Credit Card Fraud Detection

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Introduction

- Fraudulent transactions can occur at anytime whether it is online or offline.
- 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.
- Through machine learning we are trying to increase the accuracy of detecting fraudulent 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.

Tools we used

Description of the data exploration

```python
# function to convert dob to years
def age_years(born):
    return 2022 - int(born[0:4])

# replacing the dob column with age column in our data set for test and train
data_train['age'] = data_train['dob'].apply(lambda x: age_years(x))
data_train.head()
```

y	amt	first	last	gender	street	...	long	city_pop	job	dob	trans_num	unix_time	merch_lat	merch_long	is_fraud	age
et	4.97	Jennifer	Banks	F	561 Perry Cove	...	-81.1781	3495	Psychologist, counselling	1988-03-09	0b242abb623afc578575680df30655b9	1325376018	36.011293	-82.048315	0	34
s	107.23	Stephanie	Gill	F	43039 Riley Greens Suite 393	...	-118.2105	149	Special educational needs teacher	1978-06-21	1f76529f8574734946361c461b024d99	1325376044	49.159047	-118.186462	0	44
nt	220.11	Edward	Sanchez	M	594 White Dale Suite 530	...	-112.2620	4154	Nature conservation officer	1962-01-19	a1a22d70485983eac12b5b88dad1cf95	1325376051	43.150704	-112.154481	0	60
rt	45.00	Jeremy	White	M	9443 Cynthia Court Apt. 038	...	-112.1138	1939	Patent attorney	1967-01-12	6b849c168bdad6f867558c3793159a81	1325376076	47.034331	-112.561071	0	55
s	41.96	Tyler	Garcia	M	408 Bradley Rest	...	-79.4629	99	Dance movement psychotherapist	1986-03-28	a41d7549acf90789359a9aa5346dcb46	1325376186	38.674999	-78.632459	0	36

```python
clean_train = data_train[['Unnamed: 0','merchant', 'category', 'amt', 'gender', 'unix_time', 'merch_lat', 'merch_long', 'is_fraud', 'age']]
clean_train.head()
```

	Unnamed: 0	merchant	category	amt	gender	unix_time	merch_lat	merch_long	is_fraud	age
0	0	fraud_Rippin, Kub and Mann	misc_net	4.97	F	1325376018	36.011293	-82.048315	0	34
1	1	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	F	1325376044	49.159047	-118.186462	0	44
2	2	fraud_Lind-Buckridge	entertainment	220.11	M	1325376051	43.150704	-112.154481	0	60
3	3	fraud_Kutch, Hermiston and Farrell	gas_transport	45.00	M	1325376076	47.034331	-112.561071	0	55
4	4	fraud_Keeling-Crist	misc_pos	41.96	M	1325376186	38.674999	-78.632459	0	36

```python
# 5. Export the Dataframe as a new CSV file without the index.
clean_train.to_csv("Resources/clean_data_train.csv", index=False)
```

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. Are women targeted more than men?
5. What locations do 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?

ERD Diagram

```
"Age Fraud"
-
index int pk
age int
fraud int



"Gender Fraud"
-
index int pk
gender obj
fraud int

"Location"
-
index int pk
fraud int
merchant obj
merch_lat int
merch_long int


"Fraud"
-
index int pk
fraud int
category obj
amt int
```

ETL

Connect to the AWS RDS instance and write each DataFrame to its table.

In [ ]:

```
# Configure settings for RDS
mode = "append"
jdbc_url="jdbc:postgresql://finalproject.cylfu7wfg2zs.us-east-1.rds.amazonaws.com:5432/final_DB"
config = {"user":"postgres",
          "password": "fraudcc1",
          "driver":"org.postgresql.Driver"}
```

In [ ]:

```
# Write age_fraud to table in RDS
age_fraud.write.jdbc(url=jdbc_url, table='age_fraud', mode=mode, properties=config)
```

In [ ]:

```
# Write gender_fraud to table in RDS
gender_fraud.write.jdbc(url=jdbc_url, table='gender_fraud', mode=mode, properties=config)
```

In [ ]:

```
# Write location_info to table in RDS
location_info.write.jdbc(url=jdbc_url, table='location_info', mode=mode, properties=config)
```

In [ ]:

```
# Write fraud_df to table in RDS
fraud_df.write.jdbc(url=jdbc_url, table='fraud_df', mode=mode, properties=config)
```

Balanced Random Forest Classifier

```
# Import dependencies
from imblearn.ensemble import BalancedRandomForestClassifier
from sklearn.metrics import balanced_accuracy_score
from imblearn.ensemble import EasyEnsembleClassifier
```

```
# Resample the training data with the BalancedRandomForestClassifier

rf_model = BalancedRandomForestClassifier(n_estimators=100, random_state=1)
rf_model = rf_model.fit(X,y)
print(rf_model)
```

```
BalancedRandomForestClassifier(random_state=1)
```

```
# Calculated the balanced accuracy score
y_pred = rf_model.predict(X)
balanced_accuracy_score(y, y_pred)
```

```
1.0
```

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

Confusion matrix

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

Logistic Regression Preprocessing : Random Oversampling

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=1, stratify=y)
X_train.shape
```

```
(97251, 715)
```

```
# Resample the training data with the RandomOversampler
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=1)
X_resampled, y_resampled = ros.fit_resample(X, y)
Counter(y_resampled)
```

```
Counter({0: 128963, 1: 128963})
```

```
# Train the  model using the data
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(solver='lbfgs', random_state=1)
model.fit(X_resampled, y_resampled)
```

```
LogisticRegression(random_state=1)
```

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

Confusion Matrix

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

Logistic Regression Pre-Processing :SMOTE Oversampling

```
# Resample the training data with SMOTE
from imblearn.over_sampling import SMOTE
X_resampled, y_resampled = SMOTE(random_state=1,
sampling_strategy='auto').fit_resample(
    X_train, y_train)
Counter(y_resampled)
```

```
Counter({0: 96722, 1: 96722})
```

```
# Train the Logistic Regression model using the resampled data
model = LogisticRegression(solver='lbfgs', random_state=1)
model.fit(X_resampled, y_resampled)

y_pred = model.predict(X_test)
```

```
# Calculated the balanced accuracy score
from sklearn.metrics import balanced_accuracy_score
balanced_accuracy_score(y_test, y_pred)
```

```
0.868922722620266
```

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

Confusion Matrix

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

Logistic Regression Preprocessing :Undersampling

```
# Resample the data using the ClusterCentroids resampler
# Warning: This is a large dataset, and this step may take some time to complete
from imblearn.under_sampling import ClusterCentroids
cc = ClusterCentroids(random_state=1)
X_resampled, y_resampled = cc.fit_resample(X_train, y_train)
```

```
# Train the Logistic Regression model using the resampled data
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(solver='lbfgs', random_state=1)
model.fit(X_resampled, y_resampled)
```

```
LogisticRegression(random_state=1)
```

```
# Calculated the balanced accuracy score
from sklearn.metrics import balanced_accuracy_score
balanced_accuracy_score(y_test, y_pred)
```

```
0.868922722620266
```

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

Confusion Matrix

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

Logistic Regression Preprocessing :Combination (Over and Under) Sampling

```
# Resample the training data with SMOTEENN
# Warning: This is a large dataset, and this step may take some time to complete
from imblearn.combine import SMOTEENN
smote_enn = SMOTEENN(random_state=0)
X_resampled, y_resampled = smote_enn.fit_resample(X, y)
```

```
# Train the Logistic Regression model using the resampled data
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(solver='lbfgs', random_state=1)
model.fit(X_resampled, y_resampled)
```

```
LogisticRegression(random_state=1)
```

```
# Calculated the balanced accuracy score
from sklearn.metrics import balanced_accuracy_score
balanced_accuracy_score(y_test, y_pred)
```

```
0.5
```

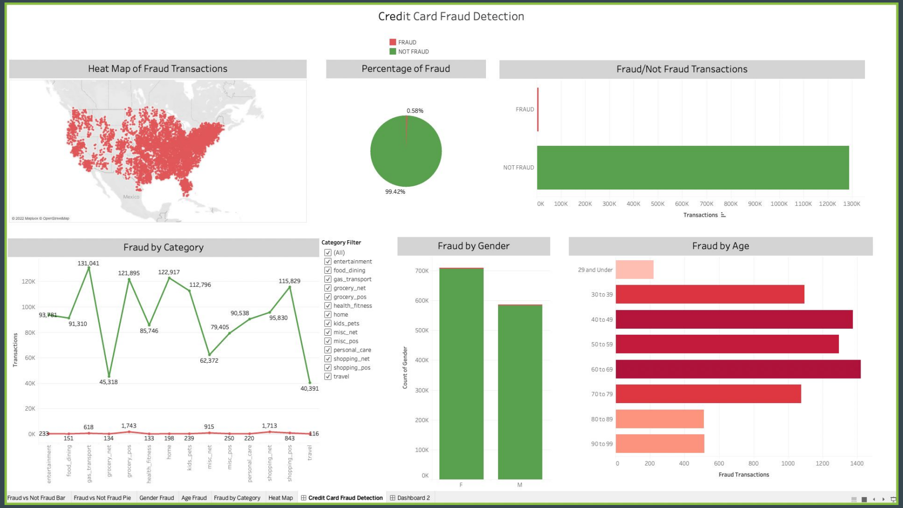
Confusion Matrix

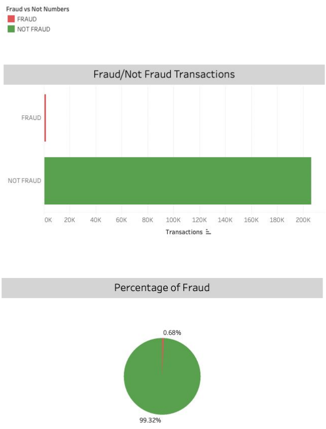
```
array([[    0, 32241],
       [    0,   176]])
```

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

Dashboard





SMOTE Oversampling

The synthetic minority oversampling technique (SMOTE) is another oversampling approach to deal with unbalanced datasets. In SMOTE, like random oversampling, size of the minority is increased.

```
In [ ]:
# Resample the training data with SMOTE
from imblearn.over_sampling import SMOTE
X_resampled, y_resampled = SMOTE(random_state=1,
sampling_strategy='auto').fit_resample(
   X_train, y_train)
Counter(y_resampled)

Out[ ]: Counter({0: 96722, 1: 96722})

In [ ]:
# Train the Logistic Regression model using the resampled data
model = LogisticRegression(solver='lbfgs', random_state=1)
model.fit(X_resampled, y_resampled)

y_pred = model.predict(X_test)

In [ ]:
# Calculated the balanced accuracy score
from sklearn.metrics import balanced_accuracy_score
balanced_accuracy_score(y_test, y_pred)

Out[ ]: 0.868922722620266

In [ ]:
# Display the confusion matrix
from sklearn.metrics import confusion_matrix
y_pred = model.predict(X_test)
confusion_matrix(y_test, y_pred)

Out[ ]: array([[30750,  1491],
       [   38,   138]])

In [ ]:
# Print the imbalanced classification report
print(classification_report_imbalanced(y_test, y_pred))

                   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
```

Logistic Regression with SMOTE preprocessing was our most accurate model. However, even with a smaller sample we took to run the model is fraud prediction was way higher at 8% compared to actual is fraud in the actual dataset at 0.58%. Logistic Regression would not be a good model for credit card fraud detection.

Summary

- Our goal was to find a machine learning model that helped detect when credit card companies should shut off credit cards due to fraudulent activity. We use Balance Random Forest Classifier which gave us a 50% accuracy. This was not a good model due to the data showing less than 1% of the transactions being fraud. The second model we used was Logistic Regression. We preformed SMOTE, Combination (SMOTEEN), Undersampling and Random Oversampler. Logistic Regression with SMOTE preprocessing was our most accurate model. However, even with a smaller sample we took to run the model is fraud prediction was way higher at 8% compared to actual is fraud in the actual dataset at 0.58%. Logistic Regression would not be a good model for credit card fraud detection.
- From the analysis, ages 40 to 70 were the most targeted for fraud. Based on the number of transactions, men were targeted more than women for fraud. According to our dataset, more fraud transactions occurred on the east coast versus the west coast. The areas that credit card companies should focus on are grocery stores and online shopping.