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Data-Driven Peer Recommendation and Its Applications in Extracurricular Learning

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Abstract: This paper introduces a system designed to enhance extracurricular learning by recommending suitable peer helpers. The system integrates educational big data of knowledge and learner models to optimize peer learning opportunities with learning analytics. Utilizing a graph-based recommendation algorithm, it incorporates three distinct indicators to dynamically match learners with suitable peers based on specific learning contexts and needs. A significant feature of the system is its capability to visualize the knowledge and proficiency levels of potential helpers, thereby empowering learners to make well-informed decisions with less bias. The system's adaptability also permits educators to tailor it to meet diverse educational goals. We are conducting an experiment with this system during a university's paper reading course to test its usability. The system aims to reduce the burden on teachers and minimize the time students spend seeking help outside of class.

Keywords: peer learning, recommendation algorithm, graph-based modelling, extracurricular learning

1. Introduction

As a supplement to regular learning, learners often seek help from peers when they are encountering difficulties in extracurricular learning (Falchikov, 2001). However, learners often struggle to find peers to help them and may find it difficult to determine if the peers can provide effective help (Dillenbourg et al., 2009). Utilizing learning analytics with educational big data in ICT platforms, we have designed a system that recommends suitable helpers based on knowledge. The recommendation system aims to assist learners in finding peer helpers in extracurricular learning, while also increasing the efficiency and scope of finding. In this way, learners are not limited to seeking help from their friends, but rather, the system recommends peer helpers from the entire learning community. Additionally, to enable learners to understand the knowledge status of potential helpers, the system provides a visualization feature to offer interpretability of peer recommendations.

The system integrates a learning management system called LEAF (Learning and Evidence Analytics Framework) (Ogata et al., 2018) and a model called OKLM (Open Knowledge and Learner Model) (Takii et al., 2023) to provide a data-driven approach to recommend suitable peers. This recommendation system utilizes an individual learning indicator currently contained within the OKLM model, and we have added two innovative indicators specific to peer learning. We designed an algorithm that uses these three indicators for each learner and the relations of knowledge to determine the recommendation score for different learning resources selected by peer seekers.

The system serves as a general system for recommending suitable peer helpers by utilizing universal learning data. In practical applications, the system allows teachers to make certain settings within the system to adapt the recommendation tendencies to different tasks. Additionally, this system is expected to effectively recommend suitable peer helpers based on various types of learning log data.

2. Theoretical Background

Vygotsky (1978) proposed the concept of the Zone of Proximal Development (ZPD), which refers to the distance between a person's current ability and their potential development when solving a specific problem. The ZPD can be narrowed with the help of a more capable other (Vygotsky, 1978). As teachers often find it challenging to help multiple learners simultaneously, collaborative learning has increasingly gained traction in educational settings (Laal & Ghodsi, 2012). Unlike traditional group learning scenarios, one-on-one peer help activities can significantly enhance engagement of learners (Topping, 2005). Moreover, since peer help activities do not require the simultaneous engagement of multiple group members, they offer greater flexibility for online implementation (Bower, 2011). Therefore, our system introduces a peer recommendation system to facilitate the implementation of peer help activities outside of class.

Data-driven methods can provide more personalized peer recommendations (Li et al, 2022). This achievement is made possible by convenient online learning platforms and learning analytics technologies. An online learning platform is a digital environment that supports various educational activities, enabling learners to access courses and resources anywhere and anytime (Al-Fraihat et al., 2020). Technologies such as knowledge graphs and learner profile analytics provide the technical foundation for personalized learning applications. Our system, based on OKLM, integrates knowledge models and learner models to facilitate this process. Thus, our system combines these technological advantages to recommend suitable peer helpers.

3. Data Model and Recommendation Algorithm

3.1 LEAF and OKLM framework

The data source of the recommendation system comes from the LEAF system, which captures and analyzes data from various learning activities when learners use it. For instance, learners can use BookRoll (Flanagan & Ogata, 2018), the key data sensor in the LEAF system, to read and annotate e-textbooks, and the LEAF system subsequently records their reading behavior data.

The recommendation algorithm of the system is based on the OKLM model. OKLM automatically constructs knowledge models and learner models using a graph data structure to represent the current state of a learner's knowledge. As shown in Figure 1, OKLM is defined by various nodes and edges. The nodes include Learner nodes representing learners and Knowledge nodes representing knowledge units contained within learning resources. Additionally, Knowledge nodes are interconnected to form a knowledge network, indicating the relations between knowledge.

Learning logs in the LEAF system are used to build knowledge models (K-K) and learner models (L-K) in OKLM. The recommendation algorithm of the proposed system follows the conceptual framework of OKLM by utilizing the K-K and L-K relations. Meanwhile, the system also feedforwards peer learning data to L-K relations in OKLM as a data-driven design.

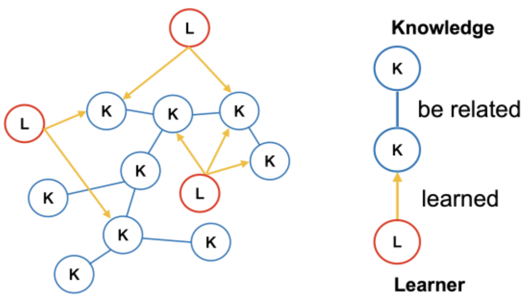

Figure 1. A simple diagram of OKLM.

3.2 Indicators and Their Evaluation

In OKLM, there exists a basic indicator from L-K relations called ***Proficiency**$_i$*, which indicates learners' proficiency of knowledge through individual learning. For peer help activities, we created two innovated indicators. Like *Proficiency$_i$* indicator, the ***Proficiency**$_p$* indicator indicates the proficiency of knowledge acquired when receiving help from peers. On the other hand, a unique indicator of peer help activities, the ***Comprehension*** indicator, indicates learners' ability acquired from interpreting knowledge and explaining it to others. The three indicators depicting L-K relations in OKLM are summarized in the Table 1.

Table 1. *The indicators in OKLM*

L-K Indicator	Meaning	Update	Evaluation
Proficiency$_i$	proficiency of knowledge	individual learning	behavior data
Proficiency$_p$	proficiency of knowledge	as help-taker	peer evaluation by help-giver
Comprehension	ability to interpret knowledge	as help-giver	peer evaluation by help-taker

During individual learning within LEAF, the OKLM construction module analyzes the learners' behavior data regarding the learning materials. The *Proficiency$_i$* indicator in OKLM will gradually increase with the exposure to the learning materials.

Regarding the two new indicators of peer help activities, their updates are evaluated through a peer evaluation component in the LEAF system (Liang et al., 2022). During each peer help activity, one learner (help-giver) helps another learner (help-taker). If the help-giver's responses in the peer evaluation suggest that the help-taker has gained a better understanding of the knowledge after taking help, then the help-taker's *Proficiency$_p$* indicator will increase. If the help-taker's responses in the peer evaluation suggest that they understood the help-giver's help well, then the help-giver's *Comprehension* indicator will increase.

3.3 Peer Recommendation Algorithm

The primary function of the peer recommendation system is to recommend appropriate peers in extracurricular learning contexts. We have developed an algorithm based on OKLM, which recommends peers from the learning community as help-givers for a problem selected by a help-taker.

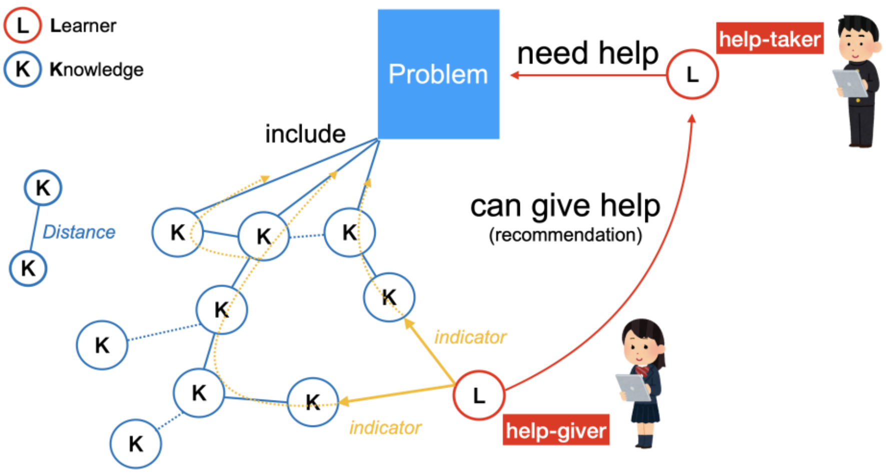

Figure 2. The peer recommendation algorithm on the graph data model.

As shown in Figure 2, the algorithm considers the K-K relations and the L-K indicators (introduced in section 3.2) to calculate recommendation scores. The algorithm searches the knowledge network to find all the knowledge units associated with the help-giver, and calculates the *Distance* to the knowledge units related to the problem selected by the help-taker. It sums up the distance attributes of the edges between the knowledge units traversed along the shortest path. Then, for each knowledge unit of the help-giver, the knowledge score is calculated using the following formula.

$$knowledge\_score = \frac{(w_1 \cdot Proficiency_i + w_2 \cdot Proficiency_p + w_3 \cdot Comprehension)}{Distance}$$

In the formula, w_1, w_2, w_3 are the weights of the three indicators and $w1 + w2 + w3 = 1$. The *Distance* variable is positioned in the denominator because greater distances imply looser relations between the knowledge units. Finally, the sum of all knowledge scores is the recommendation score of the help-giver. The peers with the highest recommendation scores are presented to the help-taker for selection.

The three L-K indicators can be assigned different weights, which can be set by teachers in the system according to a specific educational purpose. For example, if teachers want the help-giver to provide help with more knowledge, teachers can increase the weights of the *Proficiency*$_i$ indicator and the *Proficiency*$_p$ indicator. Conversely, if the goal is to provide help that is more conducive to comprehension, teachers can increase the weight of the *Comprehension* indicator.

4. Pedagogical Application

We are using the system in an academic reading course in our university, as a typical case of the application in an extracurricular learning context. In this scenario, the undergraduate students are learning how to read academic papers, where one knowledge represents an academic paper incorporated in this course. When undergraduate students begin attempting to read academic papers, they tend to find it difficult to understand (Sabat et al., 2016). At this point, the system can recommend a peer outside of class.

4.1 Recursive Recommendations

One common problem often arises in peer recommendation algorithms that high-performing learners are likely to be repeatedly recommended (Lin et al., 2017). Besides, relying solely on individual learning data to recommend for peer learning does not yield suitable results (Erdt et al., 2015). The system can fix these problems by adjusting the indicators used in the algorithm.

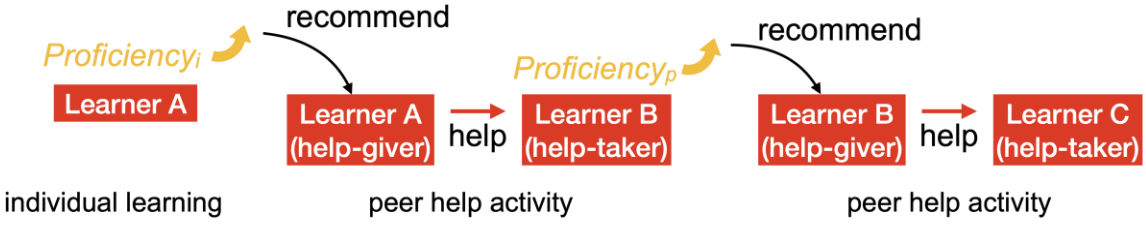

Figure 3. The process of recursive recommendations.

As shown in Figure 3, during the initial cold-start phase in a learning community, the learners' *Proficiency*$_i$ indicator increases through individual learning. Then, in the earlier rounds of peer help activities, learners who have better mastered the knowledge are recommended as help-givers. After several peer help activities, the peer-takers' *Proficiency*$_p$ indicator increases. Concurrently, the system tends to increase the recommendation weight of the *Proficiency*$_p$ indicator, allowing previously help-takers to begin being recommended as help-givers. Additionally, we also found that learners with high proficiency are not necessarily good at helping others (Topping et al., 2000). Therefore, when there is sufficient data on learners' Comprehension indicator, the system can primarily rely on it for recommendations. This approach effectively fosters social knowledge construction within the learner community through peer help activities.

4.2 Visualization

To let help-takers understand the recommended help-givers' knowledge structure in selection phase, the system offers a visualization feature. As shown in Figure 4, The system visualizes the knowledge model used by the recommendation algorithm. When a learner encounters difficulty in understanding a paper, they seek help through the system. The learner can then see which papers the recommended peers are familiar with, as well as the relations between these papers.

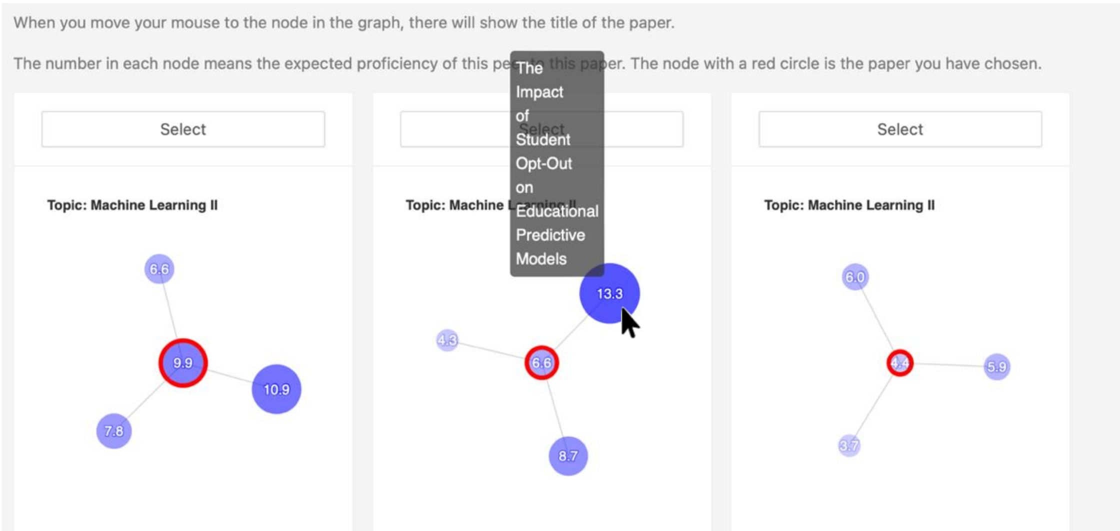

Figure 4. The UI of the visualization feature

Using visualization also allows for anonymous recommendations. This is suitable for schools or platforms adhering to certain privacy policies, such as those preferring not to disclose learners' performance. When the name is set to be hidden, learners can only see the visualized knowledge of the recommended peers, not who they are. In turn, peer help can be provided through an online chat format without physical meetings.

5. Conclusions and Future Work

This paper presented a novel data-driven peer recommendation system aimed at enhancing peer learning in extracurricular contexts. The introduction of two new indicators into the OKLM model provides a more nuanced assessment of peer learning capabilities. These indicators help in accurately matching learners with the peers most likely to enhance their learning process. By implementing a visualization feature, the system allows learners to visually comprehend the knowledge profiles of potential helpers, making the selection informed and with less bias.

As we introduced in the former section, we are currently testing this system in an authentic university course. We plan to use this system for more educational purposes in the future and conduct detailed analyses to assess its usability. Since we expect this system to be a general-purpose system, we will continue to enhance its adaptability based on the experiences from various educational settings.

In the experiment, we found that although the system effectively recommended helpers, the efficacy of peer help activities was constrained by the learners' motivation. This issue was observed on both sides of the interaction, help-takers and help-givers. Without guidance from instructors, learners (as help-takers) often lacked the initiative to seek help when encountering problems. On the other hand, learners (as help-givers), when invited to assist, sometimes found it burdensome and were reluctant to provide adequate help. Addressing the motivation problem is a key challenge that we need to focus on in future system improvements. We plan to add intelligent reminder features to the system to enhance the motivation of those seeking help, as well as reward mechanisms to increase the motivation of helpers.

Acknowledgements

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