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Twitter as Social Sensor: Dynamics and Structure in Major Sporting Events

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Abstract

Twitter often behaves like a "social sensor" in which users actively sense real-world events and spontaneously mention these events in cyberspace. Here, we study the temporal dynamics and structural properties of Twitter as a social sensor in major sporting events. By examining Japanese professional baseball games, we found that Twitter as a social sensor can immediately show reactions to positive and negative events by a burst of tweets, but only positive events induce a burst of retweets to follow. In addition, retweet networks during the baseball games exhibit clear polarization in user clusters depending on baseball teams, as well as a scale-free in-degree distribution. These empirical findings provide mechanistic insights into the emergence and evolution of social sensors.

Introduction

Online social media sites, such as Twitter and Facebook, have become increasingly popular, to the point that they are now essential tools in everyday life, thereby facilitating massive, near-realtime, networked social interactions in cyberspace. In addition, these media can have an impact not only in cyberspace but also in the physical-world. For example, it was reported that Twitter helped Arab Spring activists to spread and share information, playing a key role in the ensuing revolutionary social movements[1]. Thus, online social media can work as interfaces between cyberspace and real-world environments, connecting people and information in some nontrivial ways. Consequently, online social media form a hybrid system of users and the web, which may behave like a single organism that evolves in time, providing a new research subject for the study of artificial life.

Many social media studies have already been conducted, though not in the context of artificial life. Focusing particularly on Twitter, we see that previous studies have reported its unique characteristics, such as the structural properties of user networks (Kwak et al., 2010; Bollen et al., 2011a), the nature of social interactions (Grabowicz et al., 2012; Conover et al., 2012) and information diffusion (Romero et al., 2011; Weng et al., 2012), collective attention (Lehmann et al., 2012; Sasahara et al., 2013) and collective mood (Golder and Macy, 2011; Dodds et al., 2011), and users' dynamics related to particular real-life events (Sakaki et al., 2010; Borge-Holthoefer et al., 2011; González-Bailón et al., 2011). Twitter data were also used to detect emerging topics (Takahashi et al., 2014) and to predict the stock markets (Bollen et al., 2011b).

This paper focuses on Twitter as a "social sensor," a new type of emergent collective behavior in the social age. Twitter allows users to read, post, and forward a short text message of 140 characters or less, called "tweets," in online user networks. As shown in Fig. 1, Twitter users actively sense real-world events and spontaneously make utterances about these events by posting tweets, which immediately spread over online user networks. In addition, such information cascades can be amplified by chains of "retweets" (forwarded tweets) from other users, called followers. This is not a passive one-shot process, but rather an active process that is recurrently happening and constantly evolving due to changes both in the physical-world and in cyberspace. Consequently, the Twitter system can behave like a social sensor, exhibiting collective dynamics and a distinct structure linked with target events. This is true in principle, and the previous studies mentioned above have revealed some aspects of social sensors. However, little is known about the dynamic nature of social sensors which cannot be explained solely by "bursts of tweets."

We therefore conducted a case study of Twitter as a dynamic social sensor in major sporting events—Japan's 2013 Nippon Professional Baseball (NPB) games—by focusing on co-occurrences of tweets and retweets. These target events were suitable for our primary study because it is known that major sporting events are the subjects of strong collective attention of viewers, which gives rise to a large volume of tweets and retweets (Bagrow et al., 2011; Sasahara et al., 2013). Our study provides key insights into how and when the collective dynamics of social media users emerge and function as a social sensor.

[1] `http://www.arabmediasociety.com/?article=816`

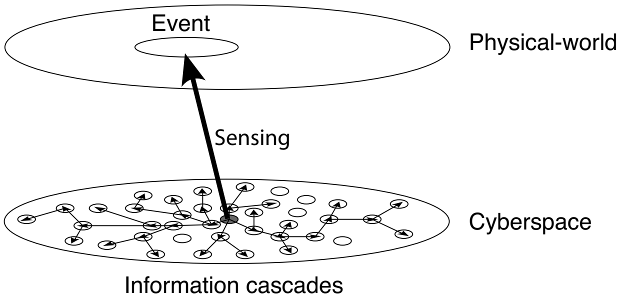

Figure 1: Schematic illustration of a social sensor. Nodes in cyberspace represent Twitter users. The thick arrow represents a user sensing a real-world event, and thin arrows represent the corresponding information cascades by means of tweet and retweet.

Methods

For this case study, we collected a comprehensive dataset by using hashtags, which are used to categorize tweets by keywords. The dataset was analyzed to explore the dynamics and structure of Twitter as a social sensor linked with major sporting events, described as follows.

Tweet Collection

We collected tweets surrounding 19 baseball games from the Climax Series (the annual playoff series in NPB) held from October 12 to 21, 2013, and from the Japan Series (the annual championship series in NPB) held from October 26 to November 3, 2013 in NPB. To this end, we selected hashtags related to Japanese professional baseball, such as `#giants` and `#rakuteneagles`, each of which represents the name of a professional baseball team by reference to a hashtag cloud site[2]. Then, we continuously crawled tweets with these target hashtags by using Twitter Search API[3]. This crawling resulted in 528,501 tweets for the baseball games in total. Each piece of tweet data contains a text message with at least one hashtag and the metadata, including the timestamp and the user profile.

Measurement of Temporal Correlation between Tweets and Retweets

The burst-like increases of tweets are often followed by those of retweets, which recurrently occur especially when positive events happen in the physical-world, as we will see later on. To measure temporal correlation between tweet and retweet count time series, we measured a cross-correlation function defined as follows (Venables and Ripley, 2002):

$$R_k(i,j) = \frac{C_k(i,j)}{\sqrt{C_0(i,i)C_0(j,j)}},$$

where

$$\begin{aligned} C_k(i,j) &= Cov(y_n(i), y_{n-k}(j)) \\ &= E[(y_n(i) - \bar{y}_n(i))(y_{n-k}(j) - \bar{y}_{n-k}(j))]. \end{aligned}$$

$R_k(i,j)$ varies between -1 and 1. In our analysis, $y_n(i)$ and $y_n(j)$ are the time series of tweets and retweets counted by 10 sec, respectively, and k is a time lag of $y_n(j)$ to $y_n(i)$. We changed k between 0 and 5 min at 10 sec intervals, because the following retweets always occur after the bursts of tweets. We adopted the maximum value of $R_k(i,j)$ as a measure of temporal correlation between tweet and retweet time series (denoted by R_{max}).

Construction of Retweet Networks

The structures of social sensors linked with major sporting events are examined using complex networks. Complex networks consist of a large number of nodes with sparse connections between them, and they are used to describe, analyze, and model real-world networks, ranging from biological systems to social systems to artificial systems (Newman, 2010).

Using official retweets (not user retweets—posts with "RT" by hand), we constructed "retweet networks," in which each node represents a user and a directed edge is attached from user B to user A if user B retweets a tweet posted originally by user A. Note that if another user C retweets a user B's retweet, a directed edge is connected from user C to user A (i.e., tweet origin). This is due to the official retweet specification of the Twitter system. Thus, influential users (also known as "hub" users) whose tweets are preferentially retweeted are represented as nodes with many incoming edges.

The resulting retweet networks are visualized in a force-directed layout algorithm called OpenOrd[4] using Gephi[5]. The size of nodes is proportional to the logarithm of the number of in-degrees. In addition, cumulative in-degree distributions are calculated from retweet networks to access their structural properties.

Results

First, we show an example of the tweet and retweet dynamics of a baseball game in the 2013 Japan Series. Then, we look into the temporal correlations of tweets and retweets as a unique feature of dynamic social sensors in 19 baseball games from the Climax Series and the Japan Series. Finally, we examine Twitter as a social sensor in terms of user interactions by constructing and analyzing retweet networks.

[2] `http://hashtagcloud.net`

[3] `https://dev.twitter.com/docs/api/1.1/get/search/tweets`

[4] `https://marketplace.gephi.org/plugin/openord-layout/`

[5] `https://gephi.org`

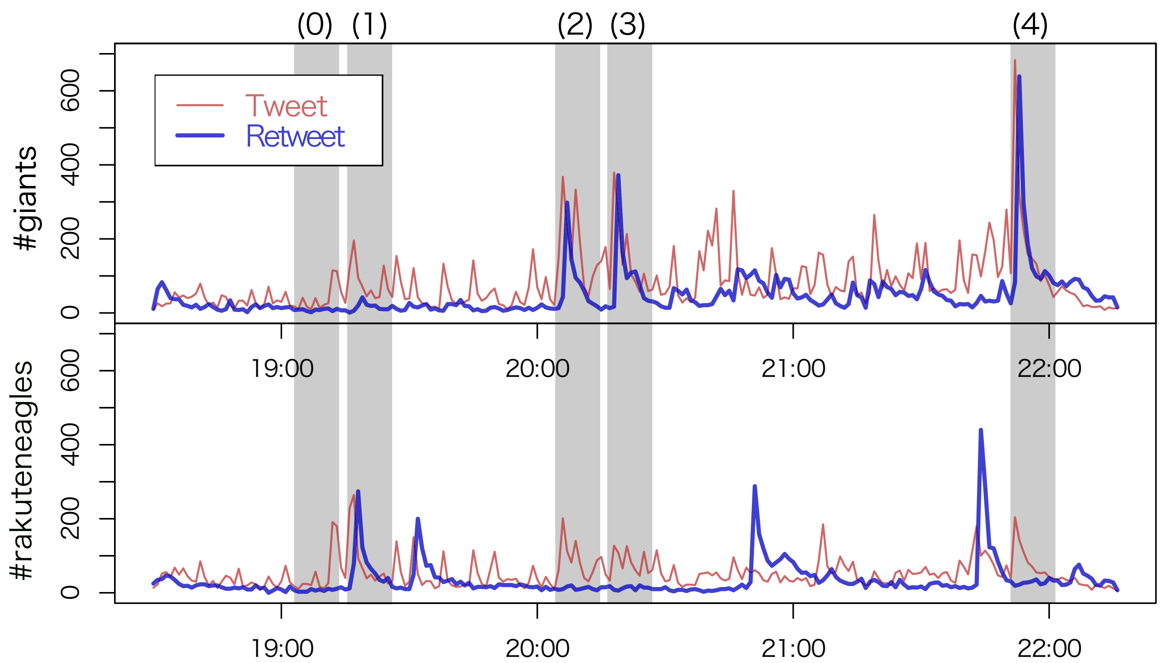

Figure 2: Example of tweet and retweet time series for the sixth round in the 2013 Japan Series in NPB. Red lines denote tweets and blue lines denote retweets. The upper panel shows tweets for the Giants (`#giants`) and the lower panel for the Eagles (`#rakuteneagles`). There is no event in (0). See the text for (1)-(4).

Dynamics of Tweets and Retweets

Figure 2 shows tweet and retweet time series for the 6th round in the 2013 Japan Series. In this game, the Yomiuri Giants beat the Tohoku Rakuten Golden Eagles by a score of 4-2. We see some co-occurrences of burst-like increases in tweets and retweets in Fig. 2 (1)-(4), each of which corresponds to the following events, respectively:

(1) The Eagles batted around in the bottom of the second inning, scoring two runs.

(2) The Giants turned the game around in the top of the fifth inning, scoring three runs.

(3) The Giants added another run in the top of the sixth inning.

(4) The Giants won the game.

In Fig. 2, the co-occurring bursts of tweets and retweets more frequently emerged in the context of the Giants (the winning team) than the Eagles (the losing team). Figure 3 exemplifies that during event (3), positive tweets such as "Oh goody!" and "go-ahead homer!" were posted with `#giants`, whereas negative tweets such as "Oh, no!" and "strike out ..." were posted with `#rakuteneagles`. Thus, once a particular event happens during a baseball game, users spontaneously post a scream of delight from the winning side and one of disappointment from the losing side. In other words, without such events, there is no strong bias against a tweet's polarity, positive or negative, as seen in Fig. 3 (0). These findings suggest that in baseball games, Twitter as a social sensor can immediately show reactions to positive and negative events by a burst of tweets, but only positive events induce a burst of retweets to follow.

On the basis of these observations, we assume that a temporal correlation between tweet and retweet time series would work as a measure of collective positive reactions of users in baseball games, which we will quantitatively examine in the next section.

Co-occurring Bursts of Tweets and Retweets

We now turn to the co-occurring bursts of tweets and retweets as a social sensor measure in major sporting events. To this end, we computed and compared a cross-correlation function for tweet and retweet time series, defined in the Methods section, from the Japan Series (seven games) and the Climax Series for the Central League (five games) and for the Pacific Leagues (seven games). We examined 19 games in total. We limited our analysis from the start time to one hour post-game for each game.

Figure 4 (left) shows the maximum values of the cross-correlation function (R_{max}) of tweet and retweet time series for the Giants (G) and the Eagles (E) across seven games in the 2013 Japan Series. In this figure, we can confirm that the winning team has R_{max} greater than that of the losing team in all games. Moreover, we found two interesting features: in the first round, R_{max} for the Giants was much larger than that of the Eagles, because this was a one-sided game and the Giants went on to win with consummate ease; in the fifth round, both teams showed an equivalent R_{max} value, because it was a close game. These results seem reasonable because, as mentioned above, a greater R_{max} value is associated with simultaneous bursts of tweets and retweets, which are in turn associated with significant game events, such as a base hit or home run. Therefore, the deviations of R_{max} are attributed to the degree of excitement of a game, which corresponds to significant scoring events.

We examined whether this notable property of a dynamic social sensor holds for other baseball games in the 2013 Climax Series. R_{max} worked as a good measure of positive reactions in the social sensor in 16 of 19 games. As shown in Fig. 4 (middle and right panels), this property holds true except in the case of three games: the second round in the Central League Climax Series and the fifth and seventh rounds in the Pacific League Climax Series. Two of these exceptions were based on the non-stationarity of tweeted and retweeted time series, in which fans generated a single sustained burst of retweets regarding a winning run after a long pitchers' duel. The other exception was based on inactive retweet reactions; for some reason, fans were not well excited or focused. Thus, R_{max} cannot be applied to both cases, which is a potential disadvantage of this measure.

We next classified the computed R_{max} values into two groups, one is the winning team group and the other the losing team group, and compared their means statistically. The result shows a significant difference between the two groups (t-test, $P < 0.05$), as shown in Fig. 5, meaning that greater R_{max} values are related to winning games. Our speculation described in the previous section has now been statistically confirmed. Therefore, we conclude that the positive collective reactions of a social sensor, measured by R_{max}, are highly indicative of winning in baseball games, and probably in other professional team sports, such as football and basketball.

Retweet Networks and Social Interactions

To quantify the structure of Twitter as a social sensor, we constructed and analyzed retweet networks related to the sixth round in the 2013 Japan Series using tweet data with `#giants` and `#rakuteneagles`. As mentioned before, nodes represent users and directed links represent official retweets between them, and colors correspond to hashtags.

The retweet network (A) corresponds to event (1) where the Eagles got two runs in the second inning, and the network (B) corresponds to event (2) and (3) where the Giants turned the game around. These networks have distinct structural features. First, the retweet networks (A) and (B)

	Fig. 2 (0)	Fig. 2 (3)
#giants	菅野頼みだのう・・・#giants 完璧に抑えられてるの .. ぅぅ ..#giants 川 ´・o ･)ﾉy-~ 今日の巨人打線はマー君相手 巨人ファンです！試合中このアカウントでつぶ バット折られすぎやん w #giants 打ててないな……(ﾟ ∀ﾟ ; ノ) ノ心配である。 いやでも絶対諦めん。#giants 150 を超えるストレート、キレッキレッの変 今、坂本選手を打ち取ったのはツーシームか。 今日の試合は 先制点をとられたらそのチーム 菅野がんばれ！！！ #giants #kyojin 巨人の攻撃終わるの早すぎるんだよなあ・・ まったく負けないって気持ち悪いぜ #giants	巨人逆転 #giants やったー！！！！！！！！！！！！ #giants ｷﾀ——(ﾟ∀ﾟ)——!! #giants 逆転きたああああああああああああああああ 最高や！ #giants 逆転！ #giants #rakuteneagles よしのぶううううううううううううううううう ｷﾀ━(ﾟ∀ﾟ)━!ｷﾀ━(ﾟ∀ﾟ)━! #giants 逆転成功！！ #giants よし！ 由伸ナイバッチ！ #giants よしのぶktkr #giants よっしゃあああああああああああああああ勝 きたああああああああああああああああああ
#rakuteneagles	先制点早く欲しい。#rakuteneagles マギムランでいいんだよ～ #rakuteneagles #t #rakuteneagles 今日決めたい!!!決める!!! そろそろマギムランみたいな #rakuteneagles 兵庫県伊丹市出身対決 凄いえええスロー映像や 巨人打線は焦っているのが明らかなバッティング 田中2回も三者凡退に抑える #rakuteneagles 今日はマギーがやってくれる気がしている。#rak マギムラン希望 #rakuteneagles 真技ー！ #rakuteneagles 先制点！！先制点！！まぎいいいい！！！ #rakute 打てない巨人が気の毒になってきた。#tbc #tbs マギー #rakuteneagles	まじか逆転 #rakuteneagles のおおおおおおおおおおおお #rakuteneagles うわああああああああああああああああああ #ra あぁ… #rakuteneagles 【239 人が実況中】プロ野球コナミ日本シリー ああああああああああああああああああああ #raku 逆転！ #giants #rakuteneagles え・#rakuteneagles #eaglenow 球が甘いんだよなぁ…。#rakuteneagles うっわ… #rakuteneagles あかん… #rakuteneagles Vai Tanaka! Vai Eagles!! #rakuteneagles マー君どうしたんだ… #rakuteneagles まーた真ん中投げちゃったよ #rakuteneagles

Figure 3: Examples of tweets' contents by `#giants` and `#rakuteneagles`. Red texts denote positive exclamations and blue ones denote negative exclamations posted by users. Without any particular events in the game (Fig. 2 (0)), there are not many positive or negative tweets from either hashtag. With an event (Fig. 2 (3)), there are many positive tweets with `#giants` and in contrast negative tweets with `#rakuteneagles`.

are composed of two main sub-networks, one is a cluster of the Giants fans (green) and the other is a cluster of the Eagles fans (blue). Within the same sub-networks there are numerous retweet interactions; however, between different sub-networks (i.e., between the Giants cluster and the Eagles cluster) there are fewer retweet interactions. A similar network topology was previously reported for the retweet networks of online political activity (Conover et al., 2012). Second, the Giants cluster involves several hub users (large nodes) who are preferentially retweeted, whereas there was a single hub user in the Eagles cluster. It turns out that these hub users are either the official account for the Giants and the Eagles or enthusiastic fans. Interestingly, there are a few retweets with both hashtags.

The bottom panels in Fig. 6 show the in-degree distributions (double logarithmic plots) of the corresponding retweet networks, respectively. These in-degree distributions exhibit a scale-free property; a long tail proofs the existence of hub users' many retweeted posts, although we have visually confirmed this above. Furthermore, it should be noted that the tails of the in-degree distributions tend to shift to the right (i.e., greater k) on the winning side. In network (A), the tail is much longer in the Eagles cluster than the Giants cluster, while in network (B) the situation is opposite. Although we used tweets with `#giants` and `#rakuteneagles` for analysis, a bipolar structure as well as a scale-free nature we have observed are not at all trivial, but rather provides hints

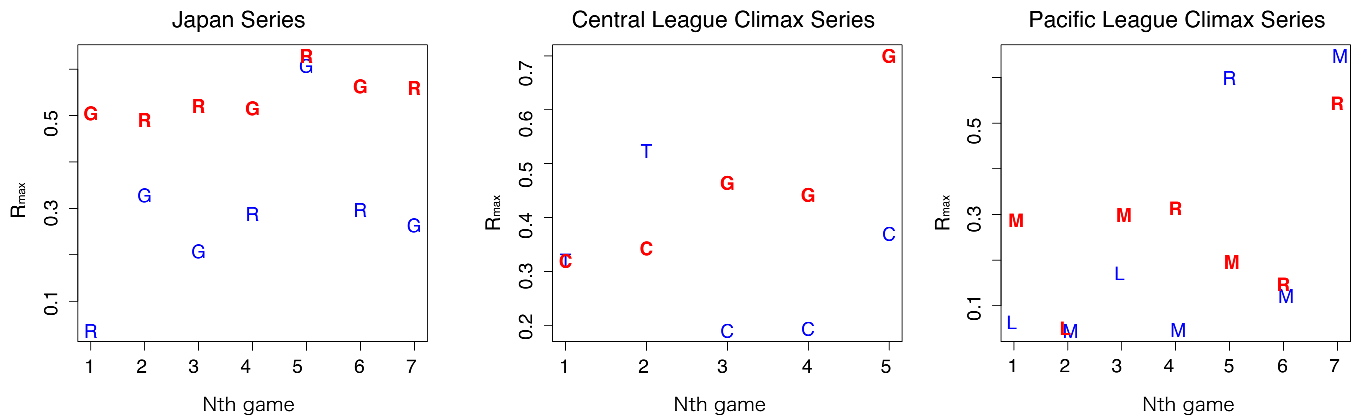

Figure 4: Cross-correlation values (R_{max}) between tweet and retweet time series for the 2013 Japan Series (left) and the 2013 Climax Series for the Central League (middle) and the Pacific League (right). Red denotes the winning term and blue denotes the losing team. G: Yomiuri Giants, R: Tohoku Rakuten Golden Eagles, T: Hanshin Tigers, C: Hiroshima Toyo Carp, M: Chiba Lotte Marines, L: Saitama Seibu Lions.

on how users interact, behaving like a social sensor.

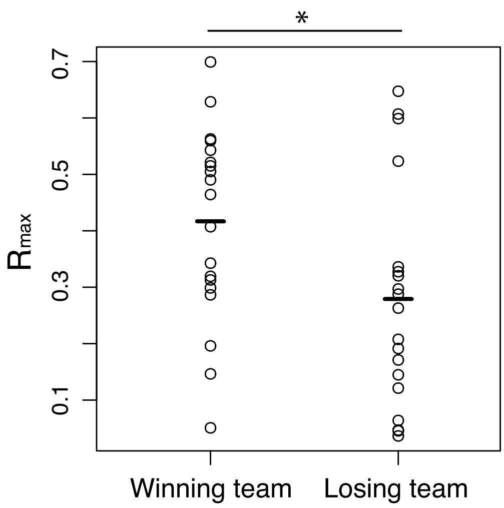

Figure 5: Distributions of R_{max} in the winning team group and the losing team group, with the mean values (crossbars).

Discussion

In this paper, we have demonstrated the temporal dynamics and structural properties of Twitter in major sporting events. Our results provide empirical evidence of how and when collective dynamics of users in the web function as a social sensor. We found that co-occurring bursts of tweets and retweets happen frequently and recurrently in winning teams in baseball games, and consequently R_{max} for these time series can be a good indicator of winning or losing the game.

This notable property, however, is not necessarily true for other sporting events, and no doubt it depends on the type of sport. This is because different sporting events may have different "affordance" (Gibson, 1977), thereby possibly inducing distinct yet coherent user reactions. For example, in two-team sports such as baseball and football, there are detailed rules with a scoring mechanism that can prompt fans to be more aware of a game's progress. This situation elicits spontaneous, polarized tweet and retweet reactions to scoring events among fans of different teams. In contrast, in multi-team sports such as car racing, rules are simple and there is no scoring mechanism, which may deprive fans of a chance to react the progress of a race. In this situation, tweet and retweet reactions can occur in a different fashion than with two-team sports. In fact, we observed such a case in the 2013 F1 Japanese Grand Prix (data not shown). Nevertheless, we think that the measurement of co-occurring bursts of tweets and retweets using R_{max} can be applied to a wider class of major sporting events, and probably other social events as well. Comparing social sensors in different types of events is thus important for the fundamental understanding of a new type of emergent collective behavior.

Furthermore, we revealed that the retweet networks for the baseball game exhibit a scale-free property, with hub users or influentials who contribute to cascades of retweets, as with other retweet networks for meme diffusion (Weng et al., 2012) and collective attention (Sasahara et al., 2013). In addition, the retweet networks for the baseball game had bipolar sub-network structures depending on the baseball teams, as with retweet networks for online political activity (Conover et al., 2012), indicating the possibility of the same underlying design principle. To assess the generality of our findings, further investigations are necessary using a wide variety of major sporting events and other types of social events across different social media.

In summary, Twitter is a "social sensor" in that it allows

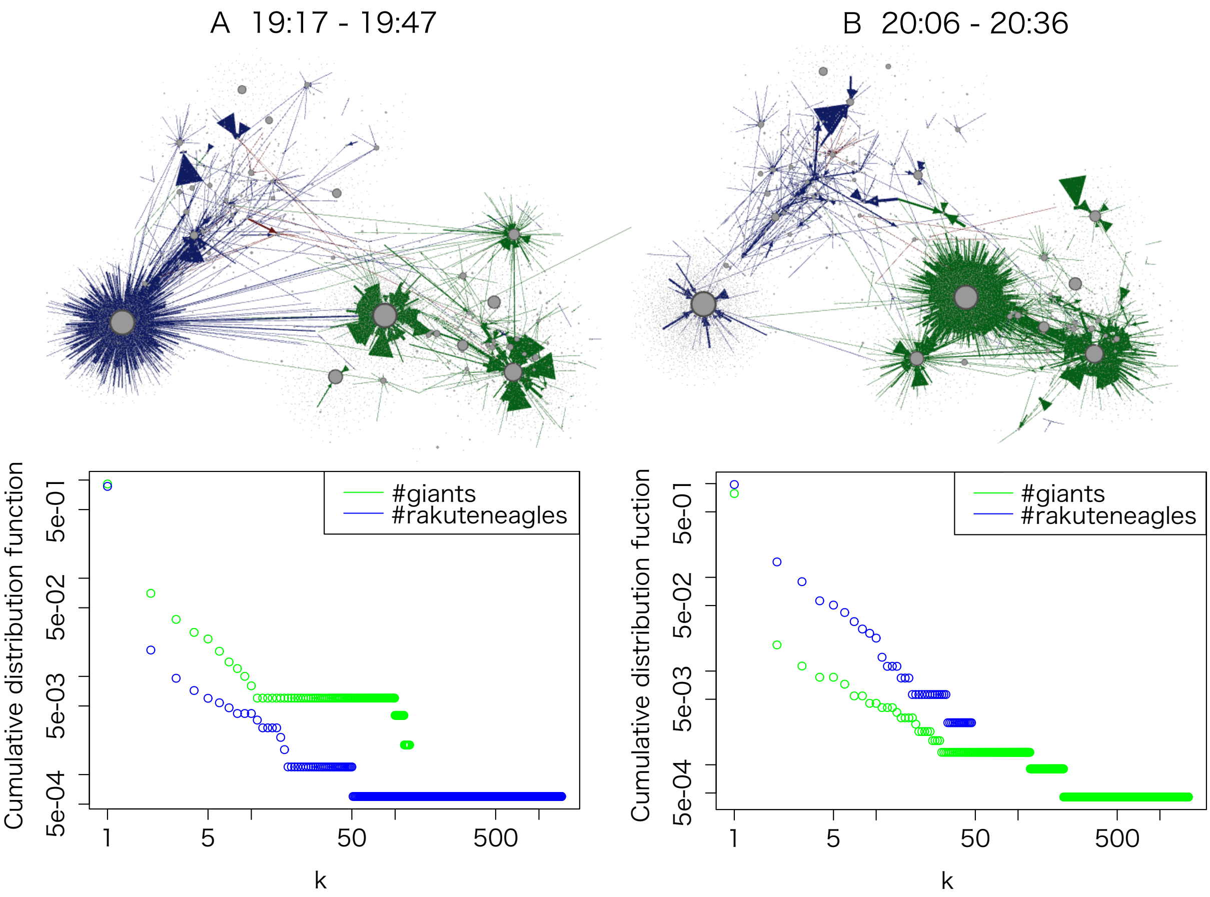

Figure 6: Retweet networks and their degree distributions in the sixth round of the 2013 Japan Series. The retweet network (A) consists of tweets generated during 30 minutes from 19:17, in which more retweets were generated with `#rakuteneagles`. The retweet network (B) consists of tweets generated during 30 minutes from 20:16, in which more retweets were generated with `#giants`. Green lines and circles denote `#giants` and blue lines and circles denote `#rakuteneagles`.

users to immediately and collectively react real-time events by tweeting and it is "active" in that users selectively retweet favorite posts, resulting in the simultaneous bursts of tweets and retweets that spread over polarized scale-free user networks. Our results offer mechanistic insights into the emergence and evolution of a dynamic social sensor. Gaining this insight is critical not only for a better understanding of the social web as a decentralized, independent, uncontrollable, living system but also for developing methods of living technology (Bedau et al., 2010) for future web-based systems. In addition, the accumulation of case studies of this kind is fundamental to artificial life study to understand a new type of complexity that arises from a collective human nature on the web.

Acknowledgements

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