Political Polarization, Emotions and Engagement on Reddit

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Abstract

This paper investigates the relationship between political polarization, emotions expressed in textual posts, and the amount of engagement those posts received on reddit. The dataset used for analysis is scraped from yearly top posts from the two partisan subreddits, and we used standard metrics for evaluating polarization, engagement, and emotion intensity. We developed a naive bayes baseline for measuring polarization along with two BERT-based models trained to more accurately measure polarization and the intensities of different emotions expressed in a post. We compared the breakdown of emotions expressed by posts, the scores our polarization models assigned to posts, and the amount of engagement posts received.

1 Introduction

Reddit is an online social-networking forum. People post on "subreddits" within reddits which are generally aligned with a particular topic, ideology, or interest group. We were interested in studying the Democrat (r/Democrats) and Republican (r/Republican) subreddits. We assume these subreddits are essentially echo chambers for the political party they correspond to.

According to the Oxford dictionary, an echo chamber is "an environment in which a person encounters only beliefs or opinions that coincide with their own, so that their existing views are reinforced and alternative ideas are not considered". Almost all posts in the Democrat and Rebuplican subreddits align with the political party assigned to the subreddit. Thus, the Democrat subreddit is an echo chamber for democrats, and the Republican subreddit is an echo chamber for republicans.

We aim to determine the amount of political polarization in a reddit post. We define political polarization as the extent to which the content of a post conveys an ideologically extreme. A post that seems politically neutral (i.e. "Go vote!") would not be classified as politically polarizing. On the other hand, a post that seems strongly republican or anti-democrat (i.e. "Joe Biden and the liberals are ruining this country because they are evil stupid fascists!") would be classified as being politically polarized in the republican direction, and a post that seems strongly democrat or anti-republican (i.e. "Mitch McConnell and the Trump supporters are ruining this country because they are evil stupid fascists!") would be classified as being politically polarized in the democrat direction.

In addition to being able to determine how polarizing a post is, we also wanted to determine which emotions are expressed by a post in order to learn more about the mechanism through which polarization occurs in social media posts. There are a variety of models, described in the sections below, that will show the extent to which emotions like anger, sadness, happiness, and fear exist in textual posts. We will apply these models to posts in the Democrat and Republican echo chambers in order to learn about the differences in the emotions that are expressed in posts that are polarizing towards either echo chamber.

Finally, we will look at the number of upvotes a post receives as a proxy for the amount of engagement that a post has gotten. A post with more upvotes is likely to have been seen and accepted by more people than a post with fewer upvotes. We want to explore the relationship between the extent to which a reddit post is politically polarizing, the emotions expressed in the reddit post, and the amount of engagement the reddit post receives, and compare the relationships between the republican and democrat echo chambers.

Our team hypothesized that for both the Democratic and Republican subreddits, posts that are more politically polarizing in-line with the political opinion dominating the subreddit will receive more engagement. We also expect that for both subreddits, posts that have more emotions expressed with larger intensities will receive more engagement than posts with less intense or fewer emotions expressed. We also expect posts with large amounts of anger and fear to receive more engagement, particularly on the Republican subreddit. We expect posts in the Republican subreddit, in general, to contain more anger, fear, and intense emotion in general than posts in the Democratic subreddit.

Our core hypothesis focuses on the relationship between political polarization, emotional intensity, and engagement for textual posts in the Democrat and Rebuplican subreddit. We chose this hypothesis because we were influenced by voices in public media which argue that republicans tend to use fear-based and anger-based techniques in order to entice viewers.

Our paper's central finding was that there is not a major difference in the emotions expressed by democrats and republicans on reddit, and the extent to which emotions like fear and anger are expressed has little impact on the amount of engagement a post receives for both subreddits.

2 Related Work

In "Analyzing Polarization in Social Media: Method and Application to Tweets on 21 Mass Shootings" (Demszky et al., 2019), the authors provide a framework for measuring polarization in textual content on social media. They aimed to create an objective, unbiased formula for calculating polarization based on (1) a leave-one-out estimator of political partisanship (democrat or republican) and (2) a user-level dot-product with a floating-point output between zero and one to measure the polarization of one user's language. These two features provide both the direction and magnitude of polarization in a post.

In contrast, "Learning Political Polarization on Social Media Using Neural Networks" (Belcastro et al., 2020) presents a neural-network based approach to measuring polarization. While the Demszky paper (Demszky et al., 2019) wants to measure partisanship and polarization in a clear, interpretable, and replicable way, the Belcastro paper (Belcastro et al., 2020) aims to measure polarization in the most accurate way possible using deep neural networks. The paper defines polarization as an inclination to speak positively about a particular faction (i.e. Democrats and republicans), and it follows that the proportion of positive words corresponding to each faction in each post is used as a proxy for the amount of polarization towards said faction in each post. Differently, in our project we define the polarization score of a comment as how likely it is published in a Democrat or Republican subreddit by leveraging the predicted probabilities of the classifier model.

We also looked at papers that studied echo chambers in general rather than isolated incidents of political polarization. In the paper "Content-Based Echo Chamber Detection on Social Media Platforms" (Calderón et al., 2019), the authors aim to formulate a model that can detect the phenomenon of "echo chamber" between a post and its related comments on Facebook pages, and then quantify the degree of "echo chamber" behavior. The paper presents two types of content-based feature extraction approaches: the first focuses on stance representation of comments on a particular discussion topic, and the second on the type and intensity of emotion elicited by a subject. The paper also defines a score, "echo chamber indexing", that measures the degree of echo chamber effects in a Facebook page. The idea of quantifying the degree of echo chamber effect using an "index" in this paper is peculiar.

It is interesting to note that the approach to measuring echo chambers by (Calderón et al., 2019) is similar to the approaches of measuring polarization by (Belcastro et al., 2020) and (Demszky et al., 2019) in that two separate calculations are performed: one calculation to determine the stance of the post (i.e. pro vs con, democrat faction vs republican faction), and another calculation to determine the emotional intensity of the post. We see that the natural phenomenon of polarization is abstractly composed of two fundamental qualities: stance and intensity. By determining the faction of the stance and the intensity of the stance stated in a social media post, one gathers all the information they need to assess the polarization in that post according to these three approaches. This leads us to believe that in our future work, we as well might benefit from exploring one system to determine the stance of the writer and one system to determine the intensity of the emotions felt by the writer.

In "Quantifying echo chamber effects in information spreading over political communication networks" (Cota et al., 2019), the authors mined 12 million Twitter messages related to the impeachment of the former Brazilian President Dilma

Rousseff to measure the effects of echo chambers in information spreading over political communication networks. An interesting notion in this paper is that the authors constructed a communication network based on users' interactions and assigned a political position score for each user to demonstrate their political geometry to quantitatively analyze the topological evidence. This user level geometrical representation provides more granularities into the polarization analysis. Similarly, Demszky's paper also defined a user-level polarization measurement by taking a user-level dot product. Both approaches can be considered if we want to include user-level polarization measurement in the future work of this project.

The paper "Echo Chambers: Emotional Contagion and Group Polarization on Facebook" studied the evolution of the size of the echo chambers by fitting daily resolution data with three growth models. The studied echo chamber evolves at a nearly constant rate after an initial spike-like growth. In the later half of the paper, the emotional behavior of the users as a function of their involvement inside the community is investigated. The study found that the more a user is active, the more likely their comments contain negative emotion. From this paper, we derived our hypothesis that larger engagement might also result in more negativity or higher intensity of the emotions.

The paper "A Sociolinguistic Study of Online Echo Chambers on Twitter" (Duseja and Jhamtani, 2019) studies the potential effect of echo chambers on user's behavior through tweet structure analysis, vocabulary analysis, and topic analysis. Different from the earlier echo chamber paper (where the author directly assumes that the communities they studied are actually echo chambers), the authors used homophily scores and fixed threshold values to determine whether a user belongs to the echo chamber.

All of the above reviewed papers studied the topics of polarization, which is also closely associated with the concept of the echo chamber, the focus of the two later papers. In many cases, the identification of echo chambers is achieved by observing the numerical manipulations of the polarization score. It is interesting to see that polarization can be defined in both user level, intra-group level, and cross-group level.

Number	Democrat	Republican
Post	811	845
Post Tokens	3852	4853
Comment	13754	15551
Comment Token	33524	34503

Table 1: Statistics from scraped data from r/democrats and r/republican

3 Data

We created our dataset by scraping the yearly top posts from the two partisan subreddits: Democrat (r/Democrats) and Republican (r/Republican). First of all, we used PRAW (Boe, 2021) to scrape top n=1000 posts from both r/Democrats and r/Republican. Then, to ensure the number of upvotes of the posts and comments are stabilized, we only included posts and comments that were created before April 1, 2021. The dates of the posts and comments in our dataset range from May 20, 2020, to April 1, 2021. Lastly, to ensure the comment section of the post contains sufficient information for us to conduct analysis, we only included posts that have more than 20 top-level comments.

3.1 Sample Data

As shown in Table 2, each post data point includes post id, post title, body text, upvote numbers, subreddit id, number of comments, and the time it was created. As shown in Table 3, for each post we scraped its top-level comments and each comment data point includes body text, upvote numbers, author id, comment, post id, subreddit id, and the time it was posted.

3.2 Data Overview

In Table 1, we show the overview of the sample data. We process the post and comment texts by splitting them by white space and removing punctuation. In Figure 8 and Figure 9 (See in Appendix), we demonstrate the top frequent tokens in Democrat posts/comments and Republican posts/comments. We noticed that the most common terms in Democrats and Republican posts/comments are highly overlapped. Notice that a primary assumption made in our study is that we assume all posts from r/Democrats are democrat leaning and all posts from r/Republican are republican leaning. By observing our dataset, we can confirm this pattern holds true for almost all data. Furthermore, both r/Democrats and r/Republican

title	score	id	subreddit	comments	body	created
Why?	34584	l2eqla	democrat	771	Why this even a question?	1611313987

Table 2: Sample Post Data

body	ups	author	id	post_id	subreddit	created
I already love this woman.	29	deadbird	gk56p2d	l2eqla	t5_2qn70	1611290395

Table 3: Sample Comment Data

communities have rules of not allowing posts or comments that promote other ideologies. We added label = -1 to Republican post and comment data while labeling = 1 to Democrat post and comment data.

4 Metrics

In our study, we are conducting an analysis of the differences in the emotions that posts express between the democratic and Republican subreddits. We want to see how these emotions relate to the popularity of posts on each subreddit. In order to complete this study, we need three different kinds of metrics. First, we need a "polarization" metric which will tell us which direction an unlabeled post leans politically. Next, we need an "emotional breakdown" metric which will tell us which emotions are present in a textual post and how intensely each of those emotions are presently expressed. Finally, we need a "engagement" metric which will tell us how popular or viral a post is.

4.1 Polarization

We define our polarization score to to automatically determine how far a reddit post leans to the right or to the left. The score is a scalar number between -1 and 1 where -1 represents a post that is extremely likely to be from the republican subreddit, +1 represents a post that is extremely likely to be from the democrat subreddit, and 0 will be a post that is likely to be neutral. In the models section, we will describe how we train a model to learn this metric by leveraging the nature of echo chambers on reddit.

4.2 Emotional Breakdown

We break down emotions into two parts: the type of emotion and the intensity of the emotion (given the type). For the type of the emotion part, there will be four different categories: joyful, fearful, angry, sad. The intensity of the emotion will be a numerical score between 0 and 1, where 0 means the least intense while 1 means the most intense. In the models section, we will describe how to train models to automatically assign the type and the intensity of emotions to posts.

4.3 Engagement

As a proxy for the amount of engagement a post receives, we look at the total number of upvotes a post has. Posts with a larger number of upvotes are assumed to have reached a larger audience than posts with a smaller number of upvotes, and thus to have caused more engagement.

4.4 Model Evaluation Metrics

We also need to define metrics that we can use to evaluate the performance and training of our models. For the political polarization model, we could transform all scores to [0,1] and use binary cross entropy loss to train the model to predict democrat or republican. When analyzing the political polarization model as a whole, we can look at the macro-averaged F1 score averaged over the democrat and republican class. We will select the model that achieves the best macro-averaged F1 score after training on the binary cross entropy loss objective.

Our emotion model has two different components: a classification component for the type of the emotion and regression component for the intensity of the given emotion. As a result, we need two different sets of the metrics to evaluate both the classification aspect and the regression aspect of the model. For the classification aspect, we can measure the classification performance using classification accuracy, measure the regression performance of the emotional intensity using Mean Absolute Error (ABE).

5 Models

5.1 Polarization

We train a model that measures the political polarization in a post. In order to do this, we will take advantage of the structure of the Democrat and Republican subreddits. Since each subreddit is essentially an echo chamber, and the posts within each echo chamber conform to a particular ideological extreme, if we train a neural network to predict which subreddit an unlabeled post belongs to, we can use the confidence of the network's prediction as a proxy for determining how polarizing a post is. In this way, our definition of polarization also entails the discrepancy between the use of languages of Democrat and Republican posts. The existence of possible discrepancies was demonstrated in (KhudaBukhsh et al., 2020).

We use the following procedure to train the neural network. We begin with a binary labeled dataset which maps reddit posts from the Republican subreddit to one label and maps posts from the Democratic subreddit to the other label. We train a neural network, which predicts an output between 0 and 1 based on a textual post that is given as input, on this dataset. Now, when the network is given an unlabeled post, it will produce an output between 1 (strongly polarizing in the republican direction) and 0 (strongly polarizing in the democrat direction). We are able to use this output as a measurement for how polarizing a post is towards either ideological extreme.

We select Naive Bayes as our baseline model. Then, we fine-tuned a pre-trained BERT network (Devlin et al., 2018) using the training procedure described above. As stated in the metrics section, we trained the BERT network using binary cross-entropy loss, and we evaluated the network based on the highest classification accuracy the models achieve.

5.2 Emotions

For the analysis of emotions behind the reddit posts, we trained deep neural networks to automatically classify the emotions into four different categories: joyful, fearful, angry, sad as well as assign an emotion intensity score between 0 to 1 given a particular type of the emotion. An emotion intensity score of 0 represents the lowest possible emotion intensity score, and the intensity score of 1 represents the highest possible emotion intensity.

We first fine tuned a pre-trained Bert model to classify the type of the emotion. Then for each specific emotion, we fine-tuned a Bert models to predict its intensity given specific emotion.

We use the dataset from WASSA'17 EmoInt shared task (Mohammad and Bravo-Marquez, 2017) to train all neural networks for emotional prediction. The dataset contains information such as tweets, the emotion it exhibits, and the intensity score of the emotion (between 0 and 1). Once we have finished training our neural networks, we would use the trained model to assign the type of the emotions and emotional intensity to each reddit post.

Accuracy	F1 Score	Precision	
		Democrat	Republican
66.77%	72.18%	70.65%	64.81%

Table 4: Naive Bayes Baseline Model Metrics

Naive Bayes	Bert Model
67%	69%

Table 5: Polarization Classification Accuracy

6 Experiments

6.1 Polarization Modeling

For the polarization model, we trained a Naive Bayes model as our baseline model using the comment data. The reason why we chose Naive Bayes as our preliminary model is its simplicity and low requirement of computation. We divided the dataset into 70/30 for training and testing. The result is shown in Table 4 and Figure 1.

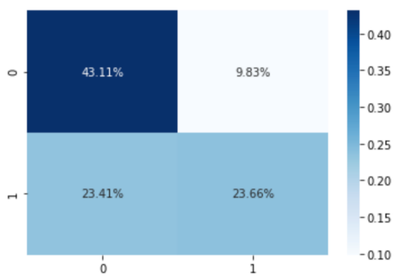

Figure 1: Naive Bayes Baseline Model Confusion Matrix

We also fine-tuned a pre-trained Bert model and obtained a slightly better overall accuracy of 69%.

6.2 Emotional Modeling

For the emotion modeling, we have downloaded and preprocessed the WASSA'17 EmoInt shared

Classification Accuracy	85%
MAE for anger dataset	0.12
MAE for fear dataset	0.11
MAE for joy dataset	0.10
MAE for sadness dataset	0.11

Table 6: Training Results for the Bert models (The MAE stands for Mean Absolute Error)

task dataset (Mohammad and Bravo-Marquez, 2017) for building the pre-trained models for both classifying the type of emotions and predicting the emotion intensity given the emotions. For the WASSA'17 EmoInt dataset, we have 857 tweets for Anger training data, 1147 tweets for Fear training data, 823 tweets for Joy training data, and 786 tweets for the sadness dataset.

For modeling both the emotional types and intensity, we fine-tuned pre-trained Bert models. We have one Bert model specifically for predicting the type of the emotion, and additional four Bert models to predict the emotional intensity of each of the following emotions: joy, fear, anger, sadness. The performance of the fine-tuned Bert model is shown in the table 6.

Once we trained our Bert models for emotion classification and emotional intensity predictions using WASSA'17 dataset. We applied the trained Bert model on the reddit Dataset to obtain the emotional type and emotional intensity of each reddit posts.

7 Analysis

7.1 Overview of Output Distributions

First, let's look at some overview statistics about our results:
Democrat mean upvotes: 18.41
Republican mean upvotes: 22.48
Democrat mean emotional intensity (across all categlories): 0.47
Republican mean emotional intensity (across all categlories): 0.47
Democrat subreddit mean polarization intensity: 0.42
Republican subreddit mean polarization intensity: -0.44

We see that republican posts tend to get an average of 4 more upvoates than democrat posts, and republican posts are overall slightly more polarizing in the republican direction than democrat posts are polarizing in the democrat direction. We find that emotional intensity averages the same across both reddits. It's unclear how significant this correlation is; we assume that based on this information, both subreddits are essentially the same in terms of polarization, emotional intensity, and mean upvotes.
Democrat standard dev upvotes: 42.34
Republican standard dev in upvotes: 50.09
Democrat std emotional intensity (across all categlories): 0.13
Republican std emotional intensity (across all categlories): 0.12
Democrat subreddit std polarization intensity: 0.45
Republican subreddit std polarization intensity: 0.44

We see the standard deviation in upvotes is slightly higher for republicans than for democrats. Besides this, the standard deviations in emotional intensity are equally small for both subreddits and equally large in polarization intensity for both subreddits.

7.2 Quantifying Emotions Expressed Across Parties

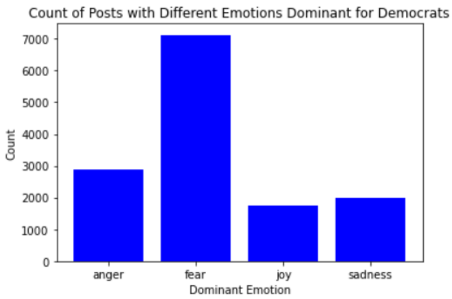

Figure 2: Count of Posts with Different Emotions Dominant for Democrats

In this section, we ask whether or not there are different breakdowns of emotions expressed with different intensities in posts between the democrat and republican subreddits. We found that posts on both reddits express almost an identical breakdown of emotions, on average.

If we look at figures 2 and 3, we see that the overall distribution of posts with different emotions dominant is essentially the same between parties. There are slightly more joyous posts relative to other posts in the democrat subreddit than in the

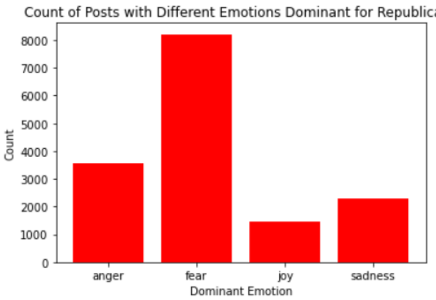

Figure 3: Count of Posts with Different Emotions Dominant for Republicans

republican subreddit, but this is the only significant difference.

Once more, in figures 10 and 11 (see in appendix), we see that both parties essentially express the same average intensities of anger, fear, joy, and sadness on each subreddit as eachother. This is fascinating given that we expected there to be big differences in the way emotions are employed in posts between the two subreddits. On both subreddits, anger was generally expressed more intensely than other emotions and fear was generally expressed less intensely.

7.3 Intensity of Emotion and Upvotes Relationships

In this section, we look at the relationship between the intensity of emotions expressed in reddit posts, as labeled by our model, and the amount of upvotes posts recieve. We compare these trends across the democrat and republican subreddits.

7.3.1 Overall

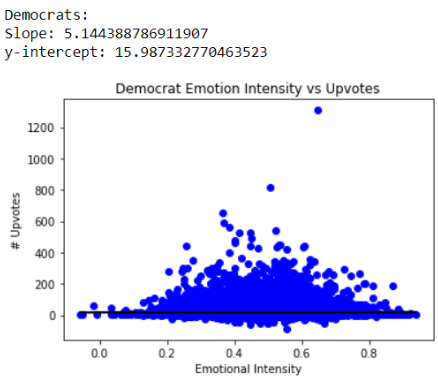

Figure 4: Overall Emotional Intensity vs Number of Upvotes for Democrats

In figures 3 and 4, we plot emotional intensity vs number of upvotes for democrats and republicans

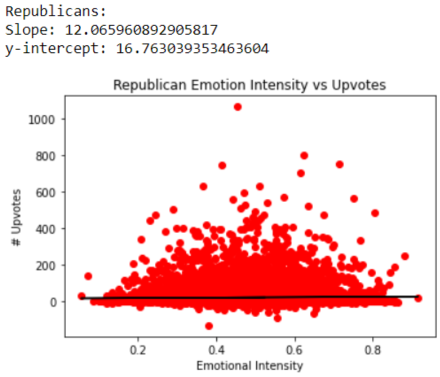

Figure 5: Overall Emotional Intensity vs Number of Upvotes for Republicans

to see how emotional intensity relates to engagement for each party. We try to fit a best fit line for both parties, however we see that a best fit line might not be the best way to model the data. Instead, it appears that the data follows a Gaussian. The Gaussian that would fit the republican graph would be wider than the Gaussian that would fit the democrat graph, suggesting that it is popular for a range of emotional intensities to become popular within the republican subreddit, while it is more likely that a narrow range of emotional intensities will become popular within the democrat subreddit.

We see that the best fit line for republicans has a much higher slope than that of democrats, and the y-intercept for each party is about the same. This means that in general, within subreddits, as posts increase in emotional intensity for the republican party, they are more likely to have an increase in engagement than posts that increase in emotional intensity for the democrat party. This aligns with our hypothesis.

7.3.2 Anger

In figures 12 and 13 (see in Appendix), we see that the best fit lines for both graphs are essentially the same, however the distribution of scatterpoints in the deomcrat party seems to suggest that posts are more likely to become more popular or surpass a threshold of virality (as shown as having significantly more likes than the average) if they have a medium amount of fear (0.3-0.6) whereas in the republican party, posts can become viral regardless of how much fear is in the post (0.1-0.8). Thus, it seems that the amount of fear in posts might be less correlated with engagement for the republican party overall than it is for the democratic party. Within the democrat subreddit, posts with a moderate but not extreme amount of fear are promoted.

7.3.3 Fear

Here, we see that there are much fewer posts in the democrat party that express small amounts anger (¡0.2) than in the republican party. The y-intercept for the republican party is higher than that of the democrat party, reflecting the fact that compared to the republican subreddit, the democrat subreddit had very few upvotes on posts that reflected low anger. The best-fit slope is significantly higher for the republican party than for the democrat party, demonstrating that posts with large amounts of anger are more likely to go viral on the republican subreddit than posts with large amounts of anger on the democrat subreddit. Generally, for both parties, more anger in posts significantly increases the likelyhood of virality.

7.3.4 Joy

The most interesting thing we see here is that posts with more joy are significantly less popular in the democrat subreddit than posts with less joy. In contrast, more joy increases the popularity of posts in the republican subreddit. Besides this, both figures 16 and 17 (seen in Appendix) are similarly shaped, reflecting similar relationships between joy and popularity.

7.3.5 Sadness

We see that posts with more sadness are significantly less likely to become popular in the democrat subreddit, while posts with more sadness are significantly more likely to become popular in the republican subreddit.

7.4 Polarization and Engagement Relationships

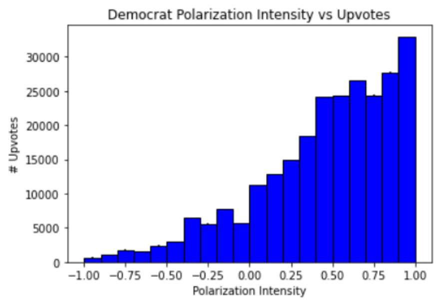

Figure 6: Intensity of Polarization vs Upvotes for Democrats

In this section, we ask how political polarization relates to levels of engagement as represented by

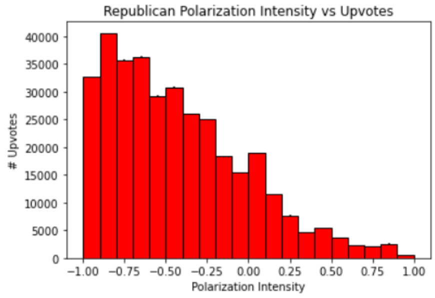

Figure 7: Intensity of Polarization vs Upvotes for Republicans

the number of upvotes each reddit post gets on each subreddit. Our model assigns posts on each subreddit with scores which we scale to be between -1 and 1 for each post. A score of +1 would be highly likely to be polarized towards the democrat subreddit and a score of -1 would be highly likely to be polarized towards the republican subreddit. We see how polarization scores relate to engagement in figures 6 and 7.

We see that for both parties, as posts become increasingly polarizing in the direction of the subreddit (i.e. more polarizingly republican for the republican subreddit), the number of upvotes the posts recieves gradually increases. Posts that are polarizing in the opposite direction of the echo chamber (i.e. republican posts on the democrat subreddit) do not tend to get very much upvotes. This is in-line with our team's hypothesis. Posts towards the middle that are politically neutral recieve a moderate amount of attention, larger than if they were from the opposite political pole but smaller than if they alligned with the echo chamber.

8 Conclusion

Our study reached several conclusions about the nature of the democrat and republican subreddits. First, we discovered that the emotional breakdowns and emotional intensities of posts are very similar between the two reddits. Also, the relationship between the emotions that are expressed in posts and the amount of upvotes posts recieves is very similar for both parties. Finally, we confirmed our hypothesis that users of one echo chamber will not tend to engage with posts that are politically polarizing in the direction of the opposing party. We hope these insights will be useful to the NLP and reddit communities.

Acknowledgement

We would like to thank Prof. Chris Potts and Dorottya Demszky for their help and advise on this project.

Authorship

All authors contributed equally to this project. Noah planned and conducted the analysis, doing the work outlined in the "overview of output distributions", "quantifying emotions expressed across parties", "intensity of emotion and upvotes relationship", and "polarization and engagement relationships" sections. He also wrote a significant portion of the final paper. Haishan is responsible for scraping the dataset for the project, training the baseline polarization model, evaluating the models and curating the final stats for the analysis. Jason collected and preprocessed the WASSA'17 dataset and trained the Bert Models for polarization prediction, emotion classification, and emotional intensity prediction.

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Appendix

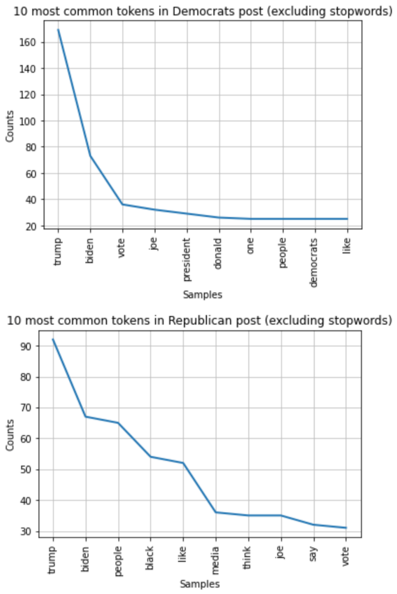

Figure 8: Top n=10 most common tokens in r/Democrats and r/Republican posts

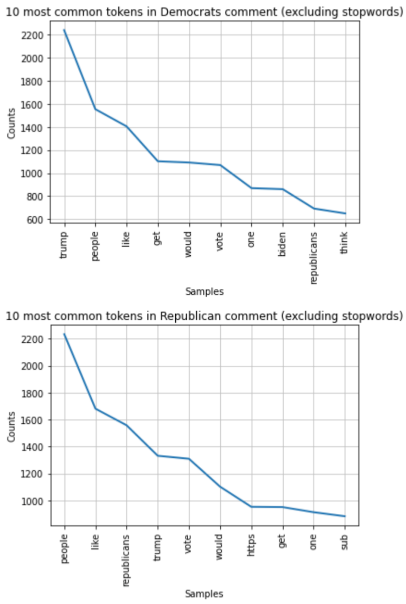

Figure 9: Top n=10 most common tokens in r/Democrats and r/Republican post comments

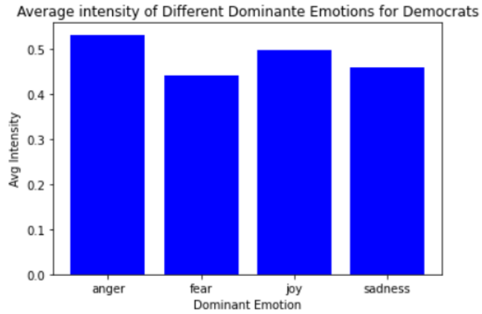

Figure 10: Average intensity of Different Dominante Emotions for Democrats

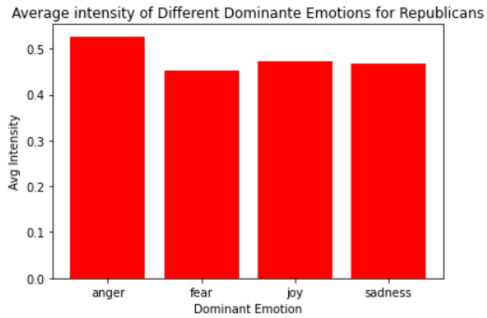

Figure 11: Average intensity of Different Dominante Emotions for Republicans

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Democrats:
Best fit Slope: 12.536602480383483
Best fit y-intercept: 14.223980473448119
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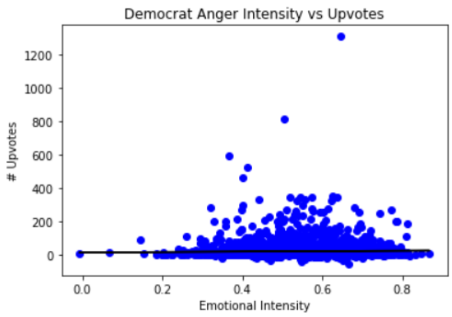

Figure 12: Emotional Intensity of Anger vs Number of Upvotes for Democrats

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Republicans:
Best fit Slope: 39.8878096339005
Best fit y-intercept: 0.3321918940849699
```

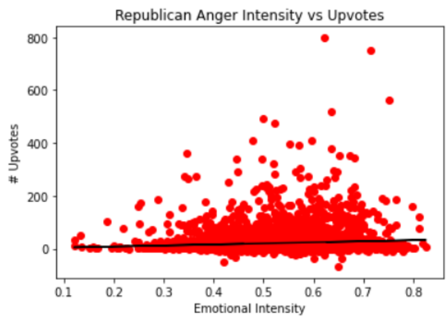

Figure 13: Emotional Intensity of Anger vs Number of Upvotes for Republicans

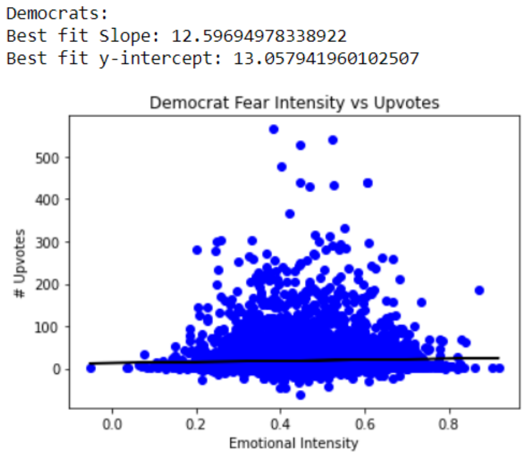

Figure 14: Emotional Intensity of Fear vs Number of Upvotes for Democrats

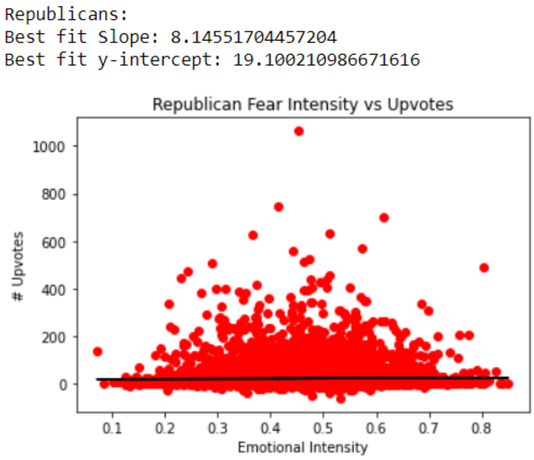

Figure 15: Emotional Intensity of Fear vs Number of Upvotes for Republicans

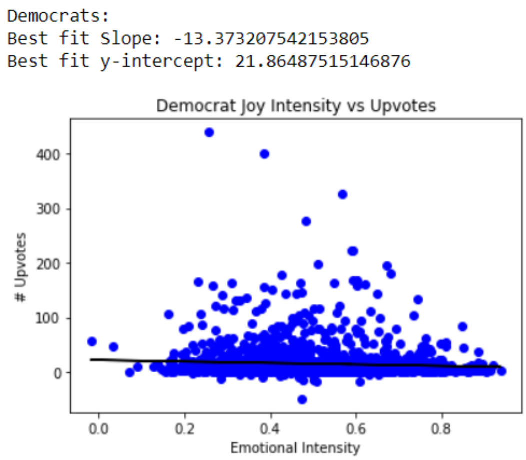

Figure 16: Emotional Intensity of Joy vs Number of Upvotes for Democrats

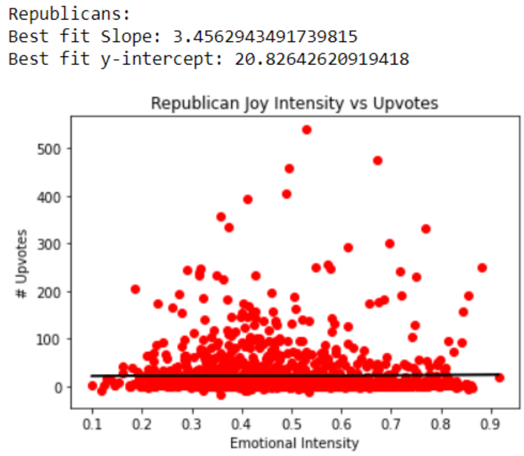

Figure 17: Emotional Intensity of Joy vs Number of Upvotes for Republicans

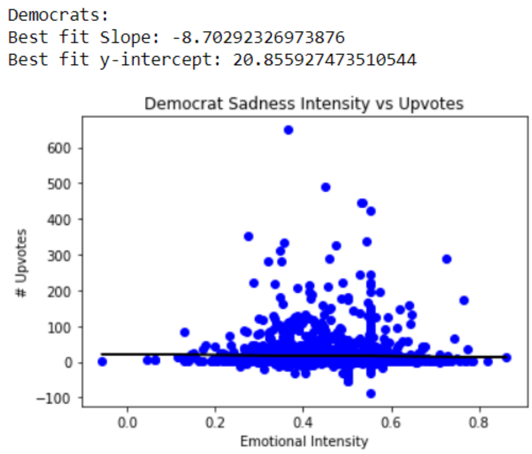

Figure 18: Emotional Intensity of Sadness vs Number of Upvotes for Democrats

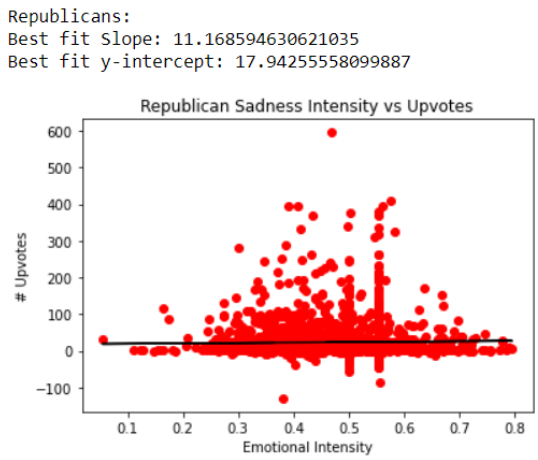

Figure 19: Emotional Intensity of Sadness vs Number of Upvotes for Republicans