Application of automatically constructed concept map of learning to conceptual diagnosis of e-learning

Chun-Hsiung Lee*, Gwo-Guang Lee, Yungho Leu

Department of Information Management, National Taiwan University of Science and Technology, Taipei 106, Taiwan

Abstract

The concept map proposed by Novak is a good tool to portray knowledge structure and to diagnose students’ misconception in education. However, most of the learning concept maps have to be constructed through the suggestions of experts or scholars in related realm. It is really a complicated and time-consuming knowledge acquisition process.

The study proposed to apply the algorithm of Apriori for Concept Map to develop an intelligent concept diagnostic system (ICDS). It provides teachers with constructed concept maps of learners rapidly, and enables teachers to diagnose the learning barriers and misconception of learners instantly. The best Remedial-Instruction Path (RIP) can be reached through the algorithm of RIP suggested in this study. Furthermore, RIP can be designed to provide remedial learning to learners. Moreover, by using statistical method, the study analyzed 245 students’ data to investigate whether the learning performance of learners can be significantly enhanced after they have been guided by the RIP.

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1. Introduction

With the popularization of information technology and computer network, the location of instruction activity has been varied from the traditional classrooms to the internet, forming the so-called e-learning. However, lacking physical teaching activity and guidance in the e-learning environment, by what means the teachers can evaluate the learning barriers, misconception and learning performance of students in the portfolio of learners would be an important research issue of today.

Nevertheless, many scholars think that online evaluation is an important learning response index for the instruction process. But most of the online evaluation system can only show the total scores, answers, solution analysis and position of the testees, they cannot help teachers to understand the students’ degree of familiarity with the knowledge from the test portfolio of testees.

Therefore, the study proposed using the algorithm of Apriori for Concept Map to develop the ICDS of an automatically constructed concept map of learning. The practice was to use the test question association rules of data mining to analyze the test portfolio of learners, and to adapt the automatically constructed concept map of learner to produce the diagnostic analysis reports. It not only shows the learning performance of students, but also provides useful clues to the learning barriers of students. Learners are able to know immediately which of their concepts should be further remedied, thus achieving the objectives of remedial learning.

The construction of concept map of learning can be generally divided into three kinds: completely manual, semi-automatic and automatic construction (Tseng, Tsai, Su, Tseng, & Wang, 2005). Among these three kinds, the completely manual construction is a constructive way through the suggestions of educational or field experts and scholars. It is really a complicated and time-consuming knowledge acquisition process.

In view of the above situations, the study was made with the following purposes:
(1) To actually develop the ICDS of an automatically constructed concept map of learning by the algorithm of Apriori for Concept Map combined with the testee’s test portfolio.
(2) Teachers were provided with the rapidly constructed concept map of learners to diagnose the learning barriers and misconception of learners.
(3) Through the analyzes of the concepts and weight in the concept map, RIP was constructed to offer remedial learning.
(4) Statistical methods were used to analyze whether the learning performance of learners can be significantly enhanced after they have been guided by the RIP.

2. Literature review

In a learning activity, each step has a learning focus, which was called “concept”. The learning of these concepts should be done in a proper sequence. We call this kind of learning sequence as epistemological order (Chen & Hsia, 1999). For example, the learning of “multiplication” must be preceded by the learning of the concept of “addition”. “Epistemological order” is used to standardize the learning order of different concepts. Let us present the epistemological order in Fig. 1. In the figure, A and B represent two concepts. The connecting line between A and B represents that there is a correlation of a certain epistemological order in between. The arrow of the connected line represents the learning order. Therefore, Fig. 1 indicates that Concept A precedes Concept B in terms of the epistemological order.

Through a series of combination of the epistemological order, a topological graph can be acquired, and is called “conceptual graph” (Novak, Gowin, & Johansen, 1983; Plotnick, 1997). Conceptual graph is proposed by Professor Novak of Cornell University of the United States to express the hierarchal structure of knowledge (Novak & Gowin, 1984).

Since “conceptual graph” can make the relationships between concepts more organized and systematic and present the learning order of concepts, the paper intended to use these properties of conceptual graph to find out the misconception of students in the learning process. For example, regarding the epistemological order shown in Fig. 2, learners should learn Concept A first, and then Concept B and Concept C. Therefore, if a learner is found to have a learning barrier during the learning of Concept B, we can presume that the learner’s learning difficulty of Concept B is caused by his/her incomplete learning of Concept A. Therefore, Concept A may be the misconception of the learner.

When a certain learner is judged to have a misconception of Concept C, the father concept that has the closest relation with the misconception of Concept C can be acquired. After repeated searching, a path that takes Concept C as the starting point and goes through a series of concepts is obtained. The concepts that the path passes through are judged by the system as the related concepts that may probably be the causes of the unsatisfactory performance in learning Concept C. This path is called the Remedial-Instruction Path (RIP) (Chung, Lin, & Wu, 2001).

Concept map is a combination of many important learning theories. In fact there are hundreds of researches papers relate to the application of concept map in education, but they hardly touch upon the application of concept map to e-learning. Therefore, concept map still has a rather great room for research in the realm of e-learning, and is worthy of making in-depth investigation.

3. Research approach

The study proposed the algorithm of Apriori for Concept Map which includes the following eight procedures that the concept map of learning has to complete.

3.1. Presetting conceptual weight of test question by teachers

In the realm of science curricula, a test question may not correspond to one concept only. A test question may at the same time include two or more than two concepts. Therefore, when a teacher presets the relevance of concepts to questions, the weight of concepts in each question has to be predetermined by the teacher. If a test question contains a single concept, the relevance degree will be represented by “1”. If a test question contains two or more than two concepts, the conceptual weight (0–1) distributed to different test questions will be presented by the degrees of strong, medium and weak. If a test question does not contain any concept, it will be represented by “0”, and the total weight of the test question is 1, as shown in the comparison chart of conceptual weight relationships in test questions in Table 1. Five test questions (Q1–Q5) cover five concepts (C1–C5) which are designed for the curriculum.

3.2. Recording the test portfolio of each testee

Suppose there is a table of test portfolio with 5 testees having given wrong answers in the test of a subject, as
shown in Table 2. In the table, testee S1 gives wrong answers to Q1 and Q2, testee S2 gives wrong answers to Q1, Q2 and Q3, and so forth. The question answering portfolio of testees is imported to the database, as shown in the chart of question answering portfolio of learners in Table 2.

Table 2 records the test portfolio of students. If a question is correctly answered, “0” will be recorded in the database; if a question is wrongly answered, “1” will be recorded in the database. The column at the right end makes a statistics on the total number of students having given wrong answers to each question, so as for analyzing the discrimination index of the question (Hwang, 1998). In order to further analyze the test portfolio of students, we converted the chart of test portfolio of learners in Table 2 into a comparison chart of learners’ wrong answers to questions, as shown in Table 3.

3.3. Using association rules of data mining to find out all the large itemsets

In Table 3, or the comparison chart of learners’ wrong answers to questions, the number of questions being wrongly answered by each testee can be calculated. Suppose that the teacher sets Min Support (MS) = 0.4 and the number of testees is 5, then the number of questions with wrong answers given by testees has to be ≥ MS × N (0.4 × 5 = 2), otherwise it would be meaningless at all. All the finally produced large itemsets are indicated in Table 4.

3.4. Ruling the test question association

The confidence level of the test question association rule Q_i → Q_j is the concept of conditional probability. It implies that under the condition that a testee gives a wrong answer to Question Q_i, there is a probability for the testee to give a wrong answer to Question Q_j, too (Hsiao et al., 2001). The estimated confidence level formula is

\[
\text{Confidence} (Q_i \rightarrow Q_j) = \frac{\text{Support} (Q_j | Q_i)}{\text{Support} (Q_i)}
\]

Let the minimum confidence level be below 70%, and based on the algorithm of Apriori for Concept Map, we can acquire the association rule between these paired test questions. As a result, seven rules are produced as follows:

Rule 1. Confidence (Q1 → Q2) = 100%.
Rule 2. Confidence (Q1 → Q3) = 100%.
Rule 3. Confidence (Q2 → Q1) = 75%.
Rule 4. Confidence (Q2 → Q3) = 100%.
Rule 5. Confidence (Q3 → Q2) = 80%.
Rule 6. Confidence (Q4 → Q3) = 100%.
Rule 7. Confidence (Q5 → Q4) = 100%.

3.5. Converting “test question association rules” into the effect of “relationship between concept and concept”

From Rule 1, it is known that Q1 → Q2 can be interpreted this way: when a testee gives a wrong answer to Q1, he/she will also give a wrong answer to Q2, and the probability is 100%. Therefore, we can further analyze Rule 1 from the comparison chart of conceptual weight relationships in test questions in Table 1 that when a testee does not understand Concept C1, he/she also will not understand Concept C2, and the probability is 100%. Nevertheless, it is known from Rule 3 that Q2 → Q1 is opposite to the explanation of Rule 1. Besides, since its confidence level is only 75%, which is lower than Rule 1’s 100%, Concept C1 is more probably the prerequisite knowledge of

<table>
<thead>
<tr>
<th>Question</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Q2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Q3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Q4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Q5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Note: 0: the student has correctly answered the test item, 1: the student failed to correctly answer the test item.
Concept C2. The conversion from “test question association rules” to the effect of “relationship between concept and concept” is as follows

\[ Q_i \rightarrow Q_j \rightarrow W_{C_iC_j} = C_x \rightarrow C_y = d \cdot \text{confidence} \]

\[ (Q_i \rightarrow Q_j) \ast R_{Q_iC_x} \ast R_{Q_jC_y} \]

where \( Q_i \) denotes the \( i \)th test question, \( C_x \) denotes the \( x \)th concept, \( R_{Q_iC_x} \) denotes the relevance degree between \( Q_i \) and \( C_x \), and \( W_{C_iC_j} \) denotes the relevance degree between \( C_x \) and \( C_y \).

1. \( Q_1 \rightarrow Q_2 \rightarrow W_{C_1C_2} = C_1 \rightarrow C_2 = \text{Confidence} \)
2. \( Q_1 \rightarrow Q_3 \rightarrow W_{C_1C_3} = C_1 \rightarrow C_3 = \text{Confidence} \)
3. \( Q_2 \rightarrow Q_1 \rightarrow W_{C_2C_1} = C_2 \rightarrow C_1 = \text{Confidence} \)
4. \( Q_2 \rightarrow Q_3 \rightarrow W_{C_2C_3} = C_2 \rightarrow C_3 = \text{Confidence} \)
5. \( Q_1 \rightarrow Q_2 \rightarrow W_{C_1C_2} = C_1 \rightarrow C_2 = \text{Confidence} \)
6. \( Q_1 \rightarrow Q_3 \rightarrow W_{C_1C_3} = C_1 \rightarrow C_3 = \text{Confidence} \)
7. \( Q_2 \rightarrow Q_4 \rightarrow W_{C_2C_4} = C_2 \rightarrow C_4 = \text{Confidence} \)
8. \( Q_3 \rightarrow Q_4 \rightarrow W_{C_3C_4} = C_3 \rightarrow C_4 = \text{Confidence} \)

3.6. Construction of preliminary concept map of learning

After converting the test question association rules into the relationship between concept and concept, the ICDS developed by the study automatically drew out a concept map of learning. In the map, each circle represents a learning concept, and the arrow direction of each line represents the priority order of learning concepts, as shown in Fig. 3.

As obviously found in Fig. 3, there is an abnormal priority order existed in the concept map of learning. For example, according to the \( Q_1 \rightarrow Q_2 \) relationship, the acquired relevance strength of the priority concept of \( C_1 \rightarrow C_2 \) is 1; but according to the \( Q_2 \rightarrow Q_1 \) relationship, the acquired relevance strength of the priority concept of \( C_2 \rightarrow C_1 \) is 0.75, implying that the tested concept from \( Q_1 \) and \( Q_2 \) is the relationship of a mutual priority. Unless the teacher makes the concepts overlap seriously when designing the test questions (the test paper designed in this way shall not be advantageous to the construction of concept map of learning), it should belong to an “unreasonable” situation.

3.7. Adjusting concept map of learning at Stage 1

In the construction process of concept map, we have to detect whether there is a “concept cycle” loop existing in the concept map of learning, e.g. \( C_1 \rightarrow C_2 \rightarrow C_1 \). If the “concept cycle” loop appears, the relationship \( (C_2 \rightarrow C_1) \) with weaker relevance degree will be firstly removed according to the strength of “relevance strength between concepts” to eliminate the existence of unreasonable situation (Tseng et al., 2005). Therefore, after deleting the relationship with weaker relevance degree the concept map of learning is shown in Fig. 4.

3.8. Adjusting of concept map of learning at Stage 2

In Fig. 4, although the unreasonable situation of the “concept cycle” loop has been removed from the concept map of learning at Stage 1, when learners are using the concept map as a guiding map for their learning, they still can-

![Fig. 3. Preliminary concept maps.](image-url)

![Fig. 4. Concept map of learning at Stage 1.](image-url)
not clearly understand which concepts are the most basic ones. Therefore, the priority relationship between concept and concept should be further analyzed in the study, and the relationship between father concept and son concept has to be found. Suppose there are five test questions, Q1, Q2, Q3, Q4 and Q5 as shown in Fig. 2, and there are five concepts, C1, C2, C3, C4 and C5 found after analyzing the whole curriculum, and the relationship between the effects of concepts is shown in Table 5.

In Table 5, NC denotes the number of son concepts contained in the father concept, and NP denotes the number of father concepts contained in the son concept. When NP = 0, it represents that the son concept, Concept C5 has no father concept. It is then the most basic concept, i.e. root. When NP = 3, it represents that Concept C3 has 3 father concepts, being C1, C2 and C3. The complete concept map is drawn in Fig. 5.

As observed from the concept map in Fig. 5, if the weight $W_{C1C2}$ is greater, Concept Ci will be the prioritized option during the establishment of the RIP. It refers that the system would select the concepts with the greatest weight as the major RIP. Therefore, it can be known that Concept C5 is the basic concept of C1, C2 and C4. Besides, when $W_{C1C2} = 1$, it represents that the relevance strength of the relationship C1 → C2 is 1, implying that if the basic concept of C1 is not understood well, the learner will not understand Concept C2. Therefore, when a teacher is diagnosing a learner’s learning barrier of Concept C2, the teacher should suggest the learner to understand Concept C1 prior than learning Concept C5 (($W_{C1C2} = 1 > (W_{C3C2} = 0.4)$). And when a teacher knows that the learner has learning barrier of Concept C1, the teacher can strongly recommend that the learner should firstly understand thoroughly the most basic concept, Concept C5.

4. Intelligent system of the automatically constructed concept map of learning

To obtain a fast and efficient result, this study used the language of APS.NET program to develop the ICDS of the automatically constructed concept map of learning so as to assist teachers in rapidly constructing the relationship chart of concepts. Its structural chart is shown in Fig. 6.

In Fig. 6, teachers have to set the corresponding concept and weight of each test question in the management interfaces of questions and conceptual weight. After a testee has done the pre-test in the interface of test system and the test portfolio is imported to the database, the system then analyze the test portfolio of the testee through the test question association rules of the algorithm of Apriori for Concept Map, thus automatically producing the “concept map of learning”. In that case, the teacher could select different Min Support (MS) and Min Confident (MC) values, and checks what relationships between concepts under the situation of different support and confidence values.

4.1. Determination of learning barrier

When using concept map to carry out remedial learning, we had to determine in which concepts that a learner has learning barrier. Multiple choices were provided for students to answer. Through the observation of the student’s answering portfolio of the questions about the concepts, we could understand the learner understands of each concept. Thus, the study was able to further determine the learning barriers of the learner. The concept diagnostic test portfolio is shown in Fig. 7.

4.1.1. Procedures

After the testee finished the test, the system calculated the ratio of wrong answers given in the test portfolio, $ER(C_j) = \frac{\sum e_{kj}}{\sum e_{ij}}$, where $e_{kj}$ denoted the weight of the jth concept of the kth test question which was wrongly answered, and $e_{ij}$ denoted the weight of the jth concept of the i th test question in the whole test paper. Suppose that in the test portfolio of one student, Q3 and Q4 were wrongly answered, and the rest of the answers were correctly answered it could be known from Table 6 that

$$ER(C1) = \frac{(0.5 + 0.3)}{1.8} = 0.44,$$

$$ER(C2) = \frac{(0 + 0.4)}{1.4} = 0.29, \ldots and so forth.

If $ER(C_j) > fail ratio$, Concept Cj is regarded as a learning barrier of the learner. Fail ratio represents the degree of endurance of the ratio of giving wrong answers. Generally
speaking, the range of failratio is $0 \leq \text{failratio} \leq 0.4$. It can be preset according to the standard of the learner. The smaller the failratio, the less the wrong answers one can endure. It implies that the expectation of the learner is relatively higher.

When $\text{ER}(C_j) > \text{failratio}$, it means that Concept $C_j$ is a learning barrier to the learner. But the fact that $C_j$ becomes a learning barrier of the learner does not represent that the learner does not understand Concept $C_j$ at all. It is very probably that the learner has not fully understood a part of Concept C only. Therefore, the system establishes a remedial-instruction path for the learning barrier (Chung et al., 2001).

### 4.2. Establishment of Remedial-Instruction Path

Suppose that a certain testee is judged to have learning barrier with Concept $C_j$, then we can find out the father

<table>
<thead>
<tr>
<th>Question</th>
<th>Concept</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C1</td>
</tr>
<tr>
<td>Q1</td>
<td>1</td>
</tr>
<tr>
<td>Q2</td>
<td>0</td>
</tr>
<tr>
<td>Q3</td>
<td>0.5</td>
</tr>
<tr>
<td>Q4</td>
<td>0.3</td>
</tr>
<tr>
<td>Q5</td>
<td>0</td>
</tr>
<tr>
<td>$\sum_k e_{ki}$</td>
<td>0.8</td>
</tr>
<tr>
<td>$\sum_j e_{ij}$</td>
<td>1.8</td>
</tr>
<tr>
<td>$\text{ER}(C_j)$</td>
<td>0.44</td>
</tr>
</tbody>
</table>
concept having greater relevance with Concept C\textsubscript{j} through
the algorithm of RIP, and search upwards repeatedly until
reaching the root node. During this time, a series of paths
that take Concept C\textsubscript{j} as the starting point can be acquired.
The node of concept that the path passes through is just the
relevance concept which is judged to be very possibly caus-
ing the vague understanding of Concept C\textsubscript{j}. This path is
called the RIP.

Here provides the algorithm of RIP searched by
FaultConcept.

010 Void main ()
020 Call Find_Remedial-Instruction_Path(k, Fault-
Concept)
030 End
040
050 //C\textsubscript{j} denotes the FaulConcept, and k denoted the
index of a father concept on C\textsubscript{j}
060 Sub Find_Remedial-Instruction_Path(k, C\textsubscript{j})
070 //judge whether the failratio of Concept C\textsubscript{j}
is greater
than the tolerance for the ratio of the giving wrong
answers.
080 If ER(C\textsubscript{j}) failratio then
090 Push C\textsubscript{j}
100 W = Max\{W_{C\textsubscript{i}C\textsubscript{j}} | 1 \leq i \leq n\}
110 While (C\textsubscript{i} RootConcept)do //Not Find to Root-
Concept
120 push Ci base on W
130 Wend
140 While Stack is not empty //Find to Root-
Concept
150 //RIP: Remedial-Instruction_Path
160 RIP = Find_Remedial-Instruction_Path(i, Pop())
170 Wend
180 End if
190 End Sub

4.3. Intelligent concept diagnostic system (ICDS)

In the study, the researcher developed an ICDS to fur-
ther analyze and diagnose the learning barriers of learners,
and provides the best RIP, as shown in Fig. 8.

The selection rule of the RIP was that the system
selected the concept with the greatest weight (W_{C2C}) as
the major RIP. It referred that concept C\textsubscript{i} with a greater
weight (W_{C2C}) would be the prioritized option during the
establishment of RIP.

For example, when ICDS diagnosed that a learner has a
learning barrier with Concept C2, ICDS would firstly sug-
gest that the learner should first of all fully understand
Concept C1, and then Concept C5 (Chung et al., 2001).
Therefore, ICDS not only provided teachers with an effec-
tive evaluation of the learning performance of students, but
also diagnosed the learning barriers and the unclear part of
students, so as to further helped students breaking
through the learning barriers, and improve the learning
performance.

Fig. 8. Intelligent concept diagnostic system (ICDS).
5. Design of experiment and data analysis

It has been proved and recorded in many literatures that the instruction paths and learning performance of students in the e-instruction system can be a reference for teachers to evaluate the learning achievements of learners and diagnose their learning difficulties as these data are very useful and are the real evaluation data Chen & Lin, 2001. Therefore, the study applied ICDS to diagnose the learning barriers of learners. The complete procedures for designing the experiment are as shown in Fig. 9.

5.1. Pre-test

The targets of the study were the Grade 1 students of a senior high school. There were 245 students participating in the study. At the beginning of the school term a pre-test of the “VB program language” in LMS was made, producing the pre-test result and the pre-test portfolio. They were for the purposes of recording the test portfolio of testees and using the pre-test result as a reference of clustering. In order to increase the prediction and diagnostic functions of tests, the analysis on the discrimination index of test questions had to be stressed, as indicated in Table 7.

In the table of discrimination index of test questions in Table 7, the discrimination index of Q9 was lower than 0.2, implying to a poor test question that had to be eliminated. Here, the study found out nine effective test questions.

5.2. Cluster

In order to understand the difference of concept maps produced from the test portfolio of students at different standards, a pre-test was held at the beginning of the school term. All the testees were clustered according to the pretest result. As proposed by Kelley (1939), under normal distribution, the optimal ratio is 27% for the high- and low-score clusters respectively. Therefore, the study divided the testees into three clusters according to the pre-test result, as shown in Fig. 10.

<table>
<thead>
<tr>
<th>Learner 1</th>
<th>Learner 2</th>
<th>...</th>
<th>Learner n</th>
</tr>
</thead>
</table>

![Fig. 9. Flow chart of data analysis of the study.](image)

![Fig. 10. Ratios of cluster under normal distribution.](image)

Table 7

<table>
<thead>
<tr>
<th>Discrimination</th>
<th>Question</th>
</tr>
</thead>
</table>
| PH             | Q1 0.93  
|                | Q2 0.93  
|                | Q3 0.93  
|                | Q4 0.93  
|                | Q5 0.71  
|                | Q6 0.86  
|                | Q7 0.64  
|                | Q8 0.14  
|                | Q9 0.79  
| PL             | Q1 0.71  
|                | Q2 0.57  
|                | Q3 0.36  
|                | Q4 0.21  
|                | Q5 0.21  
|                | Q6 0.14  
|                | Q7 0.21  
|                | Q8 0  
|                | Q9 0.07  
| Discrimination index | Q1 0.21  
|                        | Q2 0.36  
|                        | Q3 0.57  
|                        | Q4 0.71  
|                        | Q5 0.71  
|                        | Q6 0.57  
|                        | Q7 0.64  
|                        | Q8 0.43  
|                        | Q9 0.14  
|                        | Q10 0.79  |
5.3. Import the test portfolio

After the testees did the pre-test, the test portfolio was automatically and simultaneously imported to the database, offering the source of data for data mining.

5.4. Data mining

The study proposes combining the algorithm of Apriori for Concept Map with the test portfolio of testees to actually develop the ICDS of an automatically constructed concept map of learning rapidly. By using the immediate diagnosis of the learning barriers and misconception of learners, and through the analysis of the concepts and weights in the concept map, the study established the RIP.

5.5. Sub-cluster

In order to prove whether RIP could enhance the learners’ learning performance of each cluster, the study has to sub-cluster the learners of each cluster into “experimental group” and “control group”, as shown in Table 8. The way of sub-clustering is as follows.

By the way of random selection, the students were sub-clustered into two groups, “experimental group” and “control group”.

1. Experimental group: The RIP in concept map served as the learning guide.
2. Control group: Traditional non-guided network learning way was adopted.

Table 8
List of the number of students in the experimental group and control group of each cluster

<table>
<thead>
<tr>
<th>Group</th>
<th>Cluster 1 (high-score cluster)</th>
<th>Cluster 2 (medium-score cluster)</th>
<th>Cluster 3 (low-score cluster)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental</td>
<td>33</td>
<td>56</td>
<td>33</td>
</tr>
<tr>
<td>Control</td>
<td>33</td>
<td>51</td>
<td>33</td>
</tr>
<tr>
<td>Number of students</td>
<td>66</td>
<td>113</td>
<td>66</td>
</tr>
</tbody>
</table>

5.6. Post-test

It was a reference for evaluation of learning performance.

5.7. T-test

In order to test whether there was significant difference between the experimental group and the control group of each cluster after importing the RIP, t-test was adapted for data analysis. Assume that the significant standard is \( \alpha \). If \( P \)-value < \( \alpha \), then H0 is rejected, implying to a significant difference between the mean of experimental group and the mean of control group. If \( P \)-value \( \geq \) \( \alpha \), then H0 is not rejected, implying that there is no significant difference between the mean of experimental group and the mean of control group. The t-test results of the study were shown in Table 9.

5.8. Analysis

It was found that significant difference existed in the medium-score cluster and the low-score cluster (the \( P \)-values of both are less than .05) after going through the RIP, but there was no significant difference found in the high-score cluster. The study found that there was a great difference among the concept maps of learning produced by the students of different clusters. When the students belong to “high-score cluster”, no concept map was produced. Contrarily, when the students belong to “low-score cluster”, the concept maps produced are meaningless. Therefore, the study found that the test portfolio of the learners belonging to “medium-score cluster” were able to better automatically construct the concept map of learning, which would serve as the RIP for guiding the learners.

6. Conclusions and discussion

A sound ICDS not only can guide learners to achieve the instruction goals, but also can deeply analyze the learning barriers of students and provide more valuable suggestions for students. Therefore, the study mainly used the algorithm of Apriori for Concept Map to actually develop the ICDS of
an automatically constructed concept map of learning, so as to diagnose the learning barriers of learners and adaptively provided RIP to guide the learners, and ultimately enhanced the learning performance of students. In conclusion, three major contributions were induced by the study.

6.1. Discrimination index of test questions

The study found that the discrimination index of test questions was one of the major factors affecting the construction of concept map of learning. If the test questions are too difficult or too simple, they somehow cannot really test the standard of students, and the produced relationship chart of concepts would be too complicated or too simple, making it unavailable to reflect the real learning situation.

6.2. Attribute of test questions

The study discovered that the test questions of non-memorizing type had a close relationship between concept and concept, so they could more easily produce reasonable and useful concept map. The representative examples were the test questions of science subjects, such as program design, mathematics, etc. But the test questions of memorizing type had a weaker relationship between concepts. The representative examples were the test questions of the humanities subjects, such as history, geography, etc. After the test questions of memorizing type had undergone the automatic algorithm and acquired the relationship between concepts, the acquired relationship between concepts was found inconsistent with the actual relationship in real instruction.

6.3. Learning performance

The study also found that among the various clusters of learners, except the learners of “high-score cluster”, the learners of the “experimental groups” in medium-score cluster and low-score cluster had significant progress after taking the RIP as their learning guide. Although it is known from the statistical analysis of the results of medium-score cluster and low-score cluster that the “experimental group” had more significant difference than the “control group”, the P-value of “low-score cluster” was 0.003, which was less than the P-value 0.03 of “medium-score cluster”. It implies that the learners of “low-score cluster” are more in need of the learning guide of “instruction path” than the “medium-score cluster”. Therefore, when most of the learners encounter difficulties in the process of initiative construction of knowledge, the learning performance guided by the adaptive “instruction path” is significantly different from the learning performance without being guided by the adaptive “instruction path”.

References

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