SMOTEMethods

March 26, 2023

Various Synthetic Minority Oversampling Technique (SMOTE) variations to oversample the underrepresented class of Closed = No and see if that improves the accuracy of the model

[359]:
```
#Installing imblearn
!pip install -U imbalanced-learn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.9/dist-packages (0.10.1)
Requirement already satisfied: scikit-learn>=1.0.2 in
/usr/local/lib/python3.9/dist-packages (from imbalanced-learn) (1.2.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.9/dist-packages (from imbalanced-learn) (3.1.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.9/dist-
packages (from imbalanced-learn) (1.22.4)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.9/dist-
packages (from imbalanced-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-
packages (from imbalanced-learn) (1.1.1)
```

[360]:
```
import pandas as pd
import seaborn as sns
```

[361]:
```
df = pd.read_csv('/content/drive/MyDrive/CIND 820 Capstone Project/
↪merged_completedata.csv')

df = df[df['Year'] == 2019]
df.drop(['Year'], axis=1, inplace=True)
#NAICSCode back to object as it is nominal not ordinal
df['NAICSCode'] = df['NAICSCode'].astype(str)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16518 entries, 46689 to 63206
Data columns (total 28 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
```

```
 0   RecordID    16518 non-null  int64
 1   X           16518 non-null  float64
 2   Y           16518 non-null  float64
 3   FID         16518 non-null  int64
 4   BusinessID  16518 non-null  int64
 5   Name        16518 non-null  object
 6   Address     16518 non-null  object
 7   StreetNo    16518 non-null  int64
 8   StreetName  16518 non-null  object
 9   BldgNo      16518 non-null  object
 10  UnitNo      16518 non-null  object
 11  PostalCode  16518 non-null  object
 12  Location    16518 non-null  object
 13  Ward        16518 non-null  int64
 14  NAICSCode   16518 non-null  object
 15  NAICSCat    16518 non-null  object
 16  NAICSDescr  16518 non-null  object
 17  Phone       16518 non-null  object
 18  Fax         16518 non-null  object
 19  TollFree    16518 non-null  object
 20  EMail       16518 non-null  object
 21  WebAddress  16518 non-null  object
 22  EmplRange   16518 non-null  int64
 23  CENT_X      16518 non-null  float64
 24  CENT_Y      16518 non-null  float64
 25  Age         16518 non-null  int64
 26  isnew       16518 non-null  object
 27  Closed      16518 non-null  object
dtypes: float64(4), int64(7), object(17)
memory usage: 3.7+ MB
```

[362]:
```
df = df.replace(to_replace=['No', 'Yes'], value=[0, 1])
```

[363]:
```
df.describe()
```

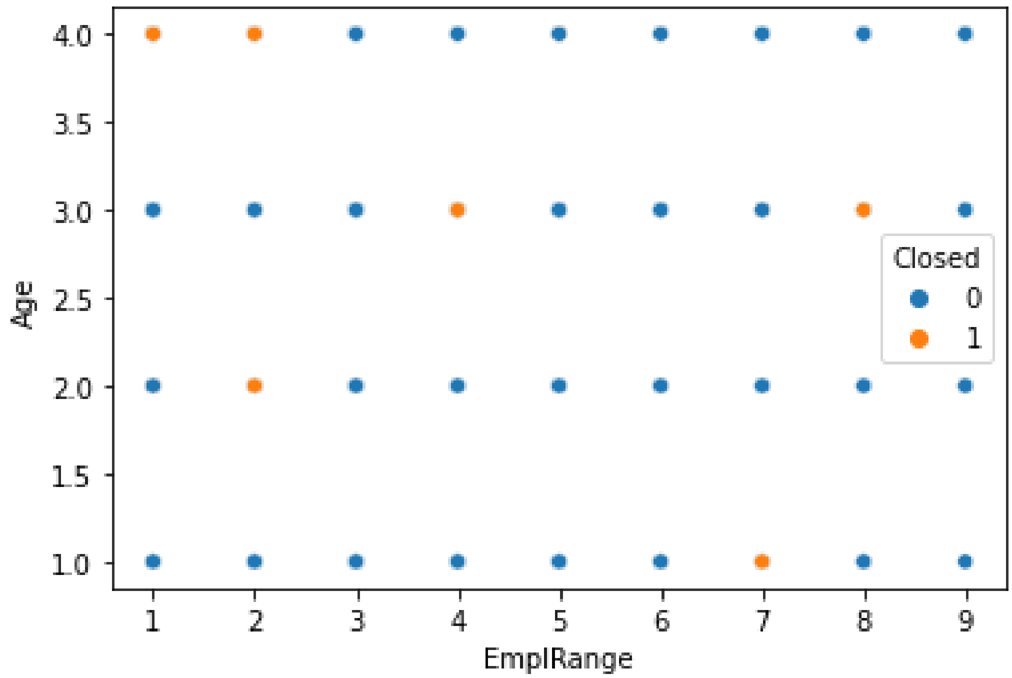
[363]:
```
           RecordID             X             Y           FID    BusinessID  \
count  16518.000000  16518.000000  16518.000000  16518.000000  16518.000000
mean   54948.500000    -79.657689     43.601356   8259.500000  38317.374803
std     4768.480209      0.046612      0.056180   4768.480209  32183.768108
min    46690.000000    -79.802980     43.485170      1.000000      7.000000
25%    50819.250000    -79.697599     43.560065   4130.250000  10300.250000
50%    54948.500000    -79.655443     43.600388   8259.500000  20467.000000
75%    59077.750000    -79.622510     43.643674  12388.750000  57398.250000
max    63207.000000    -79.550935     43.732864  16518.000000  93823.000000

           StreetNo        BldgNo        UnitNo          Ward         Phone  \
count  16518.000000  16518.000000  16518.000000  16518.000000  16518.000000
```

```
mean    2949.933285     0.050188     0.665093     5.372927     0.990314
std     2364.551005     0.218339     0.471972     2.452044     0.097945
min        1.000000     0.000000     0.000000     1.000000     0.000000
25%     1050.250000     0.000000     0.000000     5.000000     1.000000
50%     2380.000000     0.000000     1.000000     5.000000     1.000000
75%     5144.500000     0.000000     1.000000     7.000000     1.000000
max     7895.000000     1.000000     1.000000    11.000000     1.000000

                Fax      TollFree        EMail    WebAddress     EmplRange  \
count  16518.000000  16518.000000  16518.000000  16518.000000  16518.000000
mean       0.623078      0.150624      0.608911      0.738709      2.183981
std        0.484630      0.357692      0.488009      0.439351      1.450311
min        0.000000      0.000000      0.000000      0.000000      1.000000
25%        0.000000      0.000000      0.000000      0.000000      1.000000
50%        1.000000      0.000000      1.000000      1.000000      2.000000
75%        1.000000      0.000000      1.000000      1.000000      3.000000
max        1.000000      1.000000      1.000000      1.000000      9.000000

              CENT_X        CENT_Y           Age         isnew        Closed
count   16518.000000  1.651800e+04  16518.000000  16518.000000  16518.000000
mean   608803.895873  4.828662e+06      3.364451      0.105703      0.164306
std      3622.954311  6.225972e+03      1.029033      0.307466      0.370564
min    596627.934200  4.815547e+06      1.000000      0.000000      0.000000
25%    606962.728400  4.824380e+06      3.000000      0.000000      0.000000
50%    609549.255500  4.828519e+06      4.000000      0.000000      0.000000
75%    611124.363600  4.833333e+06      4.000000      0.000000      0.000000
max    616985.055200  4.843108e+06      4.000000      1.000000      1.000000
```

1) SMOTE on two continuous features - SMOTE is used to synthesize data where the features are continuous and a classification problem

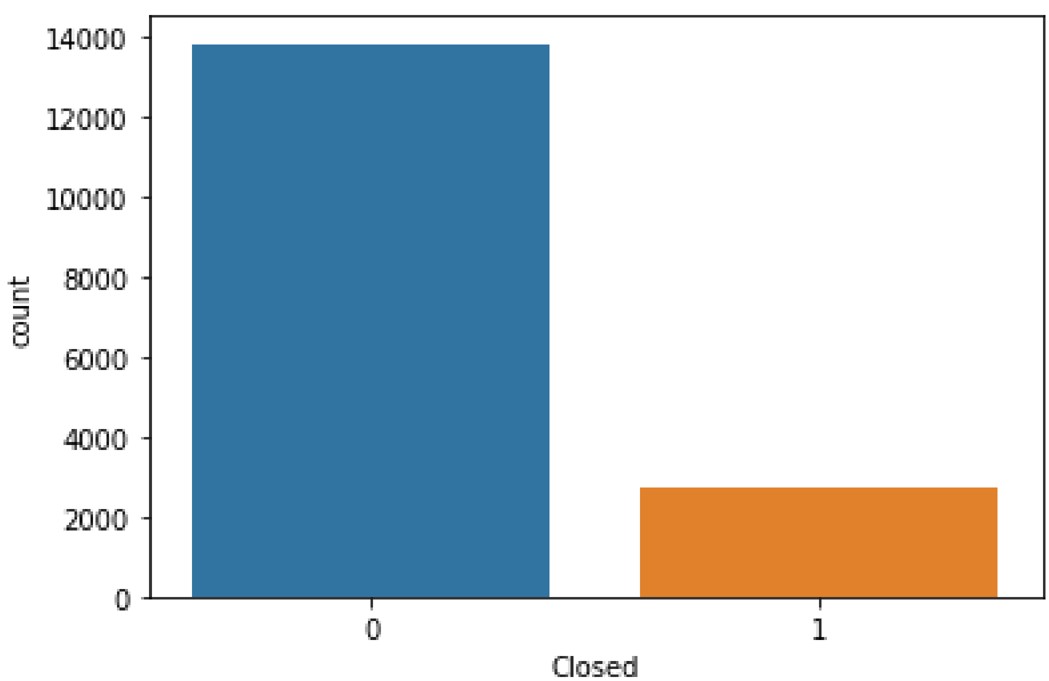
[364]:
```python
#use two continuous features EmplRange and Age with the target Closed
df_unbalanced = df[['EmplRange', 'Age', 'Closed']]
sns.scatterplot(data = df, x ='EmplRange', y = 'Age', hue = 'Closed')
```

[364]:
```
<Axes: xlabel='EmplRange', ylabel='Age'>
```



[365]:
```
sns.countplot(x=df["Closed"])
```

[365]: <Axes: xlabel='Closed', ylabel='count'>

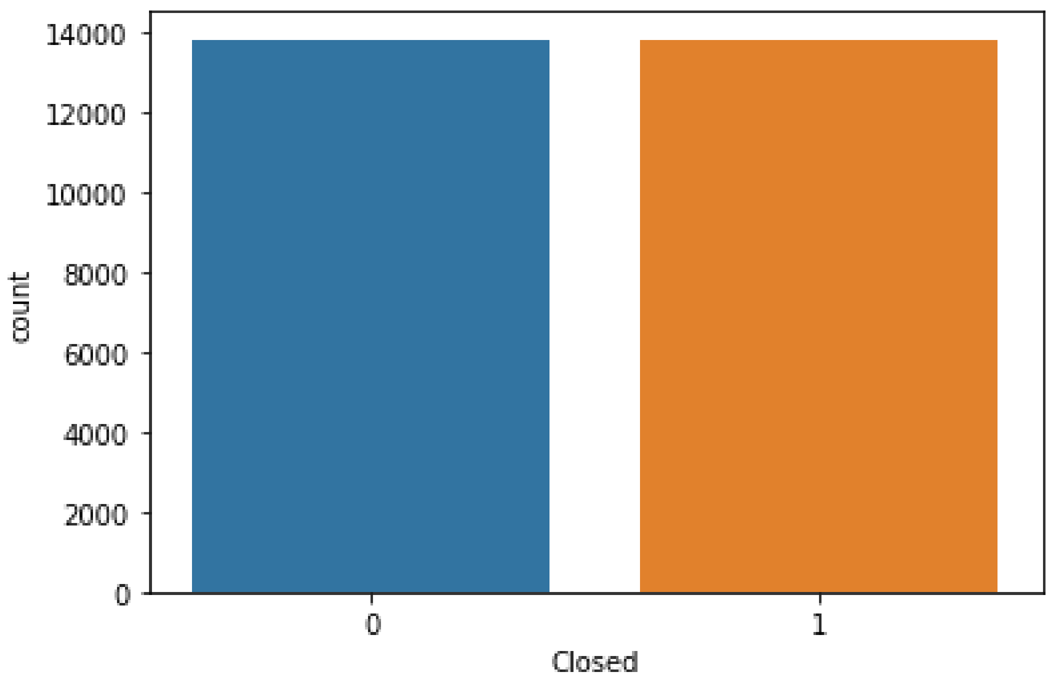


Balancing the dataset with SMOTE oversampling

[366]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state = 101)
X, y = smote.fit_resample(df[['EmplRange', 'Age']], df['Closed'])
df_oversampler = pd.DataFrame(X, columns = ['EmplRange', 'Age'])
df_oversampler['Closed'] = y
```

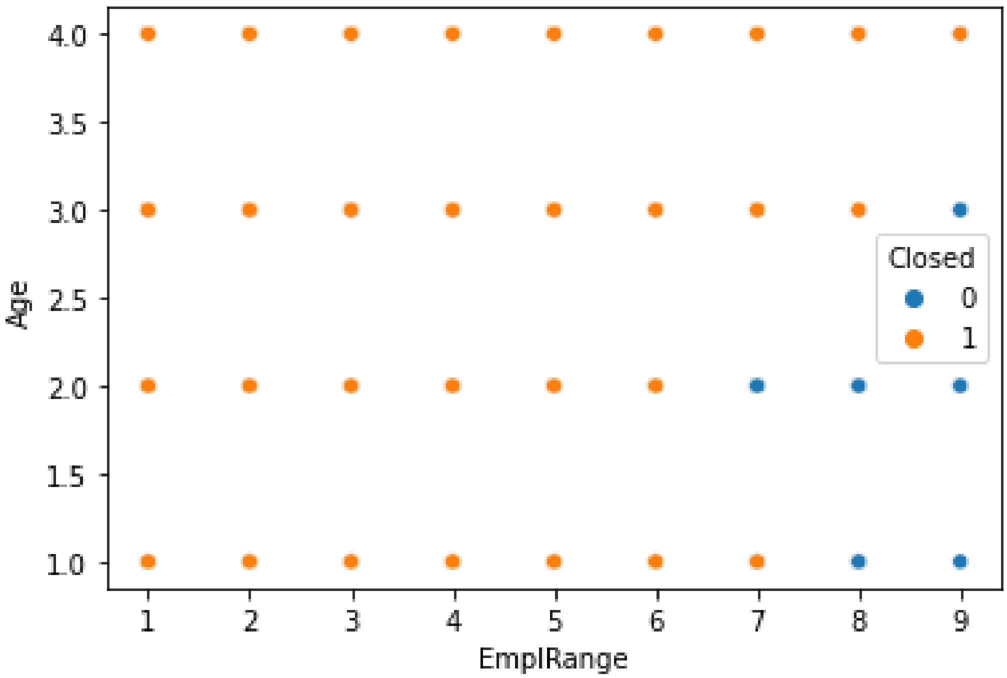
[336]:
```
sns.countplot(x=df_oversampler['Closed'])
```

[336]: <Axes: xlabel='Closed', ylabel='count'>



[367]:
```
sns.scatterplot(data = df_oversampler, x ='EmplRange', y = 'Age', hue =␣
↪'Closed')
```

[367]: <Axes: xlabel='EmplRange', ylabel='Age'>



[368]:
```
df_oversampler.describe()
```

[368]:

	EmplRange	Age	Closed
count	27608.000000	27608.000000	27608.000000
mean	2.110910	3.307556	0.500000
std	1.398145	1.061371	0.500009
min	1.000000	1.000000	0.000000
25%	1.000000	3.000000	0.000000
50%	2.000000	4.000000	0.500000
75%	3.000000	4.000000	1.000000
max	9.000000	4.000000	1.000000

[369]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
#Split the data set into test and train
X_train, X_test, y_train, y_test = train_test_split(df_unbalanced[['EmplRange',␣
↪'Age']], df['Closed'], test_size = 0.2, stratify = df['Closed'],␣
↪random_state = 101)
```

[370]:
```
#Create the oversampled training data
smote = SMOTE(random_state = 101)
X_oversample, y_oversample = smote.fit_resample(X_train, y_train)
```

[371]:
```
#Training results with imbalanced data
classifier = LogisticRegression()
classifier.fit(X_train, y_train)
print(classification_report(y_test, classifier.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.84      1.00      0.91      2761
           1       0.00      0.00      0.00       543

    accuracy                           0.84      3304
   macro avg       0.42      0.50      0.46      3304
weighted avg       0.70      0.84      0.76      3304
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[372]:
```
#Training results with oversampled data
classifier_smote = LogisticRegression()
classifier_smote.fit(X_oversample, y_oversample)
print(classification_report(y_test, classifier_smote.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.84      0.73      0.78      2761
           1       0.18      0.29      0.22       543

    accuracy                           0.66      3304
   macro avg       0.51      0.51      0.50      3304
weighted avg       0.73      0.66      0.69      3304
```

[373]:
```
from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, classifier_smote.predict(X_test))
```

```
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Confusion Matrix
[[2009  752]
 [ 383  160]]
TP:  160 , FP:  752 , TN:  2009 , FN: 383
```

2) SMOTENC ((Nominal and Continuous) - with one continuous and one categorical feature

[374]:
```
df_unbalanced = df[['EmplRange', 'NAICSCode', 'Closed']]
```

[375]:
```
X_train, X_test, y_train, y_test = train_test_split(df_unbalanced[['EmplRange',␣
↪'NAICSCode']],df['Closed'], test_size = 0.2,stratify = df['Closed'],␣
↪random_state = 101)
```

[376]:
```
from imblearn.over_sampling import SMOTENC

smotenc = SMOTENC([1],random_state = 101)
X_oversample, y_oversample = smotenc.fit_resample(X_train, y_train)
```

[377]:
```
#Classifier results with imbalanced data
classifier = LogisticRegression()
classifier.fit(X_train, y_train)
print(classification_report(y_test, classifier.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.84      1.00      0.91      2761
           1       0.00      0.00      0.00       543

    accuracy                           0.84      3304
   macro avg       0.42      0.50      0.46      3304
weighted avg       0.70      0.84      0.76      3304


/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
```

```
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[378]:
```
#Classifier results with SMOTENC
classifier_smotenc = LogisticRegression()
classifier_smotenc.fit(X_oversample, y_oversample)
print(classification_report(y_test, classifier_smotenc.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.87      0.53      0.66      2761
           1       0.20      0.59      0.30       543

    accuracy                           0.54      3304
   macro avg       0.53      0.56      0.48      3304
weighted avg       0.76      0.54      0.60      3304
```

[379]:
```
from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, classifier_smotenc.predict(X_test))
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Confusion Matrix
[[1470 1291]
 [ 220  323]]
TP:  323 , FP:  1291 , TN:  1470 , FN: 220
```

3) Borderline-SMOTE using two continuous features (only makes synthetic data along the decision boundary between the two classes.

[380]:
```
df_unbalanced = df[['EmplRange', 'Age', 'Closed']]
```

[381]:
```
X_train, X_test, y_train, y_test = train_test_split(df_unbalanced[['EmplRange',
 ↪'Age']], df['Closed'], test_size = 0.2,  stratify = df['Closed'],
 ↪random_state = 101)
```

[382]:
```
from imblearn.over_sampling import BorderlineSMOTE
bsmote = BorderlineSMOTE(random_state = 101, kind = 'borderline-1')
X_oversample_borderline, y_oversample_borderline = bsmote.fit_resample(X_train,
 ↪y_train)
```

[383]:
```
classifier_borderlinesmote = LogisticRegression()
classifier_borderlinesmote.fit(X_oversample_borderline, y_oversample_borderline)
```

```
print(classification_report(y_test, classifier_border.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.43      0.57      2761
           1       0.17      0.60      0.27       543

    accuracy                           0.46      3304
   macro avg       0.51      0.52      0.42      3304
weighted avg       0.73      0.46      0.52      3304
```

[384]:
```
from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, classifier_border.predict(X_test))
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Confusion Matrix
[[1195 1566]
 [ 218  325]]
TP:  325 , FP:  1566 , TN:  1195 , FN: 218
```

4) Borderline-SMOTE SVM (using the data from the Borderline-SMOTE example)

[385]:
```
from imblearn.over_sampling import SVMSMOTE
svmsmote = SVMSMOTE(random_state = 101)
X_oversample_svm, y_oversample_svm = svmsmote.fit_resample(X_train, y_train)
classifier_svm = LogisticRegression()
classifier_svm.fit(X_oversample_svm, y_oversample_svm)
print(classification_report(y_test, classifier_svm.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.84      0.92      0.88      2761
           1       0.18      0.09      0.12       543

    accuracy                           0.78      3304
   macro avg       0.51      0.51      0.50      3304
weighted avg       0.73      0.78      0.75      3304
```

[386]:
```
from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, classifier_svm.predict(X_test))
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
```

```
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Confusion Matrix
[[2544  217]
 [ 494   49]]
TP:  49 , FP:  217 , TN:  2544 , FN: 494
```

5) Adaptive Synthetic Sampling (ADASYN) - using the data from the SMOTE example again. ADASYN creates synthetic data according to the data density - more where density is low and less where density is high

[387]:
```
from imblearn.over_sampling import ADASYN
adasyn = ADASYN(random_state = 101)
X_oversample_adasyn, y_oversample_adasyn = adasyn.fit_resample(X_train, y_train)
classifier_adasyn = LogisticRegression()
classifier_adasyn.fit(X_oversample_adasyn, y_oversample_adasyn)
print(classification_report(y_test, classifier_adasyn.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.87      0.30      0.44      2761
           1       0.18      0.77      0.29       543

    accuracy                           0.37      3304
   macro avg       0.52      0.53      0.37      3304
weighted avg       0.75      0.37      0.42      3304
```

[388]:
```
from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, classifier_adasyn.predict(X_test))
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp,", FP: ", fp,", TN: ", tn,", FN:", fn)
```

```
Confusion Matrix
[[ 821 1940]
 [ 126  417]]
TP:  417 , FP:  1940 , TN:  821 , FN: 126
```