Long term goal oriented recommender systems

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Abstract. Recommenders assist users to find items of their interest in large datasets. Effective recommenders enhance users satisfaction and improve customers loyalty. Current recommenders concentrate on the immediate recommendations' value and are appraised as such but it is not adequate for long term goals. In this study, we propose long term goal recommenders that satisfy current needs of users while conducting them toward a predefined long term goal either defined by platform manager or by users. A goal is long term if it is going to be obtained after a sequence of steps. This is of interest to recommend learning objects in order to learn a target concept, and also when a company intend to lead customers to purchase a particular product or guide them to a different customer segment. Therefore, we believe it is beneficial and useful to develop a recommender algorithm that promotes goals either defined by users or platform managers. In addition, we also design methodologies to evaluate the recommender and demonstrate the long term goal recommender in different domains.

Keywords: Recommender System, Course generation, Course sequence, Persuasive Recommender System, Learning Design, Pattern recognition, Long Term Recommender System.

1 Introduction

Current recommenders focus on the immediate needs of users. This is insufficient to obtain long term goals. Therefore, we propose Long Term Recommender Systems (LTRS) that besides satisfying immediate needs of users, conduct them toward a predefined long term goal by generating a set of relevant recommendations step by step [12]. A goal is long term if there are intermediate goals or if there is a sequence of recommendations to attain the long term goal. This goal is domain dependent and can be defined by the owner of the system or by users. Goal can be purchasing an item, learning a course, following a specific genre or singer, etc.

LTRS can be applied in different domains. For instance, in E-learning domain, LTRS aid users (e.g. teachers and learners) to have more productive activities (teaching and learning) meanwhile consuming less time. In this case, a long term goal can be defined by a teacher as doing a relevant assignment or passing an exam after getting the long sequence of recommendations. Another example is in music domain. For example, a music company has a contract with a singer and due to some reasons the company expects to lose that singer and so it will lose a part of its music market. As a result, the company looks for solutions to retain its market and keep the same level of selling after losing that singer. One of the solutions can be diversifying the customers' taste (following other singers or other music genre) which can be done by generating a set of recommendations that influence users taste through time. Also, in the case of music, a company may use LTRS to guide the users from a preferred music genre to a target genre in order to enhance its profit on selected products. In this case, LTRS gradually influence users' interests through time.

The main research question of this study is: how can we produce recommendation sequences that successfully conduct the user to a target area in the item space, while satisfying immediate user needs? A goal can be defined as a predetermined area (in case of music, area can be a specific genre of music) in the item space of interest to both the user and the platform manager. To attain a long term goal, a recommendation algorithm must act strategically and not simply tactically. Subsequently, our main objective is to design a recommendation strategy that is able to attain strategic goals of users and platform managers.

In this study, we plan to adopt Learning Design (LD) principles and methods (such as course sequence, course generation, pattern sequence recognition) in order to build our recommender. LD is an activity to build an effective learning path by finding suitable learning objects [4]. The main advantage of LD recommenders is recommending a learning path not only based on the similarity among learning objects or among learners. It makes the generated recommendations more accurate. In addition, persuasive systems are also useful to generate our proposal. These systems were proposed by Fogg [5] in order to influence users' thoughts and behaviors, and are focused on psychological aspects of recommendations. The persuasiveness principles describes how the recommendations can be generated and represented in order to have more influence on the users [19]. Due to the fact that LTRS recommendations must be convincing for the users otherwise they do not follow the recommendations and the goal can not be obtained, therefore we believe persuasiveness principles can enhance the effectiveness of our recommendations.

The quality of a LTRS should be measured on how it can influence users' decisions and conduct the users towards a predefined target area. Although there are some techniques in order to assess the accuracy of RS such as $Precision$, *Recall* or MSE, these are not sufficient to evaluate the strategic capabilities of a LTRS. We then argue that complementary means of evaluation will be needed for LTRS.

In this 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 LDRS and persuasiveness principles. In addition, we plan to design a general evaluation framework in order to assess the results of LTRS and demonstrate our system in different domains.

The remainder of this paper is structured as follows. Section 2 surveys the related work methods and algorithms that are usable for a LTRS. The research methodology is detailed in Section 3 and then we conclude the paper with conclusion part.

2 Related work

2.1 Learning Design

In the area of e-learning, Learning Design is an activity to generate an effective learning path by an appropriate sequence of learning objects [4]. Learning object is any reusable digital resource which supports the learning process [4, 18]. Researchers have utilized LD principles in recommenders area in order to recommend a learning path (a set of connected learning objects) to users. According to our survey, all LD recommenders studies can be classified into three main categories: course generation, course sequence and pattern sequence recognition method.

2.1.1 Course generation This method is the most frequently used by researchers and it generates a well-ordered sequence of Learning Objects (LO) that is customized for a learner. In this approach, a user is evaluated before receiving a recommendation (diagnostic evaluation). The learning path is generated based on the diagnostic evaluation result and user profile information, including personal information along with extra information such as preferred language and media, etc. In course generation, the entire learning path is generated and recommended to a user in a single recommendation [16]. If a user was not able to follow the path to attain the final goal, the system recommends another path.

Several researchers have applied this method along with other techniques and algorithms. For example, Vassileva and Deters [17] applied decision rules in a tool that generates individual courses. This tool exploits on previous knowledge of a user and user's goals. This tool can be updated dynamically with respect to user progress. Markov decision [3], and fuzzy petri nets [8] are also other techniques that are used in the course generation approach in order to generate and recommend a learning path.

Although this method is fast due to generating and storing all the possible learning path for each user, it ignores a learner changes and performance during following a recommended path by a learner.

2.1.2 Course sequence In comparison with course generation that recommends the whole path in a single recommendation, course sequence recommends LOs one by one based on the user's progress [1]. Initially, as in course generation, this method recommends the first LO based on user profile and diagnostic evaluation result. Unlike in course generation, course sequence recommends LOs one by one and a user evaluation happens after recommending each LO.

Some studies such as [9, 10] utilized course sequence along with different algorithms and techniques to propose their methods. Karampiperis and Sampson [10] proposed their idea by utilizing Adaptive Educational Hypermedia Systems (AEHS). In their method, first all possible learning paths that obtain the goal are generated and then, the desired one (the shortest path) is selected adaptively according to a decision model. Also Idris et al. applied Artificial Neural Network in order to present an adaptive course sequencing method [9].

Although course sequence considers user changes and progress, which was one of the main issues in course generation, it still has several problems such as lacking of an effective automated method to update the user profile and also to determine what information in the user profile needs to be updated after each evaluation.

2.1.3 Pattern sequence recognition It is similar to the course generation method since both methods recommend a sequence of well-ordered learning objects to a learner. This method extracts a sequence of LOs (path) from the available data that was successful to guide a user toward a goal and recommends it to a user with a similar goal [11, 6].

One of the studies that used this method is conducted by Klasnja-Milicevic et al. [11]. In their system, they first cluster the learners w.r.t their learning style. Then they used *AprioriAll* algorithm [14] in order to mine the behavioral patterns of any learner. Finally, a recommendation list is generated based on the rates that is provided for frequent sequences.

Appriori is one of algorithms which is applied by researchers such as [11] in order to find patterns. Researchers who utilize pattern recognition method usually face two issues. Firstly, current pattern recognition methods are slow and secondly, they find frequent patterns and rare cases will be ignored.

In general, All LDRS methods have some problems such as (1) lack of a general framework to evaluate the result and compare different approaches, (2) researchers usually could not address the scalability (handle and work with big set of users and LOs), (3) lack of efficient user profile adaption method and (4) **Time** which is also a significant factor that is ignored by many researchers. A few studies addressed **time** in course modeling phase which is not efficient since user ability and background is ignored [2]. Course modeling is a process of finding essential knowledge units of a course and find their relations in order to build a course model.

2.2 Persuasive Recommendation System

The recommendations generated by LTRS should be convincing and persuade users to follow them otherwise the main goal of LTRS which is guiding the users toward a final goal could not be attained. Therefore, we need a technology to assist us to generate more convincing recommendations for users. Persuasive technology is initiated by Fogg in 2002 [5], applies computers to influence users' thoughts and actions. After Fogg several researchers utilized this technology in recommenders domain.

Persuasive RS are based on two theories: Media equation theory [15] and Communication persuasion paradigm [13]. According to the communication persuasion paradigm, a person can be affected by others in four different scopes (1) form and content, (2) source, (3) the receiver characteristics, (4) contextual factor [13]. In our case, if we see the recommender as a person that we communicate with (media equation theory), the system can be seen as a source, the user as a receiver and recommendations as messages. The whole process of recommending is set in a specific context. Recommendations persuade receivers whether to continue using the system or not [19]. In RS field, this technology focuses on psychological aspect of recommendations and clarifies how recommendations can be represented to have more effect on users.

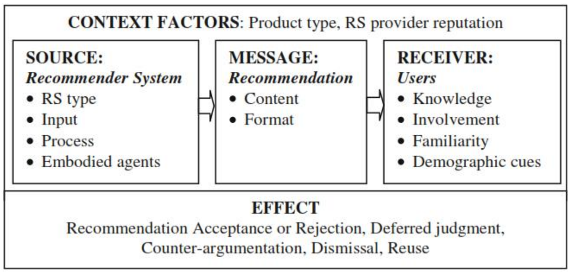

Fig. 1. Conceptual framework of persuasive RS [19].

3 Research methodology

In our proposal, we argue for the significance of LTRS to guide the users to a predefined goal in item space. The users are conducted toward a goal by generating a sequence of relevant recommendations in successive moments. We intend to design and develop a strategy that generates recommendations that guide the users toward a goal and also a framework in order to evaluate the success of our strategy. The proposed strategy is applicable in different domains such as E-learning, music, etc.

Figure 2 shows a conceptual view of our proposal. It shows an item space (a set of objects with different characteristics) that contains the type of objects in which the user is interested (gray highlighted area). Our strategy conducts the user towards the goal (green highlighted area) step by step, while dynamically calculates how far the target user is from the target area (i.e. assess the distance between the current position of the target user and target area after each recommendation). The purpose of each recommendation is to enlarge the interesting area (in case of E-learning it can be knowledge area) of the user's target until he reaches the items in the target area.

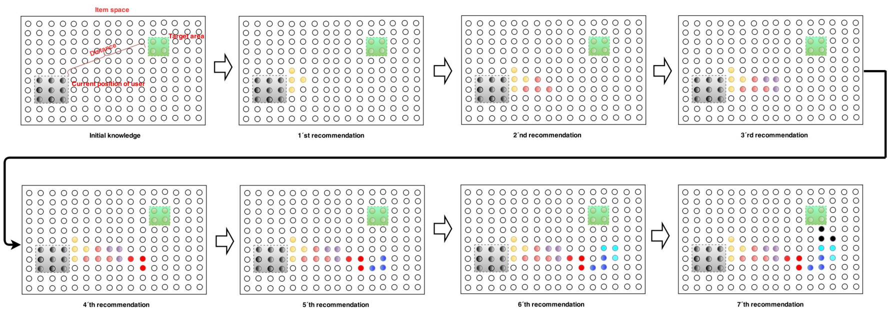

Fig. 2. Conceptual view of LTRS.

3.1 Task 1: Literature Survey and concepts definition

We already started by broadening our knowledge of the area of sequential recommender systems (e.g. learning design recommenders). Work on recommendation of structured objects in general are also of interest (sequences are a particular type of structures). User behavior studies related to recommenders such as persuasive recommender systems are also significant. In addition, in this phase, we are also interested in distance based approaches which are relevant to characterize the user trajectories in the item space and user transitions from region to region. Finally we will review existing evaluation methodologies and measures for such structured recommendation problems and specially evaluation methodologies for live environments with real users.

Furthermore, in order to design a framework for the LTRS, a few concepts should be defined: item space, target region in the item space, user location, distance between current location of user and an item and also distance between user current location and target region.

3.2 Task 2: Data feed set-up

To learn about long term interaction between users and recommenders, we are currently analyzing the log data of a music recommender that we have previously developed in the context of **Palco3.0 QREN** project. The recommender service is running for the Palco Principal website. We intend to understand how recommendations influence the evolution of users, how users react to the recommendations, their current activities and interests, etc. We collect activity data from the recommender service such as the generated recommendations and the followed recommendations.

We also look for a second application set up in the area of E-learning. We are in contact with a publishing company working in the area and also have access to programming languages tutoring environments that can be adapted to use recommendation algorithms.

3.3 Task 3: Long term user behavior and trajectory characterization

The data feed defined in Section 3.2 will be utilized in a continuous streaming fashion to identify user behavior through time and to examine the predictability of the trajectory of a user in the item space. The obtained knowledge from this phase will be significant in order to develop our strategic recommender algorithm. It will also be of interest to other researchers who are interested and work on user behavior and characterization.

3.4 Task 4: Defining a long term recommendation strategy

This phase is the main step of the study. In this phase, we plan to define a strategy that learns from user activities and generates a series of recommendations taking into account well defined long term goals and user satisfaction. Learning design recommender principles will be applied in order to generate more effective recommendations to conduct users. Furthermore, we intend to utilize distance based reasoning to make sense of the space of items and represent user's trajectories and goal in that space. Other data will also apply in order to enhance recommendations such as item features and user-item interaction ratings (preference rating or test results in the case of e-learning).

3.5 Task 5: Design an evaluation framework

Researchers evaluate their recommenders using Information Retrieval approaches (*Precision*, *Recall*, etc), Machine Learning approaches ($RSME$, MAE, etc) and Decision Support System (DSS) approaches (such as customer satisfaction and user loyalty). Although many recommenders are evaluated by IR and ML measures [19], we need to continually measure users interaction with system and DSS evaluation approaches provide more appropriate evaluation for LTRS.

Moreover, in this step, we also plan to design appropriate evaluation measures and methodologies to evaluate the success of the proposal. Due to the fact that evaluation must be performed with live recommendations on real cases (since we need to monitor how users respond to the recommendations), we see this task as a challenging one. We will determine goals to test users and evaluate the success of the methodology in guiding users toward the goals. The evaluation of results will be compared with a control group of users. In particular, we need to:

- Specify the evaluation criteria
- Define evaluation methodology
- Specify online evaluation protocols
- Perform experiments
- Statistically validate results

Furthermore, offline and user study are other methods which are applicable in order to evaluate the result of LTRS. In addition to systematic empirical evaluation of the proposed method, we also intend to demonstrate our idea on one or two real cases. Our plan is to have one e-learning case and one music recommendation case.

4 Conclusion

In this paper we propose long term goal recommender systems (LTRS) that besides satisfying immediate needs of users, conduct users toward a predefined goal. In such a scenario, user guidance would be achieved by generating a sequence of relevant recommendations through time. This strategy is applicable in different domains such as E-learning, movie, music, etc. Generating a 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.

Several methods and technologies will be utilized to build LTRS. The principles of learning design activity can be useful in order to have more effective recommendations. Another technology which is useful for this purpose is persuasive technology. Persuasive technology concentrates on the psychological aspect of recommendations and explains how recommendations can be represented in order to have more effect on users.

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

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