Budget Text Analysis

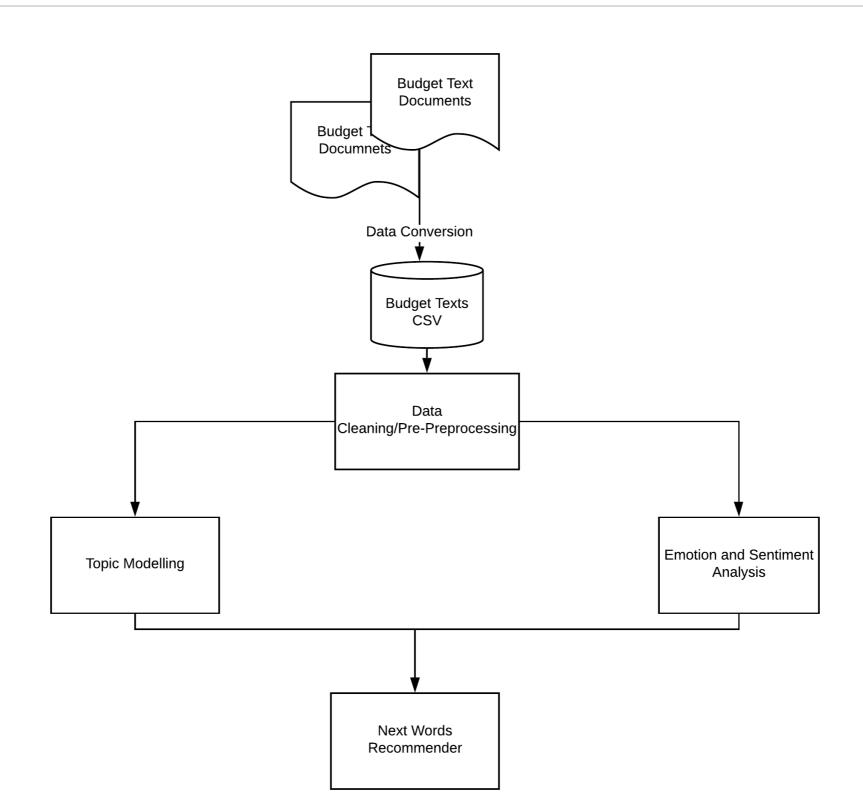
- Datatopian Visionaries

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 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.



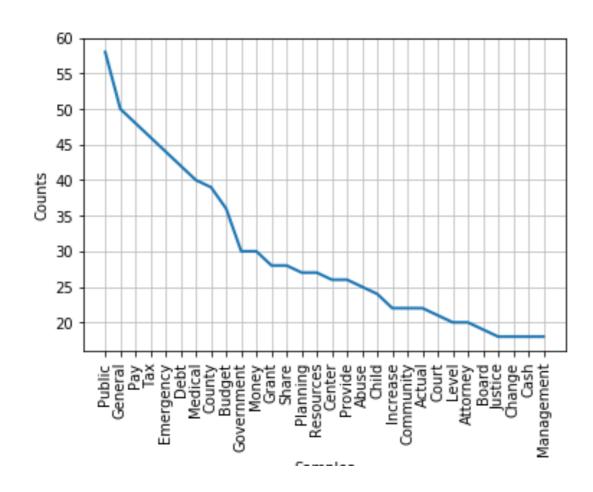
Most Influential Words in Guilford County (2020 and 2008)

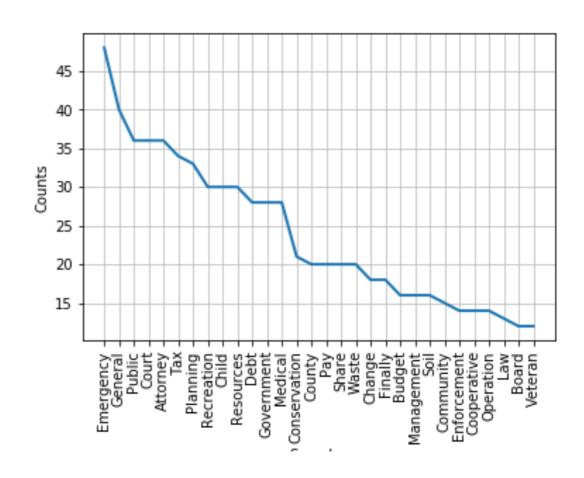
```
[('Public', 58),
  ('General', 50),
  ('Pay', 48),
  ('Tax', 46),
  ('Emergency', 44),
  ('Debt', 42),
  ('Medical', 40),
  ('County', 39),
  ('Budget', 36),
  ('Government', 30)]
```

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



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







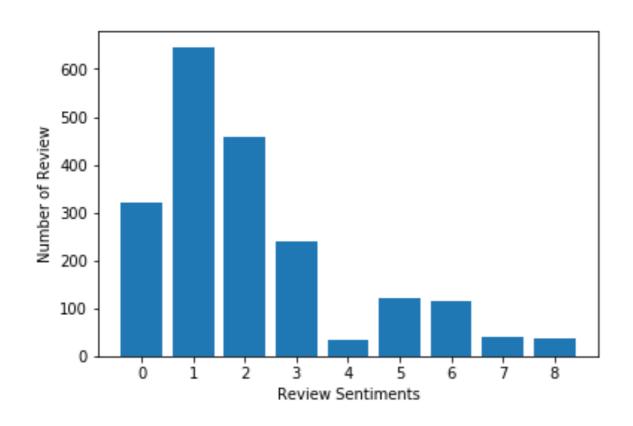
We have assigned numerical value to every emotion present in the document. Here is the list:

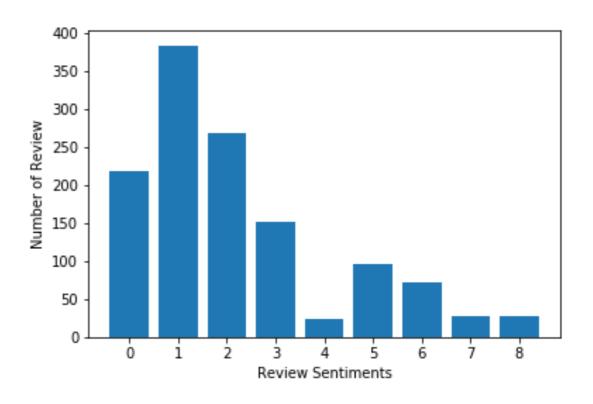
"Negative": "0","Positive":

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



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







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

```
32/8
sentiment
                                                                          5
Year
2008
           17.219589
                      30.252765
                                 21.090047
                                             11.927330
                                 22.763419 11.928429
2020
           16.003976
                      32.107356
                                                        1.689861
sentiment
                            7
Year
2008
           5.608215
                     2.211690
                               2.211690
2020
           5.715706 2.037773 1.789264
```

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



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

```
6221
sentiment
                                        2
                                                                      5
Year
2008
          16.993464 28.540305 21.241830
                                          10.130719 3.594771
2019
                     38.148218
                               26.758439
                                          12.370356 0.999434
           8.730907
sentiment
                 6
                                     8
Year
2008
          4.793028 4.793028
                              2,287582
          5.883462 1.470866 0.546860
2019
```

40 35 30 25 20 15 10 5 0 10 7 80 80 Year

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



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)]
```



- 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

```
'0.315*"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"'),
 '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"'),
 '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"'),
 '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"'),
 '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"'),
 '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"'),
 '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"'),
 '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"')]
```

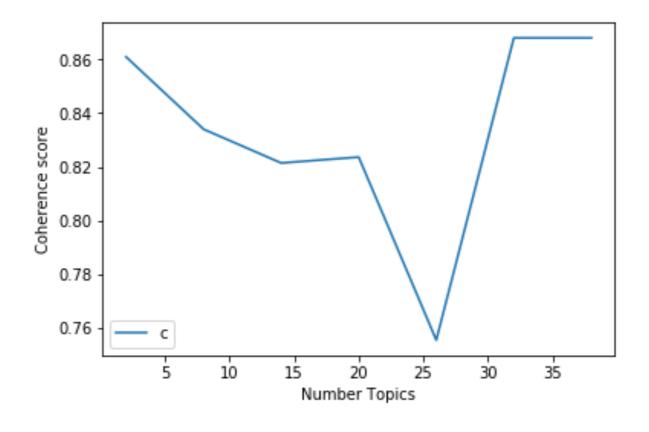


Topic Modeling

```
property resource
                             work operation
                                                major
commissioner
park policy
  security
                               information
                                  grant
   tota]
               performance
                                      change
   economic
                amend
          Topic 2
                                        Topic 3
                                                debt
                 percent
                              infrastructure
                                        base
    evel SUMMary
state <sup>estimate</sup>
  level
                                                issue
                                         unit
                             remain
        current area
                                                   goal
                                    fiscal
solid
        fund
                                             government
                               water
```

Topic 1

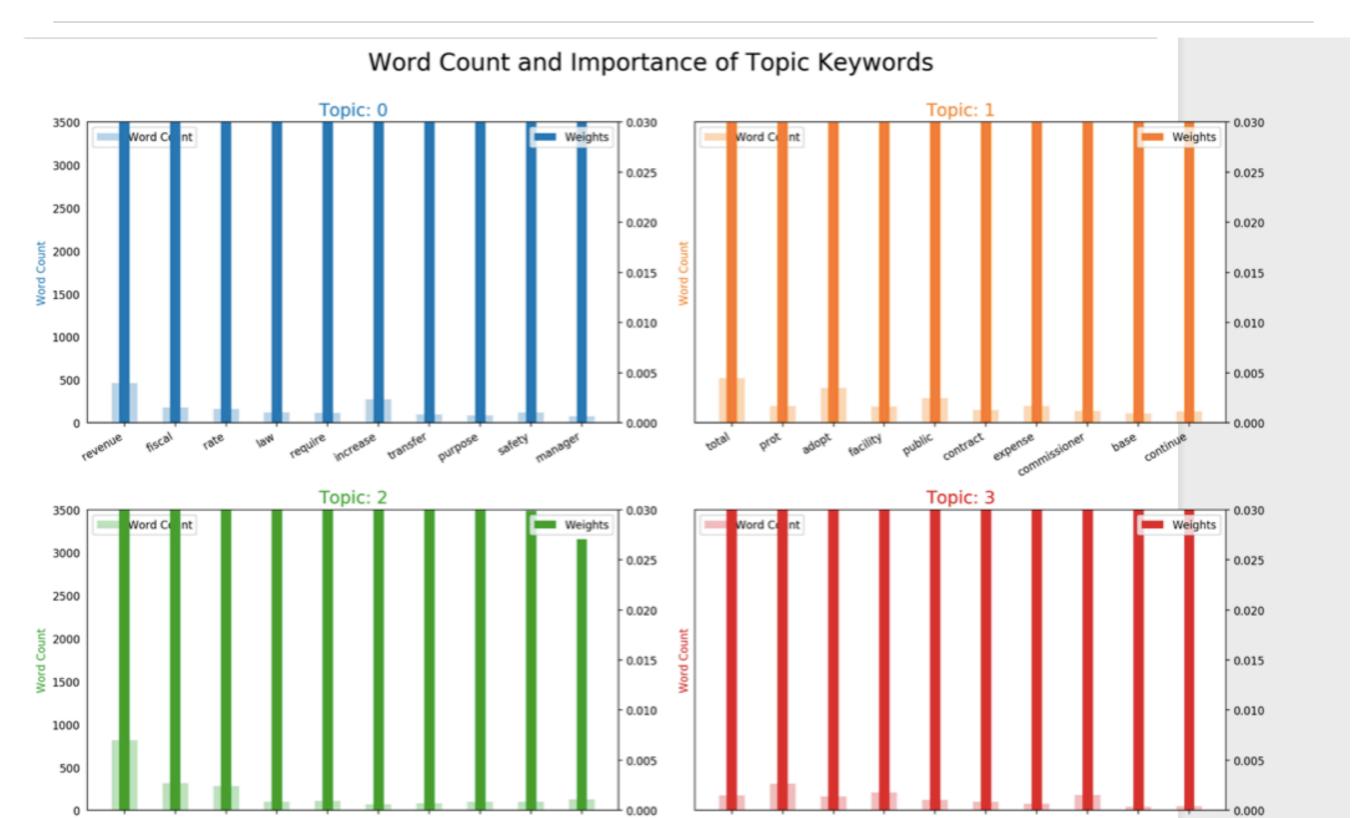
Topic 0



Coherence Score: 0.8256146597574272



Topic Modeling



Topic Modeling Comparison

```
work operation
                                             major
commissioner
                                   provide
                                    exist
park policy
                                  program
  security
                                grant
              performance
                                    change
   economic
         Topic 2
                                     Topic 3
                                              debt
               percent
                             infrastructure
    evel SUMMary
state <sup>estimate</sup>
  level
                                             issue
                                      unit
                           remain
       current area
                                                goal
                                  fiscal
solid
       fund
                                          government
                             water
```

Topic 1

Topic 0

property resource

```
Topic 0
adoptemployee
         facility
     increase
             department
project
                           student
balance
information
```

economic

administration

staff

Topic 2

area

expenditure total

law

 $\operatorname{program}^{\operatorname{work}}$

space

```
level
transportationMaintain
          tax
         technology
      base court
          Topic 3
  cost
     ordinance
 require
        bond
                  point
               fund
     system
                     result
```

incentive

Topic 1

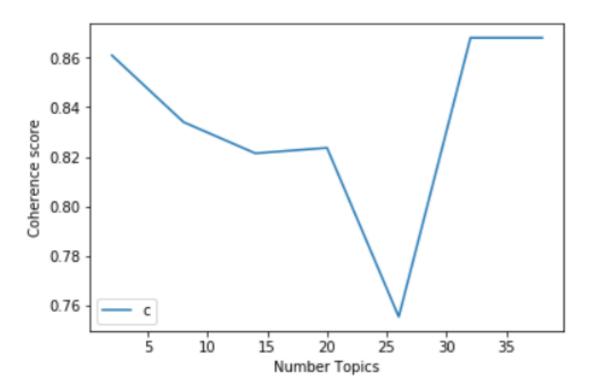
care

2019

2008

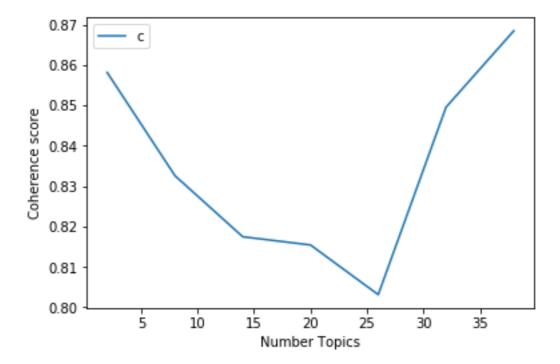


Topic Modeling Comparison



Coherence Score: 0.8256146597574272

2019



Coherence Score: 0.8247949042506306

2008



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.

