Co-Evolution of Friendship and Publishing in Online Blogging Social Networks

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ABSTRACT
In the past decade, blogging web sites have become more sophisticated and influential than ever. Much of this sophistication and influence follows from their network organization. Blogging social networks (BSNs) allow individual bloggers to form contact lists, subscribe to other blogs, comment on blog posts, declare interests, and participate in collective blogs. Thus, a BSN is a bimodal venue, where users can engage in publishing (post) as well as in social (make friends) activities. In this paper, we study the co-evolution of both activities. We observed a significant positive correlation between blogging and socializing. In addition, we identified a number of user archetypes that correspond to “mainly bloggers,” “mainly socializers,” etc. We analyzed a BSN at the level of individual posts and changes in contact lists and at the level of trajectories in the friendship-publishing space. Both approaches produced consistent results: the majority of BSN users are passive readers; publishing is the dominant active behavior in a BSN; and social activities complement blogging, rather than compete with it.

1. INTRODUCTION AND PRIOR WORK
In the past decade, blogging web sites such as Blogger [11], DreamWidth [10], LiveJournal [10], and Tumblr [13] have become more widespread, more technologically sophisticated, and more socially influential than ever. Much of this sophistication and influence stems from their network organization. Blogging social networks (BSNs) allow individual bloggers to form contact (“friend”) lists, subscribe to their friends’ blogs, comment on selected blog posts, declare and share common interests, and participate in communities, or collective blogs. Thus, a BSN is a socio-semantic network [17]—a bimodal venue where users engage in publishing (write blog posts) and social (make friends) activities.

Proper networking aspects of massive online social networks (MOSNs), including BSNs, have been extensively researched in the past ten years. MOSN static organization and macroscopic dynamics at the level of nodes and links: scale-free degree distribution, shrinking diameter, and densification—have been discussed in [15, 19, 20, 11, 10] and other papers. Analysis of microscopic behavior at the level of individual member-to-member messages and message flows can be found in [8, 11, 19], etc.

Similarly rich literature exists on blogging topics, patterns, and behaviors [15, 12]. It covers information diffusion (including epidemic diffusion), social and personal motivation for blogging, and bloggers’ anthropology.

In a recent study, Both and Cointet [17] propose that the social and semantic dimensions are co-determined. However, they do not look at the dynamics of individual friendships and posts.

In this paper, we explore the co-evolution of social and publishing activities in LiveJournal [11, 18]. LiveJournal was started in 1999 by American programmer Brad Fitzpatrick and sold to Russian media company SUP Media in 2007. At the time of writing, LiveJournal hosts approximately 40 million individual blogging accounts and communities.

Given the limited amount of time that users spend browsing social and blogging networks, it is interesting to find out the distribution of networking (social) and publishing (blogging) activities from the point of view of an individual member of a BSN, as well as the evolution of this distribution over time.

The rest of the paper is organized as follows: in Section 2, we explain the data acquisition methods and present some descriptive statistics of the acquired data; Sections 3 and 4 contain the microscopic and macroscopic data analyses, respectively. Section 5 compares the results of both studies. In Section 6, we conclude.

2. DATA COLLECTION
LiveJournal positions itself as an open blogging platform with a public application programming interface
Several trajectories in our collection had unusually large differences between consecutive values \(|G_{i+1} - G_i| \gg 1\) or unusually large overall ranges \((G_{\text{max}} - G_{\text{min}}) \gg 1\) in one or both dimensions. When designing the study, we included only the trajectories with all differences and ranges in the lower 98th percentile, the total of 1,761 trajectories\(^2\) and excluded the rest. Under the assumption that the observed processes were stationary, we translated each remaining trajectory \(T\) to the origin by subtracting \(\{t_U^i, P_U^i, F_U^i\}\) from each tuple in \(T^U \in T\).

The trajectories retained in the data set demonstrate a remarkable positive correlation between blogging and socializing: active bloggers tend to acquire new friends at a faster rate than silent network members (Figure 1). This means that publishing and social activities in LiveJournal, when present, are highly synchronized. The details of this synchronization will be discussed in the next two sections.

### 3. MICROSCOPIC ANALYSIS

At the microscopic level, we treat individual trajectories as timed sequences of events \(e \in E = \{\Pi^+, \Phi^+, \Phi^-, \Pi\Phi\}\), where symbols \(\Pi\), \(\Phi\), and \(\Pi\Phi\) represent the changes in the number of posts, friends, and posts and friends together, and the sign in the superscript represents the direction of changes (but not the magnitude). Since 97% of \(\Pi\) events constitute an addition of \(\leq 2\) posts and 97% of \(\Phi\) events constitute an addition or removal of \(\leq 7\) friends, we choose to see these events as binary—either occurring or not occurring—because the extent of variation is not significant given how minuscule it is relative to the time scope considered. The compound events \(\Pi\Phi = \{\Pi^\pm \Phi^\pm\}\) are rare. We treat them as non-directional.

The delays between consecutive events for all trajectories are distributed exponentially with the average rates of 0.45 day\(^{-1}\) for publishing events and 0.2 day\(^{-1}\) for social events.

For each trajectory \(T\) and for each pair of event types \(\{e_i, e_j\} \in E \times E\), we calculate \(\psi^T_{ij} = \psi^T(e_j|e_i)\), the probability of an event \(e_j\) immediately following event \(e_i\) along a certain trajectory \(T^U\); in other words, the conditional probability of \(e_j\) given \(e_i\). Thus, \(\psi^T = \{\psi^T_{\Pi^+\Pi^+}, \psi^T_{\Pi^+\Phi^+}, \ldots, \psi^T_{\Pi^+\Pi^+}\}\) is a vector in a 16-dimensional metric space \(\Psi\). We call this vector the signature of the trajectory. The proximity of trajectories \(T_1, T_2 \in \Psi\), defined as the Euclidean distance \(\Delta T = ||T_1 - T_2||\) between their signatures, corresponds to the similarity of the BSN users’ social and publishing behaviors.

We use the distance \(\Delta T\) to group the trajectories and the corresponding BSN users into twelve disjoint micro clusters \(\mu_k = \{T\}\) with 74 to 398 trajectories per cluster (Table I). Each directory belongs exactly to one cluster.

\(^1\)In fact, LiveJournal provides several APIs, including RSS XML and Atom XML for the most recent posts and FOAF XML and plain text interface for contact lists. It is also possible to download profile pages in HTML and parse them directly.

\(^2\)The “rough” trajectories need to be analyzed differently.
The number of micro clusters was chosen to match the number of the most significant macro clusters described in the next section. In our case, this clustering method gives acceptably good results and is substantially simpler than similar methods proposed, e.g., in [2, 14]. For each cluster $\mu_k$, we calculate its mean trajectory $T^{(k)}$ with the signature $\psi^{(k)} = \{ \psi^T | T \in \mu_k \}$.

To understand the collective behavior of cluster members, we model each cluster as a Markov chain with social and publishing events representing states, and pairs of consecutive events representing transitions. Thus, e.g., events $\Phi^-$ and $\Pi^+$ immediately following one another represent a transition between the states $\Phi^-$ and $\Pi^+$. The probability of this transition in cluster $\mu_k$ is $\psi^{(k)}_{\Pi^+\Phi^-}$.

Based on $\psi^{(k)}$, we identified four user archetypes associated with each cluster (Table 1): “mainly bloggers” (frequent publishing events), “mainly socializers” (frequent social events), “bloggers-socializers” (both publishing and social events), and “readers” (no events; the passive network members create blogging accounts simply to read other people’s blogs or leave comments).

As an example, consider clusters $\mu_{10}$, $\mu_5$, $\mu_6$, and $\mu_7$. They have 90, 187, 148, and 123 trajectories, respectively, with the dominant transition $\Pi^+\Pi^+$, “(add a post) followed by another (add a post)”. For the different clusters, this transition takes 2, 3, 5 or 9 days. These models correspond to more or less rigorous “mainly bloggers.”

The Markov chain for the cluster $\mu_7$ is shown in Figure 2. Transitions between the states $\Phi^+$, $\Phi^-$, and $\Pi\Phi$ in the cluster are very rare: they happen with the frequency of 0.01 days$^{-1}$. The self-loop around $\Pi^+$ is more frequent, which is reflected by the thickness of the arc.

According to the microscopic analysis, 45% of all users included in the study are “readers,” 20% are “bloggers-socializers,” 20% are “mainly socializers,” and 15% are “mainly bloggers.”

4. MACROSCOPIC ANALYSIS

At the macroscopic level, a unit of analysis is a blog trajectory $\{t, P(t), F(t)\}$ in the time-friendship-publishing space, representing the user’s social and blogging activities over time (Figure 3). The translated trajectories radiate from the origin approximately in the same direction. This is not very surprising, given that friends are rarely unfriended [1] and posts, once published, are rarely deleted. However, the angle between the most extreme trajectories is still large. We will use clustering again to identify similarly behaving users.

The trajectories in Figure 3 are remarkably smooth. For each component of each trajectory, we calculate the best-fit quadratic approximation $G(t) = a_0 + a_1 t + a_2 t^2$. If $|a_2/a_1| < 0.0085$, then we replace the quadratic model
Figure 4: Classification of trajectory dynamics.

with a linear model \( G(t) = a_0 + a_1 t \). Otherwise, a true quadratic model is used. Whether the trajectory bends in the direction away from the X axis or toward it, depends on the sign of \( a_2 / a_1 \). If the best-fit linear approximation of \( G(t) \) is unacceptably inaccurate with \( R^2 < 0.7 \), we treat \( G(t) \) as constant in time.

Therefore, any \( G(t) \) can be approximated using one of the following seven smooth functions (Figure 4):

- **linear** \( (G'' \approx 0) \):  
  - ascending \( (↑; G' > 0) \),
  - constant \( (↕; G' \approx 0) \) or
  - descending \( (↓; G' < 0) \),
- **quadratic locally ascending** \( (G' > 0) \) bending up \( (↑↑; G'' > 0, \text{superlinear}) \) or down \( (↓↓; G'' < 0, \text{sublinear}) \), or
- **quadratic locally descending** \( (G' < 0) \) bending up \( (↑↓; G'' > 0, \text{sublinear}) \) or down \( (↓↑; G'' < 0, \text{superlinear}) \).

Overall, there are the total of seven possible behaviors for each of \( P \) and \( F \), as described above. Each trajectory can be assigned to one of the \( 7 \times 7 = 49 \) macro clusters \( M_{PF} \), based on the publishing dynamics \( P \) and social dynamics \( F \) (Figure 5).

The largest macro clusters are \( M_{↑↑} \) (“readers,” both \( P \) and \( F \) are constant, 41%), \( M_{↑↓} \) (“mainly bloggers,” 15%), and \( M_{↑↑} \) (“bloggers-socializers,” 9%).

We assume that a trajectory belongs to a “mainly blogger” or to a “mainly socializer” if it has exactly one linear or superlinear \( P \) or \( F \) component, respectively. If both components are linear or superlinear, then the trajectory represents a “blogger-socializer.” Otherwise, it is a “reader” trajectory.

The clusters with anticorrelated publishing and social dynamics (e.g., growing number of posts vs shrinking number of friends) have negligibly small membership (3%). LiveJournal posters are motivated to gain more friends, produce more posts, and increase their presence online. Losing friends as a result of new posts may be a deterrent from writing more controversial posts. Similarly, no one will gain friends as a result of deleting posts and reducing their presence online. In other words, social activity in the selected subset of LiveJournal does not happen at the expense of publishing or the other way around.

Just as with the micro clusters, we calculated the mean trajectory for each macro cluster (Figure 6). We observed that the numbers of friends and posts along
the mean trajectories in each cluster are loosely correlated:

\[ F(t) \approx 9\sqrt{P(t)}. \]  

This relationship holds over the entire period of observation with \( R^2 \approx 0.85 \). We consider it as evidence to the mainly blogging nature of LiveJournal, with the number of posts dominating the number of friends most of the time.

5. COMPARISON

Table 2 shows the comparison between the user archetypes obtained through micro- and macroscopic analyses. While both methods confirm the dominance of the “readers” over the other three archetypes, one can see that the macroscopic method consistently underestimates the socializing component. This discrepancy is due to the averaging nature of the macroscopic procedure. A trajectory of a typical “socializer” may have a number of consecutive social events \( \Phi^+ \) and \( \Phi^- \), which will not change her number of friends at the end of the observation period and thus will not be detected by the macroscopic algorithm; such “socializers” will be mistakenly assigned to the “readers” or “bloggers” categories. In other words, if many friend events occur, yet the net change is small, the macro analysis overlooks it.

The correspondence between the micro- and macroscopic clusters is presented in Figure 7. The amount of overlap between any two clusters is used as a measure of their similarity. The twelve microscopic clusters and the twelve largest macroscopic clusters have only 21 significant relationships (of those, one is one-to-one and eleven are either many-to-one or one-to-many). This is just marginally more than the minimum of twelve one-to-one relationships but substantially less than the possible maximum of \( 12 \times 12 = 144 \) random relationships.

Most micro clusters are connected to the macro clusters that represent the same archetype. The only exceptions are the strong connections between \( M_{12} \) (“mainly bloggers”) and \( \mu_3 \) and \( \mu_{10} \) (both “bloggers-socializers”) and a weak connection between \( M_{12} \) (“mainly socializers”) and \( \mu_5 \) (readers). The first exception confirms our hypothesis about the macro method being more socially agnostic. At the moment, we do not have an explanation of the second exception.

The sparsity of the resulting bipartite graph and its cohesion with respect to the user archetypes implies that both clustering methods describe the same taxonomy, but emphasize different nuances of network dynamics.

6. CONCLUSION

We presented a study of joint social and publishing dynamics in LiveJournal—a popular blogging social network (BSN). Over eighteen hundred user accounts have been analyzed at both microscopic level (represented as timed sequences of social and publishing events) and macroscopic level (represented as trajectories in temporal-social-publishing space).

We have observed a significant general positive correlation between blogging and socializing in LiveJournal. We also identified a number of user archetypes that correspond to “mainly bloggers,” “mainly socializers,” “bloggers-socializers,” and “readers” (passive network members who create blogging accounts simply to read other people’s blogs). The analysis has been performed both at the microlevel (individual posts and changes in contact lists modeled as Markov chains) and at the macrolevel (trajectories in the time-friendship-publishing space). Both approaches produced consistent results:

- the majority of the BSN users are passive readers,
- publishing is the dominant active behavior in a

Table 2: Comparison of user archetypes obtained through micro- and macroscopic analyses.
BSN, and

- social activities, when present, complement blogging, rather than compete with it.

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