svm_model_home_credit

April 21, 2021

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.svm import LinearSVC
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import average_precision_score
from sklearn.metrics import classification_report
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
home_credit_data = pd.read_csv('home_credit_data.csv')
cleandata = pd.read_csv('cleandata.csv')
```

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

[3]:

	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	\
0	0	0	1	0	
1	0	0	0	0	
2	1	1	1	0	
3	0	0	1	0	
4	0	0	1	0	

	AMT_INCOME_TOTAL	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_RELATIVE	\
0	202500.0	24700.5	351000.0	0.018801	
1	270000.0	35698.5	1129500.0	0.003541	
2	67500.0	6750.0	135000.0	0.010032	
3	135000.0	29686.5	297000.0	0.008019	

```
4          121500.0      21865.5         513000.0                    0.028663

   DAYS_EMPLOYED  DAYS_REGISTRATION  …  CREDIT_INCOME_PERCENT  \
0         -637.0            -3648.0  …               2.007889
1        -1188.0            -1186.0  …               4.790750
2         -225.0            -4260.0  …               2.000000
3        -3039.0            -9833.0  …               2.316167
4        -3038.0            -4311.0  …               4.222222

   ANNUITY_INCOME_PERCENT  CREDIT_TERM  DAYS_EMPLOYED_PERCENT  \
0                0.121978     0.060749              -0.067329
1                0.132217     0.027598              -0.070862
2                0.100000     0.050000              -0.011814
3                0.219900     0.094941              -0.159905
4                0.179963     0.042623              -0.152418

   AMT_CREDIT_SUM_DEBT  MEAN_DAYS_APPLY  MAX_DAYS_APPLY  NUM_ACTIVE_LOANS  \
0             245781.0          -874.00          -103.0               2.0
1                  0.0         -1400.75          -606.0               1.0
2                  0.0          -867.00          -408.0               0.0
3                  0.0             0.00             0.0               0.0
4                  0.0         -1149.00         -1149.0               0.0

   TARGET  SK_ID_CURR
0       1      100002
1       0      100003
2       0      100004
3       0      100006
4       0      100007

[5 rows x 152 columns]
```

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

[4]:
```
   SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  FLAG_OWN_CAR  FLAG_OWN_REALTY  \
0      100002       1                   0             0                1
1      100003       0                   0             0                0
2      100004       0                   1             1                1
3      100006       0                   0             0                1
4      100007       0                   0             0                1

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  AMT_GOODS_PRICE  \
0             0          202500.0    406597.5      24700.5         351000.0
1             0          270000.0   1293502.5      35698.5        1129500.0
2             0           67500.0    135000.0       6750.0         135000.0
3             0          135000.0    312682.5      29686.5         297000.0
4             0          121500.0    513000.0      21865.5         513000.0
```

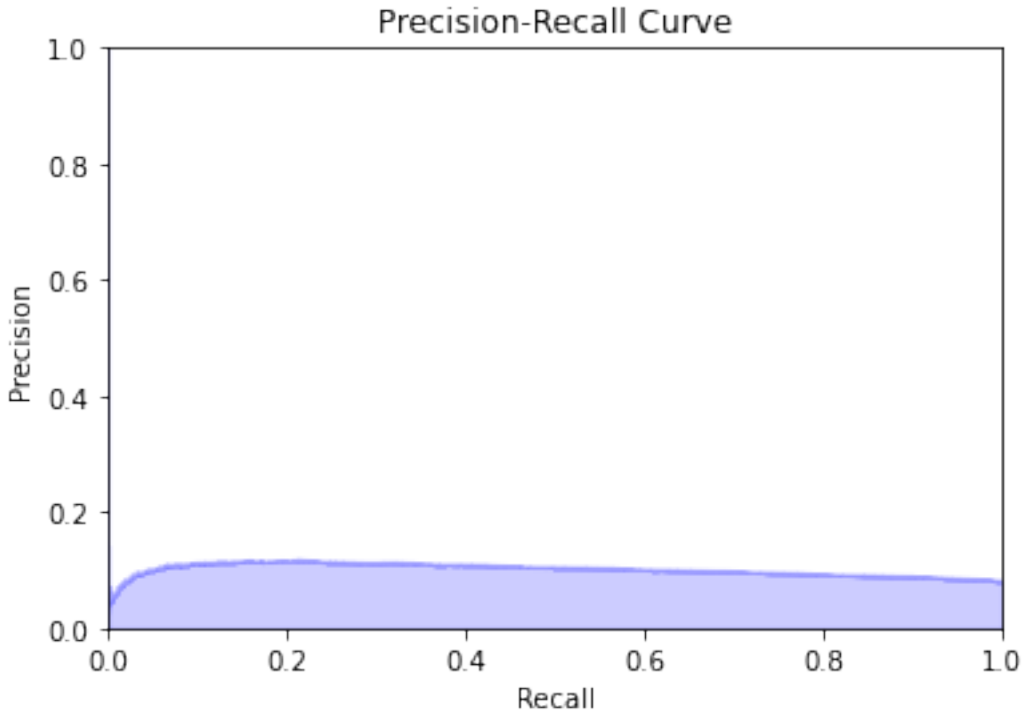
```
   …  HOUSETYPE_MODE_terraced house  WALLSMATERIAL_MODE_Block  \
0  …                               0                         0
1  …                               0                         1
2  …                               0                         0
3  …                               0                         0
4  …                               0                         0

   WALLSMATERIAL_MODE_Mixed  WALLSMATERIAL_MODE_Monolithic  \
0                         0                              0
1                         0                              0
2                         0                              0
3                         0                              0
4                         0                              0

   WALLSMATERIAL_MODE_Others  WALLSMATERIAL_MODE_Panel  \
0                          0                         0
1                          0                         0
2                          0                         0
3                          0                         0
4                          0                         0

   WALLSMATERIAL_MODE_Stone, brick  WALLSMATERIAL_MODE_Wooden  \
0                                1                         0
1                                0                         0
2                                0                         0
3                                0                         0
4                                0                         0

   EMERGENCYSTATE_MODE_No  EMERGENCYSTATE_MODE_Yes
0                       1                        0
1                       1                        0
2                       0                        0
3                       0                        0
4                       0                        0

[5 rows x 243 columns]
```

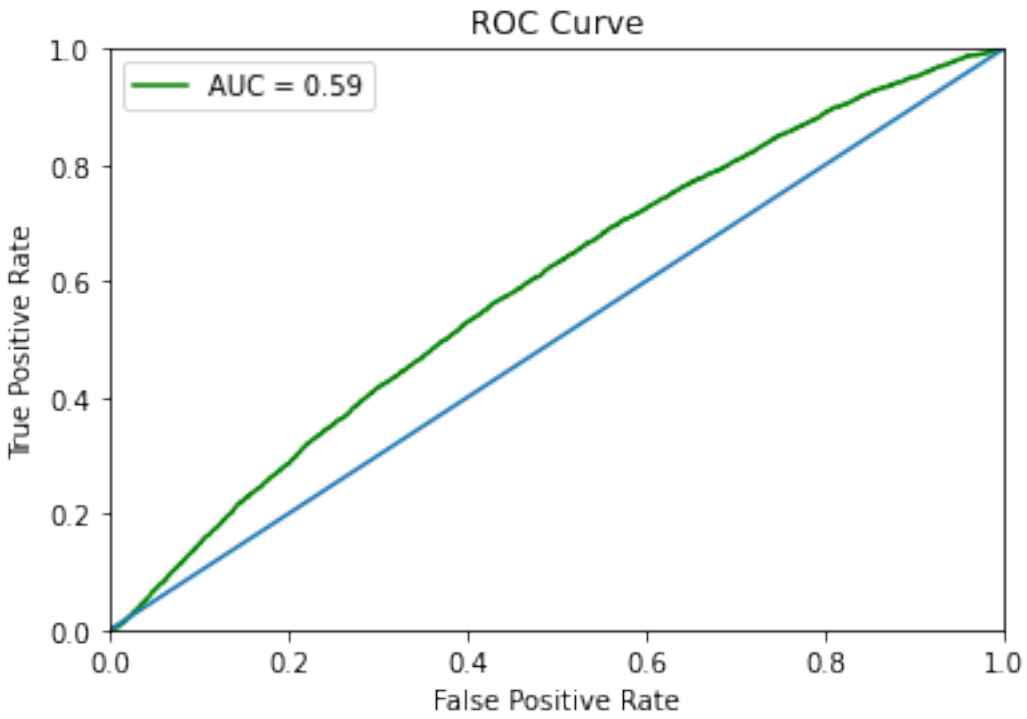
[5]:
```python
def svm(dataset):
    y = dataset['TARGET']
    X = dataset.drop(columns = ['TARGET', 'SK_ID_CURR'])

    scalar = MinMaxScaler()
    scalar.fit_transform(dataset)

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
linear_svc = LinearSVC()
model = CalibratedClassifierCV(linear_svc,
                                    method='sigmoid',
                                    cv=3)
model.fit(X_train, y_train)
predict = model.predict_proba(X_test)
print("SVM Model Accuracy Score :" ,model.score(X_test,y_test))
print("\n")


precision, recall, thresholds = precision_recall_curve(y_test, predict[:,1])
# convert to f score
fscore = (2 * precision * recall) / (precision + recall)
# locate the index of the largest f score
ix = np.argmax(fscore)
print("Precision : " ,precision)
print("Recall    : " ,recall)
print("f1_score  : " ,fscore)

plt.step(recall, precision, color='b', alpha=0.2,
     where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2,
                 color='b')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.0])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall Curve')
plt.show()

print("\n")

false_pos, true_pos, threshold = roc_curve(y_test, predict[:,1])
roc_auc = auc(false_pos, true_pos)

plt.title('ROC Curve')
plt.plot(false_pos, true_pos, 'green', label='AUC = %0.2f'% roc_auc)
plt.legend(loc='best')
plt.plot([0,1],[0,1])
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

print("SVM Model ROC Score : ", roc_auc)
```

[6]:
```
print("SVM Model on home_credit_data")
svm(home_credit_data)
```

```
SVM Model on home_credit_data
SVM Model Accuracy Score : 0.9195648992732062


Precision :  [0.08043602 0.08042106 0.08042237 … 0.         0.         1.
]
Recall    :  [1.         0.99979773 0.99979773 … 0.         0.         0.
]
f1_score  :  [0.14889548 0.14886761 0.14886985 …        nan        nan 0.
]
```

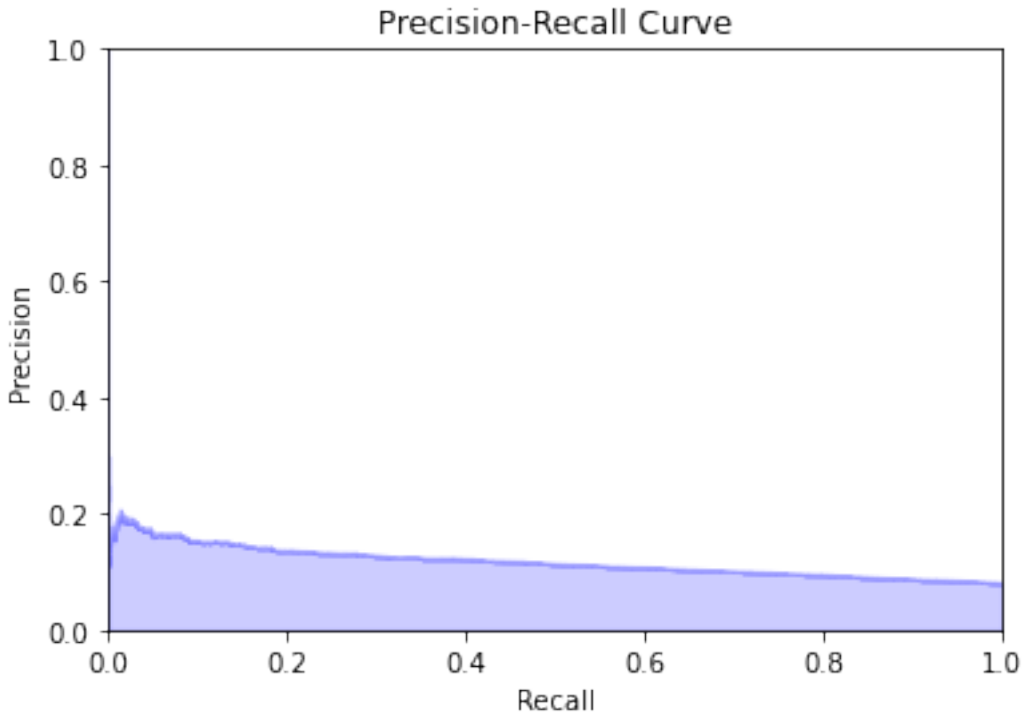


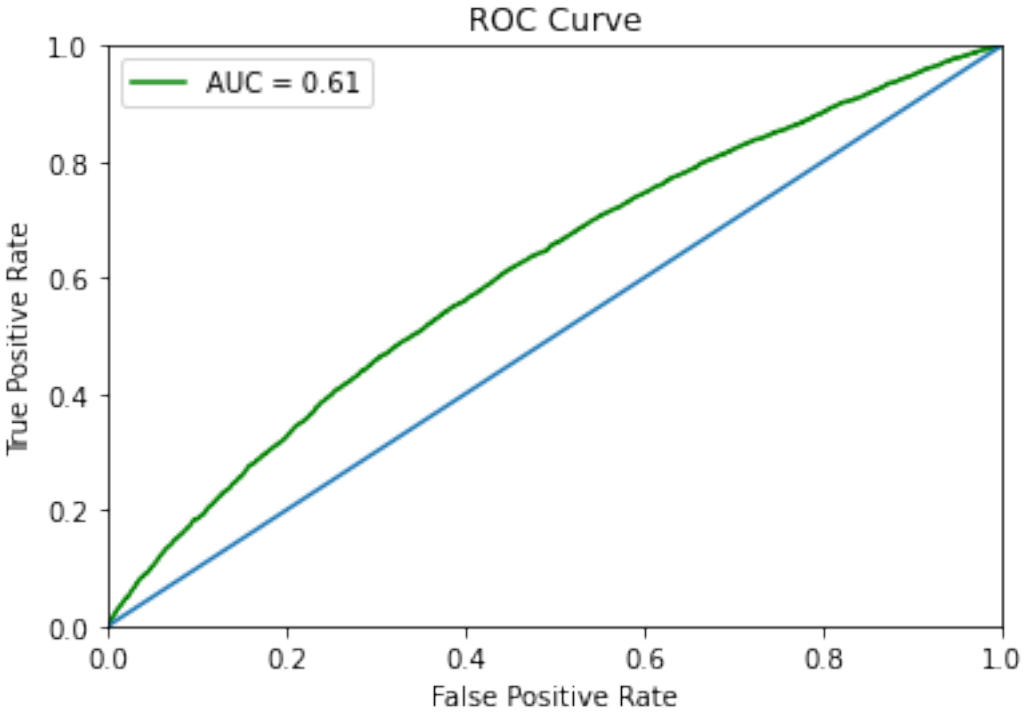



```
SVM Model ROC Score :  0.5891095351298821
```

[7]:
```
print("SVM Model on clean_data")
svm(cleandata)
```

```
SVM Model on clean_data
SVM Model Accuracy Score : 0.9202965708989805


Precision :  [0.07972158 0.07970661 0.07970791 … 0.         0.         1.
]
Recall    :  [1.       0.999796 0.999796 … 0.       0.       0.      ]
f1_score  :  [0.14767062 0.14764272 0.14764494 …        nan        nan 0.
]
```


Precision-Recall Curve
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve
AUC = 0.61
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

```
SVM Model ROC Score :  0.6114893520031359
```