Shouting at the Wall: Does Negativity Drive Ideological Cross-posting in Brexit Facebook Comments?

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ABSTRACT

Using a novel methodological approach to measure emotions in Facebook comments, this Work in Progress (WIP) paper explores the relationship between negative feelings and ideological cross-posting behavior. Using the VoxPopuli data harvester, we collect over 770,000 public Facebook comments[1] from the three major political campaign pages active during the Brexit referendum. After sorting users into ideological camps based on their reactions to campaign posts, we then examine their commenting patterns across ideological lines. Using three different methods of sentiment analysis, we identify negative and positive emotions and their fine-grained sub-categories in comments. The analysis reveals one quarter of all comments are cross-ideological posts, with Leave supporters overwhelmingly active in commenting on Remain posts. A comparison across the campaigns shows that Brexiteers are much more likely to express anger than Remainers.

CCS CONCEPTS

Information systems → Information retrieval; *Retrieval tasks and goals;* Sentiment analysis

KEYWORDS

ACM proceedings, Sentiment analysis, Emotions, Political communication, NLP, Marketing, Facebook

ACM Reference format:
Michael Bossetta, Anamaria Dutceac Segesten, Chris Zimmerman, and Duje Bonacci. 2018. Shouting at the Wall: Does Negativity Drive Ideological Cross-Posting in Brexit Facebook Comments? In Proceedings of the *International Conference on Social Media & Society,* Copenhagen, Denmark (SMSociety).
https://doi.org/10.1145/3217804.3217922

1 INTRODUCTION

Social media platforms enable citizens' participation in politics through public displays of emotion [1]. Scholars have argued previously that such expressions via social media would take place in ideological "echo chambers" [2]. However, more recent research demonstrates that users are exposed to diverse political opinions on social media [3], and social platforms enable information flows across party, ideological, and socio-cultural lines [4]. In this WIP paper, we examine the degree of ideological cross-posting in Facebook comments during the 2016 Brexit referendum campaign.

Existing research has identified a relationship between negative emotions and citizens' engagement in offline collective action [5, 6], but the role of emotions in citizens' online mobilization, particularly on social media, remains largely unexplored. Moreover, while scholars find a correlation between online political self-expression and offline participation [7], few have nuanced political self-expression on social media into distinct emotional categories. A lack of understanding therefore remains regarding which emotions influence citizens' political behavior online. In the present study, we examine multiple emotional dimensions within the Facebook comments made in response to the posts of three political campaign pages active during the 2016 Brexit referendum, in order to answer the research question: *Do negative emotions in Facebook comments drive ideological cross-posting?*

Overall, we collected 771,036 public Facebook comments to the three major campaign pages active in the referendum (Stronger In, Vote Leave, and LeaveEU) over the 10-week campaign period (April 14–June 23, 2016). Our analysis finds that 28% of comments were cross-ideological,

[1]Excluding replies

SMSociety '18, July 18–20, 2018, Copenhagen, Denmark

ACM ISBN 978-1-4503-6334-1/18/07…$15.00
https://doi.org/10.1145/3217804.3217922

but Leave supporters were overwhelmingly more active in cross-posting than Remainers. Leave supporters made 80% of the comments to the Stronger In page, whereas Remain supporters left only 3% and 5% of the comments to the Vote Leave and LeaveEU pages, respectively.

Using a triangulation of sentiment analysis methods and measures (emotionVis, LIWC, and SentiStrength), we assess the emotional content of these cross-posted comments. While each of these tools uses differing computational linguistic methods, we find that they largely agree in the overall distribution and temporal swings of sentiment polarity. Zooming in on anger as a driver of cross-ideological posting, we find that Leavers were much more likely to express anger in cross-posting than Remain supporters.

2 THEORY

2.1 Political Participation and Social Media

Political participation is fundamentally about how citizens attempt to influence politics, and citizens increasingly take to social media to support their preferred candidates and causes [8]. The act of expressing a political opinion on social media has been shown to positively correlate with offline electoral participation like canvassing or voting [7].

Online political expression incurs costs from the user in terms of time and energy. Commenting can be considered a higher degree of political participation than liking or sharing, which requires less commitment, time, and dedication [8]. We have therefore chosen to focus on commenting as a proxy for political participation online.

2.2 Mapping Emotions

In political communication studies of social media, emotions have been understudied due to methodological limitations in assessing affect automatically from text. To date, most studies only gauge the valence of emotions via standard sentiment analysis. Standard sentiment analysis predicts the implicit tone of conversation based on the words users attach to their posts [9]. Studies using this method tend to find that higher levels of emotional valence positively correlate with user engagement [10, 11].

Meanwhile, research from marketing highlights that arousal is also a significant predictor for online diffusion [12]. Emotions have more than one linear dimension of sentiment, and scholars have moved towards a circumplex approach that includes both valence and arousal [13]. However, standard sentiment analysis measures often fail to capture this two-dimensional mapping of emotions. As a result, we know little about the relationship between emotions and online political expression beyond a linear spectrum of conversation (i.e., positive or negative valence).

Our methodological contribution overcomes this problem by using the emotionVis dashboard, described further in the Method section. Based on the reviewed literature, we focus on highly aroused negative emotions (i.e., anger) and test if cross-posted comments express more anger than the average social media post. We expect that cross-posting during the referendum would be more negative than other genres of social media conversation, since ideological cross-posters in a polarized debate are likely to be strongly aligned with a partisan cause. We also explore the differences across the three campaigns to identify whose supporters express the most negative sentiments. Below, we briefly outline the context of the case before proceeding to our method and results.

3 CONTEXT

In February 2016, David Cameron, then prime-minister of the United Kingdom, announced a referendum on the UK's membership in the European Union. The question was (and remains) a polarizing one for the British society, with the two main parties, Conservatives and Labor, internally split between the Remain and the Leave camps. The desire to "break free from the EU" was an issue entirely owned by a third party, the UK Independence Party (UKIP), a more radical organization than the Conservatives or Labor.

On April 13, 2016, the British Electoral Commission announced that the UKIP-backed LeaveEU campaign was not to be the officially designated one. Instead, Vote Leave was endorsed to represent the Leave side. The official Remain campaign was Britain Stronger in Europe (shortened as Stronger In). This resulted in three major referendum campaign initiatives, each of which had launched a public Facebook page to carry their message on social media. The campaign period lasted 10 weeks, with the referendum taking place on June 23rd.

4. DATA

4. 1 Data provenance

We used the VoxPopuli harvester for data collection. The harvester has two components. The first is a scraping engine that searches for and collects articles/posts and comments from selected news portals or Facebook pages. The second is the MySQL database, into which the collected data is stored, facilitating its retrieval and subsequent analysis.

The collected Facebook data is publicly available online (even to those without a registered Facebook account), and we do not report any user names or other personally identifiable information. Therefore, we did not consult an ethics review board.

In total, we collected 771,036 Facebook comments (excluding replies) from the political campaign pages Stronger In, Vote Leave, and LeaveEU for the ten weeks comprising the campaign period (April 14 to June 23, 2016).

This timeframe includes the election day, which displayed the highest level of commenting activity. Besides the content of the comments, we also harvested metadata about the users: their unique user IDs, post IDs, time stamps, and the number of likes/reactions per post and per user.

4.2 Pre-processing

Using this metadata, we categorized users into Leave or Remain supporters based on their signaled affinity with the campaigns' position on Facebook. If a user "liked" or "loved" a post from Stronger In, that user was labeled a Remain supporter. We conflated the two Leave campaigns under the same label; Leave supporters are those who "liked" or "loved" a post from either the Vote Leave or Leave EU campaign.

Once users were classified as Leave or Remain supporters, we identified the number of comments that these users made to a post issued by the opposite ideological camp (i.e., "cross-posts"). The number of cross-posts was 214,789 – comprising 28% of the overall commenting activity. The Stronger In campaign received the most cross-posts from the opposite side (192,236), followed by Vote Leave (12,504) and LeaveEU (10,049). Brexiteers therefore left a significant portion (80%) of cross-posted comments. We removed exact duplicates to increase the validity of emotion detection, and the resulting cross-post dataset consists of 179,959 unique comments for analysis.

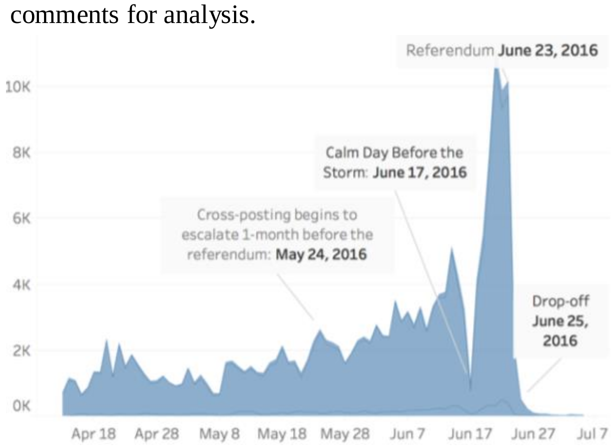

Figure 1: Volume of cross-posts over time, with callouts that signal a surge during the week leading up to the referendum. Thereafter, cross-posters typically commented only once.

5 METHOD

To meet the limitations in sentiment analysis outlined above, we utilize the emotionVis dashboard [14], a freely available research prototype analyzing several emotional dimensions: standard sentiment analysis (+/- valence), arousal detection (+/- arousal), core emotions, fine-grain feelings, as well as an overall level of emotionality. The tool is contextually appropriate to our study here, since it utilizes supervised machine learning and leverages a training set of 12 million public self-reported emotions from the Facebook platform itself.

To increase the validity of our sentiment detection, we cross-check the emotionVis results with two other established measures, namely the Linguistic Inquiry Word Count (LIWC) tool [15] and the SentiStrength algorithm using MineMyText [16]. LIWC provides complimentary measures for an overall level of emotionality (affect), sentiment analysis (tone), and specific negative emotions. MineMyText, meanwhile, provides a third corroborative measure of sentiment polarity. The overlapping dimensions offered by these tools afford a unique opportunity to compare results across systems and their underlying computational linguistic approaches.

6 RESULTS AND DISCUSSION

6.1 Emotion frequency

Of the nearly 180,000 cross-posts, over a third (63,000) contained significant levels of emotionality. As a secondary measure, we also filter for posts that LIWC detects as having some degree of emotion within the text. Looking at sentiment tone using LIWC, we find that polarity is well below normal levels used for social media texts (-23%).

	Brexit Cross-Posts	**Facebook Walls (on average)**	**+ / -**
Total Posts	179,959		
Emotional Posts	63,163		
Emotional (%)	35%	40%	-5.0%
Arousal (avg)	0.77	0.76	+1.3%
Valence (avg)	0.39	0.56	-43.5%
Probability (avg)	0.42		
Probability Range	0.19-0.97		

Table 1: Overview of the emotional frequency data for cross-posted comments. The level detected in Brexit cross-posts is contrasted against the averages for other Facebook walls analyzed by emotionVis.

While levels of arousal register roughly on par with other social media datasets, valence is lower than the historical brand levels of negativity. Thus, the cross-posted comments appear to be more negative than online conversations during brand crises (such as the United Airlines passenger assault or FIFA corruption scandal). In future analyses, we will make the more meaningful comparison against a dataset of campaign supporter-to-supporter comments, to observe any variation in emotion distribution.

Figure 2: The levels of sentiment detected by each tool over time. These pulses of conversational tone are largely in agreement, as exemplified in the final week of the referendum vote, where a strong upward climb towards positivity was detected by all three systems.

Representing the emotions of our entire dataset visually, we plot every post in a multiple dimensional space (Fig. 3). This footprint highlights the predominance of high arousal and positive valence emotions in the cross-posting sample. Arousal is plotted vertically, whereas valence is plotted horizontally. The colors correspond to the six core emotions.

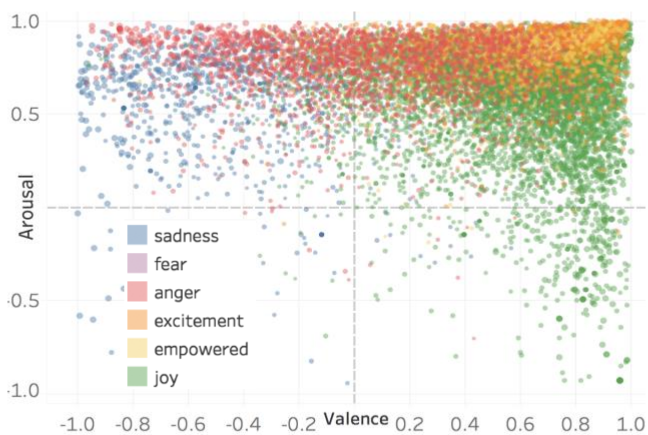

Figure 3: The automated classification of Brexit cross-posts. Our model contains all 179,759 posts mapped along a total of four dimensions: the sentiment axis (vertical), arousal axis (vertical), supplemented by two extra dimensions of color (categorical classification) and sized to subtly reflect probability (classification confidence).

To exemplify the core emotion classification, a predominantly joyful Brexit comment is: *"Great Britain was great before we joined the EU and will stay great if we leave"*. Empowerment translates into "*Will be voting out for sure*", whereas excitement is dominant here: "*Well said. IN….is the way forward"*. An example of a well-articulated angry comment: "*Another Brit told me the other day that they couldn't understand why I'm angry. […]. I'm angry that we are ruled by people who we didn't elect. In fact by people that nobody elected […].*" Most often though, the range of expressions of frustration and irritation easily crosses into uncivil territory, with this being a mild example: *"OUR GOVERNMENT IS A DISGRACE TO THE BRITISH PEOPLE! […]*" [capital letters in the original]. As with all automated sentiment analysis, even here there is a risk of missing certain nuances, in particular mixed emotion, sarcasm, and irony, for which English humor and banter is well-known. Yet, as these examples illustrate, the emotionVis classification allows for a nuanced and accurate representation of more granular and contextual emotional content than standard sentiment analysis.

Posts classified as sad (in blue) are located towards the left, showing negative sentiment. Conversely, the green joyful posts are towards the right. Low arousal emotions are generally speaking less frequent on social media, and our data follows also this pattern, with the lower area of the graph (low arousal) less populated than the upper one (high arousal). The dominance of green, orange, and yellow visually emphasizes that the valence of many of the comments was neutral or even positive.

Cross-posting maintains a great deal of positivity, even if two of our systems show that it is less than typically detected. This brings us to a point central to our argument. These results show a clear need for pushing beyond the standard sentiment analysis that only offers a vague indication of positivity and negativity. Our three sentiment classifications show average levels just above and below neutral territory. Yet, by mapping emotions along a second dimension of arousal with a third dimension of core emotion category (color), we begin to see the bigger picture beyond simple linear averages.

We expected that users crossing the ideological lines will be motivated by negative emotions. We therefore proceed to examine the most decisively negative posts to better understand the characteristics of cross-poster emotions.

6.2 Anger across the three campaigns

Since the literature outlined above suggests negativity motivates political participation, we further honed our analysis to posts expressing anger. Anger is a high negativity, high arousal emotion (depicted in the top-left quadrant of Fig. 3). We aimed to uncover whose campaign supporters expressed the most anger in our cross-posting data, as a proxy for who might be most likely to participate. In order to isolate the most "pure" angry comments, we started with identifying comments that carried negative emotions, and included only those posts classified as negative by all three systems (LIWC; SentiStrength and emotionVis). From this subset, we further distilled posts with language that was also significantly aroused (above 75%), resulting in a total of about 7,000 comments.

We used both the emotionVis and LIWC tools to filter for posts that included at least some degree of anger. Among these, emotionVis identified 1,791 categorically angry posts with anger being the dominant core emotion. Given the stringent criteria applied here, the resulting comments are few but indicate a high level of precision in our desired emotional direction as purely and categorically angry.

Campaign	'Pure' Anger Posts	Total Posts	Percen -tage Anger	Difference to Opposing Ideology
LeaveEU	64	8386	0.76%	-34%
VoteLeave	73	8963	0.81%	-26%
StrongerIn	1,654	161456	1.02%	-

Table 2: Reception of angry comments per campaign wall, from those with opposing ideologies. The two Leave campaigns both received significantly less angry posts from Remainers than the Stronger In wall received from Leave cross-posters.

The results show that Stronger In page received a 26% higher rate of angry posts than Vote Leave and 34% more than LeaveEU. In this preliminary analysis, it appears that high levels of anger were much more prevalent for Leave-to-Remain posts than vice versa.

7 CONCLUSIONS

Using a novel methodological approach that combines multiple emotion detection tools, we investigated whether negative emotions are more likely to be found in comments made to the posts of an ideological adversary on Facebook during the Brexit referendum campaign.

Cross-posting was found to be more negative than Facebook comments relating to brand crisis events. When comparing the three campaigns' supporters in terms of emotional content and patterns of cross-posting, LeaveEU emerges as having the most cross-posters driven by anger. Brexit supporters, as the outsiders and challengers of the established political system, were more likely to dive into the opposing campaign's dialogue and ignite debate by expressing anger – effectively shouting at the opposition's Facebook wall.

We plan to pursue several avenues of inquiry opened up by this initial analysis. First, we aim to examine whether posts made by ideological supporters of a campaign exhibit similar emotions. Second, we will examine the main content expressed with each primary emotion, via automated content analysis methods such as word frequencies and topic models. We expect different topic models to be associated with a variety of emotions and, moreover, expect similar topics to be discussed with different levels of arousal. Third, we will test for statistically significant correlations between emotions and levels of engagement, such as "likes", "replies", and "reactions" to comments. If the same emotions generate higher levels of engagement across the campaigns, this similarity becomes a more generalizable facet of social media communication (rather than ideological difference).

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