Naive Bayes on Donors choose dataset

Applying NB on two sets of features

Set1 - Categorical,numerical features,preprocessed_essay(Bag of Words)

Set2 - Categorical,numerical features,preprocessed_essay(TFIDF)

Naive Bayes

In [1]:
```
!pip install chart_studio
```

```
Requirement already satisfied: chart_studio in c:\programdata\anaconda3
\lib\site-packages (1.1.0)
Requirement already satisfied: requests in c:\programdata\anaconda3\lib
\site-packages (from chart_studio) (2.22.0)
Requirement already satisfied: retrying>=1.3.3 in c:\programdata\anacon
da3\lib\site-packages (from chart_studio) (1.3.3)
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site
-packages (from chart_studio) (1.14.0)
Requirement already satisfied: plotly in c:\programdata\anaconda3\lib\s
ite-packages (from chart_studio) (4.9.0)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1
in c:\programdata\anaconda3\lib\site-packages (from requests->chart_stu
dio) (1.25.8)
Requirement already satisfied: idna<2.9,>=2.5 in c:\programdata\anacond
a3\lib\site-packages (from requests->chart_studio) (2.8)
Requirement already satisfied: certifi>=2017.4.17 in c:\programdata\ana
conda3\lib\site-packages (from requests->chart_studio) (2019.11.28)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in c:\programdata
\anaconda3\lib\site-packages (from requests->chart_studio) (3.0.4)
```

In [2]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import Normalizer

%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

from chart_studio import plotly
# import plotly.offline as offline
import plotly.graph_objs as go
from collections import Counter
```

1.1 Loading Data

In [3]:
```
import pandas as pd
data  = pd.read_csv('data.csv', nrows=50000)
y = data['project_is_approved'].values
X = data.drop(['project_is_approved'], axis=1)
X.head(1)
```

Out[3]:

	school_state	teacher_prefix	project_grade_category	teacher_number_of_previously_posted_proj
0	ca	mrs	grades_prek_2	

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

In [4]:
```
# train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3
3, stratify=y)

print(X_train.shape , y_train.shape)
print(X_test.shape, y_test.shape)
print('**'*50)
```

```
(33500, 8) (33500,)
(16500, 8) (16500,)
************************************************************************
****************************
```

2) Make Data Model Ready

2.1 Encoding Textual Features using BAG OF WORDS

In [5]:
```
# encoding essay attribute using count vectorizer
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=
```

```
8000) ## taking 8000 distinct words which occure at least in 10 reviews
(min_df = 10)
vectorizer.fit(X_train['essay'].values)
essay_feature_bow=vectorizer.get_feature_names()
X_train_essay_bow=vectorizer.transform(X_train['essay'].values)
X_test_essay_bow=vectorizer.transform(X_test['essay'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_essay_bow.shape,y_train.shape)
print("test feature --",X_test_essay_bow.shape,y_test.shape)
print('**'*50)

# encoding school_state using count vectorizer
vectorizer=CountVectorizer()
vectorizer.fit(X_train['school_state'].values)
school_state_feature_bow=vectorizer.get_feature_names()
X_train_school_state_bow=vectorizer.transform(X_train['school_state'].v
alues)
X_test_school_state_bow=vectorizer.transform(X_test['school_state'].val
ues)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_school_state_bow.shape,y_train.shape)
print("test feature --",X_test_school_state_bow.shape,y_test.shape)
print('the features are : ',school_state_feature_bow)
print('**'*50)

#encoding teacher_prefix using count vectorizer
vectorizer=CountVectorizer()
vectorizer.fit(X_train['teacher_prefix'].values)
teacher_prefix_feature_bow=vectorizer.get_feature_names()
X_train_teacher_prefix_bow=vectorizer.transform(X_train['teacher_prefi
x'].values)
X_test_teacher_prefix_bow=vectorizer.transform(X_test['teacher_prefix']
.values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_teacher_prefix_bow.shape,y_train.shap
e)
```

```
print("test feature --",X_test_teacher_prefix_bow.shape,y_test.shape)
print('the features are : ',teacher_prefix_feature_bow)
print('**'*50)

#encoding project_grade_category using count vectorizer
vectorizer=CountVectorizer()
vectorizer.fit(X_train['project_grade_category'].values)
project_grade_category_feature_bow=vectorizer.get_feature_names()
X_train_project_grade_category_bow=vectorizer.transform(X_train['projec
t_grade_category'].values)
X_test_project_grade_category_bow=vectorizer.transform(X_test['project_
grade_category'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_project_grade_category_bow.shape,y_tr
ain.shape)
print("test feature --",X_test_project_grade_category_bow.shape,y_test.
shape)
print('the features are : ',project_grade_category_feature_bow)
print('**'*50)

#encoding clean_categories using count vectorizer
vectorizer=CountVectorizer()
vectorizer.fit(X_train['clean_categories'].values)
clean_categories_feature_bow=vectorizer.get_feature_names()
X_train_clean_categories_bow=vectorizer.transform(X_train['clean_catego
ries'].values)
X_test_clean_categories_bow=vectorizer.transform(X_test['clean_categori
es'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_clean_categories_bow.shape,y_train.sh
ape)
print("test feature --",X_test_clean_categories_bow.shape,y_test.shape)
print('the features are : ',clean_categories_feature_bow)
print('**'*50)

#encoding clean_subcategories using count vectorizer
vectorizer=CountVectorizer()
```

```
vectorizer.fit(X_train['clean_subcategories'].values)
clean_subcategories_feature_bow=vectorizer.get_feature_names()
X_train_clean_subcategories_bow=vectorizer.transform(X_train['clean_sub
categories'].values)
X_test_clean_subcategories_bow=vectorizer.transform(X_test['clean_subca
tegories'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_clean_subcategories_bow.shape,y_train
.shape)
print("test feature --",X_test_clean_subcategories_bow.shape,y_test.sha
pe)
print('the features are : ',clean_subcategories_feature_bow)
print('**'*50)
```

```
 after encoding in bow the size of :
 train feature -- (33500, 8000) (33500,)
test feature -- (16500, 8000) (16500,)
***********************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 51) (33500,)
test feature -- (16500, 51) (16500,)
the features are :  ['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'd
e', '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', 'ok', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx',
'ut', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
***********************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 5) (33500,)
test feature -- (16500, 5) (16500,)
the features are :  ['dr', 'mr', 'mrs', 'ms', 'teacher']
***********************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 4) (33500,)
test feature -- (16500, 4) (16500,)
the features are :  ['grades 3 5', 'grades 6 8', 'grades 9 12', 'grades
```

```
_prek_2']
****************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 9) (33500,)
test feature -- (16500, 9) (16500,)
the features are :  ['appliedlearning', 'care_hunger', 'health_sports',
'history_civics', 'literacy_language', 'math_science', 'music_arts', 's
pecialneeds', 'warmth']
****************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 30) (33500,)
test feature -- (16500, 30) (16500,)
the features are :  ['appliedsciences', 'care_hunger', 'characteredducat

ion', 'civics_government', 'college_careerprep', 'communityservice', 'e
arlydevelopment', 'economics', 'environmentalscience', 'esl', 'extracur
ricular', 'financialliteracy', 'foreignlanguages', 'gym_fitness', 'heal
th_lifescience', 'health_wellness', 'history_geography', 'literacy', 'l
iterature_writing', 'mathematics', 'music', 'nutritioneducation', 'othe
r', 'parentinvolvement', 'performingarts', 'socialsciences', 'specialne
eds', 'teamsports', 'visualarts', 'warmth']
****************************************************************************
*****************************
```

2.2 Encoding Text features using TFIDF

In [6]:

```
# encoding essay attribute
vectorizer = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=
8000)
vectorizer.fit(X_train['essay'].values)
essay_feature_TF=vectorizer.get_feature_names()
X_train_essay_TF=vectorizer.transform(X_train['essay'].values)
X_test_essay_TF=vectorizer.transform(X_test['essay'].values)

print(" after encoding in bow the size of :")
```

```
print(" train feature --",X_train_essay_TF.shape,y_train.shape)
print("test feature --",X_test_essay_TF.shape,y_test.shape)
print('**'*50)

# encoding school_state
vectorizer=TfidfVectorizer()
vectorizer.fit(X_train['school_state'].values)
school_state_feature_TF=vectorizer.get_feature_names()
X_train_school_state_TF=vectorizer.transform(X_train['school_state'].va
lues)
X_test_school_state_TF=vectorizer.transform(X_test['school_state'].valu
es)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_school_state_TF.shape,y_train.shape)
print("test feature --",X_test_school_state_TF.shape,y_test.shape)
print('the features are : ',school_state_feature_TF)
print('**'*50)

#encoding teacher_prefix
vectorizer=TfidfVectorizer()
vectorizer.fit(X_train['teacher_prefix'].values)
teacher_prefix_feature_TF=vectorizer.get_feature_names()
X_train_teacher_prefix_TF=vectorizer.transform(X_train['teacher_prefix'
].values)
X_test_teacher_prefix_TF=vectorizer.transform(X_test['teacher_prefix'].
values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_teacher_prefix_TF.shape,y_train.shape
)
print("test feature --",X_test_teacher_prefix_TF.shape,y_test.shape)
print('the features are : ',teacher_prefix_feature_TF)
print('**'*50)

#encoding project_grade_category
vectorizer=TfidfVectorizer()
vectorizer.fit(X_train['project_grade_category'].values)
project_grade_category_feature_TF=vectorizer.get_feature_names()
```

```
X_train_project_grade_category_TF=vectorizer.transform(X_train['project_grade_category'].values)
X_test_project_grade_category_TF=vectorizer.transform(X_test['project_grade_category'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_project_grade_category_TF.shape,y_train.shape)
print("test feature --",X_test_project_grade_category_TF.shape,y_test.shape)
print('the features are : ',project_grade_category_feature_TF)
print('**'*50)

#encoding clean_categories
vectorizer=TfidfVectorizer()
vectorizer.fit(X_train['clean_categories'].values)
clean_categories_feature_TF=vectorizer.get_feature_names()
X_train_clean_categories_TF=vectorizer.transform(X_train['clean_categories'].values)
X_test_clean_categories_TF=vectorizer.transform(X_test['clean_categories'].values)

print(" after encoding in bow the size of :")
print(" train feature --",X_train_clean_categories_TF.shape,y_train.shape)
print("test feature --",X_test_clean_categories_TF.shape,y_test.shape)
print('the features are : ',clean_categories_feature_TF)
print('**'*50)

#encoding clean_subcategories
vectorizer=TfidfVectorizer()
vectorizer.fit(X_train['clean_subcategories'].values)
clean_subcategories_feature_TF=vectorizer.get_feature_names()
X_train_clean_subcategories_TF=vectorizer.transform(X_train['clean_subcategories'].values)
X_test_clean_subcategories_TF=vectorizer.transform(X_test['clean_subcategories'].values)

print(" after encoding in bow the size of :")
```

```
print(" train feature --",X_train_clean_subcategories_TF.shape,y_train.
shape)
print("test feature --",X_test_clean_subcategories_TF.shape,y_test.shap
e)
print('the features are : ',clean_subcategories_feature_TF)
print('**'*50)
```

```
 after encoding in bow the size of :
 train feature -- (33500, 8000) (33500,)
test feature -- (16500, 8000) (16500,)
************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 51) (33500,)
test feature -- (16500, 51) (16500,)
the features are :  ['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'd
e', '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', 'ok', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx',
'ut', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 5) (33500,)
test feature -- (16500, 5) (16500,)
the features are :  ['dr', 'mr', 'mrs', 'ms', 'teacher']
************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 4) (33500,)
test feature -- (16500, 4) (16500,)
the features are :  ['grades_3_5', 'grades_6_8', 'grades_9_12', 'grades
_prek_2']
************************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 9) (33500,)
test feature -- (16500, 9) (16500,)
the features are :  ['appliedlearning', 'care_hunger', 'health_sports',
'history_civics', 'literacy_language', 'math_science', 'music_arts', 's
```

```
pecialneeds', 'warmth']
**********************************************************************
*****************************
 after encoding in bow the size of :
 train feature -- (33500, 30) (33500,)
test feature -- (16500, 30) (16500,)
the features are :  ['appliedsciences', 'care_hunger', 'charactereducat
ion', 'civics_government', 'college_careerprep', 'communityservice', 'e
arlydevelopment', 'economics', 'environmentalscience', 'esl', 'extracur
ricular', 'financialliteracy', 'foreignlanguages', 'gym_fitness', 'heal
th_lifescience', 'health_wellness', 'history_geography', 'literacy', 'l
iterature_writing', 'mathematics', 'music', 'nutritioneducation', 'othe
r', 'parentinvolvement', 'performingarts', 'socialsciences', 'specialne
eds', 'teamsports', 'visualarts', 'warmth']


**********************************************************************
*****************************
```

Encoding numerical features using Normalizer

In [7]:

```
normalizer = Normalizer()
normalizer.fit(X_train['price'].values.reshape(1,-1))
X_train_price_norm_1=normalizer.transform(X_train['price'].values.resha
pe(1,-1))
X_test_price_norm_1=normalizer.transform(X_test['price'].values.reshape
(1,-1))
X_train_price_norm= X_train_price_norm_1.reshape(-1,1)
X_test_price_norm= X_test_price_norm_1.reshape(-1,1)


print(" after encoding using normalizer the size of :")
print(" train feature --",X_train_price_norm_1.shape,y_train.shape)
print("test feature --",X_test_price_norm_1.shape,y_test.shape)
print('**'*50)
print(X_train_price_norm)
print('**'*50)
```

```
print(X_test_price_norm)
print('**'*50)
print(X_train_price_norm.shape)
print(X_test_price_norm.shape)

print('='*100)

normalizer = Normalizer()
normalizer.fit(X_train['teacher_number_of_previously_posted_projects'].
values.reshape(1,-1))
X_train_teacher_number_of_previously_posted_projects_norm_1=normalizer.
transform(X_train['teacher_number_of_previously_posted_projects'].value
s.reshape(1,-1))
X_test_teacher_number_of_previously_posted_projects_norm_1=normalizer.t
ransform(X_test['teacher_number_of_previously_posted_projects'].values.
reshape(1,-1))
X_train_teacher_number_of_previously_posted_projects_norm= X_train_teac
her_number_of_previously_posted_projects_norm_1.reshape(-1,1)
X_test_teacher_number_of_previously_posted_projects_norm= X_test_teache
r_number_of_previously_posted_projects_norm_1.reshape(-1,1)

print(" after encoding using normalizer the size of :")
print(" train feature --",X_train_teacher_number_of_previously_posted_p
rojects_norm_1.shape,y_train.shape)
print("test feature --",X_test_teacher_number_of_previously_posted_proj
ects_norm_1.shape,y_test.shape)
print('**'*50)
print(X_train_teacher_number_of_previously_posted_projects_norm)
print('**'*50)
print(X_test_teacher_number_of_previously_posted_projects_norm)
print('**'*50)
print(X_train_teacher_number_of_previously_posted_projects_norm.shape)
print(X_test_teacher_number_of_previously_posted_projects_norm.shape)
```

```
 after encoding using normalizer the size of :
 train feature -- (1, 33500) (33500,)
test feature -- (1, 16500) (16500,)
************************************************************************
*****************************
[[0.00074369]
```

```
 [0.00092393]
 [0.00186456]
 ...
 [0.00133543]
 [0.00094621]
 [0.00295046]]
************************************************************************
****************************
[[0.01239203]
 [0.00822029]
 [0.00865571]
 ...
 [0.00403622]
 [0.00275133]
 [0.00689957]]
************************************************************************
****************************
(33500, 1)
(16500, 1)
========================================================================
============================
 after encoding using normalizer the size of :
 train feature -- (1, 33500) (33500,)
test feature -- (1, 16500) (16500,)
************************************************************************
****************************
[[0.01096036]
 [0.        ]
 [0.00548018]
 ...
 [0.        ]
 [0.        ]
 [0.00168621]]
************************************************************************
****************************
[[0.        ]
 [0.00092454]
 [0.0181826 ]
 ...
 [0.00061636]
```

```
 [0.00061636]
 [0.00092454]
 [0.        ]]
************************************************************************

*****************************
(33500, 1)
(16500, 1)
```

2.4 Final Data Preparation- merging all the vectorized features

In [8]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
## Set 1 (Categorical+Numerical+titles(BOW)+Essays(BOW))
from scipy.sparse import hstack
X_train_BOW = hstack((X_train_essay_bow, X_train_school_state_bow, X_train_teacher_prefix_bow, X_train_project_grade_category_bow,X_train_clean_categories_bow,X_train_clean_subcategories_bow, X_train_price_norm,X_train_teacher_number_of_previously_posted_projects_norm)).tocsr()
X_test_BOW = hstack((X_test_essay_bow, X_test_school_state_bow, X_test_teacher_prefix_bow, X_test_project_grade_category_bow,X_test_clean_categories_bow,X_test_clean_subcategories_bow, X_test_price_norm,X_test_teacher_number_of_previously_posted_projects_norm)).tocsr()

print(X_train_BOW.shape, y_train.shape)
print(X_test_BOW.shape, y_test.shape)
print('**'*50)

## Set 2 (Categorical+Numerical+titles(TFIDF)+Essays(TFIDF))
X_train_TFIDF = hstack((X_train_essay_TF, X_train_school_state_TF, X_train_teacher_prefix_TF, X_train_project_grade_category_TF,X_train_clean_categories_TF,X_train_clean_subcategories_TF, X_train_price_norm,X_train_teacher_number_of_previously_posted_projects_norm)).tocsr()
X_test_TFIDF = hstack((X_test_essay_TF, X_test_school_state_TF, X_test_teacher_prefix_TF, X_test_project_grade_category_TF,X_test_clean_categories_TF,X_test_clean_subcategories_TF, X_test_price_norm,X_test_teacher_number_of_previously_posted_projects_norm)).tocsr()
```

```
print(X_train_TFIDF.shape, y_train.shape)
print(X_test_TFIDF.shape, y_test.shape)
print('**'*50)
```

```
(33500, 8101) (33500,)
(16500, 8101) (16500,)
****************************************************************************************************
(33500, 8101) (33500,)
(16500, 8101) (16500,)
****************************************************************************************************
```

3) Appling NB on different kind of featurization

Training

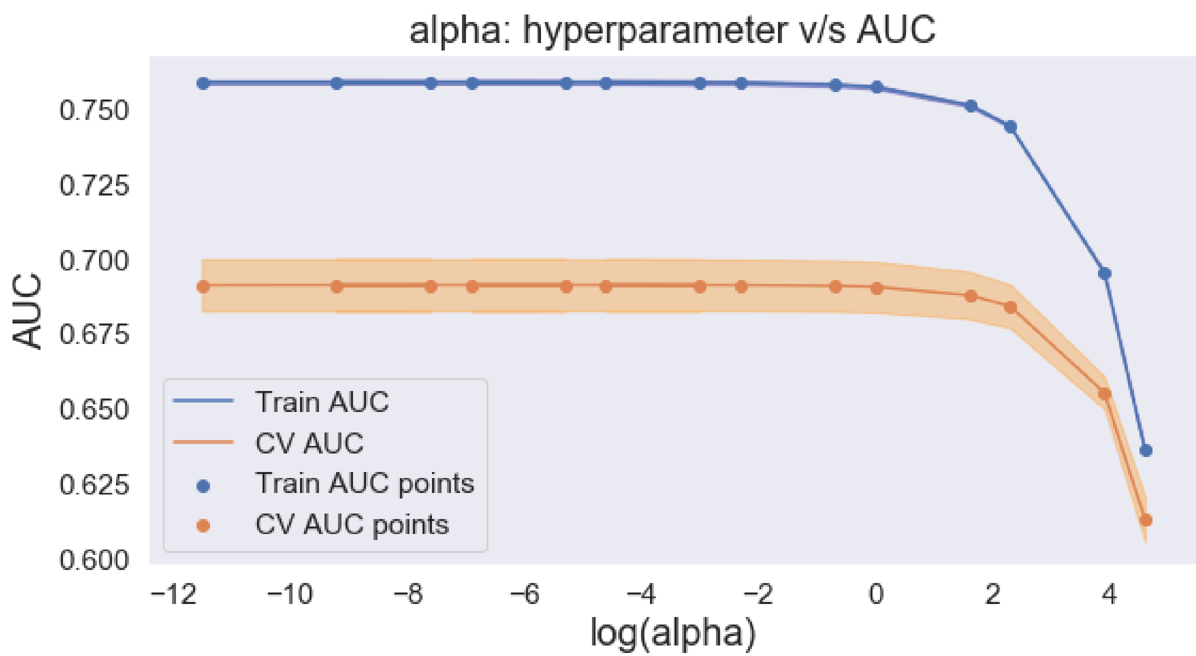
Hyper-parameter tuning on BOW features

In [40]:
```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV

model = MultinomialNB(class_prior=[0.5,0.5])
parameters = {'alpha':[0.00001,0.0005,0.0001,0.005,0.001,0.05,0.01,0.1,0.5,1,5,10,50,100]}   # values changed to interval(10^[-5] to 10^2) as suggested
clf = GridSearchCV(model, parameters, cv=10, scoring='roc_auc',return_train_score=True,n_jobs=-1) ## Usng Gridsearch
clf.fit(X_train_BOW, 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']
```

```
# Taking log of all alpha values
import math

alpha = [0.00001,0.0005,0.0001,0.005,0.001,0.05,0.01,0.1,0.5,1,5,10,50,
100]

log_alpha = []
for values in tqdm(alpha):
    a = math.log(values)
    log_alpha.append(a)
```

```
100%|██████████████████████████████████████████████████| 14/14 [00:00
<?, ?it/s]
```

In [41]:
```
# Plotting AUC vs alpha: hyperparameter curve

plt.figure(figsize=(10,5))
plt.plot(log_alpha, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4
084039
plt.gca().fill_between(log_alpha,train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.3,color='darkblue')
plt.plot(log_alpha, cv_auc, label='CV AUC')
plt.gca().fill_between(log_alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_st
d,alpha=0.3,color='darkorange')
plt.scatter(log_alpha, train_auc, label='Train AUC points')
plt.scatter(log_alpha, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log(alpha)", fontsize = 20)
plt.ylabel("AUC", fontsize = 20)
plt.title("alpha: hyperparameter v/s AUC", fontsize = 20)
plt.grid()
plt.show()

print("The Best Hyperparater is: ", clf.best_estimator_)
```




```
The Best Hyperparater is:  MultinomialNB(alpha=0.005, class_prior=[0.5,
0.5], fit_prior=True)
```

Hyper parameter tuning on TFIDF features

In [42]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV

model = MultinomialNB(class_prior=[0.5,0.5])
parameters = {'alpha':[0.00001,0.0005,0.0001,0.005,0.001,0.05,0.01,0.1,
0.5,1,5,10,50,100]}   # values changed to interval(10^[-5] to 10^2) as
 suggested
clf = GridSearchCV(model, parameters, cv=10, scoring='roc_auc',return_t
rain_score=True,n_jobs=-1) ## Usng Gridsearch
clf.fit(X_train_TFIDF, y_train)
```

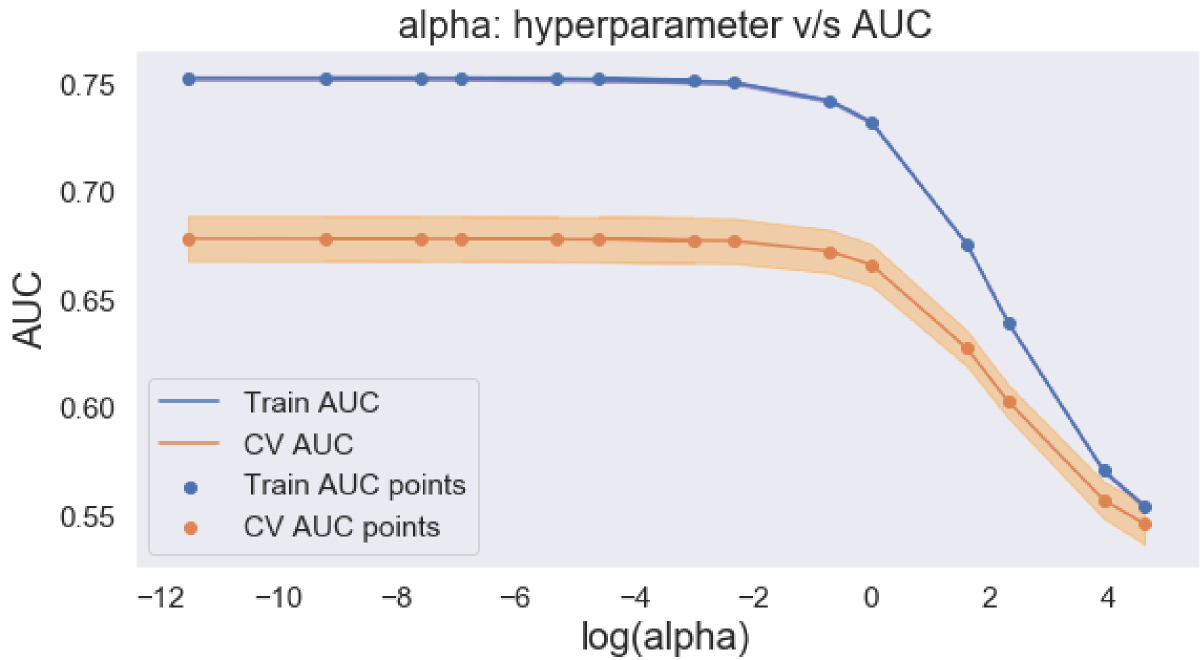
```python
train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']


# Taking log of all alpha values
import math

alpha = [0.00001,0.0005,0.0001,0.005,0.001,0.05,0.01,0.1,0.5,1,5,10,50,
100]

log_alpha = []
for values in tqdm(alpha):
    a = math.log(values)
    log_alpha.append(a)
```

```
100%|██████████████████████████████████████████████████| 14/14 [00:00
<?, ?it/s]
```

In [43]:

```python
# Plotting AUC vs alpha: hyperparameter curve

plt.figure(figsize=(10,5))
plt.plot(log_alpha, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4
084039
plt.gca().fill_between(log_alpha,train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.3,color='darkblue')
plt.plot(log_alpha, cv_auc, label='CV AUC')
plt.gca().fill_between(log_alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_st
d,alpha=0.3,color='darkorange')
plt.scatter(log_alpha, train_auc, label='Train AUC points')
plt.scatter(log_alpha, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log(alpha)", fontsize = 20)
plt.ylabel("AUC", fontsize = 20)
plt.title("alpha: hyperparameter v/s AUC", fontsize = 20)
plt.grid()
plt.show()
```

```
print("The Best Hyperparater is: ", clf.best_estimator_)
```



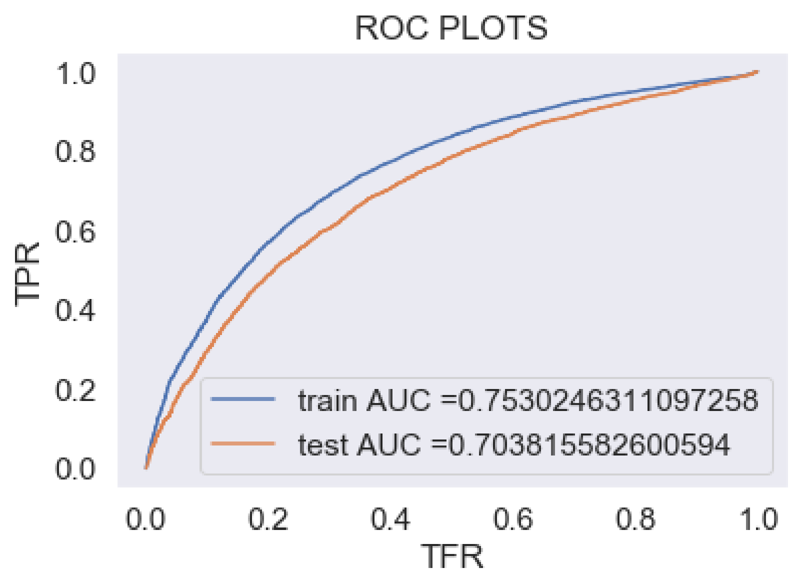

```
The Best Hyperparater is:  MultinomialNB(alpha=1e-05, class_prior=[0.5,
0.5], fit_prior=True)
```

Testing the performance of our model at alpha=0.005 (In BOW) with test data

In [44]:
```
def batch_predict(clf, data):

    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your tr_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
    if data.shape[0]%1000 !=0:
        y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

    return y_data_pred
```

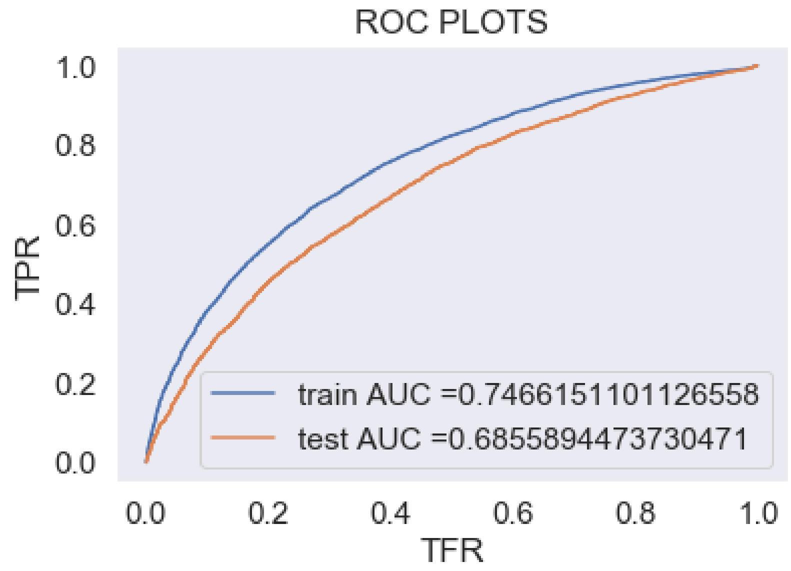
In [45]:
```
from sklearn.metrics import roc_curve, auc

best_alpha_bow=0.005
model = MultinomialNB(alpha=best_alpha_bow,class_prior=[0.5,0.5])
model.fit(X_train_BOW, y_train)


y_train_pred_BOW = batch_predict(model, X_train_BOW)
y_test_pred_BOW = batch_predict(model, X_test_BOW)

train_fpr_BOW, train_tpr_BOW, train_thresholds_BOW = roc_curve(y_train,
 y_train_pred_BOW)
test_fpr_BOW, test_tpr_BOW, test_thresholds_BOW = roc_curve(y_test, y_t
est_pred_BOW)

plt.plot(train_fpr_BOW, train_tpr_BOW, label="train AUC ="+str(auc(trai
n_fpr_BOW, train_tpr_BOW)))
plt.plot(test_fpr_BOW, test_tpr_BOW, label="test AUC ="+str(auc(test_fp
r_BOW, test_tpr_BOW)))
AUC_BOW=auc(test_fpr_BOW, test_tpr_BOW)
plt.legend()
plt.xlabel("TFR")
plt.ylabel("TPR")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



Testing the performance of our model at alpha=0.00001 (In TFIDF) with test data

In [46]:
```
from sklearn.metrics import roc_curve, auc

best_alpha_tfidf= 0.00001
model = MultinomialNB(alpha=best_alpha_tfidf,class_prior=[0.5,0.5])
model.fit(X_train_TFIDF, y_train)

y_train_pred_TFIDF = batch_predict(model, X_train_TFIDF)
y_test_pred_TFIDF = batch_predict(model, X_test_TFIDF)

train_fpr_TFIDF, train_tpr_TFIDF, train_thresholds_TFIDF = roc_curve(y_
train, y_train_pred_TFIDF)
test_fpr_TFIDF, test_tpr_TFIDF, test_thresholds_TFIDF = roc_curve(y_tes
t, y_test_pred_TFIDF)
```

```
plt.plot(train_fpr_TFIDF, train_tpr_TFIDF, label="train AUC ="+str(auc(
train_fpr_TFIDF, train_tpr_TFIDF)))
plt.plot(test_fpr_TFIDF, test_tpr_TFIDF, label="test AUC ="+str(auc(tes
t_fpr_TFIDF, test_tpr_TFIDF)))
AUC_TFIDF=auc(test_fpr_TFIDF, test_tpr_TFIDF)
plt.legend()
plt.xlabel("TFR")
plt.ylabel("TPR")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



Observation

1) As my AUC value both for train and test is >0.5, I can say that my model is sensible and good at alpha=0.005 and 0.00001

ROC curve

1) I plot ROC curve by using FPR(False positive rate) on X-axis and TPR(true positive rate) on Y-axis

2) You can understand what is TPR and FPR by looking at confusion matrix

CONFUSION MATRIX

In [47]:
```
# 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 ma
ximum if your fpr is very low and tpr is very high
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

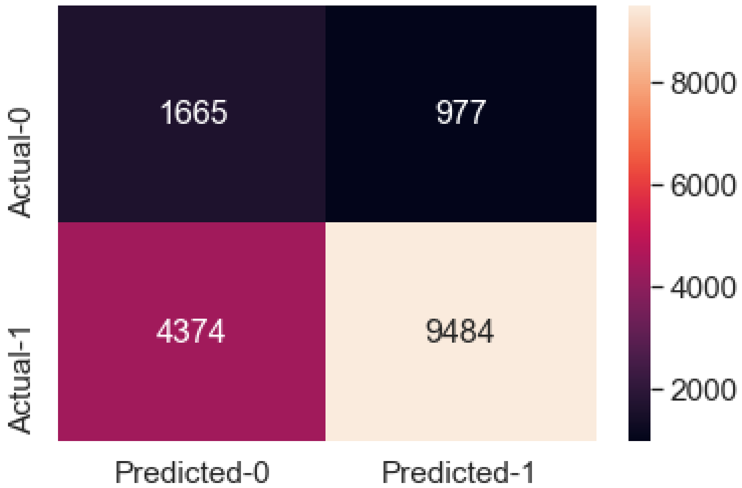
Confusion matrix for Set 1 (BOW)

In [48]:
```
print (" The confusion matrix of model with BOW vectorization")
print("**"*30)
## Function calling
best_t = find_best_threshold(train_thresholds_BOW, train_fpr_BOW, train
_tpr_BOW)
CF_MAT_BOW=pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_
test_pred_BOW, best_t)))
print(CF_MAT_BOW)
print("**"*30)
```

```python
## Ploting confusion matrix
CF_MAT_BOW.columns = ['Predicted-0','Predicted-1']
CF_MAT_BOW = CF_MAT_BOW.rename({0 : 'Actual-0', 1: 'Actual-1'})
sns.set(font_scale=1.4)
sns.heatmap(CF_MAT_BOW,annot=True,annot_kws={"size":16},fmt='g')
```

```
 The confusion matrix of model with BOW vectorization
************************************************************
      0     1
0  1665   977
1  4374  9484
************************************************************
```

Out[48]: `<matplotlib.axes._subplots.AxesSubplot at 0xd94ea08>`



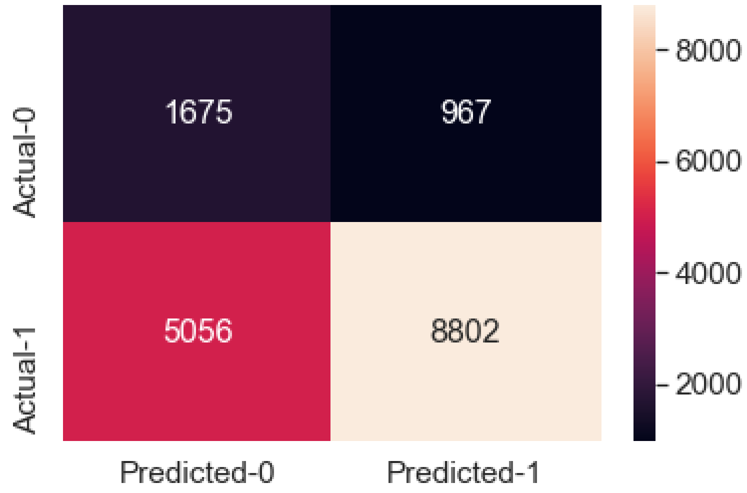
Confusion matrix for Set 2 (TFIDF)

In [49]:
```python
print (" The confusion matrix of model with TFIDF vectorization")
print("**"*30)
## Function calling
best_t = find_best_threshold(train_thresholds_TFIDF, train_fpr_TFIDF, t
```

```
rain_tpr_TFIDF)
CF_MAT_TFIDF=pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(
y_test_pred_TFIDF, best_t)))
print(CF_MAT_TFIDF)
print("**"*30)


#ploting confusion matrix
CF_MAT_TFIDF.columns=['Predicted-0','Predicted-1']
CF_MAT_TFIDF=CF_MAT_TFIDF.rename({0:'Actual-0',1:'Actual-1'})
sns.set(font_scale=1.4)
sns.heatmap(CF_MAT_TFIDF,annot= True,annot_kws={"size":16},fmt='g')
```

```
 The confusion matrix of model with TFIDF vectorization
************************************************************
      0     1
0  1675   967
1  5056  8802
************************************************************
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x11509e88>



Top 20 features of Set1 (BOW)

In [50]:
```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/40840
39
## Set 1 (Ctaegorical+Numerical+titles(BOW)+Essays(BOW))
from scipy.sparse import hstack
X_train_BOW = hstack((X_train_essay_bow, X_train_school_state_bow, X_tr
ain_teacher_prefix_bow, X_train_project_grade_category_bow,X_train_clea
n_categories_bow,X_train_clean_subcategories_bow, X_train_price_norm,X_
train_teacher_number_of_previously_posted_projects_norm)).tocsr()
X_test_BOW = hstack((X_test_essay_bow, X_test_school_state_bow, X_test_
teacher_prefix_bow, X_test_project_grade_category_bow,X_test_clean_cate
gories_bow,X_test_clean_subcategories_bow, X_test_price_norm,X_test_tea
cher_number_of_previously_posted_projects_norm)).tocsr()

print(X_train_BOW.shape, y_train.shape)
print(X_test_BOW.shape, y_test.shape)
print('**'*50)

## Set 2 (Ctaegorical+Numerical+titles(TFIDF)+Essays(TFIDF))
X_train_TFIDF = hstack((X_train_essay_TF, X_train_school_state_TF, X_tr
ain_teacher_prefix_TF, X_train_project_grade_category_TF,X_train_clean_
categories_TF,X_train_clean_subcategories_TF, X_train_price_norm,X_trai
n_teacher_number_of_previously_posted_projects_norm)).tocsr()
X_test_TFIDF = hstack((X_test_essay_TF, X_test_school_state_TF, X_test_
teacher_prefix_TF, X_test_project_grade_category_TF,X_test_clean_catego
ries_TF,X_test_clean_subcategories_TF, X_test_price_norm,X_test_teacher
_number_of_previously_posted_projects_norm)).tocsr()

print(X_train_TFIDF.shape, y_train.shape)
print(X_test_TFIDF.shape, y_test.shape)
print('**'*50)
```

```
(33500, 8101) (33500,)
(16500, 8101) (16500,)
**********************************************************************
******************************
(33500, 8101) (33500,)
(16500, 8101) (16500,)
**********************************************************************
******************************
```

In [51]:
```
MNB = MultinomialNB(alpha = 0.005,class_prior=[0.5,0.5])
MNB.fit(X_train_BOW, y_train)
```

Out[51]:
```
MultinomialNB(alpha=0.005, class_prior=[0.5, 0.5], fit_prior=True)
```

In [52]:
```
print("The total number rows & columns in our dataset: ", X_train_BOW.s
hape)
```

```
The total number rows & columns in our dataset:  (33500, 8101)
```

In [53]:
```
bow_features_probs_negative = []
for a in range(8101) :     # as number of columns in our dataset is 810
1 and so is total features
    bow_features_probs_negative.append(MNB.feature_log_prob_[0,a])
print(len(bow_features_probs_negative))
```

```
8101
```

In [54]:
```
bow_feature_names = []

for a in essay_feature_bow:
  bow_feature_names.append(a)
```

In [55]:
```
for a in school_state_feature_bow:
  bow_feature_names.append(a)
```

In [56]:
```
for a in teacher_prefix_feature_bow:
  bow_feature_names.append(a)
```

In [57]:
```
for a in project_grade_category_feature_bow:
  bow_feature_names.append(a)
```

In [58]:
```
for a in clean_categories_feature_bow:
  bow_feature_names.append(a)
```

In [59]:
```
for a in clean_subcategories_feature_bow:
  bow_feature_names.append(a)
```

In [60]:
```
bow_feature_names.append('price')
bow_feature_names.append('teacher_number_of_previously_posted_projects'
)
```

In [61]:
```
print(len(bow_feature_names))
```

```
8101
```

In [62]:
```
print("The total number rows & columns in our dataset: ", X_train_BOW.s
hape)
```

```
The total number rows & columns in our dataset:  (33500, 8101)
```

In [63]:
```
final_bow_features_negative = pd.DataFrame({'feature_names':bow_feature
_names, 'feature_probs':bow_features_probs_negative})
```

In [64]:
```
df = final_bow_features_negative.sort_values(by = ['feature_probs'], as
cending = True)
```

Top 20 important features of Negative class of Set 1

In [65]:
```
df.head(20)
```

Out[65]:

	feature_names	feature_probs
8098	warmth	-13.805614
8051	dr	-13.805614
8061	care_hunger	-13.805614
8068	warmth	-13.805614
8070	care_hunger	-13.805614

	feature_names	feature_probs
615	ball chair	-13.805614
8050	wy	-13.114958
8028	nd	-13.114958
6250	storyworks	-12.710324
1539	dash dot	-12.710324
6751	students wiggle	-12.710324
6241	stools would	-12.710324
7072	the wobble chairs	-12.710324
7277	tile	-12.423058
3429	kindle fire	-12.200164
4844	ozobots	-12.200164
1046	chromebooks allow	-12.200164
2135	every day ready learn	-12.200164
7028	the hokki	-12.200164
7029	the hokki stools	-12.200164

Top 20 important features of positive class of Set 1

In [66]:
```
bow_features_probs_positive = []

for a in range(8101) :      # as number of columns in our dataset is 810
1 and so is total features
    bow_features_probs_positive.append(MNB.feature_log_prob_[1,a])
print(len(bow_features_probs_positive))
```

8101

In [67]:
```
final_bow_features_positive = pd.DataFrame({'feature_names':bow_feature
```

```
_names, 'feature_probs':bow_features_probs_positive})
```

In [68]:
```
df = final_bow_features_positive.sort_values(by = ['feature_probs'], ascending = True)
```

In [69]:
```
df.head(20)
```

Out[69]:

	feature_names	feature_probs
8070	care_hunger	-15.523820
8098	warmth	-15.523820
8061	care_hunger	-15.523820
8068	warmth	-15.523820
8051	dr	-14.833163
8050	wy	-12.963473
8046	vt	-12.484047
8028	nd	-11.791018
8080	financialliteracy	-11.700057
8026	mt	-11.657502
8039	ri	-11.451185
8100	teacher_number_of_previously_posted_projects	-11.439126
8076	economics	-11.434379
8030	nh	-11.122027
8041	sd	-11.074402
8092	parentinvolvement	-11.051413
3362	items requested	-11.051413
8029	ne	-11.028942
4149	math materials	-11.028942

	feature_names	feature_probs
7098	these materials allow students	-11.028942

Summary

In [70]:
```
from prettytable import PrettyTable

x = PrettyTable(["Vectorization","Model", "Hyper-parameter tuning", "Hy
per-parameter" ,"AUC_SCORE"])
x.add_row([" BOW ", "MultinomialNB","GridSearchCV", best_alpha_bow, AUC
_BOW])
x.add_row([" TFIDF ","MultinomialNB", "GridSearchCV", best_alpha_tfidf,
 AUC_TFIDF])
print(x)
```

```
+--------------+--------------+------------------------+------------
----+-------------------+
| Vectorization |     Model     | Hyper-parameter tuning | Hyper-parame
ter |     AUC_SCORE      |
+--------------+--------------+------------------------+------------
----+-------------------+
|      BOW      | MultinomialNB |      GridSearchCV      |      0.005
    | 0.703815582600594  |
|     TFIDF     | MultinomialNB |      GridSearchCV      |      1e-05
    | 0.6855894473730471 |
+--------------+--------------+------------------------+------------
----+-------------------+
```

Conclusion

1) My model is resonably good when I consider confusion matrix

2) Among BOW and TFIDF, I got better results for BOW model

```
In [ ]:
```