Candidates and Memes on the Campaign Trail
Alyssa Kann
May 6, 2019

A senior thesis, submitted to the International & Global Studies Department of Brandeis University, in partial fulfillment of the Bachelor of Arts degree.
# Table of Contents

## Chapter 1: Introduction

- Terms and Questions in the Information Environment ................................................. 7
- Thesis Roadmap ........................................................................................................ 11

## Chapter 2: Literature Review

- Introduction ................................................................................................................ 13
- Presidential Races on Social Media ........................................................................... 13
- Presidential Races and Information Warfare on Social Media ................................ 15
- Detecting Manipulative Behavior Online .................................................................. 18
- Meme-Specific Information Warfare .......................................................................... 19
  - *Humanities meme studies* ...................................................................................... 19
  - *Computer science meme studies* .......................................................................... 21
- Memes, Spread, and Virality ...................................................................................... 22
- Conclusion .................................................................................................................. 23

## Chapter 3: Defining Models and Data Collection

- Introduction ................................................................................................................ 25
- Data Collection ........................................................................................................... 25
- Defining a Model ........................................................................................................ 26
- Methodology ............................................................................................................... 28
- Unused Data and Other Areas .................................................................................... 32
- Conclusion .................................................................................................................. 34

## Chapter 4: Elizabeth Warren

- Introduction ................................................................................................................ 36
- Brief Background ........................................................................................................ 36
- Presidential Bid and Pocahontas .............................................................................. 37
- Memes and Methodology ........................................................................................... 40
- Conclusion .................................................................................................................. 47

## Chapter 5: Kirsten Gillibrand

- Introduction ................................................................................................................ 48
- Brief Background ........................................................................................................ 48
- Perceptions of Hypocrisy ........................................................................................... 49
- Stance on Sexual Assault ........................................................................................... 50
- Memes and Methodology ........................................................................................... 51
Chapter 1: Introduction

The meteoric rise in social media use worldwide has created unintended consequences. Problems online are manifest and connected, from false information spread on social media, to foreign interference, to propaganda hotspots like the infamous alt-right Reddit forum “The_Donald.” Internet anonymity shields bad actors, governments, and organizations from detection by the average citizen. Significantly, malicious and shadowy influence campaigns online have targeted elections worldwide in recent years. These events make it more necessary than ever to be able to identify what influence campaigns look like. Yet there has been little academic research on this topic.

Russian interference and targeted disinformation campaigns have gained attention globally in over two dozen Western countries. From the 2016 US presidential election, to the British Brexit vote, to elections in Montenegro, influence campaigns online have perpetuated false information on social media and sown discord.¹ *The New York Times* described this as a Russian “virtual invasion.”² The Carnegie Endowment for International Peace called on the U.S. to double down on its efforts to prevent electoral interference ahead of the 2018 midterms.³

The 2018 Worldwide Threat Assessment of the US Intelligence Community listed influence campaigns as an international threat; it explicitly stated that “more governments are

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using propaganda and misinformation in social media to influence foreign and domestic audiences.”

Such comments are in light of Russian interference in the 2016 presidential elections, which inflamed the American public. Congress publicly released the Facebook ads purchased by Russia, as well as Twitter handles covertly created by Russia’s Internet Research Agency (IRA). Many of the Facebook ads were memes, meant to subtly influence voters while they used social media. Popular media outlets across the country displayed many of these memes. The idea that these memes could have had real-world effects on national security changed the zeitgeist on these popular images, making them less innocuous than previously thought.

What is a meme? The word originates from Richard Dawkins’ seminal 1976 book “The Selfish Gene,” in which he defines it as a building block of cultural transmission. Dawkins supplements his definition of the meme with the idea that it is an unconscious replicator: “memes propagate themselves in the meme pool by leaping from brain to brain via a process which, in the broad sense, can be called imitation.”

Dawkin’s original definition of the word meme has come to represent much more than he ever could have anticipated. As shown in Figure 1.1, Dawkins has himself become one.

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Memes are most commonly found, spread, and shared on social media. Their significance is more than benign. Semiotics is the study of how meaning is conveyed through everyday ‘signs.’ Memes are an example of a sign: individuals use them to communicate meaning in ways that are often beyond words. This thesis uses research from Zakem et. al to define a meme as “a culturally resonant item easily shared or spread online.” This definition encompasses the

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cultural importance of memes, while being more specific than Dawkin’s original biological characterization. Zakem’s definition is useful for its comparative specificity. Yet it is still vague, so this thesis develops a model with which to analyze relevant memes.

**Terms and Questions in the Information Environment**

While the threat of memetic interference in American elections has been established, whether or not this threat is credible is another question entirely. Could memes really influence elections, or is this an overblown concern? Different terms have been introduced to discuss these possibilities.

The term ‘memetic warfare’ was popularized in a 2015 article in NATO’s defense journal.  

10 The article’s author, Jeff Giesea, defines the term as the "competition over narrative, ideas, and social control in a social-media battlefield... a subset of 'information operations' tailored to social media... Memetic warfare could also be viewed as a 'digital native' version of psychological warfare, more commonly known as propaganda."  

11 In other words, it is meme-specific information warfare, as depicted in Figure 1.2. Giesea goes farther, and has called memetic warfare "the Wild West of asymmetric conflict."  

12 The awareness that memes could constitute a form of influence has percolated throughout the government. The State Department’s “DiplomacyLab” – which lists projects every semester to be undertaken by individuals and groups at participating colleges – had a project in Spring

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2018 calling for a “Memetic Warfare Tracker.” According to the description, the development of a memetic warfare tracker is "part of an ongoing effort" within the Department to not only identify and track memes, but also to pinpoint whether such memes are part of a more coordinated disinformation campaign, and if so where that disinformation campaign is originating from.13

‘Memetic warfare’ is a controversial term. Alternative terminologies include ‘memetic engineering,’ ‘military memetics,’ and ‘memetic engagement.’ As these recently invented terms demonstrate, mainstream internet use has caused a shift in the classical information warfare paradigm. It is necessary to revisit the information toolbox to incorporate memes within it. As Figure 1.2 shows, a March 2018 brief for Congress on the information environment classifies influence campaigns, false information, and propaganda as tools in information operations.

False information can be spread through memes, sometimes as part of an intentional campaign and sometimes accidentally. Not all false information is created equally. The Congressional brief distinguishes misinformation from disinformation: misinformation is the spread of the unintentionally false information, while disinformation is intentionally false.\textsuperscript{14} Although this definition is helpful, it is often impossible to ascertain the originator’s intentions behind sharing false information. Disinformation is used frequently as a tool in the information toolbox to achieve a specific political outcome, such as sowing confusion around an issue. In contrast to mis or disinformation, propaganda is defined as the intentional spread of an idea or

narrative to influence a group, and it can be factually true but misleading.\textsuperscript{15} The report calls the internet a “force multiplier” for information warfare.

The term ‘memetic influence campaigns’ is used in this thesis. Memetic influence campaigns are defined as the intentional attempt to influence someone through memes, as part of a broader campaign to make a certain audience believe something about a subject. In this case, the aim is influencing the public’s perceptions of a political candidate, with the ultimate objective of changing votes and the election itself. Memetic influence campaigns have been added in Figure 1.2 as another tool of information operations.

As Varol et al. point out, there are three main questions to consider when studying influence campaigns: “what, how, and who.”\textsuperscript{16} What sort of information is being perpetuated, how is it perpetuated, and who is doing it? These are large questions which each deserve significant responses. Yet before these questions can be answered, “one would need to be able to identify an information campaign in social media. But discriminating such campaigns from grassroots conversations poses both theoretical and practical challenges.”\textsuperscript{17} Therefore, the first challenge is to be able to differentiate normal internet activity from suspicious internet activity.

The question animating this thesis is how normal candidate-specific meme activity can be distinguished from memetic influence campaigns. Answering this question leads to more questions, but it is a significant first step. Little headway has been made in this area thus far.

This thesis will examine the memes targeting three politicians who were elected to Congress in the 2018 midterms and who are all current 2020 presidential candidates: Elizabeth Warren, Kirsten Gillibrand, and Tulsi Gabbard.

\textsuperscript{15} Theohary.
\textsuperscript{16} “(PDF) Early Detection of Promoted Campaigns on Social Media,” ResearchGate, accessed December 29, 2018, http://dx.doi.org/10.1140/epjds/s13688-017-0111-y.
\textsuperscript{17} “(PDF) Early Detection of Promoted Campaigns on Social Media.”
The memes targeting these politicians will be discussed, with the aim of better understanding what sort of memes target them, if any of them are part of a memetic campaign, and how the two can be differentiated. Memes will be examined from both quantitative and qualitative perspectives. The case studies will furnish examples of both positive and negative memetic influence campaigns, as well as an example of normal meme activity.

**Thesis Roadmap**

In Chapter 2, a review of relevant literature from multiple disciplines helps to better pinpoint how scholarship has thus far differentiated influence campaigns from normal internet activity. Much more research is yet to be done. Nevertheless, this pre-existing work has established that signs of influence campaigns online could include content with a high negative sentiment and the perpetuation of false information. It also indicates that the relatively high popularity of certain key themes may indicate the presence of malicious actors.

Chapter 3 presents the meme model, which supplements the definition of a meme and facilitates pattern analysis. The process of data collection, which uses the meme model in its labeling system, is explained. The meme model differentiates between true, false, and misleading information. It also distinguishes between memes which present information as fact-based and memes which present opinions.

Chapters 4, 5, and 6 are the case study chapters. Chapter 5 focuses on Kirsten Gillibrand, whose memes displays a normal pattern distribution. Her chapter is useful in establishing a sort of ‘baseline’ in a field where there is none. In Chapter 4, a possible negative memetic influence campaign is targeting Elizabeth Warren. This is established through several patterns in an analysis of her memes. Memes with a high negative sentiment and a focus on one theme could
indicate an influence campaign. Reddit and 4chan posts have corroborated this. Tulsi Gabbard is the subject of Chapter 6, which finds that she is the subject of a positive memetic influence campaign. Her memes suggest this through their suspiciously positive sentiment and wide reach. Possible Russian interference is discussed here. These case studies help to better illustrate the ultimate goal of this thesis, depicting possible differences between memetic influence campaigns and normal meme activity.
Chapter 2: Literature Review

Introduction

The online ecosystem has radically changed candidates’ political campaigns. The spread of political information on the internet is subject to different phenomena, such as false information and virality, than information spreading off-line. While some of the impacts of the internet on politics have been studied, much has yet to be examined. Misinformation, disinformation, propaganda, and more abound on social media, where the political effects of bad actors can be amplified through bubble-inducing algorithms. In order to give a complete and holistic response to the interdisciplinary question of how normal candidate-specific meme activity online can be distinguished from memetic warfare, it is necessary to examine papers from many different academic fields. This review covers previous studies of presidential campaigns on social media, memes spreading true and false information, and virality.

Presidential Races on Social Media

Two analyses of American presidential races on Twitter illustrate the different ways campaigns can be studied. In the first, “A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle,” Wang et al. conduct sentiment analysis on tweets during the 2012 presidential election. They flag tweets that were about certain candidates, and then mark the sentiment of these tweets as positive, negative, or neutral.\(^\text{18}\) The paper’s most notable achievement is their automation of sentiment analysis so that it is accessible in real time. Such a

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tool means that people could access the varying sentiments of tweets during important events, like presidential debates. The article used a data collection technique based on Twitter information that is not freely accessible. The price of access to this API could deter academic use.

In another paper, “Bumps and Bruises: Mining Presidential Campaign Announcements on Twitter,” Le et al. also look at the sentiments of tweets. However, they focus specifically on the announcements six politicians made on Twitter declaring their candidacy for president in the 2016 elections. They find an increase in attention after such announcements, of a mostly negative sentiment. The tweets are then analyzed based on three factors: party, personality, and policy. These three dimensions were established by “The American Voter,” a seminal 1960 paper on voting behavior that has impacted the study of elections since its publication. Le et al. look at how the public’s perceptions of these three factors change on Twitter before, during, and after the politicians’ announcements. One downside to this approach is that the average Twitter user may or may not represent the average American voter. Without knowing whether or not the users whose tweets were collected in this study are American voters, it is challenging to judge the importance of the study’s results.

In order to distinguish ‘normal’ internet activity from potential influence campaigns, it is important to determine a sort of ‘baseline’ social media activity. Through studying presidential campaigns on Twitter, these two papers help to establish a baseline of what normal Twitter activity looks like under such circumstances.

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Presidential Races and Information Warfare on Social Media

False information is frequently perpetuated on social media. Its effects range from benign (as shown in a confused but harmless Facebook post) to genocidal, as exemplified by events in Myanmar in 2018, where the military incited ethnic cleansing by sharing disinformation maligning Rohingya Muslims on Facebook.\(^{21}\) Unfortunately, the original perpetrators of false information are often opaque, because the internet provides a shield of anonymity.

A 2017 report by the Berkman Klein Center looks at the news shared on social media in the partisan environment of the 2016 presidential elections.\(^{22}\) They found that political divisions were sowed online through disinformation and propaganda. They discovered that the political right and left displayed different types of news sharing. The right was more susceptible to false information and propaganda, because they were more isolated and shared more fringe media sources. On the left, mainstream media attempted to be impartial, but did not give equal coverage to Hilary Clinton and Donald Trump. Trump’s coverage focused on policy issues, while Clinton’s coverage centered on the controversies she was mired in. In a previous paper from 2014, Bessi et al. uncover similar results. After analyzing Facebook users’ information consumption, they find that users who are more likely to disseminate “alternative” media sources are also more likely to interact with false information.\(^{23}\)

The Berkman Klein paper also developed mediachoice.org, which has a public API and open-source code. Mediacloud.org can be used to analyze news trajectories in real time. One


downside of the Berkman Klein report is its loose definition of disinformation; it defines it as “the communication of propaganda consisting of materially misleading information.”\textsuperscript{24} This removes the more specific direction of intention in more specific definitions of disinformation. As discussed in Chapter 1, disinformation is defined in this thesis as false information that is intentionally disseminated to mislead. However, uncovering the intentions behind the news sources would have been a challenging, if not impossible, task for the Berkman Klein report, despite the work’s impressive scope.

Another paper examines the dissemination of false news stories on Facebook during the 2016 presidential campaigns.\textsuperscript{25} Guess et al. conduct an online survey where thousands of people answered questions on their Facebook usage, demographic, and politics, and could grant researchers access to their Facebook data. The researchers examine the URLs of the links people shared, comparing them with a set list of ‘fake news’ links, where ‘fake news’ was defined as purposeful disinformation, mostly so that the links would generate ad revenue. This simple yet powerful methodology finds that sharing false news articles was rare during this time, but that with all other variables held constant, Americans over 65 shared the most. This age group is often inexperienced with the internet, so less internet literacy among this demographic makes sense. Guess et al.’s findings belie the popular conception that false information sharing on Facebook was a major issue during the 2016 elections.

Continuing the analysis of the 2016 presidential election online, a 2018 paper examined the influence and impacts of Russian information warfare on social media.\textsuperscript{26} They used a

\textsuperscript{24} “Partisanship, Propaganda, and Disinformation.”
statistical model called Hawkes processes to quantify the influence Russian Twitter accounts had on news dissemination. Congress had released the Twitter handles of the IRA, so the paper was able to easily pinpoint the originators of the information warfare for analysis.

They compare the IRA Twitter accounts to a control group of random Twitter users. They break down the two groups by URLs tweeted, language, time zone, hashtags, most common content words, location, and more. Similar to the methodology in this thesis, they made tables of the top hashtags and mentions of both troll and control Twitter accounts, to look for differences. Their findings demonstrate that the Russian account group had two more popular hashtags than the control groups’ hashtags, which were more evenly distributed. Similarly, in looking at the mentions of the two groups, they found that the Russian group had two slightly more common mentions compared to the baseline group’s mentions.

Zannettou et al. also track how the URLs shared on Twitter fared on Reddit and 4chan’s /pol/thread, ultimately finding little difference between the two in the spread of news. Since the account names for the Russian trolls were known in advance, they were able to accurately pinpoint disinformation and information warfare. However, in most cases, claims of this sort are impossible to make. It is challenging to ascertain cases of information warfare where it is uncertain who (if anyone) is perpetuating it.

These studies help to illustrate who perpetuates false information on social media when presidential elections are ongoing. By studying what the online environment looks like during such events, researchers will be better placed to determine when such online activity is ‘normal’ and when it looks suspicious. Learning more about the sometimes unwitting disseminators of

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27 Zannettou et al.
false information also helps researchers to better distinguish potential influence campaigns from unintentional confusion.

**Detecting Manipulative Behavior Online**

Other studies focus more on how detection of manipulative behavior online could work. These studies are helpful in determining how influence campaigns can be distinguished from normal internet activity.

“Account Deletion Prediction on RuNet: A Case Study of Suspicious Twitter Accounts Active During the Russian-Ukrainian Crisis,” by Svitlana Volkova and Eric Bell, is one such example. They collected Twitter accounts active during the 2014-2015 Russian-Ukrainian crisis, and then re-collected the accounts at a later date to see which had been deleted. Assuming that the accounts which were deleted were deleted because they were fake, they then compare the still-active accounts to the ones which were deleted in order to find differences. They found that the sentiment of deleted accounts’ tweets was more negative and more neutral than the sentiment of the tweets in the non-deleted accounts.\(^{28}\) It is uncertain how applicable their findings are to other social media platforms.

Another paper examines users which create multiple accounts on nine different online discussion boards. They distinguish users which make multiple accounts by identifying users’ IP addresses and session times. They then analyze the users’ networks to find the distinguishing features of users who make multiple accounts. They discover that users with multiple accounts

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are likely to comment on more controversial topics. They also find that 74% of the users with multiple accounts are both deceptive about the origins of their accounts and use their accounts to support their comments in discussions. Doing this would allow such users to manipulate discussions so that it appears that far more people support a stance or idea than in reality.

**Meme-Specific Information Warfare**

The research on memes is quickly growing as memes become more and more entrenched in daily life. Memes span many previously studied internet phenomena, and often make up another tool in the toolbox of information warfare, as shown in Figure 2.1. This literature review focuses specifically on papers where this is the case.

In general, notable highlights in meme scholarship can be divided into two categories. The first category is that of humanities. Papers that fall into this classification discuss specific memes and analyze them theoretically, historically, sociologically, and/or philosophically. In the other category, novel computer science and data techniques are developed and applied for a more comprehensive, quantitative meme analysis. Highlighted papers from both sections will be discussed here, since both categories offer unique and useful perspectives on memes.

*Humanities meme studies*

A paper explicit in memes’ roles in information warfare more broadly is “Exploring the Utility of Memes for U.S. Government Influence Campaigns,” released in April 2018. The paper is authored by a not-for-profit research organization that is a federal government contractor. Nevertheless, their work is discussed here due to its originality, creativity, and applicability.

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Zakem et al. define a meme as “a culturally resonant item easily shared or spread online.” The definition encompasses images, small bits of text, and videos. Importantly, such a definition underlines that a meme is a type of idea that can spread quickly on the internet—the ways in which it does so (text, image, etc) are less important. The authors identify three uses for memes in influence campaigns, borrowing terminology from the field of epidemiology. Various case studies illustrate preventative, offensive, and defensive meme types, which can inoculate, infect, or treat situations. Case studies include memes in influence campaigns against states like Russia and North Korea, and non-state actors like ISIS.

Using a more philosophical focus, Mihailidis and Viotty study media during the 2016 U.S. presidential election. Their work looks at the Pizzagate debacle, Pepe the Frog, and more. The paper’s focus is theoretical. They talk about the idea of ‘spectacle’ online, the role of the public in spectacle, and mainstream media’s role in perpetuating rumors. Their research highlights the interlocking roles the internet, memes, and ideas play in public expression:

Cultural transmission, or the appropriation of content online, is now embedded in digital culture, where citizens increasingly appropriate content to insert their personal ideas, opinions, and ideologies. With memes, individuals have the ability to bring their own meaning to an image, recreating or “remixing” its original content to generate new content with different meaning. Meme’s provide an accessible format for information to be shared, anchored in cultural relevance and techniques—humor, wit, and sarcasm—that are often visually pleasing and playful.

Importantly, Mihailidis and Viotty highlight that memes are often ‘remixed’ versions of past memes, where the perception of public participation is key. They also discuss the ease with which rumors with real-life political ramifications are perpetuated online.

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32 Mihailidis and Viotty.
33 Mihailidis and Viotty.
The many uses of memes are important to note in distinguishing normal meme activity from possible influence campaigns. It is necessary to understand the role memes play in digital culture in order to evaluate if an influence campaign could be credible or effective.

*Computer science meme studies*

False information is frequently perpetuated through memes. Sometimes this can be a sign of malicious activity, while other times it is not. How can the two be distinguished? Novel research techniques help to better identify and label possible influence campaigns.

At Indiana University’s Center for Complex Networks and Systems Research, a paper on “Detecting and Tracking Political Abuse in Social Media” tracks false information sharing on Twitter. Their focus is specifically political astroturfing, which they define as “political campaigns disguised as spontaneous ‘grassroots’ behavior that are in reality carried out by a single person or organization.” Ratkiewicz et al. liken it to a more harmful version of spam. Astroturfing could have significant effects on the electoral process, since it influences people’s perceptions of the popularity and legitimacy of a politician or policy. With the global resurgence of populist candidates, astroturfing is an important topic of study.

The researchers also develop a way to automatically detect and classify memes on Twitter that are related to American politics. To ensure the memes they collect are politically relevant, they compare memes to a pre-determined list of political keywords. They also ensure that the memes they collect are popular by defining a specific threshold of retweets each meme must have for inclusion in the dataset. This filtering technique is extremely important, because it ensures that memes they are collecting actually have an audience. Through such a technique

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35 Ratkiewicz et al.
these researchers are assured that any claims they make about memes influencing a population will have validity, since their memes have actually been seen by other people.

Ratkiewicz et al. then use sentiment analysis to automatically classify the information in memes as true or false. Indiana University’s research has culminated in the creation of Hoaxy, a search engine that tracks hoaxes and false information on Twitter. The front and backend code for Hoaxy is all open-source and publicly available.36

**Memes, Spread, and Virality**

The spread and virality of memes has also been a noteworthy topic of academic research.

Understanding the spread of memes is important in order to discern which memes are part of normal internet activity and which are originating from influence campaigns. Like Indiana University’s Hoaxy, many technical papers create methodologies that they empower the public to use through sleek online interfaces. The “Meme Tracker” tool was built by authors of a study that traversed 1.6 million mainstream media sources over three months, finding patterns in a whooping 90 million articles to find patterns in the spread of memes in news cycles.37 Their rigorous 2009 study, “Meme-tracking and the Dynamics of the News Cycle,” defined a meme as a short bit of text, allowing it to be tracked online without visual recognition capabilities needed. The framework they developed was novel in its enormous scale.

In a 2010 paper, “Insights into Internet Memes” Bauckhage examines the “epidemic dynamics” of 150 memes. This article uses time series data from Google Insights, Google’s user-

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friendly trend-tracking interface. They also used less known platforms including Delicious, Digg, and StumbleUpon. Unlike other papers, no automation was implemented; rather, Bauckhage typed meme phrases into Google Insights and Delicious. The shortcoming of this simple technique is that Bauckhage was at the mercy of other data collection processes’ quirks. For example, Google Insights does not allow viewers to see the actual number of hits for a meme. Using math from epidemiology, Bauckhage uses epidemiological differential equations and log-normal distributions to explain how memes spread online and then decline.

A 2017 article, “Early detection of promoted campaigns on social media,” takes a different approach to understand the popularity of viral memes on Twitter. They build a machine learning framework to ascertain whether a meme is trending because of organic spread or because of artificial advertising promotion. To do so, Varol et al. examine trending hashtags, since Twitter labels which ones are promoted. They incorporate the hashtags’ network features, user data, timing data, tweet content, and sentiment content into their algorithms. Their program works well at detecting Twitter hashtag influence campaigns early on, but does not seem to be applicable to other contexts.

Conclusion

Literature in each section of this review helps answer the question of how normal candidate-specific meme activity online can be distinguished from memetic influence campaigns. Studying what normal meme activity looks like – particularly during controversial events like presidential races – helps to create a baseline. Examining what manipulative behaviors like false information and propaganda online look like provides information about the nature of influence campaigns.

39 “(PDF) Early Detection of Promoted Campaigns on Social Media.”
Volkova and Bell’s study indicated that it is possible that a more negative and/or more neutral sentiment in content could indicate malicious activity. Zannettou et al. demonstrated that themes could be more concentrated in influence accounts over regular accounts.

Several papers used concepts from epidemiology – the spread of diseases, not ideas – to explain how memes disseminate online. Some papers implement advances in computer science to create frameworks for meme collection, while others examine memes on a case-by-case basis. Influence is defined in different ways – by relevance, different metrics for popularity, retweets, and more. Such a diverse review highlights the need for a holistic examination of memes as a part of both normal internet content and influence campaigns. Gaps in research have been identified: very little is known about how normal activity can be distinguished from influence campaigns, and the literature that responds to this gap is too narrow to apply to other cases. Anything that is too silo-ed is not relevant or useful enough to have applicable real-life findings. There is clearly much more to be done.
Chapter 3: Defining Models and Data Collection

Introduction

In order to better ascertain how memetic influence campaigns and examples of normal meme activity online can be differentiated, one must start with examples. Data collection is necessary for the three case studies. Without examples of memes targeting Elizabeth Warren, Kirsten Gillibrand, and Tulsi Gabbard, no analysis of any kind can be done. The data collection process – ie, how memes for each politician were collected – is discussed in this chapter. Then a theoretical model for labeling memes is defined and examined. The collected memes are then labeled according to this meme model methodology. Lastly, this chapter goes over data sources and collection processes that were not used in all of the case studies.

Data Collection

Google gets the most web traffic globally, making it one of the most important sites in the world. Consequently, memes aggregated on this site are viewed by many people – because the search engine sorts by popularity and relevance. On Google, the “top 30” or so memes for each case study were found by typing their name with quotation marks (ex: “Kirsten Gillibrand meme”) into Google Images. The memes that were relevant to politics and not repeats were collected. These images for each person serve as a baseline for the types of ideas that are important to discuss for each candidate, making it easy to do more targeted searching elsewhere on the internet when necessary. For each meme in the collection, information was coded according to a methodology and model discussed below.

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Defining a Model

As mentioned in Chapter 1, this thesis defines a meme as “a culturally resonant item easily shared or spread online.” Memes and other forms of political propaganda on social media use candidates as their subjects in different ways. Memes are created, shared, and viewed for many purposes. Some memes are noteworthy for conveying information, while others are notable for the strong opinions they transmit. These different methods of messaging often overlap. In order to augment this thesis’ definition of a meme with these different types of communication, a model is developed. The model – as shown in Figure 3.1 – helps to narrow down this definition of a meme. This model is specific enough to be useful in examining the memes that surround, target, and talk about different political candidates.

The meme model helps to differentiate between memes which share only an opinion and memes which convey information that is presented as fact-based. In red in Figure 3.1 are memes which only share subjective messages or opinions. For these memes, the sentiment lies somewhere on the political spectrum. Because of the infeasibility of being able to objectively code for what sort of political sentiment each displays with only one researcher, the partisanship of the sentiment was ignored. However, this does present an area for further research. In blue are memes which only share information. Since many memes convey both of these at once, memes in this category are purple in Figure 3.1.
This model does have its failings. Memes are social: they are often shared and popularized on social media, and they are created with a viewer in mind. Any influence campaign requires an audience; otherwise, it is just unimportant noise. A more precise definition of a meme or model would include this audience aspect. As mentioned in Chapter 2, this was most successfully done in Ratkiewicz’s paper, where data collection of memes was limited to memes that were already popular, as shown in retweets on Twitter. Although the audience component is not included in this thesis’ concept of a meme definitionally, it is accounted for through collecting only the popular memes on Google.

Methodology

In order to ascertain patterns, these “top 30” Google memes were coded according to the meme model. Figure 3.2 is the same model, but with the appropriate label coding highlighted in green. Each meme in the collection was given a single label that best represented what the meme was. As shown in Figure 3.2, this label was either “A,” “B1,” “B2,” “B3,” “C1,” “C2,” or “C3,” depending on the content of the meme. Letters A through C indicate the type of messaging in the meme, while numbers one through three indicate the type of information in the meme.
When a meme was clearly sentiment-only, it was given the label “A.” No attempt was made to label where on the political spectrum the sentiment lay. Memes which only included information that was presented as fact-based were given a “B” label. Many memes include both information and opinion. Those memes were given the label “C.” For “B” and “C” memes, which present either some or all of their information as fact-based, information is fact-checked.
for accuracy. This information could range from a statement about a policy, a reference to an event, or a quote. In all information checking cases, the source information was recorded.

If the information was true, it was classified as a “1” for true information. Loosely accurate information – ie, a quote that was slightly off but still conveyed the correct gist – was still coded as true information. When the information was technically “true” but misleading, memes were classified as a “2.” For example, a Gillibrand meme with an image of her and Harvey Weinstein smiling, with text overlaid about how Gillibrand condemns sexual predators, is classified as “B2,” because fact-checking the information presented shows that the image of her and Weinstein was dated prior to her statement condemning sexual predators. If the information was false, it was given a “3” label. In cases where there was both true and false information in a single meme, precedence was given to the false information.

Variables for the general sentiment of the meme and themes were also coded. Decisions about the sentiment of the meme were challenging to apply impartially, but the best attempt at objectivity was made, and every meme was given one sentiment (either positive, negative, or neutral). Notably, this sentiment was in relation to the candidate – so if a meme disparaged Tulsi Gabbard, it would be coded as negative.

Themes were individual to each case study, and were not mutually exclusive, so memes could have multiple, often over-lapping themes or no themes at all. Additionally, more themes in memes were coded than necessary, and then the final theme list for each candidate was cut down to include solely themes which have two or more memes that use that theme. Themes had to be explicit, either visually or textually. For example, if a meme depicted Elizabeth Warren depicted in Native American garb, “Native American” would be coded as a theme, but “Pocahontas” wouldn’t be – unless the text of that meme mentioned “Pocahontas,” in which case it would be.
Figure 3.3 shows an example screenshot of this meme model methodology, which was implemented in a spreadsheet. This methodology allows for certain criteria (coding and sentiment) to be quantified for all memes, and for the overarching themes of each meme set to be examined both quantitatively and qualitatively.

**Figure 3.3 Methodology Example (Kirsten Gillibrand)**

*Source:* Google Images, thesis data collection methodology

*Note:* This is a screenshot of part of Kirsten Gillibrand’s methodology.

Through this methodology, it was possible to ascertain what types of meme were being spread, and what patterns were present in popular memes. The amounts of false information (versus true, misleading, and non-information-based memes) are also calculated, as are aggregated patterns in sentiment and themes. Assuming any influence campaign must rely on patterns in information dissemination, all of this information is helpful in determining whether a
memetic influence campaign could be occurring or not. Patterns can better be ascertained through the application of a label system.

Using Google Trends allowed these impressions to be corroborated or debunked. Data was taken from Google Trends for meme keywords by geographic location, Google location (ie web search or images search), and by specific time regions. Additionally, the site source for each meme was noted down. Doing this allows for a simple way to analyze what types of sites are the more important actors in the perpetuation of candidate-specific memes, and the major sites were different for each candidate.

**Unused Data and Other Areas**

Ultimately, only some of the information collected was helpful in ascertaining the existence of a potential influence campaign. For example, the site source for the “top 30” memes, which was noted down and compiled in a table, did not appear to include any trends or patterns. Similarly, much of the social media data collected was not as aggregated as the “top 30” Google memes, and therefore not as useful.

On Facebook, searches were done for meme and candidate-specific pages, because this is one of the most common methods of meme-distribution, and it is easy to see the page that is the source of the meme, unlike through other Facebook search methods. The specific focus was on pages that had the candidate name in the title that were meme-specific, but Facebook pages that were either just candidate-specific or meme-specific were also included. For these pages, it was required for them to have at least one relevant candidate meme for inclusion. The inclusion of these Facebook pages allows for a rich examination not only on the memes themselves, but also on the spread types of memes and the possibility of astroturfing in campaigning online. Facebook groups that were both candidate and meme specific were looked at, but ultimately not
researched. Some Facebook groups are private, while some are public, which allows for uneven access to memes. Facebook pages, which are always public, were thus more useful for ensuring accessibility.

Facebook was used for data collection because it was one of the places that was most highlighted in the Russian election interference controversy. One effect of the 2016 scandals is that Facebook has tightened its use of APIs – unintentionally and paradoxically making it far more challenging for academics to study these topics. This is why such a simple data collection process was chosen – it is challenging to acquire Facebook data through the APIs nowadays, and scraping in Python or R is necessary but still not a guarantee of success.

Twitter was sparingly used in the data process. Using information on meme-specific keywords from the preliminary Google search, data was collected through Twitter and Socioviz, a social network analysis program, and then visualized in Gephi. This data centers around the meme-specific keywords used as hashtags in Twitter. Other hashtags are collected, so that it is possible to see how memes interplay with political-related content and with other, unrelated information. This data is not discussed in the case studies, however, as there were too few meme-specific keywords used on Twitter in the time frame Twitter allows researchers to scrape from.

Reddit was also used individually in case studies to examine possible outbreaks of memetic warfare. According to Storyful, a for-profit service that analyzes web content, Reddit serves as an inoculation point for the outbreak of memes. Certain forums, like the infamous alt-right forum r/The_Donald, are famed for creating memes with the express intent of influencing others. For example, on April 9, 2019, a moderator on r/The_Donald hosted a “Meet the Memers” event, where eight accounts known for their famous memes answered questions from

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fans. These eight accounts were called the “Meme Magicians,” and referred to as members of the “Meme Team.” The event garnered 442 comments.

In these instances, what was said on Reddit – particularly in support of memetic warfare – was looked at rather than the memes themselves. Preliminary searches were also done on 4chan, Instagram, and Pinterest, but these sites were not used for significant data collection. 4chan’s data is deleted after seven days, presenting a challenge for data collection, and the site had surprisingly little focus on the case studies in question.

**Conclusion**

This chapter has discussed where the memes in this thesis have been collected from. The meme model and methodology outlined here will be used in all of the case studies. Following this methodology allows for analysis of memes for each candidate both qualitatively and quantitatively. The end goal here is being able to distinguish possible memetic influence campaigns from normal meme activity. This consistently applied methodology helps to better ascertain memetic patterns for each case study.

To sum the methodology up, “A” denotes the presence of solely subjective messaging in a meme, while “B” denotes only information that was presented as fact-based. A “C” label was given to memes which have both of these elements. After the letter, a number follows based on whether not the information is true, false, or misleading. If it was true, the label given is “1;” if misleading, it is given a “2” label, and if it is false information, it is given a “3” label. For

44 “R/The_Donald - Meet The Memers AMA!!!”
example, a “B2” meme would be referencing a meme that has solely information that is presented as fact-based, and that information is misleading.
Chapter 4: Elizabeth Warren

Introduction
An examination of Elizabeth Warren’s memes has found what appears to be a negative memetic influence campaign. This campaign unduly targets Warren, specifically focusing on her claims to Native American heritage and other controversies she has been mired in. This campaign has been identified both quantitatively, through statistics derived from the data collection, and qualitatively, through various sources’ corroboration.

Brief Background
Warren was formerly a professor at Harvard Law School. In 2010 President Obama named her a presidential assistant and special advisor. In this capacity she set up the new Bureau of Consumer Financial Protection. She won a Massachusetts Senate seat in 2012 after beating Republican incumbent Scott Brown by 7% in the midterm elections. She kept her seat in the 2018 midterm elections, beating a Republican and an Independent with 60% of the vote. She ran on a platform for equal treatment and opportunity for all, health care as a basic human right, the preservation of Medicare and Medicaid, gun law reform, and increased renewable energy. Warren is a liberal

48 “President Obama Names Elizabeth Warren Assistant to the President and Special Advisor to the Secretary of the Treasury on the Consumer Financial Protection Bureau.”
50 “Elizabeth Warren/Elections.”
progressive. A British magazine named her one of the top 20 American progressives in 2012, among other names including Noam Chomsky and Rachel Maddow.\(^\text{51}\) As of 2014, she voted with the Democratic Party 98% of the time.\(^\text{52}\)

**Presidential Bid and Pocahontas**

On December 31, 2018, Warren announced she had created a committee to explore a 2020 presidential bid. She officially announced she was running for president on February 9, 2019 while giving a speech in Lawrence, Massachusetts.\(^\text{53}\) Her speech was at the site of the 1912 Bread and Roses Strike, and an estimated 3,500 people were present.\(^\text{54}\) Her speech focused on support for the middle class and emphasized action on climate change. She was very critical of both Wall Street and the Trump administration.

Her official campaign website for president strikes similar notes. There she lays out her support for a Green New Deal, Medicare for All, anti-trust enforcement, taxes on the rich, and criminal justice reform. She plays to the specifics of her constituents as well. In a November 2018 ballot proposal, Massachusetts residents voted to create a citizens commission to research how to overturn Citizens United. Warren similarly calls for overturning the law, as well as implementing anti-corruption laws to eradicate corporate funding in politics.

At the speech in Lawrence, Warren called Trump’s administration “the most corrupt in living memory.”\(^\text{55}\) That same day, President Trump tweeted a response: “Today Elizabeth Warren, sometimes referred to by me as Pocahontas, joined the race for President. Will she run

\(^{51}\) “Elizabeth Warren/Elections.”

\(^{52}\) “Elizabeth Warren.”


\(^{54}\) ptennant@eagletribune.com.

\(^{55}\) ptennant@eagletribune.com.
as our first Native American presidential candidate, or has she decided that after 32 years, this is not playing so well anymore? See you on the campaign TRAIL, Liz!”  

56 Trump first referred to Warren as Pocahontas in a 2014 tweet.  

57 He has done so in 17 ensuing tweets, all of which disparage Warren.  

Warren’s candidacy has been dogged by her claims to Native American ancestry since she first ran for office in the 2012 midterms. In 1986, Warren listed herself as a minority in the Association of American Law Schools directory. She wrote her race in a 1986 State Bar of Texas card as “American Indian.”  

59 In law positions at Harvard University and University of Pennsylvania, she was identified as a Native American on federal forms. As early as 2012 media reported that both universities said that her stated ethnicity was not a factor in the hiring process.  

61 In 2016, Trump claimed in two tweets that Warren had used her Native American heritage to advance her career.  

63 In one, he explicitly stated that this occurred at Harvard University.

56 Donald J. Trump, “Today Elizabeth Warren, Sometimes Referred to by Me as Pocahontas, Joined the Race for President. Will She Run as Our First Native American Presidential Candidate, or Has She Decided That after 32 Years, This Is Not Playing so Well Anymore? See You on the Campaign TRAIL, Liz!,” Tweet, @realDonaldTrump (blog), February 9, 2019, https://twitter.com/realDonaldTrump/status/1094368870415110145.  

57 Donald J. Trump, “@TheAme19: @realDonaldTrump @RedNationRising And the Answer ISN’T Hillary or Pocahontas Warren for $300...,” Tweet, @realdonaldtrump (blog), August 11, 2014, https://twitter.com/realdonaldtrump/status/498755228658057216.  


63 “Elizabeth Warren’s Family Has Mixed Memories about Heritage - The Boston Globe.”  

64 “Trump Twitter Archive.”  

Ahead of the 2018 midterms, Warren published an October 2018 video which defended her claims to Native American heritage and repudiated Trump. The video interweaves her family history and career story with footage of Trump. Through interviews with various former university employers, the video delineated that Warren was not hired because of her Native American claims.65

This video also included the results of a DNA test, which proves that she has Native American DNA. This was not taken well by the public, as many people define race by shared culture and history rather than through bloodlines or DNA alone. The Secretary of State of the Cherokee Nation issued a statement in response which said that “Using a DNA test to lay claim to any connection to the Cherokee Nation or any tribal nation, even vaguely, is inappropriate and wrong.”66 In a tweet right after, Trump lauded the Cherokee Nation “for revealing that Elizabeth Warren,sometimes referred to as Pocahontas, is a complete and total Fraud!”67 Warren apologized to the Cherokee Nation, and a public affairs representative of the Cherokee Nation issued another statement, saying “We are encouraged by her action and hope that the slurs and mockery of tribal citizens and Indian history and heritage will now come to an end.”68 The controversy continues to be furthered by detractors on both the right and left.

Memes and Methodology

Possible signs of memetic influence campaigns range from astroturfing, to single themes dominating the discourse, to content that is highly negative in sentiment. The numbers and patterns drawn from the application of the meme model methodology to Warren’s “top 30” Google memes lead to the conclusion that a memetic influence campaign is likely taking place.

Regardless of its existence here or not, examining the pattern of meme activity for Warren and the two other case studies will help to better illuminate the differences between normal meme activity and influence campaigns. Little research has been done on how the two are distinguished from each other, so this analysis necessarily treads some new territory in its claims and conclusions.

Table 4.1: Meme Model Applied to Warren’s Memes

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Count of Coding</th>
<th>Percentage</th>
<th>Count of Coding</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>14</td>
<td>48.28%</td>
<td>7</td>
<td>24.14%</td>
</tr>
<tr>
<td>B1</td>
<td>2</td>
<td>6.90%</td>
<td>4</td>
<td>13.79%</td>
</tr>
<tr>
<td>B3</td>
<td>3</td>
<td>10.34%</td>
<td>4</td>
<td>13.79%</td>
</tr>
<tr>
<td>C1</td>
<td>5</td>
<td>17.24%</td>
<td>24</td>
<td>82.76%</td>
</tr>
<tr>
<td>C2</td>
<td>4</td>
<td>13.79%</td>
<td>15</td>
<td>51.72%</td>
</tr>
<tr>
<td>C3</td>
<td>1</td>
<td>3.45%</td>
<td>A</td>
<td>48.28%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>29</td>
<td>100.00%</td>
<td>B</td>
<td>17.24%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>C</td>
<td>34.48%</td>
</tr>
</tbody>
</table>

*Note:* Each meme was coded with one label, according to the meme model in Chapter 3. The left side of the table depicts the breakdown of these labels. On the right side are the total counts for different types of memes, which are not mutually exclusive. On the bottom right are the totals for each label, which are mutually exclusive. Nmemes = 29.

*Source:* Google Images and thesis data collection

As shown in Table 4.1, the majority of Warren’s memes were coded as “A” – meaning the memes shared only opinion, not information. A whooping 80.00% of Warren’s memes included subjective opinions. The sentiment of these mostly-opinion memes was highly negative: 82.76% of memes studied were negative in sentiment, while only 6.90% were positive in
sentiment. Looking at the raw numbers in Table 4.2, that is two positive memes to 24 negative ones. Volkova and Bell found that malicious Twitter accounts in the 2014-15 Russian-Ukrainian crisis had far more tweets that were negative in sentiment than the control group. Such negative sentiment appears to indicate the existence of an influence campaign.

Table 4.2: Sentiment Towards Warren

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>24</td>
<td>82.76%</td>
</tr>
<tr>
<td>Neutral</td>
<td>3</td>
<td>10.34%</td>
</tr>
<tr>
<td>Positive</td>
<td>2</td>
<td>6.90%</td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>29</strong></td>
<td><strong>100.00%</strong></td>
</tr>
</tbody>
</table>

*Note:* Every meme was assigned one sentiment (negative, neutral, or positive) based on the sentiment the meme expressed towards the candidate. Nmemes = 29.
*Source:* Google Images and thesis data collection

The number of false and misleading information in memes also slightly edged out the number of memes with true information. 26.66% of memes shared either misleading information or information was totally false, compared to the 23.33% of memes which shared true information. So many of Warren’s memes were so widely shared while being misleading or false that Politifact and Snopes sometimes featured and fact-checked them.

Figure 4.1a is a great example of a meme that is extremely misleading but not entirely false. The caption about Elizabeth Warren being “1/1024th” Native American is not false, but it is not entirely true, either. Per the DNA report Warren released after having a geneticist analyze her
DNA, Warren is between 1/64\textsuperscript{th} and 1/1024\textsuperscript{th} Native American.\textsuperscript{69} The meme presents the “1/1024\textsuperscript{th}” statistic without the caveat that it is actually a range, going from that lowest end to 1/64\textsuperscript{th}. This statistic – 1/1024\textsuperscript{th} – has become a commonly cited one among many on the right. Trump tweeted the statistic in his second tweet about Warren and the Cherokee Nation in October 2018. In January 2019, he shared a “Warren 1/2020\textsuperscript{th}” meme on Twitter, which was picked up through the “top 30” Google meme methodology, as seen in Figure 4.1b. Both images in 4.1 were coded as “C2,” meaning both included opinions of Warren while also conveying misleading information.

![Figure 4.1a: “C2” coding](image1)

![Figure 4.1b: “C2” coding](image2)

**Figure 4.1: Warren’s Fraction of Native American Heritage**

Fig. 4.2a is coded as “C3” because it includes both information that is presented as fact-based in the form of a Warren quote and a subjective judgement at the bottom of the image. The quote, attributed to Warren, is: “IF WOMEN NEED TO BE RAPED BY MUSLIMS TO PROVE OUR TOLERANCE, SO BE IT -- THEN THANK GOODNESS FOR PLANNED

Parenthood.” Snopes could find no evidence of any such quote or opinion from Warren, and pinpointed the origins to a Facebook user, Tom Correa, who made the post on January 8, 2017. As of March 2019, the quote was still circulating in memes across Facebook; an article from factcheck.org published on March 27 had to again debunk it. Interestingly, a Republican official who frequently shares shocking false information and memes on his Facebook page has also shared the quote, but in a different meme, with a different font and image of Warren. The quote seems to be entirely manufactured to hit at the specific pressure points of the rightwing: Muslims, sexual assault, implied abortion, and Planned Parenthood. That fact could help to explain why the meme is so pervasive and resilient over time, despite being debunked several times over a two year period. It appears that the quote was manufactured to be as inflammatory as possible, with little regard for reality.

71 “Tom Correa - She Really Did Say This!,” archive.is, January 10, 2017, http://archive.is/zPhRo.  
Figure 4.2a: “C3” coding  Figure 4.2b: “B3” coding

Figure 4.2: False Information in Warren’s Memes

Figure 4.2b – with a coding of false information – presents another example about the pervasive and repetitive information in Warren’s memes. The statistic about Warren living in a 5.4 million dollar mansion is wrong, so the meme is coded as “B3,” since false information takes precedence over true in the labels. However, some of the other information in this meme is less easy to prove. The amount it costs to teach one class is challenging to prove; another meme in the collection provides a different statistic ($400,000 for one class, not $350,000), and both seem vaguely accurate for certain periods of Warren’s teaching career at Harvard. Deciding on a coding of “B” over “C” was also challenging; when does a visual imply an opinion? “B” was chosen because the opinion in “C” should be overt – although whether or not Warren in Native garb constitutes this is up for a bit of debate.

Table 4.3: Themes in Warren’s Memes

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/2020th</td>
<td>2</td>
<td>4.55%</td>
</tr>
<tr>
<td>Beto O’Rourke</td>
<td>2</td>
<td>4.55%</td>
</tr>
<tr>
<td>college</td>
<td>2</td>
<td>4.55%</td>
</tr>
<tr>
<td>her presidential campaign</td>
<td>3</td>
<td>6.82%</td>
</tr>
<tr>
<td>hypocrisy</td>
<td>3</td>
<td>6.82%</td>
</tr>
<tr>
<td>Native American</td>
<td>21</td>
<td>47.73%</td>
</tr>
<tr>
<td>Rachel Doozal</td>
<td>4</td>
<td>9.09%</td>
</tr>
<tr>
<td>student loans</td>
<td>2</td>
<td>4.55%</td>
</tr>
<tr>
<td>Trump</td>
<td>3</td>
<td>6.82%</td>
</tr>
<tr>
<td>white</td>
<td>2</td>
<td>4.55%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>44</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Note: These themes are not mutually exclusive; memes were coded for all of the themes present. Simultaneously, not all subjects in memes were coded; a meme had to have a theme that was repeated twice or more for the topic to be coded. \( N_{memes} = 29; \ N_{themes} = 44. \)

Source: Google Images and thesis data collection

The Native American controversy that dogs Warren is the most prevalent theme in all of Warren’s memes. A shocking 47.73% of memes are coded as being Native American themed, per Table 4.3, although there are ten possible themes found total. Several of the other themes – including the 1/2020th theme and Rachel Doe zal – are also near wholly related to the Native American theme. Rachel Doe zal gained notoriety for pretending to be a black woman. Beto O’Rourke, another 2020 hopeful, has linked himself to Mexican culture through his nickname and public statements. Figure 4.3 depicts the evolution of a meme that focuses on several of these themes. Its ending iteration, Figure 4.3c, is the most offensive version.

![Fig. 4.3a](image1)
![Fig. 4.3b](image2)
![Fig. 4.3c](image3)

**Figure 4.3: The Evolution of a Meme**

*Note:* The sentiment of all memes here is coded as negative. They are all coded as “A”.

*Source:* Google Images and thesis data collection

Such a heavy emphasis on one theme is extremely suspect. Per Zannettou et al., it is possible that this could indicate the existence of an influence campaign. It’s still possible that the Native American theme could be so prevalent because of other reasons, however. Trump’s many
tweets on the matter make this a possibility. Further, from 2012 to today, Warren continues to comment on the controversy, oftentimes in the attempt to quelch it. This could just be adding fuel to the fire.

When one considers the lack of true information in memes and the highly negative sentiment of almost all of the memes, it seems likely that an influence campaign could be occurring. Social media further corroborates the existence of a memetic influence campaign here. A year ago in Reddit’s “The_Donald” forum, a user posted a Warren Native American meme template with the exhortation that others were free to use it (Fig. 4.4a).75 In the same forum, another user posted another Warren meme on her heritage controversy, with the caption that it was one of the best Warren memes “constructed,” because it was “Under budget and ahead of schedule” (Fig. 4.4b).76

Figure 4.4: Reddit Meme Manufacturing


A 4chan post, which later ended up on Reddit, went further. It said:

Elizabeth Warren has announced a run for the presidency. Now is the time to move. Go to the New York Times comment sections. Go to Reddit. Go to Twitter. Pose as a concerned Democrat and criticize her for being white. Criticize her for being a woman. Do whatever it takes to further divide the left and prevent them from unifying behind a candidate for 2020. If we can manufacture another Bernie/Hillary split, they'll get crushed in the general election.77

Of course, such a post could have had little following – who is to say that memes were made as a result? But the mere fact that it was written is important to note, because it clearly looks like the seeds of an attempted memetic influence campaign.

**Conclusion**

As discussed in Chapter 1, a memetic influence campaign is defined as the intentional attempt to influence someone through memes. This is done as part of a broader campaign to make a certain audience believe something about a subject. In this case, it seems clear that there are indications of a memetic influence campaign against Warren, with the expressed aim being to sow discord on the left. This is proven through a highly negative sentiment in Warren’s memes, and a focus on one theme (Native American) over all others.

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Chapter 5: Kirsten Gillibrand

Introduction
Analyzing Kirsten Gillibrand’s memes dredges up a rather ordinary picture of the candidate. No theme, sentiment, or information type in her memes seems unduly represented or disproportionate to other media about her. Studying her memes is a useful exercise in what normal meme activity for a presidential candidate may look like.

Brief Background
Kirsten Gillibrand’s views and policies have evolved drastically throughout her career.

Gillibrand was a corporate lawyer in 1991, when she defended big tobacco companies. She then left private practice to clerk on the US Court of Appeals in her hometown of Albany. She served as special counsel to the Secretary of Housing and Urban Development, and was a partner at Boies, Schiller & Flexner law firm from 2001 to 2005.

From 2007 to 2009, Gillibrand was a representative for New York’s 20th congressional district in the House of Representatives. Her district swayed Republican, and during this period, she was a part of the “Blue Dog Coalition” of conservative Democrats. In 2009 she was appointed to fill a senate seat vacant because of Hillary Clinton’s Secretary of State appointment. Gillibrand had previously campaigned for Clinton’s senate election, in 1999. She was re-elected to the seat in a special 2010 election with 60% of the vote.

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80 “Kirsten Gillibrand.”
81 Nwanevu, “Kirsten Gillibrand Is Playing Her Cards Right.”
82 “Kirsten Gillibrand.”
In the 2012 midterms, she was again re-elected to the seat, defeating Republican, Green, Libertarian, and CSP candidates with 67% of the votes.\(^3\) In the 2018 midterms, she won with 67% of the vote. According to her campaign website, her platform for the midterms focused on supporting unions and small businesses, higher minimum wages, political accountability, environmental protection, health care as a basic human right (specifically, Medicare-For-All), female empowerment, and justice for sexual assault victims, particularly in the military.

Gillibrand announced her presidential candidacy on January 15, 2019 with a similar political platform. Her presidential campaign site focuses on equal pay for women, redistributive justice, and accountability. Marking a shift further to the left, Gillibrand has also pledged not to accept PAC money for financing her presidential campaign. However, she has still curried donations from larger donors, including from a former Planned Parenthood board chairwoman and former law partners.\(^4\)

**Perceptions of Hypocrisy**

Due to her political shift from a “Blue Dog” conservative Democrat to a far-left Democrat, Gillibrand has repeatedly been criticized as hypocritical. Her ideology has changed drastically in a short amount of time. She once had an “A” rating from the NRA, but her change in stance on gun control decreased her rating to an “F” in 2010.\(^5\) She has also switched positions on sanctuary cities and amnesty for immigrants. Previously she had been against the idea of

\(^3\) “Kirsten Gillibrand.”
sanctuary cities, but she has distanced herself from this viewpoint and called it embarrassing. In the 2018 midterms, part of her campaign platform focused on immigration reform, with proposed pathways for immigrants to become citizens and support of the Dreamers. As of 2014, she voted with the Democratic Party 96.9% of the time.

**Stance on Sexual Assault**

Her policy work and advocacy on sexual assault issues have also invited many accusations of hypocrisy. The law firm she was a partner at for four years, Boies, Schiller & Flexner, is the law firm that represents Harvey Weinstein. Further, Gillibrand has received campaign support from Weinstein and Bill Clinton. She appears in a 2014 picture smiling and posing with Weinstein. Despite her relationship with the Clintons, Gillibrand made comments in a 2017 New York Times podcast about how it would have been appropriate for Bill Clinton to step down after the Monica Lewinsky scandal, had it occurred today, due to the different sociopolitical climate. These comments surprised many Democrats, and she was criticized by various people close to the Clintons.

She has also come under fire for being the first senator to push for Minnesotan Senator Al Franken to resign after eight sexual assault allegations from different women came out against

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86 “Kirsten Gillibrand ‘embarrassed’ of Not Understanding ‘Gun Violence’ When NRA Gave Her an A-Rating.”
87 “Kirsten Gillibrand.”
88 “Kirsten Gillibrand.”
92 Debenedetti.
him. Former donors including Susie Tompkins Buell and George Soros were upset about Gillibrand’s push to oust Franken, although he willingly resigned. Donors described Gillibrand’s move as “duplicitous.”

In Congress, Gillibrand fervently supports and advocates for victims of sexual assault. Gillibrand went so far as to invite sexual assault survivor Emma Sulkowicz, an artist and activist, to the 2015 State of the Union address. Her platform for re-election in the 2018 midterms included justice for sexual assault cases in the military, a topic she has done much Congressional work on. Gillibrand also leads “Off the Sidelines,” a PAC promoting female leadership.

Memes and Methodology

The meme model methodology was applied to Gillibrand’s “top 30” Google memes. In a big contrast to Elizabeth Warren, the meme label breakdown is far more equitably distributed, as Table 5.1 demonstrates. The facts, figures, and themes from this methodology lead to several interesting insights and postulations, but no clues to the existence of memetic warfare, which seems negligible. It is postulated that Gillibrand’s chapter is an example of normal meme activity.

Table 5.1: Meme Model Applied to Gillibrand’s Memes

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Note: Each meme was coded with one label, according to Model 1 in Chapter 3. The left side of the table depicts the breakdown of these labels. On the right side are the total counts for different types of memes, which are not mutually exclusive. On the bottom right are the totals for each label, which are mutually exclusive. Nmemes = 31.

Source: Google Images and thesis data collection

Only 19.35% of memes were labeled with “A,” meaning that only 19.35% of memes were conveying solely a subjective sentiment. Rather, the large majority of memes – 80.65%, ie the “B” and “C” categories – include information that is presented as fact-based. Since all of these memes have information in them that could be false or true, all of them were fact-checked for veracity. This fact check shows that 58.06% of these memes had true information in them.

Misleading information was more prominent than outright false information, and false information was the least common type of information displayed.

There were challenges in applying the methodology to real-world examples. As Figures 5.1a through 5.1c show, nuanced decisions were made in applying one label over another. All three of these images are similar in theme and sentiment, yet the labels are very different. Figures 5.1a through 5.c depict the different applications of the three label types.
Figure 5.1: Sexual Assault and Hypocrisy in Gillibrand’s Memes

Figure 5.1a is coded as “A” because the information is clearly presented as a joke – the meme is not conveying any pretense of facts, but a subjective message. Nevertheless, the information in
this meme was researched to ensure that it had not been said. Figure 5.1b is solely information-based, as it juxtaposes two quotes, so it is coded with a “B” label. Figure 5.1c uses the same image of Gillibrand and Weinstein as Figure 5.1a, but uses information-based text on the top, and an opinion-based message on the bottom, so the coding for this meme is “C,” because it is both subjective and information based.

Further, despite their similarities, Figure 5.1b and 5.1c also have different numbers coded, marking different types of information disseminated. Figure 5.1b is technically all true information, but it is extremely misleading. The first part of the meme is a previous statement of Gillibrand’s, endorsing Eric Schneiderman for Attorney General. Only part of her quoted statement could be verified online, but it is true that she endorsed Schneiderman.96 However, the meme juxtaposes her statement with a quote from a woman who accused Schneiderman of sexual abuse.97 This statement is also true, but the juxtaposition of the two does not make sense chronologically.98 After Schneiderman was accused of this abuse by several women, Gillibrand called for his resignation as Attorney General. She said, “The violent actions described by multiple women in this story are abhorrent. Based on this extensive and serious reporting, I do not believe that Eric Schneiderman should continue to serve as Attorney General.” 99 The meme in Figure 5.1b is thus a great example of propaganda, because the true information was intentionally twisted to distort the facts. It is clear that this meme was made to intentionally

create the idea in uneducated viewers that Gillibrand continued to support Schneiderman after his abuse.

In contrast, Figure 5.1c is coded with a “3,” indicating false information. One of the images used in this meme – of Gillibrand and Weinstein – is also used in Figure 5.1a and 5.1b. But a few extra words mark a dramatic difference: rather than being coy about the chronology, as in Figure 5.1b, this meme implies that Gillibrand “hangs out” with Weinstein after 2014 (when the picture was taken). This meme thus demonstrates the fine line between “misleading” and outright “false” information. There were many memes like this, and this specific issue could help to explain the fact that misleading memes were more common than outright false information memes.

Figure 5.2a: “C3” coding

Figure 5.2a: “C2” coding

Figure 5.2: Bill Clinton in Gillibrand Memes
Further displaying some of the challenges of classifying memes into the three information categories is Figure 5.2a, above. Fascinatingly, information that is wrong – a picture of Gillibrand and Bill Clinton that is labeled as being of Clinton and Dr. Ford – is corrected within the meme itself. This shows how the false versus true versus ‘true but misleading’ dichotomy of the meme model is not always so straightforward: the veracity of information in a meme is not always binary true/false, but can be a spectrum. Nevertheless, Figure 5.2a was labeled as “false information,” because per the data collection methodology any false information in a meme makes the meme ‘false.’

All memes in Figure 5.1 and Figure 5.2 share a common theme of hypocrisy, and all of them except Figure 5.2a also have sexual assault as a theme. Likely because of her strong stance on sexual assault, many of the Gillibrand memes focus on this as well as her apparent hypocrisy on the issue. In fact, 23.53% of the “top 30” Google memes focused on sexual assault – the highest memes on one theme. Further, 17.65% of the memes focus on hypocrisy in some way. This is likely because Gillibrand has switched positions on so many issues throughout the course of her political career, starting as a more conservative Democrat and currently being one of the most progressive in her party. The fact that misleading information was more common than outright false information could also be a result of the specific controversies Gillibrand has been involved in and the changing postures she has taken on various issues over time. Further, the themes tracked are not mutually exclusive. Many of the themes were grouped together, such as the Kavanaugh theme – which was 5.88% of the memes – and “voting against Trump’s picks,” which was 14.71% of the memes.
Table 5.2: Themes in Gillibrand’s Memes

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;a total flunky for Chuck Schumer&quot;</td>
<td>3</td>
<td>8.82%</td>
</tr>
<tr>
<td>Chuck Schumer</td>
<td>3</td>
<td>8.82%</td>
</tr>
<tr>
<td>her presidential campaign</td>
<td>5</td>
<td>14.71%</td>
</tr>
<tr>
<td>hypocrisy</td>
<td>6</td>
<td>17.65%</td>
</tr>
<tr>
<td>Kavanaugh</td>
<td>2</td>
<td>5.88%</td>
</tr>
<tr>
<td>midterm elections</td>
<td>2</td>
<td>5.88%</td>
</tr>
<tr>
<td>sexual assault</td>
<td>8</td>
<td>23.53%</td>
</tr>
<tr>
<td>voting against Trump’s picks</td>
<td>5</td>
<td>14.71%</td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>34</strong></td>
<td><strong>100.00%</strong></td>
</tr>
</tbody>
</table>

*Note: These themes are not mutually exclusive; memes were coded for all of the themes present. Simultaneously, not all subjects in memes were coded; a meme had to have a theme that was repeated twice or more for the topic to be coded. Nmemes = 31; Nthemes = 34.

*Source: Google Images and thesis data collection*

As shown from the negative sentiments of Figures 5.1a, 5.1b, and 5.1c, negative was the most common sentiment detected in Gillibrand’s memes. 48.39% of memes were negative in sentiment, while 19.35% were positive. Examining the themes of the memes while looking at the sentiment helps indicate the relative partisan breakdown of meme creators. For example, in the five memes that were labeled voting against Trump’s picks, three of the memes were positive in sentiment, while two were neutral. This indicates that Gillibrand has garnered more praise for voting against Trump’s picks than negativity (at least in this meme collection sample).

Table 5.3: Sentiment Towards Gillibrand

```
<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>15</td>
<td>48.39%</td>
</tr>
<tr>
<td>Neutral</td>
<td>10</td>
<td>32.26%</td>
</tr>
<tr>
<td>Positive</td>
<td>6</td>
<td>19.35%</td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>31</strong></td>
<td><strong>100.00%</strong></td>
</tr>
</tbody>
</table>
```
Note: Every meme was assigned one sentiment (negative, neutral, or positive) based on the sentiment the meme expressed towards the candidate. Nmemes = 31. 
Source: Google Images and thesis data collection

Did the positive memes have more in common with each other than the negative memes? All of the positive memes were either coded as “A,” or were examples in “B” or “C” of “1” – ie, true – information. This is a notable finding. In contrast, for Elizabeth Warren, most of the negative memes had true information. Below in Figure 5.3 are two positive memes that lauded Gillibrand for not voting for any Trump picks.

![Figure 5.3: Positive Memes Voting Against Trump’s Picks](image-url)
“A Flunky for Schumer”

Gillibrand is a prominent critic of Trump, as is clear in her memes and the voting against Trump theme of certain memes. Notably, a tweet of Trump’s about Gillibrand has furthered these elements. He tweeted that Gillibrand was “a flunky for Schumer,” and this is another theme that continues to permeate Gillibrand’s memes. Figure 5.4, below, depicts examples of this. Both Figure 5.4a and 5.4b are coded as “C” – because both a subjective political sentiment is displayed and information presented as fact-based.

![Image of memes](image)

**Figure 5.4: “Flunky for Schumer” Memes**

The fact that a tweet from the president can have the effect of creating memes is notable, although not unusual, since he holds the highest office in U.S. government. These memes could show the partisanship of their creators. Figure 5.4c is unique in that it is from a source site called ‘memenews;’ because it presented a neutral photograph of Gillibrand with a caption that was solely news, it was coded as neutral in sentiment, not negative.
Conclusion

There are many interesting elements and patterns in a study of Kirsten Gillibrand’s memes. Yet little points to any possibility of memetic campaigning: compared to Warren, a much higher majority of Gillibrand memes were true, and fewer were misleading or outright false than in Warren’s case. Further, the themes in Gillibrand’s case were spread out, with several gaining attention. In contrast, in Warren’s case, one of the clearest arguments for the presence of memetic campaigning is the fact that her themes are so unequally distributed, with one having over seven times the weight of most others. Gillibrand’s popular themes – including voting against Trump’s picks, sexual assault, and hypocrisy – are also based in real actions Gillibrand has made. When true information is pervasive in memes, as is the case here, any nefarious actor’s attempt at influence is relatively moot. Rather, Gillibrand’s case study serves as a foil to the negative memetic campaigning seen in Chapter 4 with Elizabeth Warren, and the positive memetic campaigning encountered in the next chapter with Tulsi Gabbard.
Chapter 6: Tulsi Gabbard

Introduction
Positive memetic influence campaigning seems like it could be playing a role in Tulsi Gabbard’s presidential campaign. This claim is made through an analysis of Gabbard’s memes, which have an extremely positive slant, with the dissemination of absolutely no false information. This claim is further bolstered through Google search data and media sources.

Brief Background
Tulsi Gabbard is a Hawaiian politician currently in the House of Representatives. Unlike Warren and Gillibrand, who serve six year senate terms, Gabbard is up for re-election every even year. A Hawaiian and Hindu, Gabbard has been deployed in the Middle East with the National Guard.100 Before joining national politics, Gabbard was a state politician. She was elected to Hawaii’s House of Representatives in 2002 for a two year term.101 She was 21 in 2002, making her the youngest female politician ever elected to a state legislature in both Hawaii and the US as a whole.102 She ran for re-election in 2004, but her service in the National Guard conflicted with the campaign.103 So instead, she deployed to Iraq in 2004.104 She was also deployed in 2008, where she was a military police platoon leader in Kuwait. She then served on the Honolulu City

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101 “Tulsi Gabbard.”
104 Hickey, “12 Fascinating People Who Are Heading To Congress Next Year.”
Council from 2010 to 2012. She was first elected to the House of Representatives for Hawaii’s 2nd district in 2012, gaining 76% of the vote in the general elections. She is the first Hindu ever elected to Congress. She won re-election to the House of Representative in 2014, 2016, and 2018. She served as one of the five Vice Chairs of the Democratic National Committee before the 2016 presidential election, but resigned in February 2016 so that she could endorse Bernie Sanders for president. She had previously complained that the DNC did not schedule enough debates for candidates.

As a representative, she met with Syrian president Bashar al-Assad during a trip in 2017. This move was controversial for several reasons. Firstly, the US government doesn’t have diplomatic relations with Syria, so her trip was perceived as out of line by many. Further, Gabbard does not have seniority in Congress. Speaker of the House Paul Ryan and Minority House Leader Nancy Pelosi weren’t aware of the trip beforehand. Nevertheless, Gabbard has explained that the trip is a result of her principles. Gabbard is a firm anti-interventionist and strongly anti-terrorism, which she says is a result of her tour in Iraq. She is the creator of a “Stop Arming Terrorists” bill in the House.

Her campaign for re-election to the House of Representatives focused on boosting the local economy and creating jobs in Hawaii, lowered costs of housing and living, ending American involvement in the war in Syria, environmental protection, gun control, net neutrality, campaign finance reform, and protecting civil liberties. Gabbard announced her candidacy for

105 “Tulsi Gabbard.”
president on January 11. According to a Politico article, she told CNN about her intention to run before informing her own staff. In a February 2 official candidacy announcement, she emphasized her service in the National Guard, saying that she “will bring this soldier’s principles to the White House.”

Memes and Methodology

Patterns spotted in Gabbard’s memes seem to strongly hint at the existence of a memetic influence campaign. Yet unlike Warren, this campaigning seems to be boosting Gabbard’s presidential candidacy, not slandering it. A shocking 69.23% of the memes coded after the meme model methodology were positive in sentiment, as shown in Table 6.1, and a mere 3.85% of Gabbard memes were negative in sentiment.

Table 6.1: Sentiment Towards Gabbard

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>1</td>
<td>3.85%</td>
</tr>
<tr>
<td>Neutral</td>
<td>7</td>
<td>26.92%</td>
</tr>
<tr>
<td>Positive</td>
<td>18</td>
<td>69.23%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>26</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Note: Every meme was assigned one sentiment (negative, neutral, or positive) based on the sentiment the meme expressed towards the candidate. Nmemes = 26.

Source: Google Images and thesis data collection

109 “Tulsi Gabbard.”
Such a wildly positive sentiment in memes is strikingly unusual, particular when considering Warren and Gillibrand’s largely negative memes. In Warren’s case, negative memetic warfare is one likely explanation, because her memes were 82.76% negative in sentiment. But even Gillibrand – who, in the absence of the possibility of any sort of control, serves as a sort of ‘normal meme activity baseline’ – had memes that were 48.39% negative in sentiment. Positive sentiment memes were 19.35% of Gillibrand’s memes. The sweeping positivity of Gabbard’s memes is an excellent first sign that a positive influence campaign could be occurring.

Another striking statistic in Gabbard’s memes was the total absence of memes that disseminated false information, per Table 6.2. Warren and Gillibrand had 13.33% and 9.68% instances of memes sharing false information, respectively. The numbers for misleading information are similar across all three case studies, making the lack of false information for Gabbard more interesting. 11.54% of her memes do including information is misleading. If there is misleading information, why isn’t there any that is outright false?

Table 6.2: Meme Model Applied to Gabbard’s Memes

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>8</td>
<td>30.77%</td>
<td>15</td>
<td>57.69%</td>
</tr>
<tr>
<td>B1</td>
<td>5</td>
<td>19.23%</td>
<td>3</td>
<td>11.54%</td>
</tr>
<tr>
<td>B2</td>
<td>1</td>
<td>3.85%</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>C1</td>
<td>10</td>
<td>38.46%</td>
<td>20</td>
<td>76.92%</td>
</tr>
<tr>
<td>C2</td>
<td>2</td>
<td>7.69%</td>
<td>18</td>
<td>69.23%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>26</td>
<td>100.00%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Each meme was coded with one label, according to Model 1 in Chapter 4. The left side of the table depicts the breakdown of these labels. On the right side are the total counts for different types of memes, which are not mutually exclusive. On the bottom right are the totals for each label, which are mutually exclusive. Nmemes = 26.
Source: Google Images and thesis data collection
As Table 6.3 shows, the distribution of themes in Gabbard’s memes was far more equal than Warren’s case, looking more like the theme distribution of Gillibrand’s memes. Nevertheless, the content of Gabbard’s memes was notable. Since she is less well-known, one of her main claims to mainstream fame is her proposed “Stop Arming Terrorists” bill. This is reflected in the themes: condemning the American government for funding terrorists was the subject matter of 20% of the memes.

Table 6.3: Themes in Gabbard’s Memes

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Raw Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>army</td>
<td>6</td>
<td>17.14%</td>
</tr>
<tr>
<td>Bernie Sanders</td>
<td>4</td>
<td>11.43%</td>
</tr>
<tr>
<td>condemning government for funding terrorists</td>
<td>7</td>
<td>20.00%</td>
</tr>
<tr>
<td>DNC</td>
<td>3</td>
<td>8.57%</td>
</tr>
<tr>
<td>her presidential campaign</td>
<td>6</td>
<td>17.14%</td>
</tr>
<tr>
<td>left as her enemy</td>
<td>3</td>
<td>8.57%</td>
</tr>
<tr>
<td>Russia</td>
<td>2</td>
<td>5.71%</td>
</tr>
<tr>
<td>Syria</td>
<td>4</td>
<td>11.43%</td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>35</strong></td>
<td><strong>100.00%</strong></td>
</tr>
</tbody>
</table>

*Note:* These themes are not mutually exclusive; memes were coded for all of the themes present. Simultaneously, not all subjects in memes were coded; a meme had to have a theme that was repeated twice or more for the topic to be coded. Nmemes = 26; Nthemes = 35.  
*Source:* Google Images and thesis data collection

Like so many contemporary American politicians, Gabbard is also very active on Twitter. Figure 6.1a is a quote of a statement Gabbard made on Twitter, espousing non-intervention in Syria. While the meme itself is banal – its sentiment is coded as neutral, and it is coded as “B1” for presenting solely fact-based information – what happened after her tweet is unusual for a lesser known politician. After the December 16, 2016 tweet Gabbard penned in Figure 6.1a, white supremacist David Duke retweeted Gabbard. A site run by the Russian government that is known for disinformation and the dissemination of propaganda, Sputnik News, wrote and shared
an article solely based on Gabbard’s tweet.112 The first sentence of the article, which was bolded in the article, is a direct quote from the Gabbard tweet and subsequent meme. Figure 6.1b is a meme depicting the real quote of another tweet Gabbard penned on Syria.

![Fig. 6.1a: “B1” coding](image1) ![Fig. 6.1b: “C1” coding](image2)

**Figure 6.1: Gabbard Memes with a Weirdly Wide Reach**

This bizarre reach has occurred in multiple instances. Figure 6.2 is a meme that is a screenshot of a news article on Russian influence to support Gabbard. The caption at the bottom appears confused about the subject matter, but the article is legitimate, per the meme’s “C1” coding.

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An NBC News analysis conducted in February 2019 found an ongoing Russian influence campaign to support Gabbard:

Since Gabbard announced her intention to run on Jan. 11, there have been at least 20 Gabbard stories on three major Moscow-based English-language websites affiliated with or supportive of the Russian government: RT, the Russian-owned TV outlet; Sputnik News, a radio outlet; and Russia Insider, a blog that experts say closely follows the Kremlin line… The coverage devoted to Gabbard, both in news and commentary, exceeds that afforded to any of the declared or rumored Democratic candidates despite Gabbard’s lack of voter recognition… Gabbard was mentioned on the three sites about twice as often as two of the best known Democratic possibilities for 2020, Joe Biden and Bernie Sanders, each with 10 stories. Kamala Harris and Elizabeth Warren had fewer. In each case, the other contenders were treated more critically than Gabbard.\textsuperscript{113}

Such findings are aligned with the meme analysis done here, and help to explain why the sentiment of Gabbard’s memes is so unusually positive. Geopolitically, Russian support of Gabbard makes sense. Her call for the US to leave Syria is align with Russian interests in the

region. Google Trends shores up an interesting image of Russian knowledge of Gabbard. Although one may think that few in Russia would have interest in a little-known politician, Figure 6.3 depicts the popularity with which the term “Tulsi Gabbard” is searched in Russia, broken down geographically. Strikingly, the most hits are in Moscow, the capital, followed by Saint Petersburg. Saint Petersburg is where the IRA is located. The IRA conducted information operations during the 2016 American presidential election.

![Figure 6.3: Russian Google Searches of Tulsi Gabbard, Last 12 Months](image)

*Source: Google Trends*

The largest spike in Figure 6.3 corresponds to a spike in American searches of Tulsi Gabbard on Google, per Figure 6.4 – a sign that both Russian and American searches of Tulsi Gabbard went up at similar times and amounts.
Such Russian influence is difficult to pinpoint with exactitude, but it is possible to paint a potential picture of it through meme analysis. Figure 6.5 depicts what seems like a banal quote from John F. Kennedy in support of Gabbard, displaying Gabbard’s reputation for bipartisanship. The quote is from a 1958 speech Kennedy made at Loyola College in Baltimore, Maryland.
Figure 6.5: Bizarre Bipartisanship

Interestingly, Kennedy’s speech lauded Russia. He talked about how Russians had surpassed Americans in their education system and in other intellectual feats. He says,

the truth of the matter is that in many areas we are seeking to imitate the Russians… In short, we have badly deceived ourselves about Russian intellectual achievements. We have been complacent about our own supposed monopoly of know-how. We have been mistaken about their supposed ignorance. And we have completely failed to understand the crucial importance of intellectual achievements in the race for security and survival.

Could this meme count as Russian influence? It is hard to say. What is certain only is that this meme is presented as innocuous, while a closer examination presents more interesting information hidden under its banal surface.

Conclusion

Memetic influence campaigning that is positive could have played a role in uplifting Gabbard from obscurity, as shown through Google search data from the last 12 months and the strangely wide reach of an obscure candidate’s tweets. The complete lack of false information and extreme positive sentiments in the memes of Gabbard are further indications that a positive campaign could be occurring. With only Warren and Gillibrand’s meme activities available for comparison, it is difficult to make declarative statements on whether or not memetic warfare

115 “Remarks of Senator John F. Kennedy at the Loyola College Annual Alumni Banquet, Baltimore, Maryland, February 18, 1958 | JFK Library.”
certainly occurred in this instance. Along with the report, however, it appears that this claim is correct.
Chapter 7: Conclusion

The three case studies are useful not only through subject-by-subject individual analysis of Warren, Gillibrand, and Gabbard. Looking comparatively at findings that can be gathered on a macro level is also valuable. Gabbard and Gillibrand both had information was coded as true in their memes 58% of the time. In contrast, Warren’s information was true only 24% of the time. For all three case studies, a large majority of memes were ones that included opinions. All had similar amounts of memes with misleading information, around 11% to 13%. False information was in approximately 14% of memes for Warren and 10 % of memes for Gillibrand. In contrast, Gabbard had no memes with false information in them. This demonstrates that influence campaigns can occur without the existence of false information at all, contrary to popular belief. This matches the findings of Guess et al., discussed in Chapter 2.

Gabbard and Gillibrand have similar range of themes covered in their memes. For Gabbard, the most popular theme is in 20% of the memes, while for Gillibrand the most popular theme is in 23% of her memes. In contrast, for Warren, the “Native American” theme dominates her discourse, and is seen in 47% of her memes. For both Warren and Gillibrand, it appears that Trump’s disparaging tweets have influenced the themes. Interestingly, Gabbard’s themes focus far more on her policy issues than Gillibrand and Warren’s themes. This could perhaps be because so many of the memes were positive in sentiment. Gillibrand and Warren share some negative themes are negative, such as “hypocrisy.”

In terms of sentiment, Warren’s memes were 83% negative, while Gillibrand had 48% negative memes and Gabbard had a mere 4% negative memes. Gabbard was the only candidate for whom positive sentiment memes were a majority, at 69%. The sway of the influence
campaigns impacting both Warren and Gabbard is made astoundingly clear through such sentiments.

Through such trends, this thesis has argued that it is possible that Warren is the subject of a negative memetic campaign, while Gabbard is the subject of positive memetic campaign. Gillibrand was found to have normal meme activity. This argument has been made through the application of a political candidate meme model, with a coding methodology completed for each candidate’s meme collection.

Ultimately, the main question here is whether or not all of the statistics presented are meaningful or useful. Do characterizations divided by information type, theme, and sentiment actually help to illustrate normal meme activity? Do they help to demonstrate what a possible memetic influence campaign may look like? More than anything else, this thesis has helped to illustrate the challenges in being able to confidently pinpoint whether or not an influence campaign has occurred. When are trends simply trends, and when do they point to broader malfeasance? Without a lot of literature to fall back on, academics in this area have to start nearly from scratch in ascertaining what signs of influence campaigns could be. Much of this work is domain-specific: what applies to campaigning on Twitter does not necessarily apply to Facebook. This research seems to have fallen prey to the same ailment of over-specificity that has afflicted much of the scholarship reviewed in Chapter 2. Over-specificity leads to lack of applicability across platforms, politicians, and type of influence campaigns. Paradoxically, specificity is also necessary for any academic work to occur, since it must use concrete examples. Much more work, at much larger scales, is needed to counter this inherent research trap.
The meme methodology in this thesis is a good start to better examining and analyzing the signs of memetic influence campaigns and how they can be distinguished from normal meme activity. Much further research is necessary. Regressions could be run on the data in this thesis, although the small sample sizes may hamper significant results from being achieved. The meme methodology done here also lays the groundwork for potentially more groundbreaking research. The methodology could potentially be automated through image recognition, content and sentiment analysis, and machine learning. Supervised machine learning could be done using a labeled meme set similar to the one created here. Such techniques would allow for far larger sample sizes and far more candidates to be examined.

Progress in this interdisciplinary field of inquiry is slow. This thesis has helped to illuminate the difficulties in ascertaining whether or not a memetic influence campaign is occurring. But even minute progress in this field is important, maybe even imperative. Everyone must be able to become independent, critical consumers of social media. Being social media literate is difficult: memes play to our emotions and pre-conceived stereotypes. It is easy to see them as banal, as funny tidbits separated wholly from politics even as they satirize or invoke them. Our guard is not up while browsing causally through memes. A new type of media literacy, encompassing social media, must be developed. The average person should know what the signs of a memetic influence campaigning might include in order to become social media literate. This thesis serves as a cohesive brainstorm for more comprehensive research on how influence campaigns can be differentiated from normal internet activity.


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