Situating crisis in an online environment:

A semantic analysis of the #deleteuber movement on Twitter

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Social media has established a growing prevalence and influence in social change, political movements and a vehicle for crisis messages. #DeleteUber demonstrated this growing trend on January 27, 2017 when Uber was criticized regarding President Trump’s controversial executive order on immigration and the company of Uber cancelled surge pricing to JFK airport, as well as CEO Travis Kalanick’s controversial role on Trump’s advisory council. Using semantic network analysis, 23,691 tweets were analyzed in the two weeks following these acts to explore how an organization facing a crisis is situated within the network. This approach utilized text mining to clean the data and identify patterns and trends relating to organizational reputation and public response. Network figures demonstrate the strength of affiliation between an organization and crisis event, especially when compared to an individual. Additionally, competitor and political affiliation was found to be important nodes in relation to both the emergent hashtag #deleteuber and Uber the organization in regards to public response to the crisis.

*Keywords*: organizational identity, organizational reputation, framing, crisis, online activism, social media, Twitter, Uber, network theory, semantic analysis
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Crisis communication for organizations is not necessarily a new idea. However, the immediacy of news cycles, accessibility to social media and, frankly, the political environment have seen a seismic shift in recent years that has created a fundamental need to reevaluate how organizations facing crisis are situated within the conversation, particularly when leadership voices have a role within the crisis. Channels of communication are rapidly changing, integrating and evolving to meet the accelerated demand of engaging with news now. An idea of ‘virality’ has emerged as news and ideas leap to public perception at a rapid rate (Kaplan & Haenlein, 2011).

Organizations facing crisis have not been left immune to this social media phenomenon and are faced with increasing challenges of handling the onslaught of voices in an online environment and maintaining effective messaging in mitigating the crisis to best diffuse or deflect building tensions surrounding the crisis. The aim of this study is a continuation of a previous content analysis that seeks to understand how an organization is situated within a crisis, specifically when leadership is directly involved in the crisis event. Using semantic analysis, this project sought to examine what topics tie an organization or a CEO to the crisis event, and how an organization itself is situated in the midst of crisis.

A network approach can visualize this snapshot in time and not only situate an organization within the context of its own crisis, but a semantic analysis can demonstrate how stakeholders are responding to this crisis by noting common topics and perceptions regarding the crisis.
The Case: Uber and Travis Kalanick facing #deleteuber

#Deleteuber was a trending hashtag on Twitter beginning on January 27th, 2017 when Uber (the organization) was criticized for apparent support for President Trump’s widely unpopular executive order banning immigration and refugee entry from several Muslim majority countries due to several coinciding incidences. The first occurred when CEO Travis Kalanick made neutral comments not in support for nor against the order. The second incident was at JFK airport in New York City when a local group of taxi drivers planned a protest in solidarity with the ban. Uber at the same time cancelled surge pricing, which some interpreted as the company offering its support for the executive order and taking advantage of a business opportunity (Issac, 2017a). Uber claimed the message was a coincidence, but #deleteuber started trending not long after the incident. The trending message continued throughout the week, with a spike again on Thursday, February 2nd after Mr. Kalanick announced he would be resigning from the President’s Advisory Council.

The trending call to action, at least in part, was attributed, to reportedly over 200,000 users cancelling their Uber accounts. The use of the #deleteuber hashtag has not been limited to this single event, but has cropped up routinely throughout 2017 as Uber faced further allegations of sexual harassment allegations and Mr. Kalanick was further maligned and eventually ousted from his company. However, this crisis incident surrounding the incident at JFK airport sparked the most severe public response and backlash and prompted a response from Uber and Mr. Kalanick within days (Semuels, 2017).
Commonly when facing a reputational crisis, social media is the vehicle of disseminating that information. It ‘goes viral’ so to speak. Going viral is not always desirable, especially for organizations facing crisis. In times of crisis, particularly, organizations can find their message lost in the virality now afforded by social media as literally anyone can join the conversation and their reputation is threatened. Understanding how various stakeholders are oriented within a crisis can help establish patterns of communication and recognize the importance and power of crisis in an online context. Furthermore, placing an organization in the context of a crisis can be enormously helpful in strategizing how to best respond to the crisis at hand.

Crisis Communication

A crisis disrupts an entire organization with a potential for negative outcomes and attributed blame from the public, while crisis communication develops strategies that are intended to combat the negative outcomes and restore a level of order through reputation management (Coombs, 2007). In facing a crisis, organizations face a threat to their reputation so crisis communication is an organizational effort to reach external stakeholders in order to change their perception and view of the organization (Coombs, 2007). A crisis situation may spread on social media due to the share-ability of the message and the environment conditions currently facing the organization (Coombs, 2015).

Organizational Identity & Reputation in Crisis

Salient to this study is the fact that stakeholders and the general public now have direct access to engaging organizations and those in leadership positions (e.g., CEOs) in conversation. Facebook and Twitter have been invaluable tools for organizations to utilize during times of crisis or change, and have revealed benefits of two-way communication (Muralidharan,
Rasmussen, Patterson, & Shin, 2011). When Travis Kalanick publicly joined President Trump's advisory committee, the news and the opinions of the public went viral. As Kalanick received backlash and hateful comments via Twitter, so did the Uber organization. Interestingly, as one individual was responsible for an individual action, the news received a societal and collective response to the larger organization as a whole. This issue relates to the question of how the organization and its individual members are merged as one online identity and how this may affect the presence of organizational identity in the digital space. Historically, organizational identity has been defined as “that which is stable, enduring, unique, and central to the organization’s character” (Grandy & Mavin, 2011, p. 767). Often without intent or awareness, organizations create a certain identity on social media. Through this, leaders of that organization are inevitably connected to that identity—simultaneously representing and communicating for their organization through online engagement.

Reputation then becomes a matter of how identity is viewed by people outside of the organization (Coombs, 2007). It is an identity that is formed through shared information and messages from the organization out to its various stakeholders. Coombs (2007) describes that while organizations have control over their message and shape their identity, reputation is a power that’s outside of their control and rests in the perception of external stakeholders. Traditionally, crisis communication has focused on organizational response, but with social media allowing for bidirectional communication channels, reputation becomes an important consideration from external stakeholder perception (Schultz, Utz & Goritz, 2011).

**Social Media in Crisis**

Social media comprise of diverse social network sites, or bound, network systems where individuals build a profile, establish connections, and interact, including through blogs, content
communities, virtual worlds, and other collaborative projects (ie. Wikipedia) (boyd & Ellison, 2008; Kaplan & Haenlein, 2010). Social media change the media experience from passive to active media consumption. Kaplan and Haenlein (2010) argue that social media allow “continuous modify[cation] by all users in a participatory and collaborative fashion” (pg. 61). Social media enable widespread distribution and collaboration of content that moves away from individual ownership.

The import of social media to a crisis is the way social media enable the spread of opinions, garnering attention through the open accessibility and visibility of social media platforms. The online medium has shown an increasing importance in both sharing and engaging in crises (Schultz, Utz & Goritz, 2011). The notion of virality returns in considering the online word of mouth spread of information and the immediacy of that spread of information leads to exponential growth (Kaplan & Haenlein, 2011). Social media is both integrating into technology habits, as well as social habits as users continue unprecedented amounts of content across platforms (Lipizzi, Dessavre, Iandoli, & Marquez, 2016). Dialogue, discussion and interpretation on a topic becomes less controllable on social media which leads to spontaneous conversation where the message out of the creator’s hand and allows it to be reconfigured and recreated for public consumption (Husain, et al., 2014). Messages are inserted into an increasingly interconnected media space that blurs the line between organizations and the public. A network approach is appropriate here as social media continues to disrupts traditional crisis communication models with its complicated, public-engaged platform (Schultz, Utz & Goritz, 2011).
Research Questions

Based on the current literature in organizational identity, crisis communication, and social media influence this study seeks to answer the following questions utilizing a semantic network:

RQ 1: Does the public associate a crisis with an individual or leader?

RQ 2: Do users mention name of organization (i.e., @Uber, #Uber) more frequently than just CEO (i.e. Travis Kalanick)?

RQ3: Is the organization affiliated with crisis events?

RQ4: What semantic terms and patterns are affiliated with the crisis?

Method

To analyze how this crisis was influencing discussions surrounding Uber the organization and Travis Kalanick the CEO in a social media context, tweets were gathered from Twitter via hashtag (#) utilizing AP search apps. In this specific case, Uber’s trending #deleteuber hashtag emerged after President Trump’s immigration ban, CEO Travis Kalanick’s comments surrounding the ban and the incident at JFK Airport (Isaac, 2017a). The movement reportedly resulted in over 200,000 users deleting the app within weeks of the incident and CEO, Travis Kalanick, leaving his position on Trump’s Advisory Council, and eventually being ousted as a leader from the company he initially founded (Issac, 2017b).

Context of the Study

This idea developed from a completed content analysis from a sampling of the Twitter data (n=2,000). Codes in the content analysis assessed organizational identity and framing of the content in order to articulate how publics respond to a crisis. The analysis found that the
organization was typically framed as the crisis perpetrator over individuals (such as the CEO). A binomial logistic model demonstrated that mentions of CEO were linked to the organization, while mentions of the organization were not necessarily linked to the CEO. This network study expands on that attribution and framing idea in a re-analysis of the entire population of tweets to track how the crisis was discussed and how both the organization and CEO are linked to the emergent hashtag.

A network analysis is appropriate because it allows a large population of tweets (n=23,691) to be analyzed in order to identify word associations and examine how the organization is involved in a crisis discussion. Social media is also an important medium to link to the body of crisis research due to its increased usage and integration in daily communication habits and due to its large domain populations, these reactions, particularly in a crisis, are important to understand (Lipizzi, Iandoli, & Marquez, 2014). An expansion of this study could potentially involve comparing cases to see if word patterns develop in how organization reputation and attribution develops when in crisis.

**Text Mining as Method**

Text mining is one way to measure the diffusion of ideas from a large dataset. In taking large collections of unstructured data, text mining can help identify important linkages due to frequencies and co-occurrences within the network (Lipizzi, Iandoli, & Marquez, 2014). In measuring co-occurrence frequencies, relations between words can be networked and visualized in an effort to identify different clusters and topics surrounding the text population (Huang, et al., 2015). This visualization is helpful in finding meaningful ideas within a viral network, or in this specific case, a crisis network. Social media produces a lot of noise, but text mining is a tool to identify patterns and see how messages are being created in response to an issue. In a social
media context, text mining can provide meaningful connections between hashtags used and the relationship between those hashtags and other discussion topics (Turker & Sulak, 2017). While text mining is limited in fulfilling context behind messages, it is an effective measure of looking at diffusion of ideas (Lipizzi, Dessavre, Iandoli, & Marquez, 2016).

**Data Collection**

All data collected in this project was accessed using means and tools that were freely available to researchers. Utilizing API search applications, TAGS and TwitteR, 23,691 tweets were collected. Search parameters included #deleteuber between the dates of January 28, 2017 and February 10, 2017. These dates correspond to the enactment of the controversial immigration executive order signed by President Trump on Friday evening January 27, and Uber CEO Kalanick’s comments to the travel ban and Uber’s surge stalling at JFK Airport on January 28. #DeleteUber started trending later that day, with another spike on Thursday, February 2 when it was announced CEO Travis Kalanick would be stepping down from President Trump’s Advisory Board.

To collect Twitter data, the researcher created a Twitter app account to gain access to the limited API data Twitter makes freely accessible (Twitter Developer, n.d.). This is a free service available to all registered Twitter App users. TAGS and TwitteR are script software programs that are freely available online for download (Hawksey, 2014; Gentry, 2016). In this project, TwitteR was ran on StudioR (Allaire, 2016). Once proper accreditation was established for Twitter API and the proper software was downloaded specific searches for tweets incorporating the #deleteuber hashtag were conducted.

In the TAGS search, a tweet cap of 10,000 tweets was set with a total of 2,691 retrieved. TwitteR was run using RStudio and 21,000 tweets were gathered across four search queries.
Dates were broken down into three and four day stretches (1/28-1/30, 1/31-2/2, 2/3-2/6, 2/7-2/10) with a 5,000 tweet cap set. The total population size of tweets was 23,691. All tweets were consolidated into a combined excel document. It should be noted that API collection measures provide access to data, but is limited in its capacity and leads to an inevitable loss of data. API limits are set in place for number of tweets that can be collected as well as archive limit access. In this case, the event and resulting crisis was happening in real time so tweets were gathered within the two week API archive limit.

**Sample**

For the semantic network, all tweets are included from the dataset of 23,691. This includes potential duplicates from retweets because the study is focused on the dissemination of content. Duplicate tweets due to retweeting were not removed from the sample as a measure to understand what information was being repeatedly spread throughout the network in a viral capacity. This would allow measures of edge weight to show some effect on topic strength. In the context of this study, nodes will be isolated words from the tweets. Edges will be when these words interact with each other within a specified “window” (which for this case will be a tweet). The boundaries will be limited to this data set that is focusing on a very specific crisis event. Specifically, Uber and Travis Kalanick’s response to President Trump’s immigration ban policy which led #deleteuber to begin trending.

**Procedures**

While tweets are already pretty stripped down text, for a textual analysis, further data cleaning was needed to be completed before building the network. Specifically, the challenge with tweets was removing all symbols (such as @ signs and underscores), while retaining the separation of hashtag phrases from regular content phrases (ie. #Uber vs. Uber). To account for
this, before the preprocessing step all hashtag symbols were replaced by the letters ‘ht’ as a designation that can be seen in the resulting network images.

Automap (Carley, 2001) was the software used to format and preprocess the tweet data. It’s important to preprocess the data because focusing on the quality of the data over the amount of data will help the text mining process run more smoothly. Specifically the tweets were moved onto a text document (.txt) and prepped for the inclusion of a windowing algorithm. Then noise was reduced with the removal of unnecessary words, numbers and symbols. By preparing the data this way, the software used was able to prepare a word list of frequencies that was used to create a network for further analysis.

Preprocessing

To prepare text for analysis, the following measures were taken to clean the data: all letters were converted to lower case, numbers, punctuation, symbols, pronouns, noise verbs, and day and month words were all removed. Common contractions and abbreviations were also expanded before prepositions and all noise words were removed. After these steps, a concept list was created to see how the list was looking. I ran a preliminary concept list to check progress and measure how the terms were looking in order to best assess what other cleaning needed to be accomplished. In final steps, stemming was applied, common contractions were again expanded with additional removal of pronouns, prepositions, noise verbs, all noise words and I applied Automap’s delete list. Largely, text cleaning was meant to help create consistency in the data and to remove unnecessary repetition and unimportant words that don’t relate to what is being asked from the dataset. I ran another concept list and my final step was to create my own custom delete list. Words added to the delete list were primarily nonsense links or strings of letters that were
broken urls that had remained included and had not been captured in previous cleaning measures. A final concept list was ran, followed by a co-occurrence list.

The co-occurrence list matched 69,673 pairs, so to help focus the graph and analysis I limited the frequency to 50+ in migrating data over to NodeXL (Smith, et al., 2012) which limited the final network to 674 pairs for 289 total nodes.

**Network Construction**

In constructing the network, nodes are words from the tweets containing the #deleteuber hashtag and edges denote the co-occurring affiliation between the words. It is a bidirectional network where the order of co-occurrence wasn’t as important as the nearness of the words to one another. From a network perspective these linkages provide insight into tweet conversation surrounding the crisis. Four different graphs were developed from the initial created network.

**Results**

The final created network shared 289 vertices with 664 edges. The network has 26 components, with 231 vertices in the largest component. The diameter is 12, with an average geodesic distance of 3.905661 and density of 0.00795672. In this network, a very low density demonstrates that actual connections over possible connections become diluted due to the limiting interconnected of conversations. The graph fractures into pretty distinct clusters that show a wide array of discussion topics emerging from the #deleteuber hashtag. This is supported by the large diameter and average distance measures.

Diameter is a measure of the shortest distance between the most distant nodes of the network. In this context we see a diameter that tells us that the network is not well connected and
creates connections from distinct chains of nodes that don’t necessarily intersect, particularly in the outer edges of the network.

Figure 1.

#DeleteUber Co-Occurrence Semantic Network

Figure 1 is simply demonstrating the resulting network from the text mining and semantic analysis. Without knowing much data from the graph, some initial observations can be made. A star network pattern emerges around a core node, in this case the #deleteuber node. From this core node some natural clusters can be seen and suggest some branching topics of conversation.
To get a better grasp of the data, a cluster analysis was ran. Clauset-Newman-Moore was used as the clustering algorithm (Clauset, A., Newman, M. E. J., & Moore, C., 2004).

Figure 2.

Cluster Analysis of #DeleteUber Co-Occurrence Semantic Network

The algorithm found 34 clusters. In this clustered layout, about 6 distinctive groups immediately become visible as emerging topics in conversation, with the remaining groups largely clustered in various dyads and not connected to the core component. For the purpose of this study, the research questions were focused around nodes highlighting the organization or CEO. To get a closer look at this another graph exported vertex information including delete
uber, uber and chief executive officer (because it had the highest degree related to leadership) to create an interconnected ego network. Both hashtag and content affiliations were included in the network.

Figure 3.

*Interconnected Uber and CEO Ego Networks within the #DeleteUber Co-Occurrence Semantic Network*

This graph shows interconnected ego networks via clustered color and demonstrates edge width, which translates to frequency of the word co-occurrence. We see the organization (Uber), both with and without a hashtag holds a strong connection to the delete uber campaign.
Additionally, it’s interesting to note how the CEO is strongly affiliated with the organization, but removed from the crisis hashtag itself. It’s Uber, the organization that has calls for boycott, deletion, and backlash. It should also be noted that Lyft is strongly connected to the campaign as Uber’s direct competitor, affiliated with both the crisis hashtag and Uber.

These interconnected nodes show a burst pattern here, particularly surrounding the #deleteuber hashtag. There are many different topics emerging from the hashtag campaign and lend evidence to the vast amount of noise that occurs on social media. However, the edge width does provide some strength to the direction and focus of many of the conversations happening on Twitter.

Finally, a second network was pulled from the initial network for additional analysis. Groups 2-4 from the clustered network was exported to again focus on the organization and leadership. The group including #deleteuber was intentionally left out as the previous graph (Figure 3) demonstrated the amount of noise that emerges surrounding the hashtag. The purpose of this study is to understand how Uber and Travis Kalanick fit into the conversation and what topics emerge surrounding their nodes specifically.
This network shows co-occurrences within the groups mentioned. It’s a smaller single component comprised of 95 nodes and 213 edges. The diameter measure is 4, with an average geodesic distance of 2.480433, and a graph density of 0.023740202, with node size representing degree measures. This subgraph is more interconnected than the initial network showing a much tighter diameter and larger density in comparison to the initial graph (Figure 1).

Again Uber is a main focus, but interestingly Trump emerges as a node of interest. This suggests a political component is present within the crisis, which somewhat tracks based on the
event that led to the crisis itself, but somewhat surprising how much conversation branches from the node. Additionally, discussions about direct competitor, Lyft, becomes apparent as a branch of conversation.

Figure 5.

*Uber and CEO Clustered Groups within the #DeleteUber Co-Occurrence Semantic Network with betweenness and closeness centrality measures*

This final figure is the same subgraph as Figure 4, but with different measures visualized. In this graph, betweenness and closeness centrality measures are identified. Betweenness centrality is visualized by node size, while closeness centrality is visualized by color. The light
color denotes a smaller centrality measure, while the darker color denotes a higher centrality measure.

In regards to betweeness centrality, #deleteuber, Uber and Trump are nodes that show highest values within the network, which mean that many node paths pass through these three nodes in discussing the crisis event on Twitter. This puts both importance on the organization, but also the political environment surrounding the crisis.

For closeness centrality, #deleteuber, Uber (and #Uber), and Trump are joined by Lyft and CEO as core topics within the network. This centrality measure helps understand information flow and the pattern of conversation that emerges within the crisis on Twitter.

**Discussion**

This study is interested in organizational reputation and social media influence surrounding a crisis. In considering the results, organizational reputation can be linked to a crisis, even if the organization is not necessarily the perpetrator of the crisis. #DeleteUber demonstrated this as a case on January 27, 2017 when Uber was criticized regarding President Trump’s controversial executive order on immigration and the company of Uber cancelled surge pricing to JFK airport, as well as CEO Travis Kalanick’s controversial role on Trump’s advisory council. Together, these events left Uber and Kalanick in the midst of an organizational identity crisis with media, public, and political consequences. Although CEO Travis Kalanick was arguably the crux of the issue, the organization Uber was also left in crisis and had to make efforts to handle the online and offline public backlash.

The semantic network analyzed co-occurring word frequencies in an attempt to understand the crisis context in answering the following research questions.
RQ1, RQ2 and RQ3 go hand in hand asking a similar question. From the network it’s clear that the CEO is not as important in the crisis narrative, as the organization itself. Uber demonstrated high degree, betweenness, and closeness centrality measures in comparison to CEO Travis Kalanick, suggesting that the public was much more engaged in attributing blame towards the organization. In short, the public does not associate crisis with an individual, and instead the organization becomes a proxy for the crisis event. And the frequency of affiliations both including these phrases (Figure 4) and between these phrases (Figure 3) show Uber as the more frequented node.

RQ4 sought to identify patterns in the network affiliated with the crisis. Across figures, while the crisis was definitely a vein of discussion, discussion on direct competition promotion and political affiliation were other noteworthy trends to note. It’s also important to point out the use of hashtags and how conversation emerges around them. #deleteuber was clearly the focal point of this network, but the burst of noise that surrounded the hashtag in co-occurrences gave some insight into how information spreads on a crisis social network.

Conclusions and Limitations

This study was largely exploratory in measuring an entire population of collected tweets. The network analysis demonstrated how an organization is situated in an online crisis network, and perhaps most importantly highlighted what conversations are emerging from this crisis. Findings showed that the organization must be wary of direct competitors taking advantage of their plight, as well as navigating a highly politicized environment. Additionally, it was the organization itself that took the brunt of the attribution and tagging in reference to the crisis situation. All of this can be helpful as organizations adapt to an integrated social media
environment and the relentless flow of information in crafting their messages to begin the reputation recovery process.

However, while these observations are both interesting and engaging a couple limitations come to mind. One big assumption is that social media is important and Twitter is a valid data source to make claims about crisis communication. While social media is definitely an important source of information, little research has linked the effectiveness of online activity to organizational response. Furthermore, the data collection process of tweet mining is flawed, so even though quite a bit of data is being analyzed, the picture is incomplete here. This is only a sample of a much larger population, so conclusions will be tentative. Additionally, the cleaning measures also provides limitations as data was omitted from the initial population or data that was included continues to be unnecessary. Figure 5, for example, includes some unnecessary url strings in the outer edges of the graph. Finally, it’s important to note that this is a single case and as such provides a limited reaction and view to what crisis is.

Looking forward, future research connecting the importance of social media crisis response to organizational response could lead to some really interesting connections and implications in both the body of crisis literature and how practitioners respond to a crisis. There’s also an opportunity to expand this methodological approach and continue to add crisis cases to see if network trends show similar trends across crisis events.
References


