Supporting Lifelong Learning: Recommending Personalized Sources of Assistance to Graduate Students

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Abstract. Access to and effective use of relevant information and continuously learning is an integral part of graduate students' daily lives. However, when searching for learning materials, students face challenges selecting relevant information because of the tremendous increase of learning resources over the last few years. This research proposes a novel methodology that aids graduate students to find appropriate sources of information in their lifelong learning endeavors by using people-to-people recommender system (RS) techniques. The people-to-people RS aims to help graduate students by suggesting persons (peers/experts) to contact about the problems they are facing when the problems are not easily identifiable from static fact sheets (a.k.a, question and answer or frequently asked questions).

Keywords: Lifelong learning, Recommender systems, Graduate students.

1 Introduction

Lifelong Learning (LLL) refers to systematic and purposeful learning throughout a person's life involving formal (schools) and informal (work, recreation, leisure, social relations, family life) domains [1]. Though, the idea of LLL is not new, it is among the new themes of AIED research [2]. LLL as a concept has gone through a lot of changes over the years, including continuing education, adult learning, and higher education at both the undergraduate and graduate levels [3].

Graduate students generally experience challenges that go beyond their course work [4]. To address such challenges, students often seek information by asking people around them or searching online [5]. Even though advances in technology, especially the Web, enable universal and parallel accessibility to information, there are several challenges including information overload [6]. In addition, there are challenges whose solutions cannot be found online and would be better served by peers or expert help [7], such as answering situational questions or personal questions.

In an attempt to solve some of these learning challenges, researchers have developed and deployed various technological approaches. ITSs that support learning by providing environments for students to find help from others in the same university course [8], are used. Similarly, e-portfolios are employed to support and organize learning in schools and specifically LLL in a university context [9]. Furthermore, recommender systems have also been proposed in education [10].

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Recommender systems enable students to make informed decisions on what courses to take [11], help learners organize and structure their curriculum [12], recommend domain-based learning objects [13] and provide research papers to graduate students [6]. People-to-people RSs are a class of recommender technology whose focus is on recommending people to each other. Their application domains include areas where social networks and social matching are important, such as in education (e.g., I-Help, [7]), online dating, and online job seeking. When a person is expected to provide help as well as receive help, such RSs are called reciprocal RSs [14].

While there is much research that deploys recommender systems approaches to help students with their challenges such as [6, 11–15], most of this research focuses on supporting courses or learning objects recommendation. None considers recommendation in a dynamic context, such as dealing with lifelong learners' daily challenges. To address this gap, this research seeks to explore how people-to-people RS techniques can assist in finding and suggesting an expert or peer as a source of help to a lifelong learner facing challenges, in particular to a graduate student over the course of his or her graduate program. Like Bull et al. [15] the focus is on identifying factors that increase the efficacy of good recommendations. This project extends their research from a course context to a dynamic domain that extends to the entire life of graduate students.

2 Description of Our Approach

The RS will seek to predict and recommend the best person (helper) based on the characteristics of both the helper and the student. To meet this goal, the project can be broken into the four stages depicted by Figure 1 and described below:

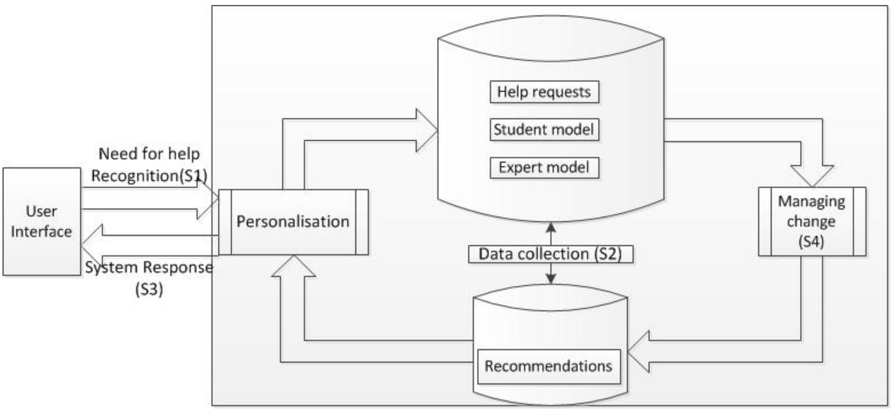

Fig. 1. Recommendation stages

S1: Recognizing the need for help. How can the system diagnose and recognise a student's need for help?

In the first stage, the system will diagnose a student's need for help by considering student information provided in explicit and implicit ways. Explicitly, a student can notify the system that he/she is in need of help by pressing a '*helpme*' button. The system then provides the student with a predefined list of challenges from which he/she can choose one. Implicitly, students' challenges can be inferred by monitoring their activities on the system and/or tracking their stated plans. An initial student model will be created based on the explicit or implicit request for help.

S2: Data Collection. What student, expert, and situational characteristics need to be collected, in order to, contextualize the need for help? How can such data be collected in the graduate studies context?

The second stage is about placing the request for help perceived from S1 into a proper context. This can be achieved by finding ways to improve the student model and problem context. Possible information sources include requesting the student to enter explicit initial information. Furthermore, information can be collected by considering the student's browsing behaviour, the time the student is seeking help, and referring to previous help requests/needs made by the same student and/or others in similar circumstances.

S3: System Response. What techniques can be used to find and suggest an appropriate expert or peer to deal with the student's issues? What factors need to be given higher consideration?

The third stage involves determining how the RS will respond to a request for help in accordance with the challenge facing the student. Two possibilities are considered: first, recommend a person straight away, or second, delay the recommendation and let the student wait. In order to build a model for finding a good helper, many factors will be considered. Such factors include availability, willingness, knowledge, social skill, compatibility, time constraints on getting an answer, knowing who seems to have helped resolve similar issues earlier, and considering later availability of a really good helper. Not every challenge is expected to need real time response, but if the help is needed in real time, and the "best" person is not currently available, then the system would have to find the next best person.

S4: Managing Change. How can the collected data in S2 be managed so that the system can update its knowledge? How can the profiles of the people in the system be maintained to keep up with the dynamic nature of lifelong learning challenges?

The fourth stage will involve managing the resulting models and data. A prominent aspect of the graduate student LLL domain is that of change. The models will have to evolve: first year grad students become second year grad students; people who have gotten help may now be able to dispense help on the same topic; courses and milestones have been achieved; and so on. It will be necessary track everybody who helped, what the help need was, and how the help was received by the person needing help (by asking for feedback from each participant after a help session). Over time, a knowledge base of helpers who would be useful for particular help needs is build.

3 Current Work and Future Research Plans

This research plan is a preliminary outline of the requirements for people-to-people RS focused on supporting graduate students. Current research work is focused on identifying the people-to-people RS system requirements. Next, a set of educational discussion forum datasets will be examined to find out if there are any relationships between older challenges and newer challenges. Furthermore, the dataset will be examined to determine the relationship between availability, time taken to respond, and individual characteristics of the helper and the person seeking help. The result of this analysis is expected to address the concerns at all stages of the RS, but especially to determine if a student's need for help can be implicitly identified.

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