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<td><strong>Author(s)</strong></td>
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Measurement-driven Temporal Analysis of Information Diffusion in Online Social Networks

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Abstract— The rapid development of online social networks (OSN) renders them a popular mechanism for information diffusion. Studying the temporal characteristics is critical in understanding the diffusion process. However, due to the lack of well-defined propagation data, hardly any study addresses the temporal feature of information diffusion in OSN. In this paper, we present a measurement study on information diffusion in the Renren social network. We investigate the latency of information propagation along social links and define the “activation time” for an OSN user, and find that the activation time follows the log-normal distribution. Based on this, we develop two new information diffusion models incorporating asynchronous activation times. Application of the models in the influence maximization problem shows that they capture the temporal diffusion behavior very well. This leads to fundamental ramifications to many related OSN applications.

Keywords—measurement; temporal; social network; diffusion; activation time

I. INTRODUCTION

The rapid development of online social networks (OSN) renders them a popular mechanism for information diffusion. In this process, information will be propagated in the so called “word-of-mouth” format. Due to the special features of online social networks, such as huge user base and explicit user demographics, leveraging the word-of-mouth effect in online social networking service is convenient. Meanwhile, viral marketing [1-2] of products, ideas, and other kinds of innovations have been conducted in OSN to spread information widely and quickly. Hence, studying the temporal diffusion behaviors is essential in understanding the mechanisms by which ideas and behaviors flow along the social links in the OSN, which is instructive for viral marketing strategy. Additionally, we could predict the failure or success of innovations in their early stages after investigating the temporal evolution of the propagation trend. Moreover, considering information could be divided into desirable ones and undesirable ones, we could maximize the desirable information by choosing the most influential targets [3] or minimize the unfavorable information by blocking certain social links [4] at the beginning. This procedure could be described as shaping the underlying propagation process so as to increase or reduce the chance of success.

Many measurement studies and diffusion models have been used to study information propagation in large scale networks. In the measurement field, a number of studies focus on information dissemination in different kinds of online social networks including blogosphere [5], recommendation network [6] and other OSN [7]. Amongst them, diffusion is studied based on keyword extraction or topic mining, because of the lack of well-defined real world propagation data. Given this diffusion data limitations, Sun et al. [8] has conducted an empirical investigation of influence diffusion through Facebook by defining the influence behavior accurately using explicit page fanning diffusion data. But the temporal propagation behavior is still not addressed. Inspired by this, we collect the shared video propagation data in Renren [9] to conduct accurate influence diffusion measurement. Moreover, we are the first to define and measure the activation time on inter-personal social links in OSN and give its empirical distribution.

A number of models have been proposed for simulating diffusions in OSN, including epidemiological models like susceptible-infected-susceptible (SIS) model [10], independent cascade model (ICM) [11], linear threshold model (LTM) [12] and the temporal model of the dynamic evolution of user interactions in OSN [13]. The widely used ones are LTM and ICM, which account for the structure of the underlying social network. However, we note that traditional ICM and LTM did not consider the time delays in diffusion or simply assume the diffusion proceeds in unit time steps, which do not reflect reality. Gruhl et al. [14] is the first to consider time delays in ICM by modeling them as discrete random variables following the geometric distribution. In reality, information propagates continuously and the diffusion rate varies at different stages. Thus, discrete time assumption is not appropriate. Another related work is given by Kazumi et al. [15]. They assumed exponentially distributed time delays in the diffusion process but they did not conduct measurement studies to learn the given distribution. By defining the time delays properly as activation time, we not only measure the activation time distribution, but also develop two new diffusion models by incorporating the activation time into ICM and LTM.

In our work, we define and measure the activation time by collecting and analyzing large-scale information propagation traces in the Renren social network which is the equivalent of Facebook in China. We find that the activation time
characteristics could be better explained by log-normal instead of the power-law distribution.

Our main contributions are summarized as follows:

- We collect a substantial dataset to study the time delay in the information propagation process and define the activation time to describe the inter-personal diffusion time through social links.
- We measure the activation time and study its distribution. We also study the temporal evolution of the propagation via social links.
- We propose new information diffusion models by incorporating the asynchronous activation time delays.
- We re-investigate the influence maximization problem using our proposed diffusion models.

II. MEASUREMENT METHODOLOGY

A. Renren

Renren, created in 2005, is the dominant online social network website in China with over 160 million registered users. It shares almost the same features, structure and layout as Facebook, so it is also called the Chinese Facebook. Users could maintain their own profiles, photo galleries and blogs, and establish bidirectional friendship links with other users. However, Renren has two unique characteristics which make it extremely attractive for our influence measurement study. Firstly, unlike Facebook, the friendship relationship in Renren is public before April 2011, which enables us to collect data to create a real world social network graph. Secondly, and perhaps more importantly, well-defined information diffusion data in Renren is public to any registered users. This allows us to crawl a substantial dataset of Renren to study the temporal propagation behaviors.

B. Mechanics of Renren Information Diffusion

Information diffusion in Renren is made possible by “sharing” activities, which include sharing friends’ posted notes, photos and external links, mainly referring to video links. Diffusion of shared information occurs as follows. Firstly, user $A$ shares a piece of information $i$, which is broadcast to his entire friend list. Upon receiving this information, one or more of his friends decide to share the information as well. Thus, we say that information $i$ is propagated from user $A$ to some of his friends.

To study how information diffuses in Renren, we concentrate on the propagation of one particular activity, namely, shared video propagation. Since the shared video links in Renren mainly come from several external video websites (see Table I, which is the statistics using our crawled dataset), and the external video URLs can be used to identify different topics (videos) directly, there is no need to conduct text mining and topic identification, which is time consuming and probably inaccurate. Meanwhile, Renren provides the timestamp of when a user shares a video, which allows us to study how the propagation of videos evolves over time.

### TABLE I. STATISTICS OF EXTERNAL VIDEO WEBSITE IN RENREN

<table>
<thead>
<tr>
<th>Rank</th>
<th>Top list</th>
<th>URLs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>youku.com</td>
<td>53.7%</td>
</tr>
<tr>
<td>2</td>
<td>tudou.com</td>
<td>23.6%</td>
</tr>
<tr>
<td>3</td>
<td>ku6.com</td>
<td>5.8%</td>
</tr>
<tr>
<td>4</td>
<td>youtube.com</td>
<td>5%</td>
</tr>
<tr>
<td>5</td>
<td>56.com</td>
<td>4.2%</td>
</tr>
<tr>
<td>6</td>
<td>Others (&gt;25 websites)</td>
<td>7.7%</td>
</tr>
</tbody>
</table>

### C. Crawling Methods

We design two efficient crawlers to collect data. One is called the “user information crawler” which analyzes the user profile webpage in order to acquire this user’s friend list, affiliation information and unique user identities. The other one is called the “video information crawler” which parses each user’s sharing activity page to obtain the user’s shared video information. The whole dataset is stored in a database for future analysis.

Considering the computational complexity of crawling the entire Renren network, we perform the crawling process on the Tsinghua community, a famous college online social network community in Renren, to obtain a sub network of the whole Renren network. In the first step, we use the “browse user” function to obtain the 50 most popular users (in terms of number of friends) in the Tsinghua community. Then, we seed the “user information crawlers” with the 50 most popular users to do a snowball sampling by breath-first search. During the crawling, we obtain the unique user IDs, network affiliations and their friend lists to construct a social graph consisting of Tsinghua users and their one-hop friends. In the second step, we seed the “video information crawler” with the obtained IDs to collect each user’s shared video information, including the exact sharing time, video URL, video title, video source, number of views, number of shares, and number of comments. Since we are limited in the number of nodes we could crawl in a finite time frame, we use multiple accounts and multiple threads to download these data.

### D. Data Description

We collect a snapshot of the Tsinghua community with one hop social graph in March 2011 which includes 4,234,561 nodes and 92,773 of them are affiliated with Tsinghua, and the rest are friends of these Tsinghua affiliates. Then, using node sampling method, we use a sub-community to collect the shared video information (see Table II). Although the friendship data is a snapshot at a particular time, the video information covers 1224 days in total, from March 2008 to July 2011. The reason is that each user’s sharing activity page keeps...
In this section, we firstly analyze the user popularity and video popularity in the aggregate sharing video activities. Then, we investigate the activation time characteristics. Finally, we apply the activation time to the existing ICM and LTM to come up with Async-ICM which is ICM with asynchronous activation time and Async-LTM which is LTM with asynchronous activation time.

A. Video Popularity and User Popularity

We study the popularity distributions for more than 3.6 million videos and the corresponding users. For a certain video \( v \), the video popularity of \( v \), denoted as \( k(v) \), is defined as the number of users who have shared video \( v \). Similarly, for user \( u \), the user popularity of \( u \), denoted as \( l(u) \), is defined as the total number of videos user \( u \) has already shared.

The complementary cumulative distribution function (CCDF) of the video popularity is shown in Fig. 1. It shows that the popularity distribution for the over 3.7 million videos roughly follows a power law distribution, with an exponential tail. Using maximum-likelihood estimation, we get the power-law curve: \( P(k) \sim k^{-\alpha} \), \( \alpha = 1.87 \). This demonstrates that only a small fraction of videos achieve high popularity and thus have the potential to spread widely through the social network. For example, the distribution of popularity shows that millions (3,378,487) of videos have fewer than 10 fans in the entire network, while two orders of magnitude fewer videos (13,892) have more than one thousand fans. Also, from the statistics in Table III, we observe that each top video enjoys a high popularity of over 50,000.

The CCDF of the video popularity is shown in Fig. 2. The user popularity roughly follows a power law distribution, except with a flat head. Using maximum-likelihood estimation, we get the power-law curve: \( P(l) \sim l^{-\alpha} \), \( \alpha = 3.5 \). This shows that there exists a comparatively small number of users with a large number of shared videos. This observation may be applied to solve the classical influence maximization problems in selecting the most influential nodes in the initial stage to spread information wider.

![Empirical Complementary Cumulative Distribution (CCDF) of the video popularity and the power-law fitting curve.](image1)

![Empirical Complementary Cumulative Distribution (CCDF) of the user popularity and the power-law fitting curve.](image2)

B. Information Diffusion Through Social Links

To distinguish the effect of video sharing activity due to social influence from other effects, we define the influence through social links in our research as follows. When user \( A \) shares a certain video \( v \) at time \( t_A \) and user \( B \) shares the same video \( v \) at time \( t_B \), if \( t_A < t_B \), we will say \( A \) has an influence on \( B \) or the influence flows from \( A \) to \( B \). Considering that user \( B \) may have some other friends who may also share the same video before \( B \), and they may exert cumulative influence on \( B \)'s sharing activity, we will investigate users’ activation time in the next section.

C. Activation Time

The social graph can be modeled as an undirected graph \( G = (V, E) \), where \( V \) is the set of nodes (users), and \( u_i \) is the unique ID of each user, and \( E = \{ (u, v) | u, v \in V \} \) is a set of edges. Note that friendship is mutual in Renren, so the edge \( (u, v) \) is undirectional, which means \( (u, v) \) is equivalent to \( (v, u) \). Besides, we assume that the Renren graph remains static during our crawling and analysis.

Through crawling, we not only obtain a sample of Renren social graph \( G' = (V', E') \), where \( V' \) is the set of users from Tsinghua University and the 1-hop friends of Tsinghua users, and \( E' \) is the set of mutual friendship relationship among these users, but also collect the shared video list of each crawled user.

After describing the social graph, we now focus on the activity of sharing videos for each user. Besides gathering a set of video objects \( O = \{ o_1, o_2, ..., o_m \} \) which have been shared among users in \( V' \), for any video object \( o_m \in O \), we also gather the users who have shared this video \( o_m \) in the following transmission path set \( P_m = \{ (u_1, t_1), (u_2, t_2), ..., (u_k, t_k) \} \), where \( t_i \) is the time that user \( u_i \) shared the video object \( o_m \).

![Graph showing the number of fans for each video with corresponding users.](image3)

<table>
<thead>
<tr>
<th>Video Rank</th>
<th>Video Popularity</th>
<th>User Popularity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>76985</td>
<td>2062</td>
</tr>
<tr>
<td>2</td>
<td>66283</td>
<td>5691</td>
</tr>
<tr>
<td>3</td>
<td>61933</td>
<td>5439</td>
</tr>
<tr>
<td>4</td>
<td>61576</td>
<td>5436</td>
</tr>
<tr>
<td>5</td>
<td>60493</td>
<td>5435</td>
</tr>
</tbody>
</table>

![Table III. The popularity of the top 5 videos](image4)
For any two different elements \((u_i, t_i) \in \mathcal{P}_m\) and \((u_j, t_j) \in \mathcal{P}_m\), we claim that a user \(u_i\) have influenced user \(u_j\) for sharing video object \(o_m\) if,

- User \(u_i\) and user \(u_j\) are friends, namely, \([u_i, u_j] \in E'\);
- User \(u_j\) shared \(o_m\) earlier than \(u_i\), namely, \(t_j \leq t_i\).

For any \((u_i, t_i) \in \mathcal{P}_m\), we further gather the sharing times of users who have influenced user \(u_i\) for sharing video object \(o_m\) into an influence time set:

\[ T_i = \{ t_j \mid (u_i, t_i), (u_j, t_j) \in \mathcal{P}_m; \{u_i, u_j\} \in E'; t_j \leq t_i \}. \]

According to the influence time set \(T_i\) we define the activation time of user \(u_i\) for video object \(o_m\) as: \(t_i = \max(T_i)\).

The physical meaning of the activation time for a certain user \(u_i\) is the time difference between when the video \(o_m\) is shared by \(u_i\) and the latest time when one of \(u_i\)'s friends shared the same video. This definition is inspired by the observation in [16] which shows that more than 80% of the Twitter users usually retweet their most recent sources.

### D. Activation Time Distribution

What is the activation time distribution like? To answer this question, we present a large scale activation time study for the aggregate propagation of all the crawled videos (including 3,675,137 distinct video URLs). Furthermore, considering that some sharing activities may happen after a long activation time interval, we did not use any time limit, which is different from the methodology used in [8] which limits the activation time to 24 hours. Fig. 3 shows the CCDF of the activation time for all the aggregate activation time in log-log scale. It shows that the obtained distributions are heavy-tailed. To better explain the observed data, we compare two approximations: the power-law hypothesis and the log-normal hypothesis. A truncated power-law continuous distribution is defined as [17]:

\[
p(x) = \frac{\alpha-1}{x_{\min}} \left( \frac{x}{x_{\min}} \right)^{-\alpha}, \quad x \geq x_{\min}.
\]

For \(x > x_{\min}\), we get a power-law distribution with exponent \(\alpha\). For \(x \leq x_{\min}\), the distribution does not hold. Hence, \(x_{\min}\) is the lower bound for the given distribution. The log-normal distribution is defined as [18]:

\[
p(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(\ln(x) - \mu)^2}{2\sigma^2}}, \quad x \geq 0.
\]

We will say \(x\) has parameters \(\mu\) and \(\sigma^2\) when the corresponding normal distribution \(ln(x)\) mean \(\mu\) and variance \(\sigma^2\). Using maximum-likelihood estimation, we get the optimal distribution parameters as shown in Table IV.

**TABLE IV. DISTRIBUTION PARAMETER ESTIMATION**

<table>
<thead>
<tr>
<th></th>
<th>Power-law</th>
<th>Log-normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>(x_{\min})</td>
<td>18.23</td>
<td>18.23</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>1.55</td>
<td>1.86</td>
</tr>
<tr>
<td>P-value</td>
<td>0.0</td>
<td>0.38</td>
</tr>
<tr>
<td>(\mu)</td>
<td>1.86</td>
<td>2.17</td>
</tr>
<tr>
<td>P-value</td>
<td></td>
<td>0.38</td>
</tr>
</tbody>
</table>

To provide goodness-of-fit for both distributions, we use the Kolmogorov-Smirnov test (KS) to compare the empirical data and the theoretical distribution. For the power-law distribution, the p-value is small (close to 0). Hence, even we use the truncation point \(x_{\min} = 18.23\) of power-law to model the tail part, the difference is still significant and we conclude that the power-law distribution cannot explain the data well. In contrast, the obtained p-value for the log-normal distribution is big, so we use the log-normal distribution to model the activation time distribution.

This finding is not surprising, since for quite a long time log-normal distribution has been used to explain the observations in social science, ecology, biology [19] and OSNs [20]. Especially, log-normal distributions are able to accurately characterize some datasets which have previously been assumed as power-law distribution [21]. And our research and findings provide some insights for the log-normal phenomenon in the OSNs. The generative models for the log-normal distributions have been discussed in the literature, among which the most popular generative process leading to a log-normal distribution was “the law of proportional effect” [18]. We will further explore this effect in the OSNs of interest in our future studies.

### E. Diffusion Models With Asynchronous Activation Time

The traditional ICM and LTM cannot handle the asynchronous time delays explicitly. They just describe how information diffuses in a graph. But when they are influenced. This is not realistic since in reality information propagates continuously in an asynchronous way. To better apply the activation time to instruct diffusion behaviors, we propose two information diffusion models by incorporating the asynchronous activation time. They are ICM with asynchronous activation time (Async-ICM) and LTM with asynchronous activation time (Async-LTM), which are extensions of the classical ICM and LTM.

The specifics of Async-ICM are as follows.

- Initially, a social graph \(G\) is given, with each edge \((u, v)\) marked with diffusion probability \(p_{u,v}\), where \(0 \leq p_{u,v} \leq 1\), and a group of nodes is initially activated randomly or following certain schemes.
• Time proceeds continuously, and when user v receives certain information i from user u at time t, firstly, v will decide whether to be activated with probability \( p_{av} \). If yes, it then chooses a random waiting time \( \delta \) distributed as follows and becomes activated at \( t + \delta \):

\[
\rho(\delta) = \frac{1}{\sqrt{2\pi}\delta} e^{-\frac{(\ln(\delta) - \mu)^2}{2\sigma^2}}, \delta \geq 0
\]

• Whether or not u succeeds, it cannot make any further attempts to activate v in subsequent rounds.

• The diffusion process continues until no more activations are possible.

The specifics of Async-LTM are as follows.

Initially, a social graph \( G \) is given, with each edge \((u, v)\) marked with weight \( w_{uv} \), and \( B(v) = \{u; (u, v) \in E\} \). For any node \( v \), a threshold \( \theta_v \) is assigned.

• A group of nodes is initially activated randomly or following certain schemes.

• Time proceeds continuously, and when the total weight from active neighbors of \( v \) becomes at least \( \theta_v \) at time \( t \) for the first time, i.e. \( \sum_{u \in B_{active}(v)} w_{uv} \geq \theta_v \), then \( v \) will become active at \( t + \delta \), with \( \delta \) distributed as follows

\[
\rho(\delta) = \frac{1}{\sqrt{2\pi}\delta} e^{-\frac{(\ln(\delta) - \mu)^2}{2\sigma^2}}, \delta \geq 0.
\]

• Note that even though some other non-active neighbors of \( v \) may become active during \([t, t + \delta]\), the activation time of \( v \) will not change.

• The diffusion process continues until no more activations are possible.

Using the proposed models, we could study the temporal features of information diffusion more accurately.

IV. EXPERIMENTS

In this section, we evaluate the effectiveness of our proposed Async-ICM and Async-LTM by applying the models to the traditional influence maximization problem, which is to find a set \( S \) of \( k \) nodes to activate initially to maximize the number of nodes active at the end \( f(S) \). Here, we compare three heuristics in identifying influential nodes and find that our models could identify the most effective heuristic not only in the final active set size but also in the temporal performance.

A. Experimental Settings

For evaluation, it is desirable to use a network which exhibits the same structural features as our social network of interest. Thus, we create a synthetic network using the structural metrics of Renren[22]. The resulting graph has 11000 nodes and 68945 bidirectional edges, with clustering coefficient 0.0419 and average distance 6.17. Meanwhile, for both models certain parameters have to be specified in advance.

In Async-ICM, the diffusion probability \( p_{av} \) is unknown and we use the value \( p_{av} = \frac{\text{number of activated edges}}{\text{total number of edges}} \) as an approximation which is 0.1074 in our measured data. In Async-LTM, both the weight \( w_{uv} \) and threshold \( \theta_v \) are unknown. We assume \( w_{uv} = 1/d_{uv} \) and \( \theta_v \sim U[0.027,0.783] \). We learn the parameters using real data and get \( \theta_v \sim U[0.027,0.783] \). The activation time distribution parameters are \( \mu=1.86, \sigma=2.17 \), which are learned by the aggregate propagation behavior.

Using both models, we compare the degree-based heuristic, the centrality-based heuristic and choosing nodes randomly to solve the influence maximization problem. The degree-based heuristic chooses nodes in decreasing degrees. The centrality-based heuristic chooses nodes in decreasing betweenness centrality [23] values. Specifically, for each heuristic, we simulate the diffusion process 2000 times, with 10 initial nodes, for both Async-LTM and Async-ICM.

B. Experimental Results

To illustrate the temporal features of information diffusion, we introduce two time-related performance metrics: the first one is the percentage of nodes influenced before time \( t \), denoted as \( p(t) \); the second one is the time taken to influence a total number of \( n \) nodes, denoted as \( t(n) \). Using these metrics, we not only compare the final active set size, but also compare how the active set size evolves with time.

Fig. 4 shows the performance of the heuristics in Async-ICM. For any given time \( t \), \( p_{\text{degree}}(t) > p_{\text{centrality}}(t) > p_{\text{random}}(t) \). Also, to activate a certain number of nodes \( n \), \( t_{\text{degree}}(n) < t_{\text{centrality}}(n) < t_{\text{random}}(n) \). It demonstrates that the degree-based heuristic outperforms the centrality-based heuristic, and the random heuristic performs the worst. However, all curves show similar trends. Before the 2000 hour point all of them show a sharp increase, and after this point the curves start to flatten out. This shows that the first 2000 hours has more significant marketing value.

Fig. 5 shows the performance of the heuristics in Async-LTM, which is similar to the Async-ICM. Although the scale is different (all values are about 40% smaller), the behavior is qualitatively the same. Obviously, both models reflect the general trend well. The slight difference is due to the network effects which suggest that the network structure will affect the final influence set size.

![Figure 4. Comparison result for Async-ICM.](image-url)
C. Discussion

Being able to include the activation time into ICM and LTM allows one to analyze the temporal features of diffusion behaviors. In particular, our findings show that, while users quickly adopt new information in the first few weeks, this trend slows down as time proceeds. Our findings also lead to insights on how a user is exposed to a shared video, since there are many possibilities: visiting friends’ profiles, browsing external web pages, or finding it via a search engine. Here, inspired by the work in [24], we make a closed world assumption that all occurrences of sharing a video other than the first one are the result of influence via edges in the social graph.

V. CONCLUSIONS AND FUTURE WORK

In this work we have presented an influence measurement study of shared video propagation on a dominant Chinese online social network. In particular, we have learned the distribution of the diffusion time and applied this parameter to the underlying process of word-of-mouth, Marketing Letters, Vol. 3, No. 12, pp. 211-223, August 2001.

Our findings are only exploratory and a number of questions are still of interest; in particular, the real mechanisms that lead to the given activation time distribution. This will be part of our future work.

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