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ORIGINAL ARTICLE

Political marketing with data analytics

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Abstract

Social media played a significant role in past Presidential elections, and it is very likely that this form of communication will continue to influence political campaigns. Can analytics uncover the linguistic "plot arcs" and resulting sentiment or emotion in political text? This paper examines how natural language processing (NLP) and data visualization tools and methods in analytics can play a key role in marketing political candidates. Using publicly available text messages, the authors employ NLP techniques to transform the text observations from the past campaigns of Hillary Clinton, Barack Obama, and Donald Trump into a linguistic "corpus" and story arc visualizations. The methodology includes the use of Syuzhet and Latent Dirichlet Allocation (LDA) models. The resulting data visualizations reveal the story arcs associated with the candidate's communications, and they provide a means to analyze the unbiased political sentiment or hidden emotion in the text. In an analysis of the results, the authors found distinctly different story arcs and vocabulary usage among the three Presidential candidates. The contribution to the literature is a methodology for extracting the story and the resulting sentiment from text messages for marketing campaigns. The authors suggest that the techniques used in this paper can assist future research on marketing other products or services that utilize computer-mediated communications.

Keywords Political marketing · Analytics · Text mining · Natural language processing · Visualization story arcs

Introduction

As happened earlier with email, socially interactive technologies have stimulated the sharing of social disclosure online (Desjarlais and Joseph 2017), and evidence points to social media serving a significant role in shaping political discussion and political opinion (Smith and Raine 2008). Through text messaging, candidates announce official statements, run presidential campaigns, declare political standpoints, and even provoke battles among candidates. As texting can shape a candidate's destiny, this paper uses advances in data science and analytics to look back at historical clues on how campaigns have shaped their destiny to their marketing advantage; in this case, it was political campaigns. To accomplish this objective, the authors focused on a public dataset containing text messages posted by three presidential candidates: Barack Obama, Hillary Clinton, and Donald Trump. The dataset provides a number of significant attributes of the candidate, such as the origin of the message, the number of times the message was designated "favorite" by the reader, and the number of "retweets." All of the data came directly from the candidate. The Natural Language Processing methodology and analytical algorithms used in the paper can transform this linguistic "corpus" into visualization story "arcs" and sentiment analysis, with the goal of examining the audience's attitudes towards a marketing campaign.

This paper contributes to the body of research and the literature on marketing analytics by presenting a methodology for topic modeling in Natural Language Processing of political text that identifies patterns in the messaging. The paper also contributes to the literature on data visualizations for extracting the story "arcs" and the resulting sentiment from the topic modeling that can be used for marketing campaigns.

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Literature review and related work

Social network sites have attracted the attention of researchers intrigued by their reach (Boyd and Ellison 2007). Since the turn of the millennium, Davis (1999) postulated that social media would control political content. Since then, scholars explored the role of computer-mediated communication in political discussion (Bimber and Davis 2003; Holt 2004; Amit-Danhi and Shifman 2018). Jungherr (2014) summarized 115 studies on the role of that media, in particular Twitter, in politics. Thus, political marketing had assumed a new medium, and Singer and Brooking (2018) referred to that medium as "weaponization," which characterizes the relationship that has evolved between social media and political marketing. At the same time, data science and analytics evolved, and Patterson (2018) helped explain why analytics would change the business of politics and running a campaign. As a result, Horacek (1990), Diakopoulos and Shamma (2010), Dang-Xuan et al. (2013), and Kumar et al. (2014) are a few who have attempted to use analytical methods for harnessing computer-mediated communication. This paper is unique in that it contributes to the literature on "topic modeling" in natural language processing and data visualizations for extracting the hidden story and the resulting sentiment.

Computer-mediated communication's main advantage is the speed with which a message spreads to reach your target audience. Using longitudinal data from ten Fortune 500 companies, Coursaris et al (2014) validated the importance of using an integrated approach to social media messaging from marketing, advertising, communications, and information systems. Soboleva et al (2015) found that Twitter can facilitate consumer engagement with a brand (person) if a popular event is involved. But, social media also has the potential for negative word of mouth. If a person "retweets," it usually implies a measure of consumer involvement or endorsement of the tweet. Ott (2017) highlights how twitter can encourage discourse that is simple, impulsive, and uncivil. In 2016, twitter became the most important communication channel for Hillary Clinton and Donald Trump to express their positions, attack each other, retweet endorsements, encourage people to vote, and give news previews (Buccoliero et al. 2020).

The role of analytics in computer-mediated communication has progressed to where there are more advanced methods for processing this form of messaging (Hirschberg and Manning 2015). Natural language processing (NLP), used in this research, has its roots with Turing (1950) and with repeated attempts at machine translation of natural language, most notably the Chinese Room (Searle 1980) and the "Georgetown-IBM Experiment" (Hutchins 1954). Also employed are the Latent Dirichlet Allocation and "syuzhet" models. Latent Dirichlet Allocation (Blei et al. 2003) is a generative probabilistic model that seeks to highlight the words in text that occur with high frequency. The "syuzhet," a term originating from the Russian Formalism school of literary criticism (Erlich 1954) during the 1910s and 1920s, has been analytically formalized in models (e.g., Phan et al. 2011) to reveal the sentiment or emotional shifts in text. Such tools provide for an exploration of political text messaging in ways that are unique. This paper contributes to that body of research, and the literature, by presenting a methodology for "topic modeling" that identifies patterns in the messaging. The paper also contributes to the literature (e.g., Rodgers et al. 1997; Berinato 2016; Liu et al. 2017; Mohammad 2020) on data visualizations for extracting the hidden story and the resulting sentiment from the topic modeling that can be used for marketing campaigns; in this case, it was political campaigns.

Methodology

Natural language processing (NLP), a branch of artificial intelligence dealing with the interaction of computers and human language, has been rapidly advancing beyond speech recognition and synthesis to analyzing marketing campaigns. In this paper, NLP was used to analyze political campaigns, but it can also be used for any marketing campaign that uses social media. Using publicly available Kaggle datasets (Hamner 2016) and Twitter datasets (accessed through the 'TwitteR' R package), the authors evaluated thousands of text observations from Barack Obama, Hillary Clinton, and Donald Trump. The methodology involved a multi-step analytical process.

First, the raw text is converted into a more readable "corpus" by removing unnecessary punctuation, web links, and unwanted syntax. To accomplish this pre-processing, or "tidying," task, readily available open-source R language packages (e.g., 'Vcorpus' to create the corpus, and 'tm_map' to remove unwanted stop-words) are readily available to automate the process. The task is not difficult, and it is unbiased. The next step is what is referred to as "topic modeling," a form of text mining, for identifying patterns in the corpus. The idea is to arrange the corpus into natural topics or groups, similar to clustering numeric data. The *Latent Dirichlet Allocation* (LDA) modeling process (Blei et al. 2003) is an (unsupervised) machine learning process for topic modeling. Hierarchical Latent Tree Analysis is an alternative to LDA, which models word co-occurrence using a tree of latent variables and the states of the latent variables, resulting in clusters of topics. Other topic models, such as MALLET (UMass Amherst 2020), incorporate LDA into its toolkit. This research uses LDA for the topic modeling phase of the project, since it is robust, common to open-source software, the easiest to use and understand, and is the most widely used technique, which would work well for other marketing campaign efforts.

Finally, sentiment analysis, otherwise known as “opinion mining,” is the last step in the modeling process. Sentiment analysis seeks to determine the emotional tone or attitude in the corpus. To extract sentiment from political messages, the authors employed “syuzhet,” which partitions the narrative into the technique behind of the narrative. Syuzhet is of more interest in this research than the “fabula,” which is the chronological order of events. Syuzhet breaks down emotions into 10 categories—anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative, and positive—and then, it scores the emotions with a standardized set of filtered and reverse-transformed values for numerical comparison. The process is automatic, not requiring human intervention. Thus, the results are not prone to human misinterpretation. This transformation of the natural language to numerical scores is the necessary and sufficient step for generating the data visualization “arcs.”

Visualization arcs are better at engaging an audience and telling the story behind the narrative than a presentation of the results in a tabular (non-visual) format. The ‘LDAvis’ toolkit and ‘Shiny’ apps in R were used to accomplish this task. LDAvis is designed to help a layperson interpret the topics resulting from the topic models. The software extracts the information with the goal of informing the audience through an interactive visualization. Shiny is an R tool that allows these visualizations to be easily distributed to an audience on the web though an app, or they can be embedded in “markdown notebooks” or “dashboards.”

While all of the steps taken in this methodology appear to be overwhelming, with the advances in data science software, the process has now become more automated. The open-source nature of languages like R and Python, and the toolkits mentioned above, mean that any layperson with a little knowledge of these tools, and access to the free scripts and tutorials on the web, can process any natural language manuscript. In this case, it is processing text messaging from political campaigns. But, the process can easily be applied to any product or service marketing campaign.

Analysis

The authors’ analysis of the messaging of the past political candidates began with a deeper understanding of the topics in the corpus by visualizing the topic modeling using the Latent Dirichlet Allocation tools created by Sievert and Shirley (2014). The corpus for each of the political candidates was merged to understand the topics with the most commonality, and then, the topics were presented in a visualization arc (Fig. 1).

The story arc of Fig. 1 attempts to answer three questions: (1) How prevalent is each topic, (2) how do the topics relate to each other, and (3) what is the meaning of each topic? Each topic’s prevalence is encoded, and the topics are sorted in decreasing order of prevalence. The left panel addresses questions (1) and (2). The topics are encoded into a circle representation whose centers are determined by computing the distance between the topics. Then, it projects the inter-topic distances onto a two-dimensional map. The right panel allows users to answer question 3, what is the meaning of each topic? The horizontal bar chart depicts the individual terms that are useful for interpreting the currently selected topic from the left panel. A nice attribute of the visualization is the ability to select a term, and investigate how that term relates to other topics. The λ in the top bar of the right panel is used to rank the terms in a given topic. Sievert and Shirley (2014) refer to λ as the “relevance,” or usefulness, to interpreting the topic. In addition to this visualization arc being interactive, it is also displayed in HTML mode for web viewing. The links between the two panels allow users to reveal aspects of the topic relationships. The topics corresponding to the numbered circles are shown in Table 1. In this paper, the authors limited the number of topics to 10 for demonstration, but there is no limit to the number of topics one wishes to investigate.

The topics are mostly similar across the three candidates chosen for this study, which may be because such topics are secular to political candidates. Note in the left panel of Fig. 1 that the circles for topics 5, 6, and 8 are separate (in distance) from the other topics. For example, topic 5 (news) contains vocabulary that is relevant to, or primarily associated with a particular candidate. Investigating this observation in further detail, the authors separated the candidate’s topics and terms. By illustration, Fig. 2 reveals what happens when Trump and Obama, separately, are compared.

When comparing the two graphs, it is interesting to note that Barack Obama uses a lot of verbs, such as ‘will’ and ‘change,’ while Donald Trump uses a lot of adjectives: ‘great’ and ‘big.’

Word clouds

A fascinating way to compare the topics between the political candidates is with the use of Word Clouds (Fig. 3).

The left word cloud is associated with Obama, and the right with Trump. It is interesting to see that both Obama and Trump tend to use their names and mention the word ‘president’ frequently in their tweets. The word cloud shows a gradation of color. Obama’s word cloud has 3 colors, while Trump’s word cloud has double that number. The difference in gradation suggests Trump has a stronger preference for specific words, whereas Obama has an even distribution of broader topics, with

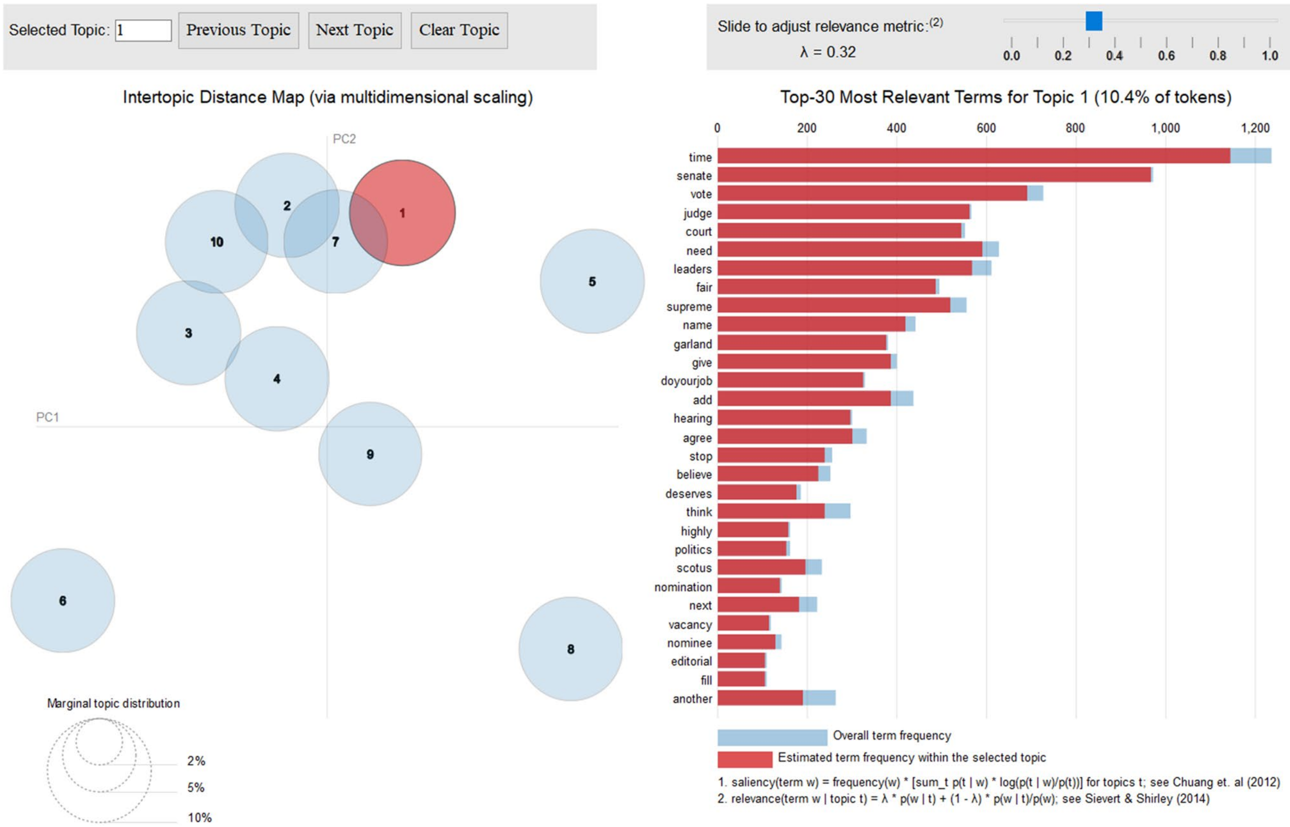


Fig. 1 The LDAvis visualization arc (author generated)

Table 1 Topics shown in the LDAvis story arc of Fig. 1

Topic number	General topic	Words used in the topic
1	Politics	Senate, Time, Judge, Vote, Court, Do Your Job, Leaders, Supreme
2	Economy	Economy, Year, Years, Record, Since, Jobs, Growth, Unemployment
3	Legislation	Watch, Congress, Live, Speaking, Address, Tune, Immigration, National, Justice, Gun, Law
4	Climate Change	Climate, Change, Action Climate, Fight, Take, Read, Way
5	News	New, News, Good, Fake, Just, States, Trade, China, Media, Deal
6	HealthCare	Now, Get, Care, Health, Don't, Obamacare, Team, Get Covered
7	Homeland Security	Border, Democrats, Security, Many, Much, Wall, Russia, Said
8	Campaigning	Will, Great, State, Done, Congratulations, Strong, Crime, Florida, Governor, Ohio, Republican
9	Work/Jobs	Make, America, Can, Work, Working, Better, Going, Still
10	People	People, Today, American, Day, World, See, Thank, Happy, Honor

the exception of the outliers of 'president' and 'Obama.' Similarly, Fig. 4 compares the Word Clouds for Hillary Clinton and Donald Trump.

Figure 4 also shows a gradation of color between the two candidates. Like Obama, Clinton's word cloud has fewer colors than Trump.

Sentiment analysis

Sentiment analysis can be very useful in social media monitoring by providing a wider public opinion behind topics. For example, shifts in sentiment on social media have been shown to correlate with shifts in the stock market (Pagolu

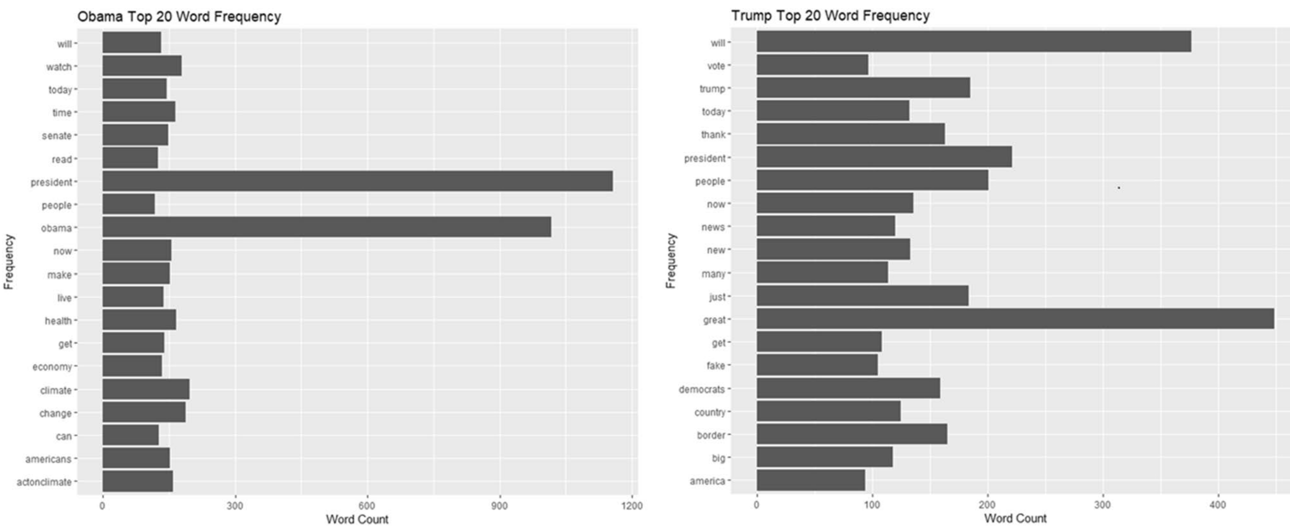


Fig. 2 Comparison of Obama and Trump's word frequency (author generated)

Fig. 3 Word cloud comparison of Obama and Trump's word frequency (author generated)

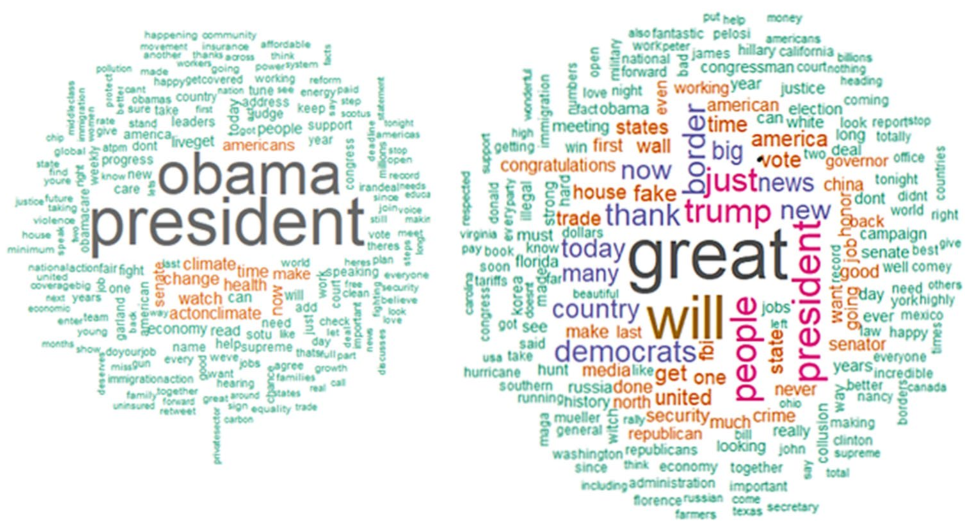
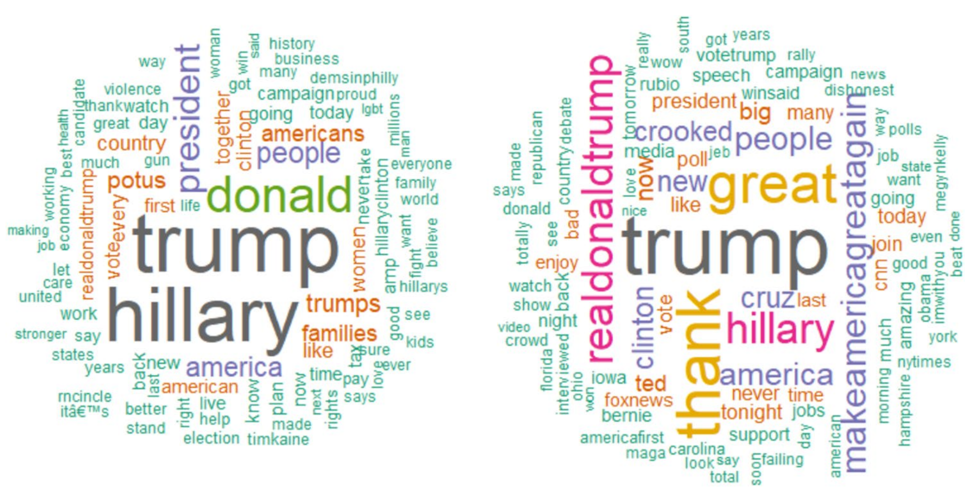


Fig. 4 Word cloud comparison of Clinton and Trump's word frequency (author generated)



2016), and the Obama administration used sentiment analysis to measure public opinion on policy during the 2012 election (Wertz 2018). Syuzhet breaks down emotions into 10 categories—anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative, and positive—and then it scores the emotions with a standardized set of filtered and reverse-transformed values for numerical comparison. The process is automatic, not requiring human intervention. Thus, the results are not prone to human bias or misinterpretation. In this case, the authors did not seek to interpret the results in a manner to evaluate one candidate over another. Rather, the intent is to demonstrate the technique.

Using syuzhet, a dynamic line chart has been constructed that displays the average sentiment scores over time for Obama and Trump (Fig. 5). Each line represents the average sentiment score.

Both Obama and Trump use more positive terms compared to negative terms. Other than the emotions displayed in Fig. 5, all of the other sentiment scores were not very high in either accounts. One conclusion reached here is that this finding may be of strategic choice, since presidential candidates try not to be overly emotional in text messaging. Thus, it would be interesting to visualize the spread and skewness of each candidate's sentiment score. Using a box plot, the authors examined sentiment ranges for Clinton and Trump (Fig. 6).

The story being told here is that the majority sentiment of Clinton and Trump's tweets were close to 0, meaning most tweets were neutral in tone. However, Trump's sentiment score variation was slightly wider than Clinton's and slightly skewed positive, while Clinton's is more normally distributed.

Exploring further, the authors created interactive scatter plots in order to visualize the relationship between retweet counts and average sentiment score (Fig. 7). Initially, the hypothesis was that the retweet counts would reach its maximum if the candidate expressed very positive or negative sentiment. However, the graphs told the opposite story arc. For both Clinton and Trump, they had the maximum retweet counts when the average sentiment was 0 (neutral expressions).

Finally, an analysis was conducted using time series comparing Clinton's and Trump's tweet popularity ('favorite' counts), retweet counts, and sentiment scores over time (Fig. 8). The visualizations are interactive: viewers are able to hover over the lines to investigate favorite count, retweet count, and sentiment score information.

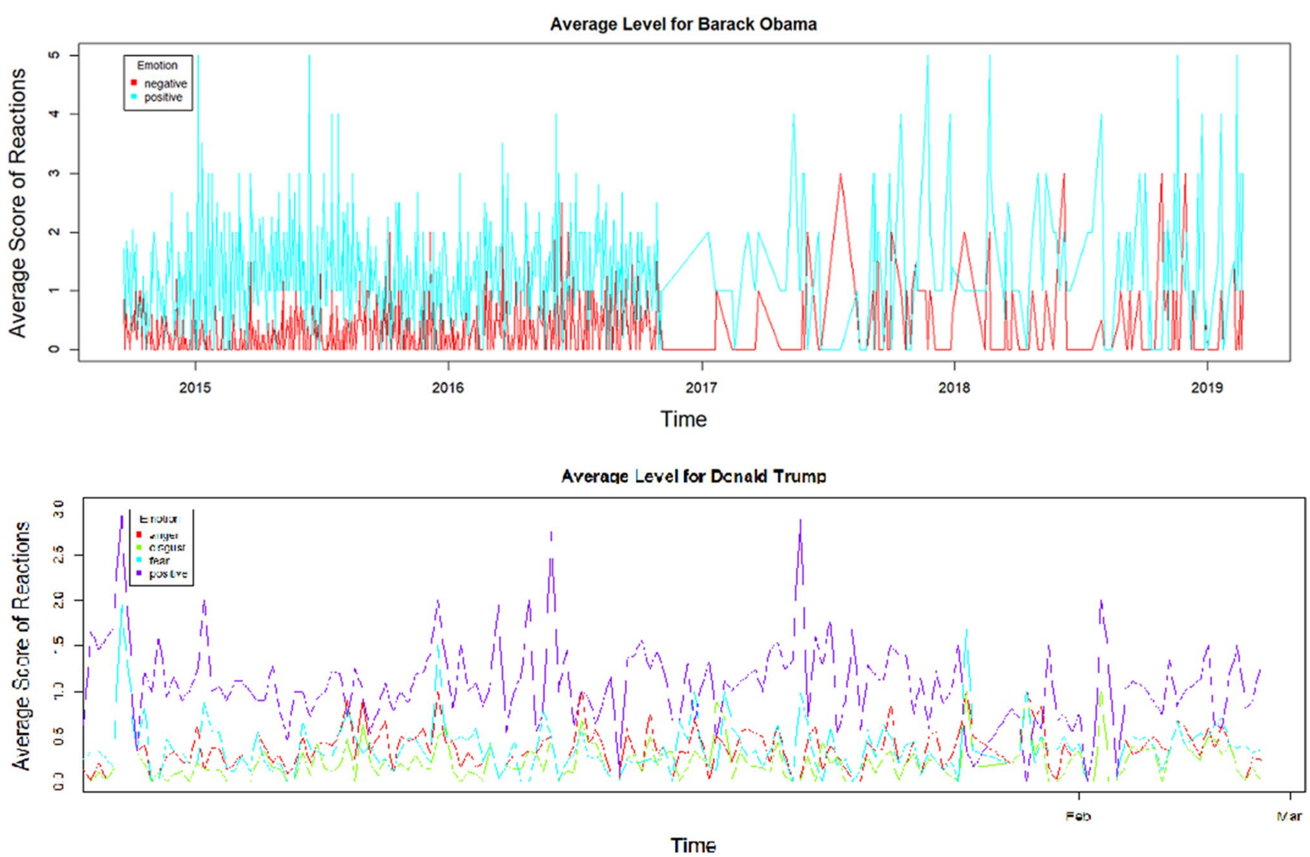


Fig. 5 Sentiment scores for Obama and Trump (author generated)

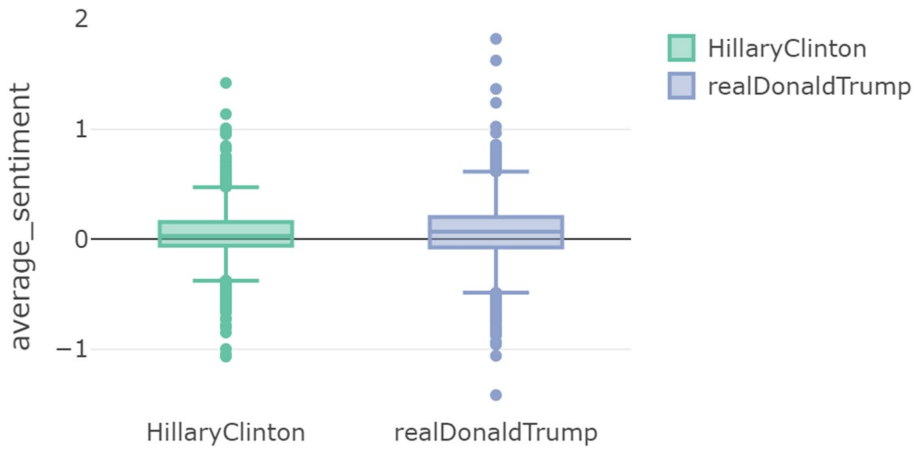


Fig. 6 Spread and skewness comparison of sentiment scores for Clinton and Trump (author generated)

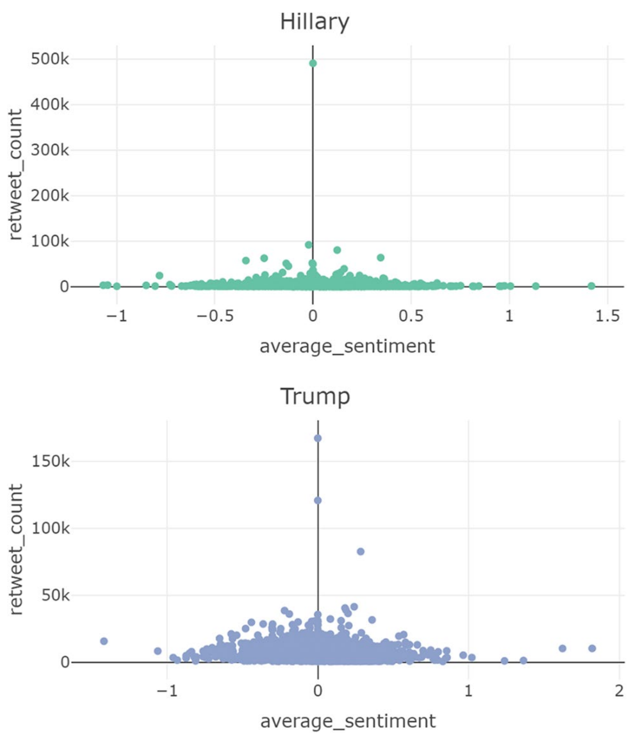


Fig. 7 Comparison of retweet counts and sentiment scores for Clinton and Trump (author generated)

The favorite counts and retweet counts story arcs of Fig. 8 reveal that Trump was consistently getting more attention—more publicity—than Clinton. The Sentiment Scores arc indicated that there were no huge sentiment differences between Clinton and Trump – a surprising result since Fig. 6 indicates that Trump had a much wider spread of sentiment than Clinton.

Marketing implications

Twitter, Facebook, and Google have been negatively impacted by the 2016 Presidential race, since their platforms were used to mount misinformation campaigns "intended to divide Americans and discourage them from voting" (Conger 2020). According to Twitter's head of Products, Kayron Beykpour (Gadde and Beykpour 2020), "our goal is to help people see what's happening, while ensuring that potentially misleading trends are presented with context." Twitter has slowed down retweets to reduce this spread of misinformation, but without the Twitter problems in the 2016 Presidential Campaign, the corrections for the 2020 Campaign may not have happened. Therefore, accurate information from Twitter, Facebook, and Google can greatly help in the promotion of any product or service. In short, marketers can now reach their target markets, engage with them, and answer their concerns more quickly because of the improvements in computer-mediated communication.

Conclusions

Analytics provides a unique set of tools by which one can gain a deeper understanding and analysis of marketing campaigns. This paper uses natural language processing (NLP) and data visualization story arc methods to explore how social media and analytics can play a role in marketing political candidates. The case involves text observations from the past campaigns of Hillary Clinton, Barack Obama, and Donald Trump with the goal of visualizing and analyzing their linguistic "corpus." The methodology includes the use of Latent Dirichlet Allocation (LDA) and Syuzhet models. The resulting data visualizations reveal the story arcs associated with the candidate's communications, and they provide a means to analyze the political sentiment or emotion hidden in the text. In an analysis of the results, the authors found distinctly different story arcs and vocabulary usage among the three Presidential candidates. The contribution to the literature is a methodology for extracting the hidden story and the resulting sentiment from text messages for all marketing campaigns; in this case, it was political campaigns.

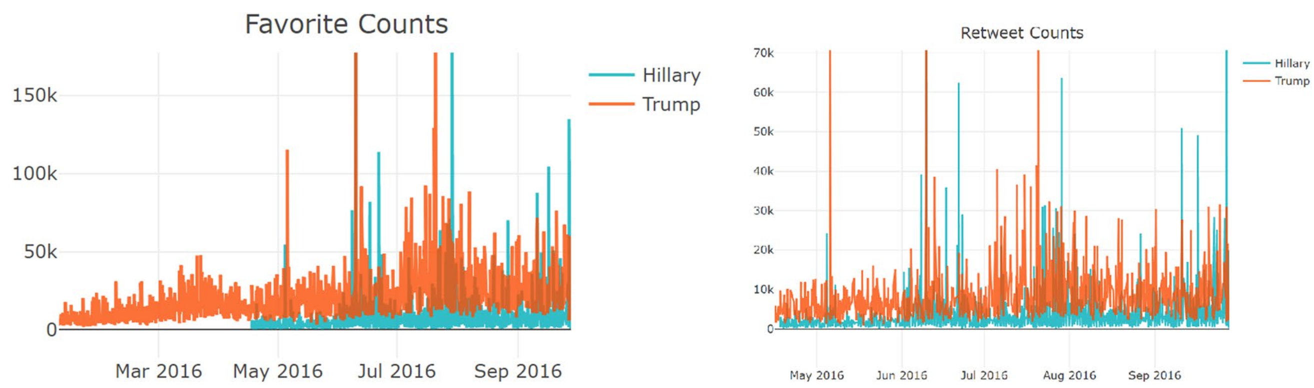


Fig. 8 Time-series comparison of 'favorite' tweet counts, retweet counts, and sentiment scores for Clinton and Trump (author generated)

Future direction

Accurate data and information from social media outlets and search engines can assist in the promotion of any product or service (Appel et al. 2020). With the contributions outlined in this paper, researchers can more easily assimilate this information. Marketers can now reach their target markets, engage with stakeholders, investigate patterns or trends, and answer concerns more quickly and visually. While this paper focused on political marketing, future research can make use of these contributions. Thus, the future direction that the authors are taking with this research is to apply these technologies and analytical methods towards marketing other products or services that utilize computer-mediated communication.

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