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An Effective Recommendation System for E-Learning Using Fuzzy Tree

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Abstract: The rapid developments of e-learning systems provide learners with large opportunities to access learning activities through online. However the issues related to e-learning systems reduces the success of its application. The enormous learning resources that are emerging online make an e-learning system difficult. The individual learners find it difficult to select optimized activities for their particular requirements, because there is no personalized system. Recommendation systems that provide a personalized environment for studying can be used to solve the issues in e-learning system. However, e-learning systems need to handle certain special requirements. They are learning activities that are often presented in tree structures; learning activities contain more uncertain categories which additionally contain unclear and uncertain data, there are pedagogical issues, such as the precedence order for a particular user cannot be given separately for each user. In our proposed system, a fuzzy tree-structured learning activity model and a learner profile model has been implemented to improve the performance of e-learning recommendation system.

Key words: E-learning · Fuzzy tree · Knowledge-based recommendation · Recommender systems

INTRODUCTION

E-learning systems are becoming popular due to the development of web-based information and communication technologies. The growth of e-learning systems has changed the traditional learning behaviour of learners and enhances learning practices online. Due to the emergence of numerous kinds of learning activities in the e-learning environment, learners find it difficult to select the learning activities that best suit them. The motivation of this study is to develop a recommendation approach to support learners in the selection of the most appropriate learning activities in an e-learning environment. Recommendation systems, as one of the most popular applications of personalization techniques, were first applied in the e-commerce.

Recommendation systems attempt to recommend items to the users by knowing the interest of the user for a particular item based on various types of information such as type of items, usage of items, popularity of items and the interactions between users and items. The basic idea of recommendation systems is that similar users like similar items. Therefore, the similarity measure for users or items is vital in the application of recommendation systems. Recommendation systems have been widely used in various web-based applications in e-commerce, e-business, e-tourism, e-government, but very few in e-learning. Both learning activities and learner profiles have complex descriptions and features [1].

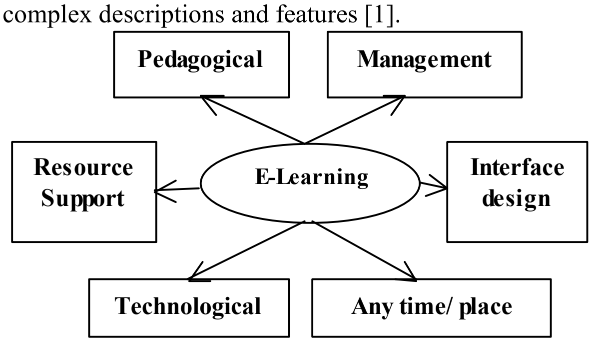

Fig 1.1: Features of E-learning

A learning activity contains several aspects of information, such as the content description and so on, while a learner profile contains the learner's background, learning goals, prior knowledge, learner characteristics and so on. Thus, the data in the e-learning environment has a hierarchical structure. In reality, learning activities and learner profiles may contain vague and uncertain data. One learning activity may be under several categories with different degrees. The tree-structured

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learning activities and learner profiles are therefore represented as fuzzy trees. The pedagogical issues must be considered in the learning activity recommendation. Some learning activities require prerequisite courses. For example, studying the subject *Data Mining* requires the pre-knowledge about database and algorithms. It is not feasible to differentiate between two learning activities just by their names, because learning activities provided from different sources may have different names [2].

Literature Survey

Personal Recommender Systems for Learners in Lifelong Learning Networks: the Requirements, Techniques and Model: Model-based techniques periodically analyze data to cluster them in estimated models. For instance, 'genre' can be a classification of a movie system and movies of the same 'genre' could be part of one cluster. The average choice of movies from a specific cluster of movies can then be used to calculate the interest of a user in a specific movie. Model-based RSs use techniques such as Bayesian models, neural networks or latent semantic analysis. The first challenge in designing an RS is to define the users and purpose of a specific context or domain in a proper way. These models require a large corpus (more than 10,000 items) to estimate their models and provide accurate recommendations.

Memory-based techniques continuously analyses all user or item data to calculate recommendations and can be classified in the following main groups: CF techniques, Content-Based techniques and hybrid techniques. User-based CF, Item-based CF, Stereotypes or demographics CF techniques benefit from the experience of user access. It allocates learners to groups (based on similar ratings). Keeps learner informed about learning goal. Attribute-based techniques and case-based reasoning is useful for hybrid Recommendation systems. User-based CF, Item-based CF, Case-based reasoning has no content analysis [3].

Personalized E-learning Material Recommender System: Content-based recommender systems provide recommendations to a customer by automatically matching his/her preferences with product content. Collaborative recommender systems estimate a customer's preferences for a product based on the overlap between his/her preference ratings for the product and those of other customers. Content-based recommender systems cannot be applied to new customers who have purchased only once, to potential customers who visited the website but have not made any purchase and customers who want to buy a product which is not frequently purchased. It is hard for collaborative filtering based recommender systems to accurately compute the neighbourhood and identify the products to be recommended.

This framework is designed to have four main components 'getting student information', 'identifying student requirement', 'learning material matching analyses' and 'generating recommendation'. In the framework, information about student requirement can essentially be obtained in two ways: extensionally and intentionally expressed. While content-based recommendation and collaborative recommendation are complementary, it would further boost the performance by integrating these two approaches. By using the framework, a learning recommender system is expected to have the capability to optimize recommendations and reduce false positive errors which are learning materials that are recommended, but the student is not satisfied with them.

Enhanced Collaborative Filtering to Recommender Systems of Technology Enhanced Learning: Efficient CF algorithms that guarantee a multiple assignment of a user to different clusters, by modifying the FCM objective function to a Matrix Factorization one. One of the major problems of RSs is the stability problem of these systems compared to the dynamic profile of the user. Due to the two major challenges for the CF based systems like scalability and scarcity problems, the real time application of traditional FCM algorithm can confront some difficulties.

A fuzzy based clustering algorithm is proposed to regroup learners, including the active learner and that guarantees a multi-affectation of learners to nearest clusters allowing them to receive partial recommendations generated in each cluster according to their membership degrees. The proposed work alleviates the stability and plasticity problem and improves the recommendation accuracy. This technique allows generating learning resources recommendations to lifelong learners that correspond to their different interests, tracking their profile's evolution [4].

An Effective Recommendation Framework for Personal Learning Environments Using a Learner Preference Tree and a GA: Case based reasoning assumes that if a user likes a certain item, she/he will probably also like similar items. This approach recommends new but similar items. Semantic recommender systems, instead of using syntactic matching techniques, use inference techniques borrowed from the Semantic Web. The performances of CBR mechanisms are closely related to the case representation and indexing approach, so their superior performances are unstable and cannot be guaranteed. Since more people usually do not spend time to rate based on each individual criterion in multi-criteria recommenders.

A new recommendation approach based on the explicit and implicit attributes of learning resources is established. Introduction of implicit attributes and optimization of the weight of these attributes by a genetic algorithm (GA) to improve the accuracy of recommendation when the information about explicit attributes is low. Alleviates the scarcity and cold-start problems and also generate a more diverse recommendation list than traditional recommender systems. In addition, the implicit attribute-based recommender which uses GAs for the weight optimization of implicit attributes can increase the accuracy of recommendations [5].

A Hybrid Attribute-Based Recommender System for E-learning Material Recommendation: The existing recommendation system like content-based system directly exploits the product's information and the collaborative filtering approach utilizes specific user rating information. The drawback is that it considers only rating matrix. Moreover Collaborative Filtering approach does not consider attribute of items and users.

An Attribute-based approach is proposed in which most frequently visited materials, most similar visited materials to target learners, most similar visited to the most similar learner, most frequently visited to the most similar learner approaches are used. The learner's real preferences were satisfied accurately according to the real-time updated contextual information [6].

Representation, Similarity Measures and Aggregation Methods Using Fuzzy Sets for Content-based Recommender System: Recommendation systems use historical data consisting of ratings from users before the recommendation begins input data such as features of items or users' ratings in order to initiate a recommendation and models and algorithms to combine the former two and generate a recommendation. A content-based recommendation requires data on the behaviour of users and features of items. Its performance depends on the data and how this data is used, i.e. represented and inferred. The Representation and reasoning about the behaviour of users and features of items raise a number of challenging issues. Features of items and users' behaviour are subjective, vague and imprecise. These, in turn, induce uncertainty on representation of and reasoning about the items' features, users' behaviour and their relationship. The uncertainty is non-stochastic or non-random and is induced from subjectivity, vagueness and imprecision in the data, the domain knowledge and the task under consideration.

A representational method, aggregation method and similarity measures for content-based recommender systems. It also develops algorithms and carries out an empirical assessment of the effect of fuzzy set theoretic method on the performance of a movie recommender system by comparing its results to the results of the baseline crisp set based method. Handles uncertainty, the performance is improved and there is a better precision [7].

Building a Recommender Agent for E-learning Systems: A log entry is automatically added when a request for a resource reaches the web server. There exist some statistical tools that give rudimentary analysis of the web logs and provide reports on the most popular pages, the most active visitors in given time periods. The log entries are not in a format that is usable by mining applications and requires reformatting and cleansing in order to identify real session information and path completion. The ability of the tools to help understand the implicit usage information and hidden trends in learners' on-line access behaviour is very limited.

An approach to build a software agent that uses data mining techniques such as association rules mining in order to build a model that represents on-line user behaviours and uses this model to suggest activities or shortcuts. This approach can help learners better navigate the on-line materials by finding relevant resources faster using the recommended shortcuts. The system assists the learner to choose pertinent learning material that improves the performance based on on-line behaviour of successful learners [8].

Existing System: A recommendation approach using fuzzy tree exists which develops a fuzzy tree-structured learning activity model for an e-learning system. In the fuzzy tree-structured learning activity model, a fuzzy category tree has been defined to specify the categories that each learning activity roughly belongs to. The precedence relations between learning activities were also handled through analysing the learning sequences and modelling the prerequisite learning activities. The efficiency of the system reduces because of the lack of groups of learners. By grouping the learners and giving group recommendations the performance of the system can be improved.

Proposed System

Proposed Recommendation Framework: Implementation of the e-learning recommender system is designed to have three types of users: system administrators, teachers and students. The roles of the users are described as follows. The role of the system administrator is to maintain the learning materials and list of staffs, which are used to support the operation of the system. The teachers are responsible for managing the learning materials. They input the learning materials with their descriptions into the system. They provide their background information when registering in the system.

As a web-based online system, the e-learning recommender system has a standard multi-tier architecture, which includes web browser, web server and database server. The database stores all the data of the system, which includes the staff data, student data and subject data. The presentation layer is generates the requested web pages and handles the user interface logic and events for the three kinds of users.

Apart from the presentation layer the web server contains four main parts: the student centre, the teacher centre, the administrator centre and the recommendation engine. The student centre collects the user's profile, tracks the user's learning behaviour and provides the recommendations of learning materials. The recommendation engine generates recommendations for the student users. Teachers upload the learning activities in the teacher centre. The administrator centre is used by administrators to manage the teachers' data and subject data. The data access layer deals with the data operations of the database.

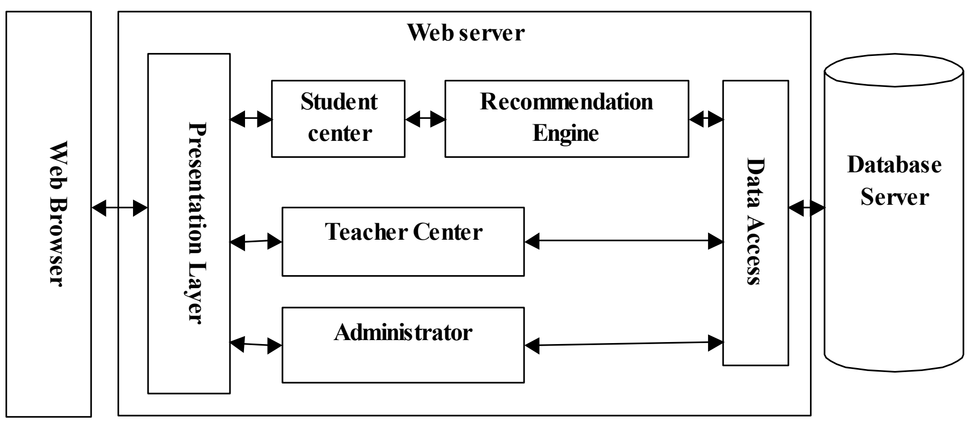

Fig. 1.2: System Architecture

Preprocess Material Database: The admin of the website manages the materials in a centralized database. The admin has privilege to upload, update and delete a document. Each action should be updated at centralized database properly. The uploaded material database is converted into a dataset by preprocessing. The requests to the website are served by retrieving results directly from the dataset instead of the database.

Grouping the Learners: The learners are grouped into clusters based on the similarity of their preferences for the learning materials. Learners with similar preferences are grouped into a single category. The learners in each cluster receive partial recommendations generated in each cluster according to their membership degrees.The recommendations given to the groups of learners are more accurate than the general recommendations.

Content Delivery: The learning materials are recommended to the learner groups based on their preferences. These learning materials are recommended based on the previous searches of the learners in the group. The recommendation list consists of a set of top learning materials which were the most preferred materials by the learners in the same cluster. The final recommendation varies for every cluster based on the interest for the learning material by the members of each cluster.

Fig 1.3: Student login page

Fig 1.4: Student search page

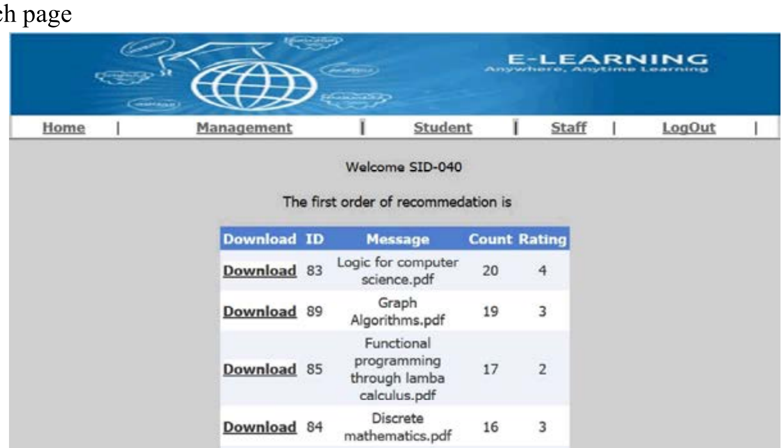

Fig 1.5: List of recommended study materials

CONCLUSION

Personalized learning is required when e-learning systems make deliberate efforts to design educational experiences that fit the needs, goals, talents and interests of their learners. The proposed personalized e-learning system takes the dynamic learner's preferences into account. The results indicate that placing the learner in an appropriate teaching style that matches with the learner's preference leads to improvement in the learning environment.

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