

Article Title: Discovering the Influence of Sarcasm in Social Media Responses

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Abstract

Sarcasm in verbal and non-verbal communication is known to attract higher attention and create deeper influence than other negative responses. Many people are adept at including sarcasm in written communication thus sarcastic comments have the potential to stimulate the virality of social media content. Although diverse computational approaches have been used to detect sarcasm in social media, the use of text mining to explore the influential role of sarcasm in spreading negative content is limited. Using tweets during a service disruption of a leading Australian organization as a case study, we explore this phenomenon using a text mining framework with a combination of statistical modeling and Natural Language Processing (NLP) techniques. Our work targets two main outcomes: the quantification of the influence of sarcasm and the exploration of the change in topical relationships in the conversations over time. We found that sarcastic expressions during the service disruption are higher than on regular days and negative sarcastic tweets attract significantly higher social media responses when compared to literal negative expressions. The content analysis showed that consumers initially complaining sarcastically about the outage tended to eventually widen the negative sarcasm in a cascading effect towards the organization's internal issues and strategies. Organizations could utilize such insights to enable proactive decision-making during crisis situations. Moreover, detailed exploration of these impacts would elevate the current text mining applications, to better understand the impact of sarcasm by stakeholders expressed in a social media environment, which can significantly affect the reputation and goodwill of an organization.

Keywords: sarcasm, social media, text mining, NLP, Kolmogorov-Smirnov test

Sarcasm in social media

The advent of social media has created a large pool of user-generated unstructured data, which capture user feelings, sentiments, and emotions. Researchers have extensively focused on analyzing sentiments to derive insights which have the potential to support the decision-making of organizations (Mostafa, 2013). This has resulted in an increased focus in the development of natural language processing (NLP) techniques able to capture and analyze sentiments, emotions, feelings and user behaviors embedded in textual data sources and the integration of such techniques into text mining (Hu & Liu, 2012). While the majority of studies focus on sentiments such as positive and negative remarks, the role of persuasive communication facets such as sarcasm is largely overlooked in current text mining. Given that sarcasm is regarded as a trait which attracts a high level of attention (Huang, Gino, & Galinsky, 2015), it is imperative to understand how this alluring nature of sarcasm can contribute to virality in social media during a crisis event. Even though there are computational models to detect and classify sarcastic expressions, studies related to more in-depth exploration of their impact and virality are limited. We address this gap in the literature by using a collection of statistical modeling and natural language processing techniques to explore the influential nature of sarcasm during a significant event recorded in social media. We selected a series of events related to an Australian telecommunications organization which encountered a series of service disruptions in the recent past. These events had caused negative ambiances among consumers which resonated and cascaded over time in social media platforms.

From an organizational point of view, during an incident such as a service disruption, the negativity could have cascading effects by spreading negative word-of-mouth, thereby harming the reputation of the organization. The use of social media further aggravates these effects given the faster information dissemination. Thus, there is a necessity to understand if the use of sarcasm in social media during a negative event could further increase the spread of negativity regarding the organization. As social media is known as a medium of faster information dispersion and a catalyst for making content viral (Hansen, Arvidsson, Nielsen, Colleoni, & Etter, 2011; Naveed, Gottron, Kunegis, & Alhadi, 2011), exploring the role of sarcasm in social media has many potential implications and value for organizations.

Text mining framework to discover the behavior of sarcasm

A text mining framework was developed to collect data from social media, pre-process and to extract knowledge relating to the impact of sarcasm. Fig 1 shows the text mining framework based on the conceptual foundations adapted from (Miner, IV, & Hill, 2012). The knowledge discovery process of the framework comprised of two main components; (1) Statistical methods to quantify the impact of sarcasm and (2) Natural Language Processing (NLP) techniques to analyze the content of sarcastic expressions. In

the statistical approach, Kolmogorov-Smirnov test was applied to analyze the correlations between the different attributes of sarcastic tweets whereas in the NLP approach, topic modelling and vocabulary-based keyword extraction techniques were used to explore the content of the sarcastic tweets. With these two approaches, the framework is able to quantify and explore the impact of sarcasm.

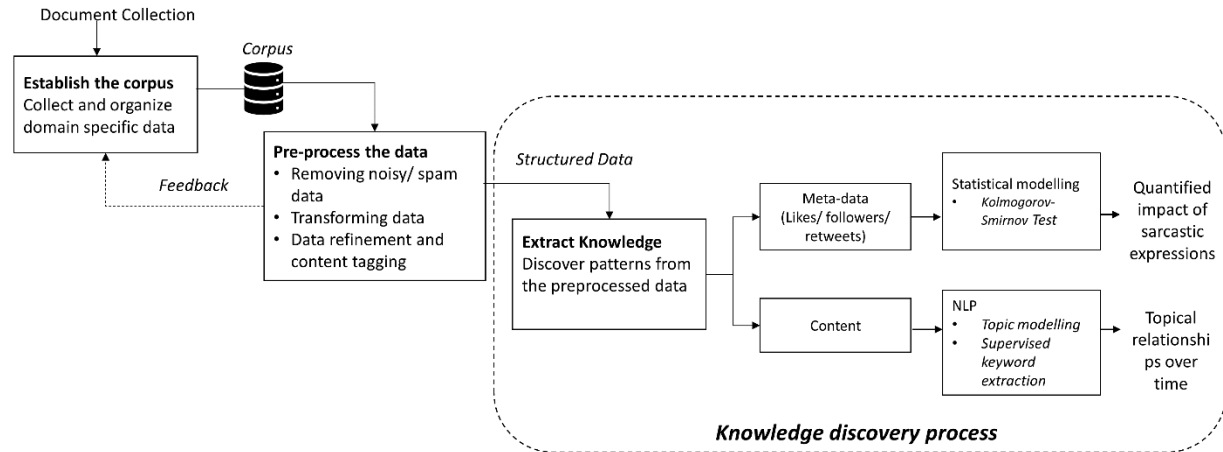


Fig 1. The text mining framework for quantifying and exploring the impact of sarcasm

In this study, we selected a leading telecommunications provider in Australia, which had a series of service disruptions in the year 2016 resulting in many consumer complaints. For this research, Twitter was selected as it is one of the most prominent social media channels for fast information dissemination and popularity (Boyd, Golder, & Lotan, 2010).

Knowledge discovery using data mining and analytics algorithms

After collecting Twitter responses, data were pre-processed to remove the spam content and posts by news channels, and generated a dataset comprised with only customers' responses. Then, the non-parametric hypothesis test approach – Kolmogorov-Smirnov test (KS) was used to determine the alluring nature of sarcasm whereas NLP techniques were used to explore the content of sarcastic tweets.

Statistical modelling

To assess the popularity of sarcastic tweets, a non-parametric test (Kolmogorov-Smirnov) was performed multiple times over the number of likes and retweets associated with sentiments. For example, the Empirical Cumulative Distribution (ECD) of the number of likes associated with a negative tweet was tested against the number of likes relating to a non-negative tweet.

NLP and Topic Modelling

Topic modelling and keyword extraction were performed to disclose prominent topic patterns during outages. First an initial seed word list was created by selecting the most frequently used keywords during the outage to identify domain-specific keywords from the content. This technical vocabulary was then used to extract similar keywords from tweets thus expand the keyword extraction process. A guided topic modelling approach (Jagarlamudi, Daumé, & Udupa, 2012) was taken to further explore topics related to these keywords. Additionally, Latent Dirichlet Allocation (LDA) was used to identify topics which are not related to the outage (Blei, Ng, & Jordan, 2012). This analysis was performed to identify subtopics and other important terms in sarcastic tweets. This enabled generating insights in order to identify recurring topics, unique topic patterns and general topics of discussion during this time period. The following figure shows the main steps of the knowledge extraction process via NLP and topic modelling.

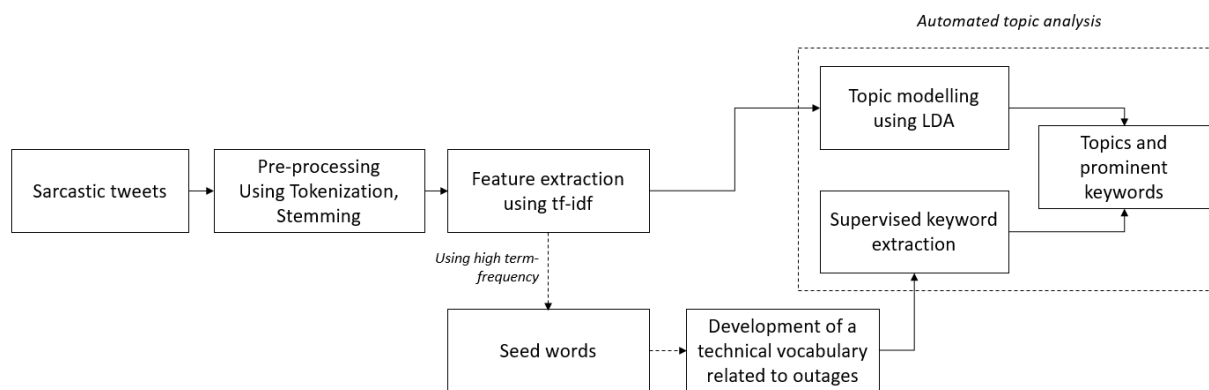


Figure 2: Knowledge extraction process using NLP and topic modelling

Findings: Discovering the influence of social media responses

Fig. 3 shows the Twitter activities during the two selected outage days. An hourly analysis of Twitter activity and corresponding sentiments expressed on the first outage clearly shows a significant rise in Twitter activity, indicating a resonance on Twitter during the outage which occurred around 2.00 PM. It was observed that during the time the aggregated Twitter activity positively peaked, the aggregated sentiment score¹ negatively peaked concurrently. It is observed that there was a significantly higher interaction on Twitter during the days of the outage. A comparison showed that the average number of

¹ Aggregated sentiment scores: 13:00: (-71), 14:00: (-346), 15:00: (-103), 16:00: (-25). A negative tweet has a sentiment score '-1' and the scores for a positive tweet and a neutral tweet are "1" and "0" respectively.

Twitter users on outage days was seven times greater than that on normal days and the average number of tweets was six times greater than tweets on normal days. The high number of negative and sarcastic tweets and the high volume of data during these outages, served as a solid foundation to conduct our analysis to investigate the impact of sarcasm on crisis situations.

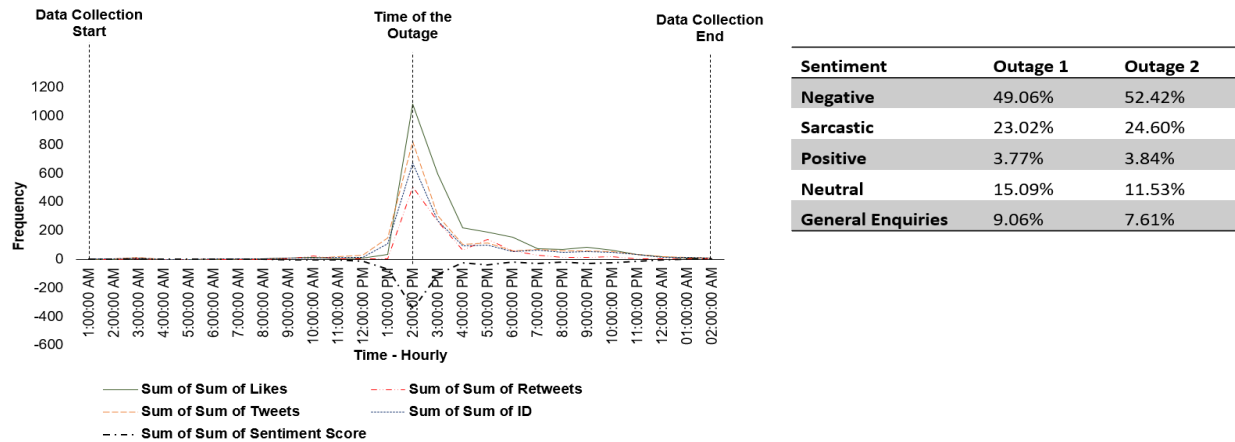


Fig. 3. The hourly trend of tweet measurements on the day of an outage.

Sarcastic expressions attract more negativity

A series of KS tests were performed for the data collected from the first outage and data collected from the second outage which was used as the control dataset. Table 1 presents the results of a series of KS tests on various variables for the outage and the control dataset respectively.

Table 1. The results of KS tests on variables' influence on engagements. The two p-values which indicate a lack of significance is denoted in bold. Significance level: $\alpha = 0.05$.

Variables	Likes		Likes		Retweets		Retweets	
	Outage Dataset		Control Dataset		Outage Dataset		Control Dataset	
	D	p	D	p	D	p	D	p
Negative vs Non_Negative	0.14	0.00	0.15	0.00	0.04	0.35	0.03	0.64
	Results: The distribution of 'Likes' associated with negative sentiment tweets are significantly different to that for non-negative tweets. However, the level of supports of negative tweets for 'Retweets' is not significant							
Sarcastic_Negative vs Non_Sarcastic_Negative	0.25	0.00	0.15	0.00	0.15	0.00	0.07	0.02
	Results: Distributions of 'Likes' and 'Retweets' associated with sarcastic negative tweets are significantly different to those for non-sarcastic negative tweets							

The results from the empirical cumulative distribution studies confirmed that the negative sentiment of the tweets has an influence on attracting more likes from consumers during the service outage. Most

importantly, from all the negative tweets, sarcastic negative tweets attracted a statistically significant number of higher likes and retweets compared to those from non-sarcastic negative tweets. These findings demonstrate that **negative sarcastic tweets are more alluring and attract a higher level of engagement (denoted in the number of likes and retweets) than regular negative tweets during a situation such as a service disruption**. This study indicates the important role of sarcasm and the popularity it gains during negative ambiances such as a service disruption.

The cascading effect of sarcastic content during outages

The NLP and topic modelling analysis showed that a significant portion of the topics (57%) were shared by both outages, within which a majority of the common topics revolved around internal process issues directly linked to outages, such as problems with signals and customer service. As a notable insight, there was a portion of sarcastic tweets diverted to strategic directions publicly announced around the time of the outage by the organization and certain government policies related to telecommunications, Fig. 4. Specifically, this behavior was predominantly observed during outages, as the **percentage of sarcastic tweets related to organizational strategy announcements and government policies were less on regular days**. These results indicate that an event such as a service outage could provoke consumers to complain about collateral issues relating to the organization but indirectly linked to a specific outage, thus creating a **cascading effect**. A cascade effect is known as an inevitable and often unforeseen chain of events which occurs due to a certain incident in the system. In this scenario, the chain of customers' opinions due to the unexpected service outage is illustrated as a cascading effect (Fig.4) via which social media responses towards a service outage at the operational level have further triggered negative responses towards corporate strategies and government policies.

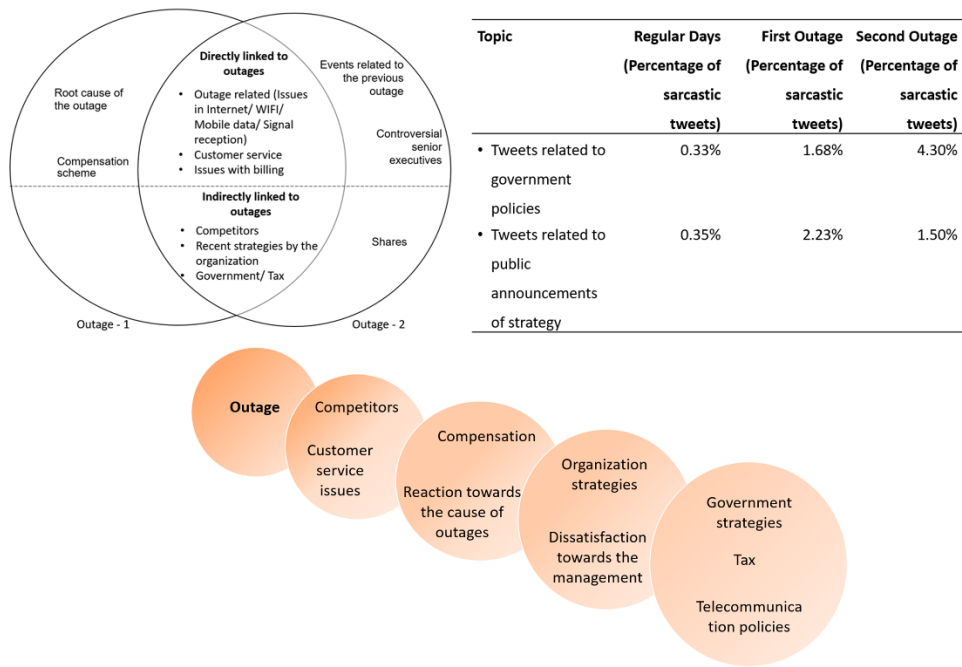


Fig. 4. The shared/unique topics from sarcastic tweets for the two outages and the distribution of sarcastic tweets related to external issues (government policies related to telecommunications and organization strategies) and the cascading effect of the topics in sarcastic tweets during an outage

Conclusion

The results of our research show that sarcasm significantly contributes to the negative popularity of a tweet during situations such as service disruptions. The findings reveal that sarcastic negative tweets attract a statistically significant higher number of likes and retweets compared to non-sarcastic negative tweets. There were over 30% of negative tweets in sarcastic or mocking nature and these sarcastic-mockery comments attracted likes and retweets significantly. This novel finding emphasizes the role of negative sarcasm as a dominant influence factor in Twitter responses towards crisis situations such as service outage. The topic analysis for these sarcastic tweets demonstrated that during the two service outages, a majority of the topics discussed were shared between both outages. The common topics revolve around internal operational process issues directly linked to the outages, for example, the problems relating to internet access and customer service. It was also noted that a portion of sarcastic tweets was cascaded to higher-level collateral issues such as corporate strategies and government telecommunications policy. This finding is salient given that sarcasm towards telecommunications policy and organization strategies is comparatively under-represented on regular days from the extracted Twitter data. This phenomenon demonstrates that, during an event which causes inconvenience, consumers tend to be sarcastic towards general practices of the organization as well. These findings can

assist organizations in public relationship management during a crisis event. We contribute to the data mining and knowledge discovery research, by quantifying and evaluating the impact of sarcasm, which is one of the under-explored linguistic features in computational studies. In addition, the proposed framework could also be adapted to quantify and explore the impact of other sentiments and language facets such as irony, humor and even emotions. As potential extensions, the framework could be expanded to automate the process of sarcasm, humor detection as well as to integrate multiple social media data sources.

Conflict of Interest

The authors have declared no conflicts of interest for this article.

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