

- When the data is imbalanced or less, it is better to use K-Fold Cross Validation for evaluating the performance when the data set is randomly split into ‘k’ groups.
- Stratified K-Fold Cross Validation is an extension of K-Fold cross-validation, in which we rearrange the data to ensure that each fold is a good representative of all the strata of the data.

MODEL EVALUATION

We will use sklearn.metrics.roc_auc_score for this as AOC and ROC metric in sklearn is used as the metric for highly imbalanced data-set, rest all fails. ROC have better false negative than the false positives. ROC-Curve = Plot between TPR and FPR The threshold with highest value for TPR-FPR on the train set is usually the best cut-off. We should not use the confusion matrix as the performance metrics as well as they have internally defined hard threshold of 0.5. We also can’t completely rely on the precision, recall and F1-score for now as they also have their strings attached of some threshold value. ROC curve takes into cognizance of all the possible threshold values. The ROC curve is used to understand the strength of the model by evaluating the performance of the model at all the classification thresholds. Because the ROC curve is measured at all thresholds, the best threshold would be one at which the TPR is high and FPR is low, i.e., misclassifications are low.

SUMMARY

Cost-Benefit Analysis:

Depending on the use case, we have to account for what we need: high precision or high recall.

For banks with smaller average transaction value, we would want high precision because we only want to label relevant transactions as fraudulent. For every transaction that is flagged as fraudulent, you can add the human element to verify whether the transaction was done by calling the customer. However, when precision is low, such tasks are a burden because the human element has to be increased. For banks having a larger transaction value, if the recall is low, i.e., it is unable to detect transactions that are labelled as non-fraudulent. So consider the losses if the missed transaction was a high-value fraudulent one, for e.g., a transaction of $10,000? So here, to save banks from high-value fraudulent transactions, we have to focus on a high recall in order to detect actual fraudulent transactions. We need to determine how much profit or dollar/rupee value we are saving with our best selected model.