The Results of Implementing Zone of Proximal Development on Learning Outcomes *

Ryan Baker
University of Pennsylvania
ryanshaunbaker@gmail.com

Wei Ma
Renmin University of China
mawei@ruc.edu.cn

Yuxin Zhao
Learnta Inc
zhaoyuxin@learnta.com

Shengni Wang
Learnta Inc
wangshengni@learnta.com

Zhenjun Ma
Learnta Inc
will@learnta.com

ABSTRACT
With the development of personalized learning in technological platforms, more data and information are given to instructors on what contents are appropriate for a learner's next step, with an aim of helping them support their students in navigating an optimized learning path that can promote an enhanced learning outcome. In this study, we collected data from an online learning platform, Learnta® TAD , which allows teachers to distribute tasks based on system recommendations. The recommendations are directed by the system's knowledge graph algorithm, determining whether the student is ready to learn the task (i.e. the task is within the student's Zone of Proximal Development), whether the student is not yet ready to learn the task, or whether the student has already mastered the task. We used the acquired data to investigate whether giving content in each of these groups results in different learning outcomes. Statistical methods such as subgroup analysis, Fisher's exact test, and logistic regression are conducted to address the proposed topic. Replicating a prior, smaller-scale study, our findings suggest that the student gains more mastery when assigned Ready-to-Learn tasks than when assigned Unready-to-Learn tasks, across Math and English, more and less successful students, and in-class and homework. Moreover, students who are given already mastered tasks perform better than those who are given Ready-to-Learn and Unready-to-Learn tasks across all groups.

Keywords
Zone of Proximal Development · Knowledge Graph · Ready-to-Learn · Unready-to-Learn

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Shengni Wang, Yuxin Zhao, Wei Ma, Zhenjun Ma and Ryan Baker "The Results of Zone of Proximal Development on Learning Outcome" In: *Proceedings of The 13th International Conference on Educational Data Mining (EDM 2020),* Anna N. Rafferty, Jacob Whitehill, Violetta Cavalli-Sforza, and Cristobal Romero (eds.) 2020, pp. 749 - 753

1. INTRODUCTION
Increasingly, teachers' decisions are driven by data [3], with increasing data becoming available from online learning environments [9]. Using reports from online learning systems, educators are able to track and evaluate each student's learning based on data [1]. However, even though data are given to teachers by these systems, instructors are still impeded by having insufficient knowledge about how to use the data [7]. In other words, teachers still have difficulties in using data effectively to decide what students need to learn next, to maximize learning outcomes and expedite the learning process.

This problem is exacerbated in online learning systems that give relatively more agency to teachers in choosing which content their students will work with. Although such systems are easier to integrate with existing pedagogical practices, they raise questions as to whether teachers will assign the best possible content. We can consider this decision in terms of whether a teacher selects content that falls within a learner's zone of proximal development (ZPD) [8]. A task within a learner's ZPD is one that he or she can succeed in, but only with external support or scaffolding. Tasks that a learner can succeed in without support, and tasks that a learner cannot succeed in even with support, fall outside of the learner's ZPD. Although the ZPD has been a popular concept in the educational literature for decades, only limited attention has been paid to ZPD in educational data mining and related communities [4].

However, recent research has found evidence that Vygotsky's concept of the ZPD can be beneficial to the design of adaptive learning systems [10]. In that work, Zou and colleagues investigated whether teachers make good instructional decisions based on student performance data. They compared "Ready-to-Learn" (RtL) content inside the ZPD to content that students were "Unready-to-Learn" (UtL), using automated assessments of student progress through a curriculum based on a knowledge graph.

We replicate and build on this work with a larger student sample, assessing whether a task is RtL for a specific student using the prerequisite structure within a knowledge graph. Our hypothesis is that, like in [10], students will gain more mastery (successfully complete more objectives within the system) if they are assigned RtL tasks instead of UtL tasks. We also investigate whether the findings in [10] are robust to whether the student is completing tasks as homework as opposed to in class. We hypothesize that students working on content in class will gain more mastery than students completing tasks as homework, due to the availability of greater learning support and scaffolding in an in-class context [6]. We also investigate whether the findings in [10] are robust to the general level of success of the student. If some students are simply faster or better learners than others in a domain (e.g. [2]), then they may be able to perform better even when given UtL. However, one could also argue that if the knowledge graph is correct, then all students should have similar (poorer) outcomes for UtL content, since regardless of their general ability they lack the building blocks to acquire the content they are given. Finally, we investigate whether the results in [10] are robust across two different learning subjects, English and Mathematics.

2. THE ONLINE LEARNING PLATFORM

The system used in this study is a learning platform for K-12 students in China, called Learnta® TAD, developed by Learnta Inc.. Learnta® TAD, an acronym of "Teacher + Artificial Intelligence + Data", is a system which gives teachers data on student learning progress and makes recommendations on optimal learning path using AI algorithms, and then allows teachers to decide which content students should work on. Learnta® TAD is primarily used in blended learning, where teachers give students face-to-face instructions in classroom.

Figure 1: Teacher's Interface of Learnta® TAD system

In TAD, teachers assign learning tasks that contain several target skills to the students. The system infers each student's mastery of each skill using Bayesian Knowledge Tracing (BKT) (Corbett & Anderson, 1995) by predicting the student's latent knowledge state according to the student's correctness on questions related to the skills. Learnta's directed knowledge graph maps content to a prerequisite structure, representing which prerequisite content is necessary to know to learn a particular piece of content. Based on the mastery of the student and the prerequisite structure of each skill, Learnta® TAD recommends RtL contents for teachers to instruct. More specifically, content is considered RtL if the student has mastered all the prerequisites of that skill; UtL indicates that the student is missing one or more of a skill's prerequisites. Whether or not the teachers choose to follow the recommendations, the system collects data on the students' performance and learning outcomes. Teachers can assign material that is RtL, UtL, or even Already Mastered (AM).

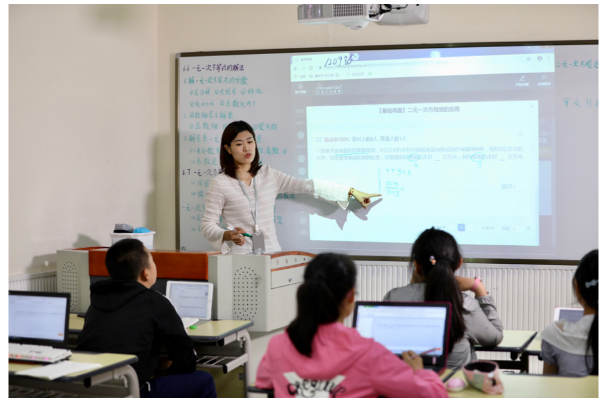

Figure 2: Teacher using Learnta® TAD in classroom

3. DATA COLLECTION

To investigate our research questions around ZPD status and students' learning outcomes, we collected data from 7913 middle school and elementary school students who studied 250,783 task cards (one task card contains several skills) in Learnta® TAD, during 2019.

In the context of both English and Math, we categorized students into different levels based on their earlier assessment test performance: 1) Excellent students; 2) Normal students; 3) Struggling students. Excellent students are those who mastered at least 80% of the skills in the assessment, according to Bayesian Knowledge Tracing. Normal students are those who mastered at least 60% but less than 80% of the skills in the assessment. Struggling students are those who mastered less than 60% of the skills in the assessment. The proportion of these three student categories is 32.39%, 53.78% and 13.83%, respectively.

In addition to that, we compare the use of the system in a classroom setting to its use as homework. In-class, students complete the assigned tasks under the supervision of their teachers during a class session. Within the homework context, students are expected to complete their tasks at home. The percentage of these two scenarios are 57.5 % and 42.5 %, respectively.

4. STATISTICAL ANALYSIS

We compare the learning outcomes of teachers' decisions of what skills the student should work on. The analyses are conducted on two topics - Math and English - separately. The outcome of interest is whether the student mastered the skill according to BKT. The percentage of skills that are mastered are tabulated for each type of teaching decisions: RtL, UtL, and AM.

In addition to descriptive statistics, we conduct Fisher's exact test to assess the association between instructional decisions and student mastery. Our hypothesis is that students are more likely to master RtL skills than UtL skills.

In addition, a logistic regression model is used, with learning outcome as the independent variable, and teacher's decision, student's level, and whether learning occurs in a classroom as predictors.

P values are calculated in R version 3.6.3 using the fisher.test() function for Fisher's exact test and the glm() function for logistic regression.

5. RESULTS

For the tasks in Math, the completion rates were 76.5%, 70%, and 65%, respectively, for the excellent, normal and struggling students. The completion rates were 79%, 72%, and 66.5% in English. Those findings indicate that the students' completion rates vary depending on overall student success, χ^2(df = 2, N = 93874) = 650.29, p < 0.001 for Math and χ^2(df = 2, N = 146127) = 1465.87, p < 0.001 for English.

The completion rates for in-class tasks were 75.7% for Math and 74.7% for English, and for homework tasks the completion rate were 65.3% for Math, and 70.3% for English (see Figures 3 and 4). Fisher's exact tests show the in-class tasks were more likely to be completed than the homework tasks for both Math (p < 0.001) and English (p < 0.001).

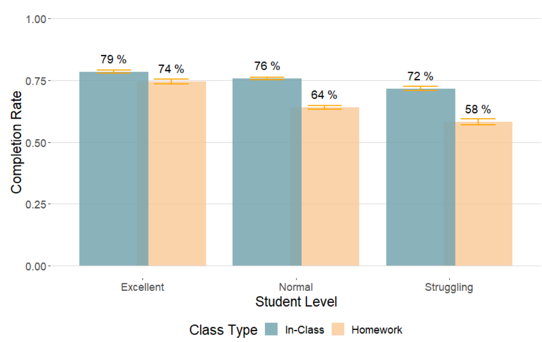

Figure 3: Completion Rate in Math

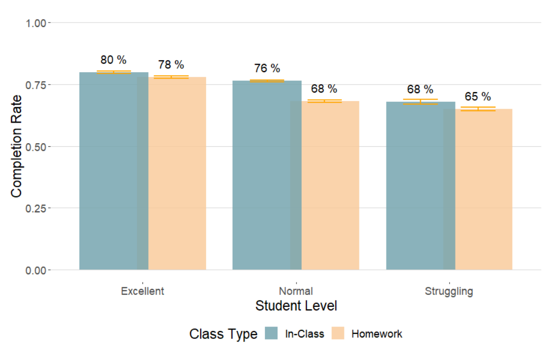

Figure 4: Completion Rate in English

The mastery rates by subject and student success level are presented in Figures 5 and 6. We conducted the Fisher's exact tests and it demonstrated that the excellent students had a better performance in terms of mastery rates compared to the normal students (Math, 68.6% vs. 52.1%, p < 0.001; English, 63.6% vs.54.7%, p < 0.001). The mastery rates were much lower for the struggling students (Math, 36.9%, p < 0.001; English, 11.9%, p < 0.001).

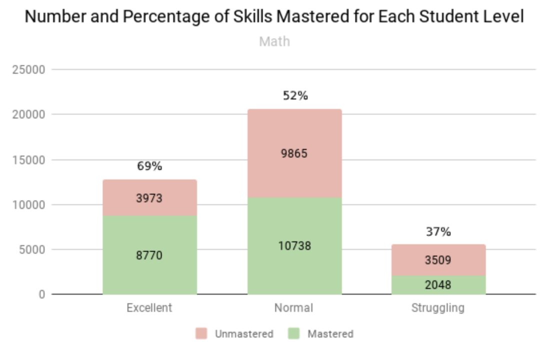

Figure 5: Mastery in Math subject

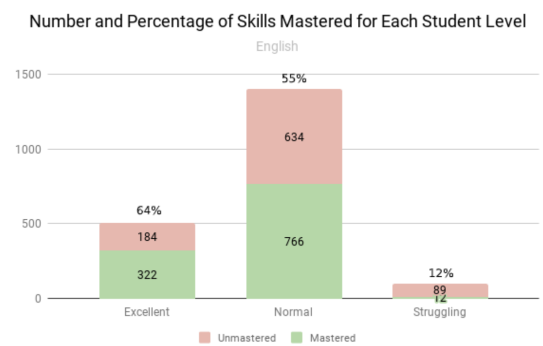

Figure 6: Mastery in English subject

Figures 7 and 8 show that the average mastery rate of RtL tasks was significantly higher than that of UtL tasks, p < 0.001 for each of the three student success levels in each subject, using Fisher's exact test.

The logistic regression provided further evidence that ZPD status was associated with students' learning outcome (F(2, 38891) = 119.85, p < 0.001 for Math and F(2, 1996) = 30.74, p < 0.001 for English), with adjustment for task type and student success levels. In particular, a RtL task was more likely to be mastered than a UtL task (Math, OR = 1.710, p < 0.001; English, OR = 7.709, p < 0.001), but was less likely to be mastered than an AM task (OR = 0.241, p < 0.001 for Math and OR = 0.185, p < 0.001 for English). Moreover, the logistic regression also suggested that students were more likely to master a math skill in class compared to homework (t(38891) = 2.676, p = 0.007), while the mastery rates of English skills were similar between the two settings (t(1996) = 0.706, p = 0.480).

Moreover, interaction terms were added to the logistic regression model in order to test the hypothesis that the relationship between ZPD status and learning outcome was

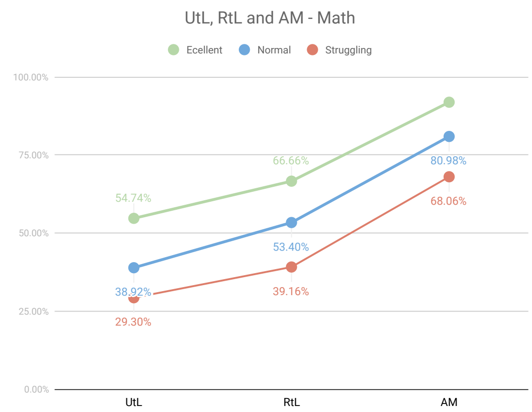

Figure 7: ZPD v.s Mastery in Math subject

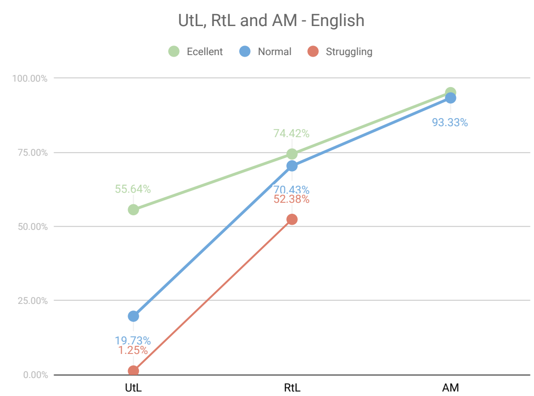

Figure 8: ZPD v.s Mastery in English subject

different for students with various success levels (i.e., excellent, normal, struggling), It turned out that, within the subject Math, the improvement on learning outcome associated with RtL status were comparable among the three student groups ($F(2, 30664) = 4.374$, $p = 0.126$), which was consistent with the observation that three lines corresponding to different success levels are almost parallel in Figure 7. Within the English subject, however, the analysis results indicated an interaction effect between RtL status and student success levels ($F(2, 1587) = 8.763$, $p < 0.001$): the excellent students tended to benefit less from being assigned a RtL task instead of a UtL task than either normal students ($p < 0.001$) or struggling students ($p = 0.002$). The conclusion with respect to AM tasks was less clear because there were fewer struggling students to begin with.

Lastly, we did not find statistical evidence for there being an interaction effect between ZPD status and whether the system was used in class or as homework ($t(38891) = -0.282$, $p = 0.778$ for Math and $t(1996) = 1.859$, $p = 0.063$ for English). This suggests that it is likely important to assign RtL content to students regardless of which setting the system is used in, although it may be warranted to continue investigating whether RtL content has more benefit for students studying English in class, based on the marginally significant p value in that analysis.

6. DISCUSSION & CONCLUSION

In the light of these results, we can re-consider our original research questions. We hypothesized that, as in [10], students would master more tasks if presented with content thought to be in their ZPD (Ready-to-Learn content) than content outside of their current ZPD (Unready-to-Learn content). Our findings are compatible with this hypothesis, providing a replication of the earlier work in [10]. We also find that this pattern replicates across two domains, Math and English.

Our second hypothesis was that students would have higher mastery rates in class than when completing homework; this hypothesis was upheld for math subject but not upheld for English subject. Our finding is that students were slightly more likely to master a math skill in class than as a homework, while the mastery rates of English skills was comparable between the two contexts. This finding may suggest that the learning support within the platform was more effective than anticipated; alternatively, it may be that the instructors using the platform in their classes have not yet learned effective pedagogies for teaching students using this type of technology. Effective teaching in these contexts involves different pedagogies than are necessary within traditional classrooms [6], and there is increasing evidence that many teachers do not adopt these pedagogies until their second year of teaching with a new technology [5].

Our third research question asked whether generally more successful students would perform better than other students, even for content seemingly outside their zone of proximal development. In line with past work by Liu and Koedinger (2015) [2], it seemed that these more successful students were more able to succeed, even on this content that was anticipated to be highly difficult. However, they still performed more poorly on this content than on content thought to be in their ZPD.

Overall, these results suggest that assigning content with regards to a student's zone of proximal development can lead to a higher probability of the student mastering the content they are given. This result, a replication of [10], appears to hold in more than one learning domain. However, there are several important areas of future work before this finding can truly be held to be robust. First, this finding should be replicated in a broader range of contexts – other learning systems, other learning domains, and a wider range of learner populations and countries. Second, it is probably warranted to look at other definitions of the ZPD to refine this finding – is there an optimal degree of prior mastery for assignment of a student within the knowledge graph? Would alternate definitions of ZPD, such as seen in Murray and Arroyo's work (2002)[4], be equally or more effective? Does this type of finding also hold within systems where content is not consolidated into skills but is more factual in nature? By learning the answer to these questions, we can improve the effectiveness of adaptive learning systems more broadly, while helping to better operationalize and understand one of the classic theories in the history of thought on education.

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