Fuzzy Logic Representation for Student Modelling

Case Study on Geometry

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Abstract. Our aim is to develop a Fuzzy Logic based student model which removes the arbitrary specification of precise numbers and facilitates the modelling at a higher level of abstraction. Fuzzy Logic involves the use of natural language in the form of If-Then statements to demonstrate knowledge of domain experts and hence generates decisions and facilitates human reasoning based on imprecise information coming from the student-computer interaction. Our case study is in geometry. In this paper, we propose a fuzzy logic representation for student modelling and compare it with the Additive Factor Model (AFM) algorithm implemented on DataShop. Two rule-based fuzzy inference systems have been developed that ultimately predict the degree of error a student makes in the next attempt to the problem. Results indicate the rule-based systems achieve levels of accuracy matching that of the AFM algorithm.

Keywords: Student model, fuzzy inference system, rule-base.

1 Introduction

Student Model is one of the primary components of an Intelligent Tutoring System (ITS). Our objective here is to study one of the AI approaches (fuzzy logic) for the conception of these kinds of models. Our methodology emphasizes the collection of real-world data for evaluating and comparing the model. Building student models is a complex and intractable task, as seen in [1]. Students pose the real challenge to a tutoring system in the sense that it is very difficult to study their minds and hence extract information under different circumstances. Moreover, recent approaches to develop an effective student model have lacked in one way or the other. Specifically, we will consider the case of Additive Factor Model (AFM) algorithm, [2], which performs the knowledge diagnosis of the student by predicting the error rate. It has been graphically shown on the learning curve diagrams on Datashop that the actual values of Error rate and the values predicted by AFM sometimes differ significantly. Later in the paper, we will compare the results obtained with the fuzzy inference systems

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with the AFM predicted values as well as with the actual error rate values coming directly from the student-computer interaction.

Fuzzy logic is an AI technique that involves the use of natural language in the form of If-Then rule paradigms which allows the modelling of complex systems using a higher level of abstraction. The main advantage of using fuzzy logic is that humans often reason in terms of vague concepts when dealing with situations in which they experience uncertainty, [3]. Hence we go for a technique that effectively maps the subjective concepts such as skilled, unskilled, average etc. (when talking about a student's skill level) into numerical values with the help of membership function curves.

2 Related Previous Work

In [4], the Brilliant Scholar Series 1 (BSS1) tutoring system has been designed based on fuzzy logic techniques. This way, it has improved the performance of the system by introducing intelligent features which can better manage the student's learning like monitoring the student's progress, trends in performance etc. A general fuzzy logic engine has been designed and implemented to support development of intelligent features for BSS1. Again in [4], it has been shown that a fuzzy logic based system offers the flexibility to manipulate the system as per the designer's need, for instance, by modelling the problem suitably, defining fuzzy variables and suitable membership functions for their fuzzy sets, and developing a comprehensive set of rules relating input and output variables.

3 The Proposed Student Model

We make use of the student-computer interaction data available on Datashop, described in [5], which is an online repository of data-sets coming from different Intelligent Tutoring Systems covering a wide variety of domains. Our approach involves the design of a student model based on Knowledge Tracing, [6], and fuzzy inference using If-Then statements for the development of the rule-base. Two rule-based systems have been designed, one for the diagnosis of student knowledge i.e. Knowledge Component (KC) diagnosis and other (using the first rule-base) for the prediction of a parameter for student performance i.e. Error Rate. Learning curves have been used that visually present measures of student performance. We have considered data of Geometry Cognitive Tutor 1996 with Geometry Area (1996-1997) as the Dataset accessed via DataShop which was tested on 59 students with an existing KC model ("Original"), [7].

3.1 Knowledge Component (KC) Diagnosis

The amount of learning that a student acquires in various concepts of geometry is an important measure for the student knowledge diagnosis, so a rule-base for the prediction of knowledge component level has been designed. In geometry domain, a student progressing through various problems encounters a total of 15 KCs when Original KC model is considered. Here, we will only consider the diagnosis of Parallelogram Area KC (given the base and height, the student is able to find the area of a parallelogram). This consideration has been generalized for the diagnosis of remaining KCs.

Input-Output Consideration and Membership Function (MF) Curves. KC diagnosis is a 3-input 1-output rule-base. The inputs are the probability that student knows the KC, the Opportunity Count (OC) and the Outcome (correct or incorrect answer) at time t. The single output considered is the probability that the student knows the KC at time t+1. With ParallelogramArea KC as an output, we can infer about the student skill level or the gaps in his knowledge about some concepts. Diagnosis results of this KC from previous step serve as an input for the KC diagnosis for current step. This information considers the fact that the current level of the student knowledge about a particular concept also depends on his previous knowledge about that concept.

Membership Function curves represent linguistic levels (non-numeric variables such as skilled, unskilled, average etc.) that a fuzzy variable can take. We have considered Universe of Discourse for ParallelogramArea from 0 to 100 as it is in terms of percentage of the KC learnt. Fig. 1 shows that a total of 7 linguistic levels have been considered for ParallelogramArea. Here, for example, the linguistic level "Above Average" has a Triangular curve with its range from 45 to 95. Opportunity Count and Outcome for the KC have 3 and 2 linguistic levels; Low, Medium, High, and Incorrect, Correct respectively.

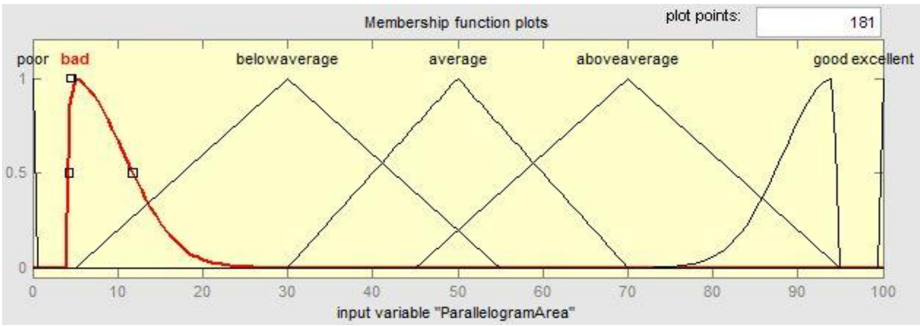

Fig. 1. Membership Function curves for ParallelogramArea

Rule-Base. For KC diagnosis, 24 If-Then rules are developed for the 3-input 1-output system. These rules allow inferring the value of the output.

Sample Rule. If ParallelogramArea is Average and OCParallelogramArea is Medium and OutcomeParallelogramArea is Correct, then ParallelogramArea is Above Average.

At Medium OC, if the student makes correct attempt with an Average level of ParallelogramArea (from previous step), then his knowledge about this KC will rise to Above Average. Following this procedure, remaining rules can also be interpreted.

3.2 Error Rate Prediction

We use the KC diagnosis for the prediction of error rate i.e. to predict about the probability that a student makes an error on a step. This will help us to compare our results with the actual values and also with the values predicted by AFM algorithm. The intuition of AFM is that the probability of a student getting a step correct depends on the response of the student on a step, the amount of knowledge that the student possess, difficulty level of the KC, skill level of student, and the amount of learning gained for each practice opportunity.

Input-Output Consideration and Membership Function Curves. Considering the variables and intuition of AFM, an analogy is applied that results in a 3-input 1-output rule-base for error rate prediction. The output considered here is the ErrorRate and the inputs are KC (Knowledge Component), Student (Skill Level of Student), and KC-DifficultyLevel (Difficulty Level of KC). KC diagnosis rule-base considers outcome of ITS and OC as two of its inputs, so we take the inferred KC level (from first rule-base) as an input. This reduces the number of input variables for error rate prediction (as compared to the number of variables in AFM). 3 linguistic levels are taken both for Student and KC-DifficultyLevel inputs; Skilled, Average, Unskilled, and Easy, Medium, Hard respectively. For the ErrorRate output, 7 linguistic levels are considered; Very Low, Low, Below Medium, Medium, Above Medium, High, Very High.

Rule-Base. 31 If-Then rules are developed for the prediction of error rate for the 3-input 1-output fuzzy inference system. The rules are developed on the basis of learning curve plots. Two such curves for error rate and assistance score are taken. On seeing the Assistance Score learning curve plot, we find those OCs which correspond to Average KC. Then values for actual error rate are computed from its learning curve plot and its average is taken for all the OCs under consideration. This mean value is then mapped to a relevant level of error rate using its MF curves and the inferred level obtained this way is assigned as the output to this rule.

Sample rule. If KC is Average and Student is Unskilled and KC-DifficultyLevel is Hard, then ErrorRate is High.

4 Results

For Fig. 2, error rates (as computed with the fuzzy inference) for all students with every KC are recorded individually. Then, all the readings are grouped so that we get values of Actual error rate, predicted error rate by AFM, and the error rate as computed by the rule-based system. Observations are then plotted as a function of Opportunity Count present in DataShop traces. Figures 2-4 show a good accuracy of the prediction; the rule-based system RMSE (Root Mean Square Error) in general is rather close to that of AFM, on Fig. 2. In particular, Table 1 indicates for Figures 2-4 the correlation between the actual error rate and the AFM prediction on one hand, between the actual error rate and the rule-based system on the other hand. The correlation is again significantly good as compared to AFM. However, our results present over-fitting issues, as we have not yet used cross-validation (i.e. to use a part of the data to train and the rest to test the model). This point is discussed in more detail in the conclusion.

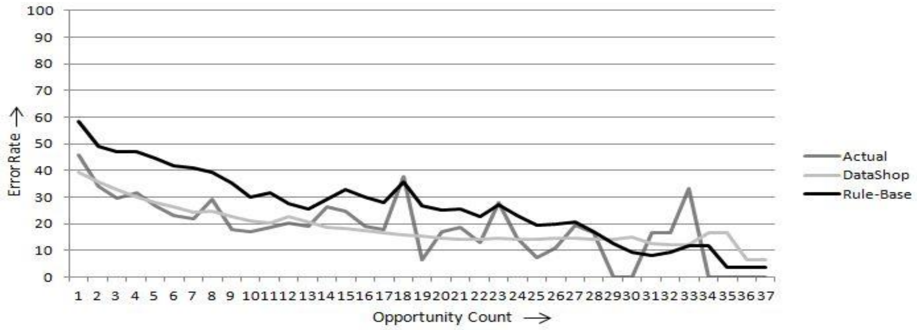

Fig. 2. General plot for all KCs and all students. Rule-Based System RMSE: 0.18635, AFM RMSE: 0.13447

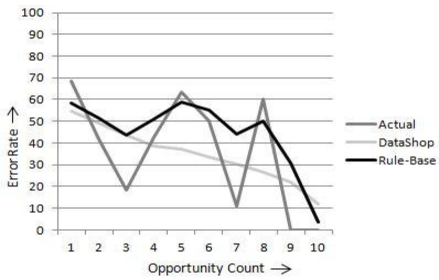

Fig. 3. Plot for Trapezoid-Base KC and all students

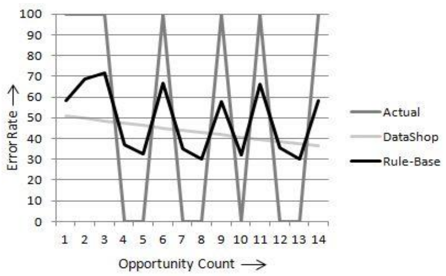

Fig. 4. Specific plot for Circle-Radius KC and Stu_0a8e3638e3c0deb4e5e49c72286

Table 1. Corresponding Pearson Correlation Coefficient (PCC) values for above plots

Fig. No	2	2	3	3	4	4
Pair of Curves	Actual-DataShop	Actual-Rule-base	Actual-DataShop	Actual-Rule-base	Actual-DataShop	Actual-Rule-base
PCC Value	0.662	0.785	0.616	0.817	0.234	0.966

5 Conclusions and Perspectives

With the fuzzy logic representation for student modelling, we have developed a student model that respects the process of knowledge tracing. This model can handle data at a higher level of abstraction and it also has the ability to deal with uncertainty. Moreover, fuzzy logic needs fewer parameters (in comparison to AFM) and this facilitates modelling with continuous variables (e.g. the membership function curves for the fuzzy variables). As the inputs and the rules are particularly comprehensible for humans due to the linguistic levels expressed in natural language, it is quite easy to adapt and refine the model (for instance by experts). In the past, knowledge tracing has been implemented with Hidden-Markov model and Logistic regression. Here, the main contribution of this paper is the design of a cognitive student model based on Fuzzy Logic. The expressive power of fuzzy inference is comparable to full Bayesian inference, but it requires fewer parameters due to the continuous Membership Functions. Moreover, the structure of this fuzzy logic model is not dependent on our domain, so it can be reused by ITS designers for another work/domain/ITS as long as the KC Model is developed. Determination of the parameters (the thresholds of each membership function) may be done either by experts or by machine learning algorithms. As said previously, validating the proposed student model in a more formal way is a crucial perspective. Our results show some over-fitting and a lack of precision in the beginning, so constructing the model with machine learning techniques is also important, this would help us improve the accuracy of the model during the initial stages. As a perspective, methods like training the model with real data (bagging algorithms) may help to overcome this issue. We also plan to compare our model with other student models (in a specific domain) both from cognitive sciences and AI, consider for example [8].

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