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#IBelieveTaraReade: Mapping Belief, Doubt, and Other Sentiment on Twitter Around a Sexual Assault Investigation

Introduction

In this project, I sought to understand the patterns of sentiment on Twitter around the discussion of Tara Reade's sexual assault allegations against Joe Biden. Reade, who had been an aide for Biden when he was a U.S. Senator, made the initial allegation in March, and the story spread virally at first: it was widely discussed on Twitter, and then in mid-April, mainstream news outlets began to post articles about the investigation. My first period of interest was in this gap between the initial news drop, which occurred on March 25, when Reade revealed to journalist Katie Halper that she had been assaulted, and the mainstream coverage of the story, which began on April 12 and included publications such as the Washington Post, CNN, and the New York Times. During this three-week period, discussion of the case was mostly limited to social media. Twitter served as a journalistic tool and a personal bullhorn; the processes of learning about the story, emotionally processing it, and situating it within the context of a larger conversation about sexual assault all took place simultaneously on the online platform. Further, by this point, lockdown had for the most part been imposed across the country, limiting the public sphere to Americans' social media feeds. I was thus interested in the way that the discussion evolved during this period. How did people feel about the case? Did the hashtags that people used indicate belief or doubt? My goal was to understand how the conversation around the story indicated different feelings, in order to extrapolate how people felt and expressed themselves.

Secondly, I wanted to compare this sentiment analysis with more recent data, to see how sentiments might have changed. Since the break of the story in the mainstream media circuit in the beginning of April, the topic's staying power has been challenged on multiple fronts. First, Biden published a response to the allegations in the Washington Post, in which he categorically denied that the assault happened and pivoted to a larger argument about his work on behalf of women. While it is not clear that this statement made a significant impact on public conversation, it is important that it was the only response by the campaign, and that it minimized the allegation rather than elevating it. Secondly, the global coronavirus pandemic, associated economic decline, the recent police killing of George Floyd in Minneapolis, and the resulting protests have all rightfully claimed space in American discursive forums, inevitably diminishing the airtime afforded to the Reade story. Third, recent allegations that Reade committed perjury have cast Reade's credibility in doubt. These developing events threw new and fascinating variables into my study, and I analyzed the data with the awareness that sentiment might change dramatically due to multiple conditions.

Research Question

Based on a sentiment analysis of Tweets following the allegations of Tara Reade in March and May, to what extent are there visible temporal patterns in language around belief and doubt, as well as other sentiments? Is there a discernable relationship with geography and the sentiments demonstrated?

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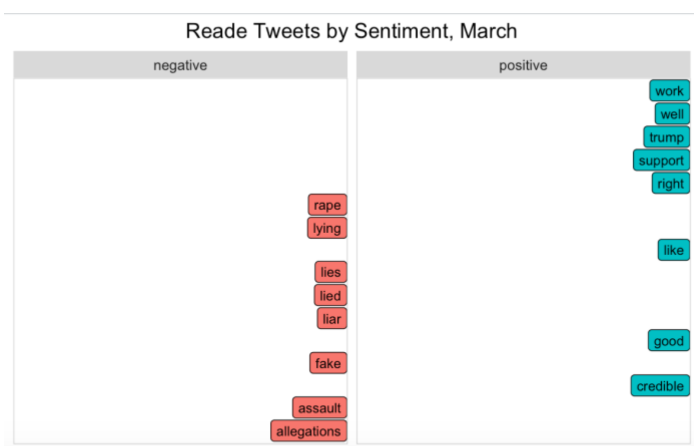
Initial Data

To pull the data, I used the "rtweet" package, which allows users to pull thousands of entries of data from publically accessible Twitter accounts. The package requires users to set up a developer profile through Twitter. The free version of this account allows for significant text mining, but unfortunately still created some limitations when it came to geocoding data. I first pulled data from March using the "search archive" function in R, and then pulled data from the past week using the "search tweets" function. I was able to retrieve about 5,000 Tweets per time period, but beyond that, I ran into an error when I tried to get more. The error had to do with the non-premium nature of my account, so I was unfortunately limited in terms of the amount of data that I could pull.

Further, in the "search tweets" function, I was able to geocode for Tweets coming from the United States, which screened for Tweets coming from within the country and able to be plotted on a map. Unfortunately, my API restricted me from applying the geolocation parameter "search archive" function, so very few of the Tweets from March are geocoded. As a result, I modified the project in order to compare the content of Tweets between March and May, with the awareness that any argument about geographic clustering could not be temporal, given the small sample size of geocoded Tweets for the month of March. For that reason, my project is divided up into three chunks. First, I analyzed the content of the March and May datasets, in order to extrapolate sentimental trends from them. Second, I mapped these sentimental trends for the May dataset. And third, I analyzed the two datasets for appearance of hashtags indicating belief and doubt.

Part I: Sentiment Analysis

For my initial sentiment analysis, I used the tidytext data package to group the Tweets by sentiment. I split the text of the Tweets by word, such that every word Tweeted had its own row. Next, I merged the data with a lexicon called Bing, which groups words based on their positivity or negativity. The following tables indicate the majority of positive and negative words in the March and May Tweets. As we can see, they're very similar.



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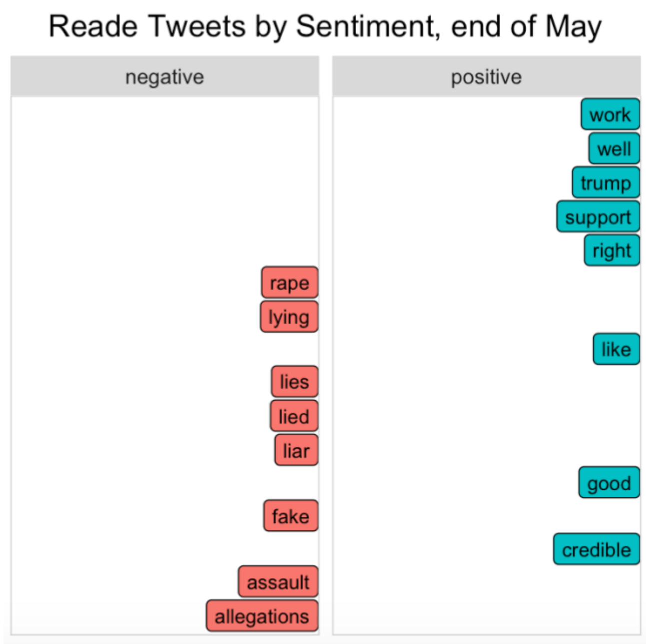

My next step was to use the NRC lexicon, which includes a broader variety of sentimental categories. Here, I used the categories "anger", "anticipation", "disgust", "fear", "joy", "sadness", "surprise", and "trust". Again, they're quite similar, although the groupings can still tell us something important. For example, "vote" is consistently in multiple sentimental categories, indicating that a call to vote is a response to a multiplicity of emotional circumstances. Further, from March to May, there's a subtle increase in the use of legal language. For example, "lawyer", "case", "expert", "investigation", "oath", "testimony", "expert", "credible" and "perjury" appear for the first time in May, although "allegation", "court", and language related to accusation was present in the first dataset as well.

I have two possible explanations for this. First, it's possible that now that the initial impact of the story has worn off, people are starting to focus more on the logistics of the process of sexual assault allegation and investigation. It's important to remember here that people are using Tweets about Tara Reade to reflect on that process, not just the particularities of her case. Second, a story appeared at the end of May that defense lawyers in Monterey County had begun an investigation into Reade's alleged perjury. It's probable that the appearance of "perjury" and other legal language is due to that story. This demonstrates an interesting conundrum in sentiment analysis, in that you're dealing with multiple levels of content processing: feelings can change, but so can the story itself. So in parsing text data as it changes over time, it's important to consider the multiple factors contributing to the shift.

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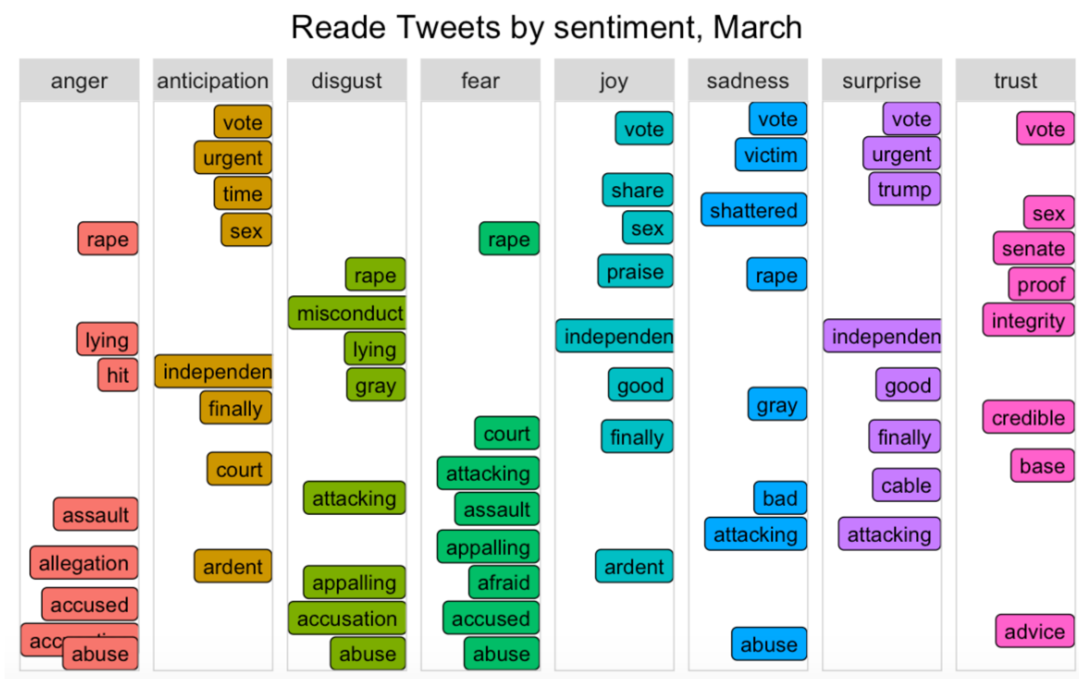
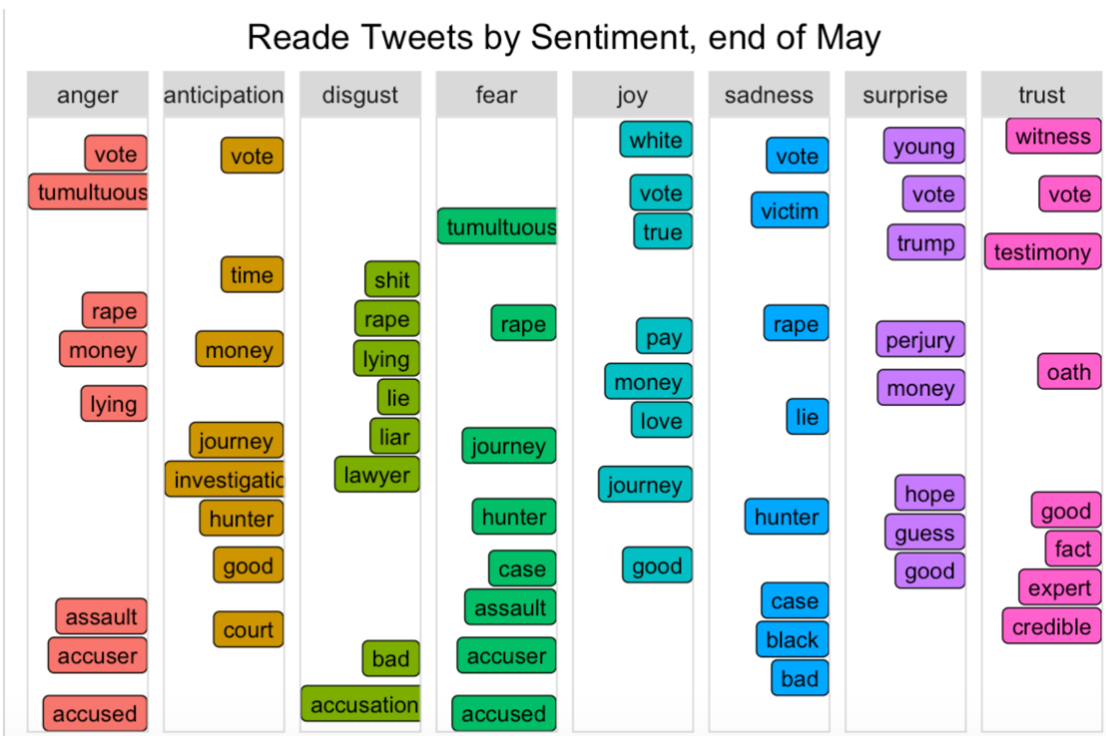
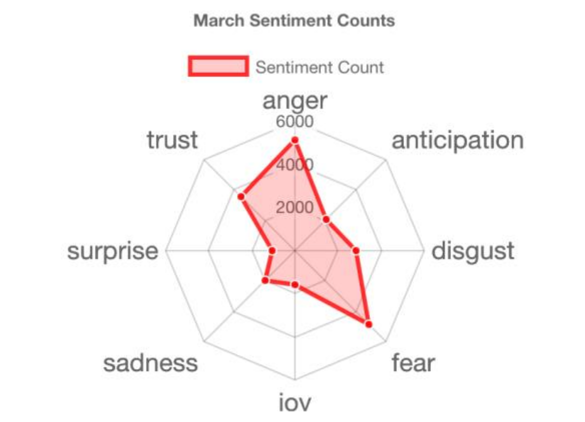
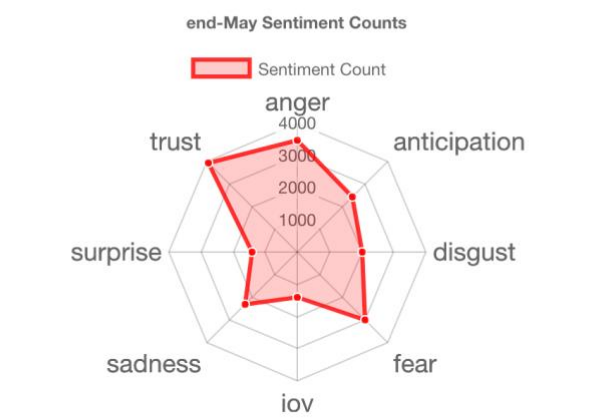




In another interesting visualization, the tidytext package allowed me to make a spider plot, which gives us an idea of the spread across the emotional spectrum of the Tweets collected. A couple of interesting things can be drawn from a comparison of the two. First, there was a spike in words indicating trust from March to May. There's also an increase in Tweets evoking anticipation, surprise, and sadness relative to the total number of Tweets. Fear seems to be static, as is anger. I'm not sure why this is, but it could be significant that trust and sadness tend to be toned-down sentiments. My assumption in reading Tweets was that outbursts of emotion would decrease over time as people processed the story over the course of several weeks, and while I can't make any conclusions about the polarity or vigor of certain emotions, it could still be significant that Tweets indicating trust increased over the two-month period.



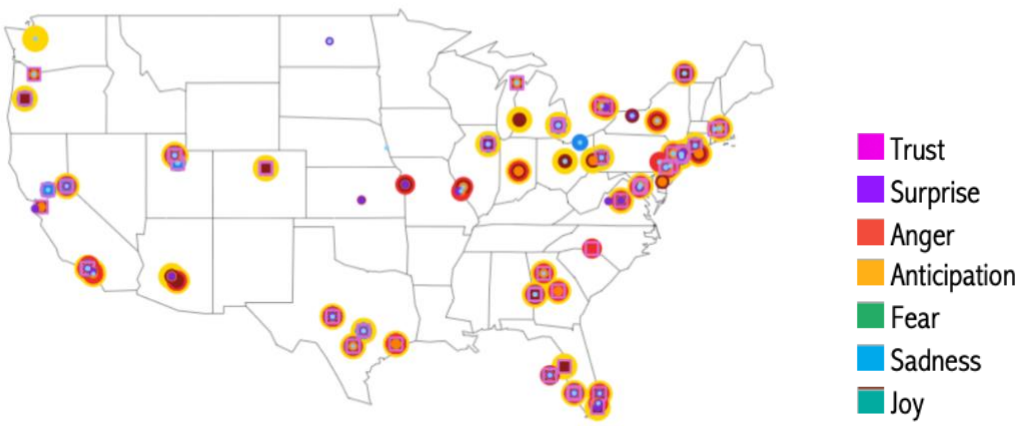


*Note that "joy" is cut off, and reads "iov" instead.

II. Mapping Sentiment Across the United States

As stated earlier, I was unable to pull an adequate sample of geocoded from the month of March to create a geospatial analysis of those Tweets. On the other hand, I was able to analysis geodata from the country as a whole. I created the following repreesentation by layering dots representing Tweets of each NRC sentimental category onto a map. To show multiple colors at once, I made the circles different sizes.

While it's not quite as visually cohesive or dispersed as would be optimal for visual interpretation, it does reflect generally that there is not a strong spatial correlation with any particular sentiment – instead, we see multiple layers on top of each other, such that hotspots represented demonstrate evidence of multiple emotions. This isn't really conclusive, but it is helpful to know that by performing this type of analysis no clear correlation was found. It's not the most exciting answer, but it is possible that there's just very little correlation.

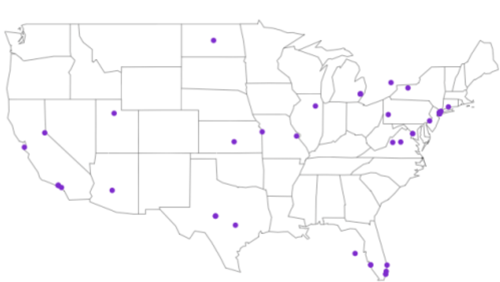


In order to make absolutely sure that the spread was approximately the same for each layer, I separated out the layers, representing each on its own map of the U.S.

Disgust

Sadness

Surprise



Joy

Trust

Fear

Anger

Anticipation

As predicted by the first map, there are no clear and significant distinctions between the spatial layout of the sentiments across the country.

III. Tracking Belief and Doubt Over Time

For my final piece of this project, I created my own lexicon to analyze patterns of belief and doubt in the datasets. To do so, I identified three hashtags that indicated allegiance with Biden, which tended to correlate with disbelief of Reade, and three hashtags that indicated belief in Reade's allegations. The belief-indicating hashtags I chose were "ibelievewomen", "ibelievetara", and "sexual predator". The doubtful hashtags were "ibelievebiden", "bluenomatterwho", and "tarareadeisafraud". I chose these hashtags based on a manual scan of Tweets that indicated either belief or doubt in the story, and fully understand that this would not be a definitive measure of either belief or doubt in the story. My goal was simply to better understand how those two sentiments might be expressed across a large sample of Tweets.

I applied that lexicon to the large datasets for March and May, and got the following result:

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	March	May
Belief	888	29
Doubt	0	5

This result is striking in some ways, and inconclusive in others. First, it's fascinating that even though both sets included approximately 5,000 entires, the use of belief-indicative hashtags dropped that dramatically. Hashtags are generally used to evoke a strong, declarative expression of feeling, so this might actually support the argument that support for Reade is dropping, or my earlier assumption that over time, discussion would become less strident and polarizing. It is true that the story initially roused passion, particularly among those knowledgeable of the structures of governance and culture that force victims to remain silent while perpetrators escape unpunished. However, as Reade's credibility as a witness has been questioned, it's possible that sentiment has tempered accordingly.

Unfortunately, there were not really enough entries in the May category to represent a strong pattern towards belief or doubt, so I'm not sure whether it's significant that 1/7 of the Tweets using one of the hashtags I indicated used a doubtful tag.

Conclusions

We have a multiplicity of tools at our disposal for analyzing the sentiment of social media data, and so much is clear in the case of Tweets discussing Tara Reade. Ultimately, this study found that sentiment remained largely static, but that the means of expressing that sentiment shifted. Further, I found no clear spatial correlation between the geography of the Tweet location and the sentiment expressed.

That said, regardless of the result, it's essential that we treat data of this kind with care. For example, we can use lexicons to extrapolate sentiment, but we must be mindful that the context and environment of the word can alter its meaning significantly. Secondly, it's essential that we consider the multiple factors that might feed into the apparent shifts in sentiment. As I've noted, the story developed signifcantly over the course of two months, and the change in feeling in Twitter discussion could have been entirely in reaction to those events. My hunch is that that the new allegations do not tell the complete story, and that sentiment morphs following the break of a story like this irrespective of new additions to the story, but in this case, it's impossible to isolate those two things. Finally, the use of Twitter by itself is insufficient in studies that aim to understand the braoder public sphere that makes its home on the Internet. It's essential to think about the ways in which the features and cultures that different platforms inculcate affect the type of posts that surface, and the ways in which people instrumentalize different platforms in order to advance their own cause or image in some way. In that sense, sentiment analysis on social media is as much an analysis of performance. While this is still fascinating, it means that we need to be careful in assuming the sentiment of a person based on what they post.

In conclusion, this type of research is inevitably incomplete, and will benefit from further study and software development. For example, additional studies might compare the distribution of sentiment across the country or another geospatial zone between two different cases of discussion around an event. One could thus pick events that are similar but for a few variables, in order to see how patterns of sentimental shift might change according to different conditions. One could also compare sentiment expression across multiple platforms, and understand how the user experiences shape online discussion. For example, although anonymity is always an option on the Internet, certain sites, like Reddit and 4chan, tend to encourage it, whereas Twitter and Facebook tend to be more available. While my assumption would be that people tend on Twitter and Facebook to express opinions that they wouldn't mind their boss seeing and feel comfortable expressing their more provocative opinions on an anonymous forum, I could be wrong about that. Finally, additional work in the world of sentiment analysis software might tackle the problem of irony and sarcasm, which further complicate meaning. It might be interesting to compare change in sentiment over time between two different cases of discussion of sexual assault allegations, only one of which was later cast in doubt by conflicting information.

In conclusion, the sentiment analysis of the Reade case provides the kernels of potentially fascinating trends in the progression of sentiment and online discussion. Further work will refine the process of sentiment analysis and extrapolate patterns in social media use.

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