Learning Ability Clustering in Collaborative Learning

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***Abstract*—Collaborative learning promotes learning motivation which encourages the active participation and leads to good learning performance. In most cases, good grade is usually a good indicator of good learner. Teachers might classify learners into various groups according to their grade. As a result, learners with poor grades are easily depressed and self-distrust. In this paper, we integrate K-means clustering method and IRT forecasting process to solve the grouping issue in collaborative learning. With a better grouping solution, teachers then can adjust the learning materials adaptively and teach students according to the learning aptitude.**

***Index Terms*—Learning ability, Item Response Theory, K-means, Collaborative Learning**

I. Introduction

Collaborative learning develops the abilities for interaction, sharing and cooperating, and emphasizes on the problem solving skills gathered from different learners. As a result, how to group learners according with similar learning ability then becomes an essential and significant issue in collaborative learning.

Traditionally, most knowledge and concepts can be compelled directly to students. The learning performance can be measured by scoring. But there is no definite linkage between learning ability and score for teachers to adjust the teaching method and learning content for different type of learners. Therefore, it does not guarantee that learners who score the same could understand the same. However, this issue has not been addressed properly yet.

Conventional test analysis techniques mainly focus on the difficulty and discrimination of the items, but the pseudo-chance parameter indicates the probability of unskilled examinees to answer items correctly. Learners might not be aware of their answer for the items. In this state, they are not supposed to understand these items. In this way, it is not easy to determine each student's study situation. Therefore, these results of the test analysis can not help teachers to enhance the effectiveness of teaching materials in class.

As the Internet and wireless networks grow up, this study presents a web-based assessment system for teachers to edit examinations online. When learners finished the test, teachers then can use Item Response Theory (IRT) to analyze and understand the learning ability of each student. According to the analysis results, teacher can adjust the learning materials adaptively and figure out the possible learning difficulties of learners. With comprehensive structure analysis, this system can help teachers to know the learning situation to achieve better teaching performance.

II. Related Work

Some e-learning technologies promote mobile learning and provide good assessment models for learners. However, whether the advanced m-learning or the traditional c-learning, the clustering method is significant for any kind of collaborative learning activity. Chang et al. [6] and Lin et al. [12] designed the influence diagram to develop courseware for collaborative learning. The work in [17] utilized SP-Chart and Bloom taxonomy in assessment method. With rapid development of ubiquitous technology, Shih et al. [16] proposed multimodel multimedia devices and Chang et al. [18] used ubiquitous technologies to enhance ubiquitous learning. The abovementioned learning platforms and intelligent tutoring methods indeed provide various innovative learning styles for learners; nevertheless, e-learning would be more practical and helpful if more educational theories and activities design were considered. This study uses the clustering method in learning ability to provide a good grouping method for collaborative learning.

Collaborative learning offers a way for learners to work together in order to reach a common goal. And collaborative learning is also a kind of group learning to increase the learning awareness for individual, as well as

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for group [5, 14]. The cooperation and teamwork are the main forces to support collaborative learning in information sharing and group processing. During the collaborative learning process, all teammates will benefit from each other [3].

Classical Test Theory [7] and Modern Test Theory [13] are both important methods to quantify the abstract data and to analyze the student's information. Classical test theory is mainly based on test score. Modern Test Theory is based on the item response theory. In these two theories, the difficulty and the discrimination are important attributes to be examined. But the most different point between these two theories exists in the impact of questions on the parameters. However, classical test theory does not put much emphasis on this issue [2].

Item Response Theory (IRT) is one of the acknowledged methods in Modern Test Theory. IRT uses the chart to demonstrate the test characteristic curve from difficulty and discrimination. Min-Ning Yu [11] mentioned that the test characteristic curve can display the student's ability and probability of correct response from learning [10]. These characteristic curves will be changed by different parameters. There are three functions to predict of student's ability and enhance the effectiveness of learning, including the one-parameter logistic model, two-parameter logistic model, three-parameter logistic model. These modules are built according to the characteristic curves. Through IRT, learners can understand their own learning ability which will not be affected by time and amount. Furthermore, IRT can collocate with other theories to perform side effect in the result. For example, IRT could be applied to analyze the test attribute and tester behavior with the student-problem chart [4].

Clustering is a method to classify scattered information into different clusters. Users can observe differences in the host easily from every distribution of the clusters. In addition, clustering is widely used in data miming to predict the behavior of information [1, 8]. Among the well-developed clustering methods, K-means is one of the most popular methods. By setting several centers, users can look for the minimum distance between any two data points in various clusters. And finally, it's easy to achieve a balance between the various clusters. K-means algorithm is often combined with other theories for further usages due to its low cost [9, 15].

III. Learning Management System

There are two parts in our proposed learning management system. One is the learner system and the other is the teacher system.

The learner system is comprised of a bulletin board system (BBS), an on-line exam system, a personal information management system and a learning history query system. The BBS shows news and learning content posted by teachers or system administrators. On-line exam system presents detailed information of each exam, such as the test range, starting time, ending time and the exam status. The exam status includes Under Preparation, Progressing and Finished. The on-line exam system shows the exam subject, exam title and remaining time. The exam items in on-line exam system focus on multiple choice questions. The personal information management system maintains learners' ID, password, name, gender, email, etc. Learners can see the class information and email to teachers directly. The learning history query system provides the service for retrieving the exam score, exam record and the three parameter model IRT information (see Figure 1) during the learning activity.

The teacher system is comprised of a bulletin board system, an item authoring system, an exam authoring system, an exam setting system, an IRT analysis system and a score management system. Teachers and system administrators can edit, delete and announce news. Teachers can edit, revise and delete the item attributes, such as item, options and answer in item authoring system. Exam authoring system supports teachers to select exam items and set the scoring criteria. The exam setting system helps teachers to manage the exam starting time and ending time. The IRT analysis system shows the difficulty and discrimination of items. Learning ability for each student will also show the one-parameter, two-parameter and three-parameter model. Regarding score management, teachers can query the students' score and check the detail answering status in each exam.

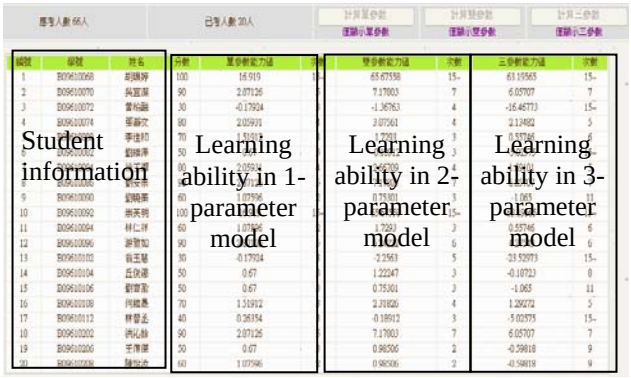

Figure 1. Three IRT parameter models and computing times for each student

IV. Main Method

There are two ways to understand the student's ability. One is to observe the performance of students in class, and the other depends on the test score. Item response theory is used to forecast the student's ability from answering questions. With the student's ability information, teachers can analyze to understand the learning status. In addition, such information also provides helpful remedial information to students and instruction hints to teachers in class.

A. Course and Item Analysis

The subjects of the experiment in this research were forty-six sophomore students in department of information management, and the target course is "Data Communications for Business". The exam was comprised of sixty multiple choice items. In order to use the item

response theory formula for forecast the student's ability after the test, we analyses the difficulty and the item discrimination in the test first. Table 1 shows the item difficulty and the discrimination in this test.

Table 1: Item difficulty and discrimination

item	(b)difficulty	(a)discrimination	item	(b)difficulty	(a)discrimination
1	1.0000	0.0000	31	1.0000	0.0000
2	0.9545	0.0909	32	0.9545	0.0909
3	0.9545	0.0909	33	0.8182	0.1818
4	0.9545	0.0909	34	0.8182	0.3636
5	0.8636	0.2727	35	0.7727	0.4545
6	0.8636	0.2727	36	0.9091	0.1818
7	0.7727	0.4545	37	0.6364	0.7273
8	0.7727	0.4545	38	0.7727	0.2727
9	0.8182	0.3636	39	0.7273	0.5455
10	0.7273	0.5455	40	0.6818	0.4545
11	0.6818	0.6364	41	0.6364	0.5455
12	0.6818	0.4545	42	0.6364	0.7273
13	0.5909	0.6364	43	0.5455	0.3636
14	0.6364	0.7273	44	0.5455	0.7273
15	0.3182	0.0909	45	0.5909	0.8182
16	1.0000	0.0000	46	1.0000	0.0000
17	1.0000	0.0000	47	0.9545	0.0909
18	0.9545	0.0909	48	0.9545	0.0909
19	0.9091	0.1818	49	0.9545	0.0909
20	0.8636	0.2727	50	0.8636	0.2727
21	0.8636	0.2727	51	0.8636	0.2727
22	0.8636	0.2727	52	0.7727	0.4545
23	0.7727	0.4545	53	0.7727	0.4545
24	0.7727	0.4545	54	0.8182	0.3636
25	0.8182	0.3636	55	0.7273	0.5455
26	0.8182	0.3636	56	0.6818	0.6364
27	0.7727	0.4545	57	0.6818	0.4545
28	0.8182	0.3636	58	0.5909	0.6364
29	0.7727	0.4545	59	0.6364	0.7273
30	0.8182	0.3636	60	0.3182	0.0909

In Formula 1, the b_i indicates the item difficulty value, and "i" is the item number in the test. Easy item has high b_i value. Formula 1 shows the difficulty function, P_H is the correct rate of the high score group, and P_L is the correct rate of the low score group. The high score group and low score group are 27% higher and lower in all of the students.

$$b_i = \frac{(P_H + P_L)}{2} \qquad \text{Formula 1}$$

In Formula 2, the a_i is item discrimination value. An item with high a_i value indicates the item has high discrimination. Formula 2 is the item discrimination function.

$$a_i = P_H - P_L \qquad \text{Formula 2}$$

B. Student's Ability Forecast

There are three functions discussed the difficulty (b_i), the item discrimination (a_i) and the pseudo-chance parameter (c_i) in Item Response Theory.

(1) One-Parameter Logistic Model: It forecasts the student's ability from difficulty (b_i). It considers the difficulty value could affect the student's ability. In Formula 3, $P_i(\theta)$ is the correct rate of the i^{th} item answered by the student with the ability value θ which ranges from 0 to 1. The value of e is 2.718. This model does not apply to the items which are too easy or too difficult.

$$P_i(\theta) = \frac{e^{(\theta - b_i)}}{1 + e^{(\theta - b_i)}} \qquad \text{Formula 3}$$

(2) Two-Parameter Logistic Model: In Formula 4, a_i is the discrimination of the i^{th} item. The learning ability could be calculated by the difficulty and the item discrimination in this model. If two students have the same number of incorrect answers with different items from this test, the $P_i(\theta)$ will not be the same. As a result, the ability of the student can be more objective.

$$P_i(\theta) = \frac{e^{a_i(\theta - b_i)}}{1 + e^{a_i(\theta - b_i)}} \qquad \text{Formula 4}$$

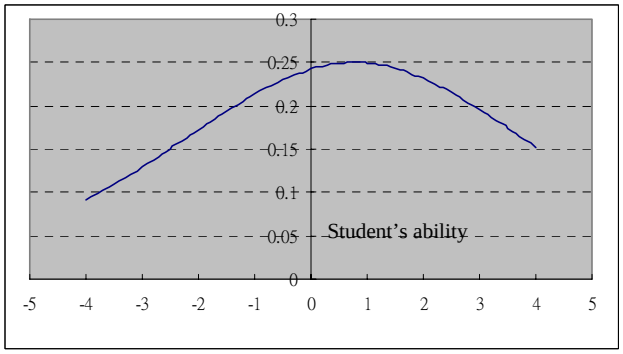

Figure 2. Test information characteristic curve of the 60th item

Table 2: Example of the 60th item

θ	P(θ)	Q(θ)	test informatiln
-4	0.102530255	0.897469745	0.019011942
-3.9	0.106789092	0.893210908	0.019707682
-3.8	0.111202912	0.888797088	0.020420831
-3.7	0.115775517	0.884224483	0.021151146
-3.6	0.120510652	0.879489348	0.021898313
-3.5	0.125411983	0.874588017	0.022661946
-3.4	0.130483082	0.869516918	0.02344158
-3.3	0.135727411	0.864272589	0.02423667
-3.2	0.141148304	0.858851696	0.025046583
-3.1	0.146748942	0.853251058	0.025870597
-3	0.152532341	0.847467659	0.026707898
-2.9	0.158501325	0.841498675	0.027557573
-2.8	0.164658507	0.835341493	0.028418612
-2.7	0.171006266	0.828993734	0.029289901
-2.6	0.177546726	0.822453274	0.030170224
-2.5	0.184281731	0.815718269	0.031058259
-2.4	0.191212821	0.808787179	0.031952578
-2.3	0.198341214	0.801658786	0.032851648
-2.2	0.205667775	0.794332225	0.033753831
-2.1	0.213193	0.786807	0.034657385
-2	0.22091699	0.77908301	0.03556047
-1.9	0.22883943	0.77116057	0.036461146
-1.8	0.236959569	0.763040431	0.037357383
-1.7	0.245276198	0.754723802	0.038247063
-1.6	0.253787635	0.746212365	0.03912799
-1.5	0.262491706	0.737508294	0.039997895
-1.4	0.271385729	0.728614271	0.040854445
-1.3	0.280466507	0.719533493	0.041695257
-1.2	0.289730311	0.710269689	0.042517904
-1.1	0.299172873	0.700827127	0.043319931
-1	0.308789387	0.691210613	0.044098864
-0.9	0.318574498	0.681425502	0.044852229
-0.8	0.328522312	0.671477688	0.045577562
-0.7	0.338626392	0.661373608	0.046272429
-0.6	0.348879771	0.651120229	0.046934437
-0.5	0.359274963	0.640725037	0.047561253
-0.4	0.369803976	0.630196024	0.048150619
-0.3	0.38045833	0.61954167	0.04870037
-0.2	0.391229082	0.608770918	0.049208448
-0.1	0.402106849	0.597893151	0.04967292
0	0.413081837	0.586918163	0.05009199
0.1	0.424143874	0.575856126	0.050464018
0.2	0.435282446	0.564717554	0.050787529
0.3	0.446486733	0.553513267	0.051061225
0.4	0.457745651	0.542254349	0.051284002
0.5	0.469047893	0.530952107	0.051454952
0.6	0.480381977	0.519618023	0.051573375
0.7	0.49173629	0.50826371	0.051638783
0.8	0.503099134	0.496900866	0.051650908
0.9	0.514458778	0.485541222	0.051609699
1	0.525803502	0.474196498	0.051515326
1.1	0.53712165	0.46287835	0.051368178
1.2	0.548401674	0.451598326	0.051168859
1.3	0.559632182	0.440367818	0.050918182
1.4	0.570801982	0.429198018	0.050617165
1.5	0.581900131	0.418099869	0.050267018
1.6	0.59291597	0.40708403	0.049869137
1.7	0.603839165	0.396160835	0.049425088
1.8	0.614659749	0.385340251	0.0489366
1.9	0.625368147	0.374631853	0.048405543
2	0.635955213	0.364044787	0.047833922
2.1	0.646412253	0.353587747	0.047223854
2.2	0.656731052	0.343268948	0.046577557
2.3	0.66690389	0.33309611	0.045897333
2.4	0.676923564	0.323076436	0.045185548
2.5	0.686783394	0.313216606	0.044444621
2.6	0.696477239	0.303522761	0.043677003
2.7	0.705999499	0.294000501	0.042885167
2.8	0.715345118	0.284654882	0.042071587
2.9	0.724509584	0.275490416	0.041238729
3	0.733488924	0.266511076	0.040389034
3.1	0.7422797	0.2577203	0.039524906
3.2	0.750878998	0.249121002	0.038648704
3.3	0.759284413	0.240715587	0.037762726
3.4	0.767494044	0.232505956	0.036869202
3.5	0.775506467	0.224493533	0.035970286
3.6	0.783320727	0.216679273	0.035068051
3.7	0.790936311	0.209063689	0.034164476
3.8	0.798353136	0.201646864	0.033261448
3.9	0.80557152	0.19442848	0.032360753
4	0.812592163	0.187407837	0.031464078

(3) Three-Parameter Logistic Model: In Formula 5, pseudo-chance parameter (c_i) is taken into consideration because some students might answer by guess in the test.

$$P_i(\theta) = (1 - c_i) + c_i * \frac{e^{a_i(\theta - b_i)}}{1 + e^{a_i(\theta - b_i)}} \quad \text{Formula 5}$$

We use the intercept to count the pseudo-chance parameter (c_i) from the characteristic curve. In order to get more accurate intercept, the test information is used in this study. In the characteristic curve, the reliability is better near the vertex. Formula 6 is the test information characteristic curve function. $I_i(\theta)$ is the test information at the i^{th} item. $P_i(\theta)$ is the correct rate of the i^{th} item derived from the ability value θ of the student.

$Q_i(\theta)$ is equal to 1-$P_i(\theta)$ and indicates the incorrect rate. The value a_i is the discrimination value.

$$I_i(\theta) = a_i{}^2 P_i(\theta) Q_i(\theta) \quad \text{Formula 6}$$

In this research, the range of validity and reliability is 0.5 units near the vertex. Figure 2 shows the characteristic curve of the 60^{th} item. Table 2 is an example of the 60^{th} item in this test. For example, when the ability value is 0.8, we can find the reliability test information in Table 2. So we get the range from 0.3 to 1.3 to count the pseudo-chance parameter which value (c_{60}) is 0.0227. Formula 7 is the student's ability function.

$$\theta_{s+1} = \theta_s + \frac{\sum_{i=1}^{N} a_i [u_i - P_i(\theta_s)]}{\sum_{i=1}^{N} a_i^2 P_i(\theta_s) Q_i(\theta_s)} \quad \text{Formula 7}$$

Table 3 demonstrates an example with 60 items in the test. Value u is the student's performance in the title. 1 means correct and 0 means incorrect. $\triangle\theta_s$ is a variation in the volume of student's ability. If this value is lower, the student's ability will be more accurate. $\triangle\theta_s$ must lower than 0.001, and θ_{s+1} predicts the value of student's ability.

Table 3: Student's ability

item	u	P	Q	a(u-P)	a*a(PQ)	Δθs	θs+1
1	1	0.5	0.5	0	0	2.24522	3.24522
2	1	0.50103	0.49897	0.04536	0.00207		
3	1	0.50103	0.49897	0.04536	0.00207		
⋮	⋮	⋮	⋮	⋮	⋮		
58	1	0.56472	0.43528	0.277	0.09954		
59	1	0.56573	0.43427	0.31583	0.12995		
60	1	0.51549	0.48451	0.04405	0.00206		
				5.79764	2.58221		

V. EXPERIEMENTAL RESULTS

In the research, we used two experiments to test the validity of the three parameter Logistic Models discussed in Item Response Theory. The first experiment explores the clustering effect of the three models tested in the result, and the second experiment examines the grouping analysis of the effectiveness in class.

A. Clustering Effect of the Three Models Tested in the result

There were forty-six students participated in this exam. In the experimental data, $\triangle\theta_s$ means the variation in the volume of student's ability, θ_{s+1} predicts the value of student's ability, and times shows the frequency of the number lower than 0.001 with $\triangle\theta_s$. Eventually with lower $\triangle\theta_s$, the student's ability will be more accurate. Accordingly we have to count the times of the $\triangle\theta_s$ converges to 0.001.

Table 4, Table 5 and Table 6 show the student's ability predicted from Item Response Theory.

In Table 4, only the difficulty (b_i) can affect the student's ability, and they do not have obvious difference. The value b_i is from 0.78 to 4.78 in the One-Parameter Logistic Model.

In Table 5, the item discrimination (a_i) is introduced, and we can see the difference obviously from student's ability. This result classifies student's ability into different levels. In Table 6, the pseudo-chance parameter (c_i) is taken to enhance the accurate student's ability (θ_{s+1}).

B. Grouping Analysis of the Effectiveness in class

There were 116 students participated this experiment. Those students were divided into two groups, including the experimental group and the control group, and took the pretest and posttest, respectively. After taking the pretest, we use the IRT to predict the student's ability of experimental group and divide them into eleven groups. The students in experimental group will have a forty minutes group discussion, and the students in the control group will not.

In the second experiment, 112 students are divided into experimental group and control group. We apply the item response theory to forecast students' learning ability and K-mean to cluster them into 11 groups. Table 7 shows the learning ability of the control group in pretest. Table 8 depicts the learning ability of the control group in posttest. Table 9 represents the learning ability of the experiment in pretest. Table 10 represents the learning ability of the experiment in posttest. Figure 3 illustrates the comparison of the control and experimental group in pretest and posttest.

After the posttest, we compared these two groups with student's ability. In experimental group, the average student's ability in pre-test is 3.84, and the average student's ability in post-test is 5.97. In control group, the average student's ability in pre-test is 2.16, and the average student's ability in post-test is 2.4.

In the test sheet reliability, we apply the Kuder-Richardson reliability.

$$r_{KR21} = \frac{n}{n-1} * \left[1 - \frac{\bar{x} - (n - \bar{x})}{n S_x^2}\right] \quad \text{Formula 8}$$

Formula 8 is the KR-21 equation. N is the number of the test questions. $\bar{x}$ is the average score, and S_x^2 is the difference of the score. If the student answers correctly, the value of x is marked as 1; otherwise, 0 is marked. The reliability of pretest and posttest is 0.86 and 0.76 respectively with KR-21 (Kuder-Richardson reliability). The reliability 0.86 and 0.76 are both between 0.7 and 0.9, so that the reliability is reliable.

Table 4: Experimental data from One-Parameter Logistic Model

Students No.	Δθs	θs+1	Times	Students No.	Δθs	θs+1	Times
B09310005	0.0003182973	2.5266153429	4	B09510060	0.0000008528	3.7385512407	6
B09510002	0.0000038764	4.8723407544	7	B09510062	0.0000072565	2.0757919977	4
B09510004	0.0000038764	4.8723407544	7	B09510064	0.0002284338	3.4328225328	5
B09510006	0.0007621270	2.6641686177	4	B09510066	0.0000008528	3.7385512407	6
B09510010	0.0000396799	3.1913124346	5	B09510074	0.0007621270	2.6641686177	4
B09510012	0.0001480262	1.5575602300	3	B09510076	0.0002284338	3.4328225328	5
B09510016	0.0005763355	1.7171410207	3	B09510078	0.0000025328	1.9798197771	4
B09510018	0.0003012618	1.6360892140	3	B09510084	0.0005763355	1.7171410207	3
B09510022	0.0001299865	2.4010987920	4	B09510088	0.0000038764	4.8723407544	7
B09510024	0.0000006101	1.1920512294	3	B09510090	0.0000038764	4.8723407544	7
B09510026	0.0002284338	3.4328225328	5	B09510094	0.0003182973	2.5266153429	4
B09510028	0.0000098386	1.3338703060	3	B09510098	0.0000396799	3.1913124346	5
B09510030	0.0000025328	1.9798197771	4	B09510100	-0.0000000012	0.7843300517	3
B09510032	0.0009367543	1.1226859435	2	B09510102	0.0005763355	1.7171410207	3
B09510034	0.0000393130	4.1617541142	6	B09510104	0.0000396799	3.1913124346	5
B09510038	0.0000012311	2.8170996563	5	B09510106	0.0003182973	2.5266153429	4
B09510040	0.0003012618	1.6360892140	3	B09510108	0.0000028713	1.2623807504	3
B09510044	0.0007621270	2.6641686177	4	B09510110	0.0001666168	1.0541039872	2
B09510046	0.0000072565	2.0757919977	4	B09510202	0.0009367543	1.1226859435	2
B09510050	0.0000197625	2.1772449792	4	B09510204	0.0000672469	1.4812088036	3
B09510052	0.0003057043	0.9186194370	2	B09510206	0.0000072565	2.0757919977	4
B09510054	0.0000070050	2.9902926337	5	B09510208	0.0000197625	2.1772449792	4
B09510056	0.0000070050	2.9902926337	5	B09510210	0.0000396799	3.1913124346	5

Table 5: Experimental data from Two-Parameter Logistic Model

Students No.	Δθs	θs+1	Times	Students No.	Δθs	θs+1	Times
B09310005	0.0006513469	3.8844103763	4	B09510060	0.0000001313	12.4676692454	8
B09510002	0.0006179281	26.1251903011	9	B09510062	0.0000068741	2.8380471539	4
B09510004	0.0000059514	10.0310927907	7	B09510064	0.0000001876	6.2405069308	6
B09510006	0.0000427374	5.1798196962	5	B09510066	0.0000002207	9.0397196891	7
B09510010	0.0004636474	5.9345921804	5	B09510074	0.0000024059	4.5007225086	5
B09510012	0.0000051332	2.7887319734	4	B09510076	0.0000094624	7.1958521005	6
B09510016	0.0000028155	2.6921158545	4	B09510078	0.0006513469	3.8844103763	4
B09510018	0.0000001355	2.2857192311	4	B09510084	0.0000002808	2.3724768134	4
B09510022	0.0000010281	4.3336664552	5	B09510088	0.0006179281	26.1251903011	9
B09510024	0.0000003948	1.2764673202	3	B09510090	0.0001258281	15.8573923198	8
B09510026	0.0001022414	7.9755397672	6	B09510094	0.0003284251	3.6834395770	4
B09510028	0.0006152862	2.1588236346	3	B09510098	0.0000094624	7.1958521005	6
B09510030	0.0000068741	2.8380471539	4	B09510100	0.0003326308	0.8867590084	2
B09510032	0.0000019971	1.3851024632	3	B09510102	0.0008932153	2.2430055056	3
B09510034	0.0002283847	8.2899912666	6	B09510104	0.0001022414	7.9755397672	6
B09510038	0.0000638316	5.2920691496	5	B09510106	0.0000055527	4.6783838523	5
B09510040	0.0006152862	2.1588236346	3	B09510108	0.0000000952	1.2047241161	3
B09510044	0.0000951625	5.4091028784	5	B09510110	0.0000018228	0.9920459721	2
B09510046	0.0006513469	3.8844103763	4	B09510202	0.0000000154	0.7470149846	3
B09510050	0.0006513469	3.8844103763	4	B09510204	0.0003378971	2.0354277621	3
B09510052	0.0000000144	0.7121444379	3	B09510206	0.0000773017	3.3178179282	4
B09510054	0.0001416425	5.5313499341	5	B09510208	0.0001267882	3.4349101507	4
B09510056	0.0000319748	10.6701589342	7	B09510210	0.0000427374	5.1798196962	5

Table 6: Experimental data from Three-parameter Logistic Model

Students No.	Δθs	θs+1	Times	Students No.	Δθs	θs+1	Times
B09310005	0.0001029703	3.5524244351	5	B09510060	0.0000060801	12.1827982556	8
B09510002	0.0000020050	25.8506371027	10	B09510062	0.0000471221	2.4719026011	5
B09510004	0.0000503266	9.7450910313	7	B09510064	0.0000295114	5.9410030227	6
B09510006	0.0004980919	4.8700760946	5	B09510066	0.0000121133	8.7521769623	7
B09510010	0.0000196924	5.6326248920	6	B09510074	0.0002037328	4.1811567825	5
B09510012	0.0009648791	2.4203306407	4	B09510076	0.0001143844	6.9022020819	6
B09510016	0.0008727186	2.3191788515	4	B09510078	0.0001029703	3.5524244351	5
B09510018	0.0005726457	1.8902613946	4	B09510084	0.0006283352	1.9823435545	4
B09510022	0.0001669787	4.0111245624	5	B09510088	0.0000020050	25.8506371027	10
B09510024	-0.0002251173	0.7894468645	4	B09510090	0.0002960735	15.5723431844	8
B09510026	0.0003790616	7.6851237927	6	B09510094	0.0000853156	3.3464123529	5
B09510028	0.0004952744	1.7550024733	4	B09510098	0.0001143844	6.9022020819	6
B09510030	0.0000471221	2.4719026011	5	B09510100	-0.0001489998	0.3432390899	5
B09510032	-0.0008208033	0.9113415585	3	B09510102	0.0005461900	1.8448113735	4
B09510034	0.0006263897	8.0005828584	6	B09510104	0.0003790616	7.6851237927	6
B09510038	0.0005845454	4.9836590075	5	B09510106	0.0002541758	4.3617156293	5
B09510040	0.0004952744	1.7550024733	4	B09510108	-0.0003328288	0.7084428627	4
B09510044	0.0006931748	5.1020097684	5	B09510110	-0.0007578597	0.4654336650	4
B09510046	0.0001029703	3.5524244351	5	B09510202	-0.0002398786	0.1791835332	5
B09510050	0.0001029703	3.5524244351	5	B09510204	0.0004217764	1.6227615491	4
B09510052	-0.0002688920	0.1378659488	5	B09510206	0.0000635678	2.9699837223	5
B09510054	0.0008313568	5.2255576177	5	B09510208	0.0000693858	3.0907919145	5
B09510056	0.0001276760	10.3847374055	7	B09510210	0.0004980919	4.8700760946	5

Table 7: The learning ability of the control group in pretest

Student No	$\triangle\theta_s$	θ_{s+1}	Times	Student No.	$\triangle\theta_s$	θ_{s+1}	Times
B09310093	-0.00054	-0.912459	7	B09610041	-2.943E-06	0.27561	12
B09410002	-4.2E-05	-0.577192	8	B09610043	2.5983E-06	2.46449	15
B09410007	-5.3E-07	0.4663465	10	B09610047	0.00037316	3.3825	16
B09410009	-1.5E-06	0.3711491	10	B09610049	8.4231E-08	0.75158	12
B09410014	0.000121	3.1228752	15	B09610051	6.2596E-05	1.64573	13
B09410018	-5.5E-07	-0.264162	8	B09610053	1.6751E-07	1.18664	11
B09410025	7.53748	16.173341	19	B09610057	0.00088222	0.8471	11
B09410034	0.000215	5.0104706	17	B09610063	-4.476E-06	0.17955	10
B09410043	7.53748	16.173341	19	B09610065	-3.724E-06	0.22765	9
B09410225	0.000112	4.8356735	17	B09610069	-0.0005381	-0.9125	8
B09410301	0.000512	1.9758595	14	B09610071	-5.587E-06	0.08279	10
B09510302	4.95E-07	3.7759545	16	B09610075	1.9921E-06	3.99934	17
B09610001	7.4E-06	6.1733407	18	B09610079	9.9716E-07	3.88504	16
B09610003	4.08E-05	1.5929062	13	B09610081	0.00011154	4.83567	18
B09610007	0.000373	3.3825031	16	B09610083	3.6684E-05	2.88624	14
B09610011	8.42E-08	0.7515791	11	B09610085	9.3471E-05	1.69912	13
B09610013	7.4E-06	6.1733407	17	B09610089	-5.784E-06	0.03409	10
B09610015	-2.4E-05	-1.695624	7	B09610093	7.53748001	16.1733	19
B09610017	2.55E-06	1.3360443	13	B09610097	-4.246E-06	-0.1136	8
B09610019	-1.6E-05	-1.622195	7	B09610099	9.9716E-07	3.88504	15
B09610021	-2.3E-06	-1.345612	7	B09610101	-5.124E-06	0.13127	10
B09610023	-1.7E-08	0.5613711	11	B09610107	0.0001209	3.12288	16
B09610027	1.15E-07	0.7039543	12	B09610201	0.0005367	3.4752	16
B09610029	-0.00054	-0.912459	7	B09610203	2.5741E-05	1.54061	13
B09610031	-6.2E-06	-1.48071	6	B09610205	2.4359E-07	3.67157	15
B09610033	0.000688	2.033475	15	B09610207	-7.707E-07	-0.3665	9
B09610035	-3.1E-06	-0.163418	10	B09610209	-5.134E-06	-0.0641	11
B09610037	-4.2E-05	-0.577192	8	B09610213	-6.638E-07	-2.6766	4
B09610039	9.35E-05	1.6991166	13				

In the 2nd experiment the score in pretest and posttest of the experiment group is more progressive than control group. One interesting to note is that we found the group members did not enjoy their discussion in each group. The relationship among students should be reconsidered and regrouped for better cooperation.

VI. DISSCUSSION

In the item response theory, there are three kinds of parameter logistic models. From the experimental results, we reveal that the item difficulty (b) and discrimination (a) influence the learning ability forecasting directly. We use T test to evaluate the difference of one-parameter, two-parameter and three-parameter logistic model to forecast learning ability.

The difference among the 3 models is compared in Table 11. In F test, the significance is 0.961, which is greater than 0.05. The T test, the significance is 0.00029, which is less than 0.001. This means the one-parameter model is much different from the two-parameter model.

For the two-parameter model and three-parameter model, the F test significance is 0.00003, which is less than 0.05, and the T test significance is 0.7564, which is greater than 0.05. The two-parameter model and three-parameter model are without obvious difference. The result also shows the one-parameter is not similar to two-parameter and three-parameter model.

Table 8: The learning ability of the control group in posttest

Student No.	$\triangle\theta_s$	θ_{s+1}	Times	Student No.	$\triangle\theta_s$	θ_{s+1}	Times
B09310093	4.1197E-08	0.82368272	11	B09610041	2.484E-06	5.5615076	18
B09410002	0.00054158	1.10433918	11	B09610043	-0.00019743	-0.663953	8
B09410007	-0.00069557	-0.85551467	6	B09610047	8.6368E-05	4.517107	17
B09410009	-1.9659E-05	-0.43705115	8	B09610049	4.5314E-06	2.4475149	14
B09410018	-2.1712E-07	-0.95539003	6	B09610051	2.1666E-05	2.6813278	15
B09410025	8.6368E-05	4.51710697	17	B09610053	2.2822E-06	9.8255541	19
B09410034	7.7938E-06	4.03151172	17	B09610057	2.2822E-06	9.8255541	19
B09410043	-1.7224E-07	0.5471949	11	B09610063	0.00070416	1.9799415	14
B09410225	9.1635E-08	0.62604873	11	B09610065	2.9287E-05	1.5229794	14
B09410301	4.7493E-05	4.38482727	17	B09610069	1.9108E-05	1.4797571	12
B09510302	0.00015021	8.59222573	19	B09610071	9.1635E-08	0.6260487	11
B09610001	3.5208E-07	3.54692059	16	B09610075	2.2943E-06	3.8246797	17
b09610003	0.00028515	4.80994127	18	B09610079	2.2943E-06	3.8246797	17
B09610007	-0.00013615	-0.61755936	8	B09610081	0.00035249	3.2226793	16
B09610011	7.1305E-08	1.14506716	12	B09610083	6.6168E-07	3.635713	17
B09610013	2.2822E-06	9.82555405	19	B09610085	0.00048771	3.2995977	16
B09610015	3.1392E-05	2.74304347	15	B09610089	1.0438E-07	0.7444741	12
B09610017	-5.191E-06	0.19009555	10	B09610093	8.0837E-07	2.231179	14
B09610019	-6.0998E-07	-1.0584306	7	B09610097	0.00054415	1.9318144	15
B09610021	-3.5926E-06	-0.09510869	9	B09610099	1.4277E-05	4.1428812	18
B09610023	1.0082E-05	2.56196963	15	B09610101	-1.9659E-05	-0.437051	8
B09610027	2.2822E-06	9.82555405	19	B09610107	1.4277E-05	4.1428812	17
B09610029	1.9577E-06	2.33741052	15	B09610201	2.484E-06	5.5615076	19
B09610031	-0.00091479	-0.90507859	6	B09610203	-5.4899E-07	-4.068839	2
B09610033	0.00012935	3.00571508	16	B09610205	6.3495E-05	1.6105738	13
B09610035	-0.00038486	-0.75846835	6	B09610207	-2.38E-06	-0.136745	8
B09610037	-9.9386E-07	-1.11125524	6	B09610209	2.5805E-05	1.0234358	12
B09610039	0.000672	3.37912613	17	B09610213	-0.00059603	-0.263387	7
B09610039	9.3471E-05	1.69911656	13				

Table 9 represents the learning ability of the experiment in pretest.

Student No.	$\triangle\theta_s$	θ_{s+1}	Times	Student No.	$\triangle\theta_s$	θ_{s+1}	Times
B09410036	1.78083E-05	2.59388382	4	B09610068	3.757381861	16.6651283	10
B09410218	-4.84062E-06	-1.24481638	4	B09610070	6.66026E-07	5.233524382	6
B09410302	-1.6938E-07	-0.88593593	4	B09610072	-1.81125E-06	0.416422149	3
B09610004	3.757381861	16.6651283	10	B09610074	1.64269E-05	4.092526076	5
B09610006	-0.000154682	-0.60249097	3	B09610080	3.25299E-06	2.351947407	4
B09610008	2.02884E-05	1.46419231	3	B09610082	-4.88698E-07	0.515429637	3
B09610010	-0.000213036	-0.64159914	3	B09610084	5.86658E-06	3.906325685	5
B09610012	0.000126247	4.5235512	5	B09610086	0.000973942	5.070147768	5
B09610014	0.000803139	3.35796403	4	B09610090	4.63511E-06	2.398673139	4
B09610018	-8.09182E-07	-0.19522555	3	B09610092	3.757381861	16.6651283	10
B09610020	-4.32895E-06	-0.33906907	3	B09610094	1.28448E-05	2.543748196	4
B09610022	0.000803139	3.35796403	4	B09610096	0.000452097	6.665128304	6
B09610024	9.20681E-06	2.49453155	4	B09610102	-6.58462E-07	-1.01541843	4
B09610026	0.000112834	2.91703512	4	B09610104	-3.62105E-08	0.581325779	3
B09610028	4.56299E-05	4.29685558	5	B09610106	-1.28137E-06	0.44945822	3
B09610030	3.757381861	16.6651283	10	B09610108	1.78083E-05	2.593883825	4
B09610032	0.000106253	1.64826718	3	B09610112	0.000111484	1.046437395	2
B09610036	3.46656E-06	1.32176856	3	B09610202	0.00058277	4.919055572	5
B09610038	-6.79437E-06	-2.71526341	5	B09610206	-0.000213036	-0.64159914	3
B09610040	3.757381861	16.6651283	10	B09610208	8.39611E-05	2.860209592	4
B09610042	3.49139E-06	3.81900583	5	B09610214	-7.40324E-05	-1.65866761	4
B09610044	1.64269E-05	4.09252608	5	B09610218	-4.84062E-06	-1.24481638	4
B09610048	4.73745E-05	6.06630358	6	B09629004	-0.000498098	-0.76155755	3
B09610052	-0.000154682	-0.60249097	3	B09629015	3.757381861	16.6651283	10
B09610054	0.000612784	3.28961728	4	B09629020	-7.20885E-06	0.149727081	3
B09610056	0.000959195	2.00238384	3	B09629023	0.000612784	3.289617283	4
B09610058	1.22375E-06	3.65432395	5	B09629026	0.000201244	3.034830938	4
B09610060	3.757381861	16.6651283	10	B09513038	6.24621E-08	0.812385775	3
B09610064	0.000112834	2.91703512	4	B09513040	0.000267208	3.095975698	4
B09610066	8.27103E-08	0.61426763	3				

Table 10: The learning ability of the experiment in the posttest

Student No.	$\triangle\theta_s$	θ_{s+1}	Times	Student No.	$\triangle\theta_s$	θ_{s+1}	Times
B09610002	1.0877E-05	1.511938398	3	B09610070	-0.6477111	-0.64771107	3
B09610004	4.684702462	20.00607457	10	B09610072	0.42348348	0.423483484	3
B09610008	0.000209579	1.905785885	3	B09610074	20.0060746	20.00607457	10
B09610010	3.34616E-07	2.334700699	4	B09610080	0.78021636	0.780216358	3
B09610012	-2.2735E-07	1.03653E-06	3	B09610082	2.2600868	2.2600868	4
B09610014	2.49163E-05	2.994593361	4	B09610084	7.26620305	7.266203047	6
B09610018	-0.00015385	-2.055634855	4	B09610088	10.0060746	10.00607457	7
B09610020	2.18369E-05	10.00607457	7	B09610090	1.32395604	1.323956037	3
B09610022	2.89494E-05	7.266203047	6	B09610092	3.28090775	3.28090775	4
B09610024	0.000150238	3.382687749	4	B09610094	4.51332057	4.513320568	5
B09610026	2.37075E-08	0.720767	3	B09610096	10.0060746	10.00607457	7
B09610028	0.00021803	1.079557272	2	B09610102	-1.2389911	-1.23899106	4
B09610030	4.684702462	20.00607457	10	B09610104	1.07955727	1.079557272	2
B09610032	0.000121739	7.743466918	6	B09610106	0.54255862	0.542558617	3
B09610036	9.74761E-05	3.28090775	4	B09610108	1.14012207	1.140122071	2
B09610038	2.49163E-05	2.994593361	4	B09610112	2.64893771	2.648937706	4
B09610040	2.14217E-05	4.844149191	5	B09610202	1.3860939	1.386093904	3
B09610042	5.59154E-06	1.448738516	3	B09610206	-1.4882153	-1.48821531	4
B09610044	4.684702462	20.00607457	10	B09610208	2.48843685	2.488436853	4
B09610048	4.684702462	20.00607457	10	B09610214	1.14012207	1.140122071	2
B09610052	1.11202E-06	4.218966523	5	B09610216	1.07955727	1.079557272	2
B09610054	4.684702462	20.00607457	10	B09629004	2.41078187	2.410781875	4
B09610056	4.97414E-06	4.513320568	5	B09629015	4.67358982	4.673589821	5
B09610058	0.000181884	5.433972936	5	B09629020	2.81724456	2.817244563	4
B09610060	4.684702462	20.00607457	10	B09629023	3.08711123	3.087111232	4
B09610064	4.97414E-06	4.513320568	5	B09629026	5.02646865	5.026468654	5
B09610066	4.97414E-06	4.513320568	5	B09513038	20.0060746	20.00607457	10

We conclude that using two-parameter model and three-parameter model to cluster learning groups is better than one-parameter model. In the one-parameter model, the learning ability scope is between 0.78 and 4.88. The cluster center is between 0.85 and 4.87. Every node is too close to find the difference. The one-parameter model makes little difference to random cluster method. In the two-parameter and three-parameter model, each group could be separated obviously.

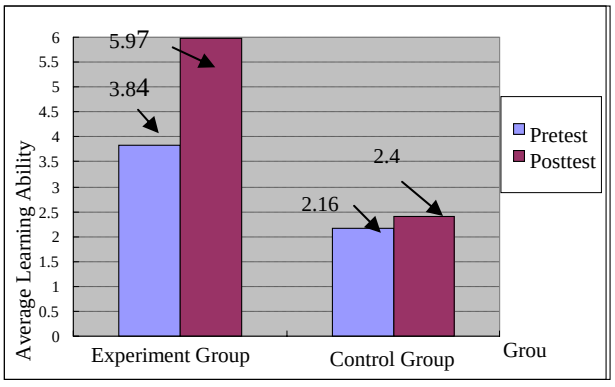

Figure 3. The comparison of pretest and posttest

After using the two-parameter and three-parameter model, the members of each learning groups cooperated and learned well in the experimental group. The posttest score of the experimental group was higher than pretest score, and the average learning ability improved from 3.84 to 5.97. On the contrary, the learning ability in the control group only improved from 2.16 to 2.4.

Table 11: Comparison among one-parameter, two-parameter and three-parameter logistic models

Comparison	Assumption	F test	Significance	t	f.d.	Significance (two-tail)
one parameter and two parameter	Assumed the differences are equal	0.00238	0.96122	-3.76949	90.00000	**0.00029**
	Assumed the differences are unequal			-3.76949	48.71873	**0.00044**
two-parameter and three-parameter	Assumed the differences are the same	19.35869	0.00003	0.31116	90.00000	0.75640
	Assumed the differences are unequal			0.31116	89.99254	0.75640
P<0.05* , P<0.01** , P<0.0001***						

Based on the two-parameter model and K-means clustering result, T test is performed to evaluate the learning efficiency in cooperative learning in experimental group and control group. Table 12 depicts the difference between pretest and posttest. The pretest F test significance is 0.98602, which is greater than 0.05. The T test significance is 0.68610, which is greater than 0.05. There is no difference between the experiment group and control group in pretest. The posttest F test significance is less than 0.05, and the T test significance is 0.0015, which is greater than 0.05. Accordingly, there is an obvious difference between the experiment group and control group in posttest.

Table 12: Comparison Table of Pretest and Posttest

	Assumption	F test	Significance	t	f.d.	Significance (two-tail)
Pretest	Assumed the differences are equal	0.00031	0.98602	-0.40523	110.00000	0.68610
	Assumed the differences are unequal			-0.40523	102.97940	0.68615
Posttest	Assumed the differences are the same	28.51689	0.00000	-3.32549	110.00000	0.00120
	Assumed the differences are unequal			-3.32549	60.79506	0.00150
P<0.05* , P<0.01** , P<0.0001***						

VII. CONCLUSION

In this study, we utilize the Item Response Theory and K-means algorithm to cluster the student's ability. It helps teachers to adjust learning materials and teaching programs adaptively according to the learning aptitude. Test is not the only way to measure the student's ability, but it indeed helps teachers to understand the student's ability. The classification information can be applied to remedial course to enhance the teaching effectiveness.

Currently we use the one-dimension and K-means in our proposed clustering method, and we are considering including other factors in the clustering method for future study. For example, the rate of student's attendance or the performance in class might be concerned. At the same time, we may choose other well-developed clustering methods, such as the Fuzzy C-means, to be compared

with the K-means. We hope to get more accurate clustering result to support the collaborative learning by integrating different data analysis methods.

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