

# Improving recommendation using meta-knowledge

Nadia BOUFARDI<sup>#1</sup>, Ouafae BAIDA<sup>#2</sup>, Abdelfettah SEDQUI<sup>#3</sup>, Abdelouahid LYHYAOUI<sup>#4</sup>

<sup>#</sup> LTI Lab, ENSA of Tangier BP: 1818, Tanger Principal. Morocco

<sup>1</sup>nadiabufardi@gmail.com

<sup>2</sup>wafaebaida@gmail.com

<sup>3</sup>abdefettah.sedqui@gmail.com

<sup>4</sup>lyhyaoui@gmail.com

**Abstract**— Usually, the user preferences change over time which implies the need to adapt the recommendation technique used in order to recommend pertinent items. For this reason, in this paper we propose a new dynamic approach that follows the change of user's interests over time to propose the appropriate recommendation technique. The proposed approach is based on meta-knowledge called explanation and a hybrid approach, and has two main phases: the first phase is to fill the meta-knowledge database with explanations using a hybrid recommendation approach. In the second phase, we calculate the average of each explanation for a user to determine the recommendation technique to use.

**Keywords**— Preference, recommendation technique, meta-knowledge, hybrid recommendation, explanation.

## I. INTRODUCTION

Recommender systems (RS) have become a fundamental tool to deal with the information overload on the Web [1]. The goal is to minimize the time spent on research for users and also to suggest relevant items that might interest them rather than simply responding to user's queries. These items can be an article to read, a book or a restaurant to choose, etc. Nowadays, recommender systems are deployed in different application domains like tourism [2], education [3] and especially in the e-commerce domain [4] in which there are very popular sites [5]. Through research, several approaches of recommendation have been proposed. There are three main approaches: collaborative, content-based Filtering systems and hybrid approaches [6]. Collaborative filtering (CF) systems produce recommendations by analyzing community data and similarities between users or items [7] while content-based filtering (CBF) recommend items that are similar to those the user liked in the past [8]. Hybrid system has been proposed to overcome the weaknesses of an approach with respect to another. [9], has identified several possibilities of hybridization or combination of different recommendation approaches. For instance, switching hybrid system chooses among recommendation components according to a switching criterion and applies the selected one. With the nature of evolution of user needs that change over time, the RS must answer the following question: What will be the best approach to use at time  $T$  to have the best results for a user  $U$ ? For example the case of a CF systems: at a time  $T$ , CF technique gives the best results for a user  $U$ . But at time  $T + 1$ , the CF does no longer meet his needs because his preferences have changed over the time. To solve this problem we need to

change the recommendation technique used at  $T + 1$ . Therefore, we introduce in this paper a new dynamic approach that proposes the best recommendation technique to use at time  $T$ . This approach will be based on the concept of meta-level knowledge, [10], represented as explanations for the recommended items. This system will use the meta-knowledge database filled with explanations provided from a hybrid approach and the scores given by the user to the recommended items. In the following section we briefly review some of the research related to our work. Section 3 presents the proposed approach. Section 4 includes dataset description and metrics. We conclude in Section 5.

## II. RELATED WORK

In literature, several researchers have suggested different approaches to adapt and yield better recommendations. As adaptive approach, Nathanson et al. [11] have developed an algorithm called Eigenstate that reorders the recommended items for a user based on the user's most recent ratings. Another approach that incorporated temporal information is given by Chu and Park [12] where a feature-based machine learning approach to personalize recommendation of new items is proposed. This approach maintains profiles for both content and users by updating their temporal characteristics, e.g. popularity and freshness over time. These approaches adapt the recommended items by considering the change of the user preferences over time. But in our approach, we recommend a technique to use for the recommendation. This allows benefiting from the advantages of the proposed technique with taking into account the temporal evolution of the user preferences.

## III. THE PROPOSED APPROACH

In recommender systems, the need to respond with a personalized way to users' preferences that changes with time has become critical. To meet this need, we have proposed in this article, an approach that will determinate the best recommendation technique to use by combining two concepts: the meta-knowledge and the hybrid approach recommendation. The meta-knowledge is knowledge about knowledge [10]. It allows the construction of new knowledge that will facilitate understanding, analyzing and learning knowledge. Pitrat [13] express very well the important role of meta-knowledge to make the system more adaptive and efficient: "At the basic level, the rules are executed in order to reach the solution; meta level, we plan and examine the advance towards the solution."

Based on this concept, we defined a meta-knowledge called an explanation. In this section, we will describe the representation of recommendation systems then we will define the concept of 'explanation' and present the two phases of our approach: filling the meta-knowledge database phase and the phase of Dynamic approach.

#### A. Recommendation system representation

In recommendation system, the data used can be represented as follows [14].  $U$  is a list of all users  $U = \{u_1, \dots, u_m\}$  and  $I$  is a list of all items  $I = \{i_1, \dots, i_n\}$ . Each user  $u_i$  has a list of items  $I_{u_i}$  which the user has expressed explicitly his opinions about the items by giving a rating score, generally integer between 1 and 5. The correspondence between users and items are usually represented in the form of matrix called rating matrix. In an  $m$ -by- $n$  rating matrix,  $m$  rows represent the users and  $n$  columns represent the items.

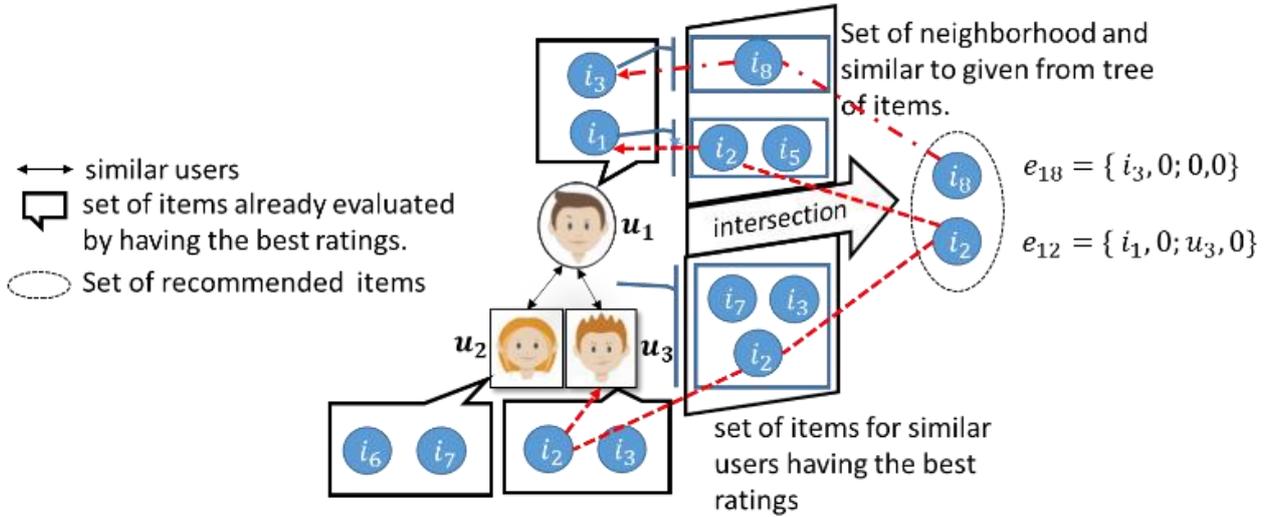


Fig. 1 Recommendation for user  $u_1$  via the approach proposed in [15]

#### B. Dynamic approach based on meta-knowledge

The meta-knowledge used in our approach called: Explanation. The explanation will be determined by the executed hybrid algorithm. For instance, the explanation  $e_{ij}$  is the explanation used to recommend the  $i_j$  item for the user  $u_i$ . It is presented as a two-line matrix, the 1st line defines the items and the 2nd line the users. It can have 3 possible forms:

- A list of Items  $e_{ij} = \{i_k, i_l; 0, 0\}$
- A list of Users  $e_{ij} = \{0, 0; u_k, u_l\}$
- A combination of a list of Items and Users  $e_{ij} = \{i_k, i_l; u_k, u_l\}$

Where  $\{i_k, i_l\} \in I$  and  $\{u_k, u_l\} \in U$ .

To determine the explanation using a hybrid algorithm, it is necessary during the execution process of the algorithm to register the user and/or the item that led to recommend the pertinent item. This process depends on the chosen algorithm, in our case, the approach proposed in [15] makes it possible to

use the graphs to record the origin user and/or item of the recommended item.

Figure 1 shows how to extract the explanation of the recommended articles. The hybrid algorithm recommended to the user the items  $\{i_2, i_8\}$ . For item  $i_2$ , it was recommended because:

- $i_2$  is similar to the item  $i_1$  with  $i_1$  belongs to the set of items already evaluated by the user  $u_1$  by having the best ratings.
- $i_2$  belongs to the set of items evaluated by the user  $u_3$  which is similar to the user  $u_1$ .

Then the explanation is  $e_{12} = \{i_1, 0; u_3, 0\}$ .

So after retrieving these explanations, we will fill the meta-knowledge database and that will be the 1st phase of our approach. In the 2nd phase, we will use these explanations to determine the best algorithm to use. The following subsections describe each of these phases.

##### 1) Phase 1: Filling the meta-knowledge database

As aforementioned, the objective of this phase is to fill the meta-knowledge database with explanations of the evaluated items. To accomplish this objective, two steps need to be followed. The first step is to run a hybrid algorithm that will generate a list  $LE_{u_k}$  of  $n$  recommended items for a user  $u_k$  and associating each item with an explanation:

$$LE_{u_k} = \{e_{k1}, e_{k2}, \dots, e_{kn}\} \text{ Or } LE_{u_k} = \{(i_1, e_1), \dots, (i_n, e_n)\}$$

In the second step, we will retrieve and store the list  $LER_{u_k}$  of  $m$  items evaluated by the user with their explanations in the meta-knowledge database:

$$LER_{u_k} = \{(i_1, e_1, r_1), \dots, (i_m, e_m, r_m)\}$$

##### 2) Phase 2: Dynamic approach

In this phase, we must determine which of the explanations stored in the database will best meet the user's needs. To do this, we will first calculate the average of each explanation for a user  $u_k$ .

Let the explanation  $e_k$  associate to a user  $u_k$  with the occurrence number  $l$  and the note set  $N_k$  :

$$N_k = \{n_1, n_2, n_3, \dots, n_l\} \text{ (where } n_i \geq 0, i = 1, 2, \dots, l \text{).}$$

The average  $\bar{n}_k$  of the note related to the explanation  $e_k$  is:

$$\bar{n}_k = \frac{\sum_{i=1}^l n_i}{l}.$$

So the explanation associated to the maximum average  $\bar{n}_{k_{MAX}}$  will identify the type of the algorithm to use:

- If Explanation is list of items then Based-Content algorithm is recommended.
- If Explanation is list of users then Collaborative Filtering algorithm is recommended.
- If Explanation is combination of items & users then Hybrid algorithm is recommended.

This last phase will generate personalized recommendations that match the user's taste. But to ensure the diversity of the recommended items and to enrich the meta-knowledge database, we will combine this last list with the list of items recommended by the hybrid algorithm in phase 1.

#### IV. CONCLUSIONS

In this paper we proposed a meta-recommender approach based on explanations to recommend items closest to the user. The approach is based on a meta-knowledge named Explanation and a hybrid recommendation algorithm as input of the system. The explanation is only an interpretation of the following fact: "*When a user gives a high value of rating to an item that was recommended because it was already liked by his friends, it shows an implicit way, the taste of the user who appreciates what his friends likes.*" So this is a way to explain the value of rating given by the user.

Thus, our approach consist in calculating the average of explanations to choose a 2nd algorithm according to the maximum average. The result of the chosen algorithm will be combined with the hybrid algorithm to ensure diversity of recommended items. Choosing as input a hybrid algorithm is based on the fact that it allows us to select one of the following algorithms: CF, CBF or hybrid. Otherwise, if for example, the system input is a FC algorithm, the choice of the 2nd algorithm will always be a FC algorithm.

As a short-term perspective, we will proceed to the evaluation of our approach. To do this, we will use as input to the system, an approach proposed by Baida [15] that contains a simple algorithmic approach that helps to easily detect the explanations at the trees covering the minimum average. And as game data we will use the MovieLens database [16]. In the long term, we will exploit the fact that we can execute separately and in parallel the two algorithms of our approach to combine it with a multi-agent systems. That will allow to have a real-time recommendation with a distribution of data and functionalities of the system.

#### REFERENCES

[1] L. Schmidt-Thieme, A. Felfernig and G. Friedrich. "Guest Editor Introduction: Recommender Systems", IEEE Intelligent Systems, pp.18-21, 2007

[2] Romain Picot-Clémente. Une architecture générique de Systèmes de recommandation de combinaison d'items : application au domaine du tourisme. Information Retrieval. Université de Bourgogne, 2011. French.

[3] ANDREAS GEYER-SCHULZ, MICHAEL HAHSLER and MAXIMILLIAN JAHN Department of Information Business, Wirtschaftsuniversität Wien, A1090Vienna, Austrian, 2011.

[4] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl. Analysis of recommendation algorithms for e-commerce. In ACM Conference on e-Commerce (EC), pages 158;167, 2000.

[5] LINDEN, Greg, SMITH, Brent, and YORK, Jeremy. Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet computing*, 2003, vol. 7, no 1, p. 76-80.

[6] MELVILLE, Prem and SINDHWANI, Vikas. Recommender systems. In : *Encyclopedia of machine learning*. Springer US, 2011. p. 829-838.

[7] SCHAFFER, J. Ben, FRANKOWSKI, Dan, HERLOCKER, Jon, and al. Collaborative filtering recommender systems. In : *The adaptive web*. Springer Berlin Heidelberg, 2007. p. 291-324.

[8] PAZZANI, Michael J. et BILLSUS, Daniel. Content-based recommendation systems. In : *The adaptive web*. Springer Berlin Heidelberg, 2007. p. 325-341.

[9] BURKE, Robin. Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 2002, vol. 12, no 4, p. 331-370.

[10] Randall Davis, Bruce C. Buchanan. Meta-level knowledge: overview and applications, *Proceedings of the 5th international joint conference on Artificial intelligence*, 1977, p.920-927, August 22-25, Cambridge, USA.

[11] NATHANSON, Tavi, BITTON, Ephrat, et GOLDBERG, Ken. Eigentaste 5.0: constant-time adaptability in a recommender system using item clustering. In : *Proceedings of the 2007 ACM conference on Recommender systems*. ACM, 2007. p. 149-152.

[12] CHU, Wei et PARK, Seung-Taek. Personalized recommendation on dynamic content using predictive bilinear models. In : *Proceedings of the 18th international conference on World wide web*. ACM, 2009. p. 691-700.

[13] PITRAT, Jacques. Des métaconnaissances pour des systèmes intelligents. *Quaderni*, 1995, vol. 25, no 1, p. 29-42.

[14] ADOMAVICIUS, Gediminas et TUZHILIN, Alexander. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, 2005, vol. 17, no 6, p. 734-749.

[15] Baida, O., Hamzaoui, N., Sedqui, A., &Lyhyaoui, A.. Recommendation based on Co-clustering Algorithm, Co-dissimilarity and Spanning Tree. *International Journal of ComputationalLinguisticsResearch*, 3(3). 2012.

[16] J. A. G. Özlem Özgöbek, Nafiseh Shabib. Data sets and news recommendation. In *Proceedings of 2nd International Workshop on News Recommendation and Analytics*, 2014.