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A Note on E-Learning Dynamic Assessment with Fuzzy Estimations

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Abstract

A model of an assessment module has been created, using intuitionistic fuzzy estimations, which render account on the knowledge of the trained objects. The final mark is determined on the basis of a set of evaluation units. An opportunity is offered no only for tracing the changes of the parameters of the trainer object, but there is also an opportunity of tracing the status of the already comprehended knowledge, as well as evaluating and changing the training themes and evaluation criteria

Key words : Dynamic ssessment, intuitionistic fuzzy estimations, knowledge comprehension.

1. Introduction

E-Learning utilizes various approaches towards organisation, implementation and management of training. These systems are intended to provide training in a certain field and additional requirements are claimed in front of them: to be easily adaptable to different users, to have open architecture, to use databases on the trained subject (training course and units, tests, training materials and schedule), as well as accumulate information about the knowledge and skills of the trainees. These demands are presented since in this type of learning the trainee lies in the center of the learning process: the trainee is motivated to define by himself the elements of the training process, the time, place, temp and ways of learning, resources utilized etc.

The process of e-Learning [3-9] investigates the set of properties, which the trained object shall acquire after each training topic. Each topic concerns a subset of object's knowledge to which a given set of assessment criteria is related.

In this paper the process of dynamic assessment during e-Learning shall be modeled, by applying modified fuzzy estimations to the answers given by students in a high school.

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In order to avoid the subjective influence of the trainer in the traditional assessment systems, here the computational method of a fuzzy estimation from [6] is modified and a modified fuzzy computation is applied over the students' answers.

The present paper expands the model of the process of machine learning from [8], which contains opportunities for alternative training strategies during the training process, as well as the chances of forgetting of parts of the information accumulated during the training, regarded in [9]. Here we shall discuss opportunities of assessment and variation of the trained material, accounting on the degree of knowledge comprehension by the trained objects, and a criterion for assessment of the material has been introduced. The training models presented in [3] have been discussed in the general case, i.e. for abstract objects (neural networks, genetic algorithms, expert systems, intellectual games, etc). [8] describes a model of a training course with an accent on the people, rather than abstract objects, while for this case in [9] there have been proposed mechanisms for evaluation of the knowledge and skills of the trained objects, such as degree of comprehension of the trained material and some of their individual characteristics.

In the model presently discussed, the history of the training course is kept, the level of adoption of certain skills for solving problems from the field. This history displays the trained object with the typical mistakes one makes. On the basis of the information collected, there have been proposed techniques for selection and variation of the topics and problems discussed during training units, their difficulty and style of the questions asked. The system keeps and analyses two main data types:

- *History of the training course* – containing facts of the following kind:

History (identifier: <object_ name>, <event>),

where "*identifier*" appoints the name of the trainee, which is used by the system to identify the trainee and differ him from the rest objects, and *<event>* is a lecture, question, problem or another training event. For each event one of the following facts is saved:

Event ([number: <event number>,
date: <event date>,
time: <event time>]).

Individual model -- contains information about the current level of comprehension of knowledge and skills which the trained object has in the trained field. Here two types of estimations are maintained: estimations of the basic skills and typical errors in the object's work, as well as estimations of the level of adoption of the separate units of the training programme.

2. Dynamic estimation due to the level of knowledge comprehension

The estimations appointing the level of comprehension $\mu(\alpha, t)$ and incomprehension $\nu(\alpha, t)$ of a certain unit of knowledge by trainee α in a moment of time t due to a time scale T, are real number s from the set [0,1]. The degree of uncertainty $\pi(\alpha, t) = 1 - \mu(\alpha, t) - \nu(\alpha, t)$ presents the cases when the answers cannot be defined exactly or a technical error has been made. Everywhere the ordered couples have been defined in the sense of the theory of temporal intuitionistic fuzzy sets [2].

At the beginning, when still no information has been extracted about the trained object α, all estimations obtain zero values. The current estimation in moment t_k, $(k+1)$ -st for $k \geq 0$, is calculated on the basis of the previous ones (if any) due to the formula:

$$<\mu(\alpha,t_{k+1}),\nu(\alpha,t_{k+1})> \; = \; <\frac{\mu(\alpha,t_k).k+m(\alpha,t_{k+1})}{k+1},\frac{\nu(\alpha,t_k).k+n(\alpha,t_{k+1})}{k+1}>$$

where $<\mu(\alpha, t_k), \nu(\alpha, t_k)>$ is the previous estimation, and $<m(\alpha, t_{k+1}), n(\alpha, t_{k+1})>$ is the estimation of the current problem for $m(\alpha, t_{k+1}), n(\alpha, t_{k+1}) \in [0,1]$ and

$$m(\alpha, tk+1) + n(\alpha, tk+1) \leq 1.$$

Thus, the evaluation of each skill contains information as about the previous events, as well as about the currently solved problem. In this way the so discussed model of electronic assessment offers not only tracing of the changes of the parameters of the trained object, but it also considers the state of the already acquired knowledge and the capability of its utilization, as well as the possibility of assessment and variation of the training topics and the criteria of evaluation.

Every testing theme can be related to a set of criteria and respective estimations, which are calculated in the process of training on this topic. The theme is related to the level of knowledge displayed by the respective trained object.

In this way are defined the themes on which the i-th trained object α_i shall be examined. Each theme is represented in the way "<*id, theme*>", where $id_{theme} \in (N)$ is a natural number which identifies the theme and each theme is related to a set of criteria C, $C \in U_c$, where U_c denotes the set of all criteria evaluating the trained objects. In order to be trained a given object on a certain new theme, then the level of one's knowledge assessed up to now shall allow the successful training.

Let X be the set of all trained objects, n in number. Time t is accounted from the initial moment 1 to the final moment F. For each trained object $\alpha_i \in X$, $i=1,...,n$ the database keeps estimations from the kind:

$$< id_{theme}, \text{estimations}\,(\alpha_i) >$$

where

$estimations\,(\alpha_i) = \{<\alpha_i, \mu(\alpha_i,t_k), \nu(\alpha_i,t_k)> \mid 1 \leq k \leq F\}$,

and $(\mu(\alpha_i,t_k), \nu(\alpha_i,t_k), \mu(\alpha_i,t_k)+\nu(\alpha_i,t_k) \in [0,1]$, i.e. these are estimations from the intuitionistic fuzzy set [2] for each associated criterion. To facilitate the calculation, this set of estimations shall be reduced to a sole intuitionistic fuzzy estimation, corresponding to the trainee's knowledge on a certain training theme.

The system makes decision depending on the obtained estimation:

The examination unit has successfully passed and for α_i the total mark $<\mu(\alpha_i), \nu(\alpha_i)>$ is calculated. The final evaluation may be determined like, for instance, the arithmetically average of all current estimations on the different themes. This will reflect the current level of trainees' knowledge on all studied themes after the cycle of lectures. The formula in use is the following:

$$<\mu(\alpha_i), \nu(\alpha_i)> \; = \; <\frac{\sum_{k=1}^{F}\mu(\alpha_i,t_k)}{F}, \frac{\sum_{k=1}^{F}\nu(\alpha_i,t_k)}{F}>.$$

The trainee has failed in successfully passing the examination unit, his training shall repeat or he shall be trained on other themes. These might be familiar to the trainee, but with low evaluations on their examination units, or these might be absolutely new for him.

The trainee has failed in successfully passing the examination unit but he has good marks on all of the previous training topics. The object obtains new examination unit on the current theme.

In this way, for every trained object, the database maintains the estimation $<\alpha_i, \mu(\alpha_i), \nu(\alpha_i)>$, where $\mu(\alpha_i), \nu(\alpha_i)$ correspond to the degrees to which the trainee has comprehended and respectively miscomprehended all themes trained up to now with $\mu(\alpha_i), \nu(\alpha_i), \mu(\alpha_i)+\nu(\alpha_i) \in [0,1]$. Here $\pi(\alpha_i) = 1 - \mu(\alpha_i) - \nu(\alpha_i)$ corresponds to the degree to which the trainee is not confident to his knowledge. The system maintains four threshold values: $M_{\max}, M_{\min}, N_{\max}, N_{\min}$. If for every object α_i $\mu(\alpha_i) > M_{\max}$ and $\nu(\alpha_i) < N_{\min}$, then the conclusion may be derived that "the training course is too easy". If for every object α_i $\mu(\alpha_i) < M_{\max}$ and $\nu(\alpha_i) > N_{\min}$, then "the training course is too difficult". In the rest of the cases the "the training course is appropriate for all trainees". Hence, on the basis of the obtained estimations for a larger number of trainees, the system is capable of making decisions on the necessity of change in the training material due to parameters volume, difficulty, etc.

The model allows the trainee to update his estimations during every examination, considering in this way the degree to which the trainee has forgotten learnt elements from the training material, as well as of the learnt new elements. The trainee may also update the estimations due to individual trainee's features in different moments of time. Let the *i*-th trainee in a given moment of time t_k has estimation $<\alpha_i, \mu(\alpha_i, t_k), \nu(\alpha_i, t_k)>$ due to the trained theme. After a certain period of time – in the moment t_s ($> t_k$), during which the theme has not been repeated, the initial estimation may be changed to estimation $<\mu(\alpha_i, t_s), \nu(\alpha_i, t_s)>$, for which the following inequalities hold: $\mu(\alpha_i, t_k) \geq \mu(\alpha_i, t_s)$ and $\nu(\alpha_i, t_k) \leq \nu(\alpha_i, t_s)$. This corresponds to the process of forgetting of "old" knowledge. On the other hand, if the most recent themes the *i*-the trainee has studied are somehow related to a theme, already learnt some time ago then the new values $<\mu(\alpha_i, t_s), \nu(\alpha_i, t_s)>$ may participate in the opposite inequalities, which would correspond to the process of complementing and affirming the "old" knowledge with new.

The so-constructed set of estimations *estimations* (α_i) may be considered a temporal intuitionistic fuzzy set [2], where index t plays the role of a time parameter. The data representation in the various moments of time is given on Figure 1.

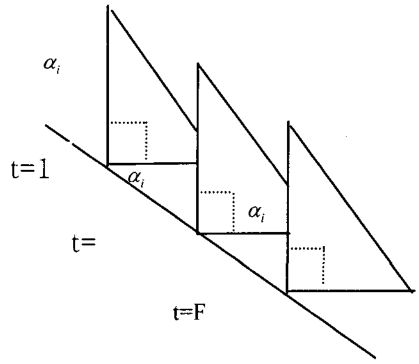

Figure 1.

Keeping time as a parameter of the estimation allows various analyses and statistics of the degrees to which the acquired and forgotten trainee's knowledge and skills vary in time and among the types of problems.

3. Dynamic estimations with weight coefficients of the assessment units

Another technique when creating an assessment module at e-Learning utilizes weight coefficients due to each assessment unit. The overall mark is determined on the basis of a set of assessment units (problem, test, examination). Each assessment unit is suggested to utilize weight coefficients, represented as fuzzy estimations, determining the importance of the unit.

For this approach of maintaining dynamic evaluation, accounting on the trainees' knowledge of a certain module, fuzzy weight coefficients <δ, ε> are introduced, so that to set weights to all assessment units, which take part in the formation of the final mark. Parameter δ is formed on the basis of the number of successive assessment units and ε is formed on the basis of the number of previous assessment units, compared to the overall number of these units. For instance, let the trainee be examined during 8 assessment units, distributed in three levels of difficulty – easy, medium and difficult. Let there be three assessment units in the first (easy) level, three units in the medium level and two in the third (difficult) one. Then the weight coefficients will be distributed in the following manner: first level $<\frac{5}{8}, 0>$, second level $<\frac{2}{8}, \frac{3}{8}>$ and third level $<0, \frac{6}{8}>$.

In this way, the (k+1)-st estimation $<\mu(\alpha_i, t_{k+1}), \nu(\alpha_i, t_{k+1})>$ for k ≥ 0 is calculated on the basis of the previous estimations $<\mu(\alpha_i, t_k), \nu(\alpha_i, t_k)>$ according to the formula:

$<\mu(\alpha_i, t_{k+1}), \nu(\alpha_i, t_{k+1})> =$

$$< \frac{\mu(\alpha_i, t_k).k + \delta_i.m(\alpha_i, t_{k+1}) + \varepsilon_i.n(\alpha_i, t_{k+1})}{k+1}, \frac{\nu(\alpha_i, t_k).k + \delta_i.n(\alpha_i, t_{k+1}) + \varepsilon_i.m(\alpha_i, t_{k+1})}{k+1} >$$

where $< m(\alpha_i, t_{k+1}), n(\alpha_i, t_{k+1}) >$ has been described above, and $<\delta_i, \varepsilon_i>$ is the weight coefficient of the *i*-th assessment unit, for $\delta_i + \varepsilon_i \leq 1$.

Conclusion

Generally, assessment unit is regarded a set of problems in a subject area, that are offered to be solved, together with a system for evaluation of the solutions. The results account on the reached level of knowledge and skills in the area at a certain moment from the pedagogical process.

Reference

[1] Atanassov, K., Generalized Nets, World Scientific, Singapore, 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, 2001.

[4] A. Shannon, E. Szmidt, E. Sotirova, I. Petrounias, J. Kacprzyk, K. Atanassov, M. Krawczak, P. Melo-Pinto, S. Melliani, T. Kim, Intuitionistic fuzzy estimation and generalized net model of e-learning within a university local network, Advan. Stud. Contemp. Math. 9 no. 1(2004), 41-46.

[5] A. Shannon, D. Langova-Orozova,, E. Sotirova, I. Petrounias, K. Atanassov, M. Krawczak, P. Melo-Pinto, S. Melliani, T. Kim, Generalized net model of intranet in an abstract university, Proc. Jangjeon Math. Soc. 7 no. 1(2004), 81-88.

[6] A. Shannon, D. Langova-Orozova,, E. Sotirova, I. Petrounias, K. Atanassov, P. Melo -Pinto, T. Kim, Generalized net model of informatiom flows in intranet in an abstract university, Advan. Stud. Contemp. Math.8 no. 2(2004), 183-192.

[7] A. Shannon, D. Langova-Orozova,, E. Sotirova, I. Petrounias, P. Melo-Pinto, K. Atanassov, T. Kim, Generalized net model of university classes schedule, Advan. Stud. Contemp. Math.8 no. 1(2004), 23-34.

[8] A. Shannon, D. Langova-Orozova,, E. Sotirova, I. Petrounias, P. Melo-Pinto, K. Atanassov, T. Kim, Generalized Net Model for Adaptive Electronic Assessment, Using Intuitionistic Fuzzy Estimations., Proc. IEE Conf. 8 no. 1(2004), 1-7.

[9] A. Shannon, D. Langova-Orozova,, E. Sotirova, I. Petrounias, P. Melo-Pinto, K. Atanassov, T. Kim, Generalized Net Model of a University Electronic Library, Using Intuitionistic Fuzzy Estimations, Notes on Intuitionistic Fuzzy Sets 10 no. 4(2004), 91-96.

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