ระเบียบวิธีการแนะนำโดยใช้ประวัติผู้ใช้แบบพลวัติและแบบลูกผสม และการทำนายคะแนนแบบการตัดสินใจหลายเกณฑ์

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RECOMMENDATION METHODOLOGY USING DYNAMIC AND HYBRID USER PROFILE, AND MULTIPLE CRITERIA DECISION MAKING SCORE PREDICTION

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ภัคพล ตังโพธิ์กลาง : ระเบียบวิธีการแนะนำโดยใช้ประวัติผู้ใช้แบบพลหวัติและแบบลูกผสม และการทำนายคะแนนแบบการตัดสินใจหลายเกณฑ์. (RECOMMENDATION METHODOLOGY USING DYNAMIC AND HYBRID USER PROFILE, AND MULTIPLE CRITERIA DECISION MAKING SCORE PREDICTION) อ. ที่ปรึกษาวิทยานิพนธ์หลัก: ผศ. ดร. ศรันญา มณีโรจน์, 68 หน้า.

ระบบผู้แนะนำได้ถูกนำมาใช้ช่วยเหลือผู้ใช้ในการเลือกสรรสารสนเทศที่มีความน่าสนใจ ระบบฯส่วนใหญ่เน้นใช้ข้อมูลคะแนนรวม (เกณฑ์เดี่ยว)ในการแนะนำไอเท็ม นักวิจัยบางกลุ่มจึงมีพยายามใช้ประโยชน์จากมุมมองในด้านต่างๆของไอเท็มเพื่อที่จะรับรู้ถึงรสนิยมความชอบของผู้ใช้ ซึ่งเทคนิคดังกล่าวเรียกว่า "การให้คะแนนแบบหลายเกณฑ์" และถูกใช้ในการทำประวัติของผู้ใช้ อย่างไรก็ดีระบบผู้แนะนำแบบหลายเกณฑ์ยังคงมีความยุ่งยากในเรื่องของการแก้ไขประวัติผู้ใช้ให้เป็นปัจจุบันเมื่อเวลาผ่านไป และในบางระบบฯประวัติผู้ใช้ไม่มีความเฉพาะเจาะจงต่อตัวผู้ใช้แต่ละคน งานวิจัยชิ้นนี้นำเสนอการสร้างประวัติผู้ใช้ที่สามารถแก้ไขให้เป็นปัจจุบันสำหรับผู้ใช้แต่ละคน และมีการพัฒนาให้ประวัติผู้ใช้นั้นมีประสิทธิภาพมากขึ้นโดยนำประวัติความชอบ และประวัติพฤติกรรมของผู้ใช้มาสร้างประวัติส่วนตัวของผู้ใช้ นอกเหนือจากนั้นเพื่อเป็นการเพิ่มความถูกต้อง งานวิจัยชิ้นนี้ยังมีการประยุกต์หลักการของการตัดสินใจแบบหลายเกณฑ์ (MCDM) มาใช้บนการให้คะแนนแบบหลายเกณฑ์ในการทำนายค่าความชอบของไอเท็ม นักวิจัยได้ทำการทดลองภายใต้สภาวะอันหลากหลายบนฐานข้อมูล "ยะฮูมูฟวี่(YahooMovies)" ซึ่งเป็นฐานข้อมูลที่มีความน่าเชื่อถือ และผลการทดลองได้แสดงให้ประจักษ์แล้วว่าวิธีการที่นำเสนอสามารถสร้างความถูกต้องให้กับระบบผู้แนะนำมากกว่าวิธีอื่นๆที่เคยมีมาก่อนหน้านี้

ภาควิชา คณิตศาสตร์ ลายมือชื่อนิสิต

สาขาวิชา วิทยาการคอมพิวเตอร์ และเทคโนโลยีสารสนเทศ ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก

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PAKPAON TANGPHOKLANG: RECOMMENDATION METHODOLOGY USING DYNAMIC AND HYBRID USER PROFILE, AND MULTIPLE CRITERIA DECISION MAKING SCORE PREDICTION. THESIS ADVISOR: ASST. PROF. SARANYA MANEEROJ, Ph.D., 68 pp.

Recommendation systems are widely used to help users acquire interesting information. Most current recommendation systems merely use the overall rating information (Single-Criteria) to recommend items. Some researchers have recently begun to exploit various aspects of an item's features to more precisely capture the users' preferences. The technique is called Multi-criteria rating. The multi-criteria ratings are usually used to construct the user profiles. However, current multi-criteria recommendation systems still have difficulty updating a user profile depending on time. This report proposes a new multi-criteria rating method that can update user profiles in a required amount of time on an individual basis, and obtain more effective user profiles by exploiting both the user's preference and behavior profiles. Moreover, to increase the accuracy, we apply Multi Criteria Decision Making (MCDM) to the multi-criteria ratings to calculate an item's prediction value. We conducted experiments under varying conditions using a reliable database, Yahoo Movies. The experimental results show that the proposed method outperforms a set of previous methods.

Department : Mathematics Student's Signature ....

Field of Study: Computer Science and Information Technology Advisor's Signature ....

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CHAPTER I

INTRODUCTION

Internet service is bringing a new chance for information distribution, and absolutely increases competitive advantages for business owners. Many organization responds to it by allowing people to reach their information from everywhere and at anytime. In the internet user's point of view, a huge amount of information from many types of sources will decrease ability to find out needed information. Many researchers tried to develop many mechanisms to support such ability. One interesting mechanism is called Recommender system. It helps users to find out what they prefer by learning their characteristics.

To learn user characteristic, most recommender system separate works into three steps. The input acquisition is the first one which explicitly or implicitly obtains user preference or behavior when rating products or item via the system. Such information will then be transferred to the second step which is neighbor formation. This is to create a set of neighbors or similar users whose interest has been in the same trend. These neighbors will share their experience in tasting products to a target user in the last step. The last step is the rating value prediction. It estimates the overall score a target user may give to an item which he/she has not evaluated before. When given an unrated item, the system predicts the user's rating value on the item using his/her neighbor's opinion as well as his/her profile. Most researchers have focused on the neighbor formation and the rating value prediction steps in order to improve the recommendation performance. Various kinds of profile construction techniques have already been proposed for finding high quality neighbors. They extract effective users' preferences or build a similarity measurement to find effective neighbors. Meanwhile, researchers proposed various techniques to better predict users' rating values on an item.

Recently, the evaluation is done by a user giving the single-criterion score to an item based on overall preference. This way has worked well with many services. However, the effort to seek out more accurate way is still in charge of the recommender system area. Many development directions have been observed. Among them, a multi-criteria recommendation technique has been interested by a lot of researchers' interest. This technique realizes that users often express their opinions based on their own aspects. The single-criterion technique which represents just the overall preference will not be able to sufficiently handle the situation. To enhance the expressive ability, multi-criteria techniques have been proposed. Adomavicius, G., et al., 2007 is the one who publicized that the multi-criteria technique is able to outperform the typical single-criteria techniques. Besides, some industries have begun studying multi-criteria systems. For example, Yahoo Movies which is a recommendation service that employs the mechanism to let user specify multi-criteria ratings for each movie, it is the place that clearly realizes the multi-criteria idea.

This work proposes a novel multi-criteria recommendation method. It concentrates three details. First, weight assignment which is in the part of neighbor formation is proposed. Generally, user profiles are created based on the item features (criteria) for neighbor formation. Since the influence of each criterion differs depending on the user, different weights to the criteria are necessary to be appointed. Although several methods were proposed to assign criteria weight, some of them assigned the same weights to all users equally, while others required user's effort to assign the criteria weights. The proposed method can automatically assign different weights to criteria according to each user's characteristics.

Second, a new user profile for the neighbor formation is concerned. Most multi-criteria systems are categorized into a user preference based system that directly utilizes the rating given on the criteria by a user, or a user behavior based system that utilizes the frequency extracted from criteria evaluation. Both of them do not completely represent the user's characteristics. The proposed profiling technique exploits both the user preference and behavior for the neighbor formation.

Third, a new method for rating value prediction from the neighbors' multi-criteria ratings is presented. In the rating value prediction step, recent recommendation systems predict the value based on weighted average technique using the single-criteria (Overall rating) of an active user's neighbors of a target user. The weights differentiating significance of neighbor's ratings are the similarity values between the active user and the neighbors. However, the idea of single-criteria, as mentioned above, lack of ability to provide accurate recommendations. The proposed method avails the multi-criteria ratings of neighbors for predicting the rating value for an active user by using the MCDM technique instead.

Last of all, the architecture of mobile multi-criteria recommender system is also designed. The case of banking services in Thailand is now considered to express the feasibility of the proposed recommendation algorithm. This is because Thai banking is a serious business domain in such the way that it increases competitive advantage. Therefore, many banking services have been presented to users by each individual bank. Besides, the trend of such services keeps going on the use of mobile facility. This brings the encouragement to help users to select a proper banking service when they are using mobile devices. In addition to the possibility that a banking service can be represented in the term of a set of criteria, the mobile multi-criteria recommender system architecture is designed in this work. The designed architecture refines, tunes, and combines ideas from a set of research works.

This work is organized as follows. The second chapter collects and explains a set of research works in the related area together with analyzing the opportunity to enhance the recommendation accuracy. The third chapter talks about the proposed methods. The fourth chapter presents the mobile architecture of the mobile banking service recommender system. The fifth chapter shoes the experimental results of the proposed methods, while the last two sections discuss the experimental results, and conclude the works. This report contains the details of recommendation algorithm and architecture which were proposed in **Tangphoklang P., Maneeroj S., et al, 2010 (IADIS 2010)**, and **Tangphoklang P., Tanchotsrinon C., et al, 2010 (KST 2010)** respectively.

1.1. Objectives

The following proposed ideas are aimed to increase opportunity of producing better recommendation in different steps of recommendation.

1. Propose dynamic weight which is varied by users, and adaptive through time.
2. Propose hybrid user profile which is the combination between preference, and behavior model

3. Propose the applied MCDM (Multi-Criteria) which is the new preference score prediction techniques.
4. Design mobile banking service recommender system architecture to ensure the feasibility of the proposed methods in real situation.

1.2. Scope

This research concentrates on movie recommender systems to enhance the quality and accuracy of recommendation by using user-variant adaptive weight, dynamic user profile, and applied MCDM rating prediction. The domain in this research is only movie. The considered criteria upon movie are overall, story, acting, direction, and visuals. These criteria are considered in user profile construction, and rating value prediction.

1.3. Research methodology

In order to achieve the defined objectives, the following tasks will be stated by means of appropriate theoretical work described below.

- Analyze the related literatures: This is to analyze the trend of research in the multi-criteria recommender system, and get the idea which is the proposed method to improve the recommendation accuracy.
- Set assumption: After investigating the idea, a set of assumptions need to be set for ensuring the idea.
- Do experiments: The experiments are done according to the assumption.
- Conclude and analyze the experimental results
- Prepare the proceedings paper
- Prepare for thesis proposal test
- Prepare the thesis report

All these steps are done in sequence through time defined in the Table 1.1.

Table 1.1: Task schedule

No	tasks	Month sequence																	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Analyze related literatures																		
2	Set assumption																		
3	Do experiments																		
4	Conclude and analyze the experimental results																		
5	Prepare the proceedings paper																		
6	Prepare for the thesis proposal test																		
7	Prepare the thesis report																		

1.4. Benefits

The proposed algorithm will help a multi-criteria recommender system produce better quality of recommendation by recognizing more closely to the user preference and behavior, getting the user model adaptive, and utilizing more reasonable neighbor suggestion.

CHAPTER II

THEORITICAL BACKGROUND

Three types of recommender systems have been observed with respect to recommendation approaches. The first one is the content-based filtering. It provides recommendations based on the similarity between user profiles and items. The user profile is the representation of user's historical data in rating items, or the requested queries in which the keywords relate to a set of items are specified. The second one analyzes user characteristic, and produce a set of similar users. A, the similar users will give opinion to a target user. This is called a collaborative filtering approach. Many works showed that only one of these two approaches have some limitations. Therefore, researchers proposed new approach which tries to combine both techniques. It is a hybrid approach that uses both previous approaches abilities to compensate for the limitations of the content-based and collaborative systems. Hybrid technique has been developed based on single-criterion rating successfully. However, the trend of making recommendation based on multi aspects of items produce much more accurate result. Therefore, the hybrid approach is now adopted in the multi-criteria rating recommendation system. For example, Yahoo Movies, which is a movie recommender system (Adomavicius, G., et al., 2007), provides four criteria for movie ratings: story, acting, direction, and visuals.

Manouselis, N., et al., 2007 proposed a framework to analyze and classify multi-criteria recommender systems. In most works, they mentioned that the user profile is merely created as a vector of the values related to each item criterion. Since different criteria affect the user's preferences unequally, they should be signified by a set of values called criteria weight. Thus, weight assignment should be the main consideration in making more accurate recommendation. Manouselis, N., et al., 2004 proposed a system for which users need to provide criteria weight manually. This will deteriorate the usability of the system and also increase the user's cost. On the other hand, many studies tried to calculate the weight automatically by using all the historical preference data. However, they did not consider the fact that a user's preference will absolutely change each time a user provide new rating information. For example, in the Lakiotaki, K., et al., 2008, and Plantie', M., et al., 2005, a set of criteria weights is assigned for all users. Moreover, Srikumar, K., et al., 2004, and Perny, P., et al., 2001 created criteria weights that is a user variant. Unfortunately, they did not take into consideration updating the weight when the preference information consecutively changed. Therefore, the criteria weight varying for different users and different times should be considered.

Another aspect of the neighbor formation step of recommendation is the profiling technique. Usually the value of each criterion in the user profile is the summarization of implicit collected by the user behavior or explicit given by the user's preference. For example, Maneeroj, S., et al., 2009, stated that the user profile is composed using only the user preference data. In a system that lets users express their preference information in term of multi-criteria ratings explicitly, it showed only one implication in the user profile. Meanwhile, some studies tried to observe the user behavior according to their behavior in item selection. Each of them can only imply the user characteristic in one aspect. This leads the system to incompletely recognizing the user. Therefore, both the preference and behavior should be incorporated in the user profile to represent the user's characteristic more correctly.

Another highly considered part is the rating value prediction step of the recommendation. In this step, a system predicts a rating value from the list of similar users (neighbors). Most researchers tried to use the weighted average technique on the single-criteria rating (overall rating toward items rated by neighbors) in order to estimate the recommendation value for a specific item unrated by the target user. However, once the multi-criteria rating idea is introduced, the motivation to develop rating prediction could be publicized. The MCDM (Multi-Criteria Decision Making) is widely used in the decision making area to help users to select good alternatives based on multiple criteria. Manouselis, N., et al., 2004 applied MCDM to their recommender system. Their work uses a content-based filtering technique that does not consider the neighbor opinion in making recommendation, and does not use MCDM specifically in the rating value prediction step. This work applies MCDM to the multi-criteria ratings of rated items acquired from the neighbors to generate a recommendation value in rating prediction step.

This chapter demonstrates a set of literatures in the related area, and navigates the opportunity for recommendation improvement. First of all, the background knowledge about three types of recommender systems is given. After that single-criteria and multi-criteria rating recommender system will be described. Then the literatures are consequently analyzed in the terms of recommendation steps point of view.

2.1. Recommender system

A recommender system applies a technique to help users select a preferred item in a large item space. Most researchers classify the system into three categories which are content-based filtering, collaborative filtering, and hybrid techniques.

2.1.1. Content-based filtering technique

This technique realizes the fact that a user is going to prefer items which is similar to the items that he or she has already evaluated. At the first time, it has its root introduced in the information retrieval area where text-based application is so much concerned, hence most recommendation is applied on the item whose content is merely textual. The evolution can be then seen after that by the development of user profile. Most systems tried to summarize the past item contents which have been evaluated by a user in the term of user profile. Generally, a user profile is represented by a vector whose elements explain the summarized content regarding of one aspect of evaluated items. Once the profile is constructed, the system finds an interesting item by measure similarity between content in a user profile and an item. Finally, item whose similarity is high will be recommended to such a user.

However, the main disadvantage of the technique is the over specification of recommendation. Since, the system matches items whose content is similar to ones that have already tasted by a user. That means the users will be recommended with a set of same old things. Hence, a user will not be recommended items that he or she does not have experience with. For example, European researchers who have not attended an international conference in Europe will never receive the recommendation for even the conference in their home town. Moreover, in other words, it is not reasonable for them to be recommended only the conferences in America, if they came to attend and evaluate such conferences just once. Therefore, variety of options is necessary to enlarge recommendation ability.

2.1.2. Collaborative filtering technique

According to real life situation, for example, when people go to see a movie. They often ask for suggestion from their friends especially who have always come with them for watching, or have similarity in taste. The idea is the logical point of collaborative view. The collaborative filtering technique form a set of neighbors or similar users based on their similar preference on a same set of items. In this kind of systems, users often express their preference in term of overall or single-criteria score. In order to calculate similarity of two users, the system first obtain a set of item that both of them have evaluated referred to as co-rated item set as shown in table 2.1. Then, their evaluation is compared whether they have the same quantitative trend in evaluation or not. In this stage, the comparison will bring out the similarity value between two users. After that, the system will obtain top n friends whose similarity value is high against a target user. From such a group of neighbors, when the target user is asking for suggestion about an unevaluated item, the system obtains the neighbors who have already evaluated the item. Neighbor evaluation will then be averaged using weight average technique where neighbor evolution weighted by the similarity values between each of them and the target user are averaged. Finally, the suggestion is in the form of score. The items which are predicted high will be recommended to that target user.

Table 2.1: single rating matrix from three users and k items

User	Item1	Item2	…	Itemk
A	5	5	…	6
B	4	3	…	N/A
C	N/A	N/A	…	N/A

co-rated items

This technique overcome the over specification problem in the sense that it uses other user opinion in order to make recommendation. Opinion from more than one user brings the variety of options to a target user, since each user even who has similar taste in common absolutely have experience with different sets of items. Unfortunately, according to the fact that the technique measure similarity between users based on just the co-rated set of items, the system will not be able to do that if there is no such an item belonging to that set. In the system that realizes this technique will suffer from the sparse matrix condition under which the co-rated set of item is hard to be found. Therefore, the similarity measurement cannot be done effectively. For example, in the table 2.1, user A and C will not be comparable.

2.1.3. Hybrid technique

Apart from content-based and collaborative filtering based, the hybrid technique combines both techniques to increase accuracy and decrease limitation of recommendation. There are many ways to combine both techniques. For example, Balabanovic, M., et al., 1997 confirmed the reliable use of the hybrid model in the web page recommendation situation (The case study of "Fab"). First of all, a user will receive a set of items whose content is really similar to his profile. After that users give items the evaluation in the term of single rating (overall score), this evaluation is then used as inputs for the collaborative filtering algorithm. That means it cascades the content-based to the collaborative filtering system. Other works based on such a model can be also found such as Basu, C., et al., 1998, Claypool, M, et al., 1999, Pazzani, M., et al., 1999, Schein, A. I., et al., 2002, Ungar, L., et al., 1998, K. Lakiotaki., et al., 2008, and Soboroff I., et al., 1999.

Recently, the way of combination is composed to measure similarity between users. This way follows the step of traditional collaborative filtering approach. It differs from the traditional one in the sense that, in order to do similarity measurement, this hybrid technique avoids using co-rated item set. On the hand, it produces content-based user profiles, and measure the similarity between users based on their profiles. After that neighbors are formed, and gives their suggestion toward unevaluated items.

The current hybrid recommendation consists of three steps as followings.

- Input acquisition: Rating information including single rating and rated item content is collected.
- Neighbor formation:
    - A user profile which is a vector is composed using such rating information.
    - A user is compared to other users using their profile and a similarity measurement (e.g. Euclidean distance, Cosine similarity, or Pearson correlation).
    - A target user is determined his neighbors who has high similarity value.
- Rating prediction: An item that a target user has not rated is given a predicted single rating using neighbor's single rating given on such an item weighted by similarity values between the target user and neighbors.

This technique is so useful, since it increases the opportunity that users are recommended the serendipitous items. Moreover, it does not use co-rated item set in similarity measurement. Therefore, the system is able to know how similar a pair of users is even the two users have not rated on a same set of item.

2.2. Single-criteria and Multi-criteria rating recommender system

Nowadays, internet applications produce large number of information. One interesting solution is a recommender system. It is a system that provides interesting information out of the whole database by trying to predict the overall score of an item generally referred to as unrated item that an active user did not evaluated before. Recommender system techniques are generally categorized into three types; content based filtering, collaborative-filtering, and hybrid recommender system. The content based recommender system proposed the idea on recommendation to introduce items by comparing the content of an unseen item to ones that an active user has already rated. Items that have much similarity are recommended to the user. This lead to its limitation called Over Specialization occurring when an active user has not been recommended with the serendipitous items which he might be interested in. One technique that was proposed to address this point is collaborative filtering. It collaborates with many users whose opinion has the similar trend as an active user's to make suggestion for an active user. Any two users are determined similar if their overlapped preferences on the set of items are close to each others. This technique came as innovative solution because it users opinion of similar users to introduce users a new set of items which are rarely faced by their own experience. Unfortunately it also has a problem called sparse rating matrix problem occurring when the overlapped opinion is not provided to the system adequately. This problem can make the collaborative filtering not so effective, because the set of similar users is hard to be formed. While the content and collaborative filtering based systems have their own benefits and limitations, the new technique applies those two techniques in many different manners to avoid limitations. It is the hybrid recommender system. Absolutely, it takes both overall score and item content as input, and has been proved undoubtedly successfully.

The three mentioned techniques mainly use the overall score in the recommendation processes, thus somehow they can be referred to as single-criteria recommender system. Single criteria technique provides a global function that represents the relation between a user and an item to a preference score. The function has the normal form as followed.

$$R(u, i) = s; s \in S, u \in U, i \in I \quad (1)$$

The global preference function *R* returns the preference score *s* to a particular pair of a user *u* and an item *i*. The set *U* and *I* represent the set of registered users and items in a specific domain, while S is a set of preference scores which are normally numbers in a bounded interval.

While such approaches have worked well in many kinds of application, but the overall score does not express the user preference well. Many users may have decided to rate the same score on an item, but they may have different reasons. For example, in an appliance recommender system, a person may rate on an iron based on the reason that it is very cheap. While another one may rate on that same iron with the reason that it can perform both dry and steam ironing. If both people give the same score on that item, that means right now they are considered similar with different reason of preference. Once those two users give the same score on the same item with different reasons, the system is going to analyze users on the same scope even the inputs are from different ones. This is not so fair and reasonable, since the system expects users to rate on an item using overall quality of its. Therefore, researchers have tried to consider letting users rate on an items with different reasons toward a given set of item criteria. A set of works consider the preference on multiple aspect in term of multi attribute content of an item. These kinds of system are called multi-attribute recommender system. They always create user profile by automatically retrieving multi-attribute content of selected items. Namely, the single ratings of all selected items are converted into the multi-attribute user preference. After that, multi-attribute user preferences of rated items are summarized, in order to match the favored attribute content, such as "Comedy" movies, for producing recommendation, such as in the work of Capphannarungsri, K., et al., 2009. Based on the idea of hybrid recommender systems, the neighbor opinion have always been used to form a high quality of neighbors which consequently affect the quality of recommendation. Therefore, letting users specify their preference toward a set of item aspects will contribute to better neighbor formation, rather than automatically transform the single rating to multi-attribute content-based preference (i.e. multi-attribute recommender system). To inherit this idea for multi aspect of preference model, some practical systems have been developed to let users rate on an item toward many aspects, such as, http://movies.yahoo.com, or http://www.hotels.com. Then these kinds of system were referred to as the multi-criteria rating recommender system.

Table 2.2 Comparing of single and multiple rating on a movie

User	Single rating	Multiple Rating
A	5	5 (3,2,10,11)
B	5	5 (9,9,8,7)
C	2	2 (3,2,10,11)

The table 2.2 illustrates how single and multi criteria are represented in the real world situation. Suppose there are three users providing scores toward a set of criteria on a movie, the single criteria method can be represented in the second column contained just the overall score. Additionally, scores toward all criteria together with the overall score visualize the idea of multi criteria method is shown in the third column. After obtaining rating table, most recommendation algorithm aim to analyze common trend of preference among users. Taking the single criteria can claim that user A and B have the same preference on such a movie, while concerning multi criteria rating the user A and C are treated as similar user. This shows that letting user provide their preference to the system in many aspect will contribute to better understanding user's characteristic.

The multiple criteria rating recommendation is defined by a set of individual local preference functions toward each item criteria. Therefore, this time the global function is used to represent the relation between *u* and *i* to a vector whose element can be consequently determined from a local preference function r_c (u, i). The local preference function in this context has the function to relate the pair of such user and item to a score provided for a specific criteria *c*. Likewise, the recommendation problem can be derived as by the local r_c (u, i) mapped to an unrated criteria score s_c. Thus r_c (u, i) = s_c , r_n (u, i) = s_n. When dealing with the *n* criteria, the systematical definition of the multi-criteria rating recommender system can be formed as followed.

$$R(u,i) = (r_c\ (u, i),\ldots, r_n\ (u, i)) \tag{2}$$

Multi-criteria rating recommender systems can be classified into two general types which are model-based and memory-based approach. The former leverage multi-criteria rating data to construct a model based on many different techniques, while the latter aim to develop the pre-defined formula utilizing such data substituted as parameters to make recommendation.

Many concepts were developed for user's model construction, and leveraging multi criteria rating data. For example, UTA algorithm (Lakiotaki K., et al., 2008) which is a method that tries to estimate the overall utility function from the sub-estimated marginal utility functions on criteria. Another approach applied probability theory on a set of latent variable to control relation between the domain of items and users. It is called FMM (Fixed Mixture Model) Si L., et al., 2003. Moreover, Li Q., et al., 2008 proposed a restaurant recommendation using the MSVD (multi-linear singular vector decomposition) to enlarge the analyzing user preference data occurring on different aspects. Among all these researches, such model-based approaches require much load for computing user model. Accordingly to the real world application which is observed that user preference can be changed along the time. Therefore, user model re-construction is not quite a good answer.

Apart from the model-based area, some people have tried to develop another approach to let the system easier to be adaptive without requiring much resource. It is the memory-based approach. In these approaches, the set of similar users are determined to make recommendation based on a multi-criteria user profile. In Roux L., et al., 2007 and Schmit, C., et al., 2002, they proposed different techniques incorporating multi-criteria preference profile of users. Schmit, C., et al., 2002 applied the MAUT (Multi-attribute utility theory, introduced in Schmitt, C., et al., 2002, and Schmitt, C., et al., 2003) on the case study of car recommender system, while Roux F. L., et al., 2007 construct the course recommender system based on multi-criteria decision making.

2.3. Three steps in making recommendation

Generally, in order to recommend an item to a target user, there are steps which are input acquisition, neighbor formation, and rating prediction. All steps will be achieved consequently when the recommendation is requested or done. The recommendation processes are done starting from input acquisition to rating prediction.

2.3.1. Input acquisition

In this step, the system aims to acquire user preference data either by using the implicit or explicit mechanism. Implicit mechanism refers to any mechanism that retrieves user preference data implicitly, such as counting the number of click in a web page, or measure the time a user spent on listening to music. For the explicit mechanism, most systems tried to let users directly specify their preference toward an item on a set of criteria. The YahooMovies is the one that realize the explicit input acquisition.

2.3.2. Neighbor formation

This step aims to characterize each user by using the past user preference data. Then the system will observe similarity among users, and form a set of similar users for a target user.

2.3.2.1. User profiling techniques

After a user kept providing his preference data to the system, now his user profile is ready to be produced using such historical preference data. A user profile which is the representation of user characteristic as well as preference data are always represented in term of a vector. Based on the concept of multi-criteria rating, a vector element is corresponding to a criterion of item. The user preference data is retrieved in the form of a vector whose elements represent rating score a user provides for an individual aspect of an item as described in Eq. (2). Therefore, an element of a user profile vector is related to and calculated using the related element in a set of user preference data.

In addition to the user profile, researchers have considered two types of user profile. They are either user preference, or behavior profile. The user preference profile refers to a user profile whose elements contain values obtained from multiple criteria rating scores. Aciar S., et al., 2007 is the one that observe this type of profile. They let users express their preference toward an item (in their case; digital camera) in term of text-based comment, and use text-mining algorithm to automatically obtain the multi-criteria numerical-based preference values from 0 to 1. After that each element of a user profile is separately calculated by summing all preference values toward the corresponding criteria of each comment. The summed value is then averaged by the number of comments a user has given.

Apart from the user preference profile, there is another profile type which is user behavior profile. This type of profile is constructed based on item selection of a user. Mostly, the system which realizes this concept will transform the initial user preference data into a binary value toward each criterion. Srikumar K., et al, 2004 realized this style. The user behavior profile is constructed when a user request for recommendation. In their work, user preference data is a vector describing multi-attribute content of a product in term of binary value. A profile element represents a binary value expressing the presence (1) or absence (0) of preference toward the corresponding criterion. After obtain the user profile based solely on the direct request from a user, it might be adjusted again to have some zero-filled elements one according to the past user preference data.

Most researches did not realize that either user preference or behavior profile expresses only one characteristic of users. The preference profile represents just only how much each user prefer a particular criterion, meanwhile the behavior profile is interested in just the selection behavior of user. Speaking of the opportunity to increase recommendation accuracy, this work considers to incorporate both aspects of user characteristic implication. The new type of user profile should cover both user preference and behavior. Thus, the system will have better ability to know users personally.

2.3.2.2. Weight calculation

In the section 2.3.2.1, user profiling techniques are mentioned. Nevertheless, just only a user profile will not well characterize a user since each element in the profile absolutely is just a summarization of preference value toward a particular criterion. This is why researchers take into consideration of criteria weight.

Both the multi-attribute and multi-criteria rating recommender systems have concerned the use of the weight assignment mechanism to give different significance level to each criteria effecting to each user. For instance, some people may agree to see a movie that James Cameron directs, such as, Avatar, or Titanic, while others may love to see a movie that has a lot of 3D effects no matter who directs the movie. Namely, having values that vary according to the users weighted on the criteria can compensate for the situation. Furthermore, according to the example, if those users are impressed by a dramatic movie, they may prefer that kind of movie without consideration of the director. Then, they may focus more on how the actor or actress acts in the dramatic movie. This means that the most important criteria for them are the acting criteria, not the direction one anymore. This means that the system needs to provide a way to monitor this preference change to closely understand the consecutively changed user's characteristic. In the work of Le Roux, F., et al., 2007 and Schmitt, C., et al., 2002, users have to provide the weight corresponding to importance of each criterion themselves manually. However, requiring user cost on weight assignment is not a good solution for nowadays. Therefore, another automatic weight calculation was then proposed. For example, in Plantié M., et al., 2005 and K. Lakiotaki., et al., 2007, the same set of weights is assigned to each criterion for all users. This is not so fair, because each user can get influenced by each criterion unequally.

Recommender systems which assign the weight variant to each user were introduced in some domains of products and services. The work of Srikumar K., et al., 2004 and Perny P., et al., 2001 tried to assign the criteria weights which vary to each user. Unfortunately, they did not provide the way for getting the criteria weight adaptive when users give more preference. Recently, there is adaptive weight assignment, but it still is hard to update the weight values. For example, M. Park H., et al., 2008 proposed a recommender system which applied the Bayesian network theory to give the set of probability values expressing how much each restaurant is likely to be selected based on each criterion. The probability values will then be used for assigning criteria weight using the pair-wise comparison on criteria formed by the AHP (Analytical Hierarchy Process). Absolutely the process of Bayesian Network Model takes so many loads on computation. In Another work, Aciar S., et al., 2007 proposed the technique to construct the ontology representing text-based preference with the numerical user preference on an item. But there is no claim that the extracted ontology will represent the actual preference of users, since extraction produces different ontology based on different text mining algorithm. Consequently, the criteria weights are produced by either counting the appearance of each content value in the ontology or directly computing from the user-specified preference. However, the criteria weights produced are in the form of fraction of appearing content on each criterion and the number of item rated by a user. This technique is really suitable for their case in which users may not provide preference toward all criteria, but if, on the other hand, users does leave any item criteria empty when commenting. The technique will not be useful in weight assignment.

It can be seen that the trend of weight assignment development keep on the user-variant, and adaptive way. Unfortunately, the weight assignments which effectively achieve the two goals have not been observed. In this work, the new candidate method for weight assignment is introduced. It is user-variant, and adaptive.

2.3.2.3. Incorporation of weight to the user profile

After the criteria weights are obtained, the system will incorporate them into the corresponding element in the user profile. The weighted user profile will then be passed to the similarity measurement.

2.3.2.4. Similarity measurement

A pair of user profile is compared using any multidimensional distance measurement method, such as, Euclidean distance, or Cosine similarity.

2.3.2.5. Neighbor selection

Finally in this step, a target user is given a set of similar users or neighbors according to their similarity value. Users who have more similarity value comparing with the target user will then be more recognized as a similar user of such a target one.

Once the criteria weight which is then incorporated to the user profile is adaptive and user-variant, that means a user may have different set of neighbors based on their updated profile.

2.3.3. Rating prediction

This step aims to predict the score a user may give to an item that he has not evaluated before or an unknown item. Researchers have used the weighted average which is introduced in Breese J. S., et al, 1998. The weighted average uses the overall score similarity value of neighbors to produce the predicted score as in Eq (3).

$$R(u,i) = \frac{\sum_{n \in N(u)} sim(u,n) \cdot R(n,i)}{\sum_{n \in N(u)} sim(u,n)} \tag{3}$$

R(u,i) represents the predicted overall score for the user *u* toward the item *i*. The set *N(u)* is the neighbors of user *u* that have already evaluated the item *i*. The *sim(u,n)* denote the similarity of the active user *u* and the neighbor *n*.

Speaking of multi-criteria rating, another interesting point is to extend the idea of multi-criteria rating to the rating prediction part. In this work, the new rating prediction technique is introduced to utilize multi-criteria rating scores in rating prediction.

CHAPTER III

PROPOSED METHOD

From the aforementioned interesting points, this work takes into consideration the neighbor formation, and the rating value prediction steps. The former consists of a weighting calculation, which is the user and the time variant, and a concatenated profile technique of both the user's preference and behavior in order to better distinguish the importance between each criterion, and produce a more representative profile, respectively. In the rating value prediction step, the MCDM is applied to the multi-criteria rating to calculate the recommendation value. First, it is much simple for understanding this work through explanation of the profile needed in our proposed method. It can be categorized into two types, *the user preference profile*, and *the user behavior profile*. These profiles need the rating information for sets of movies. For making things clear, in every step, an example for an active user will be set.

3.1. Rating information

As inputs for the method, the rating information provides the system a set of multiple rating score given by a set of user on multiple criteria toward a set of movies. Suppose there are *m* kinds of criteria. Then, for item *s*, user *a* is expected to give rating information represented by a vector

$$(r_{as0}, r_{as2}, \ldots, r_{asm}), \tag{4}$$

Where r_{as0} denotes the overall rating, whereas r_{asi} (i > 0) denotes the rating for the ith criterion. For example, the Yahoo Movies Database contains four kinds of criteria, i.e., the story, acting, direction, and visuals. For each movie, a user gives a rate ranging from 1 to 13 to each of these four criteria as well as an overall rating. As a result, the rating information is represented as a vector (r_{as0}, r_{as1},…, r_{as4}).

For the above description of rating information, it can be seen as this below example. Let a user 102 be an active users for our explanation, and user 21, 78, 125 and 15 be another users in this specific example. In this example, the rating information is collected in the form of database **tupple**. Each field starting from "overall_rating" to "visuals_rating" represents a score which a "user_id" gives on a particular "movie_id" toward particular criteria. Before rating information is transformed to numerical format, there are some tasks (described in section 4) of collecting and converting data, needed to be done. The Table 3.1 is formed from the real database, and will be used in examples along the explanation of proposed ideas.

Table 3.1 : Examples of rating information

user_id	movie_id	overall_rating	story_rating	acting_rating	direction_rating	visuals_rating
15	50	8	8	10	10	10
15	52	6	12	12	13	12
15	70	1	1	4	4	5
15	87	13	13	13	13	13
15	93	13	12	13	13	13
15	94	13	12	12	13	13
15	95	1	1	6	4	13
15	96	9	8	8	10	10
15	97	10	10	11	9	11
21	1	11	10	10	11	13
21	103	8	8	9	6	10
21	131	12	11	12	11	13
21	132	6	5	9	9	7
21	133	13	12	13	12	13
21	134	4	6	7	3	3
21	66	11	9	11	11	11
21	87	11	10	11	11	13
21	91	7	6	9	6	7
21	95	6	6	7	6	5
21	98	5	6	3	6	10
78	591	8	5	9	6	10

78	592	6	5	8	3	6
78	593	6	3	7	4	11
78	594	9	10	9	10	10
78	595	1	1	2	3	4
78	596	8	6	11	8	8
78	597	13	12	13	13	13
78	598	10	8	9	11	10
78	599	8	8	9	6	10
78	600	10	10	9	9	9
102	109	4	3	10	4	7
102	174	3	3	9	7	10
102	215	11	10	11	9	12
102	355	6	5	9	7	10
102	397	11	11	11	10	12
102	444	10	8	10	8	11
102	48	8	4	11	6	11
102	774	12	1	1	1	3
102	775	12	13	12	11	12
102	776	13	12	12	12	13
125	412	6	6	6	6	6
125	473	2	3	2	2	1
125	560	11	11	11	11	11
125	688	8	6	8	3	10
125	873	10	9	9	11	11
125	929	3	4	3	4	3
125	930	9	9	10	9	10
125	931	11	9	12	10	12
125	932	10	11	12	10	11
125	933	10	10	10	9	8
25	138	12	10	12	12	11
25	152	6	6	4	5	13
25	153	4	3	3	3	7
25	154	9	9	12	5	12
25	155	12	11	11	12	12
25	156	4	6	4	4	5
25	157	4	4	9	6	6

25	158	5	12	12	10	12
25	20	11	11	11	10	13
25	48	12	12	11	12	13
25	51	12	11	13	12	12
25	74	11	12	12	10	10
25	8	12	12	12	12	13
61	109	11	11	12	10	10
61	120	9	9	9	10	9
61	122	8	7	10	5	6
61	444	1	1	1	1	4
61	445	12	12	13	13	12
61	446	13	13	13	13	13
61	447	3	4	6	2	1
61	448	6	5	6	6	7
61	449	10	10	12	10	12
61	74	12	13	12	13	12
61	87	13	11	13	13	13
61	95	12	11	10	9	12
61	98	1	1	1	1	2
21	1	11	10	10	11	13
21	103	8	8	9	6	10
21	120	7	8	7	6	8
21	131	12	11	12	11	13
21	132	6	5	9	9	7
21	133	13	12	13	12	13
21	134	4	6	7	3	3
21	41	10	10	11	11	9
21	66	11	9	11	11	11
21	74	11	9	10	12	11
21	87	11	10	11	11	13
21	91	7	6	9	6	7
21	95	6	6	7	6	5
21	98	5	6	3	6	10

3.2. User profile

When given a set of rating information, we compose a user profile consisting of the user's preferences and the user's behavior profiles, which are updated when the users provide more rating information to the system. Two kinds of user profiles are constructed. One is in the "like" space, and the other is in the "dislike" spaces because we found that having those two spaces for the user profiles can better determine the set of similar users (neighbors) of a user, otherwise poor quality neighbors may be obtained, as stated in Maneeroj, S., et al., 2006. In this work we use both positive and negative user profiles that respectively correspond to the "like" and "dislike" spaces.

3.2.1. Space separation

Rating Information does not represent the real characteristic of user preference. Usually, human can express their in two ways; likeness, or dislikeness. In this work, space refers to a set of rating information records. The two spaces are influent upon a user in different manners in forming a set of similar users. Normally, when a user want to see which item he/she may be preferred, in this case that item should be loved and recommended by a set of similar users who have the same likeness with the active users. Thus, in order to form that set of users, the system would be able to know much more about a user likeness. On the other hand, in situations when a user ask the system to filter out items that he/she might not be preferred, the set of users who have the same taste in "dissatisfaction". Moreover, in Maneeroj, S., et al., 2009, it was stated that space separation is so important for a recommender system. The work also stated a problem called "misinterpreted same taste", found in the system that performs the recommendation without separating rating information into like and dislike space.

Additionally, in this work, it is suitable to determine the space based on a threshold "θ". The threshold is selected as a half of the possible rating information value. In case of the Yahoo Movies Database the threshold is set to 7. First of all filtering out rating information is done for records with the overall score less than or equal to Θ, and these records are obtained within the same set called "dislike", 'dissatisfied", or "negative" set. The rating information having the overall score more than or equal to Θ is formed in the "like", 'satisfied", or "positive" set. Many questions may come to point that the record having the overall score equal to Θ will be classified to both like and dislike set. It is because, for that kind of records, the probabilities of satisfaction and dissatisfaction are equal. Therefore, those records should be kept in the both spaces.

From the description of satisfied and dissatisfied spaces, user 102 rating information is now separated in to the spaces as shown in the table below. The records that belong to the satisfied space are marked with the "+", while other records that are classified into the dissatisfied space can be donated by "-".

Table 3.2 : Examples of user 102 space seperation

user_id	space	overall_rating	story_rating	acting_rating	direction_rating	visuals_rating
102	-	4	3	10	4	7
102	-	3	3	9	7	10
102	+	11	10	11	9	12
102	-	6	5	9	7	10
102	+	11	11	11	10	12
102	+	10	8	10	8	11
102	+	8	4	11	6	11
102	+	12	1	1	1	3
102	+	12	13	12	11	12
102	+	13	12	12	12	13

3.2.2. User preference profile

The user preference profile is a summarized representation of current user's preference, and represented as a vector whose components are the average rating values of the corresponding criteria. For each user *a*, we calculate a positive user preference profile (pp_{a1}, … , pp_{am}) and a negative user preference profile (np_{a1}, … , np_{am}). Let *h* denotes the possible highest rating value. In the case of the Yahoo Movies Database used in our experiment, users express a rating value from the range between 1 and 13, so the highest possible value *h* is 13. After the space separation, in order to produce the satisfied (like or positive) profile, rating information in the like set will be used. On the other hand, difference between the rating value of another set of rating information records in the dislike set, and *h* is obtained to represent the “dislikeness” or “dissatisfaction” and calculate dissatisfied (dislike or negative) profile element. Let S_a denotes the set of items that user *a* gives rating information. Then, the user preference profile for the i^{th} criterion is defined as

$$pp_{ai} = \sum_{s \in Sa} r_{asi} \Big/ h|S_a| \quad , \quad np_{ai} = \sum_{s \in Sa} (h - r_{asi} + 1) \Big/ h|S_a| \qquad (5)$$

Where r_{asi}, is the rating value of the *i*th criterion of item *s* by user *a*. Both the positive and negative profiles are normalized by the possible highest rating value *h*.

3.2.3. User behavior profile

First of all, the same thing as the section 3.2.1 is previously done before moving on producing behavior profile’s element. The all rating information records are separated into like and dislike set using the overall score. After that If the ratings in the like set (resp. dislike set) is more than (resp. less than) the threshold, it is classified into “like” (resp. “dislike”) space without considering the less-than-7 (resp. more-than-7) ratings. Finally, the occurrence in each space will be counted to produce elements of this type of profile.

For user *a*, the positive and negative user behavior profiles are represented by vectors (pb_{a1}, … , pb_{am}) and (nb_{a1}, … , nb_{am}), respectively. Each component of the positive (resp. negative) user behavior is the average number of positive or like space (resp. negative or dislike space) rating occurrences on the corresponding criterion. For the i^{th} criterion, let S_{ai+} (resp. S_{ai-}) denotes the set of movies that user *a* gives the rating value that is more than (resp. less than) the threshold Θ. Then, the user behavior profile for the i^{th} criterion is defined as

$$pb_{ai} = {|S_{ai+}|}\big/{|S_a|}\ , \qquad nb_{ai} = {|S_{ai-}|}\big/{|S_a|} \qquad . (6)$$

Here is an example of the user preference and behavior profile in both like and dislike space calculated using rating information given in the section 3.1, for a user 102. Where the field "story" to "visuals" denote the preference profile, and the field "cri1" to "cri4" represent the behavior profile. Especially for the behavior model, the cri1 to cri4 field, each of them is calculated from each particular criteria, in such a way that cri1 (resp. cri4) is computed using just only the story (resp. visuals) criteria.

Table 3.3 : Example of user 102's preference and behavior profile in like space

user_id	story	acting	direction	visuals	cri1	cri2	cri3	cri4
102	0.453846	0.523077	0.438462	0.569231	0.5	0.6	0.5	0.6

Table 3.4 : Example of user 102's preference and behavior profile in dislike space

user_id	story	acting	direction	visuals	cri1	cri2	cri3	cri4
102	0.238462	0.107692	0.184615	0.115385	0.3	0	0.1	0

Using the Eq (5), Eq. (6) and data provided in the table of rating information examples (Table 3.1), each negative and positive element of both preference and behavior profile can be computed by followed, for the user 102.

$Pp_{(102,story)}$ = (10+11+8+4+1+13+12) / (13*10) = 0.453846

$Pp_{(102,acting)}$ = (11+11+10+11+1+12+12) / (13*10) = 0.523077

$Pp_{(102,direction)}$ = (9+10+8+6+1+11+12) / (13*10) = 0.438462

$Pp_{(102,visuals)}$ = (12+12+11+11+3+12+13) / (13*10) = 0.569231

$Pb_{(102,story)}$ = |{10,11,8,13,12}| / 10 = 0.5

$Pb_{(102,acting)}$ = |{11,11,10,11,12,12}| / 10 = 0.6

$Pb_{(102,direction)}$ = |{9,10,8,11,12}| / 10 = 0.5

$Pb_{(102,visuals)}$ = |{12,12,11,11,12,13}| / 10 = 0.6

$Np_{(102,story)}$ = (11+11+9) / (13*10) = 0.453846

$Np_{(102,acting)}$ = (4+5+5) / (13*10) = 0.523077

$Np_{(102,direction)}$ = (10+7+7) / (13*10) = 0.438462

$Np_{(102,visuals)}$ = (7+4+4) / (13*10) = 0.569231

$Nb_{(102,story)}$ = |{3,3,5}| / 10 = 0.3

$Nb_{(102,acting)}$ = |{ø}| / 10 = 0

$Nb_{(102,direction)}$ = |{4}| / 10 = 0.1

$Nb_{(102,visuals)}$ = |{ ø }| / 10 = 0

3.3. Neighbor formation

The neighbor formation step consists of four sub steps, i.e., *weight calculation*, *user profile composition (hybrid user profile)*, *similarity measurement*, and *neighbor selection*. The two types of user profile defined by Eq. (5) and (6) are used in these sub steps.

3.3.1. Weight calculation

To incorporate weight with both the user preference and behavior profile, elements in a user profile are all utilized to calculate the weight.

$$wp_{ai+} = pp_{ai} \Big/ \sum_{i \in m} pp_{ai} \quad , wp_{ai-} = np_{ai} \Big/ \sum_{i \in m} np_{ai} , \qquad wb_{ai+} = pb_{ai} \Big/ \sum_{i \in m} pb_{ai} , wb_{ai-} = nb_{ai} \Big/ \sum_{i \in m} nb_{ai} \qquad (7)$$

Where the wp_{ai+} and wp_{ai-} respectively denote the calculated positive (like) and negative (dislike) weights for the user preference profiles for the i^{th} criterion of user *a*. The pp_{ai} and np_{ai}

respectively represent the calculated positive and negative criteria value for the user preference of user *a* on the *i*th criterion. On the other hand, the wb_{ai+} and wb_{ai-} respectively denote the calculated positive and negative weights for the user behavior profiles for the i^{th} criterion of user *a*. The pb_{ai} and nb_{ai} respectively represent the calculated positive and negative criteria value for the user behavior of user *a* on the i^{th} criterion. Remarkably, the weights are calculated using the element of each user profile which is updated according to the rating information of the rated movie. Therefore, the weight values are calculated individually for each user, and recalculated every time the users provide the system with more rating information.

According to our example, for a user 102, the positive preference weight of story criteria can be computed as below.

$$Wp_{(102,story)+} = 0.453846/(0.453846+0.523077+0.438462+0.569231)$$
$$= 0.228682$$

Equivalently, using the same idea another positive and negative weight values for both the preference and behavior model can be found like below.

$$Wp_{(102,acting)+} = 0.523077/(0.453846+0.523077+0.438462+0.569231)$$
$$= 0.263566$$

$$Wp_{(102,direction)+} = 0.438462/(0.453846+0.523077+0.438462+0.569231)$$
$$= 0.220930$$

$$Wp_{(102,visuals)+} = 0.569231/(0.453846+0.523077+0.438462+0.569231)$$
$$= 0.286822$$

$$Wb_{(102,story)+} = 0.5/(0.5+0.6+0.5+0.6)$$
$$= 0.227273$$

$$Wb_{(102,acting)+} = 0.6/(0.5+0.6+0.5+0.6)$$
$$= 0.272727$$

$$Wb_{(102,direction)+} = 0.5/(0.5+0.6+0.5+0.6)$$
$$= 0.227273$$

$Wb_{(102,visuals)+}$ = 0.6/(0.5+0.6+0.5+0.6)

= 0.272727

$Wp_{(102,story)-}$ = 0.238462/(0.238462+0.107692+0.184615+0.115385)

= 0.369048

$Wp_{(102,acting)-}$ = 0.107692/(0.238462+0.107692+0.184615+0.115385)

= 0.166667

$Wp_{(102,direction)-}$ = 0.184615/(0.238462+0.107692+0.184615+0.115385)

= 0.285714

$Wp_{(102,visuals)-}$ = 0.115385/(0.238462+0.107692+0.184615+0.115385)

= 0.178572

$Wb_{(102,story)-}$ = 0.3/(0.3+0+0.1+0)

= 0.75

$Wb_{(102,acting)-}$ = 0 /(0.3+0+0.1+0)

= 0

$Wb_{(102,direction)-}$ = 0.1/(0.3+0+0.1+0)

= 0.25

$Wb_{(102,visuals)-}$ = 0/(0.3+0+0.1+0)

= 0

3.3.2. User profile composition

After the criteria weights are already calculated, they will be then used for multiplying with their corresponding criteria. The weighted elements are necessary parts of the hybrid user profile, and put in order to have weighted preference elements concatenated by weighted behavior elements. The positive user profile is defined as the concatenation of the weighted positive user preference and behavior profiles

$$\boldsymbol{up}_{+}(\mathrm{a}) = (wp_{a1+} \times pp_{a1}, \ldots, wp_{am+} \times pp_{am}, wb_{a1+} \times pb_{a1}, \ldots, wb_{am+} \times pb_{am}), \tag{8}$$

where wp_{ai+} and wb_{ai+} are the positive weights for the user preference and behavior profiles defined in Eq. (7), respectively. On the other hand, pp_{ai} and pb_{ai} are the positive user preference and behavior profiles defined in Eq. (5) and (6), respectively.

Similarly, the negative user profile is defined as

$$\boldsymbol{up}_{-}(\mathrm{a}) = (wp_{a1-} \times np_{a1}, \ldots, wp_{am-} \times np_{am}, wb_{a1-} \times nb_{a1}, \ldots, wb_{am-} \times nb_{am}), \tag{9}$$

The proposed hybrid profiling technique is novel in the sense that it utilizes both the user's preference and behavior. For a user 101, after criteria weights are valued and incorporated with the corresponding criteria scores in both preference and behavior profile. The positive hybrid profile can be seen as follow. $Up_{+(102)}$ can be written in the form of a vector as (0.103786421008,0.137865233339,0.0968695835587,0.163267821766,0.113636363636,0.163636363636,0.113636363636,0.163636363636).

3.3.3. Similarity measurement

The main objective of this step is to determine the similarity between users. To do that, we use our proposed representative user profile defined in the previous section to represent a user, and measure the distance between two users as the Euclidean distance. For users *a* and *u*, the distance $d_{+}(a,u)$ between them in the "like" space is the Euclid distance of their positive user profiles , whereas their distance $d_{-}(a,u)$ in the "dislike" space is the Euclid distance of their negative user profiles.

$$, \; d_s(a,u) = \sqrt{\sum_{i=1}^{I} \left(up_s(a)_i - up_s(u)_i\right)^2} \tag{10}$$

In the Eq. (10), l denotes the number of profile elements, while s represents the space of profile (either positive, or negative). Therefore, the term $up_s(a)_i$ can be used to represent the i^{th} element in the s space user profile of the user a.

For our example, user 102 and user 21 have dissimilarity value as 0.0147131559058, in the like space when both users are prepared in term of their own positive hybrid profile. The positive hybrid user 21 profile can be found using the Eq. (8) like this (0.105403115863, 0.13610952417, 0.111888140925, 0.154862626819, 0.136363636364, 0.185606060606, 0.094696969697, 0.136363636364).

3.3.4. Neighbor selection

After the dissimilarity values between users are obtained, then the list of neighbors is proposed and sorted by the least dissimilarity value to the most dissimilarity value. In this work, it is available to select the top most N neighbors to be used in the next step. In addition, there are two kinds of neighbors' lists belonging to an active user, which are the list in the "like" space and the "dislike" space.

3.4. Estimation prediction value

The list of the top N neighbors is selected to predict the rating value for an active user. Furthermore, the calculation can be performed in two situations. First, the calculation using neighbors in the "like" (resp. "dislike") space is performed to recommend (resp. filter) items to users.

3.4.1. Applied MCDM

Single-criteria rating cannot completely explain the characteristic of the user's preference. We propose using the Multi-criteria ratings to calculate the prediction value by using MCDM. The technique can be calculated by first estimating the value of each individual criteria and then deriving the values to form the overall rating for a specific item. We utilize each neighbor's opinions toward a specific criterion as the criteria values, and their weights on such criterion, in order to estimate each unknown movie's individual criteria. After all the predicted criteria values are obtained, they are consecutively applied on the weighted average technique to calculate the overall rating of that item, where the weight is the criteria weight of the active user. The technique can be described by using Eq. (11).

$$P_{as} = \frac{\sum_{i \in m} wp_{ai} \left(\frac{\sum_{n \in N} wp_{ni} \times r_{nsi}}{\sum_{n \in N} wp_{ni}} \right)}{\sum_{i \in m} wp_{ai}}, \qquad (11)$$

Where, $P_{a,s}$ denotes the prediction value of movie *s* for active user *a.* The *m* is the set of criteria. The wp_{ai} represents the calculated weight on the i^{th} criteria by active user *a*, likely while wp_{ni} represents the calculated weight on the i^{th} criteria by neighbor *n*. Each weight value is calculated by using Eq. (7). The r_{nsi} is the actual rating of neighbor *n* toward movie *s* on criteria *i*. Finally, the *N* is the set of nearest neighbors of active user *a*. Remarkably, in the recommendation situation, the positive weight is utilized. In contrast, for filtering out items, the negative is alternatively utilized.

For a clear example on how to perform the proposed applied MCDM, let us consider the user 102 as the active user the system is going to make score prediction of the unknown movie 120 for recommendation situation. Suppose after all pairs of users are valued by a dissimilarity values, user 21, 25 and 61 are known as user's 102 similar neighbors. Fortunately, the user 21 and 61 rated the movie 120 in all criteria, and their rating information for that movie can be seen as the two vectors respectively; $r_{21,120}$=(7, 8, 7, 6, 8), and $r_{61,120}$ =(9, 9, 9, 10, 9). The term $P_{102,120}$ will be equal to 8.25714356449.

The steps before obtaining the predicted values can be shown as followed. To make every step easier to understand, some more terms are introduced for just this particular example. The term P_R_{asi} is used for representing the i^{th} criteria estimated rating score for user *a* on movie *s*.

$$P\_R_{(102,120,story)} = \frac{(0.228373556112 * 8) + (0.247104363382 * 9)}{(0.228373556112 + 0.247104363382)}$$

$$= 8.51969655917$$

$$P\_R_{(102,120,acting)} = \frac{(0.259515527352 * 7) + (0.27027046019 * 9)}{(0.259515527352 + 0.27027046019)}$$

$$= 8.02030007906$$

$$P\_R_{(102,120,direction)} = \frac{(0.235294144107 * 6) + (0.231659964222 * 10)}{(0.235294144107 + 0.231659964222)}$$

$$= 7.98443579124$$

$$P\_R_{(102,120,visuals)} = \frac{(0.276816772428 * 8) + (0.250965212206 * 9)}{(0.276816772428 + 0.250965212206)}$$

$$= 8.47550942161$$

$$P_{(102,120)} = \frac{(0.228682022114 * 8.51969655917) + (0.263565848507 * 8.02030007906) + (0.220930396611 * 7.98443579124) + (0.286821732768 * 8.47550942161)}{(0.228682022114 + 0.263565848507 + 0.220930396611 + 0.286821732768)}$$

$$= 8.25714356449$$

CHAPTER IV

PROPOSED ARCHITECTURE

Recommender systems have been integrated into many businesses especially ones that apply web-based commerce which can be referred to as electronic commerce (E-commerce) Tiwari R., et al., 2007. Once the success of E-commerce, and development of telecommunication technology brought up the new way for a business owner to service in anytime and anywhere Tiwari R., et al., 2007. It is called “Mobile commerce” (the extension of E-commerce to the wireless medium).

Mobile banking has been introduced around the world (Tiwari R., et al., 2007). In Thailand, mobility comes playing an important role on banking service. There have been three communication channels used, which are SMS (Short Message Service), EDGE/GPRS (Enhanced Data Rate for Global Evolution/General Packet Radio Service), and SOA (Service Oriented Architecture). For banking service in Thailand, SMS and EDGE/GPRS have been used for participating between the cellular network providers with the mobile phone client. For the SOA, in Thailand, most developers implements Web Service in order to communicate between cellular network provider and the bank server.

In the domain of mobile banking service, there are a lot of services which may not be seen by a user. Fortunately, a research area have introduced a technique to recommend item, called recommendation system. The current technique that has been a well-known in this kind of area is “Multiple Criteria” which has been used in many famous domain of e-business, such as http://movies.yahoo.com. The recommendation can be done using the technique which concern preference expression up on multiple criteria of an item (in this case; service). It would be a very good opportunity if the technique of recommendation which is capable of suggesting unseen items in the large item space to users is introduced to the domain of banking services. This will lead to the increase of value in mobile banking business in the sense that the never-seen service which waste a lot of cost without returning benefit will have more chance to meet users, and the time taken in searching for service (without recommendation) will be also reduced for a user. As a mobile application, there were already works which suggested a generalized way to incorporate recommender system to the mobile network framework (Liu C., et al., 2008), or the specific platform restaurant mobile recommender system (Park M. H., et al., 2008). The model was called “A Hybrid Recommendation Architecture for Mobile Commerce System”.

In addition, we suggest using of two multi-criteria recommendation techniques. They both proposed different techniques used in the web-based movie multiple criteria recommender system. Tangphoklang P., et al., 2010 proposed the multiple-aspects and adaptive user preference representation together with the way to utilize the multiple preference data to produce recommendation accurately. Unfortunately, for mobility, it is not suitable to let users express their preference directly similar to Tangphoklang P., et al., 2010. Consecutively, in this work, the proper profiling technique should be able to collect behavior data as user-specify preference data, and we suggest use of the profiling technique proposed in Rattanajitbanjong N., et al., 2009 to create this kind of profile.

Therefore, in this work, we would like to propose a design of mobile recommender system by refining the model described in Liu C., et al., 2008. Furthermore, we give the suggestion on how to combine and make the different method in Tangphoklang P., et al., 2010 and Rattanajitbanjong N., et al., 2009 possible for the designed architecture.

4.1. Multiple criteria recommendation algorithm

Recommender systems, especially for multiple-criteria consideration, were introduced in many domains of products and services, such as, e-commerce (Ben S. J., et al., 1999), restaurant (Park M. H., et al., 2008), learning quality approach (Manouselis N., et al., 2004), and course (Roux

F. L., et al., 2007), because of the introduction of effectiveness of recommendation in Adomavicius G., et al., 2007.

Multi-criteria recommendation can be done involving three steps based on Tangphoklang P., et al., 2010 , which are neighbor formation, score estimation, and recommendation. In this work, these three steps are explained to let to let reader get just the basic concepts of recommendation, the detailed process can be found in such a literature.

Generally, it is important to first know the characteristic of products (or services). In Tangphoklang P., et al., 2010 and Rattanajitbanjong N., et al., 2009 , the domain of products fall into the movie domain, and preference of user can be expressed via web-based interface by letting rate on a set movie criteria. This way is not suitable for the mobile phone context which has services as items. This reason makes the combination between methods in Tangphoklang P., et al., 2010 and Rattanajitbanjong N., et al., 2009 important.

In order to make the rating-based multi-criteria recommendation possible for mobile banking services, the detail in some step described in Tangphoklang P., et al., 2010 must be compensated by a techniques described in Rattanajitbanjong N., et al., 2009 , as follows.

4.1.1. Input acquisition and neighbor formation

A multi-criteria user profile which is the summary of user's preference must be introduced. According to Tangphoklang P., et al., 2010 and Rattanajitbanjong N., et al., 2009 , the multi-criteria user profile can be described by a vector. Let $up(a) = (e_1,e_i,\ldots,e_n)$ be an n-element user profile that belongs to the user a, and the element e_i is an element in the user profile representing the i^{th} criteria.

Computations of the profile involve profiling comparison technique Rattanajitbanjong N., et al., 2009 in the context of mobile banking service under mobile commerce environment. One type of profile introduced Rattanajitbanjong N., et al., 2009 is the movie profile which can be thought of as a service profile vector. Let $sp(s) = (c_1, c_i, \ldots, c_n)$ be an n-element service profile that belongs to the service s, and the element c_i is a numerical value toward the i^{th} criteria. The c_i can be different for each criterion, and this depends on the characteristics of the criteria. For example, if a criterion for a bank service is the service fee, numerical values for this criterion might be denoted by discrete values, i.e., 0, 1, and 2, representing "cheap", "reasonable", and "expensive", respectively.

The last input that plays a very important role in producing the user profile is the rating score that a user assessed toward a particular service. Moreover, the score might not be just capable of expressing preference of user, but also expressing the level of familiarity or friendliness. Unfortunately, in the mobile context, the user might not prefer or available to participate. So we suggest a way to address this situation. The recommender system can be performed based on the above meanings to recommend a service that might be useful and easy to get familiar by a user. The score can be obtained from the frequency of accessing the i^{th} service for user a, denoted by $r_{i,a}$.

User a's profile can be determined using the following equation

$$up(a) = \frac{\sum_{i \in S} r_{i,a} \times sp(i)}{|S|}. \qquad (12)$$

Where S represents the set of services that user a has selected. After the user profiles for all bank services are prepared, the system will try to find a set of neighbors that is similar to user a's characteristics. This can be done by measuring dissimilarity (or similarity) between multivariate user profile vectors. One well known measurement that has been used for this proposed scheme is the Euclidean distance. Finally, after the dissimilarity measurement has been done, the system will be able to determine the set of similar users by produce descending order of users according to their dissimilarity value toward a user *a.*

4.1.2. Score prediction

Realizing on the applied MCDM prediction technique used in Tangphoklang P., et al, 2010, the system will then form a set of similar users that already rated for a particular service. Their profile criteria elements, together with related element weights, are used to estimate the score for that service.

4.1.3. Recommendation

Last of all, the system will recommend top-n items that has high estimated score to the user *a*.

4.2. Mobile reference architecture design

A designed architecture on mobile hybrid recommendation system has been proposed Liu C., et al., 2008. Unfortunately, it is not suitable for recommender system inclusion to existing mobile networks in Thailand. Actually, from the mobile hybrid recommendation architecture, there are four agents working together, namely, Profile Management Agent, Customer Agent, Interface Format Agent, and Recommendation Agent. In this work, we introduce one additional agent to make the architecture applicable for Thailand situation. It is Bank Service Agent. The reference architecture is depicted in Figure 4.1.

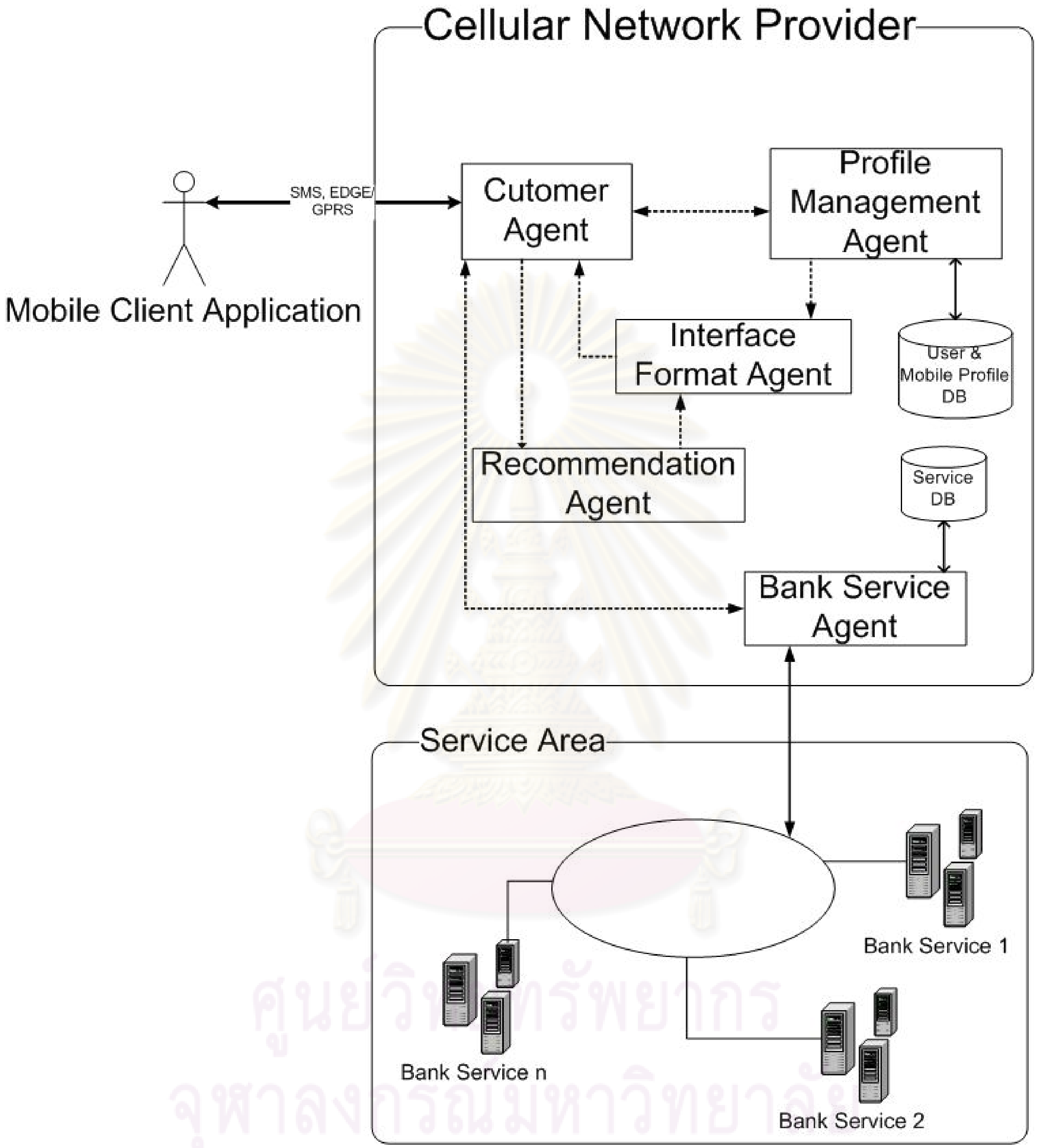

Figure 4.1. The Mobile Multi-Criteria Recommendation Architecture

4.2.1. Customer agent

The Customer Agent is responsible for communicating with users via SMS and/or EDGE/GPRS to process general bank transactions and retrieving recommendation results, working with the Profile Management Agent to manage user profiles, receiving the formatted recommendation results to be sent to users, respectively. In the scope of cellular network providers, we use the dotted arrow to represent the internal user-defined SOA message communicated with the mobile connection process, banking services, and recommendation processes.

4.2.2. Profile management agent

This Agent is capable of processing the user profile update, creating a user profile for a new member, and searching for a needed user profile. The Agent also processes general database management commands, manages the profile of user's mobile phone for the Interface Format Agent to arrange in a proper recommendation format for each specific type of mobile phone.

4.2.3. Recommendation agent

This is the flexible part because any types of recommendation modules can be put here. Additional recommendation methodologies can be added to process the set of recommendations independently aggregated by a hybrid recommendation module Liu C., et al., 2008. In our case, the multiple criteria recommendation module can be uniquely put here.

4.2.4. Interface format agent

This agent will incorporate with the profile management agent to support appropriate recommendation format for each mobile client operating system, realizing on each mobile profile and its specifications.

4.2.5. Bank service agent

The agent which is already embedded to the existing mobile banking service system has two important responsibilities. Fist, it must incorporate with the banking service server to process all necessary bank transactions via the external SOA messages represented by the arrow. Second of all, it increments the frequency of accessing various banking services. This is accomplished by a database containing all banking services registered with the cellular network providers.

4.2.6. Architecture adjustment

One aspect that has not been stated in Liu C., et al., 2008 is the mobile client application which receives data from SMS and/or EDGE/GPRS as inputs. If there are server agents who provide distinct output formats, there must also be corresponding client applications to accommodate those output formats for user display.

According to the designed architecture, when a user intends to use a service without the right services, it is helpful to let other experienced users recommend suitable services to the requesting user.

The adjustment proceeds to send the request to the customer agent. The customer agent extracts the identifiable key from the request and sends the key to obtain the active user profile from the profile management agent. The user profile will then be sent to the recommendation agent and supplied to the multi-criteria recommendation algorithm embedded in the recommendation agent. After the recommendation result is prepared as a list of banking services, it will be sent for formatting by the interface format agent. The interface format agent will require the mobile device profile from the profile management agent to process such a list properly for each mobile hardware platform. The formatted result is sent to the customer agent. Finally, as the front-end agent, the customer agent consecutively sends the formatted result to the mobile client. In a usual situation, these processes will be skipped to allow the requests passing through the bank service agent who participates with external farm of banking service servers to process general bank transactions.

From Figure 4.1, when a cellular network provider has more banking services to offer from participating banks, or more recommendation techniques, the architecture can be modified to accommodate such enhancement.

4.3. Future work

The proposed mobile multi-criteria recommendation architecture is somewhat inflexible for distributed work flow to reach wider clients or alliance banking services. As data are dispersed among SOA repositories, the resulting recommendation must be versatile and transparent to make the users feel “more decision criteria means wider service selections and reach” impressions. The issues of data warehouse and mining to arrive at satisfactory recommendation are a tall order for future mobile recommender systems to fulfill.

CHAPTER V

EXPERIMENT

These experiments are created to prove the performance of the proposed method against with a set of previous methods using these following three hypothesizes, on web-based implementation using PHP programming language and MySQL database management system.

(1) The user and time variant weights help the system produce better recommendations. This hypothesis is referred to as **claim 1**. Basically, this assumption should be set to prove the accuracy when the general preference profile (generally for most recommender systems, they use this type of profile), the preference weight, and the combination of them both are separately considered as a user profile at a time. The claim 1 will be found successful, if the idea of combination between preference weight and profile has the best quality of recommendation. Additionally since this is to observe the improvement in the neighbor formation, the traditional weighted sum technique is used to predict the rating score in the prediction step of recommendation.

(2) Concatenated profiles produce more representative user's characteristics, which will result in better accuracy. This hypothesis is referred to as **claim 2**. After the claim 1 is proved successful (if possible), the objective of the claim 2 is to prove, in neighbor formation, whether the combination of two user aspects which are preference and behavior in expressing their own subjective preference toward items will produce more accurate recommendation. The single aspect either preference, or behavior must be reasonably compared against with the combination of both of them. Considerably especially for our idea, the combination model of a user's profile is done in the way of having the preference aspect concatenated by the behavior aspect.

(3) MCDM is effective for predicting user's rating values. This hypothesis is referred to as **claim 3**, and different from the two previous assumptions. Now in this part, the experiment is done seriously in how to predict the overall rating score for users on unknown items. The current

technique is compared against with the proposed technique, called the applied MCDM (Multiple Criteria Decision Making). Logically, if the second assumption is true, the combination is then used to complete the neighbor formation, but for here now the two different techniques will be applied on prediction step alternatively.

Before the experiment is performed, there are two things which are needed to support the experiment. The first one is data, and the second one is the evaluation metric.

5.1. Data

Data were obtained from http://movies.yahoo.com, and the way the data are collected is demonstrated in the APPENDIX of this report. The data consists of 200 users and 1358 movies, which produces 2550 rating information records. The ratings are separated into two different sets, the training set (70% of the ratings) and the test set (remaining 30% of the ratings) for each variation of experiments. Originally, the Yahoo Movie System provides a way for users to be asked to give their feedback for each movie on the overall rating and **four criteria which include the story, acting, direction, and visuals.** Every user will give a score toward a particular criterion on a particular movie with respect to the meaning of each criterion as followed.

- Story: This criterion lets users give score base solely on story, plot, or scenario of each movie.
- Acting: This one represents the measurement of actors and/or actresses performance in acting characters in a movie.
- Direction: This is about the performance of the movie director.
- Visuals: This corresponds to what users can see in a movie, such as, costume of actors/actresses, location, view, or place where the movie is made.

So, there are four criteria *m* in this experiment. The possible rating values are from A+ to F. After obtaining the original information, we converted them to numeric form in such a way that the

A+ and F respectively refer to the most and least preferable values ranging from 1 to 13. We conducted experiments for various combinations of parameters: number of nearest neighbors (1, 3, and 5) and the number of users (100 and 200).

As mentioned above, the proposed ideas are combined to construct the complete recommendation method, and proved for performance using a dataset. Obtaining data from the YahooMovies is not so straightforward and automatic. Some manual processes are required using some querying techniques, because the website is just for commercial purpose, and does not provide any service for a researcher to obtain rating information.

5.1.1. Obtaining YahooMovies dataset

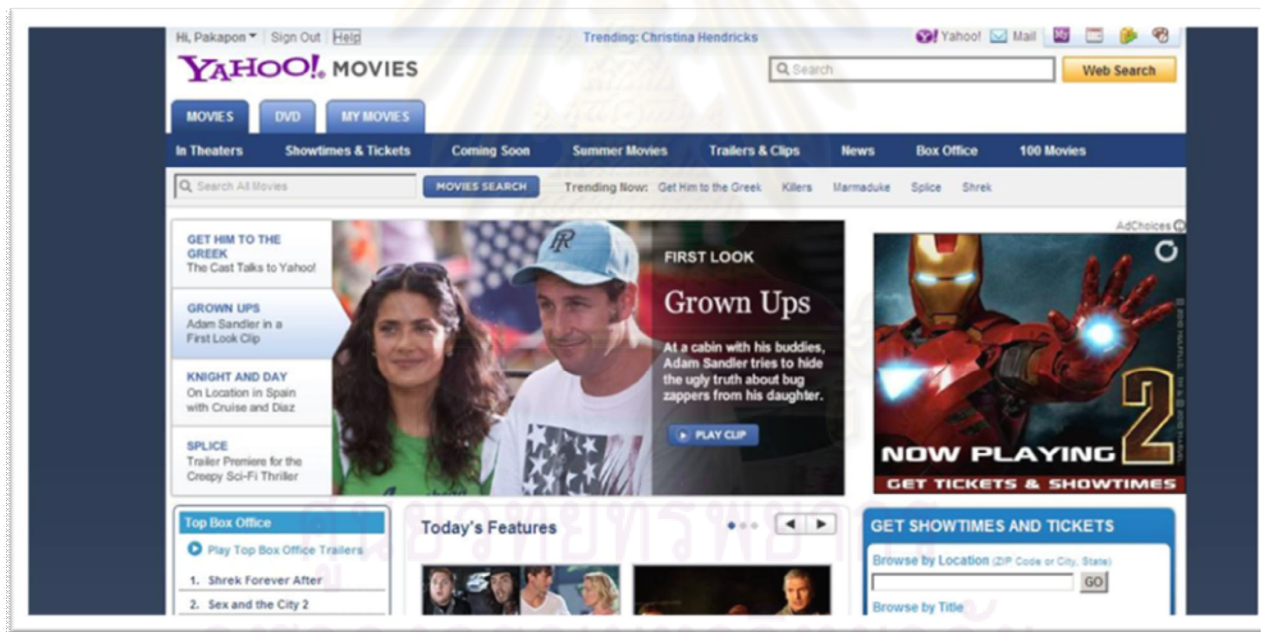

Figure 5.1 : http://movies.yahoo.com

The http://movies.yahoo.com is a website that displays the information about movies. Each movie has its own page describing the show time in different theater, comments (sometime linked from other website) from users. Especially, alike another social networking websites, the YahooMovies also provide the member system for those who want to register to take another privilege. As a recommender system, YahooMovies allows members to rate for a movie in four criteria (story, acting, direction, and visuals). Data produced from this part of YahooMovies System will be used in the experiments described in the next section, and obtained by these following steps.

1. After the main page of is displayed in a browser, Obtaining data can be started from search for a movie by supplying a word in “Movies Search” text box. In this example, the query is done for the movie, “Avatar”. The search results will be shown in another page like below.

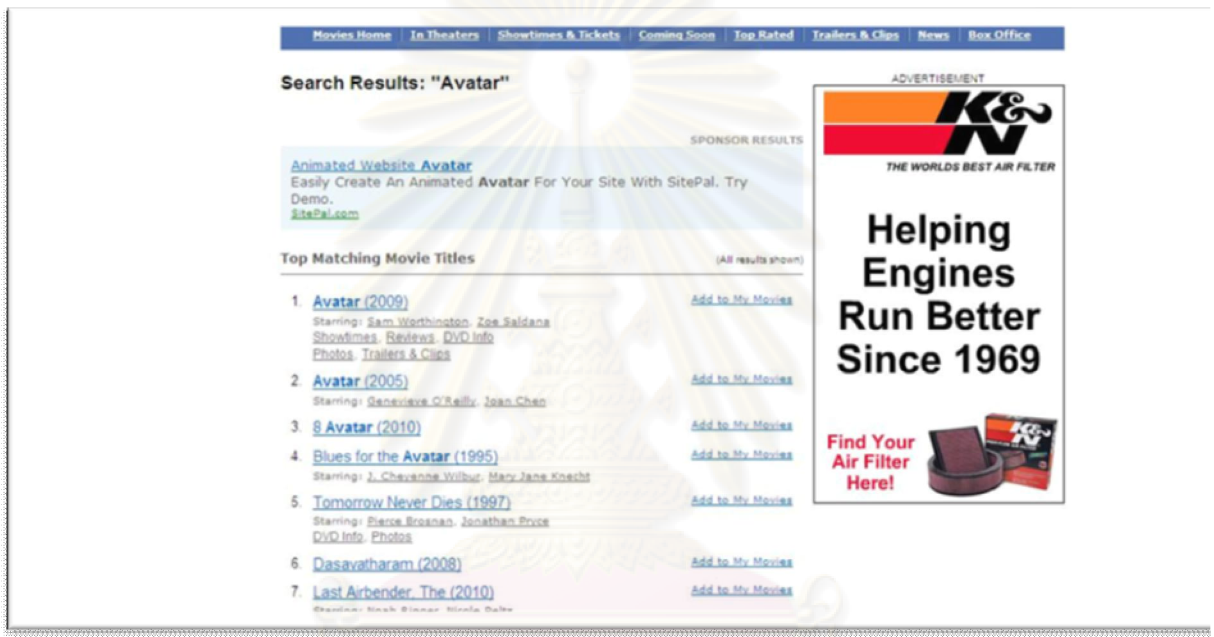

Figure 5.2 : Search results for “Avatar”

2. As shown in the search result, in some cases, if the query word provided to the system is matched or similar to more than just one movie, a list of movie information will display. In this case, the Avatar (2009) will be chosen.

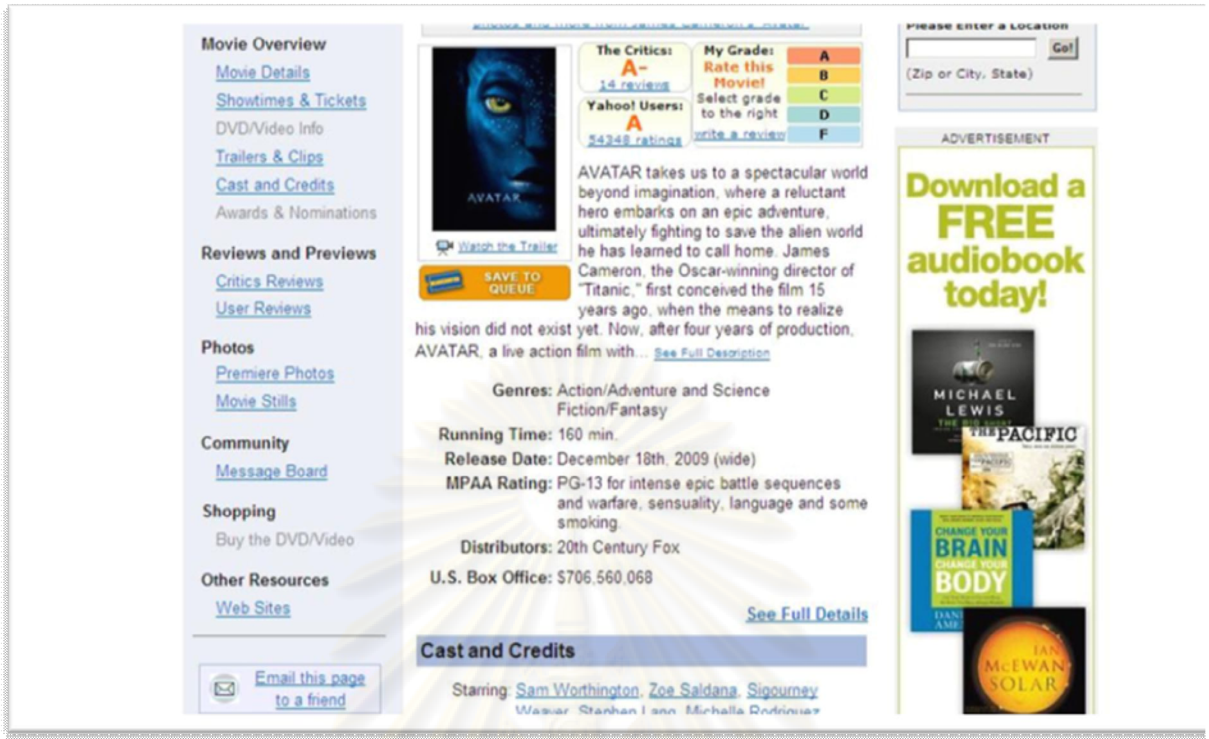

Figure 5.3 : Avatar (2009) movie information

3. Choosing a particular movie will cause the browser to redirect to a page displaying that movie information, in this case "Avatar (2009)". To see rating information, the simple way is just to click on the link on the left vertical menu, "User Reviews".

4. After clicking the link, the page of rating information will be displayed. Rating information records are display in one-column five-row tables representing expression of a user's preference on a particular movie. The first colored row represents the overall score. The color has direct relation with the score in such a way that the highest score (A+) will be colored with the red tone to the green and the blue tone for the and the lowest (F) score respectively. The second to the fifth row represent the story, acting, direction, and visuals respectively.

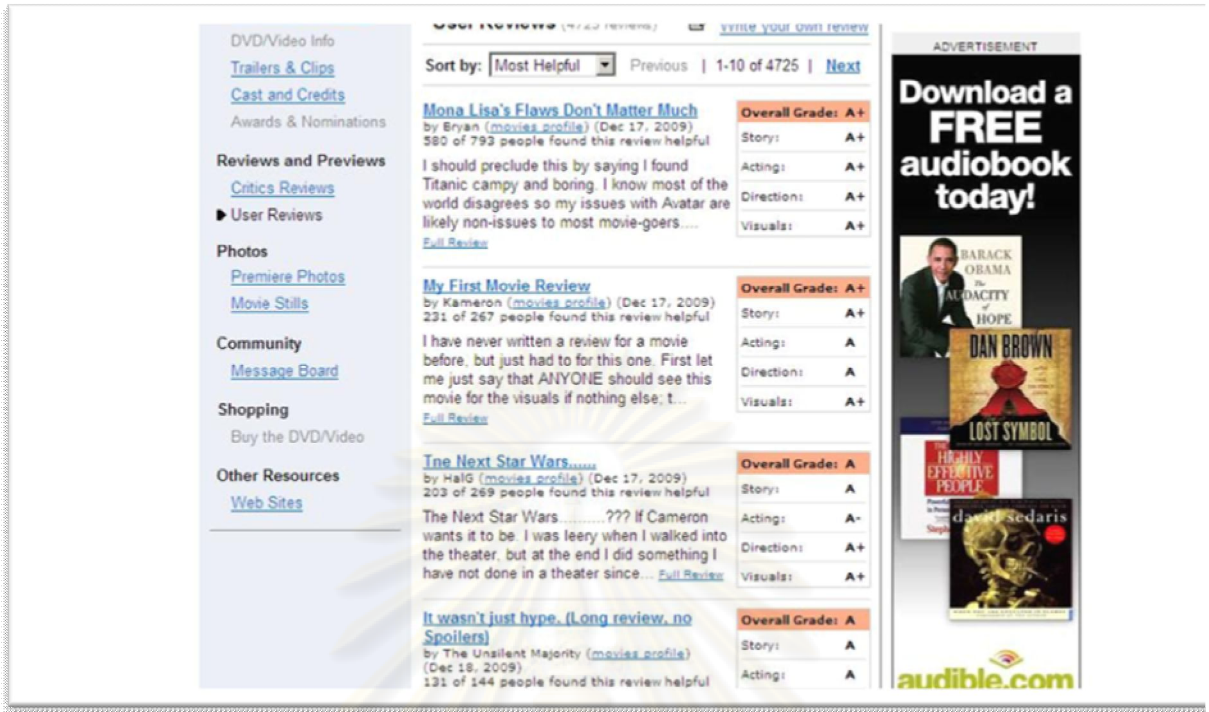

Figure 5.4 : Rating information for “Avatar (2009)”

5. Now the selection of good rating information is performed. Good rating information of a user must have been scored (one in between “A+” to “F”) on every criterion. Actually, in order to let the proposed idea work properly, the dataset should have at least ten records of rating information for each member. Therefore, after a good rating information record is found, it must be ensured that the member who produced that record must have at least another ten good rating information records too. To check the quality of other records for just one member, it is easy to click on the link, “movies profile”. The link will navigate to history of rating information one member has produced on a set of movies. A member that has good quality of records is one in the picture below.

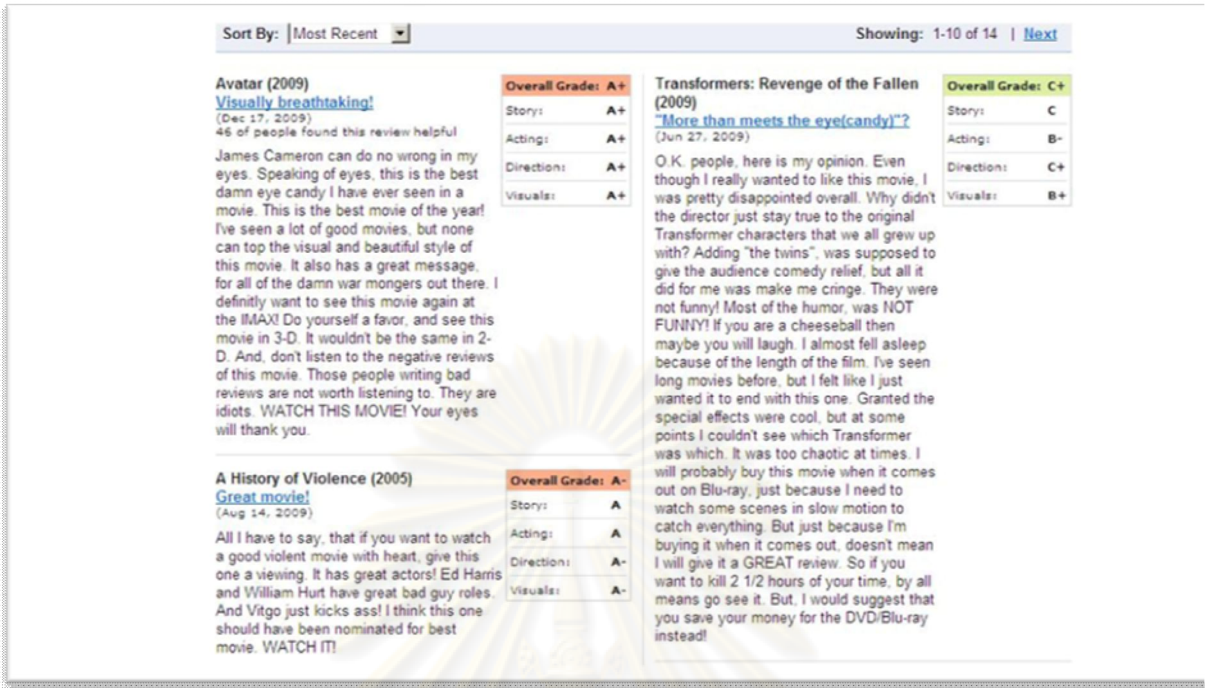

Figure 5.5 : Movies profile of a user

6. However, obtaining the record can be done by using other movies as the initial movie. The most important point is that, in the dataset consisting of too many records of rating information, any at least ten good records must belong to just one member.

While obtaining information, if some simple work sheet applications (e.g. MS EXCEL) are used to keep records which then need to be put in the rational database, characteristic of standard database record should be also maintained manually. For example, the characteristic of primary key or composed primary keys can be maintained by basically avoiding duplicated records. This is for the advantages when implementing algorithm which needs to query some data from DBMS (Database Management System).

5.1.2. Converting data

As input of the proposed method, all obtained rating information which is character format must be converted to have it numerical. The way to do that is very simple using the mapping table 5.1.

Table 5.1 : The mapping table from a character rating score to a number

From	to
A+	13
A	12
A-	11
B+	10
B	9
B-	8
C+	7
C	6
C-	5
D+	4
D	3
D-	2
F	1

After all character scores are converted to numerical scores, the rating information is now ready to perform the calculation with respect to the proposed method.

5.2. Evaluation metrics

To measure the accuracy, one possible thing to be considered is to see how different between the predicted values and the actual values on average, in the test dataset. The accurate and effective recommendation algorithm will produce really small gab between the predicted and the actual values. Therefore, when comparing a set of methods, to see which one produces the best quality of recommendation in that set, comparing of each method M.A.E. (Mean Absolute Error) value is performed. The method that produces the least M.A.E. value in the set will be considered as the best method. Each method was evaluated by using the Mean Absolute Error evaluation metric as follows.

$$MAE = \frac{\sum_{i \in I} \left| Rc_i - Rp_i \right|}{\left| I \right|} \tag{13}$$

The metric tries to calculate the error rate of the prediction performance on the test set. The Rc_i in the formula denotes the actual overall rating that the users gave on the i^{th} movie. The Rp_i represents the predicted overall rating that is produced for the i^{th} movie by our algorithm, and I denotes the set of predictable items in the test dataset.

MAE has been recognized as a acceptable metric for this area, but it does not consider carefully the performance in the situation that stability of absolute error is important. To additionally enhance the performance evaluation, in this work another metric is used. The technique is the variance of absolute error which tries to measure the variance of absolute error from the different between actual and estimated overall score in the test set.

If the term absolute error can be denoted as the equation (14), the variance of absolute error (VAE) can be derived by the equation (15).

$$AE = \left| Rc_i - Rp_i \right| \tag{14}$$

$$VAE = \frac{\sum_{i \in I} (AE_i - MAE)^2}{|I|} \quad (15)$$

The term AE_i denotes the absolute error between actual and predicted overall score for the i^{th} unknown movie in the Eq. (15). The more variance of absolute error value implies the poor stability in producing recommendation, while the least value confirms quality in producing stability of results.

5.3. Evaluation results

In order to prove **claim 1,** we compared the following three methods.

Method 1: the user preference profile without weight, i.e., we used $\boldsymbol{up}_+$ (a) = (pp_{a1}, pp_{a2}, pp_{a3}, pp_{a4}) for user *a* instead of Eq. (9).

Method 2: the profile containing only the criteria weight of the preference profile, i.e., we used $\boldsymbol{up}_+$ (a) = (wp_{a1+}, wp_{a2+}, wp_{a3+}, wp_{a4+}) for user *a* instead of Eq. (9).

Method 3: the user preference profile including weight, i.e., we used $\boldsymbol{up}_+$ (a) = ($wp_{a1+} \times pp_{a1}$, $wp_{a2+} \times pp_{a2}$, $wp_{a3+} \times pp_{a3}$, $wp_{a4+} \times pp_{a4}$) for user *a* instead of Eq. (9).

As an evaluation metric, we used both the means absolute error (MAE), which is one of the standard evaluation metrics for recommendation systems, and the variance of absolute error to analyze the stability of recommendation results. The results of using 1, 3, and 5 neighbors are listed in Table 5.2. Note that the less MAE means a better prediction of the users' rating.

Table 5.2 : MAE results for claim 1

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
1	5.18	5.83	5.88	3.40	2.56	3.01
2	4.82	6.00	**4.67**	3.59	2.45	3.03
3	**4.18**	**4.39**	4.76	**3.05**	**2.37**	**2.84**

Table 5.2 shows that method 3 produces much better accuracy than methods 1 and 2. This means that incorporation of weight, which is the user and time variant, can reliably increase the accuracy. In addition, the number of nearest neighbors has a direct effect for producing better results, while the number of users seems not to affect on the results.

Next, in order to prove **claim 2**, another two methods are invented.

Method 4: the user behavior profile *including* weight, i.e., $\mathbf{up}_+$ (a) = ($wb_{a1+} \times pb_{a1}$, $wb_{a2+} \times pb_{a2}$, $wb_{a3+} \times pb_{a3}$, $wb_{a4+} \times pb_{a4}$) for user *a* instead of Eq. (9).

Method 5: the concatenation of **user preference profile** and **user behavior profile** *including* their weights, i.e., we used the proposed user profile as Eq. (9). The results of using 1, 3, and 5 neighbors are listed in Table 5.3.

For the brief description of each method, it can be seen in the table. It expresses each method by revealing three steps inside according to the steps for recommendation mentioned in the section 3.

From Table 5.3, it can be seen that method 5, which is the concatenation of the user preference and the behavior profile with their weights, can predict the rating value more accurately than either using only the user preference or the behavior profile.

Finally, to prove **claim 3**, the proposed method is compared against with the following method.

Method 6: the concatenated user profile, similar to the one in method 5, but one that applies MCDM on the multi-criteria ratings in the prediction part. This place is to prove more about the prediction value calculation part of our method to find the exact reason that our concatenated user profile produces the best result among typical user profiles. Therefore, in the prediction value calculation step, it is necessary to apply MCDM on the Multi-criteria ratings of the neighbors, in Sec. 3.4.1, instead of the weighted average technique of the overall rating (Single-criteria rating). From Tables 5.2 and 5.3, it can be seen that good results are obtained when there are five nearest neighbors. So, in this experiment, the number of neighbors was fixed to five.

Table 5.3: MAE results for claim 2

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
3	4.18	4.39	4.76	3.05	2.37	2.84
4	<u>4.00</u>	<u>2.83</u>	4.51	3.35	2.69	2.89
5	4.09	3.39	<u>1.44</u>	<u>2.93</u>	<u>2.27</u>	<u>2.70</u>

Table 5.4. MAE results for claim 3 on number of nearest neighbor = 5

method	No. of users in Dataset	
	100	200
5	2.27	2.70
6	<u>2.02</u>	<u>2.25</u>

From the table 5.4, it can be clearly seen that when applying MCDM in the part of calculation prediction value (Method 6), the recommendation results become better accuracy.

Moreover, comparison is done on our new profiling method which is proposed in method 5 against with a typical multi-criteria recommendation technique, which is the Multi-criteria Collaborative Filtering applied on Collaborative Filtering technique and Multidimensional distance measurement on co-rated items from the work of Adomavicius, G., et al., 2007. The Multi-Criteria CF does consider only the co-rated items technique, while our method 5 absolutely does not. The table 4 shows that our concatenated user profile technique can produce better recommendation than the typical one.

Table 5.5: Comparing MAE results of current method and the proposed one on number of nearest neighbor = 5

method	number of users in Dataset	
	100	200
5	<u>2.27</u>	<u>2.70</u>
Multi-criteria CF	3.63	3.76

Using just only the MAE values, the three assumptions seem to be claimed properly. The following tables show the performance of such methods in another aspect which is the variance of absolute error. To make things easy to get followed, the VAE term are temporarily defined for the variance of absolute error.

Table 5.6: VAE results for claim 1

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
1	4.10	3.32	3.72	3.49	3.76	3.47
2	4.92	3.70	3.67	3.34	3.42	3.41
3	3.70	2.99	3.33	3.21	3.53	3.44

Table 5.7: VAE results for claim 2

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
3	3.70	2.99	3.33	3.21	3.53	3.44
4	3.33	3.45	3.29	3.87	3.83	3.95
5	3.77	3.20	3.13	3.45	3.38	3.11

Table 5.8 VAE results for claim 3

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
5	3.77	3.20	3.13	3.45	3.38	3.11
6	3.56	2.77	2.62	2.93	2.93	2.81

Table 5.9 Comparing VAE results of current method and the proposed one

method	nearest neighbor = 1		nearest neighbor = 3		nearest neighbor = 5	
	No. of users in Dataset		No. of users in Dataset		No. of users in Dataset	
	100	200	100	200	100	200
5	3.77	3.20	**3.13**	3.45	**3.38**	**3.11**
Multi-criteria CF	**3.50**	**2.95**	3.82	**3.27**	3.48	3.21

From the tables above, it can be seen that the three assumptions can still be claimed with a little excursive result in some conditions, but the excursion can be acceptable. The proposed methods produce quite the best recommendation in most conditions as they produce just little values of VAE.

Table 5.10 : Description of recommendation methods used in experiments

Method	Profiling technique	Dissimilarity measurement	Score predictions
1	user preference profile *without* weight	Euclidean distance	Weighted sum of neighbor's overall scores and similarity values.
2	profile containing only the criteria weight of the preference profile	Euclidean distance	Weighted sum of neighbor's overall scores and similarity values.
3	user preference profile *including* weight	Euclidean distance	Weighted sum of neighbor's overall scores and similarity values.
4	user behavior profile *including* weight	Euclidean distance	Weighted sum of neighbor's overall scores and similarity values.
5	concatenation of **user preference profile** and **user behavior profile** *including* their weights	Euclidean distance	Weighted sum of neighbor's overall scores and similarity values.
6	concatenation of **user preference profile** and **user behavior profile** *including* their weights	Euclidean distance	Applied MCDM incorporating neighbor's criteria scores and their corresponding weight.
Traditional Multi-criteria CF	only user multiple criteria rating information	Euclidean distance on a set of co-rated items	Weighted sum of neighbor's overall scores and similarity values.

CHAPTER VI

DISCUSSIONS

From Table 5.2, the criteria's relative user and time variant weight can produce better recommendations. This is because different users may be influenced by the movie criterion unequally. For instance, some people may agree to see a movie that James Cameron directs, such as, Avatar, or Titanic, while others may love to see a movie that has a lot of 3D effects no matter who directs the movie. Namely, having values that vary according to the users weighted on the criteria can compensate for the situation. Furthermore, according to the example, if those users are impressed by a dramatic movie, they may prefer that kind of movie without consideration of the director. Then, they may focus more on how the actor or actress acts in the dramatic movie. This means that the most important criteria for them is the acting criteria, not the direction one anymore. This means that the system needs to provide a way to monitor this preference change to closely understand the consecutively changed user's characteristic. Our method has already provided a solution for both a situation where the user's preference and behavior are changed varying by the users and time.

From Table 5.3, it can be seen that the concatenated user profile produces more accurate results. Usually, either the preference or the behavior information is used to identify the user's characteristic. The preference vector is able to imply the directly given opinion of a user, while the frequency vector, which is implicitly captured by the system, describes the user's behavior when selecting an item. Therefore, the combinations of these profile types bring us complete identification of the user preference and behavior. It implies that the system is now more efficient at recognizing the user and also has more opportunity to recommend preferred movies to users.

From Table 5.4, it can be seen the results when the MCDM technique is applied on the prediction value calculation step. First, it uses the actual criteria ratings and related weights of all neighbors to determine each criteria value of the target item. After that, the weighted average of all the derived criteria values (where the active user's weights on related criteria are used) is calculated to form the overall rating for the target item. Namely, instead of single-criteria rating, the detailed preference and their weights of the neighbors including the weight of the active user's criteria are deployed to estimate the prediction value for the target item. Consequently, a more representative preference of the neighbors is obtained. That is, a more accurate recommendation result is produced.

From Table 5.5, because co-rated items are required, the Multi-criteria CF suffers from the original problem, which is a scarcity rating problem. Therefore, it was unable to outperform the proposed method in which the concatenated user profile explaining the different aspects of the user's characteristic is used instead. Consequently, the proposed method can overcome this kind of problem, which will result in higher accuracy.

CHAPTER VII

CONCLUSION

In this paper, three aspects are proposed for the Multi-criteria recommendation system. The first aspect is the criteria's weight, which is the user and time variant. This feature enables us to support consecutively-changed individual user's preferences. The second aspect is the concatenation of the user preference and user behavior profiles. This eliminates the lack of user implication. The third aspect is the improvement of the users' rating value estimations. We applied the MCDM (Multi-criteria Decision Making) to the multi criteria ratings of movies rated by neighbors to improve the estimation accuracy. To evaluate the performance of our proposed method, we conducted a set of experiments using the Yahoo Movies database under differing conditions. The experiments were separated into three sequential parts to prove three claims related to the three proposed ideas. As a result of those experiments, we showed that our three proposed ideas on the multi-criteria ratings contributed to better recommendations when compared to a set of typical recommendation methods. Furthermore, it can be seen that the weighting technique can improve the recommendation. Other weighting techniques can be considered in our future work as well as a combination technique between the preference and behavior profiles.

Moreover, this work presents a design for a theoretically viable recommendation methodology which is suitable for mobile banking service domain. The reference architecture permits naive users to choose an unfamiliar mobile banking service without disturbing normal banking service transactions. The choice recommended by the proposed system is based on multi-criteria that entails as close to users' satisfaction as possible. Implementing the proposed architecture and performing experimental activities cannot be achieved, unless authorization for accessing both banking service systems and cellular networks are open for researchers since they are commissioned services. Fortunately, the accuracy of recommendation technique is independent from the implemented architecture. Besides, the proposed algorithm has already been proved successful in other domains, especially in the web-based movie recommendation [2] when comparing to current available methods. The adjusted part (Profiling Technique) may not be affected for any unexercised experiments if the change is taken care of in every candidate methodology. In offering a powerful recommender system for domestic mobile banking business, we envision that broader mobile-based applications will proliferate not only the banking business, but also other industries which profoundly intertwine and affect our daily lives as a whole.

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