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Tracking Knowledge for Learning Japanese as a 2nd Language

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Abstract: Most educational technologies for teaching language skills give students the same learning experience based on the assumption that every student learns at the same rate. In order to provide more individualized instruction we need to track student knowledge at a fine-grained level. This research explores how to add the ability to track knowledge in an existing educational technology system for Japanese second language learners. We explore several potential skill models based on the features available in the system and then apply a Bayesian knowledge tracing algorithm. We also make a large dataset for Japanese language learning available with no previous applied knowledge tracing.

Keywords: Knowledge Tracing, Skill modeling, 2nd Language Learning, Japanese

1. Introduction

This research is focused on improving the tracking of student second language learning knowledge from an existing question based training system for Japanese as a second language. Using established knowledge Tracing (KT) techniques, we were able to calculate the best fitting knowledge model and were able to show that by adding adaptive instruction, we could save learners from completing thousands of problems in the system that they have already mastered, allowing them to focus on skills that go unmastered.

The use of educational technology systems, such as online courseware and digital learning platforms, have been shown to be effective in helping learners acquire a second language (Webb & Doman, 2020). Research has shown that repeated practice is a key factor in successful second language learning, and many educational technology systems provide multiple opportunities for learners to practice and use the new words and skills they are learning (Nakata, 2017). Timely and corrective feedback is also an important feature of educational technology systems for second language learning, as it helps learners to identify and correct errors in real-time (Han, 2019). By leveraging adaptivity in these second language learning systems, the corrective feedback and multiple practice opportunities provided to students can be made more effective for their learning (Webb & Doman, 2020). One such way to enable this adaptivity is through KC Modeling, which not only enables adaptivity, but it also provides a way to accurately measure student knowledge. KCs are fine-grained representations of knowledge that include constraints, schemas, and production rules (Stamper & Koedinger, 2011). The KCs are typically mapped to every step of a problem, which is associated with an action the student needs to take in order to solve the problem. Each problem step provides an opportunity for students to demonstrate their mastery of the associated KCs. This mapping of KCs to the problem steps is known as a knowledge component model (KCM) and needs to be accurately designed to model student learning (Stamper and Koedinger, 2012). The use of knowledge tracing (KT) to model student learning through the progression of KCs has been proven effective in the domain of language learning (Rizvi et al., 2022). Bayesian Knowledge Tracing (BKT) is a widely used KT algorithm, which uses parameters for learning rate, along with guess and slip parameters (Corbett & Anderson, 1994). This model is used in many intelligent tutoring systems and works for any domain.

2. System and Data Collection

The edtech system used in this study is designed to quiz Japanese second language learners and is focused on paired intransitive and transitive verbs. In the Japanese language, these verbs share a stem and have pairs with each other (e.g. あつめる(atsu-meru; gather something) and あつまる (atsu-maru, people gather)). The differences of those paired intransitive and transitive verbs are basically sentence structure and the particles used with them. Intransitive verbs have the subject while the transitive verbs do not require the subject. Even if Japanese language learners master those verbs at the beginner level, they are often common mistakes from intermediate or advanced level students as they progress (Okimoto, 2021). Since it is often difficult for Japanese language learners to master those paired verbs, Japanese language teachers often have difficulty building on these concepts without first addressing the difficulties students encounter (Nakaishi, 2020).
For the present study a total of 448 items were used in a 5-week course of online study, which intermediate level Japanese language learners joined. Participants answered a total of 50 questions per access, one access per day, five days a week. For the five item types, ten items were randomly selected. The average completion time for 50 items was approximately between 20 to 30 minutes. Items were given randomly and each item appeared 65 to 140 times in a 5-week period. Corrective feedback would appear after the student answered each item. There are two types of feedback, one for correct answers, the other for incorrect answers paired with explanations and correct answers.

The participants in this study were Japanese language learners who were enrolled in courses equivalent to the late intermediate to early advanced levels at an institution of higher education in Tokyo. There were 41 participants, 10 of whom were in the control group who took only the pre-test and post-test, and 31 in the experimental group who took the pre-test, 5-week online study, and post-test. Both the control group and the experimental group joined the Japanese language course at the institution. The breakdown of native languages was 25 Chinese native speakers, 5 Korean native speakers, 8 English native speakers, and 3 speakers of other Asian languages (Tagalog, Vietnamese, and Indonesian). The item dataset consists of 448 items, testing beginner and intermediate level paired intransitive and transitive verb usage of Japanese language learners. There are additional categorizations of the items: vocabulary difficult, JLPT-level, Intransitive or Transitive verb, Teramura verb (Teramura 1990), and motion verb. The vocabulary difficulty and JLPT-level are determined by the Matsushita database (Matsushita 2011). Teramura is either 0 or h, depending whether the verb is in the Teramura verb set. In the case that the target verb is in the Teramura dataset, it is labeled “h”, if it is not present in the dataset, it is labeled “0”. Lastly, motion verbs, 0 or m, describe whether the verb in the item is a motion based verb, a verb-type Japanese second language (JSL) learners have difficulty with.

3. Skill Models and Knowledge Tracing

Initial KCMs were created by using the features of the items in the system. We report the fit of five identified KCMs by Bayesian Information Criteria (BIC) and Item Blocked Root Mean Squared Error (IB RSME) in Table 1. BIC is a model comparison metric that is widely used to compare skill models in intelligent tutoring systems (Liu et al, 2016) and adds a penalty for the complexity of a model (Stamper et al., 2013). We use BKT to identify the number of opportunities that students need to reach mastery in each knowledge component, with the 22 KC model, which was the best by BIC. A student is considered as mastering a KC if their inferred mastery of this KC at the final attempt is at least 90% (Corbett & Anderson, 1994). Based on this notion, we found that all but 4 students mastered all 22 KCs where they were given at least 30 or more opportunities on a given KC. Most of the KCs were mastered rather quickly suggesting that students are given more opportunities than they actually need and that adding adaptivity could improve learning time considerably. With the application of KC modeling and addition of Knowledge Tracing we show that we can more precisely track learning in our language questioning system.

Table 1. Proposed Skill Models based on the identified features evaluated by DataShop.

Model Name	KCs	BIC	IB RSME
beginner-JLPTlevel-itemtype	22	**27,963***	0.330442
item_type	5	27,975	**0.32979***
beginner-JLPTlevel-itemtype-Teramura-motion	85	28,242	0.330839
beginner-JLPTlevel	5	28,456	0.332392
question_item_data	448	32,920	0.334551

Our next step is to use the KT to provide feedback to the students. A longer term goal is to add true adaptivity and intelligent tutoring capabilities to our language system in order to improve the learning efficiency of students using the system (saving thousands of problems). While this initial exploration was over several KC models with BKT for knowledge tracing, we plan to do more by exploring additional KT algorithms and run some pilot tests using the models and algorithms for adaptivity. Further, we have made the dataset available here in DataShop (Koedinger et al., 2013) https://pslcdatashop.web.cmu.edu/Project?id=83, and hope others will also take advantage of this dataset that currently has many student attempts and no models or algorithms underlying the order of questions to the learners.

References

Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User modeling and user-adapted interaction*, 4(4), 253-278.

Han, Y. (2019). Written corrective feedback from an ecological perspective: The interaction between the context and individual learners. *System*, 80, 288-303.

Koedinger, K. R., Stamper, J. C., Leber, B., & Skogsholm, A. (2013). LearnLab's DataShop: A Data Repository and Analytics Tool Set for Cognitive Science. *Topics in Cognitive Science*, 5(3), 668-669.

Liu, R., Davenport, J., & Stamper, J. (2016). Beyond Log Files: Using Multi-Modal Data Streams towards Data-Driven KC Model Improvement. *International Educational Data Mining Society*.

Nakaishi, Y. (2020). Second Language Acquisition Research on Japanese Paired Imperative and Transitive Verbs. *Tokyo, Japan-China Language and Culture Publishing*.

Nakata, T. (2017). Does repeated practice make perfect? The effects of within-session repeated retrieval on second language vocabulary learning. *Studies in Second Language Acquisition*, 39(4), 653-679.

Matsushita, T. (2011). "Vocabulary Database for Reading Japanese (VDRJ) Ver. 1.1" <http://www17408ui.sakura.ne.jp/tatsum/database.html>, viewed August 12, 2018

Okimoto, T. (2021). Misuse Trends in Paired Intransitive and Transitive Verbs Comparison of two corpora from different time periods. *The Hitotsubashi journal for Japanese language education*. 10, 25-38.

Rizvi, S., Gauthier, A., Cukurova, M., & Mavrikis, M. (2022). Examining Gender Differences in Game-Based Learning Through BKT Parameter Estimation. In *International Conference on Artificial Intelligence in Education* (pp. 600-606).

Stamper, J., Koedinger, K., & Mclaughlin, E. (2013, July). A comparison of model selection metrics in datashop. In *Educational Data Mining 2013*.

Stamper, J. C., & Koedinger, K. R. (2011, June). Human-machine student model discovery and improvement using DataShop. In *Artificial Intelligence in Education* (pp. 353-360).

Teramura, H. (1990). A Collection of Examples of Japanese Misuse by Foreign Learners, Osaka University (PDF version National Institute for Japanese Language and Linguistics 2011)

Webb, M., & Doman, E. (2020). Impacts of flipped classrooms on learner attitudes towards technology-enhanced language learning. *Computer Assisted Language Learning*, 33(3), 240-274.