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Supporting Peer Help Recommendation Based on Learner-Knowledge Model

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Abstract: With the development of information technology tools and the Internet, computer-supported collaborative learning has become increasingly accessible and promising. Peer help is a popular practice of collaborative learning. In this paper, we propose a way to realize intelligently mediated peer help. We obtain open learning activity data from an integrated learning platform called LEAF for modeling. First, we create a network-based knowledge model. Then, we construct learner models associated with the knowledge model. Based on the knowledge and learner modeling, we propose a method to find problems of a learner based on the order of closeness centrality of knowledge nodes. Also, the system recommends potential peer helpers who can help with these problems. We present a scenario of physics learning at the high school level to explain the practical use of this method which is aimed to enhance learners' initiative during peer help.

Keywords: peer help, peer recommendation, learning analytics, knowledge model, learner model

1. Introduction

Collaborative learning is a situation in which particular forms of interaction among people are expected to occur, which would trigger learning mechanisms (Dillenbourg, 1999). Peer help is a major practice of collaborative learning. Assigning right peers is the key to the success of peer help, and there are several studies that show that teachers utilize some computer-assisted systems to make their students more satisfied (Urhahne, 2010).

This paper presents an approach utilizing open learning activity data from an integrated learning platform called LEAF (Ogata et al., 2018). This will achieve intelligently mediated peer help in a data-driven approach. A knowledge model is created by automatically extracting knowledge elements from the LEAF system and represents a knowledge network. Based on the knowledge model, a learner model is created from records of individual learning activities from the LEAF system. The learner model combined with the knowledge model can indicate the learner's knowledge proficiency at different stages. This paper uses a scenario of physics learning at the high school level as an example, illustrating the possibility of providing adequate peer help recommendation for learners. The peer help recommendation consists of recommending problems that can be helped by peers, as well as potential peer helpers with complementary knowledge. A learner can choose both a problem and a peer helper from the system.

2. Theoretical Background

Three cognitive dimensions were pointed out which appear to be important to the success of collaborative problem-solving and learning are learners' knowledge, information exchange, and roles (Hoppe & Ploetzner, 1999), among which knowledge is the most common consideration when assigning collaborative learning partners (Abnar et al., 2012). Knowledge network is a tool for graphically presenting a knowledge architecture that allows for a clearer understanding and organization of complex knowledge content. This network can be used to represent knowledge units in the educational area as well, and computers hold the potential to realize this representation. The concept of semantic networks was introduced by Quillian (1968), which represents semantic information such as knowledge. Furthermore, ontology was introduced as a concept for knowledge organization that considers the intrinsic associations of knowledge more than simply describing semantic information (Arroyo et al., 2003). In application areas, Khan Academy builds knowledge networks for subjects such as math and science, which guide open and personalized online learning (Meng et al., 2018).

Learner model is a representation of a real learner, representing the characteristics and level of the learner's knowledge and skills (Chrysafiadi & Virvou, 2013). Open learner modeling allows learners to compare their own models with the class as a whole and with the other learners' individual models (Brusilovsky et al., 2016). In the field of education, using data mining and other techniques to analyze learning records to construct learner portrait models allows education systems to provide more personalized support for learners (Baker & Inventado, 2014). The LEAF system, for example, provides an evidence-based dashboard to analyze and visualize learning logs of e-book reading, quizzes, etc. to demonstrate a student's learning (Majumdar et al., 2019). Experience API or xAPI (2016) is another state-of-the-art open learning record standard. Following the idea of xAPI, this paper adopts a network structure to connect the learner to the learned knowledge.

Peer help is a major practice in collaborative learning and matching an appropriate peer helper is the key to the success of peer help. In intelligently mediated peer help, the individually assessed learner models are used to match better pairs of learners (Hoppe, 1995). Related studies have made attempts to analyze and model the knowledge that learners currently have and identify theoretical correlations between their knowledge in the form of Prologs (Hoppe, 1995) and ontology (Ounnas et al., 2009; Isotani et al., 2009). It is expected that the inner connections between knowledge are considered when meditating peer helpers since these connections provide information of complementary knowledge which can contribute to effective collaborative learning (Isotani et al., 2009). However, existing peer matching methods consider students' overall performance in a certain subject or analyze students' ability to an individual knowledge topic (Liang et al., 2021). Hence, we propose a method that utilizes connections among knowledge units to recommend problems and peer helpers.

3. A Method of Peer Help Recommendation

3.1 Technical Framework and Model Construction

Learning and Evidence Analytics Framework (LEAF) presents an integrated learning platform that captures various learning activities and analyzes data to provide learners with the most appropriate support (Ogata et al., 2018). We build knowledge and learner models based on learning log data from the LEAF system. All these knowledge and learner models are built in a graph database application called Neo4j, and we use Python to access the Neo4j database and execute calculations.

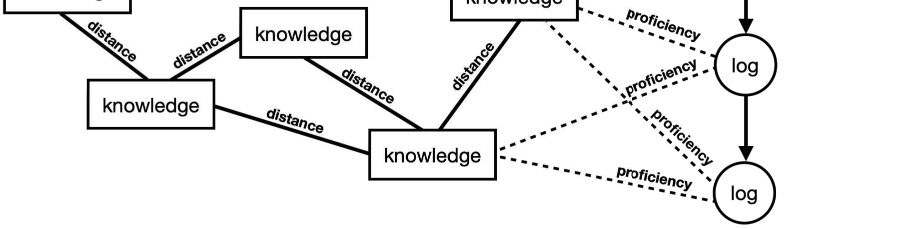

Figure 1. Learner Model and Knowledge Model

The knowledge model is a network where knowledge elements are drawn out from the LEAF system by analyzing the learning materials. These learning materials include textbooks, practice problems, etc. learned by the learners. As shown in Figure 1, knowledge elements are represented in the network as knowledge nodes. If there is relevance between two knowledge elements, these two knowledge nodes are connected by edges. Each edge connecting two knowledge nodes possesses an attribute called distance. The distance between the knowledge nodes indicates the degree of relevance. This knowledge model can thus represent complex topological associations between subject knowledge.

The learner model is constructed incorporating the knowledge model. The LEAF system stores learning analytics indicators from learners' learning records in various individual learning activities. The sources of learning records include learners' online textbook readings, homework submissions, test scores, etc. As shown in Figure 1, each learner is represented as a learner node in the network. A learning record of the learner is represented as a log node that connects some knowledge nodes. One log node indicates that the learner has learned some knowledge once. A new log node points to the most recent log node through a directed edge. Each edge connecting log nodes and knowledge nodes has an attribute called proficiency. The proficiency attribute represents a changed value of the learner's proficiency for this knowledge during this learning activity. Each log node is equivalent to a differential snapshot of the learning state. Thus, the learner model combined with the knowledge model can represent each learner at different stages of the learning process.

3.2 Recommendation Based on Closeness Centrality of Knowledge Node

The recommendation method proposed in this paper creates learner-learner connections beyond the existing knowledge and learner models mentioned above, indicating potential peer helpers for each learner. As each learner model is associated with the same knowledge model, it is possible to find learner-learner connections through the knowledge structure. The proficiency attributes for the same knowledge node by each learner are summed up as the learner's proficiency for this knowledge node. The proficiency is a numerical estimate to represent the quality of the student's specific knowledge (Hoppe & Ploetzner, 1999). If the proficiency of a knowledge node is below a certain level, but above a minimum value, it can be predicted that this learner has learned but does not understand this knowledge very well. So, these knowledge nodes are defined as weak knowledge nodes.

To find out some focused nodes among the weak knowledge nodes associated with a learner, the method of calculating closeness centrality in the weighted network is used. Closeness centrality is a measure of the distance from all other nodes in the network, hence the focused nodes tend to have high closeness centrality scores (Saqr et al., 2020). In the model of this paper, suppose there are a total of N knowledge nodes in the chosen part, each denoted as K_n $(1 \leq n \leq N)$. Define *distance*(K_n, K_i) between node K_n and node K_i as the sum of the distance attributes of the edges included in the shortest path of these two nodes. Thus, the closeness centrality of node K_i is defined as the following formula.

$$closeness\ centrality = \left[\sum_{n=1}^{N} distance(K_n, K_i)\right]^{-1}$$

The system chooses some knowledge nodes with the highest closeness centrality as candidate problems for this learner. After that, the system compares the proficiency of these knowledge nodes of other learners. If some learners have the proficiency of these knowledge nodes greater than a certain level, they are selected as candidate helpers by the system. The cut-off proficiency level, as well as the number of candidate problems and helpers, can be set flexibly based on purpose. When the candidate problems and helpers are ready, this learner can choose them from the system to get help. The following subsection will give a specific example of the method to explain the whole process.

3.3 Peer recommendation in physics learning

This subsection presents an example of physics learning at the high school level. The LEAF system extracted knowledge elements from the textbook they are learning to create the knowledge model. After these students have taken several quizzes and submitted some assignments to the LEAF system, the learner model will be created from these learning records. Thus, the models are prepared for recommending suitable problems and helpers for learners.

A portion of the knowledge model associated with Student A, B, C, D, E are shown in Figure 2, Student A has proficiency greater than 0.7 for "velocity", "uniform rectilinear motion" and others, and the system determines that Student A is already familiar with these knowledge topics. However, Student A has proficiency less than 0.5 and greater than 0.1 for "projectile motion", "horizontal projectile motion" and others, and the system identifies these as weak knowledge nodes for Student A. The system then calculates that "horizontal projectile motion" has the highest closeness centrality among these weak knowledge nodes, followed by "free-fall motion". Therefore, the system orderly selects these 2 weak knowledge nodes as the candidate problems that Student A needs help with.

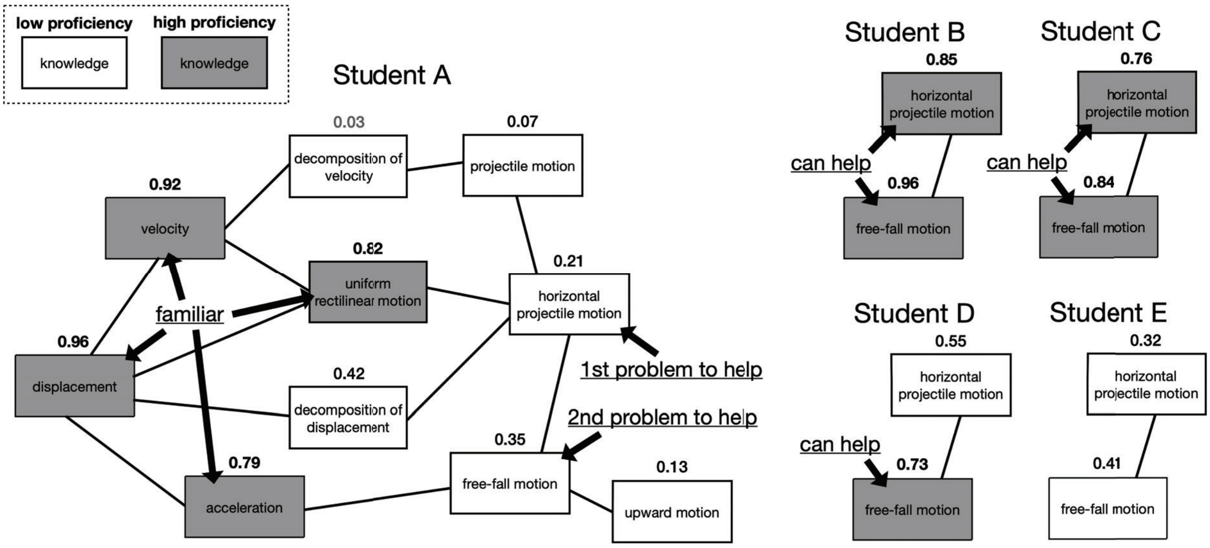

Figure 2. Knowledge Model Associated with Students

The system looks for the proficiency of other students in these 2 knowledge nodes, and finds that Student B, C have high proficiency (greater than 0.7) for "horizontal projectile motion". Besides, Student B, C, D have high proficiency for only "free-fall motion". However, Student E does not have high proficiency for these 2 knowledge nodes. In summary, the system displays the contents of Table 1 in the user interface to Student A, where Student A can select one to get help.

Table 1. *The Options of Help Recommendation*

Student	Can Help	Proficiency
B	horizontal projectile motion	0.85
C	horizontal projectile motion	0.76
B	free-fall motion	0.96
C	free-fall motion	0.84
D	free-fall motion	0.73

In Figure 3, the "horizontal projectile motion" node has the best closeness centrality, and if Student B and C are familiar with "horizontal projectile motion", theoretically, they could help explain to Student A about "decomposition of displacement" and "free-fall motion". However, some of them may not be familiar enough with "projectile motion". Finding a peer helper by focused nodes may not guarantee that all the weak knowledge nodes of Student A will be solved. However, at the same time, the helpers may explain some other related knowledge, which also benefits Student A. Such a recommendation method is an open practice of peer help, which means that it does not quantitatively predict exactly what goals should be accomplished, nor does it fully control how learners interact. Even in the case of a misdiagnosis, we can expect human-human communication to provide more flexible and ultimately more successful repair strategies (Suchman, 1987).

Finally, it should be noted that in practical implementations, the scope of knowledge and learners to be considered can be limited accordingly. For example, the scope of knowledge can be limited to knowledge related to a certain topic. Also, the range of learners can be limited to a single class, as in reality, they are more accessible.

4. Discussion and Future Work

The recommendation method in this paper is a more general way of analyzing and does not specifically analyze the characteristics of different knowledge. The characteristics of different knowledge can have an impact on the accuracy of recommendation algorithms. Closeness centrality has a lack of applicability to networks with disconnected components (Opsahl et al., 2010). We need to consider different structures for modeling knowledge from different subjects.

Besides, the method in this paper does not fully utilize the complex topological network structure of the knowledge model and the learner model when recommending problems and helpers. Other methods such as clustering may be better to select multiple problems for learners. The method in this paper initially considers creating learner connections through knowledge connections. However, we have simply considered the structural connections of knowledge but not the intrinsic associations that can imply a learning order of knowledge. If we have analyzed the learning order, a directed network can be used to represent it.

Additionally, it is challenging to mediate the interaction between learners in collaborative learning and peer help. The recommendation method in this paper considers the knowledge of the learners and assigns the roles of being helped and helping, which guides the learners' interaction to some extent. Individual tutoring ideally takes place in a "closed loop", but this is practically not feasible in rich peer interactions (Hoppe & Ploetzner, 1999). Thus, in this paper, the intelligent support system is more open that allows a learner to choose helpers as well as problems with high flexibility instead of being passively assigned. In other words, the proposed system assigns roles of peer helpers as recommendations but does not force the interaction to happen, which is aimed at diminishing the dominant role of the system and increasing the initiative of learners.

In future work, we will improve the knowledge model to make it a directed network where the pointers between knowledge nodes will be used to indicate a rational order in which knowledge is learned. Actually, there are variants for directed networks to calculate closeness centrality (Lü et al., 2016). Also, we shall look for other useful algorithms for recommending problems and helpers, making it more theoretically possible for helpers to solve problems. Finally, we will design a complete system with a user interface to implement our method in a real class. We will examine the effectiveness of our method using the peer evaluation system in LEAF (Liang et al., 2022), to figure out the advantage of the current system beyond peer matching with only learner models or random allocation.

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