Managing Bad News in Social Media: A Case Study on Domino's Pizza Crisis

Jaram Park   Meeyoung Cha   Hoh Kim   Jaeseung Jeong

Graduate School of Culture Technology, KAIST
291 Daehak-ro, Yuseong-gu
Daejeon, Republic of Korea

Abstract

Social media has become prominently popular. Tens of millions of users login to social media sites like Twitter to disseminate breaking news and share their opinions and thoughts. For businesses, social media is potentially useful for monitoring the public perception and the social reputation of companies and products. Despite great potential, how *bad news* about a company influences the public sentiments in social media has not been studied in depth. The aim of this study is to assess people's sentiments in Twitter upon the spread of two types of information: corporate bad news and a CEO's apology. We attempted to understand how sentiments on corporate bad news propagate in Twitter and whether any social network feature facilitates its spread. We investigated the Domino's Pizza crisis in 2009, where bad news spread rapidly through social media followed by an official apology from the company. Our work shows that bad news spreads faster than other types of information, such as an apology, and sparks a great degree of negative sentiments in the network. However, when users converse about bad news repeatedly, their negative sentiments are softened. We discuss various reactions of users towards the bad news in social media such as negative purchase intent.

Introduction

Social media is bringing a major headache to the corporate world because it has been shown to facilitate the spread bad news. In January 2012, a Korean-American female customer, who visited Papa John's Pizza in New York, discovered that the cashier identified her as "lady chinky eyes" on her receipt. She tweeted about the negative experience via Twitter that morning, and a local newspaper picked up the story. Within a few days, the news was reported not only in the US newspapers and broadcasts like CNN, but it also spread to other countries. The employee was fired, Papa John's in the US apologized, and even Papa John's in Korea had to apologize to Korean customers. This news started from one tweet by a customer in New York, but its impact reached all the way to Asia (ABC 2012).

In the past, only elite journalists could break bad news. Nowadays, anyone can produce bad news and spread it in

social media. From a corporate point of view, the "diffusion of bad news" often means a crisis, having a negative impact on brand reputation, word-of-mouth advertisements, and even sales. Before the social media era, companies used to respond to bad news by releasing position statements or public apologies via traditional media within days to weeks. Nowadays, however, the public expects companies to apology promptly (within 24 hours) and response directly via social media—the channel in which a crisis occurs.

Therefore, companies are interested in knowing how bad news spreads in social media. Their major concerns are on knowing how people's feelings propagate, what influences the public sentiment, and how it impacts corporate reputation. Several recent work have paid attention to analyzing public sentiments in social media. Studies have shown that online communities like Twitter can be used for predicting election results (Tumasjan et al. 2010) or even stock prices (Bollen, Mao, and Zeng 2011). Another study examined how sentiments embedded in online content affect the persistence of information, measured by decay time in the spread (Wu et al. 2011). However, sentiment analysis in the spread of corporate bad news, in particular, has not been studied. Understanding the diffusion dynamics of bad news in social media is important for crisis communication, as such knowledge can help companies and the government respond appropriately to crisis situations.

One of the first companies to experience a serious and global damage in its reputation due to the spread of bad news in social media is Domino's Pizza. The crisis started when two employees produced and uploaded a vulgar YouTube video in 2009. Within a few days, the video gained more than half a million views, major news media covered the event, and people started to discuss the incident on social media. Domino's soon released a YouTube video where its CEO apologized and explained the situation.

We paid attention to the Domino's crisis in Twitter, because from the beginning to the end the medium played a central role in spreading both the bad news and the apology. First, the crisis started in YouTube, but soon it was picked up by users in various social media sites. Twitter was one of the key places where discussions took place. Based on our estimation, more than 15,000 Twitter users posted a message about the event. Second, Domino's apologized on Twitter by sharing a link to its CEO's apology on YouTube.

Similar corporate crises have occurred causing dire consequences to various companies. Interestingly, however, crisis communication researchers have not yet conducted a systematic analysis of public sentiments in social media (Jin and Pang 2010). By conducting an in-depth analysis of public sentiments in Twitter related to the Domino's Pizza crisis, we attempted to answer the following three questions:

1. What are the temporal and spatial diffusion characteristics in the spread of corporate bad news?

2. How does the network structure determine the reactions of socially connected users?

3. What kinds of negative and positive sentiments are portrayed in Twitter conversations?

This study makes three contributions. First, we demonstrate the benefits of analyzing the actual social media conversations on a crisis situation. Before social media existed, it was extremely difficult for researchers and companies to examine the actual conversations during crises. Social media is hence called "the world's largest focus group," and the importance of decoding its content for businesses is being recognized (Talbot 2011).

Second, this is one of the first studies to conduct a systematic analysis of sentiments during a crisis situation. Researchers have pointed out the lack of systematic understanding of emotions in crisis communication research and have suggested analysis of emotions as an important future research direction in the area (Jin and Pang 2010).

Third, we not only analyzed how bad news spread in social media but also analyzed the influence of a corporate apology in social media. We used multiple methods, both quantitative and qualitative, to obtain a balanced view.

Related Work

In the past, it took a long time for companies to apologize for mistakes. Nowadays, the reaction is quicker. As social media plays a major role in the diffusion of bad news and crisis communication, companies have started to leverage social media in responding to corporate crises, such as CEO's apologies using YouTube: David Neeleman, former Chairman of JetBlue Airways responding to its Valentine's day crisis in 2007; Bob Eckert, CEO of Mattel responding to its millions of toy recalls; and Patrick Doyle, President of Domino's Pizza responding to its prank video crisis. The work in (Efthimious 2010) analyzed the case of JetBlue Airways, and the work in (HCD a) analyzed how people's perception changed after viewing the CEO's apologies of Mattel and Domino's. They found positive effects of the CEO's apologizing via YouTube.

Nonetheless, many scholars have pointed out the lack of a scientific approach in crisis communication research. Case studies have been a major research method in this area, yet it has been judged that more than half of them failed to describe a reliable data gathering method and only about 13 percent proposed research questions or hypotheses (An and Cheng 2010). In that context, the work in (Coombs 2008) emphasized the importance of building evidence-based knowledge for crisis management. This paper attempts to provide a holistic view of the crisis event in social media through both quantitative and qualitative analyses.

Case Description

On April 13th, 2009, two employees of Domino's Pizza in Conover, North Carolina, filmed a prank in the restaurant's kitchen and posted a video on YouTube, showing vulgar acts while making sandwiches. The employee in the video put cheese up his nose, nasal mucus on the sandwiches, and violated other health-code standards, while his fellow employee provided commentary. The URL of this video rapidly spread via online social media, especially through Twitter, as soon as it appeared. The video was viewed more than half a million times in the following two days and prompted angry reactions from the customers and from social media users.

Two days later, on April 15th, the president of Domino's, Patrick Doyle, shot a video directly apologizing about the incident and uploaded the apology on YouTube. Domino's also created a Twitter account with username @dpzinfo to actively address the comments and share the apology video link. The apology video also spread through social media. The original prank video was removed from YouTube because of a copyright claim, but its aliases or copies remained both inside and outside the YouTube community and continued to circulate. The company prepared a civil lawsuit, and the two employees were faced with felony charges for delivering prohibited foods to customers.

Twitter Data   In order to examine the global spreading pattern in the network, it is important to have access to all the tweet posts and the social network topology during the event period. This is because using sample tweets will not only increase biases in the measured sentiments but also result in fragmentation of information propagation patterns. In this work, we obtained and used the near-complete Twitter data in (Cha et al. 2010).

The data consists of information about 54 million users, 1.9 billion social links, and 1.7 billion tweets. The follow links are based on a topology snapshot taken in the summer of 2009, a few months after the Domino's event. The 1.7 billion tweets include all public tweets that were ever posted by the 54 million users. Each tweet entry contains the tweet content as well as the corresponding time stamp.

We extracted tweets that contained the word "domino" for an eight-day period from April 13th, 2009. A total of 19,328 tweets were identified in this way. This extraction method incurs both false positives (i.e., irrelevant tweets about the event containing the keyword) and true negatives (i.e., tweets about the event that do not include the keyword). In order to mitigate the error, we resorted to examining the tweet content and utilized the fact that the majority (60%) of these tweets contain a URL. We chose URLs that appeared more than 10 times and searched for tweets containing them from the entire Twitter data without necessarily mentioning the keyword. Encompassing the 1,445 true negative tweets found in this fashion, we analyzed a total of 20,773 tweets in this work.

Table 1 displays the number of users, tweets, mentions, re-tweets (RTs), and tweets with URLs on the Domino's case.
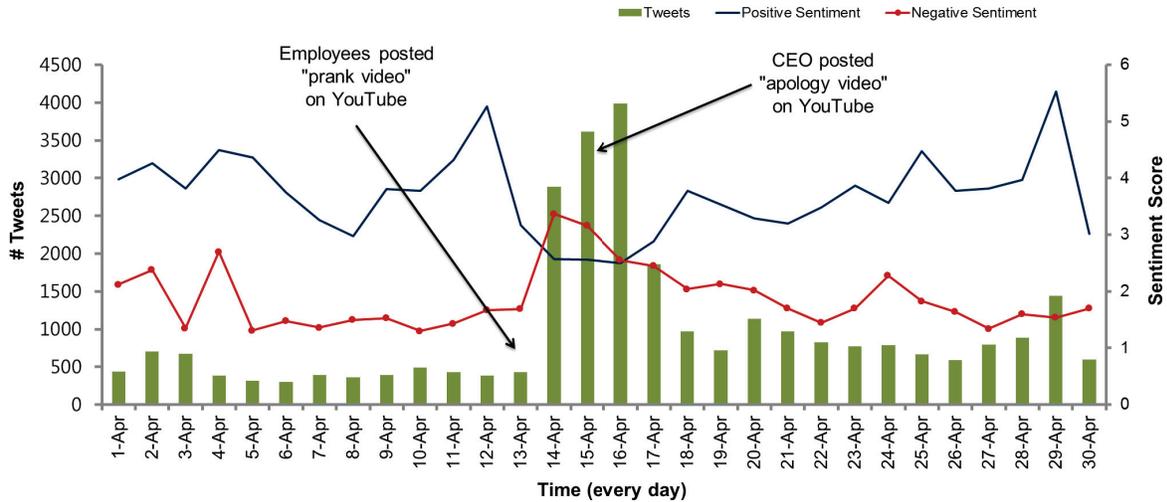
Figure 1: Temporal evolution of the positive and negative sentiment scores

The number of users who posted at least one tweet is 15,513. We found that 4,990 or 24% of the tweets were mentions, including @username in the tweet. This implies that a lively conversation took place among the Twitter users. We also found that 2,673 or 13% of the tweets were re-tweets. The most prolific tweet had been re-tweeted over 500 times.

# users	# tweets	# mentions	# RTs	URL (%)
15,513	20,773	4,990	2,673	13,132 (63%)

Table 1: Summary of the data set

Sentiment Analysis Tool   In order to quantitatively measure the mood changes of Twitter users, we used Linguistic Inquiry and Word Count (LIWC), which is a transparent text analysis program that counts words in psychologically meaningful categories. The LIWC dictionary includes around 4,500 words and word stems. It has been widely used by many social media researchers for sentiment analysis (Tumasjan et al. 2010; Wu et al. 2011; Golder and Macy 2011). This program shows the proportion of words that is related to each category (e.g., affect, cognition) in an input file. Empirical results demonstrate that LIWC can detect meanings in a wide variety of experimental settings, including attention focus, emotionality, social relationships, thinking styles, and individual differences (Tausczik and Pennebaker 2010).

In this work, we focused on the affective psychological process and examined the fraction of words in tweets that are related to the positive and negative affects. Note that typically, the levels of positive and negative affects are independent (Golder and Macy 2011). There are some limitations in using LIWC for sentiment analysis in Twitter. According to the LIWC provider, the input file should contain more than 50 words for accurate analysis. In practice, tweets written in fewer than 50 words yield extremely high or extremely low

sentiment scores. Therefore, we do not attempt to retrieve a meaningful sentiment score of a single tweet nor try to infer the moods of individuals. Since the LIWC tool calculates the sentiment scores based on just word count, capturing the subtle mood changes or the differences in tone of voice was not possible. Therefore, qualitative content analysis of sentiment propagation was needed, and we will show the results at the end of this paper.

Overall Trend   The bar plot in Figure 1 shows the daily number of tweets containing the word "domino" throughout the month of April in 2009. On the day after the prank video was uploaded, the number of tweets about Domino's Pizza increased to over 2,500 tweets per day, which is five times larger than in the previous week. Only for two days (April 14th and 15th) right after the employees posted the prank video on April 13th, there were nearly 7,000 tweets. When we account for the sheer size of the audience, a total of 16,553,169 or 30% of all Twitter users were exposed to the news during an eight-day period (April 13th–20th, 2009).

The line plots in Figure 1 show the level of positive affect (blue solid line) and negative affect (red solid line with markers) embedded in tweets over the same time period. Twitter users exhibited a stronger positive affect towards Domino's Pizza except for during the three peak days. Based on a randomly chosen set of 10,000 tweets from the same period, the level of positive and negative affects were 4.24 and 1.65, respectively.

Figure 1 shows the overall trend. We find that the amount of conversations and negative sentiments suddenly and significantly increased right after the crisis event was triggered via social media. The amount and the negative sentiments, however, dropped right after the CEO posted an apology video, indicating that the CEO's apology video was an appropriate response from a crisis management practice point of view. In fact, the apology is considered a reasonably fast one (within 48 hours) although it could have been faster.

Type	Num URLs	Num tweets	Num spreaders	Med followers	Audience size	LCC (edges)	Avg degree	Node density	Clustering coefficient	Diameter hop	Path length
Prank	24	2230	2078	169	2204175	42% (99%)	5.3	0.001	0.071	10	3.4
Apology	15	771	707	351	542161	82% (99%)	7.2	0.008	0.230	7	2.7
Commentary	44	1641	1608	367	4706032	89% (99%)	14.5	0.008	0.233	9	2.8

Table 2: Spatial characteristics of the users who spread Web links to the prank video, apology video, and critiques, respectively.

Characteristics of Bad News Spreading

We examine the temporal and spatial characteristics in the spread of Domino's news. In order to identify bad news, we manually inspected the URLs embedded in tweets. Given that the majority of tweets (63%) contained a URL, we only considered those tweets that contained a URL that appeared more than 10 times during the trace period. There were 90 distinct URLs, and the most popular one appeared 561 times. After manual inspection, we classified these URLs into three representative categories. Seven out of 90 URLs did not belong to the main categories and were discarded in the analysis. The three categories are:

- **Prank**: There were 24 URLs on the prank video, either containing a link directly to the YouTube video or containing a link to news or blog articles which had the link to the prank video, e.g., "U need 2 look @ this especially if u eat at domino's http..." and "Be careful before ordering Domino's: http.."

- **Apology**: There were 15 URLs on the apology video, either a direct link or a link to a website with relevant information, e.g., "Domino's President responds http..." and "Excellent 2-min video on YouTube from Patrick Doyle. Congrats on this move http..."

- **Commentary**: When a crisis happens, journalists, crisis management consultants, and consumers write various articles to show their points of view on the event. Furthermore, Twitter users often spread the commentaries by linking the URLs. There were 44 URLs on the commentary in total, e.g., "Apropos to the #dominos fallout, How to weather a #twitter storm http..." and "RT @briansolis: The Domino's Effect http..."

For each of these categories, we constructed a social network of users who tweeted about Domino's event based on their follow link relationships. A large fraction of users in each of these networks were connected to each other by Twitter's follow links and formed one large weakly connected component. However, some users were singletons and others formed small communities of their own and were not connected to the majority of users who talked about the crisis.

Spatial Characteristics Table 2 displays the characteristics of the prank, apology, and commentary networks. The first set of statistics are on the number of URLs, the number of tweets, the number of users who posted the URLs (whom we call "spreaders" for convenience), the median number of Twitter users who follow these spreaders, and the unique number of total followers of these spreaders (whom we call "audience"). Audience represents the maximum number of users who could have received URLs on the Domino's event through Twitter.

Hundreds to thousands of users posted URLs on the Domino's event, and more people (47%) participated in spreading the prank video than in spreading the apology video or commentaries. However, the median number of followers was the smallest for the prank network, indicating that the bad news was shared by less connected users compared to those who spread the apology news or commentaries.

Several spreaders in each of these networks had very large indegrees. As a result, the size of the audience is three orders of magnitude larger than that of spreaders and reaches from half a million to nearly 5 million users on Twitter.

The second set of statistics is on the largest connected component (LCC) of each of these networks. We focus on connected users because they have a high chance of having read about the Domino's event through followers in Twitter before their posts.[1] Hence, the LCC can be viewed as an active community that voiced the event. We show the fraction of users and edges belonging to the LCC, the average degree, density, and clustering coefficient of nodes, as well as the diameter and the average path length.

The prank network varied in its shape compared to the apology and commentary networks. Fewer than half of the nodes formed the LCC in the prank network, while a great majority (over 80%) formed the LCC in the two other networks. Furthermore, users in the LCC had sparse connections in the prank network compared to in the two other networks, as seen from small average node degree, density, and clustering coefficient values. The commentary network was the most well connected; its nodes had 13 edges on average. The diameter of these networks similarly ranged from 7 to 10, and all three networks had short average path length of between 2.7 and 3.4.

We discuss three implications of the findings. First, it is common sense that more people pay attention to an event in the beginning of a crisis, rather than later when companies respond to the crisis. Table 2 confirms this implication. The prank network receives the most number of spreaders and tweets compared to the other networks.

Second, while the prank video was more popular than the apology or commentaries, the median numbers of followers in the apology and commentary networks far exceed that in the prank network. We can reasonably assume that while normal consumers or the average Twitter users would pay more attention to the prank video, experts such as journal-

---

[1]This intuition is based on the extremely low probability for when any two randomly chosen users are connected and have shared similar content in the Twitter network.

ists, marketing consultants, and power bloggers would pay close attention to how companies or the public respond to the crisis. These experts spread corporate responses and commentaries, and they likely have more connections than people who simply spread the bad news. We could observe this power of influence, as the apology and commentary networks had denser connections than the prank network. These experts would more likely be *opinion sharers* who share their point of view, rather than *information sharers* who simply deliver news.

Third, Pete Blackshaw, the executive vice president of digital strategy services for Nielsen Online, wrote a book with an exaggerated title, "Satisfied Customers Tell Three Friends, Angry Customers Tell 3,000" (Blackshaw 2008). Crisis management consultants used to say that people deliver bad news than good news to more friends. Our analysis confirms the overall trends. Considering the audience size and the number of spreaders, one spreader tells about the prank video to 1,061 (2204175/2078) people in the audience, but the apology video to 766 (542161/707) people on average. From the difference in the number of spreaders between the prank and the apology, we can conclude that *more people deliver bad news to more friends.*

Diffusion Time Lag Given that web links are discovered at different rates depending on their topics, we next examine how the tweets containing the same URL are correlated in time. To understand this, we identify the follow links that could have been used for information diffusion. We say a piece of information diffused from user A to B if and only if (1) B follows A on Twitter, and (2) B posted the same URL only after A did so. Then the diffusion time for a piece of information to cross a social link is calculated as the time difference between the tweet posts of A and B. In case a user has multiple possible sources, we pick the user who posted the same URL the latest as the source.
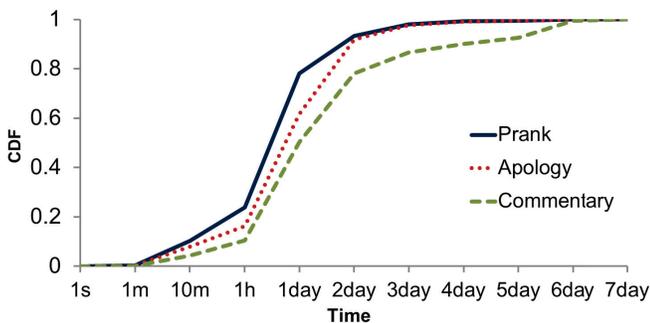

Figure 2: Time taken for information to cross a social link

Figure 2 shows the cumulative distribution function of the social diffusion times. We find that the spreading time varies widely in all three networks. A non-negligible fraction of tweets (10-25%) spread within an hour and the majority less than a day to cross a social link, indicating a rapid social diffusion process. Some tweets took several days to be found, possibly because these users did not login to Twitter every day. Notably, the prank video took the shortest time to dif-

fuse. The median spreading times were 8.0, 19.3, and 23.8 hours for the prank, apology, and commentary networks, respectively. Based on the 95th percentile values, the prank and apology news slowed down quickly in their spreading rates after 2.2-2.4 days. However, the commentary news continued to spread actively for up to 5.4 days.

Our temporal analysis has several implications. Considering the speed of spreading, we can conclude that *more people deliver bad news "faster" to more friends.* Also, compared to other types of news, commentary tweets stayed and spread for a longer period of time (more than twice the time) and reached a large audience. This means that when it comes to commentary, more people share conversation with others for a longer time period.

Social Network Determinants in Spreading

The most important characteristic of Twitter is that its users are linked to each other based on the follow feature. Under this circumstance, we tried to identify the factors that are related to the structure of social network and the interaction of users that could affect sentiment propagation.

In this section, we limit our focus to the sentiment of people in respect to the bad news. Therefore, we only considered tweets that were posted within the first 48 hours of the event prior to the CEO's apology from April 13th to 15th. We grouped tweets by the hour of their post time and ignored the time window with fewer than 100 tweets. In total, we took 23 valid time windows and analyzed sentiments of the tweets in each time window.

Connected Users We asked whether the social network structure or user interactions in Twitter can influence public sentiments (i.e., positive or negative psychological affects) on corporate bad news. Using LIWC, we conducted sentiment analysis considering different types of user relationships. We examined the difference by comparing the sentiments of tweets generated by users who independently talked about the event against those generated by users who had at least one friend who talked about the same event. We classified users into two types as follows:

- Isolated users: those who tweeted independently about the Domino's event and did not follow any other user who tweeted about the same event

- Connected users: those who are connected to other users who tweeted about the Domino's event

	# tweets	# RTs	# mentions
Isolated users	2,718	243	684
Connected users	2,009	559	535
Total	4,727	802	1,219

Table 3: Statistics for the isolated and connected users

We compared the difference in sentiments of the isolated users with the connected users. Two-sample t-tests were performed, which showed that there was no significant difference between the two groups in both positive sentiments and negative sentiments (p>.05). This observation indicates that there is no statistically meaningful level of influence of a

social link in the propagation of sentiments shared by two connected users. That is to say, the users that tweeted about the Domino's Pizza incident had similar sentiments, whether they were linked to each other or not.

Note that our finding does not deny the high level of assortativity observed in the everyday mood of social network users, where researchers found that happy or unhappy people form clusters in the offline contact network (Fowler, J.H. and Christakis 2008) as well as in the online counterpart (Bollen et al. 2011). Our finding rather supports that while there might be a great level of homophily in the general mood of users who are connected in social networks, the collective sentiments on a particular topic are strikingly in tune with one another regardless of social distance. For instance, people would collectively feel sad towards disasters like an earthquake. In the case of Domino's Pizza, most people felt disgusted watching the prank video; hence, their sentiments were similar irrespective of social distance.

Interacted Users Next, we examined the various types of user interactions on Twitter such as retweets and mentions to determine whether tweet sentiments are affected by user interactions. Figure 3 shows the level of positive and negative sentiments among different interaction groups. According to the results of analysis of variance, the tweets that were retweeted had more negative sentiment words compared to tweets without any interaction (called "statement" in the figure) tweets ($p<.05$). That is, as the tweet introducing the prank video was retweeted on Twitter, people added more negative comments in their retweets.

While retweets had more negative sentiments than the statement tweets, mentions had more positive sentiments than the statement tweets did ($p<.05$). This contrast is worth noticing because it means that when people converse with others about bad news, their choice of words are much more positive than when they simply forward the same piece of information to others.

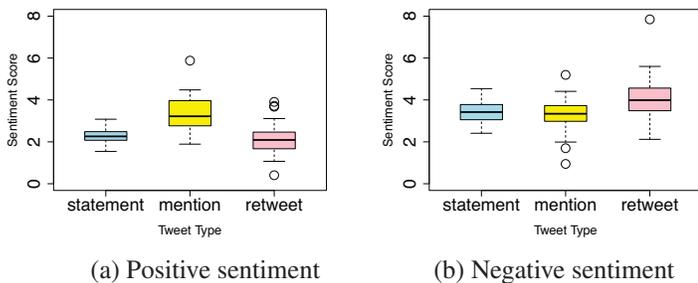(a) Positive sentiment (b) Negative sentiment

Figure 3: Sentiment difference by user interactions

For detailed analysis, we selected those users who posted at least three and no more than five tweets on the event and classified them into the following four groups: (1) statement group, if a user only posted statement tweets; (2) retweet group, if a user posted at least one retweet; (3) mention group, if a user posted at least one mention tweet; and (4) both group, if a user posted at least one retweet and one mention tweet, respectively. For example, if a user posted about

his personal thoughts (i.e., statement tweet) on the Domino's incident two times and retweeted another user's tweet once, than he is categorized as the retweet interaction group.

Figure 4 shows the sentiment scores of the first tweet and the last tweet of users in a given interaction group. Comparing the first tweet and the last tweet for each user, we found that the overall negative sentiment decreased with repeated interaction. In contrast, the positive sentiment increased slightly with repeated interaction. Users who only posted statement tweets showed the least variations in their moods over time compared to those who interacted with others.
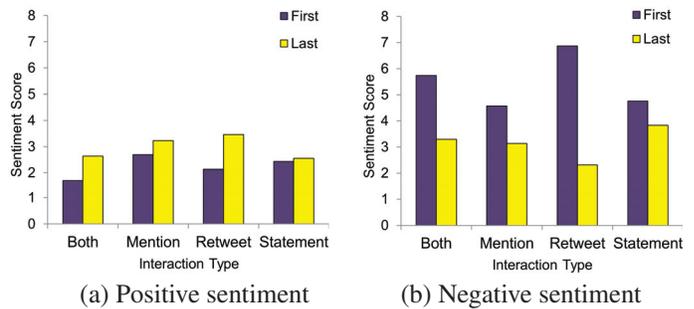

(a) Positive sentiment (b) Negative sentiment

Figure 4: Sentiment difference by repeated interactions

Qualitative Analysis of Twitter Conversations

In addition to the quantitative content analysis using LIWC, we conducted a qualitative content analysis. Qualitative analysis focuses on the meaning of the content, providing a thick description rather than quantification of the data (Geertz 1973).

Computerized quantitative content analysis has pre-structured content categories, and it can deal with mass content data. In qualitative analysis, the coding scheme is developed during the analysis, but the size of the data is limited. While quantitative analysis can provide a big picture, qualitative analysis can give a detailed picture of the data. No pre-structured coding categories were used. Instead, open coding was used so that relevant categories could emerge. Open coding is the part of analysis that pertains specifically to the naming and categorizing of phenomena through close examination of the data (Strauss and Corbin 1990).

Methods We sampled a total of 860 Twitter conversations from two peak times: 395 from 3:00–4:00, April, 15th, when the video prank by the employees spread, and 465 from 20:00–21:00, April, 16th, when the Domino's President released an apology video in YouTube.

Through continuous review of the data, we excluded tweets irrelevant to the 2009 Domino's crisis. Some tweets in this category were written in non-English and therefore, thrown out. A tweet like "I heart Lotus Domino!" also is irrelevant, because it refers to IBM's software product. Another example is "picking up Dominos for the fam. Wife called it in. Pepperoni for the kids; &Ham ; Pineapple for the grown-ups." It is about Domino's Pizza, but is not related to the crisis (in fact, the user may not know about the crisis). Furthermore, tweets like "Domino Pizza Time" were

excluded because of their ambiguity in whether they refer to the crisis or not. From the 860 tweets, 117 tweets (53 from the 1st peak and 64 from the 2nd peak) were considered as irrelevant and thus, excluded.

Results We identified two types of tweet content: facts and opinions. Tweets on facts have no sentiments, but simply state the event. This category included mere links without any text, links with the same headline of the linked website, or simple introductions of the link. Examples are:

"Shared: Dominos Pranksters Done In By Crowdsourcing: Teens have long used YouTube to post videos of them.. http://tinyurl.com/dx8kln"

"Searched Twitter for dominos: http://tinyurl.com/c4s4lx"

"See the video: http://ping.fm/9Eybi"

During the 1st peak (right after the launch of the prank video), 57 out of the 342 relevant tweets (16.7%) were categorized as facts, while in the 2nd peak (right after the launch of the apology video), 160 out of the 401 relevant tweets (39.9%) were facts.

The opinions category contained tweets that had either positive or negative sentiments. Because of the nature of the event, most opinions were negative. However, a few had positive sentiments towards the crisis:

"Yes, I read the stories about Dominoes on Consumerist today. No, that didn't stop me from just ordering a philly cheesesteak pizza."

"RT @BillieGee RT @berniebay I will continue to eat at Domino's Pizza. What about you? http://bit.ly/y3T"

Some tweets had both positive and negative sentiments, in which case the annotator questioned what the major sentiment was and then categorized the tweet. For example, the following tweet shows regret in the end. Nevertheless, the tweet was categorized as positive because its major sentiment was judged to be positive.

"liking the response by dominos... wish he would have looked at the camera tho http://tinyurl.com/c8dju3"

We make the following observations from Table 4. First, after the official corporate apology, the level of negative sentiments dropped from 82.8% to 54.6%. However, the level of positive sentiments increased marginally from 0.6% to 5.5%. In crisis management practice, when companies publicly apologize, they do not have high expectations for receiving praise or suddenly being viewed positively. Rather, they expect the public's negative sentiment to calm down and become more rational because of the apology. Our analysis confirms this expectation. The number of factual tweets increased significantly from 16.7% to 39.9%. Therefore, in Domino's case, the public apology reduced the amount of negative opinions and increased (neutral) facts in Twitter conversations.

When a crisis like this hits a company, they worry not only about its reputation damage but also and probably more importantly about its impact on sales. In fact, during the first peak, a category on negative purchase intent emerged containing the following three representative types of opinions:

	The 1st peak	The 2nd peak
Facts	57 (16.7%)	160 (39.9%)
Positive opinions	2 (0.6%)	22 (5.5%)
Negative opinions	283 (82.8%)	219 (54.6%)
Total	342 (100%)	401 (100%)

Table 4: Tweets on facts versus opinions

1. **Future intent:** Some users showed that in the future they will not to eat at Domino's, for example,

   "No more Domino's at my house"

   "and I don't think I will be eating Domino's again... *throw up in my mouth*."

2. **Persuasion:** Some recommended others not to eat at Domino's, for example,

   "This Is Why You Never Eat Dominos Pizza http://tinyurl.com/d22ubr"

   "If you didn't have a reason to not eat Domino's pizza http://tinyurl.com/cd62h3"

3. **Perception:** Some tweets confirmed people's past negative purchase intent towards Domino's, such as,

   "This is why I don't eat anything from Domino's pizza http://tinyurl.com/chxbbz"

   "@TheDLC Due to their disgusting pizza, I also haven't eaten at Domino's pizza in about 20 years. Thanks for confirming my decision!"

   "Thankfully, due to its psycho anti-abortion founder, I haven't eaten a Domino's pizza in probably 20 years."

We counted the negative purchase intent in two peaks. It significantly dropped from the 1st peak with 129 tweets (37.7%) to the 2nd peak with 26 tweets (6.5%).

Finally, our analysis confirmed that not all tweets mentioning the CEO's apology had a positive sentiment. A total of 71 tweets (17.7%) talked about the apology, out of which 34 of them (47.9%) exhibited negative sentiments, such as

"Too little too late Domino's http://tinyurl.com/c8dju3"

"Very insincere response from Domino's - http://ow.ly/31mF. Compare to Jet Blue's very sincere response 2 yrs ago - http://ow.ly/31mV"

and ten tweets (14.1%) were positive, for example,

"via @hollisthomases http://bit.ly/2lZr8m kudos to Dominos for taking swift action via social media in response to the nasty employee videos."

"Impressed w/ Domino's Response RT @lonniehodge:RT @SherryinAL: Dominos posts apology video on YouTubehttp://bit.ly/2lZr8m"

while 27 tweets (38%) were factual rather than being opinionated, such as

"Razor Report Blog: Update - Domino's Responds: Patrick Doyle, President, Domino's U.S.A., resp.. http://tinyurl.com/csls5n"

"For the PR agencies to analize, Domino's official response to the video http://tinyurl.com/cr9ak7"

It is interesting to observe that nearly half of the tweets on apology were negative. Nonetheless, slightly more than half of such tweets, including facts (38%) or positive opinions (14.1%), were non-negative.

Conclusion

When bad news spread, we could not find any statistically meaningful influence of sentiments taking place at the social network level. However, when users interacted with each other, their sentiments changed significantly. People spread and retweeted bad news with negative sentiment, but interacted with other through mentions with relatively positive sentiment. We provide one possible explanation for this result. As people interact with others in social media, they share their feelings and this act could reduce the negative sentiments. For example, it is well known in psychology that people's anger could be reduced by simply venting their sentiments (Frantz and Bennigson 2005). Also, bad news spread faster than a corporate response (i.e., apology) and by more people, while commentaries resonated in the network for a longer period of time. From our qualitative analysis, the negative purchase intent emerged as a major negative sentiment category. The CEO's YouTube apology caused a significant decrease in negative sentiments, especially the negative purchase intent, and facilitated factual and non-opinionated conversations.

Our study has practical implications for crisis managers in businesses. First, when a company makes a mistake and bad news starts to spread in social media, crisis managers should react quickly, admitting mistakes and apologizing appropriately. Several recent work confirmed the positive effect of CEO's apologies in social media, Twitter and YouTube, both in the US and in Korea (HCD b; Efthimious 2010; Park et al. 2011). Second, companies should start conversations in social media during normal times, not just after a crisis hits the organizations. Third, considering the speed at which bad news spreads, companies should prepare to respond within hours, not within days.

There are several exciting directions for future research. First, our methodology could not capture any subtle changes in sentiments of individuals, because an automated analyses tool like LIWC operates based on simple word counts. As we have demonstrated, a cross examination of both quantitative and qualitative analyses can provide a big and in-depth picture. Second, our investigation focused on only one event. Other bad news cases can be analyzed using the research framework of this study to identify commonalities and differences in the spread of bad news.

Acknowledgement

References

2012. *ABC News* Papa John's Employee Calls Woman 'Lady Chinky Eyes' on Receipt. *http://tinyurl.com/746lzko*.

An, S.-K., and Cheng, I.-H. 2010. *Crisis communication research in public relations journals: Tracking research trends over thirty years, in The handbook of crisis comm.* Handbooks in Comm. and Media. Wiley-Blackwell.

Blackshaw, P. 2008. *Satisfied Customers Tell Three Friends, Angry Customers Tell 3,000.* Crown Business.

Bollen, J.; Goncalves, B.; Ruan, G.; and Mao, H. 2011. Happiness is Assortative in Online Social Networks. *Artificial Life* 17(3):237–251.

Bollen, J.; Mao, H.; and Zeng, X.-J. 2011. Twitter mood predicts the stock market. *J. Comput. Science* 2(1):1–8.

Cha, M.; Haddadi, H.; Benevenuto, F.; and Gummadi, K. 2010. Measuring User Influence in Twitter: The Million Follower Fallacy. In *Int. AAAI Conf. on Weblogs and Social Media (ICWSM)*.

Coombs, W. T., . H. S. J. 2008. Comparing apology to equivalent crisis response strategies: clarifying apology's role and value in crisis comm. *Public Relations Review* 34:252–257.

Efthimious, G. 2010. *Regaining Altitude: A case analysis of the JetBlue Airways Valentine's Day 2007 crisis, in The handbook of crisis comm.* Handbooks in Comm. and Media. Wiley-Blackwell.

Fowler, J.H., and Christakis, N. 2008. Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the framlington heart study. *British Medical Journal* 337:a2338.

Frantz, C., and Bennigson, C. 2005. Better late than early: The influence of timing on apology effectiveness. *Journal of Experimental Social Psychology* 41(2):201–207.

Geertz, C. 1973. *The interpretation of cultures: selected essays.* Harper colophon books. Basic Books.

Golder, S. A., and Macy, M. W. 2011. Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science* 333(6051):1878–1881.

HCD Research 2007. Majority of Americans Will Continue to Purchase Mattel Toys after Recall. *http://tinyurl.com/6ujmcbu*.

HCD Research 2009. Domino's Brand Takes a Hit after YouTube "Prank" Video. *http://tinyurl.com/d4e47h*.

Jin, Y., and Pang, A. 2010. *Future directions of crisis communication research: Emotions in crisis - the next frontier in The handbook of crisis comm.* Handbooks in Comm. and Media. Wiley-Blackwell.

Park, J.; Kim, H.; Cha, M.; and Jeong, J. 2011. Ceo's apology in twitter: A case study of the fake beef labeling incident by e-mart. In *SocInfo*, volume 6984 of *Lecture Notes in Computer Science*, 300–303. Springer.

Strauss, A., and Corbin, J. 1990. *Basics of qualitative research: Grounded theory procedures and techniques.* Sage Publications.

Talbot, D. 2011. A social media decoder. *MIT Technology review* 44–51.

Tausczik, Y. R., and Pennebaker, J. W. 2010. The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. *Journal of Language and Social Psychology* 29(1):24–54.

Tumasjan, A.; O.Sprenger, T.; G.Sander, P.; and M.Welpe, I. 2010. Predicting elections with twitter: What 140 characters reveal about political sentiment. In *Int. AAAI Conf. on Weblogs and Social Media (ICWSM)*.

Wu, S.; Tan, C.; Kleinberg, J.; and Macy, M. 2011. Does bad news go away faster? In *Int. AAAI Conf. on Weblogs and Social Media (ICWSM)*.