Pro-Choice vs. Pro-Life: Tweets Exploratory Data Analysis

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I. Introduction

The 1973 Roe vs. Wade decision, legalizing abortion in all fifty states, seems to solve one of the most controversial issues in terms of abortion. However, on June 24, 2022, the Supreme Court issued a bill prohibiting women's access to out-of-state abortion services. Additionally, the Court banned abortions nationwide after 15 weeks of pregnancy, overturning the Roe v. Wade case.

The Congress's decision has drawn much attention on social media, especially from females. The argument divides into two opinions: Pro-Choice vs. Pro-Life. People who support pro-choice believe everyone has the fundamental human right to decide when and whether to have children. They think it is OK for them to have the ability to choose abortion as an option for an unplanned pregnancy – even if they would not choose abortion for themselves. The view is that a woman should have the legal right to an elective abortion, meaning the right to terminate her pregnancy.

People who support pro-life believe that the life of the fertilized egg, embryo, or fetus is much more critical. They despise children's welfare after birth and oppose child welfare legislation. The controversial issues pit people against each other like they are on two teams. Most Americans believe abortion should be legal because it is the human right to access abortion.

This paper presents an exploratory data analysis on tweets about pro-choice vs. pro-life. It is helpful for people who want a general idea about how people react to the bill that bans abortion in certain states, especially for females. The neural network model helps them to grasp a pragmatic understanding of the whole event timeline.

More specifically, the model should provide a decent result so people can learn primary online users' opinions behind the case. In addition, this model should facilitate decision-makers in Congress to pass bills involving controversial issues because it generates local and global impacts at a certain level.

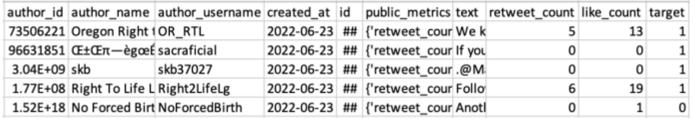
PREGNANT
Feminist Majority Foundation
KEEP ABORTION SAFE AND LEGAL
A WOMAN'S PLACE IS IN YOUR FACE!
PROSECUTING
ORTION
I AM A... PRO-CHOICER AND I REJECT abortion
I'M A WOMAN NOT
FEMINIST LOOKS LIKE
STUDENTSFORLIFE.ORG
I AM THE PRO-LIFE GENERATION

Fig 1. Abortion-rights movements

II. Data Gather

The dataset of 56,040 tweets was collected in the wake of the Roe vs. Wade cancellation sentence and analyzed the influence operations. The dataset is available to download from the Kaggle website, which lists in the reference.

The tweets are collected containing either the #prochoice or the #prolife hashtag, reflecting the two opposite poles of the discussion. The tweets with #prochoice have a target variable of 0, and the tweet with the #prolife has a target variable of 1.



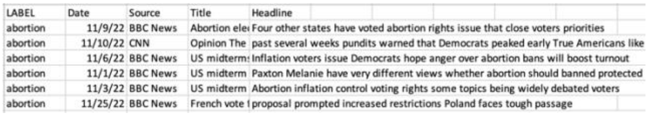
author_id	author_name	author_username	created_at	id	public_metrics	text	retweet_count	like_count	target
73506221	Oregon Right t	OR_RTL	2022-06-23	##	{'retweet_cour	We k	5	13	1
96631851	Œ±Œπ—ègœE	sacraficial	2022-06-23	##	{'retweet_cour	If you	0	0	1
3.04E+09	skb	skb37027	2022-06-23	##	{'retweet_cour	.@M	0	0	1
1.77E+08	Right To Life L	Right2LifeLg	2022-06-23	##	{'retweet_cour	Follo	6	19	1
1.52E+18	No Forced Birt	NoForcedBirth	2022-06-23	##	{'retweet_cour	Anotl	0	1	0

Fig 2. Original dataset

Other columns, such as 'created_at,' 'retweet_count,' and 'like_count,' can be valuable features for the data model. On the other hand, the 'author_name,' 'author_username,' and other columns are irrelevant to this paper and will be omitted during the data preprocessing.

In addition to the original dataset, newsapi.org provide API to gather unlabeled news titles related to Pro-Choice vs. Pro-Life. Registered a free account on newsapi.org to get the API key and set up an endpoint for the servers and the location on the server where data will be retrieved. The newspaper servers will query for all the topic names in the list: 'abortion' and 'antiabortion.'

The server will respond in JSON format with the date, title, headline, and source. Then the JSON format transforms into a large CSV file where each article is in a row. Adding one column that either abortion or antiabortion to convert this data into a labeled data frame so model train and test with the data.



LABEL	Date	Source	Title	Headline
abortion	11/9/22	BBC News	Abortion ele	Four other states have voted abortion rights issue that close voters priorities
abortion	11/10/22	CNN	Opinion The	past several weeks pundits warned that Democrats peaked early True Americans like
abortion	11/6/22	BBC News	US midterm:	Inflation voters issue Democrats hope anger over abortion bans will boost turnout
abortion	11/1/22	BBC News	US midterm	Paxton Melanie have very different views whether abortion should banned protected
abortion	11/3/22	BBC News	US midterm	Abortion inflation control voting rights some topics being widely debated voters
abortion	11/25/22	BBC News	French vote t	proposal prompted increased restrictions Poland faces tough passage

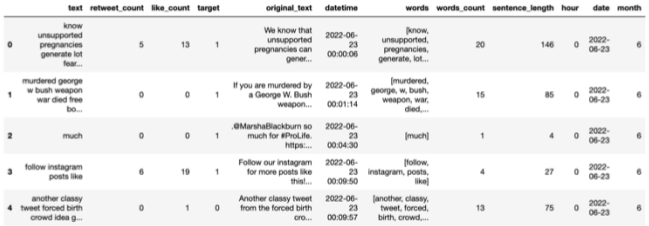
Fig3. Dataset retrieved from API

III. Data Prep

Preprocessing is a crucial step in processing text, especially for tweets. Use standard text preprocessing techniques and tweets-specific preprocessing techniques to preprocess tweets. The standard preprocessing technique uses NLTK (Natural Language Tool Kit) library. The tweets-specific preprocessing technique uses Regular Expression (re in python library).

The DateTime module transforms the 'date' column into 'hour' and 'month.' Moreover, use feature extracting to count words and sentence length to add more features to the dataset. Here is the list of tweets-specific preprocessing tasks using a regular expression:

1. Lowercasing all the letters
2. Remove mentions '@.'
3. Remove hashtags '#.'
4. Remove links. Start with 'HTTP' or 'www.'
5. Remove punctuations
6. Remove non-alphanumeric characters
7. Remove stop words



	text	retweet_count	like_count	target	original_text	datetime	words	words_count	sentence_length	hour	date	month
0	know unsupported pregnancies generate lot fear...	5	13	1	We know that unsupported pregnancies can gener...	2022-06-23 00:00:06	[know, unsupported, pregnancies, generate, lot...	20	146	0	2022-06-23	6
1	murdered george w bush weapon war died free bo...	0	0	1	If you are murdered by a George W. Bush weapon...	2022-06-23 00:01:14	[murdered, george, w, bush, weapon, war, died,...	15	85	0	2022-06-23	6
2	much	0	0	1	.@MarshaBlackburn so much for #ProLife. https:...	2022-06-23 00:04:30	[much]	1	4	0	2022-06-23	6
3	follow instagram posts like	6	19	1	Follow our instagram for more posts like this!...	2022-06-23 00:09:50	[follow, instagram, posts, like]	4	27	0	2022-06-23	6
4	another classy tweet forced birth crowd idea g...	0	1	0	Another classy tweet from the forced birth cro...	2022-06-23 00:09:57	[another, classy, tweet, forced, birth, crowd,...	13	75	0	2022-06-23	6

Fig 4. Preprocessed dataset

Then, we tokenize and vectorize text with stemming. The goal is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form. Here, we remove all columns containing numbers and any column with a name of 3 or smaller, like 'it,' 'of,' and 'pre.'

After we tokenize the text, we encode it into a 500 numeric length array to represent the original text so the model can recognize them. We use the embedding (the matrix we made in the previous steps) to encode the reader into an index inside the embedding. The padding method modifies that every encoded sentence will be the same length as 500. We append the 'pad' symbol if the distance is less than 500 and get the first 500 tokens if the size is more significant than 500.

We also split the dataset into train, valid, and test data with a ratio of 60, 20, and 20. The shape will be (33624,12), (11208,12), and (11208,12) corresponding. Using vocab to convert reviews (text) into numerical form, Replacing each word with its corresponding integer index value from the vocabulary. Assign the max length of the vocab + 1 to terms, not in the vocab. For the dataset from news API, we do similar preprocessing like tweets, but we focus on the title and headline.

IV. Baseline: Neural Net w/ Backpropagation

Use preprocessed data to train a simple, one-layer NN with backpropagation, random weights, and biases. This model aims to set up a baseline that the model describes later, ideally providing better performance. This network will not use TensorFlow/Keras, Sklearn, or other packages. Here is the network structure:

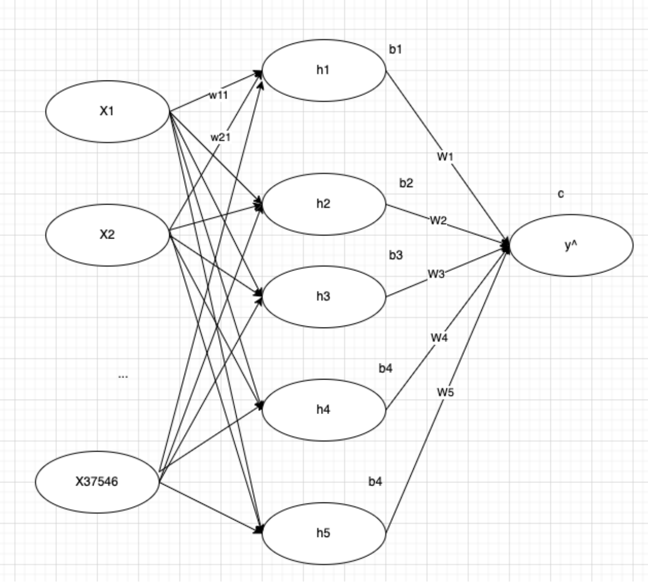


Fig 5. Neural Net structure

Backpropagation is a process that takes the error rate of forward propagation and feeds this loss backward through the neural network layers to fine-tune the weights. After iteration 1000, the total loss is 4840.21, and the average loss is 0.12. The accuracy score is 0.78, and the confusion matrix list below, along with the loss plots. There is an overfitting issue with this NN due to the simple net structure.

```
[[10232  8087]
 [   16 19211]]
```

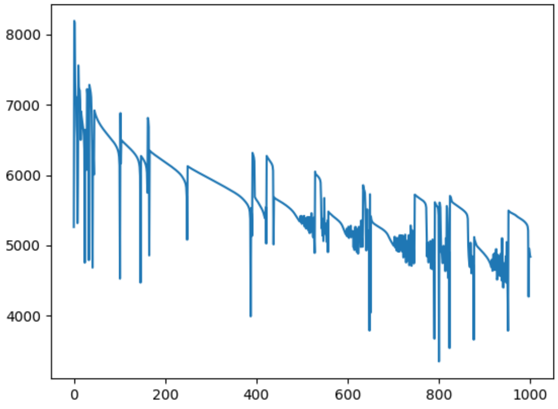


Fig 6. Total loss

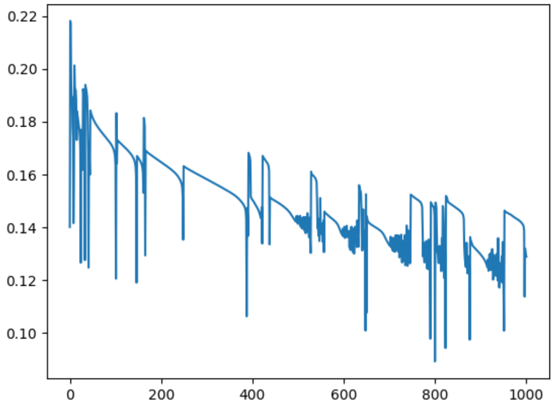


Fig 7. Average Loss

V. Neural nets

Build four neural nets with preprocessed train/validation/test datasets for predicting pro-choice and pro-life based on TensorFlow and Keras (ANN, RNN, LSTM, CNN). Evaluate the model with a confusion matrix, loss, and accuracy with the sklearn library.

The network intended to predict the tweets support pro-life or pro-choice, and the input vector is retweet_count, like_count, words_count, sentence_length, and hour.

For Convolutional Neural Networks, we need to define the convolutional layer, a generalization of the Dense layer. The convolution means sliding a flipped kernel, so most of the library use cross-correlation to implement the convolution layer because it is sliding a kernel without a flip.

Recurrent Neural Networks maintain an internal state and will update at every step. The set of weights is the same across all time steps through the sequence. The first layer is the embedding layer, which will learn embeddings for different words.

We define input with the vocabulary size and length of input sequences. We define output with a dimension of dense embedding. It is the size of the vector space in embedded words and establishes the size of the output vectors from this layer for each word.

Embedding layer, the word with similar meanings or that often occurs together in similar contexts will have a similar vector representation based on how close or far apart those words are in their meanings. The most common feature vectors are Word2Vec from Google and GloVe from Stanford.

In an embedding, each dense vector represents the projection of the word into a continuous vector space. A word's position in the learned vector space is called its embedding. The dense layers require inputs such as batch size and input size.

For Long Short Term Memory Networks, it contains computational blocks that control information flow. The gates control information is added or removed through structures. It can forget irrelevant information, store relevant information from current input, update the cell state selectively and output a filtered version of the cell state.

The encoder LSTM processes the entire input sentence and encodes it into a context vector, which is the last hidden state of the LSTM/RNN. The final state is the initial hidden state of the decoder. The decoder LSTM/RNN produces the words in a sentence one after another.

	ANN	RNN	LSTM	CNN
Train Loss	0.6287	0.4309	0.4575	**0.3532**
Train Accuracy	0.6506	0.7700	0.7421	**0.8123**
Validation Loss	**0.6375**	0.7246	0.7817	0.9974
Validation Accuracy	**0.6342**	0.6158	0.6303	0.6115
Test Loss	**0.6375**	0.7246	0.7816	0.9973
Test Accuracy	**0.6341**	0.6158	0.6302	0.6115

Table 1. Neural Nets Loss and Accuracy on Tweets

	ANN	RNN
Confusion Matrix	3227 1802 2298 3881	3503 2284 2022 3399
	LSTM	CNN
Confusion Matrix	3590 2209 1935 3474	3899 2728 1626 2955

Table 2. Confusion Matrix for detailed evaluation

	ANN	RNN	LSTM	CNN
Train Loss	0.7497	**0.5714**	0.6873	0.6715
Train Accuracy	0.5131	**0.7487**	0.5654	0.6073

Table 3. Loss and Accuracy on dataset gathered from API

CNN perform better compared to other three neural nets; RNN and LSTM perform similar result due to similar structure. ANN is unstable neural nets because it may predict all labels as 0 or 1. On the other hand, RNNs perform better among all four neural nets in relatively more minor datasets with smaller batch sizes and learning rates.

VI. Conclusion

Tweets exploratory data analysis is a challenging but also necessary task. In this paper, we have 56,040 tweets labeled pro-choice or pro-life, and 200 sample news titles and headlines labeled abortion or antiabortion. Five neural nets predict output from these data. They potentially benefit readers or decision-makers in the supreme court towards a better understanding of how the public sees and sees abortion in (digital) life.

This paper is not intended that take a position on the discussion on the right to abortion. Focus on the ethical arguments and underlying issues rather than on political considerations that might also be involved. This dataset takes its cue from this discussion to create a corpus of tweets that can be tagged a priori.

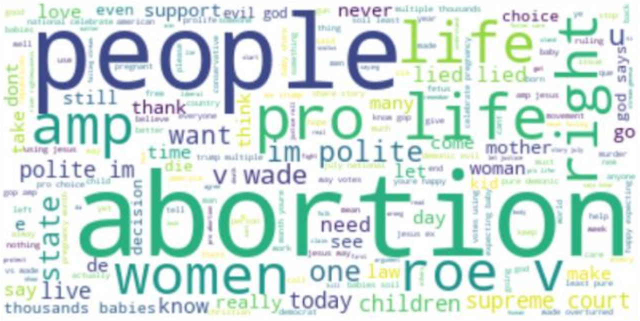


Fig 8. Pro-life Word Cloud

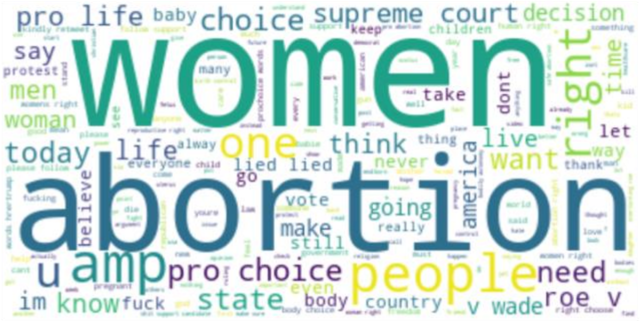


Fig 9. Pro-Choice Word Cloud

The top words for pro-life are people, right, children, and mother; meanwhile, the top words for pro-choice are women, decision, one, live, and believe. These words contribute to identifying pro-life/pro-choice labels.

Identifying pro-choice or pro-life in texts could be used in various applications like tweets sentiment analysis, argument faceted search, and value-based opinion profiling. It is important to note that these samples do not represent the user's opinion but provide a benchmark for measuring classification robustness across sources.

For now, this paper introduced five neural nets, and the best neural nets provide around 80% accuracy with reasonable training time and memory space. A more significant community effort is needed to collect more solid datasets from a wider variety of sources besides Twitter.

VII. Data Visual

This paper does not intend to provide sentimental analysis for these tweets but give a data insight behind the texts. Using NLTK library to categorize each sample into positive, negative, and neutral sentiment. Then, using seaborn and Plotly library to visual the dataset.

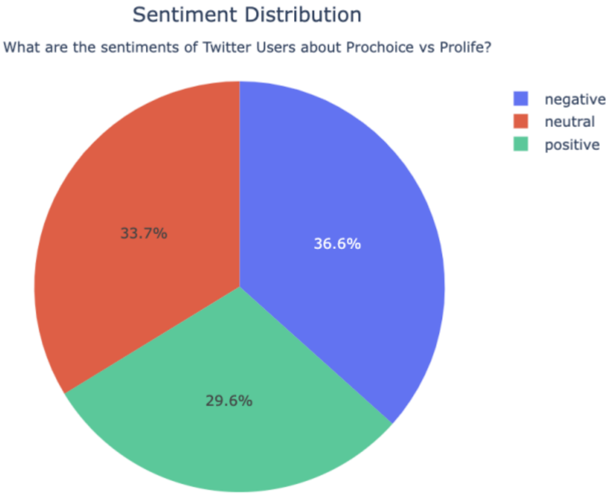


Fig 10. Count plot of sentiments of the data

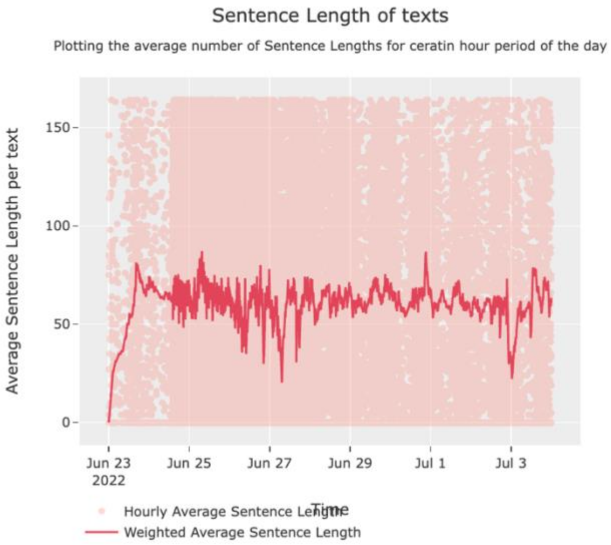


Fig 11. Sentence Length of based on date

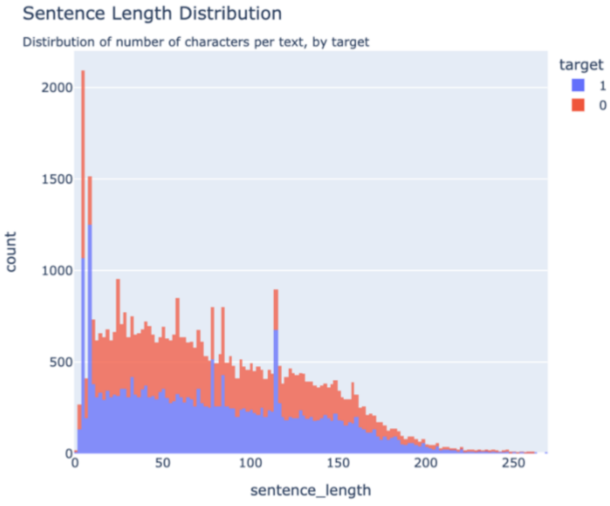


Fig 12. Sentence Length Distribution

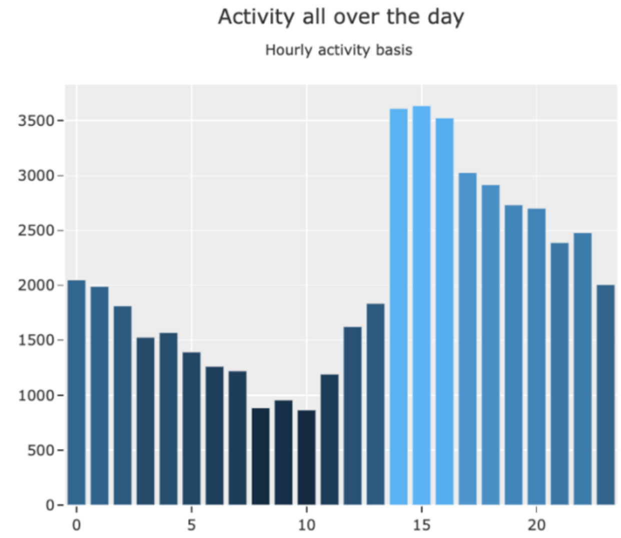


Fig 13. Activity all over the day

We can see that most tweets are negative sentiment toward to abortion topic and people continually tweets about it with length 20 ~ 50 sentence length. Most of tweets occurs afternoon or after 2 pm.

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