Information-based Item Selection with Blocking Strategy based on a Bayesian network

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Abstract: - With the rapid development of computer technology information theory has been implemented for searching optimal adaptive item sequence in computerised adaptive test systems based on Bayesian network. Information theory such as entropy between dichotomous concepts and test items generalise common intuitions about item comparison for heuristic methodology. However, the executive time and the storage space are still open problems in constructing and storing decision item trees. The blocking strategy is proposed for overcoming those problems. Experimental results show that the blocking strategy could overcome both the executive time and storage space problems.

Key-Words: Bayesian network, Information, Entropy, Computerised adaptive testing, Blocking strategy.

1 Introduction

Traditional paper and pencil tests usually yield a total score representing a student's overall performance. We can distinguish differences in competency levels among students by ranking their scores. However, the ranking cannot help teachers identify students' bottlenecks in learning and correct their misconceptions. For a high-tech generation, applying artificial intelligence technology in testing procedures has become part of each subject. By using the characteristics of computers, a computerised adaptive test (CAT) system can easily address the weaknesses of traditional paper and pencil tests and help teachers determine whether students are learning well [1-3].

Ideally, students always respond correctly to items for concepts that they already understand and can apply and always respond incorrectly otherwise. In such an ideal world, there would be few if any difficulties in diagnosing students' deficiencies by their item-response patterns [4]. In the real world, students' item-response patterns are 'fuzzy' [5] and 'uncertain' [6] because students may slip and guess.

For these reasons, the research community has admitted that uncertainty is a common challenge in many educational applications and has proposed probability-based methods to address it [4]. The strengths of a Bayesian network, a probabilistic graphical model, have been found to enable efficient uncertainty reasoning with hundreds of variables [7]. Furthermore, they help humans understand the modelled domain better [8-9]. Thus, many researchers have built models for diagnosing students' skills and bugs by analysing their performances based on a Bayesian network in a CAT system [6], [8-12].

In a CAT based on a Bayesian network, possible assessment applications include, but are not limited to, modelling diagnosis and also adaptive testing [9]. In a CAT, adaptive item selection strategy plays an important role. In such systems, adaptive testing means that questions are selected according to the examinees' performance, with the goal of diagnosing the student's state of knowledge as quickly as possible without loss of accuracy [13]. Adaptive testing offers the chance to achieve assessment goals with shorter tests [14]. In other words, a good item selection strategy for adaptive testing should attempt to select items from the item bank so that we can assess students both effectively and efficiently [4]. However, adaptive item selection is not easy, especially in real time. Given an item bank and a

Bayesian network with a trained structure and parameters, test administrators must select the proper subset of items for adaptive testing.

So far, the research community has proposed heuristic methods to cope with the problems of adaptive testing based on a Bayesian network. Vomlel applied information theory [8], specifically, the Shannon entropy equation,

$$Entropy(X) = \sum_{X=x} - P(X).\log(P(X)) \qquad (1)$$

This equation can be used to create a heuristic function for constructing a decision item tree (Figure 1) for adaptive item selection in a CAT system based on a Bayesian network. It's such as " maximum entropy method " [15]. However, this framework requires much executive time to construct the decision item tree and much storage space to store decision item trees for adaptive item selection in real time.

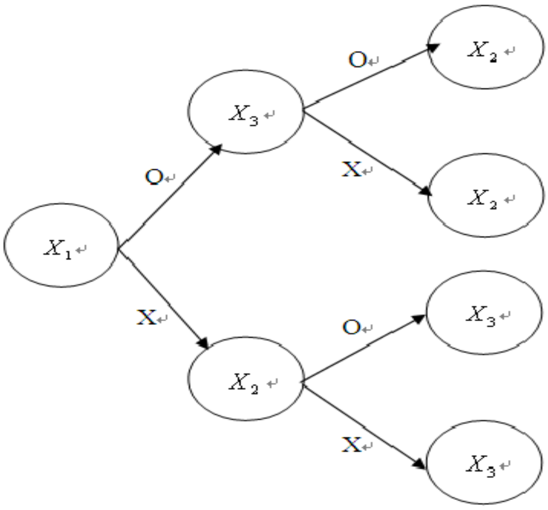

Fig. 1. Decision item tree network.

In this paper, a blocking strategy is proposed to overcome those problems. The new strategy modifies the entropy-based heuristic methodology proposed by Vomlel [8]. It clearly holds considerable potential for diagnosing students' bugs and skills with a CAT system based on a Bayesian network.

The paper is structured as follows. In the following section, we briefly review the theoretical background of our approach. We review the basic related concepts for Vomlel's methodology. Next, the blocking strategy and its implementation with Vomlel's methodology are elaborated. Then, one data set is used to evaluate this new strategy, and another is used as an example of the feasibility of Vomlel's framework with the blocking strategy. Finally, experimental results are given. The paper closes with a brief discussion presenting some conclusions and future directions.

2 Background Theories and Problem

2.1 Computerized adaptive testing

In the past two decades, advances in computer technology and psychometric theory have accelerated changes in test format from conventional paper-and-pencil tests to computerized adaptive testing [3].

In a CAT system, each examinee is presented with questions selected according to his or her performance [16], [17]. The goal is to diagnose each student's state of knowledge as quickly as possible without loss of accuracy [13]. In other words, low-ability examinees will be presented with relatively easy items, while high-ability ones will be presented with more difficult items [18]. Therefore, different participants will answer different items during the same test [19]. Although the total scores of test takers are the same, different item subsets could be administered to individual test takers.

In a CAT system, adaptive item selection strategy plays an important role in adaptive testing. A good strategy can help achieve assessment goals with shorter tests [14]. It could also reduce testing time by more than 50% while maintaining the same level of reliability [3][18].

So far, some researchers such as Collins et al. [20] and Millán et al.[13] have investigated adaptive item selection strategies relying on intuition-based heuristics with a Bayesian network. Further, Vomlel8 and Chao4 applied information theory (Shannon entropy and mutual information, respectively) to create a heuristic function based on a Bayesian network for adaptive item selection strategy in a CAT system.

The basic strategy is an iterative algorithm in which a chosen item is presented to the examinee, who answers either correctly or incorrectly. The CAT system successively selects questions that maximize the precision of the exam based on what is known about the examinee from previous questions. The estimate of the examinee's ability is then updated, based upon all prior answers. All steps are repeated until a termination criterion is met. Figure 2 illustrates the procedure.

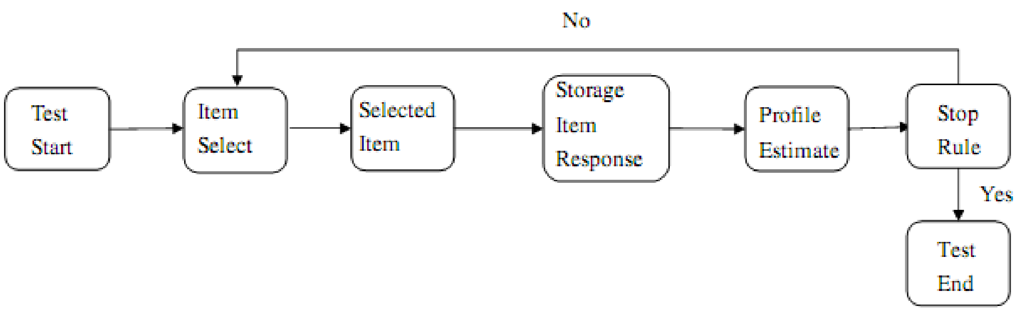

Fig. 2. Computerised adaptive testing procedure.

2.2 Bayesian network and applications

A Bayesian network is a probabilistic graphical model capable of modeling domain knowledge comprising uncertainty. Because it not only enables efficient uncertainty reasoning with hundreds of variables, but also helps humans understand the modeled domain better, it has been applied to expert systems in many fields [21]. The first applications were an expert system for electromyography, Munin, and the Pathfinder system [6].

A Bayesian network encodes the qualitative and quantitative parts of domain knowledge by means of a directed acyclic graph (DAG) $G = (E, V)$. Each node $i \in V$ corresponds to one random variable with a finite set x_i of mutually exclusive states for the qualitative part. A conditional probability table (CPT) , $P(X_i \mid (X_j)_{j \in pa(i)})$ where $pa(i)$ denotes the set of parents of node i, is the quantitative part. The joint distribution of all variables in the network can be calculated compactly and economically based on the theory and operation of a Bayesian network. That is to say, the set P defines the joint probability distribution as

$$P(X) = \prod_{i=1}^{n} P(X_i \mid (X_j)_{j \in pa(i)}) \qquad (2)$$

Using (2), any desired probabilistic information within a given Bayesian network is obtained compactly and economically.

Operation in a Bayesian network means that the network updates the probability distribution of the node of interest when it receives a piece of evidence from neighbouring nodes. This mechanism is called Bayesian network propagation. Various algorithms have been proposed to implement this mechanism [7], [12], [20], [22]. In this study, the software Bayes Net Toolbox for MATLAB [23] is used to perform the junction tree algorithm [23] for calculating all posterior probabilities.

2.3 Analyzing based on a Bayesian network

In the last few years, Bayesian networks have been applied to analysing educational assessment data and building computer-assisted test systems [6], [8-9], [10-12]. The former involves modelling the relationships between student proficiency variables and items and diagnosing students' proficiency status. Mislevy suggested a framework for model construction [10]. Three key points were described in this framework:

1. Building a Bayesian network for modelling relationships between student proficiency variables and items.
2. Constructing tasks (items) provided for students to reveal their mastery of the target knowledge.
3. Creating a Bayesian network describing how to extract the evidence of students' performance from the items.

In this study, a Bayesian network is built according to the above framework proposed by Mislevy [10].

The latter application of Bayesian networks focuses on adaptive procedures in a CAT, assuming that administrators will achieve better diagnoses with shorter tests. Adaptive procedure construction has been investigated by a number of authors. For example, Vomlel combined information theory concepts such as entropy with a Bayesian network to construct a decision item tree for adaptive item selection in a CAT [8]. (See Figure 1 for an example.) This framework shows that a decision item tree for adaptive item selection performs better. This study introduces a blocking strategy to modify the entropy-based heuristic methodology proposed by Vomlel [9]. It creates a new form, the blocking-based entropy heuristic methodology, to overcome executive time and storage space problems and improve decision item tree construction.

2.4 Item selection strategy based on a Bayesian network

According to a decision item tree constructed by Vomlel's method [8], a student will be assigned the next suitable item given his (her) prior responses. Once a test length defined by administrators is met, the testing procedure will be stopped

To construct a decision item tree for adaptive item selection, the following four steps are carried out :

1. Build a Bayesian network containing tasks (items), $X_1,\cdots,X_4$, and student's proficiency variables, $Y_1,\cdots,Y_3$. The network describes how to extract evidence regarding students' knowledge levels from their responses on the test
2. By evaluating entropy-based heuristic function (2), determine which item X should come next:
$$X = \arg\min_X \sum_x P(X = x \mid e_n) H(P(Y \mid X = x, e_n)) \quad (3)$$
Y is the variable of bugs and skills, X is the item bank and e_n is the prior sequence of item responses. $H(P(Y \mid X = x, e_n))$ is the entropy value calculated by the following equation:
$$H(P(Y \mid X = x, e_n)) = \sum_y - P(Y \mid X = x, e_n).\log(P(Y \mid X = x, e_n)) \quad (4)$$
3. By repeating step 2, construct a decision item tree (Figure 1) for adaptive testing.
4. Administer suitable items based on the decision item tree and a student's prior sequence of item responses. For example, if a student's response to X_1 was right, he or she could take the next item X_3; otherwise, he or she would get X_2. The entire procedure is illustrated in Figure 1.

An entropy-based heuristic methodology constructs the decision item tree for adaptive item selection. However, the procedure in step 2 requires much executive time for implementation in a realistic item bank with hundreds of items, bugs and skills.

For example, consider an item bank with 100 items. Because the decision item tree is fully binary with a depth of 100, the executive time problem means that the comparison procedure must be performed $2^{100}-1$ times to obtain the decision item tree. Similarly, the storage space problem means that the system requires $2^{100}-1$ space units to store the tree.

Besides, the CAT system requires much storage space to store the decision item tree.

For these reasons, it is impossible to implement adaptive testing based on entropy-based heuristic methodology or other methodologies based on a Bayesian network in the real world.

3 Problem Solution

In this study, a blocking strategy is proposed to construct decision item subtrees for adaptive item selection. In this section, the blocking strategy is elaborated, from how to construct subtrees and how to administer an adaptive test based on the subtrees.

3.1 Blocking strategy for constructing

The basic concept of a blocking strategy is that if the number of items for the decision tree is few, the executive time and storage space could be decreased. 'Blocking' means that the item bank is split based on some rules, such as the number of items per block or a content-balancing strategy. As each block contains only some items, a decision item tree could be produced for each block, yielding a subtree with fewer items to compare. In this process, a Bayesian network for the entire item bank could be used to evaluate items. Because the decision item tree is stored in many subtrees, the storage space could be decreased. To describe this procedure in detail, the length of the item bank is assumed to be 300 for diagnosing 20 skills and bugs. The corresponding Bayesian network is defined as $BN = \{\{X_1,...,X_{300}\} < -\{C_1,...,C_{20}\}\}$.

The detailed procedure is:

1. Divide the item bank into 100 blocks arbitrarily based on three items per block. The data structure will be:
$Item = \{\{X_1,...,X_3\},...\{X_{298}, X_{299}, X_{300}\}\}$.
2. Construct a subtree for block1 based on Vomlel's framework. Items belonging to block1 are compared with each other, and a Bayesian network for the entire item bank is used to evaluate the subtree.
3. Store the first subtree and repeat step 2 for block2, and so on.
4. Perform adaptive processing based on subtrees, as described in the following section.

The time required for comparisons in the above procedure is only seven time steps, and the storage space is only seven space units for constructing and storing, respectively, the subtree in each block. Therefore, the total time for all subtrees would be 700 time steps, and the total storage would be 700 storage units. In contrast, Vomlel's decision item tree would require 2300 times and 2300 storage units. Although this methodology could considerably reduce time and storage requirements, clearly the accuracy could decrease. Therefore, one real data set will to be used to experimentally evaluate this new strategy.

3.2 Blocking strategy for administering

Based on the decision item subtrees, the adaptive testing procedure could be changed to incorporate the blocking strategy. The detailed procedure for adaptive item selection based on many subtrees is:

1. The first subtree is the candidate decision item tree for adaptive item selection.
2. The first adaptive item is administrated to a test taker. The response is collected and recorded in an individual database by the computer-assisted system.
3. The second subtree is the candidate decision item tree for adaptive item selection. The test-taker's individual database must be used to determine the next suitable item. If the next suitable item is selected from the candidate decision item tree exactly, it is presented to the test-taker. Otherwise, no item from this candidate decision item tree is administrated to the test-taker.
4. Steps 2 and 3 are repeated by selecting each subtree in turn as the candidate decision item tree.
5. The adaptive procedure ends when the termination rule is met.

Figure 3 illustrates the process as following:

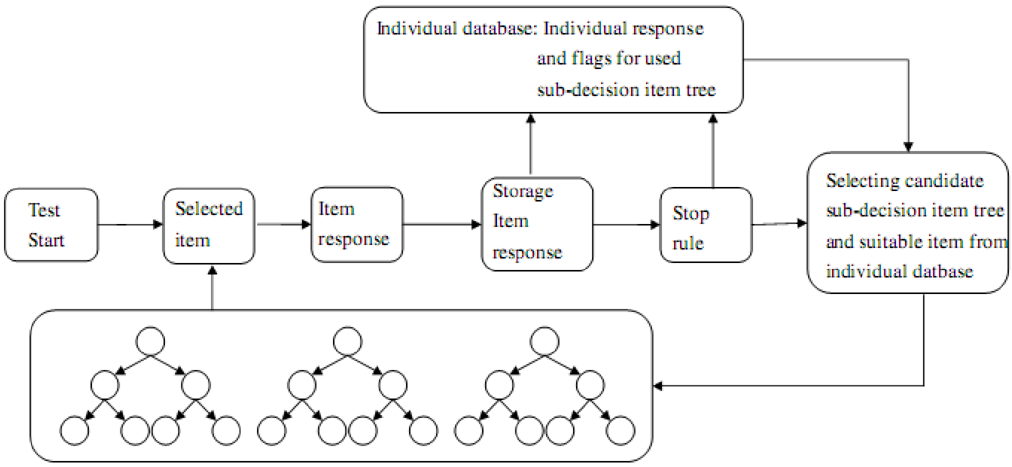

Fig. 3. CAT based on decision item subtrees

4 Experiment and Evaluation

To evaluate the blocking strategy as implemented in Vomlel's framework, two educational data sets are used. One data set, data_11, has 11 items for evaluating performance compared with that of Vomlel's framework. The other, data_18, has 18 items. It is used as an example for examining the feasibility of Vomlel's framework with the blocking strategy.

First, Bayesian networks BN_11 and BN_18 are constructed for the two educational data sets. Second, three procedures successively construct decision item trees for data_11 with BN_11 for adaptive item selection. The procedures are 'random procedure' (RM), 'entropy-based heuristic methodology' (EM) and the new implementation with the blocking strategy, 'blocking-based entropy heuristic methodology' (B-EM).

Because the blocking strategy could be affected by the number of items in each block, the B-EM methodology was separated into three kinds of procedures: blocking based on 3 items per block (B-EM-3), blocking based on 6 items per block (B-EM-6) and blocking based on 11 items per block (B-EM-11). These procedures successively construct decision item trees for data_11 with BN_11.

Finally, adaptive item selection is carried out based on those decision item trees or subtrees. The executive time, storage space, total entropy for the adaptive testing procedure and accuracy in recognising students' bugs and skills are compared. The following subsections show a Bayesian network of this domain knowledge and the evaluation method.

4.1 Experimental data and Bayesian network

4.1.1 Data_11_accounting

Educational assessment data for the unit 'Basic concepts of fractions' was collected from fifth grade students in Taiwan. Following Ref. 16, the following skills are chosen to build the student proficiency model: 'The concept of equivalent fractions' (Skill1), 'Can compare fractions' (Skill2) and 'Can transform decimal fraction into fraction' (Skill3). In addition, the three most common bugs for the basic concept of fractions are selected: 'Cannot understand equivalent fractions' (Bug1), 'Cannot compare fractions' (Bug2) and 'Cannot transform decimal fraction into fraction' (Bug3).

The presence or absence of the bugs is identified by experts' judgement using examinees' actual answers. The diagnoses of these experts serve as the external criterion variables. The assessment contains 11 problems, which were carefully constructed so that the bugs and skills can appear in various types of tasks. All items are multiple choice questions with four options (A, B, C, D). All examinees' responses are graded with binary scores (right/wrong) as the input to the Bayesian network. The Bayesian network was constructed as shown in Figure 4.

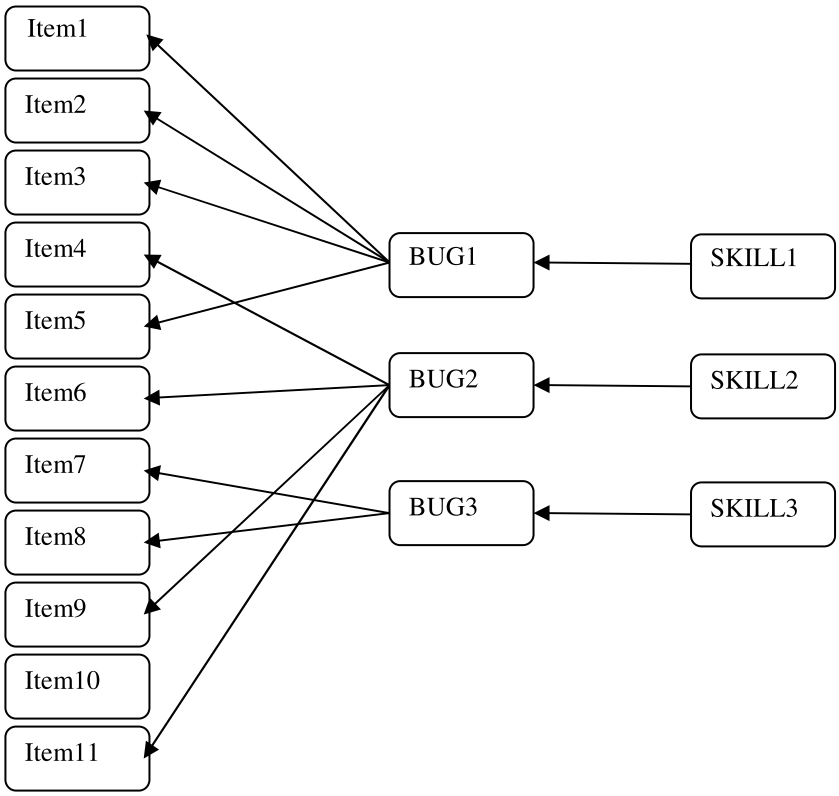

Fig. 4. Bayesian network for data_11

4.1.2 Data_18_accounting

Another educational assessment data set, from the unit 'The measure of area', was collected from fourth grade students in Taiwan. This data set is used as an example of the feasibility of Vomlel's framework with the blocking strategy. Based on the work of Hildreth,19 the five most common bugs for measure of area are selected for this study: 'Can't count to measure area' (Bug1), 'Can't multiply to measure area' (Bug2), 'Can't translate written question into mathematical equation' (Bug3), 'Can't translate one unit into the other unit' (Bug4) and 'Can't use correct formula to measure area' (Bug5).

The presence or absence of bugs is identified by experts' judgment using examinees' actual answers. The diagnoses of these experts serve as the external criterion variables. The assessment contains 18 problems, which were carefully constructed so that the bugs and skills can appear in various types of tasks. All items are multiple-choice questions with four options (A, B, C, D). All examinees' responses are graded with binary scores (right/wrong) as the input to the Bayesian networks. The Bayesian network was constructed as shown in Figure 5.

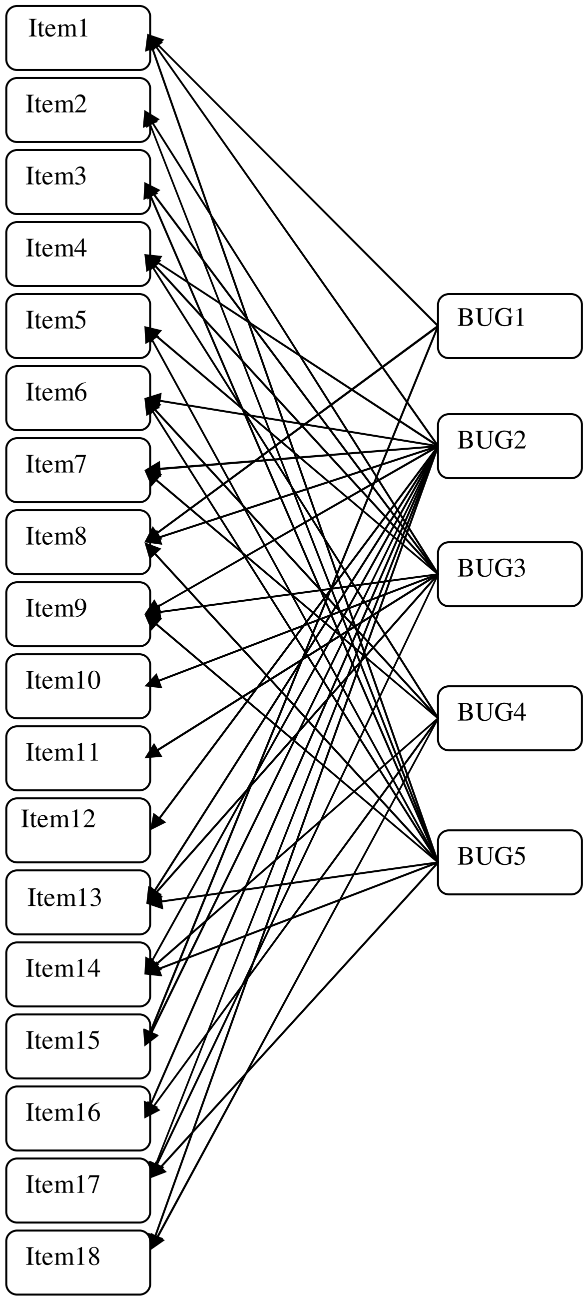

Fig. 5. Bayesian network for data_18

4.2 Evaluation Index

Although the blocking strategy used in this study could reduce the executive time and space requirements of decision tree construction considerably, clearly it could also decrease the accuracy. Therefore, data_11 was used to compare this method with Vomlel's original framework. The following criteria are defined:

1. executive time recorded by MATLAB
2. storage space units recorded by MATLAB.
3. accuracy of performance calculated by Table 1, in which N is the sample size.

Table 1. Formulation of accuracy

Artificial classification / Experts' classification	Yes(1)	No(0)
Yes(1)	f_{11}	f_{10}
No(0)	f_{01}	f_{00}

The correct prediction rate is then $\frac{f_{11}+f_{00}}{N}$.

5 Experimental Result

5.1 Comparison for Data_11

Tables 2 and 3 and Figure 5 show the comparison results for the executive time, storage space units and accuracy, respectively.

Table 2. Executive time comparison

Methodology	Executive time (s)	Proportion to EM
EM	11368.65	100%
B-EM-11	11368.65	100%
B-EM-6	544.05	4.79%
B-EM-3	63.5	0.56%
RM	0	Non

Table 3. Storage space units

Methodology	Executive time (s)	Proportion to EM
EM	2047	100%
B-EM-11	2047	100%
B-EM-6	94	4.59%
B-EM-3	24	1.17%
RM	0	Non

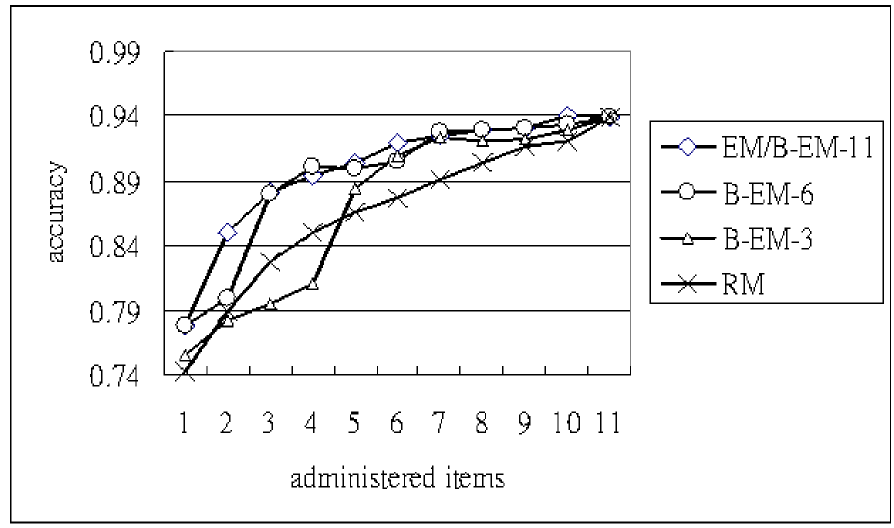

Fig. 6. Comparison of accuracy for Data_11

Figure 6 shows that the accuracy of B-EM is the same as or better than the accuracy of EM, especially B-EM-6, and the accuracy of RM is the worst. The reason is that the construction rule of the decision item tree is based on entropy values, not accuracy. Even so, the blocking strategy could be a good methodology. Tables 2 and Table 3 show that the storage space units and the executive time of B-EM-3 and B-EM-6 are smaller than those of EM. Although RM does not require any executive time or storage space units, its accuracy is the worst.

5.2 Comparison for Data_18

Here we examine data_18 as an example of the feasibility of Vomlel's framework with a blocking strategy. A decision item tree for data_18 constructed by Vomlel's framework could take four days to construct, and its storage could take 2^{18} space units. This is because it is a full binary tree with a depth of 18. In contrast, a decision item tree constructed with Vomlel's framework and a blocking strategy based on B-EM-6 requires 183.56 seconds to construct the subtrees and 2^{6} space units for storage. Although the executive time and storage space units decrease considerably, the accuracy remains almost the same, as Figure 7 shows.

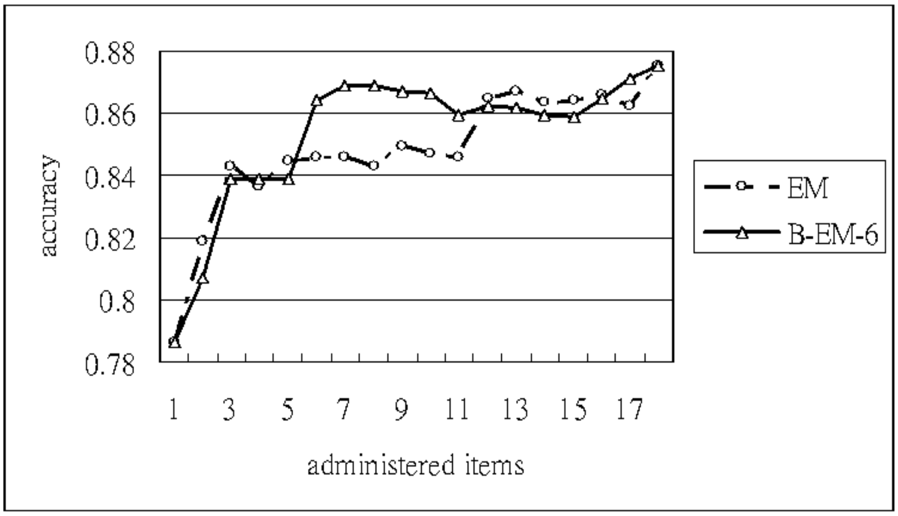

Fig. 6. Comparison of accuracy for Data_18

6 Conclusion

The adaptive testing procedure based on a decision item tree enables quicker item selection during testing in a CAT system. This procedure will administer a test with higher discrimination and fewer items than a test without it. The decision item tree is fully binary with a depth equal to the length of the item bank. Thus, the framework would require too much executive time and too many storage space units to be implemented in the real world using Vomlel's framework alone.

Some studies have covered these problems. For example, Kuo, Hsieh and Wang used the most probable explanation to speed up decision item tree construction [19]. However, those studies focused only on the dimensionality problem of bugs or skills, not including the length of the item bank.

This study proposed adding a blocking strategy to Vomlel's framework to solve the time-consumption and space-consumption problems. Experimental results show that a blocking strategy could increase the effectiveness of decision item tree construction with only a small loss of accuracy in adaptive testing. Thus, it successfully addressed the time and space problems for every size of item bank for adaptive testing.

However, some crucial points still require further study. For example, further attention should be given to the theoretical proof for the blocking strategy, the optimum number of blocks and of items in each block, which items should be included in each block and so on.

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