Classification Models

November 7, 2021

[1]:
```python
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_validate
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import StratifiedKFold
from sklearn import ensemble
import xgboost as xgb
from sklearn.metrics import mean_squared_error
```

Import Dataset

[2]:
```python
df =pd.read_csv ('/home/jovyan/Onlineshoppersdata(1).csv')
```

1 Classification Algortihms with imbalanced dataset

1.1 Random Forest

1.1.1 Separate the data into Train and Test

[3]:
```
x = df.drop(['Revenue'],axis=1).values   # independant features
y = df['Revenue'].values                                  # dependant␣
↪variable

x_trainrf, x_testrf, y_trainrf, y_testrf = train_test_split(x, y, test_size=0.
↪2, random_state=42)
```

[4]:
```
forest  = RandomForestClassifier()

forest.fit(x_trainrf,y_trainrf)

y_predrf =forest.predict(x_testrf)
```

[5]:
```
accuracy_forest = (metrics.accuracy_score(y_testrf,y_predrf)*100)
print('Acurracy is ', str(round(accuracy_forest,2)))
```

```
Acurracy is  89.05
```

[6]:
```
rmse = np.sqrt(mean_squared_error(y_testrf, y_predrf))
print("RMSE (root-mean-square error): %f" % (rmse))
```

```
RMSE (root-mean-square error): 0.330891
```

[7]:
```
# View confusion matrix for test data and predictions
matrix_rf = confusion_matrix(y_testrf, y_predrf)
print(matrix_rf )
```

```
[[1974   81]
 [ 189  222]]
```

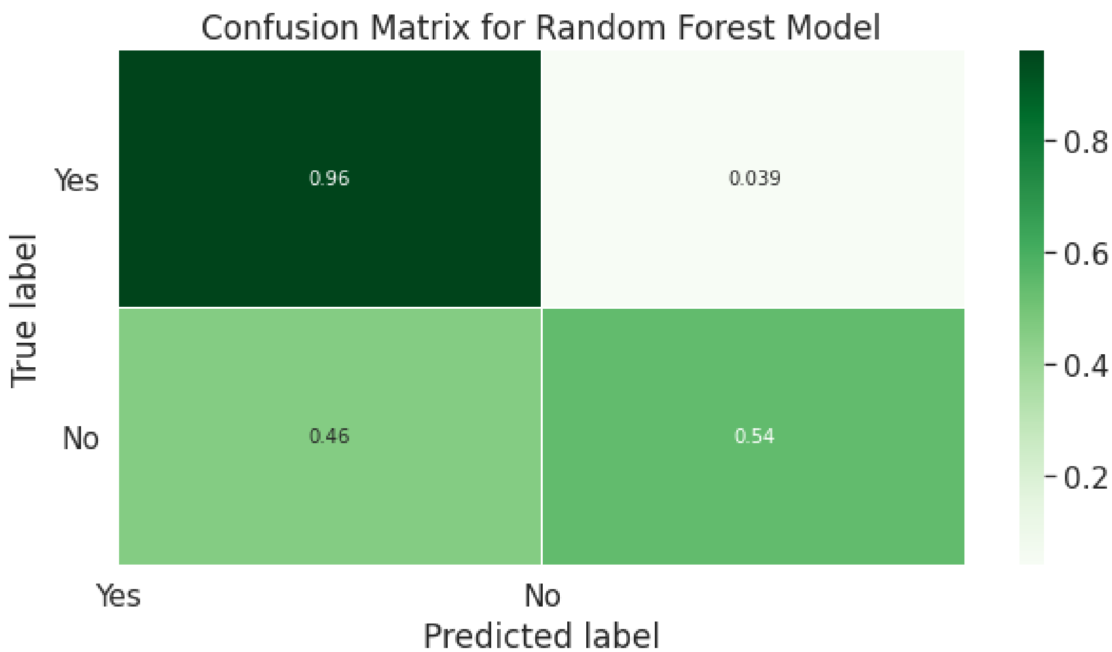
[8]:
```
# Get and reshape confusion matrix data

matrix_rforest = matrix_rf.astype('float') / matrix_rf.sum(axis=1)[:, np.
↪newaxis]

# Build the plot
plt.figure(figsize=(10,5))
sns.set(font_scale=1.4)
sns.heatmap(matrix_rforest, annot=True, annot_kws={'size':10},
            cmap=plt.cm.Greens, linewidths=0.2)

# Add labels to the plot
class_names = ['Yes', 'No']
tick_marks = np.arange(len(class_names))
tick_marks2 = tick_marks + 0.5
plt.xticks(tick_marks, class_names, rotation=0,)
plt.yticks(tick_marks2, class_names, rotation=0,  )
```

```
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix for Random Forest Model')
plt.savefig('output14.png', dpi=300, bbox_inches='tight')
plt.show()
```



[9]:
```
# View the classification report for test data and predictions
print(classification_report(y_testrf, y_predrf))
```

```
              precision    recall  f1-score   support

           0       0.91      0.96      0.94      2055
           1       0.73      0.54      0.62       411

    accuracy                           0.89      2466
   macro avg       0.82      0.75      0.78      2466
weighted avg       0.88      0.89      0.88      2466
```

1.2 K-Fold Cross Validation for Random Forest

Using Cross Validate

[10]:
```
x = df.drop(['Revenue'],axis=1).values   # independant features
```

```
y = df['Revenue'].values                                              # dependant␣
↪variable

model = RandomForestClassifier(random_state=42)
cv = cross_validate(model, x, y, cv=10)
test_score =(cv['test_score'])*100
print('The test scores are:, ' + str(test_score))
print('The average test score is :' + str(test_score.mean()))
```

```
The test scores are:, [88.24006488 90.51094891 93.18734793 88.40227088
89.6188159  87.10462287
 87.34793187 88.80778589 89.21330089 86.13138686]
The average test score is :88.85644768856449
```

[11]:
```
scores = cross_val_score(model, x, y, cv=10)
scores
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores.mean(),␣
↪scores.std()))
```

```
0.89 accuracy with a standard deviation of 0.02
```

Using Kfold to separate the data

[12]:
```
X = df.drop(['Revenue'],axis=1).values   # independant features
y = df['Revenue'].values                                              # dependant␣
↪variable

kf = KFold(n_splits=10,random_state=42,shuffle=True)
kf.get_n_splits(X)
i=1
print("confusion matrix:")
for train_index, test_index in kf.split(X):

    X_train, X_test = X[train_index], X[test_index]

    y_train, y_test = y[train_index], y[test_index]

    model.fit(X_train, y_train)

    print (i,"\n",confusion_matrix(y_test, model.predict(X_test)))
    i=i+1
    print(10* '#')
```

```
confusion matrix:
1
 [[987  43]
 [ 95 108]]
##########
```

```
2
 [[989  36]
 [ 91 117]]
##########
3
 [[1029   40]
 [  67   97]]
##########
4
 [[1007   39]
 [  79  108]]
##########
5
 [[1013   39]
 [  76  105]]
##########
6
 [[1011   28]
 [  75  119]]
##########
7
 [[1010   37]
 [  79  107]]
##########
8
 [[984  46]
 [ 89 114]]
##########
9
 [[1007   28]
 [  72  126]]
##########
10
 [[1012   37]
 [  92   92]]
##########
```

Using StratifiedKFold

[13]:
```python
X = df.drop(['Revenue'],axis=1).values   # independant features
y = df['Revenue'].values                                        # dependant␣
 ↪variable

kf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

cnt = 1
# split()  method generate indices to split data into training and test set.
for train_index, test_index in kf.split(X, y):
```

```
    print(f'Fold:{cnt}, Train set: {len(train_index)}, Test set:
↪{len(test_index)}')
    cnt+=1

score = cross_val_score(ensemble.RandomForestClassifier(random_state= 42), X,␣
↪y, cv= kf, scoring="accuracy")
print(f'Scores for each fold are: {score}')
print(f'Average score: {"{:.2f}".format(score.mean())}')
```

```
Fold:1, Train set: 11097, Test set:1233
Fold:2, Train set: 11097, Test set:1233
Fold:3, Train set: 11097, Test set:1233
Fold:4, Train set: 11097, Test set:1233
Fold:5, Train set: 11097, Test set:1233
Fold:6, Train set: 11097, Test set:1233
Fold:7, Train set: 11097, Test set:1233
Fold:8, Train set: 11097, Test set:1233
Fold:9, Train set: 11097, Test set:1233
Fold:10, Train set: 11097, Test set:1233
Scores for each fold are: [0.90186537 0.9026764  0.90024331 0.89699919
0.90510949 0.90348743
 0.9026764  0.9107867  0.89213301 0.9026764 ]
Average score: 0.90
```

After applying K-fold to Random Forest we can observe that the average score remains at 90%

1.3 XGBoost

[14]:
```
x = df.drop(['Revenue'],axis=1).values   # independant features
y = df['Revenue'].values                                      # dependant␣
↪variable

data_dmatrix = xgb.DMatrix(data=x,label=y)
X_trainxg, X_testxg, y_trainxg, y_testxg = train_test_split(x, y, test_size=0.
↪2, random_state=42)

xg_model = xgb.XGBClassifier()
print(xg_model)
```

```
XGBClassifier(base_score=None, booster=None, colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None,
              enable_categorical=False, gamma=None, gpu_id=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_delta_step=None, max_depth=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
```

```
             predictor=None, random_state=None, reg_alpha=None,
             reg_lambda=None, scale_pos_weight=None, subsample=None,
             tree_method=None, validate_parameters=None, verbosity=None)
```

[15]:
```
xg_model.fit(X_trainxg,y_trainxg)

preds_xg = xg_model.predict(X_testxg)# make predictions for test data

predictions = [round(value) for value in preds_xg]
```

```
[22:30:20] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

```
/opt/conda/lib/python3.7/site-packages/xgboost/sklearn.py:1224: UserWarning: The
use of label encoder in XGBClassifier is deprecated and will be removed in a
future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, …, [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

[16]:
```
accuracy_xg = (metrics.accuracy_score(y_testxg,preds_xg)*100)
print('Acurracy is ', str(round(accuracy_forest,2)))
```

```
Acurracy is  89.05
```

[17]:
```
rmse = np.sqrt(mean_squared_error(y_testxg, preds_xg))
print("RMSE (root-mean-square error): %f" % (rmse))
```

```
RMSE (root-mean-square error): 0.338165
```

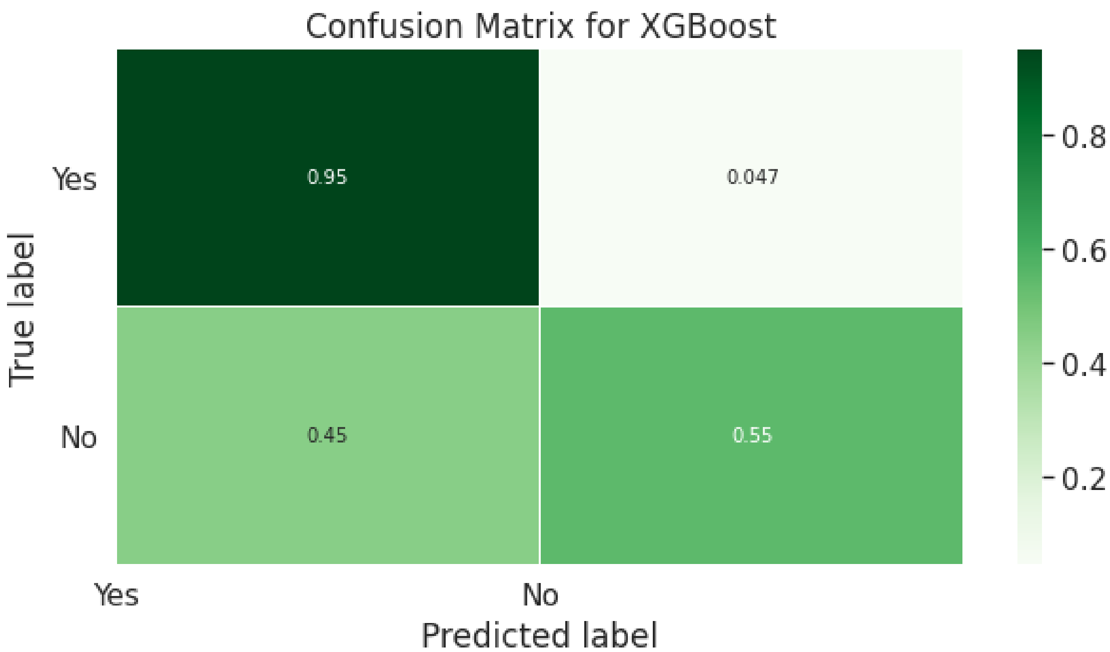
[24]:
```
# View confusion matrix for test data and predictions
matrix_xgboost=confusion_matrix(y_testxg, preds_xg)
print(matrix_xgboost)
```

```
[[1958   97]
 [ 185  226]]
```

[25]:
```
# Get and reshape confusion matrix data
matrix_xg = matrix_xgboost.astype('float') / matrix_xgboost.sum(axis=1)[:, np.
 ↪newaxis]

# Build the plot
plt.figure(figsize=(10,5))
sns.set(font_scale=1.4)
sns.heatmap(matrix_xg, annot=True, annot_kws={'size':10},
            cmap=plt.cm.Greens, linewidths=0.2)
```

```
# Add labels to the plot
class_names = ['Yes', 'No']
tick_marks = np.arange(len(class_names))
tick_marks2 = tick_marks + 0.5
plt.xticks(tick_marks, class_names, rotation=0,)
plt.yticks(tick_marks2, class_names, rotation=0,  )
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix for XGBoost')
plt.savefig('output15.png', dpi=300, bbox_inches='tight')
plt.show()
```



[26]:
```
print(classification_report(y_testxg, preds_xg))
```

```
              precision    recall  f1-score   support

           0       0.91      0.95      0.93      2055
           1       0.70      0.55      0.62       411

    accuracy                           0.89      2466
   macro avg       0.81      0.75      0.77      2466
weighted avg       0.88      0.89      0.88      2466
```

1.4 XGBoost Model With k-Fold Cross Validation

Using Kfold

[33]:
```
x = df.drop(['Revenue'],axis=1).values    # independant features
y = df['Revenue'].values                                         # dependant␣
 ↪variable

# CV model
model = xgb.XGBClassifier(use_label_encoder=False,eval_metric='mlogloss' )
kfold = KFold(n_splits=10, random_state=42, shuffle=True)
results = cross_val_score(model, X, y, cv=kfold)
print("Accuracy: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

```
Accuracy: 89.70% (0.87%)
```

Using stratified cross validation

[36]:
```
X = df.drop(['Revenue'],axis=1).values    # independant features
Y = df['Revenue'].values                                         # dependant␣
 ↪variable

# CV model
model = xgb.XGBClassifier(use_label_encoder=False,eval_metric='mlogloss' )
kfold = StratifiedKFold(n_splits=10, random_state=7,shuffle=True)
results = cross_val_score(model, X, Y, cv=kfold)
print("The Accuracy is: %.2f%% (%.2f%%)" % (results.mean()*100, results.
 ↪std()*100))
```

```
The Accuracy is: 89.75% (0.56%)
```

After applying K-fold to the XGBoost model we can observe that the average score remains at 88-89%

[ ]:
```

```