Analyzing Premeditation in Political Speech Patterns

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Word Count: 2685

Introduction:

Politicians work to garner the support of their constituents and collect as many votes as possible to win elections and join the U.S. Congress or U.S. Presidency. This paper aims to delve into the differences between political candidates for presidency and provide insights on possible connections that exists between readability and political alignment. By analyzing the tweets, debates and speeches of several Democratic and Republican politicians, we aim to try to answer the question if there exists a discrepancy between a politician through spoken language and written words. Do candidates from the two parties present themselves differently in order to appeal to different audiences? Understanding these strategies is essential to understand politicians' behaviors and distinguish between what they present to the general public and who they genuinely are.

By analyzing politicians' debate, speech and writing styles, we aim to show that politicians gain support through the careful handling of language. Readability scores can allow estimation of a person's traits and political alignment. As described by Schoonvelde et al., an averaged readability score is an indicator of linguistics habits; word and grammar choices, proportions of prepositions and pronouns are some of the concepts that make up linguistic habits. Linguistic habits, in turn, are indicators of psychological traits which influence an individual's political alignment. (Schoonvelde et al., 2019)

Literature:

This is not the first exploration into this field of analyzing politicians' spoken and written languages. The supporting literature behind our project was a study on the 2016 Presidential Election and the readability and grammatical analysis of the candidates running for office (Schumacher and Eskenazi, 2016). The standard approach method for such a study is where raw texts are collected and the readability is calculated individually on each document. There are numerous different metrics for readability suited for various needs. These scores are then averaged by author/speaker to obtain single readability scores for each. The study by Schumacher and Eskenazi employs a REAP readability model and other methods to analyze vocabulary content and syntax structure.

With millions of people regularly using social media sites to gather information, and interacting with one another, politicians around the globe have started to shift their battlegrounds from traditional media such as newspapers to social media platforms like Twitter to engage with their supporters and propagate their political ideologies. In a study that analyzes how Trump's tweets act as a source of fake news and disinformation, the authors find that politicians use tweets as a means of establishing credibility, and some, like Trump, would even position themselves as the only reliable sources of truth (Ross and Rivers, 2018). The political candidates' positive self-representation on Twitter is not difficult to understand. In a study that examines Dutch political candidates' Twitter usage and the impacts on votes, Kruikemeier collected tweets posted by candidates as well as their number of votes during the national elections. The findings of the study suggested that Twitter usage during the campaign has a positive impact on the number of votes received (Kruikemeier, 2014).

Similar to tweets that are carefully crafted, speeches that are also deliberately constructed in advance, have also been used by politicians for decades to not only pose themselves as straight-laced and confident, but also to gather support for practices of their own interests (Oddo, 2011). In contrast to tweets and speeches that are pre-prepared and possibly written by other individuals, debates force candidates to face some unanticipated questions or criticisms. Thus, debates are worth analyzing because they reveal candidates' subconscious behaviors, language usage, and offer voters a more candid view of the candidates than other messages such as speeches (Benoit et al., 2007).

Prior works analyzed political candidates' handling of language in speech, debates and online platforms separately; but the comparisons between their language use under these different settings is lacking. Our work therefore is meant to fill the gap by examining how and why politicians present themselves differently when tweeting, debating and delivering speeches.

Theory and Hypotheses:

The goal of this study is to run some sentiment analysis on politicians' tweets, speeches and debate transcripts to reveal any latent structures. Specifically, we are interested in whether and how political candidates target different groups of voters and if they handle languages differently to adapt to various situations. Our hypothesis is that candidates from the same party would have similar political ideologies and are thus likely to adopt similar language patterns to capture the same groups of voters. On the other hand, candidates from different parties generally have distinct political views and will likely adapt to different writing and speaking habits.

We also hypothesize that the candidates do not use their language in the same manner when writing, debating and delivering speeches. This is mainly due to two reasons. Firstly, politicians deliberately alter their language styles to cater to different audiences to garner support. Secondly, in contrast to tweets and speeches that are pre prepared and possibly written by other individuals, debates require candidates to construct their language in a time-limited and stressful environment. We thus expect to see a decrease in language complexity in debates for most candidates.

Data and Methods:

This portion of our project aimed to collect a breadth of data that covers the variations between a candidate's written portrayal in the form of speeches and a spoken portrayal in the form of debates. The idea in mind was to capture the premeditated and carefully planned patterns in a candidate's campaign and how they attempt to appear which contrasts with how they truly speak during a heated debate where they must draft responses quickly and with a lesser amount of deliberation.

By integrating data from various sources, we obtained a dataset of approximately 36000 tweets from six candidates of the four most recent presidential elections. From the Democrat party, Hillary Clinton, Bernie Sanders, Barack Obama, and Joe Biden’s tweets were collected and the Republican platforms of Donald Trump and Ted Cruz were collated. The dates of the tweets range from early 2007 to late 2020 to capture the presidential campaigning and outreach for each candidate.

As a contrast to the little information that is captured in a 280-character tweet we also manually collated and created two corpuses. The transcript of political debates between candidates were collated after being filtered to contain speech from a single candidate; this created our *Debates* corpus. The debates were collected for presidential candidates from the 2012 to the 2020 election. The *Speeches* corpus was created using transcripts collected from Democratic or Republican primaries or national conventions with respect to the candidates party.

The debates serve as the prompt locution while the speeches reflect the pre-written and deliberate language chosen by the writers.

Preprocessing:

We preprocessed the tweets by changing all words to lowercase, stemming and removing stop words. To only include tweets that are the candidates' original work, we also filtered out all the retweets in the dataset.

Cosine Similarity Scores:

Since we assumed that candidates from the same party target similar voters and tend to have opposing political ideologies with those from the other party, we would want to know candidates' language similarities both within and across parties. We thus calculated the cosine similarities between all candidates in the dataset and put the resulting similarity matrix into a heatmap for better visualization. It is worth noting that we chose cosine similarity as our metric because it is both widely used and easy to interpret.

Readability Analysis:

To examine which groups of voters each candidate tries to target, we need to analyze the easiness of the candidates' tweets, speeches and debates in terms of understandability. We thus calculated their average Flesch-Kinkaid scores under all three settings. Since we were also interested in whether politicians change strategies to cater to different audiences, we calculated the standard deviation of their speech readability scores. Although numerous studies have also conducted sentiment analysis on politicians' writing, speeches or debate transcripts, they were not satisfactory for our purposes since they only evaluated candidates' performances under one of the three settings. Therefore, prior methods were not sufficient to answer our question of whether politicians are disingenuous and how they present themselves distinctly to gather support when facing different situations. This is essential as for instance, compared to writing a carefully crafted tweet or pre preparing a speech, political candidates are under a higher stress level during a heated debate; they are also likely to face unanticipated questions or comments from opponents. How the candidates change their tools and strategies are thus worth exploring. Therefore, we also calculated how candidates' flesch scores change from speeches to debates.

Results:

Since we were interested in how similar the candidates are when writing, we calculated the cosine similarities of the candidates' tweets. Figure 1, shown below, is a heatmap that summarizes the results. As expected, for all candidates in the dataset, the politician they are the most similar to in terms of writing style, is a counterpart of their respective parties. For instance, Trump and Cruz have a cosine similarity score of 77%, higher than their similarities with any of the Democratic presidential candidates. Obama seems to have a relative low cosine similarity score with all other candidates except for Biden, whose tweets are 70% similar to the former president's.

Surprisingly, Joe Biden and Bernie Sanders have an exceptionally high similarity score of 96%. We think that there are two plausible explanations. First, Biden and Sanders might have attempted to appeal to the same groups of voters; therefore, they campaigned in a similar fashion. Secondly, tweets are limited to 280 characters or less, the small character limit therefore might have failed to capture the differences between Sanders and Biden's tweets.

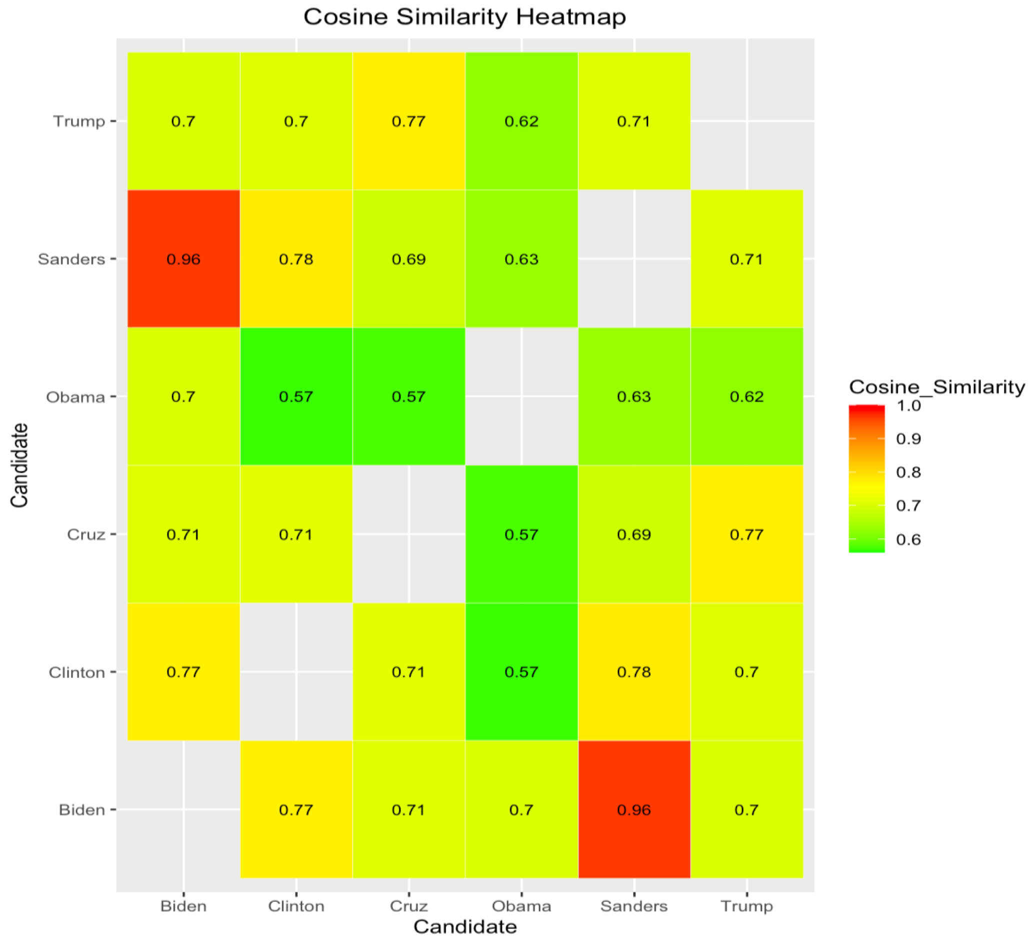

Figure 1: *Cosine Similarity between Candidates' Tweets*

Overall, the high within-party cosine similarities observed was consistent with our hypothesis, as candidates from the same parties are more likely to propose similar policies and target the same groups of voters. However, contrary to what we hypothesized, the cross-party cosine similarities were not significantly lower than the within-party ones. For example, Trump had a similarity score of 70% or higher with all Democrats except for Obama. This phenomenon might have occurred because candidates address the same issues in their tweets. Although politicians from different parties might hold completely opposing opinions, cosine similarity fails to capture this detail if the topics of discussion are the same.

The Flesch-Kinkaid scores for each candidate's individual tweets, speeches and debates, the values were calculated and then averaged together with respect to each candidate. These are shown in the tables one to three in the Appendix. Tables one to three show the mean Flesch-Kincaid scores for each candidate's tweets, speeches, and debates respectively.

Figure 2 displays the standard deviation of the readability scores of their speeches for each candidate. This could indicate how that candidate varies their speech depending on their location and audience.

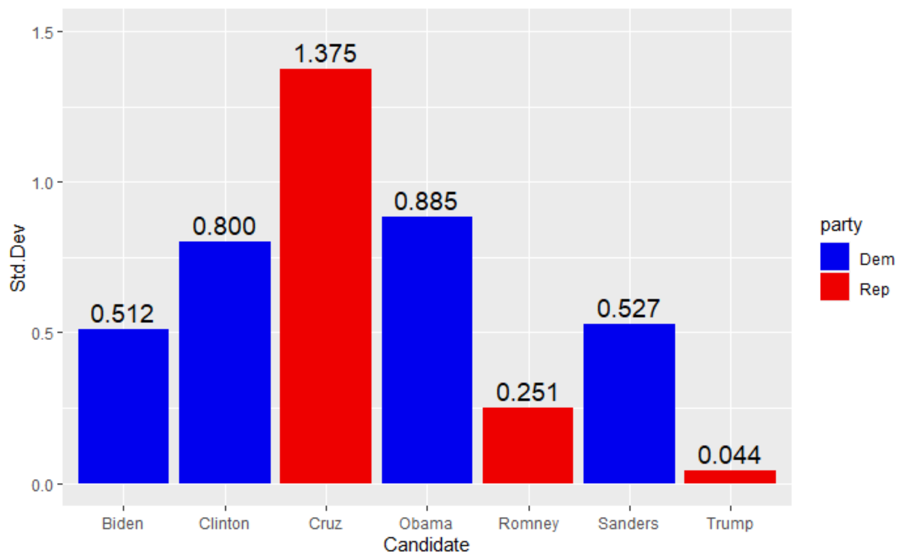

Figure 2: *Standard deviation of readability scores of speeches by candidate*

Here, we can see that Senator Cruz adapts his speeches by a large margin depending on his setting and target audience. Donald Trump has a very small deviation between his speeches; a value that is almost 0. Though speculative, it is possible that the readability is almost identical between the two speeches in our sample as they may have the same speechwriter. This brings us to Figure 3a which displays the difference between the readability of the candidates speech and the candidates debates. This difference is the change from the speeches to the debates. As an example, President Obama sees a 1.22 increase in mean Flesch-Kincaid from his written speech to his spoken language. As each candidate starts at a different initial score for speech, Figure 3b shows the absolute percent change in each candidate's scores.

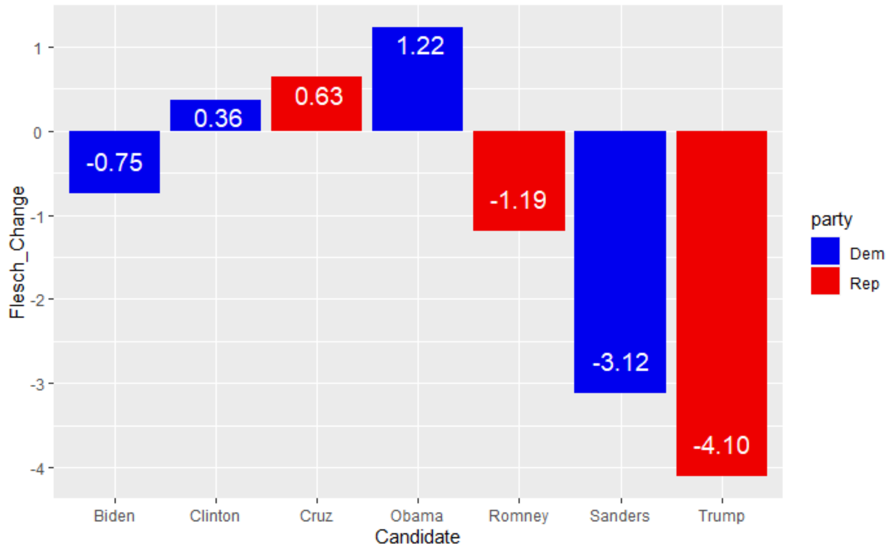

Figure 3a: *The difference between a candidate's speech and debate Flesch-Kincaid scores. In the form given by Flesch-Kincaid*$_{Speech}$ *- Flesch-Kincaid*$_{Debate}$

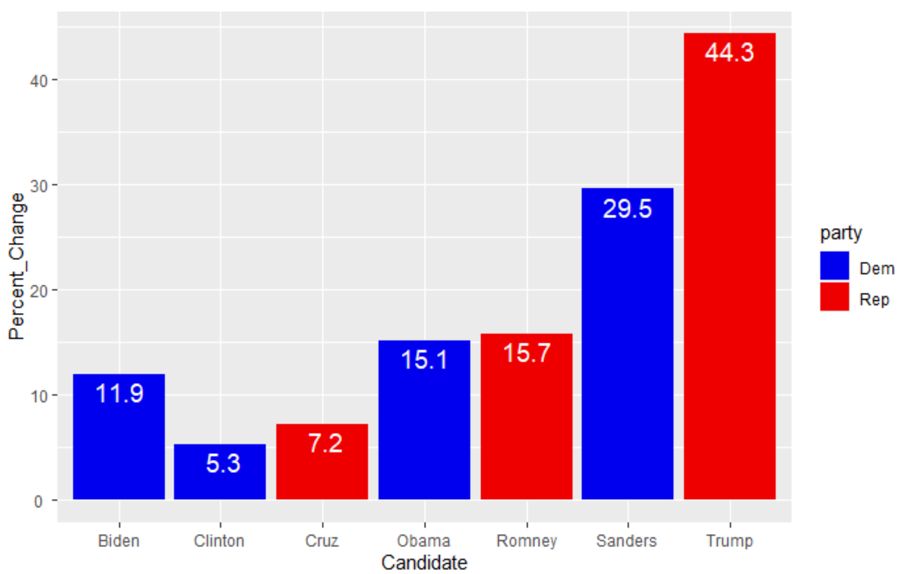

Figure 3b: *The difference between a candidate's speech and debate Flesch-Kincaid scores given in absolute percent change.*

Figure 3b details the contrast between how a politician appears in writing through speech and how they appear in conversation through debate. A higher percentage indicates a higher discrepancy between the scores. Though speculative, a large decrease, as seen with Donald Trump, may indicate that a staffer or aide is hired to write large proportions of his speeches in a noticeably different manner than his normal speech patterns.

Discussion:

This study reinforces previous studies and reconfirms their findings. Schoonvelde et al., discusses a study done that shows that American and British conservative politicians use less complex statements to convey their points as opposed to their liberal counterparts. Results shown in Table 3 agree with the previous findings as the Republican party's average readability score is 0.4 below the Democratic party. Studying readability on political candidates whose political stance and ideology is known allows a link to be formed between linguistic habits and political ideology. If studied further, it may be possible to use the average readability to find the location of a non-congressional/parliamentary individual on a political spectrum. We note that the aforementioned link would require a very large number of documents to capture the true linguistic habits and psychological traits of a person. Given more time, our next steps would be to create larger collections of documents, of both speeches and debates, to strengthen our findings.

References:

Benoit, William L., Wei-Chun Wen, and Tzu-hsiang Yu. "A functional analysis of 2004 Taiwanese political debates." *Asian Journal of Communication* 17.1 (2007): 24-39.
Kruikemeier, Sanne. "How political candidates use Twitter and the impact on votes." *Computers in human behavior* 34 (2014): 131-139.

Oddo, John. "War legitimation discourse: Representing 'Us' and 'Them'in four US presidential addresses." *Discourse & Society* 22.3 (2011): 287-314.

Ross, Andrew S., and Damian J. Rivers. "Discursive deflection: Accusation of "fake news" and the spread of mis-and disinformation in the tweets of President Trump." *Social Media+ Society* 4.2 (2018): 2056305118776010.

Schoonvelde, Martijn, et al. PLoS ONE, 2019, *Liberals Lecture, Conservatives Communicate: Analyzing Complexity and Ideology in 381,609 Political Speeches*, journals.plos.org/plosone/article?id=10.1371/journal.pone.0208450.

Schumacher, Elliot, and Maxine Eskenazi. Language Technologies Institute, 2016, *A Readability Analysis of Campaign Speeches from the 2016 US Presidential Campaign*, arxiv.org/ftp/arxiv/papers/1603/1603.05739.pdf.

Data Sources:

Tweets:

1. https://github.com/pablobarbera/social-media-workshop/blob/master/data/candidate-tweets.csv
2. https://www.kaggle.com/rohanrao/joe-biden-tweets
3. https://github.com/fivethirtyeight/data/blob/master/twitter-ratio/BarackObama.csv

Speeches and Debates:

1. J. Biden. Atlanta Convention Speech, (2020)
2. J. Biden. DNC Convention, (2020)
3. H. Clinton. Tampa Convention Speech, (2016)
4. H. Clinton. DNC Convention Speech, (2016)
5. B. Obama. Iowa Convention Speech, (2012)
6. B. Obama. DNC Convention, (2012)
7. B. Sanders. Iowa Convention Speech, (2019)
8. B. Sanders. DNC Convention Speech, (2020)
9. T. Cruz. South Carolina Convention Speech, (2016)
10. T. Cruz. RNC Convention Speech, (2016)
11. M. Romney. Ohio Convention Speech, (2012)
12. M. Romney. RNC Convention Speech, (2012)
13. D. Trump. Wisconsin Convention Speech, (2016)
14. D. Trump. RNC Convention Speech, (2016)
15. J. Biden. First Presidential Debate Transcript, (2020)
16. D. Trump. First Presidential Debate Transcript, (2020)
17. B. Sanders. Presidential Primary Speech, (2020)

18. J. Biden. Democratic Nomination Debate, (2020)
19. H. Clinton. First Presidential Debate Transcript, (2016)
20. D. Trump. First Presidential Debate Transcript, (2016)
21. B. Obama. First Presidential Debate Transcript, (2012)
22. T. Cruz. Republican Presidential Debate, (2016)
23. M. Romney. First Presidential Debate Transcript, (2012)

Appendix

Mean Flesch-Kincaid for Tweets		
Candidate	**Flesch-Kincaid**	**Party**
Biden	7.93	Dem
Clinton	7.58	Dem
Cruz	8.56	Rep
Obama	8.60	Dem
Sanders	8.69	Dem
Trump	8.90	Rep

Table 1: *Mean Flesch-Kincaid Scores that are averaged over all tweets by each candidate, respectively.*

Mean Flesch-Kincaid for Speeches		
Candidate	**Flesch-Kincaid**	**Party**
Biden	6.29	Dem
Clinton	6.87	Dem
Cruz	8.83	Rep
Obama	8.11	Dem
Romney	7.54	Rep
Sanders	10.57	Dem
Trump	9.24	Rep

Table 2: *Mean Flesch-Kincaid Scores that are averaged over all speeches by each candidate, respectively.*

Mean Flesch-Kincaid for Debates		
Candidate	**Flesch-Kincaid**	**Party**
Biden	5.55	Dem
Clinton	7.23	Dem
Cruz	9.47	Rep
Obama	9.33	Dem
Romney	6.36	Rep
Sanders	7.45	Dem
Trump	5.15	Rep
Dem Party	7.39	
Rep Party	6.99	

Table 3: *Mean Flesch-Kincaid Scores that are averaged over all debates by each candidate, respectively. The last two rows are the averages computed by party.*