Week 5 Coursework - Adrian

February 8, 2024

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

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

[2]:
```
df = pd.read_csv("/Users/adrianonggowarsito/Desktop/fraudTest.csv")
```

[3]:
```
df.head()
```

[3]:
```
   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]
```

[4]:
```
df_select = df.copy()
```

[5]:
```
df_select = df_select[
    ["trans_date_trans_time", "category", "amt", "city_pop", "is_fraud"]
]
```

[6]:
```
df_select["trans_date_trans_time"] = pd.to_datetime(
    df_select.trans_date_trans_time
)
```

[7]:
```
df_select["time_var"] = [
    i.second for i in df_select["trans_date_trans_time"]
]
```

[8]:
```
X = pd.get_dummies(df_select, columns=["category"])
X = X.drop(["trans_date_trans_time", "is_fraud"], axis = 1)
```

[9]:
```
y = df["is_fraud"]
```

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

[10]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[11]:
```
# Splitting the data between training and testing.
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.3,
```

```
    random_state=999
)
```

[12]:
```
# Splitting the testing data between testing and holdout.
X_test, X_holdout, y_test, y_holdout = train_test_split(
    X_test, y_test,
    test_size=0.5
)
```

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

[13]:
```
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
```

[14]:
```
# Create the oversampled training data
over_sampler = RandomOverSampler(random_state=999)
X_over, y_over = over_sampler.fit_resample(X_train, y_train)

# Create the undersampled training data
under_sampler = RandomUnderSampler(random_state=999)
X_under, y_under = under_sampler.fit_resample(X_train, y_train)

# Apply SMOTE to your training data
smote = SMOTE(random_state=999)
smote_X, smote_y = smote.fit_resample(X_train, y_train)
```

4 3.) Train three logistic regression models

[15]:
```
# Define the pipeline for the logistic regression model with oversampling
log_over = Pipeline([
    ('scaler', StandardScaler()),
    ('model', LogisticRegression(random_state=999))
])
# Fit the model on the oversampled dataset
log_over.fit(X_over, y_over)
```

[15]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('model', LogisticRegression(random_state=999))])
```

[16]:
```
# Define the pipeline for the logistic regression model with undersampling
log_under = Pipeline([
```

```
    ('scaler', StandardScaler()),
    ('model', LogisticRegression(random_state=999))
])
# Fit the model on the undersampled dataset
log_under.fit(X_under, y_under)
```

[16]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('model', LogisticRegression(random_state=999))])
```

[17]:
```
# Define the pipeline for the logistic regression model with SMOTE
log_smote = Pipeline([
    ('scaler', StandardScaler()),
    ('balancer', SMOTE(random_state=999)),
    ('model', LogisticRegression(random_state=999))
])
# Fit the model on the original training dataset since SMOTE is part of the␣
 ↪pipeline
log_smote.fit(X_train, y_train)
```

[17]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('balancer', SMOTE(random_state=999)),
                ('model', LogisticRegression(random_state=999))])
```

5 4.) Test the three models

[18]:
```
def print_scores(x, y, over, under, smote, title = 'Out of Sample'):
    # Calculating the score
    over = over.score(x, y)
    under = under.score(x, y)
    smote = smote.score(x, y)

    temp = f"""
    Test Scores for {title}
    Accuracy
    --------
    - Over Sample: {over:.4f}
    - Under Sample: {under:.4f}
    - SMOTE: {smote:.4f}
    """
    print(temp)
```

Testing the three models in-sample.

[19]:
```
print_scores(
    X_train, y_train,
    log_over, log_under, log_smote,
    title = 'In-Sample'
```

```
)
```

```
Test Scores for In-Sample
Accuracy
--------
- Over Sample: 0.9126
- Under Sample: 0.8948
- SMOTE: 0.9067
```

Testing the three models out-sample.

[20]:
```
print_scores(
    X_test, y_test,
    log_over, log_under, log_smote,
    title = 'Out-Sample'
)
```

```
Test Scores for Out-Sample
Accuracy
--------
- Over Sample: 0.9116
- Under Sample: 0.8949
- SMOTE: 0.9062
```

[21]:
```
# We see SMOTE performing with higher accuracy but is ACCURACY really the best␣
↪measure?
```

Accuracy is not the best measure for this dataset. We are more concerned about to detect fraud, so we want to maximize the number of true positives and minimize the number of false negatives. In other words, we want to maximize the sensitivity (recall) and minimize the false negative rate.

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

[22]:
```
print_scores(
    X_holdout, y_holdout,
    log_over, log_under, log_smote,
    title = 'HoldOut-Sample'
)
```

```
Test Scores for HoldOut-Sample
Accuracy
--------
- Over Sample: 0.9138
- Under Sample: 0.8959
```

```
- SMOTE: 0.9079
```

Analyzing the out of sample and holdout accuracy, we see that oversample is better, followed by SMOTE.

[23]:
```
# Sensitivity here in credit fraud is more important as seen from last class
```

[24]:
```
from sklearn.metrics import confusion_matrix
```

[25]:
```
y_true = y_test
```

[26]:
```
# Assuming y_test is already defined

# Over-sampling model predictions and sensitivity
y_pred_over = log_over.predict(X_test)
cm_over = confusion_matrix(y_test, y_pred_over)
print("Over Sample Sensitivity : ", cm_over[1,1] / (cm_over[1,0] +␣
↪cm_over[1,1]))

# Under-sampling model predictions and sensitivity
y_pred_under = log_under.predict(X_test)
cm_under = confusion_matrix(y_test, y_pred_under)
print("Under Sample Sensitivity : ", cm_under[1,1] / (cm_under[1,0] +␣
↪cm_under[1,1]))

# SMOTE model predictions and sensitivity
y_pred_smote = log_smote.predict(X_test)
cm_smote = confusion_matrix(y_test, y_pred_smote)
print("SMOTE Sample Sensitivity : ", cm_smote[1,1] / (cm_smote[1,0] +␣
↪cm_smote[1,1]))
```

```
Over Sample Sensitivity :  0.70625
Under Sample Sensitivity :  0.70625
SMOTE Sample Sensitivity :  0.709375
```

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

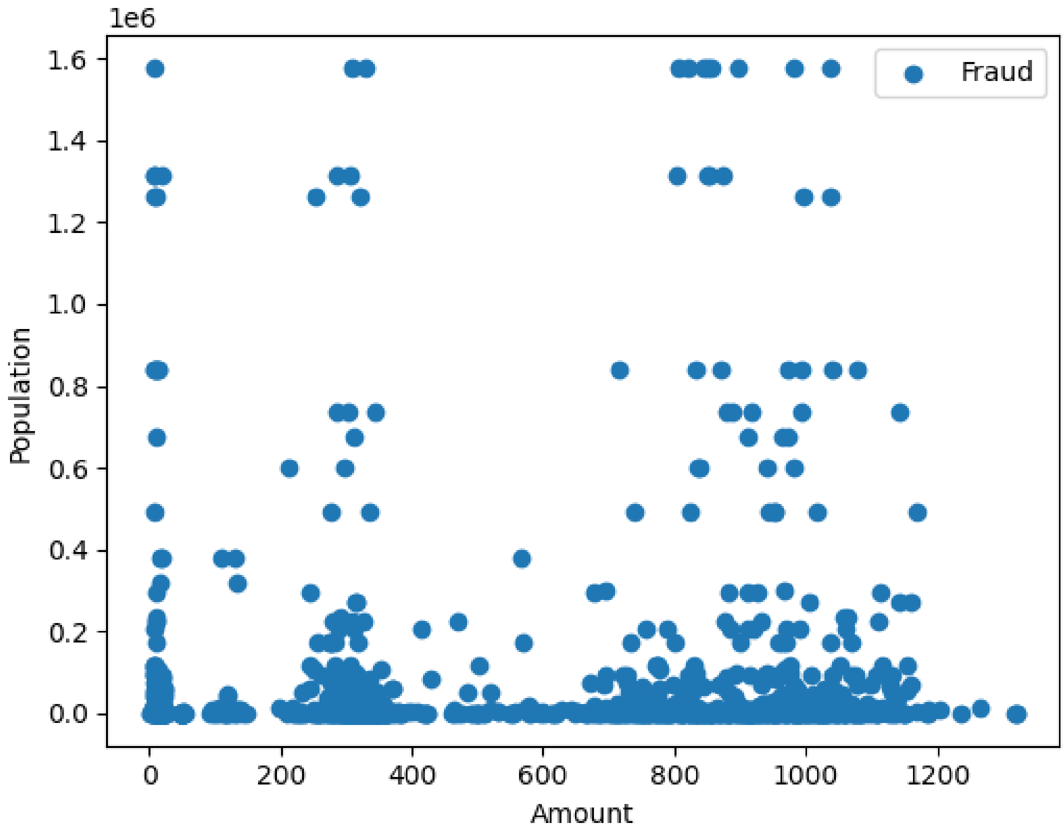
[27]:
```
raw_temp = pd.concat([X_train, y_train], axis =1)
```

[28]:
```
#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()
```



[29]:
```
raw_temp = pd.concat([smote_X, smote_y], axis=1)
```

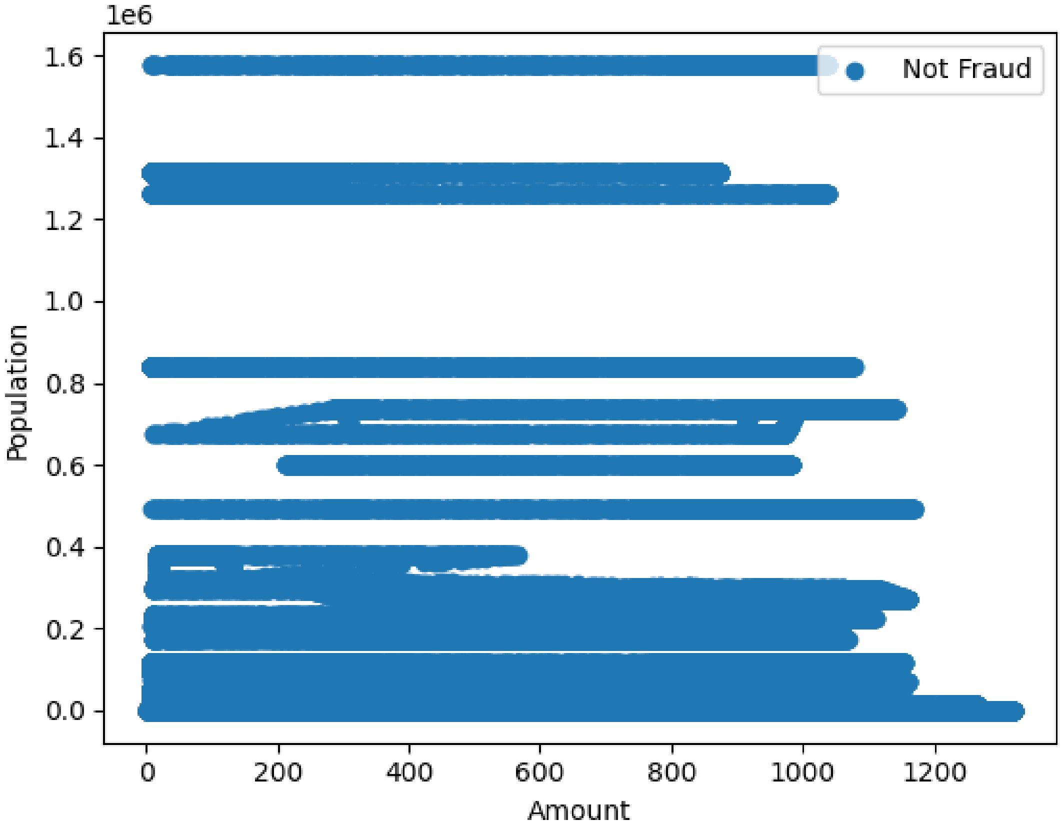
[30]:
```
#plt.scatter(raw_temp[raw_temp["is_fraud"] == 0]["amt"],␣
 ↪raw_temp[raw_temp["is_fraud"] == 0]["city_pop"])

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()
```

```
/Users/adrianonggowarsito/anaconda3/lib/python3.10/site-
packages/IPython/core/pylabtools.py:152: UserWarning: Creating legend with
```

```
loc="best" can be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



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

[31]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
↪f1_score
import pandas as pd
```

[32]:
```
model_configs = {
    'log': LogisticRegression(),
    'lasso': LogisticRegression(
        penalty = 'l1', C = 0.5, solver = 'liblinear'
    ),
    'tree': DecisionTreeClassifier()
}

balancing_configs = {
    'over': RandomOverSampler(),
    'under': RandomUnderSampler(),
    'smote': SMOTE()
}
```

[33]:
```
trained_models = {}
scores_for_df = {}
```

[34]:
```
for i,j in balancing_configs.items():
    for k,l in model_configs.items():
        pipe = Pipeline(
            steps=[
                ('scaler', StandardScaler()),
                ('balancer', j),
                ('model', l)
```

```
            ]
        )
        pipe.fit(X_train, y_train)
        trained_models[(i,k)] = pipe
        # Compute precision, recall, f1 score and store them in a dictionary
        y_pred = pipe.predict(X_test)
        cm = confusion_matrix(y_test, y_pred)
        sensitivity = cm[1,1] /( cm[1,0] + cm[1,1])
        specificity = cm[0,0] /( cm[0,0] + cm[0,1])
        accuracy = pipe.score(X_test, y_test)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)
        scores_for_df[(i,k)] = {
            'precision': precision,
            'recall': recall,
            'sensitivity': sensitivity,
            'specificity': specificity,
            'accuracy': accuracy,
            'f1': f1,
        }
```

[35]:

```
pd.DataFrame(scores_for_df).T
```

[35]:

		precision	recall	sensitivity	specificity	accuracy	f1
over	log	0.029562	0.706250	0.706250	0.910655	0.909871	0.056748
	lasso	0.029817	0.709375	0.709375	0.911053	0.910279	0.057229
	tree	0.584615	0.475000	0.475000	0.998699	0.996689	0.524138
under	log	0.030534	0.712500	0.712500	0.912823	0.912054	0.058559
	lasso	0.034721	0.706250	0.706250	0.924336	0.923499	0.066188
	tree	0.065563	0.928125	0.928125	0.949023	0.948943	0.122474
smote	log	0.029006	0.709375	0.709375	0.908488	0.907723	0.055733
	lasso	0.029573	0.709375	0.709375	0.910294	0.909523	0.056778
	tree	0.259080	0.668750	0.668750	0.992630	0.991387	0.373473

Looking at the provided scores, if we prioritize F1 score (a balanced metric for precision and recall), the Decision Tree classifier with undersampling ("under_tree") seems to perform the best. It has the highest F1 score, indicating a good balance between precision and recall. It also has the highest recall, which is crucial for fraud detection as it's more important to catch as many frauds as possible.

However, the trade-off is that it has a lower specificity compared to the other models, which means it is more likely to incorrectly label non-fraudulent transactions as fraudulent. Depending on the cost and impact of false positives, this might be an acceptable trade-off.

On the other hand, if we want to maintain higher specificity (reducing false positives), SMOTE has a slightly lower recall but better specificity than undersampling.