A tool for implementation of a domain model based on fuzzy relationships

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Abstract— The domain model is one of the important components used by adaptive learning systems to automatically generate customized courses for the learners. In this paper our contribution is to propose a new tool for implementation of a domain model based on fuzzy relationships among concepts. This tool allows the experts and teachers to find the best parameters in order to adapt the learners' differences.

Keywords—Learning path, Fuzzy Sets Theory, Fuzzy relationships, Data mining

I.   INTRODUCTION

The main aim of adaptive learning systems (ALS) is to customize the educational logic developed in their courses; those systems are considered adaptive when they can dynamically change to better suit the learning in response to information collected during the course of learning such as a learner's profile, or achievement test score.

Many adaptive learning systems for education have emerged and have even influenced a number of recent systems (Brusilovsky, 2000). We cite for example APeLS (Conlan et al., 2005), Saxon Phonics system (Duffy, 2005) , INTERBOOK system (Brusilovsky, 1998), the system WELSA (Popescu, 2008), AHA system (De Bra, 1998a), the SmexWeb system (Koch, 2000), the system ELM-ART (Weber et al., 2001), the KOD system (Sampson, 2002), the system calls (Colan 2002), the system Alfanet (Alfanet, 2005), the system Medyna (Behaz, 2008), and the OrPAF system (Yessad, 2009), GRAPPLE project , etc.

Architecture of adaptive learning systems is decomposed into three main models that are required to create or automatically generate customized courses to a learner (De Bra, 2001; Brusilovsky, 2003):
*   Domain Model (DM): represents the concepts as hierarchy of learning and relationships between the concepts

*   Learner Model (LS): describe the learner's profile such as his knowledge, his characteristics and his preference.
*   Adaptation Model (AM): defines the concept selection rules that are used for selecting appropriate concepts from the domain model, as well as, the content selection rules from the media space.

In this paper, we focus on designing domain model based on fuzzy logic approach.

The following section presents an overview of some domain model that used fuzzy logic approach.

II.   OVERVIEW OF SOME EXISTING DOMAIN MODEL BASED ON FUZZY LOGIC APPROACH

Several learning systems build their domain model by using a number of different methods of fuzzy logic (Al-Sarem et al, 2010 and Chu et al., 2010 and Chen and Bai, 2008). Sue et al., 2010, used a two-phase method that extracts the association rules between the skills by applying fuzzy logic to convert the grades learners into three levels of difficulty and construct a learning hierarchy. Bai and Chen, 2010, simplified and improved the latter method in adaptive way.
However, they don't take into account the possibility of using a learning hierarchy predefined by experts of a specific field, and those domain model considered grades obtained by learners during the process learning is a fuzzy notion.

In our previous works (Aajli and Afdel, 2014), we proposed an approach of domain model based on fuzzy logic. The idea behind it combining the hierarchy learning predefined by one expert of a specific field and that developed automatically using the fuzzy logic (Fuzzy Sets Theory), and we consider the relationships of prerequisites between the concepts in the concept map are not definitive and they are fuzzy relationships.

In this paper, we extend this idea by presenting it as a tool implements our domain model based on fuzzy logic and try to answer the following question: what are the best parameters of our model in order to adapt the learners' differences?

Before introducing the tool implements our domain model, the following section describes our approach of domain model based on fuzzy prerequisite relationship.

III.   APPROACH OF DOMAIN MODEL BASED ON FUZZY PREREQUISITE RELATIONSHIP

In this approach, we use a domain model (learning hierarchy) predefined by one or more experts of a specific field. For that we determines in first phase an initial predefined domain model, in second phase we measure the variation of grades of learners, after that we transformed the data by using the fuzzification technique, then in the next phase we mine the association rules between the concepts. In the last two phases we propose to build the final model.
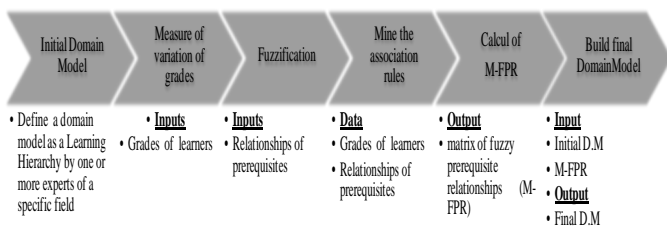

Fig. 1. *Phases of approach* based on fuzzy prerequisite relationship

IV.   A TOOL IMPLEMENTS THE DOMAIN MODEL BASED ON FUZZY PREREQUISITE RELATIONSHIP

A. Membership functions of fuzzy prerequisite relationship

CPR a fuzzy subset of prerequisite relationships that can be classified as a correct prerequisite relationships between concept « i » and concept « j ».

$$CPR = \left\{ \left(k\, , \mu_{CPR}(k) \right) / k \in X \right\}$$

Where:

$\mu_{CPR}(k)$ Is the membership function of CPR, the values of this function present the relevance degree of each link « k » in the fuzzy set CPR.

RPR a fuzzy subset of links that can be classified as wrong prerequisite relationships between concept « i » and concept « j », but can be classified also as a correct prerequisite relationships between concept « j » and concept « i ».

$$RPR = \left\{ \left(k\, , \mu_{RPR}(k) \right) / k \in X \right\}$$

$\mu_{RPR}(k)$ is the membership function of RPR, the values of this function present the relevance degree of each link « k » in the fuzzy set RPR.

The definition of the two membership functions of fuzzy sets $\mu_{CPR}(k)$ and $\mu_{RPR}(k)$ is based on the indicator expressed as « variation of grades of all prerequisite relationships of initial domain model (ΔGrades) »

Where:

$$\mu_{CPR}(k) = \begin{cases} 0 & \text{if } \Delta Grades < S1 \\ \dfrac{-1}{S1}\Delta Grades + 1 & \text{if } S1 \leq \Delta Grades \leq 0 \\ \dfrac{-1}{S2}\Delta Grades + 1 & \text{if } 0 < \Delta grades \leq S2 \\ 0 & \text{if } \Delta Grades > S2 \end{cases}$$

$$\mu_{RPR}(k) = \begin{cases} 0 & \text{if } \Delta Notes < 0 \\ \dfrac{1}{S2}\Delta Notes & \text{if } 0 \leq \Delta Notes \leq S2 \\ \dfrac{-(\Delta Notes + S3)}{S3 - S2} & \text{if } S2 < \Delta Notes \leq S3 \\ 0 & \text{if } \Delta Notes > S3 \end{cases}$$
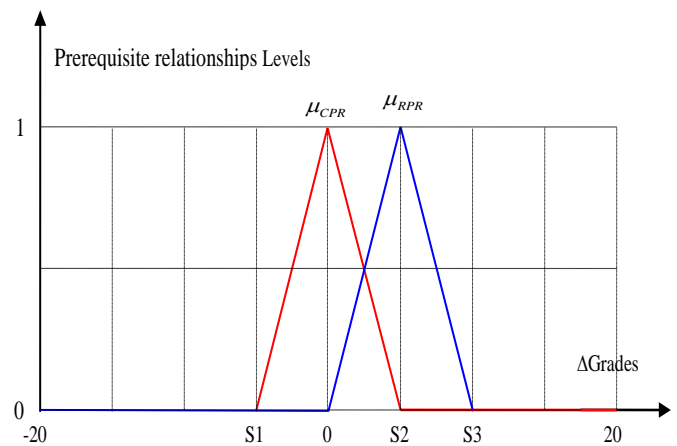

Fig. 2.   membership functions

B. Description of the Tool

The suggested tool is presented as a client-server application where experts in a specific field (Teachers of course) enable:

- Creating a new course (initial domain model) or adding a new concept to the existing courses.
- Adding the learners' grades for each concepts of initial domain model.
- Choose the three thresholds S1, S2 and S3 of the domain model based on fuzzy prerequisite relationship.
- Choose the threshold minimum of prerequisite relationships α_k, this threshold indicates the prerequisite relationships meaningful in the domain model.
- Generation the final domain model

Our tool is an implementation of the course of java programming language.

1. Creating an initial domain model of the course of Java programming language

For this course were selected following 12 concepts:

1) Elementary of Java
2) Objects and Classes
3) Packages
4) Inner Classes
5) Flux I/O
6) Exceptions
7) Inheritance
8) Serialization
9) Interfaces
10) Polymorphism
11) Threads
12) Collections

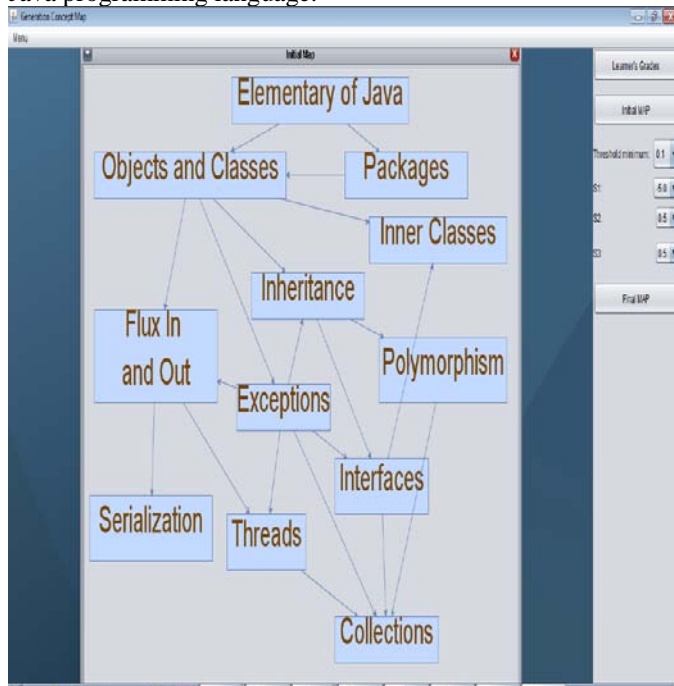Figure below shows the initial domain model of the course of Java programming language:

Fig. 3. Initial domain model of the course of Java

2. Adding the learners' grades

Figure below shows scores of 48 students obtained in the 12 concepts of the course of Java programming language:

Fig. 4. learners' grades

3. Choose the three thresholds S1, S2 and S3

The three thresholds S1, S2 and S3 are defined in collaboration with experts in the field studied.

Based on our experience feedback on course of Java programming language the values the threshold of are chosen as follows:
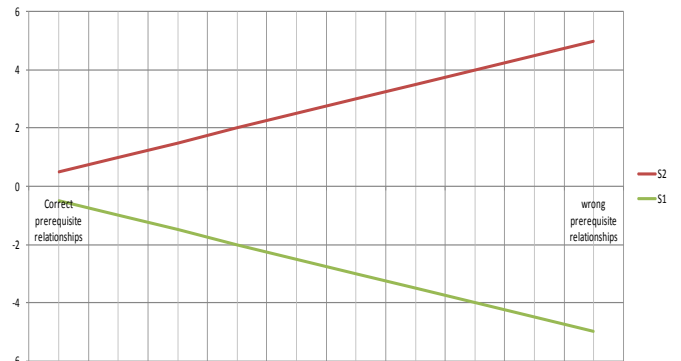

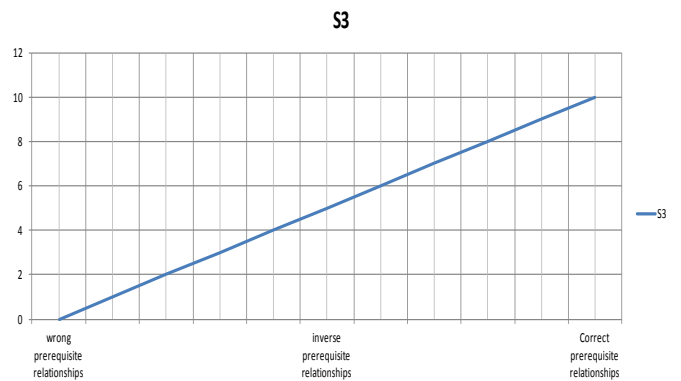Fig. 5. Possible values of threshold S1 & S2

Fig. 6. Possible values of threshold S3

The combination of S1, S2 and S3 show that:

If the absolute values of S1 and S2 tends to 5 points the detection of correct prerequisites relationships are optimal, and if the value of S3 tends to 10 points detection of inverse prerequisites relationship is optimal.

4. Choose the threshold minimum of prerequisite relationships

The threshold minimum of prerequisite relationships α_k, indicates the prerequisite relationships meaningful in the domain model.
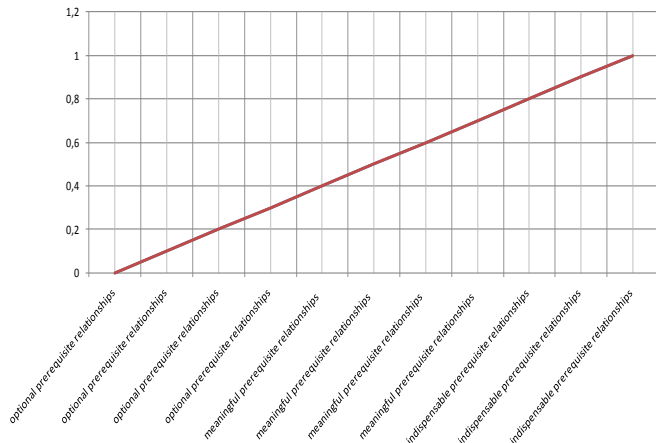

Fig. 7. Possible values of the threshold minimum of prerequisite relationship α_k

The possible values of minimum of prerequisite relationships α_k are in range: $0 \leq \alpha_k \leq 1$:

For example, if we want select the indispensable prerequisite relationship in initial domain model we chose $0,8 \leq \alpha_k \leq 1$.

5. Generation the final domain model

a. Final domain model with:

$\alpha_k = 0,5$
S1 = variation of -5 grades
S2 = variation of 5   grades
S3 = variation of 10 grades

Then the two functions $\mu_{CPR}(k)$ and $\mu_{RPR}(k)$ becomes:

$$\mu_{CPR}(k) = \begin{cases} 0 & \text{if } \Delta Grades < -5 \\ \frac{1}{5}\Delta Grades + 1 & \text{if } -5 \leq \Delta Grades \leq 0 \\ \frac{-1}{5}\Delta Grades + 1 & \text{if } 0 < \Delta grades \leq 5 \\ 0 & \text{if } \Delta Grades > 5 \end{cases}$$

$$\mu_{RPR}(k) = \begin{cases} 0 & \text{if } \Delta Grades < 0 \\ \frac{1}{5}\Delta Grades & \text{if } 0 \leq \Delta Grades \leq 5 \\ \frac{-1}{5}\Delta Grades + 2 & \text{if } 5 < \Delta grades \leq 10 \\ 0 & \text{if } \Delta Grades > 10 \end{cases}$$

And the final domain model of the course of Java programming language is:
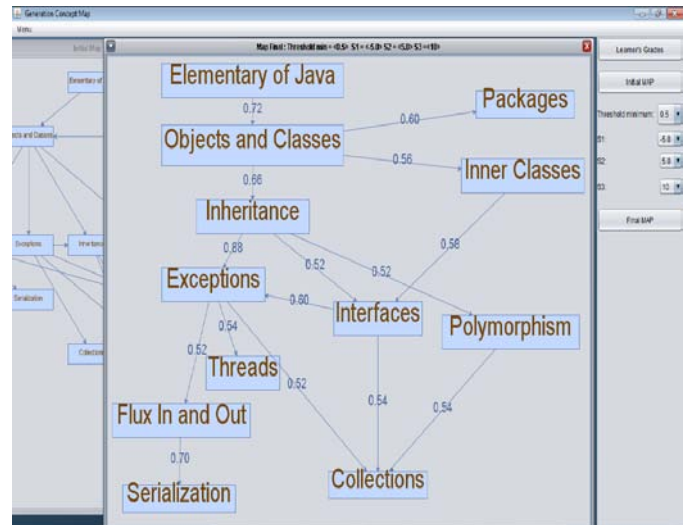

Fig. 8. *Final* domain model of the course of Java programming language (1)

These values of the parameters give the best results in practice.

b. Final domain model with:

$\alpha_k = 0,2$
S1 = variation of -5 grades
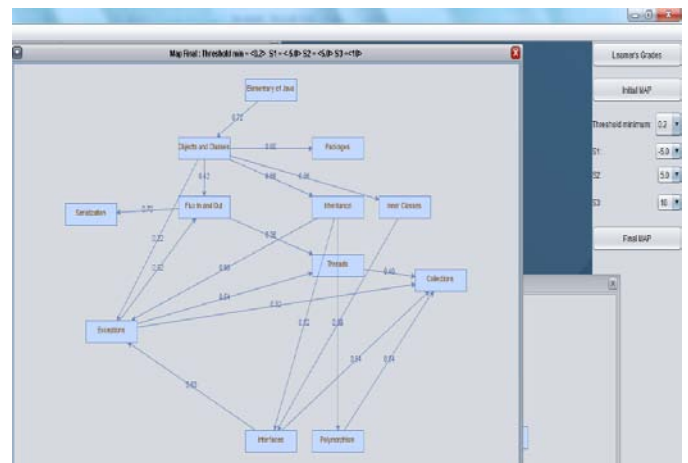S2 = variation of 5   grades
S3 = variation of 10 grades

Fig. 9. *Final* domain model of the course of Java programming language (2)

These parameter values have selected non-significant relationship.

c. Final domain model with:

$\alpha_k = 0,3$
S1 = variation of -3 grades
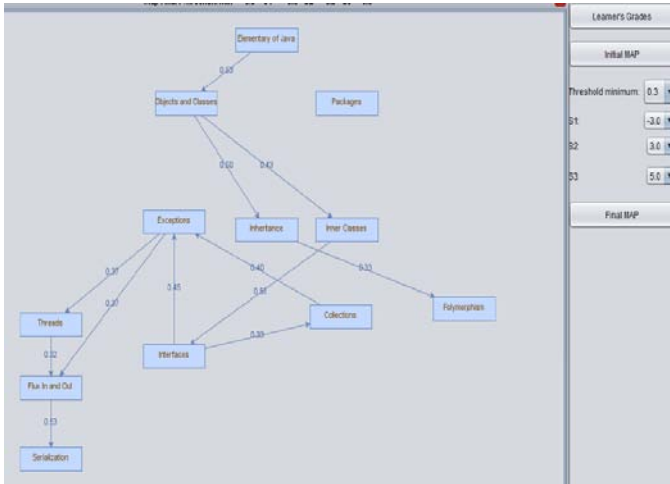S2 = variation of 3   grades
S3 = variation of 5 grades

Fig. 10. *Final* domain model of the course of Java programming language (3)

These parameter values have deleted some important relationships.

V. CONCLUSION

In this paper we present an implementation of a practical application of fuzzy logic techniques to the domain model of a specific field.

This tool allow expert in a specific field to creating an initial domain model, choose the value of the indicator of the prerequisite relationships meaningful in the domain model.
And also allow them to configure the three thresholds of the final domain model.
Based on experimental the values of the parameters that give the best adaption of the learners' differences on the course of Java programming language are:

$\alpha_k = 0,5$
S1 = variation of -5 grades
S2 = variation of 5   grades
S3 = variation of 10 grades.

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