17 "Fear in 280 characters"

A new approach for evaluation of fear over time in cyberspace[1]

Francisco J. Castro-Toledo, Tobias Gretenkort, Miriam Esteve and Fernando Miró-Llinares

17.1 Introduction

Most of the literature on fear (and fear of crime) is associated with the characteristics of spaces in cities and public realms (Castro-Toledo, 2019). This chapter focuses instead on the phenomenon of fear in cyberspace, through the analysis of emotional linguistic responses of online social media (tweets). A method to quantify fear of terrorist attacks through linguistic sentiment analysis is proposed. We analyze emotional linguistic responses to terrorist attacks over time using a sample of more than two million tweets collected on three occasions: after the attacks on Charlie Hebdo, Nice, and Barcelona between 2015 and 2017. We posit that these aspects render our understanding of fear in online social networks more fine-grained and help us understand how online social media spread messages of fear of attacks through the medium of language.

We propose that the validation of this method is of practical interest in the detection, analysis, and possibly even the prediction of waves of fear of crime in the digital realm. The relevance of tweets in this work is twofold. First of all, they're easy to gather and present an opportune option to analyze public discourse with very little delay between generation and collection of data. On the other hand, Twitter exhibits growing relevance in the public discourse as tweets are sometimes even singled out in traditional media. Furthermore, we follow Miró-Llinares & Johnson (2018) in that the social organization of cyberspace can sensibly be compared to the organization of physical space, with Twitter representing a specific macroplace in cyberspace.

In this chapter, we explore some of the traditional methodological approaches to fear and fear of terrorist attacks, after which we establish the relevance of both linguistics and its relation to emotion for this study. Subsequently, the generation of hypothesis from this interdisciplinary framework is reported, as well as testing, results and discussion of the findings. The chapter concludes with some recommendations for future research and the value of this line of investigation of research on fear of crime.

17.2 Theoretical framework

Fear of crime: definition and methodological approaches

Our investigation deals with the specific emotive response to terrorist attacks in the cyberspace, with a strong emphasis on how the authors' linguistically encoded emotion can be used to track fear across time and different "places" (i.e., hasthags) in cyberspace. In this vein, we understand fear as the emotion of fear arising in a specific moment and place upon the possibility of perceiving oneself as the victim of a crime. While this is a general definition of fear of crime (Castro-Toledo, Perea-García, Bautista-Ortuño & Mitkidis, 2017), we deem the aspect of possible victimization and the fear this creates in an individual as pertinent enough to extend this definition to the specifics of terrorist attacks.

Despite the intuitiveness of the concept, fear of crime remains a complex and hard-to-measure phenomenon (Castro-Toledo, 2018). Researchers have engaged in a methodological debate between old and new methods to measure fear of crime (Jackson 2005; Tseloni & Zarafonitou, 2008). While older approaches tackle the question of *intensity* of experiences of fear of crime, newer approaches try to observe the *frequency* with which those experiences are made in everyday life. To these authors, the methodological change from *intensity* to *frequency* seems to imply a significant improvement in the measurability of fear of crime.

Within the above-described methodological context, the major proportion of studies in crime sciences focuses on gathering information through self-reports (Castro-Toledo, 2019). Importantly, these methods of analysis have two main types of limitations. The first limitation lies in the diverse problems related to the external validity and precision of measurement instruments, in particular the presumption that research participants are able to explicate with precision the type of cognitive processes and emotional states they go through in experiencing fear of crime (Levine & Parkinson, 2014). The second limitation is that the traditional fear of crime methodologies try to collect emotional data through hypothetical scenarios of victimization or through contemplating real episodes of fear that are distant in time (Ferraro & LaGrange, 2000; Hale, 1996; Hardyns & Pauwels, 2010; Yang & Hinkle, 2012).

In contrast to data based on self-reports, new methods account for fear of crime with real-time data. This type of data is currently under-exploited, as pointed out in a recent study on physiological measures associated with the experience of fear of crime (Castro-Toledo, Perea-García, Bautista-Ortuño & Mitkidis, 2017; Noon, Beaudry, Schier, & Knowles, 2019) and app-based studies (Solymosi & Bowers, 2018), among other research contributions.

Fear in cyberspace

To date, online social networks are one of the most abundant sources of information about patterns of criminological interest (e.g., Burnap et al., 2015;

Esteve, Miró-Linares & Rabasa, 2018; Miró-Llinares, Moneva, & Esteve, 2018). In general terms, *Big data* allows us to collect data as they are generated and compared over time (Bello-Orgaz, Jung, & Camacho, 2016; McAfee, Brynjolfsson, Davenport, Patil & Barton, 2012). Twitter and other platforms put Application Programming Interface (APIs) to the users' disposition, to establish direct communication with their servers. This way, researchers can easily compile data in terms of both the discursive content (speech) of tweets and a wide array of relevant metadata (for example, IDs, hashtags, text length, geolocation, etc.). Nevertheless, research on this social media platform is still scarce or almost not existent for fear of crime (Solymosi & Bowers, 2018). To exploit this resource, we resorted to formulate an interdisciplinary paradigm of criminological Big Data analysis and computational linguistic sentiment analysis and used it to compare different crime events and Twitter users' emotional reactions over time.

Our interest in online discursive contents is based on the tightly established relationship between emotion and language on the levels of theory, neurolinguistics and computational linguistics (Wierzbicka, 1994; Van Lancker & Pachana, 1998). In this context, the analysis of linguistic material with computational methods is known as NLP, or 'natural language processing' and presents one of the most promising fields for the future of applied linguistics. Previous studies speak to the utility of the written text approach (Salas Zárate, Paredes Valverde, Rodríguez García, Valencia García, & Alor Hernández, 2017; Shivhare, 2012) and its capability of evaluating emotional content of an utterance based on non-contextual linguistic information (Asghar, Khan, Bibi, Kundi, & Ahmad, 2017). In addition, the interest in the emotive content of words led to the development of big databases in which emotional values are attributed to lexical elements by human judges without any context for the judged words to appear in (examples of databases that can be found in Spanish are: Stadthagen-Gonzalez, Imbault, Pérez Sánchez, & Brysbaert, 2015; Stadthagen-González, Ferré, Pérez-Sánchez, Imbault, & Hinojosa, 2017).

However, there are several practical and scientific restrictions with regards to sentiment analysis. On the one hand, it appears to be, from a psychological standpoint, uncertain which emotions are basic to the human psyche and how they are expressed in human vocabulary (Barrett, 1998; Christie & Friedman, 2004). The debate between those psychologists postulating clear-cut distinguished discrete basic emotions such as fear, anger, surprise, happiness and disgust (following Ekman, 1999) and those questioning and opposing the existence of basic universal discrete emotions (Barrett, 2017) is reminiscent of this uncertainty.

On the other hand, sentiment analysis functions, such as the polarity function from R's qdap package (Goodrich, Kurkiewicz, & Rinker, 2019) for linguistic analyses, often lack the appropriate scientific basis to be used in this context. The aforementioned case, for instance, makes use of predefined lists of positive and negative words, which give a given phrase a base polarity (positive or negative) which is then corrected for through the analysis of syntactic elements such as negation (inverting the base polarity), augmenting words such as "very" (boosting the base polarity value) and the like. The methodological problem at hand is that base polarity is arbitrarily assigned and does not make use of experimentally justified values as the aforementioned emotional norms do (e.g., Stadthagen-Gonzalez, Imbault, Pérez Sánchez, & Brysbaert, 2015; Stadthagen-González, Ferré, Pérez-Sánchez, Imbault, & Hinojosa, 2017).

However, the supplied parameters based on the *Theory of Constructed Emotion* as formulated by Barrett (2017) are useful to avoid some of the above limitations. She argues that the postulation of concrete basic emotions such as fear, anger, happiness, disgust and sadness cannot be held up in the light of recent psychological discoveries, and that basic emotions can and should be broken down into more primitive parameters. The title of her theory is reminiscent of the idea that "emotions" are cognitively constructed experiences that are integrated in a context from two basic "affects", that is reactions to external stimuli, namely valence and arousal. Valence is the affective positivity of a response toward a stimulus, while arousal refers to the affective activation. Higher-order emotions then are integrations of these base affects. A simple example of this is "happiness" which is the integration of "positive" and "active" (i.e., high valence and arousal) while "relaxation" integrates "positive" and "inactive" (i.e., high valence and low arousal).

This is well integrated into modern views of language, which postulate multimodal integration of word meaning from interaction memory, emotion and other parameters. In this view, a word is not stored in the brain as a linguistic description of meaning, but is integrated from the memories and emotions that are connected to its usage and interaction in the past (Barsalou, 1999). Hence, we have no reason to believe that only vocabulary which signals "fear" directly can be attributed to fear of crime. Rather, emotive information can be retrieved from language through a variety of different methods and measures, such as the valence and arousal as we have previously proposed (Gretenkort, Castro-Toledo, Esteve & Miró-Llinares, in press). In this study, we have determined that readers of tweets attribute a higher potential to promote fear of crime among readers when valence is low, and arousal is high.

Previous analysis on Twitter also have shown how linguistically encoded emotivity is organized in cyberspace. Differences in emotive response to tweets for instance vary according to hashtags mentioned in tweets and the literal meaning of hashtags, among others (Wang, Wei, Liu, Zhou, & Zhang, 2011). In particular, the hashtag *#Islam* has been found to co-occur with *#jihad*, *#terror*, and *#igiveup* (Wang et al., 2011, p. 1038). More recently, the popular hashtag *#StopIslam* has been found to be one where "[…] [e]xtremist groups can rely [on] […] with a lower expectancy of any message dilution by means of counter-narrative" (Blanquart & Cook, 2013, p. 7). The different "populations" of hashtags thus also show different reactions to different topics, both according to the hashtag as such and to the way the hashtag construes the event. That is, the hashtag #PrayForBarcelona construes the terrorist events in

2017 as one requiring solidarity with the victims, while #StopIslam construes the same event as a reason to oppose Islam in civil society.

Hypotheses of study

Given this context, the increasing interest in applied linguistics in cybersecurity and the export of the concept of place from physical space to cyberspace (Miró-Llinares & Johnson, 2018) allow us to assess new hypotheses about whether crime or fear of crime in digital contexts is randomly distributed in space and time. Specifically, we want to put forth a methodology to respond to three hypotheses generated from the previous observations. Hence, we shall analyze in this study, how the linguistically encoded emotive response to terrorist attacks changes over the course of 24 hours after these attacks, with the method proposed in Gretenkort et al. (in press). At the same time, we will compare the emotional responses across three different terrorist events in the current political panorama in Europe, namely Charlie Hebdo (2015), Nice (2016), and Barcelona (2017). Likewise, and to ensure the validity of our method, we shall attempt to replicate the findings of Wang et al. (2011) and Blanquart et al. (2013) with regards to the differences between hashtags. In summary of the previous explanations, we formulated the following three hypotheses to test:

H_1: The emotional response to a tweet can be described as a function of event, hashtag and time elapsed after the attack.

H_2: The emotive profile of each tweet will depend on the way the event is construed by the hashtag (i.e., event description, expression of solidarity, defense against Islam)

H_3: The emotive response to each tweet will depend on the hashtag that is was authored under.

17.3 Data and methods[2]

Sample

We base our study on a corpus supplied by the center CRIMINA for the study and prevention of crime at Miguel Hernández University. For the compilation of this corpus, we used the *API Search* that Twitter supplies. Implementing a Python-based algorithm that interacts with the API and specifies the filtering parameters, we obtained a JSON file, which was then exported as a CSV file with 41 attributes for each compiled tweet. The algorithm implemented to our ends mainly uses six types of data, of which four are supplied by the Twitter developer for authentication. The last two parameters were the vectors that store the language code (“es”) and the hashtags or keywords (i.e., aforementioned hashtags). With the authentication data establishing a connection to the API, a listener was implemented which, upon detection of an event matching the defined parameters, recorded and stored relevant tweets in JSON format. Upon error, the script notified the research team.

The compiled corpus contains more than two million tweets published during the first 24 hours after the attacks of Charlie Hebdo (280,000 tweets collected during 7 January 2015), Nice (720,000 tweets collected during 14 July 2016) and Barcelona (1,050,000 tweets collected during 17 August 2017). More specifically, and with a purpose of making comparative analysis, tweets were collected from the following hashtags: #charliehebdo, #nice, #barcelona, #jesuischarlie, #prayfornice, #prayforbacerlona, and #stopislam. Cleaning the data and preparing it for analysis included the steps of (1) excluding all the non-Spanish tweets, and (2) ruling out retweets; that is, keeping only unique tweets. This resulted in a database of exactly 336,960 tweets in Spanish, with 157,370 tweets in reply to the attacks on Barcelona, 64,278 concerning Charlie Hebdo, and 115,312 in reference to the Nice attacks. The distribution of tweets around different hashtags was as follows: #Barcelona 152,726, #CharlieHebdo 51,696, #JeSuisCharlie 6,396, #Niza 103,016, #PrayForBarcelona 2,926, #PrayForNice 12,056, #StopIslam 8,144.

These could be grouped according to speech acts contained in the hashtags for further analysis as follows. We regrouped those hashtags that contained (a) a mere linguistic reference to the event as such, with no further (obvious) judgement (#Niza, #Barcelona, #CharlieHebdo) under the label "event report", (b) those which carry an open expression of solidarity through a linguistically bounded association with the victims (#JeSuisCharlie) or request for support (#PrayForBarcelona, #PrayForNice) under the label "expression of solidarity", and (c) the remaining hashtag (#StopIslam) under its own category, since it carries a linguistically distinct message, namely the open request for opposition against "Islamic terror".

Procedure and analysis

As indicated before, we build upon an earlier contribution (Gretenkort et al., in press), where the effect of our measure of emotive valence and arousal was found to have an impact on the amount of fear of crime that participants read into different tweets. In this study, a low amount of valence combined with a high amount of arousal led to a perception of tweets to be more promotive of fear of crime. We shall try to expand on this paradigm to detect the effect of time passed by after a given terrorist event. To do that, we used two lists of affective norms for Spanish (Stadthagen-Gonzalez et al., 2015, 2017), two datasets in each which over 10,000 words of the Spanish language were rated with regards to their emotive content by 512 (Stadthagen-Gonzalez et al., 2015) and 2010 (Stadthagen-Gonzalez et al., 2017) participants respectively. The lists contain ratings across seven emotive dimensions (valence, arousal, happiness, disgust, anger, sadness, and fear), the first two indicating how positive (valence) or activating (arousal) a word is (Stadthagen-Gonzalez et al., 2015) and the second indicating how much happiness, disgust, anger, sadness, or fear the words contain (Stadthagen-Gonzalez et al., 2017). Note that the lists contain both explicitly emotional words ("happy", "sad") and not typically emotional words such as "monk". The lists do not discriminate between emotional and non-emotional words, but it is important to note that using these lists we can calculate emotive expressions using almost every word in a tweet (as long as it is present either list). On the other hand, in accordance with the *Theory of Constructed Emotion* (Barrett, 2017), we elaborated a measure for valence (polarity) and one for arousal (activation), such as to quantify the emotive content of each tweet.

To do so, a computer algorithm written in R (1) tokenized each tweet, (2) searched for the tokens in a list of over 10,000 experimentally generated emotive norms for Spanish words (x) (Stadthagen-González et al., 2015), and (3) calculated the emotive value for each tweet as the geometrical mean ($e = 3$) of each word's emotive value (i_x) within the tweet:

$$\textit{emotive value}_{tweet} = \left(\sum_{x=1}^{n} i_x{}^3\right)^{\frac{1}{3}} = \sqrt[3]{i_1{}^3 + i_2{}^3 + \cdots + i_n{}^3}$$

With this measure in place, calculations on the Twitter data could be made to test the aforementioned hypotheses one through three. Each hypothesis was tested for their corresponding null-hypothesis, thus enabling us to rule out random phenomena as explanatory models for our data and putting forth our alternative hypotheses.

To assess H_1, we created several linear models with the lm function of R's stats package. We will only report the best performing model. We created a model to check for the emotional profile's development (dependent variable) over time (independent variable) of tweets combined with interaction effects for events and emotions classified by a hashtag (independent variable). The corresponding model was expressed as follows:

lm(emotive value ~ created_at * emotion * event + hashtag)

To check for the significance of each of the formula's terms, we used the anova function of R's stats package.

H_2 was tested with the tweets regrouped under the classes "event description", "expression of solidarity", and "Stop Islam". We fitted a linear model to predict emotive value for each tweet from the class of hashtag it pertained to, and the emotion under investigation:

lm(emotive value ~ class of hashtag * emotion)

To address hypothesis H_3, we analogously fitted a linear model with the lm function from R's stats package (R Core Team, 2013) with the emotive value of each tweet as a dependent variable, and both hashtag and emotion (valence vs. arousal) as independent variables:

lm(emotive value ~ hashtag * emotion)

To account for the significance of the model's terms (i.e., hashtag and emotion), we applied an ANOVA over the model (Chambers & Hastie, 1992) with the anova function from R's stats package.

17.4 Results

H_1—Development over time

Our hypothesis aimed to find differences in the development of tweets' emotional profiles over time and across different events and hashtags. The corresponding variance analysis of our linear model yields significant results for all main effects plotted in the model: time elapsed after the attack F (1, 336,376) = 5,738.8382, $p < 0.001$, emotion F (1, 336,376) = 26,982.0510, $p < 0.001$, event F (2, 336,376) = 803.7335, $p < 0.001$, hashtag F (6, 336, 376) = 162.2486, $p < 0.001$. In addition, significant and meaningful interactions could be detected between emotions and time elapsed after the attack F (1, 336,376) = 411.9118, $p < 0.001$, and emotion and event F (1, 336, 376) = 2,122.1449, $p < 0.001$. The mixed linear model accounts for around 11 percent of the variance in the data $R^2 = 0.1067$, F (17, 336,380) = 2,364, $p < 0.001$, with 14 out of 17 terms (including main and interaction effects, see the Appendix for complete statistical analysis on Github) significantly contributing to the accuracy of the model. We can thus reject the null-hypothesis, namely the independence of emotive values of tweets from the terms modelled in our analysis. Our alternative hypothesis states that emotive values of tweets can be predicted from the event, hashtag and time elapsed after the terrorist attack, for each of the tested emotional base affects.

Figure 17.1 shows the development of tweets' emotional profiles during the first 24 hours after each attack and grouped by hashtags. Free scales allow for a comparison of tendencies between different events.

H_2—Emotive value by speech act classes of hashtag

The executed ANOVA shows highly significant main effects for both the class of hashtag, F(2, 336,388) = 125.8, $p < 0.001$ and the emotion to be investigated, F (1, 336,388) = 1,887.3, $p < 0.001$, including an interaction effect between these two, F(2, 336,388) = 264.0, $p < 0.001$. More concretely, this means that expressions of solidarity (#JeSuisCharlie, #PrayForBarcelona, #PrayForNice) modulate arousal in tweets by $\beta = 0.13$, t(336,338) = 49.76, $p < 0.001$ while the hashtag #StopIslam modulates arousal even stronger $\beta = 0.23$, t(336,338) = 54.22, $p < 0.001$. The opposite effect can be detected for

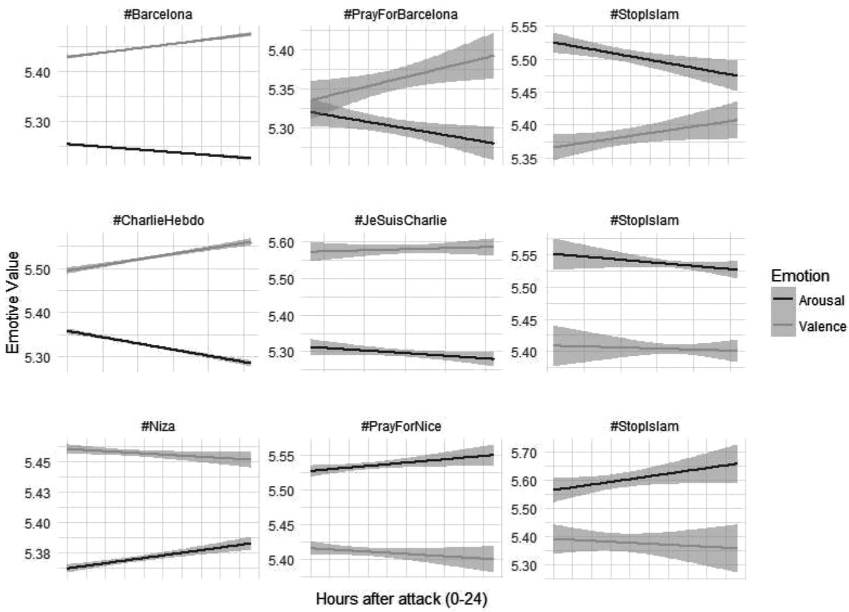

Figure 17.1 Development of tweets' emotional profiles during the first 24 hours after each attack and grouped by hashtags. Free scales allow for a comparison of tendencies between different events. The shaded areas around the linear models represent standard error.

valence in which expressions of solidarity modulate the intercept by $\beta = -0.14$, $t(336{,}338) = -37.63$, $p < 0.001$ and the hashtag #StopIslam even more so $\beta = -0.29$, $t(336{,}338) = 49.19$, $p < 0.001$ (Figure 17.2). The model furthermore explains around 9 percent of the variance in the data $R^2 = 0.0864$, $F(5, 336388) = 6{,}367$, $p < 0.001$. The null-hypothesis is thus rejected in favor of the alternative hypothesis, namely that the linguistic construction of the hashtag in question (solidarity, report, opposition) does impact the emotive profile of tweets for each emotion measured.

Figure 17.2 indicates the emotive values of tweet across different classes of hashtags (descriptive, solidary, opposed). Error bars indicate bootstrapped mean confidence intervals without assuming a normal distribution.

H_3—Emotive value by hashtag

The executed ANOVA shows that there are highly significant main effects for both the hashtag, $F(6, 336380) = 1401.1$, $p < 0.001$, and the emotion to be tested, $F(1, 336380) = 27362.5)$, $p < 0.001$. In addition, we found a highly significant interaction effect between these two variables $F(6, 336380) = 1620.7$, $p < 0.001$. We refrain from reporting the statistics of each possible combination

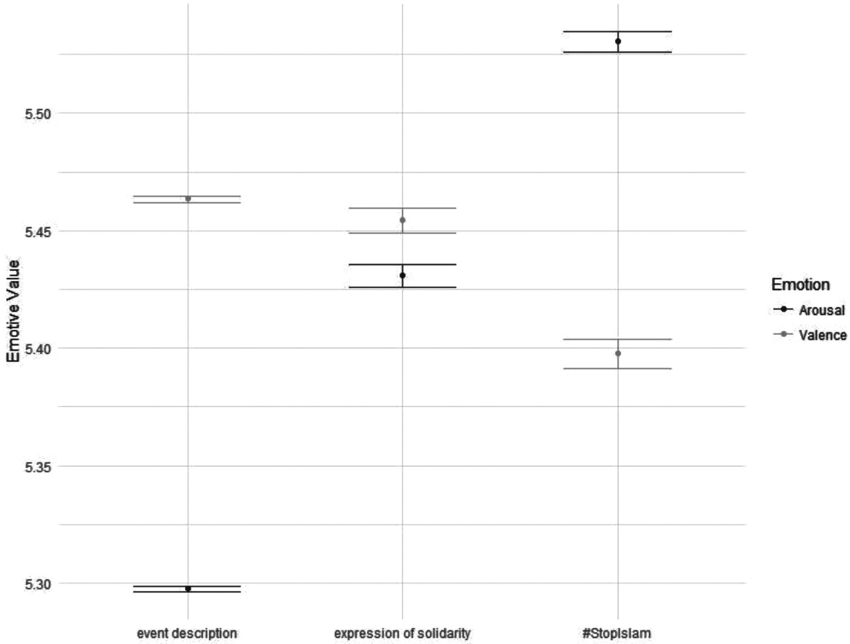

Figure 17.2 Emotive values of tweets across different classes of hashtags (descriptive, solidary, opposed). Error bars indicate bootstrapped mean confidence intervals without assuming a normal distribution.

between hashtags and emotions to maintain ease in reading. However, all of these contrasts are (as would have to be expected given the variation in data sources and events) significant and the linear model does significantly account for almost 12 percent of the variance in the data, $R^2 = 0.1191$, $F(13, 336380) = 3499$, $p < 0.001$ (Figure 17.3). We can thus reject the null-hypothesis and elaborate on our alternative hypothesis, namely that the emotional profile of tweets across the basic affects valence, and arousal does depend on the hashtag that tweets are created under. Figure 17.3 illustrates the distribution of emotive values (valence and arousal) across different hashtags. Hashtags are ordered by mean valence per tweet in descending order.

17.5 Discussion

The relevance of time

First, we observe that it was possible to model the emotive responses to terrorist events as a function of the event, the hashtag and the elapsed time after the attack. This means that our proposed method of analysis does identify all the differences that we would expect in tweets from the literature. What we

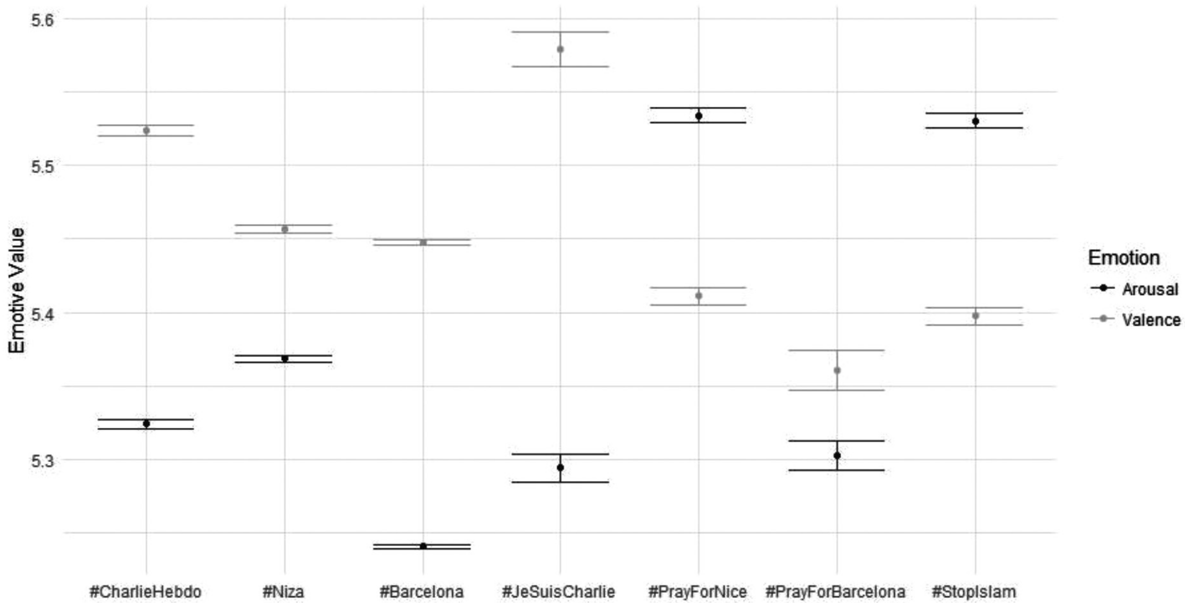

Figure 17.3 Distribution of emotive values (valence and arousal) across different hashtags. Hashtags are ordered by mean valence per tweet in descending order. Error bars indicate mean confidence intervals with an assumed normal distribution.

observe concretely in our analysis (Figure 17.1) is that, overall, valence increases as a function of time, and arousal decreases as a function of time, as if the emotional response to terrorist events was "cooling" over time, resulting in more positive and less aroused tweets after some time has elapsed. The other general rule to be observed is that valence usually has a higher value than arousal. There are two core deviations from this rule which require further investigation. First, the hashtags #PrayForNice and #StopIslam (across events) (1) show higher values in arousal than all the other hashtags. This seems to indicate that these hashtags behave fundamentally different from the other ones in that users tweet under them with more aroused vocabulary. We take this to be indicative of the fact that these hashtags are used as valves for emotional responses, while they are possibly more permissive toward radical, or anti-Islamic content.

Furthermore, the emotive responses to terrorist attacks on Nice do not develop in the same way as all the others. Tweets referring to the Nice attacks, under all hashtags, show a decrease in valence and an increase in arousal over the first 24 hours after the attack. This shows that fear of crime with regards to the Nice attacks behaves differently from the other events. We argue that the development of sentiment is a linear function of time, which can be modulated by hashtags and event, as reflected in our model. We explain this with the general attitude that authors assume toward Islam and events of terror subsequently (Blanquart et al., 2013). That is, the author's inherent interest to evoke images of terror (Wang et al., 2011) and hence fear in readers modulates the effect of discourse generally cooling down when time elapses after an event. Addressing the question of why tweets on the Nice attacks behave differently from the others, one could argue that the mediatic repercussion of this attack on Twitter is stronger, because we are here dealing with the second highly received terrorist attack in France after Charlie Hebdo. However, this assertion gives rise to new hypotheses which will have to be tested individually and is out of the scope of this chapter.

Relevance of hashtags as grouped by speech acts

First and foremost, the results of our analysis of H_2 seems to corroborate our intuitions on hashtag usage. We can observe significant differences between the three groups of hashtags in the distribution of valence and arousal. We note that, when groups are ordered in the fashion of *event description* (a), *expressions of solidarity* (b), and *#StopIslam* (c), we detect an increase in arousal, but a decrease in valence along this order. This follows our intuition on *speech acts* (Searle, 1969), namely that the linguistic expression of fear of crime, or its operationalization through valence and arousal, is not only somehow dependent on the different hashtags, but that the linguistic construction of these spaces plays a fundamental role in evoking fear of crime. It would correspond to a descriptive speech act (a) to be generally more positive (or at least less negative) than other speech acts, and to be less aroused than expressions of solidarity (b), which are almost equal in valence, but do present a more aroused vocabulary. #StopIslam, with its Islamophobic tendencies (c), is constructed even more radically, since the level of arousal surpasses the level of valence, which makes this hashtag different from the other two. There are severe limitations in this abstraction however, as we are comparing small groups of hashtags with (1) very little variation within the analyzed speech acts and (2) a superficial motivation for the analysis of these speech acts, because this study is oriented toward criminology rather than linguistics. In the future, more studies need to conclude what our findings do not contradict at least. While our study is designed to detect *if* hypertextual space on twitter is ordered (whether by hashtags or speech acts) with regards to emotional expressions of fear of crime, more conclusive studies should yield results on *what* orders this space, that is to say whether each hashtag is distinct, or whether we can abstract from this fine-grained level of appraisal through the application of speech act theory. Our analysis reproduces the findings of Wang et al. (2011) who state that the construction of the event in the hashtag itself is indicative of the discourse and the reactions that the hashtag evokes. Our method thus reproduces earlier findings and does not stand in contrast to other methodologies employed.

Relevance of hashtags

Our results uncovered furthermore that there are distinct distributions of emotive values for each hashtag, and that there are significant contrasts between them. Apparently, this makes it possible to describe different hashtags in terms of the emotional response they provoke with regards to terrorist attacks. Even though co-variance is relatively low (only 12 percent of the variance can be accounted for by our models), which hinders our method from classifying single tweets and attributing them to a hashtag a priori, we are able to distinguish the evoked emotional values by hashtags if we have a sufficiently large dataset. This means that the overall trend can be relevantly accounted for and that our method produces the anticipated results with regards to research conducted on hashtags in the past (e.g., Blanquart & Cook, 2013).

Furthermore, we can use this assessment to describe reactions in certain cyberplaces on Twitter and how they are different from one another (Miró-Llinares & Johnson, 2018). We are, for example, able to order hashtags by mean valence, resulting in #JeSuisCharlie having the highest level of valence, that is the most positive vocabulary in the analyzed corpus, while #PrayForBarcelona has the lowest. This aligns with the diagnosis that #JeSuisCharlie was a highly engaging hashtag which, first and foremost, expressed solidarity and support with the victims (De Cock & Pizarro Pedraza, 2018), while #Barcelona (even though it expresses solidarity) evokes more negative vocabulary. This could be based on the fact that we analyzed Spanish tweets exclusively and that Spanish users are more affected by terrorist events actually taking place in Spain. Also, Barcelona was the most recent of the analyzed terror attacks, meaning that responses could have become more negative over time. This could be analyzed in a separate, future study.

It is even more striking, that, usually, the response in arousal measured in the data, stays behind the response in valence, except for two hashtags, namely #PrayForNice and #StopIslam (Figure 17.3). We have discussed this under H_1. Unfortunately, it is out of the scope of this chapter to analyze the semantic fields that are used under these hashtags, because it requires a different methodology altogether. In any case, our method proves to be useful for the identification of different spaces on Twitter, that foster different images and linguistic behavior and is also in line with the observation that *#StopIslam* resorts to different emotive strategies in the construction of the topic.

Relevance to fear of crime

While our measure is not directly aimed at the identification of fear of crime, the relevance of our data analysis with this topic rests upon the results of an earlier contribution (Gretenkort et al., in press). As pointed out earlier, participants judged those tweets as more provocative or promotional of fear of crime, which exposed a great deal of arousal and little positivity. We use this to link the previously discussed features of our measure and its organization in cyberspace. Our measure of emotional variables and the attribution of certain properties goes well together with the methodological stance taken by Castro Toledo (2018) and the predictions made in the introduction to this chapter. The general contribution to a better understanding of fear of crime lies in the exploitation of large amounts of data, which corroborates the works cited, and the confirmation of its structural organization through linguistic features on Twitter.

17.6 Conclusions

This chapter has shown that, contrary to traditional research models or those based in self-reported measures, research applied to fear of terrorist attacks allows us to introduce methodological designs that can access indicators associated with emotional experiences in real time. That is, the current method does not collect the information in the very moment research participants (or Twitter users) experience fear, but instead the experience is plotted and conserved in a linguistic expression of emotivity that can be analyzed and accounted for as if it were measured at the time of experience.

Furthermore, utterances on Twitter are less cognitively shaped than self-reported entries, in that they are announced spontaneously which supports our method. However, it has to be recognized that the usage of *big data* is limited to the analysis of data. This is less trivial than it appears. Big volumes of data aren't useful in the analysis and prevention of crime unless data inputs are contrasted with those human factors that are either (a) not (yet) measurable, or (b) responsible for the pollution of data, the selection of data, and the interpretation of data. This is important to point out because the ontologies that are implemented in models of automatic data detection and classification of discursive content in social media on the scale of *big data* are limited and sometimes erroneous (Miró-Llinares et al., 2018). This is why we pointed out that the current method seems to be suitable for the analysis a posteriori of labelled data, in order to detect trends in massive data, while abstracting and classifying single data points isn't possible with the method proposed. This argument would have come into play if we had tried to predict which hashtags a Tweet includes or to build something like a hate-speech classification machine. On a slightly different note however, this method is useful to state differences between events with regards to (a) different groups articulating their concerns with regards to a given topic or event, while (b) also enabling differences between events and how they are received on a level of fear of crime.

In summary of these considerations, we state that our method aims to measure the inherent emotive dimensions of valence and arousal in the vocabulary of tweets, so as to analyze different emotive responses to terrorist attacks online and to diagnose possible differences in emotive responses according to the hashtags under which tweets are published. With this approach, we hope to take a step toward more real-time oriented research, moving away from self-reports as a measure for psychological effects of crime. Please note that our psycholinguistic analysis is not oriented toward fear as a concrete emotion, but to fear of terrorism attack as a social and criminological phenomenon. Our measurement is thus the encoding of emotive reactions in tweets that respond to a concrete crime event. We hope to contribute with this study to the construction of a bridge between 'unmeasurable' (or 'hard-to-measure') variables and data, and thus transition from mere data to actual information, which has also been termed Smart Data (George, Hass, & Pentland, 2014) and which is one of the key elements to improvement of decision making.

Future investigation in this area could lead to the identification of new interdisciplinary accounts at the intersection between criminology and linguistics. Furthermore, we suppose that this and similar types of algorithms could be used for the prediction and/or detection of fearful discourse around a given topic, when implemented in a continuously operating system on ongoing datastreams. In general, we encourage researchers to build more data-driven tools for the analysis of discourse in the context of crime research, as this will add to the replicability and validity of research by widening the scope of research and complement tools such as self-reports.

In our current situation, the different social networks (including Twitter) have ended up becoming genuine mirrors of users' emotions in cyberspace. Expressions of insecurity, of moral panic or fear of crime in general, or of terrorist attacks in particular, have found in these cyberplaces channels structurally suitable for a massive emotional diffusion, and for which we still do not have enough evidence to evaluate their impact accurately. And although the emotional experience is still embedded in the specific subjects, the characteristics of these cyberplaces force us to rethink and redefine the validity of the accumulated knowledge on the functioning of the fear of crime, especially the methodologies for measuring it in cyberspace.

Notes

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2 All relevant computer code and the statistical report appendix are available at: https://github.com/TobiDschi/linguistic_criminology. For access to the data, please contact the corresponding author.

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