Long Term Goal Oriented Recommender Systems

Amir Hossein Nabizadeh[1,3], Alípio Mário Jorge[1,3] and José Paulo Leal[2,3]
[1]*LIAAD, INESC TEC, Porto, Portugal*
[2]*CRACS, INESC TEC, Porto, Portugal*
[3]*Faculdade de Ciências, Universidade do Porto, Porto, Portugal*

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Abstract: The main goal of recommender systems is to assist users in finding items of their interest in very large collections. The use of good automatic recommendation promotes customer loyalty and user satisfaction because it helps users to attain their goals. Current methods focus on the immediate value of recommendations and are evaluated as such. This is insufficient for long term goals, either defined by users or by platform managers. This is of interest in recommending learning resources to learn a target concept, and also when a company is organizing a campaign to lead users to buy certain products or moving to a different customer segment. Therefore, we believe that it would be useful to develop recommendation algorithms that promote the goals of users and platform managers (e.g. e-shop manager, e-learning tutor, ministry of culture promotor). Accordingly, we must define appropriate evaluation methodologies and demonstrate the concept on practical cases.

1 INTRODUCTION

Current recommender systems focus on the immediate value of recommendations. This is insufficient for achieving long term goals. For that, we need Long Term Recommender Systems (LTRS) that are able to guide the users to predefined areas in item space and/or to achieve other types of goals. In such a scenario, user guidance would be achieved by generating a sequence of relevant recommendations through time. For example, in the case of music, companies may utilize these systems in order to guide the users from a preferred music genre to a target genre. Therefore, LTRS can be used to gradually influence users' interests through time. Companies can use LTRS to improve their profit on selected products (e.g. new products or products of a new segment). Another example for the potential application of LTRS is in e-learning. In this case, learning objects can be recommended to students with a higher level objective in view. By applying this system in the scope of learning, the activities can be more productive and less time consuming for both the student and teacher.

In a more abstract way, the main question we propose is: how can we generate recommendation sequences that successfully conduct the user to a goal (e.g. a target area of the item space), while satisfying user requirements? A goal can be defined as a pre-determined area in the item space of interest to both user and platform manager. To attain a long term goal, a recommendation algorithm must act strategically and not merely tactically.

The quality of a LTRS can be measured on how it can influence users' decisions and guide the users towards a predefined target area. Although there are several techniques to evaluate the accuracy of RS such as *Precision*, *Recall* or *MSE*, these are not enough to assess the strategic capabilities of a recommendation system. Therefore, we argue that complmentary means of evaluation will be needed for LTRS.

One important feature of LTRS is the ability to persuade users. Persuasive systems have been proposed by Fogg (Fogg, 2002). The aim is to use computers to positively influence how users think and act. Persuasive technology emphasizes on the social role of computers. Since then, a few studies applied this technology for recommender systems (Yoo et al., 2012), which mainly focused on psychological aspects. We believe that the use of persuasiveness principles can improve the effectiveness of recommendations in order to guide the users towards the long term goals.

LTRS must also be able to handle issues such as *Sparsity* and *Scalability* (Burke, 2002). Matrix Fac-

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torization (MF) algorithms have been successful in dealing with both problems (Gillis, 2012). Therefore, we believe that MF approaches can be use as a core of LTRS.

Finally, we plan to adopt Learning Design (LD) principles in order to generate recommendation sequences. In the e-learning field, the main goal of LD is to generate a suitable learning path (a sequence of objects) for users. Several researchers applied these principles for recommenders (Learning Design Recommender Systems (LDRS)). LDRS have several advantages such as: finding suitable learning objects, propose a well-defined order of objects (a path) and recommending not only based on the similarity among objects. Current LDRS are focused on e-learning applications and require an explicit target item (competency) (Durand et al., 2013). Different evaluation measures are used to evaluate the results of LDRS.

In this position paper, we propose the idea of Long Term Recommender Systems that guide users toward a predefined goal by generating relevant recommendations. LTRS will be supported by persuasive technology, LDRS principles and MF algorithms. In addition, we plan to design a general evaluation framework in order to assess the results of LTRS.

The remainder of this paper is structured as follows. Section 2 describes the related work of this study. The research methodology is detailed in Section 3 and then we conclude.

2 RELATED WORK

The main goal of recommender systems is to assist users in finding items of their interest in large collections. Items can be movies, news, articles, music, places to visit, etc. The creation of the World Wide Web and its later shift to the Web 2.0 in the 90s, made users face the issue of data overload (Kantor et al., 2011). Since then, the quantity of data and information has been dramatically increasing daily.

Due to the data overload issue, finding the interests of customers efficiently is a critical problem. One of the tools which help users in filtering information are search engines. To personalize the information filtering process, the community created recommender systems (RS). The main functionality of such a system is to sort and filter the items according to an acquired profile of each user (Resnick and Varian, 1997).

There are many techniques and algorithms that can be applied by recommendation systems to generate the recommendations. These techniques can be classified in 3 main categories:

- Content based recommendation (CBF): which recommends new items to users that are comparable in content with items that a user has purchased already (Balabanović and Shoham, 1997).
- Collaborative Filtering (CF): recommends items based on other users that have similar interests or other items that have the same characteristics (Balabanović and Shoham, 1997).
- Hybrid method: is a combination of CBF and CF. (Melville and Sindhwani, 2010).

2.1 Persuasive Recommendation System

LTRS are aimed at generating recommendations that satisfy users' requirements and persuade users to follow them. However, if the users do not follow them, the main goal cannot be accomplished. Persuasive technology as proposed by Fogg in 2002 (Fogg, 2002), applies computers to influence users' thoughts and actions. In RS field, this technology focuses on psychological aspect of recommendations and clarifies how recommendations can be represented that influence users more.

Persuasive RS are based on two theories: Media equation theory (Reeves and Nass, 1997) and Communication persuasion paradigm (O'Keefe, 2002). According to communication persuasion paradigm, the scope that a person influence others depends on (1) form and content, (2) source, (3) the receiver characteristics, (4) contextual factor (O'Keefe, 2002). If we see the system (in our case a RS) as a person that we communicate with (media equation theory), system can be seen as a source, user as a receiver and recommendations as messages. The whole process of recommending is about a specific context. Recommendations persuade receivers whether to continue using the system or not (Yoo et al., 2012)

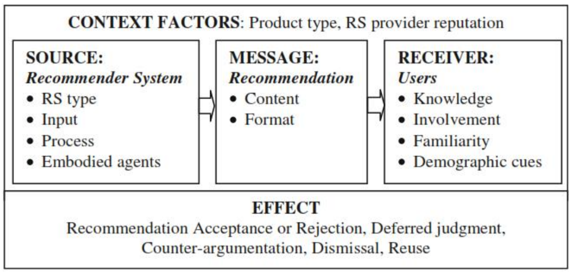

Figure 1: Conceptual framework of persuasive RS (Yoo et al., 2012).

2.1.1 Source Factors

Source is a system that generates recommendations.

According to (Xiao and Benbasat, 2007), the factors of source that have effect on persuasiveness of RS are: **type** of recommender (CBF, CF, Hybrid); **inputs** such as user preferences elicitation methods; ease of generating the recommendations and giving more control to users during their interaction with system; **process features** (like how system generates the recommendations or providing information about response time of system; **embodied agent features**: recommender systems usually include virtual character conducting the users through the process. It can be assumed that recommendations are more convicing if system is personified. Some of these features are anthropomorphism, agent demographics, style of speech and humor that influence the persuasiveness of recommendations.

2.1.2 Message Factors

According to the previous research (Cosley et al., 2003; Sinha and Swearingen, 2001) which are conducted on the same field **content** (such as discrepancy, specificity, sidedness) and **format** of messages (text, video, audio) are as important as the recommendation system (source) and have significant influence on users' evaluation and behavior.

2.1.3 Receiver Factors

User or receiver features that influence persuasiveness of recommendations such as familiarity, involvement and knowledge, are detailed as follow:

1. **Knowledge:** when users do not have sufficient information about items prefer to use a website or system which is equipped with a recommendation system (Doong and Wang, 2011; Perera, 2000).
2. **Involvement:** when users explicitly participate in the preference elicitation process, a system can generate more accurate recommendations (Zanker et al., 2006; Drenner et al., 2008).
3. **Familiarity:** users with former experience with recommenders can trust the better and results of RS can be more convincing (Swearingen and Sinha, 2002).
4. **Demographic Cues:** genders are different in acceptance of recommendations. For instance, women assess the quality of recommendations to a greater extent than men (Doong and Wang, 2011). The users' culture can also be considered as a demographic cue (Chen and Pu, 2008). For example, when a recommendation system suggests alcoholic drinks to a person who has restrictions due to his culture, it causes the user to give a lower rate to the recommendations.

2.2 Learning Design Recommendation Systems (LDRS)

In the area of e-learning, Learning Design (LD) is an activity to build an effective learning path (a set of connected learning objects) by finding suitable learning objects (Durand et al., 2013). A learning object is any reusable digital resource which supports the learning process (Wiley, 2003). Several approaches applied LD in order to recommend an efficient learning path. In other words, proposing and recommending an appropriate order of learning objects can be considered as the main functionality of LDRS (Carchiolo et al., 2010). The main advantages of these systems are the ability to find adequate learning objects (items), build an efficient path and avoid to generate recommendations only based on the similarity among objects.

Different methods and techniques have been applied to propose learning design recommenders. For example, Ullrich and Melis applied Hierarchical Task Network (HTN) to build an adaptive structured course generation framework for different goals (Ullrich and Melis, 2009). Sicilia et al. also used HTN to design learning scenarios in educational systems (Sicilia et al., 2006).

Vassileva and Deters utilized decision rules in a tool that generates individual courses. Their tool exploits on previous knowledge of a user and user's goals. This tool can be updated dynamically based on user progress (Vassileva and Deters, 1998). Markov decision (Durand et al., 2011), fuzzy petri nets (Huang et al., 2008), and production rules (Karampiperis and Sampson, 2005) are other techniques that are applied in the LD field.

Although all above studies covered LD, none built their models for a big set of objects. More recently a LD approach based on graph theory (Durand et al., 2013) has been tested on a large set of learning objects. The approaches mentioned compute the set of possible paths and suggest one path in a single static recommendation. When the user fails to proceed in the recommended path, the recommender suggests another one. Current LDRS lack a general evaluation framework that enables the comparison of different approaches.

Since Long Term Recommender Systems are concerned with guiding the user towards a goal, Learning Design principles and existing approaches are highly relevant for their development. LTRS generalize some of the LD principles to generate long term recommmendations in any domain and not only to e-learning.

2.3 Matrix Factorization (MF)

Recommender systems typically face the problems of *Sparsity* and *Scalability*. The first one is related to the fact that each user interacts with a very small fraction of the items. The second is caused by the increasingly high volumes of data found in practical applications (Burke, 2002). Collaborative Filtering (CF) techniques have been successful in dealing with both problems. The majority of CF techniques are based on the Matrix Factorization (MF) (Gillis, 2012). Since we intend to generalize our strategy for different scopes such as music (in case of music, we always face the *Sparsity*), core of our strategy will be based on matrix factorization approach.

Matrix Factorization (MF) discovers latent relations between users and items in a ratings matrix (Koren, 2008; Parambath, 2013). In the following we describe the basic MF setting. Suppose that R is a matrix with size $n \times m$ (n user and m items) that entries are ratings. By applying MF technique on the matrix:

$$R \approx \hat{R} = A.B \tag{1}$$

In (1), A represents a user matrix with size $n \times q$ and B with size $m \times q$ portrays item matrix. Value q represents the number of latent factors which are learned from past responses of user. Interpretation of factors is not easy and change tremendously depending on q selection. The following equation shows dot product can be applied to predict the rate of user u to item i:

$$\hat{R}_{ui} = A_u.B_i^T \tag{2}$$

Minimization of regularized squared error for known values in R is performed as training:

$$min_{A,B.} \sum_{(u,i) \in D} (\hat{R}_{ui} - A_u.B_i^T) + \lambda(||A_u||^2 + ||B_i||^2) \tag{3}$$

The parameter $(||A_u||^2 + ||B_i||^2)$ is used to avoid over fitting by penalizing the high dimension parameters.

3 A NEW LINE OF RESEARCH

Recommender systems usually focus on satisfying current users' requirements and are evaluated as they are. In this position paper, we argue for the importance of the study of LTRS that guide the users to a predefined goal in item space. The users are guided toward goal by generating a sequence of relevant recommendations through time. We intend to design and develop a strategy to generate the recommendations and a framework in order to evaluate the success of our strategy. The proposed strategy is applicable in different domains such as music, E-learning, etc.

To learn about long term interaction between users and recommender systems, we are currently analyzing the log data of a music recommendation system in order to see how recommendations affect the evolution of users (how they response to the recommendations, their current activities and interests and etc.). We collect activity data from the recommender service (e.g. recommendations generated, recommendations followed). Later, when our strategic recommendation method is running, we will introduce it into the recommendation service and monitor the effects of its usage with respect to the goals of this study. We will also look for a second application set up in the area of e-learning to explore more the long term goal recommender.

The data feed defined in the previous step will be used in a continuous streaming fashion to characterize user behavior over time and to test the predictability of users trajectories in the item space. The knowledge acquired in this task will be important for the development of our strategic recommendation algorithm. It will also be of potential importance to other researchers interested in user behavior and characterization.

The trajectory characterization step, we intend to define a strategy that is able to learn from user activity and make a series of recommendations taking into account well defined long term goals and user satisfaction. Learning design principles will be used to learn from the collected users' data in order to generate more effective recommendations to guide users. In addition, the recommendations will be based on a matrix factorization approach which is detailed in Section 2.3. We will use distance based reasoning to make sense of the space of items and represent user's trajectories and goal in that space. We will also exploit other data to improve recommendations, namely item features, and user-item interaction ratings (preference rating or test results in the case of e-learning).

RS researchers evaluate their proposals using the following approaches:

- Information Retrieval (IR) approaches such as *Precision* and *Recall*
- Machine Learning (ML) approaches such as *RSME*, *MAE*
- Decision Support System (DSS) approaches such as customer satisfaction and user loyalty

Although many researchers used IR and ML measures in order to evaluate the recommenders (Yoo et al., 2012), we need to continually measure users interaction with system and DSS evaluation approaches can provide more appropriate evaluation for LTRS.

Finally, we design appropriate evaluation measures and methodologies in order to assess the success of the proposed methodology. This is a particularly challenging task since, to be appropriate, evaluation must be performed with live recommendations on real situations. We will define goals for test users and assess the success of the methodology in conducting users to the goals. Results will be compared with a control group of users (A/B test). Offline, online and user study are the methods that we intend to use in evaluation phase.

Figure 2 provides a conceptual view of our idea. It shows an item space (a set of objects with different characteristics) that is included our target user who is interested in specific type of objects (gray highlighted area). Our strategy guides the target user toward goal (green highlighted area) step by step while dynamically assess how far the target user is from the target area (calculate the distance between the current position of the target user and target area after each recommendation). In this example, the goal of each recommendation is to broaden the preference area of target user until he starts to use the items in the target area (or decreasing the distance between the target user position area and target area (goal) by every recommendation).

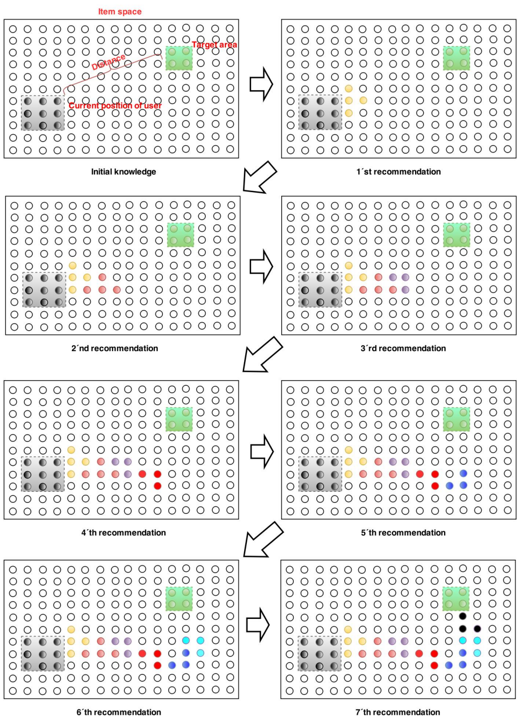

Figure 2: Conceptual view of LTRS.

4 CONCLUSION

Recommendation systems normally focus on the immediate needs of users and are evaluated as such. This is insufficient for long term goals recommenders. Generating strategy for long term goals is of interest in recommending learning resources to learn a concept, and also when a company attempts to convince users to buy certain products.

In this position paper, to face the *Sparsity* and *Scalability* problems, we propose the use of matrix factorization algorithm to handle both issues. Also, in order to have more conductive and effective recommendations, learning design principles and persuasive technology will be utilized. Learning design is selected to learn from the users' activities and since the LTRS's recommendations must persuade the users, we apply the persuasive technology.

To evaluate LTRS, we will require appropriate methods to assess the success of strategic recommendations, since existing measures such as *Precision*, and *Recall* are clearly not enough. In any case, offline and online evalution must be complemented with user studies.

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