High Negativity in Posts About Race Issues Compared to Gender and Religion: A Sentiment Analysis of Twitter Posts about Social Issues

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Introduction

In recent years, the world of social media has exploded. As of June 2016, Twitter reported to have 313 million monthly active users (MAU) as compared to 30 million in 2010 (Twitter.com, Statista.com). Social media sites such as Facebook and Twitter have transformed the way people communicate, express ideas, and get their news. It has also created a data source nearly endless in size and comprised of populations previously inaccessible to researchers. The current climate of discussion and debate on topics such as race, religion, and gender issues is lively, and quickly evolving. More than ever before, individuals have a platform and the power to publicly express their viewpoints on highly debated social issues. But how do people talk about the social issues important to them? Does the nature of the social issue effect the type of language people use?

From political science, to psychology, to linguistics, or marketing, comprehensively studying what people share on social media will lend crucial insight into what people care about, and how exactly they feel about it. What were once privately held beliefs and emotions are now available to the public via Facebook statuses, blog posts, and tweets. Researchers can begin to identify patterns between social issues and draw connections between specific issues and attitudes in order to advise legislators, advocates, and community organizers in their pursuits. This is made possible by studying not just *what* people say when posting about social issues online, but *how* they say it – the emotional value and sentiment of the language itself. As a result, organizers may be able to more effectively adapt their approaches and tactics for social justice causes when properly informed of the emotional climate surrounding the issue.

Previous research on word connotation in the English language has largely focused on cognitive aspects of language such as memory rather than emotional aspects of words (e.g., Kausler, 1994; Rubin & Friendly, 1986). Some research that does conduct an emotional analysis of English words uses measures of emotionality, from not emotional to very emotional, excluding the positive or negative valence of the emotion (e.g. Strauss & Allen, 2008). Yet surprisingly, researchers who developed the EMOTE database, a database of English emotional terms, identified only three prior-existing word norm databases that used word affect measures (Gruhn, 2016). Current research has attempted to adapt the methods for the linguistic analysis of spoken language and traditional texts to the sentiment analysis of Internet posts. Normed databases like ANEW have been modified to include internet slang (Nielson, 2011) or expanded to encompass a much larger word variety (Warriner et al, 2013). Additionally, private companies are interested in studying social media to accurately analyze what the public has to say about their products. As a result, many studies have aimed to improve the ability of sentiment analysis tools to properly identify nuanced language such as sarcasm and irony on sites like Twitter and Amazon (Davidov, Tsur & Rappoport, 2010).

Methodology

This study examined the sentiment of words used in Twitter posts across three major social issues: race issues, religious issues, and gender issues. Within group comparisons explored the most commonly mentioned related topics in addition to the most frequent positive and negative terms. Between group comparisons were also conducted to evaluate overall sentiment scores of each group over time.

The Data: Tweets

The data for this study consisted of tweets collected using Twitter's application programming interface (API) and R. Tweet text and other information such as location, retweet counts, and favorite counts were mined for posts about race issues, religious issues, and gender issues. Each social issue was broken down into three subordinate search strings to maximize the scope of the search terms. The race issues group used the terms "racism" "racial justice" and "race + America". The religious issues group included the terms "religious freedom" "freedom of religion" and "war on religion". The gender group included the terms "women's rights" "gender rights" and "gender equality". For each search string, 1000 tweets were collected daily, resulting in 3,000 tweets per social issue a day. Each group had a final sample size of 96,000 tweets.

Duration

Using a random time generator, time of day of tweet collection was varied over a span of 32 days. Tweets were collected starting on January 19, 2017. This date was chosen to capture posts during the first month of Donald Trump's presidency.

Sentiment Analysis: Coding & Cleaning

Tweets were analyzed for sentiment using the tidytext package for R. The unit of analysis was at the word level; hashtags were treated as one unit. Individual words were coded for positive or negative valence using the Bing lexicon of word sentiment. Common English stop words were removed using the SMART, snowball, and onix lexicons included with the tidytext package.

Results

Within Group Analysis: Most Mentioned Topics

The analysis of most commonly mentioned terms for Twitter posts about each social issue confirmed some anticipated related topics in addition to highlighting instances of topic overlap between issues (Figure 1). Of all the twitter posts, regardless of social issue content, the term "trump" appeared among the highest mentioned words; ranking second most mentioned for the race and religious issues groups, and fourth for posts about gender. It also appeared that there was a tendency for Twitter users posting about one social topic to mention ideas related to another social issue. The word "religion" appeared frequently in posts about race issues. "Lgbt" was among the most common terms for posts about religious issues.

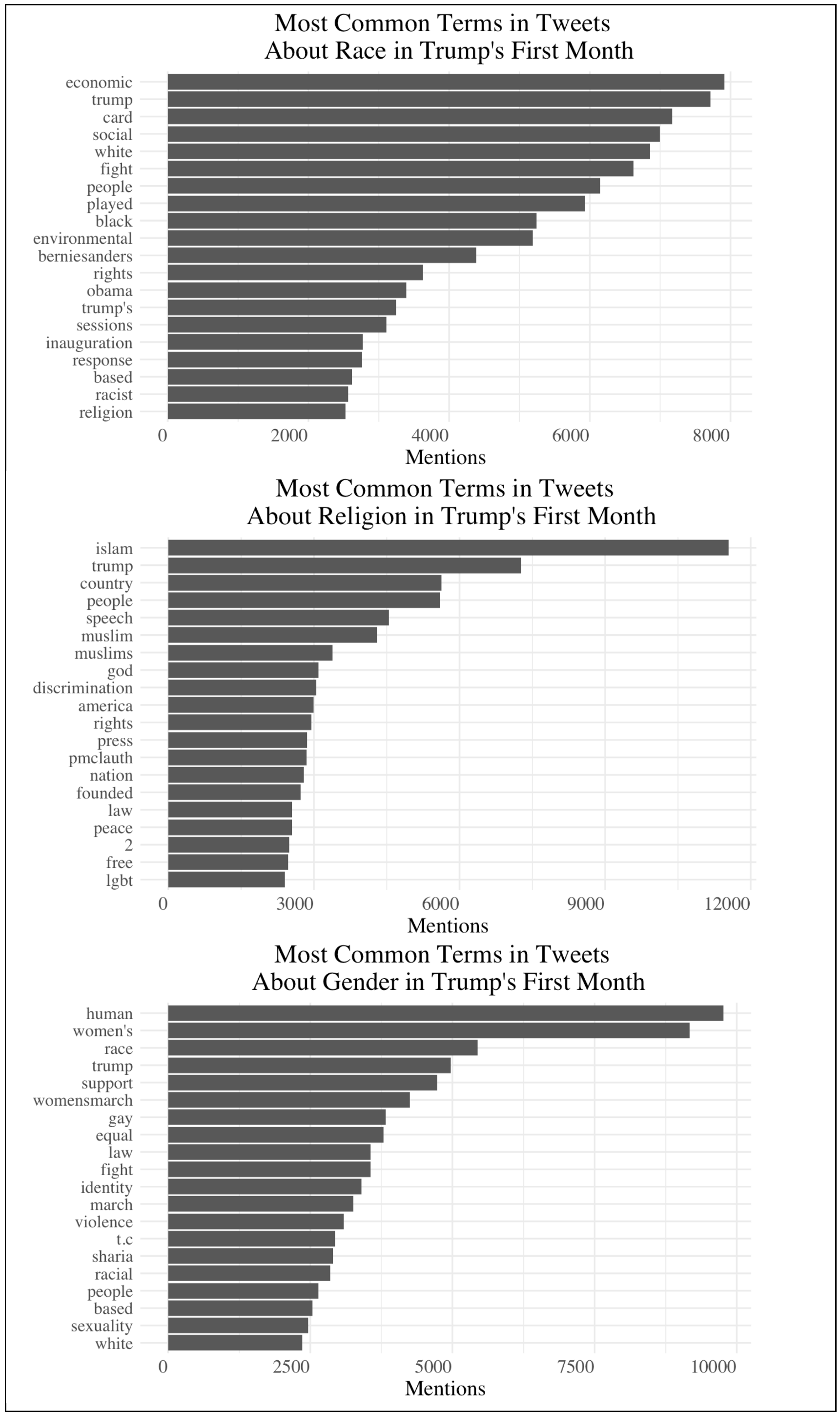

Figure 1

And finally, tweets about gender issues showed to have overlap with LGBT, religious, and race related ideas with common words including: “gay,” “identity,” “sharia,” “racial,” “sexuality,” and “white.”

While all groups mentioned Donald Trump, among those posting about race issues, we also saw high mentions of Barack Obama, Bernie Sanders, and Jeff Sessions. Among race tweets, the most commonly mentioned term overall was “economic” suggesting a possible connection between those concerned with race issues and economic interests. Many emotionally-charged terms also appeared in the frequently mentioned topics for posts about race. For instance, “card” (as in “race card”), “fight,” “played,” and “racist” were among the most mentioned terms in tweets about race. Additionally, both the terms “white” and “black” appeared frequently, with “white” showing a slightly higher occurrence.

Among religious tweets, we saw trends of mentions of Islam and American nationalism over religious ideas themselves. In fact, the only explicitly religious term to appear in the most common words of tweets about religious issues was “God.” Many Islam related ideas appeared including “Islam,” which was the highest mentioned word, appearing almost twice as often as every other term besides “Trump.” There were also very high mentions for the terms “Muslim,” “Muslims,” and a Twitter username “pmclauth”, the account for Peter McLoughlin, the co-author of a book titled “Mohammed's Koran: Why Muslims Kill for Islam” that was released during the timeframe of data collection. Nationalistic ideals were also extremely prevalent in tweets about religious issues. Terms indicating patriotic or constitutional references included:

"country," "speech," "discrimination," "America," "rights," "press," "nation," "founded," "law," and "free."

Tweets about gender issues showed the highest diversity in topics. As mentioned, ideas about race, religion, and LBGT issues appeared often in tweets about gender. The high occurrence of LGBT related ideas is attributed to the duality of the word "gender" to be used for women's causes and for ideas related to gender identity. The sample also took place during the Women's March; this hashtag had one of the highest mentions in addition to the words "women's" and "march" separately.

Within Group Analysis: Sentiment Frequency

Among tweets about race (Figure 2), positive sentiment was associated with ideas of improvement ("better," "success," and "reform) and liberty ("free" and "right") in addition to general positive evaluations and emotions ("good," "great," "love," and "proud"). Negative sentiment was related to mentions of racism ("discrimination," "bias," "bigotry," "hate," and "racist") and the justice system ("criminal" and "crime").

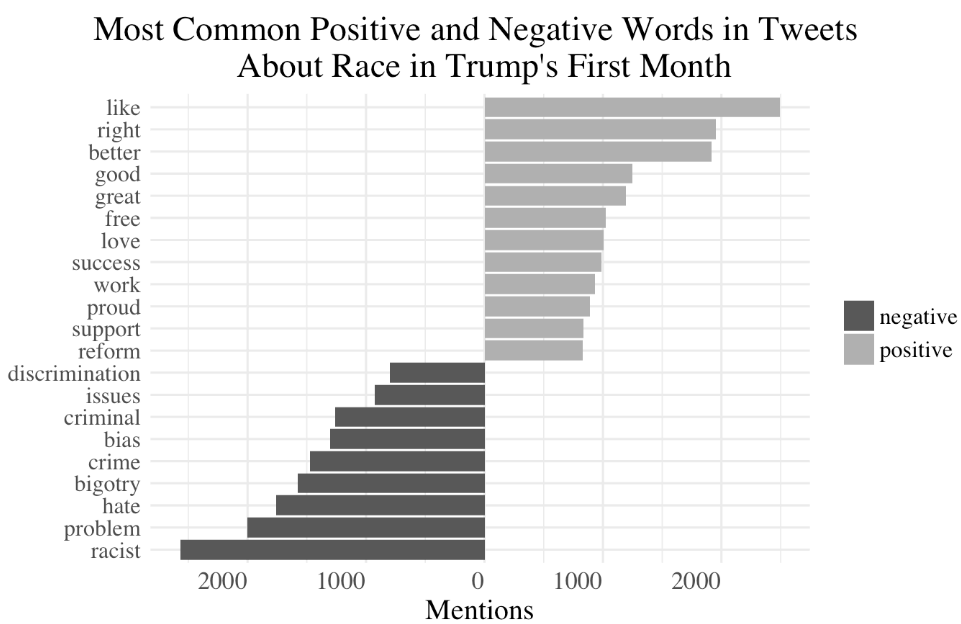

Figure 2

Positively rated words among the tweets about religion (Figure 3) were very similar to those of the race tweets in addition to the concepts of preservation (“respect” and “protect”) and religious ideas (“faith”). Negative sentiment included ideas of violence and fatality (“kill,” “hate,” and “death”) and religious persecution (“discriminate,” “persecution,” “attack,” and “discrimination”).

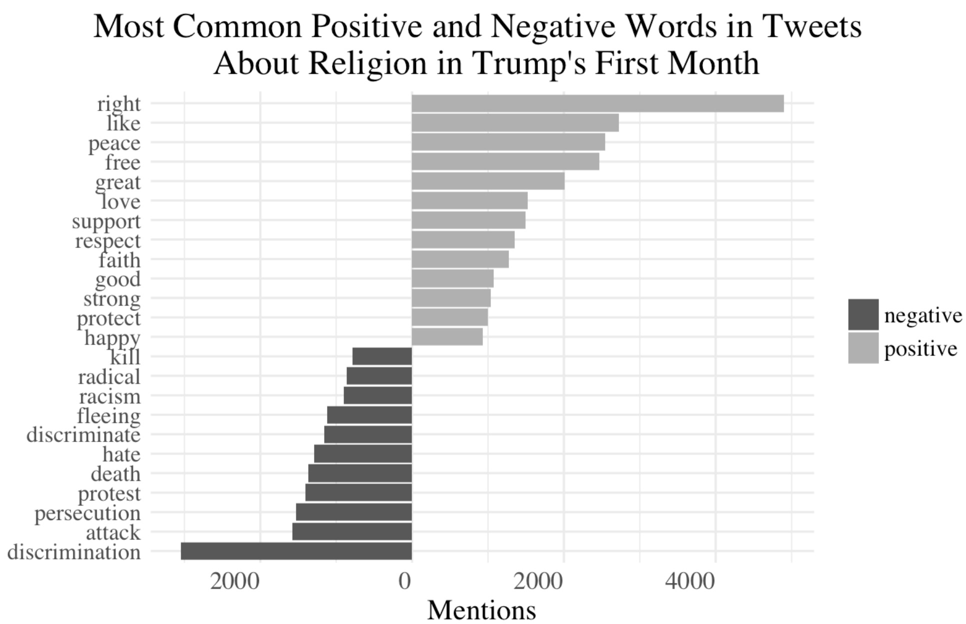

Figure 3

Of its most common words with a positive or negative sentiment, the gender tweets group showed to have a positive sentiment preference, with 75% of popular sentiment words falling into the positive category (Figure 4). The positive trends were also distinctive from that of the race and religion groups. Empowerment was a common notion (“empowerment,” “worth,” “celebrate,” “advocate,” and “important”) in addition to ideas associated with striving for social advancement (“reasonable,” “work,” and

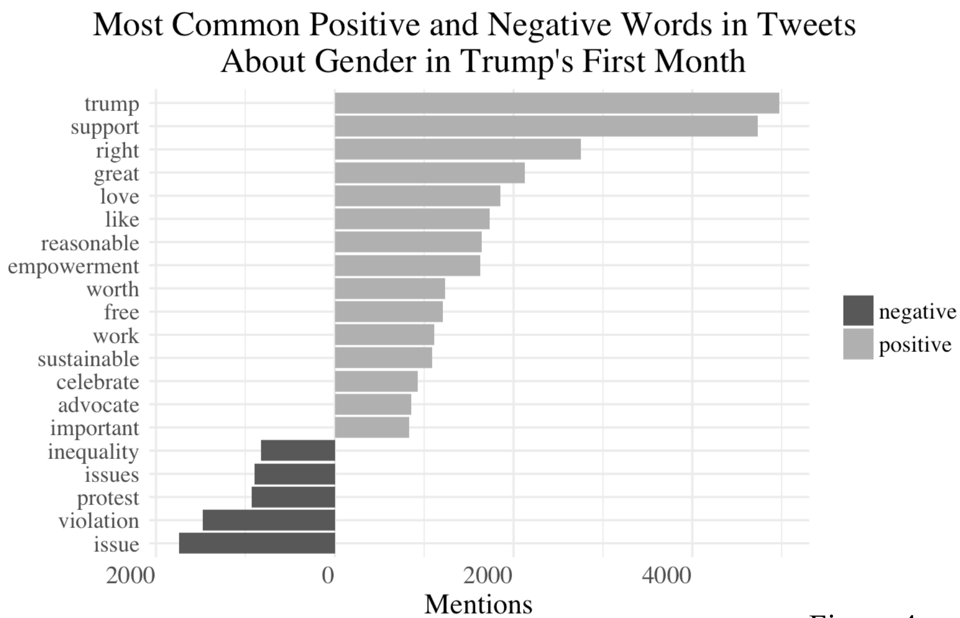

Figure 4

"sustainable"). Meanwhile, negatively charged words were indicative of mentions of the issues and organizing tactics ("issue(s)," "inequality," "violation," and "protest").

Between Group Analysis: Net Sentiment Over Time

To compare the tweets across the three issues of interest: race, religion, and gender, a net positivity score was generated for each day using the difference in daily total positive sentiment word counts and daily total negative sentiment word counts. From the most popular words that had a positive or negative sentimentality, it was anticipated that gender would have an overall positive net sentiment score. This hypothesis was confirmed. However, the tweets on religion showed to have an even greater net positivity score than did gender. While the most common sentiment words for religious tweets were evenly spread across negative and positive sentiment, the overall sentiment showed an extreme preference towards language with a positive valence. This indicates that while the extremes (most popular terms) used in religious tweets are

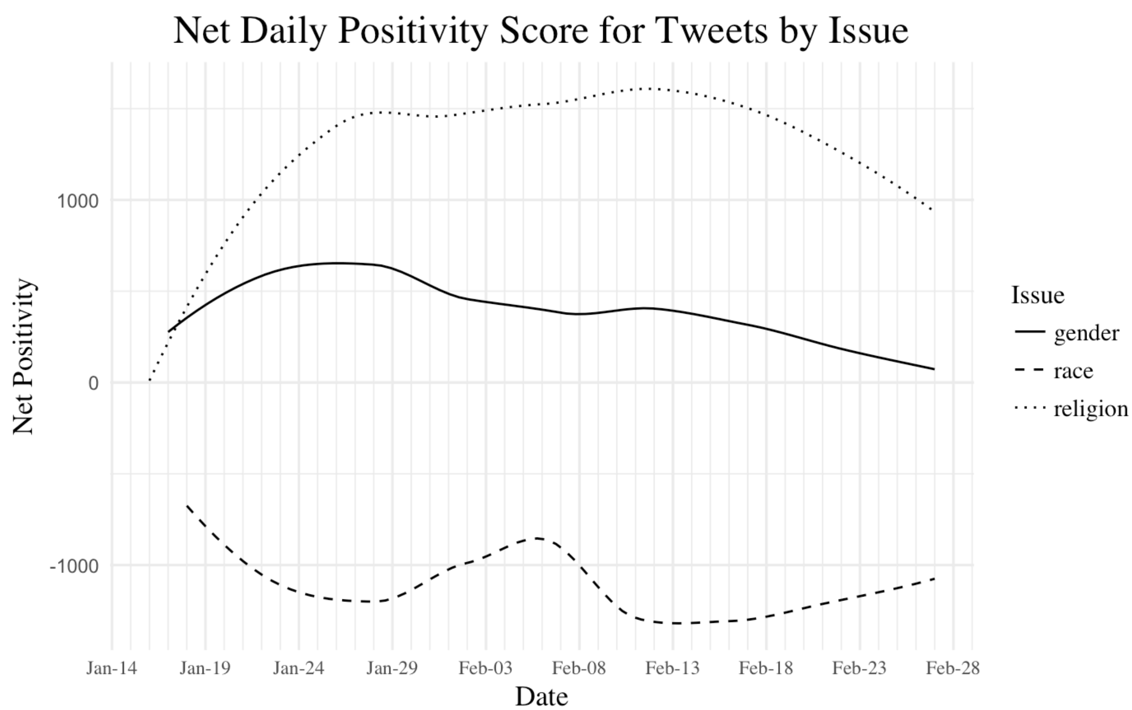

Figure 5

mixed in sentiment, the majority of posts use positive language. Finally, the race tweets group was the only group to have a consistently negative net sentiment score. This outcome was also unpredicted based on the result that the most common words that conveyed a sentiment for tweets about race appeared to be evenly distributed across positive and negative connotation.

Discussion

The analyses of the most frequently mentioned topics and sentiment words resulted in trends with an intuitive explanation, when interpreted in the context of tweet content. It was also expected to see some overlap between mentions of more than one social issue. It is likely that a person who feels strongly enough about a social issue to create a Twitter post would have opinions on other social issues. What we found was that not only is this true, but that concepts from other social issues will be referenced within the same tweet. Major trends for tweets about race included references to politicians, crime, and racial discrimination. For religion, references to nationalism, free speech, Islam, and religious persecution were highly popular. Tweets about gender issues made the most references to other social issues, and showed a bias towards positive words among the most popular terms. One possible explanation is that the data collection for gender issues happened during a major event, the Women's March, that emphasized a tone of empowerment, solidarity, and activism for this issue. However, net sentiment scores showed that it was not gender tweets that had the highest usage of positive sentiment words overall, but religious tweets.

In addition to unexpectedly positive net sentiment among tweets about religion, we also found there to be extremely high negative net sentiment for tweets about race. To say conclusively what caused this effect, a qualitative analysis of the data or a replication using a lexicon to classify words on emotional valence rather than positive or negative sentiment is recommended. However, the author does offer some cursory interpretations of these results. For one, political affiliation may be a contributing factor. Members of groups concerned with religious freedoms tend to identify conservatively, and the sentiment seen in their tweets during the first month of a new Republican party president may be indicative of a feeling of representation for their cause in political office. For tweets about race, the opposite effect may be true, with liberals expressing higher criticism and dissatisfaction with the new administration. A sample from another point in time, or spanning a longer period may be able to offer a more detailed explanation for these results.

Conclusion

The main findings from this study confirmed the hypothesis that those who post about one social issue will tend to post about multiple, with those who post about gender having the largest variety of other social issues mentioned. Tweets about gender had a positive net sentiment rating as predicted by the majority of common sentiment conveying words identifying as positive. Tweets about race had a consistently negative net sentiment rating while tweets about religion ranked consistently and extremely positive. This did not align with the most popular sentiment conveying words for each group which appeared to be evenly dispersed between positive and negative connotation. It is the author's belief that political party and outlook for advancement of the issues agenda under the current presidential administration could be one possible explanation. It is recommended that an extension be completed to evaluate the emotional content and motivations of the posts from these groups.

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