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A Recommendation System using Dynamic Profiles and Relative Quantification

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Abstract

Recommendation systems provide users with proper services using context information being input from many sensors occasionally under ubiquitous computing environment. But in case there isn't sufficient context information for service recommendation in spite of much context information, there can be problems of resulting in inexact result. In addition, in the quantification step to use context information, there are problems of classifying context information inexactly because of using an absolute classification course.
In this paper, we solved the problem of lack of necessary context information for service recommendation by using dynamic profile information. We also improved the problem of absolute classification by using a relative classification of context information in quantification step.
As the result of experiments, expectation preference degree was improved by 7.5% as compared with collaborative filtering methods using an absolute quantification method where context information of P2P mobile agent is used.

Key Words : Recommendation System, Context, Collaborative Filtering, User Profile, Quantification

1. Introduction

Recommendation systems use collaborative filtering methods in order to recommend good quality information to users[1-4]. As collaborative filtering methods need to have enormous memory because of recommended information of various users, it is difficult to use them for mobile equipment under ubiquitous environment. We can solve such problems using collaborative filtering by means of quantification of real time context information in the pure P2P[5]. But in order to provide exact recommendation, we have to solve following problems. First, even though much context information is inputted, if context information for recommendation is not sufficient, the result can be inexact. Second, there is a problem of classifying information inexactly because of absolute classification methods in the quantification step. For example, as methods of classifying age, methods of classifying age by 5 or 10 year units are used. But such methods are one-sided classification method not considering user's age. For example, a 30-year-old person has characteristics of those in their late twenties and those in their early thirties, so it is not proper to classify the person as 30-year-old group simply.

In the paper, under ubiquitous environment, we would like to propose a recommendation system using dynamic profiles and relative quantification to provide users with proper real time services. In order to solve two problems mentioned in the above, we proposes the following methods.

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First, in order to solve problems of having inexact result because of lack of contexts, we used dynamic profile information where users' service history information is saved. Second, in order to solve problems of absolute classification method, we used relative classification method.

We described relevant researches in chapter 2, recommendation system using dynamic profile and contexts in chapter 3, contents of experiment and evaluation in chapter 4 and conclusion in chapter 5.

2. Related Works

2.1 Context

Definition of context means users' ID, location, time, behaviors, emotion, environment, occupation and continuous changes of such information under the user's environment[6]. Schilit of Xerox PARC defined context as identity related to users and objects, and object information and Abowd of GATECH defined it as every information related to an individual such as users, spaces, objects and etc.[7, 8].

The course to acquire such context is called as context-awareness. Context-awareness systems are divided into the system grasping users' context through sensors around the users and providing proper services according to acknowledged context information and the system changing the execution condition or surrounding environment, etc. voluntarily and properly for context.

There are several context awareness systems as Context Toolkit[7], TEA(Technology for Enabling Awareness)[9] and ubi-UCAM(Unified Context-aware Application Model)[10], etc..

In order to make formation and services of application programs easier, Context Toolkit divided the course of acquiring context information at context awareness application. TEA used methods of changing and storing information acquired from a sensor to the form of context profile, and ubi-UCAM described a standardized context-awareness application model for development of harmonious services at ubiHome, the bed for texts under smart home environment.

Recently contexts are used for recommendation system to minimize users' burden under ubiquitous computing environment.

2.2 Collaborative Filtering

Recommendation systems are systems to recommend goods or items that users want using their preference. In the recommendation system, methods of collaborative filtering, contents-based filtering, demographical filtering and etc. are used. Among them representative technology is just collaborative filtering method.

Collaborative filtering method presupposes the degree of similarity using users' information. As formulas being used for predictability, there are methods such as Pearson Correlation Coefficient and Adjust Cosine Similarity, etc. As methods to calculate predictable proper number of people, methods of Best-n-neighborhood or Thresholding are used[2, 11].

It is a method to calculate proper neighbors using similarity and then to presuppose users' preference as to the item they want, based on similar users' preference[2, 12, 13].

2.3 User Profiles

In the profile of users, basic information of users and interesting items of them, etc. are saved, using survey or log information. Among user profiles, there are static profiles acquired directly from users and dynamic profiles acquired from users' movement patterns, etc[14]. In static profiles, name, sex, marital status, address, zip code, telephone number, occupation, age and etc. are saved; in dynamic profiles, recommendation time, route of local movement, serviced information, browsing methods, frequency of visit to homepage and staying time, etc. are saved.

Recommendation system provides users with proper presupposition services, using these user profiles.

2.4 Quantification

In order to use real time context information being acquired for collaborative filtering, it is necessary to convert the information into numeric value, such work is called as quantification. An example of arranging context information in a table is as follows.

If we quantify context information being expressed as above in numeric value, it can be expressed as Table 3.

Table 2. Context Information

User \ Item	Age	Sex	Companion	Time
User 1	18	M	Friend	Midnight
User 2	22	M	Lover	Afternoon
User 3	25	F	Single	Evening
User 4	32	F	Friend	Evening
Service User	29	M	Lover	Evening

Table 3. Quantified Value

User \ Item	Age	Sex	Companion	Time
User 1	4	5	3	4
User 2	4	5	5	5
User 3	5	4	4	4
User 5	5	4	3	4
Service User	5	5	5	5

3. Recommendation System using Dynamic Profiles and Context

In case there is insufficient context information being collected from sensors, the recommendation system that is proposed in this paper performs quantification courses by unifying users' profile and users' context information. But in case there is sufficient context information, the system performs quantification courses only using context information. Then by using quantified information in the course of collaborative filtering, the system recommends proper services to users. Fig. 1 is a flow chart of a system.

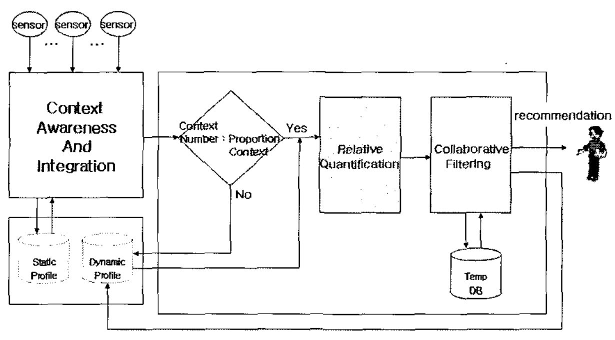

Fig. 1. System Flowchart

The course of recommending services to users using real time collected context information and users' profile information like Fig. 1 is as follows.

A. To be aware of context information being collected from outside sensors and unify it.

B. In case that the context information is proper for analysis, to perform course of "C". But in case that context information is not sufficient, to extract service history information from dynamic profile among users' profiles and then to perform course of "C".

C. To perform relative quantification course according to determined standard.

D. To recommend proper services for users by means of collaborative filtering of quantified result and then to save recommended information in dynamic profile.

3.1 Context Awareness and Integration

In the course of awareness and integration of context, to do works of awareness and classification in order to use users' context information from sensors.

The step to be aware of context is the one to confirm users by reading users' static profile and in the integration course of context, unnecessary context is filtered. In addition, if context information is insufficient, false result may be made, so it is necessary to collect context information from outside users.

In this paper, we gives examples of recommending movies in consideration of companions or watching time, etc. Necessary context information for that time is as Table 4.

Table 4. Context Information for Service

Context Type	Contents
ID	User Name
Age	Age
Sex	Man or Female
Classification	Genre
Place	Service Place
Time	Service Time
Companions	Lover, Friend, Family etc.
Service	Service Item

3.2 Dynamic Profile

Proper number of context can be different according to situation, but in this paper, it is determined as 20 for convenience of experiment. If context is not sufficient, dynamic profile information is used. Retrieved dynamic profile is feedback information being serviced previously that saves context information of service situations. Context information being saved in dynamic profiles is also like Table 4.

We can solve problems of insufficient contexts being necessary for service recommendation by using accumulated information of dynamic profiles.

3.3 Relative Quantification

The absolute quantification had problems that context information was classified in improper group. In order to solve them, in this study, we proposes relative quantification that classifies information relatively centering on users to receive services.

For example, classification method by means of absolute quantification that is used generally for object of age is as Table 5.

Table 5. Absolute Classification

Index	Age Classification	Number of Persons
1	~10	19
2	20~29	52
3	30~39	45
4	40~49	26
5	50~59	6
6	60~	2

Although a 20-year-old person may have consensus with people in their early twenties or those in their late tenth, the person belongs to the group of 20-year-old people unconditionally according to absolute quantification and receives influence of consensus of people in their twenties. In order to solve such problems, if we use relative methods on the basis of age of users to receive services, the person can belong to people with similar disposition to him.

For example, we can see that if a service requester's age is 20, the person is classified relatively as Table 6.

Table 6. Relative Classification

Index	Age Classification	Number of Persons
1	~15	8
2	16~25	49
3	26~35	61
4	36~45	23
5	46~55	6
6	56~	3

This is to select a method to allocate bigger score as the age difference from the age group to receive services is smaller and smaller score as the age difference is bigger because interest in movies is different according to age.

3.4 Collaborative Filtering

In this study, we corrected collaborative filtering from methods of comparing items with existing users to those of comparing contexts, but there is no change of the numerical formula used.

Collaborative filtering can make presupposition only when evaluation items of other customers with similar preference exist to some extent on the basis of users' evaluation value. However in collaborative filtering methods using context information, it is possible to provide a service requester with recommendation service using other context information if there is only one serviced item of same kind. Of course, insufficient context information can make inexact result.

A formula of similarity using context information is as the following Formula 1.

$$W_{x,y} = \frac{\sum_{a=1}^{n}(r_{x,a}-\bar{r}_x)(r_{y,a}-\bar{r}_y)}{\sqrt{\sum_{a=1}^{n}(r_{x,a}-\bar{r}_x)^2}\sqrt{\sum_{a=1}^{n}(r_{y,a}-\bar{r}_y)^2}} \quad (1)$$

$W_{x,y}$ is context information being evaluated by user x and user y, and $\bar{r}_x$ is evaluation average for overall context information of user x. $r_{x,a}$ is evaluation value for context information a by the user x and n is the total number of context information.

After calculating similarity, we can calculate neighbors using Best-n-neighborhood method. After calculating formula of similarity and the number of neighbor, we presuppose value, and the prediction formula is as Formula 2.

$$P_{x,b} = \bar{r}_x + \frac{\sum_{y=1}^{n}(W_{x,y})(r_{y,b}-\bar{r}_y)}{\sum_{y=1}^{n} W_{x,y}} \quad (2)$$

$P_{x,b}$ is presupposition value of preference to the user x and service item b and $\bar{r}_x$ is average of preference of the user x. $W_{x,y}$ is weight of similarity between the user x and the user y, and $r_{y,b}$ is evaluated value of service item b by the user y. $\bar{r}_y$ is average of the user y's preference, and n is the number of determined neighbors.

If we apply the above formula to quantified value, we can recommend service information by referring to the user with greatest similarity to the service user. Accordingly, service users can receive qualitatively improved services.

3.5 An example of recommendation using collaborative filtering

> Early in the morning in Sunday, Gildong decided to see a movie with his girl friend at a multiplex cinema. Because Gildong and his girl friend don't have overall knowledge of movies, they want a movie recommendation service using mobile equipment.

In order to do service recommendation using mobile equipment on the basis of the above scenario, it is necessary that information of evaluation by users who have seen movies should be saved in a server or mobile equipment either by numerical value or letters. But it is very difficult to receive evaluation information from users and save it in mobile equipments. Therefore, we can recommend service information to users who want services by means of comparative evaluation, using context information of users who have seen movies.

If it were possible to get only titles of movies from users who have seen movies first as Table 7, it would be difficult to use collaborative filtering method because of insufficient information. For collaborative filtering compares and evaluates users with similar preference to the users to receive services on the basis of users' evaluation value, but only with information in Table 7, it is difficult to make presupposition. In Table 7, users mean those who have seen movies actually and service users mean those to receive services actually.

Table 7. Service Items per User

Item / User	Service
User 1	The War
User 2	Son
User 3	Breath
User 4	Double Ticket
User 5	Robinson's Family
Service User	

In order to solve such problems, if we make recommendation by generalizing general context information together with titles of movies being seen by users, we can provide more exact recommendation service. Table 8 is an example of users' context information and service information.

Table 8. Users' Context Information and Service Information

Item / User	Age	Sex	Fellow Travelers	Time	Service
User 1	45	M	Family	Morning	The War
User 2	25	F	Friend	Evening	Son
User 3	19	F	Single	Evening	Breath
User 4	31	M	Lover	Evening	Double Ticket
User 5	25	M	Companion	Afternoon	Robinson's Family
Service User	21	F	Friend	Afternoon	?

Because only with context information as Table 8, it is difficult to use it for collaborative filtering, it is necessary to have relative quantification course of changing it as numerical value such as users' evaluation value. In Table 9, we can see that a person in his twenties has different evaluation value from people belonging to the same age group, but he has same evaluation value as people in their early thirties.

Because there aren't great difference between male and female as to taste of movies according to sex, we allocated 5 to the same sex and 4 to the opposite sex. In the case of companions, the result was made by comparing relation of upper item as the result of making respondents select the genres they want to see the most at a survey. We could find that on the basis of 'none', as we moves toward 'colleagues' and 'friends', the preference was closer to action and comedy, and 'lover' was closer to romance and drama, and 'family' was closer to family drama or drama. According to intimacy, scores from 1 to 5 were allocated. As the result of a survey, companions showed bilateral ties in the order of 'colleagues'-'friends'-'none'-'lover'-'family'.

We could find that although movie watching time has less relation than companions, there is still relation. As time is closer to forenoon, movie watchers preferred action and comedy, and as time is closer to midnight, they preferred romance or horror movies, but watching time showed less intimacy than companions, so we assigned scores from 1 to 4.

If a movie watcher sees a movie early in the morning on Sunday and real time context information of users is not sufficient, we can use dynamic profile information in the same way as real time context information.

Table 9. Improved Quantification

Item / User	Age	Sex	Fellow Travelers	Time	Service
User 1	3	5	2	3	The War
User 2	5	4	5	4	Son
User 3	5	4	4	4	Breath
User 4	4	5	3	4	Double Ticket
User 5	5	5	4	5	Robinson's Family
Service User	5	5	5	5	?

In Table 9, if the service user does collaborative filtering with other users, the service item of user, Robinson family with the most similarity with him is recommended to him.

4. Evaluation

In this paper, in order to evaluate functions under environment of Pentium IV, 2,8Ghz, 512MB, we designed experiment using C#, J2ME, and WIPI.

Although it is easy to get data set in EachMovie[15] or MovieLens[16], items to judge users' context information being necessary for experiment are insufficient, so we did survey for 241 males and 186 females, totaling to 427 and the made evaluation.

As necessary context information for services among the result of the survey, we used ID, age, genre, service, companion, time, sex, and place. Among them, we checked similarity using age, companion, time and sex. Because age has much relation, it was easy to quantify it, but because it was not easy to quantify relation of companion, time and sex, we investigated mutual relation with contents of the survey.

In order to evaluate accuracy of presupposition, as an evaluation formula in this paper, we used MAE(Mean Absolute Error). In the following formula, v_i is presupposed preference, r_i is actual preference and N is the total frequency of presupposition. MAE means average presupposition error that has occurred for the total frequency of presupposition. It means that the smaller the error is, the greater the preference is.

$$|E| = \frac{\sum |v_i - r_i|}{N} \quad (3)$$

As the result of an experiment in this study, we can see that the "Collaborative Filtering Method Using Context of P2P Mobile Agents"(CF_P2P)[17] using relative quantification method (CF_CI) and absolute quantification method shows low expectation value as the number of users is smaller as shown in Figure 2, but as the number of users is increased, the expectation value becomes higher. But in case the number of users is increased to more than 40 persons, the expectation value becomes low slowly.

As the result of experimenting on the relative quantification method proposed in this paper (CF_CI), errors were reduced by 0.039 or so in average than GroupLens method (CF_GL) and about 0.013 in average than the result of CF_P2P, which we can see in Fig. 2.

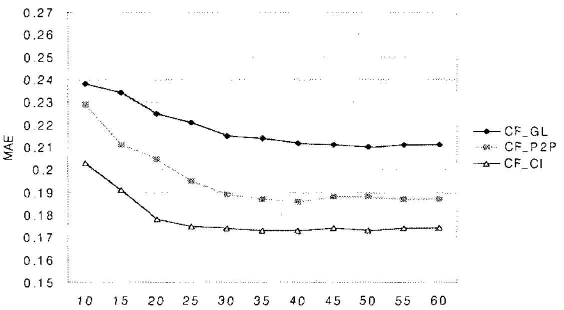

Fig. 2. Comparison According to Number of Users

5. Conclusion

Recommendation systems in ubiquitous environment recommended services to users by quantifying real time collected context information and then by doing collaborative filtering. But in case context information to be used for service recommendation is not sufficient in spite of much context information being input, there were problems of reducing accuracy of recommendation. In addition, in the quantification step to use context information, absolute classification course was used, causing problems of inexact classification of context information.

In this paper, in order to solve above problems, we solved the first problem by using dynamic profile information and the second problem by using relative classification method, so we could improve the possibility of being included in inexact group.

As the result of an experiment using CF_CI according to a proposal in this study, the researcher could find that the result was improved by 0.013 than CF_P2P using absolute quantification method. It is an average obtained by calculating difference between the expectation value using CF_CI and that using CF_P2P as to the number of users. When the researcher calculated percentage of CF_P2P and CF_CI using this value, the researcher could confirm that CF_CI showed improvement of 7.5%.

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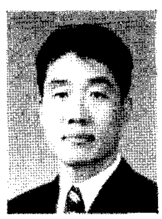

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