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Incomplete preference relations to smooth out the cold-start in Collaborative Recommender Systems

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***Abstract*—E-Commerce companies have developed tools to assist users in finding the most suitable items for their needs or preferences. The most successful tool in this area has been the Recommender Systems. This kind of software obtains information about the users' tastes, opinions, necessities, and with a recommendation algorithm, infers recommendations that lead users to the most suitable items for them. These algorithms usually require a significant quantity of information and that information is not always available or easy to obtain. Overcome this problem, known as the cold-start problem, and reduce the requirements of information is not an easy task. In this contribution, we review this topic and present our proposal: a hybrid recommender system which combines a collaborative filtering algorithm with a knowledge-based one in order to improve the cold-start problem.**

I. Introduction

The large growth of the Internet has resulted in huge amounts of on-line information, services or products that can be consulted and/or purchased on the Internet. For instance, amazon (http://www.amazon.com) sells hundreds of thousands of different books, in Game (http://www.gamegroup.plc.uk/) they offer thousands of games, or in Google (http://www.google.com) we can search among millions of web pages. At the beginning, this situation usually overwhelmed the users as they could not assimilate all the available information, and therefore, they needed to spend too much time surfing among thousand of products or pages until they find an interesting one that met their necessities.

One area affected negatively by these phenomena was the e-commerce [1]. Companies designed web-sites in order to offer their products and services. Although they expected a great success, costumers became reluctant to use them since they felt engulfed by the vast amount of products or services that were offered. In order to overcome this inconvenient, many tools were developed. The most successful one were the Recommender Systems [2], [3], [4], [5].

Recommender Systems are a kind of software that leads users to the most suitable products by means of personal recommendations. These systems use the information that users provide about their opinions or necessities to infer which items could be the most preferred for each one of them.

The process of gathering user's information usually expects users to provide a significant quantity of information about their tastes or opinions [3]. This activity is usually time-consuming, problematic and not quite enjoyable. For example, nowadays a lot of people are concerned about the invasion of privacy and they may be unwilling to provide this information if it is too much, from their point of view, and/or if they do not know how it is used.

Because of these problems, many users are reluctant to provide much information. In such situations, recommender systems are not able to provide suitable recommendation as there is not enough information available about the users. Moreover, this lack of accuracy provokes distrust in the recommendations and customers may blame the recommender system of unreliable. Thus, companies may lose many potential customers since it is very probable they look for other alternatives to meet their necessities, such as going to a traditional shop or visiting another web site.

The previous problem is so-called the *cold-start* problem and it is related to the amount of information that is needed to infer accurate recommendations and how it is obtained. Classical recommender systems, content based or collaborative ones, require an important amount of information about their users and/or the items to start making good recommendations. When new users interact with these systems, there is no information about them or it is scarce, and so, they cannot be assisted by the recommender systems.

Some solutions have been presented in order to resolve this problem [3], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15]. In this contribution we present our proposal to improve such a problem that consists of a hybrid recommender system that switches between two algorithms, a collaborative one and a knowledge-based one, depending on the available information about the user. Therefore, when a new user requires a recommendation and the collaborative method does not work properly, the system uses a knowledge-based algorithm for overcoming the cold-start problem. An important feature of our proposal is that it works with incomplete preference

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relations. That is, the user only needs to provide a few data about his/her preferences and the system will complete the preference relation automatically.

In section 2, we will review briefly how the collaborative filtering recommender systems (CFRS) work, their advantages and disadvantages. In section 3, we will show the cold-start problem and review some of the solutions proposed in the literature to get over it. In section 4, we will expose our proposal to overcome it and finally, some conclusions will be pointed out.

II. Collaborative Filtering Recommender Systems

When business were able to store data about commercial transactions, they began to analyze this information in order to understand the behavior of their customers. The term *data mining* describes a set of analysis techniques used to create rules or build models from a large set of data [16], [17].

The firsts CFRS were based on *data mining*. Most of them were designed with two phases, as *data mining* proposes: an off-line phase, when the model is built, and an on-line phase, when the model is apply to real situations providing recommendations to its customers. Nevertheless, nowadays, it is usual to build a relaxed-learning model which is updated while it is working. Thus, the customers databases grows dynamically as they interact with the system. This is the model followed by the CFRSs presented in [18], [19], [20], [21], [22].

A. Classification

CFRS can be classified in two general classes, depending on the kind of algorithms used:

- Memory-based [23], [24]: These systems work by using the complete collection of items that the user has rated. Given an item which has not been rated yet by any user, the system aggregates the rates from other users (the K more *similar* to the user), and computes the weighted average of these values to provide an estimated value that represents how much the system expect that item to be liked by that user. The similarity between two users is measured attending to the similarity between the assessments provided by these users in the past.
- Model-based [25], [26], [27], [28]: The model-based approaches use a collection of assessments to learn a model which will be used to provide recommendation. There are different techniques used to build these models: bayesian networks, clustering, etc.

B. Working description

CFRS consider that similarities in the past assessments tends to be kept in the future ones. CFRS search correlations between a user and the others in order to predict the assessments that the user could give to some unknown items. So, we can easily find interesting products, i.e., products that the user does not know but they could be liked since they have been rated favourably by other users who have affinity with the target user (see figure 1).

C. Advantages

The main benefits of these systems are:

- Do not need knowledge domain: no information or knowledge about the products is needed. The databases that these systems manage do not need any information about products' features.
- Explicit feedbacks are not required: The information needed to make the recommendations may be obtained from implicit feedbacks related to the user's actions (to purchase a product, etc.). Nevertheless, in most of the collaborative filtering recommender systems, the explicit information is preferred since this information is more accurate and trustworthy than the implicit one.
- Adaptive system: its quality is improved along the time, when the number of users and rates grow, because these systems work better in environments where the density of users and rates is relatively high in comparison with the universe of products.
- Recommendations ”outside the box”: other systems never recommend products which are ”outside the box”, that is, products very different to the ones that the user has rated positively.

D. Disadvantages

The main drawbacks that these systems present are:

- The cold-start problem: this problem is presented with both users and products. When a new user access to the system, it has not any information about him/her. Therefore, the system cannot compare him/her with the users of the database and cannot provide recommendations. When a new item is added, because it has not been assessed by any user yet, it cannot be recommended.
- The ”grey sheep” problem: This system does not work properly with ”grey sheep” users, which are in the frontier of two groups of users.
- Historical data set: Being an adaptive system can be an advantage but can be also a disadvantage when the system is starting and the historical data set is small.

III. The cold-start problem

Probably, the main disadvantage of CFRS is the ”cold-start problem”. This is related to the situation when a user enters the system and has expressed no ratings yet. CFRS cannot compute a recommendation under such situations [6]. This problem is also applied to new and obscure items and to users with eclectic tastes [7]. Given that a CFRS works making correlations between the target user and the other users, when there is not any initial information for the target user, or it is scarce, the correlation between the concepts involved is low, and then, few or no recommendations are produced. This problem decreases the overall efficiency of the CFRS and, much more important, the user confidence on the recommender system.

Several solutions have been proposed for solving this problem. Trujillo et al. [7] proposed a model with two phases: the off-line clustering phase and the on-line probabilistic phase.

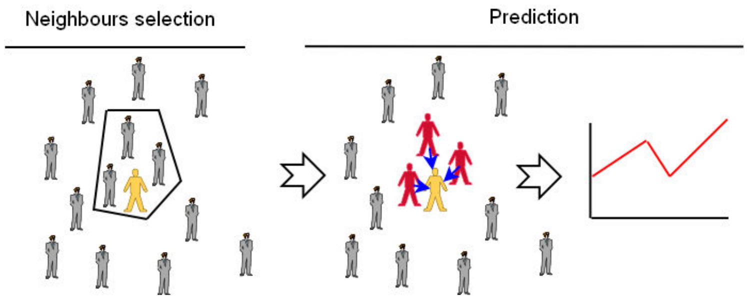

Fig. 1. Working schema of a collaborative filtering recommender system

The first one deals with two kind of features: demographics features, such as age, university relation, higher academic degree, etc. and psychographic features, such as interest areas. In this phase, the system calculates the similarity between users and classify them into clusters. The last phase calculate the probability of a user U to be interested in a product P, according to the rating that the user U did in the past and the ratings that the product P received in the past. The second phase is purely collaborative, but the first one works rightly in cold-start situations.

Rui-Qin Wang and Fan-Sheng Kong [8] proposed a semantic-enhanced collaborative filter recommendation method, in which the recommendation is produced by using the semantic information of the category features of items as well as the user demographical data.

Hyung Ahn [9] proposed a new similarity measure to alleviate the new user cold-starting problem. He proposes a measure that considers three factors: proximity, impact and popularity. In his paper, Ahn includes experimental results that prove the efficiency of his proposal when the sets of ratings per each user is small.

Wing-ki Leung et al. [10], [11] proposed a model with association rules for cold-start items. The major feature of this work is the use of associations between a given item's attributes and other domain items, when no recommendations for that item can be generated using CF. For example: the association rule ”Movie A -¿ Director: Woody Allen” indicates that ”users who liked Movie A also liked movies directed by Woody Allen”. If there exists a new (cold-start) movie, Movie Z, directed by Woody Allen, we may recommend it to users who had liked Movie A previously.

Qing Li et al. [12] described a collaborative music recommender system (CMRS) based on an item-based probabilistic model. It has been extended for improved recommendation performance by utilizing audio features that help alleviate the cold start problem for new items. Experimental results lead them to believe that content information is crucial in achieving better personalized recommendation beyond user ratings.

Diez y Villegas [13] worked in a mixed system that can take advantage of the knowledge defined in an ontology of the semantic concepts used in the items' data aquaring process. That provides two advantages. First, lessening the cold-start problem and second, it improves the guarantee of the recommendation quality.

Heung-Nam Kim et al. [14] proposed a new method of building a model, namely a user-item error matrix, for CF-based recommender systems. The major advantage of the proposed approach is that it supports incremental updating of the model by using explicit user feedback.

P. Victor et al. [15] proposed a method based on trust networks. Connecting the newcomer user to an underlying trust network among the users of the recommender system alleviates the cold start problem.

Obviously, no recommender system can work without some initial information but the system quality and efficiency depends on the capacity to work with the minimum amount of knowledge about users and items.

Models based on demographic and psychographic features need personal information about users like academic degree, age, interest areas, etc. But some users may be reluctant to provide this information and so, they will reject this kind of systems. Some solutions require some knowledge about the items, or content information, for example, for a movies recommender system, they need to know attributes like the director of the film, the genre, etc. This kind of knowledge is not always available or scarce.

Other proposed solutions are partial because improve the results when the set of ratings per user is small but do not work rightly when this set is empty (new user).

A solution that has also proved to be successful to overcome this problem is the hybridization with a Knowledge-based Recommender System [29], [30], [31]. This alternative is studied thoroughly in the following section.

IV. Hybridizing with a Knowledge-based Recommender System dealing with Incomplete Preference Relations

In the previous section, we mentioned knowledge-based recommender systems are a good solution for cold-start problem. In order to show it, first we will review the Knowledge Based Recommender System. Second, we will describe in detail an improved knowledge based recommender system that makes the recommendations from incomplete preference relations. Finally, a real example of a hybridization with this Recommender System will be exposed.

A. *Knowledge Based Recommender Systems*

Knowledge based recommender systems [29], [30], [31] present several advantages that make appropriate recommendations when there is scarce information about the user, for instance when we are dealing with casual users. That feature makes this kind of system an attractive option to hybridize with CFRS since it does not suffer from the cold-start problem.

These systems infer the recommendations from the three types of knowledge:

- *Catalog knowledge:* knowledge about the products being recommended
- *Functional knowledge:* how the features of the products meet the user's necessities.
- *User knowledge:* it is the knowledge the system has gathered about the user. It could be the necessities that the user has stated as well as all the knowledge that can be obtained by other means (for example, using demographic information).

The main disadvantage of knowledge based recommender system is that they still require knowledge acquisition. Many times this knowledge is not easy to obtain or cannot be gathered with automatic tools. In order to make easier how users states their necessities, it is usual to expect users to provide an example that represent what they are looking for. From this example, the system search similar items and allow the user navigate through them stating, removing or modifying some of the features of the original example.

B. *Knowledge-based recommender systems with incomplete preference relations*

Although it seems that cold-start problem has been solved with the aforementioned knowledge based recommender system, it has only been smooth out since the quality of the recommendation depends strongly on the example chosen. If this example is not close to the users' real expectations, they will have to refine their preferences thoroughly or otherwise, the recommendations will be not be enough accurate and therefore, users could be misleaded by the system.

A way to improve the information gathered and overcome the previous drawback is to infer the recommendation from several examples instead of a unique one. For example, in [32], [33] the recommender system presented makes the recommendations from four products and a preference relation over them.

The proposed model consists of three phases (see figure 2):

1) *Acquiring the user preference information:* The aim of this phase is to gather the user's preference information. This phase is a two-step process:
   a) *Setting the favourite examples:* The user will choose his/her favourite examples. Then, s/he will provide an incomplete linguistic preference relation providing just one row of the relation.
   b) *Filling the preference relation up:* The incomplete linguistic preference relation is filled up using the algorithm proposed in [34], whose aim is to obtain a preference relations with a consistency maximum degree.
2) *Building the user profile:* Using the complete preference relation and the descriptions of the items contained in the database, the system infers a user profile. This phase has two steps:
   a) *Building partial user profiles:* The system exploits the preference relation to obtain partial user profiles. For each column, j, of the preference relation, the system obtains a partial user profile that represents the user's preferences related to the example j.
   b) *Obtaining the user profile:* from the previous profiles, the final one is computed by aggregating all the partial profiles.
3) *Recommendation:* The user's profile is utilized to find out the items that best satisfy the user's necessities or preferences.

Perhaps, the most critical phase is the preference information acquiring. This proposal provides three main benefits regarding other knowledge-based recommender systems:

1) The task is easier and quicker for the user: s/he provides the minimum necessary information.
2) The proposed algorithm allows to build a complete preference relation starting from an only row of known values and avoiding inconsistencies.
3) Since the system uses a small number of examples, the recommendations are less dependent on the adequacy of the examples than in classical knowledge recommender system. On the one hand, on classical knowledge based recommender systems the recommendations are led by one given example. If the example is not well chosen, the recommendations are unlikely to be accurate. When recommendations are led by several examples, it is more likely that we can obtain better recommendations whenever some of the examples are good.

C. *An example of a hybridization: REJA*

The example described in this section shows how the use of a knowledge-based recommender system with incomplete preference relation can overcome the cold-start problem.

REJA is a recommender system of restaurants of the province of Jaén (Spain) (http://sinbad2.ujaen.es/?q=es/reja) (see figure 3).

In the beginning it was just a CFRS. However when we launch the system, we realize that the cold-start problem was a vital topic that had to be solved as this system deals with a great number of casual or new users.

Moreover, because of the products (restaurants) the system are dealing with, the system gathers less amount of information about the users' preferences than if it were dealing with products related to hobbies such as books, films,... For instance, a lot of users can easily provide their opinions about thousands of films, but not many of them could talk about thousands of restaurants.

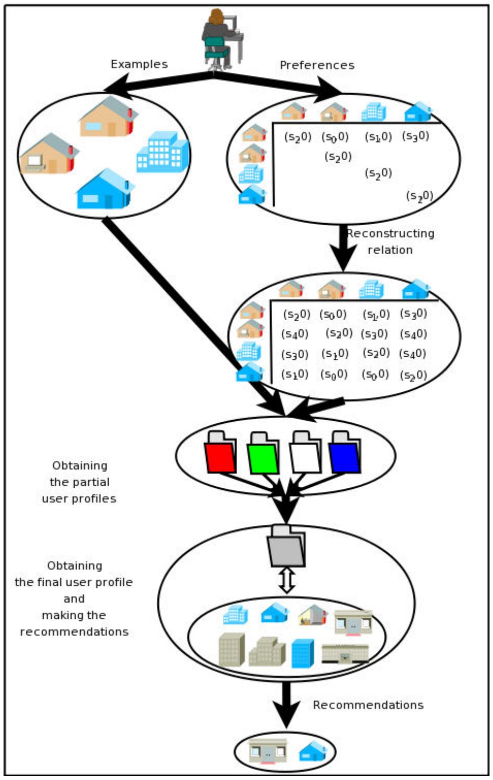

Fig. 2. Recommendation Model

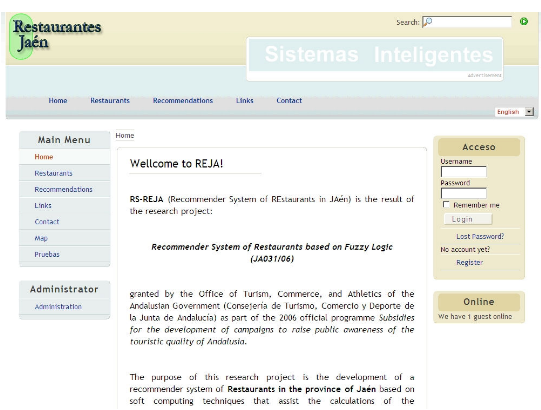

Fig. 3. REJA. A hybrid recommender system of restaurants

In order to overcome this problems, we proposed mixing the collaborative filtering recommender system with the knowledge-based recommender system with incomplete preference relations.

There are several methods to combine two or more recommender systems, each one with its advantages and disadvantages. The most well-known are: Weighted [35], [36], Switching [37], Mixed [38], [39], Feature combination [2], and Cascade [3]. There are more hybridization methods such as the *Feature Augmentation [40], [41]* or the *Meta-level [42], [43]*, however, their aims are not related to overcome or smooth out

Fig. 4. REJA. The knowledge based recommendation module

the problem of the cold-start.

In REJA, the switching technique was used: the system switch between one algorithm or another leaded by a criterion. As we wanted to overcome the cold-start problem, the criterion we used was the amount of information available about the current user. If there was not enough information to use the collaborative filtering algorithm, the system would use the knowledge-based one (see figure 4) to infer the recommendations. Thus, in REJA, new or casual users can only obtain recommendations through the knowledge-based algorithm until the system has enough information to use the collaborative filtering module.

The knowledge based module expects users to provide their preferences over a small set of well-known restaurants. With this information it infers the recommendations that are presented to the users.

This hybridization presents some interesting advantages: first of all, the cold-start problem has been solved, and furthermore, we guarantee that the recommendations obtained by the collaborative filtering module achieve a certain degree of accuracy as the collaborative filtering module cannot be use by new or casual users.

V. Conclusion

Everyday Internet is changing and expanding its possibilities offering new products, services or new ways of communications. Recommender Systems have proved to be a crucial tools for the success of many e-commerce companies and now, they are being used in other fields in order to improve the quality of the services offered to the users. However, as we have remarked, the use of this kind of software is always not straightforward as new problems have arisen that need to be dealt with. In this contribution we have studied one of the most relevant one, known as the cold-start problem, and reviewed some of the solutions presented in the literature. Finally, we have focused on one of the most promising one, the hybridization with a knowledge based recommendation algorithm and then, we have studied a real case of hybridization highlighting the advantages and disadvantages of this proposal.

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