A study of Learning Estimation using Ubiquitous Intelligence

Chang-Duk Jung

Dept Of Computer Engineering, korea University, South Korea
jcd1234@korea.ac.kr

Abstract.

Experimental results are analyzed in this paper in order to further clarify and demonstrate the benefits of the IRT system. The course unit "Perception," with the Neural Network (NN) is used to obtain these results in order to provide personalized e-learning services. This study of the Item Response Theory system estimates the abilities of on-line learners, and recommends appropriate course materials, adjusted to the learners' abilities. Course material difficulty can be automatically adjusted using the collaborative voting approach. Experimental results show that the IRT system can provide personalized on-line learning, based upon learner abilities, in a fast, efficient manner. It is very difficult for the teacher to know who understands the lecture or not in the classroom. Therefore, in this paper, it proposed the algorithm of student score evaluation algorithm using full duplex method. Moreover, it confirms that full duplex method using fuzzy rules and neural network can tell where misunderstanding of the problems in the test. The computer simulation results shows that the full duplex virtual learning system has been proven to be much more efficient than one way traditional method which unfortunately does not consider the students understanding. Moreover, In this paper, we developed adaptive feedback algorithm for each students. Purpose of this paper wishes to maximize learning effect using adaptive feedback algorithm. Adaptive feedback algorithm confirmed according to analysis result is effective than existent algorithm.

1. Introduction

Now we can know what's the name of disease by one drop of blood. Also, it's different prescriptions up to every single patient by age, sex, weight and height even though it's same disease.

For example, if they have same disease, an old person and a kid have to take 1 pill one time per a day, but for 20's healthy person has to take 1 to 2 pills 2times per a day. As the same way, if students who get over 60 points, let them pass and others who can't get over 60 points make them not pass then it will be satisfied study up level. But it causes another problem for students who get much more than 60points need to control the degree of difficulty. Because they pass the same condition - over

60points- but it's different of understanding lecture for students who get over 85 points.

Therefore, students who get 60points get class more low level of class for next lesson and students who get more than 80points should take higher level class. There are two reasons need to Full Duplex Method study : First, there are students who can understand 80% of lecture and also students who can understand 30% of lecture together in the existing school. But it's not helpful and waste of time each other. To solve this problem, middle schools and high schools run level study instead of superiority and inferiority class. Level study means students study up to their level in class.

In this article, I improve the way of evaluation algorithm and imitation test based on student's grade for level study in virtual university which doesn't need to move class room.

Second, it causes serious problem gap of questions examination relative the degree of difficulty. For example, Assume A student select Germany and B select French as a second language test for pass university. If Germany test is very easy to pass which average score is 80points but French test is hard which average score is 60 points then even if A and B got same score of 70points, it would be a disadvantage for B. To settle this problem, there's a active research about control the degree of difficulty of questions examination and using Test equating which is the way of fixing statistical data.

In other word, if some student get 90points in virtual university test but get 70points usual university then it should analyze what's actual score for this student and change score exactly to prevent from getting disadvantage of different the degree of difficulty.

I test distinction by the degree of question difficulty and then I analyze degree of question discrimination in part 2. In part 3, we will know individual ability of study and then I will show algorithm which is using by full duplex method with decision questions up to difficulty in part 3. Part 5 will be conclusion.

Problem degree On-Line Learning has one major weakness. It does not take into account learner ability, and tends to overload the student with more information than can be absorbed, resulting in the learner not being able to adapt to such quantity. The Item Characteristic Function proposed by Rasch estimates the learner's ability based upon specific learner feedback in order to determine the appropriate level of course difficulty. Many powerful information search tools have been proposed, such as Google or Citeseer search engines, which enable users to filter out uninteresting or irrelevant results. Recent surveys reveal that on-line learners frequently use search engines to find information, and moreover web-based learning is a growing trend. According to the analysis by several large, prestigious corporations, the worldwide corporate e-learning market will exceed US $24 billion by 2004. The reason for this phenomenal growth is that it provides a convenient and efficient way to learn anytime and anywhere.

Many large corporations are using e-learning for on-line employee training. Nowadays, most systems consider learner/user preferences and interests when designing an educational system. Therefore, considering learner ability and limiting information in order to prevent overload, can promote the best learning performance.

Item Response Theory (IRT) is usually applied to the Computerized Adaptive Test (CAT) domain to select the most appropriate test items based upon individual ability. The CAT can not only efficiently shorten the testing time, but provides clearer diagnosis. Currently, the CAT concept has been successfully used to replace traditional paper and pencil tests having fixed length and content, in real-world applications such as GMAT, GRE, and TOEFL. IRT provides learning paths that can be adapted to various levels of course material difficulty in order to match the different abilities of the learner. This personalized system, based upon a user profile, prevents the learner from becoming lost in the course material, resulting in more efficient and effective learning. Diagnosis of the difficulty level of individual test questions asking the learner for feedback regarding the difficulty level of each question by asking the learner to rate each question for 5 different difficulty levels, as well as yes or no feedback concerning each questions. Learners responses are then forwarded to another section called the personalized agent, which records learner responses, analyzes learner abilities, and adjusts course material difficulty. Course experts then adjust the difficulty of course materials according to the learner feedback information. After many learners use this system, course material difficulty is sufficiently adjusted to become reasonable and stable. The IRT system architecture can be divided into two main parts, which are front-end and back-end parts. The front-end part manages communications with learners, and records learner behavior, while the back-end part analyzes learner ability and determines appropriate course materials for learners. This process is based upon estimated learner ability. The front-end part identifies learner abilities, analyzes learner questions, and then selects the suggested course materials for the learner. The back-end operation is a feedback agent, which collects learner feedback, updates learner ability, and then adjusts the difficulty level of course materials. There is also an interface agent that ties the front-end and the back-end together. The interface agent provides the functions of account management, authorization, and query searching. Various graphs, charts, and equations are presented in order to further describe and clarify the Item Response System. Experimental results are analyzed in this paper in order to further clarify and demonstrate the benefits of the IRT system. The course unit “Perception,” with the Neural Network (NN) is used to obtain these results in order to provide personalized e-learning services. The principal goal of the project is to assess the students’ knowledge in the basic Informatics topics. An ordinal score ranging from 1 to 4 is assigned to each examinee for each item with respect to the solving level achieved. For every item an ordinal score is assigned to the examinee that completes with success up to a step but fails to complete the subsequent step.

2. Related Work

The amount and quality of feedback provided to the learner has an impact on learner satisfaction. Feedback is particularly important to the effective delivery of e-learning courses. E-learning delivery methods such as web-based instruction can provide barriers to traditional type classroom feedback. For instance, in a web-based course learners cannot simply raise a hand and ask for clarification about a point made by the instructor. Hence, the design and integration of feedback mechanisms impact the learners' experience and level of satisfaction.

According to Neal & Ingram (1999)[4] distance learners do not receive the day-today feedback available in traditional classroom settings. Instructor-student feedback is important as it helps the instructor to gauge the level of student satisfaction regarding a topic or an entire course. Because of the loss of traditional classroom feedback in e-learning environments, other methods to assess learner satisfaction need to be administered. Learner feedback during and after the learning event is important to successfully measure levels of satisfaction. E-learning courses, because of the lack of face-to-face contact between instructor and student, require special efforts in order to obtain information regarding learner satisfaction. For example, e-learning courses don't allow the instructor to gauge levels of learner satisfaction using traditional methods such as facial expressions or body language. **Neal and Ingram (1999)** suggested that questions related to the efficiency of what students have learned and their level of satisfaction with distance learning courses remain largely unanswered until the traditional end-of-course evaluation forms are completed and reviewed. Special attention must be given to obtain student feedback in e-learning.

Sherry, Fulford, and Zhang (1998)[3] conducted studies on two different measures of distance learners' satisfaction with instruction. The studies were held at a major University known for its early consistent involvement in distance education. The courses were delivered via live two-way audio and video technology. The first study analyzed the accuracy of a short, written survey designed to obtain learner perceptions for opportunity to interact in the distance education course. The survey included questions regarding interaction between the instructor and learner-to-leaner interaction. Results revealed that instructor-to-class interaction is positively and moderately correlated with perception of learner-to-learner interaction. The second study by Sherry et al. examined the utility and feasibility of the Small Group Instructional Diagnostic (SGID) evaluation process in distance education. SGID is an interactive evaluation process tested at the University of Massachusetts. The SGID examines broad views of the instructional environment.

In the SGID evaluation process, course instructors volunteer for a facilitated mid-semester evaluation. A trusted colleague who usually has experience in faculty development conducts the evaluation. The facilitator guides the class through three questions regarding what helps, hinders, and should be changed about the course. Comments are displayed for the whole class to consider and rank. The facilitator reviews the list with the instructor. Finally, the instructor discusses the list and planned changes with the class.

3. Item Response Theory

This study of the Item Response Theory system estimates the abilities of on-line learners, and recommends appropriate course materials, adjusted to the learners' abilities. Course material difficulty can be automatically adjusted using the collaborative voting approach. Experimental results show that the IRT system can provide personalized on-line learning, based upon learner abilities, in a fast, efficient manner. To solve these problems examining in the first chapter, we wish to present method that measure problem degree of difficulty as following. Problem degree of difficulty is numerical values which display easy military expedition and difficult degree of problem. This is student's ratios who guess right answer among whole student that apply for an examination. Formulas that calculate problem degree of difficulty is as following.

$$p = \frac{R}{N} \times 100$$

N : Whole examination candidate's number

R : Person's number who guess right answer of problem

200 students solved 5 problems. Table 1 is right answer data and each problem degree of difficulty of students.

Table1 Deduction of item difficulty

item	N	R	P
①	200	10	.05
②	200	80	.4
③	200	50	.25
④	200	180	.9
⑤	200	100	.5

Problem 1 is the most difficult. 10 people among 200 examination candidate set answer of problem. Problem degree of difficulty is 0.05. Problem 4 is the easiest. Because 180 people among 200 subjects set answer of problem, problem degree of difficulty is 0.9.

Problem degree of difficulty evaluates to hot water if it is less than 30. Degree of difficulty of problem evaluates if it is less than 80 more than 30. Degree of difficulty of problem evaluates to very easy problem if it is more than 80. Cangelosi (1990) presented valuation basis by problem degree of difficulty with table 2.

Table 2 Item evaluation for item difficulty

Problem degree of difficult	Problem evaluation
below .25	Hard problem
.25-.75	Suitable problem
more than .75	easy problem

Problem discriminate index produces by correlation coefficient. If a student is high total score, let's suppose that each subject results of the student is high averagely. That is, if correlation coefficient between two points is high, discriminate index of the problem may be high. Formula that looks for correlation coefficient is as following.

$$r_{bis} = \frac{M_R - M_W}{S_t} \times \frac{P(1-P)}{Y}$$

M_R : Student's score average (reaction to right answer
M_W : Student's score average (reaction to incorrect)
S_i : Standard deviation of whole point distribution
P : Whole student's the right answer rat
Y : In formality distribution curve P and 1 - P division

Regarding credit, variable is age, graduation availability, sex, credit etc. that is enrollment state, matriculation. Variable connected with credit is enrollment state. That is, students who credit is bad is high possibility that do leaving or encounter tail light lock removal from a register in next term, and this result is relevant statistically. Next, most, variable that interrelation is high is taking a course total credit. That is, if a student is the more credit, possibility to get good credit is high. Also, there are a lot of possibilities to get credit that there should like to be many students if class is high and there are a lot of ages. A person who solves easily hot water supposes that solve easily problem of easy degree of difficulty. Problem degree of difficulty is come for 10% on present example and number of persons is 2 people out of 20 people. Person belonging to 10% supposes almost all problems that are resolvable to whole number of persons. As a result, expectation point is 100. When this person solves next problem, a person heightens degree of difficulty.

Table 3 Calculation of score using item difficulty and number of item

step	difficult rate (%)	number of problem	score of the problem	Scorer by degree of difficulty		Point by setting a problem unit	Scorer's number by setting a problem unit
0	10	1	10	2		100	2
1	30	2	20	6		90	4
2	40	2	20	8	⇒	70	2
3	50	1	10	10		50	2
4	70	3	30	14		40	4
5	90	1	10	18		10	4
6	NONE	0	0	20		0	2

Table 3 finds out point distribution and ascertained head count by point distribution using degree of difficulty. Contrary to this, I can search relevant degree of difficulty and number of problem through point distribution and head count in table 4. Because scorer's number of ratio is ratio that dominates in degree of difficulty, degree of difficulty is decided according to scorer's number. Identification problem about a person that takes an examination in on-line estimation is the most important point in estimation of cyber education system. Cyber studying estimation method is as following.

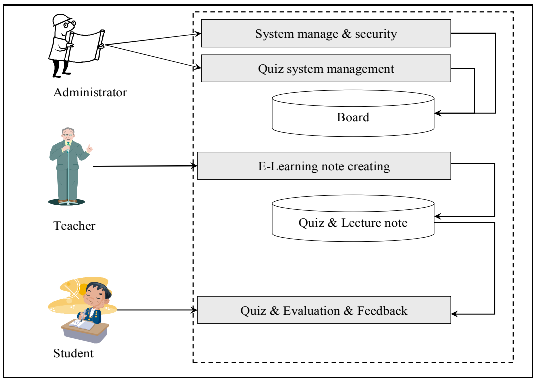

Fig. 1 on line test using item difficulty

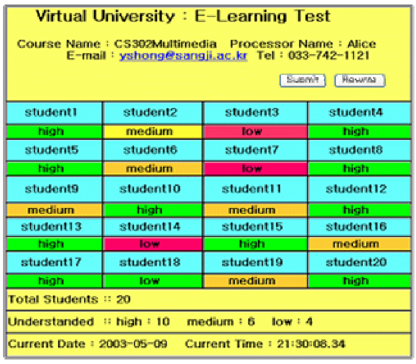

Fig.2.Test result for full duplex learning -A

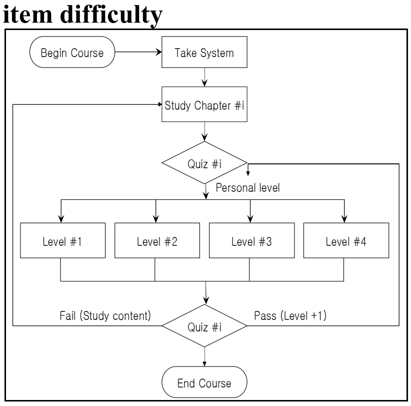

Fig.3.flowchart of adaptive feedback engine

4. Fuzzy algorithm for both direction studying

We present individual's level studying result and simulation result using neural network and fuzzy expert system in this paper. In this paper, demand estimate process that we use is as following. X shaft is time and Y shaft is value (data value past) of variable.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \varepsilon$$

Last point that consider degree of difficulty

X_1 : Element 1 that influence in dependent variable
X_2 : Element 2 that influence in dependent variable
X_3 : Element 3 that influence in dependent variable
X_4 : Element 4 that influence in dependent variable

X_5 : Element 5 that influence in dependent variable

Table.4. Input data for neural network

Neural network early input condition		
1. Learner test score during past 1 month	small	Big
2. The incorrectness rate of exam	small	Big
3. The right answer rate of exa	Big	Small
4. Degree of difficulty of exa	Big	Small
5. Learner attitude/attendance during past 1 month	Small	Big

Table 4 is expressing estimate process about 5 different conditions that serve to forecast. It is important problem that establish early value of neural network studying. It reduces studying error and quicken studying process that select value properly early. Usually, neural network's studying begins in value specification early. The studying rate how we decide parameter value is decided. As studying error is small, studying process can converge fast and can fall in saturation point at early stage. Therefore, we choose suitable parameter to data that wish to analyze. In so doing, it is very important problem that studying process does to study to be converged fast.

So, consider all cases according to each extent 0.1, 0.3, 0.5, 0.7, 0.9 with $\kappa, \theta, \phi, \mu$ (kappa, theta, phi, mu) and tried an experiment in free case.

And, limited class by each 500 number of times.

① Study test data with 10 different condition using neural network.

② Calculate test data and error of estimate data after predict about 10 test data.

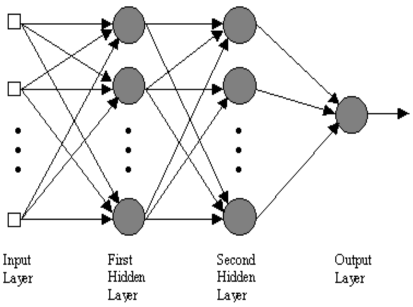

Fig. 5 Structure of neural network

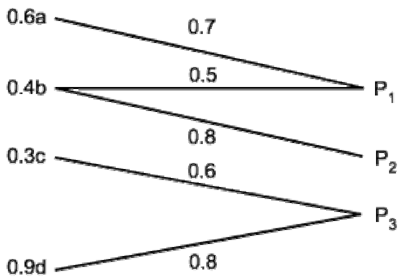

Fig. 6 Calculation of final score using Fuzzy rule

Fuzzy relation makes concept of relation that use in mathematics in fuzzy. For example, 'X and Y resembled very', relation called 'X is more active than Y' gets into purge relation. Fuzzy relation becomes important method to express fuzzy condition in fuzzy inference. Express by position function $\mu R(x, y)$ about relation of x and y. usually, we can mark fuzzy relation by fuzzy graph and fuzzy procession as we display relation by graph and procession. Fuzzy graph expresses using vertex and arc and arc means strength of relation. In <figure 3>, figure displays student point about 4 people. Examination marks means a high position student from 80 points to 100 points, and an average student can mark by 0.5 - 07 from 50 points to 70 points. Finally, a low rank student corresponds to 0.1 to 0.4 less than 40 points. Here, P_1,P_2,P_3 are denoting last results point that consider degree of difficulty. Number registered to tie line here means degree of difficulty and student studying state condition.

Therefore, we yield point that is corrected finally for estimation about a student who acquires same point. There is a student who take a course same lecture. A student understood 80%, and other student understood less than 50%. When do assumption with upside, we can classify to two groups. For lecture time, it is the almost impossible matter to grasp how much a student understood conference.

5. Conclusions

In this paper, we developed and experimented algorithm to measure weak object class of students and understanding because use fuzzy rule and neural network. Exam lowers number of standard marks automatically if degree of difficulty is difficult and I developed methods that heighten standard marks automatically if degree of difficulty was easy. In this paper, if method that we propose is applied at a cyber university, we believe firmly something to be helped to everybody to students and teacher. The purpose of this paper is to discuss the ways in which we might use on-line assessment and feedback with students. With fast development in e-learning, assessment plays an important role between teaching and learning. A good e-learning system is not only with good teaching strategy and better learning resources but also proper assessment model. In this paper, we proposed analysis feedback for recently e-learning environments. There are several proper feedbacks for teachers, students, and learning management systems. The feedback could provide proper teaching, learning resource delivering and learning progress suggestions. With the approach, assessment prompts the learning effort in e-learning. Adaptive feedback algorithm aided in results elevation more than existent studying method.

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