

Fuzzy modeling and evaluation of an ITM user

Luigi Di Lascio - Enrico Fischetti - Antonio Gisolfi

Dipartimento di Matematica e Informatica
Università di Salerno
E-mail: gisolfi@dia.unisa.it



Abstract
A suitable model of an ITM user is presented in terms of concepts and mastery of abilities. Then it is shown how, via a fuzzy algebra, it is possible to model and evaluate user's cognitive and psychological states.

Keywords
Fuzzy sets, fuzzy variable, linguistic variable, fuzzy algebraic structure, evaluation, linguistic approximation.

Introduction
Beginning in about 1960, Artificial Intelligence researchers attempted to build computerized systems that could perform in the same way as human beings. In the 1970s researchers attempted to develop intelligent computer-assisted instruction systems, so-called ITSs (acronym for Intelligent Tutoring Systems). ITSs take into consideration the individual differences of each user and provide dynamic individualization of instruction. However, even with the unquestionable success of ITSs in certain environments [Sleeman and Van Lehn, 1982, Katz *et al.*, 1992, Ohlsson, 1987], the overall performance of these systems were not adequate [Self, 1990]. ITMs (Intelligent Tutoring Multimedia) are the evolutionary successors of ITSs and they heavily rely on the recent dramatic advances in the field of multimedia. Although the

human teachers. The result of bringing together multimedia devices and AI technology represents a significant improvement in the performance of the systems that can provide more individualized instruction. This adaptation to individual students has been made possible through the development of certain modules within an ITM. A vital role is played by the *user model* module implementing the *user model* by tailoring the system's behavior to the user's needs. User modeling aims to construct a model in order to make predictions about user's behavior, so that the system can recognize misconceptions and problems, identify them and suggest suitable solutions. The user model makes hypotheses about user's conceptions, reasoning strategies employed to achieve current knowledge state.

It is apparent that the task of obtaining information about the user and inferring conclusions on the basis of what is supplied is very exacting, many interdisciplinary problems are to be tackled, and only partial solutions can be attained. However, this fact underlines the importance of improving knowledge engineering techniques to more effectively capture and portray the user's knowledge. This module plays a crucial role in the overall operation and performance of the entire system, keeping a running "snapshot" of the user and allowing

modeling problems can be found in [Silovsky, 1996].

Note that the learning process is inherently non-deterministic and this circumstance induces the necessity of managing uncertainty. The uncertainty stems from several reasons, we just mention ambiguity and multiplicity. The ambiguity is due to the fact that user's errors are anyway personal mistakes and thus the same error can be committed, in different users, by different reasons. Multiplicity, in turn, is related to the fact that a wrong behavior in order to solve a specific problem can depend on several misconceptions or skill deficiencies.

The use of fuzzy logic represents an interesting solution to the problem of dealing with uncertainty. In fact, in such way one can manage relatively different situations that the classical valued logic is unable to cope with. The basic principles of fuzzy theory are presented in [Klir, 1988] and several applications to teaching and learning problems are in [Liou and Wang, 1994, Grice-Baumont and Derognat, 1994, Sawaragi et al., 1991, Hawkes et al., 1990, Biswas, 1995].

This paper is organized as follows. Section 2 presents the basic results of fuzzy theory. Next Section 3 shows how it is possible to represent user's cognitive states and psychological characteristics through suitable strings. Section 4 presents the main features of a fuzzy algebraic structure that manages user representing strings. In Section 5 the concept of fuzzy score is introduced in Section 6 it is shown that the fuzzy structure can be utilized to monitor the evolution of the learning process. Section 7 tackles the problem of managing the learning process and last Section 8 emphasizes the expressive power of the model as compared with other educational taxonomies.

The theory of fuzzy sets

Let U be a classical not-empty set, a fuzzy subset

$\mu_A: U \rightarrow [0, 1]$. The function $\mu_A(x)$ is viewed as an extension of the concept of characteristic function. Alternatively, a fuzzy set can be denoted as follows: if $A = \{x_1, x_2, \dots, x_n\}$ is a finite set and is represented as $x_1 + x_2 + \dots + x_n$ of its elements, then $A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n$. If A is infinite then $A = \bigcup_{x \in U} \mu_A(x)/x$, where the symbol slash links each element of U with its membership grade. In both cases, a fuzzy set on U is completely characterized by the collection $\{(x, \mu_A(x)) \mid x \in U\}$.

Let $U = \{a, b, c\}$ be a set of persons. Suppose that the individual a weighs 85 kilos, b 90 kilos and c 130 kilos. This is a possible set for fat people:

$$A = 0.49/a + 0.53/b + 0.85/c.$$

A fuzzy variable is a triple $(Vf, U, R(Vf))$ where Vf is the name of the variable, U is the universe of discourse, u denotes the generic element of U and $R(Vf; u)$ is a fuzzy subset of U . For example "budget" could be the name of a fuzzy variable where $U = [0, \infty]$, and $R(Vf; u) = \{(u, s(u) = 1) \mid u \in [0, 100]\} \cup \{(u, s(u) = ((u-100)/200)^{-1}) \mid u \in [100, \infty]\}$.

A linguistic variable is, in turn, a quintuple (T, U, g, m) where Vl is the name of the variable, T is the set of values or linguistic terms of Vl , U is the universe of discourse, g is a syntactic rule (a grammar) capable of generating such linguistic values and m is a semantic rule that attaches to each element t of T its meaning $m(t)$, namely a fuzzy set on U . For example the values of the linguistic variable "age" could be young, rather young, old, very old, and so on. Each value is the name of a fuzzy variable on the universe of discourse $U = [0, 100]$. [Zadeh, 1975]. We note that adverbs such as "very", "more", "less" are called linguistic modifiers [Zadeh, 1975] because they modify the meaning of terms such as "old" and "young" which are generators of

When one gets the triangular functions, i.e. the regular symmetric numbers that are the fuzzy sets used to mathematize the terms of a linguistic variable [Pedrycz, 1994]. Lakoff [Lakoff, 1973] has shown the necessity to define the terms of a linguistic variable beginning from the generators. The following function is capable of representing the term set of a linguistic variable:

$$\mu(x) = \frac{2}{b-a} \cdot \frac{(x-a)(b-x)}{(b-a)} \cdot I_{[a, (a+b)/2]}(x) + \frac{2}{b-a} \cdot \frac{(x-a)(b-x)}{(b-a)} \cdot I_{[(a+b)/2, b]}(x),$$

$\mu \subseteq \mathbb{R}$, $a, b \in U$,

$I_{[x_1, x_2]}(x) = 1$ if $x \in [x_1, x_2]$

otherwise 0.

The terms of the linguistic variable "evaluation" are: good, fairly good, not good, very good; according to what suggested by [Schwartz, 1989], in the following Sections we use for this variable a sequence of values adjacent and uniformly distributed, rather than an infinite sequence of values. If one wishes to use n terms for evaluation, the i -th term is the fuzzy set with membership function different from zero on the interval $[(\text{Max}/n \cdot i, \text{Max}/n \cdot (i+1))/2]$, where $x \in \text{Max} \subseteq \mathbb{R}$ and $\text{Max} = \text{highest possible rating}$. The element of the variable "evaluation" can also be denoted by the triple $[a, c, b]$ where $a = (a+b)/2$ and $\mu(x) = 0$, if $x \leq a$, $\mu(x) = 1$, $\mu(x) = 0$ if $x \geq b$ [9].

Fuzzy modeling of an ITM user

Fuzzy sets can be used to model the knowledge of a concept by a generic user. In fact, introducing the notions of linguistic variable and fuzzy variable one can:

- model the inherent vagueness about the knowledge of a concept
- produce dynamically new terms (fuzzy labels) of the linguistic variable, using suitable modifiers
- obtain a rich descriptive structure of the user's cognitive, psychological and mental states

In fact, we propose that the user's cognitive state be represented by a string of the type:

$$a_n^{\alpha_n} a_{n-1}^{\alpha_{n-1}} \dots a_1^{\alpha_1}$$

where the elements of the sets $\{a_i\}$ are didactic goals related to a specific navigation within the ITM, whereas the elements $\{\alpha_i\}$ are fuzzy variables, namely values of a linguistic variable.

Let $\{C_i\}$ be the set of concepts related to the domain of the knowledge domain present in the ITM and let $\{O_i\}$ be the set of goals. We say that the mastery of the concept C_i is very good if the user, interacting with the system, generates a string $[O_{i1}, O_{i2}, \dots, O_{in}]^{vg}$ where the label vg denotes the value "very good". In general, a string such as the following represents and singles out different learning levels for each concept related to a specific concept:

$$[O_{i1}, \dots, O_{ik}]^{\alpha_n} [O_{i(k+1)}, \dots, O_{i(k+2)}, \dots, O_{ih}]^{\alpha_{n-1}} \dots [O_{i(h+1)}, \dots, O_{in}]^{\alpha_1}$$

where $\{\alpha_n\}$ are the values of the linguistic variable "evaluation".

Of course the user representation can be enriched by taking into account other variables such as the psychological state. Such state can be evaluated using the linguistic variables "attention" and "interest" associated to each node n_i visited by the user during the navigation within the ITM. In this case the elements $\{n_i\}$ are the hypermedia nodes and the labels $\{a_i\}$ are the values of the linguistic variables. For example, a couple such as (node k , very interested) could mean that the user, during the visit of the node k , has been deeply involved. In this way the learning style of a specific user can be represented by a string of linguistic variables such as the average length of the navigation path or the average navigation time for

actions, choice of a specific hypertextual link, opening on a concept, request of an example, omission of a topic already examined, access to data base. Such actions can involve one or more elements in the hypertext network and can be linked with a specific semantics, i.e. each action can be interpreted in order to get information about user's cognitive state. In such way the system can adapt its behavior to user's needs.

The following table summarizes the possible actions. To each element describing the model, "attached" the functions and variables therein used.

- Cognitive state:
 - Right translation
 - Left translation
 - Comparison
 - Change in learning states
 - Distance between cognitive states
- Psychological state:
 - Attention
 - Interest
- Base orientation:
 - Peak
 - Peak difference
 - Per cent right translation
 - Per cent left translation
- Learning styles:
 - Average length of deepening path
 - Average duration of node visits
 - Average duration of a tutoring session

When chosen the linguistic variable for evaluating cognitive states, the table shows the translations that state changes in the values of the linguistic variable. Each architectural element is linked with its own functions and linguistic variables. Each linguistic variable and each function can be interpreted depending upon the type and strength of evidence that appears in a user action. In the present work we limit our investigation to the variable "cognitive state" previously introduced.

of attributes used to classify the elements. We denote with $\alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_n$ the numbers that represent the elements of the variable evaluation. $Vt. a_{ij} = A_i^{-1}(\alpha_j)$ is the evaluation of the element α_j with respect to the attribute A_i belonging to \mathcal{A}_i . The string

$$A = \alpha_n \quad \alpha_{n-1} \quad \dots \quad \alpha_1$$

is the classification of U with respect to the attribute A_i [Gisolfi, 1992, Gisolfi and Nunez, 1993, Di Lascio *et al.*, 1998]. The symbols a_i denote the *first parts* of the string whereas α_n are the *second parts*.

Given the strings

$$A = a_n \quad a_{n-1} \quad \dots \quad a_1$$

$$\text{and } B = b_m \quad b_{m-1} \quad \dots \quad b_1$$

with $n \geq m$, the operation Π , commutative and associative, associates with A and B the string

$$\begin{aligned} & (a_n \quad a_{n-1} \quad \dots \quad a_1) \Pi \\ & (b_m \quad b_{m-1} \quad \dots \quad b_1) = \\ & = c_{m+n-1} \quad c_{m+n-2} \quad \dots \quad c_1 \end{aligned}$$

The operation Π splits in two operations: the first is denoted by $*$ and acts upon first parts of the string, the second with \bullet and acts on second parts. The traditional subsets c_i and the fuzzy numbers γ_i are obtained by applying the operators $*$ and \bullet respectively.

The operation for the first parts is defined as follows:

$$c_i = \begin{cases} a_{i-j+1} \cap b_j, & \text{if } 1 \leq i \leq m-1 \\ a_{i-j+1} \cap b_j, & \text{if } m \leq i \leq n-1 \\ a_{i-j+1} \cap b_j, & \text{if } n \leq i \leq m+n \end{cases}$$

where \cup and \cap are the usual set-theoretic operations defined on the power set $P(U)$. This operation has the following properties:

Existence of the null element, namely U.

The operation for the second parts, in turn, is defined as follows:

$$\alpha_{n-1} \dots \alpha_1 \bullet (\beta_m \beta_{m-1} \dots \beta_1) = \gamma_{m+n-1} \gamma_{m+n-2} \dots \gamma_1$$

where:

$$\begin{aligned} & 1/(k_1+k_2) d_i * \sum_{j=1 \dots i} d_{2j} * d_{1i-j+1} * \\ & (k_1 * \alpha_{i-j+1} + k_2 * \beta_j), 1 \leq i \leq m-1 \\ = & 1/(k_1+k_2) d_i * \sum_{j=1 \dots m} d_{2j} * d_{1i-j+1} * \\ & (k_1 * \alpha_{i-j+1} + k_2 * \beta_j), m \leq i \leq n-1 \\ & 1/(k_1+k_2) d_i * \sum_{j=i-n+1 \dots m} d_{2j} * \\ & d_{1i-j+1} * (k_1 * \alpha_{i-j+1} + k_2 * \beta_j), \\ & n \leq i \leq m+n-1 \end{aligned}$$

and the values d_j are obtained as

$$d_i = \sum_{j=1 \dots i} d_{1j} * d_{2i-j+1}$$

In this operation the indices k_1 and k_2 , respectively for A and B, and the arrays d_{1i} ($i=1..n$) and d_{2j} ($j=1..m$), give the distributivity of the operation \bullet with respect to \cup . The indices d_{1i} and d_{2j} represent, respectively for the first and the second string, the number of sets for which the union has been carried out in order to get the i -th class; the indices k_1 and k_2 denote the number of sets whose intersection has produced such sets.

The operation \bullet is closed in the set of numbers defined in $[0,1]$, is associative, commutative and preserves the ordering of fuzzy numbers.

Example

Consider the following matrix (concept that can be viewed as representative cognitive state of an ITM user:

	C1	C2	C3
O1	g	i	q
O2	i	g	g
O3	i	q	q
O4	s	s	q
O5	s	s	s

We can write:

$$\begin{aligned} C_1 &= [O_1]^g [-]^q [O_4, O_5]^s [O_2, O_3]^i \\ C_2 &= [O_2]^g [O_3]^q [O_4, O_5]^s [O_1]^i \\ C_3 &= [O_2]^g [O_1, O_3, O_4]^q [O_5]^s [-]^i \end{aligned}$$

Let $U = [0, 1]$ and suppose that
 $g(\text{ood}) = [0.8, 1, 1]$,
 $q(\text{uite good}) = [0.5, 0.7, 0.9]$,
 $s(\text{ufficient}) = [0.2, 0.4, 0.6]$,
 $i(\text{nsufficient}) = [0, 0, 0.2]$.

Multiplying the first parts:

$$C_1 * C_2$$

	[O1]	[-]	[O4, O5]	[O2, O3]
[O2]	[O3]		[O4, O5]	[O1]
[-]	[O1]	[-]	[-]	[-]
	[-]	[O4, O5]	[-]	

$C_1 * C_2 * C_3$

		[-]	[-]	[-]	[O1,O2]	[O3,O4,O5]	[-]	[-]
					[O2]	[O1,O3,O4]	[O5]	[-]
		[-]	[-]	[-]	[-]	[-]	[-]	[-]
	[-]	[-]	[-]	[-]	[O5]	[-]	[-]	[-]
[-]	[-]	[-]	[O1]	[O3,O4]	[-]	[-]		
[-]	[-]	[O2]	[-]	[-]	[-]			
[-]	[-]	[O2]	[O1]	[O3,O4]	[O5]	[-]	[-]	[-]

$s C_1 * C_2 * C_3 =$

$[-] [-] [O2] [O1] [O3,O4] [O5] [-] [-] [-]$

(multiplying the second parts

$= C_1 * C_2 = (g, q, s, i) * (g, q, s, i) =$

$h_6, h_5, h_4, h_3, h_2, h_1)$

note that: $dC_1 = dC_2 = (1, 1, 1, 1, 1, 1, 1)$;

$C_1 = K C_2 = 1$;

$d H_1 = 1, d H_2 = 2, d H_3 = 3; d H_4 = 4$;

$d H_5 = 3; d H_6 = 2; d H_7 = 1$

$H_1 = 2$, because the string H represents the

product of two strings:

$= 1/2 (i+i) = [0, 0, 0.2]$

$= 1/4 (i+s+i+s) = [0.1, 0.2, 0.4]$

$= 1/6 (i+d+s+i+d+i) = [0.233, 0.366, 0.5]$

$= 1/8 (i+b+s+d+d+s+b+i) =$

$= [0.375, 0.525, 0.625]$

$= 1/6 (s+b+d+d+b+s) = [0.5, 0.7, 0.833]$

$= 1/4 (d+b+b+d) = [0.65, 0.85, 0.95]$

$= 1/2 (b+b) = [0.8, 1, 1]$.

Now we carry out the multiplication

$(b, d, s, i) = (\delta_{10}, \delta_9, \delta_8, \delta_7, \delta_6, \delta_5, \delta_4, \delta_3,$

$\delta_2, \delta_1)$ and we get for the not empty first parts:

$(\delta_6, \delta_5, \delta_4) = ([0.510, 0.690, 0.810],$

$[0.417, 0.583, 0.733] [0.325, 0.475, 0.642]$

$[0.240, 0.360, 0.540])$.

applying the procedure for linguistic approximation described in [Gisolfi and Nunez,

$[0.417, 0.583, 0.733] \rightarrow IB(s,q)$,

included between "s" and "q"

$[0.325, 0.475, 0.642] \rightarrow NT(s)$, name

to "s"

$[0.240, 0.360, 0.540] \rightarrow s$

The final result is $C_1 * C_2 * C_3 =$

$[-] [O2]^q [O1]^{IB(s,q)} [O3,O4]^{NT(s)} [O5]^s$.

5. From fuzzy scores to linguistic terms

Let $t_1[a_1, c, a_2]$ and $t_1[b_1, d, b_2]$ be two

sets whose membership functions are either

s or π . In both cases two parameters

sufficient to single out univocally the fuzzy

The center of the shell of a fuzzy set

real number $m_t = 0.5 * (a_1 + b_1)$.

The function

$\Omega(t_1[a_1, c, a_2], t_1[b_1, d, b_2]) =$

$= ((a_1 + a_2 - (b_1 + b_2)) / (a_2 - a_1 + b_2 - b_1))$

is said *superposition grade* of two fuzzy

and t_1 [Hellendoorn, 1992]. It is worth

that: if $\Omega = 0$, then the center of the

the fuzzy sets is identical; if $\Omega > 0$, then

$m_{t_2} > m_{t_1}$; if $\Omega < 0$, then $m_{t_2} < m_{t_1}$. Moreover

if $\Omega = 1$, then we can affirm that $m_{t_2} >> m_{t_1}$, where

means that the evaluation expressed by t is more favorable than that expressed by t_1 .

Let $U=[0, \text{Max}]$ be the interval of possible scores. A fuzzy score is a fuzzy number FS: $U \rightarrow [0, 1]$ defined as follows:

$$S(x) = \begin{cases} l(x) & \text{if } x \in [0, a] \\ 1 & \text{if } x \in [a, b] \\ r(x) & \text{if } x \in [b, \text{Max}] \end{cases}$$

where $l(x)$ is a function defined in U and whose range is $[0, 1]$, increasing, left continuous and such that $l(x)=0$ for $x \in [0, \lambda_1] \subseteq [0, a]$ whereas $r(x)$ is also defined in U and ranges in $[0, 1]$, but is decreasing, left continuous and such that $r(x) = 0$ for $x \in [\lambda_2, \text{Max}] \subseteq [b, \text{Max}]$. A class of functions satisfying such conditions are just the above mentioned functions S and π . In this way each element of $\forall t$ is the linguistic translation of a fuzzy score.

It is easy, given a fuzzy score, to find the corresponding term of $\forall t$. Let p be a FS, if $|\Omega(p, t_0)| = \min_{t \in \forall t} |\Omega(p, t)|$, then t_0 is the term of the linguistic variable $\forall t$ corresponding to the fuzzy score.

Example

$$U = [0, 10];$$

$\forall t = \{\text{insufficient, sufficient, quite good, good, very good}\};$

$$\text{insufficient} = [0, 0, 10/5]$$

$$\text{sufficient} = [10/5, 0.5*(10/5+10/5*2), 10/5*2]$$

$$\text{quite good} = [10/5*2, 0.5*(10/5*2+10/5*3), 10/5*3]$$

$$\text{good} = [10/5*3, 0.5*(10/5*3+10/5*4), 10/5*4]$$

$$\text{very good} = [10/5*4, 10, 10]$$

Give FS = $p(u; 4; 6)$, one gets:

$$|\Omega(p, \text{insufficient})| = |(10-2)/(2+2)|$$

$$|\Omega(p, \text{sufficient})| = |(10-6)/(2+2)|$$

If FS = $p(u; 2; 3)$, one has:

$$|\Omega(p, \text{insufficient})| = |(5-2)/(1+2)|$$

$$|\Omega(p, \text{sufficient})| = |(5-6)/(1+2)|$$

$$|\Omega(p, \text{quite good})| = |(5-10)/(1+2)|$$

$$|\Omega(p, \text{good})| = |(5-14)/(1+2)|$$

$$|\Omega(p, \text{very good})| = |(5-18)/(1+2)|$$

and we get FS = sufficient

For the sake of simplicity, without generality, we use for the fuzzy score functions S and π , in such way a fuzzy score can be expressed either giving directly a fuzzy number or considering a set of values (FS(x)). We denote this choice by $\forall t$ (for example, the fuzzy set $0/0+0.2/20+0.1/40+0.5/50+0.6/60+0.9/70$ if we take seven points and $\text{Max} = 70$ is an example of discretized fuzzy set). In the first case, in order to translate the fuzzy score into a term of the variable $\forall t$, it is sufficient to compute the minimum of the function $|\Omega(p, t)|$. In the second case, the couples of values are interpolated, and the problem can be solved by applying least squares method first for $l(x)$ and then for $r(x)$. These second degree polynomial functions allow to singulate Zadeh's function represented by their values. In any way we are lead to the first case. We can improve the linguistic approximation by introducing suitable linguistic modifiers to the set $\forall t$.

6. The assessment

The first column of the following table represents the goals related to a specific concept

O_1	y_{11}	y_{12}	y_{1n}		
...		
O_j	y_{j1}	y_{jn}		

The ITM expresses for each O_i the fuzzy score, where y_{ij} belongs to the interval $[0,1]$, $s(x_i) = y_{ij}$ means that the assessment, which evaluates equal to $x_i\%$ the achievement of the goal, is assigned a credibility level equal to y_{ij} [3]. A possible range of values for x_i is the following: 0%, 20%, 40%, 60%, 80%, 100%. For the i -th row the set of couples $(x_i, \mu_{[0,1]}(x_i)=y_{ij})$ represents a fuzzy core (FSZ) and thus such set should comply with the above definition of fuzzy score (FSZ). In turn, if the score is expressed by the fuzzy number $[a,c,b]$ it means that we are sure that the goal cannot be achieved with a confidence level higher than $b\%$ and lower that $a\%$, whereas this conviction for other values is expressed by the function $l(x)$ and $r(x)$ introduced in Section 5.

Let us consider the i -th row of the previous table. The values $\{y_{ij}\}$ single out either a fuzzy set t or number S or π according to the choice made. It is possible to locate two values t_1 and t_2 of the linguistic variable V_t

such that $t_1 \leq t \leq t_2$. They can be computed by means of the Hellendoorn's function Ω :

$$t_1 = \min \left| \Omega(t, V_t) \right|$$

$$t_2 = \min \left| \Omega(t, V^*) \right|, \text{ where } V^* = V_t \setminus \{t_2\}.$$

However, in general t_1 is different from t_2 . In such case the above mentioned procedure of linguistic approximation [12] allows to single out the linguistic modifier and consequently the value of the variable V_t related to each row O_i in the table. These values are reported in the last column of E_i . By using a larger subset of V_t the problem of finding the element of V_t which best represents the linguistic translation of the values y_{ij} can be tackled. The overall evaluation can be computed as follows:

$$E = E_1 \bullet E_2 \bullet \dots \bullet E_i \bullet \dots \bullet E_m.$$

With each fuzzy number E gets associated a linguistic term. However it is also possible to state an overall assessment about the user. In fact, let

The product $A = \Pi A_k$ gives the overall evaluation of the user described by the kind reported above.

7. Monitoring learning process

Let $\{C_1, C_2, \dots, C_n\}$ be the set of concepts that can be grasped by the user during a learning session and suppose that the system classifies each concept C_j a string whose first part represents the conditions $O_i = C_j^{-1}(\alpha_i)$, where the quantities α_i are the values of the "evaluation" as defined in Section 3. In this way we have in different moments of time matrices (concept, goal). The set of these matrices describes the temporal evolution of the user's learning process. At time $t = t_k$ the representation of the cognitive state is given by the k -th matrix:

	O_1	O_2	O_h
C_1	α_{11}	α_{12}	α_{1h}
C_2	α_{21}	α_{22}	α_{2h}
.....			
C_n	α_{n1}	α_{n2}	α_{nh}

For each matrix it is possible to carry out products among rows:

$$C(t=t_1) = C_1(t=t_1) \Pi \dots \Pi C_n(t=t_1), \text{ ma}$$

$$C(t=t_2) = C_1(t=t_2) \Pi \dots \Pi C_n(t=t_2), \text{ ma}$$

$$C(t=t_k) = C_1(t=t_k) \Pi \dots \Pi C_n(t=t_k), \text{ ma}$$

Each product gives a classification of the overall evaluation referred to the instant in which the product is carried out. In turn, the product

$$C = \Pi_i C(t=t_i)$$

gives rise to a string that represents the overall cognitive state of the user.

By multiplying rows belonging to different matrices, one can get information about the cognitive levels for each concept. For

$$C^2 = C_2(t=t_1) \Pi \dots \Pi C_2(t=t_k);$$

$$C^n = C_n(t=t_1) \Pi \dots \Pi C_n(t=t_k);$$

Every C^i represents the user's learning level of the concept C_i . As every string is constructed at different instants, the product represents the final state of the cognitive evolution for a specific concept. While the previous string C gives the final evaluation for each didactic goal beginning from the representation of the conceptualization level achieved, the new product:

$$C^+ = \Pi_j C^j$$

emphasizes the temporal evolution of the learning process.

It is also possible to build strings relating goals and concepts. We note that in mastery learning the tutoring strategy [Block, 1971] aims at give students mastery about the basic elements of knowledge. By linking knowledge with concepts and abilities with goals a string, in which $C_i = O_j^{-1}(\alpha_j)$, evaluates the mastery level of each ability related to concepts. Thus a string such as the following:

$$O = [C_{i1}, \dots, C_{ik}]^{\alpha_n} [C_{i(k+1)}, \dots, C_{i(k+2)}, \dots, C_{ih}]^{\alpha_{n-1}} \dots [C_{i(h+1)}, \dots, C_{in}]^{\alpha_1}$$

adfirmes that the concepts $\{C_{i1}, \dots, C_{ik}\}$, expressed by mastery O , have been achieved with evaluation α_n . Such string gives us a computable schema to tackle the problem. For example, the ability to solve a polynomial equation is related both to the concept of zero of a polynomial and to the notion of algebraic structure on which depends the solubility of an equation. A string such as the previous one offers information about the way mastery levels of these concepts contribute to the overall ability. Thus by multiplying the columns belonging to the same matrix one gets the following string:

$$O(t=t_1) = O_1(t=t_1) \Pi \dots \Pi O_n(t=t_1), \text{ matrix 1;}$$

$$O(t=t_2) = O_1(t=t_2) \Pi \dots \Pi O_n(t=t_2), \text{ matrix 2;}$$

$$O(t=t_k) = O_1(t=t_k) \Pi \dots \Pi O_n(t=t_k), \text{ matrix k;}$$

and thus $O = \Pi_j O(t=t_j)$, and a final label expressing the contribute of each concept to the overall mastery is attached to each concept.

Moreover the product of columns belonging to different matrices:

$$O^1 = O_1(t=t_1) \Pi \dots \Pi O_1(t=t_k);$$

$$O^2 = O_2(t=t_1) \Pi \dots \Pi O_2(t=t_k);$$

$$O^n = O_n(t=t_k) \Pi \dots \Pi O_n(t=t_k);$$

expresses the overall contribution, in the interval $[t_1, t_1]$, of each concept to the goal taken into account. Thus in different strings the same concept can appear with different labels. The final product:

$$O^+ = \Pi_j O^j$$

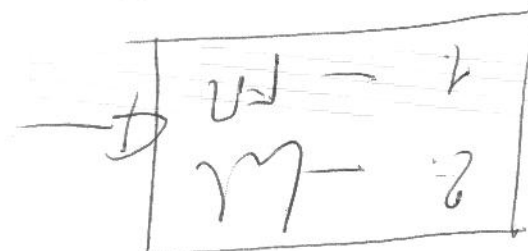
which permits to attach, at the end of tutoring sessions, one evaluation label to each concept.

8. Concluding remarks

Our approach to user modeling for ITMs allows to represent cognitive states, learning styles, psychological states, mastery levels. The fuzzy strings that are our basic elements are able to express concepts and goals presented in the taxonomies well known in the literature [De Landesheere, 1990]. The algebraic structure dealing with such strings allows to monitor and evaluate all the elements present in the learning process of an ITM user and gives us a fuzzy calculus on a set of words. We note that this model of evaluation can be used both in an ITM and during tutoring activity. In this second case the degree of subjectivity during user's assessment can be reduced so that the overall evaluation can become more objective.

References

- Biswas R., "An application of fuzzy sets to student's evaluation", *Fuzzy Sets and Systems*, Vol.74, 1995, pp.187-195
- Block J. H., "Operating Procedures for Mastery Learning" in *Mastery Learning. Theory and Practice*, Block J. H. (Ed), Holt, Rinehart and Winston Inc. 1971
- Brusilovsky P., "Methods and techniques of adaptive hypermedia", *User Modeling and User-Adapted Interaction*, 1996, Special Issue
- Clancey W. J., "Tutoring rules for guiding a case method dialogue", in D. Sleeman & J.S. Brown (Eds), *Intelligent Tutoring Systems*, London, Academic Press, 1982
- De Landesheere G., and De Landsheere V., *Definire gli obiettivi dell'educazione*, La Nuova Italia, Firenze, 1990
- Di Lascio L., Fischetti E., Gisolfi A., "A fuzzy-based approach to stereotype selection in hypermedia", *User Modeling and User-Adapted Interaction*, 1998 (in press)
- Gisolfi A., "An algebraic fuzzy structure for the Approximate Reasoning", *Fuzzy Sets and Systems*, 45 1992 pp.37-43
- Gisolfi A. and Cicalese F., "Classifying through a fuzzy algebraic structure". *Fuzzy Sets and Systems*, 3 ,1996 pp.345- 361
- Gisolfi A. and Loia V., "A complete, flexible fuzzy-based approach to the classification problem", *Int. Journal of Approximate Reasoning*, 13 ,1995, pp.151-183
- Gisolfi A. and Nunez G., "An algebraic Approximation to the Classification with Fuzzy Attributes", *Int. Journ. of Approximate Reasoning*, North-Holland, 9 ,1993, pp.75-95
- Hawkes L., W. Derry E. A. and Rundensteiner E. A., "Individualized tutoring using an intelligent fuzzy temporal relational database", *Int. J. man-Machine Studies*, 33 ,1990, pp.409-429
- Hellendoorn H., "The generalized modus ponens considered as a fuzzy relation", *Fuzzy Sets and Systems*, 46, 1992, pp.29-48.
- Katz S., Legold A., Eggan G., Gordin M., 1992, "Modelling the student in Sherlock II", *Jour. of Artificial Intelligence in Education*, 8, 1992, pp.495-518]
- Klir G. J. and Yuan Bo, *Fuzzy Sets and Fuzzy Logic. Theory and Applications*, Prentice Hall, NY, 1995
- Lakoff, G., "Hedges: a study in meaning criteria and the logic of fuzzy concepts", *Journal of Philosophical Logic*, 2, 1973, pp.458-508
- Liou T-S. and Wang M-J J., 1994, "Subjective assessment of mental workload - A fuzzy linguistic multi-criteria approach", *Fuzzy Sets and Systems*, 62,1994, pp.155-165
- Maurice-Baumont C. and Derognat I., "Fuzzy linguistic and metric formalizations of cognitive distance", *Fuzzy Sets and Systems*, 68, 1994, pp.141-156
- Ohlsson S., "Some principles of intelligent tutoring", in R. W. Lawler & M. Yazdani (Eds), *Artificial Intelligence and education (Vol. 1): Learning environments and tutoring systems*, Norwood, NJ, Ablex, pp.203-237
- Pedrycz W., "Why triangular membership function?", *Fuzzy Sets and Systems*, 64, 1994, pp.21-30
- Sawaragi T., Iwai S., Osamu K., "Controlling the process of learning from example through adaptive generalization of episodic memory", *Fuzzy Sets and Systems*, 39, 1991, pp.133-162
- Schwartz, D. G., 1989, "Outline of a naive semantics for reasoning with qualitative linguistic information", Proc. IJCAI-89, Aug., Detroit, Michigan, 1989
- Self J. A., "Bypassing the intractable problem of student modelling", in C. Frasson & G. Gauthier (Eds), *Intelligent tutoring systems: At the crossroad of artificial intelligence and education*, 1990, Norwood, NJ, Ablex, pp.107-123,
- Zadeh, L. A., "Fuzzy Sets", *Information and Control*, 12, 1965, pp.338 - 353
- Zadeh L. A., "A Fuzzy Set Theoretic Interpretation of Linguistic Hedges", *J. Cybernet.* 2, 1972, pp.4 - 34



Zadeh L. A., "The concept of a Linguistic Variable and Its Application to Approximate Reasoning, I, II, III", *Information Sciences*, 8,

1975, pp.199-249, 8, 1975, pp.301-357, 9,
1975, pp.43-80