

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
<code>project_id</code>		A unique identifier for the proposed project. Example: p036502
<code>project_title</code>	<ul style="list-style-type: none">••	Title of the project. Examples: Art Will Make You Happy! First Grade Fun
<code>project_grade_category</code>	<ul style="list-style-type: none">••••	Grade level of students for which the project is targeted. One of the following enumerated values: Grades PreK-2 Grades 3-5 Grades 6-8 Grades 9-12
<code>project_subject_categories</code>	<ul style="list-style-type: none">••••••••	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 Math & Science Music & The Arts Special Needs Warmth
		Examples: Music & The Arts Literacy & Language, Math & Science
<code>school_state</code>		State where school is located (Two-letter U.S. postal code (https://en.wikipedia.org/wiki/List_of_U.S._state_abbreviations#Postal_codes)). Example: WY
<code>project_subject_subcategories</code>	<ul style="list-style-type: none">••	One or more (comma-separated) subject subcategories for the project. Examples: Literacy Literature & Writing, Social Sciences
<code>project_resource_summary</code>	<ul style="list-style-type: none">•	An explanation of the resources needed for the project. Example: My students need hands on literacy materials to manage sensory needs!
<code>project_essay_1</code>		First application essay*
<code>project_essay_2</code>		Second application essay*
<code>project_essay_3</code>		Third application essay*
<code>project_essay_4</code>		Fourth application essay*
<code>project_submitted_datetime</code>		Datetime when project application was submitted. Example: 2016-04-28 12:43:56.245

Feature		Description
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_projects		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 <code>project_id</code> value from the <code>train.csv</code> file. Example: p036502
description		Description of the resource. Example: Tenor Saxophone Reeds, Box of 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
<code>project_is_approved</code>	A binary flag indicating whether DonorsChoose approved the project. A value of <code>0</code> indicates the project was not approved, and a value of <code>1</code> 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.

```
In [1]: %matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from chart_studio import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
```

1.1 Reading Data

```
In [2]: project_data = pd.read_csv('train_data.csv')
resource_data = pd.read_csv('resources.csv')
```

```
In [3]: print("Number of data points in train data", project_data.shape)
print('-'*50)
print("The attributes of data :", project_data.columns.values)
```

Number of data points in train data (109248, 17)

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

```
In [4]: print("Number of data points in train data", resource_data.shape)
print(resource_data.columns.values)
resource_data.head(2)
```

Number of data points in train data (1541272, 4)
['id' 'description' 'quantity' 'price']

Out[4]:

	id	description	quantity	price
0	p233245	LC652 - Lakeshore Double-Space Mobile Drying Rack	1	149.00
1	p069063	Bouncy Bands for Desks (Blue support pipes)	3	14.95

1.2 preprocessing of project_subject_categories

```

In [5]: categories = list(project_data['project_subject_categories'].values)
# remove special characters from list of strings python: https://stackoverflow.co
m/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-i
n-python
cat_list = []
for i in categories:
    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 category based on sp
ace "Math & Science"=> "Math", "&", "Science"
            j=j.replace('The', '') # if we have the words "The" we are going to re
place 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 traili
ng 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]))

```

1.3 preprocessing of project_subject_subcategories

```

In [6]: sub_categories = 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_categories:
    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 category 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 placing 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]))

```

1.3 Text preprocessing

```

In [7]: # merge two column text dataframe:
project_data["essay"] = project_data["project_essay_1"].map(str) + \
    project_data["project_essay_2"].map(str) + \
    project_data["project_essay_3"].map(str) + \
    project_data["project_essay_4"].map(str)

```



```
In [8]: project_data.head(2)
```

Out[8]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	project_submitted_date
0	160221	p253737	c90749f5d961ff158d4b4d1e7dc665fc	Mrs.	IN	2016-12-05 1
1	140945	p258326	897464ce9ddc600bcd1151f324dd63a	Mr.	FL	2016-10-25 0

```
In [9]: # 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"n't", " not", phrase)
    phrase = re.sub(r"\ 're", " are", phrase)
    phrase = re.sub(r"\ 's", " is", phrase)
    phrase = re.sub(r"\ 'd", " would", phrase)
    phrase = re.sub(r"\ 'll", " will", phrase)
    phrase = re.sub(r"\ 't", " not", phrase)
    phrase = re.sub(r"\ 've", " have", phrase)
    phrase = re.sub(r"\ 'm", " am", phrase)
    return phrase
```

```
In [10]: sent = decontracted(project_data['essay'].values[20000])
print(sent)
print("="*50)
```

My kindergarten students have varied disabilities ranging from speech and language delays, cognitive delays, gross/fine motor delays, to autism. They are eager beavers and always strive to work their hardest working past their limitations.

\r\n\r\nThe materials we have are the ones I seek out for my students. I teach in a Title I school where most of the students receive free or reduced price lunch. Despite their disabilities and limitations, my students love coming to school and come eager to learn and explore. Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting? This is how my kids feel all the time. They want to be able to move as they learn or so they say. Wobble chairs are the answer and I love them because they develop their core, which enhances gross motor and in turn fine motor skills.

\r\nThey also want to learn through games, my kids do not want to sit and do worksheets. They want to learn to count by jumping and playing. Physical engagement is the key to our success. The number toss and color and shape mats can make that happen. My students will forget they are doing work and just have the fun a 6 year old deserves.

nannan

=====

```
In [11]: # \r \n \t remove from string python: http://texthandler.com/info/remove-line-breaks-python/
sent = sent.replace('\\r', ' ')
sent = sent.replace('\\n', ' ')
sent = sent.replace('\\t', ' ')
print(sent)
```

My kindergarten students have varied disabilities ranging from speech and language delays, cognitive delays, gross/fine motor delays, to autism. They are eager beavers and always strive to work their hardest working past their limitations. The materials we have are the ones I seek out for my students. I teach in a Title I school where most of the students receive free or reduced price lunch. Despite their disabilities and limitations, my students love coming to school and come eager to learn and explore. Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting? This is how my kids feel all the time. They want to be able to move as they learn or so they say. Wobble chairs are the answer and I love them because they develop their core, which enhances gross motor and in turn fine motor skills. They also want to learn through games, my kids do not want to sit and do worksheets. They want to learn to count by jumping and playing. Physical engagement is the key to our success. The number toss and color and shape mats can make that happen. My students will forget they are doing work and just have the fun a 6 year old deserves.

nannan

```
In [12]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
print(sent)
```

My kindergarten students have varied disabilities ranging from speech and language delays cognitive delays gross fine motor delays to autism They are eager beavers and always strive to work their hardest working past their limitations The materials we have are the ones I seek out for my students I teach in a Title I school where most of the students receive free or reduced price lunch Despite their disabilities and limitations my students love coming to school and come eager to learn and explore Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting This is how my kids feel all the time The want to be able to move as they learn or so they say Wobble chairs are the answer and I love them because they develop their core which enhances gross motor and in Turn fine motor skills They also want to learn through games my kids do not want to sit and do worksheets They want to learn to count by jumping and playing Physical engagement is the key to our success The number toss and color and shape mats can make that happen My students will forget they are doing work and just have the fun a 6 year old deserves nannan

```
In [13]: # 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"]
```



```
In [21]: project_data = pd.concat([project_data, preprocessed_title,preprocessed_essay, \
                                   word_count_title, word_count_essay], axis=1)

project_data.head(1)
```

Out[21]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	project_submitted_date
0	160221	p253737	c90749f5d961ff158d4b4d1e7dc665fc	Mrs.	IN	2016-12-05 13:

1 rows x 22 columns

Calculate sentiment score of each essay

In [22]:

```
'''  
  
import nltk  
nltk.downloader.download('vader_lexicon')  
from nltk.sentiment.vader import SentimentIntensityAnalyzer  
  
# import nltk  
# nltk.download('vader_lexicon')  
  
sid = SentimentIntensityAnalyzer()  
  
sentiment_score_essays_neg = []  
sentiment_score_essays_neu = []  
sentiment_score_essays_pos = []  
sentiment_score_essays_com = []  
  
for sentence in tqdm(preprocessed_essays):  
    for_sentiment = sentence  
    ss = sid.polarity_scores(for_sentiment)  
    sentiment_score_essays_neg.append(ss['neg'])  
    sentiment_score_essays_neu.append(ss['neu'])  
    sentiment_score_essays_pos.append(ss['pos'])  
    sentiment_score_essays_com.append(ss['compound'])  
  
for k in ss:  
    print('{0}: {1}, '.format(k, ss[k]), end='')  
  
# we can use these 4 things as features/attributes (neg, neu, pos, compound)  
# neg: 0.0, neu: 0.753, pos: 0.247, compound: 0.93  
  
'''
```

Out[22]:

```
"\n\nimport nltk\nnltk.downloader.download('vader_lexicon')\nfrom nltk.sentimen  
t.vader import SentimentIntensityAnalyzer\n\n# import nltk\n# nltk.download('vad  
er_lexicon')\n\nsid = SentimentIntensityAnalyzer()\n\nsentiment_score_essays_neg  
= []\nsentiment_score_essays_neu = []\nsentiment_score_essays_pos = []\nsentimen  
t_score_essays_com = []\n\nfor sentence in tqdm(preprocessed_essays):\n    for_  
sentiment = sentence\n    ss = sid.polarity_scores(for_sentiment)\n    sentime  
nt_score_essays_neg.append(ss['neg'])\n    sentiment_score_essays_neu.append(ss  
['neu'])\n    sentiment_score_essays_pos.append(ss['pos'])\n    sentiment_scor  
e_essays_com.append(ss['compound'])\n\n    \n    \nfor k in ss:\n    print('{0}:  
{1}, '.format(k, ss[k]), end='')\n\n# we can use these 4 things as features/attr  
ibutes (neg, neu, pos, compound)\n# neg: 0.0, neu: 0.753, pos: 0.247, compound:  
0.93\n\n"
```

```
In [23]: '''  
  
print(sentiment_score_essays_neg[10])  
print(sentiment_score_essays_neu[10])  
print(sentiment_score_essays_pos[10])  
print(sentiment_score_essays_com[10])  
'''
```

```
Out[23]: '\n\nprint(sentiment_score_essays_neg[10])\nprint(sentiment_score_essays_neu[10])\nprint(sentiment_score_essays_pos[10])\nprint(sentiment_score_essays_com[10])\n'
```

```
In [24]: '''  
  
ss_neg = pd.DataFrame({'sentiment_score_essays_neg': sentiment_score_essays_neg})  
ss_neu = pd.DataFrame({'sentiment_score_essays_neu': sentiment_score_essays_neu})  
ss_pos = pd.DataFrame({'sentiment_score_essays_pos': sentiment_score_essays_pos})  
ss_com = pd.DataFrame({'sentiment_score_essays_com': sentiment_score_essays_com})  
'''
```

```
Out[24]: "\nss_neg = pd.DataFrame({'sentiment_score_essays_neg': sentiment_score_essays_neg})\nss_neu = pd.DataFrame({'sentiment_score_essays_neu': sentiment_score_essays_neu})\nss_pos = pd.DataFrame({'sentiment_score_essays_pos': sentiment_score_essays_pos})\nss_com = pd.DataFrame({'sentiment_score_essays_com': sentiment_score_essays_com})\n"
```

```
In [25]: '''  
  
project_data = pd.concat([project_data,ss_neg, ss_neu, ss_pos, ss_com], axis=1)  
  
project_data.head(1)  
'''
```

```
Out[25]: '\n\nproject_data = pd.concat([project_data,ss_neg, ss_neu, ss_pos, ss_com], axis=1)\n\nproject_data.head(1)\n'
```

```
In [ ]:
```

1.5 Preparing data for models

1.5.1 Merge project data with resource data

```
In [26]: price_data = resource_data.groupby('id').agg({'price': 'sum', 'quantity': 'sum'}).reset_index()  
project_data = pd.merge(project_data, price_data, on='id', how='left')
```



```
In [27]: project_data.columns
```

```
Out[27]: Index(['Unnamed: 0', 'id', 'teacher_id', 'teacher_prefix', 'school_state',
               'project_submitted_datetime', 'project_grade_category', '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',
               'clean_categories', 'clean_subcategories', 'essay',
               'preprocessed_titles', 'preprocessed_essays', 'word_count_titles',
               'word_count_essays', 'price', 'quantity'],
              dtype='object')
```

```
In [28]: project_data.head(1)
```

```
Out[28]:
```

Unnamed: 0	id	teacher_id	teacher_prefix	school_state	project_submitted_dat
0	160221 p253737	c90749f5d961ff158d4b4d1e7dc665fc	Mrs.	IN	2016-12-05 13:

1 rows x 24 columns

we are going to consider

- school_state : categorical data
- clean_categories : categorical data
- clean_subcategories : categorical data
- project_grade_category : categorical data
- teacher_prefix : categorical data

- project_title : text data
- text : text data
- project_resource_summary: text data (optinal)

- quantity : numerical (optinal)
- teacher_number_of_previously_posted_projects : numerical
- price : numerical

Assignment 10: Clustering

- **step 1:** Choose any vectorizer (data matrix) that you have worked in any of the assignments, and got the best AUC value.
- **step 2:** Choose any of the [feature selection](https://scikit-learn.org/stable/modules/feature_selection.html) (https://scikit-learn.org/stable/modules/feature_selection.html)/[reduction algorithms](https://scikit-learn.org/stable/modules/decomposition.html) (<https://scikit-learn.org/stable/modules/decomposition.html>) ex: selectkbest features, pretrained word vectors, model based feature selection etc and reduce the number of features to 5k features.
- **step 3:** Apply all three kmeans, Agglomerative clustering, DBSCAN
 - **K-Means Clustering:**
 - Find the best 'k' using the elbow-knee method (plot k vs inertia_)
 - **Agglomerative Clustering:**
 - Apply [agglomerative algorithm](https://stackabuse.com/hierarchical-clustering-with-python-and-scikit-learn/) (<https://stackabuse.com/hierarchical-clustering-with-python-and-scikit-learn/>) and try a different number of clusters like 2,5 etc.
 - As this is very computationally expensive, take **5k** datapoints only to perform hierarchical clustering because they do take a considerable amount of time to run.
 - **DBSCAN Clustering:**
 - Find the best 'eps' using the [elbow-knee method](https://stackoverflow.com/a/48558030/4084039) (<https://stackoverflow.com/a/48558030/4084039>).
 - Take **5k** datapoints only.
- **step 4:** Summarize each cluster by manually observing few points from each cluster.
- **step 5:** You need to plot the word cloud with essay text for each cluster for each of algorithms mentioned in **step 3**.

In []:

In []:

2.1 Choose the best data matrix on which you got the best AUC

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

In [29]:

```
#Stratify vs random sampling. oversampling for imbalanced data
#https://stats.stackexchange.com/questions/250273/benefits-of-stratified-vs-random-sampling-for-generating-training-data-in-classi

from sklearn.model_selection import train_test_split

# train = project_data.drop(['project_is_approved'], axis=1, inplace=True) # this will drop in raw data so would not work

X_train, X_test, y_train, y_test = train_test_split(project_data, project_data['project_is_approved'],
                                                    test_size=0.33, stratify = project_data['project_is_approved'])

#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, stratify=y_train)

X_train.drop(['project_is_approved'], axis=1, inplace=True)
X_test.drop(['project_is_approved'], axis=1, inplace=True)
#X_cv.drop(['project_is_approved'], axis=1, inplace=True)
```

In [30]:

```
print(X_test.shape)
print(y_test.shape)
print(X_train.shape)
print(y_train.shape)
```

```
(36052, 23)
(36052,)
(73196, 23)
(73196,)
```

2.2 Make Data Model Ready: encoding numerical, categorical features

```

In [31]: # Encoding of Categorical Features:

# Category:
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(vocabulary=list(sorted_cat_dict.keys()), lowercase=False, binary=True)
categories_one_hot_train = vectorizer.fit_transform(X_train['clean_categories'].values)
#categories_one_hot_cv = vectorizer.transform(X_cv['clean_categories'].values)
categories_one_hot_test = vectorizer.transform(X_test['clean_categories'].values)

print(vectorizer.get_feature_names())
print("category Shape of matrix after one hot encoding ",categories_one_hot_train.shape)

# Subcategory
vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowercase=False, binary=True)
sub_categories_one_hot_train = vectorizer.fit_transform(X_train['clean_subcategories'].values)
#sub_categories_one_hot_cv = vectorizer.transform(X_cv['clean_subcategories'].values)
sub_categories_one_hot_test = vectorizer.transform(X_test['clean_subcategories'].values)

print(vectorizer.get_feature_names())
print("subctg Shape of matrix after one hot encoding ",sub_categories_one_hot_train.shape)

#you can do the similar thing with state, teacher_prefix and project_grade_category also

vectorizer = CountVectorizer(lowercase=False, binary=True)
state_one_hot_train = vectorizer.fit_transform(X_train['school_state'].values)
#state_one_hot_cv = vectorizer.transform(X_cv['school_state'].values)
state_one_hot_test = vectorizer.transform(X_test['school_state'].values)

print("state Shape of matrix after one hot encoding ",state_one_hot_train.shape)

vectorizer = CountVectorizer(lowercase=False, binary=True)

tp_one_hot_train = vectorizer.fit_transform(X_train['teacher_prefix'].apply(lambda x: np.str_(x)))
#tp_one_hot_cv = vectorizer.transform(X_cv['teacher_prefix'].apply(lambda x: np.str_(x)))
tp_one_hot_test = vectorizer.transform(X_test['teacher_prefix'].apply(lambda x: np.str_(x)))

print("tp Shape of matrix after one hot encoding ",tp_one_hot_train.shape)

```

```

# Project Grade List
from collections import Counter
my_counter = Counter()
for word in project_data['project_grade_category'].values:
    my_counter.update(word.splitlines())

grade_list = dict(my_counter)
print(grade_list)

sorted_grade_list = dict(sorted(grade_list.items(), key=lambda kv: kv[1]))
print(sorted_grade_list)

# If not generating the above list and put into vocabulary, the vector will some
# mess up results ['12', 'Grades', 'PreK']

# This is because of space and new lines. Otherwise no need for vocabulary

vectorizer = CountVectorizer(vocabulary=list(sorted_grade_list.keys()), lowercase=
False, binary=True)
vectorizer.fit(X_train['project_grade_category'].values)
print(vectorizer.get_feature_names())

pg_one_hot_train = vectorizer.transform(X_train['project_grade_category'].values)
#pg_one_hot_cv = vectorizer.transform(X_cv['project_grade_category'].values)
pg_one_hot_test = vectorizer.transform(X_test['project_grade_category'].values)

print("pg Shape of matrix after one hot encodig ",pg_one_hot_train.shape)

```

```

['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning', 'Sp
ecialNeeds', 'Health_Sports', 'Math_Science', 'Literacy_Language']
category Shape of matrix after one hot encodig (73196, 9)
['Economics', 'CommunityService', 'FinancialLiteracy', 'ParentInvolvement', 'Ext
racurricular', 'Civics_Government', 'ForeignLanguages', 'NutritionEducation', 'W
armth', 'Care_Hunger', 'SocialSciences', 'PerformingArts', 'CharacterEducation',
'TeamSports', 'Other', 'College_CareerPrep', 'Music', 'History_Geography', 'Heal
th_LifeScience', 'EarlyDevelopment', 'ESL', 'Gym_Fitness', 'EnvironmentalScienc
e', 'VisualArts', 'Health_Wellness', 'AppliedSciences', 'SpecialNeeds', 'Literat
ure_Writing', 'Mathematics', 'Literacy']
subctg Shape of matrix after one hot encodig (73196, 30)
state Shape of matrix after one hot encodig (73196, 51)
tp Shape of matrix after one hot encodig (73196, 6)
{'Grades PreK-2': 44225, 'Grades 6-8': 16923, 'Grades 3-5': 37137, 'Grades 9-1
2': 10963}
{'Grades 9-12': 10963, 'Grades 6-8': 16923, 'Grades 3-5': 37137, 'Grades PreK-
2': 44225}
['Grades 9-12', 'Grades 6-8', 'Grades 3-5', 'Grades PreK-2']
pg Shape of matrix after one hot encodig (73196, 4)

```

```
In [32]: print("teacher prefix of matrix after one hot encoding ",tp_one_hot_train[0:5])
print("project grade matrix after one hot encoding ", pg_one_hot_train.shape)
print(X_train['project_grade_category'].values)
```

```
teacher prefix of matrix after one hot encoding      (0, 1)      1
  (1, 3)      1
  (2, 3)      1
  (3, 3)      1
  (4, 3)      1
project grade matrix after one hot encoding (73196, 4)
['Grades PreK-2' 'Grades PreK-2' 'Grades 6-8' ... 'Grades 3-5'
 'Grades 3-5' 'Grades PreK-2']
```

```
In [33]: # Numerical Data
```

```
from sklearn import preprocessing

# price_standardized = standardScalar.fit(project_data['price'].values)
# this will rise the error
# ValueError: Expected 2D array, got 1D array instead: array=[725.05 213.03 329.
... 399. 287.73 5.5 ].
# Reshape your data either using array.reshape(-1, 1)

#instead of standardize, try normalization since chi2 requires non-negative

#price_scalar = Normalizer()
price_scalar = preprocessing.StandardScaler()
price_scalar.fit(X_train['price'].values.reshape(-1,1)) # finding the mean and st
andard deviation of this data
#print(f"Mean : {price_scalar.mean_[0]}, Standard deviation : {np.sqrt(price_scal
ar.var_[0])}")

#Now standardize the data with above maen and variance.
price_standardized_train = price_scalar.transform(X_train['price'].values.reshape
(-1, 1))

#price_standardized_cv = price_scalar.transform(X_cv['price'].values.reshape(-1,
1))
price_standardized_test = price_scalar.transform(X_test['price'].values.reshape(-
1, 1))

print(price_standardized_train.mean())
print(price_standardized_train.std())

print(len(price_standardized_train))
```

```
1.2833180729477737e-16
1.0
73196
```

```
In [34]: previous_scalar = preprocessing.StandardScaler()
previous_scalar.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
previous_standardized_train = previous_scalar.transform(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1, 1))

previous_standardized_cv = previous_scalar.transform(X_cv['teacher_number_of_previously_posted_projects'].values.reshape(-1, 1))

previous_standardized_test = previous_scalar.transform(X_test['teacher_number_of_previously_posted_projects'].values.reshape(-1, 1))

print(previous_standardized_train.mean())
print(previous_standardized_train.std())

print(previous_standardized_train[100])
```

2.2327016397729798e-17
1.0
[-0.36463408]

```
In [35]: wc_scalar = preprocessing.StandardScaler()
wc_scalar.fit(X_train['word_count_essays'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
wc_standardized_train = wc_scalar.transform(X_train['word_count_essays'].values.reshape(-1, 1))
wc_standardized_cv = wc_scalar.transform(X_cv['word_count_essays'].values.reshape(-1, 1))
wc_standardized_test = wc_scalar.transform(X_test['word_count_essays'].values.reshape(-1, 1))

print(wc_standardized_train.mean())
print(wc_standardized_train.std())

print(wc_standardized_train[100])
```

-3.13063599489907e-17
0.9999999999999999
[0.84123827]

```
In [36]: wc_title_scalar = preprocessing.StandardScaler()
wc_title_scalar.fit(X_train['word_count_titles'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
wc_title_standardized_train = wc_title_scalar.transform(X_train['word_count_titles'].values.reshape(-1, 1))
#wc_title_standardized_cv = wc_title_scalar.transform(X_cv['word_count_titles'].values.reshape(-1, 1))
wc_title_standardized_test = wc_title_scalar.transform(X_test['word_count_titles'].values.reshape(-1, 1))

print(wc_title_standardized_train.mean())
print(wc_title_standardized_train.std())

print(wc_title_standardized_train[100])

-9.086124934032649e-17
0.9999999999999999
[-0.184783]
```

```
In [37]: quantity_scalar = preprocessing.StandardScaler()
quantity_scalar.fit(X_train['quantity'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
quantity_standardized_train = quantity_scalar.transform(X_train['quantity'].values.reshape(-1, 1))
#quantity_standardized_cv = quantity_scalar.transform(X_cv['quantity'].values.reshape(-1, 1))
quantity_standardized_test = quantity_scalar.transform(X_test['quantity'].values.reshape(-1, 1))

print(quantity_standardized_train.mean())
print(quantity_standardized_train.std())

print(quantity_standardized_train[100])
#print(quantity_standardized_train)

-3.572322623636768e-17
1.0
[0.62082931]
```


In [38]:

```
'''
ss_neg_scalar = preprocessing.StandardScaler()
ss_neg_scalar.fit(X_train['sentiment_score_essays_neg'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
ss_neg_standardized_train = ss_neg_scalar.transform(X_train['sentiment_score_essays_neg'].values.reshape(-1, 1))
#ss_neg_standardized_cv = ss_neg_scalar.transform(X_cv['sentiment_score_essays_neg'].values.reshape(-1, 1))
ss_neg_standardized_test = ss_neg_scalar.transform(X_test['sentiment_score_essays_neg'].values.reshape(-1, 1))

print(ss_neg_standardized_train.mean())
print(ss_neg_standardized_train.std())

print(ss_neg_standardized_train[100])
#print(quantity_standardized_train)
'''
```

Out[38]:

```
'\n\nss_neg_scalar = preprocessing.StandardScaler()\nss_neg_scalar.fit(X_train\n['sentiment_score_essays_neg'].values.reshape(-1,1)) \n\n# finding the mean and standard deviation of this data\n#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")\n\n# Now standardize the data with above mean and variance.\nss_neg_standardized_train = ss_neg_scalar.transform(X_train['sentiment_score_essays_neg'].values.reshape(-1, 1))\n#ss_neg_standardized_cv = ss_neg_scalar.transform(X_cv['sentiment_score_essays_neg'].values.reshape(-1, 1))\nss_neg_standardized_test = ss_neg_scalar.transform(X_test['sentiment_score_essays_neg'].values.reshape(-1, 1))\n\nprint(ss_neg_standardized_train.mean())\nprint(ss_neg_standardized_train.std())\nprint(ss_neg_standardized_train[100])\n#print(quantity_standardized_train)\n'
```

In [39]:

```
'''

ss_neu_scalar = preprocessing.StandardScaler()
ss_neu_scalar.fit(X_train['sentiment_score_essays_neu'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
ss_neu_standardized_train = ss_neu_scalar.transform(X_train['sentiment_score_essays_neu'].values.reshape(-1, 1))
#ss_neu_standardized_cv = ss_neu_scalar.transform(X_cv['sentiment_score_essays_neu'].values.reshape(-1, 1))
ss_neu_standardized_test = ss_neu_scalar.transform(X_test['sentiment_score_essays_neu'].values.reshape(-1, 1))

print(ss_neu_standardized_train.mean())
print(ss_neu_standardized_train.std())

print(ss_neu_standardized_train[100])
#print(quantity_standardized_train)
```

File "<ipython-input-39-f22aa3f395ba>", line 20

#print(quantity_standardized_train)

^

SyntaxError: EOF while scanning triple-quoted string literal

In []:

```
'''

ss_pos_scalar = preprocessing.StandardScaler()
ss_pos_scalar.fit(X_train['sentiment_score_essays_pos'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
ss_pos_standardized_train = ss_pos_scalar.transform(X_train['sentiment_score_essays_pos'].values.reshape(-1, 1))
#ss_pos_standardized_cv = ss_pos_scalar.transform(X_cv['sentiment_score_essays_pos'].values.reshape(-1, 1))
ss_pos_standardized_test = ss_pos_scalar.transform(X_test['sentiment_score_essays_pos'].values.reshape(-1, 1))

print(ss_pos_standardized_train.mean())
print(ss_pos_standardized_train.std())

print(ss_pos_standardized_train[100])
#print(quantity_standardized_train)
```

```
In [ ]: '''

ss_com_scalar = preprocessing.StandardScaler()
ss_com_scalar.fit(X_train['sentiment_score_essays_com'].values.reshape(-1,1))

# finding the mean and standard deviation of this data
#print(f"Mean : {previous_scalar.mean_[0]}, Standard deviation : {np.sqrt(previous_scalar.var_[0])}")

# Now standardize the data with above mean and variance.
ss_com_standardized_train = ss_com_scalar.transform(X_train['sentiment_score_essays_com'].values.reshape(-1, 1))
#ss_com_standardized_cv = ss_com_scalar.transform(X_cv['sentiment_score_essays_com'].values.reshape(-1, 1))
ss_com_standardized_test = ss_com_scalar.transform(X_test['sentiment_score_essays_com'].values.reshape(-1, 1))

print(ss_com_standardized_train.mean())
print(ss_com_standardized_train.std())

print(ss_com_standardized_train[100])
#print(quantity_standardized_train)'''
```

2.3 Make Data Model Ready: encoding eassay, and project_title

2.3.1 Bag of words

```
In [ ]: '''

# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = CountVectorizer(ngram_range = (2,2),min_df=10,max_features = 5000)
text_train_bow = vectorizer.fit_transform(X_train['preprocessed_essays'].values)

# should fit_transform only on train data . Transform on test data
#text_cv_bow = vectorizer.transform(X_cv['preprocessed_essays'].values)
text_test_bow = vectorizer.transform(X_test['preprocessed_essays'].values)

print("Shape of matrix after one hot encoding ",text_train_bow.shape)
print("Shape of matrix after one hot encoding ",text_test_bow.shape)
#print("Shape of matrix after one hot encoding ",text_cv_bow.shape)
print(text_train_bow[1])'''
```

```
In [ ]: '''
# you can vectorize the title also
# before you vectorize the title make sure you preprocess it

vectorizer = CountVectorizer(ngram_range = (2,2),min_df=10,max_features = 5000)
title_train_bow = vectorizer.fit_transform(X_train['preprocessed_titles'].values)
#title_cv_bow = vectorizer.transform(X_cv['preprocessed_titles'].values)
title_test_bow = vectorizer.transform(X_test['preprocessed_titles'].values)

print("Shape of matrix after one hot encodig ",title_train_bow.shape)
#print("Shape of matrix after one hot encodig ",title_cv_bow.shape)
print("Shape of matrix after one hot encodig ",title_test_bow.shape)
```

2.3.2 TFIDF

```
In [42]: from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(ngram_range=(2,2), min_df=10, max_features = 5000)
text_train_tfidf = vectorizer.fit_transform(X_train['preprocessed_essays'].values)
#text_cv_tfidf = vectorizer.transform(X_cv['preprocessed_essays'].values)
text_test_tfidf = vectorizer.transform(X_test['preprocessed_essays'].values)

print("Shape of matrix after one hot encodig ",text_train_tfidf.shape)
#print("Shape of matrix after one hot encodig ",text_cv_tfidf.shape)
print("Shape of matrix after one hot encodig ",text_test_tfidf.shape)
```

```
Shape of matrix after one hot encodig (73196, 5000)
Shape of matrix after one hot encodig (36052, 5000)
```

```
In [43]: # Similarly you can vectorize for title also
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(ngram_range = (2,2), min_df=10)
title_train_tfidf = vectorizer.fit_transform(X_train['preprocessed_titles'].values)
#title_cv_tfidf = vectorizer.transform(X_cv['preprocessed_titles'].values)
title_test_tfidf = vectorizer.transform(X_test['preprocessed_titles'].values)

print("Shape of matrix after one hot encodig ",title_train_tfidf.shape)
#print("Shape of matrix after one hot encodig ",title_cv_tfidf.shape)
print("Shape of matrix after one hot encodig ",title_test_tfidf.shape)
```

```
Shape of matrix after one hot encodig (73196, 2675)
Shape of matrix after one hot encodig (36052, 2675)
```

2.3.3 AVG W2V

```

In [44]: '''

from gensim.models import Word2Vec
from gensim.models import KeyedVectors

# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039
def loadGloveModel(gloveFile):
    print ("Loading Glove Model")
    f = open(gloveFile, 'r', encoding="utf8")
    model = {}
    for line in tqdm(f):
        splitLine = line.split()
        word = splitLine[0]
        embedding = np.array([float(val) for val in splitLine[1:]])
        model[word] = embedding
    print ("Done.", len(model), " words loaded!")
    return model
model = loadGloveModel('glove.42B.300d.txt')

# Word2Vec does not provide good result if only vectorize by letter, not words
# Need to split training to words first

'''

# Step 1: Getting each word from the sentence
def list_of_words(Sentence):
    return Sentence.split()

list_of_Sentence=list(X_train['preprocessed_essays'].values)
print(len(list_of_Sentence))
words_list_of_each_Sentence=list(map(list_of_words,list_of_Sentence))

Step 2: Apply word2vec

from gensim.models import word2vec
w2v_model = word2vec.Word2Vec(words_list_of_each_Sentence, size=100,workers=2, mi
n_count=0)
#this line of code trains your w2v model on the give list of sentences. Instead o
f train on X_train.values,
need to train individual words in it

glove_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(glove_words))
print("sample words ", glove_words)

'''

```

File "<ipython-input-44-d81c83be075c>", line 37

Step 2: Apply word2vec

^

SyntaxError: invalid syntax

```
In [ ]: with open('glove_vectors', 'rb') as f:
        w2v_model = pickle.load(f)
        glove_words = set(model.keys())
```

```
In [ ]: '''
# 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(X_train['preprocessed_essays'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length, if word2vec then use 50
    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 += w2v_model.wv[word] # this is for w2v_model from Word2Vec function
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_train.append(vector)

print(len(avg_w2v_vectors_train))
```

```
In [ ]: #this line of code trains your w2v model on the give list of sentences
'''

w2v_model=Word2Vec(X_cv['preprocessed_essays'].values,min_count=5,size=50, workers=4)

glove_words = list(w2v_model.wv.vocab)

print("number of words that occurred minimum 5 times ",len(glove_words))
print("sample words ", glove_vector[0:50])
'''
```

```
In [ ]: '''
avg_w2v_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this
list
for sentence in tqdm(X_cv['preprocessed_essays'].values): # for each review/sente
nce
    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 += w2v_model.wv[word] # this is for w2v_model from Word2Vec f
unction
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_cv.append(vector)

print(len(avg_w2v_vectors_cv))
'''
```

```
In [ ]: '''
avg_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in th
is list
for sentence in tqdm(X_test['preprocessed_essays'].values): # for each review/sen
tence
    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 += w2v_model.wv[word] # this is for w2v_model from Word2Vec
function
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_test.append(vector)

print(len(avg_w2v_vectors_test))
'''
```

```

In [ ]: '''

# Similarly you can vectorize for title also

#w2v_model=Word2Vec(X_train['preprocessed_titles'].values,min_count=5,size=50, workers=4)

#glove_words = list(w2v_model.wv.vocab)
#print("number of words that occurred minimum 5 times ",len(glove_words))
#print("sample words ", glove_words[0:50])

avg_w2v_vectors_titles_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['preprocessed_titles'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            #vector += w2v_model.wv[word] # this is for w2v_model from Word2Vec function
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_titles_train.append(vector)

print(len(avg_w2v_vectors_titles_train))
'''

```

```

In [ ]: # Similarly you can vectorize for title also

#w2v_model=Word2Vec(X_cv['preprocessed_titles'],min_count=5,size=50, workers=4)

#glove_words = list(w2v_model.wv.vocab)
#print("number of words that occurred minimum 5 times ",len(glove_words))
#print("sample words ", glove_words[0:50])
'''

avg_w2v_vectors_titles_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['preprocessed_titles']): # 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 += w2v_model.wv[word] # this is for w2v_model from Word2Vec function
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_titles_cv.append(vector)

print(len(avg_w2v_vectors_titles_cv))
'''

```



```
In [ ]: '''

# Similarly you can vectorize for title also

#w2v_model=Word2Vec(X_test['preprocessed_titles'].values,min_count=5,size=50, workers=4)

#glove_words = list(w2v_model.wv.vocab)
#print("number of words that occurred minimum 5 times ",len(glove_words))
#print("sample words ", glove_words[0:50])

avg_w2v_vectors_titles_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['preprocessed_titles'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            #vector += w2v_model.wv[word] # this is for w2v_model from Word2Vec function
            vector += w2v_model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_titles_test.append(vector)

print(len(avg_w2v_vectors_titles_test))
```

2.3.4 TFIDF WEIGHTED W2V

```
In [ ]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
#w2v_model=Word2Vec(X_train['preprocessed_essays'].values,min_count=5,size=50, workers=4)
#glove_words = list(w2v_model.wv.vocab)

# Test and train should use same tfidf model
tfidf_model_train= TfidfVectorizer()
tfidf_model_train.fit(X_train['preprocessed_essays'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train.get_feature_names(), list(tfidf_model_train.idf_)))
tfidf_words_train = set(tfidf_model_train.get_feature_names())
```

In []: '''

```
# 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(X_train['preprocessed_essays'].values): # for each review/se
ntence
    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_train):
            vec = w2v_model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf valu
e((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)

print(len(tfidf_w2v_vectors_train))
```

```

In [ ]: #w2v_model=Word2Vec(X_cv['preprocessed_essays'].values,min_count=5,size=50, workers=4)
#glove_words = list(w2v_model.wv.vocab)

'''
tfidf_model_cv= TfidfVectorizer()
tfidf_model_cv.fit(X_cv['preprocessed_essays'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_cv.get_feature_names(), list(tfidf_model_cv.idf_)))
tfidf_words_cv = set(tfidf_model_cv.get_feature_names())

tfidf_w2v_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list

for sentence in tqdm(X_cv['preprocessed_essays'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words_cv):
            vec = w2v_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_cv.append(vector)

print(len(tfidf_w2v_vectors_cv))

'''

```

In []: '''

```
#w2v_model=Word2Vec(X_test['preprocessed_essays'].values,min_count=5,size=50, workers=4)
#glove_words = list(w2v_model.wv.vocab)

# test and train should use same tfidf w2v model
#tfidf_model_test= TfidfVectorizer()
#tfidf_model_test.fit(X_test['preprocessed_essays'].values)
## we are converting a dictionary with word as a key, and the idf as a value
#dictionary = dict(zip(tfidf_model_test.get_feature_names(), list(tfidf_model_test.idf_)))
tfidf_words_test = set(tfidf_model_train.get_feature_names())

tfidf_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list

for sentence in tqdm(X_test['preprocessed_essays'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words_test):
            vec = w2v_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))
```

similarly convert title into tfidf w2v

In []: '''

```
# average Word2Vec
# compute average word2vec for each review.

#w2v_model=Word2Vec(X_train['preprocessed_titles'].values,min_count=5,size=50, workers=4)
#glove_words = list(w2v_model.wv.vocab)

tfidf_model_title_train= TfidfVectorizer()
tfidf_model_title_train.fit(X_train['preprocessed_titles'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_title_train.get_feature_names(), list(tfidf_model_title_train.idf_)))
tfidf_words_title_train = set(tfidf_model_title_train.get_feature_names())

tfidf_w2v_vectors_title_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['preprocessed_titles'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words_title_train):
            vec = w2v_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_title_train.append(vector)

print(len(tfidf_w2v_vectors_title_train))
print(len(tfidf_w2v_vectors_title_train[0]))
```

In []:

```
# average Word2Vec
# compute average word2vec for each review.

#w2v_model=Word2Vec(X_cv['preprocessed_titles'],min_count=5,size=50, workers=4)
#glove_words = list(w2v_model.wv.vocab)

'''

tfidf_model_title_cv= TfidfVectorizer()
tfidf_model_title_cv.fit(X_cv['preprocessed_titles'])
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_title_cv.get_feature_names(), list(tfidf_model_title_cv.idf_)))
tfidf_words_title_cv = set(tfidf_model_title_cv.get_feature_names())

tfidf_w2v_vectors_title_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['preprocessed_titles']): # 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_title_cv):
            vec = w2v_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_title_cv.append(vector)

print(len(tfidf_w2v_vectors_title_cv))
print(len(tfidf_w2v_vectors_title_cv[0]))

'''
```

```

In [ ]: '''

        # average Word2Vec
# compute average word2vec for each review.

#w2v_model=Word2Vec(X_test['preprocessed_titles'].values,min_count=5,size=50, wor
kers=4)
#glove_words = list(w2v_model.wv.vocab)

#tfidf_model_title_test= TfidfVectorizer()
#tfidf_model_title_test.fit(X_test['preprocessed_titles'].values)
## we are converting a dictionary with word as a key, and the idf as a value
#dictionary = dict(zip(tfidf_model_title_test.get_feature_names(), list(tfidf_mod
el_title_test.idf_)))
tfidf_words_title_test = set(tfidf_model_title_train.get_feature_names())

tfidf_w2v_vectors_title_test = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sentence in tqdm(X_test['preprocessed_titles'].values): # for each review/sen
tence
    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_title_test):
            vec = w2v_model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf valu
e((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_title_test.append(vector)

print(len(tfidf_w2v_vectors_title_test))
print(len(tfidf_w2v_vectors_title_test[0]))
'''

```

2.4 Dimensionality Reduction on the selected features

```
In [46]: # Please write all the code with proper documentation

from scipy.sparse import hstack

X_train_tfidf = hstack((categories_one_hot_train, sub_categories_one_hot_train, state_one_hot_train, pg_one_hot_train, tp_one_hot_train, price_standardized_train, previous_standardized_train, \
                        quantity_standardized_train, wc_standardized_train, wc_title_standardized_train, \
                        title_train_tfidf, text_train_tfidf)).tocsr()

X_test_tfidf= hstack((categories_one_hot_test, sub_categories_one_hot_test, state_one_hot_test, pg_one_hot_test, tp_one_hot_test, price_standardized_test, previous_standardized_test, \
                    quantity_standardized_test, wc_standardized_test, wc_title_standardized_test, \
                    title_test_tfidf, text_test_tfidf)).tocsr()

#X_cv_tfidf = hstack((categories_one_hot_cv, sub_categories_one_hot_cv, state_one_hot_cv, pg_one_hot_cv, tp_one_hot_cv, price_standardized_cv, previous_standardized_cv, \
#                    quantity_standardized_cv, wc_standardized_cv, wc_title_standardized_cv, \
#                    ss_neg_standardized_cv, ss_neu_standardized_cv, ss_pos_standardized_cv, ss_com_standardized_cv, \
#                    title_cv_tfidf, text_cv_tfidf)).tocsr()
```

In []:

```
In [47]: print(X_test_tfidf.shape)
print(y_test.shape)

print(X_train_tfidf.shape)
print(y_train.shape)

#print(X_cv_tfidf.shape)
#print(y_cv.shape)

(36052, 7780)
(36052,)
(73196, 7780)
(73196,)
```

Since model takes very long time to run, decided to only use Top 2000 features


```
In [48]: #https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html
from sklearn.feature_selection import SelectKBest, f_classif
s = SelectKBest(f_classif,k=2000).fit(X_train_tfidf, y_train)
X_train_s = s.transform(X_train_tfidf)
X_test_s = s.transform(X_test_tfidf)
#####
print("Final Data matrix on TFIDF")
print(X_train_s.shape, y_train.shape)
# print(X_cr.shape, y_cv.shape)
print(X_test_s.shape, y_test.shape)
print("="*100)
```

C:\Users\wwang26\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\feature_selection\univariate_selection.py:114: UserWarning:

Features [0 0 0 0] are constant.

Final Data matrix on TFIDF

(73196, 2000) (73196,)

(36052, 2000) (36052,)

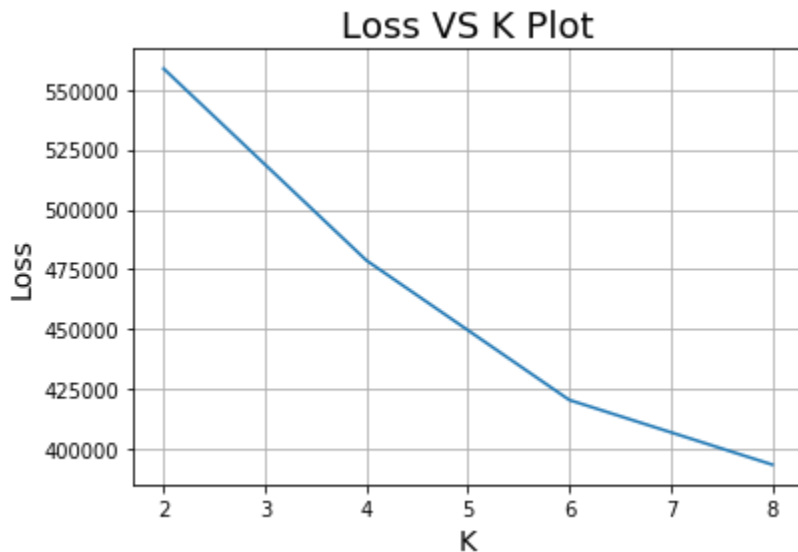
=====

2.5 Apply Kmeans

```
In [51]: from sklearn.cluster import KMeans

k_values = [2,4,6,8]
loss = []
for i in k_values:
    kmeans = KMeans(n_clusters=i, n_jobs=-1).fit(X_train_s)
    loss.append(kmeans.inertia_)
```

```
In [52]: plt.plot(k_values, loss)
plt.xlabel('K',size=14)
plt.ylabel('Loss',size=14)
plt.title('Loss VS K Plot',size=18)
plt.grid()
plt.show()
```



```
In [53]: best_k = 6
kmeans = KMeans(n_clusters=best_k, n_jobs=-1).fit(X_train_s)
```

```
In [54]: essays = X_train['preprocessed_essays'].values
cluster1 = []
cluster2 = []
cluster3 = []
cluster4 = []
cluster5 = []
cluster6 = []
for i in range(kmeans.labels_.shape[0]):
    if kmeans.labels_[i] == 0:
        cluster1.append(essays[i])
    elif kmeans.labels_[i] == 1:
        cluster2.append(essays[i])
    elif kmeans.labels_[i] == 2:
        cluster3.append(essays[i])
    elif kmeans.labels_[i] == 3:
        cluster4.append(essays[i])
    elif kmeans.labels_[i] == 4:
        cluster5.append(essays[i])
    elif kmeans.labels_[i] == 5:
        cluster6.append(essays[i])
```

```
In [56]: for i in range(3):  
         print('%s\n'%(cluster1[i]))
```

my players play public school dropped funding sports they come practice every day work hard become better players better young men they great kids maintain high standards students first athletes they work hard school taken away funding athletics this means students go fundraising every dollar comes program not school requires players pay sports fees fundraise money every piece equipment even demands players work hard learn lot grow individuals program out town located rural part arizona arizona state lowest educational funding country many schools justifiably shifted money sports classroom our program supports movement working raise money support team we requesting 3 new baseball bats season in past four years a ble purchase bats one time these get worn time some players not afford buy bats left using whatever remains even not work well these bats major benefit players not afford these bats used practice games 30 players program we also play games summer workout fall used also host youth kids camp year local youth would used we also requesting new bat grips try get life older bats worn by able get three new bats program would give players chance newest equipment we also requesting new foam rollers boxes athletic tape we trying put strong focus physical education part baseball our players need tape not full time athletic trainer school lot taping the foam rollers great addition daily stretching conditioning program nanna n

my students amazing bunch 4th graders low income high poverty inner city public elementary school pennsylvania the majority students receive free lunches my bunch includes 38 kiddies always moving asking sharing my students silly inquisitive challenging importantly world my students include general education special education students well english language learners their abilities vary greatly i always seeking resources instructional strategies individualize learning opportunities large classroom my classroom not typical i strive create opportunities all ow movement student led activities in i able creative design unique curriculum materials meet many needs students our classroom located k 5 school innovative teachers always go beyond despite challenges students i find classroom place come together feel like belong not judged we bring concept school family reality i requested close reading comprehension center reading pen students work independently guided reading these centers focus finding evidence variety texts supports ideas close reading highly effective increase students ability go back text understand structure analyze characters additionally discussion clips close reading evidence clips serve hands strategy students specifically show text found information also identify areas questions connections having kits help build stronger readers writers 4th grade classroom your donation give students access tools improve understanding complex texts nannan

the library school working hard encourage students learn fun our recently redesigned campus currently third year girls school one district initiatives focus whole child approach we see students young woman leaders working ensure maintain positive attitude every day as creed suggests girls innovative creative recognize importance strong mind body spirit every day pushing students reach next level learning journey recognize stress come the goal project provide students creative outlets relieve stress still promoting active learning experiences this project involves purchasing new spanish books library spanish collection at campus 50 students english language learners majority spanish speakers we also spanish classes available students learning language new spanish books build collection high interest reads support spanish learners well support emergent english learners imagine moving school classes taught language not understand would not enjoy escaping story written native language many students verbally bilingual speak english spanish fluently primarily spanish home language however students may not know read write spanish increased exposure language parents families reading also increase formal spanish vocabulary knowledge spanish sentence structure on top students learn appreciate beauty spanish language they exposed figurative language well many colorful illustrations help appreciate beauty stories nannan

```
In [57]: #cluster 1
words=''
for i in cluster1:
    words+=str(i)
from wordcloud import WordCloud
wordcloud = WordCloud(background_color="white").generate(words)

# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
In [ ]: from sklearn.cluster import AgglomerativeClustering
        from sklearn.metrics import silhouette_score

        n = [2, 5, 8]
        sscore = []

        #print(' '*13, '- First -', ' '*17, '- Second -', ' '*16, '- Third -', ' '*16, '- Fourth -')
        #print( end='          ')

        agg = AgglomerativeClustering(n_clusters = 5)
        agg.fit( dat)
        score = silhouette_score( x_train_s, agg.labels_, random_state=42)
        sscore.append(score)
        print( '#'*20, end = '          ' )
```

```
In [ ]: cluster1=[]
cluster2=[]
essays = X_train['preprocessed_essays'].values
for i in range(aggcl.labels_.shape[0]):
    if aggcl.labels_[i] == 0:
        cluster1.append(essays[i])
    elif aggcl.labels_[i] == 1:
        cluster2.append(essays[i])
```

```
In [ ]: for i in range(3):
        print('%s\n'%(cluster1[i]))
```

```
In [ ]: #cluster 1
words=''
for i in cluster1:
    words+=str(i)
from wordcloud import WordCloud
wordcloud = WordCloud(background_color="white").generate(words)

# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

2.7 Apply DBSCAN

```
In [49]: from sklearn.preprocessing import StandardScaler
# dat=StandardScaler().fit_transform(X_tr.toarray())
dat = X_train_s.toarray()
dat
```

```
Out[49]: array([[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., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.]])
```

```
In [50]: from sklearn.metrics.pairwise import euclidean_distances
euclidean_distances(dat, dat[1].reshape(1, -1))
```

```
Out[50]: array([[1.80738901e+00],
                [4.21468485e-08],
                [3.45203506e+00],
                ...,
                [3.89612889e+00],
                [3.51115026e+00],
                [3.54682372e+00]])
```

```
In [51]: print(X_train_s.shape)
```

```
print(X_train_s.ndim)
```

```
(73196, 2000)
```

```
2
```

```
In [69]: min_points = 5000
from sklearn.preprocessing import StandardScaler
from sklearn.metrics.pairwise import euclidean_distances

datt=StandardScaler().fit_transform(dat)
distance=[]

from tqdm import tqdm

for point in tqdm(datt):
    temp = euclidean_distances(datt, point.reshape(1, -1))
    distance.append(temp[min_points])

sorted_distance = np.sort(np.array(distance))

sorted_dist = np.sort(sorted_distance.reshape(1,-1)[0])
points = [i for i in range(len(datt))]
```


0%|
| 0/73196 [00:00<?, ?it/s]

0%|
| 1/73196 [00:00<12:16:52, 1.66it/s]

0%|
| 2/73196 [00:01<13:06:58, 1.55it/s]

0%|
| 3/73196 [00:01<12:51:17, 1.58it/s]

0%|
| 4/73196 [00:02<11:57:54, 1.70it/s]

0%|
| 5/73196 [00:02<11:35:11, 1.75it/s]

0%|
| 6/73196 [00:03<10:33:44, 1.92it/s]

0%|
| 7/73196 [00:03<9:56:43, 2.04it/s]

0%|
| 8/73196 [00:04<9:17:30, 2.19it/s]

0%|
| 9/73196 [00:04<8:40:19, 2.34it/s]

0%|
| 10/73196 [00:04<8:11:13, 2.48it/s]

0%|
| 11/73196 [00:05<8:37:52, 2.36it/s]

0%|
| 12/73196 [00:05<9:20:42, 2.18it/s]

0%|
| 13/73196 [00:06<11:06:02, 1.83it/s]

0%|

| 14/73196 [00:07<10:53:05, 1.87it/s]

0%|
| 15/73196 [00:07<9:55:50, 2.05it/s]

0%|
| 16/73196 [00:07<9:19:46, 2.18it/s]

0%|
| 17/73196 [00:08<8:56:46, 2.27it/s]

0%|
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| 561/73196 [03:45<8:20:17, 2.42it/s]

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| 562/73196 [03:46<8:39:13, 2.33it/s]

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| 563/73196 [03:46<8:24:43, 2.40it/s]

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| 564/73196 [03:46<8:10:40, 2.47it/s]

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| 565/73196 [03:47<8:14:37, 2.45it/s]

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| 566/73196 [03:47<8:12:59, 2.46it/s]

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| 567/73196 [03:47<8:10:19, 2.47it/s]

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| 568/73196 [03:48<8:15:42, 2.44it/s]

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| 569/73196 [03:48<8:07:46, 2.48it/s]

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| 570/73196 [03:49<8:04:31, 2.50it/s]

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| 571/73196 [03:49<7:58:57, 2.53it/s]

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| 581/73196 [03:53<8:13:09, 2.45it/s]

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| 589/73196 [03:56<7:59:29, 2.52it/s]

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| 593/73196 [03:58<8:14:08, 2.45it/s]

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| 599/73196 [04:00<8:16:54, 2.43it/s]

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| 601/73196 [04:01<8:18:41, 2.43it/s]

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| 678/73196 [04:32<6:57:42, 2.89it/s]

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| 725/73196 [04:51<7:37:20, 2.64it/s]

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| 815/73196 [05:32<11:25:42, 1.76it/s]

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| 816/73196 [05:32<10:58:17, 1.83it/s]

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| 817/73196 [05:33<10:46:19, 1.87it/s]

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| 818/73196 [05:33<10:20:58, 1.94it/s]

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| 819/73196 [05:33<10:06:06, 1.99it/s]

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| 820/73196 [05:34<9:48:29, 2.05it/s]

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| 821/73196 [05:35<12:42:23, 1.58it/s]

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| 822/73196 [05:36<14:26:25, 1.39it/s]

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| 823/73196 [05:37<16:13:31, 1.24it/s]

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| 824/73196 [05:38<17:57:43, 1.12it/s]

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| 825/73196 [05:39<17:19:08, 1.16it/s]

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| 826/73196 [05:39<15:24:59, 1.30it/s]

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| 827/73196 [05:40<13:19:46, 1.51it/s]

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| 828/73196 [05:40<11:23:42, 1.76it/s]

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| 829/73196 [05:41<11:58:33, 1.68it/s]

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| 830/73196 [05:41<10:54:33, 1.84it/s]

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| 831/73196 [05:42<12:18:12, 1.63it/s]

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| 832/73196 [05:43<15:37:08, 1.29it/s]

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| 833/73196 [05:44<16:57:55, 1.18it/s]

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| 834/73196 [05:45<15:20:05, 1.31it/s]

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| 835/73196 [05:45<13:27:27, 1.49it/s]

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| 836/73196 [05:45<11:55:19, 1.69it/s]

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| 837/73196 [05:46<11:51:05, 1.70it/s]

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| 838/73196 [05:46<10:23:41, 1.93it/s]

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| 839/73196 [05:47<9:50:39, 2.04it/s]

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| 840/73196 [05:47<9:19:56, 2.15it/s]

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| 841/73196 [05:48<11:43:42, 1.71it/s]

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| 842/73196 [05:49<13:15:39, 1.52it/s]

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| 843/73196 [05:50<14:40:14, 1.37it/s]

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| 844/73196 [05:51<14:40:44, 1.37it/s]

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| 845/73196 [05:51<13:00:02, 1.55it/s]

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| 846/73196 [05:51<11:50:03, 1.70it/s]

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| 847/73196 [05:52<12:18:48, 1.63it/s]

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| 848/73196 [05:53<11:34:07, 1.74it/s]

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| 849/73196 [05:53<10:13:18, 1.97it/s]

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| 850/73196 [05:53<9:34:13, 2.10it/s]

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| 851/73196 [05:54<9:22:43, 2.14it/s]

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| 852/73196 [05:54<9:33:06, 2.10it/s]

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| 853/73196 [05:55<9:40:27, 2.08it/s]

1%|█

| 854/73196 [05:55<10:23:05, 1.94it/s]

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| 855/73196 [05:56<9:53:38, 2.03it/s]

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| 856/73196 [05:56<9:15:36, 2.17it/s]

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| 857/73196 [05:57<8:58:03, 2.24it/s]

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| 858/73196 [05:57<9:05:15, 2.21it/s]

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| 859/73196 [05:57<8:28:17, 2.37it/s]

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| 860/73196 [05:58<8:12:58, 2.45it/s]

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| 861/73196 [05:58<8:15:08, 2.43it/s]

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| 862/73196 [05:59<8:00:51, 2.51it/s]

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| 863/73196 [05:59<7:43:26, 2.60it/s]

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| 864/73196 [05:59<7:28:11, 2.69it/s]

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| 865/73196 [06:00<7:15:33, 2.77it/s]

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| 866/73196 [06:00<7:13:29, 2.78it/s]

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| 867/73196 [06:01<8:29:19, 2.37it/s]

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| 868/73196 [06:01<7:58:03, 2.52it/s]

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| 869/73196 [06:01<7:37:16, 2.64it/s]

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| 870/73196 [06:02<7:21:37, 2.73it/s]

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| 871/73196 [06:02<7:11:02, 2.80it/s]

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| 872/73196 [06:03<8:57:35, 2.24it/s]

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| 873/73196 [06:03<9:21:01, 2.15it/s]

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| 874/73196 [06:04<10:06:34, 1.99it/s]

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| 875/73196 [06:04<9:42:40, 2.07it/s]

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| 876/73196 [06:04<8:59:01, 2.24it/s]

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| 877/73196 [06:05<8:32:57, 2.35it/s]

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| 878/73196 [06:05<8:18:16, 2.42it/s]

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| 879/73196 [06:06<8:02:12, 2.50it/s]

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| 880/73196 [06:06<8:47:44, 2.28it/s]

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| 881/73196 [06:07<8:31:13, 2.36it/s]

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| 882/73196 [06:07<8:09:10, 2.46it/s]

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| 883/73196 [06:07<7:56:13, 2.53it/s]

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| 884/73196 [06:08<8:32:57, 2.35it/s]

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| 885/73196 [06:08<9:07:39, 2.20it/s]

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| 886/73196 [06:09<8:56:27, 2.25it/s]

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| 887/73196 [06:09<8:29:01, 2.37it/s]

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| 888/73196 [06:09<8:21:32, 2.40it/s]

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| 889/73196 [06:10<8:04:54, 2.49it/s]

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| 890/73196 [06:10<8:02:03, 2.50it/s]

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| 891/73196 [06:11<8:02:25, 2.50it/s]

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| 892/73196 [06:11<8:32:31, 2.35it/s]

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| 893/73196 [06:12<8:49:18, 2.28it/s]

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| 894/73196 [06:12<8:48:19, 2.28it/s]

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| 895/73196 [06:12<8:34:41, 2.34it/s]

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| 896/73196 [06:13<8:30:48, 2.36it/s]

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| 897/73196 [06:13<8:22:58, 2.40it/s]

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| 898/73196 [06:14<8:17:25, 2.42it/s]

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| 899/73196 [06:14<8:07:21, 2.47it/s]

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| 900/73196 [06:14<8:11:39, 2.45it/s]

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| 901/73196 [06:15<8:20:40, 2.41it/s]

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| 902/73196 [06:15<8:09:16, 2.46it/s]

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| 903/73196 [06:16<8:11:44, 2.45it/s]

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| 904/73196 [06:16<8:06:49, 2.47it/s]

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| 905/73196 [06:17<8:12:34, 2.45it/s]

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| 906/73196 [06:17<8:09:43, 2.46it/s]

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| 907/73196 [06:17<8:01:57, 2.50it/s]

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| 908/73196 [06:18<8:01:12, 2.50it/s]

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| 909/73196 [06:18<7:57:03, 2.53it/s]

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| 910/73196 [06:18<7:50:26, 2.56it/s]

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| 911/73196 [06:19<8:13:50, 2.44it/s]

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| 912/73196 [06:19<8:10:28, 2.46it/s]

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| 913/73196 [06:20<8:02:29, 2.50it/s]

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| 914/73196 [06:20<8:00:11, 2.51it/s]

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| 915/73196 [06:21<8:08:13, 2.47it/s]

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| 916/73196 [06:21<8:07:53, 2.47it/s]

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| 917/73196 [06:21<8:06:46, 2.47it/s]

KeyboardInterrupt

Traceback (most recent call last)

<ipython-input-69-63cf1df76908> in <module>()

```
10
11 for point in tqdm(datt):
---> 12     temp = euclidean_distances(datt, point.reshape(1, -1))
13     distance.append(temp[min_points])
14
```

~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\metrics\pairwise.py in euclidean_distances(X, Y, Y_norm_squared, squared, X_norm_squared)

```
230     paired_distances : distances between pairs of elements of X and Y.
231     """
--> 232     X, Y = check_pairwise_arrays(X, Y)
233
234     # If norms are passed as float32, they are unused. If arrays are passed as
```

sed as

~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\metrics\pairwise.py in check_pairwise_arrays(X, Y, precomputed, dtype)

```
110     else:
111         X = check_array(X, accept_sparse='csr', dtype=dtype,
--> 112                        estimator=estimator)
113         Y = check_array(Y, accept_sparse='csr', dtype=dtype,
114                        estimator=estimator)
```

~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, warn_on_dtype, estimator)

```
540         if force_all_finite:
541             _assert_all_finite(array,
--> 542                               allow_nan=force_all_finite == 'allow-nan')
543
544         if ensure_min_samples > 0:
```

~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py in _assert_all_finite(X, allow_nan)

```
47     # safely to reduce dtype induced overflows.
48     is_float = X.dtype.kind in 'fc'
---> 49     if is_float and (np.isfinite(_safe_accumulator_op(np.sum, X))):
50         pass
51     elif is_float:
```

~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\extmath.py in _safe_accumulator_op(op, x, *args, **kwargs)

```
686         result = op(x, *args, **kwargs, dtype=np.float64)
687     else:
--> 688         result = op(x, *args, **kwargs)
689     return result
690
```

<__array_function__ internals> in sum(*args, **kwargs)

~\AppData\Local\Continuum\anaconda3\lib\site-packages\numpy\core\fromnumeric.py in sum(a, axis, dtype, out, keepdims, initial, where)

```
2180
2181     return _wrapreduction(a, np.add, 'sum', axis, dtype, out, keepdims=k
```



```

eepdims,
-> 2182                initial=initial, where=where)
    2183
    2184

-\\AppData\\Local\\Continuum\\anaconda3\\lib\\site-packages\\numpy\\core\\fromnumeric.py
in _wrapreduction(obj, ufunc, method, axis, dtype, out, **kwargs)
    88                 return reduction(axis=axis, out=out, **passkwargs)
    89
---> 90         return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
    91
    92

```

KeyboardInterrupt:

```

In [ ]: plt.figure( figsize=(16,5))
plt.plot(points , sorted_dist )
plt.ylabel('Distance')
plt.xlabel('Indices')
plt.title('k-distance plot')
plt.show()

from IPython.display import Image
Image( "~/DBSCAN.png" )

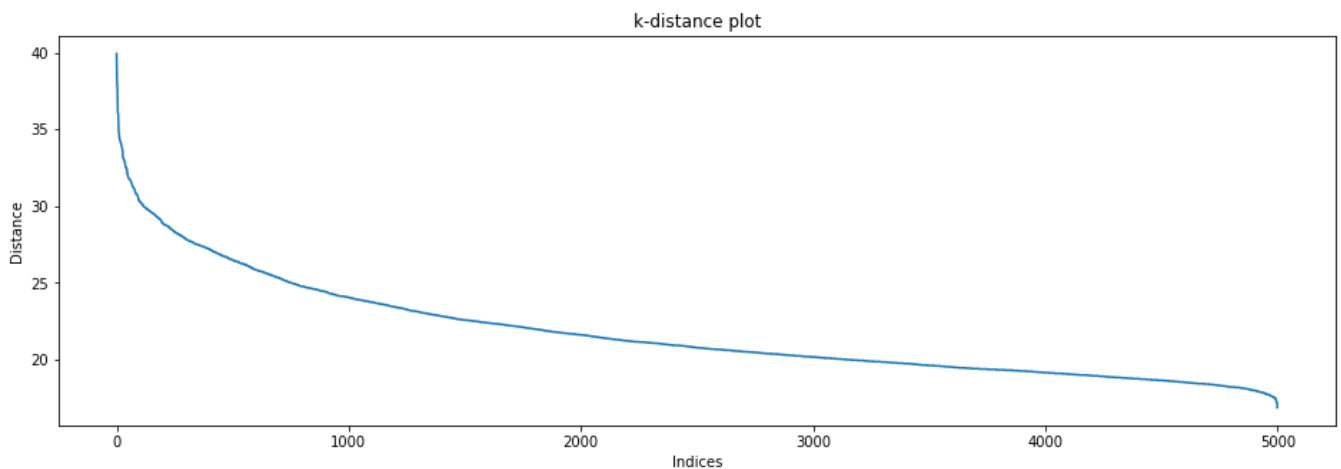
```

```

In [45]: from IPython.display import Image
Image( "DBSCAN.png" )

```

Out[45]:



In []:

```

In [ ]: #we can see that point of inflexion is at eps=90
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=90,n_jobs=-1)
dbscan.fit(dat)
print('No of clusters: ',len(set(dbscan.labels_)))
print('Cluster are including noise i.e -1: ',set(dbscan.labels_))

```

```
In [ ]: #ignoring -1 as it is for noise
cluster1=[]
noisecluster1=[]
for i in range(dbscan.labels_.shape[0]):
    if dbscan.labels_[i] == 0:
        cluster1.append(essays[i])
    elif dbscan.labels_[i] == -1:
        noisecluster1.append(essays[i])
```

```
In [ ]: for i in range(3):
        print('%s\n'%(cluster1[i]))
```

3. Conclusion

```
In [56]: # Please compare all your models using Prettytable library
# Please compare all your models using Prettytable library

from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable

x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Hyper Parameter"]

x.add_row(["TFIDF", "SGDClassifier", 6])
x.add_row(["TFIDF", "SGDClassifier", 5])
x.add_row(["TFIDF", "SGDClassifier", 90])

print(x)
```

Vectorizer	Model	Hyper Parameter
TFIDF	SGDClassifier	6
TFIDF	SGDClassifier	5
TFIDF	SGDClassifier	90

```
In [ ]:
```