RadarMath: An Intelligent Tutoring System for Math Education

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Abstract

We propose and implement a novel intelligent tutoring system, called *RadarMath*, to support intelligent and personalized learning for math education. The system provides the services including automatic grading and personalized learning guidance. Specifically, two automatic grading models are designed to accomplish the tasks for scoring the text-answer and formula-answer questions respectively. An education-oriented knowledge graph with the individual learner's knowledge state is used as the key tool for guiding the personalized learning process. The system demonstrates how the relevant AI techniques could be applied in today's intelligent tutoring systems.

Introduction

Different from the traditional classroom teaching and massive open online course (MOOC) platforms that typically provide students similar learning resources and guidance, intelligent tutoring systems (Almasri et al. 2019) emphasize more on enabling the automatic and personalized learning process. To achieve these objective, several key components are desired, such as automatic grading models and personalized guidance tools, while few existing systems have been well equipped and integrated with such capabilities (Kulik and Fletcher 2016; Roll et al. 2011; Mohamed and Lamia 2018; Wan and Niu 2018).

Driven by the latest AI techniques and the large demands from the education community, we design a novel intelligent tutoring system, named *RadarMath*, that provides learners the automatic grading service and personalized learning guidance. In particular, two grading models are designed to grade the text-answer math questions (e.g., "describe the concept of factorization") and formula-answer math questions (e.g., "extracting the common factor in the given expression"), respectively. Furthermore, an education-oriented knowledge graph with individual learner's knowledge state is designed to provide the concept-level personalized learning path, learning resource recommendation, and accordingly guide the entire learning process.

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System Overview

Figure 1 illustrates the overview of the proposed system, where the education-oriented knowledge graph can be directly accessed by learners. Through the specifically designed user interface , the system also provides learners the concept-level unit tests and micro-lecture videos. The unit tests typically consist of the text-answer questions and the formula-answer questions, which accordingly require the two different models to accomplish the automatic grading task. All the grading results together with the learner's interaction information (e.g., the frequency of watching the videos on each concept) would be collected, and then used to estimate the learner's current knowledge state and generate the diagnosis report on learning obstacle. To properly and accurately estimate individual learner's real time knowledge state, we adopt the latest knowledge tracing model (Chen et al. 2018). The derived learner knowledge state would be utilized as the key information in the education-oriented knowledge graph.

Grading Models

Unlike most of the online learning systems that cannot conduct the automatic grading or the grading models can only handle the multiple-choice or the primitive string-matching questions, our system adopts two grading models, where a deep learning based (i.e., DL-based) model is used to grade the text-answer question, and the other one (i.e., STACK-based) model is used to grade the formula-answer questions.

DL-based Grading Model

This model mainly adopts the reference-based approach to grade the text-answer questions. Simply speaking, given the reference answer r and learner's answer s, the model predicts the grade g as:

$$g^* = argmax\mathrm{P}(g|r, s) \tag{1}$$

Inspired by the prominent performance of the attention mechanism in machine comprehension and translation (Hu 2019), our DL-based grading model also adopts the attention mechanism to capture the key information from the model inputs for better scoring learner's answer. As shown in Figure 2, the model mainly consists of three layers, namely encoding layer, interaction layer and output layer. Using the

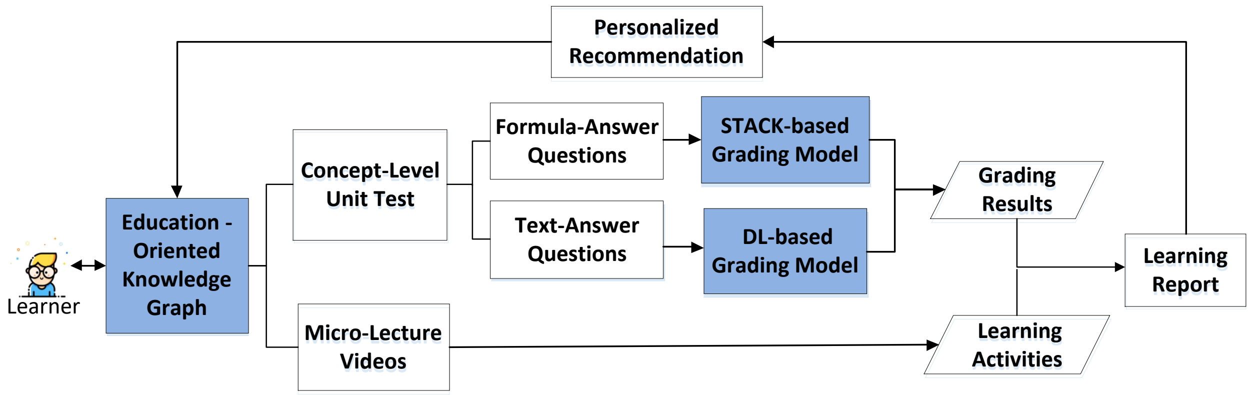

Figure 1: RadarMath System Overview

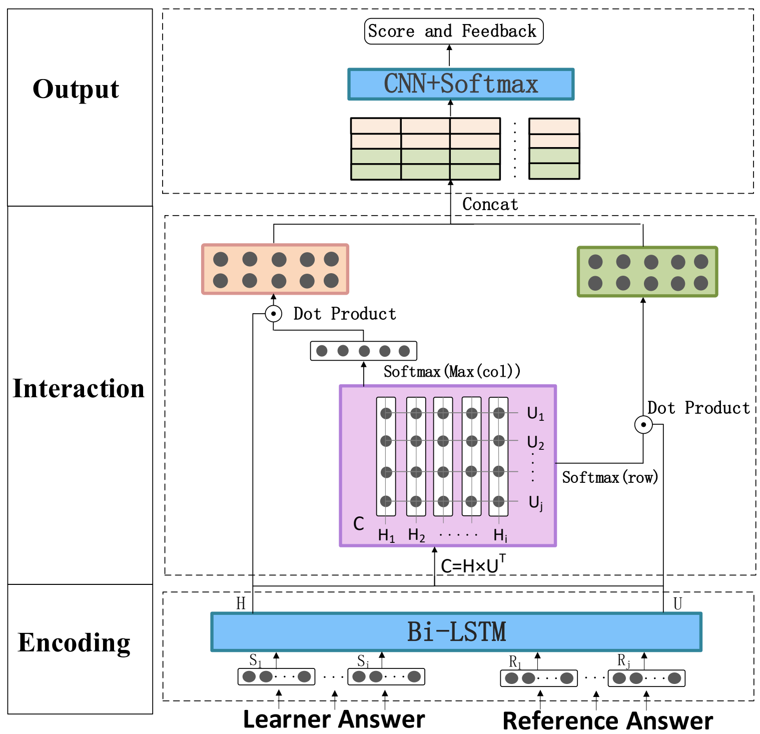

Figure 2: DL-based Grading Model

pre-trained word-embeddings, learner's answer and reference answers serve as the inputs of a bi-directional long short-term memory (Bi-LSTM) in the encoder layer. After that, the interaction layer merges learner's answer with the reference answer, where the designed attentions are computed in two directions: from learner's answer (S) to reference answer (R) and vice versa. Both are derived from a shared similarity matrix, which captures the similarity between learner's answer and reference answer. The outputs of the two attention flows would be combined into one matrix for the output layer. In the output layer, a convolutional neural network (CNN) is used to capture the local position-invariant features and utilize them as the complementary information, which eventually provides the probability distribution of the possible scores for the final grading result. The empirical experiments have shown that the quadratic weighted kappa value reaches 0.836 or above, which could satisfy the requirements on the real world deployment.

Stack-based Grading Model

This model mainly adopts a third-party open-source package, called STACK (Sangwin 2015), to accomplish the formula-answer grading tasks. STACK stands for the "System for Teaching and Assessment using a Computer algebra Kernel", which is commonly used to conduct the assessments on sophisticated formulas. A grading structure called potential response tree (PST) is designed to help specify whether two mathematic expressions are equivalent or not.

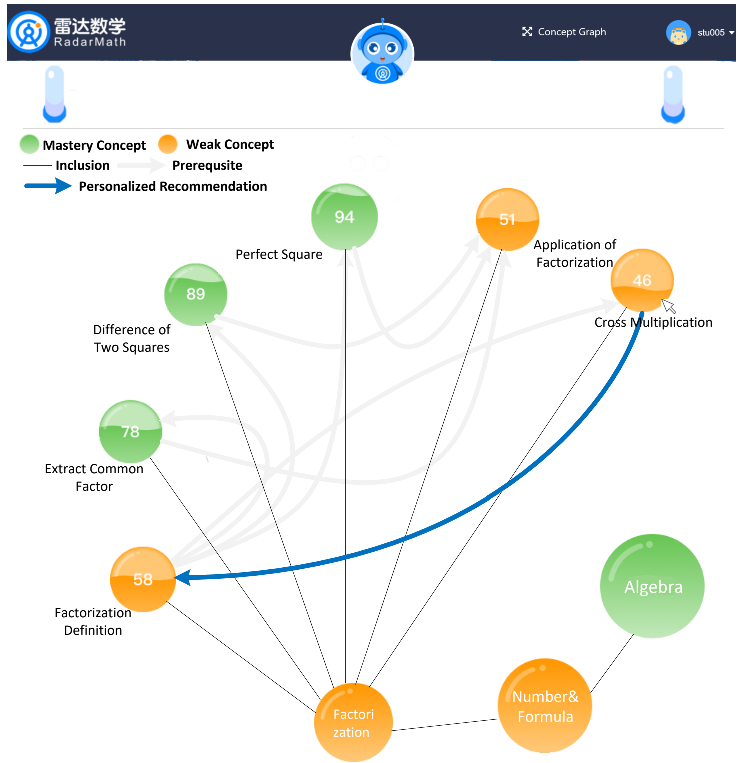

Figure 3: An Education-Oriented Knowledge Graph

The grading process is the traversal process of the PST, as its nodes is used to measure the equivalence between learner's answer and the reference expressions. Eventually, the stack-based grading model would give the score and feedback on any answers in the form of formula.

Education-Oriented Knowledge Graph

The pedagogical studies have shown that a well-structured personalized knowledge representation and an optimal learning path would directly increase the learning gain and shorten the learning time (Villano 1992). We thus design and implement an education-oriented knowledge graph (Pian et al. 2019) to fulfill such purposes and automatically guide each individual's learning process. As shown in Figure 3, the nodes represent the instructional concepts in a hierarchical structure, where different colors reflect different knowledge states (green for mastered concepts and yellow for weak concepts), and the number on each node denotes the probability derived from the automatic grading results using the knowledge tracing model. The knowledge graph could determine the learning order dynamically by considering individual learner's current knowledge states and the inherent knowledge structures using established cognitive theory. For example, when a learner attempts to start learning her weak concept "cross multiplication", the knowledge graph would present a heading arrow indicating that the concept "factorization definition" can be improved first, as it is the prerequisite concept and currently in a weak state as well. Meanwhile, the system would also make the recommendations of the corresponding micro-lecture videos and other personalized resources to the current learner.

Conclusion

We are working on deploying the system to serve more than 6,000 students in local schools[1]. The preliminary experiments have validated the accuracy of the implemented grading model and the effectiveness of the designed education-oriented knowledge graph.

Acknowledgments

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[1]The introductory video can be found at: https://www.youtube.com/watch?v=fSX16o8OuKs&feature=youtu.be

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