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Adjustment Levels for Intelligent Tutoring System using Modified Items Response Theory

A Case Study : ITS for Elementary School

Ika Widiastuti
Information Technology Department
State Polytechnic of Jember
Jember, Indonesia
ika_widiastuti@polije.ac.id

Nurul Zainal Fanani
Information Technology Department
State Polytechnic of Jember
Jember, Indonesia
zainal_fanani@polije.ac.id

Abstract—**Intelligent Tutoring System (ITS) is a computer based instructional system that assigns intelligent question depending on student's response. It is important to adjust the student level and question difficulty level to acquire an adaptive system. So, this study focus on building up a framework to automatically adjust the student level and question difficulty level using fuzzy logic and modified items response theory.**

Keywords—Intelligent Tutoring System, Intelligent Question, Fuzzy Logic, Modified Items Response Theory.

I. INTRODUCTION

Obviously, the rapid growth of information and communication technologies, has been rapidly replacing the traditional lectured-based one due to the factor of providing the multimedia enhanced learning anytime and anywhere. Computer and Electronic technology today offer myriad ways to enrich educational assessment both in the classroom and in the large-scale testing situations [1]. An Intelligent Tutoring System (ITS) is a computer based instruction tool that attempt to provide individualized instructions based on learner's background. ITSs try to satisfy all needs of an individual learner, especially with personalization and individualized instruction [2]. Each learner has their own learning style and each student's performance in learning cannot be assessed and evaluated in a unique and simple way. Context personalization can be described as adjusting learning material to align with the interests of an individual learner. It wills more productive if the system knowing about the learner characteristic. The system provides appropriate learning material and appropriate question to appropriate learner according to learner levels. The system should be identified the learner characteristic at early stage of learning like a tutor in real class environment if we would like to acquire efficient learning process. For this, the system must be intelligent and adaptive. The system should produce intelligent question depending on the learner's responses and performance during testing session. So, the difficulty of test depends on the learner's performance and level of ability. This is how the Intelligent Tutoring System (ITS) will develop. It is provides customized instruction and feedback to learners while performing a task. Learner ability in [1] can be predicted by learning through the decision tree which was built using academic attributes by ID3 algorithm. And the item difficulties of questions were estimated using item responses by Item Response Theory (IRT) model. Provision levels using IRT refers to all the questions that were ever answer, and then obtain average of each right question. This average value is used to find the standard deviation for each item. With this theory, learners are expected to answer the entire question in the question pool at least once in the right answer to adjust question level. It is causes the system slows to adapt. Beside, to predict learner ability, training dataset must be providing at early stage. It is not efficient because the system only identify learner ability at early stage not while interacting with system.

In our study, we propose fuzzy logic to predict learner ability at early stage by giving a pretest and while interacting with system. So system could adjust the learner ability while interacting with system. In order to acquire an adaptive intelligent question, we modify items response theory proposed by Kavitha [1]. In order to adjust the question level, we only consider an item that has been done by learners. So, it is not necessary to consider entire question in the question pool to adjust the question level.

Many studies have been working on development of computer based testing application. In a research study [1], proposes an intensified leveling system using items response theory and decision tree. The level of new learners predicted by using the decision tree which built by training set of data. The items in the pool are leveled on difficulty using IRT. Effective learning is achieved without any compromise which is the objective of Intelligent Tutoring System. Another study about leveling system, [3] proposes an automatic leveling system for e-learning examination pool using the algorithm of decision tree. The automatic leveling system is built to automatically level each question in the examination pool according its difficulty. In [4], develop an adaptive intelligent tutoring system based on item response theory and metrics. Metrics have been elaborated to associate the exercises of an

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activity corpus to the domain model. Previous studies have built the system that provides direct and indirect customized instruction or feedback to learners while interacting with the system.

II. SYSTEM DESIGN

A. *Intelligent Tutoring System Architecture*

This study adopts the Intelligent Tutoring Architecture developed by Zarandi [2]. We used concept of its architecture as a template of Intelligent Tutoring System which delivered the adaptive leveling of the learner. This system work as a framework for a disciplinary and could be used for another disciplinary domain.

- *Expert Model*

  According to general model of ITSs, expert model should assess learners' understanding and try to diagnose and reveals causes which might be the reason for learner misconceptions. When the learner fails to answer an assessment concept, its negative effect propagates through the whole network by its defined relation and on the other hand, if success, its lead to increasing in system's belief of learner understanding [2]. For each new student, expert model is instantiated with this new learner's ID and stored in the system's knowledge-base.

- *Student Model*

  Student model stores the information about user experiences during working with the system. This model updates during learning session. The student model is a data structure for what happened during the learning session and a fuzzy cognitive map is responsible for modeling and handling these changes [2]. Our study propose the student model could adapt

- *Pedagogical Module*

  Based on the gathered information by the student model, pedagogical module proposed comprehensive instruction in agreement with the learner's need [2]. Most of the ITSs' pedagogical module operates in the form of procedural rules. Pedagogical module by use of the updated student model presents new educational material for the learner, offers teaching suggestions or assesses the learner.

- *Communication Module*

  Communication module has two responsibilities. It visualizes student and expert model for learner's and captures environment variables like learner's allotted time for studying a specific content [2].

B. *Adaptive Leveling*

Our objective was to develop an adaptive intelligent tutoring system based on item response theory and fuzzy logic as a framework for any disciplinary fields. Along the system interacting with amount of learner, it records every even and transaction of each learner as the basis for adaptation system. Adaptation here is the enhancement of the question level automatically. Learner status or learner ability level will also update automatically during the interaction with the system. This study involved finding the learning level or capability of the learner first. Hence, their entry into the test is based on individual ability. For each new learner that uses the system for the first time, learner ability and finding information about learner background is detected while interacting with Intelligent Tutoring System. The framework proposed for this study is as follows

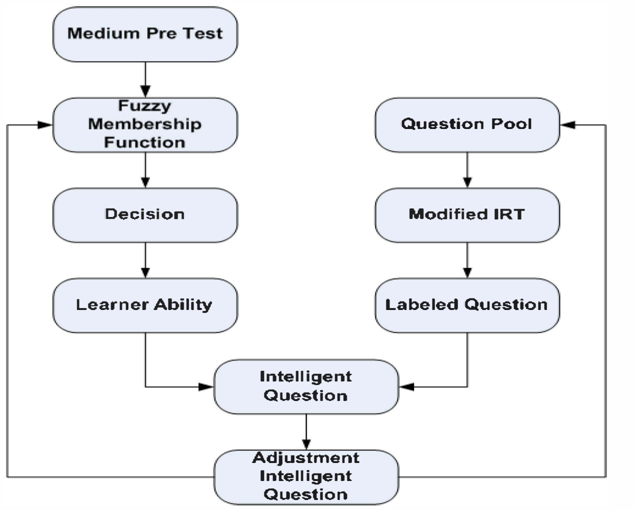

Fig 1. Proposed structure of Adaptive Leveling

a) *Adjusting Learner Level*

Fuzzy logic is used to predict learner ability at early stage by giving a pretest and while interacting with system. So system could adjust the learner ability while interacting with system. As a new learner and login to the system for the first time, the information of interaction with system is saved in knowledge-base. The system predicted the learner's ability through fuzzy logic every time the learner login to the system. First the learner login to the system, the system will detected the learner's level by giving the pretest. The item difficulty of the question on the pretest initialized with medium difficulty. This condition is for learner that login for the first time. If the learner login again in another time, the question on the pretest will adjust according to the prior result of the learner's pretest.

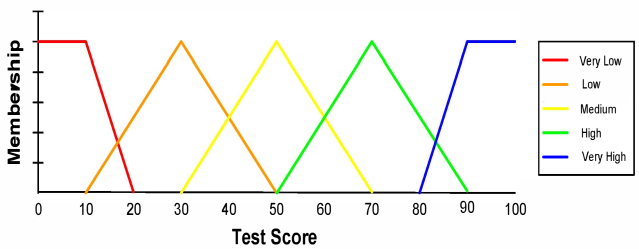

Fig 2. Membership Function of the learner's ability

This study classifies the learner ability as very low, low, medium, high, and very high as shown in Fig 2.

b) Adjusting Question Level

In our study, the system is in static condition for the first time before any interaction with learner. Items (question) difficulties are being initialized by teacher. In order to acquire an adaptive intelligent question, we modify items response theory proposed by Kavitha [1]. After amount of learners interacting with the system, appropriate items difficulty will adapt automatically according to the answers of amount of learners. A question with low level of difficulty will increase to high level automatically if few of learner (e.g. less than 10 learner) answers the question correctly. Otherwise, a question with high level of difficulty will decrease to low level automatically if amount of learner answers the question correctly. The implication of this condition is the system will give an advice to the teacher to add the question with appropriate difficulty that has changed. We inspired by [1] to used nominal question levels as shown below

TABLE 1. Nominal Question Level

Question Level	Numerical Representation
Very Easy	-1
Easy	-0,5
Middle	0
Hard	0,5
Very Hard	1

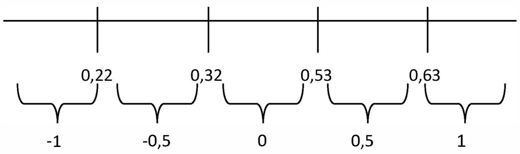

Fig 3. Nominal Question Level vs Item Difficulty scale [1]

Item difficulty can be determined by using IRT approach which uses the formula below [1]

$$ID = MSCA / SCAE \quad (1)$$

Where,

ID = item difficulty

MSCA = Minimum sum of Correct Answers

SCAE = Sum of Correct Answer of Each Question

In order to obtain the question level, a scale to placing items into nominal question level is shown in Fig. 3. It is calculated from ID values using mean and standard deviation. According to this theory, all items must be answered before calculating the question level. Our study modify this scale which shown in Fig 4. We compare a question which done by a learner with ten question which have number of right answer highest than other. So, it is not necessary waiting for entire question done correctly to change the question level.

TABLE 2. Calculation of Item Difficulty

No	SCAE	Item Difficulty	Nominal Question Level
1	12	0.83	1
2	37	0.27	-0.5
3	14	0.71	1
4	36	0.28	-0.5
5	23	0.43	0
6	23	0.43	0
7	31	0.32	0
8	45	0.22	-1
9	18	0.56	0.5
10	27	0.37	0
11	45	0.22	-1
12	12	0.83	1
13	24	0.42	0
14	47	0.21	-1
15	18	0.56	0.5
16	32	0.31	-0.5
17	35	0.29	-0.5
18	33	0.3	-0.5
19	17	0.58	0.5
20	30	0.33	0
21	10	1	1
22	45	0.22	-1
23	45	0.22	-1
24	35	0.28	-0.5
25	14	0.71	1
26	17	0.58	0.5
27	18	0.56	0.5

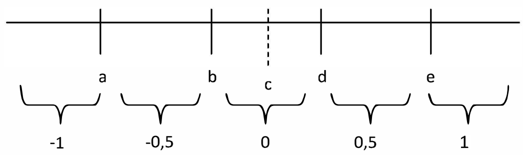

Fig 4. Propose scale to obtain question level

Calculation of item difficulty propose by this study are shown below

c = average number of correct answer from sample question (2)

b = c – standard deviation (3)
a = b – standard deviation (4)
d = c + standard deviation (5)
e = d + standard deviation (6)

III. RESULT

Our study has been implemented at an elementary school in our country. This research involves eighty student of fifth grade of elementary school. In order to obtain the student ability, we give eighty students a pre-test. The result of pre-test is seen on fig 5. About 63 % participants are in medium level, 18 % participants are in high level, 7 % participants are in very high level, 7 % participants are in low level and 5 % participants are in very low level. Based on the level, appropriate difficulty level of question that matches participants is taken from question pool. Then the system provides learning material for participants according to their level. While participants interacting with system, the difficulty level of question is evolved. It seen on table 3. Number of question is obtain from table 2 .

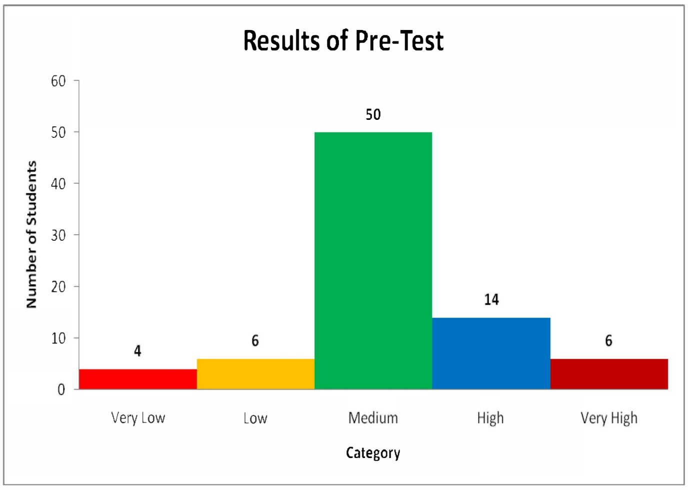

Fig 5. Pre-Test Result

TABLE 3. Number of Question with Question level

Question Level	Nominal Question Level	Number of Questions
Very Easy	-1	5
Easy	-0,5	6
Medium	0	6
Hard	0,5	5
Very Hard	1	5
Total of Questions		27

After testing, number of question on each level is change because calculation of item difficulty is running while participants answer the question which given by the system. Because distribution of participants ability based on pre-test is dominated by medium and high level so composition of changing questions for each category are low, medium and high as seen on table 4.

TABLE 4. Changes of Number of question

Question Level	Nominal Question Level	Number of Questions
Very Low	-1	5
Low	**-0,5**	**9**
Medium	**0**	**4**
High	**0,5**	**4**
Very High	1	5
Total of Questions		27

IV. CONCLUSION

There is a great need in the education area to monitor test results on a large scale as well as to identify question that are most likely to be benefited by student according to the knowledge level of the student.

More often the question is answered; the system will automatically recalculate a question level. So, in order to acquire an adaptive system could be done by adjusting learner level using fuzzy logic and adjusting question level using modified items response theory.

References

[1] Kavitha, R, "Intensified Leveling and Assessment System in Intelligent Tutoring System using Decision Tree and Item Response Theory, " International Journal Computer Technology and Application, Vol.2 (4) 736-740, July 2011

[2] Zarandi, M, H, "A Fuzzy Expert System Architecture for Intelligent Tutoring System: A Cognitive Mapping Approach," Journal of Intelligent Learning Systems and Application. Vol. 4 29-40, 2012

[3] Cheng, S, "Automatic leveling System for E-Learning Examination Pool Using Entropy-Based Decision Tree," Springer-verlag Berlin Heidelberg, 2005

[4] Conati C, "Intelligent Tutoring System: New Challenges and Direction," Department of Computer Science, University of British Columbia, 2009

[5] Samuelis L, "The Component for Intelligent Tutoring Systems," Department of Computer Science and Informatics, Technical University of Kosice Letna, Slovakia, 2007

[6] Nakakoji K, Yamada K, Yamamoto Y, Morita M, "A Conceptual Framework for Learning Experience Design," Proceeding First Conference on Publication Year, 2003

[7] Alevan V, Sewall J, McLaren BM, Koedinger K R , "Rapid Authoring of Intelligent Tutor for Real World and Experimental Use," Proceeding of the

Sixth International Conference on Advanced Learning Technologies, 2006
[8] He Y, Hui S C, Quan T.T, "Automatic Summary Assessment for Intelligent Tutoring Systems," Computer & Education, Volume 53, Issue 3, Pages 890-899, 2009