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Four new fuzzy inference rules for experience based reasoning

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Abstract

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Keywords

Experience-based reasoning (EBR), fuzzy inference rule, fuzzy reasoning, experience management.

Disciplines

Business | Social and Behavioral Sciences

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Four New Fuzzy Inference Rules for Experience Based Reasoning

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ABSTRACT: Experience-based reasoning (EBR) is a reasoning paradigm used in almost every human activity such as business, military missions, and teaching activities. However, EBR has not been seriously studied from a fuzzy reasoning viewpoint. This paper will give an attempt to resolve this issue by providing four new fuzzy inference rules for EBR. More specifically, the paper first reviews the logical approach to EBR, in which eight fundamental different inference rules for EBR are discussed. Then the paper proposes fuzzy logic-based models to the four new inference rules in EBR, which forms a theoretical foundation for EBR together with the four traditional fuzzy inference rules. The proposed approach will facilitate research and development of EBR, e-commerce, and experience management.

Keywords: Experience-based reasoning (EBR), fuzzy inference rule, fuzzy reasoning, experience management

1 INTRODUCTION

Experience-based reasoning (EBR) is a reasoning paradigm based on logical arguments [21]. EBR as a technology has been used in many applications [15][19]. Taking into account research and development of case-based reasoning (CBR) [10], Sun and Finnie [19][20][21] proposed eight different inference rules for EBR from a logical viewpoint, which cover all possibilities of EBR at a fundamental level, in order to move EBR towards a firm theoretical foundation. However, how can fuzzy logic be applied in EBR? What are the fuzzy inference rules of EBR? These questions are still open. This paper will provide some answers to these questions by providing a unified fuzzy logic-based treatment of EBR, based on our previous work on logical treatment of EBR [15][19][20]. More specifically, this paper first reviews the logical approach to EBR, in which eight different inference rules for EBR are discussed. Then the paper proposes fuzzy logic-based models for the four new inference rules of EBR. We argue that the proposed methodology will facilitate research of EBR and its applications to e-commerce, knowledge management (KM) and experience management (EM).

The rest of this paper is organized as follows: Section 2 reviews experience-based reasoning (EBR). Section 3 looks at inference rules in EBR. Section 4 examines four new fuzzy inference rules for EBR. Section 5 ends this paper with some concluding remarks.

2 Experience Based Reasoning

Experience based reasoning (EBR) is drawing increasing attention [2][19][21]. EBR is a reasoning paradigm using prior experiences to solve problems [19]. However, EBR is still at an early stage. CBR is a special kind of EBR [9][19]. But there are many different kinds of EBR, which correspond to countless different experiences in our culture and social life, which CBR can not cover. In fact, some EBR paradigms, which have not been familiarized to ordinary people, are a real foundation for inference-based deception [21]. Therefore, it is significant to examine all possible EBR paradigms, at least from a logical viewpoint. To this end, let us first look at how a human performs EBR in his social activities with the following example [21]:

Peter Hagen is a distinguished Professor of Business and Commerce at the University of Trickland (which is an invented name). He has participated in many international conferences and visited many different countries for academic travel. He teaches his student *logistics* using *modus ponens* and *modus tollens* [7][14], while he explains some social phenomena using abductive reasoning [1][22]. When he participates in business negotiation with his competition, he likes to use *modus ponens with trick* [17] (We use trick and deception interchangeably from now on) and *modus tollens with trick* [15]. He also likes to conduct some investment, in which he likes to use *inverse modus ponens* [20]. When asked for investment advice by people he does not trust, he uses *inverse modus ponens with trick* and *abduction with trick* [19].

From this example, we can see that:

- Any human activities usually involve application of many reasoning paradigms such as abduction, deduction, and reasoning with trick
- Any person has to perform many different reasoning paradigms in order to cope with different social situations or occasions
- A person uses a specific reasoning paradigm depending on his experience in different social occasions.

Further, experience is all possible past problems and corresponding solutions that a human has encountered. Therefore, only one reasoning paradigm like CBR, which only simulates an experience principle: “similar problems have similar solutions” [2][6], is insufficient to model or

simulate all experiences or all kinds of EBR, as shown in Fig. 1. Generally speaking, one of the significant contri-

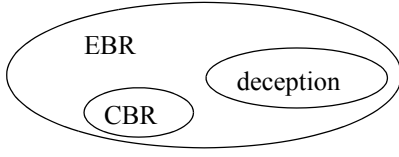


Fig. 1. CBR, EBR and deception [21].

bution of CBR research and development is that it points out the importance of experience and EBR, and provides some methodologies such as case reuse and case retention which can be used in experience reuse and experience retention in EBR and EM.

It should be noted that any EBR is based on certain inference rules, just as the basis for any reasoning paradigm discussed in AI and mathematical logic is inference rules. Therefore, it is necessary to discuss inference rules for EBR in order to improve the understanding of EBR.

3 Inference Rules for EBR

From a logical viewpoint, there are eight basic inference rules for performing EBR [19][20], which are summarized in Table 2 (see later), and are listed in the first row, and their corresponding logical forms are shown in the second row respectively. These eight inference rules cover all possible EBRs and constitute the fundamentals for all EBR paradigms [15][19][20].

From a theoretical viewpoint, the current AI models, and other computational models for problem solving are basically based on the first four inference rules: *modus ponens* (MP) [13], *modus tollens* (MT) [24], *abduction* [1], and *modus ponens with trick* (MPT) [17]. Because these four inference rules are well-known in AI, computer sciences, and fuzzy logic [13][19][24], we will not go into them any more in this paper, and turn to focus on reviewing the other four inference rules: *modus tollens with trick* (MTT), *abduction with trick* (AT), *inverse modus ponens* (IMP), *inverse modus ponens with trick* (IMPT) in some detail. These inference rules will be considered as the four new inference rules of EBR, because they are non-traditional, and have not been studied in mathematics, logic, fuzzy logic, and AI, although they are really abstractions of some EBR. The following formalization for them is a first attempt in this direction, to our knowledge [20][21].

First of all, we illustrate *modus tollens with trick* (MTT) with an example. We have the knowledge in the knowledge base (KB):

1. If Klaus is human, then Klaus is mortal
2. Klaus is immortal.

What we wish is to prove “Klaus is human”. In order to do so, let

- $A \rightarrow B$: If Klaus is human, then Klaus is mortal
- A : Klaus is human
- B : Klaus is mortal.

Therefore, we have A : Klaus is human, based on MTT, and the knowledge in the KB (note that $\neg B$: Klaus is not mortal). From this example, we can see that MTT is a kind of EBR.

Abduction with trick (AT) can be considered as a “dual” form of abduction [1][22], which is also the summary of a kind of EBR [19]. Abduction can be used to explain that the symptoms of the patients result from specific diseases [16], while AT can be used to exclude some possibilities of the diseases of the patient [20]. Therefore, AT is an important complementary part for performing system diagnosis and medical diagnosis based on abduction.

Inverse modus ponens (IMP) is also a rule of inference in EBR. The “inverse” in the definition is motivated by the fact that the “inverse” is defined in mathematical logic: “if $\neg p$ then $\neg q$ ”, provided that if p then q is given [7]. Based on this definition, the inverse of $A \rightarrow B$ is $\neg A \rightarrow \neg B$, and then from $\neg A$, $\neg A \rightarrow \neg B$ we have $\neg B$ using *modus ponens*. Because $A \rightarrow B$ and $\neg A \rightarrow \neg B$ are not logically equivalent, the argument based on IMP is not valid in mathematical logic. However, the EBR based on IMP is a kind of common sense reasoning, because there are many cases that follow IMP. For example, if John has enough money, then John will fly to Tianjin, China. Now John does not have sufficient money, then we can conclude that John will not fly to Tianjin.

It should be noted that IMP has received attention from some researchers [7]. However, they consider this inference rule as the source of fallacies in the reasoning, while we argue that it is a basic inference rule for EBR [20][21].

The last inference rule for EBR is *inverse modus ponens with trick* (IMPT) [21]. The difference between IMPT and IMP is again “with trick”, this is because the reasoning performer tries to use the trick of “make a feint to the east and attack in the west”; that is, he gets B rather than $\neg B$ in the *inverse modus ponens*.

So far, we have reviewed four new inference rules in EBR from a classic logical viewpoint. These new inference rules have not been appeared in any publications except [20][21], to our knowledge. Therefore, any research and development of each listed inference rule is significant for engineering experience and EBR.

The “with trick” is only an explanation for such models. One can give other explanations such as fraud or deception for them, depending on his/her individual preference [21]. For example, agent P has knowledge set K_P , reasoning methods set R_P , Q has knowledge set K_Q , reasoning methods set R_Q , even if $K_P = K_Q$, the agent Q can still deceive agent P if agent Q uses either of the above four new inference rules, because agent P still does not know them. Therefore, fraud and deception behaviors can be considered as special EBRs [21].

The four new inference rules are motivated by the following fact: All knowledge and experience consists of

two parts: mathematical knowledge and experience, and non-mathematical knowledge and experience as shown in Fig. 2 The former constitutes the resources for existing

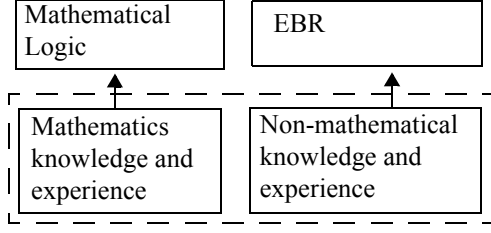


Fig. 2. Mathematics, logic and EBR.

mathematics, inference rules in mathematical logic can be considered the summary or abstraction of mathematical methods for solving problems in mathematics. The latter constitutes the resources for existing non-mathematical sciences. Although researchers have been always trying to use approaches provided by existing mathematics and mathematical logic to formalize the concepts in their own domain, there are an enormous number of theories and investigations in non-mathematical sciences that are at an empirical level, and require new logical and mathematical methodologies. The above new inference rules for EBR belong to this part.

Furthermore, from Fig. 2, we can see that mathematics can be considered one part of human knowledge and experience. Mathematics has heavily affected mathematical logic and then CBR and AI from a logical viewpoint. The rest after the abstraction are non-mathematical knowledge and experience. The latter leads to EBR. Mathematical logic is a formal meta-mathematics, it consists of all possible reasoning paradigms and inference rules occurring in mathematics for problem solving. However, from a fundamental viewpoint, only two inference rules, like the atoms of Boolean algebra [7], have been included in mathematical logic and fuzzy logic; that is, *modus ponens*, and *modus tollens*. The other existing inference rules in mathematical logic are composite. However, other above-mentioned six inference rules have not been included in mathematical logic. This is the reason why EBR is also an abstraction of non-mathematical knowledge and experience.

4 Four Fuzzy Inference Rules for EBR

This section will examine the four new inference rules for EBR from a viewpoint of fuzzy logic. Throughout this section we assume that P and Q represent fuzzy propositions. Let

$$F_0(x), F_{01}(x, y) \text{ and } F_1(y), x \in X, y \in Y$$

be fuzzy relations in $X, X \times Y, Y$, respectively, which are fuzzy restrictions on $x, (x, y)$, and y , respectively. X and Y are two ordinary non-empty sets. Let P, Q, P' , and Q' be fuzzy propositions and correspond to $F_0(x), F_1(y)$,

$F_0(x), F_1(y)$ respectively, and $P \rightarrow Q$ corresponds to $F_{01}(x, y)$. \circ is a fuzzy composition operation.

4.1 Fuzzy Modus Tollens with Trick

A direct development from *fuzzy modus ponens with trick* (FMPT) is *fuzzy modus tollens with trick* (FMTT). Although fuzzy modus tollens has drawn attention in the fuzzy logic community [12][24], nobody has studied this new kind reasoning paradigm. However, the latter is also an important part in EBR. In what follows, we will study it in some detail.

The general form of FMTT is

$$\frac{\neg Q' \quad P \rightarrow Q}{\therefore P'} \quad (1)$$

Theoretically speaking, FMTT is a variant of FMPT (see Table 2), because using FMPT, we have $\neg Q', P \rightarrow Q \Rightarrow \neg P'$. However, this variant can only be understood in a fuzzy setting. For example, if we assume, $\mu(P) = 1$, and $\mu(P') = 0.4$, then $\neg\mu(P') = 1 - \mu(P') = 1 - 0.4 = 0.6$. In this fuzzy microworld, both P' and $\neg P'$ are the intermediate states between P and $\neg P$. Therefore, such an intermediate but uncertain state is the space for performing a trick or deception [20]. It is very difficult for anyone to perform a deception in a pure two-valued world (true or false). Even though one could perform deceptions in this world, it is easy for others to recognize such deceptions. Therefore, it is significant to examine either FMPT or FMTT in a fuzzy setting, which is a closer approximation to the tricks and deceptions existing in human society.

Model (1) can be represented in the following form in fuzzy logic [24]:

$$\frac{\text{If } x \text{ is } P \text{ Then } y \text{ is } Q \quad x \text{ is } \neg Q'}{\therefore y \text{ is } P'} \quad (2)$$

For instance,

$$\frac{\text{IF Bill is the smartest THEN Bill will work at Msoft} \quad \text{Bill will not work at Msoft}}{\therefore \text{Bill is very smart}} \quad (3)$$

From a logical viewpoint, this reasoning means that we prefer to accept a fuzzy or approximate statement to the premise in the fuzzy conditional proposition (Bill is very smart), if we do not accept the conclusion resulting from performing fuzzy modus tollens.

The FMTT can be also computed using the following formula, based on the above discussion:

$$F_0(x) = F_{01}(x, y) \circ (1 - F_1(y)) \quad (4)$$

4.2 Fuzzy Abduction with Trick

Fuzzy abduction with trick (FAT) has not been drawn any attention in either medical diagnosis or system analysis,

although fuzzy abduction has been studied and applied in these fields [12][22]. In fact, it is also an important kind of EBR towards the explanation of any symptoms in clinical practice or system diagnosis, which will be seen later.

The general form of FAT is as follows:

$$\frac{Q'}{P \rightarrow Q} \quad \therefore \neg P' \quad (5)$$

Theoretically speaking, FAT is a variant of *fuzzy abduction*. In particular, when an agent A in a multiagent system (MAS) [23] may guess that another agent B in the MAS performs *fuzzy abduction*, while agent B actually performs *fuzzy abduction with trick* based on (5). Here-with agent A and agent B will suffer a trust crisis. How to resolve such a trust crisis is an important issue for MASs and web-based systems.

Model (5) can be represented in the following form in a context of fuzzy logic:

$$\frac{\text{If } x \text{ is } P \text{ Then } y \text{ is } Q}{x \text{ is } Q'} \quad \therefore y \text{ is } \neg P' \quad (6)$$

For instance,

$$\frac{\text{IF John gets fever THEN John will be dizzy}}{\text{John is a little dizzy}} \quad \text{Conclusion: John does not get any fever} \quad (7)$$

Every adult has had similar experience in a clinic: The doctor gives a wrong explanation for the symptoms. The wrong explanation leads to wrong treatment, because they sometimes do not really use fuzzy abduction with trick.

More formally, if we assume D is the set of diseases, and S is the set of symptoms, then for a patient c in a clinical practice, his symptoms (for example, SARS's symptoms) are a subset of S , S_c , and his diseases are a subset of D , D_c . Therefore,

$$D_c \subseteq D, \text{ and } S_c \subseteq S \quad (8)$$

The available medical experience can be expressed as a set of (fuzzy) rules, E ; that is,

$$E = \{f|f = \text{IF } d \text{ Then } s, d \in D, s \in S\} \quad (9)$$

The possible experience set for this patient is $E_c = \{f|f = \text{IF } d \text{ Then } s, d \in D_c, s \in S_c\}$. However, a doctor normally can not use such a medical experience-based system and performs EBR by himself. In this case, he uses any experience $f_1 \in E - E_c$ and he performs a FAT.

The fuzzy reasoning based on FAT can be computed using the following formula, based on the above discussion:

$$F_0(x) = 1 - F_{01}(x, y) \circ F_1(y) \quad (10)$$

Eq. (10) can be replaced in a more concrete form as follows: Let $D = \{d_1, d_2, \dots, d_n\}$ be the set of diseases, and $S = \{s_1, s_2, \dots, s_m\}$ the set of symptoms [12][24].

According to medical experience, disease d_i will lead to symptom s_j with certainty membership $\mu_{ij}(d_i, s_j)$; that is, fuzzy relationship between diseases D and symptom S are $\tilde{F}(D, S) = (\mu(d_i, s_j))$, $i = 1, 2, \dots, n, j = 1, 2, \dots, m$.

$\mu(d_i, s_j)$ can be considered as the confirmability of s_j for d_i , and $\mu(s_j)$ expresses the intensity of symptom s_j , for detail see [24]. If a patient is observed to have a fuzzy symptom set, $\tilde{S}_p = (\mu(s_j))^T$, where $\mu(s_j)$ is the certainty membership of the observed symptom belonging to s_j . Therefore, according to (10), the fuzzy disease set of this patient is:

$$(\mu(d_1), \dots, \mu(d_n))^T = 1 - \begin{bmatrix} \mu(d_1, s_1) & \dots & \mu(d_1, s_m) \\ \dots & \dots & \dots \\ \mu(d_n, s_1) & \dots & \mu(d_n, s_m) \end{bmatrix} \begin{bmatrix} \mu(s_1) \\ \dots \\ \mu(s_m) \end{bmatrix}$$

where $\mu(d_i)$ is the certainty membership of the disease of the patient belonging to d_i

It should be noted that FAT has still not been applied in medical diagnosis. Its research and development will help to understand why many patients suffer misdiagnosis and incorrect treatment. In particular, it can be also to exclude some possibilities of certain diseases of the patient; that is, for a certain $k \in \{1, 2, \dots, n\}$, if $\mu(d_k)$ is approximate to 0, the disease d_k can be excluded from the possible diseases from which the patient suffers. This approach is illustrated by the following example, which is borrowed from an example given in [12] and simplified:

Example 1. Fuzzy abduction with trick. Assume the set of diseases $D = \{d_1, d_2, d_3\}$, $S = \{s_1, s_2, s_3, s_4\}$.

The fuzzy confirmability of s_j for d_i , $\tilde{F}(D, S) = (\mu(d_i, s_j))$ is given as a fuzzy relation, listed in Table 1.

The observed symptoms are denoted as a fuzzy set \tilde{S} in S , and the corresponding certainty membership of the observed symptoms belonging to S_j , $\mu(s_j)$, are listed as a vector $(\mu(s_1), \mu(s_2), \mu(s_3), \mu(s_4)) = (0.6, 0.1, 0.9, 0.3)$.

Table 1: The fuzzy confirmability of s_j for d_i

$\mu(d_i, s_j)$	s_1	s_2	s_3	s_4
d_1	1.0	0.8	0	0.6
d_2	0.6	0	1.0	0
d_3	0.8	0.6	0.7	0.6

Using, we calculate $(\mu(d_1), \mu(d_2), \mu(d_3))$ (based on min-max operation [24]) and have

$$\begin{bmatrix} \mu(d_1) \\ \mu(d_2) \\ \mu(d_3) \end{bmatrix} = 1 - \begin{bmatrix} 1.0 & 0.8 & 0 & 0.6 \\ 0.6 & 0 & 1.0 & 0 \\ 0.8 & 0.6 & 0.7 & 0.6 \end{bmatrix} \begin{bmatrix} 0.6 \\ 0.1 \\ 0.9 \\ 0.3 \end{bmatrix} = 1 - \begin{bmatrix} 0.6 \\ 0.9 \\ 0.7 \end{bmatrix} = \begin{bmatrix} 0.4 \\ 0.1 \\ 0.3 \end{bmatrix}$$

Because $\mu(d_2)$ is 0.1, which is approximate to 0, the disease d_2 can be excluded from the possible diseases from which the patient suffers.

4.3 Fuzzy Inverse Modus Ponens

Fuzzy inverse modus ponens (FIMP) is another rule of inference for EBR. Its general form is as follows:

$$\frac{\neg P' \quad P \rightarrow Q}{\therefore \neg Q'} \quad (11)$$

Model (11) can be represented in the following form in the context of fuzzy logic:

$$\frac{\text{If } x \text{ is } P \text{ Then } y \text{ is } Q \quad x \text{ is } \neg P'}{\therefore y \text{ is } \neg Q'} \quad (12)$$

Example 2. Fuzzy inverse modus ponens: We have the knowledge in the knowledge base:

- If the quarter profit is increasing, then Robert invests in the Project ANP,
- The quarter profit is marginally decreased.

What we wish is to prove “Robert does not intend to invest in the Project ANA”. To this end, let $P \rightarrow Q$: If the quarter profit is increasing, then Robert invests in the Project ANA; P : The quarter profit is increasing. Therefore, we have $\neg Q'$: Robert does not intend to invest in the Project ANA based on (11) and the knowledge in the knowledge base (note that $\neg P'$: The quarter profit is marginally decreased).

In the conclusion of this example, “Robert does not intend to invest in the Project ANA” means that Robert has not yet decided to invest the project ANA, which is an intermediate state between “Robert invests in the Project ANA” and “Robert does not invest in the Project ANA”.

The fuzzy reasoning based on FIMP can be computed using the following formula, based on the above discussion:

$$F_1(y) = 1 - (1 - F_0(x)) \circ F_{01}(x, y) \quad (13)$$

4.4 Fuzzy Inverse Modus Ponens with Trick

Fuzzy inverse modus ponens with trick (FIMPT) is the last rule of inference for EBR. Its general form is as follows:

$$\frac{\neg P' \quad P \rightarrow Q}{\therefore Q'} \quad (14)$$

Model (14) can be represented in the following form in the context of fuzzy logic:

$$\frac{\text{If } x \text{ is } P \text{ Then } y \text{ is } Q \quad x \text{ is } \neg P'}{\therefore y \text{ is } Q'} \quad (15)$$

Example 3. Fuzzy inverse modus ponens with trick: We have the knowledge in the knowledge base:

- If the quarter profit is increasing, then Edward invests in the Project BMB,
- The quarter profit is not increasing much.

What we wish is to prove “Edward intends to invest in the Project BMB”. To this end, let $P \rightarrow Q$: If the quarter profit is increasing, then Edward invests in the Project BMB; P : The quarter profit is increasing. Therefore, we have Q' : Edward intends to invest in the Project BMB based on (14) and the knowledge in the knowledge base (note that $\neg P'$: The quarter profit is not increasing much). In the conclusion of this example, “Edward intends to invest in the Project BMB” is approximate to “Edward invests in the Project BMB.”

The fuzzy reasoning based on FIMPT can be computed using the following formula, based on the above discussion:

$$F_1(y) = (1 - F_0(x)) \circ F_{01}(x, y) \quad (16)$$

It should be noted that *fuzzy inverse modus ponens* and FIMPT have not drawn any attention in either fuzzy logic or computer science. We believe that the research and development of them can improve our understanding of EBR, because it is common in human society.

4.5 Summary

Table 2 summarizes the proposed eight fuzzy inference rules for experience-based reasoning (including the corresponding logical form) in the second row. It should be noted that some general forms in the table such as fuzzy modus ponens, fuzzy modus tollens, fuzzy abduction have received some attention from researchers [12][24], while the rest of them have not been studied in fuzzy logic and computer science, although they are all the summarization of EBRs. We argued that they are all the basic inference rules, like the atoms of Boolean algebra, for EBR.

5 Concluding Remarks

This paper first reviewed the logical approach to EBR, in which eight different inference rules for EBR are discussed. Then the paper proposed fuzzy logic-based models for the four new inference rules of EBR, which forms a theoretical foundation for EBR together with the four traditional fuzzy inference rules. We argued that the proposed methodology of EBR will facilitate research of EBR and its

applications to e-commerce, knowledge management (KM) and experience management (EM).

Experience management (EM) is drawing increasing attention in e-commerce, information systems, and knowledge management (KM) [2][5], and has become one of the latest hot topics in the business world [2]. EM is more useful than KM, because while every one can have a lot of knowledge, only the experience of experts is invaluable [21]. Therefore, EM can facilitate spreading

valuable experience, promoting the transition from experience to knowledge, and facilitate KM. Furthermore, from a logical viewpoint, EM is based on EBR. Therefore, we will apply the proposed approach and inference rules for EBR to EM in future work. Similarity-based reasoning (SBR) is an important operational form for performing EBR [9]. It is an important “bridge” connecting CBR and EBR [19]. We will apply SBR to examine EBR and its eight inference rules in future research.

Table 2: Fuzzy rules of inference for experience-based reasoning

	MP	MT	Abduction	MPT	IMPT	IMP	MTT	AT
<i>Logic form</i>	$\frac{P}{P \rightarrow Q} \therefore Q$	$\frac{\neg Q}{P \rightarrow Q} \therefore \neg P$	$\frac{Q}{P \rightarrow Q} \therefore P$	$\frac{P}{P \rightarrow Q} \therefore \neg Q$	$\frac{\neg P}{P \rightarrow Q} \therefore Q$	$\frac{\neg P}{P \rightarrow Q} \therefore \neg Q$	$\frac{\neg Q}{P \rightarrow Q} \therefore P$	$\frac{Q}{P \rightarrow Q} \therefore \neg P$
<i>Fuzzy form</i>	$\frac{P'}{P \rightarrow Q} \therefore Q'$	$\frac{\neg Q'}{P \rightarrow Q} \therefore \neg P'$	$\frac{Q'}{P \rightarrow Q} \therefore P'$	$\frac{P'}{P \rightarrow Q} \therefore \neg Q'$	$\frac{\neg P'}{P \rightarrow Q} \therefore Q'$	$\frac{\neg P'}{P \rightarrow Q} \therefore \neg Q'$	$\frac{\neg Q'}{P \rightarrow Q} \therefore P'$	$\frac{Q'}{P \rightarrow Q} \therefore \neg P'$

6 References

- [1]. Barrel C. Abductive reasoning through filtering, *Artificial Intelligence*, 120, 2000, 1-28
- [2]. Bergmann R: *Experience Management: Foundations, Development Methodology and Internet-Based Applications*. LAIN 2432. Berlin: Springer 2002
- [3]. Ciampolini A, Lamma E, Mello P, Stefanelli C. Abductive coordination for logic agents. ACM Symposium on Applied Computing (SAC'99) San Antonio, Texas, 1999, pp 134-140
- [4]. Console L, Theseider Dupre' D, Torasso P. On the relationship between abduction and deduction. *J. Logic Comput.* 1 (5) 1991, 661-690
- [5]. Cokes E: *Knowledge Management: Current issues and challenges*, Hershey, PA: IRM Press, 2003
- [6]. Dubois D, Esteva F, Garcia P, Godo L, López de Mántaras R, Prade H. Case-based reasoning: A fuzzy approach. In: Ralescu AL, Shanahan JG (eds). *Fuzzy logic in artificial intelligence*, IJCAI'97 Workshop. Berlin: Springer-Verlag; 1999, pp 79-90
- [7]. Epp SS: *Discrete Mathematics with Applications*, Brooks/Cole Publishing Company Pacific Grove, 1995
- [8]. Finnie G, Sun Z. R^5 model of case-based reasoning. *Knowledge-Based Syst.* 16(1) 2003, 59-65
- [9]. Finnie G, Sun Z. A logical foundation for the CBR Cycle. *Int J Intell Syst* 18(4) 2003, 367-382
- [10]. Lenz M, Bartsch-Spörl B, Burkhard HD, Wess S (eds): *Case-Based Reasoning Technology, from Foundations to Applications*, Berlin: Springer; 1998
- [11]. Magnani L. *Abduction, Reason, and Science, Processes of Discovery and Explanation*. New York: Kluwer Academic/Plenum Publishers, 2001
- [12]. Miyata Y, Furuhashi T and Uchikawa Y: A study on fuzzy abductive inference. <http://citeseer.nj.nec.com/194836.html>
- [13]. Nilsson NJ. *Artificial Intelligence: A New Synthesis*. San Francisco, California: Morgan Kaufmann Publishers, Inc. 1998
- [14]. Russell S, Norvig P. *Artificial Intelligence: A modern approach*. Upper Saddle River, NJ: Prentice Hall, 1995
- [15]. Sun Z, Finnie G: Brain-like Architecture and Experience-based Reasoning, In: *Proc. 7th Joint Conf on Information Sciences (JCIS)*, September 26-30, 2003 Cary, North Carolina, USA. 1735-1738
- [16]. Sun Z, Finnie G, Weber K. Integration of abductive CBR and deductive CBR, In: *Proc 10th IEEE Int Conf on Fuzzy Systems (FUZZ-IEEE 2001)*, Melbourne, Australia; 2-5 December 2001, pp. 1432-35
- [17]. Sun Z, Weber K. Turing test and intelligence with trick. In: *Proc 8th Ireland Conf on AI (AI-97)*, Londonderry, Ireland; 1997, 217-224
- [18]. Sun Z, Finnie G. Fuzzy rule-based models for case retrieval. *Int J Engi Intell Syst*, 10 (4) 2002, 213-224
- [19]. Sun Z. Finnie G. *Intelligent Techniques in E-Commerce: A Case Based Reasoning Perspective*, Heidelberg: Springer Verlag, 2004.
- [20]. Sun Z, Finnie G: Experience-based reasoning: A logical approach. Submission for publication at *Int. J. of General Systems*, 2004
- [21]. Sun Z, Finnie G: Experience based reasoning for recognising fraud and deception. In: *Proc. 4th Int Conf on Hybrid Intelligent Systems (HIS 2004)*, Kitakyushu, Japan, Dec 6-8, 2004, IEEE Press, pp 80-85
- [22]. Torasso P, Console L, Portinale L, Theseider D: On the role of abduction. *ACM Computing Surveys*, 27 (3) 1995, 353-355
- [23]. Weiss, G (ed.). *Multiagent Systems: A modern approach to distributed artificial intelligence*, The MIT Press, Cambridge; 1999
- [24]. Zimmermann HJ. *Fuzzy Set Theory and its Application* (3rd Edn.). Boston/Dordrecht/London: Kluwer Academic Publishers; 1996.