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Modelling of intelligent training system by a generalized net

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Abstract

A generalized net model of a training process with modified fuzzy marks in answers of the trained objects and their current and total modified fuzzy evaluation, tharning themes, estimation criteria and others are discussed and interpreted.

Key Words : Artificial intelligence, Fuzzy set, Fuzzy evaluation, Generalized net, Intelligent tutorial environment, Machine learning, User model.

I. Introduction

The idea for application the apparatus of the Generalized Nets (GNs, see[1]) for processes related to machine learning were discussed in [3,8-10]. Here we shall make the next step, extending some of our previous ideas.

In this paper we discuss the possibility to obtain modified fuzzy evaluations of the students' estimation of their mathematical training in schools and universities. In order to avoid the examinator's subjective evaluating in the traditional estimating systems, we shall modify the computational method of the fuzzy evaluation from [6] and we shall apply modified fuzzy computation over the students' answers.

In the present paper we shall extend the GN-models of the learning processes described in [3,8] with capabilities for alternating training strategy with respect to performance of the trained object and with possibility for estimation and change of the training course. Similarly to [3,8], the GN-models for learning are described in the general case, i.e., for training of abstract objects (neural networks, genetic algorithms, expert systems, intellectual games, GNs, abstract systems, etc.).

The possibility of forgetting pieces of the accumulated information during education has been discussed in [9]. Paper [10] describes the extended GN model now having the opportunity of evaluating and modifying of the tutor material, rendering an account of the educated objects' degree of assimilation. New is also the criterion of estimating the tutoring material. Represented in [3] was the general case of GN models for educational purposes - the abstract objects neuron networks, genetic algorithms, expert systems, intellectual games, abstract systems, etc. An educational GN model working over people, instead of abstract systems, has been discussed in [8] and [9]. These offer different mechanisms for estimating the objects' knowledge and the level of assimilation of the taught material, applying fuzzy sets estimations. On the basis of the information accumulated, we define some techniques of choice and change of the topics and tasks, the difficulty level and the style of stating the questions.

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As in our previous models, here we shall use the apparatus of the Intuitionistic Fuzzy sets (IFS, see [2]). IFSs are extensions of the ordinary fuzzy sets with two degrees: of membership (μ) and of non-membership (ν), such that $0 \leq \mu + \nu \leq 1$. In this case a degree of uncertainty ($\pi = 1 - \mu - \nu$) exists. In the ordinary fuzzy set case, $\pi = 0$.

The real numbers from the set $[0, 1] \times [0, 1]$ act for the estimations that indicate the level of assimilation of a certain piece of knowledge. In the ordered tuple $\langle \mu, \nu \rangle$ μ corresponds to the number of the right answers referred to the total number of the answers, and ν stays for the number of the wrong answers referred to the total number of the answers. The degree of uncertainty $\pi = 1 - \mu - \nu$ stays for the cases when the answers cannot be interpreted definitely or there have been technical mistakes.

At the beginning, when still no information has been derived about the TO, all estimations are assigned value of <0, 0>. The current estimation is calculated on the basis of the preceding estimations (if any) by means of the following formula:

$$\langle \mu_{k+1}, \nu_{k+1} \rangle \geq \langle \frac{\mu_k k + m}{k+1}, \frac{\nu_k k + n}{k+1} \rangle$$

where $\langle \mu_k, \nu_k \rangle$ is the previous estimation and $\langle m, n \rangle$ is the estimation of the current task for $m, n \in [0, 1]$ and

$m+n \leq 1$ for $k=1, 2, \cdots$.

Thus the evaluation of any skill contains information about the preceding and the last requests is contained.

2. A GN-model.

The GN-model from Fig. 1 gives possibility not only to trace the changes of the parameters of the learning object, but also a possibility for tracing of status of already studied knowledge, i.e., the degree of its remembering and the possibility of the knowledge using. We can evaluate the influence of some individual TO's characteristics, also. Moreover, the effect of training themes and criteria for their changes can be estimated. The GN represents grouping of the objects from a point of view of the different training themes.

Similarly to [8], the GN constructed here is a subnet of the First GN from [3]. We shall discuss only this subnet, that describes the process of learning which traces a concrete theme.

The places of GN E are of four types: $a-, b-, c-$ and $d-$ places.

The $a-$places represent the status of the learning objects, the $b-$places represent the status of the themes for learning, the $c-$places - the process of collecting, estimating and reproducing of previous knowledge, and the $d-$places - the criterion for estimation of the currently used themes. The learning objects are interpreted by $\alpha-$tokens that transfer in the $a-$places, the themes for learning are interpreted by $\beta-$tokens that transfer in the $b-$places, the levels of the personal knowledge are represent by $\gamma-$tokens that transfer in the $c-$places, and the criteria for estimation of training themes are represent by $\delta-$tokens that transfer in the $d-$places.

For simplicity, we shall not formalize the form of token characteristics and transition condition predicates.

Initially, one or more $\alpha-$tokens enter place a_1 with initial characteristic $x_0^\alpha=$"*identifier of the object of learning (e.g.,the student's name)*". This token splits to two tokens: one of them (marked again by α) enters place a_2 with a new characteriatic "*current training course*", while the second one (let us mark is by γ) enters place c_1 with characteristic "*level of TO's knowledge*".

When predicated W_2(see below) has a truth-value "*true*", then the $\alpha-$token is transferred in place a_3, where it obtains the characteristic "*the theme, that will be a training object.*".

This theme can be related to a set of criteria and the TO's estimations, evaluated on criteria base at the time of the training, but the theme compulsory is related with the level of TO's knowledge, represented by the $\gamma-$characteristic.

At the initial time-moment of the GN-functioning one $\beta-$token stays in place b_1 with initial characteristic $x_0^\beta=$"*list of all themes for learning.*".

When predicate W_1 is "*true*", token β splits to two tokens. One of them (let us mark it again by β) stays in the same place b_1, while the other one (let us mark it by β_i; i is its current number) enters place b_2 with a characteristic $x_1^{\beta_i}=$ "*list of themes for training of the object (student)* a_i".

So, for the i-th object α_i entering place a_2 the training themes are determined. Each theme is represented by β_j-token (shortly, $\beta-$token) with characteristic

$$x_1^\beta=\text{"}\langle id,\ theme\rangle\text{"},$$

where id is a natural number that represents the theme identifier and

$$theme=\{C | C \in U_c\},$$

where U_c denotes the set of criteria for estimation of a concrete training object according to a given training theme.

Each of the $b-$tokens can transfer from place b_2 to place b_3, if there exists at least one $\alpha-$token trained on this theme, i.e., when $W_3=true$. On the contrary, the $\beta-$token transfers to place b_4 and leaves the GN.

In place d_1-token δ with initial characteristic "*criterion for estimating the degree of theme acquirement*" enters. Then the token enters place d_3 and stays there by the end of the net functioning, when it transfers to place d_2.

The $\gamma-$token in place c_3 obtain characteristic "*level of knowledge after full course of training*", and obtain no new characteristic in place c_4. On entering place c_1 the token will obtain a new characteristic, namely "*current level of knowledge over all training themes after the previous lecturing cycle*". We shall note that here just like for the $\alpha-$ and $\beta-$token estimations we can use intuitionistic fuzzy values. We are going to discuss this matter later on.

The GN E contains five transitions having the following forms:

$$T_1=\langle a_1, a_9, b_1, c_4,\ a_2, b_1, b_2, c_1,\ r_1, \wedge(\vee(a_1, a_9), b_1, c_4)\rangle$$

where

$r_1 =$

	a_2	b_1	b_2	c_1
a_1	$true$	$false$	$false$	$true$
a_9	W_1	$true$	W_1	$false$
b_1	$false$	$true$	$true$	$false$
c_4	$false$	$false$	$false$	$true$

where $W_1=$"*There is a necessity for determining of a new topic.*".

The $\alpha-$tokens enter place a_2 with no new characteristics, while the $\beta-$token from place b_1 splits into two tokens. The first of them is the old token β that continues cycling in place b_1 without obtaining any new characteristic and a second (current) token β_{cu} (let us note it below as a $\beta-$token) with characteristic

x_1^β="*list of the current topics chosen from* x_0^β."

$$T_2 = \langle a_2, a_5, a_8, b_2, b_5,\ a_3, b_3, b_4, r_2,\ \wedge(\vee(a_2, a_5, a_8), \vee(b_2, b_5))\rangle,$$

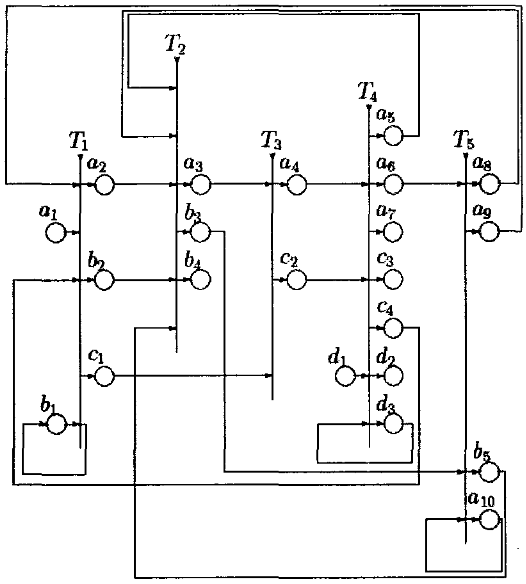

Fig. 1

where

r_2 =	a_3	b_3	b_4
a_2	W_2	*false*	*false*
a_5	W_2	*false*	*false*
a_8	W_2	*false*	*false*
b_2	*false*	W_2	*false*
b_5	*false*	W_2	W_3

W_2="*there are a learning theme for the current object and an object, to be learnt on the current theme.*".

W_3="*the training procedure has finished.*".

The tokens obtain the following current characteristics

$$x_{cu}^{\alpha} = \text{“}\langle id, id_{theme}\rangle\text{”}$$

in place a_3, where id_{theme} is the identifier of the assigned learning theme and

$$x_{cu}^{\beta} = \langle id, theme, objects\rangle$$

in place b_3, where

$$object = \{\alpha \mid \alpha \in K \ \&\ pr_2(x_0^\alpha) = id\},$$

where here and below $pr_s X$ will stay for the s-th projection of a n-dimensional set X for $s \geq n$, and an empty set for $s > n$ and β--tokens do not obtain any characteristic in place b_4.

Transition T_3 represents the process of object training by a given theme. This process is described in more details by the GN E'. The connection between both of the nets can be realized by the hierarchical operator H_1, applied over GN E, which substitutes place a_2 with subnet E'.

$$T_3 = \langle\{a_3, c_1\},\ \{a_4, c_2\},\ r_3, \vee(a_3)\rangle,$$

where

r_3 =	a_4	c_2
a_3	W_4	*false*
c_1	*false*	*true*

where W_4="*the time for learning has finished.*".

The tokens obtain characteristic in place a_4

$$x_i^\alpha = \text{“}\langle id, id_{theme}, estimations(\alpha_i)\rangle\text{”}$$

where

$$estimations(\alpha_i) = \{\langle \mu_j^{\alpha_i}, \nu_j^{\alpha_i}\rangle \mid (\forall j: 1 \leq j \leq |pr_2(x_c ur^\beta)|)\ (\mu_j^{\alpha_i}, \nu_j^{\alpha_i} \in \mathcal{R}^+ \ \&\ \mu_j^{\alpha_i} + \nu_j^{\alpha_i} \leq 1))\},$$

i.e., it is a set of intuitionistic fuzzy estimations (see [2]) for every associated criterion, where $R^+ = x \mid x \in R \ \&\ x \geq 0$.

In place d_1 a token delta with initial characteristic "*criterion for estimating the degree of theme acquirement*" enters. Then the token enters place d_3 and stays there by the end of the net functioning, when it transfers to place d_2. The g-token in place c_3 will obtain characteristic "level of kowledge after the held full course of training", while it is not going to obtain any new characteristic in place c_4. On entering place c_1 the token will obtain a new characteristic, namely "*current level of knowledge over all training themes after the previous lecturing cycle*". We shall note that here just like for the $\alpha-$ and $\beta-$tokens' estimations we can use intuitionistic fuzzy values.

To reach simplicity of the exposition, this set of estimations can be reduced to a single intuitionistic fuzzy estimation (by different manners discussed in [2]) that gives an account of all the elements of the set.

$$T_4 = \langle a_4, c_2, d_1, d_3,\ a_5, a_6, a_7, c_3, c_4, d_2, d_3,\ r_4, \wedge(a_4, c_2, \vee(d_1, d_3))\rangle,$$

where

r_4 =	a_5	a_6	a_7	c_3	c_4	d_2	d_3
a_4	W_5	W_6	W_7	*false*	*false*	*false*	*false*
c_2	*false*	*false*	*false*	$\neg W_7$	W_7	*false*	*false*
d_1	*false*	*false*	*false*	*false*	*false*	*true*	*true*
d_3	*false*	*false*	*false*	*false*	*false*	W_7	$\neg W_7$

where

W_5="*the answer of the current test is right.*"

W_6="*the answer of the current test is wrong.*"

W_7="*the answer of the current test is right and this is the final learning theme of the current object.*"

$\alpha-$token obtain in place a_5 the following characteristic:

$$x_i^\alpha = \text{“}\langle id, id_{theme}, estimations(\alpha_i)\rangle\text{”},$$

where

$$estimations(\alpha_i) = \{\langle \mu_j^{\alpha_i}, \nu_j^{\alpha_i} \rangle \mid (\forall j : 1 \le j \le |pr_2(x_c ur^{\beta})|) \\ (\mu_j^{\alpha_i}, \nu_j^{\alpha_i} \in \mathcal{R}^+ \ \&\ \mu_j^{\alpha_i} + \nu_j^{\alpha_i} \le 1))\},$$

i.e., it is a set of intuitionistic fuzzy estimations (see [2]) for every associated criterion.

To reach simplicity of the exposition, this set of estimations can be reduced to a single intuitionistic fuzzy estimation (by different manners discussed in [2]) that gives an account of all the elements of the set.

With this characteristic the token will return to transition T_2 and it will continues its training with a new theme from the list of the themes determined for it.

The α−token obtain the characteristic in place a_6 :

"a new problem for solving."

and the α−token obtain in place a_7 the final characteristic:

"final training estimation."

The last estimation can be determined, e.g., as a medium of all current estimations for the different themes.

The γ−token in place c_3 will obtain characteristic *"level of kowledge after the held full course of training"*, while it is not going to obtain any new characteristic in place c_4. On entering place c_1 the token will obtain a new characteristic, namely "current level of knowledge over all training themes after the previous lecturing cycle". We shall note that here just like for the α− and β−tokens' estimations we can use intuitionistic fuzzy values.

$$T_5 = \langle a_6, a_{10}, b_3, a_8, a_9, a_{10}, b_5, \\ r_5, \wedge(\vee(a_6, a_{10}), b_3) \rangle,$$

where

$r_5 =$

	a_8	a_9	a_{10}	b_5
a_6	W_8	W_9	W_{10}	$false$
a_{10}	W_8	W_9	W_{10}	$false$
b_3	$false$	$false$	$false$	$true$

where

W_8 =*"the problem is being correctly solved"*,

W_9 =*"the problem is not solved correctly and the TO must be re-trained or trained to other themes"*,

W_{10} =*"the problem is not solved correctly, but the TO know the previous themes."*

The α−token obtain in place a_8 the characteristic:

$$x_i^{\alpha} = \text{"}\langle id, id_{theme}, estimations(a_i) \rangle\text{"}$$

where *estimations* is as above.

The α−token obtains in place a_9 the characteristic:

"list of other themes which the TO must study (these themes may be both familiar or not familiar for the TO)"

and it obtains in place a_{10} the characteristic:

"a new problem for solving."

The β−token obtains in place b_5 the current characteristic

$$x_{cu}^{\beta} = \text{"}\langle \mu, \nu \rangle\text{"},$$

where μ and ν are estimations of the levels of assimilation and of non-assimilation of the training themes by the training object, that are calculated for the first degree, as a sum of the characteristics of the tokens in places a_5, a_7 and a_8, and for the second degree - by the sum of the characteristics of the tokens in place a_9. Finally, the degree of uncertainty can be obtained by the sum of the characteristics of the tokens in place a_{10}. Of course, we must obtain the last values directly by the previous two values, but using the last tokens characteristics we can hold the control over the estimation process.

The characteristic of the δ−token contains four level-values M_{max}, M_{min}, N_{max}, N_{min}.

If $\mu > M_{max}$ and $\nu < N_{min}$, then the β−token in place b_5 obtains characteristic "the course is very easy (elementary)."

If $\mu < M_{min}$ and $\nu > N_{max}$, then the β−token in place b_5 obtains characteristic "the course is very difficult."

In the two other cases β−token in place b_5 obtains characteristic *"the course is suitable for the training objects at whole."*

Therefore, on the basis of the respective β−characteristic, the GN-model can realize a decision making about the necessity for a change of the training themes, their volumes, their levels of difficulty, etc.

The γ−tokens also obtain intuitionistic fuzzy estimations that correspond to the degrees with which the training object "knows" μ^{γ} and, respective "does not know" ν^{γ} all themes studied by the moment. Of course, here $\mu^{\gamma} + \nu^{\gamma} \le 1$ and $\mu^{\gamma}, \nu^{\gamma} \in [0, 1]$. The number $1 - \mu^{\gamma} - \nu^{\gamma}$ determines the degree with which the training object is not assured in one's knowledge. The so constructed GN-model gives the possibility that each token γ, entering place c_1 to actualize its estimations of all themes, studied by the training object to whom/which this token corresponds. Thus, we can account the degree with which the training object has already forgotten the previous studied themes. We can also obtain the estimations of the training object's individual characteristics. This means that the estimation $\langle \mu_j^{\gamma_i}, \nu_j^{\gamma_i} \rangle$, of the level of knowledge of the i-th training object about j-th theme after some time-steps (during which this theme will not be an object of training), may be changed by the estimation $\langle \mu_j^{'\gamma_i}, \nu_j^{'\gamma_i} \rangle$, such that

$$\mu_j^{'\gamma_i} \ge \mu_j^{'\gamma_i} \text{ and } \nu_j^{'\gamma_i} \le \nu_j^{'\gamma_i}.$$

On the other hand, if the last themes, studied by the i-th training object, are related to the j-th theme (studied by the training object some time ago), for the new values of $\mu_j^{'\gamma_i}$ and $\nu_j^{'\gamma_i}$ can be valid the opposite inequalities.

3. Approach for computing of fuzzy estimations with respect to training object's

Now, we will consider modified fuzzy marks(mfm in short) in students'answerscript for performance assessment of mathematic at middle and high schools. In order to avoid any human biasness of teachers with any traditional marking system, we modify the fuzzy evaluation method in the paper [6] and the modified fuzzy evaluation (mfe in short) applies to students' evaluation. And we also discuss some examples of mfe tables.

We consider, for the purpose of an example only, the standard guidelines; (I) Letter grades according to the level of performance judged by teachers are adopted by five fuzzy variables ; excellent- E_1, very good- E_2, good- E_3, satisfactory- E_4, and unsatisfactory- E_5, (II) Each question is constructed by five steps ; from 1-step, which is an easy minor question which ask for fundamental concepts, to 5-step, which is the hardest minor question which ask for applications. Using the definition of fuzzy sets, we will define standard fuzzy marks of five fuzzy variables.

Let $X=0,20,40,60,80,100$ be an universal set. If F is one among A,B,C,D,E which are standard fuzzy marks as in the definition 2.4 , if the M_k are a student's fuzzy marks for $k=1,2,\cdots,r$ and r number of rows,and if $e_1=1$, $e_2=0.9$, $e_3=0.7$, $e_4=0.6$, $e_5=0.5$ are non-fuzzy marks of A,B,C,D,E, respectively, then the mfe table of student's fuzzy marks M_k is a $(r+2)\times 11-$matrix type structure in the below table 1, where r is the total number of questions and w_k is the weighty of the k-th question among r questions. At the bottom there is the total mark.

Standard fuzzy marks(sfm in short) of five fuzzy variables are defined by

E_1 (excellent) = {0/0, 0/20, 0.8/40, 0.9/60, 1/80, 1/100}
E_2 (verygood) = {0/0, 0/20, 0.8/40, 0.9/60, 0.9/80, 0.8/100}
E_3 (good) = {0/0, 0.1/20, 0.8/40, 0.9/60, 0.4/80, 0.2/100}
E_4 (satisfactory) = {0.4/0, 0.4/20, 0.9/40, 0.6/60, 0.2/80, 0/100}
E_5 (unsatisfactory) = {1/0, 1/20, 0.4/40, 0.2/60, 0/80, 0/100}

Tablel: The mfe table

QUESTION	m_1		m_6	GRADE	e_k	w_k	MARK $(e_k\times w_k)$
M_1							
M_2							
...							
M_r							TOTAL MARK $=\sum_{k=1}^{r} e_k\times w_k$

A sfm like {0/0, 0.1/20, 0.8/40, 0.9/60, 0.4/80, 0.2/100} in a student's answerscripts for a question including five minor questions shows to respondent the degrees 0.1, 0.8, 0.9, 0.4, 0.2 of a teacher's satisfaction for that answer in 0, 20, 40, 60, 80, 100 percent, respectively. For each $i=1,\cdots,5$, $a_i\in[0,1]$ represent a teacher's marking in a student's answerscript for i -step minor question. And we also define a mfm in student's answerscript for a question including five steps minor questions. Recall that a fuzzy mark is a fuzzy set of an universal set X whose graph is any one of the following types: (i) decreasing, (ii) increasing, (iii) at first increasing and then decreasing (see [6], definition 3.3). But we consider a mfm as a fuzzy set satisfying the following condition.

A mfm M in student's answerscript for a question including five steps minor questions is a fuzzy set M of X defined by

$$\mu_M(0)=0.8-a_1,\ \mu_M(20)=1-a_1,\ \mu_M(40)=a_2-0.2,$$

$$\mu_M(60)=a_3-0.1,\ \mu_M(80)=a_4,\ \mu_M(100)=a_5,$$

where $a_i\in[0,1]$ represent a teacher's marking in a student's answerscript for i-step minor question, for $i=1,\cdots,5$.

Therefore, we can write also:

$$M=\{(0.8-a_1)/0,\ (1-a_1)/20,\ (a_2-0.2)/40,\ (a_3-0.1)/60,\ a_4/80,\ a_5/100\}.$$

Let $X=x_1,x_2,\cdots,x_n$ be a finite universal set and F,M two fuzzy sets of X. If $f=(m_{F(x_1)},\cdots,m_{F(x_n)})$ and $m=(m_{M(x_1)},\cdots,m_{M(x_n)})$ are the vector representations of the fuzzy sets F and M, respectively, then the matching function $S(f,m)$ of f and m is defined by

$$S(f,m)=\frac{f\cdot m}{\max\{f\cdot f,m\cdot m\}}$$

where $f\cdot m=\sum_{i=1}^{n} m_F(x_i)\cdot m_M(x_i)$, $f\cdot f=\sum_{i=1}^{n} m_F(x_i)\cdot m_F(x_i)$ and $m\cdot m=\sum_{i=1}^{n} m_M(x_i)\cdot m_M(x_i)$. In this case, the value of $S(f,m)\in[0,1]$ is called the degree of similarity between two fuzzy sets F,M.

Using the degree of similarity between a student's mfm and standard fuzzy marks, we define the following mfe of student's mfm.

Let Let $X=x_1,x_2,\cdots,x_n$ be a finite universal set. If F is one among E_1,E_2,E_3,E_4,E_5 which are standard fuzzy marks as in the definition 2.4 and if M is a student's fuzzy mark, then the mfe E_{i_0} of student's mfm M is a standard fuzzy mark E_{i_0} satisfying the following condition : the number i_0 is the smallest number i such that

$$S(E_i,M)=\max\{S(E_1,M),S(E_2,M),S(E_3,M),S(E_4,M),S(E_5,M)\}$$

Now, we, construct the mfe table of student's mfm for r questions including five steps which are 5 minor questions. We denote that $\mu_M(0)=m_1$, $\mu_M(20)=m_2$, $\mu_M(40)=m_3$, $\mu_M(60)=m_4$, $\mu_M(80)=m_5$, $\mu_M(100)=m_6$.

We discuss the following example of mfe. We consider a student's answerscripts for 3 questions including five minor questions and so take $r=3$. We note that the mfe table is a 3×6-type matrix each row of which is a mfe(see Table 2 in the next example).

Let $e_1=1$, $e_2=0.9$, $e_3=0.7$, $e_4=0.6$, $e_5=0.5$ be non-fuzzy marks of standard fuzzy marks E_1, E_2, E_3, E_4, E_5, respectively. Actually these non-fuzzy marks may be suitably adopted by the concerned institution. In total there were 3 questions to be answered : TOTAL MARKS = 30, M_1 carries $w_1=9$ marks, M_2 carries $w_2=9$ marks, and M_3 carries $w_3=12$ marks. Then, we consider, for purpose of an example only, a student has the following marks of three questions $\{Q_1, Q_2, Q_3\}$ including five minor questions;

$$Q_1 ;\ a_1 = 1,\ a_2 = 0.8,\ a_3 = 0.9,\ a_4 = 0.6,\ a_5 = 0.6$$

$$Q_2 ;\ a_1 = 1,\ a_2 = 0.7,\ a_3 = 0.5,\ a_4 = 0.5,\ a_5 = 0$$

$$Q_3 ;\ a_1 = 1,\ a_2 = 1,\ a_3 = 1,\ a_4 = 0.7,\ a_5 = 0.6$$

Using above marks, we can find the mfe of a student's mfm:

(1) $M_1 = \{0,\ 0,\ 0.6,\ 0.8,\ 0.6,\ 0.6\}$ and

$$\max\{S(E_1,M_1),S(E_2,M_1),S(E_3,M_1),S(E_4,M_1),S(E_5,M_1)\} = S(E_3,M_1)$$

(2) $M_2 = \{0,\ 0,\ 0.5,\ 0.4,\ 0.5,\ 0\}$ and

$$\max\{S(E_1,M_2),S(E_2,M_2),S(E_3,M_2),S(E_4,M_2),S(E_5,M_2)\} = S(E_3,M_2)$$

(3) $M_3 = \{0,\ 0,\ 0.8,\ 0.9,\ 0.7,\ 0.6\}$ and

$$\max\{S(E_1,M_3),S(E-2,M_3),S(E_3,M_3),S(E_4,M_3),S(E_5,M_3)\} = S(E_2,M_3).$$

And then we obtain the total marks of the mfe of a student's mfm.

Table 2: The mfe table of a student' mfm.

QUESTION	m_1	m_2	m_3	m_4	m_5	m_6	GRADE	e_k	w_k	MARK $(e_k \times w_k)$
M_1	0	0	0.6	0.8	0.6	0.6	C	0.7	9	6.3
M_2	0	0	0.5	0.4	0.5	0	C	0.7	9	6.3
M_3	0	0	0.8	0.9	0.7	0.6	B	0.7	12	6.3
										TOTAL MARK = 23.4

If two students have the following mfm:

Kim ; $a_1 = 1$, $a_2 = 0.2$, $a_3 = 0.7$, $a_4 = 0.8$, $a_5 = 0.7$; $\Sigma a_i = 3.4$

Park ; $a_1 = 1$, $a_2 = 1$, $a_3 = 0.8$, $a_4 = 0.6$, $a_5 = 0$; $\Sigma a_i = 3.4$

then they have the same total sum 3.4, but they have different grades each other(see table 3).

Table 3: Comparison between two students' mfm.

QUESTION	m_1	m_2	m_3	m_4	m_5	m_6	GRADE	e_k	w_k	MARK $(e_k \times w_k)$
Kim	0	0	0	0.6	0.8	0.7	B	0.9	9	8.1
Park	0	0	0.8	0.7	0.6	0	C	0.7	9	6.3
										Kim=8.1 > Park=6.3

4. Conclusion

The proposed model can be considered as one of the possible models of the machine learning process. It gives the opportunity for monitoring the work of training procedures, for analyzing their efficiency at the different stages of the learning process, and for studying their mutual influence in their parallel work.

Many detailizations can be made by using hierarchical operators that replace a given transition or place with a sub-net with the same behavior. More of the model's parameters can be considered as a token's characteristics from an additional contour that models the training process course. In this contour one can accomplish optimizations with respect to a given aim or statistic information can be collected.

References

[1] Atanassov, K. Generalized Nets, Singapore, New Jersey, World Scientific, 1991.

[2] Atanassov, K. Intuitionistic Fuzzy Sets, Springer, Heidelberg, 1999.

[3] Atanassov, K., H. Aladjov. Generalized Nets in Artificial Intelligence. Vol.2: Generalized nets and Machine Learning. "Prof. M. Drinov" Academic Publishing House, Sofia, 2000.

[4] Atkinson, R., G. Bower, E. Crothers. An Introduction to Mathematical Learning Theory. New York,John Wiley&Sons, 1965.

[5] Banerji, R. Theory of Problem Solving and Approach to Artificial Intelligence. New York,American Elsevier Publ. Co., 1969.

[6] Biswas, R., An application of fuzzy sets in students' evaluation, Fuzzy Sets and Systems, Vol.74, pp.187-194,1995.

[7] Charniak, E., D. McDermott. Introduction to Artificial Intelligence. Reading MA, Addison-Wesley, 1987.

[8] Orozova-Langova D., H. Aladjov, K. Atanassov, Generalized nets for machine learning with current estimations, Advanced Studies in Contemp. Mathematics, Vol. 3, No. 2, pp.61-76, 2001.

[9] D. Orozova, K. Atanassov, Generalized net model of machine learning process with current estimations, Anniversary Conferention of Bourgas Free University, Vol. 2, Bourgas, pp.219-230,2001.

[10] D.Orozova, K. Atanassov, Generalized net model of intelligent tutorial system with current estimations (in press).

[11] P. Winston, Artificial Intelligence, Reading, MA, Addison-Wesley, 1977.

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