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A Situational Analytic Method for User Behavior Pattern in Multimedia Social Networks

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Abstract—The past decade has witnessed the emergence and progress of multimedia social networks (MSNs), which have explosively and tremendously increased to penetrate every corner of our lives, leisure and work. Moreover, mobile Internet and mobile terminals enable users to access to MSNs at anytime, anywhere, on behalf of any identity, including role and group. Therefore, the interaction behaviors between users and MSNs are becoming more comprehensive and complicated. This paper primarily extended and enriched the situation analytics framework for the specific social domain, named as *SocialSitu*, and further proposed a novel algorithm for users' intention serialization analysis based on classic Generalized Sequential Pattern (GSP). We leveraged the huge volume of user behaviors records to explore the frequent sequence mode that is necessary to predict user intention. Our experiment selected two general kinds of intentions: playing and sharing of multimedia, which are the most common in MSNs, based on the intention serialization algorithm under different minimum support threshold (*Min_Support*). By using the users' microscopic behaviors analysis on intentions, we found that the optimal behavior patterns of each user under the *Min_Support*, and a user's behavior patterns are different due to his/her identity variations in a large volume of sessions data.

Index Terms—multimedia social networks, situation analytics, intention prediction, behavior pattern, big data

1 Introduction

THE rapid development of Multimedia Social Networks (MSNs) causes the tremendous growth of users and digital contents. It's also convenient for users to access digital contents in MSNs with a large-scale video dataset [1]. Meanwhile, the interaction between user and user, user and system increases. Therefore, providing users with timely and rapidly personalized services considering the complex interaction [2] is now a challenge in the study of multimedia social networks. Generally speaking, multimedia computing can be decomposed into three different stages, from data-centric multimedia compression, content-centric multimedia communication and content analysis, to user-centric social media analysis till today, including user trust modeling [3, 4], propagation paths mining [5, 6] and digital right sharing [7], and digital forensics[8-10]. However, understanding and predicting what multimedia content users' real needs in different situations and contexts have not been well studied [11].

Context-Aware (CA) [12-15] was first proposed by Schilit et al in 1994. They defined context as the set of location, people nearby, objects, and the changes of the objects. Prof. Carl K. Chang [16] proposed the Situ theory by combining the service environment with situation awareness to handle the dynamic update or development of service at run time. Therefore the service can meet the changing needs of users and provide users with personalized service. In order to adapt to the dynamic service environment and make a timely respond to the feedback of service environment, social media services increasingly require situation awareness. In social media networks, the human being is a complex and open system. The individual's intention can change at any time, which also causes a change in the user's needs. Moreover, the user's context and behavior are dynamic. Some studies show that the characteristics of the dynamic change will have different effects in a user's potential needs [17, 18]. A user's intention can be reflected through the acquiring attributes of the user's situation awareness and feedback on resources. The system can formulate a timely personalized service for the user based on user's intention, which will increase the user's service experience.

In social media networks, the user has different roles in different groups. The different identifications that the user has may cause the user's intention to change. The change of intention reflects the change in user's behavior. The Situ theory [16, 19] does not fully meet the analysis of the intention of users with different identities in the social media environment. This paper's motivation is to analyze the user's intention sequence mode(s) in social media networks. The major contributions of this paper are two folds. One is to enrich and extend the Situ theory outreaching for social domain, that is the social media

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ecosystem, through newly and comprehensively considering user's changeable identity (including role and group), and the other is to propose a novel algorithm for users' behavior pattern analysis and mining. The important vision of the work is to further predict users' more and deeper intention and mental based on a large volume of previous actions.

The remaining parts of this paper are as follows: Section 2 shows the progress in related studies; the next section shows the extension of the Situ framework; Section 4 introduces the intention serialization algorithm; the experiment and its results of the serialization algorithm are in detail presented in Section 5; and finally conclusions are drawn.

2 Related Works

Chang studied the significance and influence of the situation analysis theory and Situ framework on software engineering, as well as introduced the Situ framework in detail, which could provide users with personalized service by identifying the new intention of the user and the real-time update of service [19]. Ming et al raised a spatial scenario analysis based on the Situ theory and the proposed (MR)2 paradigm promoted comprehensive decision-making which is conducive to the transformation of data, information, knowledge, and wisdom (DIKW) [20]. Rahman et al stated that, in a given environment, the user could share data with friends in the social circle through the part of the social service which they are involved in. So they put forward a SenseFacen framework to recommend services for users by using perceptual data from the user sensor network and multimedia information [21]. Shen et al put forward an algorithm which considers the surrounding environment and social network relationship. This algorithm could make use of user's recognized situation, preference, and social network relationship to acquire user's nearest neighbours through the calculation of the user's comprehensive situation similarity, and predict the potential situation user preference to make a recommendation [18]. Tong et al combined with the characteristics of Internet of things, to discuss information acquisition, modelling and intelligent processing etc by taking the situation awareness process as the main line [22]. Hence, it becomes more and more important to employ a novel situational awareness for computing services to provide users with more personalized functions, including multimedia recommendation service [23, 24], customized security and privacy one, and so forth.

Zhang et al presented an improved N-gram prediction model to predict the possible future web access request of the user through the server log data [25]. Bar-David et al stated that existing technology made an attempt to predict the location of moving user according to historical trajectory of moving objects, while ignoring the fact that the dynamic nature of the moving behavior may lead to errors in prediction. They proposed a type of context-aware position prediction algorithm based on various contexts to predict the future position of a vehicle [26]. In order to allow smart phone users to access the service easily and timely, Lee [27] et al designed a recommendation mechanism to predict user's intention and activate appropriate service; an event-condition-behavior model and a rule induction algorithm was used to find out behavior patterns of smart phone users, and then, made use of their behavior pattern to predict and recommend the appropriate service for the users. In order to better understand users' intention in MSNs, we greatly need to explore users' online social behavior patterns [28]. Users' data are high noise and discrete in MSNs, especially mobile social networks [29, 30], and these data can not be used for analysis and mining in time. So, there is a need to collect and preprocess users' data before our next work.

Chang's situation analytics theory [16, 19] is oriented toward the field of software engineering, not completely appropriate for the emerging application scenario of multimedia social networks. To sum up, in order to provide users with more personalized services in the multimedia social networks, this paper established a *SocialSitu* framework on the basis of Situ-analytics theory [16, 19] through comprehensively considering users' context and situation in MSNs. To obtain user's intention sequence, we proposed a novel algorithm for analyzing on *SocialSitu(t)* sequences of users through the improved GSP.

3 Extension of The Situ Framework in MSNs

In MSNs environment, a large number of users may be in different groups with different roles. The roles of users in groups may cause them to generate different desires. Therefore, this paper extends and enriches Situ framework in social media, as defined below：

Definition 1 [16] (*Situation(t)*): It represents the situation at t, which consists of a three-tuple, $Situation(t) = \{d, A, E\}$. Where d refers to the desire of user at t; A refers to the action of the user which achieves the d; E refers to environmental context at t.

Definition 2 (*SocialSitu(t)*): It refers to the situation at t which is the extensional *Situation(t)* for the social domain. *SocialSitu(t)* is a four-tuple $SocialSitu(t) = \{ID, d, A, E\}$. Here, ID refers to user's identity information; d refers to user's desire at t; A refers to user's behavior corresponding to d at the moment; E refers to environment information, including the terminal information which the user utilized.

Definition 3 (*ID*): *ID* refers to the user's identity information; it is a two-tuple $ID = \{Group, Role\}$. In MSNs, there is a corresponding relationship between the user's role and group. When a user's role is changed, the user's behavior may also change.

Definition 4 (*Group*): It refers to a small group formed in social media network because of a particular reason. It's a part of the whole social media network.

Definition 5 (*Role, R*): a user's role in MSNs. The role is a set $R=\{r_1, r_2, \ldots, r_n\}$, referring to RBAC96.

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Definition 6 (*Desire, D*): It refers to what users want to achieve when using a social media service, namely, the user's purpose. It consists of a series of atom-desire (*d*), namely $\{d_1, d_2, ..., d_n\}$, $d_i (1 \le i \le n)$ refers to user's desire at *i*.

Definition 7 (*Goal, G*): the user's general target $G=\{g_1, g_2, \dots, g_n\}$ for MSNs.

Definition 8 [16] (*Intention, I*): It refers to the *SocialSitu(t)* sequence of user from starting point to target achievement, namely *I={SocialSitu(1), SocialSitu(2), ..., SocialSitu(n)}*, $n \in N$, *SocialSitu(1)* refers to the starting point; *SocialSitu(n)* refers to the ending point when the target is achieved. Here, *SocialSitu(t)* sequence is directly correlated to the target achievement. Through the intention sequence, the user achieves the target, as shown in Fig.1.

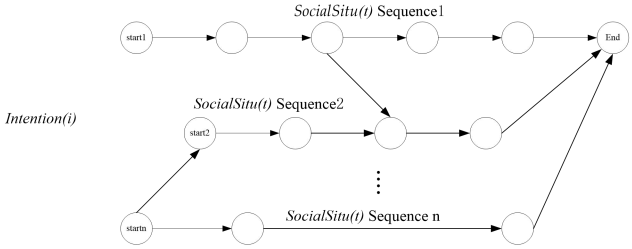

Fig.1. Intention sequence

In the figure, each point refers to *SocialSitu(t)* at a certain moment. The point *startj* ($1 \le j \le n, j \in N$) refers to the starting point of *Intention(i)*. These starting points can be the same or different. *End* refers to the ending point of *Intention(i)*. Each stripe of *SocialSitu(t)* sequence refers to the sequence composed by different *SocialSitu(t)* that the user passed from starting point to ending point. Except for the ending point, the same nodes may exist in each sequence of *Intention(i)*. In the MSNs, there is at least one sequence which corresponds to the user's intention, namely $i \in N, i \ge 1$.

4 Intention Serialization Algorithm of User

All frequent *SocialSitu(t)* related to a certain goal achievement in a user's historical access record consist of an intention sequence. The user has at least one goal in MSNs, and this corresponds to at least one intention sequence. The user's intention sequence with a specific goal is saved to the database. The current sequence of a user is compared with intention sequences of the user in the database to predict the current intention of the user to make a rapid and timely response to the user's request and provide a personalized service, intention prediction flowchart is shown in Fig.2. A key problem in this paper is how to find out the user's Intention sequence.

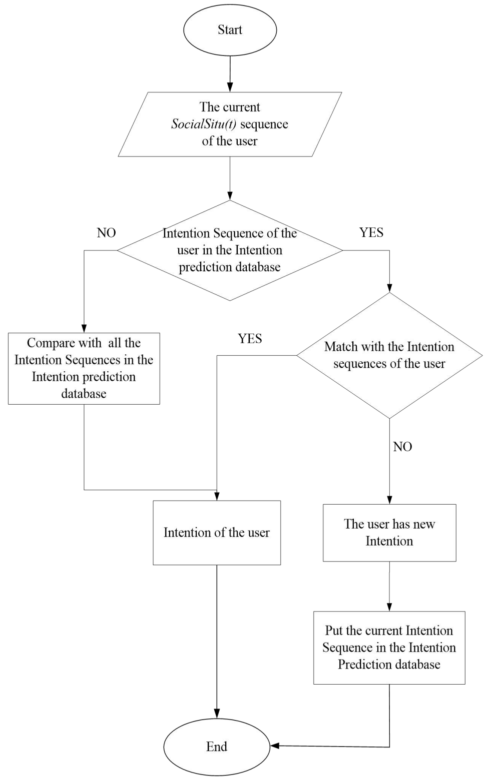

Fig.2. Intention prediction flowchart of the user

The association rule which was proposed by Agrawal et al in 1993 is used to find out the relationship among various items in a large quantity of data. *DS* is a set which represents the entire transaction set where each attribute is called as an *item*. The set including all items in a *DS* is named as the data item set, $I=\{i_1, i_2, ..., i_m\}$, $|I|$=m, m refers to the number of items in *DS*.

The association rule contains the following logic implication form: $A \Rightarrow B$, wherein, $A \subseteq I$, $B \subseteq I$ and $A \cap B = \Phi$; item set A is the antecedent of the association rule; item set B is the result of the association rule; $A \cup B$ is the item set which corresponds to this rule.

- **Support**: the number of item set R contained in the DS called as the supporting number of R, recorded as R.Support. The number of support for rule $R \Rightarrow S$ refers to number that the item sets R and S coexisting in DS. Therefore, the support for rule $R \Rightarrow S$ is Support ($R \Rightarrow S$) = P ($R \cup S$).
- **Confidence**: Confidence of rule $R \Rightarrow S$ refers to the probability that entire data set DS that contains A includes B meanwhile, recorded as Conf ($R \Rightarrow S$)=P(R|S).

The item set satisfying the *Min_Support* is called the frequent item set. The rule satisfying the *Min_Support* and the minimum confidence threshold (*Min_Conf*) is the strong association rule. Therefore, *Intention(i)* serialization in this paper adopts the method based on the association rule to find out each sequence corresponding to the intention. The ending point of each *Intention(i) sequence* is used as the result of association rule, and association rule is used to obtain the antecedent of association rule. Intention serialization algorithm is shown in Algorithm 1 and flowchart of intention serialization algorithm is shown in Fig.3. The steps of serialization algorithm based on association rule are as follows:

(1) The web log database is scanned after data processing, the goal in definition 7 was identified in the database as the ending point of user in *Intention(i)*, recorded as $G' = \{g'_1, g'_2, \quad , g'_m\}$, $1 \le m \le n$, $G' \subset G$.

(2) g_i' obtained from Step (1) is used as a result of association rule. Each *SocialSitu(t)* is used as the antecedent of the association rule to calculate the Support of each rule, and find out the rule satisfying the *Min_Support*.

(3) The antecedents of the rule obtained from Step (2) are used to build a set L_1, for set L_k in the length of k, where the link operation and pruning operation are used to generate a candidate sequence C_{k+1} in the length of k+1. Then, scan data set *DS*, calculate the Support of each candidate sequence as the antecedent and g_i' as the result of the association rule to generate sequence L_{k+1} in the length of k+1, and L_{k+1} is used as the seed set of the antecedent of new association rule.

(4) Step (3) is repeated until the new candidate sequence can no longer be generated, and all *SocialSitu(t)* sequences related the target g'_i of *Intention(i)* is obtained.

(5) All *SocialSitu(t)* sequences corresponded to target g'_{i+1} are acquired and recorded as *Intention(i+1)*. Then, Steps (2), (3), and (4) are repeated.

(6) Until there is no longer a new goal.

Link operation: if the sequence obtained after removing the first item of sequence pattern s_1 is the same as the sequence obtained after removing the last item of sequence pattern s_2, then s_1 should be connected with s_2. That is, the last item of s_2 should be added into s_1.

Pruning operation: if a certain sub-sequence of a candidate sequence pattern is not a sequence pattern, this candidate sequence pattern is unlikely to be a sequence pattern; therefore, it is deleted from the candidate sequence pattern.

Algorithm 1: Intention serialization algorithm based on situation-aware

Input: DataSet: *DS*, the Minimum Support: *Min_Support*, User's Goal: G'

Output: *SocialSitu(t)* Sequence

SituBehaviorAnalytics (*DS*, *Min_Support*, G')

Begin

for $j \leftarrow 1$ **to** n //n indicates the number of user's goal

for $t \leftarrow 0$ **to** T

Support($SocialSitu(t) \Rightarrow g'_j$) = P ($SocialSitu(t) \cup g'_j$);

endfor

if (Support ($SocialSitu(t) \Rightarrow g'_j$)>Min_Support)

$L_1 = SocialSitu(t)$; //the 1-frequent item sets L_1

endif

for $k \leftarrow 2$ **to** m **and** $L_{k-1} \neq Null$

Generate candidate sets C_k ;

Support ($C_k \Rightarrow g'_j$) = P ($C_k \cup g'_j$);

if (Support ($C_k \Rightarrow g'_j$)>Min_Support)

$L_k = C_k$;

endif

endfor

Intention(i) = $L_k \cup g'_j$;

endfor

End

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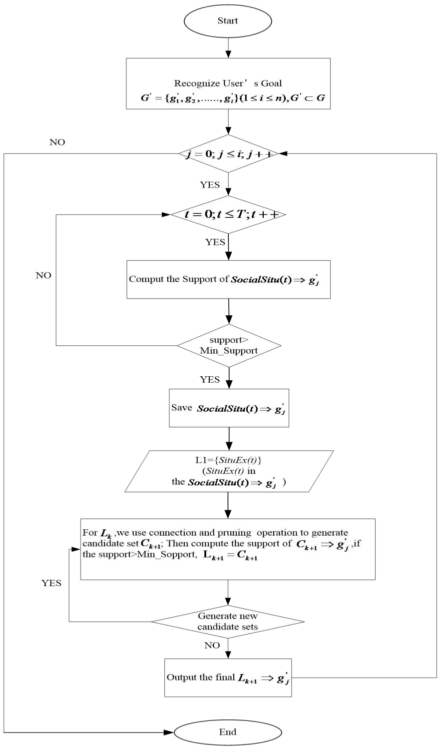

Fig.3. Flowchart of situational aware intention serialization algorithm

5 EXPERIMENT AND RESULT ANALYSIS

In the multimedia social network *CyVOD* [31] which is a prototype system we have achieved, supposing that users login and quit normally, the user first enters the goal before accessing the *CyVOD*, with the range of Goal. The user would quit the system when the goal is achieved. A complete conversation from logging in to quitting *SocialSitu(t)* sequence is tracked.

The four elements in *SocialSitu(t)* are acquired and enumerated below:

(1) *ID*: The user's role and group are acquired in the database through the session information saved in the server. Users' groups in *CyVOD* are the common registered user group and the advanced user group, which are corresponded with common users and VIP users, respectively.

(2) *d*: A user's behavior in MSNs is an observable vector. However, a user's desire is concealed. User's behaviors are reflected in various states by a probability density distribution. For example, when the user clicks into the login, the user's desire is corresponded with the login behavior access to the system.

(3) User's behavior A: In order to achieve d, the user's behavior may be an atomic action or a compound action, mainly referring to user's click and keyboard input behavior [16]. The user's behavior can be obtained through a web server log and the data change at a certain moment in the database.

(4) *e*: terminal information (mobile terminal or PC) .

In MSNs, the data in the web log are complex and irregular, so data preprocessing is required to transform these complex data into the data format required. The data preprocessing includes data cleaning, user identification, session identification, and data transformation, as shown in Fig.4, specific data preprocessing is shown as follows：

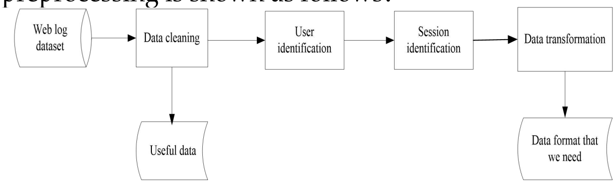

Fig.4. Data preprocessing for intention serialization algorithm

- Data cleaning: Irrelevant data record from the log should be removed. For example: browsing errors, server errors, or client errors. These log data are insignificant to this research. The error information can be found in the status code in web log, and deleted.
- User identification: All data of the current user from a large quantity of logs is identified. This paper is aimed at registered users. Therefore, the user registered ID is employed to identify the user.
- Session identification: A session is a collection of pages accessed by a user during a certain period of time. A user's complete session is identified from logging in to quitting.
- Data transformation: Log data, which is continuous, is transformed into the data type required in this paper. These data are divided into discrete data points according to the time stamp, that is, transformed to be in the *SocialSitu(t)* four-tuple in definition 2.

The most common intentions are play and share. The two users' historical *SocialSitu(t)* data of play and share intentions are collected in this experiment, respectively. We collected hundreds of sessions' data to analysis the intention sequence patterns of User #161 with different IDs and User #2. There include a large volume of actions such as logining, searching, and so on, together with environmental information in sessions data, which are from the log data of *CyVOD.net*. By using the serialization algorithm in part 4, the basic sequence patterns of two users are obtained, as shown in Table2, Table 3 and Table 4. Table 2 shows the intention sequence pattern of the User #161 with the role of common registered user with the audio and video playing intention. Table 3 shows the intention sequence pattern of User #161 with the role of VIP in the audio and video playing intention. Table 4 shows the intention sequence pattern of User #2 in the audio and video sharing intention. Table2, Table 3 and Table 4 list the Support and Confidence of sequence pattern in each minimum support threshold.

Event/Behavior-Desire control is shown in Table 1. A *SocialSitu(t)* in intention sequence pattern in Table 3 is shown as: ((V, VIP), 01, 01, n). The first element *(V, VIP)*

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presents that the user belongs to advanced user group, with the role of VIP user. The second element *01* denotes that the desire of the user is login at this moment. The third element *01* denotes that the user's behavior for achieving this desire is to click login button. The fourth element *n* indicates that the platform the user adopted is a non-mobile terminal access *CyVOD* platform.

Table 1 Event/Behavior-Desire identification symbols sheet of CyVOD

Event/Behavior	Event_ID	Desire	Desire_ID
Log in	01	Log in	01
Abnormal login	02	Abnormal login	02
Search	03	Search	03
Click audio and video	04	Play	04
My ZOE	05	My ZOE	05
Click the navigation bar	06	Browse	06
Quit	07	Quit	07
Click recommended audio and video	08	Play	04
Quick navigation	09	Browse	06
The audio and video I uploaded	10	Browse	06
Play the audio and video I uploaded	11	Play	04
Personal center sharing	24	Share	21
History of audio and video play	12	Play	04
Click modify password	13	Modify password	13
Click my collection	14	Browse	06
My share record	15	See my share record	15
Get permission record	16	See get permission record	16
Check my message record	17	Play	04
Upload media	18	Upload	18
Comments	19	Comments	19
Get online digital permission	20	Get permission	20
Share online digital permission	21	Share permission	21
Download full encryption Audio/Video	22	Download encryption	22
Get offline license	23	Get offline license	23

Table 2 Sequence pattern of User #161 with the role of common registered user

User_ID	User Intention	Min_Support	Intention Sequence Mode	Support	Confidence
161	Play	10%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n)((R,Register),20,20,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is：Login->Search->Click audio and video->Get online digital permission	52%	67.532%
			((R,Register),01,01,n)((R,Register),05,05,n)((R,Register),06,10,n)((R,Register),04,11,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is：Login->My ZOE->Click the audio and video list I uploaded->Play the audio and video I uploaded	17%	100%

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		20%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n) ((R,Register),20,20,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is： Login->Search->Click audio and video->Get online digital permission	52%	67.532%
		30%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n) ((R,Register),20,20,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is： Login->Search->Click audio and video->Get online digital permission	52%	67.532%
		40%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n) ((R,Register),20,20,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is： Login->Search->Click audio and video->Get online digital permission	52%	67.532%
		50%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n) ((R,Register),20,20,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is： Login->Search->Click audio and video->Get online digital permission	52%	67.532%

Table 3 Sequence pattern of User #161 with the role of VIP

User_ID	User Intention	Min_Support	Intention Sequence Mode	Support	Confidence
161	Play	10%	((V,VIP),01,01,n)((V,VIP),03,03,n)((V,VIP),04,04,n) ((V,VIP),04,08,n) Under the current *Min_Support*, the behavior pattern of this VIP user in non-mobile terminal is: Login->Search->Click audio and video->Click recommended audio and video	11%	100%
			((V,VIP),01,01,n) ((V,VIP),05,05,n) ((V,VIP),10,10,n) ((V,VIP),04,11,n) Under the current *Min_Support*, the behavior pattern of this VIP user in non-mobile terminal is: Login->My ZOE->Click audio and video I uploaded->Play the audio and video I uploaded	11%	100%
		20%	((V,VIP),01,01,n) ((V,VIP),03,03,n) ((V,VIP),04,04,n) Under the current *Min_Support*, the behavior pattern of this VIP user in non mobile terminal is: login->search->click audio and video play	45%	95.745%
		30%	((V,VIP),01,01,n) ((V,VIP),03,03,n) ((V,VIP),04,04,n) Under the current *Min_Support*, the behavior pattern of this VIP user in non mobile terminal is: Login->Search->Click audio and video play	45%	95.745%
		40%	((V,VIP),01,01,n) ((V,VIP),03,03,n) ((V,VIP),04,04,n) Under the current *Min_Support*, the behavior pattern of this VIP user in non mobile terminal is: Login->Search->Click audio and video play	45%	95.745%
		50%	((V,VIP),01,01,n) ((V,VIP),04,04,n) Under the current *Min_Sopport*, the behavior pattern of this VIP user in non mobile terminal is: Login->Click audio and video play	75%	76.531%

Table 4 Sequence pattern of User #2

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User_ID	User Intention	Min_Support	Intention Sequence Mode	Support	Confidence
2	Share	10%	((R,Register),01,01,n)((R,Register),05,05,n)((R,Register),06,10,n)((R,Register),18, 18,n)((R,Register),04,11,n)((R,Register),21,24,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is: Login->My ZOE->Click the audio and video list I uploaded->Upload media->Play the audio and video I uploaded->Share	21%	100%
		20%	((R,Register),01,01,n)((R,Register),05,05,n)((R,Register),06,10,n)((R,Register),18, 18,n)((R,Register),04,11,n)((R,Register),21,24,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is: Login->My ZOE->Click the audio and video list I uploaded->Upload media->Play the audio and video I uploaded->Share	21%	100%
		30%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n)((R,Register),20, 20,n)((R,Register),21,21,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is: Login->Search->Click the audio and video play->Get online digital permission->Share online digital permission	46%	100%
			((R,Register),01,01,n)((R,Register),05,05,n)((R,Register),06,10,n)((R,Register),04, 11,n)((R,Register),21,24,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is: Login->My ZOE->Click the audio and video list I uploaded->Play the audio and video I uploaded->Share	30%	100%
		40%	((R,Register),01,01,n)((R,Register),03,03,n)((R,Register),04,04,n)((R,Register),20, 20,n)((R,Register),21,21,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non-mobile terminal is: Login->Search->Click the audio and video play->Get online digital permission->Share online digital permission	46%	100%
		50%	((R,Register),01,01,n)((R,Register),04,04,n)((R,Register),20,20,n)((R,Register),21, 21,n) Under the current *Min_Support*, the behavior pattern of this common registered user in non mobile terminal is: Login->Click the audio and video play->Get online digital permission->Share online digital permission	59%	100%

Note: n: non-mobile terminal; m: mobile terminal; R: common user; V: VIP user; VIP: advanced user group; Register: common registered user group.

When a user satisfies some conditions, his authority will be higher, such as User #161 in Table 2 and Table 3. His role changes from the common registered user to the VIP. By comparing Table 2 with Table 3, User #161 has different *SocialSitu(t)* sequence in the same *Min_Support* with the same intention when his role and group change. Table 2 and Table 4 show the different intention sequences of different users with the same role and group. Thus we can acquire other users' intention sequences by using their *SocialSitu(t)* log data.

Confidence is a measure of the accuracy of intention sequence. Support is a measure of the importance of intention sequence. Support indicates the degree of representative of this intention sequence in all events. Apparently, if support is higher, then the intention sequence is more important. Some association rules have a high confidence, but the support is very low. As shown in Table 3, when *Min_Support* is 10%, the confidence of the intention sequence is 100%, but the support is only 11%. Thus, the opportunity of applying the intention sequence is lower, which makes it irrelevant.

It can be seen in Table 3 that, when *Min_Support*=50%, the support of the intention sequence pattern is high. However, the intention sequence consists of only two *SocialSitu(t)*, this has a low effect on predicting the intention of the user. When *Min_Support* is 20%, 30%, or 40%, the support and confidence of the intention sequence is same. Also, the *SocialSitu(t)* of intention sequence is the same. Therefore, the *Min_Support* of User #161 can be 20%, 30% or 40%. It can be seen in Table 3 that, when *Min_Support* is 10% or 20%, the confidence of the intention sequence is very high, but the support is very low. When *Min_support* is 30%, two intention sequence patterns are obtained, which includes the intention sequence patterns under the condition that *Min_Support* is 40% and 50%. Hence, the *Min_Support* of User #2 is 30%. Similarly, the intention sequence patterns of other users and final selection of *Min_Support* in MSNs can be concluded.

6 CONCLUSIONS

The existing MSNs environment increasingly requires situation awareness. Users' environment and behavior are dynamic, and an individual's intention is also to change. In order to adapt to the dynamic changes of user identities in the social domain, this paper extends and enriches the Situ theory, and builds a *SocialSitu* framework for the social media networks. We design and achieve the intention serialization algorithm in multimedia social networks. The user's frequent intention sequence mode is obtained through the intention serialization algorithm. When the user's identify changes, we conclude his behavior pattern with different ID, and prove that different *SocislSitu(t)* sequences are acquired in the same *Min_Support* with the same intention when his role and group change. In the future works, the existing intention sequence patterns of the user could be adopted to predict the user's more and deeper intentions. Besides, we will employ the *SocialSitu* and the proposed algorithm to improve multimedia recommendation system and some killer applications in MSNs.

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