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A Hybrid E-learning Recommendation Approach Based on Learners' Influence Propagation

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ABSTRACT
In e-learning recommender systems, interpersonal information between learners is limited, making collaborative filtering (CF) approaches challenging to employ. For proposing learning objects (LOs) to learners, we offer a hybrid filtering (HF) recommendation technique (SI IFL) that combines learner impact model (LIM), self-organization based (SOB) recommendation strategy, and sequential pattern mining (SPM). The procedure is as follows: I LIM is used to gather interpersonal data by calculating how much impact a learner has on others. Learner similarity, knowledge credibility, and learner aggregation make up LIM. LIM is unaffected by ratings. In addition, intuitionistic fuzzy logic (IFL) is used to improve the LIM in order to meet the uncertainty and fuzzy character of learners. (ii) By modelling influence propagation among learners, a SOB recommendation approach is used to propose the best learner cliques for active learners. Influence propagation occurs when a learner moves near active learners, and this activity stimulates his neighbours' movement behaviours. Based on distributed and bottom-up individual behaviours, this SOB recommendation technique provides a stable framework. (iii) Based on the proposed learner cliques, SPM is used to determine the final learning objects (LOs) and navigational pathways. The results of the experiments suggest that SI IFL is capable of providing tailored and diverse recommendations, as well as promising efficiency and flexibility in e-learning settings.

Key words:personalized e-learning, adaptive and intelligent educational systems, hybrid recommendation, influence model, self-organization, recommender system.

1. INTRODUCTION

E-learning systems, such as ELM-ART, AHA, and others, are now commonly utilised by learners to complete their studies due to the abundance of learning resources and easy access. MOOCs, such as Coursers and edX, have grown in popularity, piquing learners' interest in online learning. In turn, how to offer individualized and effective learning materials and learning paths to e learners has become a major issue, as an increasing number of learners, particularly LOs, demand to be provided with personalized learning content. Items having the lowest granularity, such as examples or multiple-choice questions, are referred to as LOs.

Learners may use an e-learning recommender system (RS) to save time looking for learning information, boost their engagement, and get suggestions that are appropriate to their aims or interests [2]. Filtering learning material is done in a variety of ways, including content-based filtering (CBF), collaborative filtering (CF), and hybrid filtering (HF). CBF recommender systems tailor goods to users' preferences based on what they've learnt. Common recommended factors include a learner's knowledge level, learning capacity, cognitive model, and learning experience [3]. Furthermore, item similarities are crucial when recommending what learners could like. Although some study used multi-dimensional learner preferences and multi-attributes of items to apply CBF suggestions, information overload is often encountered as a result of over-specifying some preferences and a significant dependence on learner-item similarity [4], [5]. The user-item rating matrix is the main criteria for assessing the similarity between users or things in the CF recommender system, which seeks to recommend goods (products, news, movies, etc) based on some other users who are similar to active users. The use of interpersonal information in CF recommender systems has resulted in high performance. They are also more effective in reducing information overload. Learner or LO information is often included in HF techniques to create a rating matrix for selecting learning materials [6], [1]. The goal of this research is to use HF approaches to enhance the quality of e-learning suggestions. Given the subjectivity and unpredictability of a learner's learning process, quantitative analysis of the learner model and learner behaviour is very challenging. The use of a heuristic technique to estimate the precise learner model is a viable option. As a result, we use certain heuristic settings to model learners' interactive behaviour and track the interactive environment's dynamic changes.

2. LITERATURE REVIEW

Shanshan Wan, ZhendongNiuet,al: In e-learning recommender systems, interpersonal information between learners is very scarce, which makes it difficult toapply collaborative filtering (CF) techniques. In this study, we propose a hybrid filtering (HF) recommendation approach (SI-IFL) combining learner influence model (LIM), self-organization based (SOB) recommendation strategy and sequential pattern mining(SPM) together for recommending learning objects (LOs) to learners. The method works as follows: (i), LIM is applied to acquire theinterpersonal information by computing the influence that a learner exerts on others. LIM

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consists of learner similarity, knowledgecredibility, and learner aggregation. LIM is independent of ratings. Furthermore, to address the uncertainty and fuzzy natures oflearners, intuitionistic fuzzy logic (IFL) is applied to optimize the LIM. (ii), a SOB recommendation strategy is applied to recommend theoptimal learner cliques for active learners by simulating the influence propagation among learners. Influence propagation means that alearner can move toward active learners, and such behaviors can stimulate the moving behaviors of his neighbors. This SOBrecommendation approach achieves a stable structure based on distributed and bottom-up behaviors of individuals. (iii), SPM isapplied to decide the final learning objects (LOs) and navigational paths based on the recommended learner cliques. The experimentalresults demonstrate thatSI-IFLcan provide personalized and diversified recommendations, and it shows promising efficiency andadaptability in e-learning scenarios.

Qian Zhang, Jie Lu, Guangquan Zhang et.al: In this era when every aspect of society is accelerating, people are always seeking improvement to stay competitive in their careers. E-learning systems fit into the ever-challenging situation and provide learners with remote learning opportunities and abundant learning resources. Facing with the numerous resources online, users need support in deciding which course to take, thus recommender systems are applied in E-learning to provide learners with personalized services by automatically identifying their preferences. This position paper systematically discusses the main recommendation techniques employed in in E-learning and identifies new research directions. Three main recommendation techniques are reviewed in this paper: content-based, collaborative filtering-based and knowledge-based recommendations. The basic mechanism of these technique together with how they are used to fulfill the specific requirements in the context of E-learning are highlighted and presented. The observations in this paper could support researchers and practitioners to better understand the current development and future directions of recommender systems in E-learning.

Anisha M Lal et.al: In recent years there has been an enormous increase in learning resources available online through massive open online courses and learning management systems. In this context, personalized resource recommendation has become an even more significant challenge, thereby increasing research in that direction. Recommender systems use ontology, artificial intelligence, among other techniques to provide personalized recommendations. Ontology is a way to model learners and learning resources, among others, which helps to retrieve details. This, in turn, generates more relevant materials to learners. Ontologies have benefits of reusability, reasoning ability, and supports inference mechanisms, which helps to provide enhanced recommendations. The

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comprehensive survey in this paper gives an overview of the research in progress using ontology to achieve personalization in recommender systems in the e-learning domain.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

- Zaiane et al. [13] applied CF techniques to some e-learning platforms which have experienced and well-established learning communities. The rating information can be obtained from the interactive evaluation records. Zapata et al. [14] attempted to add voting functionality to obtain the score of learners and items. Aleksandra et al. [15] presented an approach for the implementation of collaborative tagging techniques into online tutoring system. However, not all the learning platforms like to provide interaction entrances or communities, and it is not realistic for learners to rate or tag the large amount of resources during their continuous learning process.
- Zhu et al. applied advanced Recurrent Neural Network (RNN) to study users' behaviors based on time sequence [25], [26]. Besides, the introduction of probability and randomness based recommendation strategy is effective to improve diversity. For example, the probability-based genetic algorithm has been proposed in the context of information filtering [27].
- Yueh- Min et al.[28] studied Markov's chain model based metarules to help learners achieve effective web-based learning paths. Additionally, Bayesian Knowledge Tracing (BKT) is a common way of determining student knowledge of skills in adaptive educational systems and cognitive tutors [29].Currently, a few attempts have been made to improve the quality of recommendations using information propagation among individuals. For example, Golbeck et al. [30] studied the ripple effect of learners' behavior changes and its impact over a social network, Barsade et al. [31] researched the ripple effect of the emotional contagion on group behavior.
- Janssen et al. [32] provided recommendations for the active learners by feeding back successful learning tracks to other learners. Koper et al. [33] concentrated on the changes in some parameters, such as LOs' quality, disturbance of environment, and matching errors.

3.2 PROPOSED SYSTEM

- In the proposed system, the system proposes a hybrid filtering recommendation approach (SI IFL) to improve the personalization and diversity of recommendations. The main

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work includes: a learner influence model (LIM) is designed to address interpersonal information sparsity and cold start problems in e-learning; a SOB recommendation strategy is put forward to study the collaborative behaviors among learners and provide the optimal learner cliques; and sequential pattern mining (SPM) is applied to deciding the final LOs and navigation of recommendations. More specifically, the main contributions of this paper are listed as follows:

- (Build a learner model-LIM. LIM includes learner similarity, knowledge credibility and learner aggregation. LIM can be deduced form learning styles and learning profiles directly, so LIM is effective in addressing the extreme data sparsity normally encountered when applying CF techniques.
- Apply intuitionistic fuzzy logic (IFL) based strategy to optimizing LIM. IFL includes three functions: membership function, intuition function and non-member function. The application of IFL is conducive to building a more flexible and accurate LIM by considering the subjective and uncertain factors exiting in learners' learning process.
- Propose a self-organization based (SOB) recommendation approach to find out optimal learner cliques for active learners. This approach is a kind of CF and heuristic techniques. The self-organization behavior of learners allows some learners to move closer or farther to active learners based on influence propagation, and then the learner cliques are generated. Hence, the recommendations are based not only on similarity computation between active learners and other learners, but also the influence between other learners. SPM technique is a kind of CBF recommendation strategy, and it is applied to make final recommendations. As a result, with the application of the hybrid SI IFL, some useful but low matching learners have the possibility to be recommended.

4. RECOMMENDATION STRATEGY BASED ON INFLUENCE MODEL

4.1 Data Flow Diagram

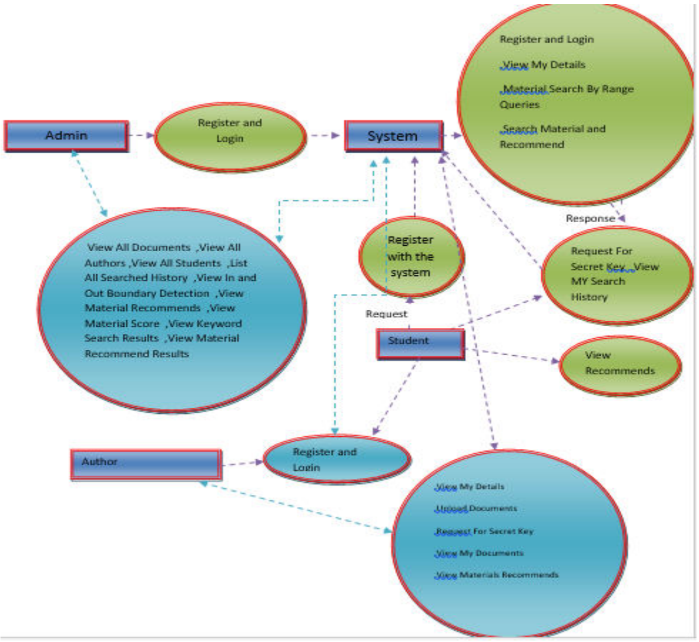

Fig 4.1: Data Flow Diagram

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4.2 Flow chart

4.2.1 Student

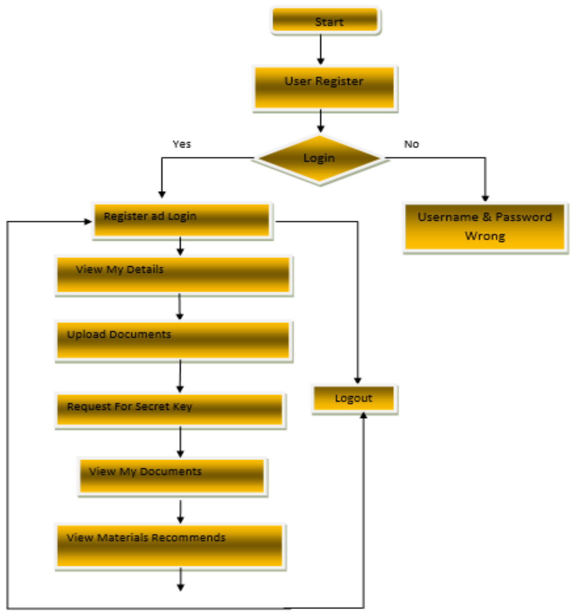

Fig4.2: Student Flow chart

4.2.2 Admin

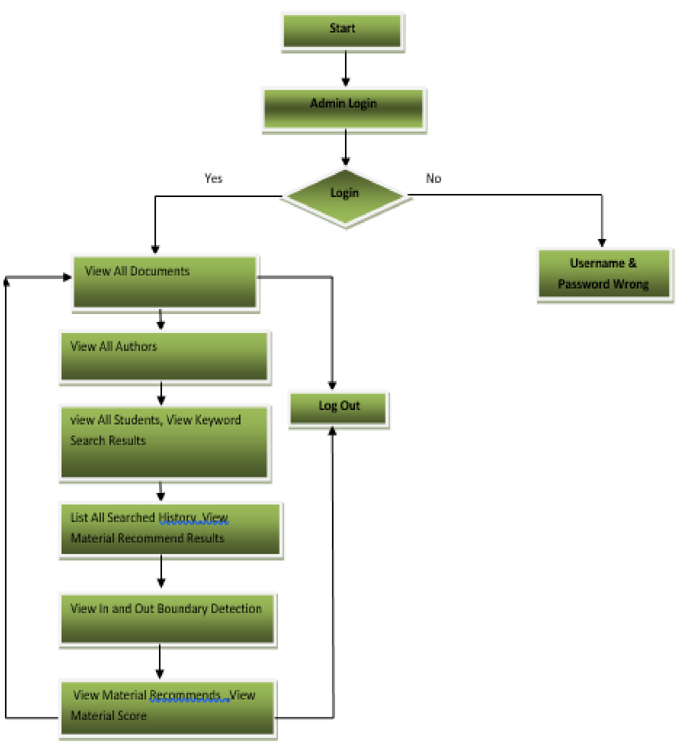

Fig 4.3: Admin Flow Chart

4.2.3 Author

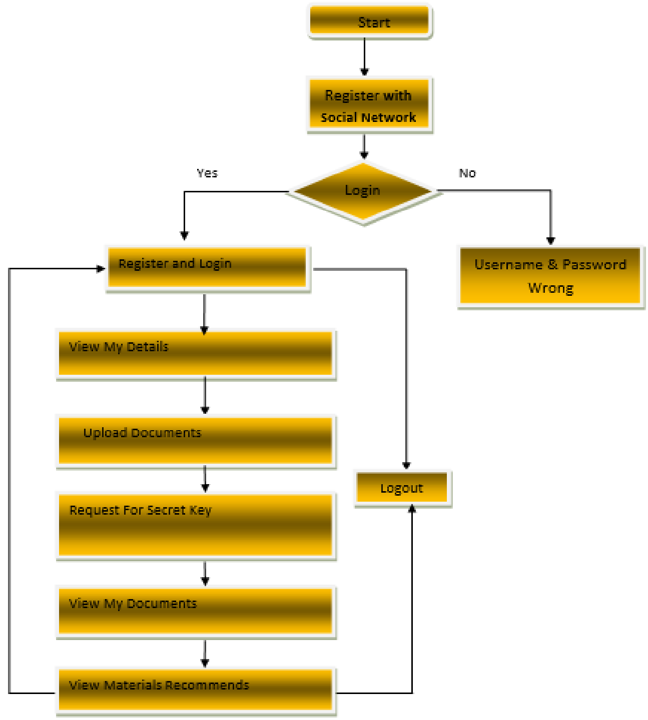

Fig 4.4: Author Flow chart

4.3 Use Case Diagram

- Use case

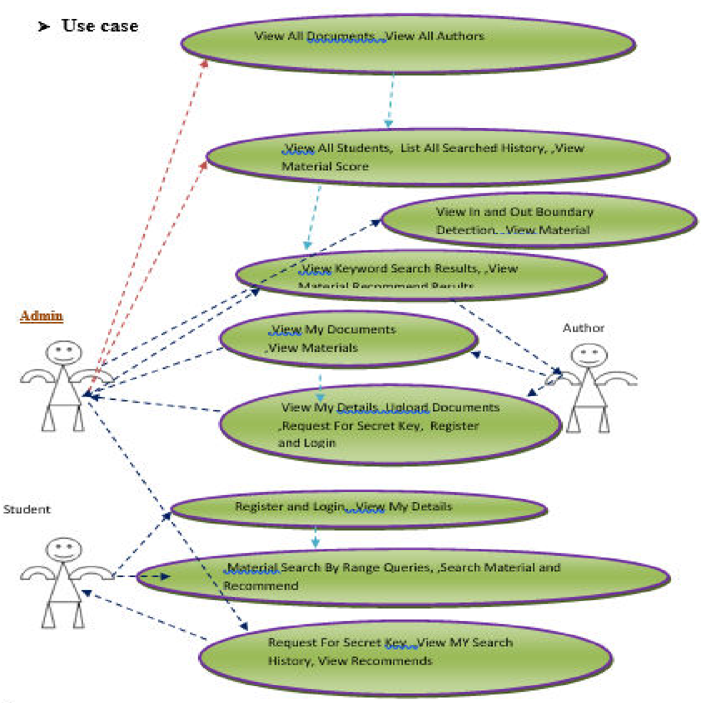

Fig4.5: Use Case Diagram

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5. MODULE IMPLEMENTATION

ADMIN

In this module,admin has to login and also performs the following operations such as View All Documents,View All Authors,View All Students,List All Searched History, View In and Out Boundary Detection, View Material Recommends, View Material Score, View Keyword Search Results, View Material Recommend Results.

AUTHOR

In this module the author has to register and login and also performs the following operations such as View My Details, Upload Documents, Request For Secret Key, View My Documents, View Materials Recommends.

STUDENT

In this module, the student has to register to admin and log in and performs the following operations such as View My Details, Material Search By Range Queries, Search Material and Recommend, Request For Secret Key, View MY Search History, View Recommends.

6. RESULTS

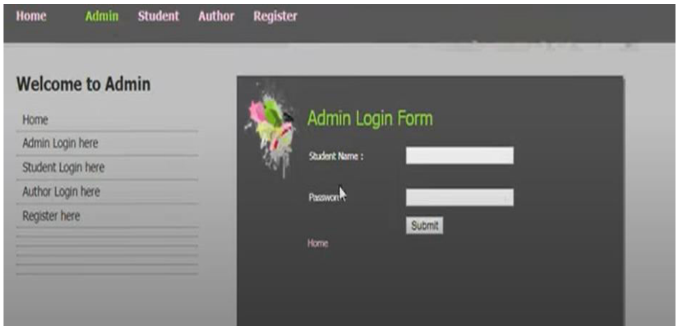

Fig 6.1: Admin Login form

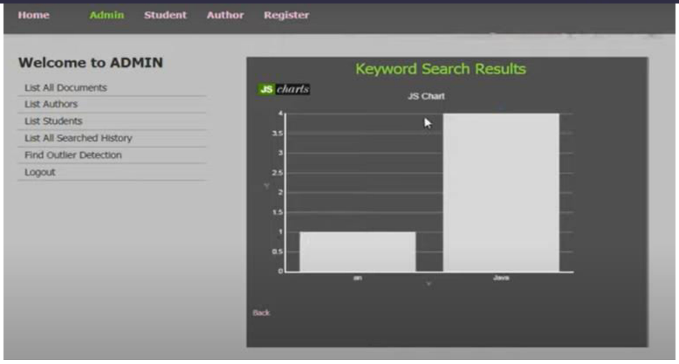

Fig 6.2: Keyword Search Result

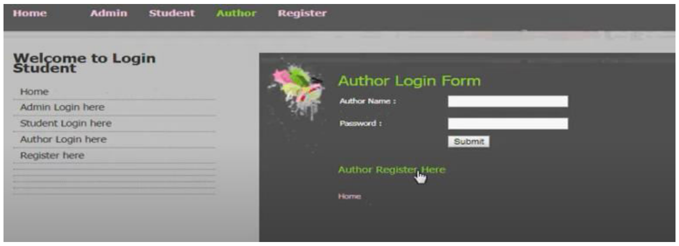

Fig 6.3: Author Login Form

Fig 6.4: Author Main

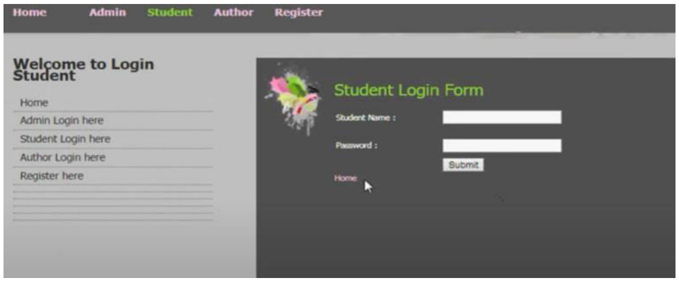

Fig 6.5: Student Login Form

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Fig6.6: Document Score

7. CONCLUSIONS

Different from e-commerce fields, e-learning faces excessive information scarcity, which hinders the application No. 61370137), the National 973 Project of China (No. 2012CB720702), Ministry of Education China Mobile Research Foundation Project (2016/2-7), Beijing emergency project (No, Z171100004417031), and the Fundamental Research Funds for Beijing University of Civil Engineering and Architecture (No. X18070).

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