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Twitter on the Anti-\$15 Democrats

Abstract

In this project, we analyze the sentiment of a sample of Twitter posts about eight Democratic and Independent US Senators in order to map changing sentiment about them before and after they voted against a Senate bill proposing an increase of the federal minimum wage to \$15. In order to achieve this, we use the Twitter API to generate a corpus by parsing tweets from the weeks before and after the Senate vote. We use two sentiment metrics to compare our documents before and after the vote, and use a statistical test to determine the significance of their separation. Additionally, we generate lists of relevant words for each period in order to determine what topics and attitudes show more prevalence for each. We conclude that, while most Senators show a clear decrease in perception on Twitter, the change is not drastic enough to be considered statistically significant.

- Daniel: Cleaned, tokenized, and formatted the corpus for our analyses. Got the sentiment analysis scores and made the respective visualizations.
- David: Scraped the tweets using tweepy, ran the TF-IDF vectorizer of before and after tweets, and performed the t-tests to see if the sentiment score decreases were statistically significant.
- Rohan: Made the data blitz presentation including the visualizations. Wrote the report.

Introduction

On March 5th, 2021, the US Senate voted on an amendment to the CARES Act—a \$2.2 trillion economic stimulus—to increase the federal minimum wage to \$15. The measure was defeated 58-42, with seven Democrats and one Independent senator joining the Republicans in voting against it. The vote was controversial and gained attention on social media, as the federal minimum wage affects millions of stakeholders on both sides of the debate. Senator Kyrsten Sinema received particular scrutiny on social media for voting against the amendment due to her spirited mannerisms on the Senate floor, as well as her prior reputation as a progressive Democrat. To that end, we ask: to what extent has Twitter users' opinion of the 8 Democratic/Independent Senators who voted against the \$15 minimum wage changed? We hypothesize that negative sentiment towards the no-voting Democrats and Independents significantly increased on Twitter in the days immediately after the vote.

Previous research on Twitter sentiment analysis is limited. A paper by E. Kouloumpios, T. Wilson, and J. Moore analyzed the ability of certain linguistic features, such as part-of-speech

tagging, and, in Twitter's case, hashtags, to predict the sentiment of Tweets¹. The study found that part-of-speech taggers display very limited usefulness, while existing sentiment lexica are more helpful when determining sentiment of microblog posts. Furthermore, a paper by H. Wang, D. Can, A. Kazemzadeh, F. Bar, and S. Narayan displayed the possibility of determining political opinions and sentiment from a large sample of tweets using real-time metrics.²

Methods

The first step of the process was data collection. We chose to use Twitter's own API to scrape relevant tweets, as it is accessible and has extensive documentation related to the needs of our study. After collecting a sample of 8,648 tweets, a comparison of TF-IDF scores was the first step of analysis. TF-IDF is helpful to the analysis because a measure of relative presence of certain words allows us to ascertain whether certain topics, attitudes, and sentiments are more present in each time period. Next, we calculated VADER and Afinn sentiment scores for each tweet. Since VADER considers a document as a whole, unlike Afinn, which calculates the sum of each words' sentiment, we decided a comparison using both metrics would be appropriate in order to give different perspectives on the change in sentiment. Finally, we performed a t-test on the VADER and Afinn sentiment scores to determine if there was a significant difference in average sentiment scores for each time period. The t-test is essential to the analysis because it allows us to differentiate between the sample means of each group and ascertain if their difference is statistically significant.

Results

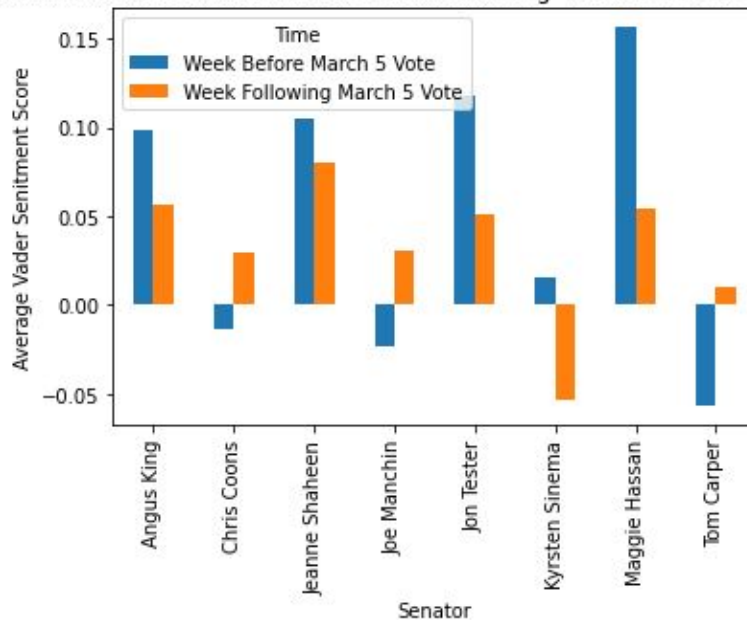
The terms with the highest TF-IDF scores were the names of the Senators in both time periods, and most of the terms at the top of these lists were sentiment-neutral, such as "senator" and "vote". In the set of tweets from before the vote, words that stood out as representing a clear sentiment were "pass" and "support", likely indicating some widespread support for the Senators in question voting in favor of the amendment. On the other hand, the word that stood out the most from tweets after the vote is "dump". Aside from these few key words, the TF-IDF scores did not reveal much change in opinion between the two time periods.

¹ Kouloumpis, E., Wilson, T., & Moore, J. (2011). Twitter Sentiment Analysis: The Good the Bad and the OMG!. *Proceedings of the International AAAI Conference on Web and Social Media*, 5(1). Retrieved from <https://ojs.aaai.org/index.php/ICWSM/article/view/14185>

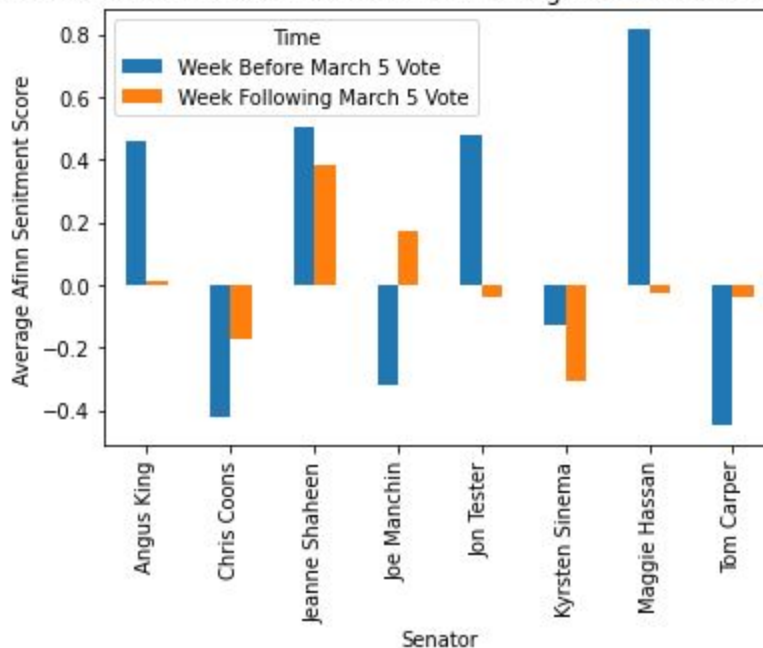
² Wang, Hao. "A System for Real-Time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle." *Association for Computational Linguistics*, 8 July 2012, A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle.

Splitting the corpus between senators, VADER and Afinn's assessment of the sentiment of the tweets can be seen in the graphs below.

Twitter Sentiment of Senators Before and After Voting "No" on Minimum Wage Increase



Twitter Sentiment of Senators Before and After Voting "No" on Minimum Wage Increase



The graphs show a clear decrease in perception of five of the Senators, whereas Chris Coons and Tom Carper of Delaware, as well as Joe Manchin of West Virginia, had an improvement in sentiment of tweets about them. Running a t-test on the sentiment analysis gave mixed results; Senators Sinema, Hassan, and Tester showed significant decreases in the sample mean, while the rest did not return a p-value within $\alpha = 0.05$.

From this data, the conclusions are clear: Senators Sinema, Hassan, and Tester saw a sharp increase in criticism following the vote, King and Shaheen saw mostly minor increases in criticism, and Coons, Carper, and Manchin saw increased positive sentiment. Since our hypothesis holds that sentiment uniformly decreased for all Senators, it is clear that it must be rejected.

Discussion

As previously stated, our data proves our hypothesis wrong; Twitter sentiment of the eight Democratic and Independent Senators voting against the minimum wage amendment did not uniformly decrease for all Senators. The data showed insignificant decreases for two of the Senators and increases for three. After briefly scanning the corpus and manually comparing tweets to their sentiment scores, it seems clear that sentiment scores accurately represent each tweet, in line with Kouloumpios et al.'s research on how existing lexica map to microblogs such as Twitter. Furthermore, the accuracy of these scores is in line with Wang et al.'s research on the possibility of mapping popular political opinion from Twitter.

A major limitation of our analysis is that the sentiment dictionaries we used are not necessarily in line with online political discourse. Certain political terms (such as "filibuster") may be attached to sentiments that are not accurately covered in VADER and AFINN, and may require a more politically-oriented dictionary (i.e. the Lexicoder Sentiment Dictionary (LSD)). Furthermore, the ability to ascertain sarcasm or humor is not a feature of these dictionaries, and tweets of these types are likely a major part of Twitter's political discussion.

With regards to future analysis, it may be possible to better answer our question by accounting for sarcastic or humorous tweets. This could be achieved by manually building algorithms to detect common joke formats or lists of terms that appear in these tweets. Additionally, analyzing a large sample of tweets from several months before and after the vote allows us to generate time series data of sentiment to more accurately model how exactly it was affected by the vote.