Personalization and Incentive Design in E-learning Systems

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ABSTRACT

My thesis focuses on the design of systems to augment existing e-learning software in a way that supports both teachers and students. It addresses three central challenges: personalization of educational content to students, techniques for machine-generated interventions, and incentive designs to enhance students' learning. For each of these problems I will synthesizes approaches from informational retrieval and social choice theory. My results thus far have included a novel algorithm for sequencing content in e-learning system that uses collaborative filtering to generate a difficulty ranking over the test questions, without needing to predict students' performance directly on these questions. The algorithm was able to outperform state-of-the-art approaches from the literature on two different data sets containing millions of records. My future efforts will be directed to extending these results and to generalize my approach to the problems of intervention and incentive designs.

1. INTRODUCTION

My thesis focuses on the design of systems for e-learning that support both students in their learning processes and teachers in their understanding of how students learn. I focus on augmenting existing educational software already used in schools where impact can be achieved and for which large amounts of data is available for analysis from past students interaction. My work addresses three central challenges in the design of such systems by synthesizing techniques from information retrieval and social choice:

The first challenge is *personalization of educational content to students.* Educational content is now accessible to student communities of varied backgrounds, learning styles[1] and needs. There is thus a growing need for personalizing educational content to students in e-learning systems in a way that adapts to students' individual needs [10, 1]. My approach towards such personalization is to sequence students' questions in a way that best matches their learning styles or gains [2, 12]. To this end, I use a collaborative filtering approach [3], to generate a difficulty ranking over a set of questions for a target student by aggregating the known difficulty rankings over questions solved by other, similar students. The difficulty rankings of similar students is combined using social choice theory [6] to produce the best difficulty ranking for the target student.

[1]learning styles: e.g. as defined by [5] covering perception, input, organization, processing and understanding aspects.

The second challenge is *intelligent intervention for students.* Two foundational principles of a collaborative system [7, 4, 8] are that (1) the system pursues all possible avenues for doing its tasks, and provides support to all participants in the system. (2) the system is lightweight and avoids disrupting other participants as much as possible. Within the context of education, such a system will guide students' interactions in a way that best adapts to their abilities and learning styles, while minimizing the amount of intervention, allowing for activities that yield educational gains through explorations. To minimize intrusion, the system must be able to model the effect of interruption on the students' behavior with the educational system over time. For example, the system should be able to decide not to intervene when the student is off-track, because it predicts that this exploratory behavior will yield further educational gains. To this end, I will use approaches from the recommendation systems literature to compare students' past interactions with that of similar students, to infer the best point in time when to interrupt the user.

The third challenge is *incentive design* for influencing the behavior of students (whether as individuals or group members). Although incentive structures have been studied extensively in psychology and economics (and most recently, human computation), there has been scarce work on the design and analysis of incentives in educational contexts. To this end, I plan to model students' uses of educational content (e.g., on-line course forums, problem sets, etc...) and to compare the efficacy of different incentives (e.g., points, badges and peer pressure) towards steering student behavior and learning.

2. INITIAL RESULTS

My research efforts thus far have focused on the first challenge, that of personalizing educational content to students in e-learning systems. I developed a novel algorithm for sequencing content in e-learning systems that directly creates a "difficulty ranking" over new questions. My approach is based on collaborative filtering [3], which generates a difficulty ranking over a set of questions for a target student by aggregating the known difficulty rankings over questions solved by other, similar students. The similarity of other students to the target student is measured by their grades on common past question, the number of retries for each question, and other features. Unlike other uses of collaborative filtering in education, this approach directly generates a difficulty ranking over the test questions, without predicting students' performance directly on these questions, which may be prone to error.[2]

The algorithm, called EduRank, weighs the contribution of these students using measures from the information retrieval literature. It allows for partial overlap between the difficulty rankings of a neighboring student and the target student, making it especially suitable for e-learning systems where students differ in which questions they solve. The algorithm extends a prior approach for ranking items in recommendation systems [9], which was not evaluated on educational data, in two ways: First, by using social choice theory to combine the difficulty rankings of similar students and produce the best difficulty ranking for the target student. Second, EduRank penalizes disagreements in high positions in the difficulty ranking more strongly than low positions, under the assumption that errors made in ranking more difficult questions are more detrimental to students than errors made in ranking of easier questions.

I evaluated EduRank on two large real world data sets containing tens of thousands of students and about a million records. I compared the performance of EduRank to a variety of personalization methods from the literature, including the prior approach mentioned above as well as other popular collaborative filtering approaches such as matrix factorization and memory-based K nearest neighbors. I also compared EduRank to a (non-personalized) ranking created by a domain expert. EduRank significantly outperformed all other approaches when comparing the outputted difficulty rankings to a gold standard.

3. FUTURE CHALLENGES AND ANTICIPATED CONTRIBUTION

My next efforts are going to focus on incentive design and intervention policies in e-learning systems. For this, I'm going to address, among others, the following topics and will be happy to get the advise of the consortium on them:

- Extrinsic vs. intrinsic motivation and respective incentives in educational systems
- Usage of persuasion technologies to steer on-line learning behavior
- Badges as an reputation incentive mechanism
- Additional game mechanics to be adapted for the context of my research
- Comparing hints to other intervention methods in the context of exploration and learning
- Influencing learning and mastery through personal vs. group incentives
- Investigating additional social choice methods for combining peers influence on personalization and intervention

My anticipated contribution will include developing novel modeling algorithms for users in e-learning systems, designing incentive mechanisms for these systems and constructing and evaluating personalization and intervention mechanisms for users by reasoning about how they respond to these interventions over time. I will evaluate my approaches in real world e-learning environments.

[2]To illustrate, in the KDD cup 2010, the best preforming grade prediction algorithms exhibited prediction errors of about 28% [11]

4. REFERENCES

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