TEXT ANALYSIS OF AIR FORCE REFERENCES IN TWITTER

THESIS

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Abstract

Social media has grown to become a rich source for opinions, authored by individuals who volunteer them, unedited and in real-time. Armed with this information, an organization like the Air Force can understand the perceptions of consumers and learn to better serve the American taxpayer. To accomplish this goal, this research takes a qualitative approach, utilizing social media analytics in combination with various Text Mining methodologies (word frequency, word relationships, sentiment analysis, topic modeling) to provide insight on Air Force related content shared on Twitter. To provide a well-rounded analysis of the overall perception of the Air Force enterprise, the methods mentioned are conducted on Tweets related to the Air Force's five core missions: *Space/Cyberspace, Nuclear Deterrence, Air Superiority, Advancements in Technology,* and *Intelligence, Surveillance, Reconnaissance*. This research also identifies the key players that publish the most engaged Tweets related to the Air Force. By understanding the types of users who possess the most influence (*Regular Users, Bloggers, Celebrities, Military Leaders, Politicians, Professional Organizations*), Air Force leaders are better equipped to react to content and protect the Air Force brand.

Dedication

I dedicate this thesis to my Family and Girlfriend, who have been a tremendous support during this experience. I would also like to dedicate this effort to my late Grandfather, who wanted nothing more than for me to succeed. I cannot express how much I love and appreciate you all.

Acknowledgments

I would like to express my gratitude to my research advisor, Dr. Daniel Ritschel, for his guidance and support throughout this thesis effort. I appreciate the confidence he has instilled in my writing, as well as the caring and patient environment that he provided. I could not have asked for a better mentor. I would also like to thank Captain Amanda McGowin for providing me critical expertise in the field of Text Mining. Finally, I would like to thank Dr. R. David Fass for his creative ideas and thorough reviews of my writing.

Seth A. Kline

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I. Introduction

Background

Social media in the early 2000s pursued a simple goal of connecting people through the internet. Myspace, once the most popular website in the world, was one of the first to enter the uncharted waters of social media networking. On Myspace, one could play a song over their profile page or alter the ranking of their top friends list; all revolutionary activities at the time. As a tool to simply interact with one another through music and entertainment, Myspace was excellent. Nevertheless, social media today has evolved to be much more. Recent generation platforms such as Twitter, Facebook, and Snapchat have grown to be highly functional resources for news and user opinions on various matters.

Fifteen years ago, it would be difficult to comprehend the dominance that social media has in the news domain over opposing sources such as newspaper and radio. According to the Pew Research Center, "two-thirds of Americans report that they get at least some of their news on social media," while at the same time nearly 50% of people under the age of 50 have online sources as their primary news outlet (Mitchell, Gottfried, Barthel & Shearer, 2016). Secondly, social media promotes the human opinion more effectively than any other avenue through sharing and promotional actions like Retweets and shares (Bruns & Burgess, 2011). More recently, the phenomenon of the hashtag has allowed social media users to post to a hashtag conversation and make it possible for them to communicate with a community of interest without needing to establish a mutual relationship (Bruns et al., 2011).

Sharing allows for several users to read one's post and continue the sharing domino effect through various actions depending on the platform. For example, someone on Facebook may like an article and share it to their profile. If this person has 100 friends, that is the potential for 100 more people to read the article and generate an opinion on the matter. If just one of those friends presses the share button, more eyes will see the article and so on. Continued sharing boosts the popularity of the message and can sway minds at a surprisingly rapid rate. According to Visual Capitalists, the internet minute was powerful in 2017 and a visual representation of what occurs can be seen in Figure 1. In one-minute last year, an average of 900,000 users logged into Facebook, 46,200 pictures were uploaded to Instagram feeds, and 452,000 tweets were posted (Desjardins, 2017).

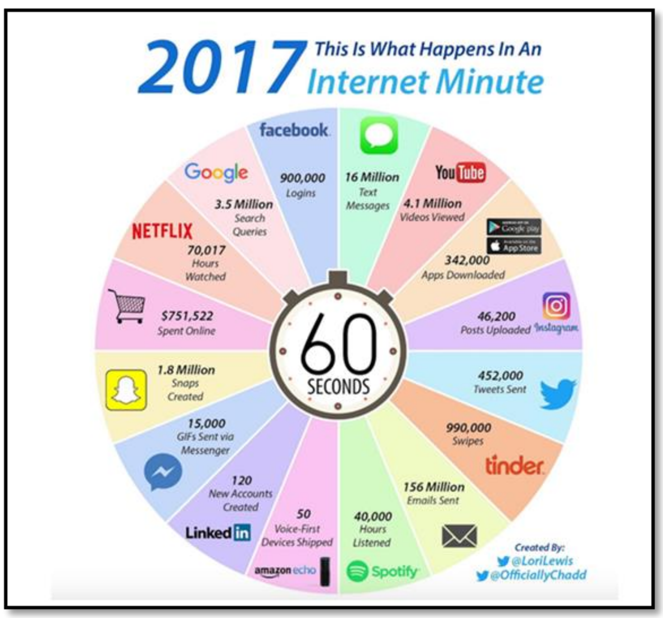

Figure 1: The Internet Minute (Desjardins, 2017)

When a message gains steam and becomes viral, a horde of consequences can occur, both positive and negative. In 2007, high school student Carly Monzo posted a creative video asking Olympic snowboarder Shaun White to her senior prom. The video received over 300,000 views within days and resulted in Shaun White escorting Monzo on her big day (Moton, 2014). The impact of social media was great for Monzo, however the same power can have a destructive outcome. In 2013, the infamous computer hacking group known as the, "Syrian Electronic Army," hacked into the Associated Press Twitter account and falsely tweeted that President Obama had been injured from explosions within the White House. Although the tweet was falsely written and removed minutes later, immediate consequences were felt around the world. The DOW Jones Industrial Average dropped an estimated value of $136 billion dollars after the tweet was posted, showcasing the unfortunate power and speed of social media (Forex Capital Markets, 2017).

Given the potential impact that social media has on the Air Force, the purpose of this research is to analyze references related to the five core missions as defined by the Air Force Strategic Master Plan (AFSMP). Those missions can be summarized into the following "buckets:" nuclear deterrence, intelligence-surveillance-reconnaissance, air combat dominance, space & cyberspace operations, and overall technological advancement. Twitter was chosen for the focus of the analysis as tweets from influential users have propagated other outlets such as television and radio. The most prominent of those users being President Donald Trump who's tweets on social and political matters can be read by the President's 51 million followers. Lastly, Twitter is widely used and accepted with over 330 million monthly active users and stands as the third most popular social networking app in the United States (Statista, 2018).

Problem Statement

The way public opinion perceives a topic on social media is powerful and can cause real consequences outside of the internet realm. How a company markets its brand is important. In addition, how a company markets its brand on social media is crucial. According to marketing strategist David Scott:

> You can buy attention [advertising]. You can beg for attention from the media [Public Relations]. You can bug people one at a time to get attention [sales]. Or you can earn attention by creating something interesting and valuable and then publishing it online for free.
> (Singh & Sinha, 2017)

Although the Air Force doesn't have the same goals as a private company, the importance of monitoring its own brand is still high. As previously mentioned, the Air Force has five distinct missions as outlined by the AFSMP. Public opinion on how these missions are being conducted is important to monitor since the Air Force is a public entity funded by tax payers eager for a return on investment. In addition, these dollars are appropriated by a Congress who could potentially be pressured by majority opinion and act on certain Air Force programs that hold a negative sentiment in social media.

Research Objectives

The following research objectives were developed in an effort to determine the effects of Twitter content posted by a variety of different users.

1. Which group of Twitter users is the most influential when it comes to Air Force missions (i.e. regular user, news/press, blogger, politician, celebrity, military leader)?
2. What sentiment was displayed for each mission area of the Air Force Strategic Master Plan, user groups, and Air Force Twitter data as a whole?
3. Which topics and/or mission areas are the most popular (Favorites + Retweets + Replies)?
4. Are number of engagements more accurately correlated to positive or negative sentiment?
5. What opportunities can the Air Force take advantage of to improve their presence in social media?

Methodology

The primary data source for this research is Twitter. Tweets were manually collected on a weekly basis between February 2018 to September 2018 (seven months). Tweets were harvested using the advanced search function within Twitter, which provides a list of the top Tweets, containing desired words. Next, Text Mining was employed on all Tweets to determine characteristics and trends of the textual data. The first Text Mining method employed is *word relationships*, which examines which words tend to follow others in order to explore word or phrase frequency. The second method, *sentiment analysis*, is used to extract the meaning or emotional intent of a tweet or conversation. And the last method, *topic modeling*, is used to identify and define the different categories or concepts within a text. By employing these Text Mining methods, tweets relating to the Air Force can be analyzed to answer the research objectives.

Scope and Limitations

For this research, Twitter data is used to generalize the public opinion of the Air Force. Although Twitter is widely used by 330 million users, the data harvested is limited by those who tweeted within the seven month period of analysis. In addition, the Tweets gathered are limited by searches that only contain words related to the five core missions. For example, an advanced search related to the *Space/Cyberspace* core mission could be "USAF Space," which would require results to contain both "USAF" and "Space." However, if a popular Tweet contained "Space" but was referenced as "US Air Force," the Tweet would not be captured according to this advanced search.

Emojis were stripped from the analysis as they could represent a vast set of emotions and it would be invalid to assume the tone of the content. Similar to this, sarcasm cannot be detected by Text Mining techniques, therefore, results would adhere to a random sample analysis to determine the amount of sarcasm among the dataset. In addition, Tweets often come in many forms (i.e. video, picture, article etc.). Because Text Mining cannot analyze these alternate forms, only those Tweets containing at least a sentence in the body of text were included in the analysis. Finally, Tweets were collected once every Friday which could limit the potential for a Tweet to go viral if it was posted minutes before collection. To limit the effect of this data collection bias, searches are backdated to the Thursday prior to account for impactful Tweets made on the previous Friday.

Thesis Overview

The next chapter discusses the current literature on social media and examines the Air Force presence in the social media arena. Chapter three delineates the methodology of the research followed by the results of the research in Chapter four. Chapter five discusses the findings of the analysis and outlines recommendations for the Air Force as well as opportunities for future research.

II. Literature Review

> *"If you make customers unhappy in the physical world, they might each tell 6 friends. If you make customers unhappy on the internet, they can each tell 6,000 friends."*
>
> *-Jeff Bezos, Amazon CEO*

Chapter Overview

The American public's views of the Air Force has shown to have real life impacts on spending (Hartley & Russett, 1992) and support for war (Page & Shapiro, 1983). As a result, public sentiment is important to Air Force leaders. Knowing the general public's stance along with the views of influential members, labeled as *influencers* for this research, can assist in understanding the outside perspective in Air Force mission execution. Twitter is a free and efficient way to gather the views of both the average American and influencer. Yet, there is currently no allocation of Air Force resources intended to analyze this information for uses outside of enemy intelligence and communication purposes.

This chapter explains the current dynamic of Air Force social media capabilities and discusses how a more in depth utilization and analysis of social media can be beneficial. As discussed in Chapter 1, the statistics behind the Internet Minute are striking and the power behind the rapid spread of information gives the people of a democracy an enhanced ability to express oneself. Evidence of this was seen in 2012 when the nation's leading breast-cancer charity, Susan G. Komen for the Cure, halted funding to Planned Parenthood due to the organization's support of abortion (Winig, 2012). The lack of funding meant that hundreds of thousands of dollars intended to pay for breast exams would no longer be available. This caused a social war between both parties and their supporters. “Over the next four days the controversy roiled the nation, drawing politicians, activists, the press and supporters of both organizations into a painful battle that pitted one venerable women’s health organization against another.” In just four days, the voice of social media put extreme pressure on the breast cancer organization to act. “Social media outlets were flooded with messages largely supporting Planned Parenthood and castigating Susan G. Komen for the Cure, which capitulated after four days of social and mass media criticism and reversed its funding decision.” By associating in mass groups via social media, Planned Parenthood supporters were able to force social change. Although using social media to promote social change is unique to the digital era, the underlying principle behind *gathering* and *associating* is fundamentally democratic and relative to ways of the past. French aristocrat, Alexis de Tocqueville, recognized American democracy and its ability to gather and promote change.

> Americans of all ages, all conditions, and all minds are constantly joining together in groups… Wherever there is a new undertaking, at the head of which you would expect to see in France the government and in England some great lord, in the United States you are sure to find an association. In America I came across types of associations which I confess I had no idea existed, and I frequently admired the boundless skill of Americans in setting large numbers of people a common goal and inducing them to strive toward that goal voluntarily. (Tocqueville, 2003)

The common way to associate in the days of Tocqueville was through a townhall. Today, the internet and social media makes it easy to express an opinion with the potential to reach millions in a short time by going “viral.” Specific to defense, there is a potential for social media to have an effect on budgets (Hartley & Russett, 1992) and public support for military intervention (Page & Shapiro, 1983). Therefore, it is critical to analyze the voice of the American public and the *influencer*, as they influence elected officials actions in the military arena. By being proactive and analyzing the information that social media provides, the Air Force can adjust to avoid a negative spotlight and maintain good standing with those that hold the purse.

To provide context to this research, it is important to understand the dynamics of social media and the methods that can be used to analyze the information. Word relationships, sentiment analysis and topic modeling are the primary Text Mining techniques utilized and a background of each will be discussed later in this thesis. Along with those methods, private industry examples will be discussed to provide real world evidence that Text Mining of social media can provide critical insight to the Air Force.

Opinion Formation

Humans are not born with innate opinions on the world around them. Inherently, this means that humans have no preconceived stance on matters of defense such as U.S. military spending or troop levels. Rather, opinions are formed over time through *social influences* and *interactions* with other people (Moussaid et al., 2013).

The opinions of others greatly affects how we generate an opinion on something. In social environments, people tend to filter and integrate information they receive and revise their own beliefs accordingly (Moussaid et al., 2013). This is especially true in the digital era today, where any place with a wi-fi signal can transform from a solitary to a social environment. Additionally, *other people* are not always weighted equally in terms of influencing your opinion (Watts & Dodds, 2007). The theory of the Two-Step Flow Model of Influence (Figure 2) demonstrates that a small minority of "stars" act as intermediaries between media and society. They find the direct exchange of information from the media to "non-stars" does not guarantee that there will be an opinion change. Rather, these "stars" or *influencers* act as trusted advisors between the two parties which help facilitate modifications to an opinion (Watts & Dodds, 2007).

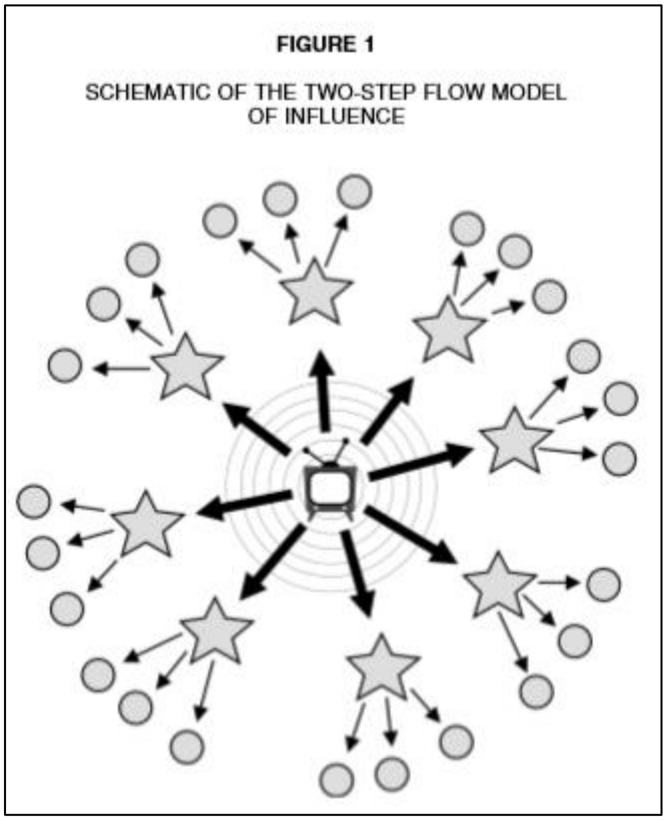

Figure 2: Two-Step Flow Model of Influence (Watts & Dodds, 2007)

War is a controversial topic that is often debated in the media. Research has found that people will initially develop their opinion on war through a cost-benefit analysis of factors such as lives lost, financial cost, or perhaps probability of winning the war (Kim, 2014). However, additional research shows that the "star" factor plays a large role in this debate as well. Berninsky (2007) demonstrates that "elites" (analogous to a "star") and the agreement or disagreement amongst other elites is the most influential factor in determining an individual's opinion on war. Berninsky (2007) found that non-stars were more likely to support war if elites were in agreement to support as well. The "star" and the "elites" are interchangeable with the concept of an *influencer* in this research. The effect that the influencer has on society is amplified through social media. By understanding the voice of various groups of influencers and non-influencers, one can understand if the same effect of intermediary influence is present in the digital age.

Once an opinion is formed, it can be shared through many outlets. Once an opinion is made known, it is then part of the overall societal opinion. Understanding the overall opinion of a society is critical in the democratic process. The Majority Rule theory states that government policy should change with the opinion of the majority stance of the populous (Hartley & Russett, 1992). Evidence of this can be seen in various research. Page and Shapiro (1983) find that where there is a change in majority opinion, there is a change to policy in the same direction (Hartley & Russett, 1992). Specific to an analysis of the effect on the military's budget, Hartley and Russett (1992) found a strong correlation between public opinion and military spending. Although the study was conducted during a time of an arms race with the Soviet Union, the evidence was strongly in favor of their hypothesis that, military spending changed with majority opinion (Hartley & Russett, 1992).

Cultural Change

> *"Progress is impossible without change, and those who cannot change their minds cannot change anything."*
>
> *-George Bernard Shaw, Playwright*

The military in general reacts to sociocultural change with careful deliberation. For instance, the Air Force tattoo policy has been strict on its members until recently. Before the policy change in February of 2017, airmen were not allowed to have a tattoo on their chest, back, arms and legs that were larger than 25 percent of the exposed body part. But due to an increased acceptance for tattoos outside of the military along with a need to "access more talent and retain qualified airmen," the Air Force adapted to sociocultural change and relaxed its policies against tattoos (Secretary of AFPA, 2017). The Army was the first U.S. military branch to implement the change. Army Chief of Staff, General Ray Odierno broke the news during his address at the Association of the U.S. Army Conference in 2015. "Society is changing its views on tattoos, and we have to change along with that…It makes sense, soldiers have grown up in an era when tattoos are much more acceptable and we have to change along with that." (Curthoys and Tan, 2015). The policy change was a constructive milestone for both the Army and Air Force and demonstrates that the military can culturally progress. The same type of change is needed for social media analytics to become a desired strategy to enhance the Air Force's cyber capabilities.

The Air Force is not fully engaged in the field of social media analytics. The Air Force's uses of social media is limited due to the amount of time and effort that would be required to analyze such large amounts of information. "There's a significant amount of that data that we collect that hits the floor and we never actually look at it because we don’t have the analytical capacity,” says General Goldfein at an Air Force Association event in Washington, D.C. “It’s not coming from something exquisite from which I’ve got to protect sources and methods, it’s coming from social media” (Harper, 2017).

Currently, the Air Force utilizes social media in two primary efforts. First, the Air Force uses a variety of social media platforms to communicate. Instagram, Facebook, Flickr, Twitter, YouTube, Vine, and the Air Force Live Blog are all platforms associated with an official Air Force account which is managed by the Air Force Public Affairs Agency (AFPAA). The Air Force Social Media Guide (AFSMG) defines the benefits and security concerns stemming from social media networking. This guidance which is authored by the AFPAA, makes it clear that the role that social media plays in the Air Force is strictly for communication, both internally and externally. “Social media not only serves as a way to communicate internally with our Airmen, but also as a means to tell the story of our Airmen to external audiences who themselves are actively engaged in social networks” (AFSMG, 2013). Although social media serves as an excellent communication tool, any capabilities to analyze social media data is not present in the mission scope of the AFPAA and the AFSMG.

Secondly, the Air Force uses social media to gather intelligence on enemy activity. At the aforementioned Air Force Association event, General Goldfein discussed the efforts of intelligence airmen that found the group responsible for shooting down a Malaysian commercial flight in 2014. “We were searching for the smoking gun and we found it a month later on Facebook when we found posted pictures on Russian blog sites that actually showed the activity” (Harper, 2017). Mirrored to mistakes on the battle field, mistakes can be made by the enemy on social media, and as shown here, the Air

Force exploited it. In a similar story, General Hawk Carlisle, Air Combat Command commander, provides an example of another intelligence gathering effort through social media. This time, a mistake was made by an ISIL soldier whose on-line post gave away the location of an Islamic State headquarters building. "So they [intelligence airmen] do some work, long story short, about 22 hours later through that very building, three JDAMS take that entire building out" (Everstine, 2015). These stories show the powerful role that social media can play when resources are allocated to analyze social media information for a specific purpose. Although social media analysis has proven exceptionally effective in the intelligence community, this remains only a fraction of its power. By using social media to track the sentiment of the public, the Air Force can be more proactive in improving deficient areas while maintaining a positive image.

Brand Management

> *"If you don't give the market the story to talk about, they'll define your brand's story for you."*
>
> *-David Brier, Shark Tank Investor*

The Air Force is a brand and its missions as outlined in the AFSMP are its products to the American taxpayer. With that comes the responsibility for the Air Force to analyze and interpret what the American public is saying about it. Tim Weber, editor from British Broadcasting Company (BBC) says it best, "these days, one witty tweet, one clever blog post, one devastating video-forwarded to hundreds of friends at the click of a mouse-can snowball and kill a product or damage a company's share price" (Weber, 2010). To counter "these days," as cited by Weber, companies are now investing resources towards social media analytics in order to avoid these misfortunes, while concurrently gathering information on customer values. "Social media analytics provides businesses with insights into customer values, opinions, sentiments and perspectives on brands" (Chamlertwat et al., 2012; IBM, 2011a; Kiron et al., 2012, as cited in Kurniawati et al., n.d.). Insight into the minds of the consumer is an invaluable benefit and growth in social media has made customer opinions more readily available.

> It's now easier than ever to connect directly with a brand and offer feedback, especially given the ability to take and share photos that support your claim with minimal effort. In this way, social media mentions can serve as quasi-reviews for both positive and negative commentary. (Annalect, 2017)

One of the more famous social media platforms that is tailored to host customer reviews is the website, Yelp. Before its inception in 2005, finding information on a local business was difficult. Besides word of mouth, the yellow pages of a phone directory listed businesses and advertisement information but inherently gave no merit to its products or services. In addition, the internet was still very new therefore finding information on a particular business was difficult. Word of mouth was the primary means of gathering knowledge according to Yelp CEO, Jeremy Stoppelman. "I got sick and needed to see a doctor. Back then there was very little information on the internet; it was frustrating. We realized the best way to find a doctor, or other services, was by word of mouth" (Loten, 2012). The troublesome experience inspired Stoppelman to co-found Yelp, which has grown its viewership nearly 300% since 2013 (Yelp, 2018). In the first quarter of 2018, Yelp had a monthly average of 174 million unique users visit the website with a total of 155 million reviews. Figure 3 displays the increase in reviews since the website's inception in 2005.

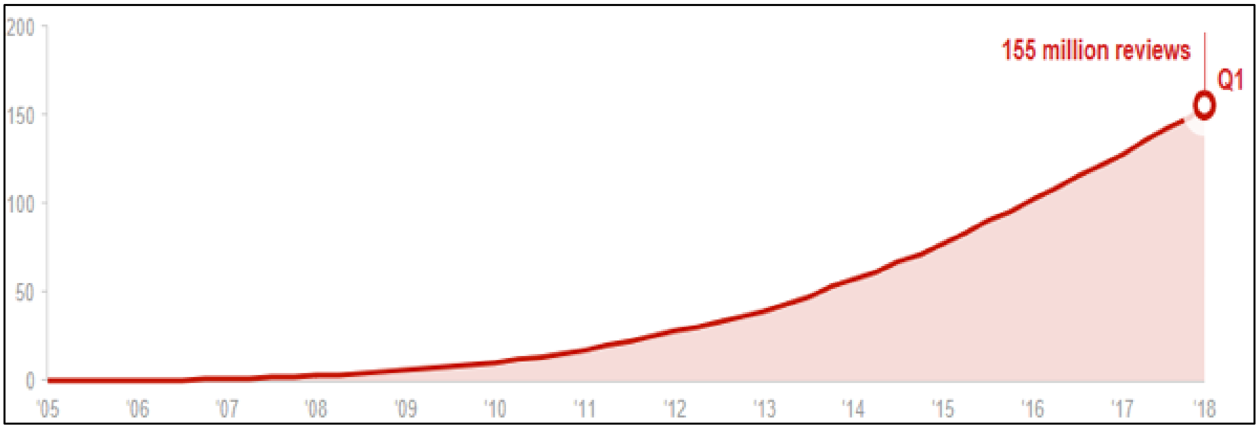

Figure 3: Yelp Reviews '05-'18 (Yelp, 2018)

Figure 3 illustrates the exponential increase of online reviews and points towards a more transparent environment between the customer and seller. This transparency allows for the customer community to be more knowledgeable before making a decision to buy from a brand. In addition, more transparency could be good or bad for a business, especially if the brand is mismanaged after an incident. An example of this came in April of 2017 when United Airlines (UA) overbooked one of its flights and forcibly removed a passenger from the plane. Video footage and tweets about the incident made the UA brand viral overnight and resulted in a drop in stock value of $1.4 billion (Shen, 2017). Additionally, the airline's social sentiment plummeted 160% and mentions of the company on social media increased by 9,968% over a span of two days (American Marketing Association, 2017). The matter was made worse when UA CEO, Oscar Munoz made a public apology that was deemed "tone deaf and insensitive" by many on social media (Shen, 2017). Additionally, the same night as the incident, Munoz sent an email out to employees to "defend his staff's actions" in the removal of the "disruptive and belligerent" passenger. This email also went viral and fueled the negative sentiment that already surrounded UA.

In contrast, businesses such as Tesla use social media to boost their brand and provide customers with quality products and first-rate service. Tesla is known for its innovative automobiles as well as its social media *presence*. The definition of social media presence is letting social media users know that you, as the company, are "available" and "accessible" (Kietzmann et al., 2011). Tesla's reputation as having solid social media presence goes far beyond the marketing team. In fact, Tesla's CEO Elon Musk, is a big part of that effort. Figure 4 shows a Twitter conversation between a Tesla customer and Musk.

Figure 4: Tesla Customer Service Tweets (Clifford, 2018)

The presence that Tesla and their CEO have with its customers pays dividends in its' corporate image. The added transparency and personal touch towards customers has made Tesla one of the best companies in social media branding. In a study of 12 automobile brands, Tesla ranked 9th in total followership for Facebook, Twitter, YouTube and Instagram (Russell, 2018). Although the ranking is in the bottom tier, it is impressive to note that Tesla is the newest brand, spends the least on advertising, and has the fewest cars being driven worldwide. In addition, Tesla was found to have the highest engagement rating (favorites + replies + retweets per post). This led to the conclusion by Russell (2018) that Tesla's social following was "generated organically" versus through paid advertisements, a feat of good brand management.

Although the Air Force is different in nature from United Airlines and Tesla, much can be learned through their examples of brand management. As Tocqueville explains, Americans voluntarily associate in order to drive social change. In the digital era, the primary venue for association is through social media and it is important to understand each association's sentiment. In the next section, we discuss the different associations of people identified in this research and how they have been sorted into various groups based off of followership and influence.

Determining Influence

Twitter contains the source of data for this research. With its rich source of public opinions, it is an excellent way to examine views on the Air Force in the form of text. However, it is important to note that Twitter is used by many types of groups. "Twitter's audience varies from regular users to celebrities, company representatives, politicians, and even country presidents" (Mehta et al., 2012). Each of these groupings have different levels of followership associated with them and with the followership comes different levels of *influence*. Although posting a tweet that 54 million people see is impressive (President Trump's followership), it is more effective if even a small fraction of those viewers propagate the message further through Retweets or replies. Because of this phenomena, it is incorrect to calculate *influence* from the amount of followers alone.

By implementing a ratio similar to the one used by Mehta et al. (2012), a more accurate way of determining influence can be constructed. The ratio developed by Mehta et al. (2012) utilized weights for various ratios of influence that included followers/following, followers/tweets, and followers/time. An influence score for each individual Twitter user is then calculated from those ratios (Mehta et al., 2012). Contrary to Mehta's exact algorithm, this research will define influence by an engagements/followers ratio, where *engagements* are defined as the sum of Favorites, Retweets, and Replies within a given Tweet. The resulting influence score can then be aggregated to an overall user or user group influence score. For instance, if a user with 100 followers generated a tweet with 10 total engagements, the influence for that particular tweet would be 0.10 and would be accumulated with all of the influence scores associated with that user or user group.

Air Force Strategic Master Plan

In May of 2015, the Air Force published a strategic framework (the Air Force Strategic Master Plan) to provide "consistent direction" across the Air Force enterprise (USAF Strategic Master Plan, 2015). This includes plans to enhance the full portfolio of Air Force resources to include programs, equipment, and an added investment in all airmen. Actionable plans to modernize concepts and capabilities to meet the needs of the future fight is a theme throughout the AFSMP. At the core of the plan lies five primary mission areas that the Air Force intends to focus on. These focus areas will be organized into subsets of data and will be gathered through focused search queries. For example, "USAF ISR" will capture all of the Tweets related to the Air Force mission area of *Intelligence, Surveillance, and Reconnaissance*. By keeping the search criteria neutral of any sentiment, the data gathered will contain unbiased results. The five mission areas of the AFMSP are as follows:

I. (Nuclear Deterrence) Provide Effective 21st-Century Deterrence: The nuclear mission remains the clear priority of Air Force leaders, but the Air Force also offers many additional capabilities to deter a wide range of actors

II. (Intelligence, Surveillance, and Reconnaissance) The Air Force will employ agile multi-domain solutions to detect, characterize, deter, and defeat adversaries. This requires an agile, coordinated multi-domain ISR approach that provides commanders with multiple options.

III. (Air Superiority) The Air Force must focus on the skills and capabilities that deliver freedom of maneuver and allow decisive action in highly-contested spaces. However, we must retain the ability to succeed in low-intensity conflict.

IV. (Space and Cyberspace) To achieve the most effective solutions across the spectrum of military operations, we will increasingly integrate and employ capabilities operating in or through the cyberspace and space domains in addition to air capabilities.

V. (Maintain Technological Dominance) We must continue to pursue radical improvements in technology, that when combined with new approaches and organizational changes, expand or maintain asymmetric advantages over adversaries.

Methodologies

Social media data collected from Twitter is utilized for the analysis. Text Mining methods will then be used to identify patterns to determine concepts and sentiments within the text (McGowin, 2018). More specifically, the Text Mining Methods of word relationships, sentiment analysis (Silge & Robinson, 2017) and topic modeling (Steyvers & Griffiths, 2007) will provide the bulk of analysis for this research.

Word relationships can provide high level insight of a text document by providing word and phrase frequency outside of commonly used words like "the," "and," or "but." In addition, word relationships can explain which words are often used together, as well as the ability to account for negation words (no, not, never, without) that flip the intent of sentiment associated words.

Sentiment analysis determines the emotion of a word, set of words, or even a body of text such as a tweet. A simple way of understanding sentiment analysis is by summing the sentiment of each individual word of a text to comprehend the sentiment of the total text. Prebuilt sentiment packages known as "Lexicons" will be used via R programming to analyze and provide various depths of sentiment for each tweet (Silge & Robinson, 2017).

Topic modeling is a method to analyze large amounts of text and generate categories, or "topics" within the text. A topic consists of a cluster of words that frequently occur together. By using contextual clues, topic modeling can identify relationships between words and establish a specific meaning (Steyvers & Griffiths, 2007).

Related Research

In other parts of the U.S. Government, there have been both successful and unsuccessful attempts at leveraging social media. This section of the chapter first explores the literature regarding impacts made by social media in government today. Next, previous research efforts employing Text Mining for defense research are detailed. Lastly, gaps in the literature are identified.

Social Media Research

As previously discussed, the Air Force maintains capabilities in social media analytics within the fields of intelligence and communication. In other government agencies, the use of social media has provided a versatile set of benefits. For instance, branches across the DoD have installations all over the world and with that comes the responsibility of maintaining good relationships with the locals of each country. Eberschloe (2017) articulates that the Army has implemented social media directives for its leadership to foster a strong social media environment. These directives provide guidance on how to communicate the Army's story to external parties such as foreign militaries and populations, which in turn, provides a place to listen to foreign populations. Eberschloe explains that the ability to listen to foreign populations gives U.S. forces the ability to self-validate reconstruction efforts and further propagate influence (Eberschloe, 2017).

As a global super power, the U.S. Government intervenes to provide relief in times of crisis (USAID Strategic Plan, 2007). Departments such as the DoD and Department of Homeland Security implement the tools that social media can offer during a major disaster (United States - FEMA, 2018). Through various applications in social media, research has found that the U.S. Government has given more effective humanitarian aid to those areas in need. Social media posts and blog websites offer crisis managers the ability to gather and disseminate information when other modes of communication are unavailable (Chan, n.d.). Geo tracking and Facebook's "safety check" have also given humanitarian personnel the information needed to provide the necessary assistance required in an identified area of concern (Statt, 2017).

Miles (2009) discusses how a NATO Supreme Allied Commander used social media to more effectively communicate guidance in a transparent style (Miles, 2009). Admiral James Stavridis used "web blogging," a form of social media journaling, to write about organizational goals for the joint effort. By using web blogging, Admiral Stavridis could constantly communicate to allied forces which provided the transparency needed to more effectively communicate the importance of cooperation.

Text Mining Research

Text Mining is the process of drawing meaning out of a written communication (Clarabridge, n.d.). Previous studies in the defense realm have shown the benefits of Text Analysis. McGowin (2018) used Text Analysis to examine a compendium of 32 expert views in comparison to five major Defense Acquisition Reforms. Through *sentiment analysis* and *topic modeling*, McGowin was able to find commonalities among expert opinions that provided recommendations for future acquisition decision makers. This research will incorporate similar Text Analysis methods to identify characteristics of Air Force referenced Tweets.

Munson (2018) used Text Mining on Twitter data to analyze content related to popular topics such as North Korea and NFL protests. By incorporating programming techniques that extracted data directly from Twitter's database, Munson was able to gather and analyze millions of Tweets to quickly identify the overall sentiment of each topic.

Hall (2016) found that Text Mining could be beneficial to the intelligence community during the planning phase of a major operation (Hall, 2016). Hall identified the inefficiency of having intelligence analysts read through extensive amounts of information to summarize for planners and decision makers. Hall's findings concluded that due to the changing threat environment, the use of Text Mining software would provide decision makers much faster and more reliable intelligence for planning.

Text Mining is also utilized in the world of DoD aircraft and vehicle maintenance. SmartArrays, an analytical software consulting company, uses Text Mining to read through millions of maintenance and repair records to specifically look for effects of corrosion (Text Mining of Maintenance Data, n.d.). The Text Mining approach that SmartArrays developed have replaced the manual method which took analysts hours to execute per maintenance record, saving both time and money for the DoD.

As demonstrated in the literature review, Text Mining has been employed in a limited manner in DoD research. However, Text Mining has *not* been applied as a way of understanding public sentiment, topics, or user groups pertaining to the AF in social media. This research intends to fill this gap in the literature.

Chapter Summary

This chapter highlighted the importance for the Air Force to have a strong presence in social media and reviewed the relevant literature focused on social media and

Text Mining in the DoD. It is clear that the Air Force and DoD have made some initial efforts in these arena's, but not to the extent of the private sector. The literature review has also identified many areas of opportunity for social media to be more effectively utilized by the Air Force. The next chapter discusses the methodologies utilized in this research to provide insight of Air Force related Tweets.

III. Methodology

Chapter Overview

The purpose of this research is to identify the topics and sentiment displayed in Air Force referenced Tweets from various user groups. The methods discussed in this chapter will provide a clear picture of what characteristics and trends are being expressed on Twitter. In addition, these methods will help provide insight on which topics are most discussed and highlight the users that are most influential among their followers. The central technique used in this analysis is Text Mining in combination with statistics to provide inferences about the data. To implement Text Mining, *R studio*, an interface to the *R* programming language is used heavily to manipulate and visualize information. Multiple applications within R, known as packages, were implemented to conduct *word relationships*, *topic modeling*, and *sentiment analysis*. Each of these methods will be discussed more thoroughly in this chapter. To provide clarity, Figure 5 displays a flow chart of the primary steps taken to gather and analyze the data.

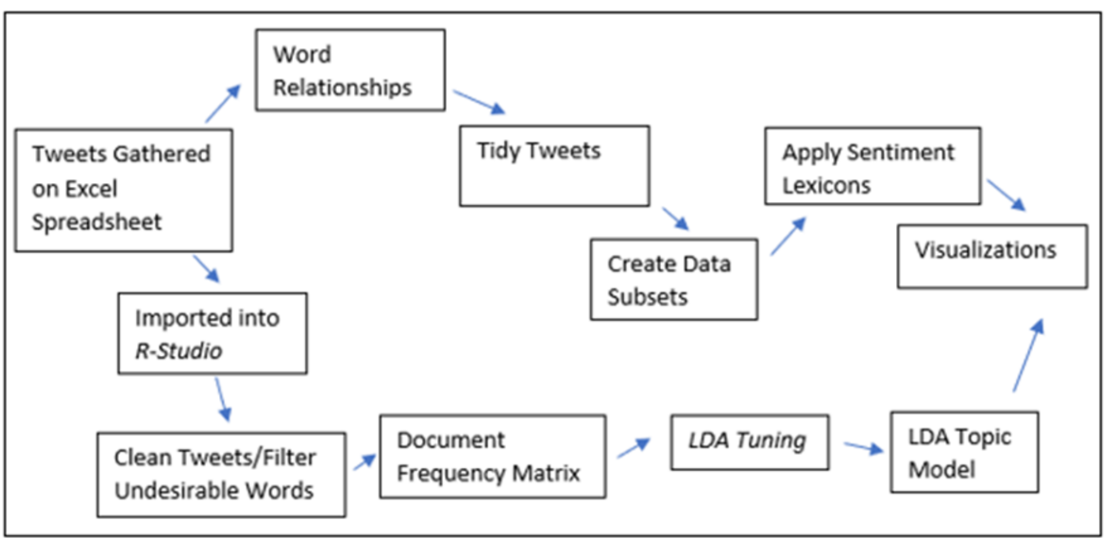

Figure 5: Methodologies Flow Chart

Text Mining

The intent of Text Mining is to extract information from written sources and then discover something that no one knows yet (Hearst, 2013). The technique is a form of data mining, but is inherently more complex as it deals with text that is both unstructured and "fuzzy" (Tan, 1999). Through Text Mining, a document of text can be analyzed to exhibit word frequencies, word relationships, categorization, sentiment and much more (Rouse, n.d.).

For this research, Tweets, will serve as individual documents of unstructured data/text. While *structured* data is created to be captured and organized (i.e. phone numbers), unstructured data is everything else, also known as "big data." (Taylor, 2017). Examples of unstructured data/text include e-mails, online customer reviews, and social media posts. Tweets, which are user generated social media posts, cannot be analyzed on a large scale due to its unstructured nature. By implementing Text Mining in the following six-step process, a way to analyze the text is possible.

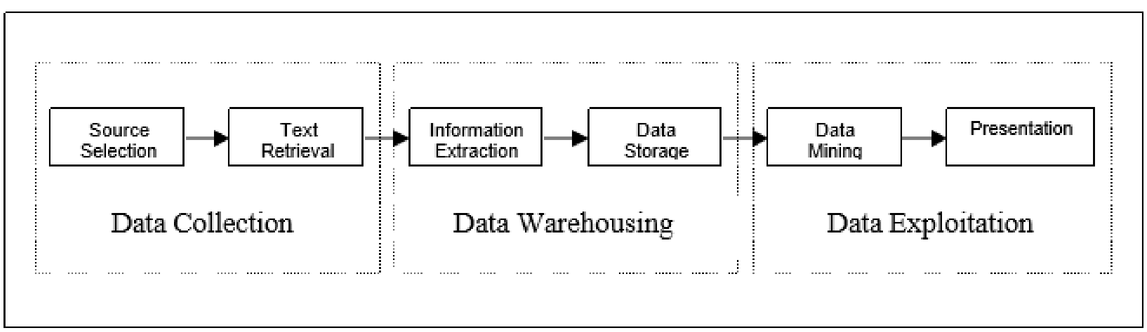

Figure 6: Six-Step Text Data Mining Process (Losiewicz et al., 2003)

Source Selection

As discussed, the intent of this research is to gain insight of Air Force referenced Twitter content. For this reason source of data derives from the Twitter website.

Text Retrieval

When utilizing Twitter as a source for research, there are many effective ways to collect data depending on the type of analysis. One way to data mine Twitter is by using its *Standard* Application Program Interface (API), which gives access to researchers to collect millions of Tweets at the click of a button (Twitter, n.d). However, a limitation of using Twitter's Standard API is that results will only show Tweets posted within the last seven days. For this research, using the API is undesirable as it would limit Tweets to a one week period, accepting the risk that a major event during that week would hinder results that would normally be displayed for an analysis over a longer duration. Another way to data mine Twitter content is by manual collection. The process of gathering Tweets manually from the website itself provides the flexibility of time. Although having a dataset containing millions of Tweets would be beneficial, having Tweets with an expanded range of time would provide improved results. For this reason, manual collection is used for this research.

Tweets were gathered over a seven month period on a weekly basis. Content was copied directly from Twitter and pasted into a formatted *Microsoft Excel* spreadsheet as exhibited in Table 1. Twitter statistics such as number of replies, Retweets (RT), and favorites for each Tweet was captured in the spreadsheet. In addition, the number of followers associated with the tweet's author, the author's user group and author's Twitter username (handle) was also included within the spreadsheet to provide more descriptive data.

Table 1: Data Organization

Tweet	Replies	RTs	Favorit	Engage	Follow	Influen	Group	Handle	Search	Indicat	Docum	Month
Air Force Maj. Raymond	0	4	14	18	138000	7666.667	PLT	GovMallo	Air Force (	SPA	1825	Sep
So where are we with tl	1	0	1	2	1280	640	RU	SmokesIn	Space For	SPA	1826	Sep
These poor #cadets hav	1	2	6	9	199	22.11111	BLG	BckgrndN	Space For	SPA	1827	Sep

To reiterate, gathering Tweets required following a meticulous process. Data collection was a 30 week effort (March 2018 – September 2018) and was conducted on every Friday afternoon. For every week, tweets were collected by using the advanced search function which filtered tweets to those that contained desired words related to either an Air Force general search, or a search related to 1 of 5 Air Force Strategic Missions. For example, the advanced search of “USAF nuclear” could return a tweet like the following: “The **USAF** is great at deterring **nuclear** threats.” In addition, searches used were of neutral sentiment. For example, the phrase “USAF nuclear” is neither positive or negative sentiment whereas, “USAF nuclear success,” would most likely show tweets with positive sentiment.

Each week resulted in 150 tweets collected. Of the 150 tweets, 50 were collected using general searches such as “USAF” aimed to gather the top 50 tweets pertaining to the overall U.S Air Force. The remaining 100 tweets were split evenly among the 5 strategic missions. Table 2 displays a detailed layout search criteria, with examples of the most utilized searches defined for each core mission. A complete list of all advanced searches are exhibited in Appendix A.

Table 2: Advanced Search Criteria

Mission	Search	Tweets/Week	Total Tweets
Overall Air Force	USAF	50	1500
Space/Cyberspace	USAF Space/Cyberspace	20 (10/10)	600
Nuclear Deterrence	USAF Nuclear/Bomber	20	600
Air Superiority	USAF Pilot, Aircraft, Tanker, Refueler, Jet, Fighter	20	600
Intelligence, Surveillance, Reconnaissance	USAF Intelligence/Surveillance/Reconnaissance	20	600
Advancements in Technology	USAF Technology, Innovation	20	600

User Group Characteristics

There are a variety of user groups in the dataset publishing tweets referenced about the Air Force. User groups developed for analysis included *Regular Users, Politicians, Celebrities, Bloggers, News/Press, Military Leaders,* and *Professional Organizations*. In order to assign an individual to a particular group, descriptions within the author's Twitter profile were used to gather information on the individual. If the user's profile contained limited descriptive information, additional online background research was conducted to find out which group the user belonged to. Furthermore, Table 3 exhibits some of the assumptions of the user group's characteristics made when categorizing users.

Table 3: User Group Assumptions

User Group	Abbreviation	Assumptions
Regular User	RU	unverified, name, typically low follower count
Politician	PLT	President Trump, Mayor, Governor, Councilman, Congressman
Celebrity	CEL	must be verified, authors, athletes, not President Trump, actors, personalities
Blogger	BLG	fan pages, pages that tweet about a specific topic, aircraft surveillance pages, explicitly say blogger, satirical pages
News/Press	NP	agencies, magazines, journalists, reporters
Military Leader	ML	official military pages, SES, 0-6 and higher, CMSgts
Professional Organization	PO	Companies, schools, sports teams

Twitter Algorithm

Once searches were made, the results were given in an order based on Twitter's *Top Tweets* algorithm (Twitter, 2018). The algorithm is exclusive to the public, however, some of the driving factors that determines a tweet's popularity is known. Results under Top tweets first display tweets that you, as the user, may "care about the most." To do this, the algorithm takes into account the engagements that the user has made in the past with other tweets and authors. To counteract this effect, a fake page was created that had no recorded history of past engagements. By using this fake page, the Top tweet algorithm could not make assumptions on what tweets this research is interested in. Aside of total number of engagement, Tweets that contained images or links also received more visibility within the Top Tweets algorithm (Twitter, 2018). Tweets that contained images or links were only added to the dataset if there was a descriptive sentence within the body of the message.

Information Extraction & Data Storage

Before applying Text Mining, the current data format must be captured in R as a data frame and then into a *Tidy Text* format. An example of a data frame is seen in Figure 7, which formats a poem into four lines containing multiple words each. Next, the text is converted into a specific type of formatting called Tidy Text, which is the base format for all of the Text Mining methods used in this analysis. The Tidy Text format conforms to a specific structure where each variable is its own column in the data frame and each observation is its own row. In this format, each word is given is own unique identification, which is the process of *tokenization.* An example of a tokenized data frame is seen in Figure 8. In this final tokenized format, capitalization and punctuation are stripped and the data frame is prepped for Text Mining.

```
## # A tibble: 4 × 2
##    line                                text
##   <int>                               <chr>
## 1     1   Because I could not stop for Death -
## 2     2             He kindly stopped for me -
## 3     3 The Carriage held but just Ourselves -
## 4     4                        and Immortality
```

Figure 7: Example Data Frame (Silge

```
## # A tibble: 20 × 2
##     line    word
##    <int>   <chr>
## 1      1 because
## 2      1       i
## 3      1   could
## 4      1     not
## 5      1    stop
## 6      1     for
## 7      1   death
## 8      2      he
## 9      2  kindly
## 10     2 stopped
## # ... with 10 more rows
```

Figure 8: Example Tidy Tokenization Format

Text Mining Methods

Exploration

Word frequency, or an analysis of word count, can be used to provide a rudimentary summary of what a collection of text looks like. Word counts can provide a beneficial comparison between subsets of data for this research, such as most used words used by different users groups or within certain mission areas. To improve on these results, highly frequent stop words ("the," "and," "but" etc.) are removed to highlight other words that are more valuable for the analysis. In addition, other words that would provide little value for the analysis can be filtered out. For this research, expected words such as "USAF" are removed. A complete list of all expected words that were removed can be found in Appendix A.

Word relationships are similar to word frequency, but are used to examine which groups of words tend to neighbor each other most often. For this research, pairs of words also known as *Bi-grams*, are utilized to determine any significant relationships between words. Bi-grams can also be used for negation handling, which highlights words that follow "no," "not," and "never."

Sentiment Analysis

Lexicons, or pre-made word dictionaries within r, can assist in providing quick analysis of text. For this research, the *NRC, BING*, and *AFINN* lexicons are used to provide different types of sentiment scoring of the data. NRC, also known as the NRC Emotion Lexicon is a dictionary that associates words to eight basic emotions (discussed in Ch. 4) in addition to positive and negative categories (Mohammad, 2017) BING, which was developed by Bing Liu, assigns words as either positive or negative (Liu, 2012). AFINN, the most used lexicon in this analysis, returns a sentiment score between -5 and 5 with 0 being neutral sentiment (Arup, 2011). For each lexicon, scores can be finalized by word, Tweet, or aggregated to different subsets of the data. By conducting sentiment analysis on subsets such as different user groups or one of the strategic missions, a summary of sentiment can be made on a focused portion of the data.

LDA Tuning and Topic Model

When dealing with a large amount of text, it is beneficial to understand the optimal number of topics within the data along with the summarization of each topic. *LDA Tuning*, which performs the *Markov Chain Montel Carlo, Density-Base, KL-Divergence* and *unsupervised Latent Concept Modeling Methods*, first returns the optimal number of topics within the data. (Nikita, 2016). With this number, the topic model can be accomplished through a *Latent Dirichlet Allocation (LDA) Topic Model* from the *Quanteda* package in R (Roberts et al,, 2018). LDA is best defined as a probabilistic model of text where documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words (Blei et al., 2003). The LDA model can then be visualized through the Quanteda package which lists the top *n* words within each topic by *beta*, a metric that signifies the importance that a word possesses within each topic.

Chapter Summary

This chapter provided the understanding of how the methods of Text Mining will be implemented in addition to a description of the data collection process. Results from these methods will be displayed and discussed in the chapter to follow. Chapter five will provide further discussion in combination with recommendations and conclusions stemming from the results and analysis.

IV. Results and Analysis

Chapter Overview

The purpose of this research is to identify the topics and sentiment of Air Force references in Twitter content. This analysis aims to convert informal text into insight that illustrates what topics are present within Tweets related to the Air Force's strategic missions, along with the sentiment and influence tied to them. To accomplish this goal, methods of Text Mining and statistics will be implemented to understand how the Air Force should best manage the effectiveness of internet blogging platforms such as Twitter. This chapter will discuss the results of the Text Mining analyses from a high level view of Air Force Twitter references, down to specific missions, user groups, and individual users.

Word Frequency

Word frequency analysis can provide insight into a large set of text. By identifying the most recurring words, a rugged understanding of the content can be made. The *Word Cloud* in Figure 9 exhibits the top 50 words used within the Twitter dataset, with some exceptions. To improve results of the Word Cloud, stop words such as "the," "and," or " but" were discarded to highlight words with more significance. In addition, expected words such as "USAF" and "AF" were also removed. The results in the Word Cloud are portrayed through font size and the color of the word. For example, "military," which has black font and is largest in size, is illustrated as the most frequently used word in the data.

Figure 9: Top 50 Word Frequency Word Cloud

KC-46

More interestingly, "kc," short for the Air Force's prized new tanker, the KC-46, was second out of all words. Tweets pertaining to the modern air refueler occurred frequently as the aircraft was set for delivery in the summer of 2018. Delays in the KC-46's delivery from Boeing to Air Force bases lead to many Tweets with criticism. However, positive tweets that highlighted the aircraft's modern capabilities were frequent. The following Tweet in Figure 10 received the most engagements (favorites + retweets + replies) out of all Tweets with KC-46 references. The Tweet, published by *Boeing Defense*, is attached to a video which shows a KC-46 refueling another KC-46, an important certification milestone. In addition, Figure 11 displays the AFINN mean sentiment scores (more thoroughly discussed in later parts of this chapter) for Tweet's containing "KC-46." The graph illustrates that the *Military*, *Politician*, and *Organization* user groups all have a mean sentiment score of one or greater indicating more positive verbiage. This makes logical sense as Military and politically affiliated Twitter accounts desire for the American taxpayer to relish the acquisition of the KC-46. In addition, Tweets from organizations such as *Boeing Defense* must validate its products through encouraging Tweets like the one seen in Figure 10.

Figure 10: Most Popular Tweet Containing "KC-46"

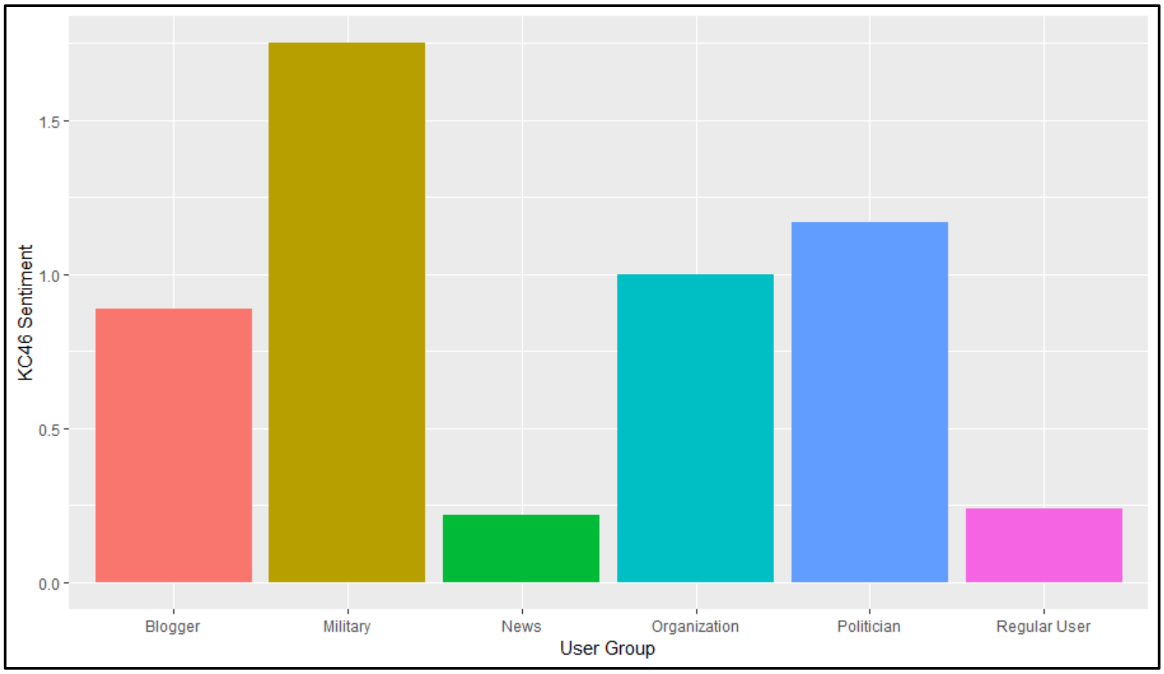

Figure 11: KC-46 Sentiment Analysis (AFINN)

Trump

Figure 9 also displays the words "Trump," "Syria," and "war" as top 20 among the most frequent words. "Trump," which references President Trump and often times family members of the President, was frequently alluded to in the dataset. The word "Trump" was referenced in 228 of the 4500 Tweets in the dataset, a rate of roughly 1 reference for every 20 Tweets. The 228 Tweets contained multiple topics with primarily negative sentiment. A summary of the sentiment of "Trump" Tweets can be seen in Figure 12. The most frequent topics observed were *Space Force* and *F-35* references. The following Tweets in Figure 13 are the top two most popular Tweets with a "Trump" reference and serve as a proper representation of "Trump" Tweets in the data. It is interesting to note that the most negative user group among "Trump" Tweets were *Politicians.*

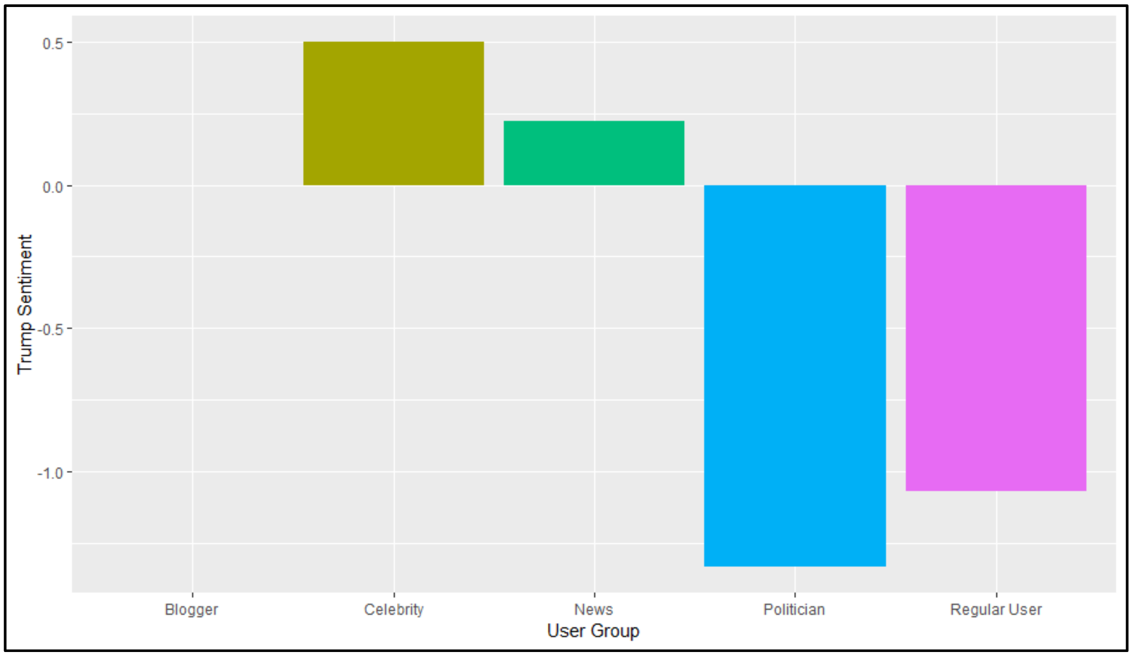

Figure 12: Trump Sentiment

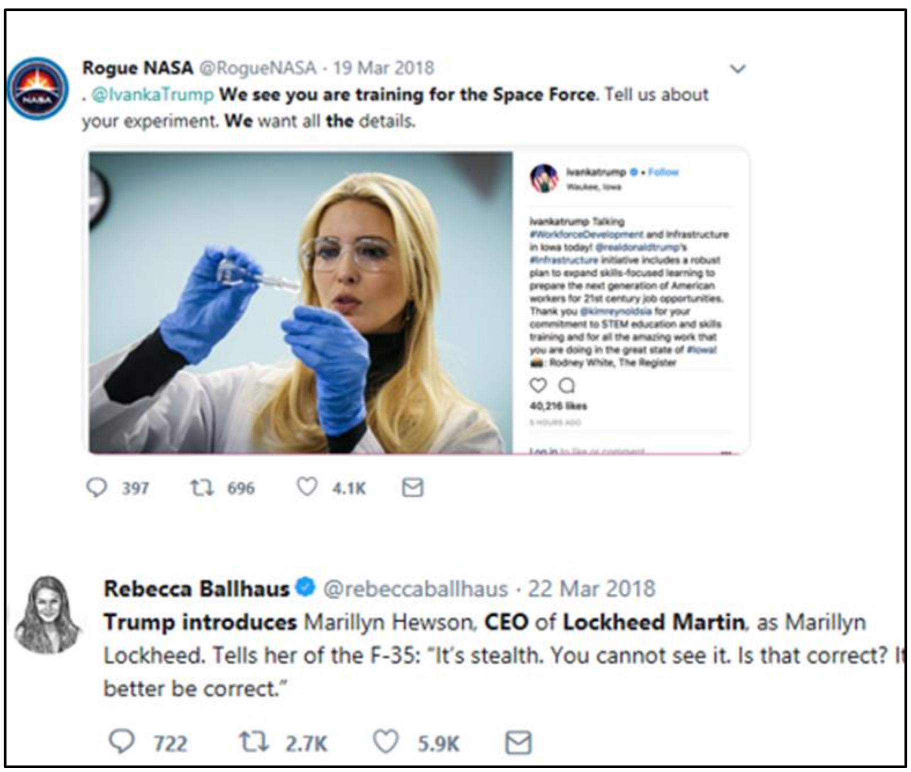

Figure 13: Most Popular Tweets Containing "Trump"

Syria and War

The word “Syria,” was mentioned in 142 of the 4500 Tweets, a rate of roughly 1 reference for every 25 Tweets. Among those, the word “war” was only mentioned seven times in conjunction with Syria, signifying that both words were rarely used together. However, the word “war” by itself was mentioned in 548 of the total dataset, a rate of roughly 1 mention for every 8 Tweets. As both words were seen frequently within the data, it is important to explore the sentiment of Tweets containing each word. Figures 14 and 15 display the mean AFINN sentiment score for Tweets containing “Syria” and “War” respectively, categorized by user group. As exhibited, the sentiment for “Syria” received negative scores across the board whereas the sentiment score for “War” received mixed results.

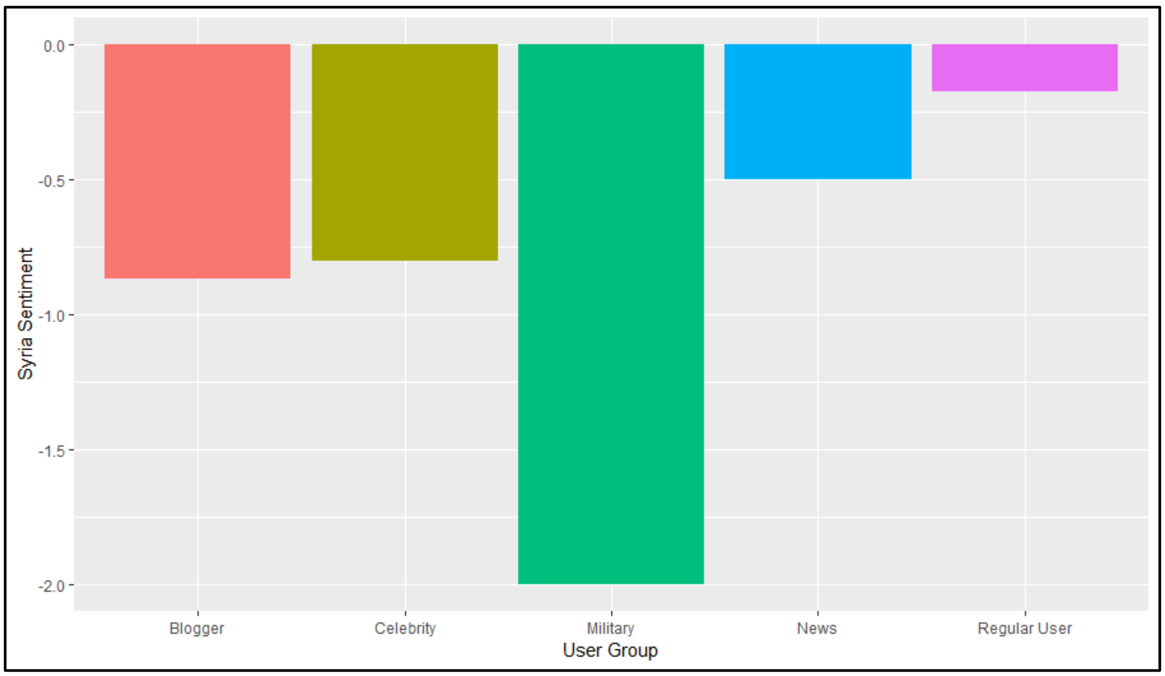

Figure 14: Sentiment of Tweets Containing “Syria”

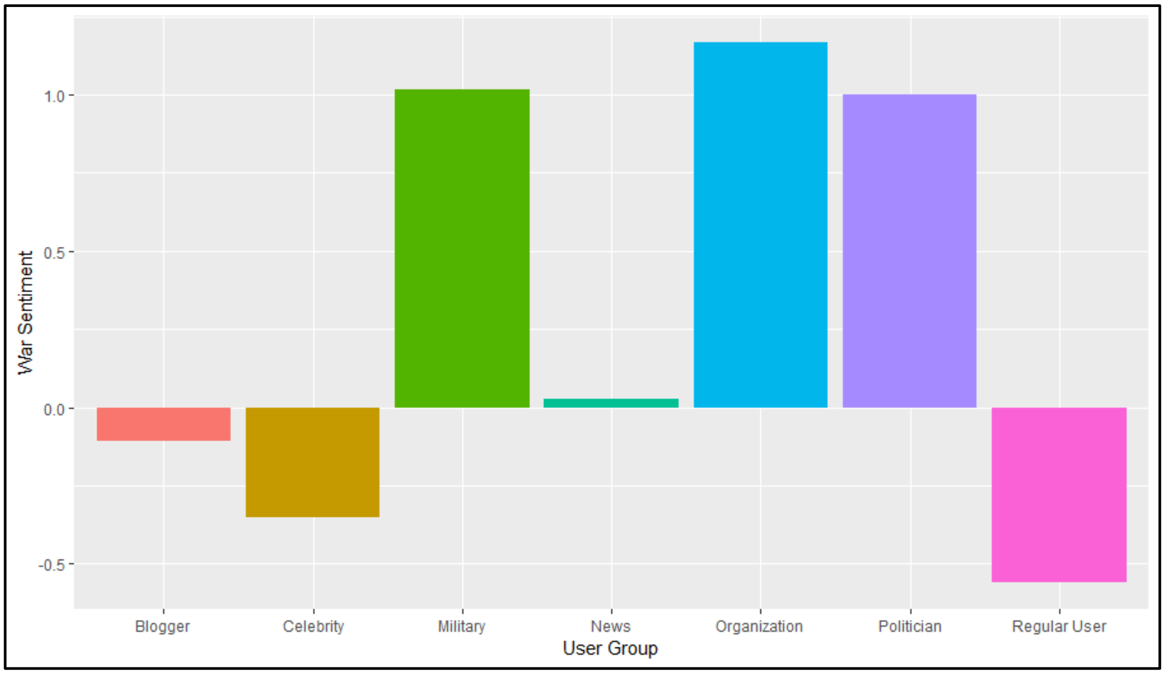

Figure 15: Sentiment of Tweets Containing "War"

Word Relationships

Context is limited in word frequency analysis. Moving to more sophisticated analyses such as word relationships can provide an enhanced understanding of a document. Consecutive sequences of words, or *N-Grams* can provide a deeper understanding of adjoining words and how they are commonly used. For this analysis, *Bi-grams*, or pairs of words are utilized to improve upon the results from the Word Cloud in Figure 9. The diagram in Figure 16 shows a Bi-gram network of the pairs of words that have over 200 occurrences together. As expected, "Air-Force" is the most frequent Bi-gram and is depicted by a solid black arrow connecting both words. The Bi-gram, "21-bomber" is an interesting result as it is short for the newest generation of bomber being developed, the B-21 Raider. Other aircraft platforms within the map include the KC-46 and the global hawk while defense industry giants like Lockheed Martin and

Northrop Grumman are themes within the data as well. A Bi-gram that stands out is "nas-sigonella," short for the U.S's *Naval Air Station Sigonella* in Sicily, Italy ("Military Bases," n.d.). The overseas base is often referenced in Tweets giving near real time updates of aircraft flying out and returning from ISR missions in the European/Middle Eastern regions.

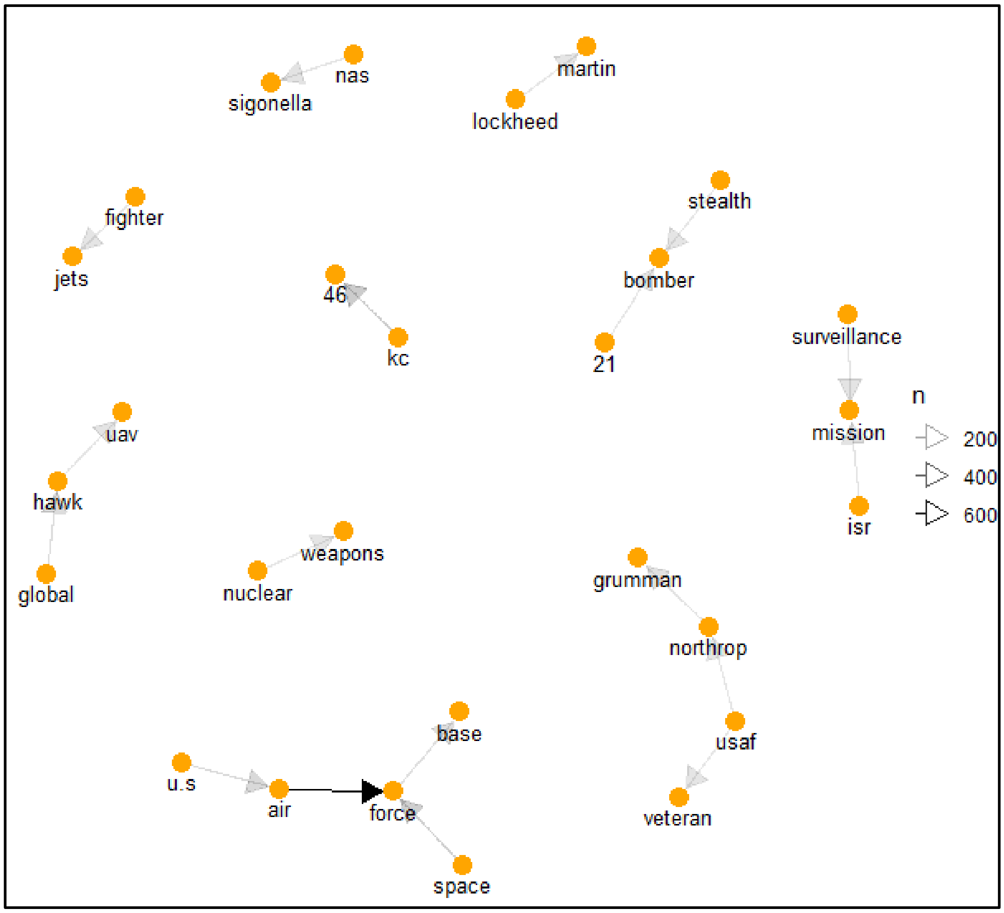

Figure 16: Bi-Gram Map (All Data)

Air Superiority Mission

To dig deeper into themes related to aircraft and aircraft producing companies, a subset of data with only Tweets related to the *Air Superiority* mission was developed into a Bi-gram network. As exhibited in Figure 17, aircrafts within the results include the

“35-fighter (F-35)”, “22-raptor (F-22),” “KC-10,” and the “KC-46.” Another interesting word pairing is the Bi-gram “flight-testing,” which has a frequency greater than 20 within the smaller subset of data. To provide substance behind this phenomena, the top two most popular Tweets with “flight-testing” are shown in Figure 18.

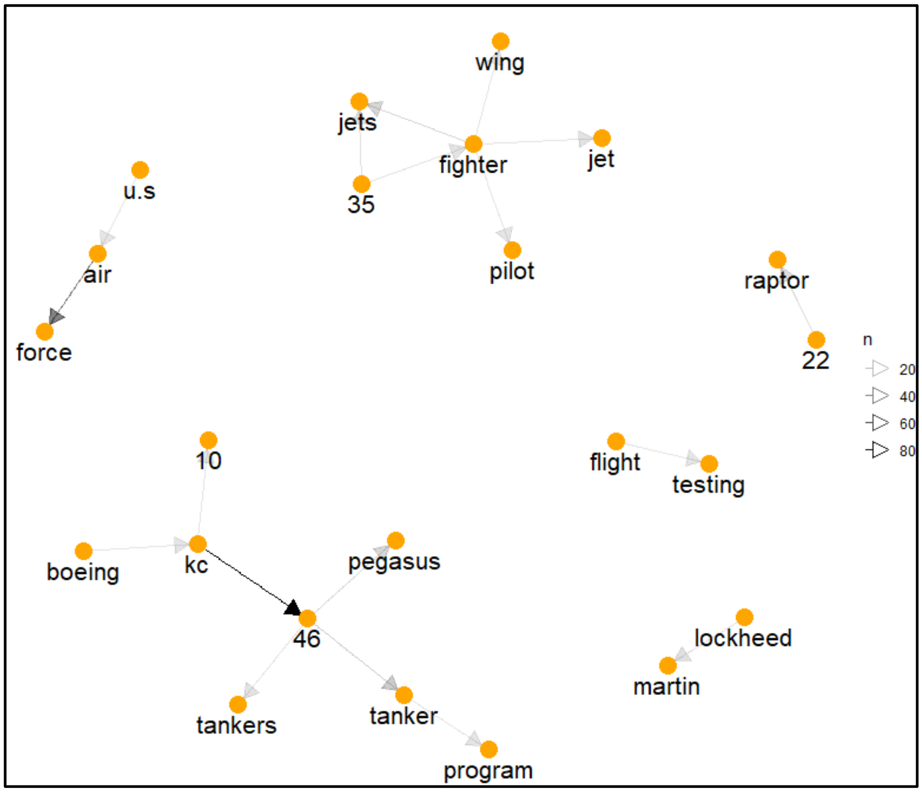

Figure 17: Air Superiority Mission Bi-grams

Figure 18: Most Popular Tweets Containing "Flight Testing"

Influence

As discussed previously, a Tweet's influence is determined by a ratio of engagements to followers. Because influence is driven by the relationship between these variables, it is important to understand one limitation. That is, if user X were to have one follower and received one engagement from a Tweet, the amount of influence for user X would be far greater than user Y who had 1,000,000 followers and received 100,000 engagements from a Tweet. Because of this dynamic, publishers of Tweets with less than 100 followers were thrown out of the dataset to help provide a more accurate representation of influence. As exhibited in Figure 19, *Regular Users* and *Bloggers* received the highest score of average influence while *Politicians* and C*elebrities* received the least amount.

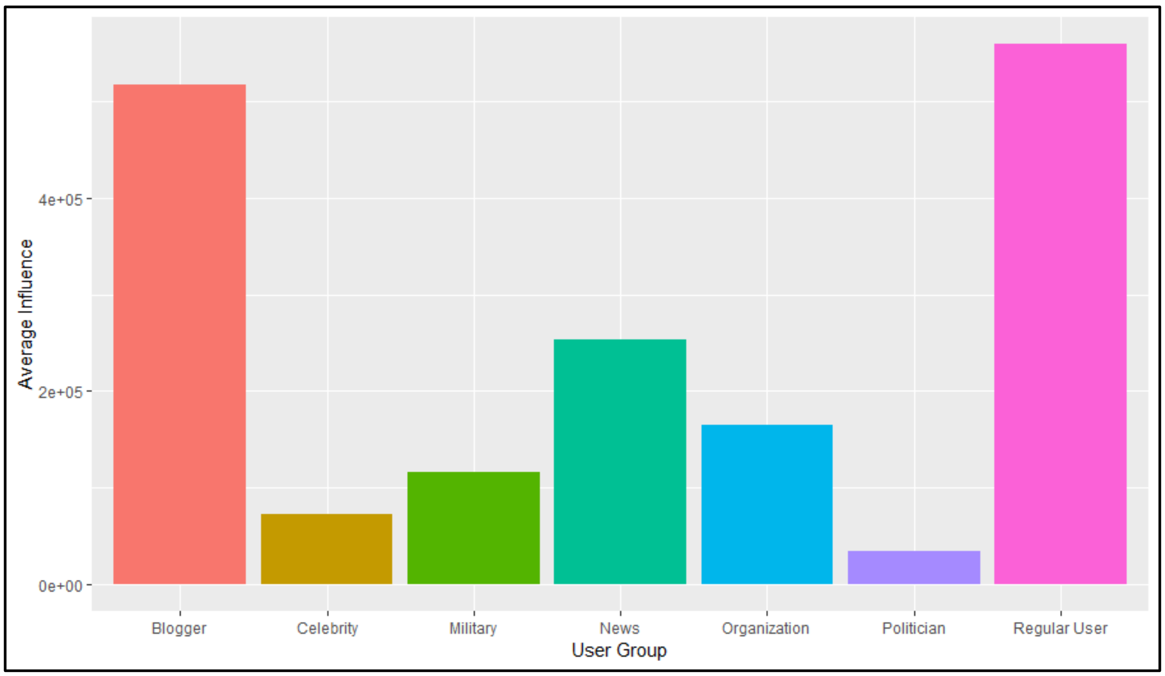

Figure 19: Average Influence By User Group

Followers Limitation

To determine the accuracy of these results, an analysis of average followers was conducted to determine if the limitation was still present in the results from Figure 19. As exhibited in Figure 20, *Regular Users* are shown to have less than 4,000 followers on average, which is hardly visible in the stacked bar chart. Because *Regular Users* have a much lower following in comparison with the other six groups, *Regular Users* should not be credited as being the most influential demographic, and are considered invalid in the influence analysis.

User Group	Avg Followers
Blogger	78,268
Celebrity	137,841
Military Leader	86,438
News	2,041,923
Organization	249,511
Politician	210,470
Regular User	3,863

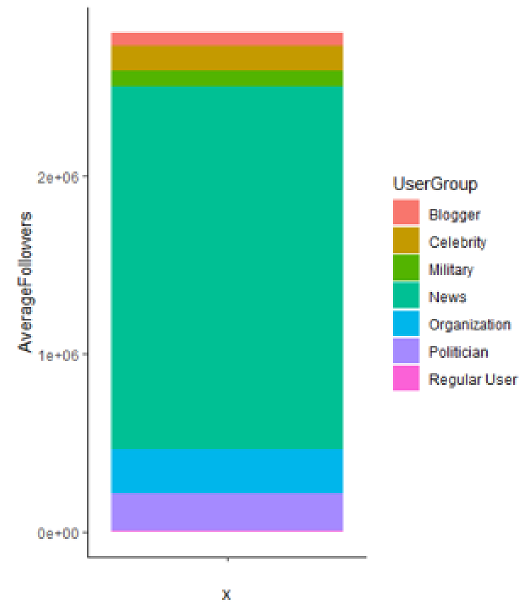

Figure 20: Average Followers Comparison

Bloggers

With *Regular Users* removed from the analysis, *Bloggers* are seen as the most influential group in the data. As discussed in Chapter 3, *Bloggers* can take on the form of many different types of users.   Although *Bloggers* possess the second lowest average follower count, it is closer in proximity to the remaining data points. In addition, it is difficult to ignore the exceptionally high influence score as shown in Figure 19. This result indicates that *Bloggers* are doing the best job at reaching their audience when it comes to Air Force related Tweets.

When it comes to *Blogger's* Tweet frequency, the entity *ItaMilRadar* recorded the most content with 50 posts within the seven month duration of data collection. ItaMilRadar constantly provides updates of aircraft flying within and near Italy. Because of the many USAF aircraft that operate out of *Naval Air Station Sigonella*, a high number of Tweets were recorded for this user from the *ISR* strategic mission search queries. In addition, Table 5 highlights *Goss30Goss*, a self-proclaimed USAF veteran who posts regularly about political affairs, as the most influential entity out of the *Blogger* user group. As exhibited in Table 5, Goss30Goss possesses an extremely large following (124^{th} of 1260 bloggers) to go with its high average influence score.

Table 4: Top 3 Entities by Number of Posts

Rank: # of Posts	Blogger Entity	Avg. Influence	# of Tweets
1	ItaMilRadar	.003132	50
2	CivMilAir	.000693	18
3	AircraftSpots	.006208	13

Table 5: Top 3 Entities by Average Influence

Rank: Avg Influence	Blogger Entity	Avg. Influence	# of Tweets
1	Goss30Goss	.104520	2
2	BckgrndNoize	.047244	2
3	SPs_MAI	.029918	3

Figure 21: Twitter Profiles (ItaMilRadar, Goss30Goss)

News/Press

As depicted in Figure 19, the average influence score for the *News/Press* users are roughly half of that of *Bloggers*. However, taking a look at the follower comparison in Figure 20, *Bloggers* have just 3% of the average followers that the *News/Press* group possesses. With such a high follower count, it would be unrealistic to accept that agencies like CNN and BBC can reach their full audience on every given Tweet. Afterall, casual news consumers are unlikely to review their favorite news social media account as much as someone who follows their favorite blogger who posts about specific topics. Regardless, Tweets from the *News/Press* are extremely influential as they have the furthest reach among any user group and received the second highest average influence.

Digging deeper into some of the key players within the *News/Press*, Tables 6 and 7 illustrate the top three entities by number of Tweets and by average influence. To limit the impact of those users who do not regularly reference the Air Force on Twitter, only those users with *more than one* Tweet in the dataset was included in Tables 6 and 7. The average influence scores within both tables were calculated by taking the influence for every post made and assigning an aggregated score for each entity. As previously mentioned, *News/Press* users can be everything from major news agencies like CNN or BBC to individual reporters posting Tweets on their personal Twitter accounts. As displayed in Table 6, the Twitter handle, *ValerieInsinna*, published the most Tweets of all *News/Press* entities with 30 total. In addition, Insinna, who works for *Defense News* also made the top three in average influence as seen in Table 7. Insinna's Tweets are both factual and opinionated and at times can be sarcastic. However, the range of topics are usually limited to news on aircraft acquisition. Larger news entities who have a vast following on Twitter did not make either top list in Tables 6 or 7. Although large agencies like CNN and FOX have follower counts in the millions, the influence rate held by news giants do not compete with smaller, more focused news entities like Insinna and company. As exhibited in Table 7, *TedLandK5,* a local news journalist from *King 5 News* in Seattle, Washington was the most influential entity out of all *News/Press* entities. Land's Tweets within the dataset all reference *Boeing Defense* and their progress in delivering the KC-46 to the Air Force. Twitter profile statistics for both Insinna and Land can be seen in Figure 22.

Table 6: Top 3 Entities by Number of Posts

Rank: # of Posts	News/Press Entity	Avg. Influence	# of Tweets
1	ValeriesInsinna	.004185	30
2	TheNatlInterest	.003674	24
3	Laraseligman	.002518	22

Table 7: Top 3 Entities by Average Influence

Rank: Avg Influence	News/Press Entity	Avg. Influence	# of Tweets
1	TedLandK5	.075921	6
2	ValerieInsinna	.004186	30
3	LucasFoxNews	.015704	6

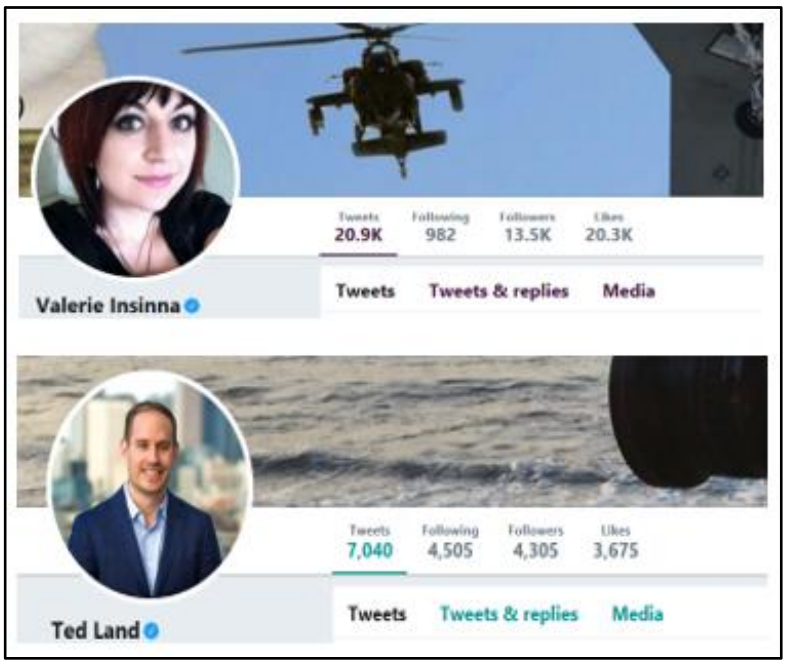

Figure 22: Twitter Profiles (Insinna, Land)

Sentiment Analysis

The ability to measure the sentiment of words is one of the most complex methods in Text Mining and can provide valuable insight into the emotion of a large text document. As previously discussed, three lexicons under the TidyText package (NRC, BING, AFINN) are applied to the Twitter dataset. By using all three sentiment lexicons, a variety of angles can be illustrated to provide a clear sentiment framework of the data.

NRC

As noted previously, the NRC lexicon provides a binary (+1 or -1) sentiment score while also putting words into eight emotional categories: anger, anticipation, disgust, fear, joy, sadness, surprise or trust.   Figure 23 illustrates the results of the NRC lexicon when applied to the entire Twitter dataset. Positive words outpaced negative words by 381 according to the NRC algorithm. In addition, the emotions *trust* and *fear* had the highest word count.

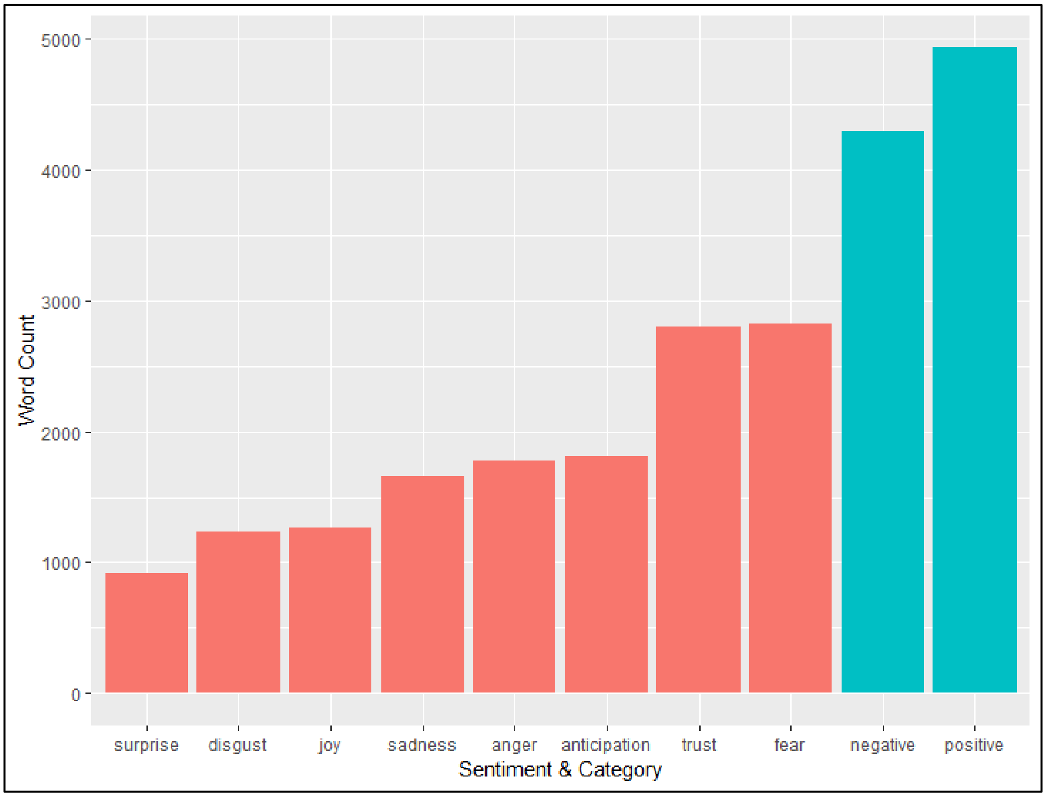

Figure 23: NRC All Data

BING

The BING lexicon is similar to NRC as it scores words in a binary manner. BING is used in this research to compare sentiments between the missions of the AFSMP and between user groups. Figure 24 displays the residual sentiment score (positive sentiment – negative sentiment) of Tweets under each strategic mission. As illustrated, the *Technology* mission received extremely positive results while the *Air Superiority* mission received fairly negative results

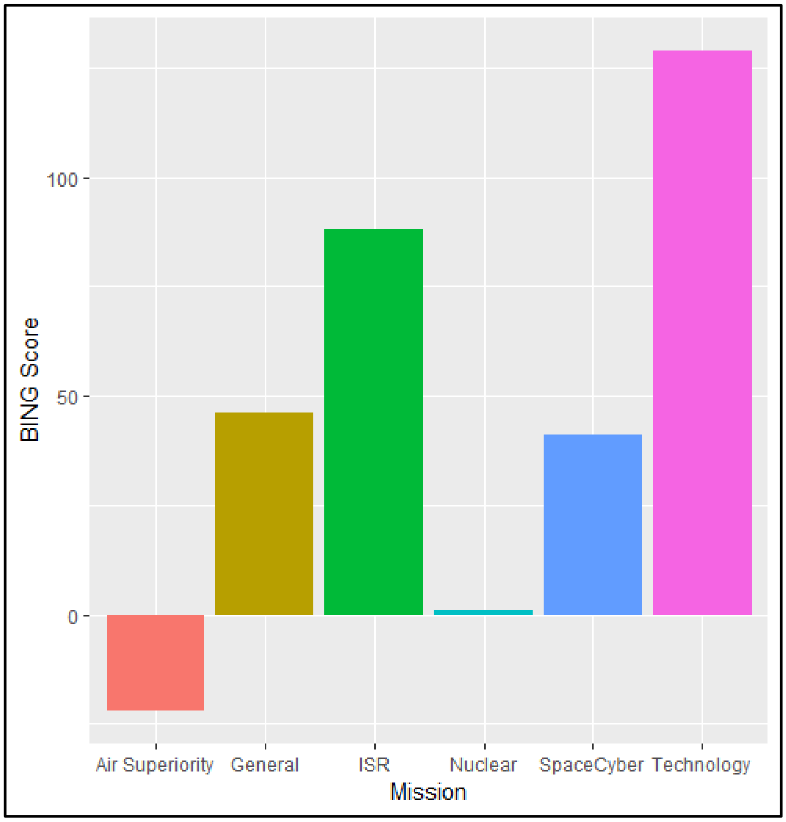

Figure 24: BING Residual Sentiment by Mission

NRC – Air Superiority Tweets

Exploring *Air Superiority* Tweets further, the NRC lexicon was applied to capture emotional changes from the NRC results of all Tweets exhibited in Figure 23. As exhibited in Figure 25, there is an expected flip between positive and negative word counts. Also exhibited is the high percentage of negative words in the Air Superiority mission that account for negative words in all of the data (77.8%). More interestingly, out of all *disgust* words used in the data, roughly 97.8% stem from the Air Superiority Tweets. Other emotions where a majority of the words came from the Air Superiority Tweets include *anticipation* (51.2%), *anger* (65.7%), *fear* (56.8%), *sadness* (73.5%), *surprise* (57.9%), and *trust* (50.3%). Results of this NRC comparison concludes that most adjectives in the data, which are the primary words that carry sentiment, originate from the Air Superiority subset of Tweets.

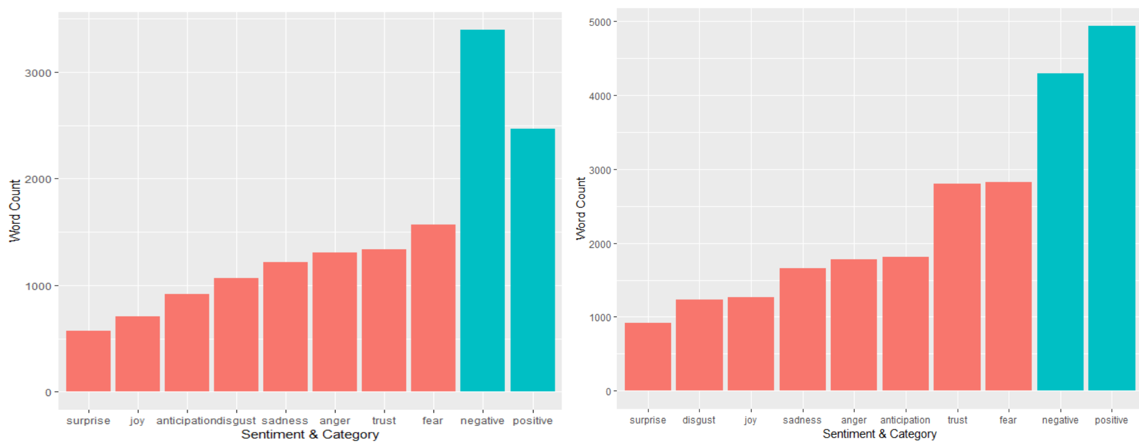

Figure 25: NRC-Air Superiority (left) vs. All Data (right)

In Figure 26, BING sentiment analysis was conducted on the data sorted by user group. *Professional Organizations* and *Military Leaders* are shown as extremely positive voices in the Twitter data while *News/Press* and *Celebrities* are amongst the most negative users.

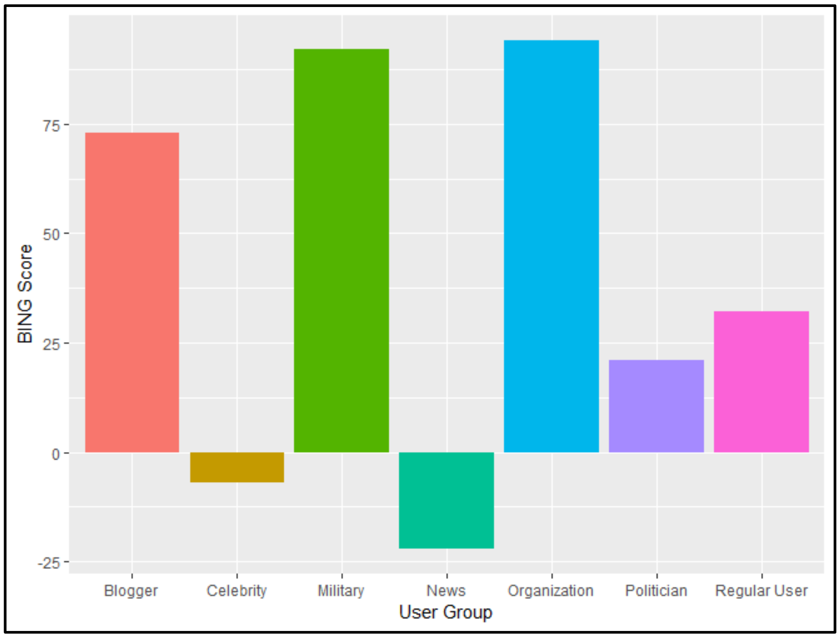

Figure 26: BING Residual Sentiment by User Group

AFINN

The AFINN lexicon provides sentiment scores on a scale of -5 to 5. Because of this, AFINN's algorithm takes into account extremely positive and negative words into its results. For this research, AFINN was used similarly to the BING lexicon, and was implemented to compare the *mean* sentiment of both the strategic missions and user groups. Figure 27 illustrates the mean sentiment calculated under each strategic mission. In this diagram, the *Technology* mission remains extremely positive, however, the *Air Superiority* mission switched from a net negative sentiment (BING) to a mean sentiment greater than zero (AFINN). This instance indicates that Tweets referencing the *Air Superiority* mission used enough extremely positive verbiage to outweigh the higher frequency of negative words seen in Figure 24.

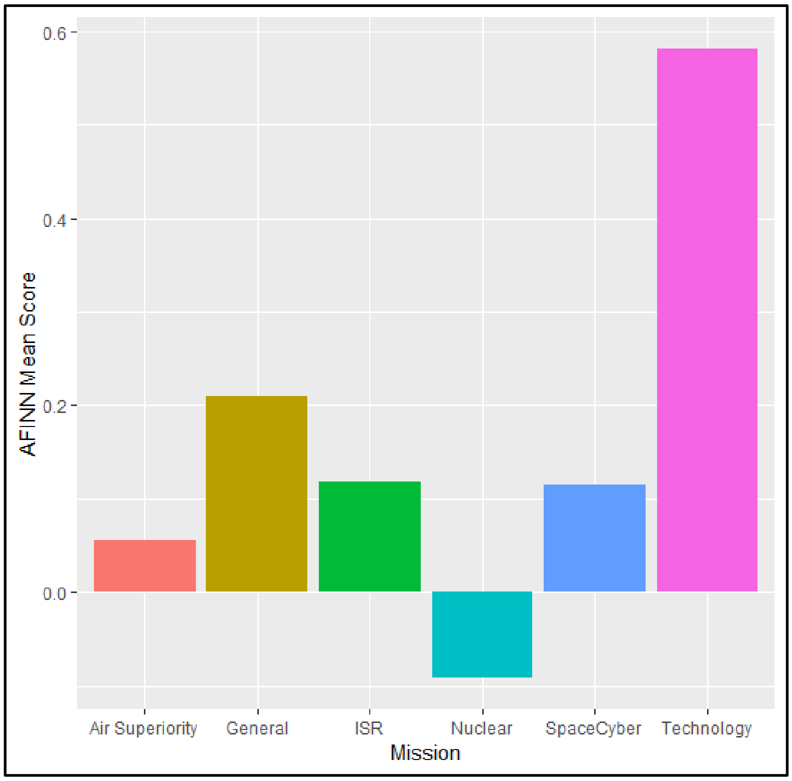

Figure 27: AFINN Mean Sentiment by Mission

Figure 28 illustrates the mean sentiment score by user groups. In comparison to its BING counterpart, the AFINN results displayed minor differences. The most extreme difference was in the intensity of the sentiment score of *Politicians*. In Figure 26, the residual sentiment score was positive but well below that of *Military Leaders* and *Professional Organizations*. In Figure 28, the mean sentiment score for *Politicians* is noticeably closer to that of *Military Leaders* and *Professional Organizations*, hinting at extremely positive verbiage used by *Politicians.*

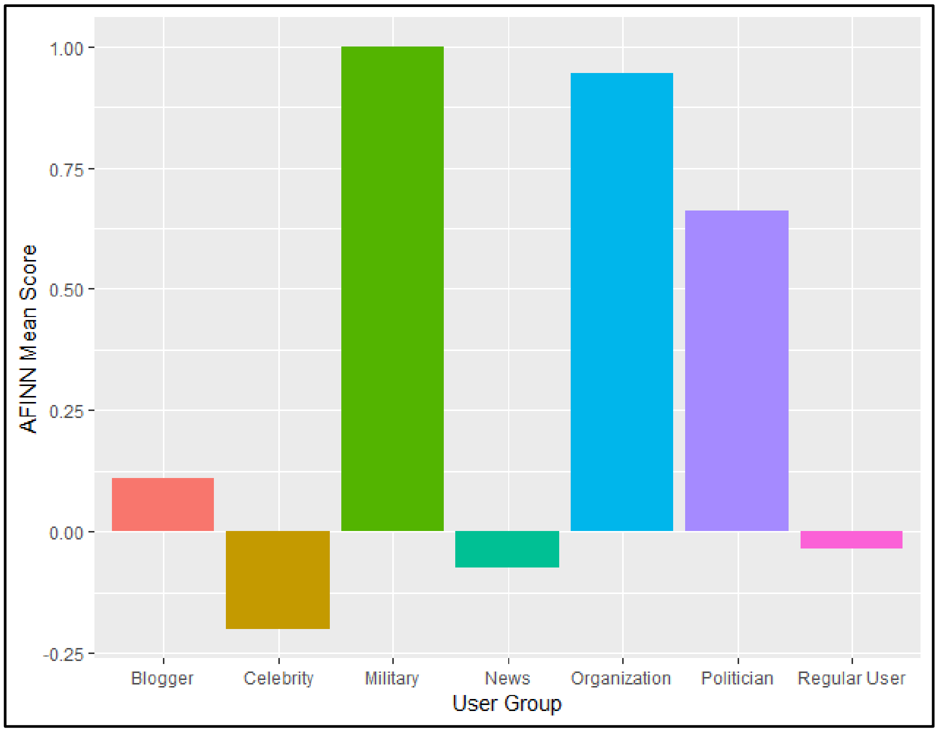

Figure 28: Mean Sentiment by User Group

Sentiment Progression

As previously mentioned, Tweets were gathered over a seven month period. With this data, a time series analysis can be conducted to measure month by month sentiment fluctuations. The chart in Figure 29 depicts the AFINN mean sentiment score for all data. The chart indicates that the sentiment is all positive sentiment outside the month of May.

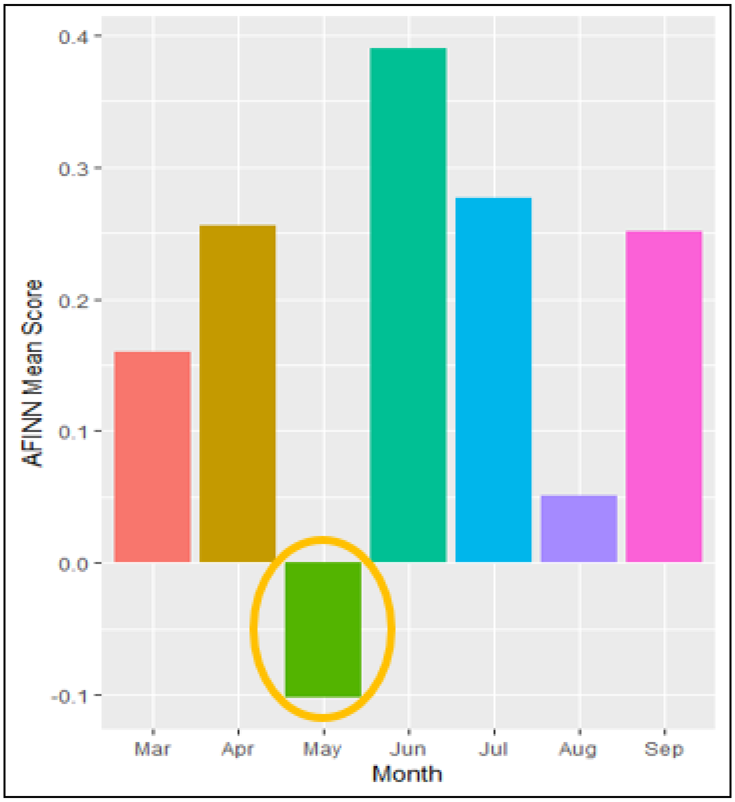

Figure 29: AFINN Time Series (All Data)

Figure 30 displays the top three most popular Tweets with a negative AFINN score from the month of May. As exhibited below, two of the Tweets reference the same incident of a woman shouting racial slurs towards an Air Force veteran. Although the story is unrelated to any of the strategic missions, the general search query "Air Force," was able to capture the Tweet. The pair of racial Tweets exemplify how much momentum a story on racism can carry on Twitter, particularly when parties are active or prior military personnel. The 3rd Tweet, which is related to the *Nuclear Deterrence* mission is a story published by *The Associated Press*. The Tweet received the 3rd most engagements by a negative Tweet in May, however, received an influence score of .0002 (406th of 1000 May Tweets) signifying a relatively small interest from *The Associated Press's* 13 million followers. In addition to these extremely viral Tweets, the pure number of negative Tweets was much greater in the month of May in comparison to the other six months. Out of the 1000 tweets captured, 674 Tweets reflected an overall negative score (67.4% negative rating). In comparison, the rest of the months together received a 39% negative rating, explaining why the month of May was the only month with a negative mean AFINN score.

Figure 30: Top 3 Negative Tweets in May

Air Superiority Sentiment Progression

An analysis of sentiment was conducted on all five strategic missions which can be found in Appendix B. One particular mission with interesting results was the *Air*

Superiority mission which can be seen in Figure 31. As illustrated, the sentiment of this subset of data was initially positive in the months of March and April. However, sentiment began to reverse in the months of May and June. Because Tweets within the Air Superiority mission often reference the Bi-grams, KC-46 and F-35, potential conclusions can be drawn from the most popular negative Tweets referencing both aircraft. Seen in Figure 32 are the top two most popular negative Tweets pertaining to the Air Superiority mission in May. As described, both Tweets reference the F-35 in different contexts. The first Tweet discusses the F-35 within the upcoming *Top Gun* sequel in a sarcastic tone. The second Tweet is more informational and explains that Congress is making an effort to block the sale of F-35's to Turkey. In Figures 33 and 34 are the top negative Tweets from the months of June and August respectively. Both Figures 33 and 34 reference the KC-46 and its issues with delayed delivery to the Air Force.

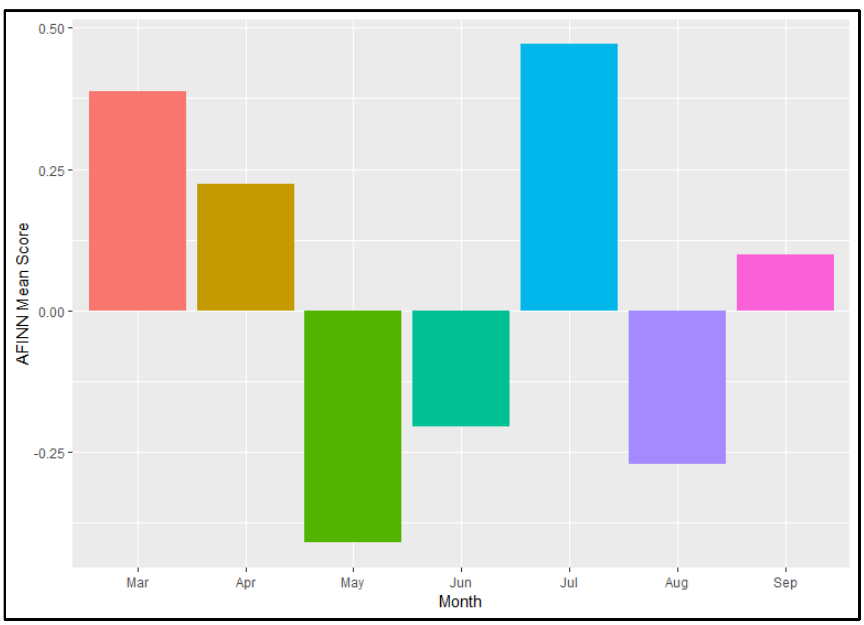

Figure 31: Air Superiority Sentiment Progression

Figure 32: Air Superiority Top Negative Tweets in May

Figure 33: Air Superiority Top Negative Tweet in June

Figure 34: Air Superiority Top Negative Tweet in August

Negation Words

So far, sentiment analysis has been described as a count or ratio between positive and negative words of a document. However, an important feature of sentiment analysis that is critical to investigate is the effect of negation words like “no,” “not,” “without,” and “never.” Negation words flip the intended sentiment of a message but is not captured in the sentiment analysis methods aforementioned. For example, the sentences “I loved you” and “I *never* loved you” should have different sentiment scores. However, the methods used thus far would capture the word “loved” in both sentences when it should be negated in the second sentence. Because of this, a potential for sentiment misrepresentation is present. To explore the impact on the sentiment analysis results, Bi-grams were utilized to isolate sentiment associated words that followed a negation word. AFINN sentiment scoring was used in combination with this technique to determine the total sentiment that was erroneously captured so far in this analysis.

Figure 35 illustrates the impact of the four negation words described. As exhibited, the sentiment impact was not significant among all four bar graphs. The sentiment associated words, “like,” and “happy” were the only erroneous positive words with a sentiment impact of 3 or greater. Of the erroneous negative words captured, “worrying” displayed the only sentiment impact of 3 or greater. In conclusion, negation word counts within the data were not substantial enough to account for a significant amount of erroneously captured sentiment. The results of the sentiment analysis, therefore, are valid.

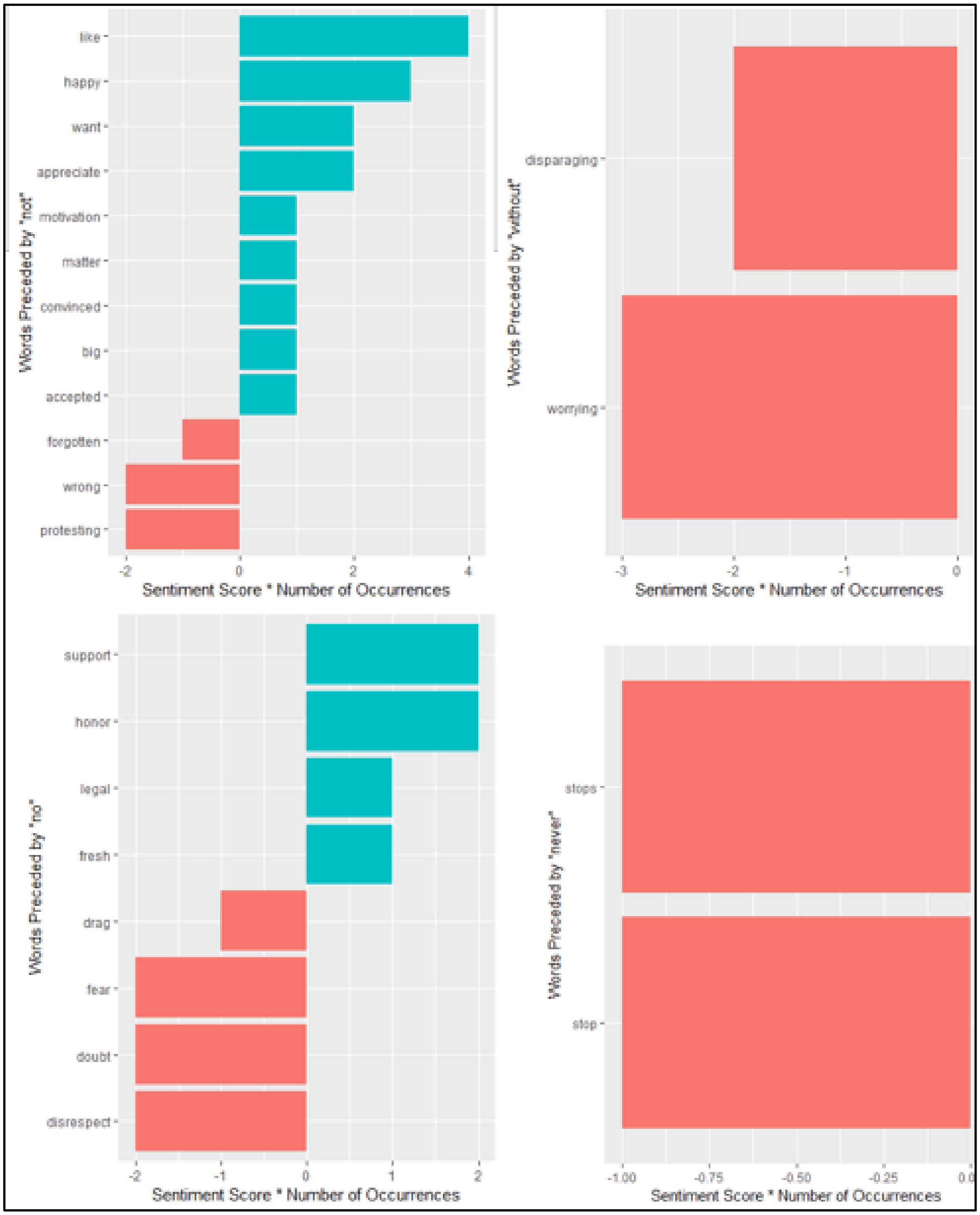

Figure 35: Negation Handling Sentiment Impact

Mission Popularity

For this research, the popularity of a Tweet is measured by the total number of engagements (favorites + retweets + replies) that the Tweet possesses. To measure which strategic mission is most popular, an average engagement per tweet was calculated for each strategic mission. Figure 36 illustrates the *Air Superiority* mission as being the most popular mission in the dataset, averaging 93 engagements per Tweet, followed by the *Space/Cyberspace* mission which had 56 engagements per Tweet.

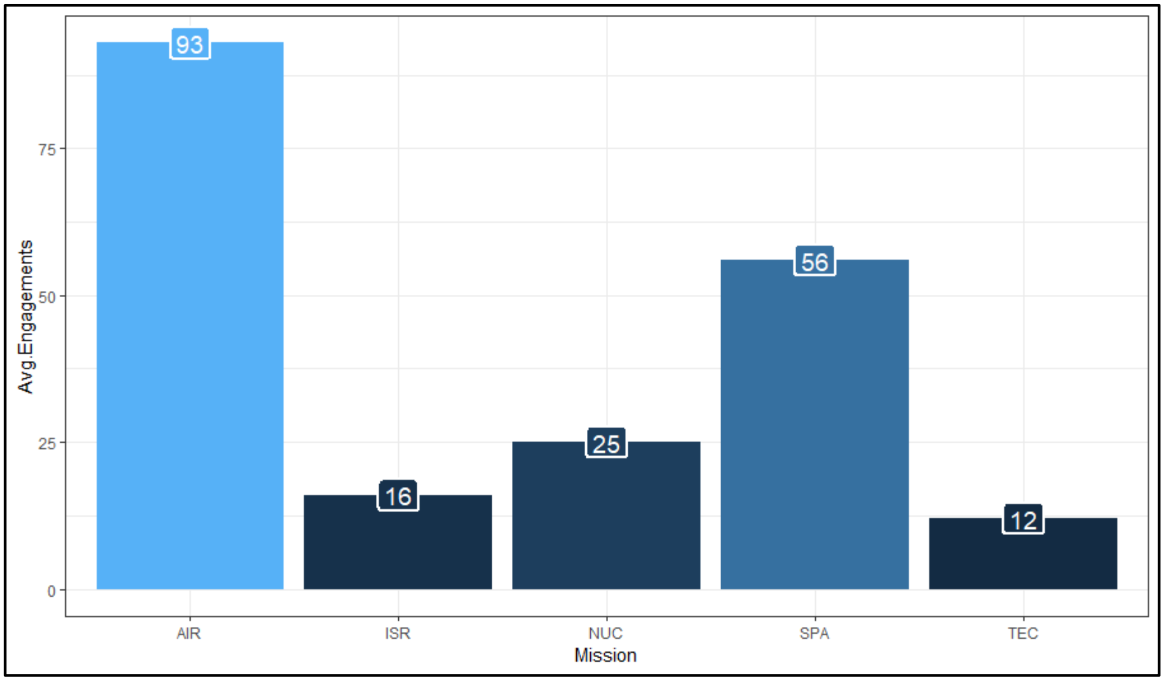

Figure 36: Mission Popularity

Popularity & Sentiment Correlation

To determine if a relationship exists between popularity of a Tweet and sentiment, residual scores from the BING and AFINN lexicons (strategic mission comparison) were used against total engagements (for each strategic mission). The result produced the Correlation Matrix in Figure 37, which illustrates Pearson Correlation

Coefficients (PCC) between each of the three variables previously stated. As expected, the two sentiment scores of BING and AFINN received a nearly perfect PCC of 0.93. When paired with the engagement variable, both BING and AFINN received a negative PCC of -0.62 and -0.37 respectively, giving some evidence that the number of engagements is negatively correlated to positive sentiment. The stronger correlation (BING vs. engagements) was tested with 95% confidence and found a corresponding P-Value of 2.2e-16, which is the default display that R uses for extremely small P-Values (Mangiafico, 2016). From this, it can be concluded that engagements and BING sentiment scores are significantly correlated with a PCC of -0.62 (output found in Appendix E).

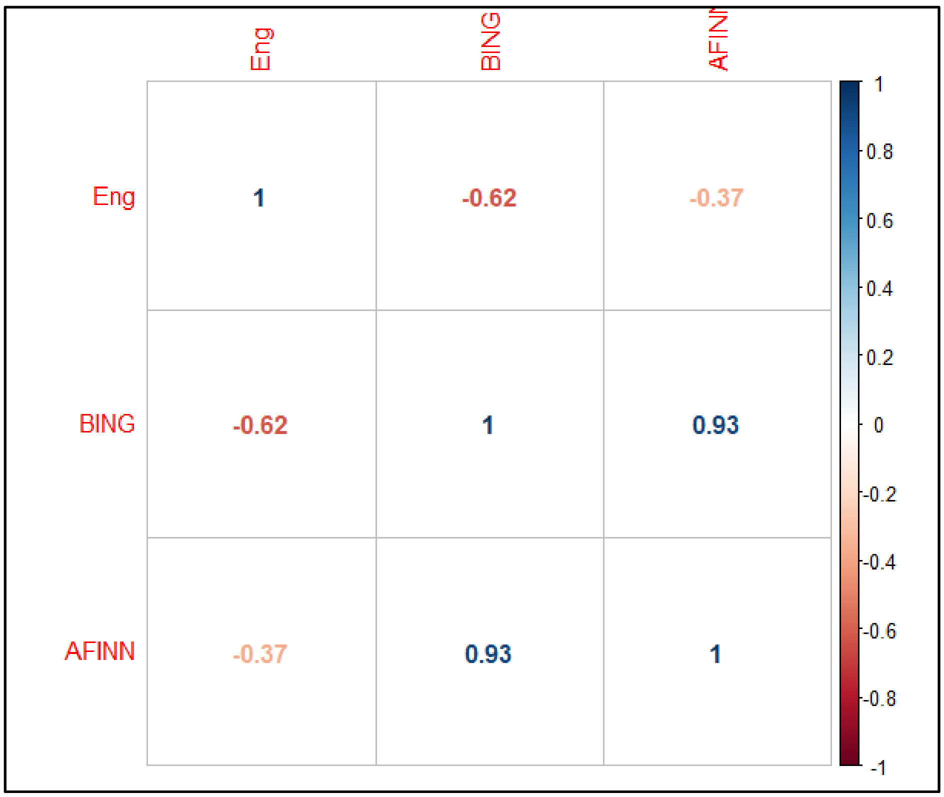

Figure 37: Engagement and Sentiment Correlation

Topic Model and LDA Tuning

As discussed, the topic model approach used in this research is the LDA Topic Model, which fits data into groups called *topics*. Topic Modeling is especially useful on Tweets that were gathered by using general search queries such as, *USAF*, because there is no prior knowledge of the content that would be returned from that search. In order to determine the hidden topics of the general search Tweets, the LDA Topic Model was trained by using the *Structural Topic Modeling (STM)* package in r. Before running the STM package on the data, the number of topics must first be calculated using the *LDA Tuning* package, which determines the range of expected number of topics in the dataset. As exhibited in the LDA Tuning plot in Figure 38, the expected number of topics is where the *CaoJuan* metric reaches its minimum point and the *Deveaud* metric reaches its maximum point. As seen in Figure 38, the two metrics converge at 6, indicating that there are 6 topics that the STM model should be using in its algorithm. The STM model which is seen in Figure 39, shows the top words within each topic. Words are sorted within each topic using *beta* scores, a metric that determines the importance of the word to the topic. Only the top four words are highlighted in the topic model as the fifth words in the majority of the topics had relatively insignificant beta scores. The summarization for each topic can be seen in the green boxes and were developed by integrating inputs from five different individuals who provided their subjective opinions for each topic.

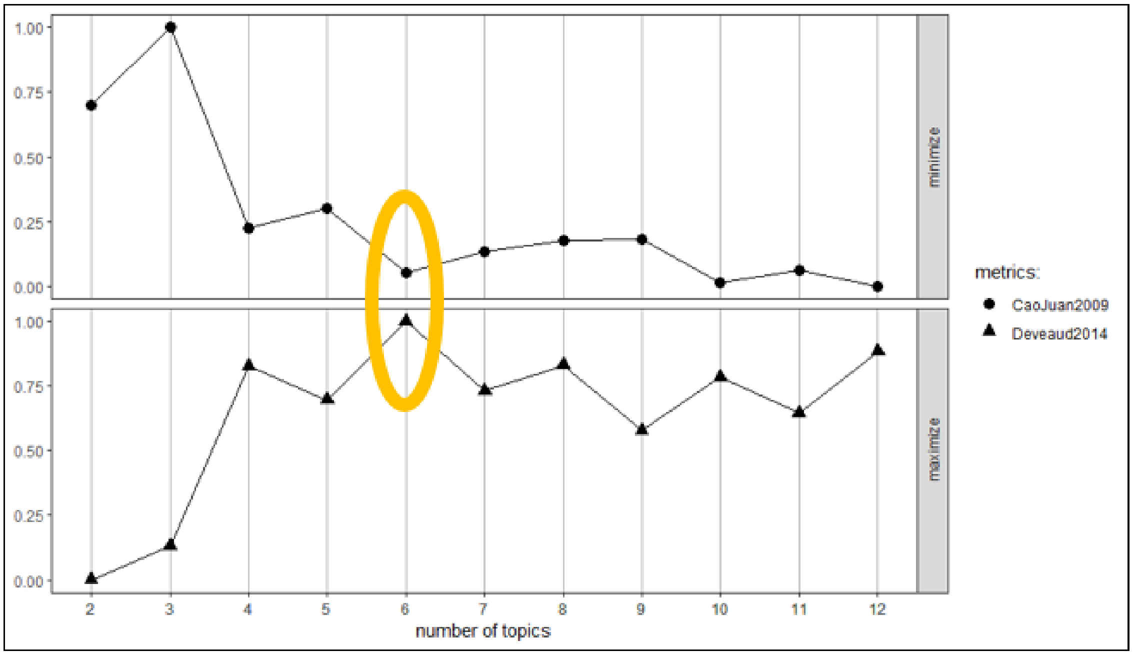

Figure 38: LDA Tuning Plot of General Searches

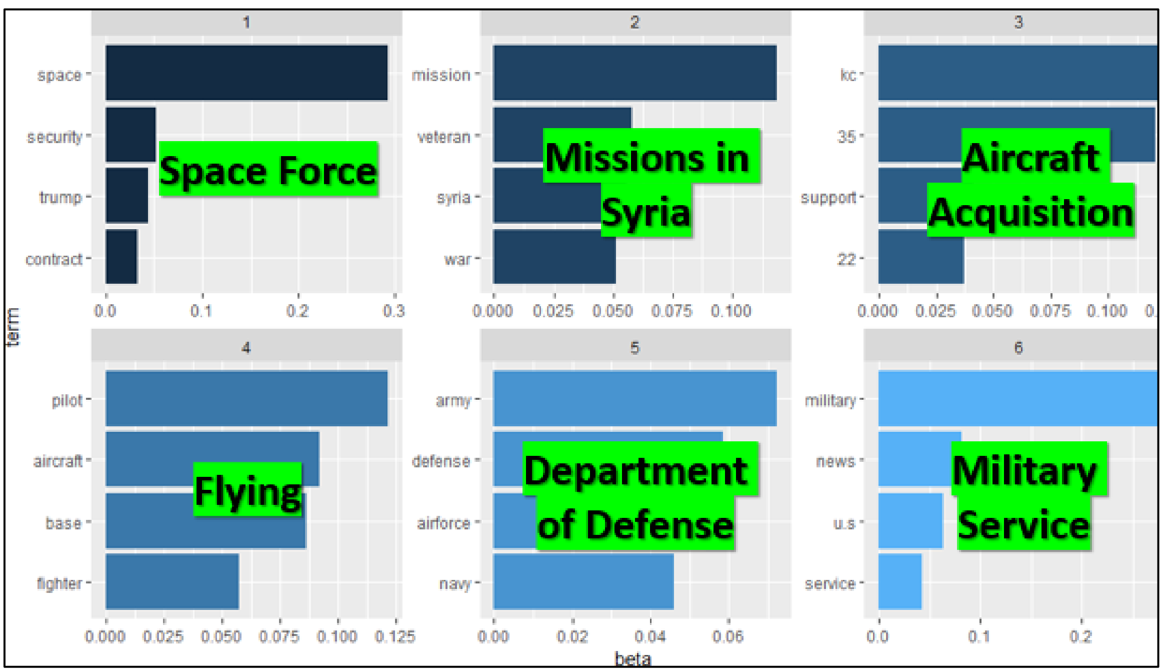

Figure 39: LDA Topic Model of General Searches

Topic Model of Celebrity Tweets

Tweets posted by celebrities received the most negative mean sentiment score (-0.18) out of all the user groups in the data. For this reason, it is interesting to understand the topics being discussed by this demographic of users. Figures 40 and 41 respectively exhibit the *LDA Tuning Plot* and topic model for the *Celebrity* subset of Tweets. As exhibited, the tuning plot suggests the optimal amount of topics to be three, which is used in the topic model of Figure 41. As illustrated, only the top two words were used in each topic to show the words with the most significant beta scores. The results make logical sense as the *Nuclear Deterrence* was the only strategic mission with a negative mean AFINN sentiment score. In addition, Tweets referencing the F-35, Russia, and Syria are primarily negative throughout the dataset. The results of this topic model provide evidence that celebrities generally vocalize their opinions on highly criticized topics and that a Tweet authored by a celebrity will more than likely be negative.

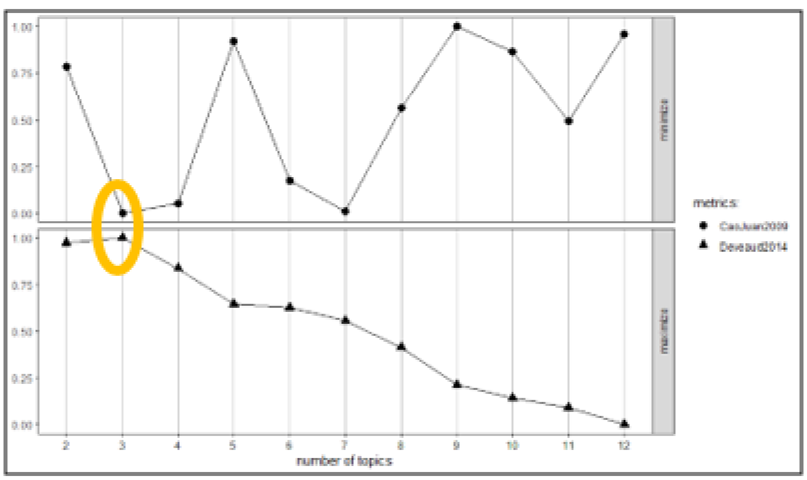

Figure 40: LDA Tuning Plot of Celebrity Tweets

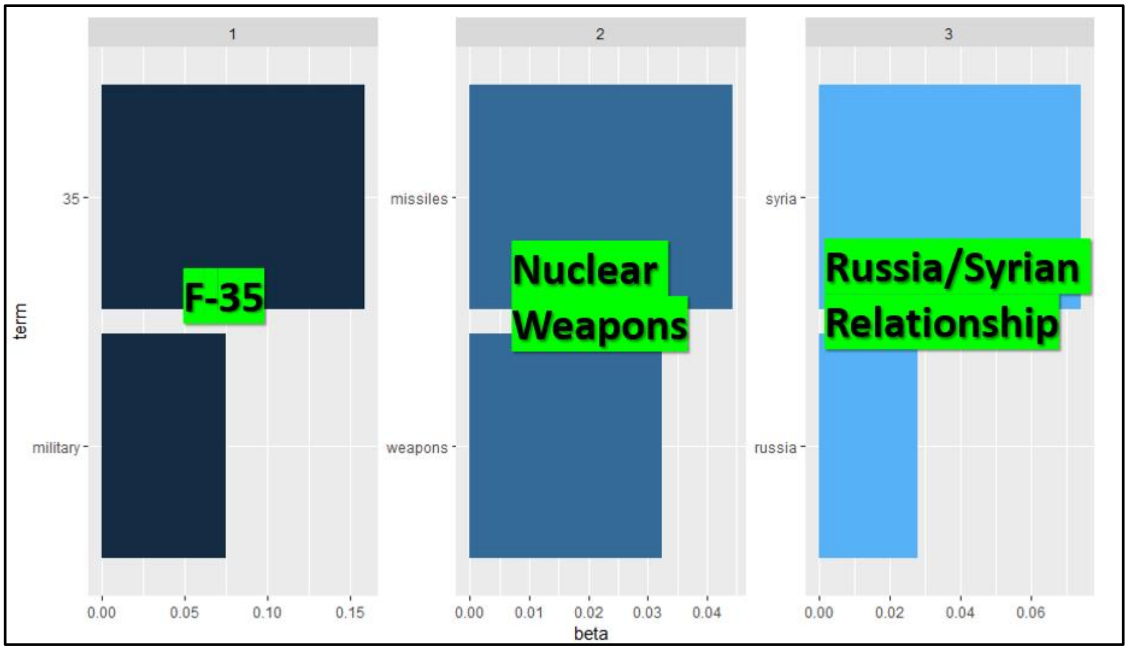

Figure 41: Topic Model of Celebrity Tweets

Topic Model of May

As discussed previously in time series analysis, the month of May was the only period with a negative AFINN mean sentiment score. The most negative Tweets were highlighted, however, a more concrete exploration of the different topics are shown in the topic model of Figure 43. As seen in the LDA Tuning Plot in Figure 42, the *Deveaud* and *CaoJuan* metrics converge at four and seven topics respectively, meaning that the optimal number of topics is within this range. Seven topics resulted in the highest average beta scores for the top five words within each topic. For this reason, seven topics is used as the input for the LDA topic model shown in Figure 43.

As exhibited, the seven topics display slight differences in comparison to the topic model of all data in Figure 39. To begin, the racist incident involving the Korean Air Force veteran was seen as its own topic within the Tweets of May. Other noticeable differences include the topics “Bombers,” “Air Force Demo Team,” and “Memorial

Day." Tweets related to the USAF demonstration team and Memorial Day were fairly positive, however, the "Bomber" topic referenced a multitude of negative Tweets pertaining to news of two Russian bombers that were intercepted near the coast of Alaska. 39% of Tweets containing the word "Bomber" referenced the interception, indicating that a considerable number of Tweets within "Bomber" topic had negative sentiment. Figure 44 exhibits the most popular negative Tweet with the word "bomber."

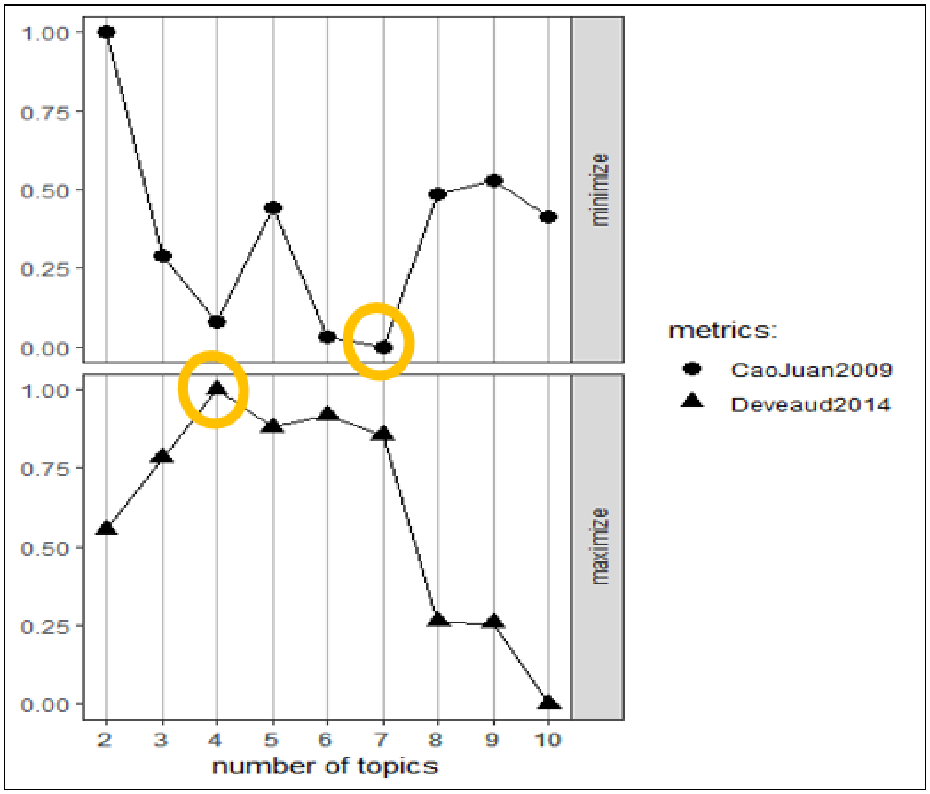

Figure 42: LDA Tuning Plot for May Tweets

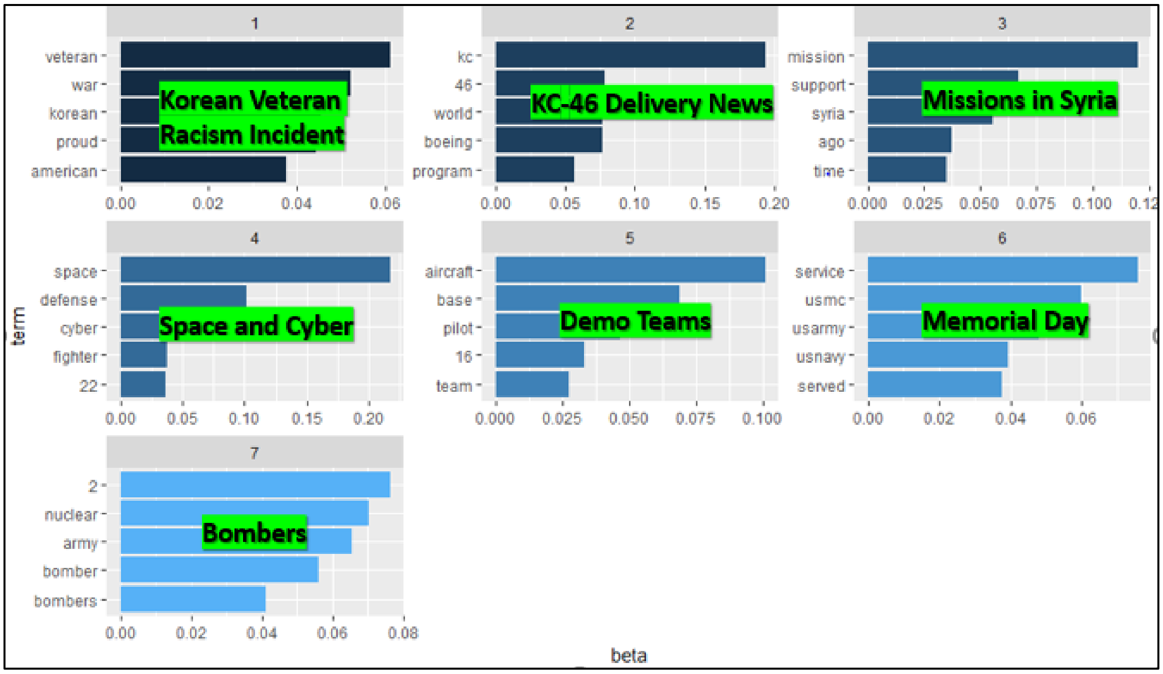

Figure 43: Topic Model of May Tweets

Figure 44: Most Popular Negative Tweet Containing "Bomber"

Sarcasm

When working with informal bodies of text like Tweets, there is the possibility of sarcasm being present within the message. As previously discussed, sentiment analysis is conducted by summing the sentiment scores of words, which can then be aggregated by sentence, Tweet etc. However, the true meaning behind a Tweet can be hidden behind sarcasm, which would hinder the accuracy of sentiment scores. For example, sentiment analysis would determine "I love the Air Force," as being an overall positive sentence. Nevertheless, the same sentence followed by a "rolling eyes" emoji would flip the intent of the message but would not be captured by sentiment analysis methods. To determine the overall impact of sarcasm, a random sample of 100 Tweets (list found in Appendix A) were examined. Of the sampled dataset, 8 Tweets were subjectively determined to contain sarcasm that countered the true intent of the message. Non-sarcastic Tweets measured to be 92% of the sampled data, which can be reflected on the entire dataset. The arguably high percentage of non-sarcastic Tweets garners confidence in the accuracy of the sentiment analysis methods used in this research.

Chapter Summary

This chapter presented the results attained from the various Text Mining methodologies and statistical inferences. The analysis began with an exploration of the data from a high level overview followed by sentiment analysis, topic modeling, and various statistical tests on multiple subsets of the data. In Chapter V, the research objectives will be addressed to include discussion, conclusions and recommendations of the findings in this research.

V. Conclusions

"As more intelligent computer assistance comes into being, it will amplify human progress."

-Paul Allen, Microsoft Co-Founder

Chapter Overview

In previous chapters we have discussed the growing popularity of social media, the potential impacts that social media presents on the Air Force, and prior research related to the benefits of Text Mining in the Department of Defense. We have also explained the Text Mining methodologies used on Air Force referenced Tweets, as well as the results found in the analysis. This chapter aims to address the five objectives set for this research, significant effects of our findings, and opportunities for future research.

Research Objectives Addressed

Social media contains a rich source of opinions readily available to review and provide insight on how the Air Force can better manage social networking platforms. The objectives for this research were designed to capture the details of what is being discussed along with the key players within the context of Air Force Tweets. To address these objectives, this research examines the following research questions:

Question 1: Which group of Twitter users is the most influential when it comes to Air Force missions (i.e. Regular User, News/Press, Blogger, Politician, Celebrity, Military Leader)?

To reiterate, influence is calculated by a Tweet's total engagements divided by the amount of followers that the Tweet's author possesses. This ratio comes with two assumptions in an attempt to deter inaccurate results:

- Tweets from users with less than 100 followers were not used in the dataset
- *Regular User*s are excluded as a candidate for the most influential user group due to low followership relative to the other user groups

After taking these assumptions into account, the results of the analysis conclude that *Bloggers* represent the most influential user group. Although all users on Twitter essentially share mini-blogs, it is important to restate what classifies a user as a *Blogger*. As defined by this research, a Blogger can assume the following forms:

- Profiles who explicitly say they are Bloggers
- Profiles who update on certain topics, but are not affiliated with a news agency
- Group profiles
- Satire profiles

Bloggers can take many forms as indicated in the assumptions of this research. However, one thing that each form has in common is its focus on a certain topic. “Blog” which is short for “Web log,” is a creation of curious and interesting information to be shared and viewed by those interested (Jenkins, 2006). Referring back to the *Stars Theory*, Bloggers act as the “stars” of this research. In other words, Bloggers are shown to be the most effective intermediaries between posted content and their followers. Although Bloggers may not possess the followership of some of the other user groups, the influence exhibited by Bloggers in this research cannot be understated. Those who have an interest in satirical content will follow and engage with a satirical Blogger. In addition, those who seek content related to the Air Force (whether factual, comical or opinionated), will follow and engage with an Air Force Blogger.

News/Press were seen as the second most influential group in the dataset. Although News/Press received an influence score that was roughly half the influence of Bloggers, News/Press entities should receive a high degree of respect when it comes to influence. To begin, News/Press entities possess the highest average follower count among all groups, with roughly 2M followers per entity. Relatively speaking, the user group with the second highest average follower count were *Professional Organizations*, with only 210K followers per entity. Considering the algorithm for influence (engagements/followers), it is impressive for the News/Press user group to maintain the second highest influence, surpassing government influencers such as *Military Leaders* and *Politicians.*

The three user groups with the least amount of influence were *Politicians, Celebrities* and *Military Leaders.* Celebrities, who possess the fourth highest follower count on average (138K), are justified in these results. Followers of Celebrities generally do not follow them for Air Force related content, therefore, it is reasonable that followers of Celebrities do not engage with such content. However, followers of government entities like Military Leaders and Politicians are more likely to have an interest in Air Force related material. The fact that Politicians have the lowest influence out of all user groups is a surprise. More interestingly, Military Leaders, who can be expected to have the most followers interested in military content, possessed the 3rd lowest influence. Additionally, Military Leaders also possessed 3rd lowest in average follower count. Combining both metrics together would indicate that although Military Leaders have a low follower count relative to other groups, a small percentage of those followers are actually engaging in Air Force related content.

Question 2: What sentiment was displayed for each mission area of the Air Force Strategic Master Plan, user groups, and Air Force Twitter data as a whole?

The sentiment of all of the Tweets collected were shown to be slightly more positive according to the analysis conducted using the NRC lexicon. However, interesting patterns were highlighted when sentiment analysis was conducted on more specific subsets of data.

When the BING lexicon was applied to Tweets filtered by mission area, results were positive outside of the Air Superiority strategic mission which displayed extremely negative results. To recap, the retrieval of Air Superiority Tweets was conducted by using the searches “USAF aircraft” and “USAF pilot.” The results of these searches highlighted an excess of negative Tweets concerning F-35 spending, blocking the sale of F-35s to Turkey, and Air Force pilot deaths. When the AFINN lexicon was applied, slightly positive results were displayed for the Air Superiority mission area, indicating that although more negative words were being used (as indicated by BING), extremely positive verbiage was captured by the AFINN lexicon. The cause of this sentiment reversal is highlighted by the analysis conducted on KC-46 Tweets. Although the KC-46 received its share of criticism relating to delivery delays, the KC-46 sentiment analysis received a positive mean sentiment score (AFINN), indicating that anticipation for the modern refueler’s capability outweighed the voice of its critics. Tweets from Boeing Defense, Politicians, and Military Leaders displayed extremely high sentiment, which resulted in a counter effect of overall sentiment within the Air Superiority mission.

The remaining four mission areas displayed varying amounts of positive sentiment, as indicated by the BING lexicon. The *Nuclear Deterrence* mission displayed positive sentiment, but was also extremely close to a residual sentiment score of zero, meaning that there were roughly the same amount of positive and negative words. When AFINN was applied to Nuclear Deterrence Tweets, the results exhibited negative mean sentiment meaning extremely negative words caused for the sentiment reversal. To recap, searches used to capture Nuclear Deterrence Tweets included "USAF Nuclear," "USAF Nuke," and "USAF Bomber." The results of these searches included many inherently negative Tweets regarding the nuclear capabilities of Russia and North Korea. However, many optimistic Tweets regarding the newest generation of bomber aircraft, the B-21, was also frequently present within the data.

The remaining three mission areas exhibited positive sentiment results in both BING and AFINN applications. *Space/Cyberspace* and *Intelligence/Surveillance/Reconnaissance* both exhibited moderately positive sentiment, while the *Technological Dominance* mission area revealed extremely positive sentiment throughout the analysis.

When sentiment analysis was conducted on the various user groups, negative sentiment was displayed throughout for the *Celebrity* and *News/Press* groups. Celebrities used slightly more negative than positive words in their Tweets, while at the same time used the most extremely negative verbiage out of all groups. New/Press exhibited an inverse relationship in comparison to Celebrity sentiment. The most negative residual sentiment was exhibited by the News/Press users, indicating that news agencies and other news entities Tweet a greater share of negative news stories over positive. However, extremely negative words are less likely to be Tweeted by a news entity, as professionalism is critical for credibility. For example, it would be unacceptable for CNN to use words like "hate" or "stupid" whereas other use groups would have little to no negative impact if these words were used. For this reason, News/Press users received a slightly negative mean sentiment score.

Regular Users received mixed results after both sentiment techniques were conducted. When BING was applied to Regular User Tweets, results indicated that more positive words were used. To provide further insight, it is critical to note that Tweets from Regular Users vastly outnumbered total Tweets by other user groups. For this reason, results of the residual sentiment score is not as significant as the AFINN lexicon which exhibited slightly negative verbiage in Regular User Tweets.

The remaining four user groups received extremely positive sentiment throughout both sentiment analysis methods. Military leaders and Politicians are positive in nature as credibility, again, is at utmost importance. In addition, defense organizations (*Professional Organizations*) such as *Boeing Defense* and *Lockheed Martin* are frequently exhibited in the data and have an obvious incentive to post positively about the DoD. *Bloggers* on the other hand, have an unknown nature but were exhibited to use slightly positive verbiage while recording the third most positive BING sentiment score behind Military Leaders and Professional Organizations.

Question 3: Which topics and/or mission areas are the most popular (Favorites + Retweets + Replies)?

The Structural Topic Model in combination with the LDA Tuning Plot highlighted six topics within the general search category. To reiterate, Tweets within the general category were captured by using the search, “USAF,” which returned the top Tweets regarding the United States Air Force for the desired time frame. Summarizations of the six topics were developed by five individuals and are listed below:

i. Space Force
ii. Missions in Syria
iii. Aircraft Acquisition
iv. Flying
v. Department of Defense
vi. Military Service

The topic model highlighted topics that were both anticipated and astonishing to see in the results. Topics such as *Flying, Department of Defense,* and *Military Service* can be reasonably expected in a pool of Air Force related Tweets. However, topics such as the *Space Force, Missions in Syria,* and *Aircraft Acquisition* provide more specificity to certain events occurring in the Air Force world.

Question 4: Are number of engagements more accurately correlated to positive or negative sentiment?

The intention of this research question was to determine which sentiment (positive or negative) was more accurately correlated with a Tweet’s popularity. Prior to the analysis, it was believed that negative news within media had a stronger chance of becoming viral. To determine if this hypothesis held true, a correlation matrix was conducted on total engagements by mission, BING sentiment by mission and AFINN sentiment by mission. As shown in Figure 37 (shown again below), the results displayed strong positive correlation (Pearson Correlation Coefficient) between the BING and

AFINN sentiments. However, -0.62 and -0.37 were the resulting coefficients when BING and AFINN sentiments were paired with the total engagements variable. Understand that although these values are far from perfect correlation, the results demonstrate that moderate negative correlation existed between sentiment and total engagement variables. This indicates that Tweets with *negative* sentiment were more strongly correlated with Popularity and that the hypothesis for this question holds true.

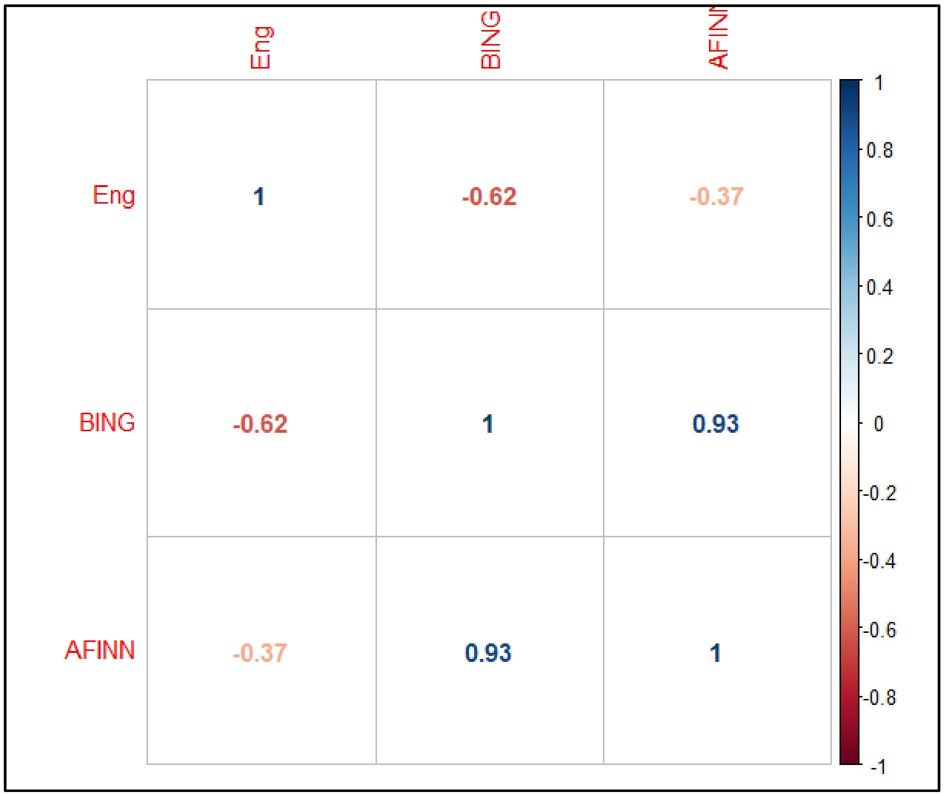

Figure 37 (repeated): Engagement and Sentiment Correlation

Question 5: What opportunities can the Air Force take advantage of to improve their presence in social media?

An analysis of social media can provide benefits to the Air Force as it does to a private corporation. Rather than turning to polls or surveys to question consumers on their opinions, social media provides a perspective from consumers who volunteer their opinions, unedited and in real-time (Curnow, 2016). When social media is combined with the Text Mining methods used in this research, the results provide insight into what topics are being discussed and who the key players are that are driving the virality of certain topics.

Bloggers

The Air Force should be aware of what is being discussed negatively within the various media avenues. Therefore, the need for topic modeling of all Air Force related social media posts may not provide significant results to Air Force leaders. However, the Influence results in our analysis indicate that a focus on *Blogger* content would be beneficial. By conducting a topic model of the most influential Air Force Bloggers, leaders would have the ability to understand which topics are most successful at "reaching" followers, or in other words, which topics are the hardest hitting. Although Bloggers do not typically have the same following as *News/Press* entities, the power of re-sharing is most efficiently conducted by the followers of Bloggers, according to Popularity analysis. By implementing sentiment analysis in combination with topic modeling, the Air Force would have a deeper understanding of the topics receiving the most negative publicity to better manage its brand.

Brand Management

The sentiment progression analysis highlighted *May* as being the only month, of seven, to have Tweets with a negative mean sentiment score. As indicated by the analysis of May Tweets, the primary driver of this result was the racist incident involving the Korean-American Air Force Veteran. Although this was negative publicity towards the female shouting racial slurs and not the Air Force, this does prove how great of an effect virality can have on an image. Additionally, sensitive topics such as racism prove to be popular as well as referenced frequently. Within the data, Tweets pertaining to this racist incident was referenced in five separate Tweets among the Top Tweets in May. In other words, the incident went viral from five different users. Sensitive topics such as racism, violence, and sexual assault are without a doubt, zero tolerance within military culture. However, when topics related to these surface on social media websites, they must be quickly handled. The Retweet is instant, therefore a continuous patrol of social media is necessary in order to be proactive and remain a step ahead of negative and viral publicity.

Air Superiority

In this research, *Popularity* was determined as the total amount of engagements (Favorites + Retweets + Replies) possessed by a particular Tweet. An aggregated sum of engagements was used to determine the average Popularity of a Tweet among the different mission areas. Results of this analysis concluded that the *Air Superiority* mission area was by far the most popular mission with 93 average engagements. As indicated in more in depth analysis of the Air Superiority mission, the F-35 and KC-46 were the most popular topics, indicating that the modern aircrafts were the most discussed Air Force topics on Twitter. Although the KC-46 received mixed sentiment that was proved to be dependent on the type of user, the F-35 was referenced almost entirely negatively in the data. References of overspending was frequent among F-35 Tweets, however, blocking the sale of the F-35 to Turkey was just as popular and contained a plethora of negative sentiment associated words. From this, it can be concluded that the American public socially engages with high ticket items such as the acquisition of new aircraft. Although this is no surprise to Air Force leaders, it is important to realize that Air Superiority is the most critical Air Force strategic mission to the American taxpayer. Therefore, acquisition of aircraft such as the new B-21 Raider, should be of utmost importance within Air Force priorities.

Limitations

The primary limitation in this research is the low number of observations in the dataset, compared to what could have been collected. As previously mentioned, Tweets were collected manually rather than through the Twitter API, which would have allowed for millions of Tweets to be collected for analysis. However, data over a longer period of time outweighed the benefits of having more data within a seven day period. For this reason manual collection was the more desired method for data collection. Additionally, 15,000 Tweets (500/week) were initially desired for the analysis. However, due to time constraints, only 4,500 Tweets (150/week) were viable.

Future Research

The original intent of this research was to conduct an analysis between Air Force Twitter sentiment and Air Force funding. Although a financial analysis was improbable due to time constraints, the idea is still a valid research opportunity that could highlight greater impacts due to public sentiment on Twitter.

Another opportunity that may improve results is an analysis of "re-shared" content. On Twitter, the process of sharing another individual's content is called Retweeting (RT). The data collected in this research includes RT data, which could be analyzed to determine another variance of Influence. For this research, popularity was calculated by summing three different Twitter engagements, however, it may be found that the RT is more impactful as it spreads content to another user's followers, increasing the amount of viewers of the Tweet. The insight that can be gathered from a RT analysis may provide a much greater accuracy of Popularity which would lead to improved influence results.

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Appendix A: Data Collection

Table 8: Advanced Searches

Mission Area	Search
Air Force in General	USAF
Air Force in General	Air Force
Air Force in General	US Air Force
Air Force in General	United States Air Force
Space/Cyberspace	USAF Space
Space/Cyberspace	USAF Cyberspace
Space/Cyberspace	USAF Satellite
Space/Cyberspace	USAF Cyber
Space/Cyberspace	USAF Cybersecurity
Nuclear Deterrence	USAF Nuclear
Nuclear Deterrence	USAF Bomber
Intelligence, Surveillance, Reconnaissance	USAF ISR
Intelligence, Surveillance, Reconnaissance	USAF Intelligence
Intelligence, Surveillance, Reconnaissance	USAF Surveillance
Intelligence, Surveillance, Reconnaissance	USAF Reconnaissance
Intelligence, Surveillance, Reconnaissance	USAF Intel
Intelligence, Surveillance, Reconnaissance	USAF Recon
Intelligence, Surveillance, Reconnaissance	USAF UAV
Intelligence, Surveillance, Reconnaissance	USAF Drone
Advancements in Technology	USAF Technology
Advancements in Technology	USAF Innovation
Advancements in Technology	USAF Modernization
Air Superiority	USAF Fighter
Air Superiority	USAF Jet
Air Superiority	USAF Refuel
Air Superiority	USAF Refueler
Air Superiority	USAF Aircraft
Air Superiority	USAF Pilot

Table 9: Expected Words Removed

Word
USAF
AF
Air
Force
http (to remove links)
https (to remove links)

2889	2895	1842	355	3392	2965
3416	1814	1415	1876	2038	2319
3064	812	747	3295	1694	1171
2725	1568	521	962	843	934
1927	2300	1373	1478	929	2077
3493	3426	2552	2674	3687	2917
1359	3378	1298	619	3200	1469
1970	3201	605	1234	1547	3070
259	1103	1098	906	261	2277
1720	2103	2843	1201	2473	990
1238	2153	3645	222	251	1865
2005	3308	2132	2492	3139	2453
1310	1074	3875	1831	1345	254
2522	2413	1856	2515	2772	1045
3546	3129	2664	522	1538	2428
3686	2893	2118	1529	1944	869
2228	2962	1488	239		

Figure 45: Random Numbers Generated for Sarcasm Analysis (random.org)

Appendix B: Text Mining – Word Frequency Results

Figure 46: Word Cloud (General Air Force)

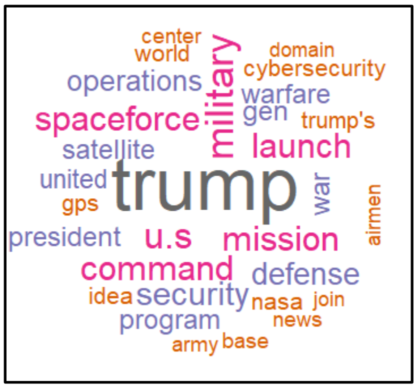

Figure 47: Word Cloud (Space/Cyberspace)

Figure 48: Word Cloud (Nuclear Deterrence)

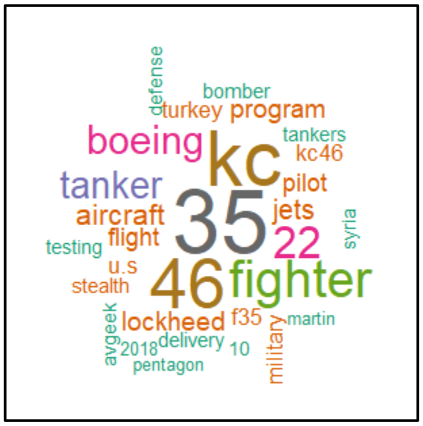

Figure 49: Word Cloud (Air Superiority)

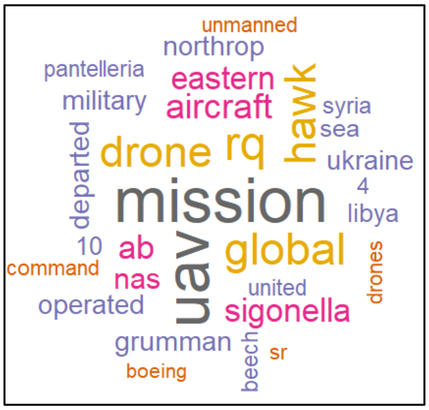

Figure 50: Word Cloud (ISR)

Figure 51: Word Cloud (Technology)

Appendix C: Sentiment Progression Results

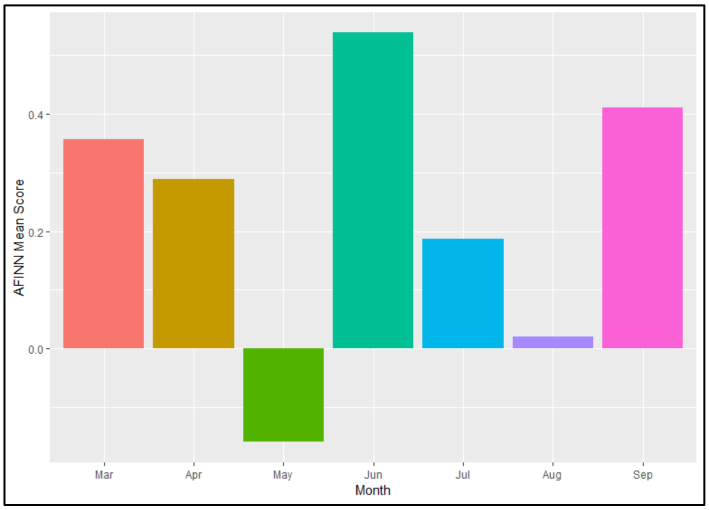

Figure 52: Sentiment Progression (General Air Force)

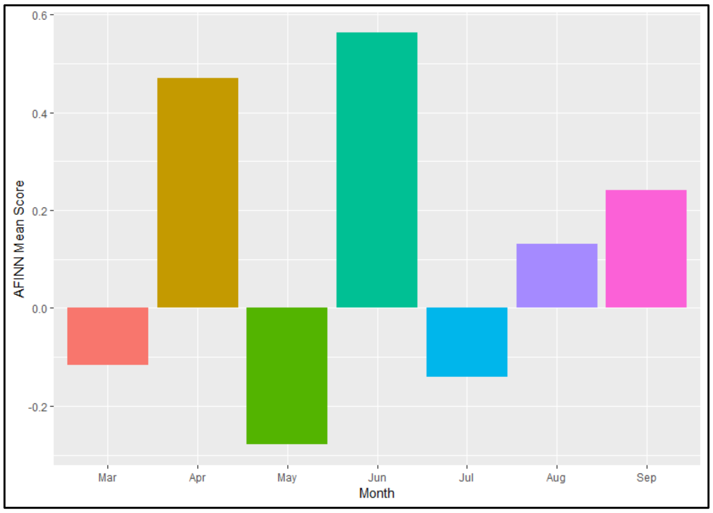

Figure 53: Sentiment Progression (Space/Cyberspace)

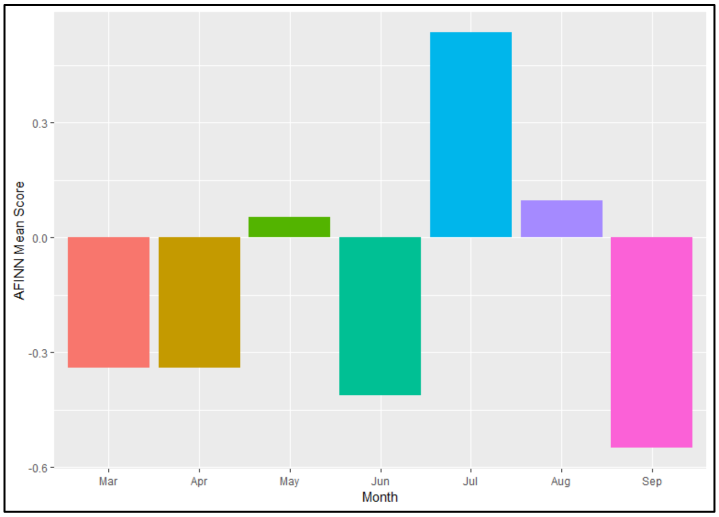

Figure 54: Sentiment Progression (Nuclear Deterrence)

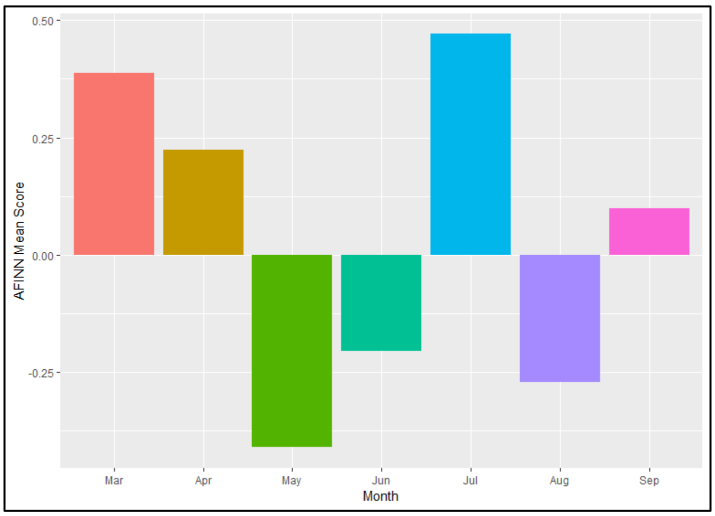

Figure 55: Sentiment Progression (Air Superiority)

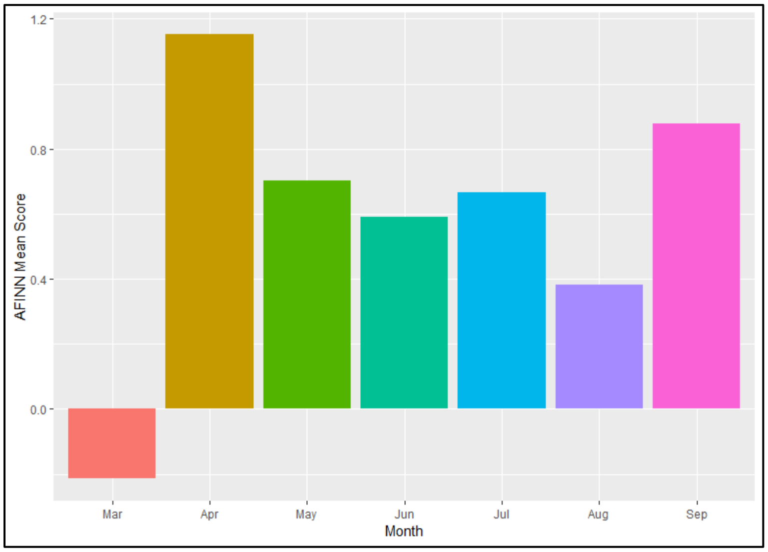

Figure 56: Sentiment Progression (Technology)

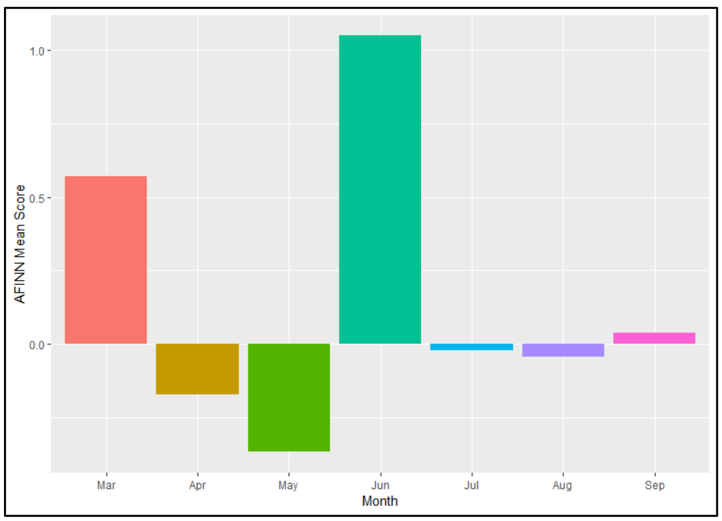

Figure 57: Sentiment Progression (ISR)

Appendix D: LDA Tuning Plots and LDA Topic Models

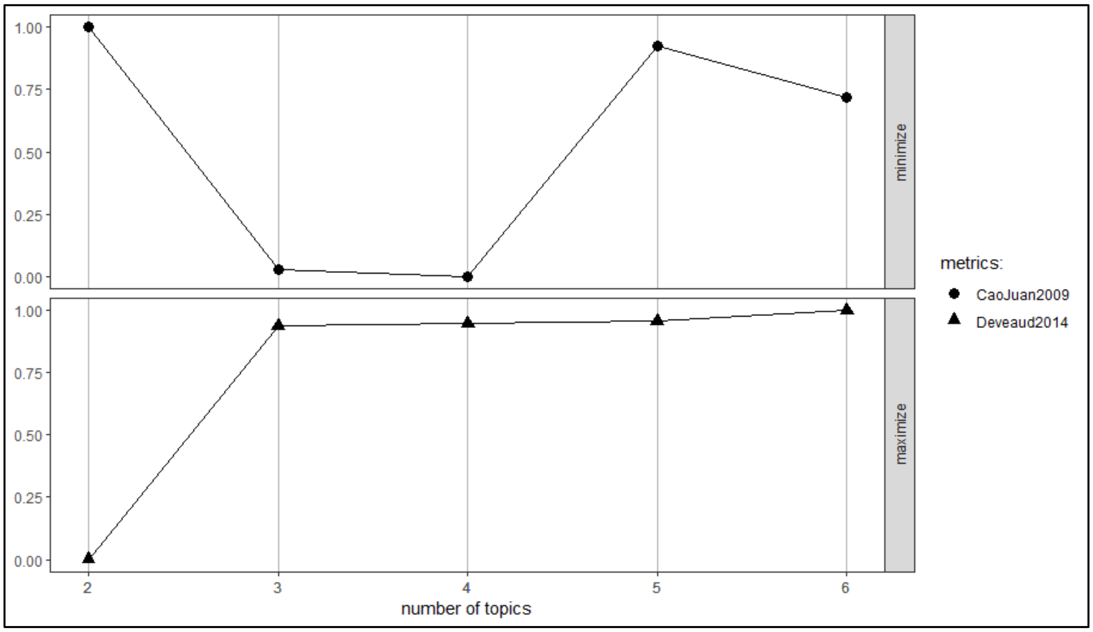

Figure 58: LDA Tuning Plot (Bloggers)

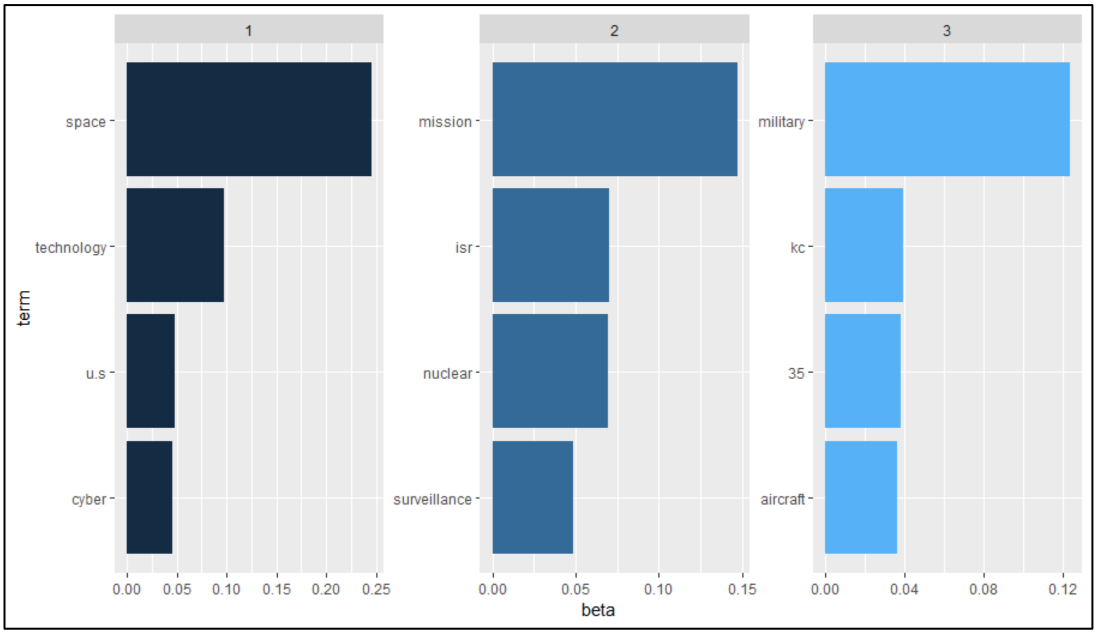

Figure 59: LDA Topic Model (Bloggers)

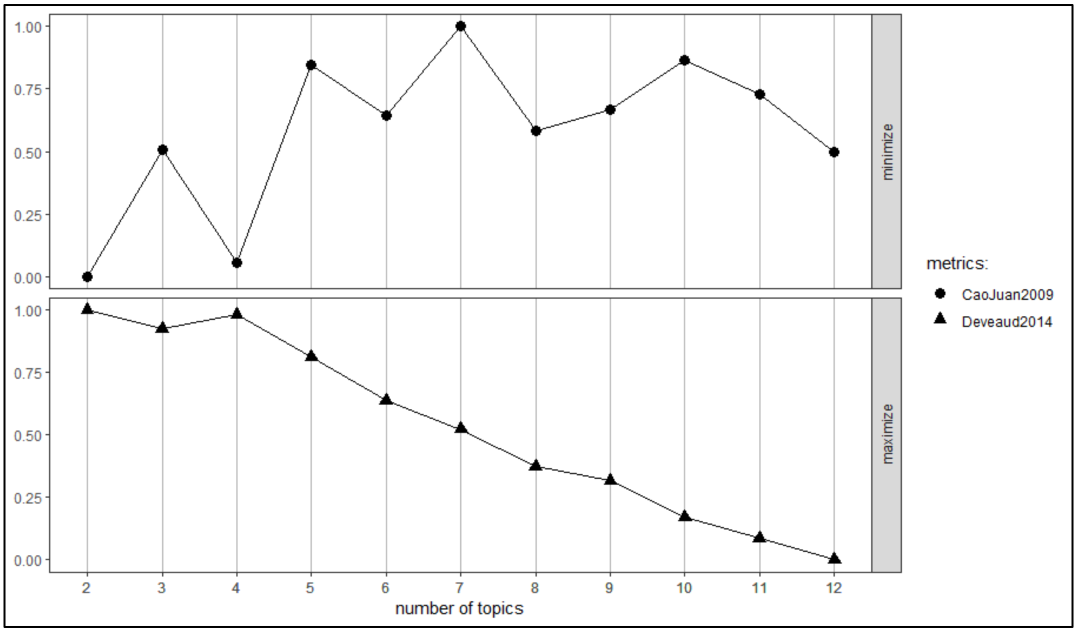

Figure 60: LDA Tuning Plot (News/Press)

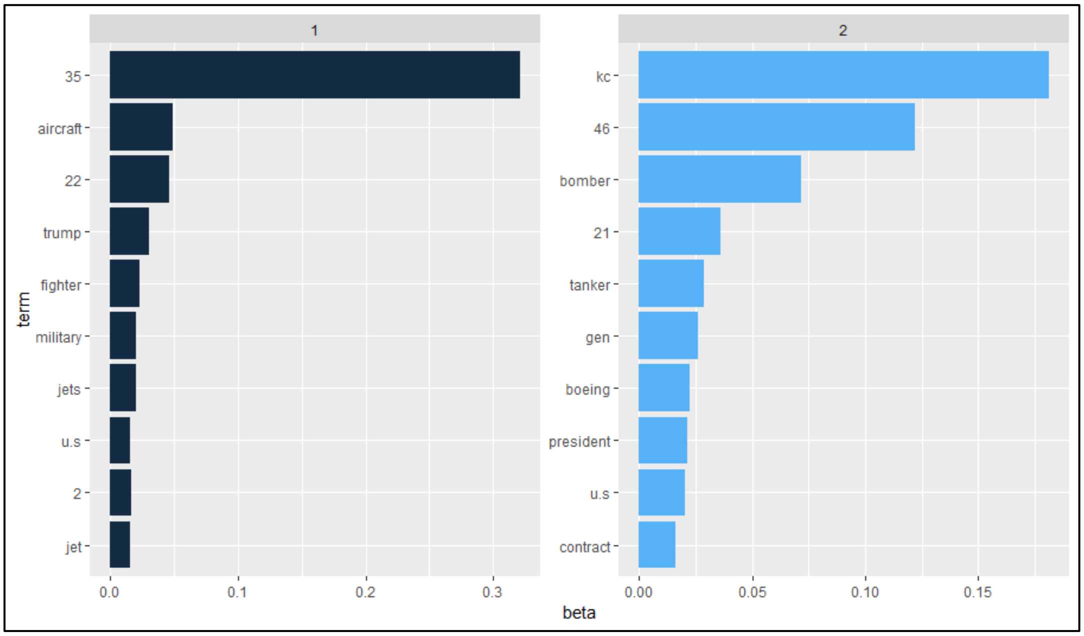

Figure 61: LDA Topic Model (News/Press)

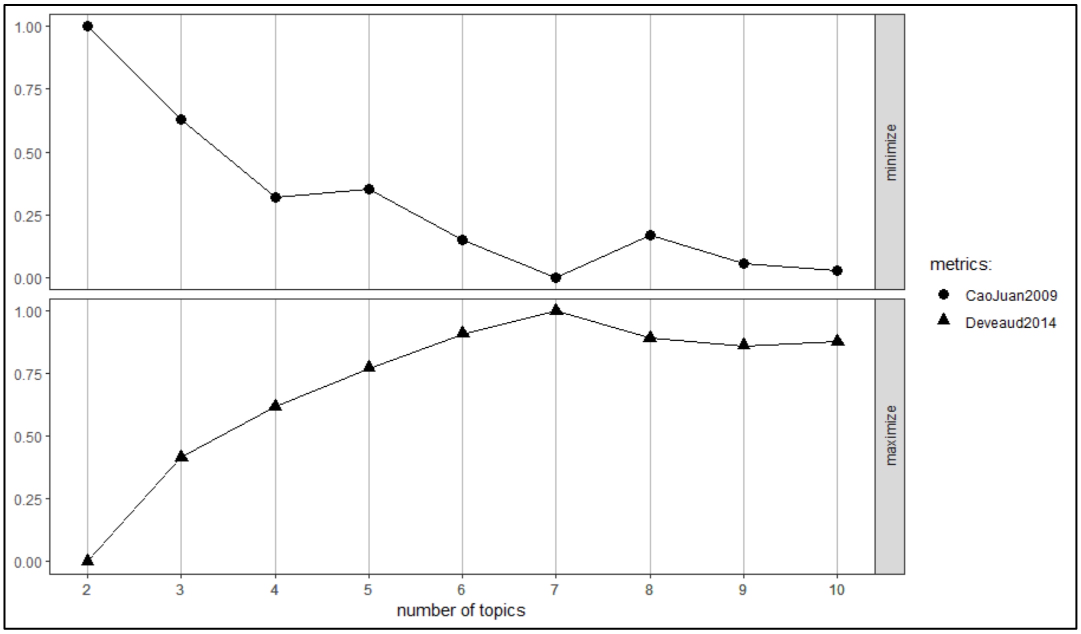

Figure 62: LDA Tuning Plot (Regular Users)

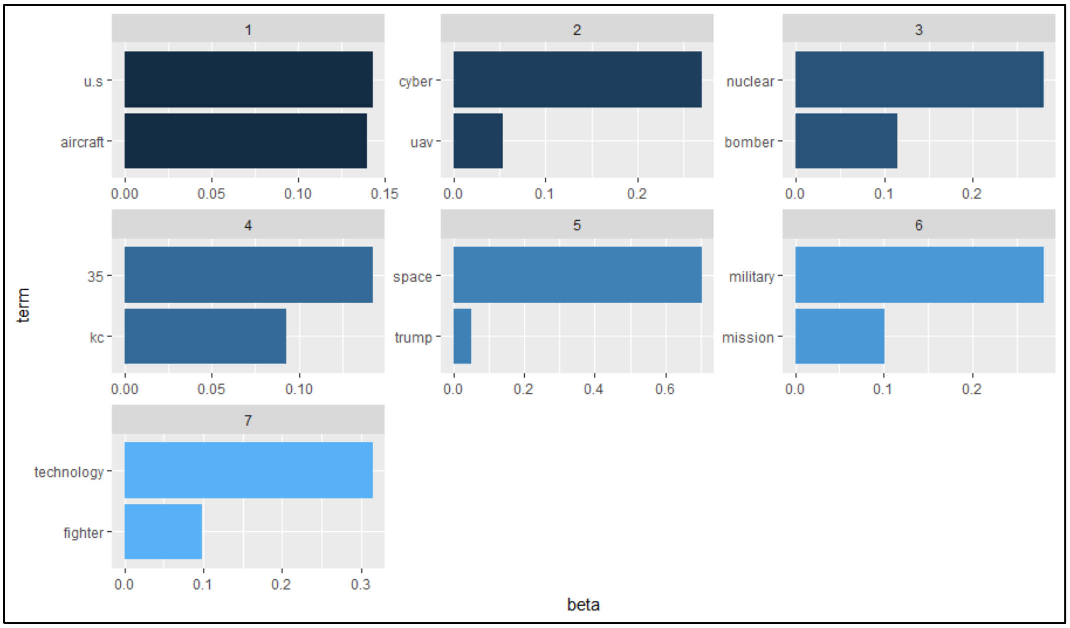

Figure 63: LDA Topic Model (Regular Users)

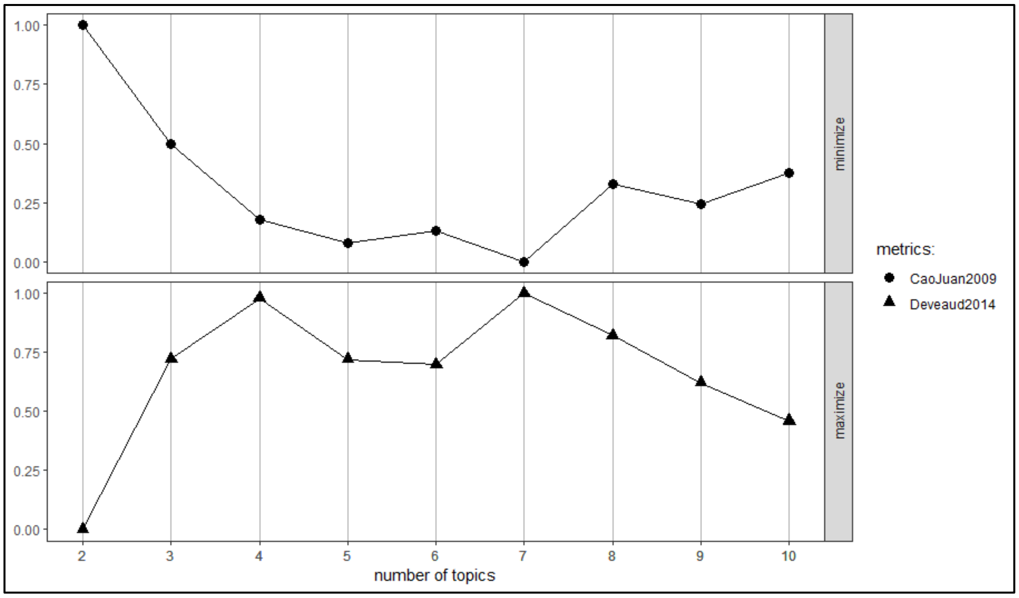

Figure 64: LDA Tuning Plot (Politicians)

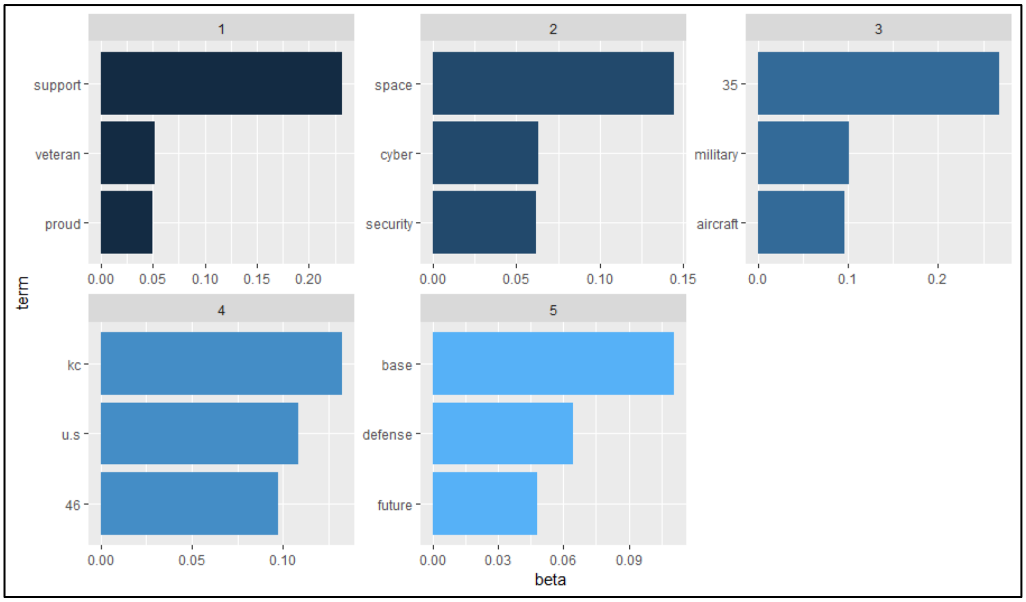

Figure 65: LDA Topic Model (Politicians)

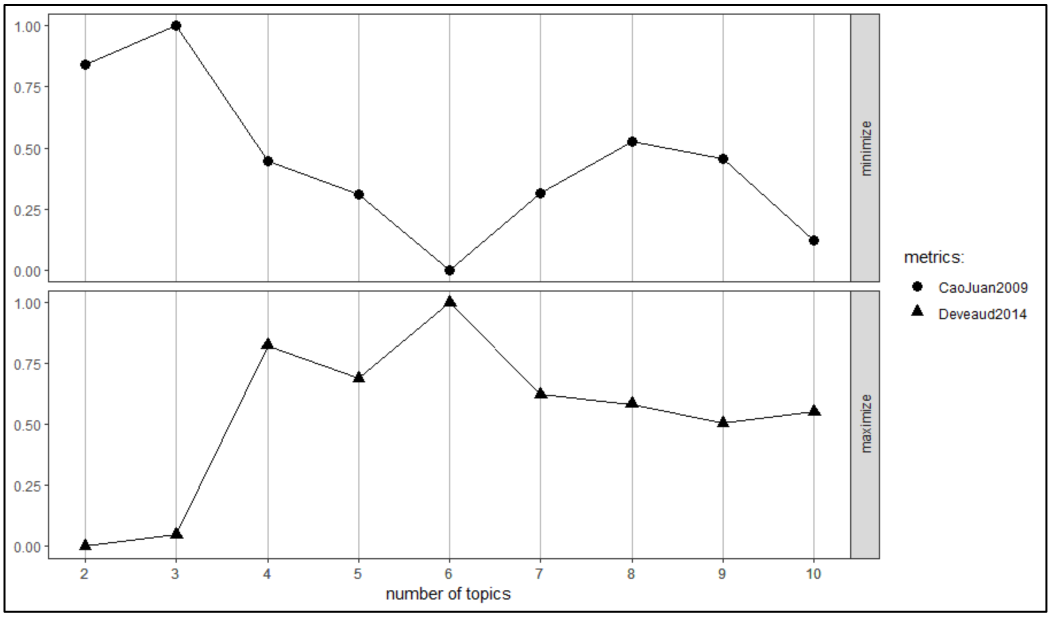

Figure 66: LDA Tuning Plot (Professional Organizations)

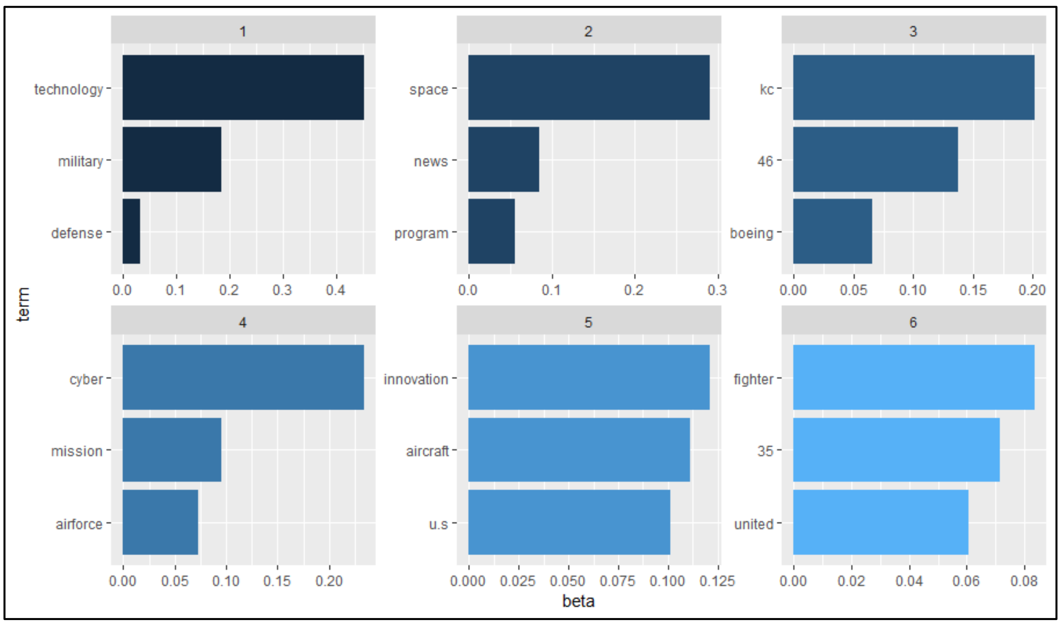

Figure 67: LDA Topic Model (Professional Organizations)

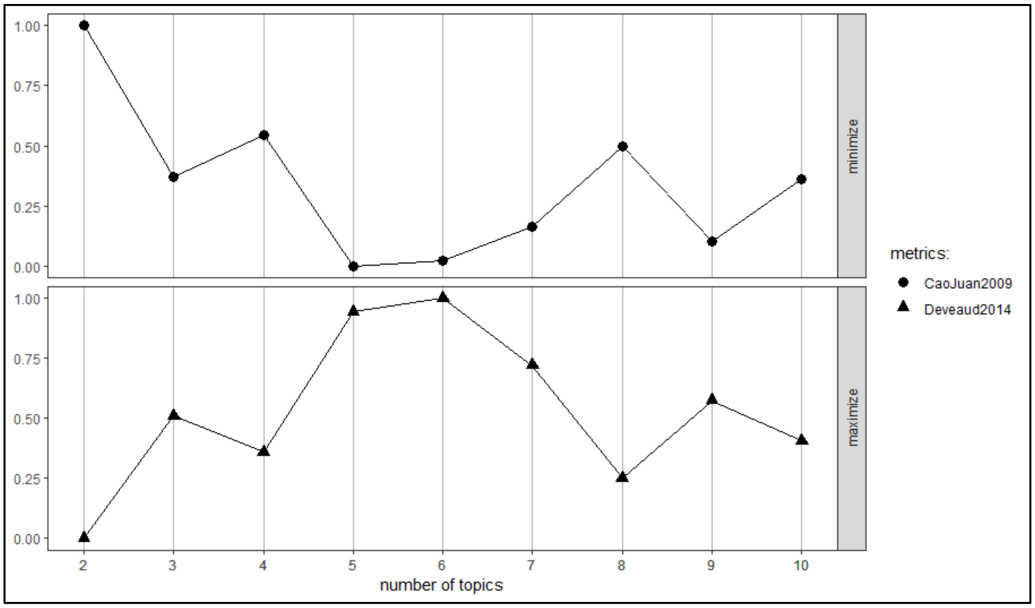

Figure 68: LDA Tuning Plot (Politicians)

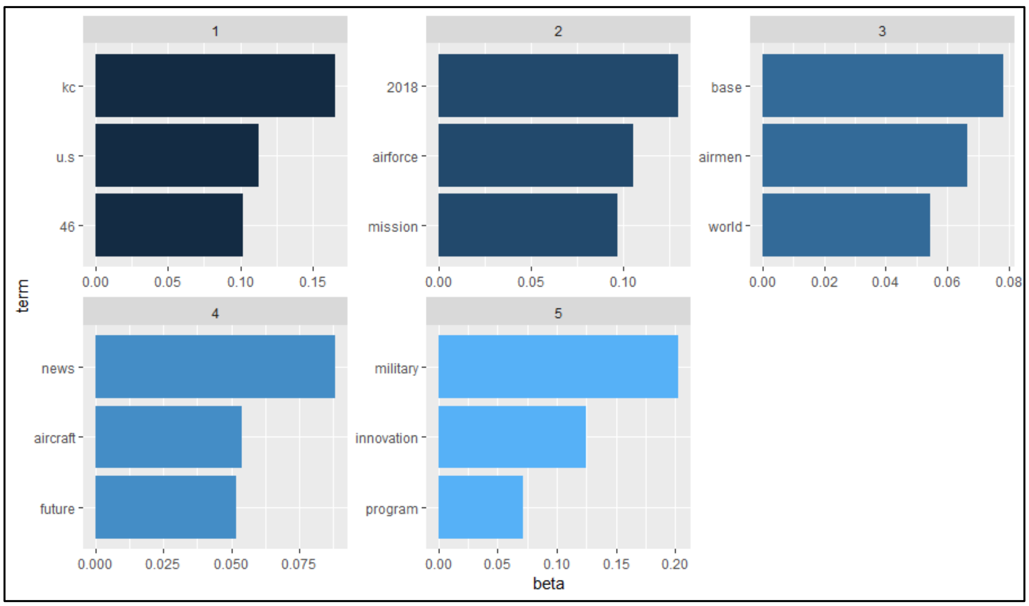

Figure 69: LDA Topic Model (Politicians)

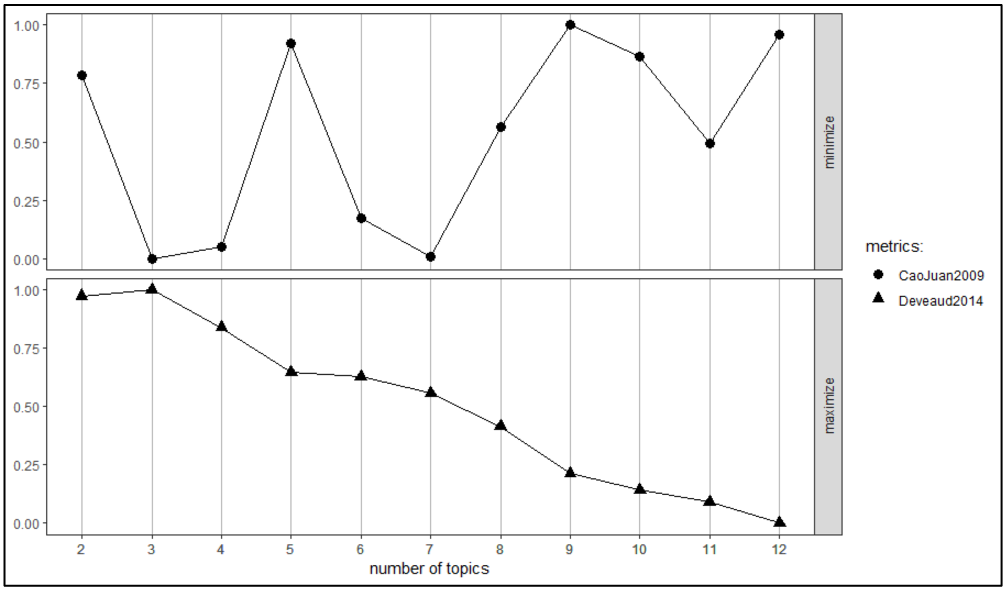

Figure 70: LDA Tuning Plot (Celebrities)

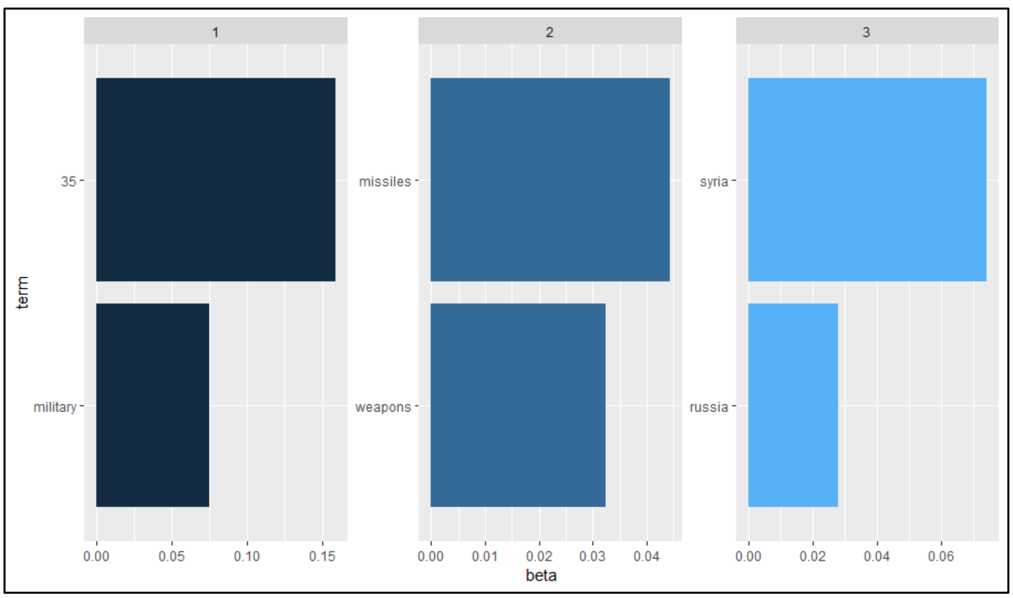

Figure 71: LDA Topic Model (Celebrities)

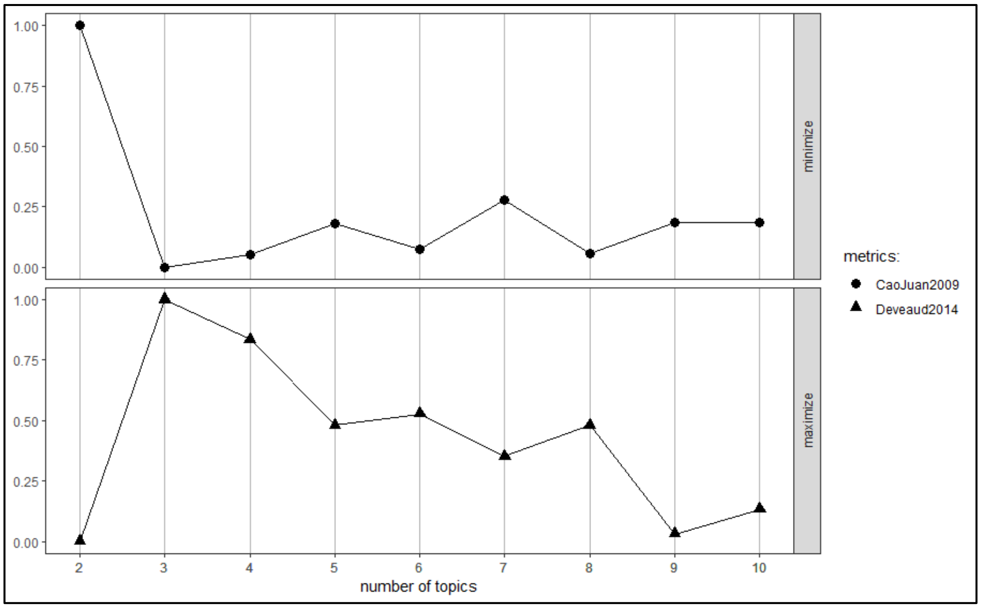

Figure 72: LDA Tuning Plot (Air Superiority)

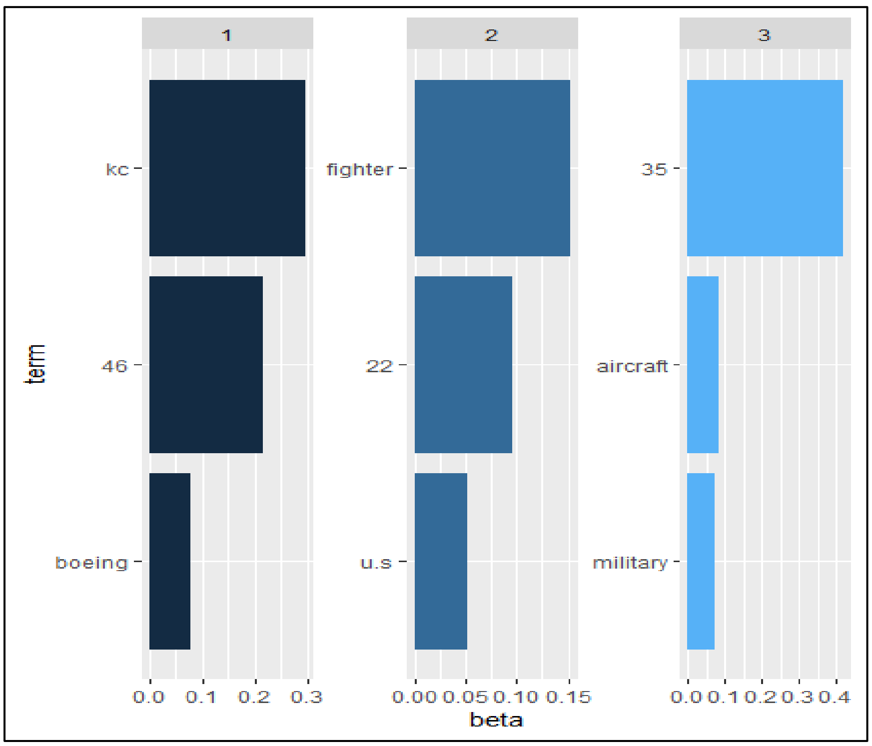

Figure 73: LDA Topic Model (Air Superiority)

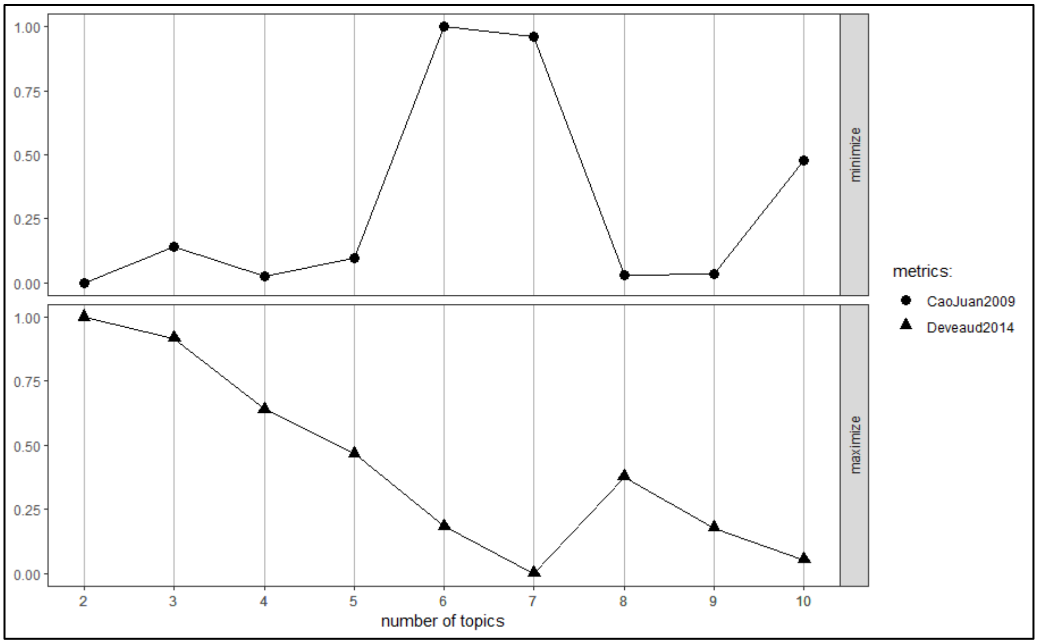

Figure 74: LDA Tuning Plot (Space & Cyberspace)

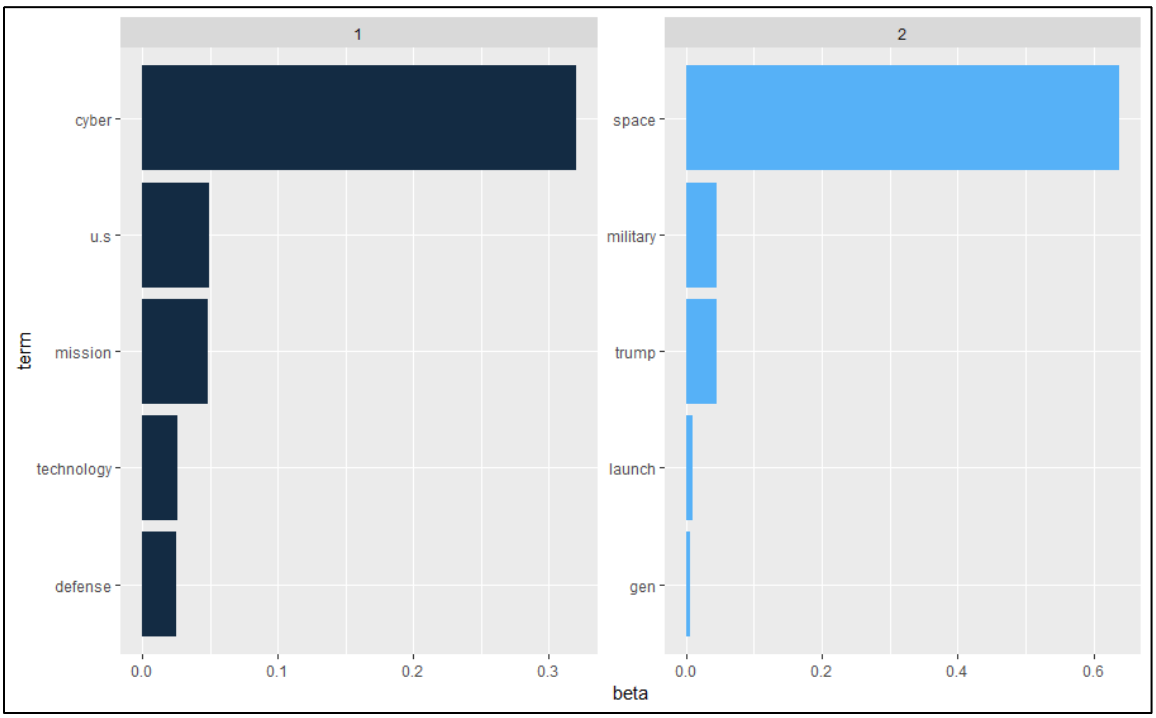

Figure 75: LDA Topic Model (Space & Cyberspace)

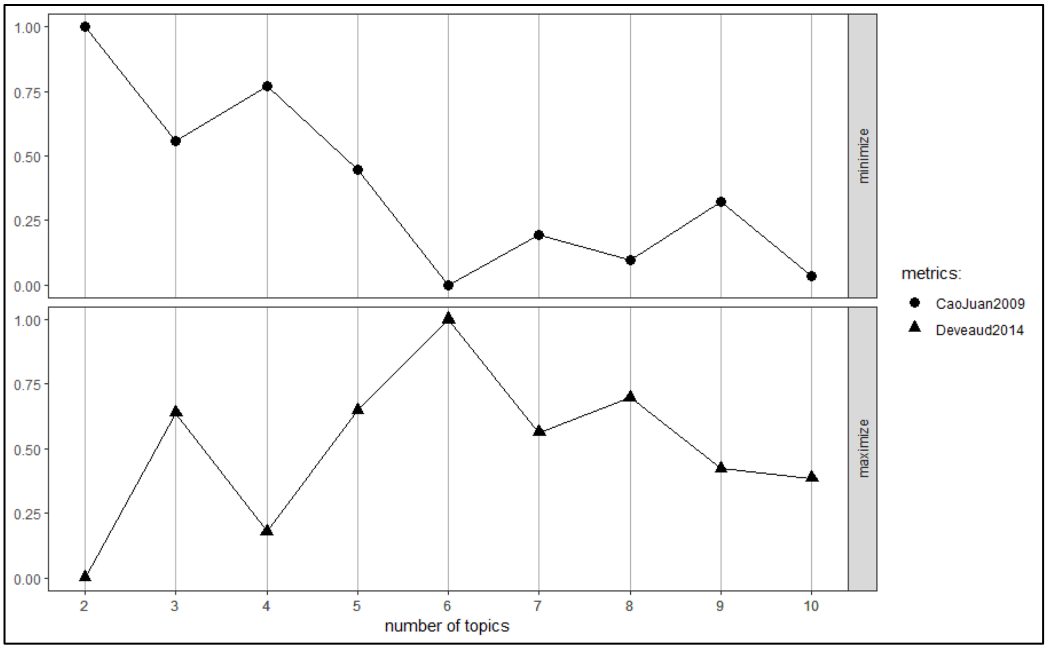

Figure 76: LDA Tuning Plot (Nuclear Deterrence)

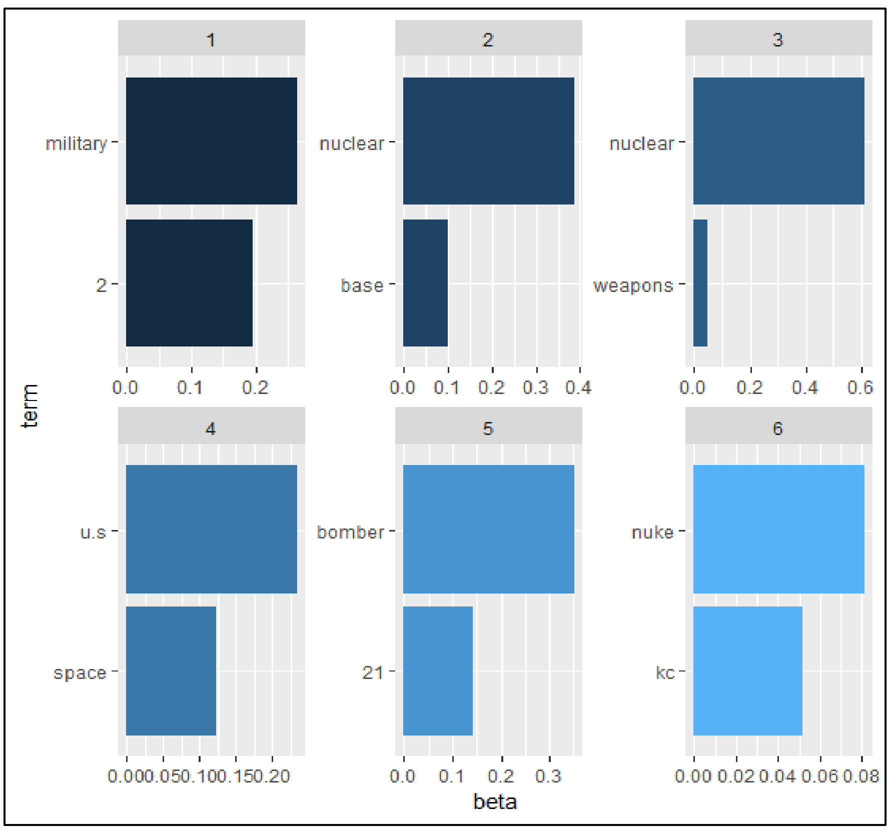

Figure 77: LDA Topic Model (Nuclear Deterrence)

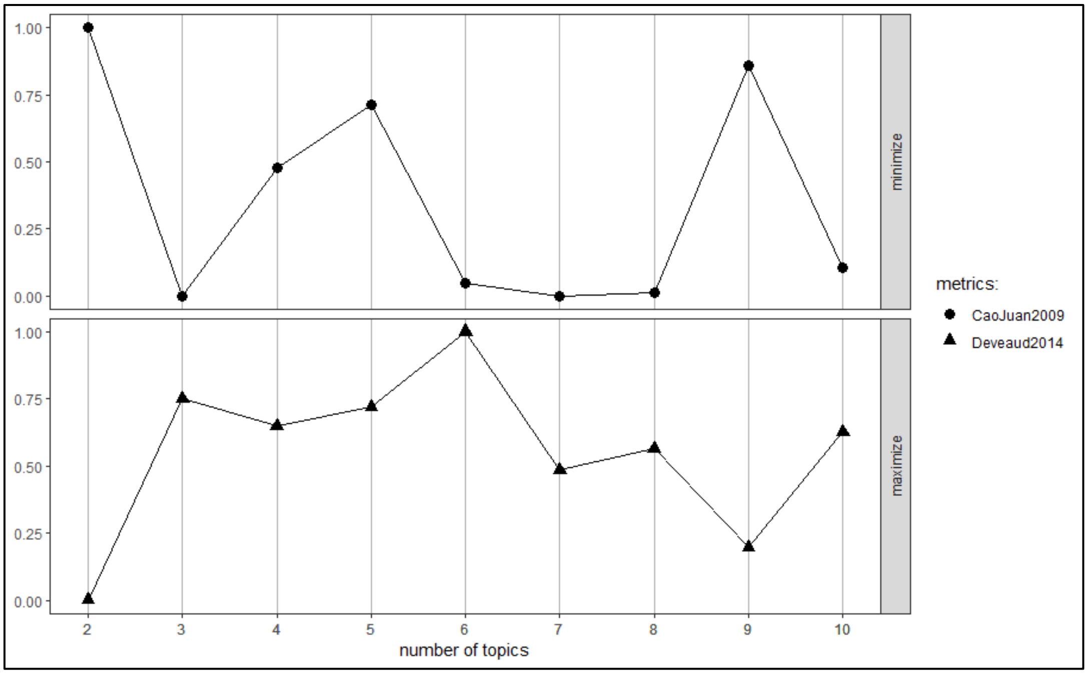

Figure 78: LDA Tuning Plot (ISR)

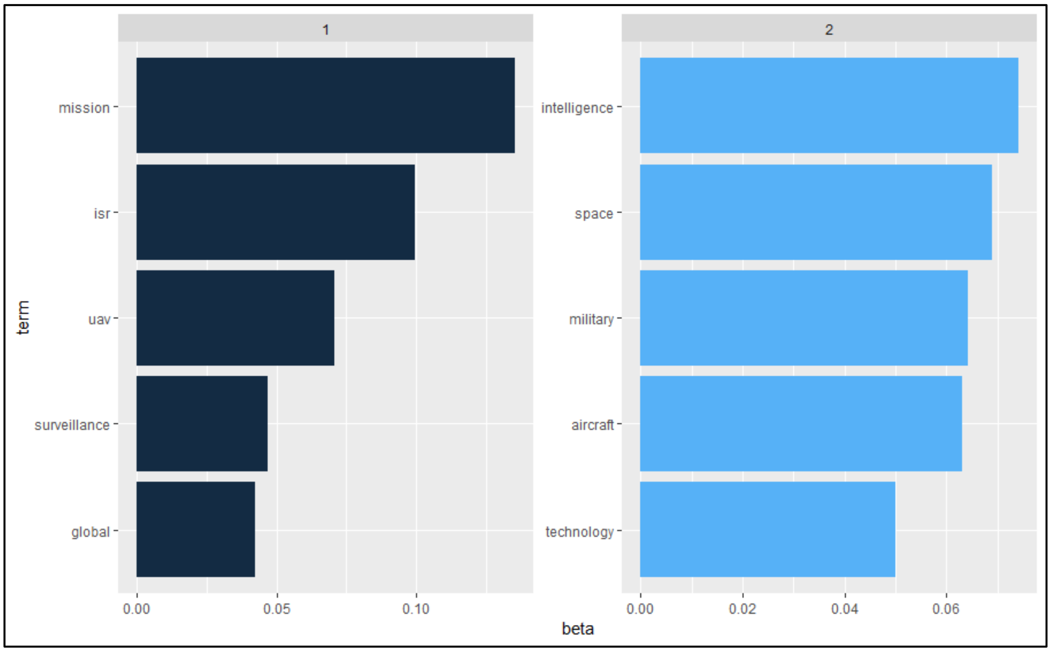

Figure 79: LDA Topic Model (ISR)

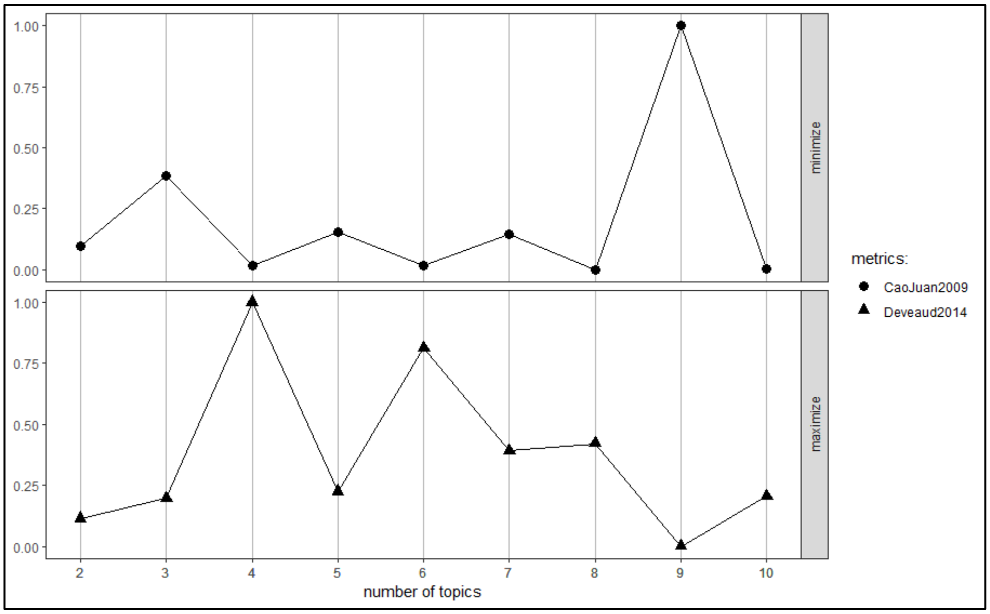

Figure 80: LDA Tuning Plot (Technology)

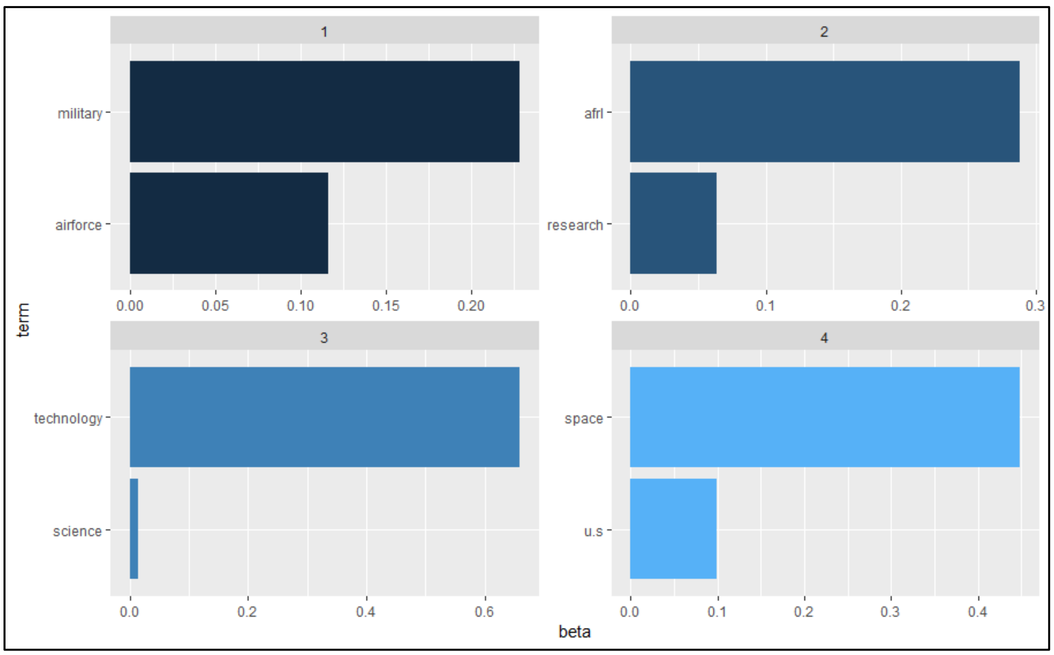

Figure 81: LDA Topic Model (Technology)

Appendix E: Correlation Significance Output

```
        Pearson's product-moment correlation

data:  CorTweets$Engagement and CorTweets$BING
t = -21.765, df = 2998, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
```

Figure 82: Pearson Correlation Significance (Engagements vs. BING)

Vita

Captain Seth A. Kline graduated from Eisenhower High School in Yakima, Washington. He entered undergraduate studies at the United States Air Force Academy, Colorado where he graduated with a Bachelor of Science degree in Business Management. Following the completion of his undergraduate degree, he was commissioned as an Officer in the United States Air Force.

His first assignment was at Laughlin AFB, Texas as Deputy Flight Commander, Budget Analysis. He entered the Graduate School of Engineering and Management, Air Force Institute of Technology in August 2017. Upon graduation, he will be assigned to the Space and Missiles Center at Los Angeles AFB, California.

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14. ABSTRACT
Social media has grown to become a rich source for opinions, authored by individuals who volunteer them, unedited and in real-time. Armed with this information, an organization like the Air Force can understand the perceptions of consumers and learn to better serve the American taxpayer. To accomplish this goal, this research takes a qualitative approach, utilizing social media analytics in combination with various Text Mining methodologies (word frequency, word relationships, sentiment analysis, topic modeling) to provide insight of Air Force related content shared on Twitter. To provide a well-rounded analysis of the overall perception of the Air Force enterprise, the methods mentioned are conducted on Tweets related to the Air Force's five core missions: *Space/Cyberspace, Nuclear Deterrence, Air Superiority, Advancements in Technology,* and *Intelligence, Surveillance, Reconnaissance*. This research also hopes to capture the key players that publish the most engaged Tweets related to the Air Force. By understanding the types of users who possess the most influence (*Regular Users, Bloggers, Celebrities, Military Leaders, Politicians, Professional Organizations*) leaders are better equipped to react to content and protect the Air Force brand.

15. SUBJECT TERMS
Text Mining, Sentiment Analysis, Topic Modeling, Word Relationships, Social Media Analytics, Qualitative

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