"Quaderni di Ricerca in Didattica (Matematica)", n. 20, 2010.
G.R.I.M. (Department of Mathematics, University of Palermo, Italy)

Combining Case-Based and Fuzzy Reasoning in Problem Solving

Michael Gr. Voskoglou
Professor of Mathematical Sciences
Graduate Technological Educational Institute of Patras
School of Technological Applications
Meg. Alexandrou 1 – 263 34 Patras, Greece
e-mail: voskoglou@teipat.gr ; mvosk@tellas.gr

Abstract

Case-Based Reasoning (CBR) and Fuzzy Systems are intended as cognitively more plausible approaches to problem-solving and learning. The two corresponding fields have emphasized different aspects that complement each other in a reasonable way. In the present paper we introduce a fuzzy model for the representation of a CBR system, which is based on the formalization of CBR as a four steps process (retrieve, reuse, revise, retain), and we use the total possibilistic uncertainty as a measurement tool for the effectiveness of the model in solving new related commercial problems. An example is also presented to illustrate our results in practice.

AMS Subject Classification (2000): 03E72, Secondary 70E05
Key words: *Case- Based Reasoning, Fuzzy sets, Uncertainty*

1. Introduction

Case-Based Reasoning (CBR) is a general paradigm for problem-solving and learning from expertise, which is not only a psychological theory of human cognition, but it also provides a foundation for a new technology of intelligent computer systems that can solve problems and adapt to new situations.

A lawyer, who advocates a particular outcome in a trial based on legal precedents, or an auto mechanic, who fixes an engine by recalling another car that exhibited similar symptoms, or even a physician, who considers the diagnosis and treatment of a previous patient having similar symptoms to determine the disease and treatment for the patient in front of him, are using CBR; in other words CBR is a prominent kind of analogy making.

As a general problem-solving methodology intended to cover a wide range of real-world applications, CBR must face the challenge to deal with uncertain, incomplete and vague information. In fact, uncertainty is already inherent in the basic CBR hypothesis demanding that similar problems have similar solutions. Correspondingly recent years have witnessed an increased interest in formalizing parts of the CBR methodology within different frameworks of reasoning under uncertainty, and in building hybrid approaches by combining CBR with methods of uncertain and approximate reasoning.

Fuzzy sets theory (Voskoglou, 2003; section 1) can be mentioned as a particularly interesting example. In fact, even though both CBR and fuzzy systems are intended as cognitively more plausible approaches to reasoning and problem-solving, the two corresponding fields have emphasized different aspects that complement each other in a reasonable way. Thus fuzzy set-based concepts and methods can support various aspects of CBR including case and knowledge representation, acquisition and modeling, maintenance and management of CBR systems, case indexing and retrieval, similarity assessment and adaptation, instance-based and case-based learning, solution explanation and confidence, and representation of context. On the other way round ideas and techniques for CBR can contribute to fuzzy set-based approximate reasoning. For special facts on fuzzy sets and on uncertainty theory we refer freely to Klir and Folger (1988).

In the present paper we shall construct a fuzzy model for the description of the CBR process and we shall also present an example to illustrate our results. For this, and in order to help the non experts on the field to have a better understanding of the paper, we shall refer first to some foundational issues of the CBR process.

2. Case- Based Reasoning

Broadly construed CBR is the process of solving new problems based on the solutions of similar past problems. The term problem-solving is used here in a wide sense, which means that it is not necessarily the finding of a concrete solution to an application problem, it may be any problem put forth by the user. For example, to justify or criticize a proposed solution, to interpret a problem situation, to generate a set of possible solutions, or generate explanations in observable data, are also problem-solving situations.

CBR has recently been developed to a theory of problem-solving and learning for computers and people Its coupling to learning occurs as a natural byproduct of problem solving. When a problem is successfully solved, the experience is retained in order to solve similar problems in future. When an attempt to solve a problem fails, the reason for the failure is identified and remembered in order to avoid the same mistake in future. Thus CBR is a cyclic and integrated process of solving a problem, learning from this experience, solving a new problem, etc.

In CBR terminology, a case denotes a problem situation. A previously experienced situation, which has been captured and learned in a way that it can be reused in the solving of future problems, is referred as a past case , previous case, stored case, or retained case. Correspondingly, a new case, or unsolved case, is the description of a new problem to be solved. The CBR systems expertise is embodied in a collection (library) of past cases rather, than being encoded in classical rules. Each case typically contains a description of the problem plus a solution and/or the outcomes. The knowledge and reasoning process used by an expert to solve the problem is not recorded, but is implicit in the solution. A case-library can be a powerful corporate resource allowing everyone in an organization to tap in the corporate library, when handling a new problem. CBR allows the case-library to be developed incrementally, while its maintenance is relatively easy and can be carried out by domain experts.

Effective learning in CBR, sometimes referred as ***case-based learning***, requires a well worked out set of methods in order to extract relevant knowledge from the experience, integrate a case into an existing knowledge structure (known, in terms of the cognitive science, as schema, or script, or frame), and index the case for later matching with similar cases.

CBR is often used where experts find it hard to articulate their thought processes when solving problems. This is because knowledge acquisition for a classical knowledge-based system would be extremely difficult in such domains, and is likely to produce incomplete or inaccurate results. When using CBR the need for knowledge acquisition can be limited to establishing how to characterize cases.

Some of the characteristics of a domain that indicate that a CBR approach might be suitable include:

- Records of previously solved problems exist
- Historical cases are viewed as an asset which ought to be preserved.
- Remembering previous experiences is useful; experience is at least as valuable as textbook knowledge.
- Specialists talk about the domain by giving examples.

CBR traces its roots in Artificial Intelligence to the work of Roger Schank and his students at Yale University, U.S.A. in early 1980's. The model of dynamic memory (Schank, 1982) was the basis of the earliest computer intelligent systems that can be viewed as prototypes for CBR systems: CYRUS (Kolodner, 1983) and IPP (Lebowitz, 1983). An alternative approach is the category and exemplar model applied first to the PROTOS system of Porter and Bareiss (1986), while some other types of memory models developed later on.

As an intelligent-systems method CBR has got a lot of attention over the last few years, because it enables the information managers to increase efficiency and reduce cost by substantially automating processes. CBR first appeared in commercial systems in the early 1990's and since then has been sued to create numerous applications in a wide range of domains including diagnosis, help-desk, assessment, decision support, design, etc. Organizations as diverse as IBM, VISA International, Volkswagen, British Airways and NASA have already made use of CBR in applications such as customer support, quality assurance, aircraft maintenance, process planning and many more applications that are easily imaginable.

CBR has been formalized for purposes of computer and human reasoning as a four steps process. These steps involve:

R_1: ***Retrieve*** the most similar to the new problem past case.

R_2: ***Reuse*** the information and knowledge of the retrieved case for the solution of the new problem.

R_3: ***Revise*** the proposed solution.

R_4: ***Retain*** the part of this experience likely to be useful for future problem-solving.

More specifically, the retrieve task starts with the description of the new problem, and ends when a best matching previous case has been found. The subtasks of the retrieving procedure involve identifying a set of relevant problem descriptors, matching the case and returning a set of sufficiently similar cases given a similarity threshold of some kind, and selecting the best case from the set of cases returned. Some systems retrieve cases based largely on superficial syntactic similarities among problem descriptors, while advanced systems use semantic similarities.

The reuse of the solution of the retrieved case in the context of the new problem focuses on two aspects: The differences between the past and the current case, and what part of the retrieved case can be transferred to the new case. Usually in non trivial situations part of the solution of the retrieved case cannot be directly transferred to the new case, but requires an adaptation process that takes into account the above differences.

Through the revision the solution generated by reuse is tested for success – e.g. by being applied to the real world environment, or to a simulation of it, or evaluated by a specialist – and repaired, if failed. When a failure is encountered, the system can then get a reminding of a previous similar failure and use the failure case in order to improve its understanding of the present failure, and correct it. The revised task can then be retained directly (if the revision process assures its correctness), or it can be evaluated and repaired again.

The final step involves selecting which information from the new case to retain, in what form to retain it, how to index the case for better retrieval in future for similar problems, and how to integrate the new case in the memory structure.

Detailed flowcharts illustrating the basic steps of the CBR process and detailed analyses of the CBR methodologies have been presented by Slade (1991), Aamodt and Plaza (1994), Lei et al (2001), Voskoglou (2008 a) and others.

3. The fuzzy model

Let us consider a CBR system whose library contains n past cases, $n\geq 2$. We denote by R_i, i=1,2,3 , the steps of retrieval, reuse and revision and by a, b, c, d, and e the linguistic labels of negligible, low, intermediate, high and complete degree of success respectively for each of the R_i's. Set

$$U=\{a, b, c, d, e\}$$

We are going to represent R_i's as fuzzy sets in U. For this, if n_{ia}, n_{ib}, n_{ic}, n_{id} and n_{ie} respectively denote the number of cases where it has been achieved negligible, low, intermediate, high and complete degree of success for the state R_i i=1,2,3, we define the ***membership function*** m_{Ri} in terms of the frequencies, i.e. by

$$m_{Ri}(x)=\frac{n_{ix}}{n}$$

for each x in U. Thus we can write

$$R_i = \{(x, \frac{n_{ix}}{n}) : x \in U\}, i=1,2,3$$

The reason, for which we didn't include the last step R_4 of the CBR process in our fuzzy representation, is that all past cases, either successful, or not, are retained in the system's library and therefore there is no fuzziness in this case. In other words keeping the same notation we have that $n_{4a}=n_{4b}=n_{4c}=n_{4d}=0$ and $n_{4e}=1$.

In order to represent all possible profiles (overall states) of a case during the CBR process, we consider a ***fuzzy relation***, say R, in U^3 of the form

$$R=\{(s, m_R(s)) : s=(x, y, z) \in U^3\}$$

To determine properly the membership function m_R we give the following definition:
DEFINITION: A profile s=(x, y, z), with x, y ,z in U, is said to be ***well ordered*** if x corresponds to a degree of success equal or greater than y, and y corresponds to a degree of success equal or greater than z.
For example, profile (c, c, a) is well ordered, while (b, a, c) is not.

We define now the membership degree of s to be

$$m_R(s)=m_{R_1}(x)m_{R_2}(y)m_{R_3}(z)$$

if s is a well ordered profile, and zero otherwise. In fact, if for example (b, a, c) possessed a nonzero membership degree, given that the degree of success at the step of reuse is negligible, how the proposed solution could be revised?

In order to simplify our notation we shall write m_s instead of $m_R(s)$. Then the ***possibility*** r_s of the profile s is given by

$$r_s=\frac{m_s}{\max\{m_s\}}$$

where max{m_s} denotes the maximal value of m_s , for all s in U^3. In other words r_s is the "relative probability" of s with respect to the other profiles.

During the CBR process it might be used reasoning that involves amplified inferences, whose content is beyond the available evidence and hence obtain conclusions not entailed in the given premises. The appearance of conflict in the conclusions requires that the conclusions be appropriately adjusted so that the resulting generalization is free of conflict. The value of total conflict during the CBR process can be measured by the ***strife function*** S(r) on the ordered possibility distribution

$$r : r_1=1 \geq r_2 \geq \ldots\ldots \geq r_n \geq r_{n+1}$$

of the profiles defined by:

$$S(r) = \frac{1}{\log 2}\left[\sum_{i=1}^{n}(r_i - r_{i+1})\log\frac{i}{\sum_{j=1}^{i} r_j}\right]$$

In general, the amount of information obtained by an action can be measured by the reduction of uncertainty that results from the action. Thus the ***total possibilistic uncertainty*** T(r) during the CBR process can be used as a measure for the system's effectiveness in solving new related problems. The value of T(r) is measured by the sum of the strife S(r) and ***non specificity*** N(r) (Klir, 1995; p.28), defined by:

$$N(r) = \frac{1}{\log 2}[\sum_{i=2}^{n}(r_i - r_{i+1})\log i$$

In contrast to strife, which, as we have already seen, expresses conflicts among the various sets of alternatives, non specificity is connected with the sizes (cardinalities) of relevant sets of alternatives. The lower is the value of T(r), the higher is the effectiveness of the CBR system in solving new related problems.

Assume now that one wants to study the combined results of the behaviour of k different systems, $k \geq 2$, designed for the solution of the same type of problems via the CBR process. Then it becomes necessary to introduce the ***fuzzy variables*** $R_i(t)$, with i=1,2,3 and t=1,2,…,k, and determine the possibilities r(s) of the profiles s(t) through the ***pseudo-frequencies***

$$f(s) = \sum_{t=1}^{k} m_s(t)$$

Namely

$$r(s) = \frac{f(s)}{\max\{f(s)\}}$$

where max{f(s)} denotes the maximal pseudo-frequency. The possibilities r(s) of all the profiles s(t) measure the degree of evidence of the combined results of the k different CBR systems..

4. An application

Let us consider a medical diagnostic CBR system that tries to retrieve past cases, whose symptom lists are similar in nature to that of the new case, and suggest diagnoses based on the best matching retrieved cases. Assume that in the system there exists a library of 105 past cases, where in no case there was a failure at the step of retrieval of a previous similar case for making a diagnosis. In fact, assume that in 51 cases we had an intermediate success in retrieving a suitable past case, in 24 cases high, and in 30 cases we had a complete success respectively. Thus the state of retrieval is represented as a fuzzy set in U as

$$R_1 = \{(a,0),(b,0),(c,\tfrac{51}{105}),(d,\tfrac{24}{105}),(e,\tfrac{30}{105})\}$$

In the same way we find that

$$R_2 = \{(a,\tfrac{18}{105}),(b,\tfrac{18}{105}),(c,\tfrac{48}{105}),(d,\tfrac{21}{105}),(e,0)\}$$

and

$$R_3 = \{(a,\tfrac{36}{105}),(b,\tfrac{30}{105}),(c,\tfrac{39}{105}),(d,0),(e,0)\}$$

It is a straightforward process then to calculate the membership degrees of all the possible profiles (see column of $m_s(1)$ in Table 1). For example, if

$$s=(c, b, a)$$

then

$$m_s=m_{R_1}(c).m_{R_2}(b).m_{R_3}(a)= =\frac{51}{105}\frac{18}{105}\frac{36}{105}\approx 0{,}029.$$

It turns out that (c, c, c) is the profile with the maximal membership degree 0,082 and therefore the possibility of each s in U^3 is given by

$$r_s=\frac{m_s}{0{,}082}$$

For example the possibility of (c, b, a) is

$$\frac{0{,}029}{0{,}082}\approx 0{,}353$$

while the possibility of (c, c, c) is of course equal to 1.

Calculating the possibilities of the 5^3=125 in total profiles (see column of $r_s(1)$ in Table 1) one finds that the ordered possibility distribution r of the profiles is:
r_1=1, r_2=0,92, r_3=0,768, r_4=0,512, r_5=0,476, r_6=0,415, r_7=0,402, r_8=0,378, r_9=r_{10}=0,341, r_{11}=0,329, r_{12}=0,317, r_{13}=0,305, r_{14}=0,293, r_{15}=r_{16}=0,256, r_{17}=0,20, r_{18}=0,195, r_{19}=0,171, r_{20}=r_{21}=r_{22}=0,159, r_{23}=0,134, r_{24}=r_{25}= =……..=r_{125}=0
Therefore the total possibilistic uncertainty is

$$T(r)=S(r)+N(r)=0{,}565+2{,}405= =2{,}97$$

Next we shall study the combined results of the behaviour of the above system and of another system, designed for the solution of the same type of problems via the CBR process, with an existing library of 90 past cases. Working as before we find for the second system that

$$R_1=\{(a,0),(b,\tfrac{18}{90}),(c,\tfrac{45}{90}),(d,\tfrac{27}{90}),(e,0)\}$$

$$R_2=\{(a,\tfrac{18}{90}),(b,\tfrac{24}{90}),(c,\tfrac{48}{90}),(d,0),(e,0)\}$$

and

$$R_3=\{(a,\tfrac{36}{90}),(b,\tfrac{27}{90}),(c,\tfrac{27}{90}),(d,0),(e,0)\}$$

The calculation of all possible profiles gives the results shown in column of $m_s(2)$ in Table 1. It turns out that (c, c, a) is the profile possessing the maximal membership degree 0,107 and therefore the possibility of each s is given by

$$r_s=\frac{m_s}{0{,}107}$$

(see column of $r_s(2)$ in Table 1).

Finally, in the same way as above, one finds that

$$T(r)=S(r)+N(r)=0{,}452+1{,}87= =2{,}322$$

Thus, since 2,322<2,97, the effectiveness of the second system in solving new related problems is better than that of the first one. This happens despite the fact that the profile (c, c, c) with the maximal possibility of appearance in the first system is a more satisfactory profile than the corresponding profile (c, c, a) of the second system.
Notice that in general, the more are the stored past cases in the system's library, the greater is expected to be its effectiveness in solving new related problems. In fact, the more are the past cases, the greater is the probability for a new problem to fit satisfactorily to one of them. Therefore the fact that the second system was found to be more effective than the first one, although not impossible to happen, it is rather unexpected in general.

We introduce now the fuzzy variables $R_i(t)$, i=1,2,3 and t=1,2. Then the pseudo-frequency of each profile s is given by

$$f(s)=m_s(1)+m_s(2)$$

Table 1: Profiles with non zero pseudo-frequencies

A_1	A_2	A_3	$m_s(1)$	$r_s(1)$	$m_s(2)$	$r_s(2)$	f(s)	r(s)
b	b	b	0	0	0,016	0,150	0,016	0,087
b	b	a	0	0	0,021	0,196	0,021	0,115
b	a	a	0	0	0,016	0,150	0,016	0,087
c	c	c	0,082	1	0,080	0,748	0,162	0,885
c	**c**	**a**	**0,076**	**0,927**	**0,107**	**1**	**0,183**	**1**
c	c	b	0,063	0,768	0,008	0,075	0,071	0,388
c	a	a	0,028	0,341	0,040	0,374	0,068	0,372
c	b	a	0,028	0,341	0,053	0,495	0,081	0,443
c	b	b	0,024	0,293	0,040	0,374	0,064	0,350
d	d	a	0,016	0,495	0	0	0,016	0,087
d	d	b	0,013	0,159	0	0	0,013	0,074
d	d	c	0,021	0,256	0	0	0,021	0,115
d	a	a	0,013	0,159	0,024	0,224	0,037	0,202
d	b	a	0,013	0,159	0,032	0,299	0,045	0,246
d	b	b	0,011	0,134	0,024	0,224	0,035	0,191
d	c	a	0,031	0,378	0,064	0,598	0,095	0,519
d	c	b	0,026	0,317	0,048	0,449	0,074	0,404
d	c	c	0,034	0,415	0,048	0,449	0,082	0,448
e	a	a	0,017	0,207	0	0	0,017	0,093
e	b	b	0,014	0,171	0	0	0,014	0,077
e	c	a	0,039	0,476	0	0	0,039	0,213
e	c	b	0,033	0,402	0	0	0,033	0,180
e	c	c	0,042	0,512	0	0	0,042	0,230
e	d	a	0,025	0,305	0	0	0,025	0,137
e	d	b	0,021	0,256	0	0	0,021	0,115
e	d	c	0,027	0,329	0	0	0,027	0,148

Note: The outcomes of Table 1 are with accuracy up to the third decimal point.

(see the corresponding column of Table 1). It turns out that (c, c, a) is the profile with the highest pseudo-frequency 0,183 and therefore the possibility of each profile is given by

$$r(s)=\frac{f(s)}{0,183}$$

The possibilities of all profiles having nonzero pseudo-frequencies are given in the last column of Table 1

5. Conclusions and discussion

The following conclusions can be drawn from the discussion presented in the paper:

- Although both CBR and fuzzy systems are intended as cognitively more plausible approaches to reasoning and problem-solving, the two corresponding fields have emphasized different aspects that complement each other in a reasonable way.
- Our fuzzy representation of a CBR system is based on the formalization of CBR as a four steps process (retrieve, reuse, revise, retain)

- Our fuzzy model is not restricted only to quantitative information (possibilities, value of T(r), etc), but it also gives a qualitative view of the behaviour of a CBR system. In fact, through it one studies all the possible profiles of the stored cases, and gets – in terms of the linguistic labels – a comprehensive idea about the degree of success of each step of the CBR process.
- Another advantage of our model is that it gives the possibility to study the combined results of behaviour of two, or more, CBR systems designed for the solution of the same type of problems.

An analogous to the above model has been constructed for a fuzzy representation of the process of learning a subject matter by a group of students in the classroom (Voskoglou, 2008 b). Analogous efforts, with different in general methodologies, to use the fuzzy sets logic in the area of student modelling and student diagnosis in particular and in education in general have been attempted by other researchers as well, e.g. Perikaris (1996), Espin and Oliveras (1997), Ma and Zhou (2000), Spagnolo and Gras (2004) etc.

We must finally underline the importance of use of ***stochastic methods (Markov chain models)*** as an alternative approach for the same purposes, e.g. Voskoglou and Perdikaris (1991), Voskoglou (1996 a,
1996 b, 2000, 2007) etc. However Markov models, although easier sometimes to be applied in practice by a non expert, are self- restricted to provide quantitative information only for the corresponding situations, e.g. measures for the problem-solving, or model-building abilities of a group of students, short and long-run forecasts (probabilities) for the evolution of various phenomena, etc. Therefore, one could claim that a fuzzy model, like the one presented in this paper, is more useful for the deeper study of a real situation, because, apart from the quantitative information, it gives also the possibility of a qualitative analysis of the corresponding phenomena.

References

1. Aamodt, A. and Plaza, E. (1994), Case-Based Reasoning:: Foundational Issues, Methodological Variations, and System Approaches // Artificial Intelligence Communications, 7/1, 39-52.
2. Espin, E. A. and Oliveras, C. M. L. (1997), Introduction to the use of fuzzy logic in the assessment of mathematics teachers' // In A. Gagatsis (Ed.), Proceedings of the 1st Mediterranean Conference on Mathematics Education (MEDCONF 97), 107-113, Nicosia, Cyprus.
3. Klir, G. J. and Folger, T. A. (1988), Fuzzy Sets, Uncertainty and Information // Prentice Hall, London.
4. Klir, G. J. (1995), Principles of uncertainty: What are they? Why do we need them?" // Fuzzy Sets and Systems, 74, 15-31.
5. Kolodner, J. (1983), Reconstructive Memory: A Computer Model // Cognitive Science, 7, 281-328.
6. Lebowitz, M. (1983), Memory-Based Parsing // Artificial Intelligence, 21, 363-404.
7. Porter, B. and Bareiss, B. (1986), PROTOS: An experiment in knowledge acquisition for heuristic classification tasks // Proceedings of the 1st International Meeting on Advances in Learning (IMAL), 159-174, Les Arcs, France.
8. Lei, Y., Peng, Y. and Ruan, X. (2001), Applying case-based reasoning to cold forcing process planning // Journal of Materials Processing Technology, 112, 12-16.
9. Ma, J. and Zhou, D. (2000), Fuzzy Set Approach to the Assessment of Student-Centered Learning // IEEE Transactions on Education, 43(2), 237-241.
10. Perdikaris, S. (1996), A system framework for fuzzy sets in the van Hiele level theory of geometric reasoning // International Journal of Mathematical Education in Science and Technology, 27(2), 273-278.
11. Slade, S. (1991), Case-Based Reasoning: A Research Paradigm// Artificial Intelligence Magazine, 12/1, 42- 55.
12. Spagnolo, F. and Gras, R. (2004), Fuzzy implication through statistic implication: A new approach in Zadeh's framework // In: Scott, D., Kurgan, L., Musilek, P., Pedrycz, W. and Reformat, M. (Eds), 23d International Conference of the North American Fuzzy Information Processing Society (NAFIPS 2004),IEEE, Vol.1, 425- 429.
13. Voskoglou, M. Gr. and Perdikaris, S. (1991), A Markov chain model in problem-solving // International Journal of Mathematical Education in Science and Technology, 24(3), 443-447.
14. Voskoglou, M. Gr. (1996 a), The use of Markov chains to describe the process of learning // Theta: A Journal of Mathematics (Manchester Metropolitan University), 36-40.
15. Voskoglou, M. Gr. (1996 b), An application of ergodic Markov chains to analogical problem solving // The Mathematics Education (India), Vol. XXX (2), 95-108.
16. Voskoglou, M. Gr. (2000), An application of Markov chains to decision making // Studia Kupieckie (University of Lodz), 6, 69-76
17. Voskoglou, M. Gr. (2003), Applications of Fuzzy Sets to Problems of Commercial Enterprises // Proceedings of the 1st International Conference on Quantitative Methods in Industry and Commerce, 654-659, T. E. I. of Athens.
18. Voskoglou, M. Gr. (2007) , A stochastic model for the modelling process // In Haines, Chr., Galbraith, P., Bloom, W., Khan, S. (Eds), Mathematical Modelling: Education, Engineering and Economics (ICTMA12), 149-157, Horwood, Chichester, UK.
19. Voskoglou, M. Gr. (2008 a), Case-Based Reasoning: A Recent Theory for Problem-Solving and Learning in Computers and People // In: Lytras, M. D., Caroll, J. M., Tennyson, R., Avison, D., Vossen, G. and Ordonez De Paplos, D. (Eds), Communications in Computer and Information Science (WSKS 08), 19, Springer, 314-319.
20. Voskoglou, M. Gr. (2008 b), Fuzziness or probability in the process of learning? A general question illustrated by examples from teaching mathematics // In Gagatsis, A. (Ed.) Research in Mathematics, Education, 275-284,
University of Cyprus, Nicosia.