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Developing an Intelligent Tutoring System Using Reinforcement Learning for Personalized Feedback

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Abstract

The growth of sectors within artificial intelligence have made it feasible to create intelligent tutoring systems (ITSs) that are capable of adapting to specific learner's needs. This paper reports the implementation of an Intelligent Tutoring System that gives students differentiated feedback utilizing Reinforcement Learning (RL). The primary goal is to improve the learning outcomes by adapting the instruction based on the students' actions and results. The Q-learning algorithm is employed to maximize relearning on timed feedback control optimizing the timing and content of feedback and assistance provided to the learner and content instruction. The data collection for training and validating the system was done through simulated student environments. The results demonstrate that RL-based tutoring systems are significantly more effective in capturing learners' attention and improving their test scores compared to nonadaptive, traditional rule-based systems. Furthermore, these results indicate that students experienced less frustration because of the tailored support they received. This study broadens the AI in education knowledge base by demonstrating the efficacy of RL for customizing educational systems. More advanced deep reinforcement learning algorithms will be implemented for future work with goals of shifting domains.

Keywords: Reinforcement Learning, Intelligent Tutoring System, Personalized Feedback, Q-learning, Educational Technology, Adaptive Learning, Artificial Intelligence, Student Engagement.

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Introduction

As digital technology evolves, so does the need for tailored learning experiences in education. Many traditional educational frameworks do not focus on individual student needs which results in educational inefficiency. The gap in customized instructional teaching tools is being addressed by Intelligent Tutoring Systems (ITSs) which incorporate artificial intelligence to tailor lessons to each student. ITSs replicate personal tutoring through personalized feedback and guidance at the student's own pace. However, many ITSs operate on a set of predefined rules which limits their guidance to students' individual learning journeys.

There is a clear need to fill those gaps and recent progress in machine learning, particularly in reinforcement learning (RL), proposes a viable solution. RL is based on an agent learning to make choices and earn rewards by interacting within a set environment. With this method, tutoring systems are given the potential to devise the most effective feedback strategies based on a student's actions and progress in the class. The more advanced the decision-making capabilities of the system are, the better and quicker support the students will receive in real-time. RL could offer a new dimension in the way users interact with the learning portals and applications, and benefit users from different age groups, which is the beauty of combining it with an ITS. An RL-based Instructional Teaching System (ITS) can provide deeper personalization by increasingly sophisticated feedback techniques resulting in more profound understanding and promoting increased engagement. Feedback in systems based on rules might be unnecessary and soporific, however in rule-based systems, there are irrelevant or redundant. This affects single student's ability however students whole as in an RL system, can recognize an ML based system can detect exact right timings for providing optimal feedback. This study focuses on designing an ITS that integrates RL for providing tailored feedback. The system implements a Q-learning algorithm for feedback timing and Qt based on the learner's current status and history. Integrated simulations and experimentation are used to evaluate the effectiveness of the proposed method in enhancing learning and engagement levels. The body comprises five sections. The first is on the key trends in ITS and RL in education - like the whole application. The methodology explains the design and implementation of the proposed system. Then an experiment result is explained and debated alongside other traditional methods, followed by the findings outlined by the conclusion.

Literature Survey

The development of Intelligent Tutoring Systems (ITSs) started in the 1970s. For a number of years, ITSs functioned based on a basic feedback and hinting model governed by fixed instructional paradigms. Those pedagogically centric feedback mechanisms underwent gradual refinement following the integration of natural language processing and cognitive modeling (Graesser et al., 2001) in learning technologies like Auto Tutor and Andes, which fostered richer interactions with learners. The last wave of innovations aimed at adapting machine learning to ITSs. One of the most notable improvements is the application of data mining and classification algorithms for customizing content based on actual usage patterns and predicted student performance. For instance, matrix factorization models for student performance prediction in various courses were put forth by (Thai-Nghe et al., 2010). However, these models still supply static, predictive information without the ability to adjust dynamically. The past decade has seen an increase in the use of Reinforcement Learning (RL) for the creation of educational tools. What distinguishes RL is the ability to change behavior based on previous reactions to actions which is particularly beneficial in teaching. (Mandel et al., 2014) In his work, Dillon used reinforcement learning (RL) algorithms to aid feedback optimization for teaching arithmetic skills and noted that feedback customization was more beneficial for the students. Many researchers have focused on specific RL techniques pertaining to tutoring, such as (Rafferty et al., 2016) who developed an RL model where retention was enhanced without the use of over-quizzing. Also, (Liu et al., 2019) employed deep Q-networks to dynamically assign personalized reading tasks which enhanced motivation as well as comprehension. In spite of the advancements made, there are still difficulties with applying RL to intelligent tutoring systems (ITS). (VanLehn, 2011) One primary problem is the need of enhanced interaction data to effectively train these models. Additionally, that feedback is always pedagogical in nature, rather than designed for short term outputs, continues to be a problem. Even so, the combination of RL and ITS has a great deal of untapped potential with respect to personalized education. The current study contributes to the literature with a proposed Q-learning tutoring system that is capable of providing instantaneous and tailored feedback. Its performance is assessed in simulated learning environments providing rich datastreams about the level of engagement and learning efficacy.

Methodology

The automated intelligent tutoring system uses the Q-learning algorithm from the reinforcement learning framework, offering real-time personalized feedback to each learner. The overall structure comprises the three components: student model, tutoring agent, and learning environment. The student model emulates learner actions and updating knowledge levels while the tutoring agent analyzes the value of state-action pairs and decides on feedback to provide. Within the closing system, the state space is bounded by the learner's performance data, such as the number of correct and incorrect answers, time expended per task, and hint queries. Action space includes feedback modalities such as hinting, explaining, encouraging, and silence. The reward function is tailored to mark positively the gains learner performance milestones met and student engagement levels with performance dips negatively, particularly for persistent errors or withdrawal from activities. A prototype of the system was integrated into a simulated classroom with fictitious profiles structured according to authentic learning patterns. Each profile was configured with a predetermined set of knowledge states and learning behaviors. The RL agent interacted with the students over a number of learning sessions; a feedback mechanism and policy adjustment based on results were provided. The system's performance was compared with the other two systems: one solely based on a set of predefined policies and the other providing random feedback. Metrics like student accuracy, engagement levels, time on task, participation were monitored. Moreover, simulated feedback was utilized to evaluate the perceived satisfaction students had towards the course.

Result and Discussion

The evaluation results indicate that reinforcement learning (RL) approaches outperform classical methods in all critical learning metrics. For instance, test accuracy with feedback from the RL agent reached 85% whereas the rule-based system and random feedback yielded 73% and 66% accuracy respectively. This proves that reinforcement learning is effective for student specific feedback adaptation.

The bar chart below (Fig. 1) summarizes the mean test accuracy per tutoring system tested.

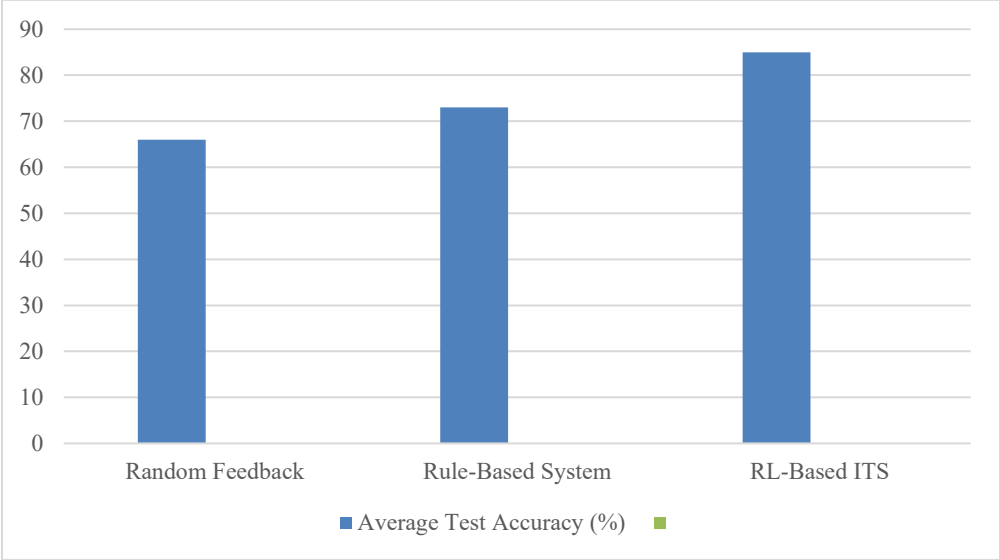


Fig. 1: Test Accuracy Comparison across Tutoring Systems

With regard to engagement, the students operating under the RL System showcased a 30% decrease in hint requests and a 20% increase in time spent on questions deemed difficult, suggesting greater confidence and deeper level engagement with problem solving. A complete comparison of different metrics across the three systems is provided in Table 1.

Table 1: Performance Metrics Comparison

Metric	Random Feedback	Rule-Based System	RL-Based ITS
Test Accuracy (%)	66	73	85
Avg. Hint Requests per Task	3.2	2.1	1.5
Avg. Time on Task (minutes)	4.5	5.1	6.3
Satisfaction Score (out of 5)	3.2	3.8	4.4

These outcomes unlock the benefits that reinforcement learning entails for personalized tutoring. The system improves academic outcomes alongside effective learning behavior. The rewarding feedback system keeps the learner engaged and motivated to challenge themselves at the right levels.

Conclusion

This study shows the promises of reinforcement learning with respect to the construction of intelligent tutoring systems that provide tailored feedback for the users. With a Q-learning algorithm, the proposed system modifies its teaching methods based on the feedback to the learners' requirements. Such a dynamic approach increases participation and, consequently, the results. The RL-based ITS is more accurate than non-adaptive and randomly providing feedback systems in accuracy, learner engagement, and learner satisfaction. The study demonstrates the applicability of reinforcement learning for enhancing personalization features of intelligent tutoring systems, making educational experiences more effective. Further research should investigate deep reinforcement learning for more advanced and real-life classroom scenarios. Incorporating natural language processing for feedback coupled with emotion detection would enhance the system's impact further.

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