Analyzing Gender, Religious, and Political Twitter Sentiment Surrounding the Death of Justice Ruth Bader Ginsburg

Data 440 Final Project

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1 Introduction

On September 18, 2020, Supreme Court Justice Ruth Bader Ginsburg passed away at the age of 87. In her 27 years on the United States Supreme Court, Justice Ginsburg had built a following as the leader of the "liberal wing," which was bolstered by her role as only the second woman, and the first Jewish woman, to be appointed to the Supreme Court. [2] This project aims to analyze Twitter sentiment in the days surrounding Justice Ginsburg's death, and to explore sentiment differences when explicitly looking at the different facets of her life and history.

2 Literature Review

There is very little literature, overall, analyzing sentiment around the death of Supreme Court Justices. This makes sense, given that, in the past decade, only two Supreme Court Justices, Ginsburg and Scalia, have died while still being sitting Justices. Furthermore, most research in the field of political polarization using Twitter sentiment analysis explores "affective polarization," which Mentzer, et al. explain is the dislike by group members of those in out-groups [4]. As such, most research around Twitter sentiment analysis aims to first label the "tweeter" as a member of a group, and then to analyze the sentiment of that individual's tweets in the context of group membership, which is not the intention of the current analysis. However, several conclusions drawn in literature adjacent to the topic are informative to potential results and processes of this analysis.

Mentzer, et al., in their 2020 paper, explored both party and gender as it related to polarization on Twitter ahead of the 2018 United States Senate Elections. They found that, on the whole, female candidates for Senate, regardless of political affiliation, were discussed less positively than their male counterparts [4]. They found that this conclusion also held across gender lines for the users, with male candidates being talked about more positively than female candidates for Senate regardless of the Twitter user's gender.

More generally, Sudhan, et al. argued that Twitter, as a platform, is a valuable source to understand the public's reaction to various external or internal events [3]. Extrapolating from this, the death of Justice Ginsburg is certainly an external event. Therefore, Twitter data is useful to explore the reactions of the "public" to this event. Further, Mondal, et al. explored hate speech on Twitter in particular. They found that hate speech is not as simple as detecting "hateful" words, because some words are hateful in certain contexts but not in others [5]. He also noted that hate speech can be based in sentence structure as much as in words [5]. However, this analysis of hate speech in sentence structure is beyond the scope of the current analysis.

Finally, in November 2019, Sandhu, et al. explored the shift in sentiment surrounding the Supreme Court before and after the confirmation of Brett Kavanaugh. They found a slightly negative sentiment in tweets mentioning derivations of "Republicans" and "Democrats" both before and after the confirmation hearings. Crucially, however, they stressed the incidence of sarcasm in tweets, where words with positive valence counter-intuitively are used to reflect negative sentiment, or vice versa [6]. This is a good warning for the current analysis, in that the results may be affected by the presence of sarcasm in tweets. However, the size of the dataset, coupled with the seriousness of the occasion, make it unlikely that such incidence of sarcasm would have a noticeable impact on the results.

3 Data

The dataset for this project was collected by Ed Summers, a member of the research faculty at the Maryland Institute for Technology in the Humanities (MITH) at the University of Maryland [7]. I found this dataset through the DocNow Tweet Catalog, where it was posted on September 25, 2020. The data set, itself, is housed in the Digital Repository at the University of Maryland (DRUM) and consists of a text file of tweet IDs. Tweets collected were from the days between September 10, 2020, and September 22, 2020, and contained the keyword “RBG,” which were Justice Ginsburg’s initials [8]. In all, the dataset contains 3,825,716 tweet IDs.

On October 8, 2020, I used the tool ”Hydrator” to turn the set of tweet IDs into a CSV file of full tweets. This resulted in a CSV file with 3,684,687 tweets in it, for a retention rate of 96.31%. The file contains 34 columns, including the text of the tweet, the URL for the tweet, the username, the verification status of the user, and other metadata.

Before moving to subset and analyze the corpus, I iterated through the CSV file and used the “detect” method from Python’s “langdetect” module to remove all tweets for which “detect” did not return English as the tweet language. This removes all tweets which are only a link, as well as all tweets with Emojis in them because “detect” does not read Emojis as English. The purpose of this was because further methods in the analysis cannot account for Emojis and are anchored in English, so only English tweets will be used. This left a total of 3,515,866 tweets, for a overall retention rate of 91.90%.

4 Methods

All analysis for this project were conducted using Python. This project was conducted using sentiment analysis methods. The sentiment dictionary used was the “VADER” dictionary [1], which was read into the notebook.

After the data was cleaned and non-English tweets were removed, I took in the CSV file of tweets and iterated through the file, separating the “text” column out into one list and then saving the text and all metadata as a dictionary into a second list. This was done to allow subsetting by metadata such as date or user verification status. Each tweet was then run through a function, “get_sentiment,” which takes in a tweet, splits the tweet on whitespace, and then, for each word in the tweet, checks the sentiment dictionary and takes the valence of the word if the word is in the dictionary. The function then outputs the sum of the valences of every word in the tweet or, if the argument “aggregation=‘scaled’” is passed into the function, then returns the sum of the valences divided by the number of words in the tweet. I also used a modified version of the function, “mod_get_sentiment,” which handled cases where each row in the CSV file was a list, rather than a string, and output the same results as the original function with the same arguments.

Once I had run the “get_sentiment” function to get a baseline for the sentiment of the corpus, I took subsets of the corpus to look at different dimensions of the sentiment of tweets about Justice Ginsburg’s death. The first subset I took was to separate the corpus in several parts, one for all tweets before September 18th and one sub-corpus for each day from September 18 and through September 22. I chose this date because Justice Ginsburg died on September 18th, and thus it would be vital to examine changes in tweet sentiment following her death. I then used the “get_sentiment” function on each subset and recorded the results.

The next subset of the corpus was to separate out all tweets containing words such as “Jew,” “Jewish,” or “Judaism,” along with some derogatory terms towards Jewish people, in order to explore whether the sentiment associated with tweets explicitly referring to Justice Ginsburg's religion was more or less negative than other tweets. These words were not within the VADER valence dictionary, and as such, they had a valence of 0 in the "get_sentiment" function. This meant that the results from the function were not biased by virtue of the keywords existing within the corpus at higher frequencies. I then used the "get_sentiment" function on this subset of "Jewish" tweets and recorded the results.

A further subset of the corpus was a subset containing all tweets with words such as "female" or "woman," along with a few gender derogatory terms that might have been used, such as "bitch". Although some of these words did exist in the valence dictionary, I chose not to remove them from the dictionary before running the results. This choice was made so that the valence of the individual tweets most accurately reflected the words included within them. I then used the "get_sentiment" function on this subset of "woman" tweets and recorded the results.

The last subset of the corpus was a subset of all tweets with words such as "liberal," "left," or "progressive". The goal of this subset was to capture tweets that discussed Justice Ginsburg's political or judiciary leanings, and see if they were commonly referenced more positively or negatively. As with the tweet of "female" referent words, I did not remove these keywords from the valence dictionary, as I felt doing so would unfairly bias the results. This was because, for example, the word "progressive" is a positive valence word in reference to Justice Ginsburg, and removing the word from the valence dictionary would intentionally suppress the results of this sub-corpus, even though the intent of the users was to have a more positive valence. I then ran the program with the "get_sentiment" function on this subset of tweets and recorded the results.

5 Expectations

The goal of this project is to analyze Twitter sentiment surrounding Justice Ginsburg's death in September 2020. I will be analyzing both the corpus of tweets as a whole, and nine subsets within the tweet corpus, for a total of ten corpora. I expect that full tweet corpus will lean slightly negative in overall sentiment, due to what I expect to be an outpouring of sadness in the tweets following Justice Ginsburg's death. The over-representation of words associated with the emotion of sadness, which have a negative valence, will drag the overall sentiment of the corpus negative. Likewise, I expect the subsets of tweets following Justice Ginsburg's death to be more negative than the subset of tweets from before September 18th, with the most negative sentiment observed the day of and day after Justice Ginsburg's death, for the same reason.

Given the analysis of the 2018 Senate elections done by Mentzer, et al., it would be reasonable to expect that, with the subset of tweets involving female referents, there is likely to be a more negative overall sentiment than the baseline corpus [4]. This is bolstered by the existence of tweets in this corpus containing derogatory referents or slurs, which were included because not including these tweets would necessarily bias the results to be more positive towards female referents by excluding common negative female referents that would likely be used in place of neutral referents, such as "female" or "woman" in denigrating or insulting tweets.

Likewise, the same explanation could be presented with the expectation that the sub-corpus of "Jewish Referent" tweets would have a more negative average sentiment than the sub-corpus of tweets not including these referents. Including religious slurs towards Jewish people certainly moves the average sentiment in the sub-corpus more negative, but not including these tweets intentionally biases the results to ignore negative sentiment simply because of its use of derogatory terms rather than "proper" referents. As such, these tweets are included in the corpus, and the sub-corpus of "Jewish referent" tweets likely has a more negative sentiment than the baseline corpus.

The final sub-corpus of tweets, those referencing Justice Ginsburg's judiciary or political leanings, is much harder to make judgement on, given the void of information on how this has interacted in the past and the lack of research on how the deaths of prominent "political" figures or "trailblazers," such as Civil Rights Activist John Lewis, was perceived by partisan users on Twitter via sentiment analysis.

6 Analysis

In order, each of the nine sub-corpora and the complete corpus of tweets were passed through the sentiment analysis function. Table 1 lists each corpus, the number of tweets within the corpus, and and the average sentiment of tweets in the corpus, both as absolute sentiment ("Avg. Simple Sentiment") and as scaled to the length of the tweets ("Avg. Scaled Sentiment").

Corpus	# of Tweets	Avg. Simple Sentiment	Avg. Scaled Sentiment
Full Corpus	3,515,866	0.058	0.001
Before September 18	9,568	0.081	0.004
September 18	125,128	0.244	0.002
September 19	2,123,737	0.048	0.000
September 20	660,130	0.081	0.003
September 21	474,365	0.023	-0.001
September 22	122,939	0.026	-0.000
"Jewish" referents	61,121	-1.898	-0.076
"Female" referents	188,005	-0.867	-0.043
"Liberal" referents	84,941	-0.402	-0.021

Table 1: Table of Sub-corpora and Sentiment

The first surprise in the results was that the average sentiment of the full corpus was positive, as was the average sentiment of each of the time based sub-corpora. I had expected that the corpus as a whole, and especially the sub-corpora for the days immediately following Justice Ginsburg's death, would be fairly negative due to increased outpouring of sadness. One of the potential causes of this could be a spike in the use of the phrases "Rest in Peace" and "May her memory be a blessing" (an alternative phrase common in Jewish culture when mourning), in conjunction with "Justice Ginsburg". An exploration of the VADER lexicon returns that the valence of "blessing" is 2.2, the valence of "peace" is 2.5, and the valence of "justice" is 2.4. As such, the phrase "Rest in Peace Justice Ginsburg" would have a valence of 4.9, since the words "rest," "in," and "Ginsburg" are not in the lexicon, a significantly higher valence than the intent of the phrase, which is mourning death, should indicate its sentiment to be.

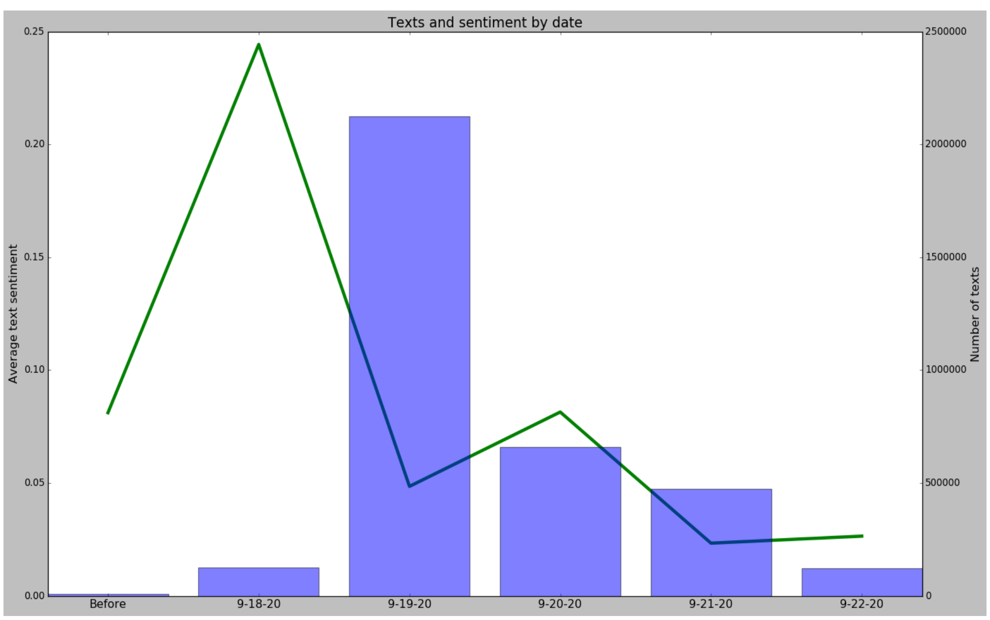

Figure 1: Average Simple Sentiment by Date Corpora

More in line with the expectations, however, was that the “Jewish” referent sub-corpus and the “female” referent sub-corpus had more negative sentiment than the corpus as a whole. I did not expect the disparity between these sub-corpora and the baseline corpus to be as wide as it was, but the expectation that both would be somewhat more negative than the corpus as a whole proved to be accurate. To further explore the strong negative sentiment of these two corpora, I looked at collocations of words in the subsets of the corpus with the keywords I used in building the original sub-corpora. By looking at which words were commonly associated with the words that I had selected as keywords, I thought it might be possible to see whether any particularly strong negative words were frequently in the subsets.

A cursory look at the collocations for both the “Jewish” referents and the “Female” referents offered some insight as to why these two sub-corpora turned out such negative sentiments. With the “Jewish” referents, in particular, the initial set of collocations includes words such as “die,” “uncomfortable,” and “holiday”. “Die,” in particular, was much more prominent in these tweets, though why this was is unclear. The other collocations relate to the timing of Justice Ginsburg’s death, which was during Prayer Services on the first night of Rosh Hashanah, the Jewish New Year. This might help explain some of the negative sentiment, however, as words such as “forbidden” and “interrupted,” common collocations for these referents, would also connect to the holiday and the interruption of services with the news.

In contrast, the collocations with the set of “Female” referents is somewhat less illuminating. There are no words in the “Female” referents which are nearly as prevalent in the sub-corpus compared to the baseline as words like “die” and “holiday” are in the “Jewish” referents. Instead, the upper portion of the list includes variations of the word “bitch,” as well as a random assortment of words, both about sadness and about strength and courage.

7 Conclusion and Further Research

In the days following the death of Justice Ruth Bader Ginsburg, the public sentiment surrounding her on Twitter was, in contrast to expectations, somewhat positive. This positive sentiment, however, did not carry into tweets from this same time period which explicitly referenced Justice Ginsburg’s gender, religion, or political leanings, with a strong negative sentiment found for references to Justice Ginsburg as a Jewish individual.

One of the major areas lacking in this analysis, being a primitive and word-based analysis of sentiment, was that the valence dictionary did not account for idiomatic phrases. This most prominently featured in the phrase “Rest in Peace,” which has a far more negative sentiment than the valence of its individual words would suggest it to have. As such, further research should likely consider phrases and the valence of those phrases. The sentiment analysis function would also then have to account for multi-word phrases, since it currently iterates through text word by word.

Another area of further research would be to incorporate Emojis within the valence dictionary and to keep tweets containing emojis within the corpus. In this analysis, such tweets were removed because the “detect” module did not perceive them as English words, and as such the tweets were not perceived as “English” and were removed from the corpus. A future analysis could include these tweets to get a more complete picture of the sentiment of the corpus and its sub-corpora. Finally, further research could also attempt to look at the users connected to these tweets, for example by gender, in order to explore the changes in sentiment relating to Justice Ginsburg’s death as it relates to the gender of the user. For example, this could explore whether or not women had, on the whole, more negative sentiment regarding Justice Ginsburg’s death compared to men.

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