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Sifting signal from noise: A new perspective on the meaning of tweets about the "big game"

Ian Graves
University of Missouri, USA

Nora McDonald
Drexel University, USA

Sean P Goggins
University of Missouri, USA

Abstract

A good deal of Twitter research focuses on event-detection using algorithms that rely on keywords and tweet density. We present an alternative analysis of tweets, filtering by hashtags related to the 2012 Superbowl and validated against the 2013 baseball World Series. We analyze low-volume, topically similar tweets which reference specific plays (sub-contexts) within the game at the time they occur. These communications are not explicitly linked; they pivot on keywords and do not correlate with spikes in tweets-per-minute. Such phenomena are not readily identified by current event-detection algorithms, which rely on volume to drive the analytic engine. We propose to demonstrate the effectiveness of empirically and theoretically informed approaches and use qualitative analysis and theory to inform the design of future event-detection algorithms. Specifically, we propose theories of Information Grounds and "third places" to explain sub-contexts that emerge. Conceptualizing sub-contexts as a socio-technical place advances the framing of Twitter event-detection from principally computational to deeply contextual.

Corresponding author:
Sean P Goggins, 303 Townsend Hall, University of Missouri, Columbia, MO, USA.
Email: gogginss@missouri.edu

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Introduction

Event-detection via Twitter is one of the most prominent cross-contextual areas of microblogging research. Many event-detection algorithms focus on anomalies in tweet volume, typically expressed in tweets-per-minute (tpm). Others use semantic modeling, coupling tpm anomaly detection with keyword identification. This technique shows promise for more fine-grained event-detection within known events such as gameplay tweeting (Chakrabarti and Punera, 2011; Zhao et al., 2011). These different approaches to event-detection identify spikes in tweet volume and report prominent words, but do not focus on the context or content of the events (Gelernter and Wu, 2012; Munro, 2011). The identification of actionable information from Twitter would have many immediate, prominent applications in disaster response, civic engagement, and other domains. Thus, the pursuit of event-detection via Twitter continues in spite of present limitations.

Here we apply theory and qualitative, empirical tweet analysis to enhance event-detection research on Twitter. Instead of focusing on tweet volume as a primary signal of actionable information, we focus on the context of tweets containing words that signal direct relevance to gameplay contexts, adding another dimension to computational framings of Twitter as a single, dynamic flood of information to monitor. This choice is motivated by socio-informational theories framing Twitter interactions; users share information through Twitter as communication intended to connect rather than merely to inform, and this act of sharing also functions as social behavior.

Two related theories of information behavior and social participation act as starting points for a theoretically informed and analytically pragmatic approach to signal detection in Twitter. Specifically, Information Grounds theory (Pettigrew, 1998, 1999) and "third place" theory are employed to operationalize Twitter analysis. We address the problem of event-detection through Tweet analysis surrounding the 2012 Superbowl, a database whose large-scale, yet compressed nature allows us to detect discrete, meaningful events during the game which serve as focal points for analysis.

An integrative analysis incorporating components of Information Grounds and third places provide a more nuanced understanding of information streams generated by Twitter during a Superbowl event than approaches focusing primarily on tweet volume. We identify gameplay phrases at the beginning of tweets to identify connections between low volumes of tweets and gameplay events. Based on these findings, we then develop an algorithm to evaluate against twitter corpuses from the 2012 Superbowl and the 2013 Baseball World Series. Both evaluations validate our initial findings.

Theoretical framing: social and information contexts

The evolution of Information Grounds theory (Pettigrew, 1998, 1999) explicitly builds on Oldenburg and Brissett's (1982) conceptualization of third places by including information behavior that emerges in social contexts. Pettigrew (1999) defines

Information Grounds as environments "temporarily created when people come together for a singular purpose" resulting in a social atmosphere that "fosters spontaneous and serendipitous sharing of information" (p. 811). Examples of Information Grounds include any public or quasi-public space in which people seek resources, such as a medical office waiting room. Oldenburg's (1999) concept of third places describes social (rather than purely functional) settings separate from primary social environments, such as the home or workplace. Examples of third places include coffee shops, community centers, bars and beauty shops. Both Information Grounds and third places are used in the literature to describe locations in the real (non-virtual) world. Steinkuehler and Williams (2006) recognize shifting conceptualizations of "place" to include virtual places like MMOs (massively multi-player online games). Twitter interaction shares some properties with MMOs—principally that interactions are ephemeral and occur as text.

Empirical framing: a thin text line as place

Information-sharing. Structurally linked strands of text enable analysis based on mimetic style rather than hashtag demarcation to identify social engagement and information-sharing on Twitter. Such textual communication is empirically well matched with theories of Information Grounds and third places. For example, we show that gameplay tweets are only linked by common sentence structures due to a limited social utility, and are therefore not technologically generative. Through these structural features, we find that users inscribe a new format, leading to common, structural expression of shared information about a distinct event.

Filling the gap left by algorithms. These formats are not easily detectable through previously described methodologies. The very structural features that characterize them as Information Grounds and third places—that is, prosaic, descriptive content focusing on events rather than social experiences—render retweets less likely. Consequently, those sub-contexts do not correspond to higher peak density of tweets, and remain undetected by algorithms relying on volume for analysis.

In the following sections, we further describe prior research on information production, filtering, and recommendation to frame our argument that tweet sentence structure aids in the identification of Information Grounds or third places on Twitter. We discuss prior research on event-detection during sporting events, and describe data sets and methods employed in our analysis. Findings illustrate structural linking behaviors, outlining new opportunities for event-detection algorithm development. Finally, we discuss implications of this work for future studies.

Related work

Twitter as information grounds

Pettigrew characterized Information grounds as "social settings in which people share everyday information while attending to a focal activity" (Fisher et al., 2007). In 2006, Fisher and Naumer considered the possibility that information grounds may include everything from health clinics to sporting events, suggesting its validity as a framework for investigating information-sharing behavior. In their Information Ground study of college students at University of Washington, Fisher and Naumer (2006) determined that students perceive the "best information" to be encountered in "restaurants and coffee shops" (Fisher et al., 2007; Fisher and Naumer, 2006: 103). At that time only 3% perceived online sources as an information ground (Fisher et al., 2007; Fisher and Naumer, 2006: 103), but the survey predates widespread use of social media and microblogging platforms.

Fisher et al. (2004) describe information grounds as comprised of seven attributes:

1. Can occur anywhere, in any type of temporal setting and are predicated on the presence of individuals;
2. Act as a gathering place intended for a primary, instrumental purpose other than information-sharing;
3. Are attended by varying social types, most if not all of whom play expected, important, diverse roles in information flow;
4. Generate information flow as a byproduct of the primary activity of social interaction;
5. Formal and informal information-sharing, with information flow occurring in many directions;
6. People use information obtained at information grounds in alternative ways, and benefit along physical, social, affective, and cognitive dimensions;
7. Contain many sub-contexts contingent on people's perspectives and physical factors, which together form a grand context (Fisher et al., 2004: 756).

On Twitter, information exists in a temporal setting and is based on the availability of many individuals sharing content where hashtags create relations among content. Social interaction may or may not be the primary activity, but is the implicit goal of any social network. Information flows in many directions on Twitter, and sub-contexts that form within Twitter information grounds are based on "perspective" and "physical factors"—that is, what users are experiencing.

Technological Information Grounds occur on Twitter when hashtags are adopted to engage in shared (findable) discourse and produce information flow as a byproduct. Hashtags link to a wider stream of discourse, a context that is itself a *linked* stream, but structurally or linguistically linked text emerges as a sub-context, forming in a location (a hashtag stream). Hashtags thus create a "virtual location". The associated event in the physical world, in this case the Superbowl, is the physical location around which experience is shared and information is exchanged. Location is construed as inclusive of both physical location and virtual participation around a hashtag.

Twitter as a third place?

Information Grounds theory has evolved to integrate Oldenburg's (1999) notion of "third places," (Fisher et al., 2005). According to Oldenburg, third places are neutral spaces where people can come and go freely without permission or invitation. In third places, individuals have no preexisting status carried over from their home, workplace, or society. These "first two characteristics of the third place ... merely set the stage" for the primary activity of third places: conversation (Steinkuehler and Williams, 2006:

892). Third places are also accessible, inviting, and populated with regulars as well as newcomers. Lack of "pretension," invites "verbal word play and wit" and gives a sense of "hominess" to the space (Oldenburg, 1999). In this way, third places are natural grounds for community building. The concept of third places has been applied in computer-mediated communication studies—for example, Steinkuehler and Williams study of MMOs (Steinkuehler and Williams, 2006).

Steinkuehler and Williams (2006) stipulate eight characteristics of "third places":

1. ***Neutral Ground****—neutral grounds where individuals are free to come and go as they please with little obligation to or entanglement with other participants.*
2. ***Leveling effects****—space in which rank and status in the workplace or society at large are of no import, where acceptance and participation is not contingent on prerequisites, requirements, roles, duties, or proof of membership.*
3. ***Conversation is Main Activity****—conversation is a main focus of activity in which playfulness and wit are collectively valued.*
4. ***Accessibility and Accommodation****—third places must be easy to access and are accommodating to those who frequent them.*
5. ***The Regulars****—a cadre of regulars attract newcomers and give the space its characteristic mood.*
6. ***A Low Profile****—third places are characteristically homely and without pretension.*
7. ***Playful Mood****—the general mood is playful and marked by frivolity, word play, and wit.*
8. ***A Home Away from Home****—third places are home-like in terms of Seamon's (1979) five defining traits: "rootedness, feelings of possession, spiritual regeneration, feelings of being at ease, and warmth*" (Steinkuehler and Williams, 2006).

Twitter meets each of these criteria. Lack of "obligation or entanglements with other participants" enabling users to "come and go as they please" creates a neutral ground. Twitter is also a "leveler" because status is ultimately irrelevant providing that the content a user provides is useful or interesting. While updates may be the main activity on Twitter, conversation is the primary focus, and "playfulness and wit" are valued in the sub-contexts that we identify. Some of the most popular tweets in our Superbowl corpora put a humorous spin on events. Twitter is also easily accessible, accommodating, and fundamentally democratic: Anyone with a computer can have an account, and one does not need followers to participate. To the extent that regulars give Twitter its "characteristic mood," they may have a role in shaping the form that information takes. In the case of celebrity tweeters, they do, indeed, shape mood of the twitter stream, often humorously, yet this tonal or mood-building content may be an inadequate lens for considering event-centered Twitter activity.

Twitter text is also "characteristically homely" in that the 140-character limit constrains use of complex prose and sophisticated words to create an inevitably casual style. Finally, Twitter is a "home away from home" in the sense of a virtual location to which people are inspired to return repeatedly for feelings of cultural participation and connection with others whom they know personally and/or are culturally relevant to them.

Hashtags share several attributes with both information grounds and third spaces. Although lacking a physical space, hashtags become highly accessible sites of culture and meaning as threaded, open streams of findable discourse. Hashtags can be seen as the textual equivalent of a casual hangout where people converge on the same topic to share and advertise their interest.

The notion of a virtual environment as a "third space" is not spared critique in the literature. Soukup (2006) opposes the inclusion of online spaces as third places, arguing that they lack "reality," are by definition not "levelers" because the Internet divide sets up barriers to entry, and that these spaces require "prerequisite" knowledge to participate and are, therefore, not open to the public. Exploring Twitter as a third place seems warranted by descriptions of Twitter in both scholarly and popular literature.

Reporting of sports events: computational approaches

Zhao et al.'s (2011) study of National Football League (NFL) football games from 2010 to 2011 sampled Twitter data from Twitter's Streaming Application Programming Interface (API) to recognize NFL game events within 40 seconds of their occurrence with 90% reported accuracy. A training data set developed during the 2010 Superbowl containing roughly half a million tweets was queried for keywords. Their real-time, live detection of game-related tweets from the Streaming API encompasses a total of roughly 20 million tweets from 3.5 million users over 9 weeks (100 games) and 1 million tweets from the 2011 Superbowl.

These tweets were ranked by "term frequency" (the duration of the game) and filtered through an algorithm to eliminate misspellings. A "two-stage solution" was employed to recognize events in real time, but it was later discovered that the Streaming API limited this model due to an implicit throughput limit, precluding detection of any increase. Zhao et al.'s two-stage model includes an adjusted sliding window that detects events based on change in tpm and lexicon-based content analysis.

Zhao et al. (2011) posit that this increase in post rate is on par with increases in post rate as related to earthquakes and celebrity deaths. When an event of similar magnitude is detected, the lexicon-based analysis is applied to the event's post rate. In contrast to other "sensor" algorithms used to monitor major events, which rely on tweet structure (number of words and context; Sakaki et al., 2010) to detect earthquakes, Zhao et al.'s model removes URLs, twitter usernames, punctuation, @username replies, and emoticons before the keyword is extracted from the tweet. This means that the final analysis is performed on spikes and keywords outside of their original context.

The event-detection algorithm determines the type of "game event" represented in the burst; in American Football, these include touchdowns and interceptions, among other events. This is accomplished through tweet analysis to determine keywords with highest post rate. In Zhao et al., two-thirds of events were detected in fewer than 30 seconds. The discovery of the limits of the Streaming API (50 tweets-per-second [tps]) during the 2011 Superbowl is reflected in a subsequent "unified" model that does not require post rate to detect events. Instead, it adapts the keyword search to a more computationally intensive real-time analysis requiring all tweets to be searched for keywords.

Other studies demonstrate potential detection of game events through fan commentary on social media. Chakrabarti and Punera (2011) study NFL game reporting on Twitter, employing a method to summarize gameplay events that reveal semantically and temporally linked structures in tweets concerning a sporting event. Chakrabarti and Punera rely on a set vocabulary and learned "hidden states" to detect co-occurring commentary. Using hashtags of team and player names to filter the data, the authors discovered Twitter users to be "remarkably consistent" in how they refer to plays. Organic categories of gameplay tweets included comment-play (and play-detail, for example, number of yards), comment-general, and comment-game. When matched within a few minutes of the actual plays in the game, their analysis reveals corresponding peaks, referred to as "sub-events," or micro-level trends measured as changes in tweet frequency.

Chakrabarti and Punera (2011) found that searching by hashtag alone is insufficient to detect emergent sub-events—action in the game that is characterized by tweeters, and for that reason supplement time-bound hashtag plots, which use frequency of team name hashtags (e.g. #jets, #steelers) with keyword detection. Keywords like "interception," "fumble," and "touchdown" are represented through a Hidden Markov Model (Chakrabarti and Punera, 2011), in which the instance of a new state (or "sub-event") depends only on the distribution of the previous states. These keywords are developed by aword alignment statistical translation tool based on the Hidden Markov Model (HMM) which models multiple events of the same type to learn parameters that best fit the data. The model parameters contain multinomial word distributions and transition probabilities, or the measure of time between sub-events. Each sub-event produces a set of top tweets. From this, Chakrabarti and Punera (2011) learn top words related to five "hidden states" discovered through their HMM-based approach. Each of these states is labeled and associated with specific words: "Touchdown" (stop, catch, drive, pass), "Field-Goal" (miss, kick, kicker, no good, score), "Interception" (int, throw, pick touchdown, defense), "Defense and Fumble" (sack, good, punt, stop, block), and "Penalty and Fumble" (challenge, run, hold, punt, call). These states are associated with player names, and computations are continually modified for each game.

Computational approaches focus on accumulating and counting specific words or total tweets without reference to the context of the tweet. Structure (or patterned text) remains an underexplored and potentially fruitful unit of Twitter data analysis that may complement keyword analysis to detect content relevant to gameplay action and actionable for participants. Moreover, keyword variability may be more than a product of different viewer vocabularies; it may also emerge as a shared vocabulary acquired during the course of the game through the mutual participation of announcers, memes, and other surrounding events.

Dataset and methods

Data set

We examine Twitter activity during the 2012 NFL Superbowl, from 23 January 2012 (following the conference championships where the competing teams were determined) through to 8 February 2012. Our sample contains 797,128 tweets including at least one of the following hashtags: #superbowl and #sb46. #superbowl was tweeted 624,454 times, roughly three times the number of tweets containing #sb46 (190,270). Those tweets that are relevant to gameplay are discussed in the following section.

We collected data using Twitter's search API (Black, Mascaro, Gallagher & Goggins, 2012) at 1-minute intervals to assemble the 1500 most recent tweets, and then parsed the data using a set of custom-built Twitter data analysis scripts (Black et al, 2012). We configured TwitterZombie to collect: #superbowl and #sb46, and selected tweets during a 16-day period from the day following the conference championship games through the Monday following the Superbowl.

Methods

We use qualitative analytical approaches from grounded theory (Strauss and Corbin, 1990; Yin, 2008) to interpret events as they are detected and connect social media information streams to in-game events. Specifically, we adapted Strauss and Corbin (1990) to our process of content analysis, following the ontological and methodological approaches outlined in Goggins, Mascaro & Valetto (2013). This approach specifically involved a reflexive process of (1) manually coding all tweets by topics that emerged from the data (open coding); (2) and from the resulting codes, refining this list and axially recoding each tweet as "gameplay," "celebrity/non-gameplay," "conversational," or "general/non-gameplay"; (3) identifying common gameplay words in "gameplay" tweets; and (4) discerning the position of these "gameplay" words in the tweet.

Through this approach, we systematically move between analyzing trace data using statistical methods and coding content associated with specific tweets. For example, we searched for #interception and #int, #td for touchdown, and all sensible keywords identified by Chakrabarti and Punera (2011). We then searched for similar keywords relating to action on the field. "Gameplay words" included player names, and more descriptive gameplay text, such as "tackle" and "first down." We verified structural patterns, such as repetitions of tweets beginning with "Manning" (a player in the game), followed by content concerning activities on the field (at the same time), which were not part of some larger retweet network. If we discovered salient keywords or hashtags, we coded their utilization in the body of the tweet. Moving between our keyword codebook and refinements based on the context of the tweet, we identified keywords and phrases that indicate structural patterns other than those revealed by hashtag or tweet volume (tpm) analysis. We then aligned these results with the physical time of the plays.

Findings

Our findings suggest novel approaches for separating signal from noise during Twitter events. Two key findings emerge from our analysis of Superbowl tweets occurring within the 16-day timeframe. First, we identify information behavior that emerges as structurally linked tweets containing descriptions about the game that are cued by starting phrases and keywords not found elsewhere—that is, outside the 7 minutes following the described event. Within the context of structurally linked communication, we show that these gameplay tweets are linked only by similar sentence structure. No structure exists to detect these events—at least, not by using Twitter signaling markers: @-replies, retweet, and @-mentions. Second, we illustrate the degree of connection between tweets and the gameplay action they describe with a time series analysis. We show that while most gameplay tweets occur within 2 minutes of the described event, they are not correlated with peaks in tweet frequency. Both of these findings illustrate factors associated with gameplay tweets that are unlikely to be detected by algorithms that do not examine full context of tweets.

Tuning into the first word

Gameplay tweets within our corpus are identified through open and axial coding as described in "Methods". The use of "gameplay words" is dominant at the *beginning* of gameplay tweets, revealing a signal that is both weak and clear: weak because these tweets represent an extremely small number of the total tweets in our corpus, and *clear* because tweets following this pattern reveal actionable information.

Finding 1: connections—social media gameplay references and events on the field

A total of 228 tweets begin with "Manning," in reference to New York Giants quarterback, Eli Manning, before and during the game. Several events occur with this time-bound structure: First, tweets occurring before the game discuss how Manning will perform, remark about his performance and whether or not he will play in the Superbowl. Second, Manning gets "sacked" during a "first drive." For example,

> *2/5/12 23:37 Manning sacked twice to end the first drive!!! #sb46#GoPats*
>
> *2/5/12 23:38 Manning sacked twice on opening drive! Way to go pats defense! #sb46*
>
> *2/5/12 23:43 Manning #sacked twice in his first offensive hahaha! #superbowl*

This "event" would not be detected by current algorithms that focus on keywords and tweet frequency not only due to obscure language, but more importantly because they represent a fraction of the total tweets referring to Manning, which are bound to overlap, and because most do not refer to action on the playing field. Although some of the other gameplay events we report are more substantial, they represent at best under 200 tweets occurring within several minutes of a key play. The interesting, actionable information is hidden within the noise of larger volumes of less game-relevant information. It is only by focusing on the content of Tweets, not merely hashtags, that this actionable information becomes visible.

The event of Manning's third touchdown pass to Cruz is tweeted but receives modest coverage in this format, potentially explained by tweet syntax that includes "Touchdown" as the first word. During the course of the game, 490 tweets beginning with "Touchdown" occur. Of those, 142 occur between 23:51 GMT and 23:58 GMT. This is around the time of Manning's touchdown pass to Cruz, and. 71% of these tweets occur between 6:51 and 6:52. Another 191 tweets capture the Patriots' touchdown between 0:47 and 0:58 GMT with 104 (54%) occurring within the first minute and 77% (148) occurring within the first 2 minutes.

Fourth, Manning is "sacked" again. For example,

> *2/6/2012 1:55 Manning sacked. Field goal time! Work on Brady in the 4th. #NFL #sb46*
>
> *2/6/2012 1:57 Manning was sacked like a BITCH! #superbowl*

Manning's 38-yard sideline throw to Mario Manningham was also captured in roughly 35 tweets between 2:33 and 2:38 GMT. These tweets are less structured: some start with Manning, others with Manningham, some refer to a "catch," others to "caught," while some simply say, "manning to manningham." For example,

> *2/6/12 2:33: Manningham caught that! #SuperBowl2012 #SB46*

> *2/6/12 2:33: Manningham just made the play of the game. That's Santonio Holmes in the corner of the endzone stuff. Amazing, amazing catch. #sb46*

> *2/6/12 2:34: Manningham makes up for the last sideline route. #SB46*

> *2/6/12 2:35: Manning to Manningham!!!!!! What a great catch! #SB46*

Touchdowns are yet another "event" captured. The 490 "touchdown" tweets tend to be quite terse. Closer examination of those reporting the event of Manning's touchdown pass to Cruz shows distinct structure: the word Touchdown (with or without a hashtag) followed by the scoring team and sometimes the score or other brief commentary. For example,

> *2/5/12 23:51: Touchdown #Giants!, TOUCHDOWN #Giants! 2 Manning to Victor Cruz!!! 9-0... Bad defense!!! Cest La Vie!!! #SB46*

> *2/5/12 23:52: Touchdown Giants! #superbowl*

In addition, as noted earlier, roughly 70% of associated tweets occur within the first 2 minutes of a touchdown event.

Between 2:03 and 2:07 GMT, 64 tweets occur beginning with the word "Interception." Many contain #giants and, like the Touchdown tweets, they are short, containing two or more hashtags. For example,

> *2/6/12 2:04: INTERCEPTION! #GIANTS #SB46*

> *2/6/12 2:04: INTERCEPTION! #Giants #SB46*

> *2/6/12 2:04: Interception! Thank you again Brady! #NYGiants #SB46*

Fewer than five tweets begin with the word "interception" at other times.

Finally, 77 tweets begin with "Welker" (wide receiver for the Patriots); 52 are during the Superbowl. Of those, 29 tweets occurring between 2:30 and 2:39 refer to Welker "dropping" a pass. Most of these tweets occurred within 2 minutes of the gameplay event.

Our results suggest that structure (i.e. use of the same first word) *in combination with* the keyword represents an event, not the keyword alone. Moreover, these keywords are hard to predict. Even if tweets containing the keyword, but not the structure, are actually depicting the event, there is yet another layer: *the adoption of identical structure reveals something about the nature of conversation in this domain*. These users are suggesting that they are aware enough of their environment (particularly exceptional given the timeframe) to mimic a format for reporting on events they are mutually observing.

Finding 2: connecting gameplay tweets to gameplay—action and recap

We looked at tweets per minute surrounding each event described in the gameplay observation section. We note that patterned structure we call “gameplay tweets” roughly occur within 6 to 7 minutes of an event on the field, but these timeframes do not correspond to increases in tweet frequency. Figure 1 shows the frequency of tweets 40 minutes before and after two major events in the game: (1) the Giants’ first touchdown (top) and (2) Eli Manning’s successful pass to Mario Manningham (bottom). Average tweets over 4 minutes are represented (in red) as well as tpm (dotted blue line).

During the touchdown time series, we see a slight spike 2 minutes *after* the Touchdown described by our gameplay tweets (top graph). This spike does not correspond to our gameplay tweets, most of which occur during the same minute as the touchdown (6:51) with 71% of our gameplay tweets occurring between 6:51 and 6:52. The spike in overall tweets doesn’t occur until 6:53, when our gameplayers are starting to dwindle. The rolling 4-minute average in the first time series graph indicates a higher average tpm in the minutes prior to the first touchdown, at the first kickoff at the start of the game (at 6:31) and following an Audi commercial (at around 6:40), but begins a slight downward trend following that first touchdown. We can only speculate that the beginning of the game and the Audi commercial account for these spikes, as we have not done content analysis of these data.

The final sideline pass to Manning described by our gameplay tweets (bottom graph) also does not result in a peak. It is followed by a very minor spike, barely detectable in the overall data set. What’s significant here is that the gameplay tweets during this event *do not peak at all.* The rolling 4-minute average shows a slight upward trend much later, during the final play of the game. Again, we are unsure what causes this spike.

Findings validation

Our results show that gameplay-specific keywords at the beginning of tweets occur at a low volume relative to overall tpm, but are a strong signal about gameplay activities. To determine if our findings related to the Superbowl were anomalous, we developed an algorithmic approach focusing on this signal identified through our manual, qualitative analysis.

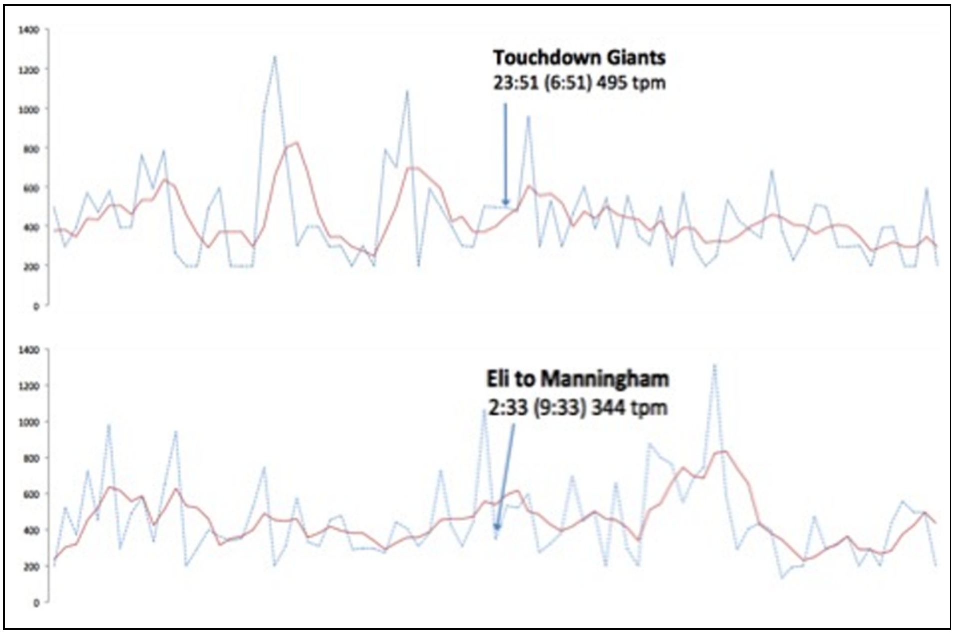

Figure 1. Time series data: number of tpm for *syntactically linked tweets* related to Giants touchdown (top) and Manning pass to Manningham (bottom). Both graphs show the frequency of tweets 40 minutes before and after two major events in the game: the Giant's first touchdown (top) and Eli Manning's successful pass to Mario Manningham (bottom). The average tweets over 4 minutes are represented (in red) as well as tpm (dotted blue line). What is notable is that the tpm does not spike in conjunction with key gameplay events.

Validation tools

We collected Tweets for the 2013 World Series between the St Louis Cardinals and Boston Red Sox using the same technology used to collect Superbowl data in 2012. We implemented the algorithm implied by our initial findings using the Haskell programming language. Haskell is a compiled, fast, strongly typed, and purely functional language. It combines benefits of very high levels of abstraction in programming languages with the speed of a low level language, allowing programmers to accurately and rapidly develop programs. Haskell includes a statistics package for basic statistical analysis and binning for histograms. In addition to Haskell, we used the MySQL database management system to execute database queries on our tweet corpus. Tweets were gathered for individual tests with our tool by batch SQL queries and saved to text files. Bags of words were also saved to text files for use by our tool.

Validation methods

Our tool treated each tweet as a list of tokens. Algorithmically building on our findings, a bag of words including player names and key events in the game of Baseball as identified on Baseball's Wikipedia page and the rosters of the Boston Red Sox and St

Louis Cardinals were read into a static data structure (Bag of World Series Words, or BWSW) for every test we ran. Our algorithm indicates words found in a tweet that are included in our BWSW. For every tweet, or list of tokens, we paired each individual token with a number into a tuple (pair) data structure indicating the token's index in the tweet. For tokens appearing at the very beginning of a tweet, a tuple would look like (0, "RT") where "RT" is the token itself. The index of a token indicates distance from the beginning of the tweet. If the index is zero, then the token is the first word.

We then filtered every index–token pair by whether or not the token portion of the pair appeared in BWSW. To the extent that a higher proportion of the words in the BWSW are found at the beginning tweets, on average, the validation of our findings in a similar, but distinct cultural event in the United States.

All index–token pairs containing a token not in the bag of words were discarded from our tabulation. We collected the indexes from the remaining pairs. This collection represented all recorded positions of a word in the bag of words appearing in our corpus. The collection was then fed to the statistics package for binning and the results outputted as a spreadsheet for data visualization.

Findings validated

Our analysis of the 2013 World Series Twitter Corpora applies qualitative findings from our analysis of the 2012 Superbowl. This analysis validates the two findings we report and provides further insight into making sense of gameplay culture as it exists on Twitter. We processed our original Superbowl corpora using the same algorithm. One key distinction between the "Bags of Words" used in each case is noteworthy. In the case of our original analysis, we identified specific player names and gameplay terms through analysis of tweet contents. In the case of baseball, we simply took common baseball terms and all player names.

Figure 2 demonstrates that baseball and player-specific terms are most heavily concentrated at the very beginning of the tweets in the corpora, consistent with our findings from the Superbowl. Figure 3 shows the Superbowl corpora reported in Findings 1 and 2 processed through the same algorithm as the 2013 World Series corpora. The 2013 World Series included six games as compared to the singular event of the Superbowl, which relates to the greater volume of World Series tweets containing gameplay words. Baseball's world series may run more than a week and include discussion of events in between games.

Figure 4 provides a clear sense of how key events in Game 3 result in the use of different, baseball-specific words, relevant to what is happening on the field, during different parts of the game. In Figure 4, we can see that the called even of an obstruction figures prominently at the very end of the game. Figure 5 provides an indication of the relationship between baseball keywords at the front of tweets, the ratio of those keywords to the tpm, and the total tpm. In order to facilitate comparisons visually, we perform a log transformation on the "keywords at front per minute" and the tpm (Cleveland, 1985). The black line represents the ratio between the two. Figure 5 shows how the ratio of keywords at the beginning of tweets to overall tpm in the baseball corpora rises first in time, followed by the total keywords at the beginning of tweets, followed by the tpm. This illustrates how an algorithmic operationalization of the findings in our article could be applied in an "early warning" type of manner during gameplay analysis.

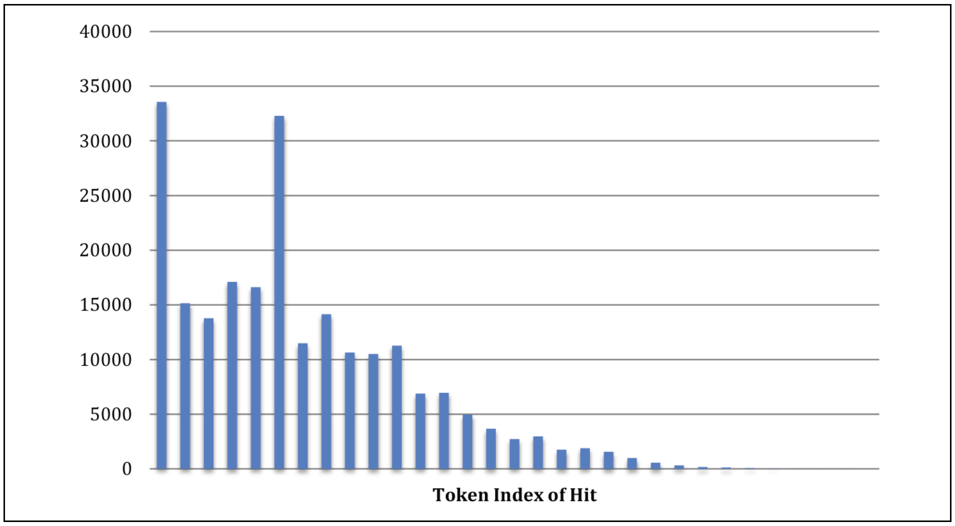

Figure 2. Baseball-specific bag of words indexical location in tweet for the 2013 world series.

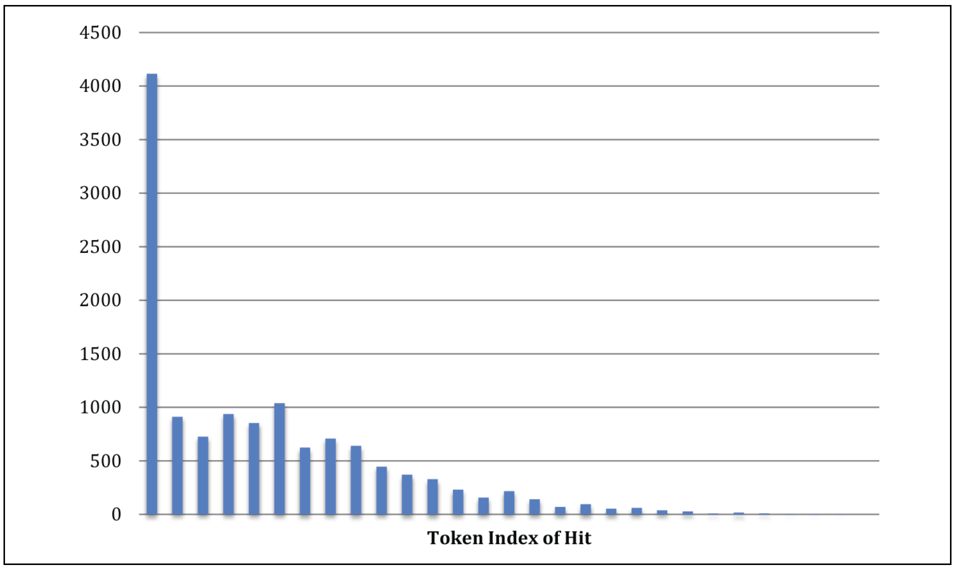

Figure 3. Football-specific bag of words indexical location for the 2012 Superbowl.

Validation caveats and considerations

A key issue in twitter analysis is filtering noise that is common to tweets. Many tweets occur in the midst of a Twitter conversation among users or in the act of rebroadcasting a message. This creates a padding at the beginning of tweets with retweet indicators and @-mention tokens unrelated to the messages we hope to observe.

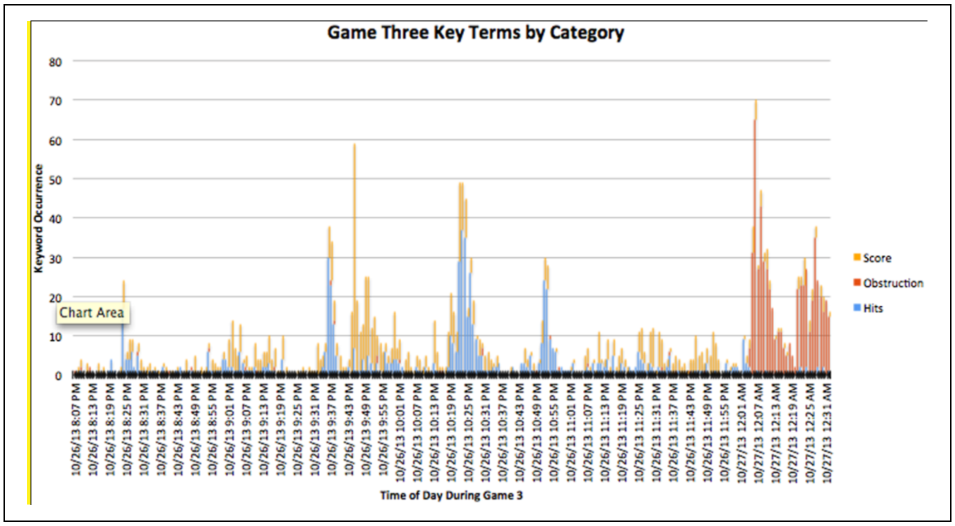

Figure 4. Top keyword occurrence at beginning of tweets during Game 3.

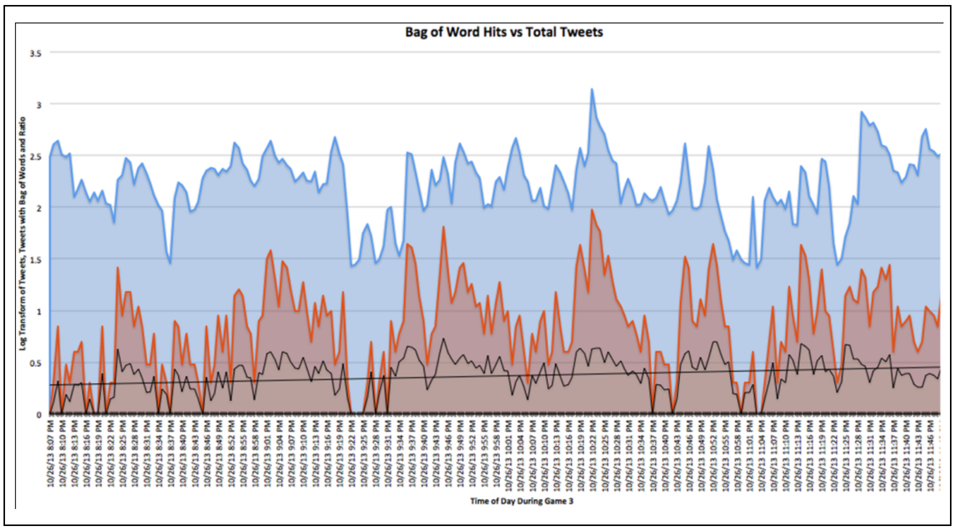

Figure 5. Comparison of total tpm in blue with number of tweets containing keywords from our bag of baseball words in the first three words of the tweet, in red. The ratio between the two is indicated by the bottom black line. To facilitate visual comparison, we perform a logarithmic transformation on the tpm and the total baseball words. This chart shows that the ratio, use of baseball words, and total tpm generally rise sequentially.

To mitigate this we added an additional cleaning function to remove this cruft from the beginning of the tweet. @-mentions not occurring at the beginning of a tweet were preserved, as they were more likely to be an integral part of the message. The function we wrote would continue to drop tokens from the beginning of the list until a token was encountered that was neither an “RT” (retweet) token or a pattern that matched an @-

mention (starting with an ampersand, alphanumerics and underscores following, potentially ending in a colon).

Game 3—we see that our bag of words is focused at the beginning of tweets across multiple games, confirming our Superbowl hypothesis. When we narrow the analysis to the two most common baseball gameplay words within a single game, we identify a slightly different trend. First, the front loading of the "big bag" holds. Second, we focus on key event words from Game 3—"Hit, Run, and Obstruction." Hit and Run are part of the original "big bag" and are top words across all games. Obstruction refers to the event that closed Game 3, where the Cardinals scored a run on a controversial play where the umpire called obstruction.

Limitations

We identified an interesting structural pattern in low-volume tweets occurring during sporting events. One advantage of sporting events compared to other event types is that these types of "virtual scenes" have a clear vernacular practice much like what Peterson and Bennett identified in hip hop culture (Peterson and Bennett, 2004). Football and baseball each have language and phrasing (vernacular practices) that go along with the games. We were able to uncover a previously unrecognized pattern of these practices on Twitter. What we do not know is whether or not less highly structured social and cultural events, like disasters or politics, have a stable enough vernacular to support this analytical strategy. Unlike games, there are not established rules or a priori "players" one can search for in the Twitter stream.

Discussion

Integration of information and social behavior theory

Our results suggest that studies approaching the examination of Twitter as a third place and Information Grounds provide a theoretically informed perspective with specific advantages for refining computational analysis of action on Twitter. This is particularly the case for social and information behavior related to events on Twitter. First, these frames aided us in distinguishing signal from noise on Twitter. The language contained in tweets alone did not provide this insight; it was only through theoretically guided *qualitative analysis*, a strategy not described elsewhere in Twitter literature, that we found the patterns we describe.

There are four salient aspects of the way Twitter can be conceptualized through the theories that we chose to integrate in this study. First, Information Grounds was critical in guiding our analysis, focusing our attention on sub-contexts based primarily on people's perspectives at various times during the game. Second, there is room for speculation regarding whether linguistic patterns are learned within the span of the event or over longer periods of Twitter use. The linguistic patterns we identify through theoretically informed examination of Tweets in our corpus lead us to confirm Twitter as a unique form of mass communication and social networking. We point out specific differences, notably the coexistence of social connection and unplanned information diffusion in a way that is explainable through our chosen theoretical constructs.

A third aspect of theory, leading us to conceptualize Twitter as *participatory mass media*, emerges from the role of word play in the construction of third places. Within this word play, the nature of gameplay tweets mediated by linguistic cues (e.g. a shared starting phrase) or phrase fragments (e.g. "Could[n't] care less about ...," "Countdown to ...," etc.) show specific promise for filtering actionable information. Algorithm developers may take special interest in this finding.

Systematic methods for applying theory to inform algorithms

Algorithm development is informed by theories related to frequency of tweets, or the frequency of specific words within tweets indicating an event. We think that measures like these, which do not consider the meaning behind the tweet, are unlikely to isolate clear, actionable information. Future research will benefit from incorporating social and information science theory more directly into algorithm development, and mapping algorithm design not only to computational phenomena, but also to social phenomena.

Recounting events and portending future consequences, gameplay tweets are a proxy for "actionable information" in our study. These gameplay tweets are patterned, but significant amounts of actionable information become invisible to conventional algorithms when structural features other than the commonly identified @-replies, @-mentions, and hashtags are used to draw attention to specific tweets. Following this recognition of underlying mechanisms for community behavior that utilize differing structure, our findings indicate that interpretations and value judgments of @-mentions, retweets, and @-reply behavior require more specific operationalization. Researchers readily draw from Twitter streams to extract data based on structural features that create something like a mainstream channel. Gameplay tweets, however, do not utilize game event-specific hashtags to create a formal "channel." Filtering by prior keywords and frequency, a method employed by Zhao et al. (2011) and Chakrabarti and Punera (2011), may not detect nuanced vocabulary that emerges during the game.

In our dataset, tweets are tagged as related to the Superbowl, but there is no sub-classification through which to discern useful, interesting, and game-relevant information. Our findings show that Zhao et al.'s (2011) strategy of removing content (username, punctuation, emoticons, etc.) from Tweets has perilous implications for modeling the social and information behavior of users during a large-scale cultural event like the Superbowl. Our analysis shows that Tweet text analysis is necessary to more fully identify information grounds emerging around gameplay events and perhaps in other large-scale contexts of Twitter use as well.

We set out to inform the development of more reliable event-detection on Twitter. Our strategy for collecting and managing data is a key component of this article's contribution. We describe our API choices and data collection strategy with a specificity and clearly stated rationale that we hope will become more common in Twitter research. Our study selects data using the Search API in order to ensure that we sample the information stream from Twitter that is most salient to our research questions. The more common use of Twitter's streaming API for Twitter research requires careful reflection, particularly when the information phenomena under study are not drawn from the full universe, but from a particular set of events.

Conclusion

Baseball and football championships as scenes in US culture

That we find similar phenomena associated with twitter use around two major sporting events in the same culture (USA) evokes similarity with the study of music scenes (Peterson and Bennett, 2004), particularly the Hip Hop music scene in the United States (Dowdy, 2007). Peterson and Bennett (2004) explore the importance of a third, virtual scene in the promulgation of music fandom in much the same way as we explore Twitter as an information grounds or third place. In essence, the corpora of discourse around a game or particular team can be thought of as a "virtual fanzine"; one needs only to search for tweets about their team, or the hashtag they are following to generate a custom, near-real-time "fanzine" to participate in during the game. In a broader sense, music scenes, like the emergence of scenes around Twitter during major sporting events, are exercises in agency and collective membership connected to individual identities. We see from our analysis of context-relevant words at the very beginning of tweets as indicators of salient events in these games that there are ways to detect growing agency. Such signals may be put to use for encouraging such third places, or for surveillance.

The media behaviors we identify on Twitter are distinct precisely because they follow a moving time window, moving through Twitter in connection with gameplay events. In a sense, these patterns are a window into the group-level activity that reflects a variety of sub-contexts. Insights about where to focus for signal in Twitter emerge from our use of theory, and our findings provide specific guidance for future algorithm development. Our main contribution is to demonstrate the advantages available to algorithm design using explicit application of relevant theory.

Future directions

Our findings lead us to pose three questions for reflection and analysis in future studies: (1) What benefits result when web researchers and Twitter users incorporate social and information behavior theories explicitly in algorithm design? (2) How and to what extent can theoretically informed, systematic, mixed methods of analysis aid us in making sense of Twitter and developing algorithms for actionable event-detection? (3) How and to what extent are computational methods not informed by social or information theories inherently limited in identifying actionable information about people?

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References

Black, A., Mascaro, C., Gallagher, M., & Goggins, S. P. (2012). *Twitter zombie: Architecture for capturing, socially transforming and analyzing the Twittersphere Proceedings of the 17th ACM international conference on Supporting group work*.

Chakrabarti D and Punera K (2011) Event summarization using tweets. In: *Proceedings of the 5th int'l AAAI conference on weblogs and social media, ICWSM*, Barcelona, 17–21 July.

Cleveland WS (1985) *The Elements of Graphing Data*. Monterey, CA: Wadsworth Advanced Books & Software.

Dowdy M (2007) Live hip hop, collective agency, and “acting in concert.” *Popular Music and Society* 30(1): 75–91.

Fisher KE and Naumer CM (2006) Information grounds: theoretical basis and empirical findings on information flow in social settings. In: Spink A and Cole C (eds) *New Directions in Human Information Behavior*. Dordrecht: Springer, pp. 93–111.

Fisher KE, Durrance JC and Hinton MB (2004) Information grounds and the use of need-based services by immigrants in Queens, New York: a context-based, outcome evaluation approach. *Journal of the American Society for Information Science and Technology* 55(8): 754–766.

Fisher KE, Landry CF and Naumer C (2007) Social spaces, casual interactions, meaningful exchanges: “information ground” characteristics based on the college student experience. Available at: http://informationr.net/ir/12-2/paper291.html (accessed 25 November 2012).

Fisher, K., Naumer, C., Durrance, J., Stromski, L., & Christiansen, T. (2005). Something old, something new: Preliminary findings from an exploratory study about people’s information habits and information grounds. *Information Research*, *10*(2), 10-12.

Gelernter, J., & Wu, G. (2012). *High Performance Mining of Social Media Data*. Proceedings from Proceedings of the 1st Conference of the Extreme Science and Engineering Discovery Environment: Bridging from the eXtreme to the Campus and Beyond, Chicago, Illinois, pp. 221-223, ACM.

Goggins, S. P., Mascaro, C., & Valetto, G. (2013). Group informatics: A methodological approach and ontology for sociotechnical group research. *Journal of the American Society for Information Science and Technology*, *64*(3), 516-539. doi:10.1002/asi.22802

Munro R (2011) Subword and spatiotemporal models for identifying actionable information in Haitian Kreyol. In: *Proceedings of the fifteenth conference on computational natural language learning*, Portland, OR, 23–24 June, pp. 68–77,Association for Computational Linguistics (ACL).

Oldenburg R (1999) *The Great Good Place: Cafés, Coffee Shops, Community Centers, Beauty Parlors, General Stores, Bars, Hangouts, and How They Get You through the Day*. New York: Marlowe & Company.

Oldenburg R and Brissett D (1982) The third place. *Qualitative Sociology* 5(4): 265–284.

Peterson RA and Bennett A (2004) Introducing music scenes. In: Peterson RA and Bennett A (eds) *Music Scenes: Local, Translocal, and Virtual*. Nashville, TN: Vanderbilt University Press, pp. 1–16.

Pettigrew KE (1998) *The role of community health nurses in providing information and referral to the elderly: a study based on social network theory*. Unpublished Doctoral Dissertation, The University of Western Ontario, London, ON, Canada.

Pettigrew KE (1999) Waiting for chiropody: contextual results from an ethnographic study of the information behaviour among attendees at community clinics. *Information Processing & Management* 35(6): 801–817.

Sakaki T, Okazaki M and Matsuo Y (2010) Earthquake shakes Twitter users: real-time event detection by social sensors. In: *Proceedings of the 19th international conference on World wide web, WWW’10*, Raleigh, NC, 26–30 April, pp. 851–860, ACM.

Seamon, D. (1979). *A geography of the lifeworld: Movement, rest, and encounter*. Croom Helm London.

Soukup C (2006) Computer-mediated communication as a virtual third place: building Oldenburg’s great good places on the world wide web. *New Media & Society* 8(3): 421–440.

Steinkuehler CA and Williams D (2006) Where everybody knows your (screen) name: online games as “Third Places.” *Journal of Computer-Mediated Communication* 11(4): 885–909.

Strauss AC and Corbin JM (1990) *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. 2nd ed. Thousand Oaks, CA: SAGE.

Yin RK (2008) *Case Study Research: Design and Methods*. 4th ed. Thousand Oaks, CA: SAGE.

Zhao S, Zhong L, Wickramasuriya J, et al. (2011) Human as real-time sensors of social and physical events: a case study of Twitter and sports games. arXiv:1106.4300. Available at: http://arxiv.org/abs/1106.4300 (accessed 10 July 2013).

Author biographies

Ian Graves is a doctoral student in the Department of Computer Science at the University of Missouri. He is studying under William Harrison. He holds a BS in Computer Science from the University of Missouri. His research interests include programming language design, formal methods, functional programming, and applications of these topics in computation, security, software engineering, and data analysis.

Nora McDonald is a doctoral student in the College of Computing and Informatics at Drexel University, where she currently studies under Susan Gasson. She holds a BA in English Literature from Cornell University. Her research interests focus on exploring social organization and technical infrastructures underpinning group work in online collaborative communities and open source software communities and the implications for community performance.

Sean P Goggins, PhD, joined the University of Missouri's iSchool faculty in 2013. He was previously on the faculty of Drexel's iSchool, from 2009 to 2013, and a tech designer and leader in a range of industries from 1993 to 2009. Goggins holds an MS in Software Engineering from the Computer Science department at the University of Minnesota and a PhD in Information Science and Technology from the University of Missouri. His research interests are focused on building context adaptive spaces to support distributed group work. Specifically, he seeks to build understanding of the emergence, development, and dissolution of technologically mediated groups in both walled gardens like those found in online learning and software engineering, and open public spaces, like those found on social media platforms. With this understanding, he is developing a methodological approach to research that focuses on interactions, performance, identity, and discourse through technology.