Towards Helping Teachers Select Optimal Content for Students

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Abstract. In a personalized learning context, teachers decide which content to assign to students on the basis of data. However, it is not clear that simply providing teachers with data is sufficient to promote good instructional decisions. In this paper, we study data from an online learning platform that gives teachers data on student test performance and then allows them to decide which new skill students should work on. We then apply a knowledge graph algorithm to infer whether the content the teacher assigned the student is a skill that the student is ready to learn (i.e. the skill is within the student's Zone of Proximal Development), whether the student is not yet ready to learn the skill, or whether the student has already learned the skill. In this paper, we study how the teacher's decision of what skills or topics the student should work on correlate to the student's learning outcomes. We study this issue using logistic regression to compare whether students master more skills based on whether they are assigned ready-to-learn skills or unready-to-learn skills according to the knowledge graph. The results demonstrate that in both mathematics and English learning contexts, if the teacher selects skills which the student is assessed by the algorithm to be ready to learn, the student gains more mastery than if he or she is assigned skills he or she is not ready to learn. We conclude by proposing a visualization that more clearly surfaces the knowledge graph predictions to teachers.

Keywords: Instructional decision, Learning outcomes, Mastery, Knowledge graph, Ready-to-learn, Unready-to-learn, Zone of Proximal Development

1 Introduction

There has been considerable interest over the last decades in providing students with adaptable, personalized learning experiences and flexible content sequencing. However, there is more to the potential of AIED systems than just automated adaptivity. Increasingly, AIED systems also inform teacher decision-making [5], part of a broader trend to support data-driven decision-making by teachers.

However, data-driven decision making within a technologically rich medium will only be effective when the right data is clearly presented by teachers, and when teachers to make the right teaching decisions. While there is increased interest in supporting teacher cognition and metacognition in the context of AIED systems [10] and creating better methods for informing teachers [5,7], it remains unknown how effective teachers are at using the information they receive. As Earl and Katz [4] note, although many school districts have established large databases, teachers typically receive little guidance in terms of how to effectively use the data for differentiated instruction. In particular, how effective are teachers at selecting material to work from when given reports on student performance? In other words, even when the data are accessible to teachers, they still have difficulties in deciding what students need next, to phrase it in affective terms, to measure what contents fall in learner's zone of proximal development (ZPD).

We consider this in the specific context of selecting content in a learner's zone of proximal development (ZPD). A learner's ZPD represents the difference between what a learner can learn with assistance, and what he or she has already mastered without help [14]. As Vygotsky [14] notes, the term "proximal" means those skills a learner is "close" to mastering; a learning task assigned within this zone is likely to be learned effectively, and content outside the ZPD is likely to either be too difficult or too easy for the student. In its original formulation, ZPD is difficult to measure without intense one-on-one scaffolding, making it difficult for teachers to use it as a basis for instructional decisions, but Murray and Arroyo [13] propose that the ZPD can be measured by adaptive learning systems. As the first group of researchers who investigated how ZPD is measured in AIED systems, they proposed to categorize a learner's learning process into several states, using data such as task performance and the number of actions needed. ZPD was identified when learners' data demonstrated that they were appropriately challenged instead of being too bored or too confused. Inspired by their work, our current study proposes to use the knowledge graph as another potential tool for determining a student's ZPD in an adaptive learning system.

In this paper, we measure the ZPD using a knowledge graph and then use this measure to investigate whether teachers make good instructional decisions based on student performance data. Specifically, we investigate the impacts on student performance and mastery when they are assigned content inside or outside their assessed ZPD. Our hypothesis is that students will gain more mastery if assigned skills they are ready-to-learn (RtL) than if the teacher assigns unready-to-learn (UtL) skills. We conclude with ideas on how to communicate ZPD to teachers.

2 Method

2.1 Platform

In the current study, we use data from an online learning platform, Learnta, that gives teachers data on student test performance and then allows them to decide which content students should work on [1]. Learnta's knowledge graph maps content to a prerequisite structure, representing which content is necessary to know to learn content. A student's mastery of each skill is assessed by Bayesian Knowledge Tracing (BKT) [3], determining whether the student has mastered a particular skill by predicting their latent knowledge. BKT has four parameters: the initial probability of knowing the skill- P(L0); the probability of learning the skill each time it is encountered - P(T); the probability of making a mistake despite knowing the skill- P(S), and the probability of guessing an unknown skill correctly- P(G). Then the prerequisite structure is used to assess which content a student is ready-to-learn (RtL), defined as when the student has not yet mastered the skill but has mastered all of its prerequisites (i.e. the skill is within the student's ZPD), versus which content the student is unready-to-learn (UtL), i.e. not all prerequisites have been mastered. We investigate whether teachers given assessment data make effective instructional decisions, by seeing whether they assign materials that fall in the student's ZPD, and what the results are for learning.

2.2 Data Collection

In an English grammar learning, the topic titled "Pronoun and Noun", used by 49 Learnta students, was randomly selected from the pool of topics. The math/Calculus topic "Integral Expression" was randomly selected from the pool of topics signed up for by the same group of students. During teaching, the teacher has access to student performance data and then makes decisions on the basis of performance data. When each action that determines what content to teach next – e.g. assigning a new skill-- was made by the teacher, the system detected and collected it as an instructional decision. We collect data on whether that skill is assessed by the learning system as mastered or not, according to BKT, by the end of the learning period. A skill was considered mastered if BKT found probability of mastery greater than 95%, and as not mastered otherwise. The teacher then selects another skill for the student to work on. Learnta's knowledge graph changes each time a new skill is encountered and assessed.

2.3 Statistical Analysis

We compare the degree to which students master skills, based on whether the teacher selects RtL skills, UtL skills, or already-mastered skills. The analyses are conducted separately for English and math. The outcome of interest is whether the student mastered the skill according to BKT. The number and percentage of skills that are mastered are tabulated for each type of teaching decision. We assess the association between instructional decisions and student mastery, looking at whether students are more likely to master RtL skills than UtL skills. The primary model is a logistic regression model with teaching decision as the single predictor variable. As a sensitivity analyses to assess the robustness of the primary model, mixed-effects logistic regressions are also conducted to adjust for the confounding effects of student and skill, either individually or both together. In these mixed-effects models, teaching decision is a ternary variable (RtL, UtL, already-mastered) and is considered as a fixed effect, while student-level and skill-level variables are treated as random effects. Odds ratios (OR) and corresponding P-values are calculated in R version 3.0.2 [5] using the glm() function for logistic regression and the lme4 package [6] glmer () function for logistic regression with mixed effects.

3 Results

For mathematics learning ("Integral Expression"), the teacher made 619 instructional decisions. Among the decisions, the teacher taught RtL skills 238 times, and the students mastered them 63% of the time. The teacher taught UtL skills 208 times, and the mastery rate was only 46%. Already-mastered skills were taught 173 times, with a mastery rate of 80%. Note that the mastery rate of these already-mastered skills was well below 95% even though the algorithm had previously assessed the skill as mastered with over 95% confidence. This may be due to the probability of slipping, or forgetting the skill after it had been learned.

For English grammar learning ("Pronoun and Noun"), the teacher made 721 instructional decisions. Among the decisions, the teacher taught RtL skills 86 times, and the students mastered them 64% of the time. The teacher taught UtL skills 497 times, and the mastery rate was only 39%. Already-mastered skills were taught 138 times, with a mastery rate of 79%. As mentioned above, forgetting or slipping may lead to an actual mastery rate that is lower than 95%.

Logistic regression analyses and sensitivity analyses confirmed that instructional decisions were significantly associated with students' learning outcomes, $p<0.001$ for both topics. Students who were taught a ready-to-learn skill were 4.34 times more likely to master an English grammar skill, and 2.78 times more likely for math.

4 Discussion and Conclusions

In a teacher-driven personalized learning environment, teachers decide which content to assign to students based on the student's performance data. However, simply providing teachers with data is not always sufficient for good instructional decision making. This paper investigates whether knowledge graphs can be used to inform and improve teacher instructional decisions within an online learning platform, in terms of Vygotsky's Zone of Proximal Development. A knowledge graph algorithm is applied to assess whether teachers assign content that a student is ready-to-learn (RtL), unready-to-learn (UtL), or already-mastered. We find that mastery is higher when teachers assign RtL skills than UtL skills, though not quite as high as if the teacher decides to re-teach a skill that the student already mastered. These findings, which generalize to both English and math, suggest steps we can take to optimize student learning outcomes and teacher decision making. Optimizing learning outcomes requires correct teaching decisions that lead students on the right path, based on the student's ZPD. As such, it would be beneficial to create an interface to communicate what students are ready to learn to teachers, and what evidence this recommendation is based on. This can be accomplished by displaying knowledge graphs showing how the system's recommendation of a skill is generated based on performance on prerequisite skills. Teacher training could emphasize the importance of using the ZPD to personalize learning and how to use knowledge graph recommendations in instructional design. While a knowledge graph may not provide a perfect operationalization of Vygotsky's ZPD, it can offer teachers information that they can use to better support student learning.

References

1. Baker, R., Wang, F., Ma, Z., Ma, W., Zheng, S. (2018) Studying the Effectiveness of an Online Language Learning Platform in China. *Journal of Interactive Learning Research, 29* (1), 5-24.
2. Bienkowski M, Feng M, Means B (2012) *Enhancing teaching and learning through educational data mining and learning analytics: an issue brief.* Washington, D.C.: Office of Educational Technology, U.S. Department of Education; 2012, 1–57.
3. Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User modeling and user-adapted interaction*, *4*(4), 253-278.
4. Earl, L., & Katz, S. (2002). Leading schools in a data-rich world. In K. Leithwood & P. Hallinger. (Eds.), Second international handbook of educational leadership and administration. (pp. 1003-1022). Dordrecht, Netherlands: Kluwer Academics.
5. Feng, M., & Heffernan, N. T. (2006). Informing teachers live about student learning: Reporting in the assistment system. *Technology Instruction Cognition and Learning*, *3*(1/2), 63.
6. Gilbert, S. W. (2000). A widening gap: the support service crisis. *Syllabus*, 14(1), 18–57.
7. Holstein, K., McLaren, B. M., & Aleven, V. (2017). Intelligent tutors as teachers' aides: exploring teacher needs for real-time analytics in blended classrooms. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 257-266). ACM.
8. Jonassen, D. H. (1993). Thinking technology: context is everything. *Educational Technology,* 31(6), 35–37.
9. Oliver, R., & Omari, A. (1999). Using online technologies to support problem-based learning: learners responses and perceptions. Australian J. of Educational Technology, 15(1), 58–79.
10. Porayska-Pomsta, K. (2016). AI as a methodology for supporting educational praxis and teacher metacognition. *Int'l Journal of Artificial Intelligence in Education*, *26*(2), 679-700.
11. Mandinach, E. B., & Jackson, S. S. (2012). *Transforming teaching and learning through data-driven decision making.* Thousand Oaks: CA: Corwin Press.
12. McLaren, B. M., & Aleven, V. (2017). Intelligent tutors as teachers' aides: exploring teacher needs for real-time analytics in blended classrooms. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 257-266). ACM.
13. Murray, T. & Arroyo I. (2002). Toward Measuring and Maintaining the Zone of Proximal Development in Adaptive Instructional Systems. *Int'l. Conf. Intelligent Tutoring Systems.*
14. Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes.* Massachusetts: Harvard University Press.