Problem Identification Based on Fuzzy Functions

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Abstract: The creation of knowledge from information can be promoted by proper representations of information which make the inherent logical structure of the information transparent. Since concepts are the basic units of human thought and hence the basic structures of logic, the logical structure of information is based on concepts and concept systems. Methods from the theory of formal concept analysis and frequent set mining are applied for automated extraction of information from students' responses to preliminary tests about their lack of knowledge or misconception of fundamental terms and skills. Personalized recommendations are suggested to each student once possible difficulties in learning a new subject are detected.

Key–Words: Decision support services, uncertainty management

1 Introduction

A single inference procedure (abduction) can operationalize a wide variety of knowledge-level modeling problem solving methods; i.e. prediction, classification, explanation, tutoring, qualitative reasoning, planning, monitoring, set-covering diagnosis, consistency-based diagnosis, validation, and verification, [24].

Association rules are widely used for detecting relationships between variables. Association rules show attribute value conditions that occur frequently together in a given dataset. They deal with statements of the form 'the presence of attributes α and β often also involves attribute γ'. This approach has an application in different fields such as market basket analysis [7], medical research [14], web clickstream analysis [27] and census data [22].

The process of determining the set of association rules that hold in a context can be broken down into two steps - finding all frequent subsets of attributes, and generating confident rules from the frequent itemsets. Traditional approaches to find frequent itemsets rely on a minimum support threshold in order to reduce the amount of candidates they have to work with [12].

Ordered weighted averaging aggregation operators (OWA) provide a parametrized class of mean type aggregation operators, [34] and [35]. Such operators are often used to model linguistically expressed aggregation instructions, [21]. OWA have two important characteristics: attitudinal (orness) and dispersion. The first one is similar to the OR operation when OR is defined as the Max, while the second one illustrates how uniformly the arguments are being used.

This paper aims at finding an efficient way for discovering which specific knowledge each student does not possess in order to successfully start a new course or to proceed with another section in a current subject. Most existing tutoring systems respond to students' mistakes by providing links to a collection of teaching materials. Such an approach does not satisfy the individual needs of each student. We believe in applying a holistic approach that involves looking at the whole system of each student knowledge within an subject rather than just concentrating on single mistakes, lack of knowledge or misconception.

Our goal is to find a way to identify those students who are exposed to a serious danger of not being able to obtain sufficient knowledge and skills in integration due to lack of preliminary knowledge in mathematics. Once these students are identified they will be suggested to take extra classes in mathematics. This will decrease the amount of students failing exams in mathematics as well as the amount of students failing exams in other subjects that require mathematical skills. In addition it will facilitate the process of allocating teaching resources at the beginning of a semester.

The rest of the paper is organized as follows. Section 2 contains definitions of terms used later on. Section 4 describes how we propose to select students that need extra classes and Section 5 is devoted to a system description. Section 6 contains the conclusion of this work.

2 Knowledge, Frequent Sets and Fuzzy Functions

2.1 Knowledge Modeling

The creation of knowledge from information can be promoted by proper representations of information which make the inherent logical structure of the information transparent. Since concepts are the basic units of human thought and hence the basic structures of logic, the logical structure of information is based on concepts and concept systems. Therefore, concept lattices as mathematical abstraction of concept systems can support humans to discover information and then to create knowledge [30].

2.2 Design and Evaluation

A uniform view of different problem solving methods is presented in [9], [10] and [6]. Abductive approach can be used for validation as well since the technique we involves both inference and testing tools. Working in vague and conflicting domains often require application of nonstandard approaches. Therefore abduction can be used for knowledge modeling.

An online application for test design and evaluation of trainees is described in [5]. An interesting analysis of the e-learning technologies used in the Italian universities can be found in [8]. Experience with using multimedia activities to improve the results of university students is presented in [20].

2.3 Concept of a Context

The mathematical preparedness of students embarking upon science and engineering degree programmes has been the subject of close scrutiny over recent years, with disheartening conclusions, [36]. Since mathematics is a key facet of all engineering degree courses it appears also to be one of the reasons for increased dropout rates and poor student progression.

Definition 1 *[13] Let P be a non-empty ordered set. If $sup\{x, y\}$ and $inf\{x, y\}$ exist for all $x, y \in P$, then P is called a* lattice.

In a lattice illustrating partial ordering of knowledge values, the logical conjunction is identified with the meet operation and the logical disjunction with the join operation.

Definition 2 *[29] A* context *is a triple (G, M, I) where G and M are sets and $I \subset G \times M$. The elements of G and M are called* objects *and* attributes *respectively.*

For $A \subseteq G$ and $B \subseteq M$, define

$$A' = \{m \in M \mid (\forall g \in A) \; gIm\},$$

$$B' = \{g \in G \mid (\forall m \in B) \; gIm\}$$

where A' is the set of attributes common to all the objects in A and B' is the set of objects possessing the attributes in B.

Definition 3 *[29] A* concept *of the context (G, M, I) is defined to be a pair (A, B) where $A \subseteq G$, $B \subseteq M$, $A' = B$ and $B' = A$.*

The *extent* of the concept (A, B) is A while its *intent* is B. A subset A of G is the extent of some concept if and only if $A'' = A$ in which case the unique concept of the which A is an extent is (A, A'). The corresponding statement applies to those subsets $B \in M$ which is the intent of some concepts.

The set of all concepts of the context (G, M, I) is denoted by $\mathfrak{B}(G, M, I)$.

Definition 4 *[29] $\langle \mathfrak{B}(G, M, I); \leq \rangle$ is a complete lattice and it is known as the* concept lattice *of the context (G, M, I).*

2.4 Frequent Sets

Frequent sets are sets of attributes that occur often enough to deserve further consideration.

Definition 5 *[12] An association rule $Q \to R$ holds if there are sufficient objects possessing both Q and R and if there are sufficient objects among those with Q which also possess R.*

The complexity of mining frequent itemsets is exponential and algorithms for finding such sets have been developed by many authors such as [3] and [12].

A context (G, M, I) satisfies the association rule

$$Q \to R_{minsup, minconf}$$

with $Q, R \in M$, if

$$sup(Q \to R) = \frac{|(Q \cup R)'|}{|G|} \geq minsup,$$

$$conf(Q \to R) = \frac{|(Q \cup R)'|}{|Q'|} \geq minconf$$

provided *minsup* $\in [0, 1]$ and *minconf* $\in [0, 1]$.

The ratios

$$\frac{|(Q \cup R)'|}{|G|}$$

and

$$\frac{|(Q \cup R)'|}{|Q'|}$$

are called, respectively, the *support* and the *confidence* of the rule $Q \to R$. In other words the rule $Q \to R$ has support $\sigma\%$ in the transaction set $\mathcal{T}$ if $\sigma\%$ of the transactions in $\mathcal{T}$ contain $Q \cup R$. The rule has confidence $\psi\%$ if $\psi\%$ of the transactions in $\mathcal{T}$ that contain Q also contain R.

Mining association rules is addressed in [2]. Algorithms for fast discovery of association rules have been presented in [1], and [33]. Association rules have applications in different fields such as market basket analysis [7], medical research [14], web clickstream analysis [27], and census data [22].

2.5 Fuzzy Functions

Fuzzy reasoning methods are often applied in intelligent systems, decision making and fuzzy control. Some of them present a reasoning result as a real number, while others use fuzzy sets. Fuzzy reasoning methods involving various fuzzy implications and compositions are discussed by many authors, f. ex. [4], and [12].

Definitions of fuzzy sets and fuzzy functions are taken from [31].

Definition 6 *Let X be a space of points (objects), and $x \in X$ being a generic element. A fuzzy set (class) A in X is characterized by a membership (characteristic) function $f_A(x)$ which associates with each point in X a real number in the interval* $[0, 1]$.

The value of $f_A(x)$ represents the "grade of membership" of x in A. This in contrast to the classical set theory where a membership function takes one of the two values 1 and 0, an element belongs the set or it does not.

The *sum-of-1-criterion* [19] states that

$$\Sigma_{i \in M_i} m_i(x) = 1, \quad \forall x \in \chi$$

where $M_i, i = 1, ..., k$ denotes all possible membership terms $\{m_i, i = 1, ..., k\}$ of a fuzzy variable in some universe of discourse χ.

An affiliation value α to a concept (A, B) is defined as

$$\alpha(A, B) = \frac{\Sigma_{o \in A, f \in B} m_{of}}{|A| \cdot |B|}$$

The affiliation value represents the relative extent to which an object belongs to this concept or an attribute is common to all objects in the concept.

In the derived graph, also known as a Hasse diagram, i.e. in the concept lattice each vertex represents a concept. The concepts are arranged hierarchically in this concept lattice, i.e. the closer a concept is to the supremum, the more attributes belong to it. Moving from one vertex to a connected vertex which is closer to the supremum means moving from a more general to a more specific description of the attributes if an object appears in both concepts.

3 Aggregation Operator

The problem of aggregating a set of numerical readings in order to obtain a mean value is addressed in [35].

If $x_1, x_2, ..., x_n$ is a set of readings then the aggregating process is denoted as

$$Agg(x_1, x_2, ..., x_n) = a$$

The aggregation operator has the following properties

1. *A natural boundary*

   $$Agg(a) = a$$

   It means that in the case of a single reading the aggregated value is taken to be that single reading.

2. *Self-identity*

   If
   $$Agg(x_1, x_2, ..., x_n) = a$$
   then
   $$Agg(x_1, x_2, ..., x_n, a) = Agg(x_1, x_2, ..., x_n) = a$$

   It implies that adding an element equal to an already existing value does not change the aggregation value.

3. *Monotonicity*

   $Agg(x_1, x_2, ..., x_n) \geq Agg(y_1, y_2, ..., y_n)$,
   $x_i \geq y_i, \forall\ 1 \leq i \leq n$

Agg is called idempotent if

$Agg(x_1, x_2, ..., x_n) = a$ whenever $x_i = a\ \forall\ 1 \leq i \leq n$ and (1) and (2) hold.

Idempotencity does not imply self-identity, [35].

If $Agg(x_1, x_2, ..., x_n)$ has a natural boundary and self-identity, is monotonic and idempotent, then

$$a \leq Agg(x_1, x_2, ..., x_n) \leq b$$

where $a = Min[x_i]$ and $b = Max[x_i]$

Theorem 7 *[35] If Agg is a monotonic and self-identity operator then*

$$\begin{array}{rl} Agg(x_1, ..., x_n, K) & \geq Agg(x_1, ..., x_n), \text{ if} \\ K & > Agg(x_1, ..., x_n) \end{array}$$

and

$$\begin{array}{rl} Agg(x_1, ..., x_n, K) & \leq Agg(x_1, ..., x_n), \text{ if} \\ K & < Agg(x_1, ..., x_n) \end{array}$$

Theorem 7 implies that addition of new elements with values greater than the current mean value results in an increased mean value and addition of new elements with values smaller than the current mean value results in an decreased mean value.

Theorem 8 *[35] If Agg is an idempotent and monotonic operator, not equal to the Max or Min operators then Agg is not associative.*

Theorem 8 implies that if Agg is idempotent and monotonic its extension to a greater cardinality does not have to be done in a consistent way. At the same time if Agg has a natural boundary and self-identity than by Theorem 7 certain requirements for consistency have to be satisfied while extending its cardinality.

The weights must satisfy the following conditions

$$\sum_{j=1}^{n} w_{nj} = 1 \;\forall\; n \text{ and } w_{nj} \geq 0 \;\forall\; n, j$$

For the case with n arguments

$$Agg(x_1, ..., x_n) = \sum_{j=1}^{n} w_{nj} x_n$$

The weights w_{nj} are uniquely determined by the formula

$$w_{ni} = w_{n1} \left(\frac{1}{w_{i,1}} - \frac{1}{w_{i-1,1}} \right), \;\; 2 \leq i \leq n$$

and the ratio

$$\frac{w_{n1}}{w_{n-1,1}}$$

between the first element in the current iteration and the first element in the previous iteration, [35].

Another approach for calculating the weights w_{nj} involves the Lukasiewicz t-conorm $S(x_1, ..., x_n)$ [15]

$$S(x_1, ..., x_n) = Min[1, \sum_{i=1}^{n} x_i]$$

Thus

$$w_{nj} = \frac{S_j - S_{j-1}}{S_n}$$

where

if $S_j < 1$ then $w_{nj} = \frac{x_j}{S_n}$

if $S_{j-1} \geq 1$ then $w_{nj} = 0$

if $S_j = 1, S_{j-1} < 1$ then $w_{nj} = 1 - S_{j-1}$.

By θ we denote the threshold for membership values above which an entry is regarded as significant, as in [19]. This is achieved by computing the arithmetic mean of all entries within a column and take it as a threshold.

4 Correlations

At the beginning of a semester students take a test with mathematical problems. The test results show a student's tendency to fail, possession of good knowledge or very good knowledge related to operations with fractions, logarithmic functions and trigonometrical functions. Our further work aims at finding out whether a student belongs to a concept containing the attribute failure in the mathematical operation integration. If affirmative the student is strongly advised to attend additional mathematical classes. The suggested approach is not limited to concepts containing the attribute failure in integration only. On the contrary, it can show to which concept any particular student belongs to.

Based on real data from previous years we first prepare Table 1 that illustrates correlations between students' preliminary knowledge and already obtained knowledge and skills in integration. Using formal concept analysis we can extract all concepts based on the data from Table 1 and build a corresponding concept lattice, see Fig 1. Concept lattice illustrating the path for the attribute If is in Fig 2.

In Table 2 the significant entries, i.e. those with values not smaller than the column's θ, are denoted by '$\star$'. We pay particular intention on the concepts that contain failure in integration (If).

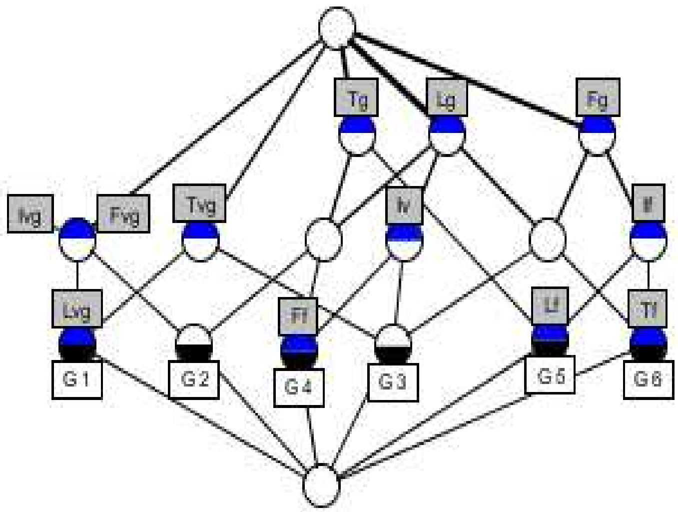

Figure 1: Concept lattice

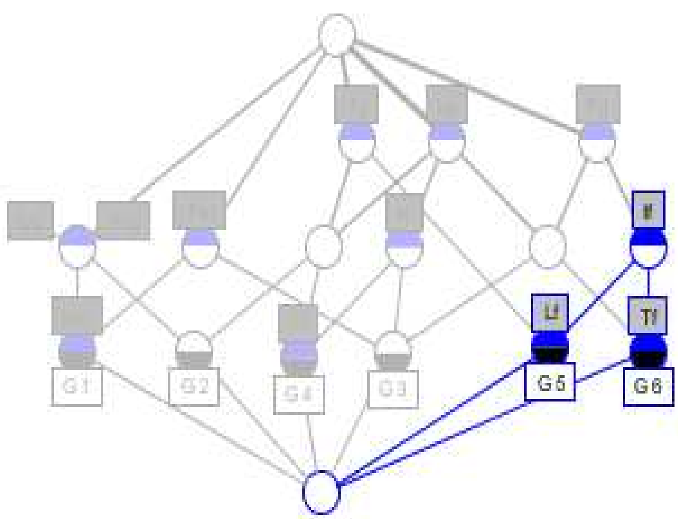

Figure 2: Concept lattice illustrating the path for the attribute If

Table 1: Context for students groups

	F			L			T			I		
	Ff	Fg	Fvg	Lf	Lg	Lvg	Tf	Tg	Tvg	If	Ig	Ivg
G1			$\star$			$\star$			$\star$			$\star$
G2			$\star$		$\star$			$\star$				$\star$
G3		$\star$			$\star$				$\star$		$\star$	
G4	$\star$				$\star$			$\star$			$\star$	
G5		$\star$		$\star$				$\star$		$\star$		
G6		$\star$			$\star$		$\star$			$\star$		

Table 2: Context for students groups with numerical values

	F			L			T			I		
	Ff	Fg	Fvg	Lf	Lg	Lvg	Tf	Tg	Tvg	If	Ig	Ivg
G1			$1^\star$	0.3	0.1	$0.6^\star$	0.1	0.1	$0.8^\star$	0.1	0.2	$0.7^\star$
G2		0.1	$0.9^\star$	0.1	$0.7^\star$	0.2	0.1	$0.7^\star$	0.2	0.2	0.3	$0.5^\star$
G3	0.2	$0.7^\star$	0.1	0.2	$0.6^\star$	0.2	0.1	0.4	$0.5^\star$	0.3	$0.5^\star$	0.2
G4	$0.7^\star$	0.2	0.1	0.3	$0.6^\star$	0.1	0.3	$0.5^\star$	0.2	0.4	$0.5^\star$	0.1
G5	0.2	$0.6^\star$	0.2	$0.8^\star$	0.1	0.1	0.4	$0.5^\star$	0.1	$0.7^\star$	0.3	0.1
G6	0.2	$0.6^\star$	0.2	0.3	$0.6^\star$	0.1	$0.8^\star$	0.2		$0.8^\star$	0.2	
θ	0.22	0.38	0.41	0.33	0.45	0.22	0.3	0.4	0.3	0.41	0.33	0.26
St 1	0.4	0.5	0.1	0.5	0.5	0	0.7	0.3				
St 2	0.2	0.6	0.2	0.6	0.2	0.2	0.1	0.8	0.1	0.33		

The following possibilities are further discussed.

4.1 A Case with One Concept

In this case student's results belong to one concept having If as an attribute or to a unique set of concepts having If as an attribute.

Suppose there is only one concept having If as an attribute. A student belongs to that concept if the attributes' values, related to his/her test result, belong to the corresponding attributes' intervals values of the concept (all attributes' values except If because the student has not been tested on integration).

If there are several concepts having If as an attribute we apply the same rule like the one with a single concept but we work with attributes' intervals values of the set of all concepts having If as an attribute (again all attributes' values except If because the student has not been tested on integration).

Example 9 *The test results of a new student ($St1$, Table 2) belong to the intervals determined by the concept*

$$I = \{Fg, If\}, \;\; E = \{G5, G6\}.$$

Therefore, the If value of $ST1$ belongs to the interval $[0.7, 0.8]$ where $\theta(If) = 0.4$. The student is therefore advised to take additional classes since $\theta(If) = 0.4$ is smaller than values in the interval $[0.7, 0.8]$.

4.2 A Case with Several Concepts

Suppose a student's results belong to more than one concept where at least one concept does not have If as an attribute. The value of the attribute $If(s)$ for that student is calculated according to the function

$$If(s) = \frac{\Sigma If(C_i) \cdot \alpha_{C_i}}{l}$$

where

- C_i are the concepts that have the same Ifvalues as the student,
- α_{C_i} are the corresponding affiliation values, and
- l is the number of the involved concepts.

If the student's results are not equal to any of the known attributes' we take the concept that has the closest attribute value. In case there are several concepts with attribute values equal to the one we are interested in, we consider all these concepts.

Example 10 *We apply the suggested approach to the tests' results of another new student ($St2$). The test results of the student $St2$, (Table 2) belong to the concepts with objects $G2, G3, G5$, and $G6$. The affiliation values for concepts with objects $G2, G3, G5$, and $G6$ are then obtained.*

The sum-of-1-criterion is applied while values of membership functions in Table 2 are determined. The order of the corresponding $If(St2)$ value is then calculated to be 0.33.

Since $0.33 < 0.41 = \theta(If)$, the second student can proceed normally without the need to attend additional classes.

4.3 Weights

Suppose new groups of students are added to the database. The value of the attribute $If(s)$ for a student is then calculated according to the function

$$If(s) = \frac{\Sigma If(C_i) \cdot \alpha_{C_i} \cdot w_{n,If}}{l}$$

where $w_{n,if}$ is the weight obtained after the nth interaction for the attribute If.

The weights $\frac{w_{n1}}{w_{n-1,1}}$ are determined via normalization of the number of elements in the two iterations:

$n-1$th iteration - ϕ elements
nth iteration - ψ elements

$$w_{n-1,1} = \frac{\phi}{\phi + \psi},$$

$$w_{n,1} = \frac{\psi}{\phi + \psi}$$

4.4 Association Rules

The following $Q \rightarrow R$ association rules have been derived from the relations in Table 1

- – Q: a student has good knowledge about trigonometrical functions
  – R: the student has good knowledge about logarithms
  support $Q \rightarrow R$ = 33%
  confidence $Q \rightarrow R$ = 66%
- – Q: a student has good knowledge about fractions
  – R: the student has good knowledge about logarithms
  support $Q \rightarrow R$ = 33%
  confidence $Q \rightarrow R$ = 66%

- – Q: a student has good knowledge about fractions
  – R: the student has insufficient knowledge (failing) about integration
  support $Q \to R$ = 33%
  confidence $Q \to R$ = 66%
- – Q: a student has good knowledge about logarithms
  – R: the student has good knowledge about trigonometrical functions
  support $Q \to R$ = 33%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about logarithms
  – R: the student has good knowledge about integration
  support $Q \to R$ = 33%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about logarithms
  – R: the student has good knowledge about fractions
  support $Q \to R$ = 33%
  confidence $Q \to R$ = 50%
- – Q: a student has very good knowledge about fractions and integration
  – R: the student has very good knowledge about logarithms and trigonometrical functions
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about logarithms and trigonometrical functions
  – R: the student has very good knowledge about fractions and integration
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about logarithms and integration
  – R: the student has very good knowledge about trigonometrical functions and good knowledge about fractions
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about fractions and logarithms
  – R: the student has very good knowledge about trigonometrical functions and good knowledge about integration
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about fractions and insufficient knowledge (failing) about integration
  – R: the student has good knowledge about trigonometrical functions and insufficient knowledge (failing) about logarithms
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about fractions and insufficient knowledge (failing) about integration
  – R: the student has good knowledge about logarithms and insufficient knowledge (failing) about trigonometrical functions
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has very good knowledge about integration
  – R: the student has very good knowledge about fractions, logarithms and trigonometrical functions
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has insufficient knowledge (failing) about integration
  – R: the student has good knowledge about fractions and trigonometrical functions, and insufficient knowledge (failing) about logarithms
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has very good knowledge about trigonometrical functions
  – R: the student has very good knowledge about fractions, logarithms and integration
  support $Q \to R$ = 16%
  confidence $Q \to R$ = 50%
- – Q: a student has good knowledge about trigonometrical functions
  – R: the student has good knowledge about fractions and insufficient knowledge (failing) about both logarithms and integration

$$\textit{support}\ Q \rightarrow R = 16\%$$
$$\textit{confidence}\ Q \rightarrow R = 33\%$$

5 System Description

A system prototype is build as a Web-based application using Apache HTTP server [37], mod_python module [38] and SQLite database [39]. The mod_python module provides programmable runtime support to the HTTP server using Python programming language. The whole application components are

1. Web-based users interface,
2. application logic, and
3. database interaction were written in Python.

The users, i.e. expert tutors, teachers, and students interact with the system using Web forms. Before any interaction with the system can take place, a user needs to be authenticated first. Experts and teachers can submit and update data, while students can only view information.

For a particular subject, an expert tutor will first submit data that will be used to construct a data table.

The system will then check that there are no duplicate attribute combinations and insert the context data in to the database.

The system provides recommendations on whether or not a student needs to take additional classes (courses) based on fuzzy dependencies.

6 Conclusion

Fuzzy systems provide the opportunity for modeling of conditions that are imprecisely defined. Various systems can be modeled and evaluated using fuzzy reasoning.

The suggested approach turns out to be quite useful for providing timely recommendations to students who might have serious problems studying a particular subject due to lack of sufficient preliminary knowledge. Even though the approach has been discussed in relation to studying one subject only, we believe that it can be applied to other subjects that require preliminary knowledge and or skills.

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