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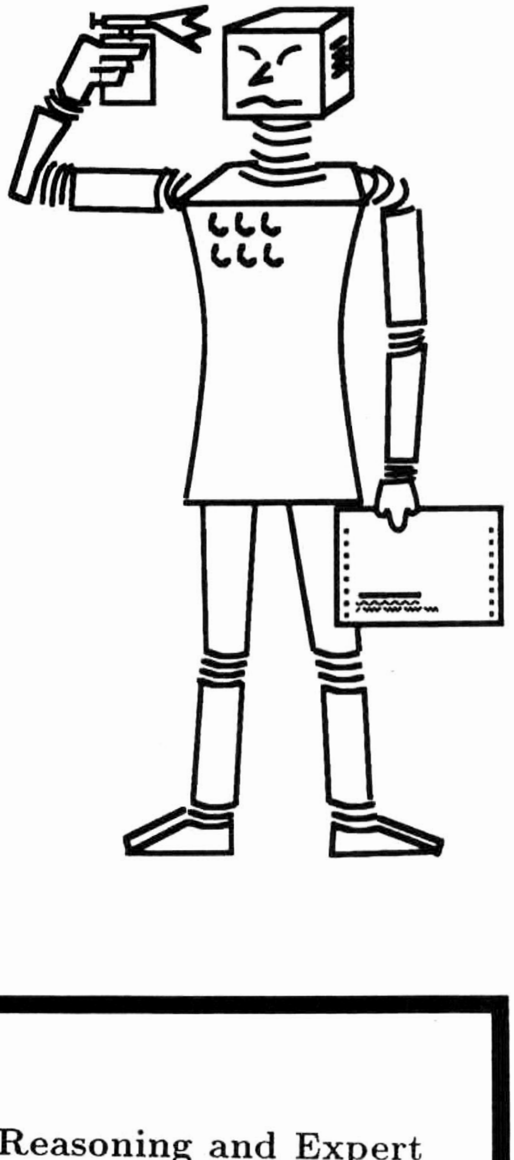

Case-Based Reasoning and Expert System Development

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Case-Based Reasoning and Expert System Development[1]

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Abstract. As a supplementation to other papers within this chapter on case-based approaches to Knowledge Engineering, we discuss some general aspects of case-based reasoning. We differentiate it from other case-using approaches and argue for the use of case-based reasoners within integrated knowledge engineering environments.

1. Introduction

Developing expert systems which can solve complex real world problems is still a difficult task. Therefore, knowledge engineering people need flexible methods and powerful tools which support them in doing this hard work. Within this paper we give a short introduction to such a flexible method, namely *case-based reasoning*, which might be one key issue in building, e.g., integrated knowledge engineering environments to offer the support needed. *Cases* are examples which have occurred in reality and consist of a problem description, a solution, and the underlying justification (derivation) for that solution. From a simplifying point of view, case-based reasoning means solving novel problems based on the adaptation of already known similar problem solutions. For being able to improve the problem solving capabilities of a system, cases must be memorized and integrated with already available empirical knowledge.

As concerned with problem solving, learning, and the acquisition of cases, case-based reasoning is within the focus of different fields of research, e.g. Cognitive Psychology, Machine Learning, and Knowledge Engineering. Apart from these strong commonalities, all those fields have their own view on the case-based reasoning approach. From a *Cognitive Psychology* point of view, it can be seen as a model of human problem solving. Within the *Machine Learning* community, case-based learning means an inductive learning method with a special kind of hypotheses generation. Verbatim examples are collected to learn (mainly) implicit con-

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cept descriptions which are then processed by the use of analogical reasoning. For the field of *Knowledge Engineering*, case-based reasoning implies a dynamic view on knowledge modeling which overcomes the strict distinction between knowledge acquisition and application which, actually, is the underlying assumption of the model-based approach to knowledge acquisition. The automation of the knowledge acquisition and adaptation processes is the transition to learning. In the sense of automatic knowledge modeling, this has already been suggested by Morik [Mor87]. Thus, the case-based reasoning approach can be roughly characterized by the notions of learning ability, adaptation, and integration of knowledge acquisition and application. Case-based reasoning is a well-suited method for dealing with any kind of inhomogeneous solution spaces.

In this paper, we discuss some general aspects of case-based reasoning. Since case-based reasoning is a hot research topic many scientific contributions within this field have to be considered. Many different research communities have, at least partially, similar interests and/or methods, e.g. Machine Learning, Cognitive Psychology, Statistics, Pattern Recognition, Neural Networks, and Knowledge Engineering. In the next section we summarize the basic characteristics of case-based reasoning. Commonalities and important distinctions between case-based reasoning and other approaches are presented in section 3. Finally, we argue for the use of case-based reasoning within integrated knowledge engineering environments.

2. Case-Based Reasoning

Introduced to the community by Kolodner [Kol80, KSS85] and Schank [Sch82], the basic problem solving model of case-based reasoning grew out of several projects at Yale University. There exists a strong overlapping with research work done so far in the field of analogical reasoning. In its simplest form, case-based reasoning is similar to approaches known from statistics and pattern recognition (e.g. nearest neighbor classification) [cf. e.g. Tou81]. A general overview of case-based reasoning is given in [Sla91] and [RS89]. Important research goals concerning case-based reasoning from a Cognitive Psychology point of view are presented in [SJ90].

2.1. Cases

What is meant by the notion of ´case´ is one of the central questions in case-based reasoning. From a psychological point of view, cases are abstractions of events or processes which can be limited within space and time. Such knowledge is also known as *episodic knowledge* [cf. Str89]. Once the abstraction mapping is fixed, cases are often identified with their underlying events or processes.

For us, a case is an "example which has occurred in reality", i.e. a problem that occurred and has been solved by a certain kind of problem solving mechanism (human expert, expert system etc.). Therefore, the "observed" solution is empirically justified. Such cases are then mapped onto the respective case representation which, of course, reflects only a part of the "problem solving reality". In this sense, cases include implicit problem solving heuristics which can be interpreted with respect to different purposes.

For being able to describe cases in more detail, at least three different levels of abstraction should be differentiated [cf. Ric89 and And89]:

- a cognitive level (knowledge level)
- a representational level (algorithmic level)
- an implementational level

Within the context of diagnosing an engineering system, a case is the behavioral result of processes that have their origin on the cognitive level. On the representation level, this could be abstracted into a sequence of attribute-value pairs. Finally, on the implementation level a case is implemented using lists, structured objects, or a special subgraphs.

Since there is no general agreement concerning formal descriptions of cases, we give a definition which is very general but, nevertheless, sufficient for our purposes here [cf. also VC89].

Definition
A case is a triple (P,S,J) where P is a problem description, S the solution for the described problem, and J the justification of the solution. A case corresponds to a real event or process which can be limited within space and time.

Justifications are an explicit representation of the problem solving process. They can be more or less complex. The simplest kind of justification is an "empty" one resulting in a case-based reasoner which could only find solutions for problems it has "seen" before. For classification tasks this approach is often sufficient and known as *case-matching* (*classification/interpretive/precedent-based*) case-based reasoning [cf. Ham89a]. E.g., in a simple diagnostic situation a case might read as follows: the problem is described by means of the observed symptoms, the solution is the achieved diagnosis, and the justification is empty.

If more than transfer of unmodified solutions is needed, justifications, as an additional knowledge source, must be available. They can range from a simple problem solving trace to a complete explanation using some kind of deep reasoning model. Thus, a justification always includes a procedure or a theory which allows the interpretation of the (static) trace. This approach is often called *case-adaptation* (*problem solving*) case-based reasoning [cf. Ham89a]. For a diagnostic task, a justification could be the temporal order by which the symptoms have been ascertained, and for a planning task, a more or less complete dependency graph.

2.2. Problem Solving

We now describe the basic problem solving cycle which characterizes the case-based reasoning paradigm (retrieve, compare, adapt, repair, generalize; cf. [Syc91]). Cases are knowledge sources as well as rules or deep models and, therefore, have to be considered during expert system development, too. Once a case has been acquired, it is stored in a case library (case memory). During problem solving it might be retrieved from the memory if its problem description is similar (enough) to the actual problem at hand. If the case can be applied to the current problem its solution must be adapted based on some simple strategies (identical solution transfer, "patching", etc.), or on a more complex underlying domain theory using the available

justifications. If the adaptation has been successful the completed case can be incorporated into the case memory. Thus, if the same problem occurs again it can be directly solved by retrieving this case and applying its stored solution. If the adaptation process has not been successful this case can be stored as a negative example to warn the problem solver not to go this direction if, e.g., the same problem has to be solved again. Additionally, if the system can find out the cause of the failure (explain the failure), it might be able to correct (repair) the wrong solution.

Both the adaptation and the repair processes require a problem solver of their own. Such problem solvers can use general strategies and a more or less complex domain theory to reach their respective goals. In the worst case, they must be as powerful as from-scratch problem solvers. Therefore, the integration of case-based reasoners into broader problem solving architectures is an important research goal (cf. section 4).

2.3. Similarity and Retrieval

Besides the underlying case representation, storage and retrieval of cases are of fundamental importance for the quality and efficiency of case-based problem solving mechanisms. Cases should be stored in memory such that fast retrieval of sufficiently similar cases is possible. They can be organized using a simple list, a data base, a discrimination [cf., e.g., Kol83a+b], or dependency graph. Similar cases can then be found by means of a similarity measure. This could be realized as an explicit mathematical function, as a pair of insert and retrieval procedures for the case memory, or as a combination of both.

2.4. Learning

A case-based reasoning system has to handle, at least, three different learning tasks. This encompasses learning from positive examples which might have been presented by an expert, learning from its own problem solving success, as well as from failure. Within the case-based reasoning community many different learning strategies have been used to handle these tasks. This includes rote learning for the integration of new cases or problem solving experiences into the case memory, explanation-based generalization to single out relevant features to be used as indices [RS89, Ham89b, BM88], generalization of implicit concept descriptions by means of partial matching (indexing, similarity functions) [Kol83a+b, PBH90, PG91], specialization of implicit concept descriptions (forgetting of cases according to certain selection criteria [AKA91], or competitive learning of feature relevances [AW91]), and generalization of feature values [Sal91].

3. Other Case-Using Approaches

Up to now, cases as a knowledge source for solving certain kinds of problems have been used in many different fields. We want to give an overview together with a rough classification of the respective approaches. This allows for an easy differentiation between them. Since many underlying notions of and connections between these approaches are not well understood up to now, we will not introduce a formal framework. Here, much work is still to be done.

Additionally, we do not want to differentiate between the case-based approach and approaches known as exemplar-based or instance-based.

One main aspect of case-based reasoning is that the underlying basic problem solving method is analogical reasoning. In general, analogical reasoning means transforming and extending existing domain knowledge to solve a similar task within another domain using similar methods. The known domain is often called *base* and the new one *target*. Fundamental characteristics of the analogical process are the mechanisms which determine the similarity of the tasks and transfer the methods and/or features from the base to the target domain, respectively. In principle, case-based reasoning can be seen as a special kind of analogical reasoning.

Historically, different research communities have concentrated on these inference mechanisms. For instance, Kolodner [cf. Kol89] points out that the focus within case-based reasoning has been mainly on case representation and retrieval, whereas within analogical reasoning the solution transfer has been treated in more depth. This is due to different basic assumptions concerning base and target domain. For case-based reasoning, they are normally identical, for analogical reasoning, on the other hand, it is mostly an essential feature to have different base and target domains [cf. Bur89, SD90]. For the rest of the paper we will not differentiate between these two approaches.

	Real-Life Connection	**Kind of Heuristic**	**Interpretation**
Rules	Abstract	Explicit	Single
Cases	Concrete	Implicit	Multiple

Fig.1 - Contrasting Cases and Rules

Case-based reasoning and inductive reasoning have in common that both reason from cases, and that the conclusions achieved are normally uncertain. Case-based, inductive, and explanation-based learning all learn from cases and can use preexisting domain knowledge for hypotheses generation. For the pure form of explanation-based learning the domain theory is assumed to be complete and correct. Here cases are used to focus the deductive process. Case-based reasoners mainly learn from the comparison of two cases (i.e. the learning procedure is fundamentally incremental) whereas inductive learners often compare several cases during one learning step. Some inductive learning systems are also able to learn incrementally. While most case-based reasoners store all the cases verbatim within an abstraction hierarchy (case memory) [cf. Sal91], most inductive learners forget all the cases which have been the basis for the generated hypotheses. Other machine learning approaches do both the learning of explicit concept descriptions, and the verbatim storing of cases [cf., e.g., SS88, Fis89]. Additionally, some

case-based reasoning approaches try to improve their implicit concept descriptions by selectively removing cases from the case library [cf. KA88, AKA91].

Cognitive Level	**Protocol of a process** Diagnostic process of Friday, the 6th of August, to find out why the lamp in our living-room was not shining.
Representation Level	**Sequence of attribute-value pairs** lamp-12 <- off switch-3 <- on bulb-7 <- okay voltage <- not available defect <- short-circuit-6
Implementation Level	**List of the respective implementation language** ((lamp-12 off) (switch-3 on) (bulb-7 okay) (voltage none) (defect short-circuit-6))

Fig.2 - An Exemplary Case

From a Machine Learning point of view, case-based reasoning is not so well understood as, e.g., inductive learning. Up to now, there is no general agreement concerning the overall learning task which is addressed by case-based reasoning. Rather, there is a focus on defining and understanding particular mechanisms like reasoning by analogy and reasoning from cases. As a reason for this, Shavlik and Dietterich point out in [SD90] that research work in the field of case-based reasoning has been mainly motivated by concerns for cognitive plausibility rather than by a desire to construct practical systems.

Another reason is that most machine learning systems make a (strong) separation between learning and problem solving [cf. SD90]. Learning involves analyzing training examples or problem solving experiences to extract functions or rules, problem solving involves applying the learned functions or rules to solve new problems. In case-based reasoning, by contrast, problem solving is performed by directly inspecting the training examples (cases) and solving new problems by analogy with these past cases. This appears to be a major distinction of case-based reasoning and other machine learning approaches. However, there are also strong similarities between case-based problem solving and the well-known rule-based approach, because often it is not possible to differentiate between cases and rules (including their processing) on

the levels of representation and implementation. Therefore, we suggest to define on a cognitive level what should be the difference between cases and rules. This allows some simple classifications which, as we hope, are helpful to answer some basic questions.

Cognitive Level	**Rule of Thumb** If you turn on a lamp and it does not shine, probably the bulb is defect.
Representation Level	**Sequence of attribute-value pairs** lamp <- off switch <- on defect <- bulb probability <- high
Implementation Level	**List of the respective implementation language** ((lamp off) (switch on) (defect bulb) (probability high))

Fig.3 - An Exemplary Rule

A production rule is a well-known knowledge representation scheme and most implemented systems within the Artificial Intelligence community have used it. We will give a very general definition of what a rule (of thumb) is, because we need it for contrasting purposes only. In section two, cases have been defined as episodic knowledge which consists of a problem description, a solution, and a justification for that solution. Normally, rules do not appear to be episodic knowledge but, rather, have been extracted from such knowledge, i.e. rules are more general than cases. Thus, a rule does not necessarily have a direct correspondence to one specific event, but is the result of a generalization process based on a number of different events.

Definition
A rule is a pair (C,A) where A is an action and C a condition which must be fulfilled to do action A.

Compared to the definition of a case, there is a correspondence between C and A, on the one hand, and problem description P and solution S, on the other hand. From another point of view, a rule could be described as an explicit kind of problem solving heuristic which can be contrasted by the more implicit heuristics being included in a case. Thus, the intended use of a

rule (normally) is clear whereas a case can be applied in many different ways to solve similar problems. The reason for this is that a case includes a justification which can be interpreted with respect to a current purpose whereas rules (normally) have lost their justification. All these aspects are summarized in figure 1.

Though cases and rules differ concerning their complexity on the cognitive level this is not necessarily reflected on the representation and implementation levels. Therefore, figures 2 and 3 present an exemplary case as well as an exemplary rule which, in principle, differ on the cognitive level only.

Of course, case representations are often much more complex (cf., e.g., [Ber91]) and, additionally, other representational and implementational descriptions would have been possible.

Based on the above definitions, figure 4 gives a rough classification of methods which use cases and/or rules. Apart from the differentiation between cases and rules, we think that the distinction of exact and partial matching is of importance as well. An underlying assumption is that the analogy-based approach applies reasoning between different domains and, therefore, needs more general knowledge than it is offered by cases. For instance, the approach Michalski describes in his paper on two-tiered concept meaning [Mic89] would be classified as an analogy-based (matching) approach.

	Exact Matching	**Partial Matching**
Rules	Standard Rule-Based Approach	Analogy-Based Approach
Cases	Standard Data Base Approach	Case-Based Approach

Fig.4 - Matching of Cases versus Matching of Rules

Using the table given in figure 4, an inductive learning system could be classified as a standard rule-based or analogy-based approach (we do not want to differentiate between the processing of decision trees and rules here). Additionally, approaches known as instance- or exemplar-based as well as those known from statistics, pattern recognition, or neural networks would be classified as case-based approaches.

The above classification can be refined by differentiating between two kinds of partial matching, namely matching based on generalized indices (as it is used in most case memories [cf. Sch82, Kol83a+b, RS89]) and graded matching based on similarity measures [cf. SW88, AKA91, AW91]. While the motivation for the indexing approach is more oriented to cognitive psychology, the second one has its roots in mathematics/statistics. It applies to both approaches

that one part of important information is represented explicitly, and another part not (cf. Fig. 5). Thus, their transparency and understandability cannot be evaluated independent from the used application.

	Similarity of Cases	**Computation of Similarity**
Case Memory	Explicit Neighbors are similar	Implicit By insert and retrieval procedures
Similarity Function	Implicit By computed value	Explicit By used Function

Fig.5 - Similarity: Computation versus Representation

In the past, many statistical and pattern recognition procedures have been developed which use similarity functions, as well as instance- and exemplar-based (case-based) reasoning approaches, but only apply pure syntactical methods for clustering or classification tasks. For a closer inspection of the relations between similarity, uncertainty, and case-based reasoning cf. [RW91].

4. Conclusions

Case-based reasoning represents a specific method for solving a certain class of problems, especially for the treatment of inhomogeneous solution spaces. Within such solution spaces, cases correspond to homogeneous (i.e. "small" changes of the problem descriptions result in "small" changes of the solutions/justifications) subspaces.

Case-based reasoning is a well-suited approach if cases are an important knowledge source within the underlying domain, and the available experts reason from cases (even a formal discipline as mathematics uses case-based reasoning, e.g. to find a certain proof [Ker89]). In addition, many domains are "case-based" in their overall structure, e.g. law, medicine, economy. Within these domains often a lot of "softcases" exist which can be easily adapted to solve novel problems. On the other hand, case-based reasoning is not well-suited in domains mainly consisting of "hardcases" (cases which can only be treated by heavily using common sense knowledge, or a huge amount of domain knowledge).

Partly in response to this problem, it is now widely recognized that a case-based reasoner can "play" different "roles" (the added lists of implemented systems are not intended to be complete, rather they represent an exemplary selection and classification) within a knowledge engineering environment:

- *Case-based reasoning can be used as a stand-alone problem solver* (no cooperation, e.g. CYRUS [Kol80], MEDIATOR [Sim85, Kol89], PROTOS [Bar89, PBH90], CASEY [Kot88], CHEF [Ham89b], PATDEX [AdM+89, Weß91, AW91])
- *Case-based reasoning can be combined with several other separate problem solvers* (input-output cooperation, e.g. GREBE [BP91], JULIA [HK91])
- *Case-based reasoning can be one among several cooperating completely integrated problem solvers* (cooperation at all levels of problem solving, e.g. PRODIGY (?) [VC91a,b], CABARET (?) [RBD+91], CREEK (?) [Aam90,91], D3 (?) [PG91, Pup90], MOLTKE (?) [AMR90, AW91, Alt91])

The first role reflects the early phase of case-based reasoning research where a lot of stand-alone systems have been implemented. Those systems cannot meet all the requirements which normally are posed by real world applications. For overcoming these shortcomings, actually the combination with other problem solving mechanisms (reasoning from rules, constraints, deep models etc.) is a hot research topic ("mixed paradigm reasoning", cf. [RSk89]). Up to now, such combinations are normally restricted to cooperations in an input-output manner. A deeper integration is an important research goal of many groups but, currently, no completely integrated systems are available. All the systems within the third list are only examples which try to achieve this goal (and, therefore, are (question-) marked). Thus, Knowledge Engineering researchers are asked to develop integrated architectures which make use of case-based reasoning.

A first suggestion for the integration of case-based reasoning and model-based knowledge acquisition is given in [JS91], whereas an overview of the integration of case-based, model-based, and compiled knowledge is given in [SZP90]. Schmalhofer et al. make a suggestion concerning the use of cases within an integrated knowledge acquisition process for the preparation of expert plans which can be reused in novel situations [SBK+91]. The MOBAL system is an interesting example for the integration of manual and automatic knowledge acquisition methods [Mor90]. In [dlO91] de la Ossa presents an approach for the automatic adaptation of a given diagnostic knowledge base with respect to changes in the physical system which is to be diagnosed. A case-based approach to theory revision using self-questions and experiments has been suggested by [Oeh91].

We mentioned above that, from a Machine Learning point of view, it is difficult to classify case-based reasoning, because its learning task is not well-defined. Shavlik and Dietterich [SD90] argue that the reason for this has been the motivation of case-based reasoning by concerns for cognitive plausibility rather than by a desire to construct practical systems. However, from a Knowledge Engineering point of view, case-based reasoning has some important advantages over standard Machine Learning approaches, namely, apart from a strong focus on cognitive plausibility, the overcoming of the separation of learning and problem solving.

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