Global Dynamics of Online Group Conversations

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Abstract

Public online groups allow individuals to carry out conversations of common interests. Study of such group conversations provides a unique opportunity to study patterns of human conversations without violating individual privacy. The observational studies conducted in this paper are an attempt to identify the main correlates of continued growth of conversations, thereby clearing the path to developing predictive models user participation.

We study temporal evolution of online group discussions. Surprisingly, we find that individual discussion groups display distinctively q-exponential shaped inter-message times to reply distributions, unlike the power law distributions seen in email conversations. We show, using simulations, that the heavy-tailed distribution of time to reply, which we also observe when all data is combined, originate from mixtures of q-exponentials. We also find that popular threads come to be so from the very beginning as opposed to evolving to be more popular as they grow. This raises new possibilities for developing generative models of thread growth.

Introduction

Online groups are an important channel of social interaction that facilitate topic-specific discussions among a limited set of individuals. Online groups thus fill the gap between person-to-person social channels like email and Instant Messages (IMs), and broadcast channels like Twitter and Facebook. In this paper, we take a global account of how group message threads evolve with time as a function of the social identities of the participants.

Our contributions:

We find that good threads in fact start off well, rather than evolving to be so! This is observation is not natural to the usual preferential attachment models which attach higher probabilities of replies to threads that have already become large.

We also analyze temporal characteristics of online group threads using a large data set. We find that the time to reply distributions have strong circadian modulations. We propose that the q-exponential distribution is a better parametric fit for individual groups, and show that a mix of individual q-

Related Work

Structure and growth of conversations:

(Backstrom et al. 2008) showed that highly engaged users in online groups start out differently from others: Users who go on to be engaged and highly active are received positively by other groups users from the beginning. Similar to the findings of Backstrom et al., we observe that highly successful conversation threads also start out differently from others and are mostly dependent more on identity of the originator of threads and the initial rate at which they receive messages rather than the users who post replies to original messages.

In hindsight, this may be obvious, since the initial rate at which replies are posted may be a correlate of the topic or the social status of the thread originator.

Inter-message time analysis:

Power-law distributions of time-delays between online social activities have been widely observed. On a large database of email conversations, Johansen (Johansen 2004) empirically showed a power-law fit for the time-difference between successive email replies. Barabasi (Barabasi 2005) proposed a priority-queue based model to explain the power-law fit observed in those email conversations. Malmgren and colleagues (Malmgren et al. 2008) showed that it is also plausible that heavy tailed reply time distributions arise as a mixture of inhomogeneous Poisson distributed arrival times. They model user posting rates as inhomogeneous Poisson distributions where the rate parameter is modulated by circadian rhythms. They show that a heavy tailed distribution of reply times arises when many individual inhomogeneous Poisson distributions are mixed. While we do not model individual users here, we draw inspiration from the work of Briggs and Beck (Briggs and Beck 2006) where the authors model train delays as q-exponentials and show how heavy-tailed distributions (e.g., q-exponentials) arise naturally as superstatisics of individual exponential (e.g., Poisson) processes with randomly distributed (e.g., \( \chi^2 \)) rate parameters.

Leskovec et al. (Leskovec et al. 2007) showed how an approximate power-law distribution was also present in the delay between blog posts linking to each-other, and provided...
a generative law that gave rise to the observed power law distributions.

**Preliminaries**

**Data description**

We use one of the world’s largest collections of online discussion boards. From this Groups data we chose only the public groups that were moderated and active at the time of data collection. Of these, we retained groups with at least 10 total messages and at least 10 unique subscribers. Roughly 10,000 groups with about 14 million total messages remained after filtering. The data was collected in January 2010 and contained all messages in the selected groups up to that time, spanning nearly 10 years.

While individual users may receive updates through different channels (email, consolidated digests, direct website visits) we do not discriminate between these in our analysis.

**Temporal dynamics of message posting**

In this section, we will present an overview of some temporal characteristics of time to reply differences that seem unique to discussion groups.

![Figure 1: Time delay between successive messages is distinctly non-power law. We also see a strong circadian rhythm and “knee points” at two hours, and one day, followed by successive daily peaks (dashed vertical lines at 2 hrs, 1 day, 1 week)](image)

**q-exponentials describe time to reply distributions**

The familiar power law distribution of the size of threads exists, with probability of observing a thread of size $k$ following distribution $p(k) \propto k^{-\alpha}$ for some $\alpha$. On the other hand, the distribution of times to reply $r(v,u)$ for individual groups, and to an extent over the whole data, follows a distinctly non-power law distribution. For example, Figure 1 shows the top 6 individual groups show lighter tailed distributions (gray lines) than what a power law distribution would predict. However, time to reply distribution accumulated over all the groups may still be closer to a power law (dark line in Figure 1). We also observe strong circadian modulations in time to reply distributions. In the overall time to reply distribution across all groups we observe distinct knee points at two hours and one day (See Figure 1). Keeping the distribution between two hours and one day as a reference, we see that there is lower mass in the distribution at less than two hours and more than one day compared to what a power law would predict. We observe more prominent circadian modulation than in some email data sets (Malmgren et al. 2008) and see traces of a weekly modulation as well, similar to blog link creation time course (Leskovec et al. 2007).

Visually, the time to reply distributions for individual groups seem to be $q$-exponentials. A random variable $X$ is $q$-exponentially distributed with shape and scale parameters $q$ and $\kappa$, respectively, if its upper cumulative (or complementary) distribution function is $Pr[X \geq x] = \left(1 - \frac{(1-q)x}{\kappa}\right)^{-\frac{1}{q-1}}$ (Picoli, Mendes, and Malacarne 2003). The $q$-exponential distribution has been used in the literature for modeling social network growth (White et al. 2006).

In Figure 2 we show reply time distributions for some of the largest groups and their corresponding $q$-exponential fits obtained by a Maximum Likelihood estimate (Shalizi 2007).

**Mixture of q-exponentials result in power law**

From the above observations, we postulate that for individual groups, time to reply are $q$-exponential distributed. We also postulate that when a right mix of $q$-exponentials is accumulated over all individual groups, it is possible to generate an overall dis-

![Figure 2: Density of the time to reply distributions of the individual groups, and their Maximum Likelihood fit to $q$-exponentials.](image)
Temporal Structure of Threads

We now turn to understanding the characteristics of individual threads. We would like to find out what may be the drivers of user participation, and whether there are any social attributes of ongoing threads that attract increased and quicker participation.

Popular threads generate high interest from start

A popular thread could be popular from the start, or it could start slow and gain popularity at a later stage. We want to understand which of these possibilities prevail. To that end we look at how time to first reply to the root message relates to the eventual thread size. Figure 5 shows the average time to first reply to a root message vs. thread size. Generally, first replies to the root message arrive much quicker for threads that grow to receive many replies. This is true within a group (not shown here due to space constraints), as well as aggregated over all the groups (Figure 5(c)). Kumar et al. (Kumar, Mahdian, and McGlohon 2010) also observed that the exponent of degree distribution power law decreases with depth in threads, i.e., thread trees tend to have fewer answers at higher depths. This suggests that popular threads usually are popular from the start, and begin receiving quicker replies right from the time the root message is posted. In other words, the root message content or the identity of its author determine, to a large extent, the eventual success of a thread.

First reply time predicts degree

We would also expect that if a message receives a quick first reply, then probably it is interesting enough to receive many more subsequent replies. Indeed this is true. Figure 5(d) shows how messages with higher degree also generally have quicker first reply times.

Mean reply time over the whole thread has no systematic relation to thread size

We saw how time to first reply to the root message correlates well with the eventual thread size. The average delay over all replies to a message, on the other hand, paints a completely different picture. For many groups, we in fact see an increase in the mean reply time...
with thread size (not shown here due to space constraints).

We also see that for some groups, the mean reply time oscillates unpredictably as the thread size grows. We looked at a large number of threads but found no systematic pattern in thread size vs. mean times to reply.

**Parent author is more predictive of time to reply**

For each group $G$ as we compute two correlation coefficients. First, we correlate the time to reply with the baseline posting rates of authors of replies, called the **author baseline**. Specifically, for each message pair ($parent(v),v$) posted in group $G$ we compute Pearson’s correlation coefficient $R_a(G)$ between quantities $r(parent(v),v)$ and $author\_baseline(author(v))$. Second, we correlate the time to reply with the average rate at which a given user’s posts receive replies, called the **parent baseline**. In other words, we compute Pearson’s correlation coefficient $R_p(G)$ between $r(parent(v),v)$ and $parent\_baseline(parent\_author(v))$. As seen in Figure 6, the **parent baseline** correlates better with time-to-replies in a thread than the **author baseline**

**Discussion and Conclusions**

The evolution of conversations when limited amount of information is visible to users is not yet completely characterized. Most of the generative models in the literature explicitly use the current degree (the number of friends a user has, total replies so far) for creating new edges. It is unknown whether users in fact take this information explicitly into consideration, or always have access to this information while creating links. Preferential attachment models are thus at best a proxy when current degree is not available to users during link creation. These aspects of evolutions of conversations remain to be investigated. In this paper, we showed how the initial few posts in a thread matter in the ultimate size of threads, and how there are non-trivial temporal aspects of thread evolution that are not captured by popular models.

**References**


Leskovec, J.; McGlohon, M.; Faloutsos, C.; Glance, N. S.; and Hurst, M. 2007. Patterns of cascading behavior in large blog graphs. In SDM. SIAM.


