A user behavior influence model of social hotspot under implicit link

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Abstract

In social networks, user behavior is affected by complex dynamic factors. Here, we investigate the internal and external factors that drive users to participate in social hotspots. By analyzing user behavior, we discover the differences between driving factors and quantify their driving strength. First, four factors that influence the user's behavior are proposed, including explicit links(E), implicit links(I), personal interest(P), and a random factor(R). In particular, based on a cloud model, an implicit link creation method is designed. This method can quantify the driving strength of the implicit relation between users, and avoid the multiple attribute weighting defects in subjective and objective aspects. Next, considering the maximum likelihood estimation theory, a user behavior influence model($EIPR$) of a hotspot topic is proposed to measure the causes of user behavior behind the social hotspots. Experimental results show that the model can be used to find different dynamic factors of user behavior in social hot topics. Among these external factors, the implicit link plays an significantly important role in driving user behavior.

Keywords: Social network, Hotspot topic, Influence analysis, Implicit link, Cloud model

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1. Introduction

What drives human behavior? This question has inspired scientists for hundreds of years. Today, in the internet and big data era, online network systems such as BBS and social networks have gradually become important platforms for investigating user behavior. In this study, we try to mine the influence factors that drive user behavior on the background of social hotspots.

The online social network is increasingly important today for social relations maintenance and user behavior diffusion in human society. In fact, hotspot topics are promoted by several factors in a social network. Discovering these factors has a profound impact on social development, social services and management, and social security. At present, the study about user behavior influence is divided into two aspects: internal influence and external influence. For the internal influence factors, Barabasi et al. [2][22] first discovered the long tail phenomenon of user behavior. And they proposed a user behavior model based on task priority to analyze the influence factors that drive user behavior. Subsequently, a variety of user behavior influence model are proposed by scholars for different application scenarios. The study of internal factors that affect user behavior is gradually clear through above research.

In addition, the external factors that influence user behavior are studied by scholars from the aspects of user behavior interaction, the neighbor node influence, common interests and behavior game etc. However, the basis of these studies is link between the social users, here we name this kind of link as explicit link. Compared to previous studies, new features of online social networking are emerging, which bring more challenges to existing methods, mainly in the following: 1) complex network structure. Group level interaction is not a simple accumulation of individual behaviors. Especially for group behavior relating to hot topics, explicit relations between online users cannot reflect real group network structure characteristics, and there are several implicit and complex relations between the groups both online and offline. 2) the group behavior dynamics are influenced by complex factors. Researches on offline individual

user behavior are already challenging. Moreover, studying online group behavior requires knowledge on multiple subjects, such as computer science, sociology, and psychology. Consequently, a number of unknown network-group behavior rules require further exploration.

35   In this study, combined with the internal and external factors, the user participation behavior of social hot topics is deeply analyzed. While discussing the interaction between users, we especially try to mine the effect of implicit links as the external factor that affects user behavior. The influence factors that drive user behavior - explicit link factor, implicit link factor, personal interest
40   factor, and random factor are extracted for modeling and analysis. Our goal is to analyze the differences between internal and external factors affecting different users, to quantify the effect of these factors, and to mine the role of the implicit link in driving user behavior.

Our contribution can be summarized as follows:

- 45   • To analyze the behavior of users to participate in hotspot topics, we propose four factors: the explicit link factor, implicit link factor, personal interest factor, and random factor. To analyze and quantify these factors, the *EIPR* influence model is proposed. It is found that different users are affected by different influence factors and the influence strength is also
50   different, as demonstrated through model analysis.
- A scheme for creating implicit link based on the cloud model is proposed. In this scheme, we give a more clear definition for implicit link. Meanwhile, the defects in the traditional weighting methods with regard to subjective and the objecting weighting and the advantage of the cloud model in
55   overcoming this problem are considered. The implicit user relation and strength of the relation are being quantified.
- The proposed method cannot only mine the dynamic factors that drive user behavior, but also make a contrast analysis between the effects of the explicit and implicit factors, which can promote topic evolution. This

60 work fully embodies the influence of the tacit role. In addition, it helps in
managing and controlling the public sentiment and providing support to
locate the online water army.

The rest of this paper is organized as follows. In section 2, we introduce
the related work. In section 3, we formulate the problem and give the neces-
65 sary definitions. In section 4, we describe the model algorithm to analyze user
behavior. In section 5, we present and analyze the experimental results of the
model. Finally, we conclude this work in section 6.

2. Related work

In a social network, user behavior is influenced by many factors. After the
70 task priority model of user behavior influence was proposed by Barabasi[2][22],
the scholars put forward different influence factors and their behavior model for
different application scenarios, such as browsing the web[34], watching online
movies[39], personal interests[20] and trust agents[18]. At present, for individ-
ual influence discovery, researchers aim to find the difference in the individuals
75 and define the opinion of leaders in a group by modeling [23]. To measure the
network structure based individual influence, early methods were mainly based
on the Degree Centrality [37], Closeness [36] and Betweenness [14]. In addition,
combined with individual influence discovery and random walk [12][24], some
representative algorithms were proposed, such as HITS [11], and PageRank [21].
80 Wang et al. [27] studied the evolution of user behavior over time, and found a
behavior influence analysis of low-literate users of a viral speech based telephone
service. Individual influence is based on user behavior. Thus, some researchers
determined the relation between users through analyzing the information dif-
fusion and user behavior [13][15], including copying, replying, retweeting and
85 so on. To study individual influence based on topic, the analysis was focused
on topic evolution and some topic model is proposed [5][9]. The abovementioned
research on the influence of individual behavior provides the academic
accumulation for the following work.

For the external factors that affect user behavior, most scholars pursue re-
 90 search on the basis of the network structure, mainly in the following aspects:
 1) Network structure based analysis of influence strength. In order to measure
 the strength of individual influence on Twitter, the following network and the
 forwarding network was analyzed [4]. Zhu, et al. [10] proposed a user behavior
 model that users affected by neighbor nodes in terrorist incidents. 2) Calcu-
 95 lation of influence strength based network structure. In order to find out the
 information dissemination path of messages, the relations between edge struc-
 ture and information pathway in the network was analyzed [7][30]. 3) User
 behavior based measurement of influence strength. Wu et al.[31][32] quantified
 the factors that affect information dissemination and topic evolution by analyz-
 100 ing the user interaction behavior in social networks. In the calculation of the
 influence strength based on topics, Tang et al. [25] studied the role of different
 groups in topic evolution. Meanwhile, they quantified the influence strength
 and predicted the evolution of topics. In addition, the implicit relation of users
 can be analyzed by combining the topic distribution, information diffusion and
 105 influence [8][19].

The abovementioned research were conducted based on the explicit link
 between users. Relation strength is considered when measuring the influence
 between users. Besides, the implicit relation between users is usually evaluated
 by user similarity. Bakshy et al. [1][3] showed the reason for information dif-
 110 fusion and sharing in social media by analyzing the strong and weak relation
 between users. They found that weak connections probably play a more impor-
 tant role in online information diffusion. Wang et al. [28] proposed the model of
 EAGR to analyze the weighting problem between adjacent points. Wang et al.
 [26] combined influence and node similarity measurement to model and analyze
 115 the most influential nodes in the network.

However, in the actual network behavior, it is possible that there is an
 implicit relationship among users - implicit link. The implicit link means implicit
 relationship, between users, which does not own nor generate explicit link in the
 future. However, we can mine the implicit relationship from the behind of user

behavior. For example, a topic hype team members may never create a link, but they have been mutual cooperation. Therefore, this implicit link cannot be calculated with traditional similarity method or link prediction. Dong et al. [6] mentioned the implicit link when they studied link prediction based on a heterogeneous network. However, the implicit link they mentioned is just a type of relationship mapping in heterogeneous networks, which is completely different from the concept of implicit link in this study. Alternately, Xiao et al. [33] have proposed the concept of implicit link, but they defined the implicit relationship only by simple statistical methods. In this paper, the implicit link will be further quantified based on the previous research. Furthermore, the influence factors that drive user behavior will be comprehensively further analyzed on the background of social network hot topics.

3. Problem definition

Figure 1: Problem overview

In the present study, we attempt to mine the factors that drive user v to participate in hotspots by analyzing the user's attribute and relation network, as shown in Figure 1. Let $G(v, E)$ be the explicit relation network of user v , that is, the following network. E is the edges connected to user v and $U(E)$ is the

set of users who have an explicit relation with v . Then, we define $A = (T_m, v, t)$ as the released topic data of user v , where T_m is the topic data that v released in time t . $B = \{(T_p, v \& U(E), t)\}$ is the topic data of user v and $U(E)$ joined in a different time. Specifically, $(T_p, v \& U(E), t)$ means that user v and $U(E)$ participated in topics T_p in time t .

3.1. Input

The input in this paper consists of: 1) the explicit relation network of user v , $G(v, E)$; 2) the topics that user v generated, $A = (T_m, v, t)$; and 3) the topics that user v and E participated in, $B = \{(T_p, v \& U(E), t)\}$.

The purpose of this paper is to make personalized analysis for each user, as well as to mine and quantify the influence factors that affect different users. In addition, we analyze the role of the implicit link in driving users to participate in hotspot topics. Taking advantage of the cloud model in weighting multiple factor weighting, a method to create the implicit link based on the cloud model is proposed.

3.2. Related definitions

3.2.1. Driving factors

We extract the influence factors explicit links factor(E), implicit link factor(I), personal interest factor(P) and random factor(R) from the data on personal attributes, the relational network, and historical behavior. The specific relationship between the factors and user v is shown in Figure 2.

Figure 2: The relation between user v and the influence factor

Definition 1. The explicit link driving factor α_e

$$\alpha_e = J_e(T_k, t_v, t_{U(E)}) / N_{T(E)} \quad (1)$$

$$J_e(T_k, t_v, t_{U(E)}) = \begin{cases} 1 & t_v \leq t_{U(E)} \\ 0 & t_v > t_{U(E)} \end{cases} \quad (2)$$

¹⁶⁰ $J_e(T_k, t_v, t_{U(E)})$ represents whether the time $t_{U(E)}$ is earlier than time t_v . $t_{U(E)}$ is the earliest time **when** users in set $U(E)$ participated in topic T_k . T_k **refers to** the topic that user v participated in. t_v represents the time **when** user v participate in topic T_k . $N_{T(E)}$ **is** the number of the topics users in set $U(E)$ participated in.

¹⁶⁵ **Definition 2. The implicit link driving factor α_i**

$$\alpha_i = (T_k, t_v, t_{U(I)}) / N_{T(I)} \quad (3)$$

$$J_e(T_k, t_v, t_{U(I)}) = \begin{cases} 1 & t_v \leq t_{U(I)} \\ 0 & t_v > t_{U(I)} \end{cases} \quad (4)$$

$J_i(T_k, t_v, t_{U(I)})$ represents whether the time $t_{U(I)}$ is earlier than time t_v . $t_{U(I)}$ is the earliest time **when** users in set $U(I)$ participated in topic T_k . T_k **refers to** the topic that user v participated in. t_v represents the time **when** user v participated in topic T_k . $N_{T(I)}$ **is** the number of topics users in set $U(I)$ participated in.

Definition 3. The personal interest driving factor α_p

$$\alpha_p = J_p(T_k) / N_{T(p)} \quad (5)$$

$$J_p(T_k) = \begin{cases} 1 & N_l \geq \ln N_T \\ 0 & N_l < \ln N_T \end{cases} \quad (6)$$

$$N_{T(p)} = g\omega \sum_L 1 \quad (7)$$

175 $J_p(T_k)$ represents whether the label l of topic T_k belongs to L where L is
the interest label set of user v . N_l is the number of topics with label l that user
 v participated in, and N_T is the total number of topics user v participated in.
Let $N_{T(p)}$ represent the number of topics with interest label. g is the increment
of topics number under every interest label, and ω is the mean topics duration
180 time.

Definition 4. The random driving factor α_r

$$\alpha_r = 1/N_{T(R)} \quad (8)$$

$N_{T(R)}$ is the number of topics that user v can participate in randomly.

3.2.2. Definition about cloud model

Due to the deficiencies of the probability theory and fuzzy mathematics
185 in dealing with uncertain data, Li et al. [16] proposed a cloud model that
illustrates the transformation of qualitative and quantitative data. The cloud
model can not only represent a qualitative concept with a quantitative value,
but also describe quantitative value with qualitative language. In addition, the
application of the model in various fields has achieved significant results [29]
190 [35].

Definition 5. Cloud and cloud droplet

We assume U is a quantitative domain, and C is a qualitative value. The
degree of membership $u(u \in [0, 1])$ is a random number with a stable tendency
which represents the qualitative relation between x and C , where $x \in U$. The
195 distribution of the membership degree $u(u \in [0, 1])$ in the domain U is called
the membership cloud, cloud for short. Thus, a cloud is a mapping from domain
 U to interval $[0, 1]$. $x \in U$ is called a cloud droplet.

The integral form of the cloud is determined by its digital features, in-
cluding expectations, entropy, and hyper entropy. These features reflect the
200 quantitative characteristics of the qualitative concepts, and they are defined as
follows respectively.

$$Ex = \frac{1}{N} \sum_{n=1}^N X_n \quad (9)$$

$$En = \sqrt{\frac{\pi}{2}} * \frac{1}{N} * \sum_{n=1}^N |X_n - Ex| \quad (10)$$

$$He = \sqrt{\frac{1}{N} \sum_{n=1}^N (X_n - Ex)^2 - En^2} \quad (11)$$

Definition 6. Cloud generator

205 Assume that U is a quantitative domain represented by precise value and C is the oriented concept of U . If the quantitative value x satisfies $x \in U$, x is a random realization of C with a qualitative concept. If $x \sim N(Ex, En'^2)$, where $En \sim e^{-\frac{(x-Ex)^2}{2(En')^2}}$ and the certainty degree μ of x for C satisfied is $\mu = e^{-\frac{(x-Ex)^2}{2(En')^2}}$, the distribution of x in the quantitative domain U is called the
210 normal cloud.

Definition 7. Cloud similarity $S_c(C_1, C_2)$

Cloud similarity measurement is a method to measure the similarity of clouds by calculating their droplet distances [17] [38]. If two clouds C_1 and C_2 generated a fixed number of cloud droplets through a normal cloud generator,
215 we regard the mean distance of all corresponding cloud droplets in C_1 and C_2 as the similarity index value between C_1 and C_2 .

3.3. Problem

Problem: Given $G(v, E)$, $G(v, I)$ and $B = \{(T_P, v \& U(E), t)\}$, we solve the following problems.

- 220 1. How can the implicit link (I) be defined and measured? How can we mine the implicit relation among users and give quantitative analysis using the concept of implicit link.
2. How can we model and analyze the difference of factors in driving different users to participate in topics, and how can we measure the driving strength.

4. Model

4.1. Framework

The model framework is shown in Figure 3. First, we analyze the data on user attributes, relational network, and historical behavior in the social network to extract the influence factors. Second, according to the influence factors, the four driving factors α_e , α_i , α_p and α_r are defined. Finally, the *EIPR* influence model is proposed to analyze the difference between the influence factors and to quantify their driving strength. Meanwhile, the role of the implicit link in driving user behavior is further analyzed.

Figure 3: Model framework

4.2. Establishing the implicit link based on the cloud model

To solve the first problem, we extract the influence factors from the personal attributes, relational network, and historical behavior. Considering the particularity of the implicit link factor, an implicit link establishment method is given.

Step 1. Improve the definition of the implicit link.

240 Implicit link: It is a game relation between users generated from different opposites, or an implicit relation generated due to a common purpose or interest. Besides, there is no explicit relation between users. For example, user A and B have different positions on topic T. They argue with each other so that the two users connect and interact, though they don't have any explicit relationship.

245 **Step 2. Candidate users extraction for the implicit link.**

Users who participated in the topics released by v are extracted as a set $U(I')$. $U(I')$ is the set of users who are likely to create an implicit link with v and $i' \in U(I')$. The existence of an implicit link is determined by the similarity between v and i' . In addition, $i' \in U(I'), i' \notin U(E)$.

250 **Step 3. User behavior cloud generation.**

Topics and labels have many-to-one relation. If the user v participated in the topics of the same label with i' , v and i' have the same label. Different candidate users i' have different quantities of the same label with user v . We assume that v and i' have two common labels l_1 and l_2 to analyze the relation between them. According to the quantity of topics that v and i' participated in, the numerical features of l_1, l_2 can be separately calculated. $v_{l_1} : \{Ex_{l_1}, En_{l_1}, He_{l_1}\}$ and $v_{l_2} : \{Ex_{l_2}, En_{l_2}, He_{l_2}\}$ are the digital features of user v in l_1 and l_2 . Similarly, $i'_{l_1} : \{Ex_{l_1}, En_{l_1}, He_{l_1}\}$ and $i'_{l_2} : \{Ex_{l_2}, En_{l_2}, He_{l_2}\}$ are the digital features of user i' . The digital features can be calculated as follows:

$$Ex_l = \frac{1}{M} * \sum_{m=1}^M x_m \quad (12)$$

260

$$En_l = \sqrt{\frac{\pi}{2}} * \frac{1}{M} * \sum_{m=1}^M |x_m - Ex_l| \quad (13)$$

$$He_l = \sqrt{\frac{1}{M} \sum_{m=1}^M (x_m - Ex_l)^2 - En_l^2} \quad (14)$$

M is the summation of the time slices divided by the month. l means a same label of user v and i' . In addition, to ignore the impact of activity on

the user's participation in topics, we normalize the number of topics that users participated in under the same label to get x_m . Then according to the digital features of v , we obtain one thousand cloud droplets by cloud generator. The same method can be used to generate the cloud droplets of i' . x, y are the normal random numbers we get by the cloud generator. The user behavior cloud is formed from the spatial distribution of cloud droplets.

$$\overrightarrow{\alpha_v(j)} = (x_{vj}, y_{vj}, \mu_v(j)) \quad j \in [1, 1000] \quad (15)$$

$$\overrightarrow{\alpha_{i'}(j)} = (x_{i'j}, y_{i'j}, \mu_{i'}(j)) \quad j \in [1, 1000] \quad (16)$$

Step 4. Similarity calculation for C_v and $C_{i'}$.

In order to make a comprehensive evaluation of user behavior, we calculate the behavior cloud similarity of C_v and $C_{i'}$ using the cloud similarity algorithm. As user behavior cloud similarity of user behavior, the calculation of $S_c(v, i')$ is as follows:

$$S_c(v, i') = 1 - \frac{1}{N} * \sum_{i=1}^N |y_v(m) - y_{i'}(n)| \quad (17)$$

$$[m, n] = \min \left\{ \sqrt{(x_{vm} - x_{i'n})^2 + (y_{vm} - y_{i'n})^2} \right\} m, n \in [1, 1000] \quad (18)$$

$|y_v(m) - y_{i'}(n)|$ is the difference of the membership degree between two corresponding cloud droplets in C_v and $C_{i'}$. The corresponding droplets mean they should satisfy $\min \left\{ \sqrt{(x_{vm} - x_{i'n})^2 + (y_{vm} - y_{i'n})^2} \right\}$ and $m, n \in [1, 1000]$. And N denotes the quantity of cloud droplets in cloud C_v or $C_{i'}$.

Step 5. Implicit links establishment.

Similarity between user v and i' is calculated, $i' \in U(I')$. Then, we rank the similarity to obtain the set $U(I)$ of users whose similarity with v are in the top $0.5N_{I'}$. The implicit link between the users v and i' is created to establish the implicit relation network $G(v, I)$ of user v , where $i \in U(I)$. The user similarity is calculated as follows:

$$(v, i') = \frac{L_v \cap L_{i'}}{L_v \cup L_{i'}} * S_c(v, i') \quad (19)$$

$N_{I'}$ is the number of user in the set of $i' \in U(I')$. $\frac{L_v \cap L_{i'}}{L_v \cup L_{i'}}$ represents the Jaccard coefficient of the labels between users v and i' . $S(v, i')$ is the similarity of the users v and i' .

4.3. Influence model

To solve the second problem, the influence model $EIPR$ is proposed based on the Maximum Likelihood theory. We convert the user behavior to the relevant probability event and estimate its parameters through $EIPR$. The model detail are shown in Figure 4.

Figure 4: Model detail

First, we assume that the behavior of user v to participate in hotspot topics is driven by independent factor. Under this assumption, we analyze the behavior of user v in an independent drive situation, including the patterns of ER , IR and PR . The ER , IR and PR patterns assume that the behavior of v is only driven by the explicit link factor, the implicit link factor or the personal interest factor. Moreover, we assume that the behavior of user v to participate in hotspot topics is driven by a combination of these factors. Under this assumption, we analyze the behavior of v in combined drive situations, including the patterns of EPR , IPR and $E&IPR$. In the EPR pattern, the behavior of user v to participate hotspot topics is driven by the explicit link factor and personal interest factor

305 together. In the *IPR* pattern, the behavior of v is driven by the implicit link factor and personal interest factor. In the *EIPR* pattern, the behavior of user v is driven by the explicit link factor, the implicit factor and the personal interest factor. Finally, we obtain the most suitable pattern for user v and the driving strength of the factors in that pattern to analyze the role of the implicit link
310 further.

1. Independent drive

Assuming that user v is driven only by the explicit link factor, the analysis with the pattern *ER* is as follows:

$$\begin{aligned} L_e(S_e) &= \prod_{T(v)} (S_e * \alpha_e + (1 - S_e) * \alpha_r) \\ &= \prod_{J_e(T_k, t_v, t_{U(E)})=1} \left(\frac{S_e}{N_{T(E)}} + \frac{1-S_e}{N_{T(R)}} \right) \prod_{J_e(T_k, t_v, t_{U(E)})=0} \frac{1-S_e}{N_{T(R)}} \end{aligned} \quad (20)$$

The estimated parameter S_e represents the driving strength of the explicit link factor. $T(v)$ refers to the set of topics that user v participated in.
315

$$\begin{aligned} LnL_e(S_e) &= \sum_{J_e(T_k, t_v, t_{U(E)})=1} \ln \left(\frac{S_e}{N_{T(E)}} + \frac{1-S_e}{N_{T(R)}} \right) + \sum_{J_e(T_k, t_v, t_{U(E)})=0} \ln \left(\frac{1-S_e}{N_{T(R)}} \right) \end{aligned} \quad (21)$$

According to the theory of maximum likelihood estimation, S_e is the driving strength of the explicit link factor when $LnL_e(S_e)$ reaches the maximum value $\max LnL_e(S_e)$ in the *ER* pattern. Similarly, the driving strengths of the implicit link factor and the personal interest factor can be obtained when
320 $LnL_i(S_i)$ and $LnL_p(S_p)$ obtain their respective maximum values $\max LnL_i(S_i)$ and $\max LnL_p(S_p)$ in the patterns *IR* and *PR*.

2. Combined drive

Assuming that user v is driven by the explicit link factor and personal
325 interest factor, the analysis with the pattern *EPR* is as follows:

$$L_{ep}(S_e, S_p) = \prod_{T(v)} (S_e * \alpha_e + S_p * \alpha_p + (1 - S_e - S_p) * \alpha_r) \quad (22)$$

$$\begin{aligned}
LnL_{ep}(S_e, S_p) = & \sum_{\substack{J_e(T_k, t_v, t_{U(E)})=1 \\ J_p(T_k)=1}} Ln \left(\frac{S_e}{N_{T(E)}} + \frac{S_p}{N_{T(P)}} + \frac{(1-S_e-S_p)}{N_{T(R)}} \right) \\
& + \sum_{\substack{J_e(T_k, t_v, t_{U(E)})=1 \\ J_p(t_k)=0}} Ln \left(\frac{S_e}{N_{T(E)}} + \frac{1-S_e-S_p}{N_{T(R)}} \right) \\
& + \sum_{\substack{J_e(T_k, t_v, t_{U(E)})=0 \\ J_p(t_k)=1}} Ln \left(\frac{S_p}{N_{T(P)}} + \frac{1-S_e-S_p}{N_{T(R)}} \right) \\
& + \sum_{\substack{J_e(T_k, t_v, t_{U(E)})=0 \\ J_p(t_k)=0}} Ln \left(\frac{1-S_e-S_p}{N_{T(R)}} \right)
\end{aligned} \tag{23}$$

S_e and S_p are the driving strength of the explicit link factor and the implicit link factor, when $LnL_{ep}(S_e, S_p)$ get the maximum value $\max LnL_{ep}(S_e, S_p)$ in the *EPR* pattern. Similarly, the driving strength of the implicit link factor and the personal interest factor can be obtained when $LnL_{ip}(S_i, S_p)$ reaches the maximum value $\max LnL_{ip}(S_i, S_p)$ in the *IPR* pattern.

In addition, we analyze the *E&IPR* pattern that the explicit link factor, the implicit link and the personal interest factor combined.

$$\begin{aligned}
& L_{e\&i p}(S_{e\&i}, S_p) \\
& = \prod_{T(v)} \left(S_{e\&i} * \frac{J_{ei}(T_k, t_v, t_{EI})}{N_{T(E) \cup T(I)}} + S_p * \frac{J_p(T_k)}{N_{T(P)}} + \frac{1-S_{e\&i}-S_p}{N_{T(R)}} \right)
\end{aligned} \tag{24}$$

$N_{T(E) \cup T(I)}$ is the number of topics that users in the set of and participated in. $S_{e\&i}$ and S_p are the driving strength when $LnL_{e\&i p}(S_{e\&i}, S_p)$ reaches the maximum value $\max LnL_{e\&i p}(S_{e\&i}, S_p)$ in the *E&IPR* pattern. Otherwise, it is difficult to obtain the optimal solution analytically. We numerically explore the values of the two parameters in the unit square to maximize the log-likelihood.

4.4. Model algorithm

In this paper, we model user behavior to determine the factors that drive users to participate in hotspot topics and quantify their driving strength. Mean-

while, the role of the implicit link factor in driving user behavior is further explored. The model algorithm is as follows.

Algorithm 1: Model algorithm

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input :

1. Network : $G(v, E)$;
2. User behavior in different time: $A = (T_m, v, t)$, $B = \{(T_P, v \& U(E), t)\}$

output:

1. The driving factors $\{E, I, P, R\}$ of user v ;
2. The driving strength of that factors;

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1 Initialize  $N_{T(E)}, N_{T(I)}, N_{T(P)}, N_{T(R)}$ 
2 for each topic  $t_k$  of user  $v$  participated in do
3   //calculate the driving factors  $\alpha_e, \alpha_i, \alpha_p, \alpha_r$ .
4   if  $v$  participated in  $t_k$  based  $E$  or  $I$  or  $P$  then
5      $J_e(T_k, t_v, t_{U(E)}) = 1, J_e(T_k, t_v, t_{U(I)}) = 1, J_p(T_k, t_v, t_P) = 1$ 
6   end
7   else
8      $J_e(T_k, t_v, t_{U(E)}) = 0, J_e(T_k, t_v, t_{U(I)}) = 0, J_p(T_k, t_v, t_P) = 0$ 
9   end
10  obtain  $\alpha_e = J_e(T_k, t_v, t_{U(E)}) / N_{T(E)}, \alpha_i = J_i(T_k, t_v, t_{U(I)}) / N_{T(I)},$ 
     $\alpha_p = J_p(T_k) / N_{T(P)}, \alpha_r = 1 / N_{T(R)}$ 
11  //Independent drive. For example  $EP$  pattern
     $L_e(S_e) * = (S_e * \alpha_e + S_r * \alpha_r)$ 
12  //Combined drive. For example  $EPR$  pattern
     $L_{ep}(S_e, S_p) * = (S_e * \alpha_e + S_p * \alpha_p + S_r * \alpha_r)$ 
13 end
14 //compute the parameters and the maximum likelihood values
     $result = \max \left\{ \begin{array}{l} \max LnL_e, \max LnL_i, \max LnL_p, \\ \max LnL_{ep}, \max LnL_{ip}, \max LnL_{e\&ip} \end{array} \right\}$ 

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In the model algorithm, the parameters $N_{T(E)}, N_{T(I)}, N_{T(P)}$ and $N_{T(R)}$ are initialized to calculate the driving factors $\alpha_e, \alpha_i, \alpha_p$, and α_r . Then, we determine the most suitable pattern for user v by analyzing the six patterns in

the independent drive and combined drive situations. According to the most suitable pattern, we can capture the driving factor that drives user to participate hotspot topics and its driving strength. In addition, the complexity of the algorithm is considered. The extraction of the driving factors $T_{extract} = O(n)$; the analysis of the patterns $T_{patterns} = O(n)$; and the calculation of the result $T_{result} = O(1)$. Based on the above analysis, the total time complexity of the model algorithm is $T = T_{extract} + T_{patterns} + T_{result} = O(n)$.

5. Experimental results

5.1. Data sets

In this study, the experimental data was collected from the social platform of *tianya* forum. The forum of *tianya* is one of the most popular social networking platforms in China. The total number of topic labels in the forum was 482. The number of topics user v can participate in randomly reached 61480000. The increment of topics reached 100000 every day. The average life cycle ω of topics is considering seven days. In order to carry out a comprehensive analysis of the influence factors, we collected the historical behavior and relation data of 1437 users in the past 12 months. Due to space constraints, use two users as examples to illustrate the results of our analysis. The related data of the two users are shown in Table 1.

Table 1: Data sets of user A and B

data sets	nodes	explicit nodes	implicit nodes	topics	topics (v)	topics (explicit)	topics (implicit)
user A	11272	11212	60	52030	403	25307	26330
user B	1732	394	1337	663553	208	34184	629369

User A: The first user is *xibeixiongying*. The related data (topics and relation) for him on December 1, 2014 and October 31, 2015 are used as the fundamental data for model. The number of related users is 11272, and the number of topics is 52030.

User B: The second user is *huachengxiaoliu*. The related data(topics and relation) for him on December 1, 2014 and October 31th 2015 are used as the fundamental data for model .The number of related users is up to 1732, and the number of topics is 663553.

375 5.2. Driving performance analysis

By observing the relation between user activity and the frequency that each user participates in topics, it becomes evident that the amount of data increases with the activity. Consequently we analyze the users that the number of topics they participate in is up to 50 in the latest year.

380 First, we show the results of three patterns *ER*, *IR* and *PR* in the independent drive situation. Then, we illustrate the results for the three patterns in the combined drive situation. Finally, we determine the most suitable pattern for the user and obtain the driving strength of every factor in that patterns.

The experimental results for the two users in independent drive situation
385 are shown in Figure 5. The x-axis represents the driving strength, and the y-axis represents the maximum likelihood function in the different driving strength.

Figure 5: (a).Independent Drive of user A. (b). Independent Drive of user B

As shown in Figure 5(a), user A has a higher maximum likelihood $\max \ln L(S)$ in pattern *PR*. Thus, *PR* is the most suitable pattern for user A in the independent drive situation, i.e., in the independent drive situation, user A prefers to participate in topics based on his personal interest factor. Similarly, as shown
390

in Figure 5(b), user B also has the $\max \ln L(S)$ in pattern *PR*. Therefore, both users exhibit the same behavior tendency in independent drive situation.

The experimental results for the two users in the combined drive situation are shown in Figure 6 and Figure 7. The abscissa and ordinate in the graphs represent the driving strength of two different driving factors. The contour indicates the value of the likelihood function.

Figure 6: (a) *EPR* for user A; (b) *IPR* for user A; (c) *E&IPR* for user A

Figure 7: (a) *EPR* for user B; (b) *IPR* for user B; (c) *E&IPR* for user B.

As shown in Figure 6(a-c), user A gets the higher $\max \ln L(S)$ in the *EPR* pattern. Thus, *EPR* is the most suitable pattern for user A in the combined drive situation, i.e., user A prefers to participate in topics based the explicit link factor and the personal interest factor. User B gets the higher maximized $\max \ln L(S)$ in pattern *E&IPR* as shown in Figure 7(a-c). User B prefers to

participate in hotspot topics based the explicit link factor, the implicit link factor and the personal interest factor.

Comparing the six patterns in the independent and in the combined drive situation, the most suitable pattern with the highest maximum value is capture. The driving strength in the different patterns and the corresponding values of the maximized log-likelihood are shown in table 2 and table 3.

Table 2: The driving strength of factors in six patterns of user A

Situation	Model	Strength	maxlnL
Independent Drive	ER	$S_e = 0.4010$	-2678.2508
	IR	$S_i = 0.3110$	-2753.2163
	PR	$S_p = 0.7460$	-2104.9619
Combined Drive	EPR	$S_e = 0.1180, S_p = 0.7060$	-2005.6420
	IPR	$S_i = 0.0360, S_p = 0.7160$	-2098.0627
	$E\&IPR$	$S_{e\&i} = 0.1220, S_p = 0.7020$	-2009.2838

Table 3: The driving strength of factors in six patterns of user B

Situation	Model	Strength	maxlnL
Independent Drive	ER	$S_e = 0.2650$	-796.8900
	IR	$S_i = 0.3050$	-807.9254
	PR	$S_p = 0.6730$	-603.9155
Combined Drive	EPR	$S_e = 0.3140, S_p = 0.6620$	-563.0384
	IPR	$S_i = 0.1040, S_p = 0.6720$	-580.0551
	$E\&IPR$	$S_{e\&i} = 0.2100, S_p = 0.6680$	-548.1718

For user A, EPR is the most suitable pattern. Consequently, user A much prefers to participate in topics based on the explicit link and his personal interest. The driving strengths of the explicit link factor and the personal interest factor are $S_e = 0.1180$ and $S_p = 0.7060$, respectively. For user B, $E\&IPR$ is the most suitable pattern. User B prefers to participate in topics based on the explicit link factor, the implicit link factor and the personal interest factor. The respective driving strengths are $S_{e\&i} = 0.2100, S_p = 0.6680$.

Then, the users like A or B are classified according to the most suitable pattern, as shown in Figure 8. First, the vast majority of users achieve higher maximized values in the ER pattern. That means users tend to participate in

hotspot topics that involve their personal interests. The *EPR* and *IPR* patterns are the most suitable patterns for 12.37% and 5.2% of the users. Finally, 2.87% of the users are driven by explicit links, implicit links and personal interest together. In terms of a single driving factor, 8.07% of the users are driven by the implicit link factors, so the implicit link plays a very important role in driving users to participate in topics.

Figure 8: The proportion of users preferring the different patterns

Finally, we compare the driving strength of the same driving factors in patterns and *EPR*, *IPR* as shown in Figure 9. The x-axis represents each user like user A or user B, and the y-axis represents the driving strength. The results indicate that personal interest as an internal factor has a greater driving strength, whereas external factors such as explicit and implicit links are relatively weak.

Figure 9: a. The driving strength of factors in *EPR*; b. The driving strength of factors in *IPR*

In order to verify the experimental results, we take the users in the *PR*,

430 *EPR* and *IPR* patterns to carry out data statistics. The obtained statistical
 result (Figure 10) allow us to verify whether the proportion of topics that users
 participate in based on the different factors is approximately the same as indi-
 cated by the results of the experiment. The x-axis in the graphs of Figure 10
 represents each user like user A or user B, and the y-axis represents the propor-
 435 tion of topics that user participated in based on the different driving factors. N_P
 is the number of topics the user participated in based on the personal interest
 factor. N_E is the number of topics the user participated in based on the explicit
 link factor. N_I is the number of topics the user participated in based on the
 implicit link factor. N presents the total number of topics user participated in.

Figure 10: a. Data statistics of users with *PR* pattern; b. Data statistics of users with *IPR* pattern; c. Data statistics of users with *EPR* pattern

440 For the users with the *PR* pattern (Figure 10(a)), the proportion of
 topics users participated based on personal interest is much higher than the
 proportion based on the implicit link factor and on the explicit link factor. For
 the users exhibiting the *IPR* pattern (Figure 10(b)), the topics based personal
 interest still occupy a higher proportion. However, compared to Figure 10(a),
 445 the proportions of topics based on the explicit link factor and on the implicit
 link factor are greater, and the proportion based on the implicit links factor
 is higher than that of the explicit links factor. Moreover, for the users with a
EPR pattern (Figure 10(c)), the proportion of topics based on the explicit link
 factor is obviously weaker than that of the implicit link factor.

450 The statistical analysis shows that, as an overall trend, the proportions of topics users participated in based on the different factors are consistent with their most suitable pattern. The experimental results of the statistical analysis.

6. Conclusion

In this paper, the user behavior is analyzed to mine the dynamic factors that drive users to participate in hotspot topics. In order to define the driving factor, we use a cloud model. Then, the *EIPR* model is established based on the theory of maximum likelihood estimation. Through the analysis of six patterns in this model, the factors that drive users to participate in hotspot topics are captured, and their driving strength are quantified. In addition, the role of implicit links in driving user behavior is investigated further.

According to the experimental result, different users are the influences by different factors in participating hotspot topics. Similarly, the driving strengths of the factors are also different. Furthermore, we divide the user group into different pattern groups according to the users' most suitable patterns. As shown in Figure 8, implicit link factors drive 8.07% of the users to participate in topics. Therefore, implicit link factor plays a very important role in driving users to participate in hotspot topics. Analyzing the driving strength of the same factor in each pattern groups. We determine that, as an internal driving factor, the personal interest factor has a higher driving strength, which is the main driver of user behavior. The driving strength of the external driving factors, such as the explicit link factor and implicit link factor, are weaker than the internal driving factor.

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