Question Generation for Adaptive Assessment for Student Knowledge Modeling in Probabilistic Domains

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Abstract. *In this paper a question generation approach for adaptive assessment is purposed to estimate the student knowledge model in a probabilistic domain within an intelligent tutoring system. Assessing questions are generated adaptively according to the student knowledge based on two factors (i) the student misconceptions that are entailed in the student knowledge model, and (ii) the information gain maximizing. Updating and verification of the student model are conducted based on the matching between the student's and model answers to assessing questions. Comparison between using the adapted questions and random questions is investigated. Results suggest that utilizing adapted generated questions increases the approximation accuracy of the student model by 40% in addition to decreasing of the required assessing questions by 50% compared to using fixed questions.*

Key words: Student Modeling, Adaptive Assessment, Item Response Theory

1 Introduction

Most adaptive tutoring systems that model the student knowledge deal with deterministic domains models. However, in the real world, a degree of uncertainty is inherent, which requires the use of probabilistic models to represent such domains. Bayesian networks (BN) are amongst the most widely used approaches to represent such domains [1]. Suebnukam et al. presented an example of modeling the student knowledge in probabilistic domains [2]. In their study, a modeling algorithm that focuses on the skill of reasoning through domain variables relations around practical patient problems in medical domains is suggested. This work suggests a student knowledge modeling algorithm that utilizes diagnostic skill. Using diagnostic questions allows inferring, not only the student knowledge, but also the student misconceptions with utilizing lower number of questions.

Generally, modeling of the student knowledge process depends on analysis of the student responses through assessing questions. Recently, trends in Intelligent Tutoring Systems (ITS) utilize Computer Adaptive Testing technology (CAT) in building of the student model [3, 4]. CAT technology considers the student knowledge and the question difficulty level to adapt the selection of the next assessing questions. That aims to decreasing of the number of required assessing questions in addition to increasing the accuracy estimation of the student knowledge. Psychometric Item Response Theory (ITR) [3] and BN modeling techniques [4] are examples of used methodologies in question selection process in the context of CAT. IRT that provides a well-founded mathematical technique in the question selection process is adopted in this work.

The main contribution of this work is a question generation approach for adaptive assessing to model the student knowledge in probabilistic domains. Student answers to the generated questions are used to update the student knowledge model. The updating process aims to express the student misconceptions in terms of modifications in the student model structure and parameters. In turn, the updated student model is utilized in the question generation process, which allows consideration of the student misconceptions when generating questions.

2 Question Generation Module

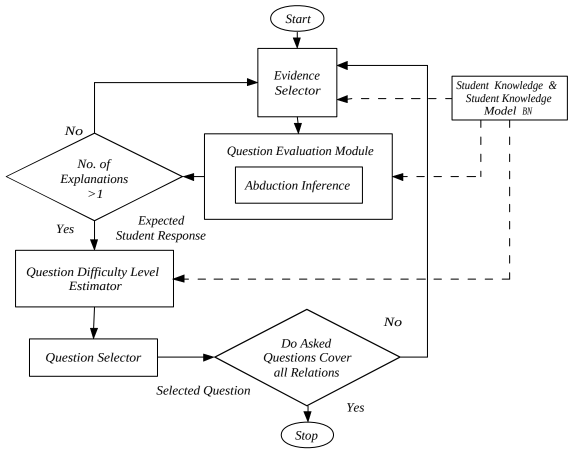

Fig. 1. Question Generation Module

Probabilistic domains are usually associated by diagnostic questions, which require identification of the most probable explanation given a set of evidences. The student is asked to provide a ranked list of possible hypotheses for the given question evidences. The question generation process accommodates the student knowledge by generating questions with different difficulty levels and evidences scope. This diversity guarantees getting informative answers from the student. The question generation process illustrated in Figure 1 is based on five components.

1. Student model: contains the student knowledge which is estimated by utilizing IRT one parameters model [7] using all responses provided by the student.
2. Evidences Selector: control the question difficulty level by identifying the suitable number of evidences. The evidences are selected from the student knowledge model conditioned by having more than one common hypotheses. This selection guarantees that the generated question has more than one explanation.
3. Question Evaluation Module: evaluates the selected evidences and checks if they constitute acceptable question with respect to the student knowledge.

4. Question difficulty level estimator: uses the question evidences and their relations with possible answers to estimate the question difficulty level.
5. Question selector: chooses a suitable question among the possible generated questions based on the Maximum Information gain [8] for the previous student knowledge level estimated.

It is worth mentioning that, updating the student knowledge model is conducted using two methods previously suggested in [6] coarse and refined updating approaches. The coarse model update is conducted by adding or removing relations of the differences in the hypotheses and swapping between relations' weights for the differences in the hypotheses order. Refined model update, on the other hand, is performed using successive increase or decrease in the weights of the different hypotheses according to the nature of the differences. Consequently, the student knowledge model entails the student misconceptions through the updating process.

3 Results and Discussion

In this paper, a question generation algorithm to assist in approximately the student model in a probabilistic domain is presented. The student's answers to student's knowledge adapted generated questions are used to estimate the actual student model. The algorithm is invoked when the student answer mismatches the expected answer evaluated using the student model. Updating and verification of the model are conducted based on the matching between the student's and model's answers. Evaluation of the proposed question generation technique is based on comparing its performance with using random assessing questions. Two evaluation criteria are used, (i) the required number of the assessing questions and, (ii) the accuracy of the obtained student BN model through measuring the difference of link weights compared with initial student model. The results indicate that utilizing adapted generated questions increases the approximation accuracy of the student model by 40% using refined updating technique in addition to decreasing the number required assessing questions by 50% using coarse updating technique.

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Student Model

- Quality of the student model directly effects the efficiency of Intelligent Tutoring Systems.
- Student answers to assessing questions is the most trustable behavior in modeling of the student knowledge.
- Adapting the assessing questions according to the student knowledge allows a fast and reliable method to bootstrap the student model.
- Many applications need probabilistic modeling and are usually associated by diagnostic questions.

Question Generation Module

•Assessing questions are generated adaptively using the updated student model
•Question Generation Module consists of:

1. <u>**Student model:**</u> estimate the student knowledge by utilizing IRT one parameters model [2] using all student responses

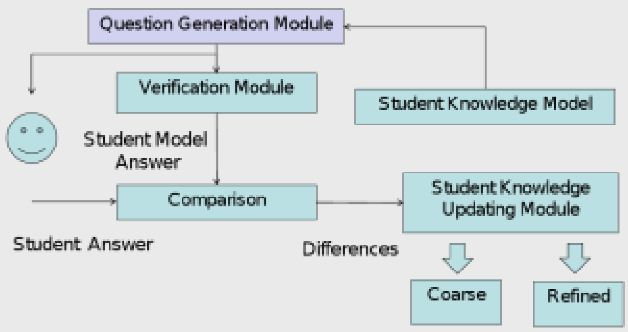
$$\hat{\theta}_{S+1} = \hat{\theta}_S + \frac{\sum_{i=1}^{N}[u_i - P_i(\hat{\theta}_S)]}{\sum_{i=1}^{N} P_i(\hat{\theta}_S)[1 - P_i(\hat{\theta}_S)]}$$

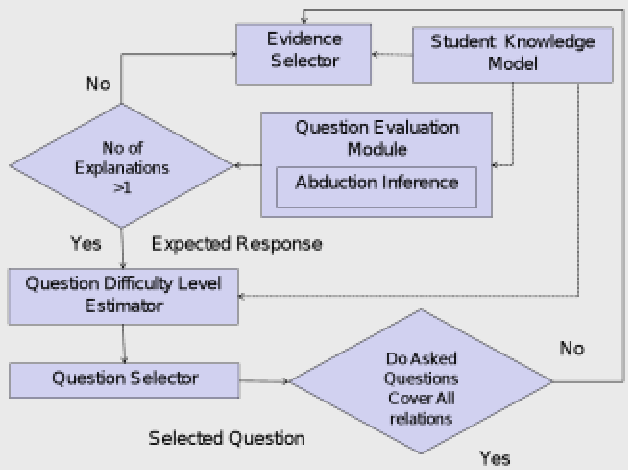
2. <u>**Evidences Selector:**</u> control the question difficulty level by identifying the evidence scope and number
3. <u>**Question Evaluation Module:**</u> evaluates the selected evidences and checks if they constitute acceptable question .
4. <u>**Question difficulty level estimator:**</u> uses the question evidences and their relations to estimate the question difficulty level.
5. <u>**Question selector:**</u> chooses a question based on the Maximum Information gain [3]

$$I_i(\hat{\theta}) = \frac{P_i(\hat{\theta})^2}{P_i(\hat{\theta}) - [1 - P_i(\hat{\theta})]}$$

Adaptive Assessment based Student Knowledge Modeling

- Student answers to student knowledge adapted generated diagnostic questions are used to estimate the actual student knowledge model.
- Student answer is a ranked list of possible hypotheses
- Modeling of the student knowledge is based on differences between the student answer and expected answer through his model [1].





RESULTS

- Fifty simulated students are generated randomly using domain knowledge representation for some diseases
  •The difference in student model BN and the simulated student BN (BN_D)
  •The number of questions required (N_Q) through different updating techniques

Verification Criteria	Coarse	Adaptive Coarse	Refined	Adaptive Refined
BN_D	10±1.58	8.5±2.26	9.50±2.60	5.73±1.27
N_Q	20	9.34±8.60	20	13.12±1.60

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