Multi-scale Dynamics in a Massive Online Social Network

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ABSTRACT

Data confidentiality policies at major social network providers have severely limited researchers' access to large-scale datasets. The biggest impact has been on the study of network dynamics, where researchers have studied citation graphs and content-sharing networks, but few have analyzed detailed dynamics in the massive social networks that dominate the web today. In this paper, we present results of analyzing detailed dynamics in a large Chinese social network, covering a period of 2 years when the network grew from its first user to 19 million users and 199 million edges. Rather than validate a single model of network dynamics, we analyze dynamics at different granularities (per-user, per-community, and network-wide) to determine how much, if any, users are influenced by dynamics processes at different scales. We observe independent predictable processes at each level, and find that the growth of communities has moderate and sustained impact on users. In contrast, we find that significant events such as network merge events have a strong but short-lived impact on users, and they are quickly eclipsed by the continuous arrival of new users.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Sciences; H.3.5 [**Information Storage and Retrieval**]: Online Information Services

General Terms

Algorithms, Measurement

Keywords

Dynamic Graphs, Online Social Networks

1. INTRODUCTION

A number of interrelated processes drive dynamics in social networks. A deeper understanding of these processes can allow us to better model and predict structure and dynamics in social networks. In turn, improved models and predictors have numerous practical implications on the design of infrastructure, applications, and security mechanisms for social networks.

Details of these dynamic processes are best studied in the context of today's massive Online Social Networks (OSNs), *e.g.* Facebook [38], LinkedIn [24], and Renren [13]. Unfortunately, the providers of large social networks generally consider their dynamic network data to be trade secrets, and have few incentives to make such data available for research. Instead, studies have analyzed citation networks [22], content sharing networks [18], and high level statistics of social networks [1]. Others [21, 26, 10] sought to validate generative models such as preferential attachment (PA) [5].

Our goal is to better understand in detail the evolutionary dynamics in a social network. This includes not only the initial growth process during a social network's formation, but also the ongoing dynamics afterwards, as the network matures. Much of the prior work in this area, including generative graph models and efforts to validate them [5, 21, 26, 10], has focused on capturing network dynamics as a single process. In contrast, we are interested in the question "how are individual user dynamics influenced by processes at different scales?" How much are the dynamics of users influenced by external forces and events, such as the activities of friends in communities they belong to, or by large-scale events that occur at the network level?

In this work, we explore these questions empirically through a detailed analysis of social network dynamics at multiple scales: at the individual user level, at the level of user communities, and at the global network level. We study a dynamic graph, *i.e.* a sequence of detailed timestamped events that capture the ongoing growth of a large Chinese online social network. With over 220 million users, it is the largest social network in China, and provides functionality similar to Facebook. We focus our analysis on first two years of its growth, from its first user in November 2005, to December 2007 when it had over 19 million members. This captures the network's initial burst of growth, as well as a period of more sustained growth and evolution. Our anonymized data includes timestamps of all events, including the creation of 19 million user accounts and 199 million edges. This dataset is notable because of three features: its scale, the absolute time associated with each event, and a rare network *merge* event, when the network merged with its largest competitor in December 2006, effectively doubling its size from 600K users to 1.3 million users in a single day.

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Our analysis of network dynamics in this dataset focuses on three different levels of granularity: nodes, communities, and networks. At each level, we search for evidence of impact on user behavior. Along the way, we also make a number of intriguing observations about dynamic processes in network communities and network-wide events.

Individual Nodes. The creation of links between individual users has been studied in a number of contexts, and is long believed to be driven by generative models based on the principle of preferential attachment, *i.e.* users prefer to connect to nodes with higher degree [5]. Our goal is to extend the analysis of this model with respect to two new dimensions. First, preferential attachment defines how a sequence of edges are created in logical order, but how do node dynamics correlate with absolute time? Second, does the strength of the preferential attachment model strengthen or weaken as the network grows in scale and matures?

Communities. Intuitively, the behavior of a user is likely to be significantly impacted by the actions of her friends in the network. This has been previously observed in offline social networks [39]. Our goal is to empirically determine if user activity at the level of communities has a real impact on individual users. To do so, we first implement a way to define and track the evolution of user communities over time. We use the Louvain algorithm [6] to detect communities, track the emergence and dissolution of communities over time, and quantify the correlation of user behavior to the lifetime, size, and activity level of the communities they belong to.

Networks. Finally, we wish to quantify the impact, if any, of network-level events on individual user behavior. By network-level events, we refer to unusual events that affect the entire network, such as the merging of two distinct social networks recorded in our dataset. We analyze user data before and after the merge of our social network and its competitor, and quantify the impact of different factors on user behavior, including duplicate accounts, and user's edge creation preferences over time.

Key Findings. Our analysis produces several significant findings. First, we find that nodes (users) are most active in building links (friendships) shortly after joining the network. As the network matures, however, we find that new edge creation is increasingly dominated by existing nodes in the system, even though new node arrivals is keeping pace with network growth. Second, we find that influence of the preferential attachment model weakens over time, perhaps reflecting the reduced visibility of each node over time. As the network grows in size, users are less likely to be aware of high degree nodes in the network, and more likely to obey the preferential model with users within a limited neighborhood. Third, at the level of user communities, we find using the Louvain algorithm that users in large communities are more active in creating friends and stay active for a longer time. In addition, we found that a combination of community structural features can predict the short-term "death" of a community with more than 75% accuracy.

Finally, in our analysis of the network merge event, we use user activity to identify duplicate accounts across the networks. Aside from duplicate accounts, we find that the network merge event has a distinct short-term impact on user activity patterns. Users generate a high burst in edge creation, but the cross-network activity fades and quickly becomes dominated by edge creation generated by new users. Overall, this quickly reduces average distance between the two networks and melds them into a single monolithic network.

2. NETWORK LEVEL ANALYSIS

We begin our study by first describing the dataset, and performing some basic analysis to understand the impact of network dynamics on first order graph metrics. Our data is an anonymized stream of timestamped events shared with us by a large Chinese social network, whose functionality is similar to those of Facebook, Google+ and Orkut. Our basic measurements in this section set the context for the analysis of more detailed metrics in later sections.

Dataset of Dynamics in a Massive Social Network. The first edge in our large social network was created on November 21, 2005. The social network was originally built as a communication tool for college students, but expanded beyond schools in November 2007.

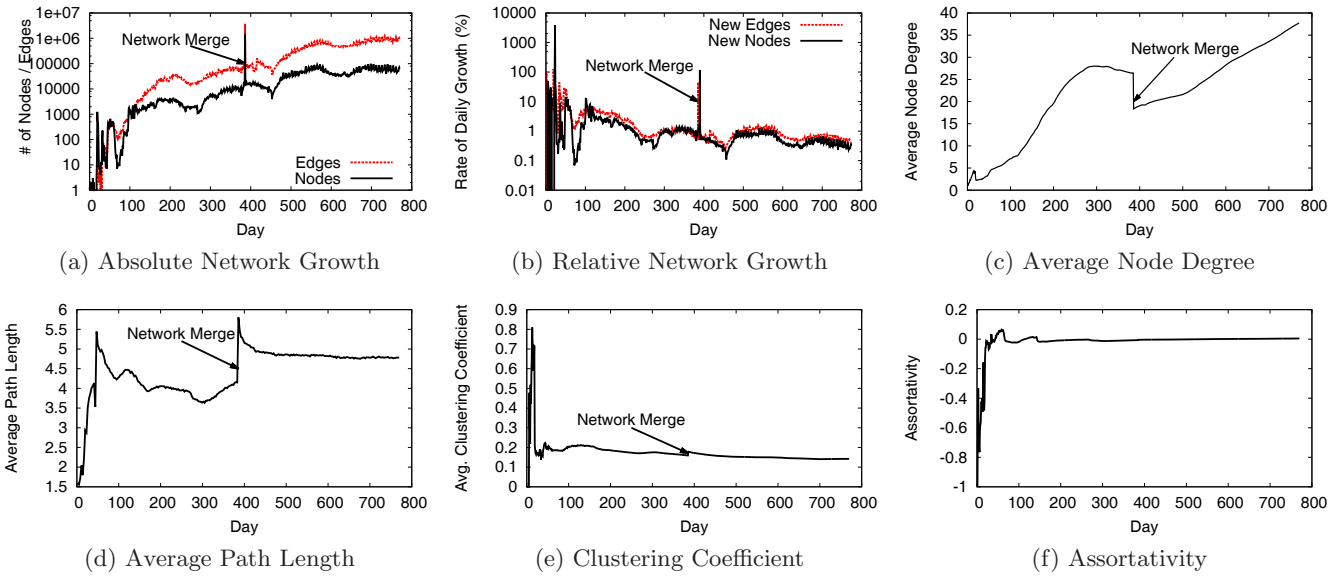
Our anonymized dataset encompasses the timestamped creation events of all users and edges in the social network. The dataset covers more than 2 years, starting on November 21, 2005 and ending December 31, 2007. In all, the dataset includes the creation times of 19,413,375 nodes and 199,563,976 edges. To perform detailed analysis on the social graph, we produce 771 graphs representing daily static snapshots from the timestamped event stream. Note that in this paper, we will use the term *node* to mean an OSN *user* and *edge* to mean a friendship link.

An unusual event happened on December 12, 2006, when our network merged with a second, competing online social network that was created in April 2006. On the merge date, our social network had 624K users with 8.2 million social links, and the second online social network had 670K users with 3 million social links. Wherever possible, we treat the merge as an external event to minimize its impact on our analysis of network growth. We also present detailed analysis of the network merge event in Section 5.

On our network, default user policy limits each user to 1,000 friends. Users may pay a fee in order to increase their friend cap to 2,000. However, prior work by the network has shown that very few users take advantage of such features. We make the same observation about our dataset: the number of users with >1,000 friends is negligibly small.

Network Growth. Figure 1(a) depicts the growth of the large Chinese social network in terms of the number of nodes and edges added each day. Day 0 is November 21, 2005. Overall, the network grows exponentially, which is expected for a social network. However, there are a number of real world events that temporarily slow the growth, and manifest as visible artifacts in Figure 1(a). The two week period starting at day 56 represents the Lunar New Year holiday; a two-month period starting on day 222 accounts for summer vacation; the merge with the competing social network causes a jump in nodes and edges on day 386; additional dips for the lunar new year and summer break are visible starting at days 432 and 587, respectively. In Figure 1(b), we plot daily growth as a normalized ratio of network size from the previous day. It shows that relative growth fluctuates wildly when the network is small, but stabilizes as rapid growth begins to keep rough pace with network size.

Graph Metrics Over Time. We now look at how four key graph metrics change over the lifetime of our data



(a) Absolute Network Growth (b) Relative Network Growth (c) Average Node Degree

(d) Average Path Length (e) Clustering Coefficient (f) Assortativity

Figure 1: Network growth over time, and its impact on four important graph metrics.

stream, and use them to identify structural changes in the large Chinese social network. We monitor average degree, average path length, average clustering coefficient, and assortativity. As before, the analysis of each metric starts from November 21, 2005.

Average Degree. As shown in Figure 1(c), average node degree grows for much of our observed time period, because the creation of edges between nodes out paces the introduction of new users to the network. When we take a closer look, we see that around days 120, 275, 475 and 650, the average degree grows faster. This means that more edges are created around this time period, which happens to match up nicely with the beginning of new academic semesters over multiple years. On day 305, however, a period of rapid growth in users starts to reduce average degree in the network. This comes from a sudden influx of new users due to several successful publicity campaigns by the social network. Next, on day 386 (December 2006), average degree drops suddenly when 670K loosely connected nodes from a competing social network merges with our social network. Average degree resumes steady growth following the event, again showing edge growth out pacing node growth and increasing network densification [22].

Average Path Length. We follow the standard practice of sampling nodes to make path length computation tractable on our large social graphs. We compute the average path length over a sample of 1000 nodes from the SCC for each snapshot, and limit ourselves to computing the metric once every three days. As seen in Figure 1(d), the results are intuitive: path length drops as densification increases (*i.e.* node degree increases). There is a significant jump when nodes from the second online social network join the large social network on day 386, but the slow drop resumes as densification continues after the merge.

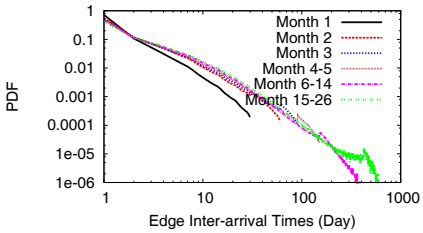
Average Clustering Coefficient. Clustering coefficient is a measure of local density, computed as the ratio of the existing edges between the immediate neighbors of a node over the maximum number of edges possible between them. We plot average clustering coefficient in Figure 1(e). In early stages of network growth (before day 60), the network was very small and contained a large number of small groups with loose connections between them. Groups often formed local cliques or near-cliques, resulting in high clustering coefficients across the network. Once the network grows in size, average clustering coefficient transitions to a smooth curve and decreases slowly. The network merge produces a small jump, since the competing social network had many small clusters of 3 or 4 nodes that boosted average clustering coefficient.

Assortativity. Finally, we plot assortativity in Figure 1(f). Assortativity is the probability of a node to connect to other nodes with similar degree, computed as the Pearson correlation coefficient of degrees of all node pairs. In the early stages of the network, the graph is sparse and dominated by a small number of supernodes connecting to many leaf nodes. This produces a strong negative assortativity that fluctuates and then evens out as the network stabilizes in structure. Assortativity evens out at around 0, meaning nodes in our network have no discernible inclination to be friends with nodes of similar or different degree.

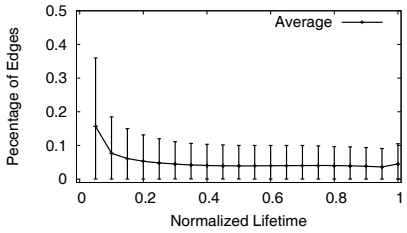
Summary. We observe that the high-level structure of our network solidifies very quickly. Several key properties stabilize after the first 2 months, with others establishing a consistent trend after 100 days. While the notable network merge with a second, competing social network introduces significant changes to network properties, the effects quickly fade with time and continued influx of new users to the merged network.

3. EDGE EVOLUTION

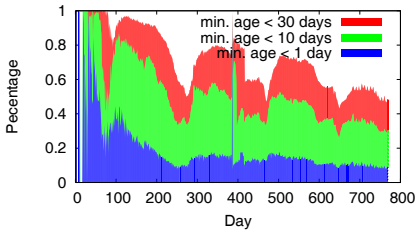
In this section, we study the behavior of individual nodes in terms of how they build edges over time. Many studies have shown that nodes build edges following the preferential attachment (PA) model [5, 21, 26, 10]. Specifically, when a new node joins the network and creates edges, it chooses the



(a) Distribution of Edge Inter-arrival Times



(b) Edge Creation vs. Normalized Lifetime



(c) Node Age and Edge Creation

Figure 2: Time dynamics of edge creation. (a) The probability distribution of the edge inter-arrival times follows a power-law distribution. (b) The normalized activity level over each user's lifetime. Users create most of her friendships early on. (c) The portion of edges created by new nodes each day. When the network is young, new edges are mostly triggered by newly joined nodes. However, as the network matures, the majority of new edges connect older users.

destination of each edge proportionally to the destination's degree. In other words, nodes with higher degrees are more likely to be selected as the destination of new edges, leading to a "rich get richer" phenomenon.

Using our dynamic network data, we extend the analysis of this model in two new dimensions. First, while PA defines how a sequence of edges is created in logical order, we seek to understand how node activities correlate with absolute time. Second, we are interested in whether, as the network evolves, the PA model's predictive ability grows or weakens over time.

3.1 Time Dynamics of Edge Creation

Edge Inter-arrival. We begin by analyzing the edge creation process in absolute time, focusing on the speed that nodes add edges. First, we look at the inter-arrival time between edge creation events. For each node, we collect the inter-arrival times between all its edges, then place them into buckets based on the age of the node when the edge was created. We then aggregate all users' data together for each bucket, *e.g.* the "Month 1" bucket contains all edge inter-arrival times where one or both of the nodes was less than 1 month old.

We plot the results in Figure 2(a). We observe that the time gap between a node's edge creation events follows a power-law distribution. The scaling exponent is between 1.8 and 2.5, shown in Figure 2(a). The exponent values can be used in an edge creation gap model. However, it is difficult to evaluate its significance without a direct comparison to data from other networks. Overall, this power-law distribution provides a realistic model of a user's idle time between edge creations at different stages of her lifetime.

Edge Creation Over Lifetime. The above result motivates us to examine the normalized activity level within each user's lifetime. We plot in Figure 2(b) the distribution of new edges based on the normalized age of the users involved. To avoid statistical outliers, we consider only nodes with at least 30 days of history in our dataset and degree of at least 20. As expected, users create most of their friendships early on in their lifetimes. Edge creation converges to a constant rate once most offline friends have been found and linked.

Node Age and Edge Creation. We observe above that nodes tend to generate a significant portion of their edges soon after joining the network. Since most generative graph models use new nodes to drive edge creation, we ask the question "What portion of the new edges created in the network are driven by the arrival of new nodes?" For each day in our dataset, we take each edge created on that day and determine its minimal age, *i.e.* the minimum age of its two endpoints. The distribution of this value shows what portion of new edges are created by new nodes.

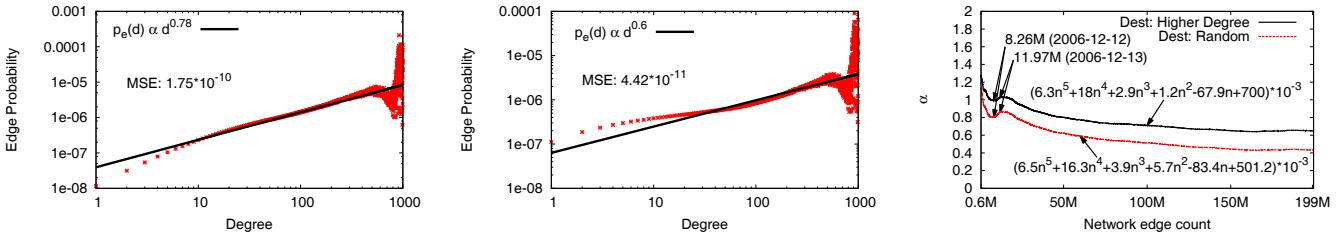
We compute and plot this distribution in Figure 2(c). We show the relative contribution by nodes of different ages by plotting three stacked percentages, showing the portion of daily new edges with minimal age $\leq$ 1 day, $\leq$ 10 days, and $\leq$ 30 days. We see that when the network is young ($\leq$ 60 days), the vast majority of new edges connect brand new nodes (*i.e.* 1 day old). As the network stabilizes and matures, that portion quickly drops, and continues to decrease over time. Edges with minimal age of 10-30 days dominate new edges for much of our trace, but their contribution steadily drops over time from 95% around day 100 to 48% by day 770. Note that this drop occurs even after the daily relative network growth has reached a constant level (see Figure 1(b)). It is reasonable to assume that in today's network (4.5 years past the end of our data), the vast majority of new edges connect mature users who have been in the network for significant amounts of time.

This result in Figure 2(c) is important, because it shows a dramatic change in the driving force behind edge creation as the network matures. Most generative graph models assume edge creation is driven by new nodes. However, our data indicates that existing models will only accurately capture the early stages of network creation. Capturing the continuous evolution of a mature network requires a model that not only recognizes the contribution of mature nodes in edge creation, but also its continuous change over time.

3.2 Strength of Preferential Attachment

Next, we take a look at the preferential attachment model and how well it predicts changes over time and network growth. We follow the method in [21] to measure the strength (or degree) of preferential attachment using edge probability $p_e(d)$. This function defines the probability that an edge chooses its destination with degree d, normalized by the total number of nodes of degree d before this time step:

$$p_e(d) = \frac{\Sigma_t\{e_t(u,v) \wedge d_{t-1}(v) = d\}}{\Sigma_t|v : d_{t-1}(v) = d|} \quad (1)$$



(a) $p_e(d)$, higher-degree node as destination

(b) $p_e(d)$, random destination selection

(c) Evolution of $\alpha(t)$

Figure 3: (a)-(b) Fitting the measured edge probability $p_e(d)$ with d^α, when our large Chinese social network reaches 57M edges. In (a), $p_e(d)$ is calculated by selecting the higher-degree node as each edge's destination. In (b) the destination is selected randomly. The mean square error (MSE) is very low, confirming the goodness of the fit. (c) As the network grows, α drops from 1.25 to 0.65. It can be approximated by a polynomial function of the network edge count n.

where $\{e_t(u,v) \wedge d_{t-1}(v) = d\} = 1$ if the destination v of the edge $e_t(u,v)$ is of degree d, and 0 otherwise.

Intuitively, if a network grows following the PA model, its edge probability $p_e(d)$ should have a linear relationship with d: $p_e(d) \propto d$. The authors of [21] verified this conclusion using synthetic graphs, and also tested the PA model on four real social networks: Flickr, Delicious, Answers, and LinkedIn. The first three networks follow the PA model $p_e(d) \propto d^\alpha$ with $\alpha \approx 1$, while for LinkedIn, $\alpha = 0.6$. From these observations, we can define a criterion for detecting preferential attachment: when $\alpha \to 1$, the network grows with a strong preferential attachment, and when $\alpha \to 0$, the edge creation process becomes increasingly random.

Using this criterion, we validate the PA model over time on our large Chinese social network by fitting $p_e(d)$ measured at time t to $d^{\alpha(t)}$ and examining $\alpha(t)$ over time. Our study seeks to answer an important question: "Does our network display the same level of preferential attachment consistently over time?" In other words, does $\alpha(t)$ stay constant over time? And if not, is the preferential attachment stronger (or weaker) at a particular stage of network growth?

We make some small adjustments to the computation of $p_e(d)$ on our dataset. First, because our data does not state who initiated each friendship link (edge directionality), we perform our test with two scenarios. The first is biased in favor of preferential attachment, because it always selects the higher degree end-point as the destination. The second scenario chooses the destination node randomly from the two end-points. Second, to make the computation tractable on our large number of graph snapshots, we compute $p_e(d)$ once after every 5000 new edges. Finally, to ensure statistical significance, we start our analysis when the network reaches a reasonable size, *e.g.* 600K edges.

Results. We start by examining whether $p_e(d) \propto d^{\alpha(t)}$ is a good fit. For this we use the Mean Square Error (MSE) between the measured $p_e(d)$ and the fitted curve. We observe that the MSE decreases with the edge count, ranging from 1.8e-5 to 3.5e-13. This confirms that the fit is tight for the measured edge probability. To illustrate the results, Figures 3(a)-(b) show the edge probability $p_e(d)$ when the network reaches 57M edges, using the two destination selection methods. The corresponding MSEs of the fit are 1.7e-10 and 4.4e-11, respectively.

Next, we examine $\alpha(t)$ over time in Figure 3(c). We make two key observations. *First*, $\alpha(t)$ when using the higher-degree method is always larger than when using random selection. This is as expected since the former is biased in favor of preferential attachment. More importantly, the difference between the two results is always 0.2. This means that despite the lack of edge destination information, we can still accurately estimate $p_e(d)$ from these upper and lower bounds.

Second, $\alpha(t)$ decays gradually over time, dropping from 1.25 (when the network first launched) to 0.65 (two years later at 199M edges). Since the number of nodes with node degree 1000 in the last snapshot is very small (0.0001% of the total nodes in the network), we believe the decrease in $\alpha(t)$ is not caused by the hard limit on node degree. This results shows that when the network is young, it grows with a strong preferential attachment. However, as the network becomes larger, its edge creation is no longer driven solely by popularity. Perhaps this observation can be explained by the following intuition. When a social network first launches, connecting with "supernodes" is a key factor driving friendship requests. But as the network grows, it becomes harder to locate supernodes inside the massive network and their significance diminishes. Alternatively, we could explain this phenomenon in another way. When the network is young, a new user is likely to find few of her offline friends to connect to, and "supernodes" easily draw users' attention because of their popularity. As the network grows, users find more and more of their offline friends on the online social network. As a result, users pay more attention to people who they may know instead of popular users.

Finally, we observe a small ripple at the early stage of the network growth, when $\alpha(t)$ experiences a surge on December 12, 2006 (8.26M edges). This is due to the network merge event, which generated a burst of new edges that produce a bump in $\alpha(t)$ for that single day.

3.3 Summary of Observations

Our analysis produces three conclusions:

- *In a node's lifetime, edge creation rate is highest shortly after joining the network and decreases over time.*
- *Edge creation in early stages of network growth is*

driven by new node arrivals, but this trend decreases significantly as the network matures.

- *While edge creation follows preferential attachment, the strength degrades gradually as the network expands and matures.*

These results set the stage for the following hypothesis. An accurate model to capture the growth and evolution of today's social networks should combine a preferential attachment component with a randomized attachment component. The latter would provide a degree of freedom to capture the gradual deviation from preferential attachment.

4. COMMUNITY EVOLUTION

In online social networks, communities can be defined as groups of densely connected nodes based on network structure. More specifically, they are groups of nodes where more edges connect nodes in the same community than edges between different communities [29]. Note that these are implicit groups based on structure, and not explicit groups that a user might join or leave. Communities effectively capture "neighborhoods" in the social network. As a result, we believe they represent the best abstraction with which to measure the influence of social neighborhoods on user dynamics. We ask the question, "how do today's social network communities influence their individual members in terms of edge creation dynamics?"

To answer our question, we must first develop a method to scalably identify and track communities as they form, evolve, and dissolve in a dynamic network. There is ample prior work on community detection in static graphs [29, 7, 37, 6]. More recent work has developed several algorithms for tracking dynamic communities across consecutive graph snapshots [17, 32, 23, 35, 34]. Some of these techniques are limited in scale by computational cost, others require external information to locate communities across snapshots of the network.

In the remainder of this section, we describe our technique for scalably identifying and tracking communities over time based on network structure. We then present our findings on community dynamics in our social network, including community formation, dissolution, merging, and splitting. Finally, we analyze community-level dynamics, and use our detected communities to quantify the correlation between node and community-level dynamics. To make computation tractable across our large dataset, we choose a modified Louvain algorithm to produce the large majority of our results. To ensure that our choice of community detection algorithm does not significantly bias our results, we validate a portion of our findings using a second community detection algorithm that does not rely on modularity.

4.1 Tracking Communities over Time

Tracking communities in the presence of network dynamics is a critical step in our analysis of network dynamics at different scales. Prior work proved that dynamic community tracking is an NP-hard problem [35]. Current dynamic community tracking algorithms [17, 32, 23, 35, 34, 11] are approximation algorithms that "track" a community over multiple snapshots based on overlap with an incarnation in a previous snapshot. For scalability and efficiency, we use the similarity-based community tracking mechanism [11] for our analysis. In this section, we first introduce background on community detection algorithms and related definitions. Then, we briefly describe our mechanism, which is a modified version of [11] that provides tighter community tracking across snapshots using the incremental version of the Louvain algorithm [6]. At a high level, we use incremental Louvain to detect and track communities over snapshots, and use community similarity to determine when and how communities have evolved.

Background. Communities can be defined based on network structure as groups of well-connected nodes. There are dense connections inside communities but sparse connections between communities [29]. Modularity [27] is a widely used metric to quantify how well a network can be clustered into communities. It is defined as the difference between the fraction of edges falling in communities and the expected fraction when edges are randomly connected. It is formally defined in Equation 2, where A is the adjacency matrix ($A_{ij} = 1$ if node i and j are connected, and $A_{ij} = 0$ otherwise), k_i is the degree of node i, m is the total number of edges and $\delta(c_i, c_j) = 1$ if node i and j are in the same community and $\delta(c_i, c_j) = 0$ otherwise. The value of modularity should be between -1 and 1, and a large modularity means the network can be well clustered into communities.

$$Q = \frac{1}{2m}\sum_{ij}(A_{ij} - \frac{k_i k_j}{2m})\delta(c_i, c_j) \quad (2)$$

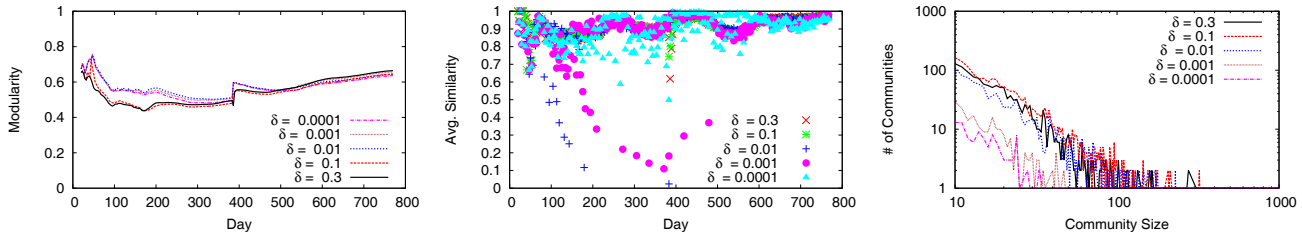
Several algorithms are designed to optimize modularity. [29] proposes a simple method to optimize modularity, reducing complexity to $O(n^3)$. [28] improves the algorithm further using hierarchical clustering method and its complexity is $O(n^2)$. [7] further reduces the complexity to $O(m \cdot d \cdot log(n))$ using balanced binary trees and max heaps. [37] improves the computation efficiency by avoiding unbalanced partitions.

Similarity-based Community Tracking. Louvain [6] is a scalable community detection algorithm that significantly improves both modularity and efficiency using greedy local modularity optimization. It uses a bottom up approach that iteratively groups nodes and communities together, and migrates nodes between communities until the improvement to modularity falls below a threshold δ. To the best of our knowledge, Louvain is the only community detection algorithm that scale to graphs with tens of millions of nodes[1].

Our approach leverages the fact that Louvain can be run in incremental mode, where communities from the current snapshot are used to bootstrap the initial assignments in the next snapshot. Given how sensitive community detection is to even small changes in modularity, this approach enables more accurate tracking of communities by providing a strong explicit tie between snapshots. Finally, we follow the lead of [11], and track communities over time by computing the similarity between communities. Similarity is quantified as community overlap and is computed using set intersection via the Jaccard coefficient.

Community Evolution Events. Using similarity to track communities allows us to detect major community events, including their birth, death, merges, and splits. We define a community A *splits* at snapshot i when A is the highest correlated community to at least two communities

[1]https://sites.google.com/site/findcommunities/



(a) Modularity (b) Average Community Similarity (c) Community Size Distribution on Day 602

Figure 4: Tracking communities over time and the impact of δ. (a) The value of modularity always stays above 0.4, indicating a strong community structure. The choice of δ has minimum impact, and $\delta = 0.01$ is sensitive enough to detect communities. (b) The value of average similarity over time at different δ values. Small δ values like 0.0001 and 0.001 produce less robust results. (c) The distribution of community size observed on Day 602. The algorithm is insensitive to the choice of δ once $\delta \geq 0.01$. The same conclusion applies to other snapshots.

B and C at snapshot $i+1$. When at least two communities A and B at snapshot i contribute most of their nodes to community C at snapshot $i+1$, A and B have merged.

When a community A splits into multiple communities $X_1, X_2 ... X_n$, we designate X_j as the updated A in the new snapshot, where X_j is the new community who shares the highest similarity with A. We say that all other communities in the set were "born" in the new snapshot. Similarly, if multiple communities merge into a single community A, we consider A to have evolved from the community that it shared the highest similarity with. All other communities are considered to have "died" in the snapshot.

Choosing δ. The δ threshold in Louvain is an important parameter that controls the trade off between quality of community detection and sensitivity to dynamics. If δ is too small, the algorithm is too sensitive, and over-optimizes to any changes in the network, needlessly disrupting the tracking of communities. If δ is too large, the process terminates before it optimizes modularity, and it produces inaccurate communities.

Choosing the best value for δ means optimizing for the dual metrics of high modularity and robustness (insensitivity) to slight network dynamics. First, we use network-wide modularity as a measure of modularity optimization for a given δ value. Second, to capture robustness to network dynamics, we use community similarity [11]: the ratio of common nodes in two communities to the total number of different nodes in both communities. More specifically, for two consecutive snapshots, we compute the average similarity between communities that exist in both snapshots. We run the Louvain algorithm on our snapshots using several different δ threshold values, and select the best δ that generates both good modularity and strong similarity. We repeat this procedure on shrinking ranges of δ until modularity and similarity can no longer be improved.

Sensitivity Analysis. We run the Louvain algorithm on our dynamic graph snapshots generated every 3 days. We start from Day 20, when the network is large enough (64 nodes) to support communities, and only consider communities larger than 10 nodes to avoid small cliques.

We scale δ between 0.0001 and 0.3, and plot the resulting modularity and average similarity in Figure 4. As shown in Figure 4(a), in all snapshots the modularity for all thresholds is more than 0.4. According to prior work [20], modularity ≥ 0.3 indicates that our social network has significant community structure. As expected, a threshold around 0.01 is sensitive enough for Louvain to produce communities with good modularity. Note that the big jump in modularity on Day 386 is due to the network merge event.

Figure 4(b) shows that thresholds 0.0001 and 0.001 produce lower values of average similarity (*i.e.* they are less robust and more sensitive) compared to higher thresholds between 0.1 and 0.3. Thus, Louvain with $\delta > 0.01$ generates relatively good stability of communities between snapshots.

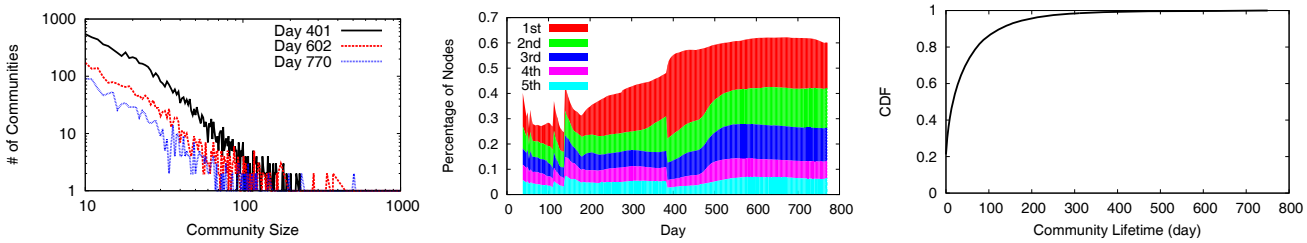
Lastly, we examine whether detected communities are highly sensitive to the choice of δ. As an example, Figure 4(c) plots the distribution of community sizes observed on Day 602. The conclusion from this figure is that once the threshold exceeds 0.01, the impact of δ on community size is reduced to a minimum. The same conclusion applies to other snapshots as well.

Based on the results in Figure 4, we repeat the Louvain algorithm within a finer threshold range of 0.01 to 0.1. We find that a threshold value of 0.04 provides the best balance between high modularity and similarity. We use $\delta = 0.04$ to track and measure dynamic communities in the rest of our analysis on the dataset.

4.2 Community Statistics Over Time

We now leverage the Louvain-based community tracking technique to analyze the dynamic properties of our social network communities. We begin in this section by looking at the community size distribution, how it changes over time, and the distribution of lifetimes for all communities. In Section 4.3, we take a closer look at the dynamic processes of community merges and splits. We explore the possibility of predicting community death from observed dynamics. Finally, in Section 4.4, we analyze the impact of community membership on individual user dynamics, and gauge how and to what extent community dynamics are observed to have influenced individual user dynamics.

Community Size. The size distribution of communities is an important property that reflects the level of clustering in the network structure. Since the network is constantly evolving, we can compute a community size distribution for each snapshot in time. We already observed in Figure 4(c) that the distribution of community sizes follows a power-law.



(a) Community Size Distribution (b) % of Nodes Covered by Top 5 Communities (c) CDF of Community Lifetime

Figure 5: Analysis on the evolution of communities. (a) Community size distribution on Days 401, 602, and 770. All three lines follow a power-law distribution, and show a gradual trend towards larger communities. (b) The portion of nodes covered by the top 5 communities grows considerably as the network matures. (c) Distribution of community lifetimes shows most communities only stay in the network for a very short time, and are quickly merged into other communities. This indicates a high level of dynamics between communities.

Our goal is to understand not only the instantaneous community size distribution, but also how the distribution changes over time as the network evolves. Thus, we compute the distributions for days 401, 602, and 770; 3 specific snapshots roughly evenly spaced out in our dataset following the network merge event. We plot the resulting community size distributions in Figure 5(a). The figure shows that the three snapshots consist of a large number of small communities and a long tail of large communities, consistent with the power-law distribution. This is consistent with other daily snapshots as well. More importantly, these snapshots show a gradual trend towards larger communities. Over the year of time between snapshots 401 and 770, the number of small communities shrunk by an order of magnitude. In turn, the sizes of the largest communities increase significantly.

To take a closer at how communities grow over time, we focus on the portion of the network that is covered by a small number of the largest communities. We take the top five communities sorted by size, and plot the percentage of the overall network they contain in Figure 5(b). We see that their coverage of the network shows a clear and sustained growth over time. They grow from less than 30% around day 100 to more than 60% of the entire network by the end of our dataset. Over time, this trend seems to indicate that as the network matures, connectivity becomes uniformly strong throughout the main connected component, while distinctions between communities fade.

Community Lifetime. In a dynamic network, how long a community remains in the network is another important statistical property. By using our community identification method between snapshots, we measure the distribution of community lifetime. Figure 5(c) shows that most of the communities only stay in the network for a very short period of time. Specifically, 20% of communities have lifetimes of less than a day, meaning that they disappear in the next snapshot after they are first detected. 60% of the communities have lifetimes less than 30 days, at which point they are merged into other communities. This shows an extremely high level of dynamics at the community level.

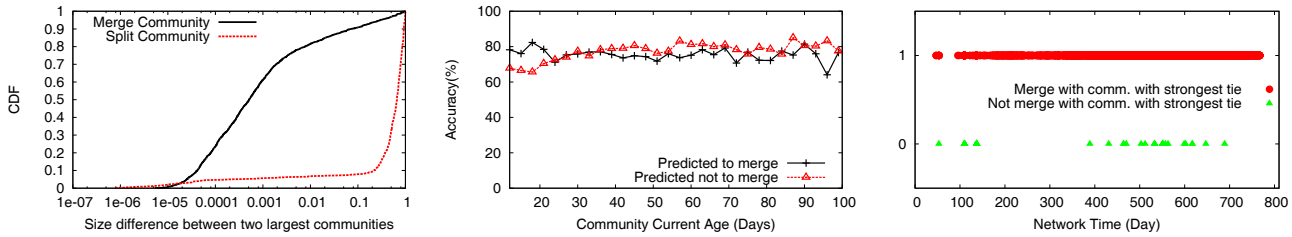
4.3 Community Merging and Splitting

Community merging and splitting are the main reasons underlying community death and birth. Therefore, understanding these processes in detail is critical to understanding dynamics at the community level as a whole. We study these processes in detail, with three questions in mind: What factors influence the split and merge processes for communities? What features, if any, are good indicators for whether a community will merge soon? Finally, can we predict which communities will merge together?

First, we study whether community size impacts splitting or merging. For splitting events, we only consider the largest two communities resulting from the split. Similarly for merge events, we focus on the two largest communities merging to become one community. We use as a metric the ratio of the size of the second largest community to the size of the largest community. The smaller the ratio is, the larger the size difference is between the two communities. In Figure 6(a), we plot the ratio of community splitting with a red line and community merging with a black line. We observe that for 78% of merged community pairs, this ratio is less than 0.005. This reflects that for most merge events, there is a large size discrepancy between the smaller community and a larger community. This is consistent with our observation that small communities tend to disappear over time, while the biggest communities continue to grow in size.

The community splitting process acts in a totally different manner. The red line in Figure 6(a) shows that the ratio for 68% split communities pairs are more than 0.5. Thus, when a community splits into smaller communities, the community tends to split into two comparable size communities. One possible explanation for this observation is that users only have a finite amount of time or energy to devote to online friendships, *e.g.* an online version of Dunbar's Number [9]. Once a community grows beyond this number, existing users cannot continue to add more friends. This leads to non-uniform distribution of new edges as users arrive, which creates pockets of stronger connectivity in the community and fragments it. The limit in social relationships has been observed in prior measurement studies [38].

Predicting Merging. Since community merge is the only reason causing the death of the communities, we are curious whether there are any structural features specific to the merge process, and whether we can accurately predict if a community is going to merge with another in the next snapshot. We identify three structural metrics, including *community size*, *in-degree ratio*, the ratio of the edges inside a community over the sum of the degrees of nodes in the



(a) Community Size Difference (b) Accuracy on Merge Prediction (c) Patterns of Merged Communities

Figure 6: Analysis of community merge and split events. (a) The distribution of the normalized size difference between the largest two components when they split or merge. Small communities always merge into large communities, and a community tends to split into two communities of comparable sizes. (b) The accuracy of our prediction on whether a community will merge with another in the next snapshot. We achieve a reasonably good accuracy of 75%. (c) With very high probability (99%), a community merges with the community that has the most edge connections (or the strongest tie) to itself.

community, and the *similarity* of a community to itself in the previous snapshot (defined in Section 4.1).

Since these metrics evolve over time, we also consider short-term changes in these features as additional factors. For example, consider the community size feature. We can identify its *first order change indicator* as a feature: if a community is smaller than its incarnation in the previous snapshot, we use -1 to indicate the decrease. Similarly, we use 1 to mark an increase and 0 to mark no change. For each metric, we can also consider its *second order change indicator*. If the change in community size from snapshot $i-1$ to i is larger than the size change from snapshot $i-2$ to $i-1$, we use 1 to indicate acceleration in this metric. Similarly, we use -1 to mark a deceleration in this metric. In total, we start with the three basic metrics and add on their standard deviation, their first order change indicator, and their second order change indicator.

Leveraging these feature metrics, we can now predict whether a community will merge with another in the next snapshot. Specifically, we apply a support vector machine over these features, together with the age of each community. For consistency, we do not consider communities created on the day of the network merge with the competing network because those changes are driven by external events. To examine the accuracy of our prediction, we compute two metrics: 1) the ratio of the number of communities predicted to merge in the next snapshot to the number of communities who actually merge, and 2) the ratio of the number of communities predicted to not merge in the next snapshot to the number of communities who do not merge.

Figure 6(b) plots our two accuracy metrics as a function of the community age. They show that our method achieves reasonable prediction accuracy. It achieves an average accuracy of 75% in predicting community merges and 77% in predicting no merges. This means that we can reliably track communities' short-term evolution.

We are also interested in predicting which destination community a given community will merge into. After examining each merged community pair, we make an interesting observation. With a very high probability (99%), a community i will merge with another community j that has the largest number of edges to i, or the strongest tie with i. Figure 6(c) illustrates this trend by plotting red dots for all merge events where a community merges with the peer with the strongest tie, and a green triangle otherwise. The results show that the trend is consistent over time. Thus, we conclude that the inter-community edge count is a reliable metric for predicting the destination of community merges.

4.4 Impact of Community on Users

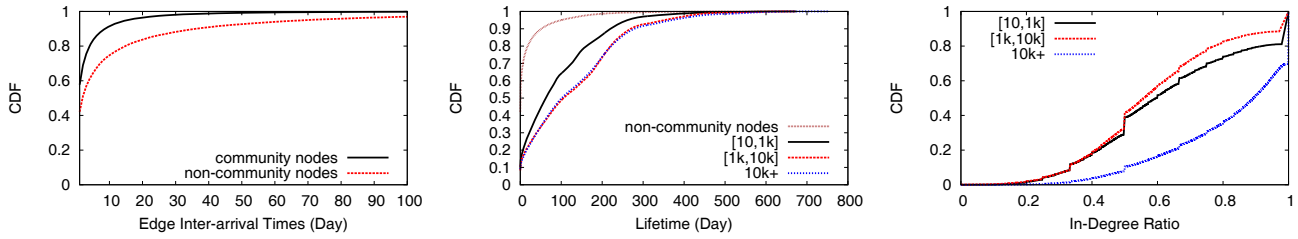
To understand how communities impact users' activity, we compare edge creation behaviors of users inside communities to those outside of any community. Overall, our results show that community users score higher on all dimensions of activity measures, confirming the positive influence of community on users.

Edge Inter-arrival Time. Figure 7(a) plots the CDF of edge inter-arrival times for community and non-community users. We observe that users within different communities display similar edge inter-arrival statistics, and merge their results into a single CDF curve for clarity. The considerable distance between the two curves confirms that community users are more enthusiastic in expanding their social connections than non-community users.

User Lifetime. Next, we examine how long users stay active after joining the network, and whether engagement in a community drives up a user's activity span. We define a user i's lifetime as the gap between the time i builds her last edge and the time i joins the network.

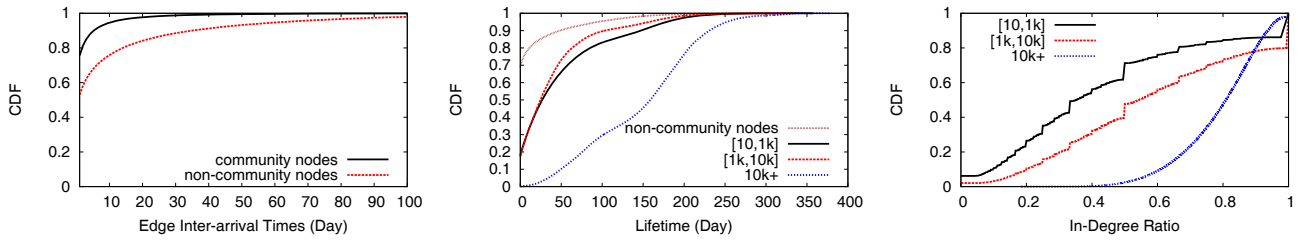
Figure 7(b) plots the CDF of user lifetime for users in different size communities as well as non-community users. $[x, y]$ represents communities of size between x and y. We find that the lifetime distribution depends heavily on the size of the community. The larger the community is, the longer its constituent user's lifetimes are. Compared to non-community users, users engaging in a community tend to stay active for a longer period of time. This confirms the positive impact of community on users.

In-Degree Ratio. Although we know that communities have more edges inside than outside statistically, we want to quantify how each user within each community connect to each other. We compute each user's in-degree ratio, *i.e.* the ratio of her edge count within her community to her degree. Figure 7(c) shows the CDF of the in-degree ratio for users in communities of different sizes. We observe that users in larger communities have a larger in-degree ratio, indicating that they form a greater percentage of edges within



(a) Edge Inter-arrival Time (b) Node Lifetime (c) Edge In-Degree Ratio

Figure 7: Comparing activity of users inside and outside communities. Community users score higher on all dimensions of activity measures, confirming the positive influence of community on users. (a) Edge inter-arrival time. Community nodes create edges more frequently than non-community nodes. (b) Node lifetime. Community users are grouped by their community sizes. $[x, y]$ represents communities of size between x and y. Community nodes stay active longer than non-community nodes. (c) Community user's in-degree ratio. Nodes in larger communities are more active within their own communities.



(a) Edge Inter-arrival Time (b) Node Lifetime (c) Edge In-Degree Ratio

Figure 8: Verification of results on the impact of communities on users' activities, using the Absolute Potts Model (APM) community detection algorithm. The results from communities detected by APM are consistent with our results using communities detected by our incremental Louvain approach.

their own community. In particular, 11-30% of nodes only interact with peers in their own communities. These results show that like offline communities, online social communities also encourage users to interact "locally" with peers sharing mutual interests.

4.5 Verification by Alternative Community Detection Algorithm

One concern with our work is whether our results are strongly biased by our choice of community detection algorithm. Since our incremental Louvain approach is the only algorithm able to process our large dataset, we choose to validate a small subset of our results using an alternative algorithm for community detection.

We select the Absolute Potts Model (APM) community detection algorithm [31]. This algorithm detects communities by minimizing a metric from Potts model, which describes the network energy under such network partition. The formal definition of this metric for unweighted graphs is shown in Equation 3, where A_{ij} is the element of adjacency matrix, $J_{ij} = (1 - A_{ij})$ is the missing edge in this network and σ_i is the community which node i belongs to. If node i and node j are in the same community, *i.e.* $\sigma_i = \sigma_j$, $\delta(\sigma_i, \sigma_j)$ is 1; otherwise, it is 0. γ is used to weight the strength of the missing edges, which is 0.0001 in our experiment.

$$H = -\frac{1}{2}\sum_{i \neq j}(A_{ij} - \gamma J_{ij})\delta(\sigma_i, \sigma_j) \quad (3)$$

Because of the significant computational costs, we run the APM community detection algorithm on our first-year network data, *i.e.* from snapshot 20 to snapshot 383. Then we run the measurement in Figure 7 on communities detected by APM, and present all of the results in Figure 8. Figure 8(a) shows the CDF of edge inter-arrival time of users in communities and users out of communities. We find that users in communities are more active in creating new connections compared to those outside of communities. Figure 8(b) shows the node lifetime distribution in communities of different sizes. We observe that users in larger communities have longer lifetimes. The edge in-degree ratio distribution in Figure 8(c) shows that users in larger communities are more likely to connect users inside the same community than users outside the community. All these results are qualitatively consistent with the observations in Figure 7. This confirms our results on community membership's impact on user activity. But more broadly, it provides evidence that our choice of that community detection algorithms does not significantly skew our analytical results.

4.6 Summary of Results

Our efforts on tracking and analyzing the evolution of communities lead to the following key findings:

- *Our social network displays a strong community structure, and the size of the communities follows the power-law distribution.*
- *The majority of communities are short-lived, and within a few days they quickly merge into other larger*

communities. These merge events can be reliably predicted using structural features and dynamic metrics.

- *The membership to a community has significant influence on users' activity. Compared to stand-alone users, community users create edges more frequently, exhibit a longer lifetime, and tend to interact more with peers in the same community.*

5. MERGING OF TWO OSNS

On December 12, 2006, our large Chinese OSN merged with a second competing online social network in China. This combined entity became the largest Chinese online social network that exists today. Our access to the graph topological and temporal data that characterizes this merge gives us a unique opportunity to study how this network-level event impacts users' activity. For clarity, we refer to our original social network as network X and the competitor it merged with as network Y.

In this section, we analyze the forces at work during the merge. First, we look at the edge creation activity of users over time in order to isolate users that have become inactive. This enables us to estimate how many duplicate accounts there were between network X and network Y. Second, we examine edge creation patterns within and between the two OSNs, and show that user preferences vary by OSN and over time. We observe that the merge is the primary driver of new edge creation for only a short time; edges to new users that joined the combined network after the merge rapidly take over as the driving force. Finally, we calculate the distance between users in each group to quantify when the two distinct OSNs become a single whole. We calculate that the average path length from one OSN to the other drops rapidly in the days following the merge, even when edges to new users are ignored. This demonstrates that the two OSNs quickly become a single, indistinguishable whole.

5.1 Background

Our original Chinese social network opened for business in November 2005 to university students. Before the two networks merged, network X counted 624K active users and 8.2M edges. Network Y was a competing OSN created in April 2006 that also targeted university students. Before the merge, network Y included 670K active users and 3M edges.

On December 12, 2006, the two OSNs officially merged into a single OSN. During the actual merge event, both OSNs were "locked" to prevent modification by users, and all information from network Y was imported and merged into network X's databases. Starting the next day, users could log-in to the combined system and send friend requests normally, *e.g.* users with profiles in network X could friend users in network Y and vice versa. New users just joining the system would not notice any difference between profiles of users from the two networks.

Since both networks targeted university students, it was inevitable that some users would have duplicate profiles after the merge. Network X used users' registration emails to identify whether a user has a duplicate profile in network Y. If a user uses one email to register both networks, the new merged social network allowed the user to choose which profile they wanted to keep during their first log-in to the site after the merge.

Definitions. In this section, we investigate the details of the merge between the two networks. To facilitate this analysis, we classify the edges created after the merge into three different groups. *External edges* connecting users from network X to users in network Y, whereas *internal edges* connect users within the same OSN. *New edges* connect a user in either OSN with a new user who joined the combined network after the merge. Time based measurements are presented in "days after the merge," *e.g.* one day after the merge is day 387 in absolute terms, since the merge occurs during day 386 of our dataset.

5.2 Measuring the Merge

User Activity Over Time. We start our analysis by examining the number of active users in both OSNs over time. We define a user as "active" if it has created an edge within the last t days. In our data, 99% of users create at least one edge every 94 days (on average), hence we use that as our activity threshold t.

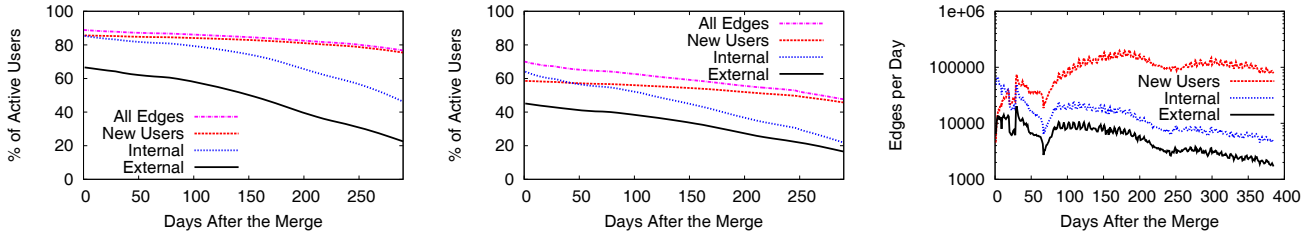
Figure 9(a) shows the number of active users over time for network X, while Figure 9(b) focuses on network Y users. Each "all edges" line highlights the number of users actively creating edges in each group. Although we have 384 days of data after the merge, the x-axis of Figures 9(a) and 9(b) only extends 290 days. Since our minimum activity threshold is 94 days, we cannot determine whether users have become inactive during the tail of our dataset.

We now address the question: *how many duplicate accounts were there on both OSNs?* Users with accounts on both services were prompted to choose one account or the other on their first log-in to the combined OSN after the merge. However, the discarded accounts were not deleted from the graph. Thus, it is likely that any accounts that are inactive on the first day after the merge are discarded, duplicate accounts.

Figures 9(a) and 9(b) reveal that 11% of network X accounts and 28% of network Y accounts are immediately inactive. Thus, it is likely that at least 39% of users had duplicate accounts between the two networks before the merge. Interestingly, users demonstrate a strong preference for keeping network X accounts over network Y accounts.

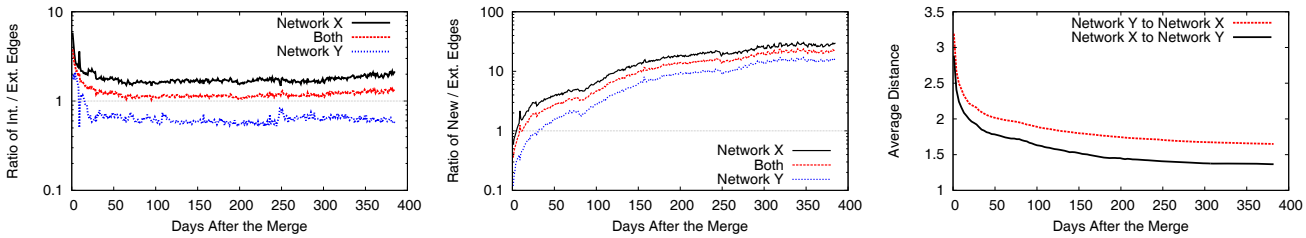
As time goes on, the number of active accounts in each group continues to drop. Presumably, these users lose interest in the merged network and stop generating new friend relationships. After 284 days, the number of inactive network X accounts doubles to 23%, while 52% of network Y accounts are inactive. The relative decrease in active accounts over time (12% on network X versus 24% on network Y demonstrates that network X users are more committed to maintaining their OSN presence. This observation corresponds to our earlier finding that users with duplicate accounts tended to keep their network X accounts. Network X users form a self-select population of more active OSN users when compared to network Y users.

The "new users," "internal," and "external" lines give the first glimpse of the types of connections favored by users in both OSNs. For each line, a user is considered active only if they have created an edge of the corresponding type in the last 94 days. Users in both graphs show similar preferences: edges to new users are most popular, followed by internal and then external edges. The large activity gap between internal and external edges highlights the strong homophily among each group of users. Internal and external edge creation activity declines more rapidly than edges to new users. This makes sense intuitively: the number of



(a) Active users over time for network X (b) Active users over time for network Y (c) Edge creation per day

Figure 9: (a)-(b) The number of active users over time. Accounts that are inactive on day 0 after the merge are likely to by discarded, duplicate accounts. Overall user activity declines over time. (c) Number of edges of different types created per day after the merge. Edges to new users quickly become the most popular edge type, although there is a small peak for external edges as well.



(a) Ratio of internal to external edges (b) Ratio of new to external edges (c) Distance between 2 OSNs over time

Figure 10: (a) Ratio of internal to external edges over time. Network X users create more edges overall, and are biased towards internal edges, weighting the average upward. (b) Ratio of new to external edges per day. Both networks overwhelmingly prefer edges to new users, although they reach this point at different rates. (c) The average distance in hops between the two OSNs drops over time as more internal and external edges are created. By day 50, the two networks are essentially one large, well connected whole.

users in the two networks is static, and hence the pool of possible friends slowly drops over time as edges are created.

Edge Creation Over Time. Next, we switch focus to look at the characteristics of edges, rather than individual users. By looking at the relative amounts of internal, external, and edges to new users that are created each day, we can identify what types of connections are driving the dynamic growth of the network after the merge.

Figure 9(c) shows the number of internal, external, and new edges created per day. Initially, internal and external edges are more numerous than edges to new users. However, 3 days after the merge new edges begin to outnumber external edges, and by day 19 new edges out pace internal edges as well. This result demonstrates that new users quickly become the primary driver of edge creation, as opposed to new edges between older, established users. This is not surprising: since the merged network is growing exponentially, the number of new users eventually dwarfs the sizes of network X and network Y, which remain static.

Note that this result does not conflict with the results presented in Section 3. Section 3 examines the edge creation patterns over the lifetime of *all* users in our data. In this section, we are comparing the edge creation patterns of users who existed before the merge to *everyone* who joined after. Thus, the age "buckets" in this section are very course.

We now ask the question: *are there differences between the types of edges created by network X and network Y users?* Although Figure 9(c) demonstrates that internal edges always outnumber external edges, the reality of the situation is more complicated when the edges are separated by OSN.

Figure 10(a) plots the ratio of internal to external edges over time for network X and network Y. Initially, users on both OSNs favor creating internal edges (*i.e.* the ratio is >1). However, by day 16, the ratio for network Y users starts to permanently favor external edges. The reason for this strange result is that network X users create more than twice as many edges than network Y users. In our dataset, network X users create 3.9 million internal edges, while network Y users only create 1.5 million. However, unlike internal edges, external edges affect the statistics for *both* groups. Thus, the number of external edges (2.2 million total in our dataset) is driven by the more active user base. Even though network X users create less external edges than internal edges, the number is still proportionally greater than the number of internal edges created between network Y users. The "both" line in Figure 10(a) is always >1 because network X users create more edges overall, which pushes the average upwards.

Figure 10(b) plots the ratio of edges to new users versus external edges over time for both networks. This plot reveals that the inflection point where users switch from preferring external edges to new edges is different for the two OSNs. The ratio becomes ≥ 1 for network X 5 days after the merge, whereas network Y takes 32 days. Despite these differences, both OSNs demonstrate the same overall trend for the ratio to eventually tip heavily in favor of edges to new users.

Distance Between the two networks. Finally, we examine the practical consequences of edge creation between the two networks. Our goal is to answer the question: *at what point do the two networks become so interconnected that they can no longer be considered separate graphs?*

To answer this question, we calculate the distance, in hops, between users in each group. Intuitively, the distance between the groups should decrease over time as 1) more external edges are created, and 2) more internal edges increase the connectivity of users with external edges. In our experiments, we select 1,000 random users from each OSN on each day after the merge and calculate the shortest path from each of them to *any* user in the opposite OSN. Thus, the lowest value possible in this experiment is 1, *e.g.* the randomly selected user has an external edge directly to a user in the opposite OSN. New users and edges to new users are not considered in these tests.

Figure 10(c) shows that the average path length between the two OSNs rapidly declines over time. Although average path lengths for both OSNs initially start above 3 hops, within 47 days average path lengths are <2. Path lengths from network X to network Y are uniformly shorter, and by the end of the experiment the average path length is <1.5.

The distance between networks X and Y rapidly approaches an asymptotic lower bound in Figure 10(c). Once this bound is reached, it is apparent that the graphs can become no closer. We conclude that by day 50, when both lines begin to approach the lower bound, the two networks can no longer be considered separate OSNs. These results demonstrate how quickly the two disjoint OSNs can merge into a single whole, even when edge creation is biased in favor of internal edges (see Figure 10(a)).

5.3 Summary of Results

Our analysis produces several high-level conclusions:

- *There were a large number of duplicate accounts between the two networks that become inactive immediately after the merge.*
- *Edges to new nodes quickly become the driving force behind edge creation.*
- *Despite user's preference against external edges, the two networks very quickly merge into a single, well-connected graph.*

We also observe that the merge alters user's edge creation patterns for a short time (until equilibrium is restored):

- *The total number of edges created per day increases, driven by the sudden appearance of so many new users.*
- *Users' preferences for internal/external edges changes drastically in the days following the merge.*
- *Network X users are more active than network Y users. Thus, the external edges created between network X and network Y force network Y users to become more active than they normally would be.*

6. RELATED WORK

Dynamic OSN Measurement. Several studies have measured basic dynamic properties of graphs. [22] analyzed four citation and patent graphs, and proposed the forest fire model to explain the observed graph densification and shrinking diameter. [21] studied details of dynamics in four OSNs to confirm preferential attachment and triangle closure features. Similar conclusions were reached by studies on Flickr [26] and a social network aggregator [10]. [16] measured network temporal radius and found out that there is a gelling point to distribution. In addition, [2] measured weighted dynamic graphs, [1] analyzed the growth of a Korean OSN, and [36] considered temporal user interactions as graph edges instead of static friendship. Finally, [12, 18] analyzed blogspace dynamics.

Some studies focused on analyzing social network dynamics through explicitly defined groups [4, 40, 14] or disconnected components [19, 25, 15]. [18] tried to identify blog communities and detect bursts in different temporal snapshots. [30] utilized the clique percolation method [8] to identify overlapping community dynamics in mobile and citation graphs. Unlike these studies, our work focuses on the evolution of implicit communities in a densely connected, large-scale social graph.

Dynamic Community Detection and Tracking Algorithms. There are two approaches to detecting and tracking dynamic communities. One approach is to minimize the self-defined temporal cost of communities between snapshots. [35] proved that this problem is NP-hard and then several works [35, 34, 23] proposed approximation algorithms. However, these algorithms only scale to graphs with thousands of nodes. [32] and [17] propose dynamic community detection algorithms that scale to graphs with hundreds of thousands of nodes. The drawback of [32] is that it cannot track individual community evolution.

The other approach is to match communities detected by static community detection algorithms across temporal snapshots. [11] maps communities between snapshots if their similarity is higher than a threshold. [3, 33] tracks communities between snapshots based on critical community events. These algorithms do not consider any temporal correlation when detecting communities between snapshots.

7. CONCLUSION

This work presents a detailed analysis of user dynamics in a large Chinese online social network, using a dataset that covers the creation of 19 million users and 199 million edges over a 25-month period. More specifically, we focus on analyzing edge dynamics at different levels of scale, including dynamics at the level of individual users, dynamics involving the merge and split of communities, and dynamics involving the merging of two independent online social networks.

Our analysis produced a number of interesting findings of dynamics at different scales. First, at the individual node level, we found that the preferential attachment model gradually weakens in impact as the network grows and matures. In fact, edge creation in general becomes increasingly driven by connections between existing nodes as the network matures, even as node growth keeps pace with the growth in overall network size. Second, at the community level, we use an incremental version of the popular Louvain community detection algorithm to track communities across snapshots. We empirically analyze the birth, growth, and death of communities across merge and split events, and show that community merges can be predicted with reasonable accuracy using structural features and dynamic metrics such as acceleration in community size. Finally, we analyze detailed dynamics following a unique event merging two comparably-

sized social networks, and observe that its impact, while significant in the short term, quickly fades with the constant arrival of new nodes to the system.

While our results from this network may not generalize to all social networks, our analysis provides a template for understanding the dynamic processes that are active at different scales in many complex networks. A significant takeaway from our work is that the actions of individual users are not only driven by dynamic processes at the node-level, but are also significantly influenced by events at the community and network levels. A comprehensive understanding or model of an evolving network must account for changes at the network and community levels and their impact on individual users.

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8. REFERENCES

[1] Ahn, Y., Han, S., Kwak, H., Moon, S., and Jeong, H. Analysis of topological characteristics of huge online social networking services. In *Proc of WWW* (2007).

[2] Akoglu, L., McGlohon, M., and Faloutsos, C. RTM: Laws and a recursive generator for weighted time-evolving graphs. In *Proc. of ICDM* (2008).

[3] Asur, S., Parthasarathy, S., and Ucar, D. An event-based framework for characterizing the evolutionary behavior of interaction graphs. *ACM TKDD 3*, 4 (2009), 16.

[4] Backstrom, L., Huttenlocher, D., Kleinberg, J., and Lan, X. Group formation in large social networks: membership, growth, and evolution. In *Proc. of KDD* (2006).

[5] Barabási, A., and Albert, R. Emergence of scaling in random networks. *Science 286*, 5439 (1999), 509.

[6] Blondel, V., Guillaume, J., Lambiotte, R., and Lefebvre, E. Fast unfolding of communities in large networks. *J. Stat. Mech* (2008).

[7] Clauset, A., Newman, M., and Moore, C. Finding community structure in very large networks. *Physical review E 70*, 6 (2004).

[8] Derényi, I., Palla, G., and Vicsek, T. Clique percolation in random networks. *Physical review letters 94* (2005).

[9] Dunbar, R. Neocortex size as a constraint on group size in primates. *Journal of Human Evolution 22*, 6 (1992).

[10] Garg, S., Gupta, T., Carlsson, N., and Mahanti, A. Evolution of an online social aggregation network: an empirical study. In *Proc. of IMC* (2009).

[11] Greene, D., Doyle, D., and Cunningham, P. Tracking the evolution of communities in dynamic social networks. In *Proc. of ASONAM* (2010).

[12] Guo, L., Tan, E., Chen, S., Zhang, X., and Zhao, Y. Analyzing patterns of user content generation in online social networks. In *Proc. of KDD* (2009).

[13] Jiang, J., Wilson, C., Wang, X., Huang, P., Sha, W., Dai, Y., and Zhao, B. Y. Understanding latent interactions in online social networks. In *Proc. of IMC* (2010).

[14] Kairam, S., Wang, D., and Leskovec, J. The life and death of online groups: predicting group growth and longevity. In *Proc. of WSDM* (2012).

[15] Kang, U., McGlohon, M., Akoglu, L., and Faloutsos, C. Patterns on the connected components of terabyte-scale graphs. In *Proc. of ICDM* (2010).

[16] Kang, U., Tsourakakis, C., and Faloutsos, C. Radius plots for mining tera-byte scale graphs: Algorithms, patterns, and observations. In *Proc. of SDM* (2010).

[17] Kim, M., and Han, J. A particle-and-density based evolutionary clustering method for dynamic networks. *Proceedings of the VLDB Endowment 2*, 1 (2009), 622–633.

[18] Kumar, R., Novak, J., Raghavan, P., and Tomkins, A. On the bursty evolution of blogspace. *World Wide Web 8*, 2 (2005), 159–178.

[19] Kumar, R., Novak, J., and Tomkins, A. Structure and evolution of online social networks. In *Proc. of KDD* (2006).

[20] Kwak, H., Choi, Y., Eom, Y., Jeong, H., and Moon, S. Mining communities in networks: a solution for consistency and its evaluation. In *Proc. of IMC* (2009).

[21] Leskovec, J., Backstrom, L., Kumar, R., and Tomkins, A. Microscopic evolution of social networks. In *Proc. of KDD* (2008).

[22] Leskovec, J., Kleinberg, J., and Faloutsos, C. Graphs over time: densification laws, shrinking diameters and possible explanations. In *Proc. of KDD* (2005).

[23] Lin, Y., Chi, Y., Zhu, S., Sundaram, H., and Tseng, B. Facetnet: a framework for analyzing communities and their evolutions in dynamic networks. In *Proc of WWW* (2008).

[24] LinkedIn Infrastructure Team. Data infrastructure at linkedin. In *Proc. of ICDE* (2012).

[25] McGlohon, M., Akoglu, L., and Faloutsos, C. Weighted graphs and disconnected components: patterns and a generator. In *Proc. of KDD* (2008).

[26] Mislove, A., Koppula, H., Gummadi, K., Druschel, P., and Bhattacharjee, B. Growth of the flickr social network. In *Proc. of WOSN* (2008).

[27] Newman, M. Analysis of weighted networks. *Physical Review E 70*, 5 (2004), 056131.

[28] Newman, M. Fast algorithm for detecting community structure in networks. *Physical Review E 69* (2004).

[29] Newman, M., and Girvan, M. Finding and evaluating community structure in networks. *Phys.Rev. E 69*, 2 (2004).

[30] Palla, G., Barabasi, A., and Vicsek, T. Quantifying social group evolution. *Nature 446*, 7136 (2007), 664–667.

[31] Ronhovde, P., and Nussinov, Z. Local resolution-limit-free potts model for community detection. *Physical Review E 81*, 4 (2010), 046114.

[32] Sun, J., Faloutsos, C., Papadimitriou, S., and Yu, P. Graphscope: parameter-free mining of large time-evolving graphs. In *Proc. of KDD* (2007).

[33] Takaffoli, M., Sangi, F., Fagnan, J., and Zaiane, O. A framework for analyzing dynamic social networks. *Applications of Social network Analysis (ASNA)* (2010).

[34] Tantipathananandh, C., and Berger-Wolf, T. Constant-factor approximation algorithms for identifying dynamic communities. In *Proc. of KDD* (2009).

[35] Tantipathananandh, C., Berger-Wolf, T., and Kempe, D. A framework for community identification in dynamic social networks. In *Proc. of KDD* (2007).

[36] Viswanath, B., et al. On the evolution of user interaction in facebook. In *Proc. of WOSN* (2009).

[37] Wakita, K., and Tsurumi, T. Finding community structure in mega-scale social networks. *CoRR abs/cs/0702048* (2007).

[38] Wilson, C., Boe, B., Sala, A., Puttaswamy, K. P. N., and Zhao, B. Y. User interactions in social networks and their implications. In *Proc. of EuroSys* (April 2009).

[39] Zachary, W. An information flow model for conflict and fission in small groups. *Journal of anthropological research* (1977), 452–473.

[40] Zheleva, E., Sharara, H., and Getoor, L. Co-evolution of social and affiliation networks. In *Proc. of KDD* (2009).