Budget Text Analysis

- Datatopian Visionaries

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Unnati Khivasara

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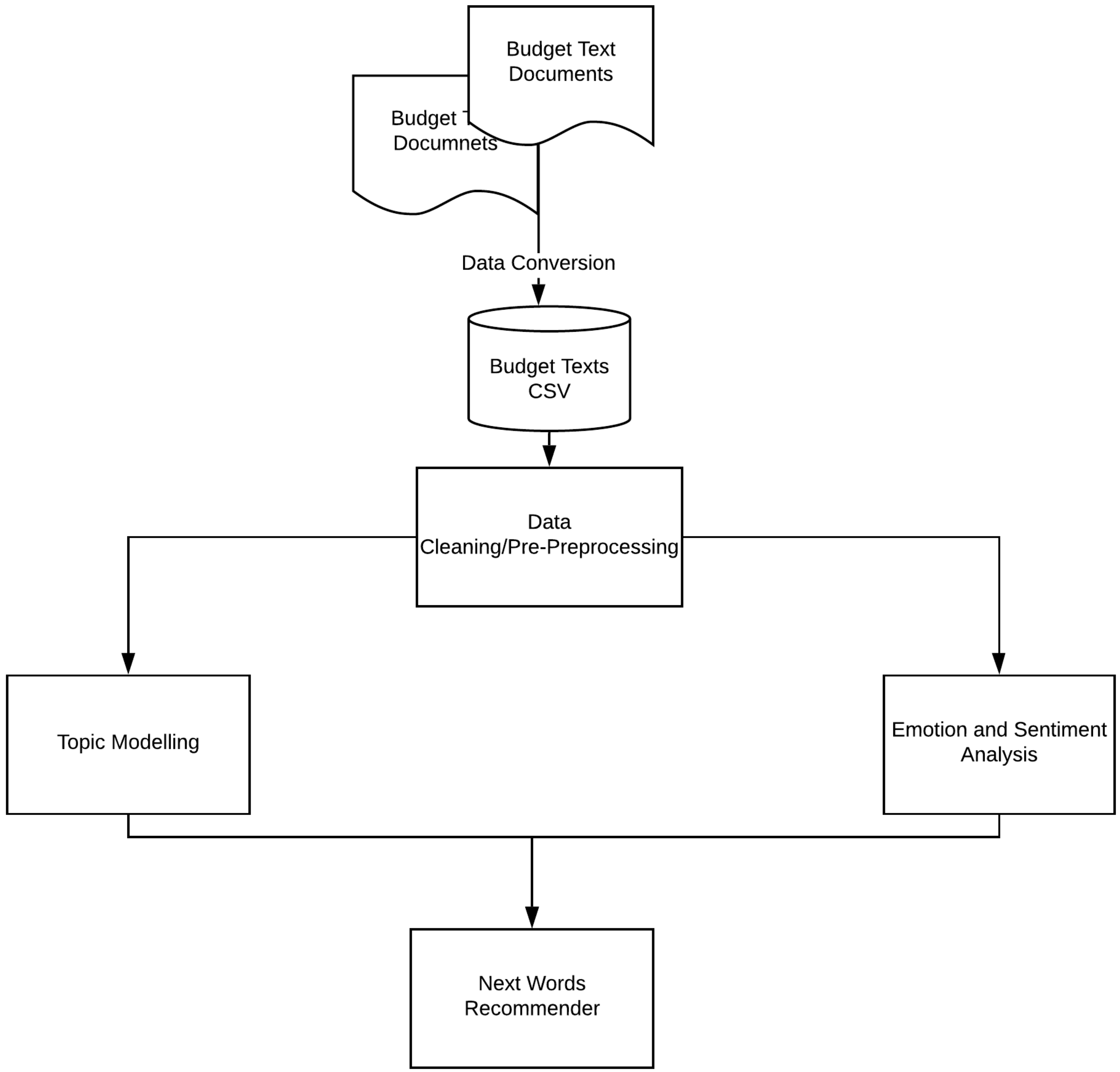
Overview of the Project



Goals (Questions Formulated)

- What are the properties of the budget text data ?
- Are there any intrusive structures and patterns in the budget texts from all the counties ?
- Does the topics change over the years (2008, 2029) ?
- Does different sections of budget text data have any common relation between them ?
- Does general funds section of Guilford county, Durham County and Charlotte City give similar sentiments or they are different ?
- How can we visualize the topics and emotions between 2008 and 2019 with proper analytics ?
- Does a topic model for one year can identify the latent semantic structure that persists over time in this budget text domain ?
- Can we formulate a next word recommender from our analysis ?

Tasks Assigned based on Objectives

- 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 ccv formats. Extract words from the documents using online tool, and classify them for further processing.
  3. Perform Statistical analysis of budget texts
- Naseeb Thapaliya
  1. Compared the topic modeling results over the years (2008,2020)
  2. Perform Supervised Machine Learning on topics from topics Modeling.
- 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 relevence.
- 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.
- Everyone
  1. Documentation of project and maintain and work on GitHub.
  2. Work on Nextword recommender

Data Overview

- **Primarily, 7 pdf files ranging from 400-500 pages long for each.**
- **Each pdf is converted to csv files by extracting all the relevant budget texts(words) from the pdf file.**
- **So, there are total of 638131 total words extracted from the budget files.**

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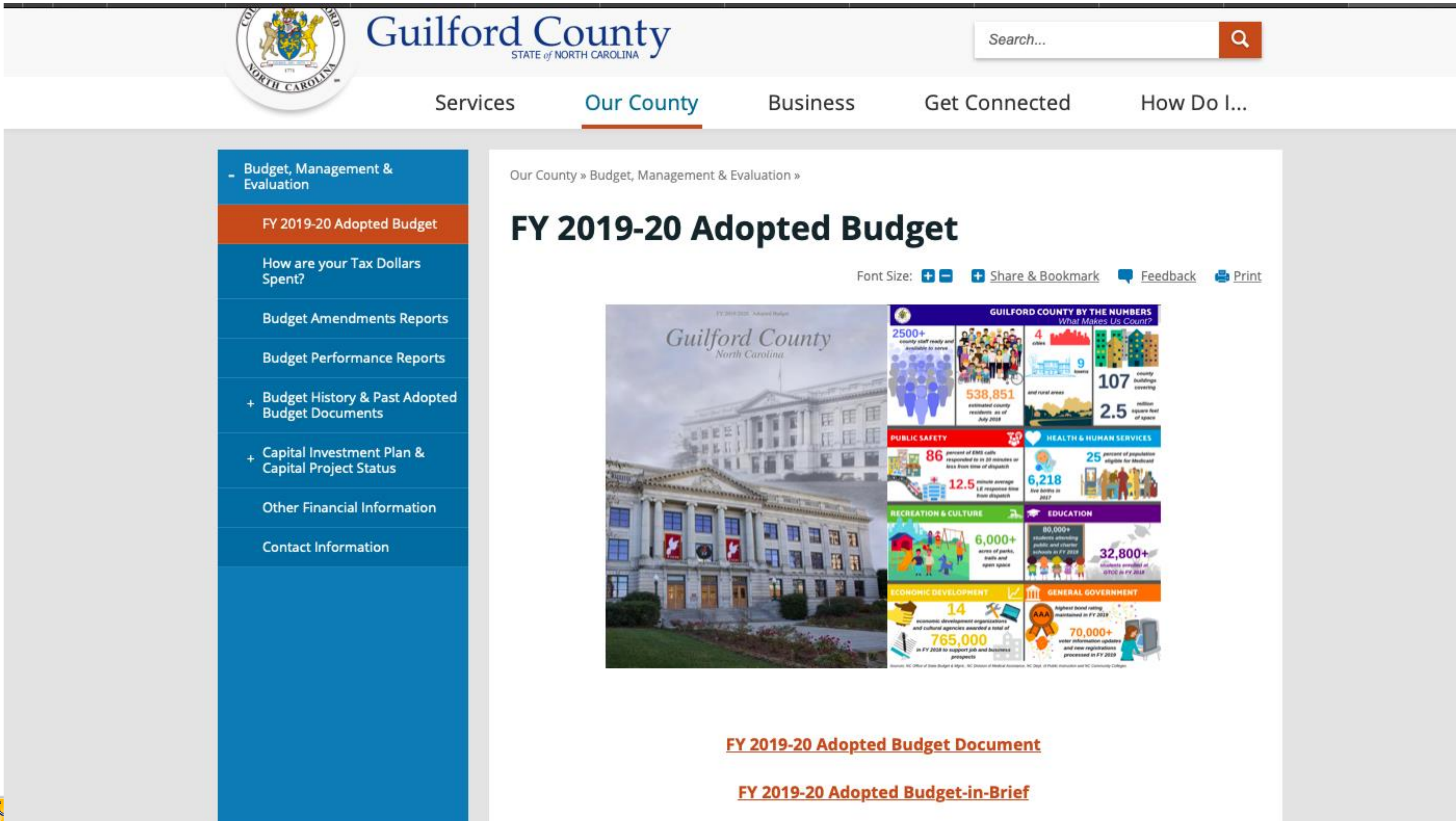
Data Source


Guilford County
STATE of NORTH CAROLINA
Search...
Services
Our County
Business
Get Connected
How Do I...
Budget, Management & Evaluation
FY 2019-20 Adopted Budget
How are your Tax Dollars Spent?
Budget Amendments Reports
Budget Performance Reports
Budget History & Past Adopted Budget Documents
Capital Investment Plan & Capital Project Status
Other Financial Information
Contact Information
Our County » Budget, Management & Evaluation »
FY 2019-20 Adopted Budget
Font Size:
Share & Bookmark
Feedback
Print
Guilford County
North Carolina
GUILFORD COUNTY BY THE NUMBERS
What Makes Us Count?
2500+
538,851
4
9
107
2.5
PUBLIC SAFETY
86
12.5
HEALTH & HUMAN SERVICES
25
6,218
RECREATION & CULTURE
6,000+
EDUCATION
80,000+
32,800+
ECONOMIC DEVELOPMENT
14
765,000
GENERAL GOVERNMENT
AAA
70,000+
FY 2019-20 Adopted Budget Document
FY 2019-20 Adopted Budget-in-Brief

Data Analysis

```
In [47]: Combined_df.shape
Out[47]: (638131, 3)
```

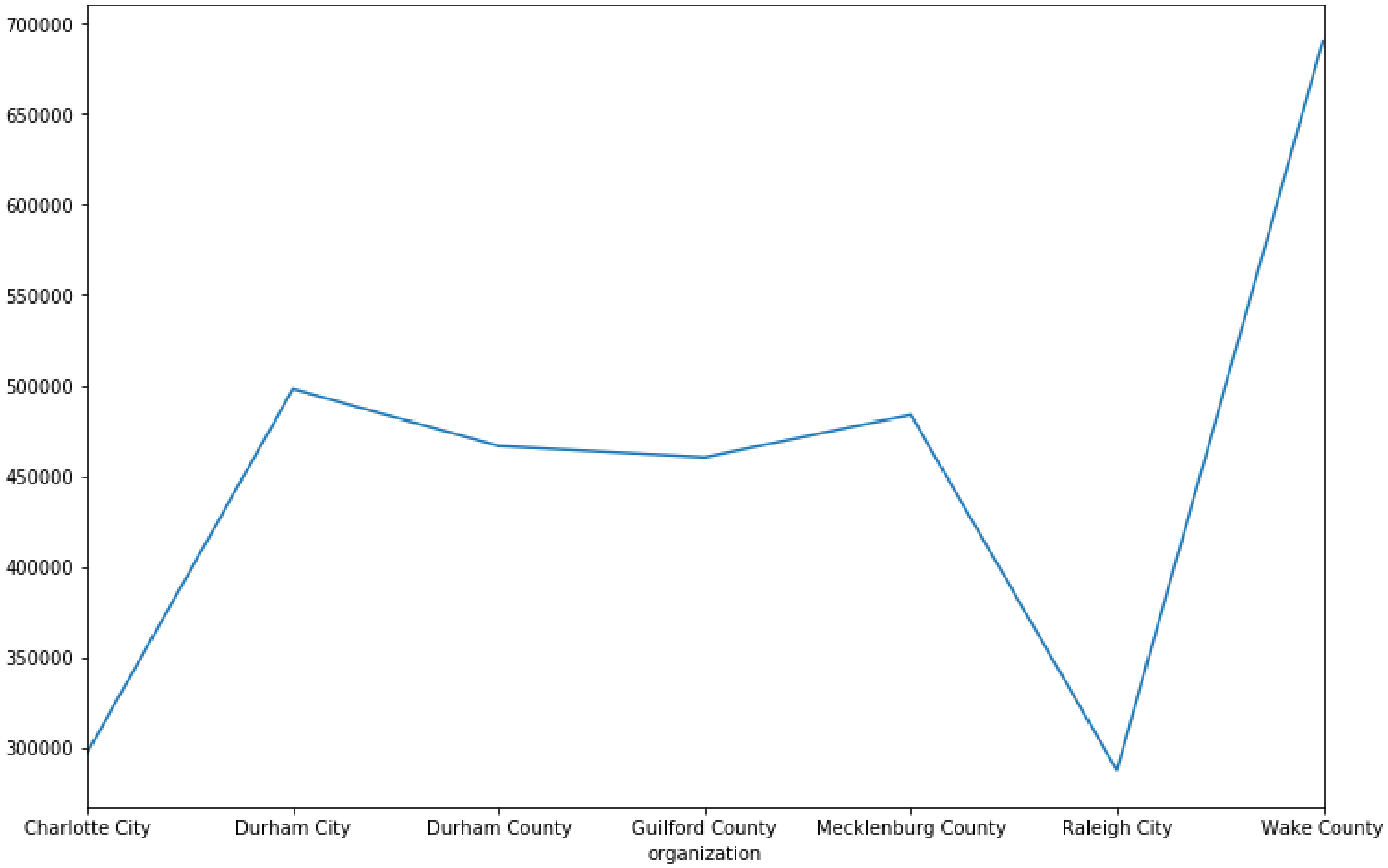
```
In [45]: Combined_df.describe()
Out[45]:
```

	page_number
count	638131.000000
mean	213.602262
std	137.058241
min	1.000000
25%	100.000000
50%	203.000000
75%	305.000000
max	537.000000

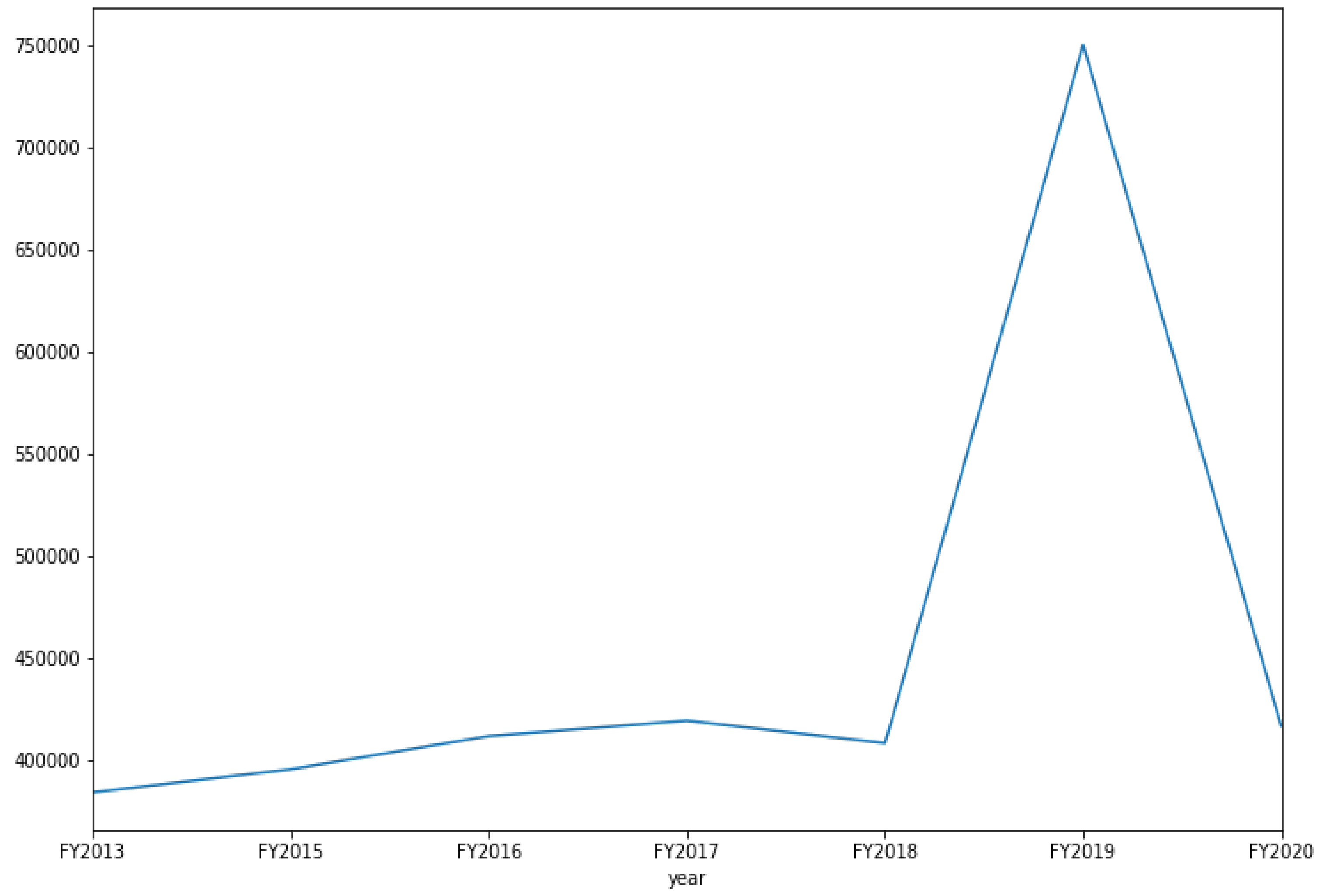
```
In [50]: Combined_df.to_csv("Combined_Counties.csv", sep='\t', encoding='utf-8')
```

```
In [ ]:
```

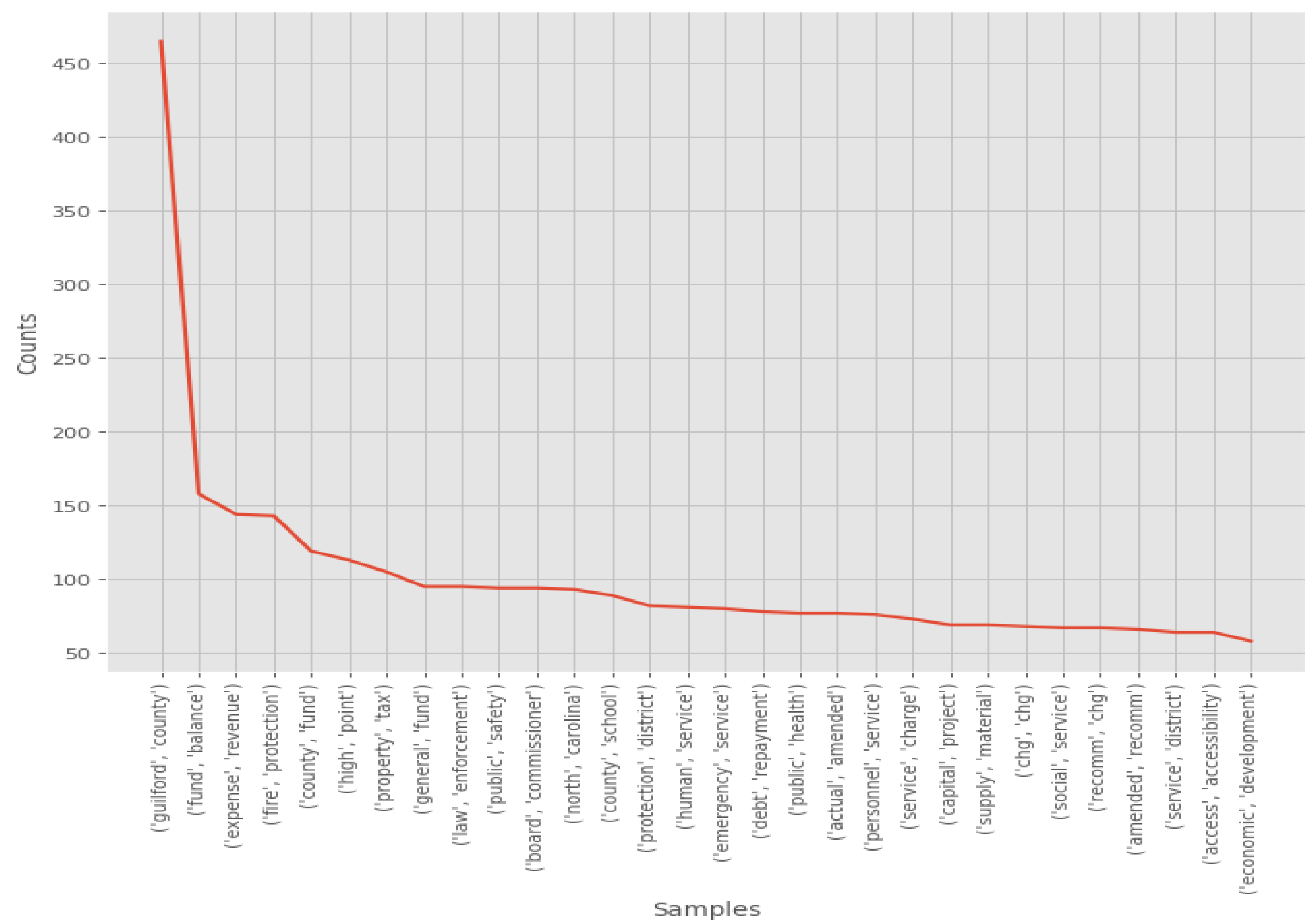
Count of words grouped by organizations.



Count of words grouped by year.



Most Frequent bigrams in Guilford County budget document From 2020



Corpus Similarity

- **Goal: Quantify the similarities between the budget documents.**

- **Method: cosine similarity is selected to determine the similarity between the documents irrespective.**
- **Why?**
  - **Other common methods find the similarities by counting the maximum number of common words between the documents.**
  - **Cosine: does not take size of the documents into account.**

Corpus Similarity

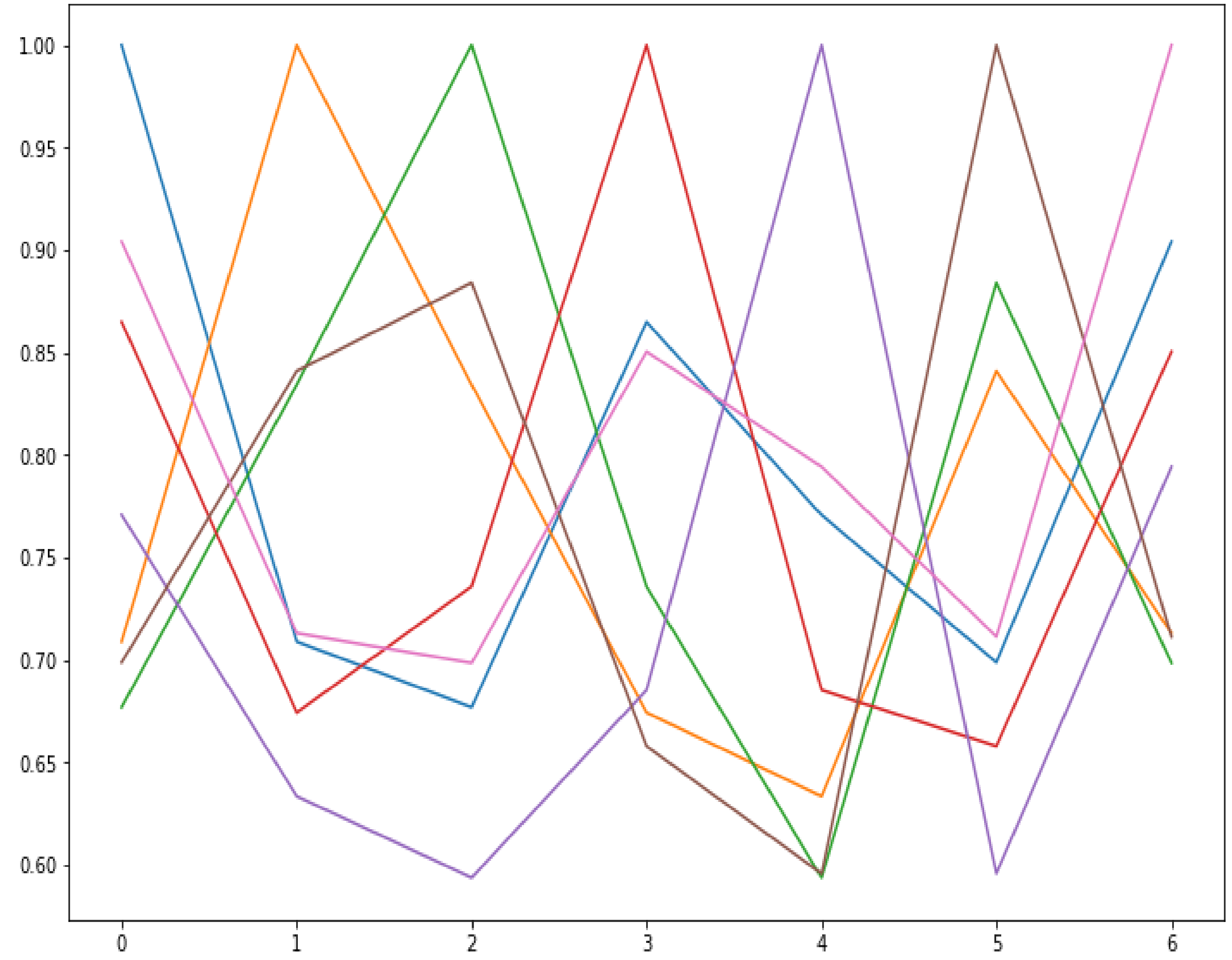
- **The steps followed to achieve the our goal are:**
  - 1. Define the documents,
  - 2. Vectorize,
  - 3. Compute cosine similarity,
  - 4. Visualize the results.

Linear relationship between words

```
In [41]: nearest_similarity_cosmul("guilford","county","year")

guilford is related to county, as fiscal is related to year

C:\Users\Sultan\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DeprecationWarning: Call to deprecate
d `most_similar_cosmul` (Method will be removed in 4.0.0, use self.wv.most_similar_cosmul() instead).
  after removing the cwd from sys.path.

Out[41]: 'fiscal'
```

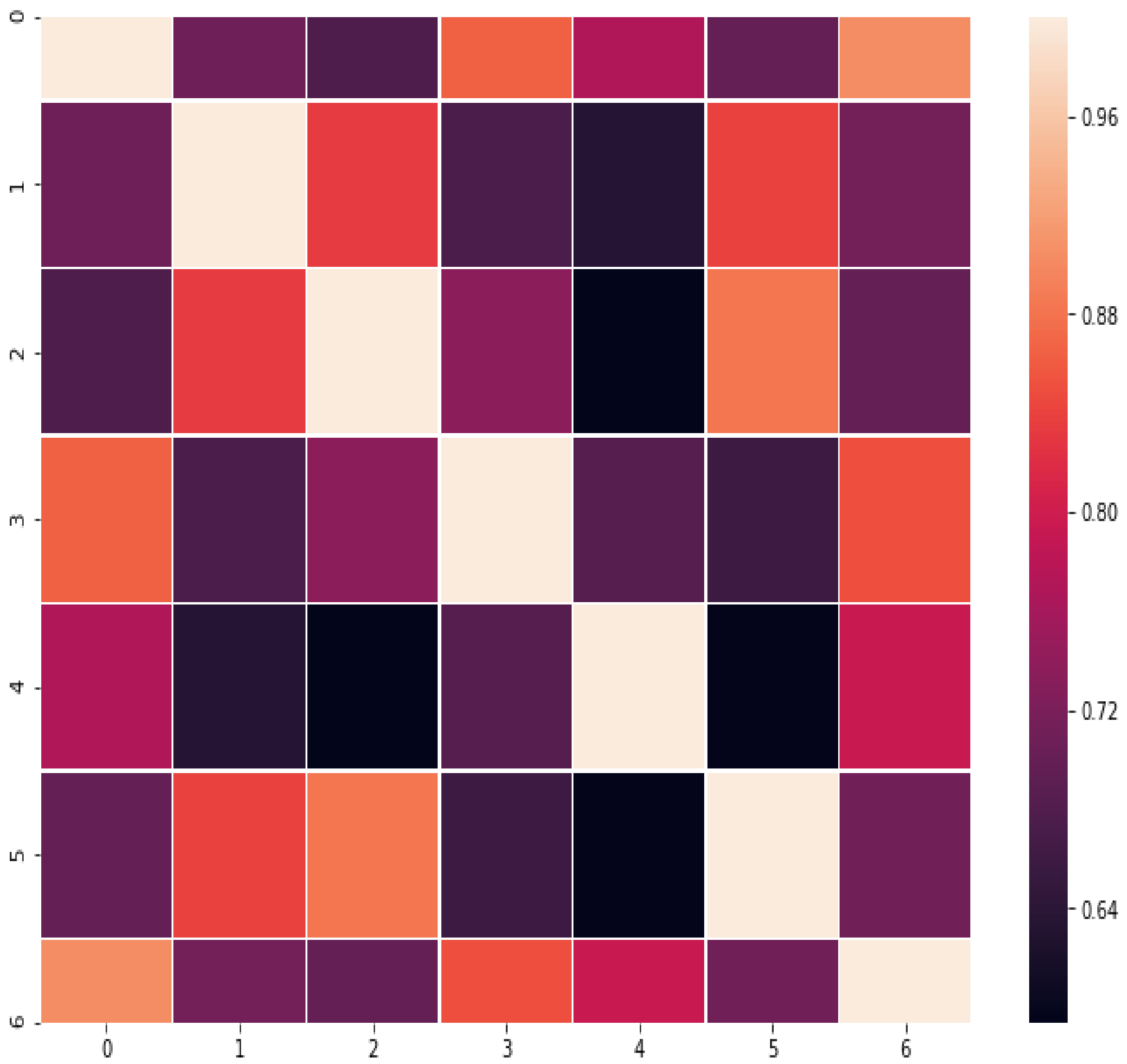
Results – Data from 2020-2013

#1- Guilford County
#2- Charlotte City
#3- Durham City
#4- Durham County
#5 -Mecklenburg County
#6- Raleigh City
#7- Wake County



Results

- #1- Guilford County
- #2- Charlotte City
- #3- Durham City
- #4- Durham County
- #5 -Mecklenburg County
- #6- Raleigh City
- #7- Wake County



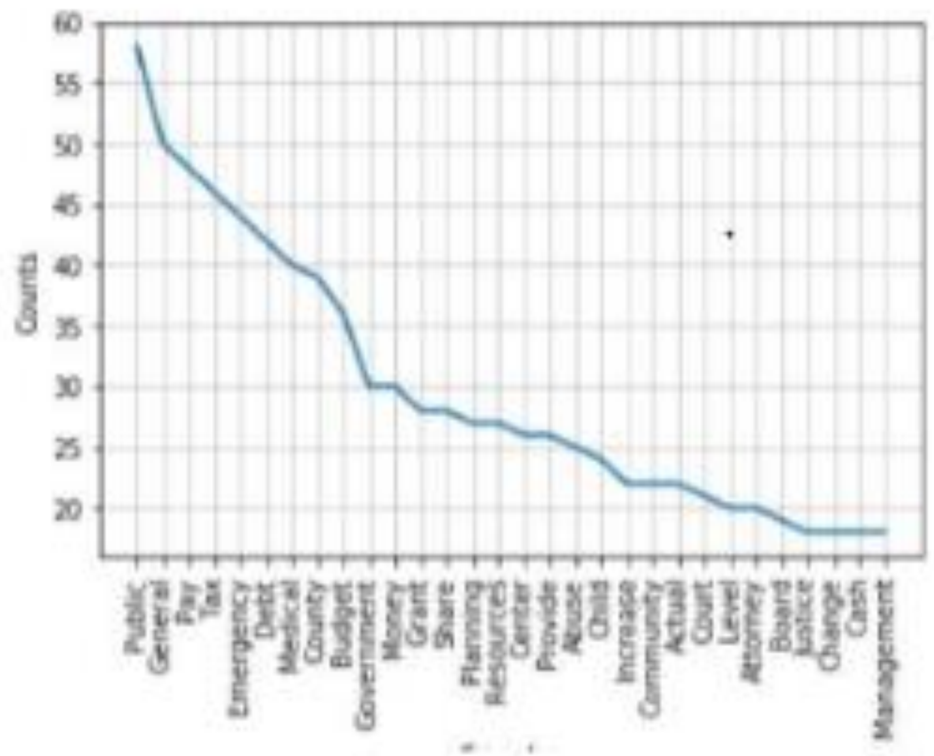
Sentiment Analysis : Influential words

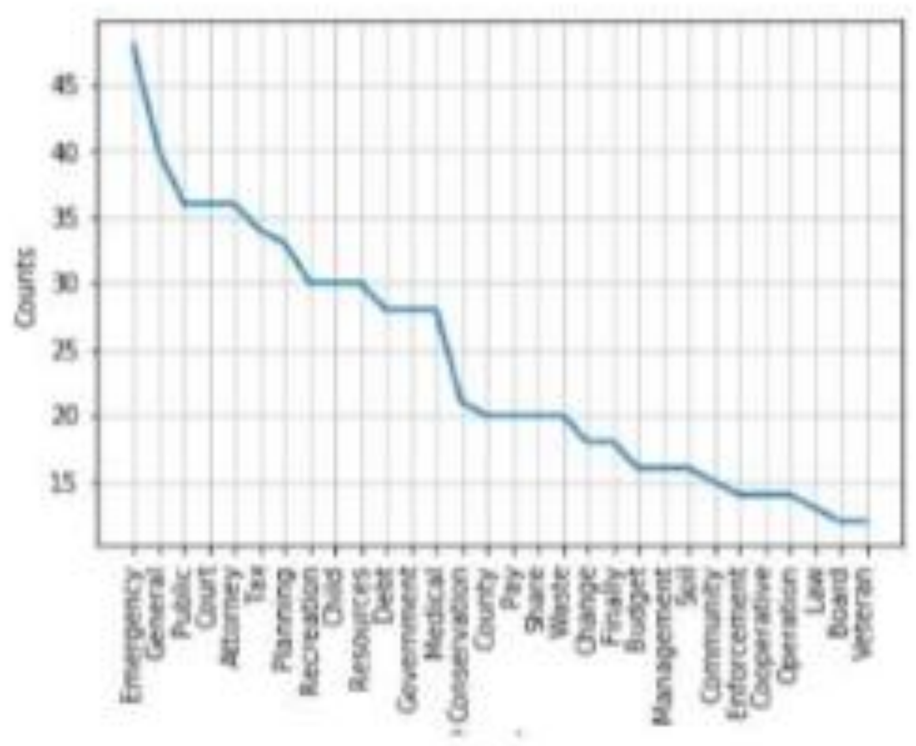
Most Influential Words in Guilford County (2020 and 2008)

```
[('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)]
```

Frequency of most influential words(2020 and 2008)





Sentiment Analysis : Sentiment renaming

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

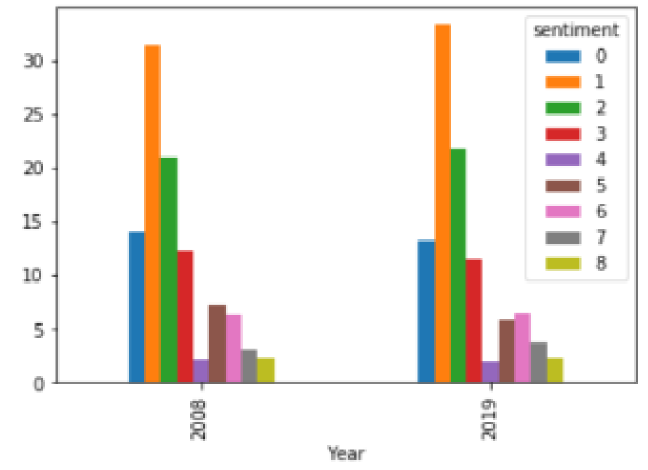
Distribution of Emotions Services section for Guilford County

Distribution of Emotions Services section for Guilford County

sentiment	0	1	2	3	4	5 \
Year						
2008	13.982430	31.442167	20.973646	12.262079	2.159590	7.320644
2019	13.250518	33.258046	21.682665	11.424807	2.051572	5.853567

sentiment	6	7	8
Year			
2008	6.368960	3.111274	2.379209
2019	6.437041	3.707886	2.333898

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1dc873ac828>



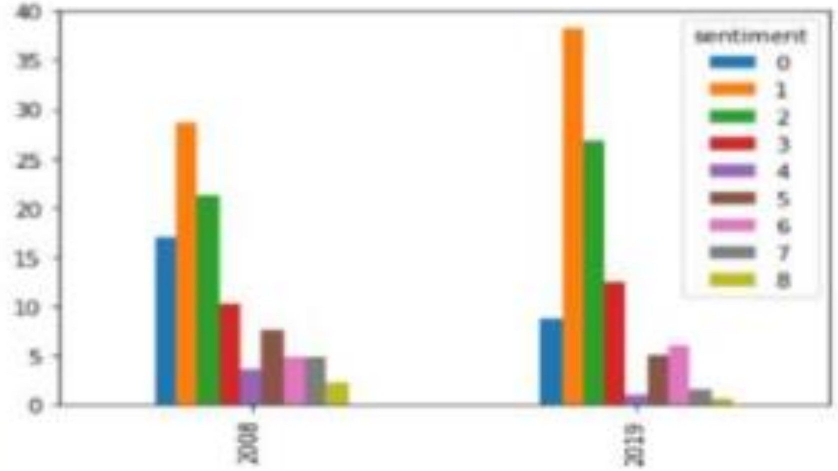
Distribution of Emotions in General Fund section (2008 and 2020) for Charlotte County

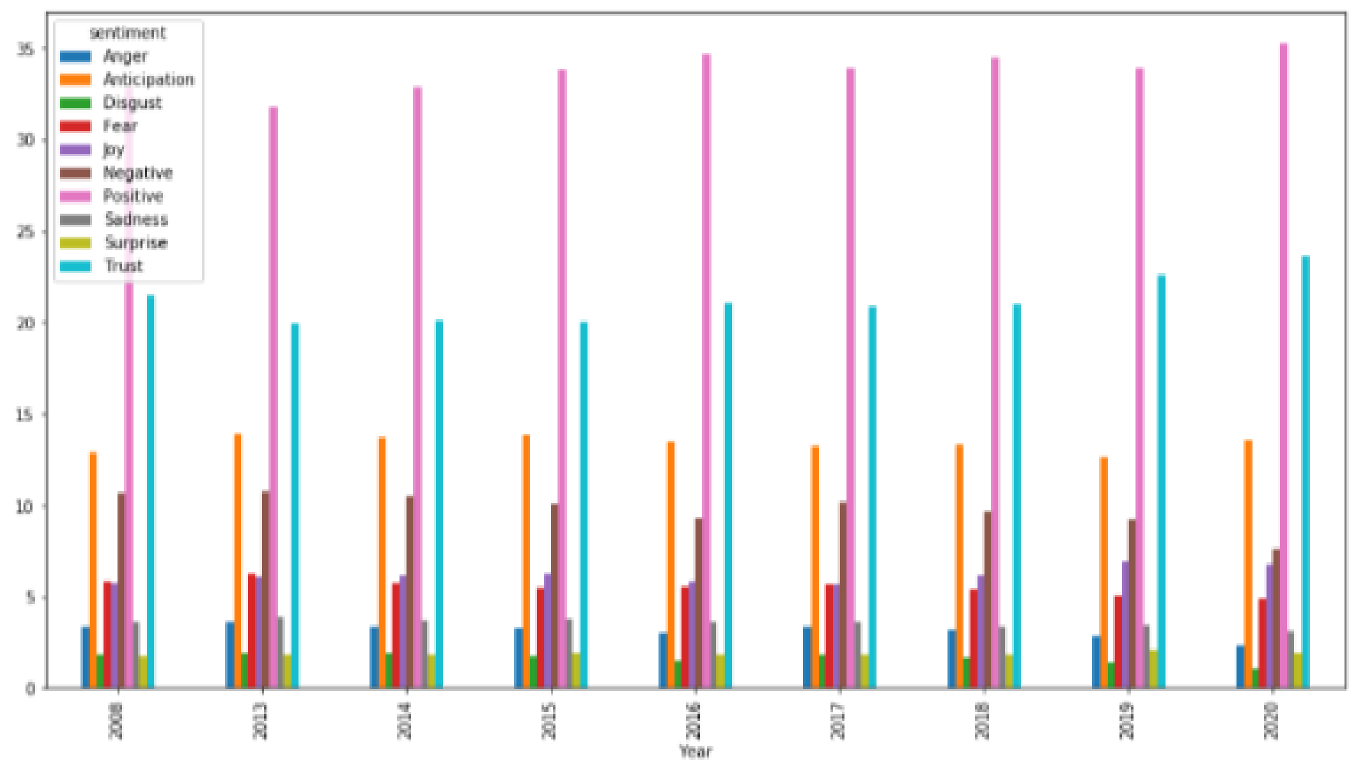
6221

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>





Charlotte sentiments and emotions distribution over the years(2008 and 2013 to 2020):

Charlotte Sentiment Continue..

- The plot shows that Positive sentiments increased after 2008 till year 2016 and slightly dropped in 2017 and remained stable in further years.
- While the Negative sentiments have reverse impact, as they dropped till year 2016 and increased in 2017 and then again dropped till 2020.
- Also the emotions like Disgust and Fear kept reducing over the years while Anticipation remained almost same for all years.

Hypothesis Testing:

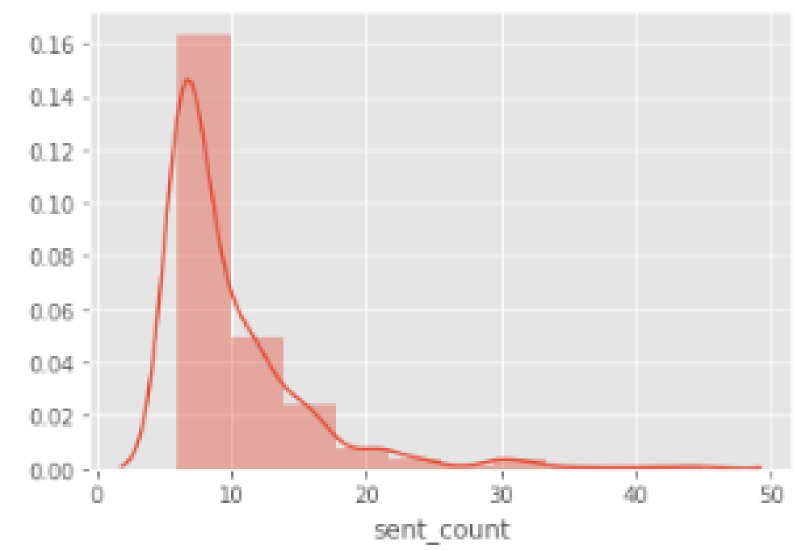
- H0 -> The sentiments remain same for service part from 2008 and 2020.

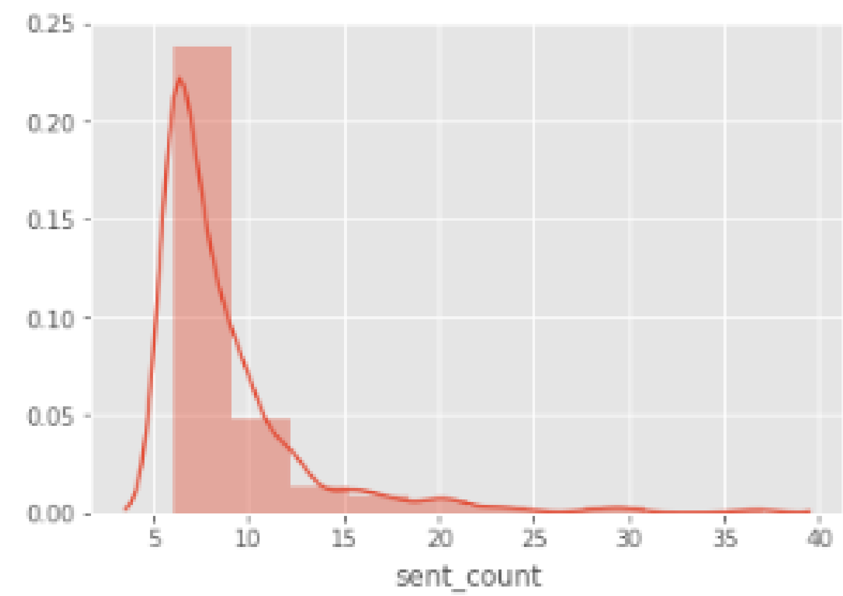
  H1 -> Sentiment changes for service part from 2008 to 2020.

- To prove this Hypothesis two sample is performed and p-value threshold is $p = 0.05$
- P-Value is greater than threshold (0.56) therefore we were failed to reject null hypothesis.

Probability Distribution:

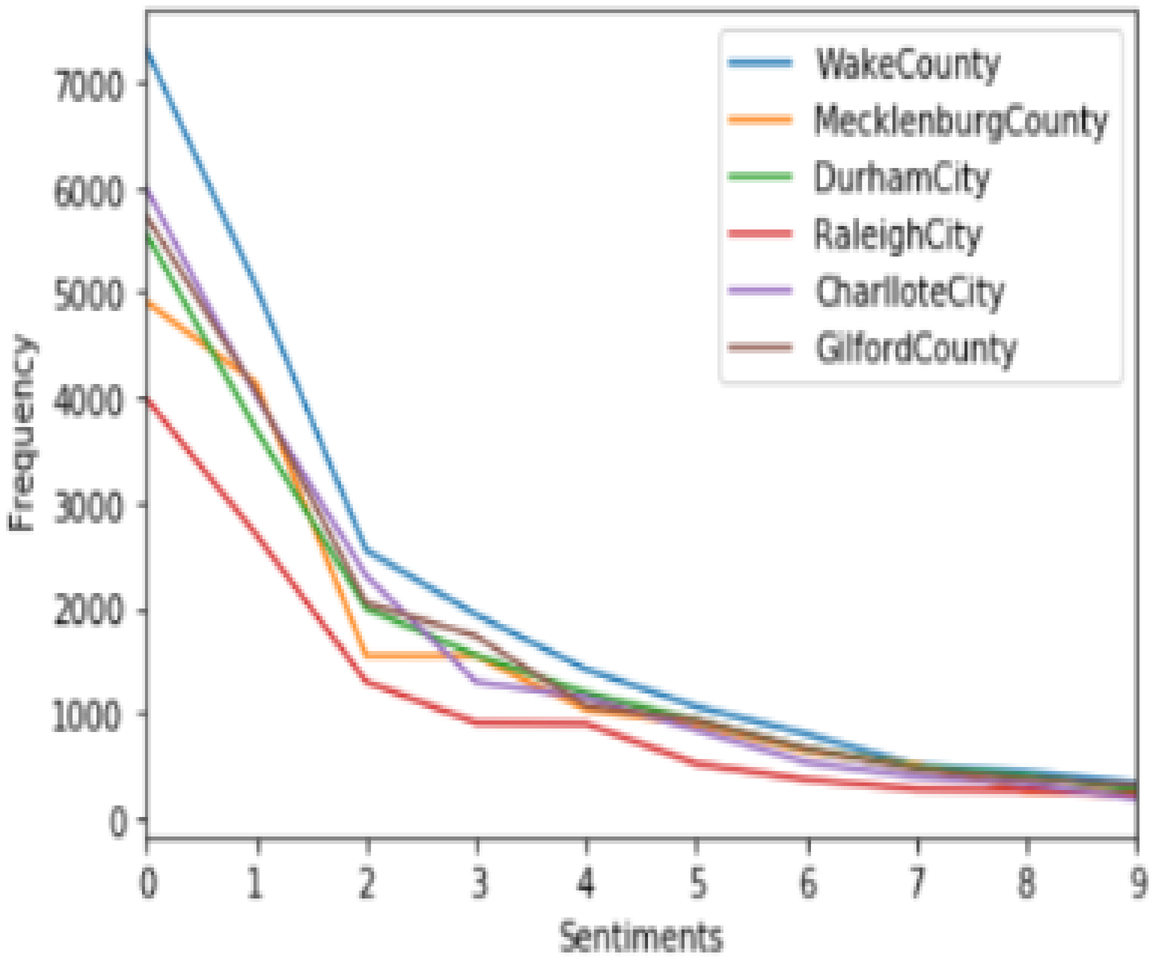
- I have concatenated Guilford county, Durham county, Durham city, charlotte city, Raleigh city :
- Took negative sentiment counts (at least more than 5 times).
- Took positive sentiment counts (at least more than 5 times):

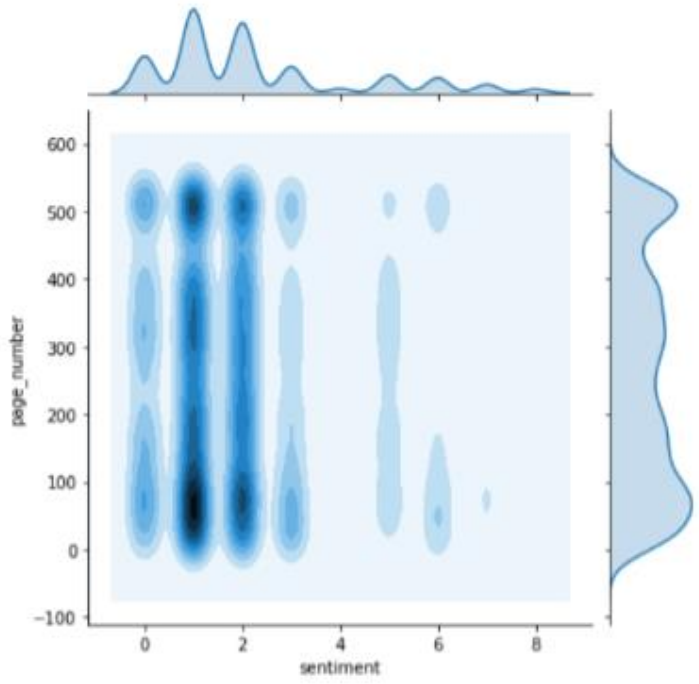


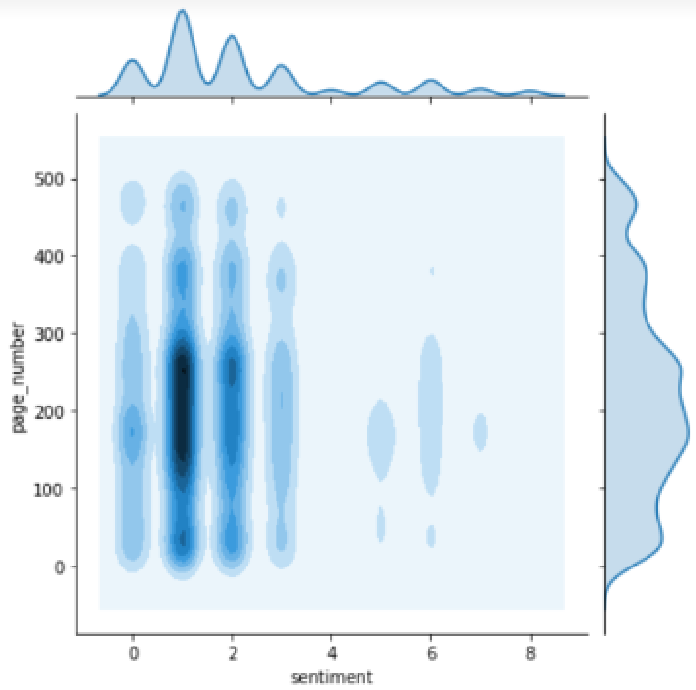


sentiments and emotions for all the cities

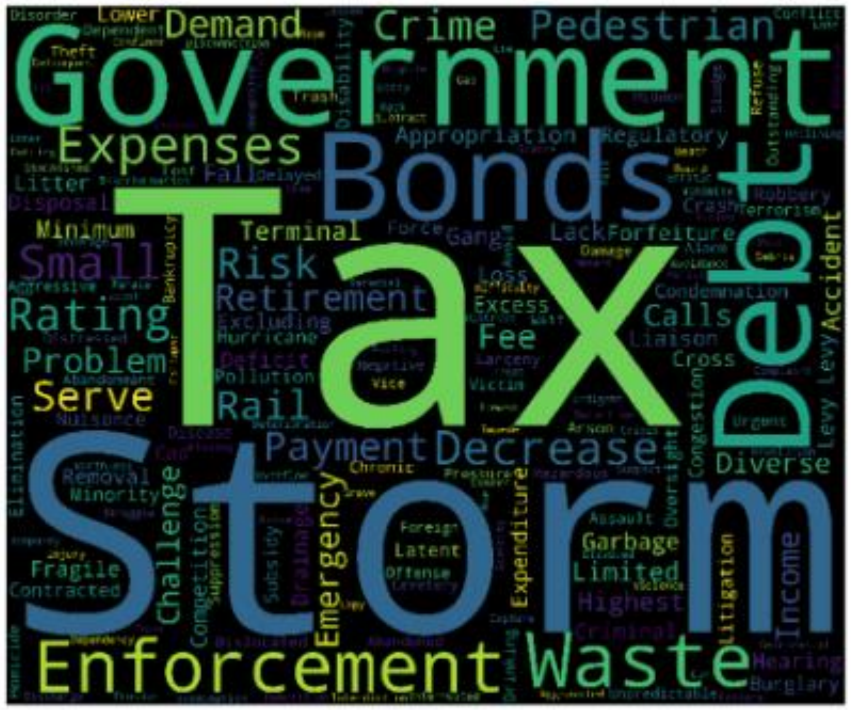
- Frequency Distribution of sentiment and emotions in the budget document remains the same.
- In Mecklenburg county it is noticed that the negative sentiment is slightly increased while this is not seen for all the cities.







Sentiment and emotion distribution with respect to page number



Charlotte city negative words (2008 and 2020)

Machine Learning

- Sample data

	text	afinn_score	emotion
0	General revenues projected rebound from econom...	0.0	1
1	City continues face limitations balancing prio...	-1.0	0
2	However City employees continue work hard prev...	-2.0	0
3	Examples prior year reductions listed below	0.0	1
4	complete listing unfunded budget requests prov...	0.0	1

Machine learning

- Split the data in 70/30 for creating train/test dataset.
- TF-IDF was used on training data. This vectorizer breaks text into single words and bi grams and create TF-IDF representation to create feature vectors.
- X -> Vectorized text
- Y-> (positive, negative)

Machine Learning

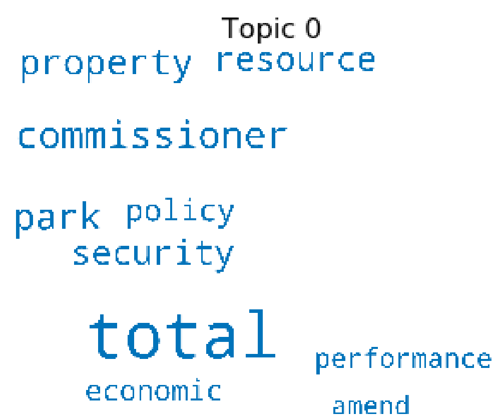
- Results

```
<class 'scipy.sparse.csr.csr_matrix'>
RMSE : 0.41633319989322654
Accuracy : 82.67%
RMSE : 0.3651483716701107
Accuracy : 86.67%
RMSE : 0.32659863237109044
Accuracy : 89.33%
```

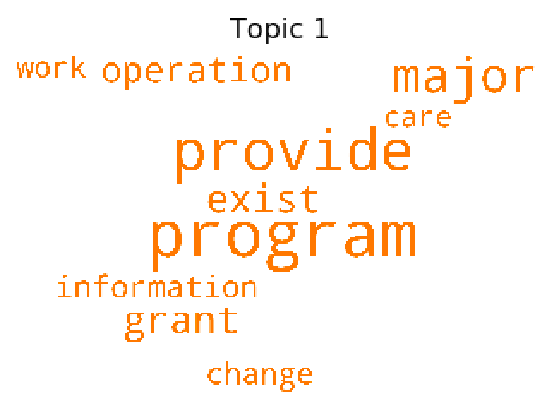
Topic Modeling

```
[(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"')]
```

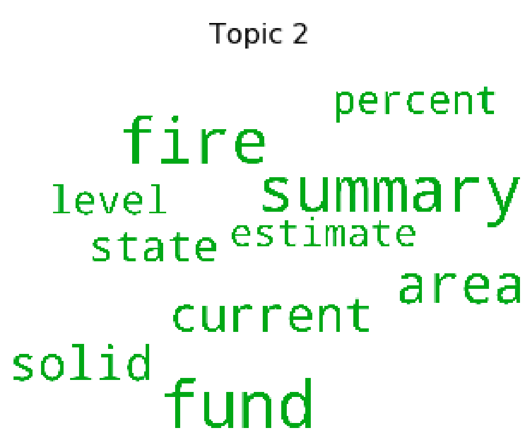
Topic Modeling



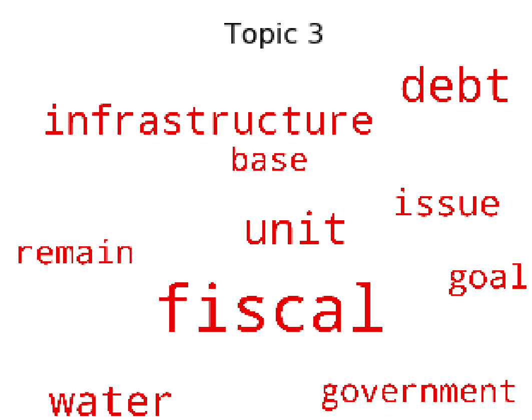
Label: Property Maintenance and Security



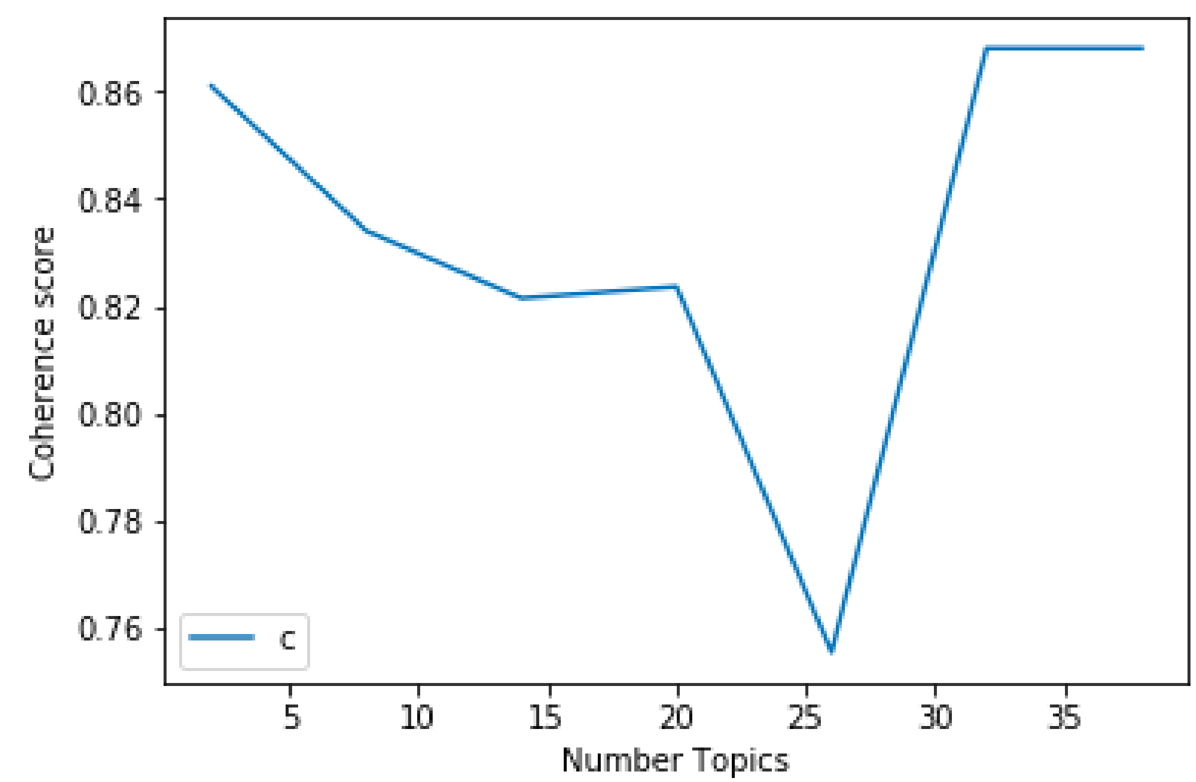
Label: Grant for Work or Program



Label: State Fire Fund

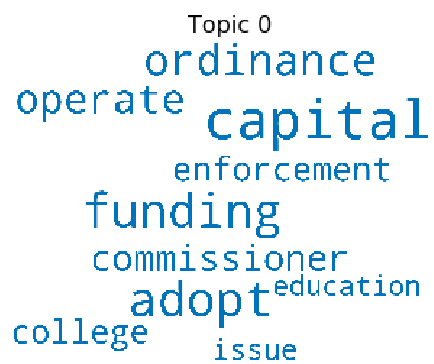


Label: Government Fiscal Year

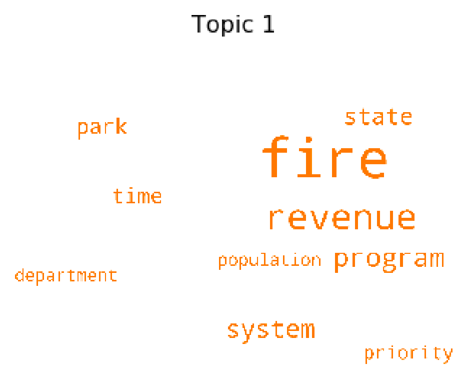


Coherence Score: 0.8256146597574272

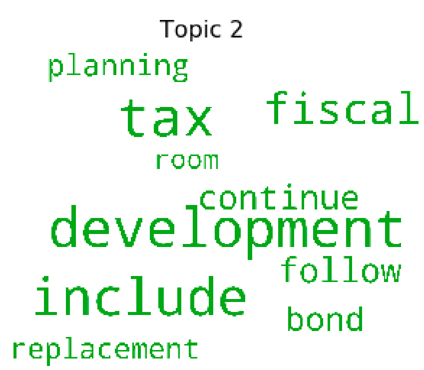
Topic Modeling Comparison



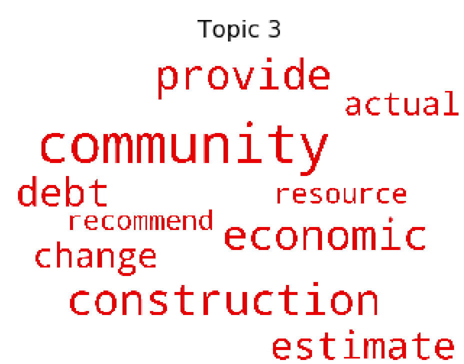
Label: Capital Funding for Education



Label: Fire Fund Program



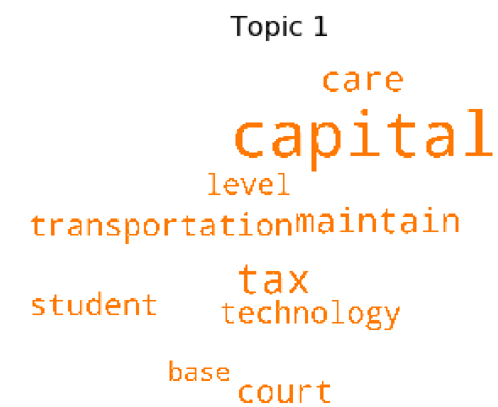
Label: Fiscal Year Planning



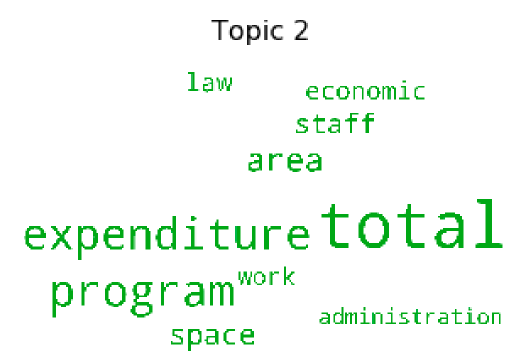
Label: Community Construction

2019

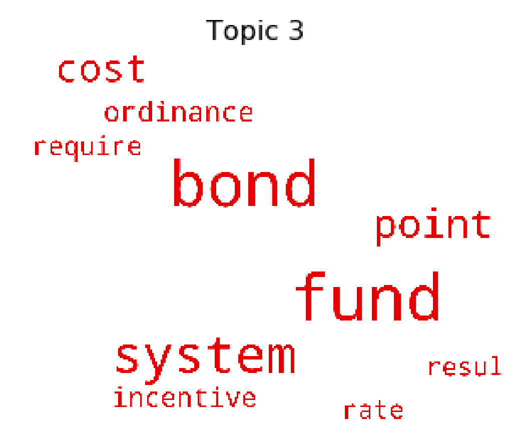
Label: Increase risk in project, department



Label: Student Tax



Label: Economic Expenditure



Label: Financial Indicators

2008

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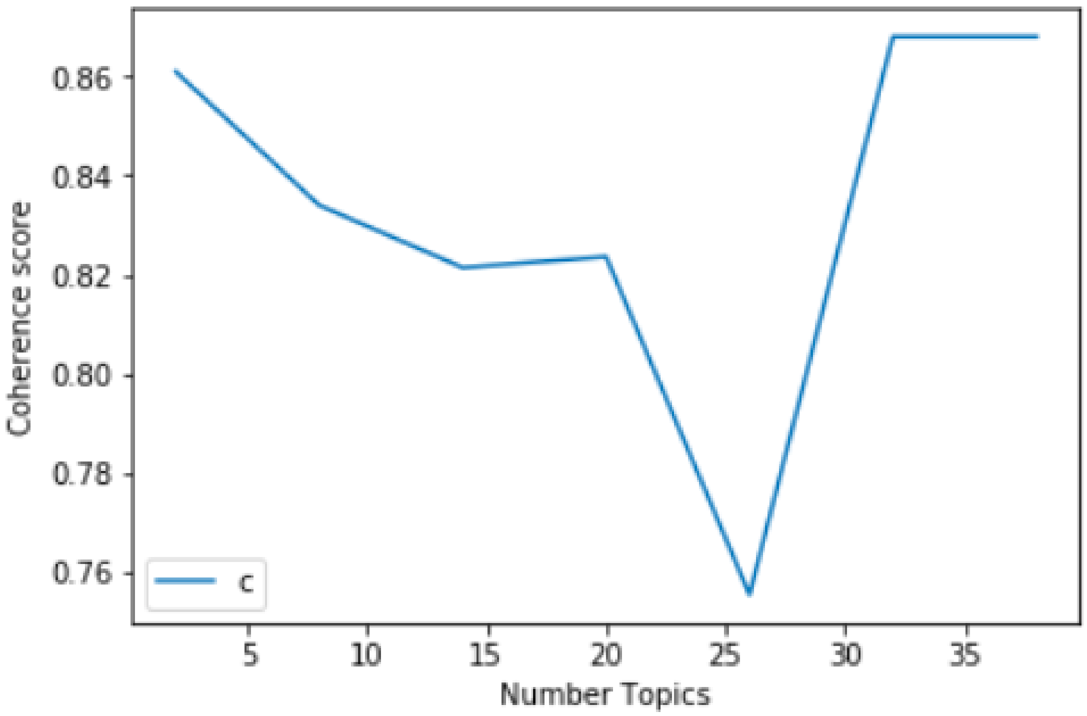
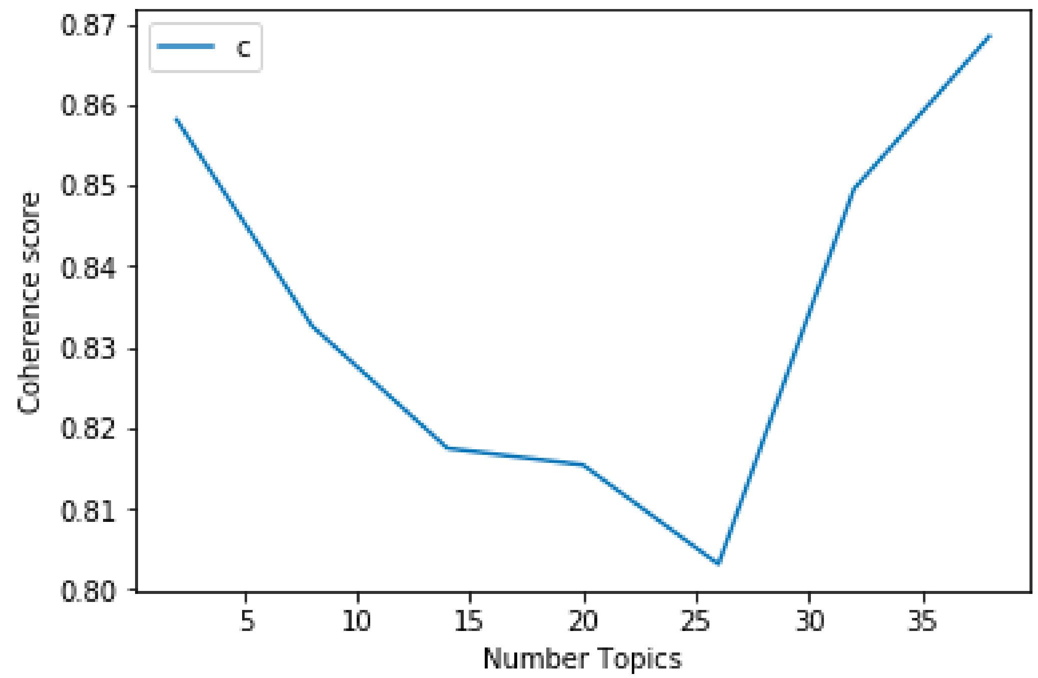
Topic Modeling Comparison



Coherence Score: 0.8256146597574272

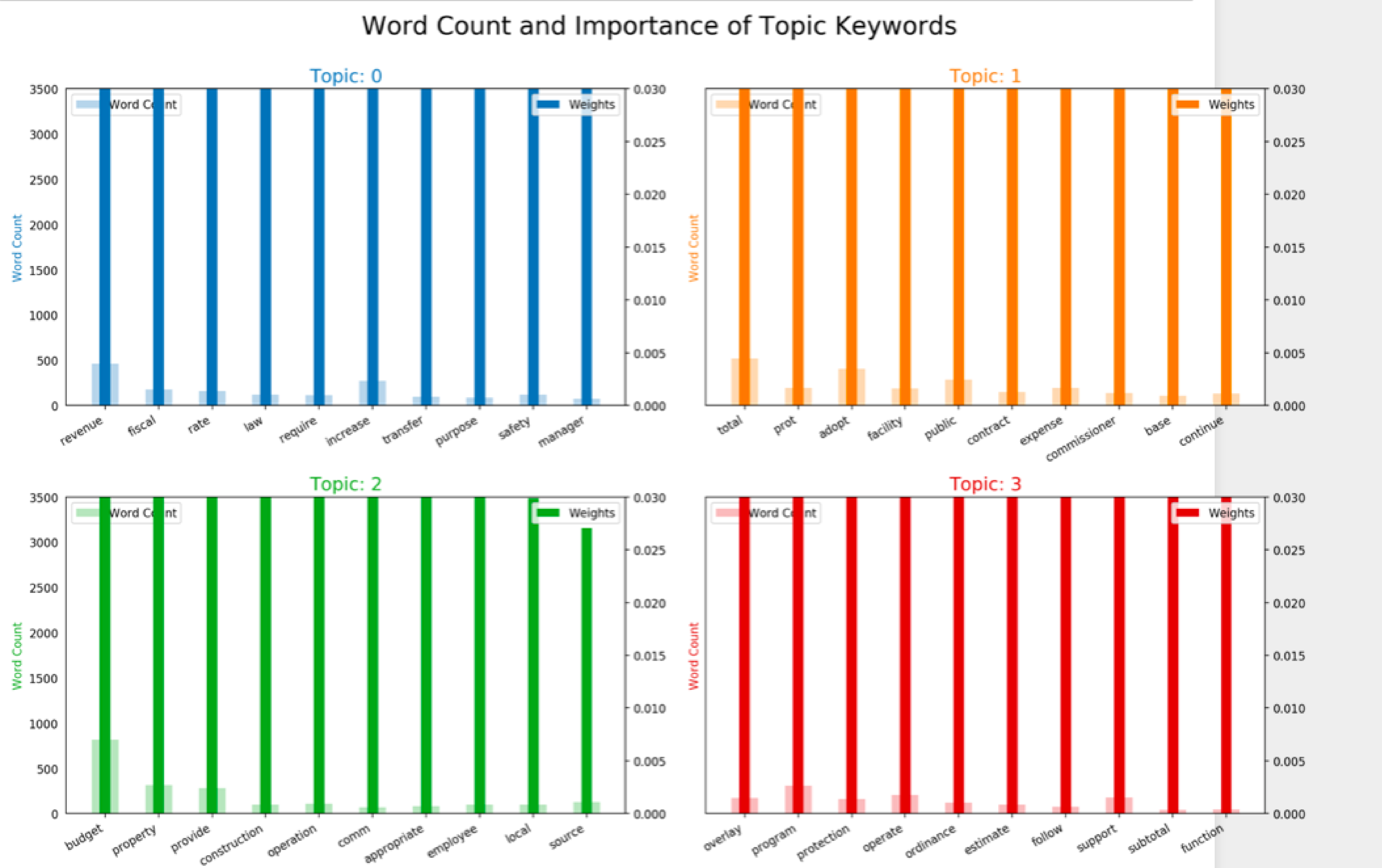
2019



Coherence Score: 0.8247949042506306

2008

Topic Modeling



Machine Learning Tasks

- Train LDA Model on the budget texts from 2019.
- Grab Topic distributions for every budget texts using the LDA Model
- Use Topic Distributions directly as feature vectors in supervised classification models (Logistic Regression, SVM, etc) and get F1-score.
- Use the same 2019 LDA model to get topic distributions from 2018 and 2020 (**the LDA model did not see this data!**)
- Run supervised classification models again on the 2018 and 2020 vectors and see if this generalizes.

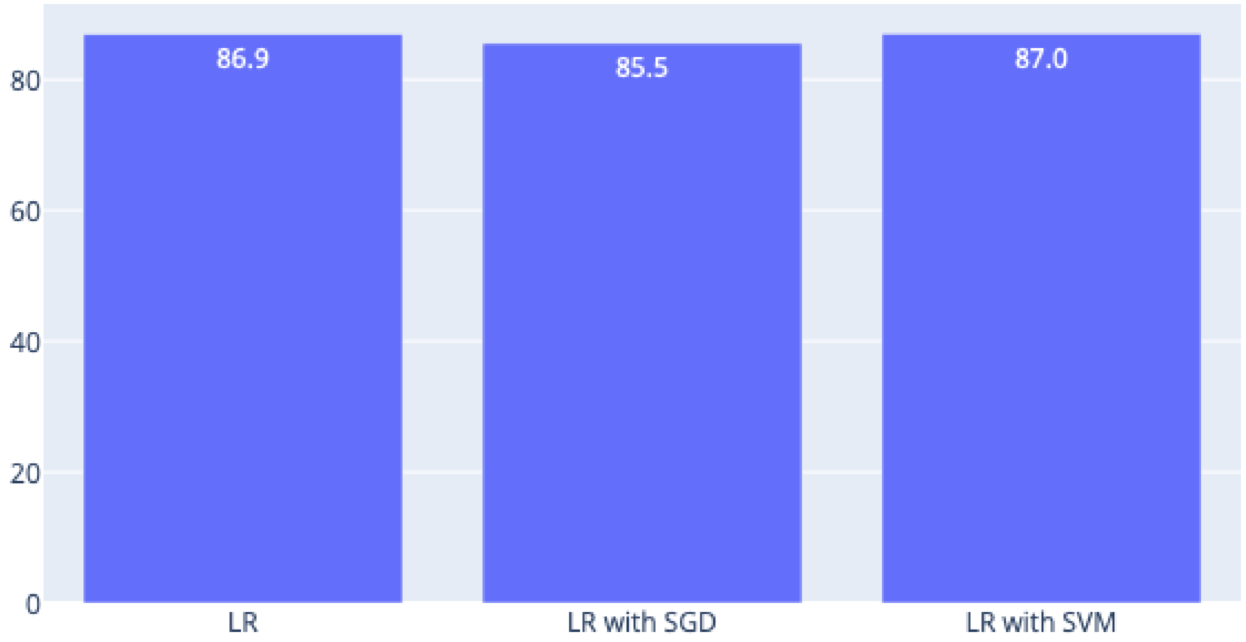
Converting Topics to Feature Vectors for Machine Learning

```
In [108]: train_vecs = []
          for i in range(len(GC_df)):
              top_topics = lda_model.get_document_topics(corpus[i], minimum_probability=0.0)
              topic_vec = [top_topics[i][1] for i in range(10)]
              topic_vec.extend([GC_df.iloc[i].sent_count]) # counts of reviews for restaurant
              topic_vec.extend([len(GC_df.iloc[i].word)]) # length review
              train_vecs.append(topic_vec)

In [109]: train_vecs[2]

Out[109]: [0.04846649,
           0.042821117,
           0.03781131,
           0.0386842,
           0.055064,
           0.050130684,
           0.043984495,
           0.087888956,
           0.54818475,
           0.046964042,
           36,
           4]
```

Supervised Classification (Training Data Result)

- X = [train_vecs];
- Y = [predicted_labels];
- Result:

```
Logistic Regression Val f1: 0.869 +- 0.003
Logisitic Regression SGD Val f1: 0.855 +- 0.008
SVM Huber Val f1: 0.870 +- 0.003
```



Supervised Classification (Testing on Unseen Data

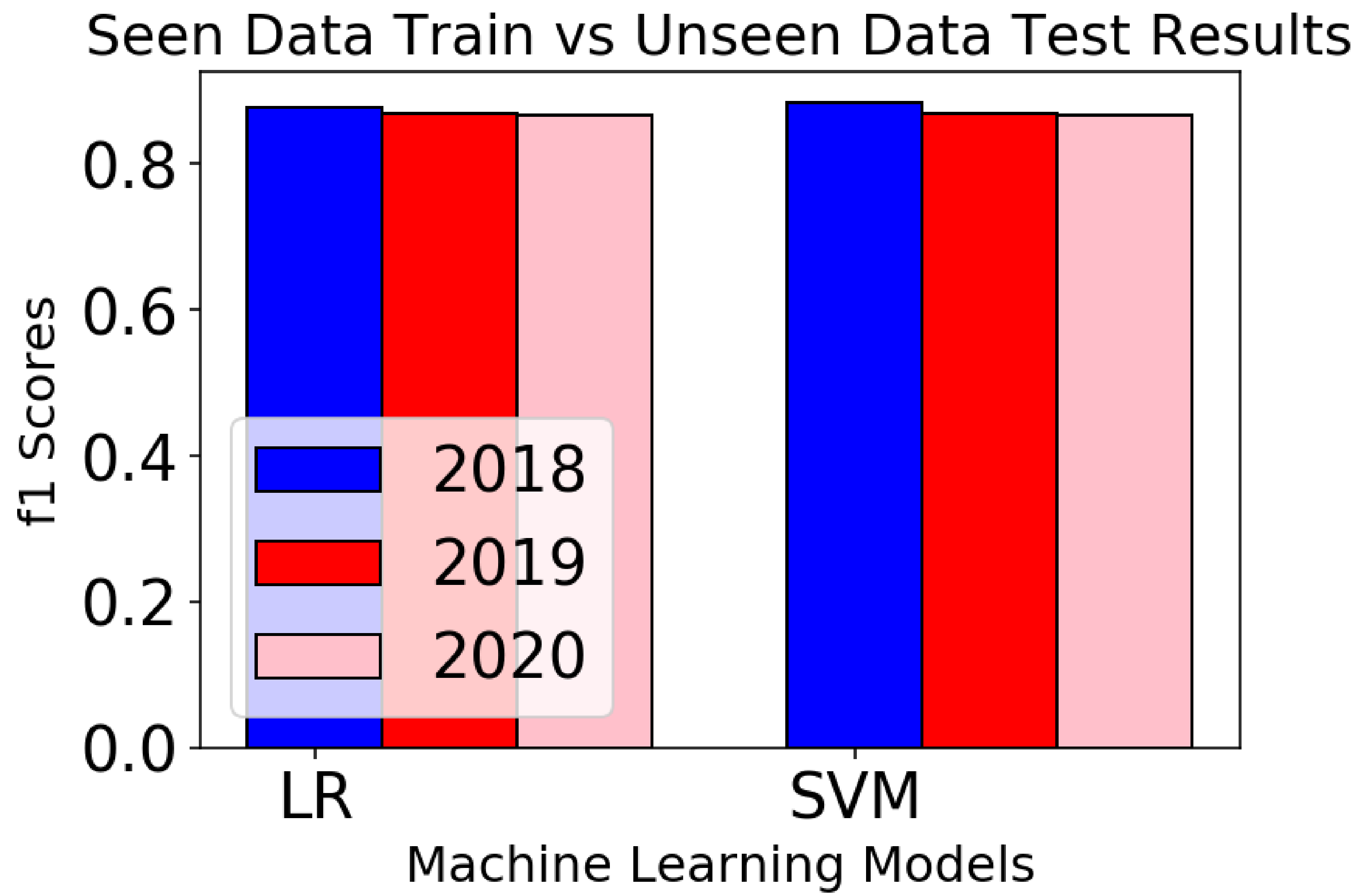
- For 2018:

```
0.8775611031997443
0.883026010151702
```

- For 2020:

```
0.8663699340718182
0.8665751454533569
```

Supervised Classification (On Test Data)



SHOCKING!!!!!!!

Hypothesis Testing

- H0(null hypothesis) -> The ML models are similar and perform for all the year .
- H1 -> The ML models are truly different and perform differently.
- Condition for Hypothesis taken such that p-value threshold is p = 0.05

```
chi-squared: 10.861150070126227
p-value: 0.0009820269000594094
```

- Hence, the null hypothesis was rejected, as the models were completely different.

Next Word Recommender

- **Simulated text with markov chain method.**
- **A Markov chain is a simulated sequence of events. Each event in the sequence comes from a set of outcomes that depend on one another.**
- **For any sequence of non-independent events in the world, and where a limited number of outcomes can occur, conditional probabilities can be computed relating each outcome to one another.**
- **To generate a simulation based on a certain text, count up every word that is used. Then, for every word, store the words that are used next. This is the distribution of words in that text *conditional on* the preceding word.**

Next Word Recommender

https://drive.google.com/open?id=1J-O3GMuii8fL9DrOM0MvREFdU9eznQYk

Conclusion

- **The topic modeling analysis implicates the topic model for 2019 year can identify the latent semantic structure that persists over time in this budget text domain**
- **Comparison between topic models showed that frequent topics between 2008 and 2016 are dissimilar to each other.**
- **Altogether mostly all the cities and counties considered showed much similarity in the type of sentiments, which was passed over the years.**
- **Even though, the topics were quite different, the sentiments were similar over the years.**
- **Next word recommender recommends a next words from a cluster based on the previous words.**