A Study on the Context-Aware Hybrid Bayesian Recommender System on the Mobile Devices

Hak-Min Lee and Jong-Seok Um

***Abstract*—The objective is to develop recommender system in mobile device to recommend proper items by combining context information obtained from mobile device, user's preference ratings, and features of items. A Bayesian hybrid recommender system is constructed by combining content-based filtering and collaborative filtering. Context information acquired from mobile devices such as GPS, whether, and time are transformed into usable data. Combining usable context information and the Bayesian hybrid recommender system, a context-aware hybrid Bayesian recommender is proposed. MovieLens data is used for simulation which contains movies with genres, user ratings, and time. Time is transformed to usable context information. This paper proposed a context-aware Bayesian hybrid recommender system which combines context information collected from mobile devices and user preference. By using canonical weights which are introduced by Campos, complex problem of computing conditional distribution is changed into simple linear sum of weights. This algorithm saves storage space and computing time, which is good for developing recommender system on the mobile devices. The objective is to develop a recommender system on the mobile device which improves accuracy of prediction by using context information. We use context information as season and time of the day for evaluating the proposed recommender. Simulation result shows that accuracy of the proposed recommender is lower than the existing recommender with small number of similar users. However, the proposed recommender improves the accuracy on predicting user preference as the number of similar users increase. Context information usable to recommender system has various types depending on the application domain. More precise prediction is possible if we use context information with a great impact on the user preference.**

We show that the proposed recommender system using context information has improved the accuracy on predicting user preference with moderate number of similar users.

***Index Terms*—Collaborative filtering, Content-based filtering, Bayesian Network, Recommender System, Mobile Device, Context Information**

I. Introduction

Many researchers have been developing recommender systems which supply meaningful information and the convenience of choice based on the large amount of data which are accumulated through SNS, IoT, supplement of mobile devices and the internet.

Manuscript received June 25, 2017, revised August 23, 2017

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Recommender systems collect information of the users such as preference, history of purchase, demographic information and context-aware information through mobile device. Based on the collected information, Recommender systems provide helpful information to users for finding appropriate items, services and content 1,2. As mobile devices have come into wide use, context and environmental information of the user on the mobile device have become ease to collect. Because of information from mobile device recommender systems on the mobile devices have become important research area and location based and context-aware recommender services are available. The goal of this paper is to recommend proper items or products to users by combining context information obtained from mobile device, user's preference rating on items, and features of items. Prediction of the user preference is made by applying content-based filtering on the features of items. Also, prediction of the user preference is computed by applying collaborative filtering to user's ratings on items by selecting similar users. Bayesian network is introduced on each recommender filtering to improve the prediction accuracy. Users, items, and features are components of the node in the Bayesian network. A Bayesian hybrid recommender system is made by combining content-based filtering and collaborative filtering. Context information acquired from mobile device such as GPS, whether, time, and many others obtained from log file are transformed into usable data by preprocessing. Combining usable context information and the Bayesian hybrid recommender system, we propose a context-aware hybrid Bayesian recommender. We divided data set into two parts, one is the context fitting data set and the other is the non-fitting data set. The Bayesian hybrid recommender system is used to predict user preference on each data set and the final prediction is made with weighted sum of each result. MovieLens data is used for simulation which is composed of movies with genres, user ratings, and time 3. Time is treated as context information, which is transformed into season and time zones. The proposed recommender system predict more accurately than the result without context information. After introduction section, we explain recommender system and related works in Section 2. In Section 3, the proposed algorithm is presented. In Section 4, we show result of the simulation and Section 5 shows conclusion on our results and future research areas.

II. Related Work

Depending on the way of recommendation, recommender systems are generally classified into two parts: collaborative filtering system and content based recommender system. Collaborative filtering recommends items based on the user's rations which show user's preference and previous purchase list of the similar users. Collaborative filtering is widely used because this algorithm is very similar to human reasoning and works well in complex objects such as movies and music. Collaborative filtering systems show a higher performance than content based system, but they require a large amount of data. Their technique has two problems to use in real world which are sparsity and scalability[4]. Content-based system recommends items similar to those previously preferred items and content information is used to find preferred items. Content-based systems evaluate similarity between items based on common features of items and this may recommend items very similar to items on which the user already has acknowledgement[5]. Many known recommendation systems as above have their own strengths and weakness. Thus, many researchers have studied the mixture of collaborative filtering system and content based filtering system. Hybrid filtering systems integrate collaborative and content information for recommending system. Collaborative filtering with content based filtering takes advantage of benefits of each algorithm[6]. Depending on the combination, various type of recommender systems are possible[7]. Collaborative filtering systems are divided into memory-based and model-based algorithms. Memory-based algorithms use the data of the user ratings of items and utilize ratings before referential point. Memory-based algorithms employ similarity measure to take into account the similarity between users and the similarity between items. User-based algorithms and item-based algorithms are the example of the memory-based algorithm. Model-based algorithms build a model for representing the relation between items for generating recommendation. Most widely used models are such as Bayesian networks[8], genetic algorithm[9], fuzzy systems[10], and aspect models[11].

This paper proposes a hybrid recommender system with Bayesian networks on the mobile devices. Luis de Campos proposed an algorithm by using Bayesian network to model the relation among user's ratings[12]. To complete the model specification, conditional distribution on each node must be estimated from the data. Since the time for computing the conditional distribution takes exponential to the number of nodes, a great amount of computing time is required in case of large dataset with many items and users. To reduce the operational time, Luis de Campos represents a conditional distribution as a sum of canonical weights which reduce the computing time proportional to the linear of the number of nodes. Also, Luis de Campos extends[13] this result to hybrid approach integrating content-based and collaborative recommendations. We use this hybrid approach combining with context information acquired from mobile device.

Mobile devices are wide spread and very personal to users so that they have very intimate and personalized information about user preference. Context information acquired from mobile device is well suited to context-aware recommendation. Mika Raento developed platform for collecting context information from mobile phone, which consist of Sensors, Communications, Customizable applications, and System services[14]. Panu presented software framework for collecting and processing context information from user's environments via mobile device. Panu's software framework manages context information obtained from various sources and enables to process to higher level context abstraction[15]. In this paper, we refer these two presentations for collecting context information.

III. Proposed Work

Here we use three information, item features and user ratings in the database and context information from mobile device. Context information contains location, season, time, a day of the week, whether, and many others extracted from log data. Data with context information enables us to split data into two part, one is a dataset which fits context environments at the recommending point of time and other dataset which does not fit to the context surroundings. In each dataset we apply hybrid filtering system which combines content based system and collaborative filtering system constructed by using Bayesian networks. After obtaining rating result of the target item of active user on each dataset, we combine each result by using weighted sum. We show the structure of the proposed recommender system as follows in Figure 1. (Figure 1)

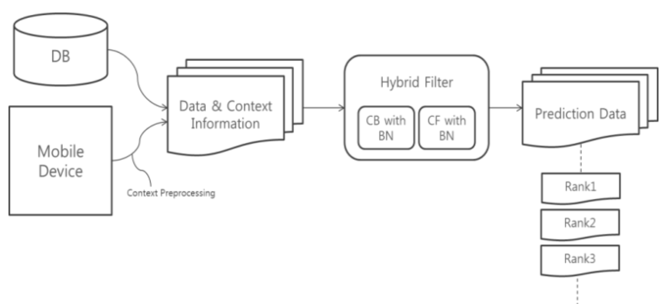

Fig. 1. Structure of the Proposed Recommender System

Mobile devices tend to have intimate relationship with their users. Thus context information obtained from mobile device is well suited for context-aware computing. Context information is collected from various resources such as system sensors, internal devices processes, Bluetooth transfer, Web, and log files. Context information has various types such as location, time, environmental information, user activity, and device activities. Context information measured from mobile device need preprocessing to be transformed into the actual world context, which has a meaning for recommender systems. Usual preprocessing includes pattern extraction, quantification and meaningful labeling. Context type, context information and sources are shown in Table 1.

TABLE I
POSSIBLE CONTEXT INFORMATION AND TYPES FROM VARIOUS SOURCES

Sources	Context type	Context information
GPS	Latitude, Longitude	Location
System	Time	Season, Day of the week, Time of the day
	User activity	Calls, SMS, Movement
Sensors	Sound	Silent, Normal, Loud
	Light	Dark, Normal, Bright
Web	Temperature	Hot, Normal, Cold
	Humidity	Dry, Humid, Normal

The detailed structure of the context-aware hybrid filter with Bayesian network (BN) is as follows in Figure 2. Here CB indicates content based filtering and CF indicates collaborative filtering. (Figure 2)

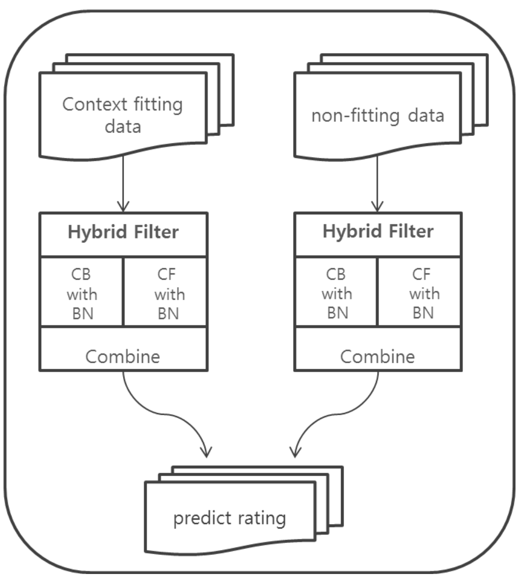

Fig. 2. Structure of the Hybrid Filter

Using Bayesian Network for estimating the preference of the active user, we first select variables which influence the preference of the user. In the Bayesian network, each node corresponds to the selected variables and if there are relationship between two variables a path must exist between them in the network. In our case, we have m items using notation, $I = \{I_1, I_2, \cdots, I_m\}$, and each item is characterized by l features using notation, $F = \{F_1, F_2, \cdots, F_l\}$, and there are n users using notation $U = \{U_1, U_2, \cdots, U_n\}$. Usually, number m and n are very large values. Luis de Campos proposed a canonical model to calculate conditional distribution on the Bayesian node by introducing canonical weighted sum. By introducing canonical weights, complex problem of computing conditional distribution is changed into simple linear sum of weights since we only need to estimate the weights related in calculating the conditional distributions. As a result, this algorithm saves storage space and computing time. Using canonical weighted sum, conditional distribution can be calculated as follows:

$$Pr\left(x_{a,j} \middle| parent(X_a)\right) = \sum_{Y_t \in parent(X_a)} w(y_{t,r}, x_{a,j}).$$

Here $y_{t,r}$ is the state of Y_t in the $parent(X_a)$ where $parent(X_a)$ is the parent node set of X_a which is a node in the Bayesian network. Also, $w(y_{t,r}, x_{a,j})$ is the weight quantifying how rth value of Y_t describe the jth state of node X_a and weights should be non-negative and the sum with respect to all the possible state of node X_a should be 1. We follow the Luis de Campos method for estimating weights 13. Our Bayesian network has information on features, items, and user and we need to define the domain of the three variables which are nodes of Bayesian network. Feature nodes consist of character node F_k which are features used to explain the item. Binary random variable is allocated to each node which takes 0 if this feature is not relevant to describe the item and 1 if this feature is relevant to describe an item. For each item, there is an item node which takes value 0 if this item is not relevant to predicting user's preference and 1 if this item is relevant. For each user, there is a user node which represents the rating of the item. These user nodes are used for predicting the rating of the target item for the active user. Range of the rating is 1 to 5 and high value indicates high preference. We have two data matrices. First one is a binary matrix which shows the relation between item and feature. The size of the binary matrix is $\mathrm{m} \times \mathrm{r}$ and its element has 1 if item is described by feature and 0 otherwise. Another matrix is user-item matrix which represents the ratings of user's preference on item.

As we have feature information of the items, recommendation by using content-based filtering is available. To represent the relation between features and items, feature nodes consist of the first layer and item nodes consist of the second layer and active user consists of the final layer which represents the active user's prediction. The diagram of the Bayesian network for the content-based filtering is as follows in Figure 3. (Figure 3)

In the content-based filtering, we have prior knowledge on the features, K_{cb}. Bayesian network shows the relation between features and items. Features which are relevant to describe items are connected to each other to show relation between them.

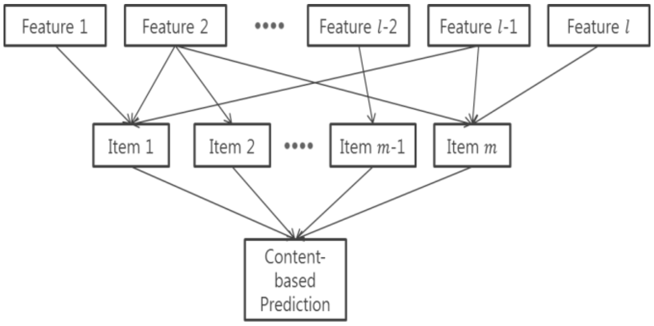

Fig. 3. Bayesian network of the content-based filtering system

Eventually, we want to compute the conditional probability distribution of how active user rates on target item given the prior knowledge, $Pr(U_{cb} = s|\, K_{cb}), s = 1,2, \cdots 5$. Luis de Campos proved following formula for computing exact posterior probabilities of node X_a having a rating s, i.e. $U_{cb} = x_{a,s}$, in the Bayesian network under certain conditions.

$$Pr\left(x_{a,s}|K_{cb}\right) = \sum_{t=1}^{m_{x_a}} \sum_{k=1}^{l_{y_t}} w(y_{t,k}, x_{a,s}) \cdot Pr\ (y_{t,k}|K_{cb})\ ,$$

Here m_{x_a} is the number of parents in the node X_a and Y_t is a node of $parent(X_a)$ and l_{y_t} be the number of states taken by Y_t. In the content-based filtering, the prior knowledge is usually comprised of a set of features for an item.

By using rating data in the user-item matrix, collaborative filtering system is applicable for preference estimation of the target item of the active user. Similar users having similar preferences to the active user are selected by using metric penalized absolute correlation. These similar users consist of the second layer and the first layer is composed with items relevant to the similar users. Similarity measure between two users we have used is as follows:

$$Similarity(U_1, U_2) = abs(corr(U_1, U_2)) \cdot \frac{|set\ of\ items\ rated\ by\ U_1 \cap set\ of\ items\ rated\ by\ U_2|}{|set\ of\ items\ rated\ by\ U_1|}.$$

Here we consider both positively and negatively correlated users for collaborative filtering Bayesian network model. The diagram of the Bayesian network for the collaborative filtering is as follows in Figure 4. (Figure 4)

Once similar users are selected, then some users among similar users have ratings on target item and some others do not have. If ratings on the target item already exist such as User 1 and User 3 in Figure 4, we use these ratings as prior knowledge for Bayesian network in the collaborative filtering recommender, K_{cf}.

If there is no rating on the target item such as User 2 in Figure 4, then rating is estimated by using content-based filtering recommender as mentioned above with prior knowledge, K_{cb}.

Our goal in the collaborative filtering recommender is to compute the conditional probability distribution of how active user rates on target item given the prior knowledge,

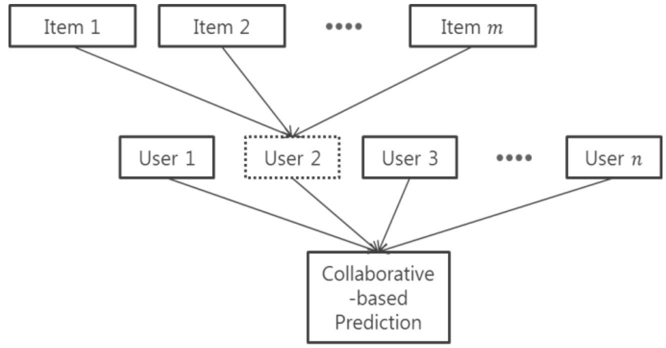

Fig. 4. Bayesian network of the collaborative filtering system

$Pr\left(U_{cf} = s\middle|\, K_{cf}\right), s = 1,2, \cdots 5$. Using Luis de Campos formula for computing exact posterior probabilities:

$$Pr\left(x_{a,s}|K_{cf}\right) = \sum_{j=1}^{m_{x_a}} \sum_{k=1}^{l_{y_j}} w(y_{j,k}, x_{a,s}) \cdot Pr\ (y_{j,k}|K_{cf}),$$

where $Pr\left(y_{j,k}\middle|K_{cf}\right) = 1$ if $y_{j,k}$ exists already in the prior knowledge K_{cf}. If $y_{j,k}$ does not exist in K_{cf}, then $Pr\left(y_{j,k}\middle|K_{cf}\right)$ becomes $Pr\left(y_{j,k}\middle|K_{cb}\right)$ and computed using content-based filtering system with prior knowledge on the relevant items K_{cb}. The formula for $Pr\left(y_{j,k}\middle|K_{cb}\right)$ is as follows:

$$Pr\left(y_{j,k}\middle|K_{cb}\right) = \sum_{a=1}^{m_{y_j}} \sum_{k=1}^{l_{i_a}} w(i_{a,b}, y_{j,k}) \cdot Pr\ (i_{a,b}|K_{cb}).$$

Here $i_{a,b} = 0$ if item a is relevant to predict to user preference of user Y_j and 0 otherwise and m_{y_j} is the number of parent nodes of user node, Y_j. K_{cb} contains relevant item information on node Y_j.

Preference predictions obtained from the content-based recommender and collaborative recommender are combined by weighted sum. The weight on the collaborative filtering is the proportion of the users among similar users having rating on the target item.

IV. SIMULATION

We use MovieLens data set for simulation. It was accumulated by the GroupLens Research project between 1997 and 1998. This data contains 1682 movies and 943 users with 100,000 records having scale 1 to 5. We have used U1.base for simulation. Each record consists of UserId, MovieId, ratings and time. Movie list shows genres of movies according to their MovieId. A movie may belong to several genres which are the features of movies. We transformed time into usable context information such as season and time of the day. Season has four values which are Spring, Summer, Autumn, and Winter. Also, time of the day has three values which are Morning, Afternoon, and Night. The result of context information preprocessing is shown in Table 2.

TABLE II
RESULT OF CONTEXT PREPROCESSING

User Id	Movie Id	Rating	Genres	Time	Season
91	683	3	Documentary	Afternoon	Spring
305	204	2	Action	Afternoon	Winter
1	229	4	Drama, Thriller	Afternoon	Autumn
193	276	4	Comedy, Romance	Morning	Winter

We divided U1.base into two parts, one data set consists of records which have identical context information when recommendation is requested and the other data set consists of remaining records. The prediction on the user preference of the target item is made by using median rating. Simulation is performed under three experimental conditions. Firstly, the proposed recommender system is performed on the data set which has identical context information among U1.base. At last, the Bayesian hybrid recommender is applied on the data set U1.base which has no context information. Mean absolute error (MAE) is used for evaluating accuracy.

$$MAE = \frac{\sum_{i=1}^{N} |\hat{r}_i - r_i|}{n}.$$

Here n is the number of ratings predicted and $\hat{r}_i$ is the predicted rating of true rating, r_i. The result of the simulation is shown in Table 3. Number of similar users (NSU) has three cases 10, 20, and 30. RS with using Context information column shows MAE of the proposed algorithm and RS without using Context information column shows the MAE of the existing Bayesian hybrid algorithm. The result shows that with small number of similar users accuracy of the proposed recommender is lower than the existing recommender. However, the proposed recommender improves the accuracy on predicting user preference as the number of similar users increase.

TABLE III
MAE OF THE CONTEXT-AWARE RECOMMENDER SYSTEM

NSU \ Method	RS with using Context information	RS without using Context information
10	0.9621	0.8267
20	0.8238	0.7181
30	0.7026	0.7331
40	0.7401	0.7425
50	0.7364	0.7501

V. CONCLUSION

In this paper, we proposed a context-aware Bayesian hybrid recommender system which combines context information collected from mobile devices and user preference data. By using canonical weights which introduced by Luis de Campos, complex problem of computing conditional distribution is changed into simple linear sum of weights. As a result, this algorithm saves storage space and computing time, which is good to be used for developing recommender system on the mobile device. The objective of this work is to develop a recommender system on the mobile device which has higher accuracy for prediction by using context information and user preference. We use context information as season and time of the day to examine the performance of the proposed recommender system. Simulation result shows that accuracy of the proposed recommender is lower than the existing recommender with small number of similar users. However, the proposed recommender improves the accuracy on predicting user preference as the number of similar users increase. Context information usable to recommender system has various types depending on the application domain such as location, whether, day of the week, and etc. More precise prediction on the user preference is possible if we use context information which has a great impact on the user preference. Discriminating influential context information in predicting user preference remains for future research.

ACKNOWLEDGMENT

This research was financially supported by Hansung University.

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