# Random Forest and GBDT on DonorsChoose

DonorsChoose.org receives hundreds of thousands of project proposals each year for classroom projects in need of funding. Right now, a large number of volunteers is needed to manually screen each submission before it's approved to be posted on the DonorsChoose.org website. Next year, DonorsChoose.org expects to receive close to 500,000 project proposals. As a result, there are three main problems they need to solve: How to scale current manual processes and resources to screen 500,000 projects so that they can be posted as quickly and as efficiently as possible How to increase the consistency of project vetting across different volunteers to improve the experience for teachers How to focus volunteer time on the applications that need the most assistance

The goal of the competition is to predict whether or not a DonorsChoose.org project proposal submitted by a teacher will be approved, using the text of project descriptions as well as additional metadata about the project, teacher, and school. DonorsChoose.org can then use this information to identify projects most likely to need further review before approval.

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
import chart studio.plotly as py
from scipy.sparse import hstack
import chart studio.plotly as py
```

### 1. LOAD AND PROCESS DATA

from collections import Counter

### 1.1 Reading Data

```
project data=pd.merge(data, price data, on='id', how='left')
                                                                                                                                                                                                                                 In [5]:
 project_data.columns
                                                                                                                                                                                                                               Out[5]:
Index(['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',
                'price', 'quantity'],
             dtype='object')
1.2 process Project Essay
                                                                                                                                                                                                                                 In [6]:
 project_data.head(3)
                                                                                                                                                                                                                               Out[6]:
      Unnamed:
                                  id
                                                                                teacher_id teacher_prefix school_state project_submitted_datetime project_grade_category pr
                   Λ
 0
          160221 p253737 c90749f5d961ff158d4b4d1e7dc665fc
                                                                                                                  Mrs
                                                                                                                                            IN
                                                                                                                                                               2016-12-05 13:43:57
                                                                                                                                                                                                                Grades PreK-2
                                                                                                                   Mr.
          140945 p258326 897464ce9ddc600bced1151f324dd63a
                                                                                                                                           FI
                                                                                                                                                              2016-10-25 09:22:10
                                                                                                                                                                                                                     Grades 6-8
            21895 p182444 3465aaf82da834c0582ebd0ef8040ca0
                                                                                                                Ms.
                                                                                                                                           Α7
                                                                                                                                                               2016-08-31 12:03:56
                                                                                                                                                                                                                     Grades 6-8
                                                                                                                                                                                                                                 In [7]:
 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 [8]:
 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"n\'t", " not", phrase)
          phrase = re.sub(r"\'re", " are", phrase)
          phrase = re.sub(r"\'s", " is", 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"\'ve", " have", phrase)
          phrase = re.sub(r"\'m", " am", phrase)
         return phrase
                                                                                                                                                                                                                                 In [9]:
 stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", \
                            "you'll", "you'd", 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'this', 'they', 'they
                            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while'
                            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'befor 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'aga. 'then', 'once', 'here', 'there', 'where', 'why', 'how', 'all', 'any', 'both', 'each',
```

In [4]:

```
'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',
              've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't
              "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", '
              "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'w
              'won', "won't", 'wouldn', "wouldn't"]
                                                                                                           In [10]:
from tqdm import tqdm
preprocessed essays = []
 # tqdm is for printing the status bar
for sentance in tqdm(project data['essay'].values):
     sent = decontracted(sentance)
     sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
    sent = sent.replace('\\n', ' ')
     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())
project_data['cleaned_essay']=preprocessed_essays
100%| 50000/50000 [00:26<00:00, 1888.95it/s]
1.2 process Project Title
                                                                                                           In [11]:
 # https://stackoverflow.com/a/47091490/4084039
from tqdm import tqdm
preprocessed_title = []
 # tqdm is for printing the status bar
for sentance in tqdm(data['project title'].values):
     sent = decontracted(sentance)
     sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
     sent = sent.replace('\\n', ' ')
     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 title.append(sent.lower().strip())
project_data['cleaned_project_title'] = preprocessed_title
100%|
              | 50000/50000 [00:01<00:00, 38272.34it/s]
1.3 teacher_prefix
                                                                                                           In [12]:
temp1=data.teacher prefix.apply(lambda x: str(x).replace('.', ''))
project data['teacher prefix']=temp1
project_data['teacher_prefix'].value_counts()
                                                                                                          Out[12]:
          26140
Mrs
Mς
           17936
Μr
            4859
Teacher
            1061
               2
nan
Name: teacher prefix, dtype: int64
1.4 project grade
                                                                                                           In [13]:
project_data.project_grade_category.value_counts()
                                                                                                          Out[13]:
Grades PreK-2
                  20316
Grades 3-5
                  16968
                  7750
Grades 6-8
                 4966
Grades 9-12
Name: project_grade_category, dtype: int64
                                                                                                           In [14]:
grade list=[]
for i in project data['project grade category'].values:
    i=i.replace(' ','_')
i=i.replace('-','_')
     grade list.append(i.strip())
```

```
project_data['project_grade_category']=grade_list
                                                                                                                                                                     In [15]:
project_data['project_grade_category'].value_counts()
                                                                                                                                                                   Out[15]:
Grades PreK 2
                           20316
Grades 3 5
                           16968
Grades 6 8
                            7750
                            4966
Grades 9 12
Name: project_grade_category, dtype: int64
1.5 project_subject_categories
                                                                                                                                                                     In [16]:
catogories = list(project_data['project_subject_categories'].values)
 # 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
cat list = []
 for i in catogories:
       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 & Science"=> '
              j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e renty j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Science"=>"Next to be a simple of the state 
              temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the trailing spaces
              temp = temp.replace('&','_') \# we are replacing the & value into
       cat list.append(temp.strip())
project data['clean categories'] = cat list
project data.drop(['project subject categories'], axis=1, inplace=True)
from collections import Counter
my counter = Counter()
 for word in project data['clean categories'].values:
       my counter.update(word.split())
cat dict = dict(my counter)
sorted cat dict = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
1.6 project_subject_subcategories
                                                                                                                                                                     In [17]:
sub catogories = list(project data['project subject subcategories'].values)
 # 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
sub cat list = []
for i in sub catogories:
       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 & Science"=> '
                    j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e rem
              j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Science"=>"N
              temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the trailing spaces
              temp = temp.replace('&',' ')
       sub cat list.append(temp.strip())
project data['clean subcategories'] = sub cat list
project_data.drop(['project_subject_subcategories'], axis=1, inplace=True)
 # count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
mv counter = Counter()
 for word in project data['clean subcategories'].values:
       my_counter.update(word.split())
```

```
sub cat dict = dict(my counter)
sorted_sub_cat_dict = dict(sorted(sub_cat_dict.items(), key=lambda kv: kv[1]))
1.7 counting words in title
                                                                                                            In [18]:
#https://stackoverflow.com/questions/49984905/count-number-of-words-per-row
project data['totalwords title'] = project data['cleaned project title'].str.split().str.len()
1.8 number of words in the essay
                                                                                                            In [19]:
project data['totalwords essay'] = project data['cleaned essay'].str.split().str.len()
1.9 sentiment score's of each of the essay
                                                                                                            In [20]:
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyser = SentimentIntensityAnalyzer()
neg=[]
compound=[]
pos=[]
neu=[]
for sent in (project data['cleaned essay'].values):
     score = analyser.polarity_scores(sent)
    neg.append(score.get('neg'))
    neu.append(score.get('neu'))
    pos.append(score.get('pos'))
    compound.append(score.get('compound'))
project data['neg']=neg
project data['neu']=neu
project data['pos']=pos
project data['compound']=compound
1.10 droping unnecesarry columns
                                                                                                            In [21]:
project_data.drop(['project_title'], axis=1, inplace=True)
project_data.drop(['project_essay_1'], axis=1, inplace=True)
project_data.drop(['project_essay_2'], axis=1, inplace=True)
project_data.drop(['project_essay_3'], axis=1, inplace=True)
project_data.drop(['project_essay_4'], axis=1, inplace=True)
                                                                                                            In [22]:
project data.head(3)
                                                                                                           Out[22]:
   Unnamed:
                iЫ
                                       teacher_id teacher_prefix school_state project_submitted_datetime project_grade_category pr
     160221 p253737 c90749f5d961ff158d4b4d1e7dc665fc
                                                                             2016-12-05 13:43:57
                                                                                                    Grades_PreK_2
                                                        Mrs
                                                                    IN
    140945 p258326 897464ce9ddc600bced1151f324dd63a
                                                         Mr
                                                                    FL
                                                                             2016-10-25 09:22:10
                                                                                                       Grades_6_8
      21895 p182444 3465aaf82da834c0582ebd0ef8040ca0
                                                         Ms
                                                                    ΑZ
                                                                             2016-08-31 12:03:56
                                                                                                       Grades_6_8
3 rows × 23 columns
                                                                                                                Þ
1.11 Making dependant (label) and independant variables
                                                                                                            In [23]:
y = project data['project is approved'].values
project data.head(1)
```

x=project\_data
x.head(3)

teacher\_id teacher\_prefix school\_state project\_submitted\_datetime project\_grade\_category pr

Unnamed: id

160221 p253737 c90749f5d961ff158d4b4d1e7dc665fc Mrs IN 2016-12-05 13:43:57 Grades\_PreK\_2

. 140945 p258326 897464ce9ddc600bced1151f324dd63a Mr FL 2016-10-25 09:22:10 Grades\_6\_8

**2** 21895 p182444 3465aaf82da834c0582ebd0ef8040ca0 Ms AZ 2016-08-31 12:03:56 Grades\_6\_8

3 rows × 23 columns

**1** 

## 1.12 Traing and Test split

In [25]:

```
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,random_state=42)
#X_train, X_cv, Y_train, Y_cv = train_test_split(X_train,Y_train, test_size=0.33, stratify=Y_train,random_state=42)
```

# 2. Text Vectorization and encoding catagories, normalization numerical features

# 2.1 converting the essay to vectors using BOW

In [28]:

```
from sklearn.feature extraction.text import CountVectorizer
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X train['cleaned essay'].values) # fit has to happen only on train data
\# we use the fitted CountVectorizer to convert the text to vector
X train essay bow = vectorizer.transform(X train['cleaned essay'].values)
#X_cv_essay_bow = vectorizer.transform(X_cv['cleaned_essay'].values)
X_test_essay_bow = vectorizer.transform(X_test['cleaned_essay'].values)
print("After vectorizations")
print(X_train_essay_bow.shape, Y_train.shape)
print(X test essay bow.shape, Y test.shape)
print (X cv essay bow.shape, Y cv.shape)
print("="*100)
After vectorizations
(22445, 5000) (22445,)
(16500, 5000) (16500,)
(11055, 5000) (11055,)
```

# 2.2 converting the title to vectors using BOW

In [29]:

```
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X_train['cleaned_project_title'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_title_bow = vectorizer.transform(X_train['cleaned_project_title'].values)

#X_cv_title_bow = vectorizer.transform(X_cv['cleaned_project_title'].values)
X_test_title_bow = vectorizer.transform(X_test['cleaned_project_title'].values)

print("After vectorizations")
print(X_train_title_bow.shape, Y_train.shape)
print(X_cv_title_bow.shape, Y_cv.shape)
print(X_test_title_bow.shape, Y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 2004) (22445,)
(11055, 2004) (11055,)
(16500, 2004) (16500,)
```

## 2.3 converting the title to vectors using TFIDF

```
In [31]:
vectorizer = TfidfVectorizer(min df=10)
vectorizer.fit(X train['cleaned project title'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train title tfidf = vectorizer.transform(X train['cleaned project title'].values)
#X cv title tfidf = vectorizer.transform(X cv['cleaned project title'].values)
X test title tfidf = vectorizer.transform(X test['cleaned project title'].values)
print("After vectorizations")
print(X train title tfidf.shape, Y train.shape)
print(X cv title tfidf.shape, Y cv.shape)
print(X_test_title_tfidf.shape, Y_test.shape)
print("="*100)
After vectorizations
(22445, 1229) (22445,)
(11055, 1229) (11055,)
(16500, 1229) (16500,)
______
```

## 2.4 converting the essay to vectors using TFIDF

```
vectorizer = TfidfVectorizer (min_df=10)
vectorizer.fit(X_train['cleaned_essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_tfidf = vectorizer.transform(X_train['cleaned_essay'].values)
#X_cv_essay_tfidf = vectorizer.transform(X_cv['cleaned_essay'].values)
X_test_essay_tfidf = vectorizer.transform(X_test['cleaned_essay'].values)

print("After vectorizations")
print(X_train_essay_tfidf.shape, Y_train.shape)
print(X_cv_essay_tfidf.shape, Y_cv.shape)
print(X_test_essay_tfidf.shape, Y_test.shape)
print("="*100)

After vectorizations
(22445, 8869) (22445,)
(11055, 8869) (11055,)
(16500, 8869) (16500,)
```

In [32]:

In [33]:

## 2.5 load glove mode

```
# 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!
# -----
```

```
1544it [00:00, 7538.34it/s]
Loading Glove Model
1917495it [03:58, 8038.90it/s]
Done. 1917495 words loaded!
                                                                                                    Out[33]:
             \nLoading Glove Model\n1917495it [06:32, 4879.69it/s]\nDone. 1917495 words loaded!\n'
'Output:\n
                                                                                                     In [34]:
words = []
for i in X train['cleaned essay'].values:
    words.extend(i.split(' '))
for i in X_train['cleaned_project_title'].values:
    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-save-and
import pickle
with open('glove vectors', 'wb') as f:
    pickle.dump(words_courpus, f)
all the words in the coupus 3499621
the unique words in the coupus 31643
The number of words that are present in both glove vectors and our coupus 29734 ( 93.967 %)
word 2 vec length 29734
                                                                                                     In [35]:
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-save-and
# make sure you have the glove vectors file
with open('glove_vectors', 'rb') as f:
    model = pickle.load(f)
    glove words = set(model.keys())
2.6 Avg w2v on essay
                                                                                                     In [36]:
Text avg w2v train essay= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['cleaned_essay'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =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:
            vector += model[word]
            cnt words += 1
    if cnt words != 0:
        vector /= cnt words
    Text avg w2v train essay.append(vector)
print(len(Text_avg_w2v_train_essay))
print(len(Text_avg_w2v_train_essay[0]))
       22445/22445 [00:07<00:00, 3001.38it/s]
22445
300
                                                                                                     In [37]:
''''Text avg w2v cv essay= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv['cleaned essay'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =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:
            vector += model[word]
            cnt\_words += 1
```

```
if cnt words != 0:
        vector /= cnt_words
    Text avg w2v cv essay.append(vector)
print(len(Text_avg_w2v_cv_essay))
print(len(Text avg w2v cv essay[0]))
        | 11055/11055 [00:03<00:00, 2936.08it/s]
11055
300
                                                                                                    In [38]:
Text avg w2v test essay= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test['cleaned essay'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =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:
            vector += model[word]
            cnt words += 1
    if cnt words != 0:
        vector /= cnt_words
    Text avg w2v test essay.append(vector)
print(len(Text avg w2v test essay))
print(len(Text avg w2v test essay[0]))
100%| 16500/16500 [00:05<00:00, 3068.97it/s]
16500
300
                                                                                                      In [ ]:
2.7 Avg w2v on title
                                                                                                    In [39]:
Text avg w2v train title= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['cleaned project title'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =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:
            vector += model[word]
            cnt words += 1
    if cnt words != 0:
        vector /= cnt words
    Text avg w2v train title.append(vector)
print(len(Text avg w2v train title))
print(len(Text avg w2v train title[0]))
100%|
       22445/22445 [00:00<00:00, 64112.56it/s]
22445
300
                                                                                                    In [40]:
''''Text avg w2v cv title= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv['cleaned project title'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =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:
            vector += model[word]
            cnt words += 1
    if cnt words != 0:
        vector /= cnt words
    Text avg w2v cv title.append(vector)
print(len(Text avg w2v cv title))
print(len(Text avg w2v cv title[0]))
100%| 11055/11055 [00:00<00:00, 62313.07it/s]
11055
300
                                                                                                    In [41]:
Text avg w2v test title= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test['cleaned project title'].values): # for each review/sentence
```

vector = np.zeros(300) # as word vectors are of zero length

```
cnt words =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:
            vector += model[word]
            cnt_words += 1
    if cnt words != 0:
        vector /= cnt words
    Text avg w2v test title.append(vector)
print(len(Text_avg_w2v_test_title))
print(len(Text_avg_w2v_test_title[0]))
        | 16500/16500 [00:00<00:00, 63445.37it/s]
16500
300
2.4 TFIDF weighted W2V on essay
                                                                                                    In [47]:
\# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf model = TfidfVectorizer()
tfidf_model.fit(X_train['cleaned_essay'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf model.get feature names(), list(tfidf model.idf )))
tfidf words = set(tfidf model.get feature names())
                                                                                                    In [48]:
Text tfidf w2v train essay= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['cleaned essay'].values): # 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),
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf va
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf idf weight
    Text tfidf w2v train essay.append(vector)
print(len(Text_tfidf_w2v_train_essay))
print(len(Text tfidf w2v train essay[0]))
100%| 22445/22445 [00:55<00:00, 401.57it/s]
22445
300
                                                                                                    In [49]:
''''Text tfidf w2v cv essay= []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['cleaned_essay'].values): # 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),
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split()))  # getting the tfidf variable.
            vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf_idf_weight
    Text tfidf w2v cv essay.append(vector)
print(len(Text tfidf w2v cv essay))
print(len(Text tfidf w2v cv essay[0]))
100%| 11055/11055 [00:27<00:00, 406.31it/s]
11055
300
                                                                                                     In [50]:
```

Text\_tfidf\_w2v\_test\_essay= [];
for sentence in tqdm(X\_test['cleaned\_essay'].values): # 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),
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf va
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf idf weight
    Text tfidf w2v test essay.append(vector)
print(len(Text_tfidf_w2v_test_essay))
print(len(Text_tfidf_w2v_test_essay[0]))
        | 16500/16500 [00:40<00:00, 411.46it/s]
16500
300
2.5 TFIDF weighted W2V on title
                                                                                                     In [51]:
                                                                                                     In [52]:
```

```
\# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf model = TfidfVectorizer()
tfidf model.fit(X_train['cleaned_project_title'].values)
 # we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf model.get feature names(), list(tfidf model.idf )))
tfidf words = set(tfidf model.get feature names())
Text tfidf w2v train title= [];
for sentence in tqdm(X train['cleaned project title'].values): # 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),
                        tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf va
                        vector += (vec * tf idf) # calculating tfidf weighted w2v
                        tf idf_weight += tf_idf
         if tf idf weight != 0:
                vector /= tf idf weight
         Text tfidf w2v train title.append(vector)
print(len(Text_tfidf_w2v_train_title))
print(len(Text tfidf w2v train title[0]))
100%| 22445/22445 [00:00<00:00, 28213.44it/s]
22445
300
                                                                                                                                                                                                   In [53]:
 ''''Text tfidf w2v cv title= [];
for sentence in tqdm(X_cv['cleaned\_project\_title'].values): # 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),
                        tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split()))  # getting the tfidf variable.
                        vector += (vec * tf_idf) # calculating tfidf weighted w2v
                        tf idf weight += tf idf
         if tf idf weight != 0:
                vector /= tf_idf_weight
        Text tfidf w2v cv title.append(vector)
print(len(Text tfidf w2v cv title))
print(len(Text tfidf w2v cv title[0]))
100%| 11055/11055 [00:00<00:00, 29009.32it/s]
11055
300
                                                                                                                                                                                                   In [54]:
Text_tfidf_w2v_test_title= [];
\textbf{for} \ \texttt{sentence} \ \textbf{in} \ \texttt{tqdm} (\texttt{X\_test['cleaned\_project\_title'].values}): \ \textit{\# for each review/sentence} \ \textbf{for 
         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),
             tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf va
             vector += (vec * tf idf) # calculating tfidf weighted w2v
             tf idf weight += tf idf
    if tf_idf_weight != 0:
        vector /= tf idf weight
    Text tfidf w2v test title.append(vector)
print(len(Text_tfidf_w2v_test_title))
print(len(Text_tfidf_w2v_test_title[0]))
        | 16500/16500 [00:00<00:00, 28295.55it/s]
16500
300
                                                                                                          In [55]:
X train.columns
                                                                                                          Out[55]:
Index(['Unnamed: 0', 'id', 'teacher id', 'teacher prefix', 'school state',
       'project_submitted_datetime', 'project_grade_category',
       'project_resource_summary',
       'teacher_number_of_previously_posted_projects', 'project_is_approved', 'price', 'quantity', 'essay', 'cleaned_essay', 'cleaned_project_title', 'clean_categories', 'clean_subcategories', 'totalwords_title',
       'totalwords_essay', 'neg', 'neu', 'pos', 'compound'],
      dtype='object')
2.6 Categories with response coding
                                                                                                          In [56]:
def Responsetable(table, col) :
    cat = table[col].unique()
    alpha=1
    freq_Pos = []
    for i in cat :
         freq Pos.append(len(table.loc[(table[col] == i) & (table['project is approved'] == 1)]))
    freq Neg = []
    for i in cat :
         freq Neq.append(len(table.loc[(table[col] == i) & (table['project is approved'] == 0)]))
    encoded Pos = []
    for i in range(len(cat)) :
         encoded_Pos.append(((freq_Pos[i]+alpha)/(freq_Pos[i] + freq_Neg[i]+alpha)))
    encoded Neg = []
    encoded_Neg[:] = [1 - x for x in encoded_Pos]
    encoded_Pos_val = dict(zip(cat, encoded_Pos))
    encoded Neg val = dict(zip(cat, encoded Neg))
    return encoded_Pos_val, encoded_Neg_val
                                                                                                          In [57]:
def Responsecode(table) :
    pos_cleancat, neg_cleancat = Responsetable(table,'clean_categories')
    pos_cleansubcat, neg_cleansubcat = Responsetable(table,'clean_subcategories')
    pos schoolstate, neg schoolstate = Responsetable(table, 'school state')
    pos_teacherprefix, neg_teacherprefix = Responsetable(table, 'teacher_prefix')
    pos_projgradecat, neg_projgradecat = Responsetable(table, 'project_grade_category')
    df = pd.DataFrame()
    df['clean cat pos'] = table['clean categories'].map(pos cleancat)
    df['clean cat neg'] = table['clean categories'].map(neg cleancat)
    df['clean_subcat_pos'] = table['clean_subcategories'].map(pos_cleansubcat)
    df['clean subcat neg'] = table['clean subcategories'].map(neg cleansubcat)
    df['school state pos'] = table['school state'].map(pos schoolstate)
    df['school state neg'] = table['school state'].map(neg schoolstate)
    df['teacher prefix pos'] = table['teacher prefix'].map(pos teacherprefix)
    df['teacher_prefix_neg'] = table['teacher_prefix'].map(neg_teacherprefix)
    df['proj_grade_cat_pos'] = table['project_grade_category'].map(pos_projgradecat)
    df['proj grade cat neg'] = table['project grade category'].map(neg projgradecat)
```

```
In [59]:
newTrain = Responsecode(X train)
newTest = Responsecode (X test)
#newCv=Responsecode(X cv)
                                                                                                       In [60]:
def mergeEncoding(table, p, n) :
    lstPos = table[p].values.tolist()
    lstNeg = table[n].values.tolist()
    frame = pd.DataFrame(list(zip(lstNeg, lstPos)))
    return frame
2.7 response code of clean_categories
                                                                                                       In [61]:
X train clean cat resposecode = mergeEncoding(newTrain, 'clean cat pos', 'clean cat neg')
X_test_clean_cat_resposecode = mergeEncoding(newTest, 'clean_cat_pos', 'clean_cat_neg')
#X cv clean cat resposecode=mergeEncoding(newCv, 'clean cat pos', 'clean cat neg')
print(X train clean cat resposecode.shape)
(22445, 2)
2.8 response code of clean_sub_categories
                                                                                                       In [63]:
X_train_clean_subcat_resposecode = mergeEncoding(newTrain, 'clean_subcat_pos', 'clean_subcat_neg')
X test clean subcat resposecode = mergeEncoding(newTest, 'clean subcat pos', 'clean subcat neg')
#X cv clean subcat resposecode = mergeEncoding(newCv, 'clean subcat pos', 'clean subcat neg')
print(X_train_clean_subcat_resposecode.shape)
print(X test clean subcat resposecode.shape)
#print(X cv clean subcat resposecode.shape)
(22445, 2)
(16500, 2)
(11055, 2)
2.9 response code of project grade
                                                                                                       In [64]:
X train grade resposecode = mergeEncoding(newTrain, 'proj grade cat pos', 'proj grade cat neg')
X_test_grade_resposecode = mergeEncoding(newTest, 'proj_grade_cat_pos', 'proj_grade_cat_neg')
#X cv grade resposecode = mergeEncoding(newCv, 'proj grade cat pos', 'proj grade cat neg')
print(X_train_grade_resposecode.shape)
print(X_test_grade_resposecode.shape)
#print(X cv grade resposecode.shape)
(22445, 2)
(16500, 2)
(11055, 2)
2.10 response code of school state
                                                                                                       In [66]:
X train state resposecode = mergeEncoding(newTrain, 'school state pos', 'school state neg')
X_test_state_resposecode = mergeEncoding(newTest, 'school_state_pos', 'school_state_neg')
#X_cv_state_resposecode = mergeEncoding(newCv, 'school_state_pos', 'school_state_neg')
print(X train state resposecode.shape)
print(X_test_state_resposecode.shape)
#print(X cv state resposecode.shape)
(22445, 2)
(16500, 2)
(11055, 2)
2.11 response code of teacher prefix
                                                                                                       In [65]:
X train teacher resposecode = mergeEncoding(newTrain, 'teacher prefix pos', 'teacher prefix neg')
X test teacher resposecode = mergeEncoding(newTest, 'teacher prefix pos', 'teacher prefix neg')
#X_cv_teacher_resposecode = mergeEncoding(newCv, 'teacher_prefix_pos', 'teacher_prefix neg')
print(X train teacher resposecode.shape)
print (X test teacher resposecode.shape)
#print(X cv teacher resposecode.shape)
(22445, 2)
(16500, 2)
(11055, 2)
```

### 2.12 Normalizing the numerical features: Price

```
In [68]:
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X train['price'].values.reshape(-1,1))
X train price norm = normalizer.transform(X train['price'].values.reshape(-1,1))
X test price norm = normalizer.transform(X test['price'].values.reshape(-1,1))
#X cv price norm = normalizer.transform(X cv['price'].values.reshape(-1,1))
print("After vectorizations")
print(X train price norm.shape, Y train.shape)
#print(X_cv_price_norm.shape, Y_cv.shape)
print(X test price norm.shape, Y test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
```

### 2.13 Normalizing the numerical features:teacher\_number\_of\_previously\_posted\_projects

```
In [69]:
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X train['teacher number of previously posted projects'].values.reshape(-1,1))
X train TPPP norm = normalizer.transform(X train['teacher number of previously posted projects'].values.r
#X cv TPPP norm = normalizer.transform(X cv['teacher number of previously posted projects'].values.reshal
X_test_TPPP_norm = normalizer.transform(X_test['teacher_number_of_previously_posted_projects'].values.res
print("After vectorizations")
print(X train TPPP norm.shape, Y train.shape)
#print(X cv TPPP norm.shape, Y cv.shape)
print(X test TPPP norm.shape, Y test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
______
```

## 2.14 Normalizing the numerical features: quantity

```
In [70]:
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X_train['quantity'].values.reshape(-1,1))
X_train_quantity_norm = normalizer.transform(X_train['quantity'].values.reshape(-1,1))
\#X\_cv\_quantity\_norm = normalizer.transform(X\_cv['quantity'].values.reshape(-1,1))
X test quantity norm = normalizer.transform(X test['quantity'].values.reshape(-1,1))
print("After vectorizations")
print(X train quantity norm.shape, Y train.shape)
#print(X_cv_quantity_norm.shape, Y_cv.shape)
print(X test quantity norm.shape, Y test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
```

## 2.15 Normalizing the numerical features: totalwords\_title

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X train['totalwords title'].values.reshape(-1,1))
X train totalwords title norm = normalizer.transform(X train['totalwords title'].values.reshape(-1,1))
X test totalwords title norm = normalizer.transform(X test['totalwords title'].values.reshape(-1,1))
#X cv totalwords title norm = normalizer.transform(X cv['totalwords title'].values.reshape(-1,1))
print("After vectorizations")
print(X_train_totalwords_title_norm.shape, Y_train.shape)
#print(X cv totalwords title norm.shape, Y cv.shape)
print(X_test_totalwords_title_norm.shape, Y_test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
_____
```

## 2.17 Normalizing the numerical features: totalwords\_essay

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()

normalizer.fit(X_train['totalwords_essay'].values.reshape(-1,1))

X_train_totalwords_essay_norm = normalizer.transform(X_train['totalwords_essay'].values.reshape(-1,1))

#X_cv_totalwords_essay_norm = normalizer.transform(X_cv['totalwords_essay'].values.reshape(-1,1))

X_test_totalwords_essay_norm = normalizer.transform(X_test['totalwords_essay'].values.reshape(-1,1))

print("After vectorizations")

print(X_train_totalwords_essay_norm.shape, Y_train.shape)

#print(X_test_totalwords_essay_norm.shape, Y_cv.shape)

print(X_test_totalwords_essay_norm.shape, Y_test.shape)

print("="*100)

After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
```

In [72]:

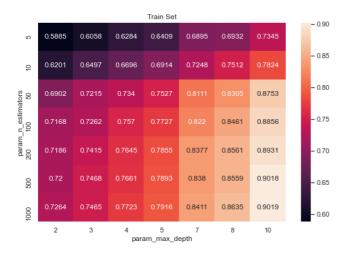
## 3. Random Forest on BOW

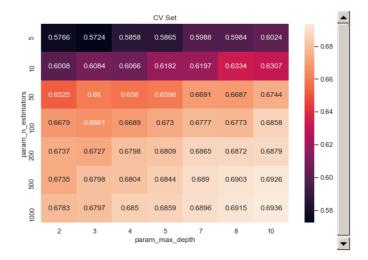
```
In [76]:
def predict (proba, threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    #(tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    \#print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
           predictions.append(0)
    return predictions
                                                                                                      In [77]:
def myplot matrix1(data):
    plt.clf()
    plt.imshow(data, interpolation='nearest', cmap=plt.cm.Wistia)
    classNames = ['Negative','Positive']
    plt.title('Approved not approved matrix')
    tick marks = np.arange(len(classNames))
    plt.xticks(tick marks, classNames, rotation=45)
    plt.yticks(tick_marks, classNames)
    s = [['TN','FN'], ['FP', 'TP']]
    for i in range(2):
        for j in range(2):
```

```
\label{eq:plt.text} \texttt{plt.text(j,i, str(s[i][j])+" = "+str(data[i][j]))} \\ \texttt{plt.show()}
```

### 3.1 BOW: Concatinating all the features

```
In [89]:
from scipy.sparse import hstack
X tr bow = hstack((X train essay bow, X train title bow, X train clean cat resposecode, X train clean subcat
#X cr bow = hstack((X cv essay bow, X cv title bow, X cv clean cat resposecode, X cv clean subcat resposecode
X te bow = hstack((X test essay bow, X test title bow, X test clean cat resposecode, X test clean subcat res
print("Final Data matrix")
print(X_tr_bow.shape, Y_train.shape)
#print(X_cr_bow.shape, Y_cv.shape)
print(X_te_bow.shape, Y_test.shape)
print("="*100)
Final Data matrix
(22445, 7017) (22445,)
(11055, 7017) (11055,)
(16500, 7017) (16500,)
______
                                                                                                     In [97]:
from sklearn.metrics import roc auc score
\textbf{import} \ \texttt{matplotlib.pyplot} \ \textbf{as} \ \texttt{plt}
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model selection import cross val score
from sklearn.tree import DecisionTreeClassifier
RF = RandomForestClassifier(class weight='balanced', min samples split=5)
parameters = {'n_estimators': [5, 10, 50, 100, 200, 500, 1000], 'max_depth': [2, 3, 4, 5, 7, 8, 10]}
model = GridSearchCV(RF, parameters, cv=3, scoring='roc auc',return train score=True)
bow= model.fit(X tr bow, Y train)
bow.cv results .keys()
print(bow.best estimator )
#Mean cross-validated score of the best estimator
print(bow.score(X_tr_bow,Y_train))
print(bow.score(X_te_bow,Y_test))
RandomForestClassifier(class weight='balanced', max depth=10,
                       min samples split=5, n estimators=1000)
0.8656591637660408
0.6992449154842851
                                                                                                      In [98]:
bow.cv results .keys()
                                                                                                     Out[98]:
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time', 'param_max_depth', 'para
m_n_estimators', 'params', 'split0_test_score', 'split1_test_score', 'split2_test_score', 'mean_test_score'
    'std_test_score', 'rank_test_score', 'split0_train score', 'split1 train score',
'split2 train score', 'mean_train_score', 'std_train_score'])
                                                                                                        - | ▶ |
                                                                                                     In [104]:
best parameters=[{'n estimators': [1000], 'max depth':[10]}]
                                                                                                     In [102]:
import seaborn as sns; sns.set()
max scores1 = pd.DataFrame(bow.cv results).groupby(['param n estimators', 'param max depth']).max().unst
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap(max\_scores1.mean\_train\_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max scores1.mean test score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```





1.Good corelation between max depth 10 and sn\_estimators 1000

2.Good corelation between max depth 10 and sample split 1000

```
In [105]:
```

```
from sklearn.metrics import roc curve, auc
clf11 = GridSearchCV(RandomForestClassifier(class weight='balanced'), best parameters)
clf11.fit(X tr bow, Y train)
#https://scikitlearn.org/stable/modules/generated/sklearn.linear model.SGDClassifier.ht
\#sklearn.linear\_model.SGDClassifier.decision\_function
y_train_pred = clf11.predict_proba(X_tr_bow) [:,1]
y test pred = clf11.predict proba(X te bow) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(Y_train, y_train_pred)
test fpr, test tpr, te thresholds = roc curve(Y test, y test pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
```



### observation

1. By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

second = [2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7,

2.By looking ROC curve of Test FPR and TPR is sensible . Model is generalize model

```
In [106]:
```

```
ax.scatter(first, second, third, c='r', marker='o')
ax.set zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set xlabel('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
  3D Scatter plot on Train AUC scores
                       0.8
                      0.6
                      10
                   6
     400 600 800 1000
   AUC Score
               2
                                                                                     In [107]:
from sklearn.metrics import accuracy score
from sklearn.metrics import classification_report
y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)
cm train=confusion matrix(Y train,y train predicted withthroshold,labels=[0, 1])
print("="*100)
from sklearn.metrics import confusion matrix
print("Train confusion matrix")
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy_score(Y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)))
cm_test=confusion_matrix(Y_test,y_test_predicted_withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm test)
print("="*100)
print("Accuracy score for Test")
accuracy_score_bow=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test fpr, test tpr))
print (accuracy score bow)
print("="*100)
______
Train confusion matrix
[[ 2858 605]
[ 4898 14084]]
Accuracy score for Train
0.7548229004232568
______
Test confusion matrix
[[ 1159 1387]
[ 2741 11213]]
Accuracy score for Test
0.7498181818181818
                                                                                     In [108]:
print("confusion matrix for train data")
```

third = list(bow.cv results ['mean train score'])

print("="\*100)

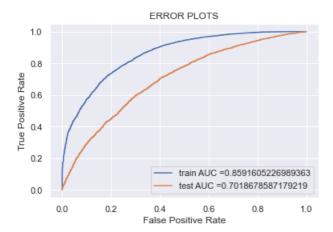
```
myplot matrix1(cm train)
  print("confusion matrix for Test data")
  print("="*100)
  myplot_matrix1(cm_test)
confusion matrix for train data
                                                   Approved not approved matrix
                                                                    TN = 2858
    Negative
                                                                    FP = 4898
                                                                                                                                    TP = 14084
       Positive
confusion matrix for Test data
                                                     Approved not approved matrix
                                                                   TN = 1159
                                                                                                                                  FN = 1387
     Negative
       Positive
observations
1.TN and TP of train data and test data is higher.
2.Accuracy score on train data is 75% and test data is 74%.
3.2 TFIDF: Concatinating all the features
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   In [109]:
  X_tr_tfidf = hstack((X_train_essay_tfidf,X_train_title_tfidf,X_train_clean_cat_resposecode,X_train_clean_
  \textbf{X\_te\_tfidf = hstack((X\_test\_essay\_tfidf, X\_test\_title\_tfidf, X\_test\_clean\_cat\_resposecode, X\_test\_clean\_subconstant (X\_test\_essay\_tfidf, X\_test\_essay\_tfidf, X\_test\_essay\_tfidf, X\_test\_clean\_subconstant (X\_test\_essay\_tfidf, X\_test\_essay\_tfidf, X\_tess\_essay\_tfidf, X\_test\_essay\_tfidf, X
```

```
print(tfidf.best params )
0.6949762987674836
RandomForestClassifier(class weight='balanced', max depth=8,
                            min samples split=5, n estimators=1000)
{'max depth': 8, 'n estimators': 1000}
                                                                                                                          In [111]:
clf2.cv results .keys()
                                                                                                                         Out[111]:
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time', 'param_max_depth', 'param_n_estimators', 'params', 'split0_test_score', 'split1_test_score', 'split2_test_score', 'mean_test_score',
e', 'std_test_score', 'rank_test_score', 'split0_train_score', 'split1_train_score',
'split2_train_score', 'mean train score', 'std train score'])
                                                                                                                          In [112]:
max scores1 = pd.DataFrame(clf2.cv results ).groupby(['param n estimators', 'param max depth']).max().uns
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap(max scores1.mean train score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max scores1.mean test score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set title('Train Set')
ax[1].set title('CV Set')
plt.show()
                         Train Set
                                                                                             CV Set
     0.5825
            0.6166
                  0.6249
                         0.6517
                                      0.7158
                                            0.7356
                                                                          0.5576
                                                                                0.5873
                                                                                       0.5725
                                                                                             0.5861
                                                                                                    0.6086
                                                                                                          0.5931
                                                                                                                 0.5918
                                                       - 0.90
                                                                                                                           - 0.68
                                                                                       0.6068
  9
                                                                      9
                                                       - 0.85
                                                                                                                            - 0.66
      0.7063
                                      0.8619
                                            0.8987
                                                                                             0.6648
                                                                                                    0.6676
                                                                                                          0.6708
                                                                                                                 0.6688
                                                                     ators
50
  8
                                                       - 0.80
                                                                                                                            0.64
                  0.7784
                                0.8555
                                      0.8777
                                            0.9184
                                                                                 0.6714
                                                                                       0.6726
                                                                                             0.6734
                                                                                                    0.6821
                                                                                                          0.6815
                                                                                                                 0.6806
  18
                                                                      100
                                                        0.75
                                                                                                                            0.62
 param.
200
                                                                     param
200
                                             0.924
                                                                                                    0.6874
                                                                                                           0.6846
                                                       - 0.70
                                                                                                                            0.60
      0.7514
                                0.8686
                                      0.8931
                                            0.9305
                                                                          0.6767
                                                                                 0.6792
                                                                                       0.6876
                                                                                             0.6887
                                                                                                    0.6907
                                                                                                          0.6934
                                                                                                                 0.6935
  200
                                                        0.65
                                                                      200
                                                                                                                            0.58
                                                                                 0.6855
                                                                                       0.6891
                                                                                              0.691
                                                                                                           0.695
                                                                                                                 0.6946
                                             0.9305
                                                                          0.6837
                                                                       000
       2
                                                                            2
              3
                           5
                                              10
                                                                                  3
                                                                                               5
                                                                                                                   10
                      param max depth
                                                                                          param max depth
observations
1.Good corelation between max depth 10 and sn_estimators 1000
2.Good corelation between max depth 10 and sample split 1000
                                                                                                                          In [113]:
best parameters=[{'n estimators': [1000], 'max depth':[8]}]
                                                                                                                          In [114]:
from sklearn.metrics import roc curve, auc
clf2 = GridSearchCV(RandomForestClassifier(class weight='balanced'),best parameters)
clf2.fit(X tr tfidf, Y train)
 #https://scikitlearn.org/stable/modules/generated/sklearn.linear model.SGDClassifier.ht
 #sklearn.linear model.SGDClassifier.decision function
y train pred = clf2.predict proba(X tr tfidf) [:,1]
y test pred = clf2.predict proba(X te tfidf) [:,1]
train fpr, train tpr, tr thresholds = roc curve(Y train, y train pred)
test_fpr, test_tpr, te_thresholds = roc_curve(Y_test, y_test_pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
```

plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")

plt.title("ERROR PLOTS")

plt.grid(True)



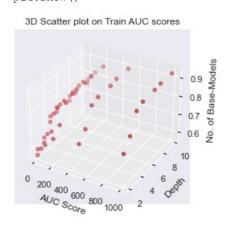
1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible . Model is generalize model

```
In [115]:
```

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
```

```
ax.scatter(first, second, third, c='r', marker='o')
ax.set_zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set_xlabel('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
```



```
In [116]:
```

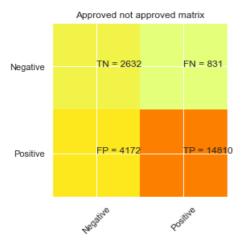
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

 $\verb|cm_train=confusion_matrix(Y_train,y_train_predicted_with throshold, labels=[0, 1])|$ 

```
print("="*100)
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
```

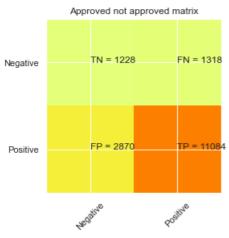
```
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm_test)
print("="*100)
print("Accuracy score for Test")
accuracy_score_tfidf=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_tpr))
print(accuracy_score_tfidf)
print("="*100)
______
Train confusion matrix
[[ 2632 831]
[ 4172 14810]]
______
Accuracy score for Train
0.7770995767431499
______
Test confusion matrix
[[ 1228 1318]
[ 2870 11084]]
______
Accuracy score for Test
0.7461818181818182
______
                                                                 In [117]:
print("confusion matrix for train data")
print("="*100)
myplot matrix1(cm train)
print("confusion matrix for Test data")
print("="*100)
myplot_matrix1(cm_test)
```

\_\_\_\_\_\_



confusion matrix for Test data

\_\_\_\_\_\_



### observations

- 1.TN and TP of train data and test data is higher.
- 2. Accuracy score on train data is 77% and test data is 74%.

## 3.3 avgw2v:Concatinating all the features

```
In [118]:
X_tr_avgw2v = np.hstack((Text_avg_w2v_train_essay,Text_avg_w2v_train_title,X_train_clean_cat_resposecode,
X_te_avgw2v = np.hstack((Text_avg_w2v_test_essay,Text_avg_w2v_test_title,X_test_clean_cat_resposecode,X_t
print("Final Data matrix")
print(X tr avgw2v.shape, Y train.shape)
print(X te avgw2v.shape, Y test.shape)
print("="*100)
Final Data matrix
(22445, 613) (22445,)
(16500, 613) (16500,)
                                                                                                     In [119]:
model = RandomForestClassifier(class_weight='balanced',min_samples_split=5)
parameters = {'n estimators': [5, 10, 50, 100, 200, 500, 1000], 'max depth': [2, 3, 4, 5, 7, 8, 10]}
clf1 = GridSearchCV(model, parameters, cv=3, scoring='roc_auc',return_train_score=True)
avgw2v = clf1.fit(X_tr_avgw2v, Y_train)
print(avgw2v.best_score_)
print(avgw2v.best_estimator_)
print(avgw2v.best_params_)
0.6842236912759052
RandomForestClassifier(class weight='balanced', max depth=7,
                       min samples split=5, n estimators=1000)
{'max depth': 7, 'n estimators': 1000}
```

In [125]:

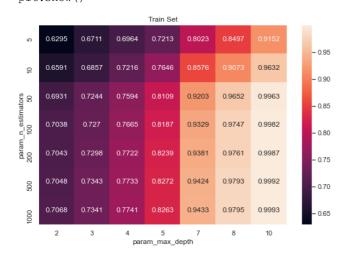
```
clf1.cv results .keys()
```

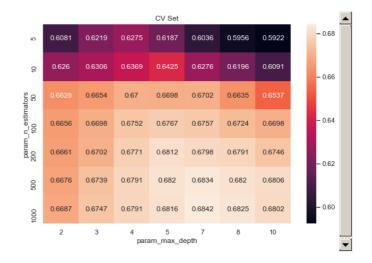
```
Out[120]:

dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time', 'param_max_depth', 'para
m_n_estimators', 'params', 'split0_test_score', 'split1_test_score', 'split2_test_score', 'mean_test_score
e', 'std_test_score', 'rank_test_score', 'split0_train_score', 'split1_train_score',
'split2_train_score', 'mean_train_score', 'std_train_score'])

[4]
```

import seaborn as sns; sns.set()
max\_scores1 = pd.DataFrame(clf1.cv\_results\_).groupby(['param\_n\_estimators', 'param\_max\_depth']).max().uns
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max\_scores1.mean\_train\_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max\_scores1.mean\_test\_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set\_title('Train Set')
ax[1].set\_title('CV Set')
plt.show()





### observations

1.Good corelation between max depth 10 and sn\_estimators 1000

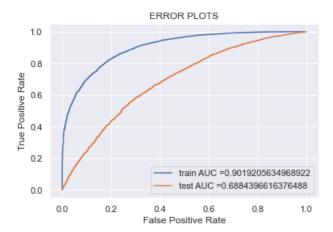
2.Good corelation between max depth 7 and sample split 1000

```
best parameters=[{'n estimators': [1000], 'max depth':[7]}]
```

```
In [124]:
```

from allegan metrics import was survey and

```
from sklearn.metrics import roc curve, auc
clf2 = GridSearchCV(RandomForestClassifier(class weight='balanced'),best parameters)
clf2.fit(X tr avgw2v, Y train)
\# https://scikitlearn.org/stable/modules/generated/sklearn.linear\ model.SGDClassifier.ht
#sklearn.linear model.SGDClassifier.decision function
y_train_pred = clf2.predict_proba(X_tr_avgw2v) [:,1]
y_test_pred = clf2.predict_proba(X_te_avgw2v) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(Y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(Y_test, y_test_pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid (True)
```



1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible . Model is generalize model

```
In [126]:
```

```
from mpl toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
```

```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
```

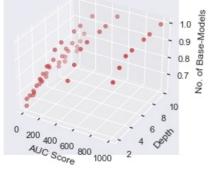
second = [2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, 8, 10,2, 3, 4, 5, 7, third = list(avgw2v.cv results ['mean train score'])

```
ax.scatter(first, second, third, c='r', marker='o')
```

```
ax.set zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set xlabel('AUC Score')
```

plt.title('3D Scatter plot on Train AUC scores') plt.show()

3D Scatter plot on Train AUC scores



In [127]:

```
from sklearn.metrics import accuracy score
from sklearn.metrics import classification report
```

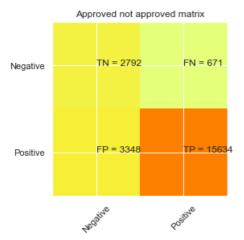
```
y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)
```

 $\verb|cm_train=confusion_matrix(Y_train,y_train_predicted_with throshold,labels=[0, 1])|$ 

```
print("="*100)
from sklearn.metrics import confusion matrix
print("Train confusion matrix")
```

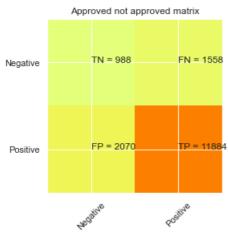
```
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm_test)
print("="*100)
print("Accuracy score for Test")
accuracy_score_tfidf=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_tpr))
print(accuracy_score_tfidf)
print("="*100)
______
Train confusion matrix
[[ 2792 671]
[ 3348 15634]]
______
Accuracy score for Train
0.8209400757406995
______
Test confusion matrix
[[ 988 1558]
[ 2070 11884]]
______
Accuracy score for Test
0.7801212121212121
______
                                                                 In [128]:
print("confusion matrix for train data")
print("="*100)
myplot matrix1(cm train)
print("confusion matrix for Test data")
print("="*100)
myplot_matrix1(cm_test)
```

\_\_\_\_\_



confusion matrix for Test data

\_\_\_\_\_\_



### observations

- 1.TN and TP of train data and test data is higher.
- 2. Accuracy score on train data is 82% and test data is 78%.

# 3.4 TFIDFw2v

```
In [129]:
 X tr tfidfw2v = np.hstack((Text tfidf w2v train essay, Text tfidf w2v train title, X train clean cat respos
  \textbf{X\_te\_tfidfw2v = np.hstack((Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_title, \textbf{X\_test\_clean\_cat\_resposecoments}) } \\ \textbf{X\_te\_tfidfw2v = np.hstack((Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_clean\_cat\_resposecoments) } \\ \textbf{X\_te\_tfidfw2v = np.hstack((Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_clean\_cat\_resposecoments) } \\ \textbf{X\_text\_tfidfw2v = np.hstack((Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_w2v\_test\_essay, Text\_tfidf\_essay, Text\_tfidf_essay, Text\_tfid
 print("Final Data matrix")
 print(X_tr_tfidfw2v.shape, Y_train.shape)
 print(X_te_tfidfw2v.shape, Y_test.shape)
 print("="*100)
Final Data matrix
(22445, 613) (22445,)
(16500, 613) (16500,)
                                                                                                                                                                                                                                                                                                                                                                                                       In [130]:
 model = RandomForestClassifier(class_weight='balanced',min_samples_split=5)
 parameters = {'n estimators': [5, 10, 50, 100, 200, 500, 1000], 'max depth': [2, 3, 4, 5, 7, 8, 10]}
 clf3 = GridSearchCV(model, parameters, cv=3, scoring='roc_auc',return_train_score=True)
 \label{eq:continuous_state} \texttt{tfidfw2v} = \texttt{clf3.fit}(\texttt{X\_tr\_tfidfw2v}, \ \texttt{Y\_train})
 print(tfidfw2v.best_score_)
 print(tfidfw2v.best estimator )
 print(tfidfw2v.best params )
```

```
0.6787674568567095
{\tt RandomForestClassifier(class\_weight='balanced',\ max\_depth=7,}
                           min samples split=5, n estimators=1000)
{'max depth': 7, 'n estimators': 1000}
                                                                                                                      In [131]:
clf3.cv_results_.keys()
                                                                                                                     Out[131]:
dict keys(['mean fit time', 'std fit time', 'mean score time', 'std score time', 'param max depth', 'para
m_n_estimators', 'params', 'split0_test_score', 'split1_test_score', 'split2_test_score', 'mean_test_score'
e', 'std_test_score', 'rank_test_score', 'split0_train_score', 'split1_train_score',
'split2 train score', 'mean train score', 'std train score'])
                                                                                                                          - ▶
                                                                                                                      In [132]:
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(clf3.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().uns
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set title('Train Set')
ax[1].set title('CV Set')
plt.show()
                                                                                           CV Set
     0.6399
            0.658
                                                                                                              0.5985
                  0.6906
                                                                        0.6128
                                                                              0.6178
                                                                                                 0.6116
                                                                                                       0.6089
                                                                                                                        - 0.67
                                                     - 0.95
     0.6613
                                           0.9603
                                                                                                              0.6186
  0
                                                                    0
                                                     - 0.90
     0.6917
           0.7216
                  0.7522
                        0.8022
                                     0.9544
                                           0.9932
                                                                              0.6645
                                                                                     0.666
                                                                                           0.6692
                                                                                                 0.6698
                                                                                                       0.6661
                                                                                                                        - 0.65
 tors
50
                                                                   tors
50
                                                     - 0.85
                                                                                                                        0.64
                        0.8084
                               0.9193
                                     0.9623
                                           0.9962
                                                                              0.6686
                                                                                    0.6707
                                                                                           0.6728
                                                                                                 0.6764
                                                                                                       0.673
  18
                                                                    18
                                                      0.80
                                                                                                                        0.63
par?
200
     0.7013
                  0.764
                                           0.9973
                                                                                           0.6763
                                                                                                 0.678
                                                                                                       0.6754
                                                                                                              0.6717
           0.7259
                        0.8098
                               0.9251
                                     0.9663
                                                                   20 par
                                                                        0.665
                                                                              0.6695
                                                                                    0.6747
                                                      0.75
                                                                                                                        0.62
                                                                                                       0.6778
      0.703
           0.7286
                  0.7649
                        0.8145
                               0.927
                                     0.9679
                                           0.998
                                                                        0.6676
                                                                              0.6716
                                                                                     0.676
                                                                                           0.6776
                                                                                                 0.6776
                                                                                                              0.6748
  500
                                                                    500
                                                                                                                        0.61
           0.7296
                                                                              0.6723
                                                                                    0.6765
                                                                                           0.6787
                                                                                                 0.6788
                                                                                                       0.6782
                                                                                                              0.6764
  000
                                                                    000
                                                      0.65
                                                                                                                        0.60
                                             10
                                                                         2
                                                                                                               10
                                       8
                                                                                3
                     param max depth
                                                                                       param max depth
observations
1.Good corelation between max depth 10 and sn_estimators 1000
2.Good corelation between max depth 7 and sample split 1000
                                                                                                                         In []:
best parameters=[{'n estimators': [1000], 'max depth':[7]}]
                                                                                                                      In [133]:
from sklearn.metrics import roc_curve, auc
clf2 = GridSearchCV(RandomForestClassifier(class_weight='balanced'),best_parameters)
clf2.fit(X_tr_tfidfw2v, Y_train)
 \# https://scikitlearn.org/stable/modules/generated/sklearn.linear\_model.SGDClassifier.ht
\#sklearn.linear\_model.SGDClassifier.decision\_function
y train pred = clf2.predict proba(X tr tfidfw2v) [:,1]
y_test_pred = clf2.predict_proba(X_te_tfidfw2v) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(Y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(Y_test, y_test_pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
```

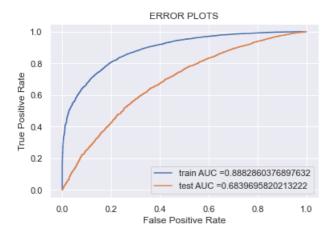
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))

plt.legend()

plt.grid(True)

plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")

plt.title("ERROR PLOTS")



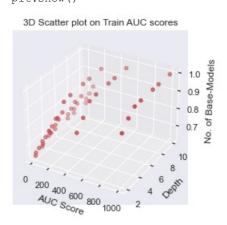
1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible . Model is generalize model

```
In [134]:
from mpl_toolkits.mplot3d import Axes3D
```

```
ax.set_zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set_xlabel('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
```

ax.scatter(first, second, third, c='r', marker='o')



import matplotlib.pyplot as plt

```
In [135]:
```

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)

cm_train=confusion_matrix(Y_train,y_train_predicted_withthroshold,labels=[0, 1])
```

```
print("="*100)
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
```

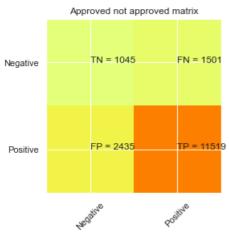
```
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm_test)
print("="*100)
print("Accuracy score for Test")
accuracy\_score\_tfidfw2v = accuracy\_score(Y\_test, predict(y\_test\_pred, tr\_thresholds, test\_fpr, test\_tpr))
print(accuracy_score_tfidfw2v)
print("="*100)
______
Train confusion matrix
[[ 2791 672]
[ 3774 15208]]
______
Accuracy score for Train
0.8019157941635108
______
{\tt Test \ confusion \ matrix}
[[ 1045 1501]
[ 2435 11519]]
______
Accuracy score for Test
0.7614545454545455
______
                                                                  In [136]:
print("confusion matrix for train data")
print("="*100)
myplot matrix1(cm train)
print("confusion matrix for Test data")
print("="*100)
myplot_matrix1(cm_test)
```

\_\_\_\_\_



confusion matrix for Test data

\_\_\_\_\_\_



### observations

- 1.TN and TP of train data and test data is higher.
- 2. Accuracy score on train data is 80% and test data is 76%.

# 4.GBDT on all vectors.

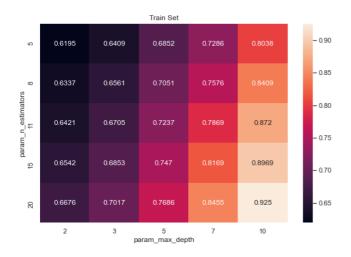
# 4.1 GBDT on Bow

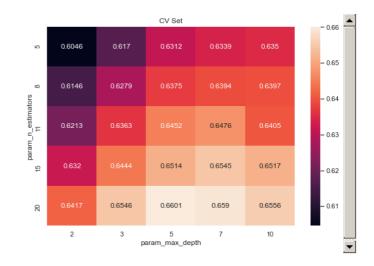
In [137]:

```
\textbf{from} \ \text{sklearn.ensemble} \ \textbf{import} \ \text{GradientBoostingClassifier}
```

```
model = GradientBoostingClassifier(min_samples_split=15)
parameters = {'n_estimators': [5, 8,11,15,20], 'max_depth':[2, 3, 5, 7, 10] }
bow_gbdt = GridSearchCV(model, parameters, cv=3, scoring='roc_auc',return_train_score=True)
bow_gbdt .fit(X_tr_bow, Y_train)

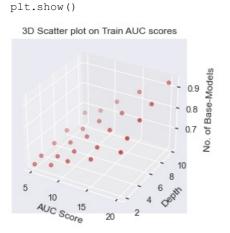
max_scores1 = pd.DataFrame(bow_gbdt .cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max(
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train_Set')
ax[1].set_title('CV_Set')
plt.show()
```





1.Good corelation between max depth 10 and sn\_estimators 20

```
2.Good corelation between max depth 5 and sample split 20
                                                                                              In [140]:
print(bow gbdt.best estimator )
#Mean cross-validated score of the best estimator
print(bow gbdt.score(X tr bow, Y train))
print(bow gbdt.score(X te bow, Y test))
GradientBoostingClassifier(max_depth=5, min_samples_split=15, n_estimators=20)
0.7534518468535307
0.6739213464372502
                                                                                              In [146]:
from mpl toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add subplot(111, projection='3d')
second = [2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10]
third = list(bow gbdt.cv results ['mean train score'])
ax.scatter(first, second, third, c='r', marker='o')
ax.set_zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set xlabel('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
```

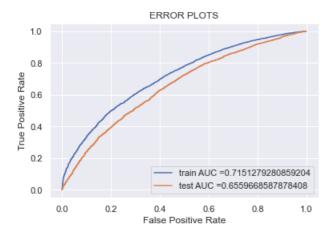


```
best_tune_parameters=[{'n_estimators': [20], 'max_depth':[5] } ]
```

In [166]:

In [167]:

```
model1 = GridSearchCV(RandomForestClassifier(class weight='balanced'),best tune parameters)
model1.fit(X_tr_bow, Y_train)
#https://scikitlearn.org/stable/modules/generated/sklearn.linear model.SGDClassifier.ht
#sklearn.linear model.SGDClassifier.decision function
y_train_pred = model1.predict_proba(X_tr_bow) [:,1]
y test pred = model1.predict proba(X te bow) [:,1]
train fpr, train tpr, tr thresholds = roc curve(Y train, y train pred)
test fpr, test tpr, te thresholds = roc curve (Y test, y test pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid (True)
plt.show()
```



1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible . Model is generalize model

```
In [168]:
from sklearn.metrics import accuracy score
from sklearn.metrics import classification_report
y train predicted withthroshold=predict(y train pred, tr thresholds, train fpr, train tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)
cm train=confusion matrix(Y train, y train predicted withthroshold, labels=[0, 1])
print("="*100)
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy_score(Y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)))
print("="*100)
cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm test)
print("="*100)
print("Accuracy score for Test")
accuracy score tfidfw2v=accuracy score(Y test, predict(y test pred, tr thresholds, test fpr, test tpr))
print(accuracy score tfidfw2v)
print("="*100)
```

Train confusion matrix [[ 2357 1106] [ 7113 11869]] Accuracy score for Train 0.6338159946535977 Test confusion matrix [[1660 886] [6135 7819]] Accuracy score for Test 0.5744848484848485 In [169]: print("confusion matrix for train data") print("="\*100) myplot\_matrix1(cm\_train) print("confusion matrix for Test data") print("="\*100) myplot matrix1(cm test) confusion matrix for train data Approved not approved matrix TN = 2357 Negative TP = 11869 Positive confusion matrix for Test data Approved not approved matrix TN = 1660 FN = 886 Negative EP = 6135TP = 7819Positive

## observations

- 1.TN and TP of train data and test data is higher.
- 2. Accuracy score on train data is 63% and test data is 57%.

## 4.2 GBDT on TFIDF

In [149]:

from sklearn.ensemble import GradientBoostingClassifier

```
parameters = {'n estimators': [5, 8,11,15,20], 'max depth':[2, 3, 5, 7, 10] }
tfidf gbdt = GridSearchCV (model, parameters, cv=3, scoring='roc_auc',return_train_score=True)
tfidf gbdt .fit(X tr tfidf, Y train)
max scores1 = pd.DataFrame(tfidf gbdt .cv results ).groupby(['param n estimators', 'param max depth']).ma
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max scores1.mean train score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set title('CV Set')
plt.show()
                       Train Set
                                                                                        CV Set
                                                                                                                     - 0.655
      0.6322
               0.6518
                                                    - 0.90
                                                                       0.6163
                                                                                0.6284
                                                                                                          0.6209
                                                                                                                     - 0.650
                                                    - 0.85
      0.6435
                                                                                                 0.6352
 80
               0.6679
                       0.7165
                                                                  80
                                                                       0.623
                                                                                0.6364
                                                                                         0.6361
                                                                                                          0.6279
                                                                                                                     - 0.645
param n estimators
                                                                 param_n_estimators
11
                                                                                                                     - 0.640
                                                    - 0.80
      0.6521
 Ε.
                                                                                                                     0.635
                                                    - 0.75
                                                                                                                     0.630
      0.6639
               0.6955
                                         0.9042
                                                                                0.6504
                                                                                         0.6539
                                                                                                 0.6509
                                                                   5
 5
                                                    - 0.70
                                                                                                                     - 0.625
                                                                                0.6576
                                                                                                          0.6493
 8
                                         0.9314
                                                                   8
                                                                                         0.6562
                                                                                                 0.6557
                                                                                                                     0.620
                                                     0.65
        2
                    5
param_max_depth
                                          10
                                                                         2
                                                                                     5
param_max_depth
                                                                                                           10
                                                                                                                         -
observations
1.Good corelation between max depth 20 and sn_estimators 10
2.Good corelation between max depth 20 and sample split 5
                                                                                                                    In [155]:
print(tfidf gbdt.best estimator )
#Mean cross-validated score of the best estimator
print(tfidf_gbdt.score(X_tr_tfidf,Y_train))
print(tfidf gbdt.score(X te tfidf,Y test))
GradientBoostingClassifier(min samples split=15, n estimators=20)
0.6978973392821376
0.6666342170622113
                                                                                                                    In [152]:
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add subplot(111, projection='3d')
first = [5,5,5,5,5,8,8,8,8,8,11,11,11,11,11,15,15,15,15,15,20,20,20,20,20]
second = [2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10]
third = list(tfidf gbdt.cv results ['mean train score'])
ax.scatter(first, second, third, c='r', marker='o')
ax.set zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set xlabel('AUC Score')
```

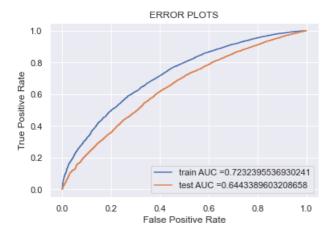
plt.title('3D Scatter plot on Train AUC scores')

plt.show()

```
3D Scatter plot on Train AUC scores

0.9 W 9 8 8 0.7 5 0.9 W 9 8 0.7 5 0.9 W 9 8 0.7 5 0.9 W 9 8 0.7 5 0.0 W 9 8 0.0 W 9 8
```

```
In [170]:
best_tune_parameters=[{'n_estimators': [20], 'max_depth':[5] } ]
                                                                                                    In [171]:
model1 = GridSearchCV(RandomForestClassifier(class_weight='balanced'),best_tune_parameters)
model1.fit(X_tr_tfidf, Y_train)
\# https://scikitlearn.org/stable/modules/generated/sklearn.linear\_model.SGDClassifier.ht
#sklearn.linear_model.SGDClassifier.decision_function
y_train_pred = model1.predict_proba(X_tr_tfidf) [:,1]
y_test_pred = model1.predict_proba(X_te_tfidf) [:,1]
train fpr, train tpr, tr thresholds = roc curve(Y train, y train pred)
test_fpr, test_tpr, te_thresholds = roc_curve(Y_test, y_test_pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
```



print("="\*100)

print("Accuracy score for Train")

plt.show()

1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible .Model is generalize model

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

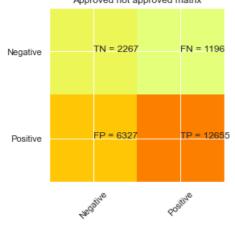
y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)

cm_train=confusion_matrix(Y_train,y_train_predicted_withthroshold,labels=[0, 1])

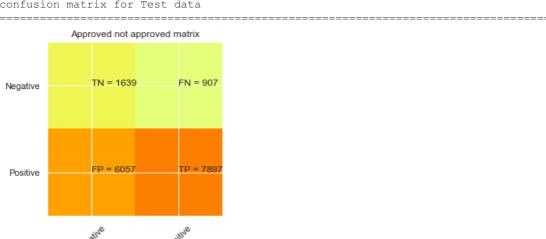
print("="*100)
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(cm_train)
```

In [172]:

```
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
print("Test confusion matrix")
print(cm test)
print("="*100)
print("Accuracy score for Test")
\verb|accuracy_score_tfidfw2v=| accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_tpr))|
print(accuracy_score_tfidfw2v)
print("="*100)
______
Train confusion matrix
[[ 2267 1196]
[ 6327 12655]]
______
Accuracy score for Train
0.6648251280908888
Test confusion matrix
[[1639 907]
[6057 7897]]
_____
Accuracy score for Test
0.577939393939394
                                                                               In [173]:
print("confusion matrix for train data")
print("="*100)
myplot matrix1(cm train)
print("confusion matrix for Test data")
print("="*100)
myplot matrix1(cm test)
confusion matrix for train data
        Approved not approved matrix
                     FN = 1196
           TN = 2267
Negative
           FP = 6327
                     TP = 12655
 Positive
```



confusion matrix for Test data



1.TN and TP of train data and test data is higher.

2.Accuracy score on train data is 66% and test data is 57%.

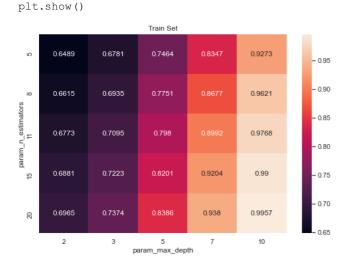
# 4.3 GBDT on avgw2v

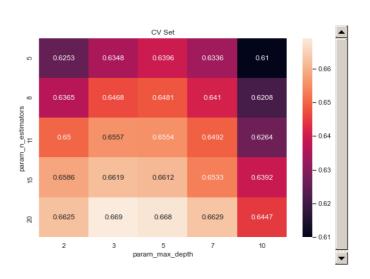
ax[1].set\_title('CV Set')

```
In [162]:
```

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

```
model = GradientBoostingClassifier(min samples split=15)
parameters = {'n_estimators': [5, 8,11,15,20], 'max_depth':[2, 3, 5, 7, 10] }
avgw2v_gbdt = GridSearchCV(model, parameters, cv=3, scoring='roc auc',return train score=True)
avgw2v gbdt .fit(X tr avgw2v, Y train)
max_scores1 = pd.DataFrame(avgw2v_gbdt .cv_results_).groupby(['param_n_estimators', 'param_max_depth']).m
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set title('Train Set')
```





### observations

plt.legend()

plt.xlabel("False Positive Rate")

1.Good corelation between max depth 10 and sn\_estimators 20

test\_fpr, test\_tpr, te\_thresholds = roc\_curve(Y\_test, y\_test\_pred)

plt.plot(train\_fpr, train\_tpr, label="train AUC ="+str(auc(train\_fpr, train tpr))) plt.plot(test\_fpr, test\_tpr, label="test AUC ="+str(auc(test fpr, test tpr)))

```
2.Good corelation between max depth 5 and sample split 20
                                                                                                       In [163]:
print(avgw2v gbdt.best estimator )
#Mean cross-validated score of the best estimator
print(avgw2v_gbdt.score(X_tr_avgw2v,Y_train))
print(avgw2v gbdt.score(X te avgw2v,Y test))
GradientBoostingClassifier(min samples split=15, n estimators=20)
0.7201905003974616
0.6719697961690083
                                                                                                       In [174]:
best tune parameters=[{'n estimators': [20], 'max depth':[5] } ]
                                                                                                       In [176]:
model1 = GridSearchCV(RandomForestClassifier(class weight='balanced'),best tune parameters)
model1.fit(X tr avgw2v, Y train)
\# https://scikitlearn.org/stable/modules/generated/sklearn.linear\_model.SGDClassifier.ht
#sklearn.linear model.SGDClassifier.decision function
y train pred = model1.predict proba(X tr avgw2v) [:,1]
y_test_pred = model1.predict_proba(X_te_avgw2v) [:,1]
train fpr, train tpr, tr thresholds = roc curve(Y train, y train pred)
```

```
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
plt.show()
```



1.By looking ROC curve of Training FPR and TPR it looks sensible as it is greater than diagonal line

2.By looking ROC curve of Test FPR and TPR is sensible .Model is generalize model

In [179]:

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

first = [5,5,5,5,5,8,8,8,8,8,11,11,11,11,11,15,15,15,15,15,20,20,20,20,20]
second = [2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10]
third = list(avgw2v_gbdt.cv_results_['mean_train_score'])

ax.scatter(first,second,third, c='r', marker='o')
ax.set_zlabel('No. of Base-Models')
ax.set_ylabel('Depth')
ax.set_xlabel('AUC Score')

plt.title('3D Scatter plot on Train AUC scores')
plt.show()
3D Scatter plot on Train AUC scores
```

In [180]:

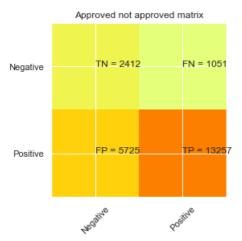
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)
```

cm train=confusion matrix(Y train,y train predicted withthroshold,labels=[0, 1])

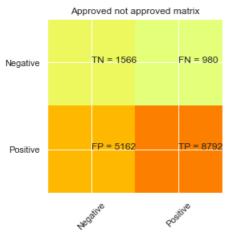
```
print("="*100)
from sklearn.metrics import confusion matrix
print("Train confusion matrix")
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
cm test=confusion matrix(Y test, y test predicted withthroshold, labels=[0, 1])
print("Test confusion matrix")
print(cm_test)
print("="*100)
print("Accuracy score for Test")
accuracy_score_tfidfw2v=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_tpr))
print(accuracy score tfidfw2v)
print("="*100)
______
Train confusion matrix
[[ 2412 1051]
[ 5725 13257]]
Accuracy score for Train
0.698106482512809
Test confusion matrix
[[1566 980]
[5162 8792]]
______
Accuracy score for Test
0.6277575757575757
_____
                                                                             In [181]:
print("confusion matrix for train data")
print("="*100)
myplot_matrix1(cm_train)
print("confusion matrix for Test data")
print("="*100)
myplot matrix1(cm test)
```

\_\_\_\_\_\_



confusion matrix for Test data

\_\_\_\_\_\_



### observations

- 1.TN and TP of train data and test data is higher.
- 2. Accuracy score on train data is 69% and test data is 62%.

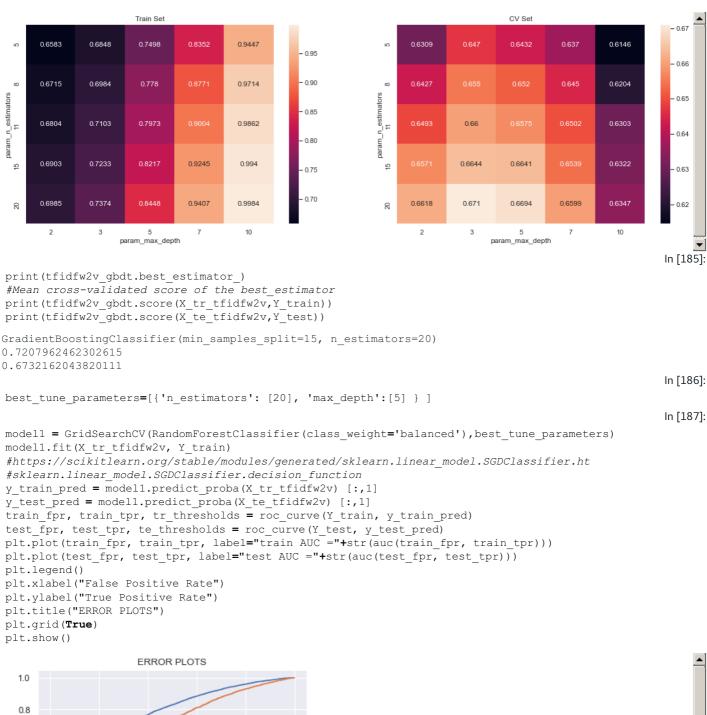
# 4.4 TFIDFW2v

In [182]:

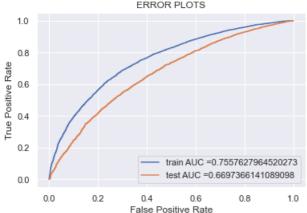
from sklearn.ensemble import GradientBoostingClassifier

```
model = GradientBoostingClassifier(min_samples_split=15)
parameters = {'n_estimators': [5, 8,11,15,20], 'max_depth':[2, 3, 5, 7, 10] }
tfidfw2v_gbdt = GridSearchCV(model, parameters, cv=3, scoring='roc_auc',return_train_score=True)
tfidfw2v_gbdt .fit(X_tr_tfidfw2v, Y_train)

max_scores1 = pd.DataFrame(tfidfw2v_gbdt .cv_results_).groupby(['param_n_estimators', 'param_max_depth'])
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train_Set')
ax[1].set_title('CV_Set')
plt.show()
```



In [192]:



from mpl\_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

first = [5,5,5,5,5,8,8,8,8,8,11,11,11,11,11,15,15,15,15,15,20,20,20,20,20]
second = [2,3,5,7,10,2,3,5,7,10,2,3,5,7,10,2,3,5,7,10]
third = list(tfidfw2v gbdt .cv results ['mean train score'])
```

```
ax.scatter(first, second, third, c='r', marker='o')
ax.set zlabel('No. of Base-Models')
ax.set ylabel('Depth')
ax.set_xlabel('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
  3D Scatter plot on Train AUC scores
                      1.0 Pase-Wodels
                       0.7
                      10
                     8
                   6
  5
     10
   AUC Score
         15
                                                                                        In [193]:
from sklearn.metrics import accuracy score
from sklearn.metrics import classification report
y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
\verb|y_test_predicted_withthroshold=| predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)| \\
\verb|cm_train=confusion_matrix(Y_train,y_train_predicted_with throshold,labels=[0, 1])|
print("="*100)
from sklearn.metrics import confusion matrix
print("Train confusion matrix")
print(cm train)
print("="*100)
print("Accuracy score for Train")
print(accuracy score(Y train, predict(y train pred, tr thresholds, train fpr, train tpr)))
print("="*100)
\verb|cm_test=| confusion_matrix(Y_test,y_test_predicted_withthroshold,labels=[0, 1])| \\
print("Test confusion matrix")
print(cm_test)
print("="*100)
print("Accuracy score for Test")
accuracy_score_tfidfw2v=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_tpr))
print(accuracy_score_tfidfw2v)
print("="*100)
______
Train confusion matrix
[[ 2438 1025]
[ 6003 12979]]
Accuracy score for Train
0.686879037647583
Test confusion matrix
[[1500 1046]
[4773 9181]]
______
Accuracy score for Test
0.6473333333333333
______
                                                                                        In [194]:
print("confusion matrix for train data")
print("="*100)
```

myplot matrix1(cm train)

```
print("confusion matrix for Test data")

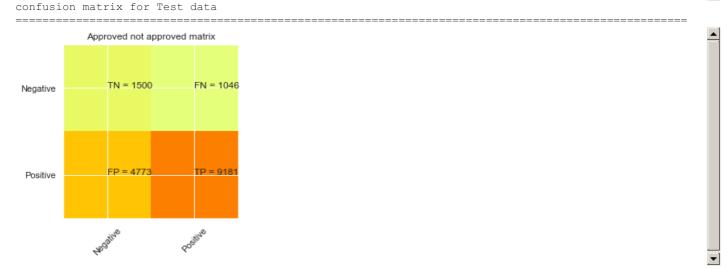
print("="*100)

myplot_matrix1(cm_test)

confusion matrix for train data

Approved not approved matrix
```





- 1.TN and TP of train data and test data is higher.
- 2.Accuracy score on train data is 68% and test data is 64%

## 5.Performance

In [183]:

```
from prettytable import PrettyTable
tb = PrettyTable()
from prettytable import PrettyTable
tb = PrettyTable()
tb.field_names= (" Model ", " Vectorizer ", " n_estimators", " max_depth "," Test -AUC")
tb.add_row([ "Random Forest", " BOW ", 1000,10, 69 ])
tb.add_row([ "Random Forest", " Tf - Idf",1000, 8, 70.3 ])
tb.add_row([ "Random Forest", " AVG-W2V", 1000, 7 , 68 ])
tb.add_row([ "Random Forest", " A VG-TfIdf",1000 , 7 , 68.2 ])
tb.add_row([ "Gradient Boosting DT", " Bow ",20 , 5 , 65 ])
tb.add_row([ "Gradient Boosting DT", " Tf-Idf",20 , 5 , 64.2 ])
tb.add_row([ "Gradient Boosting DT", " AVG-W2V", 20 , 5 , 66])
tb.add_row([ "Gradient Boosting DT", "AVG-W2V", 20 , 5 , 67 ])
```

## observation

- 1.Random forest gives best performance for n\_estimators=1000 max\_depth=8 using TFIDF
- 2.GBDT gives best performance for n\_estimators=20 max\_depth=5 using bow