Potential Topics/ Papers in Personalized Learning

Below we exemplify some potential project topics. Students are free to choose any topics related to personalized learning with AI, **NOT LIMITED** to the following examples.

1 Latent-State Modeling and Inference

At the heart of personalization lies the problem of estimating a learner's unobservable cognitive state. While classical methods like the Kalman Filter provide an optimal solution for estimating the state of linear systems from noisy, structured data [1], they are ill-suited for the non-linear dynamics and rich, unstructured data (e.g., essays, dialogues) of human learning. The open research challenge is to design hybrid neural–probabilistic models that can infer a learner's state in real time while maintaining meaningful uncertainty estimates. Modern approaches leverage large language models (LLMs) to interpret this complex data. Some works use variational autoencoders to infer latent "topics" from a text, a technique that could be applied to map student writing to concepts or misconceptions with a quantifiable uncertainty [2]. To address the noisy nature of real-world student interactions, other methods employ diffusion models to denoise the data before performing diagnosis, a general technique that could lead to more stable and accurate state estimation in education [3]. For interpretability, models like PSI-KT, combine data-driven student models with a structured prerequisite graph of the subject matter, allowing the system to infer that a struggle with "long division", for example, stems from a weakness in the prerequisite concept of "subtraction" [4]. Going a step further, general frameworks in RL can be applied to create an adaptive agent that continually interacts with a user to build and refine a dynamic profile of their knowledge and learning style over time [5].

2 Adaptive Pedagogical Control

Once a learner's state can be inferred, the next task is to decide how instruction should adapt a sequential decision-making problem under uncertainty. Reinforcement learning (RL) is a natural framework for this, but standard RL is insufficient for the high-stakes educational domain, which demands safety, fairness, and robustness. The research frontier involves adapting general RL algorithms to provide these guarantees. For safety, techniques from Constrained RL, such as CCPO, can be applied to learn versatile policies that avoid actions that might harm student motivation; for instance, by switching to a more supportive mode when a student shows signs of frustration [6]. For robustness, general algorithms like RCPO are designed to handle "model mismatch," which in an educational context ensures that a policy trained on one cohort of students remains safe and effective when deployed on a new, different group [7]. Finally, to address equity, general frameworks from Fairness-Aware RL can be used to train pedagogical agents that explicitly optimize for fairness, for example, by ensuring that learning gains are distributed equitably across students from different demographic groups [8].

3 Optimization of Scarce Resources

Even with automation, key teaching resources like instructor time remain limited. This creates a need for principled methods to allocate effort for maximum collective benefit, linking personalization with optimization. General techniques from this area might be applied to education. For instance, the "Decision Focused Learning" framework, can be used to model an end-to-end system, where a predictor predicts student needs and a solver creates an optimal schedule for a teacher's limited time [9, 10].

4 Multi-Agent and Game-Theoretic Interaction

Education is a multi-agent system where students, teachers, and AI agents interact with different, sometimes conflicting, objectives. This creates a strategic environment where incentives can shape behavior as much as pedagogy. The fields of game theory and multi-agent reinforcement learning (MARL) [11, 12] provide the tools to analyze and design the teaching system, where students may misuse hints instead of engaging in productive struggle. More advanced MARL techniques can be used to build more sophisticated agents. For example, the general principle of opponent-learning awareness, as seen in algorithms like LOLA, could be applied to create an AI tutor that strategically chooses actions to positively shape a student's future learning strategy for a better long-term outcome [13].

5 Assessment, Verification, and Content Generation

Effective personalization depends on reliable and scalable assessment. While modern AI can generate educational content, a key challenge is verifying that the content is correct and that the system can accurately evaluate a student's reasoning. This problem connects to the broader field of trustworthy and verifiable AI, which seeks to combine the fluency of generative models with the rigor of formal verifiers. A powerful general paradigm is "generate-and-test," famously used by DeepMind's AlphaCode to solve complex programming problems by generating millions of potential solutions and filtering them with a verifier (i.e., test cases) [14]. This same approach could be used in an educational tool to generate and validate hints or feedback. Furthermore, for a system to be truly trustworthy, it must understand and communicate its own limits. General techniques for training language models to express their uncertainty in words are highly applicable, as an AI tutor that can say "I am not sure, but..." is far safer and more transparent than one that presents all information with absolute confidence [15].

6 Ethical and Human-Centered Considerations

Technical success is insufficient if a system is not also private, fair, and designed to augment human teachers. These challenges require applying general techniques from several fields of responsible AI. To ensure privacy, methods from privacy-preserving machine learning like Federated Learning and Differential Privacy are critical; the foundational work in this area provides a blueprint for training models across schools without centralizing sensitive student data [16, 17]. To ensure fairness and prevent algorithmic bias from amplifying societal inequities, techniques from fairness-aware machine learning are needed. General frameworks like "equality of opportunity" provide enforceable definitions of fairness that can be used to audit and correct a model's decisions [18]. Finally, to ensure the system empowers rather than replaces educators, principles from Human-in-the-Loop (HITL) research provide a roadmap. Surveys of HITL systems offer models for designing effective teacher-AI collaborations, creating a virtuous cycle where the AI assists the teacher and the teacher's expert actions provide feedback to improve the AI [19].

7 Other related problems

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