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A Review on Different Approaches Used in E-Learning Recommender Systems

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Abstract: **As a result of internet growth users are provided with a vast amount of information. This has prompted the issue of information overload, in which users are trying to deal with an excess of information that is not useful them as they try to make sensible decision. The recommender system has been developed to overcome this issue by giving recommendations that help individual users. This paper reviews an assortment of methods that have been proposed for performing suggestion in e-learning environment. Nowadays there has been a significant development in the utilization of online learning objects by learners. Due to information overload, many learners are experiencing challenges in retrieving relevant and useful learning resources that meet their learning needs. A recommender system in an e-learning context attempts to intelligently recommend actions to a learner based on the task already done by the learner. Nowadays more people have benefited from different e-learning applications. The high variety of learners on the internet presents new difficulties to the existing e-learning models. In this paper we review the various challenges as well as techniques used in an e- learning recommender system.**

Keywords: User preferences, E-learning, E-learning Recommender Systems.

I. INTRODUCTION

Today the internet provides users with a vast amount of information that makes it cumbersome for the users to choose precisely what they actually need. The user deals with more information that does not enable them to make sensible decisions. This problem is called information overload. Recommender systems have been used to overcome the information overload problems. Recommender systems help the people to discover information that will interest them based on their needs and preferences. It provides users with suggestions of items that they may be interested in. The suggestion is based upon their past preferences or demographic information.

Recommender systems are used in a variety of areas including movies, news, books, research articles, music, social tags, search queries, and products in general. The main functions of recommendation systems include analyzing user data and extracting useful information for further predictions [1]. This paper reviews an assortment of methods that have been proposed for performing suggestion in e- learning environment. A recommender system in an e-learning platform attempts to intelligently recommend tasks to a learner based on the previous learners tasks. A recommendation seeker can be considered as a user of the system [1]. A recommendation may be directly requested by the user, or without the user's concern the system may create recommendations. The users can provide the information about their preferences to the preference provider; otherwise the preferences are requested by the system explicitly from the user. On the basis of the preferences made by the target user and those made by other similar users, the system will recommend the items that the user will possibly like. The user may utilize the recommendation to choose items from the universe or to communicate with similar users.

Recent years, the internet has witnessed an aggressive growth in the amount of learning resources. This explosion of learning resources on the internet has been accelerated by expanding interest for online learning resources by learners in e-learning environment. With this expansion of web based learning resources, learners are experiencing challenges in deciding learning resources that are valuable and significant to their learning needs. Recommender systems can overcome this issue by filtering out inappropriate learning resources and automatically recommending suitable resources to the learners according to their preferences. Learner preferences are relevant learning resources that meet their needs and interests.

An e-learning recommender system recommends a task to a learner in view of the undertakings effectively done by the learner and their successes. Certainly it is a revolutionary way to bring education in life long term comparing with the traditional learning system. The e-learning recommender system suggests online learning objects to learners, based on their preferences, browsing history of other learners with similar interest. The similarity of the learners could be established based on common previous access patterns made by other similar learners, or using user profiles.

II. TYPES OF E-LEARNING RECOMMENDER SYSTEMS

There are different approaches used to build a recommender system in e-learning context, some of them are:

A. Collaborative recommendation approach

This is one of the widely implemented recommendation techniques in data mining. It is based on the assumption that "similar users have same preferences" [2]. This technique aggregate rating of objects to recognize commonalities between learners and generate new recommendations based on inter-learner comparisons. A learner profile consists of a vector of learning objects and their ratings. Ratings indicate the degree of preference. It may be binary (likes/dislikes) or real-valued. Two classes of collaborative recommendation are:

i. Memory-based: Memory based technique can be classified into user based and item based. The user-based model is based on the fact that each learner reside on a group of similarly behaving learners and find a set of learners with similar preferences. Finally, it generates a list of recommendation for the target learner. The item-based model identifies the set of learning object that are similar or related to the target learner liked objects. After that, it computes the similarity of learning objects and finds the most similar objects to the target objects within the set of learning objects that the learner has rated.

ii. Model-based: Model based techniques provide recommendations by estimating statistical models for learner ratings. A probabilistic method can be used to compute the probability that the learner will give a particular rating to a new learning object based on previously rated objects.

Advantage: Does not need a representation of items in terms of features.

Limitations: Challenges like cold start, Sparsity problem and scalability issues.

B. Content -based recommendation

This technique is based on a comparison of the content of a learning objects and a learner profile. The content information can bridge the gap between the existing and new learner as well as the learning objects. The two classes of content based recommendation are:

i. Case based reasoning techniques: A case based reasoning technique recommends learning objects that are in highest correlation to objects the learner liked in the past. This technique does not desire a content analysis. The quality of the recommendation rises over when the learners have rated more learning objects. The new learner problem also stated to case based reasoning techniques. The limitation of this technique is overspecialization, because it recommends only the learning objects that are in higher correlation with the learner profile or interest.

ii. Attribute-based techniques: In attribute-based techniques, learning objects are recommended based on mapping of their attributes to the learner profile. Attributes could be weighted for their relevance to the learner [3]. This technique is sensitive to changes in the learner profile. Adding new learners or learner attributes will not cause any problem. The limitation of this type of recommendation is that it is static in nature and is not able to understand from the behavior of the network. Attribute-

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based technique can handle the cold-start problem because it directly maps characteristics of learners to learning attribute and the behavior data about the learners is not needed.

Advantage: Doesn't require data of other users.

Limitation: Over specialization.

C. Utility-Model based recommendation

This system does not attempt to build a long term generalization about their learners but rather base their advice on an evaluation of the match between a learner's need and the set of available options [4]. It makes suggestion based on computation function of the utility of each learning objects for the learner. The learner profile is considered as the utility function and the system employs constraint satisfaction methods to determine the finest match.

Advantage: Can factor non-object attributes.

Limitation: Learner must input utility function.

D. Demographic recommendation

This technique classifies the learners based on their personal attributes and the recommendations are based on the demographic classes. This approach is based on the assumption that all learners belonging to a certain demographic class have alike interest or preference. It uses demographic data about the learner and their point of view for the recommended learning objects. It forms people to people correlations like collaborative ones. But they use different data [4]. In systems like machine learning, it is used to reach at a classifier based on demographic data [5].The benefit of this approach is that it is independent of learner rating history.

Advantage: It does not require history of learner ratings.

Limitation: Security and privacy issue.

E. Context-aware systems

Traditional recommender systems compromise with two types of entities, users and items. The recommender system includes additional information about learners context such data can be used to change recommendations based on individual learner characteristics and additional contextual information such as available time, location, people nearby, etc. Context is information that can be used to classify the situation of an entity [6]. An entity is an object, person or place that can be considered relevant with the interaction between an application and a user [6]. The context data consists of different attributes, like physical location, date, season, emotional state, physiological state, personal history etc. This system automatically uses context data to run the system that are suitable for a specific time, places or events. It was integrated to improve the existing learner request response pattern that requires the learners to raise the wish for recommendation. The traditional recommender system focused on suggesting the most essential learning objects to learner without considering any additional contextual information, like location, emotional state and physiological state. It is necessary to combine the context data into the recommender systems so as to recommend learning objects to the learners under some circumstances. It covers the understanding of learner's objective with objects that learners might find interesting by knowing the wide area of contextual attributes.

Advantage: Based on changing contexts the recommendations can be adjusted.

Limitation: Need to integrate contextual data.

F. Hybrid recommender system

Hybrid filtering is a collaboration of two or more different recommendation approaches. Depending on domain and characteristics of data, several hybridization methods are possible to combine collaborative recommendation and content based recommendation techniques which may produce different outputs. Some of them are [7] mixed, weighted, feature augmentation, switching, feature combination, cascade etc. The widely known hybrid approach is provided by collaborative recommendation and content based recommendation. The collaborative recommendation is based on a similarity between the learner navigation path and the access patterns of similar learners. Content based recommendation is based on the correlation between the content of the learning objects and the learner taste. Hybrid recommendation tries to overcome the limitations in each approach, by making the collaborative recommendation deal with any type of content and explore new area to find something that is interesting to the learner.

Advantage: No cold start problem.

Limitation: Issue on Time complexity.

G. Knowledge-based recommendation

This recommender systems attempts to propose objects based on a learner needs and preferences. It contains knowledge about how a specific learning object meets a specific learner need. Therefore it can be a reason about the relation between a need and an achievable recommendation. The learner profile can be any knowledge structure that supports this conclusion. This technique collects knowledge about the learners and learning objects to apply them in to the recommendation activity. It is independent on learner ratings. It does not collect data about a specific learner because its intuition is independent of individual preferences. Knowledge-based techniques are suitable for hybridization with other recommendation techniques in the case of e-learning recommenders [8].

Advantage: Independent of learner ratings.

Limitation: Requirement of knowledge acquisition.

H. Ontology-based model recommendation

Ontology is an explicit specification of a conceptualization [9]. It consists of entities, attributes and relationship [9]. Ontology is used to model knowledge about the user background, item, and the domain [6]. The use of ontology can effectively improve the quality of personalized recommendation. Ontology is used to model the domain knowledge about the learner as well as the learning objects. The learner model ontology contains the personal information, learning style and knowledge level of the learner. The learning object ontology contains resource types, resource format. Personalization through ontology provides a more customized recommendation to the target learner preference. Ontology based recommendation do not experience most of the problems associated with traditional recommender systems.

Advantages: It depends on domain knowledge rather than ratings and improves the quality of personalized recommendation.

Limitation: Construction of ontology is a difficult, expensive and time consuming process.

III. GENERAL CHALLENGES AND ISSUES OF E-LEARNING RECOMMENDER SYSTEMS

Recommendation techniques have been very successful in past years but their wide use has exposed some challenges. Some of them are:

I. Cold-start problem

It is mainly based on new user or new item. This problem occurs due to an initial lack of ratings for new users who have not rated any item or new items which have not been rated by any user. Hence it becomes unattainable to make good recommendations.

New User: It occurs when there is a new learner to the system has no prior rating found in the rating table. So it is difficult to give prediction of a learning object for the new learner because it requires the learner's historic rating to calculate the similarity for determining the neighbors. Here the recommendations follows a comparison between the target learner and other learners based on their ratings, a learner with few ratings are difficult to classify.

New item: Cold start problem for a new learning object occurs when there is no enough previous rating related to that learning object exists [10].

II. Sparsity problem

Sparsity problem occurs where the number of learners who have rated learning object is too small compared to the number of available learning objects. If there is no such overlap in ratings with the target learner occurs, it is difficult to generate appropriate recommendation [9]. The main cause for data sparsity problem is that most of the learners do not rate most of the available learning objects. It has a major negative impact on collaborative recommendation approach because it is highly probable that the similarity between two given learners is zero, lay down collaborative recommendation useless.

III. Over Specialization

This is the major problem faced by the content-based recommender system. It lacks in suggesting diverse learning objects. The learners are recommended with learning objects that are already familiar with. It prevents learners from finding new learning objects and other alternatives. Additional techniques have to be added to the system to make suggestion outside the scope of learner interest. By integrating additional methods the learner will be provided with a set of different and a wide range of options [11].

IV. Scalability

As the numbers of learners and learning objects grow, traditional collaborative recommendation will suffer serious scalability issues [12]. In collaborative recommendation calculation grows linearly with the number of learners and learning objects, sometimes lead to inaccurate results.

5. Privacy

In the context of a demographic recommender, privacy is considered to be a major issue [10]. In order to provide more accurate recommendation to the learner, the most sensitive data of a learner must be acquired. It includes demographic information and information about the location of a specific learner, which may rupture the privacy of the learner.

IV. CONCLUSION AND FUTURE SCOPE

This paper surveys on various traditional recommendation techniques used in an e learning platform and also considered their advantages and limitations. A recommender system tries to intelligently recommend actions that are beneficial to the user. The development of sophisticated e-learning environments provides a path to education in life for long term. In an e-learning platform, the recommender system tries to intelligently recommend learning objects to a learner based on the task already done by the learner and their success. With the development of e-learning platforms, personalization is becoming a consequential feature in e-learning context. It is due to the dissimilarities in goals, backgrounds and capabilities of the learners. The future work will focus on incorporating intelligent technologies from field deep learning to enhance the recommendation performance and accuracy of the recommendation approach.

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