Political Propaganda on Facebook

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Introduction

The 2016 election marked the first time a foreign nation was suspected of tampering with and influencing US citizens through Social Media. Our dataset pertains directly to this issue, all of these ads are sourced by the cryptic Internet Research Agency (IRA), a Moscow-backed group that sought to sow discontent and misinformation during the presidential election. This “click” or “troll” farm focused on Facebook political advertisements to spread Kremlin-backed propaganda. Over 11 million American Facebook users were targeted as a result of the ads with over 80,000 separate pieces of created by the IRA. This dataset contains all of the Facebook Ads along with many other fields like who were they targeting, where, their creation time and date, ad text, and how many people it reached. With this information we set out to answer four questions that we believe will statistically prove that not only was there Russian meddling in the 2016 election but that it was directed to specific groups. These questions are “Do Facebook advertisement creation times coincide with elections?” which will establish a probable warrant to investigate this information. From that we will consider “Have entities outside the US supported the creation of these advertisements?” which will allow us to show a strange pattern of anomalies regarding the ads creation time and the currency used. Then we will look at “Which groups are being targeted by these advertisements?” which we can show that because of existence of certain phrases we can establish that these ads were targeted to a specific group under the pretext of a specific message. Finally, we will dive deeper into the question of targeting highlighting “Which political ideology are the advertisements meant to support?” which we will look at using different sentiment classifiers if the ads support conservatives or liberals. With all this information we will be able to conclude with our analysis that the IRA produced targeted advertisements to the US in order to sow discontent and influence the 2016 US Presidential Election.

Do Facebook advertisement creation times coincide with elections?

Approach & Methodology

We approached this problem by focusing on the `CreationDate` feature of the `FacebookAds.csv` file. The `CreationDate` had entries in the form "`MM/DD/YY HH:MM:SS AM TZ`". We wanted to see the general pattern for when the advertisements were created by month for each year, so we split the data into three separate dataframes for 2015, 2016, and 2017 advertisements. After this, we added a column to the dataframes that recorded the month of the creation date. Then, we were able to make a bar plot of the number of advertisements posted each month for each year, which can be seen below in Figures 1.1 and 1.2. We then looked at a timeline of the 2016 United States presidential election and looked for any significant events that correlated with the spikes in advertisement creation.

After finding a trend, we wanted to further prove it with a statistical learning method. At first, we attempted to use regression, but the results weren't very useful. We then realized that using clustering would be a much better approach as if there is a correlation with important election dates, all of the dates would be contained in a cluster. Rather than using months for clustering, we decided to split the data into days, as doing so would give us more data to look at and would provide more accurate results. This step was a little trickier, as the `CreationDate` entries weren't stored as unambiguous timestamps. Using the `lubridate` library to convert all of the `CreationDate` entries to PST and an unambiguous format. We then used the `lubridate` library's `yday()` function to get which day out of the year an advertisement was created. Before clustering, we used `fviz_nbclust()` from the `factoextra` library to determine the number of clusters to use for each year's plot. The plots were created using `factoextra`'s `fviz_cluster()` function and can be seen in Figure 2.1 below. In order to see which days were represented by which points we had to manually look through the unscaled data and check the dates for the corresponding points.

Conclusion

We believe that the creation times of Facebook advertisements do indeed coincide with the elections and important dates in the election timeline.

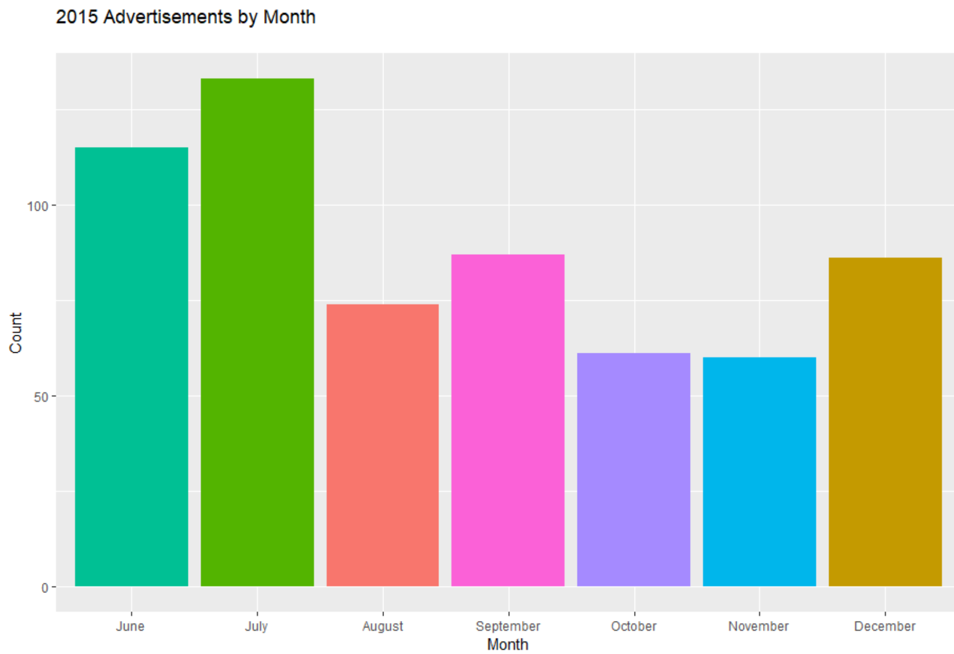


Figure 1.1: Bar graph showing the number of advertisements posted each month in 2015

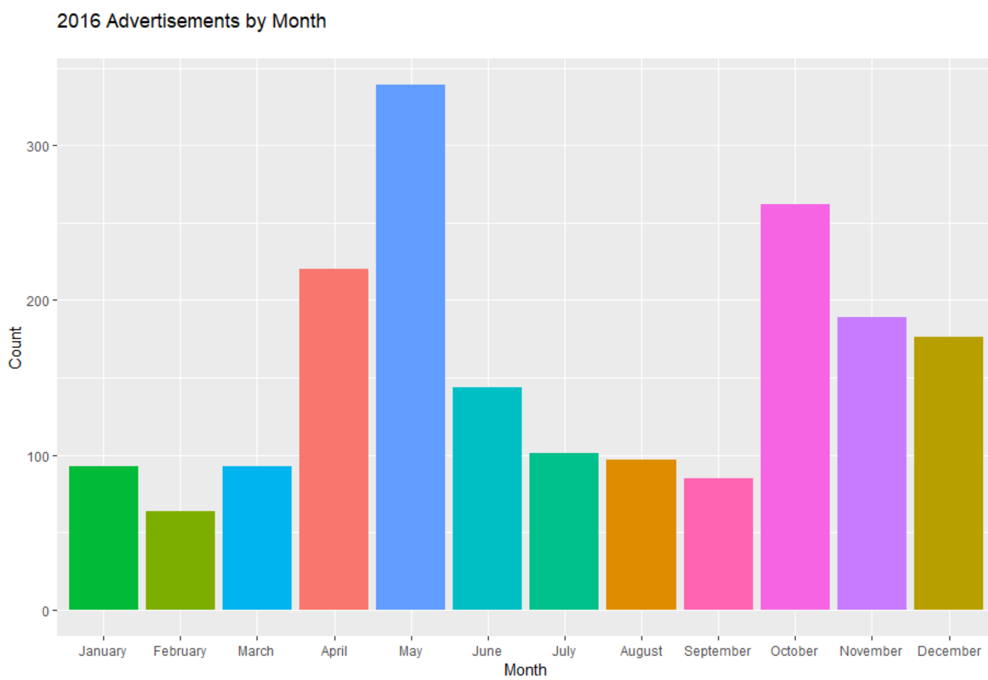


Figure 1.2: Bar graph showing the number of advertisements posted each month in 2016

As can be seen in Figure 1.1 above, there the first advertisements are posted in June of 2015, around the time when presidential campaigns begin to launch, specifically Trump's campaign, which was on June 16. The next large spike is in April and May of 2016, around the time when Trump becomes the main Republican candidate on May 3. The last spike is in October, right before the second round of presidential debates. The influx of advertisements created continued through November and election day. This shows enough correlation for us to justify diving deeper.

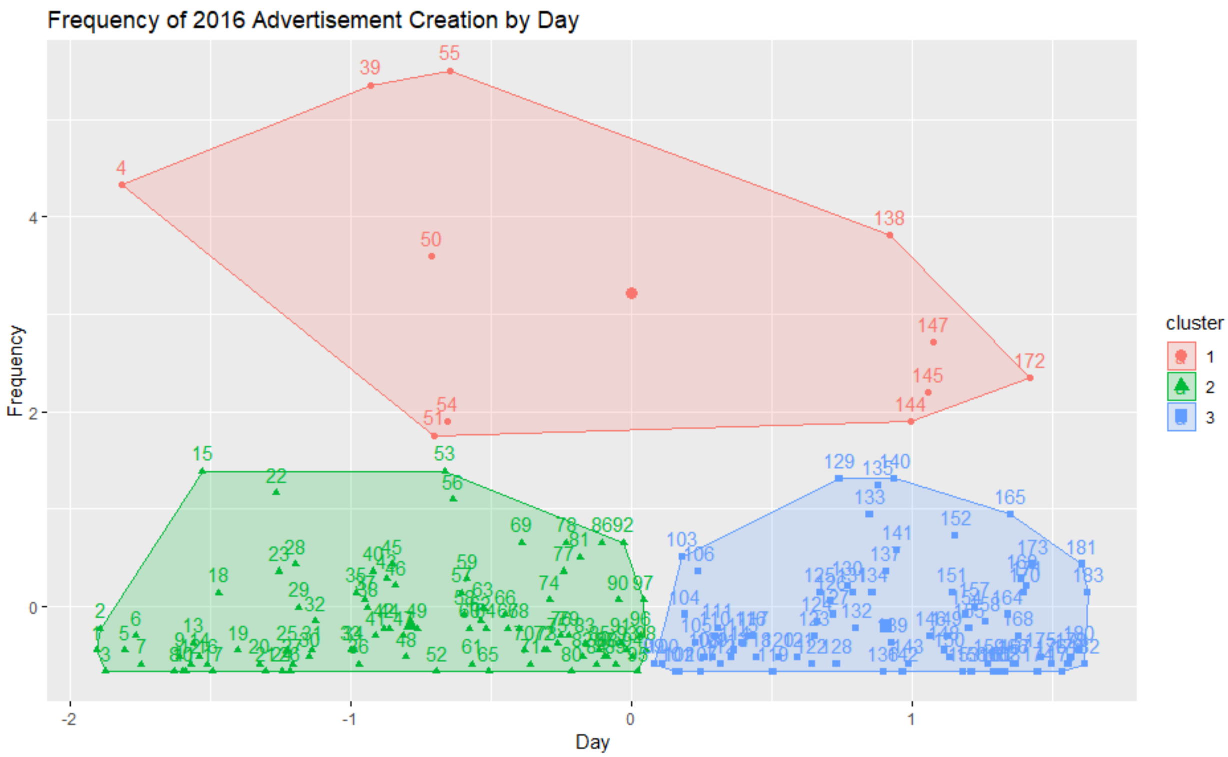


Figure 2.1: Cluster plot of the number of advertisements posted by day in 2016

As seen in Figure 2.1 above, cluster 1 contains all of the days with a higher frequency of advertisements posted. Each day in cluster 1 is just before important events in the election timeline. It is important to point out that the number for each point is not directly correlated with that day of the year, as advertisements were not posted every day. First we start with point 4, which is January 14, right before the sixth Republican debate. This debate ended up being an important debate where Trump targeted Cruz for being born in Canada. Next, on April 13 (point 39) there is a spike right before primaries start. After this we have a group of spikes in May 5, 6, 11, and 12 (points 50, 51, 54, 55). The first group is the day after John Kasich withdraws his candidacy, making lots of headlines. The second group is right in the middle of the primaries. It is worth noting that there are a decent amount of advertisements posted throughout the primaries as well, but not enough to make it into this cluster. We don't have another spike until October 18 (point 138), which is right before the final presidential debate. There are a decent amount of advertisements posted before and after this event as well, but once again, not enough to make it into the cluster. After this, there is a spike on October 26 (point 144), which is right at the beginning of the ramp up of the Hillary email scandal news. There is a group of spikes on November 1 and 3 (points 306 and 308) which correlate to the news of more emails being discovered as well as the ramp up to election day. The last spike we see is on December 8 (point 343) which is right before the electoral college meets to vote. This last point may seem odd, as the majority of people have done all they can do in terms of voting, but there were 7 unfaithful voters in the electoral college during this election, which is the greatest number in history.

We believe this provides enough evidence that the advertisements created during this time period relate to the presidential election and important events throughout the election process.

Have entities outside the US supported the creation of these advertisements?

Approach & Methodology

To determine if an outside entity supported these advertisements, there are two subsets of data that can be used to answer this question. The first useful subset of data is the currency used to purchase an ad placement. The second is the time of day the ad was created. Analysing both should yield an idea about where these ads came from. Looking at currency is a reasonable place to start our analysis.

Table 1

Number of advertisement purchases by currency

USD	RUB	*NA*
4	2534	*978*

With this table we can see only four ads were purchased using US currency. An overwhelming 2,534 ads were purchased using the Russian Rouble. However, almost 1,000 ads did not have a purchase currency listed. Thus, while almost two-thirds of the ads being purchased with Russian currency is quite convincing, the fact that roughly one-third of the data is missing means our analysis of the currency by itself is inconclusive. To remedy this, an investigation of the time of day the ads were created is needed.

To analyse the time of day, two things should be considered. The first is when the ads were created in the US, and the second is when the ads were created somewhere else, ideally where they originated. Since the majority of ads were purchased with Russian currency, a reasonable place to start is with the time in Russia. For the analysis, Moscow Time (MSK) will be will be compared to the time the data was recorded, Pacific Daylight Time. Plotting PDT vs MSK yields the following graph:

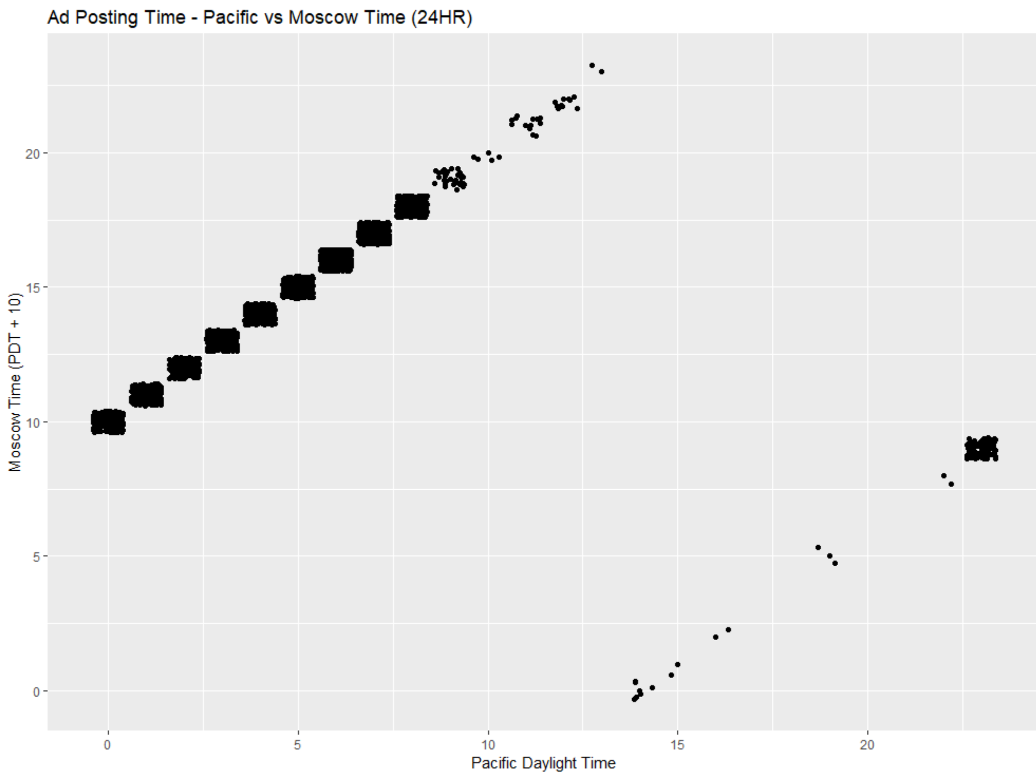


Figure 3: Cluster plot of PDT vs MSK Creation Times for IRA Facebook Ads

From this plot, it can be observed that an overwhelming majority of ads were posted between 9AM MSK and 7PM MSK. The posting time of these ads roughly coincides with what one might expect from a typical Russian workday. Just as important, the same ads were posted between 11PM PDT and 8AM PDT. If we create a table of ads created during Russian work hours (using 9AM to 7PM) vs off-hours, the following is produced:

Table 2

Number of ads created during Russian work hours (using 9AM to 7PM) vs off-hours

Off-Hours	Work Hours
37	3479

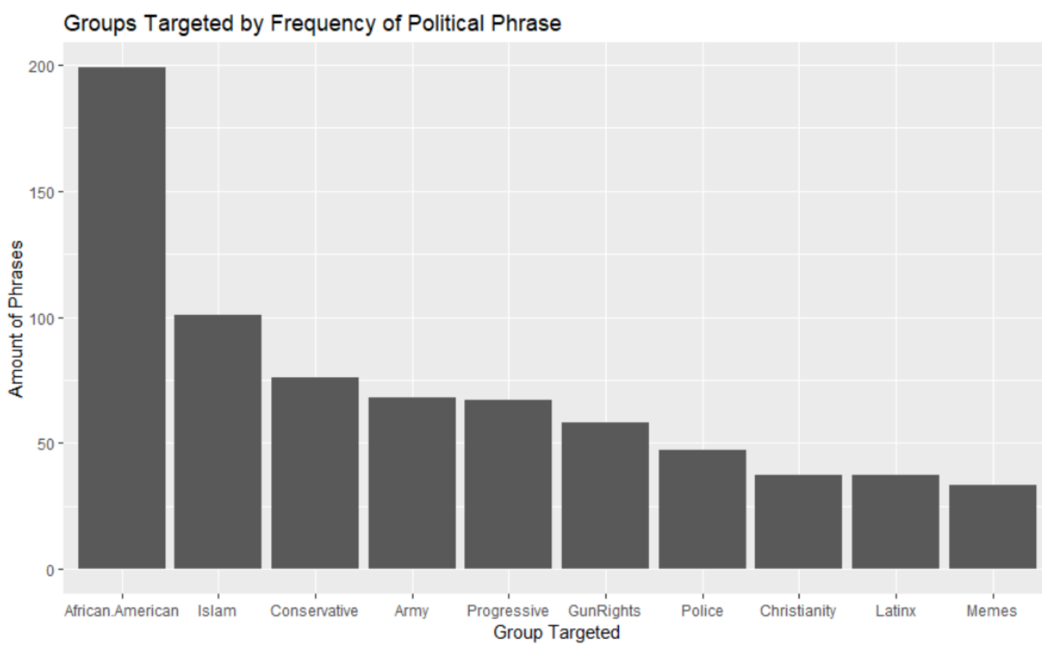
Conclusion

Since more than two-thirds of ads were listed as purchased with Roubles, and roughly 98.9% of ads were created during the Russian work day, we can conclude that not only did ads not originate from within the US, but likely came from Russia.

Which groups are being targeted by these advertisements?

Approach & Methodology

Along with the advertisement csv file we were provided from Kaggle, we also had a csv file called `interests_annotated_final.csv` that contained phrases used in Facebook advertisements that targeted different groups or ideologies. Using this csv file, we calculated the number of phrases targeting each group or ideology. This was accomplished by accessing the data items for each group and counting the number of rows. The number of rows for each of the groups in `interests_annotated_final.csv` was stored into a dataframe called `counts` so that each column would be the number of phrases that targeted each group. The `counts` dataframe was then rotated and its one column was renamed to Number of Phrases. In order to easily comprehend a visualization of the `counts` dataframe, we ordered the dataframe by the number of phrases for each group in descending order and only visualized the top 10 counts. This was stored in to another dataframe called `CountsTop10`. Lastly, we visualized the number



of phrases for the top 10 groups with a bar chart using ggplot as seen in Figure 4.1.

Figure 4: Bar graph showing the amount of phrases targeting different groups

By looking at this bar graph, we can clearly see that African Americans were targeted more by the phrases used in the IRA's Facebook advertisements. Furthermore, other major groups that were targeted in descending order are Islam, Conservatives, Army, and Progressive.

Conclusion

To truly prove that all these groups were not being evenly targeted, a suitable statistical test for significance in this situation would be the Chi-square Goodness-of-fit. After conducting the test using the dataframe called `CountsTop10`, the p-value that we got was < 2.2e-16. The observed frequencies are significantly different from the expected frequencies. Therefore, each group is not being equally targeted by IRA's Facebook advertisements.

A test that can be more compelling would be developing a probability model where we test the amount of phrases targeting African American is some number of times greater than the number of phrases targeting the other 9 groups. In other words, we are fitting a probability model to frequency data. This can be done by doing a Chi-square Goodness-of-fit to test the amount of phrases targeting African is double and triple the others. The `chisq.test` function has a parameter called p where a column vector can be passed that assigns a probability to each row and they must add up to 1. The results we got for African American targeted phrases being two or three times greater than the other 9 groups were p-values of 6.326e-15 for and 6.956e-12. Because the p-value's are less than the significance level of 0.05, we reject the null hypothesis and state that African Americans are at least being three times more targeted by these phrases compared to the other targeted groups based on IRA's Facebook advertisements.

Which candidate, group, or ideology are the advertisements meant to support?

Approach & Methodology

The first thing we wanted to do was get some exploratory information. We wanted to see how many of the ads were targeted towards liberals and conservatives. In order to do this we utilized the indico api to categorize the ad contents into either conservative or liberal by giving it a political sentiment score. As you can see in Figure 5, liberals were targeted more frequently in our sample set.

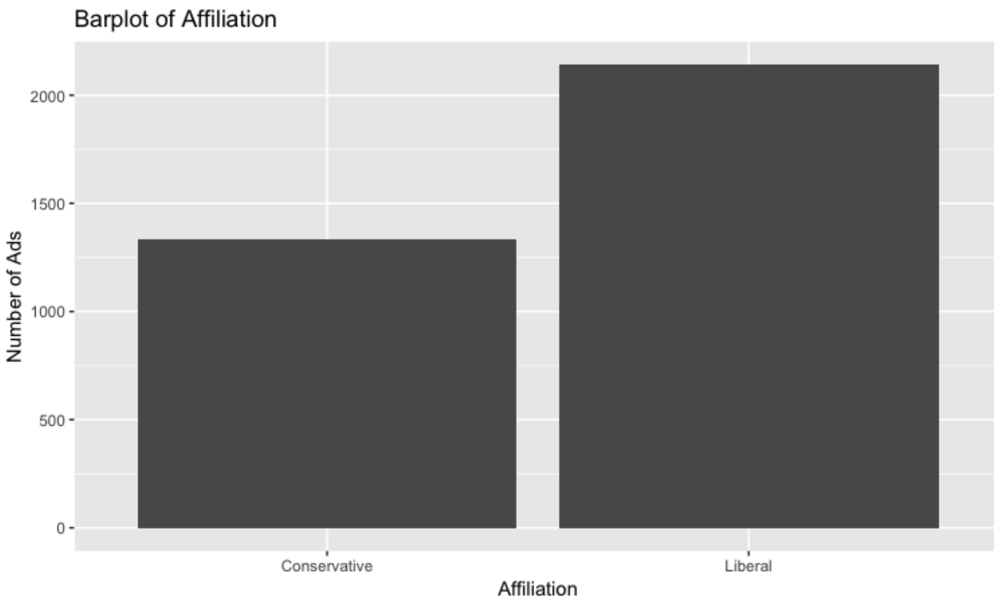


Figure 5: Bar graph showing the amount of ads targeting liberals or conservatives

We then wanted to go further and see how these scores actually looked when graphed on a scatter plot. You can see in Figure 6 that while there were a few ads that were heavily targeted at a particular affiliation most of the ads were fairly moderate. You can see this in the cluster that is circled in red.

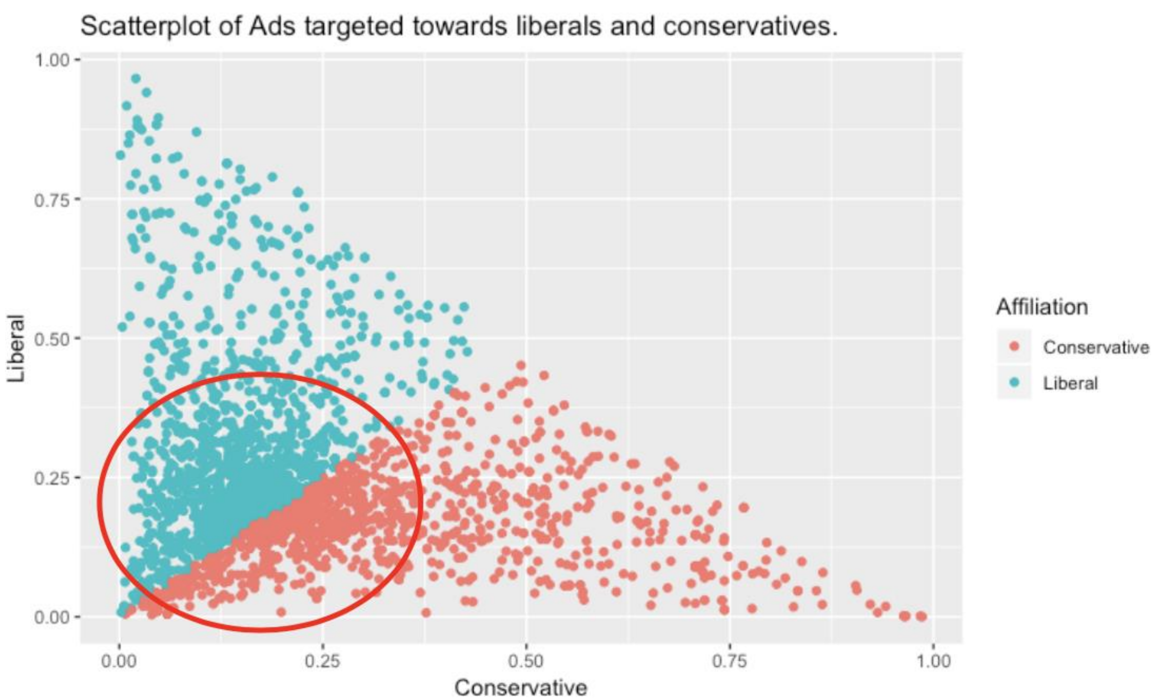


Figure 6: Scatter plot showing the political scores plotted against each other

Finally we wanted to see what some of the keywords were for both conservatives and liberals. To tackle this questions, we created a conservative and liberal subset and created a word-cloud of both datasets. After looking at the word-clouds below, it explains why there is such a large grouping in the middle, both affiliations seem to be talking about a lot of the same issues.

Figure 7: Liberal dataset word cloud

Figure 8: Conservative dataset word cloud

Conclusion

We can see that while ads are targeted more towards liberals, the majority of the ads are more moderate than extremely skewed to one side. After looking at the wordcloud, this makes sense because most of the keywords are either the same or related.

Which political ideology are the advertisements meant to support?

Approach & Methodology

Ideally, we want to know how Russia targeted specific political ideologies when advertising on Facebook during the time leading up to the election. We approached this problem by focusing on the AdText and PeopleWhoMatch features in the FacebookAds.csv file. The AdText feature consisted of advertisements by Russia during election time which were typically 40-120 words long. Each of these advertisements were connected to a political ideology in the PeopleWhoMatch feature. There were 17 different political ideologies an AdText could be classified as. A few examples of these political ideologies include “Being Patriotic”, “LGBT United”, “Don’t Shoot” amongst others. We wanted to create our own classification algorithm that would predict which of the 17 political groups a specific advertisement fell under. We decided the best way to do this was through a Naive Bayes classification algorithm for the Adtext, using each of the 17 political ideologies as classes. The Naive Bayes algorithm learns the probability of an object with certain features belonging to a particular class. It will ultimately classify Adtext based on probability and Bayesian statistics.

When coding the algorithm, our first step was to clean the advertisement text data so we can optimize the algorithm’s performance. This ultimately yielded a data set with the political ideologies associated with each Adtext. The next step was to randomize this data set so there wouldn’t be any unwarranted biases. Next, a corpus was created to clean the data even further by transforming it to lowercase, removing punctuation, removing numbers, removing stop words, and stripping any whitespace in the text. A document term matrix was generated so the Naive Bayes classification could be implemented. 75% of the data was used as training data, and 25% of the data was used as testing data.

Conclusion

The Naive Bayes classification algorithm was a good model for this data. It had a classification accuracy of 70.47%. The model yielded a Kappa statistic of .572. A Kappa statistic compares observed accuracy with an expected accuracy due to random chance. .572 can be interpreted as moderate to good agreement. If we were given a Russian advertisement, we are very confident we would be able to classify it into the correct political ideology with a classification accuracy of 70.47%.

Conclusion

Throughout our report we have sought out to understand the breadth and depth of the Russian interference in the 2016 Presidential Election through each of our four questions. Firstly, we wanted to establish through analysis of the Facebook creation times of the ads were significant in some sort of way, through a time series plot along with clustering. Through this, we were able to tie each of the clusters to events like the Presidential Debates, Presidential Primaries, or even the General Election. Each of these provided statistical and empirical reasons to dive deeper into the data. Next we wondered what factors could we use to statistically show that an entity outside of the United States sought to sow political influence. In order to do this we carried out categorical analysis with an assumption that social media ads are usually posted at peak times (3-5pm), however we saw by and large that most of the ads were posted extremely outside of that range and usually when regular Americans would be asleep. This coupled with the realization that most of the ads fall within normal Moscow time business hours gives us evidence that the IRA actively created and posted ads that targeted the US. From this point after establishing that relationship we wanted to ask who are the IRA targeting? We were able to conclude that the IRA disproportionately targeted African Americans as either being the target of the adtext or the recipient which was interesting as issues revolving African Americans were a very hotly debated topic during the 2016 Presidential Election. Finally, after seeing these results, we wanted to then see which political agenda or ideology it was meant to support, so in order to do this we used a the Indico.co Political Sentiment API to categorize the Adtext then trained a Naive Bayes Text Classifier model to classify whether or not an ad was targeted towards Liberal or Conservative ideologies, we then plotted the decision boundary which along with the bar chart shows that the primary ideology targeted was Liberal. Overall, we were able to conclude that an outside entity, specifically we believe to be the IRA, was responsible for posting the Ads that disproportionately targeted African Americans and primarily focused on Liberal Ideologies as the content of their ads.

Appendix A: Figures

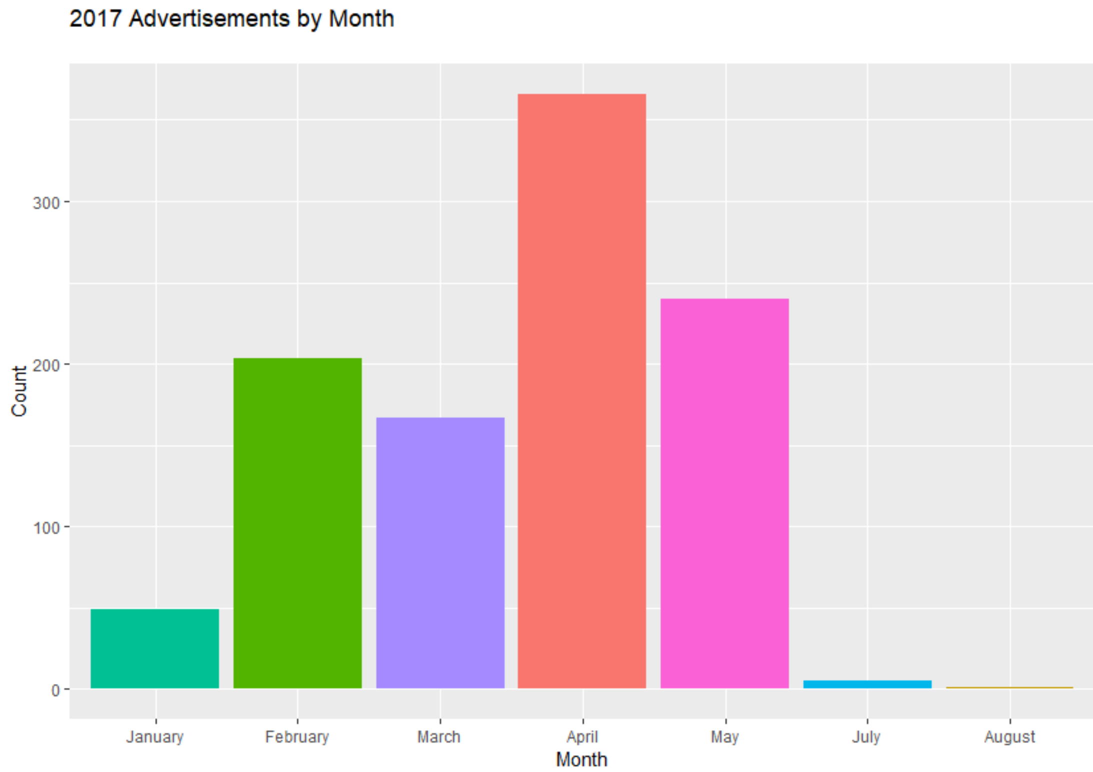


Figure 1.3: Bar graph showing the number of advertisements posted each month in 2017

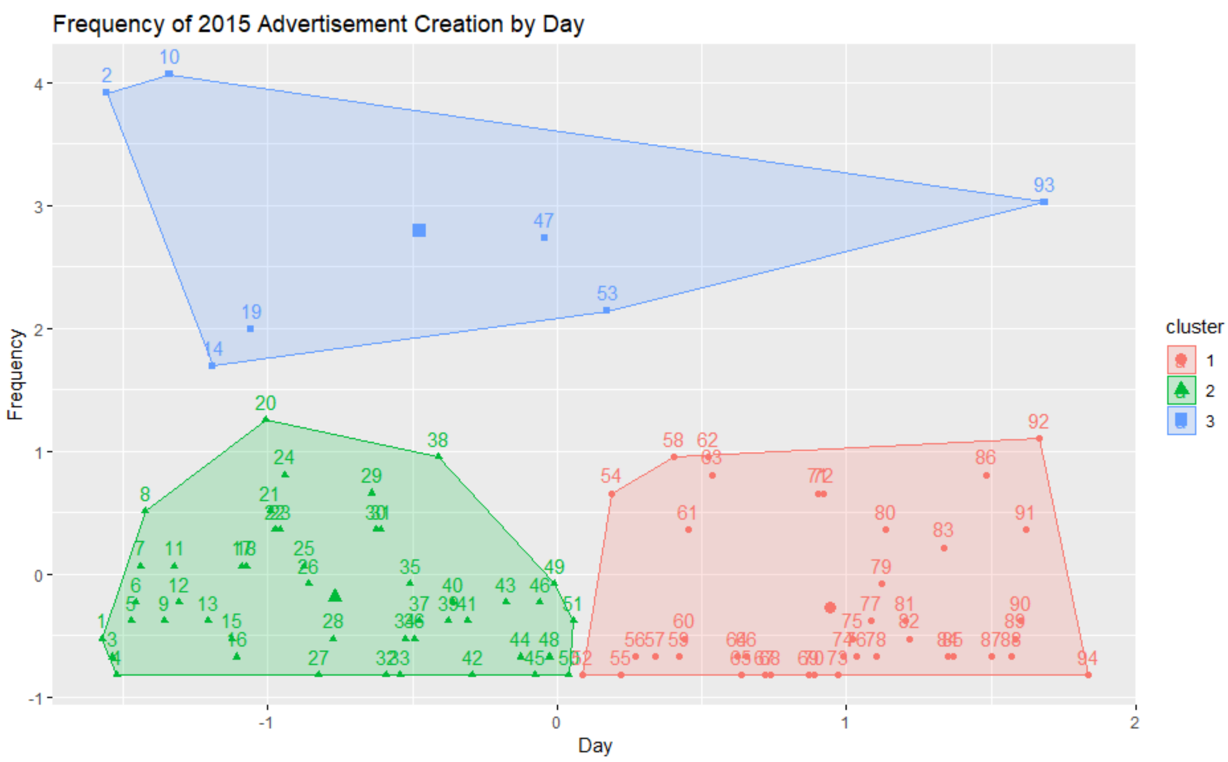


Figure 2.2: Cluster plot of the number of advertisements posted by day in 2015

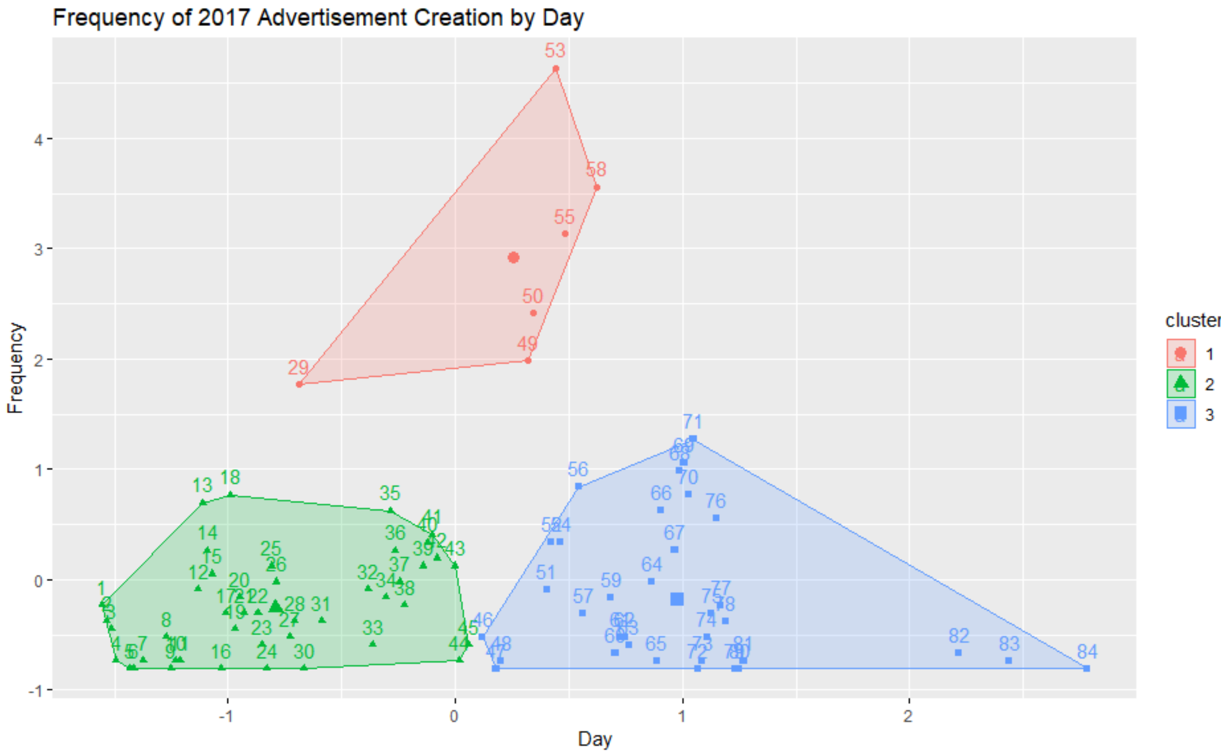


Figure 2.3: Cluster plot of the number of advertisements posted by day in 2017

Figure 3.1: Word Cloud for the 17 possible political ideologies

Figure 3.2: Word Cloud of the Adtext for Political Ideology

```
  Williams&Kalvin                                0                0

$overall
      Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull AccuracyPValue  McnemarPValue
  7.047619e-01   5.720484e-01   6.078174e-01   7.897966e-01   4.190476e-01   3.059864e-09            NaN

$byClass
                              Sensitivity Specificity Pos Pred Value Neg Pred Value Precision    Recall        F1 Prevalence
Class: Being Patriotic          0.5714286   0.9670330      0.7272727      0.9361702 0.7272727 0.5714286 0.6400000 0.13333333
Class: Black Matters            0.9318182   0.6393443      0.6507937      0.9285714 0.6507937 0.9318182 0.7663551 0.41904762
Class: Blacktivist              0.0000000   1.0000000            NaN      0.9809524        NA 0.0000000        NA 0.01904762
Class: BM                              NA   1.0000000             NA             NA        NA        NA        NA 0.00000000
Class: Born Liberal             0.0000000   1.0000000            NaN      0.9809524        NA 0.0000000        NA 0.01904762
Class: Don't Shoot              0.8666667   0.9555556      0.7647059      0.9772727 0.7647059 0.8666667 0.8125000 0.14285714
Class: Employers                       NA   1.0000000             NA             NA        NA        NA        NA 0.00000000
Class: Field of study           0.0000000   1.0000000            NaN      0.9904762        NA 0.0000000        NA 0.00952381
Class: Heart of Texas           0.0000000   1.0000000            NaN      0.9904762        NA 0.0000000        NA 0.00952381
Class: Industry                        NA   1.0000000             NA             NA        NA        NA        NA 0.00000000
Class: LGBT United              0.7058824   0.9772727      0.8571429      0.9450549 0.8571429 0.7058824 0.7741935 0.16190476
Class: Memopolis                0.0000000   1.0000000            NaN      0.9904762        NA 0.0000000        NA 0.00952381
Class: Multicultural Affinity   0.0000000   1.0000000            NaN      0.9809524        NA 0.0000000        NA 0.01904762
Class: Secured Borders          0.0000000   1.0000000            NaN      0.9904762        NA 0.0000000        NA 0.00952381
Class: Stop AI                  0.0000000   1.0000000            NaN      0.9904762        NA 0.0000000        NA 0.00952381
Class: United Muslims of America 0.0000000  1.0000000            NaN      0.9809524        NA 0.0000000        NA 0.01904762
Class: Williams&Kalvin          0.0000000   1.0000000            NaN      0.9809524        NA 0.0000000        NA 0.01904762
                              Detection Rate Detection Prevalence Balanced Accuracy
Class: Being Patriotic            0.07619048            0.1047619         0.7692308
Class: Black Matters              0.39047619            0.6000000         0.7855812
Class: Blacktivist                0.00000000            0.0000000         0.5000000
Class: BM                         0.00000000            0.0000000                NA
Class: Born Liberal               0.00000000            0.0000000         0.5000000
Class: Don't Shoot                0.12380952            0.1619048         0.9111111
Class: Employers                  0.00000000            0.0000000                NA
Class: Field of study             0.00000000            0.0000000         0.5000000
Class: Heart of Texas             0.00000000            0.0000000         0.5000000
Class: Industry                   0.00000000            0.0000000                NA
Class: LGBT United                0.11428571            0.1333333         0.8415775
Class: Memopolis                  0.00000000            0.0000000         0.5000000
Class: Multicultural Affinity     0.00000000            0.0000000         0.5000000
Class: Secured Borders            0.00000000            0.0000000         0.5000000
Class: Stop AI                    0.00000000            0.0000000         0.5000000
Class: United Muslims of America  0.00000000            0.0000000         0.5000000
Class: Williams&Kalvin            0.00000000            0.0000000         0.5000000
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Figure 3.3: Naive Bayes Classification Output for the 17 political ideologies

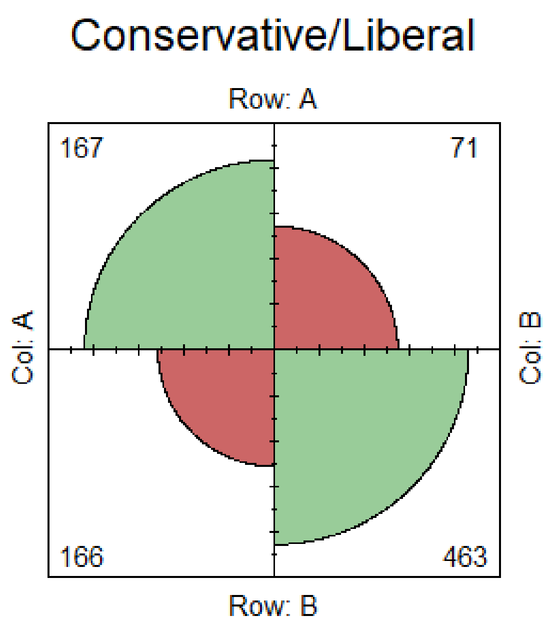

Figure 3.3: Naive Bayes Classification Output for Conservative/ Liberal

Appendix B: R Scripts

Do Facebook advertisement creation times coincide with elections?

https://drive.google.com/open?id=14SYEj-GOLls2fxUnCy3MdZCUf-4JqPCj

Have entities outside the US supported the creation of these advertisements?

https://drive.google.com/open?id=14SYEj-GOLls2fxUnCy3MdZCUf-4JqPCj

Which groups are being targeted by these advertisements?

https://drive.google.com/open?id=14SYEj-GOLls2fxUnCy3MdZCUf-4JqPCj

Which candidate, group, or ideology are the advertisements meant to support?

https://drive.google.com/open?id=14SYEj-GOLls2fxUnCy3MdZCUf-4JqPCj

Which political ideology are the advertisements meant to support?

https://drive.google.com/open?id=14SYEj-GOLls2fxUnCy3MdZCUf-4JqPCj