President Trump's Presidential Campaign Speeches

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1. Question of Interest

Due to the advancement of social media and the COVID pandemic, many offline advertising and campaigns move to online platforms, including one of the major political events: the 2020 presidential election. While online campaigns can quickly reach millions of audiences, the presidential candidates still embrace in-person rallies since speaking directly to electorates enables them to display more attention to the voters and augment their chance of winning votes in important areas by discussing local issues. Very valuing direct appeals to voters, in the 2020 presidential election, President Trump gave more than 80 in-person rally speeches from August 2019 to November 2020, which outnumbered Joe Biden's speeches by around 30. Given the election result, one of the interesting questions for the post-election analysis is to identify President Trump's in-person campaign strategy. While Trump seemed to consistently focus on the existing voter base and primarily applied psychological warfare in his campaigns, it is interesting to explore how his speeches changed in blue areas, red areas, and battlegrounds. In detail, this project studied the following hypotheses:

(a) Trump's rally speeches were not different among the four types of the states: red, blue, swing but eventually red, and swing but eventually blue.

(b) Trump's rally speeches were not different between blue counties and red counties.

(c) There is no difference in Trump's rally speeches for different combinations of state types and county types.

2. Data Collection and Preprocessing

The ideal data collection method is to acquire the speech materials directly from Trump's campaign, including scripts and audios, which allows this project to perform both text analysis and speech analysis. In order to study President Trump's in-person campaign strategy more comprehensively, it would also be ideal to collect the speeches given by his family members and important allies that are part of the campaign.

The current data set used in this project contains the 83 transcripts of President Trump's campaign speeches across 23 states and 77 cities and counties, dated from August 2019 to November 2020. The speeches were scrapped from *rev.com* using Beautiful Soup Python Package. While the data set has the most complete speech collection that can be found, it may not be sufficient to answer the research questions since it does not contain the in-person speeches given by Trump's allies as in the ideal situation. Another limitation of the data set is that since the transcripts are processed by a third party using its AI technology, there exist some inaudible words, which may have certain influence on the analysis. Also, since the majority of speeches were in swing states, the comparison between swing states and red and blue states may lack of information. Despite the limitations, this project could still serve as a prototype of future analysis and thus proceeded.

The dataset was preliminarily preprocessed as follows. First, the location (state and county) and the location type (blue, red, and battle ground) of each speech were referred from *New York Times* and hand labelled. Then, the parts of the transcript that were shown as inaudible and did not correspond to Trump's utterance (journalists' questions, introduction by another speaker, audience's reaction) were removed.

3. Methodology

To study each of the hypotheses, this project examined the length, emotions, topics, and keywords of the speeches.

3.1 Length

Each of the speeches was tokenized into sentence-tokens and word-tokens. By aggregating the speeches by the 4 state types, the average number of sentences and average number of words of speeches within each group were calculated. To compare the significance of the between-group differences, Kruskal-Wallis rank sum test, or one-way ANOVA on ranks, was used given the data is not normally distributed. Similarly, Wilcoxon rank sum test was applied to compare the significance of differences of the speech lengths between speeches in red counties and blue counties. Additionally, to examine the lengths of speech in different combinations of state and county types, two regression models were created: one with speech length against state type and county type, the other with speech length against both types and their interaction terms. The significance of the interaction terms was tested using partial F-test. If the test is significant, coefficient and significance of each interaction terms were observed.

3.2 Emotions

NRCLexicon is applied to extract 2 sentiments (positive and negative) and 8 common emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) from the speeches. Each speech would have its affect frequencies that sum up to 1. By grouping the speeches by state types and county types, I compared the mean frequency of each emotion in the speeches across location types.

3.3 Topics

Topic Modeling is performed to extract main themes of Trump's speeches. Two major topic modeling techniques --- Latent Dirichlet Allocation and Non-negative Matrix Factorization --- were tested with different parameters, and number of topics, and different input texts (tokens with different Part-of-Speech tags) to generate the model that produces the most meaningful and interpretable topics. Based on the best performing model, each speech was given a probability distribution of topics. Entropy would be used to measure the diversity of topics of a given speech. Kruskal-Wallis rank sum test was used to measure the significance of differences in median entropy of speeches among different type of states, and Wilcoxon rank sum test was applied to measure the entropy on county level. If significant results were found, post-hoc analysis would be conducted to determine which levels of the independent variable differ from each other level. Each speech would also be assigned a main topic and based on the probability distribution and compared state-wise and county-wise.

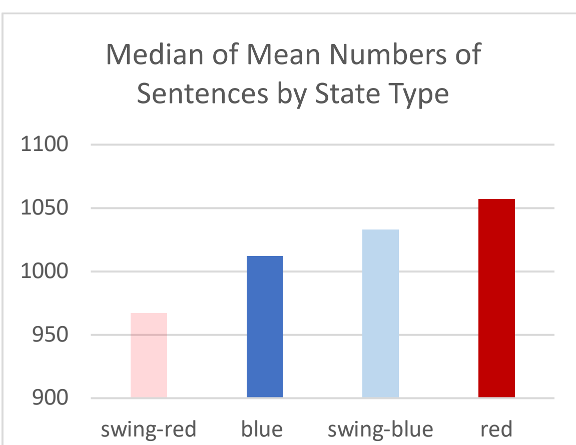
3.4 Keywords

To better understand the topic distributions among different states and counties, words that signify the topics, such as economy, and immigration, were extracted to examine in detail. I counted the number of times each word appeared in each speech and calculated the average number of appearances among speeches within each state type and county type. Similar to the comparison of speech lengths, statistical hypothesis tests were given to inform the significance of the differences in number of appearances: Kruskal-Wallis rank sum test for comparison among 4 state types, Wilcoxon rank sum test for comparison in red counties and blue counties, and Partial F-test for the regression of counts of words against different combinations of state and county types.

4. Analysis and Results

4.1 Speech Length

Figure 1 – 3 below displays the main effects and interaction effects of state type and county type on the median of average numbers of sentences within each group. We can observe that President Trump tended to speak more sentences in red states and red counties. However, the Kruskal-Wallis rank sum test and Wilcoxon rank sum test found that the medians of average number of sentences of speeches are not significantly different across different types of states ($Chisq(3) = 2.4289$, $p = 0.4883$) and different types of counties ($W = 962.5$, $p = 0.2323$). Similarly, there existed no significant interaction effect between state type and county type according to the Partial F-test with the null hypothesis that all the interaction equal 0 in the linear regression model that predicts the average numbers of sentences ($F(3,75) = 1.5172$, $p = 0.217$). The insignificant interaction effect is consistent with Figure 3 that the median of average number of sentences in red counties is consistently higher than that of blue counties across all states.



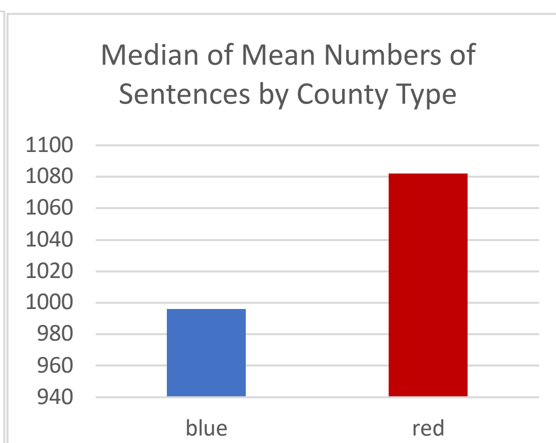


Figure 1 and 2: Median of Mean Numbers of Sentences by State (left) and County Type (right)

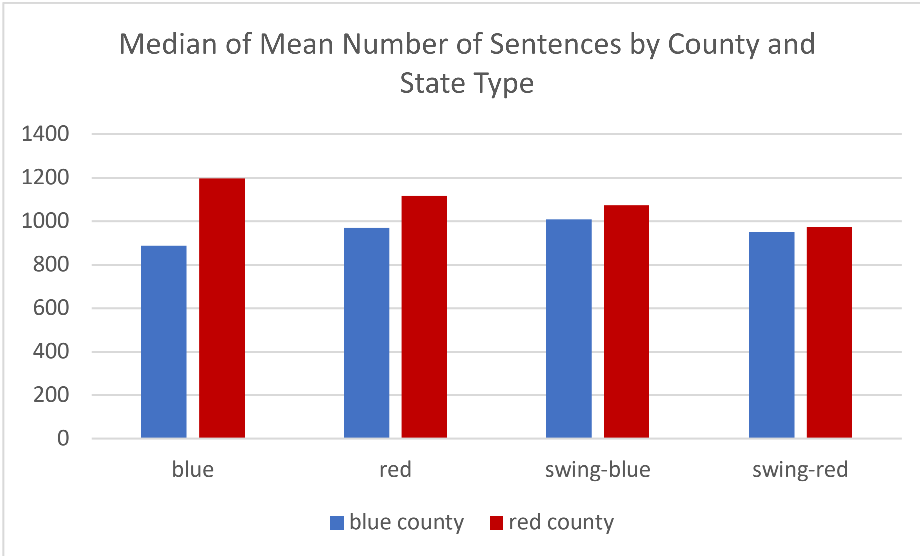


Figure 3: Median of Mean Numbers of Sentences by State and County Type

Figure 4 – 6 below displays the main effects and interaction effects of state type and county type on the median of average numbers of words within each group. The figures show that on state level, President Trump tended to use more words in blue states. However, he spoke more words in red counties on county level, and such result is approximately consistent across all states except the swing states that turned blue. As for the statistical test results, the Kruskal-Wallis rank sum test and Wilcoxon rank sum test found that the medians of average number of words of speeches are not significantly different across different types of states ($Chisq(3) = 0.43031$, $p = 0.9339$) and different types of counties ($W = 911.5$, $p = 0.4701$). Also, no significant state type x county interaction effect was found according to the Partial F-test with the null hypothesis that all the interaction equal 0 in the linear regression model that predicts the average numbers of words ($F(3,75) = 1.6322$, $p = 0.1891$).

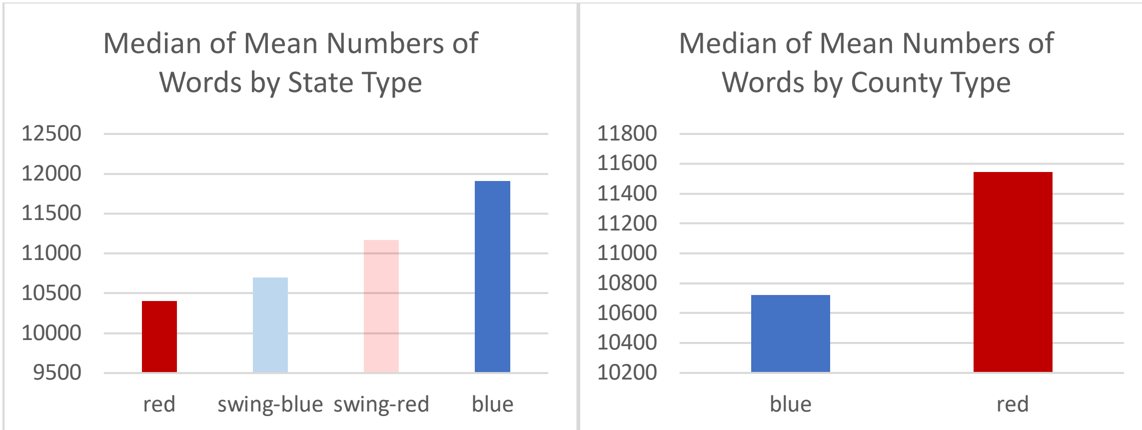


Figure 4 and 5: Median of Mean Numbers of Words by State (left) and County Type (right)

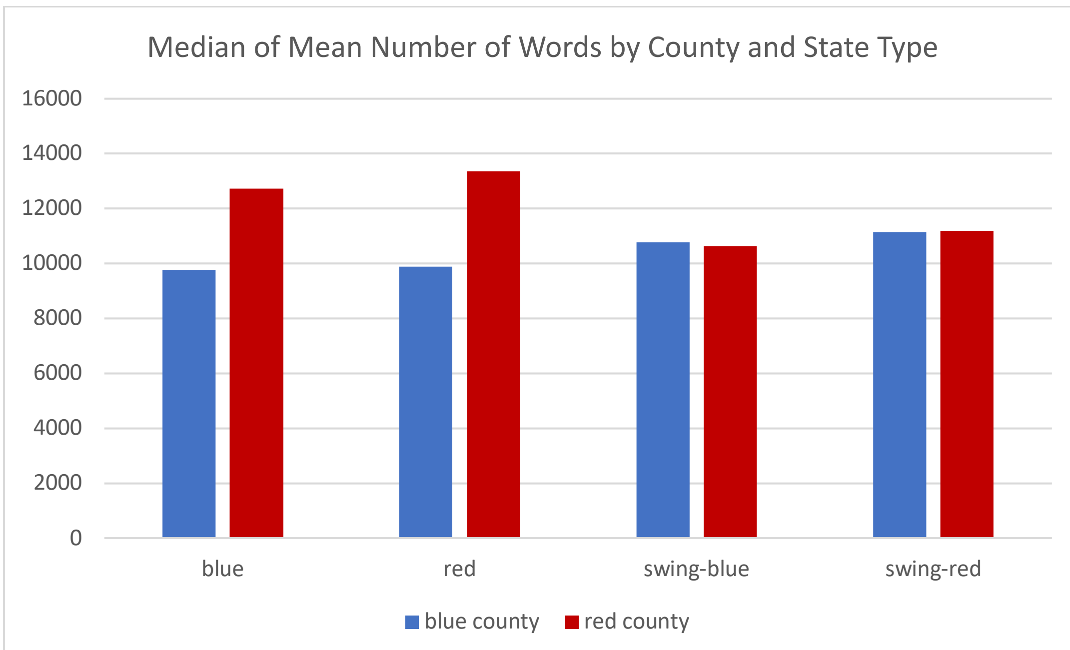
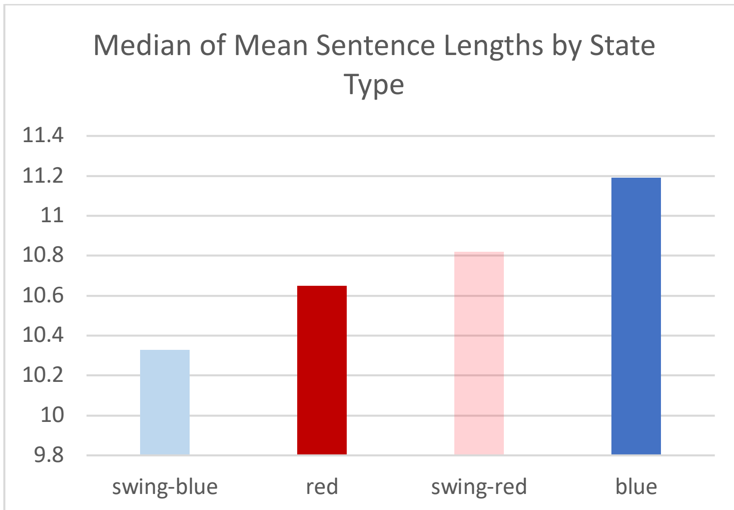


Figure 6: Median of Mean Numbers of Words by State and County Type

Despite the tests above shows no significance in differences of numbers of sentences and words across the states and counties, the visualizations of statistics for state type (figure 1 and 4) displays different patterns that President Trump seemed to use more sentences and fewer words in red states than in blue states. Therefore, statistical tests were conducted to explore the average sentence length of President Trump's speeches. However, no significant results were found by Kruskal-Wallis rank sum test (*Chisq*(3) =

6.1418, p = 0.1049), Wilcoxon rank sum test (W = 787, p = 0.6735), and partial F-test ($F(3,75)$ =1.4938 , p=0.2231). Overall, President Trump's speeches were approximately the same lengths across all rallies.



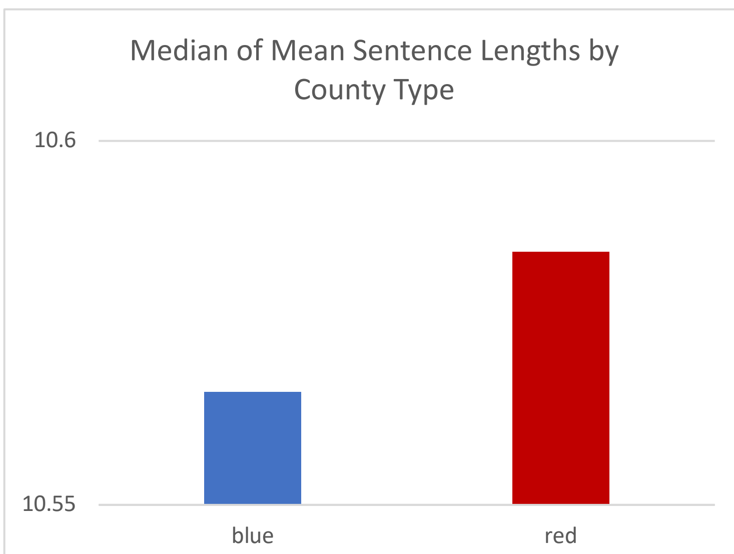


Figure 7 and 8: Median of Mean Sentence Length of Words by State and County Type

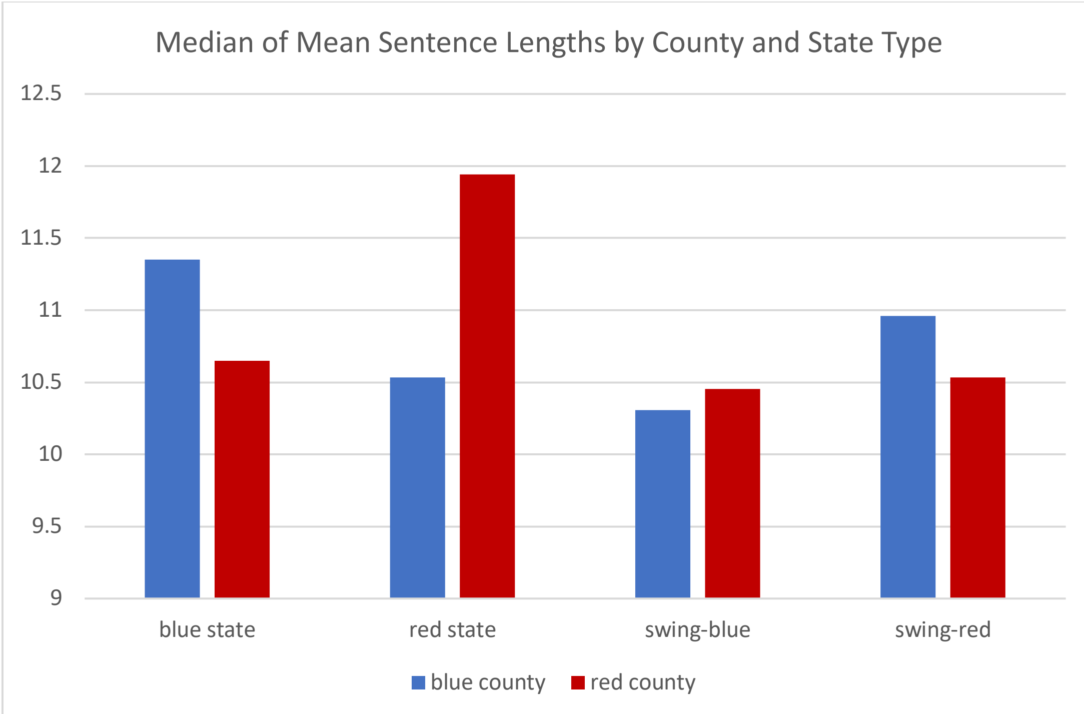


Figure 9: Median of Mean Sentence Length of Words by State and County Type

4.2 Emotion Analysis

The medians of frequencies of emotions by state type and county type are shown in figure 10 and 11. We can observe from both figures that speeches across different states and counties have similar distributions with higher frequencies of positive, trust, and negative emotions. While the differences of frequencies of emotions among states are very small, speeches in red states tended to have higher proportion of negative emotions (fear, anger, negative, sadness, and disgust) and lower proportions of positive emotions (joy, positive, trust, anticipation, and surprise). On the county level, speeches in red counties seem to express more positive emotions, but the differences are too small to declare significance. In sum, President Trump carried a similar tone across all rally speeches, which was relatively positive.

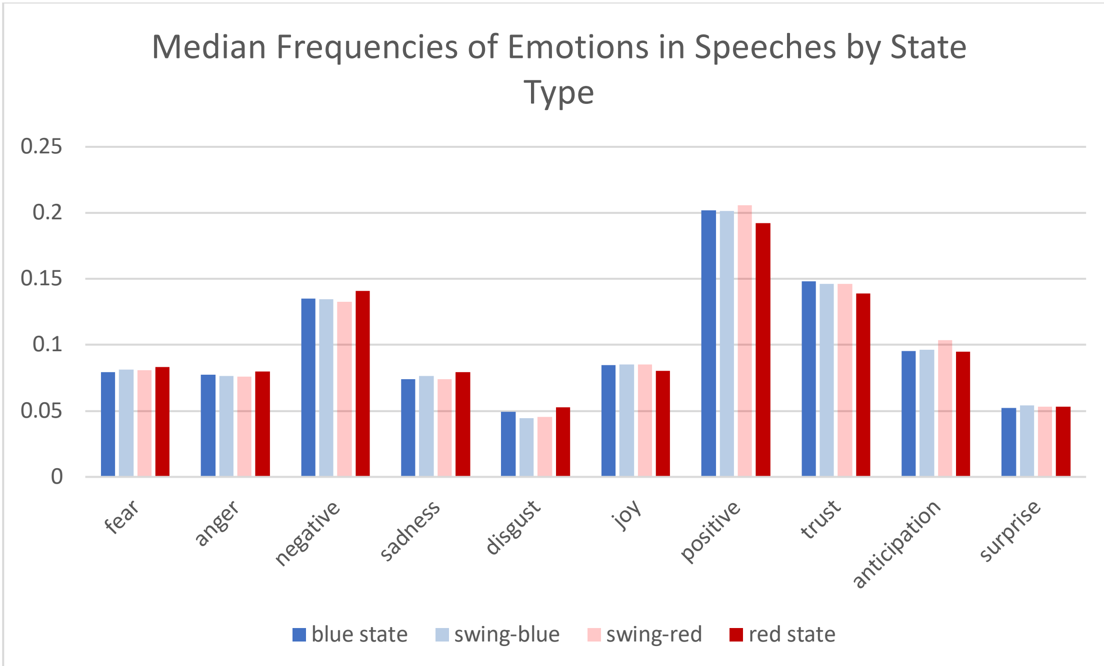


Figure 10: Median Frequencies of Emotions in Speeches by State Type

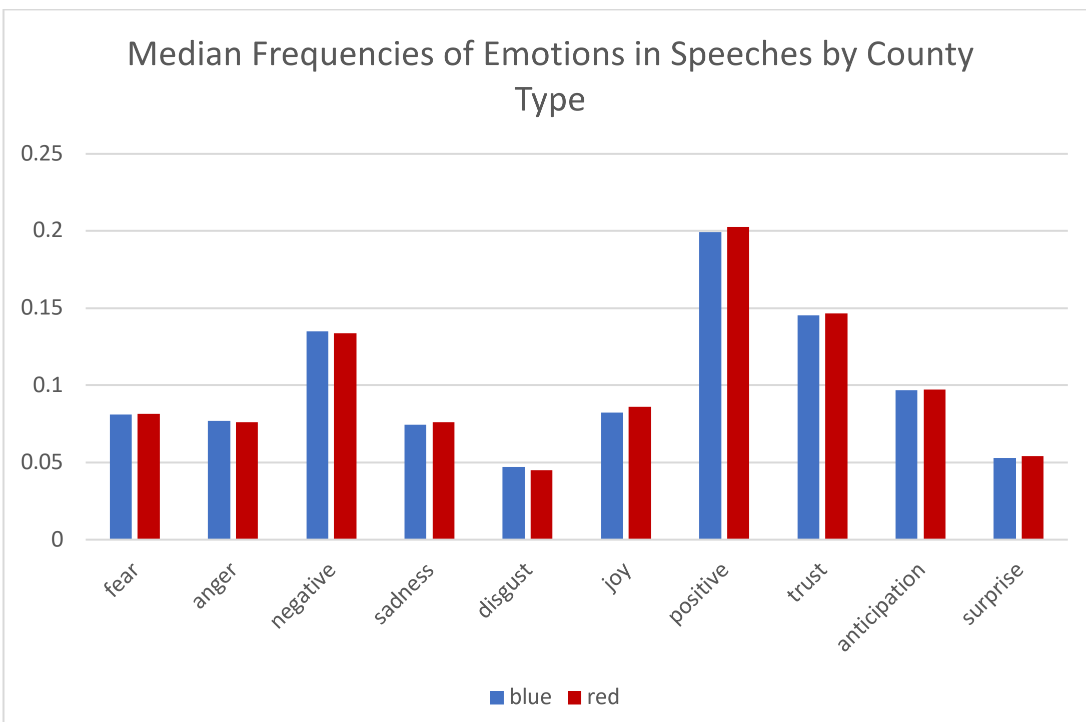


Figure 11: Median Frequencies of Emotions in Speeches by County Type

4.3 Topic Modeling

Topic modeling using nouns, adjectives, verbs and adverbs in the speeches and applying NMF on tf-idf vectors with 5 topics produced the most meaningful and interpretable topics. The topics and some of their top lemmas are shown in Table 1.

Table 1 Topics and Their Main Lemma Found by NMF

Main Topic Theme	**Main Topic Lemma**
Economy	trend, economy, lockdown, tech, school, ban, oil
Immigration	wall, illegal, unemployment, alien, immigration, welfare
Election	ballot, nominate, statue, endorse, sign, protest, corrupt
Healthcare/COVID	vaccine, doctor, immune, save, regulation, test, virus
Minority	black, community, 3rd, indian, latino, color, hispanic

Within NMF, each speech is given a probability distribution of five topics. By looking at the median entropy of the distributions for speeches across state type as shown in figure 11 and 12, we can see that the median entropy scores are very different, with the highest in swing states that turned blue and lowest in blue states. On the county level, speech topics in red counties were a bit more diverse than in blue counties.

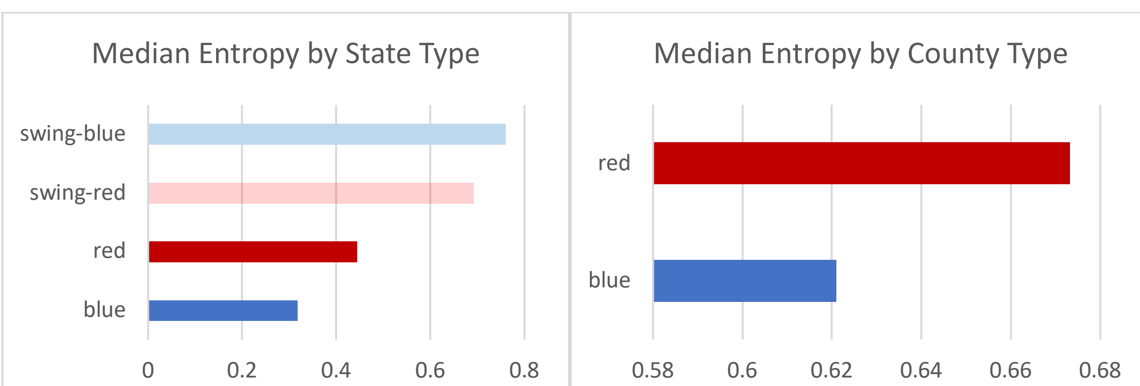


Figure 11 and 12： Median Entropy of Speech Topic Distribution by County Type

Kruskal-Wallis rank sum test found significant differences among the medians of entropy, *chisq*(3)= 10.92, $p = 0.01217$. Given such result, Dunn test (1964) for post-hoc analysis was conducted with the result shown in table 2. The table shows that the median entropy in swing states that turned blue is significantly larger than the median in blue states at the significant level of 0.05 and in swing states that turned red at the level of 0.1. The effect of county type and the state type x county type interaction effect on the median entropy are not significant according to the Wilcoxon rank sum test ($W = 877.5$, $p = 0.6837$) and partial F-test ($F(3,75) = 1.2278$, p=0.3056). The results revealed that compared to the speeches in blue states and swing states that turned red, speeches in swing states that turned blue touched on much more diverse topics.

Table 2 Dunn (1964) Kruskal-Wallis Multiple Comparison

Comparison	Z	P.unadj	P.adj
blue states - red states	-0.7585892	0.44809831	0.53771797
blue states - swing-blue	-3.0151934	0.00256815	**0.01540893****
red states - swing-blue	-1.7738299	0.07609129	0.15218259
blue states - swing-red	-2.3573312	0.01840682	**0.05522047***
red states - swing-red	-1.2550267	0.20946906	0.31420359
swing-blue - swing-red	0.7215371	0.47057911	0.47057911

Notes on Significance Level: **0.1*, 0.05**, 0.01*****

Each speech was assigned a main topic with the highest probability. Looking at the main topic of speeches as shown in figure 13, we can observe that speeches in blue and red states focused on fewer topics than in swing states and primarily on immigration. The minority topic was not shown in speeches in red states and barely discussed in swing states that turned blue. In swing states, topics related to healthcare and COVID were more frequently mentioned in speeches than other topics.

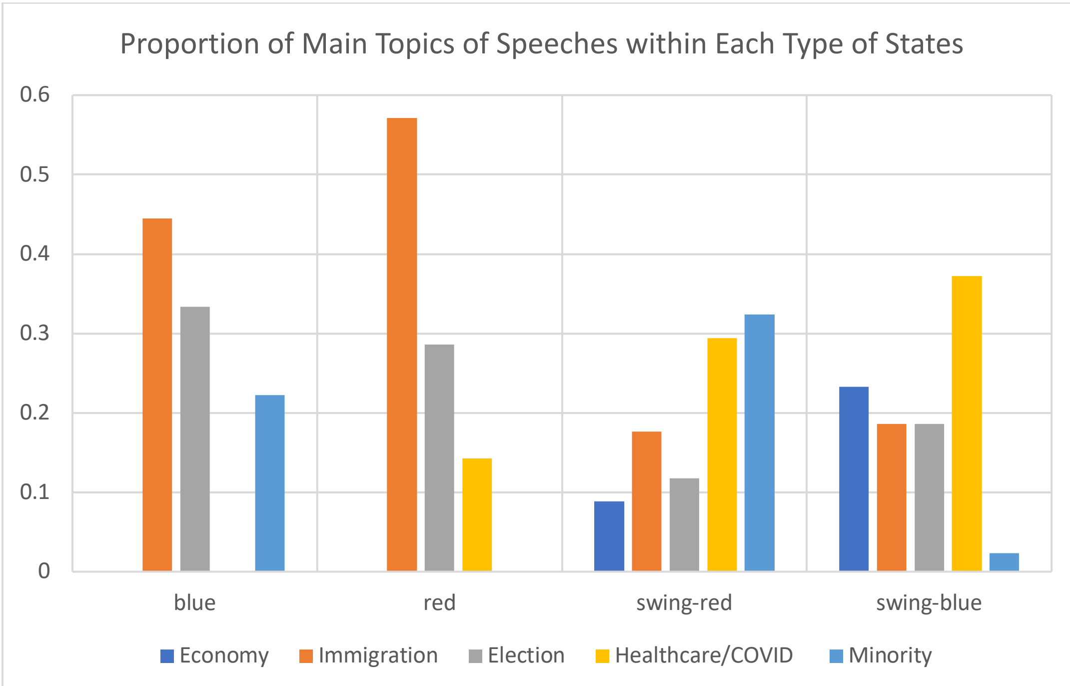


Figure 13: Proportion of Topics of Speeches within Each Type of States

Similarly, on the county level, figure 14 shows that minority did not appear as a main topic among speeches in red counties. Compared to speeches in red counties, speeches in blue counties stressed more on immigration and less on economy and healthcare.

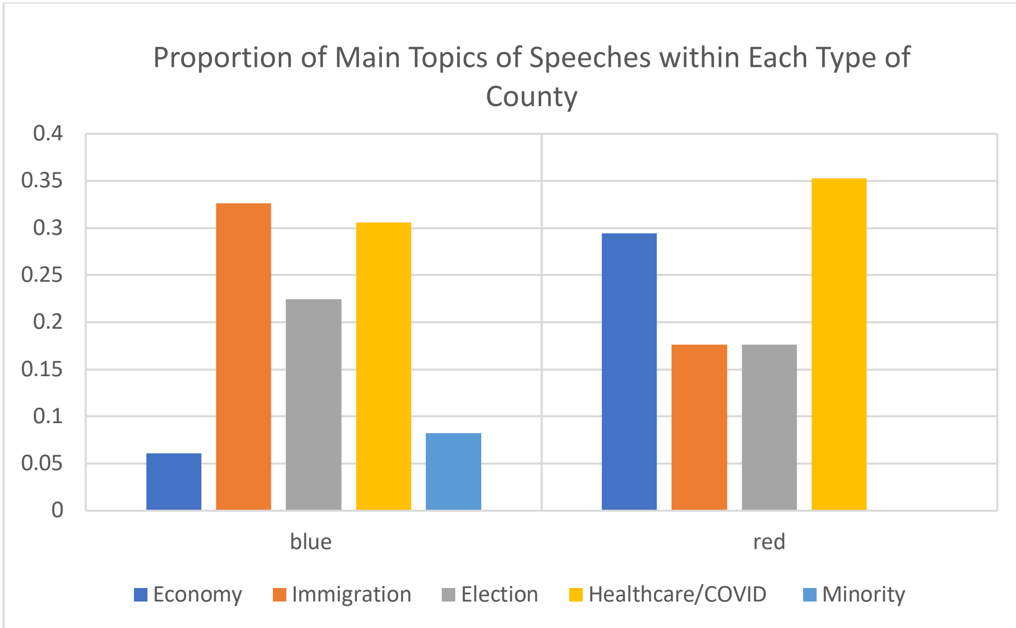


Figure 14: Proportion of Topics of Speeches within Each Type of Counties

By further grouping the speeches by state type, county type, and main topics as in table 3, we can have a clear view that President Trump mentioned minority in red states and swing states that turned red, he only talked about it in blue counties of those states, which again indicated that President Trump tailored the minority topic to blue areas.

Table 3 Speeches by State Type, County Type, and Main Topic

State Type	County type	Main Topic	Number of Speech
blue	blue	Immigration	2
		Election	2
		Minority	2
	red	Immigration	2
		Election	1
red	blue	Economy	1
		Immigration	3
		Healthcare/COVID	1

	red	Immigration	1
		Election	2
swing-blue	blue	Economy	1
		Immigration	6
		Election	6
		Healthcare/COVID	10
		Minority	1
	red	Economy	9
		Immigration	2
		Election	2
		Healthcare/COVID	6
swing-red	blue	Economy	2
		Immigration	5
		Election	3
		Healthcare/COVID	4
		Minority	1
	red	Economy	1
		Immigration	1
		Election	1
		Healthcare/COVID	6

4.4 Keyword Analysis

While the topic modeling gave an overview on the variation of topics of Trump's speeches among different locations, the lemmas that are less relevant to a topic still created noise to the topic analysis. Therefore, keywords that are closely related each of the five topics were extracted from the speeches respectively and counts of each category of words were recorded for each speech as in table 4. Statistical tests for comparison of word counts across speeches for each topic were conducted to further investigate the significance of differences in topic distributions. The results are shown in table 5.

Table 4: Keywords Related to 5 key topics

Topic	**Relevant Keywords**
Economy	economy, oil, trade, company, business, tariff
Immigration	wall, illegal, alien, immigration, immigrant, border
Election	ballot, nominate, endorse, vote, president, election, elect, biden
Healthcare/COVID	vaccine, doctor, immune, save, test, virus, patient, covid, quarantine, health, healthcare, lockdown
Minority	black, indian, latino, color, hispanic, minority

Table 5: P-values of Statistical Tests for Counts of Keywords by Topic

	Kruskal-Wallis Rank Sum Test (Main Effect for State Type)	Wilcoxon Rank Sum Test (Main Effect for County Type)	Partial F-test (Interaction Effect)
Economy	**0.004952*** **	0.8602	0.2251
Immigration	0.536	**0.03879** **	0.555
Election	0.01042**	0.00675	0.8037
Healthcare/COVID	**0.006407** **	**0.05349* **	0.4388
Minority	0.3958	0.2417	0.931
Minority (black)	0.4767	**0.01541** **	0.2582

Notes on Significance Level: **0.1*, 0.05**, 0.01*****

4.4.1 Economy

Kruskal-Wallis rank sum test found significant differences in distribution of counts of words related to economy across different types of states, *chisq*(3)= 18.594, $p<.01$. Dunn test for post-hoc analysis showed that President Trump stressed significantly more on economy in swing states that turned blue than in blue states and swing states that turned red with pairwise p-value smaller than 0.01. Such result is consistent with the figure 13. The effect of county type and the state type x county type interaction effect on word counts are not significant according to the Wilcoxon rank sum test ($W = 709.5$, $p >.10$) and partial F-test for the regression of counts against interaction terms ($F(3,75) =4863$, $p>.10$).

4.4.2 Immigration

One-sided Wilcoxon rank sum test rank sum test found that median of counts of words related to immigration in red counties were significantly smaller than those in blue counties, $W = 642$, $p <.05$, as illustrated in figure 14. However, the effect of state type and the state type x county type interaction effect on word counts are not significant according to the Kruskal-Wallis rank sum test (*chisq*(3)= 2.1795, $p >.10$), and partial F-test for the regression of counts against interaction terms ($F(3,75) = 0.7$, $p >.10$), respectively.

4.4.3 Election

Kruskal-Wallis rank sum test found significant differences in distribution of counts of words related to election across different types of states, *chisq*(3)= 11.257, *p*

$<.05$. Dunn test for post-hoc analysis showed that President Trump talked about election more frequently in swing states that turned blue than in blue states with p-value smaller than 0.05. Also, one-sided Wilcoxon rank sum test rank sum test found that median of counts of words related to election in red counties were significantly larger than those in blue counties, $W = 995.5$, $p <.10$. However, the state type x county type interaction effect on word counts are not significant according to partial F-test for the regression of counts against interaction terms ($F(3,75) = 0.3299$, $p>.10$).

4.4.4 Healthcare/COVID

Kruskal-Wallis rank sum test found significant differences in distribution of counts of words related to healthcare/COVID across different types of states, *chisq*(3)= 12.305, $p <.01$. Dunn test for post-hoc analysis showed that President Trump talked about this topic more frequently in swing states and red states than in blue states with p-value smaller than 0.05. Also, one-sided Wilcoxon rank sum test rank sum test found that median of related word counts in red counties were significantly larger than those in blue counties at the alpha level of 0.1, $W = 1007.5$, $p <.01$. However, the state type x county type interaction effect on word counts are not significant according to partial F-test for the regression of counts against interaction terms ($F(3,75) = 0.93132$, $p>.10$).

4.4.5 Minority

While no significant results were found for the differences of word counts related to the minority category as a whole, one-sided Wilcoxon rank sum test rank sum test found an interesting result that median of counts of words related to black people in red counties were significantly larger than those in blue counties, $W = 1054$, $p < .05$.

5. Conclusion and Future Studies

In sum, this project examined four main characteristics of President Trump's speeches --- length, emotions, topics, and topic keywords --- and applied statistical tests to evaluate the significance of differences of these characteristics across blue areas, red areas, and battlegrounds on both state level and county level. Results showed no significant variation in speech lengths and speech emotions. However, analysis of entropy of topic distribution over speeches displayed that speeches in swing states that turned blue included significantly more diverse topics those in blue states and swing states that turned red. Additionally, analyses of topic keywords revealed that, President Trump stressed significantly more on economy in swing states that turned blue than in blue states and swing states that turned red. He talked about healthcare related issues more frequently in swing states and red states than in blue states. On the county level, speeches in red counties discussed more frequently on topics related to healthcare/ COVID and black people and less on immigration than those in blue counties.

For future studies, it would be meaningful to look into the effect of different emphasizes on speech topics across different areas on the voting behaviors in 2020 presidential election. Also, it would be interesting to compare Trump's speeches in 2020 to those in 2016, observe potential changes in sentiments and topics, and study the correlation between these changes and shift of margin of votes.

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