Data Exploration of Trump Tweets

Barak Krakauer, July 2016

The current analysis is based on 3247 tweets pulled 7/14/2016, and 9255 retweets with scrapable geographical data selected from 10 random Trump tweets (see the scraper files for more information)

```
In [1]: import os
   import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
   import statsmodels.api as sm
   import statsmodels.formula.api as smf
   import helper as h
   from sklearn import linear_model, neighbors, ensemble, cross_validation, grid_s

pd.set_option('display.max_rows', 10)
   pd.set_option('display.notebook_repr_html', True)
   pd.set_option('display.max_columns', 10)

%matplotlib inline
   plt.style.use('ggplot')
```

```
In [2]: df = pd.read_csv('trump_tweets.csv')
    df.drop(["id"], axis=1, inplace=True)
    df.head()
```

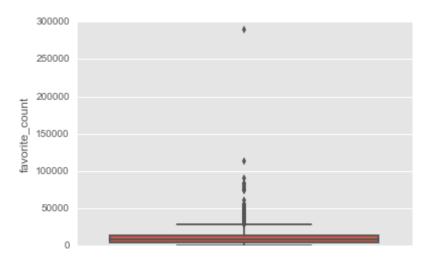
Out[2]:

	text	created_at	favorite_count	retweet_count
0	I employ many people in the State of Virginia	2016-07-14 17:23:58	13466	4401
1	Another new poll. Thank you for your support!	2016-07-14 14:53:46	15456	6047
2	Great new poll- thank you America!\n#Trump2016	2016-07-14 13:21:48	17037	5775
3	I will be making the announcement of my Vice P	2016-07-14 01:19:51	40583	15757
4	If I win the Presidency, we will swamp Justice	2016-07-13 22:28:44	22560	7167

What does the distribution of favorites look like?

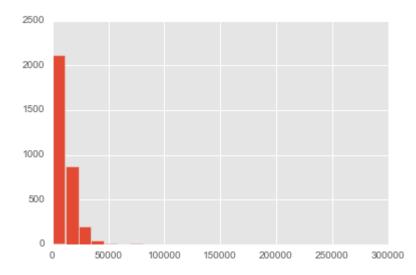
In [3]: sns.boxplot(y="favorite_count", data=df)

Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0xac613c8>



In [4]: df["favorite_count"].hist(bins=25)

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0xadbc278>



In [5]: df.sort_values("favorite_count", ascending=False)

Out[5]:

	text	created_at	favorite_count	retweet_count
324	How long did it take your staff of 823 people	2016-06-09 20:40:32	289164	170606
732	Happy #CincoDeMayo! The best taco bowls are ma	2016-05-05 18:57:30	113368	83588
293	Is President Obama going to finally mention th	2016-06-12 17:58:00	91042	39458
326	Obama just endorsed Crooked Hillary. He wants	2016-06-09 18:22:21	83089	36243
47	Prayers and condolences to all of the families	2016-07-08 11:02:41	83007	28929
			•••	
789	RT @AdrianaCohen16: Carly Fiorina no lifeboat	2016-04-29 00:32:22	0	2223
1631	RT @EricTrump: Very proud of what my father ha	2016-02-24 01:52:12	0	2123
1628	RT @TrumpNV: #NVcaucus locator -> https://t	2016-02-24 01:59:59	0	809
805	RT @DonaldJTrumpJr: An Honor to be in #Indiana	2016-04-27 22:06:11	0	4853
1681	RT @BretEastonEllis: Just back from a dinner i	2016-02-21 18:55:03	0	4384

3247 rows × 4 columns

In [6]: df[["favorite_count", "retweet_count"]].corr()

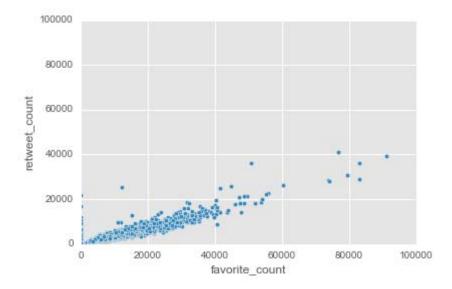
Out[6]:

	favorite_count	retweet_count
favorite_count	1.000000	0.923622
retweet_count	0.923622	1.000000

Unsurprisingly, retweets and favorites are highly correlated.

```
In [7]: a = df.plot(kind='scatter', x='favorite_count', y='retweet_count')
    a.set_ylim(0,100000)
    a.set_xlim(0,100000)
```

Out[7]: (0, 100000)



Retweets and sentiment

In [8]: from nltk import tokenize
 from nltk.sentiment.vader import SentimentIntensityAnalyzer
 sid = SentimentIntensityAnalyzer()

df["sentiment"] = 0
 df.sentiment = df.text.apply(lambda line: sid.polarity_scores(line))
 df.head()

Out[8]:

	text	created_at	favorite_count	retweet_count	sentiment
0	I employ many people in the State of Virginia	2016-07-14 17:23:58	13466	4401	{u'neg': 0.0, u'neu': 0.892, u'pos': 0.108, u'
1	Another new poll. Thank you for your support!	2016-07-14 14:53:46	15456	6047	{u'neg': 0.0, u'neu': 0.6, u'pos': 0.4, u'comp
2	Great new poll- thank you America!\n#Trump2016	2016-07-14 13:21:48	17037	5775	{u'neg': 0.0, u'neu': 0.504, u'pos': 0.496, u'
3	I will be making the announcement of my Vice P	2016-07-14 01:19:51	40583	15757	{u'neg': 0.0, u'neu': 1.0, u'pos': 0.0, u'comp
4	If I win the Presidency, we will swamp Justice	2016-07-13 22:28:44	22560	7167	{u'neg': 0.0, u'neu': 0.591, u'pos': 0.409, u'

Out[9]:

	text	created_at	favorite_count	retweet_count	sentiment	com
0	I employ many people in the State of Virginia	2016-07-14 17:23:58	13466	4401	{u'neg': 0.0, u'neu': 0.892, u'pos': 0.108, u'	0.419
1	Another new poll. Thank you for your support!	2016-07-14 14:53:46	15456	6047	{u'neg': 0.0, u'neu': 0.6, u'pos': 0.4, u'comp	0.789
2	Great new poll- thank you America!\n#Trump2016	2016-07-14 13:21:48	17037	5775	{u'neg': 0.0, u'neu': 0.504, u'pos': 0.496, u'	0.784
3	I will be making the announcement of my Vice P	2016-07-14 01:19:51	40583	15757	{u'neg': 0.0, u'neu': 1.0, u'pos': 0.0, u'comp	0.000
4	If I win the Presidency, we will swamp Justice	2016-07-13 22:28:44	22560	7167	{u'neg': 0.0, u'neu': 0.591, u'pos': 0.409, u'	0.839

In [10]: df[df.comp == min(df.comp)]

Out[10]:

	text	created_at	favorite_count	retweet_count	sentiment	comp
114	Yet another terrorist attack today in Israel	2016-07-01 15:51:46	9601	4244	{u'neg': 0.548, u'neu': 0.452, u'pos': 0.0, u'	-0.9584

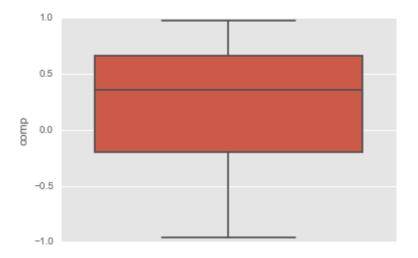
In [11]: df[df.comp == max(df.comp)]

Out[11]:

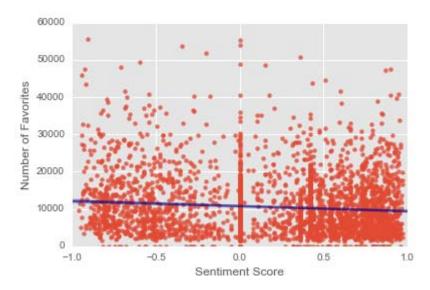
	text	created_at	favorite_count	retweet_count	sentiment	comp
2485	I would like to wish everyone A HAPPY AND HEAL	2015-12-31 23:21:49	16718	6922	{u'neg': 0.0, u'neu': 0.452, u'pos': 0.548, u'	0.9713

In [12]: sns.boxplot(y="comp", data=df)

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xd287c88>



Out[13]: <matplotlib.text.Text at 0xd55c0f0>



In [14]: # Note that we've removed a couple of outliers and forced the intercept to 0 fc
model = smf.ols(formula="favorite_count ~ comp + 0", data=df[df.favorite_count
model.summary()

Out[14]: OLS Regression Results

Dep. Variable:	favorite_count	R-squared:	0.037
Model:	OLS	Adj. R-squared:	0.037
Method:	Least Squares	F-statistic:	124.7
Date:	Fri, 22 Jul 2016	Prob (F-statistic):	1.97e-28
Time:	13:54:11	Log-Likelihood:	-35485.
No. Observations:	3245	AIC:	7.097e+04
Df Residuals:	3244	BIC:	7.098e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
comp	4625.0494	414.225	11.166	0.000	3812.881 5437.218

Omnibus:	1590.614	Durbin-Watson:	0.409
Prob(Omnibus):	0.000	Jarque-Bera (JB):	14293.547
Skew:	2.135	Prob(JB):	0.00
Kurtosis:	12.353	Cond. No.	1.00

The relation between the sentiment of a tweet and the number of favorites it gets is highly significant; a model that considers the sentiment of a tweet alone would not do a great job of predicting retweets ($r^2 = .037$). Generally speaking, however, we can say that moving from a neutral tweet to a highly negative tweet would earn Trump an addition 4600 retweets.

What words are used in the most re-tweeted tweets?

In [15]: from nltk.tokenize import TweetTokenizer

twtk = TweetTokenizer() twtk.tokenize("st")
df["tokenized"] = df.text.apply(lambda x: twtk.tokenize(x.lower())) df

Out[15]:

	text	created_at	favorite_count	retweet_count	sentiment	С
0	I employ many people in the State of Virginia	2016-07-14 17:23:58	13466	4401	{u'neg': 0.0, u'neu': 0.892, u'pos': 0.108, u'	0
1	Another new poll. Thank you for your support!	2016-07-14 14:53:46	15456	6047	{u'neg': 0.0, u'neu': 0.6, u'pos': 0.4, u'comp	0
2	Great new poll- thank you America!\n#Trump2016	2016-07-14 13:21:48	17037	5775	{u'neg': 0.0, u'neu': 0.504, u'pos': 0.496, u'	0
3	I will be making the announcement of my Vice P	2016-07-14 01:19:51	40583	15757	{u'neg': 0.0, u'neu': 1.0, u'pos': 0.0, u'comp	
4	If I win the Presidency, we will swamp Justice	2016-07-13 22:28:44	22560	7167	{u'neg': 0.0, u'neu': 0.591, u'pos': 0.409, u'	0
						Ī
3242	"@jrpantiques: @realDonaldTrump @TheFix @pbump	2015-11-22 22:33:42	2404	1009	{u'neg': 0.0, u'neu': 0.813, u'pos': 0.187, u'	0
3243	"@bloggerjulie: @FoxNews The reporter is the o	2015-11-22 22:32:42	2356	1130	{u'neg': 0.146, u'neu': 0.854, u'pos': 0.0, u'	-(

3244	"@MJP1370: @realDonaldTrump @TheFix @pbump We	2015-11-22 22:32:09	2568	1152	{u'neg': 0.0, u'neu': 1.0, u'pos': 0.0, u'comp	0
3245	"@TheFix: The Paris attacks have only made Don	2015-11-22 22:26:06	2898	1513	{u'neg': 0.147, u'neu': 0.556, u'pos': 0.297,	0
3246	"@drewtheg: Trump is the epitome of integrity	2015-11-22 20:07:10	3519	1177	{u'neg': 0.082, u'neu': 0.637, u'pos': 0.281,	0

3247 rows × 7 columns

```
In [16]: freqs = h.word_freqs(df.tokenized.tolist())
```

In [17]: import re

for every word, find the avg of retweets in the tweets in which it occurs!

```
for key, val in freqs.iteritems():
    clean_term = re.escape(key)
    avg = np.mean(df[df.text.str.lower().str.contains(clean_term)].retweet_cour
    freqs[key] = [val, avg]
```

How often does "Hillary" appear in tweets and how many retweets, on average, freqs["hillary"]

Out[17]: [292, 6938.862416107382]

```
In [18]: # Make this into a df...
freqdf = pd.DataFrame(freqs).transpose()
freqdf.columns = ["count", "avg_rts"]
freqdf
```

Out[18]:

	count	t avg_rts	
!	2509.0	4073.473920	
"	1678.0	2308.649485	
#	17.0	3651.290393	
#2016	1.0	1031.000000	
#2a	3.0	8022.666667	
	•••		
�	1.0	NaN	
�	1.0	NaN	
•	3.0	NaN	
•	1.0 NaN		
	3.0 NaN		

8065 rows × 2 columns

In [19]: # Which words appear in the most retweeted tweets?

pd.set_option('display.max_rows', 100)

(Make sure the word is used at least five times, to eliminate outliers)

freqdf[freqdf["count"] > 4].sort_values("avg_rts", ascending=False)

Out[19]:

	count	avg_rts
email	6.0	26325.555556
families	5.0	16152.400000
charges	7.0	14554.571429
prayers	5.0	14505.600000
victims	5.0	13363.400000
chicago	5.0	13329.200000
fbi	6.0	12700.833333
33	7.0	12675.388889
endorsing	6.0	12251.600000
vigilant	9.0	11851.222222

The words most associated with high numbers of retweets are "emails," "families," "charges," "prayers," and "victims." These words appear in tweets that are retweeted, on average, more than three times as much the average tweet.

Where are these retweets coming from?

```
In [20]: pd.set_option('display.max_rows', 10)
    rtdf = pd.read_csv('trumpsretweets.csv')
    rtdf.head(10)
```

Out[20]:

	text	user_location
0	RT @realDonaldTrump: Look forward to Governor	Reward if u find me! lol USA
1	RT @realDonaldTrump: Look forward to Governor	NaN
2	RT @realDonaldTrump: Look forward to Governor	NaN
3	RT @realDonaldTrump: Look forward to Governor	Tampa, FL
4	RT @realDonaldTrump: Look forward to Governor	NaN
5	RT @realDonaldTrump: Look forward to Governor	NaN
6	RT @realDonaldTrump: Look forward to Governor	Windsor, VA
7	RT @realDonaldTrump: Look forward to Governor	Long Island,NY
8	RT @realDonaldTrump: Look forward to Governor	Ohio, USA
9	RT @realDonaldTrump: Look forward to Governor	NaN

In [21]: rtdf.user_location.value_counts()

```
Out[21]: United States
                                   878
         USA
                                   432
         Texas, USA
                                   236
         California, USA
                                   232
         Florida, USA
                                   218
         Swindon, England
                                     1
         wherever I Want To Be
                                     1
         Wichita, Kansas USA
                                     1
         I'm from Earth
                                     1
         Judevine Mountain
                                     1
         Name: user_location, dtype: int64
```

In [22]: rtdf["state"] = rtdf.user_location.apply(h.get_state)
 rtdf

Out[22]:

	text	user_location	state
0	RT @realDonaldTrump: Look forward to Governor	Reward if u find me! lol USA	NaN
1	RT @realDonaldTrump: Look forward to Governor	NaN	NaN
2	RT @realDonaldTrump: Look forward to Governor	NaN	NaN
3	RT @realDonaldTrump: Look forward to Governor	Tampa, FL	FL
4	RT @realDonaldTrump: Look forward to Governor	NaN	NaN
•••			
29595	RT @realDonaldTrump: In the last 2 weeks, I ha	NaN	NaN
29596	RT @realDonaldTrump: In the last 2 weeks, I ha	NaN	NaN
29597	RT @realDonaldTrump: In the last 2 weeks, I ha	Charlotte, NC	NC
29598	RT @realDonaldTrump: In the last 2 weeks, I ha	NaN	NaN
29599	RT @realDonaldTrump: In the last 2 weeks, I ha	NaN	NaN

29600 rows × 3 columns

```
In [23]: rtdf.state.value_counts()
Out[23]: CA
                   1089
                    974
           \mathsf{FL}
           \mathsf{TX}
                    970
           NY
                    685
           ОН
                    357
           ΑK
                     19
           SD
                      9
           WY
                      8
           ND
                      6
           VT
           Name: state, dtype: int64
```

```
In [24]: rtdf.dropna(inplace=True)
len(rtdf)
```

Out[24]: 9255

```
In [25]: rtdf.groupby('state').size()
Out[25]: state
           ΑK
                      19
           ΑL
                    202
           AR
                     86
           ΑZ
                    212
           \mathsf{C}\mathsf{A}
                   1089
                   . . .
           VT
                       6
           WΑ
                    175
           WΙ
                      88
           WV
                      43
           WY
                       8
           dtype: int64
```

```
In [26]: # making a dataframe of just the states and retweet counts

rtd = pd.DataFrame(rtdf.state.unique(), columns=['state'])
 rtd["counts"] = rtd.state.apply(lambda x: len(rtdf[rtdf.state == x]))
 rtd
```

Out[26]:

	state	counts	
0	FL	974	
1	VA	206	
2	ОН	357	
3	WA	175	
4	MI	245	
		•••	
46	AK	19	
47	ME	45	
48	SD	9	
49	VT	6	
50	ND	6	

51 rows × 2 columns

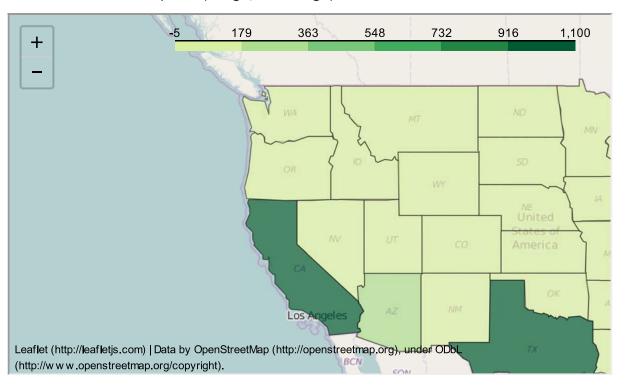
```
In [27]: rtd['population'] = rtd.state.apply(lambda x: h.pops[x])
    rtd['scaled_counts'] = rtd.counts / rtd.population
```


C:\Users\bkrak_000\Anaconda2\lib\site-packages\folium\folium.py:504: UserWa
rning: This method is deprecated. Please use Map.choropleth instead.
warnings.warn('This method is deprecated. '

C:\Users\bkrak_000\Anaconda2\lib\site-packages\folium\folium.py:506: Future Warning: 'threshold_scale' default behavior has changed. Now you get a line ar scale between the 'min' and the 'max' of your data. To get former behavi or, use folium.utilities.split_six.

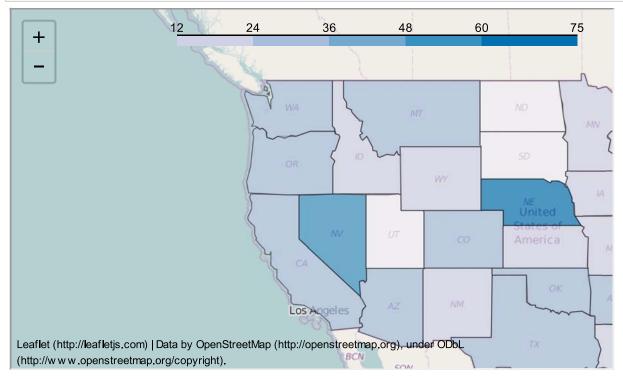
return self.choropleth(*args, **kwargs)





It's not surprising that most retweets come from high-population states like California, New York, and Texas! We need to scale this by population, which I do below...

Out[29]:



In this map, states like California and New York fade closer to average (though still somewhat high; perhaps this is due to increased penetration of Twitter?). Worryingly for Clinton, some battleground states such as Nevada and Florida are quite high!

In [30]: rtd.sort_values(["scaled_counts"], ascending=False)

Out[30]:

	state	counts	population	scaled_counts
29	DC	66	0.7	94.285714
18	ΝE	141	1.9	74.210526
24	NV	151	2.9	52.068966
0	FL	974	20.0	48.700000
20	AL	202	4.9	41.224490
			•••	•••
35	υT	35	3.0	11.666667
41	MS	32	3.0	10.666667
48	SD	9	0.9	10.000000
49	VT	6	0.6	10.000000
50	ND	6	0.8	7.500000

51 rows × 4 columns

It's notable here that DC tops the list! This is likely just do to increased presence of media and politics, rather than actual support for Trump. Many of the states toward the bottom of the list are states where Trump will probably do well, such as the Dakota and Mississippi -- this is probably due to Twitter penetration. Perhaps a third map that controls for this can confirm this hypothesis.