CLUSTERING

```
In [1]:
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6 qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0% b&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly ttps%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly

Enter your authorization code:
.....
Mounted at /content/drive

Þ

In [0]:

```
# To enable plotly plot in Google Colab
# https://stackoverflow.com/questions/47230817/plotly-notebook-mode-with-google-
colaboratory/47230966
def configure plotly browser state():
   import IPython
   display(IPython.core.display.HTML('''
        <script src="/static/components/requirejs/require.js"></script>
       <script>
          requirejs.config({
           paths: {
             base: '/static/base',
              plotly: 'https://cdn.plot.ly/plotly-1.5.1.min.js?noext',
          });
        </script>
        '''))
def enable_plotly_in_cell():
   import IPython
   from plotly.offline import init notebook mode
   display(IPython.core.display.HTML("''<script src="/static/components/requirejs/require.js"></s
cript>'''))
   init notebook mode (connected=False)
```

In [3]:

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
configure_plotly_browser_state()
init_notebook_mode(connected=False)
```

In [5]:

```
data = pd.read_csv('/content/drive/My Drive/Applied AI/Datasets/New
Donors/Preprocessed_inc_others.csv')
data.head()
```

Out[5]:

	Unnar	0			project_grade_category project_grade_category				
0		0	ca	mrs	grades_prek_2			53	1
1		1	ut	ms	grades_3_5			4	1
2		2	ca	mrs	grades_prek_2			10	1
3		3	ga	mrs	grades_prek_2			2	1
4		4	wa	mrs	grades_3_5			2	1
	[6]: ta.de		be()						
da		scri		her_number_of_p	previously_posted_projects	project_is_approved	price	quantity	sentiment_sc
da Du	ta.de	escri		her_number_of_p	previously_posted_projects 109248.000000		price 109248.000000		
da Du	ta.de	Unna	amed: 0 teac	her_number_of_r		109248.000000			109248.000
da Du	ta.de t[6]:	Unna 09248 54623 31537	amed: 0 teac .000000 .500000 .325441	her_number_of_p	109248.000000 11.153165 27.777154	109248.000000 0.848583 0.358456	109248.000000 298.119343 367.498030	109248.000000 16.965610 26.182942	109248.000 0.210 0.083
da Ou	ta.de t[6]: bunt 10 nean 9 std 3 min	Unna 09248 54623 31537	amed: 0 teac .000000 .500000 .325441	her_number_of_p	109248.000000 11.153165 27.777154 0.000000	109248.000000 0.848583 0.358456 0.000000	109248.000000 298.119343 367.498030 0.660000	109248.000000 16.965610 26.182942 1.000000	109248.000 0.210 0.083 -0.189
c m	ta.de t[6]: bunt 10 nean 4 std 3 min 25% 2	Unna 09248 54623 31537 0. 27311	amed: 0 teac .000000 .500000 .325441 .000000	her_number_of_p	109248.000000 11.153165 27.777154 0.0000000 0.0000000	109248.000000 0.848583 0.358456 0.000000 1.000000	109248.000000 298.119343 367.498030 0.660000 104.310000	109248.000000 16.965610 26.182942 1.000000 4.000000	109248.000 0.210 0.083 -0.189 0.154
da Ou m	ta.de t[6]: bunt 10 ean 9 std 3 min 25% 3	Unna 09248 54623 31537 0 27311 54623	amed: 0 teac .000000 .500000 .325441 .000000 .750000	her_number_of_p	109248.000000 11.153165 27.777154 0.000000 0.000000	109248.000000 0.848583 0.358456 0.000000 1.000000	109248.000000 298.119343 367.498030 0.660000 104.310000 206.220000	109248.000000 16.965610 26.182942 1.000000 4.000000 9.000000	sentiment_sc 109248.000 0.210 0.083 -0.189 0.154 0.208
c n	ta.de t[6]: bunt 10 nean 8 std 3 min 25% 3 75% 8	Unna 09248 554623. 331537. 0. 227311.	amed: 0 teac .000000 .500000 .325441 .000000 .750000 .500000	her_number_of_p	109248.000000 11.153165 27.777154 0.000000 0.000000 2.0000000 9.0000000	109248.000000 0.848583 0.358456 0.000000 1.000000 1.000000	109248.000000 298.119343 367.498030 0.660000 104.310000 206.220000 379.000000	109248.000000 16.965610 26.182942 1.000000 4.000000 9.000000 21.000000	109248.000 0.210 0.083 -0.189 0.154 0.208
co m	ta.de t[6]: bunt 10 nean 8 std 3 min 25% 3 75% 8	Unna 09248 554623. 331537. 0. 227311.	amed: 0 teac .000000 .500000 .325441 .000000 .750000	her_number_of_p	109248.000000 11.153165 27.777154 0.000000 0.000000	109248.000000 0.848583 0.358456 0.000000 1.000000 1.000000	109248.000000 298.119343 367.498030 0.660000 104.310000 206.220000	109248.000000 16.965610 26.182942 1.000000 4.000000 9.000000	109248.000 0.210 0.083 -0.189 0.154 0.208
co m	ta.de t[6]: bunt 10 nean 8 std 3 min 25% 3 75% 8	Unna 09248 54623. 0. 227311. 554623.	amed: 0 teac .000000 .500000 .325441 .000000 .750000 .500000	her_number_of_r	109248.000000 11.153165 27.777154 0.000000 0.000000 2.0000000 9.0000000	109248.000000 0.848583 0.358456 0.000000 1.000000 1.000000	109248.000000 298.119343 367.498030 0.660000 104.310000 206.220000 379.000000	109248.000000 16.965610 26.182942 1.000000 4.000000 9.000000 21.000000	109248.000 0.210 0.083 -0.189 0.154 0.208 0.264

```
ms
                                                                                                                                  grades_3_5
                                                                                                                                                                                                                                                                                     specialneeds
       Unnamed:
                                  school_state teacher_prefix project_grade_category teacher_number_of_previously_posted_projects clean_categories clean_catego
In [8]:
y = y.reshape(-1,1)
print(y.shape)
(109248, 1)
Splitting the data
In [0]:
from sklearn.model_selection import train_test_split
data train, data test, label train, label test = train test split(X, y, test size=0.33, stratify=y,
random state=42)
In [10]:
print(data_train.shape)
print(data_test.shape)
print(label_train.shape)
print(label_test.shape)
(73196, 14)
 (36052, 14)
 (73196, 1)
 (36052, 1)
In [0]:
X_train = data_train
X_test = data_test
y_train = label_train
y_test = label_test
In [12]:
print(X train.shape)
print(X test.shape)
print(y_train.shape)
print(y_test.shape)
(73196, 14)
 (36052, 14)
 (73196, 1)
 (36052, 1)
1. Vectorizing Features
1.1 School State
In [0]:
from sklearn.feature_extraction.text import CountVectorizer
 vectorizer 1 = CountVectorizer(list(X train['school state'].values), lowercase=False, binary=True)
```

X_train_Sstate = vectorizer_1.fit_transform(X_train['school_state'].values)

In [0]:

```
V_resr_parare - Aecrossfer T. Cranatoromm (V_resr[ schoot stare ]. Agree)
In [15]:
print(X_train_Sstate.shape)
print(X test Sstate.shape)
(73196, 51)
(36052, 51)
1.2 Clean Categories
In [0]:
vectorizer_2 = CountVectorizer(list(X_train['clean_categories'].values), lowercase=False,
binary=True)
In [0]:
X_train_cat = vectorizer_2.fit_transform(X_train['clean_categories'].values)
X test cat = vectorizer 2.transform(X test['clean categories'].values)
In [18]:
print(X train cat.shape)
print(X_test_cat.shape)
(73196, 9)
(36052, 9)
1.3 Clean sub categories
In [0]:
vectorizer 3 = CountVectorizer(list(X train['clean subcategories'].values), lowercase=False,
binary=True)
In [0]:
X_train_subcat = vectorizer_3.fit_transform(X_train['clean_subcategories'].values)
X test subcat = vectorizer 3.transform(X test['clean subcategories'].values)
In [21]:
print(X train subcat.shape)
print(X test subcat.shape)
(73196, 30)
(36052, 30)
1.4 Project Grade Category
In [0]:
vectorizer_4 = CountVectorizer(list(X_train['project_grade_category'].values), lowercase=False,
binary=True)
In [0]:
X train grade = vectorizer 4.fit transform(X train['project_grade_category'].values)
```

X test grade = vectorizer 4.transform(X test['project grade category'].values)

```
In [24]:
print(X_train_grade.shape)
print(X test grade.shape)
(73196, 4)
(36052, 4)
1.5 Teacher Prefix
In [0]:
vectorizer 5 = CountVectorizer(list(X train['teacher prefix'].values), lowercase=False,
binary=True)
In [0]:
X_train_prefix = vectorizer_5.fit_transform(X_train['teacher_prefix'].values)
X test prefix = vectorizer 5.transform(X test['teacher prefix'].values)
In [27]:
print(X train prefix.shape)
print(X test prefix.shape)
(73196, 5)
(36052, 5)
Step -1:
   - Choosing the 'TFIDF vectorizer' for Essay and Title Text
1.6 Essay
1.6.1 TFIDF
In [0]:
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer_7 = TfidfVectorizer(list(X_train['essay'].values), min_df=10)
```

In [0]:

```
X_train_essay_tfidf = vectorizer_7.fit_transform(X_train['essay'].values)
X_test_essay_tfidf = vectorizer_7.transform(X_test['essay'].values)
```

In [78]:

```
print(X_train_essay_tfidf.shape)
print(X_test_essay_tfidf.shape)

(73196, 14266)
```

1.7 Title

(36052, 14266)

1.7.1 TFIDE

```
III [U].
vectorizer 9 = TfidfVectorizer(list(X train['title'].values), min df=10)
In [0]:
X train title tfidf = vectorizer 9.fit transform(X train['title'].values)
X test title tfidf = vectorizer 9.transform(X test['title'].values)
In [33]:
print(X_train_title_tfidf.shape)
print(X_test_title_tfidf.shape)
(73196, 2617)
(36052, 2617)
1.8 Price
1.8.1 Unstandardized
In [0]:
X train price unstandardized = X train['price'].values.reshape(-1,1)
X_test_price_unstandardized = X_test['price'].values.reshape(-1,1)
In [35]:
print(X_train_price_unstandardized.shape)
print(X_test_price_unstandardized.shape)
(73196, 1)
(36052, 1)
1.8.2 Standardized
In [0]:
from sklearn.preprocessing import StandardScaler
sc price = StandardScaler()
X_train_price = sc_price.fit_transform(X_train['price'].values.reshape(-1,1))
X_test_price = sc_price.transform(X_test['price'].values.reshape(-1,1))
In [37]:
print(X_train_price.shape)
print(X_test_price.shape)
(73196, 1)
(36052, 1)
1.9 Previously Posted projects
1.9.1 Unstandardized
In [0]:
{\tt X\_train\_previous\_unstandardized = X\_train['teacher\_number\_of\_previously\_posted\_projects'].values.r}
eshape(-1,1)
X_test_previous_unstandardized =
X_test['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
```

In [39]: print(X train previous unstandardized.shape) print(X_test_previous_unstandardized.shape) (73196, 1)(36052, 1)1.9.2 Standardized In [0]: from sklearn.preprocessing import StandardScaler sc previous = StandardScaler() X_train_previous = sc_previous.fit_transform(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-X test previous = sc previous.transform(X test['teacher number of previously posted projects'].values.reshape(-1,1)) In [0]: print(X train previous.shape) print(X_test_previous.shape) In [42]: print(X train Sstate.shape) print(X_train_cat.shape) print(X_train_subcat.shape) print(X train grade.shape) print(X train prefix.shape) print(X train price.shape) print(X train previous.shape) print(X_train_essay_tfidf.shape) print(X train title tfidf.shape) print('='*50) print(X test Sstate.shape) print(X_test_cat.shape) print(X_test_subcat.shape) print(X_test_grade.shape) print(X_test_prefix.shape) print(X test price.shape) print(X test previous.shape) print(X_test_essay_tfidf.shape) print(X_test_title tfidf.shape) (73196, 51)(73196, 9)(73196, 30) (73196, 4)(73196, 5)(73196, 1)(73196, 1)(73196, 14266) (73196, 2617) _____ (36052, 51)(36052, 9)

(36052, 30) (36052, 4) (36052, 5) (36052, 1) (36052, 1) (36052, 14266) (36052, 2617)

2.1 Merging all the features

```
In [0]:
```

In [0]:

```
from sklearn.feature_selection import SelectKBest, chi2
selector = SelectKBest(chi2, k =5000)
X_train = selector.fit_transform(X_train_KB, y_train)
X_test = selector.transform(X_test_KB)
```

In [81]:

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

(73196, 5000)
(36052, 5000)
```

Step -3: Applying Clustering

3.1 K-Means

Note:

• Since the KMeans algorithm is computationally Expensive i will take 30k points for computation

```
In [0]:
```

```
X_train_1 = X_train[0:30000, :]
```

```
In [0]:
```

```
y_train_1 = y_train[0:30000, :]
```

In [0]:

```
from sklearn.cluster import KMeans
```

3.1.1 Elbow Method

```
In [0]:
```

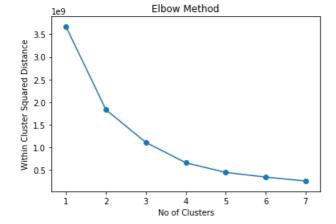
```
ss = []
for i in range(1,8):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X_train_1)
    ss.append(kmeans.inertia_)
```

```
Out[0]:

[3664288500.6005983,
1831370800.2786806,
1111414794.3491583,
660980249.8632902,
448651448.41384536,
345766077.6683432,
259129655.58727992]

In [0]:
```

```
plt.plot(range(1,8), ss)
plt.scatter(range(1,8), ss)
plt.title('Elbow Method')
plt.xlabel('No of Clusters')
plt.ylabel('Within Cluster Squared Distance')
plt.show()
```



Summary:

• It shows that the cluster distance have elbow shaped at No of clusters = 2

3.1.2 Modelling with n_clusters

```
In [0]:
```

```
kmeans = KMeans(n_clusters=2, init='k-means++', random_state=42)
y_kmeans = kmeans.fit_predict(X_train_1)
```

3.1.3 Manually Looking at the clusters

```
In [0]:
```

```
print(y_kmeans)
print(y_kmeans.shape)

[0 1 0 ... 1 1 1]
(30000,)
```

In [0]:

```
y_kmeans = y_kmeans.reshape(-1,1)
print(y_kmeans.shape)
print(type(y_kmeans))
print(y_train_1.shape)
print(type(y_train_1))
```

```
brinc (cabe (a crain t) )
(30000, 1)
<class 'numpy.ndarray'>
(30000, 1)
<class 'numpy.ndarray'>
In [0]:
#checking how many values are same in both the arrays
 #https://stackoverflow.com/questions/25490641/check-how-many-elements-are-equal-in-two-numpy-array
 s-python/25490691
 (y_train_1 == y_kmeans).sum()
Out[0]:
23795
Summary:
    • We can see that the out of 30000 data 23795 data are clustered correctly.
In [0]:
print(np.where(kmeans.labels == 0)[0])
print(len(np.where(kmeans.labels_ == 0)[0]))
                             2 10 ... 29970 29986 29991]
[ 0
3019
In [0]:
print(np.where(kmeans.labels == 1)[0])
print(len(np.where(kmeans.labels_ == 1)[0]))
      1
                       3 4 ... 29997 29998 29999]
Γ
26981
In [0]:
 # Data points belong the each cluster
 \# https://stackoverflow.com/questions/32232067/cluster-points-after-kmeans-clustering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-scikit-learngering-s
my dict = {i : np.where(kmeans.labels_== i)[0] for i in range(kmeans.n_clusters)}
In [0]:
len (my_dict[0])
Out[0]:
3019
In [0]:
len(my_dict[1])
Out[0]:
26981
```

Summary:

• It shows that out of 30k data points 26981 are clustered as one and remaining are clustered to form another

3.1.4 Plotting the Word Cloud for each cluster

```
In [0]:
X_train_essay_tfidf_1 = X_train_essay_tfidf[0:30000, :]
print(X train essay tfidf 1.shape)
(30000, 14266)
In [0]:
#https://andrew47.github.io/scikitlearn-cluster.html
\verb| essay_kmeans = KMeans(n_clusters=2 , n_jobs=-1).fit(X_train_essay_tfidf_1)| \\
In [0]:
centroids = pd.DataFrame(essay_kmeans.cluster_centers_)
centroids.columns = vectorizer_7.get_feature_names()
centroids.head(3)
Out[0]:
      00
            000
                    03
                           10
                                 100
                                       1000
                                             100th
                                                     101
                                                            102
                                                                   103
                                                                         104
                                                                                105
                                                                                       107
0 0.000104 0.000995 0.000000 0.002128 0.004715 0.000274 0.000000 0.000077 0.000036 0.000097 0.00000 0.000000 0.000083 0.
2 rows × 14266 columns
In [0]:
 #look at the top 10 words in each cluster
 for i in range(0, len(centroids)):
  print(centroids.iloc[i,:].sort values(ascending=False)[0:10])
   print('='*50)
        0.148911
0.141218
books
reading
students 0.134350
        0.092631
read
          0.056547
book
         0.051495
       0.051495
0.046745
library
school
        0.044425
love
readers 0.043976
          0.042409
Name: 0, dtype: float64
_____
           0.128708
students
          0.047591
school
learning
          0.042019
classroom
           0.039006
           0.037525
my
          0.032351
they
the
          0.031454
learn
          0.031333
          0.030540
help
not
           0.030237
Name: 1, dtype: float64
```

Note:

• To plot the word cloud for each cluster, we need to find which words are belongs to which clusters. So, here we need to find which words belong cluster_0 and which words belongs to cluster_1.

```
pd.DataFrame(centroids.iloc[0].sort_values(ascending=False).reset_index(level=0)).head()
Out[0]:
    index
               0
    books 0.148911
1 reading 0.141218
2 students 0.134350
     read 0.092631
     book 0.056547
In [0]:
#https://andrew47.github.io/scikitlearn-cluster.html
cluster 0 = pd.DataFrame(centroids.iloc[0].sort values(ascending=False).reset index()) # here i
reset index because words are in index and we want it as a column in dataframe
cluster 1 = pd.DataFrame(centroids.iloc[1].sort values(ascending=False).reset index())
In [0]:
cluster_0.head(2)
Out[0]:
    index
  books 0.148911
1 reading 0.141218
In [0]:
cluster 0 words = []
for i in cluster 0['index']:
    cluster_0_words.append(i)
cluster 1 words = []
for i in cluster_1['index']:
    cluster_1_words.append(i)
3.1.4.1 Cluster 0 word cloud
In [0]:
#https://www.geeksforgeeks.org/generating-word-cloud-python/
from wordcloud import WordCloud, STOPWORDS
stopwords = set(STOPWORDS)
comment_words_0 = ' '
for word in cluster_0_words:
    comment words 0 = comment words 0 + word + ' '
In [0]:
#Generating Word Cloud for cluster 0 words
wordcloud_0_km = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords, mi
n_font_size=10).generate(comment_words_0)
In [0]:
#plotting the Word Cloud
plt.figure(figsize=(8,8), facecolor=None)
plt.title('Cluster 0 words')
plt.imshow(wordcloud_0_km)
plt.axis('off')
```

Cluster 0 words develop ≔ kimdergarten order reader 3 つ place Lear experience pO title ome one build 0 en keep aloud see Program UT choice Speci feel make social Q anguage en best teaching no working

future

give

writing room

building

3.1.4.2 Cluster_1 word cloud

explore

```
In [0]:
```

```
comment\_words 1 = ' '
for word in cluster_1_words:
    comment_words_1 = comment_words_1 + word + ' '
```

student content project

bO

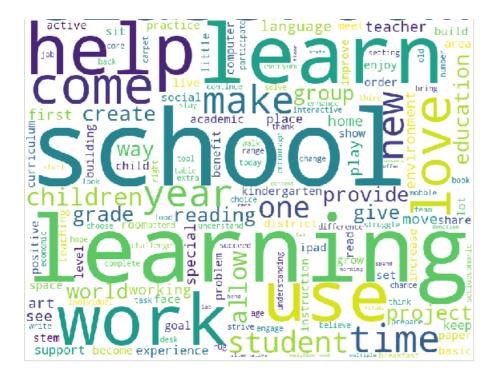
In [0]:

```
#Generating Word Cloud for cluster 0 words
wordcloud 1 km = Wordcloud (width=800, height=800, background color='white', stopwords=stopwords, mi
n font size=10).generate(comment words 1)
```

In [0]:

```
#plotting the Word Cloud
plt.figure(figsize=(8,8), facecolor=None)
plt.title('Cluster 1 words')
plt.imshow(wordcloud 1 km)
plt.axis('off')
plt.tight layout (pad=0)
plt.show()
```

Cluster 1 words equipment achieve addition titlepopulation future income well program second low boexplore find science



4. Hierarchical Clustering

```
In [0]:
```

```
# Taking only 5k points as per instructions
X_train_2 = X_train[0:5000, :]
X_test_2 = X_test[0:5000, :]
y_train_2 = y_train[0:5000, :]
```

In [0]:

```
print(X_train_2.shape)
print(X_test_2.shape)
print(y_train_2.shape)

(5000, 5000)
```

(5000, 5000) (5000, 5000) (5000, 1)

4.1 Finding Dendrogram to find the number of clusters

```
In [0]:
```

```
type(X_train_2)

Out[0]:
scipy.sparse.csr.csr matrix
```

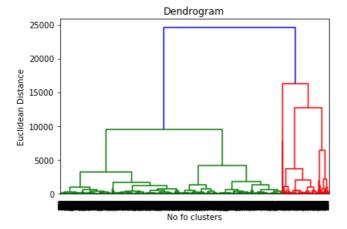
Note:

• Since it is a csr matrix we can't plot the dendrogram and we need to convert it into array as used in https://stackoverflow.com/questions/44660848/hierarchical-clustering-on-sparse-observation-matrix

In [0]:

```
#https://stackabuse.com/hierarchical-clustering-with-python-and-scikit-learn/
from scipy.cluster.hierarchy import dendrogram, linkage
linked = linkage(X_train_2.toarray(), method = 'ward')
dendrogram = dendrogram(linked)
```

```
plt.title('Dendrogram')
plt.xlabel('No fo clusters')
plt.ylabel('Euclidean Distance')
plt.show()
```



Summary:

• We can see that the number of longest vertical distance without any horizontal intersection in this dendrogram is 2. So we take the n_clusters = 2

4.2 Modelling with n_clusters

```
In [0]:
```

```
n_{clusters} = 2
```

In [0]:

```
from sklearn.cluster import AgglomerativeClustering
\verb|hc = AgglomerativeClustering(n_clusters = n_clusters, affinity='euclidean', linkage='ward')|
y_hc = hc.fit_predict(X_train_2.toarray())
```

4.3 Manually looking at the clusters

```
In [0]:
```

```
y_hc.shape
Out[0]:
(5000,)
```

```
In [0]:
y_hc = y_hc.reshape(-1,1)
print(y_hc.shape)
print(type(y_hc))
print(y_train_2.shape)
print(type(y_train))
(5000, 1)
<class 'numpy.ndarray'>
(5000, 1)
```

In [0]:

<class 'numpy.ndarray'>

```
#https://stackoverflow.com/questions/25490641/check-how-many-elements-are-equal-in-two-numpy-array
s-python/25490691
(y_train_2 == y_hc).sum()
Out[0]:
3720
Note:
 • We can see that out of 5000, 3720 are clustered correctly
In [0]:
# Data points belong the each cluster
#https://stackoverflow.com/questions/32232067/cluster-points-after-kmeans-clustering-scikit-learn
my dict 2 = {i : np.where(hc.labels == i)[0] for i in range(hc.n clusters)}
In [0]:
len(my_dict_2[0])
Out[0]:
858
In [0]:
len(my_dict_2[1])
Out[0]:
4142
Summary:
 • We can see that 858 points are clustered into one cluster and remaining 4142 cluster clustered to form another
4.4 Finding words for Essay text on each cluster
In [0]:
X_train_essay_tfidf_2 = X_train_essay_tfidf[0:5000, :]
print(X_train_essay_tfidf_2.shape)
(5000, 14266)
In [0]:
#https://andrew47.github.io/scikitlearn-cluster.html
from sklearn.cluster import AgglomerativeClustering
essay_hc = AgglomerativeClustering(n_clusters = n_clusters, linkage='ward', affinity='euclidean').f
it(X_train_essay_tfidf_2.toarray())
In [0]:
cluster_0_hc = X_train_essay_tfidf_2[np.where(essay_hc.labels_ ==0)]
In [0]:
cluster_1_hc = X_train_essay_tfidf_2[np.where(essay_hc.labels_ ==1)]
```

```
In [0]:
print(cluster 0 hc.shape)
print(cluster_1_hc.shape)
(4446, 14266)
(554, 14266)
Note:
  • We can see that the out of 5k points 4446 points are clustered into one category and remaining 554 are clustered into another
In [0]:
type(cluster_0_hc)
Out[0]:
scipy.sparse.csr.csr matrix
In [0]:
#convert csr matrix to dataframe
cluster_0_hc = pd.DataFrame(cluster_0_hc.toarray(), columns=vectorizer_7.get_feature_names())
cluster_0_hc.head(2)
Out[0]:
    00 000 03 10 100 1000 100th 101 102 103 104 105 107 10th
                                                                 11 110 1100 112 115 11th 12 120 1200 123 12
 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 0.0
                                                                                                 0.0
                                                                                                       0.0
                                                                                                           0.0
                                                                                                               0.
                               0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0
 1 0.0 0.0 0.0 0.0 0.0
                                                              00 00 00
                                                                           00 00 00
                                                                                         00 00 00
                         0.0
                                                                                                       00 00
                                                                                                               0
2 rows x 14266 columns
4
In [0]:
cluster_1_hc = pd.DataFrame(cluster_1_hc.toarray(), columns=vectorizer_7.get_feature_names())
cluster_1_hc.head(2)
Out[0]:
    00 000
            03
                10 100
                       1000 100th 101 102 103
                                               104 105 107 10th
                                                                   11 110 1100 112 115 11th
                                                                                             12 120 1200 123 12
 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
                                                                                0.0
                                                                                    0.0
                                                                                         0.0 0.0
                                                                                                 0.0
                                                                                                       0.0
                                                                                                           0.0
                                                                                                               0.
 1 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
                                                                                    0.0
                                                                                         0.0 0.0 0.0
                                                                                                       0.0 0.0 0.
2 rows × 14266 columns
4
In [0]:
#looking at the sample data point and its essay words
cluster 0 hc.iloc[0,:].sort values(ascending=False)[0:10].reset index()
Out[0]:
         index
                    0
 0
          avid 0.281376
 1 chromebooks 0.279620
 2
        college 0.179109
 3
     computers 0.178794
         pulled 0.166316
```

5

we 0.162115

```
ineed 0.161106
6
7
        paced 0.148754
8
         skills 0 147422
9
       students 0.142786
In [0]:
for i in range(0, cluster_1_hc.shape[0]):
    j = cluster 1 hc.iloc[i, :].sort values(ascending=False).reset index()
    yyy.append(j['index'].tolist())
In [0]:
#making cluster_1_words as a one flat list
cluster 1 words = []
for sublist in yyy:
    for item in sublist:
        cluster_1_words.append(item)
In [0]:
zzz = []
for i in range(0, cluster 0 hc.shape[0]):
   j = cluster_0_hc.iloc[i, :].sort_values(ascending=False).reset_index()
    zzz.append(j['index'].tolist())
In [0]:
#making cluster_1_words as a one flat list
cluster_0_words = []
for sublist in zzz:
    for item in sublist:
        cluster_0_words.append(item)
In [0]:
#to get the unique words in the list
cluster_0_words = list(set(cluster_0_words))
cluster_1_words = list(set(cluster_1_words))
In [0]:
print(len(cluster 0 words))
print(len(cluster_1_words))
14266
14266
4.6 Plotting word cloud
4.6.1 Cluster 0 words
In [0]:
#https://www.geeksforgeeks.org/generating-word-cloud-python/
```

from wordcloud import WordCloud, STOPWORDS

comment words 0 = comment words 0 + word + ' '

stopwords = set(STOPWORDS)
comment_words_0 = ' '

for word in cluster_0_words:

In [0]:

```
#Generating Word Cloud for cluster_0_words
wordcloud_0_hc = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords, mi
n_font_size=10).generate(comment_words_0)
```

In [0]:

```
#plotting the Word Cloud
plt.figure(figsize=(8,8), facecolor=None)
plt.title('Cluster 0 words')
plt.imshow(wordcloud_0_hc)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

Cluster 0 words current bilingual state aptitude organizer ign nook W knee j involve صشٍ dialect Φ work Φ accommodation S Φ aım one list fourth critique statistic cleaner § 8 stocI painting parall come owner drama tangram corporation notion | accommodate loan tresource mot

4.6.2 Cluster 1 words

In [0]:

```
comment_words_1 = ' '
for word in cluster_1_words:
    comment_words_1 = comment_words_1 + word + ' '
```

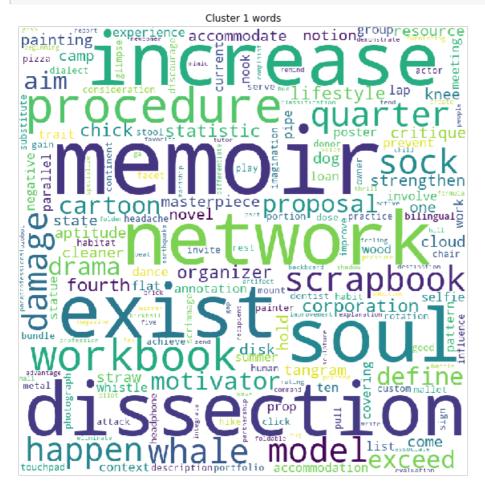
In [0]:

```
#Generating Word Cloud for cluster_0_words
wordcloud_1_hc = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords, mi
n_font_size=10).generate(comment_words_1)
```

In [0]:

```
#plotting the Word Cloud
plt.figure(figsize=(8,8), facecolor=None)
plt.title('Cluster 1 words')
```

```
pit.imsnow(wordcloud_i_nc)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



5. DBSCAN

```
In [0]:

from sklearn.cluster import DBSCAN

In [45]:

X_train.shape

Out[45]:
(73196, 14)

In [53]:

X_train_3 = X_train[0:15000, :]
y_train_3 = y_train[0:15000, :]
print(X_train_3.shape)
print(Y_train_3.shape)
print(Y_train_3.shape)

(15000, 5000)
(15000, 1)
```

5.1 Elbow method to find eps

Note:

• As dimension is 5000 and the min pts should be around 2*d. So, i am going to take min pts as 10000

```
In [54]:
```

```
# Finding nearest neighbour distance from min_pts
#to get the 100 nearest neighbor of each data points we should train with the method mentioned in
link below
#https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.NearestNeighbors.html
min_pts = 10000
from sklearn.neighbors import NearestNeighbors
neigh = NearestNeighbors(n_neighbors=min_pts, algorithm='auto', n_jobs=-1)
neigh.fit(X_train_3)
```

Out[54]:

Note:

• Once we got the nearest neighbors with the n_neighbors=min_pts, we should do with "neigh.kneighbors" to get the 10000 neighbor distance from each points as it returns the tuple of (distances, index of points) and we need only the first item in tuple and from that first item, the 100th column represents the distance from the point to 10000th neighbor as mentioned in https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.NearestNeighbors.html

In [55]:

```
\# as mentioned above the neigh.kneighbors returns the tuple of (distance of 10000 neighbors, index of data points) neigh.kneighbors (X_train_3)
```

Out[55]:

```
5.09211808, ..., 612.23987853,
(array([[ 0.
                        4.26118444.
        612.2467039 , 612.26383596],
                                       2.91805014, ..., 307.63432143,
                       2.66705629,
        307.63561732, 307.67179708],
                       2.3686349 ,
       [ 0.
                                       2.4646736 , ..., 520.59357963,
        520.63979871, 520.64468002],
       [ 0.
                       2.34817695,
                                       2.44119171, ..., 233.88279146,
        233.89206397, 233.89741496],
        [ 0. ,
                       3.61697841,
                                       4.82789578, ..., 522.66264938,
        522.66591022, 522.6774651 ],
       [ 0.
                                       2.6923055 , ..., 305.78602823,
                        2.66831236,
        306.04776049, 306.0602724 ]]),
           0, 10087, 4199, ..., 12580, 1686, 9280],
array([[
            1, 1283, 6856, ..., 12517, 2003, 8707],
2, 2984, 8155, ..., 12745, 11808, 1107],
       [
       [14997, 13364, 5756, ..., 11658, 6859, 7403],
       [14998, 2551, 7392, ..., 2876, 2268,
                                                 120],
       [14999, 7160, 7743, ..., 105, 13404, 11770]]))
```

In [56]:

```
distance = pd.DataFrame(neigh.kneighbors(X_train_3)[0])
distance.head(5)
```

Out[56]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	
0	0.0	4.261184	5.092118	5.397230	5.583272	6.815528	6.829385	6.914648	7.110555	7.251853	7.509093	8.187137	8.252110	8.5412
1	0.0	2.667056	2.918050	3.229012	3.233668	3.279749	3.432496	3.576544	3.686693	3.769418	3.847985	3.886664	3.927638	3.9637
2	0.0	2.368635	2.464674	2.613090	2.971544	3.190590	3.231828	3.265269	3.274330	3.392119	3.427837	3.617337	3.618053	3.6665
3	0.0	2.846323	2.911831	2.994461	3.035966	3.111997	3.118456	3.135570	3.218536	3.282914	3.288636	3.298813	3.306224	3.3199
4	0 0	2 318865	2 708542	2 813861	2 860198	2 912357	2 914918	2 922909	2 933845	2 989036	3 068062	3 076595	3 078355	3 1471

```
0 1 2 3 4 5 6 7 8 9 10 11 12

5 rows × 10000 columns

Note:
```

```
• Since we need the 10000th neighbor distance, so we need only 10000th column
```

```
In [0]:
```

```
distance = distance[9999]
```

In [58]:

```
Out[58]:

0    612.263836
1    307.671797
2    520.644680
```

3 175.110670 4 273.223647 ... 14995 279.192288 14996 291.540325 14997 233.897415 14998 522.677465 14999 306.060272

Name: 9999, Length: 15000, dtype: float64

In [59]:

```
pd.DataFrame(distance).describe()
```

Out[59]:

count 15000.000000 mean 311.261241 std 286.690325 min 157.852610 25% 190.148375 50% 238.259953 75% 303.531436 max 9859.842924

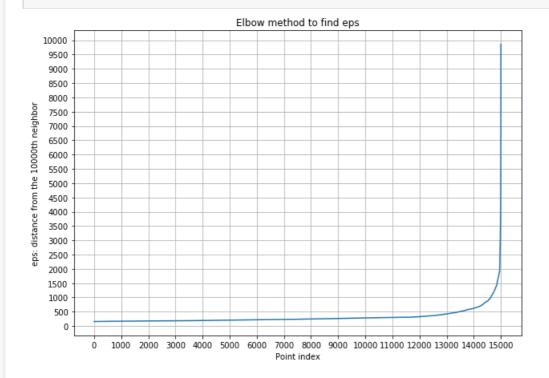
In [0]:

```
#Sort the distance in ascending order
distance = distance.sort_values(ascending=True)
```

In [66]:

```
plt.figure(figsize=(10,7))
plt.plot(range(1,15001), distance)

plt.yticks(range(0,10001,500))
plt.xticks(range(0,15001, 1000))
plt.title('Elbow method to find eps')
#plt.margins(x=0, y=-0.25)
plt.xlabel('Point index')
plt.ylabel('eps: distance from the 10000th neighbor')
plt.grid()
plt.show()
```



Note:

• It shows that the distance point around 14500 the distances start to increase over 1000 and it increases rapidly. So the distance should be taken as 1000

5.2 Modelling with parameters

```
In [0]:
    dbscan = DBSCAN(eps = 1000 , min_samples=10000)
    y_dbscan = dbscan.fit_predict(X_train_3)

In [68]:
    dbscan.labels_
Out[68]:
    array([0, 0, 0, ..., 0, 0, 0])

In [69]:

y_dbscan = y_dbscan.reshape(-1,1)
    print(y_dbscan.shape)

(15000, 1)

In [70]:

(y_dbscan == y_train_3).sum()
Out[70]:
2301
```

Summary:

It shows that our model only clustered only 2301 correctly

5.3 Finding words for Essay text on each cluster

```
In [82]:
X_train_essay_tfidf_3 = X_train_essay_tfidf[0:15000, :]
print(X_train_essay_tfidf_3.shape)
(15000, 14266)
In [0]:
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps = 1000 , min_samples=10000)
In [0]:
essay_db = dbscan.fit(X_train_essay_tfidf_3)
In [85]:
dbscan.labels_
Out[85]:
array([0, 0, 0, ..., 0, 0, 0])
In [107]:
np.unique(dbscan.labels )
Out[107]:
array([0])
Note:
 • It shows that DBSCAN plot all the points in one single cluster.
cluster_0_db = X_train_essay_tfidf_3[np.where(essay_db.labels_ ==0)]
In [0]:
#cluster_1_db = X_train_essay_tfidf_3[np.where(essay_db.labels_ ==1)]
In [113]:
print(cluster 0 db.shape)
#print(cluster 1 db.shape)
(15000, 14266)
In [0]:
type(cluster 0 hc)
Out[0]:
pandas.core.frame.DataFrame
```

```
In [91]:
#convert csr matrix to dataframe
cluster_0_db = pd.DataFrame(cluster_0_db.toarray(), columns=vectorizer_7.get_feature_names())
cluster 0 db.head(2)
Out[91]:
   00 000 03 10 100 1000 100th 101 102 103 104 105 107 10th 11 110 1100 112 115 11th 12 120 1200 123 12
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
                                                                                                        0.0
                                                                                                            0.
                                  0.0
                                               0.0
                                                   0.0
                                                       0.0
                                                            0.0
                                                               0.0
1 0.0 0.0 0.0 0.0 0.0
                        0.0
                              0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 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.
2 rows × 14266 columns
In [0]:
#cluster 1 db = pd.DataFrame(cluster 1 db.toarray(), columns=vectorizer 7.get feature names())
#cluster 1 db.head(2)
In [93]:
#looking at the sample data point and its essay words
cluster_0_db.iloc[0,:].sort_values(ascending=False).reset_index()
Out[93]:
            index
                       0
    0
             avid 0.281376
    1 chromebooks 0.279620
    2
           college 0.179109
    3
         computers 0.178794
            pulled 0.166316
          plugged 0.000000
14261
14262
             plug 0.000000
14263
             pltw 0.000000
14264
             plots 0.000000
14265
              00 0.000000
14266 rows × 2 columns
In [0]:
#for i in range(0, cluster_1_db.shape[0]):
    j = cluster_1_db.iloc[i, :].sort_values(ascending=False).reset_index()
   www.append(j['index'].tolist())
In [0]:
#making cluster 1 words as a one flat list
\#cluster\ 1\ words = []
#for sublist in www:
# for item in sublist:
         cluster 1 words.append(item)
In [0]:
xxx = []
for i in range(0, cluster 0 db.shape[0]):
    j = cluster_0_db.iloc[i, :].sort_values(ascending=False).reset_index()
    xxx.append(i['index'].tolist())
```

In [0]:

```
#making cluster_1_words as a one flat list
cluster_0_words = []
for sublist in xxx:
    for item in sublist:
        cluster_0_words.append(item)
```

In [0]:

```
#to get the unique words in the list
cluster_0_words = list(set(cluster_0_words))
#cluster_1_words = list(set(cluster_1_words))
```

5.4 Plotting word cloud

5.4.1 Cluster 0 words

In [0]:

```
#https://www.geeksforgeeks.org/generating-word-cloud-python/
from wordcloud import WordCloud, STOPWORDS
stopwords = set(STOPWORDS)
comment_words_0_db = ' '
for word in cluster_0_words:
    comment_words_0_db = comment_words_0_db + word + ' '
```

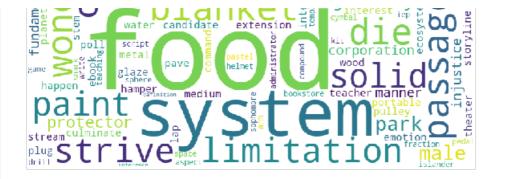
In [0]:

```
#Generating Word Cloud for cluster_0_words
wordcloud_0_db = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords, mi
n_font_size=10).generate(comment_words_0_db)
```

In [110]:

```
#plotting the Word Cloud
plt.figure(figsize=(8,8), facecolor=None)
plt.title('Cluster 0 words')
plt.imshow(wordcloud_0_db)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```





5.4.2 Cluster 1 words

```
In [0]:
```

```
#comment_words_1_db = ' '
#for word in cluster_1_words:
# comment_words_1_db = comment_words_1 + word + ' '
```

In [0]:

```
#Generating Word Cloud for cluster_0_words
#wordcloud_1_db = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords,
min_font_size=10).generate(comment_words_1_db)
```

In [0]:

```
#plotting the Word Cloud
#plt.figure(figsize=(8,8), facecolor=None)
#plt.imshow(wordcloud_1_db)
#plt.axis('off')
#plt.tight_layout(pad=0)
#plt.show()
```

Summary:

In [117]:

```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ['Model Number', 'Vectorizer', 'Model', 'Hyperparameter: n_clusters']
x.add_row(['1', 'TFIDF', 'K-Means', str(2)])
x.add_row(['2', 'TFIDF', 'Hierarchical', str(2)])
x.add_row(['3', 'TFIDF', 'DBSCAN', str(1)])
print(x)
```

+ + +	Model Number	Vectorizer	Model +	Hyperparameter: n_clusters
i	1	TFIDF	K-Means	2
	2	TFIDF	Hierarchical	2
	3	TFIDF	DBSCAN	1 1
+		+	+	++

That's the end of the code