Unfolding Dynamics in a Social Network: Co-evolution of Link Formation and User Interaction

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ABSTRACT

Measurement studies of online social networks show that all social links are not equal, and the strength of each link is best characterized by the frequency of interactions between the linked users. To date, few studies have been able to examine detailed interaction data over time, and none have studied the problem of modeling user interactions. This paper proposes a generative model of social interactions that captures the inherently heterogeneous strengths of social links, thus having broad implications on the design of social network algorithms such as friend recommendation, information diffusion and viral marketing.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Science

General Terms

Measurement

Keywords

Social Network, Graph modeling, Activity network

1. INTRODUCTION

The last few years has seen the arrival of several measurement studies of user relationships and activities on popular online social networks, such as Facebook and Twitter. A common observation made across many platforms is that the presence of a social link connecting two users is a poor estimate of the "relationship strength" between them.

To capture strength of social links, recent studies proposed the use of weighted "interaction graphs," weighted graphs where each link is labeled with some measure of interaction frequency [3]. But these studies focus on a static view of interactions, and therefore only capture a small piece of the picture. The only study to examine changing dynamics of user interactions was performed on Facebook users [2], but was limited to a sample set of 60,000 users crawled from a single geographic network.

A deeper understanding of user interactions requires the formulation of a generative model, which can explain properties observed in measured traces of user interactions, or to construct realistic arbitrary-sized user interaction traces. Such a model would also be immensely useful to a number of social network applications. For example, it can be used to make more accurate predictions in the link prediction problem, to reorder or filter user news feeds by accurately predicting the likelihood of specific user interactions.

In this paper, we seek to fill this void by building a model based on a large detailed trace of user interactions on *Renren*, the Chinese social network similar to Facebook in functionality. Our trace covers over a year in length, and contains data on the creation of 600+K users, 8+Million new links, and 29+ Million interaction events. The core contribution of this paper is a new generative model that combines the growth of social links with the generation of user interaction events on those links. The preliminary results show that our model could generate the right number of interactions and link strength distributions.

2. KEY OBSERVATIONS

We analyze of our growth data, and extract three processes that drive dynamics of social interaction during the network formation:

Interaction initiation: Users invite new friends to interact at a nearly constant rate. The reason is that interaction requires the further investment of effort (e.g., writing wall posts), but people has a finite amount of time to use.

Interaction target selection: Users prefer to interact with friends with whom they share significant overlaps in social circles.

Interaction distribution: Most social links drop in interaction frequency over time as users lose interest in the relationship.

3. A SOCIAL CO-EVOLUTION MODEL

Combining our new observations with previously studied processes of social network evolution, we propose a generative model for social and interaction networks. Our model has two different parts: one is concerned with the evolution of the social network, and the other determines growth of user interactions. We utilize the microscopic evolution model [1] for generating the social network, because that model is based on observing the temporal properties of large social networks.

Microscopic evolution model. The main ideas behind the microscopic evolution model are that nodes join the social network following a node arrival function, and each node has a lifetime, during which it wakes up multiple times and forms links to other nodes. Further details of the model can be found in the paper by Leskovec et al. [1]. We utilize the following processes:

Node arrival. New nodes $V_{t,new}$ arrive at time t according to a pre-defined arrival function $N(.)$.

Lifetime sampling. At arrival time t, u samples lifetime a from $\lambda e^{-\lambda a}$, and becomes inactive after time $t + a$. Let V_t represents set of active nodes at time t.

First social linking: u declares the first friend v based on prefer-

Algorithm 1 Social Co-evolution model.

Node set $V = \emptyset$
Interaction edge set $I = \emptyset$
for each time step $t \in T$ **do**
  Node arrival. $V = V \cup V_{t,new}$
  for each new node $u \in V_{t,new}$ **do**
    Lifetime sampling
    First social linking
    $r_u \leftarrow$ *Interaction rate sampling*
  end for
  for each active node $u \in V_t$ **do**
    if u wakes up **then**
      Social linking
      Sleep time sampling
    end if
    if $rand() < r_u$ **then** ▷ Interaction initiation
      if u has waiting interaction requests **then**
        Replies one of the senders v
      else
        Requests a friend v it has not interacted with
      end if
      $I \leftarrow I \cup (u, v, t)$
    end if
  end for
  for each interaction edge $e \in I$ **do**
    Update the weight $w_e \leftarrow n_e / a_e^{\tau}$
  end for
  for $i = 1 : \eta|V_t|$ **do** ▷ Interaction distribution
    Assign i_{th} interaction to e_s with prob. $p \propto w_e$
  end for
end for

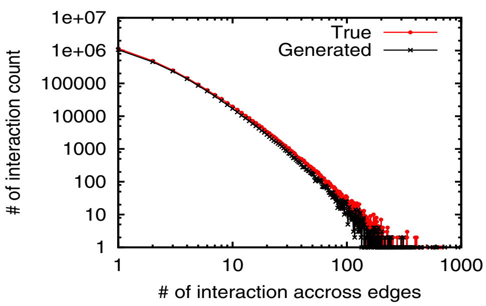

Figure 1: Distribution of the number of interactions.

ential attachment model (e.g., connecting v with prob. proportional to v's degree).

Sleep time sampling: Once creating an edge, u goes to sleep for δ time steps, where δ is sampled from a power law with exponential cut-off distribution $p(\delta) = \frac{1}{Z}\delta^{-\alpha}e^{-\beta \cdot degree(u) \cdot \delta}$.

Social linking: If u wakes up, it creates an edge to others by closing a triad two random steps away.

Co-evolution model. We augment the social graph model with the interaction processes while we grow the network. Besides befriending with others, nodes also request a certain number of friends to interact with, and distribute interactions over their interaction edges. Algorithm 1 presents our co-evolution model, which includes the following interaction processes:

Interaction rate sampling: At arrival time t, u samples interaction rate r_u from exponential distribution with an average of λ_r.

Interaction initiation: With a fixed probability r_u at each time t, u creates an new interaction edge (u, v, t) by sending/repling the first wall post along the friendship edge (u, v). u chooses the target v with the prob. proportional to their neighborhood overlap.

Interaction generation: At time t, nodes creates $\eta|V_t|$ new interactions, where $|V_t|$ is the number of active nodes and η is the average node-interaction frequency.

Params.	Processes controlled	Values
$N(.)$	Node arrival	$13,200\exp(0.01t)$
τ_a, λ_a	Node lifetime	$\tau_a = 0.1, \lambda_a = 0.004$
α, β	Edge gap	$\alpha = 1.735, \beta = 0.0008$
μ, σ	The interaction rate distribution	$\mu = -2.2, \sigma = 1.2$
η	Node interaction frequency	$\varepsilon = 0.48$
τ	Interaction decay factor	$\tau = 0.4$

Table 1: Model parameters and its values

	Real network	Co-evolution model
# of interactions	7,697,270	7,978,967
# of users have interactions	420,978	452,087
Mean # of interactions per user	18.3	17.7
# of edge have interactions	2,623,040	2,654,423
Mean # of interactions per edge	2.9	3.0

Table 2: Statistics of a real network vs. synthetic one

Interaction distribution: The system updates the weight w_e of an interaction edge e by $w_e = n_e/a_e^{\tau}$, where $n_e(n_e \geq 1)$ is the current number of interactions along the edge and a_e is the age of e. Then, the system assigns each new interaction to an interaction edge with the prob. proportional to the edge weight.

The interaction evolution part has three simple parameters: The first parameter, λ_r, controls the tendency of the node invites new friends to interact. The second parameter, τ, is an exponent controls the tendency to stop interacting with a particular friend due to losing interest over time. The final parameter is η, controls the interaction frequency during the interaction process.

4. PRELIMINARY RESULTS

We now present some preliminary results on the model accuracy. We first fit the right parameter values by measuring Renren social network, as summarized in Table 1. We then employ the model to evolve a synthetic network from the beginning, and compare the key structure properties of synthetic network with true network at the end of the evolution.

Table 2 shows that the statistics of real/synthetic interaction networks are very similar, demonstrating the co-evolution model is able to generate the right number of interactions over the social graph. We testify whether the model could generate the right link strength distribution using the interaction distribution process. Figure 1 shows the distribution of the number of interactions across interaction edges in the true and generated interaction graph, exhibiting a very good match.

5. ACKNOWLEDGEMENT

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