Modeling correlated human dynamics

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We empirically study the activity patterns of individual blog-posting and find significant memory effects. The memory coefficient [K.-I. Goh and A.-L. Barabási, EPL 81, 48002 (2008)] first decays in a power law and then turns to an exponential form. Moreover, the inter-event time distribution displays a heavy-tailed nature with power-law exponent dependent on the activity. Our findings challenge the priority-queue model [A.-L. Barabási, Nature 435, 207 (2005)] that can not reproduce the memory effects or the activity-dependent distributions. We think there is another kind of human activity patterns driven by personal interests and characterized by strong memory effects. Accordingly, we propose a simple model based on temporal preference, which can well reproduce both the heavy-tailed nature and the strong memory effects. This work helps in understanding both the temporal regularities and the predictability of human behaviors.

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I. INTRODUCTION

Human actions underly many social, technological and economic phenomena, and thus the quantitative understanding of human behavior is very significant [1,2]. Thanks to the development of the information techniques, more and more electronic records available from Internet may provide us insights into the patterns of human behavior [3,4]. In recent years, examples of empirically studied human activities include communication patterns of electronic mails [5,7] and surface mails [6–9], web surfing [10,11], short message [12], movie ratings [13], online game [14,15]. The main result, arising from all these studies, concerns the heavy-tailed natures of human activity: the inter-event and/or response times follow a power-law-like distribution at the level of both population and individual.

A possible explanation of the heavy-tailed nature is the priority-queue model firstly introduced by Barabási [3,10], in which human behavior is primarily driven by rational decision making. Another possible origin is the cascading nonhomogeneous poisson process which emphasizes the external factors such as circadian and weekly cycles [6,7,17]. Although both models can give rise to heavy-tailed distribution of inter-event and/or response times, the internal correlation of the activities of human, as the most complex creature on earth, is absent. However, in the common sense, our activities should display memory effects since the personal tastes and interests are known to have both the long-term consistence and short-term burstiness. Long-term temporal memory in some human-initiated systems has already been observed [18,19]. Moreover, the significant potential predictability found in human mobility can be considered as a complementary evidence of spatial memory of human activities [20]. Actually, our daily activities can be roughly divided into two classes: things we have to do and things we want to do. Sending emails, making calls, submitting programmes in Linux servers, printing papers can be seen as the first class, which are important yet may not be interested to us. In contrast, entertainment activities, such as listening to music, watching movies and reading books, are driven by personal interests and thus belong to the second class. Models considering adaptive interests can to some extent reproduce the memory effects [21,22]. Besides the memory effects, by extensive empirical analyses on more than 10 real systems [12,13,24,25], it is shown that the individual activity (i.e., the frequency of actions of an individual) plays an important role in determining the distribution of inter-event time distribution: the larger the activity the narrower the distribution. Both the memory effects and the activity-dependent distributions can not be reproduced by the priority-queue model with two universality classes [16].

In this paper, we empirically study the activity patterns of individual blog-posting and find significant memory effects. Moreover, the inter-event time distribution displays a heavy-tailed nature with power-law exponent dependent on the activity. We propose a simple model based on temporal preference, which can well reproduce both the heavy-tailed nature and the strong memory effects. This paper is organized as follows. In the next section, we introduce the empirical observations, followed by the model and simulation results in Section 3. We conclude this work in Section 4 with some discussion about the relevance of our work to the real human behavior.

II. EMPIRICAL ANALYSIS

Blog is a kind of so-called web2.0 application emerging in recent years, in which people post some words,
FIG. 1: (Color online) The distribution of the number of posts. There are two scaling regimes, the exponents of which are -1.48, -0.87. The part in the shadow correspond to the users whose number of posts is greater than 200.

read and comment it each other. For most ordinary bloggers (the user of blog), they post in their own interest and treat it only as an amusement or an optional way of communication with friends. This make their blogging unstable and the frequency of it could be relatively low (often once one day). Our data was collected from a campus blog website of Nanjing university (http://bbs.nju.edu.cn/blogall). Most users are current or former students and teachers of Nanjing university. As of 01/09/2009, there are 1627697 posts belonged to 20379 users in this website. The first post is at 25/03/2003 when this blog established. In fig 1, the distribution of the number of the post decays as so-called double power law. The same result was also reported by Grabowski [26] who thought that there are two groups of people which clause two scaling regimes.

The heavy-tailed nature of the global distribution of interevent times of all users is shown on the fig 2a. The exponent of this distribution is -1.98 which is very close to the one in movie rating [13] and web activities on AOL and Ebay [24]. Figure 2b is the global interevent times distribution of the users whose number of posts is more than 600. The exponent \( \beta = 2.42 \) and \( a = 1.0 \). The average of \( \text{Activity} \) is 0.76 that would be why its exponent is larger than the one of fig a.

Following the way in [19], We sort users in an ascending order of \( \text{Activity} A_i \): \( A_i = n_i/d_i \), where \( n_i \) is the total number of posts of user \( i \) and \( d_i \) is the time between the first and the last post. For simplicity, we only divide these users into two groups: one is the top 14000 users in the list above and the average of \( \text{Activity} \langle A \rangle = 0.04 \) per day, the other one is the remainder containing 6379 users and \( \langle A \rangle = 0.64 \) per day. As we can see in fig 3, the decay exponent of interevent times distribution in group level increases from 1.86 to 2.47 as the \( \text{Activity} \) from 0.04 to 0.64.

For individual behavior, we only consider users whose number of posts is more than 200 to avoid characterizing users who post too little. There are 2211 qualified users. Firstly, we choose one user for example. As shown in fig 4, both the distribution and the cumulative one of interevent times decay asymptotically as a power law. The exponents of the cumulative distribution of this user is 1.40. Correspondingly, the one of distribution of this user are 2.40. The average of the exponents of all qualified users is 2.23. The interevent times for consecutive events of this user is shown on fig 5a. As comparison, the fig 5b is another user’s. It can give us the light of the human behavior from a visual understanding. One of important features is the clustering of extreme long interevent times which also is called mountain-valley-structure and can be
found in many complex systems [27, 28]. The long-term change also can be found in these users: for fig 5b, the posting frequency is obviously lower in the span of event number 200-400.

The features above inspire us to investigate the memory coefficient of this succession, although the lack of it in human activities was already reported by [29]. The definition of it is as follow [29]:

\[
M_k = \frac{1}{n_{\tau} - 1} \sum_{i=1}^{n_{\tau} - 1} \frac{(\tau_i - m_1)(\tau_{i+k} - m_2)}{\sigma_1 \sigma_2},
\]

where \(\tau\) is the interevent time values and \(n_{\tau}\) is the number of interevent time and \(m_1(m_2)\) and \(\sigma_1(\sigma_1)\) are sample mean and sample standard deviation of \(\tau_i\)'s (\(\tau_{i+k}\)'s). The two interevent times \(\tau_i\) and \(\tau_{i+k}\) is separated by \(k\) events.

Here, we calculate \(M_k\) of all these qualified users with \(k\) ranging from 1 to 40. Because the number of posts of one single user is still so small that the decay curve of \(M_k\) of one user presents too big fluctuation, we only study the average \(M_k\) of all users. In fig 5c, \(M_1\) is 0.21 which shows there is strong memory between the nearest interevent times. Interestingly, there are two regimes in this decay curve: when \(k < 10\), it decays asymptotically as a power law: \(y = 0.23 + x^{-0.48}\); when \(k > 10\), it decreased exponentially: \(y = 0.1 + e^{-x/23.76}\). This feature shows that the short-term and long-term memory in this behavior are likely due to different mechanisms. For the part of \(k > 10\), the decay curve reminds us of the Ebbinghaus forgetting curve which also has exponential nature. It is possible that the exponential decay of memory of our behavior lead to the same decay of the long-term memory. For the part of \(k < 10\), it is much stronger and obviously has something important to do with the mountain-valley-structure above and even the heavy-tails in the distribution.

To sum up, there are three important features in this behavior: the heavy-tails distribution of interevent time with an exponent \(\beta \approx 2\); the dependence between the exponent and \(Activity\); the strong memory. It is obvious that the stochastic models, such as the priority-queue model [3, 10] and the cascading nonhomogeneous poisson process [3, 7], can’t be the mechanism of this correlated human dynamic. As to previous memory-based models, the adaptive interest model [22] only can give a distribution with the exponent \(\beta = 1\); the exponent from Vazquez’s model can more than 2 [21]. However, two other features is absent in the discussion of the both two models and the details, "overmany long intervals", also can’t get an explanation from them. Below we will try to suppose a very simple model to explain all characteristics above.

III. MODEL AND SIMULATION RESULTS

Before building our model, let’s try to gain some intuition from our daily life firstly. After along day’s work, we have some free time and need to do something that can relax ourselves. There are always many choices for us: we can do exercises outside, or see a movie, or listen to music, or write some words in your website like blogging, and so on. In most cases, we would make a choice among them basing on our personal preferences which are very diverse and different from each other. However, in one way people are alike: the more someone get interested in it, the more frequently he would do. On the other hand, in a few cases, people would like to have a change and try to do something new or something that wasn’t done for a long time.

So we assume that there are \(N\) choices which can be
regarded as different forms of entertainment. At each time step, the agent select one of them to do according to two "choosing rules" as follows:

(1) Suppose one of $N$ choices was selected $T$ times in past $M$ steps, then the probability of choosing this one at current time step is $T/M$.

(2) Picking up randomly from these $N$ choices. The probability of executing the second rule is $R$ and the one of executing the first rule is $1 - R$. Here, the interevent times $\tau$ is the number of steps between choosing the same one consecutively. From the description above, the probability of choosing $i$ in current steps $P_i$ is:

$$P_i = (1 - R)T_i/M + R/N. \quad (2)$$

where $T_i$ is the times of selecting $i$ in past $M$ steps.

In all simulations of this paper, $N$ is fixed to 6 which means that we ignore new hobbies. It is obvious that the distribution of interevent times approaches an exponential one when $R$ become rather large. So $R$ must be small but not too small. The result of following the preference rule totally is that the agent will only select one of them repeatedly and ignore the others. In our simulations, we suppose $R = 0.005$. In $M \to \infty$ limit, the distribution of interevent times become also exponential(see fig 5b). It show this preference must be temporal, otherwise there would be no heavy-tails! And $M$, as the most important parameters in our model, show how temporal this preference is. The result of following the preference rule, the agent is a "super loyal user" who would go on no matter how long he pause. That would be why the distribution given by our simulation have so many long intervals.

In order to get enough samples, we ran our program 100 times and 200,000 steps at each time. The selection made in last 60,000 steps was recorded as one individual did. So we got 100 series which belong to 100 different "users". Then we calculated the Activity $A_i$ of each "user" and sorted them by it. We choose the top 60 "users" as one group whose $\langle A \rangle$ is 0.055 per step; the other group contain the remaining 40 "users" and the $\langle A \rangle$ of it is 0.295 per step. From fig 6d, we can see similar dependence between the exponent and Activity: the exponent $\beta$ increase from 2.10 to 2.41 as the Activity from 0.055 to 0.295.

In fig 7, the corresponding memory coefficient of our simulation decays as a power law which can fit well the short-term memory obtained from the data. For the long-term one or the part of $K > 10$, the coefficient of real data goes down exponentially with $K$ and is about 0.01 smaller than the one of our model. The cause of this discrepancy for long-term part may be that we do not take into consideration the memory fading. It embodies in two aspects: for the first choosing rule, the influence of past selection within $M$ time steps is the same but in real behavior it should be decay with time; on the
FIG. 6: (Color online) The distribution of the interevent times given by our simulation. In our simulation, $N = 6$, $R = 0.005$ (the same in fig 6), we only observed the selection of one of these $N$ choices and the other’s was ignored. At first, we make $M$ choices randomly as our initial conditions. Our program ran 2,000,000 steps to get a stable exponent of the distribution. The result of simulations when $M = 1000$, $M = 20000$, and $M = 160$ is shown on (a), (b), (c). For (a), the exponent $\beta = 2.92$ and $a = 4.0$; the distribution in (b) is obviously close to exponential one; For (c), the exponent $\beta = 2.19$ and $a = 0.4$. The distribution of the interevent time of the two groups with the same parameters of (c) is shown on (d). For group 1, $\langle A_1 \rangle = 0.055$, $\beta = 2.10$ and $a = 1.5$; for group 2, $\langle A_2 \rangle = 0.295$, $\beta = 2.41$ and $a = 0.2$.

On the other hand, we actually assumed that people would never change his hobbies and be just trap in the $N$ choices and in real life there is always a possibility of finding new hobby and abandon old one. However, in our opinion, the discrepancy is too small to affect the production of heavy-tails of this behaviors. The short-term memory, which is much stronger and play a key role in the origin of heavy-tails, is reproduced well by our model.

IV. DISCUSSION

There is high complexity in human behaviors. Different activities can be conducted in different behavior pattern and the same activity can be affect by multiple factors. To fully understand the pattern of human behaviors we must investigate a wider variety of activities and further details, not just the exponent of interevent time distribution. In this paper, we investigated not only the heavy-tails in the activity pattern of blog-posting but also the memory and the role of Activity. In our opinion, it show there is another kind of activities which also have the similar heavy-tails nature but different origin. Although the influence of the seasonal cycles also would be found in this behavior, the short-term memory can’t be explained by the model like the nonhomogeneous poisson process [6, 7].

One interesting result is that the decay curve of $M_k$ have two regimes: for the short-term part ($K < 10$), it decays as a power law; for the long-term part ($K > 10$), it decreases exponentially. Based on the personal preferences rule: "the more we do it recently, the more likely we will do it next", numerical simulations give the strong short-term memory but the mechanism for long-term change is absent. That would be why $M_k$ in the real date is a little smaller than the one of our simulation for the $K > 10$ part. Recent study also pays attention to
this kind of long-term change in human activity \cite{7}. At the level of individual, this change can be the result of personal interest and need shifts which seems very unpredictable. However, at the level of population, the exponential decay of memory hint that it have something to do with the memory fading.

Another feature reproduced by our model is the dependence between the Activity and the exponent of the interevent time distribution. According to the first rule of our model, the selective probability is actually positive-linear dependent on the temporal Activity \( T_i/M \). That would be the cause of this dependence. Our model also imply that a symbiotic relationship exists between the strong short-term memory and this dependence. Further investigations are needs in this direction.

Due to the complexity of our issue it is impractical to expect this simple model to accurately match with the empirical result. One important kinds of extensions of this model would be to consider the effect of the memory fading as we discussed above. It is still a question how to do it. One easy way would be to assume that the weight of influence of the past choices decay with time. However, is there more nature ways? We mean to find the mechanism of memory and figure out why the strength of memory decay exponentially. One reason of forgetting the old hobby can be finding a new one. But the detail process of it is still unknown. Interaction is another factor needed to be into consideration. Human, as a social beings, live in a network knitted by friends and relatives and cannot avoid the effect from it. But interaction seems be secondary to the heavy-tails as the interevent time distribution of some systems without interaction also have the heavy-tails \cite{24} and the model with interactions show it just increases the value of exponent \cite{31}. If the stimulation from friends can make people more actively, our model actually include this effect naturally since the exponent from our model also increases with the activity.

In our opinion, this strong short-term memory correlation should be common in the activities which is more a matter of personality than task. We hope that more empirical studies would be made in the future. Actually, people not only have preferences for different activities, even for the same one with different types. Taking watching movies for example, when we decide to watch a DVD, there are usually many kinds of movies: romance, sci-fi, classics, horror....in this case, the \( N \) choices of our model can be regarded as different types of movies. In the dynamic evolution of social network, we also can treat one’s friends as the choices of our model when people try to choose one of their friends to contact. In our opinion, the personal preferences can be found both in many activities and at different levels.

The memory or correlation of human behavior have much to do with the predictability. One’s friends can understand and predict his behaviors better because they know his past and one’s past, present and future are interconnected. A music that many people like is probably liked by you since we are influence each other and correlation could be found in the preferences of us. Revealing it in human behaviors and uncovering the mechanism of correlated human dynamics have great significance for many fields, such as the link prediction and recommender systems. Taking the recommender systems for example. All recommendation algorithms including the famous "page-rank" algorithms used by Google is just based on the empirical hypothesis. The practice shows it works, but why it works? And how to find the best recommendation algorithm? Without fully understanding human behavior, especially the relation between one’s past behavior and present, we can not answer these questions well.

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