buy_affinity

July 26, 2020

1 Case Study - Customer Buy Affinity On E-commerce Dataset

[2]:
```
#importing for exploratory data analysis and visualization
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#importing for undersampling and oversampling techniques
import numpy as np
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.preprocessing import StandardScaler


#different models to try
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

2 Reading the data for training

[3]:
```
df = pd.read_csv('BuyAffinity_Train.txt',sep='\t',index_col='Index')
```

3 Checking the head of data

[4]:
```
df.head()
```

[4]:
```
             F1        F2        F3        F4    F5    F6    F7    F8    F9  \
Index
1      0.224506  0.500340  0.489860  0.902413  7934 -6970 -5714  9982 -5697
2      0.321128  0.281119  0.907283  0.772159 -8238  1219  1663  1287 -3658
3      0.893441  0.622005  0.998776  0.098386  8540  5266 -9377 -3504 -4511
4      0.320641  0.957234  0.346000  0.646479 -7772  -383  9681 -8661  3474
```

```
5       0.475961  0.623008  0.544988  0.159709  1571 -8039 -7961 -2385  4407

              F10  ...         F14        F15         F16  F17 F18  F19  F20  \
Index              ...
1      4227810299  ... -3433637453  10/4/1986    9/6/1992    2   1  706  305
2     -1146724819  ...   609277486  2/24/1979    1/5/1983    1   1  423  206
3      5947184989  ... -8977995005  1/12/1989  11/22/1986    2   1  703  315
4     -5724795826  ...  4868760308  2/18/1982   6/10/1992    1   1  122  304
5     -3097637172  ...  9757408267  4/10/1987  10/19/1985    1   1  486  240

       F21  F22  C
Index
1        1    2  0
2       18    7  1
3        1    4  0
4       15    1  0
5        1    1  0

[5 rows x 23 columns]
```

4 Dropping the F14,F15 date columns

[5]:
```python
df =df.drop(columns=['F15', 'F16'])
df.head()
```

[5]:
```
             F1        F2        F3        F4    F5    F6    F7    F8    F9  \
Index
1      0.224506  0.500340  0.489860  0.902413  7934 -6970 -5714  9982 -5697
2      0.321128  0.281119  0.907283  0.772159 -8238  1219  1663  1287 -3658
3      0.893441  0.622005  0.998776  0.098386  8540  5266 -9377 -3504 -4511
4      0.320641  0.957234  0.346000  0.646479 -7772  -383  9681 -8661  3474
5      0.475961  0.623008  0.544988  0.159709  1571 -8039 -7961 -2385  4407

              F10  ...         F12         F13         F14  F17  F18  F19  \
Index              ...
1      4227810299  ...   316195953  6176861823 -3433637453    2    1  706
2     -1146724819  ...  1378635942 -9031507610   609277486    1    1  423
3      5947184989  ... -9921889287 -5610051842 -8977995005    2    1  703
4     -5724795826  ...  6550322883 -4697085930  4868760308    1    1  122
5     -3097637172  ...   759031103  9984692447  9757408267    1    1  486

       F20  F21  F22  C
Index
1      305    1    2  0
2      206   18    7  1
3      315    1    4  0
```

```
4       304    15     1   0
5       240     1     1   0

[5 rows x 21 columns]
```

5 Describing the data

[6]:
```
df.describe()
```

[6]:
```
                  F1             F2             F3             F4  \
count  101180.000000  101180.000000  101180.000000  101180.000000
mean        0.502348       0.501497       0.499886       0.499839
std         0.288058       0.289017       0.288875       0.288729
min         0.000018       0.000004       0.000002       0.000006
25%         0.253819       0.251115       0.248818       0.250501
50%         0.501802       0.501095       0.499820       0.501387
75%         0.753598       0.752404       0.750281       0.748803
max         0.999986       0.999990       0.999985       0.999977

                  F5             F6             F7             F8  \
count  101180.000000  101180.000000  101180.000000  101180.000000
mean      -29.742617       1.511000       7.939118      16.434147
std      5781.829379    5796.594007    5765.581875    5782.805211
min    -10000.000000  -10000.000000  -10000.000000  -10000.000000
25%     -5045.000000   -5012.000000   -4979.000000   -4988.000000
50%       -46.000000     -11.500000      16.500000      60.000000
75%      4978.000000    5050.000000    4962.000000    5021.000000
max     10000.000000   10000.000000   10000.000000   10000.000000

                  F9           F10  …            F12           F13  \
count  101180.000000  1.011800e+05  …   1.011800e+05  1.011800e+05
mean        9.927812  1.869749e+07  …   6.921685e+06  1.127538e+07
std      5771.004738  5.769064e+09  …   5.771750e+09  5.786659e+09
min    -10000.000000 -9.999816e+09  …  -9.999754e+09 -9.999852e+09
25%     -4992.250000 -4.966961e+09  …  -4.991278e+09 -5.027003e+09
50%        22.500000  4.346691e+07  …   4.277384e+07  9.416236e+06
75%      5020.000000  5.019440e+09  …   5.008238e+09  5.032947e+09
max     10000.000000  9.999497e+09  …   9.999555e+09  9.999951e+09

                F14            F17            F18            F19  \
count  1.011800e+05  101180.000000  101180.000000  101180.000000
mean  -5.198163e+07       1.339593       1.335027     387.181479
std    5.782358e+09       0.894065       0.882435     235.939585
min   -9.999767e+09       1.000000       1.000000       1.000000
25%   -5.070403e+09       1.000000       1.000000     187.000000
50%   -8.816174e+07       1.000000       1.000000     374.000000
```

```
75%    4.947133e+09       1.000000       1.000000     560.000000
max    9.999997e+09       6.000000       6.000000     901.000000

                 F20            F21            F22              C
count  101180.000000  101180.000000  101180.000000  101180.000000
mean      387.333999       4.588031       4.598567       0.245375
std       235.374285       4.775671       4.776494       0.430311
min         1.000000       1.000000       1.000000       0.000000
25%       187.000000       1.000000       1.000000       0.000000
50%       375.000000       3.000000       3.000000       0.000000
75%       561.000000       7.000000       7.000000       0.000000
max       901.000000      21.000000      21.000000       1.000000

[8 rows x 21 columns]
```

6 Finding the percentage missing data

No data is missing for any attribute

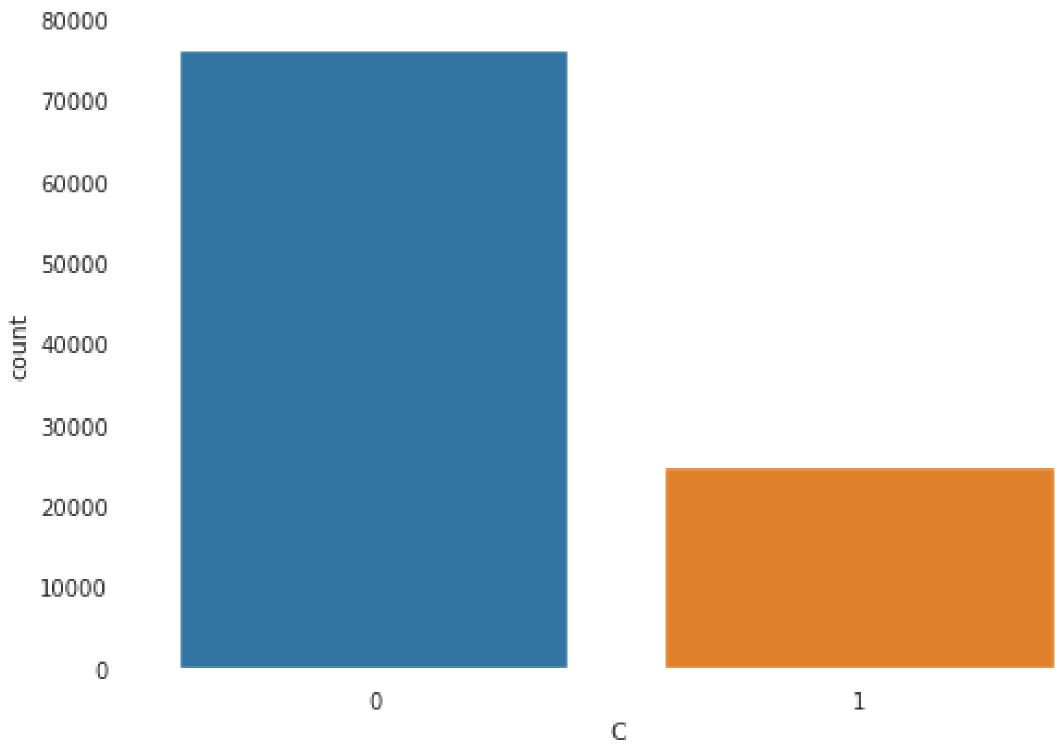
[7]:
```python
miss_per = df.isnull().sum()/df.shape[0]
print(miss_per)
```

```
F1      0.0
F2      0.0
F3      0.0
F4      0.0
F5      0.0
F6      0.0
F7      0.0
F8      0.0
F9      0.0
F10     0.0
F11     0.0
F12     0.0
F13     0.0
F14     0.0
F17     0.0
F18     0.0
F19     0.0
F20     0.0
F21     0.0
F22     0.0
C       0.0
dtype: float64
```

7 Checking distribution of positive and negative class

There is class imbalance between negative and positive class

[8]:
```
_=sns.countplot(x='C',data=df)
```



8 Training with LogisticRegression

Does not work well on imbalanced data

[9]:
```
data = df.to_numpy()
X,y = data[:,:-1],data[:,-1]
X =StandardScaler().fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪30,stratify=y)
clf = LogisticRegression(verbose=1)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
rep=classification_report(y_test, y_pred)
print(rep)
```

```
              precision    recall  f1-score   support
```

```
         0.0       0.75      1.00      0.86     22906
         1.0       0.00      0.00      0.00      7448

    accuracy                           0.75     30354
   macro avg       0.38      0.50      0.43     30354
weighted avg       0.57      0.75      0.65     30354

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s finished
/home/durgesh/miniconda3/lib/python3.7/site-
packages/sklearn/metrics/_classification.py:1221: 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))
```

9 Training With RandomForest

Performs a bit better to logistic regression on imbalanced data

[10]:

```
data = df.to_numpy()
X,y = data[:,:-1],data[:,-1]
X =StandardScaler().fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪30,stratify=y)
clf = RandomForestClassifier(verbose=1,n_jobs=80)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
rep=classification_report(y_test, y_pred)
print(rep)
```

```
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.
[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:   14.4s remaining:   19.9s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:   18.2s finished
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.
              precision    recall  f1-score   support

         0.0       0.76      0.99      0.86     22906
         1.0       0.44      0.02      0.04      7448

    accuracy                           0.75     30354
   macro avg       0.60      0.51      0.45     30354
weighted avg       0.68      0.75      0.66     30354

[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:    0.4s remaining:    0.6s
```

```
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:    0.4s finished
```

10 Performing Under Sampling And Training With RandomForest

Random forests performs better with balanced data

[11]:
```
rus = RandomUnderSampler()
data = df.to_numpy()
X,y = data[:,:-1],data[:,-1]
X =StandardScaler().fit_transform(X)
X,y = rus.fit_resample(X, y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪30,stratify=y)
clf = RandomForestClassifier(verbose=1,n_jobs=80)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
rep=classification_report(y_test, y_pred)
print(rep)
```

```
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.
[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:    6.4s remaining:    8.8s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:    8.0s finished
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.

              precision    recall  f1-score   support

         0.0       0.79      0.48      0.60      7449
         1.0       0.63      0.88      0.73      7448

    accuracy                           0.68     14897
   macro avg       0.71      0.68      0.66     14897
weighted avg       0.71      0.68      0.66     14897

[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:    0.2s remaining:    0.3s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:    0.2s finished
```

11 Performing Over Sampling And Training with RandomForest

Random forests performs better with over-sampling balanced data as there is more datapoints to train

[12]:
```
ros = RandomOverSampler()
data = df.to_numpy()
X,y = data[:,:-1],data[:,-1]
```

```
X =StandardScaler().fit_transform(X)
X,y = ros.fit_resample(X, y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪30,stratify=y)
clf = RandomForestClassifier(verbose=1,n_jobs=80)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
rep=classification_report(y_test, y_pred)
print(rep)
```

```
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.
[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:   21.0s remaining:   29.0s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:   26.8s finished
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.

              precision    recall  f1-score   support

         0.0       0.91      0.83      0.87     22906
         1.0       0.85      0.92      0.88     22906

    accuracy                           0.88     45812
   macro avg       0.88      0.88      0.88     45812
weighted avg       0.88      0.88      0.88     45812


[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:    0.7s remaining:    1.0s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:    0.8s finished
```

12 Predicting labels on BuyAffinity_Test data

[26]:
```
df_test = pd.read_csv('BuyAffinity_Test.txt',sep='\t',index_col='Index')
df_test =df_test.drop(columns=['F15', 'F16'])
data_test = df_test.to_numpy()
X_test = data_test
X_test =StandardScaler().fit_transform(X_test)
y_pred = clf.predict(X_test).astype(np.int32)
df_test = pd.read_csv('BuyAffinity_Test.txt',sep='\t',index_col='Index')
df_test['C']= y_pred
df_test.to_csv('BuyAffinity_Test_labels.txt', sep='\t', mode='w')
df_test.head()
```

```
[Parallel(n_jobs=80)]: Using backend ThreadingBackend with 80 concurrent
workers.
[Parallel(n_jobs=80)]: Done  42 out of 100 | elapsed:    0.3s remaining:    0.5s
[Parallel(n_jobs=80)]: Done 100 out of 100 | elapsed:    0.4s finished
```

[26]:

```
                 F1        F2        F3        F4    F5    F6    F7    F8  \
Index
T30234341  0.654765  0.812009  0.603190  0.391039 -5220  4825 -1784  7447
T30234342  0.694636  0.690568  0.473460  0.259760  -618 -5018  2012  9259
T30234343  0.203759  0.323301  0.492294  0.011448 -8778  6141  6965  3774
T30234344  0.319627  0.286247  0.906197  0.093840 -7929  4471  7715  9543
T30234345  0.236003  0.782784  0.285689  0.383585 -3296  4564 -1580 -8559

             F9         F10  …         F14        F15        F16  F17 F18  \
Index                        …
T30234341 -7147 -3461806391  …  5553595074  9/17/1996  8/18/1990    1   1
T30234342  9267   -36253473  …  2216284070  11/7/1985  4/11/1990    1   1
T30234343  4303  5354243488  …  -315409510   7/9/1984   5/4/1997    1   1
T30234344   335  7405036171  … -3360224957   6/3/1987   7/1/1988    1   1
T30234345   -27 -6351599280  …  7604838279  7/17/1984  12/3/1993    1   1

           F19  F20  F21  F22  C
Index
T30234341  436  478    1    1  0
T30234342  138   56   10    4  0
T30234343  117  323   10    1  0
T30234344  115  149   16   21  0
T30234345  527  281    3    1  1

[5 rows x 23 columns]
```