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Personalized advertisement system using social relationship based user modeling

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Abstract The influence of social relationships has received considerable attention in recommendation systems. In this paper, we propose a personalized advertisement recommendation system based on user preference and social network information. The proposed system uses collaborative filtering and frequent pattern network techniques using social network information to recommend personalized advertisements. Frequent pattern network is employed to alleviate cold-start and sparsity problems of collaborative filtering. For the social relationship modeling, direct and indirect relations are considered and relation weight between users is calculated by using six degrees of Kevin Bacon. Weight '1' is given to those who have connections directly, and weight '0' is given to those who are over six steps away and hove no relation to each other. According to a research of Kevin Bacon, everybody can know certain people through six depths of people. In order to improve prediction accuracy, we apply social relationship to user modeling. In our experiments, advertisement information is collected and item rating and user information including social relations are extracted from a social network service. The proposed system applies user modeling between collaborative filtering and frequent pattern network model to recommend advertisements according to user condition. User's types are composed with combinations of both techniques. We compare the performance of the proposed method with that of other methods. From the experimental results, a proposed system applying user modeling using social relationships can achieve better performance and recommendation quality than other recommendation systems.

Keywords Collaborative filtering · Recommendation system · User modeling · Social relationship · Social network

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1 Introduction

With tremendous popularity of smart devices such as smart phones or smart pads, the number of social network users has exponentially increased. Most users exchange their knowledge, ideas, opinions, and experiences about products, contents and services on social network services (SNSs) like Facebook and Myspace. Normally, users find necessary information from search engines like Google and Yahoo. However, they trust information obtained from their friends including social network friends when they want to find important or exact information [15, 29]. In other words, users seek opinions of close friends including social network friends rather than traditional search results when they purchase products like books and music, decide to visit a restaurant that serves delicious food, and choose a movie [7, 22, 26, 32, 33]. Information and relationships on social network give us an opportunity to identify the influence of social relationships in recommendation systems [2, 14, 24].

Social relationships can be applied to TV advertisement recommendation. TV advertisement exposure is broadcasted over smart TV, IPTV and VOD services. However, broadcasted advertisements are not effective because user preferences are not considered and those advertisements cannot attract user's interests. Content providers or advertisers are now beginning to study how they make a profit through advertising exposure to users. With the emergence of interactive TV, they can provide personalized advertisements in addition to content personalization. Normally, appropriate recommendation methods should be applied with users who use different types of service like Smart TV, IPTV, and VOD. However, we treat all the users in same manner under the assumption that the users using Smart TV, IPTV and VOD services watch video contents through smart device such as smart phone and smart pad. In order to provide personalized advertisements, the following points are normally considered.

1. Who are target users for advertisement?
2. How a system knows user preferences from the actions that users watch advertisement?
3. How to recommend users appropriate advertisements?

If advertisers define their target audience, then recommendation systems can easily handle the first consideration. From implicit and explicit feedback, the systems can determine the user preferences for each advertisement. Implicit feedback is updated by monitoring user behaviors such as time users spend or moving to related e-commerce web sites during providing advertisements. On the other hand, explicit feedback means that users indicate their preference for specific advertisement by rating a score from 1 to 5. Recommendation systems deal with last consideration by predicting user preferences on each advertisement based on the user group that has similar preferences.

In this paper, we propose a personalized advertisement recommendation system based on user preference and social network information. The system employs collaborative filtering (CF) and frequent pattern network (FPN) [18] to recommend personalized advertisements. CF, which is one of the information filtering techniques, became one of the most popular and effective techniques in recommendation systems after the GroupLens project [23, 25]. CF based recommendation systems predict user preferences for items based on users that have similar tendencies and some of them use social influence to their systems [17]. Some commercial web sites like Amazon.com and Netflix.com employ CF in their recommendation systems. Amazon.com recommends related goods to users based on past purchase information of users [30]. Netfilx.com provides online movie recommendations based on user movie ratings [3]. Also, Google News Personalization, which is an automated online news service, has employed a CF method to provide personalized news that is apprzaopriate for users [9]. However, predictions on unrated items can be incorrect if users just rate few items. CF also has the limitations as followings.

1) Cold Start Problem: It is not easy to predict item preferences for new users because recommendation systems cannot construct appropriate nearest neighborhood based on their few ratings.
2) Scalability Problem: If a recommendation system deals with too many users or items, it is difficult to build nearest neighborhood quickly because the system should calculate all similarities between a target user and others. It requires much time and consumes many system resources.
3) Sparsity Problem: In some cases, distribution of user-item rating matrix is too sparse due to few ratings or sparse ratings. A recommendation system cannot construct good enough nearest neighborhood because the number of concurrently rated items between users is quite small. Correlation between users then can be distorted and preference prediction on unrated item can be incorrect.

In Smart TV environment, many contents are frequently inserted and there are a huge amount of contents. This makes scalability and sparsity problems more severe. In order to solve these problems, we need effective recommendation techniques. We try to alleviate the problems like the cold-start and sparsity by applying social network-based CF and FPN methods. Normally, it is possible to provide good enough recommendation by using social relationship because friendly relations on social network are based on reliability about other users [14]. Using social network friends in CF can somehow solve the scalability problem because CF system just deals with friends of target user instead of using all users to extract nearest neighborhood. Although this approach can alleviate the scalability problem, it is difficult to construct nearest neighborhood if a target user has few friends. There still remain other two problems. If a target user has many social network friends but the user has rated few items or is the beginning user, then system cannot solve two residual problems. We apply a FPN technique for users who just rated few items. FPN is a new method to generate association rules, and the FPN based association-rule mining processes is more efficient than Apriori algorithm. Apriori algorithm is not flexible enough because the system repeats the same mining process with the change of minimum support or the update of user transaction. FPN uses network structure to flexibly handle minimum support and continuously updated user data. Once FPN is constructed based on the advertisement preferences of users, we generate association rules from FPN. We use the association rules to recommend advertisements if a user have few item ratings or few familiar friends on the social network.

The remainder of this paper is organized as follows. In Section 2, we describe related works. Then, we propose a personalized advertisement recommendation system based on social networks in Section 3. In Section 4, we present the experimental environment and evaluate the experimental results. Finally, we give our conclusions and discuss on the direction of future work.

2 Related works

Interactive TV such as IPTV and smart TV gives many researchers good environment to get and analyze user behavior and information on TV. For personalized TV program recommendations, some studies have focused on using the preference analysis of TV viewers to the recommendation systems [35, 37], and how recommendation systems utilize the user interaction with TV contents [27, 34]. The interactive TV also has influenced the advertisement market. [1, 16, 20, 28] have introduced various methods based on existing user preferences for advertisements.

[34] has developed an advertisement model that provides spontaneous and personalized advertisements. Advertisers semantically annotate their product that appeared in the contents of MPEG-7 format. A viewer watches contents without any interruptions caused by advertisement pop up. If the viewer is interested in some products, then the viewer may interact with the products on the screen. The developed system then provides personalized advertisement information through interactive services based on the user profile of the viewer. Through this approach, advertisers can reach those who are potentially interested in their products and the viewers will view the advertisements as a valuable service without any inconvenience. However, it is difficult to create a scheme related to various objects and to annotate all products at corresponding locations and frames. This approach also does not consider the social relationships among viewers.

Advertisers can easily obtain user information and feedback from interactive TV. This information makes it possible for advertisers to recommend personalized target advertisement to users. [20] proposed an ontology-based personalized target advertisement (PTA) system. Each user has an ontology-based user profile and is classified into a predefined stereotype group by calculating the similarity between the user and groups. After allocating suitable group to each user, the system tries to match the TV contents consumed by the group and advertisements using a similarity measure based on their metadata. Finally, the matched advertisements are recommended to the target user. However, the performance of personalized advertisements depends on the accuracy of user classification for the predefined stereotype. Also, although an advertisement is related to TV contents, the recommended advertisement in some cases is not suitable for a target user because personalized advertisement recommendations are only based on the contents consumed by a group that the user belongs to. Consequently, it is difficult to provide complete personalized advertisement recommendations. Unlike the PTA system, we use rating information for advertisements and social network information to recommend personalized advertisements that users have not yet rated.

[10] proposed a social network-based advertisement recommendation method using individual user social information and behaviors. They have applied three kinds of mechanisms such as CF, content-based filtering and social filtering. First, they constructed user profiles based on rating histories of advertisements and performed content-based filtering process. CF is then applied for considering relationships between users. Finally, they predicted advertisement preferences of a user by using social filtering based on user's social behavior. They could solve the sparsity problem and improve the performance of social advertising through proposed hybrid filtering methods. Although they do not treat the beginning user directly, they proposed two methods to handle cold-start problem. Commonly, new users are required to input personal information (e.g., address, city, sex, education, and other basic information) and interest (e.g., music, movies, reading, and other leisure pursuits). The first method is to analyze user interest and contents, and the second method is to select top-k nearest neighbor after user clustering based on personal information to predict user preferences. Similarly, we consider user's personal information and interest in this research. This information is used to cluster similar users and construct FPN based on a given cluster to generate association rules for advertisements.

3 Personalized advertisement system based on social network information

Facebook is one of social network services. We use basic information like birthdate, gender, name and e-mail, and activity information such as user's interest, friend list and friends' interest by requesting the authority of user accounts. Relations between users in Facebook are identified by using friend list but extracting friend list of friend using Facebook API depends on a right of access. We identify relations between users and construct relation graphs by combining user's friend list under the assumption of six degrees of Kevin Bacon [38, 40]. The promise means that everyone can know any individual within six steps.

3.1 System architecture

Our proposed system is composed of two parts as shown in Fig. 1. We provide advertisements to a user before contents are started. The user can click on the advertisement product interested in. If the user wants to view detailed information about the product, then it is possible to visit a web site to see the information.

In order to recommend personalized advertisements to a TV viewer, the system utilizes CF and FPN techniques based on user profiles, social network and advertisement information. As mentioned in introduction, we treat all the users who use Smart TV, IPTV and VOD services, in same manner.

The proposed system consists of three layers as shown in the right side of Fig. 1. The key functions of each layer are described below.
Resource Manager Layer consists of three managers:

1. User Profile Manager: It manages personal information of TV viewers who use Facebook. Basic information such as gender, age and job is contained in the personal information. A user profile also includes the preference of specific advertisements that user have watched.
2. Social Network Manager: It handles the user's SNS URL and ID. The proposed system gets the friends list from the user information of SNS and identifies relationships between social network users. Afterwards, the user modeling layer uses the information of the social network manager.

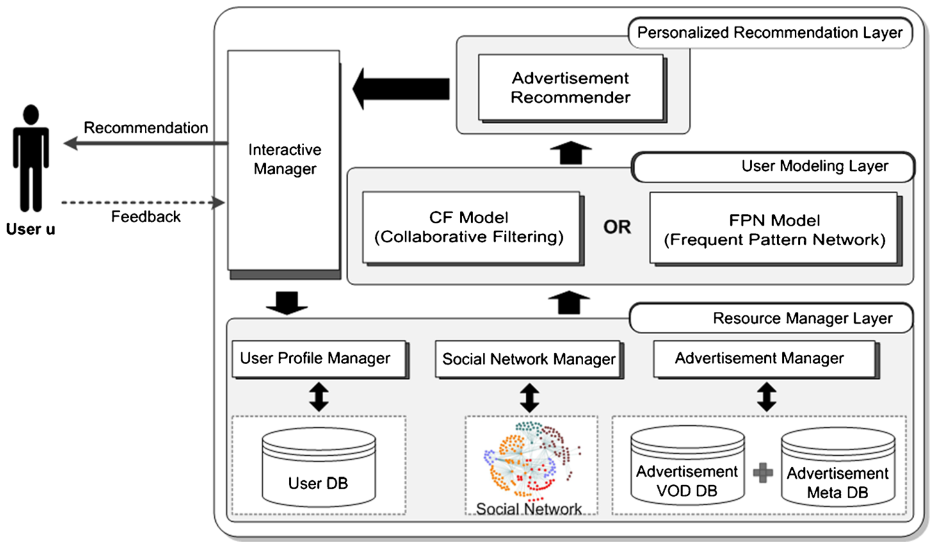


Fig. 1 Personalized advertisement recommendation system architecture

3. Advertisement Manager: We collected advertisement information from the Advertising Information Center (ADIC) of Korea Federation of Advertising Associations (KFAA) and categorized advertisements based on a classification system of ADIC. The information acquisition program provides advertisement information obtained from the advertisement manager when participants rate advertisement they have seen. Advertisement information also is used at the user modeling layer.

The User Modeling Layer consists of two models to predict the preference of advertisements that users have not yet seen.

1. CF Model: We build CF user model using the preferences on items users have rated. The proposed system recommends personalized advertisements to users through built CF model and updates user model using user feedbacks in CF model.
2. FPN Model: Our system utilizes the FPN model to recommend advertisements based on association rules generated from FPN if user condition is not suitable to apply CF model. FPN model constructs FPN based on the preferences, which are obtained from User Profile Manager, and social network information of Social Network Manager. The association rules are generated from FPN based on the given minimum support and minimum confidence thresholds. The discovered association rules are used for the personalized recommendations when our system requires FPN model for a target user.

The Personalized Recommendation Layer chooses one model from the user modeling layer, which is suitable for the current user. The main criterion to decide a user model is user cases. All users are classified into each user case depending on user condition for rating and social network information. The details of user cases will be described in Section 3.4.

The Interactive Manager interacts with user requests and responses at the Smart Client. If a user want to know detailed information of products, then the manager provide web sites to the user. The manager receives user feedback and updates user profiles.

3.2 CF model based on social network

CF system predicts user preferences for new or unrated items based on user preferences and neighbors who share similar interests with the user. Indeed, a great number of people exchange their reviews and experiences on specific items. They reflect reviews and experiences of friends if they purchase or select specific items. We can say that CF is an algorithm for automating the "Word Of Mouth (WOM)" process [36]. WOM is recognized as one of the most influential resources of information delivery and many researchers have utilized WOM information in their studies [5, 13, 31]. In the proposed CF model, we predict item preferences based on users and their neighbors on the social network, and recommend personalized advertisements to users. The proposed CF process is shown in Fig. 2.
The CF process is performed as followings.

1. Participants evaluate each advertisement they watched via the information acquisition program. The rating scale is from one to five. Our system constructs user profiles based on the social network information and user rating.
2. The similarities between all pairs of users in our CF model are calculated by using Pearson's correlation coefficient which is presented by Eq. (1).

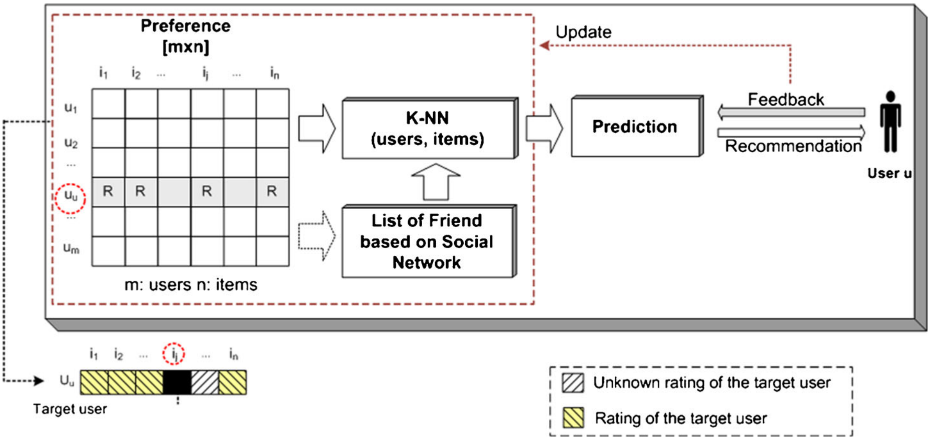


Fig. 2 Social network based CF model

$$w_p(a,i) = \frac{\sum\limits_{j\in \text{Commonly Rated Items}} \left(r_{aj}-\overline{r_a}\right)\left(r_{ij}-\overline{r_i}\right)}{\sqrt{\sum\limits_{j\in \text{Commonly Rated Items}} \left(r_{aj}-\overline{r_a}\right)^2 \sum\limits_{j\in \text{Commonly Rated Items}} \left(r_{ij}-\overline{r_i}\right)^2}} \tag{1}$$

$w_p(a,i)$ denotes similarity between two users a and i. a is a target user and denote one of the nearest neighbors. r_a means a score of an advertisement that the target user rated, and the average score of advertisements that the target user rated is represented using $\overline{r_a}$.

3. A prediction of an unrated advertisement is performed using Eq. (2) based on the user similarities and rating values of the nearest neighbors for the same advertisements. The nearest neighbors are determined by computing the similarities between a target user and the user's friends on the social network.

$$r_{aj} = \overline{r_a} + \frac{\sum\limits_i w(a,i)\left(r_{ij}-\overline{r_i}\right)}{\sum\limits_i |w(a,i)|} \tag{2}$$

After preference prediction of all unrated advertisements, the Top-N advertisements that have high prediction values are recommended to the target user.

4. A user rates a value for the recommended advertisements as feedback. The user rating is used for updating the user model to improve recommendation performance.

3.3 FPN model based on social network

As mentioned in the introduction section, FPN is used to generate association rules based on user transactions. All rated advertisements of a user become a user transaction for constructing FPN. The FPN model is used to solve cold-start and sparsity problem because the CF model does not work well if the number of user ratings is small. We define the threshold as the adequate number of user ratings in order to select an appropriate user model. The FPN model is performed if a user does not satisfy the threshold value. Our system uses FPN model for another case that a user has no or few friends on the social network. Since our recommendation is made for users based on social network information, if the number of friends on the social network is not enough to make the nearest neighbor group, then our recommendation system can not apply the CF model in advertisement recommendation. The FPN model is used for a target user who does not satisfy the CF model condition, and recommend the appropriate advertisements based on items that the user rated and association rules discovered from FPN. Figure 3 shows the process of FPN model.

The FPN model consists of an association rule generation module and an advertisement recommendation module. FPN is constructed by using the advertisement preferences that Facebook users have rated. The set of advertisements that a user rated is used as a transaction in the FPN model. The user preference matrix in Fig. 3 represents the entire user transaction. In the FPN model, we classify user groups using user profiles and construct FPNs for each group. After constructing each FPN, the association rule generation module finds frequent patterns from FPN based on the minimum support threshold and discovers the association rules that satisfy the minimum confidence threshold from the frequent patterns. All association rules for each user group are saved separately. We divided the participants into 18 groups based on gender and age obtained from the user profile manager of the resource manager layer. Age groups are divided into teenagers, twenties, thirties, forties and elderly of age over fifty. However, if a target user has many friends on social network, then we construct social network friends-based FPN and generate association rules from the FPN.

In the FPN model, our system recommends advertisements by using the discovered association rules and past user preferences. Based on advertisements users rated, the advertisement recommendation module extracts the association rules satisfying that a subset of rated items is the premise of an association rule and unrated items are the conclusion of the association rule. All rules are extracted from transactions of the relevant groups a user belongs to, or user friends. If the number of extracted rules is over the number of advertisements that will be recommended

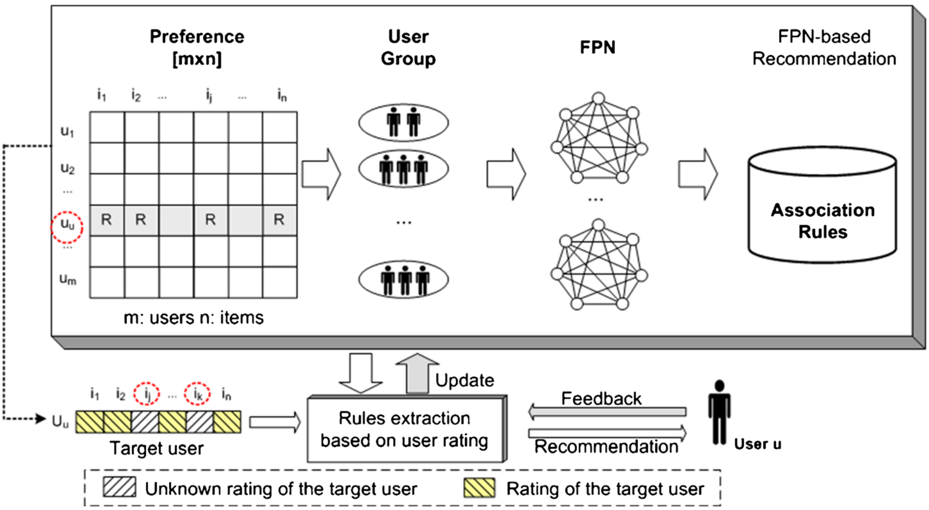


Fig. 3 Social network based FPN model

to a user, then the proposed system applies Top-N advertisement recommendation. Top-N advertisements have high prediction values compared with other advertisements. If the number of rules is small, then our system extracts more rules from extended groups. For example, there is a user who is a man in the twenties. The FPN model tries to find rules from the group of men in twenties. If the number of rules is less than N, then the FPN model supplements rest rules from the twenties by extending user group. User feedback is used for updating the FPN model like CF model.

3.4 Personalized advertisement recommendation system based on social network information

To effectively recommend personalized advertisements, we combine CF and FPN models. Normally, the performance of CF based recommendation systems depends on the number of rated items and the nearest neighbors. By using social network information in CF model, we can improve advertisement recommendation performance. If the number of commonly rated items between the users is small, then it is difficult to find the good enough nearest neighbors. The proposed system also cannot organize the nearest neighbors if the target user has few rated items. In case of users having few social network friends, we will get same results compared with traditional CF model if we only use CF model for recommendation process. Although, a user has sufficient item ratings and social network friends, it is not easy to solve the cold-start and sparsity problems. In order to alleviate the problems, we apply the FPN model instead of the CF model when the number of user ratings is not sufficient or our system cannot construct satisfactory nearest neighbors. Finally, our system can improve the recommendation performance by solving cold-start and sparsity problems based on FPN, and enriching nearest neighbors based on social relationships between users.

Figure 4 shows the flow of social network based advertisement recommendation. Let α be the appropriate number of advertisements that a user has rated. In MovieLens project, every user has rated at least 20 movies and data sets are spilt into training and test data.

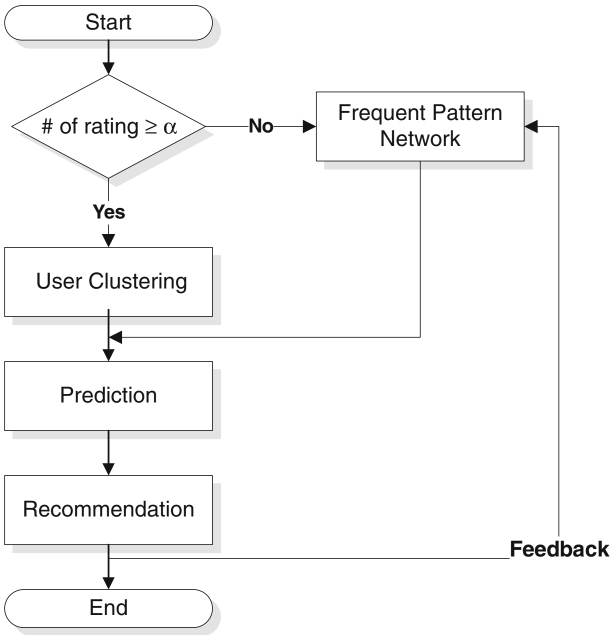


Fig. 4 The selection of recommendation model

Training data occupies 80 percentages. By considering this, we define that a threshold value of α is 15 to apply CF model to recommend advertisements. If the number of rated items is over α, then we use the CF model. If not, then the FPN model is applied to the target user.

We classify the users into four categories based on the number of rated advertisements and friends on the social network. Tables 1 shows the criteria of classification and used model with each case.

The details of each case are as follows.

1. Users who have many social network friends and sufficient rating information: A target user meets the requirements to be applied to the social network-based CF model. The CF model constructs nearest neighbors based on social network friends of the user, and then it calculates the prediction values of advertisements not yet rated by the user. Finally, Top-N personalized advertisements are recommended to the user.
2. Users who have few information on the social network and insufficient rating information: In this case, the users have enough information, but some of the user's friends have few items rated. If a target user has few friends on social network, then proposed system finds some of nearest neighbors from the friends and fills rest of the neighbors using traditional way. Then, the system recommends advertisements that have high prediction values.
3. Users who have many friends on the social network and they have sufficient rating information, but the users have few ratings on items: Although a target user has a profile with a friend list and the friends evaluate enough advertisements for CF, we apply the FPN model if the user has few rated advertisements. The social network-based FPN finds the association rules from the friend group and then it recommends advertisements using the rules which the premise of the rules is some of advertisements user ratted. However, if our system cannot match the rules and user ratings, then the system extends the scope of the rules by using the user profile.
4. Users who have few friends and insufficient rating information on the social network, and the users also have few ratings on items: In the case of a beginner, the FPN model recommends advertisements to the user using the association rules of the group that users belong to in accordance with the user profile such as age and gender, because the user has rated only few items and the system cannot get the nearest neighborhood.

4 Experiments and results

4.1 Experimental environment

In order to evaluate the proposed method, we obtained the dataset from Facebook as SNS and ADIC, as mentioned in Section 3.1. Advertisement information is provided by ADIC

Table 1 Select one of module on a case-by-case

Case	Target User # of rating≥α	Target User A lot of Friends	Friends # of rating≥α	Model
1	O	O	O	CF
2	O	X	X	CF
3	X	O	O	FPN
4	X	X	X	FPN

Table 2 The structure of advertisement database

Primary key	Date	TITLE	Advertiser	Brand	File name	1st Category	2nd Category	Model

website. We collect all information of the broadcasting advertisements ADIC provides, and refine the information in accordance with data schema. Registered advertisements consist of several attributes such as primary key, registration time, title, advertiser, brand, file name and model as shown in Table 2. The advertisements are classified into 21 categories and 166 subcategories. 218,166 advertisements are registered with advertisement videos until May, since the first advertisement is registered in 1999. For our experiment, we use 626 advertisements registered between 26 October 2010 and 29 December 2010 at the ADIC website.

We recruit 274 participants who consist of Facebook and non-Facebook users. In order to easily collect user information, we implement an information acquisition program using C# program language based on Microsoft Visual Studio .NET 2008.

Participants evaluate the advertisements via the information acquisition program to assign preferences to each advertisement they have seen.

The screen shots for information acquisition are shown in Fig. 5. The information security policy is described in Fig. 5(a). We provide log-in pages for both types of users as shown in Fig. 5(b). Participant information is automatically extracted using Facebook OpenAPI with user consent. Figure 5(c) shows an authorization access page for accessing user information through the OpenAPI. Once the user authorizes us to access a user's account, the information acquisition program starts to collect s information such as user profile, friend list and friends' profiles. We provide another page to get required information for users who do not have Facebook account. The information acquisition process is similar to participants with a Facebook account.

The information acquisition program provides a form to get user preferences for advertisements users saw. The form is shown in Fig. 6. A user can select one of three options to see the list of advertisements. Advertisement list is given by using either random selection, category classification or advertising model. They can evaluate advertisements with 5-star ratings after advertisement replay. If they want to skip the replay, then they can leave the rating directly.

The total number of advertisements rated by the participants is 8,245. The minimum and maximum numbers of the rated advertisements are 1 and 130, respectively.

4.2 Evaluation metrics

The evaluation of our personalized advertisement recommendation is carried out using the All But One protocol [4], which is an empirical analysis of predictive algorithms for CF. It is

a b c

Fig. 5 The process for gathering user information from Facebook

Fig. 6 The input form for advertisement evaluation

difficult to divide data sets into training and test data sets because our experimental data is not regular, unlike MovieLens data. We thus the All But One protocol for the evaluation.

We measure the prediction accuracy by using Mean Absolute Error (MAE) like Eq. (3). MAE is the most commonly used measure for the prediction accuracy of CF techniques. MAE value is determined using the mean of the absolute values between predicted preferences $p_i=\{p_1, \ldots, p_n\}$ and real preferences $r_i=\{r_1, \ldots, r_n\}$. The nearer the MAE is closer to the zero, the better the prediction accuracy.

$$MAE = \frac{\sum_{i=1}^{N} |r_i - p_i|}{N} \tag{3}$$

We also use the Hit Ratio (HR) to evaluate the recommendation quality of the proposed method. HR is calculated by using Eq. (4). Through the HR measurement, we can know that how many recommended Top-N advertisements are matched with real evaluation of each user.

$$HR = \frac{|Test_u \cap TopN_u|}{|Test_u|} \tag{4}$$

In Eq. (4), $Test_u$ is the advertisement list of user u in the test data, and $TopN_u$ is recommended Top-N advertisements for user u.

Although a recommendation system shows high accuracy for existing items, the system performance can be inefficient if the system shows low performance for new items. If the system recommends items that users positively rated in practice, then we conclude the recommendation is useful for the users. In other words, the higher the HR value is, the better the recommendation system is for the users who rated a small number of items.

4.3 Results and discussion

4.3.1 Prediction accuracy

In order to smoothly collect advertisement preferences of participants, we provide the information acquisition program to the participants. The evaluation of advertisement preference is performed using 5-star rating. In addition to explicit rating, we use the user's behavior for automatic evaluation as mentioned in smart client subsection. The user feedback is used to update user profiles.

We recommended personalized advertisements to the users based on user information and item preferences with social relationships between users. We performed the experiments several times to maximize the recommendation performance by adjusting the number of appropriate users. Figure 7 illustrates the variation of MAE with the size of nearest neighbors. The parameter k denotes the number of the nearest neighbors (k nearest neighbors). Our system achieves the best performance when k is seven.

Figure 8 shows the prediction accuracy measured by MAE for CF and the proposed method. We selected a thousand advertisements from all rated advertisements and make five groups similar to MovieLens data.

Overall, the proposed method shows better prediction accuracy than traditional CF method. On average, the proposed method improved MAE value 0.11. Dataset3 achieves the best performance compared to the rest of datasets.

Based on the analysis from each Dataset, we found that Dataset3 contains the users who have many social friends and most users of Dataset3 have rated over twenty advertisements. From these facts, we conclude that using social relationships influence the improvement of prediction accuracy of CF techniques.

4.3.2 Recommendation quality

To evaluate the top-N recommendation, we measure the hit rate (HR) about each method. All HR values are measured with an increasing number of advertisements. Figure 9 presents the HR results according to each user case. In Fig. 9, FPN indicates association rule based recommendation methods. The HR values are improved with the increasing number of recommended advertisements for all user cases.

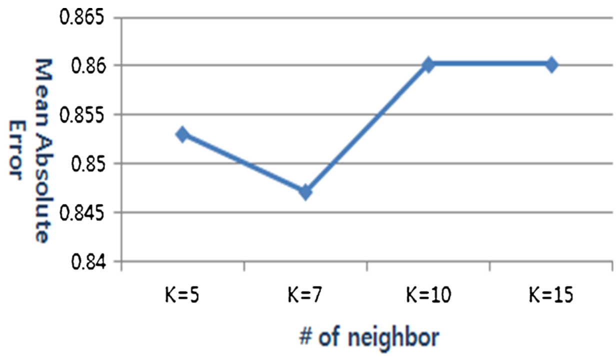


Fig. 7 The best number of nearest neighbor

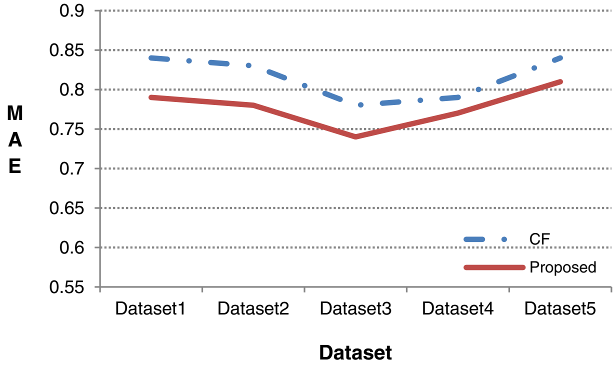


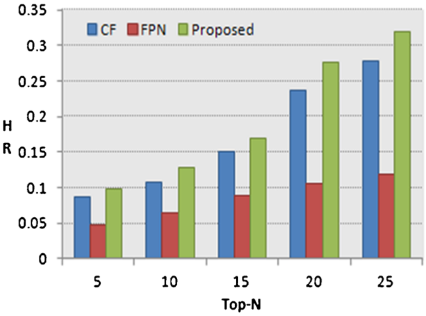
Fig. 8 The comparison of MAE

In case 1, the proposed method achieves the best performance in terms of HR. This is because the users in case 1 have sufficient social relationships and social network friends who may have similar preferences between each other. In user case 1, our system generates a number of rules from user data. The FPN method shows the lowest HR because the system chooses only N rules from the generated large rule set. From the HR results of user case 2, CF and the proposed method were not significantly different due to the lack of number of friends on the social network. If the number of friends is insufficient, then our system cannot construct the k nearest neighbor using only social network friends. The system then uses the CF to fill the rest of neighbors. This will lead to a similar HR. From the results of user case 2, we are assured that although the number of friends on the social network is insufficient, the social relationships are helpful to improve the HR results as the recommendation quality. The HR of FPN is little less than user case 1.

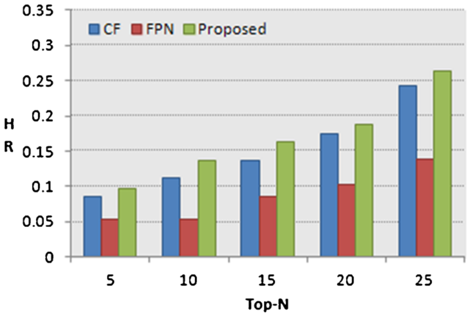
In case 3, the FPN method achieves a better HR. The association rules for user case 3 are generated based on social network friends of a target user. The prediction accuracy of CF and the proposed method are low due to the lack of target user's ratings. This is a general problem in CF fields. Although the proposed system faces the limitation of CF technique, the HR values of proposed method are slightly higher than the CF because social relationships give positive effects on recommendation quality. For case 4, FPN shows better results than the other methods. The results of case 4 are overall lower than other cases. The lack of ratings and few friends produces bad results. Through the experiments, we assure that the social network based method is more effective in improving recommendation performance and quality than other methods.

4.3.3 Discussion

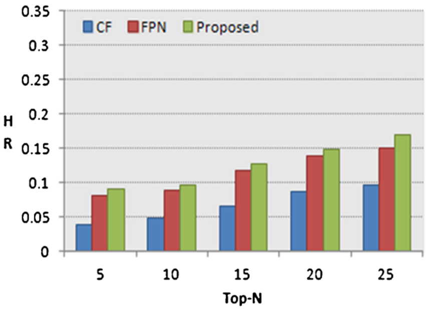
As the research and application for personalized advertisement recommendation in smart device environment, our main purpose is to improve the performance and quality of user-based collaborative filtering method. Traditional CF method has sparsity and cold-start problems. We try to alleviate the problems using friend information on social network and frequent patterns from user rating information. Indeed, from the experimental results, we can know that proposed social network-based CF method shows better performance than traditional CF method overall. In our research, we separately apply CF and FPN model to a target user according to the number of user's ratings and friend information on social network. We divide users into four cases. All users corresponding to user case 1 have rich



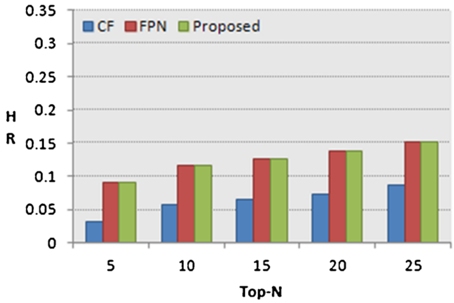
(a) User Case 1



(b) User Case 2



(c) User Case 3



(d) User Case 4

Fig. 9 Hit rate (HR) with increasing N (number of recommended advertisement)

information in terms of user' rating history and direct relationships between social network friends. Our system applies proposed method to users corresponding user case 1. For users of case 1, proposed method improved HR values of 2.62 % and 11.32 % compared with traditional CF and FPN methods, respectively from Fig. 9(a). User case 2 deals with users who have enough rating information but lack of direct friend information. We thus consider basic information of friends based on social network. The proposed method for user case 2 shows improved performances of 1.94 % and 8.26 % than traditional CF and FPN methods, respectively, as shown in Fig. 9(b). From Fig. 9(a) and (b), we can know that user case 1 and 2 give a little bit better performance than traditional CF due to rich user rating information. However, from the results, we verify that social network-based nearest neighbors provides much more reliable information than the neighbors of traditional CF. Among all users, there are cold-start users who have no rating history and lack of item rating, respectively. User case 3 and 4 cover the both types of users. Figure 9(c) shows results of user models based on rating information and frequent patterns using ratings of social network friends. Users of case 3 have no rating information or lack of item rating but many social network friends. For the users, CF using direct social relationship improves HR value of 5.94 % and 1.18 % than traditional CF and FPN, respectively. Lastly, proposed method in user case 4 uses association rules generated from FPN based on friends of social network friends because the users corresponding user case 4 have lack of item rating and their friends also have few item ratings. Our system also shows better performance than traditional CF, e.g., 6.24 % improvement. Performances of Top-5, 10, 15 of user case 4 are similar to user case 1. Despite lack of rating and friend information, the fact that user case 1 and 4 show the similar performance, means that proposed recommendation system can alleviate sparsity and cold-start problems.

We expect the improvement of recommendation quality if system uses a hybrid model which is mixed with CF and FPN models. In other words, Top-N recommendation through combining recommendation list of social network-based CF and FPN can improve the recommendation performance more [6].

5 Conclusion and future work

In order to satisfy the requirements of users and advertisers, many content providers have tried to offer intelligent and personalized advertisements to users by analyzing the user interests and past user preferences about advertisements in interactive environments. They have applied many kinds of recommendation techniques to their personalized recommendation systems.

We proposed a personalized advertisement recommendation system based on social network information. The appropriate advertisements are offered to the users by considering user personal and the social network information. Through the proposed system, advertisers and content providers can provide differentiated and personalized advertisements to users. If the users actively participate to advertisement evaluation, we can improve recommendation performance using the user feedback. We have classified users into two cases.

– If the information on user ratings and friends on the social network is sufficient, then we use the social network based CF model to recommend personalized advertisements.
– If a certain user has weak information about the ratings and friends, then the recommendation is performed via the FPN model based on the social network.

The experimental results of the MAE and HR show that the proposed method achieves better performance than other methods. The friends on the social network and ratings of a target user lead to the improvement of HR values. We also verify the fact that social network information is helpful to improve the performance of recommendation systems, and to assure that social network based recommendation is generally more effective than other methods.

In future work, we will consider the "Likes" as the user interests in Facebook. Through "Likes", we can understand user tendencies more correctly. However, since Likes information mainly consists of general information and natural languages, we need to match the meta-information of advertisements and Likes, and group the users based on "Likes". Recently, [12] have introduced SocialNews that provides more personalized news recommendations based on Facebook Likes. They compute the user similarity by applying Explicit Semantic Analysis (ESA) [11] to Facebook Likes of users. As mentioned in discussion, we will try to use hybrid model to users. User context and performance test of recommendation systems [8, 19, 21, 39] also should be considered for business. Finally, we recommend the top three fixed advertisements that have high prediction values to the users. We will try to dynamically recommend the remainder of advertisements by analyzing the user feedback about prior advertisements that the user has seen.

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