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	Descr
`project_id`	A unique identifier for the proposed project. **Example:** `p0`

Feature	Descr
`project_title`	Title of the project. **Exar** • `Art Will Make You Ha` • `First Grade`
`project_grade_category`	Grade level of students for which the project is targeted. One of the fol enumerated v • `Grades Pr` • `Grades` • `Grades` • `Grades`
`project_subject_categories`	One or more (comma-separated) subject categories for the project fr following enumerated list of v • `Applied Lear` • `Care & Hu` • `Health & Sp` • `History & Ci` • `Literacy & Lang` • `Math & Sci` • `Music & The` • `Special N` • `Wa` **Exam** • `Music & The` • `Literacy & Language, Math & Sci`
`school_state`	State where school is located (Two-letter U.S. posta (https://en.wikipedia.org/wiki/List_of_U.S._state_abbreviations#Postal_co **Exampl**

Feature	Descr
`project_subject_subcategories`	One or more (comma-separated) subject subcategories for the p **Exam** • `Lit` • `Literature & Writing, Social Scie`
`project_resource_summary`	An explanation of the resources needed for the project. **Exa** • `My students need hands on literacy materials to ma sensory needs!</`
`project_essay_1`	First application
`project_essay_2`	Second application
`project_essay_3`	Third application
`project_essay_4`	Fourth application
`project_submitted_datetime`	Datetime when project application was submitted. **Example:** `2016-0 12:43:5`
`teacher_id`	A unique identifier for the teacher of the proposed project. **Exa** `bdf8baa8fedef6bfeec7ae4ff1c`
`teacher_prefix`	Teacher's title. One of the following enumerated va • • • • • • `Tea`
`teacher_number_of_previously_posted_projects`	Number of project applications previously submitted by the same te **Examp**

[*] See the section **Notes on the Essay Data** for more details about these features.

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

Feature	Description
id	A `project_id` value from the `train.csv` file. **Example:** `p036502`
description	Desciption 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
`project_is_approved`	A binary flag indicating whether DonorsChoose approved the project. A value of `0` indicates the project was not approved, and a value of `1` indicates the project was approved.

Notes on the Essay Data

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

- **project_essay_1:** "Introduce us to your classroom"
- **project_essay_2:** "Tell us more about your students"
- **project_essay_3:** "Describe how your students will use the materials you're requesting"
- **project_essay_3:** "Close by sharing why your project will make a difference"

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

- **project_essay_1:** "Describe your students: What makes your students special? Specific details about their background, your neighborhood, and your school are all helpful."
- **project_essay_2:** "About your project: How will these materials make a difference in your students' learning and improve their school lives?"

  For all projects with project_submitted_datetime of 2016-05-17 and later, the values of project_essay_3 and project_essay_4 will be NaN.

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 plotly import plotly
```

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

```
D:\Softwares\Anaconda\envs\AAIC\lib\site-packages\gensim\utils.py:1197: UserWarning: dete
cted Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

1.1 Reading Data

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

Taking only 50K points as Training runs slower with many points

In [3]:
```
import random
project_data = project_data.loc[random.sample(list(project_data.index), 50000)]
```

In [4]:
```
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 (50000, 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 [5]:
```
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[5]:

	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 [6]:
```
catogories = list(project_data['project_subject_categories'].values)
# remove special characters from list of strings python: https://stackoverflow.com/a/473019

# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
cat_list = []
for i in catogories:
    temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "
        if 'The' in j.split(): # this will split each of the catogory based on space "Math
            j=j.replace('The','') # if we have the words "The" we are going to replace it w
        j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math
        temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the trailing spaces
        temp = temp.replace('&','_') # we are replacing the & value into
    cat_list.append(temp.strip())

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

from collections import Counter
my_counter = Counter()
for word in project_data['clean_categories'].values:
    my_counter.update(word.split())

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

1.3 preprocessing of `project_subject_subcategories`

In [7]:
```
sub_catogories = list(project_data['project_subject_subcategories'].values)
# remove special characters from list of strings python: https://stackoverflow.com/a/473019

# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python

sub_cat_list = []
for i in sub_catogories:
    temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "
        if 'The' in j.split(): # this will split each of the catogory based on space "Math
            j=j.replace('The','') # if we have the words "The" we are going to replace it w
        j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math
        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 [8]:
```
# 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 [9]:
```
project_data.head(2)
```

Out[9]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	project_submitted_c
89949	42305	p174802	ec80bfc11c25a4c96c15504709140460	Mrs.	NY	2016-12-21
88453	153498	p133636	dc2c461ba99a4f06fa391bc4bdfa474f	Mrs.	SC	2017-01-04 (

In [10]:
```
#### 1.4.2.3 Using Pretrained Models: TFIDF weighted W2V
```

In [11]:
```
# printing some random reviews
print(project_data['essay'].values[0])
print("="*50)
print(project_data['essay'].values[150])
print("="*50)
print(project_data['essay'].values[1000])
print("="*50)
print(project_data['essay'].values[20000])
print("="*50)
```

```
As a teacher in a very diverse school district, my students are faced with several challe
nges both in and out of the classroom. Despite the many challenges they face, I am lookin
g to keep things simple and provide my students with creative and meaningful learning exp
eriences.\r\n\r\nMy students are creative, caring and compassionate about learning. I loo
k everyday for ways to encourage them to keep this passion for life and learning going. T
hey love to explore different ways of learning using as many hands on materials as they c
an. One area I am very passionate about is making sure children have good literature in m
y classroom as well as some they can take home to share with their families. There are so
many different experiences that are brought into my classroom as far as the experiences l
ife has brought to our families as well as what they experience daily at home. Books and 
literature helps them to relate to many other's feelings and situations, helping my class
be a very understanding and tolerant group of children. We work together all day despite 
our many differences and needs.Many students in my class are diagnosed with ADHD or recei
ve OT and PT to build physical strength or have the need to move while working. Other stu
dents just naturally need to move while working as their bodies are growing. It is diffic
ult to stay in their traditional seats for any period of time for some kids. This distrac
ts them from their work as they are so focused on sitting still and not the task they are
working on. These wobble chairs will help my students to channel their energy to the task
they are working on and be able to move safely in their seats.\r\nBy donating to this pro
ject, my students can wiggle while they work! Wobble chairs will allow my students to wor
k without the distraction of having to sit still! Children are naturally always on the mo
ve. Moving their bodies enhances the learning process so why not help my class wiggle saf
ely!nannan
==================================================
I teach in a school that is majority free/reduced lunch.  My kids bring so many various l
```

```
ife experiences with them every day when they walk in my class.  These kids sit at tables
side by side despite their differences and each are given the same opportunities to be su
ccessful!\r\nMy Kindergarten kids come in every day ready to learn, create and explore.
Along with them they bring their wiggles.  I want to create a classroom that welcomes stu
dents to move while they learn!I have a table reserved for these 5 wobble chairs!  I am g
iving my kids the option of flexible seating & I am so excited to make wobble chairs an o
ption for them!  \r\nMy kids enter my class every day ready to become experts & wiggles s
houldn't prevent them from doing just that!  I want them to have every opportunity to cre
ate and grow each day and allow their own learning style to play a part in that adventur
e!  I need your support in making our exciting seating options a reality!  You will allow
my kids to become active learners and move on to 1st grade as experts!nannan
==================================================
I came to the \"Inland Empire\" of California to work with a difficult population in a po
or community.  My students have intellectual and behavioral challenges that I and my staf
f are trying to meet.  It's a big group for a self contained program.   They are very act
ive and need lots of positive classroom experiences, which will include hands on science
and lots of projects. \r\nMy students love hands on art activities.  Since our school foc
uses on English Language Arts and Math, they do not provide lots of materials.  As a exhi
biting artist, I can help my students learn to explore lots of media to create illustrati
ons and 3 dimensional projects to support their learning success.My students are eager to
get their hands on art materials to draw and express themselves.  By providing quality ar
t products and decent tools, I hope to really engage students in creating images to suppo
rt content including science, literature and social studies.\r\nThe students in my progra
m really benefit from project learning. Visual art creates opportunities for my students
to use their visual and drawing skills to support the academic tasks we will pursue in So
cial Studies and Science.  \r\nWe will study world history and science.  We will use our
online research to help produce lively images to illustrate what we have learned.nannan
==================================================
I teach a special education class in a low income area for kids with multiple disabilitie
s from Attention Deficit Hyperactivity to Autism.They are all amazing kids who just need
to be taught in ways that they can learn best. I have these students for several years an
d care about each one of them with there own individual personalities. I want them to gai
n the self-esteem and confidence so that they can learn and be successful in every aspect
of their lives.My student have difficulty learning due to their weak attention skills. Ma
ny of them have difficulty writing legibly due to attention and cannot compose a paragrap
h. They become frustrated and give up. I have found that if they can use a chrome book to
```

```
type their work, they have the confidence to do it because it aleves the stress of writin
g. My students can also maintain focus by using figit toys to stay on task and listen. Th
ey can also excerpt energy by using a portable exercise bike under their desks which will
help them maintain focus while staying in their seat so they can learn.nannan
==================================================
```

In [12]:

```
# 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 [13]:
```
sent = decontracted(project_data['essay'].values[20000])
print(sent)
print("="*50)
```

```
I teach a special education class in a low income area for kids with multiple disabilitie
s from Attention Deficit Hyperactivity to Autism.They are all amazing kids who just need
to be taught in ways that they can learn best. I have these students for several years an
d care about each one of them with there own individual personalities. I want them to gai
n the self-esteem and confidence so that they can learn and be successful in every aspect
of their lives.My student have difficulty learning due to their weak attention skills. Ma
ny of them have difficulty writing legibly due to attention and cannot compose a paragrap
h. They become frustrated and give up. I have found that if they can use a chrome book to
type their work, they have the confidence to do it because it aleves the stress of writin
g. My students can also maintain focus by using figit toys to stay on task and listen. Th
ey can also excerpt energy by using a portable exercise bike under their desks which will
help them maintain focus while staying in their seat so they can learn.nannan
==================================================
```

In [14]:
```
# \r \n \t remove from string python: http://texthandler.com/info/remove-line-breaks-python/
sent = sent.replace('\\r', ' ')
sent = sent.replace('\\"', ' ')
sent = sent.replace('\\n', ' ')
print(sent)
```

```
I teach a special education class in a low income area for kids with multiple disabilitie
s from Attention Deficit Hyperactivity to Autism.They are all amazing kids who just need 
to be taught in ways that they can learn best. I have these students for several years an
d care about each one of them with there own individual personalities. I want them to gai
n the self-esteem and confidence so that they can learn and be successful in every aspect
of their lives.My student have difficulty learning due to their weak attention skills. Ma
ny of them have difficulty writing legibly due to attention and cannot compose a paragrap
h. They become frustrated and give up. I have found that if they can use a chrome book to
type their work, they have the confidence to do it because it aleves the stress of writin
g. My students can also maintain focus by using figit toys to stay on task and listen. Th
ey can also excerpt energy by using a portable exercise bike under their desks which will
help them maintain focus while staying in their seat so they can learn.nannan
```

In [15]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
print(sent)
```

```
I teach a special education class in a low income area for kids with multiple disabilitie
s from Attention Deficit Hyperactivity to Autism They are all amazing kids who just need
to be taught in ways that they can learn best I have these students for several years and
care about each one of them with there own individual personalities I want them to gain t
he self esteem and confidence so that they can learn and be successful in every aspect of
their lives My student have difficulty learning due to their weak attention skills Many o
f them have difficulty writing legibly due to attention and cannot compose a paragraph Th
ey become frustrated and give up I have found that if they can use a chrome book to type
their work they have the confidence to do it because it aleves the stress of writing My s
tudents can also maintain focus by using figit toys to stay on task and listen They can a
lso excerpt energy by using a portable exercise bike under their desks which will help th
em maintain focus while staying in their seat so they can learn nannan
```

In [16]:
```
# 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'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they'
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'l
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had',
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'u
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'd
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over',
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', '
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'v
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'do
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn'
            'won', "won't", 'wouldn', "wouldn't"]
```

In [17]:
```python
# Combining all the above stundents
from tqdm import tqdm
preprocessed_essays = []
# tqdm is for printing the status bar
for sentance in tqdm(project_data['essay'].values):
    sent = decontracted(sentance)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
    sent = sent.replace('\\n', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    # https://gist.github.com/sebleier/554280
    sent = ' '.join(e for e in sent.split() if e not in stopwords)
    preprocessed_essays.append(sent.lower().strip())
```

```
100%|████████████████████████████████████████| 50000/50
000 [00:33<00:00, 1488.42it/s]
```

In [18]:
```python
# after preprocesing
preprocessed_essays[20000]
```

Out[18]:
```
'i teach special education class low income area kids multiple disabilities attention def
icit hyperactivity autism they amazing kids need taught ways learn best i students severa
l years care one individual personalities i want gain self esteem confidence learn succes
sful every aspect lives my student difficulty learning due weak attention skills many dif
ficulty writing legibly due attention cannot compose paragraph they become frustrated giv
e i found use chrome book type work confidence aleves stress writing my students also mai
ntain focus using figit toys stay task listen they also excerpt energy using portable exe
rcise bike desks help maintain focus staying seat learn nannan'
```

1.4 Preprocessing of `project_title`

In [19]:
```python
# similarly you can preprocess the titles also
```

Following Code blocks provided by me.

In [20]:
```
# Code took from original code provided.
# Also function used from original code.
preprocessed_titles = []

for sent in tqdm(project_data['project_title'].values):
    sent = decontracted(sent)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
    sent = sent.replace('\\n', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    sent = ' '.join(e.lower() for e in sent.split() if e.lower() not in stopwords)
    preprocessed_titles.append(sent.lower().strip())
```

```
100%|██████████████████████████████████████████████████| 50000/500
00 [00:01<00:00, 30939.00it/s]
```

In [21]:
```
preprocessed_titles[20000]
```

Out[21]:
```
'gaining attention confidence struggling learners'
```

Following Code blocks present in original notebook.

1.5 Preparing data for models

In [22]:
```
project_data.columns
```

Out[22]:
```
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'],
      dtype='object')
```

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
```

1.5.1 Vectorizing Categorical data

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

In [23]:
```
# we use count vectorizer to convert the values into one
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(vocabulary=list(sorted_cat_dict.keys()), lowercase=False, bina
categories_one_hot = vectorizer.fit_transform(project_data['clean_categories'].values)
print(vectorizer.get_feature_names())
print("Shape of matrix after one hot encodig ",categories_one_hot.shape)
```

```
['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning', 'SpecialNeed
s', 'Health_Sports', 'Math_Science', 'Literacy_Language']
Shape of matrix after one hot encodig  (50000, 9)
```

In [24]:
```
# we use count vectorizer to convert the values into one
vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowercase=False,
sub_categories_one_hot = vectorizer.fit_transform(project_data['clean_subcategories'].value
print(vectorizer.get_feature_names())
print("Shape of matrix after one hot encodig ",sub_categories_one_hot.shape)
```

```
['Economics', 'CommunityService', 'FinancialLiteracy', 'ParentInvolvement', 'Extracurricu
lar', 'Civics_Government', 'ForeignLanguages', 'NutritionEducation', 'Warmth', 'Care_Hung
er', 'PerformingArts', 'SocialSciences', 'CharacterEducation', 'TeamSports', 'Other', 'Co
llege_CareerPrep', 'Music', 'History_Geography', 'ESL', 'Health_LifeScience', 'EarlyDevel
opment', 'Gym_Fitness', 'EnvironmentalScience', 'VisualArts', 'Health_Wellness', 'Applied
Sciences', 'SpecialNeeds', 'Literature_Writing', 'Mathematics', 'Literacy']
Shape of matrix after one hot encodig  (50000, 30)
```

In [25]:
```
# you can do the similar thing with state, teacher_prefix and project_grade_category also
```

Following Code blocks provided by me.

In [26]:
```
# Code took from original code provided.
states = project_data['school_state'].unique()
vectorizer = CountVectorizer(vocabulary=list(states), lowercase=False, binary=True)
vectorizer.fit(project_data['school_state'].values)
print(vectorizer.get_feature_names())

school_state_one_hot = vectorizer.transform(project_data['school_state'].values)
print("Shape of matrix after one hot encoding", school_state_one_hot.shape)
```

```
['NY', 'SC', 'FL', 'TX', 'IN', 'GA', 'NC', 'ID', 'NV', 'WA', 'OH', 'MO', 'NE', 'KY', 'M
S', 'NJ', 'PA', 'IL', 'MI', 'CA', 'HI', 'OK', 'UT', 'MT', 'CT', 'MA', 'NM', 'AZ', 'ME',
'LA', 'VA', 'CO', 'AL', 'WI', 'MD', 'MN', 'VT', 'TN', 'IA', 'KS', 'OR', 'RI', 'NH', 'WV',
'AR', 'DC', 'DE', 'AK', 'ND', 'WY', 'SD']
Shape of matrix after one hot encoding (50000, 51)
```

There are some NaN's in teacher_prefix column. replacing them with 'Mrs.' as that has high occurance in that column.

In [27]:
```
print("Number of NaN's before replacement in column: ", sum(project_data['teacher_prefix'].
project_data['teacher_prefix'] = project_data['teacher_prefix'].replace(np.nan, 'Mrs.', reg
print("Number of NaN's after replacement in column: ", sum(project_data['teacher_prefix'].i

# Output may show both zeros as I re-run this several times. But there are 3 zeros in origi
```

```
Number of NaN's before replacement in column:  3
Number of NaN's after replacement in column:  0
```

In [28]:
```
# Code took from original code provided.
prefixes = project_data['teacher_prefix'].unique()
vectorizer = CountVectorizer(vocabulary=list(prefixes), lowercase=False, binary=True)
vectorizer.fit(project_data['teacher_prefix'].values)
print(vectorizer.get_feature_names())

teacher_prefix_one_hot = vectorizer.transform(project_data['teacher_prefix'].values)
print("Shape of matrix after one hot encoding", teacher_prefix_one_hot.shape)
```

```
['Mrs.', 'Ms.', 'Mr.', 'Teacher', 'Dr.']
Shape of matrix after one hot encoding (50000, 5)
```

In [29]:
```
grades = project_data['project_grade_category'].unique()
vectorizer = CountVectorizer(vocabulary=list(grades), lowercase=False, binary=True)
vectorizer.fit(project_data['project_grade_category'].values)
print(vectorizer.get_feature_names())

project_grade_category_one_hot = vectorizer.transform(project_data['project_grade_category'
print("Shape of matrix after one hot encoding", project_grade_category_one_hot.shape)
```

```
['Grades PreK-2', 'Grades 9-12', 'Grades 3-5', 'Grades 6-8']
Shape of matrix after one hot encoding (50000, 4)
```

Following Code blocks present in original notebook.

1.5.2 Vectorizing Text data

1.5.2.1 Bag of words

In [30]:
```
# We are considering only the words which appeared in at least 10 documents(rows or project
vectorizer = CountVectorizer(min_df=10)
text_bow = vectorizer.fit_transform(preprocessed_essays)
print("Shape of matrix after one hot encodig ",text_bow.shape)
```

```
Shape of matrix after one hot encodig  (50000, 12249)
```

In [31]:
```
# you can vectorize the title also
# before you vectorize the title make sure you preprocess it
```

Following Code blocks provided by me.

In [32]:
```
# Code took from original code provided.
# We are considering only the words which appeared in at least 5 documents(rows or projects
# Reduced number as title has less words
vectorizer = CountVectorizer(min_df=10)
titles_bow = vectorizer.fit_transform(preprocessed_titles)
print("Shape of matrix after one hot encodig ", titles_bow.shape)
```

```
Shape of matrix after one hot encodig  (50000, 2007)
```

Following Code blocks present in original notebook.

1.5.2.2 TFIDF vectorizer

In [33]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(min_df=10)
text_tfidf = vectorizer.fit_transform(preprocessed_essays)
print("Shape of matrix after one hot encodig ",text_tfidf.shape)
```

```
Shape of matrix after one hot encodig  (50000, 12249)
```

1.5.2.3 Using Pretrained Models: Avg W2V

In [34]:
```
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickl
# make sure you have the glove_vectors file
with open('glove_vectors', 'rb') as f:
    model = pickle.load(f)
    glove_words =  set(model.keys())
```

In [35]:
```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed_essays): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors.append(vector)

print(len(avg_w2v_vectors))
print(len(avg_w2v_vectors[0]))
```

```
100%|██████████████████████████████████████████████████| 50000/50
000 [00:19<00:00, 2510.64it/s]

50000
300
```

1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

In [36]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(preprocessed_essays)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

In [37]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(preprocessed_essays): # 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):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentenc
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # gettin
            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.append(vector)

print(len(tfidf_w2v_vectors))
print(len(tfidf_w2v_vectors[0]))
```

```
100%|████████████████████████████████████████| 50000/5
0000 [02:03<00:00, 406.32it/s]

50000
300
```

In [38]:

```
# Similarly you can vectorize for title also
```

Following Code blocks provided by me.

In [39]:
```
# Code took from original code provided.
# tfidf of project titles
vectorizer = TfidfVectorizer(min_df=10)
titles_tfidf = vectorizer.fit_transform(preprocessed_titles)
print("Shape of matrix after one hot encodig ",titles_tfidf.shape)
```

```
Shape of matrix after one hot encodig  (50000, 2007)
```

In [40]:
```
# Code took from original code provided.
# avg-w2v for project titles
avg_w2v_titles = []
for sentence in tqdm(preprocessed_titles):
    vector = np.zeros(300)
    cnt_words =0;
    for word in sentence.split():
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_titles.append(vector)

print(len(avg_w2v_titles))
print(len(avg_w2v_titles[0]))
```

```
100%|██████████████████████████████████████████| 50000/500
00 [00:00<00:00, 52863.99it/s]

50000
300
```

In [41]:
```
# Code took from original code provided.
tfidf_model = TfidfVectorizer()
tfidf_model.fit(preprocessed_titles)
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

In [42]:
```
# Code took from original code provided.
# tfidf-w2v for project titles
tfidf_w2v_titles = []
for sentence in tqdm(preprocessed_titles):
    vector = np.zeros(300)
    tf_idf_weight =0
    for word in sentence.split():
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word]
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split()))
            vector += (vec * tf_idf)
            tf_idf_weight += tf_idf
    if tf_idf_weight != 0:
        vector /= tf_idf_weight
    tfidf_w2v_titles.append(vector)

print(len(tfidf_w2v_titles))
print(len(tfidf_w2v_titles[0]))
```

```
100%|████████████████████████████████████| 50000/500
00 [00:01<00:00, 29799.92it/s]

50000
300
```

Following Code blocks present in original notebook.

1.5.3 Vectorizing Numerical features

In [43]:
```
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 [44]:
```
# check this one: https://www.youtube.com/watch?v=0HOqOcln3Z4&t=530s
# standardization sklearn: https://scikit-learn.org/stable/modules/generated/sklearn.prepro
from sklearn.preprocessing import StandardScaler

# 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.
# Reshape your data either using array.reshape(-1, 1)

price_scalar = StandardScaler()
price_scalar.fit(project_data['price'].values.reshape(-1,1)) # finding the mean and standar
print(f"Mean : {price_scalar.mean_[0]}, Standard deviation : {np.sqrt(price_scalar.var_[0])

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

```
Mean : 295.5700088, Standard deviation : 355.4632875695828
```

In [45]:
```
price_standardized
```

Out[45]:
```
array([[-0.63460846],
       [-0.07030264],
       [-0.3167416 ],
       ...,
       [ 0.15031086],
       [-0.18812072],
       [ 0.57508046]])
```

Following Code blocks provided by me.

In [46]:
```
warnings.filterwarnings("ignore")
# Code took from original code provided
scalar = StandardScaler()
scalar.fit(project_data['teacher_number_of_previously_posted_projects'].values.reshape(-1,
print(f"Mean : {scalar.mean_[0]}, Standard deviation : {np.sqrt(scalar.var_[0])}")

# Now standardize the data with above maen and variance.
previously_posted_projects_standardized = \
                scalar.transform(project_data['teacher_number_of_previously_posted_projects
print(previously_posted_projects_standardized)
```

```
Mean : 11.22942, Standard deviation : 27.96735572884215
[[-0.36576286]
 [-0.36576286]
 [-0.11547105]
 ...
 [-0.29425091]
 [-0.40151883]
 [-0.22273897]]
```

Following Code blocks present in original notebook.

1.5.4 Merging all the above features

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

In [47]:
```
print(categories_one_hot.shape)
print(sub_categories_one_hot.shape)
print(text_bow.shape)
print(price_standardized.shape)
```

```
(50000, 9)
(50000, 30)
(50000, 12249)
(50000, 1)
```

In [48]:
```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
# with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
X = hstack((categories_one_hot, sub_categories_one_hot, text_bow, price_standardized))
X.shape
```

Out[48]:
```
(50000, 12289)
```

In [49]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Computing Sentiment Scores

In [50]:
```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# import nltk
# nltk.download('vader_lexicon')

sid = SentimentIntensityAnalyzer()

for_sentiment = 'a person is a person no matter how small dr seuss i teach the smallest stu
for learning my students learn in many different ways using all of our senses and multiple
of techniques to help all my students succeed students in my class come from a variety of d
for wonderful sharing of experiences and cultures including native americans our school is
learners which can be seen through collaborative student project based learning in and out
in my class love to work with hands on materials and have many different opportunities to p
mastered having the social skills to work cooperatively with friends is a crucial aspect of
montana is the perfect place to learn about agriculture and nutrition my students love to r
in the early childhood classroom i have had several kids ask me can we try cooking with rea
and create common core cooking lessons where we learn important math and writing concepts w
food for snack time my students will have a grounded appreciation for the work that went in
of where the ingredients came from as well as how it is healthy for their bodies this proje
nutrition and agricultural cooking recipes by having us peel our own apples to make homemad
and mix up healthy plants from our classroom garden in the spring we will also create our o
shared with families students will gain math and literature skills as well as a life long e
nannan'
ss = sid.polarity_scores(for_sentiment)

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
```

```
neg: 0.01, neu: 0.745, pos: 0.245, compound: 0.9975,
```

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)/reduction algorithms (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/) and try a different number of clusters like 2,5 etc.
    ● You can take less data points (as this is very computationally expensive one) 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).
    ● You can take a smaller sample size for this as well.
- 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.

2. Clustering

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

In [51]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Following Code blocks provided by me.

Choosing best Vectorizer.

If we see the results from previous models, TFIDF seems to be doing good (even though the difference between performance of other models is less). So, proceeding with TFIDF vectorization for the models. And one hot encoding for categorical features

Bulding data matrix with required columns

Adding a column `summary_numeric_bool` instead of `project_resource_summary` column which tells if resource summary has a number in it

In [52]:
```
# ref: https://stackoverflow.com/questions/4138202/using-isdigit-for-floats
def nums_in_str(text):
    """
    Returns list of numbers present in the given string. Numbers := floats ints etc.
    """
    result = []
    for s in text.split():
        try:
            x = float(s)
            result.append(x)
        except:
            continue
    return result
```

In [53]:
```
print(nums_in_str('HE44LLo 56 are -89 I 820.353 in -78.39 what .293 about 00'))
```

```
[56.0, -89.0, 820.353, -78.39, 0.293, 0.0]
```

In [54]:
```
numbers_in_summary = np.array([len(nums_in_str(s)) for s in project_data['project_resource_
project_data['summary_numeric_bool'] = list(map(int, numbers_in_summary>0))
```

Taking Relevant columns as X (input data to model)

In [55]:
```
project_data.columns
```

Out[55]:
```
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', 'price', 'quantity',
       'summary_numeric_bool'],
      dtype='object')
```

In [56]:
```
project_data.head(2)
```

Out[56]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	project_submitted_dateti
0	42305	p174802	ec80bfc11c25a4c96c15504709140460	Mrs.	NY	2016-12-21 18:2C
1	153498	p133636	dc2c461ba99a4f06fa391bc4bdfa474f	Mrs.	SC	2017-01-04 08:31

2 rows × 21 columns

In [57]:
```
# Categorical and numerical columns are listed below.
X_columns = ['teacher_prefix', 'school_state', 'project_grade_category', 'summary_numeric_b
             'teacher_number_of_previously_posted_projects', 'clean_categories', 'clean_sub
             'price', 'quantity']
X = project_data[X_columns]
y = project_data['project_is_approved']
```

Adding preprocessed_essays and preprocessed_titles as columns to X before splitting

In [58]:
```
X['essay'] = preprocessed_essays
X['project_title'] = preprocessed_titles
X_columns.append('essay')
X_columns.append('project_title')
print('final columns used in input data are: ', X_columns)
```

```
final columns used in input data are:  ['teacher_prefix', 'school_state', 'project_grade_
category', 'summary_numeric_bool', 'teacher_number_of_previously_posted_projects', 'clean
_categories', 'clean_subcategories', 'price', 'quantity', 'essay', 'project_title']
```

2.2 Make Data Model Ready: encoding numerical, categorical features

In [59]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# make sure you featurize train and test data separatly

# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

numerical columns

- `teacher_number_of_previously_posted_projects`
- `price`
- `quantity`

Leaving `summary_numeric_bool` as it is because it only has 0's and 1's in it.

categorical columns

- `teacher_prefix`
- `school_state`
- `project_grade_category`
- `clean_categories`
- `clean_subcategories`

In [60]:
```
X_train = X
```

Normalizing teacher_number_of_previously_posted_projects column

In [61]:
```
warnings.filterwarnings("ignore")
# Code took from original Code provided.
scaler = StandardScaler()
scaler.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1))
print(f"Mean : {scaler.mean_[0]}, Standard deviation : {np.sqrt(scaler.var_[0])}")
```

```
Mean : 11.22942, Standard deviation : 27.96735572884215
```

In [62]:
```
warnings.filterwarnings("ignore")
X_train_tnppp_norm = scaler.transform(X_train['teacher_number_of_previously_posted_projects
```

Normalizing price column

In [63]:
```
# Code took from original Code provided.
scaler = StandardScaler()
scaler.fit(X_train['price'].values.reshape(-1,1))
print(f"Mean : {scaler.mean_[0]}, Standard deviation : {np.sqrt(scaler.var_[0])}")
```

```
Mean : 295.5700088, Standard deviation : 355.4632875695828
```

In [64]:
```
X_train_price_norm = scaler.transform(X_train['price'].values.reshape(-1,1))
```

Normalizing quantity column

In [65]:
```
warnings.filterwarnings("ignore")
# Code took from original Code provided.
scaler = StandardScaler()
scaler.fit(X_train['quantity'].values.reshape(-1,1))
print(f"Mean : {scaler.mean_[0]}, Standard deviation : {np.sqrt(scaler.var_[0])}")
```

```
Mean : 17.1505, Standard deviation : 27.076298302205196
```

In [66]:
```
warnings.filterwarnings("ignore")
X_train_quant_norm = scaler.transform(X_train['quantity'].values.reshape(-1,1))
```

Using a array to store column names data to use at last when interpreting the model

In [67]:
```
# when combining the input matrix the order of columns is same as cat_num_columns
cat_num_columns = ['previously_posted_projects', 'price', 'quantity', 'summary_numeric_bool
```

Encoding teacher_prefix column

In [68]:
```
# Code took from SAMPLE_SOLUTION notebook.
vectorizer = CountVectorizer()
vectorizer.fit(X_train['teacher_prefix'].values)
print(vectorizer.get_feature_names())
```

```
['dr', 'mr', 'mrs', 'ms', 'teacher']
```

In [69]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_prefix_ohe = vectorizer.transform(X_train['teacher_prefix'].values)

print(X_train_prefix_ohe.shape)
```

```
(50000, 5)
```

In [70]:
```
cat_num_columns.extend(['prefix_'+i for i in vectorizer.get_feature_names()])
```

Encoding school_state column

In [71]:
```
# Code took from SAMPLE_SOLUTION notebook.
vectorizer = CountVectorizer()
vectorizer.fit(X_train['school_state'].values)
print(vectorizer.get_feature_names())
```

```
['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi', 'ia', 'id', 'i
l', 'in', 'ks', 'ky', 'la', 'ma', 'md', 'me', 'mi', 'mn', 'mo', 'ms', 'mt', 'nc', 'nd',
'ne', 'nh', 'nj', 'nm', 'nv', 'ny', 'oh', 'ok', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx',
'ut', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
```

In [72]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_school_ohe = vectorizer.transform(X_train['school_state'].values)

print(X_train_school_ohe.shape)
```

```
(50000, 51)
```

In [73]:
```
cat_num_columns.extend(['state_'+i for i in vectorizer.get_feature_names()])
print(len(cat_num_columns))
```

```
60
```

Encoding project_grade_category column

In [74]:
```
# Code took from original Code provided.
grades = X_train['project_grade_category'].unique()
vectorizer = CountVectorizer(vocabulary=list(grades), lowercase=False, binary=True)
vectorizer.fit(X_train['project_grade_category'].values)
print(vectorizer.get_feature_names())
```

```
['Grades PreK-2', 'Grades 9-12', 'Grades 3-5', 'Grades 6-8']
```

In [75]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_grade_ohe = vectorizer.transform(X_train['project_grade_category'].values)

print(X_train_grade_ohe.shape)
```

```
(50000, 4)
```

In [76]:
```
cat_num_columns.extend(vectorizer.get_feature_names())
print(len(cat_num_columns))
```

```
64
```

Encoding clean_categories column

In [77]:
```
# Code took from original Code provided.
vectorizer = CountVectorizer(vocabulary=list(sorted_cat_dict.keys()), lowercase=False, bina
vectorizer.fit(X_train['clean_categories'].values)
print(vectorizer.get_feature_names())
```

```
['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning', 'SpecialNeed
s', 'Health_Sports', 'Math_Science', 'Literacy_Language']
```

In [78]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_categ_ohe = vectorizer.transform(X_train['clean_categories'].values)

print(X_train_categ_ohe.shape)
```

```
(50000, 9)
```

In [79]:
```
cat_num_columns.extend(['categ_'+i for i in vectorizer.get_feature_names()])
print(len(cat_num_columns))
```

```
73
```

Encoding clean_subcategories column

In [80]:
```
# Code took from original Code provided.
vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowercase=False,
vectorizer.fit(X_train['clean_subcategories'].values)
print(vectorizer.get_feature_names())
```

```
['Economics', 'CommunityService', 'FinancialLiteracy', 'ParentInvolvement', 'Extracurricu
lar', 'Civics_Government', 'ForeignLanguages', 'NutritionEducation', 'Warmth', 'Care_Hung
er', 'PerformingArts', 'SocialSciences', 'CharacterEducation', 'TeamSports', 'Other', 'Co
llege_CareerPrep', 'Music', 'History_Geography', 'ESL', 'Health_LifeScience', 'EarlyDevel
opment', 'Gym_Fitness', 'EnvironmentalScience', 'VisualArts', 'Health_Wellness', 'Applied
Sciences', 'SpecialNeeds', 'Literature_Writing', 'Mathematics', 'Literacy']
```

In [81]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_subcat_ohe = vectorizer.transform(X_train['clean_subcategories'].values)

print(X_train_subcat_ohe.shape)
```

```
(50000, 30)
```

In [82]:
```
cat_num_columns.extend(['subcateg_'+i for i in vectorizer.get_feature_names()])
print(len(cat_num_columns))
```

103

Scaling numerical features for better results

In [83]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(X_train_tnppp_norm)

X_train_tnppp_norm = scaler.transform(X_train_tnppp_norm)
```

In [84]:
```
scaler = MinMaxScaler()
scaler.fit(X_train_price_norm)

X_train_price_norm = scaler.transform(X_train_price_norm)
```

In [85]:
```
scaler = MinMaxScaler()
scaler.fit(X_train_quant_norm)

X_train_quant_norm = scaler.transform(X_train_quant_norm)
```

Combining categorical and numerical data for further use.

In [86]:
```
from scipy.sparse import hstack
cat_num_train = hstack((X_train_tnppp_norm, X_train_price_norm, X_train_quant_norm,\
                        np.array(X_train['summary_numeric_bool']).reshape(-1, 1),\
                        X_train_prefix_ohe, X_train_grade_ohe, X_train_school_ohe, X_train_
```

In [87]:
```
print(cat_num_train.shape)
```

```
(50000, 103)
```

In [88]:
```
print(len(cat_num_columns))
```

```
103
```

2.3 Make Data Model Ready: encoding eassay, and project_title

In [89]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# make sure you featurize train and test data separatly

# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Converting `essay` column to vector using TFIDF Vectorizer.

In [90]:
```
# Code took from original Code provided.
vectorizer = TfidfVectorizer(min_df=5, max_features=50000)
vectorizer.fit(X_train['essay'].values)
print(len(vectorizer.get_feature_names()))
```

```
16404
```

In [91]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_essay_tfidf = vectorizer.transform(X_train['essay'].values)

print(X_train_essay_tfidf.shape)
```

```
(50000, 16404)
```

In [92]:
```
essay_tfidf_columns = ['essay_'+i for i in vectorizer.get_feature_names()]
print(len(essay_tfidf_columns))
```

```
16404
```

Converting `project_title` column to vector using TFIDF Vectorizer.

In [93]:
```
# Code took from original Code provided.
vectorizer = TfidfVectorizer(min_df=3, max_features=10000)
vectorizer.fit(X_train['project_title'].values)
print(len(vectorizer.get_feature_names()))
```

```
4582
```

In [94]:
```
# Code took from SAMPLE_SOLUTION notebook.
X_train_title_tfidf = vectorizer.transform(X_train['project_title'].values)

print(X_train_title_tfidf.shape)
```

```
(50000, 4582)
```

In [95]:
```
title_tfidf_columns = ['title_'+i for i in vectorizer.get_feature_names()]
print(len(title_tfidf_columns))
```

```
4582
```

Joining processed `essay` and `project_title` arrays with categorical and numerical data to form matrix

In [96]:
```
tfidf_train = hstack((cat_num_train, X_train_essay_tfidf, X_train_title_tfidf)).tocsr()
print(tfidf_train.shape)
```

```
(50000, 21089)
```

In [97]:
```
tfidf_columns = cat_num_columns + essay_tfidf_columns + title_tfidf_columns
print(len(tfidf_columns))
```

```
21089
```

2.4 Dimensionality Reduction on the selected features

In [98]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Using SelectKBest for dimentionality Reduction

In [99]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

In [100]:
```
kbest = SelectKBest(chi2, k=5000)
tfidf_matrix = kbest.fit_transform(tfidf_train, y)

print(tfidf_matrix.shape)
```

```
(50000, 5000)
```

In [101]:
```
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
```

2.5 Apply Kmeans

In [102]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Function to create wordclouds given labels and number of clusters

In [103]:
```
from wordcloud import WordCloud, STOPWORDS
from IPython.display import Markdown, display

def wordclouds(labels, k, n, shape):
    fig = plt.figure(figsize = (shape[1]*6, shape[0]*6), facecolor = None)
    for l in range(k):
        inds = list(filter(lambda i: labels[i]==l, range(n)))
        ess = project_data['essay'][inds]
        concEss = ess.str.cat(sep=' ')
        wordcloud = WordCloud(width = 800, height = 800, background_color ='white', stopwor
                min_font_size = 10).generate(concEss)
        ax = fig.add_subplot(shape[0], shape[1], l+1)
        ax.imshow(wordcloud)
        ax.axis("off")
#         ax.tight_layout(pad = 0)
        ax.set_title(f"For Label: {l}", fontsize=18)
    plt.show()
```

In [104]:
```
k_s = [2, 3, 5, 8, 10]
scores = []
kmeans_models = {}
for k in k_s:
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(tfidf_matrix)
    score = kmeans.inertia_
    scores.append(score)
    kmeans_models[k] = kmeans
    print(f"score for k = {k} is: {score}")
```

```
score for k = 2 is: 200245.63959936163
score for k = 3 is: 187713.17398102183
score for k = 5 is: 171536.26395714012
score for k = 8 is: 158087.0658110251
score for k = 10 is: 151435.2718304996
```

Storing all models so that I dont need to train best model again and also use the models at end to print PrettyTable.

Adding k=20 as I observed the inertia value keeps on reducing for higher k values.

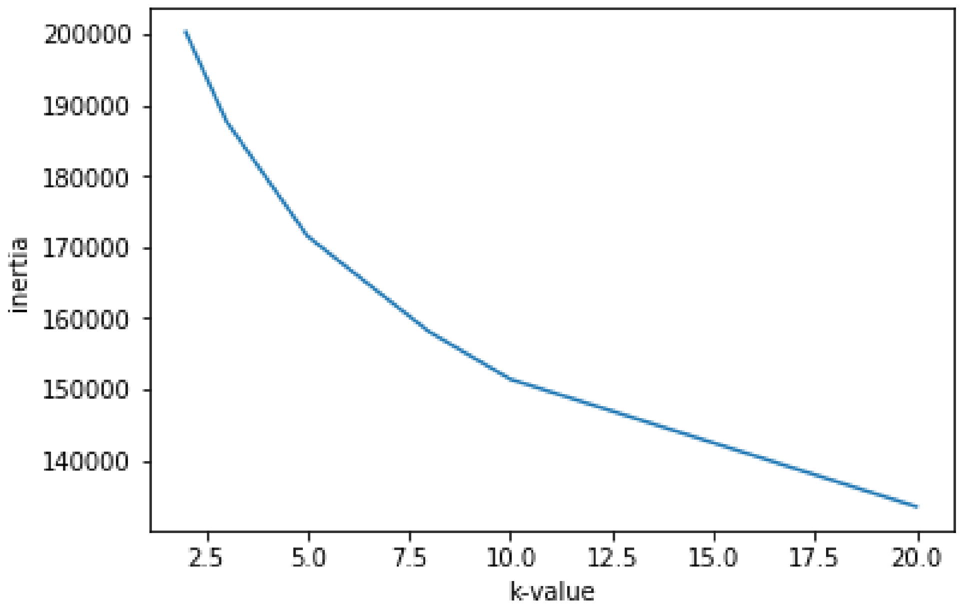
In [105]:
```
k_s.append(20)
kmeans = KMeans(n_clusters=20)
kmeans.fit(tfidf_matrix)
```

Out[105]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=20, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [106]:
```
scores.append(kmeans.inertia_)
kmeans_models[20] = kmeans
print(f"score for k = 20 is: {kmeans.inertia_}")
```

```
score for k = 20 is: 133526.57703210387
```

In [107]:
```
plt.plot(k_s, scores)
plt.xlabel('k-value')
plt.ylabel('inertia')
plt.show()
```

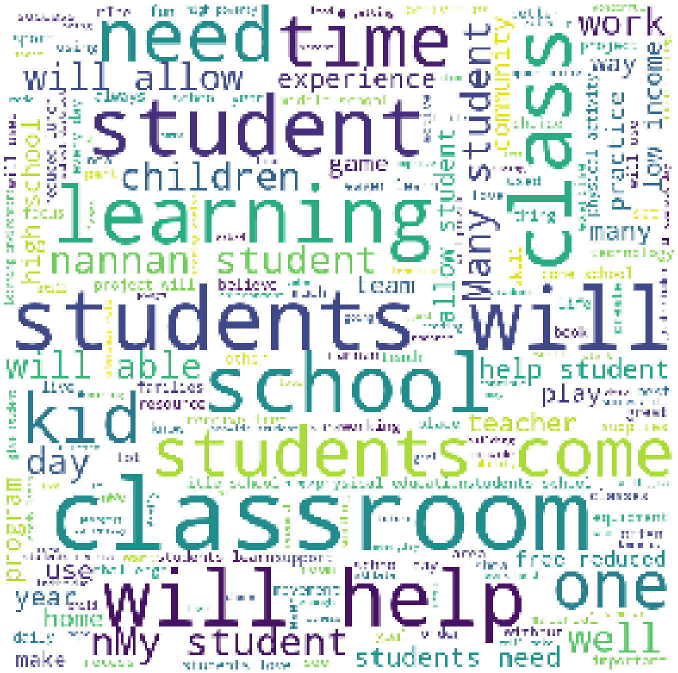


K=10 seems to be the elbow for the above graph. So taking K=10 as our best model and plotting other data.

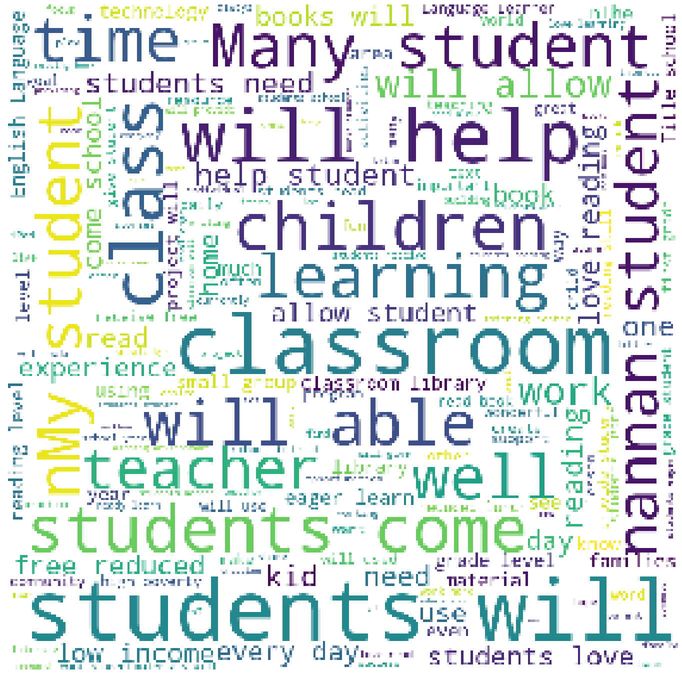
EDA on `Essay` column for different clusters

In [170]:
```
wordclouds(kmeans_models[10].labels_, 10, 50000, shape=(5, 2))
```

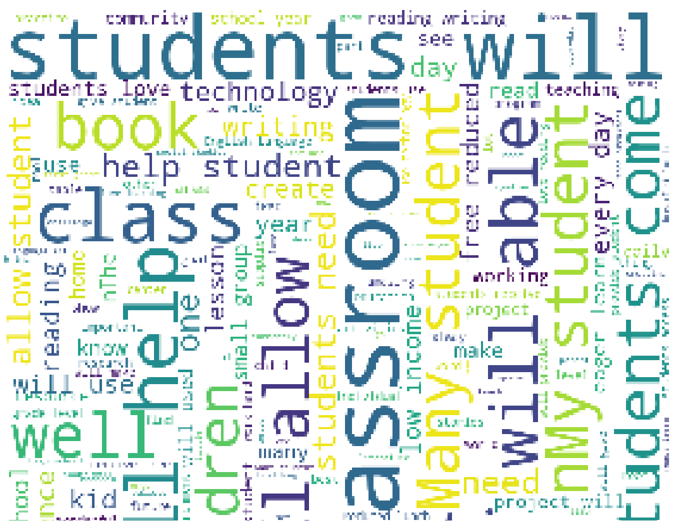
For Label: 0



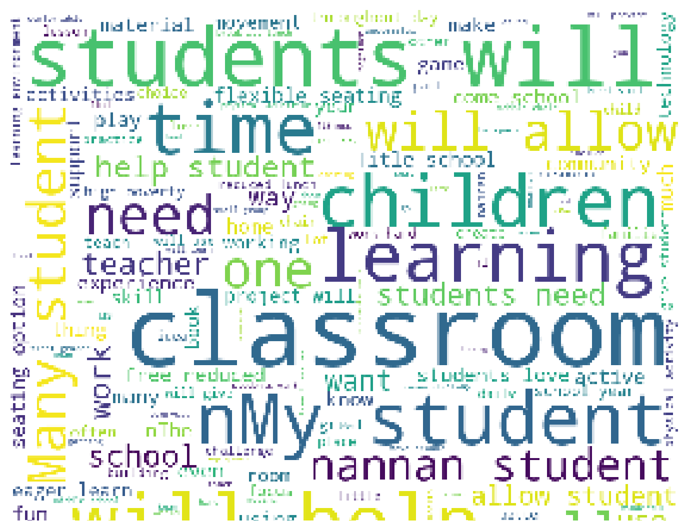
For Label: 1

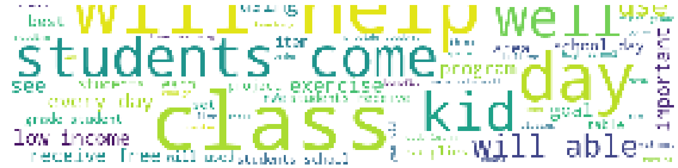


For Label: 2

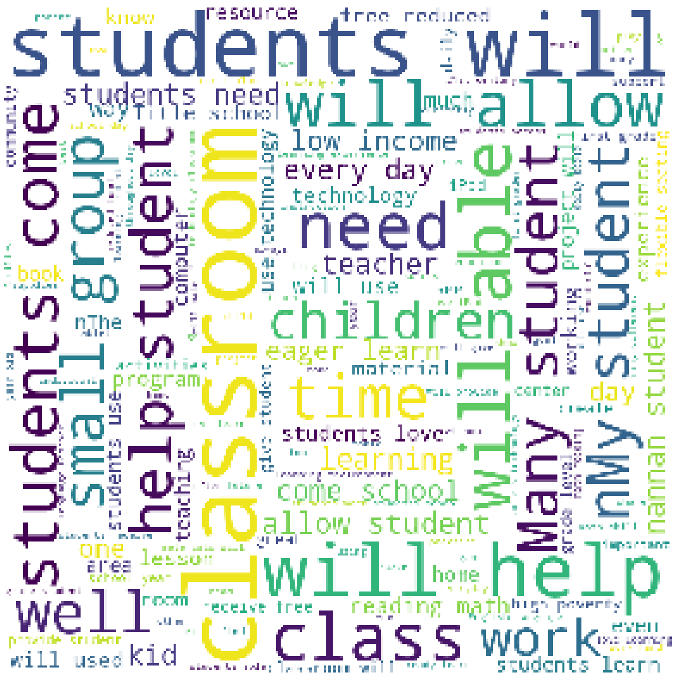


For Label: 3

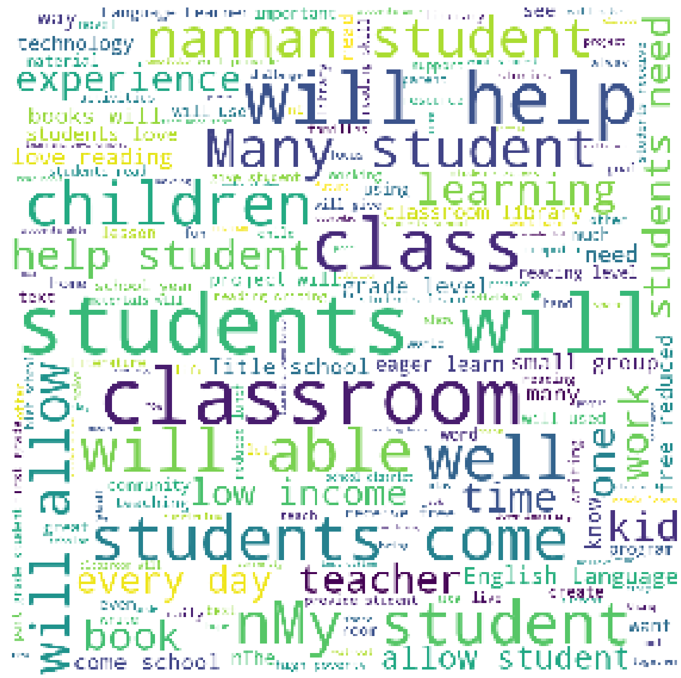




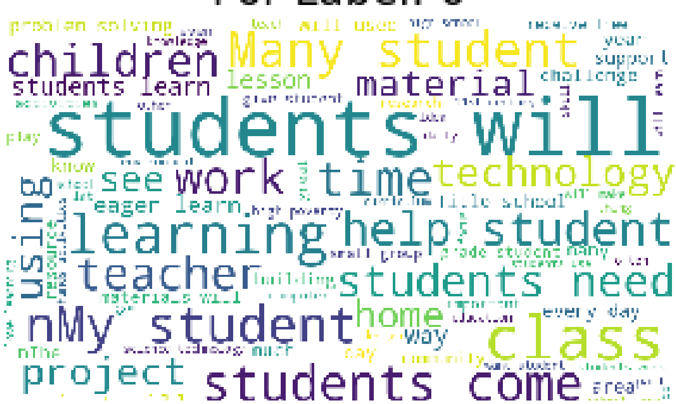
For Label: 4



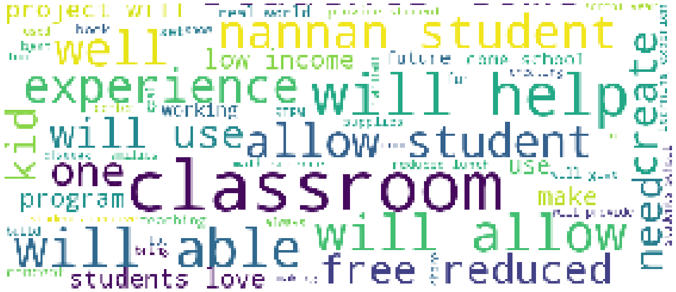
For Label: 5



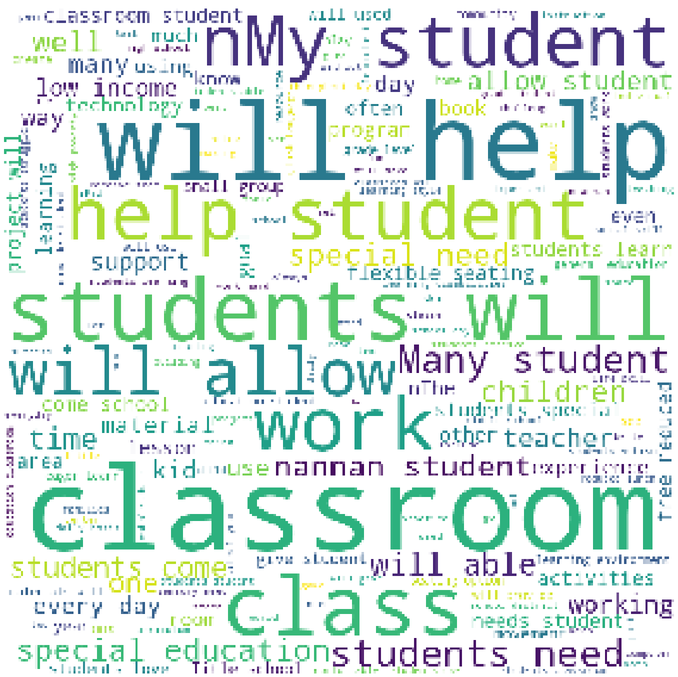
For Label: 6



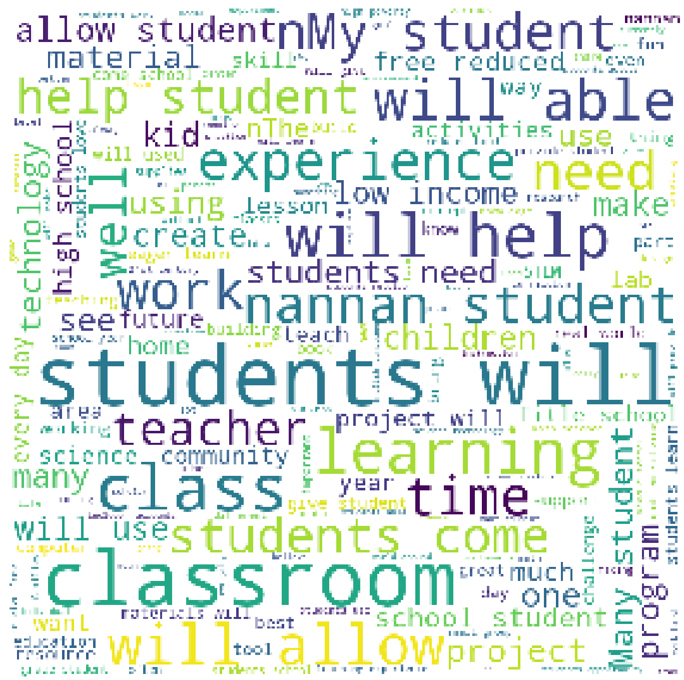
For Label: 7



For Label: 8



For Label: 9



We can see that lot of words are common for all groups. These may be due to their high frequency in the essays. Some of these words are `students` , `classroom` , `will help` . But we can see some clusters have unique words from which we may have some intuition on how these are clustered. such as Word

`music` in cluster_7 and `small group` in cluster_4 and `book` in cluster_2. To find good words, Below code block will give words which are found in high frequency in one cluster and less frequently in others.

In [394]:
```
from tqdm import tqdm_notebook
import copy
```

In [395]:
```
kmeans_essay_counters = [Counter() for i in range(10)]
lab = kmeans_models[10].labels_
all_essays = project_data['essay']
for ind, es in enumerate(tqdm_notebook(all_essays)):
    kmeans_essay_counters[lab[ind]] += Counter(es.split())
```

```
HBox(children=(IntProgress(value=0, max=50000), HTML(value='')))
```

In [396]:
```
print("len of counter keys for each cluster: ")
for i in range(10):
    print(len(kmeans_essay_counters[i].keys()))
```

```
len of counter keys for each cluster:
47395
45723
50979
44402
43523
55758
51674
43143
52272
51301
```

In [397]:
```
kmeans_counter_diff = copy.deepcopy(kmeans_essay_counters)
for i in range(10):
    for j in range(10):
        if i != j:
            kmeans_counter_diff[i] -= kmeans_essay_counters[j]
print("len of words that are highly present in one cluster")
for i in range(10):
    print(len(kmeans_counter_diff[i].keys()))
```

```
len of words that are highly present in one cluster
14286
12365
14914
12542
11275
17758
15828
13601
16121
16258
```

In [401]:
```
kmeans_most_common_sum = np.sum([len(kmeans_counter_diff[i].keys()) for i in range(10)])
print(f'Total most common words for all clusters is: {kmeans_most_common_sum}')
```

```
Total most common words for all clusters is: 144948
```

In [412]:
```
print("Top 10 most common words for each cluster and least common in other clusters: ")
print('='*100)
for i in range(10):
    print(f"Cluster {i}:")
    tpls = kmeans_counter_diff[i].most_common(10)
    print([x[0] for x in tpls])
```

```
Top 10 most common words for each cluster and least common in other clusters:
=========================================================================================
===========
Cluster 0:
['athletes', 'soccer', 'basketball', 'sports', 'baseball', 'sport', 'volleyball', 'studen
t-athletes', 'athletic', 'wrestling']
Cluster 1:
['Chicka', 'Boom', 'Yourself,', 'Ember', 'Fish,', 'mp3', 'Scrabble', 'Flashlight', 'Cran
e', 'nonfiction!']
Cluster 2:
['Kill', 'SCOPE', 'Mockingbird', "authors'", 'Bound', 'revising,', 'Common-Core', 'drafti
ng,', "Wilson's", 'MLA']
Cluster 3:
['Wii', 'nutrient', 'scooters', 'kickball', 'inclement', 'lotion', 'GoNoodle', 'hula', 't
rikes', 'sugary']
Cluster 4:
["Mini's", 'self-manager', 'GLEAM', 'Ellie', 'Starfall', '2-digit', 'Warlick\\r\\n\\r\\nM
y', 'sandpaper', 'ONLINE.', 'Epic!']
Cluster 5:
['Romeo', 'Newcomer', 'Latino/a', 'cowboy', 'cowgirl', 'dystopian', 'book!nannan', 'Lamb
s', 'I-station', 'hardcover']
Cluster 6:
['Dash', 'robots', 'Coding', 'Magformers', 'Pizza', '2016).', 'incubator', "Maker's", 'Oz
obot', '(code.org,']
Cluster 7:
['music', 'art', 'instruments', 'band', 'musical', 'instrument', 'Art', 'music.', 'Musi
c', 'instruments.']
Cluster 8:
```

```
['sensory', 'disabilities', 'Autism', 'autism', 'speech', 'therapy', 'autism,', 'severe',
'Autism.', 'Autism,']
Cluster 9:
['Physics', 'learners.Visual', 'chemistry', 'Algebra', 'DNA', 'calculators', 'physics',
'laboratory', 'Chemistry', 'biology']
```

Now this gives a clear view on how our model is clustered. You can see clearly that cluster_7 is clustered based on music related terms in essay. i.e. if there is anything related to music in the essay that project belongs to cluster_7. And Cluster_0 is clustered based on sports keywords in the essay. And cluster_8 is clustered based on the children disabilities mentioned in essay. Based on this info I will try to construct how our kmeans clustering worked.

Interpretation of 10 Clusters based on the info I got above.

- **Cluster 0: Sports Related Projects**
- **Cluster 1: Playing Materials (like Scrabble, Crane, Flashlight) Projects**
- **Cluster 2: Not Sure about this cluster**
- **Cluster 3: Mixture of Projects related to playing with vehicles, food, and health**
- **Cluster 4: Not Sure about this cluster**
- **Cluster 5: Mixture of Projects related to diverse students, books. etc.**
- **Cluster 6: Projects related to robotics and coding**
- **Cluster 7: Projects related to Music**
- **Cluster 8: Projects which have students with disabilities**
- **Cluster 9: Projects which are related to Science and mathematics (education related projects)**

Kmeans gave high interpretability when coming to how it clustered the data.

Taking average values and distributions of some features to see if they differ from each other.

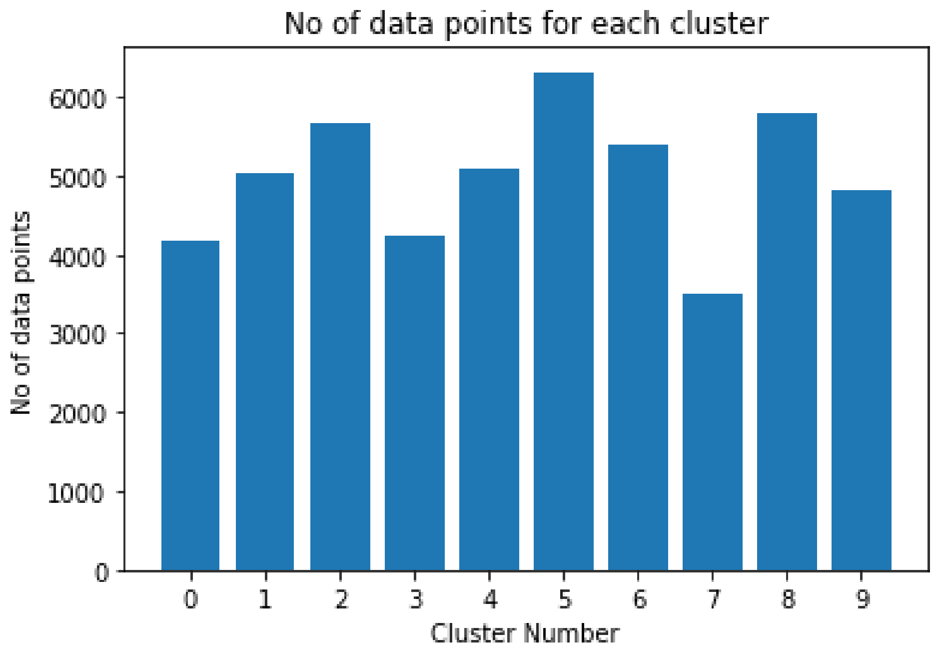
In [171]:
```
kmeans = kmeans_models[10]
```

In [172]:
```
kmeans_data = [project_data.iloc[list(filter(lambda i: kmeans.labels_[i]==j, range(50000)))

for i in range(10):
    print(kmeans_data[i].shape)
```

```
(4187, 21)
(5025, 21)
(5656, 21)
(4248, 21)
(5086, 21)
(6317, 21)
(5394, 21)
(3490, 21)
(5793, 21)
(4804, 21)
```

In [174]:
```
plt.bar(range(10), [len(kmeans_data[i]) for i in range(10)])
plt.title('No of data points for each cluster')
plt.xlabel('Cluster Number')
plt.xticks(range(10), range(10))
plt.ylabel('No of data points')
plt.show()
```



Taking below features to see the distributions of the new clustered data

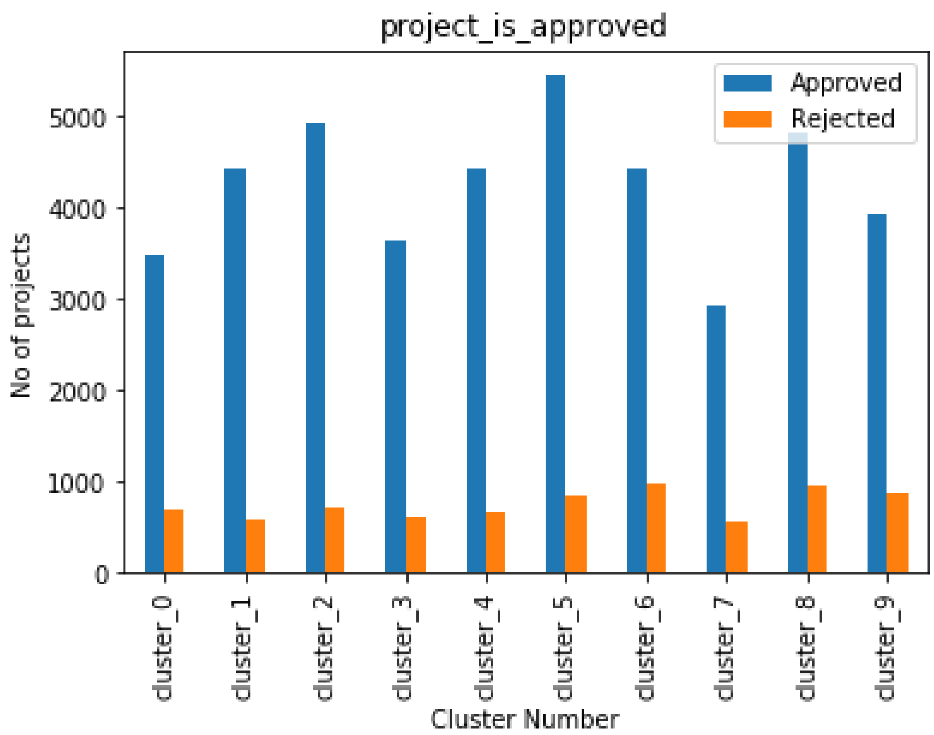
- `project_is_approved`
- `teacher_number_of_previously_posted_projects`
- `price`

EDA on `project_is_approved` column for different clusters

In [175]:
```
appr_value_counts = [kmeans_data[i]['project_is_approved'].value_counts() for i in range(10
indices = ['cluster_'+str(i) for i in range(10)]
tempDF = pd.DataFrame(appr_value_counts, index=indices)
tempDF.columns=['Approved', 'Rejected']
print(tempDF)
```

```
           Approved  Rejected
cluster_0      3498       689
cluster_1      4433       592
cluster_2      4944       712
cluster_3      3631       617
cluster_4      4427       659
cluster_5      5455       862
cluster_6      4422       972
cluster_7      2925       565
cluster_8      4831       962
cluster_9      3923       881
```

In [176]:
```
tempDF.plot.bar()
plt.title('project_is_approved')
plt.ylabel('No of projects')
plt.xlabel('Cluster Number')
plt.show()
```



The above plot shows that our data is not clustered according to the approval of projects as the approved and rejected projects are in same ratio for all clusters. To make sure that is the case we can calculate the ratio values.

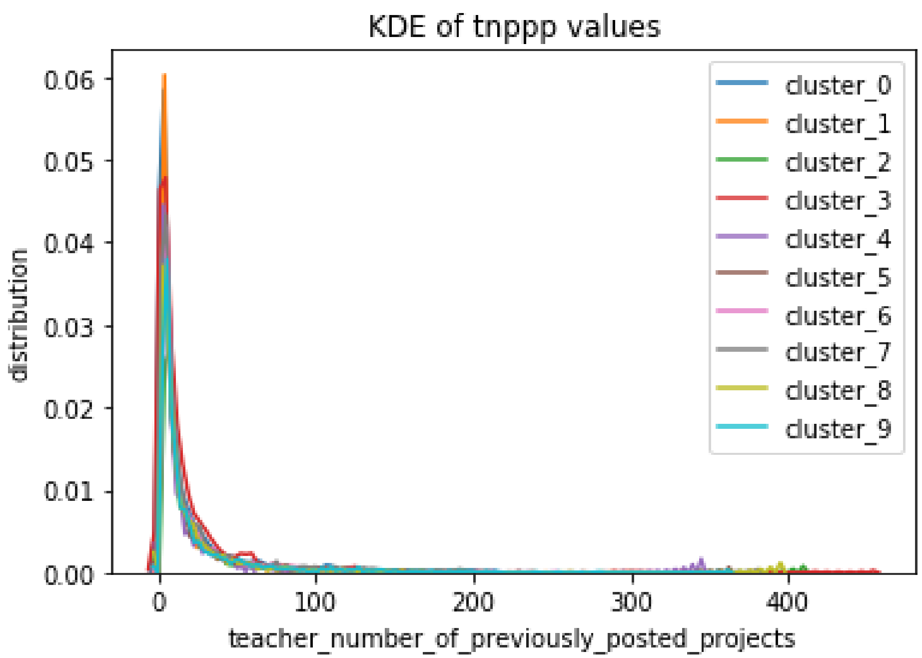
In [179]:
```
app_rej_ratio = tempDF['Approved']/tempDF['Rejected']
print(app_rej_ratio)
```

```
cluster_0    5.076923
cluster_1    7.488176
cluster_2    6.943820
cluster_3    5.884927
cluster_4    6.717754
cluster_5    6.328306
cluster_6    4.549383
cluster_7    5.176991
cluster_8    5.021830
cluster_9    4.452894
dtype: float64
```

The ratios seems to be in range 4.5 and 7.5 which is not a wide range. So, we can conclude that the clustering has no effect on the project being approved or rejected.

EDA on `teacher_number_of_previously_posted_projects` column for different clusters

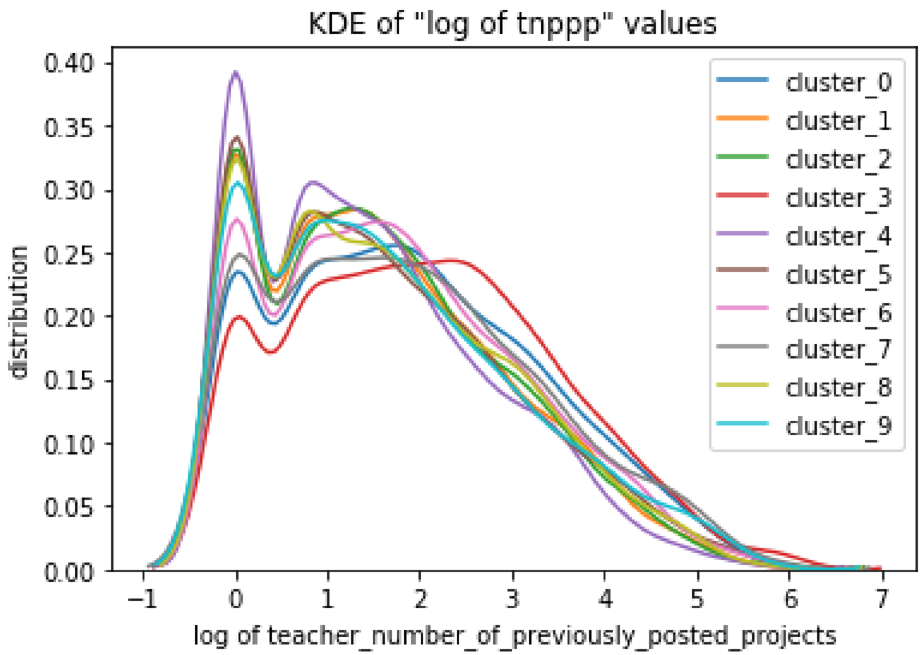
In [188]:
```
for i in range(10):
    sns.kdeplot(kmeans_data[i]['teacher_number_of_previously_posted_projects'], label='clus
plt.title('KDE of tnppp values')
plt.ylabel('distribution')
plt.xlabel('teacher_number_of_previously_posted_projects')
# plt.xlim(-10, 75)
plt.show()
```



The above graph is not that interpretable and the values seems to be following log-normal distribution. So I take log of the column values and get the mean and standard deviation values for the log values in all the clusters.

In [191]:
```
import math
```

In [211]:
```
for i in range(10):
    sns.kdeplot(np.ma.masked_invalid(np.log(kmeans_data[i]['teacher_number_of_previously_po
                  label='cluster_'+str(i))
plt.title('KDE of "log of tnppp" values')
plt.ylabel('distribution')
plt.xlabel('log of teacher_number_of_previously_posted_projects')
# plt.xlim(-10, 75)
plt.show()
```

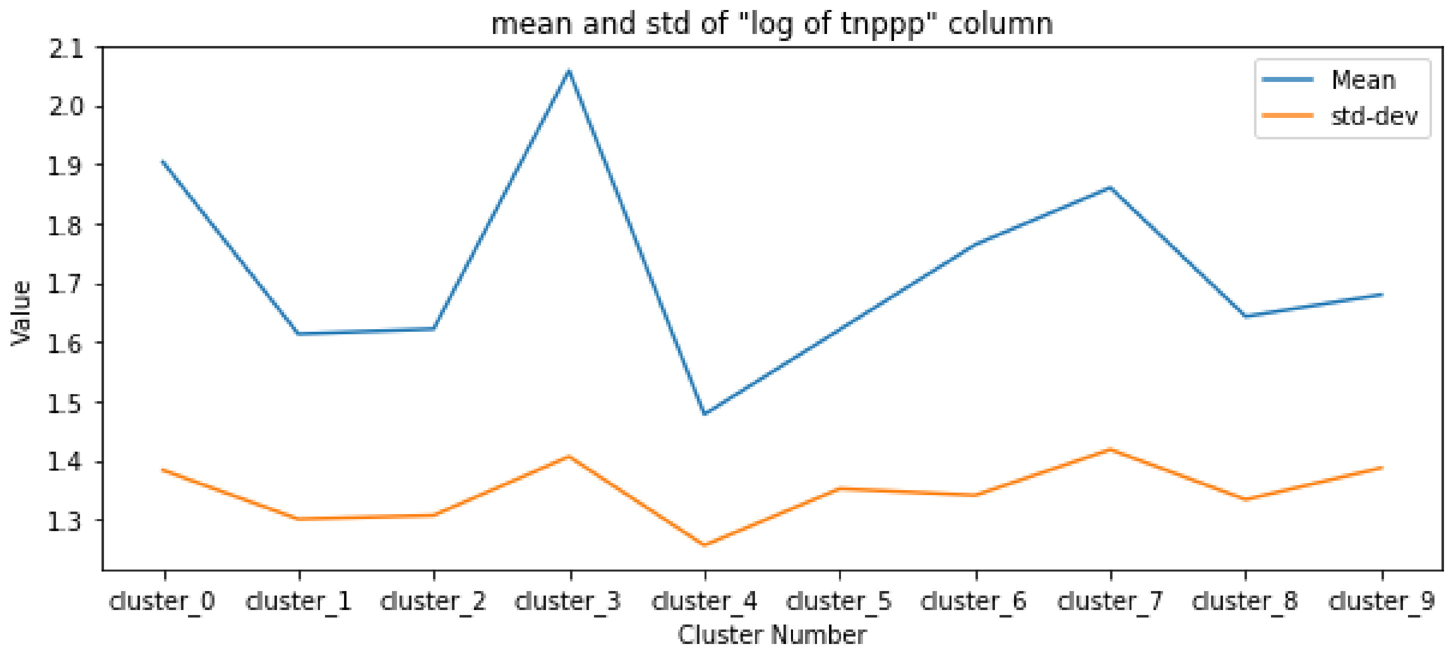


There is not much difference between the values of clusters except for cluster_3 which has slightly different `teacher_number_of_previously_posted_projects` values compared to other clusters. Let us confirm this by taking mean and standard deviation values of this column and plot them

In [273]:
```
tnppp_means = [np.ma.masked_invalid(np.log(kmeans_data[i]['teacher_number_of_previously_pos
               for i in range(10)]
tnppp_stds = [np.ma.masked_invalid(np.log(kmeans_data[i]['teacher_number_of_previously_post
              for i in range(10)]
indices = ['cluster_'+str(i) for i in range(10)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print(tempDF)
```

```
               Mean   std-dev
cluster_0  1.903602  1.383545
cluster_1  1.613550  1.300998
cluster_2  1.622134  1.307345
cluster_3  2.058067  1.406533
cluster_4  1.477773  1.256646
cluster_5  1.620850  1.352346
cluster_6  1.764175  1.341149
cluster_7  1.860558  1.418303
cluster_8  1.642981  1.334047
cluster_9  1.679812  1.387313
```

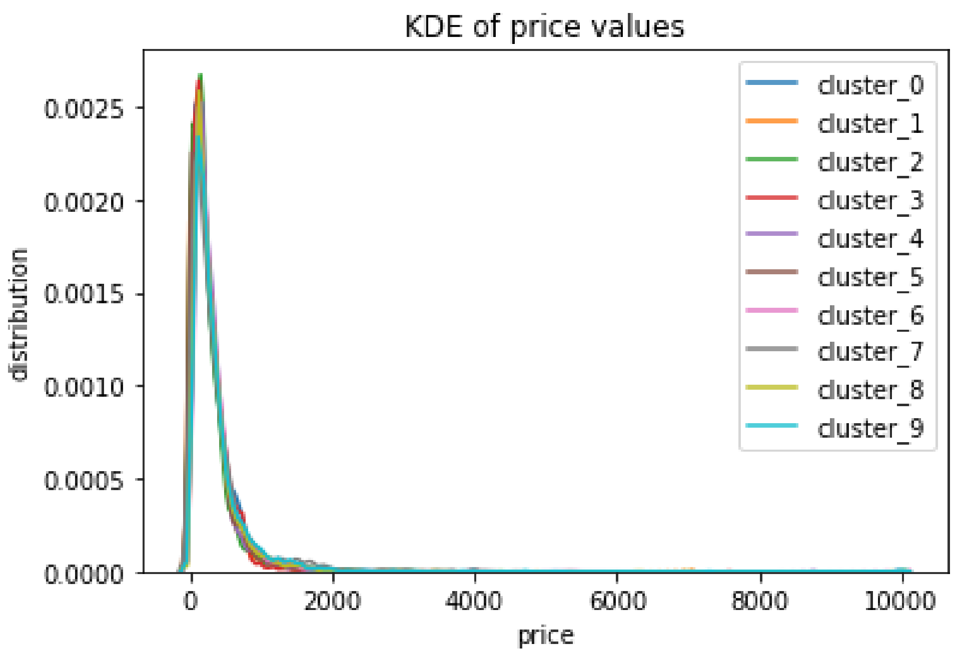
In [275]:
```
tempDF.plot(figsize=(10, 4))
plt.title('mean and std of "log of tnppp" column')
plt.ylabel('Value')
plt.xlabel('Cluster Number')
plt.xticks(range(10), indices)
plt.show()
```



According to `teacher_number_of_previously_posted_projects` column (as per above plot) the clusters are not that different from one-another except for one cluster which have slightly high values of this column. But the overlap from other clusters is high which suggests that our clustering model has no effect on this column as well.

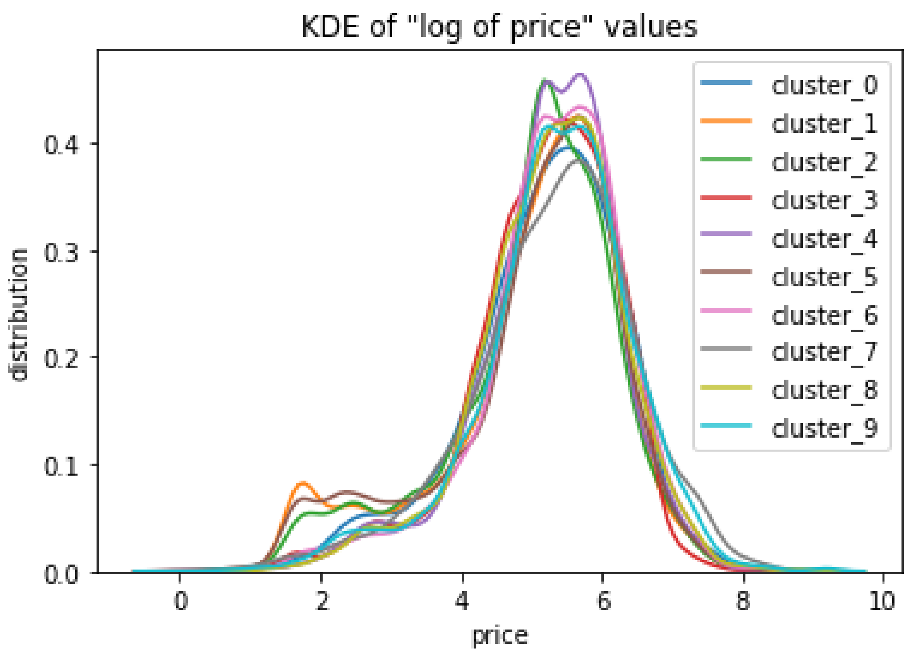
EDA on `price` column for different clusters

In [212]:
```
for i in range(10):
    sns.kdeplot(kmeans_data[i]['price'], label='cluster_'+str(i))
plt.title('KDE of price values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



seems to be log-normal distribution. So taking log values.

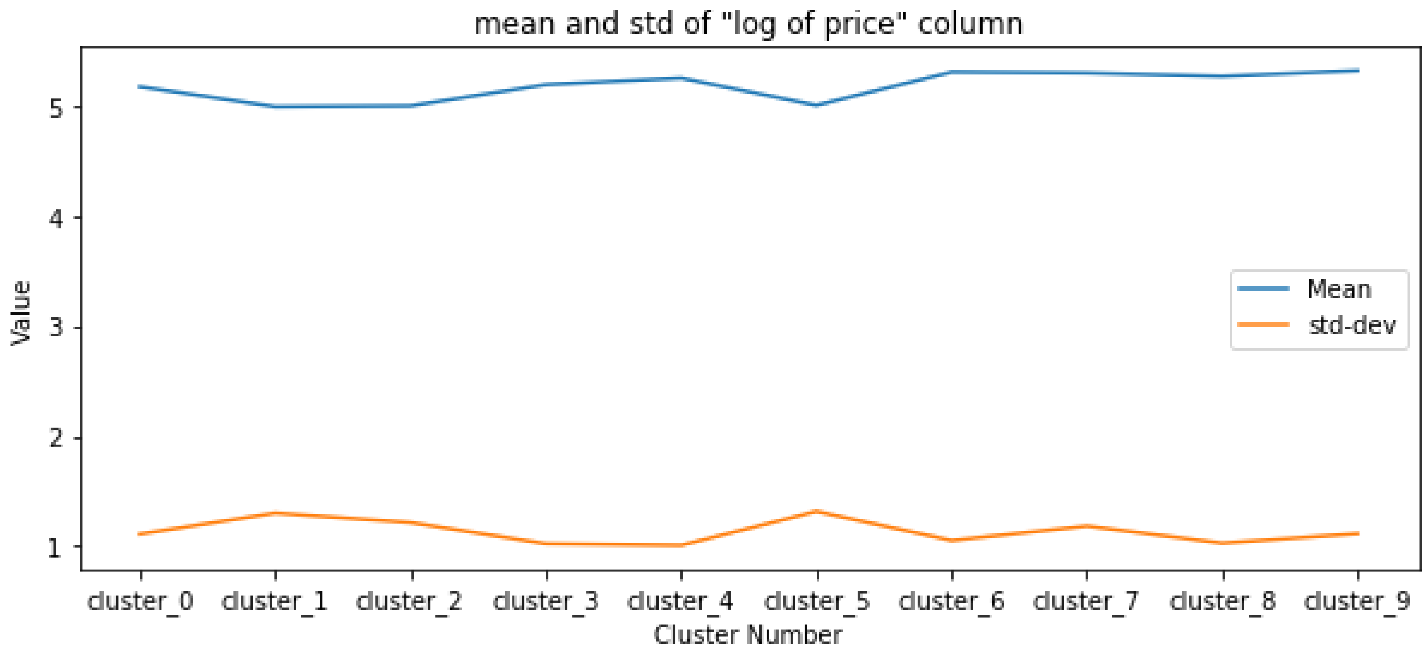
In [213]:
```
for i in range(10):
    sns.kdeplot(np.ma.masked_invalid(np.log(kmeans_data[i]['price'])), label='cluster_'+str
plt.title('KDE of "log of price" values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



In [276]:
```
tnppp_means = [np.ma.masked_invalid(np.log(kmeans_data[i]['price'])).mean() for i in range(
tnppp_stds = [np.ma.masked_invalid(np.log(kmeans_data[i]['price'])).std() for i in range(10
indices = ['cluster_'+str(i) for i in range(10)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print(tempDF)
```

```
               Mean   std-dev
cluster_0  5.172160  1.111222
cluster_1  4.991355  1.301581
cluster_2  4.998652  1.215916
cluster_3  5.190871  1.023301
cluster_4  5.250321  1.009077
cluster_5  5.003846  1.316636
cluster_6  5.305237  1.053139
cluster_7  5.297122  1.183745
cluster_8  5.267095  1.028521
cluster_9  5.318590  1.114761
```

In [277]:
```
tempDF.plot(figsize=(10, 4))
plt.title('mean and std of "log of price" column')
plt.ylabel('Value')
plt.xlabel('Cluster Number')
plt.xticks(range(10), indices)
plt.show()
```



There is no difference between the price values for clusters. This can be seen in the kdeplot as well. So our data is not clustered according to price values.

These above columns didnt show any difference which means our clustering is done mainly based on essay data. which make sense as lot of our columns are generated from essay data. This may be true for Agglomerative and DBSCAN models also.

In [121]:
```
from tqdm import tqdm_notebook
```

In [122]:
```
# from collections import Counter

# word_count_kmeans = ['', '']
# word_count_kmeans[0] = Counter()
# word_count_kmeans[1] = Counter()

# for i in tqdm_notebook(range(20000)):
#     ess = project_data.iloc[i]['essay'].lower()
#     temp_count = Counter(ess.split())
#     word_count_kmeans[kmeans.labels_[i]] = word_count_kmeans[kmeans.labels_[i]] + temp_co

# word_count_kmeans[0] = set(map(lambda x: x[0], word_count_kmeans[0].most_common(1000)))
# word_count_kmeans[1] = set(map(lambda x: x[0], word_count_kmeans[1].most_common(1000)))
```

In [123]:
```
# words_diff_0 = word_count_kmeans[0].difference(word_count_kmeans[1])
# words_diff_1 = word_count_kmeans[1].difference(word_count_kmeans[0])

# print(len(words_diff_0))
# print(len(words_diff_1))
```

2.6 Apply AgglomerativeClustering

In [124]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Reducing the dimentions of the data to train Agglomerative Clustering and DBSCAN.

In [125]:
```
tfidf_matrix.shape
```

Out[125]:
```
(50000, 5000)
```

In [126]:
```
kbest = SelectKBest(chi2, k=2000)
small_matrix = kbest.fit_transform(tfidf_matrix, y)
small_matrix = small_matrix[0:20000]
small_matrix = small_matrix.toarray()
print(small_matrix.shape)
```

```
(20000, 2000)
```

Using data with shape (20000, 2000) and taking number of clusters as (2, 5, 8) to do the Agglomerative clustering. And to compare the models we use `silhouette_score` and `davies_bouldin_score` as we dont have centers to calculate inertia

In [127]:
```
from sklearn.metrics import davies_bouldin_score, silhouette_score
```

In [128]:
```
k_s = [2, 5, 8]
silh_scores = []
db_scores = []
aggCluster_models = {}
for k in k_s:
    aggClust = AgglomerativeClustering(n_clusters=k)
    aggClust.fit(small_matrix)
    score = silhouette_score(small_matrix, aggClust.labels_)
    silh_scores.append(score)
    score = davies_bouldin_score(small_matrix, aggClust.labels_)
    db_scores.append(score)
    aggCluster_models[k] = aggClust
    print(f"score for k = {k} is: {score}")
```

```
score for k = 2 is: 2.9795516588859767
score for k = 5 is: 2.7266558900038285
score for k = 8 is: 2.2028455871266823
```

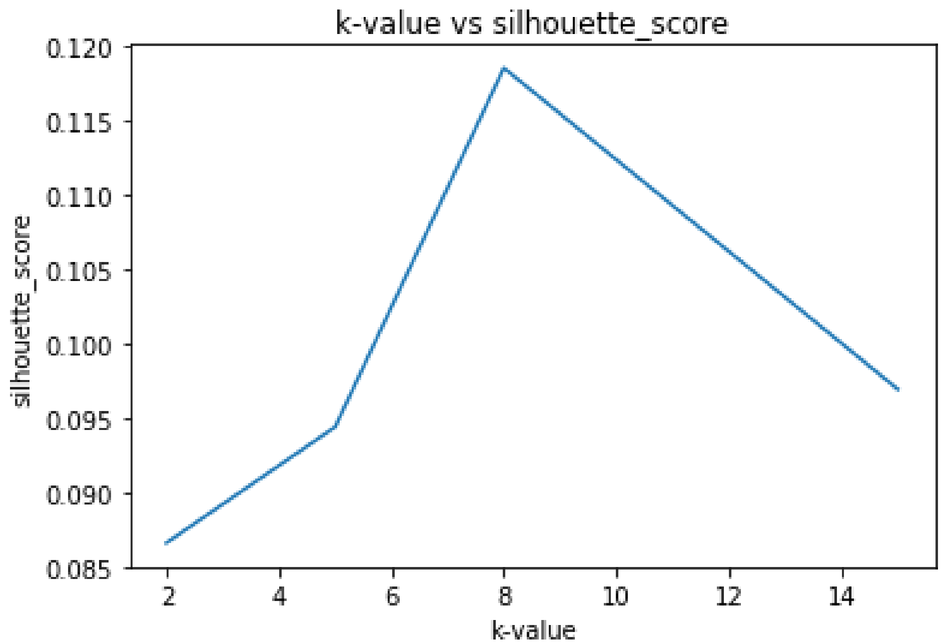
Adding k=15 to the models as the scores are improving with higher k value.

In [129]:
```
k_s.append(15)
aggClust = AgglomerativeClustering(n_clusters=15)
aggClust.fit(small_matrix)
score = silhouette_score(small_matrix, aggClust.labels_)
silh_scores.append(score)
score = davies_bouldin_score(small_matrix, aggClust.labels_)
db_scores.append(score)
aggCluster_models[15] = aggClust
print(f"davies_bouldin_score for k = 15 is: {score}")
```

```
davies_bouldin_score for k = 15 is: 2.395057238788369
```

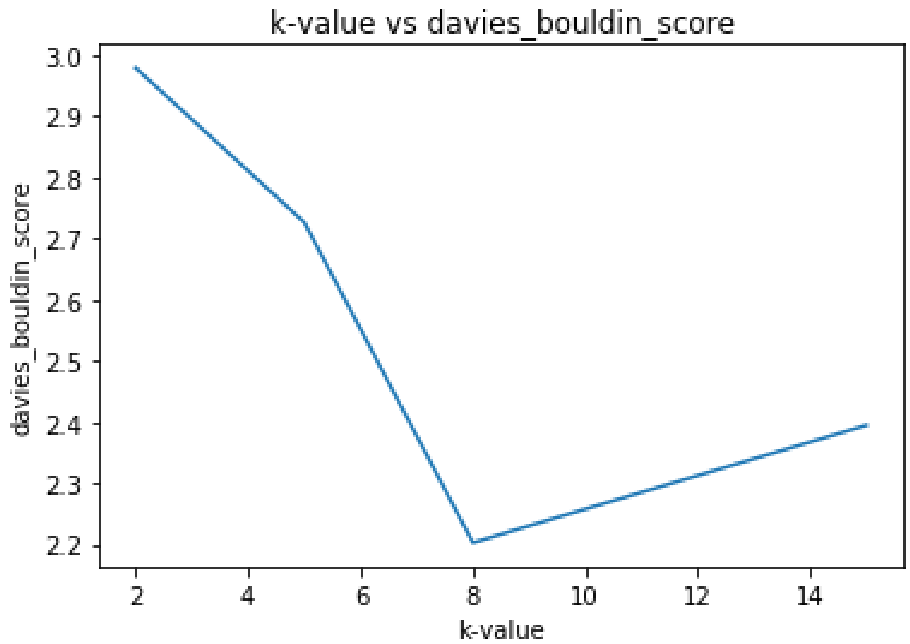
Above scores are `davies_bouldin_score` which means the lower the score the better the model is.

In [130]:
```
plt.plot(k_s, silh_scores)
plt.xlabel('k-value')
plt.ylabel('silhouette_score')
plt.title('k-value vs silhouette_score')
plt.show()
```



The above scores are `silhouette_score` which means the higher the score the better the model. which means the model with k=8 is better than other models.

In [131]:
```
plt.plot(k_s, db_scores)
plt.xlabel('k-value')
plt.ylabel('davies_bouldin_score')
plt.title('k-value vs davies_bouldin_score')
plt.show()
```



The above scores are `davies_bouldin_score` which means the lower the score the better the model. which means the model with k=8 is better than other models.

From first graph it is clear that k=8 is the best k and same k=8 can be seen in second graph as an elbow. So taking k=8 for plotting wordclouds and other data.

We can calculate the inertia for Aggleromative Clustering by creating the average of all points as the cluster centers. These inertia values can be used at end in conlusion prettytable to compare different models.

In [264]:
```
aggClust = aggCluster_models[8]
agg_mat_data = [small_matrix[list(filter(lambda i: aggClust.labels_[i]==j, range(20000)))]
```

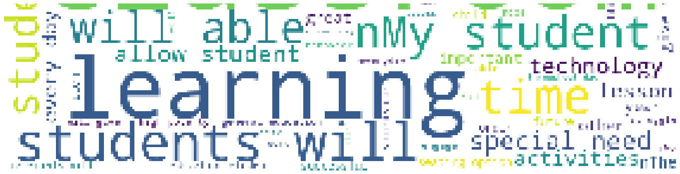
In [265]:
```
agg8_inertia = 0
for i in range(8):
    clus_cent = agg_mat_data[i].mean()
    agg8_inertia += ((agg_mat_data[i] - clus_cent)**2).sum().sum()
```

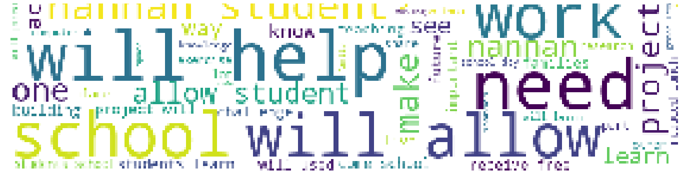
In [266]:
```
print(agg8_inertia)
```

```
94623.82897527562
```

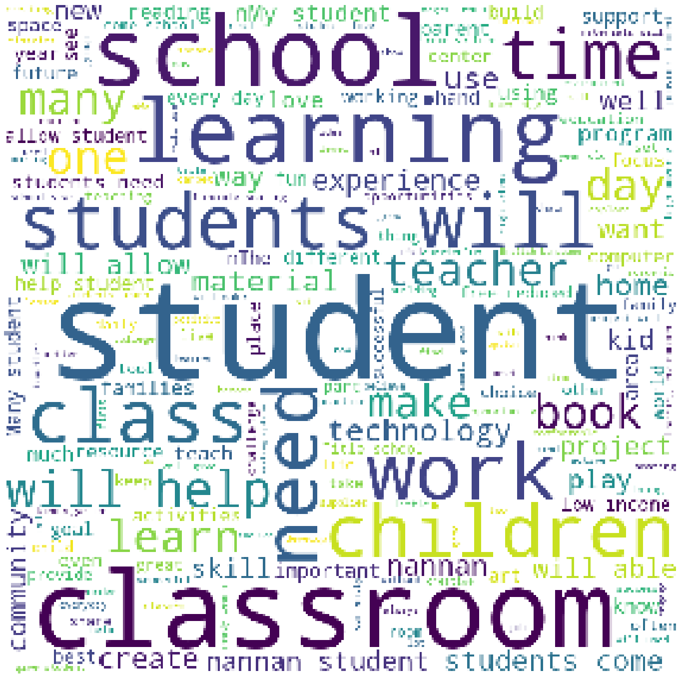
EDA on `Essay` column for different clusters

In [132]:
```
wordclouds(aggCluster_models[8].labels_, 8, 20000, shape=(4, 2))
```

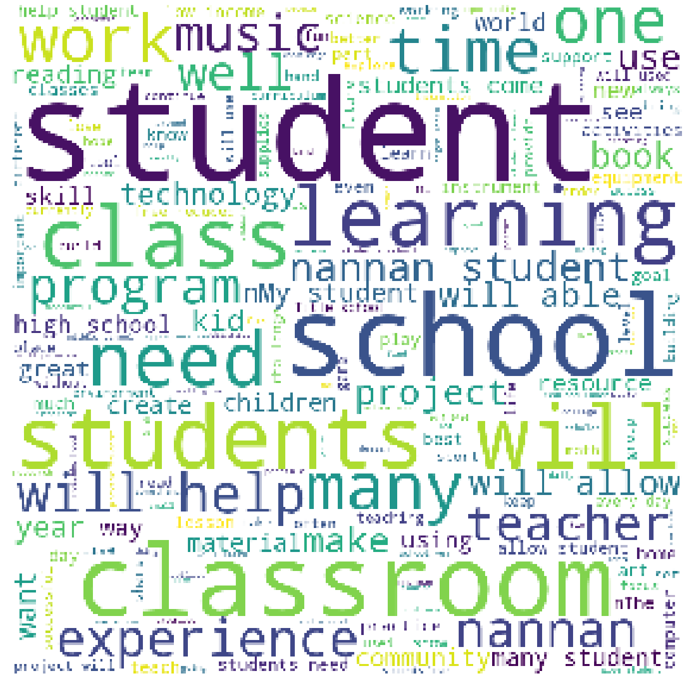




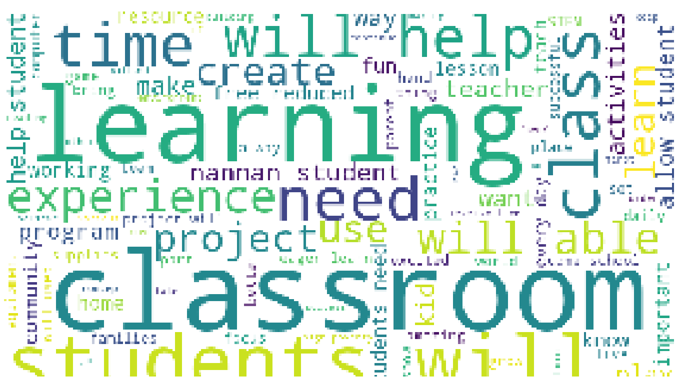
For Label: 4



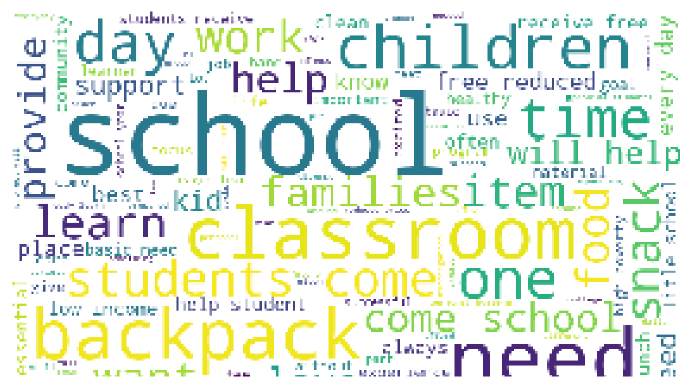
For Label: 5

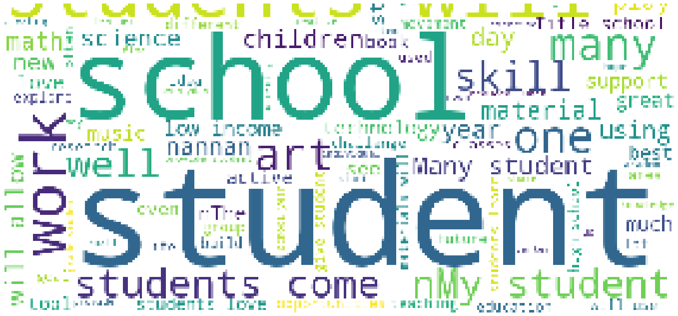


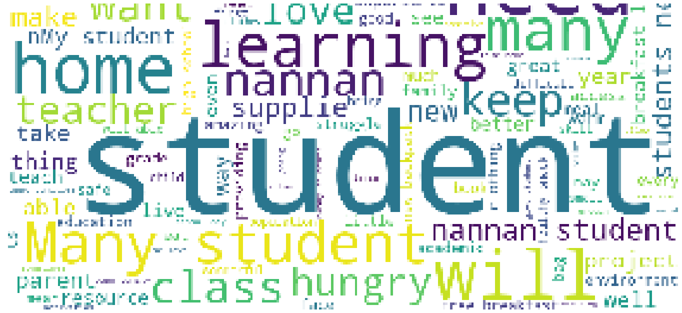
For Label: 6



For Label: 7







We can see that lot of words are common for all 8 groups. These may be due to their high frequency in the essays. Some of these words are `students` , `classroom` , `children` and `learning` . But we can see some clusters have unique words from which we may have some intuition on how these are clustered.

In [398]:
```
agg_essay_counters = [Counter() for i in range(8)]
lab = aggCluster_models[8].labels_
all_essays = project_data['essay'][:20000]
for ind, es in enumerate(tqdm_notebook(all_essays)):
    agg_essay_counters[lab[ind]] += Counter(es.split())
```

```
HBox(children=(IntProgress(value=0, max=20000), HTML(value='')))
```

In [399]:
```
print("len of counter keys for each cluster: ")
for i in range(8):
    print(len(agg_essay_counters[i].keys()))
```

```
len of counter keys for each cluster:
43786
35767
32131
40508
24797
35911
33108
7188
```

In [400]:
```
agg_counter_diff = copy.deepcopy(agg_essay_counters)
for i in range(8):
    for j in range(8):
        if i != j:
            agg_counter_diff[i] -= agg_essay_counters[j]
print("len of words that are highly present in one cluster")
for i in range(8):
    print(len(agg_counter_diff[i].keys()))
```

```
len of words that are highly present in one cluster
17265
11704
10116
14564
5935
12680
10031
956
```

In [414]:
```
agg_most_common_sum = np.sum([len(agg_counter_diff[i].keys()) for i in range(8)])
print(f'Total most common words for all clusters is: {agg_most_common_sum}')
```

```
Total most common words for all clusters is: 83251
```

In [415]:
```
print("Top 10 most common words for each cluster and least common in other clusters: ")
print('='*100)
for i in range(8):
    print(f"Cluster {i}:")
    tpls = agg_counter_diff[i].most_common(10)
    print([x[0] for x in tpls])
```

```
Top 10 most common words for each cluster and least common in other clusters:
==========================================================================================
===========
Cluster 0:
['Boogie', 'reader', 'earbuds', 'novels.', 'boogie', 'Storyworks', 'Newbery', 'containin
g', 'reading!', 'flashlights']
Cluster 1:
['cowboy', 'cowgirl', 'Newcomer', 'Pads', 'Lambs', 'book!nannan', 'SSR', 'Mobile', 'Liter
ature', 'Tank']
Cluster 2:
['sensory', 'disabilities', 'Autism', 'autism', 'speech', 'therapy', 'disabilities.', 'se
vere', 'Autism,', 'disabilities,']
Cluster 3:
['Wii', 'Magformers', 'roller', 'chicks', '3Doodler', 'kit,', 'pedal', 'gardening', 'Pizz
a', 'foldables']
Cluster 4:
['housekeeping', '\\"Comfy', 'Gelli', 'sewing', 'sew,', 'Advancement', 'Determination.',
'Shelly', 'patients', 'cloakroom']
Cluster 5:
['band', 'instruments', 'learners.Visual', 'instrument', 'drums', 'baseball', 'athletes',
'percussion', 'drum', 'ukuleles']
Cluster 6:
['belts', 'CPR', 'dissections.', '‘Move', 'dancers', 'Psychology', "K.'s", 'drumming', 'p
rintmaking', 'soldering']
Cluster 7:
['backpacks', 'hygiene', 'deodorant,', 'soap,', 'deodorant', 'shampoo,', 'socks', 'toothp
aste,', 'backpacks,', 'jackets,']
```

Now this gives a clear view on how our model is clustered. You can see clearly that some clusters (such as Cluster_2 and Cluster_5) are choosen for specific projects

Interpretation of 8 Clusters based on the info I got above.

- **Cluster 0: Projects related to Reading and libraries**
- **Cluster 1: Mixture of projects related to Students, and reading (not so sure about the cluster)**
- **Cluster 2: Projects which have students with disabilities**
- **Cluster 3: Projects which require Toys to the students**
- **Cluster 4: Projects related to housekeeping and sewing arts and etc..**
- **Cluster 5: Projects related to Music instruments and sports (related to extra-curricular activities)**
- **Cluster 6: Mix of projects related to arts (dance printmaking), and sensitive operations (i.e. CPR, dissections, soldering.. not sure about this one)**
- **Cluster 7: Projects which require bags, clothing (jackets, socks), and soap and deoderants**

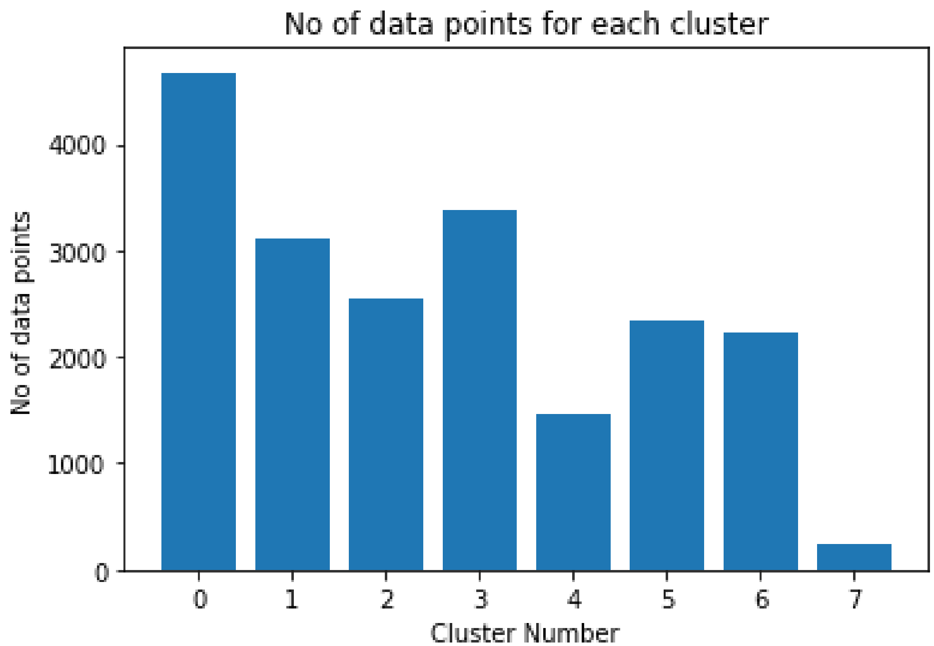
Taking average values and distributions of some features to see if they differ from each other.

In [258]:
```
aggClust = aggCluster_models[8]
aggClust_data = [project_data.iloc[list(filter(lambda i: aggClust.labels_[i]==j, range(2000
```

In [134]:
```
for i in range(8):
    print(aggClust_data[i].shape)
```

```
(4673, 21)
(3100, 21)
(2549, 21)
(3382, 21)
(1469, 21)
(2348, 21)
(2229, 21)
(250, 21)
```

In [135]:
```
plt.bar(range(8), [len(aggClust_data[i]) for i in range(8)])
plt.title('No of data points for each cluster')
plt.xlabel('Cluster Number')
plt.ylabel('No of data points')
plt.show()
```



The data in cluster 7 is very less so we may expect lot different values from other clusters.

Taking below features to see the distributions of the new clustered data

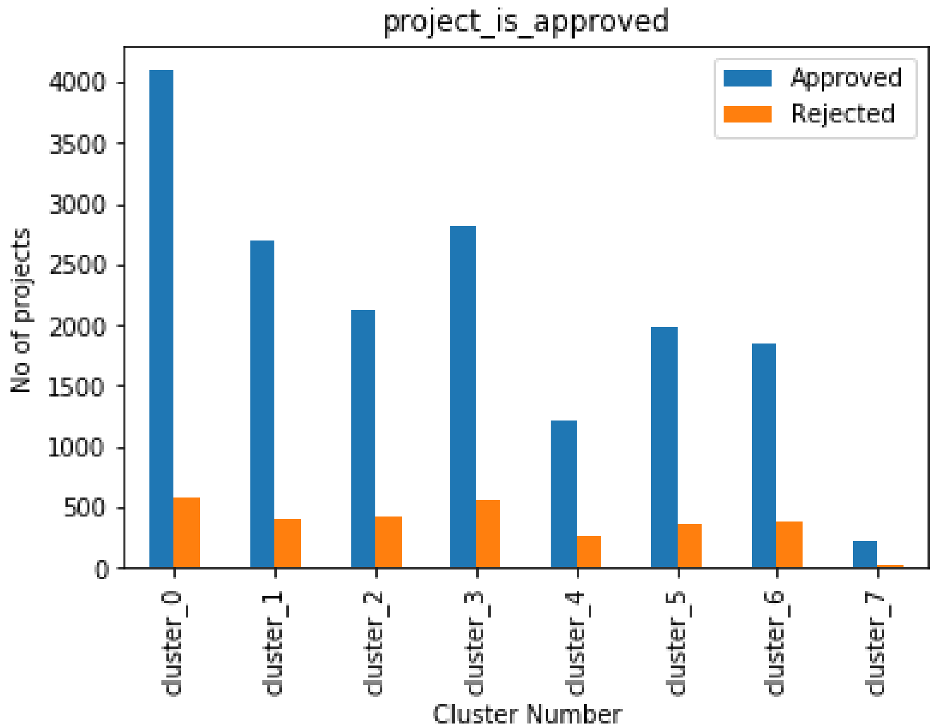
- **`project_is_approved`**
- **`teacher_number_of_previously_posted_projects`**
- **`price`**

EDA on `project_is_approved` column for different clusters

In [136]:
```
appr_value_counts = [aggClust_data[i]['project_is_approved'].value_counts() for i in range(
indices = ['cluster_'+str(i) for i in range(8)]
tempDF = pd.DataFrame(appr_value_counts, index=indices)
tempDF.columns=['Approved', 'Rejected']
print(tempDF)
```

```
           Approved  Rejected
cluster_0      4096       577
cluster_1      2690       410
cluster_2      2131       418
cluster_3      2817       565
cluster_4      1211       258
cluster_5      1992       356
cluster_6      1848       381
cluster_7       233        17
```

In [137]:
```
tempDF.plot.bar()
plt.title('project_is_approved')
plt.ylabel('No of projects')
plt.xlabel('Cluster Number')
plt.show()
```



The above plot shows that our data is not clustered according to the approval of projects as the approved and rejected projects are in same ratio for all clusters. To make sure that is the case we can calculate the ratio values.

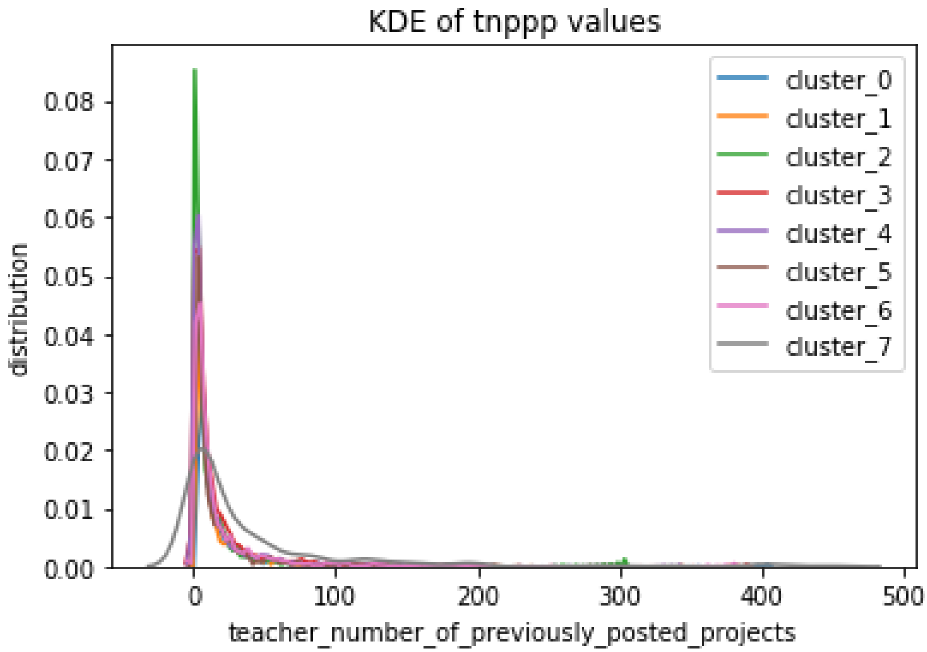
In [138]:
```
tempDF['Approved']/tempDF['Rejected']
```

Out[138]:
```
cluster_0     7.098787
cluster_1     6.560976
cluster_2     5.098086
cluster_3     4.985841
cluster_4     4.693798
cluster_5     5.595506
cluster_6     4.850394
cluster_7    13.705882
dtype: float64
```

The ratios seems to be in range 4.7 and 7.1 (except for cluster_7) which is not a wide range. So, we can conclude that the clustering has no effect on the project being approved or rejected.

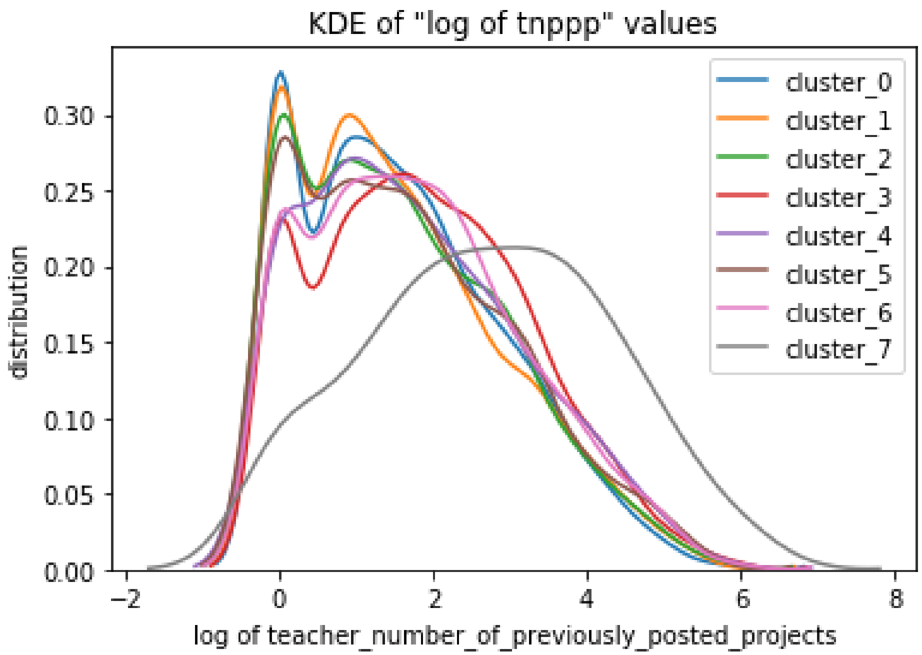
EDA on `teacher_number_of_previously_posted_projects` column for different clusters

In [268]:
```
for i in range(8):
    sns.kdeplot(aggClust_data[i]['teacher_number_of_previously_posted_projects'], label='cl
plt.title('KDE of tnppp values')
plt.ylabel('distribution')
plt.xlabel('teacher_number_of_previously_posted_projects')
# plt.xlim(-10, 60)
plt.show()
```



Taking log of teacher_number_of_previously_posted_projects column as it seems to be log-normal.

In [269]:
```
for i in range(8):
    sns.kdeplot(np.ma.masked_invalid(np.log(aggClust_data[i]['teacher_number_of_previously_
                label='cluster_'+str(i))
plt.title('KDE of "log of tnppp" values')
plt.ylabel('distribution')
plt.xlabel('log of teacher_number_of_previously_posted_projects')
# plt.xlim(-10, 60)
plt.show()
```

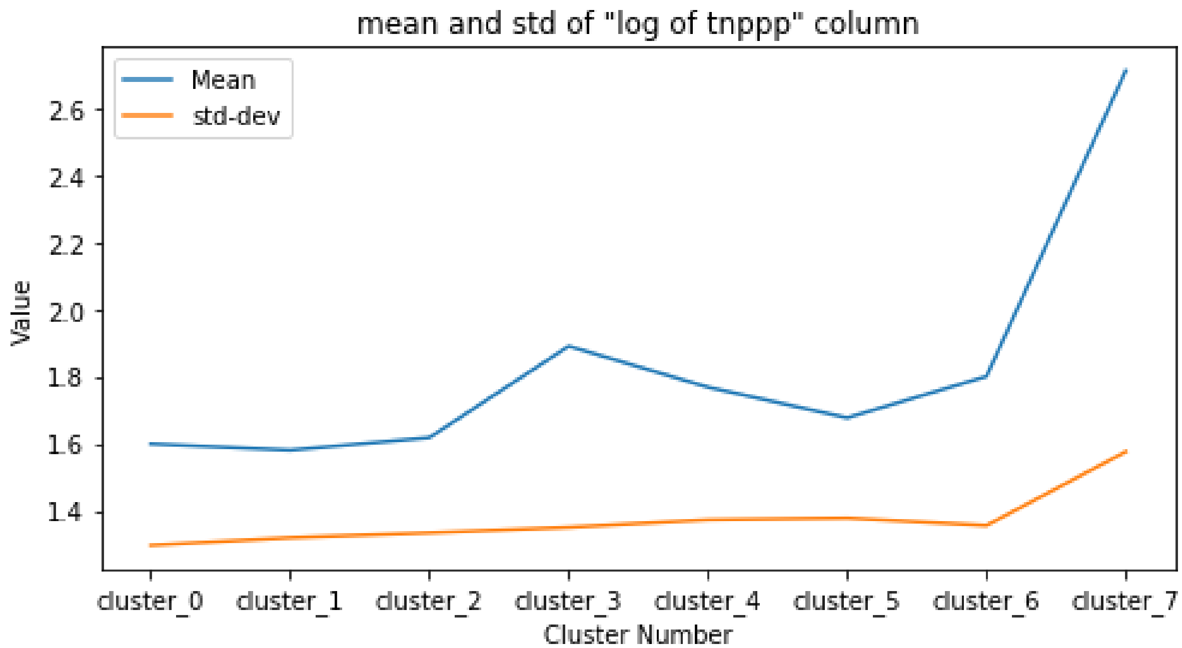


Cluster_3 seems to be different (apart from cluster_7). So taking mean and standard deviation values for this column in all the clusters.

In [270]:
```
tnppp_means = [np.ma.masked_invalid(np.log(aggClust_data[i]['teacher_number_of_previously_p
tnppp_stds = [np.ma.masked_invalid(np.log(aggClust_data[i]['teacher_number_of_previously_po
indices = ['cluster_'+str(i) for i in range(8)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print(tempDF)
```

```
               Mean   std-dev
cluster_0  1.599306  1.297170
cluster_1  1.580585  1.319702
cluster_2  1.617973  1.334303
cluster_3  1.890598  1.350776
cluster_4  1.768192  1.373228
cluster_5  1.677288  1.378174
cluster_6  1.800345  1.356202
cluster_7  2.711283  1.576097
```

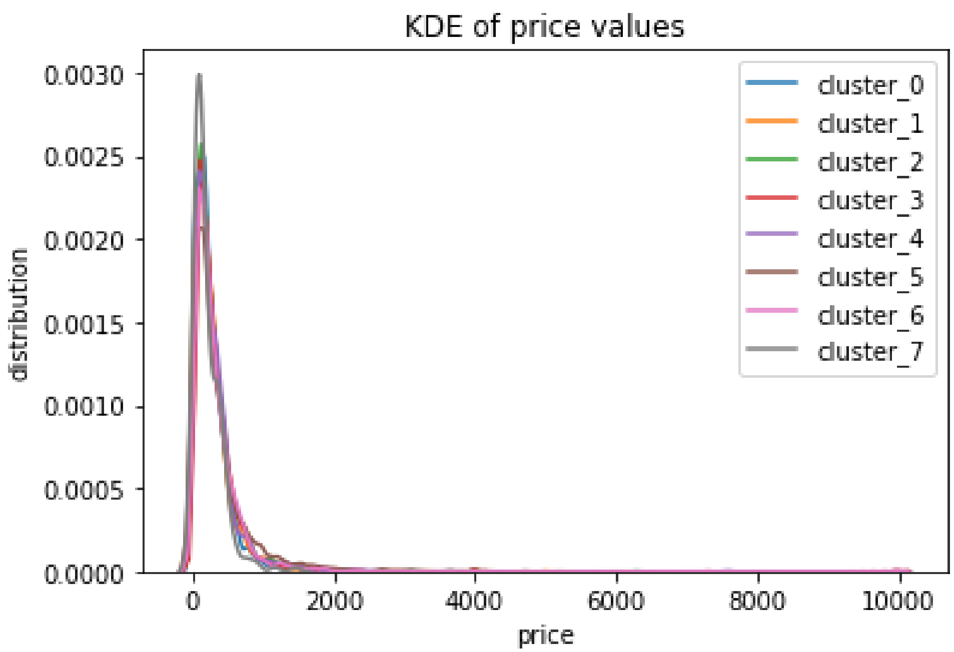
In [271]:
```
tempDF.plot(figsize=(8, 4))
plt.title('mean and std of "log of tnppp" column')
plt.ylabel('Value')
plt.xlabel('Cluster Number')
plt.xticks(range(8), indices)
plt.show()
```



This column is not divided by any of the clusters as you can see all the clusters have almost same mean values (except for cluster_7 as it has less data points this mean, std-dev is expected)

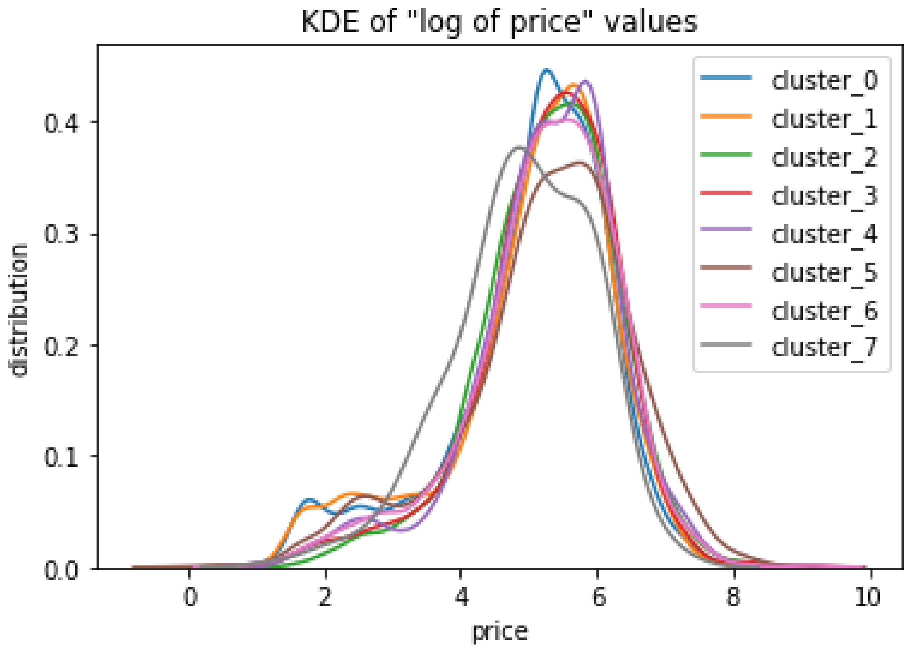
EDA on `price` column for different clusters

In [279]:
```
for i in range(8):
    sns.kdeplot(aggClust_data[i]['price'], label='cluster_'+str(i))
plt.title('KDE of price values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



Applying log to plot price.

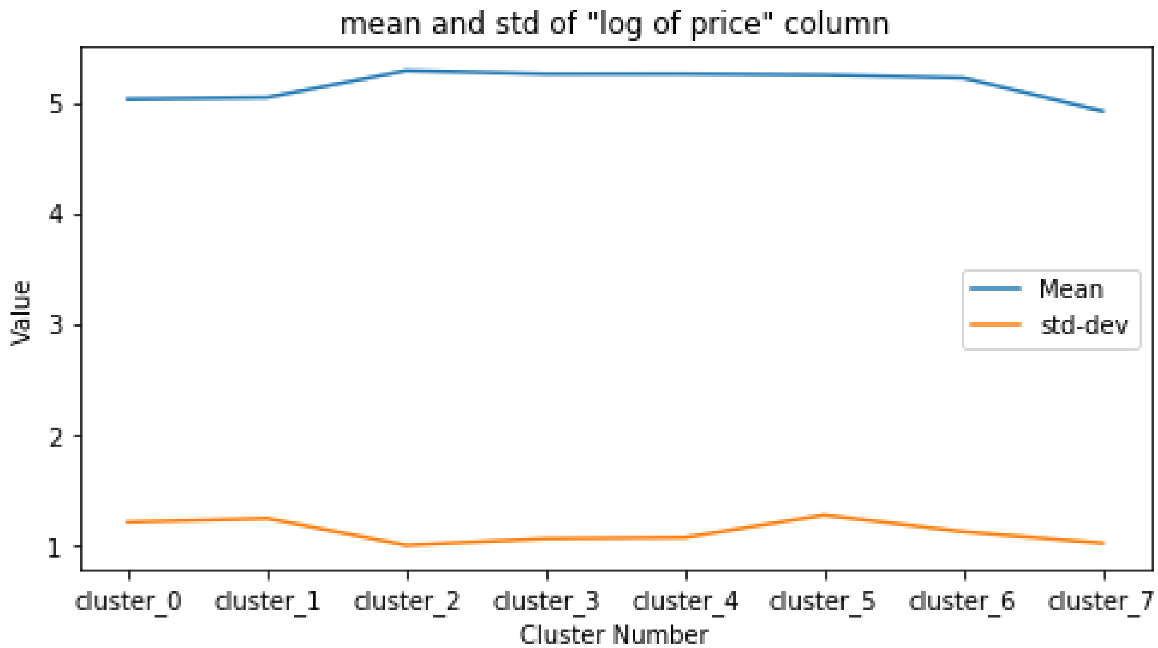
In [280]:
```
for i in range(8):
    sns.kdeplot(np.ma.masked_invalid(np.log(aggClust_data[i]['price'])), label='cluster_'+s
plt.title('KDE of "log of price" values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



In [281]:
```
tnppp_means = [np.ma.masked_invalid(np.log(aggClust_data[i]['price'])).mean() for i in rang
tnppp_stds = [np.ma.masked_invalid(np.log(aggClust_data[i]['price'])).std() for i in range(
indices = ['cluster_'+str(i) for i in range(8)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print(tempDF)
```

```
               Mean   std-dev
cluster_0  5.029477  1.207629
cluster_1  5.043506  1.241439
cluster_2  5.286397  0.997947
cluster_3  5.256561  1.058493
cluster_4  5.257313  1.068656
cluster_5  5.248063  1.271640
cluster_6  5.220311  1.120565
cluster_7  4.921120  1.017054
```

In [282]:
```
tempDF.plot(figsize=(8, 4))
plt.title('mean and std of "log of price" column')
plt.ylabel('Value')
plt.xlabel('Cluster Number')
plt.xticks(range(8), indices)
plt.show()
```



There is no difference between the price values for clusters. This can be seen in the kdeplot So our data is not clustered according to price values.

And this column is also evenly distributed accross the clusters. Showing that again this data is clustered mostly on essays data.

In [145]:
```
# from collections import Counter

# word_count_agg = ['', '', '']
# word_count_agg[0] = Counter()
# word_count_agg[1] = Counter()
# word_count_agg[2] = Counter()

# for i in tqdm_notebook(range(20000)):
#     ess = project_data.iloc[i]['essay'].lower()
#     temp_count = Counter(ess.split())
#     word_count_agg[aggClust3.labels_[i]] = word_count_agg[aggClust3.labels_[i]] + temp_co

# word_count_agg[0] = set(map(lambda x: x[0], word_count_agg[0].most_common(1000)))
```

In [146]:
```
# word_count_agg[1] = set(map(lambda x: x[0], word_count_agg[1].most_common(1000)))
# word_count_agg[2] = set(map(lambda x: x[0], word_count_agg[2].most_common(1000)))
```

In [147]:
```
# words_diff_agg_0 = word_count_agg[0].difference(word_count_agg[1]).difference(word_count_
# words_diff_agg_1 = word_count_agg[1].difference(word_count_agg[0]).difference(word_count_
# words_diff_agg_2 = word_count_agg[2].difference(word_count_agg[1]).difference(word_count_

# print(len(words_diff_agg_0))
# print(len(words_diff_agg_1))
# print(len(words_diff_agg_2))
```

2.7 Apply DBSCAN

In [148]:
```
# please write all the code with proper documentation, and proper titles for each subsectio
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your cod
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
```

Before we take a eps we need to see what is our optimal `minPts` . According to below source I take `minPts = ln(n) = ln(20000) = 9.903 ~= 10` .

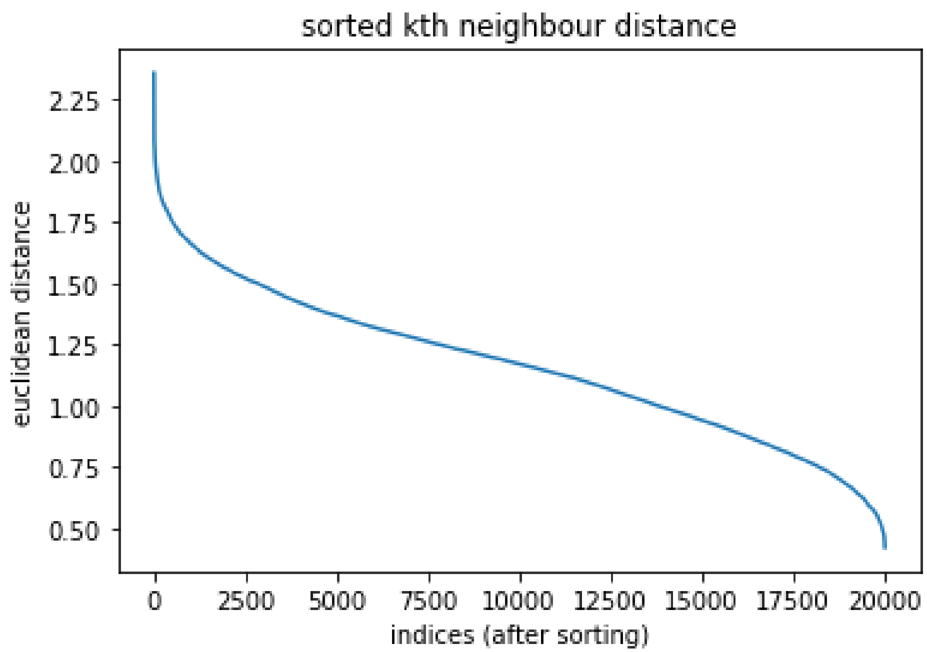
Source: [https://stackoverflow.com/questions/12893492/choosing-eps-and-minpts-for-dbscan-r/48558030#48558030 (https://stackoverflow.com/questions/12893492/choosing-eps-and-minpts-for-dbscan-r/48558030#48558030)](https://stackoverflow.com/questions/12893492/choosing-eps-and-minpts-for-dbscan-r/48558030#48558030)

Importing KDTree to get distances of kth neighbors for each point.

In [149]:
```
from sklearn.neighbors import KDTree
```

In [150]:
```
tree = KDTree(small_matrix)
dist, ind = tree.query(small_matrix, k=10)
kth_dist = dist[:, -1:].T[0]
kth_dist_sorted = sorted(kth_dist, reverse=True)
```

In [151]:
```
plt.plot(kth_dist_sorted)
plt.title('sorted kth neighbour distance')
plt.xlabel('indices (after sorting)')
plt.ylabel('euclidean distance')
plt.show()
```



According to above graph we can choose eps=1.70 as it seems to be the elbow of the graph.

In [152]:
```
k=1.7
dbscan = DBSCAN(eps=k)
dbscan.fit(small_matrix)
if max(dbscan.labels_)!=0:
    score = silhouette_score(small_matrix, dbscan.labels_)
scores.append(score)
print(f"score for eps = {k} is: {score}")
```

```
score for eps = 1.7 is: 0.14038180017264476
```

In [153]:
```
print(f"davies_bouldin_score for DBSCAN Model with eps = 1.7: {davies_bouldin_score(small_m
```

```
davies_bouldin_score for DBSCAN Model with eps = 1.7: 3.3021323178892636
```

Calculating inertia for DBSCAN model by taking mean of cluster points as cluster centers.

In [286]:
```
dbscan_matrix = [None, None]
dbscan_matrix[0] = small_matrix[list(filter(lambda i: dbscan.labels_[i]==0, range(20000)))]
dbscan_matrix[1] = small_matrix[list(filter(lambda i: dbscan.labels_[i]==1, range(20000)))]

dbscan2_inertia = 0
for i in range(2):
    clus_cent = dbscan_matrix[i].mean()
    dbscan2_inertia += ((dbscan_matrix[i] - clus_cent)**2).sum().sum()
```

In [287]:
```
print(f"Calculated inertia for DBSCAN algorithm is: {dbscan2_inertia}")
```

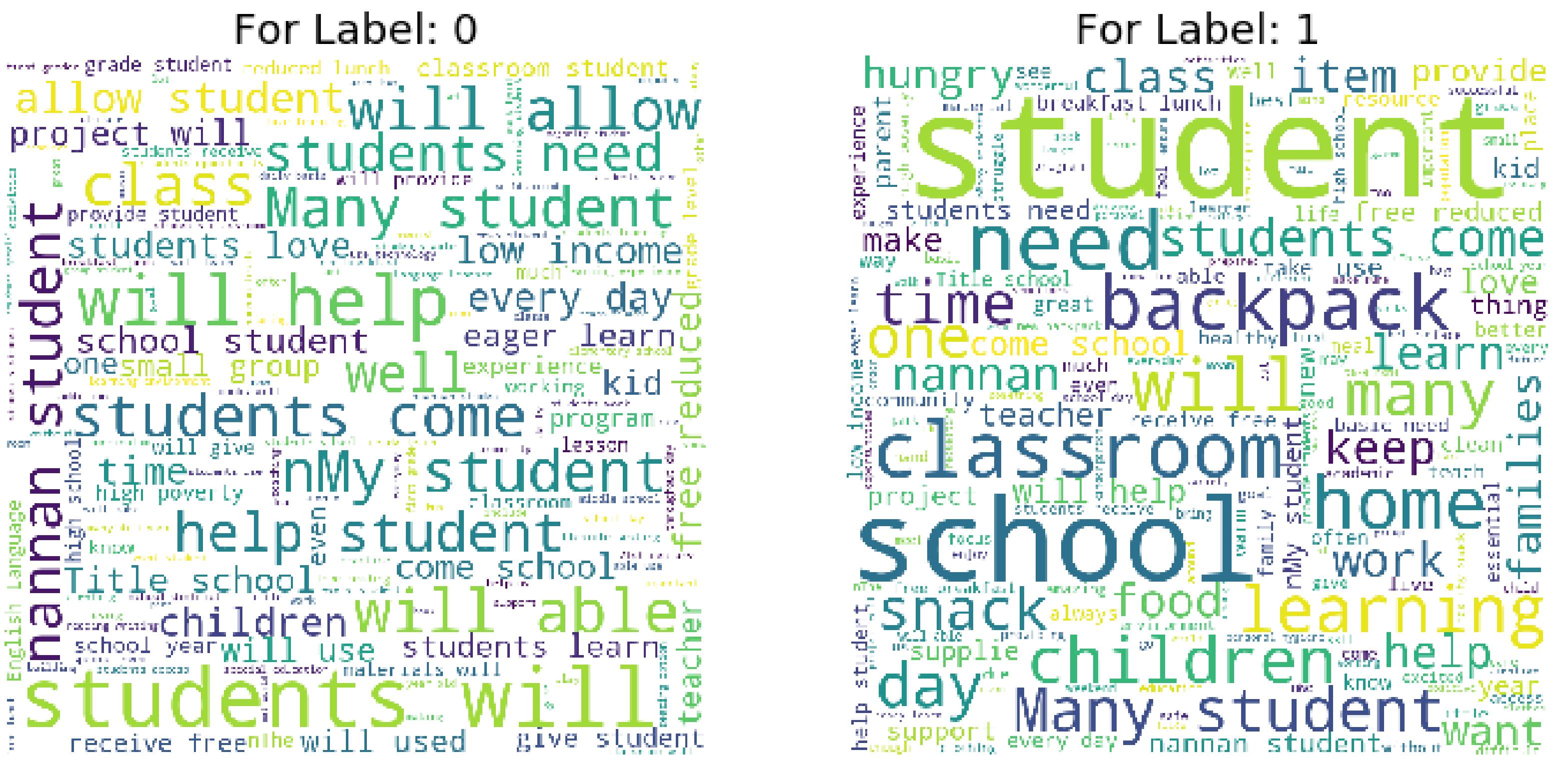
```
Calculated inertia for DBSCAN algorithm is: 94134.20973899585
```

In [288]:
```
max(dbscan.labels_)+1
```

Out[288]:
```
2
```

EDA on `Essay` column for different clusters

In [155]:
```
noc = max(dbscan.labels_)+1
wordclouds(dbscan.labels_, noc, 20000, shape=(1, 2))
```



In [386]:
```
dbscan_essay_counters = [Counter() for i in range(2)]
lab = dbscan.labels_
all_essays = project_data['essay'][:20000]
for ind, es in enumerate(tqdm_notebook(all_essays)):
    dbscan_essay_counters[lab[ind]] += Counter(es.split())
```

```
HBox(children=(IntProgress(value=0, max=20000), HTML(value='')))
```

In [391]:
```
print(len(dbscan_essay_counters[0].keys()))
print(len(dbscan_essay_counters[1].keys()))
```

```
118422
9051
```

In [389]:
```
dbscan_counter_diff = copy.deepcopy(dbscan_essay_counters)
for i in range(2):
    for j in range(2):
        if i != j:
            dbscan_counter_diff[i] -= dbscan_essay_counters[j]
print(len(dbscan_counter_diff[0].keys()))
print(len(dbscan_counter_diff[1].keys()))
```

```
117951
1281
```

In [417]:
```
dbscan_most_common_sum = np.sum([len(dbscan_counter_diff[i].keys()) for i in range(2)])
print(f'Total most common words for all clusters is: {dbscan_most_common_sum}')
```

```
Total most common words for all clusters is: 119232
```

In [418]:
```
print("Top 10 most common words for each cluster and least common in other clusters: ")
print('='*100)
for i in range(2):
    print(f"Cluster {i}:")
    tpls = dbscan_counter_diff[i].most_common(10)
    print([x[0] for x in tpls])
```

```
Top 10 most common words for each cluster and least common in other clusters:
=========================================================================================
===========
Cluster 0:
['to', 'and', 'the', 'students', 'a', 'of', 'in', 'are', 'will', 'their']
Cluster 1:
['backpacks', 'hygiene', 'deodorant,', 'soap,', 'deodorant', 'shampoo,', 'socks', 'toothp
aste,', 'backpacks,', 'jackets,']
```

Interpretation of 2 Clusters based on the info I got above.

- **Cluster 1: Projects which require bags, clothing (jackets, socks), and soap and deoderants etc..**
- **Cluster 0: All Other projects (As it has all common english words as high frequency words)**

Comparing the below numerical columns for DBSCAN clustering.

- **`project_is_approved`**
- **`teacher_number_of_previously_posted_projects`**
- **`price`**

In [156]:
```
dbscan_data_0 = project_data.iloc[list(filter(lambda i: dbscan.labels_[i]==0, range(20000))
dbscan_data_1 = project_data.iloc[list(filter(lambda i: dbscan.labels_[i]==1, range(20000))

print(dbscan_data_0.shape)
print(dbscan_data_1.shape)
```

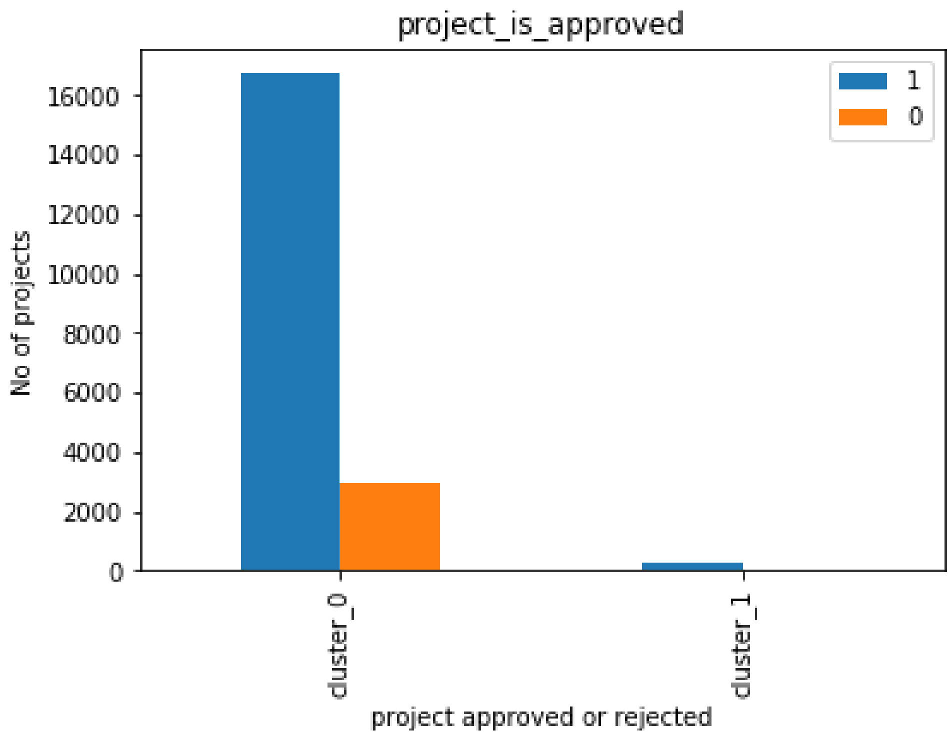
```
(19683, 21)
(243, 21)
```

EDA on `project_is_approved` column for different clusters

In [157]:
```
tempDF = pd.DataFrame([dbscan_data_0['project_is_approved'].value_counts(), dbscan_data_1['
             , index=['cluster_0', 'cluster_1'])
print(tempDF)
```

```
               1     0
cluster_0  16740  2943
cluster_1    227    16
```

In [158]:
```
tempDF.plot.bar()
plt.title('project_is_approved')
plt.ylabel('No of projects')
plt.xlabel('project approved or rejected')
plt.show()
```



The above plot shows that our data is somewhat clustered according to the approval of projects and we need to see the approval to rejection ratio which you can see in below code block

In [159]:
```
print("approval to rejected ratio (i.e. approved_projects/rejected_projects)")
print(tempDF[1]/tempDF[0])
```

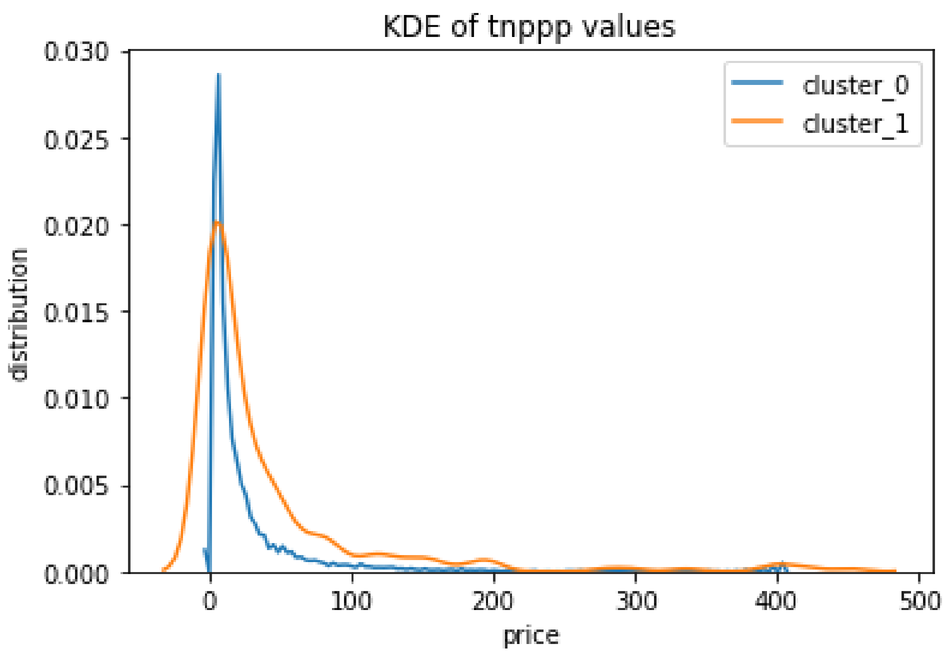
```
approval to rejected ratio (i.e. approved_projects/rejected_projects)
cluster_0     5.688073
cluster_1    14.187500
dtype: float64
```

We can see that cluster_1 has high approval rate but this doesnt say amything about the data, as we have very less values in second cluster, probability of having approval clusters is amplified than normal.

In [160]:
```
dbscan_data = [dbscan_data_0, dbscan_data_1]
```

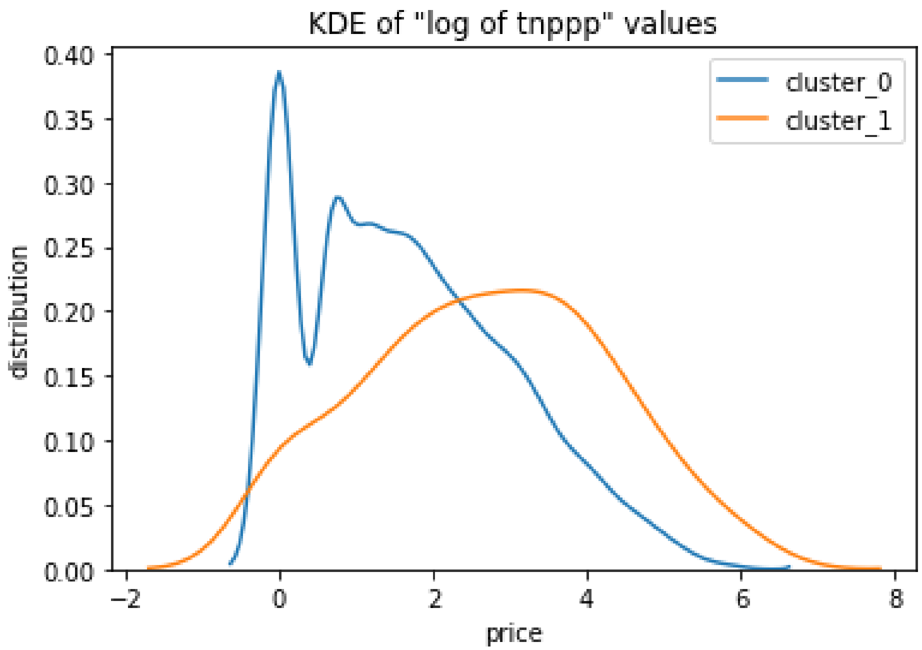
EDA on `teacher_number_of_previously_posted_projects` column for different clusters

In [289]:
```
for i in range(2):
    sns.kdeplot(dbscan_data[i]['teacher_number_of_previously_posted_projects'], label='clus
plt.title('KDE of tnppp values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 60)
plt.show()
```



Applying log for the values.

In [290]:
```
for i in range(2):
    sns.kdeplot(np.ma.masked_invalid(np.log(dbscan_data[i]['teacher_number_of_previously_po
                label='cluster_'+str(i))
plt.title('KDE of "log of tnppp" values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 60)
plt.show()
```



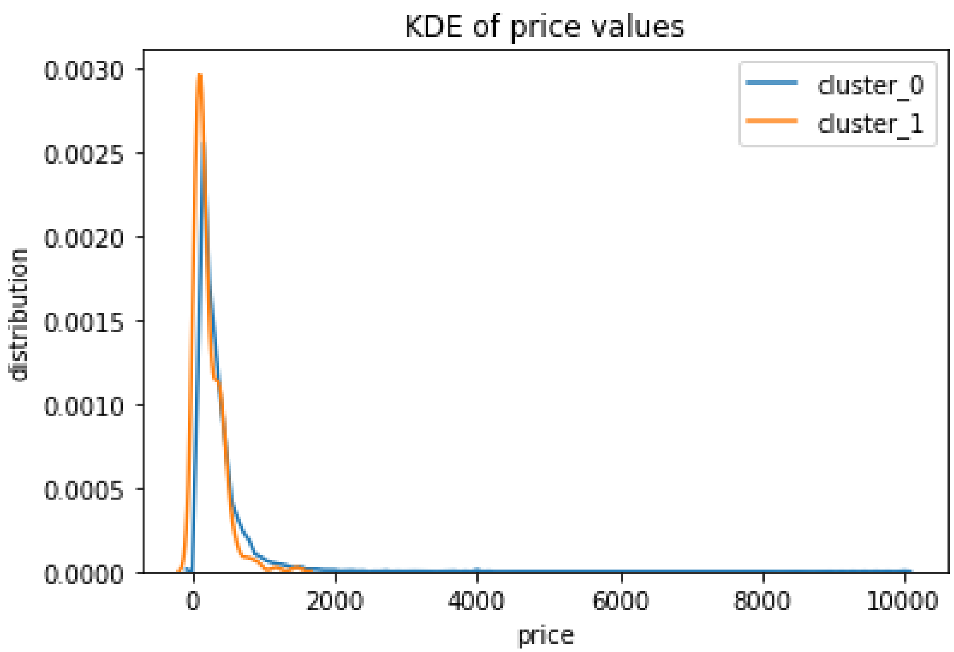
The above graph is not that interpretable. So I take mean and standard deviation values for this column in all the clusters.

In [296]:
```
tnppp_means = [np.ma.masked_invalid(np.log(dbscan_data[i]['teacher_number_of_previously_pos
               for i in range(2)]
tnppp_stds = [np.ma.masked_invalid(np.log(dbscan_data[i]['teacher_number_of_previously_post
              for i in range(2)]
indices = ['cluster_'+str(i) for i in range(2)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print("mean and std-dev values of Log of teacher_number_of_previously_posted_projects")
print('='*75)
print(tempDF)
```

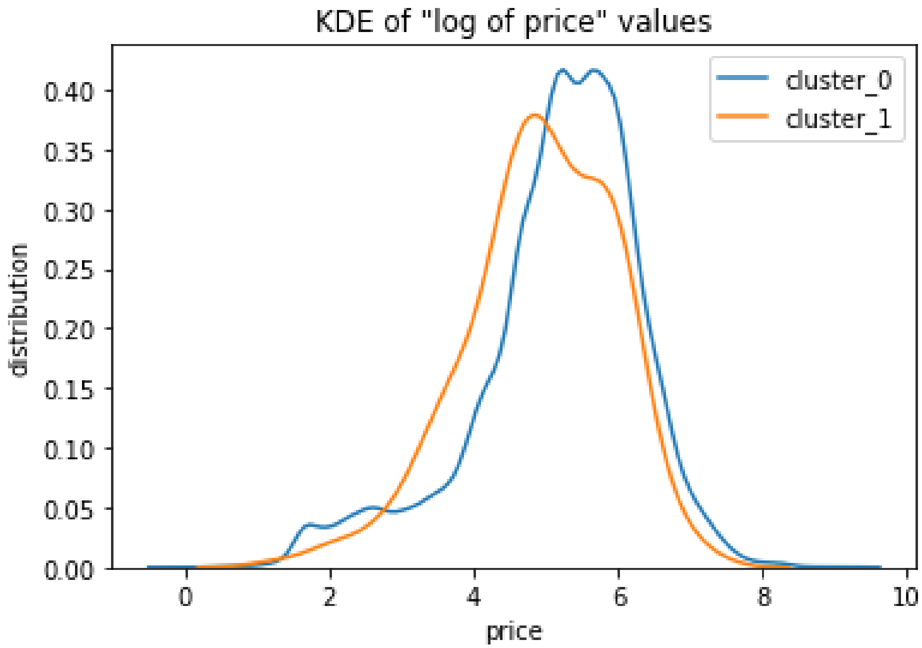
```
mean and std-dev values of Log of teacher_number_of_previously_posted_projects
===========================================================================
               Mean   std-dev
cluster_0  1.696652  1.341040
cluster_1  2.711628  1.569093
```

EDA on `price` column for different clusters

In [299]:
```
for i in range(2):
    sns.kdeplot(dbscan_data[i]['price'], label='cluster_'+str(i))
plt.title('KDE of price values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



In [301]:
```
for i in range(2):
    sns.kdeplot(np.ma.masked_invalid(np.log(dbscan_data[i]['price'])), label='cluster_'+str
plt.title('KDE of "log of price" values')
plt.ylabel('distribution')
plt.xlabel('price')
# plt.xlim(-10, 2000)
plt.show()
```



In [305]:
```
tnppp_means = [np.ma.masked_invalid(np.log(dbscan_data[i]['price'])).mean() for i in range(
tnppp_stds = [np.ma.masked_invalid(np.log(dbscan_data[i]['price'])).std() for i in range(2)
indices = ['cluster_'+str(i) for i in range(2)]
tempDF = pd.DataFrame([tnppp_means, tnppp_stds]).T
tempDF.index = indices
tempDF.columns = ['Mean', 'std-dev']
print("mean and std-dev values of Log of price")
print('='*40)
print(tempDF)
```

```
mean and std-dev values of Log of price
========================================
               Mean   std-dev
cluster_0  5.168422  1.156567
cluster_1  4.923183  1.021320
```

In [165]:
```
# from collections import Counter

# word_count_db = ['', '']
# word_count_db[0] = Counter()
# word_count_db[1] = Counter()

# for i in tqdm_notebook(range(20000)):
#     ess = project_data.iloc[i]['essay'].lower()
#     temp_count = Counter(ess.split())
#     word_count_db[dbscan2.labels_[i]] = word_count_db[dbscan2.labels_[i]] + temp_count

# word_count_db[0] = set(map(lambda x: x[0], word_count_db[0].most_common(1000)))
# word_count_db[1] = set(map(lambda x: x[0], word_count_db[1].most_common(1000)))
```

In [166]:
```
# words_diff_db_0 = word_count_db[0].difference(word_count_db[1])
# words_diff_db_1 = word_count_db[1].difference(word_count_db[0])

# print(len(words_diff_db_0))
# print(len(words_diff_db_1))
```

Even in this model the numerical columns doesnt have much significance on the clustering.

3. Conclusions

Please write down few lines of your observations on this assignment.

In [167]:
```
from prettytable import PrettyTable
```

In [308]:
```
aggClust5 = aggCluster_models[5]
agg5_mat_data = [small_matrix[list(filter(lambda i: aggClust5.labels_[i]==j, range(20000)))
```

In [309]:
```
agg5_inertia = 0
for i in range(5):
    clus_cent = agg5_mat_data[i].mean()
    agg5_inertia += ((agg5_mat_data[i] - clus_cent)**2).sum().sum()
```

Inertia for Agglomeration Clustering and DBSCAN are calculated manually by taking mean of clusters as the cluster centers and calculating the sum of squred distances for all points to thier respective nearest neighbors.

In [318]:
```
kmeans2_silh_score = silhouette_score(tfidf_matrix, kmeans_models[2].labels_)
kmeans8_silh_score = silhouette_score(tfidf_matrix, kmeans_models[8].labels_)
agg5_silh_score = silhouette_score(small_matrix, aggCluster_models[5].labels_)
agg8_silh_score = silhouette_score(small_matrix, aggCluster_models[8].labels_)
dbscan2_silh_score = silhouette_score(small_matrix, dbscan.labels_)
```

In [320]:
```
table = PrettyTable()
table.field_names = ['Model', 'hyper-parameter', 'No of clusters', 'inertia', 'silhouette_s
table.add_row(['KMeans Clustering', 'n_clusters = 2', 2, kmeans_models[2].inertia_, kmeans2
table.add_row(['KMeans Clustering', 'n_clusters = 8', 8, kmeans_models[8].inertia_, kmeans8
table.add_row(['Aggloremative Clustering', 'n_clusters = 5', 5, agg5_inertia, agg5_silh_sco
table.add_row(['Aggloremative Clustering', 'n_clusters = 8', 8, agg8_inertia, agg8_silh_sco
table.add_row(['DBSCAN Clustering', 'eps = 1.7', 2, dbscan2_inertia, dbscan2_silh_score])
print(table)
```

```
+--------------------------+-----------------+----------------+--------------------+-----
----------------+
|          Model           | hyper-parameter | No of clusters |      inertia       |   si
lhouette_score  |
+--------------------------+-----------------+----------------+--------------------+-----
----------------+
|    KMeans Clustering     |  n_clusters = 2 |       2        | 200245.63959936163 | 0.09
814386343740057 |
|    KMeans Clustering     |  n_clusters = 8 |       8        | 158087.0658110251  | 0.09
790070710872138 |
| Aggloremative Clustering |  n_clusters = 5 |       5        | 94625.17437270339  | 0.09
440044238401085 |
| Aggloremative Clustering |  n_clusters = 8 |       8        | 94623.82897527562  | 0.11
847603599777828 |
|    DBSCAN Clustering     |    eps = 1.7    |       2        | 94134.20973899585  | 0.14
038180017264476 |
+--------------------------+-----------------+----------------+--------------------+-----
----------------+
```

Forgot to Add Kmeans model with 10 clusters above which has inertia = 151435.24. I had to rerun the some prt of notebook (which takes long time in my laptop) to add this single line in the table. So please consider this.

Conclusion

- **Among all clusters DBSCAN did good in respect to score. It has a `silhouette_score` of `0.14` and `inertia (calculated)` of `94134`. But In interpretation It is very bad model.**
- **Clusters in DBSCAN is highly skewed (i.e. cluster_0 has high number of data points and cluster_1 has very low number of data points). So interpretation is not good**
- **All clustering models are clustered only based on essay data which makes sense. As we are using TFIDF vectors, lot of dimentions are from essay data**
- **Kmeans and Agglomerative Clustering did very well when it comes to Interpreting how the data is Clustered. The most common words in one cluster gave the main gist of the cluster. And from these models we can classify new projects into these clusters manually. Below are my interpretations on the clusters for different models.**

Interpretation of 10 Clusters (KMeans) based on the info I got above.

- **Cluster 0: Sports Related Projects**
- **Cluster 1: Playing Materials (like Scrabble, Crane, Flashlight) Projects**
- **Cluster 2: Not Sure about this cluster**
- **Cluster 3: Mixture of Projects related to playing with vehicles, food, and health**
- **Cluster 4: Not Sure about this cluster**
- **Cluster 5: Mixture of Projects related to diverse students, books. etc.**
- **Cluster 6: Projects related to robotics and coding**
- **Cluster 7: Projects related to Music**
- **Cluster 8: Projects which have students with disabilities**
- **Cluster 9: Projects which are related to Science and mathematics (education related projects)**

Kmeans gave high interpretability when coming to how it clustered the data.

Interpretation of 8 Clusters (Agglomerative Clustering) based on the info I got above.

- **Cluster 0: Projects related to Reading and libraries**
- **Cluster 1: Mixture of projects related to Students, and reading (not so sure about the cluster)**
- **Cluster 2: Projects which have students with disabilities**
- **Cluster 3: Projects which require Toys to the students**
- **Cluster 4: Projects related to housekeeping and sewing arts and etc..**
- **Cluster 5: Projects related to Music instruments and sports (related to extra-curricular activities)**
- **Cluster 6: Mix of projects related to arts (dance printmaking), and sensitive operations (i.e. CPR, dissections, soldering.. not sure about this one)**
- **Cluster 7: Projects which require bags, clothing (jackets, socks), and soap and deoderants**

Interpretation of 2 Clusters (DBSCAN) based on the info I got above.

- **Cluster 1: Projects which require bags, clothing (jackets, socks), and soap and deoderants etc..**
- **Cluster 0: All Other projects (As it has all common english words as high frequency words)**

In [ ]:

```
```