5 - Imbalanced Data python

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("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[["trans_date_trans_time", "category", "amt", "city_pop",␣
 ↪"is_fraud"]]

df_select["trans_date_trans_time"] = pd.
 ↪to_datetime(df_select["trans_date_trans_time"])
df_select["time_var"] = [i.second for i in df_select["trans_date_trans_time"]]

X = pd.get_dummies(df_select, ["category"]).drop(["trans_date_trans_time",␣
 ↪"is_fraud"], axis = 1)
y = df["is_fraud"]
```

```
/var/folders/8n/rplm7qjx0qq8gxp74jz2xy680000gn/T/ipykernel_48836/2282180580.py:3
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_select["trans_date_trans_time"] =
pd.to_datetime(df_select["trans_date_trans_time"])
/var/folders/8n/rplm7qjx0qq8gxp74jz2xy680000gn/T/ipykernel_48836/2282180580.py:4
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_select["time_var"] = [i.second for i in df_select["trans_date_trans_time"]]
```

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

[5]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[6]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .3)
```

[7]:
```
X_test, X_holdout, y_test, y_holdout = train_test_split(X_test, y_test,␣
↪test_size = .5)
```

[8]:
```
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)

[9]:
```
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
```

[10]:
```
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

[11]:
```
from sklearn.linear_model import LogisticRegression
```

[12]:
```
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

[13]:
```
over_log.score(X_test, y_test)
```

[13]:
```
0.923462655054104
```

[14]:
```
under_log.score(X_test, y_test)
```

[14]:
```
0.9192159120900214
```

[15]:
```
smote_log.score(X_test, y_test)
```

[15]:
```
0.9231867367259291
```

[16]:
```
# We see SMOTE performing with higher accuracy but is ACCURACY really the best␣
↪measure?
```

[ ]:
```

```

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

[17]:
```
# Sensitivity here in credit fraud is more important as seen from last class
```

[18]:
```
from sklearn.metrics import confusion_matrix
```

[19]:
```
y_true = y_test
```

[20]:
```
y_pred = over_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[20]:
```
array([[76733,  6301],
       [   79,   245]])
```

[21]:
```
print("Over Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
Over Sample Sensitivity :  0.7561728395061729
```

[22]:
```
y_pred = under_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[22]:
```
array([[76378,  6656],
       [   78,   246]])
```

[23]:
```
print("Under Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
Under Sample Sensitivity :  0.7592592592592593
```

[24]:
```
y_pred = smote_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[24]:
```
array([[76710,  6324],
       [   79,   245]])
```

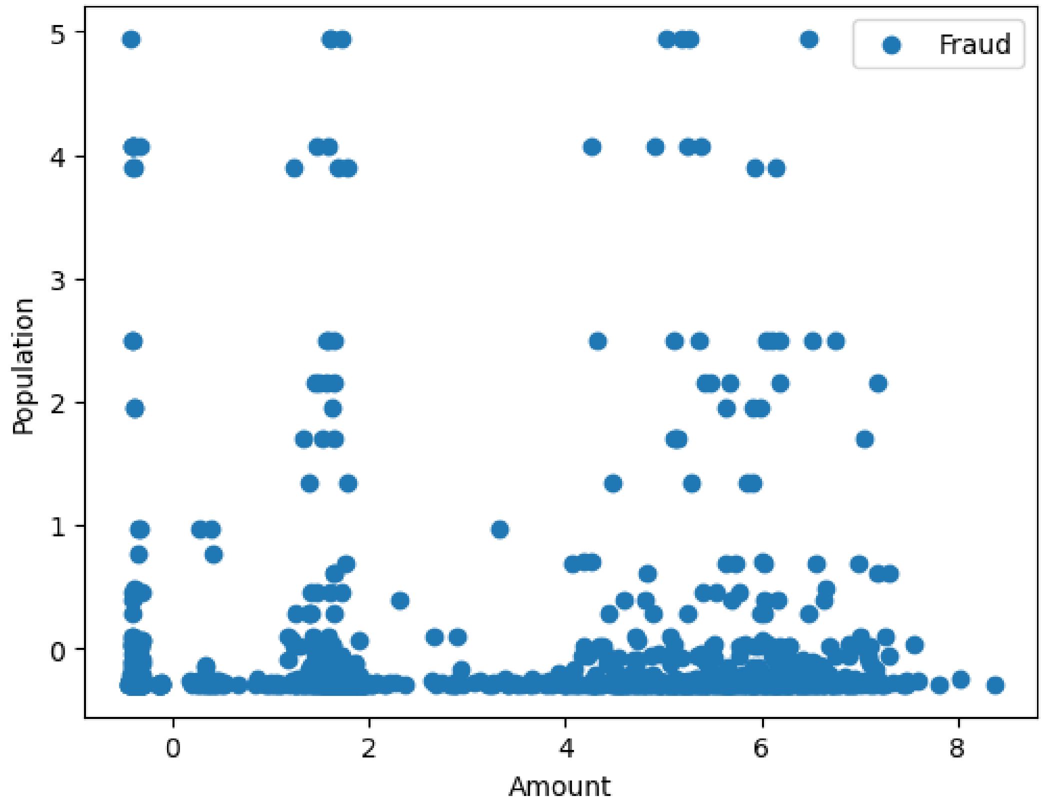
[25]:
```
print("SMOTE Sample Sensitivity : ", cm[1,1] /( cm[1,0] + cm[1,1]))
```

```
SMOTE Sample Sensitivity :  0.7561728395061729
```

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

[26]:
```
column_names = X.columns

X_train_df = pd.DataFrame(X_train, columns=column_names)

raw_temp = pd.concat([X_train_df, y_train.reset_index(drop=True)], axis=1)
```

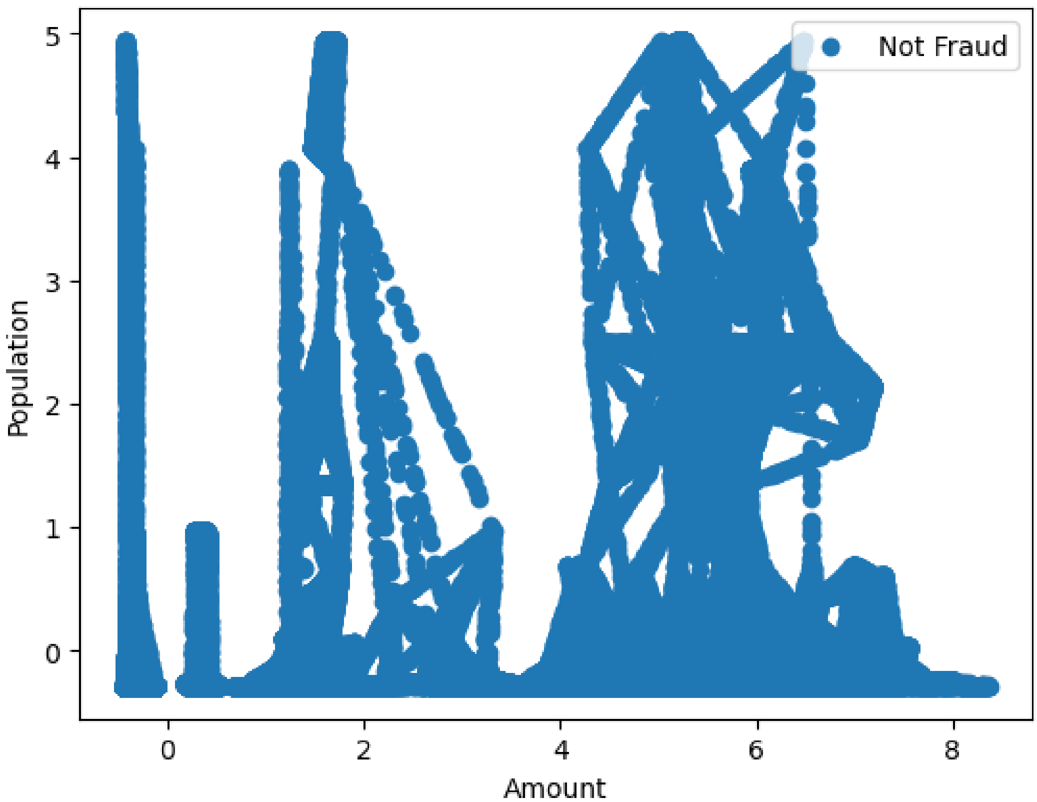
[27]:
```
#plt.scatter(raw_temp[raw_temp["is_fraud"] == 0]["amt"],␣
 ↪raw_temp[raw_temp["is_fraud"] == 0]["city_pop"])

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()
```



[28]:
```
smote_X_df = pd.DataFrame(smote_X, columns=column_names)

raw_temp = pd.concat([smote_X_df, smote_y.reset_index(drop=True)], axis=1)
```

[29]:
```
#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/zichenxu/opt/anaconda3/lib/python3.9/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)
```


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.

[30]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
↪f1_score
import pandas as pd
```

[31]:
```
resampling_methods = {
    "over":RandomOverSampler(),
    "under":RandomUnderSampler(),
    "smote": SMOTE()
}

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

[32]:
```
def calc_pref_metric(y_true,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)
```

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

[34]:
```
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

        y_pred = m.predict(X_test)

        sensitivity, specificity, precision, recall, f1 =␣
 ↪calc_pref_metric(y_test, y_pred)

        results.append({"Model": combined_key,
                        "Sentitivity": sensitivity,
                        "Specificity": specificity,
                        "Precision": precision,
                        "Recall": recall,
                        "F1": f1})
```

[35]:
```
result_df = pd.DataFrame(results)
```

[36]:
```
result_df
```

[36]:

	Model	Sentitivity	Specificity	Precision	Recall	F1
0	over_LOG	0.756173	0.926018	0.038353	0.756173	0.073004
1	over_LASSO	0.756173	0.925874	0.038281	0.756173	0.072873
2	over_DTREE	0.580247	0.998483	0.598726	0.580247	0.589342
3	under_LOG	0.759259	0.932883	0.042275	0.759259	0.080091
4	under_LASSO	0.759259	0.932847	0.042254	0.759259	0.080052
5	under_DTREE	0.950617	0.933184	0.052596	0.950617	0.099676
6	smote_LOG	0.756173	0.923658	0.037211	0.756173	0.070932
7	smote_LASSO	0.756173	0.923670	0.037217	0.756173	0.070943
8	smote_DTREE	0.737654	0.993473	0.306018	0.737654	0.432579

According to the results, there is no one model totally out perform the others. Sensitivity is relatively high for models using under-sampling, with under-sampling Decision Tree showing the highest sensitivity. Specificity is relatively higher for Decision Trees, with over-sampling Decision Tree showing the highest specificity. Precision is relatively higher for Decision Trees, with over-sampling Decision Tree showing the highest precision. Recall varies across models as Logistic Regression and LASSO perform similarly, and Decision Tree performs best using under-sampling and perform sworst using over-sampling. F1 Score is generally higher for Decision Tree models, with over-sampling Decision Tree showing the highest F1 score of all models.

In my opinion, the Smote Decision Tree model appears to be the best choice. It offers a very good balance between Sensitivity and Precision, as reflected in the higher F1 score. The model is more effective at correctly identifying both fraudulent and legitimate transactions compared to the other models.