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Optimizing Human Learning. 4th Workshop eliciting Adaptive Sequences for Learning and Educational RecSys (WASL 2024)

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ABSTRACT: Personalized learning is an educational approach that tailors the learning experience to the unique needs, interests, abilities, and preferences of individual students. There are two major tools to assist personalized learning - adaptive learning systems (ALSs) that utilizes adaptive design, data-driven algorithms and personalized approaches to tailor learning experiences for individual students, and educational recommender systems (EdRec) which can deliver personalized recommendations (e.g., course, materials, pathway, peers) to users (e.g., students, educators and other educational stakeholders). These personalized learning technologies have proved remarkable success in enhancing user experiences. This rich full-day workshop, containing a keynote and tutorials, will target stakeholders and researchers about the background, motivations, knowledge, and skills related to ALSs and EdRec. It also provides an overview of emerging trends and unresolved challenges in these fields, delving into the technical challenges of framing reward functions: how learning analytics can be used to guide instruction, inform decision making for either teachers or intelligent tutoring systems. Furthermore, we aspire to foster a productive exchange of ideas with the audience and encourage more individuals to contribute their efforts towards advancing the area of personalized learning.

Keywords: Adaptive Learning, Personalized Learning, Reinforcement Learning, Recommender Systems, Bandits, Policy Learning, Causal Inference

1 ORGANIZATIONAL DETAILS

We propose an Interactive Workshop, full-day, containing hands-on tutorials about adaptive learning and educational recommender systems, and a keynote by Aritra Ghosh (Meta) and Andrew Lan (University of Massachusetts Amherst) about learning from sequential user data. To know more, check our website <https://humanlearn.io>.

Audience: The targeted audience is anyone who is interested in personalized learning and recommender systems. To cater to the audience members without prior experience or knowledge, our tutorial will include an introductory talk about them (e.g., the background and knowledge of

recommender systems), along with more in-depth discussions about our topics, and technical details of the algorithms and implementations for the advanced users.

Program committee: Hisashi Kashima, Fabrice Popineau, Jill-Jênn Vie, Jacob Whitehill (WPI).

2 WORKSHOP OBJECTIVES

Technology-Enhanced Learning (TEL) leverages various technological tools and innovations to enhance the learning experience, making it more engaging, personalized, and effective for learners of all ages and backgrounds (Balacheff et al., 2009; Kirkwood et al., 2014). Personalized learning plays a vital role in TEL, and it was advanced by two technologies. One of them is the adaptive learning systems (ALSs) that emerge as a pioneering and promising TEL field (Bingham et al., 2018; Wang et al., 2023). ALSs enhance the scalability and resourcefulness of personalized education, a feat that would be difficult to accomplish in conventional classroom environments. Educational recommender systems (EdRec), as another TEL technology, have been utilized in education to improve personalized learning experiences, help fill students' knowledge gaps, recommend appropriate learning materials (formal and informal materials), courses, pathways and after-school programs, and adapt learning to context-aware or mobile environments, and so forth (Garcia-Martinez et al., 2013; Drachsler et al., 2015; Erdt et al., 2015; Khribi et al., 2015; Klačnja-Milićević et al., 2015; Zheng, 2023). These platforms collect a massive amount of data over various profiles, that can be used to improve learning experience: intelligent tutoring systems can infer what activities worked for different types of students in the past, and apply this knowledge to instruct new students. In order to learn effectively and efficiently, the experience should be adaptive: the sequence of activities should be tailored to the abilities and needs of each learner, in order to keep them stimulated and avoid boredom, confusion and dropout.

Implementing ALSs brings various pedagogical benefits, including accelerated learning, remediation, immediate feedback, and interactive learning (Hattie, 2008). To maximize these benefits, researchers from both academia and industry attempt to develop new systems by incorporating cutting-edge techniques (e.g., conversational AI, reinforcement learning from human feedback). As efforts to develop and implement ALSs accumulate, it becomes increasingly evident that the effectiveness in promoting learning achievement varies across different systems. While substantial progress has been made in constructing ALSs, a noticeable gap persists in our understanding of the specific architectural and design choices that contribute to their efficacy (Imhof et al., 2020; Muñoz et al., 2022). This workshop seeks to address this knowledge gap starting with an overview of the historical development and architecture of ALS and adaptive approaches, followed by a detailed analysis of the potential impact factors influencing the effectiveness of ALSs in facilitating learning achievement. In the context of reinforcement learning, we want to learn a policy to administer exercises or resources to individual students (Bassen et al., 2020; Clement et al. 2015; Lan et al. 2016; Whitehill et al., 2017). Still, framing the reward is key for making these tools effective. We will discuss future directions and persistent challenges that ALSs and LAK community must address to propel this field forward (Motz et al., 2023).

Recommender systems (RecSys) have seen widespread adoption across various internet applications. These applications encompass e-commerce platforms like Amazon.com, online streaming services such as YouTube, and social media platforms like Facebook. The remarkable

success of these applications in enhancing user experiences and aiding decision-making through personalized recommendations underscores the effectiveness of RecSys. Recently, RecSys has witnessed significant progress for optimizing interaction, click-through-rate, or profit, thanks to a range of intriguing and promising areas like multi-task learning (Zhang et al., 2023), multi-objective optimization (Zheng et al., 2022), multi-stakeholder considerations (Zheng et al., 2021), and addressing issues related to fairness, accountability, and transparency (Shin et al., 2019; Deldjoo et al., 2023), among others. However, these advancements in the realm of RecSys have not been sufficiently shared with the education community or in the development of EdRec. Can we use similar methods to enhance the performance of teaching in order to promote lifetime success? When optimizing human learning, which metrics should be optimized (Doroudi et al., 2019)? Learner progress? Learner retention? User addiction? The diversity or coverage of the proposed activities? This workshop aims to bridge this gap by providing the audience with an in-depth understanding of the background, motivations, and the essential knowledge and skills required for EdRec. Additionally, it will offer a concise overview of emerging topics and the unresolved challenges currently shaping this field. Student modeling for optimizing human learning is a rich and complex task that gathers methods from machine learning, cognitive science, educational data mining and psychometrics (Bergner et al., 2018).

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