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Approach for Constructing the Concept Effect Relation Map of Mathematics

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建構數學學科概念效應關係圖之方法

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摘要

測驗理論是一種解釋測驗資料間實證關係的系統化理論學說。當代測驗理論主要是以試題反應理論(IRT：Item Response Theory)為架構，考慮試題參數及受試者的反應等特性(包括難度、鑑別度、學生能力等)，因此在估計受試者個人能力時，能夠提供一個較精確的估計值。

以資料探勘的技術來架構概念效應關係圖(CERM：Concept Effect Relation Map)，若透過不成熟的資料前處裡將導致：(1)概念模糊化結果的單調性，(2)所探勘的關聯規則無法反映實際的概念效應關係及(3)產生循環迴圈的關聯規則。本文應用 IRT 來處裡學生概念學習的反應結果。因此，學生概念學習的反應結果加上了試題難度、鑑別度的考量下，我們提出一個基於 IRT 資料前處裡的概念效應關係圖架構系統(IRT-Based Data Preprocessing Concept Effect Relation Map Construction System)。

基於 IRT 資料前處裡的概念效應關係圖架構系統包含資料前處裡與資料探勘兩個模組。資料前處裡模組內含四個程序：試題分析、產生學習反應指標、概念分解/整合及概念學習反應指標整合結果的模糊化；資料探勘模組內含關聯規則探勘與概念效應關係圖架構兩個程序。

我們所提出的方法透過實驗的結果證明，概念效應關係圖的效應關係可以被改進且可以減少循環迴圈關聯規則的產生。

關鍵字:試題反應理論，概念效應關係圖，教學策略，概念同化效應，迷思概念，學習診斷。

Approach for Constructing the Concept Effect Relation Map of Mathematics

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Abstract

Test theory is an explanation of empirical relationships among examination data. The modern test theory is based on the **Item Response Theory (IRT),** which considers the parameters of test item and the response of test-receiver (including difficulty, discrimination, ability and so on),and the estimation of its test-receiver's ability becomes more precise.

Concept Effect Relation Map (CERM) constructed by data mining with naïve data preprocessing causes: (1) monotonous concept fuzzification result, (2) the association rules may not reflect the real concept relation and (3) the circulating association rules exit. In this thesis, we apply the IRT as the assessment of students' concept learning response. With the consideration of the difficulty and the discrimination of test item, we propose an IRT-Based Data Preprocessing Concept Effect Relation Map Construction System.

IRT-Based Data Preprocessing Concept Effect Relation Map Construction System includes two modules: the Data Preprocessing Module and the Data Mining Module. The former has four procedures: Test Item Analysis, Learning Response Index (LRI) Generator, Concept Decomposition/Aggregation and Fuzzy ACLR Generator, and the latter has two procedures: Association rule mining and concept map constructor.

The experiment results of the proposed Approach show that the CERM construction can be improved and the number of circulated association rules generated can be reduced.

Key Words: Item Response Theory, Concept Effect Relation Map, teaching strategy, concept assimilation, mis-concept, learning diagnosis.

致謝

網路學習碩士雖然是我第二個碩士學位，但卻一點也不輕鬆。回顧過去攻讀的第一個碩士學位，研讀的時間雖多，卻欠缺解決問題的脈絡與思路，而今在職念碩士專班，時間的分割雖然不易掌握，也許過去的人生閱歷，反而讓我學習更多。研究的過程不斷地印證或修正自己解決問題的策略與想法，學習因而更加踏實，凡此種種都要感謝論文指導教授曾憲雄博士，在問題研究與論文寫作上所給予的督導與幫助。同時亦感謝論文催生的推手--博士班翁瑞峰學長，從黃昏到晨曦，無怨無悔的陪我討論與修正論文，由於他不斷的鼓勵與鞭策，使得此篇論文得以順利進行迅速完成。

論文口試令人期待又怕受傷害，所幸在平時的 group meeting 與 outside meeting，有勞 KDE Lab.各位學長、同學與學弟妹提問所給予的建議與磨鍊，讓我在口試當天得以臨危不亂，從容不迫地掌握主題侃侃而談，更感謝口試委員：莊祚敏教授、葉耀明教授與曾秋蓉教授能撥冗參與給予指教。整個口試的前置作業，誠摯地感謝雅惠助理與怡靜同學的幫忙與支援，使得整個口試的活動得以順利圓滿達成。

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1. Introduction

In the last few years, the technology of Internet and database has been improved rapidly. There are a lot of teaching activities adopt the e-learning as the way of teaching. Therefore, the substitution of traditional teaching by e-learning becomes a significant trend. Among the change of teaching manner, the approach of learning assessment will then be affected inevitably. Therefore, the analysis of assessment in e-learning becomes an important issue.

With the transformation from traditional pen paper examination into the on-line examination[7], there are many researches in the assessment of e-learning. As we know, the testing records are useful in analyzing the learning status of students', e.g. analyzing student's concept effect relations [13]. The results of assessment could provide the suggestion of teaching strategy and learning guidance[5].

Test theory is an explanation of empirical relationships among examination data. There are two main developments: one is the classical test theory, which is based on the true score model. That is, observation score is the sum of the real score and the erroneous score; the other is the modern test theory, which is based on the **Item Response Theory (IRT)**[2][12]. Since IRT considers the parameters of test item and the response of test-receiver (including difficulty, discrimination, ability and so on), the estimation of its test-receiver's ability becomes more precise. Moreover, while regarding the same primitive scores, IRT may also give different ability estimation of the test-receiver.

Data mining approach is one of the assessment of learning diagnosis analysis, which usually mines the raw data directly from the students' testing result [16][22][24]. Thus the results of analyzing the testing record directly will not be able to response the students' learning status properly without considering the difficulty and discrimination of the test item. Furthermore, it may result inefficient diagnosis. To improve such situation, we propose an **IRT-Based Data Preprocessing Approach** to construct the Concept Effect Relation Map based upon the Item Response Theory (IRT). With the approach mentioned above, the testing record is firstly preprocessed before data mining with the consideration of item's difficulty and discrimination, thus the IRT-Based Data Preprocessing Approach can rectify the testing records for analysis to represent the fact of students' concept learning status. Moreover, we further visualize the effect relationships among concepts into Concept Effect Relation Map (CERM) in order to make the analysis more effective, and hence promote the consulting value of suggestion to the students' learning diagnosis and the teachers' teaching strategy.

IRT-Based Data Preprocessing Concept Effect Relation Map Construction System includes two modules: the Data Preprocessing Module and the Data Mining Module. The former has four procedures: (1) the Test Item Analysis, which calculates the difficulty and the discrimination of each item from students' testing result; (2) generates the item's Learning Response Index (LRI), which indicates the students' learning response based upon Item

Response Theory; (3) the concept decomposition and aggregation. Accordingly, the Item–Concept Relationship Table (ICRT) separates the concept with relativity weight of the test item. After the concept decomposition, the Sugeno Fuzzy Measure Function aggregates the dissociated concept with an attribute value of Weight Learning Response Index (WLRI). The aggregate valve of WLRI is an attribute value of concept called the Aggregated Concept Learning Response (ACLR); (4) transforms the ACLR from numeric into symbolic H/L by the Fuzzy membership function. The latter has two procedures: firstly, the Apriori Algorithm of data mining [11] mines the association rules from the Fuzzification of ACLR. Secondly, the scenario explanation of the mining association rule is proposed to construct CERM.

The result of the IRT-Based Data Preprocessing Approach makes the CERM much more reasonable, which is helpful for the diagnosis of student's learning problems, and teachers in adjusting their teaching strategy. The main contributions of this thesis are:

(1) The proposed Approach refines the assessment of concept learning response.

(2) The IRT-Based Measure Function is defined to quantify the learning status of concept. With the consideration of item difficulty and discrimination, the bias of the learning response is reduced.

(3) The number of circulated association rules generated can be reduced by the proposed approach.

2. Related Work

The theory and model of students' cognition often conflicts with the theory and model of science[21]. Since the student often develops individual scientific concept by experiences through their consciousness. Even if they are able to answer correctly in the examination after the teaching of scientific curriculum, only little of the mis-concept can be revised (Strike & Posner, 1985). Concept mapping is a strategy to visualize the learners' intermediate concept[1][5][8]. While elaborating Novak's Concept Mapping, Anderson(1995) pointed out that concept mapping is quite a good dialectical method in mis-concept. That is, the student may reorganize and describe the hierarchy of concepts by the approach of concept mapping[6][18].

With the development of e-learning, the technology of assessment grows[19], too, on line assessment can be also take place by Internet[7]. The effect relations among concepts can be constructed by the analysis of assessment result[15][21][24], such as assimilation effect and mis-concept effect[23]. Simultaneously, the concept mapping can be the graphical representation of learner's learning result, which indicates the connection (link) among the knowledge or concepts. Diagnosis with the assessment result[3] can improve students' learning status, and teacher can adjust the teaching strategy during tutoring[8][17][20]. As mentioned above, the assessment analysis and the concept mapping representation of the analysis result[9][10] have thus become an important issue of e-learning.

Test theory is an explanation of empirical relationships among examination data, which develops into two big schools of thought: (1) one is the classical test theory, which is based on the true score model (Gullikson, 1987; Lord & Novick, 1968). That is, observation score is the sum of the real score and the erroneous score; (2) other one is the modern test theory (Hambleton & Swaminathan, 1985; Hambleton, Swaminathan, & Rogers, 1991; Hulin, Drasgow, & Parsons, 1983; Lord, 1980), which is based on the Item Response Theory (IRT)[12]. The Item Response Theory considers the parameters of test item and the response of test-receiver (including difficulty, discrimination, ability and so on). IRT may give precisely different ability estimation to the test-receiver while regarding the same primitive scores.

To model the learning effect relationships among concepts, Hsu [15] proposed a Concept Effect Relationships (CER) as a conceptual map-based notation. In brief, if C_i is the prerequisite of concept C_j for efficiently learning, then a CER $C_i \rightarrow C_j$ exists. A single concept may have multiple prerequisite concepts, and can also be a prerequisite concept of multiple concepts. Thus, based upon CER, the learning guidance of necessary concepts to enhance their learning performance can be derived by analyzing the test results of students.

Appleby [4] proposed an approach to create the potential links among skills in Mathematics domain. The direction of a link is determined by a combination of educational judgment, the relative difficulty of skills, and the relative values of cross-frequencies. Moreover, a harder skill should not be linked forwards to an easier skill. As shown in Table 1, $f_{\bar{A}B}$ represents the amount of learners with wrong answers of skill A and right answers of skill B. If $f_{A\bar{B}} > f_{\bar{A}B}$, a skill *A* could be linked to a harder skill *B*, but backward link is not permitted.

Table 1 relative frequencies of skill

B \ A	Answer right	Answer wrong
Answer right	f_{AB}	$f_{\bar{A}B}$
Answer wrong	$f_{A\bar{B}}$	$f_{\bar{A}\bar{B}}$

Later, based upon statistical prediction and approach of Hsu [16], a CER Builder was proposed by Hwang [14]. Firstly, CER Builder finds the test item that most students failed to answer correctly and then collects the other test items, which were failed to answer by the same students. Thus, CER Builder can use the information to determine the relationships among the test items. Though the CER Builder can find the tutoring path of low learning achievement students, which may be not easy to find out from high learning achievement students, and the pattern of mis-concept from the test. Moreover, mining the testing result directly without the consideration of item’s difficulty and discrimination might cause monotone or circulating result in association rules mining.

Tsai [24] proposed a Two-Phase Fuzzy Mining and Learning Algorithm. In the first phase, **L**ook Ahead **F**uzzy **M**ining Association Rule **Alg**orithm (LFMAlg) was proposed to find the embedded association rules from the historical learning records of students. In the second phase, the AQR algorithm is applied to find the mis-concept map indicating the missing concepts during students learning. The obtained mis-concept map as recommendation can be fed back to teachers for remedy learning of students. However, because the creating mis-concept map, which is not a complete concept map of a course, only represents the missing learning concepts, its usefulness and flexibility are decreased. In addition, their approaches generate many noisy rules and only use single rule type to analyze the prerequisite relationship among learning concepts.

Sue [22] proposed a Two-Phase Concept Map Construction (TP-CMC) algorithm to automatically construct a concept map of a course by historical testing records. In the data preprocessing, Item Analysis with Norm-Referencing is applied to refine the mining result of grade fuzzy association rules. The Concept Map Constructing (CMC) Algorithm is proposed to be the post processing of the map construction. However, Item Analysis with Norm-Referencing as the data preprocessing still can't get better performance of the map construction.

In summary, there are three issues in constructing the Concept Effect Relation Map:

1. Without the consideration of test items’ difficulty and discrimination, naïve data preprocessing may cause the monotonous concept fuzzification result.

2. Without the consideration of test items’ difficulty and discrimination, naïve data preprocessing may cause the result of circulated association rule.

3. Mining with naïve data preprocessing may not reflect the physical effect relations of concepts.

3. IRT-Based Data Preprocessing Approach

For solving the problems of issue mentioned above, we apply Item Response Theory to indicate the status of concepts' learning. The Item Response Theory considers the parameters of test item and the response of test-receiver (including difficulty, discrimination, ability and so on). Therefore the estimation of its test-receiver's ability becomes more precise. Moreover, while regarding the same primitive scores, IRT may also give different ability estimation of the test-receiver.

In order to find out the cognition sequence relations among the concepts, including assimilation effect and mis-concept relation, with the consideration of difficulty and discrimination of test item, we propose an IRT-Based Data Preprocessing Concept Effect Relation Map Construction System to construct the Concept Effect Relation Map, with influence weights and effect relations among learning concepts of a course.

With the consideration of difficulty and discrimination of the test item, the status of concept learning is quantified by the Learning Response Index, which creates a fuzzy membership function between poor learning (0) and well learning (1). Thus LRI rectifies the bias of the testing result, which may cause the circulation or monotone effects among the association rules. By the rectification based upon IRT, multiple association rule types were mined and the hidden strategy of teaching is discovered. Hence applying LRI expands the further applications of Concept Effect Relation Map.

3.1 IRT-Based Concept Learning Response Function

The quality of CERM construction deeply depends on the method of data preprocessing before data mining. For example, ratio of incorrect/correct answers is a naïve way of data preprocessing to represent the learning status of concept. However, the ratio value mentioned above may be affected by the difficulty and discrimination of the test item. In order to eliminate the bias affect of concept learning response cause by the difficulty and discrimination, we propose an **IRT-Based Concept Learning Response (CLR) Function**.

Easy Difficult

	C_{T1}	C_{T2}	C_{T3}	Score
S1	✕	✓	✓	2
S2	✓	✓	✕	2

IRT-Based CLR Function

Easy Difficult

	C_{T1}	C_{T2}	C_{T3}	Score
S1	0	0.53	0.44	0.97
S2	0.24	0.53	0	0.77

Fig. 1 The difficulty effect of IRT-Based CLR Function

In Fig. 1, Two students S1 and S2 are tested by three items C_{T1}, C_{T2} and C_{T3} concerning the same concepts. As we can see, S2 has answered the C_{T1} correctly but S1 doesn't. Contrarily, S1 has answered the C_{T3} correctly but S2 doesn't. Identically, both S1 and S2 have answered C_{T2} correctly. On the left side of Fig. 1, we may say the "weight" of learning response is the same in C_{T1}, C_{T2} and C_{T3}. In other words, since S1 and S2 have the same score = 2, without the consideration of difficulty, it is hard to distinguish the learning status of the two students in learning concept C. But the situation changes while we apply the IRT-Based CLR Function. That is, S1 would have higher CLR than S2 has. Since the difficulty of C_{T3} is higher than C_{T1}. Totally, S1's CLR=0.97 is higher than S2's CLR=0.77, and we are able to say that S1 has learned the concept better than S2.

Low High

	C_{T1}	C_{T2}	C_{T3}	Score
S1	✗	✓	✓	2
S2	✓	✓	✗	2

IRT-Based CLR Function

Low High

	C_{T1}	C_{T2}	C_{T3}	Score
S1	0	0.53	0.67	1.20
S2	0.17	0.53	0	0.70

Fig. 2 The discrimination effect of IRT-Based CLR Function

In Fig. 2, Two students S1 and S2 are tested by three items C_{T1}, C_{T2} and C_{T3} concerning the same concepts. As we can see, S2 has answered the C_{T1} correctly but S1 doesn't. Contrarily, S1 has answered the C_{T3} correctly but S2 doesn't. Identically, both S1 and S2 have answered C_{T2} correctly. On the left side of Fig. 2, we may say the "difference" of the learning response is the same in C_{T1}, C_{T2} and C_{T3}. In other words, since S1 and S2 have the same score = 2, without the consideration of discrimination, it is hard to distinguish the learning status of the two students in learning concept C. Again the situation changes while we apply the IRT-Based CLR Function. That is, S1 would have higher CLR than S2 has. Since the "difference" of CLR in concept C_{T3} is larger than the "difference" of CLR in concept C_{T1}. Finally, S1's CLR=1.20 is higher than S2's CLR=0.70, Thus we are able to say that S1 has learned the concept better tha S2.

As mentioned above, it is necessary to have a fuzzy membership function of learning status which is obtained from the testing item with the value between 0~1. To build up such a

Fuzzy Learning Response Membership Function, difficulty and discrimination of test item should be considered. Meanwhile, the Fuzzy Learning Response Membership Function must have the characteristics below:

1. Positive relative to the difficulty of the test item.
2. Positive relative to the discrimination of the test item.

With the goals and characteristics mentioned above, we consider the Two-parameter Logistic Model function

$$P(\tilde{x}) = \frac{1}{1+e^{-1.7D(\tilde{x}-P)}}, \quad e = 2.719$$

of the Item Response Theory (IRT). Originally, IRT is used to estimate the aptness of the test item. The ability $\tilde{x}$ of the student is the variable of the Logistic function, which includes two parameters, difficulty P and discrimination D. The aptness of the test item is indicated by distribution of the answering probabilities of different abilities of students.

We adopted the Two-parameter Logistic model as our Fuzzy Membership Function of learning response to indicate the student's learning status responded from the testing items with the consideration of difficulty and discrimination. The definition of the Fuzzy Learning Response Membership Function is described as follows.

Definition 1 Fuzzy Membership Function of Learning Response

We define the Fuzzy Learning Response Membership Function with two parameters, the difficulty and discrimination of the item, and the variable of the function is the ability of the student. The Fuzzy Learning Response Membership Function is denoted as

$$LRI_{(P_j,D_j)}(\tilde{x}_i) = \frac{1}{1+e^{-1.7D_j(\tilde{x}_i\text{-}P_j)}},$$

where $\tilde{x}_i$: the learning ability of the student S_i,

P_j : the difficulty of the test item T_j,

D_j : the discrimination of the test item T_j.

The graph of the Fuzzy Learning Response Membership Function is shown in Fig. **3**.

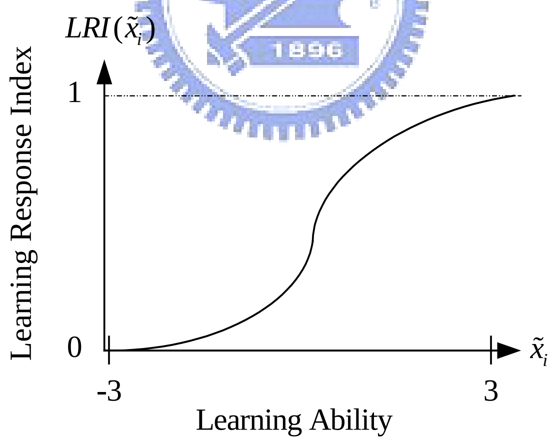

Fig. 3 The curve of the Fuzzy Learning Response Membership Function

The difficulty effect in the Fuzzy Learning Response Membership Function is shown In Fig. 4. With the same learning ability and discrimination given, the difficulty of the test item decreases cause the function's curve shift to the right, thus the student's LRI decreases as the difficulty decreases. ($P_2 > P_1 \Rightarrow LRI_2 > LRI_1$).

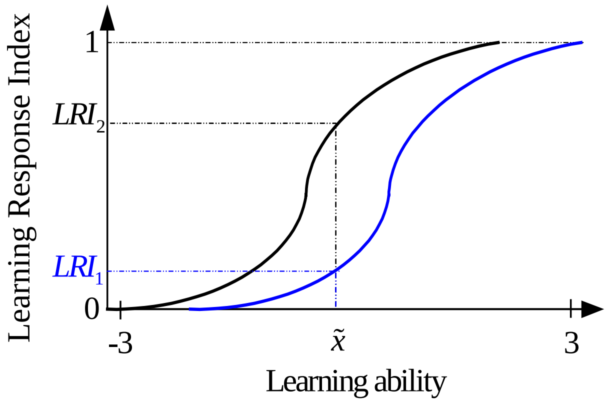

Fig. 4 The difficulty effect in the Fuzzy Learning Response Membership Function

Fig. 5 shows the discrimination effect in the Fuzzy Learning Response Membership Function. The same difficulty of the test item and the difference of students' ability were given; the curvature of the function increases while the discrimination of the test item increases. Thus the difference of the LRI increases ($D_2 > D_1 \Rightarrow \Delta LRI_2 > \Delta LRI_1$).

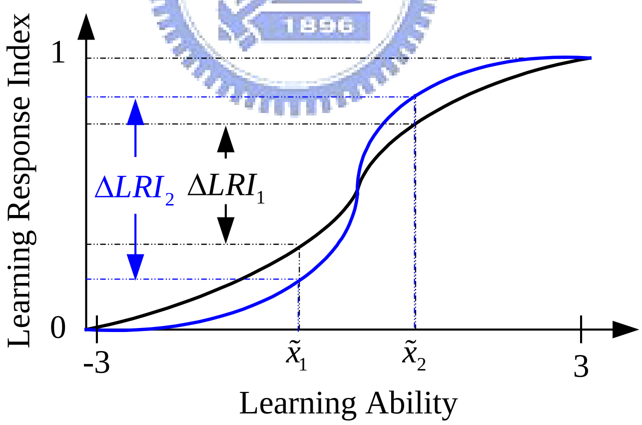

Fig. 5 The discrimination effect in the Fuzzy Learning Response Membership Function

The Fuzzy Learning Response Membership Function includes the parameter of difficult and discrimination. It is useful in indicating the actual degree of wellness in concepts learning responded from the test item, and the bias caused by the difficulty and discrimination can be rectified.

Example 1: Measures Function Of LRI

If a student has correctly answered a test item, based on the result of the testing, we say that the student learns well but no further information about how well it is. With the same situation, suppose the difficulty and the discrimination of the item is 0.813 and 0.375, respectively. If the student with learning ability of 1.8, we would have the following LRI to indicate the learning performance of the student.

$$LRI(1.8) = \frac{1}{1+e^{-1.7\times 0.375(1.8\text{-}0.813)}} = 0.65$$

3.2 System Architecture

The Concept Effect Relation Map of a course is quite useful as mentioned above. However, mining with naïve data preprocessing may not reflect the physical effect relations of concepts. Therefore, in this thesis, we propose an IRT-Based Data preprocessing approach to construct the Concept Effect Relation Map, which is a map of directional graph with influence weights among cognition learning concepts of a course. Fig.7 shows the IRT-Based Data Preprocessing Concept Effect Relation Map Construction System with two modules: Data Preprocessing Module and Data Mining Module.

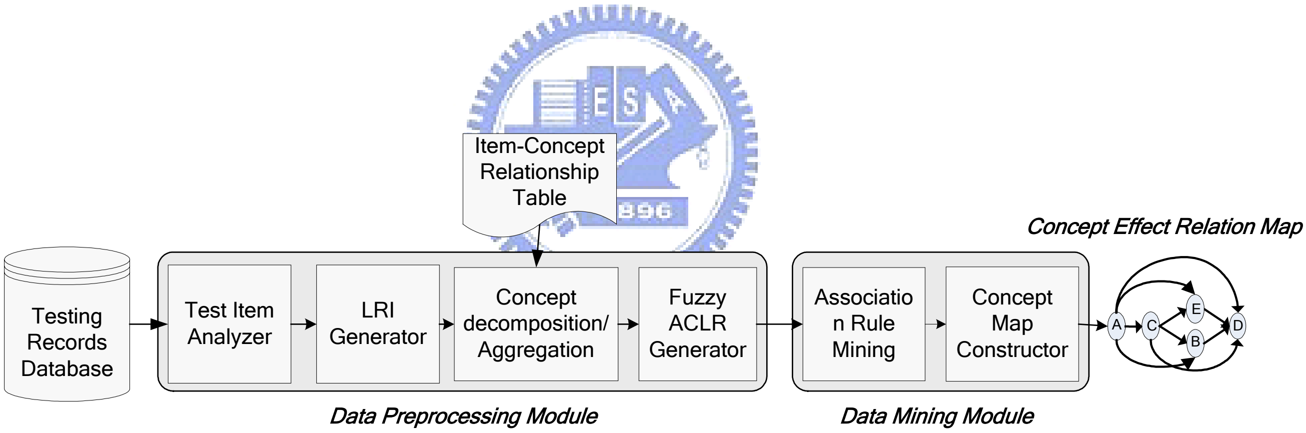

Fig. 6 IRT-Based Data Preprocessing Concept Effect Relation Map Construction System

In the module of Data Preprocessing, four procedures are held: Test Item Analysis, LRI Generation, Concept Decomposition/Aggregation and ACLR Fuzzification. In the Test Item Analysis procedure, Instruction Theory is applied to generate the difficulty and discrimination of test item and define the learning ability of the student. In the second procedure, Item Response Theory is applied to LRI in order to indicate the students' learning status responded from the test items. Concept Decomposition/Aggregation is the third procedure, which the Item-Concept Relationship Table is applied in concepts decomposition from items with Weight Learning Response Index (WLRI) and each concept has the attribute value called Aggregation Concept Learning Response index (ACLR) after the aggregation of the same concept separate in different items. The final procedure is the fuzzification of ACLR, where Fuzzy Theory is applied in transforming the numeric ACLR into symbolic “H” and ”L” to indicate well learning and poor learning, respectively.

The second module, Data Mining Module, has two procedures. In the former, applying Apriori Algorithm of data mining discovers four association rule types, L-L, L-H, H-H and H-L. In the latter, CERM is constructed based upon the scenario explanation of the mining association rule we proposed.

Base upon the historical testing records of students, we are able to preprocess the testing records with IRT-Based. Later, the embedded association rules are discovered by Data mining process. Finally, the procedure of Concept Effect Relation Map Construction Generates the Concept Effect Relation Map by scenario explanation of association rules. The procedures of the construction module are described as follows.

1) Data Preprocessing Module

- **Test Item Analyzer:**

Difficulty and discrimination of the test item are analyzed, and the students' score are normalized by the normal reference as the relative learning ability of the students'.

- **LRI Generator:**

We adopt the two-parameter Logistic model function of Item Response Theory as our Learning Response Index of item (LRI), where the difficulty and discrimination of the test item is the parameters of our Learning Response measure Function, and the relative learning ability of the student is the variable of the function. Each test item answer by a student will have a value of LRI with valve between 0 and 1. The LRI of the test item individually responses the student's learning status of the involved concepts.

- **Concept Decomposition/Aggregation:**

Usually, a test item may include several concepts; we separate the involved concepts of the test item by the test Item Concept Relationship Table (ICRT). Also, Concept may be involved in several test items. Concepts included in each test item can be separated by weight according to the entries of ICRT. The attributed value of decomposition concept is called Weight Concept Learning Response (WCLR), which are the multiple of the decomposition weight of concept and the LRI of item. Same concepts' WCLR will be aggregated by applying Sugeno Fuzzy Measure Function and are defined as the Aggregation Concept Learning Response index (ACLR).

- **Fuzzy ACLR Generator:**

In order to mine further association rules, we translate the students' ACLR into the notation of "H"(Well Learning) and "L"(Poor Learning) by the Fuzzy membership function.

2). Data Mining Module

- **Association Rule Mining**

The association rules are mined from the Fuzzy ACLR by using Apriori Algorithm. Four types of association rules ***L-L, L-H, H-L*** and ***H-H*** are used as the model to discover the assimilation and mis-concept effect relations among concepts.

- **Concept Map Constructor**

We define the direction and the weight of edge by the effect relationship and the value of support and confidence, respectively. Concept Effect Relation Map of the students' is constructed based on the scenario explanation of association rule.

4. IRT-Based Data Preprocessing CERM Construction System

IRT-Based Data Preprocessing CERM Construction System includes two modules, the Data Preprocessing Module and the Data Mining Module. There are four procedures included in the Data Preprocessing Module: Test Item Analyzer, Learning Response Index (LRI) Generator, concept decomposition/aggregation and Fuzzy ACLR Generator. The second Module includes two procedures: Association Rule Mining and Concept Map Constructor.

4.1 Data Preprocessing Module

The first module has four procedures. Sequentially, the Test Item Analysis is the first procedure, which calculates the difficulty and the discrimination of each item from students' testing result. The Learning Response Index (LRI) is generated in the second procedure. The LRI of each item indicates the students' learning response base upon Item Response Theory. The third procedure handles the concept decomposition and aggregation, while Item–Concept Relationship Table (ICRT) is applied in concept decomposition of each item with the weight of response and the Sugeno Fuzzy Measure Function is applied in concept aggregation with Weight Learning Response Index (WLRI) that is dissociated by ICRT. Several WLRI of the same concept are aggregated as the value of Aggregated Concept Learning Response (ACLR), which indicates the concept learning status of the student. The final procedure is to transform the ACLR from numeric into symbolic H/L by the Fuzzy membership function.

1) Test Item Analyzer

The Test Item Analyzer is the one who calculates the difficulty and the discrimination of each item from the result of students' testing. First of all, we build up the Testing Result Table (TRT) according to the students' answer sheet. Let $A_{m\times n}$ be the matrix of TRT, the element a_{ji} is the answered results of the test items T_j, j=1,2,…,m, from students S_i, i=1,2,…,n. The elements a_{ji}=1 and a_{ji}=0 denote the ith student having right or wrong to the jth test item, respectively. Table 2 shows the example of TRT with six students tested by seven items.

Table 2Testing Result Table (TRT)

Test item / Student ID	T_1	T_2	T_3	T_4	T_5	T_6
S_1	1	0	0	1	1	0
S_2	0	1	1	0	1	1
S_3	0	1	1	0	1	1
S_4	1	0	1	1	0	1
S_5	1	0	1	1	0	1
S_6	1	1	0	1	1	1

Definition 2 Student's Learning Ability

We standardize the score of student S_i as the student's learning ability.

$$\tilde{x}_i = \frac{x_i - \overline{X}}{S_X}, \quad i=1,2,\ldots,n,$$

where x_i : the score of students S_i.

$\overline{X}$: the average score of the students. $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} x_i$

S_X : the standard deviation of the students' scores. $S_X = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{X})^2}{n}}$

Example 2: Student's Learning Ability

If the student has the score of 92, with the class average of 62 and standard deviation of 15, then the standardized score of the student would be 2. We use the standardized score value 2 as the learning ability of the student.

Definition 3 Difficulty and Discrimination of Test Item

Based upon the theory of instruction, let *B* and *P* be the set of high achievement students (the best 27%) and low achievement students (the last 27%), respectively.

- **Difficulty of Test Item** T_j : $P_j = \dfrac{R_j^B + R_j^P}{2}$, j=1,2,…,m,
- **Discrimination of Test Item** T_j : $D_j = R_j^B - R_j^P$, j=1,2,…,m,

where R_j^B : the ratio of answering right of test item T_j in set *B*.

R_j^P : the ratio of answering right of test item T_j in set *P*.

The value of difficulty is between 0 and 1, which 0 means hard and 1 means easy of the test item. Also, the value of discrimination is between 0 and 1, which 0 means the low discrimination and 1 means the high discrimination of the test item.

2) LRI Generator

The difficulty and discrimination of each test item are computed after the Test Item Analyzer. Let $T_{m\times n}$ be the matrix of Learning Response Mapping Table, where the student S_i, i=1,2,…,n is column variable and the test item T_j, i=1,2,…,m, is the row variable. The entries t_{ji} of the matrix $T_{m\times n}$ are defined as the Learning Response Index of the test item T_j.

Definition 4 The Learning Response Index of the Test Item

Let $T_{m\times n}$ be the matrix of the Learning Response Mapping Table, and t_{ji} be the entries $T_{m\times n}$, which indicates the student's learning status obtain by the test item. We define the Learning Response Index of the Test Item as

$$t_{ji} = a_{ji} \times LRI_{(P_j,D_j)}(\tilde{x}_i),\ i=1,2,\ldots,n,\quad j=1,2,\ldots,m,$$

where a_{ji} is the answered results of the test item T_j of the student S_i, and $LRI_{(P_j,D_j)}(\tilde{x}_i)$ is defined in **Definition 1**. The value of t_{ji} which is between 0 and 1 denotes the student S_i's learning status response through test item T_j.

Example 3: Student's Learning Response Index

The difficulty and discrimination of the test item are 0.813 and 0.375 as given, respectively. If the student's ability is 1.8 and has right answer of the test item, then the student's LRI through the test item is

$$LRI_{(P_j,D_j)}(\tilde{x}_i)=LRI_{(0.813,0.375)}(1.8)=\frac{1}{1+e^{-1.7\times 0.375(1.8-0.813)}}=0.65$$

The value 0.65 indicates the learning status of the student while having the right answer of the test item.

3) Concept Decomposition and Aggregation

Intuitively, a test item may include several concepts, so we have to decompose the concepts included in a test item with the attribute called WLRI. Later, we aggregate the WLRI of the same concept involved in several test items. The aggregated value of attribute is treated as Aggregation Concept Learning Response index (ACLR).

i. Concept Decomposition :Item Concept Relationship Table

First of all, we decompose the concepts performed in the test item by the test Item - Concept Relationship Table (ICRT). If the test sheet has m test items T_j, j=1,2... m, with p concepts C_k tested, namely k=1,2... ,p. Let $B_{m\times p}$ be the matrix of ICRT, and the element b_{jk} is the weight between 0~1, which indicates the relativity of concept C_k involved in test item T_j.

Example 4: Test Item - Concept Relativity Table (ICRT)

Table 3 shows the ICRT of seven test item include five concepts, where the concept is the row variable and the test item is the column variable. By referring to the ICRT, we can see that the Test item T_3 includes Concepts C_3 、C_4 and C_5 with different relativity weight 1, 0.3, 0.4, respectively. Simultaneously, test items T_2 and T_6 have included the same concepts C_2 and C_3, but with different weight of relativity, say 0.8, 1 and 1, 0.8, respectively. Also, Concept C_3 is included in the test items T_1 、T_2 、T_3 and

T_6 with the weight of relativity, 0.75, 1, 1, 0.8, respectively.

Table 3 Test Item-Concept Relation Table (ICRT)

Test item \ Concept	C1	C2	C3	C4	C5
T1	0.9	0	0.75	0	0
T2	0	0.8	1	0	0
T3	0	0	1	0.3	0.4
T4	1	0	0	0	0
T5	0	1	0	0	0
T6	0	1	0.8	0	0
T7	1	1	0	0	1

ii. Concept Aggregation

The concepts learning response of a student through each test item are given according to the LRMT with the weight in ICRT.

Definition 5 The Weight Concept Learning Response Index

Since b_{jk} and t_{ji} are the entries of matrixes $B_{m\times p}$ and $T_{m\times n}$, respectively. Recall that $B_{m\times p}$ and $T_{m\times n}$ is the matrixes of ICRT and Learning Response Mapping Table, respectively. Let $W_{n\times m\times p}$ be the matrix of Weight Concept Learning Response mapping Table (WCLRT), and the values of entries w_{ijk} is between 0~1. We obtain w_{ijk} by the following.

$$w_{ijk} = b_{jk} \times t_{ji},\ i=1,2,\ldots,n,\ j=1,2,\ldots,m,\ k=1,2,\ldots,p,$$

where w_{ijk} indicates the concept C_k 's learning status of student S_i, which the concept C_k is involved in test item T_j.

Example 5: Weight Concept Learning Response

Suppose the student S_i has the LRI=0.6 obtain from the test item T_j which involves concepts C1 and C2 with the weight of relativity 0.75 and 1, respectively. Then the learning status indexes of the student concerning concept C1 and C2 are

$w_{ij1} = b_{j1} \times t_{ji} = 0.75\times 0.6=0.45$ and $w_{ij2} = b_{j2} \times t_{ji} =0.75\times 1=0.75$, respectively.

Since each concept C_j has a set of WCLR, which is obtain from several test items T_k, k=1,2,…,p, having concept C_j. As Fig. 7 shows, the test items T_1, T_2 and T_3 are decomposed into several concepts, like C_1, C_2 and C_3. Next, we can see that the sets of WCLR concerning concepts C_1, C_2 and C_3 are {0.64,0.69}, {0.80}, {0.35,0.87,0.69}. The aggregation WCLR of the set concerning concept C_j is defined as the Aggregation Concept Learning Response index (ACLR), which indicates the status of the student in learning concept C_j.

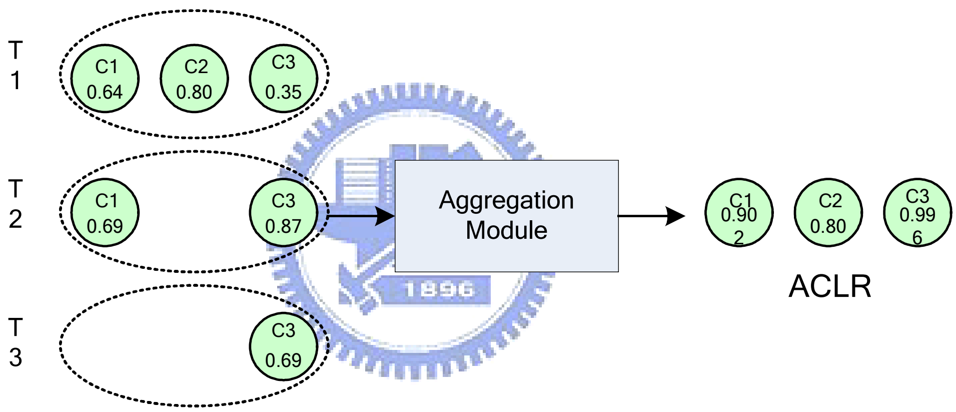

Fig. 7 ACLR index is aggregated from item's WLRI

So far, it is important to figure out the function to achieve the aggregation mention above. In this thesis, we apply the Sugeno fuzzy measure function as our aggregation function. In order to set the value between 0~1, the aggregation function must satisfy the boundary condition with (1) $g_\lambda(\phi)=0$, (2) $g_\lambda(X)=1$, and the properties, (3) if $A \subseteq B$, then $g(A) \subseteq g(B)$, where A and B are subsets of X.

Definition 6 The Function of Aggregation Concept Learning Response index (ACLR)

The Function aggregates the element of the set X_k of WCLR concerning concept C_k, and define the ACRL of concept C_k as

$$g_i(X_k) = \frac{\prod_{j=1}^{m}(1+\lambda \times w_{ijk})-1}{\lambda}, \quad \lambda=-0.97,$$

where w_{ijk} indicates the WCLR defined in Definition 5.

Example 6: Aggregation Concept Learning Response index (ACLR)

According to the ICRT, the test items T1, T2, T3 are decomposed into {C1,C2,C3}, {C1,C3}, {C3}, respectively. The learning response index of concepts in each test item is obtained by the product of the test items' LRI and the weight in ICRT. Each concept C_j has a set WLRI from several test items T_k concerning concept C_j.

Table 4 The WLRI and the ACLR of concepts

Item	C1	C2	C3
T1	0.64	0.80	0.35
T2	0.69	0	0.87
T3	0	0	0.69
ACLR	0.902	0.800	0.996

Suppose student S_i has such a table shown in Table 4 after testing. T1 includes the concepts of C1, C2 and C3 with the WLRI of 0.64, 0.80 and 0.35; T2 include the concepts of C1 and C3 with the WLRI of 0.69 and 0.87, and T3 include the concepts of C3 with the WLRI of 0.69. By looking through the columns, concept C1, C2 and C3 will have the sets of WLRI {0.64,0.69,}, {0.80,} and {0.35,0.87,0.69}through T1, T2 and T3, respectively. Then the ACLR of student S_i concerning concepts C1, C2 and C3 are calculated as below.

$$g_{\mathrm{i}}(\{0.64,0.69\}) = \frac{(1-0.97\times 0.64)(1-0.97\times 0.69)-1}{-0.97} = 0.902$$

$$g_i(\{0.80\}) = \frac{(1-0.97\times 0.80)-1}{-0.97} = 0.800$$

$$g_i(\{0.35,0.87,0.69\}) = \frac{(1-0.97\times 0.35)(1-0.97\times 0.87)(1-0.97\times 0.69)-1}{-0.97} = 0.996$$

4) Fuzzy ACLR Generator

In order to mine association rule further, it is necessary to transform the numeric data into symbolic data. We achieve the transformation by applying fuzzy Theory. Here we have two membership functions shown in Fig. 8 to transform the students' numeric ACLR into symbolic notation. The symbolic notations obtain by the fuzzification is "L" and "H", which denote "Poor Learning" and "Well Learning", respectively. $C_i.L$ and $C_i.H$ denote the value obtain from the LOW Fuzzy Function and the HIGH Fuzzy Function of the concept C_i.'s ACLR, respectively. The value of each concept's ACLR will transform into the notation "L" and "H" if $C_i.L > C_i.H$ and $C_i.L \leq C_i.H$, respectively. For example, if ACLR=0.65, by the given membership functions, we have $C_i.L$=0.2 and $C_i.H$=0.66. Since $C_i.L \leq C_i.H$ the Fuzzy ACLR is denoted as "H". Completely, fuzzification of ACLR is described in Example 4.6.

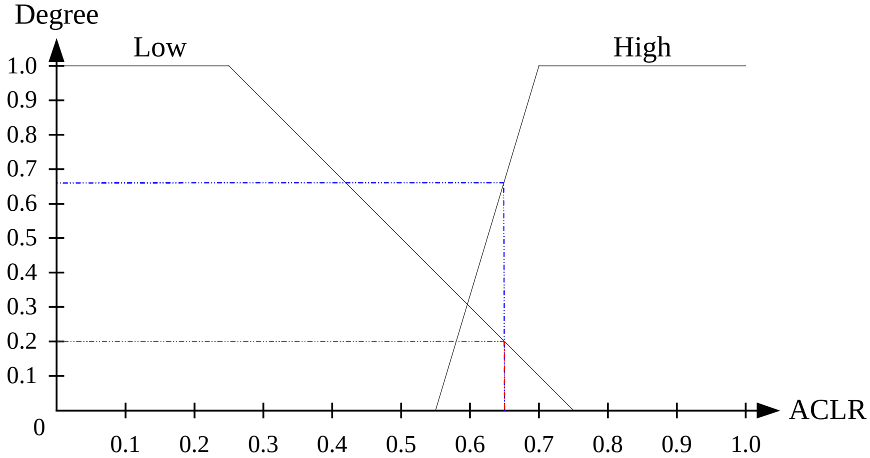

Fig. 8 The given membership functions of students' numeric ACLR.

Example 7: Fuzzy ACLR Generator

Suppose six students are tested with five concepts. Students' ACLR of each concept is shown in Table 5.

Table 5 The Students' ACLR of each concept

SCCI (Students \ Concepts)	C1	C2	C3	C4	C5
S1	1.00	0.42	0.67	0.65	0.38
S2	1.00	0.00	0.54	0.68	0.68
S3	1.00	0.30	0.55	0.53	0.77
S4	1.00	0.00	0.78	0.73	0.75
S5	1.00	0.32	0.32	0.40	0.40
S6	0.98	0.00	0.43	0.74	0.82

By the given membership functions, ACLR of each student has the degree value of $C_i.L$ and $C_i.H$. Table 6 shows the fuzzy degree values of ACLR obtain by the LOW/HIGH fuzzy membership functions.

Table 6 The degree value of ACLR translated by the LOW /HIGH fuzzy membership functions

Concept / Degree / Student	C1		C2		C3		C4		C5	
	$C_1.L$	$C_1.H$	$C_2.L$	$C_2.H$	$C_3.L$	$C_3.H$	$C_4.L$	$C_4.H$	$C_5.L$	$C_5.H$
S1	0.00	1.00	0.66	0.00	0.14	0.84	0.66	0.20	0.70	0.00
S2	0.00	1.00	1.00	0.00	0.42	0.00	0.14	0.90	0.14	0.90
S3	0.00	1.00	0.90	0.00	0.40	0.00	0.44	0.00	0.00	1.00
S4	0.00	1.00	1.00	0.00	0.00	1.00	0.04	1.00	0.00	1.00
S5	0.00	1.00	0.86	0.00	0.84	0.00	0.70	0.00	0.70	0.00
S6	0.00	1.00	1.00	0.00	0.64	0.00	0.02	1.00	0.00	1.00

We then transform the numeric ACLR into the symbolic notation of “H” if $C_i.L \le C_i.H$ and “L” if $C_i.L > C_i.H$. The notation “H” and “L” represent the meaning of “well learning” and “poor learning”, respectively. Table 7 shows the fuzzification result of ACLR.

Table 7 The Students’ fuzzy SCCI of each concept.

Concept / FACLR / Student	C1	C2	C3	C4	C5
S1	H	L	H	H	L
S2	H	L	L	H	H
S3	H	L	L	L	H
S4	H	L	H	H	H
S5	H	L	L	L	L
S6	H	L	L	H	H

4.2 Data Mining Module

After the fuzzification of ACLR, the symbolic data "H" and "L" are then process by the Data Mining Module. First, the Apriori Algorithm of data mining is adopted to discover the association rules. Finally, CERM is constructed based on the scenario explanation of the mined association rule.

Algorithm 1: Apriori Algorithm

Symbol Definition:

α : The minimum support threshold in the ℓ-large itemset.
C_ℓ : Candidate itemset of size ℓ.
L_ℓ : Frequent itemset of size ℓ.
λ : The minimum confidence threshold.

Input:

The FACLR of students.

The threshold of minimum support α.

The threshold of minimum confidence λ.

Output : The association rules of FACLR of students.

L_ℓ = {frequent items};
for (ℓ = 1; $L_\ell = \phi$; ℓ ++)
do begin
  $C_{\ell+1}$ = candidates generated from L_ℓ;
    for each transaction t in database,
    do increment the count of all candidates in $C_{\ell+1}$, that are contained in $C_{\ell+1}$
      $L_{\ell+1}$ = candidates in $C_{\ell+1}$ with min_support
end

return C_ℓ and L_ℓ

1) Association Rule Mining

We mine the association rules from the Fuzzy ACLR by using Apriori Algorithm of data mining. Four types of association rules ***L-L, L-H, H-L*** and ***H-H*** are used as the model to discover the assimilation and mis-concept effect relations among concepts.

Example 8: Apriori Association Rule Mining Algorithm

From the data shown in Table 7, Fig. 9 shows the process of mining the association rules by Apriori algorithm with minimum support 0.6 and minimum confidence 0.6.

The 1 -Candidate itemset

Itemset	Sup. count
C_1H	10
C_1L	0
C_2H	1
C_2L	9
C_3H	4
C_3L	6
C_4H	6
C_4L	4
C_5H	8
C_5L	2

The 2 -Candidate itemset

Itemset	Sup. count
{C_1H,C_2L}	9
{C_1H,C_3L}	6
{C_1H,C_4H}	6
{C_1H,C_5H}	8
{C_2L,C_3L}	6
{C_2L,C_4H}	5
{C_2L,C_5H}	6
{C_3L,C_4H}	2
{C_3L,C_5H}	5
{C_4H,C_5H}	5

The 3 -Candidate itemset

Itemset	Sup. count
{C_1H,C_2L,C_3L}	6
{C_1H,C_2L,C_4H}	5
{C_1H,C_2L,C_5H}	7
{C_1H,C_3L,C_4H}	2
{C_2L,C_3L,C_4H}	2
{C_1H,C_3L,C_5H}	5
{C_2L,C_3L,C_5H}	5
{C_1H,C_4H,C_5H}	5
{C_2L,C_4H,C_5H}	4
{C_3L,C_4H,C_5H}	2

Confidence=0.6

Confidence=0.6

Confidence=0.6

The 1 -large itemset

Itemset	Sup. count
C_1H	10
C_2L	9
C_3L	6
C_4H	6
C_5H	8

The 2 -large itemset

Itemset	Sup. count
{C_1H,C_2L}	9
{C_1H,C_3L}	6
{C_1H,C_4H}	6
{C_1H,C_5H}	8
{C_2L,C_3L}	6
{C_2L,C_5H}	6

The 3 -large itemset

Itemset	Sup. count
{C_1H,C_2L,C_3L}	6
{C_1H,C_2L,C_5H}	7

Fig. 9 Process of Apriori algorithm

Table 8 shows the Association Rule mining with minimum support 0.6 and minimum confidence 0.6 generated from large 2 itemset into L-L, L-H, H-H, and H-L types. The Confidence is used to indicate the important degree of *i*th mined association rule. For example, the Confidence of rule $C_2\mathrm{L} \rightarrow C_3\mathrm{L}$ can be obtained as follows.

$$C_2\mathrm{L} \rightarrow C_3\mathrm{L} : Confidence = \frac{\mathrm{support}\_count(\{C_2\mathrm{L}, C_3\mathrm{L}\})}{\mathrm{support}\_count(\{C_2\mathrm{L}\})} = 0.67$$

Table 8 The Mining Results (*Confidence* $\geq$ 0.6)

The Large 2 Itemset		
Rule Types	Mined Rules	Confidence
H→H	$C_1\mathrm{H} \rightarrow C_4\mathrm{H}$	0.60
	$C_1\mathrm{H} \rightarrow C_5\mathrm{H}$	0.80
H→L	$C_1\mathrm{H} \rightarrow C_2\mathrm{L}$	0.90
	$C_1\mathrm{H} \rightarrow C_3\mathrm{L}$	0.60
L→H	$C_2\mathrm{L} \rightarrow C_5\mathrm{H}$	0.78
L→L	$C_2\mathrm{L} \rightarrow C_3\mathrm{L}$	0.67

2) Concept Map Constructor

We define the direction by the effect relationship, and the weight of edge indicates the influent probability defined by the order pairs, support and confidence. According to the above concept effect direction and weight, Concept Effect Relation Map of the students' is constructed based upon the scenario explanation of the association rule shown in Table 9.

Table 9 The scenario explanation of association rule

Association Rule	Concept Effect	Relation
$C_1\text{H} \rightarrow C_2\text{H}$	Assimilation (Positive related)	$C_1 \rightarrow C_2$, C_1 is the prior concept of C_2 with support value higher then C_2 .
$C_1\text{L} \rightarrow C_2\text{L}$		$C_2 \rightarrow C_1$, C_2 is the prior concept of C_1 with support value lower then C_1 .
$C_1\text{L} \rightarrow C_2\text{H}$	Misconception (Negative related)	$C_2 \rightarrow C_1$, C_2 is the alternative concept of C_1 with higher confidence value.
$C_1\text{H} \rightarrow C_2\text{L}$		$C_1 \rightarrow C_2$, C_1 is the alternative concept of C_2 with higher confidence value.

5. Experiment

In this thesis, we applied the IRT-Based Data Preprocessing Concept Effect Relation Map Construction System in Mathematics to evaluate its effectiveness. The experiment is based upon Table 10, which is the basic data of the experiments in Mathematics, this chapter describes the experiment in detail.

Table 10 Statistics of the experiment.

Course	Mathematics
School	Senior High School
Grade	K-11
Number of students	42
Average score	62.36
Number of test item	32
Standard deviation of scores	15.43
Average difficulty of the test items	0.535
Difficulty range of the test items	0.125~0.938
Average discrimination of the test items	0.107
Discrimination range of the test items	-0.5~0.75

The experiment was based on Mathematics tests administered at a senior high school. There are 42 students participated in the experiment, and their average test score was 62.36, while the average discrimination level of the test items is 0.107. Table 11 list the notation of concepts included in the test sheet. In this experiment, the weight of concepts included in ICRT would be set to 1 to simplify our discussion. Moreover, the fuzzification threshold is set to 0.6, and the mining support and confidence are both 0.6.

Table 11 Notation of concepts included in the test sheet.

Concept Notation	Concept
C1	Spatial Relation of Points, Lines and Planes
C2	Logical Concept
C3	Symmetrical Point
C4	Distance of Two Point
C5	Trigonometric function
C6	Cosine Theorem
C7	Angle of Two Intersections Planes
C8	Coordinates Reference of Spatial Object
C9	Perpendicular Point
C10	Equations of Coordinate Planes
C11	Three Perpendicular Lines Theorem

As shown in Fig. 10, Fig. 11 and Fig. 12, the left side of the Figure shows the data preprocessing with IRT-Based, while the right side of Figure shows the data preprocessing with correct answering ratio which is un based on IRT.

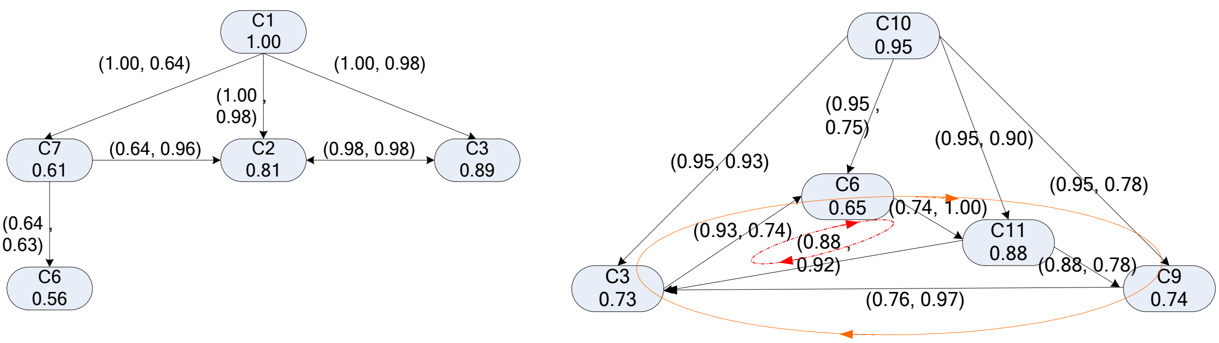

Fig. 10 H-H type CERM constructed with and without IRT-Based Data preprocessing.

Fig. 10 shows the H-H type CERM. Attention to the un IRT-Based CERM in Fig.11, the CERM has two circulated effect relationship, one is the C3➔C6➔C11➔C3 and the other one is C3→C6→C11→C9 →C3. As the experiment shows, based on the same support and confidence, the CERM construction with IRT-Based data preprocessing is better and reasonable than the one without IRT-Based data preprocessing.

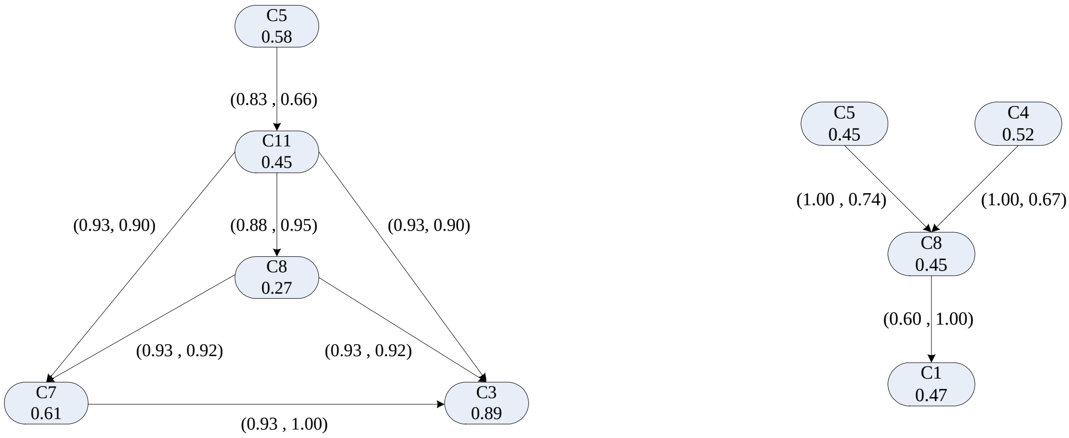

Fig. 11 L-L type CERM constructed with and without IRT-Based Data preprocessing.

Fig. 11 shows the L-L type CERM. The concept at the bottom of L-L type CERM means much more difficult than other. For example, in the left part of Fig. 11,if C3 is not well learning by student, the key problem in learning C3 is a lack of understanding of concepts C7, C8 and C11, so the student should learn concepts C7, C8 and C11 before learning C3. The left CERM suggests the learning strategy of C3: instead of learning C3 repeatedly, the learning of C11, C8 and C7 has to be firstly enhanced.

Fig. 12 shows the L-H & H-L type CERM, which indicate the mis-concept effect among concepts. The mis-concept effect may be caused by misunderstanding of concept, confuse among concept, etc. As shown in the left of Fig. 12, the concept set {C1,C2,C3,C7}is the alternative concept of the concept set {C8,C9,C10,C11}. The CERM construction with IRT-Based Data preprocessing generates more Association rules than the one without IRT-Based Data preprocessing.

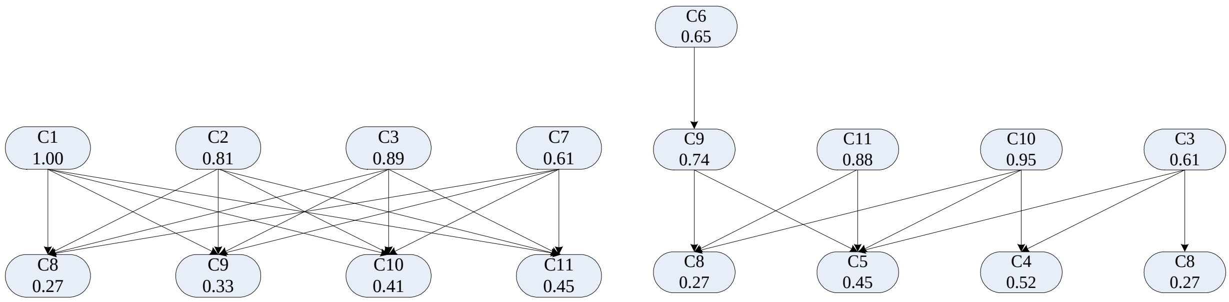

Fig. 12 L-H and H-L type CERM constructed with and without IRT-Based Data preprocessing.

6. Conclusion

The assessment analysis and the concept mapping representation of the analysis result have become an important issue of e-learning. The result of the assessment can be analyzed to discover effect relations among concepts, such as assimilation effect and mis-concept effect. Diagnoses by analyzing the result of assessment can improve students' learning status, and the teaching while tutoring.

Concept Effect Relation Map (CERM) constructed by data mining with naïve data preprocessing causes monotonous concept fuzzification result. At the same time, the circulating association rules exit, and the association rules may not reflect the concept relation physically. In this thesis, we propose an IRT-Based Data Preprocessing Concept Effect Relation Map Construction System with the consideration of the difficulty and the discrimination of test item,

IRT-Based Data Preprocessing Concept Effect Relation Map Construction System includes two modules: the Data Preprocessing Module and the Data Mining Module. The first module has four procedures: Test Item Analysis, Learning Response Index (LRI) Generator, Concept Decomposition/Aggregation and Fuzzy ACLR Generator. The second module is called Data Mining Module with two procedures. Association rule mining and concept map constructor.

The experiment of the proposed approach shows the improvement of constructing CERM and the reduction of the circulated association rules' number generated. The main contributions of this thesis are:

(1) The IRT-Based Data preprocessing Approach we proposed refines the assessment of concept learning response.

(2) Based upon the Item Response Theory, we define a fuzzy membership function to quantify the learning status of concept.

(3) The experiment of the proposed Approach indicates the improvement of CERM construction in association rules mining.

There are some interesting issues in extending the application of CERM in the nearly future:

(1) The distribution weight of the items and concepts may affect the concept learning response, CERM can be use to indicate the quality of the test sheet.

(2) The development of comparing technique: comparing the CERM of different learning groups or the CERM of teachers.

Reference

[1] Cmap Tools,IHMC, http://cmap.ihmc.us/.

[2] Item Response Theory- Theory and application, http://www.edutest.com.tw/e-irt/irt.htm

[3] Test Diagnostics, http://www.edtech.vt.edu/edtech/id/assess/diagnostics.html

[4] J. Appleby, P. Samuels, and T.T. Jones , "Diagnosis–A Knowledge-based Diagnostic Test of Basic Mathematical Skills" , *Computers & Education* , 28(2), February, 1997, pp. 113-131.

[5] J.D. Barbara, R. S.Christine, B. Toni, G. Kate, P. Linda, "Concept Maps: A Stratagy to Teach and Evaluate Critical Thinking", *Journal of Nursing Education* , 38(1), January,1999, pp. 42-47.

[6] E. Bruillard & G.L. Baron, "Computer-based concept mapping: a review of a cognitive tools for students", *International Conference on Educational Uses of Communication and Information Technologies*, Beijing, China, August 21-25, 2000, pp. 331-338.

[7] G. Frosini, B. Lazzerini, and F. Marcelloni, "Perform Automatic Exams", *Computers & Education*, 31(3), November, 1998, pp. 281-300.

[8] B.R. Gaines and M.L.G. Shaw, "Concept maps as hypermedia components", *International Journal of Human Computer Studies*, 43(3), 1995, pp. 323--361.

[9] H. Gamboa, "Designing Intelligent Tutoring Systems : A Bayesian Approach", *Proceedings of Ana Fred 3rd International Conference on Enterprise Information*

Systems (ICEIS'2001), 2001, pp. 452-458.

[10] J.L. Gordon, “Creating knowledge maps by exploiting dependent relationships”, *Knowledge-Based Systems*, 13(2000), pp.71-79.

[11] J. Han and M. Kamber, *Data mining concepts and techniques*, Morgan Kaufmann Publishers. P230-239.

[12] R.K. Hambleton and S.H. waminathan, (1985). *Item Response Theory*, Kluwer-Nijhoff Publishing, Boston, Massachusetts.

[13] G.J. Hwang, “A Conceptual Map Model For Developing Intelligent Tutoring System”, *Computers & Education*, 40(3), April, 2003, pp. 217-235.

[14] G.J. Hwang, C.L. Hsiao, and C.R. Tseng, “A Computer-Assisted Approach to Diagnosing Student Learning Problem in Science Course”, *Journal of Information Science & Engineering*, 19(2), 2003, pp. 229-248.

[15] C.L. Hsiao, G.J. Hwang, and C.R. Tseng, “An interactive concept relationship construction assisted system for learning diagnosis,” *The 5th Global Chinese Conference on Computers in Education*, 2001, pp. 925-932.

[16] C.S. Hsu, S.F. Tu, and G.J. Hwang, “A Concept Inheritance Method for Learning Diagnosis of a Network-based Testing and Assessment System”, *Proceedings of The 7th International Conference on Computer-Assisted Instructions*, 1998, pp. 602-609.

[17] D.H. Jonassen, (1996). Computer in classroom: Mindtools for critical thinking.

Englewood Cliffs, NJ: Prentice-Hall, Inc.

[18] J.D. Novak, *Learning, Creating, and Using Knowledge: Concept Maps As Facilitative Tools in Schools and Corporations*, Lawrence Erlbaum Assoc 1998.

[19] K.A. Papanikolaoua, M. Grigoriadoua, G.D. Magoulasb, and H. Kornilakisa, “Towards New Forms of Knowledge Communication: The Adaptive Dimension of a Web-based Learning Environment”, *Computers & Education*, 39(4), December, 2002, pp. 333-360.

[20] W.J. Popham, *Classroom Assessment: What Teachers Need to Know*, Pearson Allyn & Bacon, 1999, pp.222-227.

[21] H.F Schmidi and D. Volke, "Shift of meaning and students’ alternative concepts", *International Journal in Science Education*, 25(11), November, 2003, pp. 1409-1424.

[22] P.C. Sue, J.F. Weng, J.M. Su, and S.S. Tseng. “A New Approach for Constructing the Concept Map,” *IEEE International Conference on Advanced Learning Technologies*, ICALT 2004.

[23] E. Triantafllou, A. Pomportsis, and S. Demetriadis, “The Design And The Formative Assessment of An Adaptive Educational System Based on Cognitive Styles”, *Computers & Education*, 41(1), August, 2003, pp. 87-103.

[24] C.J. Tsai, S.S. Tseng, and C.Y. Lin, "A Two-Phase Fuzzy Mining and Learning Algorithm for Adaptive Learning Environment", *Proceedings of International Conference on Computational Science (ICCS'2001), Lecture Notes in Computer Science*

(LNCS 2074), Vol. 2, pp. 429-438, CA, USA, May, 2001.