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The Contagion Process of Online Negative Discourse: Case of Celebrities' Suicide

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Research-in-Progress

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Abstract

Social media discourse around shocking and highly emotive events, such as school shootings or terrorist attacks, can potentially influence individuals' real-life behaviors. Using Twitter activity following several celebrity suicides, we investigate the online propagation of negative emotions and identify factors that impact the volume and longevity of the dialogue. We find that, first, the volume of tweets and their retweets (defined as a cascade) for each celebrity, demonstrates an initial spike, then a long 'tail' that tapers off. Two, the leading negative emotions in terms of volume and timing are fear and anger, followed by sadness which was more likely to be retweeted later but over a longer period of time. Third, popular users were more likely to retweet a post during the last quarter of the cascades' lifetime. Thus, the most followed individuals have less influence in the discourse than previously understood.

Keywords

Social Contagion, Sentiment Analysis, Social Media, Suicide, Discourse

Introduction

Social media communications exhibit the contagious nature of emotions through textual messages (Ferrara & Yang, 2015; Kramer et al., 2014). In the case of celebrity suicide news, social media exposure can potentially pose a significant risk for the audience since negative messages may induce suicidal ideation in the reader's mind. Several studies provide evidence of how publicity in traditional media outlets increased consequent suicides, following the incident of celebrities' suicide (Ha & Yang, 2021; Niederkrotenthaler et al., 2012). While it is likely that social media has similar effects to traditional media (Fahey et al., 2018), many characteristics of online post-event discussions are still not studied.

This paper aims to address a number of outstanding questions. Although the antecedents of social contagion on social media (specifically, social networking sites like Twitter) have been studied (Aral et al., 2009; Berger & Milkman, 2012; Katona et al., 2011), the contagion phenomenon itself is less explored. We believe the textual, temporal, and structural characteristics of a discourse (group of communications) provide novel insights into its underlying processes. For example, the role of different actors in the communications, the emotional intensity at different stages, collective conversational patterns taking place within the lifetime of discourse, and whether these patterns follow a certain temporal order

We apply the Computer-Mediated Discourse Analysis (CMDA) method developed by Herring (2004) to analyze the discourses formed around four celebrity suicide events on Twitter. Our analysis covers three categories of textual, conversational, and structural features. The preliminary findings through this systematic analysis show that the exogenous shock coming from celebrity suicide news creates a short-lived peak in the discourse. In our dataset of 21 days post-event, half of the tweets are sent in the first 6 hours after the news is initially shared on Twitter. We observe that among negative emotions, messages containing fear and sadness are the most pronounced portion of the discourses. Also, fearful and angry messages are shared mostly in the earlier stages. Furthermore, retweeting which leads to cascading behavior is found to be a central driver of emotional contagion. Each cascade on Twitter (a chain of retweets) has made the source tweet reach 400 more users on average. Finally, we find that as the discourse evolves through time, the retweeters have a larger follower count (popularity) on average. Consequently, depending on the emotional and temporal features of the discussions, we identify different patterns of contagion taking place on social media.

Background

Herring (2003) defines computer-mediated discourse (shortly, discourse) as "*the communication produced when human beings interact with one another by transmitting messages via networked computers*". As a means of computer-mediated communication, Obar and Wildman (2015) define social media as "*user-centric spaces they could populate with user-generated content,*" which take place without physical and temporal limits through a worldwide network. Therefore, user-generated communications on social media can shape the biggest real-time discourses around the world on different topics, creating a rich source of individual- and collective-level data, for both social and organizational analytics purposes.

The propagation of suicidal behavior following the media publicity of suicide news, a.k.a. "The Werther Effect" is an important concern in today's online environments, given the evidence of emotional and behavioral contagion happening on social media (Centola, 2010; Fabrega & Paredes, 2013; Stieglitz & Dang-Xuan, 2013). The Werther Effect is named after Goethe's novel "The Sorrows of Young Werther" (1774), which at the time earned great attention among young men across Europe, who copied Werther's suicide method in the novel (Hassan, 1995). Ever since several studies have shown that the media coverage of celebrity suicides has led to contagious suicide behavior, or copycat suicides in society (Ha & Yang, 2021; Niederkrotenthaler et al., 2009, 2012). The present study aims to provide detailed discursive evidence on the textual and temporal nature of suicide communication on social media, which can motivate future theorization on the behavioral and emotional patterns of social media communications. Subsequently, these theories can be employed in intervention design and policies addressing mental health improvement in societies (La Sala et al., 2021).

Computer-Mediated Discourse Analysis (CMDA) is an established method to analyze language and its use in online social environments (Beaulieu et al., 2015; Herring, 2004). Through textual data, CMDA enables us to study micro and macro-level phenomena like interpersonal interactions, contagion, and collaboration in online communications that are otherwise harder to emerge and record in face-to-face communication (Herring, 2003). Detailed knowledge of online discourse is beneficial because discourses usually recreate recurring patterns that are shaped by the participants (Goffman, 1990; Herring, 2004). Additionally, discourses embody participant (speaker) choices that can reflect nonlinguistic features of discussions (Feng et al., 2021). Finally, a computer-mediated discourse may be shaped by technological features of the communication channel, e.g. different social media platforms (Griffith & Northcraft, 1994). We extract multiple quantitative characteristics of the discourse on celebrities' suicide events, which can potentially reveal the dynamics of language on traumatizing events, the behavior of different types of participants (e.g. contributors and audience), and the socio-material structure of supporting technologies (Cecez-Kecmanovic et al., 2014). The four-way analysis of contributors, readers, messages, and the communication channel also represents the basic mathematical theory of communication, which can now be applied to online environments (Fawkes & Gregory, 2001; Shannon & Weaver, 1949).

Research Design

In the current study, we employ Twitter data, a large Social Networking Site with 237.8 million Monetizable Daily Active Users (mDAU) as of July 2022 (Twitter, 2022), to examine online discourse characteristics in the context of celebrity suicides, and its potential implications. With Twitter's reach and scale, the impact and reputation of celebrities among Twitter users make suicide discourses highly relevant given that it poses the risk of spreading long-term negativity and inducing suicidal ideation in vulnerable users (De Choudhury et al., 2016; Fu et al., 2009). Therefore, we analyze each discourse using the CMDA method and a novel set of quantitative metrics to understand the dynamics of such online conversations.

We categorize the features of our data under Textual, Conversational, and Structural groups, in order to capture the behavior of users and subsequent discursive patterns appearing within different domains of language (Herring, 2019). Here we include linguistic structures (word Count, emotional tones, valence, words-per-sentence, and words longer than six letters, i.e. Sixltr) under the label of *Textual Features* (Pennebaker et al., 2015). Next, the *Conversational Features* are extracted to understand the interaction dimensions of language in online conversations (time, time elapsed in discourse, and retweet delay). Finally, our *Structural Features* category quantifies the network characteristic of each discourse (follower count, friends or 'followee' Count). Subsequently, this categorization allows us to frame an exploratory study toward any discourse, using the three perspectives listed below. Each approach can address a subset of questions including "What" message is being transmitted, "How" it's being shared, and "To Whom" it's delivered, as the three focal elements of computer-mediated communication research.

- **Textual**: Is there a general pattern in the structure of transmitted message text? What valence or emotional tone is embedded in the message? (Xiao et al., 2021) What platform-specific features like hashtags, URLs, mentions, photos, videos, and GIFs are included in the message?
- **Conversational**: How often are new messages added to the discourse? Does the rate of messages and retweets change over time?
- **Structural:** How many users are potentially influenced by the discourse? What factors (e.g., Influential users) increase or decrease the exposure? Through what pattern, and how much does exposure grow in the lifecycle of each discourse? Which users are contributing to the discourse?

Data Analysis

Our dataset is composed of more than 1.1 million tweets (original tweets and their retweets), recorded after the suicide incident of four prominent figures in television, cinema, and sports between 2012 and 2013 (Table 1). The names of these figures are abbreviated (DC, JS, LTY, TS). The data entries, also denoted generally as Posts, consist of both tweets (that are written by a user) or retweets (that are written by user i_1 and re-shared by user i_2). So, each tweet is a single observation in our dataset, and if retweeted, each of its retweet instances are also recorded as separate observations. For example, if tweet A is retweeted three times (rA1, rA2, rA3), then in total, there will be four posts (entries) associated with that original tweet (A). The first entry refers to the original, and the next three refer to the reshares.

Celebrity Name (Age, Gender)	**Occupation**	**Country**	**Suicide Method**	**Date of Death**	**# of Tweets (Users) involved**
Don Cornelius: DC (76, M)	TV Personality and Producer, Screenwriter	US	Gunshot in home	Feb 1, 2012	317,457 (222,698)
Lee Thompson Young: LTY (29, M)	Actor	US	Gunshot in home	Aug 19, 2013	142,621 (93,203)
Junior Seau: JS (43, M)	NFL Football Player	US	Gunshot in home	May 2, 2012	406,972 (273,344)
Tony Scott: TS (68, M)	Film Director and Producer	UK	Jumping from bridge	Aug 20, 2012	204,853 (120,670)

Table 1 - Demographics and General Characteristics of Suicide Events

In line with the earlier studies on online social media discourse (Del Vicario et al., 2016; Vosoughi et al., 2018), we define a "cascade" as the series of re-shares (retweets) occurring for a single tweet. Therefore, if a tweet is retweeted 10 times, a cascade of size 11 is generated, with its lifetime being the timespan between the last retweet and the original one. Our dataset has cascades starting from size 1 (non-retweeted tweets), up to 6,111, as the most retweeted entry, which has been posted for Junior Seau's suicide event and endured for 9,664 minutes (~7 days) since its original posting (Table 2). In the following sections, we analyze both cascades and single tweet elements from different perspectives.

Textual Analysis

Using LIWC measures of tone (Pennebaker et al., 2015), we analyzed the distribution of different sentiment and emotion types in each tweet and tracked the dynamics of each group. The emotions include anger, disgust, fear, joy, mixed/neutral, sadness and surprise, and the LIWC quantifies these tones by the means of counting relevant words and calculating the percentage of words with the respective emotional charge. For example, words like "grief", "cry" and "sad", are tagged with sadness, and "hate", "kill" and "pissed are identified with anger (*LIWC Dictionary*). Moreover, we tag each tweet by its dominant sentiment valence (positive or negative). Positive affect is identified with a set of words like "happy", "elegant", and "joy" while negativity is expressed by terms like "hate", "worthless", and "wrong" (Pennebaker & Francis, 1996). To examine emotion types, we filtered our data to include only negative and relevant emotions to suicide discourse, specifically anger, fear, sadness, and surprise.

Table 2 summarizes the cascades in our dataset in terms of size, lifetime, valence, and emotions. The composition of cascades shows that across negative emotions, fear and sadness are usually the leading emotions, followed by anger. A similar composition analysis on valence exhibits how negativity constitutes a large portion of JS-related tweets, whereas, for DC and LTY, most of the tweets are written in a relatively positive manner. In the context of microblogging applications like Twitter, the short nature of posts reduces the credibility of the tone score. As such, we make use of the dominant sentiment and emotion types relevant to the suicide discourse to alleviate this concern.

Cascades Characteristics		**Discourse** (Suicide Event)				**All**
		DC	**LTY**	**JS**	**TS**	
Count		30,976	11,456	37,315	12,134	91,881
Size (>1)	Median	2	2	2	2	2
	Max	4,489	2,416	6,111	1,463	6,111
Lifetime (minutes)	Median	9.17	13.20	12.02	31.12	12.4
	Max	28,619	13,011	20,221	20,491	28,619
Dominant Valence	Negative	3,100 (10%)	1,010 (9%)	9,068 (24%)	2,674 (22%)	15,852 (17%)
	Positive	21,430 (69%)	7,558 (66%)	7,794 (21%)	4,818 (40%)	41,600 (45%)
	Neutral	6,446 (21%)	2,888 (25%)	20,4563 (55%)	4,642 (38%)	34,429 (37%)
Dominant Negative Emotion	Anger	547 (2%)	165 (1%)	670 (2%)	175 (1%)	1,557 (2%)
	Fear	843 (3%)	127 (1%)	1,257 (3%*)	1,009 (8%*)	3,236 (3%)
	Sadness	3,291 (11%*)	196 (2%*)	1,127 (3%)	481 (3%)	5,095 (6%)
	Surprise	243 (<1%)	150 (1%)	164 (<1%)	92 (<1%)	649 (<1%)

* The leading negative emotion in each discourse (volume)

Table 2 - Characteristics of cascades within each discourse

Conversational Analysis

Timespan and Frequency of Posts (Temporal evolution of the discourse)

Next, we explore the interactions happening through each discourse, in terms of timing, sequences (or cascades in our terminology), and the frequency of communications (Herring, 2004). Our data allow us to examine the celebrity-level discourse and the cascades within each discourse up to a maximum of 21 days after the four suicide events. The time window is appropriate for capturing the discourse in line with findings from a recent study (Niederkrotenthaler et al., 2019). The fact that the frequency of communications decreases significantly after 1,000 minutes supports our selected timespan for analysis. We use a cumulative probability distribution and a corresponding frequency graph of the number of tweets over time to depict the evolution of discourse after each celebrity's suicide (Figure 2).

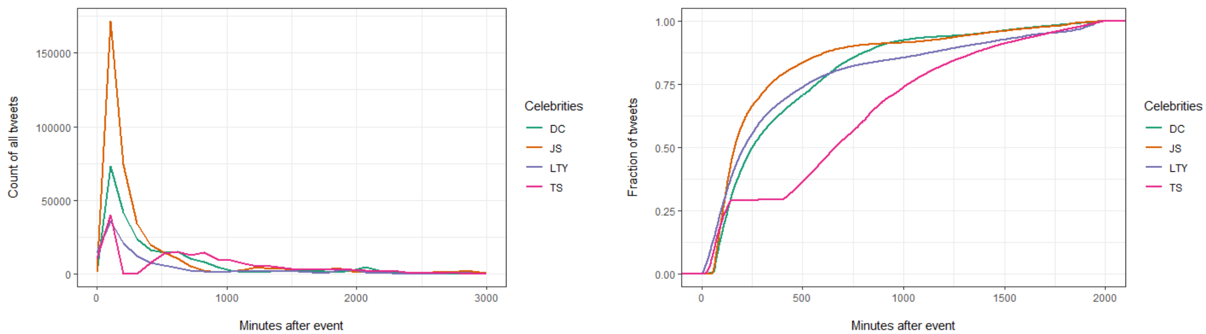

Figure 1 - (left) Frequency of Tweets over time for each suicide discourse; (right) CDF of each suicide event discourse

The surge of posts appearing shortly after the suicide news is published confirms similar patterns studied within the context of Twitter and Reddit on celebrity suicides (Kumar et al., 2015; Niederkrotenthaler et al., 2019). In all of the four examined discourses, the peak of tweet volume happens in the first six hours, followed by a sharp drop and a long tail spanning over the next two weeks. Differences in the subject of news, timing, contributors, and the social network among them can potentially define the fate of each discourse over time.

Frequency of Negative Emotions

In this step, we categorize posts with their dominant emotion and observe their behavior in the discourse for all four celebrities. The cumulative distribution of each dominant emotion group over time, as well as their distribution (Figure 2), demonstrate that fear and anger appear more in the earlier stages of these discourses. 75% of all angry tweets and retweets are posted in the first eight hours of the discourse, whereas the users seem to be more likely to write or share sad tweets for a longer time. Further statistical analysis of this pattern can reveal if the nature of emotions has any influence on the speed of reactions (Fan et al., 2018), or if users' participation in different stages of discourse reveals any information about their psychological characteristics. The same analysis however yields undifferentiated results for emotional valence, suggesting that emotional valence has probably less to do with timing and rush.

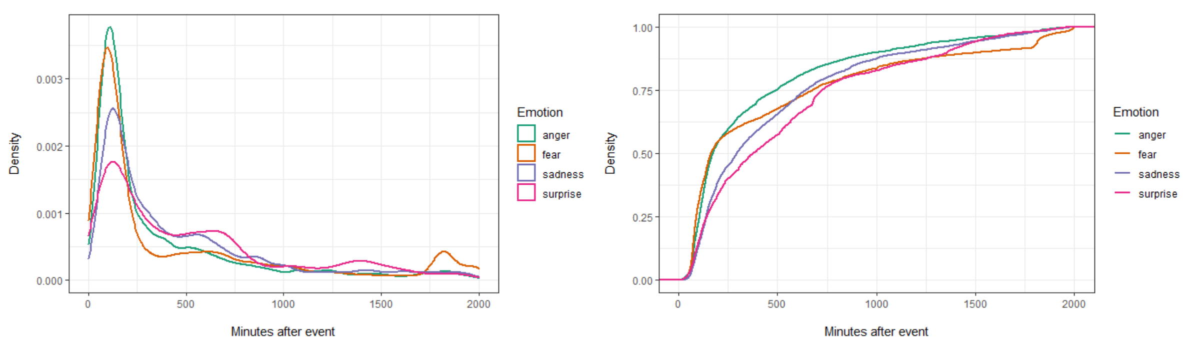

Figure 2 - (left) Distribution of Tweets over time for each dominant emotion; (right) CDF of each dominant emotion group

Structural Analysis

Maximum Potential Exposure

Exposure can drive each user's adoption or contagion of behavior or mood (Arendt et al., 2019; Kramer et al., 2014). In our analysis, we construct a measure called "Maximum Potential Exposure" representing the cumulative number of followers of all users who re-shared a tweet, within a cascade. Moreover, we define "exposure growth" as the number of additional users exposed since the beginning of a cascade, which is equal to the difference between maximum exposure and the follower count of the original author. The maximum potential exposure of cascades with different dominant emotions is depicted in Figure 3. We can observe that except in one of the discourses (TS), fear has resulted in a larger exposure.

In Table 3, we summarize the exposure growth of cascades with different emotions and valence for each discourse. The exposure growth statistics show that half of the cascades have led to an increase of 400 or more potential audiences to the primary followers of the original author. Although most of the cascades are small, the top 10% of highly viral cascades significantly increase exposure. There are a few tweets that spread widely in the network and can potentially affect a large number of users. The greatest exposure growth happens for a cascade in the JS discourse, that is retweeted 6,110 times, starting from a user with ~3.5M followers, rising to a maximum potential exposure of ~13M users. Moreover, the 90th quantile exposure growth column tells us that close to 3,100 cascades (10%) in the DC discourse have earned an additional audience of more than 3,767 users, whereas, in the JS discourse, more than 3,700 cascades (10%) have earned an increase of at least 2,629. Understanding exposure both as an opportunity for spreading marketing WoM and as a risk for negative communications and news helps us develop guidelines and knowledge for media organizations and influencers, with regard to the moderation of their content.

Discourse (Suicide Event)	**Median Exposure Growth**								**90% quantile Exposure Growth**
	Valence			**Negative Emotions**				**All**	
	Negative	Positive	Neutral	Anger	Fear	Sadness	Surprise		
DC	470	469	469	423	615*	501	458	469	3,767
LTY	660	628	602	674*	675*	596	541	625	5,062
JS	340	348	270	338	477*	377	384	300	2,629
TS	652*	510	489	476	572	617	614	523	9,268
All	414	474	341	412	545	486	464	408	3,934

* The leading group in each discourse (having the largest exposure growth)

Table 3 - Exposure growth summary of cascades in each discourse

Re-sharer Popularity

A discussion with a high exposure has either famous (more followed) participants involved, or a larger crowd of regular users involved. Re-sharer features have been suggested to be a determinative factor in the prediction of cascades (Cheng et al., 2014). We labeled each quarter in the lifetime of any cascade as a stage (from 1 to 4). Figure 3 shows how the count of followers (popularity) of the re-sharers (retweeters) is distributed across different stages of cascades. Unexpectedly, we find that the median of re-sharers popularity is largest in the last quarter of the cascades' lifetime which indicates that more famous (followed) people are attending the discourse later.

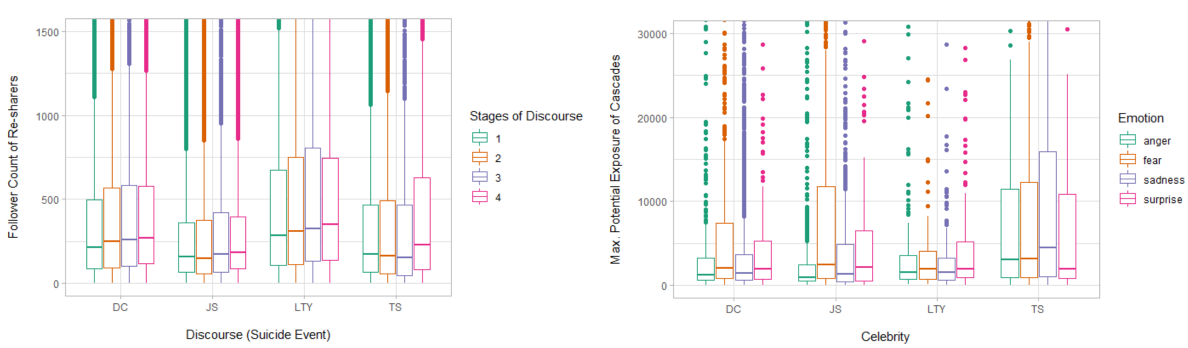

Figure 3 - (Left) The distribution of re-sharer follower count in each stage of cascades; (Right) Maximum potential exposure of cascades with different dominant emotions

Discussion and Future Steps

This study sheds light on an unexplored world of social media data and how it can be mobilized as a discourse with different textual, conversational, and structural elements and constructs. The preliminary analysis lays the foundation for a deeper theorization of the dynamics of social media influence across different topics. We respond to a call for the development of computationally intensive theories in IS (Miranda et al., 2022), using large social media data. The communication trace data recorded on these applications are a novel opportunity to study social and socio-technical phenomena, which otherwise took years to analyze, using older approaches like ethnography, surveys, and experiments. Our work can potentially lay the initial steps toward a systematic analysis of social media data on highly emotive events.

In this preliminary work, we employ the CMDA framework and show how social media communications on celebrity suicide events involve different types of emotions which spread differently and survive within varying timeframes. Unlike previous work using Twitter data, we incorporate the frequency of retweets and their temporal distance as a measure of speed in the spread of emotions, that can activate subsequent decisions and behaviors. We also observed the role of emotions and influential users in exposing the network to different content. Our next steps include further econometric modeling and the development of a theory to explain exposure growth, users' contribution and effectiveness in the discourse, re-sharing speed, and the probability of recurring emotions. The resulting insights are beneficial for the design of marketing campaigns, health interventions, and the public understanding of social media algorithms and their societal outcomes.

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