Mining Data-Logs From Intelligent Tutors to Create Learning Profiles of Students

Anita Dani

Abstract
Intelligent tutoring systems are being used to teach mathematics due to the fact that they can provide individual tutoring, instant feedback on learning and flexibility to learn at own pace. In such computer supported learning environments, it is necessary that students develop the ability to learn independently. This paper reports the result obtained after mining the data logs generated by the intelligent tutoring system, ALEKS. Three clusters were generated after using two-step cluster analysis based on a variable which represents students' ability to learn independently. It was further found that students' marks in the coursework and in the final exam differed significantly among the three clusters.
Keywords: *cluster analysis, intelligent tutor, data mining, ALEKS*

I. Introduction

In the foundation year, students experience transition from school to university. They have fewer face-to-face teaching sessions with their instructor than they have in school. Quality of learning experience that students gain in the foundation year of their higher studies is important as it lays the foundation for their learning in the later years and also develops the ability to learn independently [31,48]

Formative assessments are designed for providing feedback on actual learning and they can fill the gaps between the actual learning and expected learning outcome [10]. Formative feedback is particularly important where students are uncertain about what is expected of them and when they need guidance about how to succeed [31,47]. It may not be practical to incorporate frequent formative assessments due to some reasons, such as big class sizes and limited number of face to face teaching sessions. The results of formative assessment must be available immediately to make adjustment in teaching and learning [10]. To overcome these challenges, computer based learning environments, such as interactive applets and intelligent tutors are widely used in high schools and universities in many countries including the United Arab Emirates [3,7,14,22]. Formative assessments with appropriate feedback can be used to enhance the quality of students' learning experience.

Higher Colleges of Technology, United Arab Emirates. Email: Anita.Dani@hct.ac.ae

Another way of improving students' learning experience is to provide them individual support. It has been proven that students' learning is improved when they receive individual tutoring ([9] as quoted in [16]). Since it is difficult to provide individual support for foundation students, intelligent tutoring systems are used [26]. Intelligent tutors provide interactive and personalized learning environment for students which can facilitate student centered learning. Since these software tools are now available on mobile devices, such as iPads, their adaption in teaching and learning is changing the teacher centered learning into student centered learning. Though this change is promising it also implies that students are expected to develop self-regulatory abilities ([3,31,33].

This paper evaluates effectiveness of ALEKS and points out its limitations and provides recommendations for curriculum redesign. This evaluation is based on the student's learning patterns obtained from the data logs generated by ALEKS. The aim of this research is explore student's learning style and their impact on student's final grade. The attribute taken for investigation is student's ability to learn independently.

II. Literature Review

The name ALEKS (**A**ssessment and **Le**arning in **K**nowledge **S**paces) indicates that this software provides learning opportunities by providing learning goals and administers frequent formative assessments to provide feedback on learning. It encompasses theories of learning, assessment and theories of intelligent tutors, hence this section contains review of literature on learning theories, assessments and intelligent tutors which are used for teaching mathematics.

A. Learning theories – ZPD and scaffolding

Vygotsky formulated the concept of zone of proximal development (ZPD). It refers to the gap between 'what a student can do alone' and 'what he can achieve with the support from an expert'. The interactions between the expert and the student are termed as 'tutorial interactions' and the expert is termed as the 'tutor'. These tutorial interactions are termed as 'scaffolding'. The parallels between the notion of scaffolding and Vygotsky's concept of ZPD are given in [43]. An expert tutor establishes task-related goals and guides the learner towards them. Expert tutor also avoids setting too complex or too easy tasks to ensure that the student does not give up due to high complexity at the same time gains some new knowledge. Although, initially the student may heavily depend on the tutor's guidance eventually the responsibility of problem solving is transferred from the tutor to the student [43]. According to constructivist learning paradigm, the purpose of education is to cultivate independent and self-directed students. Scaffolding provides a strategy to implement the goals of constructivist learning paradigm [21]. Behaviorist learning theory postulates that each application must be taught as a separate learning objective, whereas constructivist learning theory emphasizes that true understanding is connected and generalizable [36]. Inability to transfer knowledge to a new situation is termed as shallow learning by [4]. Developing a metacognitive strategy, such as ability to explain acquired knowledge can avoid shallow learning [4,13].

Computer aided instructions can integrate more than one medium, provide authentic learning activities and be used to provide support to many students at the same time in a classroom setting. But it is still not as effective as human tutor. It is found by many researchers that human tutoring has an effect size of d = 2.0 relative to classroom teaching without tutoring, which is known as the 'two sigma gain' [9,33,,43]. Since intelligent tutors are developed with the aim of improving learning outcomes, developers of intelligent tutors work towards achieving the same effect. Human tutoring is more effective than computer tutoring due to appropriate feedback and scaffolding techniques based on the knowledge of the subject and the student [25,43]. After the emergence of sophisticated techniques of artificial intelligence, it is possible to embed three characteristics of human tutors into the tutoring software, which are knowledge of the subject, knowledge of the student and knowledge of teaching [25].

B. Assessments

Assessments are not just meant for giving rewards or punishment but are also a source of learning. Therefore assessment strategies and instruments should have cognitive as well as motivational purpose [36]. Assessment strategy can have one or more of the following objectives: assessment of prior knowledge, evaluation of teaching and identifying gap between expected learning and actual learning ([10,36]).

Computer based assessments have several advantages over paper based assessments [42]. They are available online providing access to any number of students anytime and anywhere. They provide a wider range of assessment techniques than the paper based assessments, such as inclusion of graphics and multimedia. Student's responses to the assessment questions can be numbers and texts as well as hotspot clicking. Evaluation and feedback is given instantly by these systems. More importantly, software can generate questions randomly from a large question bank. Random based assessments not only control copying and cheating but also provide ample practice questions required for mastering a topic [41]. This type of web-based assessment software can foster the student-centered learning by engaging students in meaningful learning activities and by fostering skills of independent learning ([11,12]). Well-designed assessment software, such as Cognitive tutor, MIM project can be used to increase students' engagement in learning mathematics [32,38].

Web-based assessment and practice lead students to have more control over their work and their effort as they get the immediate feedback and instant scoring [27]. These features might also affect the students' success or failure in mathematics learning.

Researchers have also shown that computer-based or web-based assessment and practice had positive and extraneous effects on students' mathematical learning processes . Though effectiveness of intelligent tutors to teach algebra has been confirmed by many researchers [11,12,25], some researchers also found that if a student believes that a computer can't help them learn (even though they do actually learn), then they have a high probability of disliking the system and becoming less motivated [22].

C. Intelligent tutors

The emergence of web-based technology and artificial intelligence techniques have resulted in the growth and evolution of teaching and learning of mathematics [11,12,27,28]. Intelligent tutors provide superior performance than any other computer assisted instruction program because they are developed by combining theories of cognitive science and techniques of artificial intelligence [5,26,28]. These tutoring software systems make personalized tutoring widely and inexpensively available [36,47]. Some systems allow students to write all solutions step by step as if they were solving on paper. The system gives feedback on each step [43].

Two prominent theoretical frameworks are used in the development of intelligent tutoring systems: adaptive control of thought-rational (ACT-R) and knowledge space theory.

According to the theory of adaptive control of thought rational, learning is viewed as an incremental process where declarative and procedural knowledge is acquired step by step. Rational analysis process which detects necessary procedural and declarative knowledge is applied to solve a new problem [36]. The Cognitive tutor is based on this theoretical framework whereas ALEKS is developed on the theory of knowledge spaces. It is not a cognition theory but it mimics the ability of an expert teacher and determines correctness of a student's next response based on his current response. This theory is presented in detail in the following section.

III. Background information of ALEKS

In this section, the theoretical framework of ALEKS is presented. The section begins with the definitions of key terms.

A. Definitions of key terms

(1) Set of units of knowledge: It is a large but finite set of discrete units of knowledge.
(2) Knowledge states: It is a particular set of problems that some individual is capable of solving correctly.
(3) Precedence relation: Let a and b denote two knowledge states from the set of knowledge. If the state a is a prerequisite for the state b then there is a relation defined on these two knowledge states, which is the precedence relation.

(4) A path between two states: Any two states *a* and *b* are linked if either the state *a* precedes *b* or the state *b* precedes the state *a.* Such linking develops into several paths.
(5) Knowledge structure: It is the complex structure formed by all states and all possible paths starting from one knowledge state to another knowledge state.

At the core of the analytic engine used by the software is the concept of two fringes.

(6) Inner fringe: This is the set of all problems which a student can do.
(7) Outer fringe: This is the set of all problems that a student is ready to learn.

Associated with each course of mathematics, there are several thousands of feasible knowledge states. The power set of the set of knowledge set forms a set of possible sequence one can follow to master a particular topic in the course. As described by [16] for a set of 88 knowledge units, there are 2^{88} possible subsets which form the set of knowledge states. It may appear that is impossible to enumerate all such states and then use the enumeration for accurate assessment. But not all states are feasible. In the same example, out of 2^{88}, only 60000 knowledge states are feasible. The software performs the complex task of enumerating all feasible states, storing them in an array and then sorting them to form knowledge structure. The software uses these sorted feasible states for accurate assessment and also makes the assessment adaptive. A new question in the assessment is posed to a student on the basis of his or her response to the previous question.

ALEKS is used for teaching foundation mathematics in local higher education institute in the UAE. The same software is used for formative and summative assessments. In the following section the course structure is described.

IV. Course structure

In this section, a brief description of the assessment strategy used in the foundation course is presented.

Two foundation courses covering basic arithmetic, algebra, geometry and statistics are delivered using this software. Students use their iPads to access this program. The software provides explanation and practice problems on each topic. Teachers use the same examples for classroom discussion. Students are expected to master all topics as per their learning pace. 40% weighting is assigned to completion of all topics on the Pie, which works as the formative assessment. 60% weighting is given to in-class quizzes and the final exam which form the summative assessment component. There is a risk of students getting external help in completing the homework. In order to control this, students need to write comprehensive assessments, which are individualized progress tests based on what the student has mastered. These tests are conducted in classroom under examination conditions. After each test, the software indicates which topics are retained by the student and which are not retained.

Regular course runs over 16 weeks but students who complete at least 85% of the topics after each comprehensive test are given an opportunity of exiting the course earlier. This is a motivation for students to become an independent learner. There is also a drawback of this assessment pattern. The software does not provide a formative feedback on the student's performance in the comprehensive test. Neither teacher can see student's solutions nor the student can see his (or her) own answers and know the mistake; hence student has to re-learn the topic that is dropped after each comprehensive test.

The software allows teachers to set individual or group classwork, homework, quizzes and worksheets. Students have access to their own answers, but the feedback is not detailed enough. The software only indicates that the answer is incorrect but does not indicate the justification or a direction to get the correct answer rather it displays a step-by-step solution.

V. Research aim and methodolody

This research has the following aims:

(1) To determine groups of students with similar ability to learn independently.

(2) Does the ability to learn independently affect students' marks in the coursework and in the final exam?

In this section description of the research methodology is given.

When students study, ALEKS maintains a log of their activities, such as how many topics were practiced and how many topics were mastered. A cumulative report was generated from 20-weeks data which included the following information: number of topics practiced each week and number of topics mastered each week. The ratio of these two variables, represented by the variable mtop for each week, is used as a measure of ability to learn independently. The mean of mtop values over 20 weeks was calculated. The data file also included the following variables: student's score in the initial assessment (IA), total number of topics mastered by the student after the comprehensive test (CT), student's marks in the final exam (FE) and a dichotomous variable indicating if the student passed the course in less than 12 weeks. The data file consists of 57 records from three sections of Basic Mathematics and Pre-Algebra. All students were female students who learn English as their second language.

The research question 2 is formulated into the following null hypothesis:
The means values of the CT and FE do not differ significantly for each group identified above.

Corresponding alternate hypothesis is that the mean scores for CT and FE differ significantly for each group.

Cluster analysis is applied to identify groups of people with similar attitudes [14]. Students were classified into clusters based on the mean value of the ratio of topics mastered to topics practiced. Two-step clustering method was applied since this method is appropriate when the classification variable is continuous and the number of clusters is not known apriori [18]. One-way ANOVA test was applied to test if these clusters were exclusive of each other. The results of the ANOVA test shows that the mean value of mtop is statistically different for each cluster (F=167.343, p-value=0.000).

This clustering created three different profiles based on the attitude score. All data analysis was done using SPSS 23. The software detected three clusters by applying the Log-likelihood method. The following table shows the cluster profiles and the number of cases in each cluster.

Table 1: Cluster profiles

Cluster number	Mean (mtop)	S.d. (Mtop)	Number of students
1	0.6626	0.04	21
2	0.7898	0.04	15
3	0.5430	0.05	21

Based on these cluster profiles it is observed that the students in the cluster number 2 had the highest value for the variable mtop, which means on an average they mastered 79% of the topics out of the topics that they practiced, whereas students in the cluster 3 mastered only 54% of topics.

As described in the section IV above students were given an opportunity to pass the course in less than 12 weeks if they mastered 85% of topics by studying independently. The cross-tab analysis shown in the following table shows that out of total 7 students who passed the course in less than 12 weeks, 4 students were in cluster 2 (57%), 2 were in cluster 3 (29%) and 1 student was in cluster 1 (14%). Further Chi-square analysis was done to test if the number of students who passed the course in less than 12 weeks are the same for each cluster. The result of this test show that the distribution of students is not statistically different. (Chi-square statistic= 4.132, p=0.127).

Table 2: Correlation between mtop and final marks

Correlations			
		FE	**Mean MTOP**
FE	Pearson Correlation	1	.404**
	Sig. (2-tailed)		.002
	N	57	57
MeanMTOP	Pearson Correlation	.404**	1
	Sig. (2-tailed)	.002	
	N	57	57
**. Correlation is significant at the 0.01 level (2-tailed).			

A strong positive and statistically significant correlation was found between the value of mean mtop and the marks in the final exam (FE). (Refer to the above table 2).

Table 3: Output of ANOVA test

		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
CT	Between Groups	2949.617	2	1474.809	4.885	.011
FE	Between Groups	2468.668	2	1234.334	4.283	.019

The results of ANOVA test shows that the mean value of coursework marks and final exam marks are different for all three groups. The difference is statistically significant at 0.05 level. It can be concluded that the ability to learn independently is one of the predictors of student's marks in the coursework and in the final exam.

VI. Discussion

On average, students mastered 65% of the topics they practiced. (Refer to the Figure-1 below). Students in cluster 2 have a higher rate of mastering topics. This high rate can be attributed to the regularity in studying whereas the low rate of mastering can be due to lack of regularity.

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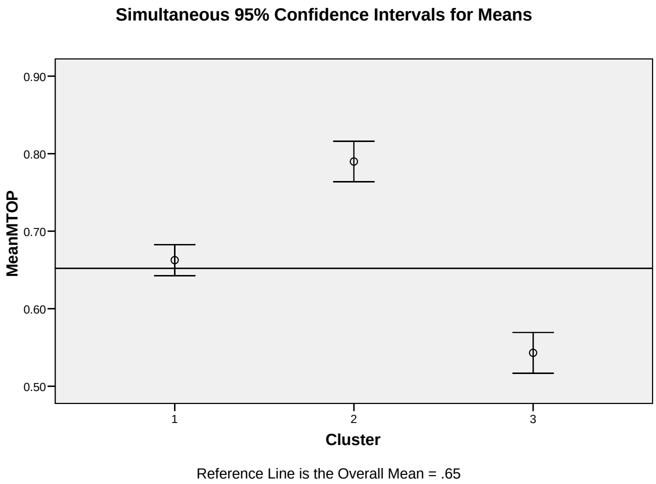

Figure 1: Confidence interval for each cluster

There are other factors affecting students' ability to learn independently, such as poor language skills and poor technology skills. Poor technology skills result into under-utilization of the features of ALEKS. A brief description of some features of ALEKS is given below.

A student can choose any topics available from the list of 'Ready to Learn Topics'. A question is presented on that topic. Student can request for explanation if needed. If a student can answer it correctly, an encouraging comment is given by the system as 'Well done'. If the student can answer three more similar questions correctly then the system shows the option of 'Done'. If student is confident about the mastery of this topic she can click the on the button 'Done', then the topic is added to the list of 'What a student can do'. If the student cannot answer three to four questions correctly, then the system does not present questions from the same topic but suggests that the student can try another topic. ALEKS has the ability to create individualized sequence of topics based on the student's background knowledge and level of cognitive development but the instructions do not account for individual learning styles. Although it allows instructor to upload customized presentations and video files.

The most important feature of ALEKS is that it designs a sequence of activities appropriate for each student and allows the student to learn at his or her own pace. As a result it builds confidence of problem solving. The novel part in the design of ALEKS is the application of the theory of Zone of Proximal Development (ZPD). The complete potential of ALEKS will be utilized, if students follow the learning paths suggested by ALEKS. Currently the ALEKS interface is not providing clear instructions about how to achieve this.

The following issue of misinterpretation is noted. According to the knowledge space theory, a student is not able to solve problems unless he or she has mastered the pre-requisite topics. There are not clear instructions presented on the home screen of the system about this fact. Student often misinterpret this representation as he or she does not need to complete those topics. This can be avoided with an improved representation, in which the student can see the list of all topics without a hyperlink to their detailed explanation.

Student knowledge component of ALEKS is responsible for the diagnostic assessment and modeling of subsequent learning profiles of each student. Upon registering into ALEKS, each student writes an initial or diagnostic assessment. Each student's learning progress is modeled in the form of a Pie. Occasional progress tests are administered by ALEKS to detect retention of knowledge. After each progress test, the previous learning score is adjusted. This mechanism provides accurate and up to date model of student's learning progress. Students tend to avoid the automatic progress tests and often request teachers to cancel it for them. It is due to two reasons: the system does not provide detail feedback about the solution submitted during automatic progress tests and they have to relearn all topics which are not retained in the progress test. These tests affects their confidence because some questions are taken from the list of topics which a student have not yet mastered but the system finds that the student is ready to learn. Weaker students fail to answer these questions which results in decreasing their previous achievement score. In order to remove these barriers in learning independently, students should be given more training about how to use the system. Also quizzes and homework assignments on ALEKS can be set as formative assessments as the system provides feedback on these assessments unlike the progress tests.

VII. Conclusion and future direction

In this paper, we established the ratio of topics mastered to topics practiced (mtop) to measure student's ability to learn independently. This measure was further applied for lassifying students. This classification formed three groups of students for which the mean mtop were 0.67, 0.79 and 0.54 respectively. A strong positive and significant correlation was found between the mtop and final exam marks and between mtop and the coursework marks, which indicates that mtop can be a predictor of student's final marks in the ALEKS based course.

These results will be tested on a larger sample. Also, other factors such students' learning styles; their attitude towards technology and towards mathematics will be measured. Based on the evaluation of the system, we found that ALEKS can measure student's attainment of factual, semantic and procedural knowledge, but it fails to measure meta-cognition, because neither ALEKS shows different strategies to solve problems nor student has to show the strategy used for problem solving. In order to develop metacognitive abilities, the ALEKS based coursework can be supplemented by project assignments.

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