Combination of Bidirectional Conceptual Map and Genetic Algorithm for E-Learning Evaluation System

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Summary

This paper mainly proposed an E-learning evaluation system to produce effective test sheets with adaptive difficulty degree and bidirectional concept. Our proposed method utilized the characteristics of optimal genetic algorithm based on a test-sheet generation model. The learner proceeded online measurement by the adoption of a measure model. Results of the measurement will be generated throughout the process of the automation analysis, feedback and recommendation. Then, the results will be feedbacked to the system, tutors and the students. For the students, the system will diagnose and lead the students to appropriate learning concept and progress. For the system, feedback model will adjust the adaptive difficulty degree of learning. For the tutors, the system will guide the tutors in the adjustment of appropriate teaching concept and difficulty degree. The simulation results showed that the proposed method was able produce the optimal test sheet that fit the learning target which helps the learners to penetrate the learning disabilities and increase the learning effectiveness.

Keywords: E-learning 、 bidirectional concept 、 genetic algorithm

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1. Introduction

In recent years, the development of internet in teaching and learning fields has penetrated the time and space limitation no matter in teaching or learning environment. Many research data showed that the applications of internet in teaching and learning lead to the development of Computer Adaptive Testing (CAT), distance learning and E-learning system [1-3]. Moreover, paper tests have transferred to online tests gradually. Therefore, the learners can learn and self-evaluate through internet without time and space limitation.

Ausubel (1968) proposed a learning theory which the prior knowledge of students should combine with new learning knowledge to form the meaningful proposition in order to generate a meaningful learning process. Novak and Gowin (1984) proposed to draw or characterize the knowledge with concept mapping [5] as an assisted tool in teaching or learning. Therefore, concept mapping was used to be the way to diagnosis the learning results of the learner in educational world. Henceforth many researchers use concept mapping as a guide in assisted learning and course guide [6-9].

The genetic algorithm is proposed by Holland in 1975 [4]. The main spirit in genetic algorithm was imitated from the rule of natural selection with the phrase "survival of the fittest". We can obtain predominance descendant (here refers to optimal solution) with the help of the evolution mechanism like reproduction, crossover and mutation. Recently, genetic algorithm is applied to all kinds of problems for optimal search. Moreover, genetic algorithm is also applied to the strategy of test items selection by some scholars as it is well suitable in solving complicated and large area problems [13-16]. Therefore, for the past five years, there are many adaptive learning and testing systems applied to concept mapping [6, 8] or genetic algorithm [15-17] for online tests and assisted instruction.

This paper mainly proposed an E-learning evaluation system with the characteristics of bidirectional concept and genetic algorithm. We generated effective test-sheet that fulfills bidirectional concept and adaptive difficulty degree. We tend to provide an effective learning and testing environment for learners by establishing an E-learning evaluation system suitable for lecturer and learner.

This paper is organized as follows. In section 2, we analyzed the proposed a system architecture, including a bidirectional concept and a difficulty degree analysis model, a test-sheet generation model, measurement model, and an automation analysis, feedback and recommend model. Section

3 presented the experimental results and analysis, followed with conclusions and future work.

2. System Architecture

This paper mainly proposed an E-learning evaluation system as shown in Figure 1. The system architecture consists of four models, which are 1) Bidirectional Concept and Difficulty Degree Analysis Model, 2) Test-Sheet Generation Model, 3) Measure Model and 4) Automation Analysis, Feedback and Recommend Model.
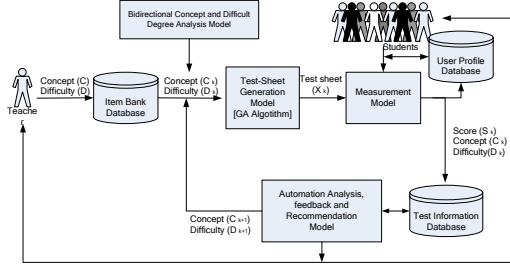

Fig. 1.　　System Architecture

The four models can be divided into front end part and back end part. In front-end part, the system will record the learning progress and learning level of the learner in order to suggest an adaptive learning level and test-sheet interface for the learner in his/her next lesson.

For back end part, we analyzed the concept degree and difficulty degree of each chapter for the current courses. Then, we generated an adaptive test sheet according to the learner's ability. Besides, the systems will feedback the learning suggestion to the learner and adjust the test sheet according to the results of evaluation.

2.1 Bidirectional Concept and Difficulty Analysis Model

In 1969, Collin and Quilian proposed the human organized knowledge in structural and stored the characteristic of different concepts in hierarchical structure. Researchers analyzed the relationship within concepts in order to depict the hierarchical relationship within concepts. In concept hierarchy, the weight of concept is accumulated with the concepts of upper and lower level, or even adjacent concepts. Hence, our research aimed to apply and improved related issues mentioned above. We proposed bidirectional concept as the relationship degree within test items and concepts to produce adaptive test items for test sheets. The definition of objective concept and difficulty vector (OCDV) are also been defined as below:

$$OCDV = [C_1,...,C_i,...,C_n, D]$$

where C_i is the concept degree of objective i, D is the difficulty degree of a target, e.g., $OCDV$

=[C1,C2,C3,C4,C5,C6,D]=[0.2, 0.4, 0.3, 0.1, 0.1, 0.6, 0.5]。

The definition of Bidirectional Concept Vector (BCV) is defined as below:

$$BCV(\underline{C},OCDV) = \left[EC(C_i,OCDV)\right]+\left[\sum_{C_K \in child(C_i)}\eta_{ik}EC(C_K,OCDV)\right]$$
$$+\left[\sum_{C_K \in parent(C_i)}\eta_{ik}EC(C_K,OCDV)\right]$$

EC: The Qjth concept set in database, Qj refers to the jth test item. $EC \in [0,1]$

$$\eta_{ik} = \frac{1}{2(level(C_i)-(level(C_k))^2},level(C_i) \neq level(C_k)$$

$$\begin{cases} chile(C_i): \text{the set of child concept} \\ parent(C_i): \text{the set of concept parent} \\ level(C_i): \text{the concept level of } C_i \end{cases}$$

where EC(C_i, OCDV) refers to the concept quantity of objective concept and difficulty vector; η is the decaying rate that accumulated by the selected concepts. However, the concepts are accumulated in bidirectional (concepts of upper and lower level). In the accumulated process, the quantity of accumulation is inversely proportional to the square of distance.

The concept degree and difficulty degree of the test items in the database are set by the lecturer referencing to other experts. After analyzed the progress of current courses, the concept degree and difficulty degree of the test items are set, as well as objective concept and difficulty vector. Meanwhile, we will find out the relationship between BCV and difficulty degree from bidirectional concept and difficulty degree analysis model.

The relationship between the test items and concepts is shown in Table 1. Test items include concept degree and difficulty relationship that forms a concept of test item and difficulty set.

$Q_j = [C_1,....,C_i,....,C_n, D]$, Q_j refers to the jth test item, C refers to concept degree of the ith test item, D refers to difficulty degree of the ith test item.

Table 1: The relationship between test item, concept degree and

difficulty degree

test\concept\difficulty	C1	C2	C3	C4	C5	C6	D
Q 1	0	0.9	0	0	0.1	0	0.5
Q 2	0.2	0.6	0	0	0.1	0.1	0.5
Q 3	0	0.3	0.5	0.1	0	0.1	0.48
Q 4	0.3	0.5	0.2	0	0	0	0.6
Q 5	0	0.3	0	0.5	0.2	0	0.4
Q 6	0	0.2	0	0	0.8	0	0.3
Q 7	0.2	0	0.5	0	0	0.3	0.7
Q 8	0.6	0.1	0	0	0.3	0	0.6
Q 9	0	0	0.1	0.2	0	0.7	0.35
Q 10	0.7	0	0	0	0	0.3	0.1

However, difficulty degree is defined from 0 to 1 with 5 grades, where D 1 : very easy [0-0.2], D 2 :easy [0.2-0.4], D 3 :moderate [0.4-0.6], D 4 : hard [0.6-0.8] and D 5 :very hard [0.8-1].

2.2 Test-Sheet Generation Model

In order to increase the speed of items selection from the huge test items database, we used real number to represent the test sheet. Each of the test sheets represents as a chromosome $TS_{(Qi)}$, where Q is the number of test item, and j is the number of test sheet. E.g., $TS_{(Q3)}$ ={29, 12, 3, 4, 5, 60, 25, 7, 8, 33, 99, 15, 16, 17, 88, 51, 73, 94, 41, 14}.

In [10-13, 19], binary code is used to represent the test sheet as 1 refers to the selected test item and 0 for the opposite way. However, extra time is needed with 0/1 coding method in determining the number of test items. Therefore, transferring 0 to 1 increased the time complicated and not a forthright way. In order to avoid the limitation of test items selection with the huge database, our research adopted the real number coding to reduce the complicated of searching and data matching. In the reproduction phase, we preserved half of the best chromosomes for reproduction. We ensured that the optimal test sheet will be reproduced forever as the best chromosome was preserved. The algorithm includes reproduction, crossover and mutation. The operation is shown as Figure 2.
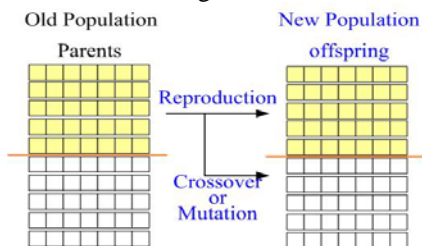

Fig. 2.   Reproduction, Crossover and Mutation operation

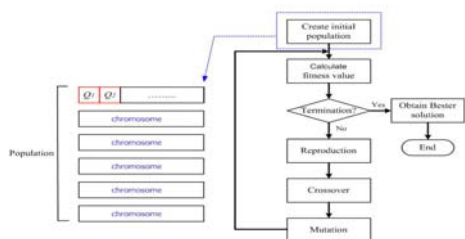The flowchart of genetic algorithm is shown as Figure 3.

Fig. 3.   Genetic Algorithm operation

The most important thing for the selection of optimal test sheet is the calculated of fitness value that closest to the information of objective concept and difficulty vector.
Ei refers to the sum of square for the differences of concept weight between *BCV* and the selected test sheet, Ei is defined as below:

$$E_I = \sum_{i=1}^{s}(o_i - O_i)^2$$

where o_i is the expected weight of concept C_i in *BCV*, s is the number of objective concept, O_i is the weight of selected test sheet for concept C_i.
Ed is the sum of square for the differences of objective difficulty between the selected test sheets, E$_d$ is defined as below:

$$E_d = \sum_{j=1}^{t}(d_j - D_j)^2$$

where d_j is the expected weight of difficulty degree for objective concept and difficulty vector, D_i is the difficulty weight of selected test sheet.

From both of the error functions that mentioned above, we get the overall error function E_{total}, $E_{total} = E_i + E_d$. Hence, the fitness function in genetic algorithm can be defined as $f = \dfrac{1}{E_{total}}$, when f increase, the error will decrease, but the fitness degree will increase.

The procedure of genetic algorithm for the test sheets is described as below:
1. Initialized setting:
    Population size
    Chromosome size, (one chromosome has several genes (test items))
    Pc=crossover rate
    Pm=Mutation rate
    The number of generation
2. Calculate the weight vector of the selected test sheet *(TS(Qi)), BCV* and the difficulty vector.
3. Evolution of test items.
    Step 1: Randomized a population (population size, chromosome), e.g. Rand (100, 200)
    Step 2: Calculate the fitness value of each chromosome, and arranged the fitness value in descending order.
    Step 3: Reproduction:
        Reproduce half of the chromosomes with higher fitness value to next generation and retain the best chromosome to next generation.
    Step 4: Crossover：
        We adopted single point crossover. Firstly, we randomized a value as the crossover node for crossover process. If the randomized value smaller than the crossover rate, crossover process will be proceeded. At the same time, we will check any duplicated number of the test item occur in a chromosome. If so, we will redo the crossover process and randomized a new number for the test item. Otherwise, no action will be taken.
    Step 5: Mutation：
        Firstly, we randomized a value as the mutation node. If the randomized value smaller than the mutation rate, then we will randomize a number for the test item to replace the mutation node. The number

of the test item is an integer (smaller than the total number of the test items).

Recalculated Step 2 to Step 5 until the evolution generation terminated. Finally, the optimal test sheet is generated.

2.3 Measure Model

The measure model provided a friendly interface for the users. It is a communication pipeline for the learner to process test evaluation, automation analysis, feedback and recommendation. The learner has to register personal message in the joining stage. Then, the learner has to take the pre-test in order to let the system get to know about his/her current abilities. After that, the system will suggest the learner places that have to be improved.

The measure model can be divided into two phases:

Pre-test：

The Pre-test is used by the lecturers after some times of lesson teaching, usually proceeded two months before mid term exam and final exam. The test items for the pre-test will be selected by the lecturers according to the teaching schedule and concepts that suitable for each chapter. The main objective of the pre-test is to let the lecturers understand the learning situation of the whole class. The learners can also realize self learning situation after taking the pre-test. The results of the pre-test will be stored in the database as the criteria for the test sheets in next examination.

Post-test：

The test items of post-test are selected according to the learning information of the learner from the pre-test. The concept and difficult of the test sheets is approximated to the pre-test in order to understanding the abilities enhancement of the

learners. After the first test, the learners can take the next examination in anytime to master their own abilities and enhance the weak sections. Besides, the tutor can also control the overall learning situation of the class by forces the students to take the tests from pre-test and post-test mechanism.

2.4 Automation Analysis, feedback and Recommend

The objective of the test is to understanding the learning situation of the learners and improves their abilities in learning. This model analyzed the learning ability of the learners from the pre-test in order to suggest the learner places that need to be improve. System will also adjust the concepts distribution and difficulty of the test sheets according to the situation of the learners. The main operations are stated as below:

1. To analyze the understanding of the learner for each chapter after test.
2. To feedback the message of the learners to the system, and decide adaptive concepts and difficulty for the test sheet in next test.
3. To feedback to the database and adjust the difficulty degree of the test items.
4. To automatically analyze the learning situation of the learner for each chapters.
5. To guide and suggest the learners to enhance their weak chapters.

>From Table 2, after evaluated 20 learners for the test, system divided those students into high scores and low scores according to their correctness of the test items. The system will examine concepts that are hard to the students and try to guide them to enhance those sections. Meanwhile, the system will adjust the difficulty degree of the test sheets according to the correctness of the answer sheets.

Table 2: The analysis of test sheet after test

	High Scores of learners														Low Scores of learners							After adjustment
Q	1	2	3	4	5	6	7	8	9	10	11	12	13	P/N	1	2	3	4	5	6	7	P/N	D
2	1	1	1	1	1	1	1	1	1	1	1	1	1	13/13=1.00	1	0	0	0	1	0	1	3/7=0.43	0.71
3	0	1	1	1	1	1	1	1	1	1	0	1	1	11/13=0.85	0	0	0	1	0	0	0	1/7=0.14	0.49
4	1	0	1	1	0	0	0	1	1	1	1	1	0	8/13=0.62	0	0	0	0	0	0	0	0/7=0.00	0.31
6	1	0	1	0	0	1	1	1	1	1	1	1	1	10/13=0.77	0	0	0	1	0	0	1	2/7=0.29	0.53
9	1	1	1	1	1	1	1	1	0	1	0	0	1	10/13=0.77	0	1	0	1	0	1	0	3/7=0.43	0.60
8	1	1	1	1	1	1	1	1	1	1	1	1	1	13/13=1.00	1	0	0	0	1	1	1	4/7=0.57	0.79
7	1	1	1	1	1	1	0	1	1	1	1	1	1	12/13=0.92	0	1	1	0	0	1	1	4/7=0.57	0.75
1	1	1	1	1	1	1	1	1	1	0	1	0	1	11/13=0.85	1	0	0	1	0	0	0	2/7=0.29	0.57

(Assume that there are 20 examines, and there are 8 test items in the test sheet.)

Feedback test items database, the adjustment of the difficulty degree of the test items is defined as below: System adjusts the difficulty degree of the test according to the results of all learners (including students with high scores and low scores) after test.

P_{iH} = The number of students with high scores that have the correct answer for the ith test item.

P_{iL} = The number of students with low scores that have the correct answer for the ith test item.

N_{iH} = Students with high scores

N_{iL} = Students with low scores

The number of students with high scores that have the correct answer for the ith test item, $P_{iH} = \dfrac{R_{iH}}{N_{iH}}$

The number of students with low scores that have the correct answer for the ith test item, $P_{iL} = \dfrac{R_{iL}}{N_{iL}}$

Difficulty degree of the test item, $(D) = \dfrac{P_i + P_H}{2}$

2. Experimental results and analysis

In the experiment, we analyzed the fitness value of the optimal test sheet and the ability enhancement of the students for post-test and pre-test. We also evaluated the satisfaction of the learners for the proposed system.

Evaluating the fitness value of the optimal test sheet

The test items were generated from 10 experiments with 1000 generations, 0.5 crossover rates, and 0.5 mutation rates. We obtained better optimal solution following with the incremental of chromosome size. However, the time for generating a better solution does not increase proportional to the increments of test items and population size. Therefore, it can be apply to huge database. The average fitness value was increased following with the incremental of test items. Hence, it is clearly shown that it is easier to obtain a better test sheet with more test items.

Table 3: Evaluating the fitness value of the optimal test sheet

chromosome size	Population size					
	50			100		
	Average	Optimum	average generation of evolution	Average	Optimum	average generation of evolution
20	0.8906	1.0058	25	0.9895	1.1943	33
50	0.9766	1.2210	37	1.1273	1.1701	46
100	0.9981	1.1891	43	1.1304	1.2102	53

Evaluating the ability enhancement of students for pre-test and post-test

The experiment of this system was tested on 45 students which taken Computer Concept course. We request those students to take both pre-test and post-test. The average score, the best score and the lowest score is shown in Table 4. From the experiment results, we can found that the learners' ability was greatly increased to 36% with the suggestions after pre-test.

Table 4: Evaluate the ability enhancement of the learner before and after pre-test and post-test

pre-test			post-test			average enhanced ability
optimum	worse	Average	optimum	worse	Average	
78	35	63	95	58	79	36%

Evaluating degree of satisfaction

In order to evaluate the satisfaction of the students about the test sheet which generated by the system, students have been asked to fill up the questionnaire with two questions. 1. Do you think the test sheet fit in with the progress of current lessons? 2. Do you think the test sheet is easy?

Table 5: Satisfaction of the test sheets which generated by the system during evaluating process

Perspective: Find out the satisfaction of the learners for the test sheets that produced by the system according to the progress of current lessons.
1. Do you think the test sheets fit in with the progress of current lessons?   Learners' perspective   0.825
Perspective: Find out the satisfaction of the learner for the difficulty level of the test sheets.
2. Do you think the test sheet is easy?   Learners' perspective   1.865

Table 6: Overall opinions of the system

Question	Answer: Learner				
	Very helpful	Helpful	Moderate	Unhelpful	Not Very helpful
(1) Do you think the system could enhance your ability?	20(9.5%)	92(43.8%)	88(41.9%)	10(4.8%)	0(0%)
(2) Do you think the learning guidance of the system could help you in your learning process?	25(11.9%)	91(43.3%)	83(39.5%)	11(5.2%)	0(0%)
	Very satisfactory	Satisfactory	Moderate	Un satisfactory	Not Very satisfactory
(3) Do you satisfy with the implementation of Pre-test and Post-test?	18(8.6%)	95(45.2%)	82(39%)	15(7.1%)	0(0%)
(4) Overall, do you satisfy with the design of the system?	3(1.4%)	105(50%)	89(42.4%)	13(6.2%)	0(0%)

The results of the questionnaire were collected by the system as shown in Table 5. The satisfaction of the learner for the test sheets that produced by the system according to current progress was 0.825, which is approximated to 1. This showed that most learners were agreed that the system is able to provide the suitable test sheets according to the progress of current lessons. By the way, we found that the satisfaction of the learners for the difficulty level of the test sheet was 1.865, which is approximated to 2 (moderate). This showed that the learners agreed that the difficulty degree of the test-sheets is moderate.

After all the lessons, we could evaluate the overall satisfaction of the learner from the questionnaire as shown in Table 6. It is clearly shown that the system gained positive reaction from the students as they felt the system is able to enhance their learning abilities.

3. Conclusions and Future Work

The proposed method combined the characteristics of bidirectional concept and genetic algorithm. We generated the effective test sheets which fulfill bidirectional concept and adaptive difficulty in order to develop an E-learning evaluation system. We hope that the lecturers could understand the learning situation of the students through the establishment of the E-learning evaluation system. In addition, the system can improve the ability of all the students as they knew their weak points in the lessons. In the future, we will combine the experiments with formative evaluation in order to understand the cognitive of the learners deeply. Hence, we can enhance student's ability by forming them individual learning habits. Our research mainly focuses on bidirectional concept and difficulty degree as the infected factors to generate the test sheet. However, the infected factors of item response theory including the discrimination, difficulty degree and guess degree of the test items. Hence, we hope that we could take consideration of the discrimination and guess degree in order to generate reliable test items.

References

[1] Fan, J. P., Tina, K. M., & Shue, L. Y. (1996). Development of knowledge-based computer-assisted instruction system. 1996 International Conference Software Engineering: Education and Practice, Dunedin, New Zealand.

[2] Johnson, W. B., Neste, L. O., & Duncan, P. C. (1989). An authoring environment for intelligent tutoring systems. IEEE International Conference on Systems, Man and Cybernetics, 1989, 761–765.

[3] Chen, C. M. (2005). Personalized e-learning system using item response theory, Computers & Education, 44, 237–255, Accepted 16 January 2004.

[4] Holland, J. H. (1975). Adaptation in natural and artificial systems. University of Michigan Press, Michigan.

[5] Novak, J. D., & Gowin, D. B. (1984). Concept mapping for meaningful learning. Cambridge: Cambridge University Press.

[6] Turns, J., Atman, C.J., & Adams, R. (2000) "Concept maps for engineering education: a cognitively motivated tool supporting varied assessment functions," Education, IEEE Transactions on, 43(2), May 2000, 164 –173

[7] Tseng, S. S. (2004), A New Approach for Constructing the Concept Map, Proceedings of the IEEE International Conference on Advanced Learning Technologies (ICALT'04)

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

[9] Hwang, G. J. (2003). A Test-Sheet-Generating Algorithm for Multiple Assessment Requirements, Ieee Transactions On Education, 46 (3), August, (329-337)

[10] Sun, k. T, & Cheng, C. F. (2003). A Study of Applying Advanced Genetic Algorithm to Select Test Items, the unpublished master's dissertation of Graduate Institute of Information and Computer Education of National Taiwan Normal University.

[11] Hwang, G. J., & Zen. S. H., (2003). On the Development of a Computer-Assisted Testing System with Genetic Test Sheet-Generating Approach, the unpublished master's dissertation of Information Management of National Chi Nan University.

[12] Chiang, M. L., & Chen, C. Y. (2003). A Study of Applying Greedy-Genetic Algorithm to Select Test Items, the unpublished master's dissertation of Information Management of National Chi Nan University.

[13] Sun, k. T., Lai, Y. H., & Day, B. C. (1999). A Study on the Test-sheet-generating Strategy Using Genetic Algorithm , National Computer Symposium (NCS' 99), 379-386.

[14] Goldberg, D.E. (1989). Genetic Algorithm in Search, Optimization, and Machine Learning, Addison-Wesley, Reading, Massachusetts.

[15] Grefenstette, J. J. (1986). Optimization of Control Parameter for Genetic Algorithms, IEEE Transactions on Intelligent Systems, 16(1), 122-128, Jan.

[16] Sun, K.T., & Fu, H.C. (1993). A Hybrid Neural Network Model for Solving Optimization Problems, IEEE Transactions on Computers, 42(2), 218-227.

[17] Sun, K. T. (1999). An Effective Item Selection Method by Using AI Approaches, in Proc. of Advances in Intelligent Computing & Multimedia Systems, 137-142, Baden-Baden, Germany, August 2-7.

[18] Collins, A. M., & Quillian, M. R. (1969). Retrieval Time from Semantic Memory, Journal of Verbal Learning and Verbal Behavior, 8.

[19] Heh J. S., & Chang, Y. W., (2003). An Item-Selection Strategy of Internet Testing Based on Knowledge Map, the unpublished master's dissertation of Department of Information & Computer Engineering of Chung Yuan Christian University

[20] Hwang, G. J. (2003). A Computer-Assisted Approach to Diagnosing Student Learning Problems in Science Courses, Journal Of Information Science And Engineering 19, 229-248.

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