Case-Based Reasoning : An Overview

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ABSTRACT

This paper contains a brief overview of case-based reasoning (CBR) with an emphasis on European activities in the field. The main objective was to have a balance between brevity and expressiveness and providing helpful pointers to the field. It identifies major open problems of CBR associated with: retrieval/selection, memory organization, matching, adaptation/evaluation, forgetting and, finally, integration with other techniques. It is intended for readers with knowledge in the area and contains a list of almost one hundred references in the field.

KEY WORDS : case-based reasoning, learning, problem solving.

1. Introduction

Case-based reasoning is a major paradigm in automated reasoning and machine learning. In case-based reasoning, a reasoner solves a new problem by noticing its similarity to one or several previously solved problems and by adapting their known solutions instead of working out a solution from scratch.

Case-based reasoning (CBR) can mean different things depending on the intended use of the reasoning: adapt and combine old solutions to solve a new problem, explain new situations according to previously experienced similar situations, critique new solutions based on old cases, reason from precedents to understand a new situation, or build a consensued solution based on previous cases. However, these different aspects can be classified into two major types: interpretative CBR, and problem solving CBR (Kolodner, 1992). In interpretative CBR the key aspect is arguing whether or not a new situation should be treated like previous ones based on similarities and differences among them. In problem solving CBR, the goal is to build a solution to a new case based on the adaptation of solutions to past cases. This division, though it is useful to present the field, is not always clear in practice because many problems have components of both types of CBR and certainly the most effective case-based learners will use a combination of both methods. For example, the labour mediation application (Sycara, 1987) needs both interpreting the situation and then deriving a solution based on precedents. Furthermore, many systems use interpretative CBR to evaluate the solutions reached since evaluation is one of the basic operations in any case-based reasoner.

In short, given a case to solve, case-based reasoning involves the following steps :

retrieving relevant cases from the case memory (this requires indexing the cases by appropriate features);

selecting a set of best cases;

deriving a solution;

evaluating the solution (in order to make sure that poor solutions are not repeated);

storing the newly solved case in the case memory.

According to these steps, Aamodt and Plaza in (Aamodt and Plaza, 1994) describe a Case-Based reasoner as a cyclic process comprising "the 4 R's" i.e. Retrieve, Reuse, Revise and Retain.

2. Case-Based Reasoning : A short description of selected early work

The case-based approach to reasoning and learning (Kolodner 83) has been growing impressively during the last few years. Today there are more than one hundred CBR systems reported in the literature. Kolodner in her very recent book (Kolodner 1993a) reports about 82 CBR systems in the USA (surprisingly, in a 650 page book, she does not report any work being done in Europe!!). Furthermore, there are specialized workshops held every year both in the US and in Europe with a quite large number of participants. In all major conferences in AI one can find several sessions devoted to this topic. The pioneering work in this field is that of Schank on Dynamic Memory (Schank, 1982), Carbonell on Analogy (Carbonell, 1983), Kolodner (Kolodner, 1983) and Rissland's (Rissland 1983) work on legal reasoning. After these pioneering works, the development of CBR continued with further work by Kolodner and students (Kolodner, Simpson and Sycara, 1985; Kolodner, 1987; and Sycara, 1988), the work of Hammond and others on case-based planning (Hammond, 1986, 1987; Collins, 1987) and the work of Ashley and Rissland with the HYPO System for legal reasoning (Ashley & Rissland, 1987), among others.

More recently, within the problem solving type of CBR, several systems have been built to do case-based planning and design, among them let us mention JULIA (Hinrichs 1988, 1989) that plans meals; CYCLOPS (Navinchandra, 1988) for landscape design; KRITIK (Goel 1989, Goel and Chandrasekaran 1989) that combines case-based and model-based reasoning for the design of mechanical assemblies; CLAVIER (Barletta and Hennessy, 1989) to lay out pieces made of composite materials in an autoclave; SMART memory model (Veloso, 1992) whose goal is to increase the planning efficiency (speed-up learning) of the system PRODIGY (Carbonell et al., 1991); and ARCHIE (Pearce et al. 1992) and CADRE (Dave et al., 1994) to help architects understand and solve conceptual design problems.

Another important application field of problem solving CBR is diagnosis. In diagnosis, just as in planning or design, it is often necessary to adapt an old case to fit a new problem. CASEY (Koton, 1988) is a well known case-based system for diagnosing heart problems of patients by adaptation of the known diagnoses of previous patients. Another early Case-based diagnosis system is PROTOS (Bareiss et al. 1988). PROTOS diagnoses hearing disorders using a learning apprentice approach. The difficulty of this diagnosis is that many different diagnoses have similar manifestations and the relevant differences are so subtle that novices miss them. In such a situation, PROTOS starts as a novice and when it makes a mistake, a teacher explains the mistake and as a result PROTOS learns such subtle differences by putting difference pointers in its memory that allow the system to switch from apparently easy but incorrect diagnose to the correct ones. Other recent representative applications to diagnosis for maintenance are CASELINE (Magaldi, 1994) for aeroplane maintenance and a system for maintenance of telecommunication networks (Deter, 1994).

In interpretative CBR, the first works are those of Rissland and Ashley with the development of a system for legal reasoning called HYPO (Ashley & Rissland 1987, Ashley 1991). HYPO retrieves cases pro and con a legal raised in a new fact situation. It uses the former to argue in support of the claim and the latter to make counter-arguments. The result is a set of three-ply arguments: arguments supporting a proposed solution, responses opposing those arguments, and a rebuttal. Many other works in interpretative CBR are also in the legal domain (Bain 1986, Branting 1988).

The latest field where CBR seems to be also useful is creativity (Turner 1993, Kolodner, 1993b). The main working hypothesis is that much creativity stems from using old solutions in novel ways or combining old solutions in a different way. A creative artificial system would need to be able to identify analogies (Boden, 1995). Kolodner in (Kolodner, 1993b) suggests that since Case-Based Reasoning offers computational tools techniques to deal with: *remembering, adapting known ideas, reinterpreting an idea, specializing an abstract idea, elaborating known ideas, merging pieces of ideas, explaining and evaluating* and these aspects seem to play a major role in creative processes, then case-based reasoning can be a research paradigm for exploring creativity.

In Europe the early work on CBR includes that of Sharma and Sleeman on a case-based aide for knowledge acquisition and refinement (Sharma and Sleeman, 1988), that of Richter and Althoff (Althoff, 1989) on complex diagnosis issues, that of Plaza and Lopez de Mantaras on a case-based learning apprentice capable of dealing with imprecise examples (Plaza and Lopez de Mantaras, 1990), that of Aamodt on knowledge intensive case-based reasoning (Aamodt, 1990) and that of Faltings in case-based representation of architectural design knowledge (Faltings et al. 1991).
Due to the late European start in CBR research, almost all the work performed in Europe addresses very open issues; for this reason, most of the European work referred to in this paper appears in the "open problems" section.

3. Case Based Reasoning as a Learning Paradigm

Learning in AI is usually taken to mean generalizing through induction or explanation. Learning is in fact inherent to any case-based reasoner not only because it induces generalizations based on the detected similarities between cases but mostly because it accumulates and indexes cases in a case memory for later use. Besides, case-based reasoning as a learning paradigm has several technical advantages. One advantage has already been stated and concerns the fact that since each new solved case is stored in the memory for later use, instead of deriving new solutions from scratch a CBR system remembers and adapts old ones. If such solutions have been adapted or combined in novel ways, then in the future, when solving another similar case, these circumstances will be remembered but not recomputed. Other advantages are that a case-based reasoner becomes more competent over time, can avoid previously made mistakes, and can focus on the most important parts of a problem first. Finally, according to DARPA : Machine Learning Program Plan, 1989, since a lot of efforts in CBR address the problem of finding techniques to analyze and select cases, perhaps some of these techniques could be used by the rest of the machine learning community to help in the selection of training instances. Inductive learning systems, for example, must rely on good training instances whose selection is often overlooked. This is a major bias that can have dramatic consequences on the behaviour of the learning system. In domains where a large number of training instances already exists one could use techniques to analyze and select instances inspired on the CBR techniques for analyzing and selecting cases. Perhaps the most important advantage of the case-based approach to learning is its affinity to human learning: people take into account and use past experiences to take future decisions.

Case-based learning algorithms have been applied to a large variety of tasks, including the following: predicting power load levels for the Niagara Mohawk Power Co. (Jabbour et al. 1987); speech recognition (Bradshaw 1987); evaluating oil prospecting sites in the North Sea (Clark 1989); robotic control (Moore 1990); molecular biology (Cost and Salzberg 1990); architectural design (Schmidt-Belz and Voss 1993); and medicine (Plaza and Lopez de Mantaras 1990, Salzberg 1990, Aha et al. 1991, Lopez and Plaza 1993, Malek and Rialle 1994).

4. Commercial Tools

Tools are needed in order to facilitate case collection, indexing, evaluation, adaptation, and for case library maintenance. Current commercial tools are mainly oriented towards acquisition and retrieval of cases and also simple adaptation and evaluation. The best known are REMIND by Cognitive Systems Inc. (USA), which is an interactive generic tool for rapid prototyping and development of CBR applications oriented to classification, prediction, and data mining tasks, and reCall by ISoft S.A. (France) which is also a generic tool that has been applied to develop applications on fault diagnosis, bank loan analysis, teaching, risk analysis, control and supervision. An interesting aspect of ReCall is that the object oriented representation language used to represent the cases allows one to represent fuzzy knowledge. Other existing tools are S3-Case by tecInno

GmbH (Germany) oriented to diagnostic problem solving and CBR-EXPRESS (see Schult, 1992 as well as Watson and Marir, 1994 for further details on software and commercial tools).

5. Open Problems

5.1. Retrieval/Selection

The most basic problems in CBR are the retrieval and selection of cases since the remaining operations of adaptation and evaluation will succeed only if the past cases are the relevant ones. The retrieval of relevant cases depends on a good indexing of the cases that select an appropriate set of indices. One way to do it is to fix the indices a priori for a given domain but the problem is a loss in generality. Among the techniques being explored to solve this problem we can mention using explanation-based techniques to identify relevant features, using instance-based learning to learn feature importance or using introspective reasoning to learn features for indexing. Explanation-based techniques are used to justify the actions of a case with respect to those features known when the case was originally executed. Demonstrably relevant features are generalized to form primary indices, inconsistencies between the domain theory and the actual case are used to determine irrelevant features and the remaining features are marked as secondary indices that are subject to refinement using similarity-based inductive techniques (Barletta and Mark, 1988). In learning feature importance, each feature is associated with a weight that is adjusted after each prediction attempt during the training process by comparing the current case with its most similar stored cases (Aha et al., 1991). The introspective approach of (Fox and Leake, 1995) consists in providing the CBR system with an introspective reasoning capability to detect poor retrievals, identify features which would retrieve more adaptable cases and refine the indexing criteria to avoid future failures.

Heuristic search techniques and Qualitative Models are also promising approaches to the indexing/retrieval problem. Heuristic search techniques (Rissland et al., 1993) are used in a graph of cases and domain knowledge to look for support for a legal argument in Rissland et al. system. The rationale is to narrow the gap that exists between an available indexing scheme and the requirements of arguments through the use of best-first search guided by evaluation functions. Richards has used the qualitative model of a physical system (a two-stage sewage treatment plant) (Richards, 1994) to derive the minimal sets of control parameters relevant to each of the desired inputs. This reduces the number of features used for indexing the cases in a case-based system that suggests the settings of the control parameters based on past experience controlling the plant.

5.2. Memory Organization

Another basic problem is that of memory organization. A good indexing is not enough. When the case memory is large, a good organization of the memory is a must because a simple linear organization, like a list, is very inefficient for retrieval. A hierarchical organization is necessary. The most commonly used approach consists in having a hierarchical structure where internal nodes are generalizations of individual cases like in the system CYRUS (Kolodner, 1983), based on Schank's dynamic memory model (Schank, 1982). The case memory in the dynamic memory model is a hierarchical structure of "episodic memory organization packets". The basic idea is to organize specific cases which share similar properties under a more general structure called a "generalized episode" (GE). A GE contains *norms, cases and indices*. Norms are features common to all cases, indexed under a GE and indices are features which discriminate between the cases of a GE. An index is composed of an index name and an index valued. The entire case memory is in fact a discrimination network where a node is either a generalized episode, an index or a case. When a new case description input is given and the best matching is searched, the input case structure is "pushed down" the discrimination network structure, starting at the root node. When one or more features of the input case match one or more features of a GE, the case is further discriminated based on its remaining features. A case is retrieved by finding the GE with most norms in common with the problem description, and the indices under that GE are then traversed in order to find the case which contains most of the remaining problem features. In case storing, when a feature of the case matches a feature of an existing case, a GE is created. The two cases can be discriminated by indexing them under different indices below the GE. If two cases or two GEs end up under the same index, a new GE is automatically created. Hence, the memory structure is dynamic in the sense that similar parts of the two cases are dynamically generalized into a GE.

In PROTOS (Porter, 1986) an alternative hierarchical organization is used. The case memory is embedded in a network structure of categories, semantic relations, cases, and index pointers. Each case is associated with a category and indices may point to a case or a category. The indices are of three types: *Feature links* pointing from problem features to cases or categories (called remindings), *case links* pointing from categories to its associated cases (called exemplars) that are sorted according to their degree of typicality in the category, and *difference links* pointing from cases to "near cases" that only differ in a small number of features. Furthermore, the categories are inter-linked within a semantic network which represents domain knowledge and enables to provide an explanatory support to some of the CBR tasks.

Finding a case in memory that matches an input description is done by combining the input features of a problem case into a pointer to the case or category that shares most of the features. If a reminding points directly to a category, the links to its most prototypical cases are traversed and these cases are retrieved. The semantic network of domain knowledge is used to enable matching of features that are semantically similar. A new case is stored by searching for a matching case and by establishing the appropriate feature indices. If a case is found with only minor differences to the input case, the input case may not be retained or the two cases may be merged by generalizing some features according to the taxonomic links in the semantic network.

Almost all the existing CBR systems use memory organizations inspired either in Schank's dynamic memory or in Porter's approach or in some combination of these two seminal approaches. This is the case of the BOLERO System (López, 1993) that uses the generalized episodes of Schank together with the exemplar links, difference links, and prototypes of Porter. The structure of the cases themselves is also an important issue. While most case-based systems store each case as a unit, others break the cases and store them into pieces along with pointers for later reconstruction (Hinrichs 1988, Lopez 1993). The advantage of this last approach is that it allows one to solve complex problems by combining partial solutions of several other problems.

Another approach, based on metaphors taken from the human immune system, is proposed in (Hunt et al., 1995). The main point is that the immune system is inherently case based and relies on its content addressable memory to identify new antigeus (new cases) which are similar to old antigeus (old cases).

5.3. Matching

Selecting the best case requires being able to match cases together. In general the match is not perfect because on the one hand, the values of the features of the new case and previous cases are not exactly the same and on the other hand there are usually missing values for some or many of the features. The usual approach, therefore, is to define some similarity metric.

The matching problem is being studied by many researchers (Bento and Costa 1993, Borner, 1993, Rougegrez 1993, etc.). An additional difficulty is that the similarity metrics must take into account that not all the features have the same importance. While it would seem that some sort of weighted similarity measure could do, in fact this is not always possible because the importance of some features is context dependent. Often, however, the context are the cases already in memory and therefore they determine which features of the new case are the most important ones. There are some methods based on this observation: the preference heuristics (Kolodner, 1988), the dimensional analysis (Rissland and Ashley, 1988), the use of dynamically changing weighted evaluation functions (Stanfill, 1987), or using domain specific knowledge to influence similarity judgements (Cain et al. 1991, Sebag and Schoenauer 1993, Surma 1994). A similar approach (Bento and Costa, 1993) uses a CBR+EBL similarity metric that is able to assign a relevance measure to each matching fact.

Up to now, practically all the existing similarity measures assume that cases are represented just by collections of attribute-value pair. However we have started to see the need for more structured representations in complex domains and therefore for new similarity measures, like for example graph similarity measures already used in pattern recognition. These measures have already started to be considered in CBR (Bunke and Messner 1993, Poole 1993).

Finally, let us mention a very interesting approach (Veloso and Carbonell, 1991) that allows one to learn incrementally better similarity metrics by interpreting the behaviour of the problem solver PRODIGY replaying retrieved cases. To do so, the problem solver provides information about the utility of the candidate cases suggested as similar. This information is used to refine the case library organization and the similarity metric. This process starts with a simple metric that is refined by analysing the derivational trace produced by the analogical problem solver.

5.4. Adaptation/Evaluation

A good adaptation of old cases to fit the new case can reduce significantly the amount of work needed to solve it. The works of Hammond, Sycara, and others in case-based planning had early addressed this important issue, however afterwards it received less attention. More recently the interest in adaptation seems to have increased. For example, quite a few papers in the first European Workshop on Case-Based Reasoning addressed this problem (see, for example Chatterji and Campbell 1993, Zeyer and Weiss 1993) and was the subject of many discussions. The existing techniques are limited to the use of generalization and refinement heuristics. An example is the plausible design adaptation (for design tasks) (Hinrichs and Kolodner, 1991). This adaptation is a process that takes a source concept, a set of constraints and constraint violations and a set of adaptation transformations and returns a new concept that satisfies the constraints. The relations between case adaptation and the case retrieval problem are also being studied (Smyth and Keane, 1993).

Evaluation consists in giving to the case-based reasoner feedback about whether or not the new case was solved adequately. If the solution is not adequate, the retrieval of additional cases may be required which may result in the need of an additional adaptation called repair. Some of the major issues involved include strategies for evaluating the cases and the assignment of blame or credit to old cases (Kolodner, 1993a).

5.5. Forgetting

Even assuming that we have solved the basic problems of retrieval and indexing there is still an additional problem resulting from an uncontrolled growth of the case memory which may result in the degradation of the performance of the system as a direct consequence of the increased cost in accessing memory. Existing approaches to this problem include: storing new cases selectively (for example only when the existing cases in memory lead to a classification error) and deleting cases occasionally (Kibler and Aha, 1987); and incorporating a restricted expressiveness policy into the indexing scheme by placing an upper bound on the size of a case that can be matched (Francis and Ram, 1993). Finally, let us mention the often proposed solution of using massive parallelism for both the parallel matching of cases and indices (Kolodner 1988, Mylymaki and Tirri, 1993). In respect to this, it is worth noticing that Thinking Machines has built a memory-based reasoning software that runs on the Connection Machine (Stanfill and Waltz, 1988).

5.6. Integration with other techniques

In some application domains there is a need to combine CBR with other reasoning techniques (Rissland and Skalak, 1989) such as model-based or rule-based reasoning. Some examples are CABARET (Rissland and Skalak, 1991) that integrates rule-based and case-based reasoning to facilitate applying rules containing ill-defined terms; CREEK (Aamodt, 1991) that integrates rules and cases and a top level control strategy decides whether to activate rules or cases to achieve a given goal; GREBE (Branting and Porter, 1991) integrating also rules and cases; PATDEX/MOLTKE (Althoff and Wess, 1991) integrating models, cases and compiled knowledge; JULIA (Hinrichs, 1988) integrating case-based reasoning and constraints for design tasks; MoCas (Pews and Wess, 1993) that combines case-based and model-based reasoning for technical diagnosis applications; Portinale (Portinale et al. 1993) who also uses a combination of models and cases for diagnosis problem solving; IKBALS (Zeleznikow et al. 1993) that integrates rule-based and case-based reasoning with intelligent information retrieval; A LA CARTE (Nakatani and Israel, 1993) that use cases to tune rules in a KBS; BOLERO (Lopez, 1993) integrating rule-based reasoning at the domain level with case-based reasoning at the meta-level in such a way that the cases guide the inference process at the domain level, allowing the system to learn control knowledge by experience; and MMA (Plaza and Arcos, 1993) a reflective architecture capable of integrating different inference and learning methods. Very recent efforts are also attempting to integrate Case-based and Inductive learning (Connolly et al. 1993, Banberger and Goos 1993, Manago et al. 1993, Armengol and Plaza 1994).

Finally, we believe that the use of Fuzzy Logic techniques may be relevant in case representation (to allow for imprecise and uncertain values in features, case retrieval by means of fuzzy matching techniques (Dubois et al. 1988) and also for case adaptation by using the concept of gradual rules (Dubois and Prade 1992). Existing work on fuzzy case-based reasoning is represented by (Plaza and Lopez de Mantaras 1990, Bonissone and Ayub 1992, Salotti 1992 and Jacinski and Trousse 1994).

6. Concluding Remarks

We have tried to give a brief overview of the main aspects of case-based reasoning both from the point of view of its short but rich history of existing systems and the main open issues for further research. Concerning this last point, although it is clear that CBR has produced very promising techniques, we want to highlight that further research is needed in all the open problems commented above, particularly in how to index cases in order to optimize their reuse, in methods for generating new indices dynamically, in structural and quantitative similarity metrics matching methods, in mechanisms for determining relevant features, in forgetting mechanisms and in the integration with other paradigms. Another missing aspect is that of the non-trivial comparison of the case-based method with other methods although there is some work addressing this aspect (Smyth 1994). A promising comparison methodology is through a knowledge-level analysis of the different systems in order to highlight differences and similarities like in (Armengol and Plaza, 1993).

Finally, perhaps the most severe limitation of existing systems is the feature-value representation that is being used for cases (Branting, 1989). The consequence is that case-based algorithms cannot be applied to knowledge-rich applications that require much more complex case representations, for example cases with higher-order relations between features. In the near future we will see fast growing research activity in such enriched representations.

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