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Assessing Students Performance Using Learning Curves

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Abstract:

Educational Data Mining is used to find interesting patterns from the data taken from educational settings to improve teaching and learning. Assessing student's ability and performance with EDM methods in e-learning environment for math education in school level in India has not been identified in our literature review. Our method is a novel approach in providing quality math education with assessments indicating the knowledge level of a student in each lesson. This paper illustrates how Learning Curve – an EDM visualization method is used to compare rural and urban students' progress in learning mathematics in an e-learning environment. The experiment is conducted in two different schools in Tamil Nadu, India. After practicing the problems the students attended the test and their interaction data are collected and analyzed their performance in different aspects: Knowledge component level, time taken to solve a problem, error rate. This work studies the student actions for identifying learning progress. The results show that the learning curve method is much helpful to the teachers to visualize the students' performance in granular level which is not possible manually. Also it helps the students in knowing about their skill level when they complete each unit.

Keywords — **Educational Data Mining (EDM), Learning Curve, Visualization method.**

I. INTRODUCTION

Educational Data Mining is an inter-disciplinary field utilizes methods from machine learning, cognitive science, data mining, statistics, and psychometrics. EDM uses computational approaches to analyze educational data to study educational questions. On the Educational Data Mining community website, www.educationaldatamining.org, educational data mining (abbreviated as EDM) is defined as: "Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in."

The increase of e-learning resources such as interactive learning environments, learning management systems (LMS), intelligent tutoring systems (ITS), and hypermedia systems, as well as the establishment of school databases of student test scores, has created large repositories of data that can be explored by EDM researchers to understand how students learn and find out models to improve their performance [30].

Baker [1] has classified the methods in EDM as: prediction, clustering, relationship mining, distillation of data for human judgment and discovery with models. Humans can make inferences about data that may be beyond the scope in which an automated data mining method provides. For the use of education data mining, data is distilled for human judgment for two key purposes, identification and classification. [1] For the purpose of identification, data is distilled to enable humans to identify well-known patterns, which may otherwise be difficult to interpret. For example, the learning curve, classic to educational studies, is a pattern that clearly reflects the relationship between learning and experience over time. Data is also distilled for the purposes of classifying features of data, which for

educational data mining, is used to support the development of the prediction model. Classification helps expedite the development of the prediction model.

The goal of distillation of data for human judgment method is to summarize and present the information in a useful, interactive and visually appealing way in order to understand the large amounts of education data and to support decision making. [29] In particular, this method is beneficial to educators in understanding usage information and effectiveness in course activities. Key applications for the distillation of data for human judgment include identifying patterns in student learning, behavior, opportunities for collaboration and labeling data for future uses in prediction models. [30]

This paper concerns with applying EDM visualization method learning curve for User knowledge modeling by distillation of data for human judgment. This paper is organized as follows: section 2 lists the related works done in this research area; section 3 explains Learning curve method used in this research; section 4 describes methodology used, section 5 discusses the results and section 6 concludes the work.

II. LITERATURE REVIEW

A number of studies have been conducted in EDM to find the effect of using the discovered methods on student modeling. This section provides an overview of related works done by other EDM researchers.

Newell and Rosenbloom[5] found a power relationship between the error rate of performance and the amount of practice. Corbett and Anderson [6] discovered a popular method for estimating students' knowledge is knowledge tracing model, an approach that uses a Bayesian-network-based model for estimating the probability that a student knows a skill based on observations of him or her attempting to perform the skill. Baker et.al [7] have proposed a new way to contextually estimate the probability that a student obtained a correct answer by guessing, or an incorrect answer by slipping, within Bayesian Knowledge Tracing. Koedinger et al [8] demonstrated that a tutor unit, redesigned based on data-driven cognitive model improvements, helped students reach mastery more efficiently. It produced better learning on the problem-decomposition planning skills that were the focus of the cognitive model improvements. Stamper and Koedinger [9], presented a data-driven method for researchers to use data from educational technologies to identify and validate improvements in a cognitive model which used Knowledge or skill components equivalent to latent variables in a logistic regression model called the Additive Factors Model (AFM). Brent et al [10] used learning curves to analyze a large volume of user data to explore the feasibility of using them as a reliable method for fine tuning adaptive educational system. Feng et al[11], addressed the assessment challenge in the ASSISTment system, which is a web-based tutoring system that serves as an e-learning and e-assessment environment. They presented that the on line assessment system did a better job of predicting student knowledge by considering how much tutoring assistance was needed, how fast a student solves a problem and how many attempts were needed to finish a problem.

Koedinger, K.R.,[13] Professor, Human Computer Interaction Institute, Carnegie Mellon University, Pittsburgh has done lot to this EDM research. He developed cognitive models and used students interaction log taken from the Cognitive Tutors, analyzed for the betterment of student learning process Better assessment models always result with quality education. Brent et al.[28] stated that measuring the efficacy of ITS can be hard because there are many confounding factors: short, well-isolated studies suffer from insufficient interaction with the system, while longer studies may be affected by the students' other learning activities. Coarse measurements such as pre- and post-testing are often inconclusive. Learning curves are an alternative tool: slope and fit of learning curves show the rate at which the student learns, and reveal how well the system model fits what the student is learning. In their study, the results suggested was to use general feedback the first few

times it is presented; if the student still had problems with a concept, switch to more specific feedback. In our paper [31] we used LFA (Learning Factor Analysis) method of EDM in an e-learning MATHSTUTOR student log and used learning curves for analyzing results of exercise problems solved by the students.

User modeling or student modeling identifies what a learner knows, what the learner experience is like, what a learner's behavior and motivation are, and how satisfied users are with e-learning. Item Response Theory and Rash model [20] is Psychometric Methods used to measure students' ability. They lack in providing results that are easy to interpret by the users. This paper studied the learners' knowledge level (knowledge modeling) using LFA and visualizing through learning curves for an e-learning environment.

Assessing student's ability and performance with EDM methods in e-learning environment for math education in school level in India has not been identified in our literature review. EDM method-Learning Curve and LFA [9][10][13] are applied only in Intelligent Tutoring System (ITS) for student modeling. We tried these methods [31] from the data taken from simple e-learning tutor. Our method is a novel approach in providing quality math education with assessments indicating the knowledge level of a student in each lesson.

III. LEARNING CURVES

A learning curve visualizes changes in student performance over time. The line graph displays opportunities across the x-axis, and a measure of student performance along the y-axis. A good learning curve reveals improvement in student performance as opportunity count (i.e., practice with a given knowledge component) increases. Here we use Learning Curve as information visualization method to improve student models by distilling data for human judgments. Teachers can make inferences about student data, when it is presented appropriately. In any e-learning platform like e-tutors or ITS , data is meaningfully organized in terms of the structure of the learning material (skills, problems, units, lessons) and the structure of learning settings (students, teachers, collaborative pairs, classes, schools). Data is distilled for human judgment in educational data mining for two key purposes: classification and identification. Identification of learning patterns and learner individual differences from visualizations is a key method for exploring educational data sets. Within the domain of student models, a key use of identification with distilled and visualized data is in inference from learning curves. . A great deal can be inferred from learning curves about the character of learning in a domain, as well as about the quality of the domain model.

Classic learning curves (Fig. 1) display the number of opportunities to practice a skill on the X axis, and display performance (such as percent correct/incorrect or time taken to respond) on the Y axis. A curve with a smooth downward progression that is steep at first and gentler later indicates that successful learning is occurring. A flatter curve, indicates that learning is occurring, but with significant difficulty. A sudden spike upwards, by contrast, indicates that more than one knowledge component is included in the model. A flat high curve indicates poor learning of the skill, and a flat low curve indicates that the skill did not need instruction in the first place. An upwards curve indicates the difficulty is increasing too fast. Hence, learning curves are a powerful tool to support quick inference about the character of learning in an educational system. It can be incorporated into tools used by education researchers.

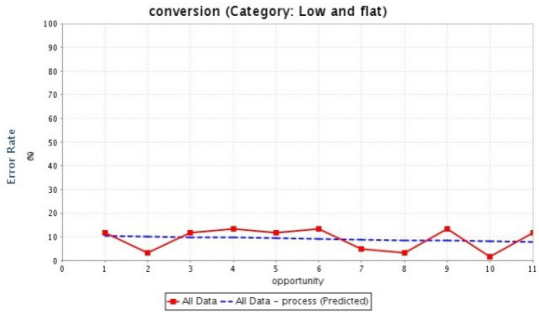

Fig. 1 A sample Learning Curve

A good cognitive model for a tutor uses a set of production rules or skills which specify how

students solve problems. The tutor should estimate the skills learnt by each student when they practice with the tutor. The power law [5] defines the relationship between the error rate of performance and the amount of practice, depicted by equation (1).This shows that the error rate decreases according to a power function as the amount of practice increase.

$$Y = aX^b \quad \text{.....} \quad (1)$$

Where

Y = the error rate

X = the number of opportunities to practice a skill

a = the error rate on the first trial, reflecting the intrinsic difficulty of a skill

b = the learning rate, reflecting how easy a skill is to learn

While the power law model applies to individual skills, it does not include student effects. In order to accommodate student effects for a cognitive model that has multiple rules, and that contains multiple students, the power law model is extended to a multiple logistic regression model (equation 2)[24].

$$\ln[P_{ijt}/(1-P_{ijt})] = \Sigma\, \alpha_i X_i + \Sigma\, \beta_j Y_j + \Sigma\, \gamma_j Y_j T_{jt} \quad \text{.....(2)}$$

Where P_{ijt} is the probability of getting a step in a tutoring question right by the ith student's t th opportunity to practice the jth KC; X = the covariates for students; Y = the covariates for skills(knowledge components); T = the number of practice opportunities student i has had on knowledge component j; α = the coefficient for each student, that is, the student intercept; β = the coefficient for each knowledge component, that is, the knowledge component intercept; γ = the coefficient for the interaction between a knowledge component and its opportunities, that is, the learning curve slope. The model says that the log odds of P_{ijt} is proportional to the overall "smarts" of that student (α_i) plus the "easiness" of that KC (β_j) plus the amount gained (γ_j) for each practice opportunity. This model can show the learning growth of students at any current or past moment.

A difficulty factor refers specifically to a property of the problem that causes student difficulties. The tutor considered for this research has metric measures as lesson 1 which requires 5 skills (conversion, division, multiplication, addition, and result). These are the factors (KCs) in this tutor (Table 1) to be learnt by the students in solving the steps. Each step has a KC assigned to it for this study.

Table 1. Factors for the Metric measures and their values

Factor Names	Factor Values
Conversion	Correct formula, Incorrect
Addition	Correct, Wrong
Multiplication	Correct, Wrong
Division	Correct, Wrong
Result	Correct, Wrong

IV. METHODOLOGY

In this paper distillation of data for human judgment method of EDM is used for data analysis. This method uses Learning curve as identification technique. The Learning Curve is illustrated using data obtained from the Metric measures lesson of Mensuration Tutor MathsTutor[18]. The tutor is practiced by two different sets of students: one from rural school and the other from urban school. Sixty students from each school participated in this study. They practiced with the tutor in solving exercise problems [27] and then moved on to the test part. Our dataset consist of two sets of 1,920(32unique steps x 60 students) transactions involving 60 students, 32 unique steps and 5 Skills (KCs) in students test log. All the students were solving 9 problems 5 in mental problem category, 3 in simple and one in big. Total steps involved are 32. While solving exercise problem a student can ask for a hint in solving a step but no help is provided in the test part. Each data point is a correct or incorrect student action corresponding to a single skill execution. Student actions are coded as correct or incorrect and categorized in terms of "knowledge components" (KCs) needed to perform that action. Each step the student performs is related to a KC and is recorded as an "opportunity" for the student to show mastery of that KC. This lesson has 5 skills (conversion, division, multiplication, addition, and result) correspond to the skill needed in a step. Each step has a KC assigned to it for this study. The table 2 shows a sample data with columns: Student-name of the student; Step – problem 1 Step1;

Success – Whether the student did that step correctly or not in the first attempt. 1-success and 0-failure; Skill – Knowledge component used in that step; Opportunities – Number of times the skill is used by the same student computed from the first and fourth column.

Table 2. The sample data

Student	Step	Success	Skill	Opportunities
X	P1s1	1	conversion	1
X	P1s2	1	result	1
X	P2s1	0	conversion	2

Learning curves [10] have become a standard tool for measurement of students' learning in intelligent tutoring systems. Here in our study we used learning curve to visualize the student performance over opportunities. Slope and fit of learning curves show the rate at which a student learns over time, and reveal how well the system model fits what the student is learning. We used learning curves to measure the performance of tutoring system domain or student models. Measures of student performance are described below in table 3. Regardless of metric, each point on the graph is an average across all selected knowledge components and students.

Table 3. Measures of student performance

Measure	Description
Error Rate	The percentage of students that asked for a hint or were incorrect *on their first attempt*. For example, an error rate of 45% means that 45% of students asked for a hint or performed an incorrect action on their first attempt. Error rate differs from assistance score in that it provides data based only on the first attempt. As such, an error rate provides no distinction between a student that made multiple incorrect attempts and a student that made only one.
Number of Incorrect	The number of incorrect attempts for each opportunity
Step Duration	The elapsed time of a step in seconds, calculated by adding all of the durations for transactions that were attributed to the step.
Correct Step Duration	The step duration if the first attempt for the step was correct. The duration of time for which students are "silent", with respect to their interaction with the tutor, before they complete the step correctly. This is often called "reaction time" (on correct trials) in the psychology literature. If the first attempt is an error (incorrect attempt or hint request), the observation is dropped.
Error Step Duration	The step duration if the first attempt for the step was an error (hint request or incorrect attempt). If the first attempt is a correct attempt, the observation is dropped.

Learning curve is categorised as follows:

- **low and flat**:. The low error rate shows that students mastered the KCs but continued to receive tasks for them
- **no learning**: the slope of the predicted learning curve shows no apparent learning for these KCs.
- **still high**: students continued to have difficulty with these KCs. Consider increasing opportunities for practice.
- **too little data**: students didn't practice these KCs enough for the data to be interpretable.
- **good**: these KCs did not fall into any of the above "bad" or "at risk" categories. Thus, these are "good" learning curves in the sense that they appear to indicate substantial student learning.

The above categorisations assist the teacher in knowing about the students' knowledge level in specific concepts to be mastered by the students.

V. RESULTS AND DISCUSSIONS

To analyse the performance of student(s), we used Datashop[13] analysis and visualization tool for generating learning curves by uploading our dataset. The teacher can view the multipurpose performance profiler to know about number of correct/incorrect attempts made for the KCs by the students as shown in fig.2a &2b. This explains that the rural students struggled in conversion step (converting from one unit to other unit in metric measures lesson).

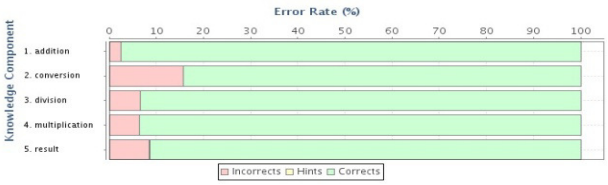

Fig. 2a. Error rate Vs KCs(Rural group)

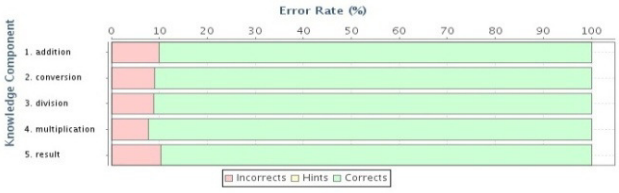

Fig. 2b. Error rate Vs KCs(Urban group)

Fig. 3a &3b shows the time taken by students to solve each KCs. Both the groups took longer time for solving the conversion steps.

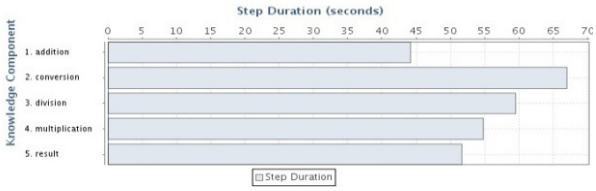

Fig. 3a Step duration Vs KCs (Rural group)

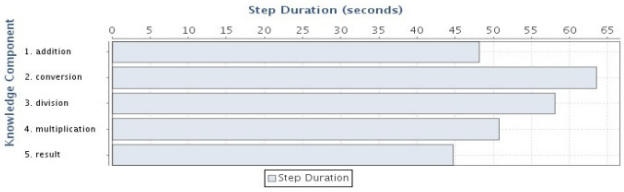

Fig. 3b Step duration Vs KCs (Urban group)

Table 4 lists out the number of correct and incorrect attempts made by both group according to the KCs and time taken for solving each KC. For example the first KC addition is required in 2 problems out of 9 and only 2 steps involve addition. Total number of observations for addition made by 60 students is 120. The rural students made 97.5 % (117/120) correct attempts and only 90% are correct attempt made by the urban students. But in conversion KC urban students performed better than rural group.

Table 4. Error report – view by KC and time taken for each KC

KC	#Unique problems	#Unique steps	No. of Observations	Correct		Incorrect		Duration(secs)	
				Rural	Urban	Rural	Urban	Rural	Urban
Addition	2	2	120	117 (97.5%)	108 (90%)	3 (2.5%)	12 (10%)	44.192	48.142
Conversion	9	11	660	556 (84.24%)	599 (90.8%)	104 (15.76%)	61 (9.2%)	66.932	63.472
Division	4	4	240	224 (93.33%)	219 (91.25%)	16 (6.67%)	21 (8.75%)	59.567	58.038
Multiplication	4	6	360	337 (93.61%)	332 (92.22%)	23 (6.39%)	28 (7.78%)	54.778	50.794
Result	9	9	540	494 (91.48%)	484 (89.63%)	46 (8.52%)	56 (10.37%)	51.652	44.743

The empirical learning curve give a visual clue as to how well a student may do over a set of learning opportunities, the predicted curves allow for a more precise prediction of a success rate at any learning

opportunity. The predicted learning curve is much smoother. It is computed using the Additive Factor Model (AFM)[25], which uses a set of customized Item-Response models to predict how a student will perform for each skill on each learning opportunity. The predicted learning curves are the average predicted error of a skill over each of the learning opportunities. The blue line in learning curves shows the predicted value and category is defined using the predicted value. The learning curve has some blips depending on error rate but the predicted line is very smooth.

The following fig. 4a &b defines that only two unique steps involves addition which is very less for prediction so it comes under category:Too little data. More than three oppurtunities are required for prediction. We can add problems for this KC or it can be merged with other KCs. From the predicted learning curve for conversion KC (Fig. 5a &b) we can infer that 'no learning' took place in rural group. There were 11 opportunities for conversion and 4th conversion has maximum error rate 33.3% 8th conversion has minimum error rate. We understood that no conversion was at 0% error rate. The teacher can better guide the students in that area. He can do changes in domain modeling by adding new problems in examples and providing more exercises. But the urban group the students performed well compared to rural students. It is predicted as 'Low and flat' with highest error rate 13% for 9th conversion. Learning curves shown in Fig. 6a &b, 7a&b, 8b and 9b are in the category 'Low and Flat' explains that students likely received too much practice for these KCs. This shows that the students were mastered in these skills and do not require any more practice. Fig.8a and 9a are in the category 'good' indicate that the students got sufficient learning in result KC Single-KC model of rural students and shows the overall performance of the rural students in all the 32 unique steps are good. In 32 steps only 2 steps used addition so fig. 10 shows 'too little data'. We can add problems for this KC or it can be merged with other KCs.

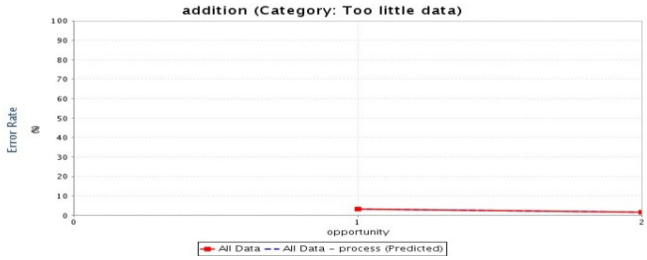

Fig. 4a Learning Curve for Addition KC(Rural)

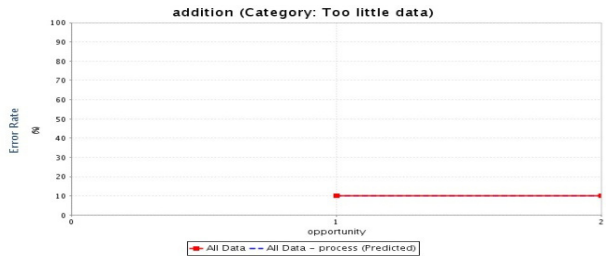

Fig. 4b Learning Curve for Addition KC (Urban)

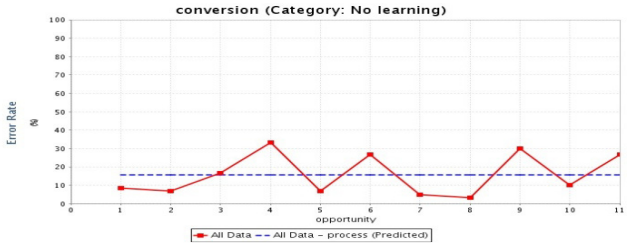

Fig. 5a Learning Curve for Conversion KC(Rura

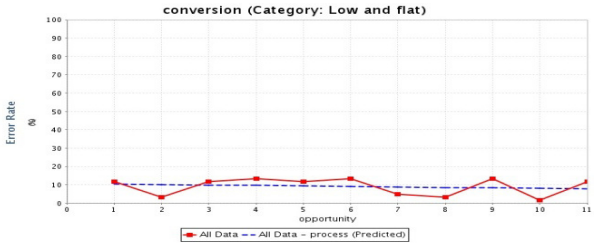

Fig. 5b Learning Curve for conversion KC (Urban)

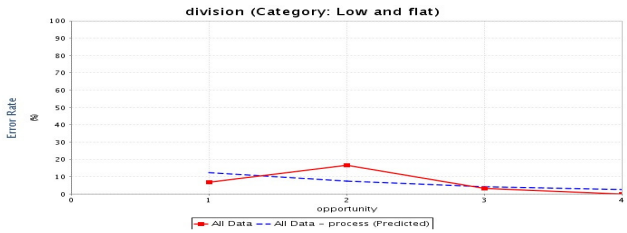

Fig. 6a Learning Curve for division KC(Rural)

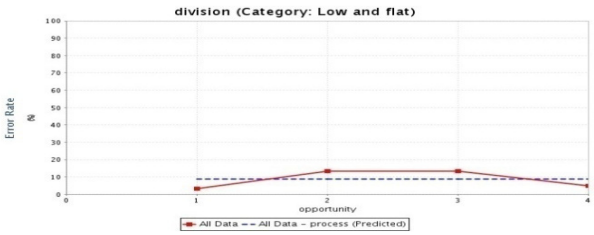

Fig. 6b Learning Curve for division KC (Urban)

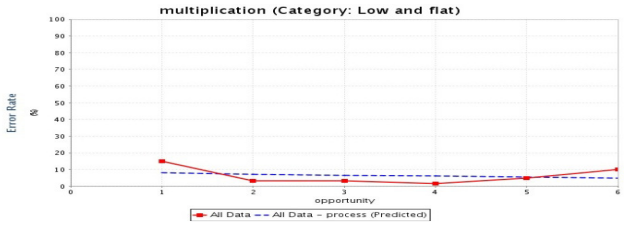

Fig. 7a Learning Curve for Multiplication KC(Rural)

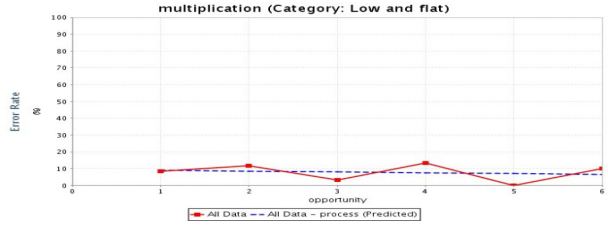

Fig. 7b Learning Curve for Multiplication KC (Urban)

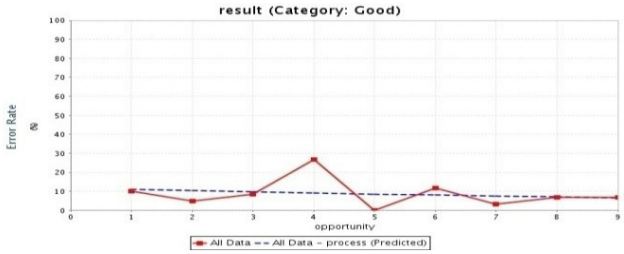

Fig. 8a Learning Curve for Result KC (Rural)

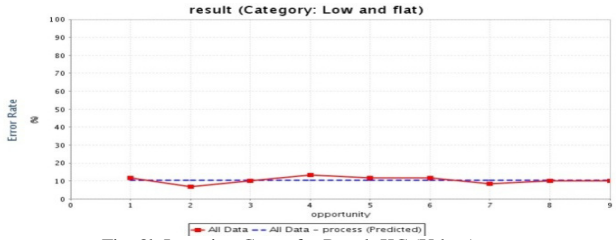

Fig. 8b Learning Curve for Result KC (Urban)

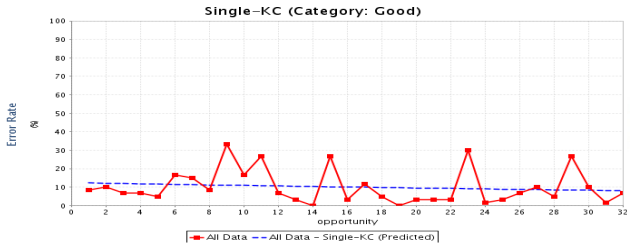

Fig. 9a Learning Curve for Single KC (Rural)

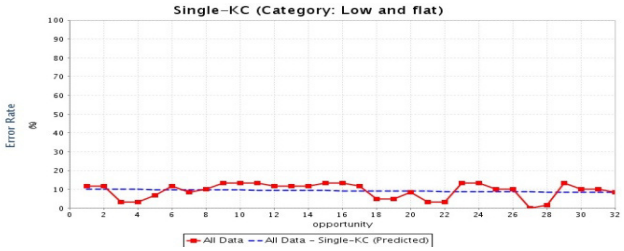

Fig. 9b Learning Curve for Single KC (Urban)

Table 5. Error Report –view by problem and time taken for each problem

Problem #	#Steps	#KC	Correct		Incorrect		Duration(secs)	
			Rural	Urban	Rural	Urban	Rural	Urban
1	2	2	53 (88.33%)	55 (91.67%)	7 (11.67%)	5 (8.33%)	39.866	45.892
2	3	3	57 (95%)	56 (93.33%)	3 (5%)	4 (6.67%)	68.05	70.822
3	3	3	54 (90%)	52 (86.67%)	6 (10.0%)	8 (3.33%)	61.572	73.272
4	3	3	52 (86.67%)	45 (75%)	8 (13.33%)	15 (25%)	60.194	72.811
5	3	3	53 (88.33%)	58 (96.67%)	7 (11.67%)	2 (3.33%)	50.0	47.578
6	4	3	52 (86.67%)	49 (81.67%)	8 (13.33%)	11 (18.33%)	57.55	63.956
7	4	3	56 (93.33%)	58 (96.67%)	4 (6.67%)	2 (3.33%)	39.033	39.622
8	6	4	55 (91.68%)	55 (91.68%)	5 (8.33%)	5 (8.33%)	53.15	53.042
9	6	4	56 (93.33%)	54 (90%)	4 (6.67%)	6 (10%)	54.308	57.036

The correct and incorrect entries in table 5 are taken from fig. 8a &b result KC. From this it is understood that the problems 1,3,4,6 have greater incorrect percentage compared with other problems. Both group took more time for solving problems 2,3 ,4 & 6. The fig.10 clearly states the individual students' performance in all 32 steps(X axis). Y axis shows the error in each step made by the individuals. 6th student in the first row was correct in all steps with 100% result. The teacher can identify the low scorers and their struggle in solving the steps and can provide remedies.

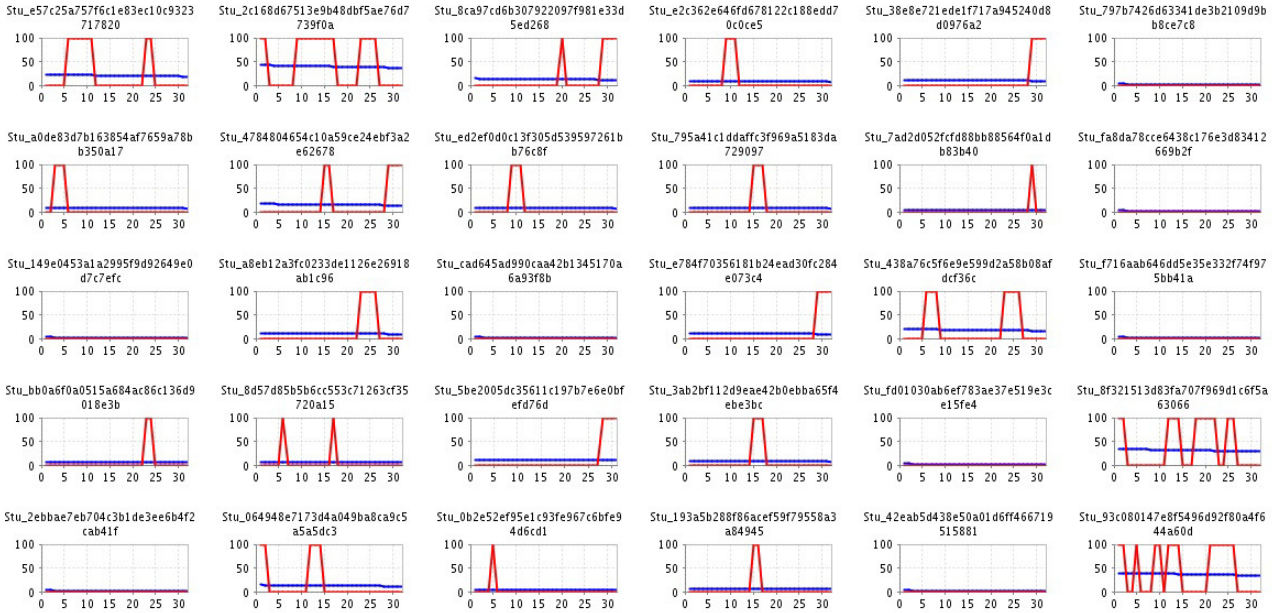

Fig. 10 Learning curve for partial list of individual Student (urban) performance in 32 steps

VI. CONCLUSION

Student knowledge models can be improved by mining students' interaction data. This paper analysed the use of Learning curve method for distillation of data for human judgment. Student knowledge modeling in mathematics education with learning curves by mining the students log data from a e-learning tool (MATHSTUTOR). This method assists the teacher in: 1) measuring the difficulty and learning rates of Knowledge Components (KCs). 2) predict student performance in practicing each KC. 3) identify over-practiced or under-practised KCs. The learners can understand what they know and do not know. The students with poor performance can be given with more problems for practicing. This method provides more insight into the performance of skills in every step for each student.

From table 5 a teacher can understood that the students were finding difficulty in attempting the mental problems than small and big problems. In 5 mental problems 3 (1, 3, &4) has more error rate than small and big problems. Also the times taken for solving mental problems were higher compared with other problems. So the teacher can concentrate on providing more mental problems for solving. From the prediction category mentioned in fig 9a &b the urban students mastered the unit and can move on to the next unit. The rural group got sufficient learning but yet to be mastered. The rural students find difficulty in conversion and division KCs, which reflects in result and single-KC components. They outperform urban in addition and multiplication KCs. The learning curves shown in fig. 10 provide individual performance of the students in the test. The next step of this research is to provide a personalized tutoring environment for the students by incorporating the results into the tutor and providing automated suggestion to improve their performance. Clustering algorithms can be used to suggest the teacher in grouping the students according to their performance.

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