Moral Emotions Drive Content Diffusion on Twitter

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Abstract

Ever since the 2016 US elections, we have been aware of how the spread of political ideas on social media can shape real-life outcomes. Yet, we still do not understand precisely how and why some political ideas spread more widely than others. In their 2017 paper, Brady et al. made one of the few groundbreaking discoveries on the topic. In this work, we replicate and extend their findings on moral-emotional contagion on social media. We studied the effects of positive and negative moral emotions on the diffusion of ideas using a large set of tweets on gun control. We further investigated the relationship between message spread and its complexity using the Gunning Fog Readability Index. We found that each additional moral emotional word increases retweet count by about 33%, while a unit increase in complexity produces only 1% decrease. We also found an asymmetric effect of positive versus negative moral-emotional words on message spread.

1 Introduction

Social media like Facebook and Twitter have played an important role in a lot of major political events, from the Arab Spring to the January 6th insurrection. Yet, little is known about how political content travels social media, and what drives people to share and retweet such messages. Brady et al. were the first to use social networks to help explain how political ideas spread from psychological viewpoint [1]. Because of the role morality and emotions play in politics, they focus on the relationship between moral emotions and the spread of tweets. Moral emotions are emotions connected with evaluations of social norms and brought about by interests that may be different from one's own [2]. For example, guilt about child death in third world countries. Brady et al. have determined that for every additional moral emotional word included in a tweet, it gets 20% more retweets on average [1]. These findings have also been confirmed by Valenzuela et al. in their research on how moral framing changes people's news-sharing behaviors [4]. We replicate as well as extend Brady's et al. analysis to help us get closer to understanding how ideas spread on social media. Since recent studies found that the scope of spread depends on how well a message captures attention, we also study how the complexity of messages influences diffusion [3]. Specifically, we have three hypothesis:

H1: The presence of moral-emotional words in tweets will increase their diffusion.

H2: The effect of moral emotions will change depending on their valence.

H3: The spread of tweets will decrease with the increase in tweet complexity.

We focused on the topic of gun control for our analysis, as it is highly discussed on Twitter. However, the tone of the discussion of this topic is relatively negative compared to others, such as gay marriage, so we do not expect our results on valence to generalize to all of Twitter political discourse.

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*Literature reveiw, data exploration and visualization, preprocessing, retweet count, modeling.
†Moral emotional word counts, Negative Binomial modeling, results presentation and visualization.

2 Methods

We tested our hypotheses on Twitter data[3], specifically on a set of 300,000 tweets about gun control. The tweets were further filtered by keywords from Brady et al. such as 'gun control', 'gun violence', '2nd amendment' etc.

	twid	rtwid	username	text
1	661664563377676288	NaN	ROCKWITHBECK	BOYCOTT NOV 4 @ABC @CMAwards > THREAT TO AL...
2	661664567940874240	6.616639e+17	BUSHADEMOCRAT	RT @AddInfoOrg: 'Responsible Gun Owner' Gives ...

Figure 1: Example tweet and retweet items.

To quantify the diffusion of tweets, we measured the spread of a given tweet by its retweet count. The raw data collected from the Twitter API did not contain a retweet count and hence we had to match every retweet to its original tweet by its retweet ID. We further matched the retweets with the originals by stripping username of the original person from the retweet ('RT @POTUS: ...') and text and matching those to the set of original tweets. We then collapsed all observations that had the same original user and text into one observation. We considered retweets whose originals where out of sample as original messages after collapsing them. In total, we ended up with $56,858$ original tweets, about 30% of which were retweeted at least once.

To count the number of moral-emotional words, we used a word dictionary developed by Brady et al., as we agreed that it was the most relevant dictionary for our analysis. After tokenizing and stemming the words in our corpus to account for the different variations of moral-emotional words, we counted the total number of such words in each tweet. We also counted the positive and negative moral-emotional words using separate positive and negative dictionaries from Brady et al.

We used the Gunning Fog Readability Index, which estimates the years of formal education required for a person to understand the text on the first reading, as a measure of tweet complexity. We chose the Gunning Fog index because it does not depend heavily on the length of the text, which works well for tweets since they are less than 280 characters. It is calculated using the equation below.

$$\text{Gunning Fog Index} = 0.4\left[\left(\frac{\text{words}}{\text{sentences}}\right) + 100\left(\frac{\text{complex words}}{\text{words}}\right)\right],$$

where complex words are words that contains 3 or more syllables. When calculating the readability index, we removed all words that began with the symbol @, as is it used for tagging or mentioning other Twitter users. We also removed all the hashtags as they are not usually read as part of the main text.

Lastly, we modeled the relationship between the retweet count of each tweets and its moral-emotional word count and readability index using a negative binomial regression. Negative binomial models are most appropriate for over-dispersed count data, which we are dealing with here.

3 Results

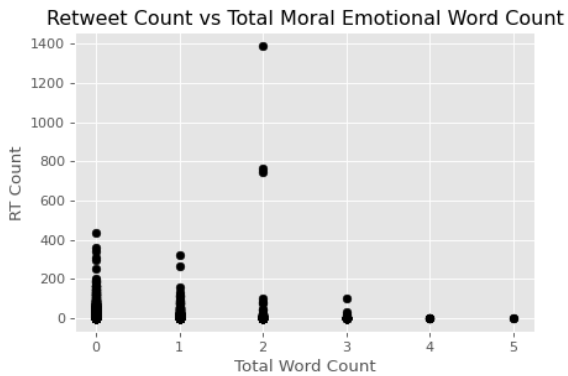
After obtaining the total, positive and negative moral-emotional word count, as well as the Gunning Fog readability index and the retweet count of each tweet, we can visualize their relationships in the scatter plots below.

In figure 2a, we observe that the retweet count of tweets in our data set span a very large range, however most tweets have a relatively small number of retweets. Furthermore, a very large percentage of the tweets collected do not contain any moral-emotional words.

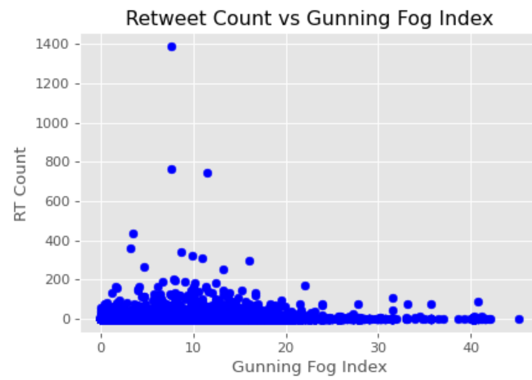
From figure 2b showing the relationship between the readability index and retweet count, we see that a large portion of the tweets have a readability index of between 5 and 15, which certain outliers that might be due to residual html. The mean Gunning Fog index of the corpus is 9.5, representing the reading level of a high school freshman or sophomore.

After fitting the negative binomial regression to the data, we can see in figure 3a that as the count of moral-emotional increases, the expected number of retweets also increases. The incidence rate ratio (IRR) of the total moral-emotional word count is 1.33, which means that an additional moral-emotional word would increase the retweet count by approximately 33%. This supports our hypothesis that the usage of moral-emotional words increases the diffusion of tweets.

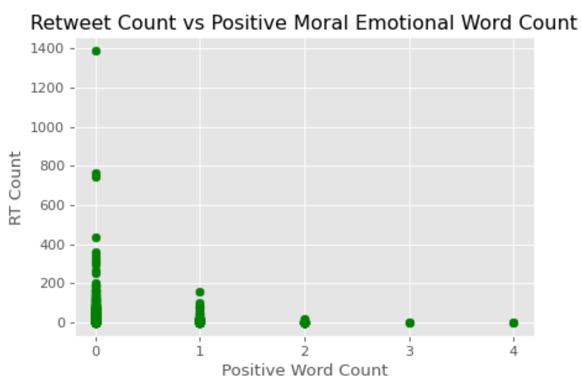
[3]Full raw data and dictionaries can be accessed at `https://osf.io/59uyz/`



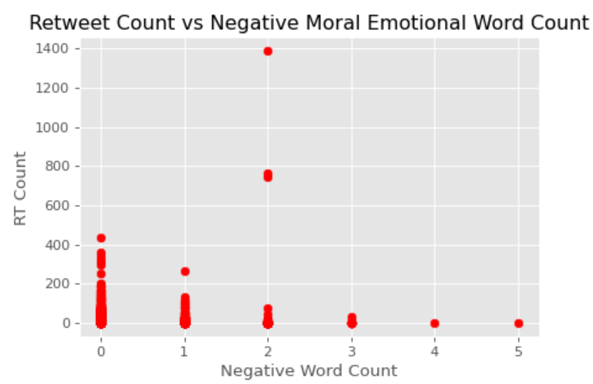
(a) Retweet count versus moral emotional word count.



(b) Retweet count versus Fog Index.

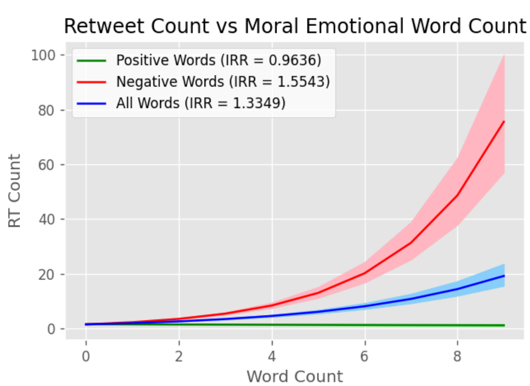


(c) Retweet count versus positive moral emotional word count.

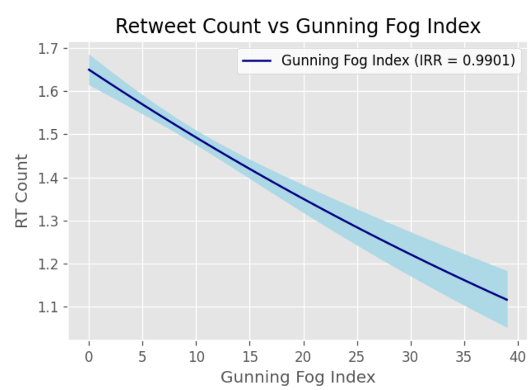


(d) Retweet count versus positive moral emotional word count.

Figure 2: Scatter plots of retweet count.



(a) The predicted retweet count as a function of moral-emotional, positive and negative words.



(b) The predicted retweet count as a function of the Gunning Fog Index.

Figure 3: Negative Binomial Regression Results.

If we analyze the use of positive and negative moral-emotional words in tweets separately, we see that the use of positive words mildly decreases the spread of the tweets. With an IRR of 0.96 for positive word counts, it is estimated that for every additional words used, there is a 4% decrease in the retweet count. On the flip side, the use of negative words in a tweets drastically increases the retweet count of the tweets. The IRR of 1.55 for negative word counts indicates that for every additional negative word in a tweet induces a 55% increase in the retweet count.

Hence, we can conclude that negative moral-emotional words have a large positive effect on the retweet count of a tweet, while positive words have a negative, but much smaller, impact on the retweet count.

Lastly, we observed a slight negative relationship between the Gunning Fog readability index and the retweet count of a tweet, as can be seen in figure 3b. However, the readability index of a tweet impacts its retweet count by a much smaller proportion as compared to the usage of moral-emotional words. The calculated IRR for the Gunning Fog index is 0.99, which represents a 1% decrease in the retweet count for every unit increase in the readability index.

4 Discussion

From our analysis, we obtained three main observations:

1. The presence of moral-emotional words in tweets increases the diffusion of tweets.
2. The usage of negative moral-emotional words increases the spread of tweets, while the usage of positive moral-emotional words decreases it, though at a lower rate.
3. The increase in tweet complexity, measured using readability, decreases the spread of tweets.

Our first and second results are consistent with the conclusions presented by Brady et al. and support the first and second hypotheses. Although, Brady et al. had different specific IRRs[4]. Our third hypothesis isn't strongly supported by the data. However, there is a slight but statistically significant negative effect of complexity on the extent of message spread.

Our analysis highlights the role that moral-emotions play in the transmission of ideas. In our particular study about discussions revolving around gun control, we see that tweets that contained more negative moral-emotional words were more likely to have a higher retweet count. However, positive words did not have the same effect, which could be representative of the users' overall negative sentiments towards the topic.

Some limitations in our research include the lack of considerations for confounding factors, such as follower count, whether or not the user is verified, the time the tweet was made and so forth. These factors could have an impact on the dispersion of a tweet. However, because a lot of their values were missing (in part due to some of the original tweets being out of sample), we did not consider them in our analysis. Additionally, we encountered three tweets in out data set which had retweet counts of over 600 – significantly higher than count of others. These extreme values might have skewed our analysis and regression model fit. Indeed, we see different results if we remove them. However, Brady et al. did not mention this in their paper and methodology. So for further analysis we could collect more data to ensure that we obtain a more representative sample of the tweets and their retweet counts.

Our work could be expanded further by considering the factors that were not accounted for as mentioned above. Furthermore, it would be interesting to investigate how the use of moral-emotional words would affect the spread of content in other subject matters, such as same-sex marriage, pro-choice, me too etc., and how the polarity of moral-emotional words would effect the spread in those topics. In our current analysis, the tweets that contain negative moral-emotional words have the highest spread, which could be explained by a general negative sentiment the users' have towards the topic of gun control. So it would be interesting to see what role these polarizing moral-emotions would play in other topics.

[4]This is probably due to the difference in filtering. In the R code of the original study, we found that the authors filter by keywords after lower-casing all the text. However, one of the keywords, "2A", is capitalized. So Brady et al. had no matches for it. We, on the other hand, chose to lowercase all keywords and text when filtering to get a more representative sample. This is why we got more tweets overall (130K versus 102K in Brady et al.).

References

[1] Brady, W. J., Wills, J. A., Jost, J. T., Tucker, J. A. & Van Bavel, J.J. (2017). *Emotion shapes the diffusion of moralized content in social networks*. Proceedings of the National Academy of Sciences - PNAS, 114(28), 7313-7318.

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Appendix

Figure 4: Gun Control political ideology visualization.