Humor, support and criticism: a taxonomy for discourse analysis about political crisis on Twitter

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ABSTRACT

The use of social networks to share information and express opinions has significantly grown in recent years. In this context, the microblogging platform Twitter has been used in the political scene by governments and citizens for different purposes. Brazil is experiencing a political crisis in recent years that led to the impeachment of Dilma Rousseff president in 2016 and the investigation of several corruption scandals in 2017. This text proposes a taxonomy for discourse analysis to help understand the intent and types of Twitter users' conversation about political scandals. In this paper, this taxonomy is described, and an analysis is presented about four political episodes that occurred in Brazil in 2017. It was possible to verify how this taxonomy can help to identify different types of user manifestations, allowing us to analyze patterns of behavior. The main contributions include: providing a new taxonomy to enable the opinion analysis about political facts and crisis; investigating the perception of social media users in Brazil about political points; and identifying the benefits of using visualizations in this context.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**;

KEYWORDS

Discourse analysis, political crisis, Twitter.

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1 INTRODUCTION

The political crisis that led to the impeachment of Brazil's president Dilma Rousseff in 2016 continued to unfold with the advancement of the Operation Car Wash towards alleged widespread corruption schemes that intertwined state-owned companies, politicians, and the private sector. In the eyes of the population, the investigation was commented online with passion, picking protagonists and antagonists, placing them in direct conflict in spontaneous narratives. Brazil, the largest country in South America, has a population of over 208 million inhabitants [6] and a growing locus for political expression online. 56% of the country's households have an Internet connection [5].This context led us to question which patterns emerged from the popular speech about such events, helping future studies about this field.

To understand the intent and types of Twitter users' speech about political scandals, the authors propose a taxonomy for discourse analysis applied on four political episodes in Brazil in 2017. Thus, it was possible to verify how this taxonomy can help to identify different types of user manifestations, allowing us to analyze patterns of behavior. The main contributions include: providing a new taxonomy to enable the opinion analysis about political facts and crisis; investigating the perception of social media users in Brazil about political points; and identifying the benefits of using visualizations in this context.

The remainder of this paper is organized as follows. Section 2 presents background and related works; section 3 describes the methodology used; section 4 shows a visual analysis of four case studies about political episodes that happened in Brazil in 2017; section 5 presents the conclusions and goals for future research.

2 BACKGROUND

Social Network Analysis has its roots in Graph Theory and Sociometric Analysis and is not related only to online studies [24]. In this field, the researcher can visualize through what channels information flows from person to person and quantify the influence these individuals have among their networks through the mapping of these structures. According to Freeman [12], Social Network Analysis is motivated by a structural intuition based on the ties that connect social actors and is based on empirical and systematic data. It also actively uses graphics and images that depend on mathematical and computational models. Recuero [22] points out that this technique stems from a series of studies that sought to overcome Cartesianism, focusing on the research of systems as a product of the interactions between its parts and the search and understanding of patterns. It also has its roots in structural-functionalism, focusing on the structural analysis. It is essential to cite these approaches because it influenced the discourse analysis of social networks, even if with a different focus. In Social Network Analysis the primary interest concerns the shape of the networks and actors relationships, influence, and nature of the ties between them. On the other hand, discourse analysis focus on more qualitative aspects of the social networks.

Two possible approaches when studying Social Network Sites that concern the present work are the discourse analysis and the content analysis. Grounded in a more qualitative field, those methodologies aid researchers to view other aspects of the social networks, especially regarding the behavior and motifs of the individual engaged in a social activity [11]. That said, it is relevant to point out the differences between these approaches and how they can be used in a complementary manner.

2.1 Computer-mediated discourse analysis

The term computer-mediated discourse analysis is closer to the linguistics field of study, as Herring [15] points out. Abbreviated, the CMDA applies to four domains of language: structure, meaning, interaction, and social behavior. Those areas display numerous topics of interest, such as: the use of distinctive typography and orthography in the structure level; meanings of words and utterances in the meaning level; turn-taking and topic development in interaction domain; and the social scale, where can be observed the linguistic expressions of play, conflict and power, for example. Herring [15] also points out that the CMDA is somewhat more of an approach than a method or a theory.

Some of the theoretical assumptions underlying CMDA are the same as the scientific field of discourse analysis. They are interesting for the present study. As Goffman [18] puts, discourse exhibits repetitive patterns, produced consciously or unconsciously. Because of that, "a basic goal of discourse analysis is to identify patterns in discourse that are demonstrably present, but that may not be immediately obvious to the casual observer or the discourse participants themselves" [15]. The proposal of a taxonomy for discourse analysis in Twitter regarding political scandals is a strategy to identify those patterns and make them visible, aiming a better understanding of the intent and types of discourses the users are propagating. It is important to notice that, according to Herring [15], a discourse also involves speaker choices that are not linked only to linguistic factors but are also of cognitive and social matter. Because of that, discourse analysis is not only applied to semantic objects, but also non-linguistic phenomena. The analyzed tweets consist of text, images, and videos, and it would be impossible to put them into categories if the non-linguistic expressions were not taken into account.

Herring [15] also points out that the technology shapes the discourse. The technologies involved in the mediation of human-computer interaction expanded the sense of community and social networks, reducing time-space barriers, for example. Another important observation is the traceable nature of the social networks that are inside these structures. Through these traces, it is possible to gather a variety of data that was impractical before [3]. As Recuero [21] notices, these networks are more stable, more complex and more significant, comprising a plurality of relationships broader than those of the offline networks. Social Network Sites differ from other social networks because of the computer-mediated nature and because they are connected to the internet. There are some other parameters brought by Boyd and Ellison [4]: it has to be a web service that allows the users to build a profile in a connected system; articulate a user list in which they share a connection and move through personal or a third party list of connections. In summary, discourse analysis mediated by technology can be a valuable tool to understand the meaning and social implications that happen through discourse.

2.2 Content Analysis

According to Bardin [2], it is a set of techniques for communications field of study and can be adaptable to a vast number of situations. The author defends the flexibility of the methodology not only to the linguistics field where it was traditionally conceived but also to objects as movies or pictorial representations.

Krippendorff [17] stated that content analysis has as objective to make replicable and accurate inferences about texts (or other significative contents), to the contexts of their uses. If it means something to someone and is produced by one or more subjects to suggest something to others, it can be considered text. The author refers to works of art, images, maps, symbols, sounds, and even numerical information as contents suitable for analysis. In the present work, not only the textual part of the tweets were regarded as text, but also the images, videos, links, and other media compose meaning - and are part of the content analysis.

Another characteristic pointed by Krippendorff [17], is the fact that the meaning of the text extrapolates its existence. For that, the researcher has to observe beyond the physicality of the text: it means to comprehend, for example, how other people use this text, what the text says about them, and what actions are encouraged by it. So, content is related to contexts, discourses, and particular purposes. As it will be seen later in this work, by understanding the Brazilian cultural background, and how technology made its part, it was possible to interpret the tweets beyond themselves.

So, if content analysis aims to validate inferences about a text, discourse analysis helps to achieve a better understanding of these documents. That said, both approaches are fundamental to the present study because they complement each other. Bardin [2] organizes the content analysis methodology in four steps: pre-analysis, coding, categorization, and analysis. These measures will be detailed further, in the methodology description. However, it is important to state that the discourse analysis will take part in the categorization.

3 RESEARCH METHODOLOGY

This section presents a summary of the methodology, including an explanation about data gathering and selection; a description of the proposed taxonomy and how the classification was conducted; finally, a presentation of the proposed visualizations to help the visual analysis.

3.1 Contextualization

Our methodology mixes qualitative and quantitative elements into an interdisciplinary strategy developed by researchers in the computer science and communication fields in the research project. According to Bardin [2], it is essential to select and organize the documents that will be analyzed. It is the first step of content analysis and is named pre-analysis. The amount of political events and tweets generated by the users is massive, so it is crucial to select a defined corpus. After that, the data was gathered, and the corpus was reduced.

Topics debated on national media usually gave the first step to trigger the data collection. The choice of a mix of politics, corruption, and economy as the primary thematic focus on this paper was motivated by the potential of such subjects to polarize audiences for and against the topics in question, along with other nuances of criticism and humor, thus leveraging online traffic. The researchers believe other subjects that provoke extensive online discussion may also be suitable to the methodology described ahead and are possible subjects of further papers. An observant look at the daily news by the research team, as well as a look ahead on what was expected for the next days, suggested the themes, keywords, and hashtags be collected. When an unexpected story broke, the team was able to fire the data gathering algorithms within a few minutes, following the peak interest of news.

3.2 Data gathering

The next step of the methodology was the gathering of tweets using a program developed in the research Lab written in Python and MySQL. The selected timeframe for collection corresponds to the initial reverberation period of the subject in Twitter. We suspended the data gathering when there was a considerable decrease in the volume of tweets related to each topic. The Google Trends online tool was used to double check the decline in traffic.

3.3 Data selection

According to Bardin [2], the second step of content analysis marks the coding. According to the author, after the objectives were set and the documents were chosen, it becomes more evident for the researcher what needs to be observed. Coding corresponds to the transformation of raw data in the representation of its content. In our case, a ranking of tweets was developed from this massive volume of data, based on the descending order of the most retweeted ones. With this methodological choice, the researchers focused the attention on the 100 most influential postings, a subset that has been retweeted more than 488,000 times, which emphasizes its relevance.

We selected as a cut off point the 100 most retweeted posts. The most retweeted messages ranged from 9k to 47k retweets. Below 100 posts, we identified a significant decrease in retweet numbers, 20 times less than the others. Thus, we considered the top 100 retweets significant enough to be re-posted in many user's timelines. As the studies by Ellison et al. [8], André et al. [1] and Recuero [20] indicate, the choice and action of retweeting is both an endorsement and the granting of symbolic capital.

Following the selection, these hundred tweets were manually classified using Excel spreadsheets according to the dominant discourse characteristics manifested and the patterns of behavior among users, following the third step of Bardin's content analysis process [2], the categorization. The author explains that it is an operation of classifying elements that constitute a group. First, the items are separated by differentiation and regrouped by analogy. They are grouped in classes or generic titles that identify common characteristics. In this work, the groups are defined by categories that constitute the taxonomy detailed in the next session.

The qualitative analysis also revealed some typical problems of the online medium. Because tweets are captured out of context (i.e., a conversation thread), there are sometimes problems in interpreting the message. If a news story were shared without other accompanying phrases, the context would need to be inferred in the conversations after the posting. Since this data is not readily available, sometimes the interpretation of posts classified as "neutral" may have some connotation that could not be interpreted. Besides, the capture never collects 100% of the messages, and a small amount is recorded incomplete or with broken links, to which they were discarded from the selected set.

3.4 Taxonomy Definition

Starting from the sample of 100 tweets, the researchers sought to identify new categories based on the collected material using the content and discourse analysis techniques. At first, all the tweets were analyzed and divided into numerous provisional categories. Next, the classes were grouped by their similar features, resulting in five general taxonomic large groups that were able to contemplate all the analyzed data.

These categories made possible for us to understand the users' behavior about the subjects. The first nominated "support," concerns messages that promote either side of the political dispute, and it does not matter which side it is: they all fall into the same category. The second: "criticism and protest," unites the notion of disapproval or holding an objection, presenting dissatisfaction about an exposed fact or situation. The third, "humor," collects tweets in a joking tone. It also includes memes, satires, cartoons, among other contents. The fourth, named "news," refers to news sharing related to the facts that had no manifestation of support, criticism, and protest, or humor. The fifth one "neutral," regards tweets that are indifferent or the position could not be inferred from the post's context. After the categories were set, a classification system was systematized and is described in the next section.

3.5 Classification

For the distribution of the categories, the criterion of peer review was used, where two different researchers qualitatively classified each tweet, and in the case of a tie, a third evaluator from the team determined the final category of the message. It was important that each reviewer chose the class of each post, even though it could be classified in others to a minor extent. In addition to the categories, the peers also organized the types of messages according to their multimedia nature, which is predominantly or only composed by animated gif, image, video, just text, and links.

3.6 Analysis

The analysis is the last step after the categorization proposed by Bardin [2]. The data is interpreted, and conclusions are made regarding what has been observed. Simple visual representations were chosen to enable a detailed analysis and at the same time allow a comparison between different collections. Bar charts, pie charts, and word clouds are examples of the graphics used to support the analysis stage. The data preprocessing and its graphical representation led us to a quick and straightforward interpretation and inferences about events.

4 VISUAL ANALYSIS OF CASE STUDIES

In this section, the selected case studies are described and then the visual analysis is presented. All the political scandals analyzed in this article are related to the Operation Car Wash. Initiated in March 2014 by Brazil's federal police, this operation is the offspring of the unification of four inquiries that investigated financial crimes with public resources. Since then, investigations have uncovered the existence of various corruption schemes involving political parties and lobby groups, politicians and private or public companies. By May 2016, more than 1,400 probes had been filed, 775 searches and seizures had been executed, 274 people were charged, 141 convictions were reached and more than R$38 billion (around U$11.5 billion) of corruption money was reclaimed and R$3.2 billion (close to U$1 billion) in defendants' assets was blocked.

4.1 Selected case studies

The team applied the methodology described in Section 3 in four cases of great national repercussion linked to politics and the Operation Car Wash in Brazil during 2017: (1) The testimony of former President Lula to Judge Sérgio Moro for the investigations of the Operation Car Wash in Curitiba on May 10, 2017 (referenced here by the nickname "Lula X Moro") [9, 23]; (2) the release of the recording of President Michel Temer's talk with Joesley Batista, owner of the multinational industry JBS, referring to Operation Car Wash in which the president allegedly approved paying for the silence of former deputy Eduardo Cunha (referenced here as "Temer") [13, 14]; (3) vote in the Federal Supreme Court for the arrest of Senator Aécio Neves, accused of requesting a U$ 2 million kickback from businessman Joesley Batista (referenced here as "Aécio") [7, 10]; (4) the discovery of 51 million Reais in cash (roughly U$15 million) stored in dozen suitcases and boxes in an apartment connected to former government minister Geddel Vieira Lima (referenced here as "Geddel") [19].

The data collections resulted in four databases, as summarized in Table 1. The collection time was established through observation of the related Twitter traffic and Google Trends data, in which we scrutinized the topics' peaks.

4.2 Visual analysis

Once the collection of tweets stopped, the researchers focused their attention on the 100 most influential postings following the methodology described in Section 3, classifying each one according to the proposed taxonomy. Based on this, multiple charts were generated and are presented below. Figure 1 shows the percentage of each post category considering all data collection. It is clear that the most significant part of the posts (85%) is split between the Criticism and Protest and Humor categories.

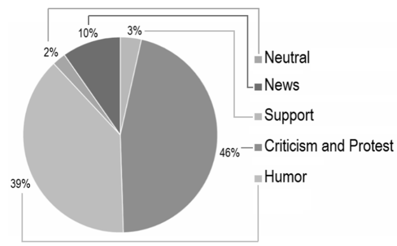

Figure 1: Post behavior categories, all datasets considered

It is possible to observe a change in the behavior of the users over time when each event is analyzed individually, a bar graph where the bars on each collection sum 100%. On the first incident, a balance between Criticism and Protest (41%) and Humor (40%) was observed, and Support is more present than in the following collections.

Next, Humor (74%) represented around 3.8 times the volume of Criticism and Protest manifestations (19%). From the third event onwards, there was an inversion of the most common type of post, as Criticism and Protest (69%) overcame Humor (18%) in around 3.8 times as well. On the last collection, Criticism and Protest (55%) keep its position over Humor (22%), having 2.5 times the volume of it. Furthermore, the News (22%) became more relevant than before. Another interesting point can be identified when analyzing how the manifestations occurred on Twitter (Figure 2). Even though plain text primarily characterizes this network as the essence of its posts, it is possible to observe that posts with visual content (Image, Gif, and Video) show substantial growth, being close to the ones that are text-only.

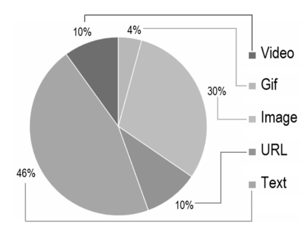

Figure 2: Types of post

It can be observed in Figure 3 that, in all cases, posts predominantly constituted of images come right after the text ones. URL and video posts also appear. The URLs often pointed to news, and videos or images were more related to humor.

For a more comprehensive visualization of the content of posts, we generated some tag clouds regarding the most common hashtags within each collection. Thus, the more frequently the hashtag was posted, the larger its size in the tag cloud. Therefore, it was possible to make some considerations from the analysis of these images.

In the tag cloud referring to the judgment of President Lula by the justice Sergio Moro, it is evident the presence of feelings

Nickname	"Lula x Moro"	"Temer"	"Aécio"	"Geddel"
Start of the collection	May 10	May 17	June 20	September 6
End of the collection	May 15	May 29	June 23	September 8
Tweet Total (RT included)	2.2 million	4.3 million	75 thousand	220 thousand
Retweet Total	1.6 million (72% of all tweets)	3 million (69% of all tweets)	53 thousand (70% of all tweets)	174 thousand (79% of all tweets)

Table 1: Summary of the collections

manifested by the crowd. The highest frequency was due to the hashtags associated with the feeling of "support", with terms such as #moroorgulhobrasileiro (or #morobrazilianpride), #lulaeuconfio (or #lulaItrust), #lulainocente (or #lulainnocent), #avantemoro (or #forwardmoro) and #brasilcomlula (or #brazilwithlula), representing more than 50% of occurrences in this collection. It was also possible to observe, with a smaller frequency (about 19%), the evidence of the feeling of "criticism and protest," present in the terms #moroperseguelula (or #moropersecuteslula), #lulanacadeia (or #lulainjail) and #lulacondenado (or #lulacondemned).

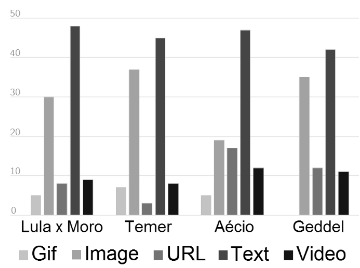

Figure 3: Types of post on each collection

In the hashtags of President Temer's case, "criticism and protest" emerges as the prominent category among the collected terms, which include the hashtags #foratemer (or #outtemer), #diretasja (or # directelectionsnow), #diretaspordireitos (or #directbyrights), and #lulanacadeia, representing more than 52%. It is also important to note the frequency of hashtags with a neutral character, which can fit both in the "neutral" and the "news" category (because they have a more descriptive bias of the fact that some positioning) as the following cases which had approximately 9% of occurrences: #temer, #g1, #politicsG1 (G1 is a Brazilian news site), #lavajato (the Operation Car Wash) and #jbs (a Brazil-based animal-protein food multinational industry).

In the case of Senator Aécio Neves, again the hashtags that somehow mention a feeling of "criticism and protest" are the most frequent, representing more than 77% frequency: #aecionacadeia (or #aecioinjail), #foratemer, #voltadilma (or #comebackdilma), #lulanacadeia and #vazatemer (or #leakouttemer). The occurrence of descriptive hashtags ("neutral" or "news") also had some prominence, with terms such as #aecio, #stf (the Federal Court of Justice), #rt, #polticag1 (or #politicsg1), #politica (or # politics) and #g1, representing more than 6%.

Geddel's case tag cloud was the only one that presented higher occurrence of descriptive hashtags ("neutral" or "news"), having as most frequent terms: #geddel, "#politicag1, #lula e #vejacolunistas (or #vejacolumnist and Veja is the bestselling Brazilian newsmagazine), with more than 28%. The exception is the term #foratemer, with more than 10%, being defined as "criticism and protest," and present in all collections.

Figure 4: Total hashtags frequency

Finally, when analyzing the tag cloud that includes all the collected hashtags (Figure 4), it is possible to have an overview of sentiments and most frequent categories. In general, the most mentioned were sentiments of "critic and protest," representing approximately 39% with the terms #foratemer, #diretasja, #lulanacadeia, #moroperseguelula, #aecionacadeia, #diretaspordireitos. It was also seen less frequently (about 16%) terms related to "support," represented by #moroorgulhobrasileiro, #lulaeuconfio, #lulainocente, #avantemoro, #brasilcomlula. Another interesting fact is related to the most popular hashtag: #foratemer, with a total of 16% of all occurrences, being regularly used in all cases.

5 FINAL CONSIDERATIONS

The data collection and analysis provided insights for many points of discussion related to discourse analysis. One important observation is regarding the number of retweets among the whole collected data. It was almost half of all tweets. In social network sites, spreadability [16] is key to understanding user's behavior. Jenkins, Ford, and Green [16] believe that most of the people are still listening to and watching media produced by others. However, they also argue that these activities are not merely "listening" or "watching" because they are part of a bigger construction - and just recognizing their potential to contribute to conversations in a participatory world shapes these "passive" activities in a whole new manner. So, even though almost half of the collected tweets were shared posts, this is also a meaningful act, because it spreads most influent posts through the network.

In these most retweeted posts, after applying our proposed taxonomy, it was observed that humor, criticism, and protest were predominant. This fact suggests that, when the analyzed users express their feelings about political happenings, their posts tend to display two distinct behaviors, whether it is a critical manifestation or some joke about the situations. It leads us to believe that the nature of the event influences how the users are most likely to behave. Not every crisis can become a joke. When involving receiving a bribe, criticism and protest posts could be seen more often, for example. Also, if the person concerned is a famous politician, such as the ex-president Lula or president Temer, humor was used broadly. Also, in Lula x Moro collection, the support category was more prominent than in the other cases. Some users "picked a side" on their tweets, using hashtags like #lulaeuconfio (#lulaitrust) for supporters of the former president and #moroorgulhobrasileiro (#morobrazilianpride) for fans of the prosecutors and the judge Moro. When facing the content of the hashtags through our visual analysis, it was apparent that in Geddel's case, the tweets were most focused on the surprise value of the event. So, even though the Brazilian audiences analyzed in this research had a behavior pattern (using humor or criticism), the event's nature shaped users' sentiments as well as cultural factors.

It is also striking to observe that although four cases were analyzed, the most frequent terms in the tag cloud indicated greater prominence of president Lula and justice Sérgio Moro. A possible explanation was that this was one of the most exploited by the Brazilian media, which prompted its more significant repercussion in social network sites.

There is one crucial observation that can be made related to the categorized tweets. The image, video and animated gif posts mostly referred to the humor category. The text predominantly ones related chiefly to criticism and protest and the other categories. It is possible to affirm that also when seeing the hashtags in the tag cloud, as most of them do not indicate any humor in their content. In most of these tweets that are supported by multimedia content, it was impossible to infer the whole meaning without taking them into account. As Twitter evolved, the service added other multimedia resources, gradually adopted by the users. Thus, growth in the use of images and other multimedia resources on Twitter was noticed. The possibilities in the social network sites influence the shape and meaning of the discourse. As said before, the computer-mediated discourse has dynamics of its own related to the technological infrastructure available that differ from face-to-face interactions.

In this context, through four case studies, we show that the proposed taxonomy and visual analysis helped in the discourse analysis about political events in the microblogging service Twitter. Thus, following the proposed methodology it is possible to have a better understanding of public opinion in social networks about important events, political facts, and crisis.

As topics for future studies, the developments suggest the use of categories to classify new political events, in different contexts and countries, given the potential of this analysis to identify trends and general sentiments of the public in these environments. For this, an interactive visualization tool is under development. It is expected to enable the identification of the top hashtags, profiles, and retweets from a data collection in a selected period through a responsive line chart that plots the total number of gathered tweets.

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