The dynamic pattern of human attention

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Abstract. A mass of traces of human activities show diverse dynamic patterns. In this paper, we comprehensively investigate the dynamic pattern of human attention defined by the quantity of interests on subdisciplines in an online academic communication forum. Both the expansion and exploration of human attention have a power-law scaling relation with browsing actions, of which the exponent is close to that in one-dimension random walk. Furthermore, the memory effect of human attention is characterized by the power-law distributions of both the return interval time and return interval steps, which is reinforced by studying the attention shift that monotonically increase with the interval order between pairs of continuously segmental sequences of expansion. At last, the observing dynamic pattern of human attention in the browsing process is analytically described by a dynamic model whose generic mechanism is analogy to that of human spatial mobility. Thus, our work not only enlarges the research scope of human dynamics, but also provides an insight to understand the relationship between the interest transitivity in online activities and human spatial mobility in real world.

PACS numbers: 89.75.Da, 05.45.Fb, 89.65.Ef

Submitted to: New J. Phys.
1. Introduction

Human activities involving with individual attention (or interest) and his/her tendency toward transitivity have been deemed to include complicated factors that affect their dynamic pattern or evolutionary process. Meanwhile, mining human dynamic patterns plays an important role on practical applications ranging from information spreading [1,2], decision making [3], advertising [4,5] to information recommendation [6]. Thanks to the rapid development of information technology providing a mass of traces of human activities in virtual social systems, we can investigate the human attention dynamics in these activities easily and comprehensively. The pioneer work made by Wu et. al. [7] suggested that a natural time scale exists in the fading process of collective attention. Following that, Crane and Sornette [8] introduced a model that incorporates an epidemic spreading process with forgetting mechanism to describe both the exogenous and endogenous bursts of attention. Recently, Weng et. al. [9] provided an agent-based model with limited attention to explain the massive heterogeneity in the popularity and persistence of memes.

Since the evolutionary process of human attention usually accompanies with the individual decision making and the tendency toward transitivity (e.g. browsing a subdiscipline, next time, stay the same or transit to another one with individual preference in an online academic communication forum), we should comprehensively analyze its dynamic pattern, especially understand how the individual attention drives his tendency toward transitivity, which is lacking in the previous works. Note that this interest transitivity in virtual social systems is not wholly identical to the movement in the human spatial mobility in real world although recent studies demonstrate that there may be some analogies between them [10, 11]. With these considerations, we empirically investigate the diverse properties of the expansion, exploration, memory effect and shift, in order to characterize the dynamic pattern of human attention. Based on these empirical results, a dynamic model is finally proposed to effectively describe the observed phenomenons in these types of human activities in virtue social systems. The rest parts of paper are organized as follows: we show the description of experimental data and measurements in section 2; the empirical results are presented in section 3; the analysis and construction of dynamic model is described in section 4; and the final section gives the conclusion.

2. Data description and measurements

As a multi-disciplinary scholarly research community in China, Sciencenet is a distinguished multi-level website including the virtual social network of users, blog post and bulletin board system (BBS) [12]. Most of the users of Sciencenet are scientists, teachers and students from diverse disciplines. The experimental dataset was collected from BBS in Sciencenet, where there were 60 different communities of subdisciplines and the users in one certain community were usually involved in similar
disciplines background. It described the browsing traces of individual user from one community to another in a period between 10/1/2007 and 7/7/2011, and was composed of 366,524 records of total 49,578 users. In addition, the structure information involved with individual user ID (anonymous for privacy protection), browsing community ID, posting/reviewing topic ID, and timestamp with time resolution of minute. Before the empirical analysis, we preprocessed the experimental dataset to pick out the 406 individual users on the condition that their browsing traces were more than 100 actions.

The human dynamic patterns are usually captured from the statistical properties of interval time between continuous activities. However, the measurements for the dynamic pattern of human attention are beyond this research scope. Instead, we characterize the individual attention by the accumulative sum of distinct subdisciplines he has browsed because the browsing/positing activities from one community to another incorporate with the individual interest and tendency toward transitivity (i.e., these activities represent the allocations of processing resources of individual time and energy [13]). Based on the aforesaid definition, we show these measurements for its dynamic pattern as follows:

1. The expansion, $S(n)$, describes the evolutionary process of human attention along with the browsing action $n$ (e.g., for a browsing order of subdisciplines with 6 actions, $C_1, C_1, C_2, C_3, C_1, C_3$, the $S(n)$ is 1, 1, 2, 3, 3, 3). Thus, It can be analogy to random walk that the number of diverse subdisciplines can be mapped into the visiting sites and the browsing actions is served as the steps.

2. The exploration, $\Delta S(n)$, is represented by the incremental process of the expansion.

3. The memory effect of human attention is characterized by the statistical properties of return interval time $\tau_m$ and return interval step (i.e., browsing action) $\Delta n_m$, where $\tau_m$ depicts that how long the individual user will return to the same subdiscipline after he previously browses it (similar to the waiting time of event occurrence in stochastic process) and $\Delta n_m$ measures how many actions the individual user will take when he sequentially visits the same subdiscipline (similar to the arrival time interval of event occurrence in stochastic process).

4. The attention shift, $\Delta Shift$ is suggested by the difference between two isometric continuous sequences, which is composed of three components

$$\Delta Shift = \Delta Drift + \Delta Shrink + \Delta Stretch.$$  

In Eq. 1, the first component $\Delta Drift$ represents the sum of frequency changes of the same elements of the isometric continuous sequences, while the second component $\Delta Shrink$ describes the sum of frequency of the elements only existing in forward sequences yet disappearing in following sequence, and the third components $\Delta Stretch$, contrary to the shrink, represents the sum of frequency of the elements missing in forward sequence but appearing in following sequence. To better understand these metrics, an illustration is presented in Fig. 1, in which there are two isometric continuous sequences $S1$ and $S2$ with length $n = 10$. Therefore, we obtain the drift set $\{1, 2\}$, shrink set $\{3\}$,
and stretch set \{4\}, respectively. According to the definitions, the following values are obtained,

\[
\begin{align*}
\Delta Drift &= \sum_{i=1}^{n} |\frac{E_{S1}^i}{2N} - \frac{E_{S2}^i}{2N}| = |\frac{4}{20} - \frac{3}{20}| + |\frac{2}{20} - \frac{4}{20}| = 0.15, \\
\Delta Shrink &= \sum_{i=1}^{n} |\frac{E_{S1}^i}{2N}| = |\frac{4}{20}| = 0.2, \\
\Delta Stretch &= \sum_{i=1}^{n} |\frac{E_{S2}^i}{2N}| = |\frac{3}{20}| = 0.15.
\end{align*}
\]

thus the \(\Delta Shift\) is 0.5 by computing these components

3. Empirical results

Based on these present measurements, we empirically investigate the dynamic pattern of human attention. The average expansion \(\langle S \rangle\) in respect to the same fixed action \(n\) is firstly presented to describe the evolution of distinct subdisciplines. As shown in Fig. 2, it can be found that the power-law relation between \(\langle S \rangle\) and \(n\) obeys the formula \(\langle S \rangle \sim n^{\alpha}\) with \(\alpha = 0.54\). Moreover, this scaling behavior of the expansion is very close to that of one-dimension random walk since these studies \[14, 15, 16, 17, 18\] on random walk have suggested that there are an instructive result about the average number of distinct sites visited corresponding to the same time steps, i) in one-dimensional, it follows \(\langle S \rangle \sim an^{1/2}\); ii) in two-dimensional, it shows \(\langle S \rangle \sim bn/\ln n\); iii) in three-dimensional, it obeys \(\langle S \rangle \sim cn\). In addition, it is also worthy to be noticed that the empirical scaling exponent approximates to that in portal browsing activity \[10\], but completely different from those in Lévy flights and human spatial mobility (i.e., \(\alpha = 1\)) \[14, 19\].

Although the expansion of human attention shows a power-law scaling behavior in analogy to one-dimension random walk, we should analyze more in depth its exploration...
to make a further confirm as the exploration corresponding to the incremental process of expansion may filter non-stationary factors. The scaled exploration, $\Delta S(n) / \langle \Delta S \rangle$, can also be regard as the rate browsing a novelty subdisciplines, where $\langle \Delta S \rangle$ is the average of $\Delta S$ from all users. In the analysis of exploration, Figure 3(a) shows that the $\Delta S(n) / \langle \Delta S \rangle$ decays in a poisson form along with $S(n)$ when its maximum are less than 10, 20, 30, respectively. This result is completely distinct from the power-law one of locating pattern in human spatial mobility [19] and thus confirms the differences of interesting transitivity between online and off-line activities [20]. Furthermore, according to these expansions in Fig. 3(a), we statistically obtain the probability $p$ browsing a novel subdiscipline at next action for each user, and give their probability distributions all following approximately a normal distribution with the center values, $\langle p \rangle \approx 0.54$, $\langle p \rangle \approx 0.52$ and $\langle p \rangle \approx 0.52$, respectively (see in Fig. 3(b)). Besides that, in Fig. 3(c), the $\Delta S(n) / \langle \Delta S \rangle$ in respect to the same fixed action $n$ performs a power-law scaling relation, $\Delta S(n) / \langle \Delta S \rangle \sim n^{-\beta}$, and $\beta \approx 0.50$ approximately consists with that in Fig. 1 because of $\alpha \approx 1 - \beta$. Note that the inset suggests the scaling behavior keeps stable when the maximum of $S(n)$ are less than 10, 20, 30, respectively.

The memory is one of the key qualities of human beings [11, 21, 22, 23, 24, 25, 26, 27], thus may has an significant influence on individual attention. To explore the memory effect during the dynamic process of individual attention, the distributions of $\tau_m$ and $\Delta n_m$ are shown in Fig. 4, which are fitted well by an approximate power-law form, respectively. The scaling exponents are estimated by the maximum likelihood method [28]. They suggest the existence of the memory effect, and show that individual user has higher probability to return to the subdisciplines browsed recently, in contrast

Figure 2. (Color online) The scaling behavior of the expansion in respect to browsing action. The fitting dash lines indicates a power-law form, $S \sim n^\alpha$ and the scaling exponent $\alpha = 0.54$ (red one) suggest that it is very close to the that ((black one) of one-dimensional random walk.
Figure 3. (Color online) (a) The scaling behavior of the scaled exploration $\Delta S(n) / \langle \Delta S \rangle$ changes with $S(n)$ when its maximum is less than 10, 20, 30, respectively, which show a distinct dynamic pattern from that in human spatial mobility again. (b) The probability distributions of parameter $p_{\text{new}}$ denoting the probability browsing a novel subdiscipline at next action. (c) The scaling behavior of the scaled exploration $\Delta S(n) / \langle \Delta S \rangle$ in respect to browsing action. Its scaling exponent approximately confirm the effectiveness of the scaling behavior in Fig. 2.

Figure 4. (Color online) The memory effect of human attention. (a) The distribution of the return interval time $\tau_m$, (b) The distribution of the return interval step $\Delta n_m$, and the guiding curve roughly follows the power law relation, $\tau_m^{-\gamma}$ and $\Delta n_m^{-\gamma}$ with the exponent $\gamma \approx 1.88$ and 1.89, respectively. Both (a) and (b) prove the existence of memory effect.

to those browsed long before. These results are consistent with our experience that people tend to be of much more interest on the activities that they engaged in most recently, rather than those they have contacted long before.
Figure 5. (Color online) The variational tendency of attention shift along with the interval orders between pairs of sequences, indicating its variational tendency and determining its memory effect. (a) The semi-adjacency matrix of $\Delta \text{Shift}$ (b) The semi-adjacency matrix of $\Delta \text{Drift}$ (c) The semi-adjacency matrix of $\Delta \text{Shrink}$ (d) The semi-adjacency matrix of $\Delta \text{Stretch}$.

At last, we turn to the empirical measurement of the attention shift $\Delta \text{Shift}$. A series of 100 records from each user are selected and then divided into 10 isometric continuous sequences. The values of $\Delta \text{Shift}$ are computed between pairs of these sequences for individual user, and the average $\Delta \text{Shift}$ for whole users are displayed in the semi-adjacency matrix (see in Fig. 5(a)). They increase monotonically along with the interval orders between pairs of sequences, which indicates the variational tendency of human attention and determines its memory effect [11, 22]. As the $\Delta \text{Shift}$ contains three components, we also present the specific variations of these components, respectively. In Fig. 5(b), it is reported that $\Delta \text{Drift}$ barely changes when the interval time increases, revealing that it maintains the intrinsic drift character of individual user no matter of the time gap between two sequences. However, another two components $\Delta \text{Shrink}$ and $\Delta \text{Stretch}$ behave different tendency from $\Delta \text{Drift}$, shown in Fig. 5(c) and (d). Similar to $\Delta \text{Shift}$, they also monotonic increase with the interval time. Thus, these phenomenons demonstrate that a longer browsing time will result in a greater divergence of individual attention $\Delta \text{Shift}$, as well as $\Delta \text{Shrink}$ and $\Delta \text{Stretch}$.

4. Model

The above empirical observations provide us deep insights to the dynamic pattern of human attention. Broadly speaking, the scaling behaviors of expansion and exploration
of human attention in respect to browsing action suggest that its dynamic process is
similar to one-dimension random walk, yet the memory effect, making the individual
user much more tend to return to the subdisciplines browsed recently, deviates from
the traditional random walk models. However, both of these properties play important
roles for characterizing the dynamic pattern of human attention.

Since the traditional random walk models are absent of memory effect, we propose a
modified model incorporating these two generic properties, i) the exploration, indicating
that the tendency to browse a novel subdiscipline decreases with steps; ii) the preferential
return with memory effect, similar with those in individual mobility model (IMM) [19]
and time order memory model (TOM) [11], taking memory effect into account when
making the return process. Note that the analogy of exploration first mentioned by
Song et. al. [19] pointed out that the longer the observed trajectory of human spatial
mobility is, the harder it is to find locations that haven’t been visited in the vicinity
of their home or workplace. However, the property of exploration shown in Fig. 3(a)
deviates from the result in human spatial mobility. Instead, the scaling behavior of
exploration in Fig. 3(c) suggests that the probability that individual user browses a
novel subsdisciplines relates much more to their activity frequency (i.e., the number
of action) than the number of browsed subsdisciplines (i.e., analogy to the length of
trajectory). Moreover, the memory effect indicates that the probability of preferential
return toward previously browsed subdiscipline $i$, $\Pi_{i}$, depends on its interval steps $\Delta n_{i}$
avay from present position. Thus, incorporating with the occurrence frequency $f_{i}$ of
subdiscipline $i$, we can infer

$$\Pi_{i} = \frac{\sum_{j=1}^{f_{i}} \Delta n_{i}^{-\gamma}}{\sum_{k=1}^{m} \Delta n_{k}^{-\gamma}},$$

(3)

where the decaying factor $\gamma$ is identical to the scaling exponent in Fig. 4(b).

With these ingredients, it is now sufficient to reproduce the dynamic process of
human attention during browsing subsdisciplines. In Fig. 5(a), a schematic description
of dynamic model on human attention is presented to illustrate how individual users
browse subdiscipline. For example, when starting at action $n$, the individual user has
two choices in next action to browse a novel subdiscipline with the probability $p_{n-\beta}$
or return to one of $m$ subsdisciplines previously browsed with the complementary probability
$1-p_{n-\beta}$. Additionally, the probability of preferential return for each specific is according
to Eq. 3. When the individual user concerns on this new subdiscipline, the number
of previously browsed subsdisciplines increases from $m$ to $m+1$ (i.e., $S(n) = m$ and
$S(n+1) = m+1$), which drives the evolution of expansion. Thus, supposing a start of
expansion of human attention with $S = 1$, the exploration $\Delta S(n)$ would evolve in the
continuous time form as

$$\frac{dS}{dn} = \langle p \rangle n^{-\beta} \equiv p_{new},$$

(4)

Thus, the expansion $S(n)$ is inferred

$$S \sim n^{-\beta+1}.$$
Figure 6. (Color online) (a) Schematic description of expansion model of human attention. Suppose that when starting at action $n$ and previously browsing $m$ distinct subdisciplines ($S(n) = m$) (up panel), an individual user is going to make an another action ($n+1$) to browsing a novel subdisciplines with probability $pn^{-\beta}$ (left panel) or return to one of the $m$ subdisciplines with complementary probability $1 - pn^{-\beta}$ (right panel). For browsing previous subdisciplines, the probability of preferential return for each of subdiscipline is mainly determined by the memory effect, $\Pi_i = \sum_{k \in m} \frac{\Delta n_{m}}{\Delta n_{m}}$. (b) The scaling behaviors of empirically, numerically, and theoretically average expansion in respect to browsing action, indicating the effectiveness of the constructed model of human attention. Here, $n = 100$, $\langle p \rangle = 0.52$, $\beta = 0.51$, $\gamma = 1.89$, and individual number is $10^3$.

In this model, the parameter $\beta = 0.51$ is determined by the empirical scaling exponent of exploration (see in Fig. 3(c)), while the parameter $\langle p \rangle = 0.52$ is estimated from the center value of probability distribution of $p$ denoting the probability browsing a novel subdisciplines (see in Fig. 3(b)). The effectiveness of model is perfectly proved in Fig. 6(b), in which the numeric and analytic results consist well with the empirical scaling behavior of expansion of human attention.

5. Conclusion

In this paper, the dynamic process of human attention involved in browsing activity in an academic community is analyzed. Here, we emphasize its dynamic pattern characterized by the statistical properties of expansion, exploration, memory effect and shift, where the properties of expansion and exploration both show a power-law behavior in respect to browsing action, especially the exponent 0.54 of expansion is similar to the theoretical one in one-dimension random walk and the empirical one in browsing portal activity. After that, the memory effect of human attention is revealed by the power-law distributions of the return interval-time $\tau_m$ and return interval-steps $\Delta n_m$, which results in the dynamic process deviating from the traditional random walk and is universal in diverse human activities. Furthermore, the shift pattern of human attention associating with memory effect is unveiled through the variational values of
\(\Delta \text{Shift}\) computed between pairs of continuous sequences along with the interval order, which shows monotonic increasing trend, proving the existence of memory effect.

Inspired by these empirical results, a dynamic model is employed to understand the evolutional mechanism of human attention. As the dynamic process of human attention is similar to random walk, and also incorporates with the preferential return with memory effect, the proposed model takeing both the properties of exploration and memory effect into consideration, which is different from those models (IMM or TOM) put forward to explain the dynamic pattern of human spatial mobility and playing online-game. Additionally, its numeric and theoretical results agree well with the empirical observations.

We conclude that the given valuable results about the dynamic pattern of human attention can help us to figure out the differences of interest transitivity between browsing activity and spatial mobility, and the proposed model provides an alternative choice to mimic the the underlying mechanisms of complexity and complicated human behaviors. However, although the comprehensive investigations on dynamic pattern of human attention is presented, we cannot ignore that the empirical data is not sufficient yet, thus richer empirical materials are expected to enlarge research scope of human dynamics in the future work.

6. Acknowledgments

We thank Xiaoyan Yuan for sharing the experimental data. This work is jointly supported by the NNSFC (Grant Nos.91024026, 61004102, and 11105025), the Fundamental Research Funds for the Central Universities (Grant Nos.ZYGX2011YB024 and ZYGX2012J075) and the startup fund of UESTC.

References

[1] Onnela J, Saramäki J, Hyvönen J, Szabó G, Lazer D, Kaski K, Kertész J and Barabási A 2007 Proc. Natl. Acad. Sci. U. S. A. 104 7332
[2] Iribarren J L and Moro E 2009 Phys. Rev. Lett. 103 038702
[3] Salganik M, Dodds P and Watts D 2006 Science 311 854
[4] Dukas R 2004 Brain Behav Evolut 63 197
[5] Reis R 2006 Journal of Monetary Economics 53 1761
[6] Guimerà R, Llorente A, Moro E and Sales-Pardo M 2012 PLoS ONE 7 e44620
[7] Wu F and Huberman B A 2007 Proc. Natl. Acad. Sci. U. S. A. 104 17599
[8] Crane R and Sornette D 2008 Proc. Natl. Acad. Sci. U. S. A. 105 15649
[9] Weng L, Flammini A, Vespignani A and Menczer F 2012 Scientific Rep. 2 335
[10] Cmiedl A, Kowal'ska K and Holyst J 2009 Phys. Rev. E 80 066122
[11] Szell M, Sinatra R, Petri G, Thurner S and Latora V 2012 Scientific Rep. 2 457
[12] [http://www.sciencenet.cn/](http://www.sciencenet.cn/)
[13] Anderson J R 2009 Cognitive psychology and its implications (Worth Publishers)
[14] Gillis J E and Weiss G H 1970 J. Math. Phys. 11 1307
[15] Stanley H, Kang K, Redner S and Blumberg R 1983 Phys. Rev. Lett. 51 1223
[16] Blumen A, Klafter J, White B and Zumofen G 1984 Phys. Rev. Lett. 53 1301
[17] Noh J D and Rieger H 2004 Phys. Rev. Lett. 92 118701
[18] Anteneodo C and Morgado W 2007 Phys. Rev. Lett. 99
[19] Song C, Koren T, Wang P and Barabási A L 2010 Nat. Phys. 6 818
[20] Conti M, Das S K, Bisdikian C, Kumar M, Ni L M, Passarella A, Roussos G, Tr?ster G, Tsudik G and Zambonelli F 2012 Pervasive and Mobile Computing 8 2
[21] Yamasaki K, Muchnik L, Havlin S, Bunde A and Stanley H E 2005 Proc. Natl. Acad. Sci. U. S. A. 102 9424
[22] Vazquez A 2007 Physica A 373 747
[23] Han X P, Zhou T and Wang B H 2008 New J. Phys. 10 073010
[24] Goh K and Barabási A L 2008 Europhys. Lett. 81 48002
[25] Cai S M, Fu Z Q, Zhou T, Gu J and Zhou P L 2009 Europhys. Lett. 87 68001
[26] Zhao Z D, Cai S M, Huang J, Fu Y and Zhou T 2012 Europhys. Lett. 100 48004
[27] Zhao Z D, Yang Z, Zhang Z, Zhou T, Huang Z G and Lai Y C 2013 arXiv preprint arXiv:1307.7796
[28] Clauset A, Shalizi C R and Newman M E J 2009 SIAM Rev 51 661