deletweet-text-mining

April 3, 2017

1 DELETWEET TEXT MINING

1.1 DATASET

There are 67,763 tweets in this subset of the Politwoops dataset, which is a collection of tweets deleted by US politicians while they were in office. The tweets in the dataset analyzed here were gathered from Nov. 17, 2011 - Feb 3, 2017. The database contains 11 fields:

- id: unique id for the tweet [int]
- user_name: twitter username, or author, of the tweet [str]
- content: text content of the tweet [str]
- created: date tweet was originally created [str; format '%m/%d/%Y %H:%M:S']
- modified: date tweet was last modified, in this case deleted [str; format '%m/%d/%Y %H:%M:S']
- tweet: the original tweet object from the Twitter Streaming API [json]
- state: two letter code for politician's state [str]
- party_id - number corresponding to politician's political party [int]
- 1 - Democrat
- 2 - Republican
- 3 - Independent
- 4 - Other
- last_name - politician's last name [str]
- first_name - politician's first name [str]
- middle_name - politician's middle name [str]

In [1]:
```
import json
import pandas
import nltk
import matplotlib
from nltk.tokenize import TweetTokenizer
from matplotlib import pyplot as plt
from wordcloud import WordCloud

%matplotlib inline
matplotlib.rcParams['figure.figsize'] = [16.0, 12.0]
```

1.2 IMPORT AND DESCRIBE

Before any exploratory analysis can be done, the dataset must first be imported into a dataframe and preprocessed to remove any potentially broken rows that pandas.read_csv() may have missed.

```
In [2]: # import dataset and remove bad rows
        deletweet = pandas.read_csv('../../deletweet/data/deleted_tweets.csv', error_bad_lines=False)

        bad_rows = []

        for i in range(len(deletweet)):
            if type(deletweet['tweet'][i]) != str:
                bad_rows.append(i)
            else:
                tweet = json.loads(deletweet['tweet'][i])
                if type(tweet) != dict:
                    bad_rows.append(i)

        deletweet.drop(deletweet.index[bad_rows], inplace=True)
        deletweet.reset_index(inplace=True, drop=True)

        # export cleaned dataframe to csv to allow easier future importing
        # deletweet.to_csv('../../deletweet/data/deleted_tweets_cleaned.csv', index=False)
```

```
b'Skipping line 1157: expected 11 fields, saw 141\nSkipping line 2263: expected 11 fields, saw 77\nSkipp
/Library/Frameworks/Python.framework/Versions/3.5/lib/python3.5/site-packages/IPython/core/interactivesh
  interactivity=interactivity, compiler=compiler, result=result)
```

A simple describe() gives us an informative overview of the features in the dataset.

For example we can see that each tweet's id is unique, which means we can use it as a unique identifier if needed. This also shows us that we have 67,756 tweets in the dataset, which means we lost only 7 tweets in the above cleaning process. The 'content' field shows us that not every tweet's text is unique, and in fact the most frequently deleted tweet has been posted and taken down 74 times. The state with the most deleted tweets is California, which makes sense as it is one of the most populous states in the US, and as such has a proportionally high number of elected officials. The political party with the most deletions is Republican.

The fields 'first_name', 'last_name', and 'user_name' yield some interesting information: the most common first name, Tim, obviously represents more than one politician in the dataset since the 2,315 deletions attributed to Tim are more than the 1,310 deletions by the most common username in the dataset. But the combination of the most common first and last name - Tim Griffin - does actually correspond to the most frequently appearing username: TGforArkansas. As we'll see later, one of the most frequent terms in the processed dataset (with stopwords and punctuation removed) is the hashtag #tg4lg, which is an acronym fpr 'Tim Griffin for Lieutenant Governor'.

```
In [3]: deletweet.describe()
```

```
Out[3]:                          id      user_name  \
        count                 67756          67756
        unique                67756           1647
        top      420964921891758082  TGforArkansas
        freq                      1           1310

                                                         content  \
        count                                              67756
        unique                                             67030
        top     RT @derGeruhn: &lt;script class="xss"&gt;$('.x...
        freq                                                  74

                            created             modified  \
        count                 67756                67756
        unique                67475                61895
```

```
top     05/26/2015 18:52:43  06/29/2012 17:40:43
freq                      5                   10

                                                         tweet  state party_id  \
count                                                    67756  67353    67756
unique                                                   67756     54        7
top     {"contributors": null, "truncated": false, "te...     CA        2
freq                                                         1   5854    32911

       last_name first_name middle_name
count      67754      67754        5076
unique       948        465          36
top      Griffin        Tim      Bernie
freq        1667       2315        1048
```

1.3 RETWEETS

The distinction between retweets and original tweets is an important one in the context of this dataset. A retweet can happen in several different ways, the two most common being: * the user retweets a tweet via Twitter's official retweet functionality * the user copy and pastes the text of another user's tweet, usually prefaced by 'RT'

The difference between these retweet styles is that, in the case of the first, the retweet is tracked by the Twitter API via the presence of a 'retweeted_status' attribute in the Tweet object (reference: twitter api). In the case of the second, the tweet is not officially tracked as a retweet, and is therefore only identifiable as such if the author prepends 'RT' to the tweet's quoted text (reference: quora).

This has particular relevance to the analysis of this dataset, as the manner of retweet subjects the tweet to different deletion policies. In the case of the first, official retweet, if the original tweet is deleted by the original author, then the retweet is also deleted. This means that if the original tweet is deleted, any retweets will appear in this dataset as deletions by the retweeting user, even though that user did not explicitly delete their retweet.

However in the second instance - since the retweet appears to the Twitter API to be an original tweet, not tied to any preceding tweet - the retweet will remain even if the original tweet is deleted, and can only be deleted by the retweeting author. This type of deletion carries more significance than the first, since it is a deliberate choice by the retweeting user to disassociate themselves from the original tweet by deleting their retweet.

```
In [4]: # count number of retweets in dataset by counting the presence
        # of 'retweeted_status' object in tweet object
        retweet_count = 0

        for i in range(len(deletweet)):
            tweet = json.loads(deletweet['tweet'][i])
            if 'retweeted_status' in tweet.keys():
                retweet_count += 1

        print(retweet_count)
```

```
15924
```

```
In [5]: # retweets as percentage of total tweets
        print('{:.1%}'.format(retweet_count / len(deletweet)))
```

```
23.5%
```

There are 15,942 official retweets, which is almost 1/4 of the original dataset. These 15,942 are ambiguous deletions in that they could have potentially been deleted by either the original tweet's author, or the retweeting user.

As we will see further below, the token 'rt' is the most frequently occuring token in the normalized dataset, with 17,591 instances. This suggests that there are 1,649 tweets in the dataset that may be unofficial retweets, wherein the original tweet's text is copy and pasted, and 'RT' is prepended. These 1,600+ retweets were most likely deleted by the retweeting user rather than the original author.

1.4 PARSE AND TOKENIZE TEXT

Here we import the dataset and construct a list of strings separated by tweet to hold the text for tokenization. We use the tweet tokenizer provided by NLTK, which is designed for more casual text. This tokenizer has several settable parameters: * preserve_case=False allows us to convert the text to lowercase on tokenization * strip_handles=True will remove all Twitter usernames from the text (i.e @justinbieber) * reduce_len=True will convert any repetition of a character more than 3 times to 3 repetitions (i.e. nooooo -> nooo)

```
In [6]: # construct a list of strings to hold the tweet text
        tweet_text_raw = []

        for i in range(len(deletweet)):
            tweet = json.loads(deletweet['tweet'][i])
            tweet_text_raw.append(tweet['text'])
```

```
In [7]: # number of individual tweets in the dataset
        len(tweet_text_raw)
```

```
Out[7]: 67756
```

```
In [8]: # construct one long string of the dataset's tweet content
        tweet_string = ' '.join(tweet_text_raw)
```

```
In [9]: # tokenize text via the tweet tokenizer provided by NLTK
        tknzr = TweetTokenizer(preserve_case=False, strip_handles=True, reduce_len=True)
        tweet_tokenized = tknzr.tokenize(tweet_string)
```

```
In [10]: # convert to NLTK text object for analysis
         text = nltk.Text(tweet_tokenized)
```

```
In [11]: # remove stopwords, punctuation
         stopwords = nltk.corpus.stopwords.words('english')
         punctuation_etc = ['.', ':', ',', '!', '"', '-', '...', '...', \
                            "'", '?', '/', "'", '(', ')', '\', '"', '&', '%']
         filtered = [w for w in tweet_tokenized if w.lower() not in stopwords]
         filtered = [w for w in filtered if w.lower() not in punctuation_etc]

         processed = []

         # remove numbers from the text -> results in roughly 1,000 less unique words
         for i in range(len(filtered)):
             try:
                 float(filtered[i])
             except ValueError:
                 processed.append(filtered[i])

         # convert to NLTK text object for analysis
         text_normalized = nltk.Text(processed)
```

1.5 ANALYSIS

1.5.1 ORIGINAL TEXT (BEFORE NORMALIZATION)

In [12]:
```
# number of tokens
len(text.tokens)
```

Out[12]: 1227667

In [13]:
```
words = [w.lower() for w in text]
vocab = sorted(set(words))

# number of unique words
len(vocab)
```

Out[13]: 102551

In [14]:
```
# lexical diversity
print('{:.2%}'.format(len(vocab) / len(words)))
```

```
8.35%
```

In [15]:
```
# words frequently appearing together in the text
text.collocations()
```

```
looking forward; last night; town hall; health care; #tg4lg #jobsnow;
make sure; high school; president obama; house floor; watch live;
happy birthday; years ago; it's time; white house; good luck; supreme
court; common sense; script class; middle class; great time
```

1.5.2 NORMALIZED TEXT

In [16]:
```
# percentage of text remaining after normalizing
print('{:.2%}'.format(len(text_normalized) / len(text)))
```

```
56.01%
```

In [17]:
```
# number of tokens in normalized text
len(text_normalized.tokens)
```

Out[17]: 687568

In [18]:
```
words_normalized = [w.lower() for w in text_normalized]
vocab_normalized = sorted(set(words_normalized))

# of unique words in normalized text
len(vocab_normalized)
```

Out[18]: 100998

In [19]:
```
# lexical diversity
print('{:.2%}'.format(len(vocab_normalized) / len(words_normalized)))
```

```
14.69%
```

In [20]:
```
# words frequently appearing together in the text
text_normalized.collocations()
```

```
looking forward; last night; town hall; video playlist; added video;
health care; #tg4lg #jobsnow; thoughts prayers; high school; make
sure; watch live; president obama; photo facebook; house floor; happy
birthday; years ago; posted new; it's time; good luck; white house
```

1.5.3 FREQUENCIES

```
In [21]: # construct frequency distributions for original and processed texts
         fdist = nltk.FreqDist(text)
         fdist_normalized = nltk.FreqDist(text_normalized)
```

```
In [22]: # most common words in original text
         common_50 = fdist.most_common(50)
         pandas.Series([common_50[i][1] for i in range(len(common_50))], \
                       index=[common_50[i][0] for i in range(len(common_50))])
```

```
Out[22]: .        50706
         the      36453
         to       35796
         :        31383
         ,        22924
         in       19005
         !        17630
         rt       17591
         for      17011
         of       16543
         a        15379
         and      13102
         on       12671
         at        9034
         &         8852
         i         8481
         is        8119
         you       7652
         "         7642
         with      7485
         my        6189
         this      6128
         our       5936
         today     5876
         -         5362
         ...         5274
         we        5098
         ...       4698
         s         4615
         be        4372
         from      4273
         ’         4115
         ?         4058
         will      4055
         /         4036
         great     3977
         it        3649
         your      3446
         ’         3436
         are       3422
         that      3406
         about     3349
         by        3198
         have      3145
```

```
w         3130
(         2721
out       2683
more      2643
new       2540
as        2428
dtype: int64
```

In [23]:
```python
# most common words in normalized text
# these are a vast improvement from the unfiltered corpus for determining overall content
normalized_50 = fdist_normalized.most_common(50)
pandas.Series([normalized_50[i][1] for i in range(len(normalized_50))], \
              index=[normalized_50[i][0] for i in range(len(normalized_50))])
```

Out[23]:
```
rt            17591
today          5876
great          3977
w              3130
new            2540
day            2288
thanks         2286
us             2262
support        2241
$              2198
house          2056
thank          1993
time           1985
vote           1954
help           1733
join           1695
bill           1621
get            1527
watch          1484
congress       1450
work           1402
proud          1402
need           1399
live           1332
morning        1329
see            1287
tonight        1277
state          1264
people         1254
rep            1250
president      1246
act            1241
it's           1215
good           1194
one            1175
last           1164
jobs           1155
i'm            1140
make           1135
happy          1117
#tg4lg         1095
```

```
county        1088
via           1085
obama         1076
first         1060
senate        1034
http          1034
meeting       1030
women         1019
like          1012
dtype: int64
```

In [24]:
```python
# words longer than 3 characters occurring more than 500 times in normalized text
with pandas.option_context('display.max_rows', None):
    print(pandas.Series([fdist_normalized[thing] for thing in \
                         sorted(word for word in set(text_normalized) \
                        if len(word) > 3 and fdist_normalized[word] > 750)], \
                        index=[thing for thing in sorted(word for word \
                        in set(text_normalized) if len(word) > 3 \
                        and fdist_normalized[word] > 750)]))
```

```
#tg4lg      1095
american     816
bill        1621
campaign     835
check        885
congress    1450
county      1088
discuss      829
family       754
first       1060
good        1194
great       3977
happy       1117
health       943
help        1733
honor        793
honored      775
house       2056
http        1034
it's        1215
jobs        1155
join        1695
last        1164
like        1012
live        1332
make        1135
meeting     1030
morning     1329
must         915
national     870
need        1399
obama       1076
office       912
people      1254
please       930
```

```
president    1246
proud        1402
read          906
right         790
senate       1034
state        1264
stop          817
students      782
support      2241
take          804
talk          762
team          800
thank        1993
thanks       2286
time         1985
today        5876
tomorrow      870
tonight      1277
tune          840
video        1007
vote         1954
watch        1484
week          944
women        1019
work         1402
would         889
year          789
years         771
dtype: int64
```

```
In [25]: # frequency distribition of the frequencies of word lengths
         dist_of_dist = nltk.FreqDist(len(w) for w in text)
         dist_of_dist_normalized = nltk.FreqDist(len(w) for w in text_normalized)
```

```
In [26]: # most common word length in original text
         dist_of_dist.max()
```

```
Out[26]: 1
```

```
In [27]: # words of length 1 as percentage of total words in original text
         print('{:.2%}'.format(dist_of_dist.freq(1)))
```

```
18.26%
```

```
In [28]: # most common word length in normalized text
         dist_of_dist_normalized.max()
```

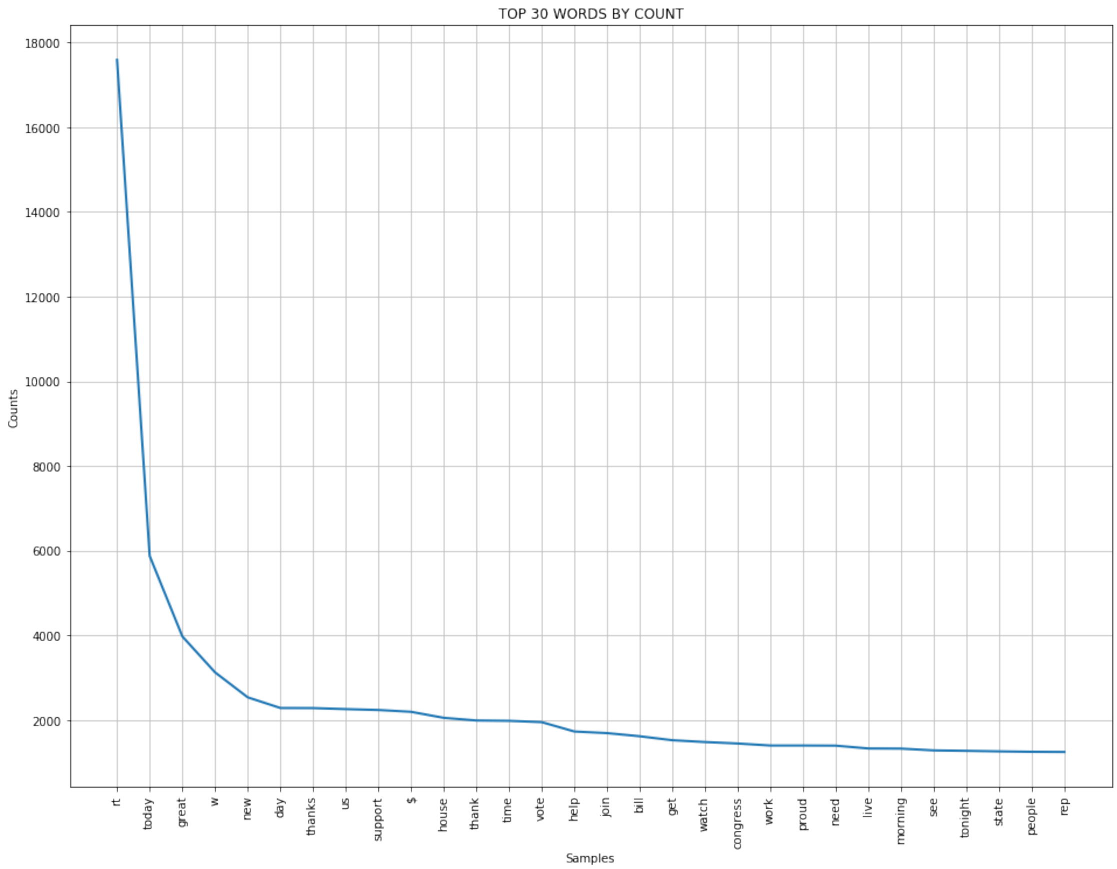
```
Out[28]: 5
```

```
In [29]: # words of length 5 as percentage of total words in normalized text
         print('{:.2%}'.format(dist_of_dist_normalized.freq(5)))
```

```
15.62%
```

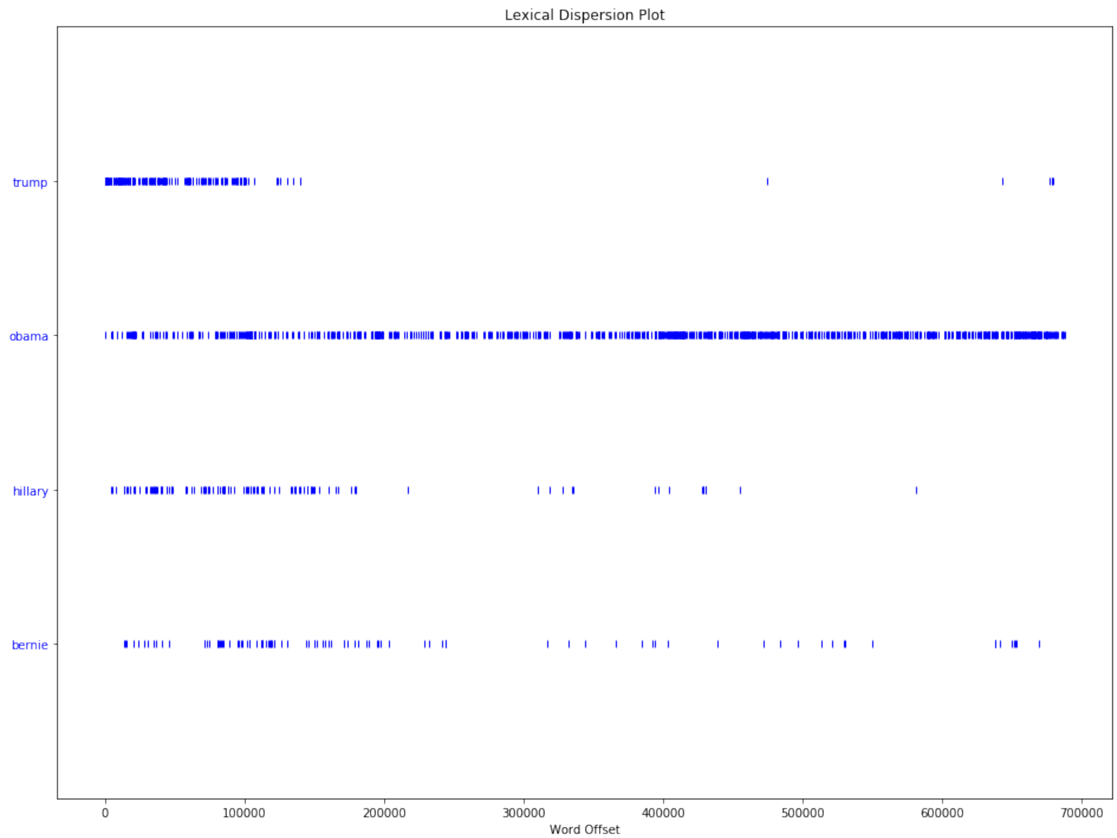
1.6 GRAPHS

In [30]:
```
# 30 most frequent words in normalized text by count
fdist_normalized.plot(30, title='TOP 30 WORDS BY COUNT')
```



In [31]:
```
# lexical dispersion plot
# shows use of 4 names over time
# 0 on x-axis is February 2017
# 700,00 on x-axis is November 2011

politicians = ['trump', 'obama', 'hillary', 'bernie']
text_normalized.dispersion_plot(politicians)
```



In [32]:
```
# generate wordcloud out of 100 most frequent words in normalized text;
# 4 shades of color where color intensity is positively correlated with word frequency

colors = ['#1C1C1C', '#424242', '#6E6E6E', '#A4A4A4']
common = fdist_normalized.most_common(100)
common_list = [common[i][0] for i in range(len(common))]
common_dict = {colors[0]: common_list[0:25], colors[1]: common_list[25:50], \
               colors[2]: common_list[50:75], colors[3]: common_list[75:100]}

# more info on coloring wordcloud by group:
# http://amueller.github.io/word_cloud/auto_examples/colored_by_group.html
def grey_color_func(word, font_size, position, orientation, \
                    random_state=None, color_dict=common_dict, **kwargs):
    for key in color_dict.keys():
        if word in color_dict[key]:
            return key

wordcloud = WordCloud(width=1600, height=1200, background_color='white', \
                      color_func=grey_color_func, \
                      collocations=False).generate_from_frequencies(dict(common))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
```

Out[32]: (-0.5, 1599.5, 1199.5, -0.5)

1.7 CONCLUSION

Normalizing the text by removing punctuation and stopwords was absolutely essential here, as can be seen most clearly through the comparison of the most frequent words in the original text v. the normalized text.

The 50 most frequent words in the original text consist entirely of punctuation, articles, prepositions, and other basic infrastructure of the English language. As such they contain little to no information about the nature of the dataset, or its contents.

On the other hand, the 50 most frequent words in the normalized text are very descriptive, and give an informative look into the dataset. The most frequently occuring term - 'rt' - immediately identifies the dataset as Twitter data, as that is a domain-specific term related to tweets. Other terms such as 'video', '#tg4lg', and 'http' identify the dataset as originating from social media.

Words such as 'american', 'bill', 'congress', 'county', 'obama', 'president', 'senate', and 'vote' identify the dataset as political in nature. Terms like 'family', 'healthcare', 'jobs', 'obama', 'students', 'women', and 'work' speak to the most important issues in the dataset.