Illinois is famous for being one of the very few states in the country with negative population growth. The objective of your final project is to:

1) Identify the key reasons for the declining population by extracting meaningful insights from unstructured text 2) Provide actionable recommendations on what can be done to r collection of a couple of months' worth of news articles in RCC located at: /project/msca/kadochnikov/news/news chicago il.pkl

The news articles are related to either Chicago and / or Illinois.

To complete your assignment, I suggest considering the following steps:

- Clean-up the noise (eliminate articles irrelevant to the analysis)
- · Detect major topics
- · Identify top reasons for population decline (negative sentiment)
  - Suggest corrective actions
- Demonstrate how the city / state can attract new businesses (positive sentiment)
- · Leverage appropriate NLP techniques to identify organizations and people and apply targeted sentiment
  - Why businesses should stay in IL or move into IL? \*\* Create appropriate visualization to summarize your recommendations (i.e. word cloud chart or bubble chart)
  - Why residents should stay in IL or move into IL? \*\* Create appropriate visualization to summarize your recommendations (i.e. word cloud chart or bubble chart)

#### Additional guidance:

- · Default sentiment will likely be wrong from any software package and will require significant tweaking
  - Either keyword / dictionary approach or
  - Labeling and classification
- You are encouraged to explore a combination several techniques to identify key topics:
  - Topic modeling (i.e. LSA, LDA and TF-IDF)
  - Classification (hand-label several topics on a sample and then train classifier)
  - Clustering (cluster topics around pre-selected keywords or word vectors)
- Please limit your work to 7 PowerPoint slides. On your slides you will want to provide:
  - Executive Summary
  - Methodology and source data overview
  - Actionable recommendations
- Please submit your actual program codes (i.e. Python Notebook) along with your PowerPoint as a separate attachment
- · Your presentation should be targeted toward business audience and must not contain any code snippets
- · You are welcome to use any software packages of your choice to complete the assignment

```
In [1]: import warnings
        warnings.simplefilter('ignore')
        import time
        import math
        import re
        from textblob import TextBlob
        import pandas as pd
        import nltk as nltk
        from nltk.stem.wordnet import WordNetLemmatizer
        import string
        import gensim
        from gensim import corpora, models
        from gensim.models.ldamulticore import LdaMulticore
        import pyLDAvis.gensim
        import numpy as np
        import pandas as pd
         from IPython.display import display
        from tqdm import tqdm
        from collections import Counter
        import ast
        import matplotlib.pyplot as plt
        import matplotlib.mlab as mlab
        import seaborn as sb
         from sklearn.feature_extraction.text import CountVectorizer
        from textblob import TextBlob
        import scipy.stats as stats
        from sklearn.decomposition import TruncatedSVD
        from sklearn.decomposition import LatentDirichletAllocation
        from sklearn.manifold import TSNE
        from bokeh.plotting import figure, output_file, show
         from bokeh.models import Label
        from bokeh.io import output_notebook
        output_notebook()
        %matplotlib inline
```

(https://www.deck.gov/deck.gov/cessfully loaded.

```
In [74]: import sklearn
    from sklearn.model_selection import train_test_split
    from sklearn.feature_extraction.text import CountVectorizer, HashingVectorizer, TfidfTransformer, TfidfVectorizer
    from sklearn.naive_bayes import MultinomialNB
    from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
    from sklearn.linear_model import LogisticRegression, SGDClassifier
    from sklearn import metrics
```

## Cleaning

In [2]: df = pd.read\_pickle("news\_chicago\_il.pkl")

In [3]: df.head(5)

Out[3]:

	crawled_date	language	text	title
0	2020-05-11	english	\nGov. Jay "Fatso" Pritzker called on all Illi	All In Illinois
1	2020-05-11	english	May 10, 2020 -The Illinois Department of Publi	The Illinois Department of Public Health Annou
2	2020-05-11	english	Gloria Lawrence said: May 10, 2020 at 1:31 AM\	Foto Friday: Alton, Illinois
3	2020-05-11	english	NBA to follow German soccer league model with	Chris Broussard on Michael Jordan returning to
4	2020-05-11	english	Search Minggu, 10 Mei 2020 Pork chops vs. peop	Pork chops vs. people: Can Americans' appetite

In [4]: df.shape

Out[4]: (177325, 4)

Checking to make sure all articles are in English.

```
In [5]: df.language.unique()
Out[5]: array(['english'], dtype=object)
```

Dropping columns not needed.

```
In [6]: df = df.drop(['crawled_date','language'], axis=1)
```

I am making the assumption that articles with the same title have the same content. I will drop duplicates in main dataframe.

I want to include the title in case there is important info.

```
In [9]: df['comb'] = df['title'] + ' ' + df['text']
In [10]: words=[]
          def stopwords(text):
               words=[w for w in text if w not in stopwords.words('english')]
               return words
In [11]: from nltk.corpus import stopwords
           #nltk.download('stopwords')
          stop = stopwords.words('english')
In [12]: #remove stop words
          \label{eq:df'comb'} \texttt{df['comb'].apply(lambda } x: ' '.join([item \ \textit{for} \ item \ \textit{in} \ x.split() \ \textit{if} \ item \ \textit{not} \ \textit{in} \ stop]))
In [13]: clean=pd.DataFrame(df['comb'])
In [14]: #lowercase
          clean = pd.DataFrame(clean['comb'].apply(str.lower))
In [15]: #remove special chars
          clean['text_clean'] = clean['comb'].map(lambda x: re.sub('[^a-zA-Z0-9 @ . , : - _]', '', str(x)))
In [16]: #only need to keep clean text
           clean=pd.DataFrame(clean['text clean'])
          clean.head()
Out[16]:
```

Out[16]

	text_clean
0	all in illinois gov. jay fatso pritzker called
1	the illinois department public health announce
2	foto friday: alton, illinois gloria lawrence s
3	chris broussard michael jordan returning chica
4	pork chops vs. people: can americans appetite

Only keep articles related to population movement in IL/Chicago.

```
In [17]: #stemmers
                          porter = nltk.PorterStemmer()
                          lancaster = nltk.LancasterStemmer()
      In [18]: #locations '(USA-IL-Chicago)', 'Illinois', 'Chicago'
                          key_words=['population','migration','exodus','moving','leaving']
                          in_stems=[porter.stem(c) for c in key_words]
                          new_stems=[]
                          for a in range(0, len(clean)):
                                  words=clean.iloc[a].text_clean
                                   stems=[porter.stem(t) for t in words.split()]
                                   if any(s in stems for s in in_stems):
                                           new_stems.append(a)
                                   else:
                                           continue
     In [19]: clean=clean.iloc[new_stems]
                          clean=clean.reset_index(drop=True)
                          len(clean)
     Out[19]: 26335
I will remove words that I don't feel explain people leaving IL.
      In [20]: #remove off-topic sports, animals, and Trump
                          words_list = ['bears','cubs','blackhawks','football','baseball','baseball','hockey','sox','Trump','deer','coyote','covi
                          p_stems = [porter.stem(x) for x in words_list]
                          l_stems = [lancaster.stem(x) for x in words_list]
                          print(p_stems)
                          print(l_stems)
                          ['bear', 'cub', 'bull', 'blackhawk', 'footbal', 'basebal', 'basketbal', 'hockey', 'sox', 'trump', 'deer', 'coyot', 'covid19', 'covid
      In [21]: porter_stems=[]
                           for a in range(0, len(clean)):
                                   words=clean.iloc[a].text_clean
                                   stems=[porter.stem(t) for t in words.split()]
                                   if any(s in stems for s in p_stems):
                                           porter_stems.append(stems)
                                           porter_stems.append(None)
      In [22]: p_articles=[i for i in porter_stems if i is not None]
                          len(p_articles)
     Out[22]: 10992
      In [23]: clean['contain_stem']=pd.Series(porter_stems)
                          clean=clean[clean['contain_stem'].isnull()]
                          clean=clean.reset_index(drop=True)
                          len(clean)
     Out[23]: 15343
      In [24]: clean_df = clean
                          clean_df.head()
     Out[24]:
                                                                                                  text clean contain stem
                           0 7 chicago officers injured altercation storage..
                                real reason nigerian vblogger, ar, tolani baj ...
                                                                                                                       None
                                families frustrated chicagoarea cemeteries clo...
                                                                                                                        None
                            3
                                illinois tool works inc. nyse:itw ceo buys 998...
                                                                                                                       None
                                tradition asset management IIc decreases stock..
```

### TF-IDF

#### https://stevenloria.com/tf-idf/ (https://stevenloria.com/tf-idf/)

- tf(word, blob) computes "term frequency" which is the number of times a word appears in a document blob, normalized by dividing by the total number of words in blob. We text into words and getting the word counts.
- n\_containing(word, bloblist) returns the number of documents containing word. A generator expression is passed to the sum() function.
- idf(word, bloblist) computes "inverse document frequency" which measures how common a word is among all documents in bloblist. The more common a word is, the lower total number of documents to the number of documents containing word, then take the log of that. Add 1 to the divisor to prevent division by zero.
- tfidf(word, blob, bloblist) computes the TF-IDF score. It's the product of tf and idf.

```
In [25]: bloblist = []
del bloblist[:]
for i in range(0,len(clean)):
    bloblist.append(TextBlob(clean['text_clean'].iloc[i]))
len(bloblist)

Out[25]: 15343
In [26]: def tf(word, blob):
    return blob.words.count(word) / len(blob.words)
def n_containing(word, bloblist):
    return sum(1 for blob in bloblist if word in blob.words)
def idf(word, bloblist):
    return math.log(len(bloblist) / (1 + n_containing(word, bloblist)))
def tfidf(word, blob, bloblist):
    return tf(word, blob) * idf(word, bloblist)
```

```
In [27]: #top 5
          for i, blob in enumerate(bloblist):
              if i == 5:
                 break
              print("Top words in news article {}".format(i + 1))
              scores = {word: tfidf(word, blob, bloblist) for word in blob.words}
              sorted_words = sorted(scores.items(), key=lambda x: x[1], reverse=True)
              for word, score in sorted_words[:10]:
                  print("\tWord: {}, TF-IDF: {}".format(word, round(score, 5)))
         Top words in news article 1
                 Word: altercation, TF-IDF: 0.2734
                  Word: officers, TF-IDF: 0.20763
                 Word: storage, TF-IDF: 0.17529
Word: injured, TF-IDF: 0.17139
                 Word: male, TF-IDF: 0.09559
                  Word: 8:16, TF-IDF: 0.09231
                  Word: injuries, TF-IDF: 0.08797
                  Word: sfgate, TF-IDF: 0.07939
                  Word: authorities, TF-IDF: 0.07871
                 Word: stabilized, TF-IDF: 0.07703
         Top words in news article 2
                 Word: tolani, TF-IDF: 0.57696
                 Word: baj, TF-IDF: 0.46157
                 Word: nigerian, TF-IDF: 0.40387
                 Word: nigeria, TF-IDF: 0.39694
                  Word: vblogger, TF-IDF: 0.37676
                 Word: ar, TF-IDF: 0.35146
                 Word: lagos, TF-IDF: 0.32829
                  Word: real, TF-IDF: 0.13276
                 Word: reason, TF-IDF: 0.12651
                 Word: entrepreneurer, TF-IDF: 0.12135
         Top words in news article 3
                 Word: mothers, TF-IDF: 0.13321
                 Word: gates, TF-IDF: 0.11302
                  Word: cemeteries, TF-IDF: 0.10206
                 Word: cemetery, TF-IDF: 0.06834
                 Word: families, TF-IDF: 0.06452
                 Word: harris, TF-IDF: 0.05731
                  Word: stood, TF-IDF: 0.05213
                  Word: console, TF-IDF: 0.05155
                 Word: smith, TF-IDF: 0.04858
                 Word: visitors, TF-IDF: 0.04773
         Top words in news article 4
                 Word: tool, TF-IDF: 0.11619
                 Word: works, TF-IDF: 0.09095
                 Word: illinois, TF-IDF: 0.0348
                 Word: rating, TF-IDF: 0.03263
                 Word: stock, TF-IDF: 0.02461
                  Word: acquired, TF-IDF: 0.02397
                 Word: quarter, TF-IDF: 0.02174
                 Word: itw, TF-IDF: 0.02147
                  Word: ratio, TF-IDF: 0.02017
                 Word: price, TF-IDF: 0.01997
         Top words in news article 5
                 Word: tool, TF-IDF: 0.09723
                 Word: works, TF-IDF: 0.07673
                  Word: shares, TF-IDF: 0.04231
                  Word: stock, TF-IDF: 0.03807
                 Word: illinois, TF-IDF: 0.02912
                 Word: quarter, TF-IDF: 0.02775
                  Word: rating, TF-IDF: 0.02467
                  Word: industrial, TF-IDF: 0.0235
                  Word: itw, TF-IDF: 0.02214
                  Word: products, TF-IDF: 0.01995
```

#### LDA

```
In [28]: df2list = clean['text_clean'].tolist()
df2list[:1]
```

Out[28]: ['7 chicago officers injured altercation storage center sfgate 7 chicago officers injured altercation storage center published 8 ven chicago police officers injured altercation saturday storage center citys near south side, authorities said. officers called storage disturbance lobby. he allegedly refused leave property, prompting altercation officers. one officer hospitalized injuries ted scene minor injuries. police said male wasnt injured taken custody. authorities said charges pending. most popular']

```
In [29]: doc_complete = []
            stop = set(stopwords.words('english'))
            exclude = set(string.punctuation)
            lemma = WordNetLemmatizer()
            def clean(doc):
                 stop_free = " ".join([i for i in doc.lower().split() if i not in stop])
                 punc_free = ''.join(ch for ch in stop_free if ch not in exclude)
normalized = " ".join(lemma.lemmatize(word) for word in punc_free.split())
                  return normalized
            doc_clean = [clean(doc).split() for doc in doc_complete]
In [30]: news_clean = [clean(doc).split() for doc in df2list]
In [31]: len(news_clean)
Out[31]: 15343
In [32]: print(*news clean[:1], sep='\n\n')
            ['7', 'chicago', 'officer', 'injured', 'altercation', 'storage', 'center', 'sfgate', '7', 'chicago', 'officer', 'injured', 'altercation', '816', 'pdt', 'sunday', 'may', '10', '2020', 'chicago', 'ap', 'seven', 'chicago', 'police', 'officer', 'injured', 'altercation', ar', 'south', 'side', 'authority', 'said', 'officer', 'called', 'storage', 'facility', 'around', '11', 'am', 'report', 'male', 'c; y', 'refused', 'leave', 'property', 'prompting', 'altercation', 'officer', 'one', 'officer', 'hospitalized', 'injury', 'shoulder' reated', 'scene', 'minor', 'injury', 'police', 'said', 'male', 'wasnt', 'injured', 'taken', 'custody', 'authority', 'said', 'charg
In [33]: dictionary = corpora.Dictionary(news_clean)
            #convert 2 corpus
            doc_term_matrix = [dictionary.doc2bow(doc) for doc in news_clean]
In [34]: #3 topic model
            numtopics = 3
            %time ldamodel = LdaMulticore(doc term matrix, num topics=numtopics, id2word = dictionary, passes=50)
            Wall time: 13min 6s
In [35]: print(*ldamodel.print_topics(num_topics=numtopics, num_words=3), sep='\n')
            (0, '0.009*"illinois" + 0.008*"state" + 0.006*"chicago"')
            (1, '0.017*"chicago" + 0.007*"said" + 0.005*"one"')
            (2, '0.034*"share" + 0.023*"company" + 0.022*"stock"')
In [36]: print(*ldamodel.print_topics(num_topics=numtopics, num_words=5), sep='\n\n')
            (0, '0.009*"illinois" + 0.008*"state" + 0.006*"chicago" + 0.005*"said" + 0.004*"year"')
            (1, '0.017*"chicago" + 0.007*"said" + 0.005*"one" + 0.004*"police" + 0.004*"time"')
            (2, '0.034*"share" + 0.023*"company" + 0.022*"stock" + 0.020*"quarter" + 0.019*"rating"')
In [37]: print(*ldamodel.print_topics(num_topics=numtopics, num_words=10), sep='\n\n')
            (0, '0.009*"illinois" + 0.008*"state" + 0.006*"chicago" + 0.005*"said" + 0.004*"year" + 0.004*"new" + 0.003*"also" + 0.003*"time"
            (1, '0.017*"chicago" + 0.007*"said" + 0.005*"one" + 0.004*"police" + 0.004*"time" + 0.003*"year" + 0.003*"like" + 0.003*"city" + 0.003*"
            (2, '0.034*"share" + 0.023*"company" + 0.022*"stock" + 0.020*"quarter" + 0.019*"rating" + 0.013*"illinois" + 0.012*"tool" + 0.012
```

```
In [38]: lda_display = pyLDAvis.gensim.prepare(ldamodel, doc_term_matrix, dictionary, sort_topics=False, mds='mmds')
              pyLDAvis.display(lda_display)
Out[38]:
              Selected Topic: 0
                                             Previous Topic | Next Topic
                                                                                  Clear Topic
                                                                                                                                            Slide to adjust relevance metric:(2)
                                                                                                                                                                                                       |
0.2
                                                                                                                                                                                              0.0
                                  Intertopic Distance Map (via multidimensional scaling)
                                                                                                                                                                          Top-30 Most Salient Term
                                                                                                                                                                      20,000
                                                                                                                                                       10,000
                                                                                                                                                                                      30,000
                                                                                                                                                                                                      40,000
                                                                                                                                     share
                                                                                                                                     stock
                                                                                                                                   quarter
                                                                                                                                 company
                                                                                                                                    rating
                                                                                                                                     price
                                                                                                                                       inc
                                                                                                                                     ratio
                                                                                                                                  research
                                                                                                                                  average
                                                                                                                                   analyst
                                                                                                                                    owns
                   PC13
                                                                                                                                     work
                                                                                                                                    valued
                                                                                                                                    target
                                                                                                                                  chicago
                                                                                                                                   holding
                                                                                                                                  dividend
                                                                                                                                    worth
                                                                                                                                 additional
                                                                                                                                    equity
                                                                                                                                    illinois
                                                                                                                                  product
                                                                                                                                    report
                                                                                                                                     stake
                                                                                                                                      said
                                                                                                                                  investor
                     Marginal topic distribtion
                                                                                                                                                               Overall term frequency
                                                                                                                                                     Estimated term frequency within the selected topic
                                              2%
                                                                                                                                          1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] f( 2. relevance(term w | topic t) = \lambda * p(w | t) + (1 - \lambda) * p(w | t)/p(w); see S
                                              5%
                                              10%
```

```
In [39]: #10 topic model numtopics = 10

%time ldamodel = LdaMulticore(doc_term_matrix, num_topics=numtopics, id2word = dictionary, passes=50)

Wall time: 14min 49s

In [40]: print(*ldamodel.print_topics(num_topics=numtopics, num_words=3), sep='\n\n')

(0, '0.018*"chicago" + 0.010*"said" + 0.007*"police"')

(1, '0.016*"illinois" + 0.014*"state" + 0.011*"said"')

(2, '0.037*"share" + 0.024*"stock" + 0.024*"company"')

(3, '0.010*"share" + 0.009*"year" + 0.006*"intel"')

(4, '0.015*"chicago" + 0.007*"music" + 0.006*"art"')

(5, '0.041*"illinois" + 0.041*"tool" + 0.039*"work"')

(6, '0.008*"illinois" + 0.007*"information" + 0.006*"court"')

(7, '0.017*"chicago" + 0.008*"city" + 0.008*"illinois"')

(8, '0.007*"chicago" + 0.005*"work" + 0.005*"school"')

(9, '0.014*"chicago" + 0.005*"food" + 0.005*"new"')
```

I tried to do coherence scores but I was unable to run the code in a reasonable amount of time.

I am choosing the 10-topic model for now because it had the best outcome.

```
In [42]: print(*ldamodel.print_topics(num_topics=numtopics, num_words=10), sep='\n\n')

(0, '0.018*"chicago" + 0.010*"said" + 0.007*"police" + 0.006*"one" + 0.005*"officer" + 0.004*"time" + 0.004*"two" + 0.004*"season

(1, '0.016*"illinois" + 0.014*"state" + 0.011*"said" + 0.006*"year" + 0.005*"new" + 0.005*"people" + 0.005*"chicago" + 0.004*"law

(2, '0.037*"share" + 0.024*"stock" + 0.024*"company" + 0.021*"quarter" + 0.020*"rating" + 0.011*"price" + 0.009*"research" + 0.005*

(3, '0.010*"share" + 0.009*"year" + 0.006*"intel" + 0.006*"index" + 0.005*"november" + 0.005*"million" + 0.005*"lilly" + 0.004*"av

(4, '0.015*"chicago" + 0.007*"music" + 0.006*"art" + 0.005*"pm" + 0.005*"back" + 0.005*"get" + 0.004*"show" + 0.004*"flight" + 0.60*

(5, '0.041*"illinois" + 0.041*"tool" + 0.039*"work" + 0.030*"share" + 0.024*"company" + 0.020*"stock" + 0.019*"quarter" + 0.018*"r

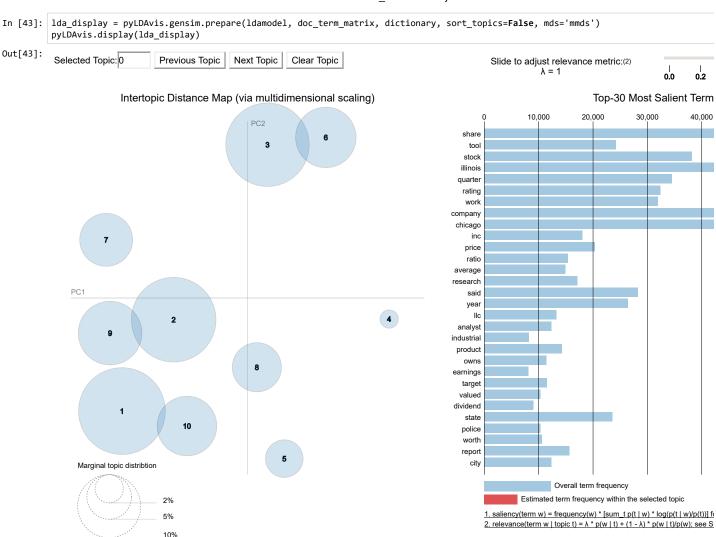
(6, '0.008*"illinois" + 0.007*"information" + 0.006*"court" + 0.006*"customer" + 0.006*"experience" + 0.006*"job" + 0.005*"team" + e"')

(7, '0.017*"chicago" + 0.008*"city" + 0.008*"illinois" + 0.007*"area" + 0.006*"building" + 0.006*"said" + 0.005*"home" + 0.005*"wc

(8, '0.007*"chicago" + 0.005*"work" + 0.005*"school" + 0.005*"student" + 0.006*"health" + 0.004*"time" + 0.004*"need" + 0.004*"prc

(9, '0.014*"chicago" + 0.005*"food" + 0.005*"new" + 0.005*"one" + 0.004*"year" + 0.004*"restaurant" + 0.004*"time" + 0.004*"like"
```

Out[43]:



```
In [44]: | #max_topics = 15
          #lda_models = []
          #n_topics = []
          #for i in range(1, max_topics):
               n_topics.append(i+1)
               %time model = LdaMulticore(doc_term_matrix, num_topics=i+1, id2word = dictionary, passes=50)
               Lda_models.append(model)
In [45]: #coherence_scores = []
          #for model in lda_models:
               coherence model = Coherence Model (model = model, texts = news\_clean, dictionary = dictionary, coherence = 'c\_v')
               coherence_scores.append(coherencemodel.get_coherence())
In [46]: #fig, ax = plt.subplots(figsize=(10,6))
          #sns.lineplot(x=n_topics, y=coherence_scores, ax=ax)
          #ax.set(xlabel='# of Topics', ylabel='Coherence Score')
```

### **LSA**

```
In [47]: n_topics = 10
```

```
In [48]: reindexed_data = clean_df['text_clean']
         reindexed_data.head(3)
Out[48]: 0
              7 chicago officers injured altercation storage...
              real reason nigerian vblogger, ar, tolani baj ...
              families frustrated chicagoarea cemeteries clo...
         Name: text_clean, dtype: object
In [49]: from sklearn.feature_extraction.text import TfidfVectorizer
         vectorizer = TfidfVectorizer(stop_words='english',
         max_features= 1000, # keep top 1000 terms
         \max_{-}^{-} df = 0.5,
         smooth_idf=True)
         X = vectorizer.fit_transform(reindexed_data)
         X.shape # check shape of the document-term matrix
Out[49]: (15343, 1000)
In [50]: from sklearn.decomposition import TruncatedSVD
         # SVD represent documents and terms in vectors
         svd_model = TruncatedSVD(n_components=10, algorithm='randomized', n_iter=100, random_state=122)
          svd_model.fit(X)
          len(svd_model.components_)
Out[50]: 10
```

```
In [51]: terms = vectorizer.get_feature_names()

for i, comp in enumerate(svd_model.components_):
    terms_comp = zip(terms, comp)
    sorted_terms = sorted(terms_comp, key= lambda x:x[1], reverse=True)[:7]
    print("Topic "+str(i)+": ")
    for t in sorted_terms:
        print(t[0])
```

Topic 0: shares stock quarter tool rating works illinois Topic 1: said illinois state police people time like Topic 2: tool works illinois itw industrial products Topic 3: police said officers state illinois man county Topic 4: police tool man officers works season said Topic 5: experience customer police service work job customers Topic 6: snow weather city area winter saturday lake Topic 7: owensillinois marijuana snow cannabis weather season sales Topic 8: marijuana said cannabis recreational city sales people Topic 9: owensillinois students school

rating industrial schools food

```
In [52]: #import umap as umap

#X_topics = svd_model.fit_transform(X)
#embedding = umap.UMAP(n_neighbors=150, min_dist=0.5, random_state=12).fit_transform(X_topics)

#plt.figure(figsize=(7,5))
#plt.scatter(embedding[:, 0], embedding[:, 1],
#c = dataset.target,
#s = 10, # size
#edgecolor='none')
#plt.show()
```

# **Sentiment Analysis (Hand-labeled)**

I want to include stopwords so the sentences are still human readable.

oucijoj.

	comb
0	All In Illinois Gov. Jay "Fatso" Pritzker call
1	The Illinois Department Public Health Announce
2	Foto Friday: Alton, Illinois Gloria Lawrence s
3	Chris Broussard Michael Jordan returning Chica
4	Pork chops vs. people: Can Americans' appetite

```
In [94]: #lowercase
    sa_df = pd.DataFrame(sa_df.comb.apply(str.lower))
In [95]: #remove special chars
    sa_df['text_clean'] = sa_df['comb'].map(lambda x: re.sub('[^a-zA-Z0-9 @ . , : - _]', '', str(x)))
In [96]: #only need to keep clean text
    sa_df=pd.DataFrame(sa_df['text_clean'])
    sa_df.head()
```

Out[96]:

	text_clean
0	all in illinois gov. jay fatso pritzker called
1	the illinois department public health announce
2	foto friday: alton, illinois gloria lawrence s
3	chris broussard michael jordan returning chica
4	pork chops vs. people: can americans appetite

Only keep articles related to population movement in IL/Chicago.

```
In [97]: #stemmers
    porter = nltk.PorterStemmer()
    lancaster = nltk.LancasterStemmer()

In [99]: #Locations '(USA-IL-Chicago)','Illinois','Chicago'
    key_words=['population','migration','exodus','moving','leaving']
    in_stems=[porter.stem(c) for c in key_words]
    new_stems=[]

for a in range(0, len(sa_df)):
    words=sa_df.iloc[a].text_clean
    stems=[porter.stem(t) for t in words.split()]
    if any(s in stems for s in in_stems):
        new_stems.append(a)
    else:
        continue
```

```
In [100]: sa_df=sa_df.iloc[new_stems]
                          sa_df=sa_df.reset_index(drop=True)
                          len(sa_df)
   Out[100]: 26335
I will remove words that I don't feel explain people leaving IL.
   In [101]: #remove off-topic sports, animals, and Trump
                          words_list = ['bears','cubs','bulls','blackhawks','football','baseball','basketball','hockey','sox','Trump','deer','coyote','covi
                          avirus'l
                          p_stems = [porter.stem(x) for x in words_list]
                          1_stems = [lancaster.stem(x) for x in words_list]
                          print(p_stems)
                          print(l_stems)
                          ['bear', 'cub', 'bull', 'blackhawk', 'footbal', 'basebal', 'basketbal', 'hockey', 'sox', 'trump', 'deer', 'coyot', 'covid19', 'covid
   In [102]: porter_stems=[]
                          for a in range(0, len(sa_df)):
                                  words=sa_df.iloc[a].text_clean
                                   stems=[porter.stem(t) for t in words.split()]
                                   if any(s in stems for s in p_stems):
                                          porter_stems.append(stems)
                                   else:
                                           porter_stems.append(None)
    In [103]: p_articles=[i for i in porter_stems if i is not None]
                          len(p_articles)
   Out[103]: 10992
   In [105]: sa_df['contain_stem']=pd.Series(porter_stems)
                          sa df=sa df[sa df['contain stem'].isnull()]
                          sa_df=sa_df.reset_index(drop=True)
                          len(sa_df)
   Out[105]: 15343
   In [106]: sa_df.head()
   Out[106]:
                                                                                                                       contain_stem
                                                                                                 text_clean
                           0 7 chicago officers injured altercation storage...
                                                                                                                       None
                               real reason nigerian vblogger, ar, tolani baj ...
                                                                                                                       None
                                families frustrated chicagoarea cemeteries clo...
                                                                                                                       None
                            3
                                illinois tool works inc. nyse:itw ceo buys 998..
                                                                                                                       None
                                tradition asset management IIc decreases stock...
                                                                                                                       None
    In [107]: #every sentence becomes it's own observavtion
                          class_sentences=[]
                          for n in range(len(sa_df)):
                                   sentences=nltk.sent_tokenize(sa_df.iloc[n].text_clean)
                                   for m in sentences:
                                           class sentences.append(m)
   In [108]: #remove non-sentences
                          class_sentences=[o for o in class_sentences if len(o) > 10]
                          len(class_sentences)
   Out[108]: 414089
   In [109]: sentences=pd.DataFrame(columns=['Sentence'], data=class_sentences)
   In [110]: sentences['Class']=""
```

```
In [111]: sentences.head(10)
```

Out[111]:

	Sentence	Class
0	7 chicago officers injured altercation storage	
1	officers called storage facility around 11 a.m	
2	he allegedly refused leave property, prompting	
3	one officer hospitalized injuries shoulder kne	
4	six officers treated scene minor injuries.	
5	police said male wasnt injured taken custody.	
6	authorities said charges pending.	
7	most popular	
8	real reason nigerian vblogger, ar, tolani baj	
9	real names, tolani shobajo the post real reaso	

```
In [112]: sentences_test, sentences_train = train_test_split(sentences, test_size=200, random_state=1)
    print(sentences_train.shape)
    print(sentences_test.shape)

    (200, 2)
    (413889, 2)
```

I'm going to hand label some of the data. Negative=0, Neutral=1, Positive=2

I choose to hand label because sentiment analysis tools (like the tweets one) are notoriously bad at predicting on data that isn't apples-to-apples. For example, it'd be a bad idea news articles. A car chase makes for a good movie, but it is not so great if it's happening in your neighborhood.

```
In [113]: train_labels=sentences_train.to_csv('train_labels.csv')
```

Reading the file back after I label.

```
In [116]: sentences_train=pd.read_csv('train_labels.csv')
    sentences_train=sentences_train.drop(['Unnamed: 0'], axis=1)
    sentences_train.head(10)
```

Out[116]:

	Sentence	Class
0	posted march 7, 2019.	1
1	jsonline.comstorynewsloc almilwaukee20191206re	1
2	the 60yearold joined paper intern 32 years ago	2
3	the deputy treated noncritical leg injuries ho	1
4	to its i leave, maray said.	1
5	this represents 4.28 annualized dividend divid	2
6	take hofmann tower, national landmark, fall 20	1
7	illinois tool works makes 2.5 fenimore asset m	2
8	i dont got speculating im getting cannabis i s	2
9	zacks investment research cut fair isaac stron	1

I ran Naive Bayes and XGB for the hand-labeled data and only got 57% and 55% accuracy.

I don't think I labeled enough data for this to work.

I will try to do auto labeling.

# **Sentiment Analysis (auto)**

```
In [253]: from collections import defaultdict
    all_reviews = sa_df['text_clean']
    all_sent_values = []
    all_sentiments = []
```

```
In [254]: from nltk.sentiment.vader import SentimentIntensityAnalyzer
              def sentiment_value(paragraph):
    analyser = SentimentIntensityAnalyzer()
                  result = analyser.polarity_scores(paragraph)
                  score = result['compound']
                  return round(score,1)
 In [256]: for i in range(0,len(sa_df)):
                  all_sent_values.append(sentiment_value(all_reviews[i]))
 In [280]:
             SENTIMENT_VALUE = []
              SENTIMENT = []
              for i in range(0,len(sa_df)):
                  sent = all_sent_values[i]
                  if (sent<=1 and sent>0.2):
                       SENTIMENT.append('Positive')
                       SENTIMENT_VALUE.append(2)
                  elif (sent<-0.2 and sent>=-1):
                       SENTIMENT.append('Negative')
                       SENTIMENT_VALUE.append(0)
                  else:
                       SENTIMENT.append('Neutral')
                       SENTIMENT_VALUE.append(1)
 In [281]: len(all sent values)
 Out[281]: 20254
 In [282]: temp_data = sa_df[0:]
  In [283]: | temp_data['SENTIMENT_VALUE'] = SENTIMENT_VALUE
              temp_data['SENTIMENT'] = SENTIMENT
  In [284]: temp_data.head()
 Out[284]:
                                                                                                                                                      text_clean
                 7 chicago officers injured altercation storage center sfgate 7 chicago officers injured altercation storage center published 8:16 pdt, sunday, may 10, 2020
                 chicago ap seven chicago police office...
                 real reason nigerian vblogger, ar, tolani baj moved chicago lagos real reason nigerian vblogger, ar, tolani baj moved chicago lagos published daily times mon,
                 11 may 2020 nigerian entrepreneurer, ..
                 families frustrated chicagoarea cemeteries close visitors mothers day dozens chicagoarea families unable pay respects lost loved ones mothers day say
                 cemeteries closed gates visitors without expla..
                 illinois tool works inc. nyse:itw ceo buys 998,046.00 stock illinois tool works inc. nyse:itw ceo ernest scott santi purchased 6,300 shares illinois tool works
                 stock transaction dated wednesday, m...
                 tradition asset management IIc decreases stock holdings illinois tool works inc. nyse:itw tradition asset management IIc lowered stake illinois tool works inc.
                 nyse:itw 1.8 1st quarter, according ...
 In [285]: le = preprocessing.LabelEncoder()
 In [286]: le.fit(clean_df.text_clean)
 Out[286]: LabelEncoder()
 In [287]: le.transform(clean_df['text_clean'])
 Out[287]: array([ 500, 12215, 6095, ..., 5765, 5277, 14633])
Classification
  In [288]: X = temp_data.text_clean
              y = temp data.SENTIMENT VALUE
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state = 8)
```

#### **Naive Bayes**

```
('clf', MultinomialNB()),
                       ])
          nb.fit(X_train, y_train)
Out[291]: Pipeline(memory=None,
                  steps=[('vect',
                         CountVectorizer(analyzer='word', binary=False,
                                         decode_error='strict',
                                         dtype=<class 'numpy.int64'>, encoding='utf-8',
                                         input='content', lowercase=True, max_df=1.0,
                                         max_features=None, min_df=1,
                                         ngram_range=(1, 1), preprocessor=None,
                                         stop_words=None, strip_accents=None,
                                         token_pattern='(?u)\\b\\w\\w+\\b',
                                         tokenizer=None, vocabulary=None)),
                         ('tfidf',
                         TfidfTransformer(norm='12', smooth_idf=True,
                                         sublinear_tf=False, use_idf=True)),
                         MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True))],
                  verbose=False)
In [298]: %%time
          y_pred_nb = nb.predict(X_test)
          print('accuracy %s' % accuracy_score(y_pred_nb, y_test))
         accuracy 0.7558114273300022
         Wall time: 1.42 s
```

## **Logistic Regression**

```
('clf', LogisticRegression()),
                         ])
          lr.fit(X_train, y_train)
Out[293]: Pipeline(memory=None,
                    steps=[('vect'
                            CountVectorizer(analyzer='word', binary=False,
                                            decode_error='strict',
                                            dtype=<class 'numpy.int64'>, encoding='utf-8',
                                            input='content', lowercase=True, max_df=1.0,
                                            max_features=None, min_df=1,
                                            ngram_range=(1, 1), preprocessor=None,
                                            stop_words=None, strip_accents=None,
                                            token_pattern='(?u)\\b\\w\\w+\\b',
                                            tokenizer=None, vocabulary=None)),
                           ('tfidf',
                            TfidfTransformer(norm='12', smooth_idf=True,
                                             sublinear_tf=False, use_idf=True)),
                           ('clf',
                            LogisticRegression(C=1.0, class_weight=None, dual=False,
                                               fit_intercept=True, intercept_scaling=1,
                                               l1_ratio=None, max_iter=100,
multi_class='warn', n_jobs=None,
                                               penalty='12', random_state=None, solver='warn', tol=0.0001, verbose=0,
                                               warm_start=False))],
                   verbose=False)
In [299]: %%time
          y_pred_lr = lr.predict(X_test)
          print('accuracy %s' % accuracy_score(y_pred_lr, y_test))
          accuracy 0.7592874212470129
          Wall time: 1.48 s
```

#### **XGBClassifier**

```
In [295]: from xgboost import XGBClassifier
In [296]: xgb = Pipeline([('vect', CountVectorizer()),
                           ('tfidf', TfidfTransformer()),
                           ('clf', XGBClassifier()),
                          ])
           xgb.fit(X_train, y_train)
Out[296]: Pipeline(memory=None,
                    steps=[('vect',
                             CountVectorizer(analyzer='word', binary=False,
                                              decode error='strict',
                                              dtype=<class 'numpy.int64'>, encoding='utf-8',
                                              input='content', lowercase=True, max_df=1.0,
                                              max_features=None, min_df=1,
                                              ngram_range=(1, 1), preprocessor=None,
                                              stop_words=None, strip_accents=None,
                                              token\_pattern='(?u)\\\\\\\\\\\),
                                              tokenizer=None, vocabulary=Non...
                             XGBClassifier(base_score=0.5, booster='gbtree',
                                            colsample bylevel=1, colsample bynode=1,
                                            colsample_bytree=1, gamma=0, learning_rate=0.1,
                                            max_delta_step=0, max_depth=3,
                                            min_child_weight=1, missing=None,
                                            n_estimators=100, n_jobs=1, nthread=None,
                                           objective='multi:softprob', random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                                            seed=None, silent=None, subsample=1,
                                            verbosity=1))],
                    verbose=False)
In [300]: %%time
           y_pred_xgb = xgb.predict(X_test)
           print('accuracy %s' % accuracy_score(y_pred_xgb, y_test))
           accuracy 0.7571149250488811
           Wall time: 1.78 s
```

LR is the winner with 0.759 accuracy.

#### Word Cloud - General

In [301]:	<pre>f = X_test.to_frame() f['prediction']=y_pred_lr.tolist()</pre>					
In [302]:		<pre>#Negative=0, Neutral=1, Positive=2 sent_df['prediction'].value_counts()</pre>				
Out[302]:	0	502 101 prediction, dtype: int64				
In [304]:	sent_d	f.head()				
Out[304]:						
	3688	chicago fire 811 review: where we end up in: one chicago shows , reviews , tv one thing i love chicago fire fact tackles realworld issues. it never fails mak				
	10916	chicago 2019: 2020 subaru legacy preview: subaru announced next week, showing allnew 2020 legacy chicago auto show. to promote announcement, ja teaser images. the ex				
	7746	illinois marijuana sales top 34 million february illinois marijuana sales top 34 million february illinois marijuana sales top 34 million february on mar 6, 202				
	9867	chubb ltd nyse:cb shares purchased chicago trust co na chicago trust co na increased holdings shares chubb ltd nyse:cb 3.3 first quarter, according rece commission				
	14173	new jersey music festival, illinois motorcycles, georgia shrimp fleet, missouri park day, , more travel the scoop travelwriter, columnist, author janet groene				

In [308]: | pos\_sentences=sent\_df[sent\_df['prediction']==2] pos\_text=pos\_sentences["text\_clean"].tolist()

Out[308]: ['chicago fire 811 review: where we end up in: one chicago shows , reviews , tv one thing i love chicago fire fact tackles realwor mportant things life. this episode particular focused cancer firefighters importance coming together midst conflict. never take li icago fire where we end up episode 811 pictured: lr david eigenberg christopher herrmann, taylor kinney kelly severide, joe minos theres one thing i could tell firehouse 20, its dont wanna mess firehouse 51 . because push comes shove, boden always gonna 51s ba as things firefighters 51 everyone 20 werent bad enough, 51 stay firehouse 20 fumigated bedbugs. stand out scene chicago fire when rosende blake gallo photo by: adrian burrowsnbc blake gallo running chicago halfmarathon firefighter gear everything. it inspirir ers. i couldnt even run halfmarathon normal clothes, let alone heavy firefighter gear. but gallo really caring person, doesn't real e blake gallo. while i still really miss otis, i really love blake gallo. i think hes great addition firehouse 51. hes definitely lake gallo might one new favorite characters. i mean, whats love him best lines captain delaney: you may based 51, youre chief whα ites gallo: two dates were already moving together watch chicago fire wednesdays 98c nbc advertisements',

chicago 2019: 2020 subaru legacy preview: subaru announced next week, showing allnew 2020 legacy chicago auto show. to promote a ple teaser images. the exterior looks evolution current shape, complete headlights 2018 legacy. previous spy photos hint larger gr a interior appears subaru going premium look. theres also large tablet screen houses number functions driver passenger. we make pl 2020 legacy move modular platform underpins new ascent, forester, impreza. source: subaru view full article']

```
In [310]: neg_sentences=sent_df[sent_df['prediction']==0]
    neg_text=neg_sentences["text_clean"].tolist()
    neg_text[0:2]
```

Out[310]: ['illinois marijuana sales top 34 million february illinois marijuana sales top 34 million february illinois marijuana sales top 54 million february illinois marijuana sales nowicki capitol news illinois springfield legal marijuana sales state remained strong february, nearly 35 million spent marijuana alization. customers spent 34.8 million 831,600 items 29day period. of that, 25.6 million spent illinois residents, outofstaters : vernors office. the numbers include taxes collected. these numbers show continues strong demand across state equitycentric cannabi aid toi hutchinson, senior cannabis advisor gov. jb pritzker. as adult use cannabis industry continues grow, number opportunities ommunities suffered failed war drugs. the numbers slightly january, saw 39.2 million sales 31day span. that generated 7.3 million 1 million retail sales taxes shared state local governments. tax numbers february yet available. the states share cannabis tax rev 35 percent state general fund, 20 percent substance abuse programs, 10 percent budget stabilization fund, 8 percent local governme tion public health data collection. another 25 percent goes special fund community development projects areas high arrest poverty s. the state also accepting applications new licenses part programs initial rollout. aspiring craft growers, cannabis infusers tra ture 5 p.m. march 16. the applications available departments website https:www2.illinois.govsitesagrplantspagesadultusecannabis.as cants, companies majority stake live disproportionately impacted areas, arrested offenses eligible expungement legalization progra category. those applicants receive additional points application eligible receive technical assistance, grants, lowinterest loans 'is injury personal injury illinois personal injury january 14, 2020 if somebody know injured, different terms may hear. one ter ding difference two phrases important. the term personal injury used civil law define claims victims peoples negligence file rece: odily injury. the defendant chicago personal injury claim person whose actions caused harm another party. the plaintiff claims per injury claim not injuries person suffers personal injuries far civil lawsuits concerned. a bodily injury occur someone fault anoth harmed, nobody blame. other times, person may something causes injury, leaving unable pursue compensation another party. four eler ts must proven order personal injury case successful. duty care . a defendant must duty exercise reasonable care plaintiff. for ex cident, driver likely duty operate vehicle care avoid accidents others. in slip fall case, business owners property owners general here. breach duty . the second element proving negligence showing breach persons duty care. for example, driver fails stop stop si property owner breaches duty care fail clean spills floor timely manner. even defendant intend cause harm plaintiff, could still h ion . the third element cases showing breach persons duty care contributed injury plaintiff sustained. following example above,  $p\varepsilon$ injuries, causation case. however, run stop sign, strike another vehicle, cause injuries, causation would present. damages . final uries personal injury claim valid. some common types damages may warrant personal injury claim include medical costs, lost income if unsure whether personal injury claim, please seek assistance qualified personal injury attorney. most individuals experience re an attorney able guide onto best path forward case. a skilled personal injury attorney work obtain maximum compensation settlement rm receive free confidential consultation experienced injury attorney. first name ']

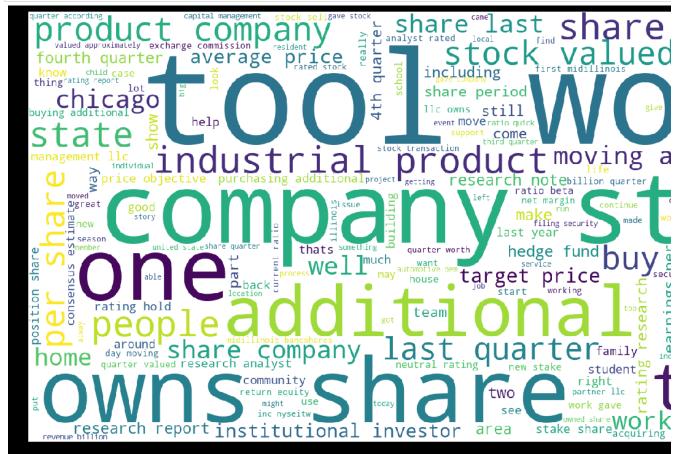
```
In [311]: pos_sentences.to_pickle('pos_sentences.pickle')
           neg_sentences.to_pickle('neg_sentences.pickle')
In [313]: stop = set(stopwords.words('english'))
           extra_stops=['chicago', 'illinois', 'city', 'said', 'say', 'year']
           stop.update(extra_stops)
           exclude = set(string.punctuation)
           lemma = WordNetLemmatizer()
In [315]: def clean(doc):
               stop_free = " ".join([i for i in doc.lower().split() if i not in stop])
               punc_free = ''.join(ch for ch in stop_free if ch not in exclude)
normalized = " ".join(lemma.lemmatize(word) for word in punc_free.split())
               return normalized
In [316]: pos_clean = [clean(doc).split() for doc in pos_text]
In [317]: neg_clean = [clean(doc).split() for doc in neg_text]
In [319]: pos_words=[]
           for u in range(len(pos_clean)):
               words=pos_clean[u]
               for v in words:
                    pos_words.append(v)
           pos_string=" ".join(pos_words)
In [321]: neg_words=[]
           for w in range(len(neg_clean)):
               words=neg_clean[w]
               for x in words:
                    neg_words.append(x)
           neg string=" ".join(neg words)
In [322]: pos text file = open("positive.txt", "w")
           pos_text_file.write(pos_string)
           pos_text_file.close()
           with open('negative.txt', 'w', encoding='utf-8') as neg_text_file:
               neg_text_file.write(neg_string)
```

```
In [332]: # Create stopword list:
    stopwords = set(STOPWORDS)
    #stopwords.update(["drink", "now", "wine", "flavor", "flavors"])

file_content=open ("positive.txt").read()

# Generate a word cloud image
    wordcloud = WordCloud(stopwords=stopwords, background_color="white", width=1600, height=800).generate(file_content)

# Display the generated image:
    # the matplotLib way:
    plt.figure( figsize=(20,10), facecolor='k')
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```

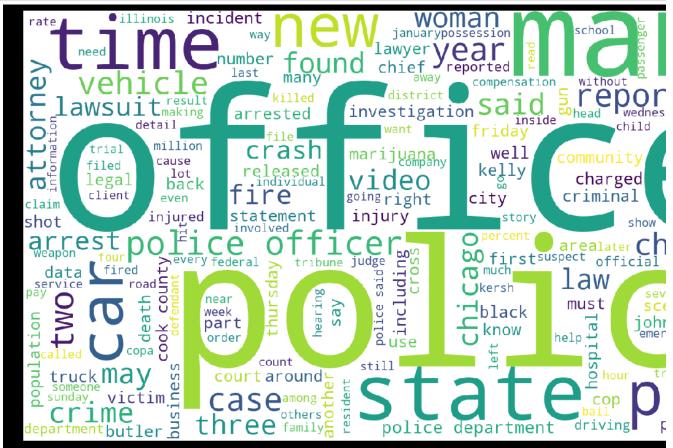


```
In [333]: # Create stopword list:
    stopwords = set(STOPWORDS)
    #stopwords.update(["drink", "now", "wine", "flavor", "flavors"])

file_content=open ("negative.txt").read()

# Generate a word cloud image
    wordcloud = WordCloud(stopwords=stopwords, background_color="white", width=1600, height=800).generate(file_content)

# Display the generated image:
    # the matplotlib way:
    plt.figure( figsize=(20,10), facecolor='k')
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```



# Name + Entity

```
In [337]: entities_df = pd.DataFrame(entities_labels)
    entities_df.columns = ["Entities", "Labels"]
    entities_df.head(20)
```

Out[337]:

	Entities	Labels
0	u.s.	GPE
1	mr. madox	PERSON
2	u.s.soviet	GPE
3	mr. kelly	PERSON
4	mr. ron	PERSON
5	john j.	PERSON
6	neighborhoods.com	ORGANIZATION
7	south	LOCATION
8	clinton	PERSON
9	trip.com	ORGANIZATION
10	mr. hamad	PERSON
11	m.b.a.	ORGANIZATION
12	d.c.	ORGANIZATION
13	russian	GPE
14	harry.harry	PERSON
15	mr. kersh	PERSON
16	mr. worsley	PERSON
17	u.n.	ORGANIZATION
18	mcdunnah.mcdunnah	PERSON
19	mr. robot	PERSON

```
In [340]: Person=entities_df[entities_df['Labels']=='PERSON']
In [356]: #there aren't any people mentioned more than once
          Person['Entities'].value_counts().sort_values(ascending=False)
Out[356]: clinton
                            1
          calif.
                            1
          mr. mcgill
          it.pitt
          harry
                            1
          mr. t.
          mr. mumbower
          mr. smollett
                            1
          mr. madox
                            1
          mr. hieronymus
                           1
          Name: Entities, Length: 66, dtype: int64
In [346]: Org=entities_df[entities_df['Labels']=='ORGANIZATION']
In [347]: #there aren't any orgs mentioned more than once
          Org['Entities'].value_counts().sort_values(ascending=False)
Out[347]: amazon.com
                                 1
                                 1
          neighborhoods.com
          1.a.
                                 1
          n.w.a.
                                 1
          s.a.
          u.s.a.
                                 1
          better.com
          d.c.
                                 1
          mlb.com
                                 1
          u.s.
          trip.com
          telegraphherald.com
          parted.the
                                 1
          m.b.a.
                                 1
          u.s
                                 1
          Name: Entities, dtype: int64
```

```
In [365]: in_terms = Org['Entities'].tolist()
    in_stems=[porter.stem(c) for c in in_terms]
    in_index=[]
    out_index=[]
    for a in range(0, len(clean_df)):
        words=clean_df.iloc[a].text_clean
        stems=[porter.stem(t) for t in words.split()]
        #if any of the keywords are in the title (stems), put those stems in the list
        if any(s in stems for s in in_stems):
            in_index.append(a)
        #if none of the keywords are present insert a Null value
        else:
            out_index.append(a)
```

### Companies

In [388]: companies=clean\_df.iloc[in\_index]
 companies.head(20)

Out[388]:

7	jushi announces beginning adultuse cannabis sales illinois dispensary normal, illinois new adultuse customers can only shop online overthephone instore instore, on
10	pope francis names father louis tylka archdiocese chicago coadjutor bishop peoria pope francis names father louis tylka archdiocese chicago coadjutor bis washingtonpope fran
28	how south holland, illinois helping residents protect properties flooding south hollands flood assistance rebate program powerful incentive proactive floodin outside
33	top 10 haunted hot spots illinois ghost stories halloween anymore. nearly every town ghost stories, obscure others however, theres locations well known particularly
34	former illinois congressman runs iowa u.s. house seat clinton a former u.s. congressman illinois one five republicans seeking partys nomination iowas 2nd co
59	investors give nod worstrated illinois with revenue growing photographer: scott olsongetty images photographer: scott olsongetty images as governor j.b. p office,
72	goodbye, new york, california illinois. hello where 1 4 goodbye, new york, california illinois. hello where bloomberg opinion new york, california illinois hemo
83	chicago public schools although ex president george bush said popular quote no child left behind , hat happening chicago public schools exactly opposite. school
85	fiat chrysler temporarily idle jeep cherokee plant illinois print fca fca invested 350 million belvidere plant, starting 2016, produce cherokee, moved toledo, o
86	activist, 23, named vacant chicagoarea state house post illinois news activist, 23, named vacant chicagoarea state house post a 23yearold community acti appoi
94	sangamon among 93 illinois counties declining populations sangamon saw population decrease 2,419, 1.2 percent, last decade, according new analysis w bureau data. san
98	ushlleading chicago stuns fighting saints last minute comeback local sports telegraphherald.com the chicago steel scored twice final minute regulation time s
114	lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plus 3 lexington betty barbecue opens saturday one eleven food hall eater chicago plu
121	iowaillinoiswisconsin news brief iowaillinoiswisconsin telegraphherald.com new hampshire general oversee wisconsin national guard changes madison, wis changes wis
122	flat idling illinois jeep plant third time six months bloomberg fiat chrysler automobiles nv pause production jeep sport utility vehicle factory third time six months
135	show review: the almost use inner light create emotional show experience chicago cait mcmahon the almosts if i believed you tour brought southern weath crowd fear call
144	400 illinois national guard soldiers say goodbye deployment ceremony pam maxey, texico, tears streaming face embraced son, spec. drake hess, last tues southern illinoi
150	chicago home price growth flat, sp corelogic caseshiller indices show crains chicago business home price growth stalled last fall chicago area. the regions perce
159	amazon buys pinnacle, saving 1,416 jobs chicago rockford airport amazon amazon buys pinnacle, saving 1,416 jobs chicago rockford airport amazon print taking pinna
165	todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith withdraws partner chicago based personal injury trial law firm power rogers smith llp out state todd smith llp out state t

In [373]: companies.shape

Out[373]: (2050, 2)

```
In [392]:
            company_sentences=[]
            for nn in range(len(companies)):
    c_sentences=nltk.sent_tokenize(companies.iloc[nn].text_clean)
                 for mm in c_sentences:
                      company_sentences.append(mm)
            company_sentences=pd.DataFrame(columns=['Sentence'], data=company_sentences)
            company_sentences['Class']="'
            company_sentences.shape
Out[393]: (81609, 2)
In [422]: company_sentences.head()
Out[422]:
               jushi announces beginning adultuse cannabis sales illinois dispensary normal, illinois new adultuse customers can only shop online overthephone instore pick
                as previously announced, jushis illinois dispensaries operate companys beyond hello brand.
                on monday, may 11, 2020 9:00 a.m., beyond hello bloomingtonnormal begin serving adultuse customers jushis newly launched online shopping experience w
                instore..
                medical patients continue shop instore well place orders online overthephone either curbside instore pickup.
                jim cacioppo, jushis chairman chief executive officer commented, on day two years ago, beyond hello opened first dispensary bristol, pennsylvania.
```

#### Residents

```
In [504]:
    in_terms = Person['Entities'].tolist()
    in_stems=[porter.stem(c) for c in in_terms]
    in_index=[]
    out_index=[]
    for a in range(0, len(clean_df)):
        words=clean_df.iloc[a].text_clean
        stems=[porter.stem(t) for t in words.split()]
        #if any of the keywords are in the title (stems), put those stems in the list
        if any(s in stems for s in in_stems):
            in_index.append(a)
        #if none of the keywords are present insert a Null value
        else:
            out_index.append(a)
```

In [505]: residents=clean\_df.iloc[in\_index] residents.head(20)

Out[505]:

Out[509]: (101901, 2)

```
families frustrated chicagoarea cemeteries close visitors mothers day dozens chicagoarea families unable pay respects lost loved ones mothers day say ce
              2
                   jushi announces beginning adultuse cannabis sales illinois dispensary normal, illinois new adultuse customers can only shop online overthephone instore p
                   instore, on...
                   pope francis names father louis tylka archdiocese chicago coadjutor bishop peoria pope francis names father louis tylka archdiocese chicago coadjutor bish
              10
                   washingtonpope fran..
                   comment chicago fire department history mike mc my dad mentioned driver ss1 article click download this entry posted may 7, 2020, 3:30 pm filed fire department
              24
                   how south holland, illinois helping residents protect properties flooding south hollands flood assistance rebate program powerful incentive proactive flooding
              28
                   top 10 haunted hot spots illinois ghost stories halloween anymore. nearly every town ghost stories, obscure others however, theres locations well known pa
              33
                   former illinois congressman runs iowa u.s. house seat clinton a former u.s. congressman illinois one five republicans seeking partys nomination iowas 2nd o
              34
                   co..
                   investors give nod worstrated illinois with revenue growing photographer: scott olsongetty images photographer: scott olsongetty images as governor j.b. pr
              59
                   office, ..
              72
                   goodbye, new york, california illinois. hello where 1 4 goodbye, new york, california illinois. hello where bloomberg opinion new york, california illinois hemo
                   chicago public schools although ex president george bush said popular quote no child left behind, hat happening chicago public schools exactly opposite.
              83
                   school...
              84
                   multiple chicago police employees under investigation for alleged coverup of eddie johnson drinking and driving incident mayor lori lightfoot. lori lightfoot sp
              85
                   fiat chrysler temporarily idle jeep cherokee plant illinois print fca fca invested 350 million belvidere plant, starting 2016, produce cherokee, moved toledo, oh
                   activist, 23, named vacant chicagoarea state house post illinois news activist, 23, named vacant chicagoarea state house post a 23 year old community activ
              86
                   appoi...
                   sangamon among 93 illinois counties declining populations sangamon saw population decrease 2,419, 1.2 percent, last decade, according new analysis wi
              94
                   bureau data. san..
                   what are the discharge dates for chicago pd then james compeau went sort scored touchdown 16 seconds board chop deficit 166 halftime. rb james todd ir
              97
                   backfield eight...
                   lexington betty barbecue opens saturday one eleven food hall eater chicago plus 2 lexington betty barbecue opens saturday one eleven food hall eater chic
              114
                   iowaillinoiswisconsin news brief iowaillinoiswisconsin telegraphherald.com new hampshire general oversee wisconsin national guard changes madison, wis
              121
              122
                   fiat idling illinois jeep plant third time six months bloomberg fiat chrysler automobiles nv pause production jeep sport utility vehicle factory third time six mon
                   show review: the almost use inner light create emotional show experience chicago cait mcmahon the almosts if i believed you tour brought southern weathe
              135
                   400 illinois national guard soldiers say goodbye deployment ceremony pam maxey, texico, tears streaming face embraced son, spec. drake hess, last tuesi
                   southern illinoi...
In [506]: residents.shape
Out[506]: (2549, 2)
In [508]:
            residents_sentences=[]
             for nn in range(len(residents)):
                  r sentences=nltk.sent tokenize(residents.iloc[nn].text clean)
                  for mm in r_sentences:
                       residents_sentences.append(mm)
In [509]:
            residents_sentences=pd.DataFrame(columns=['Sentence'], data=residents_sentences)
             residents_sentences['Class']="
             residents_sentences.shape
```

they knowledge well, said registered nurse glendra smith, for smith, familys first mothers day without mom, anna pennington, passed away less two months ac

```
In [510]: residents_sentences.head()

Out[510]:

0 families frustrated chicagoarea cemeteries close visitors mothers day dozens chicagoarea families unable pay respects lost loved ones mothers day say cem
1 but number families met locked gates sunday.they might earth, closest get mothers, said gregory harris.for harris, cemetery one place go honor mother dorott
2 they looking forward seeing moms, harris said.he said small group frustrated people jumped gates leave flowers mothers gravesides.there gentlemen went was
```

they want see loved one i understood that.when got there, 20 people so, standing out, wanting get inside.

## Sentiment Analysis - Company

```
In [448]:
           all_reviews = company_sentences['Sentence']
            all_sent_values = []
           all_sentiments = []
           from nltk.sentiment.vader import SentimentIntensityAnalyzer
            def sentiment_value(paragraph):
                analyser = SentimentIntensityAnalyzer()
                result = analyser.polarity_scores(paragraph)
                score = result['compound']
                return round(score,1)
In [450]: for i in range(0,len(all_reviews)):
                all_sent_values.append(sentiment_value(all_reviews[i]))
In [463]: SENTIMENT_VALUE = []
            SENTIMENT = []
            for i in range(0,len(all_reviews)):
                sent = all_sent_values[i]
                if (sent<=1 and sent>0.2):
                    SENTIMENT.append('Positive')
                    SENTIMENT_VALUE.append(2)
                elif (sent<-0.2 and sent>=-1):
                    SENTIMENT.append('Negative')
                    SENTIMENT_VALUE.append(0)
                     SENTIMENT.append('Neutral')
                     SENTIMENT_VALUE.append(1)
In [465]: temp_data = company_sentences['Sentence'].to_frame()
In [466]: | temp_data['SENTIMENT_VALUE'] = SENTIMENT_VALUE
            temp_data['SENTIMENT'] = SENTIMENT
In [467]: temp_data.head()
Out[467]:
               jushi announces beginning adultuse cannabis sales illinois dispensary normal, illinois new adultuse customers can only shop online overthephone instore pic
               patients can shop instore, on.,
               as previously announced, jushis illinois dispensaries operate companys beyond hello brand.
               on monday, may 11, 2020 9:00 a.m., beyond hello bloomingtonnormal begin serving adultuse customers jushis newly launched online shopping experience
               www.beyondhello.com overthephone orders instore..
               medical patients continue shop instore well place orders online overthephone either curbside instore pickup.
               jim cacioppo, jushis chairman chief executive officer commented, on day two years ago, beyond hello opened first dispensary bristol, pennsylvania.
```

# **Classification - Company**

```
In [468]: X = temp_data.Sentence
y = temp_data.SENTIMENT_VALUE

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state = 8)
```

```
In [469]: print(X_train.shape)
          print(X_test.shape)
          print(y_train.shape)
          print(y_test.shape)
          (57126,)
          (24483,)
           (57126,)
           (24483,)
In [470]: y_test.value_counts()
Out[470]: 1
               11637
                8460
                4386
          Name: SENTIMENT_VALUE, dtype: int64
In [471]: #train LR classifier
          ('clf', LogisticRegression()),
                        ])
          lr.fit(X_train, y_train)
Out[471]: Pipeline(memory=None,
                   steps=[('vect'
                           CountVectorizer(analyzer='word', binary=False,
                                           decode_error='strict',
                                           dtype=<class 'numpy.int64'>, encoding='utf-8',
                                           input='content', lowercase=True, max_df=1.0,
                                           max_features=None, min_df=1,
                                           ngram_range=(1, 1), preprocessor=None,
                                            stop_words=None, strip_accents=None,
                                           token_pattern='(?u)\\b\\w\\w+\\b',
                                           tokenizer=None, vocabulary=None)),
                           ('tfidf',
                           TfidfTransformer(norm='12', smooth_idf=True,
                                            sublinear_tf=False, use_idf=True)),
                           ('clf',
                           LogisticRegression(C=1.0, class_weight=None, dual=False,
                                              fit_intercept=True, intercept_scaling=1,
                                              l1_ratio=None, max_iter=100,
                                              multi_class='warn', n_jobs=None,
                                              penalty='12', random_state=None, solver='warn', tol=0.0001, verbose=0,
                                              warm_start=False))],
                   verbose=False)
In [472]: %%time
          y_pred_lr = lr.predict(X_test)
          print('accuracy %s' % accuracy_score(y_pred_lr, y_test))
          accuracy 0.8206919086713229
          Wall time: 387 ms
```

## **Word Cloud - Company**

```
In [474]: sent_df = X_test.to_frame()
    sent_df['prediction']=y_pred_lr.tolist()

In [475]: #Negative=0, Neutral=1, Positive=2
    sent_df['prediction'].value_counts()

Out[475]: 1    13929
    2    7530
    0    3024
    Name: prediction, dtype: int64
```

```
In [476]: sent_df.head()
```

Out[476]:

	Sentence	prediction
59288	merriman shawnee mission, ksarizona state transfer arizona state swims backstroke freestyle events.	1
36004	students may noticed changes food businesses around columbias morningside campus.	1
54078	wadlow died july 15, 1940 buried coffin measuring 10 feet, 9 inches long, 32 inches wide 30 inches deep.	1
9838	naturally, someone drunk enough volunteer.	0
40523	with valets versatile wall bedsmurphy beds, comfort lost.	0

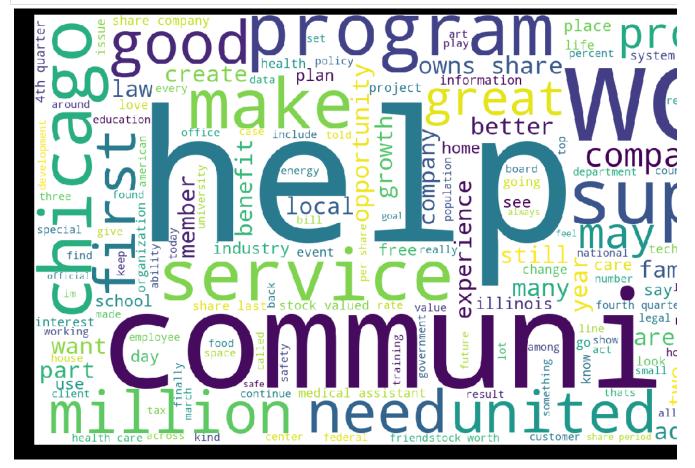
```
In [480]: pos_sentences=sent_df[sent_df['prediction']==2]
           pos_text=pos_sentences["Sentence"].tolist()
           pos_text[0:2]
Out[480]: ['but trade deals created equal, people benefit readily them.',
             restaurants facing higher costs food labor, increasing competition limits ability raise prices.']
In [481]: neg_sentences=sent_df[sent_df['prediction']==0]
           neg_text=neg_sentences["Sentence"].tolist()
           neg_text[0:2]
Out[481]: ['naturally, someone drunk enough volunteer.',
            'with valets versatile wall bedsmurphy beds, comfort lost.']
In [482]: pos_sentences.to_pickle('pos_sentences.pickle')
           neg_sentences.to_pickle('neg_sentences.pickle')
In [485]: def clean(doc):
               stop_free = " ".join([i for i in doc.lower().split() if i not in stop])
               punc_free = ''.join(ch for ch in stop_free if ch not in exclude)
normalized = " ".join(lemma.lemmatize(word) for word in punc_free.split())
               return normalized
In [486]: pos_clean = [clean(doc).split() for doc in pos_text]
In [487]: neg_clean = [clean(doc).split() for doc in neg_text]
In [488]:
           pos_words=[]
           for u in range(len(pos_clean)):
               words=pos clean[u]
               for v in words:
                   pos_words.append(v)
           pos_string=" ".join(pos_words)
In [489]:
          neg words=[]
           for w in range(len(neg_clean)):
               words=neg_clean[w]
               for x in words:
                   neg_words.append(x)
           neg_string=" ".join(neg_words)
In [490]: pos_text_file = open("positive_company.txt", "w")
           pos_text_file.write(pos_string)
           pos_text_file.close()
           with open('negative_company.txt', 'w', encoding='utf-8') as neg_text_file:
               neg_text_file.write(neg_string)
```

```
In [498]: # Create stopword List:
    stopwords = set(STOPWORDS)
    stopwords.update(["state", "new", "one",'well','time','said','people','business'])

file_content=open ("positive_company.txt").read()

# Generate a word cloud image
    wordcloud = WordCloud(stopwords=stopwords, background_color="white", width=1600, height=800).generate(file_content)

# Display the generated image:
    # the matplotLib way:
    plt.figure( figsize=(20,10), facecolor='k')
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```



```
In [499]: # Create stopword list:
    stopwords = set(STOPWORDS)
    stopwords.update(["state",'people','one'])

file_content=open ("negative_company.txt").read()

# Generate a word cloud image
    wordcloud = WordCloud(stopwords=stopwords, background_color="white", width=1600, height=800).generate(file_content)

# Display the generated image:
    # the matplotLib way:
    plt.figure( figsize=(20,10), facecolor='k')
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```



# **Sentiment Analysis - Resident**

```
In [511]: all_reviews = residents_sentences['Sentence']
    all_sent_values = []
    all_sentiments = []

In [512]: from nltk.sentiment.vader import SentimentIntensityAnalyzer
    def sentiment_value(paragraph):
        analyser = SentimentIntensityAnalyzer()
        result = analyser.polarity_scores(paragraph)
        score = result['compound']
        return round(score,1)

In [513]: for i in range(0,len(all_reviews)):
        all_sent_values.append(sentiment_value(all_reviews[i]))
```

```
In [514]: SENTIMENT_VALUE = []
            SENTIMENT = []
            for i in range(0,len(all_reviews)):
                sent = all_sent_values[i]
                if (sent<=1 and sent>0.2):
                     SENTIMENT.append('Positive')
                     SENTIMENT_VALUE.append(2)
                elif (sent<-0.2 and sent>=-1):
                     SENTIMENT.append('Negative')
                     SENTIMENT_VALUE.append(0)
                else:
                     SENTIMENT.append('Neutral')
                     SENTIMENT_VALUE.append(1)
In [519]: temp_data = residents_sentences['Sentence'].to_frame()
In [520]: | temp_data['SENTIMENT_VALUE'] = SENTIMENT_VALUE
            temp_data['SENTIMENT'] = SENTIMENT
In [521]: temp_data.head()
Out[521]:
               families frustrated chicagoarea cemeteries close visitors mothers day dozens chicagoarea families unable pay respects lost loved ones mothers day say cem
               gates visitors without expla...
               but number families met locked gates sunday.they might earth, closest get mothers, said gregory harris.for harris, cemetery one place go honor mother doroth
               cars families stood outside...
               they looking forward seeing moms, harris said.he said small group frustrated people jumped gates leave flowers mothers gravesides there gentlemen went we
               they want see loved one i understood that when got there, 20 people so, standing out, wanting get inside.
               they knowledge well, said registered nurse glendra smith.for smith, familys first mothers day without mom, anna pennington, passed away less two months ac
```

## Classification - Resident

cedar park, i tears welli..

```
In [522]: X = temp_data.Sentence
          y = temp_data.SENTIMENT_VALUE
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state = 8)
In [523]: print(X_train.shape)
          print(X_test.shape)
          print(y_train.shape)
          print(y_test.shape)
           (71330,)
           (30571,)
           (71330,)
          (30571,)
In [524]: y_test.value_counts()
Out[524]: 1
                14658
               10339
          Name: SENTIMENT_VALUE, dtype: int64
```

```
In [525]: #train LR classifier
          ('clf', LogisticRegression()),
                        ])
          lr.fit(X_train, y_train)
Out[525]: Pipeline(memory=None,
                   steps=[('vect'
                           CountVectorizer(analyzer='word', binary=False,
                                           decode error='strict'.
                                           dtype=<class 'numpy.int64'>, encoding='utf-8',
                                            input='content', lowercase=True, max_df=1.0,
                                           max_features=None, min_df=1,
                                           ngram_range=(1, 1), preprocessor=None,
                                            stop_words=None, strip_accents=None,
                                           token_pattern='(?u)\\b\\w\\w+\\b',
                                            tokenizer=None, vocabulary=None)),
                           ('tfidf',
                           TfidfTransformer(norm='12', smooth_idf=True,
                                             sublinear_tf=False, use_idf=True)),
                           ('clf',
                           LogisticRegression(C=1.0, class_weight=None, dual=False,
                                              fit_intercept=True, intercept_scaling=1,
                                              l1_ratio=None, max_iter=100,
                                              multi_class='warn', n_jobs=None,
                                              penalty='12', random_state=None,
solver='warn', tol=0.0001, verbose=0,
                                              warm_start=False))],
                   verbose=False)
In [526]: %%time
          y_pred_lr = lr.predict(X_test)
          print('accuracy %s' % accuracy score(y pred lr, y test))
          accuracy 0.8265676621634883
          Wall time: 518 ms
```

# Word Cloud - Resident

```
In [527]: sent df = X test.to frame()
            sent_df['prediction']=y_pred_lr.tolist()
In [528]: #Negative=0, Neutral=1, Positive=2
            sent_df['prediction'].value_counts()
Out[528]: 1
                 17208
                  9472
           а
                  3891
           Name: prediction, dtype: int64
In [529]: sent_df.head()
Out[529]:
                    people ineligible commission include: lobbyists persons appointed, running elected position state, federal, local government paid consultant campaign re
             87432
             70774
                    casey leins may 14, 2019 these places best america educating students levels.
             30872
                    get really upset people object pipelines oil still transported rail, aziz said
             85930
                    ethics reform the republicans best hope minimize losses, jackson said.
                    as aide schmitz, goncher served liaison constituents state agencies
           pos_sentences=sent_df[sent_df['prediction']==2]
            pos_text=pos_sentences["Sentence"].tolist()
            pos_text[0:2]
```

Out[530]: ['people ineligible commission include: lobbyists persons appointed, running elected position state, federal, local government pai

cal candidate political action committee individual ownership interest entity state, local federal contract appointed elected offi

'casey leins may 14, 2019 these places best america educating students levels.']

```
In [531]: neg_sentences=sent_df[sent_df['prediction']==0]
            neg_text=neg_sentences["Sentence"].tolist()
            neg_text[0:2]
Out[531]: ['i get really upset people object pipelines oil still transported rail, aziz said.',
             johnson, married, initially blamed failure take blood pressure medication said drinks dinner earlier evening.']
In [532]: pos_sentences.to_pickle('pos_sentences.pickle')
            neg_sentences.to_pickle('neg_sentences.pickle')
In [533]: def clean(doc):
                stop_free = " ".join([i for i in doc.lower().split() if i not in stop])
punc_free = ''.join(ch for ch in stop_free if ch not in exclude)
normalized = " ".join(lemma.lemmatize(word) for word in punc_free.split())
                return normalized
In [534]: pos_clean = [clean(doc).split() for doc in pos_text]
In [535]: neg clean = [clean(doc).split() for doc in neg text]
In [536]: pos_words=[]
            for u in range(len(pos_clean)):
                words=pos_clean[u]
                for v in words:
                    pos_words.append(v)
            pos string=" ".join(pos words)
In [537]: neg_words=[]
            for w in range(len(neg_clean)):
                words=neg_clean[w]
                for x in words:
                    neg_words.append(x)
            neg_string=" ".join(neg_words)
In [538]: pos_text_file = open("positive_resident.txt", "w")
            pos_text_file.write(pos_string)
            pos_text_file.close()
            with open('negative_resident.txt', 'w', encoding='utf-8') as neg_text_file:
                neg_text_file.write(neg_string)
```

```
In [545]: # Create stopword List:
    stopwords = set(STOPWORDS)
    stopwords.update(['people','new','one','state','well','said','time','business','make'])

file_content=open ("positive_resident.txt").read()

# Generate a word cloud image
    wordcloud = WordCloud(stopwords=stopwords, background_color="white", width=1600, height=800).generate(file_content)

# Display the generated image:
    # the matplotlib way:
    plt.figure( figsize=(20,10), facecolor='k')
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```



```
In [548]: # Create stopword List:
    stopwords = set(STOPWORDS)
    stopwords.update(["state",'people','one','said','new'])

file_content=open ("negative_resident.txt").read()

# Generate a word cloud image
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```

