IIT Stuart School of Business
ILLINOIS INSTITUTE OF TECHNOLOGY

Final Project Report

Russian Interference in the US Election via Twitter

5/6/2019

Executive Summary

Twitter has been investigating data on Russian interference in the U.S. election. There is evidence that Russian malicious automated twitter accounts spread misinformation during the 2016 presidential election, thereby exacerbating discord among Americans and attempting to interfere with the outcome of the presidential election. The project will examine how Russians specifically used twitter to impact elections, and whether there was a direct link between Russian interference and the outcome of presidential elections, by analyzing tweets from these automated accounts.

I. Background

Relevant investigations have conducted a detailed statistical study on the network environment of the United States during the 2016 presidential election, pointing out that there has been sufficient investigation and evidence proving that during the 2016 presidential election, forces from Russia unscrupulously spread information on Twitter, Facebook, YouTube and other platforms. Twitter then released more than 10 million related tweets, including more than 2 million images, gifs, video and radio shows. Many of the tweets, which date back as far as a decade, were related to Russia's efforts to sow chaos in the 2016 U.S. election and support President Trump.

II. Data Description

1. Data Source

Twitter has archived data, including tweets from Russian state-backed "Internet Research Agency" and from countries like Russia and Iran, for researchers around the world to download and analyze. We selected data from Russia for analysis.

The data set we use in this project is: Tweet information. This data set was posted on https://about.twitter.com/en_us/values/elections-integrity.html#data.

2. Dataset Field Descriptions

The data includes more than 760,000 tweets from 416 accounts. Each row corresponds to a specific tweet posted by an account. The columns contain a number of fields for the tweet, including tweetid, userid, tweet_text, tweet_time, like_count, etc. The following table describes some of these important fields.

Fields	Description
tweetid	tweet identification number
userid	user identification number
follower_count	the number of accounts following the user
following_count	the number of accounts followed by the user
account_creation_date	date of user account creation
tweet_text	the text of the tweet
tweet_time	the time when the tweet was published
is_retweet	True/False, is this tweet a retweet
retweet_userid	for retweets, the userid who authored the original tweet
retweet_tweetid	for retweets, the tweetid of the original tweet
quote_count	the number of tweets quoting this tweet
reply_count	the number of tweets replying to this tweet
like_count	the number of likes that this tweet received
retweet_count	the number of retweets that this tweet received
hashtags	a list of hashtags used in this tweet

III. Description of Analysis Methodology

1. Data Partitioning

We divided the data into four parts according to the three time points of trump's initial announcement of candidacy, trump's nomination and presidential election. The first part was before June 2015, from Trump announced his candidacy for the US President to his nomination. The second part is from June 2015 to July 2016, Hillary and Trump nominated the democratic and republican presidential candidates respectively. And Trump shift focus to general election. The third part is from July 2016 to November 2016, when the two candidates start to compete in the election of the US president. The last part was after November 2016, after Trump was officially elected president of the United States. The aim is to help explore the differences in the impact of Russian interference on the election at different times. And as the important period before the election, we will focus on the analysis of tweets in the third part of the data.

2. Sentiment Analysis

Sentiment analysis is the computational task of automatically determining what feelings a writer is expressing in text. Sentiment is often framed as a binary distinction (positive vs. negative), but it can also be a more fine-grained, like identifying the specific emotion an author is expressing (like fear, joy or anger). A sentiment analysis of the tweets in this case can give us an idea of the overall bias of the Russian tweeters towards the person or thing in the tweet.

3. Comparison with Real Data

To find out exactly what effect these malicious tweets had on the election. We originally intended to compare the existing tweet data with the analysis results of the tweet data of the entire twitter platform at that time, but we changed our thinking because we could not obtain the overall tweet data at that time. We tried to find a correlation by comparing the trend of malicious tweets to the trend of the two candidates' poll ratings.

4. Statistical Validation

Finally, we tried to use some statistical methods to verify whether there was a significant direct correlation between the number of malicious tweets and the change in Trump's and Clinton's poll ratings.

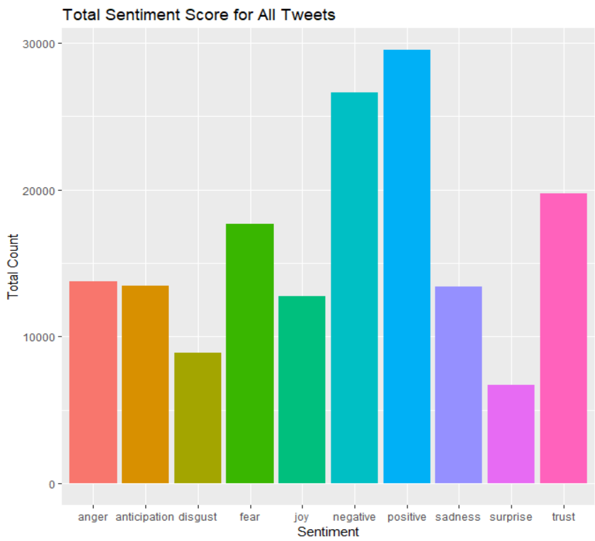
IV. Analysis by Time Division

1. Before June 2015

	tag	freq
4889	#wakeupamerica	2063
4401	#tcot	1392
3226	#obama	1317
2189	#islamistheproblem	1225
3244	#obamadestroyingamerica	1075
3519	#pjnet	979
1339	#ferguson	916
1162	#ebola	804
1818	#hillary	756
2143	#isis	741
3258	#obamahatesamerica	687
2929	#muslimsaretheproblem	676
3267	#obamalegacy	666
2154	#islam	643
314	#baltimoreriots	617

Before June 2015, public opinion pays a lot of attention to about Islamic terrorism. Obama believed that terrorist attacks should not be attributed to a religion. Islam cannot be synonymous with terrorist attacks. Obama believes that the exclusion of Islam is an act of racial discrimination. This topic has been continually debated on Twitter.

The Russian bots wasn't active enough in this period, from the data we could noticed that the hashtags such as, #wake up America, #islam is the problem, #muslimistheproblem and #tcot were against Obama's opinion on Islam. Also, some other hashtags, such as #obama destroying America and #obama hates America were directly attack to him. Any way, during that time, these bots tweeted Although they did not tweets much about Trump during this time, while these statements against Obama also indirectly supported Trump afterwards.

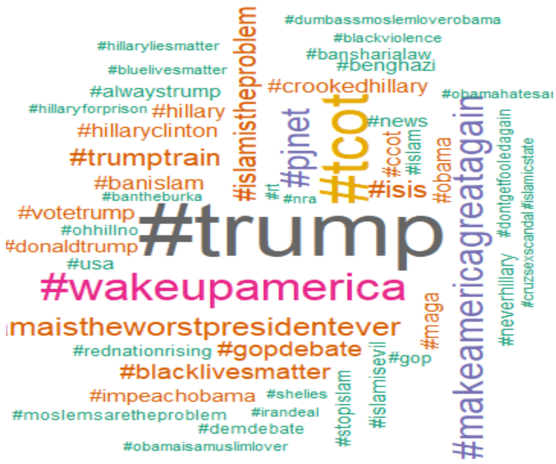


The graph shows the overall sentiments about the contents tweeted by Russian bots were more postive than negative. During this period of time, Russian bots are not active on Twitter. Firstly, the number of Twitters was small, and secondly, the sentiment bias was not strong.

Therefore, during this period, their role on Twitter was not obvious.

2. From June 2015 to July 2016

	tag	freq
22444	#trump	12193
21376	#tcot	7806
23912	#wakeupamerica	5444
13092	#makeamericagreatagain	4289
17255	#pjnet	3917
16086	#obamaistheworstpresidentever	2988
11009	#islamistheproblem	2707
22760	#trumptrain	2661
10792	#isis	2582
8611	#gopdebate	2280
2256	#blacklivesmatter	2163
3525	#ccot	2015
13026	#maga	1882
1463	#banislam	1845
9427	#hillaryclinton	1778



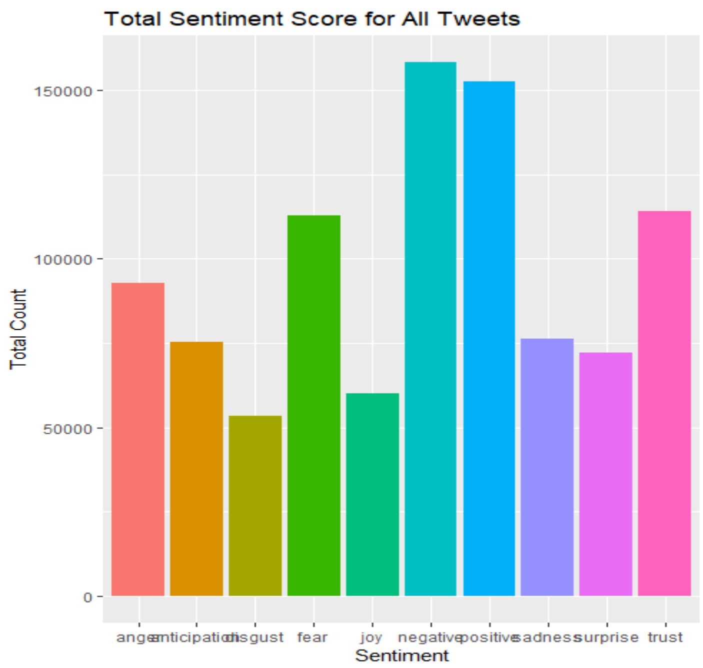
Since June 2015, Trump officially announced his candidacy for the US President, and Trump discussed illegal immigration, offshoring of American jobs, the US national debt, and Islamic terrorism in a speech, which all contains large priorities during the campaign. He also announced his campaign slogan : "Make America Great Again".

By March 2016, Trump was poised to win the Republican nomination. After a landslide win in Indiana on May 3, 2016, RNC Chairman Reince Priebus declared Trump the presumptive Republican nominee.

After becoming the presumptive Republican nominee, Trump shifted his focus the general election. Trump began campaigning against Hillary Clinton, who became the presumptive Democratic nominee on June 6, 2016.

During this period, “Trump” became a hot topic on twitter. His slogan and the topics he discussed were also focused by people. Some new hashtags were created such as #alwaystrump and #votetump,etc.

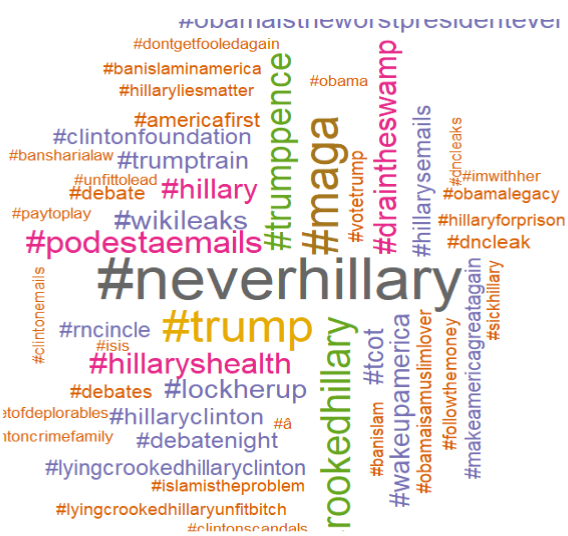
Russian bots started to active on Twitter. “Trump” was the most promoted hashtag for the bots. And from the data we could noticed that the hashtags such as, #trump, #wake up america, #islam is the problem, #make america great again and #tcot were counted the most and continuously help trump attracted great attention. Also, some other hashtags, such as #obama is the worst president ever influenced Trump indirectly. Besides, some negative hashtags about Hillary were also made such as #neverhillary and #hillary lies matter might because FBI's re-opening of its investigation into her ongoing email controversy.



In those two months, the difference between positive and negative emotions is not obvious. Negative contents showed more in Russian bots' tweets than positive contents. But from the hashtags, those about Trump were more positive or neutral, while for his rivals, such as Hillary and Obama, were more negative, which can reflect that these tweets were more beneficial to Trump.

3. From July 2016 to November 2016

	tag	freq
7747	#neverhillary	2884
6874	#maga	2168
11212	#trump	2091
2358	#crookedhillary	1753
11337	#trumppence	1476
8935	#podestaemails	1405
3064	#draintheswamp	1256
5067	#hillaryshealth	1213
4525	#hillary	1122
12276	#wikileaks	1068
6678	#lockherup	1063
10771	#tcot	1055
11967	#wakeupamerica	1041
8280	#obamaistheworstpresidentever	963
11409	#trumptrain	905

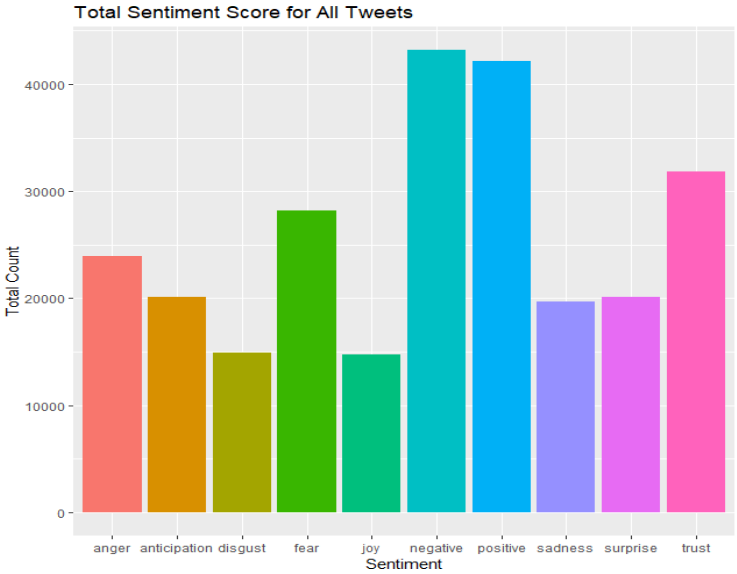


After the general election began, Trump and Hillary picked their own campaign partners.

After that, the two worked hard for their own campaigns. At the same time, Hillary's email controversy was not subsided. In September she fainted in an activity so that people questioned about her health. Subsequently, on September 26th, October 9th and October 19th, three presidential debates were held respectively. Then entering the formal election voting stage in November.

From the top hashtags of this period, the bots tweeted more about Hillary. But the contents were negative such as #neverhillary and #crookedhillary. Also some others like #hillaryshealth and #podestaemails were also related topics against Hillary.

But for those about Trump, #maga, #draintheswamp and #trumppence were his slogans and made people focus on his activities.



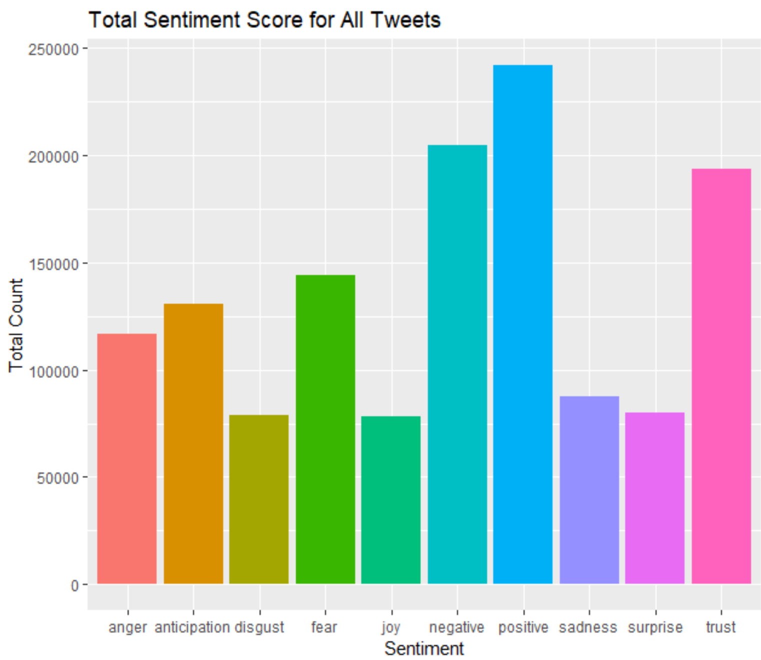
In this period, the debate on public opinion on both sides has become fierce. Negative contents showed more in Russian bots' tweets than positive contents. But from the hashtag, those about Trump were more positive or neutral. Bots tried to make more people know every Trumps' movement. While for Hillary, were more negative with doubts. From the hashtags those bots used frequently, we can also reflect that these tweets were still more beneficial to Trump.

4. After November 2016

	tag	freq
26678	#releasethememoð	31830
25729	#qanon	17507
18536	#maga	16657
15290	#islamistheproblem	15185
2309	#bansharialaw	11011
30326	#stopimportingislam	8994
2088	#banislam	7185
14930	#islam	7023
30472	#stopislam	6456
30585	#stopmakingexcusesforislam	5367
2438	#banthequran	5151
33557	#trump	4526
2016	#bancairnational	4253
764	#americafirst	4035
5467	#closeallmosquesnow	3944

After Trump was elected president of the United States and officially took office. He has carried out a series of political initiatives, such as withdrawing from TPP, building a border wall, and reaffirming "America First" policy. At the same time, Trump also signed a ban on citizens of Muslim countries from entering the United States. He also faced accusations of discussing classified information with Russian.

The Russian bots started to tweet more about Trump since he was elected. Among the hot hashtags, most of them are about supporting Trump's attitude to Islam. Also, the most frequent hashtag was #releasethememo, which was about the investigation about Russian meddling in 2016 Election and whether Trump's team colluded in that attack.



During this period, the topics were focused on the new president. People cared about Trumps' action and policies. For the sentiments about Russian bots' tweets, the positive contents counted more than negative.

From the top topics, we could see that most of the hashtags about Islam have negative feelings. Therefore, positive contents might be a support for Trump, while negative aspects might expressing opposition to Muslims or other issues to support Trump indirectly.

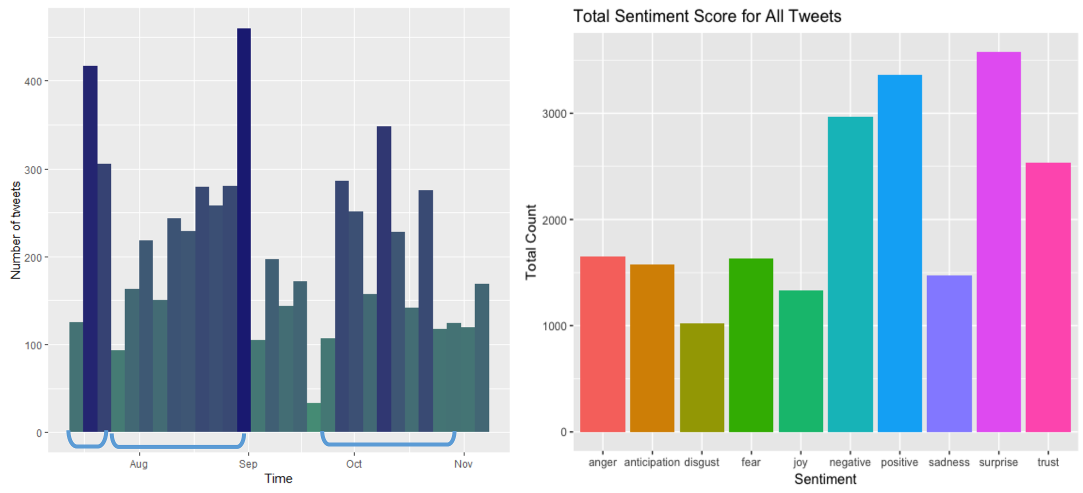
In summary, after Trump announced his candidacy to the presidency, a large amount of Russian bots' tweets and their main hashtags are beneficial to Trump. These tweets have influenced the direction of public opinion for the two presidential candidates to a certain extent. Also, at the same time, might also affect the final election to some extent.

V. Analysis of the Impact on the Election

1. Sentiment Analysis for Tweets with #hillary & #trump

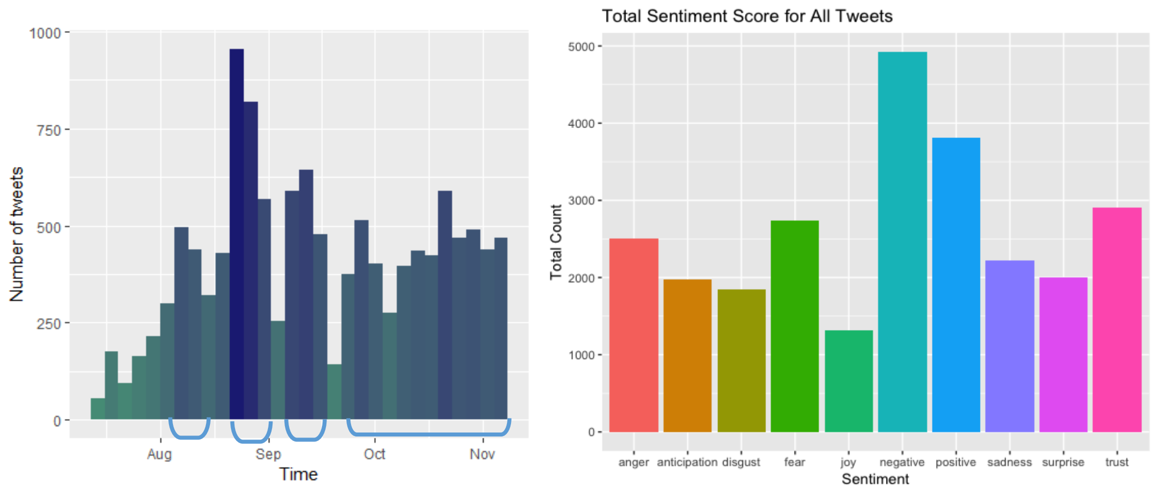
	tag	freq
7747	#neverhillary	2884
6874	#maga	2168
11212	#trump	2091
2358	#crookedhillary	1753
11337	#trumppence	1476
8935	#podestaemails	1405
3064	#drainthes wamp	1256
5067	#hillaryshealth	1213
4525	#hillary	1122
12276	#wikileaks	1068
6678	#lockherup	1063
10771	#tcot	1055
11967	#wakeupamerica	1041
8280	#obamaistheworstpresidentever	963
11409	#trumptrain	905

According to the ranking of the top hashtags of the Russian tweets, we can see most of them are talking about either Trump or Hilary. Here we use "Trump" and "Hilary" as our factors to select those tweets that have hashtags including either of these two and put them into two groups (Group T and Group H) for further analysis.



(Distribution and Sentiment Score for tweets with hashtags including "Trump" (Group T), 2016.7-2016.11)

As for Group T, we can see their distribution within this period forms 3 waves where it reached its peak at late July, early September and mid-October. And the total sentiment score shows positive sentiments (positive, surprise, trust, anticipation, joy) more than negatives (anger, fear, negative, sadness) which helps us to inform that the Russian tweets were spreading more positive comments towards Donald Trump.

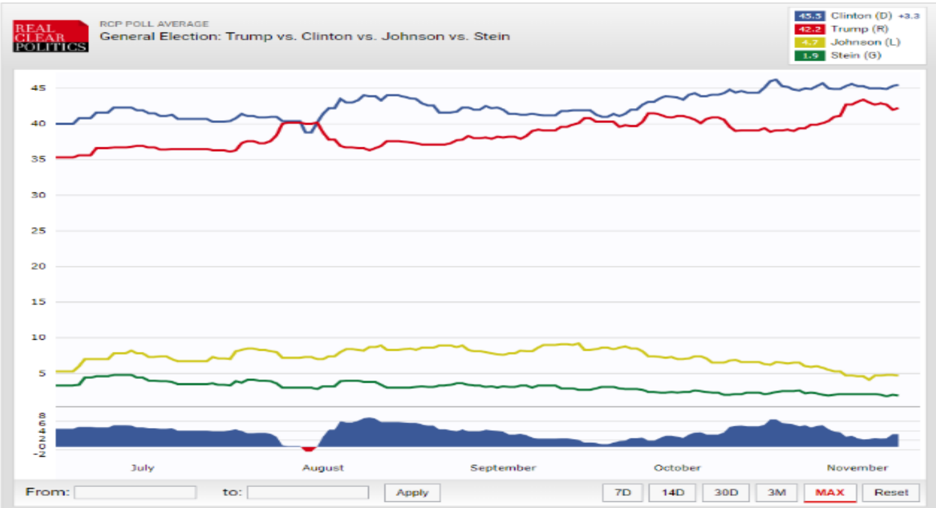


(Distribution and Sentiment Score for tweets with hashtags including "Hilary" (Group H), 2016.7-2016.11)

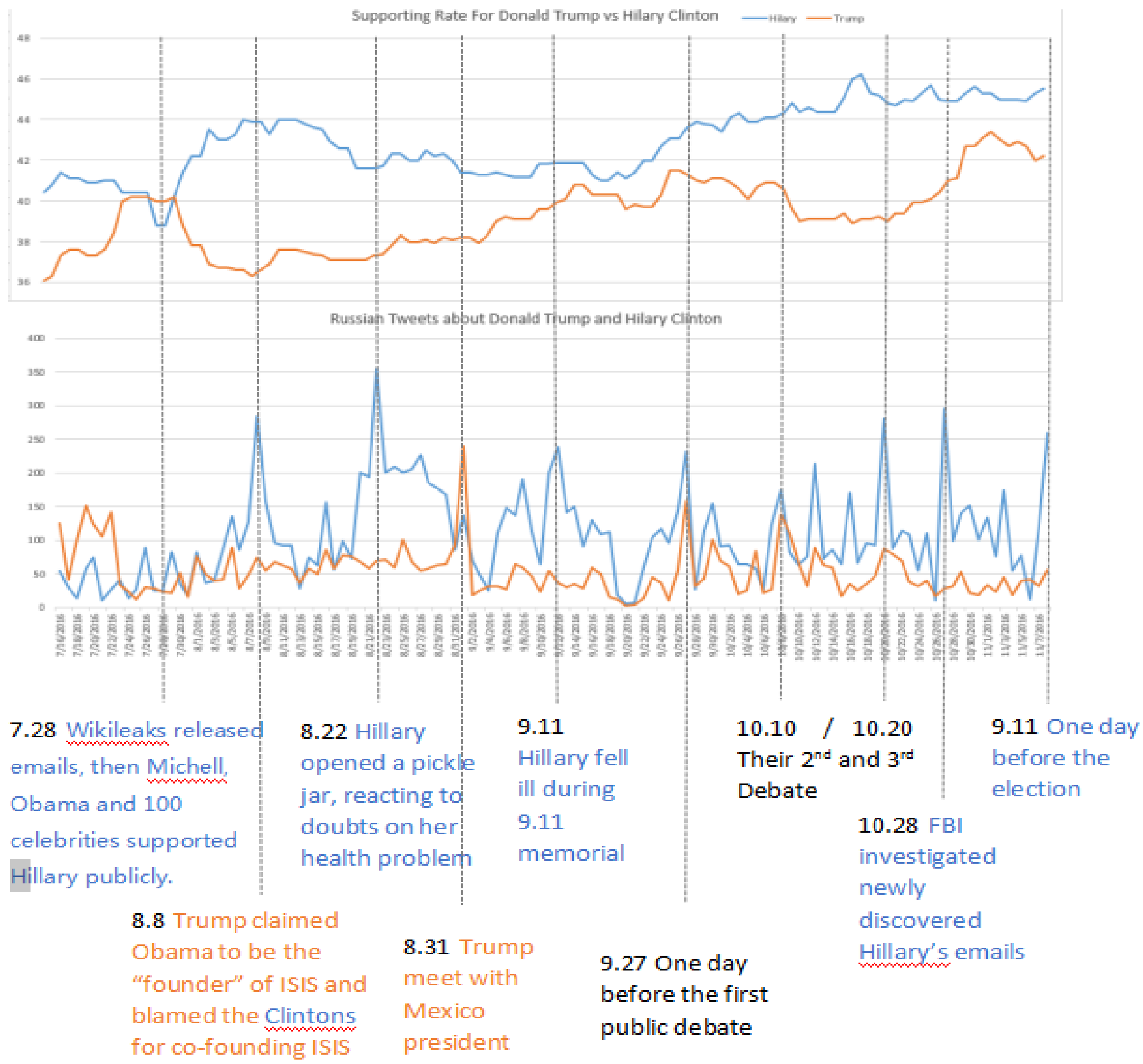
While in Group H, we can see their distribution within this period forms 3 small waves and a big one through October where it reached its peak at late August. And the total sentiment score shows negative sentiments (anger, fear, negative, sadness) more than positives (positive, surprise, trust, anticipation, joy) which helps us to inform that these Russian tweets were spreading more comments towards Hilary Clinton with negative attitude.

2. Compare that to Polling Data

By knowing what these Russian tweets were doing and implying their purpose, we step further to analyze its impact on the election. Here we took the RCP POLL AVERAGE data from Real Clear Politics that have the supporting trend of the two candidates from 2016.7.16 to 2016.11.8 as our dependent variables to compare with the trend of the Russian tweets which can be implied as the trend of Russian "marketing powers".



The data we have for the POLL and our Russian tweets trend data can both be adjusted in the unit of days which helped us to put them together.



After we slice the timeline according to the peak of the Russian tweets as well as the elbow of the candidates' supporting rate, we found those key dates are the days when these crucial events happened. News had gone viral and we can see these Russian bots put huge effort on spread them as well.

One solid proof for this conclusion is that when news involved only one candidate, only the tweets about that candidate reached its peak, while when both of them were involved, their debates, for example, drove both of their tweets trend to reach their peak and even followed the same pattern (9.27-10.28). And the proof for the Russians "hating" Hillary is that when Hillary's supporting rate gone viral with positive comments to her and "hates" to Trump all across Democrats and celebrities (7.28-8.8), the Russians bots were relatively quiet for no preferable news for them to spread, until August the 8th when Trump claimed Obama to be the founder of ISIS and blamed the Clintons for co-founding ISIS.

In addition, the Russian tweets undoubtedly took great effort on supporting Trump and dragging Hillary with their tweets spreading the crucial news which had influences on the public preference among the two candidates. They reacted quickly to spread the news that either helped to boost Trump's supporting rate or to slow down Hillary's wining process. What they had done, and their intentions were crystal clear. But does that mean their tweets had significant influence on the election or the supporting rate of the candidates? We need to pull out those data and test it statistically.

VI. Statistical Validation

1. Specification of Data Set

We select daily data from 07/16/2016 (the date Donald Trump announced Presidential candidates) to 11/8/2016 (Trump was elected President). There are 116 dates.

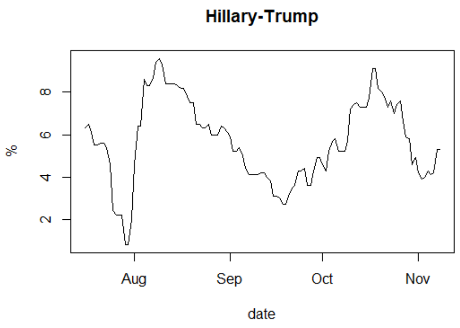
Independent variables:

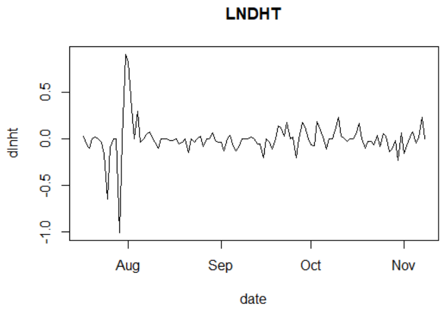
LNNOT: We calculate the daily counts of tweets from Russian Automated Dataset that contained "Trump" in their hashtags and logarithm them as LNNOT.

LNNOH: We calculate the daily counts of tweets from Russian Automated Dataset that contained "Hillary" in their hashtags and logarithm them as LNNOH.

Dependent Variables: DLNHT

In general, Trump's support rate is increasing. To get the stationary time series data that is suitable for further statistical analysis, we logarithm the support rate (%) of Trump (From Real Clear Politics Poll Average), then calculate the one-stage difference of log(Support Rate of Trump).





2. The Augmented Dickey-Fuller (ADF) Test

The augmented Dickey–Fuller test (ADF) tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is used, but is usually stationarity or trend-stationarity. It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models.

The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. If the test statistic is less (this test is non symmetrical so we do not consider an absolute value) than the (larger negative) critical value, then the null hypothesis of {\displaystyle \gamma =1} \gamma =1 is rejected and no unit root is present.

Non-stationary residuals will violate the standard assumption to apply OLS methodology. To test the stationary of the variables, we choose to use the augmented Dickey-Fuller (ADF) Test.

Following are the ADF test results of three variables:

```
> summary(adflnnot)
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend
Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
```

```
-2.43901  -0.27544   0.06951   0.36492   1.45348

Coefficients:
              Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)  2.056597   0.415177   4.954  2.68e-06  ***
z.lag.1     -0.521744   0.099152  -5.262  7.19e-07  ***
tt          -0.001832   0.001862  -0.984     0.327
z.diff.lag  -0.027901   0.095365  -0.293     0.770
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6271 on 109 degrees of freedom
Multiple R-squared:  0.2699, Adjusted R-squared:  0.2498
F-statistic: 13.43 on 3 and 109 DF,  p-value: 1.597e-07

Value of test-statistic is: -5.2621 9.2577 13.8818
Critical values for test statistics:
      1pct  5pct  10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47


> summary(adflnnoh)
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################
Test regression trend

Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min        1Q    Median        3Q       Max
-2.37416  -0.37189   0.05205   0.50808   1.79310

Coefficients:
              Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)  2.275591   0.451326   5.042  1.85e-06  ***
z.lag.1     -0.537597   0.103479  -5.195  9.60e-07  ***
tt           0.002066   0.002226   0.928     0.355
z.diff.lag  -0.129756   0.094007  -1.380     0.170
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.7539 on 109 degrees of freedom
Multiple R-squared:  0.3249, Adjusted R-squared:  0.3064
F-statistic: 17.49 on 3 and 109 DF,  p-value: 2.434e-09

Value of test-statistic is: -5.1952 9.0713 13.5132

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47


> summary(adfdlnht)
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################
Test regression trend

Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-1.00886 -0.05124 -0.00535  0.05400  0.63364

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.071e-03  3.282e-02  -0.094  0.92563
z.lag.1     -8.451e-01  1.058e-01  -7.987 1.53e-12 ***
tt           2.765e-05  4.932e-04   0.056  0.95540
z.diff.lag   2.821e-01  9.261e-02   3.046  0.00291 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.171 on 109 degrees of freedom
Multiple R-squared:  0.3823, Adjusted R-squared:  0.3653
F-statistic: 22.49 on 3 and 109 DF,  p-value: 2.077e-11

Value of test-statistic is: -7.9873 21.2669 31.899

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
```

```
phi3  8.43  6.49  5.47
```

For each variables' test results, t test-statistic value is higher than t critical value, which means there is no unit root in this time series sample. LNNOT, LNNOH and DLNHT are considered stationary, and they don't have trend effects.

3. Var Model

Vector autoregression (VAR) is a stochastic process model used to capture the linear interdependencies among multiple time series. VAR models generalize the univariate autoregressive model (AR model) by allowing for more than one evolving variable. All variables in a VAR enter the model in the same way: each variable has an equation explaining its evolution based on its own lagged values, the lagged values of the other model variables, and an error term. VAR modeling does not require as much knowledge about the forces influencing a variable as do structural models with simultaneous equations: The only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally.

To test the linear inter dependencies between these time series, we build the vector auto regression model. Before building the model, we use several ways to decide the number of lags.

```
> VARselect(df,lag.max=10,type="const")
$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
     1      1      1      1

$criteria
                 1           2          3           4           5           6           7
AIC(n) -5.41176473 -5.403255769 -5.33675177 -5.330726027 -5.216958999 -5.129526073 -5.169
919192
HQ(n)  -5.28885763 -5.188168351 -5.02948403 -4.931277965 -4.725330615 -4.545717367 -4.49
3930163
SC(n)  -5.10845497 -4.872463699 -4.57847738 -4.344969325 -4.003719982 -3.688804740 -3.50
1715543
FPE(n)  0.00446425  0.004504576  0.00481984  0.004859134  0.005462863  0.005991356  0.
```

```
005793477
                    8             9            10
AIC(n) -5.190451751 -5.143152157 -5.099574632
HQ(n)  -4.422282401 -4.282802485 -4.147044638
SC(n)  -3.294765787 -3.019983877 -2.748924036
FPE(n)  0.005727365  0.006075317  0.006439954
```

All the criteria for order selection suggests VAR(1). Following are the VAR(1) model estimation results.

```
> summary(var)

VAR Estimation Results:
=========================
Endogenous variables: dlnht, lnnot, lnnoh
Deterministic variables: const
Sample size: 114
Log Likelihood: -183.516
Roots of the characteristic polynomial:
0.457 0.457 0.342
Call:
VAR(y = df, lag.max = 1, ic = "AIC")

Estimation results for equation dlnht:
======================================
dlnht = dlnht.l1 + lnnot.l1 + lnnoh.l1 + const

           Estimate  Std. Error t value Pr(>|t|)
dlnht.l1  0.3395429  0.0907777   3.740 0.000294 ***
lnnot.l1 -0.0002038  0.0266377  -0.008 0.993910
lnnoh.l1 -0.0016085  0.0228266  -0.070 0.943951
const     0.0065590  0.1040489   0.063 0.949851
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1774 on 110 degrees of freedom
Multiple R-Squared: 0.116,   Adjusted R-squared: 0.09189
F-statistic: 4.811 on 3 and 110 DF,  p-value: 0.003466
```

From the results, we can see neither of these two variables (LNNOT, LNNOH) is significant, which means statistically the neither LNNOT nor LNNOH has the effect on DLNHT.

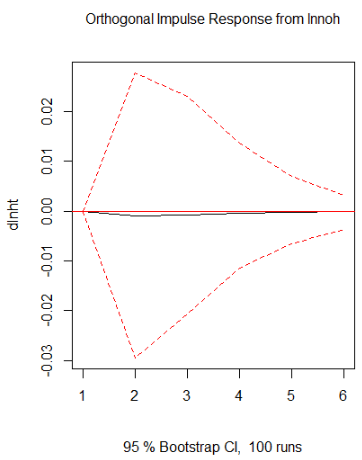
4. Impulse Response Analysis

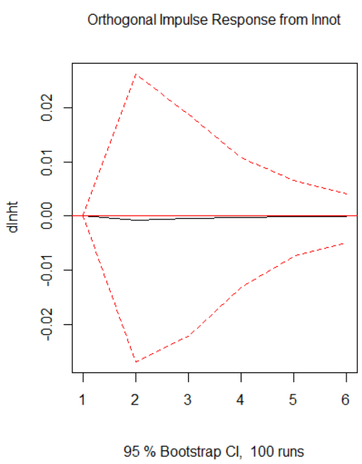
In signal processing, the impulse response, or impulse response function (IRF), of a dynamic system is its output when presented with a brief input signal, called an impulse. More generally, an impulse response is the reaction of any dynamic system in response to some external change. In both cases, the impulse response describes the reaction of the system as a function of time (or possibly as a function of some other independent variable that parameterizes the dynamic behavior of the system).

In all these cases, the dynamic system and its impulse response may be actual physical objects, or may be mathematical systems of equations describing such objects.

Since the impulse function contains all frequencies, the impulse response defines the response of a linear time-invariant system for all frequencies.

Based on the VAR model built before, we can also do the impulse response analysis. Following are the graphs of impulse response functions.





Clearly, the impulse responses show no effect of “Trump” tweets or “Hillary” tweets on Hillary-Trump support rate difference.

5. Granger Test

The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another, first proposed in 1969. Ordinarily, regressions reflect "mere" correlations, but Clive Granger argued that causality in economics could be tested for by measuring the ability to predict the future values of a time series using prior values of another time series. Since the question of "true causality" is deeply philosophical, and because of the post hoc ergo propter hoc fallacy of assuming that one thing preceding another can be used as a proof of causation, econometricians assert that the Granger test finds only "predictive causality".

A time series X is said to Granger-cause Y if it can be shown, usually through a series of t-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

```
> grangertest(dlnht ~ lnnoh, order = 2, data =df)
Granger causality test

Model 1: dlnht ~ Lags(dlnht, 1:2) + Lags(lnnoh, 1:2)
Model 2: dlnht ~ Lags(dlnht, 1:2)
  Res.Df Df      F  Pr(>F)
1    108
2    110 -2 0.0122 0.9879


> grangertest(dlnht ~ lnnot, order = 2, data =df)
Granger causality test

Model 1: dlnht ~ Lags(dlnht, 1:2) + Lags(lnnot, 1:2)
Model 2: dlnht ~ Lags(dlnht, 1:2)
  Res.Df Df      F  Pr(>F)
1    108
2    110 -2 0.1003 0.9046
```

The results of the Granger test shows neither LNNOH nor LNNOT contribute to the prediction of DLNHT, which means there isn't a statistically cause-effect relationship existing in between.

Within the selected dataset, we couldn’t find an identified relationship between what the automated Russian accounts and the support rate change of the candidates.

Conclusion

From the above analysis, we can basically see that these machine accounts from Russia seem to push the polarization of the issue of disagreement through a large number of tweets, constantly make inflammatory remarks, and attempt to interfere the public opinion direction of Americans to maximize the political division of the United States. Their more specific goal during the election was to undermine Clinton and promote Trump. Whenever negative information about Hillary and the Democratic Party is exposed, these malicious accounts reacted rapidly and tried hard to guide the online public opinion to attack Clinton and elevate Trump through pictures, video and extremely provocative language. Although we cannot find a direct relationship between the trend of the Poll rating and the trend of these tweets, these tweets played a crucial role in facilitating the dissemination of information with obvious directivity, that is, Trump is good and Hillary is not. This could subconsciously change Americans' voting preferences. The real determinants of the election were the events and news that went against Clinton, some of which came from the attacking by Russian intelligence operations. These attacks may be the core of Russian interference in the U.S. election which called "Grizzly Steppe”.

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