Industry Track

Dropout Prediction in Home Care Training

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ABSTRACT

In Washington state (WA), SEIU 775 Benefits Group provides basic home care training to new students who will deliver care and support to older adults and people with disabilities, helping them with self-care and everyday tasks. Should a student fail to complete their required training, it leads to a break in service, which can result in costly negative health outcomes (e.g. emergency rooms and hospitalization) for their clients [1].

In this paper we describe the results of utilizing machine learning predictive models to accurately identify students who exhibit a higher risk of drop out in two areas: (1) dropping out before attending first class[first class attendance]; and (2) dropping out before completing the training[training completion]. Our experimental results show that AdaBoost algorithm gives a useful result with ROC_{AUC} = 0.627±0.013 and Precision at 10 = 0.73±0.12 for first class attendance and ROC_{AUC} = 0.680±0.024 and Precision at 10 = 0.67±0.20 for training completion without relying on additional assessment data about students. In addition, we demonstrate the use case for constructing larger decision trees to help front-line training operations staff identify intervention strategies that create the most impact in preventing dropout.

1. INTRODUCTION

By 2050, the number of Americans needing long-term home care services and supports will double[2], implying increased demand for workers providing home care services (called "personal care aides" nationally and "home care aides (HCA)" in WA). This will also increase the demand of training for HCAs to provide quality care to their clients. In WA, should an individual wish to work as a home care aide, they are required to complete a 75 hour, 2 week, Basic Training (BT) course within 120 days of their hire date. In WA, an HCA can begin providing care before completing their training as long as their deadline has not passed. In the event that an HCA fails to complete BT, she or he will fall out of compliance, leading to the HCAs termination and a break in service for the clients served by the HCA [1].

Educators have frequently used assessment tools that measure cognitive skills, engagement, self-management and social support to accurately predict student successes. However, conducting assessments at scale is time consuming for both students and instructors. In the absence of a validated assessment specific to HCA profession, there is great interest in utilizing existing learning data to isolate the strongest predictors of dropout through the predictive power of machine learning algorithms. Our research questions are two-folds: 1) Can machine learning algorithms successfully predict student dropouts? 2) What are the risk factors related to early dropout from basic home care training?

Many studies[3] have been conducted to explain academic performance and to predict the success or failure across a variety of students in a wide-range of educational settings. Machine learning algorithms have been successful in predicting graduation[4], course participation[5], and other academic outcomes[6].

However current research has not fully investigated the area of using machine learning algorithms for on-the-job training, healthcare training programs, or adult education in general. In this paper, we focus on the dropout problems in home care training using machine learning methods. We were granted the latitude to be creative with our feature engineering, utilizing readily available data to meet business requirements.

2. EXPERIMENTAL SETUP

Figure 1 illustrates the four sequential time-based milestones in home care training: 1) Complete Orientation & Safety (O&S); 2) Register for a 70-hours BT course; 3) Attend the first class in this course; 4) Complete the 70-hour training. At the moment that a prospective home care aide enters the system, a 'Tracking Date' is assigned to their O&S training

*This work has been done during the author's internship at SEIU 775 Benefits Group

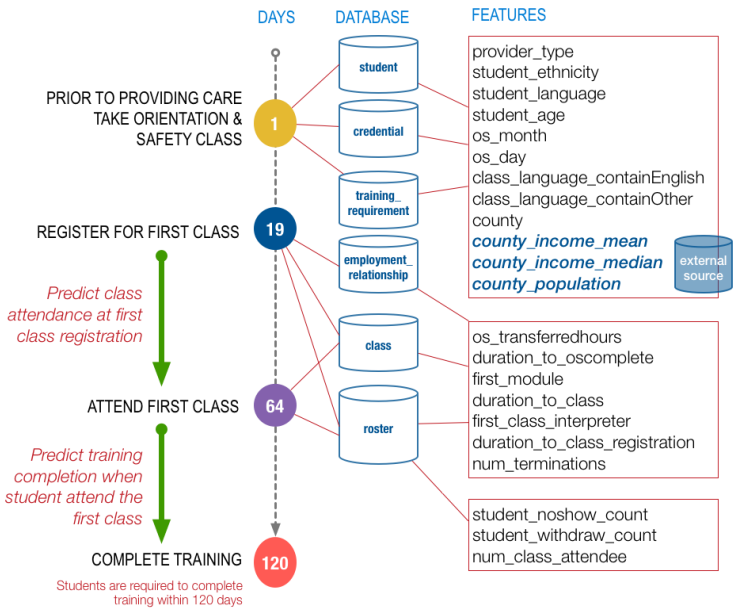


Figure 1: Predicting Targets and Features

requirement, signifying the start of their training journey. On average a student will register for his or her first class approximately 19 days after completing O&S and will actually attend his or her class about 64 days after entering our system.

Predicting dropouts at different stages has the potential to allow for timely interventions that may improve a students' learning experience. This paper focuses on two stages: First, **Class Attendance**: Will the newly hired students show up for their first scheduled class? We attempt to predict this at the point of registration. Second, **Training Completion**: Will a student complete all 70 hours of their required training? We attempt to predict this at the point that a student attends his or her first class. As shown in Figure 1, some basic but sometimes incomplete student demographic data are captured at the time a student is assigned to take O&S training. As a student progresses in his or her training journey, we are able to extract more features about learning behavior, such as the amount of time a student needed to complete O&S or the number of days it took a student to register for class. In addition, we leveraged external government census data to augment the existing feature set by adding income and population data of the student's county of residence.

We built four models – Logistic Regression, SVM, Random Forests, and AdaBoost – for the two predicting targets described above. Our final data set contained 5,303 records for predicting first class attendance and 5,182 records for predicting training completion. For both predicting targets, we reserved 2,000 records for testing data set and the remaining were utilized as the training data set. We collected 22 features to predict class completion and used the first 19 features to predict first class attendance(the last three features are not available at our prediction point of registration). Table 1 summarizes the features we used for the model.

3. EXPERIMENT RESULTS

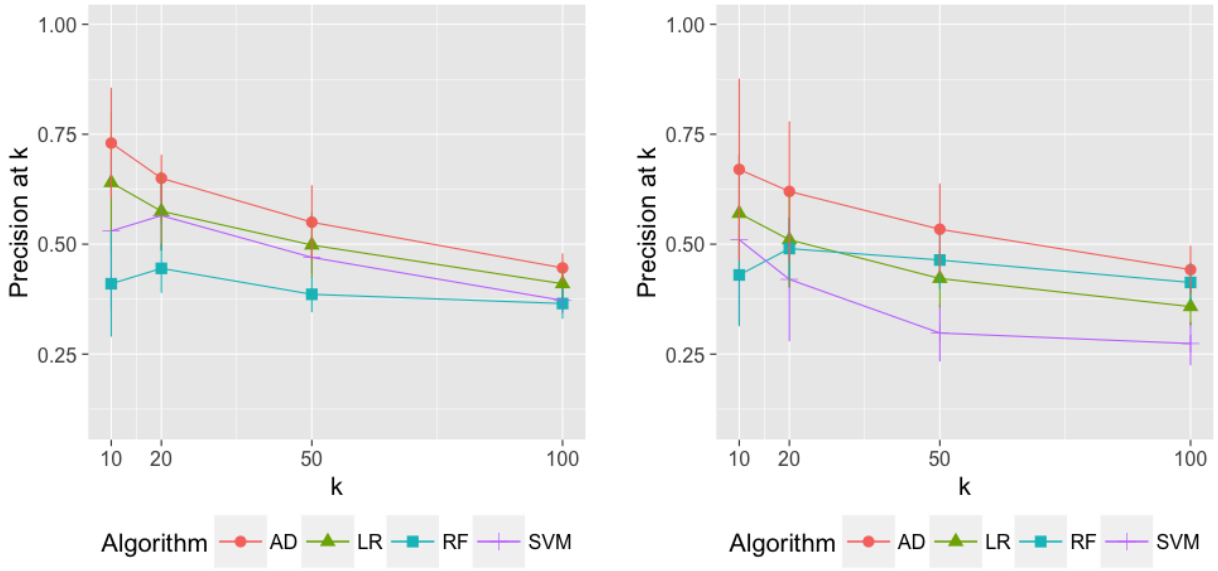
3.1 Prediction Performance: ROC-AUC and Precision at k

We use area under curve of the receiver operating characteristic (ROC_{AUC}) and precision at k (Prec@k) to evaluate prediction quality of each machine learning technique. ROC_{AUC} was used as a standard evaluation metric to measure the quality of overall ranking results. Prec@k was used to determine the quality of predicting the top k outcomes, in our case, the top k students of highest drop out risk at each stage. It is assuming that, with limited resources, front-line staff could only outreach to k number of students per week to provide support and assistance to HCAs struggling to meet their individual learning needs. Therefore, it is essential to accurately predict the first k students exhibiting the highest dropout risk.

Figures 2a and 2b depict the prediction results of our 4 models articulated by precision at k. The AdaBoost model gives the best prediction result for both targets. For predicting first class attendance, AdaBoost with tree number = 2000 has the highest precision at 10 which equals to 0.73 and AdaBoost with tree number = 1000 gives the best precision at 20, 50, 100 which equals to 0.67, 0.56 and 0.46 respectively. For predicting BT completion, AdaBoost with tree number = 100 gives the best precision at 10, 20, 50, 100, which equals to 0.67, 0.62, 0.53, 0.44 respectively. As there are more students who did not attend the first class (385/2000

Table 1: Features used for class attendance and training completion prediction

Feature	Type	Remarks
provider_type	Nominal	Individual provider (paid by the Department of Social and Health Services) or agency provider (paid by private home care agencies). {IP, AP}
student_ethnicity	Nominal	student ethnicity. {Asian Indian, White etc}
student_language	Nominal	student language. {English, Russian, etc}
student_age	Numerical	student age. {Mean = 39, Median = 37}
os_month	Numerical	Month of O&S tracking date. {1,2,$\cdots$,12}
os_day	Numerical	Day of O&S tracking date {1,2,$\cdots$, 31}
class_language_containEnglish	Boolean	Whether the student's profile includes an English language selection. {Yes, No}
class_language_containOther	Boolean	Whether the student's profile includes a language other than English.{Yes, No}
county	Nominal	student's county of residence {King County, Pierce County,etc}
county_income_mean	Numerical	The mean income(in USD) for the county.{mean = 67011, median = 65498}
county_income_median	Numerical	The medium income(in USD) for the county. {mean = 55468, median = 54727}
county_population	Numerical	The population for the county. {mean = 28672, median = 29582}
os_transferredhours	Numerical	Transferred hours for O&S. {mean = 0.9965, median = 0}
duration_to_oscomplete	numerical	Duration(in number of days) beween O&S completion date and O&S tracking date.{mean = 0.842, median = 1.500}
first_module	Nominal	The module of first registered class {Module 1, Module 2,..., Module 20, etc}
duration_to_class	Numerical	Duration(in number of days) between class date and O&S tracking date.{mean=72.05, median = 67.42}
first_class_interpreter	Boolean	Whether the student articulated a need for interpreter services.{Yes,No}
duration_to_class_registration	Numerical	duration(in number of days) between class registration date and O&S tracking date.{mean = 32.647, median = 19.784}
num_terminations	Numerical	Number of terminating employment relationships before attending first class.{0,$\cdots$,7}
student_noshow_count	Numerical	Number of class absences before attending the first class. {0,$\cdots$,58}
student_withdraw_count	Numerical	Number of class withdrawals before attending the first class. {0,$\cdots$,60}
num_class_attendee	Numerical	Number of attendees in the first class. {3,$\cdots$,33}



(a) Precision at k for first class attendance

(b) Precision at k for training completion

Figure 2: Precision at k results

ROC_{AUC}		
Model	1st Class Attendance	Training Completion
SVM(radial)	0.578±0.012	0.600±0.011
LR	0.612±0.020	0.634±0.018
AD(1000)	0.627±0.013	0.673±0.025
AD(2000)	0.626±0.015	0.680±0.024
RF(2000)	0.608±0.012	0.672±0.023

Table 2: ROC_{AUC} results

= 19.25%) than the number of students who did not complete the training (229/2000 = 11.45%), it was slightly easier to predict top k students who were likely to not show up for their first class and explains the higher Prec@k for predicting class attendance.

Table 2 shows ROC_{AUC} results. For predicting first class attendance, AdaBoost with tree number = 1000 gives the best ROC_{AUC} at 0.627. For predicting BT completion, AdaBoost with tree number = 2000 gives the best ROC_{AUC} at 0.68. Low ROC_{AUC} indicates the need for stronger inputs and feature attributes to the models. Although 19 out of 22 attributes were shared in both predicting problems, attributes such as duration to class registration, duration to class and first module were more useful in predicting BT completion than in predicting class attendance. This explains the increased ROC_{AUC} results for BT completion predictions. It provides an opportunity to understand why students choose to not attend their registered training classes and to collect more data at this early stage of the training journey.

3.2 Risk Profile Analysis

In this section, we illustrate how we use insights derived from decision tree modeling to profile students with different dropout rates, providing a tool to isolate target segments of high risk students so the business can take measures that can decrease dropout rate. Decision tree modeling enable us to acquire foundational knowledge necessary to develop educated hypotheses for customized interventions to support students with different risk profiles. Variable importance analysis using Random Forest also enhances our understanding of what factors influence training dropout and assists in our predictions.

At the root note of Figure 3a, the average first class attendance rate is almost 81% among 5,303 students. That is, the overall dropout rate is 19%. For students who didn't enroll in either module 1 or 2 as their first class[1], they demonstrated a significantly higher risk of not attending the training – 54% will not show up for their first registered class. Using the same decision tree, we are also able to infer that both county and age are important factors. For example, students who do not reside in certain counties [2] above and are younger than 49 are less likely to attend the first class compared to those who are older than 49. Younger students, English speaking students and students who take longer to complete O&S exhibit higher risk of not attending their first class. The variable importance from random forest shows that duration to class registration, duration to class are other most important indicators. The larger the time gaps, the higher the dropout rates are.

Figure 3b gives a decision tree for training completion. From the display, we can see if students have two or more class absence records before actually attending the first class, their completion rate decreases to 60%, which is much lower than the average completion rate of 89%. Among these students, if their first class is not Module 1, then the likelihood that the student will complete training drops to 27%. It shows duration to class registration and class location (i.e county) play important role for training completion. Duration to class and student age are also shown as important indicators using random forest variable importance analysis. In addtion, knowing the count of class absence record and first class module gives a much better understanding about the BT completion. Figure 3b shows that even for students who had one or zero class absences. If they register for the class too late (in our case this amounts to more than 52 days after being hired), then the probability of completing the training is even lower.

4. RELATED WORK

Prior studies([3],[7],[8]) have been conducted to explain academic performance and to predict the success or failure across a variety of students in a wide-range of educational settings. These studies focused heavily on the explanatory factors associated with a student's learning behavior and training journey and which of those may cause separation between student types. Machine learning algorithms have been successful in high school and college education settings, most helpful in predicting graduation[4], course participation[5], and other academic outcomes[6]. These algorithms also provide great value to the student success[9].

Lakkaraju et al.[6] used several classification models to identity students at risk of adverse academic outcomes and used precision_at_top_K and recall_at_top_K to predict risk early. The authors compared ROC curves for two cohorts for algorithms Random Forest, AdaBoost, Linear Regression, SVM and Decision Tree. The authors demonstrated that Random Forests outperformed all other methods. Aguiar et al.[10] selected and prioritized students who are at risk of not graduating high school on time by prediction the risk for each grade level and reported precision at top 10%, accuracy, and MAE for ordinal prediction of time to off-track.

[1]Currently, students are allowed to attend classes out of sequence in order to complete their training before the mandatory deadline.

[2]Counties include: Benton, Clark, Cowlitz, Douglas, Grays Hoarbor, Lewis, Mason, Skagit, Stevens, Walla Walla and Whatcom

Johnson et al.[11] used d-year-ahead predictive model to predict on-time graduation for different grade level. Vihavainen et al.[5] found a higher likelihood of failing their mathematics course could be detected in an early stage using Bayesian network. Radcliffe et al.[4] used logit probability model and parametric survival models to found that demographic info, academic preparation and first-term academic performance have a strong impact to graduation. Dekker et al.[12] gave experimental results which showed decision trees gave a high accuracy for predicting student success and improved prediction accuracy using cost-sensitive learning.

Other prior studies have highlighted some important indicators that influence students' performance like a student's age and absence rates[6]. Based on these features, Early Warning Indicator (EWI) systems are rapidly being built and deployed using machine learning algorithms[6]. Similar to other research in Educational Data Mining (EDM), we use precision at k to measure the prediction result([6], [10], [13]) and, like in traditional education systems, our motive is to most effectively and efficiently target our limited resources to assist and suppor students. Typically, ensemble models outperformed individual models[7] and this held true in our case as well. While random forest has proven to be an extremely useful and powerful machine learning technique in educational research[11], our results indicated that AdaBoost outperformed random forest.

5. CONCLUSION AND FUTURE WORK

In this study, we demonstrated preliminary results for predicting home care student training dropout from a large, heterogeneous dataset containing student demographics and engineered features extracted from training patterns. Predicting dropout at varying stages of an adult learner's training journey yielded promising results from a skewed dataset of over 5,303 students with AdaBoost (2,000 trees) providing the strongest predictions (prec@10 = 0.73 and ROC_{AUC} = 0.625. Prior history of class absence and time effects (duration to registration, duration to first class) were among the strongest individual predictors of dropout, as were class module sequence, county, and student age. The results demonstrate that applying machine learning techniques to demographic data and learning behavior data (e.g. duration to registration, duration to first class) can achieve adequate prediction quality in predicting the top k highest risk students out of a pool of newly hired HCAs. This enables efficient use of limited capacity and resources to support students of greatest need. Insights revealed in this study inspired training operation staff to explore alternatives, including encouraging newly hired HCAs to register for training early and strongly recommend proper class sequence to support students success in their training.

Future work will investigate collecting more information about students, such as their motivations, propensity for self-efficacy, and life circumstances to determine if there are other factors at play on a personal level that my uncover additional features that can contribute to our target predictions around training dropout.

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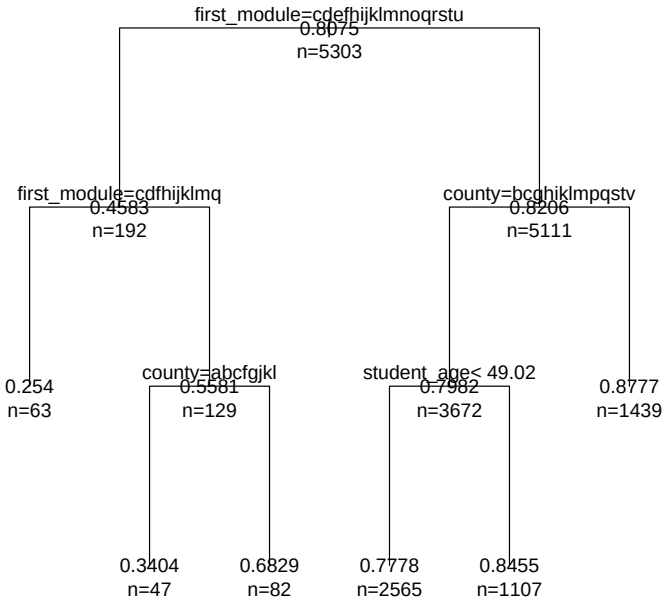
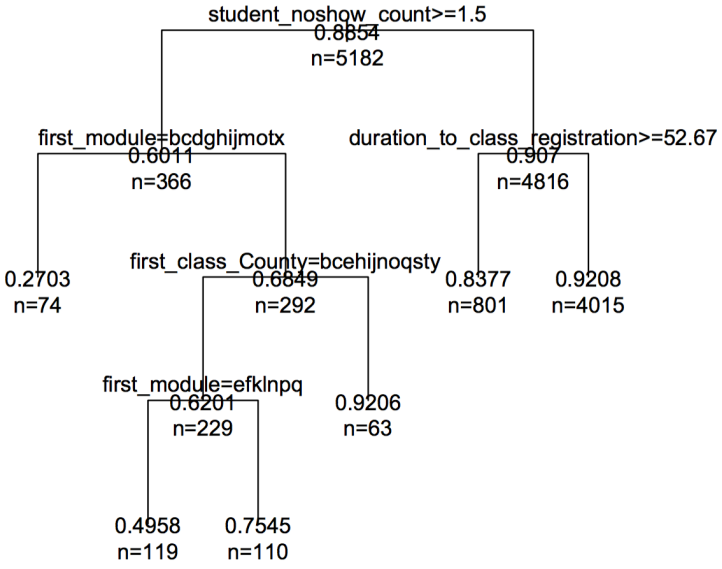


(a) First Attend



(b) Training Completion

Figure 3: Decision Trees

Few hundred parameters outperform few hundred thousand?

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ABSTRACT

Knowledge Tracing plays a key role to personalize learning in an Intelligent Tutoring System including funtoot. Bayesian Knowledge Tracing, apart from other models, is the simplest well-studied model which is known to work well. Recently, Deep Knowledge Tracing based on Deep Neural Networks, was proposed with huge promises. But, soon after, it was discovered that the gains achieved by DKT were not of significant magnitude as compared to Performance Factor Analysis [13] and BKT and its variants proposed in [6]. In the quest of examining and studying these models, we experiment with them on our dataset. We also introduce a logical extension of DKT, Multi-Skill DKT, to incorporate items requiring knowledge of multiple skills. We show that PFA clearly outperforms all the above mentioned models when the AUC results were averaged on skills while PFA and DKT, both were equally good, when they were averaged on all data points.

Keywords

Deep Knowledge Tracing, Adaptive Learning, funtoot, Bayesian Knowledge Tracing, Intelligent Tutoring System, Performance Factor Analysis

1. INTRODUCTION

An Intelligent Tutoring System's main aspect is to deliver the instruction and provide feedback as and when required. To do that, the system requires to measure the knowledge state of a student with respect to the content available. The system continuously monitors the student's performance, updates the knowledge state and based on that takes further decisions. The techniques capable of performing these functions are called Knowledge Tracing models.

Bayesian Knowledge Tracing [2] has been one of the most predominantly researched models in the educational data mining domain. BKT is a 2-state skill specific model, where the student's knowledge state can take either of the two values: learned or unlearned. Moreover, a skill once learned cannot be unlearned. These assumptions make it a very simple and constrained model and has led lots of researchers to extend the model by enhancing it with new features to improve its performance; making it less constrained so to say. For instance [10] extend BKT in the scenario where the students do not necessarily use the system in the same day.

Authors of [14] proposed an individualized BKT model which fits not only the skill specific parameters, but also student specific parameters and have reported significant gains over standard BKT.

Educational data mining techniques can now very accurately predict how much a student has learned a Knowledge Component (KC). But it doesn't give information about the exact moment when the KC was learnt. [3] discusses a technique about finding a moment of learning.

Another model Performance Factor Analysis (PFA) is a logistic regression model proposed in [7] which showed better performance than standard BKT. Unlike BKT, PFA can incorporate items with multiple skills. PFA makes predictions based on the item difficulty and historical performances of a student. [4] has compared BKT and PFA by using various model fitting parameter models like Expectation Maximization (EM) and Brute Force (BF). Knowledge tracing models with EM have shown performance comparable to PFA[4].

The most recently published model - DKT [9] is the newest technique in this area of research. DKT is an LSTM [5] network, a variant of recurrent neural network [11] which takes as input a series of exercises attempted by the student and correspondingly a binary digit suggesting if the exercise was answered correctly or not. DKT has shown significant gains over BKT which is a very tempting gain for any researcher in this community to look into and study further. Papers like [6], [13] and [12] did just that.

Authors in [13] have pointed out few irregularities in the dataset used by authors in [9] which, when accounted for, reduce the gain reported by using DKT. They also reported that DKT doesn't quite hold an edge when the results are compared with PFA.

Another standard framework for modelling student responses, Temporal extension of Item Response Theory (IRT) is compared with DKT in [12]. Authors have reported that the variants of IRT consistently matched or outperformed DKT.

Recent paper [6] studies DKT even further and explains why DKT might be better. It has been pointed out that DKT inherently exploits the characteristics of the data which standard models like BKT cannot. So, in order to make a fair comparison between the two, authors have presented three

different variants of BKT with forgetting, skill discovery and latent abilities which might help BKT make use of information from the data the way DKT does.

Having introduced these variants, the authors also make a point that Knowledge Tracing might not require the "depth" that deep learning models offer.

Being an Intelligent Tutoring System, funtoot's tutor module requires sophisticated knowledge tracing technique which models the process of knowledge acquisition and helps students achieve mastery. One such model operates at the level of LGs (discussed in section 2) which models the committance and avoidance of them with time and practice. In the context of this paper, these LG models are of prime importance to us and henceforth we will refer LGs as skills. Also, considering user experience, we need a model which can be used for predictions in real time without compromising on user latency.

In this paper, we test standard BKT, the variants of BKT, DKT and PFA on the funtoot dataset and examine the results. We also introduce a logical and trivial extension of DKT to accommodate the items which involve multiple skills. Out of all the models considered in this article, PFA is one such model which allows items with multiple skills. But in our dataset, each of the skills in the item has its own response and hence it is modelled separately in PFA.

The rest of the paper is organized as follows: section 2 gives a brief introduction to our product funtoot and its knowledge graph. Section 3 discusses the experiments on funtoot dataset and results. Section 4 discusses the future work and conclusion.

2. FUNTOOT

Funtoot[1] is a personalized digital tutor which is currently being used actively in around 125 schools all over India with the total of 99,842 students registered. The curriculum of math and science for grades 2 to 9 is covered by funtoot.

Schools in India are typically affiliated with one of the boards of education[2]. Curriculum for math and science from the following boards of education are included in funtoot:

- CBSE[3] board for grades 2 to 9,
- Karnataka State Board[4] for grades 2 to 8,
- ICSE[5] board for grades 2 to 8 and
- IGCSE[6] board for grades 2 to 3.

[1] http://www.funtoot.com/
[2] https://en.wikipedia.org/wiki/Boards_of_Education_in_India
[3] https://en.wikipedia.org/wiki/Central_Board_of_Secondary_Education
[4] https://en.wikipedia.org/wiki/Karnataka_Secondary_Education_Examination_Board
[5] https://en.wikipedia.org/wiki/Indian_Certificate_of_Secondary_Education
[6] https://en.wikipedia.org/wiki/International_General_Certificate_of_Secondary_Education

2.1 Funtoot Knowledge Graph

Pedagogy team at funtoot has created a funtoot ontology around the subjects Math and Science. This ontology represents the various learning units of any subject and their relationships, which is created based on human expertise in the subject matter. All the above mentioned curricula are later derived from this funtoot ontology based on the age group and grade.

An ontology for a subject is created as follows:

1. a subject is broken down into the smallest teachable sub-sub-concepts
2. it is then mapped to determine inter-dependencies/connections between concepts, sub-concepts (*sc*) and sub-sub-concepts (*ssc*) as shown in the figure 1,
   Consider the example shown in figure 1. Subject *Math* contains a concept *Triangle*, and *Triangle* contains a sub-concept *Congruency*. Sub-concept contains two sub-sub-concepts: *Rules of Congruency* and *Applications of Congruency*. Sub-sub-concepts are connected by "depends-on" relationship. Here, *Applications of Congruency* is dependent on *Rules of Congruency*, which suggests that the latter is a prerequisite for the former.
3. learning gaps (definition 1) are determined in the sub-sub-concepts

   DEFINITION 1. *Learning Gap (LG): "A learning gap is a relative performance of a student in a specific skill, i.e. difference of what a student was supposed to learn, and what he actually learned in a skill.* [7] *"*

   "A misunderstanding of a concept or a lack of knowledge about a concept that is required for a student to solve or answer a particular question is also a learning gap"

   For instance, a question "Solve 12 + 18" is given to student *Alice*. If *Alice* makes a mistake while adding carry and answers 20, we say that a LG (*carry-over error*) has been *committed*. Had she answered 30, this LG would have been said to be *avoided*. This question might also have other LGs which could have been committed simultaneously with the LG mentioned above. If the response is correct, all the LGs of a question are said to have been avoided.

   In figure 1, *Applications of Congruency* is an ssc containing LG_1, LG_2 and LG_3. Learning gaps can have "induce" relationships. In our example, LG_1 induces LG_2.
4. inter-dependencies get refined based on the data-points received by funtoot through the user's interaction
5. an SSC is further divided into six Bloom's Taxonomy Learning Objectives (*btlos*) using Bloom's Taxanomy [1]. Each learning objective has five difficulty

[7] http://edglossary.org/learning-gap/

Difficulty Level \ BTLO	Remember	Understand	Apply	Analyze	Evaluate	Create
1						
2						
3						
4						
5						

Table 1: Btlos, Difficulty levels ⇒ Complexities

levels as shown in table 1. Each cell (for instance, Remember1, Apply2 and so on) in table 1 is called a *complexity* in funtoot.

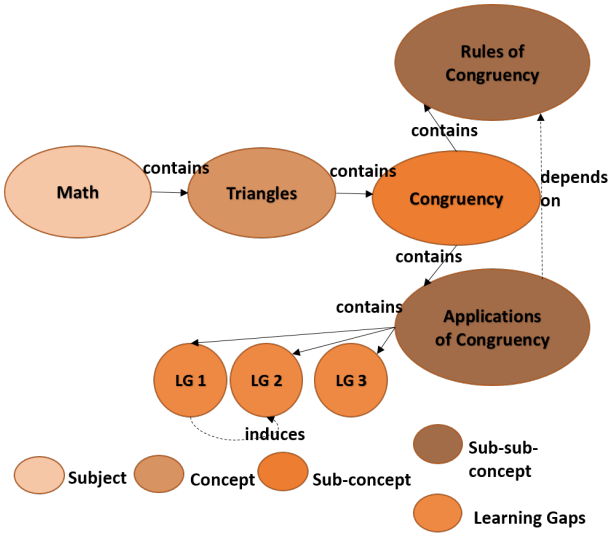

Figure 1: Funtoot Knowledge Graph

2.2 Dataset

During a student's interaction with funtoot, information like: session, the scope of the question (which includes $grade - subject - topic - subtopic - subsubtopic - complexity - question$), question identifier, start time, total attempts allowed based on the student's performance, time taken, attempts taken, information about hints, LGs committed in each attempt, assistance provided and so on is logged.

In the study presented in this paper, we model LG as a skill. We aim to predict a student's proficiency in a particular LG. When a student is presented with an item, several attempts are provided to solve it. In an unsuccessful attempt a student might commit more than one LG as explained in section 2 and the same LG can also be committed in several attempts. We know apriori the set of LGs that are exposed by a question. With this information at hand, we need an impression of each of these LGs for the student in the context of this item.

Consider a hypothetical example. *Alice* attempts an item q from a subtopic *Rules of Congruency* having skills s_1, s_2, s_3. The series of attempts is shown in table 2.

Attempt no.	s_1	s_2	s_3
1	0	1	1
2	0	1	1
3	0	0	1
4	1	1	1
Overall Outcome	0	0	1

Table 2: Attempts made by *Alice* while solving q

In the above table, 1 represents avoidance and 0 represents committance. As shown in the table, *Alice* committed s_1 in attempts 1, 2 and 3. *Alice* committed s_2 in attempt 3. *Alice* avoided s_3 in all attempts. The overall outcome of *Alice* in LGs s_1, s_2 and s_3 is $(0, 0, 1)$ which is a logical AND over all attempts. This means that s_1 and s_2 are committed and s_3 is avoided. From now on, we will refer these outcomes as committances and avoidances and they will be used for modelling. So this problem attempt of *Alice* gives rise to three data points.

For this experiment we have used data of 6^{th} grade CBSE math from date $2015-07-25$ to $2017-01-30$. Syllabus descendant hierarchy for this dataset is as follows: 22 topics, 69 subtopics, 119 sub-sub-topics, 541 complexities and $1,524$ problems. This dataset has $26,06,022$ entries of problem attempts involving 442 skills. This data is about 176 schools with $11,820$ students and $1,524$ problems. From this dataset, the data of students having less than 100 problem attempts were excluded. This gives us $24,47,027$ problem attempts involving 442 skills with 7780 students and $1,523$ problems. Finally, we have $56,04,227$ data points where $42,68,503$ are avoidances (class 1) and $13,35,724$ are committance (class 0).

In the context of the example shown in table 2, the length of $Alice's$ attempt to solve a question q can be said as three, as there are three skills involved. Given this definition, of length of the problem attempt, figure 2 shows the distribution of the length of the problem attempts in the dataset. 38.18% of the total problem attempts have 1 skill, i.e., length is 1 and 29.47% of the problem attempts have length 2.

3. EXPERIMENTS

In this section, we discuss the experiments done on our dataset and report the results. Consider a hypothetical dataset of student *Alice* attempting questions q_1 and q_2 in the same order. Question q_1 has three skills A, B and C, question q_2 has two skills B and C. *Alice* gets only one attempt for both the questions wherein she commits skill B and C and skill B in questions q_1 and q_2 respectively. This example is used in this section to explain the training datasets for each of the techniques.

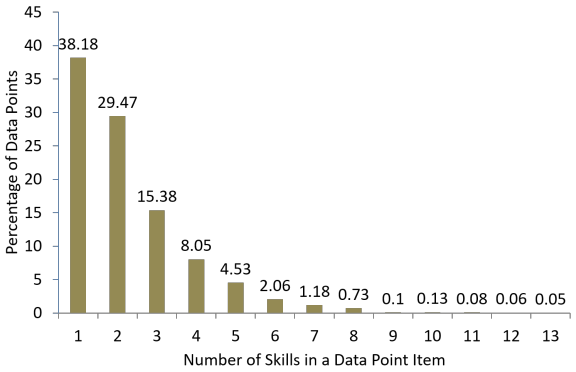

Figure 2: Data Distribution

3.1 Bayesian Knowledge Tracing

After DKT [9], authors in [6] have explored and hypothesized the properties of the data which DKT exploits while the standard BKT cannot. To equip BKT with those capabilities, the authors have proposed three variants of BKT: BKT with forgetting (BKT+F), BKT with skill discovery (BKT+S) and BKT with latent-abilities (BKT+A).

We have used the author's implementation of BKT and its three variants published on `https://github.com/robert-lindsey/WCRP/tree/forgetting` to train on our dataset. The data format required by these BKT variants is as shown in table 3. As discussed in the earlier section 1,

skill ID	response series
A	1
B	0, 0
C	0, 1

Table 3: BKT data format

BKT is a skill specific model and thus, three models need to be built one each for skills A, B and C. Each model needs the time series of responses as shown in the table 3.

All variants of BKT except the ones where skill discovery is involved, namely BKT, BKT+F, BKT+A and BKT+FA operate on the skills provided by the data. The remaining variants: BKT+S and BKT+FSA completely ignore the expert tagged skills available in the data. This is achieved by setting the non-parametric prior, β on the expert tagged skills as 0.

3.2 Performance Factor Analysis

Like BKT, PFA being a skill specific model requires a different model to be built for each skill. Logistic Regression model of [8] is used in the implementation of PFA. For each skill, the response is a function of the skill difficulty, number of prior student success (avoidances) responses and number of prior student failure (committances) responses for the skill. From the implementation point of view, the decision function has two variables - the number of prior success instances and the number of prior failure instances for the skill. Also, a bias is added in the decision function (achieved by the intercept) which serves as the skill difficulty. The data format needed by PFA is as shown in figure 4.

skill ID	no. of failures	no. of successes	response
A	0	0	1
B	0	0	0
C	0	0	0
B	1	0	0
C	1	0	1

Table 4: PFA data format

3.3 Deep Knowledge Tracing

The implementation of LSTM based DKT published on `https://github.com/mmkhajah/dkt` is used to train our dataset. The neural network of DKT requires the input as one hot encoding of skills as well as responses for each of them, while output is the probability of correctness of each of the skills. Hence the size of the input is twice the number of skills and that of the output is the number of skills. The serial number in the table 5 shows the order in which the inputs are fed into the network. The input in the table signifies the previous output while the response shows the expected output out of the network. The odd bits in the input represent one hot encoding of the skills while the even bits represent their responses. X in the output shows that the bit can take either 0 or 1.

serial no.	input	response
1	0, 0, 0, 0, 0, 0	1, X, X
2	1, 1, 0, 0, 0, 0	X, 0, X
3	0, 0, 1, 0, 0, 0	X, X, 0
4	0, 0, 0, 0, 1, 0	X, 0, X
5	0, 0, 1, 0, 0, 0	X, X, 1

Table 5: DKT data format

As discussed in subsection 2.2 that to figure out the final outcomes for the LGs in an item attempt, there is no clear or fixed ordering. But the time series to be fed into the network of DKT requires us to establish the ordering between them. We sample the orderings randomly and average the results on them. The sample dataset in the table 5 is one such ordering. Another random ordering can be seen in the table 6. The skills of the item q_1 are in the order A, B, C in table 5 while their order is B, A, C in table 6. The other way to get an ordering is to get rid of the ordering itself by merging the data points of the skills in an item which is explained in the following subsection.

serial no.	input	response
1	0, 0, 0, 0, 0, 0	X, 0, X
2	0, 0, 1, 0, 0, 0	1, X, X
3	1, 1, 0, 0, 0, 0	X, X, 0
4	0, 0, 0, 0, 1, 0	X, X, 1
5	0, 0, 0, 0, 1, 1	X, 0, X

Table 6: Shuffled skills DKT data format

3.4 Multi-skill DKT

As explained in the context of DKT, the orderings among the skills in the item are sampled randomly. In order to get rid of such orderings, we introduce an extension of DKT: Multi-skill DKT which can incorporate the items having multiple skills efficiently. It can be seen from the table 7 that the three data points of q_1 and two data points of q_2 are consolidated and we are left with two data points in total. The size and structure of the inputs and outputs still remain the

serial no.	input	response
1	0, 0, 0, 0, 0, 0	1, 0, 0
2	1, 1, 1, 0, 1, 0	X, 0, 1

Table 7: Multi-Skill DKT data

same. The only difference is that the input and output can have the information about multiple skills simultaneously.

3.5 Results

For all the algorithms, we use three replications of 2-fold cross validation, which gives us 6 folds in total on which the results are averaged. We use Area under the curve of Receiver Operating Characteristics (ROC), which we will refer as the AUC. Paper [6] discusses the inconsistent procedures used to compute and compare performance of BKT and DKT. We therefore compute AUC both by averaging on all data points and by averaging on skills. The results of our experiments on funtoot dataset are shown in figure 3.

When AUC is averaged on all the data points, the relative difference in performance between algorithms is very low, 0.83 being the lowest and 0.88 being the highest. PFA and DKT share the highest performance of 0.88 AUC. Multi-skill DKT lags a bit behind DKT by 0.03 AUC units (0.85 AUC). All the variants of BKT also lag behind DKT and PFA by not a very big margin, the highest being 0.05 AUC units. BKT has the lowest AUC of 0.83, BKT+FSA has the highest AUC of 0.85 and the rest of them have an AUC of 0.84, which depicts that they all show equivalent performance.

The relative difference in performance between algorithms is higher when AUC is averaged on skills, the lowest being 0.64 AUC of BKT+F and highest being 0.88 AUC of PFA which is 37.5% gain. PFA with an AUC of 0.88 outperforms all the methods by having a minimum gain of 17% (0.75 AUC of DKT and BKT+FSA) and maximum gain of 37.5% (0.64 AUC of BKT+F). Here also, the magnitude of difference between DKT and Multi-skill DKT is very less, 0.04 AUC units to be precise with Multi-skill DKT lagging behind.

With BKT, BTK+F, BKT+A and BKT+FA having AUCs of 0.65, 0.64, 0.68 and 0.67 respectively, it is clear that *Forgetting* adds no value. The number of skills discovered by both BKT+S and BKT+FSA are in the range of $145 - 175$ compared to 442 original skills. The *Skill Discovery* extension provides reasonable gains which are evident from the AUCs of BKT and BKT+S (9% gain) and BKT+FA and BKT+FSA (12% gain). The magnitude of the gains achieved by *Abilities* extension is very less, 0.003 AUC units in the case of BKT, BKT+A and BKT+F, BKT+FA. Finally, the different variants of BKT achieve a gain of maximum 15% over standard BKT. Notably, the best version of BKT, that is, BKT+FSA and DKT, perform equally.

4. DISCUSSION AND FUTURE WORK

Our aim of this study was to explore the performance of standard BKT, all of its variants proposed in [6], PFA and DKT on funtoot dataset. The results we have got are in sync with the results in [6]. When the AUC results were computed by averaging over skills, DKT and BKT+FSA perform equally well while DKT outperforms standard BKT with the gain of 15%. Also, BKT+S gave a performance

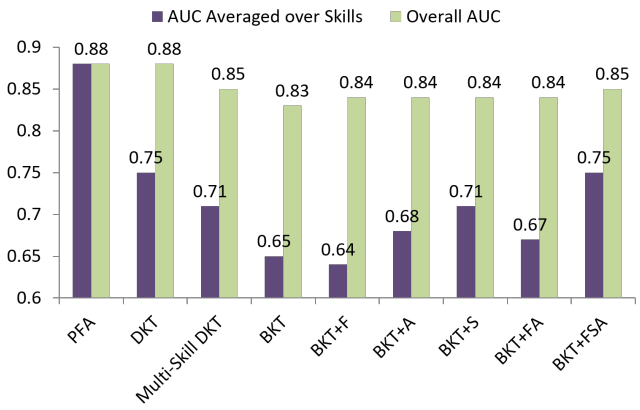

Figure 3: A comparison of PFA, DKT, Multi-skill DKT, BKT and its variants

which was very close to DKT. Though DKT does perform better when the AUC results are averaged over all data points, the magnitude of the gain is significantly low.

Similar kind of results hold true for PFA. PFA achieves a high gain compared to all the models when AUC results are averaged over skills. When AUC results are averaged over all data points, PFA equals DKT's performance and outperforms the rest of the models, though not with a very high margin. This is not consistent with the results in [13] where DKT outperforms PFA though, not overwhelmingly.

The above results reinforce the hypothesis proposed in [6] that the domain of knowledge tracing seems to be shallow and may not require the depth that the deep neural networks offer. The predictive or the explanatory power of a model can also be characterized in terms of the number of parameters the model fits. One of the reasons why DKT is expected to be more successful than other models, at the cost of interpretability, is that it has weights in the order of hundreds of thousands. Moreover, being made up of a layer of LSTM cells, DKT has the capability of looking back arbitrary number of timesteps. On the contrary, variants of BKT and PFA are very simple and interpretable models. Their simplicity can easily be attributed to the small number of parameters they fit.

Standard BKT needs four parameters: $pInit$ (the probability that the student is in learned state before the first practice), $pLearn$ (the probability that the student transitions from not learned state to the learned state at each practice), $pGuess$ (the probability that the student guesses the answer being in the unlearned state) and $pSlip$ (the probability that the student accidentally makes a mistake being in the learned state). In PFA, it is even better, only three parameters are learned per skill - item difficulty and one coefficient each for prior failures and successes. With this, the total parameters for a few hundred skills (which is true in our case) would be a few hundred parameters: $three \times number\ of\ skills$. Hence, in our context, it seems appropriate to say that few hundred parameters are better than few hundred thousand parameters.

Both BKT and DKT, in an abstract sense, are the models

which maintain the knowledge state of the student. With each response of the student, the knowledge states are updated and those states are used to generate future predictions. They both require the time series data of the student's responses. This is significantly different than the type of data required by PFA. PFA operates on abstract features of student's interactions like total number of prior successes and failures. It occurs to us that the abstract features are smoother than the time series data of responses. It seems the domain of knowledge tracing can be deciphered better if the abstract features are used instead of detailed trail of responses which might be noisy. More studies and experiments are required to validate this point.

The skills used in our experiment are the LGs from the funtoot Knowledge Graph which are tagged at the level of subsubtopic which acts as a context of LG. Also, an LG can occur in multiple subsubtopics. The discovered skills in our experiments of BKT+S and BKT+FSA were in the range of $145 - 175$ which is close to the number of subsubtopics (119) in our dataset. We suspect that there is some relation between the subsubtopics in our dataset and the skills discovered. We would like to investigate this further in future. DKT also supports skill discovery as proposed in [9] which we would look into in future to compare the skills discovered by several algorithms.

Funtoot dataset has items with multiple skills which forced us to extend DKT and come up with Multi-skill DKT. This variant of DKT underperformed marginally as compared to DKT. We do not have a clear understanding about why this is so and hence this also requires further study. Since we have used a very crude dataset, that is, does not contain features about attempts, time durations, hints, item context, etc., it would be interesting to use them with DKT and see if the depth of DKT can exploit them.

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Tell Me More: Digital Eyes to the Physical World for Early Childhood Learning

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ABSTRACT

Children are inherently curious and rapidly learn a number of things from the physical environments they live in, including rich vocabulary. An effective way of building vocabulary is for the child to actually interact with physical objects in their surroundings and learn in their context [17]. Enabling effective learning from the physical world with digital technologies is, however, challenging. Specifically, a critical technology component for physical-digital interaction is visual recognition. The recognition accuracy provided by state-of-the-art computer vision services is not sufficient for use in Early Childhood Learning (ECL); without high (near 100%) recognition accuracy of objects in context, learners may be presented with wrongly contextualized content and concepts, thereby making the learning solutions ineffective and un-adoptable. In this paper, we present a holistic visual recognition system for ECL physical-digital interaction that improves recognition accuracy levels using (a) domain restriction, (b) multi-modal fusion of contextual information, and (c) semi-automated feedback with different gaming scenarios for right object-tag identification & classifier re-training. We evaluate the system with a group of 12 children in the age group of 3-5 years and show how these new systems can combine existing APIs and techniques in interesting ways to greatly improve accuracies, and hence make such new learning experiences possible.

1. INTRODUCTION

Children learn a lot from the physical environment they live in. One of the important aspects of early childhood learning is vocabulary building, which happens to a substantial extent in the physical environment they grow up in [17]. Studies have shown that failure to develop sufficient vocabulary at an early age affects a child's reading comprehension and hence their ability to understand other important concepts that may define their academic success in the future. It is also evident from a study that failure to expose a child to sufficient number of words by the age of three years leads to a 30 million word gap between kids who have been exposed to a lot of quality conversations, versus the ones that have not been exposed as much [13].

Vocabulary building has been a theme for early childhood learning and is closely associated with its context in the physical world. The exploration of physical surroundings of the child triggers new vocabulary and vice-versa. Relating physical world objects and concepts, to digital world content requires seamless flow of information. Increasingly, availability of cheap sensors such as camera, microphone etc. on connected devices enable capture of physical world information and context, and translate them to personalized digital learning.

An envisioned system uses mobile devices to take pictures of the child's physical surroundings and make the best sense out of the picture. This is then translated to a learning session where the child is taught about the object in focus, its relation to other objects, its pronunciation, it's multiple representations, etc. Recognition of pictures for teaching a child requires high recognition accuracy. In-the-wild image recognition accuracies are in general low, especially for images taken with mobile devices. Moreover, pictures taken by a child is even more challenging given the shake, blur, lighting issues, pose etc. that come with it.

To this end, in this paper, we take a holistic approach of recognition-in-context using a combination of (a) domain restriction, (b) multi-modal fusion of contextual information, and (c) gamified disambiguation and classifier re-training using child-in-the-loop. Specifically, we use object recognition results from a custom-trained (with images from restricted domains) vision classifier, and combine them with information from the domain knowledge that is available whenever a new domain of words is taught to a child in the classroom or at home. We use a new voting based multimodal classifier fusion algorithm to disambiguate the results of vision classifier, with results from multiple NLP classifiers, for better accuracy. We show that using such a framework, we can attain levels of accuracy that can make a large majority of the physical-digital interaction experiences fruitful to the child, and also get useful feedback from the child at a low cognitive load to enable the system to retrain the classifier and improve accuracy. We tested our system with a group of 12 children in the age group of 3-5 years and show that children can play an image disambiguation game (that allows the child to verify what class label has actually been identified by the system) very easily with graceful degradation of performance on difficult images. In most cases, multi-modal context disambiguation improves object recognition accuracy significantly, and hence the human disambiguation step remains limited to one or two rounds, which ensures the child's continuing interest in the games and learning activities. The system learns from the child feedback, and the child in turn feels engaged to enable the system to learn over time. The nuggets of information made available about the object in focus at the end of playing a game were also found to be very engaging by the child.

In summary, this paper makes the following contributions:

- We take a holistic approach to address the challenges with

*these authors contributed equally to this work

automatic visual recognition for physical digital interaction to enable early childhood learning in context. Our three-stage approach includes (a) domain restriction, (b) contextual disambiguation and (c) gamified human disambiguation, which enables a platform for building a variety of early childhood learning applications with physical-digital interaction.

- We propose a novel re-ranking algorithm that uses the notion of strong vouching to re-order the output labels of a vision classifier based on strong supporting evidence provided by the additional context from semantic representation models in NLP, namely GloVe [6], Word2vec [11] and ConceptNet [5] (which can be textual cues in the form of classroom and curriculum context, domain focus, conversational input and clues, etc.). Note that, we use the terms "re-order" and "re-rank" interchangeably throughout this paper.

- We evaluate a simple disambiguation game for children to choose the right label from the Top-K labels given out by the system. Through an usability study with 12 children, we make the case that engaging user experiences can indeed be developed to bridge the gap between automatic visual recognition accuracies and the requirement of high accuracy for meaningful learning activities.

2. MOTIVATION AND RELATED WORK

Early childhood learning applications with physical-digital interaction fall into two categories: (i) *Application-initiated activities:* In this category, the child is given a context by the application and is required to find relevant physical object and take a picture [2]. For example, the application may prompt the child to take a picture of "something that we sit on", "a fruit", "something that can be used to cut paper", etc. (ii) *Child-initiated activities:* In this category, the child takes a picture of an object and intends to know what it is, where it comes from, other examples of the same type of objects, etc. For example, the child may take a picture of a new gadget or machine found in school, a plant or a leaf or a flower, etc. and wants to know more about them.

In each of these categories, the application is required to identify what the object is with Top-1 accuracy (i.e. a vision recognition solution should emit the right label at the top with high confidence). While a lot of advancement has been made in the improvement of accuracy of vision classifiers, Top-1 accuracy levels are still relatively low, although Top-5 accuracy levels (i.e. the right label is one of the top 5 labels emitted) are more reasonable. Nevertheless, the goal is to be able to work with the Top-5 list, and using the techniques described earlier, push the Top-1 accuracy to acceptable levels for a better interaction.

2.1 Vision Recognition Accuracy

To understand the efficacy of state-of-the-art solutions quantitatively, we experimented with two deep convolution neural networks (Baseline Model 1: VGGNet [18] and Baseline Model 2: Inception V3 [19]). Inception V3 has been found to have 21.2% top-1 error rate for ILSVRC 2012 classification challenge validation set [8]. Even in experiments where baseline models were custom trained with 300 training images per class and tested with images taken from iPad, we observed low Top-1 accuracy (of 72.6% in Baseline Model 1 and 79.1% in Baseline Model 2); i.e. one in about four images will be wrongly labeled. Even the Top-5 accuracy is 88.05% in Baseline Model 1 and 89.3% in Baseline Model 2. We also trained the Baseline models with the complete Imagenet[8] images for the considered classes and we observed <1% improvement. Further, when multiple objects are present in the image frame, the Top-1 accuracy degrades further (38.2% in Baseline Model 1 and 44.5% in Baseline Model 2 for 2 objects in a frame), and so does Top-5 accuracy (of 77.9% in Baseline Model 1 and 85.6% in Baseline Model 2). Note that this could be a common scenario with children taking pictures, in which multiple objects get captured in a single image frame. Observe that recent Augment Reality (AR) Applications such as Blippar [4], Layer [9], Aurasma [3] rely on similar vision recognition task, and hence run into similar inaccuracies in uncontrolled settings. While adult users of such applications may be tolerant to inaccuracies of the application, children may get disengaged when the system detects something wrongly or is unable to detect at all.

2.2 Multi-modal Information Fusion

Using additional information to identify the objects holds promise in imporving the accuracy of vision recognition. For instance, several past works ([22], [14], [15]) improve the image classification output based on the text features derived from the image. Specifically, authors in [20] propose techniques that train the model specifically with images that contain text, for efficient extraction of text and image features from the image. They also propose fusion techniques to merge these features for improving image recognition accuracies. While this may be possible in some scenarios, the application's accuracy will remain a challenge when such textual information embedded in the image is not present. Several works in literature propose indexing of images based on text annotations for efficient image search. [12] surveys and consolidates various approaches related to efficient image retrieval system based on text annotations. Likewise, [21] proposes techniques to label images based on image similarity concepts. These works are complementary, and do not address the problem of correctly determining the labels right when a picture is taken based on a context.

In summary, the early childhood learning scanarios require a holistic solution that leverages the state-of-the-art vision recognition solutions, but goes beyond in improving the detection accuracy of the image captured to make engaging applications for children. We describe one such holistic solution next.

3. PROPOSED APPROACH

Our goal is to enable a holistic solution for applications to provide as input an image taken by a child, and emit as output the final label that should be used as an *index* into the relevant learning content. A high level overview of our solution is depicted in Figure. 1. In one of the envisioned applications built for physical-digital interaction, a child takes a picture that is sent as input to the proposed ECL Image Recognition (ECL-IR) Module that emits the correct label of the image by applying the following three stages: (i) Stage 1: Domain Specific Customized Training (which improves Top-K accuracy), (ii) Stage 2: Domain Knowledge (DK) based disambiguation and reordering (which improves Top-1 accuracy) and (iii) Stage 3: Human Disambiguation game (confirmation step). We now discuss each of these stages in detail.

3.1 Stage 1: Domain Specific Customized Training of Baseline Models

The first stage of our solution strives to improve the Top-K accuracy of the vision classifiers by constraining the domain of child learning in which they are applied. In order to achieve this, we perform custom training of the baseline models with domain-specific data sets. This step is very commonly applied in most of the vision recognition use-cases for improving the Top-K accuracy and several reported statistics indicate good Top-K accuracy improvements through custom training. For example current state-of-art vision classifier [19] reports 94.6% Top-5 accuracy on ILSVRC 2012 classification challenge validation set. However, even this state-of-art vision classifier reports 21.2% Top-1 error rate on the same validation set. In the next section, we discuss how ECL-IR module improves Top-1 accuracy through contextualized reordering (Stage 2).

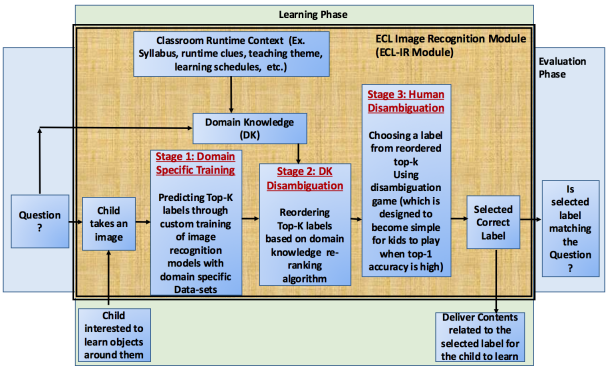


Figure 1: High Level Solution Overview

Algorithm 1: Algorithm to calculate DK Correlation Score

Input: Label, Domain Knowledge text (DK)
Output: DK Correlation Score (i.e. Semantic correlation between DK and Label)

1 For every word in DK, fetch its corresponding N-dimensional semantic vector from the semantic representation model.
2 Representation(DK) <– Compose N-dimensional vector for the complete DK by combining word level vectors to a phrase level vector using linear average technique
3 Representation(Label) <– Fetch N-dimensional vector for the label from the semantic representation model
4 DK Correlation Score = Cosine Distance between Representation(DK) and Representation(Label)
5 **return** *DK Correlation Score*

3.2 Stage 2: Domain Knowledge based Disambiguation and Reordering

In this section, we propose to improve the Top-1 accuracy through intelligent reordering of the Top-5 labels from the vision classifier. In-order to achieve this, we leverage the domain knowledge associated with the teaching activity as a second source of information to re-order the Top-5 output labels. Domain Knowledge refers to the classroom learning context (derived from teacher's current syllabus, teaching themes, object related clues, collaborative clues) based on which the learning activity is conducted. Note that the Domain Knowledge could be a *word* or a *phrase* too. We now discuss various important aspects of this stage in detail.

Enabling Semantic Capability. Domain Knowledge is a text representation of the intent or activity derived from the classroom context. However, same intent or information could be conveyed through different keywords, and hence traditional bag-of-word approaches [23] will not solve the problem in our use-cases. We leverage the support of semantic representations (i.e. distributed word representation [16]) of words for enabling keyword independent re-ranking algorithm. In distributed word representation, words are represented as N-dimensional vectors such that distance between them capture semantic information. There are various pre-trained semantic representation models (also called word embedding models such as Word2Vec [11], GloVe [6]) available which enable semantic comparison of words. Likewise, there is also ConceptNet [5] which is a multilingual knowledge base, representing words and phrases that people use and the common-sense relationships between them. This paper leverages these existing works to achieve an effective re-ranking of the output label-set with semantic capability.

Existing Approach Results. One naive way to approach the problem of re-ranking is to find the DK Correlation Score (DK-CS) using Algorithm. 1 and re-rank the Top-5 labels in descending order of their DK-CS. However, this approach has strong bias towards the semantic representation output and completely ignores the ranking that is produced by the vision classifier.

Other fusion approaches that have been tried are combining one or more of the classifier outputs (i) Word2Vec (S1), (ii) GloVe (S2), (iii) ConceptNet (S3), (iv) Vision (S4) in different ways. The most common are the product rule and the weighted average rule where the confidence scores are combined by computing either a product of them or a weighted sum of them. The improvement in Top-1 accuracy of such combinations varies from -11% to 6%. We observe that the Top-1 accuracy of the system did not increase significantly and in many cases Top-1 accuracy of the system dropped after re-ranking as compared to the original list. The reason being the need for proper and more efficient resolution of conflicts between DK-CS wins vs. vision confidence score wins. In the next section, we explain the proposed novel re-ranking algorithm which highly improves the Top-1 accuracy of the system by effectively resolving the conflicts between DK-CS and vision rankings.

Proposed Re-Ranking Approach. In our proposed approach, we fuse the inferences from various semantic models and vision model using *Majority-Win Strong Vouching algorithm* for re-ordering the Top-5 output list. There are two important aspects of this approach: (i) Strong Vouching of Semantic Models, (ii) Majority Voting across Semantic Models.

Strong Vouching of Semantic Models: As discussed earlier, the reason for failure of the traditional fusion approaches is the need for efficient resolution of conflicts between the semantic model ranks and the vision model ranks. Let us understand this problem through 2 example scenarios. (i) Scenario 1: Top-1 prediction is "orange", Top-2 prediction is "apple", domain Knowledge is "fruits"; (ii) Scenario 2: Top-1 prediction is "orange", Top-2 prediction is "apple", domain knowledge is "red fruits". In the first scenario, since the domain knowledge is semantically correlated towards both Top-1 and Top-2 predicted labels, system should maintain the same order as predicted by the vision model. However, in the second scenario, since the domain knowledge (i.e. "red fruits") is highly correlated towards Top-2 (i.e. "apple")as compared to Top-1(i.e. "orange"), system should swap the order of Top-1 and Top-2 labels. It turns out that just having a higher DK-CS to swap the labels is not enough. We show that DK-CS of one label (label-1) should override the other label (label-2) by a specific threshold value to indicate that label-1 is semantically more correlated with as compared to label-2 and hence effect a swap against the vision rank. Through empirical analysis in Section. 4.2, we show that, in the context of reordering Top-K labels, if normalized DK-CS of a label is greater than the other label by a value equal to $1/k$ (threshold value), then the former label is more semantically correlated with domain knowledge as compared to the latter.

Majority Voting across Semantic Models: As mentioned before, many semantic models exist in the literature and each of them are trained on various data-sets. Therefore, it is not necessary that the strong vouching behavior of all these semantic models to be same. In order to resolve this, our approach considers multiple semantic models together (such as GloVe, Word2Vec and ConceptNet) and enables swapping of i-th label with j-th label (i<j) in the Top-K output list only when majority of semantic models are strongly vouching that j-th label is more correlated with DK as compared to the i-th label. This makes the system more intelligent in resolving across

semantic models as well as resolving conflicts across DK correlation score wins vs. vision confidence score wins. Algorithm. 2 explains the overall flow of the proposed re-ranking algorithm.

Algorithm 2: Fusion based on Majority Win Strong Vouching Concept

Input: Top-K output label from image recognition model, Domain Knowledge(DK)
Output: Reordered Top-K output label list

```
Sort Top-K labels based on vision confidence score
Re-rank the Top-K label by sorting using the following compare logic
Compare logic (i-th label, j-th label, DK): begin
    [Note] i-th label precedes j-th label in the ranked Top-K list.
    X1 = Total number of semantic models strongly-vouching for j-th label as compared to i-th label
    X2 = Total number of semantic models strongly-vouching for i-th label as compared to j-th label
    if X1>X2 then
        swap i-th label and j-th label in the Ranked Top-K list
    else
        Maintain the same order of i-th label and j-th label
return Re-Ranked Top-K List
```

3.3 Stage 3: Human Disambiguation Game

It is important to note that, due to limitation of existing state-of-art vision models, though we achieve effective improvements, we never reach an accuracy of 100%. Even after effective custom training and DK based Top-K re-ranking, accuracy of the system is not 100% (though high improvements are observed). So, there has to be a confirmation step involving human-in-loop to confirm whether the predicted label is the right label to prevent teaching wrong objectives. Since we are dealing with Kids, this step has to be extremely light, simple, and also engaging for the Kids so that, they do not feel any extra cognitive load. In this section, we propose a simple disambiguation game which is designed in a way that, (i) Kids easily play with it correctly, (ii) Kids interaction with the game highly reduces when Top-1 accuracy of the system is high. Through enhancements as explained in previous sections, we make vision model to reach high Top-1 accuracy which in-turn reduces the Kids interactions in the disambiguation game, thereby reducing the overall cognitive overload to the Kids.

Our system leverages image matching for the disambiguation game. Re-ranked Top-K list (which is the output from Stage 2) is fed as input to the disambiguation game. This game is depicted in Figure. 2 renders reference images of the label (with possible variants of a same object) one by one in the order of the re-ranked list and asks the Kid to select the image, if it looks similar to the object clicked (through camera). If not, system show the next reference image and continues till all K labels are rendered. Since the input to the game is a re-ranked Top-K list (which has high Top-1 accuracy), Kid has high chances of encountering the right image in the first or second step itself, thus reducing the cognitive load of the kid to traverse till the end. Usability Guidelines [10] [1] for Child based Apps suggest large on-screen elements which are well spatially separated for Kids to easily interact with them. So, based on the display size of the form-factor, system could configure the no of images to be rendered in one step/cycle. Through usability study with 15 Kids, we show that Kids are able to easily play image similarity based disambiguation games. In scenarios when the right label is not in the predicted Top-K labels, system executes the exit scenarios as configured. Few possible exit scenarios could be: (i) Continue the game with other labels in the learning vocabulary set in the sorted order of DK, (ii) Request for teacher intervention, etc.

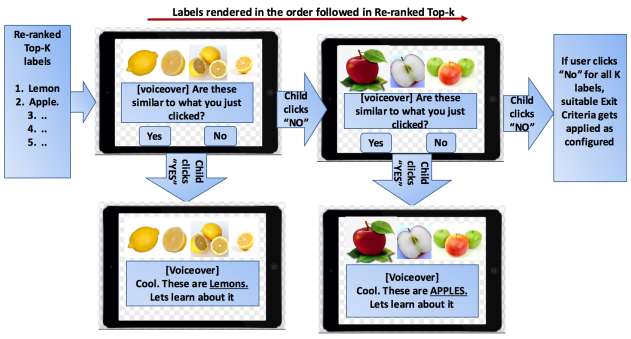


Figure 2: Basic Disambiguation Game

4. EVALUATION

We present here the experimental setup and results of improvement in the vision classifier results achieved by the re-ordering approach. We then explain and present the results of the empirical analysis to determine the value of threshold for strong vouching of the semantic models. To show that our approach is independent of domain knowledge, test set, training class set, and baseline image classification models (generality of approach), we performed various experiments as explained in following subsections. Later in this section, we present the usability study and inferences from the study conducted with a group of 12 children in the age group of 3-5 years.

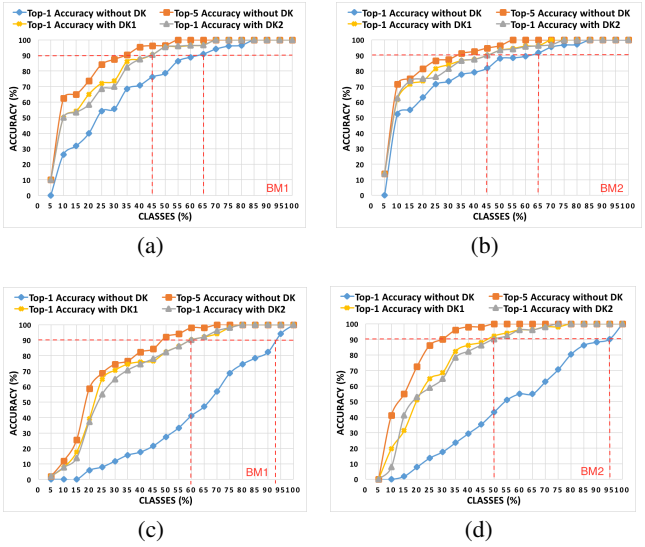
Datasets: The training dataset includes images from Imagenet [8]. We used 52 classes and approximately 400 images per class for training. These 52 selected classes are objects commonly used in early childhood learning, for example, apple, car, book, and violin, etc. The test datasets include real images taken from mobile phones and tablets. The test dataset I includes 1K images where single object (from training set) is present in an image frame. The test dataset II includes 2.6K images where two objects (from training set) are present in an image frame. All the experiments were performed using two baseline image classification models: (i) Baseline Model 1 (BM1): Model based on VGGNet architecture [18], (ii) Baseline Model 2 (BM2): Model based on Inception-V3 architecture [19].

Domain Knowledge: During all the experiments, we used two different domain knowledge (DK): Domain Knowledge 1 (DK1), which is the google dictionary definition [7] of each object class; Domain Knowledge 2 (DK2), which is the merged description of each object class collected from three different annotators (crowdsourced approach). By this way, we make sure that the domain knowledge is not keyword dependent and re-ordering happens at semantic level rather than at any specific keyword matching level.

Evaluation Metrics: In order to illustrate the performance of the proposed approach, evaluation parameters such as Top-1 accuracy, Top-5 accuracy, and improvements in Top-1 accuracy are used. The Top-1 accuracy is computed as the proportion of images such that the ground-truth label is the Top-1 predicted label. Similarly, the Top-5 accuracy is computed as the proportion of images such that the ground truth label is one of the Top-5 predicted labels.

4.1 Experimental Results

The cumulative accuracy distribution of Baseline Model 1 (BM1) and Baseline Model 2 (BM2) on test dataset I and II is shown in Figure. 3. Figures 3(a), 3(b) shows the improvement in the Top-1 accuracy after re-ordering on dataset I which has one object in an image frame. As shown in Figure. 3, for BM1, without re-ordering only 35% of object classes have Top-1 accuracy more than 90%, whereas with re-ordering using DK1 or DK2 around 55% of classes



(a) (b)

(c) (d)

Figure 3: Cumulative accuracy distribution of Baseline Model 1 & Baseline Model 2 on the data set. I(a-b), II(c-d)

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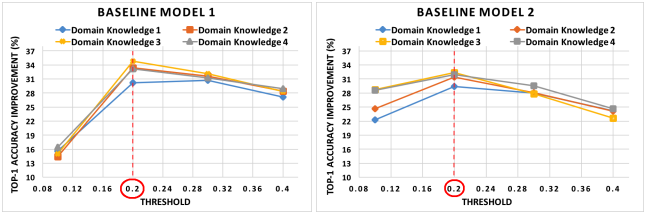
have more than 90% Top-1 accuracy. Similarly, for BM2 our approach shows 20% improvement in number of classes for 90% or above Top-1 accuracy on dataset I as shown in Figure 3(b).
When a child takes an image, it is common that multiple objects get captured in that image. If more than one object is present in an image, then the confusion of the classifier highly increases which leads to low Top-1 accuracy. Figure. 3(c), 3(d) show the improvement in Top-1 accuracy on data set II, where two objects (from training set) are present in an image frame. As shown in Figure. 3(c), for BM1, without re-ordering only 7% of object classes have Top-1 accuracy more than 90% whereas with re-ordering using DK1 or DK2 around 40% of classes have more than 90% Top-1 accuracy. Similarly, for BM2, our approach shows improvement of 45% in number of classes for 90% or more Top-1 accuracy on dataset II as shown in Figure. 3(d).

4.2 Empirical analysis to determine threshold for strong vouching of semantic models

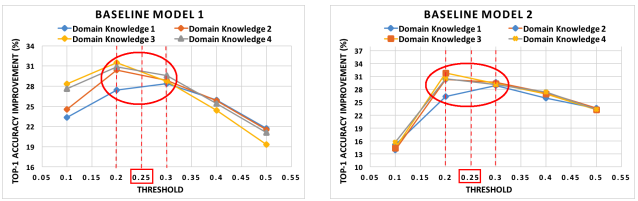
In this section, we explain the empirical analysis which determines the threshold value required by semantic models for strong vouching as discussed in Section. 3.2. In comparing two elements with respect to their semantic correlation with domain knowledge (i.e. DK-CS), the threshold stands for the minimum value by which DK-CS of one element should be higher than the other to confidently say that the element is semantically more correlated with the domain knowledge as compared to the other element. Choice of correct threshold value is very cruicial for the proposed approach. *The threshold value should be as high so as to avoid wrong swapping of labels, and as low to allow correct swapping of labels for better Top-1 accuracy improvements.*
For the empirical analysis of threshold value, we conducted experiments on dataset II with the following combinations (i) four different domain knowledges collected through crowd sourcing, (ii) four different threshold values, and (iii) for both baseline models (BM1&BM2) to make it independent of any local data-behavior. The results are shown in Figure. 4. From the results, we noticed that the correct threshold value is 0.2 for reordering Top-5 predicted labels. As observed in Figure. 4, Top-1 accuracy reaches the peak value when the threshold value is 0.2. We now discuss the reason behind this magical number.



(a) (b)

Figure 4: Improvement in Top-1 accuracy while reordering predicted Top-5 labels for different domain knowledge, threshold values and baseline models

In our approach, we use normalized DK-CS, which means if we consider equal distribution of labels while reordering Top-5 predicted labels, then the DK-CS for each label is 0.2 (i.e. 1/5). We propose that, if DK-CS of one label overrides the semantic score of another label by a value near or equal to the $1/k$ (i.e. individual DK-CS of the labels considering equal distribution of each label), then it is considered as **strong vouching** by semantic model for the former label.
In order to confirm the above proposed claim, we performed ex-



(a) (b)

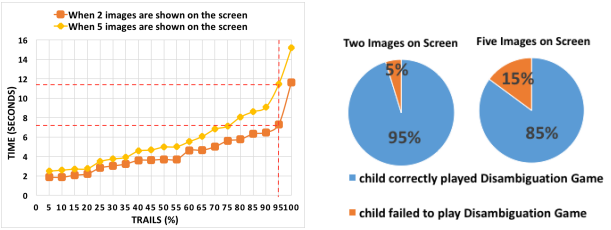
Figure 5: Improvement in Top-1 accuracy while reordering predicted Top-4 labels for different Domain Knowledge, Threshold Values and Baseline Models

periments to reorder Top-4 predicted labels (results are shown in Figure. 5). From the results, we can see that the performance is at peak for threshold between values 0.2 and 0.3, which is near to 0.25 (1/k where k is number 4). There is very noticeable degradation in performance when threshold is below 0.2 or above 0.3. Similar trends were also observed when experimenting with Top-3 re-ordering.
Therefore, the correct choice of threshold while re-ordering Top-k predicted labels is $1/k$. When system is tuned to vouch strongly using this threshold value, we observe high improvements in Top-1 accuracy.

4.3 Usability Study

The main purpose of this usability study is to observe the following key points in children of ages between 3-5 years: (i) whether they can take images using the camera of a phone or tablet, (ii) whether they can perform visual comparison between the physical object for which picture was taken, and its reference image provided by the classifier in the disambiguation game, (iii) comparison of cognitive load on children when they see less vs. more number of images on a device screen during the game. To conduct this study, we asked the child to play with our app installed on iPads, which logged the complete click stream data of the app for tracking various quantitative parameters. We also noted down the feedback from parents/observer during the activity play.

We conducted this usability study on 12 children with a total of 29 trials. In each trail, a child was allowed to play with the app as long



(a) (b)

Figure 6: (a) Cumulative distribution of time taken by children to play disambiguation game when two and five objects are shown on the device screen (b) % of times children correctly played disambiguation game when two and five objects are shown on the device screen

s(he) wanted. We observed that some children played only one time in a trial and some played upto 8 times in a trail. There were no limitations on the number of trails per child. We did not observe even a single instance where a child was asked to capture an image of a relevant object using the camera and s(he) failed to do it. This shows that children of that age group can easily take pictures. The average time taken by a child to search for an object in the environment and take picture was 20 seconds. From the collected data, we observed that around 90% of times, children are able play the disambiguation game correctly. The common feedback which we got from parents/observers is that children liked this app and wanted to play it again and again.

The comparison of cognitive load on a child when (s)he got 2 object images (from Top-2) vs. 5 object images (from Top-5) on a screen during disambiguation game is shown in Figure.6 (a). Around 95% of children took upto 7 and 11 seconds for disambiguation game when they got 2 and 5 options on a screen, respectively (as shown in figure 6a). Similarly, Figure. 6 (b) shows that on an average a child failed to make a visual comparison only 5% of time (when there were 2 images on a screen) and 15% of time (when there were 5 images on a screen). These results indicate that, child is able to easily play the disambiguation game but the cognitive load reduces when less number of images were rendered in each turn of the game. Since the proposed re-ranking algorithm increases the Top-1 accuracy of the system, the child could reach the right object in initial rounds of the disambiguation game with high chance, thereby providing a good user experience.

5. CONCLUSION

We present a holistic visual recognition system for Early Childhood Learning through physical-digital interaction that improves recognition accuracy levels using (a) domain restriction and custom training of vision classifiers, (b) a novel re-ranking algorithm for multi-modal fusion of contextual information, and (c) semi-automated feedback with different gaming scenarios for right object-tag identification & classifier re-training. Through a usability study with 12 children, we make the case that engaging user experiences can indeed be developed to bridge the gap between automatic visual recognition accuracies and the requirement of high accuracy for meaningful learning activities.

Extensive evaluations on large datasets brought forth the deficiency of existing multimodal fusion techniques in combining the domain knowledge context with the vision classification results. Using a data driven approach we show the efficacy of our proposed re-ranking algorithm based on strong vouching, and also show that the swapping threshold (derived from data) is also anchored in a physical meaning.

For future work we would like to conduct extensive pilot study with children to demonstrate evidence-of-learning for vocabulary acquisition using physical-digital interaction. We would also like to use other implicit contexts such as location, speech cues, wearable sensors etc. to derive domain knowledge for better multimodal disambiguation.

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Student Learning Strategies and Behaviors to Predict Success in an Online Adaptive Mathematics Tutoring System

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ABSTRACT

Student learning strategies play a critical role in their overall success. The central goal of this study is to investigate how learning strategies are related to student success in an online adaptive mathematics tutoring system. To accomplish this goal, we developed a model to predict student performance based on their strategies in ALEKS, an online learning environment. We have identified student learning strategies and behaviors in seven main categories: help-seeking, multiple consecutive errors, learning from errors, switching to a new topic, topic mastery, reviewing previous mastered topics, and changes in behavior over time. The model, developed by using stepwise logistic regression, indicated that requesting two consecutive explanations, making consecutive errors and requesting an explanation, and changes in learning behaviors over time, were associated with lower success rates in the semester-end assessment. By contrast, the reviewing previous mastered topics strategy was a positive predictor of success in the last assessment. The results showed that the predictive model was able to predict students' success with reasonably high accuracy.

Keywords

Help-seeking, errors, learning strategy, math, student success, adaptive tutoring system

1. INTRODUCTION

Computer-based learning environments, particularly intelligent tutoring systems (ITS), are becoming more commonly used to assist students in their acquisition of knowledge. Computer-based tutors provide tailored instruction and one-to-one tutoring, which can improve students' learning experiences and their motivation. These learning systems also provide unique and critical insight to learning science researchers by creating exhaustive archives of student learning behaviors. A central goal of investigating student learning processes is to unveil the associations between learning behaviors and performance, ultimately allowing learning system developers and researchers to predict and understand student performance. This knowledge allows for evidence-based and individually tailored feedback to be provided to students who are struggling to learn.

2. RELATED WORK

Many studies have investigated the relationships between learning behaviors and success in learning [1, 2]. The most frequent learning behaviors used in the current literature involve help-seeking, making errors, persistence, and changes in learning behaviors over time [3, 4, 5]. For example, worked examples, an effective and commonly used type of help, can be overused by students, negatively affecting learning [6]. However, asking for help after making an error has been found to be an effective help-seeking strategy, particularly for high prior knowledge students [7]. Additionally, reading a worked example after solving a problem can foster better learning than practice alone and reading a worked example before solving a problem can improve learning when compared to reading a worked example after solving a problem [8, 9].

Clearly, there is a delicate interplay between help-seeking strategies students use, their prior knowledge, and learning success. Whether students benefit from making errors often depends on how errors are approached pedagogically. Errors, when treated as stemming from student inadequacies, can trigger math anxiety, which negatively affects students' learning [10, 11]. An extreme example of making errors during learning is seen in wheel-spinning behaviors, in which students attempt ten problems or more without mastering the topic. While too many consecutive errors (i.e. wheel-spinning) undermine learning performance [12], repeated failure in the low-skill phase has been found to improve the likelihood of success in the next step [5] and to lead to more robust learning [13]. Furthermore, the errors that naturally occur from desirable difficulty are considered to be an essential element in learning [14] and facilitate long-term knowledge retention and transfer [15, 16, 17].

Many of the current computer-based tutoring systems are designed to provide students more autonomy by allowing them to learn at their own pace. In self-paced or self-regulated tutoring systems, students' learning behaviors tend to change over time during learning. These changes in learning behaviors over time represent an important aspect of learning for researchers to understand. Relatively more well-structured behavior over time is positively related to reading performance, whereas more chaotic, less-structured learning behaviors are related to poor reading performance [4].

Persistence is another increasingly studied behavior in learning research. For example, persistence is measured as time spent on unsolved problems during solving anagrams and riddles [18]. Persistence on challenging tasks is associated with mastery goals, which benefit learning [19]. Given these definitions of persistence, a contrasting learning behavior could be considered frequently switching topics within a learning system to find easier topics, an example of gaming the system [20]. Based on students' self-reports, persistence was also found to positively related to student satisfaction with the computer-based tutoring system [21]. However, unproductive persistence (i.e. wheel-spinning) impedes learning, but various formats of problems and spaced practice can reduce unproductive persistence and improve learning [22].

Reviewing previous learned materials is an efficient way to improve learning. Per Ebbinghuas' forgetting curve [23], memory retention declines over time. Repeated exposure to previously learned materials can enhance memory retention and improve learning [24]. An example of reviewing previously learned materials is seen in the retrieval practice, which was found to improve students' memory retention of reading materials [25] as well accuracy in solving "student-and-professor" algebra word problems [26].

This study aims to investigate which learning behaviors predict student success in ALEKS (Assessment and Learning Knowledge Spaces), a math tutoring system that adapts to students' knowledge [27]. Given the above literature, help-seeking behaviors, multiple consecutive errors, learning from errors, temporal behavioral changes, persistence (i.e. switch to a new topic without mastering the current topic), and reviewing previous mastered topics were selected as potential predictors of success in ALEKS. In addition, the percentage of topics that have been mastered, an indicator of learning progress, is included in the model to predict success.

3. Description of ALEKS

ALEKS is a web-based artificially intelligent learning and assessment system [27]. Its artificial intelligence is based on a theoretical framework called Knowledge Space Theory (KST) [28]. KST allows domains to be represented as a knowledge map consisting of many knowledge states, which represent the prerequisite relationships between different knowledge states (KS). Therefore, KST allows for a precise description of a student's current knowledge state, and what a student is ready to learn next. ALEKS can estimate a student's initial KS by conducting a diagnostic assessment (based on a test) when the student first begins to interact with the system. ALEKS conducts assessments during students' progress through the course to update their knowledge states and to decide what the student is ready to learn next.

For each topic within ALEKS, a problem is randomly generated, with adjustments made to several parameters for each problem type. This results in an enormous set of unique problems. Students are required to provide solutions in the form of free-response answers, rather than by selecting an answer from multiple choices. Explanations in the form of worked examples can be requested by students at any time. When an explanation is requested, a worked example for the current problem is provided and a new problem is provided to the student. The interface of ALEKS is displayed in Figure 1.

ALEKS is self-paced; students can choose topics to learn and can choose when they want to request help. All the topics that the student is most ready to learn (per the KST model) are displayed in his or her knowledge pie (Figure 2). The knowledge pie presents the student's learning progress in each math subdomain as well.

Research has shown ALEKS produces learning outcomes comparable with other effective tutoring systems for teaching Algebra [29]. Using ALEKS as an after-school program has also been observed to be as effective as interacting with expert teachers [32]. Students need less assistance during learning when using ALEKS than in traditional curricula [31]. Additionally, ALEKS has been found to reduce the math performance discrepancies between ethnicities in an after-school program [32].

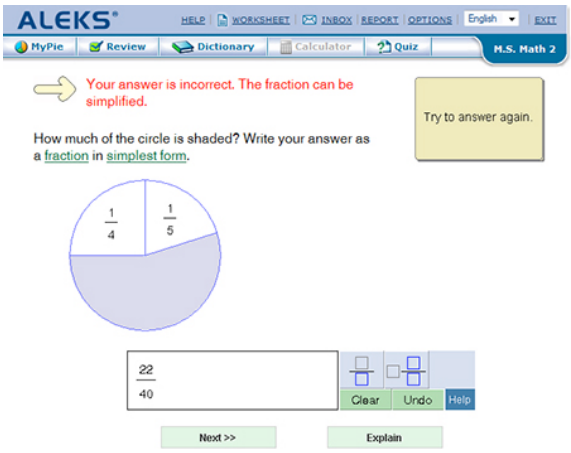

Figure 1. The ALEKS interface

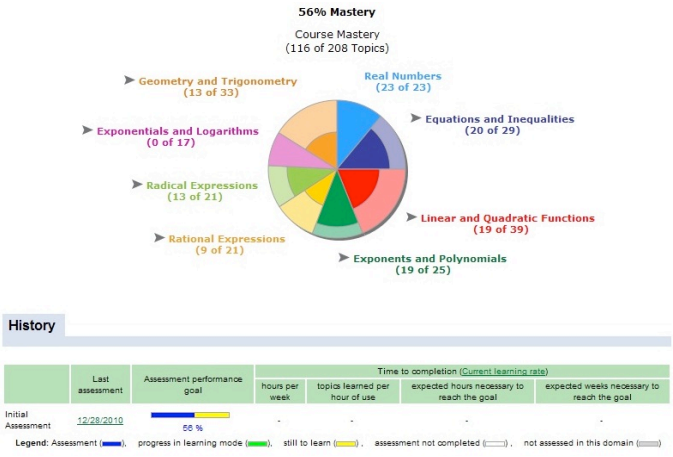

Figure 2. The ALEKS knowledge pie

4. Data

The data used in this study was collected from 179 students within 11 college classes that used ALEKS for developmental mathematics in Fall 2016. The data is comprised of information about students' learning actions and assessment scores. These actions include "correct" (C), "wrong" (W), mastering a topic (S; three C's in a row within a single topic), failing a topic (F; five W's in a row within a single topic) and explanations (E; requesting an explanation). The data also contains students' last assessment scores in ALEKS which account for students' performance in ALEKS.

5. METHODS

We employed stepwise logistic regression with backward elimination to predict students' success in ALEKS, using a training-test split. More details of this process are described below.

5.1 Student success

Success in ALEKS is defined as students knowing 60% or more of the topics in their last assessment. Therefore, we adopted 60% in the semester-end assessment as a cut-off value for success. Students whose last assessment score was 60% or greater were grouped as "successful students", whereas those with last assessment scores under 60% was grouped as "unsuccessful students". The dataset was randomly split into two parts: 60% of students' data were used to train the model (N=107), and 40% were used to test the model's generalizability (N= 72). Success was labeled as 1 and failure was labeled as 0 in the prediction model.

5.2 The features to predict success

The following behavior patterns were used to predict student success: (1) help-seeking i.e., requesting an explanation after making an error (WE), and requesting two sequential explanations (EE); (2) multiple consecutive errors i.e., making two sequential errors (WW), making an error again after an error and requesting an explanation (WEW), making an error again after an error and requesting two explanations (WEEW), and the overall percentage of failure labeled by ALEKS (PF); (3) learning from errors i.e., providing a correct answer after making an error (WC), providing a correct answer after making an error and requesting an explanation (WEC), and providing a correct answer after making an error and requesting two explanations (WEEC); (4) switching to a new topic i.e., switching to a new topic after making an error or requesting an explanation (PNew), and switching to a new topic because of failure on a topic (FNew); (5) topic mastery (PS), i.e. providing three correct responses in a row; (6) reviewing previous mastered topics (PReview); and finally, (7) changes in learning behaviors over time (measured using the entropy metric).

The features of the first four aspects mentioned above were generated by using D'Mello's likelihood metric [33] (Equation 1).

The likelihood metric is used to compute the transition probability of an event to another event. In the case of multiple events, we calculate a proportion of each sequence out of the number of sequences of that length. For example, the probability of WEEW means the transition probability of WEE to W. In this case, WEE is represented as M_t and W is represented as M_{t+1} in the formula. When the value produced by the likelihood metric is higher than 0, it signifies that M_{t+1} occurs after M_t more frequently than the base rate of M_{t+1}. Otherwise, M_{t+1} occurs after M_t at a rate lower or equal than the base rate of M_{t+1}.

$$L(M_t \rightarrow M_{t+1}) = \frac{Pr(M_{t+1}|M_t) - Pr(M_{t+1})}{1 - Pr(M_{t+1})} \quad (1)$$

Shannon entropy is used to compute the degree of regularity in the changes in students' learning behaviors over time (specifically focusing on the shifts between making an error, give a correct answer, and requesting an explanation) [34] (Equation 2). High entropy values represent disordered leaning behavior patterns. On the contrary, low entropy implies ordered pattern of learning behaviors:

$$H(x) = -\sum_{i=0}^{N} P(x_i)(\log_e P(x_i)) \quad (2)$$

The details on how the features were computed are listed below in table 1.

Table 1. Descriptions of features used to predict success

Features	Description
WE	The transition probability from making an error to requesting an explanation
EE	The transition probability from requesting an explanation to requesting another explanation
WW	The transition probability from making an error to making an error again
WEW	The transition probability from making an error and requesting an explanation to making an error again
WEEW	The transition probability from making an error and requesting two sequential explanations to making an error again
PF	The proportion of times a student made five consecutive errors
WC	The transition probability from making an error to giving a correct answer
WEC	The transition probability from making an error and requesting an explanation to giving a correct answer
WEEC	The transition probability from making an error and requesting two sequential explanations to giving a correct answer
PNew	The probability of starting a new topic after making an error or requesting an explanation on the current topic
FNew	The probability of starting a new topic after failing a topic
PS	The proportion of the mastered topics out of the number of the attempted topics during learning
PReview	The percentage of mastered topics that the student reviews after mastering them
Entropy	The entropy value produced based on students' learning behaviors

6. RESULTS

6.1 Description of features

Before building the prediction model, we calculated basic descriptive statistics. The mean and standard deviations are listed in Table 2.

Table 2. Feature means and standard deviations

Features	M	S.D.
WE	.40	.11
EE	-.07	.07
WW	-.02	.08
WEW	.15	.09
WEEW	.06	.25
PF	.07	.07
WC	-.69	.37
WEC	-.07	.18
WEEC	-.22	.46
PNew	.001	.01
FNew	.76	.33
PS	.87	.10
PReview	.14	.11
Entropy	.51	.11

6.2 Model development

Stepwise logistic regression with backward elimination was used to generate the predictive model of students' success. The final model included requesting an explanation after making an error (WE), requesting two sequential explanations (EE), making an error again after making an error and requesting an explanation (WEW), changes in learning behaviors over time (entropy) and review on the topic (PReview). Each of these metrics were statistically significant predictors of students' success (i.e. the score in the last assessment is greater or less than 60%) in ALEKS. The details on the prediction model are displayed in Table 3.

Table 3. The results of multi-feature logistic regression on students' success

	B	S.E.	Z value	p
Intercept	3.32	1.63	2.04	.04*
WE	4.25	2.31	1.84	.07
EE	-8.31	4.05	-2.06	.04*
WEW	-11.33	3.40	-3.33	.00***
Entropy	-10.34	2.91	-3.55	.00***
PReview	9.44	2.57	3.67	.00***

Note. p<.000 ***, p<.05 *

The results of multicollinearity indicated that there were low correlations between features. The VIF value (i.e. variance inflation factor) for each feature is illustrated in Table 4.

Furthermore, logistic regressions that only include one single feature were conducted to examine suppression effect. The results were listed in Table 5. The results showed that compared to the results of multi-feature logistic regression, the direction of relationship between each feature and success did not change in the single-feature logistic regression. Therefore, the relationship between features and success was not impacted by suppression effect.

Then, based on the results of logistic regressions, students were less likely to be successful in the last assessment if they tend to read two consecutive explanations, or made an error after making an error and requesting an explanation, or demonstrated irregularity in their learning behaviors. By contrast, the more frequently students reviewed topics they have already mastered, the more likely they were to pass the last assessment in ALEKS.

Table 4. Multicollinearity between features in the prediction model

	WE	EE	WEW	entropy	PReview
VIF	1.02	1.32	1.17	1.66	1.50

Table 5. The summary of single-feature logistic regressions on students' success

	B	Z value
WE	4.40	2.32
EE	-0.61	-.23
WEW	-9.12	-3.44
Entropy	-5.01	-2.62
PReview	5.24	2.60

6.3 Model goodness

The fitness index of the prediction model (i.e. AIC) of training data was 115.67. McFadden pseudo r^2 of training data was .30, indicating that this model predicts a substantial amount of the variance in student success.

The model's accuracy of prediction on test data was 0.71. The AUC of test data (area under the ROC curve) was 0.77. The plot of the ROC curve is illustrated in Figure 3.

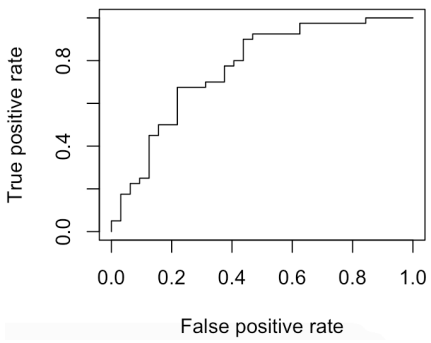

Figure 3. The ROC plot of the prediction model

7. DISCUSSIONS

The current study developed a logistic model to predict student overall success in ALEKS, as well as the relationship between various learning behaviors and success. Our findings contribute to the current understanding of the relationship between student learning behaviors and their delayed performance in adaptive tutoring systems, as well as provide evidence-based suggestions for improving the feedback and interventions in ALEKS.

Requesting two sequential explanations (EE) had a negative relationship with success in the last assessment, a finding in line with previous research on the negative effect of overusing help on learning [8]. However, the EE behaviors may suggest that students did not understand the first explanation rather than indicating that the students were "gaming the system". This can be concluded for the following reason. After requesting a worked-examples explanation, the student typically receives a new problem. Making an error again after making an error and requesting an explanation (WEW) was negatively related to students' success. The relationship between WEW and success suggests that students frequently make multiple consecutive errors, even after receiving the provided worked examples. These students may have trouble understanding the example. Therefore, if students frequently demonstrate those two behaviors on a specific problem, more individually-tailored and deeper-level instructions may be needed to provide the necessary help to overcome the impasse, such as concept-specific conversations with tutor agents that are integrated in ALEKS.

Another finding conforming to the previous research was that regular behaviors during learning is positively related to students' performance [cf. 5]. In this study, the measurement of changes of behaviors over time (via Shannon entropy) is relatively coarse-grained. Moving forward, deeper and finer-grained investigations of changes in behavior over time may shed further light on why regularity is associated with better outcomes.

Another finding worth noting was that the percentage of topics mastered (PS) during learning was not found to be a significant predictor of success on the last assessment. An explanation of this finding may lie in the adaptive design of ALEKS. During learning, ALEKS continually matches students' existing knowledge with topic difficulty and provides the topics that students are most ready to learn, so students focus their time on topics that have an appropriate level of difficulty [22]. Thus, the percentage of topics being mastered may not differ much between students who were successful in the last assessment and those who failed the last assessment. Finally, reviewing previously mastered topics (PReview) was found to be positively linked to students' success in the last assessment, which confirmed the findings of literature [24].

Our model was able to accurately predict student success. However, some improvements can be made in the future. The current model only includes percentages or probabilities of behaviors without considering the time spent on these behaviors. In the future, adding the time duration of behaviors may increase the prediction accuracy of the model. Additionally, refining the measurements of behaviors may increase the prediction accuracy of the model. For example, changes in learning behaviors over time could be measured during different learning phases or in specific temporal sequences.

By better understanding the factors associated with success in ALEKS, we can design interventions that will improve student success – the ultimate goal of any intelligent tutoring system.

8. ACKNOWLEDGMENTS

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Adaptive Assessment Experiment in a HarvardX MOOC

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ABSTRACT

We report an experimental implementation of adaptive learning functionality in a self-paced HarvardX MOOC (massive open online course). In MOOCs there is need for evidence-based instructional designs that create the optimal conditions for learners, who come to the course with widely differing prior knowledge, skills and motivations. But users in such a course are free to explore the course materials in any order they deem fit and may drop out any time, and this makes it hard to predict the practical challenges of implementing adaptivity, as well as its effect, without experimentation. This study explored the technological feasibility and implications of adaptive functionality to course (re)design in the edX platform. Additionally, it aimed to establish the foundation for future study of adaptive functionality in MOOCs on learning outcomes, engagement and drop-out rates. Our preliminary findings suggest that the adaptivity of the kind we used leads to a higher efficiency of learning (without an adverse effect on learning outcomes, learners go through the course faster and attempt fewer problems, since the problems are served to them in a targeted way). Further research is needed to confirm these findings and explore additional possible effects.

Keywords

MOOCs; assessment; adaptive assessment; adaptive learning.

1. INTRODUCTION

Digital learning systems are considered adaptive when they can dynamically change the presentation of content to any user based on the user's individual record of interactions, as opposed to simply sending users into different versions of the course based on preexisting information such as user's demographic information, education level, or a test score. Conceptually, an adaptive learning system is a combination of two parts: an algorithm to dynamically assess each user's current profile (the current state of knowledge, but potentially also affective factors, such as frustration level), and, based on this, a recommendation engine to decide what the user should see next. In this way, the system seeks to optimize individual user experience, based on each user's prior actions, but also based on the actions of other users (e.g. to identify the course items that many others have found most useful in similar circumstances). Adaptive technologies build on decades of research in intelligent tutoring systems, psychometrics, cognitive learning theory and data science [1, 3, 4].

Harvard University partnered with TutorGen to explore the feasibility of adaptive learning and assessment technology implications of adaptive functionality to course (re)design in HarvardX, and examine the effects on learning outcomes, engagement and course drop-out rates. As the collaboration evolved, the following two strategic decisions were made: (1) Adaptivity would be limited to assessments in four out of 16 graded sub-sections of the course. Extra problems would be developed to allow adaptive paths; (2) Development efforts would be focused on Harvard-developed Learning Tools Interoperability (LTI) tool to support assessment adaptivity on edX platform. Therefore, in the current prototype phase of this project, adaptive functionality is limited to altering the sequence of problems, based on continuously updated statistical inferences on knowledge components a user mastered. As a supplement to these assessment items, a number of additional learning materials are served adaptively as well, based on the rule that a user should see those before being served more advanced problems.

While the prototype enabled us to explore the feasibility of adaptive assessment technology and implications of adaptive functionality to course (re)design in HarvardX, it is still challenging to judge its effects on learning outcomes, engagement and course drop-out rates due to the prototype limitations. However, we believe that the study will help to establish a solid foundation for future research on the effects of adaptive learning and assessment on outcomes such as learning gains and engagement. [5]

2. SETUP AND USER EXPERIENCE

The HarvardX course in this experiment was "Super-Earths and Life". It deals with searching for planets orbiting around stars other than the Sun, in particular the planets capable of supporting life. The subject matter is physics, astronomy and biology. Roughly speaking, the course aims at users with college-level knowledge of physics and biology. Some of the assessment material in the course requires calculations, and some requires extensive factual knowledge (e.g. questions about DNA structure).

Two versions of the course have already run in the edX platform, our adaptivity was implemented as part of the course re-design for the third run.

A number of subsections in the course contained assessment modules (homeworks). The experiment consisted of making four of these homeworks adaptive for some of the users. At the moment of their registration, the course users were randomly split 50%-50% into an experimental group and into a control group. When arriving to a homework, users in the control group see a predetermined, non-adaptive set of problems on a page. The same is true for the experimental group in all homeworks except the four where we deployed the adaptive tool. In these homeworks, a user from the experimental group is served problems sequentially, one by one, in the order that is individually determined on-the-fly based on the user's prior performance. In addition to problems, some instructional text pages were also included in the serving sequence.

To enable adaptivity, we manually compiled a list of knowledge components (KCs, for our purposes synonymous with "learning objectives", "learning outcomes", or "skills") and tagged problems in the course with one or several knowledge components. This tagging was done for *all* assessment items in the course (as well as for some learning materials), enabling the adaptive engine to gather information from any user's interaction with any problem in the course, not only with those problems that are served adaptively. Additionally, the problems in the 4 adaptive homeworks were tagged with one of three difficulty levels: advanced, regular and easy (other problems in the course were tagged by default as regular). No pre-requisite relationships or other connections among the knowledge components were used.

The adaptive engine (a variety of Bayesian Knowledge Tracing algorithm) decides which problem to serve next based on the list of KCs covered by the homework and course material. Additional rules could be incorporated into the serving strategy. Thus, we had a rule that before any problem of difficulty level "Advanced", the user should see a special page with advanced learning material.

The parity between experimental and control groups was set up as follows. In the pool from which problems are adaptively served to the experimental group, all the regular-difficulty problems were the ones that the control group saw in these homework. The control group had access to the easy and advanced problems as well: students in this group saw a special "extra materials" page after each of the 4 experimental homeworks. This page contained the links to all the advanced instructional materials and advanced and easy problems for this homework, for no extra credit. Thus, all the materials that an experimental user can see, were also available to the control students. There were two main reasons for this: obvious usefulness for comparative studies, and enabling all students, experimental and control, to discuss all problems in the course forum.

When an experimental group user is going through an adaptive homework, the LTI tool loads edX problem pages in an iFrame. Submitting ("checking") an answer to the problem triggers an update of user's mastery, but does not trigger serving the next problem. For that to happen, the user has to click the button "Next Question" outside the iFrame. The user always can revisit any of the previously served problems.

In edX, users usually get several attempts at a problem. Thus, it may be possible for a user to submit a problem after the next problem has already been served. Fig. 1, for instance, shows a situation, where so far 4 problems have been served (note the numbered tabs in the upper left), but the user is currently viewing problem 2 in this sequence, not the latest one. The user is free to re-submit this problem, which will update the user's mastery (although in this case there is no need to do so, since it appears that problem 2 has been answered correctly). It will not alter the existing sequence (problems 3 and 4 will not be replaced by others), but it may have effect on what will be served as 5 and so on.

The user interface keeps track of the total number of points earned in a homework (upper right corner in Fig. 1). The user knows how many points in total are required and may choose to stop once this is achieved (earning more points will no longer affect the grade). Otherwise, the serving sequence ends when the pool of questions is exhausted. Potentially, it could also end when the user's probability of mastery on all relevant KCs passes a certain mastery threshold (a high probability, at which we consider the mastery to be, in practical terms, certain; it was set to 0.9). However, in this particular implementation, due to having only a modest number of problems, this was not done.

In order to explore possible effects of adaptive experiences on learners' mastery of content knowledge competence-based pre- and post-assessment were added to the course and administered to study participants in both experimental and control groups. Typical HarvardX course clickstream time-stamped data and pre-post course surveys data was collected.

2.1 Course Design Considerations

Adaptive learning techniques require the development of additional course materials, so that different students can be provided with different content. For our prototype, tripling the existing content in the four adaptive subsections was considered a minimum to provide a genuine adaptive experience. This was achieved by work from the project lead and by hiring an outside content expert. This did not provide each knowledge component with a large number of problems, reducing the significance of knowledge tracing, but it was sufficient for the purpose of our experiment. The total time outlay was ~200 hours. Keeping the problems housed within the edX platform avoided substantial amounts of software development.

The tagging of content with knowledge components was done by means of a shared Google spreadsheet, which contained a list of content items in one sheet (both assessment and learning materials), a list of knowledge components in another, and a correspondence table (the tagging itself), including the difficulty levels, in the third.

Most of the time was spent on creating new problems based on the existing ones. For these the tagging process was "reversed": rather than tag existing content with knowledge components, the experts created content targeting knowledge components and difficulty levels. Commonly, an existing problem was considered to be of "regular" difficulty, and the expert's task was to create an "easy" and/or an "advanced" version of it.

103 distinct knowledge components were used in tagging. The experts used their judgement in defining them. 66 of these were used in tagging problems, and in particular the 39 adaptively served problems were tagged with 25 KCs. The granularity of KCs was such that a typical assessment problem was tagged with one learning objective (which is desirable for knowledge tracing). Namely, among the adaptively served problems, 31 were tagged with a single KC, 7 problems – with 2 KCs, and 1 problem – with 3.

2.2 LTI Tool Development

To enable the use of an adaptive engine in an edX course, Harvard developed the Bridge for Adaptivity (BFA) tool (open-source, GitHub link available upon request). BFA is a web application that uses the LTI specification to integrate with learning management systems such as edX. BFA acts as the interface between the edX course platform and the TutorGen SCALE (Student Centered Adaptive Learning Engine) system, and handles the display of problems recommended by the adaptive engine. Problems are accessed by edX XBlock URLs.

This LTI functionality allows BFA to be embedded in one or more locations in the course (4 locations in our case). The user interface seen by a learner when they encounter an installed tool instance is that shown in Fig. 1.

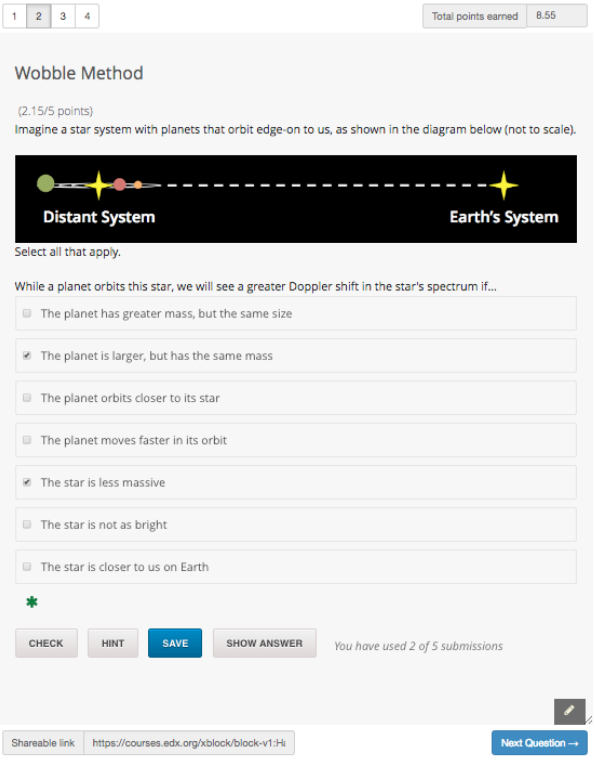

Figure 1. Adaptive assessment user interface

Problems from the edX course are displayed one at a time in a center activity window, with a surrounding toolbar that provides features such as navigation, a score display, and a shareable link for the current problem (that the learner can use to post to a forum for help). The diagram in Fig. 2 describes the data passing in the system. The user-ids used by edX are considered sensitive information and are not shared with SCALE: we created a different user-id system for SCALE, and the mapping back and forth between the two id-systems happens in the back end of the app.

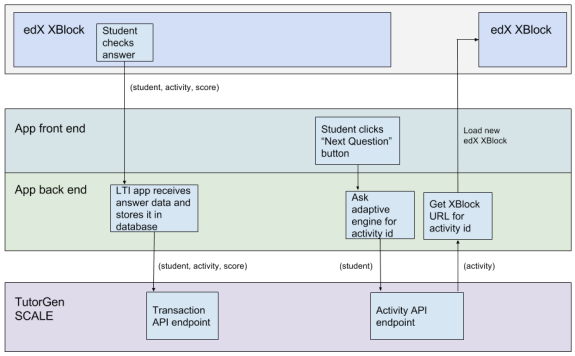

Figure 2. Diagram of data passing in the system

Every problem-checking event by the user (both inside and outside the adaptive homeworks) sends the data to SCALE, to update the mastery information real-time. Every "Next Question" event in an adaptive homework sends to SCALE a request for the next content item to be served to the user (this could be instructional material or a problem). SCALE sends back the recommendation, which is accessed as an edX XBlock and loaded.

The edX support for LTI is highly stable. The challenge is that edX exports data on a weekly cycle, but we needed to receive the information about submits in real time. We achieved this by creating a reporting JavaScript and inserting it into every problem.

2.3 TutorGen Adaptive Engine

TutorGen SCALE is focused on improving learning outcomes using data collected from existing and emerging educational technology systems combined with the core technology to automatically generate adaptive capabilities. Key features that SCALE provides include knowledge tracing, skill modeling, student modeling, adaptive problem selection, and automated hint generation for multi-step problems. SCALE engine improves over time with additional data and/or with the help of human input by providing machine learning using a human-centered approach. The algorithms have been tested on various data sets in a wide range of domains. For successful implementation and optimized adaptive operations, it is important that the knowledge components be tagged at the right level of granularity.

SCALE has been used in the intelligent tutoring system environment, providing adaptive capabilities during the formative learning stages. SCALE with HarvardX for this course is being used more as in the assessment stage of the student experience. In order to accomplish the goals of the prototype for this pilot study, we extended our algorithms to consider not only the knowledge components (KCs), but also problem difficulty. This will accommodate the needs for this course by providing an adaptive experience for students while still supporting the logical flow of the course. Further, the flexible nature of the course, having all content available and open to students for the duration of the course, presents some additional requirements to ensure that students are presented with problems based on their current state and not necessarily where the system believes they should navigate.

A variety of serving strategies are available in SCALE and can be swapped in and out. In this particular implementation, while the algorithm did trace the students' knowledge, the results were used minimally in the serving strategy: it did not make sense to do otherwise given the small size of the adaptive problem pool. SCALE was configured to consider after each submit: the probability of the learner has mastered the KCs from the problem most recently worked, the difficulty of that problem, and the correctness of the submitted answer. A general and simplified explanation of the process is as follows. Each of the four adaptive modules was treated as a separate instance, with its own pool of problems. Each problem can be served to each learner no more than once. Given the last problem submitted by a learner in the module, the candidate to be served next is the (previously unseen) problem, whose KC tagging overlaps with the KCs of the last submitted problem and includes at least one KC, on which the user has not yet reached the mastery threshold. If multiple candidates are available, SCALE will serve the one with a KC closest to mastery. If no candidates are available, other problems of the same difficulty within the same module will be served (i.e. SCALE switches to another KCs). The difficulty level of the next served problem is determined by the last submit correctness. As long as problems of the same difficulty level as the last one are available, the learner will remain at that difficulty level. Once such problems are exhausted, SCALE will serve a more or less difficult problem, depending on whether the last submit in the module was correct or incorrect.

2.4 Quantitative Details and Findings

The course was launched on Oct 19, 2016. The data for the analysis presented in this paper were accessed on Mar 08, 2017 (plus or minus a few days, since different parts of the data were extracted at different times), after the official end date of the course.

Table 1. Number of students attempting assessment items of different difficulty level

	Experimental group	Control group
Regular level only	58	73
Easy level only	0	0
Advanced level only	1	0
(Regular ∪ Easy) levels only	1	35
(Regular ∪ Advanced) levels only	105	0
(Easy ∪ Advanced) levels only	0	1
(Regular ∪ Easy ∪ Advanced) levels	99	145
Total students attempting new problems	264	254

We will refer to the list of problems from which problems were served adaptively to the experimental group as "new problems". The control group may have interacted with these as well, although not adaptively (as additional problems that do not count towards the grade). There were 39 new problems, out of which 13 were regular difficulty (these formed the assessments for the control group of students), 14 were advanced and 12 were easy. For the control group, the advanced and easy problems were offered as extra material after assessment, with no credit toward the course grade. The numbers of students attempting assessment problems of different difficulty levels are given in Table 1.

To get a sense of how the two groups of students performed in the course, we compared the group averages of the differences in scores in the pre-test and post-test. For reasons unrelated to this study, both tests were randomized: in each test each user received 9 questions, randomly selected from a bank of 17. All questions were graded on the 0-1 scale. The users knew that the pre- and post- tests do not contribute to the grade, and so only about ~40% of users took both. Moreover, not all of these questions were *relevant* for (i.e. tagged with) those 25 knowledge components, with which the adaptively served problems were tagged. So the number of offered *relevant* questions varied randomly from user to user. For these reasons the pre- and post-test are not the most reliable measure of knowledge gain, but it was still important for us to make sure that adaptivity did not have any adverse effect. Each question was graded on the scale 0-1, and in Fig. 3 we subset the student population to those individuals who attempted a "new problem" *and* a relevant pre-test question *and* a relevant post-test question, and used the average score from relevant questions as the student's relevant score. For instance, if one user attempted two relevant questions in a pre-test, and another user attempted three, and the questions were answered correctly, both users have the relevant score 1: (1+1)/2=(1+1+1)/3.

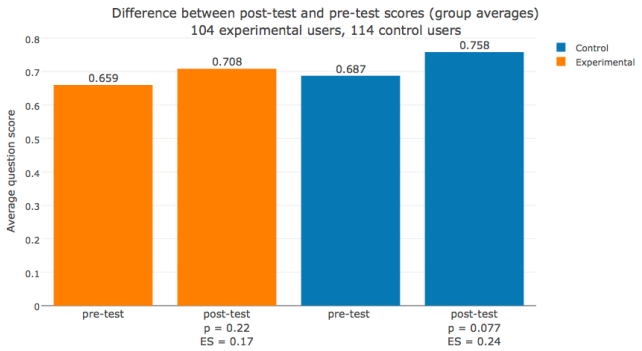

Figure 3. Comparison of relevant post-test and pre-test scores. Here and everywhere below, the p-values are two-tailed from the Welch two-sample t-test, and the effect size is the Cohen's d (Cohen suggested to consider d=0.2 as "small", d=0.5 as "medium" and d=0.8 as "large" effect size).

There is no significant between-group difference, neither in the pre-test scores (p-value 0.49, effect size 0.093) nor in the post-test scores (p-value 0.21, effect size 0.17). The two populations of pre-test takers remain comparable after subsetting to those who attempted new problems and the post-test and we see no statistically significant difference in the knowledge gaining between the experimental and control groups.

We did not see a difference in the final grade of the course: the mean grade was 83.7% in the experimental group vs. 82.9% in the control group, which is not a significant difference (p-value 0.76, effect size 0.06). Likewise, there is no significant between-group difference in the completion and certification rates (about 20%), or in demographics of students who did not drop out.

Students in the experimental group tended to make more attempts at a problem (Fig. 4), and they tried fewer problems (Fig. 5), most strikingly among the easy new problems: for these we have 1,162 recorded scores in the control group and only 423 in the experimental group.

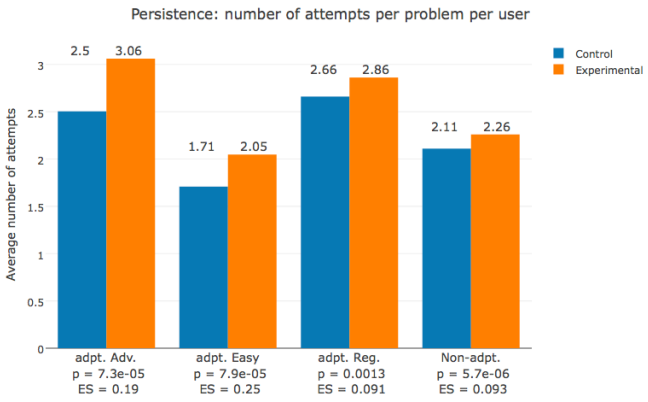

Figure 4. Comparison of attempt numbers between the experimental and control groups in the chapters where adaptivity was implemented. The attempt numbers are averaged both over the problems and over the users. Non-adaptive problems are problems not from the 4 experimental homeworks but from the same two chapters of the course as the experimental homeworks.

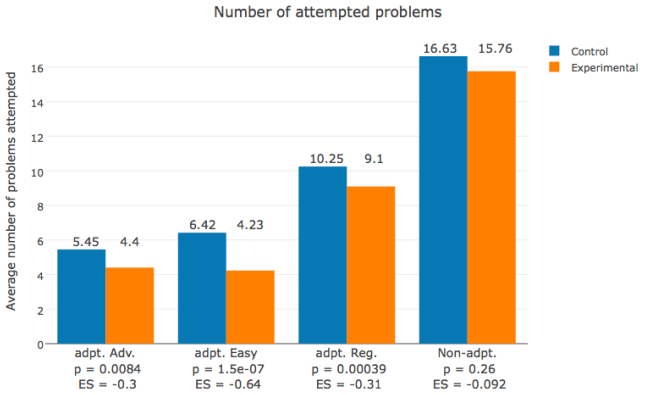

Figure 5. Comparison of attempt numbers between the experimental and control groups in the chapters where adaptivity was implemented. Non-adaptive problems are problems not from the 4 experimental homeworks but from the same two chapters of the course as the experimental homeworks.

The interpretation emerges that the students who experienced adaptivity showed more persistence by giving more attempts per problem (presumably, because adaptively served problems are more likely to be on the appropriate current mastery level for a student), while taking a faster track through the course materials. We also observed that the experimental group students tended to have a lower net time on task in the course: an average of 5.47 hours vs. 5.85 in the control group (although in this comparison the p-value is high, 0.21, and the effect size is –0.11).

Thus, we conjecture that the adaptivity of this kind leads to a higher efficiency of learning. Students go through the course faster and attempt fewer problems, since the problems are served to them in a targeted way. And yet there is no evidence of an adverse effect on the students' overall performance or knowledge gain. Given the limited implementation of adaptivity in this course, it is not surprising that we cannot find a statistically significant effect on student overall performance in the course. We expect to refine these conclusions in the future courses with a greater scope of adaptivity.

3. FUTURE WORK

Our implementation of adaptivity provided some insights for future work. For instance, assessment questions in MOOCs can vary greatly in nature, difficulty and format (multiple choice, check-all-that-applies, numeric response, etc.), and may often be tagged with more than one knowledge component. To be suitable for a MOOC, an adaptive engine should be able to handle these features.

There appear to be extensive opportunities to expand adaptive learning and assessment in MOOCs. The low total number of problems was the most severe restriction on the variability of learner experience in this study. In the future applications, larger sets of tagged items could provide a more adaptive learning experience for students, while also providing a higher degree of certainty of assessment results. Interestingly, in some MOOCs (for example, those teaching programming languages) it may be possible to create very large numbers of questions algorithmically, essentially by filling question templates with different data.

In this study, adaptivity was implemented mostly on assessment problems. Given the structure of many MOOCs, more integration between learning content and assessment could provide an adaptive experience that would guide students to content that could improve their understanding based on how they perform on integrated assessments.

Affective factors could be included to provide a more personalized learning experience. We can conceive an adaptive engine which decides what item to serve next based not just on the mastery but also on the behavioral patterns interpreted as boredom or frustration.

Finally, this work could lead to improved MOOC platform features that would contribute to improved student experiences, such as optimized group selection [2]. In addition, we anticipate expanding this adaptive assessment system to work with other LTI-compliant course platforms. Enabling use in a platform such as Canvas, the learning management system used university-wide at Harvard (and many other schools), would enable adaptivity for residential courses on a large scale. An adjustment to the current system architecture would be the use of OpenEdX as the platform for creating and hosting problems.

4. ACKNOWLEDGMENTS

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