

Assignment 6: Apply NB

1. Apply Multinomial NB on these feature sets

- **Set 1**: categorical, numerical features + preprocessed_eassay (BOW)
- **Set 2**: categorical, numerical features + preprocessed_eassay (TFIDF)

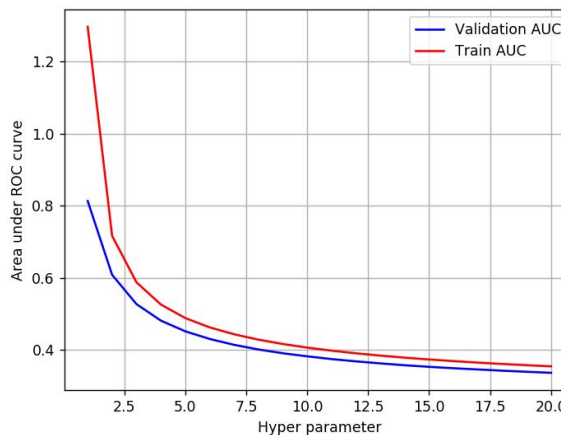
2. The hyper paramter tuning(find best alpha:smoothing parameter)

- Find the best hyper parameter which will give the maximum [AUC \(https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/\)](https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
- find the best hyper paramter using k-fold cross validation(use GridsearchCV or RandomsearchCV)/simple cross validation data (write for loop to iterate over hyper parameter values)

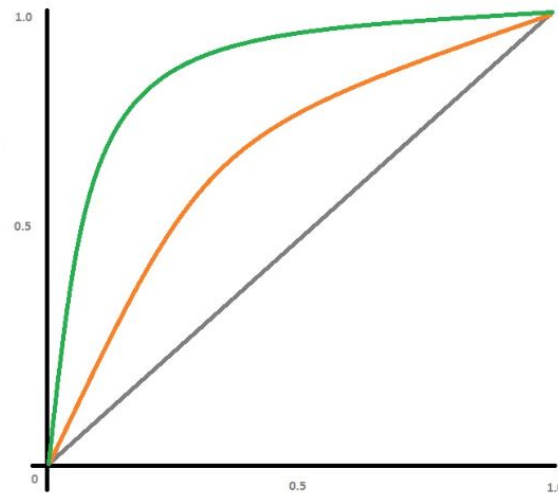
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3. Representation of results

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure



- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.



- Along with plotting ROC curve, you need to print the [confusion matrix](https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tp-rr-fpr-fnr-tnr-1/) (<https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tp-rr-fpr-fnr-tnr-1/>) with predicted and original labels of test data points

	Predicted: NO	Predicted: YES
Actual: NO	TN = ??	FP = ??
Actual: YES	FN = ??	TP = ??

- fine the top 20 features from either from feature **Set 1** or feature **Set 2** using absolute values of `feature_log_prob_` parameter of `'MultinomialNB'` (https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html) and print their corresponding feature names
- You need to summarize the results at the end of the notebook, summarize it in the table format



2. Naive Bayes

1.1 Loading Data

```
In [1]: %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.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc

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

import pickle
from tqdm import tqdm
import os
```

```
In [2]: from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import math
```

```
In [3]: import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
import plotly
```

```
In [4]: from chart_studio import plotly
```

```
In [5]: #reading the data
```

```
In [6]: data = pd.read_csv('preprocessed_data.csv')
data.shape
```

Out[6]: (109248, 9)

```
In [7]: data.head()
```

Out[7]:

	school_state	teacher_prefix	project_grade_category	teacher_number_of_previously_posted_projects	project_is_approved	clean_category
0	ca	mrs	grades_prek_2	53	1	math_scienc
1	ut	ms	grades_3_5	4	1	specialneed
2	ca	mrs	grades_prek_2	10	1	literacy_language
3	ga	mrs	grades_prek_2	2	1	appliedlearning
4	wa	mrs	grades_3_5	2	1	literacy_language



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

```
In [8]: y = data['project_is_approved'].values #making the required label and gievn the calss abel as y
X = data.drop(['project_is_approved'], axis=1)
X.head(1)#printing the data
```

```
Out[8]:
```

	school_state	teacher_prefix	project_grade_category	teacher_number_of_previously_posted_projects	clean_categories	clean_subcategory
0	ca	mrs	grades_prek_2	53	math_science	appliedscienc health_lifescien

```
In [9]: # train test split
#this code is taken from the refrence notebook
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify=y)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, stratify=y_train)
```

```
In [10]: #printing the shapes of the x,y ies train,test and cv data
```

```
In [11]: X_train.shape
```

```
Out[11]: (49041, 8)
```

```
In [12]: X_cv.shape
```

```
Out[12]: (24155, 8)
```

```
In [13]: X_test.shape
```

```
Out[13]: (36052, 8)
```

```
In [14]: y_train.shape
```

```
Out[14]: (49041,)
```

```
In [15]: y_test.shape
```

```
Out[15]: (36052,)
```

```
In [16]: y_cv.shape
```

```
Out[16]: (24155,)
```

1.3 Make Data Model Ready: encoding eassay

BOW

```
In [17]: print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)

print("="*100)
```

```
(49041, 8) (49041,)
(24155, 8) (24155,)
(36052, 8) (36052,)
```

```
=====
```

```
In [19]: vectorizer_bow = CountVectorizer(min_df=10)
vectorizer_bow.fit(X_train['essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_bow = vectorizer_bow.transform(X_train['essay'].values)
X_cv_essay_bow = vectorizer_bow.transform(X_cv['essay'].values)
X_test_essay_bow = vectorizer_bow.transform(X_test['essay'].values)
```

```
In [24]: print("After vectorizations")
print(X_train_essay_bow.shape, y_train.shape)
print(X_cv_essay_bow.shape, y_cv.shape)
print(X_test_essay_bow.shape, y_test.shape)
print("="*100)
#print(vectorizer_bow.get_feature_names())
#printing the featured names in the essay
```

After vectorizations

(49041, 12164) (49041,)

(24155, 12164) (24155,)

(36052, 12164) (36052,)

=====

TFIDF

```
In [25]: from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer_tfidf = TfidfVectorizer(min_df=15)
vectorizer_tfidf.fit(X_train['essay'])

# we use the fitted CountVectorizer 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)
X_cv_essay_tfidf=vectorizer_tfidf.transform(X_cv['essay'].values)
```

```
In [26]: print("after vectorization")
print(X_train_essay_tfidf.shape,y_train.shape)
print(X_test_essay_tfidf.shape,y_test.shape)
print(X_cv_essay_tfidf.shape,y_cv.shape)
```

after vectorization

(49041, 10255) (49041,)

(36052, 10255) (36052,)

(24155, 10255) (24155,)

In []:

1.4 Make Data Model Ready: encoding numerical, categorical features

```
In [27]: # 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
# make sure you featurize train and test data separatly

# 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
```

Categorical features

one hot encoding the catogorical features: school_state


```
In [29]: vectorizer_ss = CountVectorizer()
vectorizer_ss.fit(X_train['school_state'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_state_ohe = vectorizer_ss.transform(X_train['school_state'].values)
X_cv_state_ohe = vectorizer_ss.transform(X_cv['school_state'].values)
X_test_state_ohe = vectorizer_ss.transform(X_test['school_state'].values)

print("After vectorizations")
print(X_train_state_ohe.shape, y_train.shape)
print(X_cv_state_ohe.shape, y_cv.shape)
print(X_test_state_ohe.shape, y_test.shape)
print(vectorizer_ss.get_feature_names())
print("="*100)

After vectorizations
(49041, 51) (49041,)
(24155, 51) (24155,)
(36052, 51) (36052,)
['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi', 'ia', 'id', 'il', 'in', 'ks', 'ky',
'la', 'ma', 'md', 'me', 'mi', 'mn', 'mo', 'ms', 'mt', 'nc', 'nd', 'ne', 'nh', 'nj', 'nm', 'nv', 'ny', 'oh', 'o
k', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx', 'ut', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
=====
```

one hot encoding the catogorical features :teacher_prefix

```
In [30]: vectorizer_tp = CountVectorizer()
vectorizer_tp.fit(X_train['teacher_prefix'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_teacher_ohe = vectorizer_tp.transform(X_train['teacher_prefix'].values)
X_cv_teacher_ohe = vectorizer_tp.transform(X_cv['teacher_prefix'].values)
X_test_teacher_ohe = vectorizer_tp.transform(X_test['teacher_prefix'].values)

print("After vectorizations")
print(X_train_teacher_ohe.shape, y_train.shape)
print(X_cv_teacher_ohe.shape, y_cv.shape)
print(X_test_teacher_ohe.shape, y_test.shape)
print(vectorizer_tp.get_feature_names())
print("="*100)
```

After vectorizations

(49041, 5) (49041,)

(24155, 5) (24155,)

(36052, 5) (36052,)

['dr', 'mr', 'mrs', 'ms', 'teacher']

=====

one hot encoding the catogorical features: project_grade_category

```
In [31]: vectorizer_pgc = CountVectorizer()
vectorizer_pgc.fit(X_train['project_grade_category'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_grade_ohe = vectorizer_pgc.transform(X_train['project_grade_category'].values)
X_cv_grade_ohe = vectorizer_pgc.transform(X_cv['project_grade_category'].values)
X_test_grade_ohe = vectorizer_pgc.transform(X_test['project_grade_category'].values)

print("After vectorizations")
print(X_train_grade_ohe.shape, y_train.shape)
print(X_cv_grade_ohe.shape, y_cv.shape)
print(X_test_grade_ohe.shape, y_test.shape)
print(vectorizer_pgc.get_feature_names())
print("="*100)
```

After vectorizations

(49041, 4) (49041,)

(24155, 4) (24155,)

(36052, 4) (36052,)

['grades_3_5', 'grades_6_8', 'grades_9_12', 'grades_prek_2']

=====

one hot encoding the catogorical features: clean_categories

```
In [32]: vectorizer_cc = CountVectorizer()
vectorizer_cc.fit(X_train['clean_categories'].values) # fit has to happen only on train data
```

```
# we use the fitted CountVectorizer to convert the text to vector
X_train_ccat_ohe = vectorizer_cc.transform(X_train['clean_categories'].values)
X_cv_ccat_ohe = vectorizer_cc.transform(X_cv['clean_categories'].values)
X_test_ccat_ohe = vectorizer_cc.transform(X_test['clean_categories'].values)
```

```
print("After vectorizations")
print(X_train_ccat_ohe.shape, y_train.shape)
print(X_cv_ccat_ohe.shape, y_cv.shape)
print(X_test_ccat_ohe.shape, y_test.shape)
print(vectorizer_cc.get_feature_names())
print("="*100)
```

After vectorizations

(49041, 9) (49041,)

(24155, 9) (24155,)

(36052, 9) (36052,)

['appliedlearning', 'care_hunger', 'health_sports', 'history_civics', 'literacy_language', 'math_science', 'music_arts', 'specialneeds', 'warmth']

=====

one hot encoding the catogorical features: clean_subcategories

```
In [33]: vectorizer_csc= CountVectorizer()
vectorizer_csc.fit(X_train['clean_subcategories'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_csubcat_ohe = vectorizer_csc.transform(X_train['clean_subcategories'].values)
X_cv_csubcat_ohe = vectorizer_csc.transform(X_cv['clean_subcategories'].values)
X_test_csubcat_ohe = vectorizer_csc.transform(X_test['clean_subcategories'].values)

print("After vectorizations")
print(X_train_csubcat_ohe.shape, y_train.shape)
print(X_cv_csubcat_ohe.shape, y_cv.shape)
print(X_test_csubcat_ohe.shape, y_test.shape)
print(vectorizer_csc.get_feature_names())
print("="*100)
```

After vectorizations

(49041, 30) (49041,)

(24155, 30) (24155,)

(36052, 30) (36052,)

['appliedsciences', 'care_hunger', 'charactereducation', 'civics_government', 'college_careerprep', 'community service', 'earlydevelopment', 'economics', 'environmentalscience', 'esl', 'extracurricular', 'financialliteracy', 'foreignlanguages', 'gym_fitness', 'health_lifescience', 'health_wellness', 'history_geography', 'literacy', 'literature_writing', 'mathematics', 'music', 'nutritioneducation', 'other', 'parentinvolvement', 'performingarts', 'socialsciences', 'specialneeds', 'teamsports', 'visualarts', 'warmth']

=====

Numerical features

Normalising numerical features: price

```

In [46]: import warnings

warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler
#https://machinelearningmastery.com/rescaling-data-for-machine-learning-in-python-with-scikit-Learn/
standard_vec_p = StandardScaler(with_mean = False)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.

standard_vec_p.fit(X_train['price'].values.reshape(-1,1))

X_train_price_std = standard_vec_p.transform(X_train['price'].values.reshape(-1,1))
X_cv_price_std = standard_vec_p.transform(X_cv['price'].values.reshape(-1,1))
X_test_price_std = standard_vec_p.transform(X_test['price'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_price_std.shape, y_train.shape)
print(X_cv_price_std.shape, y_cv.shape)
print(X_test_price_std.shape, y_test.shape)
print("=*100)

```

After vectorizations

(49041, 1) (49041,)

(24155, 1) (24155,)

(36052, 1) (36052,)

=====

Normalising numerical features: teacher_number_of_previously_posted_projects

```
In [47]: import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler
#https://machinelearningmastery.com/rescaling-data-for-machine-learning-in-python-with-scikit-learn/
standard_vec_tpps = StandardScaler(with_mean = False)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.
standard_vec_tpps.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))

X_train_pre_project_std = standard_vec_tpps.transform(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))
X_cv_pre_project_std = standard_vec_tpps.transform(X_cv['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))
X_test_pre_project_std = standard_vec_tpps.transform(X_test['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_pre_project_std.shape, y_train.shape)
print(X_cv_pre_project_std.shape, y_cv.shape)
print(X_test_pre_project_std.shape, y_test.shape)
print("=="*100)
```

After vectorizations

(49041, 1) (49041,)

(24155, 1) (24155,)

(36052, 1) (36052,)

=====

1.5 Applying 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 instructions

Concatinating all the features

Set 1: categorical, numerical features + preprocessed_eassay (BOW)

```
In [49]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
#here in set 1 i am consideribng the essay_bow ,all categoricala nd all numerical values
from scipy.sparse import hstack
X_tr = hstack((X_train_essay_bow, X_train_state_ohe, X_train_teacher_ohe, X_train_grade_ohe,
               X_train_ccat_ohe,X_train_csubcat_ohe, X_train_price_std,X_train_pre_project_std)).tocsr()

X_cr = hstack((X_cv_essay_bow, X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe,
               X_cv_ccat_ohe,X_cv_csubcat_ohe, X_cv_price_std,X_cv_pre_project_std)).tocsr()

X_te = hstack((X_test_essay_bow, X_test_state_ohe, X_test_teacher_ohe, X_test_grade_ohe,
               X_test_ccat_ohe,X_test_csubcat_ohe,X_test_price_std,X_test_pre_project_std)).tocsr()

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
print("=*100)
```

Final Data matrix

```
(49041, 12265) (49041,)
(24155, 12265) (24155,)
(36052, 12265) (36052,)
```

=====

```
In [50]: def batch_predict(clf, data): #using the batch predition metod
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

y_data_pred = []
tr_loop = data.shape[0] - data.shape[0]%1000
# consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
# in this for loop we will iterate unti the last 1000 multiplier
for i in range(0, tr_loop, 1000):
    y_data_pred.extend(clf.predict_proba(data[i:i+1000]))[:,1])
# we will be predicting for the last data points
y_data_pred.extend(clf.predict_proba(data[tr_loop:]))[:,1])

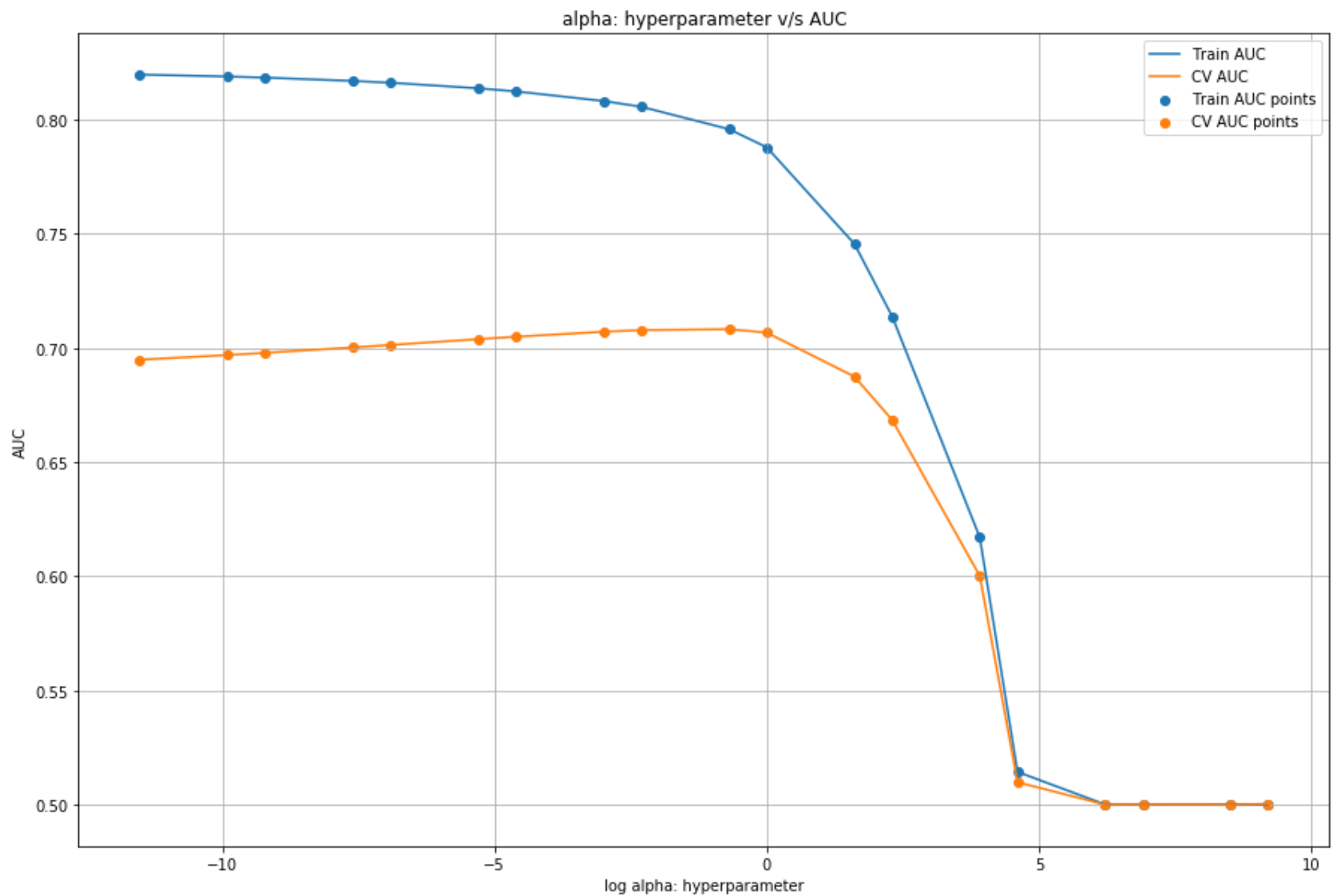
return y_data_pred
```



```
In [52]: # plotting the graphn b/w train and cv
plt.figure(figsize=(15,10))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("log alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("alpha: hyperparameter v/s AUC")
plt.grid()
plt.show()
```

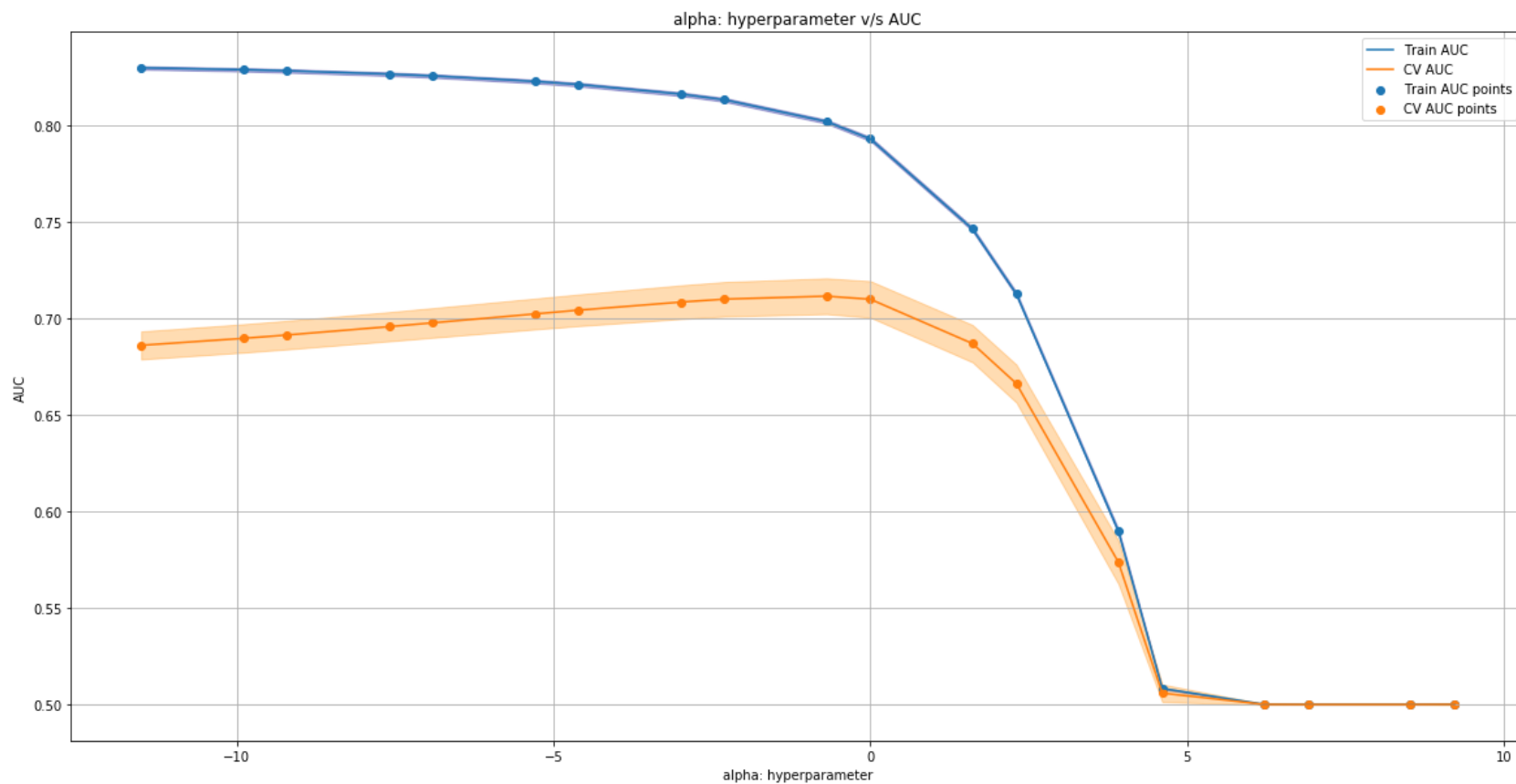


```
In [55]: from sklearn.model_selection import GridSearchCV

#using the grid search cv for the creoss validation of the model
nb = MultinomialNB()

parameters = {'alpha':[10000,5000,1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001,0.00005,0.00001]}
#taking the valies of alpha fro 10^4 to 10^-4 for the better hyperparaeter tunning
clf = GridSearchCV(nb, parameters, cv= 10, scoring='roc_auc',return_train_score=True)
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

```
In [57]: print('Best score: ',clf.best_score_)  
print('k value: ',clf.best_params_)  
print('='*10)
```

```
Best score:  0.7116797222248861  
k value:  {'alpha': 0.5}  
=====
```

```
In [58]: best_k_1 = 0.5
```

```
In [59]: print('Train AUC scores')
print(clf.cv_results_['mean_train_score'])
print('CV AUC scores')
print(clf.cv_results_['mean_test_score'])
```

Train AUC scores

```
[0.50006258 0.5          0.5          0.50005532 0.50828169 0.58991726
 0.71281137 0.74651529 0.7931575   0.80218895 0.81348439 0.81645642
 0.82142243 0.82302015 0.82587931 0.82682403 0.82852308 0.82908202
 0.83007256]
```

CV AUC scores

```
[0.50006259 0.5          0.5          0.50005529 0.50586215 0.57385746
 0.66639573 0.68711952 0.71005032 0.71167972 0.71012484 0.70859465
 0.70442195 0.70246053 0.69785198 0.69587373 0.69153133 0.68980147
 0.68618202]
```

```
In [60]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html#sklearn.metrics.roc\_curve
from sklearn.metrics import roc_curve, auc

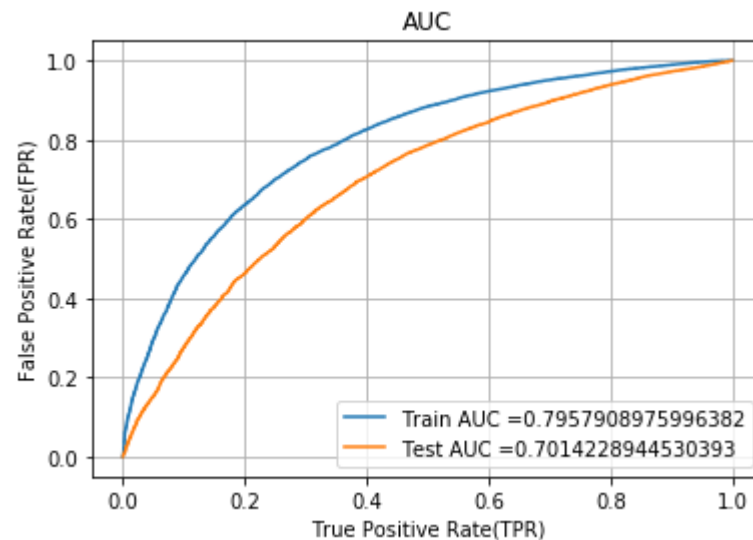
nb_bow = MultinomialNB(alpha = best_k_1)

nb_bow.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

y_train_pred = batch_predict(nb_bow, X_tr)
y_test_pred = batch_predict(nb_bow, X_te)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="Train AUC =" + str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="Test AUC =" + str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("True Positive Rate(TPR)")
plt.ylabel("False Positive Rate(FPR)")
plt.title("AUC")
plt.grid()
plt.show()
```




```
In [61]: def predict(proba, threshold, fpr, tpr):

    t = threshold[np.argmax(fpr*(1-tpr))]

    # (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))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Confusion matrix for train data set

```
In [62]: #confusion matrix for train data set
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr)))
```

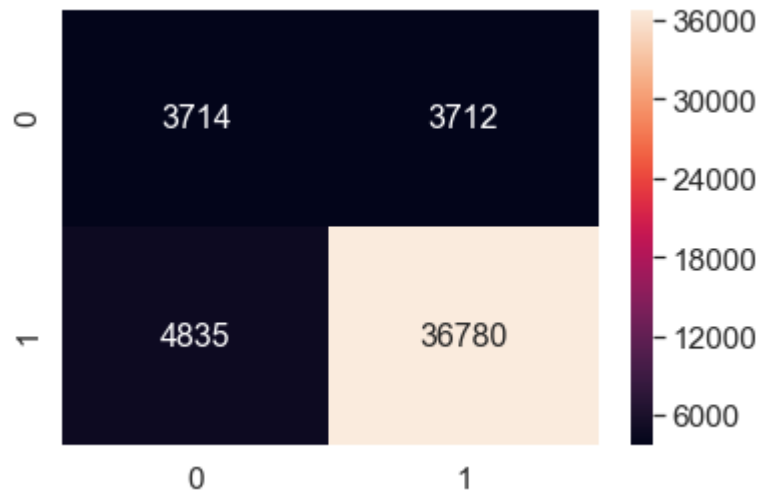
```
Train confusion matrix
the maximum value of tpr*(1-fpr) 0.2499999818661462 for threshold 0.133
[[ 3714  3712]
 [ 4835 36780]]
```

```
In [63]: conf_matr_df_train_1 = pd.DataFrame(confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, tr
                                             range(2),range(2)))
```

```
the maximum value of tpr*(1-fpr) 0.2499999818661462 for threshold 0.133
```

```
In [64]: #for the better vizulation of the confusion matrix  
#this plot is build by using the seaborn  
#https://seaborn.pydata.org/generated/seaborn.heatmap.html  
  
sns.set(font_scale=1.4)#for label size  
sns.heatmap(conf_matr_df_train_1, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x1cf014af4a8>



Confusion matrix for TEST data set

```
In [65]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr)))
```

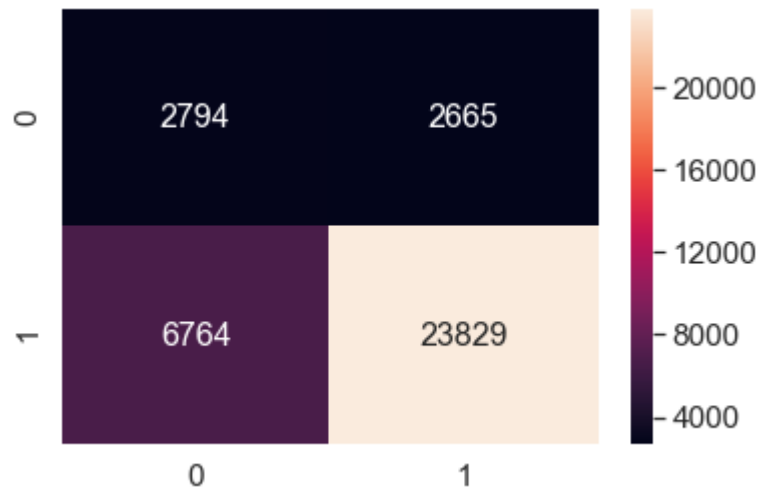
Test confusion matrix
the maximum value of $tpr \cdot (1 - fpr)$ 0.24999999161092995 for threshold 0.567
[[2794 2665]
 [6764 23829]]

```
In [66]: conf_matr_df_test_1 = pd.DataFrame(confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.24999999161092995 for threshold 0.567

```
In [67]: #for the better vizulation of the confusion matrix
#this plot is build by using the seaborn
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df_test_1, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x1cf0154c1d0>



Set 2: categorical, numerical features + preprocessed_eassay (TFIDF)

```
In [68]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr = hstack((X_train_essay_tfidf, X_train_state_ohe, X_train_teacher_ohe, X_train_grade_ohe,
               X_train_ccat_ohe, X_train_csubcat_ohe, X_train_price_std, X_train_pre_project_std)).tocsr()

X_cr = hstack((X_cv_essay_tfidf, X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe,
               X_cv_ccat_ohe, X_cv_csubcat_ohe, X_cv_price_std, X_cv_pre_project_std)).tocsr()

X_te = hstack((X_test_essay_tfidf, X_test_state_ohe, X_test_teacher_ohe, X_test_grade_ohe,
               X_test_ccat_ohe, X_test_csubcat_ohe, X_test_price_std, X_test_pre_project_std)).tocsr()

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
print("=="*100)
```

Final Data matrix

(49041, 10356) (49041,)

(24155, 10356) (24155,)

(36052, 10356) (36052,)

=====

```
In [69]: def batch_predict(clf, data):
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

y_data_pred = []
tr_loop = data.shape[0] - data.shape[0]%1000
# consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
# in this for loop we will iterate until the last 1000 multiplier
for i in range(0, tr_loop, 1000):
    y_data_pred.extend(clf.predict_proba(data[i:i+1000]))[:,1])
# we will be predicting for the last data points
y_data_pred.extend(clf.predict_proba(data[tr_loop:]))[:,1])

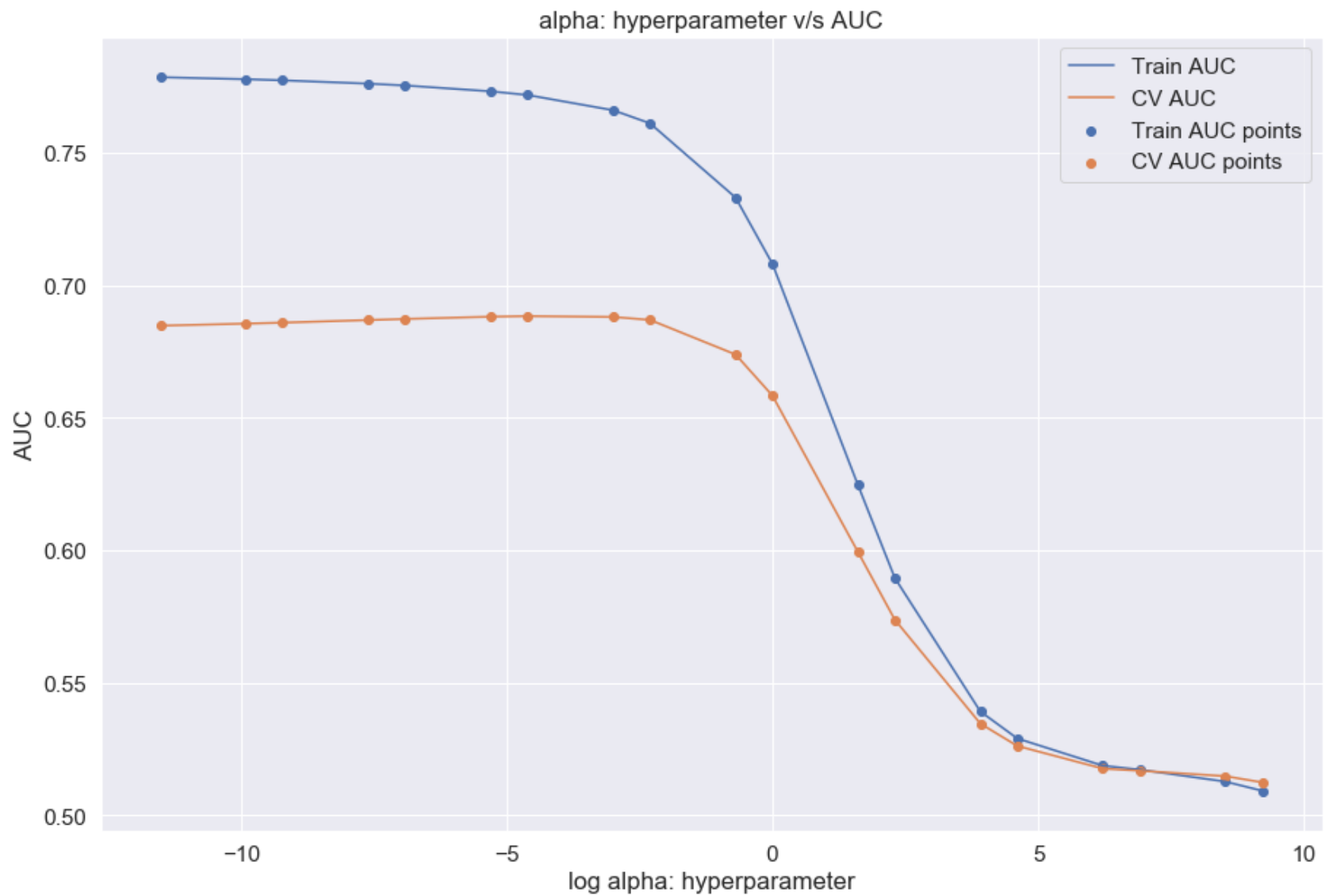
return y_data_pred
```

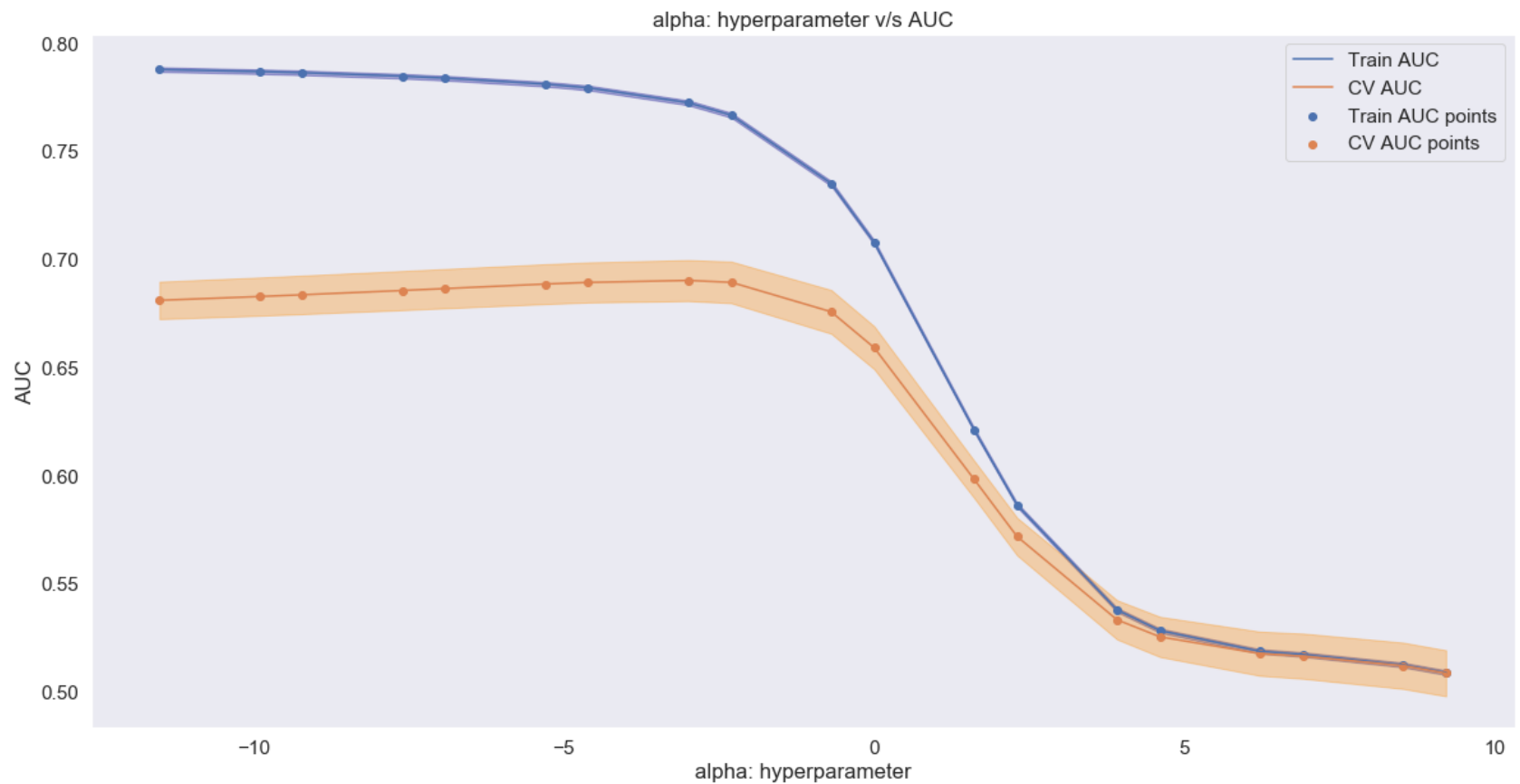


```
In [71]: plt.figure(figsize=(15,10))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("log alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("alpha: hyperparameter v/s AUC")
#plt.grid()
plt.show()
```





```
In [74]: print('Best score: ',clf.best_score_)  
print('k value: ',clf.best_params_)  
print('='*10)
```

```
Best score: 0.690169164405337  
k value: {'alpha': 0.05}  
=====
```

```
In [75]: best_k_1 = 0.05
```

```
In [76]: print('Train AUC scores')
print(clf.cv_results_['mean_train_score'])
print('CV AUC scores')
print(clf.cv_results_['mean_test_score'])
```

Train AUC scores

```
[0.50877954 0.51234951 0.51717129 0.51861261 0.52819717 0.5377839
0.5862645 0.62111304 0.70776382 0.73504566 0.76663951 0.77237942
0.77928396 0.78100398 0.78379268 0.78467766 0.78626595 0.78679571
0.78776437]
```

CV AUC scores

```
[0.50850318 0.51199743 0.51643092 0.51755553 0.52531768 0.53321373
0.57169871 0.5982098 0.65907504 0.67569235 0.68932114 0.69016916
0.68927958 0.68850328 0.68643281 0.68552942 0.683546 0.68273514
0.68099308]
```

```
In [77]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html#sklearn.metrics.roc\_curve
from sklearn.metrics import roc_curve, auc

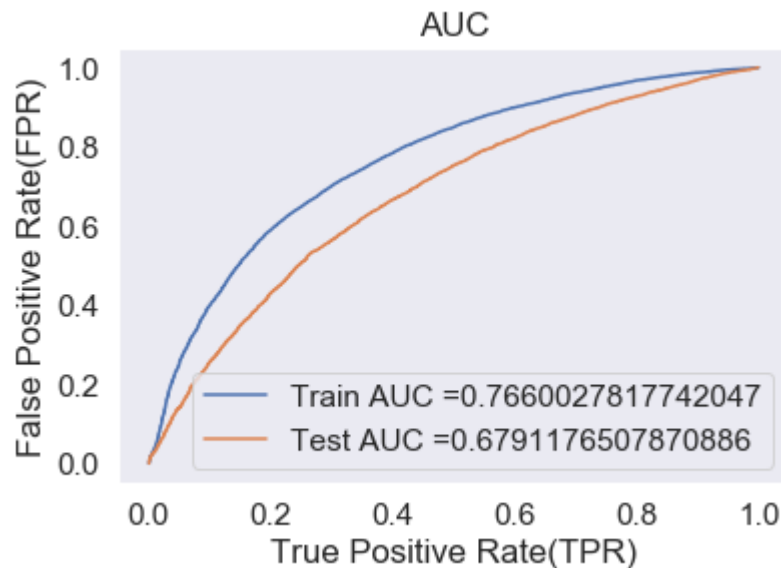
nb_bow = MultinomialNB(alpha = best_k_1)

nb_bow.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

y_train_pred = batch_predict(nb_bow, X_tr)
y_test_pred = batch_predict(nb_bow, X_te)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="Train AUC =" + str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="Test AUC =" + str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("True Positive Rate(TPR)")
plt.ylabel("False Positive Rate(FPR)")
plt.title("AUC")
plt.grid()
plt.show()
```



```
In [78]: def predict(proba, threshold, fpr, tpr):

    t = threshold[np.argmax(fpr*(1-tpr))]

    # (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))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Confusion matrix for train data set

```
In [79]: from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr)))
```

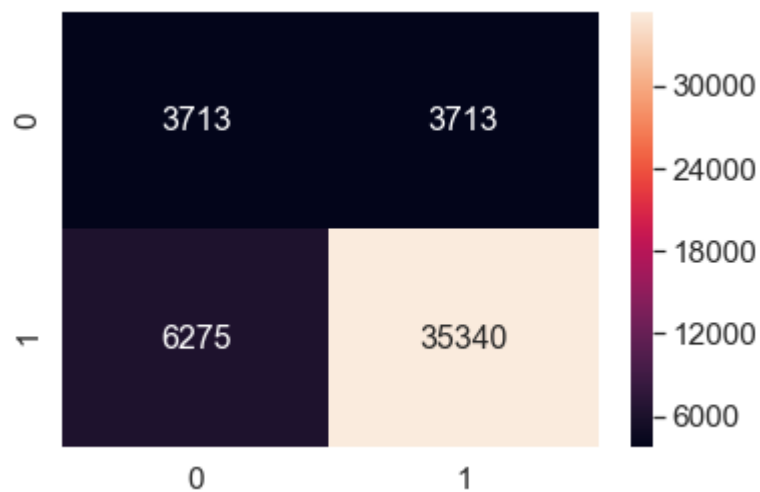
```
Train confusion matrix
the maximum value of tpr*(1-fpr) 0.25 for threshold 0.779
[[ 3713  3713]
 [ 6275 35340]]
```

```
In [80]: conf_matr_df_train_1 = pd.DataFrame(confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, tr
                                             range(2),range(2)))
```

```
the maximum value of tpr*(1-fpr) 0.25 for threshold 0.779
```

```
In [81]: #for the better vizulation of the confusion matrix  
#this plot is build by using the seaborn  
#https://seaborn.pydata.org/generated/seaborn.heatmap.html  
sns.set(font_scale=1.4)#for label size  
sns.heatmap(conf_matr_df_train_1, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x1cf5dea1630>
```



Confusion matrix for TEST data set

```
In [82]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr)))
```

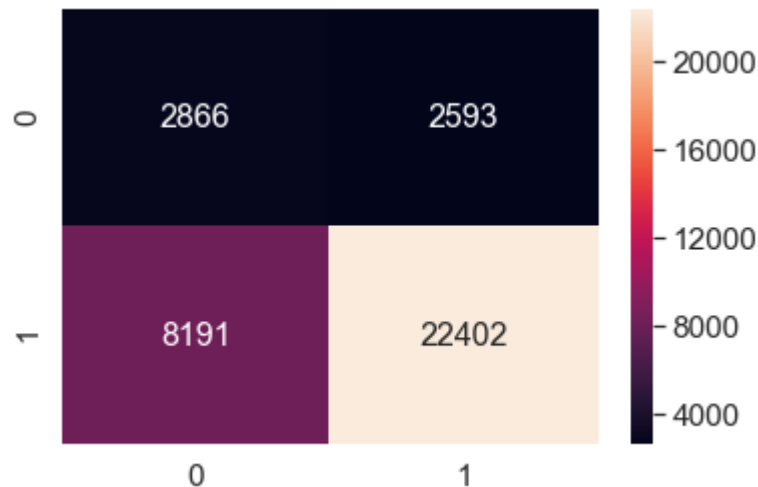
Test confusion matrix
the maximum value of $tpr \cdot (1 - fpr)$ 0.24999999161092998 for threshold 0.827
[[2866 2593]
[8191 22402]]

```
In [83]: conf_matr_df_test_1 = pd.DataFrame(confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr)),
range(2),range(2))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.24999999161092998 for threshold 0.827

```
In [84]: #for the better vizulation of the confusion matrix
#this plot is build by using the seaborn
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df_test_1, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1cf5de0e438>



Top 20 features from BOW i.e SET 1 using absolute values of feature_log_prob_ parameter of MultinomialNB

```
In [37]: from scipy.sparse import hstack
X_tr = hstack(( X_train_essay_bow,X_train_state_oh, X_train_teacher_oh, X_train_grade_oh,
                X_train_ccat_oh,X_train_csubcat_oh)).tocsr()

X_cr = hstack(( X_cv_essay_bow,X_cv_state_oh, X_cv_teacher_oh, X_cv_grade_oh,
                X_cv_ccat_oh,X_cv_csubcat_oh)).tocsr()

X_te = hstack(( X_test_essay_bow,X_test_state_oh, X_test_teacher_oh, X_test_grade_oh,
                X_test_ccat_oh,X_test_csubcat_oh)).tocsr()
```

```
In [38]: print("Final Data-matrix:")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
```

Final Data-matrix:

```
(49041, 12263) (49041,)
(24155, 12263) (24155,)
(36052, 12263) (36052,)
```

```
In [39]: NBModel = MultinomialNB(alpha=0.05, class_prior=[0.5,0.5])
NBModel.fit(X_tr, y_train)
```

```
Out[39]: MultinomialNB(alpha=0.05, class_prior=[0.5, 0.5], fit_prior=True)
```

```
In [40]: # For positive class
sorted_prob_class_1_ind = NBModel.feature_log_prob_[1, :].argsort()
# For negative class
sorted_prob_class_0_ind = NBModel.feature_log_prob_[0, :].argsort()
```

```
In [41]: features_lst = list(vectorizer_ss.get_feature_names() + vectorizer_bow.get_feature_names()+\
                             vectorizer_tp.get_feature_names() + vectorizer_pgc.get_feature_names()+\
                             vectorizer_cc.get_feature_names()+vectorizer_csc.get_feature_names() )
```



```
In [42]: Most_imp_words_1 = []
Most_imp_words_0 = []

for index in sorted_prob_class_1_ind[-20:-1]:
    Most_imp_words_1.append(features_lst[index])

for index in sorted_prob_class_0_ind[-20:-1]:
    Most_imp_words_0.append(features_lst[index])
```

```
In [43]: print("20 most imp features for positive class:\n")
print(Most_imp_words_1,)

print("\n" + "-"*100)

print("\n20 most imp features for negative class:\n")
print(Most_imp_words_0)
```

20 most imp features for positive class:

```
['70', 'cuties', 'log', 'untapped', 'random', 'wires', 'naked', 'wands', 'multiple', 'makeup', 'hdmi', 'latel
y', 'texts', 'nice', 'tender', 'church', 'latino', 'movin', 'saves']
```

20 most imp features for negative class:

```
['simplicity', 'random', '70', 'log', 'colds', 'wires', 'naked', 'wands', 'makeup', 'multiple', 'tender', 'hdm
i', 'texts', 'lately', 'nice', 'church', 'movin', 'latino', 'saves']
```

```
In [44]: Most_imp_words=Most_imp_words_0+Most_imp_words_1
#comibiningb the +ve and -ve class
```

```
In [45]: np.sort(Most_imp_words)# srtoring the new Lsit
```

```
print(Most_imp_words)#printing the new List
```

```
['simplicity', 'random', '70', 'log', 'colds', 'wires', 'naked', 'wands', 'makeup', 'multiple', 'tender', 'hdm  
i', 'texts', 'lately', 'nice', 'church', 'movin', 'latino', 'saves', '70', 'cuties', 'log', 'untapped', 'rando  
m', 'wires', 'naked', 'wands', 'multiple', 'makeup', 'hdmi', 'lately', 'texts', 'nice', 'tender', 'church', 'l  
atino', 'movin', 'saves']
```

```
In [221]: #refrence of the code
```

```
In [ ]: #https://stackoverflow.com/questions/30522724/take-multiple-lists-into-dataframe  
#https://stats.stackexchange.com/questions/266031/what-is-log-probability-of-feature-in-sklearn-multinomialnb  
#https://stackoverflow.com/questions/7271385/how-do-i-combine-two-lists-into-a-dictionary-in-python  
#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://datascience.stackexchange.com/questions/65219/find-the-top-n-features-from-feature-set-using-absolute-v
```

3. Summary

as mentioned in the step 5 of instructions

```
In [85]: # Please compare all your models using Prettytable library
from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable

x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Alpha:Hyper Parameter", "AUC"]

x.add_row(["BOW", "Naive Bayes", 0.5, 0.7116])
x.add_row(['TFIDF', 'Navie Bayes', 0.05, 0.6901])
print(x)
```

Vectorizer	Model	Alpha:Hyper Parameter	AUC
BOW	Naive Bayes	0.5	0.7116
TFIDF	Navie Bayes	0.05	0.6901

References

```
In [ ]: #https://stackoverflow.com/questions/56416576/getting-keyerror-from-sklearn-model-selection-gridsearchcv
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.html#sklearn.metrics.roc_auc_score
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.average_precision_score.html#sklearn.metrics.average_precision_score
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.html
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
#https://stackoverflow.com/questions/19710602/concatenate-sparse-matrices-in-python-using-scipy-numpy/19710648#19710648
#https://www.appliedaicourse.com/Lecture/11/Applied-Machine-Learning-course/2971/handling-categorical-and-numerical-features
#https://stackoverflow.com/questions/50526898/how-to-get-feature-importance-in-naive-bayes
#https://stackoverflow.com/a/19710648/4084039
#https://stackoverflow.com/a/48803361/4084039
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#http://zetcode.com/python/prettytable/
#https://github.com/vishalgupta1996/Naive-bayes-donor-choose/blob/master/NaiveBayes.ipynb
#https://classroom.appliedcourse.com/classrooms/JQ0Z47Em/assignments/Jg05JAP8/
```

