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Content Analysis of Russian Trolls' Tweets Circa the 2016 United States Presidential Election

Introduction

In the past decade, Twitter has steadily grown as an important resource that allows ordinary citizens to "follow" the thoughts and opinions of journalists, newspapers, celebrities, politicians, and even the current President of the United States. The most recent Pew Center Research report of Social Media Use in 2018 found that 24% of the U.S. population now uses Twitter (Smith and Anderson, 2018). As a digital forum that allows users to "like" and "retweet" individual posts, the website has helped spawn the proliferation of salient hashtag movements that have entered the public consciousness. From issues diverse as economic inequality in the Occupy Wall Street movement, racial injustice and law enforcement behavior in the Black Lives Matter movement, as well as calls to overthrow long-standing dictatorships in the Arab Spring movement, Twitter is a powerful tool that individuals can use to communicate, coordinate, and spread their thoughts to other users of the platform (Conover, et al., 2013; Anderson and Hitlin, 2016; Kassim, 2012).

However, the power of social media—and Twitter in particular—has not gone unnoticed by nefarious actors that are working to spread disinformation and sow discord in the American public. For instance, as of February 2018, Twitter has contacted more than one million users to inform them that they directly engaged with tweets from known Russian propaganda bots during the 2016 presidential election (Kirby, 2018). At a Senate Intelligence Committee hearing on February 13th, 2018, U.S. Director of National Intelligence Dan Coats was quoted as saying, "We expect Russia to continue using propaganda, social media, false-flag personas, sympathetic spokespeople and other means of influence to try to exacerbate social and political fissures in the United States" (Rosenberg, et al., 2018).

In February of 2018, NBC News released a database of approximately 200,000 tweets from the Internet Research Agency, which is a “Kremlin-linked propaganda outfit” (Popken, 2018). Hereafter, the Internet Research Agency will be shortened to its IRA acronym. The database of IRA-affiliated tweets expanded dramatically with the release of a dataset from Clemson professors Darren Linvall and Patrick Warren. The Clemson-based researchers collected almost 3 million tweets from 2012 to May 2018 by known Russian trolls (Roeder, 2018), and “identified five handle categories: *right troll*, *left troll, news feed, hashtag gamer*, and *fearmonger*.”

My research uses the NBC News published dataset of 200,000 tweets, with the tweets categorized based on race/ethnicity, sex, and religion. Analyzing the content of the tweet dataset revealed categories of identity that were tweeted about more frequently than other identities, troll tactics for spreading messages, the most retweeted messages and the accounts with the broadest messaging reach, and the preference for either the Democratic or Republican presidential candidate based on characteristics like identity, occupation, location, and personalistic qualities.

Literature

The Robert Mueller led indictments of IRA operatives explain in detail the processes and functions of the IRA. It’s clear from the research done by both Linvall and Warren (2018) and the description of IRA structure and functions in the IRA indictments that the IRA had broad directives and used sophisticated methods to realize their agenda. A report published by the independent Russian media station Novaya Gazeta in September 2013 provides an in-depth look at the early formation and agenda of the IRA. Alexandra Garmazhapova—a correspondent for Novaya Gazeta—went undercover and was interviewed by the IRA for a job, and she reported her experiences for the paper (Garmazhapova, 2013).

The interviewer for the IRA explained that the job was based on the “Yandex-Market” principle. The "Yandex-Market" is an online store that explains the best places to buy products based on price, and it allows users to post reviews of the products (Garmazhapova, 2013). The interviewer explained what the function of the IRA was for when he stated, “We need to increase the attendance of the site. This can be done by robots, but robots do their work mechanically, and sometimes a system like "Yandex" bans them. Therefore, it was decided to do it by people. Write a comment from yourself with the vector indicated by us. For example, about the G-20, you can write that it is very honorable for Russia" (Garmazhapova, 2013). The reporting done by Alexandra Garmazhapova reveals how the IRA started as a digital propaganda project, one that was intended to promote pro-Kremlin figures and denigrate any person that was a threat to the Putin regime. Linvill and Warren (2018) note the industrial structure of the agency, which is given further credence by details included in the February 2018 indictment issued against several IRA affiliated individuals (United States of America v. Internet Research Agency LLC).

In the context of Twitter, the means by which false information spreads gives insights into the potential effectiveness of the IRA led propaganda and misinformation campaign around the 2016 presidential election. For instance, Vosoughi et al. (2018) studied the diffusion of both verified false and true news stories on Twitter, and the researchers found that false political news tends to travel deeper, faster, and more broadly than both any other type of false information or true news stories. Furthermore, the researchers noted that "The spread of falsehood was aided by its virality, meaning that falsehood did not simply spread through broadcast dynamics but rather through peer-to-peer diffusion characterized by a viral branching process," noting that the novelty and information uniqueness of false information has explanatory power for why false rumors tend to diffuse differently than the truth (Vosoughni, et al., 2018). Shin et al. (2017) studied political rumoring on Twitter during the 2012 presidential election and found that "rumors were mainly shared with the spreader's own followers rather than interest-oriented publics organized around hashtags," and that the "rumors were relatively resilient to debunking and continued to propagate despite the emergence of countervailing information." In the context of the 2016 presidential election and the IRA tweets, the *Troll Tactics* and *Most Retweeted* sections highlight the heightened emotional tweet content sent out by the trolls and the effectiveness of these tactics in garnering retweets.

Data Analysis

To understand the political motivations of those hired by the Internet Research Agency in relation to the 2016 presidential election, I used the qualitative analysis software *QDA Miner* to analyze more than 203,451 tweets from confirmed IRA-affiliated Twitter accounts. I also used the quantitative analysis software *WordStat* to discover co-occurrences between words or phrases within the dataset. This dataset is taken from the work done by "three sources familiar with Twitter's data systems [who] cross-referenced the list of [IRA account] names released by Congress, excluding any account that Twitter later restored." (Popken, 2018). The tweets in the dataset are taken from the period between 2014 through late 2017.

Methods

1a.) *Identity Category Counts*

Categories were created in the software to code for identities based on superficial and limited identity-related keywords. The categories were created based on race, sexual orientation, sex, and religion. The categorical identities that were coded for "Racial/Ethnic Identity" include: *White*, *Native American*, *Asian*, *Mexican*, *Hispanic/Latino,* and *Black.* The categorical identities that were coded for "Sexual Orientation Identity" include: *LGBT General*, *Bisexual*, *Homosexual*, *Heterosexual*. The categorical identities that were coded for "Sex" include: Male, Female. The categorical identities that were coded for "Religious Identity" include: *Muslim*, *Christian*, and *Jew*. Accounting for total count of keywords discovered in the categories, *Black Identity, Muslim Identity,* and *Female Identity* were chosen as the primary identities to analyze.

1b.) *Three Categories from Race, Sex, and Religion*

I calculated the ideal sample size with a confidence level of 95% and a margin of error +/- 5% for the tweet identities with the most keyword hits in relation to "Racial/Ethnic Identity," "Sex Identity," and "Religious Identity." I analyzed the tweet content of these categories and further subdivided them into categories relating to support of, or opposition to, the Republican or Democratic presidential candidate. A further category included tweets that included both support of one candidate and opposition of another candidate.

2.) *Troll tactics*

The trolls use many different methods to spread their message, including: tweeting to the Twitter-based television show @midnight, focusing on emotionally charged issues like rape and murder, using different accounts to send the same tweet, and sending out the same tweet with minor variations over time. Examples of each are shown in the *Results* section.

3.) ***Most Retweeted***

This research question of most retweeted tweets focused on tweets made by trolls that were retweeted at least 1000 times. The tweets were taken by filtering tweets that garnered over 1000 retweets, and this was narrowed further to a list of the accounts with the greatest number of retweets. This type of retweet analysis highlights the most prolific and unique troll messages that found the greatest audience. At least 467,000 unique retweets resulted from the parameters defined above.

4.) ***Candidate Preferences***

The *Candidate Preferences* category focuses on explicit support for either the Democratic or Republican presidential candidate based on searching the dataset for the keywords “4Trump,” “forTrump,” “forHillary,” and “4Hillary.”

Results

1a.) ***Categories and Counts of Identity***

Categories for identities were derived from reading the tweets and developing keywords for each identity. The categorical counts of tweets containing at least one keyword for the category give an indication of which groups the trolls were intending to target in order to spread their message and agenda. The qualitative identity types with the most promise based on keyword hits per category were “Race/Ethnic Identity,” “Religious Identity,” and “Sex Identity” “Sexual Orientation Identity” was excluded from the final analysis. The total counts of keyword hits per identity reveal that African-Americans, Muslims, and females were the identities with the greatest number of results. I attempted to manually remove any keyword codes that contained words that weren’t explicitly tied to identity characteristics, although categorical keyword search rarely revealed a tweet that contained a keyword (e.g., “black”) that was not tied to the categorical identity defined by the keywords used for an identity. The keyword hits for each identity are listed below.

"<u>Race/Ethnic Identity</u>"

White (Caucasian): 1760	*Native-American*: 67	*Hispanic/Latinx*: 423
Black (African-American): 3770	*Mexican*: 301	*Asian*: 45

"<u>Religious Identity</u>"

Jew: 355	*Christian*: 1081	*Muslim*: 3335

"<u>Sexual Identity</u>"

Male: 3920	*Female*: 4622

1b.) <u>*Identity and Support or Opposition of a Candidate*</u>

The three identities with the largest population size were *Black Identity* (3770), *Female Identity* (4662), and *Muslim Identity* (3335). I calculated the ideal sample size for each with a margin of error +/-5% and a confidence level of 95%. I manually went through all the tweets in the sample size and developed a coding system[1] for tweets that explicitly mentioned the Republican or Democratic presidential candidate and an identity in the same tweet, with the same tweet either positively or negatively reflecting an opinion about the candidate. I took special care to be as diligent and restrictive with my selections as possible. For instance, if a tweet didn't mention the candidate explicitly by name or include information that would make it beyond a reasonable doubt as to who the reference was about, it was excluded and put in the *Other* category. Tweets

[1] Terms for the coding system: "P" refers to positive support for a candidate; "A" refers to anti or negative references to a candidate; "t" refers to the candidate Donald Trump; "h" refers to the candidate Hillary Clinton; "(Ph′ ∩ At′)" refers to the intersection of a tweet containing both pro-Hillary and anti-Trump sentiments that are not included in the "Pt" or "At" counts, and vice-versa for "(Pt′ ∩ Ah′)"; "Other" refers to excluded tweets; "Total (T)" refers to the total number of tweets analyzed for the identity.

that may have been ambiguous, ironic, or lacked a definitive position about the candidate and his or her relationship to an identity were excluded. Categorizing intent based exclusively on text lacks the cues that come from interpersonal exchange in physical spaces, so I categorized this subdivision of identity and candidate mentions in a tweet in the narrowest means. The total counts are listed below.

Black Identity

Trump:	Pt: 40	At: 8	$Pt' \cap Ah'$: 11	Other: 298
Hillary:	Ph: 0	Ah: 22	$Ph' \cap At'$: 0	Total (T): 379

The value of the equations below shows the overall support or disapproval of a candidate in relation to the *Black Identity* category, with a positive result showing positive support for a candidate and vice-versa. The further away the result is from 0, the greater the support or opposition to a candidate there is.

$$\text{Trump: } Pt + (Pt' \cap Ah') - At = 43$$

$$\text{Hillary: } Ph + (Ph' \cap At') - Ah = -22$$

The results show that for roughly every two tweets that indicated *Black Identity* support of Donald Trump, there is one tweet that indicated *Black Identity* opposition to Hillary Clinton. Tweets that were critical of Hillary would highlight her “super predators” remark from the 1990s as well as other actions during her husband’s presidency. Tweets that tied black identity to support of Trump almost exclusively proffered superficial support of *Black Identity* for Trump. For instance, “This black Trump supporter” and similar constructions would be used as a contextual base to support the rest of the tweet in support of Donald Trump. The base of “This [identity] Trump supporter” is a recurrent pattern across identities, with identities often being stacked to cover groups that are generally loyal voters for the Democratic Party to instead be in support of Donald Trump. It should be noted that there were no tweets that contained both *Black Identity* and explicit support for Hillary Clinton.

Taking the total counts for black identity and the candidates (Bi) divided by the total (T) counts of tweets analyzed for the category reveals the percentage of tweets about either candidate in relation to *Black Identity*:

$$(Pt + (Pt' \cap Ah') + At) + (Ph + (Ph' \cap At') + Ah) = 65$$

$$Ic/T = 21.3\%$$

This relationship between a categorical identity and candidate support or opposition was the strongest of the three categorical identities that were analyzed. In the *Black Identity* sample, political parties rarely appeared. There were no tweets that were critical of the GOP. However, there were a non-trivial number of tweets that were critical of the Democratic Party. The tweets that were critical of the Democratic Party would call it the "Democratic plantation," and similar tweets critical of the Democratic leaders of the past like Barack Obama and Bill Clinton would attack their policies that were addressed to help African-Americans in particular.

Other tweets contained a diverse range of issues tied to race, like generalities about strained African-American and Caucasian relations. Similarly, contentious relations between African-Americans and the police were heightened by accounts that would focus on the division between the social justice group Black Lives Matter and the pro-police group Blue Lives Matter. For instance, accounts that were supportive of Blue Lives Matter would retweet a right-leaning supporter account like @SheriffClarke, while those supportive of social justice issues and Black Lives Matter would retweet a left-leaning account like @DeRay or @TalibKweli. One account that pretended be interested in African-American issues was Crystal1Johnson, who also appears in the *Most Retweeted* section.

Female Identity

Trump:	Pt: 9	At: 14	$Pt' \cap Ah'$: 3	Other: 281
Hillary:	Ph: 2	Ah: 24	$Ph' \cap At'$: 1	Total: 355

The value of the equations below shows the overall support or opposition to a candidate in relation to *Female Identity*, with a positive result showing positive support and vice-versa. The further away the result is from 0, the greater the support or opposition to a candidate there is.

$$\text{Trump: } Pt + (Pt' \cap Ah') - At = -2$$

$$\text{Hillary: } Ph + (Ph' \cap At') - Ah = -21$$

There are several results for female identity that are different from the *Muslim Identity* and *Black Identity* categories that were analyzed. As the results above show, for every tweet that contained *Female Identity* and was critical of candidate Donald Trump, there were 10 tweets that were critical of Hillary Clinton. The tweets critical of Hillary Clinton and contained *Female Identity* attempted to either connect her relationship to predominantly Muslim countries that have poor records on women's right issues, or the tweets attempted to criticize her relationship to her husband and his prior indiscretions while in office. The tweets that were critical of Trump and his relationship to *Female Identity* were primarily retweets of other accounts. However, it's important to note that instead of attempting to create the perception of Donald Trump as a vanguard for women's rights, these accounts attempted to attack Hillary Clinton by her association to other groups or individuals.

Taking the total of counts for each identity and candidate (Ic), divided by the total (T) counts of tweets, shows the percentage of tweets about either candidate in relation to an identity:

$$(Pt + (Pt' \cap Ah') + At) + (Ph + (Ph' \cap At') + Ah) = 53$$

$$Ic/T = 14.9\%$$

There was a noticeable connection between *Muslim Idenity* and *Female Identity* categories, particularly in regards to women's rights issues. Tweets would often portray Muslim refugees in Western Europe, especially in Germany and Sweden, as individuals that rape women and children.

Muslim Identity

Trump:	Pt: 16	At: 2	$Pt' \cap Ah'$: 0	Other (O): 169
Hillary:	Ph: 0	Ah: 28	$Ph' \cap At'$: 0	Total (T): 355

The value of the equations below shows the overall support or disapproval of a candidate in relation to *Muslim identity*, with a positive result showing positive support and vice-versa. The further away the result is from 0, the greater the support or opposition to a candidate there is.

$$\text{Trump: } Pt + (Pt' \cap Ah') - At = 14$$

$$\text{Hillary: } Ph + (Ph' \cap At') - Ah = -28$$

The gap in support and disapproval of candidates in relation to Muslim identity is striking. As the results show, for every tweet that contained *Muslim Identity* and were supportive of Donald Trump, there were two tweets that contained *Muslim Identity* and were opposed to Hillary Clinton. Some of these tweets that were critical of Hillary Clinton accuse her of being a hypocrite for taking money from Middle Eastern countries that have poor records on women's rights issues. There are also tweets that accuse her of having an open border policy for immigrants from predominantly Muslim-majority countries. In contrast, the tweets in support of Donald Trump the contain *Muslim* Identity are predominantly tied to his immigration policy of restricting immigrants and refugees from predominantly Muslim-majority countries.

Taking the total of counts for each identity and candidate (Ic), divided by the total (T) counts of tweets, shows the percentage of tweets about either candidate in relation to an identity:

$$(Pt + (Pt' \cap Ah') + At) + (Ph + (Ph' \cap At') + Ah) = 46$$

$$Ic/T = 12.9\%$$

Prior to doing the counts for this identity, and as a result of reading the tweets before creating the categorization schema based on identities and candidate support or opposition, I made a separate group for *Muslim Identity* consisting of Islamophobic (Ip) tweets. This group contains tweets that directly denigrate Islam as a religion, Muslims as a people, or refugees and immigrants from Middle Eastern countries. As with the candidate groupings based on *Muslim Identity*, I grouped tweets into this category in as restrictive a way as possible. Any tweets that mentioned both a candidate and an Islamophobic sentiment were categorized in relation to candidate support/opposition instead of the Ip category. Taking the total count for the Islamophobic (Ip) category (105), divided by the Total (T) number of tweets, reveals the percentage of the sample that contained some form of Islamophobic sentiment: $Ip/T = 29.5\%$

The European migrant crisis that began in 2015 was often used to create a theme of tweets that portrayed Muslims and refugees as being an existential threat to Western society. The tweets that had explicit support for Trump’s policy of banning people from predominantly Muslim countries often tied the migrant crisis in Europe and the character of Muslims as empirical support for his immigration policy proposal. Furthermore, an agglomeration of “IslamKills” and “Refugees” showed that there was a similarity of 0.218—the scale ranges from 0 to 1, where 0 means the phrases do not appear in the same tweet together and 1 means the phrases appear in all of the tweets together.

2.) *Troll Tactics*

@midnight

One of the surprising findings in this database was the trolls' engagement with the Comedy Central late-night program @midnight. The show—which was discontinued in late 2017—allows and encourages users of Twitter to actively engage in the show. The show was based around humorous wordplay, and one segment called "Hashtag Wars" let viewers send a tweet to the @midnight twitter handle, which could potentially be shown live on air. An example of this engagement with the show can be seen in the tweet sent by @traceyhappymom, who tweeted in September of 2016, "Dr. Fin, Medicine Woman #FishTV @midnight." This tweet is a play on words and homage to the show Dr. Quinn, Medicine Woman. For those that play the game on Twitter, they can also view what others are tweeting into the show by searching "@midnight" on Twitter. A search for "@midnight" in the dataset returned 2685 hits.

Emotionally Charged Content

There were many accounts that focused on retweeting emotionally charged content. For instance, @jacquelineisbest retweeted a post by @Nottinghams1 that reads, "Muslim Pedophile Gang Kidnaps Random Christian Boy, Then They Take Turns Raping Him Before Murder." Words like "BREAKING" (1524 hits), "Rape" (429 hits), "Kill" (600 hits), and "Death" (748 hits) highlight the use of emotionally charged content the trolls used to gain attention to their accounts.

Same Tweet, Different Troll

Although rare, there were some instances of different troll accounts repeating the same tweet. This practice was used less often over time, and so my working conjecture is that it was used less often as the IRA messaging process became more sophisticated. An example of this can be seen in the tweet sent by @c_wells on August 4th, 2015, and the tweet sent by @Laurabaeley on August 8th, 2013, both of which read, "#TrumpBecause Get these damn mexicans out so we can have our jobs back. #Trump2016."

Trolls Retweeting Trolls

Pamela_moore13, who is one of the three most retweeted troll accounts, offers an enlightening example of two troll tactics: a troll repeating the same message over time with different hashtags and a troll retweeting another troll. For example, 33 minutes after the Pamela_moore13's initial tweet of "This Hispanic Trump supporter came to the US legally. And this needs to be normal!" was posted on September 1st, 2016 at 12:52 a.m., Missourinewus—another confirmed troll account—retweeted Pamela_moore13's tweet at 1:25 a.m. Similarly, the hashtags that were used as a supplement for the tweet's base message (e.g., #TrumpEnMexico, #HispanicHeritageMonth, #EvangelicalTrump) were changed to reflect a twitter trend and drive engagement with the content of the tweet. Trolls retweeting other trolls to expand their message to their own followers, and potentially recruit other users to spreading their message, was a common tactic that I discovered through my research.

Retweet Counts

One of the features of Twitter that trolls used to expand their message to others is Twitter's retweet function, which allows a user to take someone else's tweet and put it on their own account page. There are many purposes and reasons for retweeting a comment, but for this paper it is important to note its value in spreading a message. The more a tweet gets retweeted, the likelihood of others seeing that tweet increases. A search for "RT" returns 148181 hits of the total 203451 tweets in the dataset, which allows one to infer that the troll accounts were actively searching for other users and keywords to amplify those messages and messengers. In some instances, troll accounts that focused on a specific identity or issue would retweet popular America-based Twitter users that were consistently engaged with an aspect of that identity or issue.

3.) *<u>Most retweeted</u>*

To get an idea of the spread and efficacy of messages that were created by troll accounts, I filtered tweets for retweets that garnered over 1000 unique retweets. Filtering cases for retweets that have a value > 1000 retweets yielded 417 results. Three bots consistently appeared in this list, including: @pamela_moore13, @crystal1johnson, and @ten_gop. @pamela_moore13 had 16 tweets with over 1000 total retweets; @crystal1johnson had 36 tweets with over 1000 total retweets; and @ten_gop had 272 tweets with over 1000 total retweets. Combined, these three accounts had 369 of the total 417 tweets that were retweeted over 1000 times.

@southlonestar, @trayneshacole, @gloed_up, @usa_gunslinger, @jennaabrams, and @thefoundingson combined to have 34 total tweets that were retweeted at least 1000 times. When the retweets garnered by these accounts are added to the three accounts listed above, these 9 troll accounts accounted for 96.6% of all tweets that were retweeted over 1000 times.

Crystal1Johnson is the clearest example of a troll focusing on portraying itself as an identity, which in this instance would correspond to an activist-oriented African-American person. Pamela_moore13 attempts to portray itself a supporter of Donald Trump. Ten_gop, which is pretending to be a political branch of the Republican Party operating in Tennessee, has the most explicitly antagonistic and conspiratorial tweet content of the three. As noted in the Mueller indictment of the IRA operators, this account had over 100,000 followers (United States of America v. Internet Research Agency LLC).

Filtering tweets that were retweeted over 3000 times for **pamela_moore13** gives 12 cases, of which the top 10 are presented below:

1. Former Navy Officer Peggy Hubbard endorses Trump!
   "Something needs to Change and that's why I'm Voting Trump! I'm[missing]¦
   https://t.co/qf28hDm04h
2. I would rather take care of TEN homeless US Veterans, than 50,000 migrants/illegal aliens.. How About You? https://t.co/Fa3H2Krxix
3. 65 Top "Journalists" from MSNBC, CNN, ABC, CBS & Politico have been submitting their work to Hillary for approval [missing] https://t.co/zlVtNwZHaR
4. Former FBI Asst Director James Kallstrom endorses Donald Trump
   "Our country is going down the tubes"
   Listen to what[missing] https://t.co/HXPPMp1QHz
5. France is lost. #French police try to enter a muslim no-go zone.
   We can not allow this in America! https://t.co/JtQyiPMhE1
6. Man PROVES software stole votes in ALL 'Hillary won' counties! DNC rigged elections https://t.co/Asw0xKcny1
7. Crowd chanting "Podesta! We got your emails, Podesta!" live on @CNN during discussion. Podesta: "Uh, uh, uh, it uh, [missing] https://t.co/8Me1LvHTsq
8. Detroit residents speak out against the failed policies of Obama, Hillary & democrats #ImGoingToMissObamaBecause https://t.co/aGMH2NroNV
9. I prefer Trump's platform for our community. He can put America back to work back to church back to school! ~ Alved[missing] https://t.co/MbLaqjwmdf
10. This is a movement for ALL Americans. Join the Trump Train 4 a better future, for Americans first! https://t.co/6AB4jO1zWT

Filtering tweets that were retweeted over 3k for **Crystal1Johnson** gives 12 cases, of which the top 10 are presented below:

1. There are bodies in the street and people getting paid leave and getting away with murder." -- Colin Kaepernick https://t.co/ltDtnlBx9O
2. 3 Black children carrying their daily water allowance. Flint, Michigan - 2016 https://t.co/widOHGok0F
3. These emotions... You can hear the pain in her voice https://t.co/K98Fzep7K3
4. ABC gives the KKK an interview... Welcome to America
   A racist trying to say his organization isn't racist https://t.co/E47qm885xr
5. "His life mattered."
   #TerenceCrutcher's twin sister demands justice: https://t.co/OCRHS6wfYr
6. This is the image you will not on the media. https://t.co/spz3M4OrRW
7. Muhammad Ali, the only person whose Hollywood Walk of Fame Star is hanging on a wall, not for anyone to step on https://t.co/OLw89EDEIU
8. So who was #TerenceCrutcher?
   #BlackLivesMatter https://t.co/lOQjlJiQZJ

9. Let this picture sink in. Maximize it. Zoom in. Stare at it. Take several moments. Now get angry. Be angry. https://t.co/WxwHddMJSE
10. When It's slowly becoming illegal for black people to work #BlackTwitter https://t.co/syvZeCnsxR

Filtering tweets that were retweeted over 5k for **ten_gop** gives 11 cases, of which the top 10 are presented below:

1. RT if you also think that @LorettaLynch should be impeached for blocking the FBI investigation & abetting a criminal[missing] https://t.co/KHBe5AthJC
2. OMFG! This is EXPLOSIVE! THE MOST IMPORTANT VIDEO OF THE ELECTION! Retweet! Takes 2 sec but will change everything https://t.co/18PtBuQr2h
3. BREAKING Hillary caught using a child actor [missing] at her townhall in Haverford, PA Please, RT to expose this fraud! https://t.co/UoBB20RAoB
4. OMG, this new Anti-Hillary ad is brilliant! It's fantastic!!!!!! Spread it far & wide! https://t.co/v7zrP8iDl7
5. RT the hell out of it: Dem party operatives: 'We've been bussing people in.. for 50 yrs and we're not going to stop’ https://t.co/tO0NKGEJE2
6. BREAKING Thousands of names changed on voter rolls in Indiana. Police investigating #VoterFraud. #DrainTheSwamp https://t.co/JdLzKTt4cC
7. DISGUSTING Watch: Hillary laughing when Trump said gays get thrown off buildings in Muslim counties [missing] https://t.co/Opp7AlA9lF
8. This is sickening. Hillary using the "Mentally Ill" to incite violence at Trump rallies. #FreeJulian #BirdDogging [missing] https://t.co/xed9LyNR8j
9. BREAKING: #VoterFraud by counting tens of thousands of ineligible mail in Hillary votes being reported in Broward C[missing] https://t.co/UC6ydIpU9b
10. BREAKING
    Hillary shuts down press conference when asked about DNC Operatives corruption & #VoterFraud https://t.co/PMXHRWxiMy

4.) *Candidate Preferences*

The prior findings in this paper highlighed the intentional focus of the IRA on manufacturing perceptions of identity groups as being supportive or opposed to either Donald Trump or Hillary Clinton. To discover whether candidate support holds outside of the identity categorization system, I searched the dataset for the most explicit declaration of support for a candidate by searching for the phrases “forTrump,” “4Trump,” “forHillary,” and “4Hillary.”

The results that were discovered lend further support to the idea that aspects of identity played a key role in the manufactured support for candidate Donald Trump. The results are also notable for the lack of results for candidate Hillary Clinton. For instance, searching for "___4Hillary" yields 17 results, 3 of which retweet @lovemywife4eva's tweet that reads, "#voted #HillaryClinton #PedophilesForHillary #SpiritCookersForHillary #SexOffendersForHillary #Satanists4Hillary." In contrast, a search of "4Trump" yields 712 hits.

The hashtags that appear before the phrase "4Trump" or "forTrump" consist of the words "pray," "vote," "onevote," "march," and "unite." Identities, occupations, qualities, and locations generally appear in handles before the phrase "4Trump." Locations that appear before the phrase "4Trump" or "forTrump" include the following: Florida, Southern California, New York City, New York Maryland, Miami, Texas, Alaska, California, Brooklyn, West Virginia, and Michigan. Occupation, identities, and qualities that appear before the phrase "4Trump" or in account handles include the following: *FeminineAmerica*, *LGBT*, *Veteran*, *Blacks*, *immigrant*, *military*, *america*, *gays*, *italians*, *vets*, *YoungDems*, *bikers*, *workers*, *cubans*, *ladies*, *military*, *hotties*, *citizens*, *students*, *woman*, *cops*, *lgbtq*, *Mexican*, *Berners*, *NavyVets*, *Latinos*, *Pilots*, *Dems*, *Vegans*, *gays*, *lesbians*, *Catholic*, *youth*, and *patriots*.

Analysis of this broad support for Trump and lack of support for Hillary also revealed a relationship between tweets that were simultaneously supportive of Donald Trump and critical of Hillary Clinton. For instance, an agglomeration of "HillaryforPrison" and "TrumpforPresident" have a similarity of 0.253. As mentioned earlier in this report, a result of 0 means the phrases do not appear in the same tweet together and a result of 1 means the phrases appear in together in all the tweets where the phrases are used.

Concluding Thoughts

As partisanship and party sorting based on qualitative aspects of identity become increasingly common, identity as a lens of shared experience and understanding becomes susceptible to the anonymity that the internet provides its users. Voting bloc coalitions that are sorted by identity are particularly vulnerable to social media platforms, because social media can be used as a political tool to express and influence people based on manufactured identities. The intersection and stacking of identities was used by IRA trolls to give the impression of support or opposition for the candidates. An example of a stacked identity can be seen in the troll account @kateritterrr's retweet of another troll account, @nestormotojr, whose tweet reads, "I am a gay Latino man voting for Trump. He's not bought & is fighting for all of us! #MAGA #GaysForTrump #Trump2016." @usa_gunslinger also stacks identities in its tweet sent on September 18th, 2016, when it tweeted "CNN interviews Muslim woman, hopes she will destroy Trump live. Turns out she is a Trump supporter!"

Social media allows for users to engage and act in a digital environment of bits, and this engagement has the potential to manifest itself into real world action. This becomes a problem when information in the digital social media environment that's based on false information and fake news spreads faster and further than factually accurate information. For instance, the IRA promoted a rally in Washington, D.C. called "Support Hillary. Save American Muslims" and "recruited a real U.S. person to hold a sign depicting Clinton and a quote attributed to her stating that "I think Sharia Law will be a powerful new direction of freedom" (*United States v. Internet Research Agency LLC*). Furthermore, troll accounts engaged in and amplified the #pizzagate conspiracy theory, which purported that Hillary Clinton was running a secret pedophile organization in the basement of a pizzeria called Comet Ping Pong (Aisch, Huang, Kang, 2016).

In December, 2016, a 28-year-old man from North Carolina acted upon this politically motivated rumor, taking an assault rifle and firing it in the restaurant (Haag, Salam, 2017).

The results from this research highlight two general vulnerabilities that can be taken advantage of in the digital environment. First, social media websites do not have a rigorous authentication process. This lack of authenticating an individual's identity allows trolls and other actors to take advantage of this by masquerading as someone else, which allows the troll to push an agenda that's intended to suit their own purposes. Second, the IRA trolls took advantage of the fact that false information tends to diffuse further and faster than true information. Prolific accounts like @ten_gop would send out information that was salacious, exciting, and false. However, as noted above, this troll account gathered an extensive following of over 100,000 Twitter users. Until and unless these vulnerabilities are addressed, the public remains vulnerable to organizations that want a cheap and relatively easy way to engage in American political processes and discourse.

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