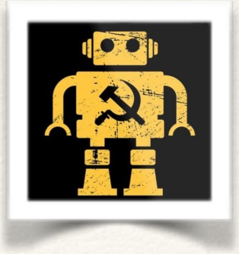
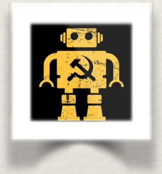


IST 718 Big Data Analytics Final Project, Spring 2019

Identifying Russian Troll Accounts on Twitter



Adil Gokturk
Drew Howell
Scott Snow

Story & Hypothesis

- According to the House Intelligence Committee investigation, Russia's Internet Research Agency attempted to interfere with the 2016 U.S. election by running fake accounts on known as **"Russian trolls"**.
- Our hypothesis Questions
  - Would it be possible to demonstrate whether these tweets used to manipulate/target the 2016 U.S. election to favor on any presidential candidate?
  - Would it be possible by developing machine learning models to predict whether a Twitter account is a Russian troll/fake?

Russian Troll Tweets

Data

Source:

- NBC News
  - https://www.nbcnews.com/tech/social-media/now-available-more-200-000-deleted-russian-troll-tweets-n844731
- Kaggle - Russian Troll Tweets
  - https://www.kaggle.com/vikasg/russian-troll-tweets

Dimension:

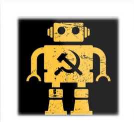
- 203,482 tweets
- 16 variable columns

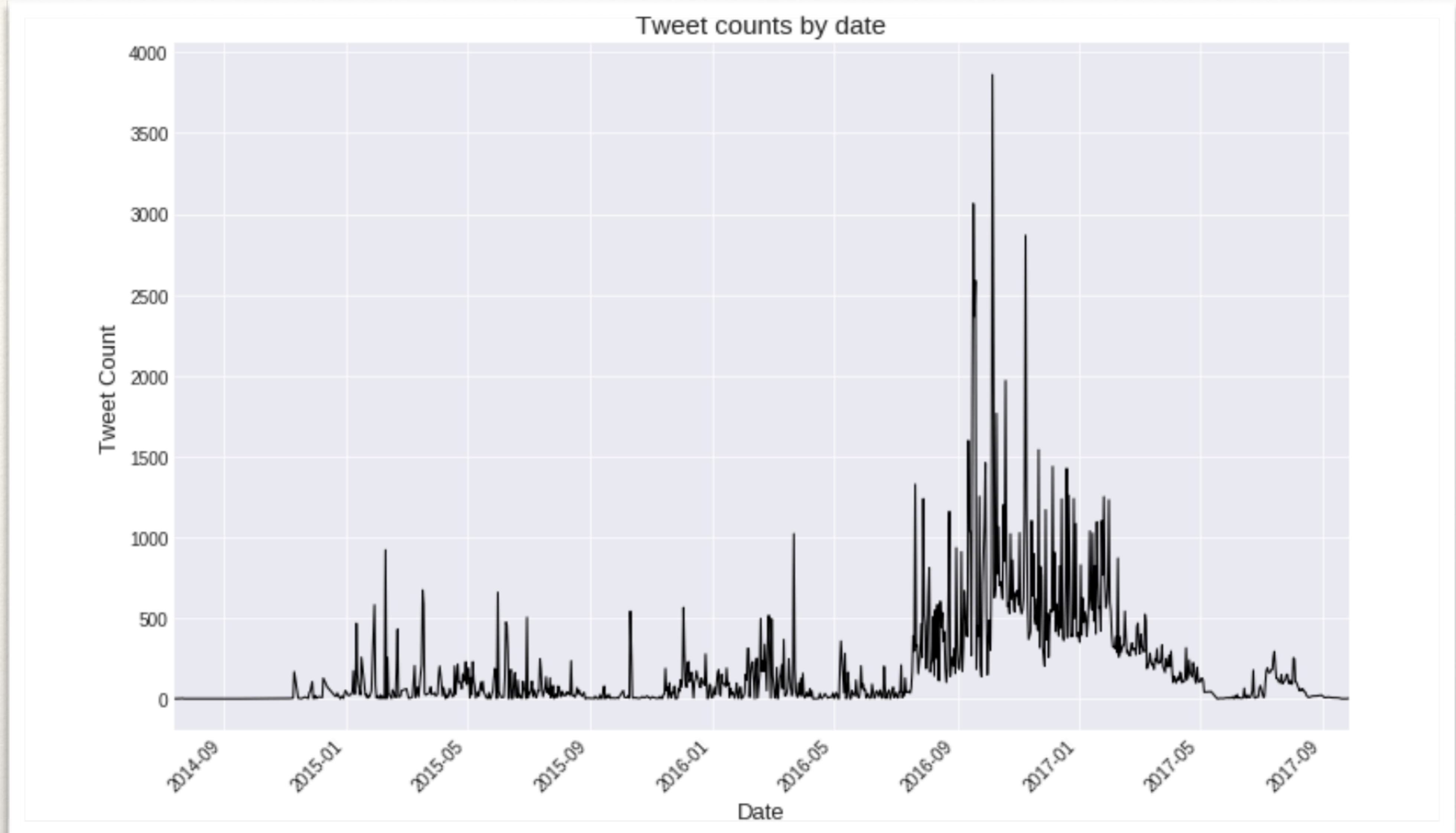
Data Sets:

- tweets.csv
- users.csv

Columns

- # user_id
- A user_key
- # created_at
- created_str
- A retweet_count
- A retweeted
- A favorite_count
- A text
- # tweet_id
- A source Utility used to post the Tweet, as an HTML-formatted string. Tweets from the Twitter website have a source value of web.
- A hashtags
- A expanded_urls
- A posted
- A mentions
- A retweeted_status_id
- A in_reply_to_status_id

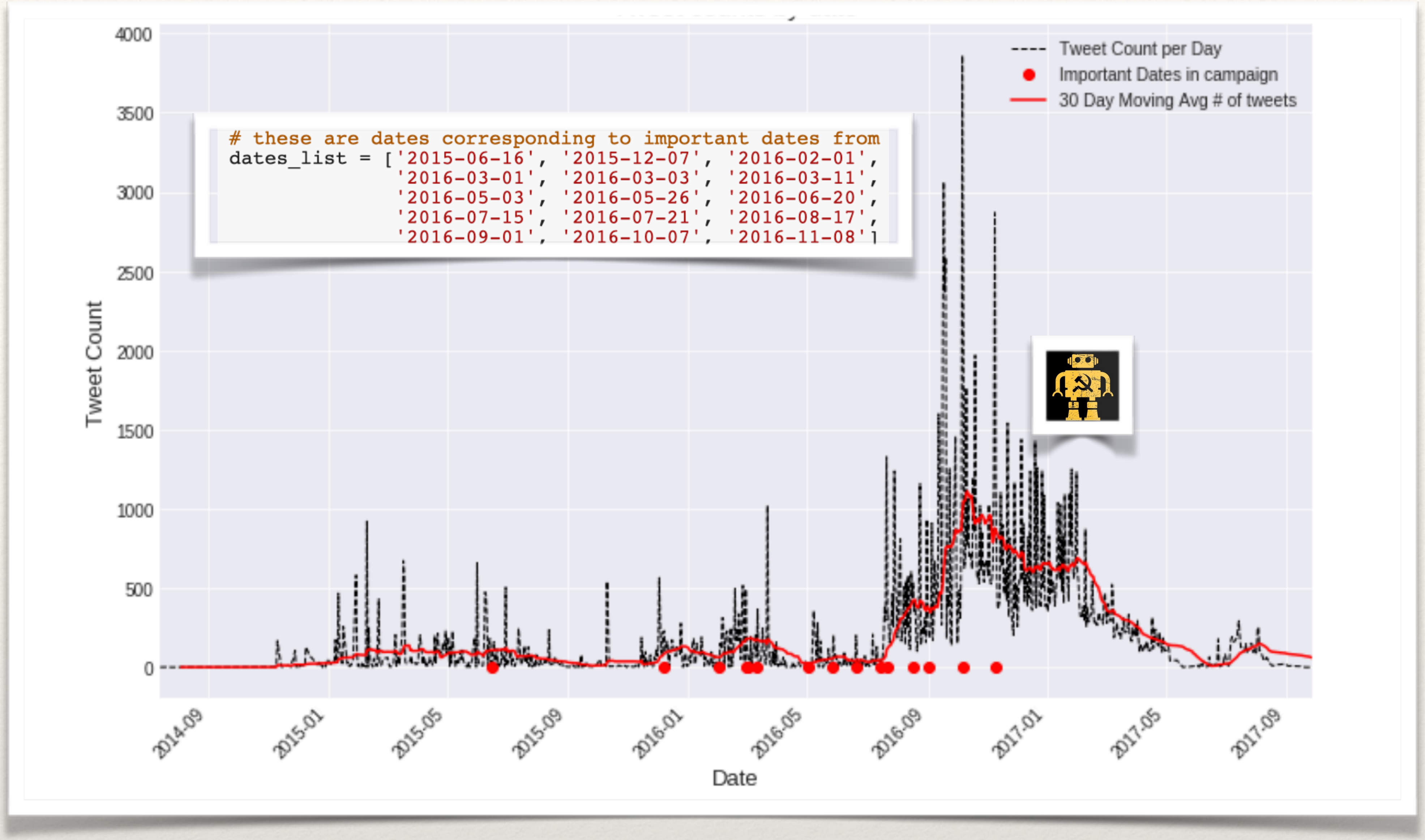




Time line of the tweets

Exploratory Analysis

3 years of tweets starts on **July 14th, 2014 and ends on of September 26th, 2017**

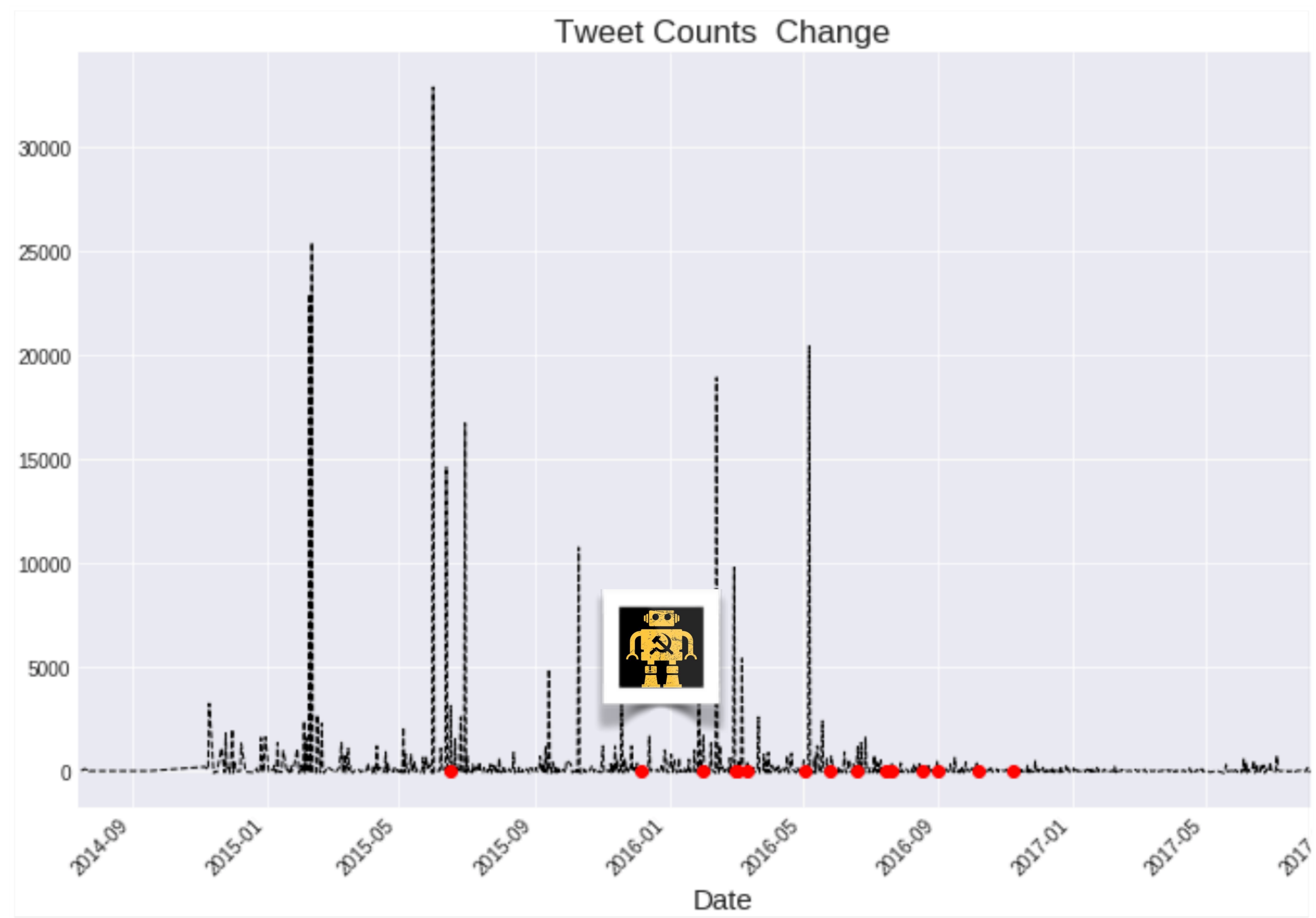


Time line of the tweets comparison to the Trump's campaign important event days

Time Line Comparison

Relatively similar tweet trend activity between the Campaign and the troll accounts.

	tweet_count	Pct_Chg_tweets
2015-06-16	3	50.000000
2015-12-07	219	204.166667
2016-02-01	18	1700.000000
2016-03-01	143	-71.052632
2016-03-03	6	-92.105263
2016-03-11	64	-69.523810
2016-05-03	38	216.666667
2016-05-26	6	-50.000000
2016-06-20	201	1156.250000
2016-07-15	47	17.500000
2016-07-21	1327	349.830508
2016-08-17	534	20.270270
2016-09-01	337	-63.918630
2016-10-07	2222	-42.450142
2016-11-08	2867	145.042735



Time line of the tweets comparison to the Trump's campaign important event days

Percentage Change in Tweet Counts

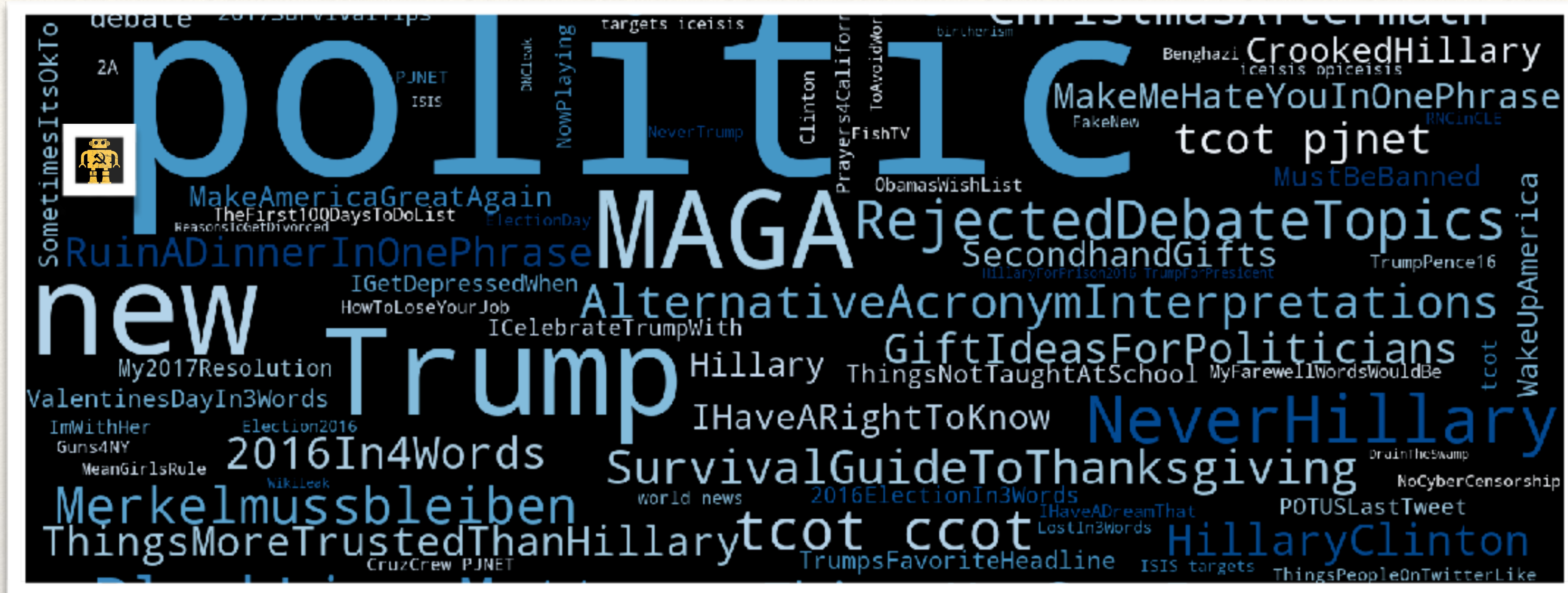
The US president was elected on **November 8th, 2016** - the last red dot on the chart.
The tweet activity near the end of the campaign was **increased**.

```
0     #IslamKills Are you trying to say that there w...
1     Clinton: Trump should've apologized more, atta...
2     RT @ltapoll: Who was/is the best president of ...
3     RT @jww372: I don't have to guess your religio...
4     RT @Shareblue: Pence and his lawyers decided w...
5                            @ModicaGiunta me, too!
6     RT @MDBlanchfield: You'll never guess who twee...
7     RT @100PercFEDUP: New post: WATCH: DIAMOND AND...
8     RT @AriaWilsonGOP: 3 Women Face Charges After ...
9     One of the ways to remind that #BlackLivesMatt...
```

Sample troll tweets

Text Analytics

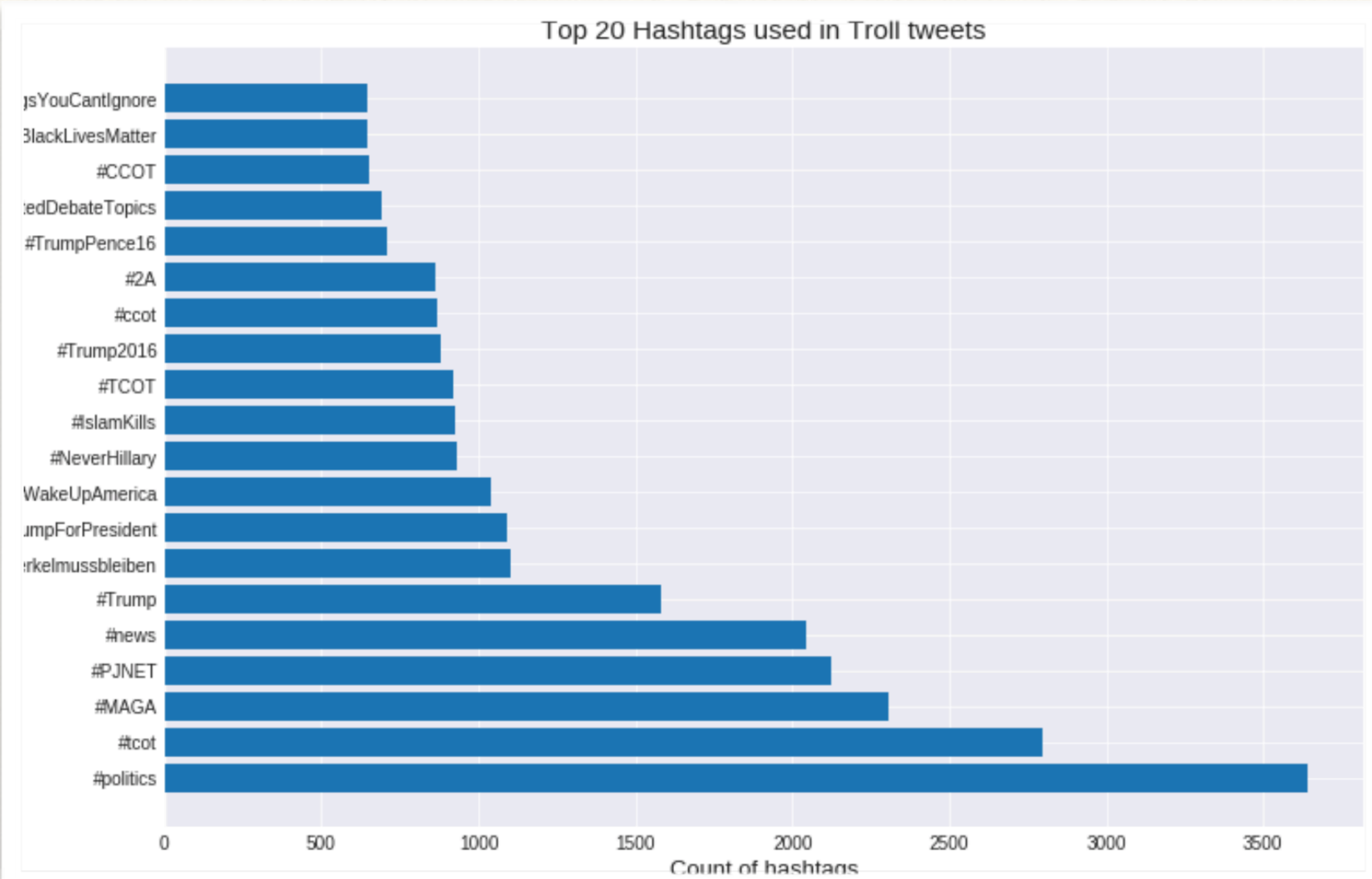
Need to **scrub** some column features from the data, such as **RT mentions, links, hashtags, extra spaces**



Most Commonly used words

Word Cloud

Word Cloud provides a general context of 200,000 troll tweets.



1. #POLITICS
2. #TCOT
3. #MAGA
4. #PJNET
5. #news
6. #Trump

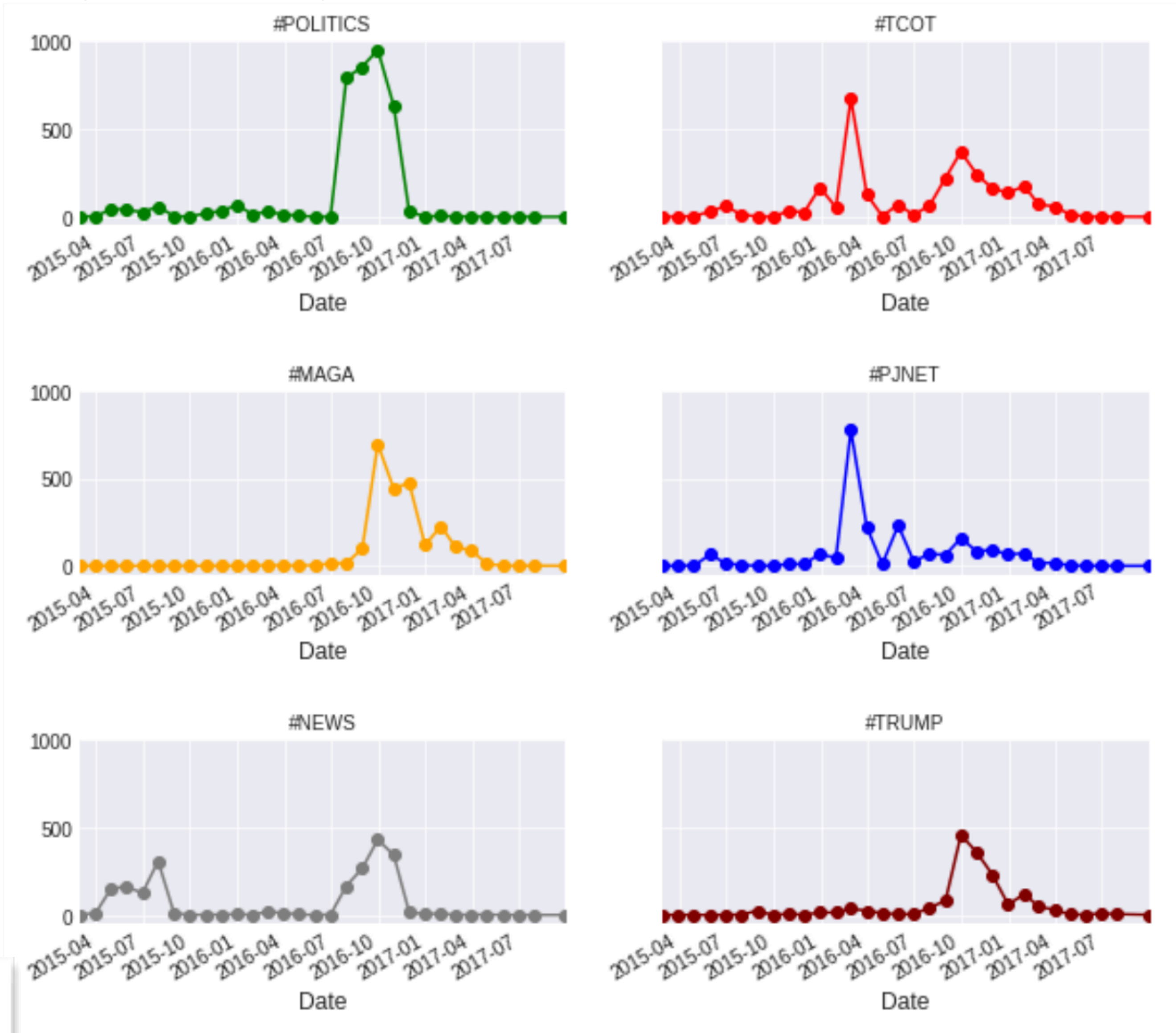
Most Commonly used hashtags

Top 20 Hashtag used in Troll Tweets

Trolls seems highly supported to the Trump's Presidential Campaign

TCOT:Top conservatives on Twitter

CCOT: Christian conservatives on twitter



1. #POLITICS
2. #TCOT
3. #MAGA
4. #PJNET
5. #news
6. #Trump

Were these hashtags used most before the president's campaign?

Prior usage of the most common hashtags

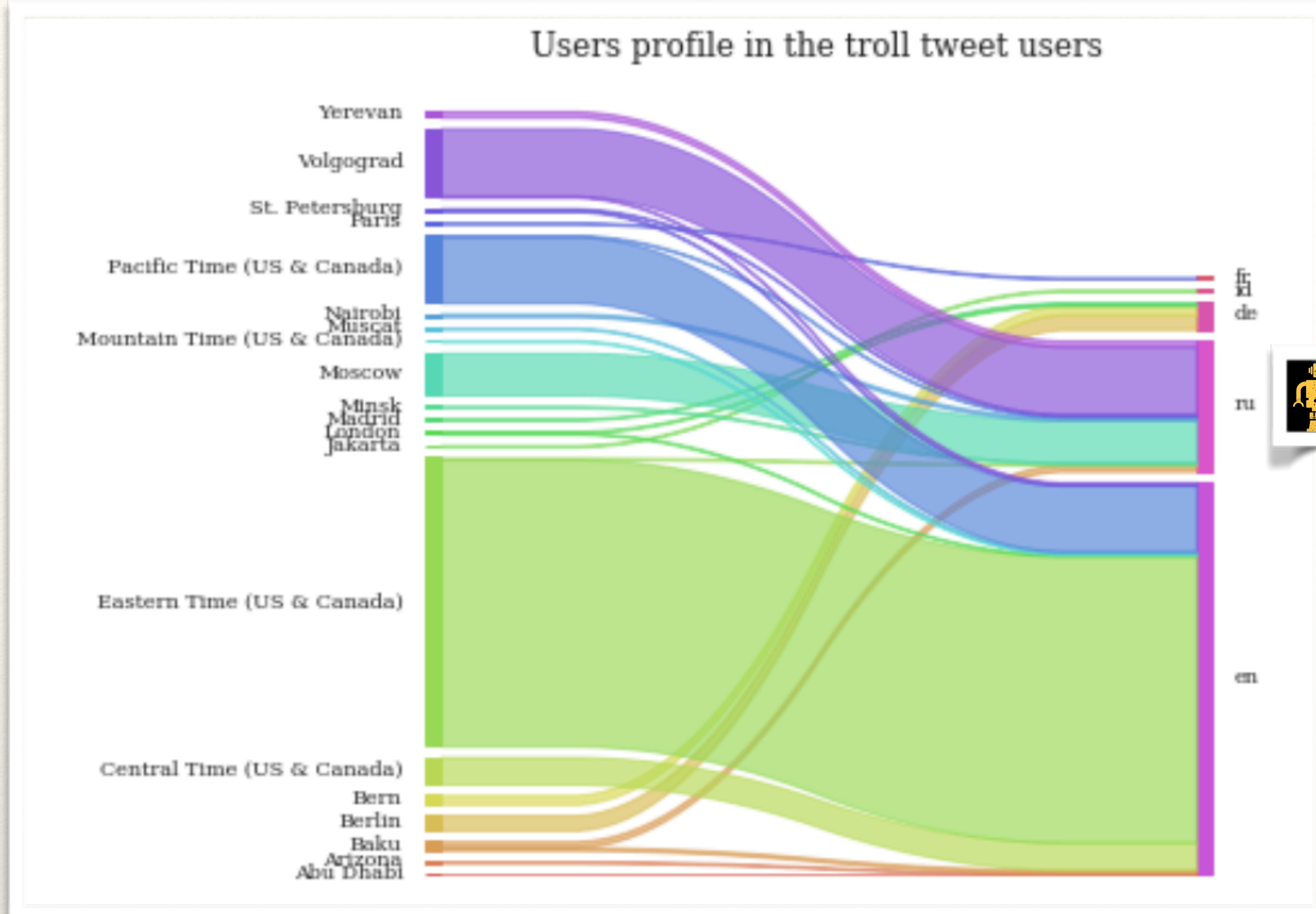
Apparently, most of these hashtags picked up in the year **2016 near March or later in July, close to the elections.**

Most used Hashtags

Clustering by HashTags

- More than 28,000 unique hashtags
- Qualified hashtags
  - tweeted > 50 times
  - 435 hashtags tweeted

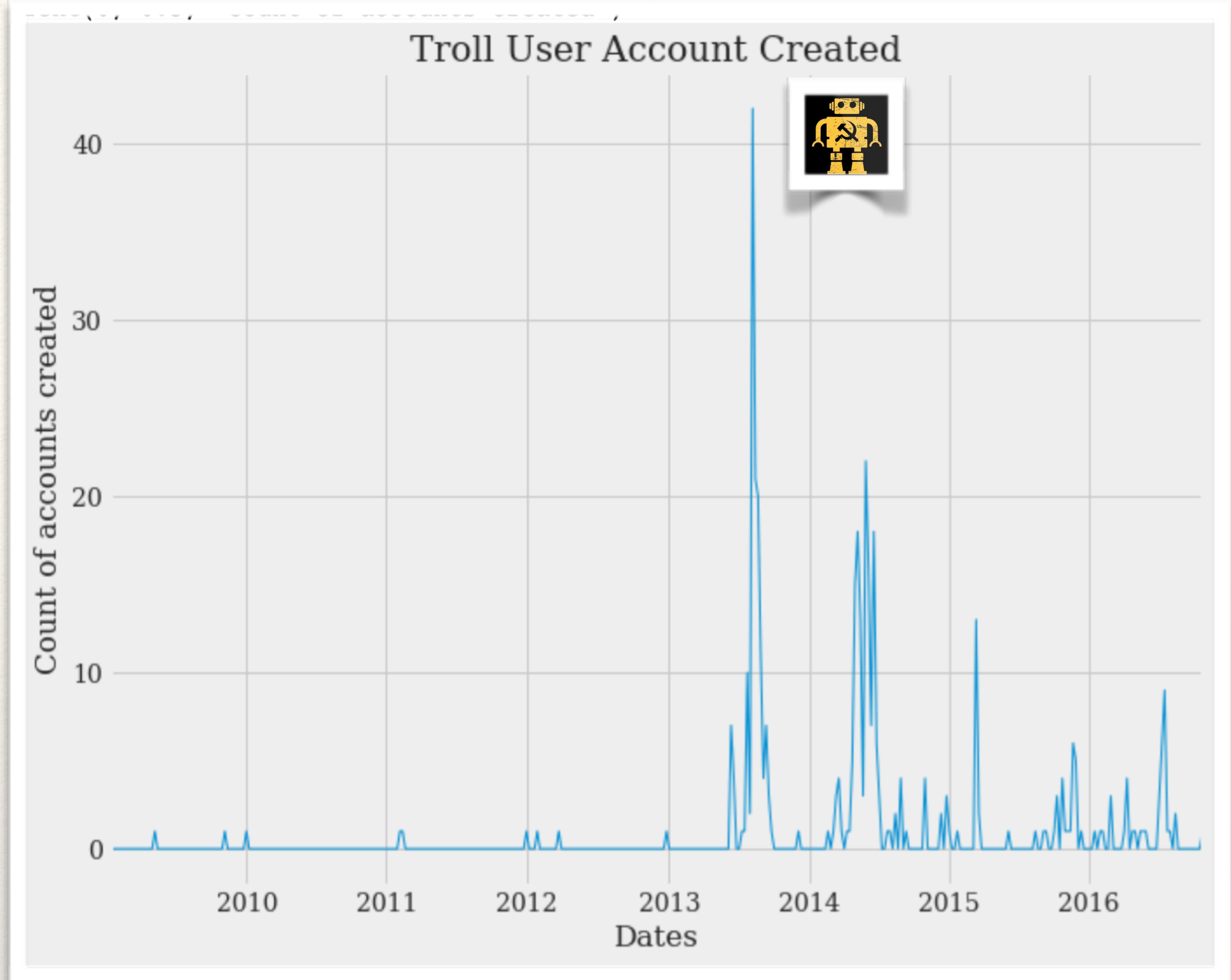
#politics	3638
#tcot	2799
#MAGA	2306
#PJNET	2121
#news	2046
#Trump	1583
#Merkelmussbleiben	1104
#TrumpForPresident	1088
#WakeUpAmerica	1038
#NeverHillary	932
#IslamKills	926
#TCOT	921
#Trump2016	882
#ccot	867
#2A	865
#TrumpPence16	710
#RejectedDebateTopics	691
#CCOT	651
#BlackLivesMatter	648
#ThingsYouCantIgnore	643



Sankey Plot - Count of users from each time-zone and language combination

Users Locations and Languages

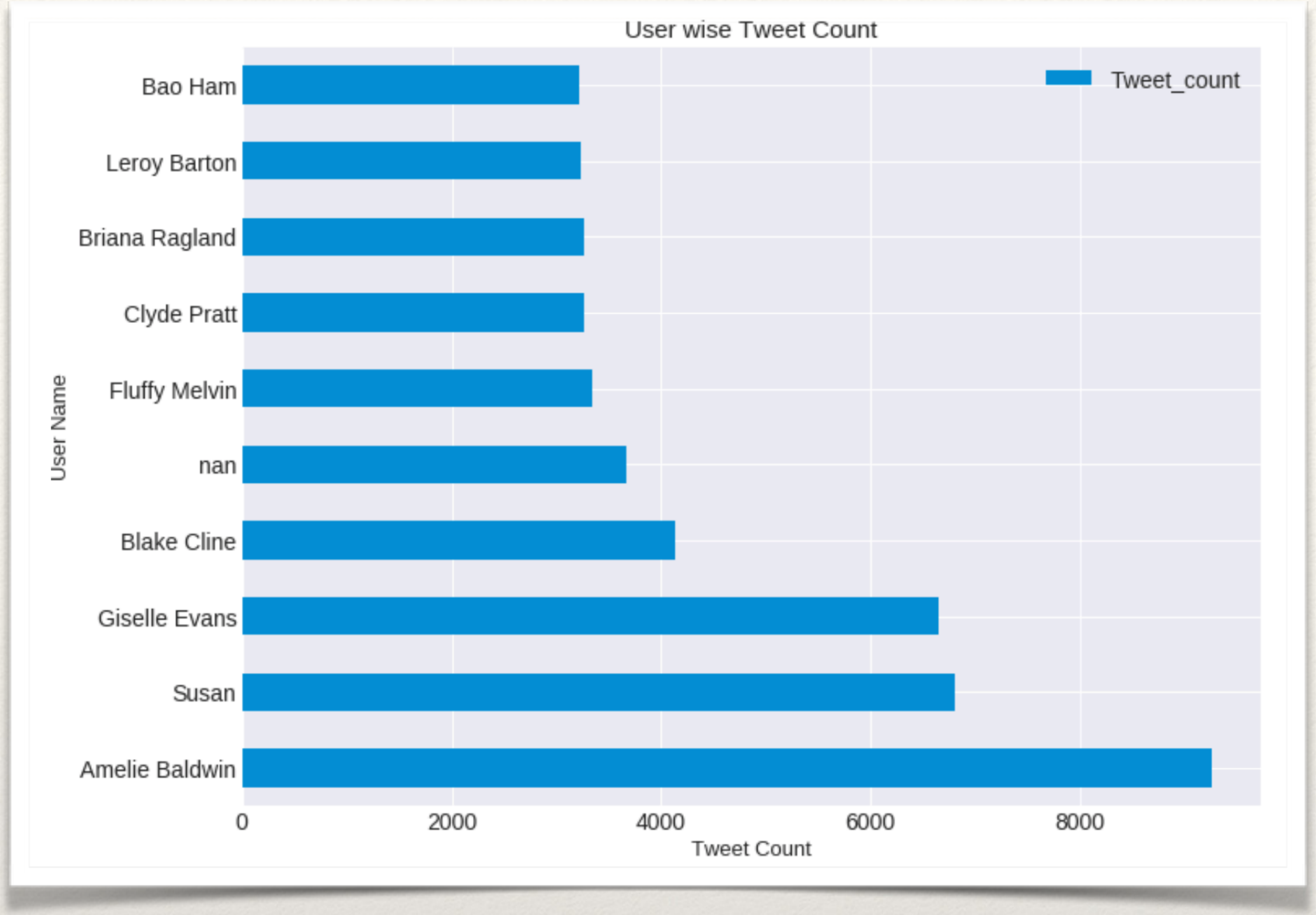
Apparently, English speaking users come from **US & Canada .**
Russian speaking users come from **Moscow, Volgograd, Yerevan and Minsk**.

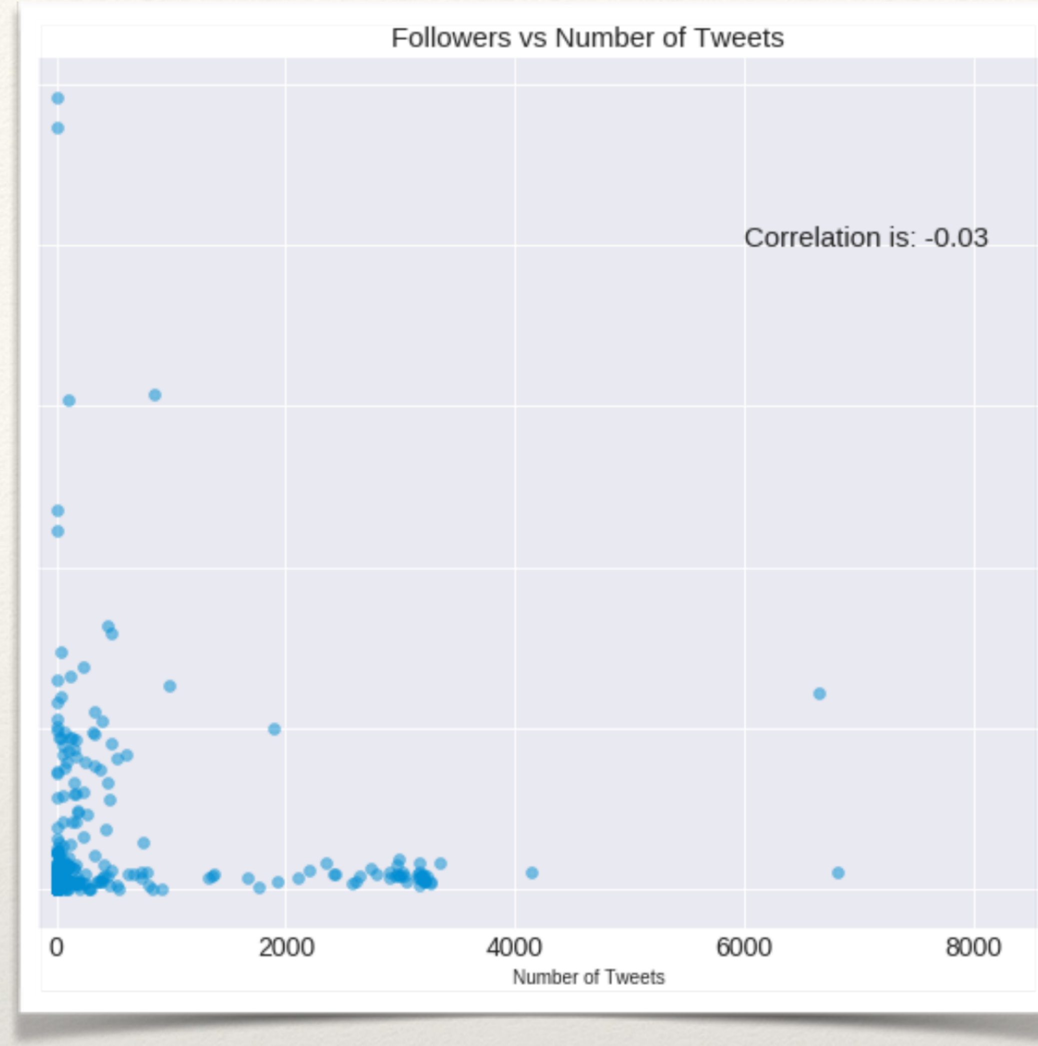


The created_at column in the users dataframe provides this information

Twitter Accounts creation dates

Most accounts were created in the second half of 2013 or first half of 2014





Many users have very low tweets count

Correlation between higher number of followers and large number of tweets

No such correlation exists.

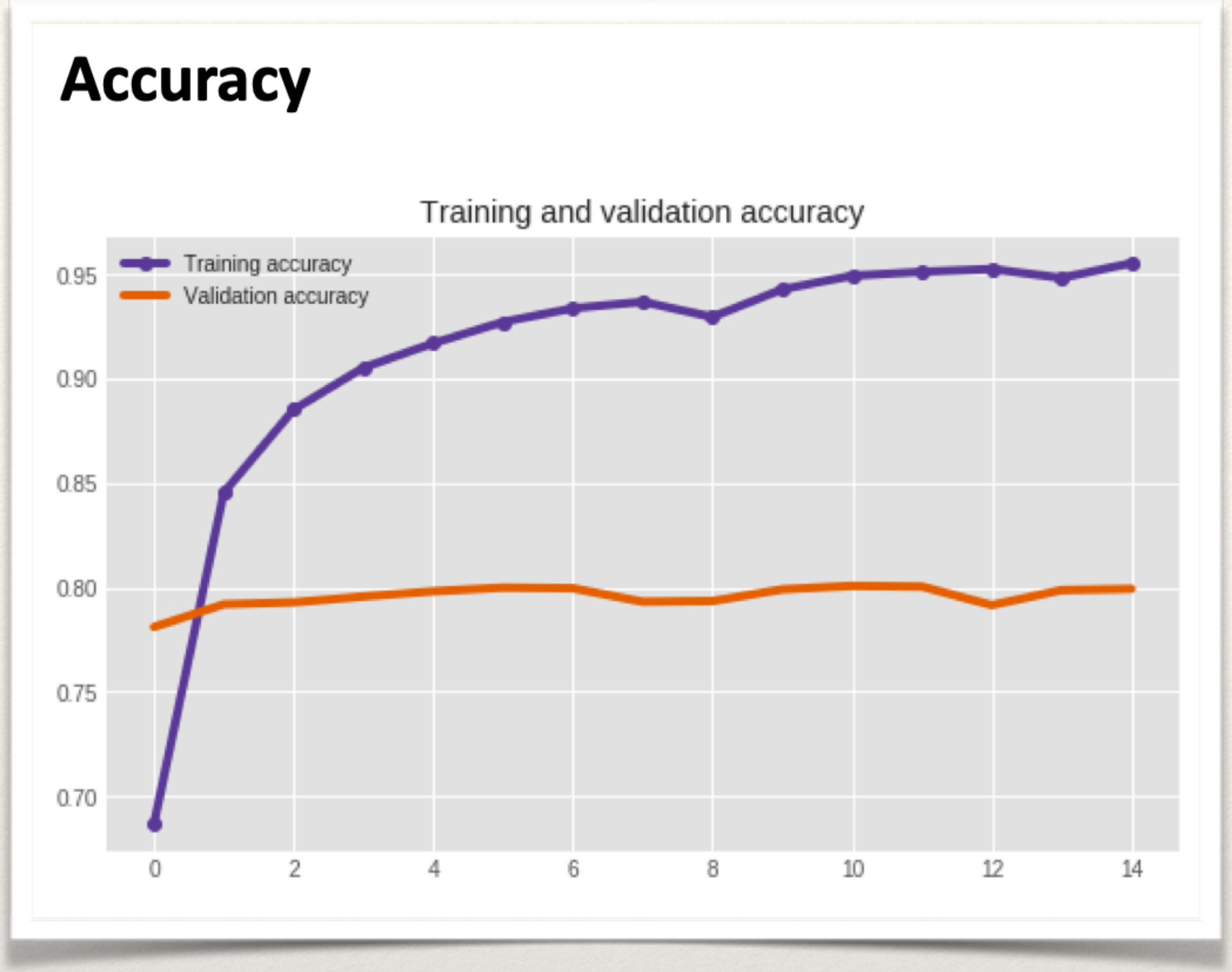
Deep Learning Learning Library

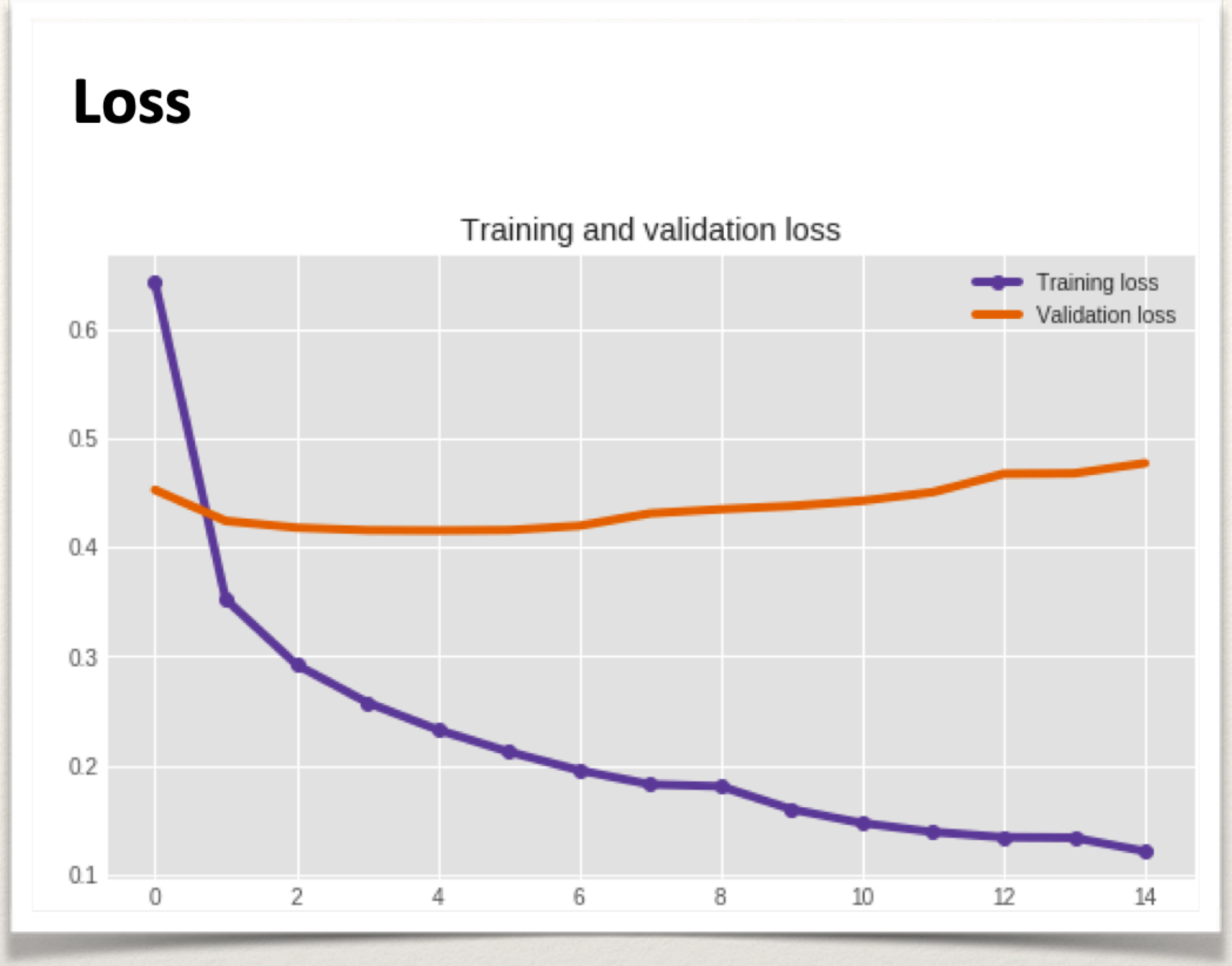
Keras Model

- Ran in Google Colab
- Combined Troll tweets data with generic political tweets from Election day
- Original combined size: 601,090 tweets
- Sampled due to RAM Restrictions on Colab
- Sample Size 75,136
- Train/Test Split – 50%
- 7304 features

Keras Sequential Configuration

- 1 Inner Layer
  - Activation – Rectified Linear Unit
  - Input Dimensions – 7304
- Final Layer
  - Activation – Sigmoid
  - Input Dimensions – 1
- Fit configuration
  - Batch Size – 10000
  - Epochs – 16
  - Val_loss callback patience - 10





Keras Deep Learning Learning Library

Model Performance by Epoch

Accuracy & Loss

22162	2656
4880	7870

	precision	recall	f1-score	support
Real	0.82	0.89	0.85	24818
Troll	0.75	0.62	0.68	12750
accuracy			0.80	37568
macro	0.78	0.76	0.77	37568
weighted	0.80	0.80	0.79	37568

Keras Deep Learning Learning Library

Model Accuracy

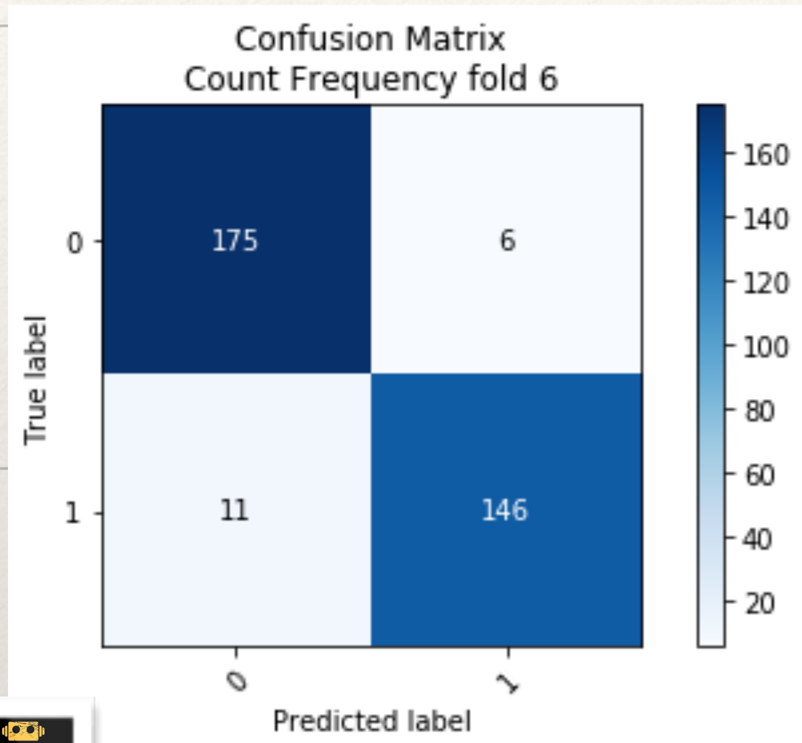
- Having the additional tweets likely reduces the potential for accuracy.
- There is unfortunately a time mismatch between the data sets. All of the Real twitter posts were entirely from election day.
- More activation models and more layers will be attempted.

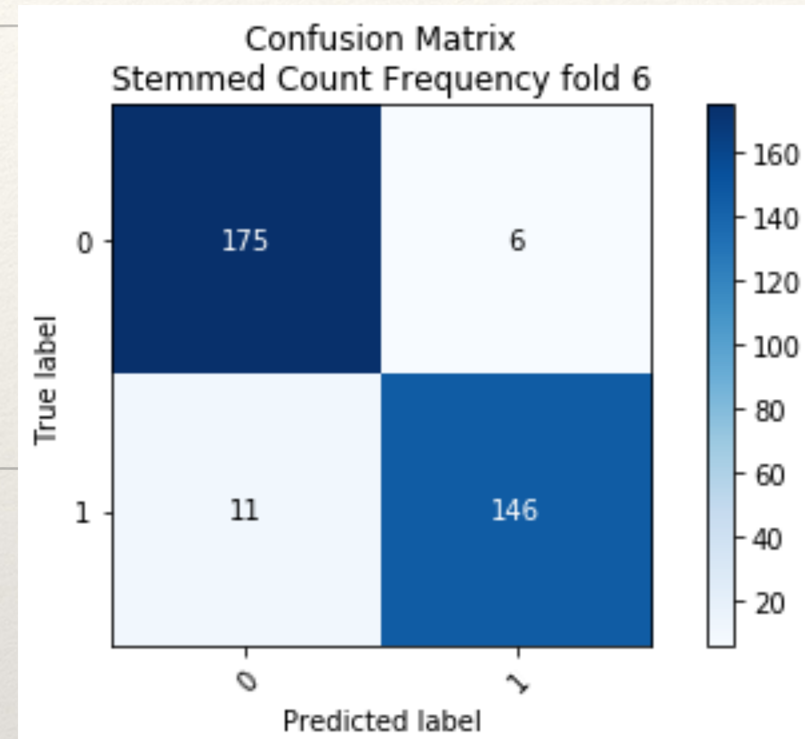
Multinominal Naive Bayes

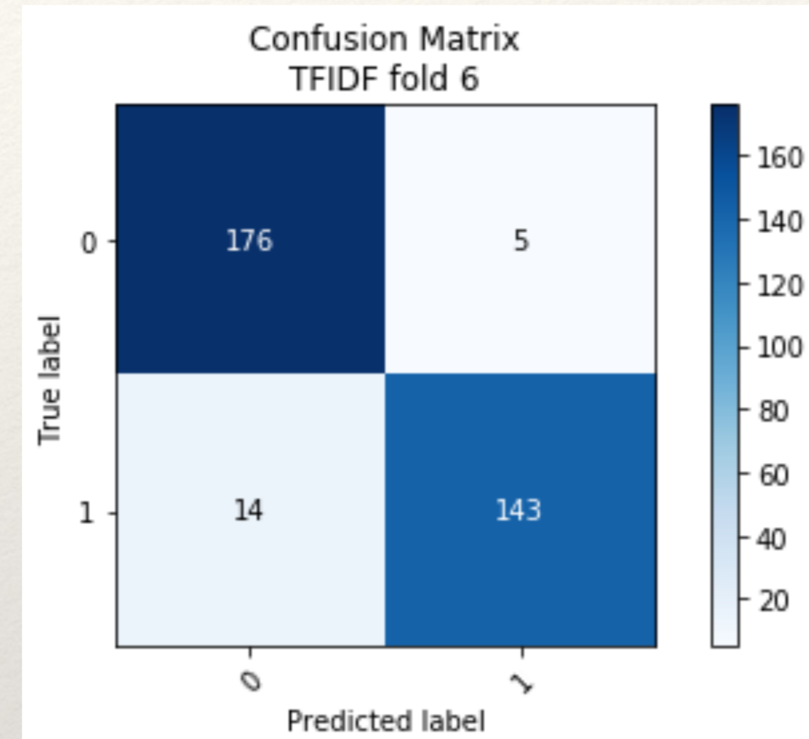
Real/Fake Prediction Average Accuracy:

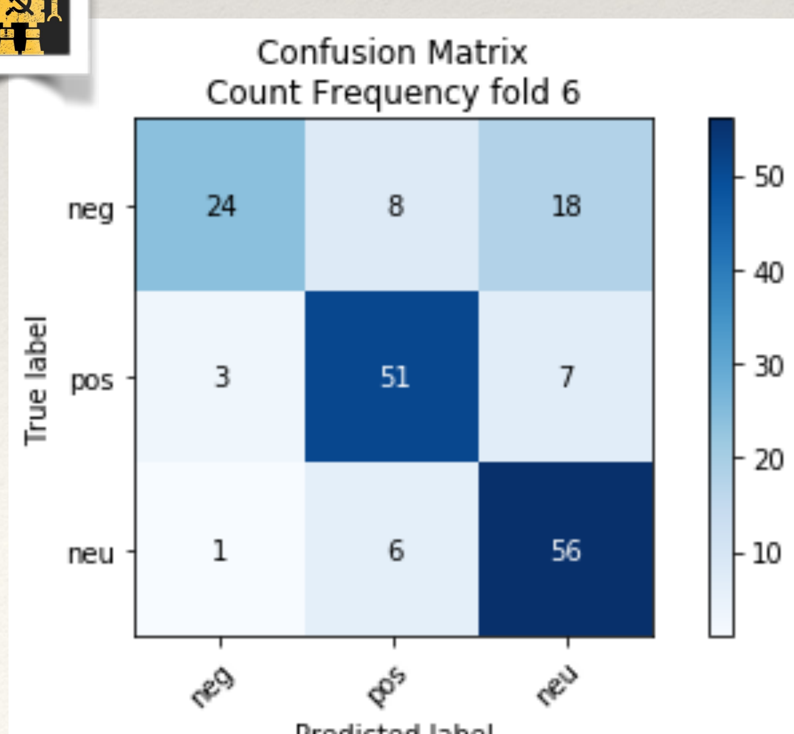
- Count frequency - 94.9%
- TF-IDF - 92.7%
- Stemmed count freq. - 94.6%

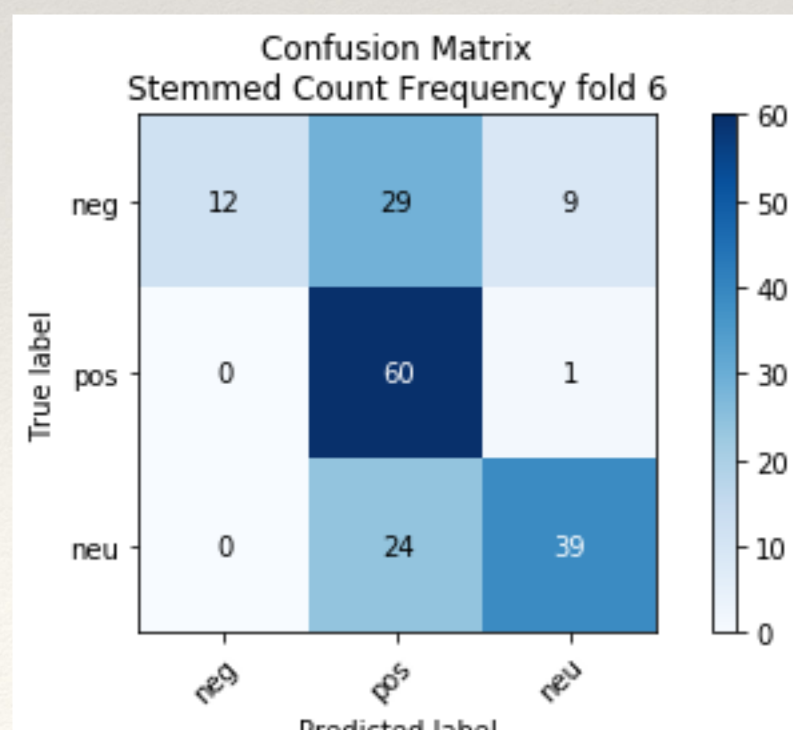
- Sentiment Prediction Average Accuracy:
  - Count frequency - 73.1%
  - TF-IDF - 73.9%
  - Stemmed count freq. - 68.6%

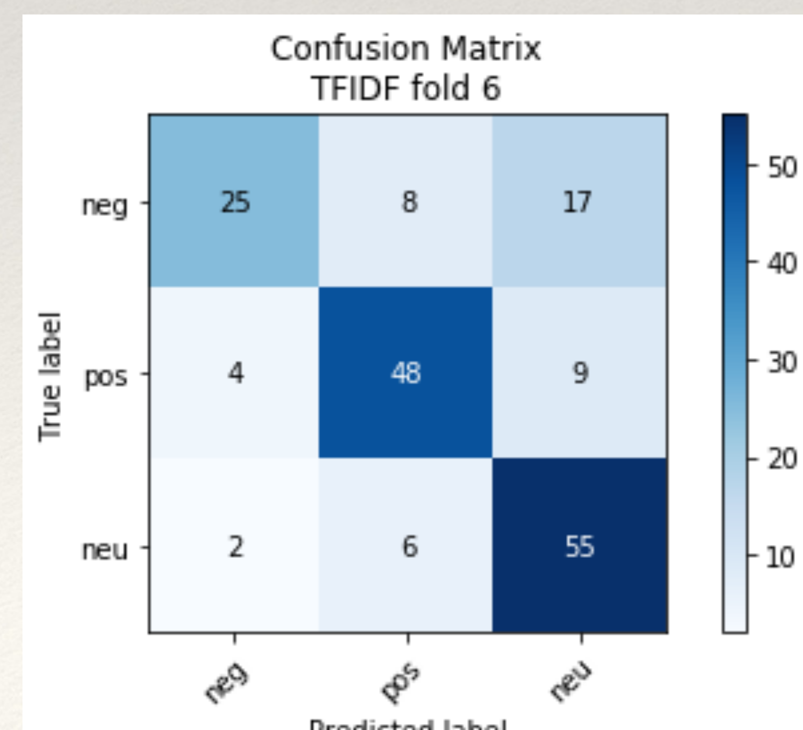






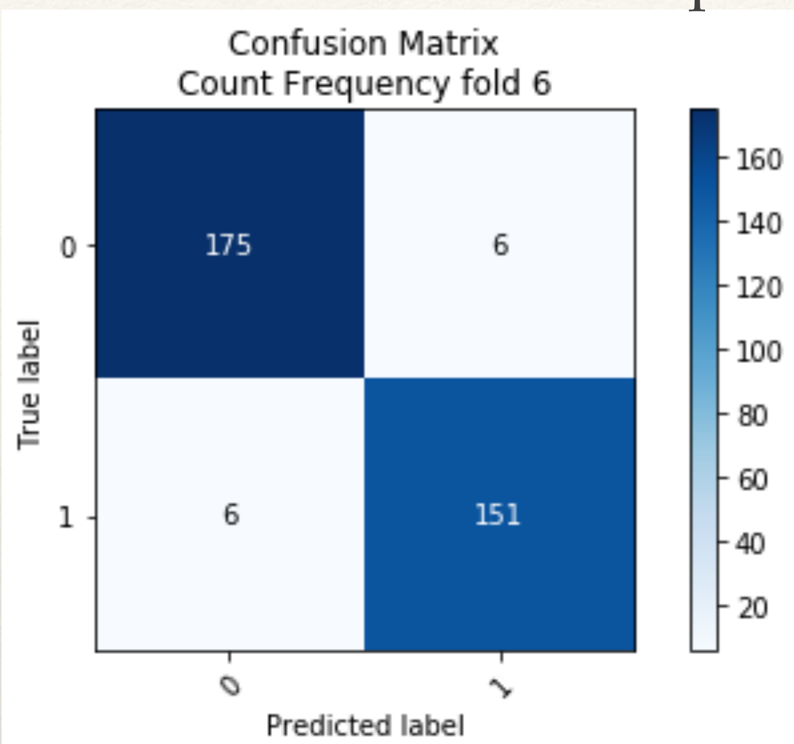


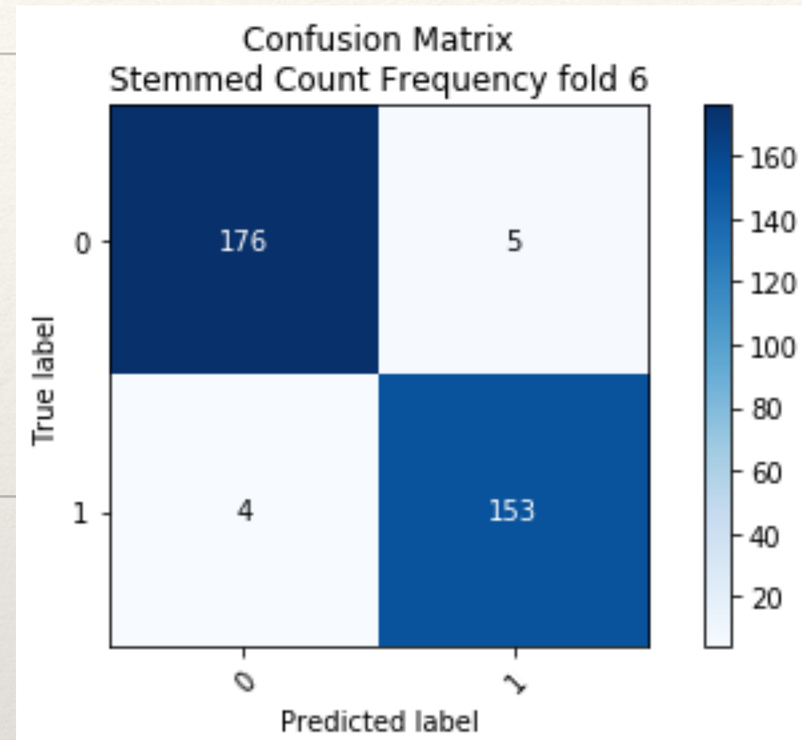


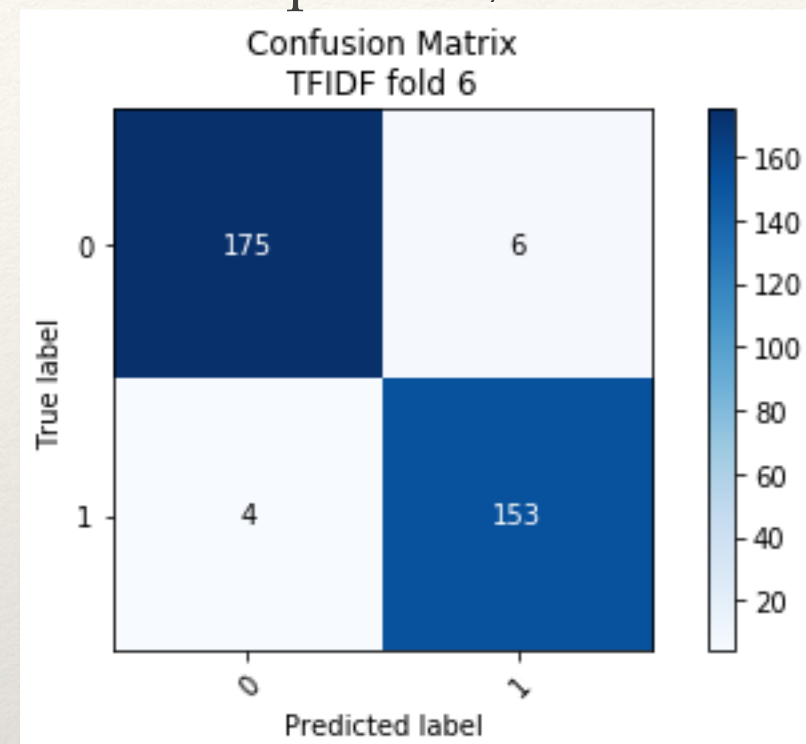


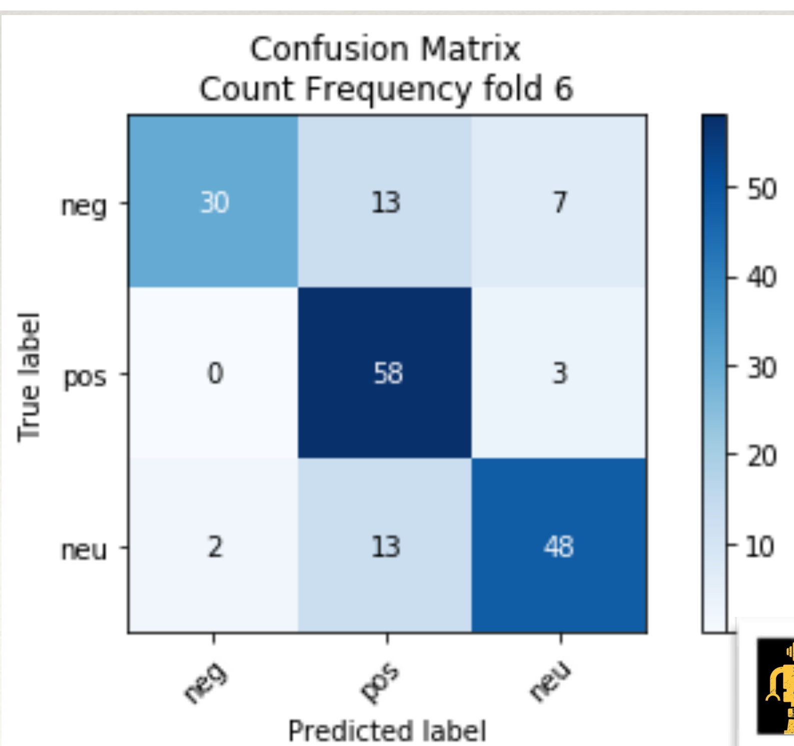
Linear Support Vector Machine

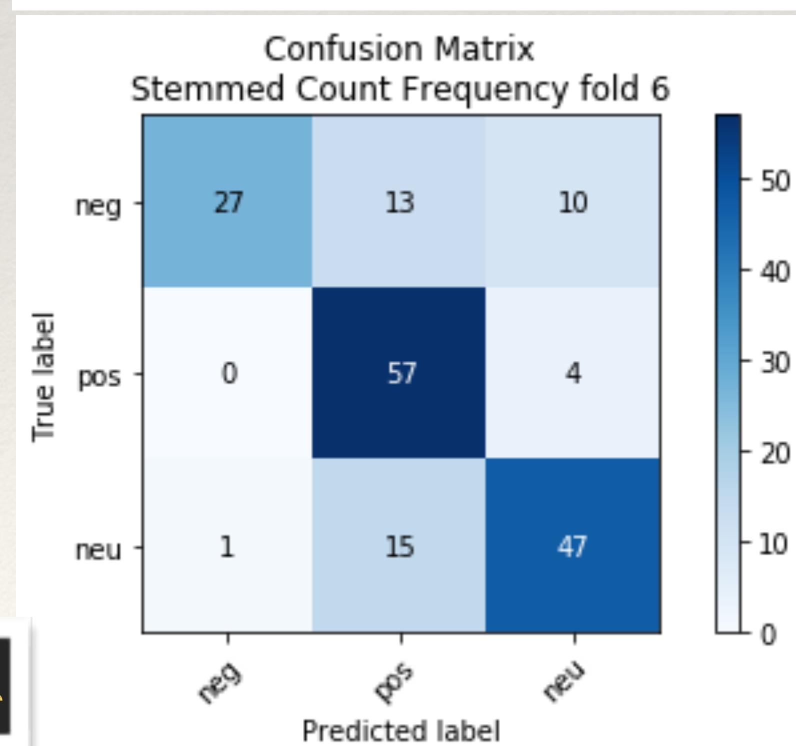
- Real/Fake Prediction Average Accuracy:
  - Count frequency - 96.2%
  - TF-IDF - 96.4%
  - Stemmed count freq. - 96.3%
- Sentiment Prediction Average Accuracy:
  - Count frequency - 78.4%
  - TF-IDF - 80.0%
  - Stemmed count freq. - 77.2%

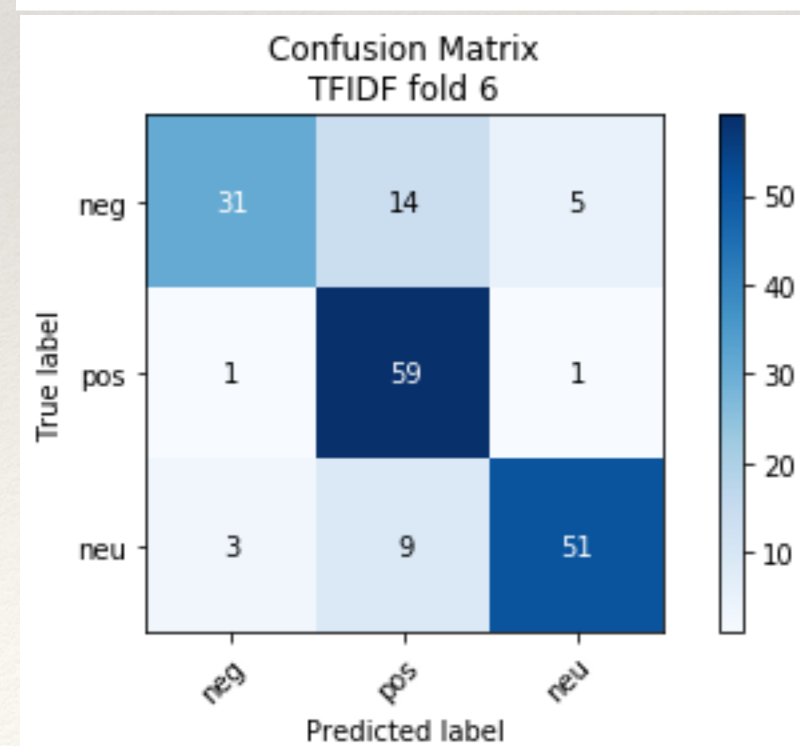






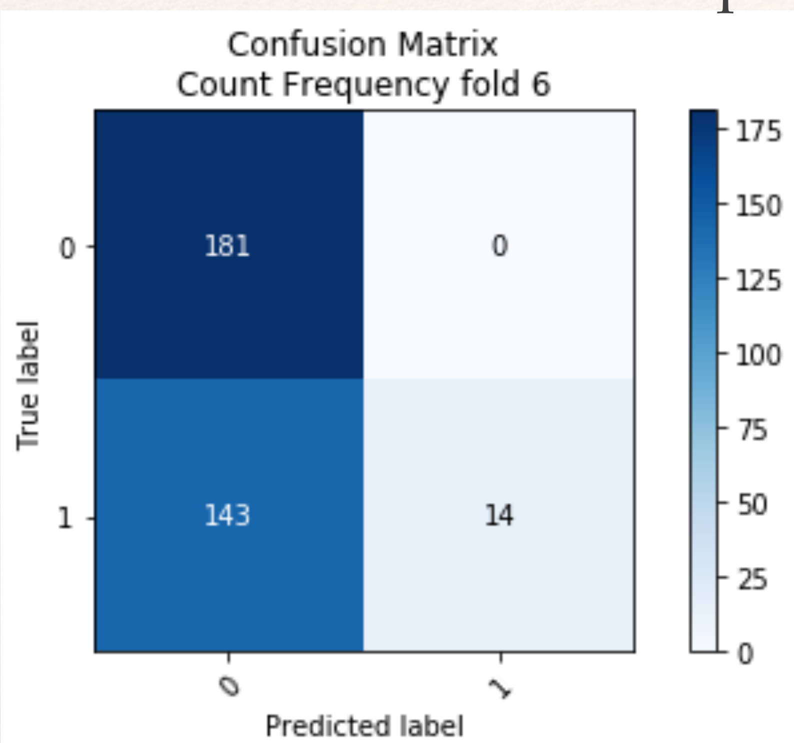


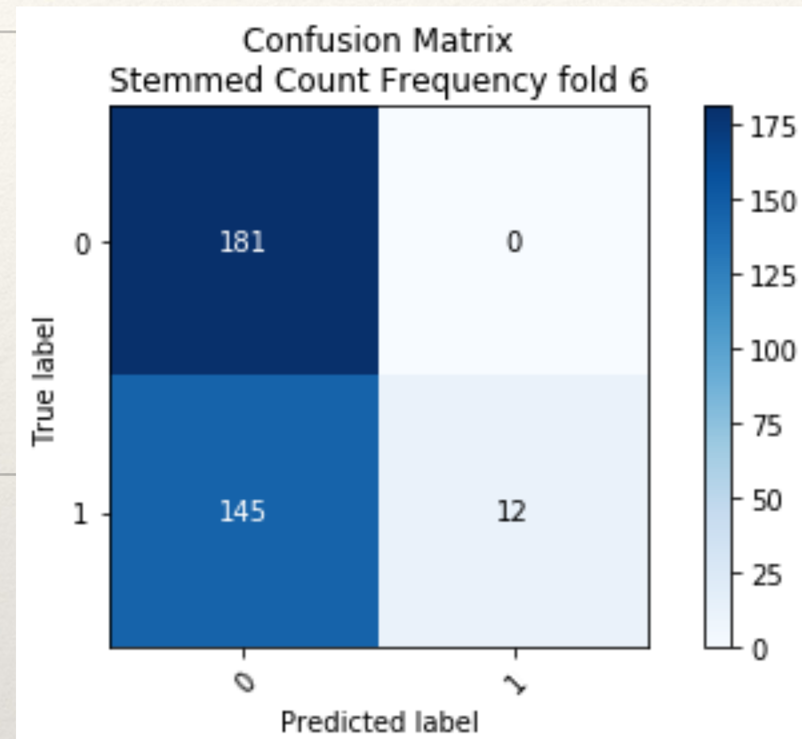


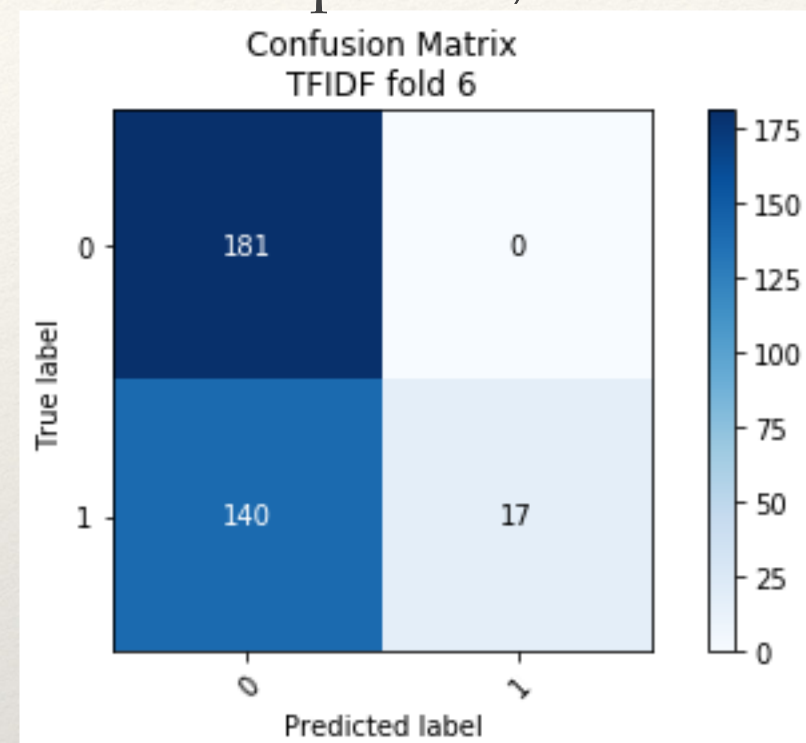


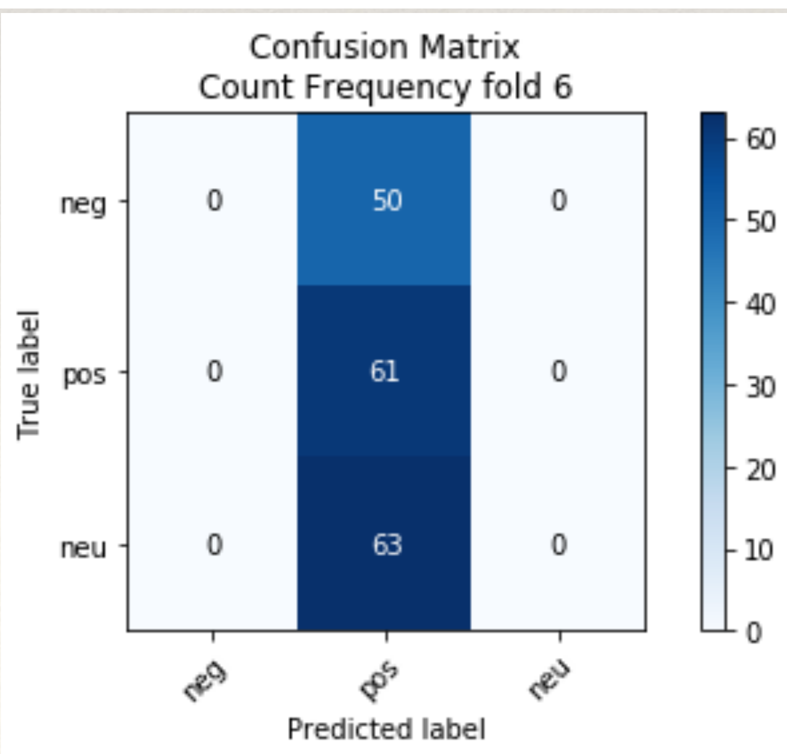
Random Forest

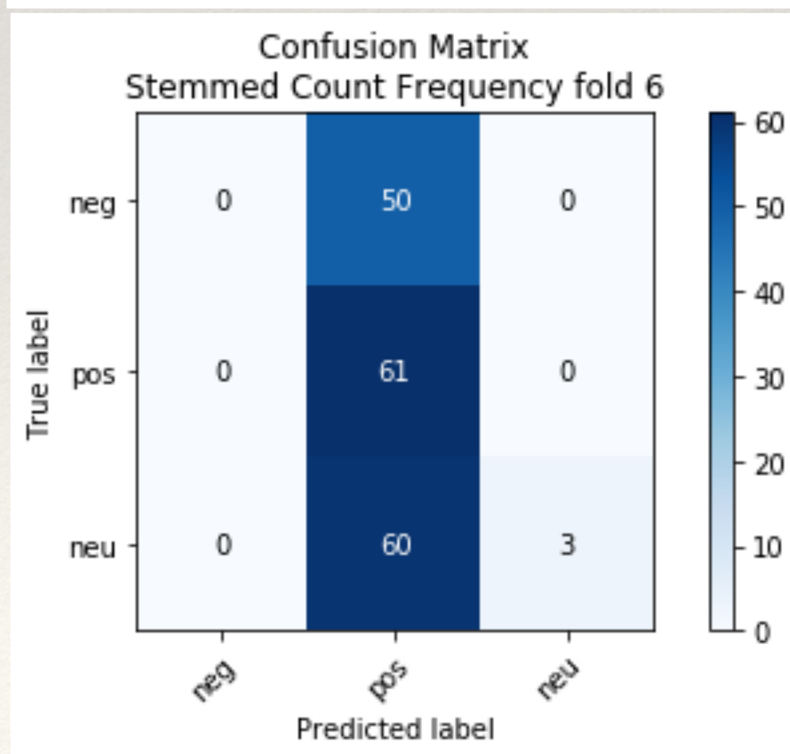
- Real/Fake Prediction Average Accuracy:
  - Count frequency - 70.4%
  - TF-IDF - 70.5%
  - Stemmed count freq. - 67.1%
- Sentiment Prediction Average Accuracy:
  - Count frequency - 42.4%
  - TF-IDF - 42.8%
  - Stemmed count freq. - 42.6%

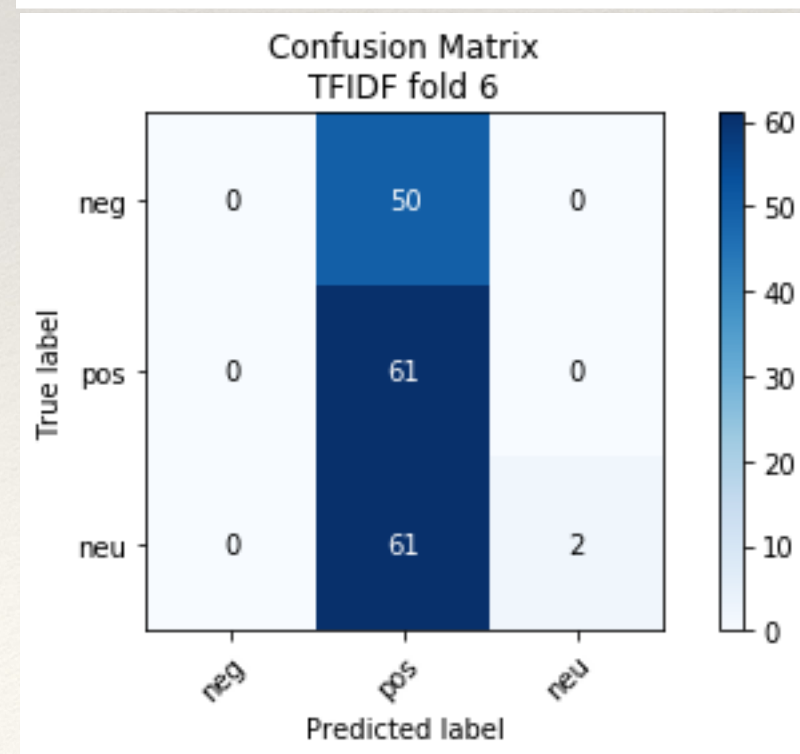






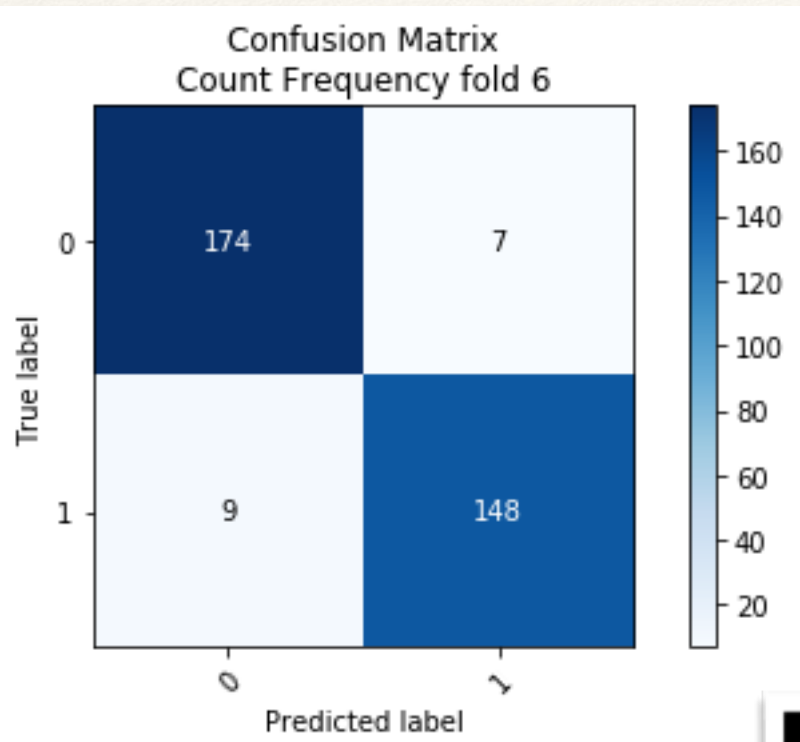


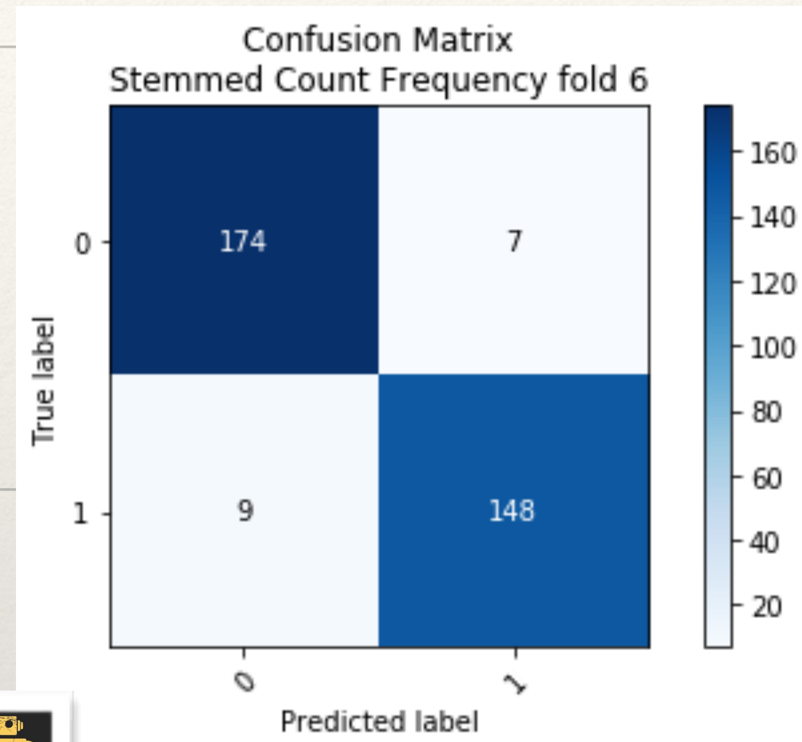


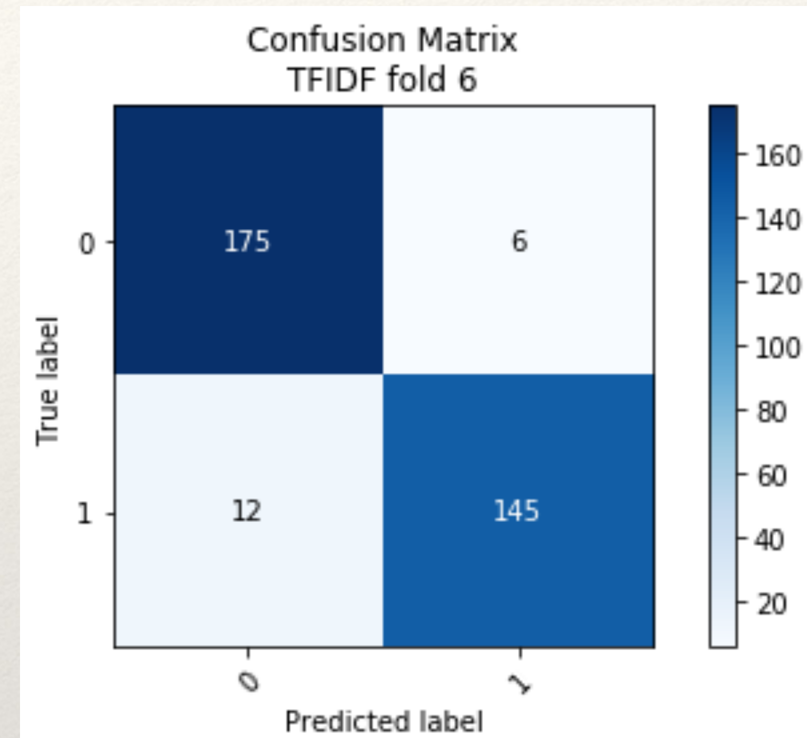


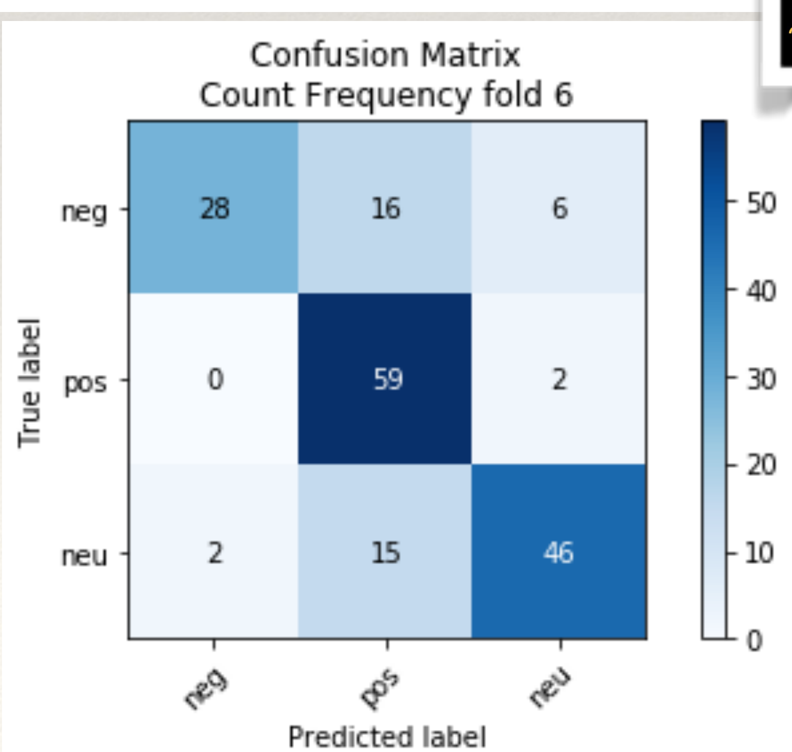
Logistic Regression

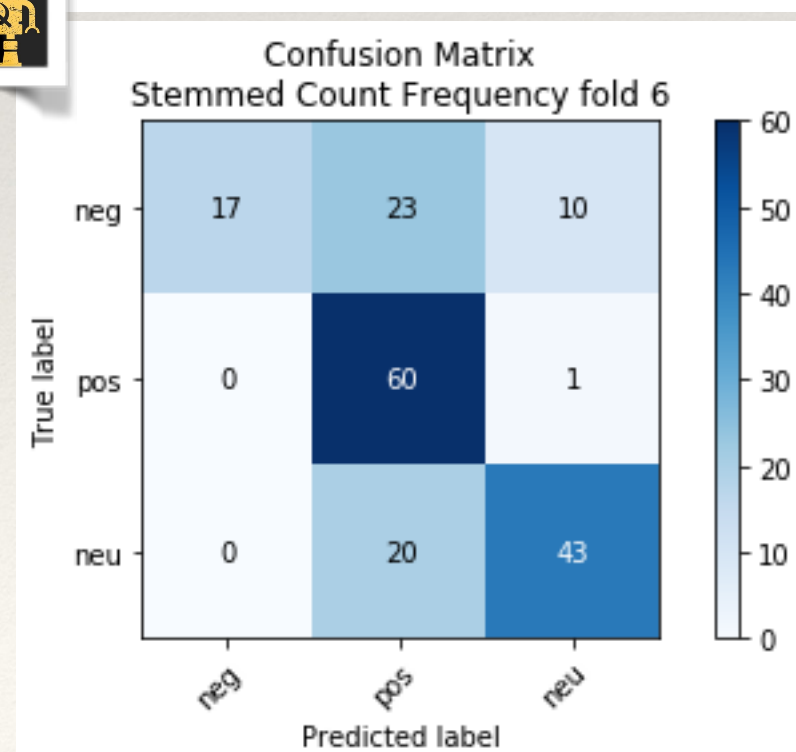
- Real/Fake Prediction Average Accuracy:
    - Count frequency - 96.2%
    - TF-IDF - 95.8%
    - Stemmed count freq. - 96.3%
- Sentiment Prediction Average Accuracy:
    - Count frequency - 76.0%
    - TF-IDF - 78.1%
    - Stemmed count freq. - 70.7%

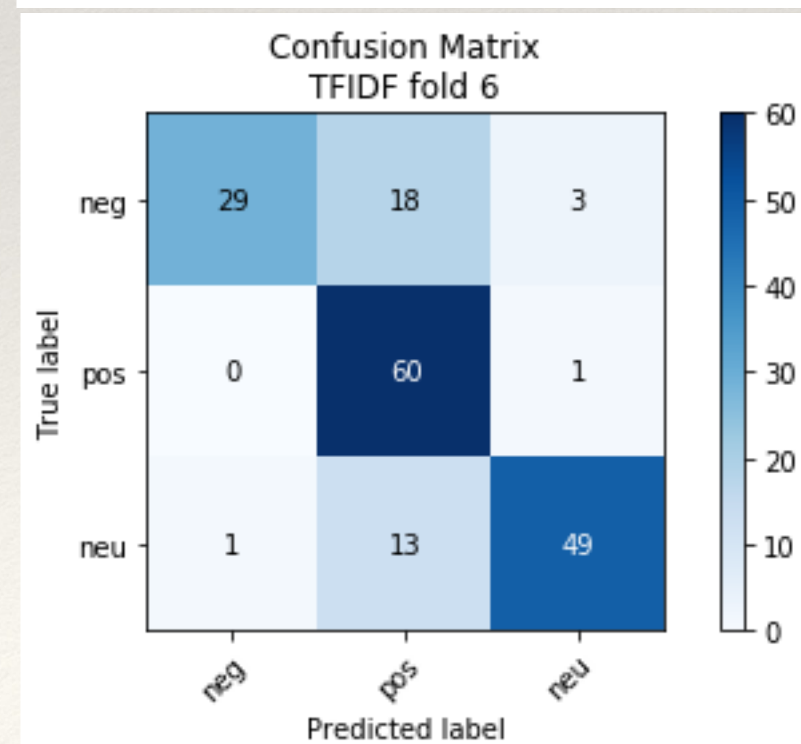












Results

MNB Real	SVM Real	RF Real	Logistic Real	MNB Sent	SVM Sent	RF Sent	Logistic Sent	VecType
0.948817	0.962722	.704142	0.961538	0.73127	0.78421	.424646	0.760026	Count Frequency
0.927219	0.964497	.70503	0.957692	0.738748	0.799744	.428088	0.781324	TFIDF
0.94645	0.962722	.671302	0.962722	0.685822	0.772131	.425796	0.706544	Stemmed Count Frequency

MNB Real Top 5 Feature Importance

```
{'Count Frequency': [{'congress': 5.759759701563032,
   '2016electionin3words': 4.892782663471337,
   'trumpforpresident': 4.8038351774548405,
   'thingspeopleontwitterlike': 4.607461867205235,
   'rt': 4.143370644325254},
  {'congress': 5.765685446818899,
   'trumpforpresident': 5.483495801988313,
   '2016electionin3words': 4.957714087068672,
   'thingspeopleontwitterlike': 4.608836453589971,
   'rt': 4.140772689162062},
  {'congress': 5.780156408593282,
   '2016electionin3words': 4.8593462247299675,
   'thingspeopleontwitterlike': 4.489986121263919,
   'trumpforpresident': 4.3735319894575895,
   'rt': 4.152449488586919},
  {'congress': 5.746033046902089,
   '2016electionin3words': 4.917746183823315,
   'trumpforpresident': 4.750380718183011,
   'thingspeopleontwitterlike': 4.519107040785551,
   'rt': 4.06770483749036},
  {'congress': 5.760270831488239,
   'trumpforpresident': 5.4621285205784735,
   '2016electionin3words': 4.969298241031561,
   'thingspeopleontwitterlike': 4.604400317912397,
   'rt': 4.2325897302644995},
```

Conclusion

- Social media and society in general are negatively impacted by trolls. It's helpful to know who is real and who isn't.
    - The trolls attempted to influence and disrupt a broad range of local and global political debates
    - Most but not all of the content favors the extremist right wing
- Some of our models were surprisingly good at predicting bots. Three models consistently *predicted with mid-90% accuracy* in cross-validation tests *(10 folds)*, independent of vectorization methods
- They were also good at predicting sentiment (around 75%, kappa = 0.73).
- Keras model predicted with 80% accuracy . We are still looking at the best optimization for the Keras model

References

- NBC News
  - https://www.nbcnews.com/tech/social-media/now-available-more-200-000-deleted-russian-troll-tweets-n844731
- Kaggle - Russian Troll Tweets
  - https://www.kaggle.com/vikasg/russian-troll-tweets
- Identifying Tweets Written by Russian Troll Accounts
  - https://cs230.stanford.edu/projects_spring_2018/reports/8289223.pdf
- Still Out There: Modeling and Identifying Russian Troll Accounts on Twitter
  - https://arxiv.org/pdf/1901.11162.pdf