Apply Random Forest Classifier and Gradient Boosted Decision Trees

In [1]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature extraction.text import TfidfTransformer
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
from nltk.stem.porter import PorterStemmer
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
from tqdm import tqdm
import os
from chart_studio.plotly import plotly
import plotly.offline as offline
import plotly.graph objs as go
offline.init notebook mode()
from collections import Counter
```

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

```
In [2]:

project_data = pd.read_csv("train_data.csv", nrows = 30000)
resource_data = pd.read_csv("resources.csv", nrows = 30000)

In [3]:

print("Number of data points in train data", project_data.shape)
print('-'*50)
print("The attributes of data :", project_data.columns.values)

Number of data points in train data (30000, 17)

The attributes of data : ['Unnamed: 0' 'id' 'teacher_id' 'teacher_prefix' 'school_state'
'project_submitted_datetime' 'project_grade_category'
'project_subject_categories' 'project_subject_subcategories'
'project_title' 'project_essay_1' 'project_essay_2' 'project_essay_3'
'project_essay_4' 'project_resource_summary'
```

```
'teacher number of previously posted projects' 'project is approved']
In [4]:
# Let's check for any "null" or "missing" values
project_data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 17 columns):
                                                30000 non-null int64
Unnamed: 0
id
                                                30000 non-null object
                                                30000 non-null object
teacher_id
teacher prefix
                                                29999 non-null object
school state
                                                30000 non-null object
project submitted datetime
                                                30000 non-null object
                                                30000 non-null object
project grade category
project_subject_categories
                                                30000 non-null object
{\tt project\_subject\_subcategories}
                                                30000 non-null object
                                                30000 non-null object
project title
project_essay_1
                                                30000 non-null object
project essay 2
                                                30000 non-null object
project essay 3
                                                1013 non-null object
                                                1013 non-null object
project_essay_4
project resource summary
                                                30000 non-null object
                                                30000 non-null int64
teacher_number_of_previously_posted_projects
                                               30000 non-null int64
project is approved
dtypes: int64(3), object(14)
memory usage: 3.9+ MB
In [5]:
project data['teacher prefix'].isna().sum()
Out[5]:
1
In [6]:
# "teacher prefix" seems to contain 2 "missing" values, let't use mode replacement strategy to fil
1 those missing values
project data['teacher prefix'].mode()
Out[6]:
   Mrs.
dtype: object
In [7]:
# Let's replace the missing values with "Mrs." , as it is the mode of the "teacher_prefix"
project_data['teacher_prefix'] = project_data['teacher_prefix'].fillna('Mrs.')
In [8]:
price_data = resource_data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset_index()
project_data = pd.merge(project_data, price_data, on='id', how='left')
In [9]:
# Let's select only the selected features or columns, dropping "project resource summary" as it is
project data.drop(['id','teacher id','project submitted datetime','project resource summary'],axis
=1, inplace=True)
project data.columns
Out[9]:
```

.

```
Index(['Unnamed: 0', 'teacher prefix', 'school state',
       'project_grade_category', 'project_subject_categories',
       'project_subject_subcategories', 'project_title', 'project_essay_1',
       'project essay 2', 'project essay 3', 'project essay 4',
       'teacher_number_of_previously_posted_projects', 'project_is_approved',
       'price', 'quantity'],
      dtype='object')
In [10]:
# Data seems to be highly imbalanced since the ratio of "class 1" to "class 0" is nearly 5.5
project_data['project_is_approved'].value_counts()
Out[10]:
    25380
    4620
Name: project is approved, dtype: int64
In [11]:
number_of_approved = project_data['project_is_approved'][project_data['project_is_approved'] == 1].
number of not approved = project data['project is approved'][project data['project is approved'] =
= 0].count()
print ("Ratio of Project approved to Not approved is:", number of approved/number of not approved)
Ratio of Project approved to Not approved is: 5.4935064935064934
In [12]:
# merge two column text dataframe:
project_data["essay"] = project_data["project_essay_1"].map(str) +\
                        project_data["project_essay_2"].map(str) + \
                        project data["project essay 3"].map(str) + \
                        project data["project essay 4"].map(str)
In [13]:
project data.head(2)
```

Out[13]:

0 160221 Mrs. IN Grades PreK-2 Literacy & Language ESL, Lite History & Civics, Health & Civics &	subject_subcateg
History & Civics, Health & Civics &	:racy
1 140945 Mr. FL Grades 6-8 Sports Sports	Government, Team

In [14]:

Let's drop the project essay columns from the dadaset now, as we have captured the essay text da ta into single "essay" column project data.drop(['project essay 1','project essay 2','project essay 3','project essay 4'],axis=1

```
In [15]:

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

Out[15]:
```

	Unnamed: 0	teacher_prefix	school_state	project_grade_category	project_subject_categories	project_subject_subcatego
0	160221	Mrs.	IN	Grades PreK-2	Literacy & Language	ESL, Literacy
4	·	<u> </u>		1		

In [16]:

```
# 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=0.33, stratify=y)
```

2) Make Data Model Ready: encoding numerical, categorical features

In [17]:

```
def cleaning_text_data(list_text_feature,df,old_col_name,new_col_name):
    # remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
   # https://www.qeeksforgeeks.org/removing-stop-words-nltk-python/
    # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
    # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
    feature list = []
    for i in list_text_feature:
       temp = ""
        # consider we have text like this "Math & Science, Warmth, Care & Hunger"
       for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care
& Hunger"]
            if 'The' in j.split(): # this will split each of the catogory based on space "Math & Sc
ience"=> "Math", "&", "Science"
               j=j.replace('The','') # if we have the words "The" we are going to replace it with
''(i.e removing 'The')
           j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Sc
ience"=>"Math&Science"
            temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the trailing spaces
            temp = temp.replace('&',' ') # we are replacing the & value into
       feature list.append(temp.strip())
    df[new_col_name] = feature_list
    df.drop([old col name], axis=1, inplace=True)
    from collections import Counter
    my counter = Counter()
    for word in df[new_col_name].values:
       my counter.update(word.split())
    feature dict = dict(my_counter)
    sorted feature dict = dict(sorted(feature dict.items(), key=lambda kv: kv[1]))
    return sorted feature dict
                                                                                                •
```

```
def clean project grade(list text feature, df, old col name, new col name):
    # remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
    # https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
    # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
    # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
   feature_list = []
   for i in list text feature:
       temp = i.split(' ')
       last dig = temp[-1].split('-')
       fin = [temp[0]]
       fin.extend(last dig)
       feature = ' '.join(fin)
       feature list.append(feature.strip())
   df[new col name] = feature list
   df.drop([old col name], axis=1, inplace=True)
   from collections import Counter
   my_counter = Counter()
   for word in df[new col name].values:
       my counter.update(word.split())
   feature_dict = dict(my_counter)
   sorted feature dict = dict(sorted(feature dict.items(), key=lambda kv: kv[1]))
   return sorted feature dict
```

2.1) Text Preprocessing: project_subject_categories

```
In [19]:
```

```
x_train_sorted_category_dict = cleaning_text_data(X_train['project_subject_categories'], X_train, 'p
roject_subject_categories', 'clean_categories')
x_test_sorted_category_dict =
cleaning_text_data(X_test['project_subject_categories'], X_test, 'project_subject_categories', 'clean_categories')
[4]
```

2.2) Text Preprocessing: project_subject_subcategories

```
In [20]:
```

```
x_train_sorted_subcategories = cleaning_text_data(X_train['project_subject_subcategories'], X_train
,'project_subject_subcategories','clean_subcategories')
x_test_sorted_subcategories = cleaning_text_data(X_test['project_subject_subcategories'], X_test,'p
roject_subject_subcategories','clean_subcategories')
```

2.3) Text Preprocessing: project_grade_category

```
In [21]:
```

```
x_train_sorted_grade =
clean_project_grade(X_train['project_grade_category'], X_train, 'project_grade_category', 'clean_grade
')
x_test_sorted_grade =
clean_project_grade(X_test['project_grade_category'], X_test, 'project_grade_category', 'clean_grade'
)
```

2.4) Text Preprocessing (stowords): project_essay, project_title

```
In [22]:
```

```
# https://stackoverflow.com/a/47091490/4084039
import re
def decontracted(phrase):
```

```
# specific
phrase = re.sub(r"won't", "will not", phrase)
phrase = re.sub(r"can\'t", "can not", phrase)

# general
phrase = re.sub(r"\'r", " are", phrase)
phrase = re.sub(r"\'s", " is", phrase)
phrase = re.sub(r"\'d", " would", phrase)
phrase = re.sub(r"\'d", " would", phrase)
phrase = re.sub(r"\'ll", " will", phrase)
phrase = re.sub(r"\'t", " not", phrase)
phrase = re.sub(r"\'t", " have", phrase)
phrase = re.sub(r"\'ve", " have", phrase)
phrase = re.sub(r"\'m", " am", phrase)
return phrase
```

In [23]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', '&
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"]
4
                                                                                                 ▶ |
```

In [24]:

```
# Combining all the above stundents
from tqdm import tqdm
def process_text(df,col_name):
    preprocessed_feature = []
    # tqdm is for printing the status bar
    for sentance in tqdm(df[col_name].values):
        sent = decontracted(sentance)
        sent = sent.replace('\\r', ' ')
        sent = sent.replace('\\", ' ')
        sent = sent.replace('\\", ' ')
        sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
        # https://gist.github.com/sebleier/554280
        sent = ' '.join(e for e in sent.split() if e.lower() not in stopwords)
        preprocessed_feature
```

In [25]:

```
100%|
[00:06<00:00, 1435.06it/s]

In [26]:

x_train_title_preprocessed = process_text(X_train,'project_title')
x_test_title_preprocessed = process_text(X_test,'project_title')

100%|
100%|
100:00<00:00, 27107.65it/s]
100%|
100:00<00:00, 27890.32it/s]</pre>
```

2.5) Response Coding for Categorical Data

```
In [27]:

# We have following categorical features
# 1) school_state, 2) project_categories(clean_categories), 3)
project_subcategories(clean_subcategories),
# 4) project_grade_categories(clean_grade), 5) teacher_prefix
```

```
In [28]:
```

```
def response_coded(x_train,y_train,x_test,y_test,col_name):
    train_list = []
    test list = []
    if (len(x train[col name]) != len(y train)) or (len(x test[col name]) != len(y test)):
       return "rows mismatch"
    train_set = list(set(x_train[col_name]))
    test set = list(set(x test[col name]))
    # Let's process train data
    for index in range(len(train set)):
       label_1 = 0
       label_0 = 0
        temp = {}
        for attr,label in zip(x_train[col_name],y_train):
            if train set[index] == attr:
                if label == 0:
                    label 0 += 1
                else:
                    label 1 += 1
        temp['attribute'] = train set[index].lower()
        temp['prob_label_1'] = label_1 / (label_1 + label_0)
        temp['prob_label_0'] = label_0 / (label_1 + label_0)
        train list.append(temp)
    # Let's process test data
    for index in range(len(test_set)):
       label 1 = 0
       label_0 = 0
        temp = {}
        for attr,label in zip(x test[col name], y test):
            if test set[index] == attr:
                if label == 0:
                    label 0 += 1
                else:
                    label_1 += 1
        temp['attribute'] = test set[index].lower()
        temp['prob label 1'] = label_1 / (label_1 + label_0)
        temp['prob label 0'] = label 0 / (label 1 + label 0)
        test_list.append(temp)
    # let's check for elements in test data that is not there in train data
    in test = list(set(x test[col name]) - set(x train[col name]))
    if len(in test) != 0:
        for attr in in test:
         train list.append({'attribute':attr.lower(),'prob label 1':0.5,'prob label 0':0.5})
```

```
test list.append({'attribute':attr.lower(),'prob label 1':0.5,'prob label 0':0.5})
    train list 1 = [0] * len(x train[col name])
    train list 0 = [0] * len(x train[col name])
    train_attr = ["-"] * len(x_train[col_name])
    for index,value in enumerate(x_train[col_name]):
        for tr in train list:
            if tr['attribute'] == value.lower():
                train list 1[index] = tr['prob label 1']
                train_list_0[index] = tr['prob_label_0']
                train_attr[index] = tr['attribute']
    test list 1 = [0] * len(x_test[col_name])
    test list 0 = [0] * len(x test[col name])
    test attr = ["-"] * len(x test[col name])
    for index, value in enumerate(x test[col name]):
        for te in test_list:
            if te['attribute'] == value.lower():
                test list 1[index] = te['prob label 1']
                test_list_0[index] = te['prob_label_0']
                test attr[index] = te['attribute']
    return train_list_1, train_list_0, test_list_1, test_list_0
school_state
In [29]:
x_train_school_state_1,x_train_school_state_0, x_test_school_state_1,x_test_school_state_0 =
response coded(X train, y train, X test, y test, 'school state')
In [30]:
X train['train school state 1'] = x train school state 1
X train['train school state 0'] = x train school state 0
X_test['test_school_state_1'] = x_test_school_state_1
X test['test school state 0'] = x test school state 0
In [31]:
X train['train school state 1'][:10]
Out[31]:
10010
         0.857675
         0.847015
       0.835214
26899
6909
        0.848485
7151
        0.847015
         0.861533
12755
         0.886878
15456
25829
         0.813688
       0.879828
22949
2244
        0.850099
Name: train_school_state_1, dtype: float64
In [32]:
X train['train school state 0'][:10]
Out[32]:
10010
        0.142325
         0.152985
868
```

26899

0.164786

```
6909
      0.151515
7151
        0.152985
12755
        0.138467
15456
        0.113122
       0.186312
25829
      0.120172
22949
2244
        0.149901
Name: train_school_state_0, dtype: float64
In [33]:
X_test['test_school_state_1'][:10]
Out[33]:
3779
        0.826783
      0.806985
22936
10115
      0.849029
29791
        0.822674
11587
        0.849029
7617
        0.826783
27165
        0.876761
24916
        0.831169
24849
       0.865385
21430
        0.857143
Name: test school state 1, dtype: float64
In [34]:
X test['test school state 0'][:10]
Out[34]:
3779
       0.173217
22936
        0.193015
        0.150971
10115
29791
        0.177326
        0.150971
11587
7617
        0.173217
27165
      0.123239
        0.168831
24916
24849
        0.134615
21430
        0.142857
Name: test_school_state_0, dtype: float64
project_categories (clean_categories)
In [35]:
x_train_pro_cat_1,x_train_pro_cat_0, x_test_pro_cat_1,x_test_pro_cat_0 =
response_coded(X_train,y_train,X_test,y_test,'clean_categories')
In [36]:
X_train['train_pro_cat_1'] = x_train_pro_cat_1
X train['train pro cat 0'] = x train pro cat 0
X_test['test_pro_cat_1'] = x_test_pro_cat_1
X_test['test_pro_cat_0'] = x_test_pro_cat_0
In [37]:
X_train['train_pro_cat_1'][:10]
Out[37]:
      0.930894
10010
        0.870438
868
26899
        0.843127
        0.500000
6909
7151
        0.866491
12755
        N 212021
```

```
14177
        U • U ± U ⊅ J ±
15456
        0.870438
25829
      0.848326
22949 0.800000
2244
       0.866491
Name: train_pro_cat_1, dtype: float64
In [38]:
X_train['train_pro_cat_0'][:10]
Out[38]:
10010
        0.069106
       0.129562
      0.156873
26899
6909
        0.500000
7151
        0.133509
12755
        0.181069
15456
       0.129562
25829
       0.151674
      0.200000
22949
2244
        0.133509
Name: train pro cat 0, dtype: float64
In [39]:
X test['test pro cat 1'][:10]
Out[39]:
3779
       0.861368
22936
        0.862297
        0.861368
10115
29791
        0.915423
       0.791209
11587
7617
        0.862297
27165
       0.827302
        0.848073
24916
24849
        0.827302
21430
        0.862297
Name: test_pro_cat_1, dtype: float64
In [40]:
X_test['test_pro_cat_0'][:10]
Out[40]:
      0.138632
3779
22936
        0.137703
10115
        0.138632
29791
        0.084577
11587
       0.208791
7617
        0.137703
27165
        0.172698
24916
        0.151927
24849
        0.172698
       0.137703
21430
Name: test pro cat 0, dtype: float64
project_subcategories (clean_subcategories)
In [41]:
x train pro subcat 1,x train pro subcat 0, x test pro subcat 1,x test pro subcat 0 =
response_coded(X_train,y_train,X_test,y_test,'clean_subcategories')
In [42]:
```

X train['train pro subcat 1'] = x train pro subcat 1

```
X_train['train_pro_subcat_0'] = x_train_pro_subcat_0
X_test['test_pro_subcat_1'] = x_test_pro_subcat_1
X_test['test_pro_subcat_0'] = x_test_pro_subcat_0
In [43]:
X train['train_pro_subcat_1'][:10]
Out[43]:
        0.930894
10010
868
         0.866536
      0.857741
26899
6909
        0.000000
7151
         0.826087
12755
        0.819376
15456
       0.881449
25829
       0.796163
      0.800000
22949
        0.874675
2244
Name: train_pro_subcat_1, dtype: float64
In [44]:
X_train['train_pro_subcat_0'][:10]
Out[44]:
10010 0.069106
868
        0.133464
26899
        0.142259
6909
        1.000000
7151
       0.173913
12755
        0.180624
15456
        0.118551
25829
        0.203837
22949
        0.200000
2244
        0.125325
Name: train_pro_subcat_0, dtype: float64
In [45]:
X_test['test_pro_subcat_1'][:10]
Out[45]:
3779
        0.873294
22936
        0.863818
        0.873294
10115
29791
       0.914286
11587
       0.875000
        0.865149
7617
        0.858896
27165
24916
        0.771084
24849
        0.815735
      0.863818
Name: test pro subcat 1, dtype: float64
In [46]:
X_test['test_pro_subcat_0'][:10]
Out[46]:
3779
        0.126706
       0.136182
22936
       0.126706
10115
29791
        0.085714
11587
        0.125000
7617
        0.134851
        0.141104
27165
24916
        0.228916
```

```
24849 0.184265
21430 0.136182
Name: test pro subcat 0, dtype: float64
project grade categories (clean grade)
In [47]:
 x\_train\_grade\_1, x\_train\_grade\_0, \ x\_test\_grade\_1, x\_test\_grade\_0 = response\_coded(X\_train, y\_train, X\_train\_grade\_1, x\_t
est,y_test,'clean_grade')
In [48]:
X_train['train_grade_1'] = x_train_grade_1
X_train['train_grade_0'] = x_train_grade_0
X_test['test_grade_1'] = x_test_grade_1
X_test['test_grade_0'] = x_test_grade_0
In [49]:
X_train['train_grade_1'][:10]
Out[49]:
10010 0.832957
868
                           0.832957
26899
                           0.846456
                         0.846456
6909
7151
                        0.837961
12755
                     0.846456
15456
                         0.846456
25829
                           0.853715
22949
                          0.846456
                         0.846456
2244
Name: train grade 1, dtype: float64
In [50]:
X train['train grade 0'][:10]
Out[50]:
10010
                         0.167043
868
                           0.167043
                    0.153544
26899
                        0.153544
6909
7151
                         0.162039
                         0.153544
12755
15456
                           0.153544
                      0.146285
25829
22949
                    0.153544
2244
                        0.153544
Name: train_grade_0, dtype: float64
In [51]:
X_test['test_grade_1'][:10]
Out[51]:
                     0.850442
3779
22936 0.844942
10115
                    0.841229
                         0.842742
29791
11587
                           0.844942
7617
                           0.844942
27165
                       0.850442
24916 0.841229
24849 0.842742
21430
                       0.844942
Mamos toot arada 1 dtimos floated
```

```
Name: cest_grade_1, dtype: 110at04
In [52]:
X_test['test_grade_0'][:10]
Out[52]:
3779
       0.149558
22936 0.155058
10115
      0.158771
        0.157258
29791
11587
        0.155058
        0.155058
7617
27165 0.149558
24916 0.158771
      0.157258
24849
21430
        0.155058
Name: test_grade_0, dtype: float64
teacher_prefix
In [53]:
x_train_prefix_1,x_train_prefix_0, x_test_prefix_1, x_test_prefix_0 = response_coded(X_train,y_train_
n,X_test,y_test,'teacher_prefix')
In [54]:
X train['train prefix 1'] = x train prefix 1
X train['train prefix 0'] = x train prefix 0
X test['test prefix 1'] = x test prefix 1
X test['test prefix 0'] = x test prefix 0
In [55]:
X train['train prefix 1'][:10]
Out[55]:
10010
        0.846304
868
        0.846304
26899
      0.846586
6909
       0.846586
7151
       0.846586
12755
        0.846586
15456
        0.846304
      0.846586
25829
22949 0.846586
2244
       0.846586
Name: train_prefix_1, dtype: float64
In [56]:
X_train['train_prefix_0'][:10]
Out[56]:
      0.153696
10010
       0.153696
868
26899
      0.153414
6909
        0.153414
        0.153414
7151
12755
        0.153414
15456
       0.153696
25829
      0.153414
22949 0.153414
2244
        0.153414
Name: train prefix 0, dtype: float64
```

```
In [57]:
X_test['test_prefix_1'][:10]
Out[57]:
3779 0.839867
22936 0.853163
10115 0.853163
      0.840659
0.853163
29791
11587
       0.839867
7617
27165 0.853163
24916 0.853163
24849 0.853163
21430
        0.853163
Name: test_prefix_1, dtype: float64
In [58]:
X_test['test_prefix_0'][:10]
Out[58]:
       0.160133
3779
22936 0.146837
10115
        0.146837
29791
        0.159341
      0.146837
11587
7617
       0.160133
27165
      0.146837
24916
        0.146837
24849
        0.146837
      0.146837
21430
Name: test_prefix_0, dtype: float64
2.6) Vectorizing text Data
2.6.1) Bag of Words (essay)
In [59]:
def bow_vectorizer(X_train,col_name,df):
   vectorizer = CountVectorizer()
    vectorizer.fit(X_train[col_name].values)
   df bow = vectorizer.transform(df[col name].values)
   return df bow, vectorizer.get feature names()
In [60]:
x train essay bow, x train essay feat = bow vectorizer(X train, 'essay', X train)
x_test_essay_bow, x_test_essay_feat = bow_vectorizer(X_train,'essay',X_test)
In [61]:
print(x_train_essay_bow.shape)
print(x_test_essay_bow.shape)
(20100, 31041)
(9900, 31041)
2.6.2) Bag of Words (title)
```

In [62]:

def bow vectorizer title(X train.col name.df):

```
vectorizer = CountVectorizer()
    vectorizer.fit(X train[col name].values)
    df bow = vectorizer.transform(df[col name].values)
    return df_bow, vectorizer.get_feature_names()
In [63]:
x_train_title_bow, x_train_title_feat = bow_vectorizer_title(X_train,'project_title',X_train)
x test title bow, x test title feat = bow vectorizer title(X train, 'project title', X test)
In [64]:
print(x train title bow.shape)
print(x test title bow.shape)
(20100, 7857)
(9900, 7857)
2.6.3) TFIDF (essay)
In [65]:
from sklearn.feature extraction.text import TfidfVectorizer
def tfidf_vectorizer(X_train,col_name,df):
    vectorizer = TfidfVectorizer()
    vectorizer.fit(X train[col name].values)
    df tfidf = vectorizer.transform(df[col name].values)
    return df_tfidf, vectorizer.get_feature_names()
In [66]:
# Lets vectorize essay
x train essay tfidf, x train essay tfidf feat = tfidf vectorizer(X train, 'essay', X train)
x test essay tfidf, x test essay tfidf feat = tfidf vectorizer(X train, 'essay', X test)
In [67]:
print(x train essay tfidf.shape)
print(x_test_essay_tfidf.shape)
(20100, 31041)
(9900, 31041)
2.6.4) TFIDF (title)
In [68]:
from sklearn.feature_extraction.text import TfidfVectorizer
def tfidf vectorizer_title(X_train,col_name,df):
    vectorizer = TfidfVectorizer()
    vectorizer.fit(X_train[col_name].values)
    df tfidf = vectorizer.transform(df[col name].values)
    return df tfidf, vectorizer.get feature names()
In [69]:
# Lets vectorize essay
x train title tfidf, x train title tfidf feat =
tfidf vectorizer title (X train, 'project title', X train)
x test title tfidf, x test title tfidf feat =
tfidf_vectorizer_title(X_train,'project_title',X_test)
```

In [70]:

print(x train title tfidf.shape)

```
print(x_test_title_tfidf.shape)

(20100, 7857)
(9900, 7857)
```

2.6.5) Using Pretrained Models: Avg W2V

```
In [71]:
```

```
# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039
def loadGloveModel(gloveFile):
   print ("Loading Glove Model")
   f = open(gloveFile,'r', encoding="utf8")
   model = \{\}
   for line in tqdm(f):
       splitLine = line.split()
       word = splitLine[0]
       embedding = np.array([float(val) for val in splitLine[1:]])
       model[word] = embedding
   print ("Done.",len(model)," words loaded!")
   return model
model = loadGloveModel('glove.42B.300d.txt')
# ===============
Output:
Loading Glove Model
1917495it [06:32, 4879.69it/s]
Done. 1917495 words loaded!
words = []
for i in preproced texts:
   words.extend(i.split(' '))
for i in preproced titles:
   words.extend(i.split(' '))
print("all the words in the coupus", len(words))
words = set(words)
print("the unique words in the coupus", len(words))
inter words = set(model.keys()).intersection(words)
print("The number of words that are present in both glove vectors and our coupus", \
     len(inter words),"(",np.round(len(inter words)/len(words)*100,3),"%)")
words courpus = {}
words glove = set(model.keys())
for i in words:
   if i in words glove:
       words_courpus[i] = model[i]
print("word 2 vec length", len(words_courpus))
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
import pickle
with open('glove vectors', 'wb') as f:
   pickle.dump(words courpus, f)
. . .
```

Out[71]:

```
'\n# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039\ndef loadGloveModel(gloveFile):\n print ("Loading Glove Model")\n f = open(gloveFile,\'r\', encoding="utf8")\n model = {}\n for line in tqdm(f):\n splitLine = line.split()\n word = splitLine[0]\n embedding = np.array([float(val) for val in splitLine[1:]])\n rodel[word] = embedding\n print ("Done.",len(model)," words loaded!")\n return model\nmodel = loadGloveModel(\'glove.42B.300d.txt\')\n\n# =============nOutput:\n \nLoading G love Model\n1917495it [06:32. 4879.69it/sl\nDone. 1917495 words loaded!\n\n#
```

===========\n\nwords = []\nfor i in preproced_texts:\n words.extend(i.split(\'\'))\n\nfor i in preproced_titles:\n words.extend(i.split(\'\'))\nprint("all the words in the coupus", len(words))\nwords = set(words)\nprint("the unique words in the coupus", len(words))\n\ninter_words = set(model.keys()).intersection(words)\nprint("The number of words that are present in both glove vectors and our coupus", len(inter_words),"

(",np.round(len(inter_words)/len(words)*100,3),"%)")\n\nwords_courpus = {}\nwords_glove = set(model.keys())\nfor i in words:\n if i in words_glove:\n words_courpus[i] = model[i]\r print("word 2 vec length", len(words_courpus))\n\n\n# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-save-and-load-variables-in-python/\n\nimport pickle\nwith open(\'glove_vectors\', \'wb\') as f:\n pickle.dump(words_courpus, f)\n\n\n'

In [72]:

```
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
# make sure you have the glove_vectors file
with open('glove_vectors', 'rb') as f:
    model = pickle.load(f)
    glove_words = set(model.keys())
```

In [73]:

```
# Combining all the above stundents
from tqdm import tqdm

def preprocess_essay(df,col_name):
    preprocessed_essays = []
    # tqdm is for printing the status bar
    for sentance in tqdm(df[col_name].values):
        sent = decontracted(sentance)
        sent = sent.replace('\\r', ' ')
        sent = sent.replace('\\"', ' ')
        sent = sent.replace('\\"', ' ')
        sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
        # https://gist.github.com/sebleier/554280
        sent = ' '.join(e for e in sent.split() if e not in stopwords)
        preprocessed_essays.append(sent.lower().strip())
    return preprocessed_essays
```

In [74]:

In [75]:

In [76]:

```
x_train_preprocessed_title = preprocess_essay(X_train,'project_title')
x_test_preprocessed_title = preprocess_essay(X_test,'project_title')
```

```
| 20100/20100
[00:00<00:00, 26177.59it/s]
                                                                              1 9900/9900
[00:00<00:00, 26318.96it/s]
In [77]:
x_train_avg_w2v_essay = compute_avg_W2V(x_train_preprocessed_essay)
x test avg w2v essay = compute avg W2V(x test preprocessed essay)
                                                                              20100/20100
[00:09<00:00, 2138.78it/s]
                                                                               1 9900/9900
[00:04<00:00, 2188.44it/s]
In [78]:
x train avg w2v title = compute avg W2V(x train preprocessed title)
x test avg w2v title = compute avg W2V(x test preprocessed title)
100%|
                                                                      20100/20100
[00:00<00:00, 38925.02it/s]
                                                                     9900/9900
[00:00<00:00, 40226.97it/s]
```

2.6.6) Using Pretrained Models: TFIDF Weighted W2V

```
In [79]:
```

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
def get_tfidf_dict(preprocessed_feature):
    tfidf_model = TfidfVectorizer()
    tfidf_model.fit(preprocessed_feature)
    # we are converting a dictionary with word as a key, and the idf as a value
    dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
    tfidf_words = set(tfidf_model.get_feature_names())
    return dictionary, tfidf_words
```

In [80]:

```
# average Word2Vec
# compute average word2vec for each review.
def compute tfidf w2v vectors(preprocessed feature):
   tfidf w2v vectors = []; # the avg-w2v for each sentence/review is stored in this list
    dictionary, tfidf_words = get_tfidf_dict(preprocessed_feature)
    for sentence in tqdm(preprocessed feature): # for each review/sentence
        vector = np.zeros(300) # as word vectors are of zero length
       tf_idf_weight =0; # num of words with a valid vector in the sentence/review
       for word in sentence.split(): # for each word in a review/sentence
            if (word in glove words) and (word in tfidf words):
               vec = model[word] # getting the vector for each word
                # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
               tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting
the tfidf value for each word
               vector += (vec * tf idf) # calculating tfidf weighted w2v
               tf idf weight += tf idf
       if tf idf weight != 0:
            vector /= tf_idf_weight
       tfidf w2v vectors.append(vector)
    return tfidf_w2v_vectors
```

In [81]:

```
100%|
                                                                                      1 9900/9900
[00:28<00:00, 351.94it/s]
In [82]:
x train weighted w2v title = compute tfidf w2v vectors(x train title preprocessed)
x test weighted w2v title= compute tfidf w2v vectors(x test title preprocessed)
100%|
                                                                                20100/20100
[00:00<00:00, 22871.70it/s]
100%|
                                                                                   1 9900/9900
[00:00<00:00, 23178.65it/s]
2.7) Vectorizing Numerical Features
We have 2 numerical features left, "price" and "teacher number of previously posted projects". Let's check for the "missing" or
"NaN" values present in those numerical features and use "Mean Replacement" for "price" and "Mode Replacement" for
"teacher_number_of_previously_posted_projects".
In [83]:
print("Total number of \"Missing\" Values present in X train price:",X train['price'].isna().sum()
print("Total number of \"Missing\" Values present in X test price:",X test['price'].isna().sum())
Total number of "Missing" Values present in X train price: 19718
Total number of "Missing" Values present in X test price: 9715
In [84]:
print("Total number of \"Missing\" Values present in X train previous teacher number:",X train['te
acher_number_of_previously_posted_projects'].isna().sum())
print("Total number of \"Missing\" Values present in X_test previous teacher number:",X_test['teac
her_number_of_previously_posted_projects'].isna().sum())
Total number of "Missing" Values present in X train previous teacher number: 0
Total number of "Missing" Values present in X test previous teacher number: 0
In [85]:
print("Total number of \"Missing\" Values present in X train quantity:",X train['quantity'].isna()
print("Total number of \"Missing\" Values present in X test quantity:",X test['quantity'].isna().s
um())
Total number of "Missing" Values present in X train quantity: 19718
Total number of "Missing" Values present in X_test quantity: 9715
"teacher_number_of_previously_posted_projects" does not have any "missing" values.
In [86]:
X train['price'].mean()
Out[86]:
274.02664921465987
In [87]:
X_train['price'] = X_train['price'].fillna(274.0266)
```

In [88]:

```
X test['price'].mean()
Out[88]:
288.2436756756755
In [89]:
X test['price'] = X test['price'].fillna(288.2436)
In [90]:
print(X train['quantity'].mean())
print(X test['quantity'].mean())
18.020942408376964
19.967567567567567
In [91]:
X train['quantity'] = X train['quantity'].fillna(18.0209)
X_test['quantity'] = X_test['quantity'].fillna(19.9675)
In [92]:
# check this one: https://www.youtube.com/watch?v=0HOqOcln3Z4&t=530s
# https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html
from sklearn.preprocessing import StandardScaler
def scaler_function(df,col_name):
    scaler = StandardScaler()
    scaler.fit(df[col\_name].values.reshape(-1,1)) \ \# \ finding \ the \ mean \ and \ standard \ deviation \ of \ this
data
    # Now standardize the data with above maen and variance.
    print(f"Mean : {scaler.mean [0]}, Standard deviation : {np.sqrt(scaler.var [0])}")
    scaled = scaler.transform(df[col name].values.reshape(-1, 1))
    return scaled
teacher_number_of_previously_posted_projects
In [93]:
x train teacher number = scaler function(X train, 'teacher number of previously posted projects')
x_test_teacher_number = scaler_function(X_test,'teacher_number_of_previously_posted_projects')
Mean: 11.35726368159204, Standard deviation: 28.634018915945607
Mean: 10.915959595959595, Standard deviation: 26.43942586821415
price
In [94]:
x train price = scaler function(X train, 'price')
x_test_price = scaler_function(X_test,'price')
Mean: 274.02660093532336, Standard deviation: 60.03146833870624
Mean : 288.2436014141413, Standard deviation : 41.114941277013656
quantity
In [95]:
x_train_quantity = scaler_function(X_train,'quantity')
x test quantity = scaler function(X test, 'quantity')
```

Mean: 18.020900805970157, Standard deviation: 3.2232352374733524
Mean: 19.967501262626257, Standard deviation: 4.44596974919204

2.8) Merging all the features and building the sets

In [96]:

```
# train dataset
print("After Vectorization and One hot encoding train dataset shape becomes:")
print(np.asarray(X_train['train_pro_cat_1']).shape)
print(np.asarray(X_train['train_pro_cat_0']).shape)
print(np.asarray(X train['train pro subcat 1']).shape)
print(np.asarray(X_train['train_pro_subcat_0']).shape)
print(np.asarray(X train['train school state 1']).shape)
print(np.asarray(X_train['train_school_state_0']).shape)
print(np.asarray(X_train['train_prefix_1']).shape)
print(np.asarray(X_train['train_prefix_0']).shape)
print(np.asarray(X train['train grade 1']).shape)
print(np.asarray(X train['train grade 1']).shape)
print(x train essay bow.shape)
print(x_train_title_bow.shape)
print(x_train_essay_tfidf.shape)
print(x train title tfidf.shape)
print(np.asarray(x train avg w2v essay).shape)
print(np.asarray(x train avg w2v title).shape)
print(np.asarray(x_train_weighted_w2v_essay).shape)
print(np.asarray(x_train_weighted_w2v_title).shape)
print(x train teacher number.shape)
print(x train price.shape)
print(x_train_quantity.shape)
print("="*50)
# test dataset
print ("After Vectorization and One hot encoding test dataset shape becomes:")
print(np.asarray(X test['test pro cat 1']).shape)
print(np.asarray(X test['test pro_cat_0']).shape)
print(np.asarray(X test['test pro subcat 1']).shape)
print(np.asarray(X_test['test_pro_subcat_0']).shape)
print(np.asarray(X test['test school state 1']).shape)
print(np.asarray(X test['test school state 0']).shape)
print(np.asarray(X test['test prefix 1']).shape)
print(np.asarray(X test['test prefix 0']).shape)
print(np.asarray(X_test['test_grade_1']).shape)
print(np.asarray(X_test['test_grade_1']).shape)
print(x test essay bow.shape)
print(x test title bow.shape)
print(x test essay tfidf.shape)
print(x_test_title_tfidf.shape)
print(np.asarray(x_test_avg_w2v_essay).shape)
print(np.asarray(x_test_avg_w2v_title).shape)
print (np.asarray (x test weighted w2v essay).shape)
print(np.asarray(x_test_weighted w2v title).shape)
print(x test teacher number.shape)
print(x_test_price.shape)
print(x test quantity.shape)
print("="*50)
```

```
After Vectorization and One hot encoding train dataset shape becomes: (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100,) (20100, 31041) (20100, 7857) (20100, 7857)
```

```
(20100, 300)
(20100, 300)
(20100, 300)
(20100, 300)
(20100, 1)
(20100, 1)
(20100, 1)
______
After Vectorization and One hot encoding test dataset shape becomes:
(9900,)
(9900,)
(9900,)
(9900,)
(9900,)
(9900,)
(9900,)
(9900,)
(9900,)
(9900, 31041)
(9900, 7857)
(9900, 31041)
(9900, 7857)
(9900, 300)
(9900, 300)
(9900, 300)
(9900, 300)
(9900, 1)
(9900, 1)
(9900, 1)
_____
In [97]:
def enable plotly_in_cell():
  import IPython
  from plotly.offline import init_notebook_mode
  display(IPython.core.display.HTML("''<script src="/static/components/requirejs/require.js"></scr
ipt>'''))
  init_notebook_mode(connected=False)
In [98]:
%matplotlib inline
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
def plot_3d_plot(x_tr, y_tr, x_te, y_te, depth_list, split_list,algo):
```

```
auc tr = []
   auc_te = []
   y_train_pred_prob = []
   y_test_pred_prob = []
   for depth, split in zip(depth_list ,split_list):
       if algo == 'RF ':
           clf_ = RandomForestClassifier(max_depth = depth ,min_samples_split = split,
class weight = "balanced")
            clf_.fit(x_tr,y_tr)
       elif algo == "GB ":
            clf = GradientBoostingClassifier(max depth = depth ,min_samples_split = split)
            clf .fit(x tr,y tr)
       y train pred = clf .predict proba(x tr)
       y_test_pred = clf_.predict_proba(x_te)
       for index in range(len(y train pred)):
            y_train_pred_prob.append(y_train_pred[index][1])
       for index in range(len(y test pred)):
            y_test_pred_prob.append(y_test_pred[index][1])
```

```
train fpr, train tpr, tr thresholds = roc curve(y tr, y train pred prob)
    test_fpr, test_tpr, tc_thresholds = roc_curve(y_te, y_test_pred_prob)
   y train pred prob = []
   y test pred prob = []
   auc tr.append(auc(train fpr,train tpr))
   auc te.append(auc(test_fpr,test_tpr))
X = split list
Y = depth_list
Z1 = auc tr
Z2 = auc te
# https://plot.ly/python/3d-axes/
trace1 = go.Scatter3d(x=X,y=Y,z=Z1, name = 'train')
trace2 = go.Scatter3d(x=X,y=Y,z=Z2, name = 'cv')
data = [trace1.trace2]
enable plotly in cell()
layout = go.Layout(scene = dict(
        xaxis = dict(title='min samples split'),
        yaxis = dict(title='max_depth'),
        zaxis = dict(title='AUC'),))
fig = go.Figure(data=data, layout=layout)
offline.iplot(fig, filename='3d-scatter-colorscale')
```

3.1) Random Forest Classifier

Set 1) categorical(response coding: use probability values), numerical features + project_title(BOW) + preprocessed_eassay (BOW)

```
In [99]:
```

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
# with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
X train set 1 = hstack((X train['train pro cat 1'].values.reshape(-1,1), X train['train pro cat 0']
.values.reshape(-1,1), X train['train pro subcat 1'].values.reshape(-1,1),
X train['train pro subcat 0'].values.reshape(-1,1), X train['train school state 1'].values.reshape(
-1,1), X_train['train_school_state_0'].values.reshape(-1,1), X_train['train_grade_1'].values.reshap
e(-1,1), \setminus
                                                                     X train['train grade 0'].values.reshape(-1,1),X train['train prefix 1'].val
es.reshape(-1,1), X train['train prefix 0'].values.reshape(-1,1), x train teacher number, x train pric
e,x_train_quantity,x_train_title_bow,x_train_essay_bow)).tocsr()
 \textbf{X\_test\_set\_1} = \textbf{hstack((X\_test['test\_pro\_cat\_1'].values.reshape(-1,1),X\_test['test\_pro\_cat\_0'].value } . \\  \textbf{X\_test\_set\_1} = \textbf{hstack((X\_test['test\_pro\_cat\_0'].values.reshape(-1,1),X\_test['test\_pro\_cat\_0'].value } . \\  \textbf{X\_test\_set\_1} = \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1} . \\  \textbf{X\_test\_set\_1} = \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1} . \\  \textbf{X\_test\_set\_1} = \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1} . \\  \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1} . \\  \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1} = \textbf{A.S.test\_set\_1
s.reshape(-1,1), X_test['test_pro_subcat_1'].values.reshape(-1,1), X_test['test_pro_subcat_0'].values
 .reshape(-1,1), X test['test school state 1'].values.reshape(-1,1), X test['test school state 0'].val
ues.reshape(-1,1),X_test['test_grade_1'].values.reshape(-1,1),\
                                                         X test['test grade 0'].values.reshape(-1,1),X test['test prefix 1'].values.resha
pe(-1,1),X_test['test_prefix_0'].values.reshape(-1,1),x_test_teacher_number,x_test_price,x_test_qua
ntity,x test title bow,x test essay bow)).tocsr()
```

In [100]:

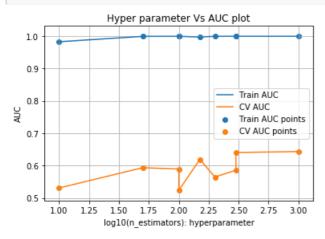
```
from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestClassifier
import math
```

Calculating Combine Hyper-Parameters

```
In [104]:
```

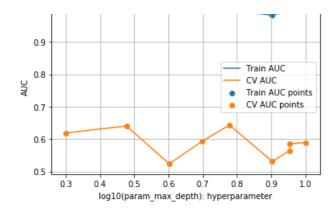
```
RF_ = RandomForestClassifier(class_weight = "balanced")
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,10]
```

```
clf = RandomizedSearchCV(RF_, parameters,n_iter = 9, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_1, y_train)
results = pd.DataFrame.from dict(clf.cv results )
results = results.sort values(['param n estimators'])
train auc= results['mean train score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv auc std= results['std test score']
C_ = results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C , train auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C , train auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [105]:

```
results = results.sort values(['param max depth'])
train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std= results['std_test_score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C , train auc, label='Train AUC points')
plt.scatter(C , cv auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(param_max_depth): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [106]:

results

Out[106]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
3	0.247100	0.008275	0.020599	0.002960	150	2	{'n_estimators': 150, 'max_depth': 2}
4	0.548963	0.056624	0.036501	0.000896	300	3	('n_estimators': 300, 'max_depth': 3)
7	0.214821	0.020349	0.013902	0.000196	100	4	{'n_estimators': 100, 'max_depth': 4}
8	0.094000	0.006139	0.007700	0.000402	50	5	('n_estimators': 50, 'max_depth': 5)
5	2.074884	0.107347	0.122921	0.008777	1000	6	{'n_estimators': 1000, 'max_depth': 6}
6	0.022691	0.002152	0.002804	0.000236	10	8	{'n_estimators': 10, 'max_depth': 8}
0	0.536196	0.059843	0.028605	0.005120	200	9	{'n_estimators': 200, 'max_depth': 9}
2	0.689265	0.051618	0.043516	0.012311	300	9	{'n_estimators': 300, 'max_depth': 9}
1	0.228352	0.006613	0.014297	0.001160	100	10	{'n_estimators': 100, 'max_depth': 10}

9 rows × 22 columns

I I

In [107]:

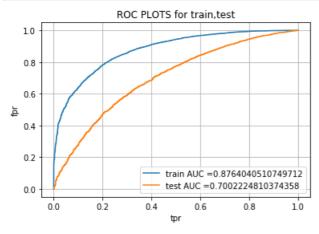
```
# the best value for n_estimators and max_depth from the above table
best_n_estimator = 200
best_max_depth = 9
```

n [108]:

from sklearn.metrics import roc_curve, auc

```
In [109]:
```

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
from sklearn.metrics import roc_curve, auc
RF_ = RandomForestClassifier(n_estimators = best_n_estimator, max_depth = best_max_depth, class_wei
ght = "balanced")
RF .fit(X train set 1, 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 = RF_.predict_proba(X_train_set_1)
y_test_pred = RF_.predict_proba(X_test_set_1)
y train pred prob = []
y_test_pred_prob = []
for index in range(len(y train pred)):
    y train pred prob.append(y train pred[index][1])
for index in range(len(y test pred)):
    y_test_pred_prob.append(y_test_pred[index][1])
train fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



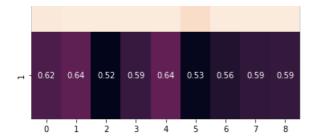
In [110]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores), annot = True, cbar=False)
```

Out[110]:

<matplotlib.axes._subplots.AxesSubplot at 0x25c85f3f588>

```
0-1 1 1 1 1 0.98 1 1 1
```



In [111]:

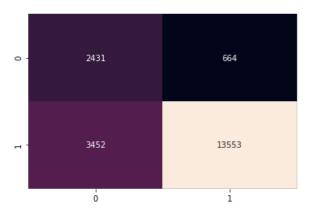
In [112]:

```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.6260126476152837 for threshold 0.501 Train confusion matrix

Out[112]:

<matplotlib.axes._subplots.AxesSubplot at 0x25c85e140b8>



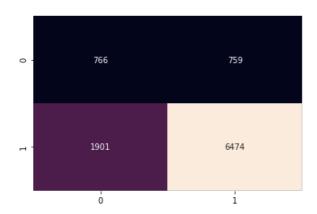
In [113]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Our[II3]:

<matplotlib.axes. subplots.AxesSubplot at 0x25c85d70978>



In [114]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_1, y_train, X_test_set_1, y_test, depth, estimators, "RF_")
```

Set 2) categorical(response coding: use probability values), numerical features + project_title(TFIDF)+ preprocessed_eassay (TFIDF)

In [115]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
# with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
from scipy.sparse import hstack
X_train_set_2 = hstack((X_train['train_pro_cat_1'].values.reshape(-1,1), X_train['train_pro_cat_0'].values.reshape(-1,1), X_train['train_pro_subcat_1'].values.reshape(-1,1),
X_train['train_pro_subcat_0'].values.reshape(-1,1), X_train['train_school_state_1'].values.reshape(-1,1), X_train['train_school_state_0'].values.reshape(-1,1), X_train['train_grade_1'].values.reshape(-1,1), X_train['train_prefix_1'].values.reshape(-1,1), X_train['train_prefix_1'].values.reshape(-1,1), X_train['train_prefix_0'].values.reshape(-1,1), X_train_tacher_number, X_train_price.x_train_grade_1').tocsr()
```

```
X_test_set_2 = hstack((X_test['test_pro_cat_1'].values.reshape(-1,1),X_test['test_pro_cat_0'].value
s.reshape(-1,1),X_test['test_pro_subcat_1'].values.reshape(-1,1),X_test['test_pro_subcat_0'].values
.reshape(-1,1),X_test['test_school_state_1'].values.reshape(-1,1),X_test['test_school_state_0'].val
ues.reshape(-1,1),X_test['test_grade_1'].values.reshape(-1,1),X_test['test_prefix_1'].values.resh
pe(-1,1),X_test['test_prefix_0'].values.reshape(-1,1),X_test_test_prefix_1'].values.resh
pe(-1,1),X_test['test_prefix_0'].values.reshape(-1,1),X_test_test_prefix_1'].values.resh
pe(-1,1),X_test_test_prefix_0'].values.reshape(-1,1),X_test_test_prefix_1'].values.resh
pe(-1,1),X_test_test_prefix_0'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_test_test_prefix_1'].values.reshape(-1,1),X_te
```

Calculating Combine Hyper-Parameters

```
In [116]:
```

```
RF_ = RandomForestClassifier(class_weight = "balanced")
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,10]}
clf = RandomizedSearchCV(RF_, parameters,n_iter = 9, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_2, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
```

In [117]:

results

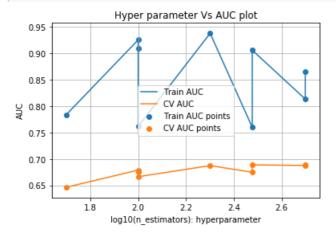
Out[117]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
0	7.640406	0.227881	1.144224	0.112074	500	4	{'n_estimators': 500, 'max_depth': 4}
1	1.137128	0.068535	0.136805	0.015658	50	5	{'n_estimators': 50, 'max_depth': 5}
2	4.007514	0.278102	0.270112	0.012062	100	10	{'n_estimators': 100, 'max_depth': 10}
3	2.704006	0.123833	0.683220	0.056569	300	2	{'n_estimators': 300, 'max_depth': 2}
4	3.466756	0.098852	0.241555	0.016177	100	9	{'n_estimators': 100, 'max_depth': 9}
5	1.271650	0.053347	0.224548	0.011704	100	3	{'n_estimators': 100, 'max_depth': 3}
6	7.544095	0.177640	0.540696	0.026809	200	10	{'n_estimators': 200, 'max_depth': 10}
7	10.873345	0.097874	1.123981	0.030397	500	6	{'n_estimators': 500, 'max_depth': 6}
8	8.924304	0.096602	0.671370	0.013667	300	8	{'n_estimators': 300, 'max_depth': 8}

9 rows × 22 columns

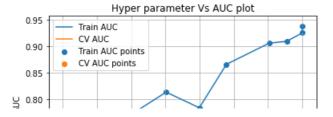
(<u>)</u>

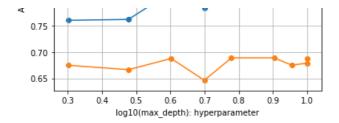
```
results = results.sort values(['param n estimators'])
train auc= results['mean train score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv auc std= results['std test score']
C_{=} results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C , train auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n_estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [119]:

```
results = results.sort_values(['param_max_depth'])
train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv auc = results['mean test score']
cv_auc_std= results['std_test_score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(max_depth): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



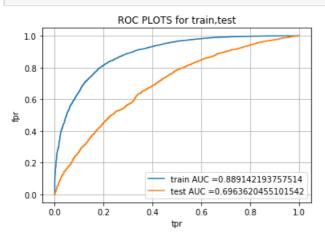


In [120]:

```
# the best value for n_estimators and max_depth from the above table are
best_n_estimator = 300
best_max_depth = 8
```

In [121]:

```
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
RF = RandomForestClassifier(n estimators = best n estimator, max depth = best max depth, class wei
ght = "balanced")
RF_.fit(X_train_set_2, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
# not the predicted outputs
y_train_pred = RF_.predict_proba(X_train_set_2)
y_test_pred = RF_.predict_proba(X_test_set_2)
y_train_pred_prob = []
y_test_pred_prob = []
for index in range(len(y_train_pred)):
   y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y_test_pred)):
    y test pred prob.append(y test pred[index][1])
train fpr, train tpr, tr thresholds = roc curve(y train, y train pred prob)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



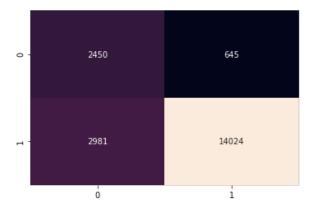
```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.6528308931279833 for threshold 0.506 Train confusion matrix \blacksquare

. ▶

Out[122]:

<matplotlib.axes. subplots.AxesSubplot at 0x25c85fb6a90>



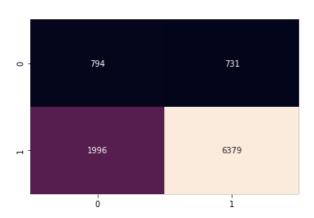
In [123]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[123]:

<matplotlib.axes._subplots.AxesSubplot at 0x25c9039e898>



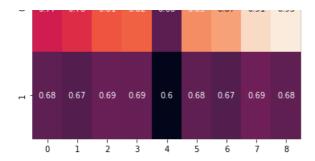
In [194]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores), annot=True, cbar= False)
```

Out[194]:

<matplotlib.axes. subplots.AxesSubplot at 0x2208a5ea550>





In [98]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_2, y_train, X_test_set_2, y_test, depth, estimators, "RF_")
```

Set 3) categorical(response coding: use probability values), numerical features + project_title(AVG W2V)+ preprocessed_eassay (AVG W2V)

In [195]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
 # with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
from scipy.sparse import csr matrix
X train set 3 = hstack((csr matrix(X train['train pro cat 1'].values).reshape(-1,1), csr matrix(X t
rain['train pro cat 0'].values).reshape(-1,1),csr matrix(X train['train pro subcat 1'].values).resh
ape(-1,1), csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_0'].values).reshape(-1,1),csr_matrix(X_train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['train['t
  school state 1'].values).reshape(-1,1),csr matrix(X train['train school state 0'].values).reshape(
 -1,1),\
                                                                                       csr matrix( X train['train grade 1'].values).reshape(-1,1),csr matrix( X tr
in['train_grade_0'].values).reshape(-1,1),csr_matrix(X_train['train_prefix_1'].values).reshape(-1,1)
), csr_matrix(X_train['train_prefix_0'].values).reshape(-1,1), x_train_teacher_number, x_train_price, x_train_price, x_train_teacher_number, x_train_te
  train quantity, x train avg w2v title, x train avg w2v essay)).tocsr()
X_test_set_3 = hstack((csr_matrix(X_test['test_pro_cat_1'].values).reshape(-1,1),csr_matrix(X_test[
 'test_pro_cat_0'].values).reshape(-1,1),csr_matrix(X_test['test_pro_subcat_1'].values).reshape(-1,1)
),csr matrix(X test['test pro subcat 0'].values).reshape(-1,1),csr matrix(X test['test school state
1'].values).reshape(-1,1),csr_matrix(X_test['test_school_state_0'].values).reshape(-1,1),csr_matrix
 (X test['test grade 1'].values).reshape(-1,1), \
                                                                        csr matrix(X test['test grade 0'].values).reshape(-1,1),csr matrix(X test['test
```

```
prefix_1'].values).reshape(-1,1),csr_matrix(X_test['test_prefix_0'].values).reshape(-1,1),x_test_te
acher_number,x_test_price,x_test_quantity, x_test_avg_w2v_title,x_test_avg_w2v_essay)).tocsr()
[4]
```

Calculating Combine Hyper-Parameters

```
In [197]:
```

```
RF_ = RandomForestClassifier(class_weight = "balanced")
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,10]
}
clf = RandomizedSearchCV(RF_, parameters,n_iter = 9, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_3, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_n_estimators'])
```

In [198]:

results

Out[198]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
3	0.396966	0.005997	0.021812	0.013566	10	7	{'n_estimators': 10, 'max_depth': 7}
8	2.017022	0.041508	0.056501	0.009760	50	9	{'n_estimators': 50, 'max_depth': 9}
4	2.239859	0.178913	0.117862	0.013082	100	4	{'n_estimators': 100, 'max_depth': 4}
1	5.408265	0.405228	0.170044	0.049033	150	7	{'n_estimators': 150, 'max_depth': 7}
7	3.004580	0.010015	0.176151	0.022817	200	3	{'n_estimators': 200, 'max_depth': 3}
2	4.847715	0.271939	0.313647	0.042912	300	3	{'n_estimators': 300, 'max_depth': 3}
5	3.368393	0.124852	0.313928	0.053726	300	2	('n_estimators': 300, 'max_depth': 2)
0	10.127935	0.536526	0.522066	0.086801	500	4	{'n_estimators': 500, 'max_depth': 4}
6	10.946567	0.305066	0.809621	0.036345	1000	2	{'n_estimators': 1000, 'max_depth': 2}

9 rows × 22 columns

In [199]:

```
results = results.sort_values(['param_max_depth'])

train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std= results['std_test_score']
```

```
plt.plot(C_, train_auc, label='Train AUC')

plt.plot(C_, cv_auc, label='CV AUC')

plt.scatter(C_, train_auc, label='Train AUC points')

plt.scatter(C_, cv_auc, label='CV AUC points')

plt.scatter(C_, cv_auc, label='CV AUC points')

plt.legend()

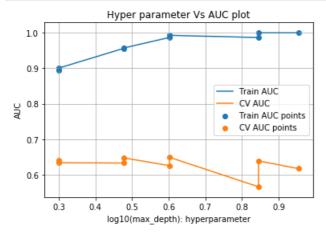
plt.xlabel("log10 (max_depth): hyperparameter")

plt.ylabel("AUC")

plt.title("Hyper parameter Vs AUC plot")

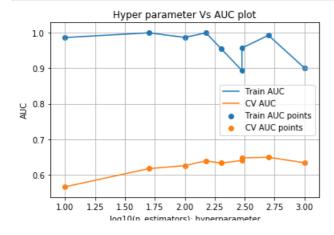
plt.grid()

plt.show()
```



In [200]:

```
results = results.sort_values(['param_n_estimators'])
train auc= results['mean train score']
train auc std= results['std train score']
cv auc = results['mean test score']
cv auc std= results['std test score']
C_ = results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C_, cv_auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n_estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```

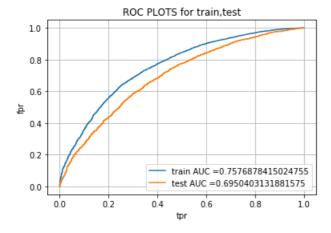


In [201]:

```
# the best value for n_estimators and max_depth from the above graphs are best_n_estimator = 500 best_max_depth = 4
```

In [202]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
RF = RandomForestClassifier(n estimators = best n estimator, max depth = best max depth, class wei
ght = "balanced")
RF_.fit(X_train_set_3, 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 = RF_.predict_proba(X_train_set_3)
y test pred = RF .predict proba(X test set 3)
y_train_pred_prob = []
y test pred prob = []
for index in range(len(y_train_pred)):
   y train pred prob.append(y train pred[index][1])
for index in range(len(y test pred)):
   y_test_pred_prob.append(y_test_pred[index][1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



In [203]:

```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train_confusion_matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

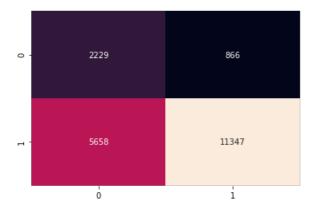
the maximum value of tpr*(1-fpr) 0.48056687689024274 for threshold 0.508 Train confusion matrix

- 333 ▶

Out[203]:

4

<matplotlib.axes. subplots.AxesSubplot at 0x2208a3a66a0>



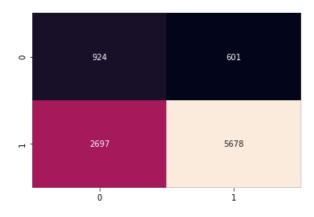
In [204]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[204]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208a5df5c0>

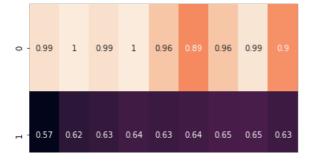


In [205]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores), annot = True, cbar=False)
```

Out[205]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208a77f208>



```
0 1 2 3 4 5 6 7 8
```

In [108]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_3, y_train, X_test_set_3, y_test, depth, estimators, "RF_")
```

Set 4) categorical(response coding: use probability values), numerical features + project_title(TFIDF W2V)+ preprocessed_eassay (TFIDF W2V)

In [206]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
# with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
X train set 4 = hstack((csr matrix(X train['train pro cat 1'].values).reshape(-1,1), csr matrix(X t
rain['train_pro_cat_0'].values).reshape(-1,1),csr_matrix(X_train['train_pro_subcat_1'].values).resh
ape(-1,1), csr matrix(X train['train pro subcat 0'].values).reshape(-1,1),csr matrix(X train['train
school state 1'].values).reshape(-1,1),csr matrix(X train['train school state 0'].values).reshape(
                      csr_matrix( X_train['train_grade_1'].values).reshape(-1,1),csr_matrix( X_tr
),csr_matrix(X_train['train_prefix_0'].values).reshape(-1,1),x_train_teacher_number,x_train_price,x
train quantity, x train weighted w2v title, x train weighted w2v essay)).tocsr()
X_test_set_4 = hstack((csr_matrix(X_test['test_pro_cat_1'].values).reshape(-1,1),csr_matrix(X_test[
'test_pro_cat_0'].values).reshape(-1,1),csr_matrix(X_test['test_pro_subcat_1'].values).reshape(-1,1)
),csr matrix(X test['test pro subcat 0'].values).reshape(-1,1),csr matrix(X test['test school state
1'].values).reshape(-1,1),csr_matrix(X_test['test_school_state_0'].values).reshape(-1,1),csr_matrix
(X_test['test_grade_1'].values).reshape(-1,1), \
                   csr_matrix(X_test['test_grade_0'].values).reshape(-1,1),csr_matrix(X_test['test_grade_0'].
prefix_1'].values).reshape(-1,1),csr_matrix(X_test['test_prefix_0'].values).reshape(-1,1),x_test_te
acher number, x test price, x test quantity, x test weighted w2v title, x test weighted w2v essay)).t
ocsr()
4
```

In [211]:

```
RF_ = RandomForestClassifier(class_weight = "balanced")
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,10]}
clf = RandomizedSearchCV(RF_, parameters,n_iter = 9, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_4, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_n_estimators'])
```

In [212]:

results

Out[212]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params	
3	0.371997	0.008068	0.011294	0.000687	10	8	{'n_estimators': 10, 'max_depth': 8}	
1	1.079607	0.037545	0.031998	0.002531 50 5		5	{'n_estimators': 50, 'max_depth': 5}	
6	0.470455	0.007614 0.034295 0.000977 50 2		{'n_estimators': 50, 'max_depth': 2}				
8	1.278673	0.067645	0.037629	0.003479	50	6	{'n_estimators': 50, 'max_depth': 6}	
7	3.509688	0.026575	0.064440	0.001643	100	9	{'n_estimators': 100, 'max_depth': 9}	
0	5.057817	0.343219	0.106022	0.018510	150	8	{'n_estimators': 150, 'max_depth': 8}	
5	4.367771	0.087024	0.107195 0.021847 150 7		{'n_estimators': 150, 'max_depth': 7}			
2	2.898401	0.142856	0.177992	0.017325	300	2	{'n_estimators': 300, 'max_depth': 2}	
4	5.676710	0.443878	0.230635	0.034477	300	4	{'n_estimators': 300, 'max_depth': 4}	

9 rows × 22 columns

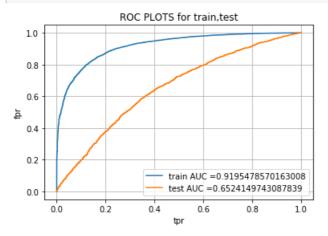
In [213]:

```
# the best value for n_estimators and max_depth from the above table are
best_n_estimator = 10
best_max_depth = 9
```

In [214]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
RF_ = RandomForestClassifier(n_estimators = best_n_estimator, max_depth = best_max_depth, class_wei
ght = "balanced")
RF_.fit(X_train_set_4, 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 = RF_.predict_proba(X_train_set_4)
y_test_pred = RF_.predict_proba(X_test_set_4)
y_train_pred_prob = []
y test pred prob = []
for index in range(len(y train pred)):
    y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y_test_pred)):
    y_test_pred_prob.append(y_test_pred[index][1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



In [215]:

```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.7069230517110097 for threshold 0.521 Train confusion matrix \blacksquare

Out[215]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208a61dba8>

○ - 2578 517



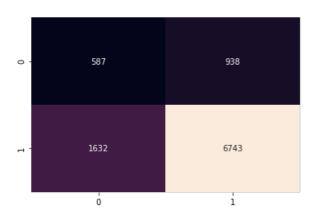
In [216]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[216]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208a5eac18>

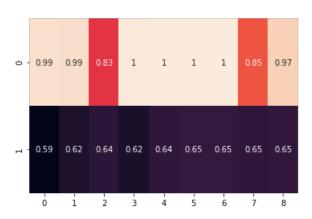


In [218]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores),annot = True,cbar=False)
```

Out[218]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208a639978>



In [117]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_4, y_train, X_test_set_4, y_test, depth, estimators, "RF_")
```

3.2) Gradient Boosted Decision Trees

Set 1) categorical(response coding: use probability values), numerical features + project_title(BOW) + preprocessed_eassay (BOW)

```
In [219]:
```

```
from sklearn.ensemble import GradientBoostingClassifier
```

Calculating Combine Hyper-Parameters

```
In [232]:
```

```
GB_ = GradientBoostingClassifier()
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,1
0]}
clf = RandomizedSearchCV(GB_, parameters,n_iter = 8, scoring='roc_auc', return_train_score=True)
clf.fit(X_train_set_1, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_n_estimators'])
```

In [233]:

```
results
```

Out[233]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
3	0.803711	0.079007	0.003598	0.000373	10	9	{'n_estimators': 10, 'max_depth': 9}
5	0.528480	0.048005	0.004008	0.000318	10	5	{'n_estimators': 10, 'max_depth': 5}
6	2.080649	0.133949	0.004305	0.000808	50	4	{'n_estimators': 50, 'max_depth': 4}
							{'n estimators':

0	ភ ាទ ឧភ <u>ិទ្</u> ទាវ_time	9ta9ft51fime	meanoscore_time	St00_S4€50Pe_time	papam_n_estimators	param_max_depth	100, params
							'max_depth': 7}
1	7.742294	0.273951	0.004285	0.000583	300	2	{'n_estimators': 300, 'max_depth': 2}
4	17.355465	0.679673	0.007097	0.002400	300	7	{'n_estimators': 300, 'max_depth': 7}
7	22.236497	0.838947	0.006911	0.001243	300	9	{'n_estimators': 300, 'max_depth': 9}
2	26.305203	1.319721	0.008696	0.002461	500	7	{'n_estimators': 500, 'max_depth': 7}

8 rows × 22 columns

```
· ·
```

```
In [236]:
```

```
train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std= results['std_test_score']
C_= results['param_n_estimators'].apply(lambda x: math.log10(x))

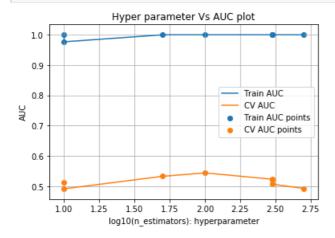
plt.plot(C_, train_auc, label='Train AUC')

plt.scatter(C_, cv_auc, label='Train AUC points')

plt.scatter(C_, cv_auc, label='Train AUC points')

plt.legend()
plt.scatter(C_, cv_auc, label='CV AUC points')

plt.legend()
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [237]:

```
results = results.sort_values(['param_max_depth'])

train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std= results['std_test_score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))

plt.plot(C_, train_auc, label='Train AUC')
```

```
plt.plot(C_, cv_auc, label='CV AUC')

plt.scatter(C_, train_auc, label='Train AUC points')

plt.scatter(C_, cv_auc, label='CV AUC points')

plt.legend()

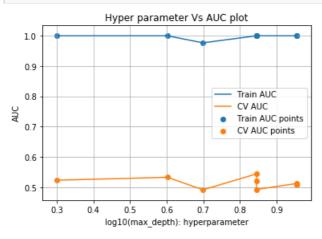
plt.xlabel("log10 (max_depth): hyperparameter")

plt.ylabel("AUC")

plt.title("Hyper parameter Vs AUC plot")

plt.grid()

plt.show()
```

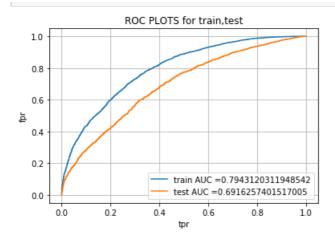


In [234]:

```
# the best value for n_estimators and max_depth from the above graphs are
best_n_estimator = 50
best_max_depth = 4
```

In [235]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.metrics.h
GB_ = GradientBoostingClassifier(n_estimators = best_n_estimator, max_depth = best_max_depth)
GB .fit(X train set 1, 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 = GB .predict proba(X train set 1)
y test_pred = GB_.predict_proba(X_test_set_1)
y_train_pred_prob = []
y_test_pred_prob = []
for index in range(len(y_train_pred)):
          y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y_test_pred)):
          y_test_pred_prob.append(y_test_pred[index][1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



In [238]:

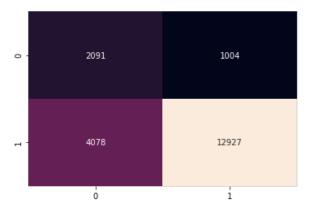
```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.5135875554989766 for threshold 0.829 Train confusion matrix \blacksquare

| P

Out[238]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208d7bda90>



In [239]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[239]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208d87ed68>



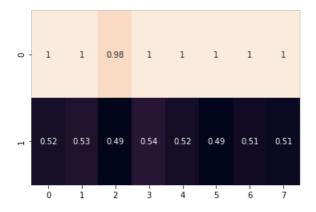


In [240]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores),annot = True, cbar=False)
```

Out[240]:

<matplotlib.axes._subplots.AxesSubplot at 0x2208d8d7cc0>



In [241]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_1, y_train, X_test_set_1, y_test, depth, estimators, algo = "GB_")
```

```
In [242]:
```

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestClassifier
import math
```

Calculating Combine Hyper-Parameters

In [279]:

```
GB_ = GradientBoostingClassifier()
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,10]}
clf = RandomizedSearchCV(GB_, parameters,n_iter = 9, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_2, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_max_depth'])
results
```

Out[279]:

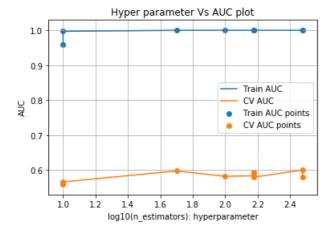
	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
2	12.869973	0.069965	0.004296	0.000398	150	4	{'n_estimators': 150, 'max_depth': 4}
1	1.093199	0.053436	0.003795	0.001113	10	5	{'n_estimators': 10, 'max_depth': 5}
6	8.060015	0.314129	0.002496	0.000441	100	5	{'n_estimators': 100, 'max_depth': 5}
8	26.884331	1.973777	0.004499	0.000444	300	6	{'n_estimators': 300, 'max_depth': 6}
3	24.769889	0.596861	0.005410	0.000382	150	8	{'n_estimators': 150, 'max_depth': 8}
0	9.732167	0.502142	0.004898	0.001117	50	9	('n_estimators': 50, 'max_depth': 9)
5	53.651707	5.584866	0.008706	0.001992	300	9	{'n_estimators': 300, 'max_depth': 9}
7	1.520379	0.065109	0.002502	0.000448	10	9	{'n_estimators': 10, 'max_depth': 9}
4	31.370350	0.579829	0.005707	0.000245	150	10	{'n_estimators': 150, 'max_depth': 10}

9 rows × 22 columns

```
# the best value for n_estimators and max_depth from the above graphs are
best_n_estimator = 50
best_max_depth = 9
```

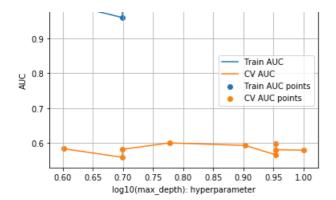
In [281]:

```
results = results.sort_values(['param_n_estimators'])
train_auc= results['mean_train_score']
train auc std= results['std train score']
cv auc = results['mean test score']
cv_auc_std= results['std_test_score']
C_ = results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C_, cv_auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n_estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



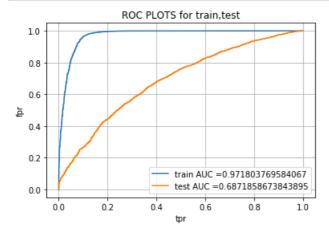
In [282]:

```
results = results.sort_values(['param_max_depth'])
train auc= results['mean train score']
train auc std= results['std train score']
cv_auc = results['mean_test_score']
cv auc std= results['std test score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))
plt.plot(C , train auc, label='Train AUC')
plt.plot(C_, cv_auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(max_depth): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [283]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.metrics.h
GB_ = GradientBoostingClassifier(n_estimators = best_n_estimator, max_depth = best_max_depth)
GB_.fit(X_train_set_2, 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 = GB_.predict_proba(X_train_set_2)
y_test_pred = GB_.predict_proba(X_test_set_2)
y train pred prob = []
y_test_pred_prob = []
for index in range(len(y train pred)):
          y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y_test_pred)):
           y_test_pred_prob.append(y_test_pred[index][1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



In [284]:

```
print("="*100)
from sklearn.metrics import confusion_matrix
boot t = find boot throughold/tr througholds train for train tor)
```

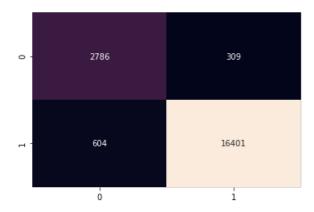
```
pest_t = lind_best_threshold(tr_thresholds, train_lpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.8681887442589109 for threshold 0.808 Train confusion matrix \blacksquare

| | | | | | | |

Out[284]:

<matplotlib.axes._subplots.AxesSubplot at 0x220984f0fd0>



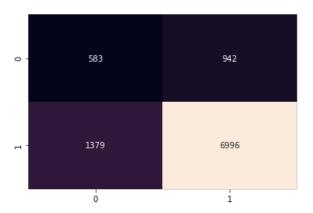
In [285]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[285]:

<matplotlib.axes._subplots.AxesSubplot at 0x2209846e780>

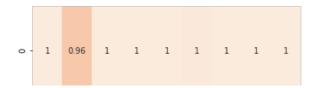


In [287]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores),annot = True, cbar=False)
```

Out[287]:

<matplotlib.axes. subplots.AxesSubplot at 0x220983e9438>



```
- 0.58 0.56 0.58 0.6 0.59 0.57 0.6 0.58 0.58
```

In [151]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_2, y_train, X_test_set_2, y_test, depth, estimators, algo = 'GB_')
```

Set 3) categorical(response coding: use probability values), numerical features + project_title(AVG W2V)+ preprocessed_eassay (AVG W2V)

Calculating Combine Hyper-Parameters

In [261]:

```
GB_ = GradientBoostingClassifier()
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,1
0]}
clf = RandomizedSearchCV(GB_, parameters,n_iter = 8, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_3, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_n_estimators'])
results
```

Out[261]:

		mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
								{'n_estimators':
1:	2	0.659660	0.024315	0.003902	0.001110	10	2	10,

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	ˈmax_d pataˈm͡s
5	1.251189	0.021426	0.003403	0.000376	10	4	{'n_estimators': 10, 'max_depth': 4}
1	20.470414	0.633090	0.006907	0.002611 100 6		{'n_estimators': 100, 'max_depth': 6}	
3	10.095314	0.721341	0.004967	0.001814	150	2	{'n_estimators': 150, 'max_depth': 2}
4	14.488546	0.815637	0.004400	0.000974	150	3	{'n_estimators': 150, 'max_depth': 3}
6	36.070863	5.697585	0.005698	0.001070	300	5	{'n_estimators': 300, 'max_depth': 5}
7	37.875498	0.954277	0.005904	0.000749	300	4	{'n_estimators': 300, 'max_depth': 4}
0	27.377544	3.319729	0.005572	0.000985	1000	7	{'n_estimators': 1000, 'max_depth': 7}

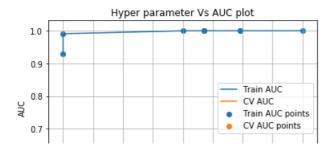
8 rows × 22 columns

In [262]:

```
# the best value for n_estimators and max_depth from the above graphs are
best_n_estimator = 150
best_max_depth = 3
```

In [263]:

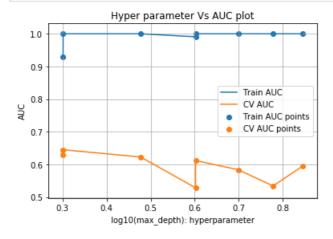
```
results = results.sort_values(['param_n_estimators'])
train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv auc = results['mean test score']
cv_auc_std= results['std_test_score']
C_ = results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n_estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



```
0.6 0.5 1.00 1.25 1.50 1.75 2.00 2.25 2.50 2.75 3.00 log10(n_estimators): hyperparameter
```

In [264]:

```
results = results.sort_values(['param_max_depth'])
train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv auc = results['mean test score']
cv_auc_std= results['std_test_score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C , cv auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(max_depth): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```

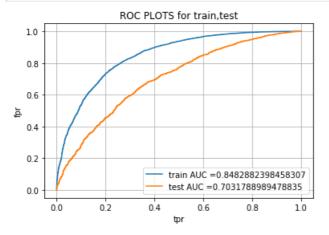


In [265]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html \# sklearn.html \# sklea
GB_ = GradientBoostingClassifier(n_estimators = best_n_estimator, max_depth = best_max_depth)
GB_.fit(X_train_set_3, 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 = GB_.predict_proba(X_train_set_3)
y test pred = GB .predict proba(X test set 3)
y train pred prob = []
y test pred prob = []
for index in range(len(y train pred)):
             y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y test pred)):
              y_test_pred_prob.append(y_test_pred[index][1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred_prob)
test fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
```

```
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train,test")
plt.grid()
plt.show()
```



In [266]:

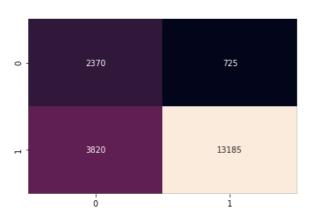
```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

.....

the maximum value of tpr*(1-fpr) 0.5937330035497496 for threshold 0.831 Train confusion matrix \P

Out[266]:

<matplotlib.axes._subplots.AxesSubplot at 0x22098634f98>



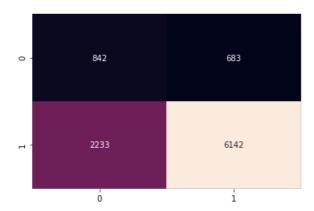
In [267]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[267]:

<matplotlib.axes._subplots.AxesSubplot at 0x220986c7780>

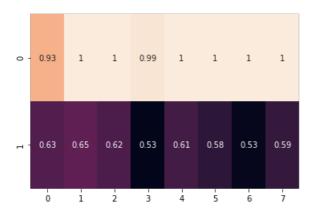


In [269]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores), annot = True, cbar=False)
```

Out[269]:

<matplotlib.axes._subplots.AxesSubplot at 0x220986e6588>



In [118]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_3, y_train, X_test_set_3, y_test, depth, estimators, algo = "GB_")
```

Set 4) categorical(response coding: use probability values), numerical features + project_title(TFIDF W2V)+ preprocessed_eassay (TFIDF W2V)

Calculating Combine Hyper-Parameters

In [278]:

```
GB_ = GradientBoostingClassifier()
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2,3,4,5,6,7,8,9,1
0]}
clf = RandomizedSearchCV(GB_, parameters,n_iter = 8, scoring='roc_auc', return_train_score = True)
clf.fit(X_train_set_4, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)
results = results.sort_values(['param_n_estimators'])
results
```

Out[278]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_depth	params
0	0.949910	0.016993	0.003100	0.000200	10	3	{'n_estimators': 10, 'max_depth': 3}
3	1.244781	0.026956	0.003100	0.000188	10	{'n_estimato 4 10, 'max_depth'	
4	12.358133	0.226298	0.004489	0.000711	50	8	{'n_estimators': 50, 'max_depth': 8}
1	6.395110	0.078714	0.003395	0.000379	100	2	{'n_estimators': 100, 'max_depth': 2}
2	23.609481	0.533504	0.004304	0.000238	150	5	{'n_estimators': 150, 'max_depth': 5}
5	25.645134	1.874733	0.004691	0.000235	150	7	{'n_estimators': 150, 'max_depth': 7}
7	14.532658	0.386343	0.004300	0.000677	150	3 ('n_esti 150, 'max_d	
6	19.416899	0.542825	0.005507	0.000531	300	2	{'n_estimators': 300, 'max_depth': 2}

8 rows × 22 columns

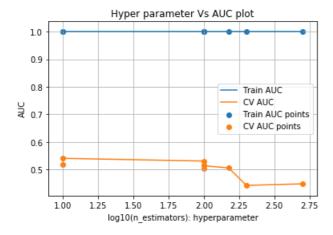
| d |

In [271]:

```
# the best value for n_estimators and max_depth from the above graphs are
best_n_estimator = 10
best_max_depth = 10
```

In [272]:

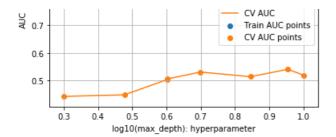
```
results = results.sort_values(['param_n_estimators'])
train auc= results['mean train score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv auc std= results['std test score']
C_ = results['param_n_estimators'].apply(lambda x: math.log10(x))
plt.plot(C , train auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(n_estimators): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```



In [273]:

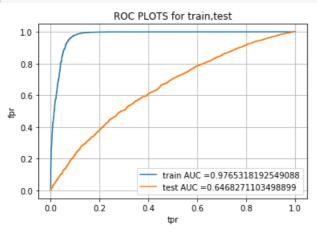
```
results = results.sort_values(['param_max_depth'])
train auc= results['mean train score']
train_auc_std= results['std_train_score']
cv auc = results['mean test score']
cv_auc_std= results['std_test_score']
C_ = results['param_max_depth'].apply(lambda x: math.log10(x))
plt.plot(C_, train_auc, label='Train AUC')
plt.plot(C , cv auc, label='CV AUC')
plt.scatter(C_, train_auc, label='Train AUC points')
plt.scatter(C_, cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log10(max_depth): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```





In [274]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
GB = GradientBoostingClassifier(n estimators = best n estimator, max depth = best max depth)
GB .fit(X_train_set_4, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
# not the predicted outputs
y_train_pred = GB_.predict_proba(X_train_set_4)
y_test_pred = GB_.predict_proba(X_test_set_4)
y_train_pred_prob = []
y test pred prob = []
for index in range(len(y train pred)):
   y_train_pred_prob.append(y_train_pred[index][1])
for index in range(len(y_test_pred)):
    y_test_pred_prob.append(y_test_pred[index][1])
train fpr, train tpr, tr thresholds = roc curve (y train, y train pred prob)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred_prob)
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("tpr")
plt.ylabel("fpr")
plt.title("ROC PLOTS for train, test")
plt.grid()
plt.show()
```



In [275]:

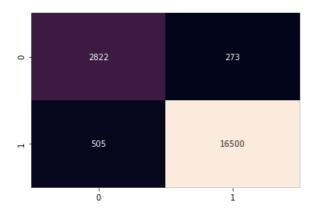
```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train_confusion_matrix")
sns.heatmap(confusion_matrix(y_train, predict_with_best_t(y_train_pred_prob, best_t)),annot = True,
fmt = "d", cbar=False)
```

the maximum value of tpr*(1-fpr) 0.8847155569088061 for threshold 0.83 Train confusion matrix



Out[275]:

<matplotlib.axes. subplots.AxesSubplot at 0x220986916a0>



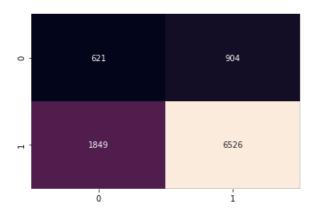
In [276]:

```
print("Test confusion matrix")
sns.heatmap(confusion_matrix(y_test, predict_with_best_t(y_test_pred_prob, best_t)), annot = True,
fmt = "d", cbar=False)
```

Test confusion matrix

Out[276]:

<matplotlib.axes._subplots.AxesSubplot at 0x22098596860>

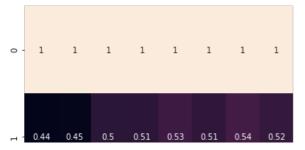


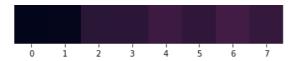
In [277]:

```
scores = [results['mean_train_score'].values, results['mean_test_score'].values]
sns.heatmap(np.asarray(scores), annot = True, cbar=False)
```

Out[277]:

<matplotlib.axes._subplots.AxesSubplot at 0x2209856ab70>





In [94]:

```
depth = [2,3,4,5,6,7,8,9,10]
estimators = [10,50,100,150,200,300,500]
plot_3d_plot(X_train_set_4, y_train, X_test_set_4, y_test, depth, estimators, algo = 'GB_')
```

In [124]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Dataset", "best_n_estimator", "best_max_depth", "Train AUC", "Test AUC"]

x.add_row(["RandomForestClassfier", "BOW", 200, 9, 0.8760, 0.7002])

x.add_row(["RandomForestClassfier", "TFIDF", 300, 8, 0.8891, 0.6963])

x.add_row(["RandomForestClassfier", "AVG W2V", 500, 4, 0.7576, 0.6950])

x.add_row(["RandomForestClassfier", "TFIDF W2V", 10, 9, 0.9195, 0.6524])

x.add_row(["GradientBoostingClassifier", "BOW", 50, 4, 0.7943, 0.6916])

x.add_row(["GradientBoostingClassifier", "TFIDF", 50, 9, 0.9718, 0.6871])

x.add_row(["GradientBoostingClassifier", "AVG W2v", 150, 3, 0.8482, 0.7031])

x.add_row(["GradientBoostingClassifier", "TFIDF W2V", 10, 10, 0.9765, 0.6468])

print(x)
```

	Model	+ Dataset	best_n_estimator	1	'	+ Test AUC
+	RandomForestClassfier	+ BOW	200	-+ 9	0.876	0.7002
	RandomForestClassfier	TFIDF	300	8	0.8891	0.6963
	RandomForestClassfier	AVG W2V	500	4	0.7576	0.695
i	RandomForestClassfier	TFIDF W2V	10	9	0.9195	0.6524

			+		+		-+-	Þ
GradientBoostingClassifier TFID	F W2V	10	1	10	I	0.9765	I	0.6468
GradientBoostingClassifier AVG	W2v	150	1	3	1	0.8482	I	0.7031
GradientBoostingClassifier TF	IDF	50	1	9	1	0.9718	I	0.6871
GradientBoostingClassifier Be	I WC	50	1	4	1	0.7943		0.6916