NB_Assignment_instructions

May 9, 2022

1 Assignment 6: Apply NB

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[2]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import Normalizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from scipy.sparse import hstack
from scipy import sparse

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/

import pickle
from tqdm import tqdm
import os

from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
import math
```

```python
from prettytable import PrettyTable
```

```
<li>Minimum data points need to be considered for people having 4GB RAM is <strong>50k</strong
<li>When you are using ramdomsearchcv or gridsearchcv you need not split the data into X_train
<li>If you are writing for loops to tune your model then you need split the data into X_train,X
<li>While splitting the data explore stratify parameter. </li>
<li><strong>Apply Multinomial NB on these feature sets</strong></li>
    <ul>
        <li>Features that need to be considered</li>
            <dl>
              <dt>essay</dt>
                <dd>while encoding essay, try to experiment with the max_features and n_grams p
              <dt>categorical features</dt>
              <dd> - teacher_prefix</dd>
              <dd> - project_grade_category</dd>
              <dd> - school_state</dd>
              <dd> - clean_categories</dd>
              <dd> - clean_subcategories</dd>
              <dt>numerical features</dt>
              <dd> - price</dd>
              <dd> - teacher_number_of_previously_posted_projects</dd>
              <dd>while encoding the numerical features check <a href='https://imgur.com/ldZA1z
            </dl>
        <li><font color='red'>Set 1</font>: categorical, numerical features + preprocessed_essa
        <li><font color='red'>Set 2</font>: categorical, numerical features + preprocessed_essa
    </ul>
<li><strong>The hyper paramter tuning(find best alpha:smoothing parameter)</strong>
    <ul>
<li>Consider alpha values in range: 10^-5 to 10^2 like [0.00001,0.0005, 0.0001,0.005,0.001,0.05
<li>Explore class_prior = [0.5, 0.5] parameter which can be present in MultinomialNB function(g
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>For hyper parameter tuning using k-fold cross validation(use GridsearchCV or RandomsearchCV
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='https://i.imgur.com/hUv6aEy.jpg' width=300px><dd>-while plotting take log(alpha) on y
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='https://imgur.com/q2P65L5.jpg' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
    <img src='https://i.imgur.com/IdN5Ctv.png' width=300px><dd>-plot the confusion matrix in he

    </ul>
```

find the top 20 features from either from feature Set 1 or feature Set 2 using values of `feature_log_prob_` parameter of `MultinomialNB` (https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html) and print BOTH positive as well as negative corresponding feature names.

- go through the link
  You need to summarize the results at the end of the notebook, summarize it in the table format

2. Naive Bayes

1.1 1.1 Loading Data

[3]:
```
#make sure you are loading atleast 50k datapoints
#you can work with features of preprocessed_data.csv for the assignment.
# If you want to add more features, you can add. (This is purely optional, not␣
↪mandatory)

import pandas
data = pandas.read_csv('/content/drive/MyDrive/Dataset/preprocessed_data.csv')

print(data.shape)

#data.head(3)
```

```
(109248, 9)
```

[4]:
```
data.head(2)
```

[4]:
```
  school_state teacher_prefix project_grade_category  \
0           ca            mrs          grades_prek_2
1           ut             ms             grades_3_5

   teacher_number_of_previously_posted_projects  project_is_approved  \
0                                            53                    1
1                                             4                    1

  clean_categories                 clean_subcategories  \
0     math_science  appliedsciences health_lifescience
1     specialneeds                        specialneeds

                                               essay   price
0  i fortunate enough use fairy tale stem kits cl…  725.05
1  imagine 8 9 years old you third grade classroo…  213.03
```

##

1.2 Splitting data into Train and cross validation(or test): Stratified Sampling

[5]:
```
data.columns
```

[5]:
```
Index(['school_state', 'teacher_prefix', 'project_grade_category',
       'teacher_number_of_previously_posted_projects', 'project_is_approved',
       'clean_categories', 'clean_subcategories', 'essay', 'price'],
      dtype='object')
```

Numerical Features:

- Price
- teacher_number_of_previously_projects

Categorical Features - school_state - teacher_prefix - project_grade_category - clean_categories - clean_sub_categories

Text Features - essay

[6]:
```
# 1. Split your data.

y = data['project_is_approved'].values
X = data.drop(['project_is_approved'],axis = 1)

print(X.shape, y.shape, 'This is X and y ')

X_train,X_test,y_train,y_test = train_test_split(X,y,stratify = y,test_size = 0.
↪3 ,random_state = 10)

print(X_train.shape,X_test.shape, 'This is X train and test')
print(y_train.shape,y_test.shape,'This is  y train and test')
```

```
(109248, 8) (109248,) This is X and y
(76473, 8) (32775, 8) This is X train and test
(76473,) (32775,) This is  y train and test
```

1.2 1.3 Encoding Text Features

[7]:
```
# write your code in following steps for task 1
# 1. Split your data.
# 2. Perform Bag of Words Vectorization of text data.
# 3. Perform tfidf vectorization of text data.
# 4. perform one-hot encoding of categorical features.
# 5. perform normalization of numerical features
# 6. For set 1 stack up all the features using hstack()
# 7. For set 2 stack up all the features using hstack()
# 8. Perform hyperparameter tuning and represent the training and␣
↪cross-validation AUC scores for different 'alpha' values, using a 2D line␣
↪plot.
# 9. Find the best hyperparameter 'alpha' and fit the model. Plot ROC-AUC␣
↪curve(by obtaining the probabilities using 'predict proba' method)
# 10. Plot confusion matrix based on the best threshold value
# 11. Either for the model in set 1 or in set 2, print the top 20 features(you␣
↪have to print the names, not the indexes) associated with the positive and␣
↪negative classes each.
# 12. Summarize your observations and compare both the models(ie., from set 1␣
↪and set 2) in terms of optimal hyperparameter value, train AUC and test AUC␣
↪scores.
```

```
# 13. You can use Prettytable or any other tabular format for comparison.


# please write all the code with proper documentation, and proper titles for␣
↪each subsection
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in␣
↪debugging your code
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the␣
↪reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

[8]:
```
# Split the dataset
# 1) If you want to apply simple cross-validation, split the dataset into 3␣
↪parts (ie., train, CV and test sets)
# 2) If you want to apply K-fold CV (or) GridSearch Cross Validation (or)␣
↪Randomized Search Cross Validation, just split the dataset into 2 parts (ie.
↪, train and test sets)
```

[9]:
```
# Apply Bag of Words (BOW) vectorization on 'Preprocessed_Essay'
# Apply Bag of Words (BOW) vectorization on 'Preprocessed_Title' (Optional)


vect1 = CountVectorizer(min_df=10,ngram_range=(1,4), max_features = 5000)
vect1.fit(X_train['essay'])
X_train_preprocessed_essay_bow = vect1.transform(X_train['essay'])

X_test_preprocessed_essay_bow = vect1.transform(X_test['essay'])

print("Shape after Transform")
print(X_train_preprocessed_essay_bow.shape)
print(X_test_preprocessed_essay_bow.shape)
```

```
Shape after Transform
(76473, 5000)
(32775, 5000)
```

[10]:
```
# Apply TF-IDF vectorization on 'Preprocessed_Essay'
# Apply TF-IDF vectorization on 'Preprocessed_Title' (Optional)


vect2 = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features = 5000)
```

```
vect2.fit(X_train['essay'])
X_train_preprocessed_essay_tfidf = vect2.transform(X_train['essay'])

X_test_preprocessed_essay_tfidf = vect2.transform(X_test['essay'])

print("Shape after Transform")
print(X_train_preprocessed_essay_tfidf.shape)
print(X_test_preprocessed_essay_tfidf.shape)
```

```
Shape after Transform
(76473, 5000)
(32775, 5000)
```

##

1.4 Make Data Model Ready: encoding categorical features

[11]:
```
# Apply One-Hot Encoding on the categorical features either using␣
↪OneHotEncoder() (or) CountVectorizer(binary=True)
# Apply Normalization on the numerical features using Normalizer().

# School_state
print('School State')

vect = CountVectorizer()
vect_ss = vect.fit(X_train['school_state'].values)
X_train_school_state = vect.fit_transform(X_train['school_state'].values)
X_test_school_state = vect.transform(X_test['school_state'].values)

print('X_train shape:' ,X_train_school_state.shape)
print('X_test_shape:', X_test_school_state.shape)

print('\n')

# Teacher_prefix
print('Teacher Prefix')

vect = CountVectorizer()
vect_tp = vect.fit(X_train['teacher_prefix'].values)
X_train_teacher_prefix = vect.fit_transform(X_train['teacher_prefix'].values)
X_test_teacher_prefix = vect.transform(X_test['teacher_prefix'].values)

print('X_train shape:' ,X_train_teacher_prefix.shape)
print('X_test_shape:', X_test_teacher_prefix.shape)

print('\n')
```

```python
print('Project_grade_category')

vect = CountVectorizer()

vect_pgc = vect.fit(X_train['project_grade_category'].values)
X_train_pgc = vect.fit_transform(X_train['project_grade_category'].values)
X_test_pgc = vect.transform(X_test['project_grade_category'].values)

print('X_train shape:' ,X_train_pgc.shape)
print('X_test_shape:', X_test_pgc.shape)

print('\n')

print('Clean_category')

vect = CountVectorizer()

vect_cc = vect.fit(X_train['clean_categories'].values)
X_train_cc = vect.fit_transform(X_train['clean_categories'].values)
X_test_cc = vect.transform(X_test['clean_categories'].values)

print('X_train shape:' ,X_train_cc.shape)
print('X_test_shape:', X_test_cc.shape)

print('\n')

print('Clean_subcategory')

vect = CountVectorizer()

vect_cs = vect.fit(X_train['clean_subcategories'].values)
X_train_cs = vect.fit_transform(X_train['clean_subcategories'].values)
X_test_cs = vect.transform(X_test['clean_subcategories'].values)

print('X_train shape:' ,X_train_cs.shape)
print('X_test_shape:', X_test_cs.shape)

X_train_cat =␣
↪hstack((X_train_school_state,X_train_teacher_prefix,X_train_pgc,X_train_cc,X_train_cs)).
↪tocsr()
X_test_cat =␣
↪hstack((X_test_school_state,X_test_teacher_prefix,X_test_pgc,X_test_cc,X_test_cs)).
↪tocsr()

print('\n')
print('Th final categorical variables')
print('X_train_cat shape:' ,X_train_cat.shape)
```

```
print('X_test_cat shape:', X_test_cat.shape)
```

```
School State
X_train shape: (76473, 51)
X_test_shape: (32775, 51)


Teacher Prefix
X_train shape: (76473, 5)
X_test_shape: (32775, 5)


Project_grade_category
X_train shape: (76473, 4)
X_test_shape: (32775, 4)


Clean_category
X_train shape: (76473, 9)
X_test_shape: (32775, 9)


Clean_subcategory
X_train shape: (76473, 30)
X_test_shape: (32775, 30)


Th final categorical variables
X_train_cat shape: (76473, 99)
X_test_cat shape: (32775, 99)
```

1.3 1.5 Encoding Numerical Features

[12]:
```
#Normlaizer
# By default works on row not on column like standardscaler
#So transfrom the to row form then transform using 1 -1 which is 1 row and numb␣
↪of cols

#Numerical Feature

print('For Price Feature')

norm = Normalizer()
norm.fit(X_train['price'].values.reshape(-1,1)) #Converts to
X_train_price_norm = norm.transform(X_train['price'].values.reshape(-1,1))
X_test_price_norm = norm.transform(X_test['price'].values.reshape(-1,1))
```

```
print('X_train_price shape_norm',X_train_price_norm.shape)
print('X_test_price shape_norm',X_test_price_norm.shape)
print('\n')

print('For Teacher number of previously posted projects')

norm = Normalizer()
X_test_pp = norm.fit(X_train['teacher_number_of_previously_posted_projects'].
 ↪values.reshape(-1,1))
X_train_pp = norm.
 ↪transform(X_train['teacher_number_of_previously_posted_projects'].values.
 ↪reshape(-1,1))
X_test_pp = norm.
 ↪transform(X_test['teacher_number_of_previously_posted_projects'].values.
 ↪reshape(-1,1))

print('X_train_pp',X_train_pp.shape)
print('X_test_pp',X_test_pp.shape)
```

```
For Price Feature
X_train_price shape_norm (76473, 1)
X_test_price shape_norm (32775, 1)


For Teacher number of previously posted projects
X_train_pp (76473, 1)
X_test_pp (32775, 1)
```

##

1.5 Appling NB on different kind of featurization as mentioned in the instructions

Apply NB on different kind of featurization as mentioned in the instructions For Every model that you work on make sure you do the step 2 and step 3 of instrucations

1.4 Set 1

[13]:
```
#Data
X_train =␣
 ↪hstack((X_train_preprocessed_essay_bow,X_train_cat,X_train_price_norm,X_train_pp)).
 ↪tocsr()
X_test =␣
 ↪hstack((X_test_preprocessed_essay_bow,X_test_cat,X_test_price_norm,X_test_pp)).
 ↪tocsr()
```

```
print('Train',X_train.shape,'y:',y_train.shape)
print('Test',X_test.shape,'y:',y_test.shape)
```

```
Train (76473, 5101) y: (76473,)
Test (32775, 5101) y: (32775,)
```

[14]:
```
#Training model
model = MultinomialNB(class_prior = [0.5,0.5])
alpha_values = [0.00001,0.0005, 0.0001,0.005,0.001,0.05,0.01,0.1,0.
↪5,1,5,10,50,100]
param = {'alpha':alpha_values}

#Iinstantiate grid
grid = GridSearchCV(model,param, scoring='roc_auc',cv= 5,return_train_score=␣
↪True)
grid.fit(X_train,y_train)
```

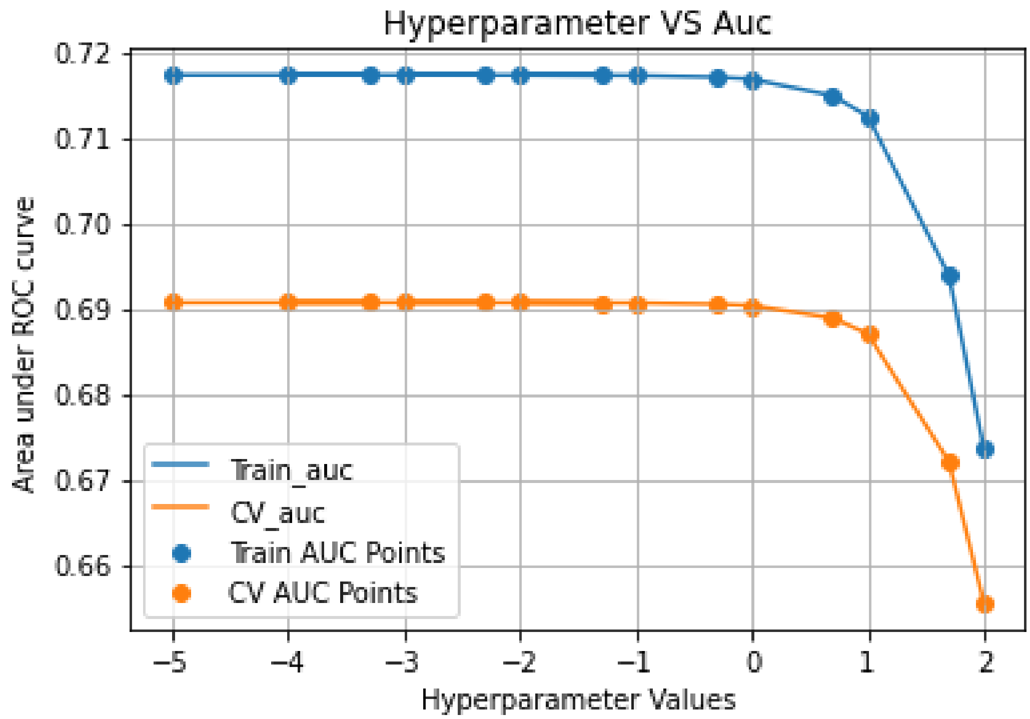
[14]:
```
GridSearchCV(cv=5, estimator=MultinomialNB(class_prior=[0.5, 0.5]),
             param_grid={'alpha': [1e-05, 0.0005, 0.0001, 0.005, 0.001, 0.05,
                                   0.01, 0.1, 0.5, 1, 5, 10, 50, 100]},
             return_train_score=True, scoring='roc_auc')
```

[15]:
```
train_auc = grid.cv_results_['mean_train_score']
train_auc_std = grid.cv_results_['std_train_score']

cv_auc = grid.cv_results_['mean_test_score']
cv_auc_std = grid.cv_results_['std_test_score']
```

[16]:
```
alpha_values = [0.00001,0.0005, 0.0001,0.005,0.001,0.05,0.01,0.1,0.
↪5,1,5,10,50,100]
alpha  = [math.log10(i) for i in alpha_values]
#print(alpha)
```

[17]:
```
# Perform Hyperparameter Tuning.
# Plot the training and the CV AUC scores, for different values of 'alpha',␣
↪using a 2D line plot3

plt.plot(alpha,train_auc,label = 'Train_auc')
plt.plot(alpha,cv_auc,label = 'CV_auc')

plt.scatter(alpha,train_auc,label='Train AUC Points')
plt.scatter(alpha,cv_auc,label='CV AUC Points')

plt.xlabel('Hyperparameter Values')
plt.ylabel("Area under ROC curve")
plt.title("Hyperparameter VS Auc")
plt.legend()
```

```
plt.grid()
```



[18]:
```
#From graph we have maximum AUC and leats gap at approx alpha = 0.5
print('The best alphh after trainin:',grid.best_params_)

#Getting the auc score at highest alpha
print('AUC score of the best alpha:',grid.best_score_)
```

```
The best alphh after trainin: {'alpha': 1e-05}
AUC score of the best alpha: 0.6906557619488548
```

1.4.1 Testing performance on Test and plotting ROC for train and test

[19]:
```
model = MultinomialNB(alpha = grid.best_params_['alpha'],class_prior = [0.5,0.
 ↪5])
model.fit(X_train,y_train)
```

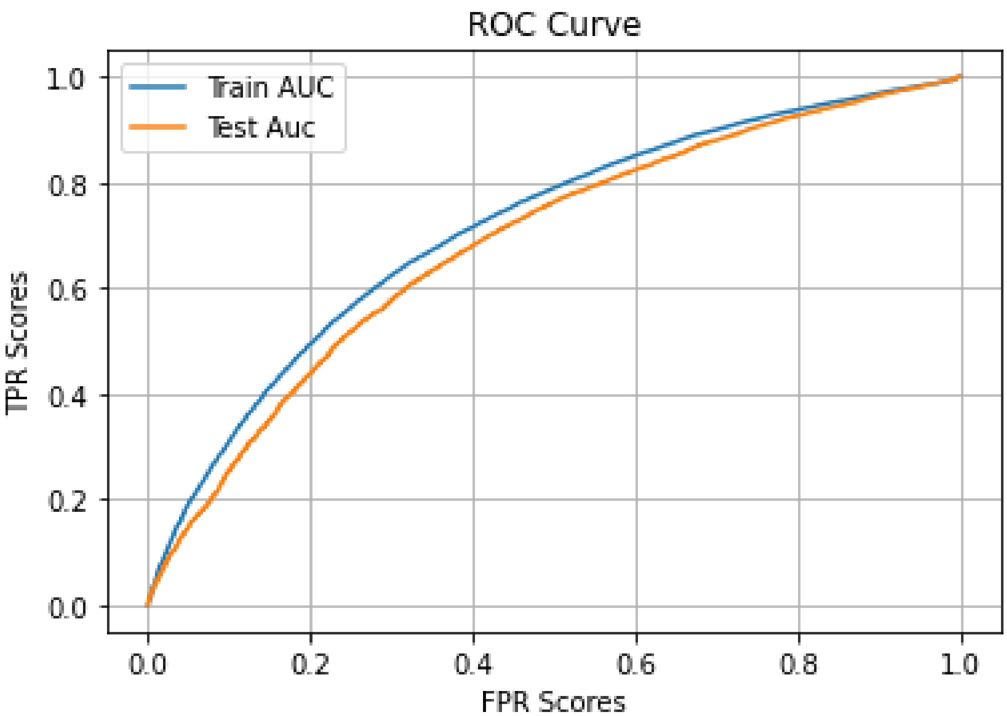
[19]:
```
MultinomialNB(alpha=1e-05, class_prior=[0.5, 0.5])
```

[20]:
```
# Obtain the optimal value for 'alpha' and using the obtained optimal 'alpha'␣
 ↪value, fit a multinomial naive bayes model, on the train data,
```

```
# Note: If you have split the datase into 3 parts (ie., train, cv and test␣
↪sets) in the beginning, then the training datafor this final model would be␣
↪(train set + cv set)
# Make class label and probability predictions on the train and test data.
#Choosing the best parameters from grid search to train the model


model = MultinomialNB(alpha = grid.best_params_['alpha'],class_prior = [0.5,0.
↪5])
model.fit(X_train,y_train)

# Plot the ROC-AUC curves using the probability predictions made on train and␣
↪test data.
y_train_prob = model.predict_proba(X_train)[:,1]
y_test_prob = model.predict_proba(X_test)[:,1]

train_fpr,train_tpr,train_thresholds = roc_curve(y_train,y_train_prob)

test_fpr,test_tpr,test_thresholds = roc_curve(y_test,y_test_prob)

plt.plot(train_fpr,train_tpr,label = 'Train AUC')
plt.plot(test_fpr,test_tpr,label = 'Test Auc')
plt.title('ROC Curve')
plt.xlabel('FPR Scores')
plt.ylabel('TPR Scores')
plt.legend()
plt.grid()

print('Train AUC ',auc(train_fpr,train_tpr))
print('Test AUC ',auc(test_fpr,test_tpr))
grid.best_params_['alpha']
```

```
Train AUC  0.7125686358152559
Test AUC  0.6834340080930832
```

[20]: 1e-05



[21]:
```
# Pick the best threshold among the probability estimates, such that it has to␣
↪yield maximum value for TPR*(1-FPR)
# Plot the confusion matrices(each for train and test data) afer encoding the␣
↪predicted class labels, on the basis of the best threshod probability␣
↪estimate.
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t


# Predicting output with threshold from least fpr
def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
```

```
            predictions.append(0)
    return predictions
```

[22]:
```
best_t = find_best_threshold(train_thresholds, train_fpr, train_tpr)

print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_prob, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_prob, best_t)))
```

```
the maximum value of tpr*(1-fpr) 0.43984773984713327 for threshold 0.492
Train confusion matrix
[[ 7838  3741]
 [22727 42167]]
Test confusion matrix
[[ 3180  1783]
 [ 9958 17854]]
```

1.5 Set 2

[23]:
```
#Data

X_train =␣
↪hstack((X_train_preprocessed_essay_tfidf,X_train_cat,X_train_price_norm,X_train_pp)).
↪tocsr()
X_test =␣
↪hstack((X_test_preprocessed_essay_tfidf,X_test_cat,X_test_price_norm,X_test_pp)).
↪tocsr()

print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
```

```
X_train shape: (76473, 5101)
X_test shape: (32775, 5101)
```

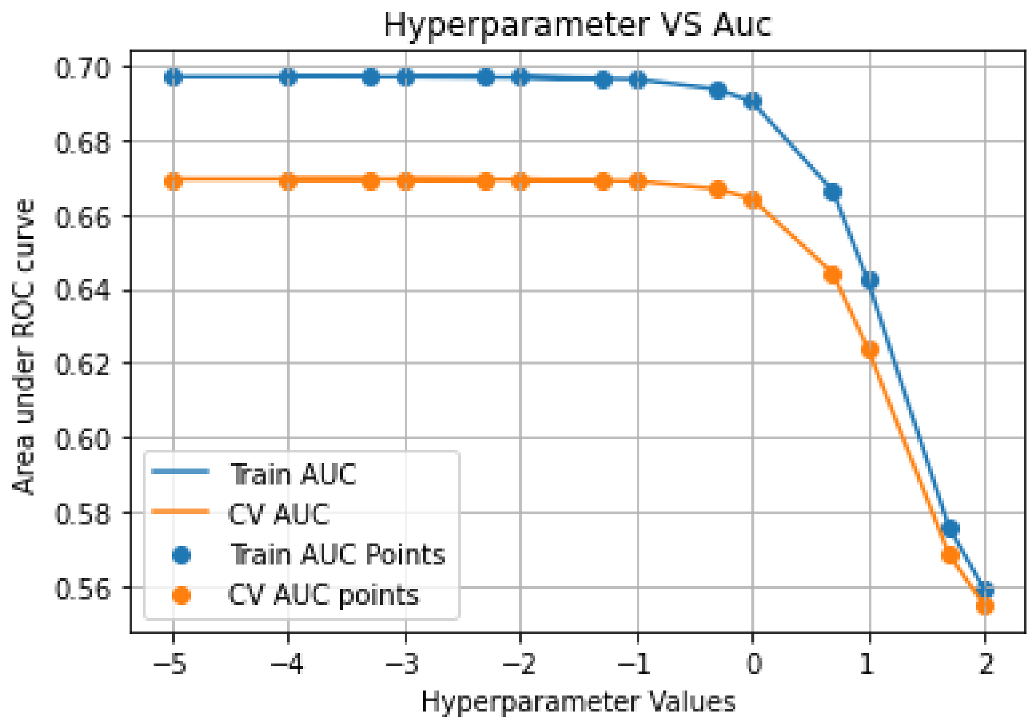
[24]:
```
# Perform Hyperparameter Tuning.
# Plot the training and the CV AUC scores, for different values of 'alpha',␣
↪using a 2D line plot


alpha_values = [0.00001,0.0005, 0.0001,0.005,0.001,0.05,0.01,0.1,0.
↪5,1,5,10,50,100]

model = MultinomialNB(class_prior =[0.5,0.5])
param = {'alpha':alpha_values}
```

```
grid = GridSearchCV(model,param, scoring = 'roc_auc',cv = 5,return_train_score␣
 ↪= True)
grid.fit(X_train,y_train)
```

```
[24]: GridSearchCV(cv=5, estimator=MultinomialNB(class_prior=[0.5, 0.5]),
             param_grid={'alpha': [1e-05, 0.0005, 0.0001, 0.005, 0.001, 0.05,
                                   0.01, 0.1, 0.5, 1, 5, 10, 50, 100]},
             return_train_score=True, scoring='roc_auc')
```

```
[25]: # Obtain the optimal value for 'alpha' and using the obtained optimal 'alpha'␣
 ↪value, fit a multinomial naive bayes model, on the train data,
# Note: If you have split the datase into 3 parts (ie., train, cv and test␣
 ↪sets) in the beginning, then the training datafor this final model would be␣
 ↪(train set + cv set)
# Make class label and probability predictions on the train and test data.

train_score = grid.cv_results_['mean_train_score']
val_score = grid.cv_results_['mean_test_score']

alpha = [math.log10(i) for i in alpha_values]

plt.plot(alpha,train_score,label = 'Train AUC')
plt.plot(alpha,val_score,label='CV AUC')
plt.scatter(alpha,train_score,label  = 'Train AUC Points')
plt.scatter(alpha,val_score,label = 'CV AUC points')
plt.xlabel('Hyperparameter Values')
plt.ylabel("Area under ROC curve")
plt.title("Hyperparameter VS Auc")
plt.grid()
plt.legend()
```

```
[25]: <matplotlib.legend.Legend at 0x7f7a011b8990>
```



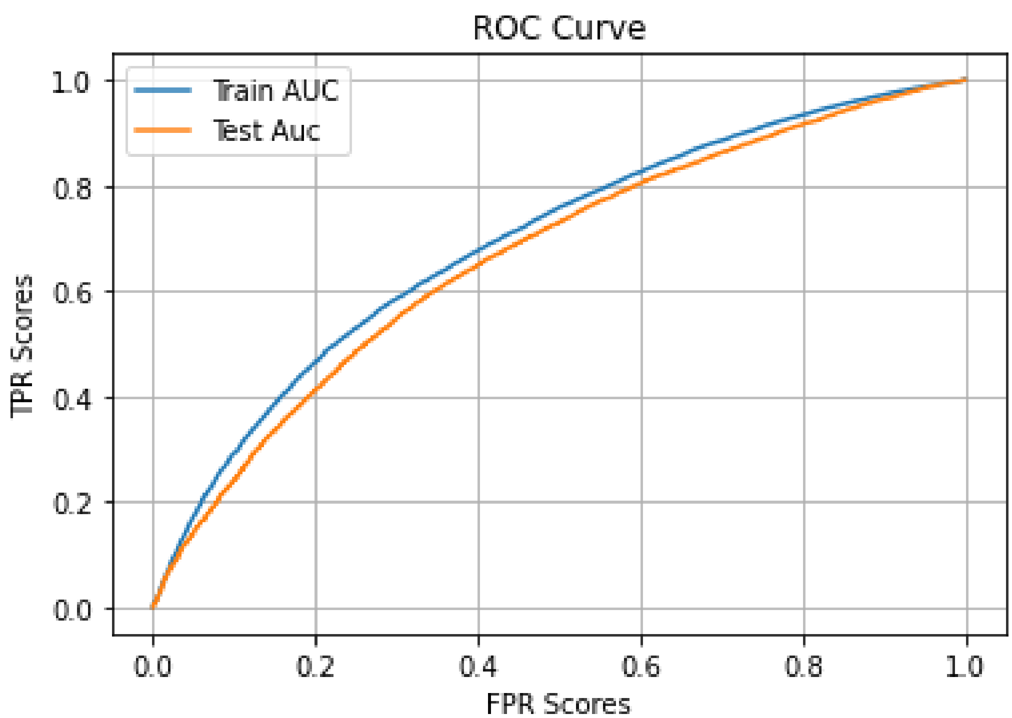
[26]:
```
#From graph we have maximum AUC and leats gap at approx alpha = 0.5
print('The best alphh after trainin:',grid.best_params_)

#Getting the auc score at highest alpha
print('AUC score of the best alpha:',grid.best_score_)
```

```
The best alphh after trainin: {'alpha': 1e-05}
AUC score of the best alpha: 0.6694005297402958
```

[27]:
```
# Plot the ROC-AUC curves using the probability predictions made on train and␣
↪test data.

model = MultinomialNB(alpha = grid.best_params_['alpha'],class_prior = [0.5,0.
↪5])
model.fit(X_train,y_train)

y_train_prob = model.predict_proba(X_train)[:,1]
y_test_prob = model.predict_proba(X_test)[:,1]

train_fpr,train_tpr, train_thres = roc_curve(y_train,y_train_prob)
test_fpr,test_tpr, test_thres = roc_curve(y_test,y_test_prob)

plt.plot(train_fpr,train_tpr,label = 'Train AUC')
```

```
plt.plot(test_fpr,test_tpr,label = 'Test Auc')
plt.title('ROC Curve')
plt.xlabel('FPR Scores')
plt.ylabel('TPR Scores')
plt.legend()
plt.grid()


print('Train AUC ',auc(train_fpr,train_tpr))
print('Test AUC ',auc(test_fpr,test_tpr))
print(grid.best_params_['alpha'])
```

```
Train AUC  0.6921893423796579
Test AUC  0.6654928261164836
1e-05
```



[28]:
```
# Pick the best threshold among the probability estimates, such that it has to
 ↪yield maximum value for TPR*(1-FPR)
# Plot the confusion matrices(each for train and test data) afer encoding the
 ↪predicted class labels, on the basis of the best threshod probability
 ↪estimate.

best_t = find_best_threshold(train_thresholds, train_fpr, train_tpr)
```

```
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_prob, best_t)))

print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_prob, best_t)))
```

```
the maximum value of tpr*(1-fpr) 0.4123565655693785 for threshold 0.534
Train confusion matrix
[[ 8293  3286]
 [27944 36950]]
Test confusion matrix
[[ 3409  1554]
 [12152 15660]]
```

1.6 20 features

[29]:
```
#https://stackoverflow.com/questions/50526898/
↪how-to-get-feature-importance-in-naive-bayes
#https://stackoverflow.com/questions/16486252/
↪is-it-possible-to-use-argsort-in-descending-order
#https://numpy.org/doc/stable/reference/generated/numpy.take.html
# Either from set 1 (or) set 2, print the names of the top 20 features␣
↪associated with the positive and negative classes each. (You have to print␣
↪the names of the features, but not the indexes)

#Creating list for adding all features the using argsort to find them

features = []

for i in vect1.get_feature_names():
  features.append(i)

for i in vect_ss.get_feature_names():
  features.append(i)

for i in vect_tp.get_feature_names():
  features.append(i)

for i in vect_pgc.get_feature_names():
  features.append(i)

for i in vect_cc.get_feature_names():
  features.append(i)

for i in vect_cs.get_feature_names():
```

```
  features.append(i)


features.append('price')
features.append('teacher_number_of_previously_posted_projects')


print(len(features))
```

5101

[42]:
```
#Argsor is in ascending using indexing to take 20 feature from back
#Using feature_log_prob to filter max feature

top_20_class_0 = np.take(features,model.feature_log_prob_[0,:].argsort()[-20:] )
print('top_20_class_0:', top_20_class_0)
print('\n')
top_20_class_1 = np.take(features,model.feature_log_prob_[1,:].argsort()[-20:] )
print('top_20_class_1:', top_20_class_1)
```

```
top_20_class_0: ['grades_9_12' 'appliedsciences' 'students' 'appliedlearning'
'ca'
 'health_sports' 'specialneeds' 'specialneeds' 'grades_6_8'
 'literature_writing' 'literacy' 'mathematics' 'grades_3_5' 'ms'
 'math_science' 'grades_prek_2' 'literacy_language' 'mrs'
 'teacher_number_of_previously_posted_projects' 'price']


top_20_class_1: ['appliedsciences' 'grades_9_12' 'appliedlearning'
'specialneeds'
 'specialneeds' 'students' 'health_sports' 'ca' 'grades_6_8'
 'literature_writing' 'mathematics' 'literacy' 'grades_3_5' 'ms'
 'math_science' 'grades_prek_2' 'literacy_language' 'mrs'
 'teacher_number_of_previously_posted_projects' 'price']
```

##

3. Summary

as mentioned in the step 5 of instructions

[35]:
```
#Summarize your assignment work here in a few points, and also compare the␣
↪final models (from set 1 and set 2), in terms of optimal hyperparameter␣
↪value 'alpha', training AUC and test AUC scores.
# You can either use a pretty table or any other tabular structure.
# Reference Link for Pretty table:  https://pypi.org/project/prettytable/

myTable = PrettyTable(["Model", "Vectorizer", "Hyperameter", "Train AUC","Test␣
↪AUC"])
```

```
myTable.add_row(["NB", "BOW", "1e-05","71.2 %", "68.3 %"])
myTable.add_row(["NB", "TFIDF", "1e-05", "67.1 %","67 %"])

print(myTable)
```

```
+-------+------------+-------------+-----------+----------+
| Model | Vectorizer | Hyperameter | Train AUC | Test AUC |
+-------+------------+-------------+-----------+----------+
|   NB  |    BOW     |    1e-05    |   71.2 %  |  68.3 %  |
|   NB  |   TFIDF    |    1e-05    |   67.1 %  |   67 %   |
+-------+------------+-------------+-----------+----------+
```

Conclusion:

- Final Models:
- Set 1: Train Auc: 71.2 % Test Auc: 68.3% alpha: 1e-05
- Set 2: Train Auc: 67.1 % Test Auc: 67% alpha:1e-05
- From the table we can conclude that the tfidf is better fit than BOW vectorization as the train and test auc are almost similar.
- Also the test auc of BOW is slightly greater than TFIDF Vectorizer but the gap is more between the train and test auc
- Both the models get the values of alpha as 1e-05
- The accuracy remains almost same when we consider all the feature and when we consider 80k points.
- The top features for both the classes are aslo almost similar.
- To further increase accuracy we need to work on feature engineering.