Sydney Siege, December 2014:
A Visualisation of a Semantic Social Media Sentiment Analysis

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ABSTRACT

Sentiment Analyses are widely used approaches to understand and identify emotions, feelings, and opinion on social media platforms. Most sentiment analysis systems measure the presumed emotional polarity of texts. While this is sufficient for some applications, these approaches are very limiting when it comes to understanding how social media users actually use language resources to make sense of extreme events. In this paper, the authors apply a Sentiment Analysis based on the Appraisal System from the theory of communication called Systemic Functional Linguistics to understand the sentiment of event-driven social media communication. A prototype was developed to code and visualise geotagged Twitter data using the Appraisal System. This prototype was applied to tweets collected during and after the Sydney Siege, a hostage situation in a busy café in Sydney's inner city at the 15th of December 2014. Because the Appraisal System is a theorised functional communication method, the results of this analysis are more nuanced than is possible with traditional polarity based sentiment analysis.

Keywords

Social Media, Sentiment Analysis, Systemic Functional Linguistics, Extreme Events, Crisis Communication

INTRODUCTION

In the morning of the 15th of December 2014, a hostage situation unfolded at Sydney's Martin Place (Commonwealth of Australia 2015; State Coroner of NSW 2017). A gunman took eighteen hostages in a busy café and chocolate shop (Lindt Café). After seventeen hours, the gunman executed one of the hostages and the police were forced to resolve the situation violently. In the resulting firefight, the gunman and a further hostage were killed. The event attracted a worldwide interest and large media and social media coverage. In this study, the sentiment of Twitter communication generated during and after the event is analyzed and visualized based on the Appraisal framework (Martin and White 2005).

Social media microblogging services, such as Twitter, are a common channel for communication and distribution of facts, rumors, and opinions in extreme events (e.g.: Chatfield et al. 2014; Fraustino et al. 2012; Hughes and Palen 2009; Jeannette et al. 2013; Liu et al. 2014; Oh et al. 2013; Sutton et al. 2008; Sutton et al. 2012; Westerman et al. 2014). Examining social media channels can provide insights into how social media communities are feeling and reacting towards specific extreme events. These insights can be used to infer the sentiment of the broader population of citizens. In extreme events like the Sydney Siege, emergency management organizations are interested in how the effects of the event are influencing the communities in order to better tailor their response online and offline. Armed with knowledge of sentiment, these organizations can fight rumors being spread using social media or provide information concerning how to provide or receive assistance. Analyzing social media data offers the potential for fostering better situational awareness for

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Proceedings of the 15th ISCRAM Conference – Rochester, NY, USA May 2018
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Emergency Management Organizations by providing novel information about the event, how the general public is reacting towards the event, or revealing abnormal and emergent patterns of human behavior. One way in which social media can help Emergency Management Organizations is by providing indications of sentiment, a broad term that can indicate feelings and emotions, opinion and reactions or indicate outlooks or perspectives of those who are communicating.

Part of the difficulty in determining the utility of sentiment analyses is how to actually define the concept of 'sentiment'. The usual ways of determining social media sentiment are based on algorithms where words are classified according to a presumed emotional polarity (Medhat et al. 2014; Montoyo et al. 2012). Unfortunately, these approaches can only provide a rather limited view of the attitudes and sentiments expressed by social media users. In this paper, the authors adopt an different approach to the analysis of social media sentiment by adopting a functional theory of communication called Systemic Functional Linguistics (Halliday 1985; Martin 1992) to unpack the attitudes and sentiment of social media messages during extreme events. A functional theory of language is employed because we are interested in how social media users actually use language resources to create meanings (Sampson 1980). Of particular interest, here is the language resource called Appraisal that includes those features that encode attitudes and feelings.

In this paper we use the Appraisal System (Martin and White 2005) as a form of sentiment analysis which can better help to understand sentiment in extreme event social media data in comparison to traditional polarity based approaches. We developed a prototype which helps us to conduct an Appraisal analysis and visualization of Twitter data. We use this prototype to illustrate the utilisation of the Appraisal System based on extreme event data.

The remainder of the paper is structured as follows. First, the appraisal system used as a novel form of sentiment analysis is described. Second, the case event of the Sydney Siege 2014 is described in more detail. Third, the Twitter dataset is introduced. Fourth, a detailed description of the developed prototype is provided. Fifth, the findings of the Appraisal-based social media sentiment analysis are summarized. In the final section, the findings are discussed and the contributions of this approach are outlined.

SENTIMENT ANALYSIS EMPHASIZING APPRAISAL RESOURCES

Information Systems applications of sentiment analysis have been employed in applications as diverse as assessing the sentiment surrounding political actors (Bakliwal et al. 2013; Ceron et al. 2014; Unankard et al. 2014), sport events (Yu and Wang 2015), brand perception (Morinaga et al. 2002), product perception (Jansen et al. 2009; Mostafa 2013), or stock market predictions (Das and Chen 2007). Our application involves determining the sentiment within social media posts surrounding an emergency incident, the Sydney Siege that occurred December 2014. Unfortunately, the usual approaches to sentiment analysis are extremely limited. They mostly utilize approaches based on emotional polarity that is assumed to be associated with particular words occurrences in messages (Medhat et al. 2014; Montoyo et al. 2012). A determination of emotion based simply on polarity yields a very limited view of what social media users are feeling about an extreme event. Construing polarity as an indication of emotion, conflates the potential analysis to only one dimension of sentiment. Perhaps more importantly for organizations- especially in this context, emergency management agencies- polarity sentiment analysis while arguably providing the means for organizations to 'socially listen' renders them simultaneously incapable of acting on what's been heard.

Issues with Polarity-based Sentiment

Many problems associated with the reported poor performance of polarity sentiment applications and systems are due to the fact that they ignore how language is functionally organised in order to be used. There are several issues which can easily be considered here. These issues include a fundamental misunderstand of how language is organised, another involves the fact that lexis-based (word-based) polar sentiment fails from the perspective of construct validity, and finally that polar based approaches to sentiment analysis cannot distinguish any other dimensions of evaluative language. Sentiment analysis, as it is developed in the polar sentiment literature, seems only concerned with emotions (affect) and incapable of dealing with any of its consequences in the form of appreciation or judgements.

The problem with almost all polarity-based sentiment analysis products is that they do not come to grips with what sentiment actually is. Polarity-based sentiment is assumed to be a property of words; it is the static attribution of a polarity to a word that is the basis of all polarity-based sentiment analysis system. However from a functional perspective - that is when developing accounts of language that involve how it is used to make meanings - language comprises a number of compositionally organized layers of units, the so-called *rank scale*, that starts at words classes (nouns, verbs and so on) and proceeds to successively large units associated with the

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group/phrase rank that are in turn organized into complete messages at the *clause/clause complex rank*. Likewise any sentiment attached to the messages in social media posts will not just involve word classes but also potentially other ranks. This is why the expression 'being between a rock and a hard place' can be associated with a single sentiment in this case at the group/phrase rank. In this example, the specific sentiment cannot be identified by using the constituent words of constitute the expression considered separately.

From a functional perspective, sentiment is an evaluative attitude to a situation or thing, so employing a *scalar* +, 0 - (a direction without a magnitude) does not in and of itself shed any light on which construct is being referred to. This limitation is referred to here as the *missing referent problem*. By comparing contrasting words like 'love' and 'hate' some of the problems of polar-based sentiment become apparent. For example, neither in kind or extent, is a little bit of 'hate' anything like any kind of 'love'. Different kinds of sentiment exist as distinct kinds of category- 'love' and 'hate' do belong to the same class- they are both examples of emotions (affect), but they are not co-terminus categories (extreme endpoints of the same kind of thing). From a classical *construct validity perspective* (Cronbach and Meehl 1955), the notion of 'polar sentiment' seems inadequate to the task of accessing the specific mood or opinion experienced by an individual or group engaged in evaluative language- the superset of language resources of which sentiment is apart.

Usually what is meant by the term 'sentiment' is actually strictly limited to considering a kind of emotional assessment of a word. But is that really all we want to know when we conduct a sentiment analysis? Clore and Huntsinger (2007) correctly point out that while "theorists commonly assume that people's attitudes and judgments reflect information about the object of judgment, people's evaluations also reflect information from their own affective reactions". Businesses want to know how customers are emoting because they want to know how they view our products, services and organisation is relation to others, and also what kinds of impressions they may form as a consequence. Emotion is one thing but these other forms of appreciation and judgement are equally as important for a useful sentiment analysis. For this reason, the remainder of this article concentrates on semantic sentiment which includes affect, judgement and appreciation.

The Appraisal System

In order to understand what communicated sentiment can be, a functional model of communication theory called Systemic Functional Linguistic (SFL) is selected (Eggins 2004; Halliday 1985). The reasons for selecting this model of language are beyond the scope of this paper, but the reader is directed to Clarke (2001) for a review of semiotic and communication-based approaches employed in Information Systems. While there has been a great deal of work in linguistics that concerns the description of interactional aspects of talk, there has been almost no theoretical or methodological development concerning communicated evaluative meanings. However, SFL accounts for communicated evaluative meanings using its Appraisal system. The Appraisal system is employed in this paper to provide a more elaborate and nuanced sentiment analysis than is usually applied in the Information Systems discipline. The term 'system' in SFL refers to a collection of meaning-making resources that are employed by communicators to create meanings. System networks like those shown in Figure 1 are read from left to right from the most general option in the network- the so-called point of entry-to the most specific or right-most option. The square brackets indicate options that are in logical OR (selection) relationships between each other while the curly bracket indicate options that are in logical AND (combination) relationship with each other.

Figure 1 shows the system network for the Appraisal system. The Appraisal system was developed in order to account for the interpersonal assessment of speakers (or social media users) and associated attitudes (Martin and White 2005). Attitude includes different options for expressing evaluative statements in language. In particular, attitude is relevant to the evaluation of things, people's character and their feelings (Martin and Rose 2007; Martin and White 2005). This system is divided into three semantic regions covering "affect" (synonymous with emotion), "appreciation", and "judgement" (Martin and Rose 2007; Martin and White 2005). Each one of the semantic resources facilitates evaluation and is defined below:

Appreciation concerns the speakers' reactions to and evaluations of reality; typically, of a process of some kind or a completed act of communication. There are three specific types of appreciation, valuation, composition and reaction. These are organized in the system network using square brackets that indicate a logical OR relation exists between these options. This implies that if a stretch of language (in a tweet or other social media message) is being coded as an instance of 'appreciation' then it can be a 'valuation', 'composition', or a 'reaction'.

Affect involves a speakers' expression of emotional states, either positive or negative. This is the option that most closely resembles traditional sentiment analysis in Information Systems, although there are three specific kinds of affect recognized in Systemic Functional Linguistics. They include satisfaction, security and happiness.

Judgement relates to the speakers' judgements about the ethics, morality, or social values of others. The two types of judgement are social esteem and social sanction.

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For the remainder of this paper, traditional sentiment analysis approaches are abandoned in favor of the Appraisal system from SFL (Martin and White 2005)
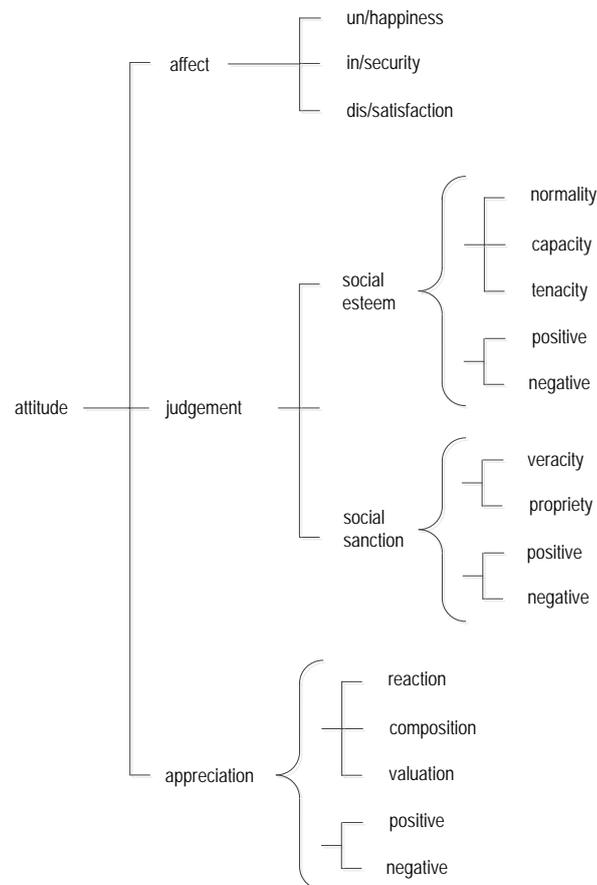
Figure 1. The Appraisal System (Martin and White 2005)

CASE STUDY: SYDNEY SIEGE 2014

The Sydney Siege of 2014 was hostage situation which unfolded at the 15th of December. The event was violently resolved by the police in the morning hours of the 16th December after a hostage was shot by the gunman. The event started at around 9:40 am as a lone gunman took eighteen hostages (eight employees of the café and ten customers) in the Lindt Café at Sydney's Martin Place.

While the Sydney Siege was unfolding the media perception was that this event was part of a broader organized terror attack and the police was treating it as such (Ralston and Partridge 2014). During the event, it was never clear whether the gunman was working alone or whether there were others working in the background. It was as well not clear whether the perpetrator was the only gunman within the café.

Apart from the immediate threat within the cafe, the gunman had claimed that there were several bombs located at Martin Place, Circular Quay, and George Street. These places are some of the busiest in Sydney's central business district and are also the locations of famous sightseeing spots frequented by tourists during that time of the year.

Only in the aftermath of the event it became evident that the gunman was a 'lone wolf' (Commonwealth of Australia 2015; State Coroner of NSW 2017) working without additional support. A provisional timeline for the Sydney Siege is provided in Table 1 to provide an overview about the event. This table was derived from media coverage and the official reports resulting from the event.

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Table 1. Timeline for the Sydney Siege derived from media coverage (ABC-News 2014; Commonwealth of Australia 2015; Fallon 2014; Ralston and Partridge 2014; Safi 2015; State Coroner of NSW 2017)

| Timeline	Description
15th December 2014	
08:33 am	later hostage-taker enters the café
~09:40 am	hostage-taker speaks to the manager; hostage situation unfolds
09:41 am	forced call to 000 (Australia's emergency phone number)
09:49 am	Police arrives at Martin Place
10:20 am (approx.)	Hostages were forced to hold black flag against the window
10:45 am	Sydney Opera House was evacuated (caused by suspicious package)
03:37 pm	Three hostages escaped the building
04:58 pm	Two more hostages escaped through another exit
16th December 2014	
2:00 am	Six hostages were fleeing out of the building; followed by one gun shot.
2:11 am	Second gun shot. Hostage escapes.
2:13 am	One hostage was shot. Police are storming the café.
2:14 am	Ongoing firefight; One further hostage was killed by stray bullet
2:44 am	Hostage situation is declared resolved through a NSW Police Tweet. "Siege over. More details to follow"

DATASET

In this study, we are exploring the sentiment of the Twitter community during and after the Sydney Siege through assessing the Twitter communication concerning the event. The corpus for this study comprised Tweets collected over a span of two weeks starting from the 15th of December 2014. These Tweets were harvested according to the following keywords "sydneysiege", "martinplace", "sydney", "lindt", and "chocolate shop". This yielded an initial corpus of 5,429,345 Tweets globally. From these tweets, we selected Tweets which were in English. As we are interested in the geographic distribution of sentiment, only geotagged tweets were used for the analysis. The final dataset consists of a corpus size of 50,670 tweets.

TWEET APPRAISAL CODING AND VISUALIZATION PROTOTYPE

A Tweet Appraisal Coding and Visualization Prototype was built to assist in (I) coding tweets using the Appraisal system and (II) visualizing Appraisal globally as the event unfolds. The prototype consists of three major components: A (1) User Interface to annotate Tweets, a (2) Classification Tool, and an (3) Visualization Tool for Twitter Datasets. The classifier (1) is a tool that helps the user to code Tweets according the Appraisal framework. With these manually (expert) coded tweets, the prototype can use different machine learning approaches (2) to learn the sentiment of tweets according to the Appraisal Framework. The third part of the prototype (3) is a tool that the user can employ to discover the spatial and temporal distribution of Appraised tweets for a given event. The classifier and visualization tool are described in the following sections.

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User interface to annotate Tweets

The Interface to annotate Tweets in the existing prototype is shown in Figure 2. The appraisal analysis requires that individual tweets are segmented into their constituent messages called clauses. The tweet in Figure 2 consists of two clauses, "thinking of the hostages" and another dependent clause "in this terrible and frightening time". The second clause is dependent because it cannot stand alone as a sensible message. Its job is to elaborate upon the situation being described. The segmentation of clauses is a simple manual procedure involving selecting where the boundaries between clauses should occur in the tweet. Once this first step has been completed, the next step involves locating the appraisal items. As shown in Figure 2, the first clause has 'hostages' as an appraisal item, while the dependent clause has 'terrible' and 'frightening'. Indicating one or more appraisal items is very easy in this prototype. By simply clicking anywhere inside a word, that word will be selected. Alternatively dragging the mouse pointer across multiple words will select multiple words. The final step- the actual classification itself- involves determining what kind of appraisal should be assigned to each appraisal item, see Figure 2.
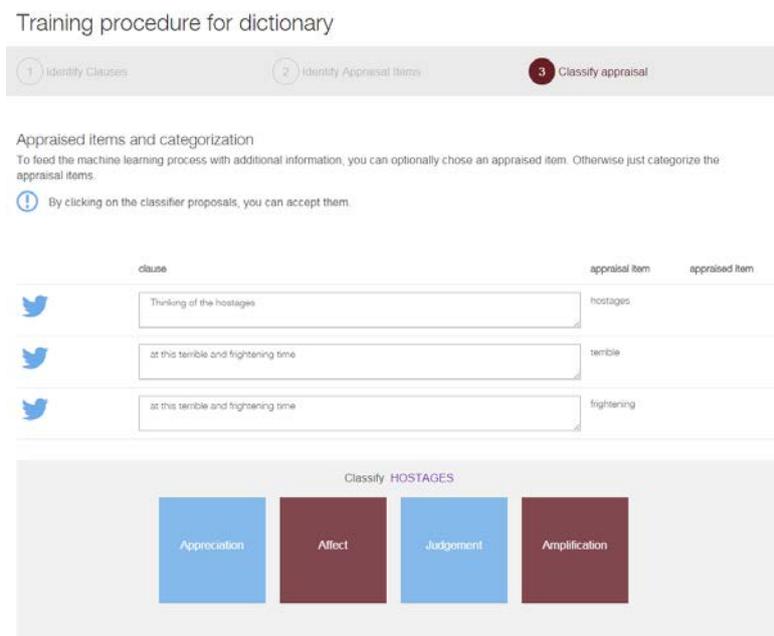
Figure 2. Classifying Appraisal Items

The examined dataset included 50,670 geotagged Tweets. With the help of the prototype we manually coded 792 Tweets according to the appraisal framework. The corpus was coded by a single expert, skilled in performing the clause boundary analysis and the use of systemic functional linguistics in general and appraisal in particular. Intercoder reliability measures did not need to be performed on this corpus as a consequence.

Classification of Tweets

The classification tool works as an environment to apply and test different classifier approaches. The prototype is modularly designed which allows us to add or exchange the classifiers. For this analysis, we initially evaluated a multinomial logistic regression and a Naïve Bayes classifier in different configurations, as shown in table 2.

The different configuration is allowing for different feature types and an up-weighting of appraisal items. In this initial case, the feature type for classification was either a binary bag of words model, where a document is represented as a vector of 0s and 1s representing the absence/presence of a word, a TF/IDF weighted feature vector, or a word frequency based vector. Increasing the weighting of relevant appraisal items, a classifier setting was introduced that increases the weight of features which were marked as appraisal items during the annotation process by a configurable factor which defaults to 1.7. The up-weighting of appraisal items is an idea borrowed from Liang (2006), who was able to improve classification results on sentiment in movie reviews by up-weighting the relevance of adjectives.

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Table 2. Overview and evaluation of classifier settings

Setting	Base Classifier	Feature Type	Appraisal Boost	MAP	MR
Setting 1	Naïve Bayes	binary	X	46.59%	47.58%
Setting 2	Naïve Bayes	TF/IDF	X	45.53%	46.20%
Setting 3	Naïve Bayes	frequency	X	49.26%	49.70%
Setting 4	Naïve Bayes	TF/IDF	1.7	45.98%	45.63%
Setting 5	Naïve Bayes	frequency	1.7	49.72%	48.92%
Setting 6	Logistic Regression	binary	X	48.59%	49.82%
Setting 7	Logistic Regression	TF/IDF	X	44.63%	46.33%
Setting 8	Logistic Regression	frequency	X	50.24%	52.04%
Setting 9	Logistic Regression	TF/IDF	1.7	48.92%	47.72%
Setting 10	Logistic Regression	frequency	1.7	51.46%	50.92%

In the configuration to classify the Sydney Siege dataset of this study a multinomial logistic regression classification approach was used which was utilizing a frequency 'bag of words model' with an up-weighting of appraisal items (setting 10). The setting was identified through 10-fold cross-validation (Burman 1989) and comparison of the mean average precision (MAP), i.e. the averaged proportion of correct classifications in all classifications per fold over all folds and all iterations, and the mean recall (MR) of each setting. The latter is a metric which is used in information retrieval to describe the proportion of retrieved relevant documents to the total amount of relevant documents (Goel and Yadav 2012).

Visualization of Appraisal in Space and Time

The visualization tool helps to analyze the sentiment of an event through the location and time of the event. The left-hand side panel of Figure 3 (a) shows a set of controls that are used to operate the visualization component of the prototype. Corpora for different events can be selected, and maps can be centered on different parts of the world for example Australia, Europe, United Kingdom, or the United States. Another control in this panel displays the chronology of the event. Significant events that have been entered into the system can be displayed in chronological order. The Twitter traffic associated with these events can be shown on the tweet appraisal map on the right-hand panel of Figure 3 (a). Controls can be used to select a time/date interval of interest, for example only the daytime hours, and this selection in turn is used for displaying only those classified tweets that were communicated during the selected interval. The temporal unfolding of the event, as revealed through its tweets, can be animated. This visualization reveals the extent to which this siege captured a great deal of international media exposure.

Various metrics can be displayed on the right-hand side panel as a visualization. The first of these is provided by showing aggregated data for the overall dataset or a region, or the data for a specific location on a map, Figure 3 (b). The display is in the form of a pie chart that shows the proportion of tweets classified according to the appraisal system (breakdown of categories and an associated key), a proportional timeline that shows the change over time, the percentage of different categories of tweet appraisal, and the actual classified tweets themselves. Figure 3 (c), shows the possibility to look into the actual Tweets and their appraisal category. The findings of the analysis of the Sydney Siege tweet corpus are provided in the next section.

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(a)

(b)   **(c)**

Figure 3. Global visualization of different appraisal categories over time (Sydney Siege 2014)

FINDINGS

The examined dataset included 50,670 geotagged Tweets. With the help of the prototype we manually coded 792 Tweets according to the appraisal framework. These classified Tweets were used to train the prototype and subsequently preliminary classify the entire dataset. The prototype and several keyword filters were then used to analyze the Sydney Siege dataset.

All of the Tweets in the dataset are geocoded and this permits an analysis of the communicative behavior of citizens in specific regions and countries over time. However, the dataset was limited to Tweets in which the language setting of the individual users was English. This resulted in a higher Tweet activity from countries in which English is predominantly spoken and excludes other countries.

While the dataset included Tweets from all over the world, in this paper we focus on the Australian perspective. In particular, we are analyzing four facets of the Twitter communication behavior accompanying the Sydney Siege extreme event:

- Overall Sentiment - Australia;
- Sentiment towards Victims - Australia;
- Sentiment towards Islam - Australia;
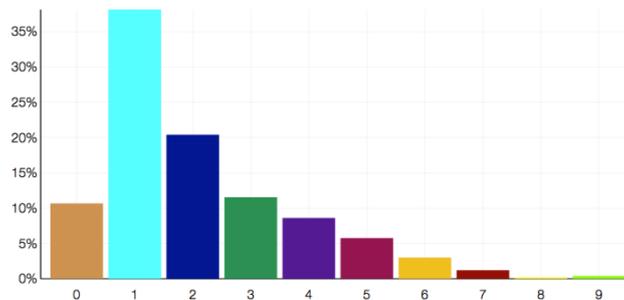- and Sentiment around #Illridewithyou - Australia.

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Overall Sentiment - Australia

As shown in Figure 4, the Twitter communication in Australia peaked shortly after noon of the 15th of December and then decreased over the subsequent development of the event. In contrast to the behavior in Australia, the Twitter communication in the overall dataset increases over time. We can account for these contrasting patterns through the assumption that most people in Australia went to bed before the major event changes occurred. The police were forced to storm the café shortly after 2 am. At 2:44 am local time the Siege was declared over. This resulted in a small increase of the Twitter communication in Australia. Communication participants at other parts of the world were at this time awake and commented much more about the extreme event. In Australia, the communication increased again after people were waking up.
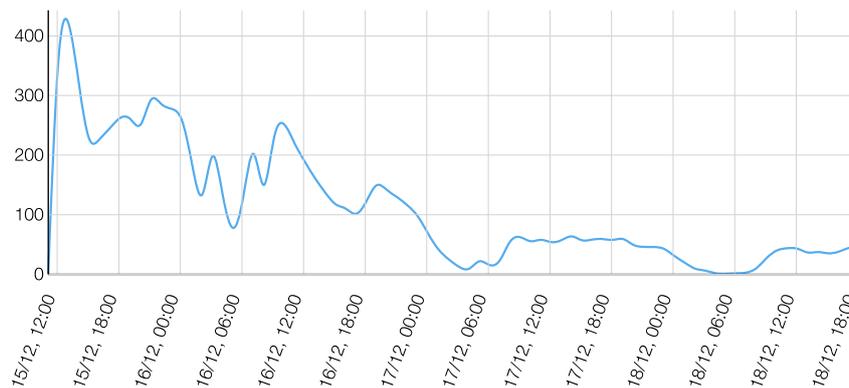
Figure 4. Hourly tweet rates in Australia, December 15 - 18

The distribution of the appraisal categories of the overall Australian dataset is shown in Figure 5. The most dominant appraisal categories in Australia were "Appreciation" in form of a "positive reaction" followed by "Affect" in form of "Insecurity" and "Security", and "Judgement" in form of a "negative social sanction". At first it sounds counterintuitive that such an overwhelmingly negative extreme event would create a lot of positive reactions. However, a deeper investigation into the content of the Tweets reveals that the positive reactions were given in the form of emotional support and the expression of hope for a positive outcome in the short term.

Figure 5. Overall sentiment proportions - Australia

Figure 6 shows the proportion of the sentiment over time. While the event was unfolding "negative social sanctions" are most dominant, closely followed by the "positive reactions" towards the event. Before the situation needed to be resolved by force there was a high level of "positive reactions" in the Tweets. A closer investigation into these types of Tweets revealed that they were in the form of emotional support and the hope that the situation could be resolved without a further escalation. The moment the situation changed and the police needed to storm the café, the reaction turned mostly into "Judgement" in form of "negative social sanctions". In the aftermath of the event most Tweets were classified towards "Appreciation" in form of "positive reactions". Most of these tweets were some derivation of "*praying for the victims*".
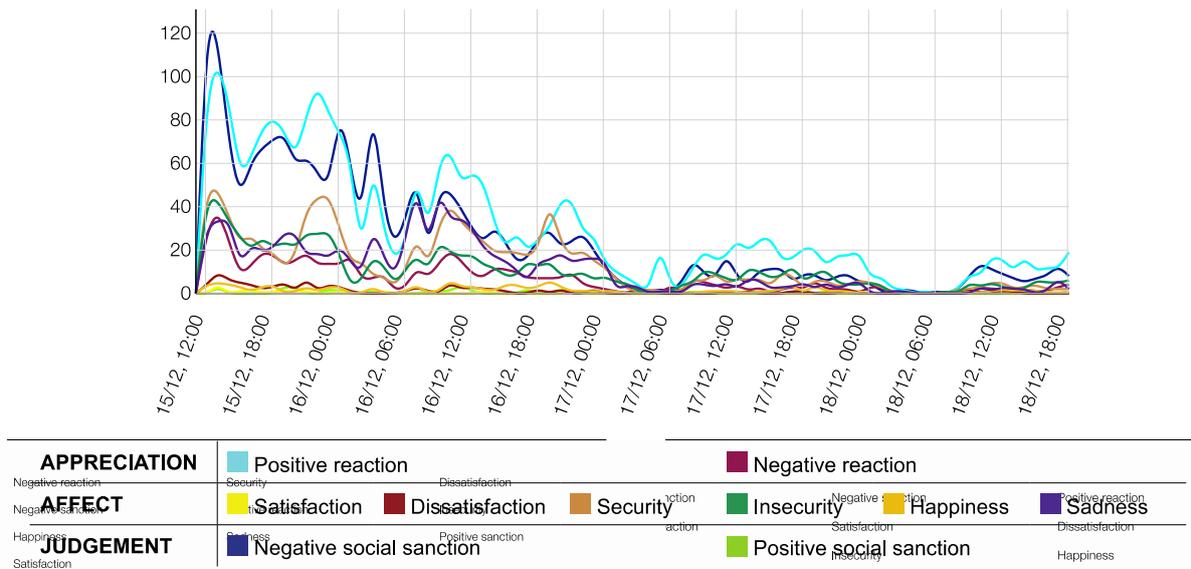
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Figure 6.   **Hourly sentiment rates in Australia, December 15 – 18**

SENTIMENT TOWARDS VICTIMS - AUSTRALIA

To explore the sentiment towards the casualties of the event, we filtered for Tweets that included at least one of the following keywords: "Katrina Dawson", "lawyer", "Tori Johnson", "innocent", and "funeral" (the names are those of the victims). As shown in Figure 7, the Appraisal categories reveal that the sentiment regarding the killed hostages comprised a high level of "Affect" in form of "Sadness" and "Insecurity", as well as "Appreciation" in the form of "positive reactions" and "Judgement" in form of "negative social sanctions". It is not surprising that the proportion of messages that express "sadness" in this subset of the data is more than double that in the overall dataset. The frequent "positive reactions" can be explained through prayers for the victims and expression of emotional support for the families. The negative social sanctions show the resentment against the event.
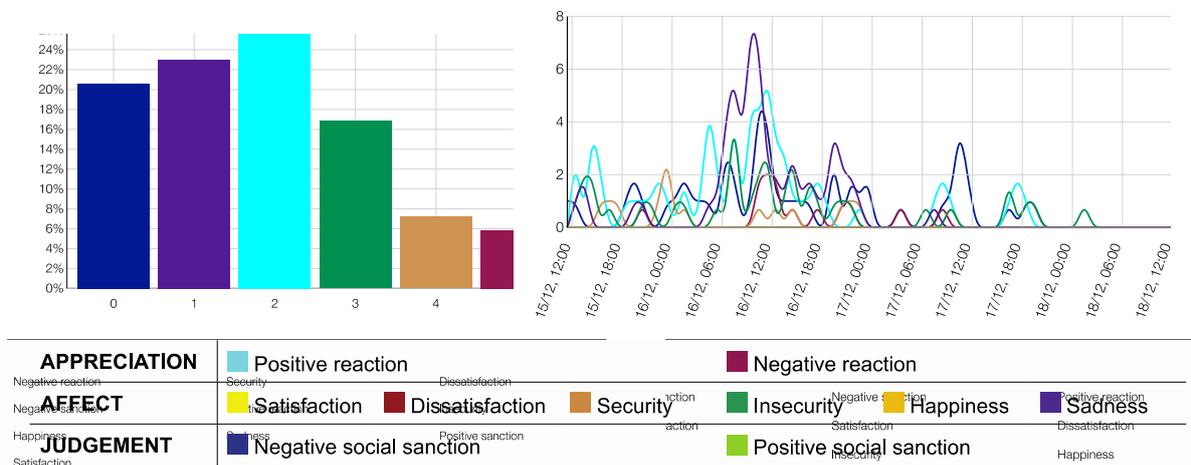

Figure 7. Sentiment proportions towards victims – Australia

More surprising in this specific subset, is the higher proportion of insecurity especially in the morning after the event. "Insecurity" in the Appraisal framework is a representation of fear that is expressed through these Tweets and might serve as a potential explanation for the observed pattern.

SENTIMENT TOWARDS ISLAM - AUSTRALIA

To filter for Tweets related to a sentiment towards Islam we applied the neutral keywords "Islam", "Muslim", "Koran", "Quran", "Qur'an", and "Allah". We intentionally excluded negative connoted Tweets which included the keywords "ISIL", "ISIS", "terror", "jihad", and "djihad". Figure 8 shows that the resulting sentiment proportions is negative and categorized under "negative social sanction" and are a form of "Judgement" in the appraisal framework.

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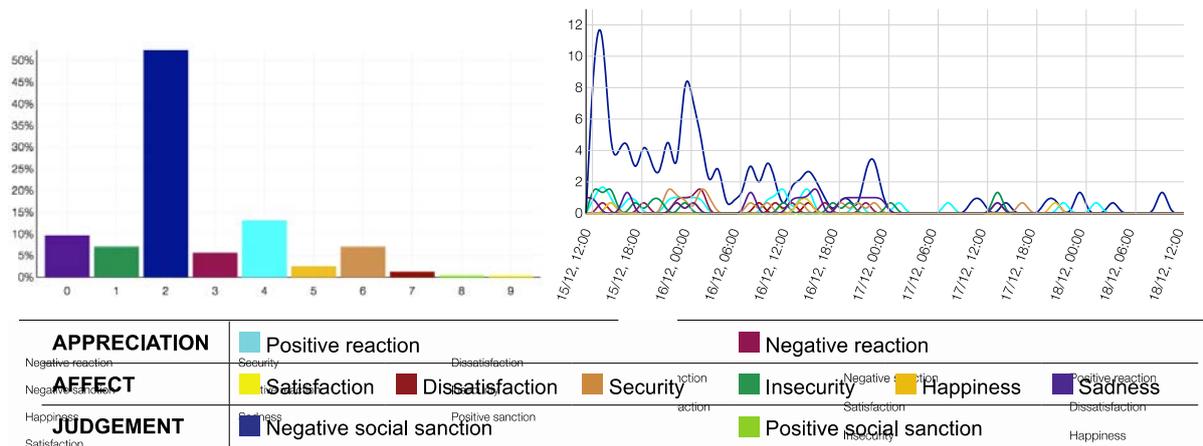|			
APPRECIATION	Positive reaction		Negative reaction
AFFECT	Satisfaction	Dissatisfaction	Security	Insecurity	Happiness	Sadness
JUDGEMENT	Negative social sanction		Positive social sanction

Figure 8. Sentiment proportions towards Islam - Australia

A closer examination of the relevant Tweets reveals three main groups. The first group are individuals who anticipate that Muslims will be demonized and they communicate their disapproval towards this kind of behavior. An example of such a Tweet is *"The people holding hostages in Sydney do not in any way represent all Muslims, and hating them for the act of a minority is wrong"*. The second group consists of Muslims who distance themselves and their religion from the gunman and his action. The last group are individuals who show anger towards Islam and attempt to spread hate; for example: *"Why is it that all terrorists are of a particular faith #sydneysiege #morningexpress"*.

SENTIMENT AROUND #ILLRIDEWITHYOU – AUSTRALIA

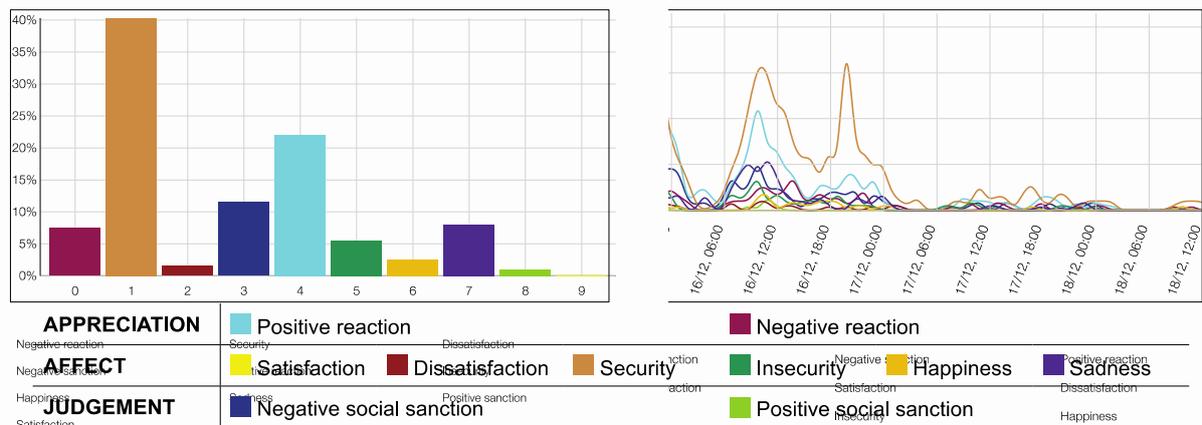|			
APPRECIATION	Positive reaction		Negative reaction
AFFECT	Satisfaction	Dissatisfaction	Security	Insecurity	Happiness	Sadness
JUDGEMENT	Negative social sanction		Positive social sanction

Figure 9. Sentiment proportions towards #Illridewithyou – Australia

The last pattern considered here is the hashtag #Illridewithyou. The hashtag emerged in Australia and was then picked up worldwide to support and build community cohesion as well as opposing any fear concerning Muslims during the Sydney Siege and its immediate aftermath. The hashtag started as a result of a Facebook post in which a user reported that a distressed Muslim woman was removing her hijab on public transport (ABC 2014). The Facebook user told her to put it back on and that they would travel together for safety. Following the Facebook post, a Twitter user offered to ride with Muslims who were using a specific bus line and who feared reprisals or hostility based on their religion. This Twitter user suggested the hashtag "#illridewithyou" and this immediately went viral. In our corpus, this hashtag showed a high level of use during the Sydney Siege and in the two days after the event. As shown in Figure 9, "Affect" in form of "Security" and "Appreciation" in form of "positive reactions" dominates the Tweets that included the #illridewithyou hashtag. An exemplar Tweet employing this hashtag was *"Praying for the safe release of the #sydneysiege victims, C'mon Aussies, of all religions, we will all stick together #illridewithyou"*.

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DISCUSSION AND CONCLUSION

Our study involved a corpus of 50,670 Tweets collected during the Sydney Siege with a view to developing and applying a for extreme event social media communication new class of social media sentiment analysis (using Appraisal resources) developed within a functional and semantic theory of communication (Systemic Functional Linguistics). The analysis utilized the appraisal system and revealed patterns that would have stayed invisible with a pure polarity measuring sentiment analysis approach. At first, some of the observed patterns seemed counterintuitive to what would have been expected to see in such an extreme event. It was assumed that the communication would be categorized negatively with an overall high degree of sadness and judgement. In fact, the unexpected result was that a high proportion of Australian Tweets were classified with a "positive reaction" towards the event. A closer investigation of the relevant Tweets revealed that this behavior could be explained through statements of 'hopes and prayers' for a positive outcome of the event. While the event created a noticeable amount of fear ("insecurity") in the communication, an equal amount of the tweets involved attempts to comfort ("security") users of the social media platform. Attempts to build solidarity, comfort and security were especially prominent with the #illridewithyou subset of the data.

Unexpectedly there was a relatively low amount of anti-Muslim sentiment within the tweets of the Australian cohort. A more detailed analysis of the tweets with neutral Islam related keywords nonetheless showed a high amount of Judgement in form of "negative social sanctions". However not all of these Tweets were against Muslims or Islam in general, some of them showed resentment toward, and condemnation of, racism directed at members of the Muslim community because of the actions of one individual. Also, these Islam related Tweets did not show a high amount of "insecurity" that would have indicated fear.

Another surprising result was the development of hashtags and associated societal action like the #illridewithyou hashtag that actively promoted the support of Muslim women on public transport who chose to wear Islamic identified garments. This kind of sentiment promoted inclusive community cohesion evident in the "security" category in the Appraisal Framework. This movement generated a noticeable amount of Tweets especially in the two days following the hostage situation. The communication regarding Islam was prominent both during the event and for a day after.

The communication around the two casualties of the event showed a relatively equal distribution "positive reactions" in form of prayers and expression of emotional support, "negative social sanctions", "sadness" and "insecurity". While we were expecting the former categories, the high amount of fear ("insecurity") in the messages was unexpected.
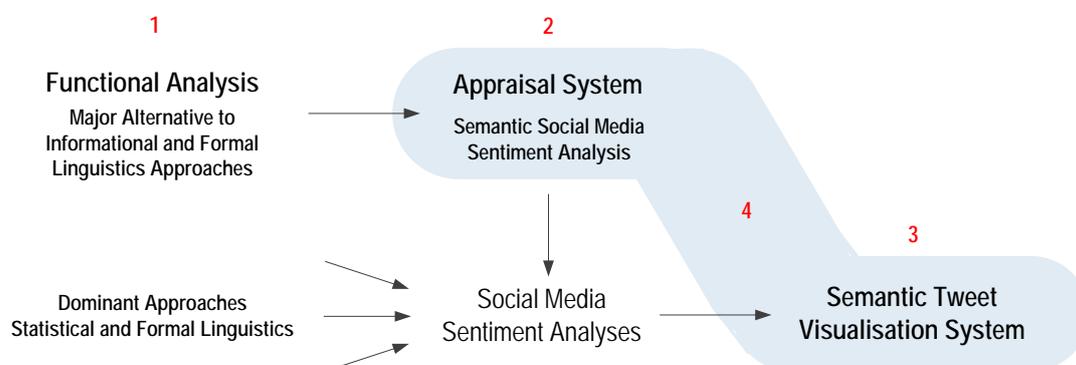
Figure 10. Functional Analysis using Appraisal together with global visualization

These results while interesting would not have been possible without a substantial change to the kind of approach used to determine the sentiment associated with these Tweets. The major and distinct theoretical contribution arising out of this study is the application of a functional linguistics to social media sentiment analysis (see 1 in Figure 10). A methodological contribution to social media sentiment analysis is the use of appraisal resources to identify different types of interpersonal assessment (see 2 in Figure 10). Another methodological contribution of this study includes the ability to visualize the semantics of social media messages over space and time, specifically the meanings associated with reactions to a crisis event (see 3 in Figure 10). The world of functional linguistics is a world centered on meanings in social and institutional settings. The detailed training necessary to understand these ideas is not usually available to computer scientists, likewise the disciplines of text mining classification and visualization is not usually accessible to those who study social systems. Much of the knowledge we have acquired conducting this research lies at the bridges we built between these worlds (see 4 in Figure 10), which needs to be further explored in ongoing research.

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REFERENCES

ABC-News. 2014. "Sydney Siege: What We Do and Don't Know About Hostage Situation in Martin Place." from http://www.abc.net.au/news/2014-12-15/sydney-siege-what-we-know/5967610

Bakliwal, A., Foster, J., van der Puil, J., O'Brien, R., Tounsi, L., and Hughes, M. 2013. "Sentiment Analysis of Political Tweets: Towards an Accurate Classifier," Association for Computational Linguistics.

Burman, P. 1989. "A Comparative Study of Ordinary Cross-Validation, V-Fold Cross-Validation and the Repeated Learning-Testing Methods," *Biometrika* (76:3), pp. 503-514.

Ceron, A., Curini, L., Iacus, S. M., and Porro, G. 2014. "Every Tweet Counts? How Sentiment Analysis of Social Media Can Improve Our Knowledge of Citizens' Political Preferences with an Application to Italy and France," *New Media & Society* (16:2), pp. 340-358.

Chatfield, A. T., Scholl, H. J., and Brajawidagda, U. 2014. "#Sandy Tweets: Citizens' Co-Production of Time-Critical Information During an Unfolding Catastrophe," *System Sciences (HICSS), 2014 47th Hawaii International Conference on*, pp. 1947-1957.

Clarke, R. 2001. "Studies in Organisational Semiotics: An Introduction," *Australasian Journal of Information Systems* (8:2).

Clore, G. L., and Huntsinger, J. R. 2007. "How Emotions Inform Judgment and Regulate Thought," *Trends in Cognitive Sciences* (11:9), pp. 393-399.

Commonwealth of Australia. 2015. *Martin Place Siege: Joint Commonwealth – New South Wales Review*. Canberra, Australia:

Cronbach, L. J., and Meehl, P. E. 1955. "Construct Validity in Psychological Tests," *Psychological Bulletin* (52:4), pp. 281-302.

Das, S. R., and Chen, M. Y. 2007. "Yahoo! For Amazon: Sentiment Extraction from Small Talk on the Web," *Management Science* (53:9), pp. 1375-1388.

Eggins, S. 2004. *An Introduction to Systemic Functional Linguistics*, (2nd. ed.). New York: Continuum.

Fallon, D. 2014. "Lindt Chocolat Cafe Hostage Drama in Martin Place, Sydney."   Retrieved 10.06, 2015, from http://www.smh.com.au/nsw/lindt-chocolat-cafe-hostage-drama-in-martin-place-sydney-20141215-1278cx

Fraustino, Daisy, J., Liu, B., and Jin, Y. 2012. "Social Media Use During Disasters: A Review of the Knowledge Base and Gaps," Final Report to Human Factors/Behavioral Sciences Division, Science and Technology Directorate, U.S. Department of Homeland Security. College Park.

Goel, S., and Yadav, S. 2012. "An Overview of Search Engine Evaluation Strategies," *International Journal of Applied Information Systems* (1), pp. 7-10.

Halliday, M. A. K. 1985. *An Introduction to Functional Grammar*. London: Edward Arnold.

Hughes, A. L., and Palen, L. 2009. "Twitter Adoption and Use in Mass Convergence and Emergency Events," *International Journal of Emergency Management* (6:3-4), pp. 248-260.

Jansen, B. J., Zhang, M., Sobel, K., and Chowdury, A. 2009. "Twitter Power: Tweets as Electronic Word of Mouth," *Journal of the American society for information science and technology* (60:11), pp. 2169-2188.

Jeannette, S., Emma, S., Carter, B., Sean, F., Britta, J., and Matt, G. 2013. "Tweeting the Spill: Online Informal Communications, Social Networks, and Conversational Microstructures During the Deepwater Horizon Oilspill," *International Journal of Information Systems for Crisis Response and Management (IJISCRAM)* (5:1), pp. 58-76.

Liang, A. 2006. "Rotten Tomatoes: Sentiment Classification in Movie Reviews," *CS* (229), p. 15.

Liu, F., Burton-Jones, A., and Xu, D. 2014. "Rumors on Social Media in Disasters: Extending Transmission to Retransmission," *PACIS 2014*.

Martin, J. R. 1992. *English Text: System and Structure*. John Benjamins Publishing.

Martin, J. R., and Rose, D. 2007. *Working with Discourse: Meaning Beyond the Clause*, (Second ed.). London: Continuum.

CoRe Paper – Social Media Studies
Proceedings of the 15th ISCRAM Conference – Rochester, NY, USA May 2018
Kees Boersma and Brian Tomaszewski, eds.

Martin, J. R., and White, P. R. 2005. *The Language of Evaluation: Appraisal in English*. Palgrave Macmillan: New York.

Medhat, W., Hassan, A., and Korashy, H. 2014. "Sentiment Analysis Algorithms and Applications: A Survey," *Ain Shams Engineering Journal* (5:4), pp. 1093-1113.

Montoyo, A., Martínez-Barco, P., and Balahur, A. 2012. "Subjectivity and Sentiment Analysis: An Overview of the Current State of the Area and Envisaged Developments," *Decision Support Systems* (53:4), pp. 675-679.

Morinaga, S., Yamanishi, K., Tateishi, K., and Fukushima, T. 2002. "Mining Product Reputations on the Web," *Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining*: ACM, pp. 341-349.

Mostafa, M. M. 2013. "More Than Words: Social Networks' Text Mining for Consumer Brand Sentiments," *Expert Systems with Applications* (40:10), pp. 4241-4251.

Oh, O., Agrawal, M., and Rao, H. R. 2013. "Community Intelligence and Social Media Services: A Rumor Theoretic Analysis of Tweets During Social Crises," *Mis Quarterly* (37:2), pp. 407-426.

Ralston, N., and Partridge, E. 2014. "Martin Place Siege Being Treated as Terrorist Attack, Police Confirm." Retrieved 10.06, 2015, from http://www.smh.com.au/nsw/martin-place-siege-being-treated-as-terrorist-attack-police-confirm-20141215-127mh5

Safi, M. 2015. "Sydney Siege Inquest: Katrina Dawson Killed by Fragments of Police Bullets – as It Happened." from http://www.theguardian.com/australia-news/live/2015/jan/29/sydney-siege-coroners-inquest-rolling-report#block-54c9677be4b089fc37336577

Sampson, G. 1980. *Schools of Linguistics*. Stanford University Press.

State Coroner of NSW. 2017. "Inquest into the Deaths Arising from the Lindt Café Siege - Findings and Recommendations." from http://www.lindtinquest.justice.nsw.gov.au/Documents/findings-and-recommendations.pdf

Sutton, J., Palen, L., and Shklovski, I. 2008. "Backchannels on the Front Lines: Emergent Uses of Social Media in the 2007 Southern California Wildfires," *Proceedings of the 5th International ISCRAM Conference*: Washington, DC, pp. 624-632.

Sutton, J. N., Spiro, E. S., Johnson, B., Fitzhugh, S. M., Greczek, M., and Butts, C. T. 2012. "Connected Communications: Network Structures of Official Communications in a Technological Disaster." *Proceedings of the 9th International ISCRAM Conference*

Unankard, S., Li, X., Sharaf, M., Zhong, J., and Li, X. 2014. "Predicting Elections from Social Networks Based on Sub-Event Detection and Sentiment Analysis," in *Web Information Systems Engineering–Wise 2014*. Springer, pp. 1-16.

Westerman, D., Spence, P. R., and Van Der Heide, B. 2014. "Social Media as Information Source: Recency of Updates and Credibility of Information," *Journal of Computer-Mediated Communication* (19:2), pp. 171-183.

Yu, Y., and Wang, X. 2015. "World Cup 2014 in the Twitter World: A Big Data Analysis of Sentiments in Us Sports Fans' Tweets," *Computers in Human Behavior* (48), pp. 392-400.

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