

A Student-oriented Physics E-tutorial System

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Abstract: - E-tutorial systems recently played important roles in the teaching and learning of both online and conventional courses. Students have opportunities to study and practice exercises under guidance of the systems. A challenge in the development of e-tutorial systems is the design and implementation of the student guidance system. The guidance system should take into consideration the ability of individual students and give appropriate questions according to the student's ability. The students should finally reach the solution and gain better understanding of the learning topic. This paper presents the student guidance system of ESBO, a knowledge-based Physics e-tutorial system. This system considers individual student's ability in a different approach from other existing systems.

Key-Words: - E-tutorial system, Intelligent tutoring system, Bayesian networks, Bayes' theorem, Solution graph, Student guidance.

1 Introduction

The ESBO (E-tutorial System Based on ORM) project [1] is a project aimed to develop an intelligent e-tutorial system that uses the Object Role Model (ORM)[5] as its knowledge representation. The e-tutorial system is viewed as an expert system that needs to access a large knowledge base. Instead of referring directly to base relations, the system refers to ORM fact types so that a predicate instance is actually an ORM fact instance.

The ESBO student's guidance system is based on the Bayes' theorem and also takes into consideration individual student's responses such as the time that the student uses to answer a question and the number of incorrect answers for a question.

Experiments have been conducted to test if the guidance and evaluation given by ESBO reflects the actual ability of the students. The result is found to be satisfactory.

2 Bayesian Networks as Solution Graphs

Bayesian Network is a kind of diagram that describes events and the result of the events. There is a value that reflects the probability of each event attached to each event node. This probability value can be obtained from statistics, previous research results or

calculations using the Bayes' theorem. Such a value is called the posterior probability.

There are five kinds of nodes. The first one is the Goal node (G). It shows the objective of the work such as the objective of each solution step of a tutorial question. The second one is the Rule node (R). It shows rules that are required in order to reach the objective such as the equations which are required to solve each step of a tutorial question. The third one is the Rule Application node (RA). It shows the result of the application of a rule node. The forth one is the Fact node (F). It shows facts which are related to the rules such as variables of relevant equations. The fifth one is the Strategy Node (S). This one is optional. It can influence the result so that more than one result is produced under the same objective.

From Fig.1, $P(F1)$, $P(F2)$, $P(F3)$ and $P(F4)$ are prior probabilities of the Fact node (F1,F2,F3,F4) respectively. These probabilities have to be obtained a prior probability. $P(RA1 | R1, F1!)$ is the conditional probability of the result RA1 when R1,F1,F2,F3 and F4 take place. $P(RA1 | R1, \sim F1!)$ is the conditional probability of the result RA1 when R1 takes place but F1,F2,F3 and F4 do not all exists. These conditional probabilities also have to be predefined.

After the result RA1 is obtained and R1, F1, F2, F3 exist, the posterior probability is calculated using the Bayes' theorem as follows:

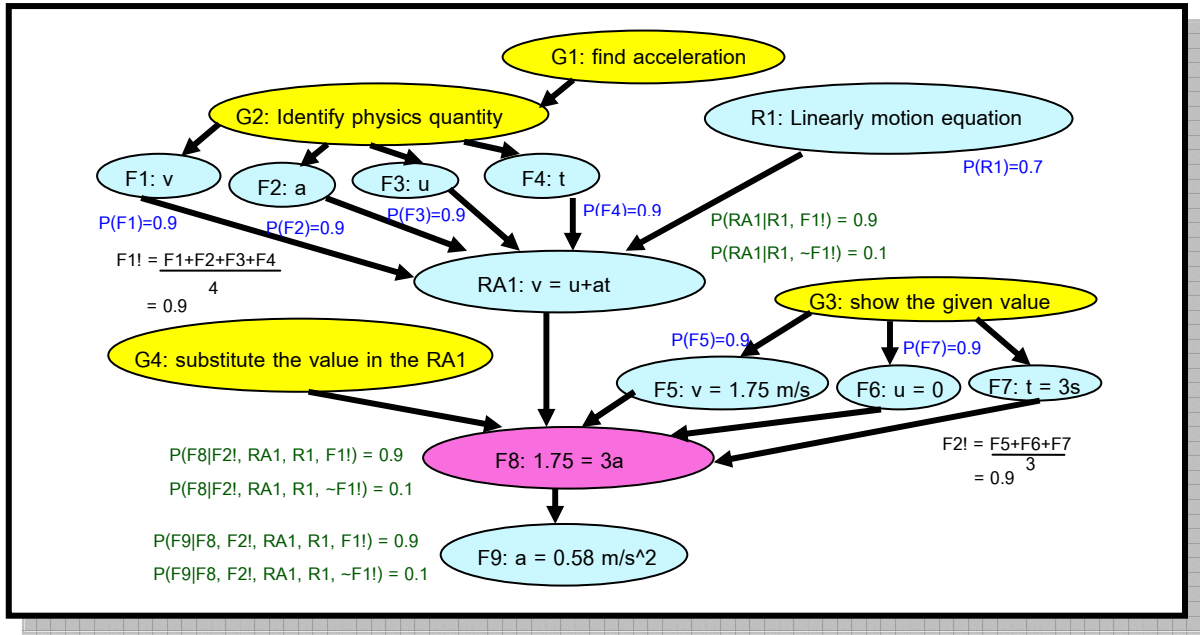


Fig.1 A Bayesian Network as a solution graph for the calculation of the observer's acceleration.

$$P\langle X|Y\rangle = \frac{P\langle Y|X\rangle P(X)}{P(Y)} \quad (1)$$

where $P\langle X|Y\rangle$ is the probability of having X under the condition of having Y. This is the posterior probability.

$P\langle Y|X\rangle$ is the probability of having Y under the condition of having X. This is the conditional probability.

$P(X)$ is the probability of having X. This is the prior probability.

$P(Y)$ is the total probability of having Y. This is the marginal probability.

Fig. 2 shows the solution graph for solving a physics (object acceleration) problem.

Fig.3 shows the application of Bayes' theorem for the calculation of the posterior probability of knowing the node F8.

3 The ESBO Student Environment

This part of the ESBO system serves student users. For each selected problem, the system asks the student to select formulae which are related to the problem being solved. This formulae selection process is a part of the student's skill evaluation. For each formula, related variables are selected and applied. The student guidance system guides

students according to individual skill on the given problem.

The skill level calculation comprises 2 parts. The first one calculates the ability to solve each problem.

Each solution step is considered using the Bayes' Theorem. The second one calculates the total skill of the students for the given subject area.

The ESBO system not only uses the Bayes' Theorem for the probability calculation but also utilizes other factors such as the time required to enter an answer and the numbers of help. The equation is shown as follows:

$$P\langle X|Y\rangle = P\langle X|Y\rangle_{actual} - T - H \quad (2)$$

T is the quantity of posterior probability that has to be removed because the longer time used in answering the question.

The system uses a table which relates the time used to answer a step answer and the value T which is to be deduced. It then further checks the time a student uses to answer a question and determines the corresponding T value which is to be deduced.

the duration time (second)	T
< 60	0
60-119	10%
120-179	20%

Table 1 The relationship between the time used to answer a step question and its corresponding value T

H is the quantity of posterior probability that has to be removed because of the number of helps used in answering the question.

The system uses a table which relates the number of helps required and the H value which is to be deduced. Table 2 shows some sample entries of the table.

Numbers of help	H
0	0
1	10%
2	15%

Table 2 The relationship between number of helps and the H value

The total ability of each student by using problem solving histories can be obtained as follows:

$$P_{\text{accumulation}} = \frac{\sum_{i=1}^N P\langle X|Y \rangle_i}{N} \quad (3)$$

where $P\langle X|Y \rangle_i$ is the ability to solve each problem successfully.

N is the number of problems which are successfully solved.

4 The ESBO Student Guidance System

This part of the system gives advices to students upon requests. At any stage, the students may request for help. The system then examines the next possible steps. In the case that there is only one step, the system will then recommend that step. If there are several possible next steps, the system examines the current skill level of the student and the skill level required for each possible next step. The skill level of each path and the skill level of the student are as follow:

$$P(\text{potential}) = \frac{\sum P(X|Y)_{\text{actual}}}{\sum \text{Finish_Solution}} \quad (4)$$

$$P(\text{Path})_i = \frac{\sum P(X_j)_i \times \text{weight}_j}{\sum j} \quad (5)$$

Fig. 4 shows part of a solution graph of a physics question for finding power and prior probability of some nodes which are required in the calculation of any P(Path).

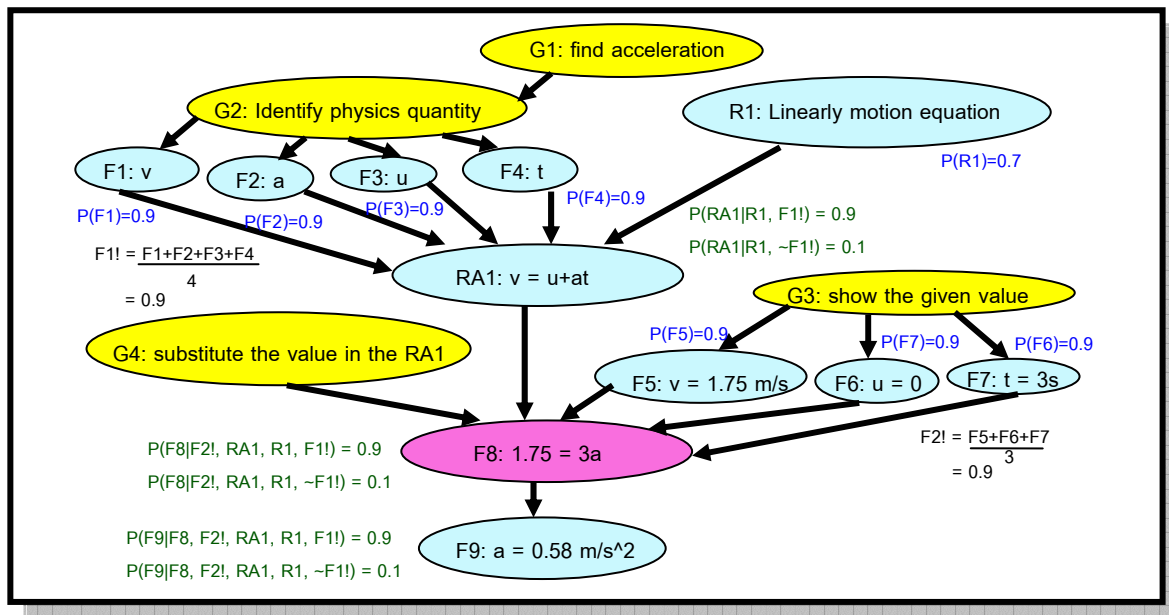


Fig.2 An ESBO solution Graph.

$$\begin{aligned}
 & P(F2!, RA1, R1, F1! | F8)_{\text{actual}} \\
 &= \frac{P(F8 | F2!, RA1, R1, F1!) * P(F2!) * P(RA1 | R1, F1!) * P(R1) * P(F1!) (-T- H)}{P(O) + P(F8 | F2!, RA1, R1, \sim F1!) * P(F2!) * P(RA1 | R1, \sim F1!) * P(R1) * P(\sim F1!)} \\
 &= \frac{0.9 * 0.9 * 0.9 * 0.7 * 0.9 (- 0.045 - 0.045)}{(0.9 * 0.9 * 0.9 * 0.7 * 0.9) + (0.1 * 0.9 * 0.1 * 0.7 * 0.1)} \\
 &= 0.802 \\
 &P(F2!, RA1, R1, F1! | F8) = P(F2!, RA1, R1, F1! | F8)_{\text{actual}} * \text{solution_probability} \\
 &= 0.802 * 0.8 = 0.6416
 \end{aligned}$$

Fig.3 The application of Bayes' Theorem for the node F8 of Fig.2

5 System Evaluation

The ESBO student environment and guidance systems are evaluated by using it with first year science students. Correlations between the calculated probability of ESBO users and the actual marks the same group of students obtained from conventional examination are established. Such

nonparametric statistics are obtained using the Spearman's Rank Correlation Coefficient [9].

Since this evaluation is about the measurement of Physics skill using the Bayes' Theorem, there must be collections of basic Physics skill and determine the prior probability and conditional probability.

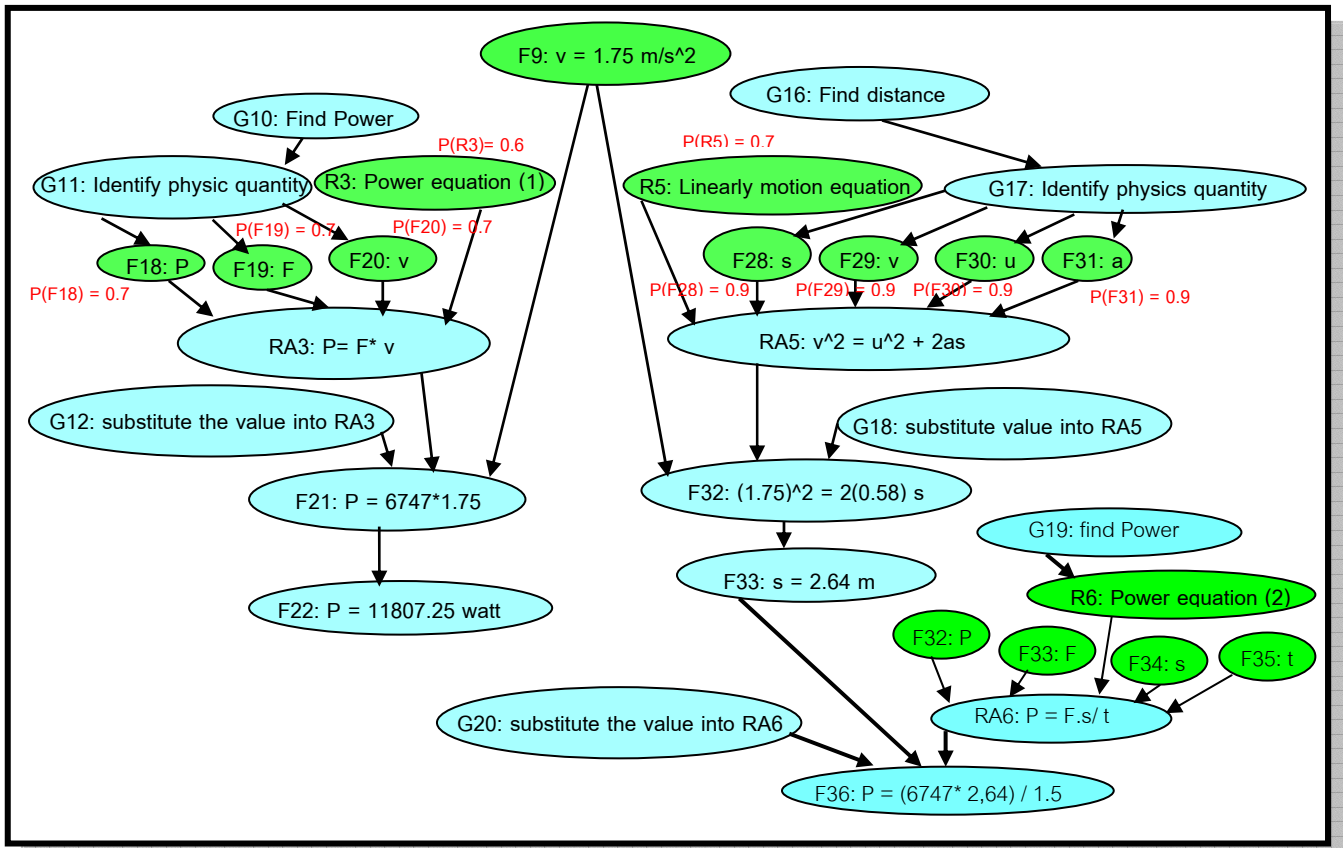


Fig.4 A solution graph that shows the prior probability of each step.

The prior probability is obtained by having students work on test problems and variables and check if the students know them. The ratio between the number of students who know each formula/variable and the total number of students are calculated. The result is the prior probability of the formula/variable.

The conditional probability is the value that shows conditional relationships between 2 nodes. A Bayesian network may describe the fact that Proposition 1 and Rule 1 must exist before Rule Application 1 can exist. This project uses the conditional probability as suggested in ANDES [6].

There are three evaluation rounds. Each of them comprises two tests. For the first one, the students work on ten Physics questions using the ESBO system. The second one the students work on actual exam papers. For each round, the probabilities and marks are compared and the Spearman's Rank Correlation Coefficient is computed. The results of the three rounds are 0.9153, 0.8283 and 0.8744. The ESBO system reflects similar skill level to the marks obtained in conventional tests.

6 Conclusions

This paper presents the application of Bayesian Network as the solution graph in the ESBO (E-tutorial System Based on ORM) system. Individual student's skills on a given problem are used as part of the guidance through the solution graphs. The evaluation results of the approach shows that the ESBO system reflects similar skill level to the one obtained from conventional tests.

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