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Improving the Revision Stage of a CBR System with Belief Revision Techniques

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This paper presents a method for automating the revise phase of case-based reasoning systems. The revision is carried out using a rule-based system, which adapts its rules or knowledge base as the working environment, to which the system is applied, evolves in time. This actualisation is carried out by a belief revision technique. An example has been introduced to illustrate the working mode of the revision technique.

1. INTRODUCTION

Case-based Reasoning (CBR) systems have a life cycle formed by four well known phases which take place in sequence [Aamodt, 1994]: Retrieve, Reuse, Revise and Retain. Huge amounts of work have been carried out with the aim of identifying techniques that automate such stages. Although there have been identified a considerable number of successful retrieval and reuse (adaptation) techniques, still much work have to be done to identify adequate revision and retain methods [Corchado, 2000]. These both stages are normally carried out by human experts in most experimental and commercial CBR systems.

This paper shows how a rule based system could be used to review automatically the initial solution obtained by the case-based reasoning system after the reuse phase. So the CBR system could achieve a higher degree of autonomy. This approach presents some problems related to the evolution of the knowledge. In the retain phase the CBR system will learn by introducing new cases. So the rule based system, which reviews the solution must evolve in the same way**.**

The previously exposed idea is the main topic of this paper and has not been address many times in literature [Pal, 2000]. The most usual way in which actualisation of knowledge has been solved is reanalysing the available data for obtaining a completely new system, as if the previous one had never existed [Lenz *et al.*, 1998]. Nevertheless, it is thought that this remaking is an effort wasteful task. Another way of achieving a change in the knowledge would be to employ techniques for revising the existent rules with incoming information. The AGM (Alchourron, Gärdenfors and Makinson) Belief Revision (BR) paradigm is a powerful framework for modelling such revision process [Alchorron *et al.*, 1985]. Particularly, the maxi-adjustment method offers a sound, robust and computational mechanism to develop BR systems [Antoniou, 1997b].

The present work is focused in the use of the maxi-adjustment Belief Revision method for changing the knowledge base of a rule-based system which could substitute a human expert in the revise phase of a CBR system. The paper is organised as follows. Sections 2 and 3 present some of the CBR and BR concepts. Section 4 describes how the combination of such techniques can be used in the revise stage of a CBR system. A simplified problem will be used to present the "hybrid" system. Future work and Conclusions are presented in section 5.

2. CBR DESCRIPTION

The idea which impelled the development of Case-based reasoning (CBR) systems is centred in the fact that human beings employ what they have learned in previous experiences to solve present problems [Kolodner 1983a, 1983b; Aamodt, 1994]. Case-based reasoning systems solve problems through the adaptation of solutions previously given to similar problems [Riesbeck *et al.*, 1989].

The CBR systems analyse and obtain solutions through algorithms of index, recuperation, comparison techniques and adaptation of problems to a certain situation. To do this, they are based on the knowledge stored in their memory, in the form of cases or problems.

Figure 1 shows the reasoning cycle of a typical CBR system that includes four steps that are cyclically carried out and in a sequenced way: R*etrieve, Reuse,* R*evise, and Retain (training)* [Kolodner, 1993; Aamodt, 1994; Watson *et al.*, 1994]. The mission of the algorithm of *retrieve* consists of looking for and selecting in the memory of the CBR the cases that are more similar to the present problem. The recovered cases are *adapted* to generate a possible solution. Such solution is *reviewed* and if it is appropriated a new case is created and *stored* in the memory. A CBR is a system of increasing training since each time a problem is solved, it is possible to create a new case and store it in the CBR memory for its further use.

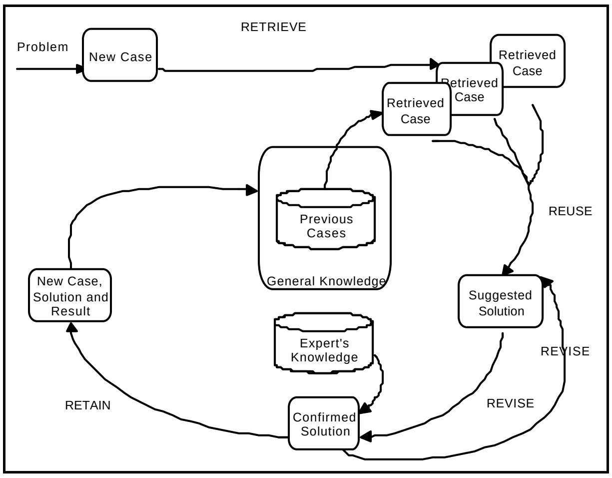

Figure 1. CBR Life Cycle

Of particular interest is the phase of revise, which checks the proposed solution in accordance with an expert in the domain. If the solution is considered to be correct then the system produces it as output, otherwise the CBR system turns back to the *reuse* phase and searches for other possible solutions.

Whereas the CBR system gives the appropriate solutions, the expert's knowledge must be considered right. But when the results of putting into effect these solutions are not the expected ones, the knowledge should be updated. Section 4 of this paper presents a method for automating the revision step of such systems.

3. BELIEF REVISION

The theory of Belief Revision deals with the dynamics of belief states, that is, it aims at modelling how an intelligent system updates its state of belief as a result of receiving new information [Antoniou, 1997a], [Gärdenfors, 1995]. Of particular interest is the case where the new information is incompatible with the old state of belief.

The AGM paradigm [Alchorron *et al.*, 1985], so named after its founders Alchourron, Gärdenfors and Makinson, is a powerful framework for modelling and implementing BR systems based on the principle of *Minimal Change*. Technically, a belief state can be seen as a *theory K* and changes as *functions* that take a theory and a logical sentence to another theory. In the AGM approach one can distinguish three main kinds of belief changes: *Expansion* (K+α), a new sentence α is added to a belief systems K regardless of the consequences of the larger set so formed. *Revision* (K*α), a new sentence that is inconsistent with a belief system K is added in such a way as to ensure the consistency of the resulting belief system. *Contraction*: (K-α), the sentence α in K and all other beliefs that imply this sentence are retracted without adding any new fact.

The process of Belief Revision can be derived from de process of belief contraction and vice versa through the so-called *Levy Identity* (K*α) = ((K−¬α)+α) and the *Harper Identity* (K-α) = K∩(K*¬α).

It is not possible to give a definition of revision and contraction based only in logical and set-theoretical notions. Logical considerations alone do not identify which beliefs to give up and which to retain, so this has to be decided by some other means. There are two general approaches to deal with belief revision:

- *Axiomatic*: this approach formulates postulates for the changes of belief, which are supposed to be rationality criteria for revision and contractions of belief states. These postulates do not uniquely determine a change function, rather their purpose is to identify the set of possible new belief states that might reasonable result when new information is received.
- *Constructive*: This approach presents explicit ways of constructing the revision process [Gärdenfors, 1995]. In order to choose a particular function of change, extralogical information is required. There are several constructive models for belief states such as epistemic entrenchment, selection functions, systems of spheres or safe contraction. *Epistemic entrenchment* will be the referential model in this paper.

3.1 Epistemic entrenchment

Intuitively, epistemic entrenchment (≤) is a preference ordering of beliefs according to importance in the face of change [Gärdenfors, 1988]. For instance, if α and β are beliefs in a belief set K, α≤β means that β is at least as entrenched as α. If inconsistency arises after applying changes to a belief set, beliefs with the lowest degree of epistemic entrenchment are given up.

Technically, a relation of epistemic entrenchment is a relation over all sentences satisfying the following postulates: **(EE1)** If α=β and β=γ, then α=γ. **(EE2)** If α? β, then α≤β. **(EE3)** For any α and β, α≤α∧β or β≤α∧β. **(EE4)** When $K \neq K_\perp$ α∉K iff α≤β,for all β. **(EE5)** If β≤α for all β, then ? α.

The condition (EE1) requires that an epistemic entrenchment ordering be transitive. (EE2) says that if α is logically stronger than β, then β is at least as entrenched as α. The condition (EE3) together with (EE1) and (EE2) implies that a conjunction is ranked at the same level as its least ranked conjunct. The condition (EE4) indicates that sentences not in theory are minimal and (EE5) says that the tautologies are maximal.

It has been proved that an ordering of epistemic entrenchment determines a contraction function:

$$\text{(C-)} \qquad \beta \in K\text{-}\alpha \text{ iff } \beta \in K \text{ and either } \alpha < \alpha \vee \beta \text{ or } \alpha \notin K \text{ or not } \alpha < T$$

Moreover, a contraction function and a belief set determine an ordering of epistemic entrenchment:

$$\text{(C<)} \qquad \alpha < \beta \text{ iff } \alpha \notin K\text{-}\alpha \wedge \beta \text{ and } \beta \notin K\text{-}\alpha \wedge \beta$$

In order to develop computational models based on entrenchment construction, two problems must be solved: a finite representation for epistemic entrenchment ordering and a strategy of iterated revisions where epistemic entrenchment ordering must be propagated.

3.1.1. Finite partial entrenchment ranking

In [Williams 1995], the first problem is solved using a *finite partial entrenchment ranking* (B) that grades the content of a finite knowledge base according to its epistemic importance. Intuitively, the higher the value assigned to a sentence the more firmly held it is. Formally, this ranking maps a finite set of sentences to natural numbers, such that the following conditions are satisfied for all $\alpha \in \text{dom(B)}$:

$\{\beta \in \text{dom(B)}: B(\alpha) < B(\beta)\}$? α

If ? $\neg\alpha$, then $B(\alpha) = 0$

$B(\alpha)=1$ iff ? α

The set of all finite partial entrenchment ranking is denoted ? . $B(\alpha)$ represents the *degree of acceptance* of α. The explicit information content of $B \in$? is $\exp(B) = \{\alpha \in \text{dom(B)}: B(\alpha)>0\}$. Similarly, content(B) = Cn(exp(B)) define the implicit information content of B (Cn is the classical consequence operator). Not only the degree of acceptance of explicit information is interesting, but also the degree of acceptance of sentences they entail. The following function derives the minimum possible degree of acceptance for implicit information as specified by a partial entrenchment ranking:

$$\text{degree}(B,\alpha) = \begin{cases} \text{largest } j \text{ such that } \{\beta \in \exp(B): B(\beta) \geq j\} \text{ ? } \alpha \\ \qquad\qquad \text{if } \alpha \in \text{content}(B) \end{cases}$$

3.1.2. Maxi-Adjustment

Williams [Williams,1996] solves the problem of iterated revisions transmuting epistemic entrenchment ordering where the emphasis is not only on acceptance or removal of beliefs from a theory, but also on raising and lowering of the degree of acceptance of beliefs. Maxi-adjustment repeatedly transmutes B using an absolute measure of minimal change under *maximal information inertia*, i.e. information stays at its current rank unless there is a *reason* to change it. According to Spohn's [Spohn, 1983] β is a reason for α if and only if raising the epistemic rank of β would raise the epistemic rank of α.

Then the (α,i) maxi-adjustment of B is [Williams,1996]:

$$B^*(\alpha, i) = \begin{cases} (B^-(\alpha, i)) & \text{if } i \leq j_m \\ (B^-(\neg\alpha, 0))^+(\alpha, i) & \text{otherwise} \end{cases}$$

4. AUTOMATING THE REVISE PHASE

This work addresses some useful ideas for the development of a model capable of carrying out the theory actualisation of a rule-based system. Such system will validate, during the revise phase of the CBR life cycle, the output of the reuse phase and will identify if the output of the reuse stage (adaptation) is consistent with the rules of the system (see Figure 1). This system will be constructed using Knowledge Engineering techniques and updated using the previously introduced belief revision technique.

Interesting areas of application of these ideas are dynamic systems, that is, systems which evolve in time, like e-commerce or Internet search, where the likes of users may change during a period of time.

The model will be illustrated using as example a system, which help to identify potential buyers, taking into account a number of characteristics, which determine his profile. A possible set of cases for this determination is shown in Table 1. These cases will form the hypothetical case base of the CBR system.

Salary	Have Children	Age	Item one bought
H-M	Yes	20-35	Yes
H-M	No	20-35	Yes
H-M	No	20-35	No
H-M	No	36-50	No
H-M	No	36-50	No
M-L	Yes	36-50	Yes
M-L	Yes	36-50	Yes
M-L	No	36-50	Yes
M-L	No	36-50	No
M-L	Yes	36-50	No
M-L	Yes	36-50	Yes
M-L	Yes	36-50	Yes
H-M	No	36-50	Yes
H-M	No	36-50	No

Table 1: Collected data.

Where three attributes defining customer characteristics are selected: salary, have children and age, with the following domains:

V_{Salary} = {High-Medium, Medium-Low}

$V_{HaveChildren}$ = {Yes, No}

V_{Age} = {20-35, 35-50}

The customer decision attribute indicates the customer decision about buying or not the considered item.

$V_{customer\ decision}$ = {Yes, No}

4.1. Knowledge representation

Expert's beliefs are represented as rules with an associated credibility. For example, a belief that item one is required by 85% persons which have a children, is represented as a rule like this one: (0.85,children→item one). This rule has a credibility value associated. Section 4.2 will introduce a mechanism that can be used to calculate such credibility.

It is possible to induce a preference ordering between rules using such credibility. Once this order is induced, it can be taken as the epistemic entrenchment ordering of the corresponding beliefs.

4.2. Construction of the Rule -based System

0,83	*Children Þ item one*
0,75	*HM Ù Ø young Þ Ø item one*

Figure 2. Initial theory obtained from the cases

The rule-based system is created using the cases stored in the CBR case base[1]. From the cases and using variable precision rough sets [Ziarko, 1993], rules can been extracted. This rules have an associated error *i* such that *0 £ i <0.5* which is interpreted as its credibility and allows the ordering of the rules in the way epistemic entrechment requires. Such rules constitute de initial rule-based system. The rules obtained for the example presented in Table 1 are shown in figure 2. These rules state that persons who have children buy item one in a 83% of the cases, while people between 36 and 50 years old, with high or medium salary, do not buy this product in a 75% of the cases.

4.3. Revision of the Rule -based System

Since the CBR is a dynamic system, it will store new cases. In order to adapt the rule-based system to the changes in the environment, these new cases will be used as input for revising the rules.

Figure 3 describes the proposed life cycle for the rule based system. The new cases are used to obtain a new theory, as it has been done before for creating the initial one. New rules will appear and/or the degree of credibility of rules will change. Then, the old rules are revised with these ones. The result is a new knowledge base, which incorporates the evolution of knowledge in time.

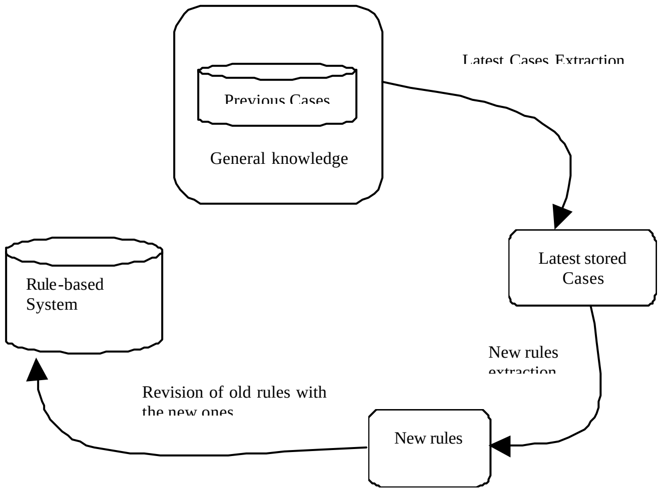

Figure 3. Proposed Rule Based System Life Cycle.

4.4. Empirical results

Three examples have been selected for illustrating what happen when new cases are stored in the retain phase of CBR system and, in consequence, new rules are identified. These new rules are used as incoming information for revising the old rule-based system using belief revision. For making revision SATEN, a tool for BR available on the net, has been used [Williams, 1997].

Examples start from the initial rule-based system presented in figure 2.

Example 1:

Salary	Have Children	Age	Item one bought
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
M-L	Yes	20-35	Yes
M-L	Yes	20-35	Yes
M-L	Yes	20-35	Yes
M-L	Yes	20-35	Yes
M-L	Yes	20-35	No
M-L	No	20-35	No
H-M	No	20-35	No
H-M	No	20-35	Yes

Table 2: Collected Data

[1] The results achieved by the process of revision will be the same as if the system had been built using traditional techniques of Knowledge Engineering. The only requirement needed is that knowledge is represented in the way previously described.

.Table 2 shows 13 new cases from which a new rule has been obtained, applying variable precision rough sets (*0,9 Children Þ item one*). This rule states that people who have children buy item one with a higher degree of credibility than before. Applying BR to the old rules with this rule will yield to a new theory in which the credibility of the first rule is incremented (Figure 4).

0,9 Children Þ item one
0,75 HM Ù Ø young Þ Ø item one

Figure 4. Revised theory.

Example 2:

Salary	Have Children	Age	Item one bought
M-L	Yes	20-35	No
H-M	Yes	20-35	No
M-L	Yes	20-35	No
M-L	Yes	20-35	No
M-L	Yes	20-35	No
H-M	Yes	20-35	No
H-M	Yes	20-35	No
H-M	Yes	20-35	No
M-L	Yes	20-35	No
H-M	Yes	20-35	Yes
H-M	No	20-35	Yes
M-L	No	20-35	Yes
M-L	No	20-35	No

Table 3: Collected Data

.Table 3 presents cases which generate a contradictory rule (*0,9 Children Þ Ø item one*) with respect to initial rules. In this case, the application of BR introduces the new rule and the old one, which is in conflict, is eliminated (Figure 5).

0,9 Children Þ Ø item one
0,75 HM Ù Ø young Þ Ø item one

Figure 5. Revised theory.

Example 3:

Salary	Have Children	Age	Item one bought
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
H-M	Yes	20-35	Yes
M-L	Yes	20-35	No
H-M	Yes	20-35	No
M-L	Yes	20-35	Yes
M-L	Yes	20-35	Yes
M-L	Yes	20-35	Yes
H-M	Yes	20-35	No
H-M	No	20-35	No
H-M	No	20-35	No
H-M	No	20-35	Yes

Table 4: Collected Data

In the last example (Table 4), the new rule is identical to one of the initial theory, but has a lower degree of credibility (*0,75 Children Þ item one*). In this case, as BR considers that the rules used for revision must always remain in the final theory, the result is a decrease in the rule credibility (Figure 6). This solution which may seem a bit strange is very useful, because allows giving a higher importance to the newest information.

0,75 Children Þ item one
0,75 HM Ù Ø young Þ Ø item one

Figure 6. Revised theory

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5. CONCLUSIONS AND FUTURE WORK

This paper has shown that Belief Revision can be applied in a CBR environment to address the possibility of representing the change in time. The main advantage of the system proposed is the automation of the revise phase of the CBR. Other useful feature is that the system gives automatically more importance to the latest cases, because of the properties of BR, which is very adequate for the exposed applications.

Other utility of the system can be to use the rules in order to decide what cases to store in the CBR case base or to prune the case base in accordance to them, reducing the amount of information the CBR system has to manage.

Nevertheless a drawback is related with the amount of rules and cases. In a simple example like the one shown, BR is a useful technique, but when the number of rules increases its computational complexity grows. So further work must be done in order to address this drawback and achieve a system useful with any number of cases and rules. This is a current field of study in BR.

References

[Aamodt, 1994] Aamodt A. and Plaza E. *Case-Based Reasoning: foundational Issues, Methodological Variations, and System Approaches*, AICOM. Vol. 7. n. 1, March. 1994.

[Alchorron *et al*., 1985] C. Alchourrón, P. Gärdenfors. and D. Makinson. *On the logic of theory change: Partial meet contraction and revision functions*. Journal of symbolic logic, Vol. 50, pag. 541-530, 1985.

[Antoniou, 1997a] G. Antoniou. *Belief Revisión*. In Nonmonotonic Reasoning. The MIT Press, pag. 183-196, 1997.

[Antoniou, 1997b] G. Antoniou. *Implementing Belief Revisión*. In Nonmonotonic Reasoning. The MIT Press, pag. 197-211, 1997.

[Corchado, 2000] J. M. Corchado and B. Lees. *Adaptation of Cases for Case-based Forecasting with Neural Network Support*. S.K Pal, T.S. Dillon and D.S. Yeung (Eds.), Soft Computing in Case Based Reasoning, Springer Verlag, London. 2000.

[Gärdenfors, 1988] P. Gärdenfors and D. Makinson. *Revision of Knowledge Systems using Epistemic Entrenchment*. Proceedings of the Second Conference of Theoretical Aspects of Reasoning about Knowledge, pag. 83-96, 1988.

[Gärdenfors, 1995] P. Gärdenfors and H. Rott. *Belief Revision*. In Dov M. Gabbay, C.J. Hogger and J. A. Robinson, Handbook of logic in Artificial Intelligence and Logic Programming, pag. 35-132, 1995 Oxford University Press.

[Joh, 1997] Joh D. Y. *CBR in a Changing Environment*. Case-based Reasoning Research and Development. ICCBR-97. Providence, IR, USA. 1997.

[Kolodner, 1983a] Kolodner J. *Maintaining organization in a dynamic long-term memory*. Cognitive Science. Vol. 7, pag.. 243-280. 1983.

[Kolodner, 1983b] Kolodner J. *Reconstructive memory, a computer model. Cognitive Science*. Vol. 7, pag. 281-328. 1983.

[Kolodner, 1993] Kolodner J. *Case-Based Reasoning*. Morgan Kaufmann. 1993.

[Lenz *et al*., 1998] Lenz M., Auriol E., Manago M. *Diagnosis and Decision Support*. Springer. 1998.

[Pal, 2000] S.K Pal, T.S. Dillon and D.S. Yeung (Eds.), Soft Computing in Case Based Reasoning, Springer Verlag, London. 2000.

[Spohn, 1983] W. Spohn. *Deterministic and probabilistic Reasons*. Erkenntis 19, pag. 371-396. 1983.

[Watson, 1994] Watson I., Marir F. *Case-Based Reasoning: A Review*. The knowledge Engineering Review. Vol. 9.n.3. Cambridge University Press, 1994.

[Williams, 1995] M. A. Williams. *Iterated theory base change: A computational model*. Proceedings of the 14th IJCAI, pag. 1541-1547. San Francisco, 1995.

[Williams, 1996] M. A. Williams. *Toward a practical approach to belief revision: Reason-Based Change*. KR'96: Principles of Knowledge representation and reasoning, pag. 412-420, 1996.

[Williams, 1997] M. A. Williams, D. M. Williams, *A Belief Revision System for the World Wide Web*, IJCAI Workshop on Artificial Intelligence and the Internet, 1997.

[Ziarko, 1993] W. Ziarko, *Variable Precision Rough Set Model*. Journal of Computer and System Sciences, Vol. 46, pag. 39-59, 1993.

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