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.

About the DonorsChoose Data Set

The train.csv data set provided by DonorsChoose contains the following features:

Feature	Description						
project_id	A unique identifier for the proposed project. Example: p036502						
	Title of the project. Examples:						
project_title	• Art Will Make You Happy!						
	• First Grade Fun						
	Grade level of students for which the project is targeted. One of the following enumerated values:						
	• Grades PreK-2						
project_grade_category	• Grades 3-5						
	• Grades 6-8						
	• Grades 9-12						
	One or more (comma-separated) subject categories for the project from the following enumerated list of values:						
	Applied Learning						
	• Care & Hunger						
	• Health & Sports						
	• History & Civics						
	• Literacy & Language						
project_subject_categories	• Math & Science						
, <u></u> ,	• Music & The Arts						

Feature	Description Needs					
	• Warmth					
	Examples:					
	• Music & The Arts					
	• Literacy & Language, Math & Science					
school_state	State where school is located (<u>Two-letter U.S. postal code</u>). Example: WY					
	One or more (comma-separated) subject subcategories for the project. Examples:					
project_subject_subcategories	• Literacy					
	• Literature & Writing, Social Sciences					
project_resource_summary	An explanation of the resources needed for the project. Example: • My students need hands on literacy materials to manage sensory needs!					
project_essay_1	First application essay*					
project_essay_2	Second application essay*					
project_essay_3	Third application essay*					
project_essay_4	Fourth application essay*					
project_submitted_datetime	Datetime when project application was submitted. Example: 2016-04-28 12:43:56.245					
teacher_id	A unique identifier for the teacher of the proposed project. Example: bdf8baa8fedef6bfeec7ae4ff1c15c56					
	Teacher's title. One of the following enumerated values: • nan • Dr.					
teacher_prefix	Mr.Mrs.Ms.Teacher.					
teacher_number_of_previously_posted_projec	Number of project applications previously submitted by the same teacher. Example: 2					

^{*} See the section **Notes on the Essay Data** for more details about these features.

Additionally, the resources.csv data set provides more data about the resources required for each project. Each line in this file represents a resource required by a project:

Feature	Description
id	A project_id value from the train.csv file. Example: p036502

Feature -description	Description the resource. Example: Tenor Saxophone Reeds, Box of						
-description-	25						
quantity	Quantity of the resource required. Example: 3						
price	Price of the resource required. Example: 9.95						

Note: Many projects require multiple resources. The id value corresponds to a project id in train.csv, so you use it as a key to retrieve all resources needed for a project:

The data set contains the following label (the value you will attempt to predict):

Label	Description
project_is_approved	A binary flag indicating whether DonorsChoose approved the project. A value of 0 indicates the project was not approved, and a value of 1 indicates the project was approved.

Notes on the Essay Data

Prior to May 17, 2016, the prompts for the essays were as follows:

- project essay 1: "Introduce us to your classroom"
- __project_essay_2:__ "Tell us more about your students"
- project essay 3: "Describe how your students will use the materials you're requesting"
- project essay 3: "Close by sharing why your project will make a difference"

Starting on May 17, 2016, the number of essays was reduced from 4 to 2, and the prompts for the first 2 essays were changed to the following:

- project essay 1: "Describe your students: What makes your students special? Specific details about their background, your neighborhood, and your school are all helpful."
- project essay 2: "About your project: How will these materials make a difference in your students' learning and improve their school lives?"

For all projects with project submitted datetime of 2016-05-17 and later, the values of project essay 3 and project essay 4 will be NaN.

```
%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 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
import scipy
# 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
import plotly.offline as offline
import plotly.graph objs as go
offline.init notebook mode()
from collections import Counter
from scipy.sparse import hstack, vstack
from sklearn.model selection import train test split
from sklearn.metrics import accuracy score
from sklearn.model selection import cross val score
from sklearn import model selection
from sklearn.metrics import roc auc score
from sklearn.model selection import GridSearchCV
from sklearn.model selection import RandomizedSearchCV
from prettytable import PrettyTable
from sklearn.preprocessing import Normalizer
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader lexicon')
from sklearn.ensemble import RandomForestClassifier
from mpl toolkits.mplot3d import Axes3D
from xgboost import XGBClassifier
from sklearn.ensemble import GradientBoostingClassifier
import pdb
```

1.1 Reading Data

```
In [0]:
```

(1541272, 4)

```
Project_data = pd.read_csv('train_data_50K.csv')
Resource_data = pd.read_csv('resources.csv')
#Bk=Project_data
#print(Bk.shape)
print(Project_data.shape)
print(Resource_data.shape)
(50000, 17)
```

```
In [0]:
```

```
# how to replace elements in list python: https://stackoverflow.com/a/2582163/4084039
cols = ['Date' if x=='project_submitted_datetime' else x for x in list(Project_data.columns)]
#sort dataframe based on time pandas python: https://stackoverflow.com/a/49702492/4084039
Project_data['Date'] = pd.to_datetime(Project_data['project_submitted_datetime'])
Project_data.drop('project_submitted_datetime', axis=1, inplace=True)
Project_data.sort_values(by=['Date'], inplace=True)
# how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4084039
Project_data = Project_data[cols]
Project_data.head(2)
```

Out[0]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	Date	project_grade_category	project_subject_categories	project_subject_subcatego
31477	47750	p185738	3afe10b996b7646d8641985a4b4b570d	Mrs.		2016- 01-05 01:05:00		Math & Science	Mathematics
40132	91045	p161351	40c9c33254a39827d6908ae9a6103c04	Teacher		2016- 01-05 01:59:00		Special Needs	Special Needs

1.2 preprocessing of project subject categories

```
In [0]:
```

```
y = Project_data['project_is_approved'].values
# Project_data.drop(['project_is_approved'], axis=1, inplace=True)
lpd = len(Project_data)
ys = np.zeros(lpd, dtype=np.int32)
X = Project_data
X = Project_data
```

```
#Spliting the Dataset into three Train and Test
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X, y, test_size=0.33, random_state=0, stratify=ys)
print('Shape of the X_Train data is {0} and Y_Train data is: {1}'.format(X_Train.shape,Y_Train.shape[0]))
print('Shape of the X_Test data is {0} and Y_Test data is: {1}'.format(X_Test.shape,Y_Test.shape[0]))
```

```
Shape of the X_Train data is (33500, 17) and Y_Train data is: 33500 Shape of the X_Test data is (16500, 17) and Y_Test data is: 16500
```

```
# 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
catogories = list(X Train['project subject categories'].values)
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"=> "Math", "&", "Science"
           j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Science"=>"Math&Science"
       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())
X Train['clean categories'] = cat list
X Train.drop(['project subject categories'], axis=1, inplace=True)
from collections import Counter
my counter = Counter()
for word in X Train['clean categories'].values:
   my counter.update(word.split())
cat dict = dict(my counter)
sorted cat dict Train = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
print(len(sorted cat dict Train))
#*******************
Data*****************************
catogories = list(X Test['project subject categories'].values)
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"=> "Math", "&", "Science"
           j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Science"=>"Math&Science"
       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())

X_Test['clean_categories'] = cat_list
X_Test.drop(['project_subject_categories'], axis=1, inplace=True)
```

1.3 preprocessing of project subject subcategories

```
# 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 catogories = list(X Train['project subject subcategories'].values)
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"=> "Math", "&", "Science"
           j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math & Science"=>"Math&Science"
       temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the trailing spaces
       temp = temp.replace('&',' ')
   sub cat list.append(temp.strip())
X Train['clean subcategories'] = sub cat list
X Train.drop(['project subject subcategories'], axis=1, inplace=True)
# count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
my counter = Counter()
for word in X Train['clean subcategories'].values:
   my counter.update(word.split())
sub cat dict = dict(my counter)
sorted sub cat dict Train = dict(sorted(sub cat dict.items(), key=lambda kv: kv[1]))
print(len(sorted sub cat dict Train))
sub catogories = list(X Test['project subject subcategories'].values)
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"=> "Math", "&", "Science"
        j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e removing 'The')
    j = j.replace('','') # we are placeing all the ''(space) with ''(empty) ex:"Math & Science"=>"Math&Science"
    temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the trailing spaces
    temp = temp.replace('&','_')
    sub_cat_list.append(temp.strip())

X_Test['clean_subcategories'] = sub_cat_list
    X_Test.drop(['project_subject_subcategories'], axis=1, inplace=True)
```

1.3 Text preprocessing

In [0]:

```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
    # general
    phrase = re.sub(r"\'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"\'ll", " will", phrase)
    phrase = re.sub(r"\'ll", " not", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'re", " am", phrase)
```

In [0]:

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

```
# Combining all the above stundents
# tgdm is for printing the status bar
                  ----- of Essays in Train data set-----
preprocessed essays Train = []
for sentance in tqdm(X Train['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.lower() not in stopwords)
   preprocessed essays Train.append(sent.lower().strip())
# pdb.set trace()
     -----PreProcessing of Essays in Test data set-----
preprocessed essays Test = []
for sentance in tqdm(X Test['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.lower() not in stopwords)
   preprocessed essays Test.append(sent.lower().strip())
```

```
# pdb.set trace()
100%|
           | 33500/33500 [00:18<00:00, 1848.60it/s]
              | 16500/16500 [00:08<00:00, 1834.83it/s]
In [0]:
word count essay Train = []
for a in tqdm(X Train["essay"]) :
   b = len(a.split())
    word count essay Train.append(b)
X Train["word count essay Train"] = word count essay Train
word count essay Test = []
for a in tqdm(X Test["essay"]) :
    b = len(a.split())
    word count essay Test.append(b)
X Test["word count essay Test"] = word count essay Test
100%|
      | 33500/33500 [00:00<00:00, 66475.46it/s]
              | 16500/16500 [00:00<00:00, 65650.70it/s]
```

1.4 Preprocessing of `project_title`

```
In [0]:
```

```
# Combining all the above stundents
# tqdm is for printing the status bar
                 ------PreProcessing of Project Title in Train data set------PreProcessing of Project Title
preprocessed titles Train = []
for sentance in tqdm(X Train['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 titles Train.append(sent.lower().strip())
# pdb.set trace()
          -----PreProcessing of Project Title in Test data set-----
preprocessed titles Test = []
for sentance in tqdm(X Test['project title'].values):
```

```
sent = decontracted(sentance)
sent = sent.replace('\\r', ' ')
sent = sent.replace('\\", ' ')
sent = sent.replace('\\", ' ')
sent = sent.replace('\\", ' ')
sent = re.sub('\^A-Za-z0-9]+', ' ', sent)
# https://gist.github.com/sebleier/554280
sent = ' '.join(e for e in sent.split() if e not in stopwords)
preprocessed_titles_Test.append(sent.lower().strip())
# pdb.set_trace()

100%| | 33500/33500 [00:00<00:00, 42123.97it/s]
100%| | 16500/16500 [00:00<00:00, 42023.42it/s]</pre>
```

In [0]:

1.5 Preparing data for models

1.5.1 Vectorizing Categorical data

https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/

```
def ResponseCoding(Train, Test, Column_Name):
    Unique_Category = Train[Column_Name].unique()
    Accept=[]
    Reject=[]
    Prob_Accept=[]
```

```
Prob Reject=[]
Net=[]
for i in Unique Category:
  Accept.append((len(Train.loc[(Train[Column Name] == i) & (Train['project is approved'] == 1)])))
for i in Unique Category:
  Reject.append((len(Train.loc[(Train[Column Name] == i) & (Train['project is approved'] == 0)])))
for i in range(len(Accept)):
  try:
    Prob Accept.append(Accept[i]/(Accept[i]+Reject[i]))
  except ZeroDivisionError:
    Prob Accept.append(0)
for i in range(len(Reject)):
  try:
    Prob Reject.append(Reject[i]/(Accept[i]+Reject[i]))
  except ZeroDivisionError:
    Prob Reject.append(0)
Prob Accept dict = dict(zip(Unique Category, Prob Accept))
Prob Reject dict = dict(zip(Unique Category, Prob Reject))
acc=Column Name+' accept'
rej=Column Name+' reject'
df = pd.DataFrame()
df[acc] = Train[Column Name].map(Prob Accept dict)
df[rej] = Train[Column Name].map(Prob Reject dict)
acce Train = df[acc].values.tolist()
reje Train = df[rej].values.tolist()
Train R = pd.DataFrame(list(zip(acce Train, reje Train)))
df1 = pd.DataFrame()
df1[acc] = Test[Column Name].map(Prob Accept dict)
df1[rej] = Test[Column Name].map(Prob Reject dict)
acce Test = df1[acc].values.tolist()
reje Test = df1[rej].values.tolist()
Test R = pd.DataFrame(list(zip(acce Test, reje Test)))
Test R.fillna(0.5, inplace = True) #Filling the unseen values with 0.5 values.
return Train R, Test R
```

project_subject_categories,project_subject_subcategories, School State, Prefix, project_grade_category

```
In [0]:
```

```
X_Train_clean_cat_raw,X_Test_clean_cat_raw=ResponseCoding(X_Train,X_Test,'clean_categories')
X_Train_clean_subcat_raw,X_Test_clean_subcat_raw=ResponseCoding(X_Train,X_Test,'clean_subcategories')
X_Train_grade_raw,X_Test_grade_raw=ResponseCoding(X_Train,X_Test,'school_state')
X_Train_state_raw,X_Test_state_raw=ResponseCoding(X_Train,X_Test,'teacher_prefix')
X_Train_teacher_raw,X_Test_teacher_raw=ResponseCoding(X_Train,X_Test,'project_grade_category')

X_Train_clean_cat= scipy.sparse.csr_matrix(X_Train_clean_cat_raw.values)
```

```
| X Train clean subcat= scipy.sparse.csr matrix(X Train clean subcat raw.values)
X Train grade= scipy.sparse.csr matrix(X Train grade raw.values)
X Train state= scipy.sparse.csr matrix(X Train state raw.values)
X Train teacher= scipy.sparse.csr matrix(X Train teacher raw.values)
In [0]:
X Test clean cat = scipy.sparse.csr matrix(X Test clean cat raw.values)
X Test clean subcat = scipy.sparse.csr matrix(X Test clean subcat raw.values)
X Test grade = scipy.sparse.csr matrix(X Test grade raw.values)
X Test state = scipy.sparse.csr matrix(X Test state raw.values)
X Test teacher = scipy.sparse.csr matrix(X Test teacher raw.values)
1.5.2 Vectorizing Numerical features
In [0]:
price data = Resource data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset index()
X Train = pd.merge(X Train, price data, on='id', how='left')
X Test = pd.merge(X Test, price data, on='id', how='left')
In [0]:
price norm = Normalizer(norm='12', copy=False)
price norm.fit(X Train['price'].values.reshape(1,-1))
p=price norm.transform(X Train['price'].values.reshape(1,-1))
price norm.transform(X Test['price'].values.reshape(1,-1))
price norm Train = (X Train['price'].values.reshape(-1,1))
price norm Test = (X Test['price'].values.reshape(-1,1))
print("-"*120)
print('Shape of Train normalized price dataset matrix after one hot encoding is: {0}'.format(price norm Train.shape))
print('Shape of Test normalized price dataset matrix after one hot encoding is: {0}'.format(price norm Test.shape))
Shape of Train normalized price dataset matrix after one hot encoding is: (33500, 1)
Shape of Test normalized price dataset matrix after one hot encoding is: (16500, 1)
In [0]:
quantity norm = Normalizer(norm='12', copy=False)
quantity norm.fit(X Train['quantity'].values.reshape(1,-1))
quantity norm.transform(X Train['quantity'].values.reshape(1,-1))
quantity norm.transform(X Test['quantity'].values.reshape(1,-1))
quantity norm Train = quantity norm.transform(X Train['quantity'].values.reshape(-1,1))
quantity norm Test = quantity norm.transform(X Test['quantity'].values.reshape(-1,1))
```

```
print ("-"*120)
print('Shape of Train normalized quantity dataset matrix after one hot encoding is: {0}'.format(quantity norm Train.shape))
print('Shape of Test normalized quantity dataset matrix after one hot encoding is: {0}'.format(quantity norm Test.shape))
Shape of Train normalized quantity dataset matrix after one hot encoding is: (33500, 1)
Shape of Test normalized quantity dataset matrix after one hot encoding is: (16500, 1)
In [0]:
teacher prev post norm = Normalizer(norm='12', copy=False)
teacher prev post norm.fit(X Train['teacher number of previously posted projects'].values.reshape(1,-1))
teacher prev post norm.transform(X Train['teacher number of previously posted projects'].values.reshape(1,-1))
teacher prev post norm.transform(X Test['teacher number of previously posted projects'].values.reshape(1,-1))
teacher prev post norm Train = teacher prev post norm.transform(X Train['teacher number of previously posted projects'].values.reshape(-1,1))
teacher prev post norm Test = teacher prev post norm.transform(X Test['teacher number of previously posted projects'].values.reshape(-1,1))
print("-"*120)
print ('Shape of Train normalized previously posted project dataset matrix after one hot encoding is: {0}'.format(teacher prev post norm Train.shape
))
print ('Shape of Test normalized previously posted project dataset matrix after one hot encoding is: {0}'.format(teacher prev post norm Test.shape))
Shape of Train normalized previously posted project dataset matrix after one hot encoding is: (33500, 1)
Shape of Test normalized previously posted project dataset matrix after one hot encoding is: (16500, 1)
In [0]:
title norm = Normalizer(norm='12', copy=False)
title norm.fit(X Train['word count title Train'].values.reshape(1,-1))
title norm.transform(X Train['word count title Train'].values.reshape(1,-1))
title norm.transform(X Test['word count title Test'].values.reshape(1,-1))
word count title Train = title norm.transform(X Train['word count title Train'].values.reshape(-1,1))
word count title Test = title norm.transform(X Test['word count title Test'].values.reshape(-1,1))
print("-"*120)
print('Shape of Train normalized title dataset matrix after one hot encoding is: {0}'.format(word count title Train.shape))
print('Shape of Test normalized title dataset matrix after one hot encoding is: {0}'.format(word count title Test.shape))
Shape of Train normalized title dataset matrix after one hot encoding is: (33500, 1)
Shape of Test normalized title dataset matrix after one hot encoding is: (16500, 1)
In [0]:
essay norm = Normalizer(norm='12', copy=False)
essay norm.fit(X Train['word count essay Train'].values.reshape(1,-1))
essay norm.transform(X Train['word count essay Train'].values.reshape(1,-1))
essay norm.transform(X Test['word count essay Test'].values.reshape(1,-1))
```

```
word_count_essay_Train = essay_norm.transform(X_Train['word_count_essay_Train'].values.reshape(-1,1))
word_count_essay_Test = essay_norm.transform(X_Test['word_count_essay_Test'].values.reshape(-1,1))
print("-"*120)
print('Shape of Train normalized title dataset matrix after one hot encoding is: {0}'.format(word_count_essay_Train.shape))
print('Shape of Test normalized title dataset matrix after one hot encoding is: {0}'.format(word_count_essay_Test.shape))
```

Shape of Train normalized title dataset matrix after one hot encoding is: (33500, 1) Shape of Test normalized title dataset matrix after one hot encoding is: (16500, 1)

1.5.3 Vectorizing Text data

1.5.3.1 Bag of words

```
In [0]:
```

```
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer_essays_bow = CountVectorizer(min_df=10)
text_bow_Train = vectorizer_essays_bow.fit_transform(preprocessed_essays_Train)
text_bow_Test = vectorizer_essays_bow.transform(preprocessed_essays_Test)
print("-"*120)
print("Applying Bag Of Words for Text Data")
print("-"*120)
print('Shape of Train dataset matrix after one hot encoding is: {0}'.format(text_bow_Train.shape))
print('Shape of Test dataset matrix after one hot encoding is: {0}'.format(text_bow_Test.shape))
```

Applying Bag Of Words for Text Data

Shape of Train dataset matrix after one hot encoding is: (33500, 10323) Shape of Test dataset matrix after one hot encoding is: (16500, 10323)

Bag of Words for Project Title

```
In [0]:
```

```
# you can vectorize the title also
# before you vectorize the title make sure you preprocess it
vectorizer_titles_bow = CountVectorizer(min_df=10)
title_bow_Train = vectorizer_titles_bow.fit_transform(preprocessed_titles_Train)
title_bow_Test = vectorizer_titles_bow.transform(preprocessed_titles_Test)
print("-"*120)
print("Applying Bag Of Words for Project Title Data")
print("-"*120)
print('Shape of Train dataset matrix after one hot encoding is: {0}'.format(title_bow_Train.shape))
print('Shape of Test dataset matrix after one hot encoding is: {0}'.format(title_bow_Test.shape))
```

Applying Bag Of Words for Project Title Data

Shape of Train dataset matrix after one hot encoding is: (33500, 1626)

Shape of Test dataset matrix after one hot encoding is: (16500, 1626)

1.5.2.2 TFIDF vectorizer

In [0]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer_essays_tfidf = TfidfVectorizer(min_df=10)
text_tfidf_Train = vectorizer_essays_tfidf.fit_transform(preprocessed_essays_Train)
text_tfidf_Test = vectorizer_essays_tfidf.transform(preprocessed_essays_Test)
print("-"*120)
print("Applying TFIDF for Text Data")
print("-"*120)
print("Shape of Train dataset matrix after one hot encoding is: {0}'.format(text_tfidf_Train.shape))
print('Shape of Test dataset matrix after one hot encoding is: {0}'.format(text_tfidf_Test.shape))
```

Applying TFIDF for Text Data

Shape of Train dataset matrix after one hot encoding is: (33500, 10323) Shape of Test dataset matrix after one hot encoding is: (16500, 10323)

TFIDF vectorizer for Project Title

In [0]:

```
vectorizer_titles_tfidf = TfidfVectorizer(min_df=10)
title_tfidf_Train = vectorizer_titles_tfidf.fit_transform(preprocessed_titles_Train)
title_tfidf_Test = vectorizer_titles_tfidf.transform(preprocessed_titles_Test)
print("-"*120)
print("Applying TFIDF for Project Title")
print("-"*120)
print("-"*120)
print('Shape of Train dataset matrix after one hot encoding is: {0}'.format(title_tfidf_Train.shape))
print('Shape of Test dataset matrix after one hot encoding is: {0}'.format(title_tfidf_Test.shape))
```

Applying TEIDE for Droject Title

Applying TFIDF for Project Title

Shape of Train dataset matrix after one hot encoding is: (33500, 1626)

Shape of Test dataset matrix after one hot encoding is: (16500, 1626)

1.5.2.3 Using Pretrained Models: Avg W2V

In [0]:

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

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v vectors Train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed essays Train): # 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
    avg w2v vectors Train.append(vector)
avg w2v vectors Test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed essays Test): # 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
    avg w2v vectors Test.append(vector)
print(len(avg w2v vectors Test))
print(len(avg w2v vectors Test[1]))
      | 33500/33500 [00:10<00:00, 3320.55it/s]
              | 16500/16500 [00:05<00:00, 3290.15it/s]
```

AVG W2V on project title

```
In [0]:
```

```
# Similarly you can vectorize for title also
# compute average word2vec for each title.
avg w2v vectors title Train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm (preprocessed titles Train): # for each review/sentence
    vector title = np.zeros(300) # as word vectors are of zero length
    cnt title 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 title += model[word]
            cnt title words += 1
    if cnt title words != 0:
        vector title /= cnt title words
    avg w2v vectors title Train.append(vector title)
avg w2v vectors title Test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm (preprocessed titles Test): # for each review/sentence
    vector title = np.zeros(300) # as word vectors are of zero length
    cnt title 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 title += model[word]
            cnt title words += 1
    if cnt title words != 0:
        vector title /= cnt title words
    avg w2v vectors title Test.append(vector title)
print(len(avg w2v vectors title Test))
print(len(avg w2v vectors title Test[0]))
      | 33500/33500 [00:00<00:00, 63778.12it/s]
              | 16500/16500 [00:00<00:00, 60001.70it/s]
```

16500 300

1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

```
tfidf_model_essays = TfidfVectorizer()
tfidf_model_essays.fit(preprocessed_essays_Train)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_essays.get_feature_names(), list(tfidf_model_essays.idf_)))
tfidf_words_essays = set(tfidf_model_essays.get_feature_names())
```

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors Train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed essays Train): # 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 essays):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf idf weight
    tfidf w2v vectors Train.append(vector)
tfidf w2v vectors Test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed essays Test): # 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 essays):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector /= tf idf weight
    tfidf w2v vectors Test.append(vector)
print(len(tfidf w2v vectors Test))
print(len(tfidf w2v vectors Test[0]))
                33500/33500 [00:58<00:00, 568.94it/s]
100%|
               | 16500/16500 [00:29<00:00, 563.88it/s]
```

Using Pretrained Models: TFIDF weighted W2V on project title

16500/16500 [00:00<00:00, 33814.70it/s]

```
In [0]:
# Similarly you can vectorize for title also
tfidf model title = TfidfVectorizer()
tfidf model title.fit(preprocessed titles Train)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf model title.get feature names(), list(tfidf model title.idf )))
tfidf words title = set(tfidf model title.get feature names())
# compute tfidf word2vec for each title.
tfidf w2v vectors title Train = []; # the avq-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed titles Train): # for each review/sentence
    vector title = 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 title):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf value for each word
            vector title += (vector title * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector title /= tf idf weight
    tfidf w2v vectors title Train.append(vector title)
tfidf w2v vectors title Test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed titles Test): # for each review/sentence
    vector title = 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 title):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf value for each word
            vector title += (vector title * tf idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf idf weight != 0:
        vector title /= tf idf weight
    tfidf w2v vectors title Test.append(vector title)
print(len(tfidf w2v vectors title Test))
print(len(tfidf w2v vectors title Test[0]))
                33500/33500 [00:01<00:00, 33090.71it/s]
100%1
```

Calculating the sentiment score's of each of the essay

```
sid = SentimentIntensityAnalyzer()
essays = X Train['essay']
essays sentiment TR P = []
essays sentiment TR N = []
essays sentiment TR NE = []
essays sentiment TR C = []
for essay in tqdm(essays):
    res = sid.polarity scores(essay)
    essays sentiment TR P.append(res['pos'])
    essays sentiment TR N.append(res['neg'])
    essays sentiment TR NE.append(res['neu'])
    essays sentiment TR C.append(res['compound'])
X Train['sentiment essay TR P'] = essays sentiment TR P
X Train['sentiment essay TR N'] = essays sentiment TR N
X Train['sentiment essay TR NE'] = essays sentiment TR NE
X Train['sentiment essay TR C'] = essays sentiment TR C
essays = X Test['essay']
essays sentiment TS P = []
essays sentiment TS N = []
essays sentiment TS NE = []
essays sentiment TS C = []
for essay in tqdm(essays):
    res = sid.polarity scores(essay)
    essays sentiment TS P.append(res['pos'])
    essays sentiment TS N.append(res['neg'])
    essays sentiment TS NE.append(res['neu'])
    essays sentiment TS C.append(res['compound'])
X Test['sentiment essay TS P'] = essays sentiment TS P
X Test['sentiment essay TS N'] = essays sentiment TS N
X Test['sentiment essay TS NE'] = essays sentiment TS NE
X Test['sentiment essay TS C'] = essays sentiment TS C
sentiment norm P = Normalizer(norm='12', copy=False)
sentiment norm N = Normalizer(norm='12', copy=False)
sentiment norm NE = Normalizer(norm='12', copy=False)
sentiment norm C = Normalizer(norm='12', copy=False)
sentiment norm P.fit(X Train['sentiment essay TR P'].values.reshape(1,-1))
```

```
sentiment norm N.III(A Irain) Sentiment essay IK N' | Values resnape(1, -1) |
sentiment norm NE.fit(X Train['sentiment essay TR NE'].values.reshape(1,-1))
sentiment norm C.fit(X Train['sentiment essay TR C'].values.reshape(1,-1))
sentiment Train P = sentiment norm P.transform(X Train['sentiment essay TR P'].values.reshape(1,-1))
sentiment Test P = sentiment norm P.transform(X Test['sentiment essay TS P'].values.reshape(1,-1))
sentiment Train N = sentiment norm N.transform(X Train['sentiment essay TR N'].values.reshape(1,-1))
sentiment Test N = sentiment norm N.transform(X Test['sentiment essay TS N'].values.reshape(1,-1))
sentiment Train NE = sentiment norm NE.transform(X Train['sentiment essay TR NE'].values.reshape(1,-1))
sentiment Test NE = sentiment norm NE.transform(X Test['sentiment essay TS NE'].values.reshape(1,-1))
sentiment Train C = sentiment norm C.transform(X Train['sentiment essay TR C'].values.reshape(1,-1))
sentiment Test C = sentiment norm C.transform(X Test['sentiment essay TS C'].values.reshape(1,-1))
sentiment Train P = (X Train['sentiment essay TR P'].values.reshape(-1,1))
sentiment Test P = (X Test['sentiment essay TS P'].values.reshape(-1,1))
sentiment Train N = (X Train['sentiment essay TR N'].values.reshape(-1,1))
sentiment Test N = (X Test['sentiment essay TS N'].values.reshape(-1,1))
sentiment Train NE = (X Train['sentiment essay TR NE'].values.reshape(-1,1))
sentiment Test NE = (X Test['sentiment essay TS NE'].values.reshape(-1,1))
sentiment Train C = (X Train['sentiment essay TR C'].values.reshape(-1,1))
sentiment Test C = (X Test['sentiment essay TS C'].values.reshape(-1,1))
print ("Shape of sentiment Train matrix after one hot encodig ", sentiment Train P.shape)
print("Shape of sentiment Test matrix after one hot encodig ", sentiment Test P.shape)
print("Shape of sentiment Train matrix after one hot encodig ", sentiment Train N. shape)
print("Shape of sentiment Test matrix after one hot encodig ", sentiment Test N.shape)
print("Shape of sentiment Train matrix after one hot encodig ", sentiment Train NE.shape)
print("Shape of sentiment Test matrix after one hot encodig ", sentiment Test NE.shape)
print("Shape of sentiment Train matrix after one hot encodig ", sentiment Train C.shape)
print("Shape of sentiment Test matrix after one hot encodig ", sentiment Test C.shape)
                 33500/33500 [01:28<00:00, 377.05it/s]
               | 16500/16500 [00:44<00:00, 369.82it/s]
Shape of sentiment Train matrix after one hot encodig (33500, 1)
Shape of sentiment Test matrix after one hot encodig (16500, 1)
Shape of sentiment Train matrix after one hot encodig (33500, 1)
Shape of sentiment Test matrix after one hot encodig (16500, 1)
Shape of sentiment Train matrix after one hot encodig (33500, 1)
Shape of sentiment Test matrix after one hot encodig (16500, 1)
Shape of sentiment Train matrix after one hot encodig (33500, 1)
Shape of sentiment Test matrix after one hot encodig (16500, 1)
```

1.5.4 Merging all the above features

• we need to merge all the numerical vectors i.e catogorical, text, numerical vectors

```
In [0]:

BOW_Train = hstack((X_Train_clean_cat, X_Train_clean_subcat, X_Train_grade, X_Train_state, X_Train_teacher, text_bow_Train, title_bow_Train, price_norm_Train, quantity_norm_Train, teacher_prev_post_norm_Train, word_count_title_Train_word_count_essay_Train, sentiment_Train_P, sentiment_Train_N, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_N, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Train_NE, sentiment_Test_NE, sen
```

```
TFIDF_Train = hstack((X_Train_clean_cat, X_Train_clean_subcat, X_Train_grade, X_Train_state, X_Train_teacher,text_tfidf_Train,title_tfidf_Train, price_norm_Train, quantity_norm_Train, teacher_prev_post_norm_Train, word_count_title_Train, word_count_essay_Train,sentiment_Train_P,sentiment_Train_N,sentiment_Train_NE,sentiment_Train_C))

TFIDF_Test = hstack((X_Test_clean_cat,X_Test_clean_subcat,X_Test_grade,X_Test_state,X_Test_teacher,text_tfidf_Test,title_tfidf_Test, price_norm_Test, quantity_norm_Test,teacher_prev_post_norm_Test,word_count_title_Test,word_count_essay_Test,sentiment_Test_P,sentiment_Test_N,sentiment_Test_NE,sentiment_Test_C))

print(TFIDF_Train.shape)

print(TFIDF_Test.shape)
```

(33500, 11968) (16500, 11968)

In [0]:

AVG_W2V_Train = hstack((X_Train_clean_cat, X_Train_clean_subcat, X_Train_grade, X_Train_state, X_Train_teacher,avg_w2v_vectors_Train,avg_w2v_vectors_title_Train, price_norm_Train, quantity_norm_Train, teacher_prev_post_norm_Train, word_count_title_Train, word_count_essay_Train,sentiment_Train_P, sentiment_Train_N, sentiment_Train_NE, sentiment_Train_C))

AVG_W2V_Test = hstack((X_Test_clean_cat, X_Test_clean_subcat, X_Test_grade, X_Test_state, X_Test_teacher, avg_w2v_vectors_Test, avg_w2v_vectors_title_Test, price_norm_Test, quantity_norm_Test, teacher_prev_post_norm_Test, word_count_title_Test, word_count_essay_Test, sentiment_Test_P, sentiment_Test_N, sentiment_Test_NE, sentiment_Test_C))

print(AVG_W2V_Train.shape)

print(AVG_W2V_Test.shape)

(33500, 619) (16500, 619)

In [0]:

TFIDF_W2V_Train = hstack((X_Train_clean_cat, X_Train_clean_subcat, X_Train_grade, X_Train_state, X_Train_teacher,tfidf_w2v_vectors_Train,tfidf_w2v_v ectors_title_Train, price_norm_Train, quantity_norm_Train, teacher_prev_post_norm_Train, word_count_title_Train, word_count_essay_Train,sentiment_Train_P, sentiment_Train_N, sentiment_Train_NE, sentiment_Train_C))
TFIDF_W2V_Test = hstack//Y_Test_clean_cat Y_Test_clean_subcat Y_Test_crade Y_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_crade Y_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_Test_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_title_Test_ctate Y_Test_teacher_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfidf_w2v_vectors_tfi

```
price_norm_Test,quantity_norm_Test,teacher_prev_post_norm_Test,word_count_title_Test,word_count_essay_Test,sentiment_Test_P,sentiment_Test_N,sentiment_Test_NE,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,sentiment_Test_N,
```

Assignment 9: RF and GBDT

Response Coding: Example

(16500, 619)

The response tabel is built only on train dataset. For a category which is not there in train data and present in test data, we will encode them with default values Ex: in our test data if have State: D then we encode it as [0.5, 0.05]

1. Apply both Random Forrest and GBDT on these feature sets

- Set 1: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project_title(BOW) + preprocessed_eassay (BOW)
- Set 2: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project_title(TFIDF)+ preprocessed_eassay (TFIDF)
- Set 3: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project_title(AVG W2V)+ preprocessed_eassay (AVG W2V)
- Set 4: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project title(TFIDF W2V)+ preprocessed eassay (TFIDF W2V)

2. The hyper paramter tuning (Consider any two hyper parameters preferably n estimators, max depth)

- Find the best hyper parameter which will give the maximum AUC value
- find the best hyper paramter using k-fold cross validation/simple cross validation data
- use gridsearch cv or randomsearch cv or you can write your own for loops to do this task

3. Representation of results

• You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure with X-axis as n_estimators, Y-axis as max_depth, and Z-axis as AUC Score, we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive 3d_scatter_plot.ipynb



- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure seaborn heat maps with rows as n_estimators, columns as max_depth, and values inside the cell representing AUC Score
- You can choose either of the plotting techniques: 3d plot or heat map

- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
- Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points

4. Conclusion

• You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

Note: Data Leakage

- 1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
- 2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
- 3. While vectorizing your data, apply the method fit transform() on you train data, and apply the method transform() on cv/test data.
- 4. For more details please go through this link.

2. Random Forest and GBDT

```
In [0]:

n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000]

max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

MD=[j for j in max_depth for i in n_estimators]

ES=[i for j in max_depth for i in n_estimators]

'''for i in max_depth:
    for j in n_estimators:
        MD.append(i)
        ES.append(j)

print(ES)
print(MD)'''
print(ES)
print(MD)
```

2.4 Applying Random Forest

Apply Random Forest on different kind of featurization as mentioned in the instructions

2.4.1 Applying Random Forests on BOW, SET 1

```
In [0]:
```

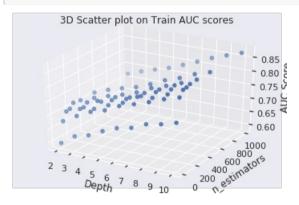
```
RF_clf = RandomForestClassifier(class_weight='balanced',n_jobs=-1)
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
RFRan_clf = RandomizedSearchCV(RF_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
RFRan_clf.fit(BOW_Train, Y_Train)
print("-"*120)
print(RFRan_clf.best_estimator_)
print("-"*120)
BOW_Best_ES=RFRan_clf.best_params_['n_estimators']
BOW_Best_MD=RFRan_clf.best_params_['max_depth']
AUC_TR= RFRan_clf.cv_results_['mean_train_score']
AUC_CV = RFRan_clf.cv_results_['mean_test_score']
```

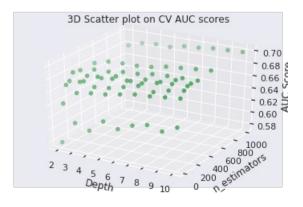
Fitting 3 folds for each of 72 candidates, totalling 216 fits

3D PLOT

```
In [0]:
```

```
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES,AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
                                       -----3D-Plot for CV Dataset-----
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```





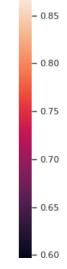
HEATMAP

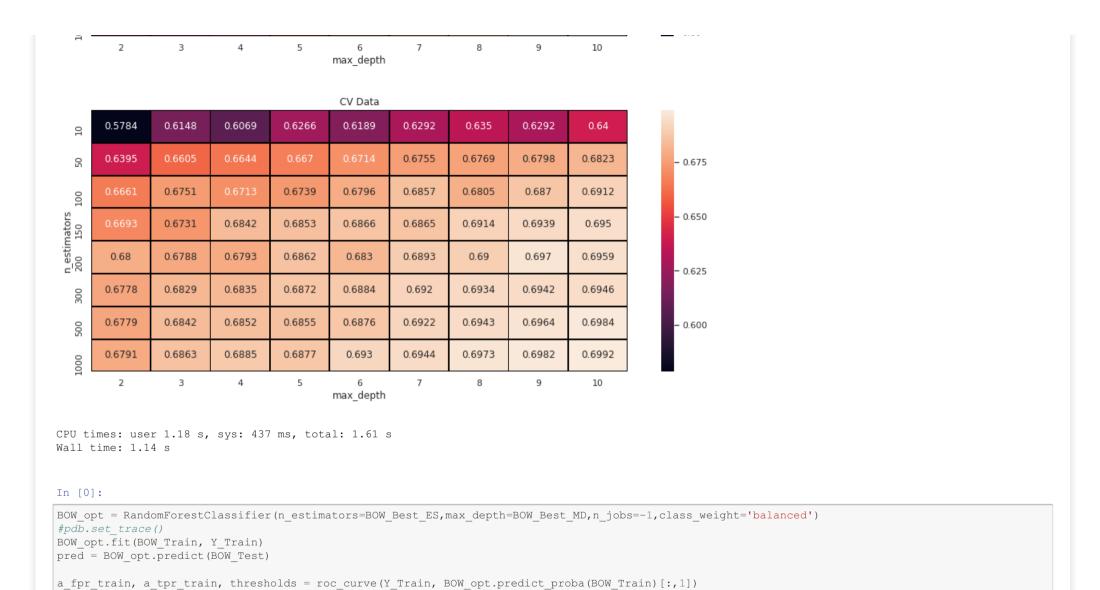
In [0]:

```
%%t.ime
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC TR':AUC TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
#------#
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC CV':AUC CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4q',linewidths=1,linecolor='black')
plt.title('CV Data')
plt.show()
```

Train Data

10	0.5958	0.6318	0.6467	0.6724	0.6941	0.7057	0.7291	0.7396	0.7551
100 50	0.6719	0.7015	0.7267	0.7421	0.7677	0.7843	0.8014	0.8217	0.8372
	0.7007	0.7198	0.7303	0.7534	0.772	0.8032	0.8092	0.8311	0.8565
nators 150	0.7033	0.7187	0.7522	0.7648	0.7788	0.7987	0.8224	0.8416	0.858
n estimators 200 150	0.7186	0.7299	0.7424	0.7684	0.7775	0.803	0.8249	0.8489	0.8627
300	0.7143	0.7323	0.7492	0.7638	0.7818	0.8066	0.824	0.8433	0.8645
200	0.7155	0.735	0.7504	0.7644	0.7845	0.8078	0.8253	0.8481	0.8642
000	0.7197	0.7382	0.7546	0.769	0.7898	0.8106	0.8329	0.8511	0.8687





BOW ROC PLOT

```
In [0]:
```

```
%%time

#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
```

a fpr Test, a tpr Test, thresholds = roc curve(Y Test, BOW opt.predict proba(BOW Test)[:,1])

```
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a_fpr_train, a_tpr_train, label="BOW AUC Train", color='green')
plt.plot(a_fpr_Test, a_tpr_Test, label="BOW AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("BOW ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a_fpr_train, a_tpr_train))
print("AUC Test (for best estimator and depth) =", auc(a_fpr_Test, a_tpr_Test))
BOW_AUC=round(auc(a_fpr_Test, a_tpr_Test)*100)
pred1 = BOW_opt.predict(BOW_Train)
pred2 = BOW_opt.predict(BOW_Test)
```



```
AUC Train (for best estimator and depth) = 0.8357237027801431 AUC Test (for best estimator and depth) = 0.6830153857549816 CPU times: user 24.2 s, sys: 605 ms, total: 24.8 s Wall time: 2.31 s
```

BOW CONFUSION MATRIX

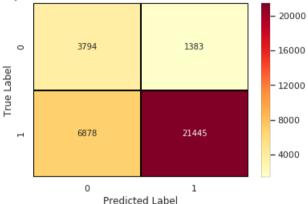
```
In [0]:
```

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
```

```
Train = confusion_matrix(Y_Train, pred1)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')

CPU times: user 88.2 ms, sys: 44.7 ms, total: 133 ms
```

Project is APPROVED or NOT Confusion Matrix - Train Data



OBSERVATION:

Wall time: 82.9 ms

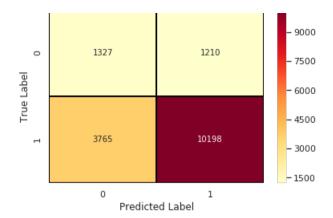
True Negative = 3794; False Negative = 6878; True Positive = 21445; False Positive = 1383 Accuracy (Overall, how often is the classifier correct) = 0.76 Precision(When it predicts yes, how often is it correct) = 0.94 Misclassification (Overall, how often is it wrong) = 0.25

In [0]:

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred2)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
```

CPU times: user 74.2 ms, sys: 46.9 ms, total: 121 ms Wall time: 69.3 ms

Project is APPROVED or NOT Confusion Matrix - Test Data



OBSERVATION:

True Negative = 1327; False Negative = 3765; True Positive = 10198; False Positive = 1210 Accuracy (Overall, how often is the classifier correct) = 0.70 Precision(When it predicts yes, how often is it correct) = 0.90 Misclassification (Overall, how often is it wrong) = 0.31

2.4.2 Applying Random Forests on TFIDF, SET 2

```
In [0]:
```

```
RF_clf = RandomForestClassifier(class_weight='balanced',n_jobs=-1)
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
RFRan_clf = RandomizedSearchCV(RF_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
RFRan_clf.fit(TFIDF_Train, Y_Train)
print("-"*120)
print(RFRan_clf.best_estimator_)
print("-"*120)
TFIDF_Best_ES=RFRan_clf.best_params_['n_estimators']
TFIDF_Best_ES=RFRan_clf.best_params_['max_depth']
AUC_TR= RFRan_clf.cv_results_['mean_train_score']
AUC_CV = RFRan_clf.cv_results_['mean_test_score']
```

Fitting 3 folds for each of 72 candidates, totalling 216 fits

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 40 concurrent workers.

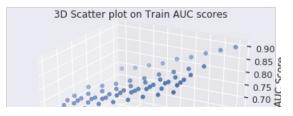
[Parallel(n_jobs=-1)]: Done 120 tasks | elapsed: 36.7s

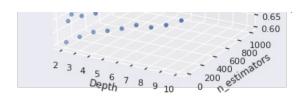
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 1.5min finished
```

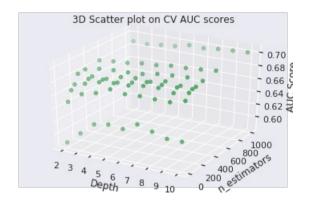
3D PLOT

```
In [0]:
```

```
%%t.ime
#https://stackoverflow.com/questions/53311685/difference-between-ax-set-xlabel-and-ax-xaxis-set-label-in-matplotlib-3-0-1
#-----3D-Plot for Train Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
#------3D-Plot for CV Dataset-------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```







```
CPU times: user 428 ms, sys: 397 ms, total: 825 ms Wall time: 348 ms
```

HEATMAP

```
%%time
                   ------ dat Map for Train data------
____
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC TR':AUC TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
                plt.close()
d={'n estimators':ES,'max depth':MD,'AUC CV':AUC CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
```

```
plt. Ilgure (Ilgslze=(15,6))
sns.heatmap(result,annot = True, fmt='.4q',linewidths=1,linecolor='black')
plt.title('CV Data')
plt.show()
                                                                                                                                                                                         Þ
4
                                                    Train Data
                                                                                                                     - 0.90
         0.6084
                    0.6417
                                0.6725
                                           0.6892
                                                      0.7092
                                                                 0.7339
                                                                             0.7365
                                                                                        0.7568
   2
                                                                                                                     - 0.85
         0.6874
                    0.7187
                               0.7397
                                           0.7678
                                                                                        0.8456
                                                                                                   0.8651
   20
         0.7064
                     0.741
                               0.7554
                                           0.7801
                                                                             0.8489
                                                                                        0.861
                                                                                                   0.8838
                                                                                                                     - 0.80
 n estimators
200 150
                    0.7442
                                0.7612
         0.7154
                                                                             0.8499
                                                                                        0.8732
                                                                                                   0.8862
                                                                                                                     - 0.75
         0.7271
                    0.7454
                               0.7592
                                                                              0.85
                                                                                        0.8712
                                                                                                   0.8894
         0.7298
                    0.7485
                                0.7694
                                           0.7885
                                                                             0.855
                                                                                        0.8739
                                                                                                   0.8926
                                                                                                                     - 0.70
         0.7353
                    0.7506
                                0.769
                                                                 0.8359
                                                                             0.8558
                                                                                        0.8772
                                                                                                   0.8964
   200
                                                                                                                     - 0.65
         0.7394
                    0.7523
                                                                             0.8587
                                                                                        0.8801
                                                                                                   0.9014
   1000
           2
                       3
                                                                                          9
                                  4
                                             5
                                                         6
                                                                    7
                                                                               8
                                                                                                     10
                                                    max depth
                                                     CV Data
                                                                                                                    - 0.70
                                                                             0.6305
         0.5865
                    0.6053
                                0.6239
                                           0.6279
                                                      0.6257
                                                                 0.6371
                                                                                        0.6242
                                                                                                   0.6242
   10
         0.6475
                                           0.6787
                                                      0.6756
                                                                  0.677
                                                                             0.6764
                                                                                        0.6763
                                                                                                   0.6824
                                                                                                                     - 0.68
   22
                    0.6762
                                0.6824
                                           0.685
                                                      0.6856
                                                                  0.689
                                                                             0.6902
                                                                                        0.6867
                                                                                                   0.6911
   100
                                                                                                                     - 0.66
 n estimators
200 150
                    0.6806
                                0.6833
                                           0.6831
                                                      0.6872
                                                                 0.6917
                                                                             0.6916
                                                                                        0.692
                                                                                                   0.6936
                                                                                                                     - 0.64
         0.6815
                    0.6815
                               0.6818
                                           0.6885
                                                      0.6907
                                                                 0.6895
                                                                             0.694
                                                                                        0.6917
                                                                                                   0.6942
         0.6828
                    0.6875
                                0.6893
                                           0.6899
                                                      0.6914
                                                                 0.6954
                                                                             0.6971
                                                                                        0.6982
                                                                                                   0.6971
   300
                                                                                                                     - 0.62
         0.6857
                    0.6879
                                0.6893
                                           0.6925
                                                      0.6937
                                                                 0.6967
                                                                             0.6972
                                                                                        0.6989
                                                                                                   0.7009
                                                                                                                     - 0.60
         0.6892
                    0.6884
                                0.6907
                                           0.6925
                                                      0.6976
                                                                 0.6967
                                                                             0.6992
                                                                                        0.7004
                                                                                                   0.7016
   1000
           2
                                             5
                                                                    7
                                                                                          9
                       3
                                  4
                                                         6
                                                                               8
                                                                                                     10
                                                    max depth
```

```
CPU times: user 1.2 s, sys: 448 ms, total: 1.65 s
Wall time: 1.17 s

In [0]:

%%time
TFIDF_opt = RandomForestClassifier(n_estimators=TFIDF_Best_ES,max_depth=TFIDF_Best_MD,n_jobs=-1,class_weight='balanced')
#pdb.set_trace()
TFIDF_opt.fit(TFIDF_Train, Y_Train)
pred = TFIDF_opt.predict(TFIDF_Test)
a_fpr_train, a_tpr_train, thresholds = roc_curve(Y_Train, TFIDF_opt.predict_proba(TFIDF_Train)[:,1])
a_fpr_Test, a_tpr_Test, thresholds = roc_curve(Y_Test, TFIDF_opt.predict_proba(TFIDF_Test)[:,1])

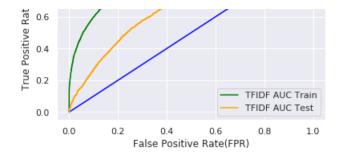
CPU times: user lmin 35s, sys: 2.93 s, total: lmin 38s
Wall time: 7.54 s
```

TFIDF ROC PLOT

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="TFIDF AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="TFIDF AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("TFIDF ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
TFIDF AUC=round(auc(a fpr Test, a tpr Test)*100)
pred3 = TFIDF opt.predict(TFIDF Train)
pred4 = TFIDF opt.predict(TFIDF Test)
```





AUC Train (for best estimator and depth) = 0.8678407507381374 AUC Test (for best estimator and depth) = 0.6890352370252921 CPU times: user 24.2 s, sys: 582 ms, total: 24.8 s Wall time: 2.17 s

TFIDF CONFUSION MATRIX

```
In [0]:
```

Wall time: 83.5 ms

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred3)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=l,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
CPU times: user 88.5 ms, sys: 45.5 ms, total: 134 ms
```

Project is APPROVED or NOT Confusion Matrix - Train Data



```
0 1
Predicted Label
```

OBSERVATION:

True Negative = 3700; False Negative = 4695; True Positive = 23628; False Positive = 1477

Accuracy (Overall, how often is the classifier correct) = 0.82

Precision(When it predicts yes, how often is it correct) =0.95

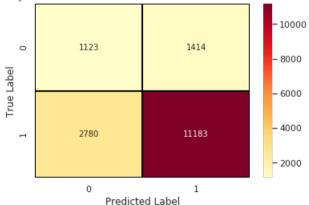
Misclassification (Overall, how often is it wrong) =0.19

In [0]:

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred4)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
```

CPU times: user 75.6 ms, sys: 41.7 ms, total: 117 ms Wall time: 68.4 ms

Project is APPROVED or NOT Confusion Matrix - Test Data



OBSERVATION:

True Negative = 1123; False Negative = 2780; True Positive = 11183; False Positive = 1414

Accuracy (Overall, how often is the classifier correct) = 0.75

Precision(When it predicts yes, how often is it correct) =0.89

2.4.3 Applying Random Forests on AVG_W2V SET 3

```
In [0]:
```

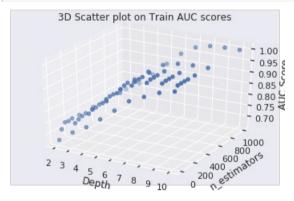
```
RF_clf = RandomForestClassifier(class_weight='balanced',n_jobs=-1)
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
RFRan_clf = RandomizedSearchCV(RF_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
RFRan_clf.fit(AVG_W2V_Train, Y_Train)
print("-"*120)
print(RFRan_clf.best_estimator_)
print("-"*120)
AVG_W2V_Best_ES=RFRan_clf.best_params_['n_estimators']
AVG_W2V_Best_MD=RFRan_clf.best_params_['max_depth']
AUC_TR= RFRan_clf.cv_results_['mean_train_score']
AUC_CV = RFRan_clf.cv_results_['mean_test_score']
```

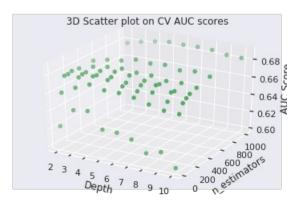
Fitting 3 folds for each of 72 candidates, totalling 216 fits

3D PLOT

```
In [0]:
```

```
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
                         -----3D-Plot for CV Dataset-----
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```





```
CPU times: user 1.02 s, sys: 4.06 s, total: 5.08 s Wall time: 369 ms
```

HEATMAP

```
In [0]:
```

```
%%t.ime
plt.close()
d={'n estimators':ES,'max_depth':MD,'AUC_TR':AUC_TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
#-------# data-----
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC CV':AUC CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('CV Data')
plt.show()
```

- 0.96

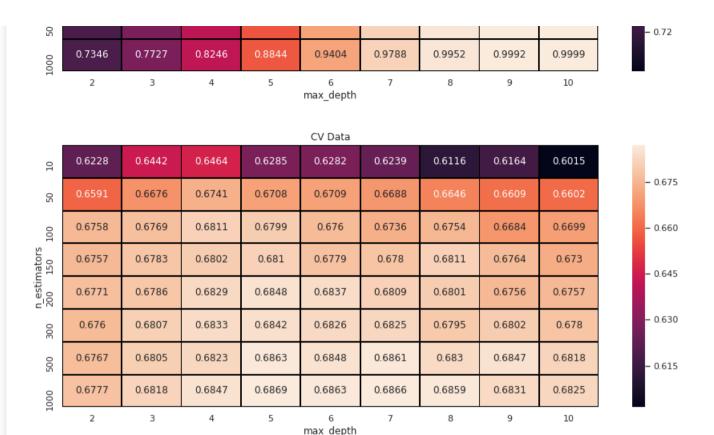
- 0.90

- 0.84

- 0.78

	Dat

10	0.6699	0.7174	0.7535	0.8013	0.8519	0.9042	0.9346	0.9633	0.9805
20	0.7117	0.752	0.8069	0.866	0.9197	0.9635	0.986	0.9954	0.9989
100	0.7341	0.7605	0.8159	0.8737	0.9285	0.9721	0.9921	0.9983	0.9997
nators 150	0.7312	0.7662	0.8176	0.8774	0.9355	0.974	0.9928	0.9985	0.9998
n estimators 200 150	0.7343	0.7702	0.8219	0.8781	0.939	0.9753	0.9937	0.9988	0.9998
300	0.7328	0.7708	0.8195	0.8825	0.9371	0.9773	0.9945	0.999	0.9999
0	0.7346	0.773	0.8233	0.8826	0.9391	0.9784	0.9949	0.9992	0.9999



CPU times: user 1.17 s, sys: 447 ms, total: 1.62 s

Wall time: 1.14 s

In [0]:

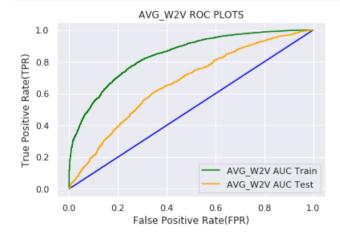
```
%%time
AVG W2V opt = RandomForestClassifier(n estimators=AVG W2V Best ES, max depth=AVG W2V Best MD, n jobs=-1, class weight='balanced')
#pdb.set trace()
AVG W2V opt.fit(AVG W2V Train, Y Train)
pred = AVG W2V opt.predict(AVG W2V Test)
a fpr train, a tpr train, thresholds = roc curve(Y Train, AVG W2V opt.predict proba(AVG W2V Train)[:,1])
a fpr Test, a tpr Test, thresholds = roc curve (Y Test, AVG W2V opt.predict proba(AVG W2V Test)[:,1])
```

CPU times: user 4min 36s, sys: 1.85 s, total: 4min 38s Wall time: 9.63 s

AVG W2V ROC PLOT

```
In [0]:
```

```
%%t.ime
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="AVG W2V AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="AVG W2V AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("AVG W2V ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
AVG W2V AUC=round(auc(a fpr Test, a tpr Test)*100)
pred5 = AVG W2V opt.predict(AVG W2V Train)
pred6 = AVG W2V opt.predict(AVG W2V Test)
```



AUC Train (for best estimator and depth) = 0.8408032063349351 AUC Test (for best estimator and depth) = 0.6638840874428062 CPU times: user 19.4 s, sys: 390 ms, total: 19.8 s Wall time: 1.76 s

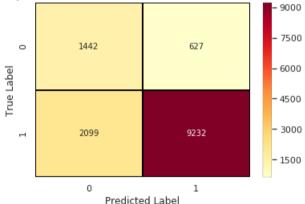
AVG_W2V CONFUSION MATRIX

In [0]:

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred5)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=l,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
```

CPU times: user 71.9 ms, sys: 49.2 ms, total: 121 ms Wall time: 68.4 ms

Project is APPROVED or NOT Confusion Matrix - Train Data



OBSERVATION:

True Negative = 1442; False Negative = 2099; True Positive = 9232; False Positive = 627 Accuracy (Overall, how often is the classifier correct) = 0.80 Precision(When it predicts yes, how often is it correct) = 0.94 Misclassification (Overall, how often is it wrong) = 0.21

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred6)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
```

```
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
CPU times: user 71.4 ms, sys: 42.3 ms, total: 114 ms
Wall time: 62.1 ms
 Project is APPROVED or NOT Confusion Matrix - Test Data
                                                 4000
   0
                                 521
                                                - 3200
 Frue Label
                                                - 2400
                                                -1600
              1371
                                 4249
                                                - 800
               0
                                  1
                   Predicted Label
```

OBSERVATION:

True Negative = 459; False Negative = 1371; True Positive = 4249; False Positive = 521 Accuracy (Overall, how often is the classifier correct) = 0.72 Precision(When it predicts yes, how often is it correct) = 0.90 Misclassification (Overall, how often is it wrong) = 0.29

2.4.4 Applying Random Forests on TFIDF W2V SET 4

In [0]:

```
%%time

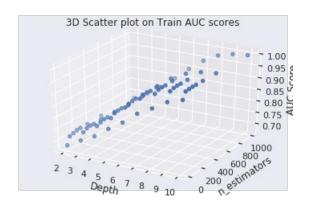
RF_clf = RandomForestClassifier(class_weight='balanced',n_jobs=-1)
parameters = ('n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
RFRan_clf = RandomizedSearchCV(RF_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
RFRan_clf.fit(TFIDF_W2V_Train, Y_Train)
print("-"*120)
print(RFRan_clf.best_estimator_)
print("-"*120)
TFIDF_W2V_Best_ES=RFRan_clf.best_params_['n_estimators']
TFIDF_W2V_Best_MD=RFRan_clf.best_params_['max_depth']
AUC_TR= RFRan_clf.cv_results_['mean_train_score']
AUC_CV = RFRan_clf.cv_results_['mean_test_score']
```

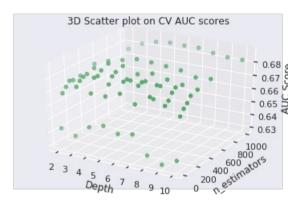
Fitting 3 folds for each of 72 candidates, totalling 216 fits

receing o rotable for each of 12 banaracco, cocarring fro from

3D PLOT

```
%%time
#https://stackoverflow.com/questions/53311685/difference-between-ax-set-xlabel-and-ax-xaxis-set-label-in-matplotlib-3-0-1
#-----3D-Plot for Train Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES,AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
#-----3D-Plot for CV Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```





CPU times: user 407 ms, sys: 403 ms, total: 810 ms Wall time: 332 ms

HEATMAP

Train Data

10	0.6805	0.7141	0.7457	0.7894	0.8282	0.877	0.9103	0.9473	0.9675
20	0.7136	0.7431	0.7827	0.8281	0.884	0.9314	0.9627	0.984	0.9945
100	0.718	0.7516	0.7893	0.8402	0.8919	0.9389	0.9714	0.9895	0.9965
estimators 00 150	0.7228	0.7547	0.7943	0.8434	0.8945	0.9414	0.9732	0.9907	0.9975
n estin 200	0.7244	0.7538	0.7944	0.8444	0.8964	0.9394	0.9732	0.9909	0.9977
300	0.7238	0.7558	0.7971	0.844	0.8968	0.9431	0.9755	0.9913	0.998
200	0.7278	0.7574	0.7967	0.8454	0.8971	0.9438	0.9748	0.9916	0.9982
1000	0.7263	0.7575	0.7979	0.8471	0.8991	0.9447	0.9767	0.9924	0.9983
ī	2	3	4	5	6 max_depth	7	8	9	10

CV Data

10	0.6428	0.639	0.6479	0.651	0.6471	0.649	0.6353	0.6306	0.6359
20	0.6678	0.6745	0.6716	0.6714	0.6755	0.6699	0.6771	0.6728	0.6674
100	0.6711	0.6775	0.6817	0.6787	0.6827	0.6818	0.6742	0.6751	0.6714
n estimators 200 150	0.6743	0.6791	0.6815	0.6832	0.683	0.6828	0.6827	0.6793	0.674
n estin 200	0.6734	0.6798	0.6843	0.685	0.6808	0.6822	0.6808	0.6817	0.6778
00	0.6739	0.6814	0.6865	0.6866	0.6826	0.685	0.6826	0.6808	0.6794

- 0.84 - 0.78

- 0.96

- 0.90

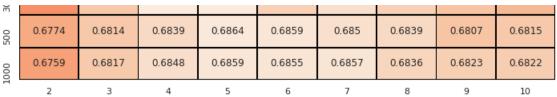
- 0.72

- 0.68

- 0.67

- 0.66

- 0.65



```
CPU times: user 1.32 s, sys: 446 ms, total: 1.77 s
Wall time: 1.29 s

In [0]:

%%time
TFIDF_W2V_opt = RandomForestClassifier(n_estimators=TFIDF_W2V_Best_ES,max_depth=TFIDF_W2V_Best_MD,n_jobs=-1,class_weight='balanced')
#pdb.set_trace()
TFIDF_W2V_opt.fit(TFIDF_W2V_Train, Y_Train)
pred = TFIDF_W2V_opt.predict(TFIDF_W2V_Test)
a_fpr_train, a_tpr_train, thresholds = roc_curve(Y_Train, TFIDF_W2V_opt.predict_proba(TFIDF_W2V_Train)[:,1])
a_fpr_Test, a_tpr_Test, thresholds = roc_curve(Y_Test, TFIDF_W2V_opt.predict_proba(TFIDF_W2V_Test)[:,1])

CPU times: user 43.6 s, sys: 640 ms, total: 44.3 s
```

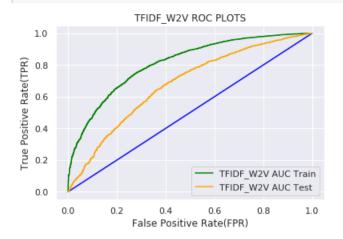
- 0.64

```
Wall time: 2.57 \text{ s}
```

TFIDF W2V ROC PLOT

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="TFIDF W2V AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="TFIDF W2V AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("TFIDF W2V ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
TFIDF W2V AUC=round(auc(a fpr Test, a tpr Test)*100)
pred7 = TFIDF W2V opt.predict(TFIDF W2V Train)
pred8 = TFIDF W2V opt.predict(TFIDF W2V Test)
```



AUC Train (for best estimator and depth) = 0.8106247445224307 AUC Test (for best estimator and depth) = 0.6773669111772823 CPU times: user 3.27 s, sys: 164 ms, total: 3.43 s Wall time: 781 ms

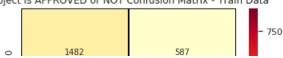
TFIDF_W2V CONFUSION MATRIX

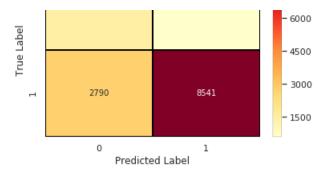
```
In [0]:
```

Wall time: 76.2 ms

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred7)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
CPU times: user 86.1 ms, sys: 61.3 ms, total: 147 ms
```

Project is APPROVED or NOT Confusion Matrix - Train Data





OBSERVATION:

Wall time: 62 ms

True Negative = 1482; False Negative = 2790; True Positive = 8541; False Positive = 587

Accuracy (Overall, how often is the classifier correct) = 0.75

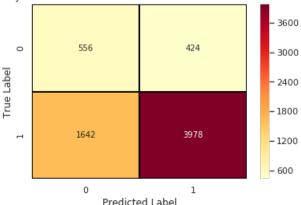
Precision(When it predicts yes, how often is it correct) =0.94

Misclassification (Overall, how often is it wrong) =0.26

In [0]:

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred8)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
CPU times: user 65.3 ms, sys: 51.2 ms, total: 117 ms
```

Project is APPROVED or NOT Confusion Matrix - Test Data



OBSERVATION:

True Negative = 556; False Negative = 1642; True Positive = 3978; False Positive = 424 Accuracy (Overall, how often is the classifier correct) = 0.69 Precision(When it predicts yes, how often is it correct) = 0.91 Misclassification (Overall, how often is it wrong) = 0.32

Gradient Boosting

2.4.5 Applying Gradient Boosting on BOW SET 1

```
In [0]:
```

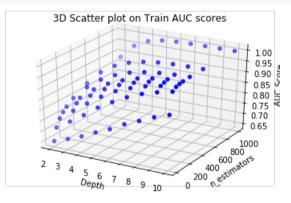
```
%%time
GBDT_clf = GradientBoostingClassifier()
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
GBDTRan_clf = RandomizedSearchCV(GBDT_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
GBDTRan_clf.fit(BOW_Train, Y_Train)
print("-"*120)
print(GBDTRan_clf.best_estimator_)
print("-"*120)
BOWG_Best_ES=GBDTRan_clf.best_params_['n_estimators']
BOWG_Best_MD=GBDTRan_clf.best_params_['max_depth']
AUC_TR= GBDTRan_clf.cv_results_['mean_train_score']
AUC_CV = GBDTRan_clf.cv_results_['mean_test_score']
```

Fitting 3 folds for each of 72 candidates, totalling 216 fits

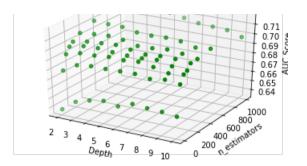
3D PLOT

```
In [0]:
```

```
%%t.ime
#https://stackoverflow.com/questions/53311685/difference-between-ax-set-xlabel-and-ax-xaxis-set-label-in-matplotlib-3-0-1
#-----3D-Plot for Train Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```







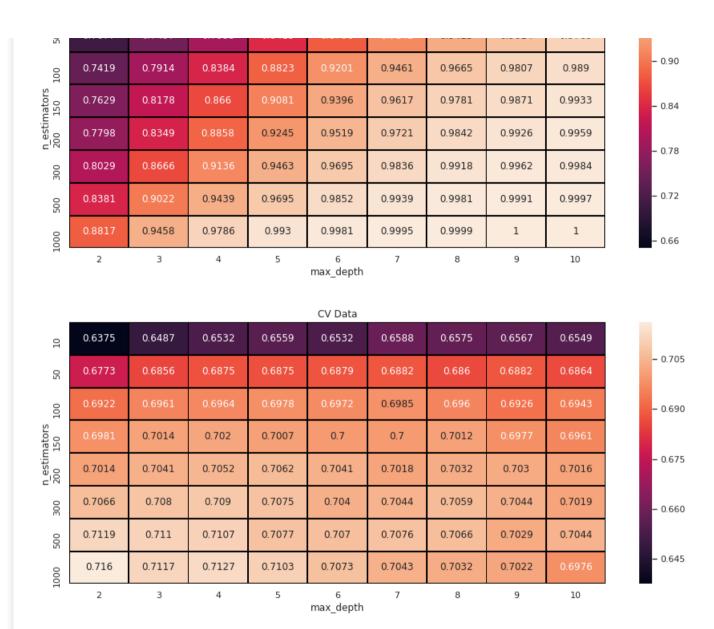
CPU times: user 1.34 s, sys: 3.56 s, total: 4.9 s Wall time: 800 ms

HEATMAP

```
%%time
                          -------Heat Map for Train data-----
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC TR':AUC TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
#------#
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC CV':AUC CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4q',linewidths=1,linecolor='black')
plt.title('CV Data')
plt.show()
```

T	rai	ın		-	ta.

10	0.6496	0.6738	0.7007	0.733	0.762	0.7984	0.8271	0.8569	0.8811
0	0.7077	0.7497	0.7933	0.8413	0.8798	0.9142	0.9415	0.9614	0.9769



CPU times: user 1.2 s, sys: 446 ms, total: 1.65 s $\,$

Wall time: 1.18 s

In [0]:

```
%%time
BOW_opt = GradientBoostingClassifier(n_estimators=BOWG_Best_ES,max_depth=BOWG_Best_MD)
BOW_opt fit(ROW_Train, V_Train)
```

```
pred = BOW_opt.predict(BOW_Test)

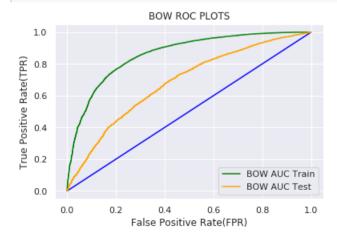
a_fpr_train, a_tpr_train, thresholds = roc_curve(Y_Train, BOW_opt.predict_proba(BOW_Train)[:,1])
a_fpr_Test, a_tpr_Test, thresholds = roc_curve(Y_Test, BOW_opt.predict_proba(BOW_Test)[:,1])
```

```
CPU times: user 4min 40s, sys: 376 ms, total: 4min 40s Wall time: 4min 40s
```

BOW ROC PLOT

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="BOW AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="BOW AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("BOW ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
G BOW AUC=round(auc(a fpr Test, a tpr Test)*100)
pred9 = BOW opt.predict(BOW Train)
pred10 = BOW opt.predict(BOW Test)
```



```
AUC Train (for best estimator and depth) = 0.8600601960724177 AUC Test (for best estimator and depth) = 0.6817789969216181 CPU times: user 1.14 s, sys: 7.04 ms, total: 1.15 s Wall time: 1.14 s
```

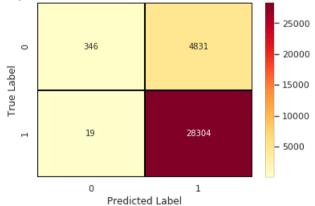
BOW CONFUSION MATRIX

```
In [0]:
```

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred9)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
```

CPU times: user 90.4 ms, sys: 55.1 ms, total: 145 ms Wall time: 88.4 ms

Project is APPROVED or NOT Confusion Matrix - Train Data



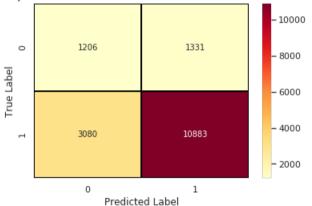
OBSERVATION:

True Negative = 346; False Negative = 19; True Positive = 28304; False Positive = 4831 Accuracy (Overall, how often is the classifier correct) = 0.86 Precision(When it predicts yes, how often is it correct) = 0.856 Misclassification (Overall, how often is it wrong) = 0.15

```
In [0]:
```

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred10)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
CPU times: user 76.7 ms, sys: 44.1 ms, total: 121 ms
```

Project is APPROVED or NOT Confusion Matrix - Test Data



OBSERVATION:

Wall time: 70.4 ms

True Negative = 1206; False Negative = 3080; True Positive = 10883; False Positive = 1331 Accuracy (Overall, how often is the classifier correct) = 0.74 Precision(When it predicts yes, how often is it correct) = 0.90 Misclassification (Overall, how often is it wrong) = 0.27

2.4.6 Applying Gradient Boosting on TFIDF SET 2

```
In [0]:
```

```
%%time

GBDT_clf = GradientBoostingClassifier()

parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}

GBDTRan_clf = RandomizedSearchCV(GBDT_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)

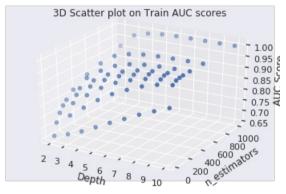
GBDTRan_clf.fit(TFIDF_Train, Y_Train)

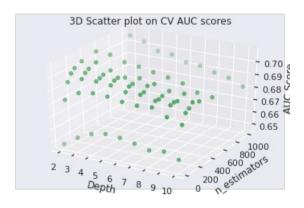
print("-"*120)
```

```
print(GBDTRan clf.best estimator )
print("-"*120)
TFIDFG Best ES=GBDTRan clf.best params ['n estimators']
TFIDFG Best MD=GBDTRan clf.best params ['max depth']
AUC TR= GBDTRan clf.cv results ['mean train score']
AUC CV = GBDTRan clf.cv results ['mean test score']
Fitting 3 folds for each of 72 candidates, totalling 216 fits
[Parallel (n jobs=-1)]: Using backend LokyBackend with 40 concurrent workers.
[Parallel(n jobs=-1)]: Done 120 tasks | elapsed: 25.2min
[Parallel (n jobs=-1)]: Done 216 out of 216 | elapsed: 104.3min finished
GradientBoostingClassifier(ccp alpha=0.0, criterion='friedman mse', init=None,
                          learning rate=0.1, loss='deviance', max depth=2,
                           max features=None, max leaf nodes=None,
                           min impurity decrease=0.0, min impurity split=None,
                           min samples leaf=1, min samples split=2,
                           min weight fraction leaf=0.0, n estimators=500,
                           n iter no change=None, presort='deprecated',
                           random state=None, subsample=1.0, tol=0.0001,
                           validation fraction=0.1, verbose=0,
                           warm start=False)
CPU times: user 8min 12s, sys: 1.14 s, total: 8min 13s
Wall time: 1h 52min 26s
```

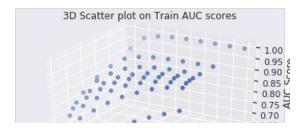
3D PLOT

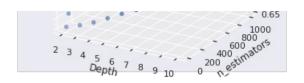
```
ax = rigure.add_supplot(lil, projection='sd')
ax.scatter(MD, ES, AUC_CV, c='g', marker='o')
ax.set_xlabel('Depth')
ax.yaxis.set_label_text('n_estimators')
ax.zaxis.set_label_text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```

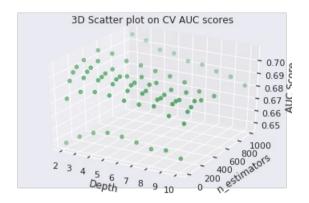




CPU times: user 1.07 s, sys: 4.05 s, total: 5.12 s Wall time: 389 ms







```
CPU times: user 1.07 s, sys: 4.05 s, total: 5.12 s Wall time: 389 ms
```

HEATMAP

```
%%time
                          ------Heat Map for Train data-----
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC TR':AUC TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
plt.close()
d={'n estimators':ES,'max_depth':MD,'AUC_CV':AUC_CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
plt.figure(figsize=(15,6))
```

Þ

					CV Data				
10	0.6478	0.6553	0.6605	0.6628	0.6621	0.66	0.657	0.6584	0.6543
20	0.6819	0.6893	0.6912	0.6907	0.6889	0.6881	0.689	0.6838	0.6802
100	0.6942	0.6985	0.6988	0.6978	0.6949	0.6949	0.6925	0.6912	0.6877
n_estimators 200 150	0.6994	0.7018	0.6998	0.7	0.6976	0.6955	0.6921	0.692	0.6896
n_estin 200	0.7022	0.7035	0.701	0.7007	0.6981	0.6987	0.6932	0.6914	0.6927
300	0.7046	0.7058	0.7015	0.6981	0.6996	0.6972	0.694	0.6941	0.6903
200	0.7068	0.7061	0.7024	0.701	0.6986	0.6966	0.694	0.689	0.6875
1000	0.7063	0.7032	0.6977	0.6968	0.6926	0.6918	0.6884	0.6862	0.6814
á '	2	3	4	5	6 max_depth	7	8	9	10

- 0.70

- 0.69

- 0.68

- 0.70

- 0.69

- 0.67

- 0.66

					CV Data				
10	0.6478	0.6553	0.6605	0.6628	0.6621	0.66	0.657	0.6584	0.6543
20	0.6819	0.6893	0.6912	0.6907	0.6889	0.6881	0.689	0.6838	0.6802
100	0.6942	0.6985	0.6988	0.6978	0.6949	0.6949	0.6925	0.6912	0.6877
nators 150	0.6994	0.7018	0.6998	0.7	0.6976	0.6955	0.6921	0.692	0.6896
n estimators 200 150	0.7022	0.7035	0.701	0.7007	0.6981	0.6987	0.6932	0.6914	0.6927
300	0.7046	0.7058	0.7015	0.6981	0.6996	0.6972	0.694	0.6941	0.6903
200	0.7068	0.7061	0.7024	0.701	0.6986	0.6966	0.694	0.689	0.6875
1000	0.7063	0.7032	0.6977	0.6968	0.6926	0.6918	0.6884	0.6862	0.6814
ñ	2	3	4	5	6 max_depth	7	8	9	10

CPU times: user 1.21 s, sys: 425 ms, total: 1.64 s Wall time: 1.17 s $\,$

CPU times: user 1.21 s. svs: 425 ms. total: 1.64 s

```
Wall time: 1.17 s

In [0]:

%%time

TFIDF_opt = GradientBoostingClassifier(n_estimators=TFIDFG_Best_ES,max_depth=TFIDFG_Best_MD)

TFIDF_opt.fit(TFIDF_Train, Y_Train)

pred = TFIDF_opt.predict(TFIDF_Test)

a_fpr_train, a_tpr_train, thresholds = roc_curve(Y_Train, TFIDF_opt.predict_proba(TFIDF_Train)[:,1])

a_fpr_Test, a_tpr_Test, thresholds = roc_curve(Y_Test, TFIDF_opt.predict_proba(TFIDF_Test)[:,1])

CPU times: user 8min 13s, sys: 146 ms, total: 8min 13s

Wall time: 8min 13s, sys: 146 ms, total: 8min 13s

Wall time: 8min 13s
```

TFIDF ROC PLOT

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="TFIDF AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="TFIDF AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("TFIDF ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
G TFIDF AUC=round(auc(a fpr Test, a tpr Test)*100)
pred11 = TFIDF opt.predict(TFIDF Train)
pred12 = TFIDF opt.predict(TFIDF Test)
```

AUC Train (for best estimator and depth) = 0.83113411064781

AUC Test (for best estimator and depth) = 0.83113411064781

AUC Train (for best estimator and depth) = 0.83113411064781

AUC Test (for best estimator and depth) = 0.6740369297979392

CPU times: user 881 ms, sys: 12 ms, total: 893 ms

Wall time: 888 ms

CPU times: user 881 ms, sys: 12 ms, total: 893 ms

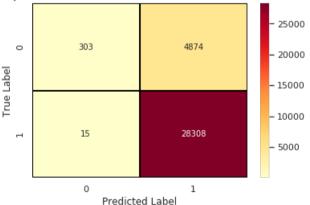
TFIDF CONFUSION MATRIX

In [0]:

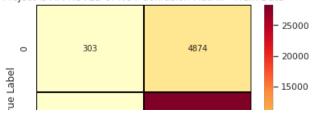
```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred11)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
CPU times: user 334 ms, sys: 55 ms, total: 389 ms
```

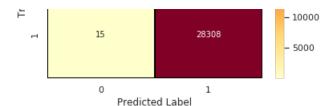
Wall time: 335 ms, sys: 55 ms, total: 389 ms
CPU times: user 334 ms, sys: 55 ms, total: 389 ms
Wall time: 335 ms

Project is APPROVED or NOT Confusion Matrix - Train Data



Project is APPROVED or NOT Confusion Matrix - Train Data





OBSERVATION:

True Negative = 303; False Negative = 15; True Positive = 28308; False Positive = 4874

Accuracy (Overall, how often is the classifier correct) = 0.86

Precision(When it predicts yes, how often is it correct) =0.86

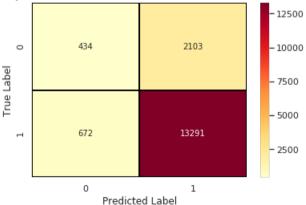
Misclassification (Overall, how often is it wrong) =0.15

In [0]:

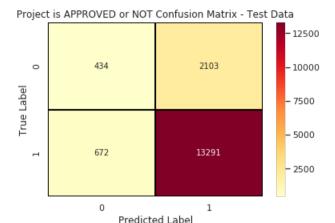
```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred12)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
CPU times: user 76 ms, sys: 45 ms, total: 121 ms
```

Wall time: 69.5 ms

Project is APPROVED or NOT Confusion Matrix - Test Data



CPU times: user 76 ms, sys: 45 ms, total: 121 ms Wall time: 69.5 ms



OBSERVATION:

True Negative = 434; False Negative = 672; True Positive = 13291; False Positive = 2103 Accuracy (Overall, how often is the classifier correct) = 0.84 Precision(When it predicts yes, how often is it correct) = 0.87 Misclassification (Overall, how often is it wrong) = 0.17

2.4.7 Applying Gradient Boosting on AVG_W2V SET 3

```
In [0]:
```

```
%%time
GBDT_clf = GradientBoostingClassifier()
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
GBDTRan_clf = RandomizedSearchCV(GBDT_clf, parameters, cv=3, scoring='roc_auc',n_jobs=-1,return_train_score=True,verbose=1,n_iter=100)
GBDTRan_clf.fit(AVG_W2V_Train, Y_Train)
print("-"*120)
print(GBDTRan_clf.best_estimator_)
print("-"*120)
AVG_W2VG_Best_ES=GBDTRan_clf.best_params_['n_estimators']
AVG_W2VG_Best_MD=GBDTRan_clf.best_params_['max_depth']
AUC_TR= GBDTRan_clf.cv_results_['mean_train_score']
AUC_CV = GBDTRan_clf.cv_results_['mean_test_score']
```

Fitting 3 folds for each of 72 candidates, totalling 216 fits

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 40 concurrent workers.

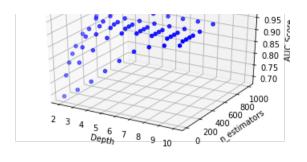
[Parallel(n_jobs=-1)]: Done 120 tasks | elapsed: 58.5min

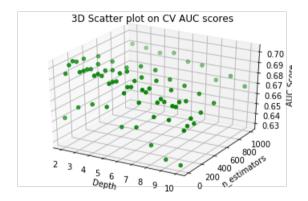
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 200.1min finished
```

3D PLOT

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/53311685/difference-between-ax-set-xlabel-and-ax-xaxis-set-label-in-matplotlib-3-0-1
#-----3D-Plot for Train Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES,AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.vaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
                 -----3D-Plot for CV Dataset------
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```





CPU times: user 1.15 s, sys: 4 s, total: 5.15 s Wall time: $469~\mathrm{ms}$

HEATMAP

```
df=pd.DataFrame(d)
result = df.pivot(index='n_estimators',columns='max_depth',values='AUC_CV')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('CV_Data')
plt.show()
```

Train Data

					II alli Data				
10	0.6893	0.7292	0.7763	0.832	0.885	0.9332	0.9619	0.9787	0.9899
20	0.7719	0.8368	0.899	0.9592	0.9878	0.998	0.9997	1	1
100	0.8175	0.8921	0.9554	0.9913	0.9988	1	1	1	1
n estimators 200 150	0.8466	0.9281	0.9802	0.9981	1	1	1	1	1
n estin 200	0.8706	0.9516	0.9917	0.9997	1	1	1	1	1
300	0.9059	0.9789	0.9988	1	1	1	1	1	1
200	0.9493	0.9972	1	1	1	1	1	1	1
1000	0.9906	1	1	1	1	1	1	1	1
ā	2	3	4	5	6 max_depth	7	8	9	10

CV Data

10	0.6528	0.6655	0.6711	0.6713	0.6549	0.6574	0.6431	0.6321	0.6295
20	0.6932	0.6971	0.6963	0.6914	0.6852	0.679	0.6684	0.6683	0.6611
100	0.6994	0.6965	0.6961	0.6912	0.689	0.689	0.6799	0.6794	0.6635
nators 150	0.7014	0.6962	0.6926	0.6901	0.6874	0.685	0.6814	0.6767	0.6686
n estimators 200 150	0.6992	0.6948	0.6959	0.6958	0.6912	0.6867	0.6769	0.6793	0.6619
300	0.6987	0.6961	0.6928	0.694	0.691	0.6904	0.6843	0.6765	0.6685
200	0.6944	0.6919	0.6885	0.6921	0.6909	0.6846	0.6812	0.6762	0.67

- 0.96

- 0.90

- 0.84

- 0.78

- 0.72

- 0.690

- 0.675

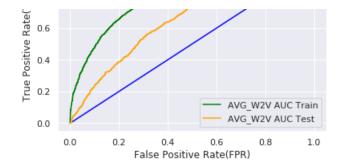
- 0.660

- 0.645

AVG_W2V ROC PLOT

```
%%t.ime
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="AVG W2V AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="AVG W2V AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("AVG W2V ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
G AVG W2V AUC=round(auc(a fpr Test, a tpr Test)*100)
pred13 = AVG W2V opt.predict(AVG W2V Train)
pred14 = AVG W2V opt.predict(AVG W2V Test)
```





AUC Train (for best estimator and depth) = 0.8160369127257701 AUC Test (for best estimator and depth) = 0.6618643329217808 CPU times: user 724 ms, sys: 4.03 ms, total: 728 ms Wall time: 723 ms

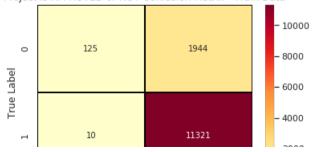
AVG_W2V CONFUSION MATRIX

```
In [0]:
```

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(y_Train, pred13)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
CPU times: user 91.7 ms, sys: 69 ms, total: 161 ms
```

CPU times: user 91.7 ms, sys: 69 ms, total: 161 ms Wall time: 84.8 ms

Project is APPROVED or NOT Confusion Matrix - Train Data





OBSERVATION:

Wall time: 75.3 ms

True Negative = 125; False Negative = 10; True Positive = 11321; False Positive = 1944

Accuracy (Overall, how often is the classifier correct) = 0.86

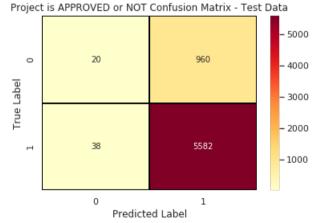
Precision(When it predicts yes, how often is it correct) =0.86

Misclassification (Overall, how often is it wrong) =0.15

In [0]:

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred14)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')
```

CPU times: user 85.8 ms, sys: 64.1 ms, total: 150 ms



OBSERVATION:

True Negative = 20; False Negative = 38; True Positive = 5582; False Positive = 960 Accuracy (Overall, how often is the classifier correct) = 0.85

Precision/When it predicts was how often is it correct) = 0.86

2.4.8 Applying Gradient Boosting on TFIDF_W2V SET 4

```
In [0]:
%%time
GBDT clf = GradientBoostingClassifier()
parameters = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
GBDTRan clf = RandomizedSearchCV(GBDT clf, parameters, cv=3, scoring='roc auc',n jobs=-1,return train score=True,verbose=1,n iter=100)
GBDTRan clf.fit(TFIDF W2V Train, Y Train)
print("-"*120)
print(GBDTRan clf.best estimator )
print("-"*120)
TFIDF W2VG Best ES=GBDTRan clf.best params ['n estimators']
TFIDF W2VG Best MD=GBDTRan clf.best params ['max depth']
AUC TR= GBDTRan clf.cv results ['mean train score']
AUC CV = GBDTRan clf.cv results ['mean test score']
Fitting 3 folds for each of 72 candidates, totalling 216 fits
[Parallel(n jobs=-1)]: Using backend LokyBackend with 40 concurrent workers.
[Parallel(n jobs=-1)]: Done 120 tasks
                                        | elapsed: 29.4min
[Parallel(n jobs=-1)]: Done 216 out of 216 | elapsed: 82.8min finished
GradientBoostingClassifier(ccp alpha=0.0, criterion='friedman mse', init=None,
                           learning rate=0.1, loss='deviance', max depth=2,
                           max features=None, max leaf nodes=None,
                           min impurity decrease=0.0, min impurity split=None,
                           min samples leaf=1, min samples split=2,
                           min weight fraction leaf=0.0, n estimators=300,
                           n iter no change=None, presort='deprecated',
                           random state=None, subsample=1.0, tol=0.0001,
                           validation fraction=0.1, verbose=0,
                           warm start=False)
CPU times: user 5min 46s, sys: 1.29 s, total: 5min 47s
```

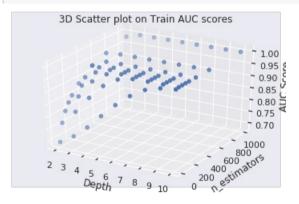
3D PLOT

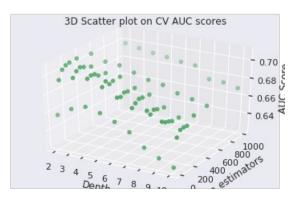
Wall time: 1h 28min 35s

```
In [0]:
```

```
%%time
#https://stackoverflow.com/questions/53311685/difference-between-ax-set-xlabel-and-ax-xaxis-set-label-in-matplotlib-3-0-1
```

```
-----3D-Plot for Train Dataset-----
figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC TR, c='b', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
plt.close()
                         figure = plt.figure()
ax = figure.add subplot(111, projection='3d')
ax.scatter(MD, ES, AUC CV, c='g', marker='o')
ax.set xlabel('Depth')
ax.yaxis.set label text('n estimators')
ax.zaxis.set label text('AUC Score')
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
plt.close()
```





```
CPU times: user 1.08 s, sys: 4.03 s, total: 5.12 s Wall time: 381 ms
```

HEATMAP

```
In [0]:
```

```
%%t.ime
     plt.close()
d={'n estimators':ES,'max depth':MD,'AUC TR':AUC TR}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC TR')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('Train Data')
plt.show()
plt.close()
d={'n estimators':ES,'max depth':MD,'AUC CV':AUC CV}
df=pd.DataFrame(d)
result = df.pivot(index='n estimators',columns='max depth',values='AUC CV')
sns.set()
plt.figure(figsize=(15,6))
sns.heatmap(result,annot = True, fmt='.4g',linewidths=1,linecolor='black')
plt.title('CV Data')
plt.show()
```

- 0.96

- 0.90

- 0.84

Tra	ain	Da	ıta.

10	0.692	0.7288	0.778	0.836	0.892	0.9391	0.9737	0.991	0.9976
20	0.767	0.8242	0.8924	0.9507	0.9866	0.9991	1	1	1
100	0.8082	0.8791	0.9505	0.9893	0.9996	1	1	1	1
nators 150	0.8355	0.9157	0.9791	0.9987	1	1	1	1	1
n estimators 200 150	0.8576	0.9417	0.9916	0.9999	1	1	1	1	1
300	0.8909	0.9729	0.9992	1	1	1	1	1	1

200	0.9362	0.9955	1	1	1	1	1	1	1	
1000	0.9845	1	1	1	1	1	1	1	1	- 0.72
п.	2	3	4	5	6 max_depth	7	8	9	10	_

CV Data

Cv Data										
10	0.6575	0.6672	0.6725	0.6688	0.6623	0.6542	0.6404	0.6318	0.6247	
22	0.694	0.6991	0.701	0.6951	0.6869	0.6787	0.6789	0.6703	0.6563	
100	0.7032	0.7044	0.7027	0.6993	0.6856	0.6818	0.6727	0.6674	0.6622	
estimators 00 150	0.7059	0.7066	0.702	0.6943	0.6882	0.6843	0.6758	0.6662	0.6628	
n estin 200	0.707	0.705	0.6987	0.6958	0.6874	0.6837	0.6741	0.6643	0.6623	
1000 200 300	0.7076	0.7017	0.6974	0.6962	0.6869	0.6827	0.6719	0.6638	0.6692	
	0.7053	0.6992	0.6979	0.6927	0.6877	0.6851	0.6788	0.6754	0.6711	
	0.6983	0.6954	0.6927	0.6907	0.6882	0.6868	0.6743	0.6735	0.6699	
ī	2	3	4	5	6 max_depth	7	8	9	10	

CPU times: user 1.18 s, sys: 417 ms, total: 1.6 s

Wall time: 1.13 s

In [0]:

```
%%time
TFIDF_W2V_opt = GradientBoostingClassifier(n_estimators=TFIDF_W2VG_Best_ES,max_depth=TFIDF_W2VG_Best_MD)
TFIDF_W2V_opt.fit(TFIDF_W2V_Train, Y_Train)
pred = TFIDF_W2V_opt.predict(TFIDF_W2V_Test)

a_fpr_train, a_tpr_train, thresholds = roc_curve(Y_Train, TFIDF_W2V_opt.predict_proba(TFIDF_W2V_Train)[:,1])
a_fpr_Test, a_tpr_Test, thresholds = roc_curve(Y_Test, TFIDF_W2V_opt.predict_proba(TFIDF_W2V_Test)[:,1])
```

- 0.705

- 0.690

- 0.675

- 0.660

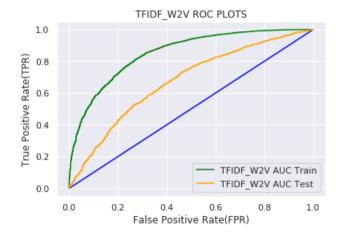
CPU times: user 5min 46s, sys: 198 ms, total: 5min 46s

Wall time: 5min 46s

TFIDF_W2V ROC PLOT

```
In [0]:
```

```
%%t.ime
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn-machine-learning-algorithm-using-python-and-sci
plt.plot([0,1],[0,1],'k-', color='blue')
plt.plot(a fpr train, a tpr train, label="TFIDF W2V AUC Train", color='green')
plt.plot(a fpr Test, a tpr Test, label="TFIDF W2V AUC Test", color='orange')
plt.legend()
plt.ylabel("True Positive Rate(TPR)")
plt.xlabel("False Positive Rate(FPR)")
plt.title("TFIDF W2V ROC PLOTS")
plt.show()
print("-"*120)
print("AUC Train (for best estimator and depth) =", auc(a fpr train, a tpr train))
print("AUC Test (for best estimator and depth) =", auc(a fpr Test, a tpr Test))
G TFIDF W2V AUC=round(auc(a fpr Test, a tpr Test)*100)
pred15 = TFIDF W2V opt.predict(TFIDF W2V Train)
pred16 = TFIDF W2V opt.predict(TFIDF W2V Test)
```



AUC Train (for best estimator and depth) = 0.8523021762775286 AUC Test (for best estimator and depth) = 0.6735076984530467 CPU times: user 629 ms, sys: 7.03 ms, total: 636 ms Wall time: 631 ms

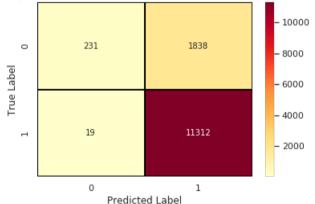
TFIDF_W2V CONFUSION MATRIX

```
In [0]:
```

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
%matplotlib inline
from sklearn.metrics import confusion_matrix
Train = confusion_matrix(Y_Train, pred15)
sns.heatmap(Train,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=l,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Project is APPROVED or NOT Confusion Matrix - Train Data')
```

CPU times: user 77.5 ms, sys: 45.1 ms, total: 123 ms Wall time: 69.7 ms

Project is APPROVED or NOT Confusion Matrix - Train Data



OBSERVATION:

True Negative = 231; False Negative = 19; True Positive = 11312; False Positive = 1838

Accuracy (Overall, how often is the classifier correct) = 0.87

Precision(When it predicts yes, how often is it correct) =0.87

Misclassification (Overall, how often is it wrong) =0.14

```
%%time
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://getaravind.com/blog/confusion-matrix-seaborn-heatmap/
Test = confusion_matrix(Y_Test, pred16)
sns.heatmap(Test,annot=True,cbar=True,fmt='d',cmap='YlOrRd',linewidths=1,linecolor='black')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
```

```
Plt.title('Project is APPROVED or NOT Confusion Matrix - Test Data')

CPU times: user 75.3 ms, sys: 46 ms, total: 121 ms

Wall time: 65.5 ms

Project is APPROVED or NOT Confusion Matrix - Test Data

- 5000
- 4000
- 3000
- 2000
- 1

Predicted Label
```

OBSERVATION:

True Negative = 32; False Negative = 63; True Positive = 5557; False Positive = 948 Accuracy (Overall, how often is the classifier correct) = 0.85 Precision(When it predicts yes, how often is it correct) = 0.86 Misclassification (Overall, how often is it wrong) = 0.16

Conclusion

```
In [0]:
```

```
%%time
# Please compare all your models using Prettytable library

pt = PrettyTable()
pt.field_names= ("S.No","Vectorizer", "Model", "n_estimators","max_depth", "AUC")
pt.add_row(["1","BOW", "RandomForest",BOW_Best_ES, BOW_Best_MD, BOW_AUC])
pt.add_row(["2","TFIDF", "RandomForest", TFIDF_Best_ES, TFIDF_Best_MD, TFIDF_AUC])
pt.add_row(["3","AVG_W2V", "RandomForest",AVG_W2V_Best_ES, AVG_W2V_Best_MD, AVG_W2V_AUC])
pt.add_row(["4","TFIDF_W2V", "RandomForest", TFIDF_W2V_Best_ES, TFIDF_W2V_Best_MD, TFIDF_W2V_AUC])
pt.add_row(["5","BOW", "GradientBoosting",BOWG_Best_ES, BOWG_Best_MD, G_BOW_AUC])
pt.add_row(["6","TFIDF", "GradientBoosting", TFIDFG_Best_ES, TFIDFG_Best_MD, G_TFIDF_AUC])
pt.add_row(["7","AVG_W2V", "GradientBoosting", AVG_W2VG_Best_ES, AVG_W2VG_Best_MD, G_TFIDF_W2V_AUC])
pt.add_row(["8","TFIDF_W2V", "GradientBoosting", TFIDF_W2VG_Best_ES, TFIDFF_W2VG_Best_MD, G_TFIDF_W2V_AUC])
pt.add_row(["8","TFIDF_W2V", "GradientBoosting", TFIDF_W2VG_Best_ES, TFIDF_W2VG_Best_MD, G_TFIDF_W2V_AUC])
pt.add_row(["8","TFIDF_W2V", "GradientBoosting", TFIDF_W2VG_Best_ES, TFIDF_W2VG_Best_MD, G_TFIDF_W2V_AUC])
```

4		+	+	+	+	++
	S.No	Vectorizer	Model	n_estimators	max_depth	AUC
Ì	1	BOW	RandomForest	1000	10	0.68
	2	TFIDF	RandomForest	1000	10	0.69
	3	AVG_W2V	RandomForest	1000	5	0.66
	4	TFIDF_W2V	RandomForest	300	5	0.68
	5	BOW	GradientBoosting	1000	2	0.68
	6	TFIDF	GradientBoosting	500	2	0.67
	7	AVG_W2V	GradientBoosting	150	2	0.66
-	8	TFIDF_W2V	GradientBoosting	300	2	0.67
- 4		+	+	+	+	++

CPU times: user 1.43 ms, sys: 0 ns, total: 1.43 ms

Wall time: 1.37 ms

SUMMARY:

- 1. After applying the Gradient Boosting over the Random Forest, we can see **"Accuracy, Precision were improved"** for the TFIDF, AVG W2V and TFIDF W2V.
- 2. Also we can see the **"Misclassfication is dropped around 10%"** approx.After applying the Gradient Boosting over the Random Forest.
- 3. Comparatively after applying the Gradient Boost**" TFIDF,AVG_W2V and TFIDF_W2V"** vectorizer are performing very well.
- 4. Both Random Forest and Gradient Boosting are giving more or less same AUC score.
- 5. Gradient Boosting take more time and space complexity when compare to the Random Forest.
- 6. Compare to the Random Forest the Gradient Boosting is taking small value of the Estimators and Depth.
- 7. Due to memory constraints issue only 50K data points were used for BOW/TFIDF and 20K points were used for AVG W2V/TFIDF W2V.