**MGT 6203 Project Proposal Team 36**

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Abstract

E-commerce fraud is defined as any type of fraudulent transactions that occur on e-commerce platforms. Many data mining techniques and machine learning algorithms can be used to detect fraudulent transactions based on various features about the transaction. This study is intended to test several machine learning classification techniques for determining if a transaction is fraudulent or not. Fraud Detection dataset from Kaggle is used in the research. The algorithms that we are planning to use are classification techniques like logistic regression, KNN, Random Forest, SVM etc. The aim is to find the best model that predicts the test data accurately. The results will be measured by confusion matrix and/or mean classification error.

Introduction

According to the new “State of Fraud 2023” study from fraud prevention solution provider Signifyd, the total cost of e-commerce fraud in 2023 will reach $206.8 billion. These frauds affect both companies as well as customers. Although most banks will reimburse fraudulent transaction cost, it gets passed to the customer. To identify and stop potential financial loss for both the businesses and their clients, high accuracy fraud detection is essential. Effective fraud detection can protect customer data and maintain trust between companies and their clients. In this project, we are using e-commerce transaction data to detect fraudulent transactions. The aim is to find out whether a transaction is fraud or not. Identifying this will help banks and payment providers alert their customers in case of suspicious activities, so they can block these transactions.

Literature Review

  The simplicity and ability to explain the model are typically ignored in favor of focusing on predictive performance. Most papers focus on predictive performance as opposed to the interpretation of the model - while predictive performance is important, interpreting a model is equally important to make critical business decisions. As fraud detection occurs in the financial services industry, many datasets will include masked columns for privacy concerns. Both Varmedja et al and Awoyemi et al used methods like Principal Component Analysis to keep the data anonymous. Due to this, they were able to make accurate predictions, but the model's interpretability suffered.

Fraud detection being a key factor in gaining and maintaining customer trust, businesses come up with various machine learning techniques to predict fraudulent transactions. Numerous researchers are trying their best to better the existing methods. Varmedja et al used machine learning techniques like logistic regression, Naïve Bayes, Random Forest and Multilayer perception to obtain high accuracy in credit card fraud detection. Awoyemi et al used Naïve Bayes, logistic regression and K-nearest neighbour techniques to obtain high predictive performance.

Most fraud detection datasets are imbalanced. An imbalanced dataset is a dataset where the number of records belonging to one class is much higher than the other. This usually occurs in the fraud detection use case as the number of fraudulent transactions are much lesser than that of the number of non-fraudulent ones. It is extremely important to balance the dataset to get good predictive performance. Varmedja et al used SMOTE technique to balance the dataset by a technique called oversampling where the records in the smaller class is increased in a balanced way to make sure that the samples of both classes are equal. While other research papers like Awoyemi et al explored a combination of oversampling and undersampling to achieve balance in the dataset.

Problem Statement and Data Sources

The datasets for this project are from [Kaggle](https://www.kaggle.com/datasets/vbinh002/fraud-ecommerce?select=Fraud_Data.csv). There are two datasets used here. First, a transaction dataset that contains the fraudulent as well as non-fraudulent transactions. Next, ip address to country cross reference table to find out the country associated with transactions in the transaction dataset. The objective of the assignment is to predict whether a transaction is fraudulent or not. Accurately predicting this will help increase the customers’ trust on the companies and help reduce losses for both the customers as well as the companies.

Planned Approach

Regarding data preparation, we plan to do some Exploratory Data Analysis to understand the raw data better. As a result, we may identify outliers, erroneous data or some cleaning tasks that need to be done prior to model training. After that, we will create features that may be found useful in model training. Indicator variables and encoding text variables as numbers or dummy variables may be done at this point.

Fraud detection datasets tend to be imbalanced as there are considerably more legitimate transactions than fraudulent ones. For this reason, we are thinking about balancing by under sampling legitimate transactions or by oversampling fraudulent ones. This serves the purpose of making more relevant the class that we are interested in identifying (frauds). We will experiment with different combinations of these techniques, especially SMOTE to synthesize new positive cases.

To test and compare various models, we will use K-fold Cross Validation (KCV) and F1 measure as the comparison metric. To use KCV we will need to split the data into K chunks instead of only splitting it into train and test sets as done when only one model will be tested. The decision to use F1 measure as metric comes from the article “A Gentle Introduction to Threshold-Moving for Imbalanced Classification” by Jason Brownlee. The precision-recall curve focuses on correctly identifying positive cases (which is what is desired in fraud detection models) and F1 measure is the harmonic mean between these 2 metrics.

A higher F1 indicates a better balance between precision and recall. This balance is the goal because we want to correctly identify a high percentage of frauds to mitigate losses, but we do not want to saturate clients by blocking their accounts/credit cards when they are making legitimate transactions.

This problem calls for classification models. We will start by testing logistic regression, random forest, KNN and SVM models. Many variations of these models may be tested along the way.

Progress, Analysis and Results

<Include EDA results. In-line figures. Include figure numbers, figure captions and notations in the text>

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