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

Shanshan Wan and Zhendong Niu

Abstract—In e-learning recommender systems, interpersonal information between learners is very scarce, which makes it difficult to apply collaborative filtering (CF) techniques to achieve recommendations. In this study, we propose a hybrid filtering 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 the interpersonal information by computing the influence that a learner exerts on others. LIM consists of learner similarity, knowledge credibility, and learner aggregation, meanwhile, LIM is independent of ratings. Furthermore, to address the uncertainty and fuzzy natures of learners, intuitionistic fuzzy logic (IFL) is applied to optimize the LIM. (ii) A SOB recommendation strategy is applied to recommend the optimal learner cliques for active learners by simulating the influence propagation among learners. Influence propagation means that a learner can move towards active learners, and such behaviors can stimulate the moving behaviors of his/her neighbors. This SOB recommendation approach achieves a stable structure based on distributed and bottom-up behaviors of individuals. (iii) SPM is applied to decide the final learning objects (LOs) and navigational paths based on the recommended learner cliques. The experimental results demonstrate that $SI-IFL$ can provide personalized and diversified recommendations, and it shows promising efficiency and adaptability in e-learning scenarios.

Index Terms—Personalized e-learning, adaptive and intelligent educational systems, hybrid recommendation, influence model, self-organization, recommender system

1 Introduction

Currently, owing to the plentiful learning materials and the convenient access, e-learning platforms have been widely used by learners to accomplish their study, such as ELM-ART, AHA, etc. [1]. The popularity of MOOCs, such as Coursers and edX, further increase learners' interests on e-learning. Correspondingly, how to recommend personalized and effective learning resources and learning paths to e-learners has become an important problem, because more and more learners expect to be recommended with personalized LOs to facilitate their learning. LOs refer to items with smallest granularity, such as examples or multiple-choice questions.

E-learning recommender system (RS) offers flexibility for learners to decrease the time for searching learning content, increase the learner's interest, and provide the recommendations relevant to the learner's goals or interests [2]. Content-based filtering (CBF), collaborative filtering (CF) and hybrid filtering (HF) are common methods to filter the learning content. CBF recommender systems customize items for users according to what they have learned. Learners' knowledge level, learning ability, cognitive model and learning experience are common recommendation criteria [3]. Furthermore, the similarities between items are critical to recommend what learners might like. However, although some research implemented CBF recommendations by combining multi-dimensional preferences of learners and multi-attributes of items, information overload is normally encountered due to the over specification for certain preferences and the high reliance on learner-item similarity [4], [5]. CF recommender system aims to recommend items (products, news, movies, etc.) according to some other users who are similar to active ones, in addition, the user-item rating matrix is the basic criterion for calculating the similarity between users or items. CF recommender systems have achieved good performance by utilizing interpersonal information. Moreover, they are more efficient in decreasing information overload. HF approaches often combine information of either learners or LOs to rating matrix for recommending learning resources [1], [6]. In this study, we focus on applying HF techniques to improve the quality of e-learning recommendations. Considering the subjectivity and randomness in learner's learning process, it is very difficult to make quantitative analysis on learner model and learner behaviors. Heuristic approach is a possible way to approximate the exact learner model. Hence, we adopt some heuristic settings to model learners' interactive behaviors.

It has been noticed that the characteristic of extreme data sparsity and the demands of diversity exert difficulties on realizing personalized recommendations for learners. Our study attempts to address the above problems and improve

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Manuscript received 24 May 2018; revised 28 Nov. 2018; accepted 8 Jan. 2019. Date of publication 25 Jan. 2019; date of current version 1 Apr. 2020. (Corresponding author: Zhendong Niu.)
Recommended for acceptance by D. Cai.
Digital Object Identifier no. 10.1109/TKDE.2019.2895033

the effectiveness and efficiency of e-learning recommender systems. The detailed problems we devote to solving are listed as follows:

1) Compared with e-commerce fields, the explicit interpersonal information in e-learning environment is particularly scarce, which makes it hard to compute the similarity of learners for applying CF techniques [7]. Some of the reasons of information scarcity include: (i) during the continuous learning process, learners do not actively make ratings or give comments because they aim to achieve their goals within scheduled but limited learning time. (ii) the rating entrance is not common in e-learning platforms because of the existence of the massive LOs with small granularity. (iii) the scarcity of implicit interpersonal information is caused by a lack of community environments where learners can post comments or engage in discussions, as well as a lack of common learning activities. As a result, learners' learning profiles often seem isolated from each other. The extreme data sparsity caused by the above factors poses a great challenge to the realization of CF based recommendations.
2) The recommendation mechanisms which excessively depend on similarity and ratings cause the lack of diversity. In many commercial fields, the recommendations aim to meet users' specific demands at a certain point of time, without the need to consider the long-term requirements. However, e-learning presents a continuous process. Besides the personalization, diversity is necessary to ensure the long-term learning experience of learners. In addition, learners have inherent motivations for self-improvement and self-challenge, as well as desires for curiosity and intrinsic interests, etc. To achieve these requirements, learners often show subjectivity and uncertainty natures in their learning process. These situation makes it paramount that there is a high diversity of recommendations [8]. Nevertheless, the complete dependence on high matching in CBF recommendations and the similarity computation in CF recommendations decrease the possibility of diverse recommendations. Such approaches are not conducive to ensuring the flow learning experience during the whole learning process.

In this paper, we propose a hybrid filtering recommendation approach ($SI - IFL$) to improve the personalization and diversity of recommendations. The main 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:

1) Build a learner model-LIM. LIM includes learner similarity, knowledge credibility and learner aggregation. LIM can be deduced from learning styles and learning profiles directly, so LIM is effective in addressing the extreme data sparsity normally encountered when applying CF techniques.
2) Apply intuitionistic fuzzy logic (IFL) based strategy to optimizing LIM. IFL includes three functions: membership function, intuition function and non-member function. The introduction of IFL is conducive to building a more flexible and accurate LIM by considering the subjective and uncertain factors exiting in learners' learning process.
3) 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 clustered into the cliques for active learners.

Such SOB recommendation strategy is bottom-up, distributed and probability-based, it is promising to address the problems of information overload and lack of diversity.

The remainder of the paper is organized as follows: Section 2 describes some researches related to data sparsity and self-organization theory for e-learning recommender systems. Section 3 introduces details regarding the proposed recommendation approach, especially the learner influence model and the self-organization based recommendation strategy. Section 4 presents the experimental setup of the study. Section 5 presents the experimental results and discussions. Finally, Section 6 summarizes the characteristics of the proposed approach and introduces future work.

2 Related Works

In this section, we summarize relevant research on interpersonal information scarcity, the approaches for optimizing learner model, and the recommendation strategies based on self-organization theory.

2.1 Interpersonal Information Acquisition

Some methods have been proposed to process the data sparsity caused by the lack of rating information. The research focuses on matrix factorization method, or fusing trust and friendship relationship into rating matrix [9], [10]. These methods show good performance on e-commerce fields, such as catering, entertainment, shopping and tourism [11]. However, in e-learning recommender systems, the problem of data sparsity is more severe than it in other fields [7], [12]. Due to the lack of community environments and the fact that learners have seldom common learning activities on the same LOs, it is difficult to deduce the trust or friendship relationships between learners.

Some strategies are taken to acquire the rating information directly. For example, 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.

The context-aware information of learners, such as knowledge level and some kind of learning styles, is often applied as auxiliary information to strengthen the similarity rating matrix in CF recommender systems [6], [16], [17]. Dwivedi et al. [18] pointed out that the trustworthy learners having greater knowledge and similar learning style patterns as that of the active learner have greater weightage in the recommendation strategy. However, such research is still based on rating matrix. How to realize CF recommendations when there is no effective rating information still needs further study.

2.2 Learner Model Optimization

E-learning environment has its peculiarities which are different from other fields. The peculiarities include time continuity, knowledge consecutiveness and learner's craving for a multidimensional learning experience, etc. To ensure a long-term learning experience for learners, the recommendations should not only have high accuracy, but also some level of diversity. One possible solution to increase diversity is to use multi-attribute learner models [8], [19]. Another method is the introduction of fuzzy mechanism to describe learner's uncertainty behaviors which are difficult to be analyzed and modeled qualitatively. Fuzzy theory is appropriate to effectively cope with the inherent vagueness, uncertainty, and subjectivity of human decision-making process [20]. In e-learning, fuzzy set theory has been used to deal with the uncertain natures of learners, such as learners' uncertain responses [21], the fuzzy matching between learning resources and learners' needs [22], [23]. Yet, because of the complicated and multidimensional requirements of learners, learners may select the learning resources in an intuitive way. Until now, there is seldom research considering applying the intuitionistic fuzzy characteristics on learner modeling.

2.3 Self-Organization Based Recommendation Strategy

In CBF recommendations, the high dependence on the similarity matching between learners and LOs causes learners have little possibility of receiving LOs that they might wish to receive but may not be aware of their existence [24]. The similarity and rating-based CF recommendation criteria also have little inherent mechanisms for recommending something unexpected but interesting. To improve the performance of recommendations, 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 meta-rules 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.

To a certain extent, the above methods can increase the diversity of recommendations by applying the randomness mechanism. However, the computation complexity is high in updating the influence between each pair of learners. It is also observed that learner structure in the above approaches keep static before the clusters are presented, and these researches didn't consider the useful communications among others. Hence, learners may miss important and useful recommendations. Moreover, the fully active learner-oriented computation strategy decreases the diversity of recommendations.

In this study, we apply self-organization theory to simulate learners' behaviors. The self-organization theory refers to the self-organizing phenomenon that the subsystems or individuals can form certain structures according to some rules without external instruction [34]. In real learning environments, in spite of the fact that the rating information is scarce, learners are able to extract useful information from others, and find the favorite cliques to facilitate their study. Learners' behaviors present the natures of self-organization. Hence, we model learners as entities which have the ability to receive information, transmit information, and move towards other learners. All students exhibit the self-organization-based nature which drives them to move towards some cliques which can help them optimize their learning process. Self-organization theory has achieved significant results in image recognition, virus propagation, traffic control and population development [35], [36]. How to find out an effective and efficient mechanism to stimulate collaborative behaviors of learners is still under-explored.

3 Recommendation Strategy Based on Influence Model

In this section, we first give the model of e-learning recommendation problem; second, we introduce the recommendation framework of $SI-IFL$; third, we describe the LIM and introduce how to optimize the model with IFL, and finally we describe how the recommendation strategy is implemented.

3.1 Recommendation Framework

E-learning recommendation problem is complex due to the existence of many constraints, such as learning goals, learning preferences and time limitation. The recommender system aims to satisfy those constraints simultaneously. The recommendation framework of $SI-IFL$ is shown in Fig. 1. There are three major components in this framework, which are learner module, recommendation module, and interaction module.

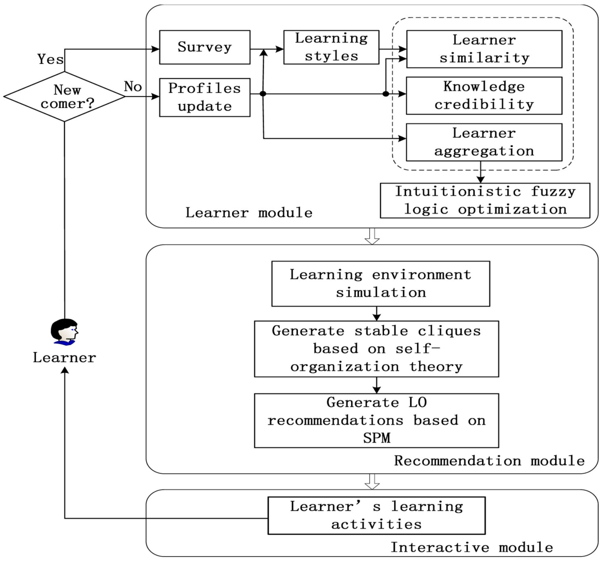


Fig. 1. Recommendation diagram for the proposed recommendation approach.

In learner module, learner similarity, knowledge credibility and learner aggregation constitute LIM, and LIM is used to quantitatively evaluate the relationship among learners. Among LIM, learner similarity consists of personality similarity and profile similarity. Knowledge credibility is computed by analyzing leaners' learning process, such as scores and learning behaviors. Learner aggregation is obtained by analyzing the existing access transactions of learners. IFL method is applied to optimizing the influence model. In recommendation module, the SOB recommendation approach is used to simulate learners' collaborative behaviors and give learner cliques. Then, SPM is applied to deciding the final LO representation by mining the sequential access pattern among the learners in same cliques. In interaction module, learners' activities, such as studying records and possible tagging behaviors, are recorded.

3.2 Learner Influence Model

The completely cold-start problem has hindered the direct application of CF recommender systems. Some research implemented CF recommendations by analyzing users' behaviors. In [37], authors used an active learning model to handle users' implicit feedback, and consider users' time-sensitive responsiveness for active learning based recommendations. In [38], authors combined the overlap of users, feedback pattern similarity and coverage of users to study the broadcast email prioritization. To address the problems of cold start and data sparsity, we propose LIM to mine the explicit and implicit behaviors. LIM consists of three parts: learner similarity, knowledge credibility and learner aggregation. The motivation is based on real life experiences that people are willing to take suggestions from those who show similar preferences or those who are excellent in learning, or those who are highly recognized by the public [39].

3.2.1 *Learner Similarity*

To address the scarcity of the user-item ratings, learner similarity in $SI-IFL$ is obtained from personality similarity and profile similarity.

1) Personality similarity. Personality refers to the inherent learning habits of learners. Based on the fact that, in order to enjoy a smooth learning experience, active learners tend to follow other learners who show similar preferences, abilities, and learning experiences. We use learners' individual preferences and learning goals as the indexes to measure the personality similarity of learners.

Personality similarity is obtained from questionnaires, which are designed to acquire the learning styles and learning goals of learners. Learning styles are defined as how a learner behaves during learning process, and what kind of preferences the learner has. In our previous work, a questionnaire has been designed to test the learning styles of learners [19], [40]. The questionnaire is designed referring to some learning style quantitative tables and psychology questionnaires which are highly acknowledged. The detailed constituents of learning styles include $Competency\ level$ (CL), $Media\ Preference$ (MP), $Content\ Preference$ (FP), $Learning\ Purpose$ (PU), $Learning\ Attitude$ (AT), $Learning\ Feeling$ (LF), $adaptability$ (AC), $tolerance\ of\ repeatedly\ recommended\ LOs$ (DC) and $Preference\ priority$ (HP). These metadata are represented as digits or digital sequences, and they can be updated according to learner profiles. Specifically, AC indicates the extent of a learner's acceptance for the LOs which show low-matching degree with learners' preferences; DC represents learners' tolerance for repeatedly recommended LOs; LF reflects learners' current learning experiences, such as being attracted, being impatient or feeling difficult to follow; HP is a sequence of the above preferences for a certain learner.

Learners' learning goals are a combination of the candidate concepts, named as LG. For example, $LG = \{C_1, C_2, \ldots, C_i, \ldots, C_n\}$. C_i represents ith concept.

A learner U_a is represented as $u_a = \{CL, MP, FP, PU, AT, LF, AC, DC, HP, LG\}$. u_a^i represents the ith attribute in u_a. It is clear that there are kinds of heterogeneous properties of learners: discrete values, ordered sequences, and sets. Referring to our previous study in computing the matching degree between learners and LOs [40], three methods are applied here to compute the personality similarity of learners—Cosine similarity, Hamming distance, and Jaccard coefficient. Cosine similarity is used to calculate the similarity of some attributes which have unique and discrete values. Hamming distance is used to calculate the similarity of some attributes which present sequential pattern. For these attributes, the matching degree of digital sequential patterns is critical to computing attribute similarity. Jaccard coefficient is applied to compute the similarity for the attributes which are represented as discrete vectors, hence, the intersection of attributes is critical to the similarity evaluation.

The personality similarity of two learners U_a and U_b, S_{ab}, is computed following Algorithm 1.

In Algorithm 1, norm() is a normalization function. $norm(sim_{ab}) = 0.5 + 0.5 * sim_{ab}$, $norm(sim_{ab}^{'}) = sim_{ab}^{'} \sum_{j=2,3,9} Max(Len(u_a^j), Len(u_b^j))$. $Len(u_a^j)$ is the length of sequence in attribute u_a^j Max means taking the maximum of $Len(u_a^j)$ and $Len(u_b^j)$. $norm(sim_{ab}^{''}) = sim_{ab}^{''}/Max(Len(u_a^k), Len(u_b^k))$. $Len(u_a^k)$ is the length of set LG in u_a.

w, $w^{'}$, and $w^{''}$ are the weights. $w + w^{'} + w^{''} = 1$, $0 \leq w, w^{'}, w^{''} \leq 1$. These weights are determined according to the attributes' order ranked in HP. If CL plays an important role to learner's learning effectiveness, then the weight associated with CL will be increased. Hence, the attributes which are preferred by the learners will achieve high weights in similarity computation.

Algorithm 1. Compute Personality Similarity

Input: Learning styles of U_a and U_b
Output: S_{ab}
1: Obtain u_a and u_b by analyzing learners' learning styles.
2: For the attributes with discrete values, such as CL, PU, AT, LF, AC and DC, the similarity, sim_{ab}, is calculated using Cosine similarity equation. $sim_{ab} = \sum_{i=1,4,5,6,7,8}(u_a^i * u_b^i)/(\sqrt{\sum_{i=1,4,5,6,7,8}(u_a^i)^2} * \sqrt{\sum_{i=1,4,5,6,7,8}(u_b^i)^2})$
3: For the attributes with ordered sequences, such as MP, FP and HP, the similarity, $sim_{ab}^{'}$, is computed using Hamming Distance. $sim_{ab}^{'} = \sum_{j=2,3,9} HamDis(u_a^j, u_b^j)$. $HamDis(u_a^j, u_b^j)$ is obtained by calculating the minimum number of operations required to turn u_a^j into u_b^j, including shifting and replacing operations
4: For the attributes which are presented in sets, such as LG, the similarity $sim_{ab}^{''}$, is computed by the Jaccard coefficient. $sim_{ab}^{''} = \sum_{k=10}(u_a^k \bigcap u_b^k)/(u_a^k \bigcup u\ b^k)$
5: $S_{ab} = w * norm(sim_{ab}) + w^{'} * norm(sim_{ab}^{'}) + w^{''} * norm(sim_{ab}^{''})$

2) Profile similarity. More and more users are using online tagging services to organize their resources [41]. In this study, besides the possible tags existing in e-learning platform, we extract learners' implicit tags from learners' learning profiles. When learners begin to study, profile similarity can be computed based on their learning profiles. Vector H represents the related information included in learners' learning profiles, $H = \{H_1, H_2, \ldots, H_7\}$. The implication of each element is described as follows:

- $H_1 = \{l_i | i \in [1, n]\}$. H_1 is the LO set that a learner has visited. l_i means the ith LO in LO set.
- $H_2 = \{m_1 \succ \cdots \succ m_k\}$. H_2 is a set of media types. The media types are sorted in descending order according to the frequency of their being accessed. The accessed frequency F_{m_i} can be computed as, $F_{m_i} = (AccessN(m_i)/\sum_{i=1}^{k} AccessN(m_i)) * (CandidateN(m_i)/\sum_{i=1}^{k} (CandidateN(m_i))$. $m_i \in \{m_1, m_2, \ldots, m_k\}$, m_i may take the following values, $1 - Chart$, $2 - Animation$, $3 - Audio$, $4 - Video$, $5 - Office\ document$, $6 - Web\ file$. $AccessN(m_i)$ means the number that the LOs with m_i attribute have been accessed. $CandidateN(m_i)$ means the number of LOs which have the attribute of m_i.
- $H_3 = \{f_1 \succ \cdots \succ f_p\}$. f_i takes the following values, $1 - Theory$, $2 - Explanatory$, $3 - Objective\ test$, $4 - Subjective\ test$, $5 - Example$, $6 - Module\ test$. Similar to H_2, H_3 is a set of LO content attributes according to descending frequency of being accessed.
- H_4 represents the average difficulty of the resources that the learner has accessed. The difficulty of LOs is annotated according to expert experience and learners' feedback given in advance [42].
- H_5 is the time that learner has spent to finish the specific module.
- H_6 is the normalized score the learner has obtained in a specific module.
- $H_7 = \{t_i | i \in [1, q]\}$. q tags are considered here. H_7 is a ordered tag set, that is, the tags in H_7 are placed in descending order according to the quantity that the tags have been used. If there is no label or tag in the learning platform, H_7 can be ignored.

For a learner U_a, his/her attributes in H can be denoted as $H_{U_a} = \{H_a^1, H_a^2, \ldots, H_a^7\}$. The profile similarity between U_a and U_b, named as H_{ab}, can be computed in the same way as S_{ab} in Algorithm 1. To be specific, the attributes of H_4, H_5 and H_6 are discrete values, and their similarity, h_{ab}, is calculated using Cosine similarity equation. The attributes of H_2, H_3 and H_7 are ordered sequences, and their similarity, $h_{ab}^{'}$, is computed using Hamming distance. H_1 is presented in the way of sets, and the similarity, $h_{ab}^{''}$, is obtained using the method of Jaccard coefficient.

Finally, the profile similarity of U_a and U_b is computed as follows:

$$H_{ab} = \Theta * norm(H_{ab}) + \Theta^{'} * norm(H_{ab}^{'}) + \Theta^{''} * norm(H_{ab}^{''}). \tag{1}$$

In which, $\Theta + \Theta^{'} + \Theta^{''} = 1$, $0 \leq \Theta, \Theta^{'}, \Theta^{''} \leq 1$. The values of Θ, $\Theta^{'}$ and $\Theta^{''}$ are determined in the same way as w, $w^{'}$ and w''.

Profile similarity is incorporated to personality similarity to determine the similarity of U_a and U_b. Hence, US_{ab} is computed as follows:

$$US_{ab} = w_1 * S_{ab} + w_2 * H_{ab}, \tag{2}$$

where, $w_1 + w_2 = 1$.

3.2.2 Knowledge Credibility

Knowledge Credibility (UC) is applied to evaluate the extent that a target learner can be trusted by a specific active learner. Ghauth et al. [43] proved that the ratings of good learners are important to help active learners access to important learning resources more efficiently, further on, the good learners always show high knowledge credibility. UC aims to evaluate the importance of target learners based on learner's learning profiles. UC includes scores, time efficiency, ranking information, ability for solving difficult questions etc. The symbol and meaning of each item are shown in Table 1.

The UC of the learner U_a can be determined as follows:

$$\begin{aligned} UC_a = {} & w_1 * TC^{'} + w_2 * MC^{'} + w_3 * LP^{'} \\ & + w_4 * TP^{'} + w_5 * EP^{'} + w_6 * LU^{'}, \end{aligned} \tag{3}$$

wherein, $TC^{'}$, $MC^{'}$, $LP^{'}$, $TP^{'}$, $EP^{'}$, $LU^{'}$ are all normalized values and their ranges are [0, 1]. w_i is the weight for each component, $\sum_{i=1}^{6} w_i = 1$. The weights are set according to expert suggestions and empirical values.

UC_{ab} refers to the UC value that a target learner U_b exerts on U_a. Considering that in real learning environment, the influence between learners can be positive or negative, and this almost depends on the influence contrast between active learners and target learners. The formula to calculate UC_{ab} is listed as follows:

$$UC_{ab} = (UC_b - UC_a) * (1 + |Rank_{U_a} - Rank_{U_b}|/N). \tag{4}$$

TABLE 1
The Constituents of UC

No	Symbol	Explanation
1	TC	The rank of a learner's average score in all the modules
2	MC	The rank of a learner's average score in a specific module
3	LP	The ratio of score/time in whole modules
4	TP	One-time accuracy rate in answering questions in specific module
5	EP	The rank of learner's score in solving test with high difficulty
6	LU	The number of LOs that a learner has studied in unit time

In this formula, UC_a and UC_b refer to the knowledge credibility of U_a and U_b. New comers have the UC value of zero. N represents the number of learners who have studied or are studying the same learning module as the active learner. $Rank_{U_i}$ means the rank order of U_i sorted by UC.

From the above equation, it is clear that only the target learner whose UC is larger than that of the active learner, has he/she the possibility to exert positive influence on the active learner. Otherwise, the influence is negative.

3.2.3 Learner Aggregation

In order to avoid the aimless and ineffective following behaviors of active learners, it is important to evaluate the influence that a learner has exerted on his/her followers. Learner aggregation (UF) is designed to describe the extent to which a learner is followed and approved by others. Besides the number of a learner's followers, we still focus on the number of TRUE followers. TRUE followers of U_a refer to the learners who focus on U_a and adopt the same access sequence as U_a. The factors of UF are listed in Table 2. Overlap modules correspond with the modules which have been studied by both active learners and target learners.

For a target learner, TO refers to the proportion of his/her accessed items out of the items of active learner. The greater the TO is, the higher the matching degree with the active learner. The threshold of TO to decide a high match is represented as T_{To}. In IC, the effective followers mean such learners who are followers of the targeted learner, and their TO is larger than T_{To}.

Similar to UC, the UF of learner U_a can be computed as follows:

$$UF_a = w_1 * SF' + w_2 * TF' + w_3 * TO' + w_4 * VT' + w_5 * FT' + w_6 * IC' + w_7 * FN'. \tag{5}$$

Similar to UC_{ab}, if an active learner U_a has his/her UF_a already, the UF that a target learner U_b exerts on U_a, UF_{ab}, is computed as follows:

$$UF_{ab} = (UF_b - UF_a) * (1 + |Rank_{U_a} - Rank_{U_b}|/N). \tag{6}$$

$Rank_{U_i}$ means the rank order of U_i sorted by UF.

US, UC and UF are normalized and added together to give the initial influence between learners.

3.2.4 IFL Based Influence Model

Due to the subjective natures of learners, the behaviors of learners show the characteristics of uncertainty and vagueness. We apply IFL theory to modeling learners more accurately. Fuzzy set theory was first proposed by Zadeh [44], which can be extended to describe the fuzzy concept that is not clearly defined, specifically, the fuzzy concept of an element belonging to set A or not belonging to set A. Atanassov proposed the concept of intuitionistic fuzzy sets [45], in which, a new attribute parameter, non-membership function, is added. Non-membership function can describe the fuzzy concept of betwixt situation, that is, the neutral state of an element's belonging to set A or not belonging to set A. Therefore, IFL is suitable to represent the uncertainty and intuition characteristics of learners.

TABLE 2
The Constituents of UF

No	Symbol	Explanation
1	SF	The number of the followers in all the modules
2	TF	The number of the followers in overlap modules
3	TO	The overlap proportion of topic items in LG
4	VT	Times that a learner has been accessed in overlap modules
5	FT	Time that a learner has been accesses in overlap modules
6	IC	The number of the effective followers in overlap modules
7	FN	The number of TRUE followers in overlap modules

If X is a given domain, an intuitionistic fuzzy A in X is computed as follows:

$$A = \{ <x, u_A(x), v_A(x)> \; |x \in X\}. \tag{7}$$

In which, $u_A : X \in [0,1]$, $v_A : X \in [0,1]$, $0 \leq u_A(x) + v_A(x) \leq 1$, $\forall x \in X$. Membership function, $u_A(x)$, represents the degree that element x in X belongs to A, and non-membership function, $v_A(x)$, represents the degree that x does not belong to A. $u_A(x)$, $v_A(x) \in [0,1]$. For each fuzzy set A in x, $\pi_A(x)$ is defined as the intuition index of X in A, it also indicates the hesitancy degree of x to A:

$$\pi_A(x) = 1 - u_A(x) - v_A(x). \tag{8}$$

In learning process, learners present different acceptances and desires for target learners. For example, a beginner shows high reliance on learner credibility, but after a period of time, he/she turns to learners who have high similarity; a learner who seeks for flow learning experience always focuses on target learners who show high similarity with him/her; a learner who has low learning ability likes to follow the target learners who have high learner aggregation. Moreover, besides like and dislike behaviors, learners show certain hesitation and uncertainty in learning decisions. Intuition fuzzy logic coefficients $<u_i, v_i, \pi_i>$ are able to represent learners' like, dislike and hesitation for the three influence factors (learner similarity, knowledge credibility and learner aggregation) in LIM. Considering learners' different requirements for US, UC and UF, we extract three indexes to help determining $<u_i, v_i, \pi_i>$. The indexes are learning requirement (LR), learner stage (LS) and learning ability (LA). The indexes are decided through questionnaire survey and feedback from e-learning platform. The information of these indexes is detailed as follows:

1) LR means learners primary requirements for recommendations. Three kind of requirements are introduced here, they are flow experience (FE), self-challenge (SC) and quick knowledge acquisition

TABLE 3
Allocations of the Experimental Methods and Groups

	LR	LS	LA
US	$< 0.5, 0.3, 0.2 >$	$< 0.8, 0.1, 0.1 >$	$< 0.6, 0.2, 0.2 >$
UC	$< 0.8, 0.1, 0.1 >$	$< 0.7, 0.1, 0.2 >$	$< 0.9, 0.05, 0.05 >$
UF	$< 0.5, 0.3, 0.2 >$	$< 0.6, 0.2, 0.2 >$	$< 0.7, 0.2, 0.1 >$

(QKA). FE means learners achieve their goals in a smooth and easy way, learners like to find similar learners to follow; SC means learners aim to achieve high ability improvements, hence, they tend to follow learners with high credibility; QKA means learners want to achieve their goals as soon as possible, hence, they will focus on target learners with high aggregation.

2) LS refers to the stages of the learning process. According to LS, learners are classified into beginners, ordinary learners, and senior learners. To explain LS, we define the average quantity of LOs that have been learned by all the learners in specific module as AQ. Beginners mean learners who are newcomers, or the LOs they have learned are lower than AQ; ordinary learners refer to the learners who have learned LOs which are approximate to AQ; senior learners refer to the learners whose learned LOs are higher than AQ. For learners in different stages, the three factors in LIM exert different importance to them. Similarity has the greatest effect on ordinary learners; credibility is more valuable to senior learners; aggregation is desired for the beginners.

3) LA mainly refers to the knowledge acquisition ability. It includes low, medium and high levels. Low LA means learners are passive to acquire knowledge, hence, they focus on similar learners for help; medium LA means learners are able to follow the learning path of the public, hence, they like the recommendations from leaners with high aggregation; high LA means learners have strong self-learning ability, therefore, they will choose the recommendations from learners with high credibility.

Table 3 is an example of IFL coefficients to optimize LIM. In this example, the active learner U_a is assumed as an ordinary learner who desires for self-challenge and who has high learning ability. US, UC and UF are taken as three domains, and LR, LS and LA are taken as three indexes for evaluating learners' reliance on US, UC and UF. Based on grey correlation analysis theory [46], we compute U_a's association degrees with US, UC and UF. The association degrees are mapped into the weights assigned for each factor in LIM. According to the data in Table 3, we apply intuitionistic fuzzy positive ideal schemes to compute the relevance of a learner for different domains (US, UC and UF). Then, the relevance is normalized as weight, and the LIM model is finally optimized.

3.2.5 Learner Behavior Description

In e-learning recommender systems, motivated by the desires for smooth learning experiences, as well as the demands for knowledge acquisition, active learners move closer towards target learners who exhibit high influences. The interactive

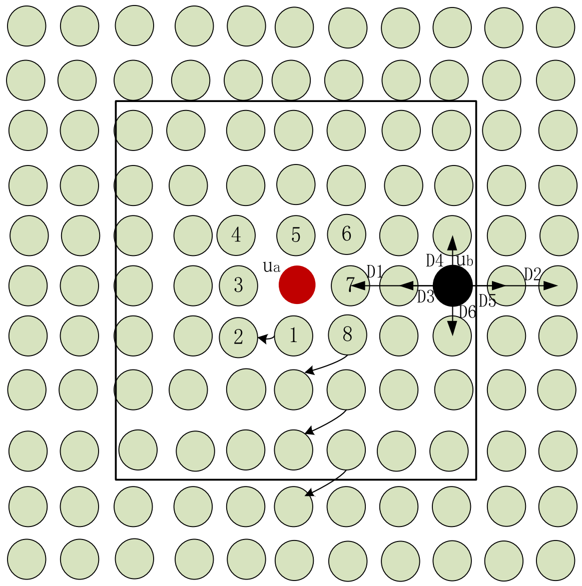
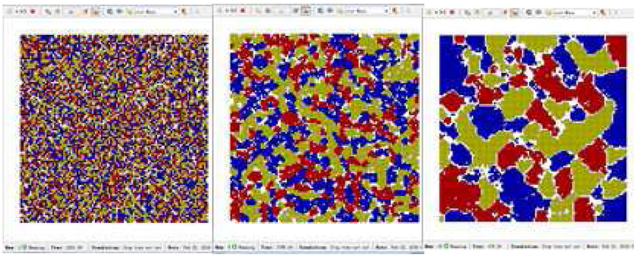


Fig. 2. Demo of learner's behaviors: U_a is an active learner, U_b is one of target learner U_a, directed arrows: The ascending distance between neighbors and active learner.

information carried by these movements can be propagated within a certain scope and time duration, and other learners make corresponding movements according to the information they receive. Consequently, such self-organization process helps build orderly and effective social cliques when the learner structure becomes stable. For each clique, they should have minimum distance of intra-cluster.

In Fig. 2, we give a demo to explain learners' behaviors. The active learner is placed in the middle and denoted as a red dot. The gray dots represent the neighbors of the active learner. Each learner is surrounded by his/her neighbors and each learner has his/her effective learners. Effective learners mean those learners who can communicate with the active learner directly during the information propagation. Further, for each active learner, only the effective learners are evaluated on how they affect the active learner and what kind of movements they will have. The effective learners transmit their movement information to their own neighbors. Such movement information conveys the demands and preferences of the active learner. Hence, all the learners may be informed with the requirements of active learners based on information propagation. Usually, for each learner, some layers around him/her are taken as his/her effective learners, and the quantity of layers are decided according to the problem scale. In Fig. 2, the three layers of learners surrounded by black boxes are regarded as effective neighbors of the active learner U_a. If m is assumed as the total number of the effective learners for an active learner. The value of m in Fig. 2 is 48. At the beginning of the recommendation process, the learners are randomly distributed in the interactive environment, that is, the effective learners are also initialized randomly. When learners begin to move after being influenced by others, the effective neighbors also change. When the frequency of movement decreases, the learner structure is stable and learner cliques are given.

It is needed to be explained that the digits labeled on the learners of the nearest level to active learner, 1 to 8, are used for marking the distance between neighbors and active



(a) Initial state (b) Intermediate state (c) Stable state

Fig. 3. The self-organization process of generating learner cliques.

users. In which, 1 means the nearest neighbor and 8 is the farthest one. Similarly, directed arrows are applied to simulate how close or how far the target learner in the same layer moves from the active learner.

Algorithm 2. Generate Stable Learner Cliques

Input: Profiles of all the learners
Output: Stable learner cliques

1: Set a learner as an active learner. Find his/her effective learners according to the influences between the active learner U_a and his/her effective learners. Obtain Inf_{amax}, Inf_{ab}, US_{ab}, UC_{ab}, UF_{ab}
2: **for all** $l_i, i \in [1, m]$ **do**
3: If $Inf_{ab} \in Inf^h$, then U_b crosses one layer closer to U_a with a probability $p1$. In Fig. 2, this kind of movement is labeled as $D1$
4: If $Inf_{ab} \in Inf^l$, then U_b crosses one layer far away from U_a with a probability $p2$. In Fig. 2, this kind of movement is labeled as $D2$
5: If $Inf_{ab} \in Inf^m$, and it satisfies two conditions of $US_{ab} \in US^h$, $UC_{ab} \in UC^h$ and $UC_{ab} \in UC^h$, then U_b moves one layer closer to U_a with a probability $p1$. In Fig. 2, this kind of movement is labeled as $D3$
6: If $Inf_{ab} \in Inf^m$, and it satisfies at least one condition among $US_{ab} \in US^h$, $UC_{ab} \in UC^h$ and $UC_{ab} \in UC^h$, then U_b moves closer to U_a in the same layer with a probability $p1$. In Fig. 2, this kind of movement is labeled as $D4$
7: If $Inf_{ab} \in Inf^l$, and it satisfies one condition of $US_{ab} \in US^m$, $UC_{ab} \in UC^m$ and $UC_{ab} \in UC^m$, then U_b moves one layer far away from U_a with a probability $p2$. In Fig. 2, this kind of movement is labeled as $D5$
8: If $Inf_{ab} \in Inf^l$, and it satisfies two conditions of $US_{ab} \in US^m$, $UC_{ab} \in UC^m$ and $UC_{ab} \in UC^m$, then U_b moves one layer far away from U_a in the same layer with a probability $p2$. In Fig. 2, this kind of movement is labeled as $D6$
9: If the above conditions are not satisfied, U_b moves in a random direction with a random probability.
10: **end for**
11: Update m according to the results. Select one learner among m neighbors as the subordinate active learner (assumed as A'). Update A to A'. If system entropy is larger than ET, then jump to line 2, else, jump to line 12.
12: Output the learner cliques with corresponding influence values. A stable cluster refers to a clique which still has low distance of intra-cluster.

Algorithm 2 shows how to generate stable learner cliques based on self-organization behaviors of learners. Some parameters in Algorithm 2 are explained as follows:

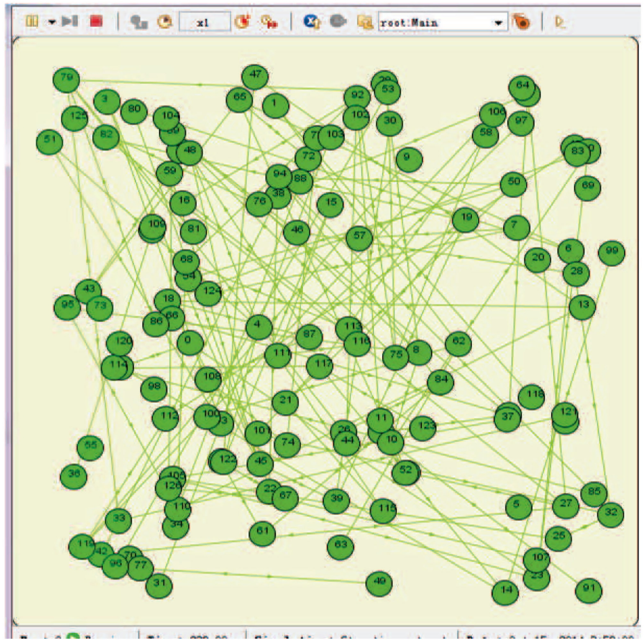


Fig. 4. Learner cliques in the stable learner structure.

Inf_{ab} - The influence value that U_b exerts on U_a.

Inf_{amax}, Inf_{amin} - The maximum and minimum influence values between learner U_a and his/her effective neighbors.

US_{ab}, UC_{ab}, UF_{ab} are values of the learner similarity, knowledge credibility and learner aggregation that U_b exerts on U_a respectively.

US_{amax}, UC_{amax}, UF_{amax} are the maximum values that U_a has been exerted by all his/her effective neighbors in learner similarity, knowledge credibility and learner aggregation respectively.

US_{amin}, UC_{amin}, UF_{amin} are the minimum values that U_a has been exerted by all his/her effective neighbors.

ph and pl are the proportion thresholds for defining high and low influence matching between learners. $0 < pl < ph < 1$. We give some definitions: if $Inf_{ab} \geq Inf_{amin} + (Inf_{amax} - Inf_{amin}) * ph$, U_b has high influence on U_a, $Inf_{ab} \in Inf^h$; if $Inf_{ab} \leq Inf_{amin} + (Inf_{amax} - Inf_{amin}) * pl$, U_b has low influence on U_a, $Inf_{ab} \in Inf^l$; otherwise, U_b has a moderate influence on U_a, $Inf_{ab} \in Inf^m$. For US_{ab}, UC_{ab} and UF_{ab}, they have the same definitions. US^h, US^m and US^l refer to the high, mediate and low similarity extents respectively.

ET is the threshold of system entropy. The learner structure is considered as stable when the entropy is less than ET.

$p1'$ and $p2'$ represent the probabilities of a neighbor moving near or far away from active learners respectively.

Fig. 3 gives a simulation of the self-organization process. There are 8,000 learners in this e-learning environment. Three kinds of colors are used to distinguish the adjacent cliques. Fig. 3 (a) is the initial state of the learners. Fig. 3 (b) is one of the intermediate states. Fig. 3 (c) is a stable state of learner cliques. It is clear that in Fig. 3 (c), cliques are distinct clearly from the other cliques.

Fig. 4 shows the learner clique for an active learner based on Fig. 3(c). There are 127 learners in this clique. The line between two learners is a directed line. If it is a directed line that points to from learner U_b to learner U_a, it indicates that the influence of U_b on U_a exceeds the given threshold. For any learner in Fig. 4, the learners who are connected together constitute his/her optimal neighbor clique.

3.3 LO Recommendation Presentation

When the learner cliques are recommended, the final LOs can be subsequently acquired. In this study, the PrefixSpan algorithm is applied to providing personalized LOs and learning navigations for active learners. PrefixSpan is a projection-based pattern mining algorithm, and it has been proved to have good performance in pattern discovery [47], [48]. Because of the advantages in time and space complexity, PrefixSpan algorithm is suitable for deciding the LO recommendations in a real-time e-learning environment.

Algorithm 3 shows the procedure of generating the final LO presentations for an active learner. As for a target learner in this clique, his/her influence value with the active learner is taken as a local reference; the influence who exerts on the other members in this clique is taken as a global reference. The local and global references decide the importance of the clique members together.

Algorithm 3. Generate LO Presentations Based on SPM

Input: Learners in clique - UL and LO set LS. $UL = \{U_a, U_1, U_2, \ldots, U_i, \ldots, U_{n-1}\}$, in which, the active learner is U_a. The direct influence matrix of learners is $Infn \times n$. Inf_{ij} is the influence that learner U_j directly exerts on U_i. $LS = \{S_a, S_1, S_2, \ldots, S_i, \ldots, S_{n-1}\}$. S_i means the LO set visited by U_i.
Output: Final hybrid recommendations

1: Compute the local influence between U_a and U_j - Inf_{aj}, $j \in [1, n-1]$. If Inf_{ai} = 0.9, Inf_{ij} = 0.8, Inf_{aj} = 0, then $Inf_{aj} = Inf_{ai} \times Inf_{ij}$ = 0.72. With the updated influence matrix, a learner set is ranked as L_{seq} according to the descending local influence with U_a
2: Compute the global influence of each learner in this clique. If $Inf_{ij} \neq 0$, the link from U_i to U_j, R_{ij}, is initialized as 1. The global influence of the members is computed based on PageRank algorithm. Then, a learner set $L^{'}_{seq}$ is generated according to descending global influence
3: Rank $\{U_1, U_2, \ldots, U_i, \ldots, U_{n-1}\}$ as $UL^{'}$ in descending order according to weighted L_{seq} and $L^{'}_{seq}$
4: Weighting the importance of LS according to the sorted $UL^{'}$. Apply PrefixSpan algorithm on LS
5: Output the sequenced learning objects for learner U_a

4 Experiment Setup

4.1 Recommendation Platform Design

Anylogic is used to study the propagation of interactive information. The Anylogic modeling approach enables us to study the behaviors of intelligent entities from an observable and controllable way [49].

The interaction module provides learners with the following functions:

1) Parameter presetting. The parameters of $\{CL, MP, FP, PU, AT, LF, AC, DC, HP\}$ for a learner are preset according to the questionnaire results mentioned in Section 3.2.1. Learners are permitted to fine-tune some parameters according to their current study situations and feelings.
2) Interactive settings. During the learning process, learners can mark LOs with check boxes. The tags are provided as *More difficult*, *Important*, *Pass* and *Later*. Learners can browse other learners' learning state. The learner's learning activities, such as tagging LOs and following other learners, are applied to update the influence among learners. These strategies ensure adaptive and dynamic interactions for learners' learning process.

4.2 Experiment Data

Since there are no suitable public data that we can use to implement the expected e-learning recommender system, we applied the proposed approach to the formal e-learning setting, that is, a learning environment offered by educational institutions (e.g, universities and schools) within a curriculum [50]. Our recommender system aims to recommend open educational resources for university students to achieve their learning goals. Experimental data are taken from a course of C Programming language (C). C is a required course and it is the first programming course for freshmen.

C includes 4 main modules: the *Fundamental module* (*Fund*) which includes *Operator*, *Expression*, *Input and output*; the *Structure module* (*Stru*), which includes *Sequence structure*, *Selection of structure*, *Loop structure*; the *Advanced module* (*Adva*), which includes *Array*, *Function*, *Pointer*; and the *Hard module* (*Hard*) which includes *Structure*, *Union*, *Bit operation*, *Files*. Digital resources are in the form of video, audio, PPT, Word documents, HTML pages, etc. The content of the digital resources includes pretest, theory explanation, example, quiz, analysis, summary, module test, etc. The number of LOs with the smallest granularity is 2,386. LOs are annotated by the instructors with empirical values in advance.

Students from six institutions in the Beijing University of Civil Engineering and Architecture are recruited for the experiment. Each institution is taken as a group, and the groups are marked as group 1, 2, 3, 4, 5, and 6. Each group consists of many classes. The total number of the participants is 1,119. The composition of the groups is shown in Table 5. The average age of participants was 18.6 years old, 74 percent of the participants were male and 26 percent were female.

In order to ensure the effectiveness of the implementation, students who are unable to complete courses due to force majeure (such as illness, leave, etc.) are excluded in advance. Moreover, due to the special mechanism of university enrollment, the participants did not show great difference in enrollment scores. Furthermore, the equilibrium strategy of class assignment further narrowed these gaps. As well, through the analysis on the scores of other courses in last semester, these six groups did not show significant differences. Hence, we do not carry out experimental comparisons on classes in a group.

All students completed the C course and participated in the final exam. Before the beginning of the curriculum, all the students received a survey, thus their learning goals and learning styles can be initialized.

4.3 Experiment Design

Besides $SI-IFL$, Table 4 lists the main comparison strategies used in this study. For example, $SS-IFL$ only considers

TABLE 4
Recommendation Strategies

Strategy	Influence			Fuzzy factor		Methods	
	US	UC	UF	FL	IFL	Self-organization	Others
SI-IFL	✓	✓	✓		✓	✓	
SSC-IFL	✓	✓			✓	✓	
SS-IFL	✓				✓	✓	
SI-FL	✓	✓	✓	✓		✓	
Prefix							PrefixSpan
SI-Top	✓	✓	✓				Top-N

TABLE 5
Allocations of the Experimental Methods and Participants

Group	Classes	Learner quantity	Fund	Stru	Adva	Hard
1	4	128	Tra	SI-IFL	SI-IFL	SI-IFL
2	8	264	Tra	SSC-IFL	SSC-IFL	SSC-IFL
3	5	165	Tra	SS-IFL	SS-IFL	SS-IFL
4	4	132	Tra	SI-FL	SI-FL	SI-FL
5	6	174	Tra	Prefix	Prefix	Prefix
6	8	256	Tra	SI-Top	SI-Top	SI-Top

the similarity factor in LIM, and IFL is applied for similarity optimization; $Prefix$ uses the PrefixSpan algorithm to mine sequential access pattern, the history profiles of all the learners are the only criteria; $SI-Top$ uses the influences to decide the target learners and give recommendations based $Top-N$ method.

Table 5 lists the different recommendation strategies applied on the groups of participants. Tra refers to the traditional classroom teaching strategy, that is, teachers primarily use one-for-all teaching strategy. Learners can determine the LO presentation and LO sequence by themselves based on teachers' recommendations. In order to promote the validity of the experimental results, the learners are not allowed to repeat the learning process, even if they fail the module tests or final exam.

4.4 Parameter Setting

In the recommendation strategies, some parameters are critical to ensure the quality of recommendations, such as the ph, pl, $p1^{'}$, $p2^{'}$ and ET in Algorithm 2. We use simulation experiments to decide the optimal parameters.

To be specific, first, we simulate the entity attributes and the environment parameters to generate entities in the recommendation environment according to the characteristics of learners and learning resources in the real learning environment. Entity attributes include the learning profiles, learning styles of learners and LO attributes. Environment parameters mainly refer to the real-time and dynamic parameters caused by the possible learning and marking behaviors of learners. In which, the number of entities is the same with the entities in real recommendation problem.

Second, if the value of ph needs to be decided, the value of ph keeps changing, however, other parameters are fixed as empirical values. Through evaluations on the simulation experiments with specific scale of learners, the rough range of ph is obtained. Similarly, we acquire the values of other parameters.

TABLE 6
The Comparisons of Complete Status

	SI-IFL	SSC-IFL	SS-IFL	SI-FL	Prefix	SI-Top
Ave score	84	82	81	79	76	80
PassP	90%	88%	85%	86%	81%	83%
Ave time	78.2	85.3	88.1	89.5	102.1	92.6
LOsP	75%	81%	83%	80%	86%	91%

Finally, the optimal parameter combination which can ensure the stable and successful clusters are decided through the method of grid search. The metrics which are applied to evaluate the performance of different parameters include entropy, evolution time, distance of inter-class and intra-class, and, also the evaluations on learning process, including learning time, scores, etc. Most of these metrics are introduced in Section 5.

5 Results and Discussions

There is no public dataset applied to our e-learning experiments, and therefore, we use some indexes which are appropriate to evaluate our approach, such as matching degree, diversity, score and experience. Then, we design several evaluation methods to analyze the performances of these approaches. Specifically, we use effectiveness, efficiency, and learner satisfaction to evaluate the recommendation approaches first [16], [51]; then we focus on the personalization and diversity performances; finally, system entropy is utilized to evaluate the proposed approaches.

5.1 Complete Status

To study the performances of different methods, the following data of different groups are recorded: students' average scores ($Ave\ score$), the proportion of students who passed the exam ($PassP$), the average learning time ($Ave\ time$) and the proportion of the resources that learners had visited out of the total number of resources ($LOsP$). Among them, $LOsP$ and $PassP$ are applied to the last three modules of the C course.

From the results shown in Table 6, it can be seen that $SI-IFL$ shows slightly better performances in $Ave\ score$ and $PassP$. Meanwhile, the results of $Ave\ time$ and $LOsP$ in $SI-IFL$ group are obvious lower than other groups. The situation indicates that learners in $SI-IFL$ group can complete the learning process through studying relatively fewer resources in a shorter time, and with the consideration of $Ave\ score$ and $PassP$, it can be concluded that $SI-IFL$ is able to help learners complete learning objectives more quickly and efficiently. The comparison of $SI-IFL$ and $SI-FL$ shows that the introduction of the IFL improves the completion rate and learning efficiency. The results of $SSC-IFL$ group are slightly better than $SS-IFL$, and both of them are lower than the $SI-IFL$. It shows that with the consideration of more influence factors, the recommended strategies perform better in helping learners achieve their learning goals.

5.2 Learning Experience Evaluation

In order to obtain learners' subjective experience with the recommender systems, a survey is designed to obtain the learner's evaluation of personalized recommendation and

TABLE 7
Evaluations of Learners' Experiences

Content	Items	SI-IFL	SSC-IFL	SS-IFL	SI-FL	Prefix	SI-Top	Tra
Personal realization evaluation	Difficulty	3.8	3.6	3.7	3.3	3.2	3.4	3.7
	Media	3.6	3.7	3.4	3.6	3.0	3.8	4.3
	Content	4.2	4.1	4.0	3.6	3.4	3.5	4.4
	Time	4.4	4.3	4.2	3.9	4.1	4.1	3.8
Flow experience evaluation	Control	4.2	4.3	4.3	4.1	3.6	4.0	3.5
	Attention focus	3.9	4.1	3.9	3.6	3.4	3.7	3.5
	Curiosity	3.7	3.5	3.2	3.0	3.1	3.3	2.6
	Intrinsic interest	4.0	3.8	3.8	3.3	3.8	3.7	3.3
Quality evaluation	Usefulness	4.4	4.0	3.7	3.5	3.3	3.7	3.3
	Satisfaction	4.3	4.1	3.8	3.4	3.3	3.2	3.5

learning experience [19]. Table 7 lists each index's average score. The ratings of each question range from 1 to 5. The digits mean that, $1 - Very\ unsatisfied, 2- Unsatisfied, 3 - Just\ ok, 4 - Satisfied, 5 - Very\ satisfied$.

As for the results of $Personal\ realization\ evaluation$, Tra group shows higher scores in media and content matching; however, the score for time evaluation is lower. It indicates that although the learners can choose their wanted resources according to their own preferences, their choices may not be comprehensive enough if they do not balance those requirements. Consequently, learners spend more time to complete their study. The comparisons also show that due to the consideration of the learner's influence and intuitionistic fuzzy evaluation, the $SI - IFL$ can provide learners with more personalized learning resources.

In the evaluation of $Flow\ experience\ evaluation$, the four dimensions test of Trevino and Webster are applied here, that is, control, attraction focus, curiosity, and intrinsic interest [52]. By analyzing the results in Table 7, it can be learned that, $SI - IFL$ group shows higher satisfaction in flow experience. That is, learners are immersed and engrossed in the learning process, and the recommended resources can satisfy learners' personalized and multiple demands. The $SI - IFL$ and $SSC - IFL$ groups also significantly outperform the other strategies on attention focus and curiosity, which is attributable to the randomness and probability mechanisms included in the self-organization approach. However, in Tra, the learners do not take the initiative to select some diverse resources.

In the $Quality\ evaluation$, a user-centric evaluation framework of recommender is adopted to test the qualities of recommenders such as their usefulness and users' satisfaction of the systems [53]. The results denote that the proposed approach has highly useful qualities, and the learning satisfaction of students is relatively high.

The results in Table 7 show that learners in $SI - IFL$ shows high affirmation on the personalized realization, and learners rated high on his/her $Flow\ experiences\ evaluation$ and $Quality\ evaluation$. The main reason for the excellent results of $SI - IFL$ is that the proposed approach balances the diverse and complex demands by applying influence model. The influence-based learner model improves the accuracy and efficiency of the recommendations. The intuitionistic fuzzy logic in learner model and the probability mechanism of self-organization are effective to address the fuzzy and random factors implied in learners' behaviors. The SPM algorithm applied on LO presentation also ensures a high matching of the recommendations.

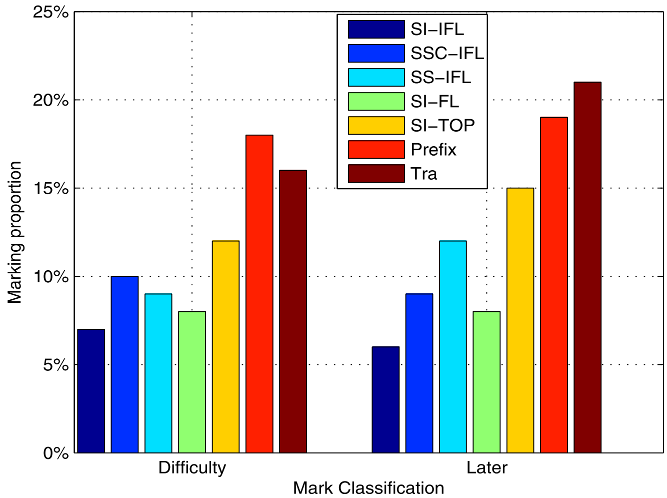


Fig. 5. Comparisons of marking proportions.

5.3 Personalization Evaluation

In this part, the proportions of learners who marked $Difficult$ and $Later$ on the experimental LOs are recorded.

In Fig. 5, it is noticed that the learners in $Prefix$ and Tra group have a higher proportion in both $Difficult$ and $Later$. It must note that in the traditional one-for-all teaching method, teachers cannot fully consider each student's knowledge level and learning preferences, furthermore, the learners passively process the recommendations, as a result, they are easily bored. In $Prefix$ group, the sequential access pattern is mined from all the other existing learner profiles, thus recommendations are not one-for-one, so the marking proportions are higher than other algorithm groups. $SI - Top$ has better results than $Prefix$ and Tra group. It indicates that the learner influence model is very helpful to improving the quality of recommendations. The results of $SI - IFL$, $SSC - IFL$ and $SS - IFL$ show that if more influence factors are considered, the recommendations are more personalized. The comparisons of $SI - IFL$ and $SI - FL$ shows that intuitionistic fuzzy logic can guarantee higher acceptance for learners.

5.4 Diversity Evaluation

The diversity of recommendations is evaluated by analyzing the constitutes of recommendations from two different aspects: (i), the matching degree between LOs and learners. (ii), the equilibrium of the attributes of recommendations.

1) The evaluation of matching degree.

The matching degree between LOs and learners is studied to evaluate the diversity of recommendations. If the recommendations are completely focused on the main preferences preferred by learners, information overload will ensue, and the diversity of recommendations will be reduced. Considering that the CBF recommendations mainly satisfy the learners' primary preferences by minimizing the matching difference, we take the Top-N recommendations given by CBF recommendation approach as basic comparison data,

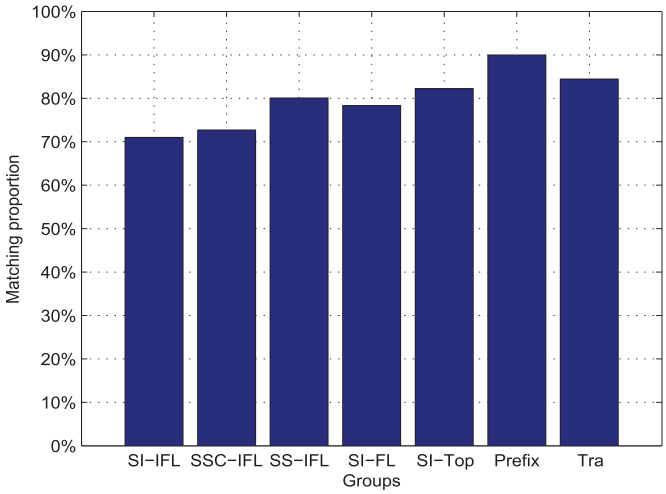


Fig. 6. Matching degree evaluation.

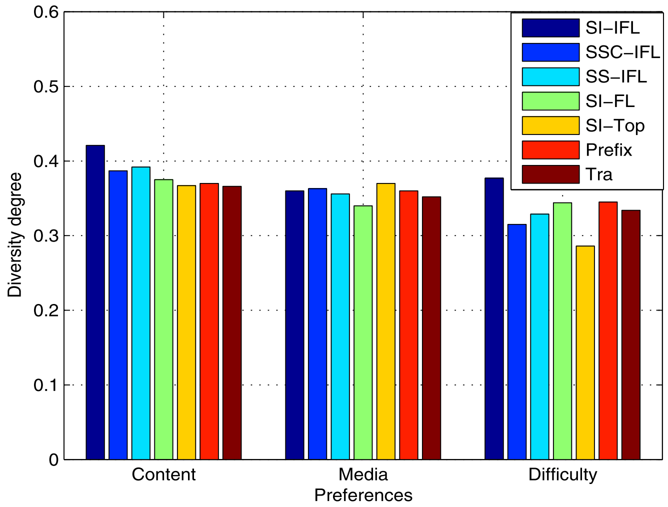


Fig. 7. Diversity evaluation on LOs' attributes.

and the recommendation set is named as CBD [19]. Then, we compute how many LOs in CBD are also included in the recommended LO set R in our experiment. The proportion, $Pro(R)$, is calculated as follows:

$$Pro(R) = \sum_{i=1}^{N} sim(i)/N. \tag{9}$$

In which, N is the number of LOs being compared. i means the ith LO - l_i in R. If $l_i \in R$, and $l_i \in CBD$, then $sim(i) = 1$, otherwise, $sim(i) = 0$. So, higher Pro means higher matching degree between R and the CBF recommendations.

The statistical results are shown in Fig. 6. It is interesting to notice that all the recommendations of the experimental groups include a certain proportion of LOs which do not belong to CBD. $Prefix$ group has the highest consistency proportion. $SS-IFL$, $SI-FL$, $SSC-IFL$ and $SI-IFL$ present a descending order in similarity matching degree. It can be seen that $SI-IFL$ has the most excellent performance in decreasing the similarity matching degree, and the lower matching degree is conducive to addressing the information overload.

2) The diversity of LO attributes.

The diversity of LO attributes can be calculated by analyzing whether the recommendations are not non-centralized in attributes [54]. If the attributes of the recommendation are too concentrated on some specific values, such recommendations are unbalanced and the coverage of attributes is reduced, hence, the diversity of the recommendations is low. Since the diversity function may correspond to the inverse of the similarity measure in terms of the item features [55], the equation to evaluate the diversity is listed as follows:

$$\begin{aligned} DI(R) = normalize((1/(N*(N-1)))* \\ \sum_{i\in R}\sum_{j\in R, j\neq i} div(i,j)), \end{aligned} \tag{10}$$

i, j refer to l_i and l_j. R is the LO set of recommendations for a specific learner and the size is N. We compute $div(i,j)$ as the complement the similarity between l_i and l_j - $sim(i,j)$. $div(i,j) = 1/sim(i,j)$. In which, the similarity is related to some basic attributes of LOs which are specified as content attribute M, media attribute F and the difficulty D. $D \in \{1, 2, 3, 4, 5\}$. $sim(i,j)$ is calculated with Euclidean distance.

The results in Fig. 7 are the average value of diversity statistics in a period of learning time. It is surprising to find that the $SI-IFL$ group has a high proportion of diversity in terms of content and difficulty. The $SI-IFL$ recommendation strategies also shows higher diversity than $SI-FL$ which does not include intuitionistic fuzzy logic.

Generally, improving the diversity is often combined with the cost of accuracy [56]. In this study, compared with the personalized experimental results, it is found that the diversity degree of the $SI-IFL$ still keeps high without reducing learners' experience on personalization. The reasons owe to the combination of IFL and content-based influence model and the bottom-up self-organization mechanisms of the $SI-IFL$ approach.

5.5 Entropy

In SOB recommendation system, lower entropy means the frequency and magnitude of information exchange have decreased, and it also means that the recommended LO's sequence tends to be stable. Entropy provides a quantitative way to measure whether the recommended results reach a stable combination and sequence. The formula for calculating entropy is listed as follows:

$$S_{entropy} = -\sum_{i=1}^{N}\sum_{j=1}^{m} log \triangle P_{ij}, \tag{11}$$

$\triangle P_{ij} = |P_{ij}^t - P_{ij}^{t-1}|$, $\triangle P_{ij}$ is the change in influence between U_i and his/her neighbors. m is the number of effective neighbors of U_i, and N is the total number of learners.

Fig. 8 shows that the system entropies of different groups decrease significantly. This is because the information transmission is more frequent at the beginning of the learning process, it is also because changes in both influence and positions of the learners are frequent. When the learner cliques tend to be stable, the information transmission frequency begins to slow down. That is, the position of each learner is relatively fixed, and the learner structure tends to be orderly and stable. It is clear that the entropies of those three strategies, $SI-IFL$, $SSC-IFL$ and $SS-IFL$, show quick

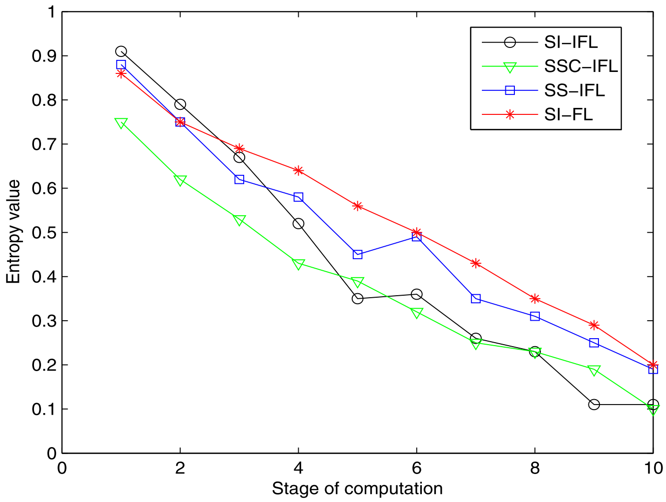


Fig. 8. Comparisons of entropy.

convergence trend, and the entropies of these approaches have obvious fluctuations. As a comparison, the entropy curve of $SI-FL$ is relatively smooth. It shows the fact that with the application of intuitionistic fuzzy logic, the learners' selections become more varied, so the learners' states change more frequently. The intuitionistic fuzzy logic-based influence model simulates learners' psychological needs well and increases the diversity of recommendations to some extent.

6 Conclusions and Future Work

Different from e-commerce fields, e-learning faces excessive information scarcity, which hinders the application of CF recommendation approaches. In addition, e-learning process has the characteristics of time continuity. In such situation, diversity plays an important role in ensuring a long-term learning experience and improving learner satisfaction. In this study, a hybrid recommendation strategy is proposed to achieve personalized and diversified e-learning recommendations. As answers to the above problems, (i), we first propose an influence-based learner model, which is independent of rating information. This influence model is available to fill the deficiency gaps in the underlying data for CF recommendations. (ii), with the uncertainty and vagueness features considered, IFL is applied to optimize the learner model, which helps to present a more adaptive and accurate learner influence model. (iii), in order to cluster the optimal learner clique for an active learner, we use self-organization theory to simulate the collaborative behaviors of learners. Different with other recommendation strategies which are fully active learner-oriented, in this study, the clusters are generated through the dynamic interaction of learners caused by information propagation. Hence, $SI-IFL$ performs well at increasing the diversity of recommendations and decreasing the computation complexity of influence transitivity. (iv), given the learning profiles in the learner cliques, the recommendations are provided with the application of PrefixSpan algorithm, so the personalization of recommendations is further ensured. Based on the experimental results, the proposed hybrid approach is proved to be effective, efficient, highly adaptable, capable of personalized and diversity realizations.

Our future research will focus on learner modeling first, for example, we will consider more explicit and implicit characteristics of learners, and study more learning behaviors of learners. We will further study the self-organization based hybrid recommendation strategies to improve the recommendation results. As well, we will design more detailed experiments, including the composition and grouping of participants, learning resources, and evaluation methods. The proposed approach can also be applied to other fields for improving diversity of recommendations and addressing the problem of information overload.

Acknowledgments

The authors wish to acknowledge the support of the National Natural Science Foundation of China (Project No. 61370137), the National 973 Project of China (No. 2012CB720702), Ministry of Education China Mobile Research Foundation Project (2016/2-7), the Major Science and Technology Project of Press and Publication (No. GAPP ZDKJ BQ/01), the Beijing Municipal Party Committee and Municipal Government Key Work and District Government Emergency Project (No. Z171100004417031), and the Fundamental Research Funds for Beijing University of Civil Engineering and Architecture (No.X18070, X18044, and X18065).

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