It is not only about Grievances - Emotional Dynamics in Social Media during the Brazilian Protests

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Abstract

In the summer of 2013, Brazil experienced a period of conflict triggered by a series of protests. While the popular press covered the events, little empirical work has investigated how first-hand reporting of the protests occurred and evolved over social media and how such exposure in turn impacted the demonstrations themselves. In this study we examine 42,280,539 tweets shared during the three months of conflict in order to connect patterns in online and offline protest-related activity and uncover language-use related to the emotions and motivations of protesters. Our findings show that peaks in Twitter activity coincide with days in which major protests took place, the emotions that users expressed on Twitter reflect the protest-related events, and in days in which major protests took place a massive number of users were expressing positive emotions when referring to the protests.

Introduction

Social media has emerged as a powerful resource during periods of collective political action — both for the individuals involved in those movements as well as for observers aiming to better understand their dynamics. For instance, websites such as Facebook and Twitter have been extensively used to facilitate mobilizations against autocratic regimes (e.g., Egypt, Iran, Tunisia) as well as during demonstrations in democratic countries (e.g., Austria, United Kingdom, United States) (**?**; **?**; **?**). Indeed, the impact of social media for protest-related purposes is so powerful that several governments have imposed internet restrictions during periods of conflict (**?**). At the same time, such usage of social media in order to organize action and express viewpoints leaves behind a record of information that enables researchers from across disciplines to explore questions surrounding human nature in newfound ways, at broader scales, and in real-time.

One such question that has long intrigued social scientists is: what drives people to protest? Similarly in this research, a primary pursuit is to investigate what motivating factors are behind the willingness of people to join a movement, even when involvement may risk injurious and adverse personal consequences. Driven by these questions, in this study we focus our attention on the Brazilian riots that occurred from June - July 2013 and involved millions of people across more than 100 cities.

The protests began on June 6, when over 2000 people protested in the city of São Paulo because of a bus fare increase equivalent to 10 cents. The Free Fare Movement (Movimento Passe Livre in Portuguese), the organization behind the protest, has organized similar protests in the past and achieved partial victories during some (**?**). The day's protests were marked by police violence, and many arrests were made. In the following weeks, the movement continued, seeing larger numbers of protesters and increased police violence — including against journalists (**?**). This police brutality was largely responsible for bringing the country's wider attention to the protests. In rapid succession, the demonstrations subsequently exploded in size and spread across Brazil. On June 17, over 100,000 people gathered to protest in Rio de Janeiro. In response to this pressure, the federal government eventually pushed local authorities in São Paulo and Rio de Janeiro to reverse the transport fare increases on June 19. Still, the protests continued to grow, at one point reaching over 1 million protesters in numerous cities on June 20. Over time, the movement also became increasingly splintered, with protesters complaining about more diverse issues such as the high cost of hosting the upcoming World Cup, cases of government corruption, and the ways in which gay rights were being handled by some members of the government. In addition to such serious grievances, individuals participating in the protests would also sometimes display bizarre statements on placards such as "I want a Louis Vuitton Bag" (**?**). After some time, the movement dwindled in size and ended as suddenly at it had begun.

Examining the circumstances, pressures, and perceptions that spurred citizens to demonstrate in this context is particularly compelling given that such broad societal upheaval is relatively uncommon in Brazil, a country with a political culture described as more accepting of long standing social problems than other neighboring South American countries (**?**). Further, unlike other movements from recent history in which the demands of protesters were reasonably apparent and explicit, the turmoil in Brazil did not have a single motivation and also witnessed demonstration of a larger set of

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grievances as the conflict grew (**?**). We undertake this investigation by analyzing the emotions conveyed and motivations expressed through the protest-related tweets posted by Twitter users in Brazil during the protest period. Our findings offer new perspectives on the role that both positive and negative emotions play during times of societal conflict and mass action.

Specifically, we make the following contributions:

- We present computational approaches to automatically and reliably identify protest-related tweets and perform large-scale sentiment classification;
- We demonstrate how Twitter reflects changing protest dynamics by analyzing both trends in Twitter activity levels throughout the course of the conflict period as well as how users' detected emotions change over time and in response to protest milestones;
- We analyze what words people tend to use to express their emotions and how tweet content reveals triggers for bursts in protest-related collective action in real life;
- Finally, we discuss the design and practical implications of our findings.

Related Work

Studying the dynamics of protests is of keen interest to researchers across domains, including sociology (**?**), political science (**?**), and social psychology (**?**). The recent adoption of social media as a communication and coordination tool by protesters during periods of demonstration has lately inspired researchers to begin turning to these online traces as a means of inquiry. Protest-related communication along with how protest movements grow over time are core topics commonly explored in such work. For instance, analysis of the evolution of Twitter communication activity related to the Occupy Wall Street (OWS) movement found that OWS elicited participation from a set of strongly interconnected individuals with pre-existing interests in politics and foreign social movements but that those people apparently lost interest in OWS-related communication after some time (**?**). In another case, researchers leveraged Twitter activity levels to analyze patterns of protest recruitment surrounding the Spanish protests of 2011, finding evidence of social influence and contagion and helping to elucidate how social networking sites play a role in triggering the start and subsequent growth of protests (**?**).

Beyond communication and growth, another component crucial in understanding individual and collective behaviors during protests is the emotional dynamics of individuals involved, associated, or exposed to the movement (**?**). Throughout the lifecycle of these social movements, emotions are a key driver behind why individuals join protest events or groups, what motivates them to maintain or abandon involvement, and what influences whether a movement persists or eventually declines (**?**). Indeed, a protest detached from emotions, especially anger, is likely inconceivable (**?**) considering that a main reason people participate in protests is to express grievances resulting from frustrations due to injustices or other forms of affliction and hardship (**?**). However, while anger, indignation, and outrage may be the most obvious emotions associated with protester motivations (**?**), other emotions play a role as well. Positive feelings such as pride in participating or hope for a better future can also encourage people to engage in protest movements, and it is argued that the interplay between negative and positive emotions in fact compels people to action and sustains participation in protest movements (**?**). Activists and protest recruiters are fully aware of the importance of this interplay and in fact carefully design their dissemination of information in order to arouse certain emotions and motivate individuals transition from bystanders roles to active participation (**?**). For example, animal protectionists have utilized both happy stories of rescued animals together with images of dead or suffering animals to propel people to action (**?**).

Methodologies that utilize social media data to analyze large scale public sentiment is becoming increasingly common and reliable. For instance, researchers have inferred daily happiness levels from the content of blog posts (**?**), measured societal happiness through messages shared on Facebook (**?**), and examined Twitter data to determine how public mood changes on scales from hours to seasons (**?**). Other analyses of publicly broadcast tweets have revealed the impact of social, political, cultural, and economic events such as stock market fluctuations or a U.S. Presidential election on six dimensions of public mood (**?**). Such online content has not only been used for population-level sentiment assessment but also for prediction purposes, for instance from text-based content in blog posts (**?**) or from image-based content on Twitter (**?**).

Researchers have also used social media to examine the emotional characteristics of individuals during times of social turmoil and tension in particular, for instance finding moods expressed on Twitter to be correlated with rioting activity and economic downturns (**?**). Researchers studying affective reactions to violence associated with the Mexican Drug War similarly found negative sentiment in tweets to be correlated with levels of violence, though only initially, with negative emotional expression declining over time despite a rise in violence — suggesting that people become emotionally desensitized and that individuals' reactions to events depend on multiple factors, including previous exposure to similar events (**?**). A final area of emotion research highly relevant to protest dynamics is how emotions spread from one individual to another, and researchers have studied such phenomenon through social media systems as well — for instance finding the emotions expressed by users via computer and technology-mediated communication tools to be contagious (**?**) and that different emotions spread at different rates and scales of diffusion, with anger spreading the fastest and farthest (**?**).

Thus while numerous studies have established the value of social media data both for analyzing patterns of protest communication and growth as well as for performing large scale sentiment assessment, few studies have attempted to utilize social media to explore the emotions expressed by individuals as protest events unfold. Further, the few existing experiments have taken into account only negative emotions to explain protest-related activities and reactions rather than considering the wider emotional profile central to the experi-

ence of protesters (**?**). Our study aims to merge these strands of research by leveraging social media content posted during times of protest to assess societal mood, protesters' motivations for involvement, and the changes in protest characteristics over time.

Method

Data Collection

For this study, we used Twitter's Firehose API, which was made available to us through a partnership with an organization with access. Through the API, we collected 42,280,539 million tweets shared in Brazil from May 1, 2013 to July 31, 2013 using the tweets' geo-coordinates to identify their location. We included all tweets, including retweets, since retweets can be considered endorsements of the message being shared and typically express a similar sentiment (**?**).

Since one of the main goals of this study is to analyze the emotions that Twitter users express during periods of protest, our first step was to determine whether a tweet is relevant or not to our case study, the Brazilian protests of 2013.

Protest classification

Since one of the main goals of this study is to analyze the emotions that Twitter users express during periods of protest, our first step was to determine whether a tweet is relevant or not to our case study, the Brazilian protests of 2013. To do so, we mined hashtags used during these protests as an initial indicator of tweet relevance and built a co-occurrence graph between hashtags that occurred more than 8 times in the dataset. We used the Jaccard measure to weight the edges, normalized the outgoing edges from each node, and ran the Pagerank algorithm with 5 seeds having equal probability of 0.2. The following hashtags were used for seeds and are all highly correlated; they were very popular during the protests and many news articles mentioned their use (**?**): *#ogiganteacordou* (the giant woke up), *#vemprarua* (come to the street), *#verasqueumfilhoteunaofogealuta* (you will see that your son does not run away from the fight), *#protesto* (protest) and *#protestosp* (protest São Paulo).

We used the assumption that the co-occurrence graph had a sparse cut between nodes corresponding to protest-related and non-related hashtags and therefore by running the Pagerank algorithm using power iterations with a 0.1 chance of teleporting back to a starting node by random, the probability on each node would be a good indicator of whether a hashtag is related to protest or not. In other words, if the graph was dense over the nodes related to protest hashtags, then the probability mass would stay inside. However, this method did not yield a satisfactory result due to the high expansion of the graph. In response, we used a random walk with a constant depth of 5 to find a large number of relevant hashtags. We considered the top 150 hashtags with the highest probability for depths 1 through 5 as protest-related hashtags. To ensure the resulting hashtags were actually relevant to the protest movements, we trained an external annotator who is a native speaker of Portuguese to manually remove all irrelevant hashtags. In the end, we obtained a list of 478 protest-relevant hashtags.

Using this list to find protest-related tweets (tweets using those hashtags), we obtained 72,083 candidate tweets. Since some tweets could of course also be related to the protests without using these hashtags, we then manually confirmed a randomly selected subset of them in order to obtain 800 protest-related tweets as a training set for automatically classifying tweets as related or unrelated to the protests. For this task, we used an SVM classifier with unigram features to determine whether a tweet is relevant to the protests or not, regardless of the presence of one of our hashtags. By training the classifier with the aforementioned 800 verified protest-related tweets along with 4000 randomly sampled non-relevant tweets our classifier achieved an accuracy of 98.8% — much higher than its baseline performance of 83.3%.

Sentiment classification

We next turned our attention to assessing the sentiment expressed in our dataset of tweets. To perform sentiment classification, we collected a random subset of these tweets and again trained an external annotator to label the tweet's sentiment as negative, positive or neutral. Through this process, we obtained over 3100 labeled tweets. We then took a random sample of 1000 tweets for each class (positive, neutral, negative) and applied both SVM and Naive Bayes for classification, using words found in tweets from the training set as the classifiers' features. Results of this classification are presented in the following sections.

Naive-Bayes classifier We use a multinomial Naive Bayes classifier with 9003 binary features (presence/absence), specifically unigrams occurring in the training set. Since the data was not fully balanced, equal priors would not yield favorable results. Instead, we randomly sampled 300 tweets from the entire protest-tweet corpus and manually labeled the emotions of each tweet present in the sample as positive, negative, or neutral. We then defined the priors of each class based on the ratios of labeled emotions. In order to test the accuracy of our classifier, we trained on 900 tweets from each class and tested on 100 tweets from each class, achieving an overall accuracy of 83%. Table 1 shows the confusion matrix of the classifier.

	Negative	Neutral	Positive
Negative	81	10	9
Neutral	7	83	10
Positive	6	9	85

Table 1: Confusion matrix of Naive Bayes Classifier for sentiment classification

SVM Classifier For our SVM classifier we used SVM-light (**?**) to train on the same tweets and features, which are words appearing in the training set. Since SVM is a binary classifier we used a voting method. We learned three classifiers for all pairs of classes, and for classifying each tweet we have three outcomes. If two of the outcomes agree,

we have a winning class; otherwise, each class received exactly one vote and so we assign a neutral sentiment to the tweet. The latter case happens in less than 0.7% of the data and does not change results significantly. Although we introduced cost factors favoring the positive and negative classes in comparison to the neutral class, we still observed large numbers of false-positives for the neutral class in the output of our SVM and as a result worse performance than with the Naive Bayes classifier with the set priors. We therefore opted to use the Naive Bayes classifier to identify the sentiment of tweets going forward.

Results

Social media usage

We began our analysis by exploring how individuals used Twitter throughout the period of the protests. To do so, we analyzed how the total number of tweets, the number of protest-relevant tweets, the number of protest-relevant hashtags, and the number of authors (users posting tweets) changed over time.

Figure **??** shows the number of tweets posted in Brazil per day. The X axis represents the day, and the Y axis represents the number of tweets posted. As the graph shows, the number of tweets shared is higher in June and July compared to the month of May, with the overall number of tweets increasing month to month — the average number of tweets in May is 429,498, in June 465,485, and in July 483,919. June 30 saw more tweets posted than any other day during the protests. Protests happened on this day, but it was also marked by the final of the Confederations Cup, an international soccer league in which Brazil was the champion(**?**).

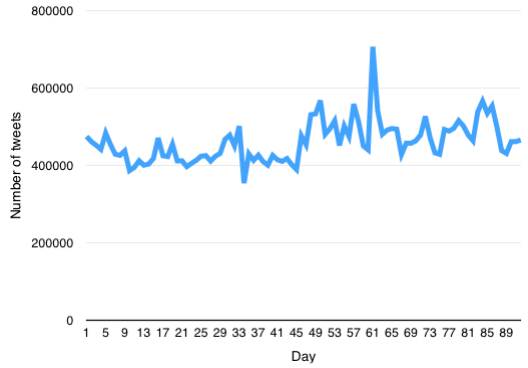

Figure 1: Tweets from Brazil per day

In addition to the number of tweets per day, we analyzed how the number of hashtags changed over time. In Figure **??**, the higher, blue line represents the total number of hashtags related to protests per day, and the lower, green line represents the number of new protest related hashtags per day. As the figure shows, most hashtags about protests were used during the month of June, especially after June 13. Even though the protests started on June 6, the movement started to become more violent after June 13, a day that became known as "bloody Thursday", due to the brutality that the police displayed against protesters (**?**). This disproportionate violence fueled mobilizations in additional cities and served to recruit more supporters to the movement — both in the streets and on social media (**?**). Further, we found that the peaks in the line representing the total number of hashtags (higher, blue line) correspond to the period from June 17 to June 20, which was one of the most intense periods of protest activity. Over 100 thousand people protested in Rio de Janeiro on June 17, and over 1 million individuals from various cities protested on June 20 (**?**). Regarding the new hashtags created over time (the lower, green line), we see that the peak in posting happened on June 17. Thus despite the fact that several protests happened after this date, people continued mostly using the same hashtags rather than new hashtags. Specifically, 93% of the hashtags related to protests were used for the first time before June 22.

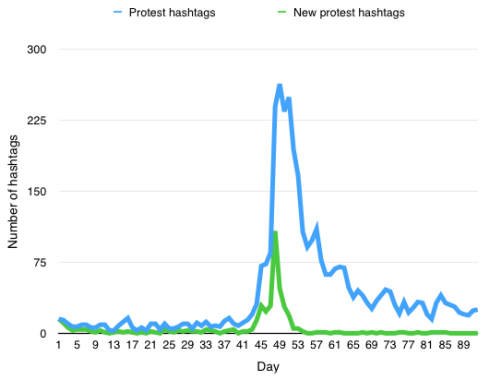

Figure 2: Number of hashtags related to protests per day

Finally, we analyzed the number of tweets related to protests per day. To do so, we performed two different methods to collect the data. In the first method, we collected all tweets that contained at least one of the 478 hashtags identified as protest-relevant. By using this method, we obtained 72,083 tweets over the entire period. Figure **??** shows the number of protest-related tweets per day using this method. As the spike reveals, most of tweets about protests were shared in the middle of June.

Our second method to obtain the protest-related tweets was to train a SVM classifier to determine whether a tweet is about a protest or not. Using this classifier, we obtained 199,039 tweets. Despite the higher number of tweets, Figure **??** illustrates that the pattern remains similar and helps to confirm observed trends — the number of tweets about protests is very low in May, achieves its peak in the middle of June, and begins to decrease by the end of June. As previously mentioned, the majority of protest-relevant tweets were posted in June, especially from June 17 to June 21, during which time users tweeted a total of 121,652 messages about protests (61% of all tweets).

Sentiment over time

Our analysis of social media usage revealed how protest-related communication varied considerably over time,

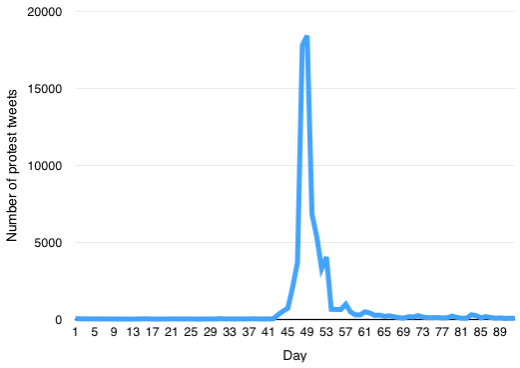

Figure 3: Number of protest-related tweets using the hashtag-based sampling

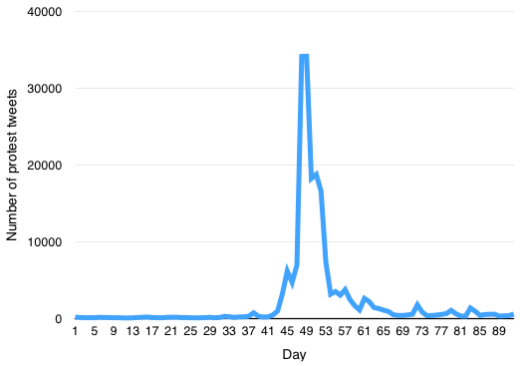

Figure 4: Number of protest-related tweets using the classifier of tweets about protests

achieving its peak in the middle of June. A key question that follows is how the *emotions* expressed by Twitter users fluctuated over time. To pursue this question, we next performed sentiment analysis on all tweets from Brazil and all tweets related to protests.

Table **??** presents statistics based on the ratio of the number of tweets per day expressing an emotion in relation to the total number of tweets shared in the day. During the three months of protesting, the average is 50% for neutral tweets, 29% for positive tweets, and 19% for negative tweets. In all cases the standard deviation is very low, indicating that the ratio of each emotion remains relatively stable. Figure **??** illustrates how the ratio of emotions changes over time, providing a fine-grained view of the dynamics of public mood during the protests. As can be observed from the figure, even though the ratio of each emotion is reasonably stable, there are several peaks and drops of emotions during the entire time period. For instance, we see an increase in the ratio of negative emotions and a drop of neutral emotions in the middle of June, which coincides with the period of greater intensity of protest activity. Further, there is an increase in the ratio of neutral emotions and a drop of positive and negative emotions by the end of June.

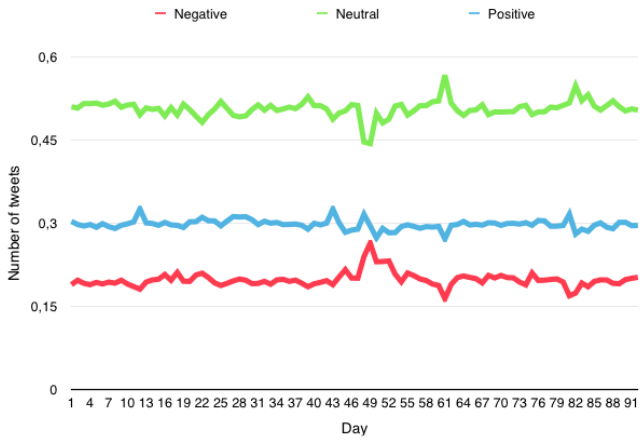

Figure 5: Sentiment classification for all tweets shared in Brazil

All tweets				
	Mean	Std Dev	Max	Min
Positive	0.29	0.008	0.32	0.27
Neutral	0.50	0.015	0.56	0.44
Negative	0.19	0.013	0.26	0.16

Table 2: Descriptive statistics of all tweets from Brazil

After running our sentiment classifier over all tweets from Brazil, we ran the sentiment classifier over the 199,039 tweets that were related to protests. Table **??** presents descriptive statistics based on the ratio of emotions over the three months analyzed. On average, 45% of the tweets related to protests express negative emotions, 30% neutral emotions, and 23% positive emotions. This higher percentage of negative emotions is to be expected given that protests are generally associated to negative emotions such as anger (**?**). Neutral emotions also make sense considering that news media articles generally report on the topic of the protests with relatively impartial prose. The fact that on average 23% of the protest tweets express positive emotions is a more surprising result.

Delving a little deeper in the emotions expressed in the protest-related tweets, we analyzed how these emotions varied over time. The results are shown in Figure **??**. As can be observed, the number of negative tweets is higher than the number of positive tweets on most days except one (June 17), on which day the positive class beats the negative class by 4890 tweets. This is an intriguing and again potentially counterintuitive result, since June 17 was one of the most intense days of protests. We pursue these questions further in the following section on Representative Words.

One possible explanation for the sizable number of tweets expressing positive emotions is the fact that users may be sharing positive tweets, such as jokes, when referring to protests. Given that Twitter bots repeatedly share a large number of tweets, a small number of users sharing positive content could be significantly influencing the overall

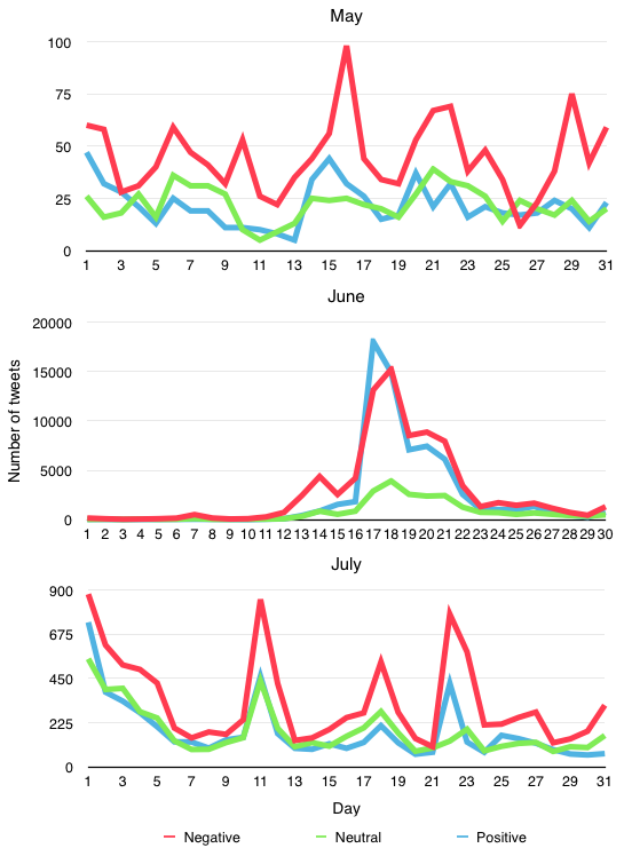

Figure 6: Number of protest-related tweets using the classifier of tweets about protests

results (**?**). In order to investigate whether this is the case, we analyzed the number of users that tweeted about protests either expressing positive or negative emotions. Figure **??** shows how the number of authors expressing each emotion changed over time. The slopes of the two lines clearly show that a large amount of users tweeted about protests during the time period analyzed. Even though in most days the number of users expressing negative sentiment is higher than the number of users expressing positive sentiment, there are two days in which the number of authors expressing positive emotions was higher: June 18 and June 19.

Given these results, a new question arises: Why were users expressing positive emotions during periods of protest? In addition, another key goal of this research is to understand the driving factors of protests and the underlying motives of those involved. Thus to pursue these questions, we next analyzed the representative words for the positive and negative classes over the entire time frame of our dataset, in order to gain a better understanding of how the users were using language to convey their ideas and emotions.

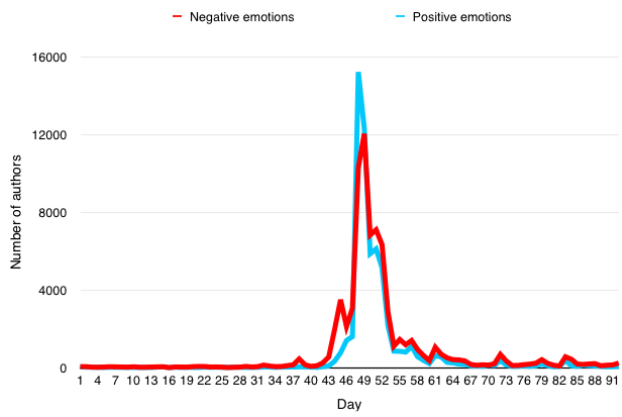

Figure 7: Number of users over time that express either positive or negative emotions in their tweets

Protest-related tweets				
	Mean	Std Dev	Max	Min
Positive	0.23	0.057	0.47	0.13
Neutral	0.30	0.068	0.47	0.11
Negative	0.45	0.063	0.68	0.31

Table 3: Descriptive statistics of all protest-related tweets

Representative words

To investigate the most representative words or hashtags used by Twitter users to express their positive and negative emotions, we used the log-odds-ratio to identify the most representative words and Informative Dirichlet priors to polarize words between two categories. This method assigns scores to each word, in which negative scores relate to negative sentiment and positive scores relate to positive sentiment. A more detailed description of this approach can be found in (**?**). By observing the words with the highest scores in each category, we attempt to interpret the most important factors that influence people's emotions during the protests.

Tables **??** and **??** show the top 10 words/hashtags resulting from this analysis and provides a representative tweet for each word. These words help to shed light on the reasons behind users' expression of negative as well as positive emotions when referring to the protests.

The results for negative-sentiment words (see Table **??**) indicate that users tended to refer to events happening during the protests in these cases. In particular, many words were used to refer to how the police were handling the protests, for instance: atacou (attacked), dispersa (spread), atirou (shot), incitar (incite), inaceitável (unacceptable), and gari (street-sweeper). The lattermost word was used in response to the death of a street-sweeper after having inhaled tear gas thrown by the police (**?**). The remaining 4 words were used to refer to violent and illegal actions of some protesters. For instance, veículo (vehicle) was used to reference the fact that protesters set fire at vehicles, and depredada (vandalized) was used to refer to the vandalism done by protesters.

Next, Table **??** shows the words used in the protest-related

WORD	TRANSLATION	TWEET EXAMPLE TRANSLATED
saques	spoliations	Group that vandalized the city hall performs spoliations in the region. several young men wielding weapons #protest #riot #brazil #protestsp
dispersa	spread	Police spread protesters with bombs and fans suffer with gas
incitar	incite	Free Fare Movement suspects that police infiltrate agents to incite violence in protests
atirou	shot (verb)	Police threw tear gas without warning and without even tense atmosphere between protesters and cops. aggression is systematic.
atacou	attacked	Shock troops attacked protesters at pampulha and cameras from bh trans were deactivated! dictatorship, is that you?
gari	street-sweeper	Police bomb causes the death of a street-sweeper during manifestation in Belem
inaceitável	unacceptable	”Protests cause discomfort and setbacks. But this is part of democracy. unacceptable is the brutality with which the police acted.”
depredada	vandalized	Paulista Avenue dawns vandalized after demonstration against bus fare increase in SP http://t.co/nyvpnkfqts # r7
atropela	tramples	A playboy impatient aboard a land rover runs over 14 protesters and one of only 20 years dies in Ribeiro Preto.
veculo	vehicle	Tense situation in SP. Protesters set fire to a vehicle in front of the city hall and turnstile in front of the municipal theater.

Table 4: Discriminant words for negative emotions

WORD	TRANSLATION	TWEET EXAMPLE TRANSLATED
esplendido	splendid	Brazil changed their status as ”eternally laid in a splendid cradle” to “thou wilt see that a son of thine flees not from battle”. #changebrazil
chegadecorrupo	no more corruption	Bye PEC 37! Congratulations Brazil, you won another one! #nomorecorruption
verasqueumfilhoteunaofogealuta	Thou wilt see that a son of thine flees not from battle	”How beautiful you are! I thought I wouldn’t live to see this in my generation!!! #thegiantwokeup #thouwiltseethatasonofthinefleesnotfrombattle
vemprajanela	come to the window	It is very exciting to see all people united like this. This is what is a wonderful city #cometothewindow
gratificante	gratifying	Few things are more gratifying than being in the middle of 100 thousand people and feel peace in the committed struggle of the Brazilian population! Today I will sleep calmly...
orgulho	pride	I feel so proud to see people in the street protesting for their rights
patriaamadabrasil	beloved country Brazil	Before so many protests Brazil is doing a pretty job... #belovedcountrybrazil!
vamosmudar	let’s change	Look at the hashtag #wakeupbrazil. it is beautiful to see the reaction of the population!!! #neveristoolate #letschange #revolution
paz	peace	To all of you that will go to the manifestation today in Sao Paulo: be careful, let’s all go for peace and for a better country! let it be peaceful!
acreditamos	we believe	We are the children of the revolution, we believe in a good future for the nation! #cometothestreet #riohasstopped

Table 5: Discriminant words for positive emotions

tweets with positive-sentiment. These words suggest that people also expressed positive emotions in order to exhibit pride (orgulho), peace (paz), and satisfaction (gratificante). Other words express patriotic feelings, such as the words esplendido (magnificent), verasqueumfilhoteunaofogealuta (thou wilt see that a son of thine flees not from battle), and patriaamadabrasil (loved country Brazil), all of which refer to parts of the Brazilian national anthem. Some words express hope for a better future, such as vamosmudar (let’s change) and acreditamos (we believe). The word vemprajanela (come to the window) was used to invite people that were not protesting into the streets to see what was taking place. Finally, the word chegadecorrupção (no more corruption) does not express a positive emotion itself but was used in tweets that express positive affect, for instance to refer to the abandonment of PEC 37, a controversial project extensively criticized by protesters.

Discussion and Conclusion

In this paper we undertook an analysis of how Twitter reflects protest dynamics in Brazil throughout May, June, and July of 2013, a period in which major demonstrations happened across the country. While previous studies have analyzed the emotions expressed on social media during periods of conflict and protest, our research is the first to explore how societal mood changes over time and in the context of the Brazilian protests. Furthermore, in this work we analyzed both negative, neutral and positive emotions during the period of protests, which contrasts with previous works that focused mostly on the analysis of negative emotions.

Specifically, we analyzed Twitter activity levels throughout the protests, finding that peaks in Twitter activity coincide with days in which major protests took place, and in particular on days when significant violence and police brutality was reported. Looking to the emotions users ex-

pressed on Twitter and how those emotions changed over time, we again found inferred sentiment to reflect protest-related events. A surprising finding was that users tweeted a large amount of tweets related to protests that express positive emotions, and in one day the number of tweets expressing positive emotions even surpassed the number of negative tweets. Our analysis of words commonly found in tweets with particular emotions more fully revealed that many negative tweets tended to refer to violence, injury, and destruction resulting from brutality from police and vandalism by protesters, while positive tweets tended to refer to sensations of peace, pride, patriotism, and gratification.

Practical and Design Implications

The findings of this research bears implications for government leaders and authorities. In order to take the right measures during periods of protest, authorities often communicate with leaders of social movements to understand their grievances and make agreements based on that. Social media, however, has contributed to the occurrence of large protests without key leaders, and with protesters complaining about different issues (**?**). Therefore, it can be hard for authorities to communicate with the protesters and respond to their expectations. By knowing the emotions that users express online during periods of protest, and identifying what people are referring to when expressing these emotions, authorities can have a better understanding about the reasons that lead people to protest, and to what extent their measures will take effect or not. For instance, if people are joining a protest because they are angry about the violence of the police in previous protests, then revoking a bus fare increase will not take any effect. Similarly, if individuals are participating of a protest mostly because they feel happy of being part of a collective movement with the goal of changing Brazil for the better, then the authorities should not react by asking shock troops to prevent the protest. In Brazil, the protests continued to happen even after the government revoked the increase in bus fares, which shows that people had different reasons for participating in the protests. Gilberto Carvalho, which was the general secretary of the Brazilian president in 2013, said a phrase that shows that the government leaders did not know how to react during the protests: "It would be pretentious to say we understand what is going on" (**?**).

Given the need of understanding the interests and expectations of the population, one possible implication of this study is the development of tools that monitor in real-time the emotions that people express when referring to protests or political issues. Prior work has shown that tools that continuously present information about events identified from social media can assist the work of journalists (**?**). Therefore, a similar tool could be developed for authorities and government leaders. This tool could guide the way that a manifestation or conflict is handled, giving more time to anticipate the right resources and measures needed, which can make a big difference in the way that protests unfold.

Limitations and Future Work

In our research there is a concern with sampling biases. Our data and findings are based on people who purposefully shared messages on social media expressing their emotions and opinions, so it is possible that the emotions expressed by individuals on Twitter are different from the emotions expressed by protesters in the streets. Furthermore, individuals who do not have the technological infrastructure to access Twitter or do not have a Twitter account are underrepresented. Even though we were unable to account for bias in this study, we recognize the importance of addressing this, and emphasize that future directions involve additional validation work. For instance, a key next step is to analyze the correlation between online Twitter activity and offline protest-related information such as reports from authorities and news media about the number of protests and protesters on a given day, the number of people who got arrested, and number of people who were injured. In particular, it is desirable to analyze the extent to which the negativity we see expressed in tweets actually correlates with violence happening in the streets.

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