Credit Card Fraud Detection

By Charmiece, Princy, Afreen, Prachi

Reason for selecting the topic

Using Python and Machine learning, we plan to detect credit card fraud. As eCommerce sales rise, payment fraud continues to plague customers and merchants. We all have been targeted or known someone whose been targeted. It'll be interesting to know how the companies detect when this happens. Also to try and see how credit card companies detect fraudulent websites. Online fraud has widespread business impacts and requires an effective end-to-end strategy to prevent account takeover (ATO), deter new account fraud, and stop suspicious payment transactions.

Description of the source of data

- fraudTrain.csv
- https://www.kaggle.com/code/chethanbr86/credit-card-fraud-capstone/data
- This is a simulated credit card transaction dataset containing legitimate and fraud transactions from the duration 1st Jan 2019 - 31st Dec 2020. It covers credit cards of 1000 customers doing transactions with a pool of 800 merchants. This was generated using Sparkov Data Generation | Github tool created by Brandon Harris. This simulation was run for the duration - 1 Jan 2019 to 31 Dec 2020. The files were combined and converted into a standard format.

Description of the data exploration

- We used fraud train csv to make a clean data csv to perform machine learning models.
- For the clean csv, we made an age column from the date of birth column using lambda function and then we took the index column, merchant column, merchant latitude and merchant longitude columns, amount column, category, unix time, is_fraud and gender columns.
- From this we performed multiple machine learning models including balanced random forest classifier, a SMOTE oversampling, undersampling, random oversampling and combination (over and under) sampling.
- We also extracted, transformed and loaded the data from aws to pgadmin.

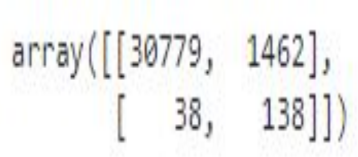
Questions we hope to answer with the data

1. When should the credit card companies shut off a card when it detects fraud?
2. What we are trying to accomplish through this data?
3. Which age group are targeted by credit card fraud?
4. Is women targeted more than man?
5. What locations frauds occur?
6. What areas do the company need to pay attention to in order to catch the detection?
7. what machine learning works the best?

Random Oversampling

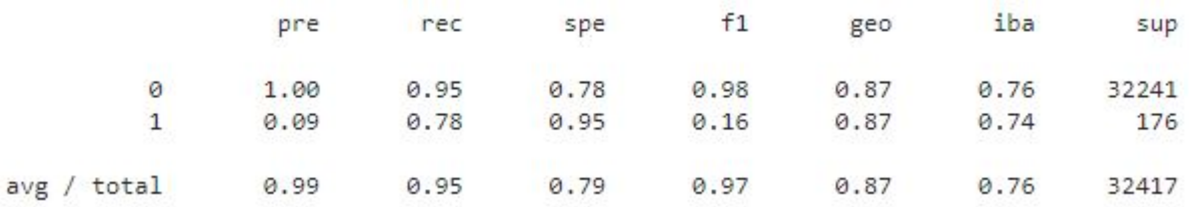
- In random oversampling, instances of the minority class are randomly selected and added to the training set until the majority and minority classes are balanced.
- The accuracy score was 87%. It matched with SMOTE and undersampling. It was a good model to run.

Confusion Matrix



```
array([[30779,  1462],
       [   38,   138]])
```

Classification Report

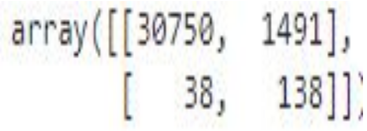


```
                   pre       rec       spe        f1       geo       iba       sup

          0       1.00      0.95      0.78      0.98      0.87      0.76     32241
          1       0.09      0.78      0.95      0.16      0.87      0.74       176

avg / total       0.99      0.95      0.79      0.97      0.87      0.76     32417
```

SMOTE Oversampling

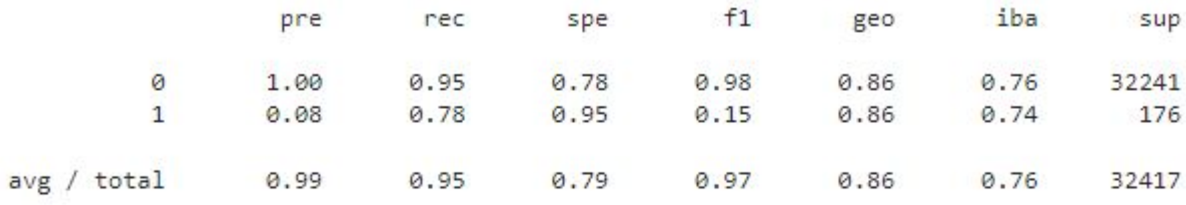
- The synthetic minority oversampling technique (SMOTE) is another oversampling approach to deal with unbalanced datasets. In SMOTE, like random oversampling, the size of the minority is increased.
- The accuracy score was 87%. It matched with Random oversampling and undersampling. It was a good model to run.

Confusion Matrix



```
array([[30750,  1491],
       [   38,   138]])
```

Classification Report

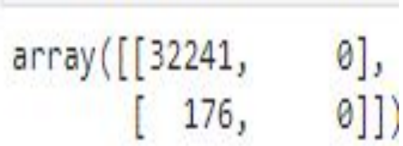


```
                   pre       rec       spe        f1       geo       iba       sup

          0       1.00      0.95      0.78      0.98      0.86      0.76     32241
          1       0.08      0.78      0.95      0.15      0.86      0.74       176

avg / total       0.99      0.95      0.79      0.97      0.86      0.76     32417
```

Undersampling

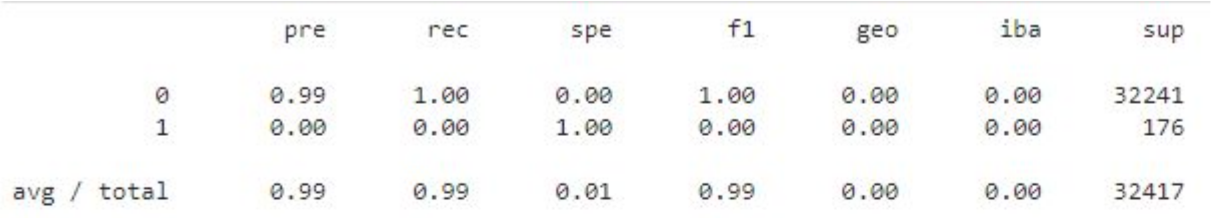
- Undersampling is another technique to address class imbalance. Undersampling takes the opposite approach of oversampling. Instead of increasing the number of the minority class, the size of the majority class is decreased.
- The accuracy score was 87%. It matched with SMOTE and Random Oversampling. It was a good model to run.

Confusion Matrix



```
array([[32241,     0],
       [  176,     0]])
```

Classification Report



```
                   pre       rec       spe        f1       geo       iba       sup

          0       0.99      1.00      0.00      1.00      0.00      0.00     32241
          1       0.00      0.00      1.00      0.00      0.00      0.00       176

avg / total       0.99      0.99      0.01      0.99      0.00      0.00     32417
```

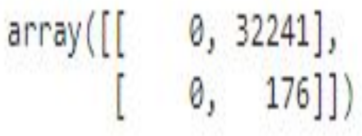
Combination (Over and Under) Sampling

- SMOTEENN combines the SMOTE and Edited Nearest Neighbors (ENN) algorithms. SMOTEENN is a two-step process:

1. Oversample the minority class with SMOTE.
2. Clean the resulting data with an undersampling strategy. If the two nearest neighbors of a data point belong to two different classes, that data point is dropped.

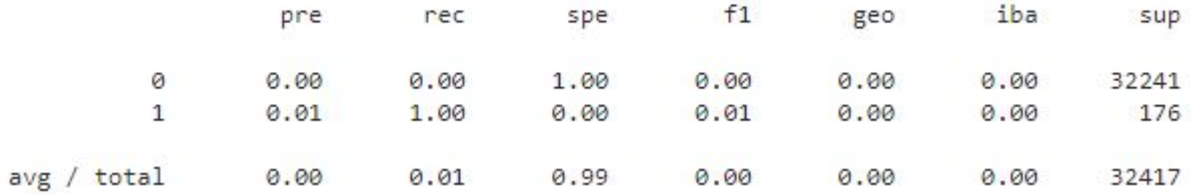
- The accuracy score was 50%.

Confusion Matrix



```
array([[    0, 32241],
       [    0,   176]])
```

Classification Report

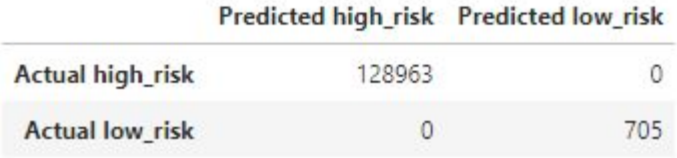


```
                   pre       rec       spe        f1       geo       iba       sup

          0       0.00      0.00      1.00      0.00      0.00      0.00     32241
          1       0.01      1.00      0.00      0.01      0.00      0.00       176

avg / total       0.00      0.01      0.99      0.00      0.00      0.00     32417
```

Balanced Random Forest Classifier

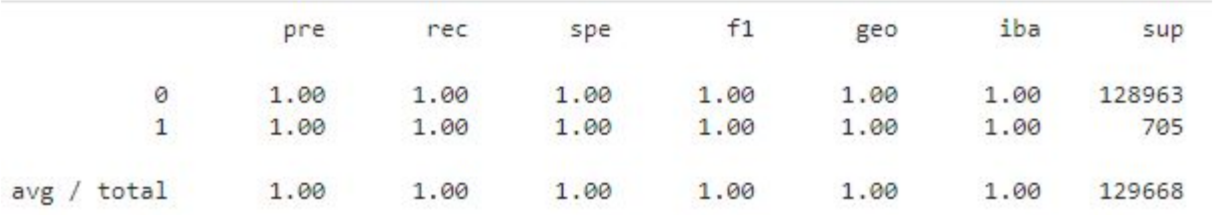
- Random forest algorithm will sample the data and build several smaller, simpler decision trees.
    1. Are robust against overfitting as all of those weak learners are trained on different pieces of the data.
    2. Can be used to rank the importance of input variables in a natural way.
    3. Can handle thousands of input variables without variable deletion.
    4. Are robust to outliers and nonlinear data.
    5. Run efficiently on large datasets.
- After cleaning the data we put the data to aws and connected it to google colab notebook and performed balanced random forest classifier machine learning model. The accuracy score was 100%.

Confusion matrix



	Predicted high_risk	Predicted low_risk
Actual high_risk	128963	0
Actual low_risk	0	705

Classification Report

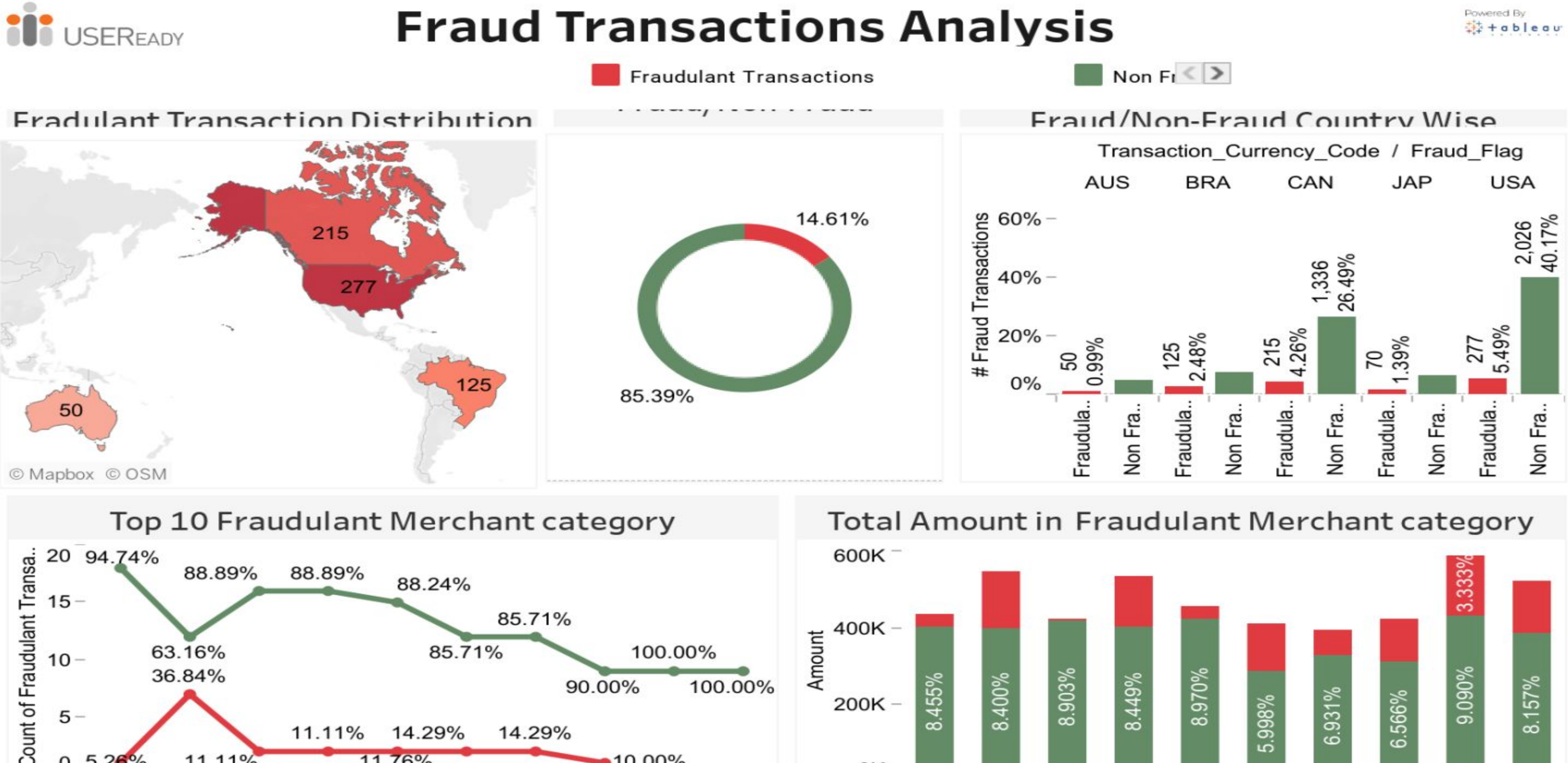


```
                   pre       rec       spe        f1       geo       iba       sup

          0       1.00      1.00      1.00      1.00      1.00      1.00    128963
          1       1.00      1.00      1.00      1.00      1.00      1.00       705

avg / total       1.00      1.00      1.00      1.00      1.00      1.00    129668
```

Dashboard

- We are gonna use tableau for our dashboard.
- We are going to create filters for different genders, age group, category, heatmaps and bar graph of fraud vs not fraud.

Dashboard contd….



Summary

- The Balanced Forest and the Combination were not good models because of the accuracy scores (100% and 50% respectively). Even though the SMOTE, Undersampling and Random Oversampling all had 87% accuracy scores, we would recommend SMOTE because it predicts both high and low risks as opposed to undersampling and combination.
- Fraud is a major problem for the whole credit card industry that grows bigger with the increasing popularity of electronic money transfers. To effectively prevent the criminal actions that lead to the leakage of bank account information leak, skimming, counterfeit credit cards, the theft of billions of dollars annually, and the loss of reputation and customer loyalty, credit card issuers should consider the implementation of advanced Credit Card Fraud Prevention and Fraud Detection methods. Machine Learning-based methods can continuously improve the accuracy of fraud prevention based on information about each cardholder’s behavior.