An Evolutionary Computation Approach for Automatically Constructing Concept Map to Evaluate the Quality of Test Question Establishment

Ta-Cheng Chen[1], Peng-Sheng You[2], Yi-Chih Hsieh[3], and Chih-Chung Lo[1,4]

[1]Department of Information Management, National Formosa University, Taiwan

[2] Graduate Institute of Marketing and Logistics/Transportation, National Chiayi University, Taiwan.

[3]Department of Industrial Management, National Formosa University, Taiwan

[4] Mailiao Elementary School, Taiwan

Abstract

Concept map is useful for evaluating students learning and helping to illuminate where learning has occurred and where invalid or the wrong concepts are held by the students. A good concept map is very important to describe students' learning portfolio. However, most learning concept maps have to be formed through the suggestions of experts or scholars in their related fields. The concept map can also be built through the test analysis process and the relationship between learners and concepts. But the issues of how to find the optimal association rule for building the concept map are not considered in the past studies. In this study, a novel data mining based approach has been proposed for constructing a most appropriate concept map in the study. Moreover, the logic of contraposition is applied in the proposed approach to optimize the fuzzy membership function so as to dig out the optimal fuzzy association rules. Based on the proposed approach, it is to investigate that whether the test question banks provided by the elementary school textbook publishers are appropriate or not. In other words, it is to know whether the test question establishment based on the test bank is suitable to evaluate students' achievement or not. According to the proposed approach, it is able to find out the important association rules to form the learning concept map. The test questions can be then evaluated to see whether the confidence, difficulty and discrimination are appropriately considered in the test questions. The experimental result demonstrates that the well organized test problems are with better concept map similarity to the ideal concept map.

Key words: concept map, fuzzy association rule, test question establishment

1. Introduction

This study is to investigate the issue of reconstructing concept map accurately which help students integrate new concepts into their existing set of knowledge. Concept map is useful for evaluating students learning and helping to illuminate where learning has occurred and where invalid or the wrong concepts are held by the students. Concept mapping was developed by Novak for assessing student understanding and learning of scientific topics (Novak, 1998) (Novak and Gowin, 1984). Concept maps are directed graphs in which labeled nodes represent concepts and labeled arcs represent relations between each pair of concepts (Cline *et al.*, 2010). The learning concepts should be ordered in a proper sequence. This kind of learning sequence is called as the epistemological order (Novak, 1981), see Figure 1. Through a series of combination of the epistemological order, a topological graph is then acquired, and is called "conceptual graph" (Plotnick, 1997).

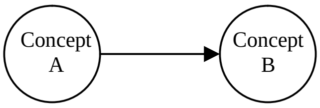

Figure 1. Epistemological order of concept map

Through the test analysis process and the relationship between learners and concepts, the concept can be then built. Concept can provide the remedial-instruction path for students and teachers to promote the learners' learning, and then help them to overcome the obstacles and difficulties during their learning. So, how to build the most appropriate concept map becomes the significant issue for doing researches. A good concept map is very important to describe students' learning portfolio. Based on the literature, the concept maps were generally constructed by the teachers and scholars. However, they are gradually constructed by using various algorithms and are developed automatically (Tseng et al., 2007), (Bai and Chen, 2007; 2008) (Chen and Bai, 2010) (Chen and Sue, 2013). For example: Chen et al. (2007) presented a remedy learning approach based on the discovered common learning misconceptions to promote the learning performance. Lee et al. (2009) presented a method to automatically construct concepts maps for conceptual diagnosis. But it is with some shortages that it constructs unnecessary concepts-relationships in concept map. The construction of concept maps based on the fuzzy rules has been proposed for adapting learning systems (Chen and Bai, 2010) and their approach can overcome the drawbacks of Lee et al.'s method (2009). For overcoming the drawbacks of Chen and Bai's method (2010) and Lee et al's method (2009), an improved approach has been proposed by Chen and Bai (2013). It provides us with a useful way to construct concept maps for adaptive learning systems based on data mining techniques.

However, the issues of how to find the optimal association rules for building the concept map are seldom considered in the past studies. So, the inappropriate linkages between concepts are always generated improperly while the parameters in their approaches were set in many values including the definition of membership functions, and the setting of threshold minimum support, confidence level. For overcoming the above difficulties, a bi-directional approximate reasoning evolutionary approach based on the logic of contraposition has been proposed in this study.

Moreover, another aim of this study is using the proposed approach to evaluate the quality of quality of test question establishment from the elementary school textbook publisher. Based on the proposed approach, it is to investigate that whether the test question banks provided by the elementary school textbook publishers are appropriate or not. In other words, it is to know whether the test question establishment based on the test bank is suitable to evaluate students' achievement or not. According to the proposed approach, it is able to find out the important relation rules to form the learning concept map precisely.

2. Research approach

The procedure of constructing the learning concept map is described as shown in Figure 2. The test questions in a subject of specified topic domain should be designed by qualified teachers. All the learning concepts should be included in the questions of the test. While the tests are given to the students, all the testing results are then recorded an analyzed. The testing results are as the input of the proposed approach to generate the association rules so that the concept association matrix can be determined. Finally, the concept map is able to be constructed based on the association matrix.

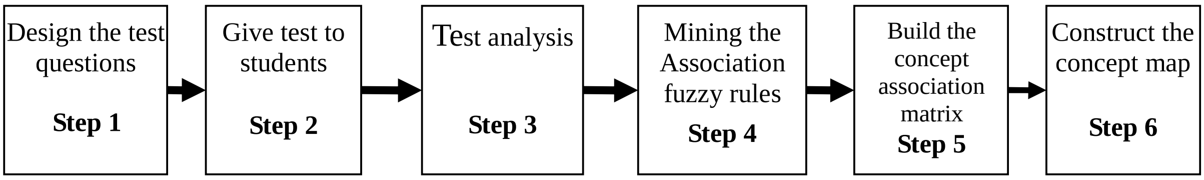

Figure 2. The basic steps to construct the concept map

The fuzzy theory has been applied in this study in which the membership functions are to be optimized by a bi-directional approximate reasoning evolutionary approach based on the logic of contraposition. Through the proposed approach, the optimal membership functions based on the test results are obtained. The confidence values of both forward inference reasoning and backward inference reasoning will become similar. The contraposition theory is supposed that the bi-directional inference including the forward inference "*If X is A then Y is B*" and the backward inference "*If Y is not B then X is not A*". Both the forward inference and backward inference should be the same, so that it is supposed that the confidence values of the two should be very close to each other or even become equal. According to the above assumption, the membership function with the corresponding shapes and parameters are then adjusted by using genetic algorithm so as to minimize the difference of confidence values between the forward inference and backward inference. So that the evaluation function can be defined as follows:

$$Evaluation = \sum_{l=1}^{L} \left| CF_l - CB_l \right| \quad (1)$$

where, L represents the number of rules, l=1, 2., …, L. CF_l is the confidence value of the l^{th} forward fuzzy rule, and CB_l is the confidence value of the l^{th} backward fuzzy rule. The value of Evaluation is to be minimized. It means that the difference between the CF_l and CB_l should be the smaller the better. In this study, the genetic algorithm (Holland, 1975) has been applied as the optimization mechanism to minimize the above function in equation (1). The optimization procedure has been described in Figure 3.

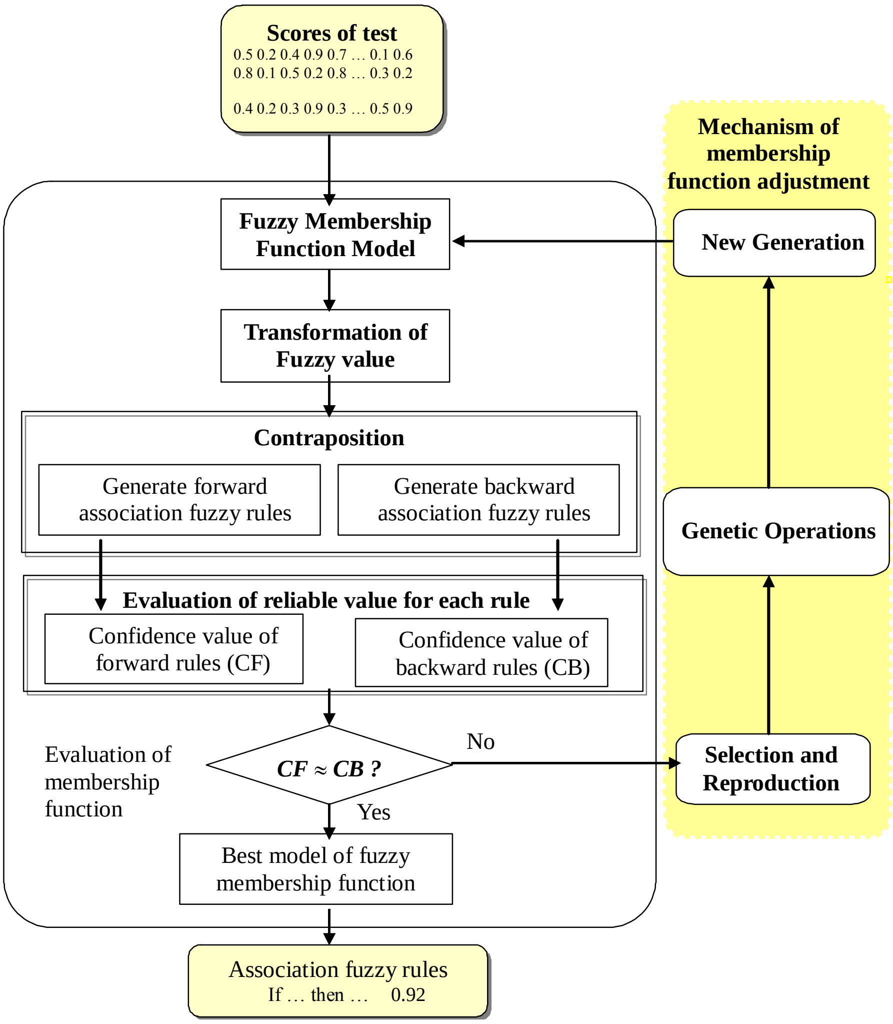

Figure 3. The bi-directional approximate reasoning evolutionary approach based on the logic of contraposition

All the fuzzy membership functions can be represent by the specified solution representation as shown in Figure 4. The solution representation is represented by a 0-1 binary stream. Each membership function can be defined by different shape of function with the corresponding parameters. The 0-1 sub-stream of function shape is decoded as a integer number which represents the shape of function and every parameter is decoded as the real value.

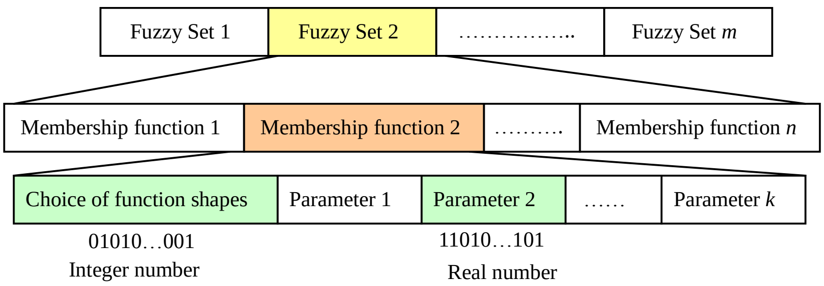

Figure 4. The solution representation of the proposed approach

For better understanding to the proposed approach, a simple example is illustrated in Table 1. It is assumed that there are four kinds of questions Q1~A4 in an examination paper. The four questions contain four concepts A~D respectively. In the table, five students took the test and the scores they get for each question. It is supposed that the best Membership function is obtained as Figure 5 and then the fuzzy relative grade for each student's testing results can be represented as in Table 2.

Table1. Imitating the answering questions condition of students.

	Test questions			
Students no.	Q1	Q2	Q3	Q4
S_1	100	100	60	90
S_2	90	60	55	65
S_3	80	85	90	85
S_4	50	30	30	70
S_5	95	80	70	100

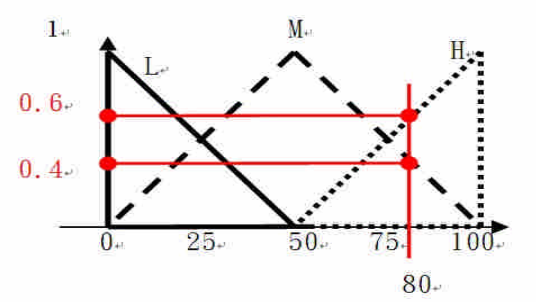

Figure 5. Assumption of ideal membership function

For example, if the student (S_3) got 80 points of score in question Q1 of the test, through the membership function (see Figure 5) and then the fuzzification values for three levels (L, M and H) is (0.0, 0.4, 0.6). By keeping doing so, we get Table 2. Then we can find out large 2-itemsets, after calculating formula (1) and (2) we can get the confidence level of Fuzzification question, for example, Table 3 and Table 4. If the threshold of confidence level is set as 0.6, the concept map is constructed as shown in Figure 6.

Table 2 Fuzzy relative grade table for the students' testing records.

Student No.	Q1			Q2			Q3			Q4		
	L	M	H	L	M	H	L	M	H	L	M	H
S_1	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.8	0.2	0.0	0.2	0.8
S_2	0.0	0.2	0.8	0.0	0.8	0.2	0.0	0.9	0.1	0.0	0.7	0.3
S_3	0.0	0.4	0.6	0.0	0.3	0.7	0.0	0.2	0.8	0.0	0.3	0.7
S_4	0.0	1.0	0.0	0.4	0.6	0.0	0.4	0.6	0.0	0.0	0.6	0.4
S_5	0.0	0.1	0.9	0.0	0.4	0.6	0.0	0.6	0.4	0.0	0.0	1.0
Total	0.0	1.7	3.3	0.4	2.1	1.6	0.4	3.1	1.5	0.0	1.8	3.2

$$Support(Qi \cup Qj) = \sum_{1}^{n} Min(Qi, Qj) \quad (2)$$

where, n is the numbers of student; i & j are the question number and $i \neq j$. While the support values are calculated, the confidence values are then obtained by the equation (3).

$$Confidence(Qi \rightarrow Qj) = \frac{Support\ (Qi \cup Qj)}{Support\ (Qi)} \quad (3)$$

Table 3. Large 2-itemsets and support

Min(Q1(H),Q2(M))	Min(Q1(H),Q3(M))	Min(Q1(H),Q4(H))	Min(Q2(M),Q3(M))	Min(Q2(M),Q4(H))	Min(Q3(M),Q4(H))
0.0	0.8	0.8	0.0	0.0	0.8
0.8	0.8	0.3	0.8	0.3	0.3
0.3	0.2	0.6	0.2	0.3	0.2
0.0	0.0	0.0	0.6	0,4	0.4
0.4	0.6	0.9	0.4	0.4	0.6
1.5	2.4	2.6	2.0	1.4	2.3

Table 4 Confidence level of fuzzification question (CL⩾0.6)

Rule	Confidence level
If Q1(H) Then Q2(M)	0.455
If Q1(H) Then Q3(M)	**0.727**
If Q1(H) Then Q4(H)	**0.788**
If Q2(M) Then Q3(M)	**0.952**
If Q2(M) Then Q4(H)	**0.667**
If Q3(M) Then Q4(H)	**0.742**

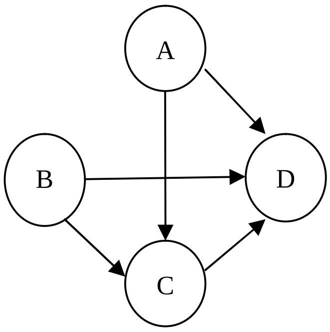

Figure 6. Concept map of the simple example

3. Experimental Results and Discussion

In this research, a fourth grade class of elementary school in Yunlin County, Taiwan was given the mathematic tests. There are 64 students in the class and two tests were given in the same field. In domain of the field, seven major concepts should be learned clearly by students. On test questions are well designed by a group of qualified teachers and these test questions have been checked to be with qualifications. This test is called as “Test A”. The other test problems are extracted from a test bank from a reference book of a publisher. This is called “Test B Two tests are given to the same class and then the results of the two tests are then obtained respectively. Based on the two test results, the respective concepts are then generated, analyzed and compared. According to the ideal concept map for the above test domain generated by experts, the two test questions are evaluated to understand which test questions establishment is more ideally.

The learning concepts of the subject are illustrated in Table 5 and the corresponding learning concept map is defined by a group of experts and described as shown in Figure 7.

Table 5. The learning concepts in the test subject

Concept code	Conceptual meaning
C1	divide equally
C2	Fractional notation
C3	Unit quantity
C4	Equivalent
C5	Equivalent Fractional
C6	The same denominator decomposition synthesis
C7	Improper、mixed decomposition synthesis

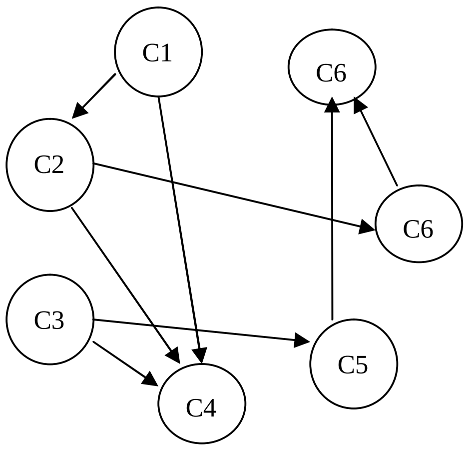

Figure 7. Concept map suggested by experts

After give the tests to the same 64 students, that grades becomes the way to evaluate students' learning achievement. However, is it a pragmatic method to judge the students' learning by using any kind of testing questions? Therefore, we prove the above method that can establish objective and correct concept map by this research. At the same time, testified a test question which has confirmed by reliability and validity, through this test, we can know the real learning condition for students, by means of this study, we can emphasize the importance of formulation of examination questions.

By giving students the two tests, we can get the grades form students, then follow the proposed approach, if we set threshold value as 0.55 for the confidence Level, we can get the concept maps from question Test A and Test B as shown in Figure 3 and Figure 4 respectively.

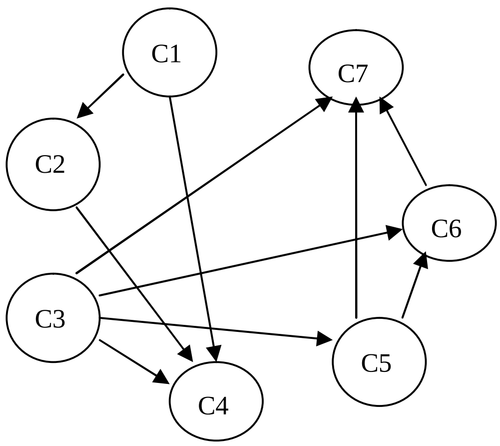

Figure 3. The concept map for Test A.

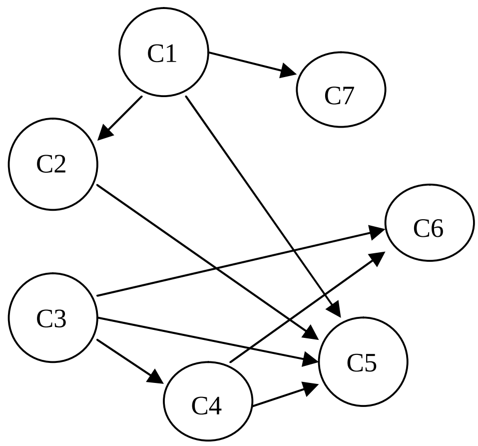

Figure 4. The concept map for Test B.

Through the Closeness analyze Table 6 and Table 7, we can compare the similarity with concept maps suggested by experts and those obtained by giving tests including Test A and Test B. The similarity value of Test A is (19/4)/7=0.68, and that of Test B is (47/30)/7=0.22. Obviously, the quality of test questions in Test A is much better than those of in Test B. That means the well designed and organized test questions are very important to show students' learning condition. Surely, it indicates that the proposed approach can evaluate how good the test questions are.

Table 6 The concept map for Test A and the corresponding Node ratio.

	Neighboring nodes		Intersection		United set		
node	Expert	A-test	set	number	set	number	ratio
C1	{C2, C4}	{C2, C4}	{C2, C4}	2	{C2, C4}	2	1
C2	{C1, C4, C6}	{C1, C4}	{C1, C4}	2	{C1, C4, C6}	3	2/3
C3	{C4, C5}	{C4, C5, C6, C7}	{C4, C5}	2	{C4, C5, C6, C7}	4	2/4
C4	{C1, C2, C3}	{C1, C2, C3}	{C1, C2, C3}	3	{C1, C2, C3}	3	1
C5	{C3, C7}	{C3, C6, C7}	{C3, C7}	2	{C3, C6, C7}	3	2/3
C6	{C2, C7}	{C3, C5, C7}	{C7}	1	{C2, C3, C5, C7}	4	1/4
C7	{C5, C6}	{C3, C5, C6}	{C5, C6}	2	{C3, C5, C6}	3	2/3
Total							19/4

Table 7 The concept map for Test B and the corresponding Node ratio

	Neighboring nodes		Intersection		United set		
node	Expert	B-test	set	number	set	number	ratio
C1	{C2, C4}	{C2, C5, C7}	{C2}	1	{C2, C4, C5, C7}	4	1/4
C2	{C1, C4, C6}	{C1, C5}	{C1}	1	{C1, C4, C5, C6}	4	1/4
C3	{C4, C5}	{C4, C5, C6}	{C4,C5}	2	{C4, C5, C6}	3	2/3
C4	{C1, C2, C3}	{C3, C5, C6}	{C3}	1	{C1, C2, C3, C5, C6}	5	1/5
C5	{C3, C7}	{C1, C2, C3, C4}	{C3}	1	{C1, C2, C3, C4, C7}	5	1/5
C6	{C2, C7}	{C3, C4}	{ }	0	{C2, C3, C4, C7}	4	0
C7	{C5, C6}	{C1}	{ }	0	{C1, C5, C6}	3	0
Total							47/30

4. Conclusions

A good concept map is very important to describe students' learning portfolio. In this study, a novel data mining based approach has been proposed for constructing a most appropriate concept map in the study. Moreover, the logic of contraposition is applied in the proposed approach to optimize the fuzzy membership function so as to dig out the optimal fuzzy association rules for constructing the concept map for reflecting students' learning in a specified subject. Based on the proposed approach, the test questions can be then evaluated to see whether the confidence, difficulty and discrimination are appropriately considered in the test questions. The experimental result demonstrates that the well organized test problems are with better concept map similarity to the ideal concept map.

Acknowledgement

This work was supported by the National Science Council, Taiwan, under Grant NSC 99-2628-E-150-043

References

1. Bai, S.M., and Chen S.M. (2007), "Evaluating students' learning achievement using fuzzy membership functions and fuzzy rules," *Expert Systems with Applications*, 34, pp. 339-410.
2. Bai, S.M, and Chen S.M. (2008), "Automatically constructing concept maps based on fuzzy rules for adapting learning systems," *Expert Systems with Applications*, 35, pp. 41-49.
3. Chen, S.M., & Bai, S.M. (2010), "Using data mining techniques to automatically construct concept maps for adaptive learning systems," *Expert Systems with Applications*, 37(6), pp. 4496-4503.
4. Chen, S.M., Sue P.J. (2013), "Constructing concept maps for adaptive learning systems based on data mining techniques," *Expert Systems with Applications*, 40, pp. 2746-2755.
5. Cline, B.E., Brewster C.C., and Fell R.D. (2010), "A rule-based system for automatically evaluating student concept maps," *Expert Systems with Applications*, 37, pp. 2282-2291.
6. Holland, J.H. (1975), "Adaptation in natural and artificial system," University of Michigan Press, Ann Arbor, MI; reprinted by MIT Press, Cambridge, MA, 1992.
7. Lee, C. H., Lee, G. G., and Leu, Y. (2009), "Application of automatically constructed concept map of learning to conceptual diagnosis of e-learning," *Expert Systems with Applications*, 36(2), pp. 1675-1684.
8. Novak, J.D. (1981), "Applying learning psychology and philosophy of science to biology teaching," *The American Biology Teacher*, 43, pp. 12-20.
9. Novak, J.D. (1998), "Learning, creating, and using knowledge: Concept maps as facilitative tools in schools and corporations," Mahweh, NJ; Lawrence Erlbaum Associates.
10. Novak, J.D., and Gowin, D.B. (1984), "Learning how to learn," Cambridge, England: Cambridge University Press.
11. Plotnick, E. (1997), "Concept mapping: a graphical system for understanding the relationship between concepts," I*nformation and Technology*, ED407938, pp. 122-137.
12. Tseng, S.S., Sue, P.C., Su, J.M., Weng, J.F. and Tsai, W.N. (2007), "A new approach for constructing the concept map," *Computer and Education*, 49, pp. 691-707.