TOXIC TWEETS: CORRELATING POLITICIANS' EMOTION WITH FEEDBACK ON TWITTER

by

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A THESIS

Presented to the School of Journalism and Communication
and the Robert D. Clark Honors College
in partial fulfillment of the requirements for the degree of
Bachelor of Science

June 2021

An Abstract of the Thesis of

Lilika Sandra Hanson for the degree of Bachelor of Science
in the School of Journalism and Communication to be taken June 2021

Title: Toxic Tweets: Correlating Politicians' Emotion with Feedback on Twitter

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As one of the most popular social media platforms, Twitter attracts many journalists and politicians. This popularity is concerning because traditional journalism adapts to its medium, and the growing polarization of American politics seems to be facilitating a toxic environment on Twitter. By over-relying on Twitter trends and discussion for their stories, journalists could be perpetuating a feedback loop that rewards negativity among American politicians. By psychometrically analyzing the tweets of twelve United States senatorial candidates campaigning in swing states throughout 2020, I found a statistically significant positive correlation between negative emotion and all forms of Twitter feedback and a statistically significant negative correlation between positive emotion and all forms of Twitter feedback. These findings support my theory that politicians are rewarded for toxic behavior on the platform, which should discourage journalists from fixating on Twitter-based stories. To leverage the positive qualities of Twitter without validating the toxic behavior encouraged among politicians on the platform, journalists should primarily use Twitter as a networking platform.

Acknowledgements

I would like to thank Associate Professor Nicole Dahmen, Assistant Professor David Markowitz, and Professor of Practice Barbara Mossberg for their time and support in my honors thesis committee and throughout my undergraduate education. Not only have they served as excellent advisors that helped this project reach its full potential, but they also taught me how to be a better scholar of the world. I hope that, by writing this thesis, I have captured a fraction of the passion they displayed for their fields while I was enrolled in their courses.

I would also like to thank my partner and fellow Robert D. Clark Honors College student Adriann Bechtle for his continued love and support in writing this thesis. My work would not be half as polished as it is now without his frequent proofreading, as well as his generosity in lending his desktop computer to help my data scraping efforts on Twitter.

I am eternally grateful for the love and support my parents have provided throughout my academic career. They have always believed in me and encouraged me to reach my full potential, and I would not be where I am today without them and my siblings standing by my side.

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Introduction

Personal Perspective

Over the past four years I have studied ways computers and humans communicate amongst themselves and between each other. Technology is designed with humans in mind and humans alter their behaviors in relation to the technologies they use. This intersection of technical and mass communication has continued to fascinate me in and out of the classroom, which is one of the many reasons I chose to undertake this project.

My research involves essential concepts relating to journalism and communication, computer science, and political science – all of which will be explained throughout this introduction. Such a wide berth of disparate fields is daunting to describe and synthesize, but I believe my multidisciplinary studies have uniquely prepared me for the task.

I first discuss the mechanisms that govern Twitter and its importance as a social media platform, which are followed by an overview of the history of journalism in relation to technology and the working political science models I used to rationalize my hypothesis and findings. My thesis statement is properly contextualized with this background information in mind; this foundation allows me to discuss the methods and findings of this project in detail.

A Guide to Twitter

The social networking platform Twitter receives an average of roughly 500,000,000 public messages – called “tweets” – from its users every day (Smith, 2020). As one of the most popular microblogging services on the internet, politicians and journalists are increasingly using Twitter to advance their careers. Now roughly 22% of all Americans use the platform, 71% of which rely on Twitter for news, and 42% of which use it to discuss politics according to the Pew Research Center (Hughes & Wojcik, 2019). Prominent politicians, such as former American President Barrack Obama, and news organizations like CNN rank among the Twitter accounts with the largest followings (Boyd, 2021). It should come as no surprise that a platform that allows its users to rapidly disseminate political messages would draw the attention of major news outlets and politicians alike considering the nature of their professions.

Whether their aim is to promote their campaign for a political position or to educate the public, Twitter users want to reach the broadest possible audience by maximizing the feedback their tweets receive. Users offer feedback on other tweets in up to four forms: likes, quotes, replies, and retweets. Liking a tweet indicates that a user enjoys or supports its message. Quoting a tweet allows a user to post a new tweet with a reference to the original. Replying to a tweet creates a chain of messages other users can see below the original tweet. Retweeting a post increases its visibility by sharing it with the users following the retweeter as well as the original poster.

History of Online Journalism

Technological advancements have always influenced the field of journalism, and the rise of online platforms such as Twitter is the most recent example of this historical trend. The “inverted pyramid” technique in journalism – a way of structuring an article so the most important information is succeeded by less and less pressing details – was a product of the telegraph’s highly compressed messages (Friend & Singer, 2007, p. 6).

Twitter's strings of emojis and images are no different than the telegraph's dots and dashes of morse code.

> "Though it would be overly simplistic to make too much of the parallels, both the telegraph and the Internet threatened the hegemony of established media not only be creating new storytelling possibilities accompanied by new economic models, but also by bringing a degree of practical reality to the time-honored ideal of journalism as a public conversation. Internet technology has empowered anyone with a computer to create a media outlet with a potential audience of millions. And millions have." (Friend & Singer, 2007, p. 13)

Traditional newspapers, magazines, radio stations, and television programs were previously the only groups that had access to the wide, interested audiences that Twitter now affords its most influential users. Although many journalists continue to debate what constitutes journalism in a digital age of hyperconnectivity, it is irrefutable that these novel digital platforms are significantly influencing modern news cycles (Eldridge, 2018, pp. 74-75). The emails poached from Sony Pictures' private servers in 2014 and Hillary Clinton's 2016 presidential campaign, while gathered by hackers and other non-journalists, still ended up serving as sources for novel stories from major news outlets (Eldridge, 2018, p. 91). Similarly, former President Donald Trump's tweets fueled news cycles and shaped the discourse around his presidential campaign in 2016 and the early months of his presidency (Ingram, 2017).

Many journalists' growing reliance on digital platforms is problematic because it risks corroding journalistic ideals with the biases and limitations of said online mediums. Géraldine Muhlmann, a French political scientist and author of *A Political History of Journalism* stipulates that there are two forms of journalism: the witness-ambassador and the de-centerer (Muhlmann, 2008, pp. 4-5). The witness-ambassador is the archetype of a journalist whose news coverage aims to unify the populace under a single, agreeable truth that is detached from the writer's own biases (Muhlmann, 2008, pp. 22-28). The decentering journalist, by contrast, seeks to oppose conventional truths by embracing the subjectivity of their own views and the experiences of their subjects (Muhlmann, 2008, pp. 135-139). Of these two archetypes, the witness-ambassador is most vulnerable to the biases and limitations of technological mediums. This weakness stems from the archetype's typical lack of a personal voice – unlike the de-centerer – and its focus on representing current issues as fairly and objectively as possible.

> "To quote opinions and give their source does not exonerate journalists from the choices they make in presenting them, and is hardly cause for self-congratulation on their part. For example, in the 1950's, the American press published lists of 'suspects' compiled by Senator Joseph McCarthy; the journalists may have believed that, by specifying the source of these lists ('he said'), they were not giving aid to McCarthy, but it is clear that, in practice, this precaution hardly clears them from blame because, by publishing these lists, the press gave McCarthyism a huge boost." (Muhlmann, 2008, p. 12)

This weakness of the witness-ambassador archetype still holds true in the digital era. The mainstream press, which still primarily follows the tenets of the witness-ambassador archetype, covered former President Donald Trump's tweets so thoroughly during his 2016 presidential campaign that many journalists argue these efforts contributed to his victory in November of that year (Ingram, 2017). If journalists aren't careful, their efforts to fairly document current events can unintentionally benefit the involved political actors.

Not only can journalists following the witness-ambassador approach give undue publicity to the figures they cover, but their coverage can also accidentally spread traits that are implicit to their sources and the digital mediums they use. Many journalists that used to frequent Twitter have quit using the platform because they claim that the platform's latent toxicity is damaging their mental health (Lieberman, 2020). According to the Pew Research Center, roughly 80% of all tweets are written by only 20% of Twitter's users (Hughes & Wojcik, 2019). These two facts, in combination, spell dire consequences for the growing number of reporters that use Twitter to gather and distribute their content. Journalists might be giving undue attention to a disproportionately toxic minority that produces the most content on Twitter. No differently than how reporters in the 1950's popularized McCarthyism by publishing his accusations, reporters that rely on Twitter might be perpetuating a positive feedback loop by giving attention to its most popular and toxic accounts.

> "No good journalists would go to the library and check the best-seller list to research an issue, but that is essentially what they are encouraged to do online. The Web is, among other things, a massive, ongoing popularity contest. Search engines rank sites, in part, on the basis of how many other sites link to them and how often they are viewed. Visitor counters roll up hits. Quantity parades as quality. The popularity of a site may reflect a hard-won reputation for credibility and accuracy, or it may be a product of a pack mentality." (Friend & Singer, 2007, p. 69)

As one of the internet's most popular websites, Twitter can provide journalists with an invaluable well of information to guide their stories (Neufeld, 2021). But those following the witness-ambassador form of journalism need to be wary that their content is not unintentionally popularizing the views of the figures they cover or spreading toxicity.

Partisanship and Political Hostility

Since its first publication in 1957, Anthony Downs' *An Economic Theory of Democracy* has strongly influenced how many political scientists rationalize the United States' two-party political system and the behavior of both its electorate and politicians. Expanding upon the Median Voter Theorem first posited by Duncan Black in 1948, Downs claims:

> "…In a two-party system, both parties nearly always adopt any policy that a majority of voters strongly prefer, no matter what strategies the parties are following. Neither party can gain from holding the minority view unless the majority hold their opinions lukewarmly; hence a passionate majority always determines policy." (Downs, 1957, p. 64)

Although this theory is well-rationalized and was consequently held in high esteem among political scientists for decades, many now question its validity as American politics continue to drift toward political extremes (Drezner, 2015). In fact, modern research has found that candidates are just as likely to appeal to the extremes of their party base – not the sensibilities of a median voter – in highly contested elections as uncontested elections (Adams, Brunell, Grofman, & Merill, 2009, p. 417). Only 39% of Americans who hold mixed political views always vote compared to the 58% and 78% of Americans with consistently liberal and conservative views that always vote, respectively (Pew Research Center, 2014). This distribution of voter engagement rewards candidates' appeals to their party base more than appeals to centrism.

In addition to contesting the Median Voter Theorem, political scientists have also questioned whether policy responsiveness is as significant in American politics as many people believe. Policy responsiveness is an incumbent politician's ability to pass laws that align with the interests of their electorate (Hogan, 2008, p. 858). A common tenet of American democracy is that the electorate will vote for candidates whose lawmaking goals align with their own and vote out the same candidate if they diverge from said goals. Although it's true that policy responsiveness has a non-negligible impact on a candidates' reelection chances, other factors like national party support, campaign spending, and past support from local partisans have a much greater influence on their likelihood of victory (Hogan, 2008, p. 871).

The erosion of the Median Voter Theorem, as well as importance of party support being greater than that of policy responsiveness, paints a picture of American democracy that is profoundly and inextricably partisan. According to Hogan, “Policy voting does play a role, albeit in a fashion that does not necessarily reward responsiveness to median district voters” (Hogan, 2008, p. 871).

Such intense partisanship in American politics is significant to my research because it promotes the acceptance of aggressive, hostile behavior among both politicians and their electorate. Roughly 40% to 60% of partisan Americans are inclined toward some level of moral disengagement – the belief that certain moral principles are not applicable under specific circumstances – when matters of the opposite party are involved (Kalmoe & Mason, 2019, p. 37). While moral disengagement isn’t inherently problematic, it makes it much easier for people to justify violent or aggressive actions under the applicable circumstances. According to Kalmoe and Mason, “As more Americans embrace strong partisanship, the prevalence of lethal partisanship is likely to grow” (Kalmoe & Mason, 2019, p. 37).

The negative emotion and general hostility that heavy partisanship promotes is further evidenced by how politicians employ aggressive metaphors when communicating with their constituents. When politicians employ such language, like promising to battle for their constituents or fight for their beliefs, they are likely to motivate aggressive-minded partisans to vote for them and simultaneously demotivate unaggressive partisans to vote for them (Kalmoe, 2019, p. 423). Although the net effect of this phenomenon is relatively minor, it still supports a “general model of trait resonance in which aggressive metaphors reinforce the role of predispositions among high-aggression citizens and disrupt the same predispositions among low-aggression citizens" (Kalmoe, 2019, pp. 422-423).

Although partisanship and hostility are not explicitly connected, these findings seem to indicate that there is a significant relationship between the two traits among politicians and their electorates. Heavily partisan Americans seem to be sufficiently morally disengaged because they condone aggressive acts against their political opposition and are more easily rallied by the aggressive language of the politicians they support. These findings, when combined with the research indicating that the country's politics are latently hyper-partisan, provide good reason to believe that American politicians are significantly motivated to be hostile toward the opposing party when they connect with their constituents.

Position Premise

While testing the Linguistic Inquiry and Word Count program – often abbreviated as LIWC – in 2015, its creators tested its performance by analyzing sample texts in five different communication mediums (Pennebaker, Boyd, Jordan, & Blackburn, 2015, pp. 9-10). These mediums were blogs, expressive writing, natural speech, the *New York Times,* and Twitter (Pennebaker, Boyd, Jordan, & Blackburn, 2015, p. 10). Their findings were what prompted me to pursue this research project, because they found that Twitter had the highest rate of angry language out of all the mediums they tested: 0.75% of words in the average Tweet were angry compared to the 0.68%, 0.51%, 0.49%, and 0.36% of words in the tested blogs, novels, expressive writing, *New York Times* articles, and natural speech excerpts that were angry, respectively (Pennebaker, Boyd, Jordan, & Blackburn, 2015, p. 11). That is a 0.07%

and greater increase in aggressive language across all tested mediums. Since Twitter is a microblogging platform, the fact that it and blogs ranked the highest in analyzed anger percentages among several disparate mediums suggests that there are latent qualities to blogging platforms that incentivize or prompt angry language.

Thesis Statement

I am concerned that journalists' growing reliance on Twitter as a platform to research and distribute news is skewing their coverage of current events toward the campaigning efforts of American politicians, who seem to be incentivized by the heavily polarized state of American politics and the nature of the platform to be as aggressive and negative as possible in their tweets. If my hypothesis is correct and there is significant reason to believe that politicians benefit from embracing these toxic traits on the platform, then journalists would do well to heavily restrict their coverage of politicians' tweets.

To test whether my concerns are well-founded, I devised a means of extracting a large corpus of tweets from American politicians and the types of feedback that said tweets received, which I discuss in the methods section. Since politicians on Twitter are trying to garner as much attention and support as possible, a positive correlation between increased feedback – more likes, quotes, replies, and retweets – and the presence of negative emotion in their tweets would suggest that politicians have a strong impetus to consistently tweet in a hostile, toxic fashion. A negative correlation would indicate the opposite effect, suggesting that politicians should behave in a respectful, positive manner to garner the most attention on Twitter.

By testing the relationship between feedback on Twitter and negative and positive emotion in the tweets of American politicians, I aim to inform online journalists of how they should handle their coverage of these politicians on the platform.

Methods

Determining the Sources

The 15,878 total public tweets posted throughout 2020 by twelve United States senatorial candidates in five swing states comprised the corpus of my data. To avoid skewing the results of my research toward swing states with larger populations, I limited my research to prospecting senators instead of representatives. I chose to focus on politicians competing in swing states because their races tend to attract more competition and, consequently, stronger emotional appeals to their party bases (Adams, Brunell, Grofman, & Merill, 2009, p. 427).

There is no consensus among political analysts on which states qualify as swing states (Rakich, 2020). Despite this limitation, I feel confident in my selection of Georgia, Iowa, Maine, Montana, and North Carolina as the target states of my research. Politico listed these states as “true toss-ups” prior to the 2020 election and each of them had close results between their competing candidates (Arkin, et al., 2020).

In the Georgian runoff elections, Jon Ossoff and Raphael Warnock beat David Purdue and Kelly Loeffler by approximately 1.2% and 2% of the total vote, respectively (CNN, 2021). In Iowa, Joni Ernst beat Theresa Greenfield by a margin of approximately 6.6% (The Washington Post, 2020). Maine’s senatorial election left incumbent Susan Collins in power with a margin of 8.6% over her challenger, Sara Gideon (The Washington Post, 2020). Steven Daines beat Steve Bullock by roughly 10% of the total vote in Montana (The Washington Post, 2020). North Carolina was a much closer race that Thom Tillis won over Cal Cunningham by only approximately 1.8% of the total vote (The Washington Post, 2020).

Some of these twelve senators use multiple Twitter accounts for different purposes, such as Raphael Warnock seemingly using both @ReverendWarnock and @RaphaelWarnock. In these instances, I selected only accounts that Twitter had "verified," which indicates that the owner of the account has submitted proof to Twitter that its owner is the same person, as well as looking at which account contained primarily political content (Twitter, 2021). In every instance, the verified account contained significant content relating to senatorial campaigns, making me confident that I could trust that the accounts @CalforNC, @GovernorBullock, @GreenfieldIowa, @KLoeffler, @ossoff, @ReverendWarnock, @SaraGideon, @SenatorCollins, @sendavidperdue, @SenJoniErnst, @SenThomTillis, and @SteveDaines accurately displayed the activity of these politicians on Twitter.

Gathering the Data

I used a free Python script on GitHub called snscrape to gather the relevant data for every Tweet posted by the chosen twelve Twitter accounts throughout 2020. This tool was the best option available to me because it was more affordable and less restrictive than other tools. Twitter's standard developer API – which stands for Application Programming Interface and serves as a set of tools to help programmers access content on websites – only permits scraping programs to gather data from tweets that seven days old at most (Twitter, 2021). The snscrape program has no such restrictions and is free to use under an open license, unlike the prohibitively expensive historical API's that Twitter offers for developers to access older tweets (Twitter, 2021).

After specifying the Twitter account name and date range for each of the twelve politicians, snscrape returned a JSONL file containing the tweets and their metadata.

JSONL stands for JavaScript Object Notation List, which is a versatile data storage format that both humans and computers can easily interpret. However, I needed to convert it to a CSV file – a format commonly used to represent large matrices of data that stands for Comma Separated Values – so that I could more easily read and analyze my findings in other programs.

To convert this data to a CSV, I programmed a short Python script in a Jupyter Notebook. For every tweet in each JSONL file, it extracted the link to the tweet, the date it was posted, the text content of the tweet, and the number of likes, quotes, replies, and retweets it received and stored the output in a CSV. I then compiled these CSV files into a single Microsoft Excel spreadsheet with a new column designating the account name of each tweet and cleaned the data of textual errors to prepare it for analysis. Since each my dataset displayed a skewed distribution with certain tweets attracting far more attention than others, I applied the natural logarithm to each tweet's likes, quotes, replies, and retweets to normalize their distribution and stored these values in separate columns of the Excel spreadsheet.

Conducting the Analysis

I sent my dataset to Professor Markowitz, who used LIWC to quantify the levels of positive and negative emotion in each tweet. The program quantifies the psychometric and linguistic properties of bodies of text. It is a rigorously tested source of automated text analysis in the field of linguistics and psychology (Pennebaker & Tausczik, 2010, p. 24)

The program accepts text in a CSV file as an input and searches through the 6,400 words in its dictionary for matches the supplied text (Pennebaker, Boyd, Jordan,

& Blackburn, 2015). Each word has associated sub-dictionaries and traits, and the proportional representation of each trait and sub-dictionary compared to the total length of the text is displayed as the program's output, which can then be stored in a CSV file (Pennebaker, Booth, Boyd, & Francis, 2015).

The last component of my methodology employed IBM SPSS, a program whose name stands for Statistical Package for the Social Sciences. Its suite of tools allowed me to plot each tweet's adjusted sums of likes, quotes, replies, and retweets with their corresponding LIWC variables. Using these graphs to gauge the data visually, I then used SPSS's bivariate correlation tests to calculate the Pearson correlation coefficients and their statistical significance for my desired Twitter feedback and LIWC emotional value pairings.

Results

Anger

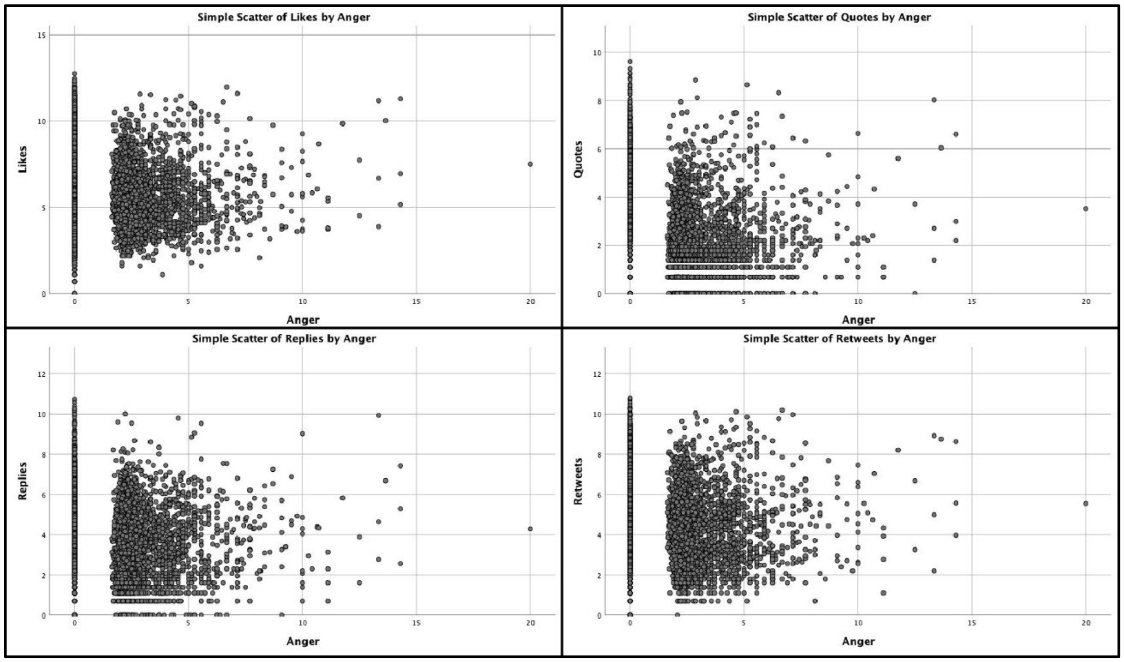

Figure 1: Anger Scatterplots

From top to bottom and left to right, these graphs plot the natural-logarithm-adjusted number of likes, quotes, replies, and retweets each tweet received with its corresponding LIWC anger value.

The first of LIWC's three subsets of negative emotion is anger, which was by far and away the most prevalent form of negative emotion. Across all twelve candidates' tweets, LIWC returned a sum of 8,909.53 anger. Out of all four forms of feedback, anger was most strongly positively correlated with retweets ($r = +0.035$, $n = 15{,}878$, $p < 0.0005$). Anger's second strongest positive correlation was with likes ($r = +0.022$, $n = 15{,}878$, $p = 0.005$). The last statistically significant correlation was shared with quotes ($r = +0.017$, $n = 15{,}878$, $p = 0.03$). No significant correlation was found between anger and replies ($r = +0.013$, $n = 15{,}878$, $p = 0.1$).

Anxiety

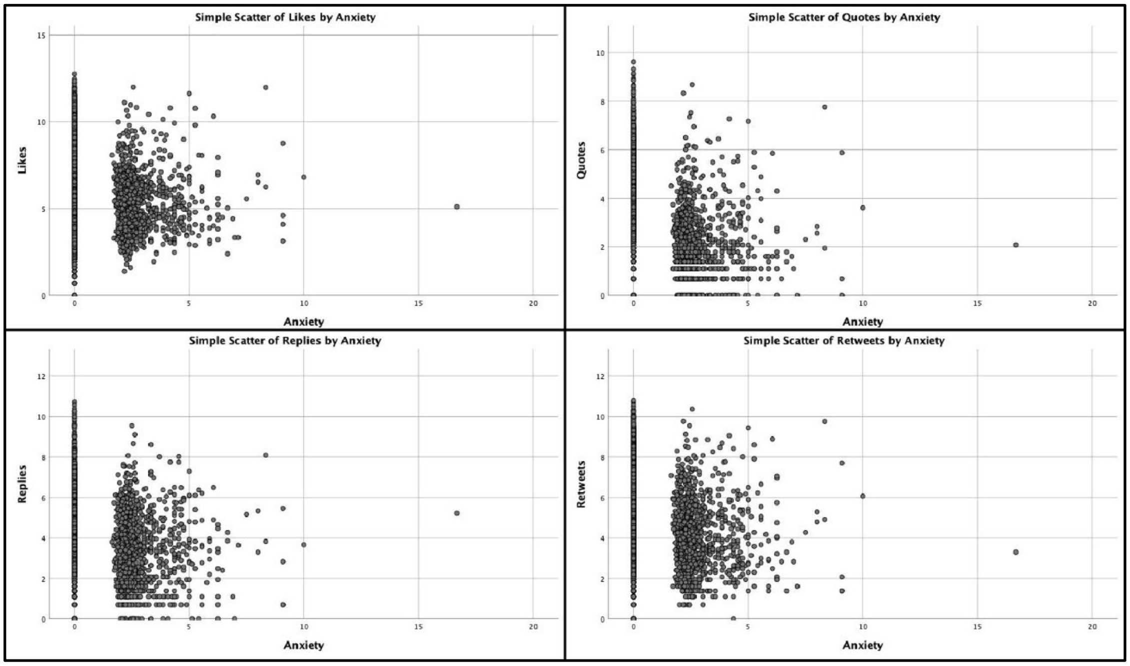

Figure 2: Anxiety Scatterplots

From top to bottom and left to right, these graphs plot the natural-logarithm-adjusted number of likes, quotes, replies, and retweets each tweet received with its corresponding LIWC anxiety value.

Anxiety was the least prevalent subset of negative emotion among the twelve candidates' tweets with a sum of 3,207.88 returned by LIWC. All types of feedback were negatively correlated with anxiety, especially likes (r = -0.019, n = 15,878, p = 0.017). Although the second strongest negative correlation was with quotes, the result was not statistically significant (r = -0.013, n = 15,878, p = 0.101). Neither of the remaining two forms of feedback had statistically significant relationships with anxiety, Retweets, of the two remaining, had the stronger negative correlation (r = -0.006, n = 15,878, p = 0.456). The weakest negative correlation and least significant finding was between anxiety and replies (r = -0.005, n = 15,878, p = 0.524).

Sadness

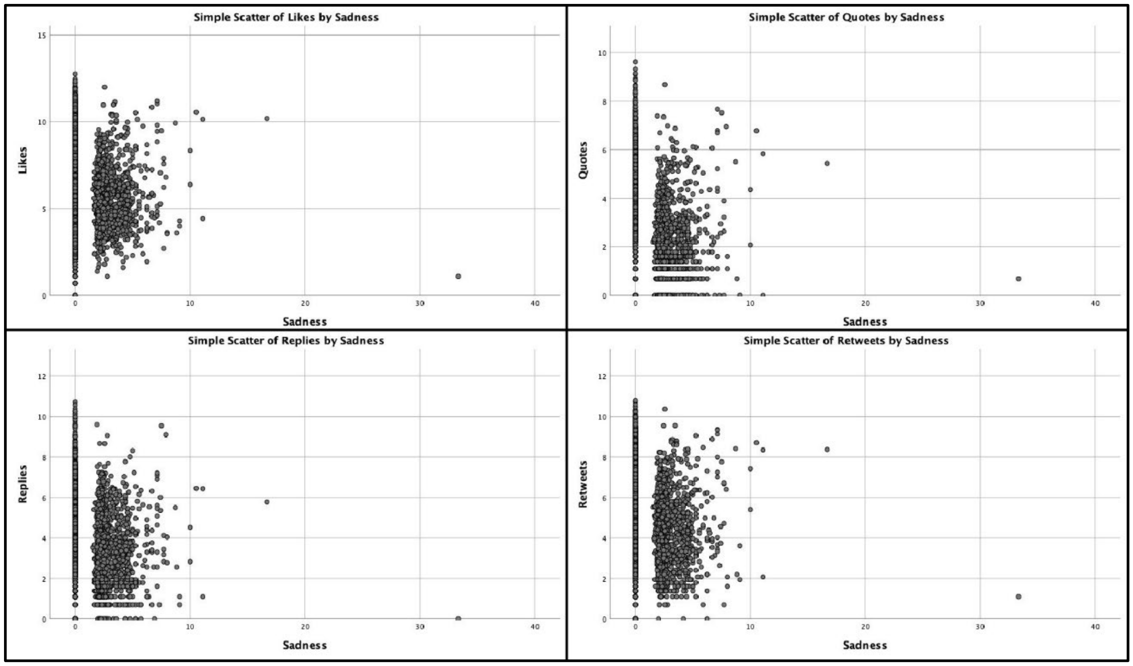

Figure 3: Sadness Scatterplots

From top to bottom and left to right, these graphs plot the natural-logarithm-adjusted number of likes, quotes, replies, and retweets each tweet received with its corresponding LIWC sadness value.

LIWC returned a sum of 3,992.75 sadness across the tweets of all twelve candidates, giving it slightly more prevalence than anxiety but only 44.81% of anger's total. Interestingly, it displayed a mixture of positive and negative correlations depending on the variety of feedback. Sadness had the strongest positive correlation with retweets ($r = +0.029$, $n = 15,878$, $p < 0.0005$). It also shared a positive correlation with likes ($r = +0.018$, $n = 15,878$, $p = 0.024$). The positive correlation it shared with quotes was not statistically significant, however ($r = +0.011$, $n = 15,878$, $p = 0.161$). Out of the four forms of feedback, replies stand out considering their negative correlation with sadness ($r = -0.017$, $n = 15,878$, $p = 0.035$).

Negative Emotion

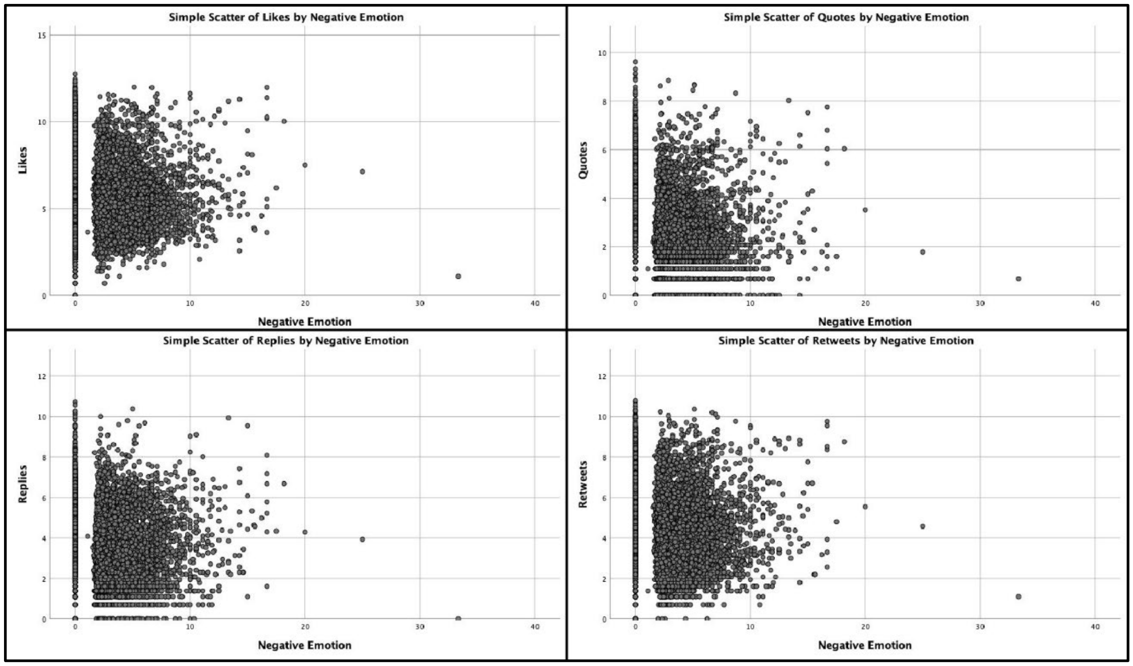

Figure 4: Negative Emotion Scatterplots

From top to bottom and left to right, these graphs plot the natural-logarithm-adjusted number of likes, quotes, replies, and retweets each tweet received with its corresponding LIWC negative emotion value.

Negative emotion, the aggregate of anger, anxiety, and sadness in LIWC's analysis, was surprisingly dwarfed by its counterpart positive emotion. Across the twelve senators' tweets throughout 2020, there was a sum of 22,247.73 negative emotion. Much like anger, its strongest positive correlation was with retweets ($r = +0.051$, $n = 15,878$, $p < 0.0005$). Unlike anger, though, its second strongest positive correlation was with quotes ($r = +0.035$, $n = 15,878$, $p < 0.0005$). Likes was within a few hundredths of a decimal place, however ($r = +0.031$, $n = 15,878$, $p < 0.0005$). Much like all three of its subsets, negative emotion had the weakest positive correlation with replies out of all four feedback forms ($r = +0.027$, $n = 15,878$, $p = 0.001$).

Positive Emotion

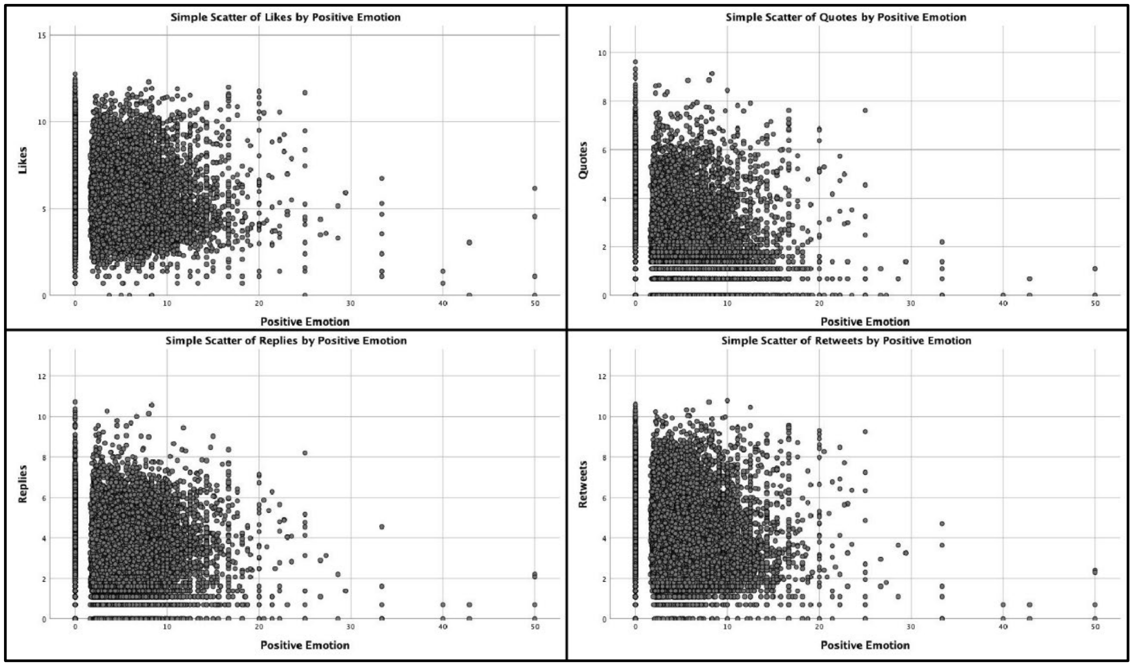

Figure 5: Positive Emotion Scatterplots

From top to bottom and left to right, these graphs plot the natural-logarithm-adjusted number of likes, quotes, replies, and retweets each tweet received with its corresponding LIWC positive emotion value.

Positive emotion was by far and away the most prevalent affective language type I analyzed with LIWC, which returned a sum of 64,451.03 positive emotion – just shy of three times the amount of negative emotion in the same dataset. All its correlations were negative and very statistically significant. Paralleling negative emotion, its strongest negative correlation was with retweets ($r = -0.133$, $n = 15,878$, $p < 0.0005$). Quotes shared the second strongest correlation ($r = -0.117$, $n = 15,878$, $p < 0.0005$). Its third strongest negative correlation was with likes ($r = -0.087$, $n = 15,878$, $p < 0.0005$). Continuing to parallel negative emotion and its three subsets, positive weakest correlation was with replies ($r = -0.057$, $n = 15,878$, $p < 0.0005$).

Conclusion

Discussing the Findings

Emotion	Feedback	Correlation
Negative Emotion	Retweets	+0.051
Anger	Retweets	+0.035
Negative Emotion	Quotes	+0.035
Negative Emotion	Likes	+0.031
Sadness	Retweets	+0.029
Negative Emotion	Replies	+0.027
Anger	Likes	+0.022
Sadness	Likes	+0.018
Anger	Quotes	+0.017
Anger	Replies	+0.013
Sadness	Quotes	+0.011
Anxiety	Replies	-0.005
Anxiety	Retweets	-0.006
Anxiety	Quotes	-0.013
Sadness	Replies	-0.017
Anxiety	Likes	-0.019
Positive Emotion	Replies	-0.057
Positive Emotion	Likes	-0.087
Positive Emotion	Quotes	-0.117
Positive Emotion	Retweets	-0.133

Table 1: Correlation Summary

A sorted list of all twenty tested relationships between LIWC's affective emotional values and the natural-logarithm-adjusted Twitter feedback values. Correlations that were not statistically significant are highlighted in grey.

Not only do these findings indicate that politicians' toxic behavior on Twitter is seemingly rewarded by other users with increased feedback, the stronger negative correlation between all forms of feedback and positive emotion actively disincentivizes pleasant discussion among politicians on the platform. Although the statistical principle that correlation does not imply causation is still relevant, the context that user feedback is in direct response to the tweets – and consequently their affective language – strongly suggests that the variables and their correlations are not products of coincidence. This explicit relationship between tweet content and feedback, while not fully representative of every factor that might influence a user to respond to a tweet, represents a statistical causality that lends significance to these correlations (Kelleher, 2016).

Even with a selection of 15,878 distinct datum, the number of tweets that displayed any significant amount of anxiety or sadness was shockingly low. As Figure 2 and Figure 3 indicate, the twelve senators I selected seemed very hesitant throughout 2020 to indicate any amount of those two emotions in their messages. The absence of sadness and anxiety was especially apparent in relation to the amount of anger present in their tweets as indicated in Figure 1, which comprised the bulk of the negative emotion data superset. I theorize that this emotional disparity stems from the public's stigmatic perception of anxiety and sadness, which typically associates it with weakness. Given that politicians are heavily concerned with their public image, their attempts at minimizing the amount of weakness they display might account for this pattern. Expanding my research to include a more diverse body of politicians might shed light on whether these emotional patterns hold true throughout American politics.

As discussed briefly in the results section, I was greatly surprised to find that positive emotion had a much stronger presence in the tweets I scraped compared to negative emotion. While this finding might have challenged my initial concerns in isolation, its negative correlation with feedback supports my hypothesis. Even if positive emotion has a stronger presence on the platform among politicians in this current dataset, the fact that negative emotion is the more rewarding behavior suggests that politicians will trend toward negative emotion as they become more adept at using social media to advance their careers. If I expanded my research to include time slices of American politicians' tweets in the past as well as the present, I would be able to test whether negative language is trending upward or downward with time.

Perhaps the most interesting pattern among my findings is that anger, negative emotion, and positive emotion are all most strongly correlated – either negatively or positively – with retweets. This pattern is significant because, out of all four forms of feedback, retweets increase a tweet's visibility the most by sharing its contents with the retweeting account's followers in addition to the original poster's followers. The extra publicity that retweets afford their target tweets is especially relevant to campaigning politicians that are striving to rally their electorates, as well as online journalists that are content with mainly reporting on the platform's most popular tweets and subjects. Retweeting's significance as arguably the most important means of feedback on the platform lends my findings greater gravitas and strengthens my argument that journalists should refrain from relying on Twitter to conduct and distribute their work.

Takeaway for Journalists

As the fourth most popular website and second most trafficked social media platform in the world, it is not surprising so many journalists and politicians have flocked to Twitter (Neufeld, 2021). Both political candidates and newsrooms are in the business of communicating with the public, and as one of the internet's premier hubs of online discourse it is fertile ground for campaigning and dissemination news.

> "Hundreds of American news organizations are turning their own journalists loose to blog. Are they cashing in on the cachet surrounding blogs, or do they recognize the value of less formal and more participatory ways to communicator with readers and viewers? Probably both." (Friend & Singer, 2007, p. 136)

Although Twitter presents great opportunities for journalists to interface with their audiences, elevate their voices, and advance their careers, it also imposes great costs (Lieberman, 2020). No differently than past technological advancements like the telegraph, these toxic aspects of Twitter have the capacity to change how journalists draft their stories. Many reporters' fascination with keeping up to date on Twitter is exploitable by Twitter-savvy politicians like former President Donald Trump, who leverage the attention to advance their agendas (Ingram, 2017).

Even when journalists are cautious and restrained in their approach to reporting on Twitter, my research has demonstrated that the platform is inextricably a hostile environment that facilitates negativity among prospecting political candidates. Consequently, attempts to report on the world through Twitter will always be colored by this toxic lens. As Muhlmann laid out in her book *A Political History of Journalism*, publishing Joseph McCarthy's accusations furthered the spread of McCarthyism in the United States (Muhlmann, 2008, p. 12). Sourcing news from tweets likely has a similar effect by poisoning political discourse with the platform's latent toxicity and the overt partisanship that fuels its aggressive language.

It's unrealistic to ask for all journalists to stop using Twitter or to expect politicians to conduct themselves in a less attention-seeking manner on the platform, but that doesn't mean there aren't potential ways to curtail the spread of toxic tweets.

A solution might lie in Muhlmann's second posited form of journalism: the de-centerer. Unlike their counterparts, witness-ambassadors, which aim to unify the news narrative under objective truths, de-centering journalists "seek to make the public which 'receives' their gaze feel something very different, something deeply disturbing to the ‘we’” (Muhlmann, 2008, p. 29). In essence, de-centering journalism emphasizes specific narratives on the periphery of society, typically guided by the writer’s strong voice as they relate their story to the audience (Muhlmann, 2008, pp. 28-33). Twitter is at its best when it is giving a voice to marginalized groups, thereby allowing their stories to go further than they might otherwise have spread within cultural enclaves. Many journalists rightly recognize this capacity to connect and empower the voices of minority groups as one of Twitter’s greatest strengths (Lieberman, 2020). Instead of primarily tracking popular discourse, journalists could focus on using it to form connections with unheard voices. It could be possible for journalists to avoid the problems of a Twitter-reliant news cycle by using these voices’ stories to fuel a de-centering narrative outside of the platform and its toxic inclination.

Final Thoughts

Through this research I aimed to guide not only how journalists approach Twitter, but how everyone interacts with digital mediums. By demonstrating how politicians in my dataset are seemingly rewarded with increased feedback for negative language and punished with decreased feedback for positive language, I hope that I have demonstrated the extent to which the environment of social media platforms can influence the speech of their users.

If I had time to continue my research, I would not only have expanded my selection of politicians to observer and timeframe for posts, I also would have looked at other platforms such as Facebook. This project was focused on the implications of its findings in the context of journalism not only because communication is one of my specialties, but also because journalists comprise a large portion of Twitter’s most active users (Stocking, Barthel, & Grieco, 2018). Had the scope of this project been larger, I could have examined the way other groups of people interface with social media.

The intersection of humanity and technology, as well as the competing means by which the two communicate, continues to be an object of fascination for me. With my conceptualization of Twitter seemingly validated by my findings, I am eager to test it further with future research.

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