# A Space-time Dimension User Preference Calculation Method for Recommendation in Social network


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***Abstract*— Under the background of the Mobile Internet Age, location service has been developed rapidly. On the basis of modeling the space-time dimension and the study of users' personalized preference combined with the preference of similar user groups, this paper proposes the information selection model of location service and relevant algorithms. In this model, a space-time dimensional model is firstly constructed to process the information of users' personalized location service in the time and spatial dimension. Then, a new user preference model is constructed based on the existing study on user preference.**



***Keywords*— location service, space-time dimension, personalized, user preference**


## I. General Introduction

With the rapid development of global mobile Internet applications, LBS (Location Based Service) has not only become one important developing direction for the mobile network communication and personalized preference, but also, it draws increasing attention from more and more researchers [1]. Personalized recommendation algorithm is applied very broadly. Its application in the e-commerce sector has specially played a significant role [2]. From the viewpoint of application, personalization algorithm solves the problem of the insufficiency of traditional personalized recommendation algorithm, which promotes the development of personalized location-based service to a new stage. Technically, the personalized recommendation technology is based on the existing mature recommendation algorithms and meets the diverse needs of different users according to such information as the users' actual needs and interest. However, the existing personalized recommendation algorithms have neglected location-based service [3]. Usually, they tend to focus on meeting the needs of individual users, but rarely take into account such factors as the user's current location, time, seasonal climate, and the service requested by users based on those factors. As a result, they cannot meet the requirement of providing personalized location-based service to users.

Facing the gradual improvement of the Internet and the tidal wave of abundant information, how to choose from the vast and complex information on location service in order to meet the users' service requests is a major problem in location service that needs to be addressed at the current stage. However, many existing research on time or space in personalized recommendation algorithms mainly focus on the study of time complexity or user behavior tracking. It lacks the distribution of the associated information on time and space context for users and service projects as well as the combination of spatial dimension and time dimension.

Combining the concept theory of space-time dimension, this paper firstly defines and summarizes time dimension and space dimension respectively and constructs space-time recommendation model on the basis of combing the two dimensions. Then, the paper focuses on the modeling of user preference and the construction of user preference model based on users' historical location data. Finally, the location service selection framework basing on space-time dimension and user preference is built with the combination of space-time dimension and the modeling of user preference so as to meet the personalized demands of users.

## II. Related work

The early location recommendation technology includes the recommendation algorithms based on content filtering and collaborative filtering. As a variety of studies on the recommendation system algorithm gradually rise, various personalized recommendation algorithms emerge and the recommendation system is applied more widely. The author of the [4] establishes a recommendation system meeting the users' personalized demands on the basis of the existing recommendations. The author firstly analyzes the problem that the user's interests are prone to deviate, and then propose an interest offset model constantly monitored based on the network complexity. The author also backs up the current recommendation algorithm according to the actual environmental of events [4].

Though the Information Age has brought a lot of conveniences to peoples' lives, it also creates certain problems, such as how to effectively process data facing massive information data [5]. The authors of [6] proposed a system which provides the security to the user's location as well as uses compression algorithm to compress and decompress the message so that that the message retrieval time will be lesser than other system. Their system cost of the server database will decrease and the time required for transmitting the message is also decreases. Their system also uses keyed tags and random tags which balance the privacy and performance of the system. The keyed tag provides strong privacy and random tags provide privacy and high efficiency to the system [6]. The authors of [7] proposed a Facebook application and an Android application that recommend places based on the number of check-ins of those places, the distance of those places from the current location, the number of people who like Facebook page of those places, and the number of talking about of those places. They found that the users' satisfaction can increase by adding the app features that support personalization in terms of interests and preferences [7]. Yang-Chieh Chin investigate and compare what recommendation sources influence the intention to use LBS and to combine gender, daily internet hour usage and past use experience to infer the usage of LBSs decision rules using a dominace-based rough-set approach. [8]The authors of [9] proposed a framework of map search service using Region-of-Interest as the query result, which can greatly reduce users shopping distance among multiple stores. High order Voronoi diagram is used to reduce the time complexity of Region-of-Interests generation [9].

## III. The Users' Personalized Preference

### A. The Definition of the Users' Personalized Preference

The user preference can be divided into long-term and short-term preference. The former one is also known as the historical preference. In general, the users' long-term preference is gradually evolved and relatively stable, and it can be obtained from the historical data analysis. The users' short-term preference is relatively stable at a certain period time, and it can be analyzed through relevant characteristics of time dimension [10]. If the data is far from enough for some users, establishing a similar preference user group can solve the problem.

This paper firstly constructs the user preference. User preference $h(Pi)$ refers to the corresponding value of the users' preference to the service $i$. $P_i$ stands for the users' requested services, such as the taste, environment, and price of a certain restaurant. $h(P_i)$ represents the users' preference for the service $i$. $h_L(P_i,t)$ represents the long-term preference, while $h_S(P_i,t)$ is for the short-term.

The users' long-term and short-term preference can be mutually transformed. For example, supposing a user has a low preference for the Sichuan cuisine, he only enjoys it occasionally at first. However, due to some reasons, he starts to eat Sichuan cuisine on a regular basis. Thus, Sichuan cuisine becomes the user's long-term preference. Besides, under certain conditions, the user's long-term preference may be converted to short-term preference. The transformation formula is shown below:

$$h(P_i)=\begin{cases} h_L(P_i);t<t_0 \\ \dfrac{h_L(P_i,t_0)}{t_0}+\lambda h_L\left(P_i,(t-t_0)\right);t_0\leq t\leq t_1 \\ h_S(P_i);t>t_1 \end{cases} \tag{1}$$

Where $\lambda$ is the transformation factor between long-term and short-term preference, as is shown in Formula 2:

$$\lambda=f\left(\frac{1}{t}\right) \tag{2}$$

Conversion Algorithm of User Preference is give as follows,

| Conversion Algorithm of User Preference: |
|---|
| Input: get $<P_1$、$P_2\ldots P$n$>$;// Obtain service requested by users<br>get $U_m<h(P_1)$、$h(P_2)\ldots\ h(P_n)>$;// Preference based on User M's historical data<br>Output: $h(P_i)$;// User Preference<br>$t_0=7$, $t_1=14$;// Initialize $t_0$ & $t_1$<br>if $t<t_0$ // $t_0$&$t_1$ are the threshold of transformation from short-term preference to long-term preference<br>$h(P_i)\ =\ h_L(P_i,t)$; // short-term preference<br>else if $t_0<=t<=t_1$<br>$h(P_i)\ =\ h_L(P_i,\ t_0)/\ t_0+\lambda h_L(P_i,(t\ -\ t_0))$// decay from short-term preference to long-term preference<br>else if $t>t_1$<br>$h(P_i)\ =\ h_S(Pi)$ long-term preference |

### B. The Modeling of the Users' Personalized Preference

Assuming that the historically stored service project requested by the users is $S[P_2, P_3...P_n]$ and $P_2$, $P_3...P_n$ refer to each of the different specific services, then the corresponding recommendation value of the location service requested by the users is $h_1(P_1),h_2(P_2),h_3(P_3)......,\ h_n(P_n)$.

Supposing that different users are represented as $U[P_1, P_2 ... P_n]$ and the personalized preferences corresponding to the services requested by each user is $h(P_1), h(P_2) ... h(P_n)$, then the preference value of the users' requested services is $V_1(h(P_1)) ... V_n(h(P_n))$.

Recommendation computing refers to the calculation of the recommendation score of users' personalized preferences. Assuming that the recommendation score is Sim, then the formula for the users' personalized recommendation score is as follows:

$$Sim = \begin{cases} 1; V(p_i) \geq V(h(p_i)) \\ 0.5; \alpha < V(p_i) - V(h(p_i)) < 0 \\ 0; others \end{cases} \tag{3}$$

As is shown in Formula 3, $\alpha$ represents the users' tolerance. When the recommendation value of the service $V_i(P_i)$ is greater than or equal to the preference value of the service requested by the users, the recommendation score is 1. When the result for the recommendation value $V_i(P_i)$ subtracting the preference value of the requested service belongs to $(\alpha, 0)$, the recommendation score is 0.5. Under other circumstances, the recommendation score is 0. However, for calculating the recommendation score of the service projects for the users, Formula 3 only applies to the computing of one user's recommendation score. To further meet the demands of the users' personalized preference, Formula 3 can be optimized and the formula for the service recommendation score meeting the demands of individual users is shown in Formula 4:

$$Sim = \frac{\sum_{i=1}^{n} Sim(U(P_i))}{n} \tag{4}$$

In Formula 4, $n$ represents the total number of users who have similar preferences. The denominator calculates the recommendation score of different users with reference to Formula 3. To achieve the final recommendation score of the users, the recommendation score of all the users having similar preferences needs to be summed up, and then the obtained number will divide the number of users $n$.

## IV. USER GROUP PREFERENCE

### A. The Modeling of User Group Preference

The purpose of establishing user group preference model is to solve the scarcity of the service data requested by single users. Firstly, the model of user group preference should be established. Assuming that user group preference is represented as $G_x([P_1, L_1], [P_2, L_2] \ldots [P_i, L_i])$, $P_i$ indicates the service requested by users, $G_i$ refers to the preference model of user $i$, and $L_i$ represents the corresponding preference degree of service $P_i$. Preference degree adopts 10-point system. Then, the historical data will be analyzed and the user group model will be established through finding out the data of similar user groups.

Before building user preference model, standard preference model should be established on the basis of historical data. To take the example shown above, the established user group preference model includes the number of users indicated as $x$ and the service projects as $y$. In the existing standard model, supposing that the number of users is m and n represents the service projects requested by users, and then the preference model of standard user group can be expressed as $S\tan dard_i([P_1, L_1], [P_2, L_2] \ldots [P_i, L_i])$ .After the establishment of the user preference model, the user preference degree can be estimated by computing the preference of the users and the similar ones. The formula that calculates the similarity between them according to cosine similarity is shown as below:

$$sim\left(\overrightarrow{G_i}, \overline{S\tan dard_j}\right) = \frac{\sum_{a=1}^{n} G_a(P_i, L_i) \times S\tan dard_a((P_j, L_j))}{\left|\overrightarrow{G_i}\right| \left|\overline{S\tan dard_j}\right|} \tag{5}$$

As is shown in Formula 5, it computes the similarity degree of the preference between the users and similar users. For a certain user $a$, the standard user group preference model should be looked up thoroughly and then the standard preference model that is similar to this particular user should be found out in order to calculate the similar preference from the standard user group preference model. After discovering the similar preference to the user $a$, the correspondent user group will also be verified. It will be recorded as follows: $\Pr es_i([User_1, S\tan dard_1], [User_2, S\tan dard_2] \ldots [User_i, S\tan dard_i])$. Then it comes to the calculation of the user group preference.

For the calculation of user group preference, one method is based on the property research of user group model. Another one is to obtain the preference information of the user group through the statistical analysis of the preference information of the group members. Though there are lots of methods to calculate the user group preference, this paper adopts the second one. For the second method, first of all, the user group that is similar to the target user should be identified from the standard preference model $\Pr es_i([User_1, S\tan dard_1], [User_2, S\tan dard_2] \ldots [User_i, S\tan dard_i])$, and then the user group preference can be calculated on the basis of the user group collection recorded. Assuming that the number of users is $User_i$ and the preference of user group is $SP([P_i, L_i])$, $total(User_i)$ then indicates the number of users in the user group where $i$ belongs to, and the formula for computing the user group preference that user $i$ belongs to is as follows:

$$S_p([P_i,L_i]) = \frac{\sum_{a\in User_i} G_a(P_i,L_i)}{total(User_i)} \tag{6}$$

In this formula, the user preference is firstly calculated and then comes the total number of users. Finally, the result is obtained. But for the user $i$ , different users have different similarity with $i$ . To begin with, with the help of cosine similarity, the similarity degree should be looked up thoroughly among the members in the user group and then the comparison between the similarity degree of the members and that of user $i$ shall be drawn upon as shown in the following formula:

$$sim\left(\overrightarrow{person_i}, \overrightarrow{person_j}\right) = \frac{\overrightarrow{person_i} \bullet \overrightarrow{person_j}}{\left|\overrightarrow{person_i}\right|\left|\overrightarrow{person_j}\right|} \tag{7}$$

After obtaining the result based on formula 4-7 and the difference between target user and similar user group members on similarity degree, different weight ratio shall be added before similar user group members when computing the user group preference. Since the similarity degree between target user and similar user group members ranges from 0 to 1 as the calculated degree between them is greater than 0, the proportion that similar user group members obtain is distributed based on the similarity degree.

According to the division of the similarity degree into different sections represented by $n$ , supposing that the weight ratio for the user group member whose similarity degree is close to 1 is 1, then in the second section, the weight ratio of the member is $1-t$ . By this analogy, the weight ration of the members in the section n should be $1-(n-1)t$ . Besides, after obtaining the similarity degree between target user and similar user group member through formula 7, the order of the members in the user preference group will be rearranged based on the ascending numerical order of the similarity degree, and the order of the new user group will be shown as $New\left(\left[G(P_1,L_1)\right],\left[G(P_2,L_2)\right]\ldots\left[G(P_m,L_m)\right]\right)$ . As a result, Formula 6 can be further optimized into Formula 8 to calculate the preference value of the new user group.

As is shown in Formula 8, the value of t can be set according to the actual circumstance, and $G(P_i, L_i)$ means that the preference degree of user to service Pi is Li. Such improvement will lead to more accurate calculation of user groups' preference value.

$$S_P = \frac{G(P_1,L_1)*1+G(P_2,L_2)*(1-t)+...+G(P_i,L_i)*(1-(i-1)*t)+...}{\mathrm{total}(\mathrm{User}_i)} \tag{8}$$

Calculation of User Group Preference:

Input: Get $G_a([P_i, L_i])$ ;// Preference of User $a$

Get $\Pr es_i\left(\left[User_1, S\tan dard_1\right],\left[User_2, S\tan dard_2\right]\ldots\left[User_i, S\tan dard_i\right]\right)$ ;// Obtain the preference of standard user group $i$

Output: $S_P$ ;// user group preference

For $i\in n$ ;// $n$ stands for the number of users in the standard user group

$$sim\left(\overrightarrow{G_i}, \overrightarrow{S\tan dard_j}\right) = \frac{\sum_{a=1}^{n} G_a(P_i,L_i)\times S\tan dard_a((P_j,L_j))}{\left|\overrightarrow{G_i}\right|\left|\overrightarrow{S\tan dard_j}\right|}$$

End for // End for loop to find out standard user group similar to the target user

For $i\in n$ ;// n stands for the number of users in the standard user group

$$sim\left(\overrightarrow{person_i}, \overrightarrow{person_j}\right) = \frac{\overrightarrow{person_i} \bullet \overrightarrow{person_j}}{\left|\overrightarrow{person_i}\right|\left|\overrightarrow{person_j}\right|}$$

*Group*

$G[(P_i,L_i)] = New\left(\left[G(P_1,L_1)\right],\left[G(P_2,L_2)\right]\ldots\left[G(P_m,L_m)\right]\right)$;

End for // End for loop, find out the similarity degree between each member in the similar user group and the target user, and then rearrange in a descending order according to similarity degree

$$S_P = \frac{G(P_1,L_1)*1+G(P_2,L_2)*(1-t)+...+G(P_i,L_i)*(1-(i-1)*t)+...}{\mathrm{total}(\mathrm{User}_i)}$$

// Calculate the user group preference, i.e. preference of the target user

### *B. User Preference Update and Cold Boot*

Finishing the calculation of user preference and user group preference, the user model and user preference value previously established wouldn't be able to adapt to the new calculation with the increasing of new data. As a result, it is very important to update the calculation for user preference. This section mainly focuses on relevant algorithm for updating user preference on the basis of the original calculation of user preference.

The record of users' requested service would be stored in the database in chronological order. Let $N$ represents the newly added user service record, $Dim$ refers to the dimensions of user preference in the standard user model, thus the matrix $M[N, Dim]$ is constructed. The following formula 9 indicates the preference degree of the new users.

$$GN(P_i, L_i) = \frac{\sum_{N=1}^{N_{\max}} M_{Nj}}{\sum_{N=1}^{N_{\max}} \sum_{Dim=1}^{Dim} M_{NDim}} \tag{9}$$

As is shown in Formula 9, the denominator refers to the newly added user preference record in the service of category $J$, and the numerator represents the all the newly added users' preference. When building matrix $M[N, Dim]$, $MN_j = 1$ means that the user likes the particular service, and $MN_j = 0$ means dislike. After getting the preference of the newly added user $GN(P_i, L_i)$, the user's update preference will be obtained on the basis of the former user preference, as is shown in Formula 10:

$$GL[P, L] = \alpha G(P_i, L_i) + (1-\alpha) GN(P_i, L_i) \tag{10}$$

Formula 10 represents the newly added preference obtained from the added number of records known as $N$, andα is the weight value.

Cold boot: there are many ways to deal with cold boot, for instance, basing on the combination of collaborative algorithm and project score, adopting data mining etc. In this paper, cold boot will be dealt with by means of creating user group similar to the target user.

Assume that the number of the records for user requested service is $S$, $S_1$ is the threshold of user group preference and $S_2$ is preference threshold of a single user, then the user preference can be demonstrated as:

*1）when* $S < S1$

$h(P_i) = Pg(P)$ $Pg(P)$ *represents user group preference*

*2）when* $S_1 < S < S_2$

$h(P_i) = aPg(P) + b\,Ps(P)$ $Ps(P)$ *represents the user's personal preference*

*3）when* $S > S_2$

$h(P_i) = Ps(M)$

Given that the record of services requested by users is increasing, the personal preference of the users will be increasingly stable and the weight of user group preference required will be smaller. So the formula sets the value of $a$, $b$ .To summarize the personalized recommendation algorithm by combining the space-time dimensional algorithm and user preference algorithm, firstly, the recommendation score is obtained basing on space-time dimension, which is formed by the recommendation score of time dimension and the location information of space dimension. $Service(i) = \alpha ServiceT(i) + \beta ServiceL(i)$ ; secondly, personalized recommendation is calculated as shown in Formula 11 on the basis of space-time dimension and user preference according to the recommendation score of user preference in Formula 4.

$$PU = \lambda \frac{Sim(U(P_i))}{n} + \theta Service(i) \tag{11}$$

As is shown in Formula 11, $\lambda$ and $\theta$ are the weight value. The range of recommendation score of space-time dimensional recommendation algorithm is [0, 10], so is the recommendation score of user preference algorithm. $\lambda$ and $\theta$ ranges from 0 to 1, the value of which can be directly affirmed by input.

## V. EXPERIMENT AND RESULT ANALYSIS

This experiment makes use of the date from the website called DianPing through the technology of web crawler.

*1) Analysis of the users' personalized preference degree*

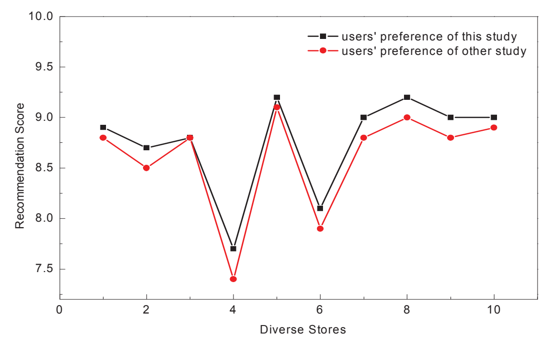


Fig. 1. Comparison of Users' Preference.

To calculate the recommendation score of users' personalized preference, this paper adopts the core algorithm according to the calculation of user preference in Formula 3 & 4. In the second reference, the writer Kuo M H adopts the compensatory recommendation algorithm of users' personalized preference. To verify the accuracy of algorithm in this paper, a comprehensive comparison will be made with the recommendation algorithm of Kuo M H, using the recommendation score as the criteria. The comparison of users' preference is shown in Figure 1.

*2) Analysis & Processing of Space-time dimension and preference degree of users*

To analyze users' personalized preference, this paper analyzes the preference degree of users from the factors of both time and space. Firstly, the information concerning the recommendation score of 20 different stores from the DianPing database is selected; then, the space-time dimension and user preference is calculated based on Formula 11; lastly, the recommendation diagram based on the calculation result of the space-time dimension and user preference is shown in

Figure 2. As is shown in Figure 2, the blue curve stands for the distribution of the recommendation score of the taste service for the listed 20 stores, and the black curve shows the distribution for the recommendation score of the 20 stores on the basis of space-time dimension and the user preference algorithm. Through the contrast of space-time dimension and the user reference algorithm, the feasibility of this algorithm is confirmed.

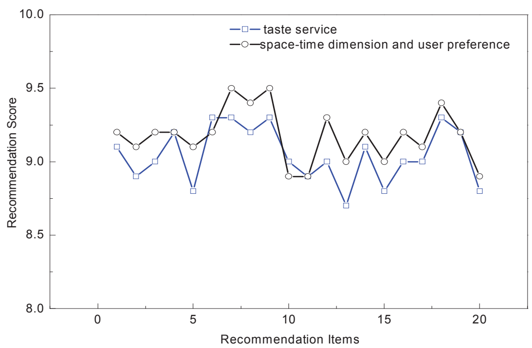


Fig. 2. Comparison between Space-time dimension and User Preference.

*3) Analysis of User Group Preference*

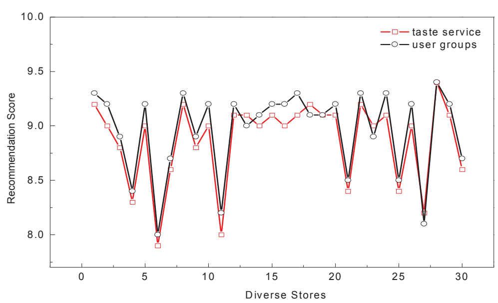


Fig. 3. Recommendation Score for User Groups.

For the recommendation system, the improvement of the recommendation accuracy plays a key role in meeting the users' personalized preference. This paper calculates the errors of the recommendation results brought by the scarcity of data through analyzing similar user groups. A contrast between the recommendation score calculated through Formula 6, 7, & 8 and the recommendation score of the 30 stores randomly selected from the database is shown in Figure 3:

To sum up, seeing from the above experimental analysis, it is feasible to construct the recommendation model based on space-time dimension and the users' personalized preference. Under the condition of space-time dimension, the user preference varies with the changing of time, location, and personal factors. To meet the demands of users' personalized location service, the impact of context factor should also be taken into consideration, with the assistance of analyzing similar user groups.

## VI. CONCLUSION

The main research topic of the modern recommendation system is to meet the users' personalized demands. Starting from the time dimension and space dimension, this paper firstly focuses on the study of the intrinsic relationship between time dimension and space dimension as well as its impact on users' personalized preference. Secondly, the user preference model and update model are constructed on the basis of the historical data to present the algorithm of user recommendation score. The effectiveness of the designed model is also verified by the experimental results.

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