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# Prerequisite structure discovery for an intelligent tutoring system based on intrinsic motivation

Louis Annabi<sup>1</sup> and Sao Mai Nguyen<sup>1</sup>

**Abstract**—This paper addresses the importance of Knowledge Structure (KS) and Knowledge Tracing (KT) in improving the recommendation of educational content in intelligent tutoring systems based on intrinsic motivation. The KS represents the relationships between different Knowledge Components (KCs), while KT predicts a learner’s success based on her past history. The contribution of this research includes proposing a KT model that incorporates the KS as a learnable parameter, enabling the discovery of the underlying KS from learner trajectories, and studying its impact on the performance of intelligent tutoring systems based on intrinsic motivation. The quality of the uncovered KS is assessed by using it to recommend content and evaluating the recommendation algorithm with simulated students.

**Index Terms**—Intelligent Tutoring Systems, Knowledge Tracing, Knowledge Structure Discovery

## I. INTRODUCTION

We explore the use of machine learning techniques to uncover the knowledge structure (KS) of an educational domain, focusing on the prerequisite relations between different skills – called Knowledge Components (KCs) – that learners must acquire. The goal is to develop a method that can accurately estimate the KS based solely on learners’ interactions with an educative platform. The discovered KS can then be used to enhance intelligent tutoring systems (ITS) by providing personalized recommendations and adaptive curricula tailored to the learners’ individual needs. We study the impact of this discovered KS on intelligent tutoring algorithms.

Previous research on tutoring models formulate the recommendation task as a Partially Observable Markov Decision Process (POMDP) [1] or Multi-Armed Bandit (MAB) [2] problem, often with the goal of maximizing the learning progress of the student. This reward is both: from the teacher’s point of view, the natural extrinsic reward a tutor would try to maximize, and from the learner’s point of view – according to theories of intrinsic motivation in developmental psychology [3] – an intrinsic drive for artificial agents to choose what to learn [4] and when and whom to choose as teachers [5]. Typically, pedagogical activities (in our case exercises) that maximize learning progress should not be too hard nor too easy for the learner. This idea aligns nicely with the concept of Zone of Proximal Development (ZPD) suggested by Vygotsky [6]. The ZPD refers to the set of activities a learner can do with some assistance but is unable to do independently. Because learning is most effective in the ZPD, several works have proposed implementations of this concept in tutoring models,

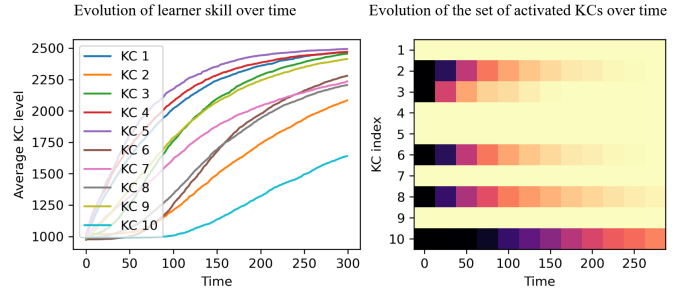


Fig. 1: Results with the ZPDES algorithm on one of the dataset, with the KS discovered by the PKT-L method. Left: evolution of the learner skills over time, averaged on 300 learners. Right: evolution of the set of activated KCs in the ZPDES algorithm over time, averaged on 300 learners (clear=activated, dark=deactivated).

exploiting domain knowledge and student models to construct and dynamically adapt the ZPD during tutoring. For instance, [7] exploit a given curriculum, while [8] and [9] use student models to estimate respectively student forgetting and student probability of success on given exercises.

We build upon the Zone of Proximal Development and Empirical Success (ZPDES) model [7] and focus on the automatic discovery of the prerequisite relations driving the evolution of the estimated ZPD. We propose the Prerequisite Knowledge Tracing (PKT) model, a knowledge tracing model conditioned on the prerequisite relations between knowledge components (KCs). The PKT model predicts the probability of success for a student on an exercise, given the prerequisite relations between the KCs. By setting the prerequisite relations graph as a learnable parameter, we can uncover the KS by training the model on observed student trajectories.

We evaluate our approach in two stages. We first measure the ability of the method to correctly retrieve the ground truth KS from learner trajectories. Then, we perform a comparative evaluation of ZPDES and other tutoring algorithms based on a KS-based discovered graph, or KT.

## II. METHODS

### A. Prerequisite structure learning

We propose the Prerequisite Knowledge Tracing (PKT), a straightforward KT model conditioned on the prerequisite relations between the KCs. The prerequisite relations are represented by an adjacency matrix  $A$  such that  $A_{ij} = 1$  if the KC  $i$  is a prerequisite for the KC  $j$ . The model predicts the probability of success of a student  $s$  on an exercise  $e$  as:

$$p_{e,s,t} = \sigma \left( \text{softmax}_{k \in PKC_e} (\lambda_{s,k,t}) - \delta_e \right) \quad (1)$$

<sup>1</sup>Flowers Team, U2IS, ENSTA Paris, Institut Polytechnique de Paris & Inria, Palaiseau, France nguyensmai@gmail.com

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TABLE I: Evaluation of the tutoring models.

Tutoring model	Random	ZPDES						MBT		
		GT	PKT-L	KI	DKT-H	SKT-H	SKT-L	PKT	DKT	SKT
Average level	1414	<b>1629</b>	<u>1528</u>	1480	1402	1406	1450	1412	1411	1425
Final level	1737	<b>2034</b>	<u>1894</u>	1826	1713	1727	1788	1738	1700	1796

where  $\sigma$  denotes the sigmoid function,  $\lambda_{s,k,t}$  denotes the estimated learner  $s$  skill level on KC  $k$  at time  $t$ , and  $\delta_e$  denotes the exercise  $e$  difficulty level. Finally,  $PKC_e$  denotes the set of KCs corresponding to the exercise  $e$ , and parent KCs in the prerequisite graph  $A$ . Thanks to the softmax aggregation, if the learner skill on one of the prerequisite KCs is insufficient, the probability of completing the exercise will be low.

The parameters  $\{p_g, p_s, \delta_e, \mu_{s,k}, \alpha_s, \beta_s \text{ and } A\}$  are optimized in order to minimize the binary cross entropy loss between the predicted probability of success  $p_{e,s,t}$  and the ground truth learner response.

### B. ZPDES Tutoring

The ZPDES algorithm [7] uses a progression graph on exercises to structure the curricula of learners. We adapt this method to be able to use it with a prerequisite graph on the KC level. The ZPDES algorithm builds and updates a personalized pool of exercise with a potential for progress. We propose the following rules to build and update the ZPD:

- 1) The ZPD is initialized with exercises for which all the KCs have no prerequisite in the prerequisite graph.
- 2) If the empirical success on one exercise reaches a threshold value  $\epsilon_v$ , we consider the exercise to be validated.
- 3) A KC is validated if it has at least one validated exercise.
- 4) A KC is activated if all its parent KCs are validated.
- 5) An exercise is added if all its KCs are activated.
- 6) If the empirical success on one exercise reaches a threshold value  $\epsilon_r$ , it is removed from the ZPD.

The empirical success  $\hat{S}_{s,e}$  of the learner  $s$  on the exercise  $e$  is initialized at zero, and updated whenever the exercise  $e$  is taken by the learner. Exercises are recommended to the learner based on a multi-armed bandit algorithm, using as reward function the empirical progress  $\hat{P}_{s,e}$  made by the learner  $s$  on the exercise  $e$ .

To encourage recommendation of exercises within the ZPD, we add a reward  $r_{ZPD}$  to those exercises. The recommendation algorithm then samples the exercise to recommend using a softmax distribution based on this reward function.

This tutoring model exploits a given KS in order to build an adaptive curriculum of exercises personalized to the progress speed of each learner. Next we describe an algorithm using a student model (i.e. a KT trained model) to optimize the recommendation of exercises.

### C. Model-Based Tutoring

We propose a greedy recommendation algorithm using a given student model, that we call Model-Based Tutoring (MBT). This tutoring model aims at maximizing at each time step the expected progress of the learner, estimated using the given student model. For each exercise, the algorithm simulates the evolution of the knowledge state of the learner, and estimates the resulting progress on each KC.

## III. EXPERIMENTS

To evaluate our method and compare it with other approaches, we generate synthetic learner trajectories with random exercise sequences. We measure the quality of discovered graphs as a basis to drive the evolution of the ZPD in the ZPDES tutoring model.

We display in figure 1 example results obtained with the ZPDES tutoring model using the prerequisite relations found with the PKT-L method. Initially, only half the KCs are activated. The learners quickly progress on these KCs, which unlocks new KCs and adds new exercises in the ZPD.

We report in table I the average proficiency level throughout practice, and the average proficiency level at the end of practice, using the ZPDES tutoring model with prerequisite graphs obtained with different KS discovery methods. We also provide the results obtained when using the ground truth KS with ZPDES (labeled GT), and results obtained with the MBT using different KT methods as student models. Our results demonstrate the efficacy of our method for KS discovery on synthetic data. The proposed approach yields both the most accurate prerequisite relation prediction, and the best tutoring with the ZPDES algorithm.

## IV. CONCLUSION

In summary, this work proposes a new method for discovering the prerequisite relations within an educational domain without relying on expert knowledge. The discovered prerequisite graph can then drive the estimation of learners' individual Zone of Proximal Development by tutoring models, improving the learners' progress when interacting with the ITS.

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