Retrieval, reuse, revision, and retention in case-based reasoning

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Abstract

Case-based reasoning (CBR) is an approach to problem solving that emphasizes the role of prior experience during future problem solving (i.e., new problems are solved by reusing and if necessary *adapting* the solutions to similar problems that were solved in the past). It has enjoyed considerable success in a wide variety of problem solving tasks and domains. Following a brief overview of the traditional problem-solving cycle in CBR, we examine the cognitive science foundations of CBR and its relationship to analogical reasoning. We then review a representative selection of CBR research in the past few decades on aspects of retrieval, reuse, revision, and retention.

1 Introduction

While much of the inspiration for the study of case-based reasoning (CBR) came from cognitive science research on human memory (e.g., Schank, 1982), the resulting methodology has been shown to be useful in a wide range of applications (e.g., Watson, 1997; Aha, 1998; Bergmann, 2002). Unlike most problem solving methodologies in artificial intelligence (AI), CBR is memory based, thus reflecting human use of remembered problems and solutions as a starting point for new problem solving. An observation on which problem solving is based in CBR, namely that similar problems have similar solutions (e.g., Leake & Wilson, 1999), has been shown to hold in expectation for simple scenarios (Faltings, 1997b), and is empirically validated in many real-world domains.

Solving a problem by CBR involves obtaining a problem description, measuring the *similarity* of the current problem to previous problems stored in a *case base* (or *memory*) with their known solutions, *retrieving* one or more similar cases, and attempting to *reuse* the solution of one of the retrieved cases, possibly after *adapting* it to account for differences in problem descriptions. The solution proposed by the system is then *evaluated* (e.g., by being applied to the initial problem or assessed by a domain expert). Following *revision* of the proposed solution if required in light of its evaluation, the problem description and its solution can then be *retained* as a new case, and the system has learned to solve a new problem.

Figure 1 shows Aamodt & Plaza's (1994) classic model of the problem solving cycle in CBR. The individual tasks in the CBR cycle (i.e., *retrieve*, *reuse*, *revise*, and *retain*) have come to be known as the "4 REs". Because of the pivotal role of retrieval in the CBR cycle, a considerable amount of research has focused on retrieval and similarity assessment. As illustrated in Figure 2, Leake (1996b) expresses the role of similarity through the concepts of retrieval and adaptation distances. Also captured in Leake's diagram is the relationship between problem and solution spaces in CBR.

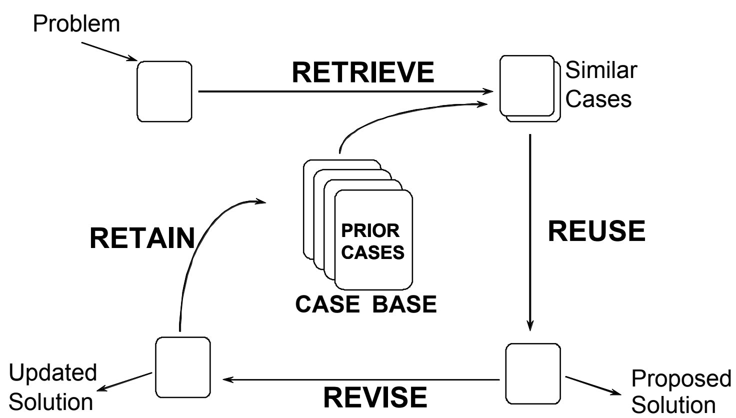
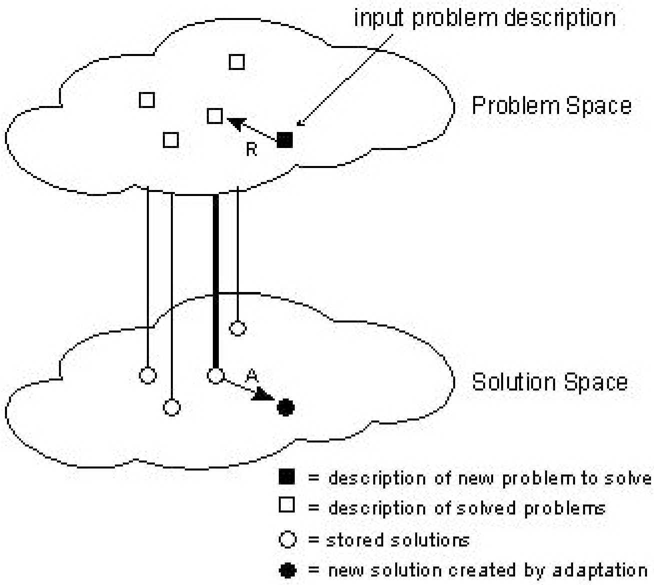


Figure 1 The CBR cycle. Adapted from (Aamodt & Plaza, 1994).

In Figure 2, the retrieval distance *R* increases as the similarity between the input problem description and a stored problem description decreases (i.e., lower similarity means greater distance). A common assumption in CBR is that the retrieval distance *R* is commensurate with *A*, the adaptation distance (or effort). However, several authors have questioned this assumption and its implication that the most similar case is the easiest to adapt (e.g., Smyth & Keane, 1998). This is an issue that we will return to in our discussion of retrieval methods in Section 3.



.**Figure 2** Relationship between problem and solution spaces in CBR. Adapted from (Leake, 1996b)**.**

As will be clear from the literature review we present in this article, aspects of reuse and retention, and to a lesser extent revision, have also attracted significant research interest. Several books examine fundamental aspects of CBR and present case studies of research and applications (e.g., Riesbeck & Schank, 1989; Kolodner, 1993; Leake, 1996a; Watson, 1997; Lenz e*t al*., 1998; Bergmann, 2002). However, our aim in this article is to present a concise summary of research that focuses on the problem-solving cycle in CBR, including some of the most recent advances. In Section 2, we briefly examine the cognitive science foundations of CBR and the relationship between CBR and analogical reasoning. In Sections 3, 4, and 5, we review a representative selection of CBR research on aspects of retrieval, reuse and revision, and retention. Our conclusions are presented in Section 6.

2 CBR and cognitive science

The study of CBR has been strongly influenced by research in cognitive science. A major current underlying early CBR research was the study of human story understanding (Schank & Abelson, 1977), especially as it led to investigations of the role of memory in understanding (Schank, 1982). Initial work on story understanding examined the knowledge structures underlying understanding and their role in providing expectations for the events in stories. These knowledge structures also provide a causal structure that links the states and events in stories and explains agent behaviors. Dynamic memory theory (Schank, 1982) focused on the interplay of understanding, learning, and memory. Memory Organization Packets, or MOPs, organize sequences of events, but individual MOPs may share structure and inherit information from other MOPs. MOPs organize individual events which can be recalled as *remindings*. These remindings can play many roles in interpretation and problem solving. For example, during planning, a problem may prompt the reminding of a past plan that can be adapted to help solve a new problem. This forms a basis for CBR. Reminding may sometimes occur across contexts, enabling lessons from one situation to be applied to a situation that is superficially quite different.

When expectations fail during understanding, remindings of prior explanations may be useful to help resolve the anomalies present in the input (Schank, 1986; Schank *et al*., 1994). The SWALE system (Kass *et al*., 1986; Schank & Leake, 1989), which models case-based explanation generation, uses MOP-based expectations to guide understanding until it encounters an anomaly, and then retrieves prior explanations to adapt to the new situation. The system's namesake was a star race horse whose unexpected death with no warning after a major race shocked and intrigued the racing community. Experts were immediately reminded of similar cases; one vet's reaction to the news was "*This sounds like an aneurysm. I've seen this sort of thing before*." The death also prompted less routine remindings among students at the Yale AI lab, such as the death of the rock star Janis Joplin due to an overdose of recreational drugs. While recreational drug use was unlikely for Swale, adaptation to another type of drug use known to be associated with racing (i.e., performance-enhancing drugs) led to a more plausible explanation, though not one that was borne out by later investigation. SWALE modeled the role of CBR in explanation-building and modeled creativity through methods to perform the flexible retrieval and reuse processes needed to apply explanations in unusual ways.

Another major current contributing to the study of CBR stems from examinations of the use of *precedents* in legal reasoning. Issues addressed include handling multiple cases and the use of hypothetical cases in legal arguments (e.g., Rissland *et al*., 2005). Several other studies have explored the role of CBR in human reasoning and learning, giving rise, for example, to teaching systems shaped by lessons from CBR (Schank *et al*., 1993-1994; Kolodner *et al*., 2003). A core part of medical diagnostic reasoning is also shown to follow a type of *pattern matching* (Patel & Groen, 1986), which in essence is a case-based process of reasoning from experiences with previous patients. This has given rise to a number of medical CBR systems that support this type of decision making (Holt *et al*., 2005). See (Kolodner, 1994) and (Leake, 1998) for more extensive discussions of CBR as a cognitive model.

2.1 CBR and analogical reasoning

CBR is also fundamentally related to research in analogical reasoning, an active area of research in cognitive science. Analogical reasoning research focuses on basic mechanisms such as matching and retrieval, and how those mechanisms are used in other cognitive processes, including reasoning and learning. Psychological studies have shed light on some basic properties of human analogical reasoning. For example, there is ample evidence that, for people, retrieval is heavily influenced by surface properties more than by deep similarities, unlike most CBR systems. Yet when people are given the analogues, they find the comparisons easy (e.g., Gick & Holyoak, 1980; Keane, 1988; Gentner *et al*., 1993). The centrality of relational information in human similarity judgments is now reasonably well-established (e.g., Gentner *et al*., 2001; Markman & Gentner, 2001; Kokinov & French, 2003). This reinforces the practice of using structured representations that was common in early CBR, but it also suggests that CBR and machine learning systems that use feature vectors are unlikely to be good models of human cognition.

Psychological theories of analogical processes have led to computational models that can be used for building CBR systems. For example, the Structure-Mapping Engine (SME) (Falkenhainer *et al*., 1986; Forbus *et al*., 1994a) is based on Gentner's (1983) structure-mapping theory. SME has been used as a cognitive modeling tool to account for some existing psychological findings, and several predictions made based on SME have been subsequently confirmed in psychological experiments (Forbus, 2001). SME has also been used in a variety of performance-oriented systems, ranging from a case-based tutor for engineering thermodynamics (Forbus, 2001) to sketch understanding systems (Forbus *et al*., 2003). The Incremental Analogy Machine (Keane & Brayshaw, 1988; Keane *et al*., 1994) was first to explore incremental mapping of analogies, crucial for extended problem solving. Some computational models have focused on how such computations can be implemented in neural architectures, such as Hummel & Holyoak's (1997) LISA model and Larkey & Love's (2003) CAB model. Other computational models explore how statistical association models can be combined with structural models (e.g., Ramscar & Yarlett, 2003).

One of the major differences in approach between CBR and analogy research is their focus on generality. In analogy research, processes like matching and retrieval are typically assumed to be broadly general cognitive processes, operating universally (or nearly so) over people's mental representations. In contrast, CBR often focuses on creating a system to perform a specific task well on existing computing hardware, and generality is often traded off for efficiency or other performance measures, with an emphasis on *content theories* that reflect the knowledge required for particular task domains. Domain-specific matchers, retrieval systems, and even similarity metrics are fair game. This can lead to controversies between the two communities. This dissociation between similarity-based reminding and analogical inference was greeted with great skepticism and shock in the CBR community because it contradicted a common assumption that human memory retrieval relied on extensive indexing, using abstract principles. Forbus *et al*.'s (1994b) MAC/FAC model captures this dissociation by postulating a first stage of retrieval that is non-structural, a cheap filter that generally lets highly similar items through, followed by a much more constrained structural match stage using SME. If the MAC/FAC model is correct, then CBR index-based retrieval schemes would best be viewed as good engineering tools, rather than as cognitive models. This is still an open question.

CBR also differs from analogy research in its treatment of adaptation. Case adaptation is a major issue for CBR, and must often be addressed in CBR applications. Consequently, it is possible that the experience of CBR in this area will suggest fruitful questions to consider in the context of analogy. Studies focusing on integrating adaptability concerns with other CBR processes include Smyth & Keane's (1998) adaptation-guided retrieval and Leake *et al.*'s (1997) use of adaptation cases to reuse prior adaptations and predict adaptability.

2.2 Discussion

How closely should CBR systems mirror what people do? It can be argued that organizing CBR systems to operate differently from people in some ways might make them more useful. Just as eyeglasses and cars help us see and move farther than we can unaided, carefully designed CBR systems could help us retrieve more relevant memories more often, and help us to work through problems that we could not solve unaided due to working memory limitations. On the other hand, no CBR system approaches the amount of knowledge and experience that people accumulate, nor has any CBR system ever operated over the breadth of problems that people can solve. The processes of human cognition may well hold the key to creating such capabilities.

3 Retrieval in CBR

An important step in the CBR cycle (Figure 1) is the retrieval of previous cases that can be used to solve the target problem. As will be clear from our discussions in Sections 3.1 and 3.2, improving retrieval performance through more effective approaches to similarity assessment has been the focus of a considerable amount of research. However, several authors have questioned the basic assumption on which similarity-based retrieval is based, namely that the most similar cases are most useful for solving the target problem. In Section 3.3, we examine alternative approaches to retrieval that have been motivated by a growing awareness of the limitations of similarity-based retrieval, particularly in light of new application requirements.

3.1 Similarity assessment

In some applications of CBR, it may be adequate to assess the similarity of the stored cases in terms of their *surface* features. The surface features of a case are those that are provided as part of its description and are typically represented using attribute-value pairs. In other applications, it may be necessary to use *derived* features obtained from a case's description by inference based on domain knowledge. It is worth noting, though, that whether or not a feature is readily available has no bearing on whether or not it is predictive of a case's relevance (Kolodner, 1996). In yet other applications, cases are represented by complex structures (such as graphs or first-order terms) and retrieval requires an assessment of their *structural* similarity. As might be expected, the computation of derived features or use of structural similarity is computationally expensive. However, the advantage is that more relevant cases may be retrieved.

One way to help assure that useful cases are retrieved without extensive computation is to develop carefully crafted *indexing vocabularies* to describe cases, so that the explicit description of a case captures the features that determine its relevance. In fact, the focus of considerable early

CBR work concerned the development of such indexing vocabularies (Schank *et al*., 1990; Domeshek, 1992; Leake, 1992) as a way to avoid the need for computationally expensive structure mapping and case matching procedures.

3.1.1 Assessment of surface similarity

In approaches to retrieval based on surface features, the similarity of each case to the target problem, typically represented as a real number in [0, 1], is computed according to a given similarity measure. Usually the retrieved cases are the k most similar to the target problem, an approach often referred to as "k nearest neighbor" retrieval or simply k-NN (e.g., Cover & Hart, 1967). Alternatively, the retrieved cases may be those whose similarity to the target problem exceeds a predefined threshold.

There are many ways of measuring similarity and different approaches are appropriate for different case representations. For example, it is common practice for each case to be represented as a simple feature vector (or set of attribute-value pairs). With this representation, a *local* similarity measure is usually defined for each attribute and a *global* similarity measure is computed as a weighted average of the local similarities. The weights assigned to case attributes allow them to have varying degrees of importance and may be selected by a domain expert or user, or as we shall see in Section 3.2, determined by an adaptive learning process.

A CBR system can guarantee that it retrieves the k cases that are maximally similar to the target problem by computing the similarity of the target problem to every case in memory. However, sequentially processing all cases in memory has complexity $O(n)$, where n is the number of cases. This may not be an acceptable overhead if n is very large. One approach to reducing retrieval time, as in the pioneering work of Stanfill & Waltz (1986), involves the use of massively parallel computers. While the requirement for expensive hardware is an obvious drawback, the approach still guarantees finding the maximally similar cases by performing an exhaustive memory search. Stanfill & Waltz describe the implementation of a memory-based reasoning algorithm on a fine-grained SIMD parallel machine. Their Connection Machine performs a highly parallel search for similar cases and was applied to the problem of pronouncing English words using a case memory containing thousands of examples of correctly-pronounced words.

Another approach to reducing retrieval time relies on the organization of cases in memory. For example, Wess *et al*. (1993) propose an approach to retrieval in which organization of the case memory is based on similarities *between* cases. A binary tree called a *k-d* tree is used to split the case memory into groups of cases in such a way that each group contains cases that are similar to each other according to a given similarity measure. To ensure that the most similar cases are retrieved, the retrieval algorithm computes similarity bounds to determine which groups of cases should be considered first.

Smyth & McKenna (1999a; 2001b) propose an alternative model of case retrieval that is informed by the availability of an explicit model of case-base competence (Smyth & McKenna, 1998; 2001a). The so-called *footprint-based retrieval* algorithm is a two-stage retrieval approach that searches two distinct populations of cases. First, it involves the search of a small subset of so-called *footprint* cases which have been identified as providing a covering set for the entire case base (i.e., can solve the same set of problems). They are drawn from the key competence groups that exist within the case base as made available by the competence model. The first stage of retrieval identifies the footprint case that is most similar to the target problem as the *reference* case, and the second stage of retrieval searches another small subset of cases that are related to this reference case. This *related set* is chosen because its cases either cover (solve) the reference case or because they can be covered by a reference case. The final case chosen for retrieval is the related set case that is most similar to the target problem. The approach has produced significant retrieval efficiency benefits by searching only a small fraction of the cases in the case base, while at the same time guaranteeing the selection of near optimal cases. Footprint-based retrieval is related to Shaaf's (1996) *fish and shrink* strategy in which cases are linked according to specific aspect similarities. The latter approach assumes that if a case does not fit a query then this will reduce the likely usefulness of its neighbors. This allows for the efficient elimination of many cases during retrieval.

Simoudis & Miller (1990) argue that retrieval based only on surface similarity may not be sufficiently discriminating when applied to large case memories, and needs to be combined with other techniques to reduce the number of cases considered for adaptation. They present an approach called *validated retrieval* that can dramatically reduce the number of potentially relevant cases. Retrieval based on surface similarity is combined in the approach with validation of the retrieved cases to determine if they are applicable to the target problem. Associated with each case in memory is a *validation procedure* consisting of a set of domain-specific tests and their results for that case. To validate a retrieved case, its associated tests are applied to the target problem. The retrieved case is deemed relevant to the target problem only if all the tests give the same results for the target problem as they do for the retrieved case.

The validation phase that follows the initial retrieval of cases in validated retrieval resembles the *justification* phase in CASEY, a CBR system for medical diagnosis (Koton, 1988). The goal of CASEY's justification component is to determine whether the causal explanation of a retrieved case applies to the target problem. Often this enables CASEY to avoid invoking its causal model when creating an explanation for the target problem. Other systems that combine retrieval based on surface similarity with an additional filter to improve retrieval performance include CHEF (Hammond, 1986), SWALE (Kass *et al.*, 1986), KRITIK (Goel & Chandrasekaran, 1989), and PROTOS (Porter *et al.*, 1990).

3.1.2 Assessment of structural similarity

Though computationally expensive because it relies on extensive use of domain knowledge, retrieval based on structural similarity has the advantage that more relevant cases may be retrieved. As in Forbus *et al.*'s (1994b) MAC/FAC model (Section 2.1), one way of mitigating the extra cost is to combine surface and structural similarity in a two-stage retrieval process. Experiments based on human assessment of similarities and analogies have confirmed that both surface and structural similarity assessment are necessary for sound retrieval (Forbus *et al.*, 1994b). Inspired by previous work by Gentner & Forbus (1991), Börner (1993) proposes an approach to retrieval in which fast retrieval of candidate cases based on their surface similarity to the target problem is followed by a more expensive assessment of their structural similarity. She defines structural similarity as the most specific graph structure that the target problem has in common with a stored case, and a set of transformation rules, given as background knowledge, needed to determine this common structure.

Object-oriented case representations generalize simple attribute-value representations. Cases are represented by sets of objects. Objects belong to classes, which are organized in a class hierarchy. An object's class determines the attributes it may have. Attributes may be *relational*, which means that their values will themselves be objects. Thus, the class hierarchy must contain useful similarity knowledge. For example, objects that are close to each other in the hierarchy are likely to be more similar than objects that are far apart. However, Bergmann & Stahl (1998) suggest that because there is no clear view about how the similarity between objects of different classes should be determined, similarity assessment is often restricted to objects of the same class. To address this issue, they present a framework for computing similarities for object-oriented case representations that enables objects of different classes to be compared and accounts for the knowledge implicit in the class hierarchy.

Creek (Aamodt, 1994; 2004) uses an object-oriented, frame-based representation system to capture both cases and general domain knowledge, which together can be viewed as a multi-relational semantic network. Similarity assessment is once again a two-step process in which indices are first used to retrieve a set of potentially similar cases and then a closer examination of the cases takes place in which general domain knowledge is utilized to generate explanations for feature-to-feature matches. A method inspired by Cohen's (1985) work on endorsement theory and plausible inference constitutes a core part of the inference machinery underlying the generation and evaluation of explanatory structures.

Spreading activation methods (e.g., Brown, 1994) represent case memory as an interconnected network of nodes capturing case attribute-value combinations. Activation spreads from target attribute-value nodes across the network to cause the activation of case nodes representing similar cases to the target. The approach is efficient and flexible enough to handle incomplete case descriptions, but can incur a significant knowledge engineering cost in constructing the activation network. Furthermore, the spreading activation algorithm requires specific knowledge to guide the spread of activation throughout the network. Related network-based retrieval methods are proposed by Wolverton & Hayes-Roth (1994) and Lenz (1996).

Another way of representing relations between attributes uses the concept of *generalized cases* (Bergmann *et al*., 1999; Bergmann, 2002; Mougouie & Bergmann, 2002). A generalized case covers a subspace of the problem-solution space, providing solutions to a set of closely-related problems, rather than just a single problem. Dependencies between attributes are explicitly represented to support the extension of similarity measures. For example, Bergmann (2002) defines the similarity between a query and a generalized case as the similarity between the query and the most similar case contained in the generalized case. Mougouie & Bergmann (2002) formulate the similarity assessment problem for generalized cases described by continuous attributes as a nonlinear programming problem and introduce an optimization-based retrieval method. Tartakovski *et al*. (2004) extend the case representation to support mixed, discrete, and continuous attributes. They also formulate similarity assessment as a special case of a mixed integer nonlinear optimization problem, and propose an optimization-based retrieval method operating on a given index structure.

Bunke & Messmer (1993) propose one of several structural similarity measures for domains in which cases are represented as graph structures. Their measure is based on *graph editing* operations (i.e., inserting, deleting, and substituting nodes and edges in the graph). To improve the practical efficiency of the approach, they introduce a *subgraph matching* algorithm that works on a compact version of the case memory in which subgraphs that are common to multiple cases are stored only once. In a similar vein, Champin & Solnon (2003) propose a similarity measure, based on graph editing operations within a modification of Tversky's (1977) *contrast model*, to compare cases represented by labeled graphs where vertices and edges can have more than one label. To account for the intractability of this representation, they propose a heuristic greedy algorithm.

Arcos & López de Mántaras (1997) describe a retrieval mechanism called *perspectives* for structured case representations. Cases and degrees of similarity are represented as feature terms, which are equivalent to first-order terms and can also be viewed as directed acyclic graphs labeled by features and values (Plaza, 1995). Their knowledge-intensive approach to retrieval uses a *subsumption* mechanism between the feature terms to obtain an order relation between case descriptions on the basis of a set of user-defined relevant aspects of the target problem. The system is implemented in an object-oriented language (Arcos, 1997) based on feature terms and has been applied to the problem of synthesizing expressive music (Arcos & López de Mántaras, 2001; López de Mántaras & Arcos, 2002).

Emde & Wettschereck (1996) propose an alternative way of measuring the similarity of first-order terms. They also present a generalization of a propositional instance-based learner (distance-weighted *k*-NN) to first order representations. Issues addressed in the approach, which the authors refer to as *relational* instance-based learning (RIBL), include the generation of cases from the knowledge base, assessment of similarity between arbitrarily complex cases, and estimation of the relevance of predicates and attributes. Their empirical results suggest that RIBL can achieve high levels of classification accuracy in a variety of domains.

3.1.3 Similarity frameworks

With so many ways of measuring similarity, it is not surprising that some researchers view similarity in a general way, independent of any specific algorithm. For example, Richter (1992) discusses the notion of similarity in the context of a formal mathematical framework. He describes approaches to modeling similarities with increasing complexity and informativeness. These range from simple predicates (least informative) to relations and functions (most informative). He also discusses general forms of distance functions and similarity measures, including a generalization of Tversky's (1977) contrast model, which uses a set-theoretic approach to express the similarity between objects as a linear combination of their numbers of matching and mismatching features. One limitation of Tversky's model is that all features are assumed to be equally important, whereas Richter's generalization allows different weights to be assigned to features. However, Richter emphasizes that to allow for changes in the problem-solving environment, the parameters of a similarity measure should be the result of an adaptive learning process, an idea we explore further in Section 3.2.

Osborne & Bridge (1996) present another general framework that distinguishes, in particular, between *ordinal* and *cardinal* similarity measures. Ordinal measures use a description of the target problem to induce a partial ordering over the cases in the case memory. No information about the degree of similarity is given; the cases are merely ordered, with the implication that cases higher in the ordering should be retrieved prior to any that are lower in the ordering. On the other hand, cardinal measures are functions that score the cases, returning real numbers to denote degrees of similarity. Osborne & Bridge present a set of operators that allows the flexible and systematic construction of both ordinal and cardinal similarity measures. In later work (e.g., Osborne & Bridge, 1997), the framework is generalized to accommodate similarity measures in which the degree of similarity is denoted by any value drawn from an ordered set. With this extension, the framework accounts for similarity measures in which the degree of similarity is denoted by common subgraphs (Börner, 1993) or feature terms (e.g., Jantke, 1994; Plaza, 1995).

3.2 Improving and evaluating retrieval performance

Several techniques for improving the *speed* of retrieval were mentioned in our discussion of similarity assessment in Section 3.1. Another important aspect of retrieval performance is its impact on *solution quality*. Measures used to evaluate retrieval performance in terms of solution quality are likely to depend on the type of problem-solving task (e.g., classification, recommendation, planning) for which the system is designed. For example, evaluation in terms of *classification accuracy* is possible only if the outcome classes to be predicted in the *test set* are represented in the *training set*. This is not the case in domains such as product recommendation in which each outcome class (a unique product or service) is represented by a single case in the case base (McSherry, 2001c; 2001d). Evaluation of classification accuracy is similarly compromised in *conversational* CBR (Aha *et al*., 2001), where it is typical for most cases to have unique solutions. Appropriate measures of retrieval performance for datasets of this type include precision, recall, and the average length of problem-solving dialogues (Aha *et al*. 2001; McSherry, 2001c; 2001d; 2003a; McGinty & Smyth, 2003).

Problems likely to affect solution quality include the use of inadequate similarity measures, noise, missing values in cases, unknown values in the description of the target problem, and the so-called *heterogeneity* problem that arises when different attributes are used to describe different cases (Aha, 1998; Aha *et al*., 2001; McSherry, 2001d; Stahl & Gabel, 2003; Bogaerts & Leake, 2004). Bogaerts & Leake (2004) propose and evaluate a variety of possible strategies for handling missing information in similarity assessment. Retrieval based on incomplete information is an important challenge in conversational CBR, where a description of the target problem is incrementally (and often incompletely) elicited in an interactive dialogue with the user. Aha *et al*. (2001) evaluate an approach to incremental query elicitation that takes account of the heterogeneity that is typically found in domains such as fault diagnosis. McSherry (2003a) proposes a conversational CBR approach to product recommendation that includes a mechanism for ensuring that the dialogue is terminated only when it is certain that a more similar case will not be retrieved if the dialogue is allowed to continue.

Retrieval performance can often be improved by making the similarity measure the subject of an adaptive learning process. Focusing on variants of *k*-NN that automatically learn the weights assigned to features, Wettschereck & Aha (1995) propose a multi-dimensional framework for the categorization and comparison of feature weighting methods in CBR. The proposed framework can be used to categorize new methods, thus facilitating their comparison with existing methods. However, it cannot be applied to *k*-NN methods that incorporate domain specific knowledge and complex representations. Noting that most feature weighting methods are designed to optimize classification accuracy, Wilke & Bergmann (1996) argue that decision costs should also be considered in many applications. Experimental results support the hypothesis that classification based on weights learned using cost optimization leads to lower decision costs than classification based on weights learned by accuracy optimization.

Improving the *adaptability* of retrieved cases can also be the subject of an adaptive learning process. In case-based planning, for example, Muñoz-Avila & Hüllen (1996) extend the *foot-printed* similarity metric used in Prodigy/Analogy (Veloso, 1994; Veloso & Carbonell, 1994) by incorporating feature weights in a new metric which counts the weights of relevant features that match features in the target problem. A feature is considered relevant to a planning goal with respect to a solution if it contributes to achieving the goal in the solution. The authors also present an algorithm for analyzing the performance of retrieved cases to identify features whose weights need to be recomputed. The algorithm provides a bridge between the new similarity metric and a feature weighting model based on incremental optimizers. Experimental results show that integrating the proposed similarity metric and analysis algorithm in the feature weighting model improves the adaptability of the retrieved cases by converging to best weights over a period of multiple problem-solving episodes.

Many CBR applications rely on domain knowledge encoded in the similarity measures used by the system to guide the retrieval of relevant cases. Such a *knowledge-intensive* approach to similarity assessment typically relies on knowledge acquired from a domain expert. Stahl & Gabel (2003) and Gabel & Stahl (2004) investigate the use of machine learning techniques to reduce the knowledge-acquisition overheads associated with the construction and maintenance of domain-specific similarity measures. Feedback about the quality of retrieval results provided by a domain expert is used in the approach to guide the automatic refinement of similarity measures.

3.3 Alternatives to similarity-based retrieval

Much of the research we describe in this section was motivated by a growing awareness of the limitations of retrieval based purely on similarity. While continuing to play a prominent role in retrieval, similarity is increasingly being combined with other criteria to guide the retrieval process, such as how effectively the solution space is *covered* by the retrieved cases (McSherry, 2003b), how easily their solutions can be *adapted* to solve the target problem (e.g., Smyth & Keane, 1998), or how easily the proposed solution can be *explained* (Doyle *et al*., 2004).

3.3.1 Adaptation-guided retrieval

While many factors may affect retrieval performance in a CBR system, often what matters most is whether the retrieved cases can be used to solve the target problem. Thus effective retrieval is not simply a matter of finding cases that are *similar* but cases that are *usefully* similar. This view is perhaps most formally expressed by Bergmann *et al*. (2001), who argue that similarity is used as a proxy for solution *utility*. However, this raises the question of whether similarity is always an adequate proxy for solution utility. In situations where it is not, it may be necessary for other forms of knowledge available to a case-based reasoner to be brought to bear on the retrieval task.

For example, Smyth & Keane (1994; 1995a; 1996; 1998) question the assumption that the most similar case is the one that is easiest to adapt. They argue that sometimes the most similar case may be impossible to adapt, for example if adaptation knowledge is incomplete, as is often the case in weak-theory domains that are commonly targeted by CBR. To address this issue, they introduce the notion of *adaptation-guided retrieval* in which the adaptation requirements of cases are explicitly assessed during retrieval by means of domain-specific adaptation knowledge. In contrast to traditional approaches that relied on heuristics to predict the ease with which a given case could be adapted, adaptation-guided retrieval combines local and global measures of adaptability to ensure that the most adaptable case is always selected. In this way, it bridges the gap between retrieval (and similarity knowledge) and reuse (and adaptation knowledge). Empirical results show that the approach can significantly reduce adaptation failures and adaptation costs by performing preliminary adaptation work during retrieval. Leake *et al*. (1997) propose a case-based approach to this problem, predicting adaptation effort based on prior adaptation experiences.

3.3.2 Diversity-conscious retrieval

In CBR recommender systems, descriptions of available products are stored in a product case base and retrieved in response to a query describing the user's requirements. An important advantage of similarity-based retrieval in this context is that if there is no case that exactly matches the user's requirements, she can be shown the cases that are most similar to her query. However, one problem is that the most similar cases are often very similar to each other, with the result that the user is offered a limited choice (Smyth & McClave, 2001). In other words, the recommended cases may be lacking in *diversity*. To address this issue, retrieval algorithms have recently been introduced that combine measures of similarity and diversity in the retrieval process to achieve a better balance between these often conflicting characteristics (e.g., Smyth & McClave, 2001; McSherry, 2002; McGinty & Smyth, 2003). For example, Smyth & McClave (2001) propose an approach to retrieval that incrementally selects a diverse set of cases from a larger set of similarity-ordered cases. Experimental results have shown that major gains in diversity can often be achieved at the expense of relatively small reductions in similarity.

3.3.3 Compromise-driven retrieval

McSherry (2003b; 2004a) proposes a *compromise-driven* approach to retrieval in recommender systems inspired by the observation that the cases that are most similar to the user’s query are often not sufficiently representative of compromises (i.e., unsatisfied requirements) that the user may be prepared to accept. A basic assumption in similarity-based retrieval is that a given case (or product) is more acceptable than another if it is more similar to the user’s query. Compromise-driven retrieval is based on the weaker assumption that a given case is more acceptable than another if it is more similar to the user’s query *and* it involves a subset of the compromises that the other case involves. As well as being less likely to be contradicted by user behavior, this weaker assumption provides the basis of a more principled approach to deciding which cases are included in the retrieval set than arbitrarily limiting the number of retrieved cases as in *k*-NN. For example, no case is included in the retrieval set if there is a more similar case that involves a subset of the compromises it involves.

Though not relying on an explicit *measure* of diversity in the retrieval process, compromise-driven retrieval shares with other approaches to enhancing diversity (e.g., Smyth & McClave, 2001; McSherry, 2002) the goal of offering users a better choice of alternatives. Also, it guarantees that the retrieval set provides full *coverage* of the available cases; that is, for any case that is not included in the retrieval set, one of the recommended cases is at least as good in terms of its similarity to the user's query and the compromises it involves.

3.3.4 Order-based retrieval

Order-based retrieval is another approach with particular application to recommender systems (Bridge & Ferguson, 2002a). Rather than scoring the cases, it offers an expressive query language for defining and combining ordering relations, and the result of query evaluation is to partially order the cases in the case base. The query language supports queries that naturally combine preferred values with other preference information such as maximum values, minimum values, and values that the user would prefer not to consider. As in compromise-driven retrieval (McSherry, 2003b), there is no need for an explicit measure of recommendation diversity because the set of retrieved cases is *inherently* diverse (Bridge & Ferguson, 2002b).

3.3.5 Explanation-oriented retrieval

It is often important for CBR systems to explain their reasoning and to justify their suggestions or solutions (e.g., Rissland, *et al*. 1984; Ashley & Aleven, 1992; Leake, 1996b; McSherry, 2001b; Cunningham *et al*., 2003; Doyle *et al*., 2004; McSherry, 2004b; Leake & McSherry, 2005). Explanations serve many different *goals*, such as teaching the user about the domain or explaining the relevance of a question the user is asked (Leake, 1991; 1992; Sørmo & Cassens, 2004; Sørmo *et al*., 2005). For example, McSherry (2003a; 2005) proposes a conversational CBR approach to product recommendation in which the system can explain why a question is being asked in terms of its ability to discriminate between competing cases. Explaining *retrieval failures* is another potential role of explanation in CBR recommender systems (e.g., McSherry, 2004c).

More commonly, the goal is to explain how the system reached its conclusions. In applications such as classification and diagnosis, an attractive feature of CBR is the ability to explain the predicted outcome by showing the user one or more of the target problem's nearest neighbors. As noted by Leake (1996b), "... *the results of CBR systems are based on actual prior cases that can be presented to the user to provide compelling support for the system's conclusions*". Such explanations are known as *precedent-based* explanations and have long been a feature of case-based models of legal argumentation (e.g., Ashley, 1991; Branting, 1991; Rissland & Skalak, 1991). An empirical study by Cunningham *et al*. (2003) has shown that they are often more compelling than alternative forms of explanation. However, several authors have questioned the effectiveness of precedent-based explanations in which the user is simply shown the case that is most similar to the target problem.

For example, McSherry (2004b) argues that such explanations are often less informative than might be expected, and should ideally be supported by an analysis of the *pros* and *cons* of the proposed solution. Case-based legal argumentation (Ashley, 1989, 1991; Ashley & Aleven, 1992; 1997; Aleven, 2003) broadens the notion of case similarity to include other considerations (e.g., noteworthy distinctions among cases, the existence of counterexamples) with a view to explaining and distinguishing the strengths and weaknesses of relevant cases, providing examples to resolve conflicts, presenting counterexamples to proposed solutions, and posing hypothetical variations of problems to illustrate their effects on the analysis.

Doyle *et al*. (2004) argue that the most compelling explanation case may not necessarily be the one that is most similar to the target problem. In particular, they demonstrate how cases that lie between the target problem and the decision boundary can often be more useful for explanation. This has motivated the development of *explanation-oriented* retrieval. The approach remains precedent-based, but once a classification or diagnosis has been reached on the basis of the nearest neighbors, the system performs an additional retrieval step, using an explanation utility metric, to obtain the explanation case. Doyle *et al*. (2004) also report the results of an empirical study that show their explanation cases to be generally more compelling than the nearest neighbor.

4 Reuse and revision in CBR

The reuse process in the CBR cycle is responsible for proposing a solution for a new problem from the solutions in the retrieved cases. In the "4 REs" of Aamodt & Plaza's (1994) classic CBR cycle (Figure 1), *reuse* appears second, after *retrieve*, and is followed by *revise* and *retain*. Reusing a retrieved case can be as easy as returning the retrieved solution, unchanged, as the proposed solution for the new problem. This is often appropriate for classification tasks, where each solution (or class) is likely to be represented frequently in the case base, and therefore the most similar retrieved case, if sufficiently similar, is likely to contain an appropriate solution. But reuse becomes more difficult if there are significant differences between the new problem and the retrieved case's problem. In these circumstances the retrieved solution may need to be adapted to account for these important differences. Medical decision making is one domain in which adaptation is commonly required.

Adaptation becomes particularly relevant when CBR is used for constructive problem-solving tasks such as design, configuration, and planning. For such tasks it is unlikely that each solution (design, configuration, or plan) will be represented in the case base. Thus the retrieved solution is simply an initial solution and any differences between the new problem and the retrieved case's problem are likely to alter the retrieved solution.

Adaptation methods differ in complexity with respect to two dimensions: what is changed in the retrieved solution, and how the change is achieved. *Substitution* adaptation simply reinstantiates some part(s) of the retrieved solution, whereas *transformation* adaptation alters the structure of the solution (Kolodner, 1993). Adaptation is commonly achieved by altering the retrieved solution directly, but the more complex *generative adaptation* replays the method of deriving the retrieved solution on the new problem. These three adaptation methods will be used to structure this section. The contributions we discuss are different approaches to adaptation for reuse (i.e., adaptation during solution formulation). Adaptation can also be used when feedback about a proposed solution indicates that a repair is needed; this is part of the revise stage in the

CBR cycle.

Hammond (1990) describes the reuse of recipes in CHEF, a menu-planning system. Substitution adaptation is used to substitute ingredients in the retrieved recipe to match the menu requirements (e.g., when a recipe containing beef and broccoli is retrieved for a meal requiring chicken and snow peas, the meat component is replaced by chicken and the vegetable component is substituted by snow peas). Transformation adaptation may also be needed to amend the proposed recipe further by adding or removing steps in the recipe that result from any ingredient substitutions (e.g., for chicken, rather than beef, a new skinning step should be added). Further transformations may occur at the revise stage where *critics* analyze the failure of a recipe and repair strategies are applied to the proposed recipe to add or remove steps in the failed recipe. CHEF's learning of critics introduced the topic of case-based planning and many of its themes (e.g., indexing, use of cases in memory, failure-driven learning).

SWALE (Schank & Leake, 1989) is a case-based explanation system for story understanding that reuses old explanations by applying substitution adaptation to amend the actor, their role or the action in the retrieved explanation (Kass, 1989). Transformation adaptation may again be needed to add or remove components in the current explanation resulting from these substitutions.

Déjà Vu (Smyth & Keane, 1995a; 1998) is a CBR system for the automated design of plant-control software. It builds on some of the ideas proposed in CHEF (Hammond, 1990) by utilizing transformation adaptation knowledge in the form of general *adaptation strategies* and more specialized *adaptation specialists.* An important and novel contribution of Déjà Vu is its representation of complex plant-control software designs as hierarchies of related cases and its adoption of a hierarchical model of case retrieval and reuse. For example, complex target problems lead to the retrieval and adaptation of the solutions to *abstract cases*, the elements of which in turn lead to the retrieval and adaptation of more detailed sub-cases. In this way, the solution transformation is performed by a combination of problem decomposition, sub-case adaptation, and solution re-integration. A unique feature of Déjà Vu, as discussed in Section 3.3, concerns its ability to leverage existing adaptation knowledge during retrieval to evaluate the adaptability of cases. This alleviates some adaptation problems by guaranteeing the retrieval of cases that can be adapted easily.

Model-based adaptation is a popular approach to transformation adaptation in which causal reasoning is integrated with CBR. Koton's (1988) CASEY is an early example of model-based adaptation, in a medical diagnosis CBR system that utilizes domain independent repair strategies to adapt the retrieved explanation to account for differences between the symptoms of new and retrieved patients. KRITIK (Goel & Chandrasekaran, 1989) relies on model-based transformation adaptation to reuse designs for physical devices. Model-based reasoning creates a causal explanation for the new design by transforming the explanation of the retrieved one. Faltings' (1997a) CADRE also applies model-based reasoning in case-based design. Reuse involves the combination of retrieved design cases and the transformation adaptation of the retrieved design. This approach was evaluated in two design prototypes: CADRE for architectural design and FAMING (Faltings & Sun, 1996) for mechanism design.

Evolutionary methods have also been explored for adaptation, in the context of architectural design (Gómez de Silva Garza & Maher, 2000). The retrieved designs become the initial population for a *genetic algorithm* and mutation and crossover operators are used to generate new designs for the population. Mutation is a substitution adaptation that randomly alters parts of one design to produce a new design. Crossover is a transformation adaptation that can alter the structure of the design. It generates two new designs from two parent designs by interchanging parts of the design in each parent. The genetic algorithm's fitness function evaluates the designs by calculating how well they match the design requirements. The design with the highest match to the requirements is the new design.

Purvis & Pu (1995) present adaptation as a *constraint satisfaction problem*. The design cases are represented as constraint satisfaction problems, where the design requirements are the constraints and the design is the solution. The retrieved designs are adapted by applying a minimum conflicts heuristic to guide the repair of the design to match the new design requirements.

The work discussed so far in this section has been devoted to substitution and transformation adaptation. Based on studies of several CBR systems that use adaptation, Fuchs & Mille (1999) propose a knowledge-level task model for substitution and transformation adaptation processes. Their reuse task is composed of *copy* and *adapt* subtasks. The adapt subtask comprises selecting a problem difference, *modify*ing the solution, and finally verifying the solution. The modify task can remove or *substitute/add* part of the solution, and finally the substitute/add task searches for a suitable replacement by using additional cases, applying a heuristic, or accessing domain knowledge such as explanations, abstractions or specializations.

Generative adaptation differs from substitution and transformation adaptation in that it does not adapt the retrieved solution directly, but instead derives the new solution by replaying the method used to derive the retrieved solution. Generative adaptation may result in a reinstantiation of parts of the retrieved solution, like substitution, or in a transformation that alters the structure of the solution. Prodigy/Analogy (Veloso, 1994; Veloso & Carbonell, 1994), a general purpose planning system, applies *derivational replay* to recompute a replacement for a faulty element of the retrieved solution by recalling how the element was computed and replaying the computation for the new problem. Derivational replay is a variant of *derivational analogy* (Carbonell, 1986) in which the complete solution is recomputed. In this work an analogy between the new and retrieved problems is used to adapt the method of deriving the solution.

Although CBR systems avoid reasoning from first principles by remembering and reusing past solutions, substitution and transformation adaptation of retrieved solutions is often achieved by reasoning about how the problem differences should be reflected in the adaptation to the proposed solution. Therefore the acquisition of adaptation knowledge can require a substantial knowledge engineering effort. The difficulty of acquiring adaptation knowledge was identified in early CBR research but, until recently, relatively little effort has been devoted to automating the acquisition of adaptation knowledge. Leake *et al.*'s (1995) DIAL system for disaster response planning builds up its adaptation knowledge as it applies case-based planning. The adaptation knowledge it learns is a set of adaptation cases that capture the steps in successful manual plan adaptations. DIAL applies a mixed-initiative adaptation process: if an adaptation case matches the current adaptation need it is reused by a CBR process, otherwise DIAL attempts to apply a general rule to revise the plan (e.g., add or remove a step), but as a final option it resorts to manual adaptation. This last option offers the opportunity to acquire a new adaptation case when the manual adaptation generates a successful plan.

Several systems exploit the knowledge already captured in the cases as a source of adaptation knowledge. McSherry (1999) reuses pairs of cases from the case base that contain the same differences as those found between the new problem and the retrieved case. The solution difference from the pair of cases is replayed on the retrieved case. Rather than reusing differences directly from cases, Hanney & Keane (1997) use the case base as a source of case pairs that are used as training data to learn rule-based adaptation knowledge that generalizes the adaptations represented in the case pairs. Wilke *et al.*'s (1997) *knowledge-light* learning provides a framework for such approaches, in which knowledge contained elsewhere in the CBR system, like the case base, is used to learn or improve the adaptation knowledge. Jarmulak *et al.* (2001) use a set of adaptation cases created from the original case-base as the knowledge source of a case-based adaptation system. Further work has applied different learning methods to assemble an ensemble of rule-based adaptation experts learned from these adaptation cases (Wiratunga *et al.*, 2002).

5 Retention in CBR

In the classic review paper by Aamodt & Plaza (1994), retention is presented as the final step in the CBR cycle, in which the product of the most recent problem-solving episode is incorporated into the system's knowledge. To a great extent this has traditionally translated into a variety of approaches for recording the product of problem solving as a new case that can be added to the case base. Of course, there are various issues concerning how best to learn a new case and different systems record different types of information in their cases. Most, for example, simply record the target problem specification and the final solution, with the implicit assumption that the outcome was successful. For example, when CBR is integrated with a generative problem-solving system for speed-up learning, the success of the system's solutions may be guaranteed (e.g., Veloso, 1994; Veloso & Carbonell, 1994). When outcomes are less reliable or when the criteria for success are more complex, case representations must include additional information on the *outcome* of the solution, which may also include fine-grained information on how well the solution addressed many dimensions of the system's goals (e.g., Goel *et al*., 1991). Another question is what to store concerning the solution itself. Many systems store only the solution, but others record a much deeper representation of the problem solving process that brought about the particular solution. In Veloso & Carbonell's work, for example, *derivational traces* are stored in cases. These rich knowledge structures describe precisely how a given solution was derived, providing a trace of the decision-making processes that led to a particular solution.

In general, the modern view of retention accommodates a much broader perspective of what it means for a CBR system to learn from its problem solving experience, a view that is largely a response to certain critical issues that have arisen during the practical application of CBR systems in complex problem solving scenarios. In this section we will review this body of work, highlighting many of the critical issues associated with open-ended case learning policies and how these issues have been resolved by novel approaches to case-base optimization. Moreover, we will argue that these issues have served as an important catalyst for research in the area of case-base maintenance and the maintenance of other aspects of a CBR system, which accommodates a broader perspective on case learning and retention.

5.1 The utility problem in CBR

In the past the prevailing view of case learning in CBR was based on the assumption that learning would occur as a by-product of every problem solving episode. However, as CBR systems were developed and deployed for real-world application scenarios, the potential pitfalls of long-term case learning became apparent, especially in relation to the impact of case-base growth on retrieval costs. This is an example of the *utility problem* identified in explanation-based learning research (e.g., Minton, 1990). This problem refers to the performance degradation experienced by speed-up learners as a result of learning control knowledge. In brief, Minton demonstrated how rules learned for reducing problem solving time, by directing the search more carefully, might ultimately degrade overall system performance as the time spent considering the application of a speed-up rule eventually overtakes the time needed for first principles problem solving. For example, overly specific rules that are seldom applicable, or rules with a high match cost, or rules that offer limited speed-up were all found to contribute to a decline in problem solving efficiency.

At the heart of the utility problem is a natural trade-off between the benefits of speed-up knowledge and the cost of its application. A similar trade-off also exists in CBR systems (Francis & Ram, 1995; Smyth & Keane, 1995b; Smyth & Cunningham, 1996). Cases correspond to a form of speed-up knowledge in the sense that retrieval and reuse of similar cases are expected to provide more efficient problem solving than first-principles methods, with additional cases increasing the range of problems that can be solved rapidly. However, this rather naive view of case knowledge fails to consider retrieval costs. In CBR systems the utility problem is caused by the conflict between (1) the average savings in adaptation effort due to the availability of a particular case, which tends to increase efficiency as the case base grows, and (2) the average retrieval time associated with a given case-base size, which tends to decrease efficiency. Smyth & Cunningham (1996) demonstrate the inevitability of the utility problem in CBR under reasonable general assumptions about the retrieval and reuse characteristics of a CBR system. They show that as a result of case learning, retrieval efficiency (mean retrieval time) tends to degrade while adaptation efficiency (mean adaptation time) is seen to improve, but at an ever decreasing rate. Initially, as a case base grows each newly learned case can have a significant impact on adaptation as it is more likely to improve overall case-base coverage. However, as the case base grows new cases are more likely to overlap with existing cases and so offer little in the way of new coverage and minimal adaptation savings. As new cases are added retrieval costs become progressively greater but adaptation savings progressively less. Eventually the increase in retrieval time as a result of a new case addition is greater than the adaptation savings offered. At this critical case-base size, overall problem solving efficiency begins to degrade.

5.2 Harmful cases, competence models, and selective retention

Once the relevance of the utility problem to CBR became clear, researchers began to look to the machine learning literature as a source of coping strategies. The starting point for this research effort includes early work by the pattern recognition community on nearest neighbor classification (Cover & Hart, 1967), focusing on a number of ways to remove harmful training examples from a set of instances. For example, Hart's condensed nearest neighbor (CNN) approach (Hart, 1968) is an early attempt to eliminate redundancy from a collection of instances, which in turn led to a family of related redundancy detection methods (e.g., Gates, 1972; Tomek, 1976b). Wilson (1972) adopts a complementary stance, focusing on the elimination of noise rather than redundancy from training data. For example, Wilson's edited nearest-neighbor (ENN), and Tomek's (1976a) repeated edited nearest neighbor (RENN) techniques represent the genesis of a variety of noise reduction techniques that remain as valuable coping strategies even today.

In the 1990's, with the revival of lazy learning techniques and a renewed interest in nearest neighbor methods, researchers from the machine learning community once again focused their attention on ways to eliminate harmful data from training sets. Algorithms proposed by Aha *et al.* (1991) and Wilson & Martinez (1997) are good examples of a new breed of machine learning inspired coping strategies that ultimately came to have a significant influence on the CBR community. Markovitch & Scott (1993) propose a unifying framework for the systematic discussion of all of the various strategies for coping with *harmful knowledge* in general, and the utility problem in particular. Their framework is based on different types of filters for eliminating harmful knowledge at various stages in the problem solving cycle. One approach that is especially relevant in CBR is to simply delete harmful cases from the case base so that they cannot actively contribute to ongoing problem solving costs – deletion policies in CBR correspond to *selective retention filters* in the Markovitch & Scott framework. Surprisingly enough, in many speed-up learners even the apparently naive random deletion of knowledge items (to maintain the knowledge base to some predefined size) works quite well for optimizing efficiency. Even though random deletion removes both useful and redundant items it can equal the success of more sophisticated methods (Markovitch & Scott, 1993). More sophisticated deletion policies have been developed and are guided by some assessment of the utility of individual knowledge items. For example, Minton (1990) uses a utility metric that takes into account the cost of including the item in the set of candidates to consider (match cost) and the expected savings offered by the item (average savings multiplied by its application frequency) to deliver even greater protection against the damaging effects of the utility problem.

Unfortunately it soon became clear that the same type of coping strategies would not translate directly over to case-based reasoners. The problem stems from the fact that many case-based reasoners are not simply using case knowledge as a form of speed-up knowledge. Instead, cases are often a primary source of problem solving knowledge. Without cases, certain problems cannot be solved and thus the act of deleting cases may irrevocably reduce the competence of the system to solve new problems; CBR systems may not be able to reconstruct deleted cases from an internal domain model. To address this problem, Smyth & Keane (1995b) proposed the use of a *competence model* to evaluate the contributions of individual cases to problem solving competence. In particular, they developed methods for categorizing cases according to their competence characteristics with a view to guiding the selection of cases for deletion. These categories facilitate the preservation of key cases (called *pivotal cases*) that might otherwise be deleted, in favor of deleting less critical cases whose loss is expected to least harm system competence. Competence-guided case deletion provides a safe way to eliminate cases from a growing case base to stave off the harmful effects of the utility problem while at the same time protecting against reductions in competence.

Later work brought the introduction of a more fine-grained model of case competence (Smyth & McKenna, 1998) as a pre-cursor to a variety of related retention models and other forms of case-base editing (e.g., McKenna & Smyth, 2000a; 2000b; Smyth & McKenna, 2000). For example, as an alternative to case deletion, Smyth & McKenna (1999b) use their competence model to develop a competence-guided case addition algorithm. In related work, Zhu & Yang (1999) describe a case addition algorithm that has the added advantage of providing a guaranteed lower bound on resulting competence. Leake & Wilson (2000) highlight the importance of considering both competence *and* performance during case-base optimization. They argue the need for more fine-grained performance metrics with which to guide the maintenance of a case base and show how one such metric can help to guide case-base editing in a way that gives due consideration to competing factors such as case-base size, coverage, and adaptation performance.

Over the past few years there has been a broad range of research addressing these key issues of case deletion, addition, and case-based editing in general. Further discussion is beyond the scope of this article but the interested reader is referred to work by Surma & Tyburcy (1998), Lei *et al*. (1999), Portinale & Torasso (2001), Yang & Zhu (2001), Salamó & Golobardes (2002), Wiratunga *et al*. (2003), and Woon *et al*. (2003).

5.3 Case-base maintenance

As researchers began to recognize that there was more to case retention than simply which cases to learn, and how they should be encoded, the importance of case-base maintenance quickly came into focus (Smyth, 1998; Leake *et al*., 2001; Wilson & Leake, 2001). Maintenance issues arise when designing and building CBR systems and support tools that monitor system state and effectiveness to determine whether, when, and how to update CBR system knowledge to better serve specific performance goals. Understanding the issues that underlie the maintenance problem and using that understanding to develop good practical maintenance strategies is crucial to sustaining and improving the efficiency and solution quality of CBR systems as their case bases grow and as their tasks or environments change over long-term use. And today there is a general recognition of the value of maintenance to the success of practical CBR systems.

To begin to appreciate the issues involved in developing maintenance strategies, as well as to understand maintenance practice and identify opportunities for new research, it is useful to understand the nature of the maintenance process and its relationship to the overall CBR process. Wilson & Leake (2001) characterize case-base maintenance in terms of the components of maintenance policies and the dimensions along which alternative maintenance policies may differ, using this characterization to examine a range of concrete maintenance strategies and proposals. Their framework categorizes case-base maintenance policies in terms of how they gather data relevant to maintenance decisions, how they determine when to trigger maintenance operations, the types of maintenance operations available, and how the selected maintenance operations are executed. For example, data collection might be restricted to gathering information on individual cases (e.g., the number of times a case has been used, or has been used and produced an unsuccessful result) or about the case base as a whole (e.g., its current size, or its growth trends over time). Maintenance policy triggering may be done periodically (e.g., at every case addition), conditionally (e.g., when retrieval time increases to a pre-specified threshold), or on an *ad hoc* basis (e.g., by unpredictable intervention by a human maintainer). The available maintenance operations may target different knowledge containers (e.g., indices, the cases themselves, or adaptation knowledge) and may be applied at different times or to varying portions of the case base. They use this framework to characterize existing strategies according to the framework's dimensions, providing both a snapshot of the current state of the art in case-base maintenance and suggestions of unexplored strategies.

Of course, the success of maintenance depends not only on the maintenance policies themselves, but also on how maintenance is integrated with the overall CBR process. Reinartz *et al*. (2001) propose to extend the classic 4-stage CBR cycle shown in Figure 1 to include two new steps, a *review* step to monitor the quality of system knowledge, and a *restore* step which selects and applies maintenance operations. Their revised model, shown in Figure 3, emphasizes the important role of maintenance in modern CBR and indeed proposes that the concept of maintenance encompass the retain, review and restore steps (Iglezakis *et al*., 2004).

A considerable body of maintenance research has developed directly from earlier work on how best to control the addition and deletion of cases in a CBR system (Section 5.2), but case addition/deletion is just one aspect of maintenance, and maintenance policies can be applied to a variety of other knowledge sources beyond the case base. For instance, Hammond (1990) uses explanations of case application failures to determine additional indices to assign to a new case to focus future retrievals. Fox & Leake (1995; 2001) and Cox & Ram (1999) use introspective learning techniques to examine the issue of index refinement triggered by retrieval failures. Muñoz-Avila (2001) looks at index revision (and case retention) policies in the context of a derivational replay framework. Index revision is guided by a policy that is based on an analysis of whether the results of retrievals can be extended for new problem scenarios without revising the planning decisions suggested by the retrieved case. Craw *et al*. (2001) examine the use of a genetic algorithm for refining indexing features and matching weights; see also (Wettschereck & Aha, 1995) and (Bonzano *et al*., 1997). Maintenance can also involve adaptation. Leake & Wilson (1999) propose adding adaptation rules as a "lazy" strategy for updating the case base as future cases are retrieved, and Shiu *et al*. (2001) generate new adaptation rules while compressing the case base as a means to protect against knowledge loss.

In multi-agent scenarios, a CBR system's own case retention process may be bolstered by drawing on the case bases of cooperating agents, raising questions of when to access those cases and to retain them in the agent's own case base This requires strategies for addressing questions such as when external cases may be useful, how to process them to maximize their value to a particular agent, and when multiple case bases should be merged into a single case base (Ontañon & Plaza, 2003; Leake & Sooriamurthi, 2004).

Techniques have been developed for detecting inconsistencies in the case base, either to avoid storing inconsistent cases during initial case retention (McSherry, 1998) or to enable correction of inconsistencies when maintaining the case base as a whole (e.g., Shimazu & Takishima, 1996;

Racine & Yang, 1997). More generally, Leake & Wilson (1999) look at the use of CBR in changing environments where key challenges exist in relation to the predictability of problem-solution regularity and distribution. They argue that to avoid inconsistent problem-solving performance a CBR system must be able to examine how well these key regularity assumptions hold and take corrective maintenance action when they do not. The study of case retention is therefore inextricably tied to many related issues for managing the multiple forms of knowledge within CBR systems and adapting CBR systems to the needs of the environments in which they function.

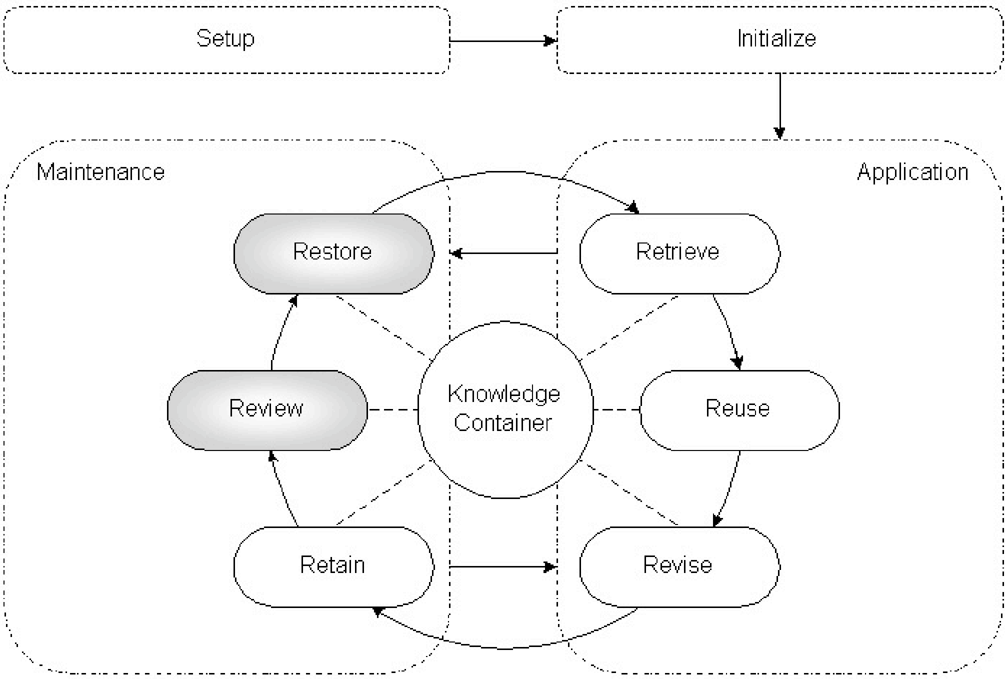


Figure 3 An extension of the classical 4-stage CBR model to emphasize the importance of maintenance in overall system performance, illustrating the setup, initialization, application and maintenance phases of the SIAM methodology for maintaining CBR systems. Adapted from (Iglezakis *et al*., 2004).

Maintenance strategies can also be used to assist the case author during the early stages of case acquisition. For example, Ferrario & Smyth (2001) describe a distributed approach to case authoring in which a community of authors contribute to the validation of new case knowledge. McSherry (2000; 2001a) also focuses on the case acquisition task, and presents CaseMaker, a system that performs background reasoning on behalf of the case author while new cases are being added, in order to help the user determine the best cases to add in light of their competence contributions. The system uses its evaluations of the contributions of potential cases to suggest cases to add to the case library. McKenna & Smyth (2001) propose an approach to providing authoring support that attempts to identify *competence holes* within an evolving case base. They demonstrate how their model of competence (Smyth & McKenna, 1998; 2001a) can be used to prioritise gaps in case knowledge and, like McSherry (2000; 2001a), propose a technique for automatically suggesting the type of cases that an author might want to consider to fill these gaps with a view to maximizing the potential coverage and contributions that are available. To provide a systematic framework for organizations needing to capture and maintain case-based knowledge, Nick *et al*. (2001) developed systematic practical strategies for guiding the maintenance of corporate experience repositories.

In this section we summarized research in the area of retention and maintenance in CBR. Due to space limitations, we could only scratch the surface of this dynamic and rich area of research. Retention and case-base editing and, more generally, case-base maintenance, continues to be a rich source of research ideas, and even recent developments could not be discussed here in the detail they deserve. The interested reader is referred to Wilson & Leake (2001) for a thorough examination of the dimensions of maintenance strategies and survey of additional maintenance research in terms of those dimensions. In addition, a recent collection of maintenance articles addressing numerous facets of maintenance is available in Leake *et al*. (2001).

6 Conclusions

Our aim in this paper has been to provide a concise overview of the cognitive science foundations of CBR and of the four main tasks involved in the CBR cycle, namely retrieval, reuse, revision, and retention. Rather than presenting a comprehensive survey, we have focused on a representative selection of work from the CBR literature in the past few decades. We have tried to strike a balance between research that can be seen as laying the foundations of CBR and more recent contributions. The fact that many of the cited papers were published in the last few years is also evidence of a significant amount of ongoing research activity. It should be clear from our discussion that much of the recent research has been motivated by an increased awareness of the limitations of traditional approaches to retrieval, reuse, and retention. This is a trend that seems likely to continue with the emergence of new and more demanding applications of CBR, and we look forward to the challenges and opportunities that lie ahead.

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