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EXPERT SYSTEMS USING FOR ANSWERS ANALYSIS IN AUTOMATED KNOWLEDGE CONTROL SYSTEMS

This article proposes the use of an expert system to analyze answers to test questions of different types: open questions, closed questions, questions for compliance, questions for the correct sequence. The Cartesian distance between answers, Levenshtein distances and the relative number of errors were used to build the computer mathematical model. The models of an expert system and logical inference micromachines are considered. The proposed model does not carry out a direct dialogue with the testee (user). Interaction with the testee (user) will be carried out through the automated knowledge control system interface and its database - analysis of answers, generation of additional questions, saving the progress of the inference (solution), etc. In order to speed up development and facilitate the expansion of the system's functionality, we implemented the logical inference machine in the form of a controller and several logical inference micromachines. The inference machine analyzes the testee answers and if necessary, it generates additional questions for him or marks his answers as guessed. Each of the logical inference micromachines solves only one task and can be launched a limited number of times within the same testing session. The described expert system makes the testing process more similar to the procedure of interaction between a teacher and a student, allowing to clarify or discard the received answers. The proposed expert system and logical inference micromachines were implemented as the software module for automated knowledge control system "Antonov Students Test System (A.S.T.S)" and was used in practice more than 5 years. As a result of the operation of the logic inference machine 1, it was found that 4.59% of the answers received needed clarification. From all of the re-asked questions 20.68% were able to get completely correct answers and thus improve the result. As a result of the operation of the logic inference micromachine 2, the following patterns were revealed: 60.54% are for pairs who do not need to clarify the results; 25.14% are pairs of answers, according to which the expert system made a decision to guess the answer (5.24% of the total number of answers). As a result of the operation of inference micro-machines 1 and 2, 6.19% of the total number of answers were changed.

Keywords: Levenshtein distance, Cartesian distance, answer completeness.

АНТОНОВ ЮРІЙ, СМОКТІЙ КИРИЛО
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ВИКОРИСТАННЯ ЕКСПЕРТНИХ СИСТЕМ ДЛЯ АНАЛІЗУ ВІДПОВІДЕЙ У АВТОМАТИЗОВАНИХ СИСТЕМАХ КОНТРОЛЮ ЗНАНЬ

У цій статті запропоновано використання експертної системи для аналізу відповідей на тестові питання. Розглянуто модель експертної системи і микромашин логічного висновку. При побудові комп'ютерно-математичної моделі використано Декартову відстань між відповідями, відстань Левенштейна та відносну кількість помилок. Описана експертна система робить процес тестування більш схожим на процедуру взаємодії викладача та студента, дозволяючи уточнювати, чи відкидати отримані відповіді.

Ключові слова: відстань Левенштейна, Декартова відстань, повнота відповідей.

Introduction

Testing of knowledge by using automated knowledge control systems (AKCS) is currently used in various fields, for example: in the process of teaching students and schoolchildren, employment, taking various courses. The use of such systems makes it possible to reduce subjectivity and bias in the process of knowledge control.

Problem formulation

One of the disadvantages of AKCS can be considered their limitations in assessing the response given by testee. The simplest AKCS for each of the answers to the test questions make decisions of the form "Correct" / "Incorrect" and counts only completely correct answers. More sophisticated and advanced systems for closed-ended or matching questions can count the answer as partially correct and even give the testee a certain score for this.

According to the classical method of conducting knowledge control, the examiner (a human) may ask additional clarifying questions to the examinee. In addition, the examiner can determine whether a mistake (typo) that does not affect the correct answer was made and general understanding of the topic. On the one hand, the examiner may get tired, feel bad, have a personal dislike or antipathy towards the examinee, which also makes this process not ideal. On the other hand, a simple AKCS cannot determine whether the examinee gave the wrong answer, because he does not own the material, or a minor inaccuracy or mistake was made. If the answer is correct, such a system cannot determine the test testee has a sufficient level of knowledge or he simply guessed it.

Analysis of recent researches and publications

So, the problems of adaptive control of knowledge are considered in the works [1, 2, 3]. The works [4, 5, 6] are devoted to the automatic generation of test questions. In work [7] it is proposed the method of assessing the completeness of answers to test questions based on the Cartesian distance [8] and the Levenshtein distance [9]. The longest common subsequence algorithm usage for open questions is proposed in work [10]. The question of using expert systems or knowledge bases in AKCS was considered earlier in the works [1, 4, 6, 11].

Purpose of the article

The purpose of this work is to show that the use of expert systems in AKCS will increase their efficiency by obtaining more accurate answers, and reduce the guessing effect.

Main material

One of the ways to create AKCS, allowing to combine the positive features of knowledge assessment, both with the help of computers and in the classical way, is the introduction of a decisive expert system and knowledge base in AKCS [11] as shown in Fig. 1.

Such AKCS functioning algorithm can be described as follows:

1. The testing system generates questions for the testee.
2. The testee answers all the questions generated for him.
3. The inference machine analyzes the responses of the testee. If necessary, generates additional questions for him or marks the answers given to him as guessed.
4. The testee answers additional questions.
5. Depending on the settings, go to step 3 or 6.
6. Completion of testing, calculation of test scores.

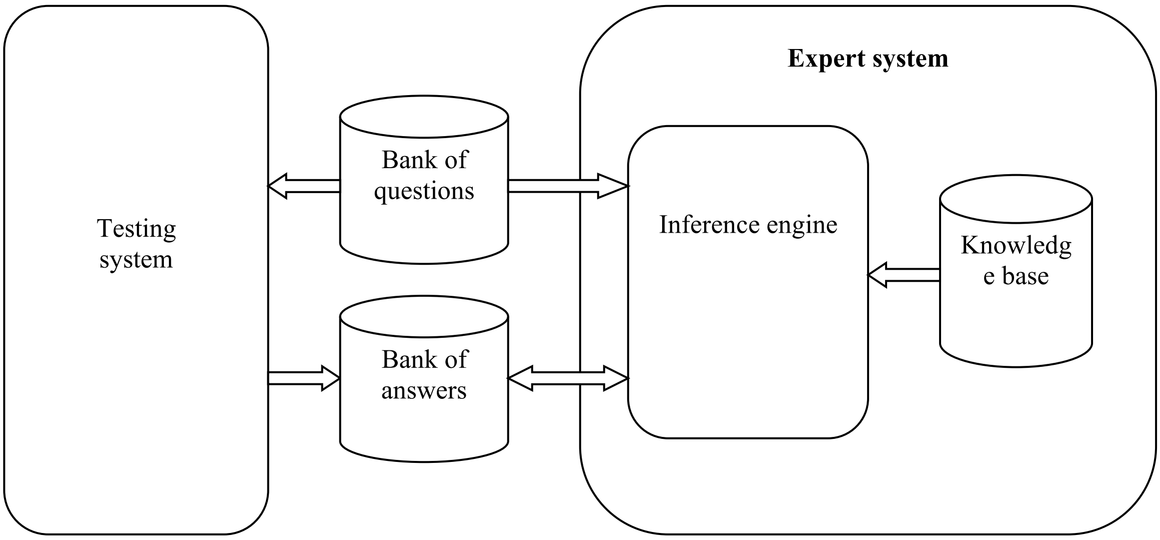

Fig. 1. Interaction of the testing system and the expert system

It should be noted that, unlike classical expert systems [12, 13], the proposed model does not carry out a direct dialogue with the user. Interaction with the user will be carried out through the AKCS interface and its database – analysis of answers, formation of additional questions, saving the progress of the solution, etc.

In the work of E.V. Popov [12] it is noted that huge rules should be broken down into smaller ones. Therefore, in order to accelerate the development and facilitate the expansion of the system's functionality, in this paper the inference engine will be implemented in the form of a controller and several inference micromachines (Fig. 2).

All inference micromachines will operate according to point 3 of the above algorithm. When starting the logical inference machine, the controller, based on the current state of the system, determines the most suitable logical inference machine and transfers control to it. Each of the inference micromachines solves only one task and can be launched no more than P_i times within the same testing session.

With no statements generality limitation, lets consider the example of creating two inference micromachines that will process answers to four types of questions: open, closed, to choose a match and to choose the correct sequence.

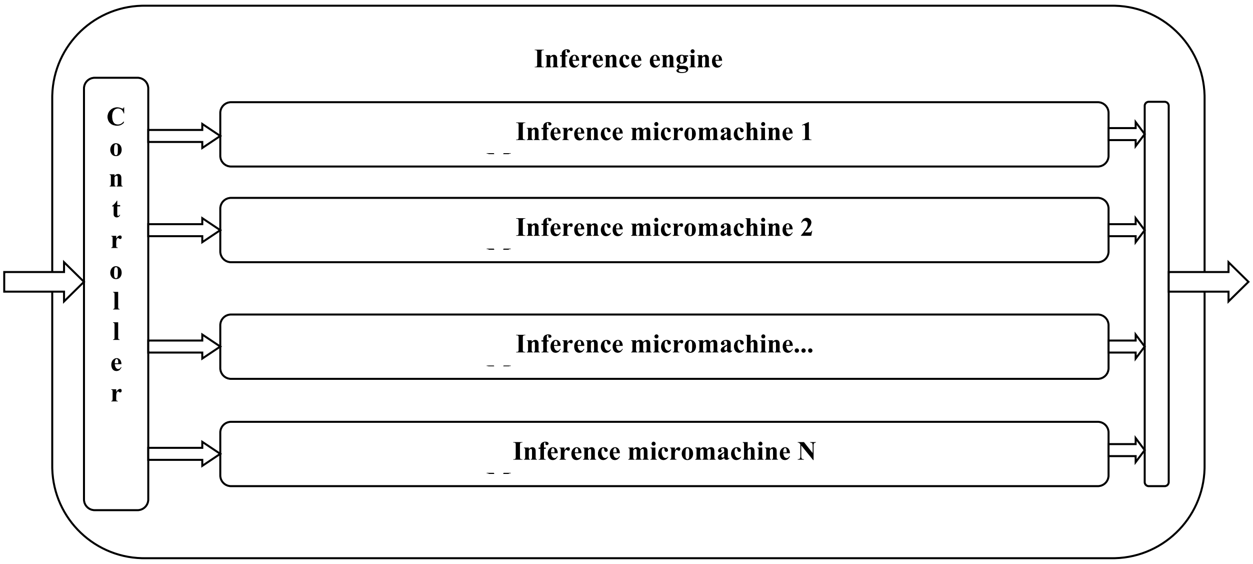

Fig. 2. Conceptual diagram of an inference machine

The task of the inference micromachine 1 is to assess the degree of the answer completeness and make decisions about the need of asking the same question again. To assess the answer completeness the expert system uses the relative number of errors calculated by the formula [7]:

$$\varepsilon(i,j)=\begin{cases}\dfrac{\sum_{k=1}^{M}\left(a_{ik}-b_{ijk}\right)^2}{\sum_{k=1}^{M}a_{ik}^2}, & qtype(i)\neq 3\\ \min\limits_{T_{ir}\in\Omega_i}\left(\dfrac{\rho_{Lev}\left(T_{ir},S_{ij}\right)}{(T_{ir}(}\right), & qtype(i)=3\end{cases} \tag{1}$$

Here $A_i(a_{i1}, a_{i2}, a_{i3},..., a_{iM})$ – the point corresponding to the pattern of the correct answer to the i-th question; $B_{ij}\left(b_{ij1}, b_{ij2}, b_{ij3},..., b_{ijM}\right)$ – j-th answer to i-th question [8], $a_{ij} \in \{0;1\}$, $b_{ijk} \in \{0;1\}$, $j=\overline{1,P_i}$ M – the number of answer options in a closed-ended question, or $M = N^2$ for questions to choose the correct match or the correct sequence, where N – number of events / sequences; $\Omega_i = \left\{T_{ir}, |T_{ir}| > 0, r = \overline{1,Q}\right\}$ – many templates for correct answers to open-ended questions; T_{ir} – correct answer template; $|T_{ir}|$ – length of the pattern of the correct answer in characters; Q – number of response templates [7]; S_{ij} – j-th answer to i-th open question; ρ_{Lev} – Levenshtein distance between two lines [9]; $qtype(i) = 0$, if i - th closed question, $qtype(i) = 1$ – for questions to choose the correct sequence, $qtype(i) = 2$ – choosing the right match, $qtype\ (i) = 3$ – for open-ended questions.

Inference micromachine 1 will generate additional questions if the relative number of errors in the answer does not exceed the value $\varepsilon_{1\max}$, set by the experts:

$$\varepsilon(i,j) \le \varepsilon(qtype(i))_{1max}. \tag{2}$$

The total number of errors in the answer can be calculated using the formula [7]:

$$d(i,j)=\begin{cases}\sum_{k=1}^{M}\left(a_{ik}-b_{ijk}\right)^2, & qtype(i)\neq 3\\ \min\limits_{T_{ir}\in\Omega_i}\left(\rho_{Lev}\left(T_{ir},S_{ij}\right)\right), & qtype(i)=3\end{cases}, \tag{3}$$

To obtain expert assessments ε_{1max} necessary:

1) for each of the answers already available in the database, calculate $\varepsilon(i,j)$ and$d(i,j)$;
2) group questions and answers by type;
3) order questions in ascending order of $\varepsilon(i,j)$ value;
4) invite experts to analyze the answers for each type of question and determine the values $\varepsilon(i,j)$ on which you can ask the same question again;
5) average the values obtained at step 4 for each of the types of questions and save them in the database as $\varepsilon(q)_{1max}\ \left(q=\overline{0,\ 3}\right)$.

The task of the inference micromachine 2 is to analyze the answers to logically related to each other questions. It can be stated that any pair of questions (A, B) stored in the database exists in the following logical relationship:

1) there is no logical connection between the questions;

2) $A \Rightarrow B$ – correct answer to question A implies correct answer to question B;

3) $B \Rightarrow A$ – correct answer to question B implies correct answer to question A;

4) $A \Leftrightarrow B$ – the correct answer to question A implies the correct answer to question B and vice versa.

Thus, in the testing process, it is necessary to additionally analyze the answers to those questions between which there is a connection. If the testee gave answers to such pairs of questions with the same correctness, then we will not analyze them in the future anymore (Table 1). The presence of both correct and incorrect answers in a pair may indicate that the correct answer was guessed or a small inaccuracy was made in the wrong answer.

Table 1

Expert system response to answers for logically related questions

The answer to the question A	The answer to the question B	A?B	Response
Wrong	Wrong	$A \Rightarrow B$	Does not need clarification
Correct	Wrong	$A \Rightarrow B$	Does not need clarification
Wrong	Correct	$A \Rightarrow B$	Clarification needed
Correct	Correct	$A \Rightarrow B$	Does not need clarification
Wrong	Wrong	$A \Leftrightarrow B$	Does not need clarification
Correct	Wrong	$A \Leftrightarrow B$	Clarification needed
Wrong	Correct	$A \Leftrightarrow B$	Clarification needed
Correct	Correct	$A \Leftrightarrow B$	Does not need clarification

Obviously, there is no need to store information about unrelated to each other issues in the knowledge base. Therefore, in the knowledge base it is enough to store information about relationships in the form 2-4. Thus, for the formation of the knowledge base, it is necessary:

1) group the questions by the semantic blocks to which they relate;
2) form a group of experts for each subtopic / topic;
3) perform an expert analysis of test questions in order to identify dependencies of the form 2-4;
4) add information about dependencies to the knowledge base.

In the result it will be many pairs of related questions. Examples of some of these pairs are given in table. 2.

If, after passing the test and analyzing the paired answers, the expert system determines the presence of inconsistencies in them (Table 1), it will intervene in the testing process, considering both answers as incorrect. This approach will partially solve the problem of guessing, but without a micromachine logic output 1 does not consider almost correct answers and mistakes.

If such an intervention is not enough then instead of the micromachine of logic output 2 it can be taken the different one , which is analyzing paired responses in the same way, but intervening in one of the following ways:

1) ask again the question to which the wrong answer was given - partially solves the problem of guessing, independently takes into account almost correct answers and mistakes;
2) ask both questions again - solves the problem of guessing, independently takes into account almost correct answers and mistakes;
3) using the knowledge base, choose an equivalent question for the wrong answer and ask it as an additional;
4) to form a new pair of questions as follows: from the initial pair of questions it should be taken that one to which the correct answer was given. Using the knowledge base, it should be selected a completely equivalent question from the original pair for the wrong answer and added to the new pair.

Table 2

Logically related questions examples

Question A	Question B	A?B
The computer's IP address (IPv4) must have the following properties	Which of the IP addresses is incorrect	$A \Leftrightarrow B$
The computer's IP address (IPv4) must have the following properties …	Which of the IP addresses is correct	$A \Leftrightarrow B$
The table is in the third normal form if …	Which normal form has the table with attributes: people_id, Last name, First name, Patronymic, Age, Date of birth?	$A \Rightarrow B$

It should be noted that the logic output logic machines created based on the micromachine 2 can form additional questions, both considering the completeness of the correctness of the answer and without. To consider the completeness of the answers, it is necessary to use a system of inequalities instead of inequality (2)

$$\begin{cases} \varepsilon(i,j) < \\ \varepsilon(qtype(i))_{2max}\ , \\ \\ \varepsilon(p,k) < \\ \varepsilon_{2max}(qtype(p)).\{ \end{cases} \qquad (4)$$

Here ε_{2max} – values that are determined by experts.

Entering information about the links between questions or additional questions into the knowledge base is the most time-consuming and routine process. This activity can be automated using the ideas suggested in the works [5, 6, 14].

The proposed expert system and logic output machines were implemented as a module for AKCS "A.S.T.S." [7, 15]. For this purpose, at the first stage, changes were made to the structure of the database - existing database tables were changed and a number of new ones were created (Fig. 3). Thus, the expsys_type attribute describes the AKCS component to which the expert system belongs; expsys_decision - decisions that can be made by an expert system; description - description of the logic output micromachine; max_passing - the maximum number of passes in one test session (P_i); order_number – the sequential number of the logic output micromachine in the general start sequence; micromachine_id – the number of the logic output micromachine that was run last to analyze the responses in this test session; last_passing – the number of the last pass of the corresponding micromachine; ESPassing – the number of the micromachine that made the decision on the relevant issue; ESPassingNum – the number of the launch during which the decision was made on this issue; ESDecision – the number of the made decision.

This system was used in the real educational process to test the knowledge of students of various specialties.

As a result of the operation of the logic machine 1, it was found that 4.59% of the answers received needed clarification (Table 3). As you can see from the table. 3, for closed-ended questions 3.89% account for additional questions, and for compliance and open-ended questions - 5.83% and 11.23%, respectively.

Among all additional questions, 81.38% are closed-ended questions, 16.81% - open-ended questions and 1.81% - to establish the correct sequence.

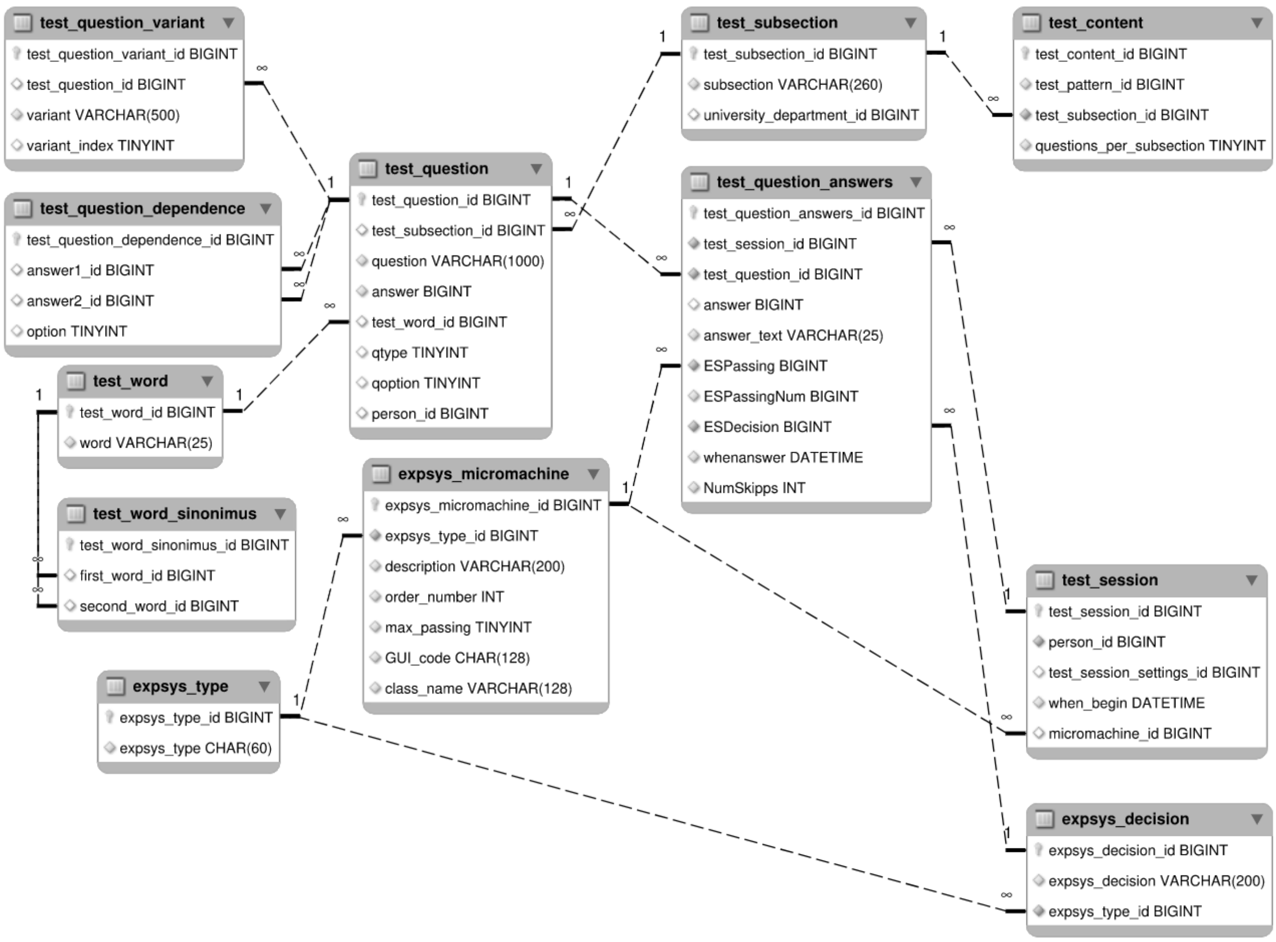

Fig. 3. Fragment of the scheme of the database AKCS "A.S.T.S."

Table 3

General information about the expert system's working results for various types of questions

Indicator	Meaning
Answers received	104074
Answers to the main questions were received	99761
Additional questions generated	4580
Blank answer sheets for additional questions	267
Answers to closed questions were received	95793
Additional questions (closed) generated	3727
Answers to additional closed questions were received	3461
Improved answers to additional closed questions	504
Answers to questions on choosing the correct sequence have been received	1423
Generated additional questions (by choosing the correct sequence)	83
Answers to additional questions on choosing the correct sequence have been received	82
Improved answers to additional questions on choosing the correct sequence	70
Answers to open-ended questions were received	6858
Additional questions (open) generated	770
Answers to additional open-ended questions were received	770
Improved answers to additional open-ended questions	373

From all of the re-asked questions, 5.83% were ignored by the students, and 20.68% were able to get completely correct answers and thus improve the result. The largest percentage of improved answers is accounted for by questions to establish the correct sequence - 85.37%, followed by open-ended questions - 48.44%, and closed-ended questions - 14.56%.

Let's consider in more details in what cases the expert system made the decision that the received answers are needed to be specified. We are most interested in open-ended questions.

So the table. 4 shows extended information for open-ended questions, on which the template of the correct answer consists of one word, and in table.5 - from several words. The % column in these tables shows the proportion of the answer among all the answers that match the correct answer pattern. For questions of this type $\varepsilon_{1\max}(3)=0{,}5$.

Table 4

Extended information for open-ended questions answers with a one-word correct answer template

	i	T_{ir}	S_{ij}	$\varepsilon(i,j)$	$d(i,j)$	%
1	671	switch	swithch	0,1667	1	6,25
2			switc	0,1667	1	31,25
3			swich	0,1667	1	25,00
4			Svitch	0,3333	2	6,25
5		commutator	communicator	0,1500	3	9,30
6			hub	0,2500	5	90,70
7		switch	comutator	0,0556	1	2,08
8			commutetor	0,0556	1	2,08
9			communicator	0,1667	3	2,08
10			comunicator	0,1667	3	2,08
11			hub	0,2222	4	2,08
12			computer	0,2222	4	2,08
13			comeputer	0,2222	4	2,08
14			concentrator	0,2778	5	81,25
15		switch	swich	0,1000	1	50,00
16		switch	switcch	0,1000	1	81,82
17	672	attribute	attribude	0,0714	1	7,69
18			atribute	0,0714	1	15,38
19			attribut	0,1429	2	23,08
20	673	record	request	0,2000	2	50,00
21		record	rekord	0,0833	1	14,29
22			recordes	0,2500	3	28,57
23		cortege	cortiege	0,0833	1	66,67
24			corteege	0,1667	2	33,33

Table 5

Extended information for open-ended questions answers with a multi-word correct answer template

		T_{ir}	S_{ij}	$\varepsilon(i,j)$		
1	675	Common data	Data Common	0,0345	1	1,35
2			Common Date	0,0690	2	6,76
3			Comon Data	0,1034	3	1,35
4			share data	0,1379	4	1,35
5			data integrity	0,2069	6	5,41
6			data availability	0,2069	6	1,35
7			Common	0,2414	7	1,35
8			database	0,2414	7	2,70
9		Data community	Date community	0,0968	3	1,72
10			Data comunity	0,1290	4	1,72
11			data integrity	0,1290	4	5,17
12			data set	0,1613	5	1,72
13			data availability	0,1935	6	1,72
14	699	22:ssh (en)	21:ssh	0,1667	1	28,57
15			80:ssh	0,3333	2	14,29
16			4251:ssh	0,5000	3	14,29
17			Ssh	0,5000	3	42,86
18	700	3389:rdp (en)	3389:tcp	0,2500	2	57,14
19			tcp3389:rdp	0,3750	3	14,29
20			tcp 3389:rdp	0,5000	4	14,29
21	712	function parameters (ua)	function parameters	0,0909	3	1,54
22			function arguments	0,1515	5	1,54
23			function argument	0,1818	6	1,54
24			parameters	0,2424	8	46,15

As can be seen from table. 4 and table. 5, the proposed technique allows to determine quite effectively the minor errors or typos when $\varepsilon(i,j) \leq 0{,}15$. It should be considered that when $\varepsilon(i,j) \in 0{,}15; 0{,}5$ the additional questions are also generated for answers that are similar in spelling but have a completely different meaning.

As a result of the operation of the inference micro-machine 2, based on the received answers and data from the knowledge base, corresponding pairs of answers to interrelated questions were formed. As you can see from the table. 6, as a result of the analysis of the received pairs of answers, the following patterns were revealed:

60.54% are for pairs who do not need to clarify the results;

6.92% - cases when the answer to at least one of the questions was not given by the testee (lack of time and other reasons);

32.54% - pairs in which the answer to one of the questions is correct and the other is not correct.

Table 6

Analysis of answers to logically related questions

Index	Meaning	%
Total Pairs of Answers	10403	100
Pair of species (True, True)	2715	26,10
Pair of species (False, False)	3583	34,44
Pair of species (True, False)	1401	13,47
Pair of species (False, True)	1984	19,07
Did not receive an answer to one of the questions in a pair	720	6,92
Pair of species (True, False) for dependencies $A \Rightarrow B$, $A \Leftrightarrow B$ and pairs (False, True) for $A \Leftrightarrow B$	2615	25,14

Note that 25.14% are pairs of answers, according to which the expert system made a decision to guess the answer (the last line of Table 6). Therefore, the number of guessed answers is 5230, which is 5.24% of the total number of answers.

Thus, as a result of the operation of inference micro-machines 1 and 2, 6177 answers were changed, which amounted to 6.19% of the total number of answers.

Conclusions and further research directions.

The given model of the expert system can be effectively used in automated knowledge control systems or training systems, making the testing process more similar to the procedure of interaction between a teacher and a student, allowing you to refine or reject the received answers. The considered inference micromachines do not limit the generality of reasoning and can be further replaced or supplemented by other inference micromachines.

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