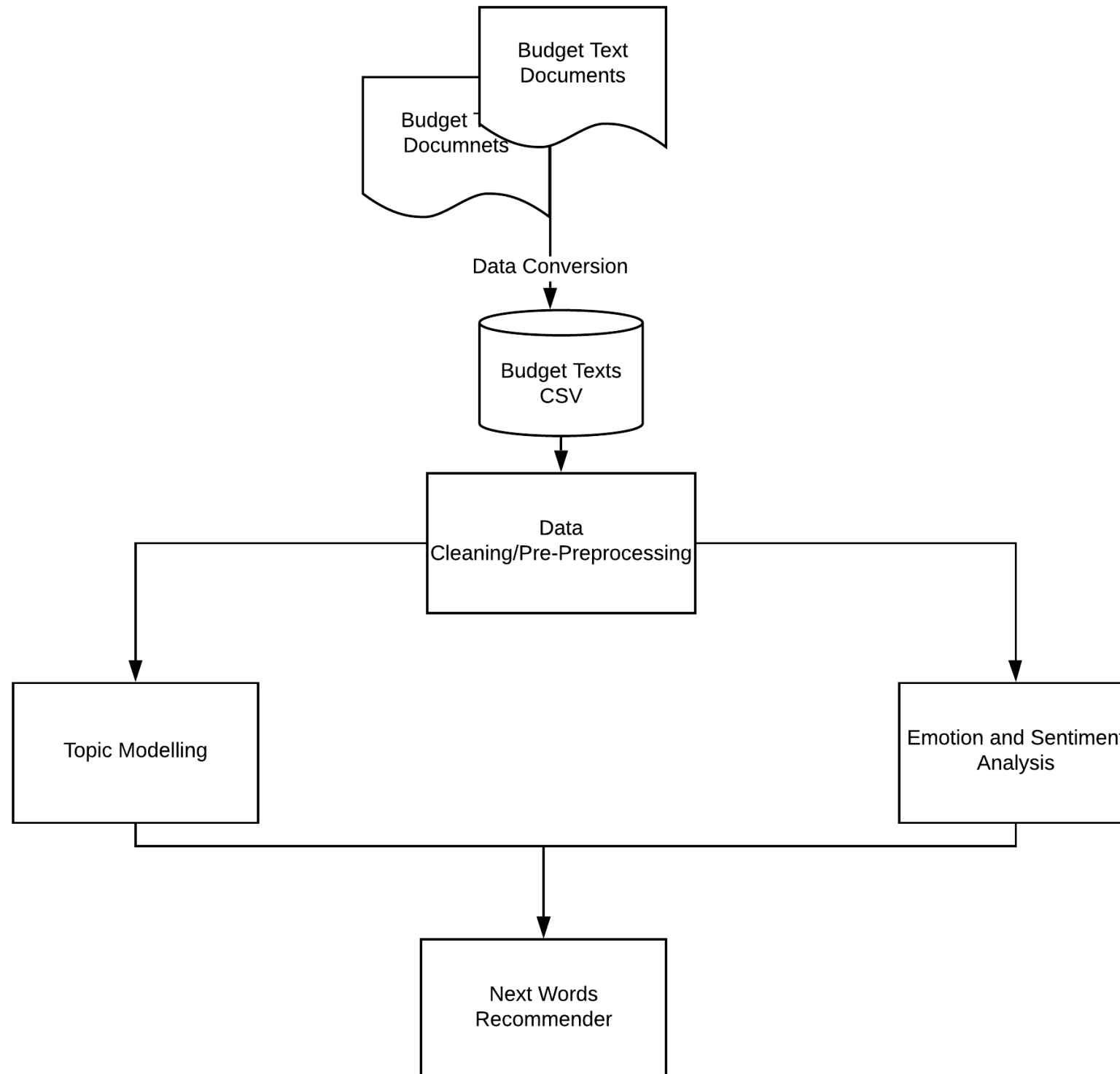

Budget Text Analysis

- Datatopian Visionaries

Akash Meghani,
Miguel Gaspar Utrera,
Naseeb Thapaliya,
Sultan Al Bogami,
Unnati Khivasara

Mentors: Dr. Soumya Mohanty
Jason Jones (Guilford County)

Overview of the Project



Goals

- ❖ Understand the Different sections of budget text data from different counties and create a relation between them.
- ❖ Compare the general funds section of Guilford county, Durham County and Charlotte City (2008 and 2019) and understand the difference between them.
- ❖ Visualization of emotions between 2008 and 2019.
- ❖ Understand the different relevant topics from all the counties 2019 and with computed their coherence score with proper visualization.
- ❖ Compared the topic modeling results over the years (2008,2012,2016,2020)

Team Structure

- ❖ All the individuals will work on preparing data i.e. Perform Data cleaning and Data preprocessing.
- ❖ Team will be divided into 2 groups to perform different tasks:
 - Team 1: Topic Modelling
Members:
 1. Naseeb Thapaliya
 2. Miguel Gasper Utrera
 - Team 2: Emotion and Sentiment Analysis
Members:
 1. Akash Meghani
 2. Unnati Khivasara

Individual Tasks Done

❖ **Sultan Al Bogami**

1. Collected Budget Documents from all the different Counties websites and other sources(2008 to 2020) and organization of github.
2. Converted the pdf documents to csv formats. Extract words from the documents using online tool, and classify them for further processing.

❖ **Naseeb Thapaliya**

1. Compared the topic modeling results over the years (2008,2012,2016,2020)

❖ **Miguel Gasper Utrera**

1. Applied Topic modeling on different relevant topics from all the counties and computed their coherence score with proper visualization.
2. Applied Davis model and showed top 30 words in each topic and their relevance.

❖ **Unnati Khivasera**

1. Analyzing sentiment intensity using Vader.
2. Performed visualization of emotions from different sections of documents.

❖ **Akash Meghani**

1. Applied Emotional and Sentiment analysis with NLTK and got meaningful results.
2. Performed visualization of emotions from different sections of documents.

Emotion And Sentiment Analysis

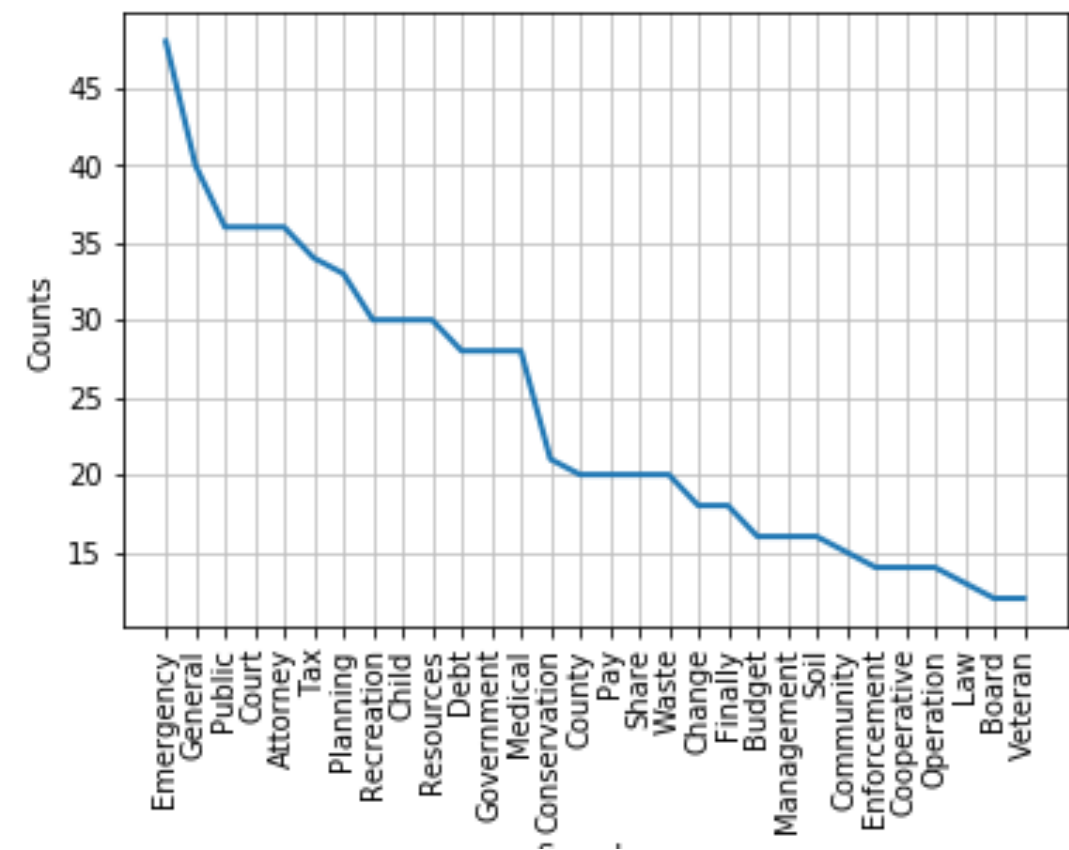
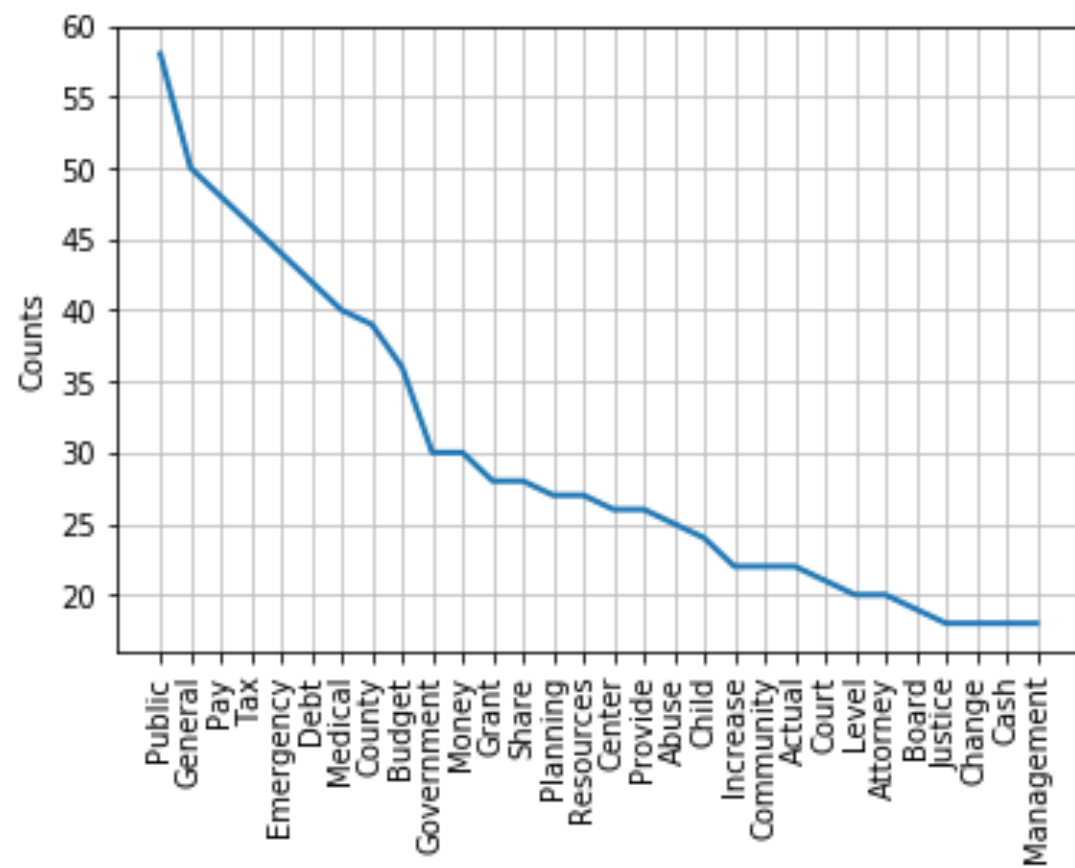
Most Influential Words in Guilford County (2020 and 2008)

```
[('Public', 58),  
 ('General', 50),  
 ('Pay', 48),  
 ('Tax', 46),  
 ('Emergency', 44),  
 ('Debt', 42),  
 ('Medical', 40),  
 ('County', 39),  
 ('Budget', 36),  
 ('Government', 30)]
```

```
[('Emergency', 48),  
 ('General', 40),  
 ('Public', 36),  
 ('Court', 36),  
 ('Attorney', 36),  
 ('Tax', 34),  
 ('Planning', 33),  
 ('Recreation', 30),  
 ('Child', 30),  
 ('Resources', 30)]
```

Emotion And Sentiment Analysis

Distribution of most influential Words in Guilford County (2020 and 2008)



Emotion And Sentiment Analysis

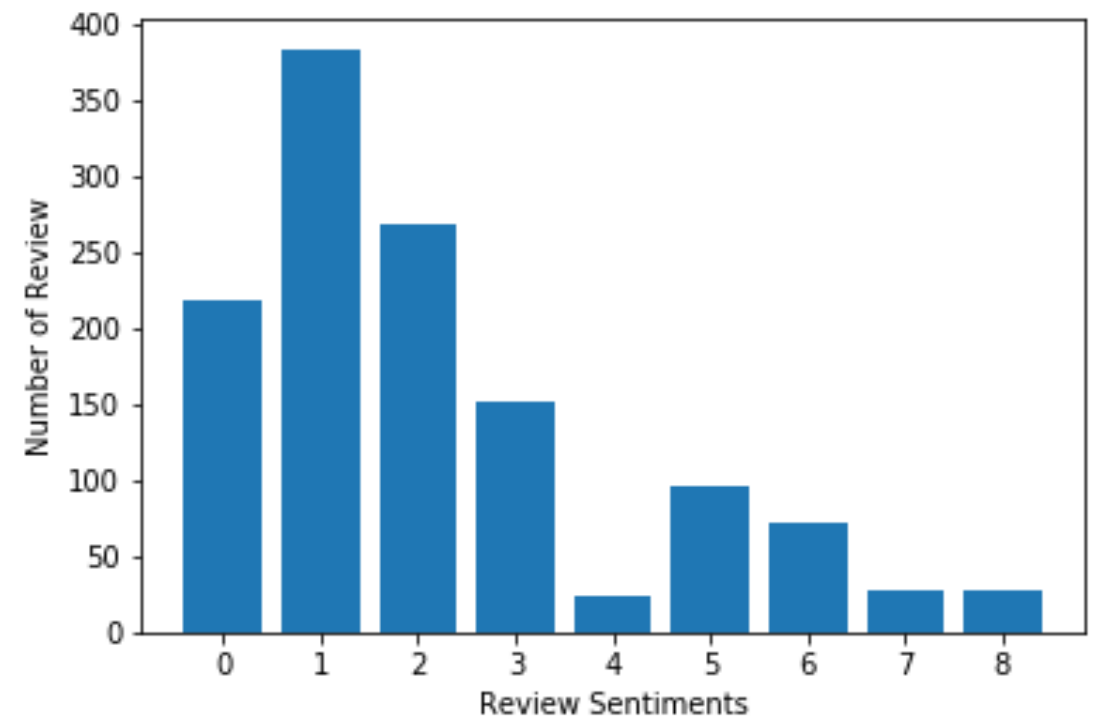
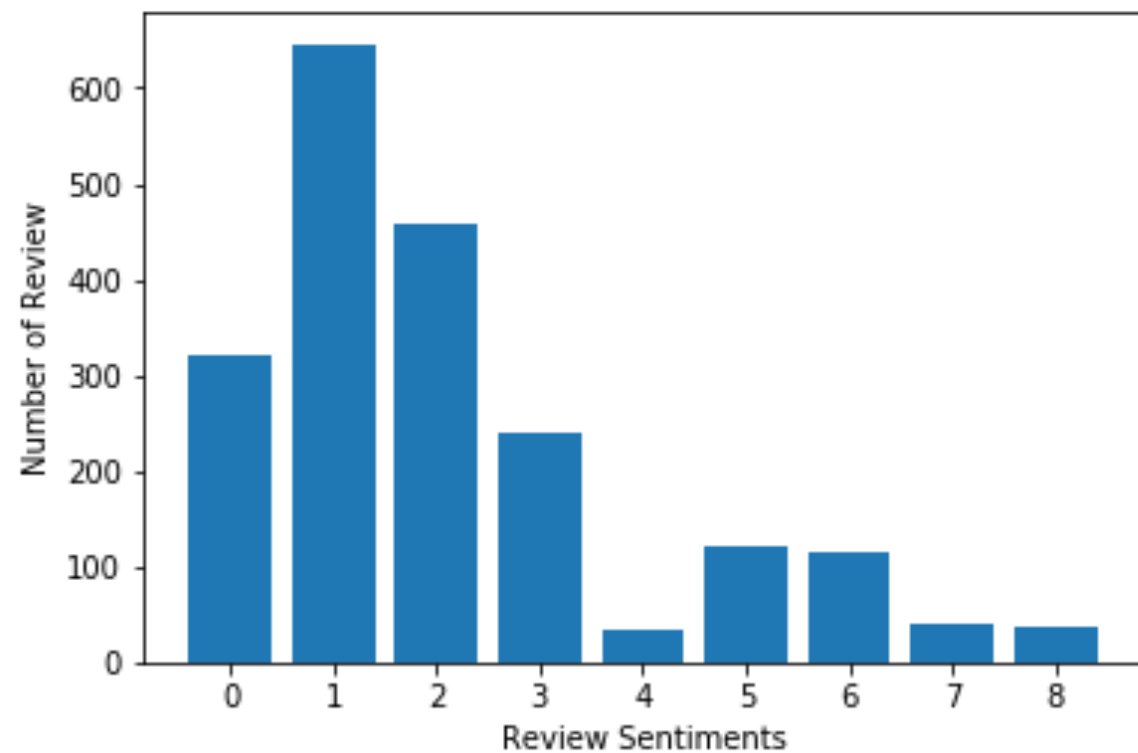
We have assigned numerical value to every emotion present in the document. Here is the list :

"Negative": "0", "Positive":

"1", "Trust" : "2", "Sadness": "0", "Anticipation": "3", "Surprise": "4", "Fear": "5", "Joy": "6", "Anger": "7", "Disgust": "8"

Emotion And Sentiment Analysis

Distribution of Emotions in General fund summary section (2020 and 2008)



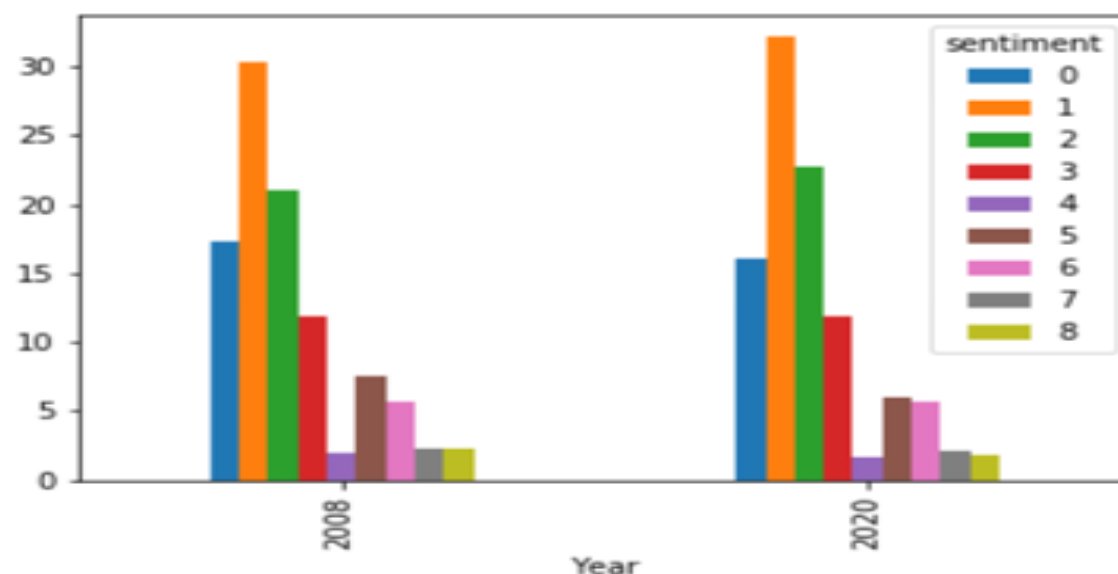
Emotion And Sentiment Analysis

Distribution of Emotions in General fund summary section (2020 and 2008) for Guilford County

32/8						
sentiment	0	1	2	3	4	5
Year						
2008	17.219589	30.252765	21.090047	11.927330	1.895735	7.582938
2020	16.003976	32.107356	22.763419	11.928429	1.689861	5.964215

sentiment	6	7	8
Year			
2008	5.608215	2.211690	2.211690
2020	5.715706	2.037773	1.789264

<matplotlib.axes._subplots.AxesSubplot at 0x20cf2a6e4a8>



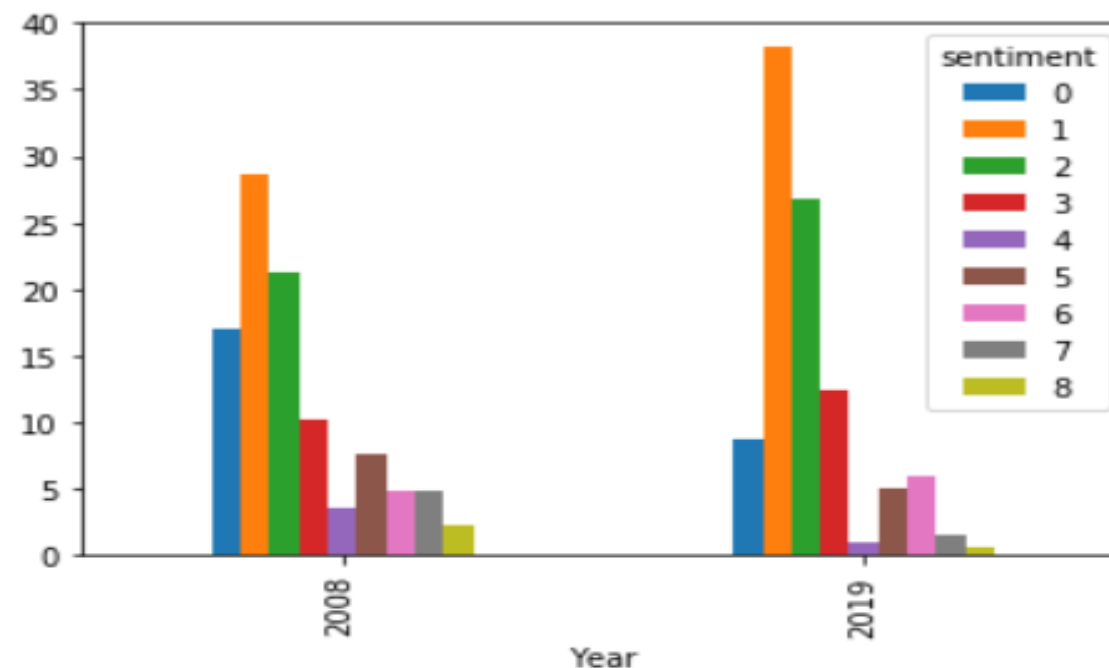
Emotion And Sentiment Analysis

Distribution of Emotions in General fund summary section (2020 and 2008) for Charolette

6221						
sentiment	0	1	2	3	4	5
Year						
2008	16.993464	28.540305	21.241830	10.130719	3.594771	7.625272
2019	8.730907	38.148218	26.758439	12.370356	0.999434	5.091458

sentiment	6	7	8
Year			
2008	4.793028	4.793028	2.287582
2019	5.883462	1.470866	0.546860

<matplotlib.axes._subplots.AxesSubplot at 0x20cf2b25780>



Emotion And Sentiment Analysis

Most Influential Words in Charlotte City (2020 and 2008)

```
[('Retirement', 210),  
 ('Provide', 138),  
 ('Pay', 120),  
 ('Public', 118),  
 ('Salary', 116),  
 ('General', 110),  
 ('Planning', 93),  
 ('Change', 81),  
 ('Risk', 78),  
 ('Efficient', 78)]
```

```
[('Emergency', 40),  
 ('Medical', 40),  
 ('Director', 40),  
 ('Public', 38),  
 ('Planning', 36),  
 ('Continue', 36),  
 ('Management', 34),  
 ('Provide', 34),  
 ('County', 33),  
 ('Resources', 33)]
```

Emotion And Sentiment Analysis

- ❖ We have used multiple methods like NLTK, Text blob and Vader to figure out what make sense with our data.
- ❖ We have applied NLTK on multiple sections of the document but we have only presented interesting things.

Topic Modeling

```
[(0,
 '0.315*"total" + 0.056*"commissioner" + 0.052*"park" + 0.051*"property" + '
 '0.044*"security" + 0.044*"resource" + 0.035*"policy" + 0.032*"economic" + '
 '0.027*"performance" + 0.026*"amend"'),
 (1,
 '0.196*"program" + 0.153*"provide" + 0.106*"major" + 0.064*"grant" + '
 '0.063*"exist" + 0.053*"operation" + 0.039*"information" + 0.037*"change" + '
 '0.035*"work" + 0.034*"care"'),
 (2,
 '0.115*"fund" + 0.110*"summary" + 0.108*"fire" + 0.078*"area" + '
 '0.062*"current" + 0.060*"solid" + 0.048*"state" + 0.041*"level" + '
 '0.040*"percent" + 0.039*"estimate"'),
 (3,
 '0.187*"fiscal" + 0.086*"debt" + 0.074*"unit" + 0.068*"water" + '
 '0.060*"infrastructure" + 0.050*"issue" + 0.044*"goal" + 0.042*"remain" + '
 '0.042*"government" + 0.041*"base"'),
 (4,
 '0.206*"adopt" + 0.107*"replacement" + 0.090*"support" + 0.083*"increase" + '
 '0.075*"number" + 0.044*"charge" + 0.041*"planning" + 0.038*"additional" + '
 '0.038*"require" + 0.038*"site"'),
 (5,
 '0.219*"capital" + 0.134*"expenditure" + 0.100*"management" + '
 '0.072*"equipment" + 0.050*"balance" + 0.044*"vehicle" + 0.040*"begin" + '
 '0.036*"improve" + 0.030*"identify" + 0.026*"law"'),
 (6,
 '0.242*"include" + 0.164*"community" + 0.095*"school" + 0.075*"impact" + '
 '0.037*"rate" + 0.033*"maintain" + 0.027*"recommend" + 0.027*"associate" + '
 '0.026*"pay" + 0.024*"resident"'),
 (7,
 '0.259*"year" + 0.150*"funding" + 0.117*"public" + 0.080*"development" + '
 '0.077*"actual" + 0.044*"plan" + 0.029*"annual" + 0.024*"life" + '
 '0.021*"address" + 0.019*"help"'),
 (8,
 '0.047*"service" + 0.019*"system" + 0.013*"building" + 0.012*"improvement" + '
 '0.012*"operate" + 0.011*"transfer" + 0.010*"cost" + 0.010*"source" + '
 '0.010*"complete" + 0.009*"future"'),
 (9,
 '0.260*"budget" + 0.207*"project" + 0.180*"facility" + 0.133*"revenue" + '
 '0.052*"tax" + 0.024*"appropriate" + 0.024*"control" + 0.015*"specific" + '
 '0.014*"population" + 0.011*"food"')]
```

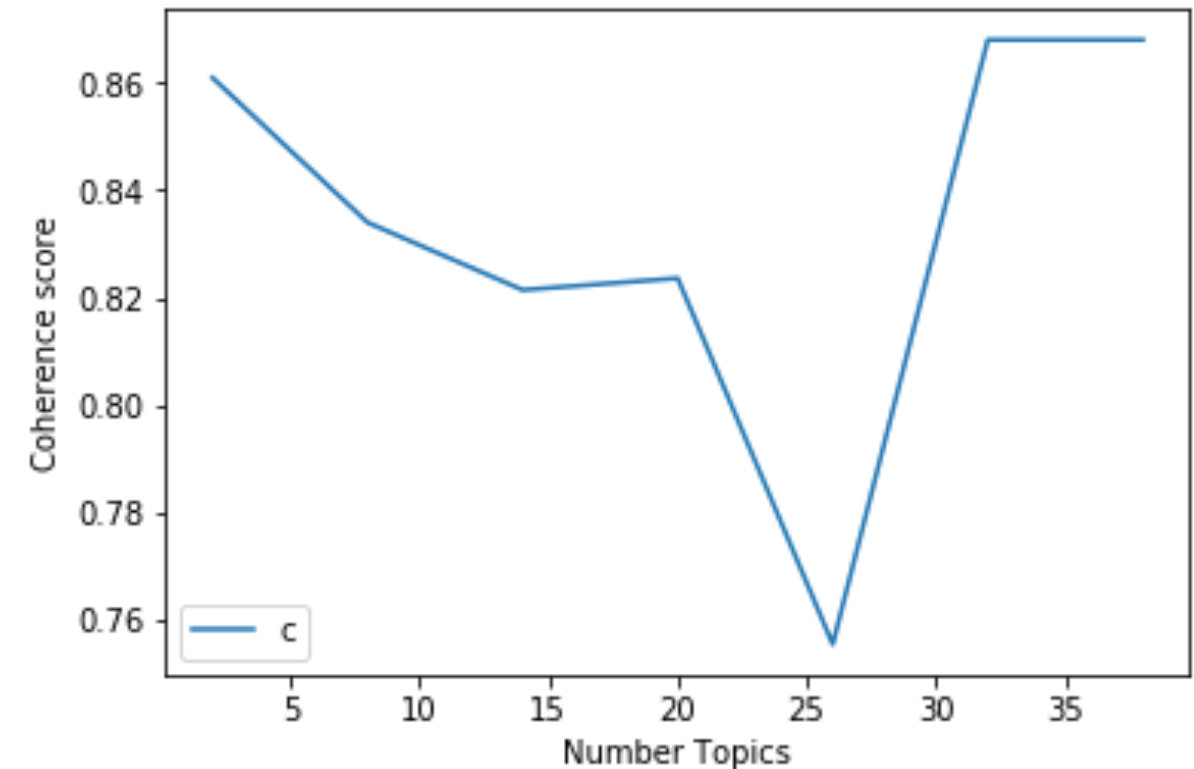
Topic Modeling

Topic 0
property resource
commissioner
park policy
security
total
economic performance
amend
Label: Property Maintenance and Security

Topic 1
work operation major
care
provide
exist
program
information grant
change
Label: Grant for Work or Program

Topic 2
percent
fire
level summary
state estimate
current area
solid fund
Label: State Fire Fund

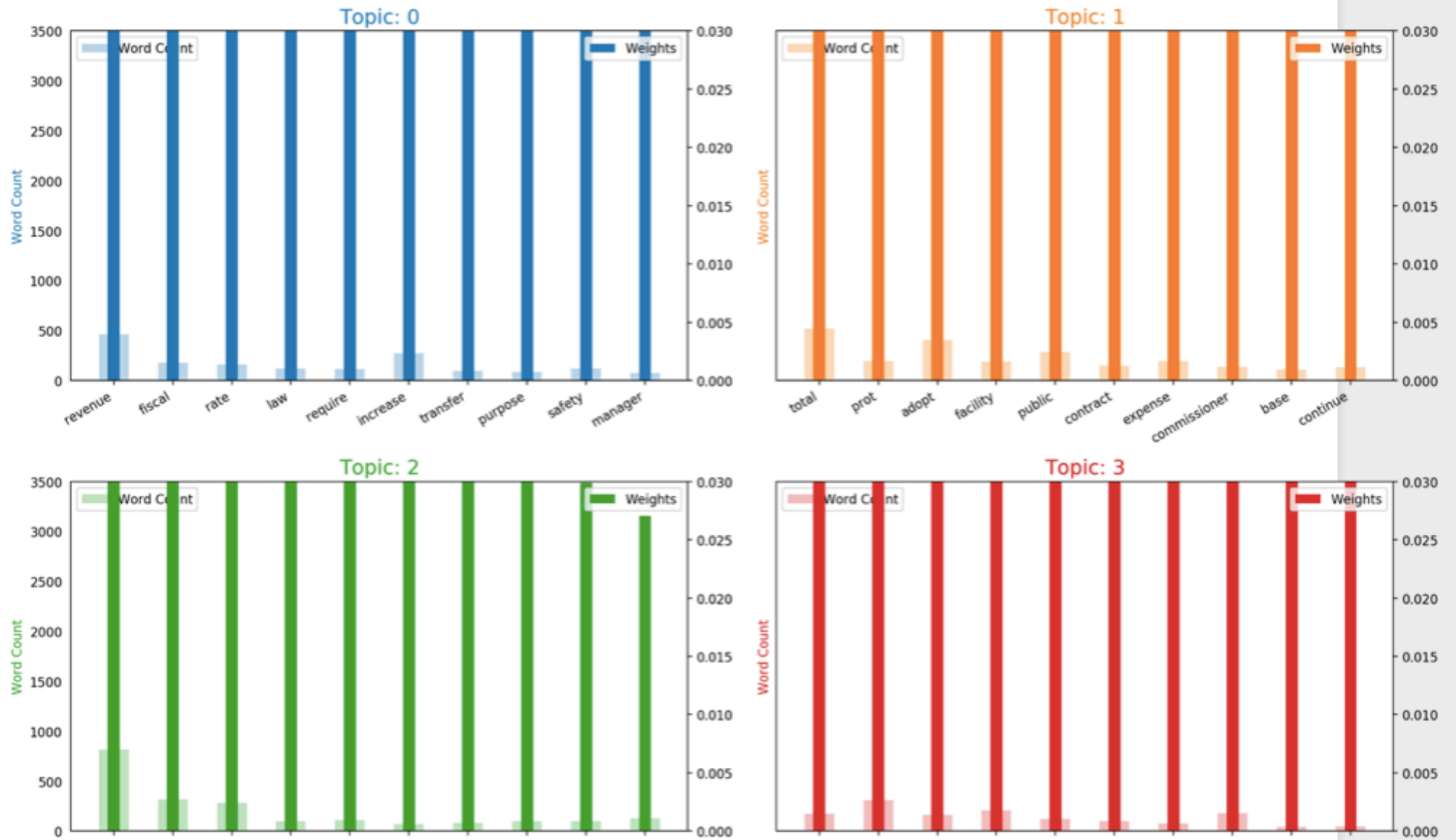
Topic 3
infrastructure debt
base
unit issue
remain goal
fiscal
water government
Label: Government Fiscal Year



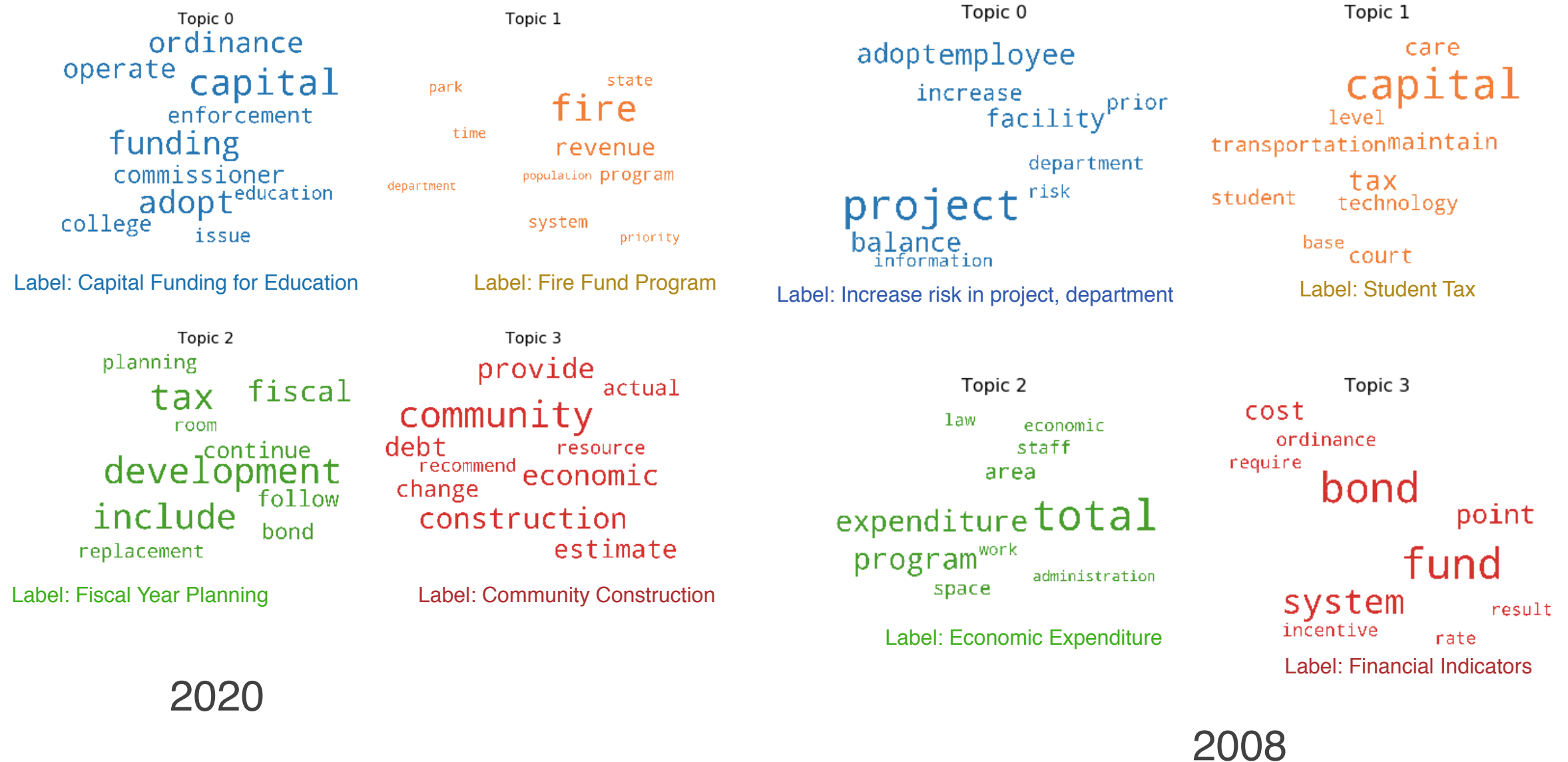
Coherence Score: 0.8256146597574272

Topic Modeling

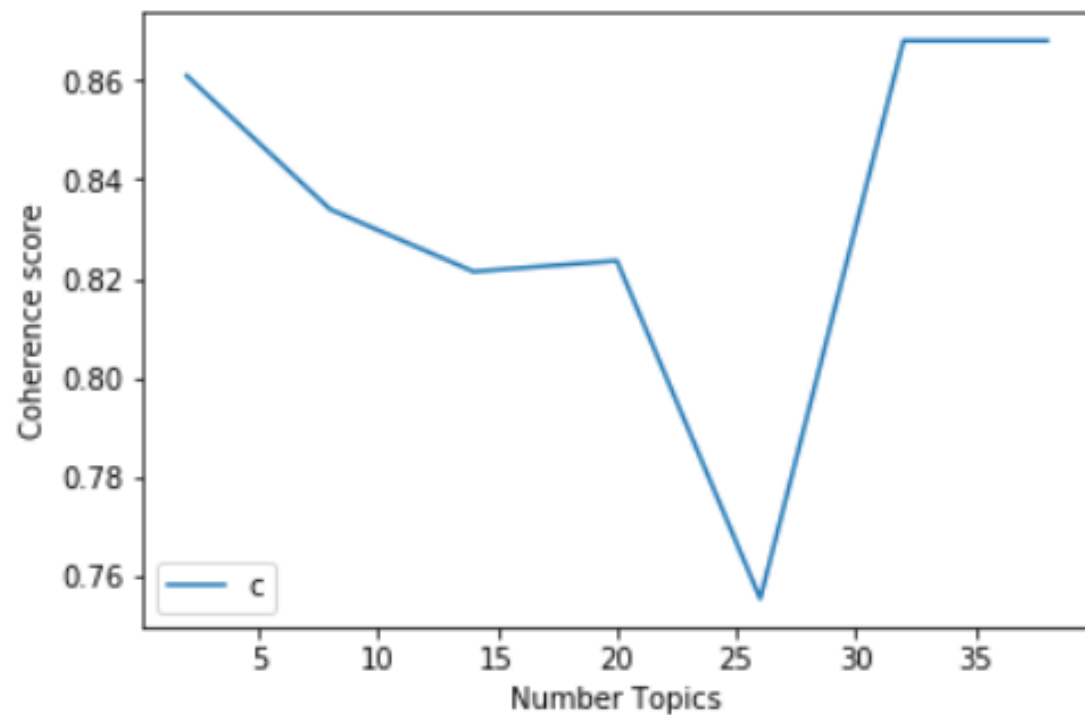
Word Count and Importance of Topic Keywords



Topic Modeling Comparison

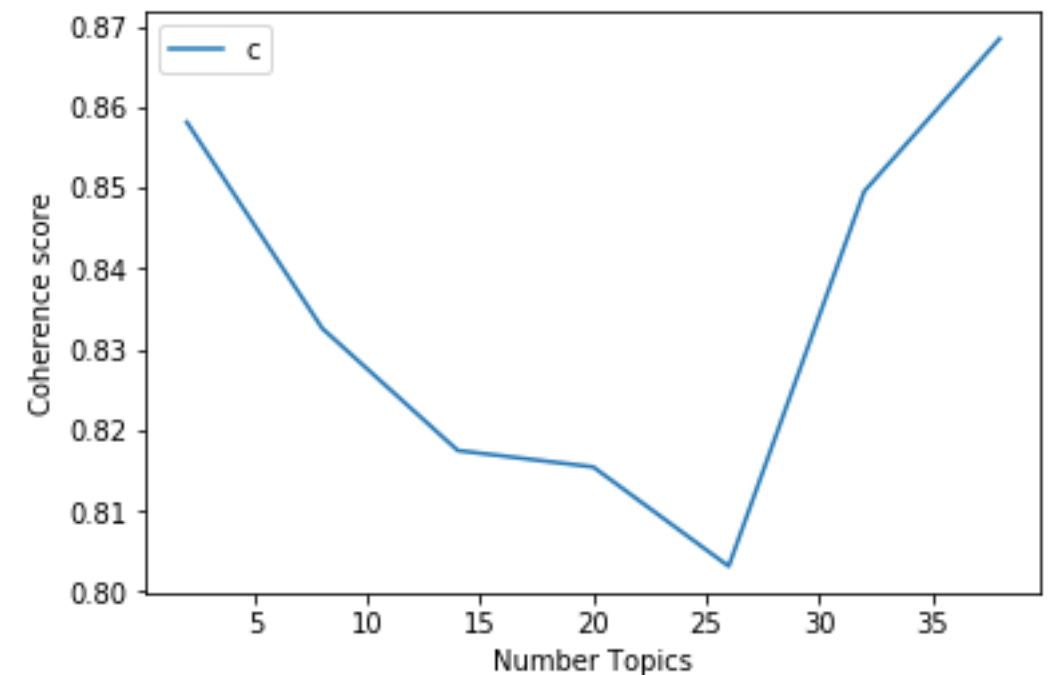


Topic Modeling Comparison



Coherence Score: 0.8256146597574272

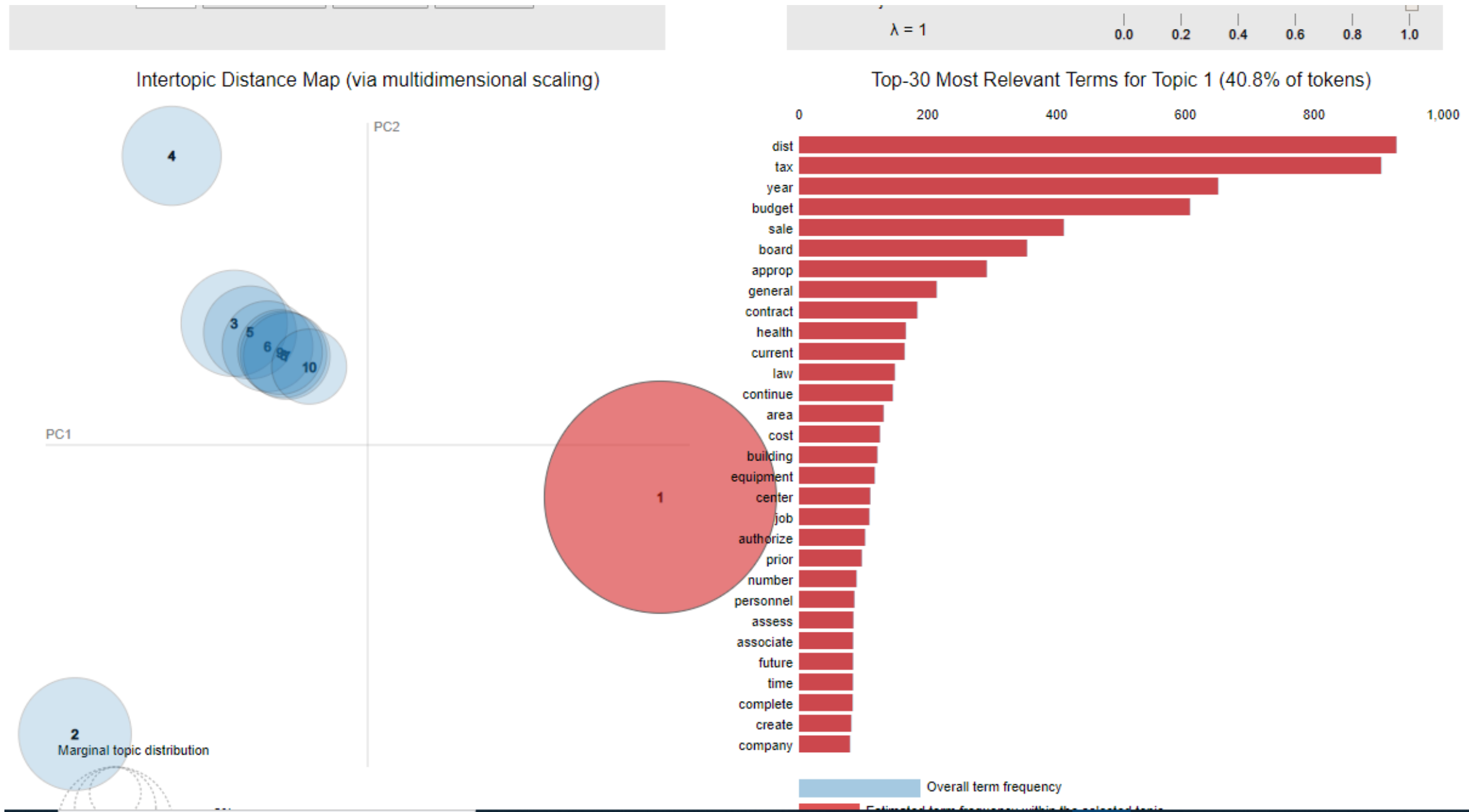
2019



Coherence Score: 0.8247949042506306

2008

Topic Modeling Comparison



Next Word Recommender

- Whenever a user tries to enter a word/s suggest the next word based on combination of words used as input in previous searches.
- Use results from Topic modeling to predict the recommended word/topic which are important.