Social Sensing Model and Analysis for Event Detection and Estimation with Twitter

Kardelen Cepni **Ozgur B. Akan**
Next-generation and Wireless Communications Laboratory (NWCL)
Department of Electrical and Electronics Engineering
Koc University, 34450, Istanbul, Turkey
Email: {kcepni, akan}@ku.edu.tr

***Abstract*—Twitter is an Online Social Networking (OSN) service, in which users instantly share short messages with their followers. Active use of Twitter during major events turns it into a *participatory sensor network*, where each user acts as a sensor by sharing its observation through Twitter, and the observations may be utilized for estimation of various events. There are several studies on event detection in Twitter, which are primarily based on semantic analysis of collected tweets. To the best of our knowledge, there exists no analytical study on the accuracy of event detection and estimation of event signal with Twitter using observations collected. In this study, a communication theoretical model is developed for tweet propagation, and the accuracy of the estimated signal is explored with mean square error analysis. The results indicate that, in addition to user observations and network conditions, the accuracy of the estimation is also affected by user behavior patterns.**

***Index Terms*—Twitter, Social Sensing, Twitter, Estimation Error, Event Detection**

I. Introduction

Beside their networking aspects, Online Social Networking (OSN) services recently came into use as a platform for collecting data from people. People share information with their contacts through mediums such as Facebook, Twitter, Flickr, LinkedIn, Instagram and other similar services. Active use of OSN and resulting accumulated data leads to a recently new field called *participatory sensing* or *social sensing*, which is based on the utilization of the information shared in OSN for sensing a physical phenomenon [1]. Main attributes of participatory sensing are the type of observed phenomena, type of information shared in OSN and the features of OSN. Then, aggregated data in OSN can be used to estimate the phenomena considering those aspects.

Twitter is one of most favorable OSN for participatory sensing, in which users simply share short text messages with their followers. Two main uses of Twitter are broadly defined [2]. First, people use it to share instances about their lives. Second, both individual users and news companies use it for disseminating news or observations about an event. The latter use of Twitter makes it an efficient platform for information sharing and spreading news online during major events [2]. Twitter use in mass protests in Iran, Tunisia and Egypt during 2011 Arab Spring has been investigated in [3]. It is found that people used Twitter to instantly learn the latest updates about the mass protests, and act accordingly. Furthermore, they used it to share their observations with others during the protests.

With its popularity and significant role in participatory sensing, research on Twitter exists in some directions. User behavior statistics and network characteristics are investigated in [2] and [4], respectively. Several event detection systems are proposed in [5], [6], [7] and [8], where event detection is mainly realized via sentiment analysis of tweets along with their location and time information. Although they are proposed for event detection, to the best of our knowledge, their detection and estimation accuracy have not been investigated based on a theoretical communication network model of Twitter.

In fact, Twitter may be considered as a Wireless Sensor Network (WSN), where users are sensors and they share observations about the event, i.e., samples of the event signal, to be observed. Observations including same hashtag are collected in hashtag timeline in Twitter. Here, timelines refer to webpages where various tweets are collected, i.e., tweets with the same hashtag are collected in hashtag timeline or a user reads the tweets created by its followees in its home timeline. Hashtag timeline is similar to the sink node in sensor networks since both are many-to-one receivers, where observations are collected.

Beside similarities, there are also some differences between Twitter and WSNs. In general, sensors nodes in WSNs interact with each other only when relaying information from source nodes to the sink nodes. However, the sensors interact by communicating with each other in Twitter. Namely, a user communicates with other users by following and receiving their tweets. Furthermore, while sensors send their own observations to the sink in WSNs, users do not have to send their own observations in Twitter. They may simply relay other users' observations by retweeting their tweets, which is an important feature of Twitter.

The main objective of this paper is to investigate the accuracy of event detection and estimation based on the utilizing the tweets collected in Twitter. The estimate is prone to errors since there may be fake users in the network or users' biased observations may hamper the accuracy of the information shared. In addition, network structure of Twitter, user behavior patterns and network conditions may change the accuracy of information. For the first time in the literature, we develop an analytical model for tweet propagation and information fusion in Twitter by incorporating all these factors, and we investigate the accuracy of the estimated signal.

The remainder of the paper is organized as follows. In Section II, we develop an analytical model for tweet propagation in Twitter. In Section III, we define the estimate signal and derive distortion function. In Section IV, error analysis is performed and the results are presented. Finally, we conclude the paper in Section V.

II. Twitter as a Sensor Network

Twitter is a directed social network in which users simply send and read short messages called tweets. Interactions are directed in Twitter based on following/follower relationships. Hashtag use during major events turns Twitter into a natural sensor network by enabling Twitter to collect observations in a single pool. The function of Twitter as a sensor network depends on user preferences to include hashtag in their tweets or not. There may be users sharing their observations without a hashtag. However, in [9], it is shown that majority of Twitter users add hashtag during major events in order to increase the visibility of their tweets.

During major events, the observations collected in hashtag timeline in Twitter are widely used by users. Unlike the event detection systems, observations are available to all users. A user, who does not directly observe the event, may make an estimate about the event reading through the tweets in the hashtag timeline, and take decisions based on its estimate. Hence, consensus formed in Twitter may govern people's actions during critical situations. Therefore, it is vital to understand the accuracy of estimated signal in Twitter.

While modeling, we use a discrete time framework and make the following assumptions. Although there are various features of Twitter such as reply, mention and favorite, in the model, we assume that users may only tweet, retweet and use geotag/hashtag in their tweets. Users may take a single action during each time interval. For this study, we approximate the average time a user spends in Twitter including reading tweets in its home timeline and/or creating a tweet as a minute assuming that a dynamic event is occurring, which needs to be observed in minute intervals. For simplicity, we assume that tweets include text messages and users do not have a memory. Namely, their current observations are not affected by the previous observations. In the model, all accounts are taken to be public. Namely, user may follow people without requiring an approval. Lastly, we assume that if a user inserts a hashtag, then it tweets about the event related to that hashtag.

A. Tweet Propagation Model

We investigate the information propagation in Twitter by modeling the path of a tweet after it is created until it reaches follower timelines and hashtag timeline. Suppose there exists a social event or a disaster in the region R. The source of the event signal to be observed is located at (x_0, y_0), and i^{th} user, i.e., U_i resides at the location (x_i, y_i). Every $U_i \in E$ for $i = 1...N$, where E is the set of Twitter users observing the event or interested in the observations. Note that E does

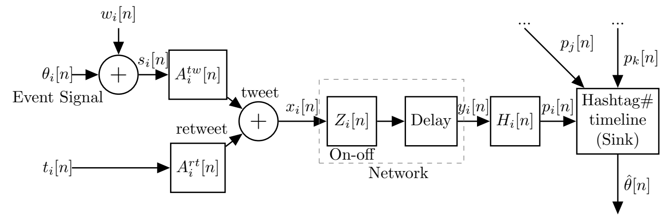


Fig. 1. Information flow model in Twitter.

not include all Twitter users but only the ones participating in social sensing. Furthermore, users do not need to be around the event region R. They may be following the event in a far location from R. The set of people followed by U_i is named as *followees of* U_i and defined as

$$F_i = \{U_x \in E, U_x \neq U_i \mid U_i \rightarrow U_x\}, \tag{1}$$

where $\rightarrow$ means *follows* and $|F_i|$ is the number of followees of U_i at time n. F_i may change with time as U_i follows and unfollows users. Thus, the observation of U_i at time n is denoted as

$$s_i[n] = \theta_i[n] + w_i[n], \tag{2}$$

where $\theta_i[n]$ is event signal at U_i's location (x_i, y_i), and $w_i[n]$ is the observation noise. The noise can be considered as user's bias on the source event or it may be due to sensual impairments, i.e., visual, hearing impairments. The noise prevents U_i from observing the pure event signal $\theta_i[n]$.

If U_i wants to share the observation $s_i[n]$ with its followers, it has several options. $x_i[n]$ is signal sent to the Twitter network after U_i's action, i.e., tweet or retweet, as shown in Fig. 1. User's possible actions are discussed in the following part.

1) Users and their actions: When a user logs in to Twitter, it has several options. First, it may not take any action, i.e., log off after checking its account. In this case, sensor is considered as inactive. Second, it can take only the following actions based on our assumptions:

Tweet: U_i only tweets its observation, and the message $s_i[n]$ may appear in the timelines of its followers depending on the network availability.

Retweet: U_i prefers to share one of the messages in its home timeline, where the messages from U_i's followees are stored. Note that the observations do not have to be created by its followees. The reason is that the messages in U_i's home timeline may also include retweets. A message may be retweeted several times before it reaches to U_i's home timeline, but it appears with its original author name and original creation time in U_i's home timeline.

Regarding retweets, we make the following assumptions. At time n, a user reads all messages in its timeline that are created at time $n-1$, and retweets one of these messages. Here, all messages are equally likely to be selected by the user. We also assume that user retweets messages created up to time $n-a$. For example, if a=3, then user may retweet observations created within 3 minutes from the current time

$$
\begin{aligned}
E\Big[(\hat{\theta}[n]-\theta_0[n])^2\Big] &= \sigma_\theta^2+\sum_{i=1}^{N}\frac{p_i^{ht}p_i^s}{N^2}\Bigg[(p_i^{tw}+p_i^{rt})(\sigma_\theta^2+\sigma_w^2)-2N\Big(p_i^{tw}\sigma_\theta^2(e^{\frac{-d_{i,0}}{c_s}}e^{\frac{-|n_d|}{c_t}})+p_i^{rt}\sigma_\theta^2(e^{\frac{-d_{m,0}}{c_s}}e^{\frac{-|n_d+n_m|}{c_t}})\Big)\Bigg] \\
&+\sum_{\substack{i,j=1\\ i\neq j}}^{N}\frac{p_i^{ht}p_j^{ht}p_i^s p_j^s}{N^2}\Bigg[p_i^{tw}p_j^{tw}\Big(\sigma_\theta^2(e^{\frac{-d_{i,j}}{c_s}})+\sigma_w^2\delta(i-j)\Big)+p_i^{rt}p_j^{rt}\Big(\sigma_\theta^2(e^{\frac{-d_{m,u}}{c_s}}e^{\frac{-|n_m-n_u|}{c_t}})+\sigma_w^2\delta(m-u)\delta(n_m-n_u)\Big) \\
&+p_i^{tw}p_j^{rt}\sigma_\theta^2(e^{\frac{-d_{i,u}}{c_s}}e^{\frac{-|n_u|}{c_t}})+p_i^{rt}p_j^{tw}\sigma_\theta^2(e^{\frac{-d_{j,m}}{c_s}}e^{\frac{-|n_m|}{c_t}})\Bigg] \qquad (11)
\end{aligned}
$$

B. Tweet Delivery Failures

Tweets may not be delivered to users (followers) and the hashtag timeline because of network failures. Low Internet speed may incur delay in the delivery of tweets. Furthermore, tweet of a user may be blocked by the following factors: (i) most Twitter users are mobile during major events [3], and if the battery of a mobile device runs out, the user may not send its observation; (ii) due to imperfections in the Internet network, the connection may be lost suddenly. These factors can be modeled as an on/off channel. U_i's message $x_i[n]$ may be blocked or delayed due to imperfections in the network as shown in Fig. 1. Thus, the resulting signal of U_i at time n is

$$y_i[n] = Z_i[n]x_i\Big[n-n_d[n]\Big], \qquad (8)$$

where $n_d[n]$ is the amount of delay such that $n_d[n] \in Z$. Here, $Z_i[n]$ is an i.i.d. Bernoulli process, which either allows message to pass through the network or blocks it such that $Z_i[n] = 1$ with probability $p_i^s[n]$ and $Z_i[n] = 0$ with probability $1-p_i^s[n]$.

III. Event Estimation in Twitter

An estimate about the event signal at time n can be made by reading the tweets accumulated in hashtag timeline. For a tweet to appear in hashtag timeline, a hashtag should be added. As shown in Fig. 1, the output signal to sink becomes

$$p_i[n] = H_i[n]y_i[n] \qquad (9)$$

where $H_i[n]$ is a Bernoulli random process, which corresponds to U_i's action of adding the event related hashtag to its tweet at n, and $H_i[n] = 1$ with probability $p_i^{ht}[n]$ and $H_i[n] = 0$ with probability $1-p_i^{ht}[n]$.

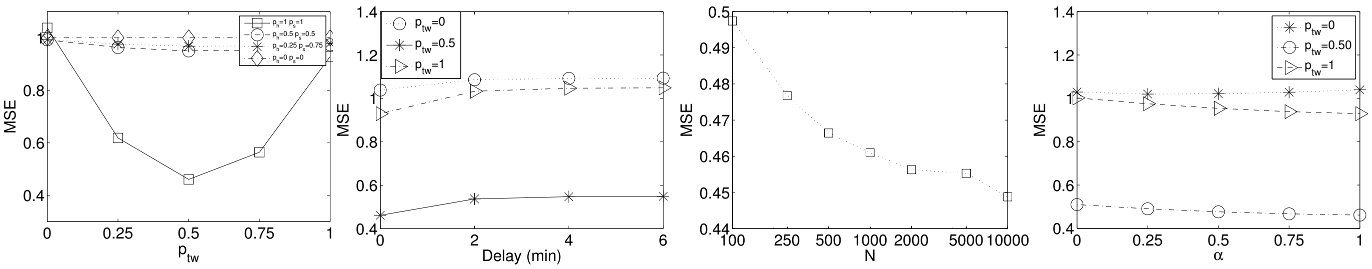
The estimate $\hat{\theta}[n]$ is formed by individuals who read the tweets in hashtag timeline and learn from these tweets about the event signal. Various learning models for social networks exist in literature [11]. We use De Groot's learning model, in which users utilize a weighted average. The weights may be described as the trust factor of corresponding users. Namely, if a user cares more about its contacts' observations than strangers' observations, then the user does not pay attention to them. Broadly, in this work, we assume that users assign equal weights on the observations of the other users, and thus

$$\hat{\theta}[n] = \frac{1}{N}\sum_{n=1}^{N} p_i[n]. \qquad (10)$$

In order to measure the accuracy of the event signal estimation based on tweets, we define mean square error (MSE) of the estimate signal as $D[n] = E[(\hat{\theta}-\theta_0)^2]$ and derive it. In the derivation, user observation noise is taken as i.i.d. zero-mean Gaussian noise with variance σ_n^2, and it is assumed all $(A_i^{tw}[n], A_i^{rt}[n], A_i^{na}[n])$, $Z_i[n]$, $H_i[n]$ are i.i.d. uncorrelated processes for every U_i. User behavior pattern, network characteristics and delay stay constant during period of observation transmission and event detection, therefore time index n is dropped in expressions, and (11) is obtained for $D[n]$, that is, MSE of the estimation of event signal at time n. Here, $\delta(.)$ is Kronecker delta function and two sets of variables $\{m, n_m\}$, $\{u, n_u\}$ appear in (11). These sets of variables originate from $t_i[n]$ and $t_j[n]$, which are defined in II-A, respectively. Considering $t_i[n]$, i.e., retweet signal of U_i at n, m is the user index of the selected message and n_m determines the creation time of the message such that $t_i[n] = s_m[n-n_m]$. Similar explanation holds for the set of variables $\{u, n_u\}$ for $t_y[n]$.

IV. Error analysis

In analysis, we calculate MSE in the estimation of the event signal (11) in MATLAB for various cases. During evaluations, an iterative approach is used since MSE depends on both directed network structure, i.e., who follows whom, and the locations of the users. Most of the social networks including Twitter [4] have the characteristics of scale free random graphs. From the perspective of Twitter, these graphs imply that while a large number of users have less number of followers, a small number of users in the network have high number of followers. We generate random scale free graphs using [12] and randomly locate users in 100 x 100 m^2 square grid area. Source signal is assumed to be located at the center of grid area. For each analysis, we iterate MSE over for 1000 different network and deployment configurations, and then take average in order to obtain the final MSE. The variables related to retweet signal u, n_u, m and n_m are chosen randomly out of possible message sets X_i, X_j defined by network graph and a=2 min. In the correlation model, we set $f = 1$ observation/minute, $c_s = 10$ and $c_t = 10$. Note that MSE is unitless in the results as the event signal to be observed is not physically defined in the model. In order to observe the effect of behavior patterns explicitly, we set p_i^{na}=0 for all users since the estimated signal is formed by the observations of active users. During analysis, unless opposite is stated we assume that (i) default network size is 1000 users ($N = 1000$), (ii) all users behave the same and (iii) network conditions are the same for all users, these conditions imply that $p_i^{ht}[n]$=p_h, $p_i^s[n]$=p_s, $p_i^{tw}[n]$=p_{tw}, and $p_i^{rt}[n]$=p_{rt}



(a) (b) (c) (d)

Fig. 2. MSE for varying (a) p_h, p_s and p_{tw} (b) n_d and p_{tw}, (c) N, (d) α

for all $U_i \in E$. Default values for p_h, p_s and n_d are taken as p_h=1, p_s=1 and n_d=0 for all users.

A. Spatially-correlated Users

In the first analysis, we assume that all users insert geotag in their tweets and investigate MSE for varying tweeting probabilities (p_{tw}), hashtag use (p_h) and network blockage probabilities (p_s).

In Fig. 2(a), we observe that unless both p_h and p_s are high, MSE stays close to 1 since path of tweet to hashtag timeline may also be blocked if hashtag is not used. Furthermore, MSE does not fall below 0.5 all the time, which is likely due to user observations noise. When p_h=1 and p_s=1, MSE decreases as p_{tw} increases, reaches its minimum by decreasing 50% when p_{tw}=0.5, and then increases with p_{tw}. Note that when p_{tw}=1 MSE is better (by 9%) than the case when p_{tw}=0. Thus, we deduce that only retweeting does not improve MSE since randomly retweeted observations may include many repeated tweets, but distinct observations are required for a better estimate of the event signal. However, the number of distinct observations are likely to be bounded since the case p_{tw}=0.5 outperforms the case p_{tw}=1, which shows that all distinct user observations are not required for improving accuracy, repeated observations may also improve MSE. In Fig. 2(b), MSE is calculated for varying tweeting probabilities (p_{tw}) and delays (n_d). It is observed that when p_{tw}=0.5, MSE increases by approximately 20% with increasing delay, but still remains below the values when p_{tw}=1 and p_{tw}=0 for n_d=0. In the following analysis, we investigate the effect of number of the active users on MSE for $p_{tw} = 0.5$. MSE improves approximately by 10% as N goes from 100 to 10000 as shown in Fig. 2(c),. Increasing the number of active sensors ultimately improves MSE, however, the number of users may change depending on the type of physical phenomena to be observed.

B. α Spatially-correlated Users

In the last analysis, we investigate the effect of geotag use on MSE. Being α spatially-correlated means that the first αN of the users, i.e., $U_i \in E$ for i=1..αN, use geotag in their tweets. In Fig. 2(d), MSE is calculated for varying tweeting probabilities and α values. It is observed that as α increases as MSE decreases. As users use geotag, the accuracy of information aggregated at hashtag timeline improves approximately 7-10% for $p_{tw} = 0.5$ and $p_{tw} = 1$ since correlated observations reduce the effect of noise in MSE expression (11). When all users retweet, the result indicates that geotag use does not improve MSE.

V. Conclusions

Twitter is a naturally formed sensor network where user observations are collected, and event estimation may be performed using collected tweets during major events. In this study, a theoretical communication model for Twitter is developed for the first time and the accuracy of estimate signal formed by collected tweets at hashtag timeline has been investigated. While the accuracy of the estimate signal is mostly dependent on users observation noise and adversely affected by network conditions, i.e., delays or blocks, the results also indicate that the accuracy of the estimation varies with user behavior patterns due to Twitter's features, as well.

References

[1] O. Aulov and M. Halem, "Human sensor networks for improved modeling of natural disasters," *in Proc. IEEE*, vol. 100, no. 10, pp. 2812–2823, Oct 2012.

[2] A. Java, X. Song, T. Finin, and B. Tseng, "Why we twitter: Understanding microblogging usage and communities," *in Proc. 9th WebKDD and 1st SNA-KDD 2007*, pp. 56–65, 2007.

[3] A. Kavanaugh, S. Yang, S. Sheetz, L. Li, and E. Fox, "Microblogging in crisis situations: Mass protests in iran, tunisia, egypt," *in Proc. ACM. CHI'2011*, 2011.

[4] H. Kwak, C. Lee, H. Park, and S. Moon, "What is twitter, a social network or a news media?" *in Proc. WWW'2010*, pp. 591–600, 2010.

[5] R. Li, K. H. Lei, R. Khadiwala, and K.-C. Chang, "Tedas: A twitter-based event detection and analysis system," *in Proc. ICDE'2012*, pp. 1273–1276, April 2012.

[6] T. Sakaki, Y. Matsuo, T. Yanagihara, N. Chandrasiri, and K. Nawa, "Real-time event extraction for driving information from social sensors," *in Proc. IEEE CYBER'2012*, pp. 221–226, May 2012.

[7] T. Sakaki, M. Okazaki, and Y. Matsuo, "Earthquake shakes twitter users: Real-time event detection by social sensors," *in Proc. 19th International Conference on WWW'2010*, pp. 851–860, 2010.

[8] D. Thom, H. Bosch, S. Koch, M. Worner, and T. Ertl, "Spatiotemporal anomaly detection through visual analysis of geolocated twitter messages," *in Proc. IEEE PacificVis'2012*, pp. 41–48, Feb 2012.

[9] M. Mendoza, B. Poblete, and C. Castillo, "Twitter under crisis: Can we trust what we rt?" *in Proc. First Workshop on SOMA'2010*, pp. 71–79, 2010.

[10] M. C. Vuran and O. Akan, "Spatio-temporal characteristics of point and field sources in wireless sensor networks," *in Proc. IEEE ICC'2006*, vol. 1, pp. 234–239, June 2006.

[11] D. Acemoglu and A. Ozdaglar, "Opinion dynamics and learning in social networks," *Dynamic Games and Applications*, vol. 1, no. 1, pp. 3–49, 2011.

[12] L. Muchnik, "Complex networks package for matlab (version 1.6)," http://levmuchnik.net/Content/Networks/ComplexNetworksPackage.html, 2013.