Twitter Diplomacy in the Trump Administration: Comparing @realDonaldTrump and @SecPompeo

Applied Statistical Methods Final Project

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11/10/19

I. Background, Research Question, and Ideal Data

a. Background: Twitter Diplomacy

U.S. President Donald Trump has received a great deal of attention for his frequent use of Twitter, as well as for the aggressive tone with which he tweets about his political allies, perceived enemies, and world events. In particular, Trump's use of Twitter to directly address other nations and announce foreign policy changes, a practice referred to as "Twitter diplomacy," has raised alarm in the general public, as well as among international relations scholars. Though the majority of national governments and/or world leaders do have active Twitter accounts (as of 2018, 97% of United Nations member states have an official Twitter presence), these leaders and nations typically only use Twitter diplomacy cautiously and as a secondary tool to supplement official statements on foreign policy, and private communications with other world leaders.[1] Trump appears to use Twitter as a primary mode of communication with the general public and foreign governments rather than a secondary tool, which has resulted in headlines such as: "Addiction to Twitter Diplomacy is Unwise,"[2] published in 2017 by the Chinese state media, and "Trump's Twitter diplomacy with China is no substitute for clear policy," published in 2019 by the Washington Post.[3]

b. Research Question: Trump's vs. Pompeo's Twitter Diplomacy

Though many international relations studies have compared Trump's Twitter diplomacy usage to that of Obama and that of other nations, few have compared Twitter diplomacy usage by officials *within* the Trump administration. A within-administration analysis is necessary, because the consistency, or lack thereof, between the Twitter diplomacy practices of top administration officials may impact the U.S.'s ability to execute a cohesive foreign policy agenda. Therefore, my research question for this project is: do Secretary of State Mike Pompeo and President Donald Trump use Twitter diplomacy with similar frequency, and do their diplomacy-related tweets discuss/ address similar nations and world regions with similar frequencies as well?

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[1] "Twiplomacy Study 2018," *Twiplomacy* (blog), July 10, 2018, https://twiplomacy.com/blog/twiplomacy-study-2018/.

[2] Kristin Huang, "State Media Criticism of Trump's 'addiction to Twitter Diplomacy' Signals China's Frustration," South China Morning Post, January 4, 2017, https://www.scmp.com/news/china/diplomacy-defence/article/2059200/chinas-state-media-slams-trump-conducting-twitter.

[3] David Ignatius, "Trump's Twitter Diplomacy with China Is No Substitute for Clear Policy," *Washington Post*, September 5, 2019, https://www.washingtonpost.com/opinions/trumps-twitter-diplomacy-with-china-is-no-substitute-for-clear-policy/2019/09/05/2d5afda8-d011-11e9-8c1c-7c8ee785b855_story.html.

c. Ideal Data vs. Actual Data

My ideal dataset for answering this question would be one that included all tweets sent by President Trump (@realDonaldTrump) and all tweets sent by Secretary Pompeo (@SecPompeo) during the time they have held their respective governmental positions. This dataset would also ideally include a binary label of diplomacy related or non-diplomacy related for each tweet, as well as a label indicating which diplomatic entities or foreign nations are referenced in each diplomacy-related tweet. This would allow me to analyze the Twitter diplomacy practices of both officials in their entirety, and having the tweets pre-labeled for their diplomatic content would minimize both the potential researcher bias created by doing it myself, and the time required to pre-process this data.

Luckily, the respective Twitter timelines of Donald Trump (user @realDonaldTrump) and Mike Pompeo (user @SecPompeo) are relatively easily obtainable through the Twitter Developer API and GET statuses/user_timeline endpoint. However, the Twitter API imposes a limit on the number of tweets you can request for a given user through this endpoint (3,200), which allowed me to retrieve the entirety of Pompeo's Twitter timeline (his first tweet being in March 2018), but only Trump's tweets as far back as August 7, 2019, as he is quite prolific on Twitter. Additionally, the API does not pre-label tweets as diplomacy-related or non-diplomacy-related, nor does it extract the diplomatic entities referenced in each tweet (outside of direct @ mentions, which Trump often doesn't use in his diplomatic tweets). This obtainable dataset is still related to my research question, however, this analysis is limited to the time period for which I have tweets for both users (August 7, 2019 – November 18, 2019), and some bias may have been introduced by the process of manually labeling tweets as diplomacy-related or not, and labeling the diplomatic entities referenced within each tweet as discussed in section 2b.

II. Data: @realDonaldTrump and @SecPompeo Twitter Timelines

a. Data Collection and Source

Using my personal Twitter Developer authentication keys and a Python script, I requested the Twitter timelines of @realDonaldTrump and @SecPompeo, and was able to retrieve a json containing data on 2909 tweets by Trump, and a json of data containing 1553 tweets by Pompeo. As mentioned in the previous section, the time period coverage of these two datasets was quite different: Trump's tweets only spanned from August 7, 2019 to November 18, 2019, while Pompeo's tweets spanned from May 1, 2018 to November18, 2019 (the data collection date). Though there were no anomalies in the data, the datasets included each user's retweets of other users' tweets, which I was not interested in for the purposes of this study: I simply wanted to analyze the original Twitter content generated by these two officials. The json returned by Twitter also included a number of variables that were not immediately relevant to my specific research question, such as the media included in a given tweet, the tweet link, etc.

b. Pre-Processing Steps

I first wanted to convert the dense json file returned by the Twitter API to a data frame object that included useful and interesting variables, and only included original tweets by each user for the time frame being studied. In order to achieve this, I read in each json file to a Python pandas DataFrame, and wrote functions that would allow me to extract key information from the 'extended_entities' and 'entities' dictionaries returned for each tweet, which included the type of media displayed with each tweet, if any (photo, video, etc.), hashtags, and users mentioned in the given tweet using the @ function. Though I did not end up using this information, it may be useful for future analyses. I also wrote functions to remove links from tweet text, as well as to retrieve the length of a cleaned tweet. Finally, I subsetted these large DataFrames based on three conditions: that the contained tweets were only original tweets and not retweets, that the tweet id was no smaller than that of the oldest Trump tweet I was able to retrieve (thus only including tweets in the desired date range), and that the contained, cleaned tweets were no less than 5 characters in length (thus removing tweets that contained only a link and no text and otherwise uninformatively short tweets). I then saved the cleaned, subsetted DataFrames for each user as csv files, which left me with a final sample size of 1583 tweets for @realDonaldTrump, and 407 tweets for @SecPompeo.

Next came the tedious task of manually labelling each tweet as diplomacy related or non-diplomacy related, for which I applied a set of simple criteria through which I hoped to minimize the subjectivity and researcher bias created by labeling the tweets myself. Tweets were given a value of 1 under the variable 'is_diplomatic' if the tweet included one or more of the following: the name of a foreign nation or city, the name of a leader of a foreign nation, the name or acronym of an inter-governmental organization (such as the UN), the name of a world region (such as the Middle East), or the name or acronym of a commonly recognized foreign sub-national group (such as the Kurds) or terrorist group (such as ISIS). The name in question could be merely stated in the body of the tweet text, or could be contained in a direct mention of a specific user or entity through the @ function or a hashtag. Application of these criteria resulted in the creation of a binary 'is_diplomatic' variable in each data csv file, coded as 1 if the tweet met my Twitter diplomacy criteria, and 0 otherwise.

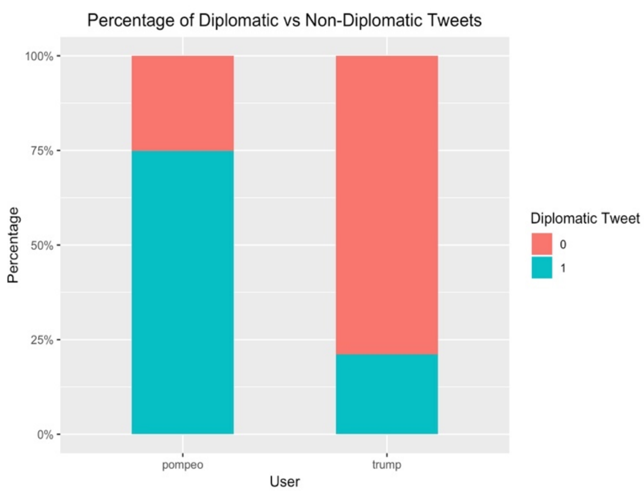
Finally, as I also wanted to analyze the relative frequency with which Trump and Pompeo referenced specific diplomatic entities in their diplomacy-related tweets, I manually labeled the diplomatic entities referenced in each tweet for which the 'is_diplomatic' variable had a value of 1. However, I also decided to apply a set of criteria for determining the entity label of a tweet, when I realized after examining my data that Trump and Pompeo use a number of names to refer to a single nation when discussing foreign policy, for example: using "Beijing," "President Xi," "Xi," and "China" to refer to the government of the People's Republic of China. Therefore, the 'entities_mentioned' variable was created as follows: if, in the body of a tweet, the user explicitly used the name of a foreign nation, a city in a foreign nation, or the name of a leader or official of a foreign nation, the diplomatic entity or subject of the tweet was defined as the name of the corresponding nation. For example, if President Xi or the city of Beijing were mentioned in a tweet, the diplomatic entity or subject of the tweet was defined as merely "China." Additionally, sub-groups of international organizations were simplified to the acronym of the international organization itself, for example, "UN Security Council" was simplified to "UN." This simplifying coding scheme was applied identically to both Secretary Pompeo and President Trump's diplomacy-related tweets for ease of comparison.

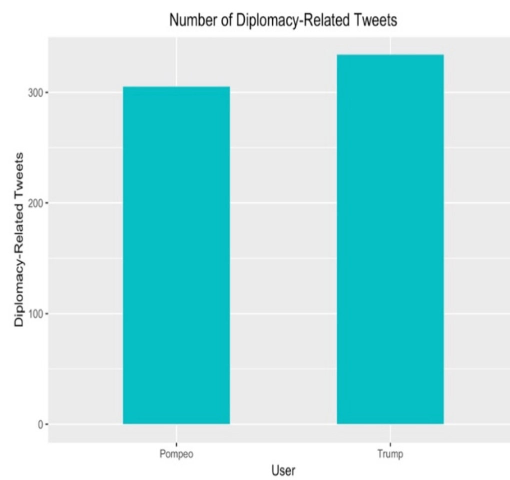
Though both of these labelling steps may have introduced a degree of subjectivity into this analysis and were therefore not ideal, I believe that they were necessary in the interest of making these data applicable to my research question. Additionally, writing code that would perform these labeling steps manually would have been arguably even more time-intensive.

c. Graphical Summaries of Data

After pre-processing and labelling the data, I wanted to visualize key elements of the data. The first element I wanted to visualize was the comparative proportion of original tweets sent during the study period that were diplomacy related vs non-diplomacy related for Trump and Pompeo, which is visualized in Figure 1. This figure makes clear that when labelled according to my criteria, Secretary Pompeo uses Twitter diplomacy in a much greater proportion of his overall tweets than does President Trump. This is not altogether surprising given that foreign relations composes most of Secretary Pompeo's job description while President Trump must contend with domestic American politics as well as foreign relations, yet is interesting to observe. However, as visualized in Figure 2, though the proportion of tweets sent during the study period that were diplomacy-related varied greatly between users, the raw count of diplomacy-related tweets for each user was roughly similar: 305 for Pompeo, and 334 for Trump.

Figures 1 and 2: Visualizing Proportions and Counts of Diplomacy Related Tweets





I also wished to visualize and examine the frequency and relative frequency with which Pompeo and Trump referenced specific diplomatic entities in their diplomacy-related tweets, which I take as an indicator of the importance they afforded to that specific nation or issue area during the study period. This will allow me to assess whether Trump and Pompeo afforded importance to similar diplomatic entities in their diplomacy related tweets. Tables 1 and 2 show the top 5 most-referenced diplomatic entities by Trump and Pompeo respectively, with the reference counts of the other official included for comparison. Notably, the officials share zero entities in common in their 5 most-referenced entities, and seem to have prioritized mentions of different entities in their diplomacy-related tweets. For a similar purpose, Figure 4 shows the relative frequency with which each official referenced specific diplomatic entities in diplomacy-related tweets. Because the two officials, when combined, referenced 118 distinct nations/ issue areas in total, I only included diplomatic entities that were referenced by both Trump and Pompeo more than four times each in this visualization (however, I included all entities that were referenced by either official in my analysis, as described in Section II). Figure 4 further supports the shows that Pompeo and Trump seem to have afforded importance to diplomatic entities differently: among the entities referenced by Pompeo and Trump at least 4 times, Trump appears to have prioritized references to China while Pompeo appears to have prioritized mentions of Iran.

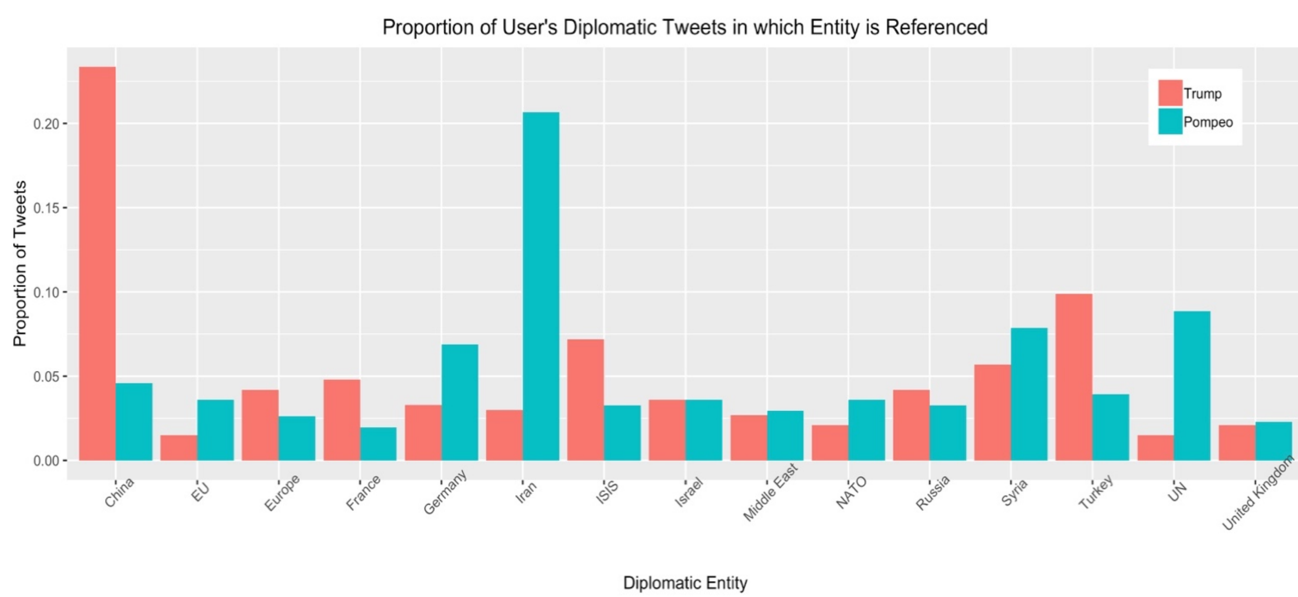
Table 1: The 5 Most-Referenced Diplomatic Entities by @realDonaldTrump

Diplomatic Entity	References by @realDonaldTrump	References by @SecPompeo
Ukraine	91	4
China	78	14
Turkey	33	12
ISIS	24	10
Kurds	24	0

Table 2: The 5 Most-Referenced Diplomatic Entities by @SecPompeo

Diplomatic Entity	References by @realDonaldTrump	References by @SecPompeo
Iran	10	63
UN (United Nations)	5	27
Venezuela	1	26
Syria	19	24
Germany	11	21

Figure 4: Visualizing Proportion of User's Diplomacy-Related Tweets in which Specific Diplomatic Entities are Mentioned



III. Analysis

The visualizations in the previous section suggest that President Trump and Secretary Pompeo use Twitter diplomacy differently, both in terms of the proportion of tweets they post that are diplomacy-related, and in terms of the emphasis they place on various diplomatic entities in their diplomacy-related tweets. However, in order to make the case that Trump and Pompeo truly do use Twitter diplomacy differently, I needed to both quantify this difference through specific metrics, and show the statistical significance (or lack thereof) of the metrics. I chose three metrics through which to show the difference in frequency of use, breadth of diplomatic entities mentioned, and specific entity focus of Trump and Pompeo's Twitter Diplomacy: 1) the difference between users in proportion of tweets sent that are diplomacy-related, 2) The difference between users in number of unique diplomatic entities mentioned in diplomacy-related tweets, and 3) For every diplomatic entity referenced by either user, the difference between users in the proportion of diplomacy-related tweets that mention that entity.

I then needed to obtain a p-value for the observed value of each of these metrics. However, I did not want to make any assumptions about the distribution of tweets in the dataset, as any assumption of independence or distribution would likely not suit these data. Tweets posted close together in time are likely to have similar subject matter and thus mention similar diplomatic entities, because Twitter users tend to tweet about events that occur in the world, as they occur.

Therefore, I decided to perform a non-parametric test of significance in the form of a permutation test for each of these metrics, which would allow me to obtain a p-value without assumptions. As each metric involved taking a difference of some sort between two samples (Trump's vs Pompeo's), to perform the permutation test for each metric, I shuffled the tweets attributed to each user at random and re-calculated the metric 10,000 times. I then calculated the p-value as the proportion of times the permutation metric was greater than or equal to the observed metric or test statistic. I used the Python libraries pandas (for dataframe operations), numpy (for performing and storing permutations in an array), and random (for randomly selecting dataframe indices to attribute to each user). The results of the permutation test for each metric are below. I hypothesize that the results of the permutation tests for both the difference in proportion of diplomacy-related tweets and the difference in number of unique diplomatic entities referenced will be significant at the 0.05 alpha significance level, but that only some diplomatic entities will have statistically significant differences in proportion of references between users.

a. Analysis of Difference in Proportion of Diplomacy-Related Tweets

$$\boldsymbol{test\ statistic = \frac{trump\ diplomatic\ tweet\ count}{total\ trump\ tweets} - \frac{pompeo\ diplomatic\ tweet\ count}{total\ pompeo\ tweets}}$$

$$\boldsymbol{observed\ test\ statistic\ value\ = \frac{334}{1583} - \frac{305}{407}\ =\ -0.5384}$$

$$permutation\ test\ p - value\ (2 - sided)\ = 0.000$$

b. Analysis of Difference in Number of Unique Diplomatic Entities Referenced

$$test\ statistic\ =\ (trump\ \#\ unique\ entities\ referenced\ )\ -\ (pompeo\ \#\ unique\ entities\ referenced)$$

$$observed\ test\ statistic\ value\ =\ 52-11\ =\ -59$$

$$permutation\ test\ p-value\ (2-sided)\ =\ 0.0608$$

c. Analysis of Difference in Proportion of User's Diplomacy-Related Tweets that Reference Each Diplomatic Entity

$$\boldsymbol{test\ statistic_{entity}\ =\ \frac{\#\ trump\ entity\ references}{\#\ trump\ diplomatic\ tweets}-\frac{\#\ pompeo\ entity\ references}{\#\ pompeo\ diplomatic\ tweets}}$$

$$*\ \boldsymbol{as\ there\ are\ 118\ entities\ total, and\ 118\ observed\ test\ statistics\ and\ permutation\ test\ p-values, I\ have\ not\ included\ them\ here. See\ code\ for\ full\ list.}$$

Summary of Permutation Test Results: (2-sided, $\alpha\ =\ 0.05$)

- 24 diplomatic entities with significant p-value
- 94 diplomatic entities with insignificant p-value

IV. Conclusion

My analysis was both conclusive, and inconclusive. The difference between the proportion of Trump's tweets that were diplomacy-related and the proportion of Pompeo's tweets that were diplomacy related was highly significant, indicating that it is likely that Trump and Pompeo do in fact use Twitter Diplomacy with different relative frequencies. However, surprisingly, the difference in the number of unique diplomatic entities mentioned by Trump vs. Pompeo was just barely insignificant, and therefore I cannot reject the null hypothesis that there is no difference in the number of diplomatic entities mentioned between the two users. Gauging by this p-value, I cannot rule out the possibility that Trump and Pompeo use Twitter Diplomacy to discuss the same number of issue areas/ nations. Finally, the permutation test returned both significant and insignificant values for the difference in the proportion of each user's diplomacy-related tweets that reference a given diplomatic entity: 24 significant p-values, 94 insignificant. Unsurprisingly, when observing these values in my code, I saw that the entities with the largest observed difference in proportion also were those with significant results (such as Iran, China, and Turkey, as observed in the visualizations of section 2c). Therefore, when it comes to those 24 specific diplomatic entities, we can infer a significant difference in the importance afforded to each entity by Trump vs. Pompeo in their respective practices of Twitter Diplomacy.

My project certainly changed from my initial proposal, and throughout the process of completing this project, though mainly in a manner that made my question more specific, and my metrics more applicable to the question I wanted to answer. My project was also much more time-consuming and ambitious than I originally realized, but I overall found it rewarding.

**My code review partner was Maddie Covino.*