HW #5

February 9, 2024

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

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

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

[45]:
```python
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]:
```
# 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]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

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

[49]:
```
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

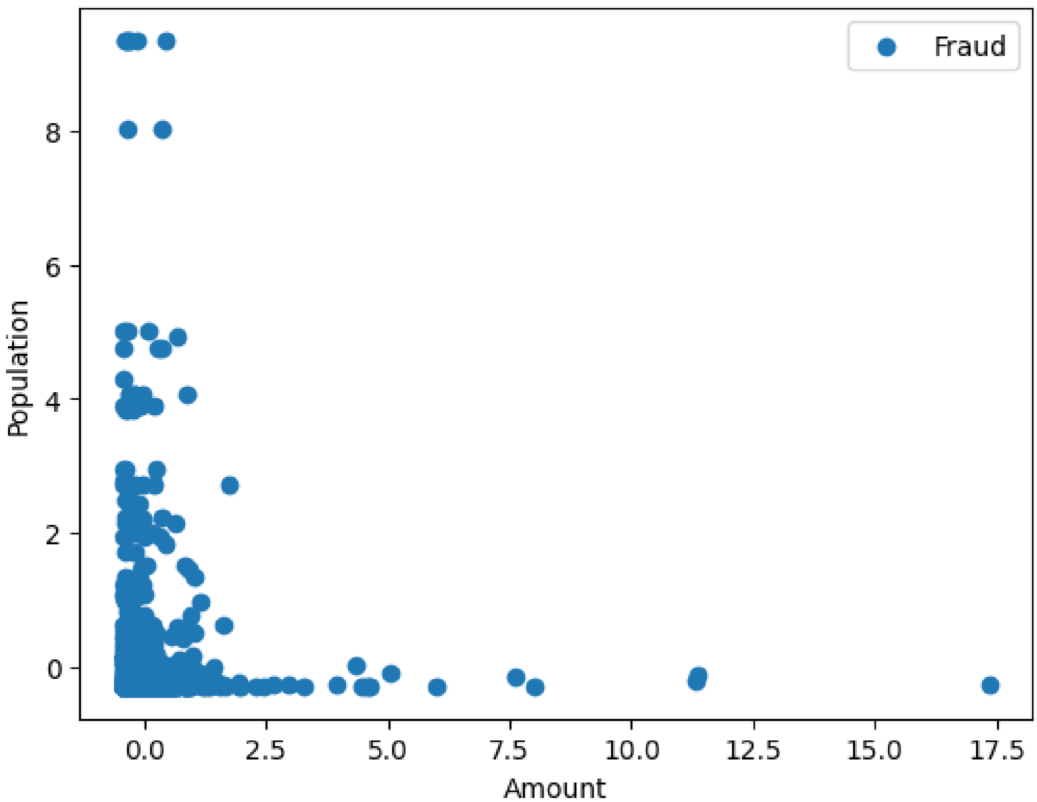
7 6.) Pick two features and plot the two classes before and after SMOTE.

[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()
```

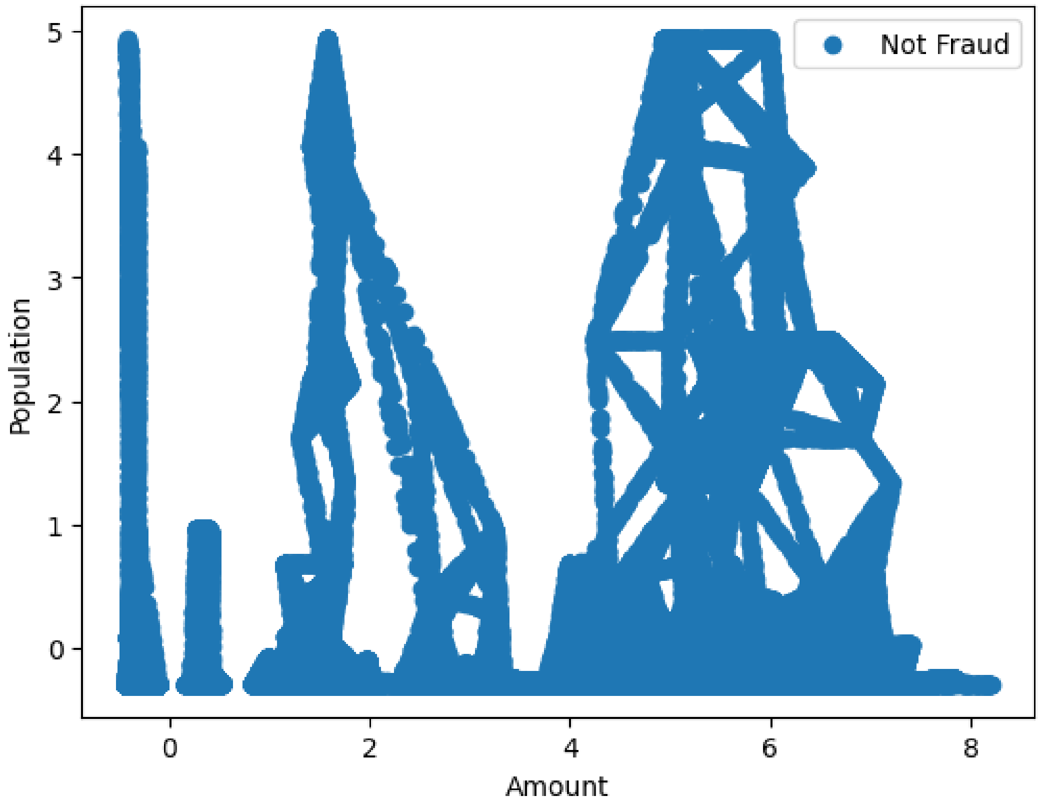


[125]:
```
raw_temp = pd.concat([smote_X, smote_y], axis =1)
```

[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()
```



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

- Make a dataframe that has a dual index and 9 Rows.
- Calculate: Sensitivity, Specificity, Precision, Recall and F1 score. for out of sample data.
- 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?
- 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]:
```
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
        })
```

```python
        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	Holdout
0	over_LOG	0.776730	0.903504	0.029903	0.776730	0.057589	0.903573
1	over_LASSO	0.776730	0.903613	0.029936	0.776730	0.057650	0.903669
2	over_DTREE	0.547170	0.998386	0.564935	0.547170	0.555911	0.996845
3	under_LOG	0.776730	0.898784	0.028548	0.776730	0.055072	0.898006
4	under_LASSO	0.776730	0.898374	0.028437	0.776730	0.054865	0.897490
5	under_DTREE	0.962264	0.946484	0.064421	0.962264	0.120758	0.947815
6	smote_LOG	0.776730	0.902469	0.029595	0.776730	0.057018	0.902541
7	smote_LASSO	0.776730	0.902505	0.029606	0.776730	0.057037	0.902553
8	smote_DTREE	0.663522	0.993064	0.268107	0.663522	0.381900	0.992310

The decision tree model trained on the under-sampled data (under_DTREE) emerges as the top-performing model, showcasing commendable F1-score, sensitivity, and consistent performance across diverse metrics and sampling techniques. It effectively identifies fraudulent transactions while maintaining a balanced trade-off between precision and recall.

Logistic regression consistently yields reliable results across various resampling methods, demonstrating resilience to different data characteristics. Its sensitivity and F1-score exhibit minimal fluctuations, indicating stable performance. This steadfastness suggests potential for superior out-of-sample performance. The resemblance between logistic regression and Lasso may arise from disparities in their underlying models. Despite decision tree models achieving high scores in numerous categories, they demonstrate variance across metrics and sampling approaches.

8.0.1 Testing on Holdout

[139]:
```
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 outcomes on the holdout dataset are in line with anticipated results, with metrics generally exhibiting strong performance compared to those on the in-sample dataset. This reaffirms the earlier observation that logistic regression remains the most dependable model, offering consistent outcomes even when dealing with unseen data. With its sensitivity reaching close to 75%, logistic regression outperforms all other models, underscoring its efficacy in accurately detecting positive cases. In summary, logistic regression emerges as the preferred option due to 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)
```