ModelTune_LogReg-XGBoost_ComboPlots

October 1, 2022

[ ]:
```
!pip install xgboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: xgboost in /usr/local/lib/python3.7/dist-packages
(0.90)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from xgboost) (1.21.6)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages
(from xgboost) (1.7.3)
```

[2]:
```
%cd /content/drive/MyDrive/Github/ml-blog
```

```
/content/drive/MyDrive/Github/ml-blog
```

[3]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
```

0.1 Import Scaled Data

[ ]:
```
filename = 'taiwan-credit-col-transform-FULL.csv'
```

[ ]:
```
DATA = os.path.relpath('/content/drive/MyDrive/Github/ml-blog/credit/data/' +␣
↪filename)

df = pd.read_csv(DATA, index_col='ID', header=0)
df.head()
```

[ ]:
```
    category__SEX_1  category__SEX_2  category__EDUCATION_0  \
ID
1               0.0              1.0                    0.0
2               0.0              1.0                    0.0
```

```
3              0.0             1.0                     0.0
4              0.0             1.0                     0.0
5              1.0             0.0                     0.0

    category__EDUCATION_1  category__EDUCATION_2  category__EDUCATION_3  \
ID
1                     0.0                    1.0                    0.0
2                     0.0                    1.0                    0.0
3                     0.0                    1.0                    0.0
4                     0.0                    1.0                    0.0
5                     0.0                    1.0                    0.0

    category__EDUCATION_4  category__EDUCATION_5  category__EDUCATION_6  \
ID
1                     0.0                    0.0                    0.0
2                     0.0                    0.0                    0.0
3                     0.0                    0.0                    0.0
4                     0.0                    0.0                    0.0
5                     0.0                    0.0                    0.0

    category__MARRIAGE_0  …  nums__BILL_AMT4  nums__BILL_AMT5  \
ID                        …
1                    0.0  …        -0.672497        -0.663059
2                    0.0  …        -0.621636        -0.606229
3                    0.0  …        -0.449730        -0.417188
4                    0.0  …        -0.232373        -0.186729
5                    0.0  …        -0.346997        -0.348137

    nums__BILL_AMT6  nums__PAY_AMT1  nums__PAY_AMT2  nums__PAY_AMT3  \
ID
1         -0.652724       -0.341942       -0.227086       -0.296801
2         -0.597966       -0.341942       -0.213588       -0.240005
3         -0.391630       -0.250292       -0.191887       -0.240005
4         -0.156579       -0.221191       -0.169361       -0.228645
5         -0.331482       -0.221191        1.335034        0.271165

    nums__PAY_AMT4  nums__PAY_AMT5  nums__PAY_AMT6  default payment next month
ID
1        -0.308063       -0.314136       -0.293382                           1
2        -0.244230       -0.314136       -0.180878                           1
3        -0.244230       -0.248683       -0.012122                           0
4        -0.237846       -0.244166       -0.237130                           0
5         0.266434       -0.269039       -0.255187                           0

[5 rows x 92 columns]
```

[ ]:
```
X = df.iloc[:, :91]
y = df.iloc[:, 91]
X.columns, y.name, y.shape
```

[ ]:
```
(Index(['category__SEX_1', 'category__SEX_2', 'category__EDUCATION_0',
        'category__EDUCATION_1', 'category__EDUCATION_2',
        'category__EDUCATION_3', 'category__EDUCATION_4',
        'category__EDUCATION_5', 'category__EDUCATION_6',
        'category__MARRIAGE_0', 'category__MARRIAGE_1', 'category__MARRIAGE_2',
        'category__MARRIAGE_3', 'category__PAY_0_-2', 'category__PAY_0_-1',
        'category__PAY_0_0', 'category__PAY_0_1', 'category__PAY_0_2',
        'category__PAY_0_3', 'category__PAY_0_4', 'category__PAY_0_5',
        'category__PAY_0_6', 'category__PAY_0_7', 'category__PAY_0_8',
        'category__PAY_2_-2', 'category__PAY_2_-1', 'category__PAY_2_0',
        'category__PAY_2_1', 'category__PAY_2_2', 'category__PAY_2_3',
        'category__PAY_2_4', 'category__PAY_2_5', 'category__PAY_2_6',
        'category__PAY_2_7', 'category__PAY_2_8', 'category__PAY_3_-2',
        'category__PAY_3_-1', 'category__PAY_3_0', 'category__PAY_3_1',
        'category__PAY_3_2', 'category__PAY_3_3', 'category__PAY_3_4',
        'category__PAY_3_5', 'category__PAY_3_6', 'category__PAY_3_7',
        'category__PAY_3_8', 'category__PAY_4_-2', 'category__PAY_4_-1',
        'category__PAY_4_0', 'category__PAY_4_1', 'category__PAY_4_2',
        'category__PAY_4_3', 'category__PAY_4_4', 'category__PAY_4_5',
        'category__PAY_4_6', 'category__PAY_4_7', 'category__PAY_4_8',
        'category__PAY_5_-2', 'category__PAY_5_-1', 'category__PAY_5_0',
        'category__PAY_5_2', 'category__PAY_5_3', 'category__PAY_5_4',
        'category__PAY_5_5', 'category__PAY_5_6', 'category__PAY_5_7',
        'category__PAY_5_8', 'category__PAY_6_-2', 'category__PAY_6_-1',
        'category__PAY_6_0', 'category__PAY_6_2', 'category__PAY_6_3',
        'category__PAY_6_4', 'category__PAY_6_5', 'category__PAY_6_6',
        'category__PAY_6_7', 'category__PAY_6_8', 'nums__LIMIT_BAL',
        'nums__AGE', 'nums__BILL_AMT1', 'nums__BILL_AMT2', 'nums__BILL_AMT3',
        'nums__BILL_AMT4', 'nums__BILL_AMT5', 'nums__BILL_AMT6',
        'nums__PAY_AMT1', 'nums__PAY_AMT2', 'nums__PAY_AMT3', 'nums__PAY_AMT4',
        'nums__PAY_AMT5', 'nums__PAY_AMT6'],
       dtype='object'), 'default payment next month', (30000,))
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

0.2 Logistic Regression Baseline

[ ]:
```
lr_base_clf = LogisticRegression(penalty='l2', tol=0.0001,
                                 C=1, solver='lbfgs',
                                 max_iter=500, multi_class='ovr').fit(X_train,␣
 ↪y_train)
```

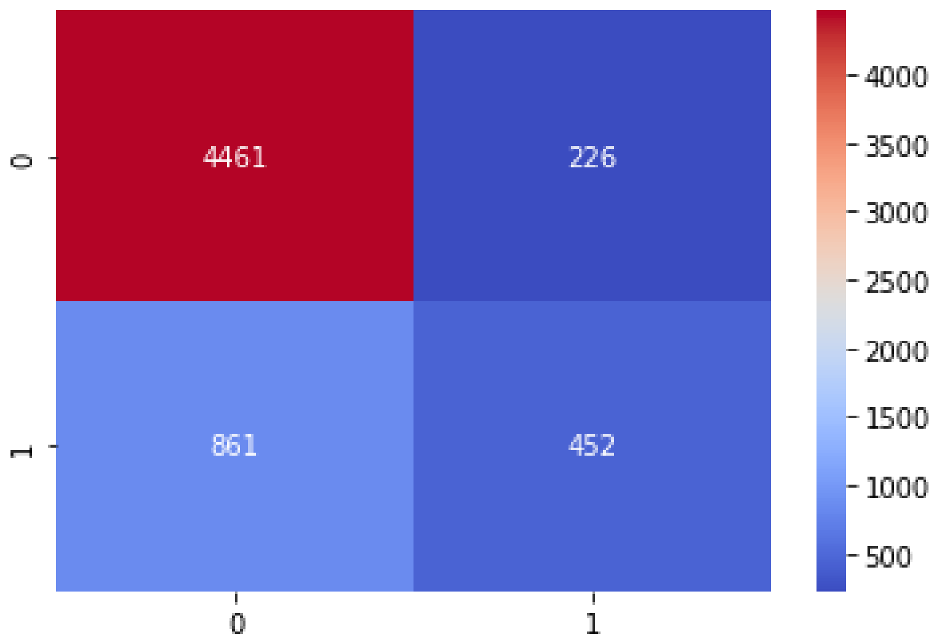
[ ]:
```python
y_lrbase_preds = lr_base_clf.predict(X_test)
```

[ ]:
```python
print(confusion_matrix(y_test, y_lrbase_preds))
```

```
[[4461  226]
 [ 861  452]]
```

[ ]:
```python
sns.heatmap(confusion_matrix(y_test, y_lrbase_preds), cmap='coolwarm',␣
 ↪annot=True, fmt='g')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10f0898b50>



[ ]:
```python
print(classification_report(y_test, y_lrbase_preds))
```

```
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      4687
           1       0.67      0.34      0.45      1313

    accuracy                           0.82      6000
   macro avg       0.75      0.65      0.67      6000
weighted avg       0.80      0.82      0.80      6000
```

It's about what we expected….

0.3 GridSearchCV to compare hyperparameter settings

[ ]:
```
lr_param_grid = [
    {'penalty': ['l2'], 'C': [0.1, 1.0, 5.0, 10.0, 100.0], 'tol': [0.001, 0.01,␣
↪0.5, 1.0]},
    {'penalty': ['l1'], 'C': [0.1, 1.0, 5.0, 10.0, 100.0], 'tol': [0.001, 0.01,␣
↪0.5, 1.0]},
    {'penalty': ['none'], 'tol': [0.001, 0.01, 0.5, 1.0]},
]

xgb_param_grid = [
    {'max_depth': [2], 'n_estimators': [25, 50, 100, 500], 'learning_rate': [0.
↪01, 0.05, 0.075, 0.1]},
    {'max_depth': [4], 'n_estimators': [25, 50, 100, 500], 'learning_rate': [0.
↪01, 0.05, 0.075, 0.1]},
    {'max_depth': [6], 'n_estimators': [25, 50, 100, 500], 'learning_rate': [0.
↪01, 0.05, 0.075, 0.1]},
]

lr = LogisticRegression(max_iter=2000, solver='saga')

xgb = XGBClassifier(use_label_encoder=False)
```

[ ]:
```
lr_clf = GridSearchCV(lr, param_grid=lr_param_grid, scoring='roc_auc')
lr_clf.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(estimator=LogisticRegression(max_iter=2000, solver='saga'),
             param_grid=[{'C': [0.1, 1.0, 5.0, 10.0, 100.0], 'penalty': ['l2'],
                          'tol': [0.001, 0.01, 0.5, 1.0]},
                         {'C': [0.1, 1.0, 5.0, 10.0, 100.0], 'penalty': ['l1'],
                          'tol': [0.001, 0.01, 0.5, 1.0]},
                         {'penalty': ['none'], 'tol': [0.001, 0.01, 0.5, 1.0]}],
             scoring='roc_auc')
```

[ ]:
```
print(lr_clf.best_params_, lr_clf.best_estimator_, round(lr_clf.best_score_, 3))
```

```
{'C': 0.1, 'penalty': 'l2', 'tol': 0.001} LogisticRegression(C=0.1,
max_iter=2000, solver='saga', tol=0.001) 0.768
```

[ ]:
```
xgb_clf = GridSearchCV(xgb, param_grid=xgb_param_grid, scoring='roc_auc')
xgb_clf.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(estimator=XGBClassifier(use_label_encoder=False),
             param_grid=[{'learning_rate': [0.01, 0.05, 0.075, 0.1],
                          'max_depth': [2],
                          'n_estimators': [25, 50, 100, 500]},
                         {'learning_rate': [0.01, 0.05, 0.075, 0.1],
                          'max_depth': [4],
```

```
                                 'n_estimators': [25, 50, 100, 500]},
                                {'learning_rate': [0.01, 0.05, 0.075, 0.1],
                                 'max_depth': [6],
                                 'n_estimators': [25, 50, 100, 500]}],
             scoring='roc_auc')
```

[ ]:
```
print(xgb_clf.best_params_, xgb_clf.best_estimator_, round(xgb_clf.best_score_,␣
 ↪3))
```

```
{'learning_rate': 0.05, 'max_depth': 6, 'n_estimators': 100}
XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False) 0.783
```

0.4 Evaluation, Graphs, etc.

[ ]:
```
from sklearn.metrics import roc_curve, auc, roc_auc_score
```

[ ]:
```
y_lr_probas = lr_clf.predict_proba(X_test)[:, 1] # using the 'greater label', i.
 ↪e., 0 for 'No default'.
```

[ ]:
```
y_xgb_probas = xgb_clf.predict_proba(X_test)[:, 1]
```

[ ]:
```
y_xgb_probas.shape
```

[ ]:
```
(6000,)
```

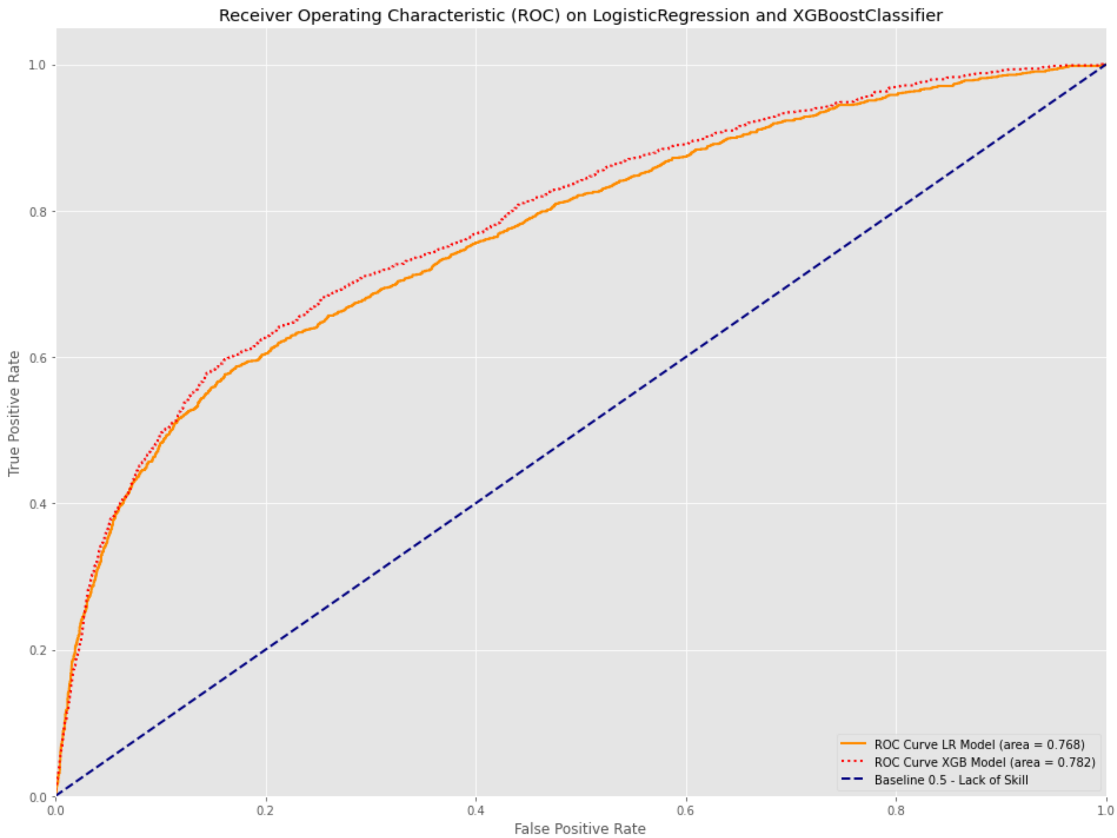
[ ]:
```
y_test_np = y_test.to_numpy()
```

[ ]:
```
y_test_np.shape
```

[ ]:
```
(6000,)
```

[ ]:
```
truePR_lr = dict()
falsePR_lr = dict()
roc_auc_lr = dict()

truePR_xgb = dict()
falsePR_xgb = dict()
roc_auc_xgb = dict()


falsePR_lr, truePR_lr, _ = roc_curve(y_test_np, y_lr_probas)
roc_auc_lr = auc(falsePR_lr, truePR_lr)

falsePR_xgb, truePR_xgb, _ = roc_curve(y_test_np, y_xgb_probas)
roc_auc_xgb = auc(falsePR_xgb, truePR_xgb)


plt.style.use('ggplot')
```

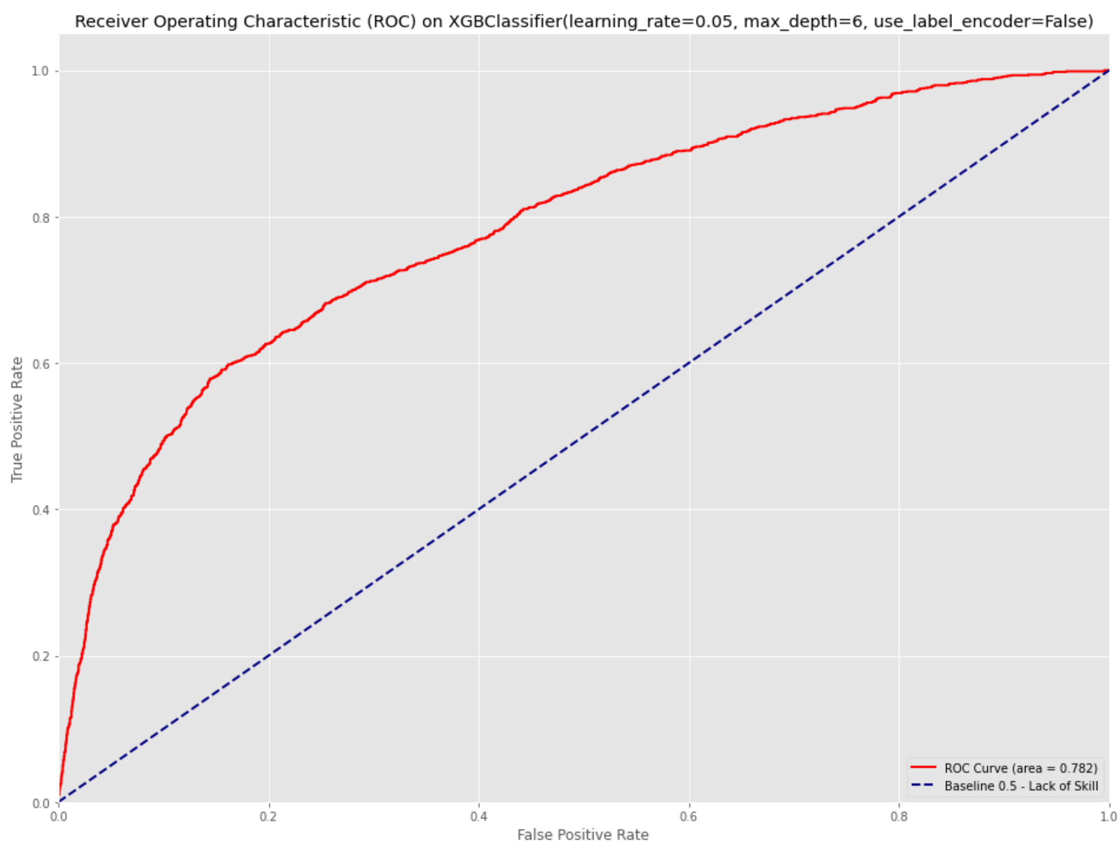
```
plt.figure(figsize=(16,12))
lw = 2

plt.plot(
    falsePR_lr,
    truePR_lr,
    color='darkorange',
    lw=lw,
    label="ROC Curve LR Model (area = %0.3f)" % roc_auc_lr,
)

plt.plot(
    falsePR_xgb,
    truePR_xgb,
    color='red',
    linestyle='dotted',
    lw=lw,
    label="ROC Curve XGB Model (area = %0.3f)" % roc_auc_xgb,
)

plt.plot([0,1], color='navy', lw=lw, linestyle='--', label='Baseline 0.5 - Lack␣
 ↪of Skill')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) on LogisticRegression and␣
 ↪XGBoostClassifier')
plt.legend(loc='lower right')
plt.savefig('./credit/model/best-combo-model-auc.png')
plt.show()
```



[ ]:
```
y_xgb_probas = xgb_clf.predict_proba(X_test)[:, 1] # using the 'greater label',␣
↪i.e., 0 for 'No default'.
```

[ ]:
```
truePR = dict()
falsePR = dict()
roc_auc = dict()


falsePR, truePR, _ = roc_curve(y_test_np, y_xgb_probas)
roc_auc = auc(falsePR, truePR)

plt.style.use('ggplot')
plt.figure(figsize=(16,12))
lw = 2
plt.plot(
    falsePR,
    truePR,
    color='red',
    lw=lw,
    label="ROC Curve (area = %0.3f)" % roc_auc,
```

```
)

plt.plot([0,1], color='navy', lw=lw, linestyle='--', label='Baseline 0.5 - Lack␣
 ↪of Skill')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) on␣
 ↪XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False)')
plt.legend(loc='lower right')
plt.savefig('./credit/model/best-xgb-model-auc.png')
plt.show()
```



[ ]:
```
y_lr_preds = lr_clf.predict(X_test)
y_xgb_preds = xgb_clf.predict(X_test)
```

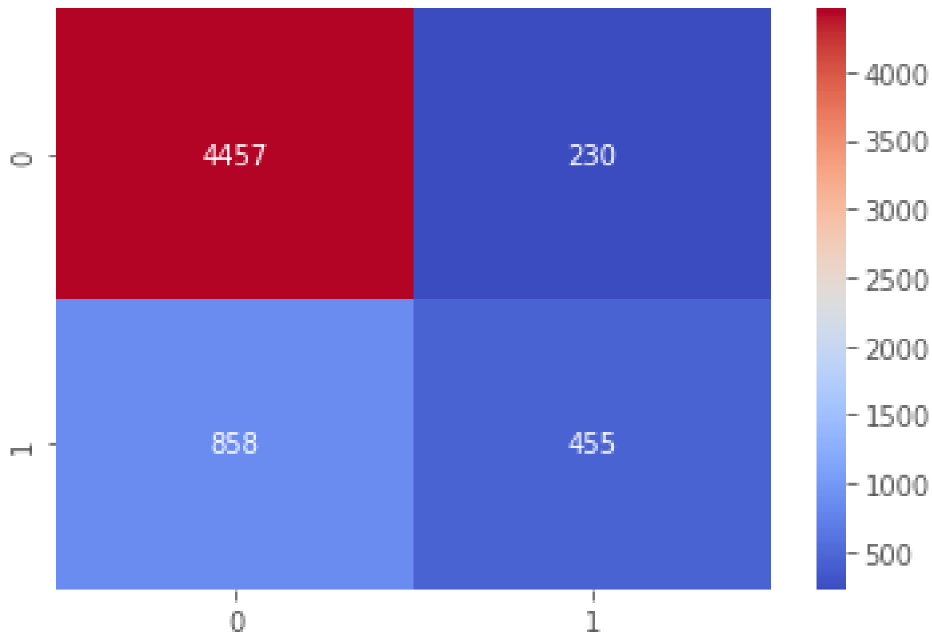
[ ]:
```
print(classification_report(y_test_np, y_lr_preds))
```

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

```
              0       0.84      0.95      0.89      4687
              1       0.66      0.35      0.46      1313

       accuracy                           0.82      6000
      macro avg       0.75      0.65      0.67      6000
   weighted avg       0.80      0.82      0.80      6000
```

[ ]:
```python
sns.heatmap(confusion_matrix(y_test, y_lr_preds), cmap='coolwarm', annot=True,
 fmt='g')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10ecd18c50>

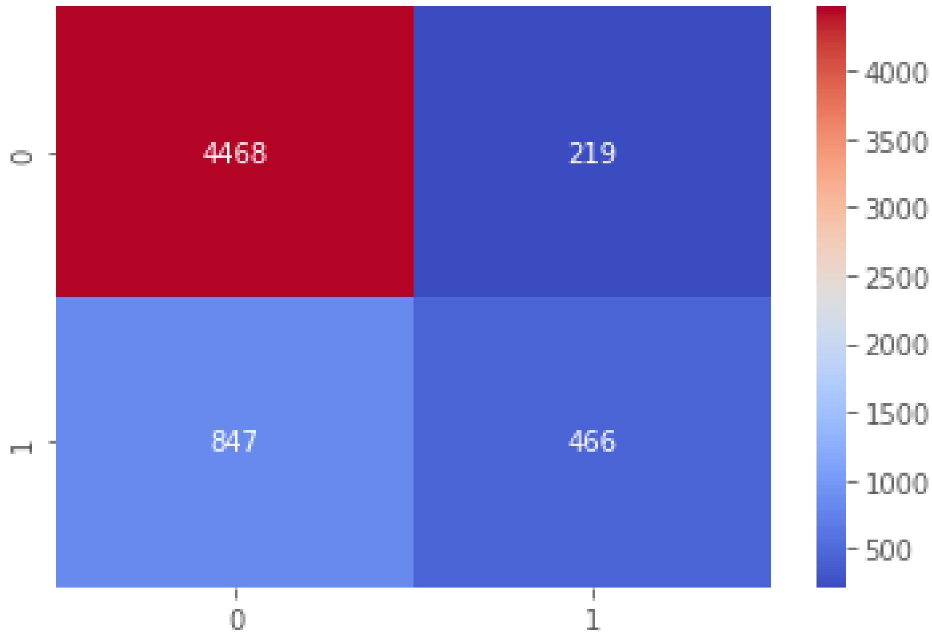


[ ]:
```python
print(classification_report(y_test_np, y_xgb_preds))
```

```
              precision    recall  f1-score   support

              0       0.84      0.95      0.89      4687
              1       0.68      0.35      0.47      1313

       accuracy                           0.82      6000
      macro avg       0.76      0.65      0.68      6000
   weighted avg       0.81      0.82      0.80      6000
```

```
[ ]: sns.heatmap(confusion_matrix(y_test, y_xgb_preds), cmap='coolwarm', annot=True,␣
       ↪fmt='g')
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10eb332210>
```



0.5 SMOTE to Address Class Imbalance

- The dataset has a clear imbalance in the label counts. This means our models will have trouble discerning a **minority class** instance clearly.
- We can use the **SMOTE** method to improve class balance.

```
[ ]: from imblearn.under_sampling import RandomUnderSampler
     from imblearn.over_sampling import SMOTE
     from imblearn.pipeline import Pipeline
     from sklearn.metrics import classification_report
```

```
[ ]: ov = SMOTE(sampling_strategy=0.5, random_state=42)
     und = RandomUnderSampler(sampling_strategy=0.35, random_state=42)
```

```
[ ]: from collections import Counter
```

```
[ ]: count = Counter(y)
     print(count, 'Ratio: ', round(count[1]/count[0], 4), '% minority class (1)')
```

```
Counter({0: 23364, 1: 6636}) Ratio:  0.284 % minority class (1)
```

[ ]:
```
count_train = Counter(y_train)
print(count_train, 'Ratio: ', round(count_train[1]/count_train[0], 4), '%␣
↪minority class (1)')
```

```
Counter({0: 18677, 1: 5323}) Ratio:  0.285 % minority class (1)
```

[ ]:
```
test_pipe = Pipeline(steps=([('und', und), ('ov', ov)]))
```

[ ]:
```
X_res, y_res = test_pipe.fit_resample(X_train, y_train)
```

[ ]:
```
count_res = Counter(y_res)
print(count_res, 'Ratio: ', round(count_res[1]/count_res[0], 4), '% minority␣
↪class (1)')
```

```
Counter({0: 15208, 1: 7604}) Ratio:  0.5 % minority class (1)
```

[ ]:
```
# {'learning_rate': 0.05, 'max_depth': 6, 'n_estimators': 100}␣
↪XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False) 0.783
xgb = XGBClassifier(n_estimators=100, max_depth=6, learning_rate=0.05,␣
↪use_label_encoder=False)
over = SMOTE(sampling_strategy=0.5, random_state=42)
under = RandomUnderSampler(sampling_strategy=0.35, random_state=42)

steps = [('under', under), ('over', over), ('xgb_clf', xgb)]
smote_model = Pipeline(steps=steps)
```

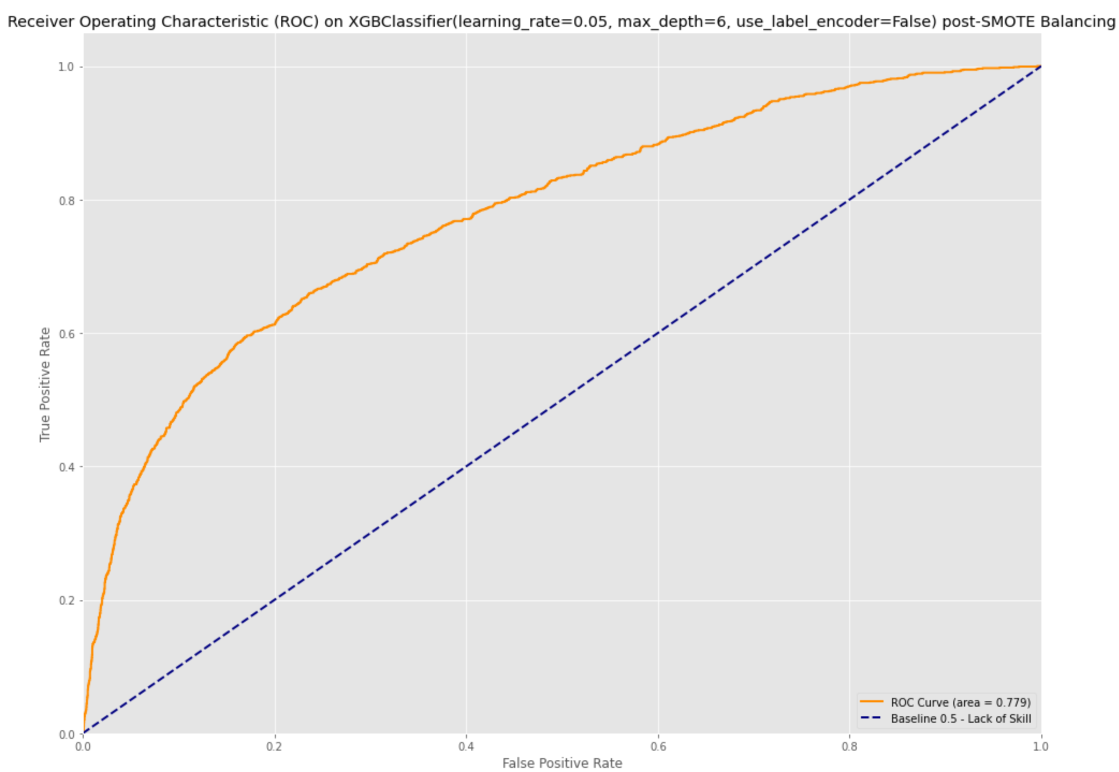
[ ]:
```
smote_model.fit(X_train, y_train)
```

[ ]:
```
Pipeline(steps=[('under',
                 RandomUnderSampler(random_state=42, sampling_strategy=0.35)),
                ('over', SMOTE(random_state=42, sampling_strategy=0.5)),
                ('xgb_clf',
                 XGBClassifier(learning_rate=0.05, max_depth=6,
                               use_label_encoder=False))])
```

[ ]:
```
y_smote_probas = smote_model.predict_proba(X_test)[:, 1] # using the 'greater␣
↪label', i.e., 0 for 'No default'.
```

[ ]:
```
truePR = dict()
falsePR = dict()
roc_auc = dict()


falsePR, truePR, _ = roc_curve(y_test, y_smote_probas)
roc_auc = auc(falsePR, truePR)

plt.style.use('ggplot')
plt.figure(figsize=(16,12))
```

```
lw = 2
plt.plot(
    falsePR,
    truePR,
    color='darkorange',
    lw=lw,
    label="ROC Curve (area = %0.3f)" % roc_auc,
)

plt.plot([0,1], color='navy', lw=lw, linestyle='--', label='Baseline 0.5 - Lack of Skill')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) on XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False) post-SMOTE Balancing')
plt.legend(loc='lower right')
plt.savefig('./credit/model/best-xgb-model-auc-smote.png')
plt.show()
```



[ ]:
```
y_smote_preds = smote_model.predict(X_test)
```

[ ]:
```
print(classification_report(y_test, y_smote_preds))
```

```
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      4687
           1       0.63      0.42      0.50      1313

    accuracy                           0.82      6000
   macro avg       0.74      0.67      0.69      6000
weighted avg       0.80      0.82      0.80      6000
```

- The **precision** of **class 0** : 0.85
- The **recall** (sensitivity) of class 0 : 0.93
- The **false discovery rate** of class 0 : $1 - 0.85 = 0.15$
- The **precision** of **class 1**, the **minority class** : 0.63
- The **recall** of class 1 : 0.42
- The **false discovery rate** of class 1 : $1 - 0.63 = 0.37$
- The **False Negative Rate** of **Class 1** is $1 - recall$, or $1 - 0.42 = 0.58$ This is **the rate of missing credit defaults**.

[ ]:
```
from imblearn.under_sampling import NeighbourhoodCleaningRule
```

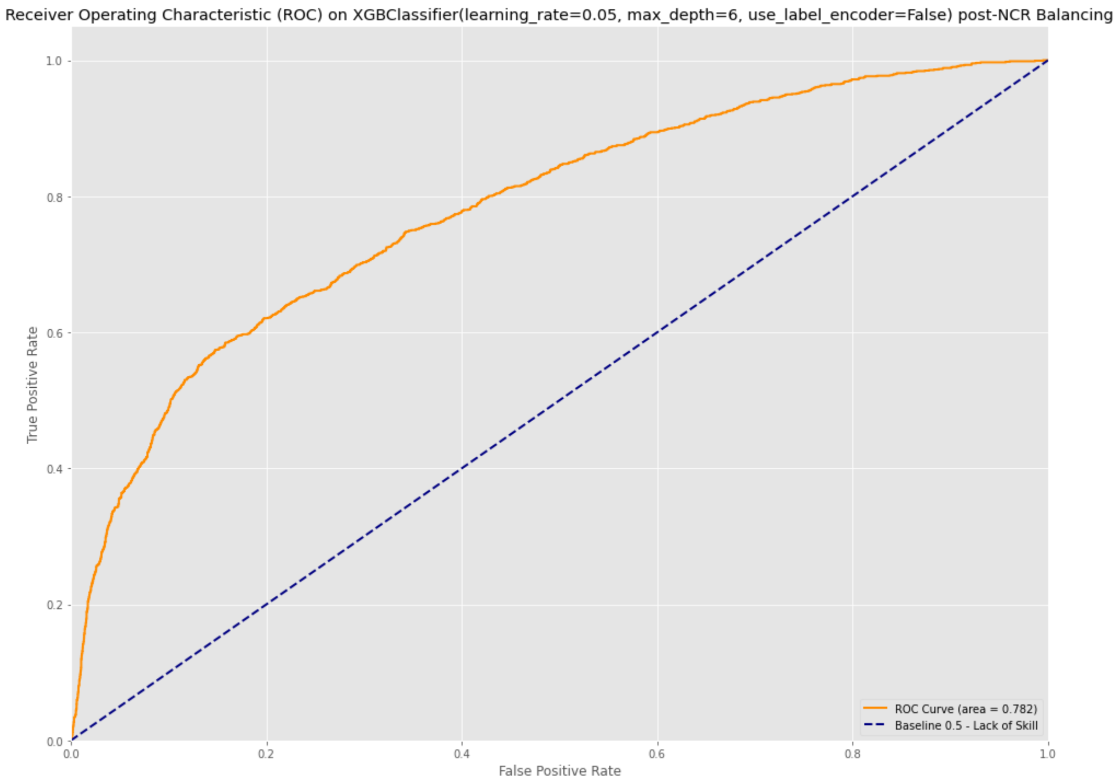
[ ]:
```
# {'learning_rate': 0.05, 'max_depth': 6, 'n_estimators': 100}␣
 ↪XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False) 0.783
xgb = XGBClassifier(n_estimators=100, max_depth=6, learning_rate=0.05,␣
 ↪use_label_encoder=False)
over = SMOTE(sampling_strategy=0.5, random_state=42)
under = NeighbourhoodCleaningRule(sampling_strategy='auto', n_neighbors=3,␣
 ↪n_jobs=1)

steps = [('under', under), ('over', over), ('xgb_clf', xgb)]
ncr_model = Pipeline(steps=steps)
```

[ ]:
```
ncr_model.fit(X_train, y_train)
```

[ ]:
```
Pipeline(steps=[('under', NeighbourhoodCleaningRule(n_jobs=1)),
                ('over', SMOTE(random_state=42, sampling_strategy=0.5)),
                ('xgb_clf',
                 XGBClassifier(learning_rate=0.05, max_depth=6,
                               use_label_encoder=False))])
```

```
[ ]: y_ncr_probas = ncr_model.predict_proba(X_test)[:, 1] # using the 'greater␣
     ↪label', i.e., 0 for 'No default'.
```

```
[ ]: truePR = dict()
     falsePR = dict()
     roc_auc = dict()


     falsePR, truePR, _ = roc_curve(y_test, y_ncr_probas)
     roc_auc = auc(falsePR, truePR)

     plt.style.use('ggplot')
     plt.figure(figsize=(16,12))
     lw = 2
     plt.plot(
         falsePR,
         truePR,
         color='darkorange',
         lw=lw,
         label="ROC Curve (area = %0.3f)" % roc_auc,
     )

     plt.plot([0,1], color='navy', lw=lw, linestyle='--', label='Baseline 0.5 - Lack␣
     ↪of Skill')
     plt.xlim([0.0, 1.0])
     plt.ylim([0.0, 1.05])
     plt.xlabel('False Positive Rate')
     plt.ylabel('True Positive Rate')
     plt.title('Receiver Operating Characteristic (ROC) on␣
     ↪XGBClassifier(learning_rate=0.05, max_depth=6, use_label_encoder=False)␣
     ↪post-NCR Balancing')
     plt.legend(loc='lower right')
     plt.savefig('./credit/model/best-xgb-model-auc-ncr.png')
     plt.show()
```



[ ]:
```
y_ncr_preds = ncr_model.predict(X_test)
```

[ ]:
```
print(classification_report(y_test, y_ncr_preds))
```

```
              precision    recall  f1-score   support

           0       0.88      0.86      0.87      4687
           1       0.53      0.57      0.55      1313

    accuracy                           0.79      6000
   macro avg       0.70      0.71      0.71      6000
weighted avg       0.80      0.79      0.80      6000
```

- The **precision** of **class 0** : 0.88;
- The **recall** (sensitivity) of class 0 : 0.86
- The **false discovery rate** of class 0 : $1 - 0.88 = 0.12$
- The **precision** of **class 1**, the **minority class** : 0.53
- The **recall** of class 1 : 0.57
- The **false discovery rate** of class 1 : $1 - 0.53 = 0.47$

[ ]:

```

```