Detecting Corporate Social Media Crises on Facebook using Social Set Analysis

Raghava Rao Mukkamala[1] and Jannie Iskou Sørensen[1] and Abid Hussain[1] and Ravi Vatrapu[1,2]
[1]*Copenhagen Business School, Denmark and* [2]*Westerdals Oslo School of Arts, Comm & Tech, Norway*
{*rrm.itm, –, ah.itm, rv.itm*}*@cbs.dk*

***Abstract*—Social media crises pose significant challenges for organizations in terms of their rapid rate of spread and potential persistent negative associations in terms of brand parameters and sustained negative advocacy by internet users and/or consumers. This paper reports on a technique for detecting social media crises using social set analysis- an approach to computational social based on associational sociology and set theory. Based on a conceptual and formal model of social data, we conduct social set analysis of the facebook wall data of four diferent Danish companies. Findings show the voluminous but also transient nature of social media crises and aggregate user behavioural patterns. We discuss the implications of our findings and the application of the crisis detetction technique for analyzing other epiosodic activities such as product promotions, election campaigns.**

***Keywords*-Big social data, Social set analysis, Social business, Social media crisis, crisis communication.**

I. INTRODUCTION

All companies can experience various types of crises and these crises are by nature unpredictable, but not unexpected as wise organizations are aware of the fact that crises can befall them. The crisis of an organization can trigger negative reactions from stakeholders and thereby affect the overall performance of the company. Therefore, it is important for the companies to respond to the crises in order to limit the damage [1], [2]. This paper addresses the topic of corporate social media crises detection using a multidimensional data model approach for Facebook data. Specifically, it addresses the research question, *how to detect corporate social media crisis using interactions of social media users on corporate Facebook walls?*

A. Selected Corporate Social Media Crises

In order to address the above research question, we selected four recent social media crises. The objective was to study user interactions on corporate Facebook walls of the companies that have experienced a social media crisis in the recent years. We purposefully limited the selection of social media crises to Denmark to hold the linguistic and socio-cultural attributes of interacting with social media [3], [4] invariant to the extent possible: Copenhagen Zoo, Telenor, Jensen's Bøfhus (translation: Jensens Steak House), and Imerco.

Copenhagen Zoo experienced a social media crisis, which started on February 8th 2014 (week 06/2014), due to an impending euthanizing of a young giraffe they had chosen to call Marius and lasted until February 13th 2014 (week 07/2014). Also, major international media has also participated in the case of Marius. British BBC and The Guardian newspaper has also referred to the killing, CNN followed the case on both network and TV, and The New York Times has also written about Marius' death.

Jensen's Bøfhus experienced a social media crisis on Facebook, which started on September 19, 2014 (week 38/2014) and lasted until September 27, 2014 (week 39/2014), due to a dispute between Jensen's Bøfhus, and a fish restaurant named *Jensens Fiskerestaurant* (ed. Jensen's Seafood Restaurant). The case involved a conviction in the Supreme Court that caused great debate in Denmark, since Jensen's Bøfhus were successful at that the name, Jensen Fiskerestaurant, is too similar to the steakhouse chain restaurant. This meant that the owner of Jensen's Fiskerestaurant, Jacob Jensen, had to change the name of his restaurant. According to Jensen's Bøfhus they were trying to protect their trademark in the catering industry as Jensens Fiskerestaurant were planning to expand with new restaurants in other cities[1]. According to the judgment, the small restaurateur, Jacob Jensen, had to pay 200,000 Danish kroner to Jensen's Bøfhus, 150,000 Danish kroner to the costs that Jensen's Bøfhus have had his own lawyer, and the practical arrangements for the defeat[2].

Imerco experienced a social media crisis, which started on August 25th, 2014 (week 35/2014) and lasted until August 26th 2014, due to a fast sold out anniversary vase from the brand Khler. 16,000 customers wanted to buy a special anniversary vase from the company Khler on offer at Imerco's website. However, this tumbled the website, after which angry customers vented their displeasure on Imerco's Facebook page[3].

Telenor experienced a social media crisis on Facebook, which started on August 3rd 2014 (week 31/2014) and lasted until August 8, 2014 (week 32/2014), due to a farewell salute from an unsatisfied customer, named Anders Brinkmann. Anders Brinkmann wrote in the evening on August 2nd 2014 at Telenor's Facebook page that he had ended his mobile subscription with the telecom company. In his post, he described that Telenor could not manage to collect money

[1]Jensen's Bøfhus on tv2.dk
[2]Jensen's Bøfhus on politiken.dk
[3]Imerco on politiken.dk

by Direct Debit and that the company had repeatedly sent reminders before he had received the normal expense. This post brought Telenor into a social media crisis on Facebook [4] and more than 30,000 "liked it"[5].

The remainder of the paper is organized as follows. Section II presents the methodology of our approach, where as findings of case studies are presented in sec. III. Finally, a brief discussion is presented in sec. IV.

II. Methodology

In this section, we will briefly outline methodology adopted to process user interactions data on corporate Facebook walls to detect social media crisis. Facebook data for all four companies is collected using a new purpose-built software application Social Data Analytics Tool, SODATO [4]. SODATO allows to examine public interactions on the Facebook walls by extracting several core pieces of information.

A. Data Collection and pre-processing

The Facebook data is collected for all the four companies since inception of their corporate Facebook walls till to the time of analysis i.e. 02/2015 as shown in Table. I. In the analysis, we distinguish between admin-actor, who manages the Facebook wall of an enterprise from non-admin actors, who are the social media users. To simply the matters, we have excluded *share* action from our analysis as we also did not noticed any share actions in the datasets. Moreover, the terms *user* and *actor* are used interchangeably throughout the paper without any difference in semantics.

Out of the four datasets, the dataset for Copenhagen Zoo is the largest containing closer to one million user interactions that were performed by 162000 unique actors or users. As one can observe from the datasets (Table. I), majority of user interactions are likes on the artifacts and the artifacts comprise of posts and comments made by both admin and non-admin actors. The collected interactions are processed

company	period	users	user interactions		
			total	artifacts	likes
Zoo	12/2011-02/2015	162708	848413	80013	768400
Telenor	09/2011-02/2015	36032	107510	37248	70262
Jensen	05/2012-02/2015	73087	216274	90282	125992
Imerco	06/2011-02/2015	76003	254657	127108	127549

Table I
Details of Facebook data of four companies

according to methodology of Social set analysis [5]–[7], segmented them into *during*, *before* and *after* the crisis period to further conduct temporal analysis of the artifacts.

[4]Telenor on tv2.dk
[5]Telenor on politiken.dk

B. Temporal Analysis of Artifacts for Crisis Detection

Social media crises are characterized by marked increase in interaction levels on the social media channels. Further, based on traditional crisis communication and management theories and frameworks, we conducted temporal analysis of interactions in terms of two kinds of actions (like and comment) with respect to two kinds of artifacts (posts and comments) made by two different kinds of actors (admins/companies and non-admins) over temporal dimension of daily, weekly, monthly and yearly.

We have used data warehousing and on-line analytical processing (OLAP) [8] technology using Microsoft SQL server database to conduct temporal analysis. We have designed multidimensional data model for Facebook data using interactions as numeric/fact measures. The interactions measure data is further processed across several dimensions: *temporal* (daily, weekly, monthly, yearly), *actions* (post, comment, like), *actors* (admin, non-admin) and *artifacts* (posts, comments). Since the type of interactions that can be performed by various actors on a *post* artifact are comment and like, using a multidimensional approach, we have performed the analysis along data slices listed in Table II.

artifact (post) by	actions	by actor
admin	comment, like	admin actor
non-admin		
admin		non-admin actor
non-admin		

Table II
Actions of admin/non-admin actors on post artifact

When it comes to *comment* artifact, like is the only type of interaction that can be performed. Therefore, we have conducted analysis along the data slices of like interaction (by admin vs non-admin actors) on comments made (by admin vs non-admin actors) over the posts (made by admin vs non-admin actors) as shown in Table III, on a temporal dimension of daily, weekly, monthly and yearly as shown in figures 1 and 2.

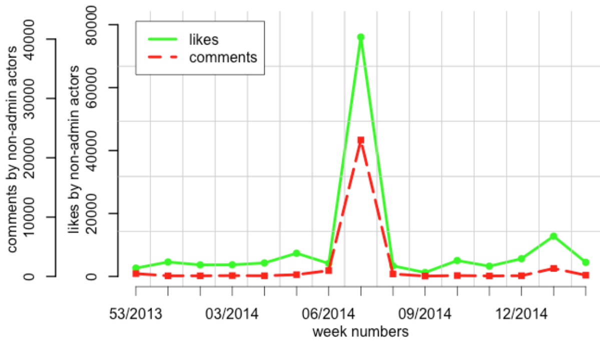
artifact (post) by	artifact (comment) by	action
admin actor	admin	like by admin/non-admin actor
	non-admin	
non-admin actor	admin	
	non-admin	

Table III
Likes on comments by admin/non-admin actors over posts by admin/non-admin actors

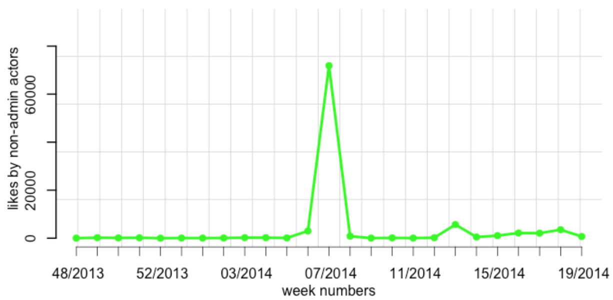
III. Findings

In this section, we first present identified peeks in interactional patterns revealed by the temporal analysis of artifacts as shown in figures. 1 and 2.

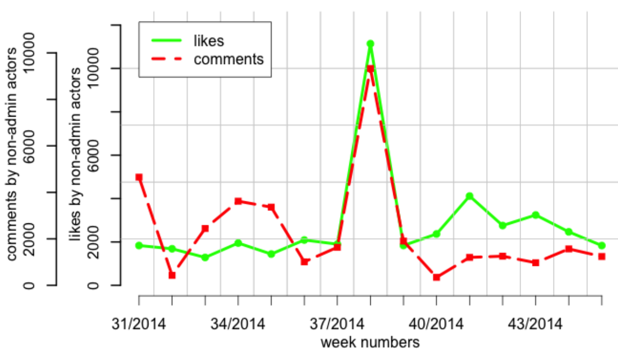
Figures 1(a) and 1(b) reveal the interactional spikes by non-admin actors on the Copenhagen Zoo's posts as well



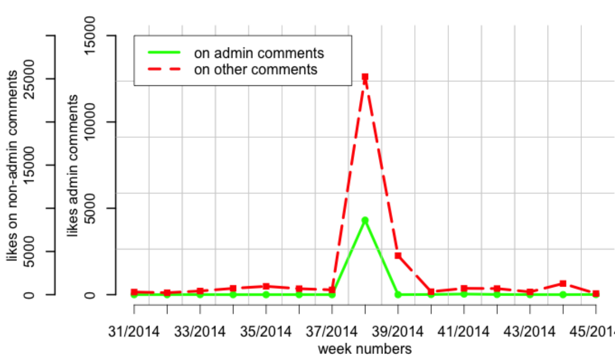
(a) Zoo - comments, likes by non-admin actors on admin posts



(b) Zoo - likes on comments made by non-admin actors on admin posts

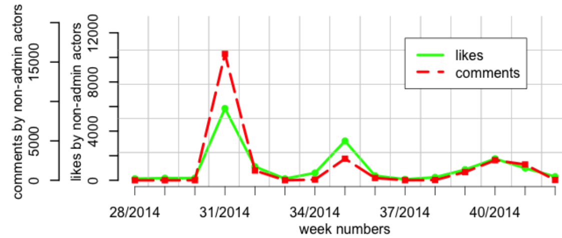


(c) Jensen Bøfhus - comments, likes by non-admin actors on admin posts

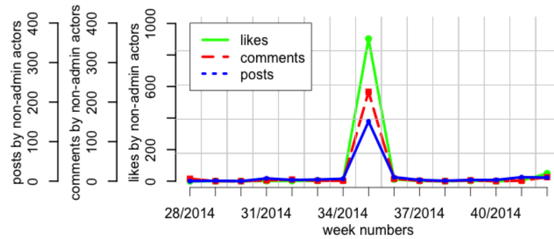


(d) Jensen Bøfhus - comparison of likes on comments made by admin vs non-admin actors

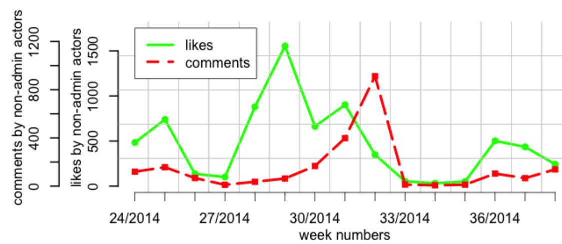
Figure 1. Artifact Analysis of Copenhagen Zoo and Jensen Bøfhus Crises



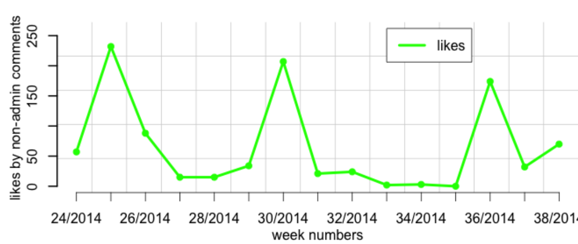
(a) Imerco - comments, likes by non-admin actors on admin posts



(b) Imerco - posts, comments, likes by non-admin actors on non-admin posts



(c) Telenor - comments, likes made by non-admin actors on admin posts



(d) Telenor - likes on comments by non-admin actors on admin posts

Figure 2. Artifact Analysis of Imerco and telenor Crises

as an preliminary indication of the nature of the crises. To be specific, the spike of likes on the admin's posts and comments is an indicator of positive endorsement of the

Copenhagen Zoo's activities during the crises. As can be in seen from figure 1(d), the admin comments on Jensen's Bøfhus received much fewer likes than the likes on the comments by non-admin users during the interactional peak, which indicates negative endorsement of Jensen's Bøfhus activities during the crisis.

In case of Imerco, our technique detects two interactional peaks. The first peak refers to the huge interest expressed by many customers in the form of comments and likes on admin posts (Figure. 2(a)) towards buying the anniversary vase few weeks before the crisis, the second interactional peak. But during week 35/2014, when Imerco's website couldn't fulfill al of the orders for the promoted product, facebook users and customers expressed their displeasure in the form of posts, comments, likes by non-admin actors (Figure. 2(b)).

Finally, in case of Telenor, the crisis (week 31-32/2014) was indicated by the number of comments by non-admin actors exceeded the likes on the admin posts as shown in Figure. 2(c).

Thus, we can not only detect the interactional peaks (in this case, known social media crises) but also obtain indicators of the nature of net user associations towards the companies duing the crises in terms of likes (positive associations) and comments (negative associations when like count is significantly lower) on admin (=company posts).

IV. Discussion

Our empirical findings on detecting corporate social media crises can be understood in the wider context of extant literature on social media analytics that shows the bursty nature of social media interactions as well as detection of real-world events [9]–[11]. That said, our paper makes two small but seminal ad substantial contributions to the extant literature: (a) we analyze Facebook data that is relatively under-examined, and (b) we not only model the conceptual and formal aspects of social data but also attempt to exploit the inherent logic of the socio-technical interactions in terms of the different kinds of social actors (admins, non-admins) and different kinds of actions (likes, comments and posts) and different associations (likes on admin vs. non-admin posts/comments).

Our follow-up analyses included netnographic observations, topic detection and sentiment identification during, before and after the crises. We also investigated the crisis communication and management strategies employed by the companies, if any. We cannot discuss the findings from these follow-up analyses in this paper due to space constraints but mention briefly that they yielded in an management framework for dealing with social media crisis.

One implication of our findings is that embedding sociological and/or social psychological rationale into the design of big social data analytics techniques has the potential to yield better insights compared to a purely technical focus in modelling structural properties such as network characteristics or agentic dynamics such as sentiments expressed. A second implication of our findings is that big social data analytics in particular and computational social science in general need to move towards a "thick model" of human actors online. That is, not all users are alike in terms of their psychographic, demographic, geographic and lifestyle characteristics and this needs to be explicitly addressed or implicitly incorporated in to big social data analytics for applied domains such as business or education.

We believe that our technique for detecting corporate social media crises on Facebook can be applicable and extensible for other episodic activities such as marketing campaigns, elections and real-world events. For example, there might be structural isomorphisms and agentic similarities between social media crises and successful social media marketing episodes such as viral videos.

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