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US Hashtag Diplomacy During Russia's Invasion of Ukraine

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Background:

The ongoing conflict in Ukraine remains a major global issue since 2014, highlighting the importance of understanding the impact of Russian disinformation on social media. Russia's alleged interference in the 2016 US Presidential Election contributed to lasting suspicion and concern regarding the use of disinformation tactics to influence public opinion in the US and Europe. Although discussions of Russian disinformation are expanding in research and news media, there is still a significant gap in understanding the function and impact of the countermeasures used by US political figures to combat Russian informational tactics. This project will argue that to counterbalance Russian spin tactics used to legitimize the war, as a form of opposing spin, political messages disseminated on social media by American politicians will tend to be calls-to-action, intended to mobilize and sway opinion. By using charged language, it can be anticipated that such messages will involve more uplifting, opinionated terms, rather than less enthusiastic language.

Methods:

To evaluate this, Tweet sentiment is analyzed. Sentiment analysis takes in some sort of text data–in this case, Tweets–and determines for every word if its polarity is negative, neutral, or positive (scoring them between -1 and 1) and then compounds these values to result in an overall evaluation of sentiment for the text. Subjectivity can also be a useful tool in text analysis to determine if content is subjective or objective. 1000 Tweets were pulled from @POTUS and 10 Tweets from each Senator's account (1880 Tweets) and then the Tweets were analyzed. In order to have at least 150 lines of data after filtering, 5000 Tweets from @POTUS were pulled and 100 Tweets from each Senator's account. Then, these Tweets were filtered by the keyword "Ukraine," yielding 168 and 178 Tweets respectively.

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Results:

There is a greater percentage of positive sentiment Tweets compared to negative or neutral ones overall.

The set of Tweets that mention Ukraine have a smaller percentage of positive or neutral sentiment Tweets and are more negative instead.

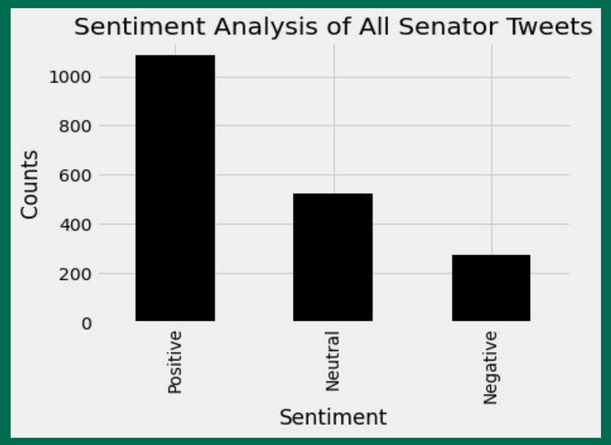

Figure 1 plots the number of positive, neutral, and negative Tweets in Senator-All. Most Tweets are positive. Few Tweets are negative. Specifically, 57.7% of Tweets are positive and 14.5% of Tweets are negative. The rest are neutral.

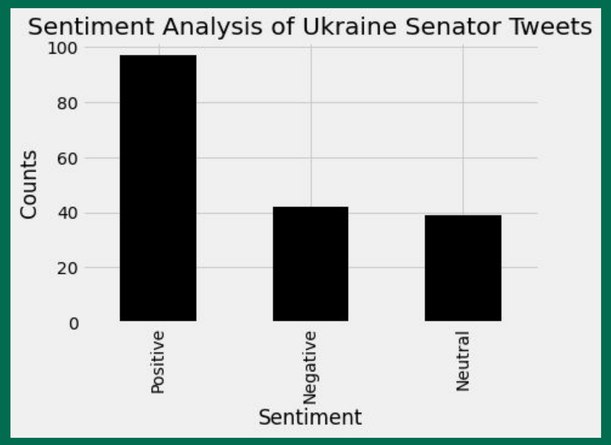

Figure 2 plots the number of positive, neutral, and negative Tweets in Senator-Ukraine. Most Tweets are positive. Few Tweets are neutral. Specifically, 54.5% of Tweets are Positive and 23.6% of Tweets are negative. The rest are neutral.

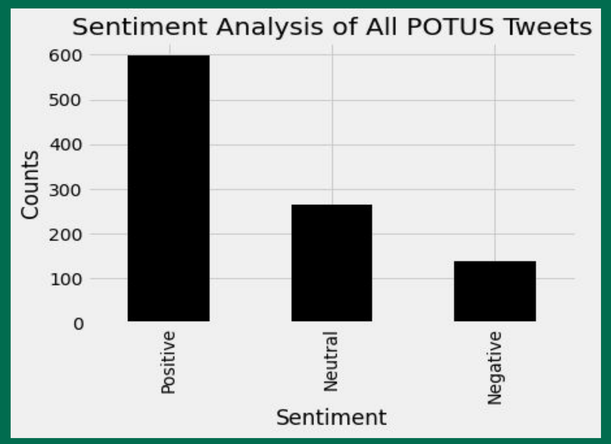

Figure 3 plots the approximate number of positive, neutral, and negative Tweets in POTUS-All. Most Tweets are positive. Few Tweets are negative. Specifically, 59.8% of Tweets are Positive and 13.7% of Tweets are negative. The rest are neutral.

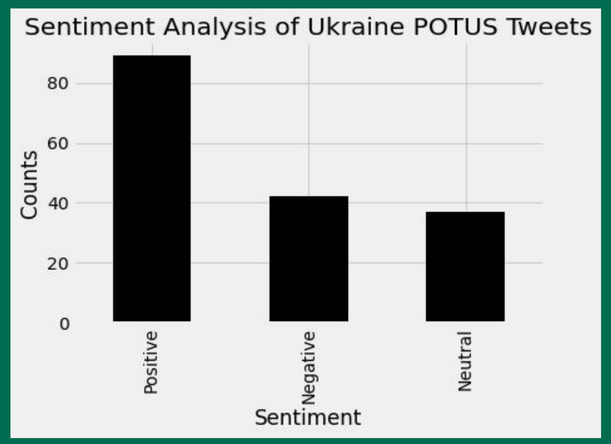

Figure 4 plots the approximate number of positive, neutral, and negative Tweets in POTUS-Ukraine. Most Tweets are positive. Few Tweets are neutral. Specifically, 53.0% of Tweets are Positive and 25.0% of Tweets are negative. The rest are neutral.

Analysis:

There is an overwhelmingly positive sentiment for all Tweets, however, ones that mention "Ukraine" are less neutral. This shows that for more contentious issues, the sentiment will also be elevated and thus will be less neutral. In this case, Tweets mentioning the conflict ("Ukraine") were more negative for both POTUS and Senators. This is indicative of the US tactics as a whole: combat disinformation with optimistic proclamations and condemnation of disagreeable conflicts. Given how similar the @POTUS and Senator data is for all sets, this strategy seems to be consistent for a large number of US politicians on Twitter, suggesting a new informational trend in global politics and conflicts.

How The Program Evaluates Tweets:

Sample Sentiment Program:

```
# Import and download the Natural Language Processing Toolkit (nltk)
import nltk
nltk.download()
# Initialize the sentiment analyzer
from nltk.sentiment import SentimentIntensityAnalyzer
# Assign the sentiment analyzer to an easy to write variable, sia
sia = SentimentIntensityAnalyzer()
# Get text data (in this case, I wrote it!)
my_text = "Political science is so exciting! I love learning about such a great subject!
# Analyze the text for sentiment
sentiment_score = sia.polarity_scores(my_text)
# Print the sentiment score
print(sentiment_score)
# Do any additional calculations (i.e. subjectivity)...
```

The program evaluates the sample text as follows: {'neg': 0.0, 'neu': 0.376, 'pos': 0.624, 'compound': 0.9358}

If the text was changed to "Political science is so exciting! However, some people think it's boring," the results are as follows: {'neg': 0.146, 'neu': 0.573, 'pos': 0.281, 'compound': 0.4781}.

Sample Results From @JoeBiden:

Negative: "Donald Trump failed America."
Polarity: **-0.5** Subjectivity: 0.3

Neutral: "Folks, get vaccinated."
Polarity: **0.0** Subjectivity: 0.0

Positive:"My message to all LGBTQ+ youth. Be you. You are loved. You are understood. You belong. And we have your back."
Polarity: **0.4** Subjectivity: 0.4

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