Farmers’ Protests: An Analysis of Discourse on Twitter

Data Science Major Capstone
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Background & Significance

In September of 2020, the government introduced three acts that would deregulate the existing system of agriculture markets, allowing farmers to sell directly to food processors. While these bills were claimed to be in the interest of farmer welfare, many farmers and farmer unions argued that these were suited to private companies. In fear of being at the mercy of corporations, these laws elicited a response from farmers in India that led to one of the longest and largest protests the world has ever seen. Conversation and sentiment of both news outlets and the general public regarding the recent Farmers’ Protests was shared on social media, especially on Twitter. This study aims to investigate public reaction to the protest at the Delhi border that occurred on India’s Republic Day.

This study details the training and testing of a Naive Bayes classifier on tweets published on India’s Republic Day to answer the following research questions:

1. Is there polarization in stance of the discourse expressed on Twitter regarding the Republic Day Protest at the Delhi border and Red Fort?
2. Does this polarization on Twitter, differ for verified users and unverified users? How?
3. Did the language used differ? What were the most common words used?

Data

The data, titled ‘Farmers Protests Tweets Dataset,’ used in this analysis was collected, compiled and made publicly available by Pratham Sharma on Kaggle. [1] It includes two *csv* files, one containing tweets with the hashtag ‘#FarmersProtest’ and the other containing the users who have tweeted using this hashtag. The latest version of this dataset contains over 1 million tweets from November 1, 2020, to November 21, 2021. This was collected using *snscrape* and the *Twitter API*.

This dataset was limited to tweets published on January 26, 2021, India’s Republic Day, when there was a large protest against the bills passed at the Delhi border. This trimmed dataset was merged with the dataset of users by *userId* and, then, duplicate tweets were dropped to obtain a dataset of 7914 rows.

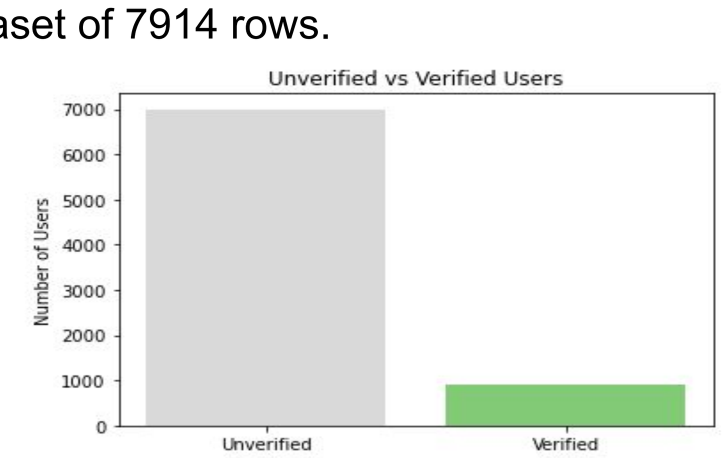

Fig 1. Bar Chart of Percentages of Verified and Unverified Users

Feature engineering is used to create inputs for the machine learning model and it is important for improving its performance. Before creating features, data preprocessing is conducted for consistency. This includes:

1. Removal of special characters like *\r*, *\n* and **
2. Making the words lowercase so the same word in different cases are not considered different
3. Elimination of punctuation like *?*, *!*, *;*
4. Conversion of emojis to text to preserve information that might be important for classification eg. ‘I won 🥇 in 🏏’ would become ‘I won *1st_place_medal* in *cricket*’

[1] Sharma, P. (2021, February). Farmers Protest Tweets Dataset (CSV). Version 17. Retrieved on December 20, 2021 from Kaggle

Methods

Preliminary Analysis

To understand the language used on Twitter, a word cloud was created to visualize the most common words used during the protests that occurred on Republic Day, where thousands of farmers protested at the Delhi border. This day was marked with a clash between the farmers and the police. From the word cloud (not pictured), it is clear that the rhetoric online was polarized with the most common words being ‘violence,’ ‘people,’ and ‘Delhi Police.’

Modelling Polarization of Stance

The initial analysis identified polarization in the language used online, indicating that further analysis should be conducted. To detect polarity of opinion in text, a multinomial Naive Bayes classifier was trained and fitted to measure the attitude, opinion and emotion of the tweets.

In order to train this classifier, a training dataset of 600 randomly sampled tweets was used. This training dataset was inspected and stances were assigned manually to reflect the nuances of opinion of the tweets. After manual assignment, the dataset was balanced with 201 tweets labelled as ‘for’, in support of the Farmers’ Protests, 200 labelled as ‘against’, against the Farmers’ Protests, and 203 as ‘neutral,’ neither for nor against the protests. The Naive Bayes classifier was then trained on this dataset.

Model Evaluation

Using cross-validation, the average accuracy of this classifier was found to be 61.92% which is far better than randomization at 33.33%. In an attempt to increase the accuracy, the tweets that were not clearly classified into one of the three categories, i.e., those with probabilities of being each of the three stances being between 0.2 and 0.55 (around random), were also classified. After adding these manually classified tweets to the training set, the accuracy of the classifier dropped to 59.18%. The classifier trained on the initial 600 tweets had higher accuracy so this model was tested on the rest of the tweets that weren’t used for training.

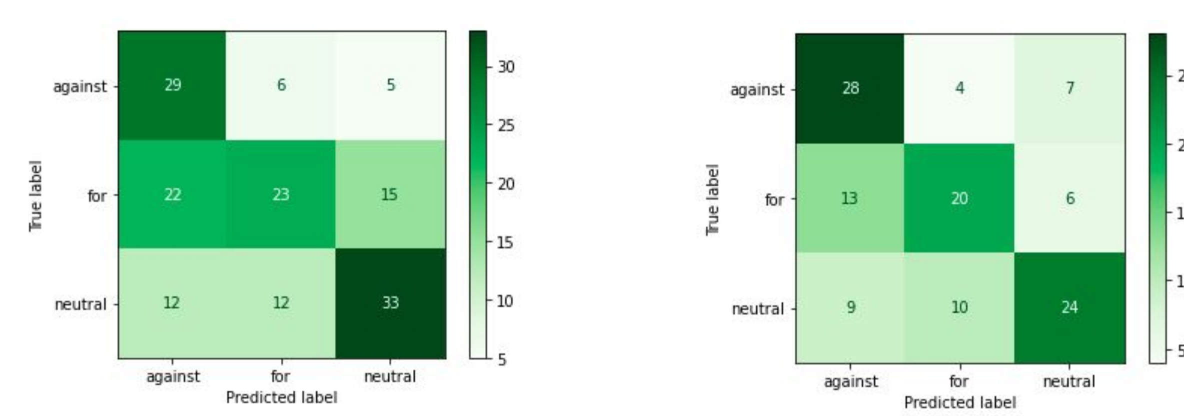

Fig 2. *(left)* Confusion matrix of classifier of accuracy of 61.92% (~600 tweets)
(right) Confusion matrix of classifier of accuracy of 59.18% (~850 tweets)

Testing the Model

On creating a bar chart of the distribution of tweets according to their predicted stances, it was found that the tweets were quite evenly distributed. The majority of tweets were against farmers at 41.6%, followed by tweets in support of farmers at 31.8% and then neutral tweets at 24.6%. This shows a fairly polarized rhetoric on Twitter regarding the Farmers’ Protest.

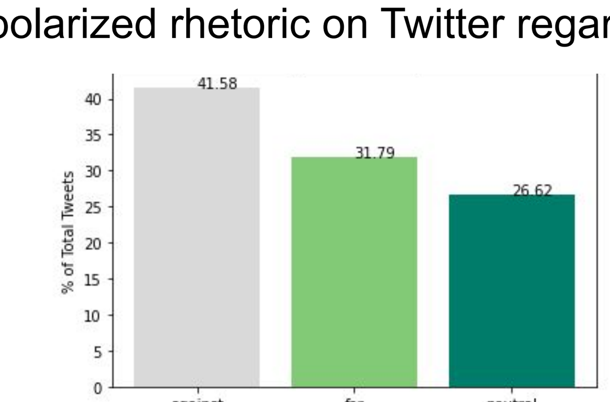

Fig 3. Bar chart of distribution of predicted labels of tweets after fitting classifier

Results

Verified vs. Unverified

The distribution of polarization of tweets published for verified vs. unverified users were very different. Tweets by verified users tended to be neutral at 72.5%, while 11.5% of the tweets were pro farmers and 16% against. This is perhaps due to the large number of accounts representing news companies. Unlike this case, there were barely any neutral tweets published by unverified accounts with neutral tweets making up just 20.6%. There were 34.4% tweets for the protests and 45% tweets against the protests.

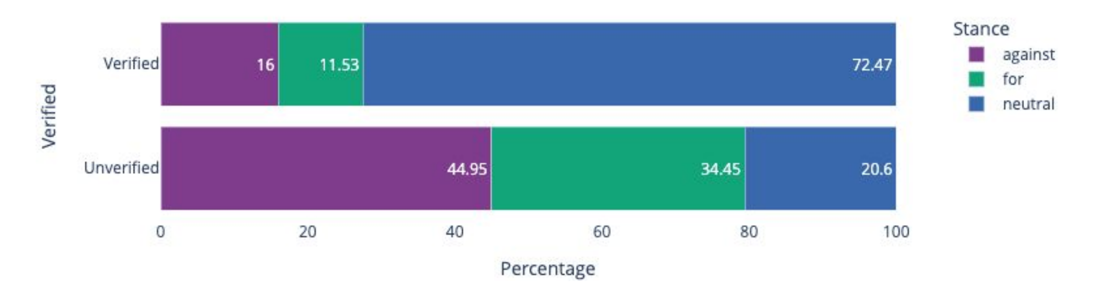

Fig 4. Stacked bar chart of distribution of predicted labels of tweets by verified vs. unverified users

Word Frequency Analysis

The 25 most common words in tweets by verified users and unverified that were labelled ‘for’, ‘neutral’ and ‘against’ were visualized using word clouds and side-by-side bar charts. In general, for verified users, all the tweets used similar language, but the neutral tweets often used words like ‘live updates,’ confirming that these tweets are from news sources. Unverified users followed a similar trend, but tweets against the protests contained violent and divisive language like ‘khalistan terrorist’ and ‘farmers protests hijacked.’

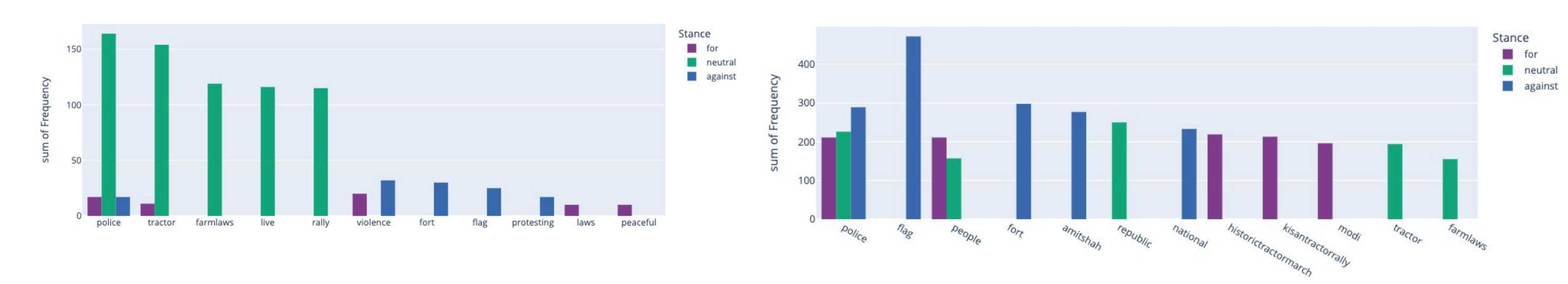

Fig 5. Side-by-side bar plots of top 10 words of tweets ‘for’, ‘neutral’ and ‘against’ by verified vs unverified users

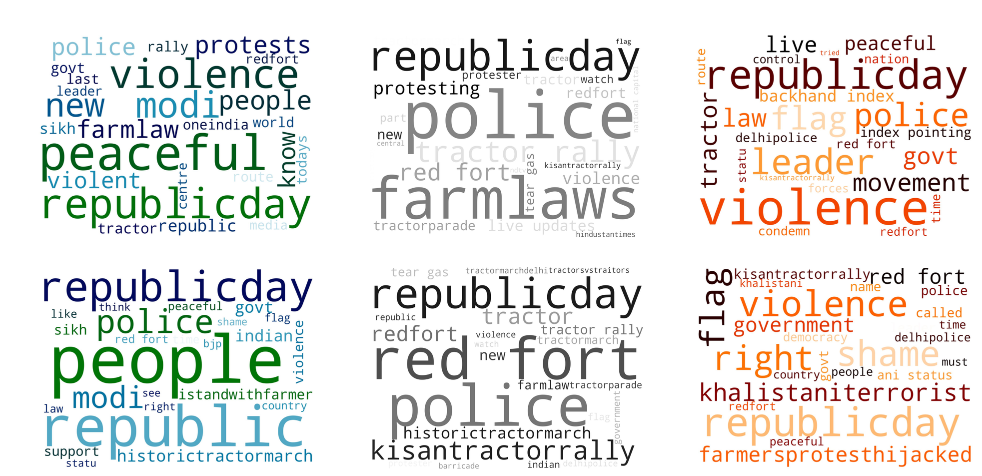

Fig 4. *(top)* Word clouds of top 25 words of tweets ‘for’, ‘neutral’ and ‘against’ by verified users
(bottom) Word clouds of top 25 words of tweets ‘for’, ‘neutral’ and ‘against’ by unverified users

Further Considerations

1. Naive Bayes classifiers have their own drawbacks and others might be more accurate.
2. The model was trained on a small dataset (~4%) which could be improved with more training data. A larger and less-biased training dataset make for a more effective model.
3. Since the study uses bag-of-words approach where two dictionaries are compared and the classifier uses vector space models, words can easily be assigned wrong stances.
4. The tweets included only those set to English on Twitter and does not consider tweets in other regional languages like Hindi which are very important in India. Many tweets have some Hindi words or Hindi words written in English which are not accounted for.