SVD on Donors Choose dataset

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.

```
%matplotlib inline
In [1]:
         import warnings
         warnings.filterwarnings("ignore")
         import sqlite3
         import pandas as pd
         import numpy as np
         import nltk
         import string
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.feature extraction.text import TfidfTransformer
         from sklearn.feature extraction.text import TfidfVectorizer
         from sklearn.feature extraction.text import CountVectorizer
         from sklearn.metrics import confusion matrix
         from sklearn import metrics
         from sklearn.metrics import roc curve, auc
         from nltk.stem.porter import PorterStemmer
         # 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 tgdm import tgdm
import os
import chart studio.plotly as py
from scipy.sparse import hstack
import chart studio.plotly as py
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 collections import Counter
```

1. LOAD AND PROCESS DATA

1.1 Reading Data

```
project data=pd.merge(data, price data, on='id', how='left')
In [4]:
          project data.columns
In [5]:
Out[5]: Index(['Unnamed: 0', 'id', 'teacher id', 'teacher prefix', 'school state',
                 'project_submitted_datetime', 'project_grade_category',
                 'project subject categories', 'project subject subcategories',
                 'project_title', 'project_essay_1', 'project_essay_2', 'project_essay_3', 'project_essay_4', 'project_resource_summary',
                 'teacher number of previously posted projects', 'project is approved',
                 'price', 'quantity'],
                dtype='object')
        1.2 process Project Essay
          project data.head(3)
In [6]:
Out[6]:
            Unnamed:
                            id
                                                    teacher id teacher_prefix school_state project_submitted_datetime project_grade_category project_
               160221 p253737
                                c90749f5d961ff158d4b4d1e7dc665fc
                                                                       Mrs.
                                                                                     IN
                                                                                                2016-12-05 13:43:57
                                                                                                                          Grades PreK-2
                                                                                                                                          Histo
                                                                                     FI
                                                                        Mr.
                                                                                                2016-10-25 09:22:10
                                                                                                                             Grades 6-8
               140945 p258326 897464ce9ddc600bced1151f324dd63a
         2
                21895 p182444 3465aaf82da834c0582ebd0ef8040ca0
                                                                       Ms.
                                                                                     A7
                                                                                                2016-08-31 12:03:56
                                                                                                                            Grades 6-8
          project data["essay"] = project_data["project_essay_1"].map(str) +\
In [7]:
                            project data["project essay 2"].map(str) + \
                            project data["project essay 3"].map(str) + \
                            project data["project essay 4"].map(str)
```

```
In [8]:
          import re
          def decontracted(phrase):
              # specific
              phrase = re.sub(r"won't", "will not", phrase)
              phrase = re.sub(r"can\'t", "can not", phrase)
              # general
              phrase = re.sub(r"n\'t", " not", phrase)
              phrase = re.sub(r"\'re", " are", phrase)
              phrase = re.sub(r"\'s", " is", phrase)
              phrase = re.sub(r"\'d", " would", phrase)
              phrase = re.sub(r"\'ll", " will", phrase)
              phrase = re.sub(r"\'t", " not", phrase)
              phrase = re.sub(r"\'ve", " have", phrase)
              phrase = re.sub(r"\'m", " am", phrase)
              return phrase
          stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", \
In [9]:
                      "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', 'whoo', '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', 'furthe
                      'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'moi
                      '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', "were
                      'won', "won't", 'wouldn', "wouldn't"]
         from tgdm import tgdm
In [10]:
          preprocessed essays = []
          # tqdm is for printing the status bar
          for sentance in tgdm(project data['essay'].values):
              sent = decontracted(sentance)
              sent = sent.replace('\\r', ' ')
```

```
sent = sent.replace('\\"', ' ')
sent = sent.replace('\\n', ' ')
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
# https://gist.github.com/sebleier/554280
sent = ' '.join(e for e in sent.split() if e not in stopwords)
preprocessed_essays.append(sent.lower().strip())
project_data['cleaned_essay']=preprocessed_essays
100%| 50000/50000 [00:27<00:00, 1847.94it/s]
```

1.2 process Project Title

```
In [11]:
          # https://stackoverflow.com/a/47091490/4084039
          from tgdm import tgdm
          preprocessed title = []
          # tqdm is for printing the status bar
          for sentance in tqdm(data['project title'].values):
              sent = decontracted(sentance)
              sent = sent.replace('\\r', ' ')
              sent = sent.replace('\\"', ' ')
              sent = sent.replace('\\n', ' ')
              sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
              # https://gist.github.com/sebleier/554280
              sent = ' '.join(e for e in sent.split() if e not in stopwords)
              preprocessed title.append(sent.lower().strip())
          project data['cleaned project title']=preprocessed title
                          50000/50000 [00:01<00:00, 38276.23it/s]
```

1.3 teacher_prefix

```
Name: teacher prefix, dtype: int64
        1.4 project grade
In [13]:
          project data.project grade category.value counts()
Out[13]: Grades PreK-2
                          20316
         Grades 3-5
                          16968
         Grades 6-8
                           7750
         Grades 9-12
                           4966
         Name: project grade category, dtype: int64
In [14]:
         grade_list=[]
          for i in project data['project grade category'].values:
              i=i.replace(' ','_')
              i=i.replace('-','-')
              grade list.append(i.strip())
          project data['project grade category']=grade list
          project data['project grade category'].value counts()
In [15]:
Out[15]: Grades PreK 2
                          20316
         Grades 3 5
                          16968
         Grades 6 8
                           7750
         Grades 9 12
                           4966
         Name: project grade category, dtype: int64
        1.5 project subject categories
          catogories = list(project data['project subject categories'].values)
In [16]:
          # remove special characters from list of strings python: https://stackoverflow.com/a/47301924/4084039
          # https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
          # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
          # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
          cat list = []
```

Dr

```
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", "&",
           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())
project data['clean categories'] = cat list
project data.drop(['project subject categories'], axis=1, inplace=True)
from collections import Counter
my counter = Counter()
for word in project data['clean categories'].values:
   my counter.update(word.split())
cat dict = dict(my counter)
sorted cat dict = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
```

1.6 project_subject_subcategories

```
In [17]:
         sub catogories = list(project data['project subject subcategories'].values)
         # remove special characters from list of strings python: https://stackoverflow.com/a/47301924/4084039
          # https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
          # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
         # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
          sub cat list = []
          for i in sub catogories:
             temp = ""
             # consider we have text like this "Math & Science, Warmth, Care & Hunger"
             for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care & Hunger"]
                  if 'The' in j.split(): # this will split each of the catogory based on space "Math & Science"=> "Math", "&",
                     i=i.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())

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

# count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
my_counter = Counter()
for word in project_data['clean_subcategories'].values:
    my_counter.update(word.split())

sub_cat_dict = dict(my_counter)
sorted_sub_cat_dict = dict(sorted(sub_cat_dict.items(), key=lambda kv: kv[1]))
```

1.7 counting words in title

```
In [18]: #https://stackoverflow.com/questions/49984905/count-number-of-words-per-row
project_data['totalwords_title'] = project_data['cleaned_project_title'].str.split().str.len()
```

1.8 number of words in the essay

```
In [19]: project_data['totalwords_essay'] = project_data['cleaned_essay'].str.split().str.len()
```

1.9 sentiment score's of each of the essay

```
project_data['pos']=pos
project_data['compound']=compound
```

1.10 droping unnecesarry columns

```
In [21]: project_data.drop(['project_title'], axis=1, inplace=True)
    project_data.drop(['project_essay_1'], axis=1, inplace=True)
    project_data.drop(['project_essay_2'], axis=1, inplace=True)
    project_data.drop(['project_essay_3'], axis=1, inplace=True)
    project_data.drop(['project_essay_4'], axis=1, inplace=True)
```

1.11 Concate Essay and title

```
In [22]: project_data['essay_title']=project_data['cleaned_essay']+" "+project_data['cleaned_project_title']
    essay_title=project_data['essay_title']
```

1.12 TFIDF vectorizer of concatinated Essat_titile

```
In [23]: #https://stackoverflow.com/questions/48431173/is-there-a-way-to-get-only-the-idf-values-of-words-using-scikit-or-any-
tf = TfidfVectorizer(use_idf=True,min_df=10)
    tf.fit_transform(project_data['essay_title'].values)
    feature = tf.get_feature_names()

idf = tf.idf_ #print numerical idf

indexes = np.argsort(idf)[::-1] #sorting as per value w.r.t indexes
indexes = indexes[0:2000]
idf_feature=[]
fet_2000=[]
for i in indexes:
    fet_2000.append(feature[i])
    idf_feature.append([feature[i],idf[i]])
In [24]: len(fet_2000)
```

Out[24]: 2000

1.13 Co-occurance matrix

```
def get co occur matrix(data, vocab, context window=5):
In [25]:
               a = pd.DataFrame(np.zeros((len(vocab), len(vocab))), index=vocab, columns=vocab)
               for review in data:
                    words = review.split()
                   for idx in range(len(words)):
                        if a.get(words[idx]) is None:
                             continue
                        for i in range(1, context window+1):
                             if idx - i >= 0:
                                 if a.get(words[idx-i]) is not None:
                                     a[words[idx-i]].loc[words[idx]] = a.get(words[idx-i]).loc[words[idx]] + 1
                                     a[words[idx]].loc[words[idx-i]] = a.get(words[idx]).loc[words[idx-i]] + 1
                            if idx+i < len(words):</pre>
                                 if a.get(words[idx+i]) is not None:
                                     a[words[idx+i]].loc[words[idx]] = a.get(words[idx+i]).loc[words[idx]] + 1
                                     a[words[idx]].loc[words[idx+i]] = a.get(words[idx]).loc[words[idx+i]] + 1
               np.fill diagonal(a.values, 0)
               return a
           co matrix = get co occur matrix(project data['essay title'], fet 2000)
           co matrix
In [26]:
                     kelly detention devises devotion symphonic dilemmas susceptible disappearing ditching sunday ... keepers medias shovels
Out[26]:
                                                                                                            0.0 ...
               kelly
                      0.0
                                0.0
                                        0.0
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                                                           0.0
                                                                     0.0
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                                                                                            0.0
                                                                                                     0.0
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                                                                                                                                        0.0
            detention
                      0.0
                                0.0
                                        0.0
                                                0.0
                                                           0.0
                                                                     0.0
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                                                                                            0.0
                                                                                                     0.0
                                                                                                            0.0 ...
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                                                                                                                                        0.0
             devises
                      0.0
                                0.0
                                        0.0
                                                0.0
                                                           0.0
                                                                     0.0
                                                                                0.0
                                                                                            0.0
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                                        0.0
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                                                                     0.0
                                                                                0.0
                                                                                                            0.0 ...
            devotion
                      0.0
                                0.0
                                                           0.0
                                                                                            0.0
                                                                                                     0.0
                                                                                                                        0.0
                                                                                                                               0.0
                                                                                                                                        0.0
                                                                                                            0.0 ...
          symphonic
                      0.0
                                0.0
                                        0.0
                                                0.0
                                                           0.0
                                                                     0.0
                                                                                0.0
                                                                                            0.0
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```

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heal

royal

rub

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0.0

0.0

0.0

0.0

	kelly	detention	devises	devotion	symphonic	dilemmas	susceptible	disappearing	ditching	sunday	 keepers	medias	shovels
ordinarily	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0
moderately	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0

2000 rows × 2000 columns

←

1.14 SVD on cooccurance matrix

```
In [27]:
          from sklearn.decomposition import TruncatedSVD
          n components=[10,20,50,60,100,200,300,400,500,1000,1200,1500,1600,1700,1800,1900,1999]
          explained variance=[]
          for i in n components:
           svd=TruncatedSVD(n components=i,random state=42)
           svd.fit(co matrix)
           exp var=svd.explained variance ratio .sum()
           explained variance.append(exp var)
           print('n components=',i,'variance=',exp var)
         n components= 10 variance= 0.40607391483910527
         n components= 20 variance= 0.5129279118824488
         n components= 50 variance= 0.6722847588030308
         n components= 60 variance= 0.7047263478101818
         n components= 100 variance= 0.7781856441556061
         n components= 200 variance= 0.8549650520220569
         n components= 300 variance= 0.9014224986700434
         n components= 400 variance= 0.9324144628011418
         n components= 500 variance= 0.9531639495527733
         n components= 1000 variance= 0.9988219060277594
         n components= 1200 variance= 1.0000000000000084
         n components= 1500 variance= 1.000000000000115
         n components= 1600 variance= 1.0000000000000095
         n components= 1700 variance= 1.0000000000000093
         n components= 1800 variance= 1.000000000000142
         n components= 1900 variance= 1.000000000000147
         n components= 1999 variance= 1.0000000000000093
```

1.15 components vs variance

```
plt.plot(n components, explained variance)
In [28]:
          plt.xlabel('n components')
          plt.ylabel("Explained variance")
          plt.title("n components v/s Explained variance")
          plt.show()
                      n components v/s Explained variance
            1.0
            0.9
          Explained variance
            0.8
            0.6
            0.5
            0.4
                     250
                          500
                                    1000
                                        1250 1500 1750 2000
                               750
                                 n components
          from sklearn.decomposition import TruncatedSVD
In [29]:
          tsvd=TruncatedSVD(n components=1500, random state=42)
          final co matrix=tsvd.fit transform(co matrix)
          print(final co matrix.shape)
In [30]:
          (2000, 1500)
          co_matrix.columns
In [31]:
Out[31]: Index(['kelly', 'detention', 'devises', 'devotion', 'symphonic', 'dilemmas',
                 'susceptible', 'disappearing', 'ditching', 'sunday',
                 'keepers', 'medias', 'shovels', 'footrest', 'zoned', 'heal', 'royal',
                 'rub', 'ordinarily', 'moderately'],
                dtype='object', length=2000)
          word names = list(co matrix.columns)
In [32]:
```

1.16 Making dependant(label) and independant variables

```
In [33]:
           project data=project data[:2000]
           y = project data['project is approved'].values
           x=project data
           x.head(3)
Out[33]:
              Unnamed:
                             id
                                                      teacher_id teacher_prefix school_state project_submitted_datetime project_grade_category project_
                        p253737
                                  c90749f5d961ff158d4b4d1e7dc665fc
                                                                          Mrs
                                                                                        IN
                                                                                                   2016-12-05 13:43:57
                                                                                                                             Grades PreK 2
                                                                                                                                               op
                                                                                                                               Grades 6 8
                140945 p258326 897464ce9ddc600bced1151f324dd63a
                                                                                        FL
                                                                                                   2016-10-25 09:22:10
                                                                           Mr
           2
                 21895 p182444 3465aaf82da834c0582ebd0ef8040ca0
                                                                                       ΑZ
                                                                                                   2016-08-31 12:03:56
                                                                                                                               Grades 6 8
                                                                           Ms
         3 rows × 24 columns
          1.17 Traing and Test split
```

In [34]: from sklearn.model_selection import train_test_split
 X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.33, stratify=y,random_state=42)

```
\#X\_train,\ X\_cv,\ Y\_train,\ Y\_cv=train\_test\_split(X\_train,Y\_train,\ test\_size=0.33,\ stratify=Y\_train,random\_state=42)
```

- 2.Text Vectorization using co_matrix and encoding catagories,normalization numerical features¶
- 2.1 essay and title with matix words

```
In [35]:
          Text avg w2v train essay co matrix= []; # the avg-w2v for each sentence/review is stored in this list
          for sentence in tqdm(X train['cleaned essay'].values): # for each review/sentence
              vector = np.zeros(1500) # 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 word names:
                      vector += final co matrix[word_names.index(word)]
              Text_avg_w2v_train essay co matrix.append(vector)
          print(len(Text avg w2v train essay co matrix))
          print(len(Text avg w2v train essay co matrix[0]))
         100%|
                          1340/1340 [00:05<00:00, 244.72it/s]
         1340
         1500
          Text avg w2v test essay co matrix= []; # the avg-w2v for each sentence/review is stored in this list
In [36]:
          for sentence in tqdm(X test['cleaned essay'].values): # for each review/sentence
              vector = np.zeros(1500) # 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 word names:
                      vector += final co matrix[word names.index(word)]
              Text avg w2v test essay co matrix.append(vector)
          print(len(Text avg w2v test essay co matrix))
          print(len(Text avg w2v test essay co matrix[0]))
                          660/660 [00:02<00:00, 243.85it/s]
         100%
         660
         1500
```

```
In [37]: Text avg w2v train title co matrix= []; # the avg-w2v for each sentence/review is stored in this list
          for sentence in tqdm(X train['cleaned project title'].values): # for each review/sentence
              vector = np.zeros(1500) # 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 word names:
                      vector += final co matrix[word names.index(word)]
              Text avg w2v train title co matrix.append(vector)
          print(len(Text avg w2v train title co matrix))
          print(len(Text avg w2v train title co matrix[0]))
         100%
                        | 1340/1340 [00:00<00:00, 8070.28it/s]
         1340
         1500
         Text avg w2v test title co matrix= []; # the avg-w2v for each sentence/review is stored in this list
In [38]:
          for sentence in tqdm(X test['cleaned project title'].values): # for each review/sentence
              vector = np.zeros(1500) # 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 word names:
                      vector += final co matrix[word names.index(word)]
              Text avg w2v test title co matrix.append(vector)
          print(len(Text avg w2v test title co matrix))
          print(len(Text avg w2v test title co matrix[0]))
         100%|
                          660/660 [00:00<00:00, 8047.09it/s]
         660
         1500
```

2.2 Categories with response coding

```
In [39]: def Responsetable(table, col) :
    cat = table[col].unique()
    alpha=1
    freq_Pos = []
    for i in cat :
```

```
freq Pos.append(len(table.loc[(table[col] == i) & (table['project is approved'] == 1)]))
              freq Neq = []
              for i in cat :
                  freq Neq.append(len(table.loc[(table[col] == i) & (table['project is approved'] == 0)]))
              encoded Pos = []
              for i in range(len(cat)) :
                  encoded Pos.append(((freq Pos[i]+alpha)/(freq Pos[i] + freq Neg[i]+alpha)))
              encoded Neg = []
              encoded Neg[:] = [1 - x \text{ for } x \text{ in encoded Pos}]
              encoded Pos val = dict(zip(cat, encoded Pos))
              encoded Neg val = dict(zip(cat, encoded Neg))
              return encoded Pos val, encoded Neg val
          def Responsecode(table) :
In [40]:
              pos cleancat, neg cleancat = Responsetable(table,'clean categories')
              pos cleansubcat, neg cleansubcat = Responsetable(table, 'clean subcategories')
              pos schoolstate, neg schoolstate = Responsetable(table, 'school state')
              pos teacherprefix, neg teacherprefix = Responsetable(table, 'teacher prefix')
              pos projgradecat, neg projgradecat = Responsetable(table, 'project grade category')
              df = pd.DataFrame()
              df['clean cat pos'] = table['clean categories'].map(pos cleancat)
              df['clean cat neg'] = table['clean categories'].map(neg cleancat)
              df['clean subcat pos'] = table['clean subcategories'].map(pos cleansubcat)
              df['clean subcat neg'] = table['clean subcategories'].map(neg cleansubcat)
              df['school state pos'] = table['school state'].map(pos schoolstate)
              df['school state neg'] = table['school state'].map(neg schoolstate)
              df['teacher prefix pos'] = table['teacher prefix'].map(pos teacherprefix)
              df['teacher prefix neg'] = table['teacher prefix'].map(neg teacherprefix)
              df['proj grade cat pos'] = table['project grade category'].map(pos projgradecat)
              df['proj grade cat neg'] = table['project grade category'].map(neg projgradecat)
              return df
```

```
newTrain = Responsecode(X train)
In [41]:
          newTest = Responsecode(X test)
          #newCv=Responsecode(X cv)
         def mergeEncoding(table, p, n) :
In [42]:
             lstPos = table[p].values.tolist()
             lstNeg = table[n].values.tolist()
             frame = pd.DataFrame(list(zip(lstNeg, lstPos)))
              return frame
        2.3 response code of clean categories
         X train clean cat resposecode = mergeEncoding(newTrain, 'clean cat pos', 'clean cat neg')
In [43]:
         X test clean cat resposecode = mergeEncoding(newTest, 'clean cat pos', 'clean cat neg')
         #X cv clean cat resposecode=mergeEncoding(newCv, 'clean cat pos', 'clean cat neg')
         print(X train clean cat resposecode.shape)
         (1340, 2)
        2.4 response code of clean sub categories
         X train clean subcat resposecode = mergeEncoding(newTrain, 'clean subcat pos', 'clean subcat neg')
In [44]:
         X test clean subcat resposecode = mergeEncoding(newTest, 'clean subcat pos', 'clean subcat neg')
          #X cv clean subcat resposecode = mergeEncoding(newCv, 'clean subcat pos', 'clean subcat neg')
          print(X train clean subcat resposecode.shape)
          print(X test clean subcat resposecode shape)
          #print(X cv clean subcat resposecode.shape)
         (1340, 2)
         (660, 2)
```

2.5 response code of project grade

```
In [45]: X_train_grade_resposecode = mergeEncoding(newTrain, 'proj_grade_cat_pos', 'proj_grade_cat_neg')
X_test_grade_resposecode = mergeEncoding(newTest, 'proj_grade_cat_pos', 'proj_grade_cat_neg')
#X_cv_grade_resposecode = mergeEncoding(newCv, 'proj_grade_cat_pos', 'proj_grade_cat_neg')
print(X_train_grade_resposecode.shape)
print(X_test_grade_resposecode.shape)
#print(X_cv_grade_resposecode.shape)
```

```
(1340, 2)
(660, 2)
```

2.6 response code of school state

```
In [46]: X_train_state_resposecode = mergeEncoding(newTrain, 'school_state_pos', 'school_state_neg')
    X_test_state_resposecode = mergeEncoding(newCv, 'school_state_pos', 'school_state_neg')
    #X_cv_state_resposecode = mergeEncoding(newCv, 'school_state_pos', 'school_state_neg')
    print(X_train_state_resposecode.shape)
    print(X_test_state_resposecode.shape)

#print(X_cv_state_resposecode.shape)

(1340, 2)
(660, 2)
```

2.7 response code of teacher prefix

```
In [47]: X_train_teacher_resposecode = mergeEncoding(newTrain, 'teacher_prefix_pos', 'teacher_prefix_neg')
    X_test_teacher_resposecode = mergeEncoding(newTest, 'teacher_prefix_pos', 'teacher_prefix_neg')
    #X_cv_teacher_resposecode = mergeEncoding(newCv, 'teacher_prefix_pos', 'teacher_prefix_neg')
    print(X_train_teacher_resposecode.shape)
    print(X_test_teacher_resposecode.shape)
    #print(X_cv_teacher_resposecode.shape)
    (1340, 2)
    (660, 2)
```

2.8 Normalizing the numerical features: Price

2.9 Normalizing the numerical features:teacher_number_of_previously_posted_projects

2.10 Normalizing the numerical features: quantity

2.11 Normalizing the numerical features: totalwords_title

```
In [51]:
    from sklearn.preprocessing import Normalizer
    normalizer = Normalizer()

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

X_train_totalwords_title_norm = normalizer.transform(X_train['totalwords_title'].values.reshape(-1,1))

X_test_totalwords_title_norm = normalizer.transform(X_test['totalwords_title'].values.reshape(-1,1))

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

print("After vectorizations")

#print(X_cv_totalwords_title_norm.shape, Y_train.shape)

#print(X_test_totalwords_title_norm.shape, Y_cv.shape)

print("="*100)

After vectorizations
(1340, 1) (1340,)
(660, 1) (660,)
```

2.12 Normalizing the numerical features: totalwords_essay

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

print("After vectorizations")
print(X_train_totalwords_essay_norm.shape, Y_train.shape)
#print(X_cv_totalwords_essay_norm.shape, Y_cv.shape)
print(X_test_totalwords_essay_norm.shape, Y_test.shape)
print("="*100)
After vectorizations
(1340, 1) (1340,)
(660, 1) (660,)
```

2.13 Finally merge all data

3.XGB classifier

3.1 model on data

```
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import learning_curve, GridSearchCV
xgb = XGBClassifier(n_jobs=-1,class_weight='balanced')
```

```
parameters = {'n estimators':[10, 50, 100, 150, 200, 300,500], 'max_depth': [2,4,5,6,7,8]}
          clf=GridSearchCV(xgb, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
          clf.fit(X tr svd, Y train)
         [10:33:58] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.4.0/src/learner.cc:573:
         Parameters: { "class weight" } might not be used.
           This may not be accurate due to some parameters are only used in language bindings but
           passed down to XGBoost core. Or some parameters are not used but slip through this
           verification. Please open an issue if you find above cases.
         [10:33:58] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.4.0/src/learner.cc:1095: Starting in XGB
         oost 1.3.0, the default evaluation metric used with the objective 'binary: logistic' was changed from 'error' to 'logl
         oss'. Explicitly set eval metric if you'd like to restore the old behavior.
Out[63]: GridSearchCV(cv=3,
                      estimator=XGBClassifier(base score=None, booster=None,
                                              class weight='balanced',
                                              colsample bylevel=None,
                                              colsample bynode=None,
                                              colsample bytree=None, gamma=None,
                                              gpu id=None, importance type='gain',
                                              interaction constraints=None,
                                              learning rate=None, max delta step=None,
                                              max depth=None, min child weight=None,
                                              missing=nan, monotone constraints=None,
                                              n estimators=100, n jobs=-1,
                                              num parallel tree=None, random state=None,
                                              reg alpha=None, reg lambda=None,
                                              scale pos weight=None, subsample=None,
                                              tree method=None, validate parameters=None,
                                              verbosity=None),
                      n iobs=-1.
                      param grid={'max depth': [2, 4, 5, 6, 7, 8],
                                  'n estimators': [10, 50, 100, 150, 200, 300, 500]},
                      return train score=True, scoring='roc auc')
         clf.cv results
In [65]:
Out[65]: {'mean fit time': array([ 0.84325306,  3.02359247,  5.665277 ,  8.22885354,  10.42034737,
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                 11.80232588, 14.9517018 , 21.4161582 , 35.75172305, 1.06757315,
                  4.40999468, 8.93234603, 13.67374754, 17.55428799, 25.50741561,
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```

```
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      0.00124719, 0.00047148, 0.00205477, 0.00205598, 0.0024943 ,
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'param max depth': masked array(data=[2, 2, 2, 2, 2, 2, 4, 4, 4, 4, 4, 4, 5, 5, 5, 5,
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                  150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
```

```
10, 50, 100, 150, 200, 300, 500],
            mask=[False, False, False, False, False, False, False, False,
                  False, False],
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{'max depth': 8, 'n estimators': 10},
```

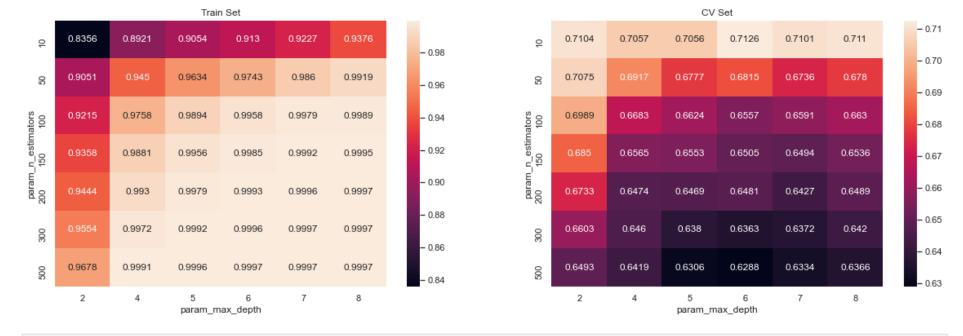
```
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```

```
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      0.99791164, 0.99923218, 0.99955238, 0.99965046, 0.99965699,
      0.93755782, 0.99192422, 0.99887743, 0.99953111, 0.99965852,
      0.99968137, 0.99969115]),
```

```
'std_train_score': array([0.00585995, 0.00947447, 0.01137846, 0.01182329, 0.01194202, 0.01072208, 0.0076775, 0.01251754, 0.01104109, 0.0053373, 0.00187903, 0.00145225, 0.00092806, 0.00041779, 0.00660413, 0.01038242, 0.00308525, 0.00176024, 0.00101946, 0.00042571, 0.00019878, 0.01200082, 0.00485973, 0.00157671, 0.00061703, 0.0002946, 0.00018656, 0.0001663, 0.00870079, 0.00406178, 0.0010974, 0.00034366, 0.0002152, 0.000179, 0.00017494, 0.00395143, 0.00235828, 0.00057513, 0.0002212, 0.00019151, 0.00018439, 0.00018194])}
```

3.2 heatmap

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



```
In [68]:
          # Print params
          print(clf.best estimator )
          print(clf.score(X tr svd, Y_train))
          print(clf.score(X te svd, Y test))
         XGBClassifier(base score=0.5, booster='gbtree', class_weight='balanced',
                       colsample bylevel=1, colsample bynode=1, colsample bytree=1,
                       gamma=0, gpu id=-1, importance type='gain',
                       interaction constraints='', learning rate=0.300000012,
                       max delta step=0, max depth=6, min child weight=1, missing=nan,
                       monotone constraints='()', n estimators=10, n jobs=-1,
                       num parallel tree=1, random state=0, reg alpha=0, reg lambda=1,
                       scale pos weight=1, subsample=1, tree method='exact',
                       validate parameters=1, verbosity=None)
         0.9006855870121283
         0.841984911503628
          def batch predict(clf, data):
In [75]:
              data pred = []
              tr loop = data.shape[0] - data.shape[0]%1000
              for i in range(0, tr loop, 1000):
                  data pred.extend(clf.predict proba(data[i:i+1000])[:,1])
              data pred.extend(clf.predict proba(data[tr loop:])[:,1])
              return data pred
```

3.3 ROC curve

```
In [89]: from sklearn.metrics import roc_curve, auc
import xgboost as xgb

gbdt = xgb.XGBClassifier(max_depth = 6, n_estimators = 10,n_jobs=-1,class_weight='balanced')
gbdt.fit(X_tr_svd, Y_train)

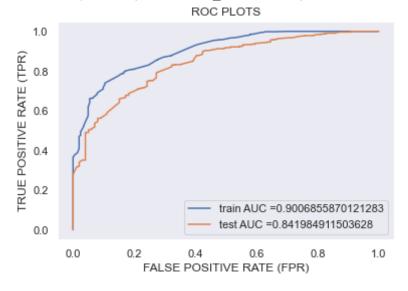
y_train_pred = clf.predict_proba(X_tr_svd)[:,1]
y_test_pred = clf.predict_proba(X_te_svd)[:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(Y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(Y_test, y_test_pred)
```

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```

[11:19:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:573: Parameters: { "class weight" } might not be used.

This may not be accurate due to some parameters are only used in language bindings but passed down to XGBoost core. Or some parameters are not used but slip through this verification. Please open an issue if you find above cases.

[11:19:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:1095: Starting in XGB oost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl oss'. Explicitly set eval_metric if you'd like to restore the old behavior.



observation

1. Model perform good on train data than test data

```
def predict(proba, threshould, fpr, tpr):
In [85]:
              t = threshould[np.argmax(tpr*(1-fpr))]
              #(tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
              \#print("the maximum value of tpr*(1-fpr)", \max(\text{tpr*}(1-\text{fpr})), "for threshold", \text{np.round}(t,3))
              predictions = []
              for i in proba:
                  if i>=t:
                      predictions.append(1)
                  else:
                       predictions.append(0)
              return predictions
          def myplot matrix1(data):
In [60]:
              plt.clf()
              plt.imshow(data, interpolation='nearest', cmap=plt.cm.Wistia)
              classNames = ['Negative', 'Positive']
              plt.title('Approved not approved matrix')
              tick marks = np.arange(len(classNames))
              plt.xticks(tick marks, classNames, rotation=45)
              plt.yticks(tick marks, classNames)
              s = [['TN', 'FN'], ['FP', 'TP']]
              for i in range(2):
                  for j in range(2):
                       plt.text(j,i, str(s[i][j])+" = "+str(data[i][j]))
              plt.show()
```

3.4 confusion matrix

```
In [90]: from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

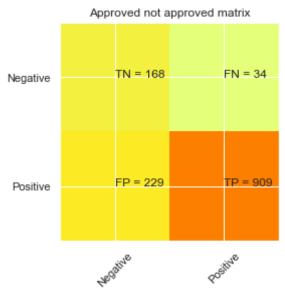
y_train_predicted_withthroshold=predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)
y_test_predicted_withthroshold=predict(y_test_pred, tr_thresholds, test_fpr, test_tpr)

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

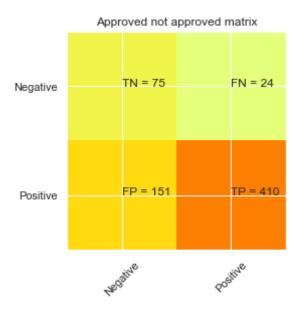
```
print("="*100)
        from sklearn.metrics import confusion matrix
        print("Train confusion matrix")
        print(cm train)
        print("="*100)
        print("Accuracy score for Train")
        print(accuracy score(Y train, predict(y_train_pred, tr_thresholds, train_fpr, train_tpr)))
        print("="*100)
        cm test=confusion matrix(Y test,y test predicted withthroshold,labels=[0, 1])
        print("Test confusion matrix")
        print(cm test)
        print("="*100)
        print("Accuracy score for Test")
        accuracy_score_bow=accuracy_score(Y_test, predict(y_test_pred, tr_thresholds, test fpr, test tpr))
        print(accuracy score bow)
        print("="*100)
       Train confusion matrix
       [[168 34]
        [229 9091]
       Accuracy score for Train
       0.8037313432835821
       ______
       Test confusion matrix
       [[ 75 24]
        [151 410]]
       Accuracy score for Test
       0.7348484848484849
        print("confusion matrix for train data")
In [91]:
        print("="*100)
        myplot matrix1(cm train)
        print("confusion matrix for Test data")
```

```
print("="*100)
myplot_matrix1(cm_test)
```

confusion matrix for train data



confusion matrix for Test data



4. Model Performance Table

5.Observation

1.Using svd we get 84% accuracy in test data

2.True postive number in confusion matrix is good for test data	
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