HIGH SCHOOL EDITION
Journal of Student Research

Volume 12 Issue 1 (2023)

A Sentiment Analysis on Roe v. Wade Twitter Data

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ABSTRACT

In May of 2022, the US Supreme Court case *Dobbs v. Jackson Women's Health Organization* threatened to and did overturn *Roe v. Wade*, the historic 1973 Supreme Court case that created prenatal healthcare guidelines, including specifications for regulation of abortion. This work aims to investigate tweets on *Roe v. Wade* during a period of interest through posts on Twitter to provide an understanding of general public opinion. This was done primarily by running sentiment analysis on a dataset of 35,999 tweets from May 1st, 2022 to July 8th, 2022 from the #RoeVWade, separating them into negative, positive, and neutral sentiments, then finding collocations and often used hashtags in each category. Although the sentiment analysis model used classified sentiment rather than "pro-choice" versus "pro-life," negative and neutral tweets were more likely to use phrases associated with "pro-choice" beliefs. In contrast, positive tweets often used hashtags aligned with Republican or conservative views.

Introduction

Roe v. Wade originated in 1970 in the district court of the Northern District of Texas before being brought up to the Supreme Court. The decision set new guidelines for handling prenatal healthcare in the states. The case was between the plaintiff "Jane Roe," a single pregnant woman, and the defendant Henry Wade, a district attorney for the Texas ND. Roe wished to terminate her pregnancy by abortion "performed by a competent, licensed physician, under safe, clinical conditions" but could not get one legally under Texas law because the pregnancy didn't pose a serious risk to her life. She wasn't in a financially viable position to travel to a different territory to get an abortion. In return, Roe claimed that the Texas law was unconstitutionally vague and abridged her right to personal privacy (*Roe v. Wade*, 1970). When the District Court declared the abortion statutes void and dismissed the application for an injunction, Roe et al. appealed to the Supreme Court in 1973 about the injunction denial, leading to *Roe v. Wade*.

The Supreme Court decision mandated new guidelines for prenatal healthcare. Until the end of the first trimester, the decision to have an abortion must be up to the medical judgment of the pregnant woman's physician. After the first trimester, the State could regulate abortion but only in reasonable ways for women to get them if they need to for health reasons, whether fatal or not. From when the fetus is viable, the State can choose to regulate or even proscribe abortion except in cases where a physician decides it is necessary for the health or life of the pregnant woman (*Roe v. Wade*, 1973). *Planned Parenthood of Southeastern Pennsylvania v. Casey*, another Supreme Court case regarding the right to an abortion held, upheld the right in 1992. However, in May 2022, *Dobbs v. Jackson Women's Health Organization* overturned both aforementioned cases.

On May 2nd, 2022, a working draft of the Supreme Court's decision for *Dobbs v. Jackson* was leaked, revealing the potential overturning of *Roe v. Wade*. On May 24th, 2022, *Dobbs v. Jackson* was decided, fully overturning both *Roe v. Wade* and *Planned Parenthood v. Casey*. The original draft leak sparked mass criticism and public outcry, which continued past the actual decision. The main focus of this paper is on analyzing sentiment in public opinion from the first draft leak to the next two months by running sentiment analysis on tweets made under the #RoeVsWade hashtag at the time.

Overview of Sentiment Analysis

Sentiment analysis is contextual text mining that extracts subjective phrasing and information from data or source materials. There are many use cases for sentiment analysis, and many models are tuned for different topics and subjects, for example, politics versus Facebook posts. Sentiment analysis models that use deep learning use multiple classification layers to extract features. Additionally, sentiment analysis models built for different use cases, such as Twitter data, fine tunes additional classification layers to have more accurate data, as seen in figure 1. The BERT model is an unsupervised model used for unstructured data such as encyclopedias and Wikipedia then, additional layers of training are added for specific text styles. For example, some sentiment analyses have separate classification layers that train emoji or multilingual sentiments.

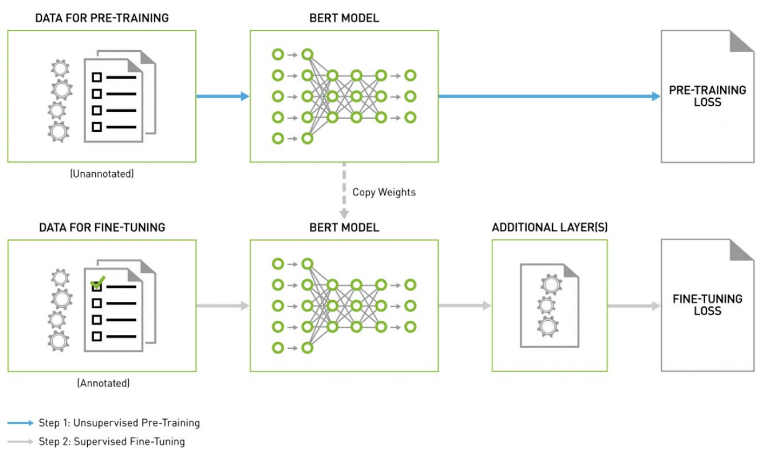

Figure 1. Sentiment Analysis BERT Model Training Flow Chart. Source: https://www.nvidia.com/en-us/glossary/data-science/sentiment-analysis/

Methodology

The data is a set of 35,999 tweets in English from May 1st, 2022 to July 8th, 2022, picked for containing #RoeVsWade. Of the 1.6 million tweets during that time period, about 500 to 1000 tweets were selected per day, depending on the day's activity. The data set was provided by *FollowersAnalysis*'s historical tweet data service, which pulls old tweets for any date range going back to 2006 that contains a specific hashtag or keyword. The date range (05/01/2022–07/08/2022) was decided because the Supreme Court work draft was leaked on May 2nd, 2022, and the last time the hashtag appeared in the top 10 trend list was June 26th, 2022 (adding a dozen days to account for the discussion being ongoing but not trending).

The sentiment analysis model used is cardiffnlp's xlm-twitter-politics-sentiment, found on the Hugging Face Hub. The model is an extension of twitter-xlm-roberta-base-sentiment (Barbieri et al., 2022), trained with a focus on sentiment from politicians' tweets. The original model's sentiment fine-tuning was done in 8 languages, including English. Still, the model was further trained using tweets from members of Parliament from the UK, Spain, and Greece (Antypas et al., 2022). This model was chosen because of its focus on classifying politicians' tweets.

The model takes an input of a sentence and gives the whole phrase a decimal score between 0 and 1 for negative sentiment, positive sentiment, and neutral sentiment, 0 being none and 1 being very strong. The model gives an output from "Negative," "Positive," and "Neutral," depending on which sentiment is strongest.

The second type of analysis is collocations, expressions of multiple words that often appear together. This analysis was done using Natural Language ToolKit. Bigram, trigram, and fourgram association measures were run on the negative, positive, and neutral tweets. Lastly, the hashtags and frequency from each tweet list (Negative, Positive, and Neutral) were extracted.

Results

Sentiment Analysis Word Clouds

The data was first cleaned, removing all mentions to other users, hashtags, links, most punctuation, and words derived from "Roe V. Wade" or "Supreme Court." The latter was done to ensure that the later collocations would not become clogged with the same repeated phrase. A separate tokenized version of the now-cleaned tweet was created, in which each tweet was split into separate words and stopwords (common words and phrases in English such as conjunctions and prepositions) were removed.

After running cardiffnlp's xlm-twitter-politics-sentiment sentiment analysis model on the cleaned data, the data was collected in a data frame. The columns were the "label" (Negative, Positive, or Neutral), the "score" (how well the tweet matched the sentiment label from the aforementioned scale of 0 to 1), the "tweet" (the tweet after cleaning), the "tokenized tweet" (the tweet after cleaning and tokenization), and the original tweet (the tweet before cleaning).

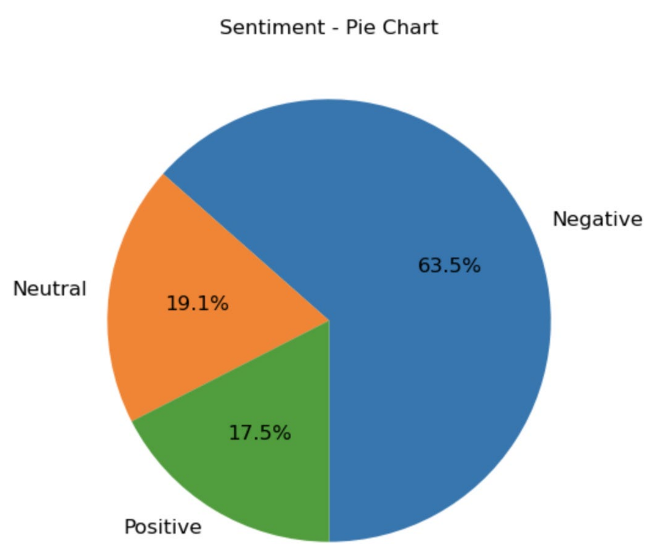

Figure 2. A pie chart displaying the percentages of tweets marked Negative, Positive, and Neutral by the sentiment analysis model in the data set

61.7% of the 35,999 tweets were marked negative, 19.9% were marked neutral, and 18.4% were marked positive.

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Figure 3. A word cloud of words used in tweets classified as "Negative"

The most frequent words in the tweets marked negative were: STRIKE, Defend, WALK, SOMETHING, SICK, murder, one, Close, talking, and WTF.

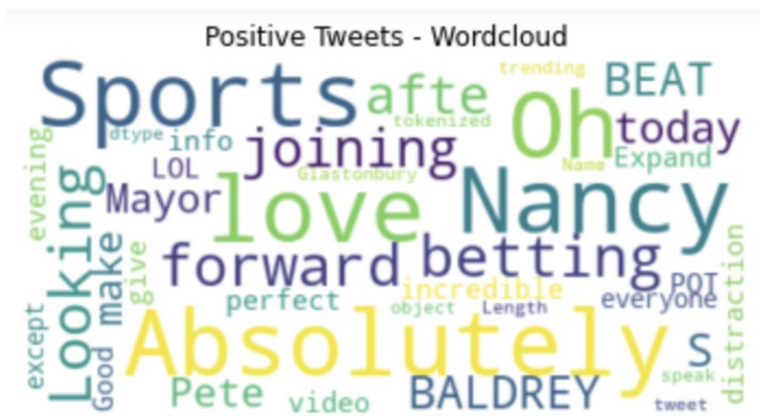

Figure 4. A word cloud of words used in tweets classified as "Positive"

The most frequent words in the tweets marked positive were: Absolutely, Nancy, Sports, love, betting, forward, Looking, Oh, today, and joining.

Figure 5. A word cloud of words used in tweets classified "Neutral"

The most frequent words in the tweets marked neutral were: STRIKE, SOMETHING, Defend, Close, talking, SICK, murder, WALK, ok, and WTF. The word clouds from negative and neutral overlapped, though their frequencies weren't the same. The words STRIKE, Defend, SICK, SOMETHING, WTF, WALK, and murder, though in different frequencies.

Collocations

The tokenized tweets were run through Natural Language Toolkit's collocation analysis. Bigrams (sets of two words often appearing together), trigrams (sets of three words often appearing together), and fourgrams (sets of four words often appearing together were found for each of the different sentiments.

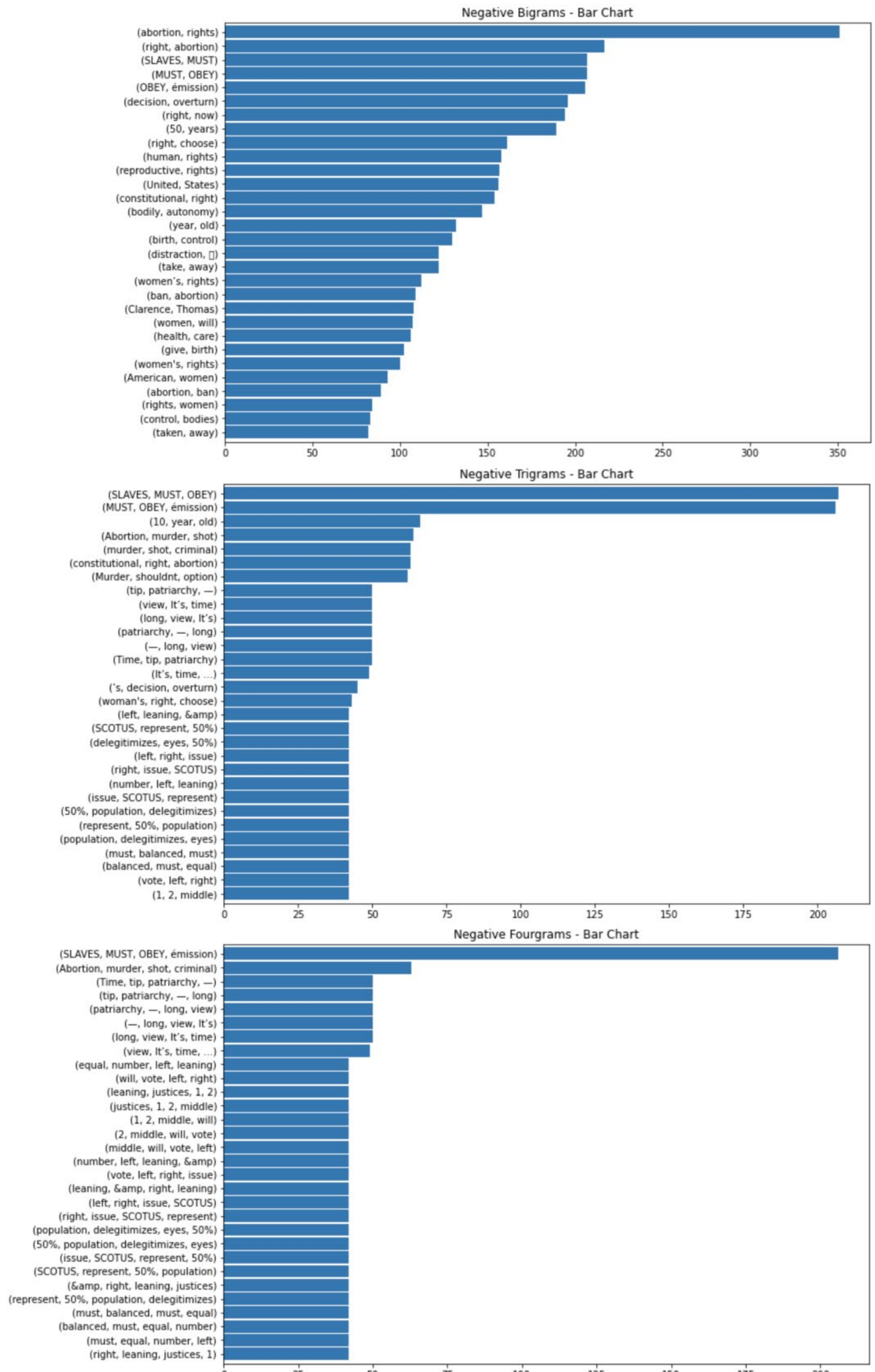

Figure 6. Three horizontal bar charts containing the bigram, trigram, and fourgram analysis for tweets marked for negative sentiment

The most frequent bigrams for tweets marked negative were mostly two-word phrases such as "abortion rights," "right now," "human rights," "reproductive rights," "United States," "constitutional right," "bodily autonomy," "birth control," and "abortion ban." The two most frequent trigrams were from the phrase "SLAVES MUST OBEY émission," which was also the most frequent fourgram.

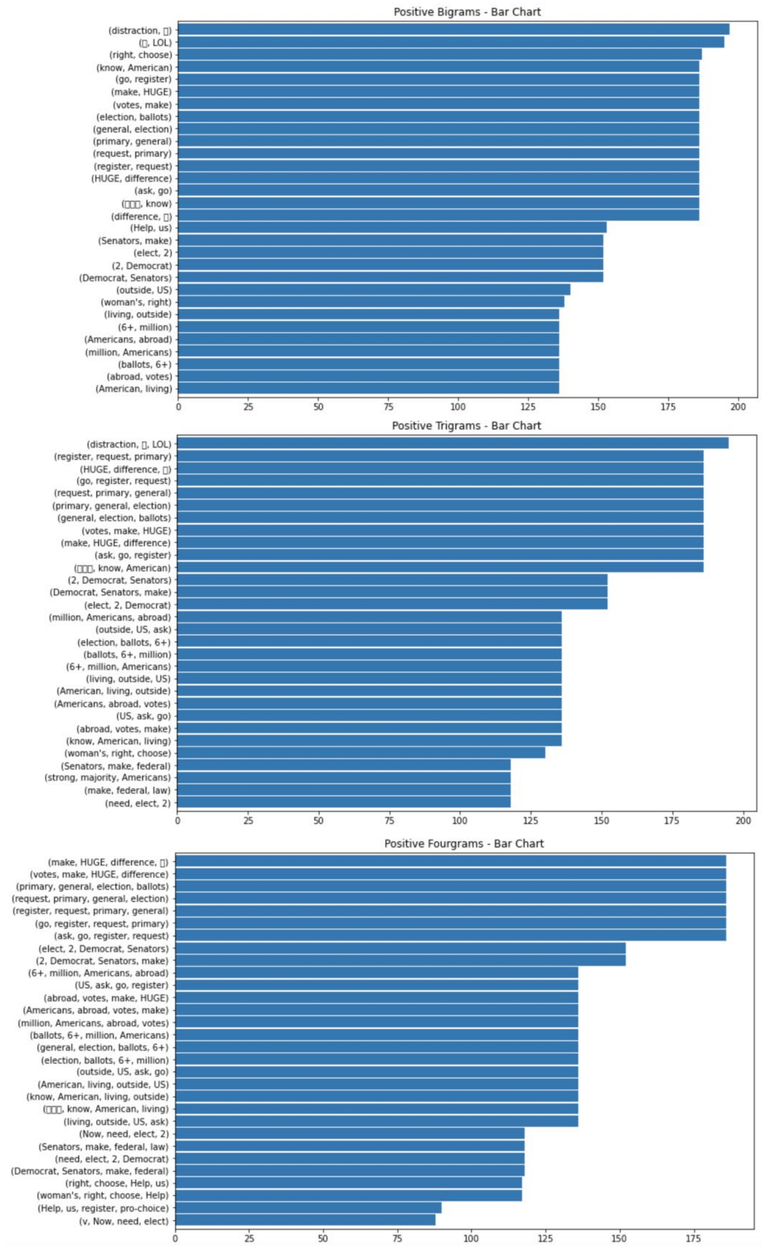

Figure 7. Three horizontal bar charts containing the bigram, trigram, and fourgram analysis for tweets marked for positive sentiment

The most frequent bigrams from tweets marked positive are political language about elections: words like "register," "primary," "general," "request," "difference," "Democrat," "senators," "right," and "votes." The most frequent trigrams and fourgrams follow the same trend.

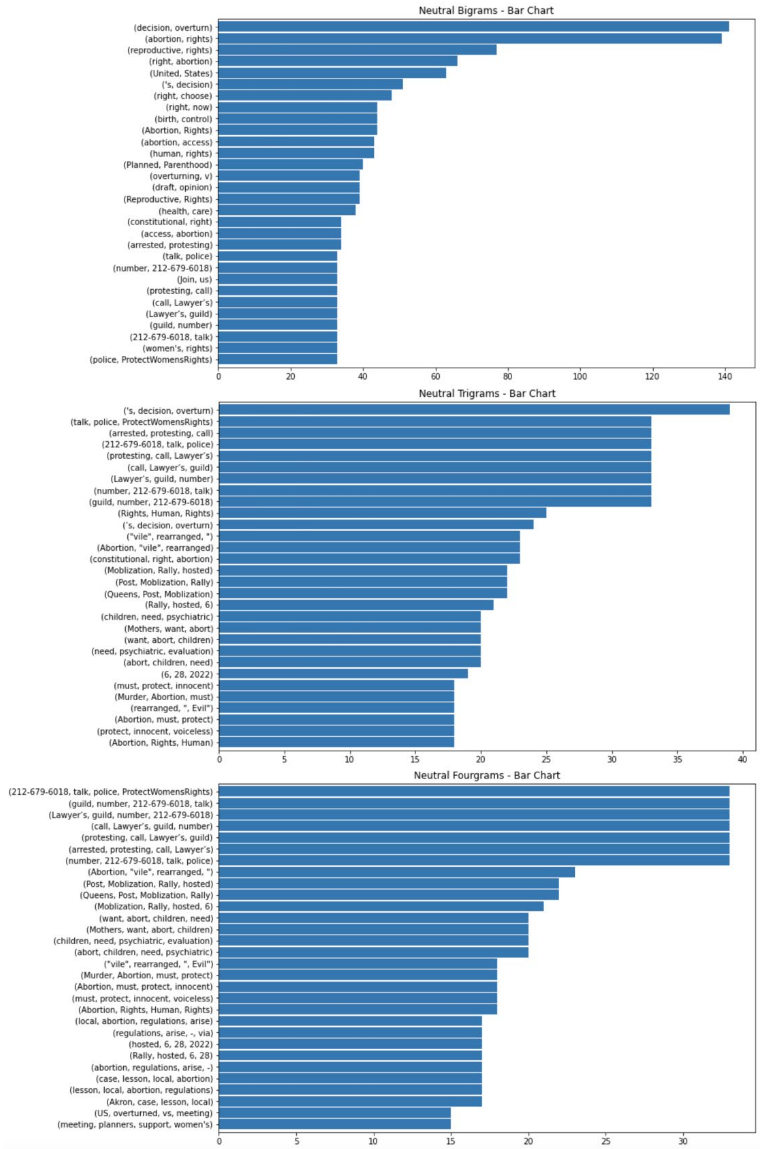

Figure 8. Three horizontal bar charts containing the bigram, trigram, and fourgram analysis for tweets marked for neutral sentiment

In bigram's analysis of neutral tweets, the most frequent words used together were (decision, overturn) and (abortion, rights). The rest of the frequent bigrams are phrases such as “abortion access,” “human rights,” “Planned Parenthood, “Reproductive Rights,” and “health care.” The most frequent trigrams, except for the most frequent (‘s, decision, overturn), are about the NY Lawyer’s Guild’s number. The next-most frequent trigram is (Rights, Human, Rights). The most frequent fourgrams are also about the NY Lawyer’s Guild’s number. The next-most frequent fourgrams are about mobilization rallies. The following fourgrams use the words “Mothers,” “want,” “abort,” “children,” “need,” “psychiatric”, and “evaluation.” If accounting for removed stopwords, these fourgrams might add up to “Mothers who want to abort children need psychiatric evaluation.”

Hashtags

For each of the lists of negative, positive, and neutral tweets, hashtags were extracted and turned into a dictionary, with keys being the hashtags and values being the number of times they appeared in the list in total. The hashtags #RoeVsWade and #RoeVWade were excluded. The first, #RoeVsWade, was excluded because every single tweet contained it, as it was the criteria for which tweets were selected. The second, #RoeVWade, was also excluded because of both its prevalence and lack of meaning.

Hashtags from negative tweets were displayed if they appeared more than 150 times, while hashtags from positive tweets were displayed if they appeared more than 100 times.

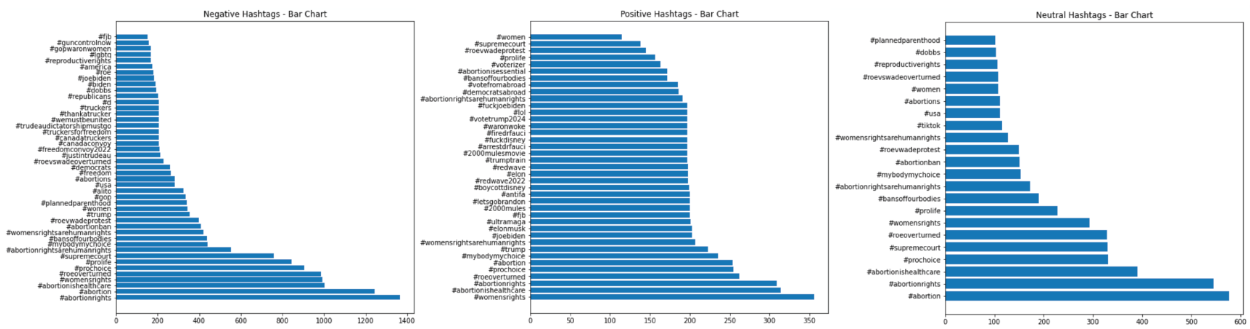

Figure 9. Three horizontal bar charts listing hashtags used in tweets marked "Negative" with a frequency of over 150, hashtags used in tweets marked "Positive" with a frequency of over 100, and hashtags used in tweets marked "Neutral" with a frequency of over 100

The hashtags #abortion, #abortionishealthcare, #prochoice, #womensrights, and #roeoverturned appeared highly frequently in all negative, positive, and neutral tweets. All hashtags that appeared with frequency in tweets marked "Neutral" had sentiments against the overturning of Roe V. Wade. Tweets marked "Positive" had more hashtags aligned with Republican ideas, namely #redwave2022, #redwave, #trumptrain, #votetrump2024, and #fuckjoebiden. Tweets marked "Negative" had a wide variety of hashtags. Still, the hashtags #abortionrights and #abortion notably had over 1200 mentions each, while the third most frequent sat at less than 1000 mentions.

Conclusion

The model classified sentiment rather than "pro-choice" versus "pro-life," and tweets on both sides held all of the negative, positive, and neutral sentiments. However, positive and negative sentiments can show a strong correlation between the belief of pro-lifers and pro-choicers. Negative and neutral tweets were more likely to use phrases such as "abortion rights," "human rights," "reproductive rights," and "health care," which points towards those with pro-abortion views tweeting with the negative sentiment more often. Unlike negative and neutral tweets, positive tweets often use hashtags aligned with Republican views. The collocations for positive tweets mostly encompassed political language, a significant portion of which concerned voting. The collocations for neutral tweets had more neutral tones and informative information about the situation surrounding Roe vs. Wade. However, there are some limitations to this study. The results of the collocations have been skewed due to the multiple tweets in the data that were not accounted for. Additionally, the model was more fit for sentiment analysis instead of the classification of pro-choice or pro-life. An example of this would be that it seems that abortion was classified to be a negative sentiment, when it is just the subject of the matter. This study can be further extended by correcting these data mistakes and using other models or adding further classification layers to identify the pro-choice and pro-life tweets correctly.

Acknowledgments

I would like to thank my advisor for the valuable insight provided to me on this topic.

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