MEASURING SOCIAL MEDIA: BENCHMARKING AN INDIVIDUAL TWITTER TIMELINE

Dr Stephen

About our Speaker
Dr Stephen Dann is a Senior Lecturer in the School of Management, Marketing and International Business, College of Business and Economics at the Australian National University. He has been recognized as one of world’s senior social marketing researchers by the National Centre for Social Marketing (UK). His research has been published in Social Marketing Quarterly, Monash Business Review, Quality Assurance in Education, Journal of Public Affairs, Marketing Theory and Journal of Business Research. He has published a range of marketing text books including eMarketing, Competitive Marketing Strategy and is a regular contributor to the Australian and New Zealand Marketing Academy Conference. His research interests include social marketing, consumer behaviour, internet marketing, marketing strategy, and innovation adoption.

Dr Stephen Dann
Senior Lecturer, Marketing
School of Management, Marketing & International Business
ANU College of Business & Economics
The Australian National University
Canberra ACT 0200 Australia
Stephen.dann@anu.edu.au
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

This paper outlines a method of converting Twitter content into useful numerical data that can be applied in a range of metric, measurement and planning purposes. The method outlined acknowledges the organic nature of Twitter account use in practice, the interplay between the organizational objectives of the account holder, and the conversational nature of the platform. The measurement technique focuses on the production of an introspective corporate assessment of the historical use of the individual account timeline, and as such, is a novel approach to benchmarking that examines how a Twitter account has been used in practice, with a content based analysis process that contextualizes the conversation into categorical structures that in turn can form the basis of future strategic and tactical decisions.

The paper consists of six parts – a brief history of Twitter use, an outline of the method of Twitter analysis, details of the analysis procedure including the coding framework, the method of analysis including procedure for data collection, results and the implications from the findings. The paper uses data from three accounts heavily engaged in the Queensland extreme weather events - Brisbane City Council (@brisbanecityqld), Queensland Police (@QPSMedia) and Energex (@energex) – to demonstrate the functionality of the account analysis protocols. The collected data period covers the extreme weather events of the Brisbane Floods, the interim disaster recovery periods between flood and cyclone, and the Severe Tropical Cyclone Yasi (#TCYasi). Using these periods as interval measures, it is possible to apply the benchmark to demonstrate shifts in account use, communication style and messaging strategy during the weather events to respond to the needs of the community.

A Brief history of Twitter

Twitter was founded in 2006 as a group broadcasting platform for short messages, and has developed into a global communications network, micro-blogging and lifestreaming platform. Corporate use of the service has varied from highly successful through to abject failure, and all combinations between. Prior studies in Twitter have examined best practice use of the service, public timeline content analysis, consumer interaction dynamics and end user research.

Best practice papers have focused on anecdotal evidence and limited case studies which cast the role of Twitter as a platform for engagement for organization such as public libraries (Cahill 2009), or as a social communications platform for political campaigns (Cetina 2009), civil unrest and protests (Fahmi 2009) and social activism (Galer-Uni 2009). Related to the idea of the communications network as a citizen empowerment technology has been work on Twitter as a form of journalism platform for the live coverage of major events (Gay et al 2009) and eyewitness accounts of breaking news stories (Lariscy et al 2009) or detection of natural disasters such as forest fires (Longueville et al 2009) or earthquakes (Okazaki and Matsuo 2010).

Public timeline analysis has approached Twitter as a form of sentiment collection engine that captures public opinion on a large scale. Referred to as the “age of big data” by Dodds et al (2011), these types of research studies apply large scale automated content analysis of the public timeline
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

date for insight into the real life application of Twitter (Zhao and Rosson 2009; Java et al 2007). Work has also focused on specific behavioural patterns with Twitter such as the use of hashtags to create temporary communities of content (Lariscy et al 2009; Gay et al 2009; boyd et al 2010). Recent studies have also applied predictive modeling technologies to large scale sentiment analysis to use Twitter as a social barometer (Bollen et al 2009, Thelwall et al 2011) and predictive insight platform (Bollen et al 2011). These studies work on the premise of Twitter as a data set that can be accurately described as a holistic unit through selectively sampled analysis. However, limitation in both sampling (English language tweets only) and coding (automated machine coding for several million tweets) restrict the applicability of these studies.

Consumer interaction dynamics research has focused on the follower/following count as a measure of account behaviours (Java et al 2007; Krishnamurthy et al 2008). Additional studies focus on the application of Twitter as an interpersonal and group communication tool through the use of the @ symbol (Pear Analytics, 2009; Java et al 2007; Jansen et al, 2009; Naaman et al 2010; Honeycutt and Herring, 2009). Studies have also examined the message endorsement and message relay through the “retweet” protocol (RT) Java et al 2007; Pear Analytics, 2009; Naaman et al 2010; boyd et al 2010.

Consumer research is emerging from a marketing perspective as to the consumption of Twitter as a service product through end user motive research which likens Twitter to radio as a casual listening platform (Crawford 2009), a means for creating an illusion of physicality (Hohl 2009), a sense of connectedness with others (Henneburg et al 2009), and as a venue for conversation (Steiner 2009). Other studies have looked at the consumption of Twitter as a broadcast platform for consumer to consumer conversations (Efron 2011) and as a platform to report daily life to connected friends to maintain a sense of community and connectedness over distance (Fernando 2010).

A Current Project

The paper outlines the testing and refinement of the Dann (2010) Twitter content analysis framework for use as a third party audit system for assessing Twitter account activity between time periods. This is an extension of the prior work which focused on the use of the account for a single personal timeline over the length of the account history.

The paper addresses two research questions

RQ1: Can the coding framework be used to assess a third party timeline operated by multiple users?
RQ2: Can the data produced from the analysis method be used to detect patterns in timeline content production?

B Method

The breadth and depth of the existing literature on Twitter consumption and use indicates that any model, framework or methodology for analysis will need to be both robust and versatile to be able to
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

be adapted to the environment it seeks to describe. The method presented in this paper is an extension and improvement of a prototype published in Dann (2010) which was developed as a proof of concept that content classification could be applied to an individual Twitter account's timeline data. The timeline analysis approach was developed to supplement the large scale data sets approach with an analysis framework suited to classify an individual timeline as a measurement system to benchmark the performance of their Twitter use over time. The outline below extends the original Dann (2010) historical timeline analysis by testing its application in measurement and observation of community practice during crisis events, and crisis communications. The method is based on qualitative content analysis using a preset coding structure balanced by the grounded theory approach that allows for alteration to the categories, and increased numbers of subcategories based on patterns and trends emerging from the data set. The ground theory approach was chosen both for the academic pedigree in research literature, and for the robust nature of the approach in dealing with evolving requirements identified in the research process.

B The Framework

The paper outlines a revised and revisited content classification framework based on the existing work from Dann (2010) who applied a qualitative content analysis to his own personal twitter timeline. This paper extends the prior work by applying the content classification to third party accounts where contextual information about the intention and meaning of a tweet is unavailable to the researcher. The Dann (2010) Twitter Analytics framework is based on prior studies by Java et al 2007; Jansen et al 2009; Pear Analytics, 2009; Honeycutt and Herring 2009 and Naaman et al 2010, all of which analyzed large volumes of Twitter public timeline content to generate classification schemes to predict the use of Twitter at the aggregate level. For this study, an extensive review of existing literature on Twitter use, analysis and application was undertaken to expand and enhance support for each of the categories and sub categories of the original Dann (2010) framework. Table 1 is a summary overview of the six top level content frameworks, their sub classifications, definition of each type and the supporting references for each classification category.
### Table 1: Content Categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Supporting References</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1 Conversational</strong></td>
<td>Uses an @statement to address another user</td>
<td>Cahill 2009, Cranefield and Yoong 2009, Honeycutt and Herring 2009, Java et al 2009, Perlmutter 2009, Steiner 2009, Ratkiewicz 2010</td>
</tr>
<tr>
<td>1.1 Action</td>
<td>Activities involving other Twitter users, or tweets which describe the presence of other Twitter users.</td>
<td>Hohl 2009, Honeycutt and Herring 2009, Jansen et al 2009, Efron 2011</td>
</tr>
<tr>
<td>1.3 Referral</td>
<td>@response which contains URLs or recommendation of other Twitter users. (Excludes RT @user)</td>
<td>Honeycutt and Herring, 2009, Pear Analytics, 2009, Naaman et al 2010, Ratkiewicz 2010, Efron 2011</td>
</tr>
<tr>
<td>2.1 Announcement</td>
<td>Announcement of a forthcoming event including dates, venue or location, but without links or URLs.</td>
<td>Mischand 2007, Cahill 2009, Henneburg et al 2009, Doherty 2010, Jackson and Lilleker 2011</td>
</tr>
<tr>
<td>2.2 Hashtagged Event</td>
<td>Any tweet which represents the live discussion of an identified or identifiable event such as a conference, live television or live event collected under a consistent #hashtag</td>
<td>Cuddy 2009, Lariscy et al 2009, Gay et al 2009, Phelan et al 2009, Dann 2010, Efron 2011, Rath 2011</td>
</tr>
</tbody>
</table>
# Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Supporting References</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>descriptive recount without overt opinion or comment</td>
<td></td>
</tr>
<tr>
<td>2.4 Sport</td>
<td>Identifiable results of sporting events. Factual or descriptive recount</td>
<td>Java et al 2007, Pear Analytics, 2009</td>
</tr>
<tr>
<td></td>
<td>without overt opinion or comment</td>
<td></td>
</tr>
<tr>
<td>disaster</td>
<td>related extreme weather events</td>
<td></td>
</tr>
<tr>
<td>2.6 Transport</td>
<td>Traffic, transport, flight, road or rail related announcements including</td>
<td>Parslow 2009, Sakaki et al 2010</td>
</tr>
<tr>
<td></td>
<td>delays, accidents, postponements or other details of schedule changes</td>
<td></td>
</tr>
<tr>
<td>3.1 Automated</td>
<td>Status announcements triggered by third party applications which also publish</td>
<td>Honeycutt and Herring, 2009, Chu et al 2010</td>
</tr>
<tr>
<td>Endorsement</td>
<td>the URLs of content</td>
<td></td>
</tr>
</tbody>
</table>
### Category | Description | Supporting References
--- | --- | ---

3.4 Secondary Social Media | Links to Facebook (fb.me) or similar social media platform content created by the account owner | Butcher 2010

3.5 User generated content | Links to own content created by the user including use of third party photo or video hosting, or identifiable blog posts, or content. | Honeycutt and Herring 2009, Pear Analytics 2009, Butcher 2010, Dong et al 2010, Naaman et al 2010


4.2 Fourth wall | Textual equivalent of comments made directly to camera in television or cinema | Honeycutt and Herring 2009, Marwick and boyd 2010

4.3 Greetings | Statements of greetings to the broader Twitter community, including emotional connections with the audience, well wishes, congratulations or thanks. | Miller, 2008, Hohl 2009, Honeycutt and Herring, 2009, Java et al 2009, Naaman et al 2010


5 Status | Tweets which address the statement "What are you doing?" and "What's | Gaonkar et al 2008, Bollen et al 2009, Java et al 2009, Chu
# Measuring Social Media: Benchmarking an Individual Twitter Timeline

**Stephen Dann, Australian National University**

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Supporting References</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>happening?</strong></td>
<td><em>in terms of an account holder’s experiences</em></td>
<td>et al 2010, Dodds et al 2011, Naaman et al 2010, Zhang et al 2010</td>
</tr>
<tr>
<td><strong>5.1 Activity</strong></td>
<td>Activity statements answering “What are you doing now?”</td>
<td>Mischaud 2007, Honeycutt and Herring 2009, Chu et al 2010, Marwick and boyd 2010, Naaman et al 2010</td>
</tr>
<tr>
<td><strong>5.2 Automated</strong></td>
<td>Status announcements triggered by third party applications which do not contain a URL</td>
<td>Dann (2010)</td>
</tr>
<tr>
<td><strong>5.3 Location</strong></td>
<td>Geographic references and location statements. Addresses a question of “Where are you?”</td>
<td>Longueville et al 2009, Makice, 2009, Naaman et al 2010</td>
</tr>
<tr>
<td><strong>5.4 Mechanical</strong></td>
<td>Statements relating to any form of technology or mechanical systems</td>
<td>Mischaud 2007</td>
</tr>
<tr>
<td><strong>5.6 Physical</strong></td>
<td>Sensory experiences of a physical nature which cover the “What are you physically experiencing?” rather than “What are you feeling emotionally?”</td>
<td>Mischaud 2007, Naaman et al, 2010, Dodds et al 2011, Sullivan et al 2011</td>
</tr>
<tr>
<td><strong>5.7 Temporal</strong></td>
<td>Statements of temporal nature (waiting) and temporal action (“Time to”)</td>
<td>Longueville et al 2009, Marwick and boyd 2010, Naaman et al 2010</td>
</tr>
<tr>
<td><strong>6.1 Administered Malcontent</strong></td>
<td>Links to malware or related hostile websites</td>
<td>Chu et al 2010</td>
</tr>
</tbody>
</table>
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Supporting References</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.2 Keyword response</td>
<td>Automated context free responses to keywords and brands</td>
<td>Chu et al 2010</td>
</tr>
<tr>
<td>6.3 Mention</td>
<td>Replies using the @ command from accounts which do not follow the user, and which only send @ replies to other unfollowed accounts</td>
<td>Grier et al 2010</td>
</tr>
<tr>
<td>6.4 Trend hijacking</td>
<td>One or more #hashtags of trending events in a tweet unrelated to the trend</td>
<td>Grier et al 2010, Zhou et al 2010</td>
</tr>
<tr>
<td>6.5 Truthiness</td>
<td>Astroturfing message originating from an automated account.</td>
<td>Ratkiewicz 2010</td>
</tr>
</tbody>
</table>

The framework has been extended from Dann (2010) as a response to content elements that were presented by commercial and government Twitter use that were not present in content from individual, personal or character accounts. These extensions are based on the grounded theory approach of extending the classifications based on the content and context of the data – for example, the “News – Transport” was developed based on @QPSMedia and @Brisbanecityqld reports of traffic accidents, delayed public transport and blocked roads. The extensions are noted in context of the details of the six categories outline below.

B Conversational

*Uses an @statement to address another user*

The conversational category is the social interaction between Twitter users (Perlmutter 2009). There are four sub-categories incorporating action, query, referral and response. Action is the rhetorical presence of the other user which creates an illusion of physicality between twitter users (Hohl 2009; Jansen et al 2009), and acknowledges a connection (physical, social or temporal) with other participants on Twitter (Cranefield and Yoong 2009, Efron 2011). Query is the active engagement in information seeking from the community by broadcasting questions (Mischaud 2007; Cahill 2009, Efron, 2011, ), opinion seeking (Jackson and Lilleker 2011), advice seeking (Wilson 2008), conversation starting (Zhang et al 2010) or other use of tweets ending with question marks (Naaman et al, 2010). Referrals are where the reply comment contains a web address or similar URL information (Naaman, Boase and Lai, 2010; Honeycutt and Herring, 2009), recommendations of other Twitter users (Efron 2011), or reference to a Twitter user which is not a directed response to that person (Honeycutt and Herring 2009, Ratkiewicz 2010). Response which uses the principle of addressivity (Honeycutt and Herring 2009) to reply to another user including direct answers to questions (Cahill 2009), conversations (Ratkiewicz 2010, Honeycutt and Herring 2009; Java et al 2009; Steiner 2009), or directed advice in response to a previous statement or question (Wilson 2008)
B News Events

Identifiable newsworthy content

News tweets incorporate coverage of mainstream media issues, breaking news events, liveblog coverage, social media news, and other identifiable factual orientated newsworthy information content (Phelan et al 2009, Chu et al 2010, Petrovic et al 2010, Zhou et al 2010 Phuvipadawat and Murata 2011). The category of “newsworthiness” also incorporates media releases, event announcements and related content of interest to others, for which the point of origin is the original poster either as citizen journalist (Mäkinen and Wangu Kuira 2008, Java et al 2009) media source (Cheong and Lee 2011), or authoritative voice in emergency response (Cheong and Lee 2011). Rebroadcasts of content from other news sources are part of the Pass Along category. There are seven categories of news items including announcements, hash tagged events, headlines, sport, natural disasters, transport and weather.

Announcements are statements of forthcoming events including dates, venues, locations either for the account holder or a third party such as political rallies (Henneburg et al 2009), job announcements (Doherty 2010), opening hours (Cahill 2009) or public appearances (Mischand 2007). Viewed as a 140 character press release, these tweets do not use links to an external site (Pass Along) or reference to another Twitter user (Conversational) in the announcements. Hashtagged Event is any tweet which represents the live discussion of an identified or identifiable event such as a conference, live television or live event collected under a consistent #hashtag (Lariscy et al 2009; Gay et al 2009; Efron 2011; Rath 2011). Headlines are eye-witness accounts of news events (Fahmi 2009; Lariscy et al 2009; Gay et al 2009) such as the Hudson River Plane crash (Krums, 2009) or other breaking news stories (Pear Analytics, 2009; Java et al 2007; Cheong and Lee 2011) that are factual or descriptive recount without overt opinion or comment (Zhou et al 2010, Phuvipadawat and Murata 2011). Sport is a specific class of headline or breaking news based on the factual identification of scores, placing or results at a sporting event without commentary as to the nature of the performance (Java et al 2007, Pear Analytics, 2009). Natural disasters are reports of geological occurrences such as earthquakes (Power and Forte 2008, Okazaki and Matsuo 2010, Petrovic et al 2010, Sakaki et al 2010), extreme storms and weather events (Bryce and Pieper 2010) or forest fires (Longueville et al 2009, Parslow 2009). This category was added after needing to distinguish between the cyclones, floods, earthquakes and thunderstorm warnings in terms of the size, scale and severity of a weather event that would distinguish a thunderstorm from a tropical cyclone.

Transport covers reports from commuters as to traffic conditions (Parslow 2009), traffic jams (Sakaki et al 2010) or announcements from service providers as to delays in flight, buses, or trains. This category emerged from observation of recurring patterns of traffic reports (#bnetraffic) and transport conditions (#bnept) within the data set coded for this paper. Weather is a combination of reports of weather condition as factual event, rather than a pejorative commentary (Honeycutt and Herring, 2009), and includes storm tracking (Bryce and Pieper 2010), reports of weather events such as hail or lightning (Longueville et al 2009), discussion of weather (Mischaud 2007) and locations of single rainbows (Okazaki and Matsuo 2010) or heavy rainfall (Sakaki et al 2010).
B Pass along

Tweets as endorsement of content

The pass-along category recognizes both the desire of the user of Twitter to access human curated content of interest, and the desire to provide such content to others (Heany and McClurg 2009). Social networks are used as a meta filter system to share information and found news with others (Mischaud 2007, Java et al 2009, Naaman et al 2010, Zhang et al 2010). Twitter authors are regarded by their readers with a certain level of trust, credibility and perceived expertise so that the inclusion of third party’s message, external URL or other content counts as an act of endorsement (Java et al 2007; Pear Analytics, 2009). Pass-Along consists of five content areas – automated endorsements, endorsement, retweet, secondary social media, and user generated content. Automated Endorsement is the type of content update triggered automatically by a third party application such as Live.fm, foursquare or other services that have permission to post to the Twitter account (Honeycutt and Herring, 2009, Chu et al 2010).

Endorsement is where Twitter users act as editors and filters of content for their followers by posting full length or shortened URLs, offline content such as phone numbers or other online materials (Ratkiewicz 2010 Zhao and Rosson 2009; Naaman et al 2010; Honeycutt and Herring, 2009; boyd et al 2010, Bakshy et al 2011, Wilson 2008, Sullivan et al 2011, Welch et al 2011).

Retweets are any posts that partially or fully reproduces another Twitter status using the retweet (RT) protocol as detailed by boyd et al (2010). The purpose of the RT is to acknowledge and reference the original source tweet (Java et al 2007; Pear Analytics, 2009; Naaman et al 2010) in order to propagate the idea from the individual’s timeline to the timeline of their followers (Dodds et al 2011, Lerman and Ghosh 2010, Ratkiewicz 2010, Welch et al 2011). It also represents a proxy measure of the interestingness and relevance of the original content (Lauw et al 2010, Phuvipadawat and Murata 2011) or its perceived value such as shared information during an emergency (Longueville et al 2009).

Secondary Social Media is a specific type of user generated content where the twitter message is a headline or reference to a more detailed post on another social media platform such as Facebook (Butcher 2010). This also emerged from the coding of data for this paper as @QPSMedia refer to Facebook pages as their primary distribution outlet for detailed information. User generated content is a link to content created by the timeline owner either on their own website or blog (Butcher 2010), or hosted through a secondary service provider for video (YouTube, Vimeo), picture (Flickr, TwitPic, Yfrog) or audio hosting (Soundcloud) as a form of self promotion (Pear Analytics 2009, Naaman et al 2010) or distribution of new ideas (Honeycutt and Herring, 2009) which are as yet unavailable to search engines (Dong et al 2010)

B Phatic

Content independent connected presence

Phatic is one of the most important interpersonal aspects of Twitter, and which is often misunderstood by critics of the service. It represents the passive acknowledge of membership of the community both by casual participation in posting updates and observing updates from
community members (Miller, 2008). This category covers the participation in the daily life of fellow twitter users which can foster a sense of connectivity (Henneburg et al 2009), address the human need for community, exchange and collaboration (Fernando 2010), and generate ambient connectivity through status updates (Keenan and Shiri 2009), ceremonial commentary (Makice 2009) and engaging the imagined audience of Twitter followers (Marwick and boyd 2010, Zhang et al 2010).

Phatic communications are divided into four categories – broadcasts, fourth wall, greetings and unclassifiable tweets. Broadcasts are statements made in observation of life (Marwick and boyd 2010), stated opinions (Honeycutt and Herring 2009), or general monologue style streams of consciousness which maintain a connected presence with others (Miller 2009). The phatic broadcast category is the opinionated answer of “What am I thinking now?” rather than descriptive “What am I doing?”. This allows for expressions of opinion (Jackson and Lilleker 2011) public displays of attitude (Jansen et al 2009) declarations of moral perspectives (Thelwall et al 2011) and emotive personal statements (Mischaud 2007, Phuvipadawat and Murata 2011) that represents the first line in an open conversation (Longueville et al 2009, Perlmutter 2009). The purposes of the commentary is provide content for the ambient listening readership (Crawford 2009, Naaman et al 2010) rather than factual recounts (News) or curated content (Pass Along). Fourth wall is a sub-class of phatic commentary that is meta-commentary either directed to the author through “Note to self” “FYI” or “Just for the record” thought bubble style comments (Honeycutt and Herring 2009), or which is the textual equivalent of comments made directly to camera in television or cinema to an imagined audience (Marwick and boyd 2010). Greetings are a sub class of phatic statement that engage an emotional connection with the imagined audience (Marwick and boyd 2010) through presence maintenance (Naaman et al 2010) which is where the community is addressed indirectly as a whole with the greeting or statements of gratitude. By addressing followers indirectly through generic statements of time, place and greetings to the broader community it creates and maintains a sense of telepresence (Hohl 2009) and virtual community (Miller, 2008). Unclassifiable is the catchall category for garbled texts, posts in error, cat-on-keyboard input and unclassifiable strings of text (Honeycutt and Herring, 2009, Miller, 2008). In the coding structure, where a tweet cannot be placed anywhere else, it defaults to being part of the Phatic – Unclassifiable category.

B Status
Tweets which address the statement "What are you doing?” and "What's happening?” in terms of an account holder's experiences
Status messages take the form of an answer the question Twitter used to pose on the update page on their website (“What are you doing now?”). This is the use of Twitter by the account holder to outline their own activity in a public record as a lifestreaming process (Gaonkar et al 2008), to micro-blog about themselves (Bollen et al 2009) and their current state of being (Chu et al 2010, Dodds et al 2011). It supports the phatic communications in the sense that it provides ambient intimacy through connections in text that would normally be visible through inter personal activity (Java et al 2009, Naaman et al 2010, Zhang et al 2010). This is the largest category with eight items - activity, automated, location, mechanical, personal, physical, temporal and work.
Activity answers the question “What are you doing now?” in the most direct sense as a diary of daily life (Marwick and boyd 2010) which describes actions underway (Naaman et al, 2010) or being experienced by the individual (Chu et al 2010). Automated are announcements from third party systems such as media players, games or other services which do not post URLs but are otherwise functionally identical to Pass Along-Automated posts. Location answers the question of “Where are you?” as part of “What are you doing?” and incorporates references to traveling and location changes that function as social network ‘ping’ commands to notify followers of changes in the author’s locations (Makice, 2009; Naaman et al 2010), or where the contextual location of the author is necessary to support other aspects of communication such as discussing an event within the context of it being nearby, or geographically distant from the author (Longueville et al 2009).

Mechanical tweets cover any technology or mechanical systems such as computers, cars, phones or equipment, data, and related technical issues of these devices functioning or malfunctioning (Mischaud 2007). Personal tweets are positive or negative sentiments in personal opinions or emotional status. Covers the sense of “What are you feeling?” rather than “What are you doing?”. These are recognizable through the use of personal pronouns, statements of positive or negative sentiment, personal opinions or emotional status (Jansen et al, 2009; Naaman et al 2010; Honeycutt and Herring, 2009), shared subjectivity such as statements of the author’s mood (Bollen et al 2009) or other emotional tweets (Pak and Paroubek 2010, Phuvipadawat and Murata 2011).

Physical tweets convey the sensory experiences that address “What are you physically experiencing?” rather than “What are you feeling emotionally?” (Sullivan et al 2011). They can range from small talk about the weather as experienced by the author in terms of heat or cold (Mischaud 2007) and physical states of the body such as tiredness, hunger or food consumption (Naaman et al, 2010, Dodds et al 2011). Temporal tweets related to specific dates, times, statements of temporal nature (waiting) and temporal action (“Time to” ) but exclude materials that can be classified as “News – Announcement”. The distinguishing aspect is the emphasis on the experience of time as part of an event (Naaman et al 2010), or as context for personal activity (Marwick and boyd 2010) or location data (Longueville et al 2009). Work tweets are any reference to work related activity, particularly references to jobs, employment or related content, and incorporates both the style of office water cooler chat (Heany and McClurg 2009; DiMicco, et al 2008) and the use of Twitter as status update for coworkers (Zhao and Rosson 2009), discussions of the work place (Mischaud 2007), and achievements in the day job (Jackson and Lilleker 2011, Marwick and boyd 2010).

B Spam

Unsolicited content that could win a Free iPad! Unbelievable!
Spam is included in the framework to classify junk traffic, unsolicited automated posts, and other tweets generated without user consent due to malware or unethical sites (Pear Analysis, 2009). Four categories of spam have been identified from the literature, although the nature of the spam process is external to the user timeline, these have not been confirmed from the individual account.
analysis. Instead, these types of messages would be detected in a public timeline or hashtag analysis. Identified types of spam include administered malcontent, keyword response, mentions, trend hijacking, and truthiness. Administered malcontent are links to malware or related hostile websites (Power and Forte 2008). Keyword triggered conversational responses which are automated context free responses to keywords and brand name (Chu et al 2010). Mention spam which use the structure of Conversation – Referral for the purpose of encouraging a user to engage the account to increase the perceived credibility of the spammer (Grier et al 2010). Trend hijacking which is where malicious content is appended with one or more #hashtags of trending events in a tweet unrelated to the trend (Grier et al 2010, Zhou et al 2010). Finally, a recently developed spam trend is the concept of “Truthiness” which uses Twitter accounts to generate an astroturfing meme or trending topic by automated posting amongst multiple accounts for the purpose of influence real time search engine results (Ratkiewicz 2010).

A Case Studies.
The revised coding structure was tested on three accounts heavily involved in the use of social media during the 2011 Queensland floods and cyclone season. These accounts were selected for three reasons. First, the extreme weather events provided a set of key dates that could be identified as pre-event, crisis event, and post-event. Second, significant media and political interest surrounds the crisis communications use of Twitter by the Queensland Police and Brisbane City Council. Third, permission was sought and received from the account holders to conduct an independent content audit, and whilst public timelines are available for use in research within the general conditions of Twitter’s acceptable use policy, it was preferable to have positive support from the account holders.

B Procedure
The data collection and coding process requires a three step process of archiving the original timeline, converting that archive into a coding framework, and the actual coding process. These steps are outlined in detail below, with the results from applying this process to the case study timelines detailed in the subsequent section.

C Archiving the Timeline
One limitation of Twitter is the current absence of a download function to draw the timeline data directly from their servers. This also raises an issue with Twitter’s terms of service – notably, if large volumes of timeline data is captured, the original data may not be redistributed without breaching Twitter’s guidelines. However, Twitter permits capture and analysis of timeline data sing the described method to collect your organizational or individual timeline for analysis and benchmarking will be within acceptable use policies. Archiving of a timeline requires a third party application such as TwapperKeeper's automated search function which can be set in advance to capture timeline
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

data, or Twitter to PDF for capturing historical timeline. Twitter to PDF (http://twitter-to-pdf.sourceforge.net/) is the preferred system for the method described below.

Twitter to PDF is a Windows software package that captures Twitter feed content for the previous 3200 tweets (Twitter’s maximum search history) on the first search. Subsequent searches of the same timeline using the data will be added to a consolidated history, so high volume twitter accounts can be captured by carefully timed frequent use of the software. Downloading, installing and operating the software is relatively straightforward, with instructions provided both onsite and within the archival software setup. Timelines to be captured are designed by entering the account names into the “Following.txt” file without using the @ symbol (stephendann rather than @stephendann). Activating the software with the “run.bat” will start the download process which can vary from a few minutes (incremental updates) to hours (original searches, large number of accounts). Twitter to PDF stores the collected data in three formats – an XML file, Text document, and PDF format. For the purpose of the analysis, the TXT file is the primary data source, although many of the manual data cleaning steps may be able to be automated in later iterations of the method which is an aspect of the method that requires further research and development.

C Converting to coding format

Data is presented in the text file in two lines
Day, Date, Time, Offset Year.
StatusID:StatusContent

An example of the data set drawn from the author’s own timeline is illustrated as follows:
Tue May 24 00:08:41 +0000 2011
72816248249004032:Spending the day working on my #AMSRS2011 conference paper.

The status ID number (72816248249004032) can be used to identify the live URL of the tweet (http://twitter.com/#!/stephendann/statuses/72816248249004032) which allows for confirmatory inspection of the original data if required. To enable the coding process, the data is imported into Microsoft Excel via a manual data cleaning process which returns the content as a single line tab delimited CSV file for import with the following headings:

<table>
<thead>
<tr>
<th>Date Block</th>
<th>ID</th>
<th>Content</th>
</tr>
</thead>
</table>

On import to Excel, addition data headings are inserted so the data set resembles the following table

<table>
<thead>
<tr>
<th>ID</th>
<th>date</th>
<th>SLI</th>
<th>Content</th>
<th>Timeline</th>
<th>Category</th>
<th>SubCat</th>
<th>N</th>
</tr>
</thead>
</table>

Table 2 describes the details of each header within the data fields.

Table 2: Data Heading

| ID | Each tweet is numbered sequentially to allow for sorting, resorting and restoration to the original order of the content. |
### Measuring Social Media: Benchmarking an Individual Twitter Timeline

**Stephen Dann, Australian National University**

<table>
<thead>
<tr>
<th>Date</th>
<th>The date block is preserved in current format.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SLI</td>
<td>The 17 digit identifier for the tweet within Twitter's database (and forms part of the tweet's unique URL)</td>
</tr>
<tr>
<td>Content</td>
<td>The tweets to be analysed</td>
</tr>
<tr>
<td>Timeline</td>
<td>This is an optional column that can be used to define measurement periods in terms of pre-event, event and post-event</td>
</tr>
<tr>
<td>Category</td>
<td>Top level category for the first pass analysis</td>
</tr>
<tr>
<td>Sub Category</td>
<td>Sub domain of tweets within the primary category</td>
</tr>
<tr>
<td>N</td>
<td>Column for counting the number of tweets in category or subcategory.</td>
</tr>
</tbody>
</table>
C Coding Procedure

Manual timeline coding is undertaken in a three stage format starting with the allocation of timeline periods (pre/event/post) for any significant milestones or marker dates in the timeline. Timeline coding is followed by sorting the data set by the “content” column by alphabetical order to cluster the @ replies, tweets that start with #hashtags and similarly structured tweets for initial coding into the six top level domains. Coding process is assisted by the use of search functions in Excel which can highlight individual cells based on search terms by using the Find/Replace function (Figure 1) to highlight the cells containing key determinants:

- “http” and “RT” for Pass Along categories
- @symbols for Conversational category items
- # for identify tweets with hashtags for News

Figure 1 Find/Change

Using the find/replace function to change the format of the cells assists in the recognition of these four key identifying marks in the large volume of text data. In addition, this method may be applied to any keyword to be observed, highlighted or tracked (for example, brand names, product names or web addresses). In the case studies outlined below, @QPSMedia’s extensive use of Facebook pages was easily identified using the find/replace function to highlight any URL with the "http://fb.me" structure.

Data can be coded either visually as “Conversation” and “Conversational – Reply” or through a code book structure (eg Conversation = 1, Phatic = 2, Pass-along = 3) for statistical analysis. For this paper, top level coding of the six main categories was undertaken, with further sub-classification restricted to areas of noticeable difference between each distinct time period. Further research will examine the data at the secondary level of coding for all time periods and top level categories.
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

A Case Study

The paper focuses on the application of the methodology to examine the Twitter account use during the Queensland Floods, and Severe Tropical Cyclone Yasi. The selected accounts were recruited based on their respective roles in the severe weather events - @QPSMedia represents the Queensland Police service who have a state wide responsibility for the safety of the population, @Brisbanecityqld is the communication outlet for the Brisbane regional area which was directly impacted by the flooding of the Brisbane River, and @Energex who have the responsibility for the state-wide power grid.

B Data Collection and Aggregate results

Data collected from the three twitter accounts was downloaded from the public timeline on March 24 for all three services. In the case studies for this paper, the timeline was divided into five periods (pre-crisis, flood, inter-crisis, cyclone, post-crisis). For this case study, time periods were set around key dates in the January – February storm season.

<table>
<thead>
<tr>
<th>Period</th>
<th>Date Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-crisis</td>
<td>Start date in the captured timeline to 9/1/11</td>
</tr>
<tr>
<td>Flood</td>
<td>10/1/11 to 14/1/11</td>
</tr>
<tr>
<td>Inter-crisis</td>
<td>15/1/11 – 29/1/11</td>
</tr>
<tr>
<td>Cyclone</td>
<td>30/1/11 – 3/2/11</td>
</tr>
<tr>
<td>Post Crisis</td>
<td>4/2/11 – 24/3/11</td>
</tr>
</tbody>
</table>

Post-crisis was defined as the date of downgrading of Severe Tropical Cyclone Yasi to a rain depression by the Bureau of Meteorology to the point of data collection. All three accounts have continued in operation, and no further data has been collected post March 24.

Data coding was undertaken in two processes – each timeline was individually assessed against the content classification framework top level categories (conversational, phatic, news, pass-along, status and spam) with each category then placed into the respective subcategory as a confirmatory process. Using the two stage coding process also improves the classification of the twitter content as each tweet must conform to the requirements of the major category, and the minor subcategory. Across the entire process, Status and Phatic proved to be the most difficult to identify in the initial coding pass, with Conversational, Pass-along proving to be the most easily identifiable category. The News category was expanded from the original Dann (2010) four categories to the more nuanced seven category structure with the inclusion of “Natural Disaster”, “Transport” and “Announcement”.

The overall data set consists of 7239 twitter status updates divided between @QPSMedia (4344), @Brisbanecityqld (1823) and @Energex (1072) with a relatively high proportion of the overall coded content within the Pass Along (64%) followed by Conversational (21%) and News Events (11%) category, and lower than expected levels of Phatic and Status updates (~3%). Pass-Along notably strongest in the @Energex timeline as their account provided power loss and power recovery status updates which directed traffic to their own website. QPSMedia’s extensive use of Facebook to host
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

full updates resulted in significant redirecting of traffic away from Twitter for detailed updates. Finally, @BrisbaneCityqld’s twitter account was a mix between a switchboard for council enquiries and wide ranging set of curated links.

Table 3 Data overview

<table>
<thead>
<tr>
<th>Category</th>
<th>@QPSMedia</th>
<th>@brisbanecityqld</th>
<th>@energex</th>
<th>Sum</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conversational</td>
<td>585</td>
<td>785</td>
<td>115</td>
<td>1485</td>
<td>21%</td>
</tr>
<tr>
<td>News Events</td>
<td>784</td>
<td>31</td>
<td>10</td>
<td>825</td>
<td>11%</td>
</tr>
<tr>
<td>Pass along</td>
<td>2780</td>
<td>949</td>
<td>896</td>
<td>4625</td>
<td>64%</td>
</tr>
<tr>
<td>Phatic</td>
<td>69</td>
<td>24</td>
<td>20</td>
<td>113</td>
<td>2%</td>
</tr>
<tr>
<td>Status</td>
<td>126</td>
<td>34</td>
<td>31</td>
<td>191</td>
<td>3%</td>
</tr>
<tr>
<td>Total</td>
<td>4344</td>
<td>1823</td>
<td>1072</td>
<td>7239</td>
<td></td>
</tr>
<tr>
<td>Days</td>
<td>95</td>
<td>665</td>
<td>306</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tweets per day</td>
<td>45.7</td>
<td>1.2</td>
<td>3.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall, the three accounts reflect relatively similar styles with all tend to use a concierge model of content curation. That said, each has a distinctively secondary style with the Brisbane City Council having a higher level of community engagement as a secondary portfolio, in contrast to @QPSMedia’s journalistic role as a primary media source and @Energex’s limited communication activity. As the accounts were able to codified, classified and reported in Table 3, this confirms that the method can be used on third part accounts in answer to Research Question 1 (RQ1).

C Queensland Police Service Media (@QPSMedia)

The Queensland Police twitter account is one piece of a broader social media communications strategy that makes extensive use of the Facebook community platform, livestreaming and YouTube as part of a comprehensive portfolio of communication outlets. It should be noted that the sub-category “Pass Along – Secondary Social Media” was created in recognition of the @QPSMedia use of Twitter to direct traffic to detailed reports on their Facebook group via the fb.me shortened URLs. Historically, @QPSMedia is one of the older accounts in use, with an observable trial period in 2009 and early 2010.

Figure 2: Tweetstats report for @QPSMedia
The site was relatively active prior to the Queensland floods, and whilst it experienced a major uptake in followers and activity, it has remained considerably active in the post-crisis period.

<table>
<thead>
<tr>
<th>Dates</th>
<th>Total</th>
<th>Pre-crisis</th>
<th>Flood</th>
<th>Inter-crisis</th>
<th>Cyclone</th>
<th>Post Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
</tr>
</tbody>
</table>
| Conversational | 585   | 13%        | 32    | 4%           | 35      | 6%          | 92   | 16%|330|19%
| News Events  | 784   | 18%        | 182   | 22%          | 138     | 23%         | 86   | 15%|195|34%|183|10%
| Pass along   | 2780  | 64%        | 547   | 67%          | 399     | 66%         | 380  | 64%|254|44%|1200|68%
| Phatic       | 69    | 2%         | 24    | 3%           | 15      | 2%          | 4    | 1% |11|2%|15|1%
| Status       | 126   | 3%         | 35    | 4%           | 19      | 3%          | 24   | 4% |24|4%|24|1%
| Total        | 4344  |            | 820   |              | 606     |             | 590  |    |756|    |1752|

Data from the coding process also indicated that the style of account was relatively stable with the exception of the cyclone period.
The rise in News Events during the cyclone related to the increased use of single line statement of the weather conditions, cyclone tracking information, and safety status of the cyclone affected areas. Severe Tropical Cyclone Yasi updates were able to be summated into single line statements due to the nature of the event - geographic tracking, time to impact and affected regions were more concise than was the experience of the Brisbane Flood information which required more frequently references to detailed information on the QPS media Facebook page. Research Question 2 is answered in the affirmative for the QPSMedia account data analysis.

Brisbane City Council

The Brisbane City Council Twitter account is an example of the adaptive nature of the Twitter services, and the value to be found in community engagement during crisis situations. The BrisbaneCityQLD account is unique in that it represents a clearly geographically defined area, and as such, it was not expected to be impacted by the Severe Tropical Cyclone Yasi, compared to QPSmedia (statewide) or Energex (South East QLD). As with all accounts in the study, the flood period produced a peak of activity that is a distinctive, and largely self contained period of high volume traffic as demonstrated in Figure 4.

Figure 4 Tweetstats report for @Brisbanecityqld
The @Brisbanecityqld account activity spike is directly related to community engagement as the level of conversational interaction spiked during the flood peaks, and immediate post-flood recovery. As the account is geographically located by representing the City council districts, the peak activity centers around the flood period, and the post-flood clean up period (intercrisis).

Table 5  Brisbane City Council Data

<table>
<thead>
<tr>
<th>Dates</th>
<th>Total</th>
<th>Pre-crisis</th>
<th>Flood</th>
<th>Inter-crisis</th>
<th>Cyclone</th>
<th>Post Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td>Conversational</td>
<td>785</td>
<td>43%</td>
<td>231</td>
<td>24%</td>
<td>279</td>
<td>76%</td>
</tr>
<tr>
<td>News Events</td>
<td>31</td>
<td>2%</td>
<td>28</td>
<td>3%</td>
<td>1</td>
<td>0%</td>
</tr>
<tr>
<td>Pass along</td>
<td>949</td>
<td>52%</td>
<td>650</td>
<td>68%</td>
<td>88</td>
<td>24%</td>
</tr>
<tr>
<td>Phatic</td>
<td>24</td>
<td>1%</td>
<td>17</td>
<td>2%</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Status</td>
<td>34</td>
<td>2%</td>
<td>27</td>
<td>3%</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Total</td>
<td>1823</td>
<td></td>
<td>953</td>
<td></td>
<td>368</td>
<td></td>
</tr>
<tr>
<td>Days</td>
<td>665</td>
<td>591</td>
<td>5</td>
<td>15</td>
<td>5</td>
<td>49</td>
</tr>
<tr>
<td>Tweet per day</td>
<td>1.2</td>
<td>1.6</td>
<td>73.6</td>
<td>20.0</td>
<td>3.0</td>
<td>3.8</td>
</tr>
</tbody>
</table>
Two noticeable shifts in communication patterns are evident in the data. First, conversation replaces Pass Along during the Flood, and steadily declines after the intercrisis period indicating that the community has not maintained the engagement with the council. Second, the level of the Pass-Along content pre-crisis and post-crisis indicates a return to the previous style of information brokerage is underway. As an aside, many of the Pass-Along information tweets were event announcements for council activities around Brisbane – the return of the Pass-Along category mirrors the rebuilding and reconstruction of Brisbane, and a return to the pre-flood levels of activity that were unavailable during the intercrisis period due to infrastructure damage.

The brief spike in News Events was traffic related as the council announced timetable changes, and returns to service for the various public transport functions that were damaged during the flood. Research Question 2 is answered in the affirmative for the @Brisbanecityqld account data analysis.

**B Energex**

Energex is a power supply company for the South East Queensland region, and their Twitter account appears superficially to be a “broadcast only” system for network status, power outages and repair announcements. The usage patterns are distinctively weather related with existing spikes of activity noticeable around months associated with the storm seasons in Queensland (November - February).
As with the other accounts, the spike of activity associated with the Brisbane floods is recognizable, although less pronounced than the @Brisbanecityqld and @QPSMedia accounts. Data from the period indicates that community engagement was a significant factor in driving traffic levels (Table 6).

### Table 6 Energex Data

<table>
<thead>
<tr>
<th>Dates</th>
<th>Total</th>
<th>Pre-crisis</th>
<th>Flood</th>
<th>Inter-crisis</th>
<th>Cyclone</th>
<th>Post Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N %</td>
<td>N %</td>
<td>N %</td>
<td>N %</td>
<td>N %</td>
<td>N %</td>
</tr>
<tr>
<td><strong>Conversatio</strong></td>
<td>115</td>
<td>11%</td>
<td>12 2%</td>
<td>68 40%</td>
<td>25 27%</td>
<td>0 0%</td>
</tr>
<tr>
<td><strong>News Events</strong></td>
<td>10</td>
<td>1%</td>
<td>4 1%</td>
<td>3 2%</td>
<td>0 0%</td>
<td>0 0%</td>
</tr>
<tr>
<td><strong>Pass along</strong></td>
<td>896</td>
<td>84%</td>
<td>551 95%</td>
<td>73 43%</td>
<td>62 67%</td>
<td>13 93%</td>
</tr>
<tr>
<td><strong>Phatic</strong></td>
<td>20</td>
<td>2%</td>
<td>8 1%</td>
<td>5 3%</td>
<td>2 2%</td>
<td>0 0%</td>
</tr>
<tr>
<td><strong>Status</strong></td>
<td>31</td>
<td>3%</td>
<td>5 1%</td>
<td>19 11%</td>
<td>3 3%</td>
<td>1 7%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>1072</td>
<td></td>
<td>580 168</td>
<td>92 15%</td>
<td>14 5%</td>
<td>218</td>
</tr>
<tr>
<td><strong>Days</strong></td>
<td>306</td>
<td>232</td>
<td>5</td>
<td>15 5%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: [http://tweetstats.com/graphs/energex#tstats](http://tweetstats.com/graphs/energex#tstats)
As with the Brisbane City Council, Energex is a geographically bounded entity which was not impacted by Severe Tropical Cyclone Yasi, and as such, did not have information to report during the cyclone period. Similarly, the end of the summer storm season in February is noticeable with the decline in traffic and content for the account.

Figure 7 Performance over Time

Energex has the most overt shift in styles from a broadcast platform of network status downtime (Pass Along) into a community hub for a brief period directly connected to Brisbane floods and the post-flood recovery. The return to the original account style post-crisis recovery indicates that the capacity exists for Energex to use community engagement when required by the marketplace, however, the marketplace has not required high levels of communication with their power provider. Research Question 2 is answered in the affirmative for the @Energex account data analysis.

C Overall summary

All three Twitter accounts experience peak content concentrations during the extreme weather events of the Queensland 2011 summer period. The spikes in activity coincide with the geographic coverage of the accounts – the two South East Queensland region accounts peaked with the flood and post-flood recovery period - @BrisbaneCityqld's peak occurred immediately post-flood and @Energex peaking during the flood conditions. In contrast, the state wide coverage for @QPSMedia resulted in a dual peak for the flood (SE Queensland) and the Severe Tropical Cyclone Yasi (North Queensland). Overall, each account demonstrated a consistent pattern of emergency crisis response – moving from a relatively low Tweet per day count for @Energex (3.5) @Brisbanecityqld (4.8) and @QPSMedia (15.8) over the full history of the account into an intense burst of content around the flood period with @Energex (33) @Brisbanecityqld (73) and
C Limits, restrictions and restraints

There are three limitations governing the development of the method. First, the coding of the data is in a positive format, as the mechanism is designed to categorize and classify what exists rather than to pass judgment on the quality of the content. This is based on the strategic belief that Twitter is a sufficiently versatile platform (140 characters delivered across web, mobile, and other formats) that proscribing a “best/worst” or “right/wrong” analysis method would fail to reflect the reality of the platform’s flexibility. Second, the account coding processes are intentionally open for subjective classification as a feature of the reflection process. The aim of the method is to allow for insight and discovery, and self reflection of the actual behavior of the account as interpreted by the account holder. Finally, at the time of writing, the testing of the methodology has been restricted to timeline specific analysis using single accounts. Future research will apply the framework to hashtag analysis for event analysis, market research applications for consumer insight, and potentially to the public timeline. However, at present, the mechanisms has only been applied to the subjective historical analysis of individual timelines.

A The Social Impact of Twitter in a crisis

Although not measurable within the context of the research method proposed, it is worth mentioning several outcomes from the use of social media within the crisis communications environment created by the flood conditions. The role of Twitter as a leading headline service which was then used by more traditional media was noted by QPSMedia’s representatives. The protocol used by the Police also involved their senior communications staff being present at high level briefings for the state emergency services, and deciding which information presented in the briefing should be available immediately, often before the briefing was finalized, and well before the press releases were drafted. Consequently, radio and television media channels were using the Twitter account for breaking headlines and news updates, with live television coverage periodically scrolling items from QPSMedia Twitter feed across the bottom of the screen. Even if the Twitter content was not reaching sections of the population directly, the information was relayed through conventional channels, meaning that the value of the communication was not just in the primary exchange between followers and following, but also the secondary exchanges through rebroadcast by media, or retweets by followers.

An additional social impact of QPSMedia’s use of Twitter and Facebook during the crisis was to spark a significant growth in social media engagement by South East Queensland residents. For example, prior to the crisis period, the QPS media Facebook page had approximately 60,000 followers – during and immediately post crisis this rose to 330,000 followers and has settled around
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

220000 ongoing followers. An unintended consequence of the use of the social media has been the increased sense of community around the police. This has been reflected both in the level of conversation and engagement around posts on Facebook, anecdotal data from the communications representatives about levels and rates of information in response to public requests for assistance, and in the sheer volume of tributes and personal turnout to a recent public funeral for an office killed in the line of duty.

Even if the messages during the floods were did not have a significant impact in terms of information, behaviour or value to the population, it has created a sense of engagement with the police that has not been as visible, or as present. By participating in the community, talking to concerned individuals over Facebook and Twitter, and being part of the community in crisis and recovery, the police have changed their public perception, and have built a reputation for feedback and engagement. If nothing else, the use of Twitter to talk to individual members of the community gives a perception of phatic connectedness which is often absent in non-community policing engagement. The strategic value of being part of the community, and providing an open line of communication enhanced the reputation of the police force, and reintroduced a sense of connectedness with the service. For this aspect alone, it was worth the engagement during the peak crisis period – particularly the use of @responses to personalize their engagement, and the humanity of the posts including apologies for errors and the occasional frustration at the continuing decline in weather conditions. These glimpses of humanity behind the mostly professional face of the media service helped humanize both the police and their media services.

A Conclusions

This paper outlined the extension and testing of the Dann (2010) personal timeline history into the context of an audit and review process of a third party twitter account. The paper outlines how the Dann (2010) method can be applied to external accounts through the measurement and assessment of the timelines of QPSMedia, Brisbane Cityqld and Energex. The method was successfully applied to the content of three external accounts to which the author had not additional contextual insight to explain the type of message posted, and produces a positive resolution to research question 1. Further, as demonstrated by the respective case studies, data produced from the analysis method can detect patterns in the content production over time. The three accounts each displayed noticeable trends and patterns within the data collection period, including recognizable shifts between pre- and post- crisis communication styles. These are demonstrated in the data trends tables, and the charts for each account. Although developed for a personal timeline written by an individual author, the timeline coding framework was robust when applied to a commercial and corporate account setting. Three additional categories in News (Natural Disaster, Announcement, Transport) and two categories in Pass Along (Automated, Secondary Social Media) were discovered during the process of the data collection, and supported through additional literature scans.
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

References

Bakshy, E, HofmanJ, Mason, W and Watts, D (2011) Everyone’s an influencer: Quantifying Influence on Twitter, WSDM’11, February 9–12, 2011, Hong Kong, China

Bollen, J Mao, H and Zeng, X (2011) Twitter mood predicts the stockmarket, Journal of Computational Science 2 (1) 1-8


Bryce T and Pieper C (2010) Using Twitter to Receive Storm Reports, 38th Conference on Broadcast Meteorology, June 2010,

Butcher, L, (2010) Using Twitter to Advance Cancer Knowledge, Oncology Times, 32 (1) 8-10

Cahill, K, 2009 Building a virtual branch at Vancouver Public Library using Web 2.0 tools, Program: electronic library and information systems 43 (2) 140-155


Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University


Doherty, R (2010) Getting social with recruitment, Strategic HR review, 9 (6) 11-15


Fahmi, W S 2009, Bloggers' street movement and the right to the city. (Re)claiming Cairo's real and virtual "spaces of freedom", Environment and Urbanization 2009; 21; 89-107


Galer-Unti, R 2009, Guerilla Advocacy: Using Aggressive Marketing Techniques for Health Policy Change, Health Promotion Practice, 10; 325-327


Grier, C, Thomas, K., Paxson, V and Zhang, M (2010) @spam: The Underground on 140 Characters or Less, CCS’10, October 4–8, 2010, Chicago, Illinois, USA

Heany, M and McClurg, S 2009, Social Networks and American Politics: Introduction to the Special Issue, American Politics Research 37, 727-741

Henneburg, S. Scammell, M and O’Shaughnessy, N (2009) Political marketing management and theories of democracy, Marketing Theory 2009; 9; 165-188

Hohl, M (2009) Beyond the screen: visualizing visits to a website as an experience in physical space, Visual Communication, 8 (3) 273-284

Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University


http://ist.psu.edu/faculty_pages/jjansen/academic/jansen_twitter_electronic_word_of_mouth.pdf


Krums, 2009 “There's a plane in the Hudson. I'm on the ferry going to pick up the people”, http://twitpic.com/135xa, January 16, 2009


Longueville, B, Smith, R., and Luraschi, G., “OMG, from here, I can see the flames!”: a use case of mining Location Based Social Networks to acquire spatiotemporal data on forest fires" ACM LBSN '09, November 3, 2009

Makice, K, 2009 Phatics and the Design of Community, CHI 2009, April 4-9, 2009, Boston, Massachusetts


Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University


Mischaud, E 2007, Twitter: Expressions of the Whole Self An investigation into user appropriation of a web-based communications platform, MSc Dissertation, London School of Economics


Phuvipadawat, S and Murata, T (2011) Detecting a Multi-Level Content Similarity from Microblogs Based on Community Structures and Named Entities, Journal of Emerging Technologies in Web Intelligence, 3 (1), 11-19

Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University


Steiner H, 2009 Reference utility of social networking sites: options and functionality, Library Hi Tech News 5/6, 4-6


Welch, M., Schonfeld, U., He., D and Cho, J., Topical Semantics of Twitter Links, WSDM’11, February 9–12, 2011, Hong Kong, China

Wilson, D (2008) Monitoring technology trends with podcasts, RSS and Twitter, Library Hi Tech News, 10, 8-12


Twitter Accounts

Brisbane City Council @brisbanecityqld
Energex @energex
Measuring Social Media: Benchmarking an Individual Twitter Timeline

Stephen Dann, Australian National University

Queensland Police @QPSMedia

Web pages
Twitter to PDF http://twitter-to-pdf.sourceforge.net/
TweetStats http://tweetstats.com/graphs/brisbanecityqld#tstats
TweetStats http://tweetstats.com/graphs/energex#tstats
TweetStats http://tweetstats.com/graphs/qpsmedia#tstats