Conceptual Design of WHALE: A Wise Helper Agent for the LEAF Environment

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Abstract: This approach introduces and elaborates the idea of combining learning path recommendations with the use of pedagogical agents in computer-based learning environments. For this purpose, we conceptualize and propose a pedagogical agent named WHALE (Wise Helper Agent for the LEAF Environment) together with a suite of multiple educational tools enhancing the LEAF learning platform. The main idea is to generate learning path recommendations based on a multi-layered background model comprising an action sequence layer, a resource item layer, and a knowledge graph layer. We expect the acceptability of recommendations to be enhanced by transmitting them through a personalized pedagogical agent. Based on this idea, we describe the design of a pedagogical agent that can recommend what to learn next, what materials to use for that purpose, and what to do with the materials in a multi-facetted educational tool environment.

Keywords: Pedagogical agent, learning path recommendation, knowledge graph

1. Introduction

To guide students in their learning in online environments generating recommendations for the learning process itself (i.e., what to learn next) beyond micro-level assistance within given tasks and exercises is important but difficult to implement. Coordinating these activities into a continuous learning process can be a daunting task without assistance (Zimmerman, 2002). Such assistance is usually provided by teachers, but there are challenges: teachers' resources are limited and online learning, where teachers are not usually there, is growing.

Pedagogical agents, digital entities designed to support learning, have the potential to solve this problem. Pedagogical agents are attractive to learners due to their social presence (Haake & Gulz, 2008; Mayer & DaPra, 2012; Woo, 2009), which promotes learners' acceptance of recommendations and other instruction (Castro-Alonso et al., 2021).

However, scaffolding by pedagogical agents has been limited to domain-specific application contexts so far. Usually, pedagogical agents have functionalities to provide pedagogical assistance in the form of scaffolds, such as nudges, explanations, feedback, prompts, support for metacognitive reflection/planning, or error reports/hints (Martha & Santoso, 2019). According to VanLehn (2006), these scaffolds can be classified into two types: guiding problem-solving steps within specific problems (inner-loop scaffolding) and guiding learners to an appropriate next unit through sequential problems or item sets (outer-loop scaffolding).

In order to enable pedagogical agents to guide learning activities, they need to be equipped with capabilities to adaptively sequence multiple learning-related activities as well as to support problem-solving. To complete the learning process, other important activities besides problem-solving, such as reading, taking notes, discussing with peers, self-reflection have to be considered and included. For example, if an educational agent recommends a quiz to a learner with no evidence of prior knowledge, the educational value is limited because the quiz would not be a meaningful indicator for formative assessment.

Therefore, our suggestion aims to address these challenges by developing a pedagogical agent capable of adaptively supporting individual learning paths for expanding learners' knowledge by identifying and recommending adequate learning actions. The ultimate objective is the development of a pedagogical agent that can guide learners in selecting appropriate activities, considering the array of available options, the learner's habit, and the learner's both state of knowledge and affect. As a part of this objective, in this paper, we proposed a first conceptual design of an agent for guiding the learner's learning path in the LEAF environment (Ogata et al., 2023) which is a suite of multiple educational tools enhancing a learning platform. We design the concept of our agent namely WHALE (Wise Helper Agent for the LEAF Environment) which is an agent for guiding a learner's next action that considers both the learner's habitual learning flow and learning target (topic)-specified general learning flow. We believe that learners will learn what to learn next through our recommendations and be able to adjust their learning paths.

2. Background

Several pedagogical agents have been proposed and their effectiveness has been verified. For instance, there are AutoTutor (Graesser et al., 2005), Betty's Brain (Biswas et al., 2005; Leelawong & Biswas, 2008), and SimStudent (Matsuda et al., 2013) as well-known agents. The benefits of introducing pedagogical agents as metaphors, in general, are widely known. In particular, the explicit presence of agents is known to give learners a sense of social presence. Equipping social presence is more effective than only show prompting and feedback, and eliciting engagement (Haake & Gulz, 2008; Mayer & DaPra, 2012; Woo, 2009). Also, it is known that in the recommendation context including education, the existence of an agent affects the acceptance of recommendations (Castro-Alonso et al., 2021).

However, there have been no attempts to assist in the sequencing of learning activities. Accordingly, clarifying what kind of recommendations can be accepted in comprehensive guidance may be an important contribution to the study of pedagogical agents. Learning requires not only resolving impasses in problem-solving or making decisions about specific activities but also deciding what to learn next and how to do it from a more holistic viewpoint. Until now, pedagogical agents have been limited to assisting in the problem-solving process and recommending problems to be solved. Thus, the range of recommendations and support that has been handled by pedagogical agents has been limited.

Individual differences in sequencing learning activities can affect the learner's academic achievement and efficiency (Pintrich, 2000). Such learning sequence have also been conceptualized as learning paths (or learning pathways), i.e., the learner's developmental trajectories towards reaching given learning goals (Cheng et al., 2023; Ortiz-Vilchis & Ramirez-Arellano, 2023; Pintrich, 2000). The selection of adequate learning paths has been based on Vygotsky's notion of Zone of Proximal Development (ZPD) as a theoretical background (Shabana et al., 2022). ZPD theory distinguishes between problems that learners can solve on their own, problems that they can solve with help, and problems that they cannot solve even with help, depending on their learning situation. Furthermore, this theory promotes development by having learners work on the second one with support. If the learner's current knowledge is represented as a subset of a general knowledge graph, the nodes most promising for "knowledge expansion" can be selected from the outer fringe of the student's current knowledge. The next knowledge item should not yet be part of the learner's knowledge, yet should be maximally connected to nodes that have already been learned. This idea has, e.g., been operationalized using the theory of Knowledge Spaces (Falmagne et al., 2013) and recently using a "curriculum graph" in combination with an optimization strategy (Shabana et al., 2022). For instance, methods for giving learning path are proposed with: graph network (Raj & Renumol, 2022); ontology description (Rahayu et al., 2023); bayesian knowledge tracing (Pelánek, 2017); model tracing (Blessing, 1997); and so on. Also, each of these methods depends on some granularity: steps in problem-solving (Blessing, 1997); problem in problem sequence (Falmagne et al., 2013; Raj & Renumol, 2022), and item bag (Pelánek, 2017); problems in a unit(topic) of curriculum (Shabana et al., 2022); but no method of action level.

However, in the context of learning path recommendations, the question is not only which knowledge should be learned next but also how knowledge should be acquired using available resources and actions in the environment. Effectively coordinating the timing and action among various learning activities presents its own set of challenges for learners. To form a learner's learning path, thus, it is important to decide both what to learn and how to learn.

To design the pedagogical agent with recommendations that consider both what to learn and how to learn, a learning environment with multiple options for both topic and learning activities is needed in advance. One such learning environment is the LEAF system, a large-scale educational platform (Ogata et al., 2023). LEAF is a packaged platform that can be extended through LTI connections to an LMS system. An LMS with the LEAF platform comprises multiple modules supporting different learning activities: (1) regular LMS activities (e.g., forum discussions and assignment submissions); (2) learning activities in an e-book reader (e.g., highlighting and memo functions) (Kannan et al., 2022); (3) learning activities in the GOAL subsystem supporting individual learning management across formal and informal spaces (Li et al., 2021); and (4) learning activities in the AI-enabled EXAIT subsystem (e.g., recommending problems to be solved, self-explanation of solved problems, etc.) (Flanagan et al., 2021); (5) learning activities in GLOBE supporting cooperative learning based on automated group formation (Liang et al., 2022). The LEAF system is equipped with multiple learning activities and their support functions, but since there are multiple types of learning activities, it is difficult for the learner to coordinate the activities as in the before discussion.

On the other hand, LEAF's characteristic that all activities in all tools are recorded in the form of xAPI logs can be advantageous for the design of general recommendations. By recording the habitual learning activities of learners, it is possible to extract examples of what worked well in the aggregate and to attempt perturbations from individual habits. Furthermore, the LEAF system has been installed in several schools and is used daily. Therefore, a large amount of data necessary for designing and training the agent that this research aims for has already been accumulated.

3. Conceptual Design of WHALE for Learning Action Path Recommendation

We focused on developing a pedagogical agent capable of supporting learners' learning path for expanding learners' knowledge and options for learning actions. Thus, we propose a concept of a pedagogical agent named WHALE that combines the technologies of a pedagogical agent and learning path recommendation in the LEAF environment. To make learning action path recommendations, at the level of knowledge expansion, WHALE stands on ZPD theory. Falmagne et al. (2013) and Shabana et al. (2022), by applying the theory of ZPD to the knowledge map, state that knowledge nodes with links to the learner's current knowledge nodes (called "fringe") are the easiest knowledge to learn. Therefore, WHALE also aims for the learner to learn knowledge in a way that the node is approached step by step from the learner's current knowledge node toward the knowledge node that is set as the destination. However, the remaining challenges are which material and how to learn. To develop a pedagogical agent for addressing these challenges, we raised some working hypotheses as follows: (1) Certain actions on certain material can learn certain knowledge nodes; (2) Between materials and knowledge nodes can make N-to-N relations; (3) Each material limits allowed actions; (4) actions can be discussed independently from materials; (5) There can be an ideal sequence of actions represented as a semi-ordered structure. Based on these working hypotheses, we propose multi-layered learning path recommendations combined from three layers: an action sequence layer, a resource item layer, and a knowledge graph layer (Fig. 1).

The knowledge graph layer is a layer that represents the so-called knowledge graph, a graph that expresses the connections between knowledge and its parent-child relationships.

In several studies, recommendations based on the knowledge graph have been realized (Falmagne et al., 2013; Shabana et al., 2022).

The resource item layer is a layer where items such as textbooks, workbooks, class videos, and teacher's class materials reside. These resource items are the learning contents uploaded in the LEAF environment. There is no connection between these items in this layer alone, and the order relationship in the resource item layer is inferred through the knowledge graph layer. In addition, there is usually an N-to-N relationship between resource items and nodes in the knowledge graph. This is because a textbook contains multiple pieces of knowledge and there are multiple learning materials for a given piece of knowledge.

The action sequence layer is a layer in which a sequence of learned actions is represented as a directed graph. The learning actions are based on the primitive actions that a recommender system can represent. In the LEAF environment, we are considering representing them based on the type of verb represented by xAPI. We also assume that learning actions are sequential: for example, it should make little sense to perform a formative test when no knowledge has been learned. The types of learning actions that can be taken depend on the resource items: simply reading the question booklet or solving the teacher's material is unlikely to be considered.

By implementing a reasoning mechanism based on these three layers, WHALE aims to provide step-by-step recommendations for specific primitive actions to acquire knowledge of goals set by the learner, teacher, and system. In other words, finally, we believe that WHALE can recommend what to learn next, what materials to use for that purpose, and what to do with the materials.

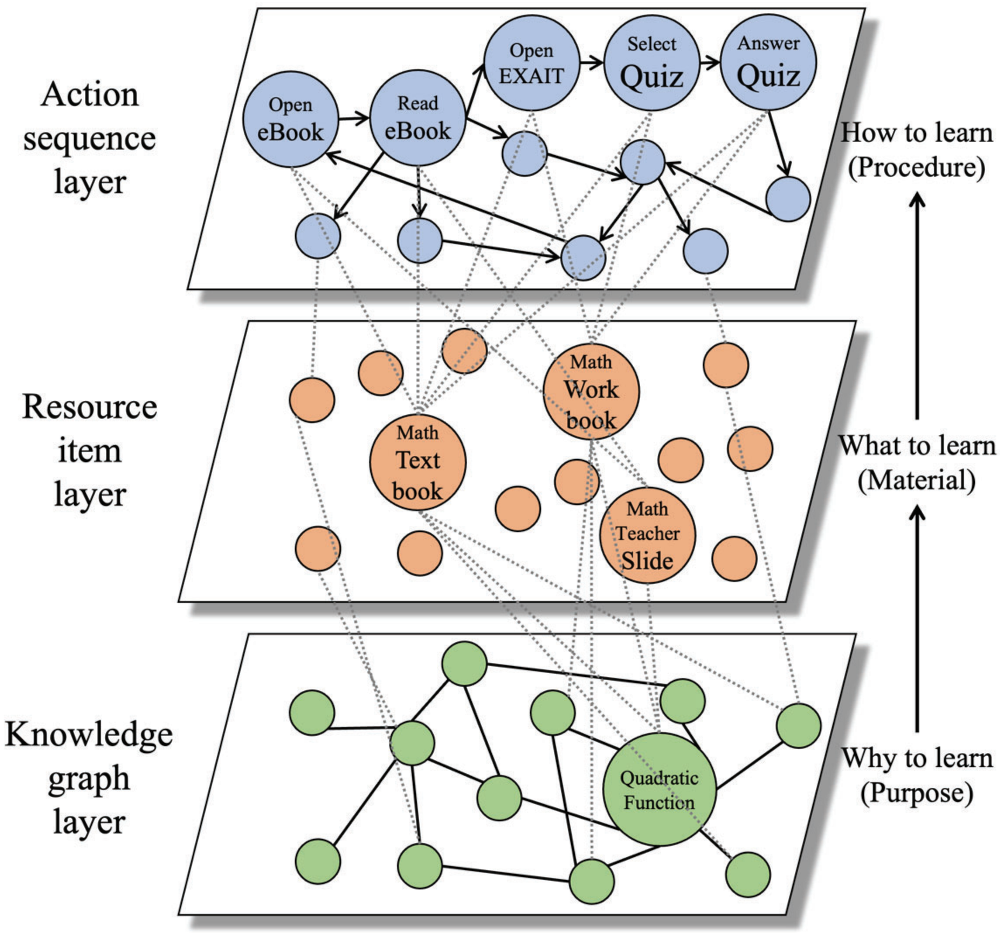

Figure 1. Concept of three layers for inference of recommendation.

As an example, our architecture supports a kind of "means-ends analysis" that spells out through the three layers starting with the identification of "ZPD anchors" and generating the actual suggestions by a mapping from the knowledge layer to the action (sequence) layer. This is the generative part of the process, which can be broken down into the following steps:

(1) The knowledge graph is static in its underlying structure, but dynamically annotated according to the individual learner's assumed knowledge state (overlay type student model).
(2) The ZPD / "fringe" analysis selects candidate nodes (knowledge items) for knowledge expansion.
(3) Based on the selected knowledge item, learning resources supporting this knowledge item are selected (making use of metadata labels such as "Introduction to knowledge X").
(4) The selected resources are suggested to be accessed using appropriate tools or apps, possibly also including usability support on the concrete action level.

Furthermore, we propose the following strategy to diagnose and update knowledge states based on the results of a certain action of the learner and the connections between each action:

(1) When any action is performed by the learner, (regardless of whether it is a recommended action or not), it is represented in the model as having gained some degree of experience with that knowledge.
(2) After that, effective/connective action is diagnosed and recommended based on the action sequence.
(3) By repetition of (1) and (2), when the "number of experiences" of the knowledge node or when the percentage of correctness to the quiz related to the knowledge exceeds a certain level, the next knowledge node is recommended based on the ZPD fringe.

Our agent equipped with these two mechanisms is provided along with an anthropomorphic agent, and the learner interacts with this agent by selecting recommended actions. For example, the agent can provide these options for the learner's inquiry: “I want to set a goal.”, “I do not know what to do next.”, “Which knowledge would be good for the next learning?”, etc.

4. Discussion and Future Work

This paper describes the design of WHALE, a pedagogical agent for learning action path recommendation. However, several issues remain to be solved in order to implement and deploy WHALE. First, it is necessary to introduce and implement the three layers (an action sequence layer, a resource item layer, and a knowledge graph layer) as part of the LEAF environment. For this purpose, we believe that both extraction of the most frequently occurring patterns in each resource item and top-down modeling are necessary for the action sequence. For resource items, from a practical point of view, it is necessary to be able to define semi-automatically what kind of action each resource item is associated with. As for the knowledge graph, we believe that technology to automatically extract the hierarchy of knowledge from the table of contents of textbooks and other sources will be a central issue.

In addition, although we mainly discussed the recommendation mechanism in this paper, we have not yet discussed how to utilize social cues by pedagogical agents. This is also an issue to be addressed in the future.

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