# POSTER AND DEMO PAPERS

# Automatic Grading of Short Answers for MOOC via Semi-supervised Document Clustering

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## ABSTRACT

Developing an effective and impartial grading system for short answers is a challenging problem in educational measurement and assessment, due to the diversity of answers and the subjectivity of graders. In this paper, we design an automatic grading approach for short answers, based on the non-negative semi-supervised document clustering method. After assigning several answer keys, our approach is able to group the large amount of short answers into multiple sets, and output the score for each answer automatically. In this manner, the effort of teachers can be greatly reduced. Moreover, our approach allows the interaction with teachers, and therefore the system performance could be further enhanced. Experimental results on two datasets demonstrate the effectiveness of our approach.

## Keywords

Clustering, semi-supervised learning, short-answer grading

## 1. INTRODUCTION

Grading short answers is a challenging problem in the conventional educational measurement and assessment [6, 4], due to the diversity of answers and the subjectivity of graders. Especially, in the era of the massive open online course (MOOC), this problem becomes critical. MOOC provides plenty of courses, and has attracted over 10 million users during the past few years. However, traditional assessments are not suitable for MOOC. For example, in most MOOC platforms, short answers appear frequently in various quizzes and exams. Obviously, hiring lots of graders is not a feasible solution. Thus, it is very necessary to develop an automatic grading system for short answers. The automatic grading system for short-answers has been widely studied during the past decade [2]. Most recently, a system named "Powergrading" was presented by Microsoft Research, which achieved quite impressive performance [1].

We would argue that clustering is a straightforward solution to automatic grading. For short answer grading, the motivation of using clustering is that, the similar short answers should have high similarity values, while the dissimilar ones should have low similarity values. Therefore, those similar short answers could be assigned into the same group. We can then infer the final scores of those answers according which groups they belong to.

In this paper, we aim to design an automatic grading approach for short answers. Our approach is expected to solve the assessment challenge in MOOC. Moreover, it can also be applied to traditional educational assessment scenario, to reduce the efforts of teachers. We will present the methodology of our approach, discuss its influence in online education, and report the quantitative results and analysis.

## 2. METHODOLOGY

### 2.1 Feature Representation

In our problem, each short answer can be treated as a short document. Let $W = \{f_1, f_2, \cdots, f_m\}$ denote a complete vocabulary set of the short answers after the stopwords removal and words stemming operations. We can get the term-frequency vector $X_i$ of short answer $d_i$ as follows

$$X_i = [x_{1i}, x_{2i}, \cdots, x_{mi}]^\top \tag{1}$$

$$x_{ji} = t_{ji} \times \log(\frac{n}{\text{idf}_i}) \tag{2}$$

where $t_{ji}$, $\text{idf}_i$, $n$ denote the term frequency of word $f_j$ in short answer $d_i$ , the number of short answers containing word $f_j$, and the total number of documents in the corpus, respectively.

By using $X_i$ as a column, we can construct the term-short-answer matrix $X$.

### 2.2 Semi-Supervised Clustering for Short-answer Grading

We observe that, the label information of short answers is neglected in the basic document clustering approach. However, by leveraging the expertise of teachers, we can usually get some useful information. For example, teachers will tell us which two answers are essentially similar to each other, although they look quite different on the first sight.

To make use of such useful information, we propose a semi-supervised document clustering approach. The basic idea

is to add some constraints, including positive ones and negative ones. The former one shows us which short answers are similar, and we can always put them into the same cluster. On the other hand, the latter one tells us which short answers cannot be grouped together.

Inspired by the semi-supervised clustering algorithm [3, 5], we present the non-negative semi-supervised document clustering (SSDC) algorithm for short-answer grading as follows.

Let $A = X^\top X$ denote the document (e.g., short-answer) similarity matrix. In our approach, we first employ the symmetric non-negative tri-factorization as follows

$$A = QSQ^\top \tag{3}$$

where $Q$ is the cluster indicator matrix. Each element in $Q$ represents the degree of association of the short-answer $d_i$ with cluster $j$. The cluster membership information is determined by seeking an optimization matrix $S$.

In the semi-supervised setting, we are given two sets of pairwise constraints on the short-answers, including the must-link constraints $C_{ML}$ and cannot-link constraints $C_{CL}$. Every pair in $C_{ML}$ means this pair of short-answers should belong to the same cluster; every pair in $C_{CL}$ means this pair of short-answers should belong to different clusters.

Then, the objective function of SSDC algorithm is

$$\begin{aligned} &J = \arg\min \|\bar{A} - QSQ^\top\|^2 \\ &s.t., S \geq 0, Q \geq 0, \end{aligned} \tag{4}$$

where $\bar{A} = A - R_+ + R_-$. $R_+$ and $R_-$ are two penalty matrices, considering the two constraint sets $C_{CL}$ and $C_{ML}$.

The problem (4) can be solved efficiently using the standard gradient descent algorithm. The update rules of $S$ and $Q$ are given below

$$S_{ij} = S_{ij} \frac{(Q^\top \bar{A} Q)_{ij}}{(Q^\top QSQ^\top Q)_{ij}} \tag{5}$$

$$Q_{ij} = Q_{ij} \frac{(\bar{A}QS)_{ij}}{(QSQ^\top QS)_{ij}}. \tag{6}$$

After obtaining the optimized $S$ and $Q$, we can use them to infer the cluster labels for each short answer.

Finally, we can assign the score for each short-answer. For example, we know that the score of one template answer is 8.0. If another short-answer and this template answer belong to the same cluster, then the score of this short-answer should be close to 8.0. We also design a weighting strategy to adjust this score, based on the distance to the template answer.

# 3. EXPERIMENTS

We utilize the data set provided by Microsoft Research, which is also analyzed in the paper (Basu, Jacobs & Vanderwende, 2013). It contains the responses from 100 and 698 crowdsourced workers to each of 20 short-answer questions. These questions are taken from the 100 questions published by the United States Citizenship and Immigration Services as preparation for the citizenship test. It also contains labels of response correctness (grades) from three judges for a subset of 10 questions for the set of 698 responses (3 x 6980 labels).

**Table 1: The Results on MSR Dataset and MOOC Dataset.**

| Method | MSR Dataset | MOOC Dataset |
|---|---|---|
| DC | 85.2% | 74.1% |
| Semi-supervised DC | 87.5% | 78.9% |

Besides, we also collect some short answers from MOOC websites. We will evaluate the performance of our approach on both datasets.

We evaluate the performance of our approach on the MSR dataset and MOOC dataset. As we have the ground truth information, we can report the accuracy of clustering algorithms. Table 1 shows the accuracies of our approach and the baseline method DC under different settings. It shows that our semi-supervised document clustering method always achieves better performance than DC on two datasets.

# 4. CONCLUSIONS AND FUTURE WORK

We studied the educational assessment problem in MOOC. In this paper, we proposed an automatic grading approach for short answers. By leveraging the benefits of document clustering, our approach was able to assign a large amount of short answers into different groups, and infer their scores accordingly. Moreover, we designed a semi-supervised approach, which is able to incorporate the expertise of teachers. The proposed approach fits the requirements of MOOC. Results on two datasets showed the effectiveness of our approach. Our paper provides an effective solution to the educational assessment problem. In the future, we will design more computer-aided systems to address the educational assessment problem.

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# Discovering students' navigation paths in Moodle

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## ABSTRACT
In this paper, we apply clustering and process mining techniques to discover students' navigation paths or trails in Moodle. We use data from 84 undergraduate Psychology students who followed an online course. Firstly, we group students using on Moodle's usage data and the students' final grades obtained in the course. Then, we apply process mining with each cluster/group of students separately in order to obtain more specific and accurate trails than using all logs together.

## Keywords
Clustering, process mining, navigation paths, trails in education.

## 1. INTRODUCTION
One of the current promising techniques in EDM (Educational Data Mining) is Educational Process Mining (EPM). The main goal of EPM is to extract knowledge from event logs recorded by an educational system [4]. It have been observed that students show difficulties when learn in hypermedia and Computer Based Learning Environments (CBLEs) due to these environments seems to be highly cognitive and metacognitive demanding [1]. In this sense, the models discovered by EPM could be used: to get a better understanding of the underlying educational processes, to early detect learning difficulties and generate recommendations to students, to help students with specific learning disabilities, to provide feedback to either students, teachers or researchers, to improve management of learning objects, etc. In a previous work [2], we found two problems when using EPM: 1) the model obtained could not fit well to the general students' behaviour and 2) the model obtained could be too large and complex to be useful for a student or teacher. In order to solve these problems, we proposed to use clustering to improve both the fitness and comprehensibility of the obtained models by EPM. However, in this paper we propose to use a Hypertext Probabilistic Grammar (HPG) algorithm instead of Heuristics Net [2] because it provides more informative graphs.

## 2. METHODOLOGY
A traditional approach would use all event log data to reveal a process model of student's behaviour . Nevertheless, in this paper, we propose an approach that uses clustering for improving EPM (see Figure 1). The proposed approach firstly applies clustering in order to group students with similar features. And then, it applies process mining for discovering more accurate models of students' navigation paths or trails. In fact, we propose to use two different grouping methods:

1) Clustering students directly by using the students' grades obtained in the final exam of the course.
2) Clustering students by using a clustering algorithm over the student's interaction with the Moodle's course.

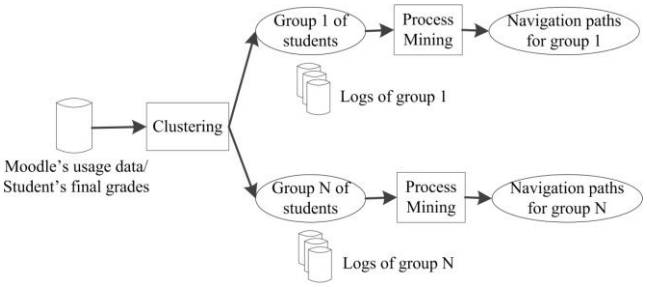


**Figure 1: Proposed approach for discovering students' navigation paths.**

## 3. DESCRIPTION OF THE DATA AND EXPERIMENTS
In this work we have used real data collected from 84 undergraduate Psychology students who followed a Moodle course. Firstly, we have divided the student's log provided by Moodle in two different ways. In a first way, we divided directly the original log file into two datasets: one that contains the 68 students who passed the course and other with the 16 students who failed. In the second way, we have used the Expectation-Maximization (EM) clustering algorithm provided by Weka [6] in order to group together students of similar behaviour when using Moodle. In this case we have obtained three clusters/datasets with the following distribution:

- **Cluster 0**: 23 students (22 pass and 1 fail).
- **Cluster 1:** 41 students (39 pass and 2 fail).
- **Cluster 2**: 20 students (13 fail and 7 pass).

After clustering, we applied EPM through HPG over the previous datasets. We have used the HPG model in order to efficiently mine trails or navigation paths [3]. HPG uses a one-to-one mapping between the sets of non-terminal and terminal symbols. Each non-terminal symbol corresponds to a link between Web pages. Moreover, there are two additional artificial states, called *S* and *F*, which represent the start and finish states of the navigation sessions respectively. The probability of a grammar string is given by the product of the probability of the productions used in its derivation. The number of times a page was requested, and the number of times it was the first and the last page (state) in a session, can easily be obtained from the collection of student navigation sessions. The number of times a sequence of two pages appears in the sessions gives the number of times the corresponding link was traversed. The aim is to identify the subset of these trails that correspond to the rules that best characterize the student's behavior when visiting the Moodle course. A trail is included only if its derivation probability is above a cut-point.

The cut-point is composed of two distinct thresholds (support and confidentiality). The support (Sup) value is for pruning out the strings whose first derivation step has low probability, corresponding to a subset of the hypertext system rarely visited. The confidence (Con) value is used to prune out strings whose derivation contains transitive productions with small probabilities. Support and confidence thresholds give the user control over the quantity and quality of the obtained trails, while α (Alp) modifies the weight of the first node in a student navigation session: when α is near 0, only those routes that start in a node which started a session are generated; when α is near 1, all weights are completely independent of the order within the session.

# 4. RESULTS

We have carried out several experiments with the HPG algorithm to test several configurations of number of Nodes, Links, Routes, and average route length (Avg). Results obtained when using different datasets and parameters are displayed in Table 1.

**Table 1. Results with different datasets and configurations.**

| Dataset | Alp | Sup | Con | Nodes | Links | Routes | Avg |
|---|---|---|---|---|---|---|---|
| Fail | 0,2 | 0,05 | 0,5 | 8 | 7 | 12 | 3,85 |
| Pass | 0,2 | 0,05 | 0,5 | 12 | 11 | 20 | 3,81 |
| Cluster0 | 0,2 | 0,05 | 0,5 | 8 | 6 | 12 | 4,16 |
| Cluster1 | 0,2 | 0,05 | 0,5 | 9 | 7 | 14 | 4,14 |
| Cluster2 | 0,2 | 0,05 | 0,5 | 5 | 4 | 6 | 2,75 |
| Fail | 0,4 | 0,06 | 0,3 | 15 | 15 | 27 | 3,8 |
| Pass | 0,4 | 0,06 | 0,3 | 25 | 27 | 47 | 3,96 |
| Cluster0 | 0,4 | 0,06 | 0,3 | 13 | 12 | 21 | 3,66 |
| Cluster1 | 0,4 | 0,06 | 0,3 | 15 | 17 | 29 | 4,11 |
| Cluster2 | 0,4 | 0,06 | 0,3 | 12 | 9 | 18 | 3,66 |
| Fail | 0,5 | 0,06 | 0,3 | 20 | 19 | 36 | 4 |
| Pass | 0,5 | 0,06 | 0,3 | 37 | 41 | 72 | 4,07 |
| Cluster0 | 0,5 | 0,06 | 0,3 | 19 | 17 | 31 | 3,7 |
| Cluster1 | 0,5 | 0,06 | 0,3 | 20 | 21 | 38 | 4,19 |
| Cluster2 | 0,5 | 0,06 | 0,3 | 12 | 9 | 18 | 3,66 |

Table 1 show that the smaller and more comprehensible models were obtained using logs from students who failed (Fail dataset) and students of Cluster 2. On the other hand, the models obtained with the other datasets were much bigger and complex. We think that this may be due to:

- Both dataset Fail and Cluster 2 contain mainly information about bad students who failed the course. This type of students has a low interaction with Moodle and so, they show only some frequent navigation paths.
- Datasets Pass, Cluster0 and Cluster1 contain mainly information about good students who pass the course. This type of students has a high interaction with Moodle and so, they show more frequent navigation paths.

Finally, we show an example of obtained model when using the Cluster2 dataset. In Figure 2, each node represents a Moodle's Web page, and the directed edges (arrows) indicate how the students have moved between them. These paths can be stochastically modeled as Markov chains [5] on the graph, where the probability of moving from one node to another is determined by which Web page the student is currently visiting. Edge thickness varies according to edge weight; this allows the learning designer to quickly focus on the most important edges, ignoring those that have very low weights. In addition, line widths and numerical weights are also available.

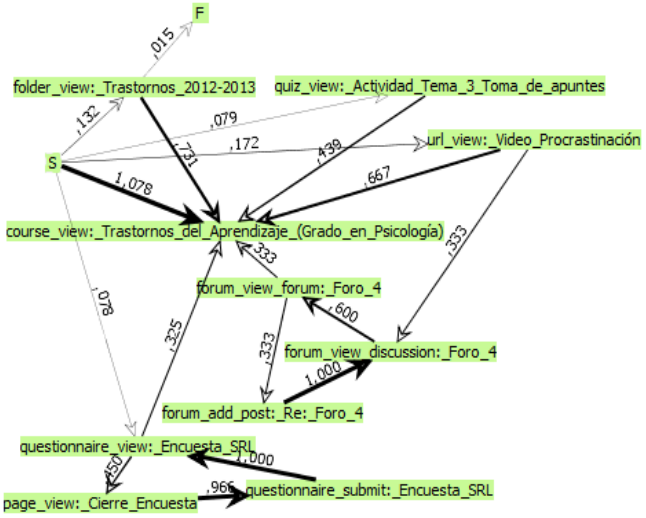


**Figure 2: Navigation paths of Cluster 2 students.**

Starting from Figure 2 we can see and detect what are the most frequent actions (view forum X, view questionnaire Y, view quiz Z, etc.) and in which order (navigation paths or trails) were done/followed by Cluster 2 students (normally fail students).

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# Teacher-Student Classroom Interactions: A Computational Approach

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## ABSTRACT
Teacher-student interactions are key to most school-taught lessons. We present a new approach to studying these interactions; this approach is based on a fine-grained data collection, using quantitative field observations (QFOs), which relies on a well-established theoretical framework. The data collected can be analyzed in various methods to address different types of research questions; we give some examples to demonstrate this potential.

## Keywords
Teacher-student interactions, quantitative field observations, different analysis approaches.

## 1. INTRODUCTION
Since the early days of Plato, over 2,300 years ago, dialogues were at the heart of the teaching practice. For as long as classroom teaching exists, teacher-student interactions have been the key to most school-taught lessons, hence studying these interactions is decades-old. Many studies in this field that have used classroom observations, often manually documented each occurrence of a teacher-student interaction, usually by observing a small cohort of students at a time or by observing individual students based on an interval-based protocol (e.g., Good & Brophy, 1970; Cameron, Cook & Tankersley, 2012; Luckner & Pianta, 2011). We use a digital data collection tool—a tablet app developed specifically for this purpose—in order to conduct quantitative field observations (QFOs). Although documenting each occurrence of a teacher-student interaction, data is not collected at the student-level (i.e., students are not labeled, only interactions), which makes it feasible to have a single person observing a whole class and still document every interaction during it. Once the class is over, the data is ready to be analyzed. More than that, this fine-grained data is time-stamped, which allows for advanced, including temporal, analyses.

## 2. THEORETICAL FRAMEWORK
Good and Brophy's (1970) method, developed in the context of mathematics education, was probably the first to refer to a single student—as opposed to the whole class—while recording public classroom interactions, hence focusing on dyadic teacher-student interactions**. T**his protocol was later modified by Reyes and Fennema (1981), who considered non-public teacher-student interactions too.

These validated protocols have been in use to study various variables at different grade levels and in many learning settings. Due to their validity, fine granularity and popularity, we find these protocols very suitable for our research. Adapting and extending the original protocols to better fit to our research setting—mainly to the whole class being observed at all times—we categorize each teacher-student interaction to one of the categories described in the next sub-sections.

### 2.1 Response Opportunity
A response opportunity is a public attempt by an individual student or a group of students to deal with a question posed by the teacher. Interactions that fall under this category take one of four possible values: **Direct** – the teacher asks a direct question of an individual student; **Volunteer** – the teacher asks a question, waits for the students to raise their hands, then calls on one of the children who has his hand up; **Call Out Single** – the teacher asks a question and a student calls out an answer without waiting for permission to respond; **Call Out 2+** – the teacher asks a question and more than one student call out an answer without waiting for permission to respond.

### 2.2 Immediate Contact
An immediate interaction is a public, content-related interaction initiated by the teacher, a student or a group of students that is not preceded by a teacher's question. This category again has four values based on the interaction initiator and the number of students involved in it: **Teacher to Single**, **Teacher to 2+**, **Single to Teacher**, **2+ to Teacher**.

### 2.3 Behavioral Contact
These are public, behavior-related comments of the teacher. Here too, four values are defined, based on the type of behavior commented and on the targeted audience: **Discipline to Single**, **Discipline to 2+**, **Appraisal to Single**, **Appraisal to 2+**.

### 2.4 Procedural Contacts
These interactions are public, non-content related; they are related to students' management or to the class management, e.g., permission, supplies, or equipment. Like *Immediate*, we distinguish the interaction initiator and the number of students involved, hence its four values are: **Teacher to Single**, **Teacher to 2+**, **Single to Teacher**, **2+ to Teacher**.

### 2.5 Non-Public Interactions
Non-public interactions are held privately between the teacher and one or more students. As such, we assume not being able to categorize them, therefore we only code whether they were **Teacher-Afforded** or **Student-Initiated**.

## 3. DATA COLLECTION APP
As mentioned above, a dedicated data collection app was developed for the purpose of this study. The app, Q-TSI

(Quantifying Teacher-Student Interactions), is available for free via Google Play Store[1]. Besides coding the interaction categories, the app allows documenting the following contextual variables:

- **Learning Configuration** (whole class discussion, group work, pair work, individual work);
- **Technologies in Use by the Teacher** (blackboard, projector, smart board, book – any combination of these are allowed);
- **Technologies in Use by the Students** (book, computer, book and computer);
- **Teacher Location** –on a 4x4 division of the classroom.

Furthermore, the app allows the user to enter any (time-stamped) comment s/he finds useful. These comments might be useful to interpret the results of analyses. The data is stored locally on the observer device as a CSV file.

# 4. ANALYSES APPROACHES

The collected data can be analyzed in various ways in order to address a wide range of research questions. We now describe a few potential research directions we are currently considering (some will be demonstrated in the poster).

## 4.1 Visualization

Visualization can be a powerful tool to have an overall understanding of the classroom dynamics. Teachers can gain awareness and reflect upon their interactions with their students during the class. A typical visualization may include a time-ordered representation of the interactions, differentiated by type (e.g., by color, marker), along with values of the contextual variables. Such visualizations may assist in initially having an overview of the kinds of interactions that happen, exploring differences within classes, based on, e.g., learning configuration or technologies in use, or between classes, based on, e.g., teacher, school, grade-level, subject matter, time of day, etc.

## 4.2 Statistics

Basic statistics may shed light on the overall distribution of the different types of interactions in a lesson, as well as on differences within and between classes (based on variables as such as were mentioned in *4.1 Visualization*).

## 4.3 Time-based Patterns

Association rules, time series, statistical discourse analysis and epistemic network analysis may assist in understanding whether there are specific interactions that often occur jointly or in connection, possibly, in some specific order or in a specific context, and how occurrences of interactions evolve over time. Time in our context has at least two levels of granularity: the lesson granularity (i.e., what happens during one lesson) and the school year granularity (i.e., what happens in lessons over the weeks).

## 4.4 Cluster Analysis

Clustering techniques can be used to explore whether classes can be classified according to typical patterns of interactions. Several ways of describing a lesson and, consequently, of comparing lessons, can be investigated. For instance, a mere quantitative analysis can be used to characterize a lesson, that is, counting interactions and using the Euclidean distance (or alike) for clustering. A lesson can also be described as a sequence of different interactions over time, then using the Levenshtein distance (or alike) for clustering. It might be necessary to define several abstraction levels for the interactions.

## 4.5 Prediction

It might be possible to predict different types of interactions based on historical data, or based on contextual variables. A possible prediction might look like: "three <Response opportunity: Call out 2+> interactions and two <Procedural: Teacher to single> interactions are followed by a <Discipline: Single> interaction in 85% of the instances." Several techniques will be considered to investigate this kind of patterns, in particular, classification techniques enriched with time series and statistical discourse analysis.

## 4.6 Collecting More Data

In the future, additional data will be collected, such as students' log files, performance, meta-cognitive and affective measures, in order to enrich the data with more layers. These layers will allow, in turn, to ask even more questions about the data and to better investigate the role of teacher-student interactions in the learning/teaching process.

# 5. ACKNOWLEDGMENTS

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# Modeling Student Learning: Binary or Continuous Skill?

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## ABSTRACT

Student learning is usually modeled by one of two main approaches: using binary skill, with Bayesian Knowledge Tracing being the standard model, or using continuous skill, with models based on logistic function (e.g., Performance Factor Analysis). We use simulated data to analyze relations between these two approaches in the basic setting of student learning of a single skill. The analysis shows that although different models often provide very similar predictions, they differ in the impact on student practice and in the meaningfulness of parameter values.

## Keywords

student modeling; learning; Bayesian Knowledge Tracing; simulated data

## 1. INTRODUCTION

In this work we focus on modeling of student learning in the basic setting: we assume that for each student we have a sequence of answers related to a single skill and we consider only correctness of these answers, i.e., we do not take into account additional information like response times or partial correctness due to the use of hints. We work only with basic models and focus on experiments with simulated data. This setting is of course a coarse simplification, since in a real application we typically have some additional information on student answers, questions are related to multiple skills, and model extensions are used. But in order to successfully use complex models, it is necessary to have deep understanding of the base case and this understanding is still lacking. There are many feasible modeling approaches, but they are usually proposed and studied independently and their relations, similarities, and differences have not been well studied. The use of simulated data allows us to analyze behaviour of models in detail thanks to the knowledge of "ground truth" values; moreover, we can manipulate in controlled way generation of data and thus easily evaluate behaviour of models under different assumptions.

## 2. MODELING STUDENT LEARNING

Most approaches to modeling of student learning can be viewed as hidden Markov models (also called latent process models, state-space models). We assume a hidden (latent) state variable (called "skill") and two types of equations. Observation equation describes the dependence of observed variables (correctness of answers) on the hidden variable (skill). State equation describes the change of the hidden variable (i.e., learning). There are two main types of models depending on whether the latent skill is binary or continuous. It is in principle possible to consider discrete skill with more than two states, but such models are not commonly used. The standard form of a binary skill model is Bayesian Knowledge Tracing (BKT) [1]. Models based on continuous latent skill typically use logistic function for observation equation, they differ in their approach to skill estimation.

Bayesian Knowledge Tracing assumes a sudden change in knowledge. It is a hidden Markov model where skill is a binary latent variable (either learned or unlearned). Figure 1 illustrates the model; the illustration is done in a non-standard way to stress the relation of the model to the model with continuous skill. The estimated skill is updated using a Bayes rule based on the observed answers; the prediction of student response is then done based on the estimated skill. Note that although the model is based on the assumption of binary skill, the skill estimate is actually continuous number (in the $[0, 1]$ interval).

Models which utilize the assumption of continuous latent skill consider skill in the $(-\infty, \infty)$ interval and for the relation between the skill and the probability of correct answer use the logistic function $\sigma(x) = \frac{1}{1+e^{-x}}$. Although it would be possible to consider also other functions, the logistic function is currently the standard choice. As a simple model of learning we consider a simple linear growth of the skill (Figure 1). More specifically, for the initial skill $\theta_0$ we assume normally distributed skill $\theta_0 \sim N(\mu, \sigma^2)$ and for the change in learning we consider linear learning $\theta_k = \theta_0 + k \cdot \Delta$, where $\Delta$ is either a global parameter or individualized learning parameter (in that case we assume a normal distribution of its values). This model is a simplified version of the Additive Factors Model [3]; the original additive factor model uses multiple skills. A principled way of estimating continuous skills is the Bayesian approach, which computes not just a point estimate of skill, but a distribution over skill capturing also the uncertainty of the estimate. This approach be implemented for example using particle filter, i.e., discretized

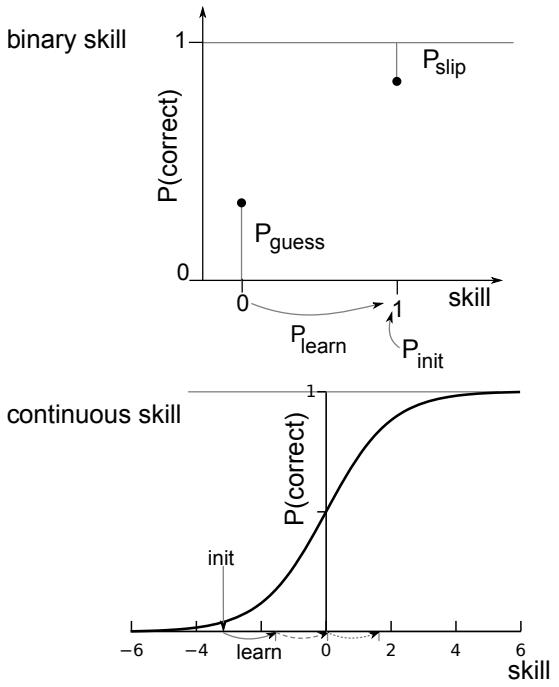


**Figure 1: Binary and continuous skill models of student learning – high level overview.**

representation of posterior distribution. A more pragmatic approach to skill estimation is Performance Factor Analysis [5], which computes the skill estimate as a linear combination of the number successes and failures of a student. This approach can be extended to take into account ordering of attempts and time intervals between them [2, 4].

Which type of model is better depends on the learning situation. Binary skill models assume a sudden switch from unlearned to learned state. Such assumption is appropriate mainly for fine-grained skills which require understanding or insight (such as "addition of simple fractions"). Models with continuous skill assume gradual increase of skill. This is appropriate either for modeling coarse-grained skills (e.g., "fractions" as a single skill) or for situations where gradual strengthening happens (e.g., memorizing facts).

## 3. EXPERIMENTS

To analyze the described models and relations between them we performed experiments with simulated data. We generated simulated data by one of the models and then analyzed the generated data using both models with binary and continuous skills. For generating data we used 10 scenarios with different parameter settings.

With respect to accuracy of predictions the results show that both types of models bring consistent improvement over baselines like moving average and time decay models [6]. The basic comparison of binary and continuous skill models is also not surprising: each approach dominates in scenarios which correspond to its assumptions. Nevertheless, in many cases the differences are small and the predictions are actually highly correlated.

Models are not used only for predictions, but they may be useful in themselves for system developers and researchers. Plausible and explainable model parameters may be used to get insight into behaviour of tutoring systems and also for "discovery with models" (higher level modeling). Results of our analysis show that in the case when there is a mismatch between source of the data and a model, interpretation of parameters may be misleading. As a specific example consider simulated students behaving according to the continuous model with $\theta_0 \sim N(-1, 1), \Delta = 0.2$. Here the fitted BKT guess and slip parameters are 0.24 and 0.16. Intuitive interpretation of BKT parameters would thus suggest high chance of guessing an answer. In the ground truth model, however, chance of guessing converges to zero for unskilled students.

One of the main applications of student models is to guide the behaviour of adaptive educational systems. A typical example is the use of student models for mastery learning – students have to practice certain skill until they reach mastery, the attainment of mastery is decided by a student model. Mastery is declared when a skill estimate is higher than a given threshold. How does the choice of student model and a threshold impact student practice? Our results show that the BKT model is relatively insensitive to the choice of the threshold and that the model provides weak decisions for scenarios with continuous learning, specifically when the learning rate is low. Continuous skill models can provide good decision for all scenarios if used with a good threshold. However, optimal thresholds differ significantly for scenarios with binary skill and continuous skill.

To summarize, our study with simulated data suggests that the choice between models with binary and continuous skill does not seem a key concern as long as we are interested only in predictions of students' answers, but it can have significant impact on parameter interpretation and mastery learning.

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# An Analysis of Response Times in Adaptive Practice of Geography Facts

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## ABSTRACT

Online educational systems can easily measure both answers and response times. Student modeling, however, typically focuses only on correctness of answers. In this work we analyze response times from a widely used system for adaptive practice of geography facts. Our results show that response times have simple relationship with the probability of answering correctly the next question about the same item. We also analyze the overall speed of students and its relation to several aspects of students' behaviour within the system.

## 1. INTRODUCTION

When students use computerized educational systems, we can easily store and analyze not just their answers and their correctness, but also the associated response times. Response times carry potentially useful information about both cognitive and affective states of students.

Response times have been studied thoroughly in item response theory in the context of computerized adaptive testing, for an overview of used models see [5]. But testing and learning settings differ in many aspects, including response times – for example we would expect students to think for longer time in the case of high stake testing than in practice session (there are differences even between high-stakes and low-stakes testing [2]).

Response times have been used previously in the context of student modeling for intelligent tutoring systems, e.g., for modeling student knowledge in the extension of Bayesian Knowledge Tracing [6] or for modeling student disengagement [1]. But overall the use of response times has been so far rather marginal. In this work we analyze response times from an adaptive system for practice of facts, which is a specific application domain where response times have not been analyzed before.

## 2. THE USED SYSTEM AND DATA

For the analysis we use data from an online adaptive system `slepemapy.cz` for practice of geography facts (e.g., names and location of countries, cities, mountains). The system uses student modeling techniques to estimate student knowledge and adaptively selects questions of suitable difficulty [4]. The system uses open questions ("Where is Rwanda?") and multiple-choice questions ("What is the name of the highlighted country?") with 2 to 6 options.

The system uses a target success rate (e.g., 75 %) and adaptively selects questions in such a way that the students' achieved performance is close to this target [3]. The system also collects users' feedback on question difficulty – after 30, 70, 120, and 200 answers the system shows the dialog "What is the difficulty of asked questions?", students choose one of the following options: "Too Easy", "Appropriate", "Too Difficult".

For the reported experiments we used the following dataset: 54 thousand students, 1458 geography facts, over 8 million answers and nearly 40 thousand feedback answers.

## 3. RESULTS

We provide basic analysis of response times, and their relation to student knowledge and to students' behaviour within the adaptive practice system.

### 3.1 Basic Characterization of Response Times

Distribution of response times is skewed, in previous work it was usually modeled by a log-normal distribution [5]. Our data are also approximately log-normal, therefor as a measure of central tendency we use median or mean of log times.

Response times clearly depend on the type of question and on specific item. Our results for example show, that response times are higher for cities and rivers than for countries and regions (states are larger than cities on the used interactive map and therefore it is easier to click on them). Response times are also on average higher for countries in Asia than in South America (there is larger number of countries on the map of Asia).

For the below presented analysis we use percentiles of response times over individual items – these are not influenced by skew and provide normalization across different items.

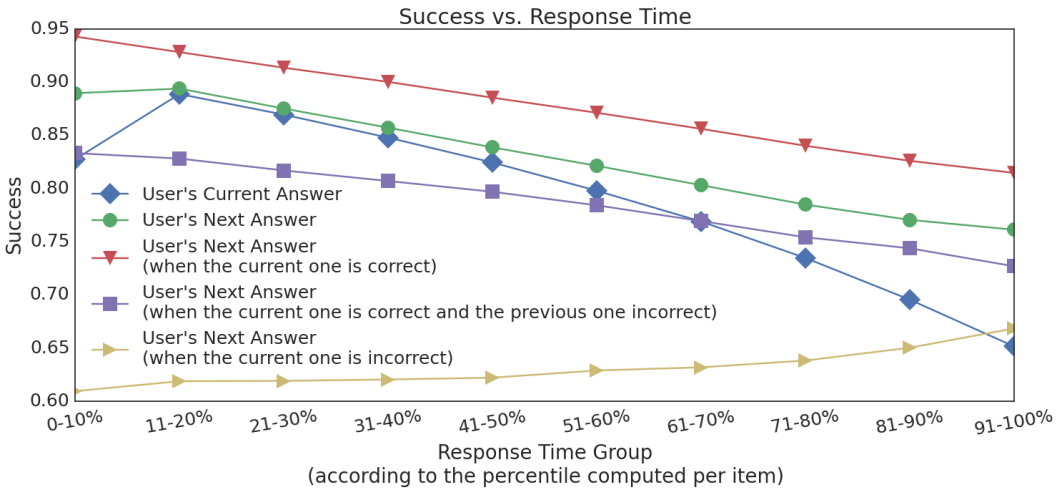


**Figure 1: Response times and probability that the (next) answer is correct.**

## 3.2 Response Times and Students Knowledge

Figure 1 shows the relationship between response times and correctness of answers. The relationship between response time and correctness of the *current* answer is non-monotonic – very fast responses combine "solid knowledge" and "pure guessing", long responses mostly indicate "weak knowledge". The highest change of correct answers is for response times between 10th and 20th percentile, i.e., answers that are fast, but not extremely fast.

We get a more straightforward relationship when we analyze correctness of the *next* answer (about the same item) based on both the correctness and response time for the current answer. If the current answer is correct then the probability of correct next answer is linearly dependent on the response time – it goes from 95% for very fast answers to nearly 80% for slow answers. If the current answer is incorrect then the dependence on response time is weaker, but there is still (approximately linear) trend, but in this case in the other direction. When the current answer is incorrect, longer response time actually means higher chance that the next answer will be correct!

A limitation of the current analysis is that we do not take into account types of questions (the number of available choices and the related guess factor) or the adaptive behaviour of the system (the system asks easier questions when knowledge is estimated to be low). However, we do not expect these factor to significantly influence the reported results, which quite clearly show that response times are useful for modeling knowledge and that it is important to analyze response times separately for correct and incorrect answers.

## 3.3 Speed of Students

As a next step we analyze not just response times for single answers, but over longer interaction with the system. Statistics of response times may indicate affective states or characterize a type of student. For this preliminary analysis we have classified students as fast/slow depending on their median response time and we analyzed correlations with other aspects of their behaviour (in similar way and with analogical results we have also analyzed variance of response time). The reported results do not necessary imply direct relationship as they may be mediated by other factors (like difficulty of presented items).

Slower students answer smaller number of questions in the system. In fact the overall time in the system is nearly the same for students with different speeds, i.e., slower students just solve smaller number of questions during this time. Faster students have higher prior skill and are more likely to return to the system to do more practice. In the feedback on question difficulty slower students report more difficult impression. Possible application of these results is incorporation of students' speed into the algorithm for adaptive selection of questions (e.g., by selecting easier questions for slower students).

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# Achievement versus Experience: Predicting Students' Choices during Gameplay

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## ABSTRACT

This study investigates how we can effectively predict what type of game a user will choose within the game-based environment iSTART-2. Seventy-seven college students interacted freely with the system for approximately 2 hours. Two models (a baseline and a full model) are compared that include as features the type of games played, previous game achievements (i.e., trophies won, points earned), and actions (i.e., iBucks/points spent, time spent on games, total games played). Using decision tree analyses, the resulting best-performing model indicates that students' choices within game-based environments are not solely driven by their recent achievement. Instead a more holistic view is needed to predict students' choices in complex systems.

## Keywords

Game-based environments, Modeling, Decision tree analysis

## 1. INTRODUCTION

Game-based environments often afford fine-grained examinations of patterns in students' behaviors during gameplay and how they are related to cognitive skills and learning outcomes [1,2]. However, such previous work has not examined the driving force behind *why* a student chooses a specific activity or interaction within a game environment. In the current work, we compare two models. The first model is a parsimonious "1-back" model that assumes that students' choices are directly related to (and predicted by) their most recent game choice within the system and their achievements (in terms of the type of trophy won). Thus, if a student is performing well in one activity, they will continue to play that activity (or one similar to it) – *achievement behavior* [3]. The second, full model assumes that students' choices (of game type in this case) are related more comprehensively to a holistic combination of their previous *experiences* within the environment, including the types of games played, game achievements, and actions. This model follows the assumption that students' choices are influenced by a range of factors that is broader than their most recent choice and achievements. This paper is an exploratory study that attempts to answer: *what impacts students' choices within game-based environments?*

### 1.1 iSTART-2

Our analysis is conducted within the context of the Interactive Strategy Training for Active Reading and Thinking-2 (iSTART-2) system, designed to provide students with self-explanation strategy instruction to improve reading comprehension [1, 4]. After viewing five instructional videos, each covering a reading strategy, students are transitioned to a practice interface in which they can engage with a suite of educational games. Games involve either *generative* or *identification* practice. Generative practice games require students to type their own self-explanations while reading a text. Identification mini-games require students to read self-explanations that are ostensibly written by other students, and select which of the five strategies was used to generate each self-explanation. Students receive feedback about whether their choice was correct or incorrect.

iSTART-2 offers an ideal environment to explore questions about choice within open learning environments because students are free to choose which practice games to play. During each of the practice games, students earn points for writing high quality self-explanations or selecting the correct strategies. Based on students' score at the end of each game, theycan earn trophies (gold, silver, bronze), *iSTART Points,* and *iBucks*. iSTART Points determine students' current level within the system. iBucks are the system currency and can be spent to customize players' avatars, change background colors, or buy access to the identification games. In the current study, they were provided with an abundance of iBucks to allow them to freely interact with all features.

## 2. METHODS

### 2.1 Participants and Procedure

The study included 77 students (18-24 years) from a large University in the Southwest US. We conducted a 3-hour session consisting of a pretest, strategy training (via iSTART-2), extended game-based practice within iSTART-2, and a posttest. For our analyses here, we solely examined data from the time students spent in the game-based practice menu of iSTART. Each student spent approximately 2 hours interacting freely within the game-based interface, with his or her actions logged into the iSTART-2 database.

### 2.2 Development of Machine-Learned Models of Game Choice

To develop models that predict next game choice from previous achievement in an iSTART-2 game, we distilled features from the interaction logs of the 77 students who interacted with iSTART-2. A total of 1,562 action records were created for these 77 students, where each action record had 13 distilled features. Each record was labeled with the current game choice (at time *n*; 1 = identification game, 0 = generative game), having features corresponding to information about previous gameplay actions (at time *n-1*) in either an identification game or a generative game. In developing the two models to predict students' game choice, we employed student-level cross-validation for a decision tree classifier that uses the J48 implementation [5] that builds a

decision tree from a set of labeled training data. The baseline 1-back model included 2 features: previous type of game played, and type of trophy earned on the previous game. The full model included 11 additional features. The features that involved prior gameplay achievements and actions included: the number of iBucks won/spent, the number of iBuck bonus points won/spent, and the number of iSTART points won/spent the previous time the student played that game type. The remaining five features were aggregates of a student's achievements and actions so far: number of trophies achieved, number of generative games played, number of identification games played, average time played in a generative game, and average time played in an identification game.

# 3. RESULTS

For the 1-back model that predicts game choice based solely on previous game choice and achievement, students in our data set played a total of 1,562 games in iSTART – 1,144 instances of an identification game played and 418 instances of a generative game. The baseline model performed poorly under student-level cross-validation (see Table 1). This results in an imbalance, with precision of 38.46% and recall of 4.78%. The cross-validated A' is 0.603 (correctly predicted a game choice to be an identification game 60.3% of the time) and cross-validated Cohen's Kappa is 0.208 (model's accuracy was only 2.8% better than chance). This baseline model mainly predicts that students who have just played an identification game will select another identification game, regardless of their trophy achievement. It also predicts that many students who have just played a generative game, but did not receive any trophy, will select an identification game next.

**Table 1.** Cross-validated confusion matrix of baseline model

| | Identification Game (True) | Generative Game (True) |
|---|---|---|
| Identification Game (Predicted) | 1112 | 398 |
| Generative Game (Predicted) | 32 | 20 |

The second model resulted in the best-performing J48 tree with six features: (1) type of trophy from previous game played, (2) number of identification games played so far, (3) number of generative games played so far, (4) iSTART bonus iBucks spent in previous interaction, (5) iSTART points won in previous game, and (6) iSTART iBucks spent in previous interaction.

**Table 2**. Cross-validated confusion matrix of comprehensive model

| | Identification Game (True) | Generative Game (True) |
|---|---|---|
| Identification Game (Predicted) | 1069 | 125 |
| Generative Game (Predicted) | 75 | 293 |

This second model performed significantly better under cross-validation, classifying 1194 game choices as identification games, and 368 game choices as generative games (see Table 2), with a precision of 80.45% and recall of 70.10%. Our cross-validated A' and Cohen's Kappa also increased considerably, to A' = 0.907 and Cohen's Kappa = 0.660. Our second model yields a decision tree size of 61, with 34 decision rules (paths from root to leaf). Some examples of rules within this model include:

1) IF a student has at least played one generative game so far, AND spent more than 50 iSTART iBucks, THEN the next game the student will play is an IDENTIFICATION GAME (Confidence: 99.5%).
2) IF in a previous game the student won more than 610 iSTART points in a previous game, but spent 861 or fewer iSTART iBucks in a previous game, THEN the next game the student will play is an IDENTIFICATION GAME (Confidence: 97.0%).
3) IF a student has not played any generative game so far, AND spent no iSTART iBucks in a previous game, AND has received a BRONZE trophy in the previous game played, THEN the next game the student will play is an GENERATIVE GAME (Confidence: 83.33%).
4) IF a student has not played any generative game so far, AND spent no iSTART iBucks in a previous game, AND has received a SILVER trophy in the previous game played, THEN the next game the student will play is an GENERATIVE GAME (Confidence: 100%).

# 4. DISCUSSION

Results from this exploratory analysis suggest that students' choices in activities do not rely solely on previous game trophy achievement or previous game choice (first baseline model), but instead students' choices seem to be guided by their overall experience and interactions within the system (second comprehensive model). While this finding is not entirely surprising, it does help researchers shed light upon which features in a game-based environment are impacting students' choices. Indeed, there are many factors that impact students' choices within game-based environments. Thus, within environments where students are afforded a high amount of agency, user models will benefit by incorporating a more complete set of interaction features as a means to represent students' game experience more completely. In the future, we will employ Markov analyses in combination with decision tree analysis in an effort to gain a deeper understanding of what drives students' choices within a game-based environment. Although interactions within agency-driven environments are highly complex, this project demonstrates that they are predictable using machine learning algorithms.

# 5. ACKNOWLEDGMENTS

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# How to Aggregate Multimodal Features for Perceived Task Difficulty Recognition in Intelligent Tutoring Systems

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## ABSTRACT

Currently, a lot of research in the field of intelligent tutoring systems is concerned with recognising student's emotions and affects. The recognition is done by extracting features from information sources like speech, typing and mouse clicking behaviour or physiological sensors. Multimodal affect recognition approaches use several information sources. Those approaches usually focus on the recognition of emotions or affects but not on how to aggregate the multimodal features in the best way to reach the best recognition performance. In this work we propose an approach which combines methods from feature selection and ensemble learning for improving the performance of perceived task difficulty recognition.

## 1. INTRODUCTION

Some research has been done in the area of intelligent tutoring systems to identify useful information sources and appropriate features able to describe student's emotions and affects. However, work on multimodal affect recognition in this area focuses more on engineering appropriate features for affect recognition than on the problem of aggregating the features from the different information sources in an good way. The usual approach is to use one classification model fed with one input vector containing the concatenated features (maybe reduced by feature selection) like in [3] or using standard ensemble methods on the features of the sources separately like in [4]. In this paper instead we propose to mixing up the different feature types and combining methods from feature selection and ensemble approaches to reach a classification performance improvement compared to using only either methods from feature selection or ensemble approaches. Feature selection methods can be used to reduce the number of features and find good combinations of features. They take advantage of statistical information like correlations. Ensemble methods like stacking use multiple learning models to obtain a better prediction performance.

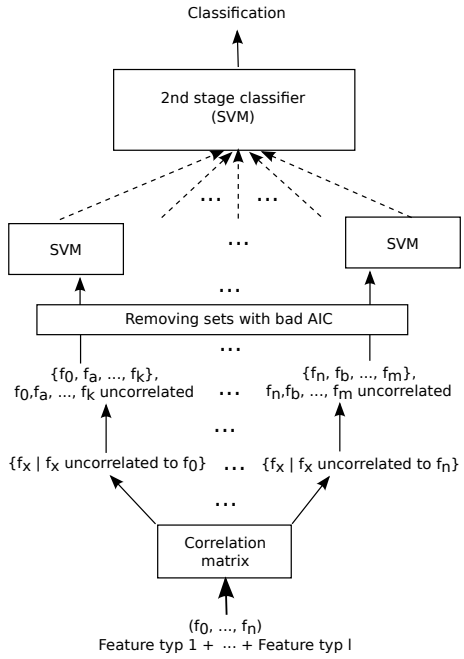


**Figure 1: Multimodal feature aggregation approach.**

Stacking learns to combine the classification decisions of several single classifiers by a further classifier which gets as input the outputs of the other classifiers.

## 2. MULTIMODAL FEATURE AGGREGATION

We propose to profit from the advantages of both feature selection methods and ensemble methods. Hence, we combine both (see fig. 1): In a first step the feature vectors of all $l$ feature types are concatenated to reach one input feature vector $(f_0, \ldots, f_n)$. However, there could be dependencies between the different features. Hence, we create the correlation matrix reporting about the correlations between each pair of features. By means of this matrix we extract for each single feature $f_y$ a set $uncorr_y$ containing all other features $f_x$ not correlated to $f_y$. *Not correlated* means in this case that the correlation value $v_{x,y}$ of the pair $(f_x, f_y)$ in the correlation matrix is near to 0.0, or more explicitly, $|v_{x,y}|$ is smaller than some positive thresh-

**Table 1: Classification errors and F-measures.**

| | |
|---|---|
| (1) | SVM applied to amplitude features<br>31.25% (0.75, 0.59)<br>SVM applied to articulation features<br>22.92% (0.81, 0.72) |
| (2) | SVM applied to all concatenated features<br>27.08% (0.77, 0.67) |
| (3) | SVM applied to most uncorrelated features<br>20.83% (0.81, 0.77) |
| (4) | Stacking applied to $uncorr_y$ sets<br>20.83% (0.83, 0,74) |
| (5) | Stacking applied to $uncorr2_y$ sets<br>16.67% (0.86, 0.80) |
| (6) | Stacking applied to $uncorr2_y$ sets with best AIC<br>**8.33% (0.92, 0.91)** |

old $t$, i.e. $uncorr_y := \{f_y\} \cup \{f_x \mid t > |v_{x,y}|\}$. The set $uncorr_y$ contains all features uncorrelated to $f_y$ but between the features within this set there could still be correlations. Consequently, we compute for each feature $f_y$ a set $uncorr2_y := \{f_y, f_a, \ldots, f_k\}$ where $f_y, f_a, \ldots, f_k$ all are uncorrelated. These sets $uncorr2_y$ are gained for each feature $f_y$ by sequentially intersecting $uncorr_y$ with the sets belonging to the features within $uncorr_y$, or the intersection respectively. Different to feature selection, our goal is not to create one feature vector with reduced dimensionality but we aim at creating one feature vector per feature which will be fed into an own classifier, to consider each feature and to deliver as many input as needed for the ensemble method. Nevertheless, we remove some of the $uncorr2_y$ sets. The reason is that there is still some statistical information which we did not yet use: the quality of the models using these sets as input. Hence, for each set $uncorr2_y$ we compute the Akaike information criterion (AIC) – indicating the quality of a model. Subsequently, we remove the worse quarter of the sets. The remaining sets are fed into an support vector machine (SVM) each. In the next step we apply a stacking ensemble approach by feeding the outputs, i.e. the classification decisions, of the SVMs into a further SVM, which learns how to generate one common classification decision.

## 3. EXPERIMENTS

We prove our proposed multimodal feature aggregation approach by experiments with a real data set and multimodal low-level speech features. The data were gained by conducting a study in which the speech of ten 10 to 12 years old German students was recorded and their perceived task-difficulties were labelled by experts. During the study a paper sheet with fraction tasks was shown to the students and they were asked to explain their observations and answers. The acoustic speech recordings were used to gain two kinds of low-level speech features: *amplitude* and *articulation* features. The *amplitude features* ([1]) are taken from the raw speech data, or information about speech pauses respectively: ratio between (a) speech and pauses, (b) number of pause/speech segments and number of all segments, (c) avg. length of pause/speech segments and max. length of pause/speech segments, (d) number of all segments and number of seconds, and percentage of pauses of input speech data. The idea behind this kind of features is that depending on how challenged the student feels, the student makes more or less and shorter or longer speech pauses. The *articulation features* ([2]) are gained from an intermediate step of speech recognition which delivers information about vowels and consonants: ratio between (a) number of silence tags and number of all tags, (b) avg./min. length of vowels/obstruents/fricatives/silence tags and max./avg. length of vowels/obstruents/fricatives/silence tags. The idea behind this kind of features is that depending on how challenged the student is, the student shortens or lengthens vowels and consonants. The data collection resulted in 36 examples labelled with *over-challenged* or *appropriately challenged*, respectively 48 examples after applying oversampling to the smaller set of examples of class *over-challenged* to eliminate unbalance within the data. We conducted a 3-fold cross validation and we applied SVMs with an RBF-kernel and for each SVM used we conducted a grid search on each fold to estimate the optimal values for the hyper parameters. As baseline experiments we applied an SVM separately to both feature types. The classification test errors and F-measures (harmonic mean of *recall* and *precision*) for both classes (*over-challenged*, *appropriately challenged*) are reported in tab. 1, (1). An aggregation of both feature types only makes sense, if we can improve this results. A straight forward way to combine different feature types is to concatenate the features of all types and putting them into one feature vector which serves as input for one classification model. However, this approach does not deliver good results (see tab. 1, (2)) in cases where some features may be correlated and may disturb each other. Hence, one should restrict the input vector by considering the correlations. The results of using only features uncorrelated with most of the other features are shown in tab. 1, (3). As one can see considering correlations helps to improve the classification performance. But still there is space for improvement. Hence, in the following we combine ensemble methods with feature selection which takes into account correlations. In a first step we applied stacking ensemble to the outputs of SVMs applied to the $uncorr_y$ sets (see tab. 1, (4)). However, there could still be correlations within the $uncorr_y$ sets. Hence, as next step we computed for each feature the $uncorr2_y$ set and applied again stacking ensemble, resulting in a classification test error of 16.67 % (tab. 1, (5)). This result is already very good but there is one more statistical information to use: the AIC. We computed for each $uncorr2_y$ set the AIC, threw out the worst quarter of these sets and applied stacking to the remaining sets resulting in a very good classification test error of 8.33 % and F-measures $0.92, 0.91$ (tab. 1, (6)). In summary, the experiments have shown that our multimodal feature aggregation approach is able to improve the classification performance significantly.

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# Teacher and learner behaviour in an online EFL workbook

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## ABSTRACT

In this paper, we present selected findings from our usage analysis of an online English Language Teaching (ELT) workbook. We focus on how teachers assign activities and how learners complete them.

## Keywords

ELT, network analysis, time on task

## 1. BACKGROUND

MyEnglishLab for Speakout Pre-intermediate is an ELT workbook that accompanies a paper textbook. The aim of the product is for the teacher to assign auto-graded homework. On average, about 10 practice activities are assigned by the teachers within a week, with a 30% chance of assigning more than the average. Speakout consists of twelve units that cover 90-120 hours of teaching. Each unit contains about thirty assignable activities centred around grammar, vocabulary, listening, reading and writing. This paper is an exploratory study about how teachers assign such activities and how learners complete them.

## 2. TEACHER PROGRESSION

### 2.1 Method

To analyse how teachers progress through units within Speakout, we wanted to show which pairs of units were assigned together. By assigning a unit we mean assigning at least one activity from that unit. In Figure 1 (created using Gephi [1]), a node represents teachers who assigned at least one activity in a given unit. The edges represent those teachers that, having assigned some activities in one unit, moved to another unit. A thicker edge means two units were assigned together more frequently (by more teachers). For example, 185 teachers assigned both Unit 1 and Unit 2. The thickness and length of each edge refers to normalised co-appearance (geometric mean) calculated after Newman [2] as:

$$\frac{n(u_i,u_j)}{\sqrt{n(u_i)\cdot n(u_j)}}$$

where $n$ (…) is the number of teachers that assigned activities in all listed units, and $u_i$ is the $i$-th unit. Different unit types were highlighted for better readability, namely the regular Units 1-6 (U1-U6) and Units 7-12 (U7-U12) are shown separately from Review and Check 1-4 (R&CH1-R&CH4). The role of the former units is to enable regular day-to-day homework practice, while the role of the latter is to allow the learner to review a larger portion of the material from the three previous units before a test.

### 2.2 Results

Figure 1 shows that there is no prominent community structure. Teachers tend to focus on smaller chunks of material, especially Units 1-3 and Units 7-9. Figure 2 shows that teachers assign either the regular Units or just the Review and Check units, rarely both. There are more connections between the Review and Check units themselves than between the regular Units. For example, more teachers assign Review & Check 3 together with Review & Check 4 than they assign Units 10-12 together with Review & Check 4.

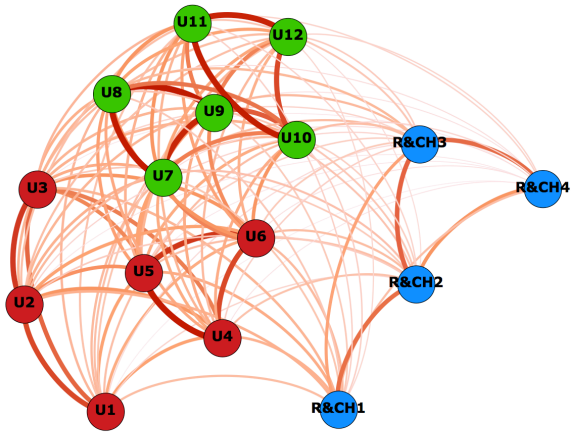


**Figure 1. Network graph of relations between units in Speakout Pre-intermediate with edge as a normalised value (geometric mean)**

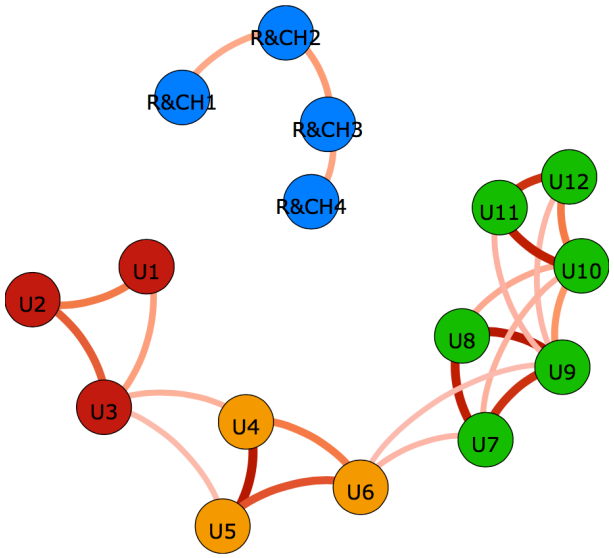


**Figure 2. Network graph of relations between units in Speakout Pre-intermediate with edge as a normalised value (geometric mean); only the 24 strongest edges shown**

## 3. QUESTION TYPE AND TIME SPENT

When it comes to learners, we wanted to analyse the time needed for completing a language-learning activity. Speakout contains 15 main question types. Figure 3 (created using RStudio [3]) shows that for most of them the average time spent on the first submission of an activity is of the order of 3 minutes. Learners spend the least time on multiple choice activities (about 1.5 minutes), and most time on jumble words activities (over 4 minutes). We stress that these times do not necessarily correspond to the *optimal* duration it takes a learner to complete all the questions within such an activity, which needs future exploration.

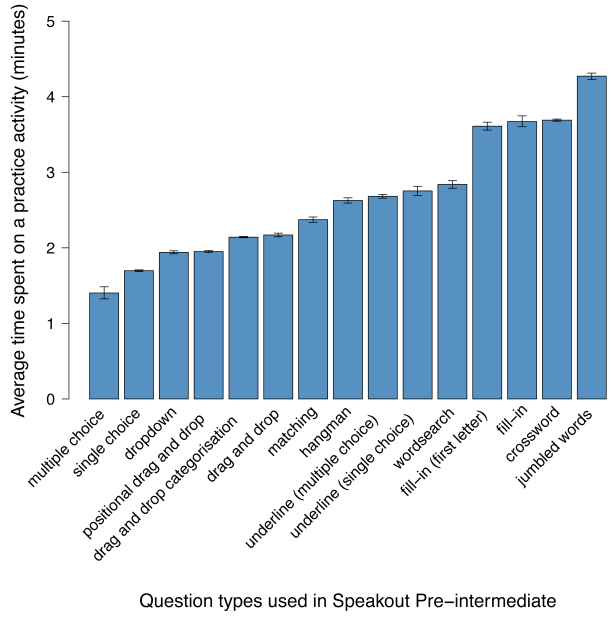


**Figure 3. Geometric average of time spent on completing an activity of a given type, with 95% confidence intervals.**

Due to space constraints, we present only one figure that presents a question type in more detail, namely *fill-in* (gap completion).

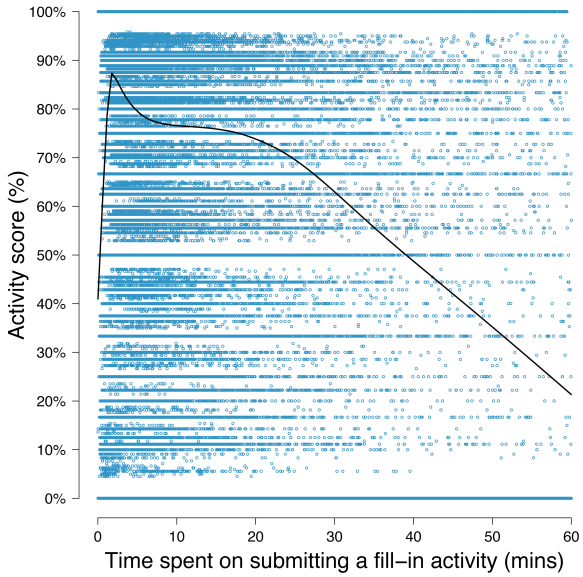


**Figure 4. Correlation between the time in which a learner submits a fill-in activity and the score received for that activity; cutoff at 60 minutes**

Figure 4 shows that, except for the solid lines at activity score 0% and 100%, most of the observations are placed in the top left part of the plot. The smoothed line shows a peak in activity score at 1.5 minutes spent on a fill-in activity, after which the score visibly decreases. This means many learners need 1.5 minutes to submit a simple fill-in activity (for example, without a text or audio) and receive a relatively high score. An analysis of the top four question types that account for about 76% of Speakout activities (fill-in, drag-and-drop, dropdown and single choice – the last three are not shown here) shows that there is a negative correlation between the time spent on activities and the scores received for those activities. On average, the score decreases by about 8% for each 10 minutes spent on the activities with these question types.

## 4. FUTURE WORK

Regarding teacher usage, our next step is to segment teachers according to course types and institutions. Regarding learner usage, we will investigate if activities consisting of many questions that are completed within a very short time need to be further analysed to identify whether their format encourages guessing or copying.

## 5. ACKNOWLEDGMENTS

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# Skill Assessment Using Behavior Data in Virtual World

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## ABSTRACT
Highly interactive game-like virtual environment has gained increasing spotlight in academic and educational researches. Besides being an efficient and engaging educational tool, virtual environment also collects a lot of behavior data which can be used with Educational Data Mining (EDM) techniques to assess students' learning competencies. In this paper, we propose an assessment system that seamlessly integrates EDM techniques with functionality and affordance of a virtual environment to assess students' learning competency through analyzing their behavioral data and patterns. The virtual environment can record not only students' learning outcome, but also their detailed learning process information, which has the potential to depict the full set of students' learning activity. We also propose a set of metrics which can be used for judging students' Self-Directed Learning skills and how these metrics can be evaluated computationally by capturing students' behavioral data in a virtual environment. The field study, which is conducted in Xinmin Secondary School in Singapore, preliminarily illustrates the effectiveness of our approach.

## Keywords
Educational Data Mining; Virtual Environment; Competency Assessment; Self-Directed Learning

## 1. INTRODUCTION
In the fast changing and increasingly globalized society, students nowadays need to become more conscious, controlled, independent and active in their learning. The new requirements of education urge the creation of new assessment approaches. Besides being an efficient and engaging educational tool, virtual environment also collects a lot of behavior data which can be used with Educational Data Mining (EDM) techniques to assess students' learning competencies. Many researchers have worked in this area [1-3]. The system that we proposed is based on a full-scale 3D virtual environment to assess students' learning competencies. Among all kinds of learning competencies, we focus on Self-Directed Learning (SDL) competency in our research study because it is among the most important learning competencies students need to excel in the knowledge society of the 21st century [4]. SDL skills are important indicators of students' learning competencies as they are the fundamental philosophy behind life-long learning. The proposed system uses Evidence Centered Design (ECD) approach to assess students' SDL competency through analyzing their behavioral data in virtual learning environment. With the Competency Model, Evidence Model, and corresponding Task Model, the system can provide opportunities for students to elicit behavioral indicators of certain SDL skills. These behavioral indicators can be used for assessing the skill levels which cannot be discerned from traditional academic assessment. Moreover, we conducted a pilot study in Xinmin Secondary School Singapore to demonstrate how to evaluate the SDL metrics. The study illustrates the preliminary effectiveness of our approach.

## 2. MODELING SDL SKILLS
The overall system architecture consists of two main modules: the Virtual Singapura II (VS-II) System and Assessment Automation module. VS-II System is a full-scale 3D virtual world to promote intelligent agent mediated learning. As an open environment, VS-II allows students to explore and learn in a self-directed manner. By recording student's behaviors in the virtual environment, the system provides a convenient and effective setting to elicit students' behavior evidence of their learning skills through the whole learning process.

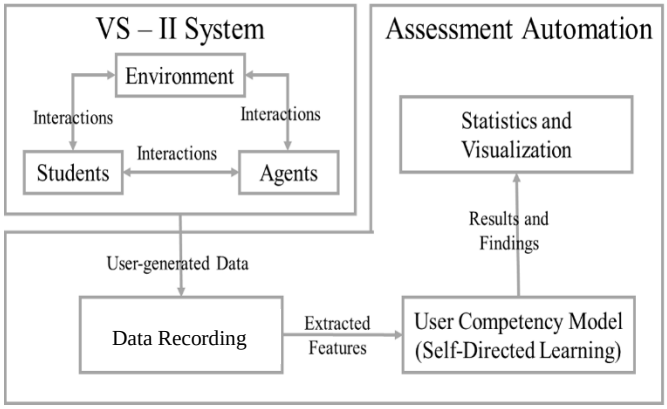


**Figure 1. System Architecture for Assessing Students' Learning Competency.**

The Assessment Automation module has three sub-modules as shown in Figure 1. The first module – Data Recording meticulously records a wide range of student learning behavior data. There are totally 78 types of events being tracked in the system, and the data collected in the virtual environment consists of three categories: 1) Student learning behavior data, such as locations, timestamps, mouse clicks, etc. 2) Student learning achievement data, such as collected items, fulfilled missions, etc. 3) Student knowledge data, such as correctness of responses, hints required, etc. The second module – User Competency analyzes students' behavioral data through Evidence Centered Design (ECD) approach. Evidence Centered Design (ECD) is the framework for assessment that makes explicit the interrelations among substantive arguments, assessment designs, and operational processes [5]. Similar to the approach Shute has adopted in her study [6], we utilize ECD methodology in our system design to track and interpret students' behavioral data to assess students' SDL competency. The system is designed in a

three-layered model. The three layers are: 1) ***Competency Model*** identifies what should be assessed in terms of skills. The competence of Self-Directed Learning (SDL) is denoted as $C_1$, where $C_1$ consists of three aspects of skills $\mathbf{S}^{C_1}$, and $\mathbf{S}^{C_1} = \{S_1, S_2, S_3\}$, where $S_1$ denotes Ownership of Learning, $S_2$ denotes Management and Monitoring of Own Learning, and $S_3$ denotes Extension of Learning. 2) ***Evidence Model*** identifies behaviors that demonstrate the skills defined in 1). The essential student behavioral indicators for SDL are defined as $\mathbf{B}^{S_i} = \{\text{behavioral indicators of } S_i\}$, where $i \in \{1, 2, 3\}$. 3) ***Task Model*** identifies the tasks that would draw out behaviors defined in 2). Let T = {tasks completed by students in the learning environment}, and $\mathrm{T} = \{T_1, T_2, \ldots, T_L\}$. Each task $T_i$ is an n-tuple, which consists of an ordered list of learning activities. Let $T_i = (A_1, A_2, \ldots, A_n)$, and $A_i \in \mathbb{A}$ denotes a learning activity. $\mathbb{A}$ is the set of learning activities and each $A_i$ is atomic and cannot be further decomposed into other learning activities.

In our implementation, we focus on the assessment of SDL skills in one of its three aspects, "Management and Monitoring of Own Learning". We illustrated the assessment process by emphasizing one of the skills of SDL competency,$S_2$, i.e. Management and monitoring of own learning skills. This skill is defined with three behavioral indicators. For each behavioral indicator, we designed several evidence variables to capture a student's performance (as Figure 2). The Last module Statistics and Visualization module visualizes all the results and findings through our user interface.

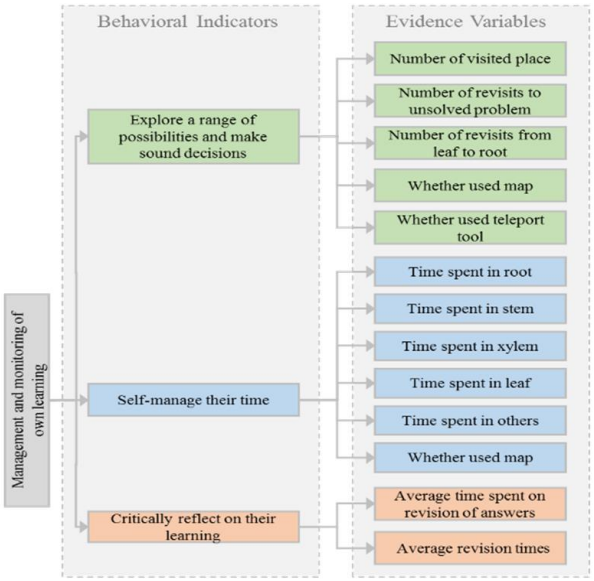


**Figure 2. List of Behavioral Indicators and Evidence Variables on Management and Monitoring of Learning.**

## 3. PILOT STUDY AND FINDINGS

The assessment prototype has been deployed in Xinmin secondary school in Singapore. The field study on one side aims to examine whether the whole system is technically workable (data transmission, real time data recording, network setting, client response, etc.), on the other side aims to examine whether the SDL skills can be identified among students with students' real behavioral data. 26 students from Secondary 2 (age 12-13) have participated in our study. In order to get the benchmark, we collected students' SDL skills markings from three of their teachers, and calculated the average scores on each perspective. We also let students fill in a SDL self-report questionnaire.

Significant results have been found. For time management, students who used the virtual map to plan their learning path completed a significantly higher number of learning tasks during the same sessions as compared to those who did not. About 50% of the students in the group with the virtual map completed 4 learning tasks, while for the other group, most students (close to 60% of them) only managed to complete 2 or 3. The average number of learning tasks completed by the group with the map is 3.83, while that of the other group is 2.5. Also, students who more tended to rely on the mobility tools provided in the game (i.e. the teleporting gates, the virtual passport, etc.) tended to limit themselves in terms of self-exploring wide range of possibilities. In contrast, students who were more selective of the tools tend to explore more widely and make better decisions. The correlation coefficient between mobility tool usage and the form teacher's assessment of individual students' exploration skills is -0.5404, indicating a strong negative relationship. These findings support that our system is promising in identifying useful learning behavior metrics, and also has the capability to identify different SDL skills from different behavior patterns.

## 4. CONCLUSIONS

This paper proposed a virtual environment enabled assessment system for assessing student's SDL skills through personal learning behavior informatics. We provided a set of tools from theoretical models to system implementations to analyze student's behavior data and managed to evaluate the connections between behavioral indicators and student's SDL skills. The proposed three-layered model bridges the gap between definitions of SDL skills and how they can be quantified and evaluated computationally. The seamless integration with VS-II system enables the collection of students' behavioral data in the virtual environment. With the application of educational data mining, the Assessment Automation module analyzes collected behavioral data, consolidates and presents the findings graphically. In the future work, with more and more student data collected, we will gradually refine the benchmarks of student skills and improve the whole assessment process.

**Acknowledgement.** This research is supported in part by Interactive and Digital Media Programme Office (IDMPO), National Research Foundation (NRF).

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# Pacing through MOOCs: course design or teaching effect?

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## ABSTRACT

Despite the original tenets about openness and participatory characteristics of MOOCs [1], the majority of MOOCs are delivered in a semi-structured asynchronous way bridging the strong structure of traditional courses -signposted by lectures, tutorials/seminars and activities/assignment deadlines- and open courseware in which student are able to select their own learning paths and goals. Looking at the activity of students in three different MOOCs delivered on the Coursera platform, we considered the effects of different course design to observe variations in the way students pace through the courses. The analysis (in progress) suggests that the course design and the mode of teaching strongly influence the way in which students progress and complete the courses. However, more research needs to be done on the individual variations and on the supporting mechanisms which could be put in place to scaffold students' development of their own learning paths and matching their intended goals.

## Keywords

MOOCs, learning design, behavioural analysis, learning

## 1. INTRODUCTION

Following Gartner's hype cycle [2], MOOCs are currently in the 'sliding into the trough' phase, quickly moving into a consolidation stage, which should lead to the establishment of best practices. This is evident also in the research domain, in which MOOCs have taken centre stage in the recent LAK and Learning@scale conferences. Despite the hype of big data in education and the potential associated with the ability to collect and analyse large amount of information about students' learning behaviours, one of the biggest limitation in the field are the lack of systematicity in the creation of MOOCs –perhaps with the exemption of the limitations of the various platforms- and the lack of strong collaborations leading to sharing data across the sector. As mentioned in [3], at most, researcher might have access to a few MOOCs to analyse; this is echoed in the recent call for a special issue of the JLA (Siemens) to open up and describe large datasets in order to enable research. Yet, the biggest limitation in many published works is a full description of the context, i.e. the course design and philosophy behind it -which is the first stage of any data mining process in the industry-standard CRISM-DM model [4].

Even though the philosophies behind the MOOCs movement range from the instructivist (xMOOC, [5]) to the social-constructivist (cMOOC, [6, 7]), a key assumption is that most MOOCs are built as a 'course': normally there is an instructor/facilitator, a set of resources, activities, support and other participants; content can be curated by instructors or shared among participants. As Cormier [8] put it, a MOOC is 'an event' which provides an opportunity for participants 'to connect and collaborate' and to 'engage with the learning process in a structured way'. But, if it is an *event* and it is *structured*, then the way in which *it* is designed is fundamental and the design is what trumps the teacher role and/or presence. From an academic development's perspective, not only the way in which elements and components are selected and structured makes a difference, but also the philosophy of teaching behind how the course should be delivered drive the learners' experiences.

## 2. DIFFERENT COURSE DESIGN

At our university, a large, public, research-intensive university in Australia, one of the key reasons to enter the MOOC space was to be able to experiment with pedagogical innovation, learn from it and bring it back to mainstream (i.e. what we do on campus). The selection of courses to be delivered is driven by the awareness of a different target audience, disciplines and the ways in which academics imagined the best ways of teaching a course at scale. Here we only refer to the first 3 courses completed: INTSE (Introduction to System Engineering), LTTO (Learning to Teach Online) and P2P (From Particles to Planets -physics) which are broadly characterised in the table below.

**Table 1. Overview of courses**

| | INTSE | LTTO | P2P |
|---|---|---|---|
| **Target group** | Engineers | Teachers at all levels | High school and teachers |
| **Course length** | 9 weeks | 8 weeks | 8 weeks |
| **Total videos** | 110 | 224 | 98 |
| **Total quizzes** | 10 | 22 | 42 |
| **Assignments** | 7 | 3 | 2 |
| **Forums** | 54 (14 top level) | 105 (17 top-level) | 63 (15 top-level) |
| **Design mode** | All-at-once | All-at-once | Sequential |
| **Delivery mode** | All-at-once | Staggered | Staggered |
| **Use of forums** | Tangential | Core activity | Support |
| **N in forum** | 422 | 1685 | 293 |
| **Tot posts** | 1361 | 6361 | 1399 |
| **Tot comments** | 285 | 2728 | 901 |
| **Registrants** | 32705 | 28558 | 22466 |
| **Active students[1]** | 60% | 63% | 47% |
| **Completing[2]** | 4.2% (0.3% D) | 4.4% (2.4 D) | 0.7% (0.2%) |

*1. Active students are those appearing in the log; 2. Completing are those who achieve the pass grade or earn Distinction (D)*

At the surface all three course lean toward an instructivist approach in which the content is essential. However, the educational developers supporting the design ensured that each course was characterised by a mix of content, activities, support tools and evaluation. There are some key differences by design: the way in which content is released; the way in which the course is taught; the function of activities and forums. In INTSE and LTTO all content is released at the start all together, however in LTTO the teaching occurred in a staggered way with regular announcements and feedback videos in response to the top voted comments in each week. P2P used a sequential release of content every week with a staggered delivery and interaction. The activities focus on self-test in INTSE and P2P, while in LTTO these had a teaching function structuring personal development and reflection in the forums. Finally forums were not the focus of the course in INTSE, but had an important role in LTTO and as support in P2P.

# 3. RESULTS

## 3.1 Patterns of activity

As it can be seen from the charts some patterns are quite evident. For the P2P course (figure 1), which was designed and delivered on a week-on-week basis, the darker diagonal shows that students are following the course in a linear fashion. LTTO (figure 2) shows a tendency to follow activity along the diagonal. However, this pattern is reduced by individuals who jump between sections/components in the same week (earlier in the course rather than later). In the INTSE (figure 3), patterns are a lot more diluted: in the use of content (videos) the stronger patters occur in the first week, last week and in part across the diagonal. The forums don't seem to have a time-based dependency and the quizzes follow the diagonal and are more frequent in the last week of the course, it is evident that the majority of students tend to follow a fairly linear pattern. Further analysis will be required to test the significance of these patterns, but this early visualization clearly suggest that there is an interaction between the design and delivery of the course and that despite the freedom of determining their learning paths, students like the pacing provided by instructors.

## 3.2 'Ontrackness' and dedication

In their analysis [3] 'on-trackness' is defined as 'the degree to which students cohere with the recommended syllabus'. Similar metrics have been used in learning analytics as signals for possible support/interventions in order to reduce dropout (i.e. attendance, timely submission etc.). In sequential courses this is simple to identify, however when all the material is available at once, this could be less meaningful. Figure 4 shows the patterns in the three courses by mapping the weeks in which a resource is expected to be used (i.e. design) and when it was actually used. Once again the linear pattern around the diagonal for P2P clearly show how participants follow the course week-on-week; in INTSE and LTTO the videos use are more scattered with quite a few participants looking ahead in the course, but this is not reflected in the quizzes/acitivities and the forums As well as the overview of ontrackness, we have started to consider other metrics, which will require further modelling and analysis. *Dedication* is defined as the regularity of engagement. Given a time period T and the distribution of activity during T, dedication d is the ratio of activity and course length. *Assiduity* is a measure of the patterns of activity over time and it is characterised by the skewness and kurtosis of the distribution of activity. Looking into individual distributions of activity and the relations with other measures will provide a better insight on the individual preferences and how these are related to the teaching and course design.

# 4. CONCLUSION & DIRECTIONS

Bearing in mind the differences in the cohorts of students taking the courses taken into consideration, which leads to a limited ability to draw conclusions, the striking similarities between the patterns of engagement in the different MOOCs suggests that the method of teaching/delivery is a key element in the way students take a MOOC. The structure of the MOOC 'event' has got a strong impact in the way students engage, but more analysis is necessary to determine the level of flexibility afforded.

At the group level it is apparent that student follow the pace of the course as set by the instructors, however many questions remain open about the effectiveness when it comes to achievement levels. In particular, the goals/intents of students might not be to complete the course and therefore the skipping behaviours could be aligned with what they want to achieve and hard to relate to the measure of success of a MOOC. In fact [9] argue that we need to review and reconceptualise what we mean with student success in this space. More analysis, especially at the individual student level will be necessary to extract meaningful insights.

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# Integrating a Web-based ITS with DM tools for Providing Learning Path Optimization and Visual Analytics

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## ABSTRACT
We present an improved version of our web-based intelligent tutoring system integrated with data mining tools. The purpose of the integration is twofold; a) to power the systems adaptivity based on SPM, and b) to enable teachers (non-experts in data mining) to use data mining techniques on a daily basis and get useful visualizations that provide insights into the learning process/progress of their students.

## Keywords
Web based intelligent tutoring system, data visualizations, visual analytics.

## 1. INTRODUCTION
Our proposed solution to objectives put forth in [5] is the integration of our web-based ITS with standalone data mining tools Weka[3] and SPMF[2]. We developed an integration module that enables continuous communication with the DM tools without implementing any specific algorithm into our application or changing the original DM code. The architecture of the integrated system is displayed in Figure 1. Functionalities that rely on data mining results for students and teachers are marked with asterisks. We will elaborate on these in the next sections. Our web-based intelligent tutoring system (ITS) provides a platform for learning on ill-defined domains [4] i.e. domains that consist of a number of knowledge units (KUs) that do not have a set order in which they have to be learned, but instead the system relies on a domain expert to define the structure of the domain. The learning process is started by selecting a KU to which the system responds by displaying the various types of learning materials created by the teacher. Afterwards, the student proceeds to the assessment module. The system will first ask the student a question about the KU that was learned, followed by an initial question for every KU that is below the current KU in the domain structure created by the teacher. In this way the system checks whether the student understands all the underlying concepts. This list of KUs is currently the same for all students. We aim to make this part dynamic (see Section 3) in order to make the system more adaptive and increase the efficiency of the whole system. If the student offers an incorrect answer to any of the initial questions, he/she is transferred to learning that KU and the whole process is repeated.

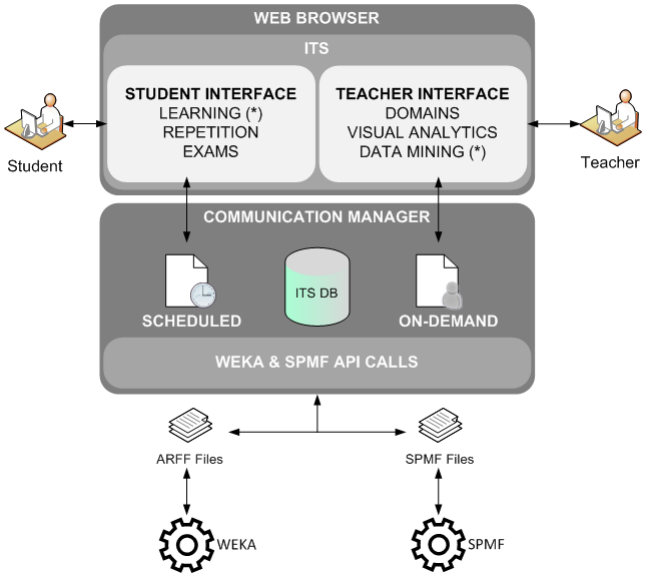


**Figure 1. Overall system architecture**

No matter how many levels down the hierarchy the student is taken by answering initial questions incorrectly, the system will always return to the starting KU and finish when all the initial questions have been answered. Once the student reaches the KU threshold, the system will stop displaying that KU later in the learning process in order to avoid tediousness and repetition.

## 2. VISUAL ANALYTICS FOR TEACHERS
At the time of writing the visual analytics section for teachers had a number of visualizations and a clustering section that provide useful insights into the activity of the students and the learning process as a whole. When they start the analytics module, teachers are presented with a compact report containing columns on the number of learning and repetition activities the student performed, number of correct, incorrect and unanswered questions, and the total time spent learning. Each of the columns can be expanded into a sortable, searchable, heat mapped table to get a detailed view about the student's activity. Figure 2 represents the expanded report on the number of learning sessions and repetitions for all the KUs in the domain. Another part of the visual analytics module is the chart section. There are a number of

activity charts that can reveal the activity levels of the whole group or individual students (Figure 3).

**Figure 2. Detailed report on learning (all KUs,all students)**

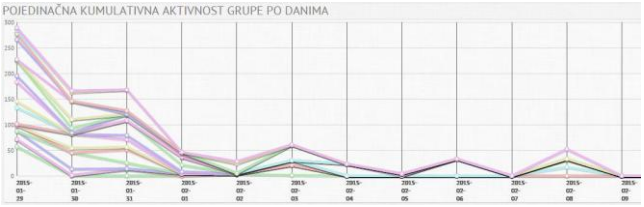


**Figure 3. Cumulative group activity by days**

The clustering analysis is currently based on a fixed number of features (the ones mentioned in the compact report), but in the next development iteration it will be completely interactive so that the teacher will be able to select features as well as the number of clusters before starting the analysis. When the teacher starts the clustering, the system invokes the communication manager which converts the data to the appropriate file format for either Weka or SMPF, writes the file to the file system and then performs the appropriate API call in the shell command line.

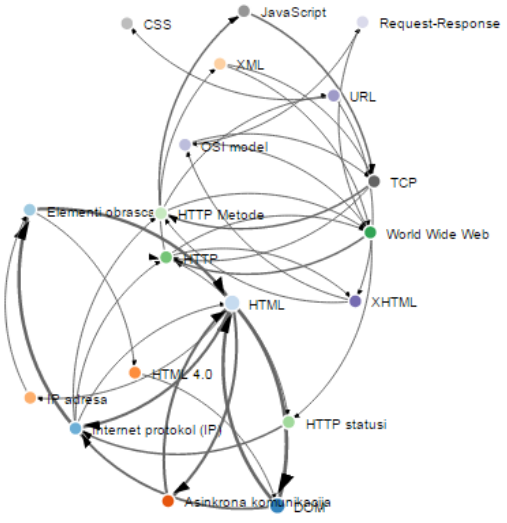


**Figure 4. Visualization of student learning paths**

The DM tool runs the required algorithm on the data using the sent parameters, and produces the output file. The file is then read, formatted and then returned to the teacher interface where they are displayed as a table with five columns containing cluster names, clusters centroids and students belonging to each cluster. The teachers using the system had no problem identifying inactive students, best students, the average students (largest cluster) and students that were "gaming" the system - students with low number of questions answered and very small amount of time spent learning – they started using the system at the last minute and probably obtained the answers to some questions. This can be confirmed by analyzing the heat maps and activity charts of those students.

## 3. DM-POWERED PATH OPTIMISATION

The next goal of our research is to create a more adaptive tutoring system in order to: a) increase the quality of learning, b) reduce time needed to acquire the domain knowledge. The set hypothesis is that each student creates a unique path through the structure of KUs. By scheduling a daily analysis of all these paths using SPM algorithms, we can find frequent learning paths. Next, we need to evaluate these paths in order to differentiate between paths that are frequent because a number of students are struggling with a difficult KU without making much progress through the domain from paths that show efficient behaviors that result in significant progress. We are currently developing an algorithm that will perform these evaluations by taking into account a number of learning performance indicators in order to produce a path score. When we get a list of evaluated frequent sequences and students clustered by their activity and effectiveness levels, we can alter the list and order of KUs to be learned in order to help the student follow an optimized path through the knowledge domain. Clustering of students gives us a finer level of granularity so we can offer different modifications to different groups of students. At this moment we run the SPM algorithms to get the frequent patterns and visualize them (Figure 4) using D3JS [1].

## 4. CONCLUSION

The main advantage of the system is that we can use any of the many SPM and clustering algorithms provided by integrated DM tools. In the future we will complete the SPM based adaptive path optimization component and perform experiments to verify its efficiency.

## 5. ACKNOWLEDGMENTS

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# Different patterns of students´ interaction with Mooodle and their relationship with achievement

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## ABSTRACT
This work tends to broaden the knowledge about the learning process in LMSs from an EDM approach. We examine students' interactions with Moodle and their relationship with achievement. We analyzed the log data gathered from a Moodle 2.0 course corresponding to the different interaction patterns of 140 undergraduate students with the LMS in an authentic learning context. We found out 4 different patterns of learning related to different academic achievement.

## Keywords
Learning process, LMSs, Moodle, higher education, log analysis.

## 1. INTRODUCTION
In traditional learning settings, instructors can easily get an insight into the way that the students work and learn. However, in LMSs, it is more difficult for teachers to see how the students behave and learn in the system [2]. Since learner activities are crucial for effective online teaching-learning process, it is necessary to search for empirical methods to better observe patterns in the online environment. In recent years, researchers have investigated various data mining methods to help instructors to improve e-learning process and systems [1]. As shown in the review of Romero and Ventura [3], a good number of quality works have been conducted with techniques similar to the ones used at this work. Most of them were carried out in laboratory settings with concrete tasks, but just a few in real settings or during an extended period of time [2]. These work aims to go beyond laboratory contexts and researcher-controlled settings. Therefore we set two research questions: 1. Are there sense different patterns of students' interaction when they learn in an LMS in a real context? 2. Are those patterns related to students' final marks?

## 2. METHODOLOGY
### 2.1 Participants and procedure
The datasets used in this work have been gathered from a Moodle 2.0 course that enrolled 140 undergraduate university students in a psychology degree program at a state university in Northern Spain. The experience was an assignment in the curriculum of a third year mandatory subject. Students were asked to participate in an eTraining program about self-regulated learning related to the subject's topic. The program was composed of 11 different units that were delivered to the students on a weekly basis. Students get an extra point in their final subject grade if they complete the assignments. We have used 12 actions that make the most sense to represent the students' performance in the particular Moodle course described (See Table 1). The variables selected can be grouped into two different groups: Variables related to effort and time spent working (*Time task, Time Span, Relevant Actions,* and *Word Forums)* and Variables related to procrastination (*Day's task* and *Day's Hand-in*). *Final marks* were extracted from the performance in the subject that is the grade of the e-Training program and the sum of the grade in an objective final exam of the subject.

### 2.2 Data Analysis
First, as an exploratory approach to the optimal number of behavioral patterns or clusters in the LMS, the expectation-maximization (EM) algorithm was used. Second, we sought a similar solution to the one provided by EM for the cluster classification but through the k-means algorithm. The objective of these two first steps is to obtain a clustering solution based on coherence among EM and k-means. Through the clustering, we aim to get high similarity intra-cluster and maximize the differences between them. Finally, ANOVA analyses were run to observe if there were differences between the inter-clusters, and the predictive validity of those clusters to predict final marks.

## 3. RESULTS
After analyzing the data with the EM algorithm, with k-means and with the elbow method, k = 4 was found to be the optimal number of clusters for this sample. Fig. 1 graphically represents the characteristics of the four groups. The second question was to bring up the chances of those patterns being related to students' final marks. For this purpose, an ANOVA analysis was carried out. The results obtained with final marks as the dependent variable and the different clusters the independent ones where $F(3,136) = 13.31$; $p < .00$; $\eta^2_p$ .227, indicates that there are statistically significant differences between the four student groups in final marks. The post hoc comparisons showed the following statistically significant differences: cluster 1 vs cluster 2 (d = 0.82, large effect), cluster 2 vs cluster 4 (d = 1.43, very large effect), and cluster 3 vs cluster 4 (d = 1.01, large effect).

**Table 1. Name of variables considered in the study with their description and extraction method**

| Name | Description | Extraction Method under *Moodle nomenclature* | Additional information |
|---|---|---|---|
| **Variables related to effort and time spent working** | | | |
| Time Tasks | Total time spent | Sum of the periods between *quiz view/quiz attempt/quiz continue attempt/quiz close attempt* and the next different action | Students have a period of 15 days to complete the tasks. |
| Time Span | Total time spent working in every unit | Sum of the variables related to the time spent in the three different type of contents: *Time tasks*, *Time Theory* and *Time Forum* | Students have a period of 15 days to work in a declarative knowledge level (*Theoretical contents*), procedural knowledge level (*Practical tasks*), and conditional knowledge level (*Discussion forums*). |
| Words Forums | Number of words in forum posts | Extracting the number of *forum add discussion* OR *forum add reply* words | Students do not have a minimum/maximum number of words. |
| Relevant Actions | Number of relevant actions in the LE | Total of relevant actions considered | Actions such as log in, log out, profile updating, check calendar, refresh content, etc. are dismissed. |
| **Variables related to procrastination** | | | |
| Day's Tasks | How long students wait to check the task since it was made available in the LE (in days) | Date of task *view* since the task was made available | Students have a period of 15 days to complete the tasks. |
| Day's "hand-in" | The time taken to hand in the task since the task was made available at in LE (in days) | Date of *quiz close attempt* since the task was made available | Students have a period of 15 days to hand in the tasks. |

Regarding the comparisons between cluster 1 vs cluster 4 and cluster 2 vs cluster 3, the inter-cluster differences' effect size was medium.

# 4. DISCUSSION

Four different patterns of learning with different final marks were found in this course; it is interesting how students with very different patterns in the LMS end with a very similar achievement. Cluster 1 is characterized by a small amount of time allocated to work in general but particularly in the practical task. The variables regarding procrastination and the participation in the forums are low, nevertheless, the overall number of significant actions in the LMS is high. Considering that their achievement is medium-low these results may indicate that students in this cluster work quickly but not efficiently. The students in the Cluster 2 could be described as strategic due to the small amount of time and low number of actions in the LMS that led them to very good results. The pattern for working variables is very suitable, too, with a high quantity of time invested in the tasks and they do not procrastinate. Cluster 3 is similar to the previous one in terms of achievement but not in the remaining variables. This group's achievement is a bit lower than Cluster 2's, it could be labeled as medium-high. There is nothing remarkable about procrastination variables, in contrast, the participation in the forums is really low. The number of relevant actions is also the lowest for this cluster; however, the time that they spent in the LMS was the highest. These results may indicate that they are not strategically efficient and do not make the most of the time spent, but they are still ultimately profitable in terms of achievement. Finally, Cluster 4 is characterized by the lowest marks. The most defining characteristic is that they are extreme procrastinators with really low levels in the variables related to the time spent working. Moreover, they make a significant number of relevant actions but do not benefit from them at all, which denotes a maladaptive approach to learning.

On one hand, these results may help an instructor better understand students' learning process, identify at-risk students (e.g., Cluster 1 and 4) and intervene. On the other hand, the information provided by Clusters 2 and 3 could guide the future development of recommendation systems; having a similar performance in terms of achievement the underlying interaction with the LMS denote different patterns that could be modeled by a recommendation systems in very different terms.

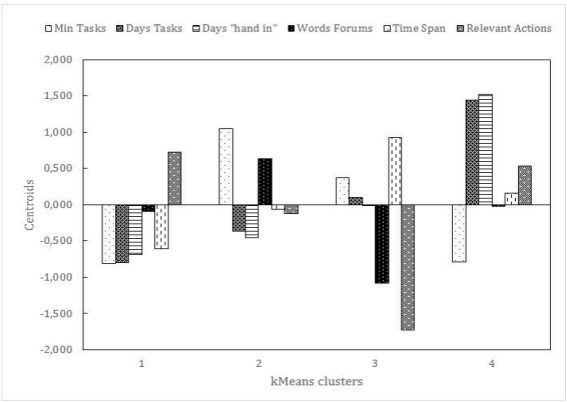


**Figure 1. Graphic representation of clustering**

# 5. ACKNOWLEDGMENTS

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# Educational Data Mining in an Open-Ended Remote Laboratory on Electric Circuits. Goals and Preliminary Results

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## ABSTRACT
WebLab-Deusto is a learning environment used at the University of Deusto as the landing platform to several remote laboratories currently used in high school and university level courses. One of these remote labs is VISIR, a remote electricity kit that can be used in teaching DC and AC circuits. As happens in any open-ended educational environment, it is difficult to assess the learning effects of this tool. Fortunately the communication between the users and the VISIR remote lab in the Weblab-Deusto leaves behind a set of log information that can be analyzed. This contribution presents our current work-in-progress in analyzing these logs for better understanding the learning processes that take place when using this remote lab.

## Keywords
Remote lab, logging, learning, physics, electric circuit

## 1. INTRODUCTION
WebLab-Deusto [1] is an open-source management system for remote laboratories in development at DeustoTech, Universidad de Deusto since 2001. Its features web and mobile access to several remote laboratories in different topics, e.g. programming or physics.

One of the remote labs that is used through this platform is VISIR [2], a remote laboratory which supports experimentation with electric circuits (see Figure 1).

As is common in using open-ended educational environments, it is difficult for students, teachers and researchers alike to understand and to assess how to use them to improve learning.

Fortunately, the use of VISIR through the WebLab allows collected each of the circuits made by the students and sent to the remote lab for its construction.

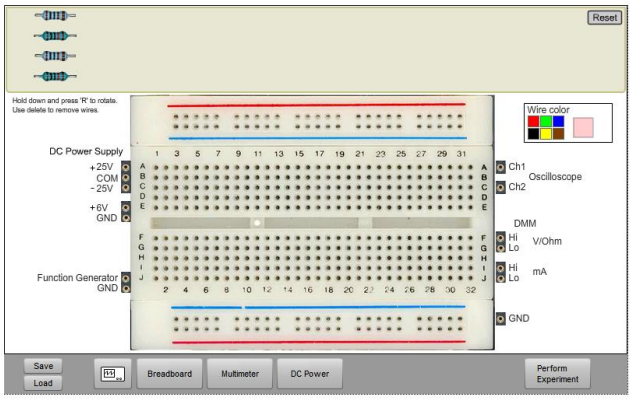


**Figure 1. Web interface to VISIR in WebLab-Deusto**

This work describes the data collected in WebLab-Deusto for the VISIR remote lab and it presents our efforts to provide (a) a tool for teachers to check students' work, and (b) a toolbox for a quick understanding of the students' activity when the lab is used in medium-to-large class settings.

## 2. WEBLAB-DEUSTO VISIR DATA COLLECTION
As indicated above, any call to the VISIR remote lab in the WebLab-Deusto system is collected to a database.

Each register in the collected data includes the following fields:

- **studentId**, a key corresponding to each student,
- **sessionId**, a WebLab-Deusto session key,
- **requestTime**, a date/time indicating when the request was made,
- **responseTime**, a date/time indicating when the response was sent back to the web client,

- **queryXML**, the information sent from the client to the remote lab and,
- **answerXML**, the digitized information of the measures collected in the remote lab and sent back to the client.

In this data, the electric circuit made by the user is encoded in character string in the queryXML field. For example, the text "W_X DMM_VHI A11 W_X DMM_VLO A7 R_X A7 A11 10k" indicates that a 10 kΩ resistance is connected to the voltage plugs of the digital multimeter.

## 3. ASSESSMENT TOOL FOR TEACHERS

The assessment tool for teachers allows selecting a specific call to the remote lab and retrieving in friendly interface the most significant information about the circuit that was constructed and, if it's the case, measured.

This tool, detailed in an earlier publication [3], allows to compare a specific circuit built by a student with a teacher's proposed solution. It automatically evaluates the main characteristics of both circuits and tries to estimate whether both circuits are equivalent.

## 4. DATA MINING FOR ACTIVITY EVALUATION

The data mining part of the effort implies querying the database for all the actions done by a group of students in solving a predesigned educational hands-on activity.

The results shown here correspond to an educational activity carried in the second semester of the 2013-14 academic year in an introductory physics course in a first-year undergraduate program. It belongs to the teaching of DC circuits, i.e. to the measure of voltage and current in simple DC circuits and Ohm's law. The activity included two 1.5-hour sessions of using the VISIR remote lab.

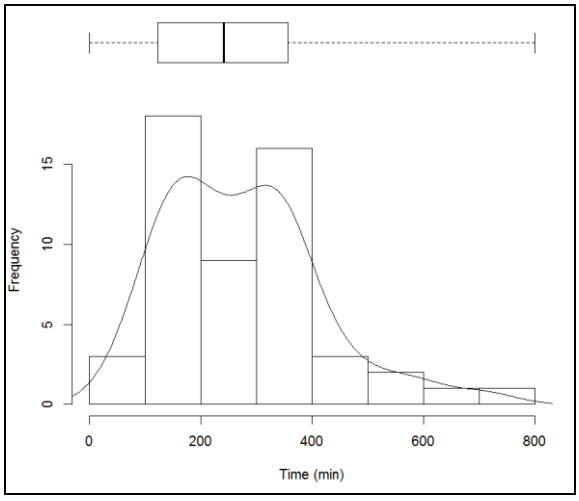


**Figure 2. Time spent per student**

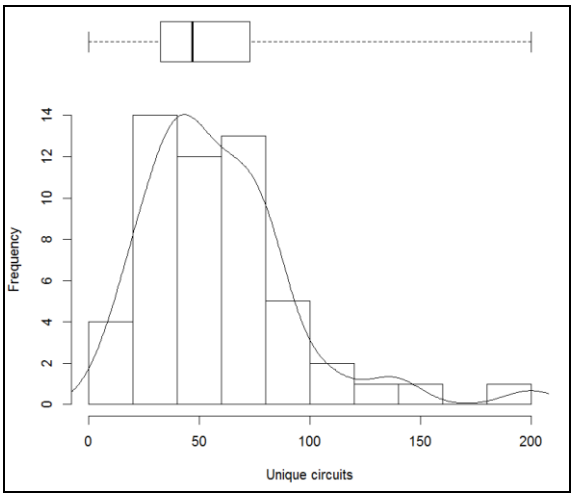


**Figure 3. Unique circuits per student**

From the pooled data (53 students, 18064 registers, 12114 circuits), a data-based evaluation of the activity has been carried on. For example, the teacher can know the distribution of time-on-task per user (Figure 2), the number of different circuits built per user (Figure 3) or, if required, identify the students who did not take enough profit from the lab session.

Other information that we are currently able to analyze include which circuits are more often built, what measure is attempted in each of them and the correctness of this measure.

## 5. CONCLUSIONS AND FURTHER WORK

Current logged data in remote laboratories delivers enough information to provide better feedback to students and teachers to support learning in these open environments.

Work is in progress to offer the users of these resources, analytic tools that allow for detecting learning difficulties and affordances for educational improvement.

## 6. ACKNOWLEDGMENTS

Our thanks to Obra Social "La Caixa" for the funding provided to support this research.

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# Discovering Process in Curriculum Data to Provide Recommendation

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## ABSTRACT

Process mining is an emerging technique that can discover the real sequence of various activities from an event log, compare different processes and ultimately find the bottleneck of an existing process and hence improve it. Curriculum data is the history of the courses effectively taken by students. It is essentially process-centric. Applying process mining on curriculum data provides a means to compare cohorts of students, successful and less successful, and presents an opportunity to adjust the requirements for the curriculum by applying enhancement of process mining. This can lead to building recommenders for courses to students based on expected outcome. In this paper we first discover a process model of students taking courses, then, compare the paths that successful and less successful students tend to take and highlight discrepancies between them. The conclusion we reached is that process mining indeed has a great potential to assist teachers and administrators to understand students behavior, to recommend the correct path to students, and at last to enhance the design of a curriculum.

## 1. INTRODUCTION

The term curriculum often refers to a predefined recommended or mandatory sequence of actions including courses or resources for students. It is designed by a school or a university in order to achieve some educational goals. To maximize this goal, some constraints are frequently imposed, e.g., students must take some specified courses before taking others. Given the liberal approach for selecting courses and taking into account these prerequisites for the courses and the requirements for the programs, students can follow different paths from start to finish. Discovering and understanding the process students follow, or some cohort, such as the most successful learners, can be very indicative to curriculum administrators and can also be the basis for a recommender system to recommend appropriate paths to students in terms of courses to take and in terms of prioritizing the sequence of courses. The common way to analyze educational data is using simple statistics and traditional data mining. However statistics and conventional data mining techniques do not focus on the process as a whole, and do not aim at discovering, analyzing, nor providing a visual representation of the complete educational process [3]. Process mining consists of extracting knowledge from event logs recorded by an information system and is inherent in discovering business process from these event logs, comparing and conforming processes, and providing mechanisms for improvements in these processes[4]. Process mining techniques are often used in the absence of formal description of the process and can provide a visualization with a flowchart as a sequence of activities with interleaving decision points or a sequence of activities with relevance rules based on data in the process.

Some attempts have already been made to exploit the power of process mining in curriculum data, historical data encompassing the sequence of courses taken by students. For instance, the authors of one chapter in [2] give a broad introduction of process mining and indicate that it can be used in educational data. The first paper that proposes to utilize process mining on curriculum data is [3]. The main idea is to model a curriculum as a Colored Petri net using some standard patterns. [1] directly targets curriculum data and brings up a notion called curriculum mining. Similar to the three components of process mining, it clearly defines three main tasks of curriculum mining, which are curriculum model discovery, curriculum model conformance checking and curriculum model extensions.

The application of process mining on curriculum data offers a wide range of possibilities. First it can help the educators understand and make better decisions with regard to the offered curriculum. For example, what is the real academic curriculum? Are there paths seldom used and others more popular? Do current prerequisites make sense? Are the particular curriculum constraints obeyed? How likely is it that a student will finish the studies successfully or will drop out? It can also assist students to choose among different options and even make recommendations to students. For instance, How can I finish my study as soon as possible? Is it more advantageous to take course A before B or B before A? Should I take courses A and B or courses B and D this semester in order to maximize my GPA? Answering such questions to both educators and students can greatly enhance the educational experience and improve the education process. We show in this paper how some of these questions can be answered using the history of courses taken.

## 2. CURRICULUM DATA

Although the data about courses have already been collected by the Computing Science department of the University of Alberta, we cannot publish any result related to such data due to lack of ethical approval. However, we wrote a curriculum simulator to mimic the behaviors of different kinds of students from the department and be as close as possible to the real data. First, we predefined a set of rules or requirements similar to those in the offered programs in the department. For example, prerequisites, i.e. some specified courses must be taken before the student takes another one. Other requirements include the first and the last course a student must take, mandatory courses, and non-coexisting courses, i.e. if the student takes one course in the group then they cannot take any other course belonging to the same group. Then, we generated students in three categories: the responsible students who always satisfy the course constraints; the typical students who seldom violate course constraint rules; and the careless students who often do not follow the set rules. Moreover, we differentiated the students based on the range of marks they are assigned in courses they take creating clusters of successful and less successful students. We generated the historic courses data for each student adding some probability that a student withdraws from a course giving the course load and previous withdrawing behavior.

## 3. DATA ANALYSIS

The final goal is to examine what kind of paths successful students tend to take and what is the discrepancy between successful students and less successful students so that we can make recommendations to steer the students to the successful paths. Since we have predefined rules for different types of students in our simulations, the goal is to verify whether we can discern these rules purely from the model we discover by process mining. If we can find the rules from the model, then we are safe to say it is possible to distinguish the "correct path" that can yield the best result by means of process mining, thus a recommendation, that closes the gap among students, can be achieved.

The several process models that were discovered from the curriculum log are close portrayal of real curriculum models in our computing science department. Each model covers the most frequent activity paths, given some thresholds. This is because the model map would be too dense and cluttered to recognize patterns if we present all of them. We added an additional activity at the end of each case to indicate the type of the student. In practice, this type can be any cohort of students such as based on the GPA ranges, based on graduation distinction, withdrawal, or other criteria. To inspect students' behavior patterns in more detail, we further filtered the model with their last activity, i.e., partitioning students based on their type so that we can compare them. The rules we imposed while generating the curriculum data can indeed be easily verified. For the students who seldom violate course constraint rules, the frequent paths appear very similar to those of the first group. However, contrasting the complete graphs of these groups reveals peculiar paths specific to one or the other group. The contrast is even more pronounced when comparing the responsible students and the careless students, as defined in the data. This grouping can be a placement test in some other cases. The categorization can also be done at the end of the paths based on the outcome at the end of the program or the end result for a given course. This allows contrasting the paths taken by successful students with other paths at the end of a program, or comparing the initial paths of students who dropped out of a course to paths leading to the same course taken by those who finish that course. The result of contrasting paths of different cohorts of students stresses out desired and undesired paths specific to some groups, the analysis of which can highlight recommendations for new prerequisites to align new students from a potentially undesired path to the desired one. In the case of drop-outs from courses, this analysis provides insights on the potentially faulty sequence of courses or lack of certain courses in the sequence that lead to higher risk of dropping out. In addition to providing better understanding of the curriculum data and a way to discern between behaviors of different cohorts of students, contrasting between process models from different groups of students presents an opportunity for a course recommender system. By contrasting between the processes followed by students grouped based on their course outcome or based on final GPA, we can find and visualize the sequences of courses that lead to the highest probability of success for a given course. Based on the courses already taken by a student, the system can indicate the options to take that have the highest chance to improve the GPA. Similarly, the system can recommend to take a course before another to maximize outcome. The same data can also be used by administrators to define new prerequisites for courses and thus improve the chance for the adoption of better paths. We are currently building such a recommender system for students. The system would use evidence from historical data to provide comparison of average ranges of prospective marks if a student follows one path or the other when selecting courses.

## 4. CONCLUSION

Process mining, to discover sequences of courses taken by students, is indeed a powerful tool to analyze curriculum data. By this means, we can visualize and formalize the real paths students actually take, and reveal the underlying patterns such as prerequisites and other constraints. Moreover, conformance in process mining can reveal paths that are unexpectedly not followed by students. Furthermore, contrasting processes from different cohorts of students discloses hidden specificity that we can act upon. Most importantly, contrasting processes provides means to recommend more appropriate sequences of courses to students personalized to their own cases and exposes new insights to administrators.

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# Improving Long-Term Retention Level in an Environment of Personalized Expanding Intervals

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## ABSTRACT
The ability to retain a skill long-term is one of the three indicators of robust learning. Researchers in Intelligent Tutoring Systems (ITS) and Educational Data Mining (EDM) have focused increasing attention on predicting students' long-term retention performance as well as attempting to find effective methods to help improve student knowledge retention. But traditional practices of spacing and expanding retrieval practices have typically fixed their spacing intervals to one or few predefined schedules. In this work, we introduce the Personalized Adaptive Scheduling System (PASS) in ASSISTments' retention and relearning workflow and we have evidence to show that the PASS is helping to improve students' long-term retention performance.

## Keywords
Robust learning, spacing effect, knowledge retention, educational data mining

## 1. INTRODUCTION

### 1.1 Robust learning and long-term retention
Robust learning is a desirable instructional outcome that goes beyond typical answering a problem correctly immediately following instruction or tutoring. The level of robust learning is assessed by at least one of the three criteria: whether students will be able to transfer their knowledge, whether they will be prepared for future learning, and whether they will retain their knowledge over the long-term [1]. Expanding retrieval practice is often regarded as a superior technique for promoting long-term retention relative to equally spaced retrieval practice [2]. This is specifically crucial to subjects such as mathematics where we are more concerned with students' capability to recall the knowledge they acquired over a long period of time.

### 1.2 Automatic Reassessment and Relearning System
Inspired by the importance of long-term retention and the design of the enhanced ITS mastery cycle proposed by Wang and Beck [3], we developed and deployed a system called the Automatic Reassessment and Relearning System (ARRS) [4] to make decisions on when to review skills students have mastered in ASSISTments, a non-profit, web-based tutoring system. ARRS is an implementation of expanding retrieval in the ITS environment. ARRS assumes that if a student mastered a skill with three correct responses in a row, such mastery is not necessarily an indication of long-term retention. Therefore, ARRS will present the student with retention tests on the same skill at expanding intervals spread across a schedule of at least three months: the first level of retention tests takes place seven days after the initial mastery, the second level of retention tests 14 days after successfully passing the first retention test, then 28 days, and 56 days. If a student answers incorrectly in one of these retention tests, ASSISTments will give him an opportunity to relearn this skill before redoing the same level of test.

### 1.3 Personalized Adaptive Scheduling System
Although ARRS helps students review knowledge after a time period, it neither knows a student's knowledge level nor does it have the mechanism to change the retention schedule based on a particular student's performance. Here we formed a hypothesis that we can improve students' long-term retention levels by adaptively assigning students with gradually expanding and spacing intervals over time and we proposed to design and develop such a system, called Personalized Adaptive Scheduling System (PASS), as shown in Figure 1. In the spring of 2014, we enhanced the traditional ARRS with the PASS and deployed it in ASSISTments.

The current workflow of PASS aims to improve students' long-term retention performance by setting up personalized retention test schedules based on their knowledge levels. Here we rely on the *mastery speed* of a skill [4] (number of problems required achieving three consecutive correct responses) as an estimate of the student's knowledge. We retained the ARRS design of 4 expanding intervals of retention tests for each skill; however, PASS alters how tests behave within each interval, especially for the first interval. When a student finishes initially learning a skill, PASS uses his mastery speed to decide when to assign his first level 1 retention test. The longest delay is seven days as students' mastery speed can be as good as three and shortest delay is one day for students who spend seven or more opportunities to achieve initial mastery.

When a student passes the first test, PASS will schedule another test with a longer delay. Once the student passes the seven-day test, he will be promoted to Level 2 with a delay of 14 days. From that point on the intervals are the same as in ARRS system. Note that mastery speed can be extracted from both students' initial learning and relearning processes. Therefore, when a student fails a retention test, a relearning assignment will be assigned to the student immediately and how quickly the student relearns this assignment will be used to set the interval for his next test. The mechanism of Level 2 to Level 4 tests is simpler. When a student fails a retention test, the retention delay will be reduced

to the previous level (e.g., from 56 days to 28 days). It will be increased to the next level if the student passes the delayed retention test.

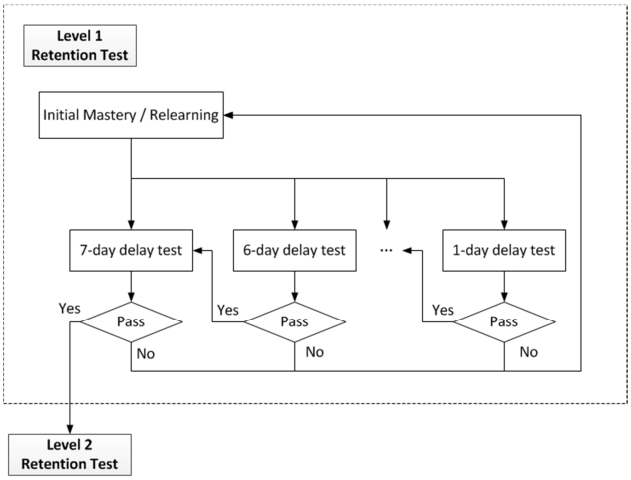


**Figure 1. Design of Personalized Adaptive Scheduling System (PASS)**

## 2. IMPACT OF PERSONALIZED EXPANDING RETENTION INTERVALS

A previous study [5] on Level 2 retention tests revealed that students in the PASS condition outperformed those in the ARRS condition and PASS helped to close the performance gap between two groups of students. In fact, in the PASS condition, the long-term performance of medium-knowledge students even slightly outperformed the high-knowledge students.

In this work, we extended our investigation to how students performed on much longer delay after the initial mastery. We collected data that recorded between May 2014 and Feb 2015, which consisted of 4,352 students who have worked on PASS retention tests. We calculated the percentage of correctness on retention tests that within 10 weeks after the completion of a homework assignment, as shown in Figure 2. The data was grouped by the three identified mastery speed bins to represent high-, medium- and low-knowledge students on their initial mastery levels.

It is important to notice that since PASS strictly requires students to achieve a certain level of retention of skills before promoting to the next level of practice, a longer delay doesn't mean a student was working at a higher level of retention test. As we have observed in the previous study [5], some students had to spend four weeks to reach Level 2 retention test while high knowledge level students only need 18 days on average.

The relationship between retention performance and delays in Figure 2 contradicts the general assumption that with strong prior knowledge, performance should decrease as delays get longer. What is seen here is the performance trends got slightly better compared to how students performed at the beginning of PASS workflow. We fitted the performance lines with linear regression trend lines and received positive slopes (0.0057 on average) for all three groups of retention performance. This is can be explained by PASS aggressively assigning short-delay retention tests to weaker students during the first retention level. Another observation is that we again see the persistence of performance differential across three group of students; however, we also noticed the gap between different levels of students was reduced from 12.04% to 7.98% at the end of Week 10. This is further evidence that PASS helps to improve students' retention performance in a classroom context.

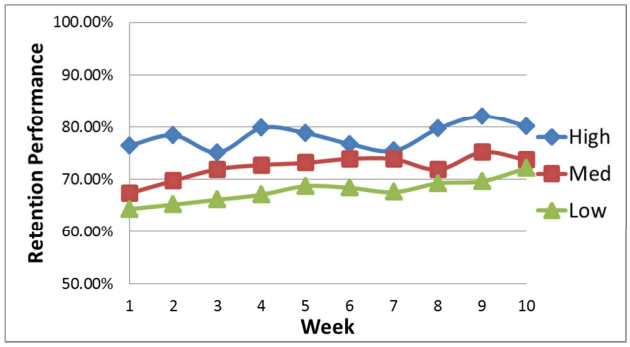


**Figure 2. Scatter plot of long-term retention performance in PASS**

## 3. CONCLUSIONS AND FUTURE WORK

This experiment improved the enhanced ITS mastery-cycle model with a personalized expanding interval-scheduling system and explored a simple but effective approach for using ITS to help students achieve better long-term mastery learning. Next, we will work on modeling students' long-term retention performance with data gathered from PASS.

## 4. ACKNOWLEDGMENTS

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# Exploring Problem-Solving Behavior in an Optics Game

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## ABSTRACT

Understanding player behavior in complex problem solving tasks is important for both assessing learning and for the design of content. Previous research has modeled student-tutor interactions as a complex network; researchers were able to use these networks to provide visualizations and automatically generated feedback. We collected data from 195 high school students playing an optics puzzle game, Quantum Spectre, and modeled their game play as an interaction network. We found that the networks were useful for visualization of student behavior, identifying areas of student misconceptions, and locating regions of the network where students become stuck.

## 1. INTRODUCTION

This work presents preliminary results from our attempts to derive insight into the complex behaviors of students solving optics puzzles in an educational games using a complex network representation of student-game interactions. An *Interaction Network* is a complex network representation of all observed student-tutor interactions for a given problem in a game or tutoring system [3]. Professors using *InVis* were successful in performing a series of data searching tasks; they were also able to create hypotheses and test them by exploring the data [5]. *InVis* was also used to explore the behavior of students in a educational game for Cartesian coordinates. Exploration of the interaction networks revealed off task behavior, as well as a series of common student mistakes. The developers used the information gained from the interaction networks to change some of the user interface to reduce these undesirable behaviors [4]. Regions of the network can be discovered by applying network clustering methods, such as those used by Eagle et al. for deriving maps high-level student approaches to problems [2]. This paper reports gameplay data from 195 students in 15 classes collected as part of a national Quantum Spectre implementation study in the 2013-14 academic year.

The Education Gaming Environments (EdGE @ TERC) research group studies how games can be used to improve learning of fundamental high-school science concepts. EdGE games use popular game mechanics embedded in accurate scientific simulation so that through engaging gameplay, players are interacting with digitized versions of the laws of nature and the principles of science. We hypothesize that as players dwell in scientific phenomena, repeatedly grappling with increasingly complex instantiation of the physical laws, they build and solidify their implicit knowledge over time. Previous work for a game *Impulse* used an automated detector of strategies in the game [1]. In this study, we examine how interaction networks can be used to visually measure the implicit science learning of students playing *Quantum Spectre*, a puzzle-style game that simulates an optics bench students might encounter in a high school physics classroom.

## 2. QUANTUM SPECTRE

Quantum Spectre is a puzzle-style designed for play in browsers and on tablets. Each level requires the player to direct one or more laser beams to targets while (potentially) avoiding obstacles. For each level, an inventory provides the player with access to resources, such as flat and curved (concave, convex, and double-sided) mirrors, (concave and convex) lenses, beam-splitters, and more, that can be placed and oriented within the puzzle and that interact with and direct the laser beams in a scientifically accurate manner. When the appropriate color laser beam(s) have reached all the targets, a level is complete. The player earns three "stars" if the puzzle has been solved in the fewest possible moves, two "stars" for a low number of extra moves, and one "star" for any solution. Each placement or rotation of an object on the game board counts as one move. A player can go onto to the next level as soon as a puzzle is complete, regardless of the number of moves used, but the stars system provides an incentive for level replay and an understanding of the puzzle's solution. The game includes a range of scientifically accurate optical instruments and related science concepts, but for the research, three key scientific concepts were identified: The Law of Reflection; Focal Point and Focal Length of Concave Mirrors; and Slope.

## 3. RESULTS AND DISCUSSION

To construct an Interaction Network for a problem, we collect the set of all solution attempts for that problem. Each solution attempt is defined by a unique user identifier, as well as an ordered sequence of interactions, where an interaction is defined as {initial state, action, resulting state}, from the start of the problem until the user solves the prob-

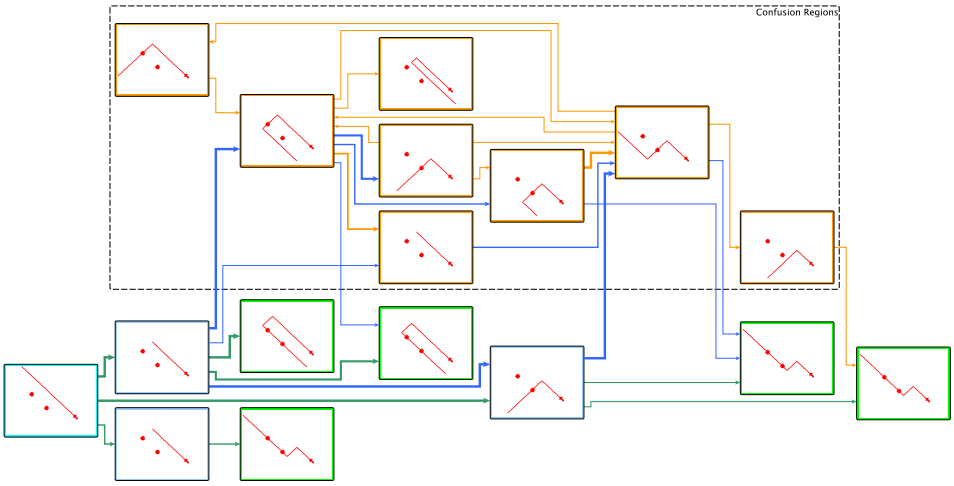


**Figure 1: The approach map for problem number 18. This is a high-level view at student approaches to this puzzle. The vertices represent sub-regions of the overall interaction network. Vertices are colored according to their game "star" score, with green being the optimal score, blue the less optimal, and orange for very suboptimal states. The approach map is capturing students with poor approaches to the problem, these regions are indicated by the dotted line.**

lem or exits the system. The information contained in a *state* is sufficient to precisely recreate the tutor's interface at each step. Similarly, an *action* is any user interaction which changes the state, and is defined as {action name, pre-conditions, result}. We chose to use only objects the player can interact with. We ignore the distinction between objects of the same type, so the order of placement does not matter. An example state could be {Flat_Mirror(4,1,90), Flat_Mirror(5,5,180)}: which would be a state describing two mirror objects with the first two numbers representing the X and Y coordinates and the last representing the mirrors angle.

The full graph of every state space and every action taken was large, complex, and difficult to interpret in terms of player understanding. In order to provide a high-level view that game designers and instructors could use to gauge players' mastery of game concepts, we clustered states using the Approach Map method from Eagle et al. [2]. The interaction network for problem 18, which had over 1000 unique states, is concisely represented as 17 region-level nodes as seen in figure 1.

This image is a simplified representation of the game board, with a mirror drawn in every location where a mirror was placed by an edge entering the cluster. "Active" pieces (the piece that was moved or rotated to enter the cluster was considered active for that move) were shown in blue, and inactive pieces (any pieces that remained unmoved on the board during that action) were in black. The intention was to show a milestone for each cluster: by looking at how each student who entered a cluster got into that cluster, the reader could trace a given path from cluster to cluster and get an idea of how the students on that path had progressed through the puzzle.

Using the approach map we are able to derive an overview of the student behaviors. Several of the derived regions represent poor approaches to solving the problem, this mirrors the results from Eagle et al. [2]. The region vertices are particularly useful for discovering the locations where students transfer into the confusion regions, as these highlight the places where student approaches contain misunderstandings. These results support the use of approach maps and interaction networks for use in this game environment. In future work we will look for differences in student performance on pre and posttest measures to see if there are differences in overall approach that are predicted by pretest score or can predict posttest score.

## 4. ACKNOWLEDGMENTS

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# Simulating Multi-Subject Momentary Time Sampling

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## ABSTRACT

This paper presents software for examining measurement error in Momentary Time Sampling—an interval time sampling method commonly used in research domains (e.g., classroom observations) where continuous recording is not feasible. The Parameters for Optimizing Scientific Sampling Using Momentary-time-sampling Simulator (POSSUMS) produces Monte Carlo simulations (based on user-specified values) and automatically generates statistics relevant to understanding the extent to which measurement error may be expected within multi-subject design parameters.

## Keywords

Momentary Time Sampling, Monte Carlo simulation, student behaviors, classroom observations.

## 1. INTRODUCTION

Educational research and other investigations of behavior often rely on sampling procedures when continuous observation is not viable [4]. As researchers in Educational Data Mining (EDM) have sought training labels for affect/engagement detectors to study the effects of student classroom behaviors on long-term outcomes, they have also relied on sampling procedures (e.g., [6]'s review). These include momentary time sampling (MTS), where researchers divide the observation session into intervals, recording whether a particular behavior occurs at the end of each. MTS, also known as *instantaneous time sampling* or *point sampling*, proves more accurate than similar techniques, including whole interval recording (WIR, where behavior is only recorded if it was present throughout the sampling interval) or partial interval recording (PIR, where behavior is recorded as present if it occurs at any time during the interval) [8]. Still, MTS is prone to substantial measurement error for some study designs [5].

Measurement error in MTS—the difference between *actual* and *observed* values for specific behaviors—is influenced by a large number of interacting factors [14], but research focuses on the duration of the behavior being observed and the length of the observation interval (e.g., [1]). Although the method does not introduce bias, the sometimes substantial variation in apparently transient measurement error has led to highly conservative suggestions, including [11], who suggest that MTS should only be used after continuous observations first determine typical values for factors known to influence MTS measurement error.

A different approach to dealing with the uncertainty in MTS is to model measurement error through simulation (see extensive review in [14]), sometimes to study particular conditions and other times to make more general recommendations (e.g., [10], [13], [12], [3]). However, existing simulators [7] have focused on single-subject designs, which is inadequate for modeling measurement error in observation systems where an observer is coding multiple students in the same session (e.g., BROMP [6], a common method for EDM research; but also classroom observation schemes used by many public schools in the U.S.). In this poster, we present a freely available simulator that addresses this gap: the Parameters for Optimizing Scientific Sampling Using Momentary-time-sampling Simulator (POSSUMS).

## 2. Prior Research

Prior research has shown that measurement error in MTS may be induced by a number of interacting factors, including: (a) the *sampling interval* (how often observations are recorded) (b) the *observation session's length*, (c) *bout-length* (the duration of each event/behavior being observed) and (d) *prevalence*, the percentage of an observation session that a behavior occupies (as [6] and [14] review). Previous research with simulations has led to practical recommendations, such as specific limits on sampling intervals (e.g., less than every 60 seconds [2] or 120 seconds [9]), or more general suggestions (e.g., sampling intervals must be shorter than mean bout-length [1], [14]), but these recommendations are based on simulations involving single-subject design. That is, these are recommendations for estimating the amount of time that a single research subject (e.g., a student) spends engaging in a particular behavior (e.g., on-task conversation) over a given observation session (e.g., an hour long class). They have not been demonstrated to be appropriate for estimating prevalence in multi-subject research designs (e.g., the amount of time that students in a particular classroom spend engaged on on-task conversation over the course of a class session). What's more, simulators that are currently publically available for single-subject design (e.g., [7]) require programming skills, limiting their use to researchers familiar with that programming language.

## 3. POSSUMS 1.0

In this paper, we present POSSUMS 1.0: a java-based tool that allows researchers using MTS in multi-subject design to run Monte Carlo simulations to study potential measurement error. POSSUMS, which is freely available on the 1st author's webpage (http://www.columbia.edu/~lp2575/tools.html), allows users to set parameters which it models, automatically generating metrics needed to understand potential sources of error. In the sections that follow, we present the user interface and the output.

### 3.1 User Interface

POSSUMS presents users with an interface that allows them to set several relevant parameters. As shown in Figure 1, users first add

target behaviors to be observed, specifying projected bout-length and prevalence for each. They then specify how many subjects (students) will be coded and the length of the observation window. (These values are used to run a Monte Carlo simulation that represents the *actual*, continuous values that might be found *en vivo*.) The user also specifies multiple sampling intervals, in seconds, which are used to simulate MTS *estimates*—the values that would be obtained based on sampling at those intervals across multiple subjects. Finally, the user indicates how many simulations should be run.

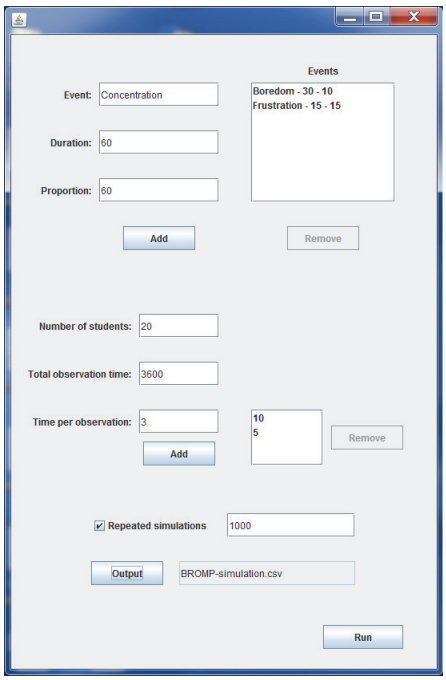


**Figure 1. POSSUMS 1.0 User Interface**

## 3.2 Output

POSSUMS 1.0 outputs to .csv files, which import easily into Excel or other widely-used analyses tools. The exact format depends on how many simulations are run. When only a single simulation is executed, the output file summarizes how many time each target behavior was observed, providing percentages for each behavior's contribution to the total observations at the classroom and the student level. These files also contain a detailed list of the behaviors associated to each student at each second in the simulated observation period. When multiple simulations are executed, the output file is different, providing summary measures that average across all simulations. Those values include the average and standard deviations for the number of time the behavior was observed across simulations, and the average and standard deviation for the percentage of observations for each behavior across simulations.

# 4. Discussion/Conclusions

Educational research, like other domains that sometimes require observational research, has long relied on sampling methods to estimate actual values. As EDM research begins to make use of observational methods to estimate the prevalence of relevant behaviors or events in classroom settings (cf. [6]), it is important that researchers understand possible sources of measurement error. Because this error in MTS appears to be influenced by a large number of factors working in concert, to date efforts to quantify it have focused on single-subject design (e.g., [7], [14]). Unfortunately, these studies are insufficient for understanding measurement error in many observational studies of classroom conditions, which involve multi-subject designs. POSSUMS 1.0 represents a step forward in this effort, simulating pertinent field conditions and automatically generating metrics needed to understand potential sources of error.

# 5. ACKNOWLEDGMENTS

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# Analyzing Students' Interaction Based on their Responses to Determine Learning Outcomes

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## ABSTRACT
Online learning platforms such as Moodle and MOOC (Coursera, edX, etc) have become popular in higher education. These platforms provide information that are potentially useful in developing new student learning models. One source of information provided by these platforms is in the form of student interaction with one another, instructors, and the platform itself. These interactions contain various activities such as: participation in forum discussion, how frequently a student is logged into their account, and frequency of reading posted activities, etc. Using Data Mining techniques, namely clustering algorithms to find students with similar behavior patterns, our goal is to develop a student model that can be conducted by learning these interaction patterns. In doing so, we aim to develop a method by which to provide students with different guidelines and instructions that will help to improve their performance. This research is in progress and our data include Moodle online courses in computer science in different semesters.

## Keywords
Online Learning, Student Behaviors, Student Outcomes, Moodle, Data Mining, Clustering, Educational Data Mining

## 1. INTRODUCTION
Detecting students' performance is one of the most crucial tasks in online learning and educational data mining (EDM), a task which falls under the scope of classification/clustering or other algorithms. Various learning methods have been applied to detect course results and academic performance with each learning algorithm performing differently with different datasets [4]. The No Free Lunch Theorem states that it is difficult to choose a specific model or classification algorithm for this difficult task [2]. Therefore, discovering and applying appropriate methods for a specific dataset should yield a significant improvement in the effectiveness of a given learning algorithm. Our approach will apply learning algorithms based on metadata, as they have proven to be sufficient to address this problem [2]. These meta-learning algorithms have been studied by exploring metadata to adopt suitable algorithm based on data mining and machine learning techniques [5]. In this research, we propose to apply various classifications/clustering models, evaluation measurements, and statistical analysis test to predict the performance of students' learning outcomes based on new dataset. This paper focuses on a portion of our statistical analysis, namely the examination of student response times to professor activity.

## 2. DATASET
Our dataset contains student and professor metadata from eleven courses over two semesters at Southeast Missouri State University. The metadata is in the form of log data from the online learning platform that the school uses, Moodle. In order to determine which of the features the metadata provides, we have performed rudimentary statistical analysis using SPSS. A basic overview of our dataset is provided in Table 1.

**Table 1. Course Overview**

| Course | Number of Students | Number of interactions | Average Interactions |
|---|---|---|---|
| CS1 | 12 | 4281 | 356.75 |
| **CS2** | **53** | **14006** | **264.26** |
| CS3 | 23 | 3891 | 169.17 |
| IS1 | 33 | 26682 | 808.55 |
| IS2 | 31 | 20049 | 646.74 |
| IS3 | 10 | 7906 | 790.60 |
| IS4 | 13 | 13311 | 1023.92 |
| IS5 | 19 | 10986 | 578.21 |
| IS6 | 30 | 31433 | 1047.77 |
| IS7 | 7 | 13150 | 1878.57 |
| UI1 | 27 | 7127 | 263.96 |

### 2.1 Data Processing
For this portion of analysis, we analyze CS2 (bold in Table 1.) for students' interaction response times; this was due to the large sample size it provided with respect to the other courses in our dataset. There were five students that failed to complete this course, so they were dropped from the dataset for this particular portion of analysis to prevent data skewing in the later weeks of the class.

## 3. METHODOLOGY

We propose that applying data mining techniques and statistical analysis of metadata from an online learning platform will allow us to derive insights into student interaction patterns. Using these insights, we theorize that a student learning model can be developed by learning these interaction patterns. In doing so, we aim to develop a method by which to provide students with different guidelines and instructions that will help to improve their performance.

### 3.1 Feature Selection

Our dataset explicitly provides the following features: the course in which an activity occurred, the time of occurrence, the IP address from which an activity originated, the user which performed the action, the action occured (course, user, assignment, and grade view), and information about the action completed.

There are also metadata that are not explicitly provided in the dataset but can be extracted. For example, our dataset does provide with specifics of the activity that the student is performing (e.g. posting to a forum, content of their posts, etc.) . However, we aware that a student is automatically logged out from their Moodle account if they have not performed an activity within 15 minutes. Using this knowledge, we can then determine when a student is logged out, approximately number of times they login, and the time interval between logins. We are aware that that there may be more metadata hidden within our dataset that maybe found upon closer examination that we plan to consider for future research.

Finally, we consider statistical features that have been extracted. For this portion of the analysis we considered how quickly the students responded to activities made by the professor; these activities include: updates to materials, posting of assignments, and updating student grades. We have computed the average student response time per activity, a sample standard deviation for the response time per activity, the total average response time and a sample standard deviation for the course during the first two weeks and the entirety of the course. We have also computed the top ten activities that resulted in the quickest average response times and the top ten activities that resulted in the slowest average response times.

## 4. RESULTS AND DISCUSSION

One of our goals was to explore trends in how students interact with their course over the duration of a semester and, more specifically, how quickly they react to activities performed by their professor. We noticed that when a professor interacts with Moodle, they typically perform a lot more than one action. For our statistics, we counted the time it took for each student in the course to respond to the last update to the course page that a professor made in a continuous block of interactions. For each of these interactions, we then calculated the average response time per student and the overall average response time for that particular activity. The average response times per activity are shown in Figure 1. We can see that student activity has fluctuates throughout the semester, but further analysis is needed to determine possible causes for these fluctuations. The only readily explainable peak is activity thirty, which occurred during a five day break.

## 5. RELATED WORKS

Wang [6] has indicated a need for the examination of log analysis within online learning platforms, namely the examination of

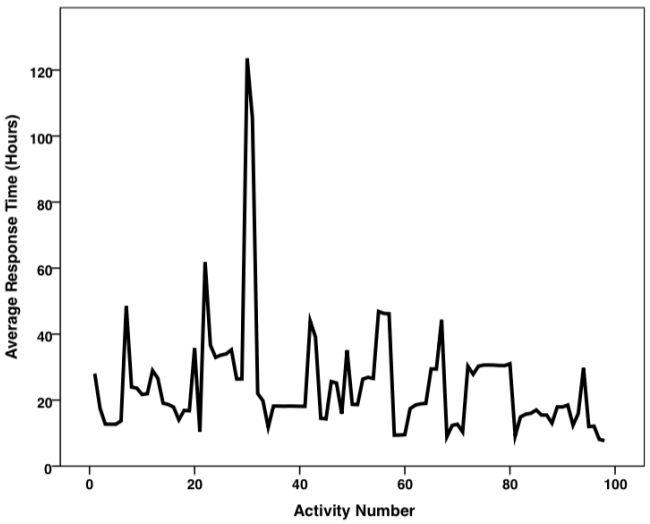


**Figure 1. Average response times per activity.**

indicators of participation such as use of discussion forums, quiz completion rate, and video usage. The research of Yudelson et al [7]. indicates that finding and analyzing certain sub-populations within a student body can produce a better predictive model than that of examining the entire population; importantly, these sub-populations tend produce a more substantial data footprint [7]. The research of Coffrin et al. indicates that student interactivity and success during the first two weeks of a course strongly related to their outcomes at the end of the course. They also suggested that identifying students based on their patterns of engagement presents the opportunity of tailored feedback to these sub-populations [1].

## 6. ACKNOWLEDGMENTS

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# Exploring the Impact of Spacing in Mathematics Learning through Data Mining

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## ABSTRACT

Laboratory studies suggest that long term retention of Mathematics learning is enhanced by spaced, as opposed to massed, practice. However, little evidence has been evinced to demonstrate that such spaced learning has a positive impact in real world learning environments, at least partly because of entrenched pedagogy and practice, whereby students are encouraged to engage with Mathematics in a very sequential manner - thus leading to massed learning episodes. Indeed, much educational practice and the structure of Mathematics textbooks lend themselves to massed rather than spaced learning. However, in online learning such spaced practice is possible and more practically achieved. Predicting learner outcomes from data in a popular online Mathematics learning site shows that in this data set spacing seems to have a negative effect on retention at a later time.

## Keywords

Mathematics, spaced learning, learning science, online learning

## 1. INTRODUCTION

Learning efficiently is one of the main drivers of personalized instruction. By ensuring that students engage with material only for as long as they need to in order to master it, intelligent instruction can push students further in less time, allowing outcomes to be improved more rapidly, and also to reduce the risk of boredom and loss of motivation. In addition, retention over longer time scales is important to the goals of Education as a whole. While the old adage "Education is what is left once what is learned has been forgotten" is oft quoted, in many Educational contexts, and in particular Mathematics, the necessity of prerequisite knowledge for learning higher order material means that such forgetting is far less desirable.

Until relatively recently in pedagogical practice (as shown by the design of Mathematics textbooks), it was thought that the most efficient way for a student to learn Mathematics in a way that facilitated later retrieval was *overlearning* - the continued practice of a procedure after mastery has been achieved. This *massed* (as opposed to *spaced*) practice model explains the design of Mathematics textbooks, where, by chapter, exercises are massed by a small number of procedures that need to be applied. By contrast, a spaced learning methodology would require intermingled exercises requiring application of different kinds of procedure, but with procedures recurring multiple times over several study sessions.

Spacing has been a core component of recent advances in our understanding of the Science of Learning. Rohrer and Pashler[7], drawing on work by Rohrer and Taylor[8], identify the empirical support for using such spaced learning episodes in the learning of Mathematics. Rickard et al.[6] examined the role of spacing in promoting retrieval over calculation in mathematics, and spacing of learning has been assessed in the college Mathematics classroom by Butler and colleagues[1]. Both found spacing to have positive effects on Mathematics learning. However, most recent work has focused more on the effect of spacing on declarative fact learning, with much of the successful practical application focused on foreign language vocabulary learning[4][5][9]. If these techniques can be extended to Mathematics learning, then considerable learning gains could be achieved.

Such hypotheses are best tested through a more controlled manipulation of the spacing regime - in the online learning context, using an A/B test common in most website implementations. Exposing some subset of users to a spaced learning regime, while recommending massed learning to the remainder. However, it is also possible to examine the impact of spaced learning in a somewhat more confounded way by looking at spaced learning that has occurred naturally during the course of student engagement.

## 2. DATA

The data being analysed are logs from Khan Academy's interactive Mathematics exercise platform. Students answer exercises, and are given instant feedback. The data recorded for each attempt includes the exercise type, the instance of the exercise, the answers given by the student, the time the student spent on the page while answering, the time it was attempted, and whether the student used a hint or not.

## 2.1 Spaced Learning

Khan Academy has attempted to implement spaced learning within its site design mostly derived from the spaced repetition algorithm popularized by Leitner[3]. In the Leitner System cards that have been correctly memorized are pushed back into a later set, whereas incorrectly answered cards are placed into the first set. The first set is reviewed on every cycle, with each set beyond being reviewed one less time per cycle (for N boxes, a cycle will consist of N review sessions).

The variable implementation of this spacing design over time in the Khan Academy site (including the use of A/B testing for various implementations of this spaced repetition algorithm), in addition to the voluntary engagement with the software by student users has served to create a data set with a large variety of spacing schemes (although somewhat confounded by other variables). Using this data, we are conducting a post hoc analysis of spaced versus massed practice. This will help to shed light on the impact of spaced repetition on learning of particular Mathematics skills.

# 3. ANALYSIS

Recent experimental studies on spaced learning have generally been constructed around one or more temporally separated (by periods of more than a day) study sessions, followed by a further temporally separated recall session, where retention of what has been learned is measured[2]. In order to emulate this design for each student, data, subdivided by exercise, were separated into study sessions (any gaps of a day or more were assumed to constitute a separate study session). In order to have an outcome measure by which to measure student learning, the final session was taken to be the retention session.

## 3.1 Data Selection

In order to ensure more meaningful comparisons, all student/exercise pairings with only one session associated with them (and therefore no differentiable outcome measure) were discarded, as were students who had made less than ten attempts across all sessions on that particular exercise. A random subsample was chosen for analysis, with data from 13528 students, and a total of 155602 student/exercise pairs. All data were normalized before fitting in order to render model coefficients more meaningful.

# 4. RESULTS

In order to assess the potential contribution of the effect of spacing, a logistic regression model using L2 regularization (strength parameter set by 10-fold cross validation) was fitted to predict student performance during the retention session. The independent variables included in the model were: mean accuracy across all study sessions, mean accuracy in the most recent study session, total time spent on exercises during study sessions, total number of study sessions, and total number of attempts during study sessions. While the model performed relatively poorly, (achieving approximately 58% accuracy on the test data) similar performance was seen predicting from most subsets of the independent variables. Only total time spent failed to lend any power to the model.

**Table 1: Coefficients for Normalized Variables**

| | |
|---|---|
| Mean Study Accuracy | 38.25 |
| Recent Accuracy | -15.61 |
| Total Study Time | 0.74 |
| Number of Study Sessions | -13.36 |
| Study Attempts | 8.59 |

# 5. CONCLUSIONS

The results seem to indicate that, at least in the case of the Khan Academy data, that spaced learning does not help with later retention. However, as much of the engagement takes place over relatively short time scales (with the median interval between study and retention being ten days). Further analysis will look at the impact of spaced learning not only on later retention of that skill, but also on learning skills for which the learned skill is a prerequisite. This will allow the impact of spaced learning to be assessed absent the compressed nature of engagement with individual exercises.

# 6. ACKNOWLEDGMENTS

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# Toward Data-Driven Analyses of Electronic Text Books

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## ABSTRACT

We present data-driven log file analyses of an electronic text book for history, called the mBook, to support teachers in preparing lessons for their students. We represent user sessions as contextualised Markov processes of user sessions and propose a probabilistic clustering using expectation maximisation to detect groups of similar (i) sessions and (ii) users.

## 1. INTRODUCTION

Electronic text books may offer a multitude of benefits to both teachers and students. By representing learning content in various ways and enabling alternative trajectories of accessing learning objects, electronic text books offer great potentials for individualised teaching and learning. Although technological progress passed by schools for a long time, inexpensive electronic devices and handhelds have found their way into schools and are now deployed to complement traditional (paper-based) learning materials.

Particularly text books may benefit from cheap electronic devices. Electronic versions of text books may revolutionise rigour presentations of learning content by linking maps, animations, movies, and other multimedia content. However, these new degrees of freedom in presenting and combining learning materials may bring about new challenges for teachers and learners. For instance, learners need to regulate and direct their learning process to a greater extent if there are many more options they can choose from. Thus, the ultimate goal is not only an enriched and more flexible presentation of the content but to effectively support teachers in preparing lessons and children in learning. To this end, not only the linkage encourages users to quickly jump through different chapters but intelligent components such as recommender systems [4] may highlight alternative pages of interest to the user. Unfortunately, little is known on the impact of these methods on learning as such and even little is known on how such electronic text books are used by students.

In this article, we present insights on the usage of an electronic text book for history called the mBook [5]. Among others, the book has been successfully deployed in the German-speaking Community of Belgium. We show how data-driven analyses may support history teachers in preparing their lessons and showcase possibilities for recommending resources to children. Our approach is twofold: Firstly, we analyse user sessions to find common behavioural patterns across children and their sessions. Secondly, we aggregate sessions belonging to the same user to identify similar types of users. This step could help to detect deviating learners requiring additional attention and instructional support.

## 2. THE MBOOK

The *mBook* is guided by a constructivist and instructional-driven design. Predominantly, the procedural model of historical thinking is implemented by a structural competence model that consists of four competence areas that are deduced from processes of historical thinking: (i) the competency of posing and answering historical questions, (ii) the competency of working with historical methodologies, and (iii) the competency of capturing history's potential for human orientation and identity The fourth competency includes to acquire and apply historical terminologies, categories, and scripts and is best summarised as (iv) declarative, conceptual and procedural knowledge.

Imparting knowledge in this understanding is therefore not about swotting historic facts but aims at fostering a reflected and (self-)reflexive way of dealing with our past. The underlying concept of the multimedia history schoolbook implements well-known postulations about self-directed learning process in practice. The use of the mBook allows an open-minded approach to history and fosters contextualised and detached views of our past (cf. [3]). To this end, it is crucial that a purely text-based narration is augmented with multimedia elements such as historic maps, pictures, audio and video tracks, etc. Additionally, the elements of the main narration are transparent to the learners. Learners quickly realise that the narration of the author of the mBook is also constructed, as the author reveals his or her construction principle.

## 3. METHODOLOGY

For lack of space, we only sketch the technical contribution. We devise a parameterised mixture model with $K$ components to compute the probability of a user session. The

browsing process through chapters is modelled by a first-order Markov chain so that pages are addressed only by their chapter. The category model depends on the chapters as we aim to observe correlations between different types of pages. This may show for example whether galleries of some of the chapters are more often visited (and thus more attractive) than others and thus generate feedback for the teachers (e.g., to draw students attention to some neglected resources) and developers (e.g., to re-think the accessibility or even usefulness of resources). The model for the connection times is inspired by the approach described in [2] to capture repetitive behaviour across weeks. The final model is optimised by an EM-like algorithm.

## 4. EMPIRICAL RESULTS

In our empirical analysis, we focus on about 330.000 sessions collected in Belgium between March and November 2014 containing approximately 5 million events.

**Session-based View:** Figure 1 (top) shows the results of a session-based clustering. User sessions are distributed across the clustering according to the expressed behaviour. Clusters can therefore be interpreted as similar user behaviours at similar times. The visualisation shows that all categories are clearly visible for all clusters, indicating a frequent usage of all possible types of resources by the users. Cluster *C6* possesses half of the mass on the weekend of category *text*. This indicates more experienced users who like to form their opinion themselves instead of going to summary pages. The same holds for cluster *C8* that possesses in addition only a vanishing proportion of the *home* category. Small probabilities of category *home* as well as large quantities of category *text* indicate that users continuously read pages and do not rely on the top-level menu for navigation.

**User-based View:** Our approach can also be used to group similar users. To this end, we change the expectation step of the algorithm so that sessions by the same user are processed together. That is, there is only a single expectation for the sessions being in one of the clusters. Clusters therefore encode similar users rather than similar behaviour as in the previous section.

Figure 1 shows the results. Apparently, the main difference of the clusters is the intensity of usage during working days and weekends. Cluster *C2* for instance clearly focuses on working day users who hardly work on weekends compared to Cluster *C1* whose users place a high emphasise on Saturdays and Sundays. Cluster *C3* contains low frequency users who rarely use the mBook and exhibit the smallest amount of sessions and page views per session. Cluster *C8* contains heavy (at night) users with high proportions of category *text*. In general, we note that transition matrices are consistent between chapters in contrast to the session-based clustering, that is, test takers interact with most of the chapters.

## 5. DISCUSSION

Our results illustrate potential benefits from clustering learners for instructional purposes. In the first place, the probabilistic clustering approach shows a way how to condense a huge amount of logfile information to meaningful patterns of learner interaction. Classifying a student into one of several clusters reveals whether, when, and how the learner used

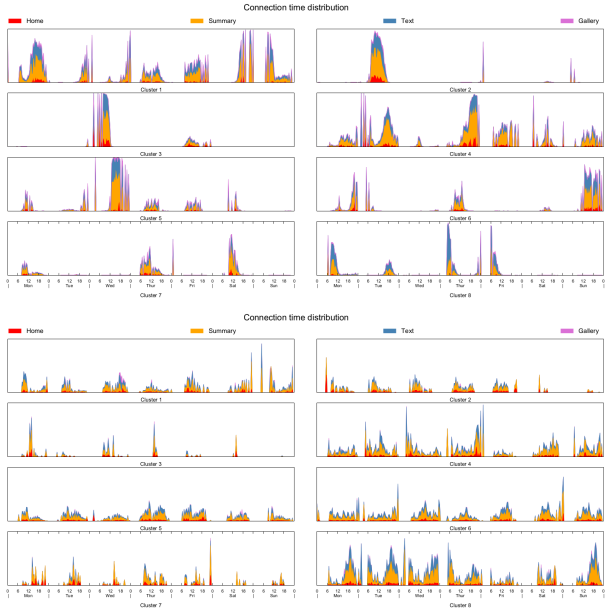


**Figure 1: Resulting clusters for the session- (top) and user-based (bottom) clustering.**

the materials offered by the electronic text book. Thus, the teacher can get information about the learners' navigation speed, whether part of the content was used in self-directed learning processes as expected, whether learners came up with alternative learning trajectories, and so on and so forth. This information can be used by the teacher in a formative way (cf. the concept of formative assessment, e.g., [1]), that is, it is directly used to further shape the learning process of students. For instance, in a follow-up lesson the teacher could simply draw the students attention to some parts of the book that have not or only rarely been visited. Moreover, history and learning about history could be reflected in a group discussion of learners who used the mBook resources of a particular chapter in different ways.

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# How to Visualize Success: Presenting Complex Data in a Writing Strategy Tutor

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## ABSTRACT
Intelligent tutoring systems (ITSs) have been successful at improving students' performance across a variety of domains. To help achieve this widespread success, researchers have identified important behavioral and performance measures that can be used to guide instruction and feedback. Most systems, however, do not present these measures to the teachers who employ the systems in classrooms. The current paper discusses visualizations that will be displayed to teachers using the writing strategy tutor, Writing Pal. We present visualizations for both classroom and student level data and offer descriptions of each.

### Keywords
Visualizations, intelligent tutoring systems, writing instruction.

## 1. INTRODUCTION
Over the past several decades, intelligent tutoring systems (ITSs) have been successfully developed for and implemented across a variety of domains [1]. These computer-based systems are often designed to record every interaction, behavior, and performance marker a student achieves while using the system. Research in educational data mining has used these system logs to identify what data are most predictive of overall performance and learning [2], while research in the learning sciences has used system logs to tailor instruction to individual students [3]. The synthesis of this work yields more adaptive, effective systems.

The analysis of log data has helped develop complex computational algorithms that improve adaptability within ITSs by modeling the learner [4]. Learner models can be difficult to understand without experience in modeling and educational research, and as a result, researchers have developed visualization tools to render components of these models more accessible [5]. Such tools are important because of the potential disadvantages that may emerge when the teachers who use ITSs have little understanding of their underpinnings. For instance, teachers may be less likely to use a system if they do not understand a system's feedback or what drives the feedback [6]. Moreover, if a system does not convey appropriate and timely information about students, the instructor may be unable to intervene [7].

Visualizations provide one means of aiding teachers in deciphering the complexity of ITSs and making data-driven classroom decisions [e.g., 8]. Our team is working toward providing visualizations of student progress within the Writing Pal (W-Pal), a writing strategy ITS designed for high school students. Writing Pal provides strategy instruction via lesson videos, game-based strategy practice, and essay practice with automated, formative feedback [9]. In this paper, we describe visualizations we have developed and implemented as well as those we are currently prototyping.

## 2. VISUALIZING DATA
Our initial goal is to provide the most relevant and understandable data to teachers through intuitive visualizations. The following sections describe visualizations that we are developing for W-Pal's *teacher interface*, where teachers view students' progress.

### 2.1 Classroom Level Visualizations
In a recent classroom implementation of W-Pal, five ninth grade classes with the same teacher used the system for approximately four months. We analyzed data from 90 consenting students. For the study, W-Pal's teacher interface included a spreadsheet in which teachers could track students' progress through the system activities (see Figure 1). However, during the study, this page did not provide a visual summary of the progress across students. Broadcasting the average number of activities attempted in a classroom of students who have generally stalled in their progression might prompt teachers to request that students not linger on particular topics or switch their focus. Future iterations of W-Pal will provide easily discernible bars that indicate the overall progress of classes. In Figure 1, the darker blue bars in the first four columns represent the percentage of activities attempted for those modules (a black rectangle highlights this feature).


**Figure 1. Visualization of a classroom's progress in W-Pal's teacher interface; dark blue bars represent progress.**

An important strength of W-Pal is the automated feedback it provides on students' essays. The teacher interface allows teachers

to view each student's submitted essays along with the feedback and score received. Currently, however, teachers do not have access to a summary of all students' performance. For example, if the majority of students are struggling to properly structure their writing in W-Pal, teachers would remain unaware until they carefully perused students' feedback messages. To provide teachers with a quickly consumable summary of the feedback that students are receiving, we are developing a visualization that displays the percentage of feedback triggered across all essays in a W-Pal class (see Figure 2). Using this information, teachers might adjust their own classroom instruction or assign students to interact with appropriate W-Pal lessons.

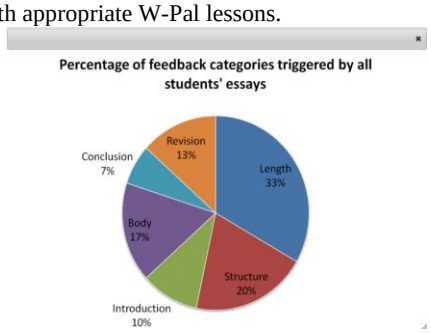


**Figure 2. Visualization of the type of essay feedback students in a classroom have received.**

## 2.2 Student Level Visualizations

Our recent classroom study also revealed that the percentage of time that students selected different activities related to their persistence in the system. For example, there was a positive correlation between the percentage of *game* activities that students selected and the number of days they used the system [$r(90) = .49$, $p < .001$]. Thus, the percentage of activities attempted (i.e., videos, games, and essay practice) could be indicative of how likely students are to persist in the system. Teachers will be presented with this information via pie charts, which are useful for visualizing proportions of a whole [10] (see Figure 3).

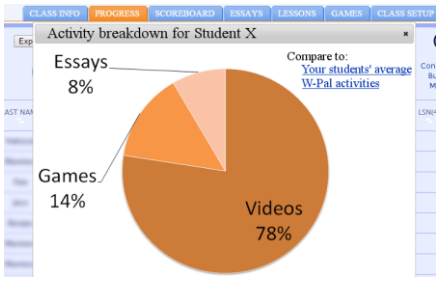


**Figure 3. Visualization of the activity breakdown for an individual student.**

Similar to the activity breakdown available for each student, teachers will be able click students' names in the essay window to see breakdowns of essay feedback (see Figure 2 for a similar example). If a student is struggling with writing assignments in class, this visualization will give teachers a quick view of how W-Pal has assessed areas of weakness.

# 3. CONCLUSION

In this paper, we argue for the importance of using visualizations to communicate data from ITSs to the teachers. Specifically, we describe classroom and student level visualizations that we are developing for the writing strategy tutor, W-Pal. When equipped with these visualizations, teachers may be more likely to use a system appropriately and to intervene when a student is not performing optimally. Future empirical work must test these visualizations, through techniques ranging from surveys to eye tracking [8], to determine their effectiveness in conveying information to teachers. As the understanding of how teachers use such visualizations grows, systems can provide teachers with intelligent tutors that better support classroom instruction.

# 4. ACKNOWLEDGMENTS

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# Adjusting the weights of assessment elements in the evaluation of Final Year Projects

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## ABSTRACT
The authors of this paper have defined a continuous evaluation methodology for Final Year Projects, in which six different evaluable items are involved. However, establishing the weights of each assessment element in the evaluation of Final Year Projects is a complex process, especially when several teachers are involved [3] like in this case. In this paper, the experiment carried out in order to establish the weight each assessment element should have in the final mark of a Final Year Project is described.

## Keywords
Final Year Projects, weight adjustment, experts' validation

## 1. INTRODUCTION
Finishing a Final Year Project (FYP) is a challenging task for all the involved actors, either students or lecturers. In a previous work, the authors conducted a study and concluded that the main problems during projects' development are related to the evaluation process [7].

In many universities, the evaluation of the FYPs has been mainly based on a final dissertation of the work and a public oral defense in front of an examination board. This approach presents several drawbacks [6]. In order to overcome them, a set of 8 experts (teachers from the University of the Basque Country, with more than 10 years supervising FYPs) defined six elements to be taken into account and the responsible for their evaluation.

The supervisor of the project evaluates: an initial report including the project planning and requirements (*Init_Report*), the result of the design phase of the project (*Design*) and the students' attitude during the process (*Attitude).*

The evaluation board evaluates: the final report of the project (*End_Report*), the oral defense (*Defense*) and the complexity of the project (*Complexity*).

To avoid the subjectivity, an evaluation rubric was created for each of the evaluable elements [4].

## 2. ADJUSTING THE WEIGHTS OF THE EVALUABLES
According to the proposed FYP grading proposal [7], the final grade is computed as the weighted mean of the scores achieved in the assessable elements. Next, the experiment carried out to adjust those weights is described.

### 2.1 Data Set & Techniques
In order to develop a model to accurately predict the mark of a FYP, a set of graded FYPs, including the final grade provided by the evaluation board using the traditional grading way and the grades for each of the items for those projects, are required.

In this experiment, 32 FYPs were evaluated. The collected data was randomly split into two data sets, *training set*, which contained 2/3 of the collected data, and the *validation set*, entailing the remaining data.

Adjusting the weight to compute the grade as accurate as possible in relation to the grades given by the evaluation board is a regression problem. Therefore, the first technique tested was the linear regression. In this experiment the target variable is the final mark and the features are the 6 items that according to experts should influence the final mark. The objective is to determine to which extent affects each element the final mark.

During this experiment, negative coefficients were inferred (see Table 1, *LRModel)*. In the case of FYP, a negative value is not applicable as the assessable elements refer to aspects the FYP must satisfy, whilst a negative weight would mean that an undesirable or wrong feature is being evaluated. To overcome this problem, non-negativity constraints in the model should be enforced. Therefore, the Lawson-Hanson Non-negative least-squares technique [2] was used in the second phase of the experiment.

**Table 1. Weights of each item in the final mark**

| | Weights | | | | | | Analysis results | |
|---|---|---|---|---|---|---|---|---|
| | **Init_Report** | **Design** | **Attitude** | **End_Report** | **Defense** | **Complexity** | **Correlations** | **RMSE** |
| LRModel | 0.24 | 0.18 | -0.08 | 0.37 | 0.11 | 0.15 | 0.95 | 0.49 |
| NNLSModel1 | 0.1 | 0.26 | 0 | 0.31 | 0.19 | 0.14 | 0.97 | 0.31 |
| NNLSModel2 | 0.25 | 0.08 | 0.08 | 0.46 | 0.13 | 0 | 0.85 | 0.55 |
| NNLSModel3 | 0 | 0 | 0 | 0.52 | 0.32 | 0.16 | 0.96 | 0.35 |

## 2.2 Validation Procedure

The validation process consisted in analyzing the extent to which the obtained model fits the data. With this objective, evaluation boards' judgments and the marks obtained using the weights of the different models were compared computing two different metrics: Pearson correlation coefficients [5] and Root-Mean-Squared Error (RMSE) [1].

The admissible error for the model has to be defined taking into account the peculiarities of the process. In this case, according to the experts, it is a common practice to round the grades to 0.5 points intervals, being very unusual to find grades not matching this criterion. For example, grades such as 7 or 7.5 were observed in the training set, whereas intermediate grades similar to 7.2 were not found. Taking this into account, for this experiment 0.5 has been asset as the maximum admissible error.

## 2.3 Exploratory Analysis and Working Hypothesis

The identified 6 features are considered independent factors for the final score, as they are evaluated in different stages of the FYP process. To determine the new models to compute the final grades of the FYPs, the authors stated the following hypotheses:

- **H1**: The factors identified by the expert board are appropriate predictors for the final grade of the FYPs.
- **H2**: the complexity of the FYPs is implicitly considered in the other evaluable elements.
- **H3**: The evaluation board can infer all the information needed from the *End_report* and the *Defense*.

Considering these starting hypotheses, the following models were defined for this experiment:

- **LRModel**: Model derived using linear regression and considering all the features. (Hypothesis H1)
- **NNLSModel1**: Model derived using the Lawson-Hanson Non-negative least-squares technique and considering all the features. (Hypothesis H1)
- **NNLSModel2:** Model derived using the Lawson-Hanson Non-negative least-squares technique and considering all the features except *Complexity*. (Hypotheses H1 and H2)
- **NNLSModel3**: a model derived using the Lawson-Hanson Non-negative least-squares technique only considering the *End-report*, the *Defense* and the *Complexity*. (Hypothesis H3)

# 3. RESULTS

In this experiment, the models described above were derived using the *training set* and tested on the *validation* set.

As it can be observed in Table 1, the linear regression technique, used for *LRModel,* led to a model with negative coefficients for some features (*Attitude*). Although the performance was remarkably good, this is not an admissible model to grade FYPs because it would mean that negative aspects of the project are being measured.

*NNLSModel2* had an RMSE of 0.55 points, which did not fit in the defined admissible error range. *NNLSModel1* computed grades with 0.97 correlation with the evaluation boards' and 0.31 RMSE, whereas *NNLSModel3* achieved 0.35 RMSE.

Taking into account the calculated RMSE, the best model is *NNLSModel1* where all the features identified by the expert board are used (including *Complexity*). However, in this model *Attitude* has a weight of 0, i.e., it is not a statistically significant predictor for the final mark. Moreover, as shown in Table 1, with *NNLSModel1* an error of 0.31 in a 10-point scale has been achieved. As previously mentioned, this is an admissible error for the evaluation of FYPs because it is inferior to 0.5.

# 4. CONCLUSIONS AND FUTURE WORK

This paper has presented the experiment carried out in order to adjust the weights of assessment elements for the evaluation of FYPs. Several models have been evaluated, achieving a model with an error of 0.31 in a 10-point scale. One of the main results of the experiment is that the student's attitude *(Attitude)* is not statistically significant to predict the final mark.

The best performing model considers elements that must be evaluated by the supervisor of the FYP in addition to the elements assessed by the evaluation board. This suggests that, even if the evaluation board can give a grade, for a detailed evaluation, the opinion of the person who better knows the project is required.

The main future work is related to the adjustment of weights for each dimension of the rubrics. Additionally, the authors will continue validating the obtained model with new evaluations.

# 5. ACKNOWLEDGMENTS

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# Predicting students' outcome by interaction monitoring

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## ABSTRACT
In this paper we propose to predict the students' outcome by analyzing the interactions that happen in class during the course. PresenceClick lets teachers and students register their interactions during learning sessions in an agile way to give feedback in return about the students' learning progress by means of visualizations. Some of the registered interactions are the students who are attending class and a subset of the students' emotions felt during learning sessions. We have found correlations among attendance, emotions and performance in the final exam. This paper presents the study carried out to build a prediction model for the students' mark in the final exam based on these interactions. The purpose is to advice teachers about students in risk to fail.

## Keywords
F2F interactions, mark prediction, linear regression, decision tree

## 1. INTRODUCTION
Drop out or failure is a common issue related to university students. Many studies have been carried out to detect students' problems, or even to predict the students' outcome, by applying data mining techniques to their interactions with intelligent tutoring systems [1] or course management systems [2] [3]. Other works include a wide range of potential predictors –i.e. personality factors, intelligence and aptitude tests, academic achievement, previous college achievements, or demographic data– to predict drop out and students' performance in high school [4] [5]. However, these works leave aside all the information that can be collected from the interactions that happen in face-to-face learning, the most extended way of education.

During traditional learning courses there is no way to detect problems or to know the performance of students in the final exam, except applying the teacher's intuition on the in-class students' interactions. This is even more difficult as the number of students in class grows, which is a current common issue at university worldwide. In this line, this papers aims to answer the next research questions: *Is it possible to predict the students' outcome by analyzing the interactions that happen in class? And, can we detect any interaction that especially influences the mark?*

## 2. PRESENCECLICK
PresenceClick is a distributed and modular environment that captures the interactions in learning sessions in an agile way. On the one hand, the *AttendanceModule* automatically captures the list of attendees to class. On the other hand, the *EmotionsModule* lets teachers capture the emotional state of the classroom related to whatever specific activity of the course. Students quantifies their emotions (six positive *–enjoyment, hope, pride, excitement, confidence* and *interest–* and six negative *–anxiety, anger, shame, hopelessness, boredom* and *frustration–*) in a 6-likert scale questionnaire based on the models described in [6] and [7]. The analyzed data belong to two subjects of Computer Science:Modular and Object Oriented Programming, (MOOP) and Basic Programming (BP). In MOOP 97 students were enrolled whereas 81 students participated in BP. The data were collected asking students to fill different event questionnaires. The MOOP students were asked three times to fill events where 41, 20 and 41 students responded respectively. The BP students were asked six times and 56, 36, 57, 48, 29 and 13 students participated (last event participation was low due to a server problem).

## 3. PREDICTING OUTCOME
Building a predicting model for students' outcome in the final exam was aimed to let teachers foresee those students that could be in risk to fail in the subject or even drop out.

In MOOP 44 students out of 97 enrolled attended the exam and 50 responded at least one emotion event, while 59 students attended the exam from 81 students enrolled in BP and 68 responded at least one emotion event. As the students dropping out the subject precisely are an important sample set to study, and as a considerable number of students did not attend the exam in both subjects, three different cases were studied: (Case1 - NA=F) Students non attending the exam were not considered; (Case2 - NA=T; mean=F): Students non attending the exam were assigned 0 as mark; (Case3 - NA=T; mean=T): Students non attending the exam were assigned the mean of the fails as mark, where fails are all the students with mark<5.

The three phase experiment that follows was carried out.

### 3.1 Phase 1: Correlation analysis
Pearson-correlation analysis was conducted between mark-attendance and mark-emotions. All the positive/negative emotions were gathered together, and the mean from all the events where each student participated was calculated in order to normalize the data. Table 1 shows the correlations for the three cases between mark-attendance, mark-positive emotions and mark-negative emotions. In both subjects *attendance and students' negative emotions influence the mark in the final exam* (except when non

attendees to exam were not considered in BP) according to literature ($p$>|0.3|) [8]. Student's positive emotions influence the mark only in MOOP. This could be due to the fact that being aware of the negative emotions is usually easier than being aware of the positive ones. In addition, we could also suppose that students expressing negative emotions in questionnaires are not lying, whereas students could increase the value of their positive emotions in order to be closer to the group feelings.

**Table 1. Correlations with the mark in MOOP**

| | Case | Attendance | Pos emo | Neg emo |
|---|---|---|---|---|
| MOOP | NA=F | 0.45 (p=0.0048) | 0.45 (p=0.0056) | -0.46 (p=0.0034) |
| | NA=T, mean=F | 0.6 (p=4.02e-06) | 0.46 (p=0.0008) | -0.65 (p=3.78e-07) |
| | NA=T, mean=T | 0.54 (p=4.7e-05) | 0.46 (p=0.0008) | -0.59 (p=5.45e-06) |
| BP | NA=F | 0.25 (p= 0.071) | 0.13 (p= 0.35) | -0.29 (p=0.034) |
| | NA=T, mean=F | 0.48 (p=0.0004) | 0.28 (p=0.019) | -0.34 (p=0.0042) |
| | NA=T, mean=T | 0.39 (p=0.0009) | 0.23 (p=0.054) | -0.33 (p=0.006) |

## 3.2 Phase 2: Multiple linear regression

In this stage of the experiment we looked for a model with a multiple linear regression analysis to predict the numeric mark of the student. For both subjects, 2/3 of the population was taken for training while the remaining was taken for validation. The three variables together were tested as dependent in order to predict the mark ($w$+ $x$* attend.+ $y$* posEmotions+ $z$* negEmotions). However, for all cases the standard deviation of the model prediction error rounded two points, which implies a margin too big (in a scale grade from 0 to 10, where fails are above 5). All the emotions were also studied individually to check if any of them could explain the mark, but the error rounded the two points.

## 3.3 Phase 3: Classification tree

Finally, we ran a decision tree to predict whether a student drops out, fails or passes the exam. Data from both subjects were normalized and gathered in a unique dataset, and different models were tested taking into account different variables in order to find the one that better predicted the students' performance. Figure 1 presents the decision tree for the training set that best predicted the students' performance taking into account the *attendance* and the *students' negative emotions*.

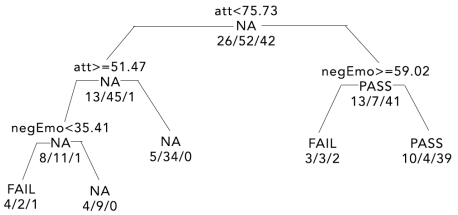


**Figure 1. Training set's classification tree**

As we can see in table 2 failed students are not well predicted with a 30% precision and 50% recall ($F_1$=37,5%), but dropping out students ($F_1$=86,36%) and passing students are quite well predicted ($F_1$=81,63%). The low correction of the fails could be due to the fact that few students are in this category and more data is required to refine the model. However, we consider that the most important measure is the recall for drop out and fail, in order to discover the students in risk and make the teacher aware. Taking into account that only 16% of failed students and 8,4% of drop out students have been predicted with PASS, we can conclude that the model is quite good, although a major sample is needed in order to adjust it for a better prediction.

**Table 2. Predictions table**

| | | Real | | | | |
|---|---|---|---|---|---|---|
| | | FAIL | NA | PASS | Precis. | Recall |
| Class | FAIL | 3 | 3 | 4 | 30% | 50% |
| | NA | 2 | 19 | 2 | 82,61% | 90,48% |
| | PASS | 1 | 2 | 20 | 86,96% | 76,92% |

# 4. CONCLUSIONS

This paper has presented the preliminary study developed to propose a predicting model for the students' outcome in the final exam based on the interactions captured by the PresenceClick system. Those interactions data give teachers and students the possibility to avoid failure and drop out. So far, we have tested the *attendance to class* and *the students' emotions* as model predictors. The study was divided in three phases: correlation analysis, multiple linear regression and decision trees. We founded that *attendance* as well as *student's emotions* influence the mark. In particular, the *negative emotions* together with the *attendance* seem to be the interactions with bigger influence on the mark, although the multiple linear regression did not provide an accurate model. However, the decision tree brought us the possibility to foresee the students' performance in the final exam according to these factors, although a major sample is needed in order to refine the model.

# 5. ACKNOWLEDGMENTS

This work has been supported by the Govern of the Basque Country (IT722-13), the EHU/UPV university (PPV12/09, UFI11/45) and Gipuzkoako Foru Aldundia (FA-208/2014-B).

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# Hierarchical Dialogue Act Classification in Online Tutoring Sessions

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## ABSTRACT
As the corpora of online tutoring sessions grow by orders of magnitude, dialogue act classification can be used to capture increasingly fine-grained details about events during tutoring. In this paper, we apply machine learning to build models that can classify 133 (126 defined acts plus 7 to represent unknown and undefined acts) possible dialogue acts in tutorial dialog from online tutoring services. We use a data set of approximately 95000 annotated utterances to train and test our models. Each model was trained to predict top level Dialogue Acts using several learning algorithms. The best learning algorithm from top level Dialogue Acts was then applied to learn subcategories which was then applied in multi-level classification.

## Keywords
Dialogue Act, Tutoring dialog, Machine Learning, Classification

## 1. INTRODUCTION
A speech or dialogue act is a construct in linguistics and the philosophy of language that refers to the way natural language performs actions in human-to-human language interactions, such as dialogues. [1] [6] In order to represent the Dialogue Act of an utterance, a set of Dialogue Act categories is defined. The set of categories is also known as the Dialogue Act taxonomy.

In this paper we examine different models on a relatively large data set which is extracted from one-on-one online tutoring sessions. The taxonomy used in our work is based on a hierarchical structure, i.e., each Dialogue Act has a set of sub-categories (subacts). The size of our training data is larger than the data presented in most of the previous work on Dialogue Act classification, which helps support this more fine-grained structure. We used WEKA toolkit [2] and the CRF++ package to train and test the models and Mallet [3] java library was used to train and test Logistic Regression models. Since our data is within the domain of human one-on-one tutoring sessions, this work enables further analysis of models to investigate the impact of dialog moves on learning. The feature sets used to train these models include the leading tokens of an utterance in addition to contextual information (i.e., features of previous utterances).

## 2. METHOD
The taxonomy used in this work was developed with the assistance of 20 subject matter experts (SMEs), all experienced tutors and tutor mentors. The resulting hierarchical taxonomy includes 15 main categories where each main dialog act category consists of different sub-categories which resulted in 133 distinct dialog acts out of which 7 categories were defined to represent unknown and undefined cases.

Once the taxonomy was available, a set of 1,438 sessions were manually tagged. The human tagging process included 4 major phases: development of taxonomy, 1st round tagging, reliability check, 2nd round tagging, reliability check, and final tagging phase.

The experts were divided into two groups: Taggers and Verifiers. In the first 2 tagging phases, each tagger was given a session transcript and asked to annotate the utterances. The resulting tagged session was then assigned to a verifier who went through the annotations, reviewed the tags and made necessary changes. In the reliability check steps, experts tagged each transcript independently.

Since the Verifiers were modifying tags already established by the Taggers in the 1st and 2nd round cases, the agreement was expected to be high. The agreement of Taggers and Verifiers was approximately 90%, with a slightly higher agreement on the second round. This shows to what extent the verifiers made changes to the initial annotations (about 10% of tags changed). The reliability checks involved completely independent tagging, in which human experts yielded an agreement of approximately 80% on top level and 60% on subact level. The final annotations were used as training data for our machine learning models. In order to build the Dialogue Act classifier, we applied the following 3 kinds of feature sets.

**- Simple features:** Based on previous research, 3 leading tokens of an utterance were shown to be good predictors for Dialogue Act [4]. Thus, we extracted the following features of each utterance: 1st token, 2nd token, 3rd token, last token, and length of utterance (i.e., number of tokens).

**- Extended features:** Using the Correlation Feature Selection (CFS) measure, we found that 1st and last token are the most predictive features and in order to add contextual information (features of prior utterances) we extended the simple features by adding the 1st and last token of three previous utterances to our feature set.

The above feature sets were used to create different models with multiple learning algorithms. Four learning algorithms were used and evaluated: Naïve Bayes, Bayesian Networks, Logistic Regression, and Conditional Random Fields (CRF). Each of the algorithms has certain properties that take into account different characteristics of data.

## 3. RESULTS & DISCUSSION
Based on the division of taxonomy in top-level and subcategories, we first trained and tested the models to predict the top-level Dialogue Act. Table 1 shows the results of 10-fold cross validation on the top-level classification models.

**Table 1. 10-fold Cross Validation of Algorithms with Different Features for Top-level Dialogue Act Classification.**

| Algorithm | FeatureSet | Accuracy% | Kappa |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Naïve Bayes | Simple | 72.5 | 0.65 |
| Naïve Bayes | Extended | 72.3 | 0.64 |
| Bayes Net | Simple | 72.6 | 0.65 |
| Bayes Net | Extended | 72.5 | 0.65 |
| Logistic Regression | Simple | 76.6 | 0.70 |
| **Logistic Regression** | **Extended** | **77.4** | **0.71** |
| CRF | Simple | 72.7 | 0.45 |
| CRF | Extended | 71.9 | 0.44 |

As seen in table 1, the best performance on top-level classification is achieved by the Logistic Regression algorithm; however, all the algorithms yield and accuracy of more than 70%. It is interesting to note that the extended feature set does not improve the algorithms significantly which implies that adding the contextual information, i.e., prior utterances, is either not useful or not sufficiently representing the context. The diminished role of contextual features is not surprising. It has been previously indicated that they do not play a significant role in Dialogue Act classification models on a multi-party chat based tutoring system [5].

We further trained and tested models to classify utterances in the second level of Dialogue Act categories. For each Dialogue Act a classifier was trained to predict its corresponding subcategories. Table 2 shows the performance of these classifiers which were trained on 70% and tested on 30% of the dataset. A 10-fold cross-validation was not possible in this case due to too few instances for some subcategories.

**Table 2. Performance of Subact Classifiers within each Dialogue Act Category using Logistic Regression algorithm.**

| Model | N | Accuracy% | Kappa |
|---|---|---|---|
| **Answer** | 1130 | 52.8 | 0.43 |
| **Assertion** | 29890 | 57.6 | 0.42 |
| **Clarification** | 609 | 40.4 | 0.17 |
| **Confirmation** | 6620 | 92.6 | 0.77 |
| **Correction** | 2065 | 62.3 | 0.43 |
| **Directive** | 2006 | 61.7 | 0.52 |
| **Explanation** | 1941 | 54.4 | 0.25 |
| **Expressive** | 22198 | 76.8 | 0.74 |
| **Hint** | 341 | 67.6 | 0.34 |
| **Promise** | 303 | 95.6 | 0.00 |
| **Prompt** | 6186 | 64.2 | 0.30 |
| **Question** | 2553 | 60.7 | 0.49 |
| **Reminder** | 337 | 47.7 | 0.25 |
| **Request** | 14243 | 56.2 | 0.49 |
| **Suggestion** | 2028 | 70.2 | 0.43 |

As shown in Table 2, the subact classifiers yield an average accuracy of approximately 65% and kappa of 0.4. Next we created a single model to classify Dialogue Act and Subact. By combining the top-level dialogue acts with their subacts, this produced a flat taxonomy with 133 categories. Table 3 shows the performance of our models with flat taxonomy using 10-fold cross validation.

**Table 3. Performance of models with flat taxonomy.**

| Algorithm | FeatureSet | Accuracy | Kappa |
|---|---|---|---|
| Naïve Bayes | Simple | 51% | 0.49 |
| Naïve Bayes | Extended | 48% | 0.45 |
| **Bayes Net** | **Simple** | **53%** | **0.50** |
| Bayes Net | Extended | 51% | 0.48 |
| Logistic Regression | Extended | 44% | 0.42 |
| Logistic Regression | Simple | 43% | 0.41 |

Table 3 shows that the flat taxonomy classification improved the accuracy of our model significantly when compared to the the multi-level classification. It is worth noting that these results approach the agreement of human experts when they annotated independently, which was 66%.

# 4. CONCLUSION

The results of the different models and algorithms showed that the top-level Dialogue Acts can be predicted with a reasonable accuracy. However to be able to tag utterances with both top-level and subcategories a combined classification needed to be applied, rather than a hierarchical approach. Multiple classification algorithm were effective, such as Naïve Bayes, Bayesian Networks, Logistic Regression, and Conditional Random Fields (CRF).

The ultimate goal of this work is to build a model to be applied to a set of not-seen and untagged data and use the Dialogue Acts as means of modeling the discourse. The proposed models in this paper can be used as initial models for a semi-supervised classifier which will ultimately identify Dialogue Acts in real time.

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# Towards Freshmen Performance Prediction

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## ABSTRACT

In this paper, we deal with freshmen performance prediction. We analyze data from courses offered to students at Faculty of Informatics, Masaryk University. We supposed that the success rate of our predictions increases when we omit freshmen from our experiments as we have no study-related data about them. However, we disproved this hypothesis because there was generally no significant difference in prediction of freshmen and non-freshmen students. We also presented the attributes that were important for freshmen performance prediction.

## Keywords

Student Performance, Prediction, Freshmen, Social Network Analysis, Educational Data Mining.

## 1. INTRODUCTION

Universities are faced with the problem of a high number of students' drop outs. Thus, researches explore what influences students' performance, and identify weak students in order to help them to improve their achievements. It is important to predict student failure as soon as possible. The task is difficult because the less data about students we have the less accurate the prediction we obtain is.

Data mining techniques represent a typical way for discovering regularity in data [3]. It allows us to build predictive models by defining valid and exact corresponding rules. Authors in [2] explored the drop-out prediction after the first year at Electrical Engineering department. Their data contained the study results of students enrolled in selected courses or the average grades gained in different groups of courses. Their results showed that decision trees belong to the most suitable algorithms. They also demonstrated that the cost-sensitive learning methods helped to bias classification errors towards preferring false positives to false negatives. Authors in [4] also investigated the prediction after the first year. They used questionnaires to get more detailed information about student habits.

We are interested in a similar problem but our task involves the prediction of student success in a course not in the whole study. Our aim is to identify the combinations of students and courses that could be predicted with a high accuracy. Due to the lack of data, we supposed that omitting freshmen (students in the first semester in their first study at the faculty) from the investigation should significantly increase the prediction accuracy. We also investigated how accurately we are able to predict the success or failure of freshmen.

## 2. DATA

The data used in our experiment originated from the Information System of Masaryk University. Our aim was to reveal useful attributes characterizing students in order to predict student performance in every particular course. Our data comprised of study-related and social behavior data about students. We explored the freshmen performance prediction and the observations were verified on 62 courses offered to students of the Faculty of Informatics of Masaryk University. The data sets comprised of students enrolled in courses in the years 2010-2012 and their grades. We constructed three data sets: (1) All students – 3,862 students with 42,677 grades, (2) Without freshmen – 2,927 students with 32,945 grades, (3) Only freshmen – 935 students with 9,732 grades.

### 2.1 Study-related data

This kind of data contained personal attributes (e.g. gender, year of birth, year of admission at the university) and data about study achievements (e.g. the number of credits to gain for enrolled, but not yet completed courses, the number of credits gained from completed courses, the number of failed courses). This data contained 42 different attributes in total.

### 2.2 Social Behavior Data

This kind of data described students' behavior and co-operation with other students. In order to get additional social attributes, we created sociograms. The nodes denoted users and the edges represented ties among them. The ties were calculated from the communication statistics, students' publication co-authoring, and comments among students. Particularly, we applied social network analysis methods on the sociograms to compute the values of attributes that represent the importance of each user in the network, e.g. centrality, degree, closeness, and betweenness. We also calculated the average grades of students and their friends. Finally, the social behavior data contained 131 attributes in total. We already proved that this type of data increases the accuracy of student performance prediction [1].

## 3. EXPERIMENT

**Hypothesis.** The accuracy of the student success prediction will significantly increase when we omit freshmen.

**Evaluation.** We utilized nine different classification algorithms implemented in Weka. We built a classifier for each investigated course because courses differ in their specialization, difficulty, and student occupancy rate. In the first place, we had to select suitable methods and compare the results of data sets with and without freshmen. We used the accuracy and coverage for comparing the results. Generally, the accuracy represents the percentage of correctly classified students. The coverage represents the amount of students for whom we can predict the success or failure.

**Observations**. In all cases, SMO reached the highest accuracy (with and without freshmen). We computed also baseline (the prediction into the majority class) in order to compute the percentage of successful grades. In all cases, we used 10-fold cross-validation for evaluation the results. The results comparison

can be seen in Table 1. Surprisingly, the results indicate that there is no significant improvement when we omit the freshmen. We improved the results only by 1% but for almost 10,000 grades we did not give any prediction.

**Table 1. Comparison of results with and without freshmen**

| ALL COURSES | Accuracy | | Coverage |
|---|---|---|---|
| | SMO | Baseline | |
| All students | 80.04% | 73.45% | 100% |
| Without freshmen | 81.26% | 75.79% | 77.2% |

Naturally, the increase can be distorted by the large amount of non-freshmen students. No freshman has enrolled in 8 courses. Less than 10 freshmen were enrolled in 22 courses. Moreover, freshmen did not constitute 10% of all students in the next 18 courses. For the next investigation we selected only 14 courses where the number of freshmen is not negligible.

The results of selected 14 courses can be seen in Table 2. As can be seen, the improvement was 3.3%. However, there was a significant difference in baseline – about 7%. SMO was the most suitable method again but the results were difficult to interpret. For this reason, we also presented the accuracy using J48 for the purpose of comparison the success rate of the both approaches. We considered the J48 model to be similar enough for indication the attributes that influenced the results.

**Table 2. Comparison of results for 14 courses**

| 14 COURSES | Accuracy | | | Coverage |
|---|---|---|---|---|
| | SMO | J48 | Baseline | |
| Without freshmen | 82.07% | 80.24% | 77.82% | 59.27% |
| All students | 78.77% | 77.48% | 70.66% | 100% |
| Only freshmen | 76.56% | 75.10% | 67.11% | 40.73% |

When comparing the results presented in Table 1 and Table 2, freshmen decreased the overall accuracy in all cases. However, the difference was insignificant. The model based on J48 algorithm was explored for each course. We also investigated trees built only for the freshmen. The classifiers classified the data based on using the following attributes:

*Known study-related attributes***:** field of study, programme of the study, if the student passed the entrance test or the student was accepted without taking any entrance test, score of the entrance test, if the course is mandatory, elective, or voluntary for the student.

*Social behavior attributes***:** degree, centrality, betweenness, number of friends / average of grades of friends that already passed investigated course, number of friends / average of grades of friends that are enrolled in the course with the investigated student.

It was very interesting that the freshmen can be characterized by social attributes. They got the access to the system in June during the enrollment to their studies. During the enrollment of courses in September when we investigated their probability to pass the courses, we already had some data about their activity in the system. In order to measure the influence of the social behavior data on the freshmen performance prediction, we removed different types of data from the data set. The comparison can be seen in Table 3. SMO reached all presented results. The accuracy obtained by mining social behavior attributes was surprisingly slightly better than by mining only known study-related attributes. The best result was obtained when we used the both data types together.

**Table 3. Freshmen performance prediction using different types of data**

| Data set | Accuracy |
|---|---|
| All attributes | 76.56% |
| Only known study-related attributes | 73.95%. |
| Only social behavior attributes | 74.72% |

**Decision**. The results indicated that the accuracy of the prediction was almost the same for all students regardless the status of freshmen. The freshmen passed through the similar classification paths as the non-freshmen. When we consider only the courses with a high proportion of the freshmen, the difference is higher but not significant. As a result, the hypothesis was not confirmed.

# 4. CONCLUSION

In this paper, we were dealing with the freshmen performance prediction. The hypothesis was that the success rate of the predictions will increase when we omit the freshmen. We disproved this hypothesis because the results sustained almost the same. The freshmen passed through the similar classification path as the non-freshmen. When we inspected the possibility of estimation only the freshmen grades, surprisingly, mining the social behavior data collected from students in the information system only in two months reached better results than mining data about results in the entrance test, course category, and the basis of the study specialization.

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# Generalising IRT to Discriminate Between Examinees

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## ABSTRACT

We present a generalisation of the IRT framework that allows to discriminate between examinees. Our model therefore introduces examinee parameters that can be optimised with Expectation Maximisation-like algorithms. We provide empirical results on PISA data showing that our approach leads to a more appropriate grouping of PISA countries than by test scores and socio-economic indicators.

## 1. INTRODUCTION

Developments in Psychometrics have led to a multitude of logistic models, ranging from simple classical test theory to sophisticated multidimensional generalizations (e.g., [2]). Usually, these generalizations focus on items and the success of solving an item depends on a particular set of skills. On the contrary, examinees are only represented by their ability although, according to the original theoretical IRT problem, items and examinees are supposed to be treated symmetrically.

In this paper, we propose to balance this asymmetry by including a discrimination parameter for examinees. We present a *homographic* parametrization that preserves symmetry and allows to derive characteristics of examinees. We report on empirical results on PISA 2012 data showing that the use of *examinee discrimination parameters* reveals insights that cannot be identified with traditional approaches.

## 2. A SYMMETRIC AND LOGISTIC MODEL

The traditional 1PL model [5] is given by

$$IRF_{1PL}(i,j) = \frac{1}{1+e^{\theta_i+\beta_j)}}, \tag{1}$$

where the real numbers $\theta$ and $\beta$ represent the examinee's ability and the item difficulty, respectively. These parameters can be related to the score $x_i$ and the rate of success of the question $a_j$ by using the transformations $\beta_j = \log\left(\frac{1-a_j}{a_j}\right)$ and $\theta_i = \log\left(\frac{1-x_i}{x_i}\right)$. Note that $x_i$ and $a_j$ are real numbers bounded by 0 and 1. After substitution, the model can be expressed as

$$IRF_{1PL}(i,j) = \frac{a_j x_i}{a_j x_i + (1-a_j)(1-x_i)}. \tag{2}$$

A similar transformation can be applied to the 2PL [1], where $\alpha_j = b_j$ are non negative real numbers called *item discrimination*,

$$\begin{aligned} IRF_{2PL}(i,j) &= \frac{1}{1+e^{\alpha_j(\theta_i+\beta_j)}} \\ &= \frac{(a_j x_i)^{b_j}}{(a_j x_i)^{b_j} + ((1-a_j)(1-x_i))^{b_j}}. \end{aligned} \tag{3}$$

The multidimensional two-parameter logistic model (M2PL) [2] splits the items in $k$ different skills. The examinee has an ability parameter for each skill that is affected by a skill discrimination parameter. The ability is now a vector of real numbers $\boldsymbol{\theta}_i = (\theta_{i,1}, ..., \theta_{i,k})$ and the item discrimination a vector of non-negative real numbers $\boldsymbol{\alpha}_j = (\alpha_{j,1}, ..., \alpha_{j,k})$,

$$\begin{aligned} IRF_{M2PL}(i,j) &= \frac{1}{1+e^{\boldsymbol{\alpha}_j\boldsymbol{\theta}_i+\beta_j}} \\ &= \frac{a_j \mathbf{x}_i^{b_j}}{a_j \mathbf{x}_i^{b_j} + (1-a_j)(\mathbf{1}-\mathbf{x}_i)^{b_j}}. \end{aligned} \tag{4}$$

The appealing use of *item discrimination parameters* can be translated to examinees, for instance to distinguish between a regular scholarly student and a talented, yet slacking one. Let us introduce an *examinee discrimination parameter* denoted by the non-negative real number $y_i$ that acts as the analogue of its peer $b_j$. The discrimination parameters will also be decoupled from the other item or examinee parameter. This assures the identifiability of the model. The resulting model is called the *Symmetric Logistic Model* (SyLM) and given by

$$\begin{aligned} IRF_{SyLM}(i,j) &= \frac{1}{1+e^{b_j\theta_i+y_i\beta_j}} \\ &= \frac{a_j^{y_i} x_i^{b_j}}{a_j^{y_i} x_i^{b_j} + (1-a_j)^{y_i}(1-x_i)^{b_j}}. \end{aligned} \tag{5}$$

At first sight, the logistic parametrization of the SyLM appears as a special case of the M2PL by setting $\beta_j = 0$ and renaming the parameters, however, the homographic parameterization renders them intrinsically different. Actually, SyLM is closer to the 2PL as it does not subdivide items into skills although a multidimensional extension could be easily derived. For lack of space, we will thus only compare SyLM to the 1PL and 2PL.

**Table 1: Synthetic results**

| Model | Param. | log.Lik | AIC | BIC |
|---|---|---|---|---|
| 1PL | Log. | -3847.1 | 8504.3 | 10100.1 |
| 1PL | Hom. | -3836.6 | 8483.2 | 10079.0 |
| 2PL | Log. | -3809.2 | 8478.5 | 10172.8 |
| 2PL | Hom. | -3724.3 | 8308.7 | 10002.9 |
| SyLM | Log. | -3809.2 | 9238.5 | 12430.1 |
| SyLM | Hom. | -3455.5 | 8531.1 | 11722.6 |

# 3. EMPIRICAL EVALUATION

## 3.1 Synthetic Comparison

For each approach, logistic and homographic parameterizations are tested. Parameters are inferred by a Maximum Likelihood [4] algorithm supported by a Newton-Raphson optimization. The dataset consists of the results to the first Mathematic booklet of PISA 2012 study in France (380 examinees, 25 items). For items having two degrees of success, both cases are considered as a success. Similarly, answers entered as "not reached" or "NA" are considered as failures.

Although the results shown in Table 1 should be independent of the paramtetrization, estimations using homographic parametrizations produce better results throughout all settings. As expected, the additional parameters brought into the optimization by SyLM are crucial for the information criteria. However, comparing SyLM with the 1PL shows SyLM as the winner in two out of three cases. The decrease of the log-likelihood exceeds the increase of the AIC due to the significantly higher number of parameters.[1] The difference is even stronger for BIC and increases with the number of samples, hence naturally penalizing SyLM.

## 3.2 PISA Analysis

We now analyse the PISA 2012 ranking [3] and its associated country clustering with SyLM. The original grouping is based on the scores in the different tests and on social and economical variables of the countries. We focus on four pairs of countries/economies and shown in Table 2. Although Shanghai and Singapore are not reported similar, we study them together as they are the top ranked and the only ones without a similar peer. Our analysis is again performed on the Mathematics test. For each country, booklets are analyzed separately before the results are merged.

For the the twelve countries listed in Table 2, Figure 1 focuses on the distribution of *examinee's discrimination* given the *examinee's ability*. The coloring indicates the ratio of pupils having a high or a low *normalized*[2] discrimination given the fact that they have a low or a high *normalized* ability. We consider values below .25 as a low *normalized* characteristic and above .75 as a high one.

Although Switzerland and Japan are in the same PISA group, their figures are very different. The Japanese distribution is closer to the other Asiatic countries while the Swiss is similar to the German one. The geographic argument holds for Brazil and Argentina but not for USA and Russia, which are geographically and culturally very different. Again the two neighbors Canada and USA produce very different results. While the distribution for USA is closer to the British one, the Canadian one shows very different. Based on our results, an improved clustering can be proposed. Shanghai, Singapore and Japan constitute the first group; Switzerland, Germany the second. Great Britain, the USA and Russia form the third group while Brazil and Argentina make a group of their own. Canada and France remain outsiders.

[1]The 2PL counts $N+2M$ parameters, SyLM has $2N+2M$.
[2]Data is normalized by $y_i \to \frac{y_i}{1+y_i}$ and $\theta_i \to \frac{1}{1+e^{\theta_i}} = x_i$.

**Table 2: PISA country grouping**

| | | |
|---|---|---|
| QCN Shanghai<br>SGP Singapore | CHE Switzerland<br>JPN Japan | GER Germany<br>CAN Canada |
| FRA France<br>GBR Great Britain | USA USA<br>RUS Russia | BRA Brazil<br>ARG Argentina |

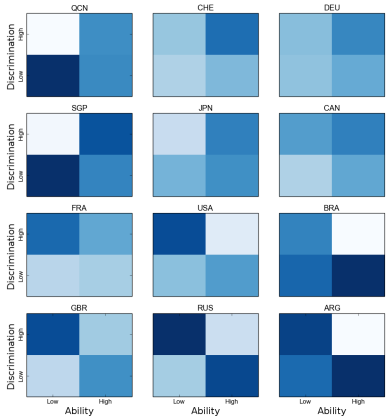


**Figure 1: SyLM results for PISA**

# 4. CONCLUSION

We proposed the Symmetric Logistic Model as a generalization of the Rasch model. Our approach can be interpreted as a symmetric 2PL at the cost of additional parameters. Empirically, our Symmetric Logistic Model showed that the PISA grouping of countries based on score and socio-economic backgrounds is suboptimal. More appropriate groups could be formed by taking examinee discrimination parameters into account.

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# Detection of learners with a performance inconsistent with their effort

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## ABSTRACT

Motivation is essential to learning and performance in e-learning environments. Designing strategies to intervene in the learning process as soon as possible with the aim of keeping the learner engagement high is thus remarkably important. This paper proposes a method which allows instructors to discover learners with a performance inconsistent with the activity carried out, enabling teachers to send personalised messages to these students.

## 1. INTRODUCTION

Motivation is essential to carry out any kind of task successfully but, this is even more necessary for activities which require a great cognitive and time effort such as the acquisition and understanding of new knowledge to be applied suitably and rightly to problem solving. This is the case of learning processes supported by e-learning platforms where learners must adopt an active role and guide their self-learning.

To offer support and individualised help to learners, teachers need tools that help them to detect students who require advice. We, in this work, present a method which aims at detecting learners whose effort performed in the e-platform is comparable or higher than that one done by their peers but, unlike them, they do not pass the assessable assignments. These learners require a feedback different from those who are not interested in the course, thus being at risk of dropout. These feedback messages should be automatically generated by the e-learning system in order to provide students with personalized guidance, tailored to their inhomogeneous needs and requirements [1].

To our knowledge, the relationship between effort and performance has never been studied. The closest topic researched is the detection of undesirable student behaviours [3, 2] whose goal is to discover those students who have some type of problem or unusual behavior such as dropping out or academic failure. For instance, Ueno [4] proposed an animated agent which provided adaptive messages to the learners with an irregular learning process and Vellido et al. [5], characterised atypical student behaviors through robust generative relevance analysis.

Next, we describe our method and discuss the results achieved.

## 2. METHOD AND RESULTS

Our approach aims at detecting students who have carried out a great effort but, however, they have failed. These are thus a subset of the students that a performance classifier would classify wrongly since their activity is very similar to that performed by students who passed. Therefore our method works in two phases: first, a classifier is built in order to detect misclassified instances and next, a clustering technique is applied on the misclassified instances set of "fail" class with the aim of detecting these learners. The instances from the cluster whose weighted Euclidean distance to "fail" class prototype is the largest are our target students.

We apply our method on students' activity data from two e-learning courses hosted in Moodle with 43 and 119 learners respectively. In both, the students must carry out four assignments to pass the course. We generated two data sets, one for each course, with the activity data corresponding to the period of the first assignment(named "d1" and "d2"). The attributes used were: N# of actions performed by the student ("act"), N# of visits to the content-files ("v-re"), the SCORM resources ("v-sc"), the statistics page ("v-da"), the feedback messages provided by the instructor ("v-fe") and the html pages ("v-co"); N# of messages read ("v-fo"), posted ("a-di") and answered ("p-fo") by the student in the forum and the sum of the attributes "a-di" and "p-fo" ("pa-fo"). As class attribute, we used the mark achieved by the learner in the first assignment, pass or fail.

We configured our method for using J48 as classifier and k-means as clustering technique. The accuracy of the classifiers, evaluated with 10-CV, were 69.77% and 85.17%, with 7 and 13 instances misclassified respectively, that means, there were 7 and 13 learners who could have carried out an activity (effort) similar to those who passed the first assignment, but however they failed. To determine if these misclassified students had really a similar activity to those who passed, we performed a clustering process with these

**Table 1: Clustering process on "d1"**

| attr. | relevance | C1 | C2 | Avg. |
|---|---|---|---|---|
| act | 9 | 0.1835 | 0.4639 | 0.1245 |
| v-re | 4 | 0.093 | 0.438 | 0.1270 |
| v-co | 1 | 0.1017 | 0.3785 | 0.1239 |
| v-fe | 1 | 0 | 0.1667 | 0.0385 |
| v-da | 6 | 0.0435 | 0.3732 | 0.0920 |
| a-di | 2 | 1 | 0.1667 | 0.0769 |
| p-fo | 4 | 0 | 0.2 | 0.0308 |
| pa-fo | 1 | 0.1667 | 0.1944 | 0.0385 |
| v-fo | 2 | 0.3061 | 0.3299 | 0.0597 |
| v-sc | 3 | 0.075 | 0.3417 | 0.0952 |
| N# ins. | - | 1 | 6 | - |
| dist. to avg. | - | 2.0183 | 3.8936 | - |

**Table 2: Clustering process on "d2"**

| attr. | relevance | C1 | C2 | C3 | C4 | Avg. |
|---|---|---|---|---|---|---|
| act | 10 | 0.679 | 0.049 | 0.163 | 0.137 | 0.07 |
| N# ins. | - | 2 | 5 | 2 | 4 | - |
| dist. to avg. | - | 0.609 | 0.021 | 0,093 | 0,067 | - |

instances. Two and four clusters were created for dividing up these students. The number of clusters was manually selected by comparing the different clusters built with k ranges from 2 to 5. Next, we calculated the weighted Euclidean distance from each centroid to the mean of the well-classified instances of class "fail", being the contribution of each attribute weighted according to its relevance. Those instances which belonged to the cluster with a larger distance to the average were marked as outliers. The prototype of each cluster is shown in Tables 1 and 2. These tables also gather the relevance of each attribute ("relevance") calculated with the ClassifierSubSetEval method provided by Weka and the average value ("Avg.") of each attribute corresponding to the well-classified instances of the fail class.

As can be observed, in "d1", the cluster C1 only contains one instance which represents the activity of one of the students with the lowest activity in all course and similar to that performed by the students who failed and were well-classified. The centroid of cluster C2 is further from the average of the well-classified instances of the fail class and these, thus, are marked as outliers. In "d2", the only relevant attribute is the N# of total actions, and the instances of the cluster C1 therefore were marked as outliers.

Table 3 collects the most relevant activity performed by the six and the two students misclassified in each course respectively. In "d1", the value of most attributes is larger than the average of their class, being this difference remarkable for the attribute "act". On the one hand, the students labelled as d1s3, d1s4, d1s5 and d1s6 performed a significant activity, but failed the first assignment (q1) with a low qualification, from 0 to 4 out of 10. However, they passed the second assignment (q2) with a good mark, 9 out of 10. That means that the feedback given to them by the instructor was useful and effective, being clearly reflected the importance of giving a good feedback to the students. On the other hand, student named d1s2, even having an appreciable activity, failed the first assignment and dropped out before sending the second task. In this case, the instructor's advice was not successful. If the teacher had known the activity performed at the same time that he assessed the assignment, the message could have been written in a more motivating tone, expressly mentioning the activity already undertaken. Finally, d1s1 was detected by the method but the learner

**Table 3: Students' activity**

| student | act | v-re | v-da | p-fo | v-sc | q1 | q2 |
|---|---|---|---|---|---|---|---|
| d1s1 | 0.23 | 0.30 | 0.24 | 0.00 | 0.19 | 0 | 0(dropout) |
| d1s2 | 0.20 | 0.16 | 0.15 | 0.00 | 0.34 | 3 | 0(dropout) |
| d1s3 | 0.91 | 1.00 | 0.72 | 0.60 | 0.63 | 4 | 9 |
| d1s4 | 0.50 | 0.44 | 0.20 | 0.20 | 0.23 | 0 | 9 |
| d1s5 | 0.58 | 0.42 | 0.43 | 0.40 | 0.31 | 3 | 9 |
| d1s6 | 0.37 | 0.30 | 0.50 | 0.00 | 0.36 | 0 | 9 |
| d2s1 | 0.84 | | | | | 3 | 8 |
| d2s1 | 0.51 | | | | | 4.5 | 8.5 |

did not receive feedback because he did not deliver the assignment. In this case, the teacher missed the opportunity to rescue him. Regarding d2, the N# of actions performed by both students is very high in comparison with the average of the students who failed. Indeed, one of these students had a mark of 4.5 out of 10, being very close to pass. In this scenario, the feedback provided by the instructor was successful since this learner passed the second assignment with a qualification of 8.5 out of 10.

The experimentation carried out shows that our method helps to discover students whose performance do not match with the effort performed. Being able to automatically detect them would allow teachers to act quickly, sending them personalised messages oriented to keep their engagement high and avoid the dropout.

As future work, our aim is to apply this method to other virtual courses and support the teacher during the learning process in order to validate the goodness of our proposal in real online contexts. Another issue which will be addressed shortly is to evaluate the effect of using different classifiers and clustering algorithms in our proposal.

## 3. ACKNOWLEDGMENTS

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# A Probabilistic Model for Knowledge Component Naming

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## ABSTRACT

Recent years have seen significant advances in automatic identification of the Q-matrix necessary for cognitive diagnostic assessment. As data-driven approaches are introduced to identify latent knowledge components (KC) based on observed student performance, it becomes crucial to describe and interpret these latent KCs. We address the problem of naming knowledge components using keyword automatically extracted from item text. Our approach identifies the most discriminative keywords based on a simple probabilistic model. We show this is effective on a dataset from the PSLC datashop, outperforming baselines and retrieving unknown skill labels in nearly 50% of cases.

## 1. OVERVIEW

The Q-matrix, introduced by Tatsuoka [9], associates test items with attributes of students that the test intends to assess. A number of data-driven approaches were introduced to automatically identify the Q-matrix by mapping items to latent *knowledge components* (KCs), based on observed student performance [1, 6], using, e.g. matrix factorization [2, 8], clustering [5] or sparse factor analysis [4]. A crucial issue with automatic methods is that latent skills may be hard to describe and interpret. Manually-designed Q-matrices may also be insufficiently described. A data-generated description is useful in both cases.

We propose to extract *keywords* relevant to each KC from the textual content corresponding to each item. We build a simple probabilistic model, with which we score keywords. This proves surprisingly effective on a small dataset obtained from the PSLC datashop.

## 2. MODEL

We focus on extracting keywords from the textual content of each item (question, hints, feedback, Fig. 1). We denote by $d_i$ the textual content (e.g. body text) of item $i$, and assume a Q-matrix mapping items to $K$ skills $c_k$, $k = 1 \dots K$.

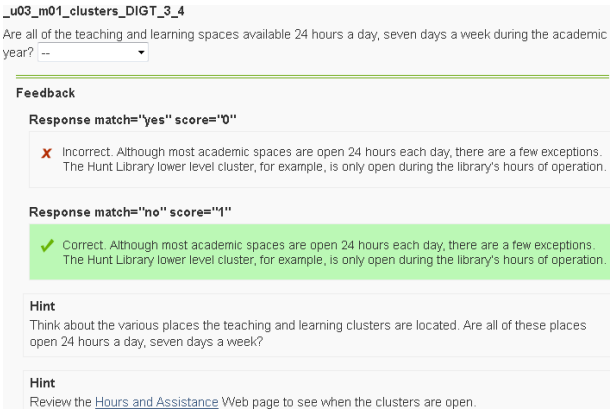


**Figure 1: Example item body, feedback and hints.**

These may be latent skills obtained automatically or from a manually designed Q-matrix. For eack KC we build a unigram language model estimating the relative frequency of words in each KC [7]:

$$P(w|c_k) \propto \sum_{i, d_i \in c_k} n_{wi}, \qquad \forall k \in \{1 \dots K\} \tag{1}$$

with $n_{wi}$ the number of occurrences of word $w$ in document $d_i$. $P(w|c)$ is the *profile* of $c$. Important words are those that are high in $c$'s profile and low in other profiles. The symmetrized Kullback-Leibler divergence between $P(w|c)$ and the profile of all other classes, $P(w|\neg c)$, decomposes over words: $KL(c, \neg c) = \sum_w \left(P(w|c) - P(w|\neg c)\right) \log \frac{P(w|c)}{P(w|\neg c)}$. We use the contribution of each word to the KL divergence as score indicative of keywords. In order to focus on words significantly *more* frequent in $c$, we use the signed score:

$$\text{KL score:} \quad s_c(w) = |P(w|c) - P(w|\neg c)| \log \frac{P(w|c)}{P(w|\neg c)}. \tag{2}$$

Figure 2 illustrates this graphically. Words frequent in $c$ but not outside (green, right) receive high positive scores. Words rare in $c$ but frequent outside (red, left) receive negative scores. Words equally frequent in $c$ and outside (blue) get scores close to zero: they are not specific enough.

## 3. EXPERIMENTAL RESULTS

We used the 100 student random sample of the "Computing@Carnegie Mellon" dataset, *OLI C@CM v2.5 - Fall 2013, Mini 1.* This OLI dataset is well suited for our study because the full text of the items is available in HTML format

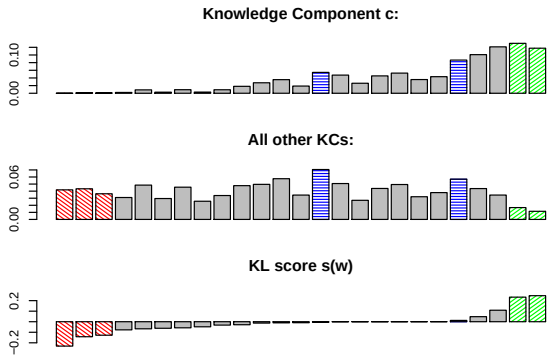


**Figure 2: From KC profile, other KCs, to KL scores.**

| KC label | #it | Top 10 keywords (body text only) |
|---|---|---|
| identify-sr | 52 | phishing email scam social learned indicate legitimate engineering anti-phishing indicators |
| print | 12 | quota printing andrew print semester |
| quota | | consumed printouts longer unused cost |
| penalties | 1 | maximum limitations exceed times |
| bandwidth | | bandwidth suspended network access |

**Table 1: Top 10 keywords for 3 KC of various sizes.**

and can be extracted. Other datasets only include screenshots. There are 912 unique steps, 31k body tokens, 11.5k hints tokens, and 41k feedback tokens, close to 84k tokens total. We pick a model in PSLC that has 108 distinct KCs with partially descriptive labels. That model assigns 1 to 52 items to each KC, for 823 items with at least 1 KC assigned. All text is tokenized, stopwords are removed, as well as tokens not containing one alphabetical character.

We estimate three different models, using Eq. (1), depending on the data considered: body text only ("body"), body and hints ("b+h"), all text ("all"). For each model, we extract up to 10 words with highest KL score (2) for each KC. Table 1 shows that even for knowledge components with very few items, the extracted keywords are clearly related to the topic suggested by the label. Although the label itself is not available when estimating the model, words from the label often appear in the keywords: this happens in 44 KCs out of 108 (41%), suggesting that the retrieved keywords are relevant. Note that some labels are vague (e.g. *identify-sr*) but the keywords provide a clear description (*phishing scams*).

We now focus on two desirable qualities for good keywords: *diversity* (keywords should differ accross KCs) and *specificity* (keywords should describe few KCs). Table 2 compares KL scores with the common strategy of picking the most frequent words (MP), using various metrics. Good descriptions should have a high number of different keywords, many of which describing a unique KC, and few KCs per keyword. The total number of keyword is fairly stable as we extract up to 10 keywords for 108 KCs. It is clear that KL extracts many more different keywords (up to 727) than MP (352 to 534). KL yields on average 1.4 (median 1) KC per keyword, whereas MP keywords describe on average 3.1 KC. There are also many more KL-generated keywords describing a unique

| | total | different | unique | max |
|---|---|---|---|---|
| KL-body | 995 | **727** | **577** | **9** |
| KL-b+h | 1005 | 722 | 558 | 10 |
| KL-all | 1080 | 639 | 480 | 19 |
| MP-body | 995 | 534 | 365 | 42 |
| MP-b+h | 1005 | 521 | 340 | 34 |
| MP-all | 1080 | 352 | 221 | 87 |

**Table 2: Keyword extraction for KL vs. max. probability (MP) using text from body, b+h and all fields; total keywords, # different keywords, # with unique KC, and maximum KC per keyword.**

KC. These results support the conclusion that our KL-based method provides better *diversity* and *specificity*.

Note that using more textual content (adding hints and feedback) hurts performance accross the board. We see why from the list of words describing most KCs from two methods:
**KL-body**: use (9) following (8) access, andrew, account (7)
**MP-all**: incorrect(87) correct(67) review(49) information(30)

"correct" and "incorrect" are extracted for 67 and 87 KCs, respectively, because they appear frequently in the feedback text. The KL-based approach discards them because they are equally frequent everywhere.

## Acknowledgement

We used the 'OLI C@CM v2.5 - Fall 2013, Mini 1 (100 students)' dataset accessed via DataShop [3]. We thank Alida Skogsholm from CMU for her help in choosing this dataset.

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# An Improved Data-Driven Hint Selection Algorithm for Probability Tutors

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## ABSTRACT

Data-driven systems such as the Hint Factory have been successful at providing student guidance by extracting procedural hints from prior user data. However, when only small amounts of data are available, it may be unable to do so. We present a novel hint-selection algorithm for coherent derivational domains, such as probability, which addresses this problem by searching a frontier of viable, partially matching student states. We tested this algorithm on a dataset collected from two probability tutors and performed a cold start comparison with direct state matching. We found that our algorithm provided higher value hints to students in unknown states 55.0% of the time. For some problems, it also provided higher value hints in known states.

## 1. INTRODUCTION

Adaptive feedback is one of the hallmarks of an Intelligent Tutoring System. This feedback often takes the form of hints, pointing a student to the next step in solving a problem. While hints can be authored by experts, more recent data-driven approaches, such as the Hint Factory [1] have shown that this feedback can be automatically generated from prior student data. The Hint Factory operates on a representation of a problem-specific dataset called an interaction network [3], where each vertex represents the state of a student's solution at some point during the problem solving process, and each edge represents a student's action. A complete solution is represented as a path from the initial state to a goal state. A new student requesting a hint is matched to a previously observed state and directed along a path to the goal state.

If too few students have been recorded, the Hint Factory is unable to match new students to existing states in the network. This is known as the *cold start problem*, a fundamental challenge in many domains. For example, when Hint Factory's original state matching algorithm was applied to BOTS, an educational programming game, a dataset of nearly 100 students provided only 40% hint coverage [4].

This paper focuses on two probability tutors in which many actions have no ordering constrains. This can produce an exponentially large state space, making the cold start problem even harder to overcome. We present a novel state matching mechanism that helps address this problem in *coherent derivational domains*. These are problem-solving domains, such as probability, physics, and logic, where: *a*) a solution $S$ is constructed by repeated applications of domain rules to derive a goal value; *b*) taking any valid action cannot prevent the student from taking another valid action; and *c*) if $S$ is a complete solution to the problem, then any superset of $S$ is also a complete solution. Note that this does not prevent rule applications within a solution from having ordering constraints.

## 2. SELECTION ALGORITHMS

For our purposes, we assume a hint selection algorithm takes the following inputs: *a*) an interaction network, $N=(V,E)$ of previously observed states and actions; *b*) a value or ordering function $f: V \rightarrow \mathbb{R}$, which assigns "desirability" to each of the states in $V$; and *c*) the current state $s_c$ of a student who is requesting a hint. In coherent derivational domains, each state $s \in V$ can be defined by the set of derived facts. Each edge $e \in E$ is annotated with an action $a_e$, the derivation or deletion of a fact.

Given this information, a selection algorithm attempts to find the optimal action $a$, such that $a$ is a valid action in state $s_c$, and the value of the resulting state $f(s_a)$ is maximized. Here we derive $f$ from the Hint Factory's value iteration procedure [1], but other functions could be used instead.

The selection algorithm employed by the Hint Factory requires that $s_c \in V$, meaning the student is in a known, or previously observed state. The algorithm then selects the successor of $s_c$ with the highest value and returns the action which leads to this state.

In the case that $s_c$ is unknown, meaning $s_c \notin V$, Barnes and Stamper [1] suggest using a student's previous state to generate a hint. This approach can be generalized to walking back to the last recognized state in the student's path, and using that to generate a hint. We refer to this as the "Backup Selection" algorithm.

In our selection algorithm, we first mark all $v \in V$ such that $v \subseteq s$. Beginning with the start state $s_0$, we traverse the graph in a depth-first fashion, following an edge $e$ only if $a_e$ is a deletion or derives a fact which is present in $s_c$. Let us call the set of states traversed in the manner $T$. Note that we do not *generate* states here, but explore only the previously observed states in $N$. We know that for any $t \in T$, $t \subseteq s_c$ and $t$ is reachable by a known path from the start state. We define the Frontier $F$ as the set of all states which can be reached by a single action from a state in $T$. A student in $s_c$ can reach any state in the Frontier – or some superset of the Frontier state – in a single action. We then find the edge $\overrightarrow{tu}$ which maximizes $f(u)$ and return its annotated action.

## 3. EVALUATION

Our evaluation was based on the cold start experiment originally used to evaluate the Hint Factory [1], which was designed to measure how much data was required to provide hints to new students. Because we can always provide *some* hint by applying the Backup algorithm, we are instead interested in measuring the quality of the hints being given. Since we cannot directly measure hint quality, we will use the value function, $f$, described in Section 2, as an approximation of the quality. Here we use the value iteration method employed by the Hint Factory [1]. We do not make the claim this is an ideal metric, and this experiment can be easily adapted to work with any value function.

We evaluated our algorithm using combined log data from the Andes and Pyrenees probability tutors [2]. The Andes data was drawn from a prior experiment [2] and included 394 problem attempts by 66 students over 11 problems. The Pyrenees data included 999 problem attempts by 137 students on the same problem set. The tutors contain the same knowledge base, problems and solutions, allowing their data to be merged. This allowed us access to a wider variety of data than a single tutor would afford.

### 3.1 Procedure

For each problem, a student was selected at random and removed from the population to represent a previously unobserved student. We will call this student's path $P$. The remaining students who successfully solved the problem were added, one at a time and in a random order, to the network, $N$. Let $n$ be the number of students added this way. After each addition, for each non-solution state in $P$, we calculated hints with the Backup selection algorithm and with our algorithm. We gave each of these hints a value, equal to $f(s)$, where $s$ is the resulting state of applying the hint. In the case that this state was not in $N$, we used the value of the Fringe state selected by the algorithm (a superset of the resulting state). If our algorithm showed an improvement, we also recorded whether or not the state requesting a hint was known, meaning it was in $N$. This process was repeated 500 times to account for ordering effects.

### 3.2 Results

For each problem, we averaged the the percentage of *unknown* states with improved hints over all values of $n$. This average ranges from 33.5% to 69.8%, with an average of 55.0%. This indicates that our algorithm accomplishes its intended purpose of improving hint selection when insufficient data makes it difficult to find matching states in the network. However, while we were able to improve hints for a large *percentage* of these unknown states, the number of unknown states dropped off rapidly as $n$ increased.

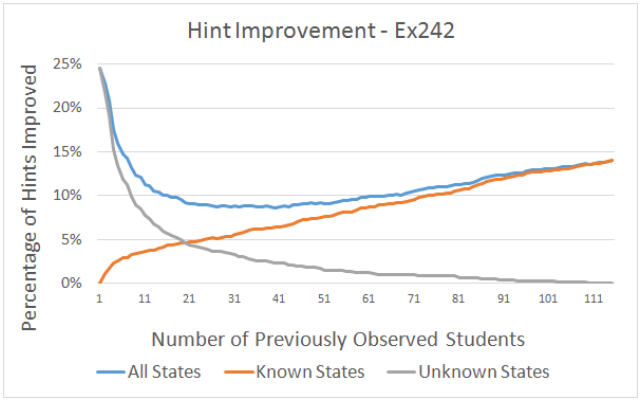


**Figure 1: One cold start curve, showing the percent of hints which are improved by our algorithm (y-axis), given the number of students in $N$ (x-axis).**

For 7 of the 11 problems, our algorithm also produced improved hints for *known* states. Notably, the percentage of improved hints *increases* as more students are added to $N$, meaning additional data strengthens our algorithm's advantage. After all of the students were added to $N$, this number ranged from 3.6% to 49.7%, with an average of 17.8%. The improvement for known states seems to depend largely on the graph structure, and occurs infrequently in smaller graphs. Figure 1 depicts one cold start graph demonstrating the trends for known and unknown states.

## 4. CONCLUSIONS

We have presented a novel algorithm for selecting among possible data-driven hints. We have demonstrated that on average our algorithm gives a higher value hint 55.0% of the time when a student is in an unknown state, and 17.8% of the time for known states in a subset of problems.

## 5. ACKNOWLEDGMENTS

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# Good Communities and Bad Communities: Does membership affect performance?

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## Keywords
MOOC, social network, online forum, community detection

## 1. INTRODUCTION
The current generation of Massive Open Online Courses (MOOCs) are designed to leverage student knowledge to augment instructor guidance. Activity in these courses is typically centered on a threaded forum that, while curated by the instructors, is largely student driven. When planning MOOCs, it is commonly hoped that open forums will allow students to interact freely and that better students will help the poorer performers. It has not yet been shown, however, that this occurs in practice.

In our ongoing work, we are investigating the structure of student communities and social interactions within online and blended courses [1]. Our focus in this poster is on the structure of student communities in a MOOC and the connection between those communities and students' performance in the course. Our goal was to determine whether students in the course form strong sub-communities and whether a student's community membership is correlated with their performance. If students do form strong communities and community membership is a predictor of performance, then it would suggest either that students are forming strong relationships that help to improve their performance or that they are clustering by performance. If they do not, then it suggests that they may be able to connect freely in the forums at the expense of persistent and beneficial relationships.

## 2. BACKGROUND
Course-level relationships have been shown to influence students' performance and the overall success of a course. Fire et al. examined the impact of immediate peers in a traditional class and found that students' performance was significantly correlated with that of their closest peer [4]. Eckles and Stradley analyzed dropout rates and found that students with strong relationships with students who dropped out were more likely to do so themselves [3].

Rosé et al. [7] examined students' evolving social interactions in MOOCs using a Mixed-Membership Stochastic Block model which seeks to detect partially overlapping communities. They found that dropout likelihood was strongly correlated with community membership. Students who actively participated in forums early in the course were less likely to drop out later. Dawson [2] studied blended courses and found that students in the higher grade percentiles tended to have larger social networks within the course and were more likely to be connected to the instructor.

## 3. METHODS
Big Data in Education is a MOOC offered by Dr. Ryan Baker through the Teacher's College at Columbia University [8]. This is a 3-month long course composed of lecture videos, forum interactions, and 8 weekly assignments. All of the assignments were structured as numeric or multiple-choice exams and were graded automatically. Students were required to complete assignments within two weeks of their release and were given three attempts to do so, with the best score being used. 48,000 students enrolled in the course with 13,314 watching at least one video, 1,380 completing at least one assignment and 778 posting in the forums. Of that 778, 426 completed at least one assignment. 638 students completed the course, some managed to do so without posting in the forums.

We extracted a social network from the forums, each student, instructor, and TA was represented by a node. Each student node was annotated with their final grade. Forum users could: start new threads, add to existing threads, or add comments below existing posts. We added directed edges from the author of each item to the author of the parent post, if any, and to the authors of the items that preceded it in the current thread. We then elimi-

nated all self-loops and collapsed all parallel edges to form a simple weighted graph for analysis. We extracted two different classes of graphs. The *ALL* graphs include everyone who participated in the forums while the *Student* graphs omit the instructor and TAs. We produced two versions of each graph: one containing all participants and one that excluded students with a course grade of 0.

We identified communities using the Girvan-Newman Edge Betweenness Algorithm [5]. This algorithm takes as input an undirected graph and a desired number of communities. It operates by identifying the edge with the highest *edge-betweenness* score: the edge that sits on the shortest path between the most nodes. It then removes that edge and repeats until the desired number of disjoint graphs have been made. We applied exploratory modularity analysis to identify the *natural* number of communities [1].

Having generated the graphs and determined the natural cluster numbers, we clustered the students into communities. We treated the cluster assignment as a categorical variable and tested its correlation with final course grades. An examination of the grade distributions showed that they were non-normal, so we applied the Kruskal-Wallis (KW) test to evaluate the relationship [6]. The KW test is a non-parametric analogue of the ANOVA test.

## 4. RESULTS AND DISCUSSION

The raw graph contained 754 nodes and 49,896 edges. After collapsing the parallel arcs and removing self-loops we retained a total of 17,004 edges. Of the 754 nodes, 751 were students. Of those, 304 obtained a grade of 0 in the course leaving 447 nonzero students. The natural cluster number for each of the graphs is shown in Table 1 along with the result of the KW tests. As Table 1 illustrates, cluster assignment was significantly correlated with the students' grade performance for all of the graphs. A sample visualization of the student graph is shown in Figure 1.

The students formed detectable communities, and community membership was significantly correlated with performance. While the structure of the communities changed when non-students and zero-students were removed, the significance relationships held. Thus while the specific community structure is not stable under deformations, students are still most connected to others who perform at a similar level. This is consistent with prior work on traditional classrooms and issues such as dropout. It runs counter to the naïve assumption that good students will help to improve the others. While it may be the case that the better performing communities contain poorer-performing students who increased their grades through interaction with better students, the presence of so many low-grade clusters suggests that students do fragment into semi-isolated communities that do not perform very well.

More research is required to determine why these communities form, whether it is due to motivational factors or similar incoming characteristics. We present some work along these lines in [1]. We will also examine the stability of the communities over time to determine whether they can be changed or if they are a natural outgrowth of the forums and must be accepted as is.

**Table 1: Community cluster numbers and Kruskal-Wallis test of student grade by community.**

| Users | Zeros | Clusters | $K$ | df | p-value |
|---|---|---|---|---|---|
| All | Yes | 212 | 349.03 | 211 | $< 0.005$ |
| All | No | 173 | 216.15 | 172 | $< 0.02$ |
| Students | Yes | 184 | 202.08 | 78 | $< 0.005$ |
| Students | No | 169 | 80.93 | 51 | $< 0.005$ |

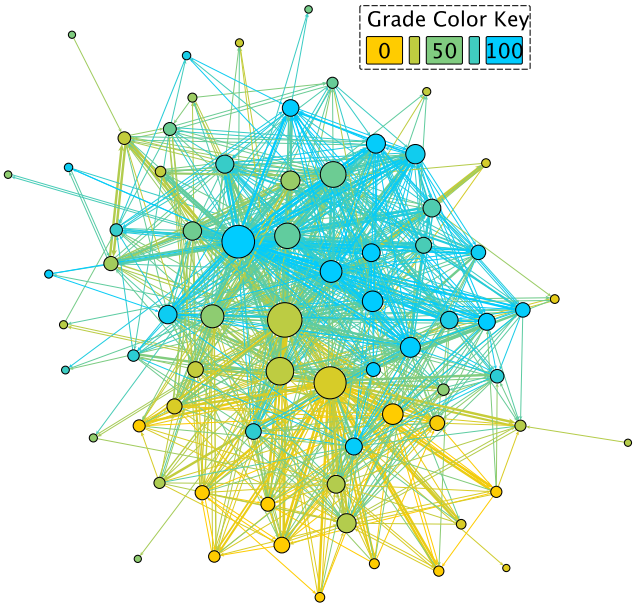


**Figure 1: Student communities with edges of weight 1 removed. Nodes represent communities. Size indicates number of students. Color indicates mean grade.**

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# A Model for Student Action Prediction in 3D Virtual Environments for Procedural Training

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## ABSTRACT

This paper presents a predictive student action model, which uses student logs generated by a 3D virtual environment for procedural training to elaborate summarized information. This model can predict the most common behaviors by considering the sequences of more frequent actions, which is useful to anticipate common student' errors. These logs are clustered based on the number of errors made by each student and the total time that each student spent to complete the entire practice. Next, for each cluster an extended automata is created, which allows us to generate predictions more reliable to each student type. In turn, the action prediction based on this model helps an intelligent tutoring system to generate students' feedback proactively.

## Keywords

Intelligent Tutoring Systems, Educational Data Mining, e-learning, procedural training, virtual environments

## 1. INTRODUCTION

Interactive simulations or virtual environments (VEs) have been used as tools to improve the learning by facilitating the "learning by doing" approach. Some of them show information to students through pictures, videos, interactive objects or help teachers make virtual lectures. However, there are some educative environments that can also supervise the execution of students' tasks by employing Intelligent Tutoring Systems (ITS), which provide tutoring feedback to students.

As a preamble to this work, a 3D biotechnology virtual lab was developed by our research group [4]. After evaluating this virtual lab, we saw opportunity to include the power of data mining to improve its automatic tutor by taking advantage of student logs.

Despite the work that has already been done about ITS in Educational Data Mining (EDM), the community misses more generic results [5]. Furthermore, it is also remarkable the lack of ITSs that take advantage of models developed by EDM [1].

The work presented in this paper represents a step forward towards the development of an ITS that leverages a predictive model computed by means of EDM to offer a better tutoring feedback. Moreover, this ITS is intended for procedural training in VEs and is domain independent.

Section 2 describes the proposed architecture for the ITS, which leverages the predictive student model (section 3). Finally, in section 4 we show the conclusions of this work.

## 2. ITS ARCHITECTURE PROPOSAL

The ITS architecture proposal is inspired on MAEVIF architecture [3], which is an extension of the ITS classical architecture for VEs.

Our main contribution resides in the Tutoring Module, which has a Tutoring Coordinator that validates the students' actions and shows error messages or hints. This module also comprises the Student Behavior Predictor (SBP) and within it lies the Predictive Student Model, which is used to find out the next most probable action from the last action made by the student. This information is used to anticipate probable students' errors, which provides a mechanism to avoid them as long as it is pedagogically appropriate.

## 3. PREDICTIVE STUDENT MODEL

Predictive student model uses historical data from past students and is continually refined (as Romero and Ventura recommend [5]) with actions that students under supervision are doing. In the context of the KDD Process and its adaptation into EDM formulated by Romero and Ventura [5], this model is created in Models/Patterns phase.

The model contains summarized data from historical registries of actions made by past students, and it is used to obtain the next most probable student's action. It consists of several clusters of students where each of them contains an extended automata, detailed in section 3.1. These clusters help to provide automatic tutoring adapted to each type of student. For example, if the student is committing few errors, it is more probable that his/her next action will not be an error. However,it will happen the opposite to a student who has failed more times.

The process of creation of this model is similar to the one

proposed by Bogarín et. al. [2], and it is executed at the tutor start-up. Basically, this process consists in taking events from student logs and from them data clusters of students are created based on the number of errors and the time they spent to complete the entire training process. Then, an automata for each cluster is built from the logs of the students using an incremental method. Later, at training time the SBP component updates the model with each new student's action attempt.

## 3.1 Extended Automata Definition

This automata consists of states (represented by circles) and transitions (represented as arrows) as shown in figure 1. Furthermore, states are grouped into three zones: Correct Flow, Irrelevant Errors and Relevant Errors Zone.

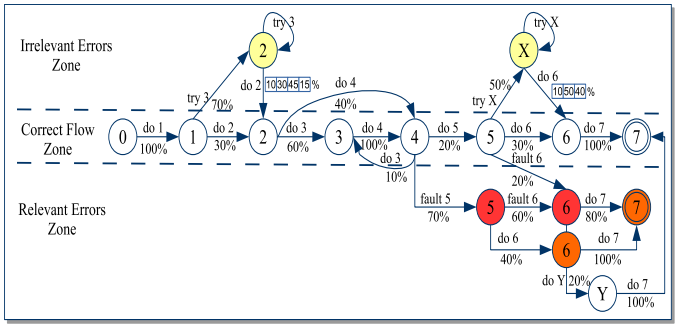


**Figure 1: Example of an extended automata**

Transitions denote events across an exercise such as actions or action attempts that past students have performed so far and new students may repeat in the future. An event may be a valid action of an exercise or an error detected by the tutor at the time of validating an action attempt. Accordingly, states represent the different situations derived from the events provoked by students.

Each state, and each transition, contains the number of students whose logged sequences of events have passed through, which becomes into event probabilities between states. In the case of states with loops, event frequencies to next state are reflected in a vector. In this way, the probability that a student leaves the loop on each iteration can be represented.

### 3.1.1 Correct Flow Zone

In this area, events represent the valid sequence of actions for an exercise, which ends up with a final satisfactory state. These states are represented by white circles.

### 3.1.2 Irrelevant Errors Zone

This zone groups states derived from error events that do not influence in the final result. These error events are associated with action attempts blocked by the automatic tutor (blocking errors [4]). These are graphically represented by a yellow circle.

### 3.1.3 Relevant Errors Zone

This area encompasses states derived from error events that actually influence in the final result, i.e. if an event of this type occurs the final result will be wrong unless a repairing action is done (non-blocking errors [4]). In this case there will be an error propagation to the subsequent states, because it does not matter what the student does later (except for some repairing action), the subsequent states will be considered also erroneous. The states derived directly from these errors are graphically represented by red circles and the subsequent correct states by orange circles.

In addition, repairing actions can be found in this area. These actions fix errors occurred earlier and redirect to one state in the correct flow.

# 4. CONCLUSIONS

Our proposal achieves an automatic tutoring in procedural training more adapted to each type of student by applying methods of extraction and analysis of data, which can anticipate possible errors depending on its configuration.

The principal application of the presented predictive model is to help students with preventing messages. For this, we have designed an ITS, presented above, which leverages the predictive model to provide that kind of tutoring.

We consider that the advice of an expert educator or teacher of the subject is essential at design time, despite this ITS may become very independent once its tutoring strategy is configured. This is because the resulting predictive model need to be analyzed for refining the tutoring strategy. In order to facilitate this task, it will be necessary to develop an application that displays the model to the expert or professor. In this way, he/she could visualize where students make more mistakes or where the practice is easier for them, and with this information he/she could decide where and what tutoring feedback is needed. Additionally, this could also help teacher to improve his/her own teaching.

# 5. ACKNOWLEDGEMENTS

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# The Impact of Instructional Intervention and Practice on Help-Seeking Strategies within an ITS

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## ABSTRACT

Within intelligent tutoring systems, instructional events are often embedded in the problem-solving process. As students encounter unfamiliar problems there are several actions they may take to solve it: they may explore the space by trying different actions in order to 'discover' the correct path or they can request a hint to get 'direct instruction' about how to proceed. In this paper we analyze experimental data from a tutoring system that provides two different kinds of hints: (1) interface specific hints that guide students attention to relevant portions of a worked example, supporting student discovery of next steps, and (2) procedural hints that directly tell students how to proceed. We adapted a method of sequence clustering to identify distinct hinting strategies across the two conditions. Using this method, we discovered three help-seeking strategies that change due to experimental condition and practice. We find that differences in strategy use between conditions are greatest for students that struggle to achieve mastery.

## 1. INTRODUCTION

As an instructional practice, tutoring supports students as they learn by doing. The tutor passively observes while the student is successful, but intervenes when the student struggles. Merrill et al. [2] describe the act of tutoring as allowing students to "reap the rewards of active problem solving while tutors minimize the dangers". In this paper, we explore data from two intelligent tutoring system (ITS) experimental conditions that take different approaches to assisting students. The conditions utilized adaptations of two common instructional perspectives, direct instruction and independent student discovery. These methods are often discussed in contrast to one another. Direct Instruction (DI) involves explicitly identifying and teaching the key principles, skills, and procedures for performing a specific task. The Discovery Method (DM), on the other hand, fosters a student's discovery of these principles, skills, and procedures by referring to content in the learning environment and providing indirect feedback and guidance.

To explore how DI and DM impact student learning we analyzed data two algebra equation solving tutors [1]. In both tutors students were provided with a worked example. However, in the DI condition, students were provided with explicit procedural hints whereas in the DM condition, hints provided general information about the interface. In their initial analysis, Lee et al. looked at average actions per problems across several units and found that on some early units students in the DM tutor showed a higher proportion of mastered skills than students in the DI tutor. This effect did not persist in later units of the tutor. They concluded that, in the early units, students in the DM condition were able to learn faster with the non-verbal worked examples scaffolding than with the informative hints of the DI condition. In the current paper we aim to take a more nuanced look at how the two experimental conditions impacted help-seeking strategies and how these strategies change over the course of problem solving.

## 2. METHODS

The experiment was conducted within the Carnegie Learning Algebra tutor. Twenty-two high school classes were randomly assigned to the DI condition and sixteen classes were randomly assigned to the DM condition. We restricted this sample to students who had completed all experimental problems in the 'Two-step linear equation solving' unit (DI=136, DM=138). Tutors in both conditions featured a worked example that faded as students achieved mastery. In the DI condition students were provided with hints that instructed them on what procedure to do and why to do it (e.g. "To eliminate -1, add 1 to both sides of the equation because -1 +1=0"). In the DM condition students were provided with hints about how to use the interface (e.g. "Select an item from the transform menu and enter a number"). Unlike the traditional Cognitive Tutor, the initial hint was a bottom out hint. Finally, in both tutors students could make two types of mistakes, which received different feedback. If they selected off-task actions (e.g. choosing to multiply when they should have divided), they received a 'bug' telling them to undo their action and ask for a hint. If they selected an on-task action, but incorrectly applied it (e.g. dividing by an incorrect amount), they would receive 'error' feedback that their action was incorrect.

To identify distinct strategic behaviors within these tutors we first generated a matrix of all problem-solving sequences for each participant. We had a total of 5541 sequences for the DI condition and 5430 sequences for the DM condition. Correct actions were coded as 'Success', off-path actions as 'Bug', on-path actions as 'Error', and hints as 'Hint'. Next, we used a clustering method previously used to detect strategy use within an ITS [3]. This method consists of fitting a Markov Chain (MC) to each sequence, evaluating the fit of each sequence's MC to every other sequence's MC to derive

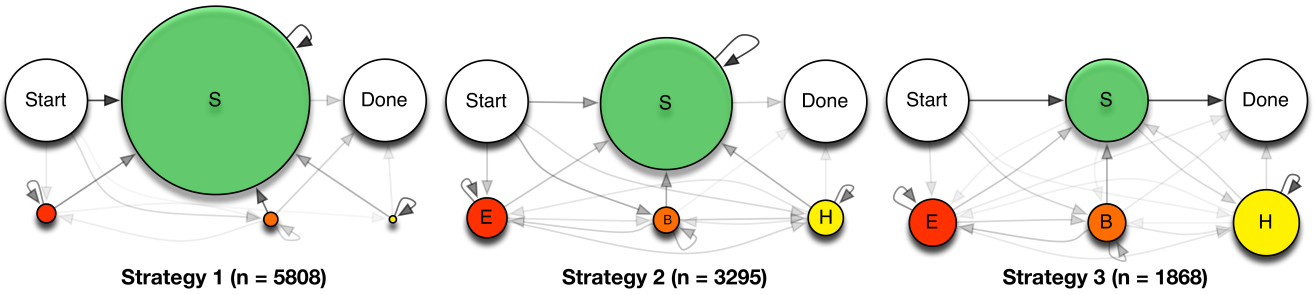


**Figure 1:** The student behavior for each cluster. Arrow gradients denote transition probability. Green nodes represent success, red error, orange bugs, and yellow hints.

a dissimilarity matrix, and using k-mediods to cluster the sequences. We found that fitting 3 clusters produced the highest average silhouette coefficient. Then, for each cluster we re-fit a single MC using all sequences assigned to that cluster to generate transition probabilities between states used to make Figure 1. After clustering the sequences we fit a binomial mixed-effects model to each cluster to better understand how students moved through the strategic clusters. Our models included fixed effects for experimental condition, the number of problems students solved (we refer to this as Practice Opportunity), and an interaction between experimental condition and practice opportunity. The models also included a random intercept for student to account for individual differences, and a random intercept for each specific problem to account for differences between the specific problems.

## 3. RESULTS

Figure 1 illustrates the occupancy and transitions between the different actions of the three clusters. A Chi-Squared test found that the cluster assignment of sequences from the two conditions are significantly different ($\chi^2(2) = 131.7$, $p < .001$). More sequences in the DM condition were observed in Strategy 1 (DI=2886, DI=2922) and Strategy 3 (DI=765, DM=1103) than students in the DI condition, whereas the reverse was true for Strategy 2 (DI=1890, DM=1405). Modeling Strategy 1 use, we found that the level of variability between conditions was not sufficient to include a random effect of problem. We found a marginally significant effect of intercept ($z = 1.94, p = 0.053$) along with a marginally significant interaction between the DM condition and practice opportunity ($z = 1.89, p = 0.059$). In modeling the use of Strategy 2, we found that there was a significant fixed effect of intercept ($z = -7.8, p < .001$) and of practice opportunity ($z = 3.4, p < .001$). Finally, in modeling the use of Strategy 3, we found that the random effect of practice opportunity was invariant across the different problems and model fit was improved by removing it. After removal, we found a significant fixed effect of intercept ($z = -11.2, p < .001$) as well as a significant effect of the DM condition ($z = 3.0, p < .005$). Figure 2, while not capturing the full nuanced relationship between the different factors and strategy assignments, offers some reference for understanding the model results.


**Figure 2:** The average usage of strategies across practice opportunity for the two conditions. The solid vertical and dashed lines indicate the average point of mastery for DM (M=39,SD=11.5) and DI (M=41, SD 14).

In conclusion, our approach enabled us to build a picture of the strategies students use and how they change over time. Our results suggest that strategy use in the DM and DI conditions is similar, with differences appearing after higher performing students begin to reach mastery. This suggests that students who do not need help and are not exposed to the experimental manipulations have similar strategies across the two conditions. In contrast, students who achieve mastery more slowly ask for more hints, receive the manipulation, and consequently vary in their use of strategy. Future work might benefit from focusing on students that take longer to reach mastery and from coding problem type.

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# Predicting Performance on Dichotomous Questions: Comparing Models for Large-Scale Adaptive Testing

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## ABSTRACT

Computerized adaptive testing (CAT) is a mode of testing which has gained increasing popularity over the past years. It selects the next question to ask to the examinee in order to evaluate her level efficiently, by using her answers to the previous questions. Traditionally, CAT systems have been relying on item response theory (IRT) in order to provide an effective measure of latent abilities in possibly large-scale assessments. More recently, from the perspective of providing useful feedback to examinees, other models have been studied for cognitive diagnosis. One of them is the q-matrix model, which draws a link between questions and examinee knowledge components. In this paper, we define a protocol based on performance prediction to evaluate adaptive testing algorithms. We use it to evaluate q-matrices in the context of assessments and compare their behavior to item response theory. Results computed on three real datasets of growing size and of various nature suggest that tests of different type need different models.

## Keywords

Adaptive assessment, computerized adaptive testing, cognitive diagnosis, item response theory, q-matrices

## 1. INTRODUCTION

Automated assessment of student answers has lately gained popularity in the context of online initiatives such as massive online open courses (MOOCs). Such systems must be able to rank thousands of students for evaluation or recruiting purposes and to provide personal feedback automatically for formative purposes.

For computerized adaptive tests (CAT), item response theory (IRT) provides the most common models [3]. IRT provides a framework to evaluate the performance of individual questions, called *items*, on assessments [6]. When the intention is more formative, examinees can receive a detailed feedback, specifying which knowledge components (KCs) are mastered and which ones are not [1]. Most of these models rely on a q-matrix specifying for each question the different KCs required to solve it.

We propose a protocol to evaluate adaptive testing algorithms and use it to compare the performances of the simplest IRT model, the 1-parameter logistic one, commonly known as Rasch model, with the simplest Q-matrix model. We expect to answer the following question: given a budget of questions of a certain dataset asked according to a certain adaptive selection rule, which model performs the best at predicting the answers of the examinee over the remaining questions? We managed to get satisfactory results, enabling us to state that no model dominates in all cases: according to the type of test, either the Rasch model or the q-matrix performs the best.

## 2. BACKGROUND AND RELATED WORK

### 2.1 Item Response Theory: Rasch Model

The Rasch model estimates the latent ability of a student by a unique real number $\theta$ modeled by a random variable and characterizes each question by one real number: its difficulty $d$, corresponding to the ability needed to answer the question correctly. Knowing those parameters, the probability of the event "the student of ability $\theta$ answers the question of difficulty $d$ correctly", denoted by *success*, is modeled by:

$$\Pr\{success|\theta\} = \frac{1}{1 + e^{-(\theta - d)}}.$$

The aim is first to optimize the parameters $d_j$ for each question $j$ and $\theta_i$ for each student $i$ in order to fit a given train dataset. Then, throughout the test, a probability distribution over $\theta_i$ is updated after each question answered, using the Bayes' rule.

### 2.2 Cognitive Diagnosis Model: Q-matrix

We now present a model that tries to be more informative about the student's knowledge components. Every student is modeled by a vector of binary values $(a_1, \ldots, a_K)$, called *knowledge vector*, representing her mastery of $K$ distinct KCs. A q-matrix $Q$ [7] represents the different KCs involved in answering every question. In the NIDA model considered here [3], $Q_{ij}$ is equal to 1 if the KC $j$ is required to succeed at question $i$, 0 otherwise. More precisely, we denote by $s_i$ ($g_i$) the *slip* (*guess*) parameter of item $i$. The probability of a correct response at item $i$ is $1 - s_i$ if all KCs involved are mastered, $g_i$ if any required KC is not mastered.

The KCs are considered independent, thus the student's knowledge vector is implemented as a vector of size $K$ indicating for each KC the probability of the student to master it. Throughout the test, this vector is updated using Bayes' rule. From this probability distribution and with the help of our q-matrix, we can derive the probability for a given student to answer correctly any question of the test.

# 3. ADAPTIVE TESTING FRAMEWORK

Our student data is a dichotomous matrix of size $N_S \times N_Q$ where $N_S$ and $N_Q$ denote respectively the number of students and the number of questions, and $c_{ij}$ equals 1 if student $i$ answered the question $j$ correctly, 0 otherwise.

We detail our random subsampling validation method. Once the model has been trained, for each student of the *test* dataset, a CAT session is simulated. In order to reduce uncertainty at most, at each step we pick the question that maximizes the Fisher information and ask it to the student. The student parameters are updated according to her answer and a performance indicator at the current step is computed. To compare it to the ground truth, we choose the negative log-likelihood [5], that we will denote by "mean error".

# 4. EVALUATION

We compared an R implementation of the Rasch model (IRT) and our implementation of the NIDA q-matrix model (Q) for different values of the parameter $K$, the number of columns of the q-matrix. Our algorithms were tested over three real datasets:

**SAT dataset [4].** Results from 296 students on 40 questions from the 4 following topics of a SAT test: Mathematics, Biology, World History and French.

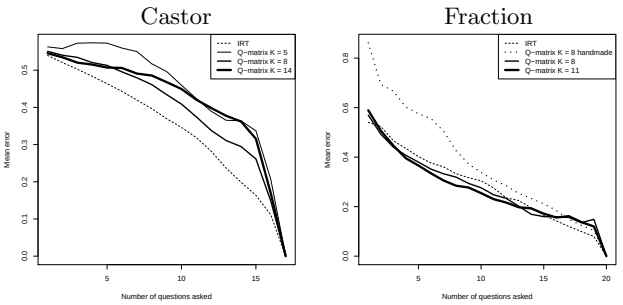
**Fraction dataset [2].** Responses of 536 students to 20 questions about fraction subtraction.

**Castor dataset.** Answers of $6^{\text{th}}$ and $7^{\text{th}}$ graders competing in a K-12 Computer Science contest which was composed of 17 tasks. It is a $58939 \times 17$ matrix, where the $(i, j)$ entry is 1 if contestant $i$ got full score on task $j$, 0 otherwise.

Results are presented in Table 1 where the best performances are shown in bold. As a reference, 1.0 is the error obtained by the trivial algorithm affecting 1/2 to every probability. On the Castor dataset, IRT performs better than Q for any value of $K$ throughout the whole test. On the Fraction dataset, the handmade q-matrix achieves the highest error. In the early questions of the test, Q algorithms for $K = 8$ and 11 perform slightly better than IRT. The Fraction dataset is a calculus test: it requires tangible, easy-to-define knowledge components. Therefore, after a few carefully chosen questions Q can estimate reasonably the performance of an examinee over the remaining ones. On the SAT dataset, IRT achieves the lowest error among all tested algorithms. We also observe that the variance increases throughout the test, probably because the behavior of the algorithm may vary substantially if the remaining questions are from a different topic than the beginning of the test.

# 5. DISCUSSION AND FUTURE WORK

Our comparison of the cognitive diagnosis model with IRT seems to indicate that q-matrices perform better on a certain type of tests; in the Fraction test, there are redundancies from one question to another in order to check that a notion is known and mastered. Conversely, IRT performs better on both the SAT test and Castor contest, which is remarkable given its simplicity. The fact that the SAT test is multidisciplinary explains the difficulty of all considered algorithms in predicting the answers, and the nature of Castor as a contest may require a notion of level instead of knowledge mastery. Therefore, in those cases, we will prefer to use the Rasch model. In order to confirm this behavior, we plan to test our implementation on many other datasets.




| **Castor** | After 4 q. | After 10 q. | After 16 q. |
|---|---|---|---|
| Q $K = 2$ | 0.555 ± 0.004 | 0.456 ± 0.005 | 0.167 ± 0.012 |
| Q $K = 5$ | 0.574 ± 0.004 | 0.460 ± 0.006 | 0.206 ± 0.016 |
| Q $K = 8$ | 0.520 ± 0.004 | 0.409 ± 0.006 | 0.148 ± 0.013 |
| Q $K = 11$ | 0.519 ± 0.004 | 0.462 ± 0.007 | 0.218 ± 0.014 |
| Q $K = 14$ | 0.515 ± 0.003 | 0.449 ± 0.006 | 0.169 ± 0.014 |
| IRT | **0.484 ± 0.003** | **0.346 ± 0.005** | **0.111 ± 0.010** |
| **Fraction** | | | |
| Q $K = 2$ | 0.464 ± 0.012 | 0.326 ± 0.013 | 0.196 ± 0.017 |
| Q $K = 5$ | 0.440 ± 0.011 | 0.289 ± 0.014 | **0.146 ± 0.013** |
| Q $K = 8$ | 0.407 ± 0.011 | 0.276 ± 0.015 | 0.159 ± 0.015 |
| Q $K = 11$ | **0.395 ± 0.009** | **0.255 ± 0.013** | 0.156 ± 0.015 |
| Q $K = 14$ | 0.422 ± 0.009 | 0.274 ± 0.014 | 0.180 ± 0.018 |
| IRT | 0.435 ± 0.012 | 0.304 ± 0.013 | **0.142 ± 0.012** |
| Q* $K = 8$ | 0.596 ± 0.008 | 0.346 ± 0.007 | 0.182 ± 0.007 |
| **SAT** | | | |
| Q $K = 2$ | 0.522 ± 0.007 | 0.417 ± 0.010 | 0.315 ± 0.018 |
| Q $K = 5$ | 0.469 ± 0.007 | 0.365 ± 0.012 | 0.306 ± 0.019 |
| Q $K = 8$ | 0.463 ± 0.007 | 0.367 ± 0.013 | **0.242 ± 0.018** |
| Q $K = 11$ | 0.456 ± 0.008 | 0.364 ± 0.013 | 0.331 ± 0.023 |
| Q $K = 14$ | 0.441 ± 0.007 | 0.350 ± 0.012 | 0.296 ± 0.021 |
| IRT | **0.409 ± 0.008** | **0.285 ± 0.012** | **0.248 ± 0.022** |

Table 1: Mean error of the different algorithms over the remaining questions of the Castor and Fraction datasets, after a certain number of questions have been asked. The dashed curve denotes the Rasch model (IRT), while the curves of growing thickness denote q-matrices (Q) of growing number of columns. The dotted curve in Fraction denotes the handmade q-matrix (Q*) [2].

# 6. ACKNOWLEDGEMENTS

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# The Effect of the Distribution of Predictions of User Models

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## ABSTRACT

We hypothesize that there are two basic ways that a user model can perform better than another: 1.) having test data averages that match the prediction values (we call this the *coherence* of the model) and 2.) having fewer instances near the mean prediction (we call this the *differentiation* of the model). There are several common metrics used to determine the goodness of user models; these metrics conflate coherence and differentiation. We believe that user model analyses will be improved if authors report the differentiation, as well as to include an ordering metric (e.g. AUC/A' or $R^2$) and an error measurement (Efron's $R^2$, RMSE or MAE). Lastly, we share a simplified spreadsheet that enables readers to examine these effects on their own datasets and models.

## 1. INTRODUCTION AND BACKGROUND

One of the goals of many in the online educational community is to more accurately predict whether a student will get the next question correct. In order to predict student responses, algorithms such as Knowledge Tracing [2], Performance Factors Analysis [6], and tabling methods [10] etc. have been developed. (See [3] for a thorough review of various user models.) Looking at only papers presented at EDM 2014, we find more than 6 new models or modifications proposed in the full papers alone [14]. Common metrics used to determine when a model is better than another include AUC/A', RMSE, MAE, and R-squared. There has been some work done (e.g. [1, 4]) looking into what metrics to use and how to interpret them [5, 11].

One can argue that current models predict the probability that a student-problem-instance (hereafter "instance") will be correct. Models such as Knowledge-Tracing ("KT"), Performance Factors Analysis ("PFA"), and their derivatives create a theoretically continuous range of predictions from 0.00 to 1.00. Even tabling models (eg. [10]) may predict a (near) continuous range of values through regressions. We argue that there are two properties of a model that will make it more accurate: 1.) How well a prediction matches the aggregate test-data, and 2.) How well the model can make predictions away from the mean.

### 1.1 Our Definitions

#### *1.1.1 "Coherence"*

Given a large enough data-set, we argue that an accurate model's predictions should match the test data average for a given group of instances. For example, if a model were to identify a group of instances and give that group a predicted value of 0.25, we argue that the model is most accurate when exactly one out of every four students in that condition gets the correct answer. If the model predicts 0.25, but only one out of every ten gets it right, the model's "scores" by most metrics will be improved, however, it is not as accurate as a similar model that groups that same instances together, but predicts 0.10.

#### *1.1.2 "Differentiation"*

A naive model of student knowledge might use the average score from a training dataset and predict with that probability for all instances. Arguably, more complicated user models seek to find reasons *not* to do this. The more features that a model can incorporate to move predictions away from the mean value, the better a model is at not making the mean prediction. We use the term "differentiation" in much the same way as "distribution", but do so to avoid possible confusion with the distribution of the training data.

## 2. METHODS

In order to visualize the impact of differentiation and coherence on the various metrics, we generate not synthetic data, but rather synthetic model outputs. To examine the effect of differentiation, a spreadsheet was created that allows the user to input prediction value, test group average, and number of instances within that group, for up to eleven groups. The spreadsheet then calculates values for AUC, A', $R^2$, Efron's $R^2$, RMSE, and MAE. A publicly shared copy of the spreadsheet can be found at: http://tinyurl.com/kznthk7. In addition to using synthetic data, the results of three models fitted to real data are explored.

## 3. RESULTS AND DISCUSSION

Figure 1 is a plot of the six metrics as a differentiation changes from an exceptionally steep "V" to flat to increasingly steep "A". All "models" have perfect coherence. E.g., when the model predicts 0.20, exactly 2/10 students are correct. From Figure 1, we can see that differentiation plays a role in user model "scores".

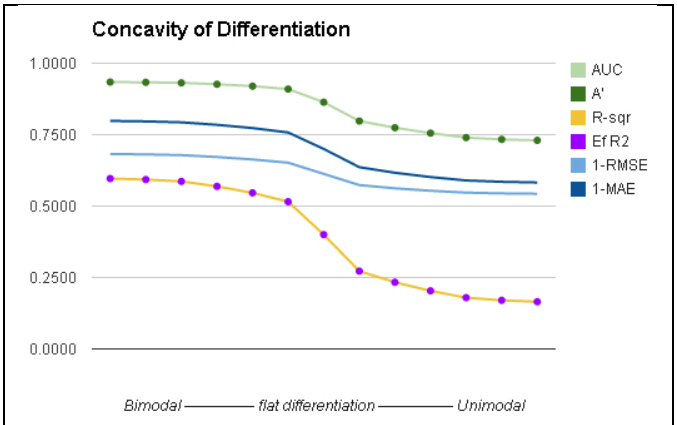


**Figure 1:** Chart of synthetic model outcomes showing the basic effect of changing differentiation.

To see if these ideas have merit on real data, we analyze three different models fitted to the same (~400K instance) dataset. In another paper [16], we have submitted a new user model. In that paper, the new model, called "SuperBins" (SB), is compared to Knowledge Tracing and Performance Factors Analysis, and found to be "better", according to RMSE, $R^2$, and AUC. If we create a frequency table of 11 groups, we will certainly lose precision, but the analysis is useful. To do so, we average the prediction values (according to their frequency) across eleven equal lengths *of prediction values* of the data set; we do the same for the test data

**Table 1:** A coherence-frequency table of results from three knowledge models trained and tested on the same real dataset (80/20). Model results have been averaged across 11 intervals for demonstration purposes. The prediction and test values are the weighted averages of each model within the ranges on the left.

| | **SB** | | | | *KT* | | | | PFA | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Range | **pred** | **test** | **n** | | *pred* | *test* | *n* | | pred | test | n |
| 0.0000 - 0.0909 | **0.08** | **0.00** | **5** | | *n/a* | *n/a* | *0* | | 0.01 | 0.78 | 9 |
| 0.0910 - 0.1818 | **0.14** | **0.13** | **516** | | *0.16* | *0.75* | *4* | | 0.13 | 0.53 | 17 |
| 0.1819 - 0.2727 | **0.22** | **0.23** | **892** | | *0.24* | *0.30* | *64* | | 0.23 | 0.46 | 56 |
| 0.2728 - 0.3636 | **0.31** | **0.32** | **1829** | | *0.33* | *0.28* | *704* | | 0.31 | 0.49 | 168 |
| 0.3637 - 0.4545 | **0.41** | **0.41** | **3235** | | *0.40* | *0.36* | *2565* | | 0.41 | 0.42 | 643 |
| 0.4546 - 0.5454 | **0.50** | **0.51** | **4878** | | *0.51* | *0.48* | *6978* | | 0.50 | 0.49 | 3539 |
| 0.5455 - 0.6363 | **0.60** | **0.60** | **6355** | | *0.60* | *0.61* | *8776* | | 0.61 | 0.59 | 7376 |
| 0.6364 - 0.7272 | **0.69** | **0.69** | **9772** | | *0.69* | *0.71* | *12149* | | 0.70 | 0.70 | 25819 |
| 0.7273 - 0.8181 | **0.79** | **0.79** | **25296** | | *0.78* | *0.78* | *18518* | | 0.77 | 0.78 | 25580 |
| 0.8182 - 0.9090 | **0.86** | **0.87** | **23347** | | *0.87* | *0.85* | *23600* | | 0.87 | 0.87 | 13811 |
| 0.9091 - 1.0000 | **0.97** | **0.97** | **3074** | | *0.95* | *0.95* | *5841* | | 0.97 | 0.96 | 2181 |
| Metrics | **AUC** **0.728** | **$R^2$** **0.145** | **RMSE** **0.406** | | *AUC* *0.710* | *$R^2$* *0.115* | *RMSE* *0.413* | | AUC 0.653 | $R^2$ 0.058 | RMSE 0.426 |
| | **stdev (pred): 0.166** | | | | *stdev(pred): 0.147* | | | | stdev(pred): 0.107 | | |

averages. E.g.., the average prediction value from 0 to 0.0909, as weighted by the frequency of each prediction was found to be 0.08 for the SuperBins model. There were no predictions in that range for KT. There were nine for PFA (eight were right), with an average prediction value of 0.01.

The analysis of coherence shows that, from 0.60 and up, all three models are reasonably accurate; i.e., the predictions closely match the test data averages. However, KT has over-predicted in the three largest of the 6 groups below 0.60. PFA appears to be reasonably consistent; however, one could argue that PFA consistently *under*-predicts in this range. Others [7] have previously reported on KT over-reporting. With this analysis, we can say that PFA has done the worst of the three at moving instances away from the mean. The major reason why SB scores so well against the other two could be its ability to bring more predictions below 0.50, while maintaining coherence.

The easiest way to measure the differentiation of the prediction values might be to report the standard deviation of prediction values. As a way to compare to the "ideal" (for that dataset), we could report either the standard deviation of the test data (0.439), or the standard deviation of the training data (0.440).

# 4. CONCLUSION

There are times when the metrics "scoring" user models disagree; in addition, it may be helpful for a deeper comparison.

We conclude that, if we are to accurately compare knowledge predicting models to each other, we need to look at new metrics, in addition to a mix of old metrics. We do not believe that we are proposing the "ultimate" single metric that will definitively state which model is "better". We are stating that we believe model comparison is improved when it contains (AUC or A', or $R^2$), and (Efron's $R^2$, RMSE, or MAE) and the standard deviation of the predictions. A more thorough comparison might also include coherence-frequency table analysis in an attempt to identify regions of habitual over or under prediction.

# 5. ACKNOWLEDGEMENTS

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# Predicting Student Aptitude Using Performance History

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## ABSTRACT

Many tutoring systems currently in use provide a wealth of information pertaining to student learning over long periods of time. Providing meaningful representations of student performance can indicate levels of knowledge and understanding that can alert instructors to potential struggling students in order to provide aid where it is needed; it is the goal of many researchers to even provide such indication preemptively in order to intervene before students become frustrated when attempting new skills. The goal of this work is to utilize student performance history to provide a means of quantizing student aptitude, defined here as the speed at which a student learns, and then using this measurement to predict the speed at which each student will learn the next skill before beginning. Observing a dataset of 21 skills, we compare two methods of predicting aptitude to majority class predictions at the skill level. Our results illustrate how our proposed methods exhibit different strengths in predicting student aptitude when compared to majority class, and may be used to direct attention to a struggling student before attempting a new skill.

## Keywords

Aptitude, Student Knowledge, Intelligent Tutoring Systems

## 1. INTRODUCTION

Many instructors rely on intelligent tutoring systems (ITS) as a means of extending student learning outside the classroom. Many such systems, such as the ASSISTments system used in this work, provide a wealth of student performance data that is often underutilized. While many systems have focused on and have shown success in predicting next problem correctness, such information is only useful to instructors in a short time-span as students are completing assignments. Furthermore, many of these models rely on latent variables that leas to problems of identifiability [1] when attempting to draw conclusions of student knowledge.

The purpose of this work is to observe and predict student learning rates, referenced throughout this paper as aptitude; this value is expressed as a metric in terms of completion speed (cs), or the number of problems a student needs to complete the assignment (described further in the next section). Such a measure of aptitude in prerequisite skills has shown to be successful in predicting initial knowledge, represented as correctness, on a subsequent skill [2], illustrating that the two concepts are related, but from that work, it is unclear as to whether student aptitude is transitive across skills. In this work, therefore, we strive to answer the following research questions:

1. Do students exhibit similar degrees of aptitude across skills?
2. Are changes in student aptitude across skills predictable?
3. Can a student's aptitude in previous skills be used to construct a reliable prediction of completion speed in a new skill before it is begun?

## 2. METHODOLOGY

The dataset[1] used in this work is comprised of real-world data from PLACEments test data reported from the ASSISTments tutoring system. Data pertaining to 21 unique observable skills was extracted. Here, we define a skill as observable if it contains data from more than 10 unique students, and no less than half of the students must have completed the skill. ASSISTments defines skill completion in terms of 3 consecutive correct answers.

We used a simple binning method implemented in similar research [2][3] to place students into one of five categories based on completion speed in order to represent different levels of aptitude. As aptitude is an independent concept of domain knowledge, a student's entire recorded performance history, regardless of the prerequisite structure, was used to categorize each student. Observing each student's performance over several skills, we used a moving average of student completion rates of each skill ordered from oldest

[1]The original raw dataset can be found at the following link: http://bit.ly/1DVbHdB.

to most recent. Equation 1 displays the formula for this method. For our implementation, we used a value of 0.3 for alpha.

$$A_t = ((1 - \alpha) * A_{t-1}) + (\alpha * V_t) \quad (1)$$

**Table 1: The ranges of completion speed represented by each bin with corresponding the quantized aptitude value.**

| Bin Number | Completion Speed(cs) | Quantized Value |
|---|---|---|
| 1 | $3 \leq$ cs $\leq 4$ | 1 |
| 2 | $4 <$ cs $< 8$ | 0.75 |
| 3 | $8 \leq$ cs | 0.5 |
| 4 | DNF, pcor $\geq .667$ | 0.25 |
| 5 | DNF, pcor $< .667$ | 0 |

Once an average completion speed, in terms of number of problems needed to reach three sequential correct responses, each student is placed in the corresponding bin described in Table 1. Bins 4 and 5 contain students that did not finish (DNF) at least one previous skill, and are instead split based on the average percent correctness (pcor) across all previous skills. The quantized values are chosen arbitrarily to discretize the learning rate that is intended to be represented by each bin.

## 2.1 Experiments

Our first prediction method, referenced as Same Bin Prediction (SBP) in our results section, simply uses the average completion speed of each student's performance history to determine in which bin to place each student. The method then simply uses that bin's quantized value as a prediction for the new skill. Both the SBP and majority class are then compared to each student's actual completion speed, expressed as a quantized bin value, to determine both error rates.

Our second experiment attempts to make predictions again using each student's performance history, but by also taking into account changes in aptitude across skills. Our first experiment assumes that most students will exhibit the same level of aptitude in a new skill as in previous skills. This experiment takes into account the realization that differences in skill difficulty may cause fluctuations in our aptitude measurements. Our second method, referenced as Transitioning Bin Prediction (TBP) in our results section, builds off of the previous SBP prediction by calculating an offset transition value. For example, if half the students in bin 1 (value = 1) remained in that bin for the new skill, while half transitioned to bin 2 (value = 0.75), an offset value of -0.125 would be applied to all predictions of bin 1. A negative offset indicates that many students required more opportunities to complete than normal, while a positive offset indicates the reverse. The prediction is normalized to a value between 0 and 1 to make full use of our quantized values

# 3. RESULTS AND CONCLUSIONS

Table 2 contains the RMSE results of each prediction method divided by each bin of the new skill. The success of the majority class predictions extends across higher aptitude students, while the TBP method provides the most accurate predictions over students in the lower aptitude bins.

**Table 2: Average RMSE of the skill level analysis divided by bin.**

| Bin of New Skill | Majority Class | SBP | TBP |
|---|---|---|---|
| 1 | 0.230 | 0.498 | 0.358 |
| 2 | 0.120 | 0.356 | 0.170 |
| 3 | 0.284 | 0.362 | 0.205 |
| 4 | 0.307 | 0.526 | 0.251 |
| 5 | 0.571 | 0.659 | 0.497 |

**Table 3: Percent correctness at the skill level divided by bin.**

| Bin of New Skill | Majority Class | SBP | TBP |
|---|---|---|---|
| 1 | 0.709 | 0.479 | 0.500 |
| 2 | 0.280 | 0.245 | 0.268 |
| 3 | 0.102 | 0.251 | 0.200 |
| 4 | 0 | 0.029 | 0.129 |
| 5 | 0 | 0.041 | 0.333 |

Each method described in this work exhibited different strengths, including the simple majority class predictions. It is often for the benefit of both teachers and students that a model represent meaningful information beyond the provision of predictive accuracy. The SBP method, for example, while not excelling in any one category, illustrates tendencies of aptitude mobility. Such methods may act as a means of better understanding and developing course structure and skill relationships.

The fact that the proposed prediction methods fail to outperform majority class overall suggests that using all performance history is not by itself a strong predictor of future performance, and is instead dependent to some degree on skill-based attributes. This work ignores prerequisite skill hierarchies available in many tutoring systems and MOOCs, using all previous performance history. Using prerequisite data may lead to stronger predictions, or at the very least provide indications of strong and weak skill relationships. Knowing more information about such skill relationships could provide better indications of when performance history is most useful as a predictor.

# 4. ACKNOWLEDGMENTS

We acknowledge funding for ASSISTments from the NSF (1316736, 1252297, 1109483, 1031398, 0742503, 1440753), the U.S. Dept. of Ed. GAANN (P200A120238), ONR's "STEM Grand Challenges," and IES (R305A120125, R305C100024).

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# Discovering Concept Maps from Textual Sources

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## ABSTRACT

Concept maps and knowledge maps, often used as learning materials, enable users to recognize important concepts and the relationships between them. For example, concept maps can be used to provide adaptive learning guidance for learners such as path systems for curriculum sequencing to improve the effectiveness of learning process. Generation of concept maps typically involve domain experts, which makes it costly. In this paper, we propose a framework for discovering concepts and their relationships (such as prerequisites and relatedness) by analyzing content from textual sources such as a textbook. We present a prototype implementation of the framework and show that meaningful relationships can be uncovered.

## 1. INTRODUCTION

In any given learning setting, a hierarchy of concepts (set by experts) is provided and the learner is expected to follow through these concepts in the specified order, e.g., Table of Contents (ToC), which indicates that concepts appearing in earlier chapters *are* (sometimes *'may be'*) pre-requisites for the concepts discussed in the later chapters. Similarly, end-of-the-book index indicates prominent occurrences of the main concepts (and some relationships between them) discussed in the book. In both the cases, the relationship is static, is designed by the experts and is restricted to the pre-populated list of concepts. As we move towards personalized learning, such a knowledge-driven static elicitation is inadequate. e.g., if the immediate goal of the learner is to understand concepts in chapter L, s/he may only have to go through a select 'n' sections of some chapters till L. Consider another example, if a learner has to know which concepts co-occur or which concepts predominantly occur before a particular concept C and are relevant to the concept C. This information is not easily available either from the ToC or from the "end-of-the-book index".

Concept map is a knowledge visualization tool that represents concepts and relationships between them as a graph. Nodes in the graph correspond to concepts and edges depict the relationship between concepts. In recent years, concept maps are widely used for facilitating meaningful learning, capturing and archiving expert knowledge, and organizing and navigating large volumes of information. In adaptive learning, concept maps can be used to give learning guidance by demonstrating how the learning status of a concept can possibly be influenced by learning status of other concepts [3]. Construction of concept maps is a complex task and typically requires manual effort of domain experts, which is costly and time consuming.

In this paper, we propose a framework for automatic generation of concept maps from textual sources such as a textbook and course webpages. We discover concepts by exploiting the structural information such as table of contents and font information and establish how closely two concepts are related to each other where the relation is defined on how strongly one concept is being referred to/discussed in another. The proposed approach is implemented and applied on several subjects. Our initial results indicate that we are able to discover meaningful relationships.

The remainder of this paper is organized as follows. Related work is presented in Section 2. We discuss our approach of discovering concept maps in Section 3. Section 4 presents some experimental results. Section 5 concludes with some directions for future work.

## 2. RELATED WORK

Concept map mining refers to the automatic or semi-automatic creation of concept maps from documents [4]. Concept map mining can be broadly divided into two stages: (i) concept identification and (ii) concept relationships association. Concept identification is typically done using dictionaries or statistical means (e.g., frequent words). Relation between concepts is typically defined over word-cooccurrences. In our work, we do not use any dictionary of terms. Instead, we rely on structural information such as bookmarks, table of contents, and font information manifested in data sources to discover concepts. Furthemore, when discovering relationships, we not only look at co-occurence of concepts within a sentence but scope it to larger segments such as a section and chapter.

## 3. GENERATION OF CONCEPT MAPS

Concept maps should provide support for modular nature of the subject matter and the interconnections between knowledge modules (concepts). Formally, a concept map can be defined as a tuple $< C, R, L >$ where $C = \{c_1, c_2, \ldots, c_n\}$ is a set of concepts; $L = \{l_1, l_2, \ldots, l_k\}$ is a set of labels. $R = \{r_1, r_2, \ldots, r_m\} \subseteq C \times C \times L$ is a set of relationships among concepts. Each relation $r_j = (c_p, c_q, l_s) \in R, p \neq q, 1 \leq p, q \leq n, 1 \leq j \leq m, 1 \leq s \leq k$ defines a relation-

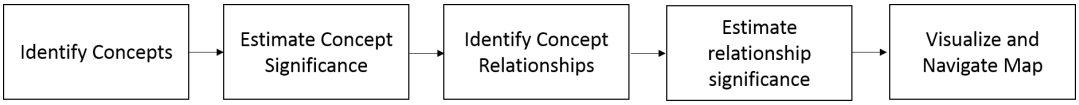

Figure 1: Approach Overview

ship between concept $c_p$ and $c_q$ which is labeled $l_s$. Optionally each relation $r_j$ can also be associated with a weight $w_j \in \Re^+$. Figure 1 presents an overview of our approach and is comprised of five steps:

**1. Identify Concepts:** We exploit structural and font information such as bookmarks, table of contents, and index (glossary) in e-textbooks, and headers and font information in html pages for this step. Text processing such as tokenizing, stemming, and stop word removal are then applied. Concepts are identified as either individual words or n-words ($n > 1$)

**2. Estimate Concept Significance:** We estimate the significance of concepts automatically using different criteria: (i) frequency of occurrence (frequent concepts are more significant than infrequent ones) (ii) importance of a concept w.r.t the examinations/evaluations and (iii) font related information (larger font concepts are more significant than smaller fonts). The three criteria mentioned above can be grouped together using weights.

**3. Identify Concept Relationships:** Several types of relationships can be defined among concepts, e.g., superclass-subclass (one concept is *more general* than another), pre-requisite relation (a concept A is said to be a pre-requisite for concept B), etc. The table of contents in a document directly gives a (partial) hierarchical structure among concepts. Apart from the hierarchical relationship, concepts can also be horizontally related e.g., *relevant to* and *mentioned by* as discussed in [1]. We consider the *mentioned by* relation, which is used to express the fact that two concepts are related of the type A *refers-to* B, A *discusses* B, A *mentions* B. Note that *mentioned by* is an *asymmetric* and *not necessarily transitive* relation.

**4. Estimate Relationship Significance:** Relationship significance is estimated using *term co-occurrence* as a basis. For each concept, in the pages where it manifests, we also estimate which other concepts manifest in those pages and how often do they manifest. The degree of relatedness is obtained by the frequency at which the concept is used, e.g., if concept $c_j$ manifests $f_j$ times when describing concept $c_i$ and if $f_i$ is the frequency of occurrence of concept $c_i$, then the weight of the edge between $c_j$ and $c_i$ can be defined as $f_j/f_i$. We also consider normalized weights.

**5. Visualize and Navigate Map:** The concepts and their relationships can be visualized as a graph $G = (V, E)$ where $V$, the set of vertices, correspond to the concepts and $E$, the set of edges, correspond to the relationship between concepts. Nodes and edges can be annotated to provide rich information and enable the navigation of these maps e.g., size of the node can be used to depict the significance of a concept, color of the node can be used to indicate its importance w.r.t student examinations/evaluation, thickness of the node can be used to depict the relative knowledge of the student on the concept. Similarly, edges can be annotated to reveal different kinds of information e.g., thickness of an edge can be used to signify the relatedness between two concepts.

# 4. EXPERIMENTS AND DISCUSSION

We have implemented the proposed framework in Java and Python and tested it on several examples. Visualization of concept maps is implemented using d3js. In this section, we present the results of one such experiment of generating concept maps using the pdf textbook on databases [2]. Figure 2 depicts a subgraph corresponding to the concepts related to relational algebra. We showed the uncovered concept maps

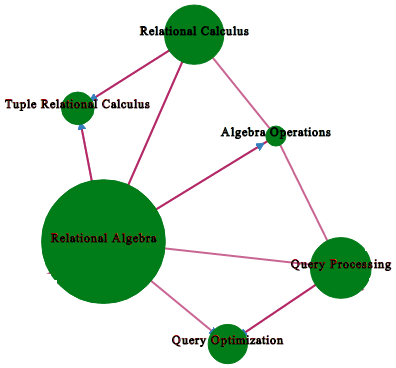

Figure 2: Concept map pertaining to the core concept relational algebra

to a few experts in databases and they mostly agree to the discovered relations. We have applied our approach to several subjects (e.g., operating systems, computer networks etc.) and found that in each of those, we are able to uncover meaningful and important relations. We realize that there is a need for an objective evaluation method to automatically assess the goodness of discovered concept maps, e.g., using gold standard.

# 5. CONCLUSIONS

Generation of concept maps is an important means of supporting deep understanding of a subject matter. In this paper, we presented an approach for identifying concepts and establishing how closely two concepts are related to each other. We believe that these concept maps enable users to quickly get knowledge about the centrality or importance of each concept and its significance in understanding other concepts. As future work, we would like to further enrich the discovered concept maps with additional information based on the user of the application. For example, upon clicking on a node, teachers/faculty can be provided with information such as the average/distribution score of students on this concept in various tests conducted; students can be provided with links to lecture material, questions/solutions asked in previous exams, etc.

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# Integrating Product and Process Data in an Online Automated Writing Evaluation System

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## ABSTRACT
We explore how data generated by an online formative automated writing evaluation tool can help connect student writing product and processes, and thereby provide evidence for improvement in student writing. Data for 12,337 8th grade students were retrieved from the *Criterion* database and analyzed using statistical methods. The data primarily consisted of automated holistic scores on the student writing samples, and the number of attempts on a writing assignment. The data revealed trends of positive association between the number of revisions and the mean writing scores. User logs were sparse to support study of additional behaviors related to the writing processes of planning and editing, and their relation to the writing scores. Implications for enhancing automated scoring based feedback with learner analytics based information are discussed.

## Keywords
Automated scoring, learner analytics, formative writing, automated feedback, process and product

## 1. INTRODUCTION
The *Criterion*® *Online Writing Evaluation Service* [3], is a web-based writing tool that allows easy collection of writing samples, efficient scoring, and immediate feedback through the *e-rater*® automated essay scoring (AES) engine [2].

*Criterion* supports essay writing practice with a library of more than 400 essay assignments in multiple discourse modes (expository and persuasive) for students in elementary, middle, and high schools as well as in college. These prompts are used for classroom writing assignments and their scoring is supported by AES models. As a formative writing tool, *Criterion* has several features to facilitate writing processes and help learners improve their writing. These include planning templates, immediate feedback, multiple attempts to revise and edit, and resources such as a Writer's Handbook, a spell checker, a thesaurus and sample essays at different score points. The holistic scoring and feedback in *Criterion* is supported by *e-rater*. The analyses of errors and feedback are available for linguistic features of grammar, usage, mechanics, style and organization and development. There are limited studies on the pedagogical effectiveness of *Criterion* and AES systems in general [1, 5], and examining relation of product and process data for assessing writing quality [4]. Our motivation for this study was to analyze product data (holistic scores) in relation to process data (for revising) to provide evidence for effectiveness of the tool and automated feedback and scoring for improving writing. We report the observed trends for association between the two types of data, the cautions warranted in making strong claims based on these data, and the next steps.

## 2. METHODS
Data were extracted for 8th grade students for one school year from the *Criterion* database. The data spanned 295 days, and included 12,337 students from 183 schools; a total of 95,261 attempts were made across 41,473 assignments on 2,447 prompts.

Mean holistic scores by the *assignment* and by the *attempt* were examined to relate the revising behavior with improvement in writing scores. The results from the assignment and the attempt level analyses can easily be preliminary indicators of the tool's usefulness and effectiveness, and enhanced data logging capabilities of student actions in the system can provide richer information on writing processes.

## 3. RESULTS
### 3.1 Assignment Level
Of the 12,337 students who submitted assignments in the system, a little over 4,000 students submitted only one assignment over the full school year. About half of the students (N=6,663) completed a total of 2 to 6 assignments. A handful of students submitted as many as a total of 15 assignments. We identified groups of students who completed 2 to 5 unique assignments over the period of the full school year (the Ns were small for groups of students completing 6 or more assignments and hence excluded). The assignments in *Criterion* can be scored on a 4-point or a 6-point scale. We analyzed the data for responses evaluated on a 6-point scale only, and hence after filtering out the responses scored on the 4-point scale, the remaining sample size was 5,235 students. It should be noted that within each assignment, a user can have multiple attempts.

Figures 1a and 1b present the trends for the mean writing scores across assignments for the different groups based on the first attempt and the last attempt on the assignment, respectively. We draw quite a few interesting observations from the two graphs. The mean writing scores on the last attempt are always higher than the mean writing scores on the first attempt across all the assignments. Further, the mean writing score on the last attempt of the first assignment (first data point in Figure 1b) is almost always higher than the mean writing score on the first attempt of the fifth assignment (last data point in Figure 1a), suggesting that multiple attempts on an assignment is associated with a higher mean writing score than the total number of assignments completed by a user in the system.

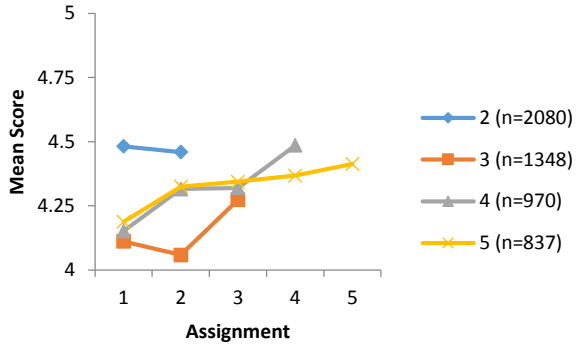


**Figure 1a. Mean holistic score on the first attempt, per ordered assignment conditioned on total number of assignments**

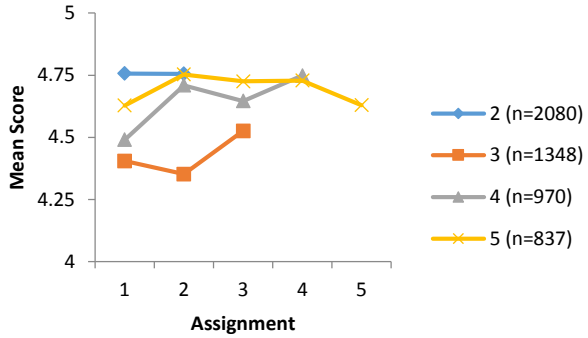


**Figure 1b. Mean holistic score on the last attempt, per ordered assignment conditioned on total number of assignments**

## 3.2 Attempt Level

After filtering for responses evaluated using 6-point scale, a total of 34,196 completed attempts were recorded in the system over the full school year. 15,841 of these attempts were instances of one attempt only per assignment. A few students completed as many as 10 attempts on an assignment which is the maximum limit by default. We identified groups of 2 to 6 attempts per assignment that included 16,846 instances (the Ns were small for groups of 7 or more attempts and hence excluded). Figure 2 presents the trends of mean writing scores across attempts for the different groups. The uniform trend of increase in the mean writing scores across the attempts for all the groups once again suggests that the revising process is associated with gains on the writing scores.

# 4. LIMITATIONS

The data on which trends have been reported were derived from a non-experimental setting. Large groups of students completed only one assignment or submitted only one attempt. Students who did engage in multiple assignments and/or multiple attempts hint at self-selection. The data are unbalanced and highly non-normal, and hence do not support rigorous statistical analyses but rather only lend themselves to exploration for trends.

Server log files were sparse for digital traces of student actions to support nuanced analyses of the corresponding writing processes. Information on students such as background variables is

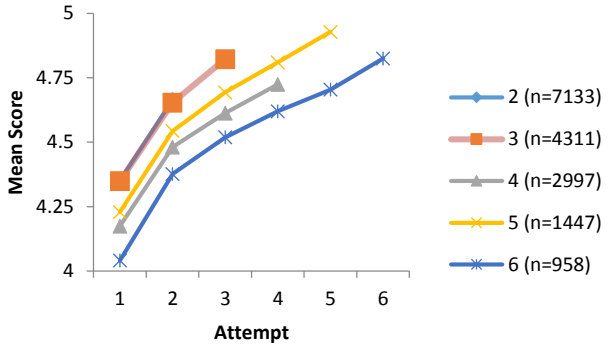


**Figure 2. Mean holistic score, per ordered attempt by total number of attempts**

not available in the system. We analyzed data for only one grade level, but it would be of interest to examine if and how the trends based on product data as well as students' usage of the system vary across the different grade levels. Similar analyses of linguistic feature values or error analyses on the product can provide further insight into the process of improvement in student writing.

# 5. CONCLUSION

Data currently available from *Criterion* are primarily on the work product; limited data are available for writing processes based on user actions. The additional data from our ongoing work on extension of *Criterion* to capture extended learner usage data will support further analysis of associations between the writing product and the processes, and their relation to change in student writing ability over time. This work has implications for extending application of automated scoring systems in formative contexts with the potential to provide richer feedback on product as well as processes, and enhancing the validity argument for automated scores as supported by response process data.

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# Application of Sentiment and Topic Analysis to Teacher Evaluation Policy in the U.S.

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## ABSTRACT

We examine the potential value of Internet text to understand education policy related to teacher evaluation. We discuss the use of sentiment analysis and topic modeling using articles from the New York Times and Time Magazine, to explore media portrayal of these policies. Findings indicate that sentiment analysis and topic modeling are promising methods for analyzing Internet data in ways that can inform policy decision-making, but there are limitations to account for when interpreting patterns over time.

## Keywords

Teacher evaluation, topic modeling, sentiment analysis

## 1. MOTIVATION

In the United States and abroad, teacher evaluation systems are increasingly becoming a common component of school reform efforts. Because teacher effectiveness is central to improving student learning, education policy in the U.S. has targeted teacher evaluation systems, with the rationale that evaluating teachers will lead to improved effectiveness. The result is an often contentious debate among researchers, educators and policy-makers about the utility of these systems in improving teacher effectiveness. Issues include which performance measures to use, how to collect and combine the data, and how it will be used with teachers.

A significant arena for debate about education policy, including teacher evaluations, occurs via the Internet. As the 2013 report "Social Media and Public Policy" notes [Leavy, 2013], use of data produced by Internet users may be useful in understanding policy issues and social problems, and perhaps ultimately, can provide insight to enable governments to develop more informed and better policy. The data may lead to better understanding of policy impact, and could potentially inform the different organizations that deliver public services, such as public education systems.

Given the potential value of Internet data to inform policy, our aim for this study is to conduct a preliminary analysis of publicly available Internet data from media outlets reporting on U.S. education policy, to evaluate what might be learned from such data that could inform policy-making regarding teacher evaluation. Therefore, we narrowed the focus to two popular media sources that cover national as well as local education policy – the NY Times, and Time Magazine–to analyze public sentiment and topics of concern regarding education policy focused on teacher evaluation. Given the increased emphasis on teacher evaluations over the past decade, we gathered data from 2004 - 2014. We used two approaches for analyzing data from the online media articles: a topic modeling approach [Blei, 2012] and sentiment analysis [Liu, 2010, pan, ]. The research questions we addressed included:

1. What trends, if any, exist in public sentiment regarding teacher evaluation policy over the past decade?
2. What are the recurring topics most associated with media portrayal of teacher evaluation policies?

## 2. DATA COLLECTION AND ANALYSIS

We used the NY Times API and Time Magazine search query using "teacher evaluation" as the search term. Because there are no tools for collecting the full NY Times and Time Magazine articles,we scraped the websites after retrieving the relevant URLs. We retrieved a total of 348 articles on "teacher evaluation" from the NY Times during the period 2004 to 2014, and 292 articles from Time Magazine during the same period. We examined the articles for their relevance and removed those for which the focus was not primarily on teacher evaluation. The resulting dataset included 171 NY Times articles from 2009 to 2014, and 45 Time Magazine Articles from 2010 to 2014.

For the current study, we used the "topicmodels" package in R [Grün and Hornik, 2011]. We compared two variants of topic modeling: latent dirichlet allocation (LDA) and Correlated Topic Models (CTM). Both approaches are based on Blei [Blei et al., 2003, Blei and Lafferty, 2007]. To determine the number of topics to specify, we used the perplexity score.For our analyses, we specified a ten topic model, i.e. we set $k = 10$ to interpret results. In addition to the entropy measure, we used word clouds to display and make

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(a) Topic 1 (b) Topic 2

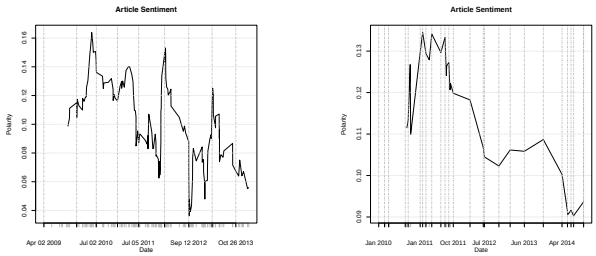
Figure 1: Word clouds for generated from NY Times articles.

sense of the topics generated from topic models. Figure illustrates word clouds for topic 1 and 2 generated from the New York Times articles. The topics that appeared to dominate the NY Times reporting included focus on federal requirements for teacher evaluation systems (e.g., reliance on student test data and relatedly, value-added models, for evaluating teachers); the impact of those requirements on teachers at both a federal and local (NYC) level, e.g., accountability, merit pay, lay offs and budgets; and the reaction of teacher unions to federal and local legislation (e.g., Chicago's teachers strike). In Times Magazine, where coverage of teacher evaluation policy was often combined with coverage of other federal education policies, the focus appeared to be on student achievement testing; changing education policies by the Obama Administration and in Washington DC, led by DC's former Chancellor of Education Michelle Rhee; and policy proposals during the 2012 presidential campaign. Teacher union reactions to teacher evaluation policy were also of focus, including the Chicago teachers strike.

We use the Natural Language Toolkit (NLTK) [Bird, 2006], a leading python platform to harvest textual data. The sentiment analysis tool in NLTK uses naive Bayes classifiers trained on both twitter sentiment as well as movie reviews. In Figure 2, a time series of the sentiment polarity of both the New York Times (left) and Times Magazine (right) articles is presented for 2009 - 2014. We used a simple moving average to plot the sentiment over time. In these graphs, we observe a similar trend in both the NY Times and Times Magazine articles. In both, we see somewhat similar peaks and troughs, as well as a similar trend of decreasing positive sentiment from 2010 to 2014.

## 3. DISCUSSION & FUTURE WORK

A number of federal and local (to NY) events took place over that period of time, that could be related to the sentiment trends. Nationally, the Obama Administration's Race To the Top (RTTT) legislation was initiated in July 2009, which among other policies, required states to develop and implement teacher evaluation systems that included student achievement as a "significant" component of a teacher's effectiveness rating. In 2010, RTTT was rolled out and the states awarded funding were announced. The state of New York was awarded 700M dollars in August, 2010. A result of this legislation was a contentious battle between lawmakers and the teachers union over the details of the evaluation system, among other policies. In September 2012 in Chicago, teachers took to the streets and went on strike against a range of education policies, including the teacher evaluation system that was to be put in place. NYC and the teachers union settled on an evaluation system in March, 2013.




(a) Topic 1 (b) Topic 2

Figure 2: Article Sentiment over Time

In the case study for this paper, issues regarding the use of student test scores for evaluating teachers; the response of teacher unions to federal and local teacher evaluation system requirements; and the budgets for implementing these systems were just some of the more prominent issues reflected in the results. Our ultimate goal is to advance the understanding of the impact of new policies on the well-being of public schools and teachers. While the methodology is promising, it needs to be harnessed through a useful visualization interface to facilitate the exploration and analysis of the topics produced to make it more useful to leverage in decision making. We acknowledge that there are limitations and potential problems with these approaches. A known challenge is choosing the granularity level of the topics that is related to the number of topics $k$ provided as a parameter. A second challenge is in the interpretation and labeling of the derived topics that require a manual human intervention. In some cases, what is rated as positive or negative analytically might not reflect how human raters would code those words. Moreover, in our example, although sentiment appeared to decline in the negative direction, it still remained on the positive end of the polarity continuum.

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# Defining Mastery: Knowledge Tracing Versus N- Consecutive Correct Responses

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## ABSTRACT
Knowledge tracing (KT) is well known for its ability to predict student knowledge. However, some intelligent tutoring systems use a threshold of consecutive correct responses (N-CCR) to determine student mastery, and therefore individualize the amount of practice provided to students. The present work uses a data set provided by ASSISTments, an intelligent tutoring system, to determine the accuracy of these methods in detecting mastery. Study I explores mastery as measured by next problem correctness. While KT appears to provide a more stringent threshold for detecting mastery, N-CCR is more accurate. An incremental efficiency analysis reveals that a threshold of 3 consecutive correct responses provides adequate practice, especially for students who reach the threshold without making an error. Study II uses a randomized- controlled trial to explore the efficacy of various N-CCR thresholds to detect mastery, as defined by performance on a transfer question. Results indicate that higher thresholds of N-CCR lead to more accurate predictions of performance on a transfer question than lower thresholds of N-CCR or KT.

## Keywords
Intelligent Tutoring System, Knowledge Tracing, Mastery Learning.

## 1. INTRODUCTION

Intelligent tutoring systems are known for their ability to personalize the learning experience for students. One way that learning is individualized is by providing just the right amount of practice to meet the student's needs. Determining the correct amount of practice is critical because over-practice might bore students and take an un-necessarily long time, while under-practice might not provide enough opportunities for a student to learn a skill. To determine the correct amount of practice, systems must identify the point in time when students have learned the skill, otherwise referred to as reaching mastery.

Defining mastery may vary between systems. One measure of mastery includes next problem correctness, another is performance on a transfer question, and yet another is performance on a delayed retention test. Some systems rely on knowledge tracing (KT) [1-2], others use a predetermined number of consecutive correct responses (N-CCR) [3, 4, 9}. In each case, mastery status is used by the system to determine the end of an assignment.

## 2. METHODOLOGY
This research is comprised of two studies, the first was a data analysis of large data sets provided by ASSISTments, and the second was a randomized controlled trial. Study I of the present study leverages data generated by an intelligent tutoring system to explore the ability of N-CCR and KT to detect mastery. Mastery will be measured by next problem correctness. Additionally, an incremental efficiency analysis will also be presented that sheds light on the number of additional questions students must answer to reach a given threshold.

Next problem correctness is arguably a weak measure of mastery as slips are possible. A measure of more robust learning is performance on a transfer task [10]. Therefore, in Study II, a randomized-controlled trial was conducted to compare the accuracy of different potential thresholds of number of consecutive correct responses. This data was then used to further explore KT predictions, compared to N-CCR in an attempt to determine which method should be used in intelligent tutoring systems who rely on mastery to determine amount of practice.

## 3. RESULTS

### 3.1 NCCR
When mastery is defined by next problem correctness, results indicate that 3-CCR is an adequate threshold for accurately detecting mastery. Table 1 shows that 80% of students who answer three questions correctly, go on to answer the fourth and fifth correctly as well.

**Table 1: Percentage of students with each response combination of the fourth and fifth question following 3-CCR.**

| 3 Consecutive No Errors | | Fourth Question | |
|---|---|---|---|
| | | Incorrect | Correct |
| Fifth Question | Incorrect | 1.8% (5) | 9.8% (24) |
| | Correct | 8.4% (28) | 80.0% (228) |

When mastery is defined by performance on a transfer question, results indicate that 5-CCR (Table 3) more accurately detects mastery than 3-CCR (Table 2). Accuracy is defined by the percentage of students who met the threshold and were successful on the transfer questions combined with the percentage of students who failed to meet the threshold and answered the transfer questions incorrectly. Identifying students who met the threshold yet answered the transfer incorrectly are considered false positives and students who answered the transfer question

correctly yet failed to meet the threshold are considered false negatives.

**Table 2: Student performance on transfer question based on 3-CCR.**

| Percent(Number) of students | Threshold Met | Threshold Not Met |
|---|---|---|
| Transfer Correct | 46%(17) | 0% |
| Transfer Incorrect | 43%(16) | 11%(4) |

**Table 3: Student performance on transfer question based on 5-CCR.**

| Percent(Number) of students | Threshold Met | Threshold Not Met |
|---|---|---|
| Transfer Correct | 43%(16) | 8%(3) |
| Transfer Incorrect | 19%(7) | 30%(11) |

## 3.2 KT

When mastery is defined by next problem correctness, results indicate that KT is comparable to 3-CCR in accurately detecting mastery for students who do not make an error (Table 4).

**Table 4: Accuracy of KT detecting mastery for students who answered three consecutive questions correctly without an error. (n=287)**

| | Threshold Met (>95%) | Threshold Not Met (<95%) |
|---|---|---|
| Next Question Correct | 80.5% (231) | 9.4% (27) |
| Next Question Incorrect | 8.4% (24) | 1.7% (5) |

When mastery is defined by performance on a transfer question, results indicate that KT is comparable to 3-CCR, but less accurate than 5-CCR (Table 5).

**Table 5: . Student performance on the transfer question based on KT's 95% threshold.**

| Percent(Number) of students* | Threshold Met | Threshold Not Met |
|---|---|---|
| Transfer Correct | 42%(31) | 7%(5) |
| Transfer Incorrect | 39%(29) | 12%(9) |

## 3.3 Incremental Efficiency Analysis

Using the data generated from the students reaching the 5-CCR threshold, we determined how many additional questions were required to reach each incremental threshold. This provides insight into the tradeoff between potential increased mastery detection and time consumption, as measured by number of questions completed. 3-CCR is a sufficient threshold, as over 90% students go on to reach the higher threshold. Of the students who reached the final 5-CCR threshold, 90% of them reached it without an error. Those who made at least one error, tended to reach the threshold with N attempts following the error. This suggests that the error was a slip.

# 4. DISCUSSION

Accurately predicting or detecting mastery status is critical to intelligent tutoring systems, because the amount of practice provided to students depends on this. An overly cautious prediction will lead to unnecessary practice (false negatives), while less strict criteria will not provide enough (false positives). N-CCR, specifically 3-CCR, is a simple, yet effective way to determine mastery within an ITS. This threshold has been found to predict next problem correctness with at least 80% accuracy. However, when predicting performance on a transfer task, a higher threshold (5-CCR) is more effective. Both thresholds of N-CCR were more accurate than the more complicated method, knowledge tracing, when determining mastery.

# 5. ACKNOWLEDGMENTS

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# A Toolbox for Adaptive Sequence Dissimilarity Measures for Intelligent Tutoring Systems

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## ABSTRACT

We present the *TCS Alignment Toolbox*, which offers a flexible framework to calculate and visualize (dis)similarities between sequences in the context of educational data mining and intelligent tutoring systems. The toolbox offers a variety of alignment algorithms, allows for complex input sequences comprised of multi-dimensional elements, and is adjustable via rich parameterization options, including mechanisms for an automatic adaptation based on given data. Our demo shows an example in which the alignment measure is adapted to distinguish students' Java programs w.r.t. different solution strategies, via a machine learning technique.

## 1. INTRODUCTION

Systems for computer-aided education and *educational data mining* (EDM) often process complex structured information, such as learner solutions or student behavior patterns for a given learning task. In order to abstract from raw input information, the given data is frequently represented in form of sequences, such as (multi-dimensional) symbolic strings, or sequences of numeric vectors. These sequences may represent single solutions, as in some *intelligent tutoring systems* (ITSs) [2, 6]; or may encode time-dependent data, like learner development or activity paths [1, 7].

Once a meaningful sequence representation is established, there are many possibilities to process sequential data with existing machine learning or data mining tools. A crucial component for this purpose is a (dis)similarity measure for pairs of sequences, which enables operations like finding closest matches in a given data set, clustering all instances, or visualizing their neighborhood structure [5]. One particularly flexible approach to determine the (dis)similarity of sequences is *sequence alignment* [3].

For applications in the context of EDM and ITSs, sequence alignment offers two key features: On the one hand, the structural characteristics of sequences are taken into account, while calculation remains efficient, even with complex parameterization options. On the other hand, alignment provides an intuitive matching scheme for a given sequence pair, since both sequences are extended, so that similar parts are *aligned*. However, we believe the full potential of sequence alignment is rarely utilized in EDM or ITSs.

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## 2. ALIGNMENT TOOLBOX

We present the *TCS Alignment Toolbox*[1], an open-source, Matlab-compatible Java library, which provides a flexible framework for sequence alignments, as follows:

**Multi-dimensional input sequences** are possible, such that every element of the sequence can contain multiple values of different types (namely discrete symbols, vectors or strings).

A **variety of alignment variants** is implemented, covering common cases, such as *edit distance*, *dynamic time warping* and *affine sequence alignment* [3].

The **parameterization** of the alignment measure is defined by costs of operations (replacement, insertion, and deletion) between sequence elements, which can be adjusted by the user, or left at reasonable defaults. Users can even plug in custom functions to yield meaningful problem-specific costs.

A **visualization feature** displays the aligned sequences in a comprehensive HTML view, as well as the dissimilarity matrix for an entire set of input sequences.

An approximate **differential of the alignment functions** w.r.t. its parameters is provided, which enables users to automatically tune the rich parameter set with gradient-based machine learning methods, e.g. to facilitate a classification [4].

**In this demo**, we present an example for a set of real student solutions for a Java programming task: After programs are transformed to sequences, the parameters of an alignment algorithm are automatically adapted to distinguish between different underlying solution strategies, and the resulting alignments are visualized. Thus, the adapted measure improves the classification accuracy for the given data.

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# Carnegie Learning's Adaptive Learning Products

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## ABSTRACT

Carnegie Learning, developers of the widely deployed Cognitive Tutor, has been working on several new adaptive learning products. In addition to demoing the Cognitive Tutor, an educationally effective intelligent tutoring system for mathematics that has been the subject of a great deal of educational and educational data mining research, we demo two iPad apps, an equation solving app that recognizes hand writing and a game for developing math fluency using fraction comparison tasks. A wide variety of datasets over the years have been analyzed from the Cognitive Tutor, and in recent years several new features have been introduced that may be important to researchers. This demonstration will introduce those unfamiliar with Cognitive Tutor to the system and serve as a refresher for those unaware of recent developments. It will also introduce our new iPad apps to researchers.

## Keywords

Cognitive Tutor, intelligent tutoring systems, real-world implementation, mathematics education, educational games, iPad, mathematics fluency, fractions, decimals, multiple representations, equation solving, cognitive modeling

## 1. COGNITIVE TUTOR

Carnegie Learning's Cognitive Tutor (CT) [7] is one of the most widely used intelligent tutoring systems (ITSs) in the world, with hundreds of thousands of users in middle schools, high schools, and universities throughout the United States and abroad. CT has been demonstrated effective in one of the largest randomized trials of its kind involving educational software, providing substantive and significant improvement in learning gains, compared to a control group using traditional textbooks, in the second year of implementation for a large cohort of high school students from diverse regions of the United States [6].

A variety of datasets providing information about learner interactions with the CT have been made available by Carnegie Learning via the Pittsburgh Science of Learning Center LearnLab's DataShop repository [5]; the learning sciences community and others have used these and other datasets in a correspondingly wide variety of educational and educational data mining (EDM) research projects, including many throughout the history of the *International Conference on EDM*. Some datasets used are from relatively older versions of the CT software. Even relatively old data can enable discovery and insight into issues likes improving cognitive models and improving the predictive accuracy of models of student behavior, but as can be expected, CT, like any other piece of widely deployed software, evolves over time. Elements of this evolution may impact the types of substantive conclusions that can be drawn from CT data or contribute to creative new modeling approaches and target educational phenomena. In this demonstration, we will provide an overview of the basic interface of the CT and its approach to mathematics education as well as highlighting several newer features that have been deployed in the last few years. We will also, as appropriate, highlight several nuances and issues that arise when CT and Carnegie Learning's middle school math product based on CT, called MATHia, are deployed in real-world classrooms. Some of these nuances and issues may have important implications for how EDM analyses are conducted using CT data.

Our demo will provide a general overview with CT and focus on the following features of CT and MATHia: lesson content and manipulatives, step-by-step examples, review mode, promotion & placement changes, interest area & name customization (MATHia), and math "Fluency Challenge" Games (MATHia).

## 2. AN IPAD RACING GAME TO ENHANCE MATH FLUENCY

Developers at Carnegie Learning are also developing an iPad car racing game (Figure 1) to enhance math fluency for tasks like comparing fractions. The game integrates with the Hyper-Personalized Intelligent Tutoring (HPIT) system [4], a distributed web service plugin architecture that enables "on-the-fly" personalization based on (non-)cognitive factors. Gameplay is predicated on learners rotating the iPad to direct a car to the right, left, and in between "flags" that display values of fractions (or decimals, etc.) based on whether a value displayed on the car is greater than or less than values displayed on flags, creating a sort of number line on the game's "road."

Time pressure, introduced via a countdown clock, serves gameplay and cognitive functions. Time pressure on tasks like fraction comparison will encourage learners to develop dynamic

strategies to carry out such tasks (e.g., imagining slices of a pie vs. finding common denominators). Learners' successful adoption of diverse strategies is a marker of math fluency that will decrease working memory load on such tasks. We posit that fluent math learners are more likely to succeed in more advanced math.

Game content and behavior are configurable to allow education researchers, without programming, to rapidly prototype and build a range of experiments. Researchers can, for example, specify number sequences encountered as well as "level" structure that groups similar content together. We support in-game feedback (e.g., text displayed after questions, pausing after incorrect actions for review) via an XML run-time scripting engine.


**Figure 1. Sample problem: The player's value is 1/9, and since 1/9 < 1/7 the player moves to the left lane before passing the flags.**

A conceivable experiment uses multiple graphical representations to develop fluency [1]. Curricula can begin with a level containing common numerator fractions, then common denominator fractions, and then mixed fractions. Scripting provides for dynamic annotations of each fraction with pie slice or number line images above flags to help players visualize the comparison (e.g., loading web images and reacting to each level's content). Help can be offered only when a student is struggling (e.g., making at least one error), and HPIT can drive A/B tests, distributing content/scripts to control and experimental groups.

## 3. AN IPAD APP FOR EQUATION SOLVING

Researchers at Carnegie Learning are also working on an iPad app to support math equation solving practice. The app combines technology from CT with an interface that recognizes human handwriting (Figure 2). Following the lead of CT and building on earlier work on handwriting-based tutors [2], the app provides context sensitive feedback and hints while also providing the capability to "trace" student knowledge using, like CT, the Bayesian Knowledge Tracing (BKT) [3]. Integrating the app with HPIT provides the ability to adapt to cognitive factors (e.g., BKT) and non-cognitive factors (e.g., grit, self-efficacy, etc.).

The app will advance student learning about equation solving and our understanding of that learning in at least two ways. First, handwriting recognition will provide for an experience that is more akin to a traditional "pencil and paper" approach to equation solving practice than the approach provided by CT in which actions like "combining like terms" to manipulate sides of an equation are chosen from a drop-down menu. Second, logging such equation solving will provide rich data to better understand the learning of equation solving in this more natural setting.

Moving away from the menu-based CT approach introduces challenges. Handwritten equation solving allows for a variety of math errors that simply are not allowed by CT. Further, new knowledge components (or skills) must be introduced to the cognitive/skill model for this app; skills, for example, related to the understanding of equality (e.g., that the equation symbol must persist from line to line as the student works toward an equation solution) should be tracked. Such skills are not tracked in CT's menu-based equation solving because the equation symbol persists from step-to-step in CT. Comparing skill models and learner performance across platforms is a key area for future research; translation of skill models across platforms is an important issue as technology permeates teaching and instruction.

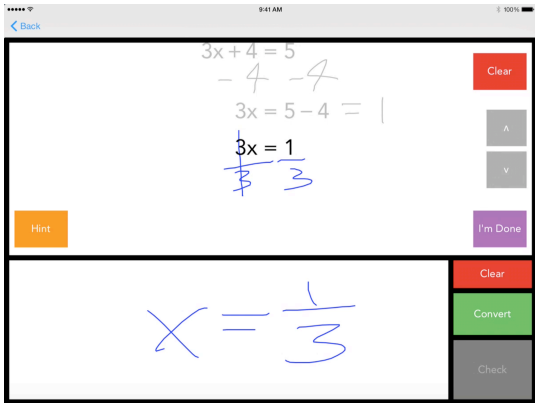


**Figure 2. A user solves the equation 3x+4 = 5, writing the final step of the equation as x = 1/3.**

## 4. ACKNOWLEDGMENTS

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# SAP: Student Attrition Predictor

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## ABSTRACT

Increasing rates of student drop-outs with increase in popularity of Massive Open Online Courses (MOOCs) makes predicting student attrition an important problem to solve. Recently, we developed an algorithm based on artificial neural network for predicting student attrition in MOOCs using student sentiments. In this paper, we present a web-based tool based on our algorithm which can be used by educators to predict and reduce attrition during a course and by researchers to design and train their own system to predict student attrition.

## Keywords

Student Attrition, MOOC, Sentiment Analysis, Neural Network, Educational Data Mining, Student Drop-out

## 1. OVERVIEW

Growing popularity of MOOCs is attributed to their accessibility, scalability and flexibility. With scalability, MOOCs also provide huge amounts of data of student activity which can be used to predict their behavior. We have developed an algorithm to predict student attrition [4] which uses clickstream log and forum posts from MOOCs to extract features such as number of page views, clicks, study sessions, etc. as suggested by previous studies [1, 3, 5, 6]. A unique feature used by our algorithm is student sentiments in forum posts, which is calculated using lexicon-based Sentiment Analysis with SentiWordNet 3.0 [2] as the knowledge resource. The values of all these features for current week are passed as inputs into an artificial neural network, whose output indicates whether student is going to drop out in the following week. Using data from Coursera course 'Introduction to Psychology', we get 74.4% accuracy with false negative ratio of 0.136, leading to a Cohen's Kappa value of 0.435.

## 2. STUDENT ATTRITION PREDICTOR

We present a web tool having three interfaces for educators and researchers to predict and study student attrition.

### 2.1 Sentiment Analysis

Sentiment Analysis of student's forum posts is the unique feature which wasn't used by previous algorithms and improves the Cohen's Kappa value of our algorithm by about 13%. Effectiveness of using sentiment analysis can be seen by the changes in results from neural network when student sentiments are added as input. Our tool also provides option to get the Sentiment score of any student's forum post.

### 2.2 Pre-trained Neural Network

Users have the option to use our pre-trained neural network to predict student drop-out. This allows our tool to be used freely by educators to predict student attrition. Since we predict whether student is going to drop-out in the following week and not whether student is going to complete the course, our algorithm pin-points the exact week when student is predicted to drop-out and thus, educators can use our tool during the course in order to take necessary student-specific actions to prevent or reduce attrition. Apart from MOOCs, Student Attrition Predictor can also be used by traditional classroom setting educators, using digital mediums for study and interaction in schools, which are becoming increasingly popular in recent years.

### 2.3 Design new Neural Network

Our tool also provides an interactive graphical interface for the users to design their own unique neural network. A screenshot of design interface is shown in Figure 1. It shows an input panel, training and testing data panels, a neural network design canvas and a results panel. The process of using Design interface can be divided into 3 phases:-

- **Design:** Users can add their own nodes in the 'Input' panel and select any number of hidden layer nodes. The canvas in the middle of Figure 1 shows the structure of designed neural network.
- **Train:** Training data can be uploaded in 'Training Data' panel and used to train the designed neural network. Options for selecting number of training iterations, classification boundary and learning heuristic (like back-propagation, resilient propagation, etc.) for training Neural Network will also be provided.
- **Test:** After training, individual input values can be entered in the input panel or test data can be uploaded in 'Test Data' panel to get results from trained neural network. 'Results' panel shows metrics such as Accuracy, False Negative Rate and Cohen's Kappa value.

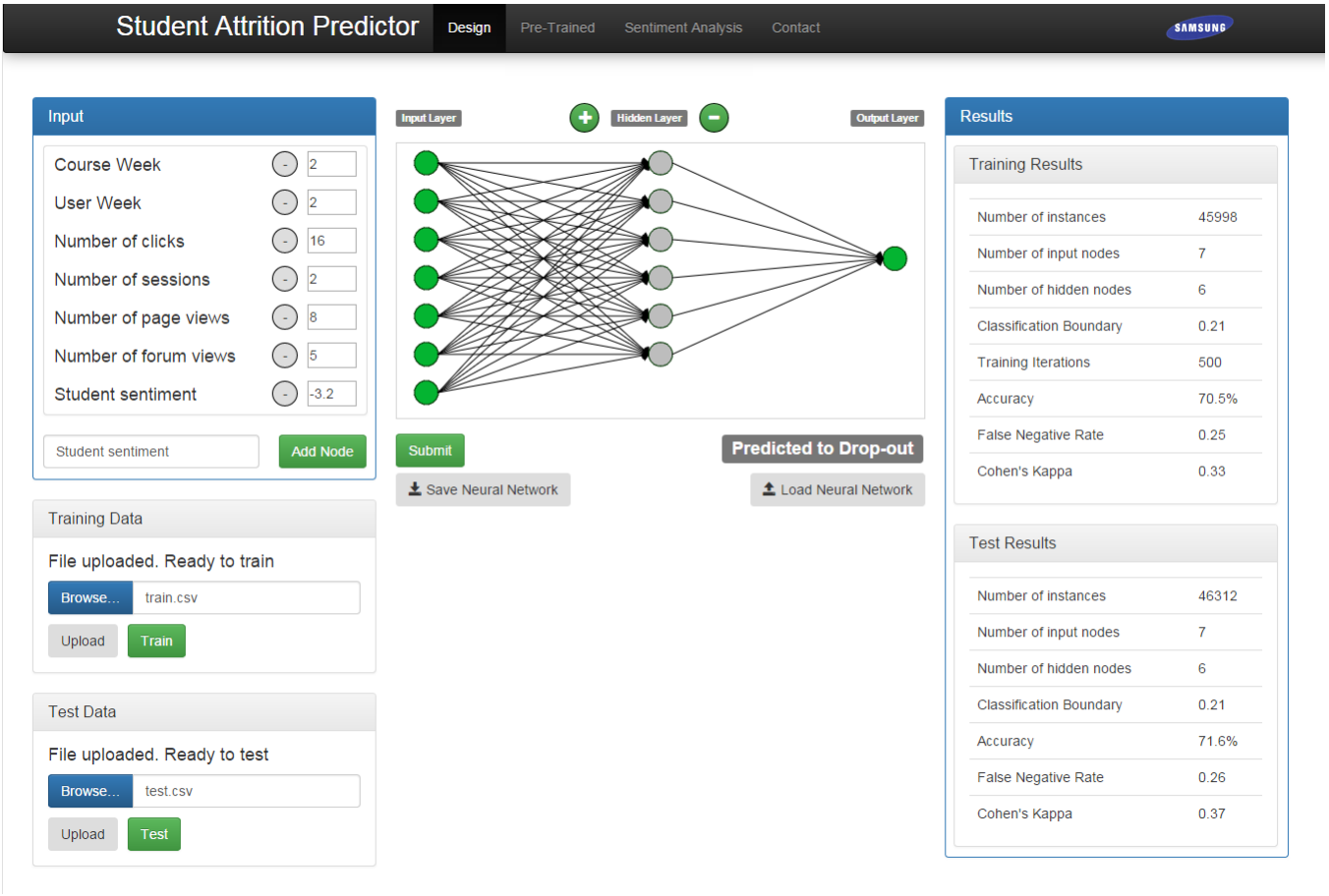


**Figure 1: Screenshot of Design Interface of Student Attrition Predictor**

This interface is especially useful for researchers who can decide the input features and structure of their own neural network, train and test it by uploading their own data and optimize the parameters and learning heuristic according to their application. The designed and trained neural network can be saved and loaded into the tool at any point.

## 3. CONCLUSION

There has been lot of research in recent years on predicting student attrition. In contrast to many studies trying to find reasons behind attrition, we focus on predicting and reducing attrition. Student Attrition Predictor not only predicts student drop-out, but also identifies the precise week when student is likely to drop-out in order to reduce attrition during the course. To the best of our knowledge, there is no direct way for educators to benefit from years of research on predicting student attrition. This tool acts as a medium for educators to directly utilize our research in this field. The tool also provides an easy graphical interface to researchers for further experiments.

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