importing required libraries / packages

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
import re
import pickle
import os
nltk.download('vader lexicon')
from scipy, sparse import csr matrix
from xgboost import XGBClassifier
from sklearn import tree
from nltk.corpus import stopwords
from sklearn.tree import DecisionTreeClassifier
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from collections import Counter
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.feature extraction.text import CountVectorizer
from sklearn.metrics import confusion matrix, roc curve, auc,
ConfusionMatrixDisplay, RocCurveDisplay, roc auc score,
accuracy score, classification report
from sklearn.model selection import train test split, cross val score,
KFold, StratifiedKFold, GridSearchCV, RandomizedSearchCV
from sklearn import metrics
from tgdm import tgdm
from sklearn.preprocessing import Normalizer, StandardScaler,
MinMaxScaler
from scipy.sparse import hstack
from sklearn.naive bayes import MultinomialNB
from scipy.stats import randint
from prettytable import PrettyTable
[nltk data] Downloading package vader lexicon to /root/nltk data...
from sklearn.experimental import enable halving search cv
from sklearn.model selection import HalvingGridSearchCV,
HalvingRandomSearchCV
!pip install ipython-autotime
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
```

```
Collecting ipython-autotime
  Downloading ipython autotime-0.3.1-py2.py3-none-any.whl (6.8 kB)
Requirement already satisfied: ipython in
/usr/local/lib/python3.7/dist-packages (from ipython-autotime) (7.9.0)
Requirement already satisfied: pygments in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (2.6.1)
Requirement already satisfied: pexpect in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (4.8.0)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (57.4.0)
Requirement already satisfied: prompt-toolkit<2.1.0,>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (2.0.10)
Requirement already satisfied: backcall in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (0.2.0)
Requirement already satisfied: pickleshare in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (0.7.5)
Collecting jedi>=0.10
  Downloading jedi-0.18.1-py2.py3-none-any.whl (1.6 MB)
ent already satisfied: decorator in /usr/local/lib/python3.7/dist-
packages (from ipython->ipython-autotime) (4.4.2)
Requirement already satisfied: traitlets>=4.2 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (5.1.1)
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
/usr/local/lib/python3.7/dist-packages (from jedi>=0.10->ipython-
>ipython-autotime) (0.8.3)
Requirement already satisfied: wcwidth in
/usr/local/lib/python3.7/dist-packages (from prompt-
toolkit<2.1.0,>=2.0.0->ipython->ipython-autotime) (0.2.5)
Requirement already satisfied: six>=1.9.0 in
/usr/local/lib/python3.7/dist-packages (from prompt-
toolkit<2.1.0,>=2.0.0->ipython->ipython-autotime) (1.15.0)
Requirement already satisfied: ptyprocess>=0.5 in
/usr/local/lib/python3.7/dist-packages (from pexpect->ipython-
>ipvthon-autotime) (0.7.0)
Installing collected packages: jedi, ipython-autotime
Successfully installed ipython-autotime-0.3.1 jedi-0.18.1
%load ext autotime
time: 530 µs (started: 2022-11-08 01:27:54 +00:00)
#please use glove vectors if you are using TFIDF + W2V vectorization
in this code
with open('glove vectors', 'rb') as f:
```

```
model = pickle.load(f)
    glove words = set(model.keys())
time: 2.32 s (started: 2022-11-08 01:27:54 +00:00)
# loading the preprocessed data, can check number of records using
'nrows'
data = pd.read csv('preprocessed project data.csv', nrows = 50000)
time: 2.23 s (started: 2022-11-08 01:30:20 +00:00)
# checking for any Null values
data.isnull().sum()
teacher prefix
                                                  0
school state
                                                  0
project grade category
                                                  0
project subject categories
                                                  0
project subject subcategories
                                                  0
project title
                                                 23
project resource summary
                                                  0
teacher number of previously posted projects
                                                  0
project_is_approved
                                                  0
                                                  0
essay
price
                                                  0
quantity
                                                  0
negative score
                                                  0
positive score
                                                  0
neutral score
                                                  0
compound score
                                                  0
dtype: int64
time: 44 ms (started: 2022-11-08 01:30:38 +00:00)
data.shape
(50000, 16)
time: 4.51 ms (started: 2022-11-08 01:30:42 +00:00)
# we are removing null values present in project title column since
they are of very small in number
data = data.dropna( axis=0, how="any", thresh = None, subset = None,
inplace = False)
time: 43.8 ms (started: 2022-11-08 01:30:44 +00:00)
data.shape
(49977, 16)
time: 4.85 ms (started: 2022-11-08 01:30:47 +00:00)
```

```
data.isnull().sum() # now we have no null values in our data
teacher prefix
                                                 0
school state
                                                 0
project grade category
                                                 0
project subject categories
project subject subcategories
                                                 0
project title
                                                 0
project resource summary
                                                 0
teacher_number_of_previously_posted_projects
                                                 0
                                                 0
project is approved
                                                 0
essay
                                                 0
price
                                                 0
quantity
negative score
                                                 0
positive score
                                                 0
neutral score
                                                 0
                                                 0
compound score
dtype: int64
time: 51.6 ms (started: 2022-11-08 01:30:50 +00:00)
y = data['project is approved'].values # storing the values of the
column 'project is approved' in a variable 'y'
x = data.drop(['project is approved'], axis = 1) # droping the column
'project is approved' from our original data and storing rest of the
values in 'x'
time: 11.4 ms (started: 2022-11-08 01:30:53 +00:00)
\#vv = pd.DataFrame(v)
time: 1.11 ms (started: 2022-09-02 05:36:53 +00:00)
#yy.value counts()
1
     29614
      5366
0
dtype: int64
time: 9.83 ms (started: 2022-09-02 05:36:53 +00:00)
x.head(1)
  teacher prefix school state project grade category \
                                       grades prek 2
             mrs
                           in
  project subject categories project subject subcategories \
           literacy language
                                               esl literacy
                               project title \
  educational support english learners home
```

```
project resource summary \
  students need opportunities practice beginning...
   teacher number of previously posted projects \
0
                                                essay price quantity
   students english learners working english seco... 154.6
                                                                    23
   negative score positive score neutral score compound score
0
            0.013
                            0.154
                                            0.833
                                                           0.9694
time: 30.7 ms (started: 2022-11-08 01:30:55 +00:00)
Task 1
Splitting the data into Train and Test
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.25, stratify = y ) # splitting the data into train, test with test
data= 25% of values and strtify on 'Y' label
time: 36.1 ms (started: 2022-11-08 01:30:57 +00:00)
1.1.1
y testtt = pd.DataFrame(y test)
y_testtt.value_counts()
     7404
1
     1341
dtype: int64
time: 8.38 ms (started: 2022-09-02 05:36:53 +00:00)
print(" Number of rows and columns in Training data ", x_train.shape)
print(" Number of rows and columns in Test data ", x test.shape)
 Number of rows and columns in Training data (37482, 15)
 Number of rows and columns in Test data (12495, 15)
time: 1.11 ms (started: 2022-11-08 01:31:11 +00:00)
Applying TFIDF to the 'essay' column
vectorizer tfidf = TfidfVectorizer(min df = 10, max features = 5000)
vectorizer tfidf.fit(x train['essay'].values)
```

```
# we use fitted TFIDF to convert the text to vector
x train essay tfidf =
vectorizer_tfidf.transform(x_train['essay'].values)
x test essay tfidf =
vectorizer tfidf.transform(x test['essay'].values)
time: 9.35 s (started: 2022-11-08 01:31:19 +00:00)
type(x_train_essay_tfidf)
scipy.sparse.csr.csr matrix
time: 4.81 ms (started: 2022-11-08 01:31:31 +00:00)
print("Using TFIDF representation on 'Essay' column")
print("="*30)
print("Before Vectorization:")
print("-"*22)
print("Number of rows and columns in Train data are", x_train.shape)
print("Number of rows and columns in Test data are", x test.shape)
print('\n')
print("After Vectorization:")
print("-"*21)
print("Number of rows and columns in Train data are",
x train essay tfidf.shape)
print("Number of rows and columns in Test data are",
x test essay tfidf.shape)
print('\n')
Using TFIDF representation on 'Essay' column
_____
Before Vectorization:
- - - - - - - - - - - - - - - - - - -
Number of rows and columns in Train data are (37482, 15)
Number of rows and columns in Test data are (12495, 15)
After Vectorization:
Number of rows and columns in Train data are (37482, 5000)
Number of rows and columns in Test data are (12495, 5000)
time: 3.54 ms (started: 2022-11-08 01:31:34 +00:00)
Applying TFIDF to the 'project title' column
vectorizer_tfidf_title = TfidfVectorizer(min_df = 10, max_features =
vectorizer tfidf title.fit(x train['project title'].values)
# we use fitted TFIDF to convert the text to vector
```

```
x train title tfidf =
vectorizer tfidf title.transform(x train['project title'].values)
x test title tfidf =
vectorizer tfidf title.transform(x test['project title'].values)
time: 551 ms (started: 2022-11-08 01:31:39 +00:00)
type(x train title tfidf)
scipy.sparse.csr.csr matrix
time: 4.2 ms (started: 2022-11-08 01:31:41 +00:00)
print("Using TFIDF representation on 'Project Title' column")
print("="*30)
print("Before Vectorization:")
print("-"*22)
print("Number of rows and columns in Train data are", x train.shape)
print("Number of rows and columns in Test data are", x test.shape)
print('\n')
print("After Vectorization:")
print("-"*21)
print("Number of rows and columns in Train data are",
x_train_title_tfidf.shape)
print("Number of rows and columns in Test data are",
x test title tfidf.shape)
Using TFIDF representation on 'Project Title' column
Before Vectorization:
Number of rows and columns in Train data are (37482, 15)
Number of rows and columns in Test data are (12495, 15)
After Vectorization:
Number of rows and columns in Train data are (37482, 1694)
Number of rows and columns in Test data are (12495, 1694)
time: 10.5 ms (started: 2022-11-08 01:31:44 +00:00)
Applying TFIDF to the 'project resource summary' column
vectorizer tfidf project resource summary = TfidfVectorizer(min df =
10, max features = 5000)
vectorizer tfidf project resource summary.fit(x train['project resourc
e_summary'].values)
# we use fitted TFIDF to convert the text to vector
x_train_project_resource_summary_tfidf =
vectorizer_tfidf_project_resource summary.transform(x train['project r
esource summary [].values]
```

```
x test project resource summary tfidf =
vectorizer tfidf project resource summary.transform(x test['project re
source summary'].values)
time: 1.17 s (started: 2022-11-08 01:31:47 +00:00)
print("Using TFIDF representation on 'Project Resource Summary'
column")
print("="*65)
print("Before Vectorization:")
print("-"*22)
print("Number of rows and columns in Train data are", x_train.shape)
print("Number of rows and columns in Test data are", x Test.shape)
print('\n')
print("After Vectorization:")
print("-"*21)
print("Number of rows and columns in Train data are",
x_train_project_resource_summary_tfidf.shape)
print("Number of rows and columns in Test data are",
x test project resource summary tfidf.shape)
print('\n')
Using TFIDF representation on 'Project Resource Summary' column
_____
Before Vectorization:
Number of rows and columns in Train data are (37482, 15)
Number of rows and columns in Test data are (12495, 15)
After Vectorization:
-----
Number of rows and columns in Train data are (37482, 3342)
Number of rows and columns in Test data are (12495, 3342)
time: 5.21 ms (started: 2022-11-08 01:31:49 +00:00)
Applying TFIDF + W2V to the 'essay' column
# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf model = TfidfVectorizer()
tfidf model.fit(x train['essay'])
# we are converting a dictionary with word as a key, and the idf as a
value
dictionary = dict(zip(tfidf model.get feature names(),
list(tfidf model.idf )))
tfidf words = set(tfidf model.get feature names())
time: 4.01 s (started: 2022-11-08 01:31:53 +00:00)
```

```
# average Word2Vec
# compute average word2vec for each review.
train essay tfidf w2v = []; # the avg-w2v for each sentence/review is
stored in this list
for sentence in tqdm(x_train['essay']): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
   tf idf weight =0; # num of words with a valid vector in the
sentence/review
   for word in sentence.split(): # for each word in a review/sentence
        if (word in glove words) and (word in tfidf words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and
the tf value((sentence.count(word)/len(sentence.split())))
            tf idf =
dictionary[word]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
           vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf idf weight
   train_essay_tfidf_w2v.append(vector)
print(len(train essay tfidf w2v))
print(len(train essay tfidf w2v[0]))
100%| 37482/37482 [01:23<00:00, 450.63it/s]
37482
300
time: 1min 23s (started: 2022-11-08 01:32:00 +00:00)
x train essay tfidf w2v = csr matrix(train essay tfidf w2v)
time: 537 ms (started: 2022-11-08 01:33:25 +00:00)
for Test data
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
test essay tfidf w2v = []; # the avg-w2v for each sentence/review is
stored in this list
for sentence in tqdm(x test['essay']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
   tf idf weight =0; # num of words with a valid vector in the
sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove words) and (word in tfidf words):
```

```
vec = model[word] # getting the vector for each word
           # here we are multiplying idf value(dictionary[word]) and
the tf value((sentence.count(word)/len(sentence.split())))
           tf idf =
dictionary[word]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
           vector += (vec * tf idf) # calculating tfidf weighted w2v
           tf idf weight += tf idf
   if tf idf weight != 0:
       vector /= tf idf weight
   test essay tfidf w2v.append(vector)
print(len(test essay tfidf w2v))
print(len(test essay tfidf w2v[0]))
100%| 12495/12495 [00:27<00:00, 459.42it/s]
12495
300
time: 27.2 s (started: 2022-11-08 01:33:26 +00:00)
x test essay tfidf w2v = csr matrix (test essay tfidf <math>w2v)
time: 144 ms (started: 2022-11-08 01:33:53 +00:00)
print("Training data of 'Essay' column:")
print("="*30)
print("total rows in our Test data :",x train essay tfidf w2v.shape)
print('\n')
print("Testing data of 'Essay' column:")
print("="*30)
print("total rows in our Train data :",x test essay tfidf w2v.shape)
print('\n')
Training data of 'Essay' column:
total rows in our Test data: (37482, 300)
Testing data of 'Essay' column:
_____
total rows in our Train data: (12495, 300)
time: 3.2 ms (started: 2022-11-08 01:33:53 +00:00)
x train.head(1)
     teacher_prefix school_state project_grade_category \
4840
                                            grades 6 8
               mrs
                             fl
```

```
project_subject_categories project_subject_subcategories \
4840
                   math science
                                                  mathematics
                  project title \
4840
      algebraic thinkers action
                               project resource summary \
4840
      students need laptop class things make success...
      teacher number of previously posted projects
4840
                                                  essay
                                                          price
quantity \
4840 students wonderful bunch bright motivated year...
      negative score positive score neutral score compound score
4840
               0.017
                               0.306
                                              0.677
                                                              0.9932
time: 24.1 ms (started: 2022-11-08 01:33:53 +00:00)
Applying TFIDF + W2V to the 'project_title' column
# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf model = TfidfVectorizer()
tfidf model.fit(x train['project title'].values)
# we are converting a dictionary with word as a key, and the idf as a
dictionary = dict(zip(tfidf model.get feature names(),
list(tfidf model.idf )))
tfidf words = set(tfidf model.get_feature_names())
time: 293 ms (started: 2022-11-08 01:33:53 +00:00)
for Train data
# average Word2Vec
# compute average word2vec for each review.
train title tfidf_w2v = []; # the avg-w2v for each sentence/review is
stored in this list
for sentence in tqdm(x train['project title']): # for each
review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight =0; # num of words with a valid vector in the
sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and
```

```
the tf value((sentence.count(word)/len(sentence.split())))
            tf idf =
dictionary[word]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
   if tf idf weight != 0:
        vector /= tf idf weight
   train title tfidf w2v.append(vector)
print(len(train title tfidf w2v))
print(len(train title tfidf w2v[0]))
100% | 37482/37482 [00:01<00:00, 21866.18it/s]
37482
300
time: 1.73 s (started: 2022-11-08 01:33:54 +00:00)
x train title tfidf w2v = csr matrix (train title tfidf w2v)
time: 512 ms (started: 2022-11-08 01:33:55 +00:00)
for Test data
# compute tfidf word2vec for each review.
test title tfidf w2v = []; # the avg-w2v for each sentence/review is
stored in this list
for sentence in tqdm(x_test['project_title']): # for each
review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
   tf idf weight =0; # num of words with a valid vector in the
sentence/review
   for word in sentence.split(): # for each word in a review/sentence
        if (word in glove words) and (word in tfidf words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and
the tf value((sentence.count(word)/len(sentence.split())))
            tf idf =
dictionary[word]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
   if tf idf weight != 0:
        vector /= tf idf weight
   test title tfidf w2v.append(vector)
```

```
print(len(test title tfidf w2v))
print(len(test title tfidf w2v[0]))
100% | 12495/12495 [00:00<00:00, 26541.04it/s]
12495
300
time: 484 ms (started: 2022-11-08 01:33:56 +00:00)
x test title tfidf w2v = csr matrix (test title tfidf w2v)
time: 155 ms (started: 2022-11-08 01:33:56 +00:00)
print("Training data of 'Project title column':")
print("="*37)
print("Shape of our Test data :",x train title tfidf w2v.shape)
print('\n')
print("Testing data of 'Project title column':")
print("="*37)
print("Shape of our Train data :",x test title tfidf w2v.shape)
print('\n')
Training data of 'Project title column':
Shape of our Test data: (37482, 300)
Testing data of 'Project_title column':
Shape of our Train data: (12495, 300)
time: 2.29 ms (started: 2022-11-08 01:33:57 +00:00)
Applying TFIDF + W2V to the 'project_resource_summary' column
\# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf model = TfidfVectorizer()
tfidf_model.fit(x_train['project_resource_summary'].values)
# we are converting a dictionary with word as a key, and the idf as a
value
dictionary = dict(zip(tfidf model.get feature names(),
list(tfidf model.idf )))
tfidf words = set(tfidf model.get feature names())
time: 669 ms (started: 2022-11-08 01:34:06 +00:00)
for Train data
# average Word2Vec
# compute average word2vec for each review.
```

```
train project resource summary tfidf w2v = []; # the avg-w2v for each
sentence/review is stored in this list
for sentence in tqdm(x train['project resource summary']): # for each
review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight =0; # num of words with a valid vector in the
sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove words) and (word in tfidf words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and
the tf value((sentence.count(word)/len(sentence.split())))
            tf idf =
dictionary[wor\overline{d}]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
            vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf_idf_weight != 0:
        vector /= tf idf weight
    train project resource summary tfidf w2v.append(vector)
print(len(train_project_resource_summary_tfidf_w2v))
print(len(train project resource summary tfidf w2v[0]))
          | 37482/37482 [00:04<00:00, 8233.93it/s]
100%
37482
300
time: 4.56 s (started: 2022-11-08 01:34:11 +00:00)
x train project resource summary tfidf w2v = csr matrix
(train project resource summary tfidf w2v)
time: 529 ms (started: 2022-11-08 01:34:17 +00:00)
for Test data
# compute tfidf word2vec for each review.
test project resource summary tfidf w2v = []; # the avg-w2v for each
sentence/review is stored in this list
for sentence in tqdm(x test['project resource summary']): # for each
review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight =0; # num of words with a valid vector in the
sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and
```

```
the tf value((sentence.count(word)/len(sentence.split())))
           tf idf =
dictionary[word]*(sentence.count(word)/len(sentence.split())) #
getting the tfidf value for each word
           vector += (vec * tf idf) # calculating tfidf weighted w2v
           tf idf weight += tf idf
   if tf idf weight != 0:
       vector /= tf idf weight
   test project resource summary tfidf w2v.append(vector)
print(len(test project resource summary tfidf w2v))
print(len(test project resource summary tfidf w2v[0]))
100% | 12495/12495 [00:01<00:00, 7551.98it/s]
12495
300
time: 1.67 s (started: 2022-11-08 01:34:19 +00:00)
x test project resource summary tfidf w2v = csr matrix
(test_project_resource_summary_tfidf_w2v)
time: 158 ms (started: 2022-11-08 01:34:23 +00:00)
print("Training data of 'Project resource summary column':")
print("="*37)
print("Shape of our Test
data :",x train project resource summary tfidf w2v.shape)
print('\n')
print("Testing data of 'Project title column':")
print("="*37)
print("Shape of our Train
data :",x test project resource summary tfidf w2v.shape)
print('\n')
Training data of 'Project resource summary column':
Shape of our Test data: (37482, 300)
Testing data of 'Project_title column':
_____
Shape of our Train data: (12495, 300)
time: 8.6 ms (started: 2022-11-08 01:34:23 +00:00)
Normalization of numerical features
```

1. price

- 2. Quantity
- 3. teacher_number_of_previously_posted_projects
- 4. Sentiment score related columns

```
standard scaler = StandardScaler() # using standardization as I can
use either Normalizer or MinMaxScaler on the price column
# Standardization of 'Price' column
price train = standard scaler.fit transform(x train[['price']])
price test = standard scaler.transform(x test[['price']])
# Standardization of 'teacher number of previously posted projects'
column
teacher number of previously posted projects train =
standard scaler.fit transform(x train[['teacher number of previously p
osted projects']])
teacher number of previously posted projects test =
standard_scaler.transform(x_test[['teacher_number_of_previously posted
projects']])
# Standardization of 'quantity' column
quantity train = standard scaler.fit transform(x train[['quantity']])
quantity test = standard scaler.transform(x test[['quantity']])
# Standardization of 'negative score' column of Sentiment score
neg score train =
standard scaler.fit transform(x train[['negative score']])
neg score test = standard scaler.transform(x test[['negative score']])
# Standardization of 'positive score' column of Sentiment score
pos score train =
standard scaler.fit transform(x train[['positive score']])
pos score test = standard scaler.transform(x test[['positive score']])
# Standardization of 'neutral score' column of Sentiment score
neu score train =
standard scaler.fit transform(x train[['neutral score']])
neu score test = standard scaler.transform(x test[['neutral score']])
# Standardization of 'compound score' column of Sentiment score
comp score train =
standard scaler.fit transform(x train[['compound score']])
comp score test =
standard scaler.transform(x test[['compound score']])
time: 61.4 ms (started: 2022-11-08 01:35:44 +00:00)
print(type(comp score train))
```

```
<class 'numpy.ndarray'>
time: 1.06 ms (started: 2022-11-08 01:35:47 +00:00)
Encoding of Categorical features using Response coding:
Categorical features are:
     teacher_prefix
 1.
 2.
     project_grade_category
 3.
     school_state
 4.
     clean_categories
 5.
     clean_subcategories
# function for generating response code
def response code(xtr,ytr,xte):
    pos = []
    neg = [1]
    dictionary = dict(xtr.value counts())
    cat = dictionary.keys()
    cat values = dictionary.values()
    for k in cat:
        po count = 0
        neg count = 0
        for n,i in enumerate(xtr.values):
            if k == i and ytr[n]==0:
                neg count += 1
            elif k == i and ytr[n]==1:
                po count += 1
            else:
                continue
        pos.append(po count)
        neg.append(neg count)
    pos prob = np.divide(pos,list(cat values))
    neg prob = np.divide(neg,list(cat values))
    xtr 0 = np.zeros(len(xtr))
    xtr 1 = np.zeros(len(xtr))
    for n,k in enumerate(cat):
        for m,i in enumerate(xtr.values):
            if i == k :
                xtr 0[m] = neg prob[n]
                xtr_1[m] = pos_prob[n]
            else:
                 continue
    only xte cat = set(xte.values)-set(xtr.values)
```

xte_0 = np.zeros(len(xte))
xte_1 = np.zeros(len(xte))
for cat in only xte cat:

```
for m,i in enumerate(xte.values):
            if i == cat:
                xte 0[m] = 0.5
                xte 1[m] = 0.5
            else:
                continue
    for n.k in enumerate(cat):
        for m,i in enumerate(xte.values):
            if i == k :
                xte 0[m] = neg prob[n]
                xte 1[m] = pos prob[n]
            else:
                continue
    return xtr 0.reshape(-1,1),xtr 1.reshape(-1,1),xte 0.reshape(-
1,1), xte 1. reshape(-1,1)
time: 4.88 ms (started: 2022-11-08 01:35:48 +00:00)
Response encoding for the Categorical columns
# project subject categories project subject subcategories
# implementing Response encoding for the column 'teacher prefix'
teacher_prefix_tr_0_rc, teacher_prefix_tr_1_rc,
teacher_prefix_te_0_rc, teacher_prefix_te_1_rc = response_code
(x train['teacher prefix'],
y train,
x test['teacher prefix'])
# implementing Response encoding for the column
'project grade category'
project_grade_cat_tr_0_rc, project_grade_cat_tr_1_rc,
project_grade_cat_te_0_rc, project_grade_cat_te_1_rc = response_code
(x train['project grade category'],
y_train,
x_test['project_grade_category'])
# implementing Response encoding for the column 'school state'
school state tr 0 rc, school state tr 1 rc, school state te 0 rc,
school state te 1 rc = response code (x train['school state'],
y train,
x test['school state'])
# implementing Response encoding for the column
```

```
'project subject categories'
clean cat tr 0 rc, clean cat tr 1 rc, clean cat te 0 rc,
clean cat te 1 rc = response code
(x train['project subject categories'],
y train,
x test['project subject categories'])
# implementing Response encoding for the column
'project subject subcategories'
clean subcat tr 0 rc, clean subcat tr 1 rc, clean subcat te 0 rc,
clean subcat te 1 rc = response code
(x train['project subject subcategories'],
y train,
x test['project subject subcategories'])
time: 4.55 s (started: 2022-11-08 01:35:52 +00:00)
# Performing One Hot encoding on Categortical features
# shud use alternatively fit tranform and transfomr for each column or
else we get wrong values as the fit will be updated with the latest
values
vectorizer oneHot = CountVectorizer(binary = True)
school state oneHot tr =
vectorizer oneHot.fit transform(x train['school state'].values)
school_state oneHot te =
vectorizer oneHot.transform(x test['school state'].values)
teacher prefix oneHot tr =
vectorizer oneHot.fit transform(x train['teacher_prefix'].values)
teacher prefix oneHot te =
vectorizer oneHot.transform(x test['teacher prefix'].values)
project_grade_category_oneHot_tr =
vectorizer oneHot.fit transform(x train['project grade category'].valu
es)
project grade category oneHot te =
vectorizer oneHot.transform(x test['project grade category'].values)
clean categories oneHot tr =
vectorizer oneHot.fit transform(x train['clean categories'].values)
```

```
clean categories oneHot te =
vectorizer oneHot.transform(x test['clean categories'].values)
clean subcategories oneHot tr =
vectorizer oneHot.fit transform(x train['clean subcategories'].values)
clean subcategories oneHot te =
vectorizer oneHot.transform(x test['clean subcategories'].values)
1.1.1
time: 390 ms (started: 2022-08-30 06:09:18 +00:00)
print("Shape of various columns after performing One Hot encoding on
Train data are:")
print("="*79)
print("school state after One hot encoding:
 ,school state oneHot tr.shape)
print("teacher_prefix after One hot encoding:
",teacher prefix oneHot tr.shape)
print("project grade category after One hot encoding:
", project grade category oneHot tr.shape)
print("clean categories after One hot encoding:
",clean categories_oneHot_tr.shape)
print("clean subcategories after One hot encoding:
", clean subcategories oneHot tr.shape)
print('\n')
print("Shape of various columns after performing One Hot encoding on
Test data are:")
print("="*79)
print("school state after One hot encoding:
", school state oneHot te.shape)
print("teacher prefix after One hot encoding:
",teacher prefix oneHot te.shape)
print("project grade category after One hot encoding:
", project grade category oneHot te.shape)
print("clean categories after One hot encoding:
,clean categories oneHot te.shape)
print("clean subcategories after One hot encoding:
",clean subcategories oneHot te.shape)
```

Concatinating all the above features

Set 1:

```
Categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project_title(TFIDF)+ preprocessed_eassay (TFIDF)+sentiment Score of eassay(check the bellow example, include all 4 values as 4 features)
```

from scipy.sparse import hstack x tr tfidf = hstack((x train essay tfidf, school state tr 0 rc, school_state_tr_1_rc, teacher_prefix_tr_0_rc, teacher_prefix_tr_1_rc, project grade cat tr 0 rc, project_grade_cat_tr_1_rc, clean_cat_tr_0_rc, clean_cat_tr_1_rc, clean subcat tr 0 rc, clean subcat tr 1 rc, price train, teacher number of previously posted projects train, x train title tfidf, x train project resource summary tfidf, neg score train, pos score train, neu score train, comp score train, quantity train)).tocsr() x_te_tfidf = hstack((x_test_essay_tfidf, school_state_te_0_rc, school state te 1 rc, teacher prefix te 0 rc, teacher prefix te 1 rc, project_grade_cat_te_0_rc, project grade cat te 1 rc, clean cat te 0 rc, clean cat te 1 rc, clean_subcat_te_0_rc, clean subcat te 1 rc, price test, teacher_number_of_previously_posted_projects_test, x_test_title_tfidf, x test project resource summary tfidf, neg_score_test, pos_score_test, neu_score_test, comp_score_test, quantity test)).tocsr() time: 667 ms (started: 2022-11-08 01:35:56 +00:00) Set 2: Categorical (instead of one hot encoding, try response coding: use probability values), numerical features + project title(TFIDF W2V)+ preprocessed eassay (TFIDF W2V) from scipy.sparse import hstack x tr tfidf w2v = hstack((x train essay tfidf w2v, school_state_tr_0_rc, school_state_tr_1_rc, teacher_prefix_tr 0 rc, teacher_prefix_tr_1_rc, project grade cat tr 0 rc, project_grade_cat_tr_1_rc, clean_cat_tr_0_rc, clean_cat_tr_1_rc, clean_subcat_tr_0_rc, clean subcat tr 1 rc, price train, teacher number of previously posted projects train, x_train_title_tfidf_w2v, quantity_train, x_train_project_resource_summary_tfidf_w2v ,neg_score_train,

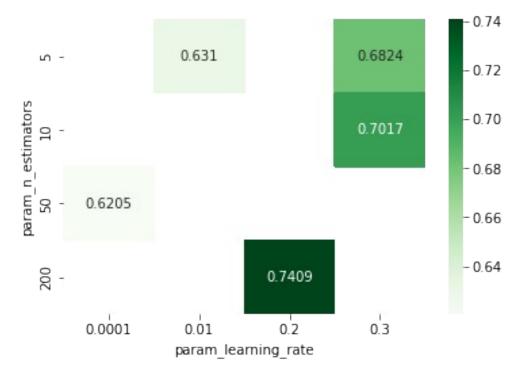
```
pos score train, neu score train, comp score train)).tocsr()
x te tfidf w2v = hstack((x test essay tfidf w2v, school state te 0 rc,
school_state_te_1_rc, teacher_prefix_te_0_rc, teacher_prefix_te_1_rc,
                        project grade cat te 0 rc,
project grade cat te 1 rc, clean cat te 0 rc, clean cat te 1 rc,
clean subcat te 0 rc,
                        clean subcat te 1 rc, price test,
teacher_number_of_previously_posted_projects_test,x_test_title_tfidf_w
2v, quantity test,
                        x_test_project_resource_summary tfidf w2v,
neg score test, pos score test, neu score test,
comp score test )).tocsr()
time: 1.68 s (started: 2022-11-08 01:35:59 +00:00)
print("Final Data Matrix is :")
print('*'*22)
print('\n')
print("Using TFIDF:")
print('='*12)
print("Training data:",x_tr_tfidf.shape, y_train.shape )
print("Testing data:",x te tfidf.shape, y test.shape )
print('\n')
print("Using TFIDF + W2V:")
print('='*20)
print("Training data:",x_tr_tfidf_w2v.shape, y_train.shape )
print("Testing data:",x te tfidf w2v.shape, y test.shape )
print('\n')
Final Data Matrix is :
*********
Using TFIDF:
Training data: (37482, 10053) (37482,)
Testing data: (12495, 10053) (12495,)
Using TFIDF + W2V:
Training data: (37482, 917) (37482,)
Testing data: (12495, 917) (12495,)
time: 11 ms (started: 2022-11-08 01:36:01 +00:00)
```

```
Function to Evaluate our Model using different metrics
# function to evaluate our model using different metrics
# values to be passed :
# model name = Our Model name, model = classifier used used to
predict, y_train_pred, y_test_pred, x_train, x_test
def evaluate model(model name, model, y train pred, y test pred,
x train, x test):
   # Printing Train & Test Accuracy scores
   print("Train Accuracy :", accuracy_score(y_train,
model.predict(x train)))
   print("Test Accuracy :", accuracy_score(y_test,
model.predict(x test)))
   print('\n')
   print("="*60)
   print('\n')
# Printing Confusion Matrix for Train & Test data
   print("Train Confusion Matrix:")
   print(confusion matrix(y train, model.predict(x train)))
   print("Test Confusion Matrix:")
   print(confusion matrix(y test, model.predict(x test)))
   print('\n')
   print("="*60)
   print('\n')
************************************
   # Printing classification reports
   # For Train Data
   print("Classification report for our Model's Training data:")
   print(classification report(y train, model.predict(x train)))
   print('\n')
   print("="*60)
   print('\n')
   # For Train Data
   print("Classification report for our Model's Test data:")
```

```
print("-"*52)
   print(classification report(y test, model.predict(x test)))
   print('\n')
   print("="*60)
   print('\n')
# Calculating AUC ROC scores
   auc_train_data = roc_auc_score(y_train, y_train_pred[:,1])
   auc test_data = roc_auc_score(y_test, y_test_pred[:,1])
   print("AUC scores for \nTrain data is :", auc_train_data," & \
nTest data is :", auc_test_data)
   print('\n')
   print("="*60)
   print('\n')
   # Plotting AUC ROC scores for Train & Test data
   # ROC Curve using predict proba method
   print("Plotting AUC ROC curves for Train and Test Data")
   tr fpr, tr tpr, tr thresh = roc curve(y train, y train pred[:,1],
pos label=1)
   te fpr, te tpr, te thresh = roc curve(y test, y test pred[:,1],
pos label=1)
   plt.style.use('seaborn')
   # plot roc curves
   plt.plot(tr_fpr, tr_tpr, linestyle='--', color='orange',
label='Train AUC ='+str(auc(tr fpr, tr tpr).round(3)))
   plt.plot(te_fpr, te_tpr, linestyle='--', color='green',
label='Test AUC ='+str(auc(te fpr, te tpr).round(3)))
   # title
   plt.title('ROC curve using '+str(model name)+' model')
   # x label
   plt.xlabel('False Positive Rate')
   # v label
   plt.ylabel('True Positive rate')
   plt.legend(loc='best')
   plt.show();
   print('\n')
```

```
# https://www.quantinsti.com/blog/creating-heatmap-using-python-
seaborn
   # Plotting Train & Test Confusion matrices
   print("Plotting Train and Test Confusion matrices")
   sns.set()
   con m train = confusion matrix(y train, model.predict(x train))
   con m test = confusion matrix(y test, model.predict(x test))
   key = (np.asarray([['TN','FP'], ['FN', 'TP']]))
   fig, ax = plt.subplots(1,2, figsize=(12,5))
   labels train = (np.asarray(["{0}] = {1:.2f}]" .format(key, value)
for key, value in zip(key.flatten(),
con m train.flatten())])).reshape(2,2)
   labels_test = (np.asarray(["{0}] = {1:.2f}]" .format(key, value) for
key, value in zip(key.flatten(), con m test.flatten())])).reshape(2,2)
   sns.heatmap(con m train, linewidths=.5, xticklabels=['PREDICTED :
0', 'PREDICTED : 1'], yticklabels=['ACTUAL : 0', 'ACTUAL : 1'], annot
= labels_train, fmt = '', ax=ax[0], cmap='Blues')
   sns.heatmap(con m test, linewidths=.5, xticklabels=['PREDICTED :
0', 'PREDICTED : 1'], yticklabels=['ACTUAL : 0', 'ACTUAL : 1'], annot
= labels test, fmt = '', ax=ax[1], cmap='Blues')
   ax[0].set title('Train Data')
   ax[1].set_title('Test Data')
   plt.show()
time: 7.69 ms (started: 2022-11-08 01:36:09 +00:00)
Performing Hyperparameter tuning and plot either heatmap or 3d plot.
using Set 1 TFIDF
model = XGBClassifier()
param = \{ learning rate' : [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3], \}
```

```
'n_estimators' : [5, 10, 50, 75, 100, 200]
        }
clf gbdt = RandomizedSearchCV(model, param distributions = param,
scoring='roc auc', cv = 3,
                              return train score = True, n jobs = -1,
n iter = 5, verbose = 3)
clf gbdt.fit(x tr tfidf, y train)
print("Best value of Parameters for our XGBoost GBDT with TFIDF model
are :", clf_gbdt.best_estimator_)
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Best value of Parameters for our XGBoost GBDT with TFIDF model are :
XGBClassifier(learning rate=0.2, n estimators=200)
time: 6min 20s (started: 2022-11-08 01:36:27 +00:00)
clf gbdt.score(x te tfidf, y test) # just to test the values
0.7390945344871613
time: 600 ms (started: 2022-11-08 01:44:51 +00:00)
0.00
#clf gbdt.cv results
results = pd.DataFrame.from dict(clf gbdt.cv results )
results.groupby(['param n estimators', 'param learning rate']).max()
results = pd.DataFrame.from dict(clf gbdt.cv results )
max scores = results.groupby(['param n estimators',
'param_learning_rate']).max()
max scores = max scores.unstack()[['mean test score',
'mean train score']]
sns.heatmap(max scores.mean test score, annot=True, fmt='.4g', cmap =
'Greens');
```



time: 348 ms (started: 2022-11-08 01:44:59 +00:00)

time: 1min 48s (started: 2022-11-08 01:45:15 +00:00)

Applying our Best parameters obtained by Hyperparameter tuning to our Model

```
# best parameters for our Decision Tree
```

Best Learning rate = 0.2 &
Best estimator tfidf = 200

model_name = Our Model name, model = classifier used used to predict, y_train_pred, y_test_pred, x_train, x_test

evaluate_model ('XG Boost GBDT (TFIDF)', gbdt_tfidf,
y_train_pred_tfidf, y_test_pred_tfidf, x_tr_tfidf, x_te_tfidf)

Train Accuracy: 0.8648684701990289 Test Accuracy: 0.8462585034013606

Train Confusion Matrix:
[[842 4935]
 [130 31575]]
Test Confusion Matrix:
[[7 1919]
 [2 10567]]

Classification report for our Model's Training data:

	precision	recall	f1-score	support
0 1	0.87 0.86	0.15 1.00	0.25 0.93	5777 31705
accuracy macro avg weighted avg	0.87 0.87	0.57 0.86	0.86 0.59 0.82	37482 37482 37482

Classification report for our Model's Test data:

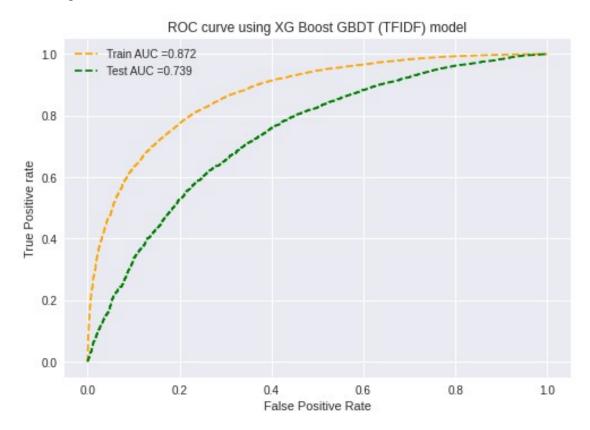
support	f1-score	recall	precision	
1926 10569	0.01 0.92	0.00 1.00	0.78 0.85	0 1
12495 12495	0.85 0.46	0.50	0.81	accuracy macro avg

weighted avg 0.84 0.85 0.78 12495

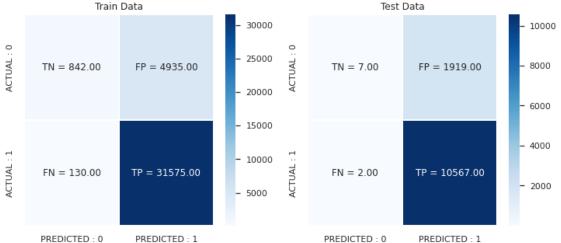
AUC scores for

Train data is : 0.8721273777428817 & Test data is : 0.7390945344871613

Plotting AUC ROC curves for Train and Test Data

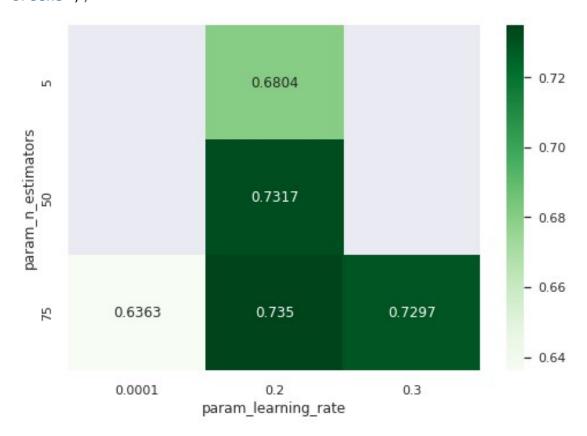


Plotting Train and Test Confusion matrices



```
time: 8.43 s (started: 2022-11-08 01:47:25 +00:00)
using Set 2 TFIDF + W2V
model W2V = XGBClassifier()
param = { 'learning_rate' : [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3],
          'n estimators' : [5, 10, 50, 75, 100, 200]
clf gbdt W2V = RandomizedSearchCV(model W2V, param distributions =
param, scoring = 'roc auc',
                                  cv = 5, n jobs = -1, n iter = 5,
return train score = True, verbose = 10)
clf gbdt W2V.fit(x tr tfidf w2v, y train)
print("Best value of Parameters for our XGBoost GBDT with TFIDF + W2V
model are :", clf_gbdt_W2V.best_estimator )
Fitting 5 folds for each of 5 candidates, totalling 25 fits
Best value of Parameters for our XGBoost GBDT with TFIDF + W2V model
are : XGBClassifier(learning rate=0.2, n estimators=75)
time: 55min 58s (started: 2022-11-08 01:48:21 +00:00)
clf_gbdt_W2V.score(x_te_tfidf_w2v, y_test) # just to test the
values
0.7173001588630792
time: 3.56 s (started: 2022-11-08 02:48:09 +00:00)
results w2v = pd.DataFrame.from dict(clf gbdt W2V.cv results )
max scores = results w2v.groupby(['param n estimators',
'param learning rate']).max()
max scores = max scores.unstack()[['mean test score',
```

```
'mean_train_score']]
sns.heatmap(max_scores.mean_test_score, annot=True, fmt='.4g', cmap =
'Greens');
```



time: 358 ms (started: 2022-11-08 02:48:24 +00:00)

Applying our Best parameters obtained by Hyperparameter tuning to our Model

best parameters for our Decision Tree

```
# predicting on train and test data using predict_proba method
y_train_pred_tfidf_w2v = gbdt_tfidf_w2v.predict_proba(x_tr_tfidf_w2v)
y test pred tfidf w2v = gbdt tfidf w2v.predict proba(x te tfidf w2v)
 Best parameters for our XG Boost GBDT model based on TFIDF are:
 Best Learning rate = 0.2 &
 Best estimator tfidf = 75
time: 3min 51s (started: 2022-11-08 02:49:10 +00:00)
# model name = Our Model name, model = classifier used used to
predict, y train pred, y test pred, x train, x test
evaluate model ('XG Boost GBDT (TFIDF + W2V)', gbdt tfidf w2v,
y train pred tfidf w2v, y test pred tfidf w2v, x tr tfidf w2v,
x te tfidf w2v )
Train Accuracy : 0.8564644362627395
Test Accuracy: 0.8458583433373349
```

Train Confusion Matrix: [[524 5253] [127 31578]]

Test Confusion Matrix:

1 19251 1 1056811

Classification report for our Model's Training data:

	precision	recall	f1-score	support
0 1	0.80 0.86	0.09 1.00	0.16 0.92	5777 31705
accuracy macro avg weighted avg	0.83 0.85	0.54 0.86	0.86 0.54 0.80	37482 37482 37482

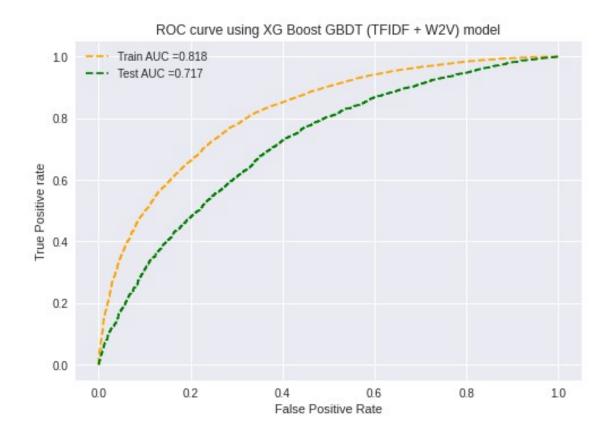
Classification report for our Model's Test data:

	precision	recall	f1-score	support
0 1	0.50 0.85	0.00 1.00	0.00 0.92	1926 10569
accuracy macro avg weighted avg	0.67 0.79	0.50 0.85	0.85 0.46 0.78	12495 12495 12495

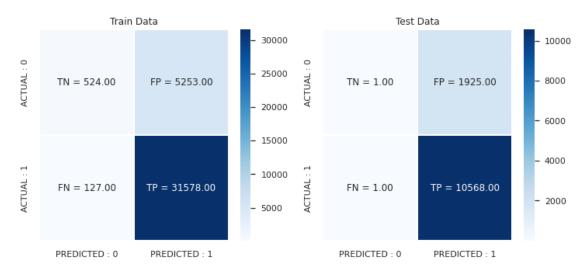
AUC scores for

Train data is : 0.8184661059740816 & Test data is : 0.7173001588630792

Plotting AUC ROC curves for Train and Test Data



Plotting Train and Test Confusion matrices



time: 50.2 s (started: 2022-11-08 02:55:33 +00:00)

initializing a table
table = PrettyTable()

adding title to our table

time: 2.61 ms (started: 2022-11-08 02:56:51 +00:00)