Apply K means, Agglomerative & DBSCAN clustering algorithms on Donors Choose dataset

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
import 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.plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
```

1.1 Loading Data

Due to compuational resource constraints ,I will be considering 5k data points to run all the algorithms.

In [2]:

```
data = pd.read_csv('preprocessed_data.csv', nrows=5000)
data.head(2)
```

Out[2]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_s
0	160221	p253737	c90749f5d961ff158d4b4d1e7dc665fc	Mrs.	IN
1	140945	p258326	897464ce9ddc600bced1151f324dd63a	Mr.	FL

2 rows × 29 columns

In [3]:

```
data.columns
```

Out[3]:

```
Index(['Unnamed: 0', 'id', 'teacher_id', 'teacher_prefix', 'school_state',
       'project_submitted_datetime', 'project_grade_category', 'project_ti
tle',
       'project_essay_1', 'project_essay_2', 'project_essay_3',
       'project_essay_4', 'project_resource_summary',
       'teacher_number_of_previously_posted_projects', 'project_is_approve
d',
       'clean_categories', 'clean_subcategories', 'essay', 'price', 'quant
ity',
       'Numerical digits in summary', 'titles_sw', 'essays_sw',
       'preprocessed_project_grade_category', 'preprocessed_essays',
       'preprocessed_titles', 'sentimental_score',
       'preprocessed_essay_word_count', 'preprocessed_title_word_count'],
      dtype='object')
```

In [4]:

```
data['project_is_approved'].value_counts()
```

Out[4]:

```
1    4237
0     763
Name: project_is_approved, dtype: int64
```

In [5]:

```
y = data['project_is_approved'].values
X = data.drop(['project_is_approved'], axis=1)
X.head(2)
```

Out[5]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_s
0	160221	p253737	c90749f5d961ff158d4b4d1e7dc665fc	Mrs.	IN
1	140945	p258326	897464ce9ddc600bced1151f324dd63a	Mr.	FL

2 rows × 28 columns

1.2 Make Data Model Ready: encoding essay, and project_title using BOW

- In the Logistic Regression assignment I gor the highest test AUC for BOW vectorization compared to others
- Hence, I will be considering the data matrix obatined from BOW to select top 5K features

In [6]:

```
# preprocessed essays
print(X.shape, y.shape)
print("="*100)

vectorizer = CountVectorizer(min_df=10,ngram_range=(1,2), max_features=7000)
vectorizer.fit(X['preprocessed_essays'].values)  # fit has to happen only on train data

# we use the fit CountVectorizer to convert the text to vector
X_train_essay_bow = vectorizer.transform(X['preprocessed_essays'].values)
```

```
(5000, 28) (5000,)
==========================================================================
==========================
```

essay_info = (vectorizer.get_feature_names(), X_train_essay_bow.toarray())

In [7]:

```
f1=vectorizer.get_feature_names()
print("After vectorization")
print(X_train_essay_bow.shape)
print("="*100)
```

```
After vectorization
(5000, 7000)
==========================================================================
==========================
```

In [8]:

```
#project_title
vectorizer1 = CountVectorizer(min_df=10,ngram_range=(1,2), max_features=5000)
vectorizer1.fit(X['preprocessed_titles'].values.astype('U'))

X_train_title_bow = vectorizer1.transform(X['preprocessed_titles'].values.astype('U'))
```

In [9]:

```
f2=vectorizer.get_feature_names()
print("After vectorization")
print(X_train_title_bow.shape)
print("="*100)
```

```
After vectorization
(5000, 373)
==========================================================================
==========================
```

1.3 Make Data Model Ready: encoding numerical, categorical features

1.3.1 Encoding categorical features: School State

In [10]:

```
vectorizer = CountVectorizer()
vectorizer.fit(X['school_state'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_state = vectorizer.transform(X['school_state'].values)
f5=vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_state.shape)
print(f5)
print("="*100)
```

```
After vectorizations
(5000, 51)
['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi',
'ia', 'id', 'il', 'in', 'ks', 'ky', 'la', 'ma', 'md', 'me', 'mi', 'mn', 'm
o', 'ms', 'mt', 'nc', 'nd', 'ne', 'nh', 'nj', 'nm', 'nv', 'ny', 'oh', 'o
k', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx', 'ut', 'va', 'vt', 'wa', 'w
i', 'wv', 'wy']
===========================================================================
==========================
```

1.3.2 Encoding categorical features: teacher_prefix

In [11]:

```
X['teacher_prefix'].unique()
```

Out[11]:

```
array(['Mrs.', 'Mr.', 'Ms.', 'Teacher'], dtype=object)
```

In [12]:

```
vectorizer = CountVectorizer()
vectorizer.fit(X['teacher_prefix'].values)

X_train_teacher = vectorizer.transform(X['teacher_prefix'].values)
f6=vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_teacher.shape)
print(f6)
print("="*100)
```

```
After vectorizations
(5000, 4)
['mr', 'mrs', 'ms', 'teacher']
===========================================================================
==========================
```

1.3.3 Encoding categorical features: project_grade_category

In [13]:

```
#This step is to intialize a vectorizer with vocab from train data
#Ref: https://www.kaggle.com/shashank49/donors-choose-knn#Concatinating-all-features-(T
FIDF)
from collections import Counter
my_counter = Counter()
for word in X['project_grade_category'].values:
    my_counter.update([word[i:i+14] for i in range(0, len(word),14)]) #https://www.geek
sforgeeks.org/python-string-split/

# dict sort by value python: https://stackoverflow.com/a/613218/4084039
project_grade_category_dict = dict(my_counter)
sorted_project_grade_category_dict = dict(sorted(project_grade_category_dict.items(), k
ey=lambda kv: kv[1]))
```

In [14]:

```
vectorizer = CountVectorizer(vocabulary=list(sorted_project_grade_category_dict.keys
()), lowercase=False, binary=True,max_features=4)
vectorizer.fit(X['project_grade_category'].values) # fit has to happen only on train da
ta

# we use the fitted CountVectorizer to convert the text to vector
X_train_grade = vectorizer.transform(X['project_grade_category'].values)

f7=vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_grade.shape)
print(f7)
```

```
After vectorizations
(5000, 4)
['Grades 9-12', 'Grades 6-8', 'Grades 3-5', 'Grades PreK-2']
```

1.3.4 Encoding categorical features: clean_categories

In [15]:

```
vectorizer = CountVectorizer()
vectorizer.fit(X['clean_categories'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_cat = vectorizer.transform(X['clean_categories'].values)

f8=vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_cat.shape)
print(f8)
print("="*100)
```

```
After vectorizations
(5000, 9)
['appliedlearning', 'care_hunger', 'health_sports', 'history_civics', 'lit
eracy_language', 'math_science', 'music_arts', 'specialneeds', 'warmth']
==========================================================================
==========================
```

1.3.5 Encoding categorical features: clean_subcategories

In [16]:

```
vectorizer = CountVectorizer()
vectorizer.fit(X['clean_subcategories'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_subcat = vectorizer.transform(X['clean_subcategories'].values)

f9=vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_subcat.shape)
print(f9)
print("="*100)
```

```
After vectorizations
(5000, 30)
['appliedsciences', 'care_hunger', 'charactereducation', 'civics_governmen
t', 'college_careerprep', 'communityservice', 'earlydevelopment', 'economi
cs', 'environmentalscience', 'esl', 'extracurricular', 'financialliterac
y', 'foreignlanguages', 'gym_fitness', 'health_lifescience', 'health_welln
ess', 'history_geography', 'literacy', 'literature_writing', 'mathematic
s', 'music', 'nutritioneducation', 'other', 'parentinvolvement', 'performi
ngarts', 'socialsciences', 'specialneeds', 'teamsports', 'visualarts', 'wa
rmth']
==========================================================================
==========================
```

1.3.6 Encoding numerical features: Price

In [17]:

```
from sklearn.preprocessing import Normalizer
normalizer1 = Normalizer()
# normalizer.fit(X_train['price'].values)
#this will rise an error Expected 2D array, got 1D array instead:
normalizer1.fit(X['price'].values.reshape(-1,1))

X_train_price_norm = normalizer1.transform(X['price'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_price_norm.shape)
print("="*100)
```

```
After vectorizations
(5000, 1)
==========================================================================
==========================
```

1.3.7 Encoding numerical features: Quantity

In [18]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X['quantity'].values.reshape(1,-1))

X_train_quantity_norm = normalizer.transform(X['quantity'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_quantity_norm.shape)
print("="*100)
```

```
After vectorizations
(5000, 1)
============================================================================
==========================
```

1.3.8 Encoding numerical features: teacher_number_of_previously_posted_projects

In [19]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X['teacher_number_of_previously_posted_projects'].values.reshape(1,-1))

X_train_projects_norm = normalizer.transform(X['teacher_number_of_previously_posted_pro
jects'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_projects_norm.shape)
print("="*100)
```

```
After vectorizations
(5000, 1)
============================================================================
==========================
```

1.3.9 Encoding numerical features: sentimental_score

In [20]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X['sentimental_score'].values.reshape(-1,1))

X_train_senti_norm = normalizer.transform(X['sentimental_score'].values.reshape(-1,1))

print("After vectorizations")
print(X_train_senti_norm.shape)
print("="*100)
```

```
After vectorizations
(5000, 1)
============================================================================
==========================
```

1.3.10 Encoding numerical features: preprocessed_essay_word_count

In [21]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X['preprocessed_essay_word_count'].values.reshape(-1,1))

X_train_ewc_norm = normalizer.transform(X['preprocessed_essay_word_count'].values.resha
pe(-1,1))

print("After vectorization")
print(X_train_ewc_norm.shape)
print("="*100)
```

```
After vectorization
(5000, 1)
==========================================================================
==========================
```

1.3.11 Encoding numerical features: preprocessed_title_word_count

In [22]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X['preprocessed_title_word_count'].values.reshape(-1,1))

X_train_twc_norm = normalizer.transform(X['preprocessed_title_word_count'].values.resha
pe(-1,1))

print("After vectorization")
print(X_train_twc_norm.shape)
print("="*100)
```

```
After vectorization
(5000, 1)
==========================================================================
==========================
```

1.4 Concatinating all categorical features + numerical features + preprocessed_titles(BOW) + preprocessed_essays(BOW)

In [23]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

X_stack = hstack((X_train_essay_bow, X_train_title_bow, X_train_state, X_train_teacher,
X_train_grade, X_train_cat, X_train_subcat, X_train_price_norm, X_train_quantity_norm,
X_train_projects_norm,X_train_senti_norm,X_train_ewc_norm,X_train_twc_norm )).tocsr()

print("Final Data Matrix")
print(X_stack.shape)
```

```
Final Data Matrix
(5000, 7477)
```

2. Dimensionality Reduction on the selected features using sklearn selectkbest

In [24]:

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.feature_selection import SelectKBest, f_classif

X_final = SelectKBest(f_classif, k=5000).fit_transform(X_stack,y)
```

In [25]:

```
print("Shape of the data matrix after dim reduction :", X_final.shape)
```

```
Shape of the data matrix after dim reduction : (5000, 5000)
```

In [32]:

```
#saving the sparse matrix
# https://stackoverflow.com/questions/8955448/save-load-scipy-sparse-csr-matrix-in-port
able-data-format
from scipy import sparse

sparse.save_npz("X_final.npz", X_final)
np.save('y', y)
```

In [ ]:

```
#Loading the files
y = np.load('y.npy')
X_final = sparse.load_npz("X_final.npz")
```

3. Apply K-Means

3.1 Find best 'k' using using the elbow-knee method (plot k vs inertia_)

In [42]:

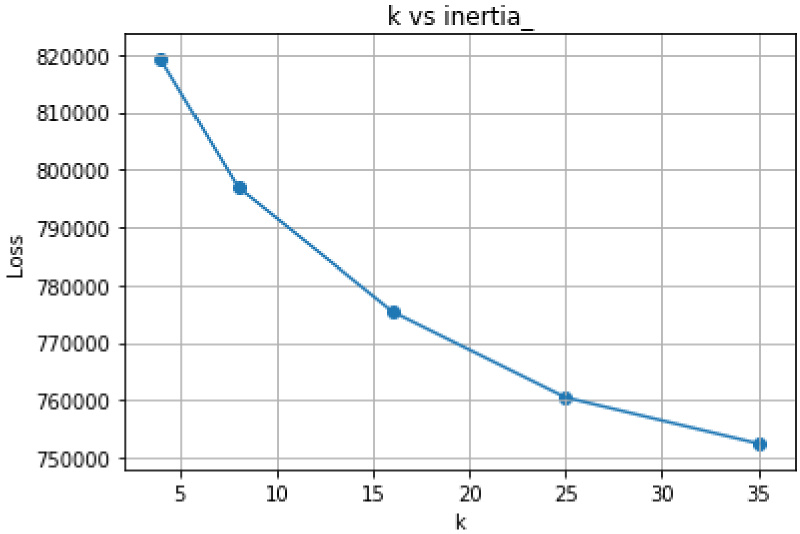
```
from sklearn.cluster import KMeans

loss=[]
k=[4, 8, 16, 25, 35]

for i in tqdm(k): #using simple for loop
    clf1 = KMeans(n_clusters=i, n_jobs=-1)
    clf1.fit(X_final)
    loss.append(clf1.inertia_)
```

```
100%|█████████████████████████████████████████████████████████████████████
████████████████████████████████████████████████████████████| 5/5 [32:26<0
0:00, 379.05s/it]
```

3.2 plot k vs inertia_

In [44]:

```
plt.plot(k, loss)
plt.scatter(k, loss)
plt.xlabel("k")
plt.ylabel("Loss")
plt.title("k vs inertia_")
plt.grid()
plt.show()
```



From the above plot I shall consider k=15

In [27]:

```
# Applying best n_clusters
from sklearn.cluster import KMeans
clf2 = KMeans(n_clusters=15, random_state=0, n_jobs=-1).fit(X_final)
#cluster_dict = getClusterDict(essay_info, clf2.labels_)
#cluster_dict = dict(sorted(list(cluster_dict.items()), key=lambda x: x[0]))
```

for key, val in cluster_dict.items(): plotWordCloud(val, key,'KMeans')

3.3 Dataframe contaning the cluster numbers and the text

In [28]:

```
#Ref: https://stackoverflow.com/questions/36195457/python-sklearn-kmeans-how-to-get-the
-samples-points-in-each-clusters

cluster_map = pd.DataFrame()
cluster_map['data_index'] = X.index.values
cluster_map['essay']= X['preprocessed_essays'].values
cluster_map['cluster'] = clf2.labels_
```

In [29]:

```
cluster_map.head(5)
```

Out[29]:

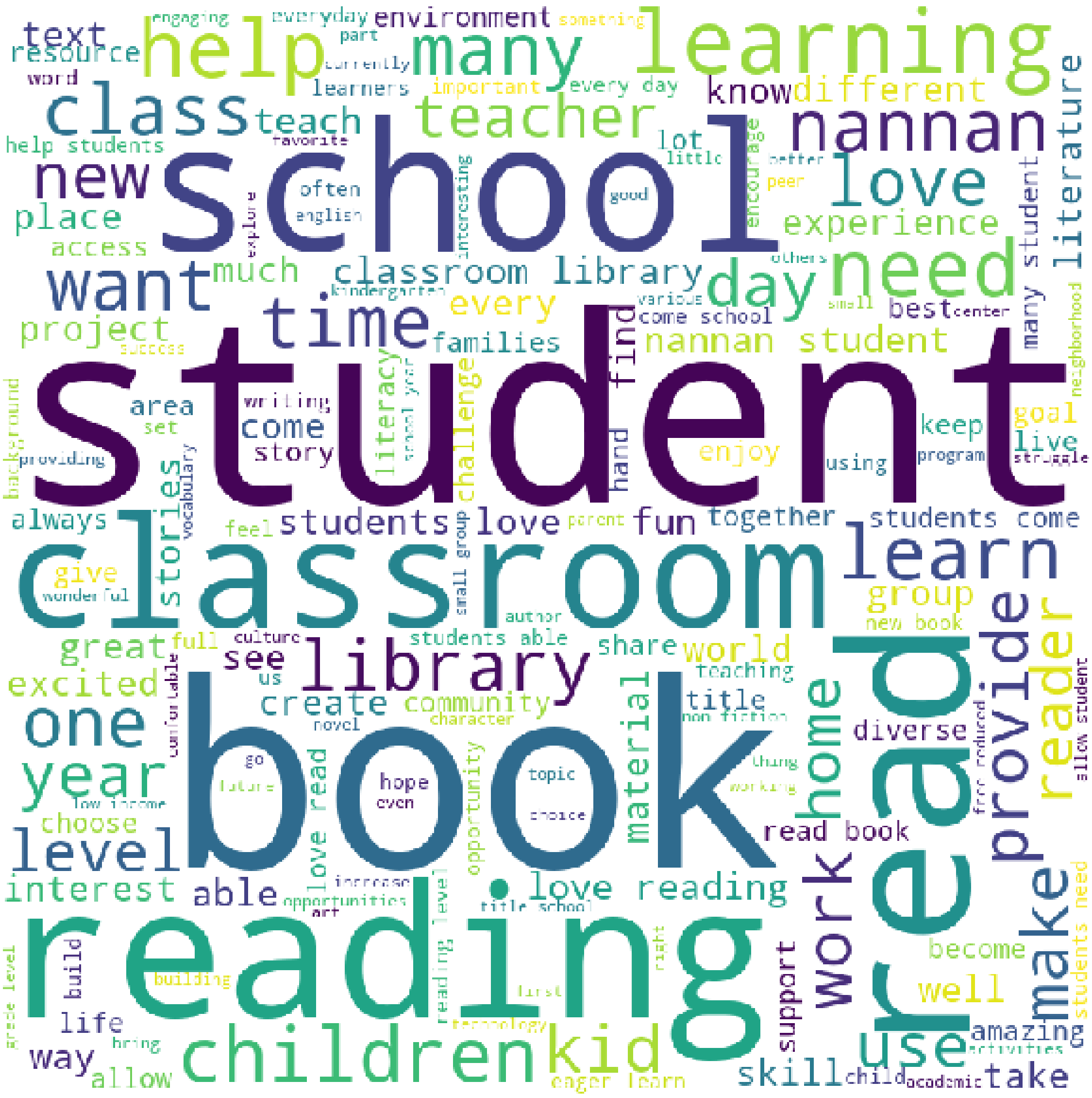
	data_index	essay	cluster
0	0	students english learners working english seco...	7
1	1	students arrive school eager learn polite gene...	7
2	2	true champions always ones win guts mia hamm q...	14
3	3	work unique school filled esl english second l...	10
4	4	second grade classroom next year made around 2...	11

3.4 Essay Wordcloud

In [30]:

```
for i in range(0,15):
    dfi=cluster_map[cluster_map.cluster == i]
    print("Essay Wordcloud for cluster {} :".format(i))
    from wordcloud import WordCloud
    from collections import Counter

    words = ' '
    for row in dfi['essay'].values:
        tokens = row.split()
        for t in tokens:
            words += t + ' '

    wordcloud = WordCloud(width = 800, height = 800, background_color ='white', min_fon
t_size = 10).generate(words)

    # plot the WordCloud image
    plt.figure(figsize = (8, 8), facecolor = None)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad = 0)
    plt.show()

    word_count=len(words.split())  #https://www.geeksforgeeks.org/find-k-frequent-words
-data-set-python/
    Counter = Counter(words.split())
    most_occur = Counter.most_common(10)
    print("Summary of words in Cluster {} :".format(i))
    print("Number of words in the cluster: {}".format(word_count))
    print("Most frequent words in the cluster: {}".format(most_occur))
    print('\n\n')
```

Essay Wordcloud for cluster 0 :

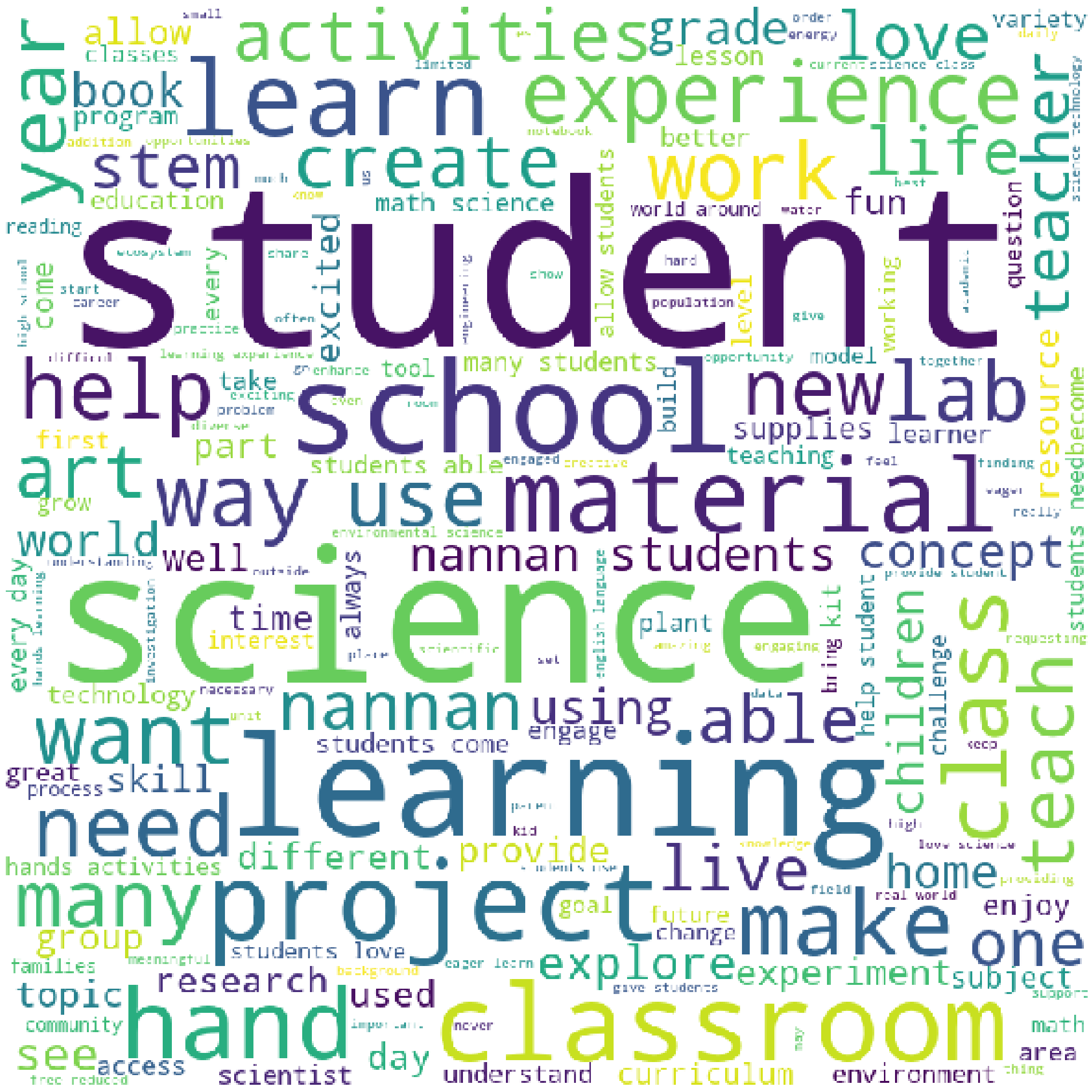


Summary of words in Cluster 0 :
Number of words in the cluster: 33246
Most frequent words in the cluster: [('students', 1435), ('books', 925), ('reading', 656), ('school', 567), ('read', 553), ('classroom', 423), ('love', 408), ('learning', 310), ('learn', 291), ('help', 265)]

Essay Wordcloud for cluster 1 :

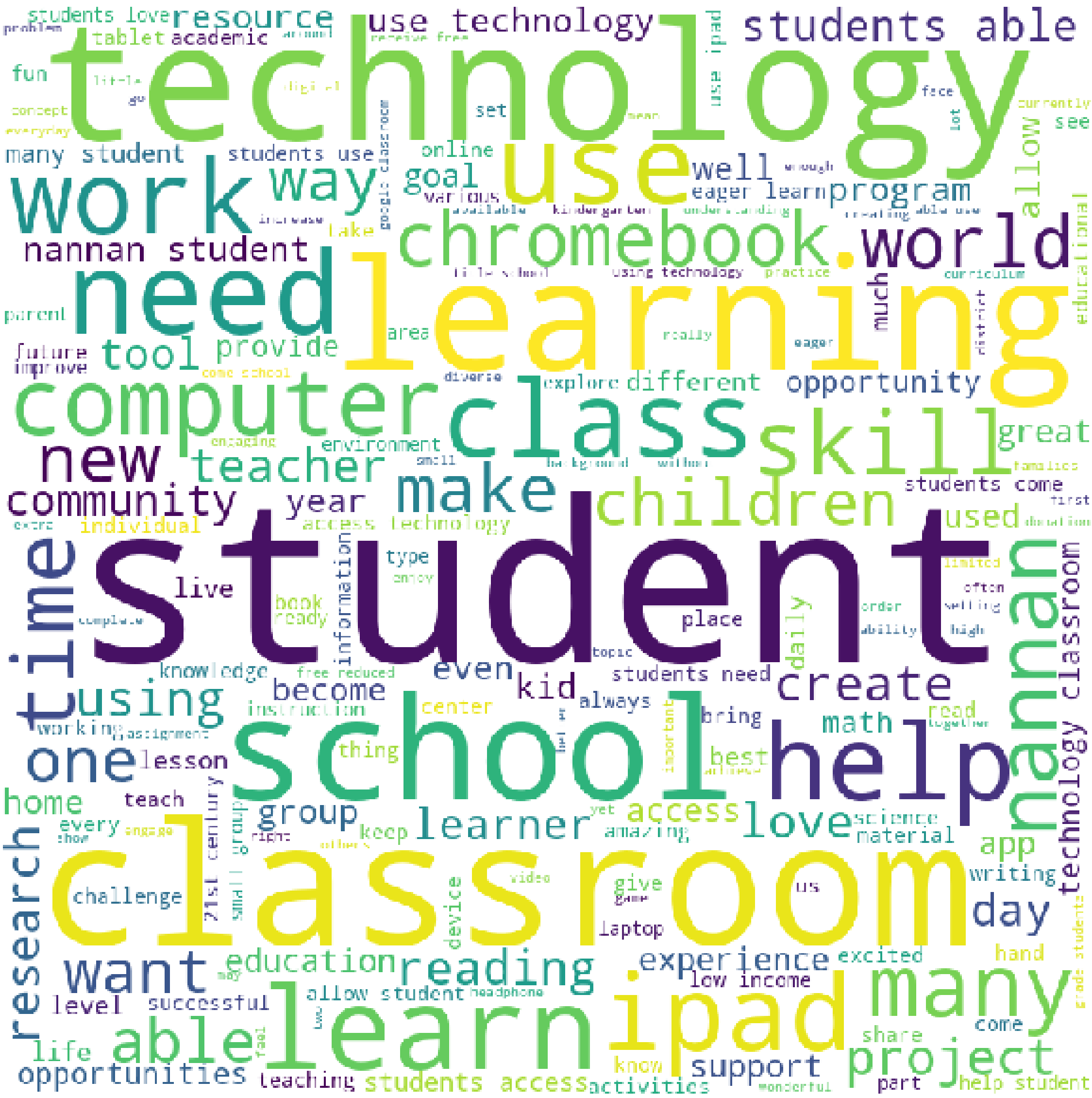
Summary of words in Cluster 1 :
Number of words in the cluster: 13058
Most frequent words in the cluster: [('students', 628), ('music', 601), ('school', 262), ('instruments', 134), ('learning', 119), ('learn', 112), ('class', 100), ('play', 97), ('many', 95), ('band', 94)]

Essay Wordcloud for cluster 2 :



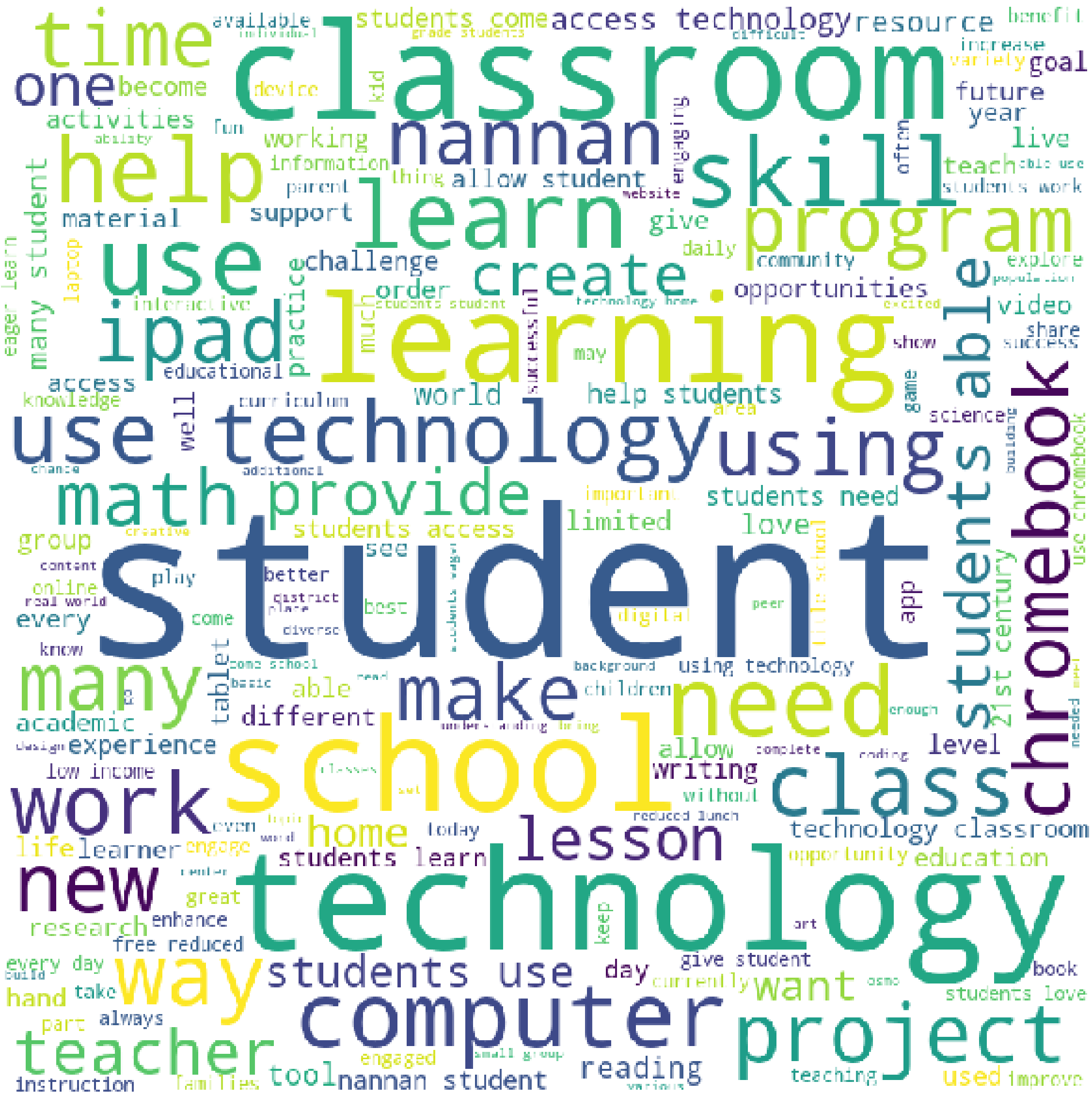
Summary of words in Cluster 2 :
Number of words in the cluster: 19445
Most frequent words in the cluster: [('students', 1033), ('science', 616), ('school', 283), ('learning', 276), ('hands', 156), ('learn', 148), ('clas sroom', 127), ('nannan', 119), ('help', 111), ('materials', 109)]

Essay Wordcloud for cluster 3 :



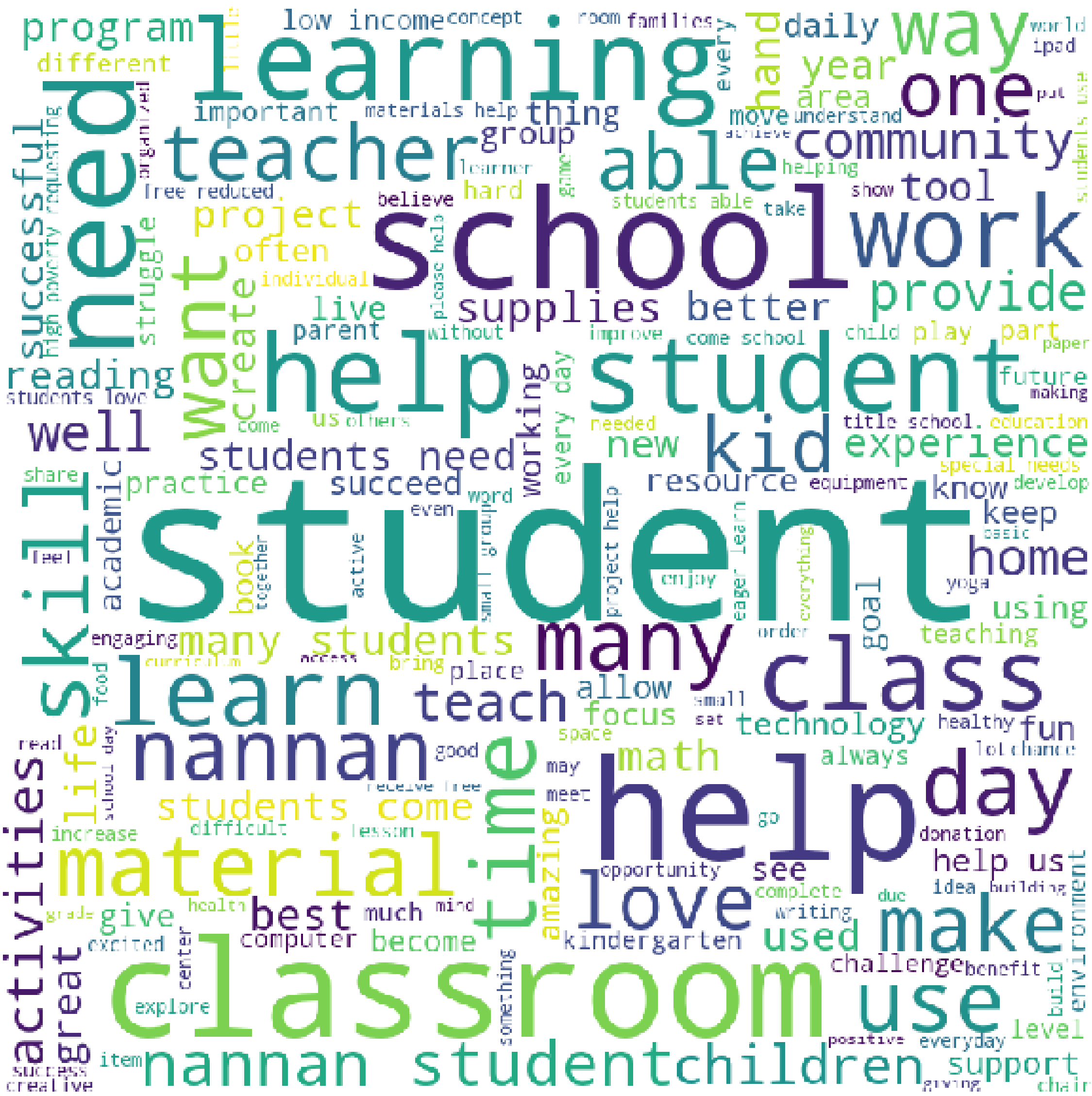
```
Summary of words in Cluster 3 :
Number of words in the cluster: 42503
Most frequent words in the cluster: [('students', 1890), ('technology', 94
6), ('classroom', 799), ('learning', 685), ('school', 644), ('use', 502),
('learn', 362), ('nannan', 321), ('able', 308), ('help', 295)]
```

```
Essay Wordcloud for cluster 4 :
```

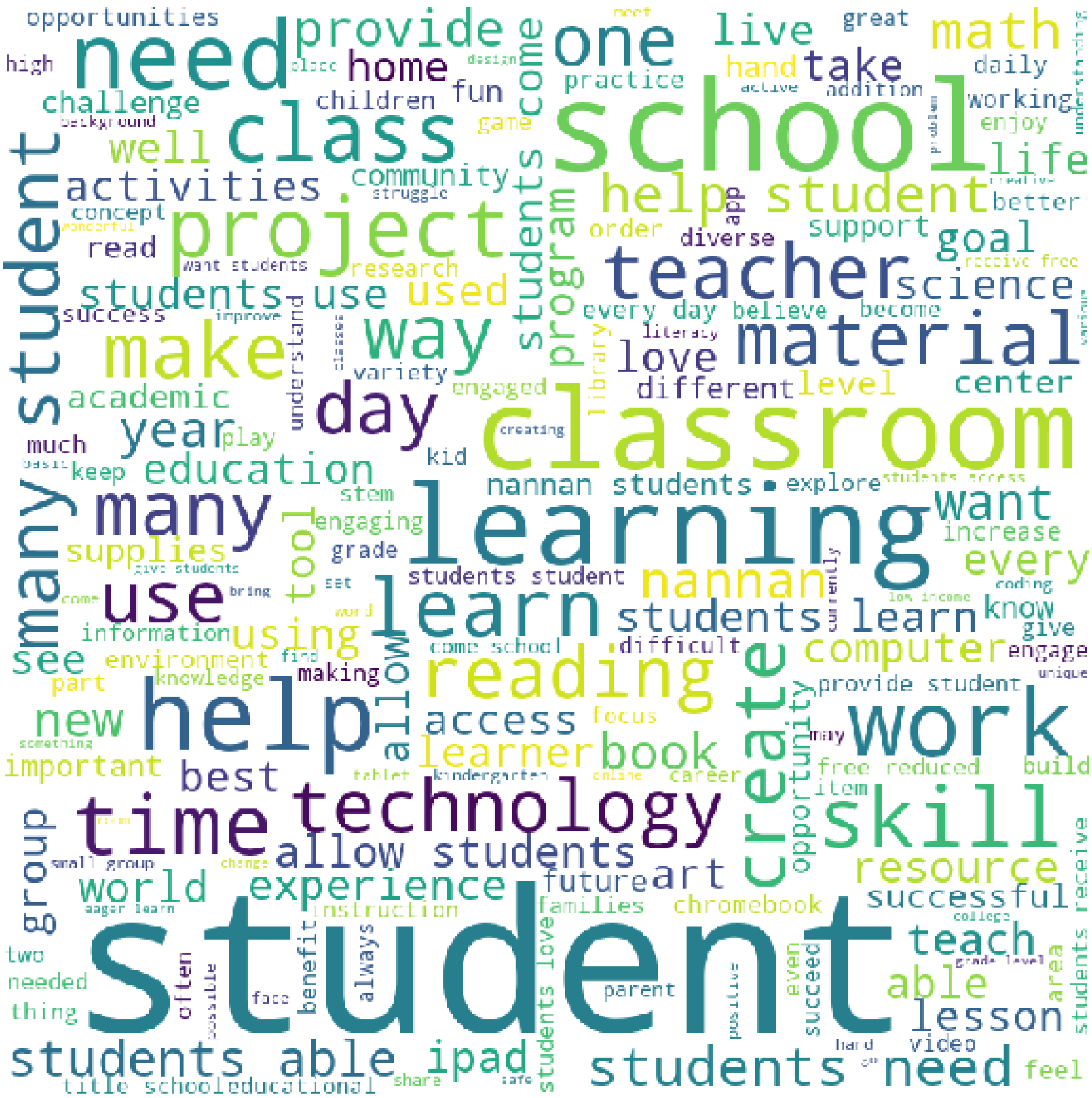


Summary of words in Cluster 4 :
Number of words in the cluster: 37666
Most frequent words in the cluster: [('students', 2383), ('technology', 1006), ('school', 604), ('use', 573), ('classroom', 562), ('learning', 510), ('learn', 331), ('access', 313), ('many', 295), ('help', 273)]

Essay Wordcloud for cluster 5 :

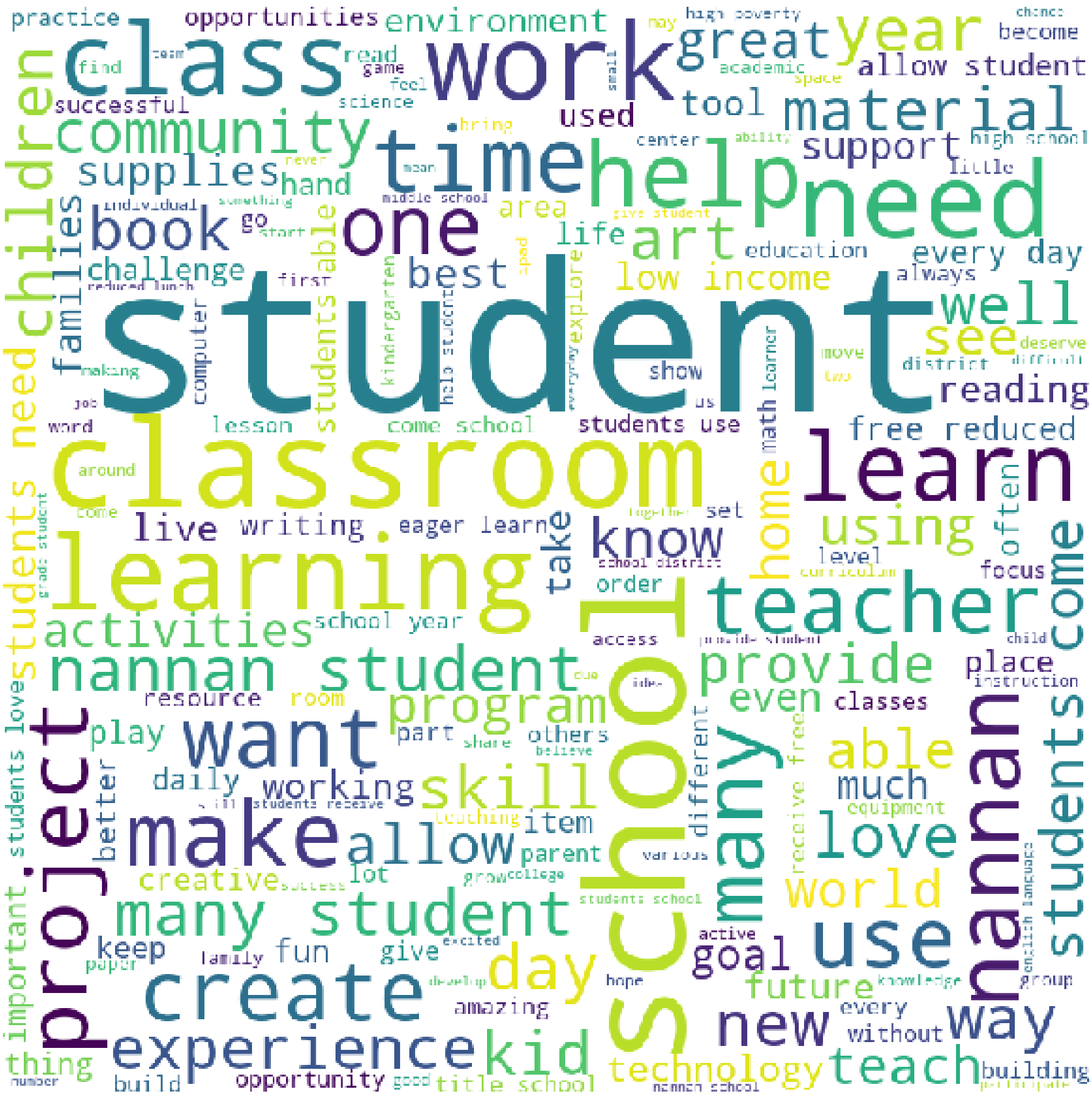


```
Summary of words in Cluster 5 :
Number of words in the cluster: 41309
Most frequent words in the cluster: [('students', 2151), ('help', 1129),
('school', 722), ('classroom', 436), ('learning', 407), ('learn', 343),
('need', 342), ('many', 307), ('nannan', 297), ('skills', 270)]


Essay Wordcloud for cluster 6 :
```



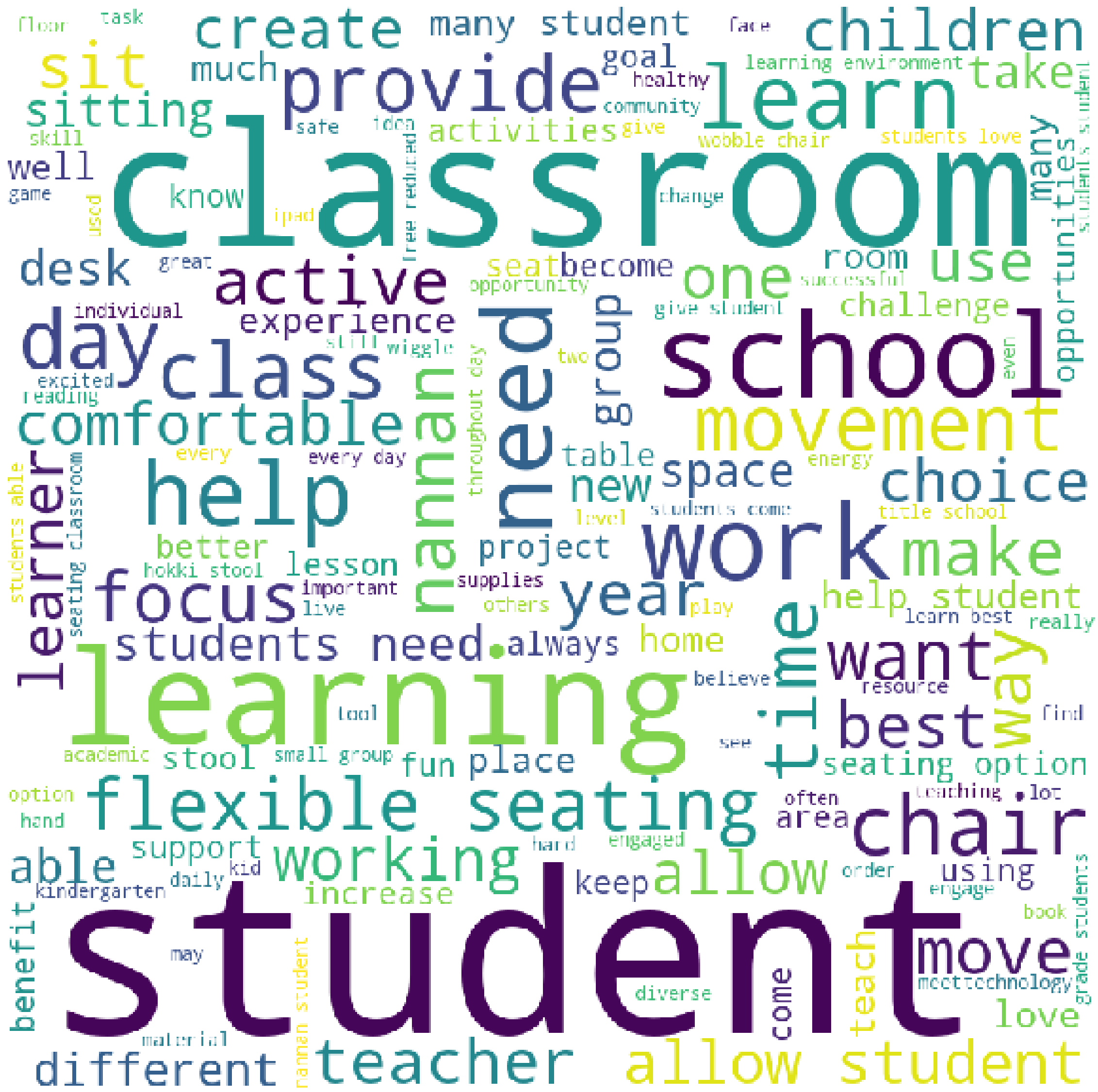
Summary of words in Cluster 6 :
Number of words in the cluster: 37900
Most frequent words in the cluster: [('students', 2854), ('school', 664), ('learning', 448), ('help', 372), ('learn', 356), ('classroom', 322), ('ma ny', 321), ('need', 254), ('skills', 239), ('use', 237)]

Essay Wordcloud for cluster 7 :



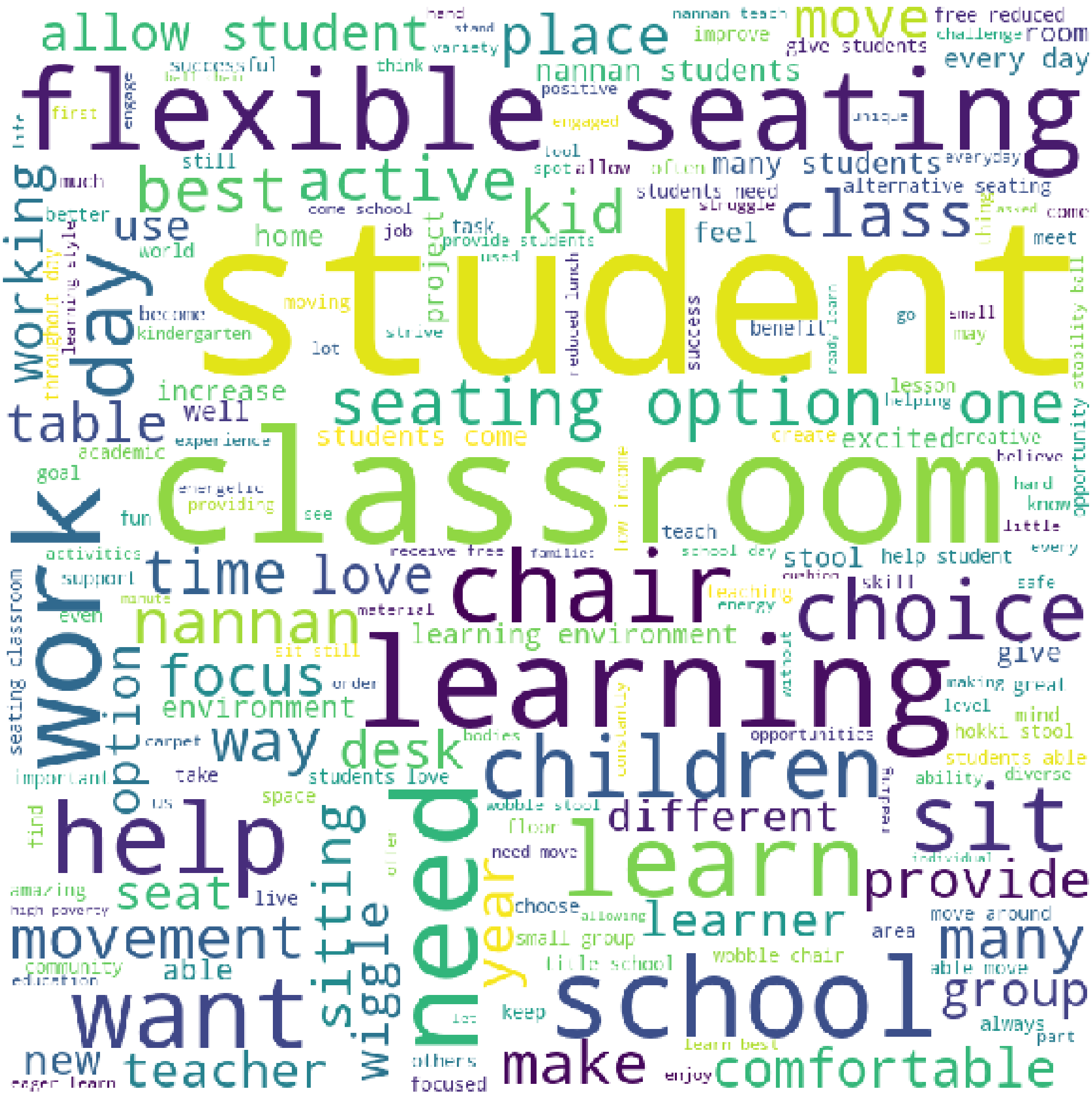
```
Summary of words in Cluster 7 :
Number of words in the cluster: 113188
Most frequent words in the cluster: [('students', 5873), ('school', 2403),
('many', 913), ('learn', 901), ('nannan', 901), ('classroom', 865), ('lear
ning', 751), ('work', 685), ('need', 683), ('come', 599)]
```

```
Essay Wordcloud for cluster 8 :
```



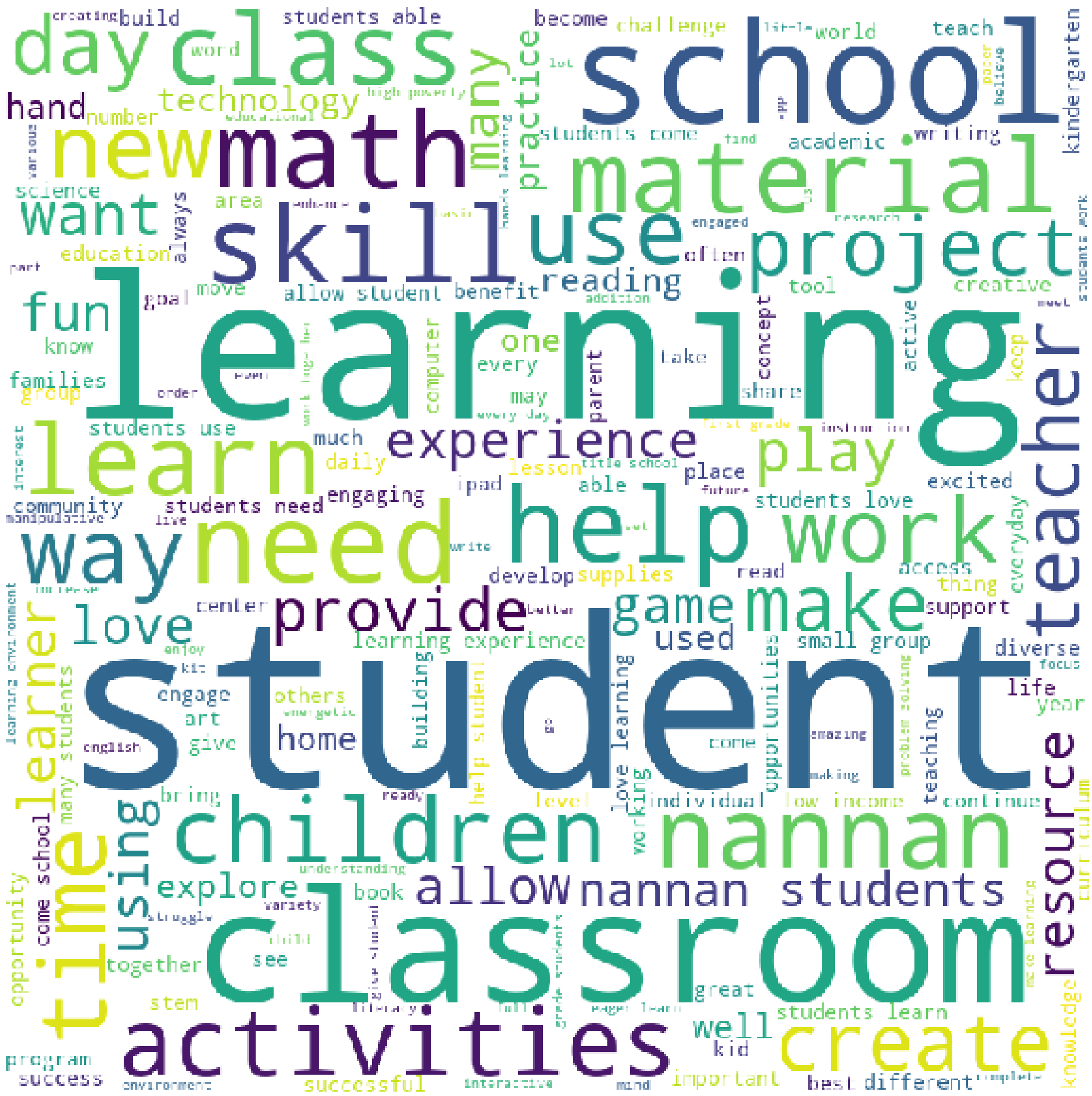
```
Summary of words in Cluster 8 :
Number of words in the cluster: 35291
Most frequent words in the cluster: [('students', 2310), ('classroom', 96
8), ('learning', 674), ('school', 503), ('learn', 331), ('seating', 318),
('work', 303), ('day', 297), ('help', 265), ('need', 222)]
```

```
Essay Wordcloud for cluster 9 :
```



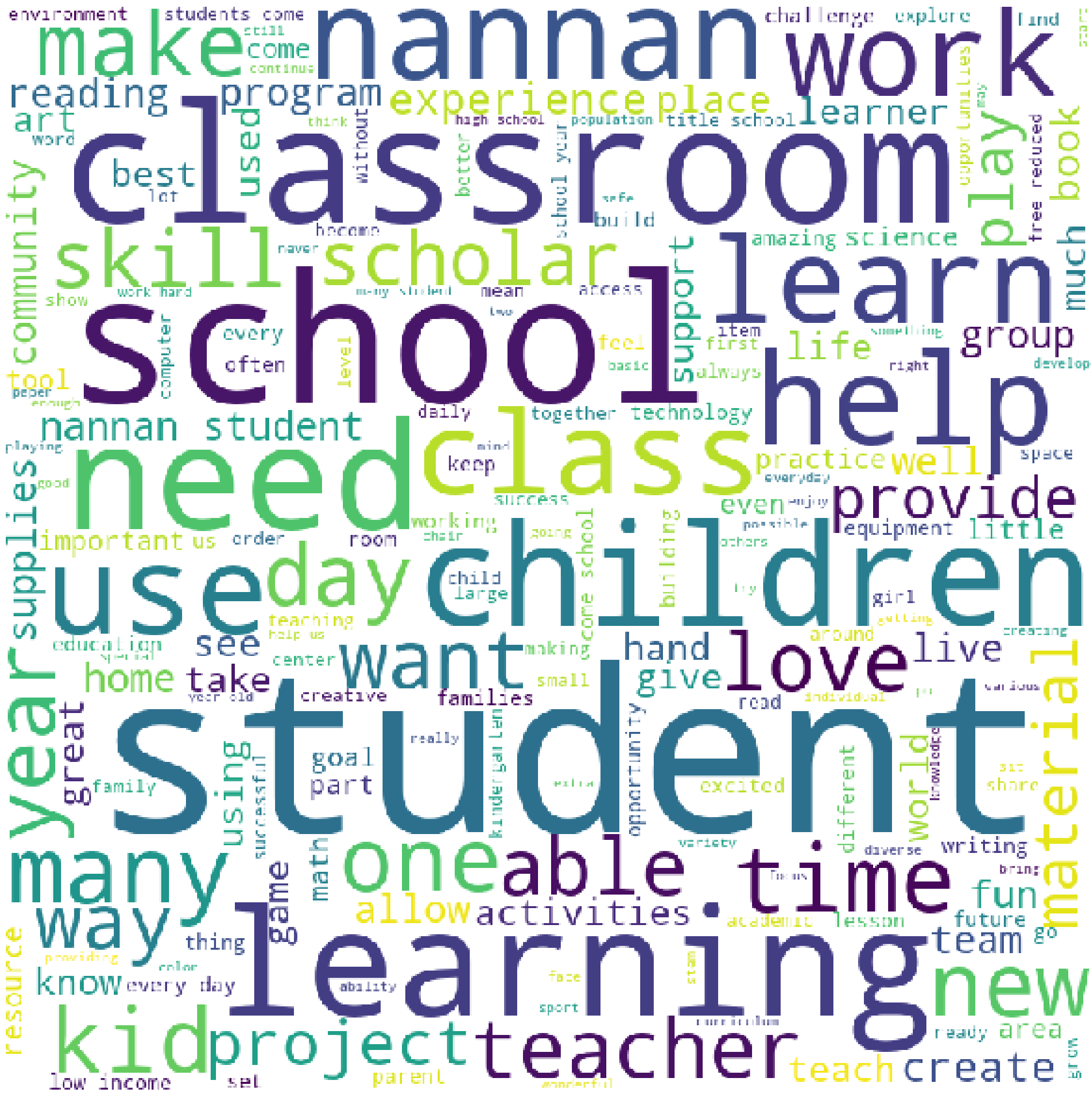
Summary of words in Cluster 9 :
Number of words in the cluster: 41743
Most frequent words in the cluster: [('students', 2039), ('classroom', 79
8), ('learning', 677), ('seating', 602), ('school', 510), ('learn', 426),
('work', 386), ('day', 355), ('move', 355), ('flexible', 324)]

Essay Wordcloud for cluster 10 :

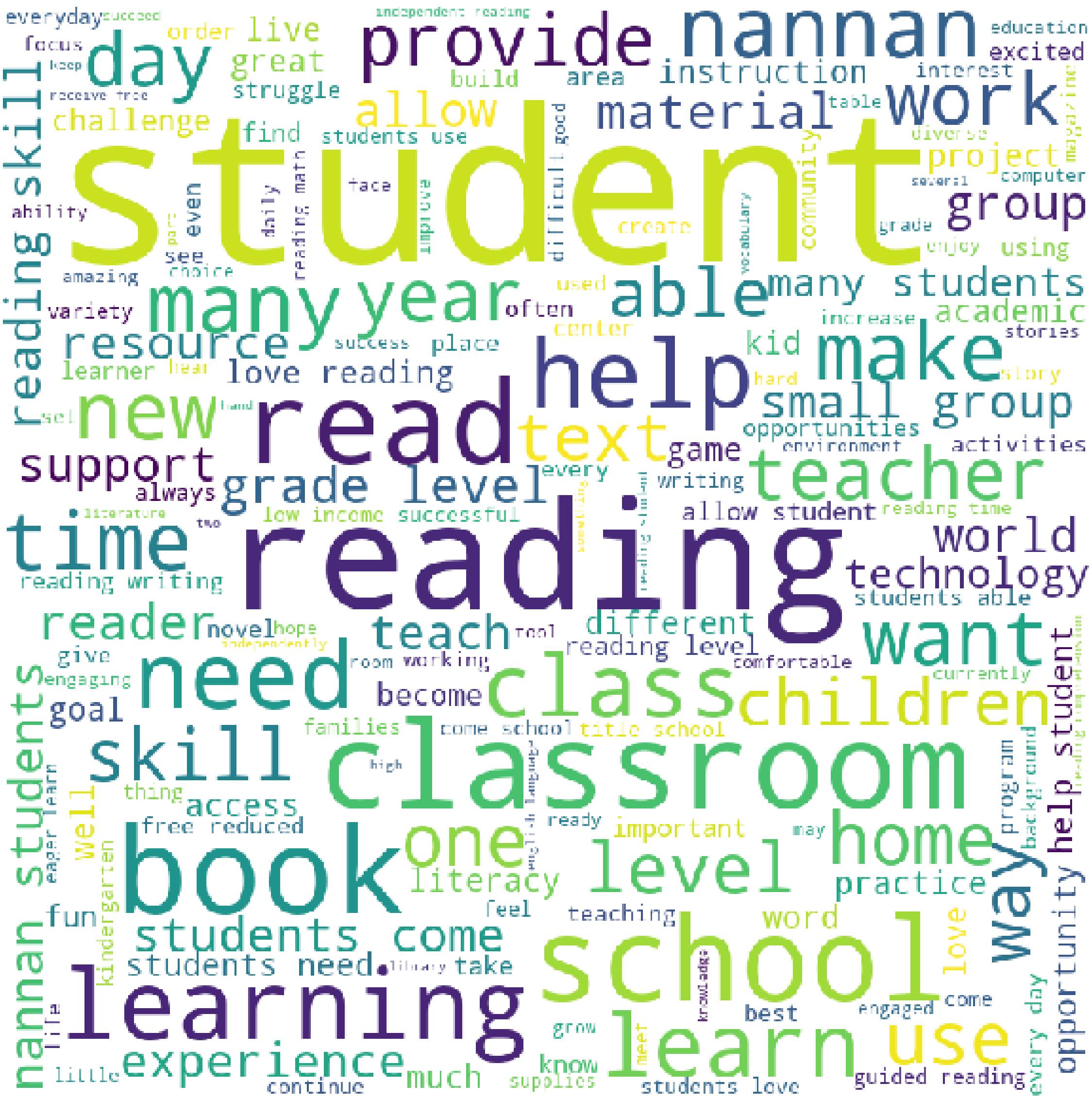


Summary of words in Cluster 10 :
Number of words in the cluster: 43451
Most frequent words in the cluster: [('students', 2265), ('learning', 1442), ('school', 645), ('classroom', 523), ('math', 436), ('learn', 401), ('skills', 320), ('nannan', 305), ('materials', 297), ('help', 283)]

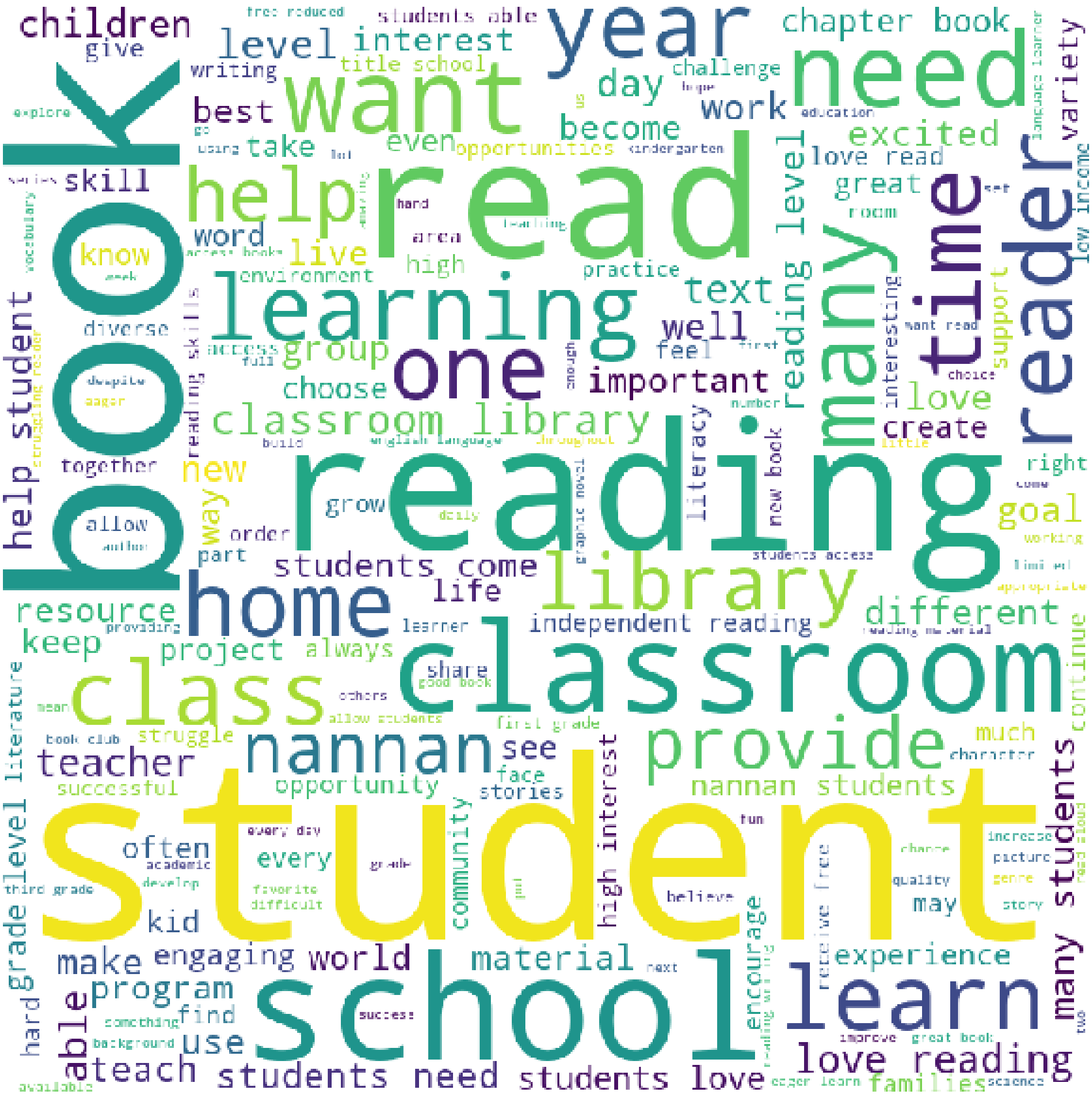
Essay Wordcloud for cluster 11 :



```
Summary of words in Cluster 11 :
Number of words in the cluster: 83323
Most frequent words in the cluster: [('students', 1935), ('school', 1484),
('learning', 753), ('classroom', 736), ('nannan', 649), ('children', 623),
('learn', 596), ('help', 577), ('need', 535), ('many', 521)]


Essay Wordcloud for cluster 12 :
```

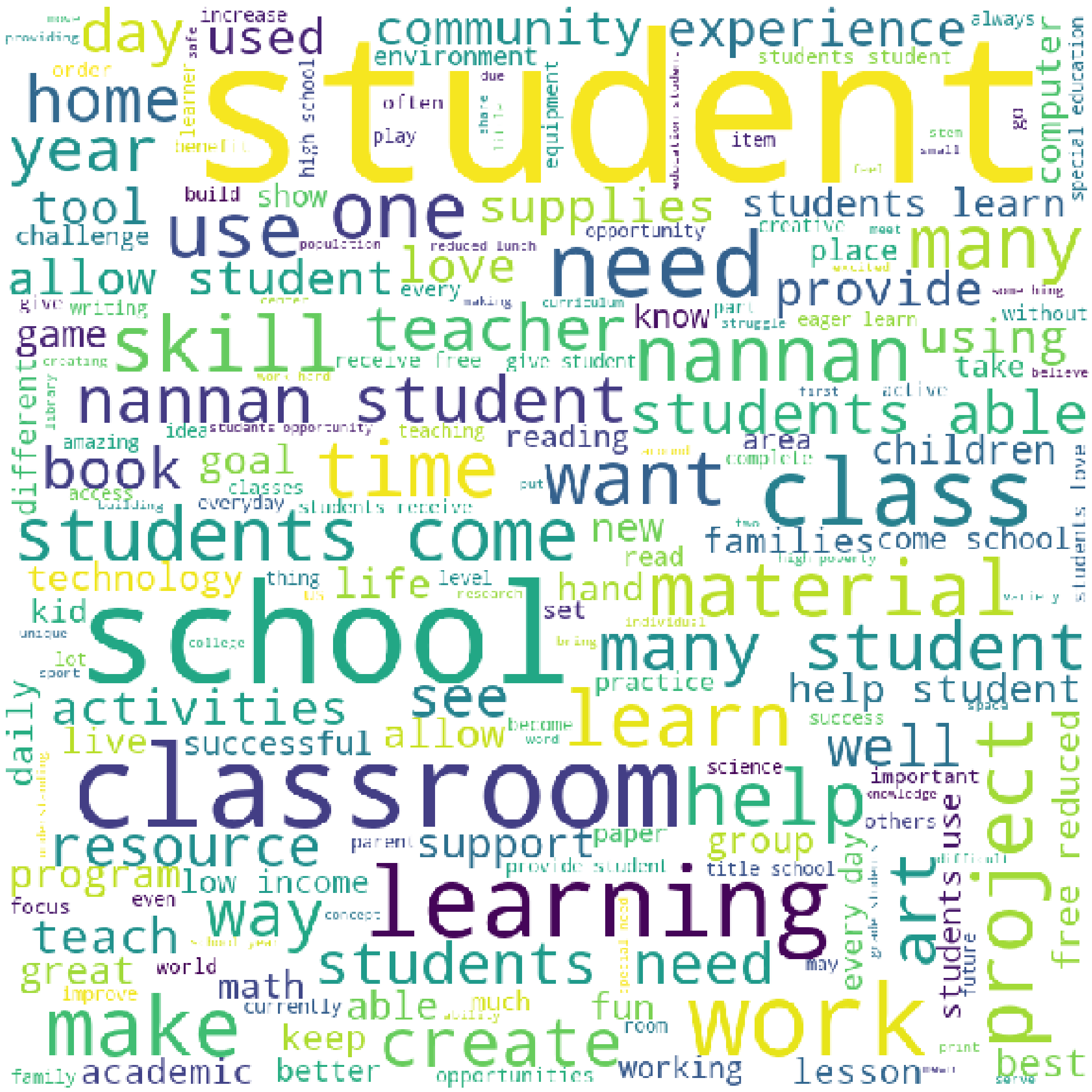


```
Summary of words in Cluster 12 :
Number of words in the cluster: 31025
Most frequent words in the cluster: [('students', 1775), ('reading', 110
4), ('school', 455), ('classroom', 311), ('read', 282), ('help', 275), ('m
any', 233), ('learning', 231), ('skills', 224), ('nannan', 223)]


Essay Wordcloud for cluster 13 :
```



Summary of words in Cluster 13 :
Number of words in the cluster: 23706
Most frequent words in the cluster: [('students', 1409), ('books', 900), ('reading', 762), ('read', 488), ('school', 386), ('classroom', 277), ('love', 242), ('book', 229), ('many', 201), ('library', 184)]

Essay Wordcloud for cluster 14 :



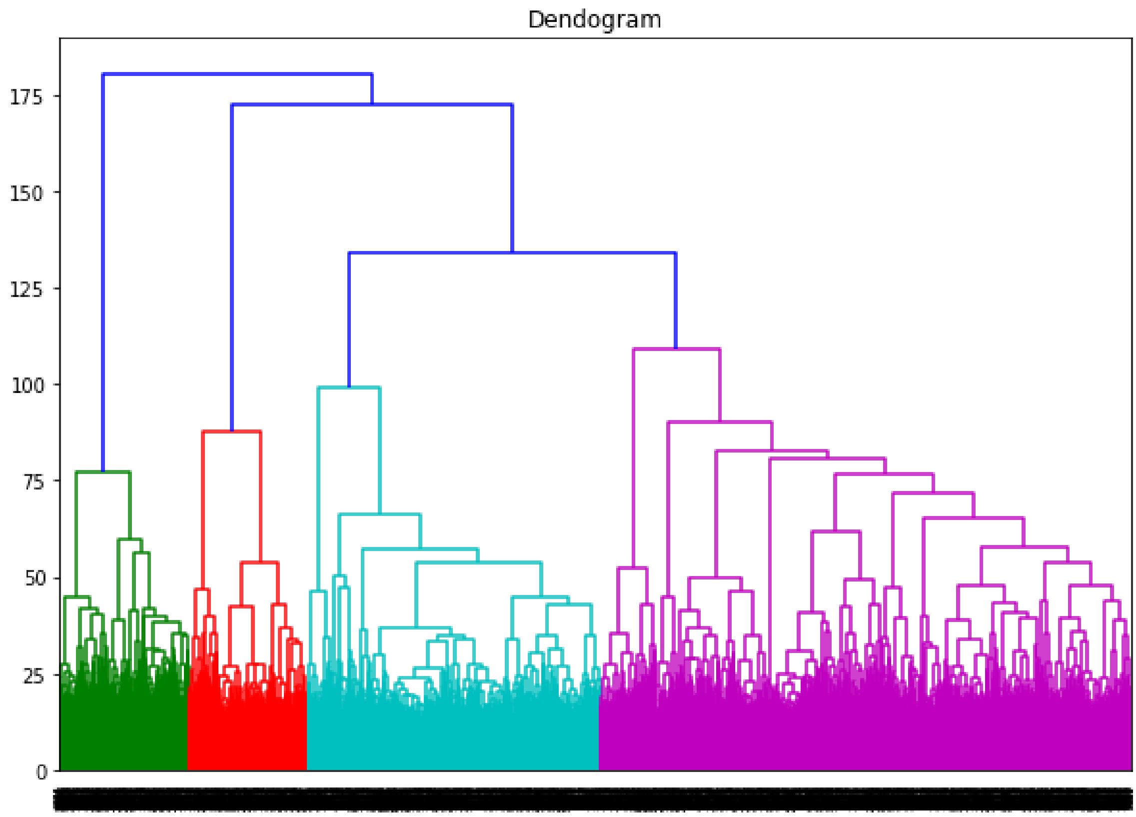

```
Summary of words in Cluster 14 :
Number of words in the cluster: 90506
Most frequent words in the cluster: [('students', 6344), ('school', 1764), 
('learn', 724), ('learning', 720), ('classroom', 680), ('work', 647), ('ma
ny', 634), ('need', 602), ('nannan', 594), ('help', 563)]
```

4. Apply Agglomerative Clustering

4.1 Estimate the number of clusters using a Dendogram

In [37]:

```
# Ref: https://stackabuse.com/hierarchical-clustering-with-python-and-scikit-learn/

import scipy.cluster.hierarchy as shc

X_agg = X_final.todense() #was getting a value error, hence converted to dense matrix

plt.figure(figsize=(10, 7))
plt.title("Dendogram")
dend = shc.dendrogram(shc.linkage(X_agg, method='ward'))
```



- From the above dendrogram clearlyn_clusters= 4

In [38]:

```
np.save('dense',X_agg)
```

In [40]:

```
X_new=np.load('dense.npy')
```

4.2 Agglomerative Clustering on n_clusters

In [41]:

```
from sklearn.cluster import AgglomerativeClustering

clf3 = AgglomerativeClustering(n_clusters= 4, affinity='euclidean', linkage='ward')
clf3.fit_predict(X_new)
```

Out[41]:

```
array([0, 0, 0, ..., 1, 2, 1], dtype=int64)
```

4.3 Dataframe contaning the cluster numbers and the text

In [42]:

```
#Ref: https://stackoverflow.com/questions/36195457/python-sklearn-kmeans-how-to-get-the
-samples-points-in-each-clusters

cluster_map = pd.DataFrame()
cluster_map['data_index'] = X.index.values
cluster_map['essay']= X['preprocessed_essays'].values
cluster_map['cluster'] = clf3.labels_
```

In [43]:

```
cluster_map.head(5)
```

Out[43]:

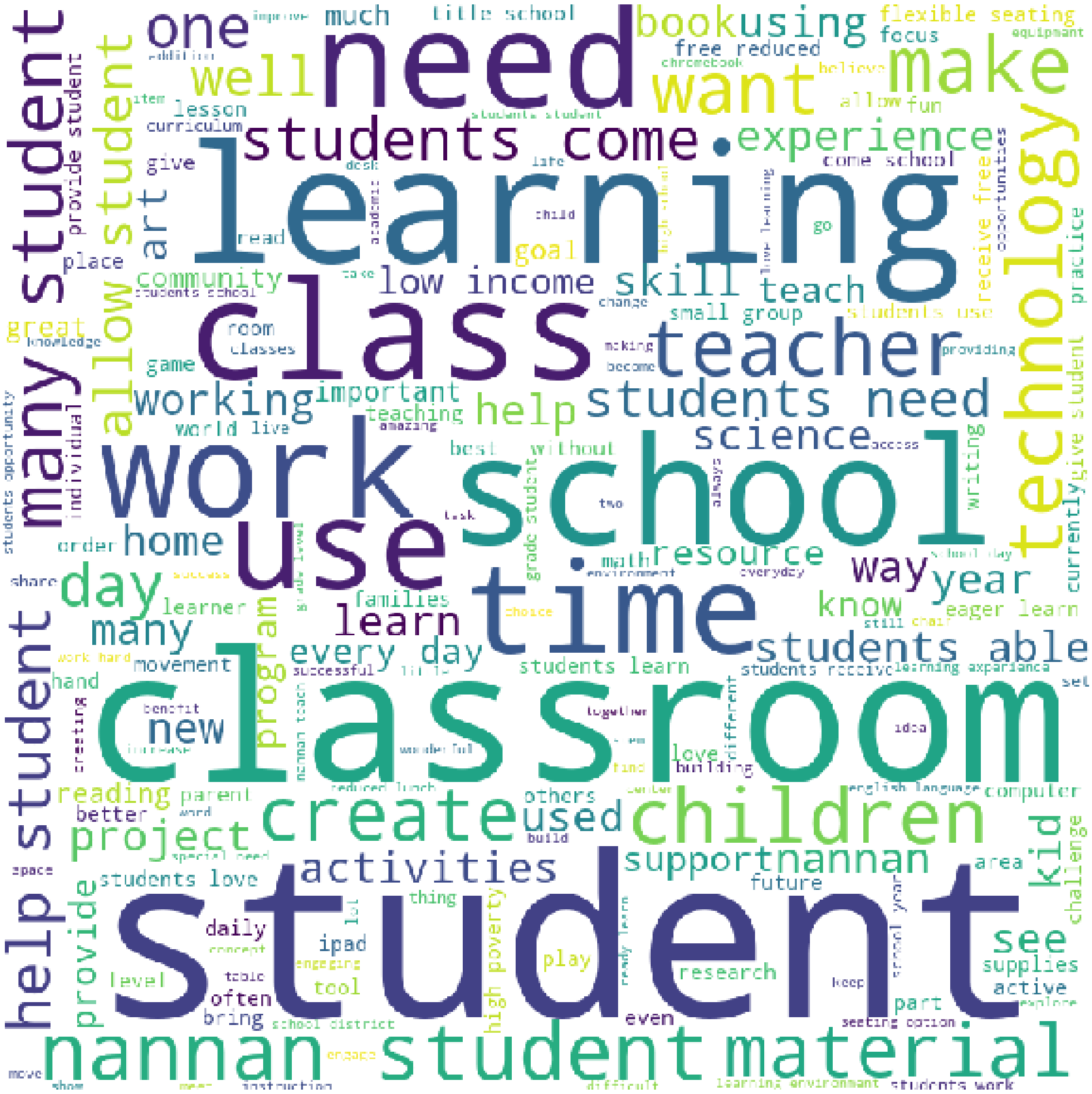
	data_index	essay	cluster
0	0	students english learners working english seco...	0
1	1	students arrive school eager learn polite gene...	0
2	2	true champions always ones win guts mia hamm q...	0
3	3	work unique school filled esl english second l...	0
4	4	second grade classroom next year made around 2...	0

4.4 Essay Wordcloud

In [45]:

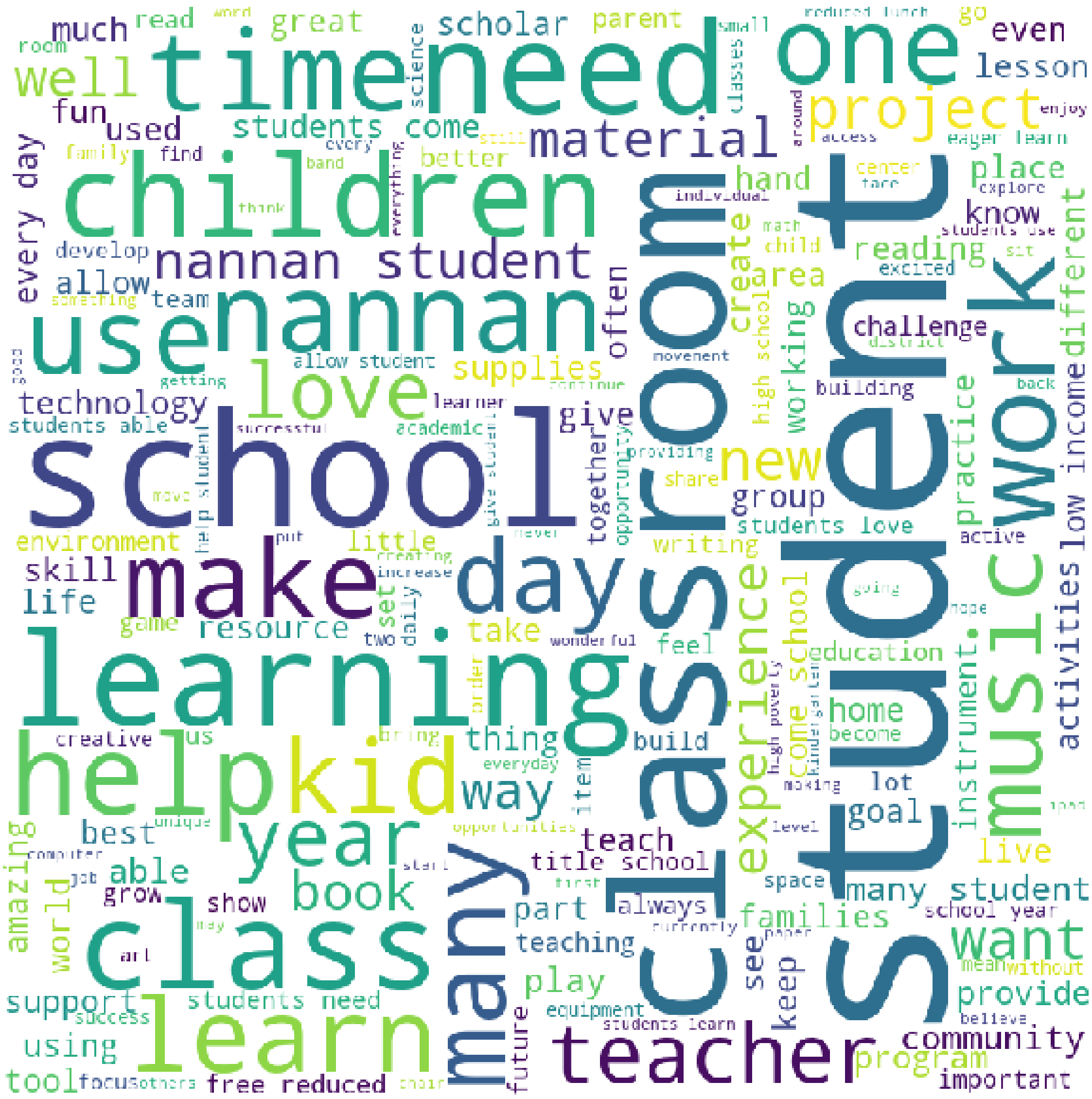
```
for i in range(0,4):
    dfi=cluster_map[cluster_map.cluster == i]
    print("Essay Wordcloud for cluster {} :".format(i))
    from wordcloud import WordCloud
    from collections import Counter

    words = ' '
    for row in dfi['essay'].values:
        tokens = row.split()
        for t in tokens:
            words += t + ' '

    wordcloud = WordCloud(width = 800, height = 800, background_color ='white', min_fon
t_size = 10).generate(words)

    # plot the WordCloud image
    plt.figure(figsize = (8, 8), facecolor = None)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad = 0)
    plt.show()

    word_count=len(words.split())  #https://www.geeksforgeeks.org/find-k-frequent-words
-data-set-python/
    Counter = Counter(words.split())
    most_occur = Counter.most_common(10)
    print("Summary of words in Cluster {} :".format(i))
    print("Number of words in the cluster: {}".format(word_count))
    print("Most frequent words in the cluster: {}".format(most_occur))
    print('\n\n')
```

```
Essay Wordcloud for cluster 0 :
```

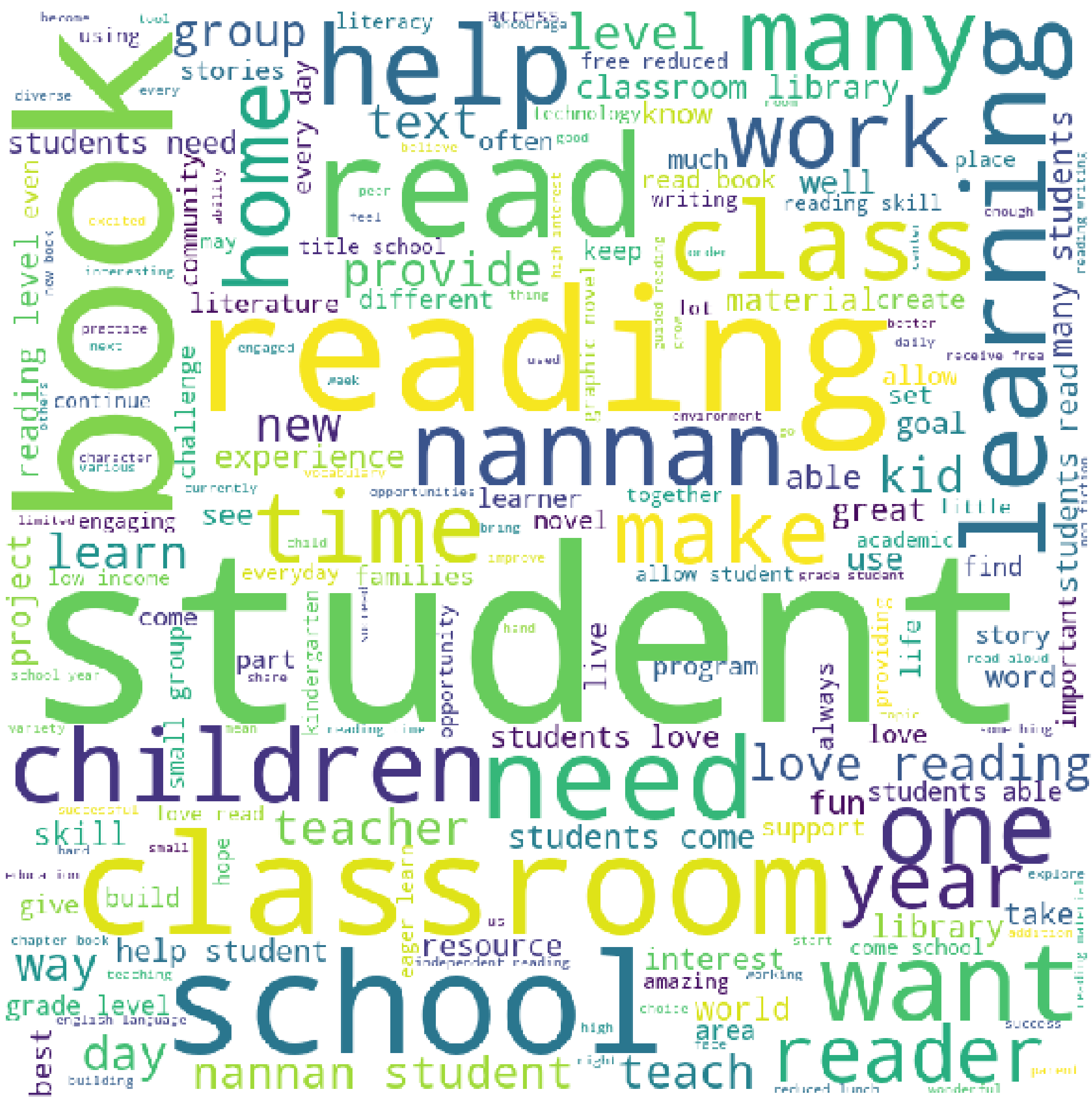


```
Summary of words in Cluster 0 :
Number of words in the cluster: 342371
Most frequent words in the cluster: [('students', 18837), ('school', 569
9), ('learning', 4672), ('classroom', 4120), ('learn', 2911), ('help', 281
8), ('nannan', 2371), ('many', 2340), ('work', 2237), ('need', 2107)]
```

```
Essay Wordcloud for cluster 1 :
```

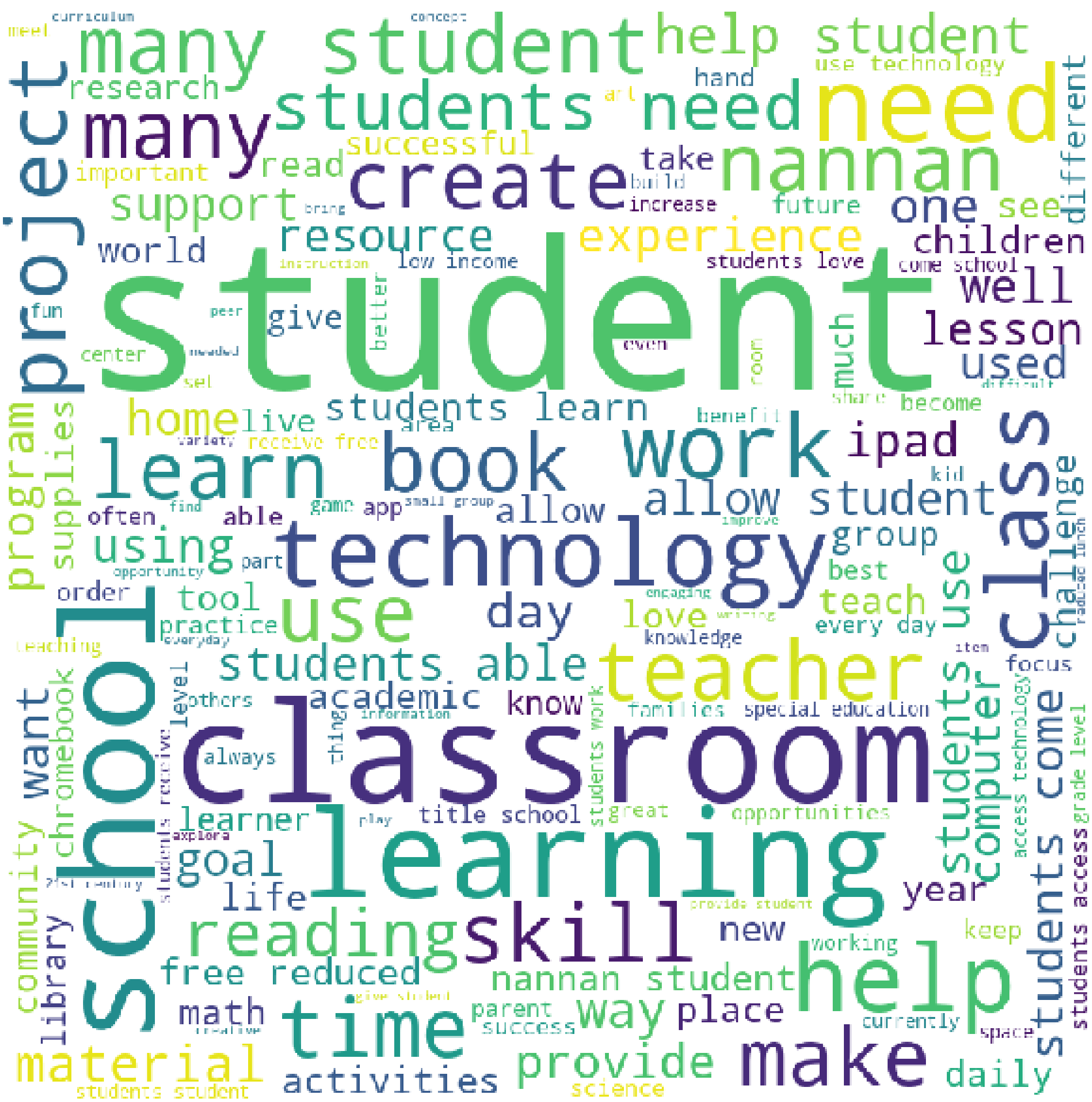


```
Summary of words in Cluster 1 :
Number of words in the cluster: 170258
Most frequent words in the cluster: [('students', 6721), ('school', 3339),
('classroom', 1665), ('learning', 1572), ('learn', 1362), ('nannan', 131
7), ('many', 1258), ('help', 1227), ('need', 1063), ('work', 990)]



Essay Wordcloud for cluster 2 :
```



```
Summary of words in Cluster 2 :
Number of words in the cluster: 72973
Most frequent words in the cluster: [('students', 3704), ('reading', 207
0), ('books', 1762), ('read', 1210), ('school', 1143), ('classroom', 790),
('love', 698), ('help', 605), ('learning', 537), ('learn', 530)]
```

```
Essay Wordcloud for cluster 3 :
```




```
Summary of words in Cluster 3 :
Number of words in the cluster: 101758
Most frequent words in the cluster: [('students', 7062), ('school', 1715),
('learning', 1343), ('classroom', 1342), ('technology', 1019), ('help', 90
2), ('learn', 876), ('use', 767), ('many', 756), ('need', 683)]
```

5. Apply DBSCAN

In [33]:

```
import math
print(math.log(5000))
```

```
8.517193191416238
```

- Ref: https://stackoverflow.com/questions/12893492/choosing-eps-and-minpts-for-dbscan-r/48558030#48558030 (https://stackoverflow.com/questions/12893492/choosing-eps-and-minpts-for-dbscan-r/48558030#48558030)
- Heuristic approach to determine minPts is ln(n), where n is the total number of points to be clustered.
- Therefore minPts = ln(5000) = 8

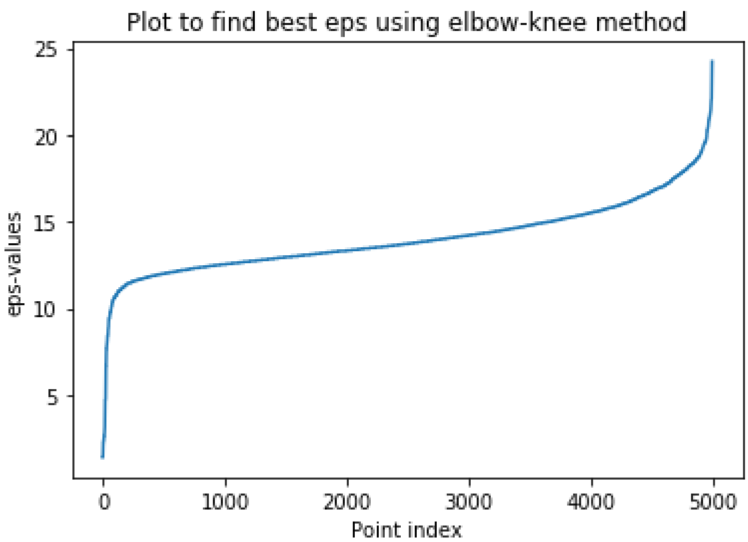
5.1 Best ‘eps’ using the elbow-knee method

In [50]:

```
#Ref:https://datascience.stackexchange.com/questions/10162/knn-distance-plot-for-determ
ining-eps-of-dbscan
#https://towardsdatascience.com/machine-learning-clustering-dbscan-determine-the-optima
l-value-for-epsilon-eps-python-example-3100091cfbc

from sklearn.neighbors import NearestNeighbors

nbrs = NearestNeighbors(n_neighbors=8).fit(X_new)
distances, indices = nbrs.kneighbors(X_new)

distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)

#plt.plot(indices, distances)
plt.title("Plot to find best eps using elbow-knee method")
plt.xlabel('Point index')
plt.ylabel('eps-values')
```

Out[50]:

```
Text(0, 0.5, 'eps-values')
```



5.2 DBSCAN on best eps

In [51]:

```
from sklearn.cluster import DBSCAN

clf4 = DBSCAN(eps=15, min_samples=8).fit(X_new)
```

5.3 Dataframe contaning the cluster numbers and the text

In [52]:

```
#Ref: https://stackoverflow.com/questions/36195457/python-sklearn-kmeans-how-to-get-the
-samples-points-in-each-clusters

cluster_map = pd.DataFrame()
cluster_map['data_index'] = X.index.values
cluster_map['essay']= X['preprocessed_essays'].values
cluster_map['cluster'] = clf4.labels_
```

In [53]:

```
cluster_map.head(5)
```

Out[53]:

	data_index	essay	cluster
0	0	students english learners working english seco...	-1
1	1	students arrive school eager learn polite gene...	0
2	2	true champions always ones win guts mia hamm q...	-1
3	3	work unique school filled esl english second l...	0
4	4	second grade classroom next year made around 2...	0

In [55]:

```
cluster_map['cluster'].unique()
```

Out[55]:

```
array([-1,  0], dtype=int64)
```

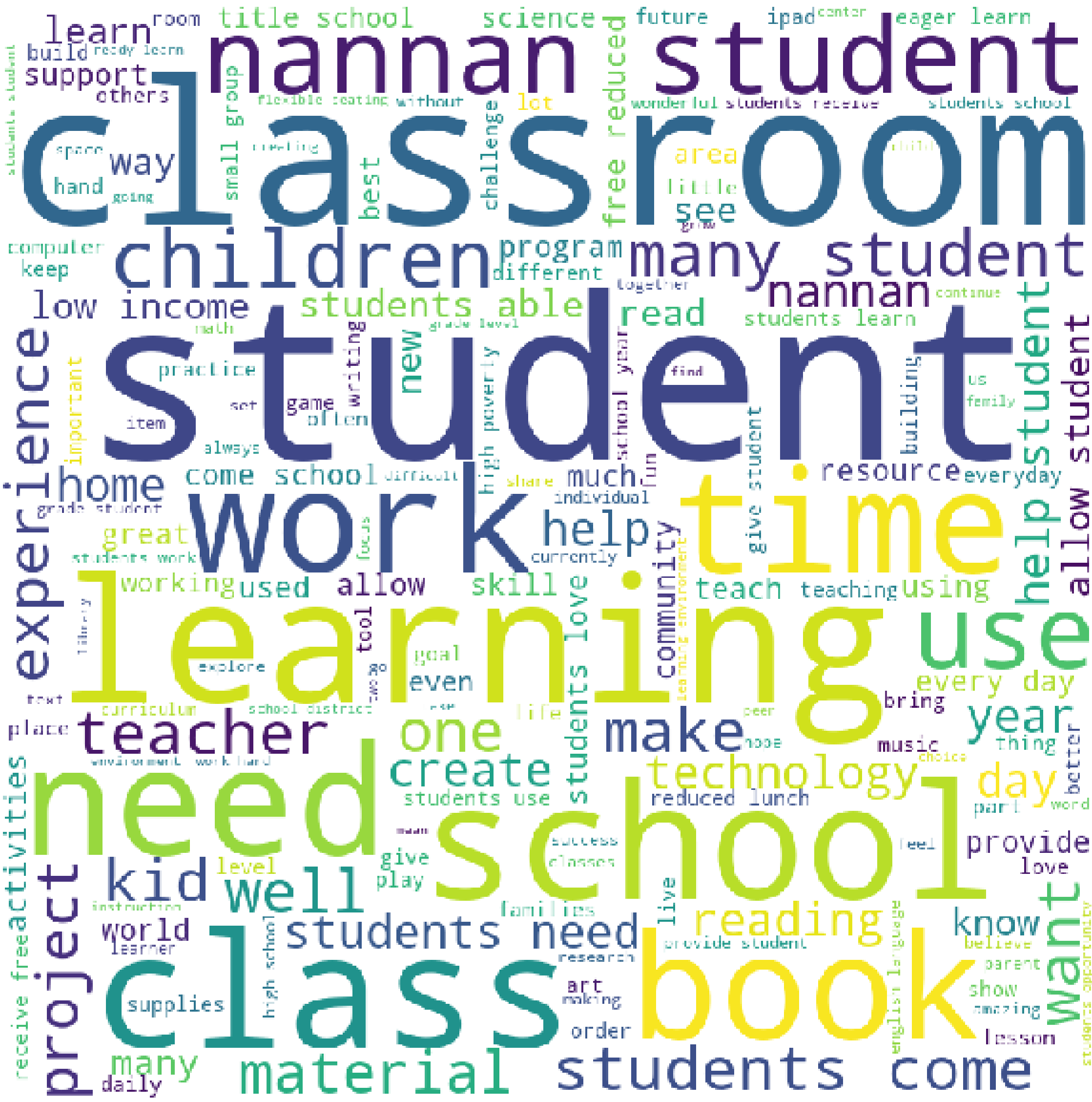
- There are just 2 clusters with one being a noise cluster. Therefore n_clusters=1

5.4 Essay Wordcloud

In [61]:

```
for i in range(0,1):
    dfi=cluster_map[cluster_map.cluster == i]
    print("Essay Wordcloud for cluster {} :".format(i))
    from wordcloud import WordCloud
    from collections import Counter

    words = ' '
    for row in dfi['essay'].values:
        tokens = row.split()
        for t in tokens:
            words += t + ' '

    wordcloud = WordCloud(width = 800, height = 800, background_color ='white', min_fon
t_size = 10).generate(words)

    # plot the WordCloud image
    plt.figure(figsize = (8, 8), facecolor = None)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad = 0)
    plt.show()

    word_count=len(words.split())  #https://www.geeksforgeeks.org/find-k-frequent-words
-data-set-python/
    Counter = Counter(words.split())
    most_occur = Counter.most_common(10)
    print("Summary of words in Cluster {} :".format(i))
    print("Number of words in the cluster: {}".format(word_count))
    print("Most frequent words in the cluster: {}".format(most_occur))
    print('\n\n')
```

```
Essay Wordcloud for cluster 0 :
```


classroom
student
nannan student
learning
school
need
class
book
work
time
children
many student
experience
use
teacher
project
kid
well
material
students come
students need
one
create
make
technology
help
reading
want
home
learn
support
way
program
nannan
low income
students able
read
title school
science
future
eager learn
activities
help student
allow student
year
day
provide
know
supplies
world
many
order
resource
everyday
teach
teaching
using
skill
allow
used
working
great
come school
much
individual
every day
bring
community
students love
free reduced
small group
best
challenge
area
see
new
writing
game
often
practice
item
always
important
keep
computer
different
together
students learn
reduced lunch
students use
even
goal
explore
tool
curriculum
school district
life
music
thing
better
part
word
love
show
lesson
parent
believe
high school
art
making
research
provide student
families
give
play
level
receive free
daily
learner
instruction
success
classes
school year
high poverty
give student
fun
currently
building
us
family
find
others
room
build
hand
space
going
little
lot
ipad
without
wonderful students receive
students school
flexible seating
continue
grade level
math
set
grade student
students work
focus
share
difficult
teach
peer
hope
choice
feel
english language
students opportunity
environment
work hard
place
text
library

```
Summary of words in Cluster 0 :
Number of words in the cluster: 443120
Most frequent words in the cluster: [('students', 23505), ('school', 812
1), ('learning', 5241), ('classroom', 5025), ('learn', 3775), ('help', 365
7), ('nannan', 3496), ('many', 3302), ('need', 2833), ('work', 2713)]
```

- It can be seen that DBSCAN did not perform well on my data set as there was only 1 cluster