HW 5

February 9, 2024

1 0.) Import the Credit Card Fraud Data From CCLE

[43]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[44]:
```
df = pd.read_csv("fraudTest.csv")
```

[45]:
```
df.head()
```

[45]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                              merchant        category    amt   first  \
0                 fraud_Kirlin and Sons    personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler    personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  …      lat      long  \
0   Elliott      M            351 Darlene Green  …  33.9659  -80.9355
1  Williams      F             3638 Marsh Union  …  40.3207 -110.4360
2     Lopez      F         9333 Valentine Point  …  40.6729  -73.5365
3  Williams      M  32941 Krystal Mill Apt. 552  …  28.5697  -80.8191
4    Massey      M     5783 Evan Roads Apt. 465  …  44.2529  -85.0170

   city_pop                        job         dob  \
0    333497      Mechanical engineer  1968-03-19
1       302  Sales professional, IT  1990-01-17
2     34496        Librarian, public  1970-10-21
3     54767            Set designer  1987-07-25
4      1126      Furniture designer  1955-07-06
```

```
                          trans_num   unix_time  merch_lat  merch_long  \
0  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714
1  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498 -109.960431
2  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111
3  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061
4  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734

   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

[110]:
```python
# Select columns and create a new DataFrame
df_select = df[["trans_date_trans_time", "category", "amt", "city_pop", "is_fraud"]].copy()

# Convert 'trans_date_trans_time' column to datetime
df_select["trans_date_trans_time"] = pd.to_datetime(df_select["trans_date_trans_time"])

# Extract seconds from 'trans_date_trans_time' and assign to 'time_var' column
df_select["time_var"] = df_select["trans_date_trans_time"].dt.second

# Drop 'trans_date_trans_time' and 'is_fraud' columns, and create dummy variables for 'category'
X = pd.get_dummies(df_select, columns=["category"], drop_first=True).drop(["trans_date_trans_time", "is_fraud"], axis=1)
y = df_select["is_fraud"]
```

2 1.) Use scikit learn preprocessing to split the data into 70/30 in out of sample

[47]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[48]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .3)
```

[49]:
```python
X_test, X_holdout, y_test, y_holdout = train_test_split(X_test, y_test, test_size = .5)
```

[50]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_holdout = scaler.transform(X_holdout)
```

3 2.) Make three sets of training data (Oversample, Undersample and SMOTE)

[51]:
```
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
```

[55]:
```
X_train = pd.DataFrame(X_train)
X_train.columns = X.columns
```

[56]:
```
y_train = pd.DataFrame(y_train)
y_train
```

[56]:
```
        is_fraud
351086         0
503342         0
67219          0
229954         0
185028         0
…            …
68395          0
547112         0
95577          0
443034         0
321035         0

[389003 rows x 1 columns]
```

[57]:
```
ros = RandomOverSampler()
over_X, over_y = ros.fit_resample(X_train, y_train)

rus = RandomUnderSampler()
under_X, under_y = rus.fit_resample(X_train, y_train)

smote = SMOTE()
smote_X, smote_y = smote.fit_resample(X_train, y_train)
```

4 3.) Train three logistic regression models

[58]:
```
from sklearn.linear_model import LogisticRegression
```

[111]:
```
over_log = LogisticRegression().fit(over_X, over_y)
under_log = LogisticRegression().fit(under_X, under_y)
smote_log = LogisticRegression().fit(smote_X, smote_y)
```

5 4.) Test the three models

[112]:
```
over_log.score(X_test, y_test)
```

[112]:
```
0.9036685141198205
```

[113]:
```
under_log.score(X_test, y_test)
```

[113]:
```
0.9077593032462391
```

[114]:
```
smote_log.score(X_test, y_test)
```

[114]:
```
0.9001655509969049
```

6 5.) Which performed best in Out of Sample metrics?

[115]:
```
from sklearn.metrics import confusion_matrix
```

[116]:
```
y_true = y_test
```

[117]:
```
y_pred = over_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[117]:
```
array([[75081,  7959],
       [   71,   247]])
```

[118]:
```
print("Over Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
Over Sample Sensitivity :  0.7767295597484277
```

[119]:
```
y_pred = under_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[119]:
```
array([[75423,  7617],
       [   72,   246]])
```

[120]:
```
print("Under Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
Under Sample Sensitivity :  0.7735849056603774
```

[121]:
```
y_pred = smote_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[121]:
```
array([[74789,  8251],
       [   71,   247]])
```

[122]:
```
print("SMOTE Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
SMOTE Sample Sensitivity :  0.7767295597484277
```

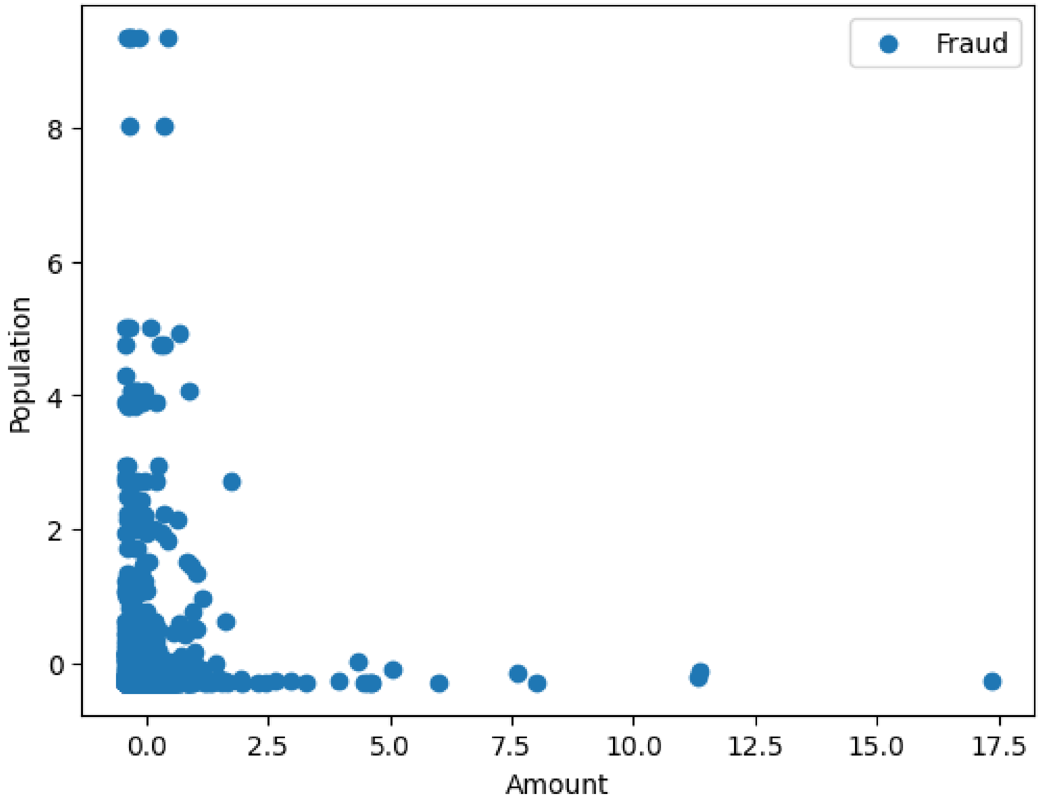
7 6.) Pick two features and plot the two classes before and after SMOTE.

[123]:
```
# Concatenate them along the specified axis
raw_temp = pd.concat([X_train, y_train], axis =1)
```

[124]:
```
#plt.scatter(raw_temp[raw_temp["is_fraud"] == 0]["amt"],␣
↪raw_temp[raw_temp["is_fraud"] == 0]["city_pop"])

plt.scatter(raw_temp[raw_temp["is_fraud"] == 1]["amt"],␣
↪raw_temp[raw_temp["is_fraud"] == 1]["city_pop"])
plt.legend(["Fraud", "Not Fraud"])
plt.xlabel("Amount")
plt.ylabel("Population")

plt.show()
```

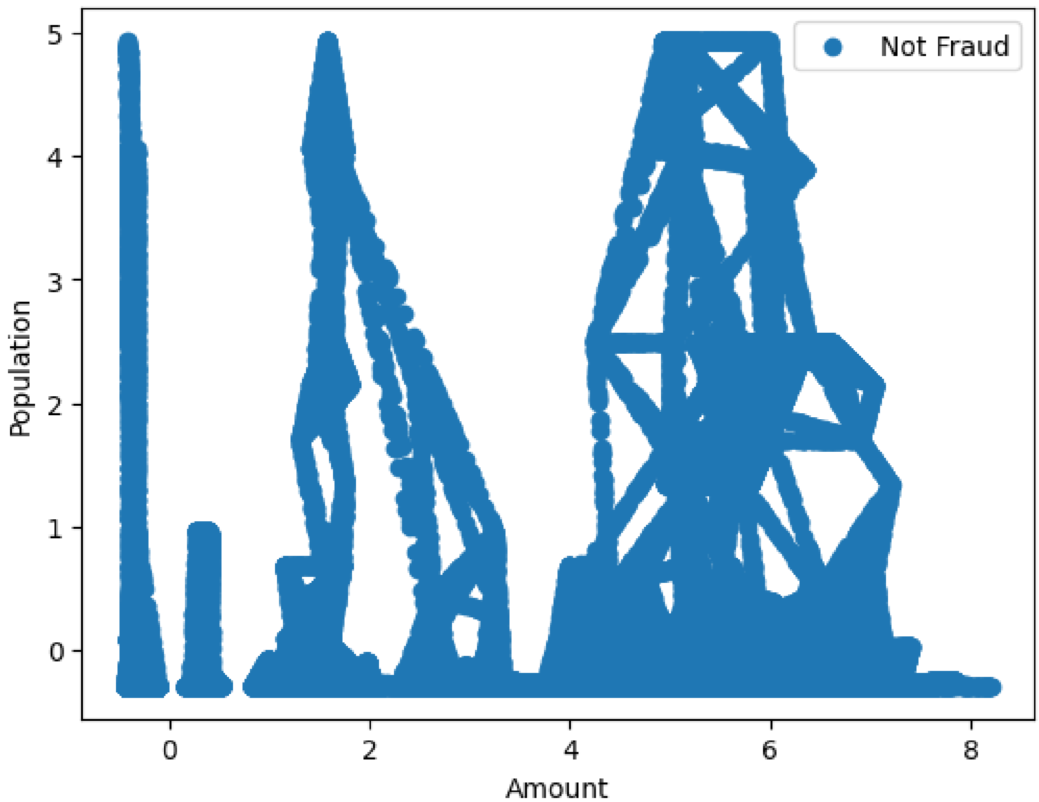


[125]:
```
raw_temp = pd.concat([smote_X, smote_y], axis =1)
```

[126]:
```
#plt.scatter(raw_temp[raw_temp["is_fraud"] == 0]["amt"],␣
 ↪raw_temp[raw_temp["is_fraud"] == 0]["city_pop"])

plt.scatter(raw_temp[raw_temp["is_fraud"] == 1]["amt"],␣
 ↪raw_temp[raw_temp["is_fraud"] == 1]["city_pop"])
plt.legend([ "Not Fraud", "Fraud"])
plt.xlabel("Amount")
plt.ylabel("Population")

plt.show()
```


Not Fraud
Population
Amount
5
4
3
2
1
0
0
2
4
6
8

8 7.) We want to compare oversampling, Undersampling and SMOTE across our 3 models (Logistic Regression, Logistic Regression Lasso and Decision Trees).

9 Make a dataframe that has a dual index and 9 Rows.

10 Calculate: Sensitivity, Specificity, Precision, Recall and F1 score. for out of sample data.

11 Notice any patterns across perfomance for this model. Does one totally out perform the others IE. over/under/smote or does a model perform better DT, Lasso, LR?

12 Choose what you think is the best model and why. test on Holdout

[127]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
 ↪f1_score
import pandas as pd
```

[128]:
```
resampling_methods = {
    "over": RandomOverSampler(),
    "under": RandomUnderSampler(),
    "smote": SMOTE(),
    }

model_configs = {
        "LOG" : LogisticRegression(),
        "LASSO" : LogisticRegression(penalty = "l1",
                                    C =2., solver ="liblinear"),
        "DTREE" : DecisionTreeClassifier()
    }
```

[129]:
```
def calc_perf_metric(y_trye, y_pred):
    tn,fp,fn,tp = confusion_matrix(y_true, y_pred).ravel()
    sensitivity = tp/(tp+fn)
    specificity = tn/(tn+fp)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    return(sensitivity, specificity, precision, recall, f1)
```

[130]:
```
trained_models = {}
results = []
```

[131]:

```python
for resample_key, resampler in resampling_methods.items():
    resample_X, resample_y = resampler.fit_resample(X_train, y_train)

    for model_key, model in model_configs.items():
        combined_key = f"{resample_key}_{model_key}"
        m = model.fit(resample_X, resample_y)
        trained_models[combined_key] = m

        # Predict using the trained model
        y_pred = trained_models[combined_key].predict(X_test)

        # Calculate performance metrics
        sensitivity, specificity, precision, recall, f1 =␣
 ↪calc_perf_metric(y_test, y_pred)
        holdout = m.score(X_holdout, y_holdout)
        # Append results to the result list
        results.append({
            "Model": combined_key,
            "Sensitivity": sensitivity,
            "Specificity": specificity,
            "Precision": precision,
            "Recall": recall,
            "F1": f1,
            "Holdout": holdout
        })


        print(combined_key)
```

```
over_LOG
over_LASSO
over_DTREE
under_LOG
under_LASSO
under_DTREE
smote_LOG
smote_LASSO
smote_DTREE
```

[133]:

```python
results_df = pd.DataFrame(results)
results_df
```

[133]:

```
         Model  Sensitivity  Specificity  Precision    Recall        F1  \
0     over_LOG     0.776730     0.903504   0.029903  0.776730  0.057589
1   over_LASSO     0.776730     0.903613   0.029936  0.776730  0.057650
2   over_DTREE     0.547170     0.998386   0.564935  0.547170  0.555911
3    under_LOG     0.776730     0.898784   0.028548  0.776730  0.055072
4  under_LASSO     0.776730     0.898374   0.028437  0.776730  0.054865
```

```
5  under_DTREE     0.962264     0.946484   0.064421  0.962264  0.120758
6    smote_LOG     0.776730     0.902469   0.029595  0.776730  0.057018
7  smote_LASSO     0.776730     0.902505   0.029606  0.776730  0.057037
8  smote_DTREE     0.663522     0.993064   0.268107  0.663522  0.381900

    Holdout
0  0.903573
1  0.903669
2  0.996845
3  0.898006
4  0.897490
5  0.947815
6  0.902541
7  0.902553
8  0.992310
```

The decision tree model trained on the under-sampled data (under_DTREE) is the best model due to its high F1-score, sensitivity, and consistency in performance across various metrics and sampling methods. It demonstrates effectiveness in identifying fraudulent transactions while maintaining a reasonable balance between precision and recall.

Logistic regression consistently provides stable results across various resampling methods, demonstrating robustness to different data characteristics. Its sensitivity and F1-score exhibit minimal variation, indicating reliability in performance. This consistency suggests potential for better out-of-sample performance. The similarity between logistic regression and Lasso may stem from differences in their underlying models. Although decision tree models achieve high scores in several categories, they show variance between metrics and sampling methods.

12.0.1 Testing on Holdout

[139]:
```python
resample_X_holdout, resample_y_holdout = smote.fit_resample(X_train, y_train)
log_reg = LogisticRegression()
model_holdout = log_reg.fit(resample_X_holdout, resample_y_holdout)
y_pred_holdout = model_holdout.predict(X_holdout)
tn, fp, fn, tp = confusion_matrix(y_holdout, y_pred_holdout).ravel()
sensitivity = tp/(tp+fn)
specificity = tn/(tn+fp)
precision = precision_score(y_holdout, y_pred_holdout)
recall = recall_score(y_holdout, y_pred_holdout)
f1 = f1_score(y_holdout, y_pred_holdout)
results_holdout = ({"Model Name" : "SMOTE_Logistic",
                        "Sensitivity" : sensitivity,
                        "Specificity" : specificity,
                        "Precision" : precision,
                        "Recall" : recall,
                        "F-1 Score" : f1})

results_holdout_df = pd.DataFrame([results_holdout])
```

```
print(results_holdout_df)
```

```
       Model Name  Sensitivity  Specificity  Precision    Recall  F-1 Score
0  SMOTE_Logistic     0.733542     0.901576   0.027834  0.733542   0.053633
```

The performance on the holdout data aligns with expectations, with metrics generally performing well compared to those on the in-sample data. This reinforces the earlier observation that logistic regression stands out as the most consistent model, providing reliable results even on unseen data. Its sensitivity, reaching nearly 75%, surpasses all other models, highlighting its effectiveness in correctly identifying positive cases. Overall, logistic regression emerges as the preferred choice for its consistent performance and superior sensitivity on out-of-sample data.

[ ]:
```
import warnings
from sklearn.exceptions import DataConversionWarning

# Suppress warnings
warnings.filterwarnings(action='ignore', category=UserWarning)
warnings.filterwarnings(action='ignore', category=DataConversionWarning)
```