Credit Card Fraud Detection

https://github.com/Raihana90/Credit-Card-Fraud-Detection

Prepared By: TEAM 4: Giraffe Theory

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Problem Overview

Facts:

- About 270,000 cases of identity theft in the United States occurred in 2019.
- During the coronavirus pandemic the rate, of credit card fraud increased by 30%.

Problem:

- Early detection of fraudulent transaction at the time of occurrence is the best method for stopping credit card fraud as this reduces the liability for the customer, credit card company, and the merchant.

Goal:

- Create machine learning algorithms to classify fraudulent credit card transactions.

Solution Process

-Our dataset, obtained from Kaggle, consists of 284,807 credit card transactions, of which 492 (.172%) are fraudulent and 31 features (V1,V2,..., V28, Time, Amount, Class).

-The target feature is Class. It takes 1 in case of fraud and 0 otherwise.

-We apply 3 supervised machine learning algorithms (LR,RF,SVM) and ANN to obtain models predicting fraud.

STEP 01

Analyse Data:

We first acquired, analyzed, visualized the data and preprocessed it using the StandardScaler pipeline for the first 3 models.

STEP 02

Analytical Approach

4 different models were decided on to have a diverse selection: LR (RM),RF(MDS),SVM(ADP), ANN(MDS).

STEP 03

Models Preparation

We train the models on our split of training data.

STEP 04

Models Validation

Several measures were used in the validation. Accuracy, precision, f1 score and recall were all compared.

CLASSIFICATION MODELS COMPARISON

	LR	RF	SVM
	Testing	Testing	Testing
F1 Score	64%	93%	73%
Precision	86%	93%	85%
Recall	52%	93%	64%
Accuracy	99%	94%	99%

Key Insights

Key insight 1

The data consists of 248,807 classified instances of credit card transactions (fraud or not). The features are 28 anonymized and preprocessed (via PCA) attributes for each transaction due to confidentiality issues, except the time, the amount and the class.

Key insight 2

Due to the unbalanced nature of the data our 3 initial classification algorithms did not perform well uniformly well across performance measures.

Key insight 3

Following lackluster results from traditional classification, an ANN was trained and performed better than our 3 individual classification algorithms across the board.

Key insight 4

False negatives provide the greatest risk in practice and these account for unnoticed cases of credit card fraud the dangers of which are laid out in slide 3.

Key insight 5

When implementing the algorithms in practice, false positives cause some inconvenience to users -- for example accounts may be closed temporarily if fraud is suspected until the situation is cleared up.

Recommendations

Recommendation 1 (Done by MDS)

Artificial Neural Networks may have the potential to perform better at handling the unbalanced classification task than traditional algorithms.

Utilize an ANN.

Recommendation 2 (Done by ADP)

A further analysis can be done on those data points that give false negatives and a classification model can be fit for that case.

Handle false negatives.

Recommendation 3 (Done by RM)

Precision-recall curves and AUC are more appropriate for analyzing classifiers on unbalanced data sets.

Use PR-curve and AUC.

Comparison with Neural Network

- The idea here was to compare the previous models' results with a neural network.
- Instead of applying the usual train/test split to the heavily imbalanced data set, a random sample of 492 valid transactions were paired with the 492 fraudulent transactions to obtain a balanced (albeit undersampled) data set.
- The threshold for a valid transaction in this model was chosen to be 90%.*
- While ANN appeared to have performed worse in some categories, it had the lowest FNR (5.2%) when compared with the previous 3 models.**
- The FPR, on the other hand, was bout 9%. This is bad.***
- The AUC value for ANN was 0.9812

ANN

	Testing
F1 Score	91%
Precision	91%
Recall	90%
Accuracy	90%

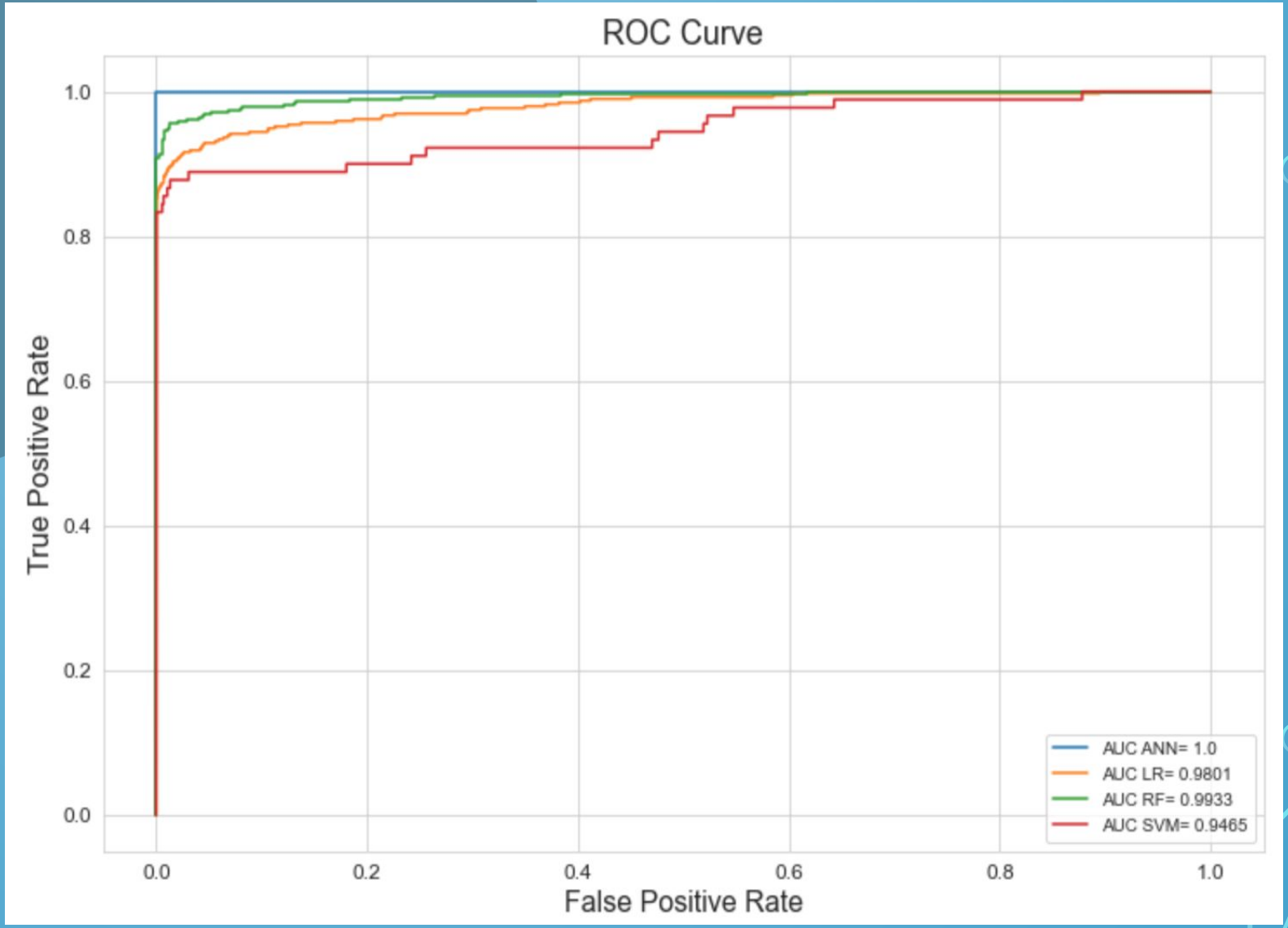
Further Information

- A false negative is a “worst case” for fraudulent credit card data.
- This corresponds to a fraudulent charge that isn’t detected and can lead to costs from the vendor who handled the charge, the credit card issuer, or the customer.

Recommendation

- A model that is more robust to the false negative error could be created. Some ideas for this are:
  - Holdout all the data points which resulted in negatives and create a new classifier that determines those false negatives. An ANN may be a good suggestion here as we’ve seen it handles the unbalanced classification well.
  - Reduce the dimensions of the holdout data set of false negatives and find the features that account for the most variability in this case.
  - Bootstrapping could be done to help alleviate the unbalanced nature of the data set.

Recommendations



Recommendations

Thank You!

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