F4.3 Fuzzy Case-Based Reasoning Systems

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Abstract

Case-based Reasoning (CBR), a method of analogical reasoning which is common and extremely important in human cognition, has only recently emerged as a major reasoning methodology. CBR involves solving new problems by identifying and adapting solutions to similar problems stored in a library of past experiences. The important steps in the inference cycle of CBR are to retrieve cases from the library which are most relevant to the problem at hand and adapt the retrieved cases to the current input. First we will review the history of CBR and discuss two types of CBR systems (interpretive and problem-solving). Then, we will analyze the most important CBR issues, such as case retrieval and selection, memory organization, matching and similarity measures, case adaptation, evaluation, and integration. Finally, we will explore some of Fuzzy Logic contributions to CBR and focus on the computation of abstract features for case indexing and their use in computing similarity measures to retrieve the most relevant cases.

F4.3.1 Introduction

F4.3.1.1 Problem Description

Rule-based Reasoning (RBR) systems solve problems by following a generative approach, typically rule-chaining, in which they create a deductive path from the evidence (facts) to the hypotheses (goals). Case-based Reasoning (CBR) systems, on the other hand, follow an analogical rather than a deductive approach. In this new paradigm, a reasoner solves a problem by noticing its similarity with one or several previously solved problems and by adapting their known solutions instead of developing a solution from scratch. The problem descriptions and their solutions are stored in the CBR Case Base and are the basis for the CBR performance. Therefore, a CBR system is only as good as the cases within its Case Base and its ability to retrieve the most relevant cases in response to a new situation.

Case-based reasoning can provide an alternative to rule-based expert systems, and is especially appropriate when the number of rules needed to capture an expert's knowledge is unmanageable or when the domain theory is too weak or incomplete. CBR can work in problem domains where the underlying models used for solutions are not well understood. Historically, CBR has shown its greatest success in areas where individual cases or precedents govern the decision-making processes, as in case law (Ashley, 1988), (Rissland and Skalak, 1989b), medical (Koton, 1988), financial (Dutta and Bonissone, 1993) and engineering (Barletta and Hennessy, 1989).

F4.3.1.2 CBR Types

Case-based reasoning systems can be used to 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, reasoning from precedents to understand a new situation, or build a solution based on previous cases.

These different aspects of CBR can be classified into two major types: interpretive (or classification) CBR, and problem-solving CBR (Kolodner, 1992). In interpretive 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. In practice, however, this division does not create a crisp dichotomy, since many problems, such as the most effective case-based learners, will use a combination of both types of CBR. For instance, the labor mediation application (Sycara, 1987) needs both interpreting the situation and then deriving a solution based on precedents. Furthermore, many systems use interpretive CBR to evaluate the solutions reached, since evaluation is one of the basic operations in any case-based reasoner.

F4.3.1.3 CBR Process

In general, CBR systems are comprised of a case-memory, indexing, matching and retrieval mechanisms, and a reasoning component. The matching and retrieval mechanisms, driven by the current context (reasoner's goal and probe), return the most similar cases from the case memory. Similarity among cases is based on an evaluation of salient and relevant features. In interpretive CBR systems, the output of the matching process provides a complete solution to the input problem, and no additional reasoning is required. In problem-solving CBR, the reasoning component processes the retrieved cases, adapting their solutions (plans, explanations, interpretations) to apply in the current situation.

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

- retrieving relevant cases from the case memory (this requires to index 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.

F4.3.1.4 Uncertainty in CBR

Uncertainty and incompleteness pervade the CBR process. Uncertainty is present in the semantics of *abstract features* used to index the cases, in the evaluation of the *similarity measures* computed across these features, in the determination of *relevancy and saliency* of the similar cases, and in the *modification rules* used in the case adaptation phase. Incompleteness is present in the partial domain theory used in the indexing and retrieval, in the usually sparse coverage of the problem space by the existing cases, and in the description of the probe. After a brief review of CBR history and components, we will focus on Fuzzy Logic based approaches to address some of the above issues.

F4.3.2 Review of CBR Systems

F4.3.2.1 CBR as Reasoning Systems: A Brief History

The case-based approach to reasoning and learning (Kolodner 83) has been growing impressively during the past fifteen years. In 1983, Kolodner reported in her book (Kolodner 1993a) about 82 CBR systems in the USA alone. Today we can find hundreds of CBR systems reported in the literature. The pioneering work in this field is that of Schank on Dynamic Memory (Schank, 1982), Carbonell on Analogy (Carbonell, 1983) and Kolodner, who was the first to build a case-based reasoning and learning system called CYRUS (Kolodner, 1983). After these early works, the development of CBR continued with further work by Kolodner and students (Kolodner, Simpson and Sycara, 1985; Kolodner, 1987; and Sycara, 1988) as well as the work of Hammond and others on case-based planning (Hammond, 1986, 1987; Collins, 1987).

Among the problem-solving CBR types, several systems have been built to address planning and design: JULIA (Hinrichs 1988, 1989) to plan meals; CYCLOPS (Navinchandra, 1988) to design landscapes; KRITIK (Goel 1989, Goel and Chandrasekaran 1989) to combine 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; a system developed by Faltings to represent architectural design knowledge (Faltings et al. 1991); SMART (Veloso, 1992) 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. PROTOS (Bareiss et al. 1988) diagnoses hearing disorders using a learning apprentice approach. The difficulty of this diagnosis is that many difference diagnoses have similar manifestations and the relevant differences are so subtle that novices tend to miss them. In such a situation, PROTOS plays the role of a novice. When the CBR system makes a mistake, a teacher explains the mistake. As a result PROTOS learns these subtle differences by creating difference pointers in its memory that allow the system to switch from an apparently trivial but incorrect diagnosis to the correct one. Another historical CBR work in diagnosis is that of Richter and Althoff (Althoff, 1989) on complex diagnosis issues. Other more recent representative applications to diagnosis for maintenance are CASELINE (Magaldi, 1994) for airplanes maintenance and a system for maintenance of telecommunication networks (Deter, 1994).

In interpretive CBR, the first works are those of Rissland and Ashley with the development of a system for legal reasoning called HYPO (Ashley 1988). In HYPO, the cases retrieved are of two different types, those supporting the new situation which are used to argument in favor and those against the new situation which are used as counter-arguments. The result is a set of three-ply arguments supporting the proposed solution. Many other works in interpretive 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 and Wills 1993b). The main working hypothesis is that much creativity stems from using old solutions in novel ways.

F4.3.2.2 CBR 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 also because it accumulates and indexes cases in a case memory for later use.

Case-based reasoning as a learning paradigm has several additional advantages.

- Since each new solved case is stored in memory for later use, instead of deriving new solutions from scratch, a CBR system remembers and adapts old solutions. If such solutions have been adapted in a novel way or combined in a different way then, when solving another similar case, these circumstances will be remembered rather than re-derived.
- 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.
- 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.

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, such as: 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); knowledge acquisition and refinement (Sharma and Sleeman, 1988); robotic control (Moore 1990); molecular biology (Cost an 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).

F4.3.3 CBR Components, Issues, and Open Problems

F4.3.3.1 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 selected 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. A predetermined set of indices could solve this problem but would severely constraint the system's abilities to generalize. Several techniques have been explored to solve this problem: *inductive learning* methods to identify predictive features which will then be used as indices (Lebowitz, 1987) and *explanation-based learning* (EBL) techniques to identify relevant features (Barletta and Mark, 1988). Recently, several researchers have taken the approach of defining vocabularies for describing different types of problems in an attempt to discover the content of indices that allow reminding across particular domains (Hinrichs et al. 1993, Cuthill and McCartney 1993, Goldweic and Hammond 1993). Heuristic search techniques (Rissland et al. 1993) and Qualitative Models (Richards 1994) are also very promising approaches to the indexing/retrieval problem (Rissland et al. 1993).

F4.3.3.2 Memory Organization

Another basic problem is that of memory organization. A good indexing scheme is not enough when the case memory is large. Therefore, the proper organization of case memory is another crucial point for the success of a CBR system. One approach to his problem consists in having a hierarchical structure where internal nodes are generalizations of individual cases like in the system BOLERO (Lopez, 1993). 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 to solve complex problems by combining partial solutions of several other problems.

F4.3.3.3 Matching and Similarity Measures

Selecting the best case requires being able to match cases together. In general the match is not perfect, since the values of the features of the new and previous cases are not exactly the same. Furthermore, there are usually missing values for some or many of the features. The most usual approach to solve this issue is to define a set of similarity metrics. The matching problem has been 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 the different importance of the features. Sometimes, a weighted similarity measure can be used to perform this aggregation (Bonissone and Cheetham, 1998). Other times, however, this is not possible because the importance of some features is context dependent. Usually, the context is represented by the cases already in memory and therefore they can be used to determine which features of the new case are the most important ones. There are some methods based on this observation: the preference heuristics (Colander, 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 judgments (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 existing similarity measures assume that cases are represented by collections of attribute-value pairs. However we also see the need for more structured representations in complex domains and therefore for new similarity measures, like 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, we should mention the approach described in (Veloso and Carbonell, 1991) that allows to incrementally learn better similarity metrics by interpreting the behavior of the problem solver replaying retrieved cases.

F4.3.3.4 Adaptation/Evaluation

A good adaptation of old cases to fit the new one can significantly reduce the amount of work needed to solve it. In spite of its importance, little attention had been devoted to the adaptation problem until the first European Workshop on Case-Based Reasoning where this problem was addressed by several papers (e.g., Chatterji and Campbell 1993, and 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 Colander, 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 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 using cases and the assignment of blame or credit to old cases (Colander, 1993).

F4.3.3.5 Forgetting

Even assuming that we have solved the basic problems of retrieval and indexing, there is still an additional, somehow unexpected 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, we should mention the often proposed solution of using massive parallelism for both the parallel matching of cases and indices (Colander 1988, Mylymaki and Tirri, 1993).

F4.3.3.6 Integration with other techniques

In some application domains there is a need to combine CBR with other reasoning techniques (Rissland and Skalak, 1989a) such as model-based or rule-based reasoning. Some examples are Aamodt's work on knowledge intensive case-based reasoning (Aamodt, 1990); CABARET (Rissland and Skalak, 1991),which integrates rule-based and case-based reasoning to facilitate applying rules containing ill-defined terms; CARS - Combining Approximate Reasoning Systems (Bonissone et. al. 1990), which explores the integration of case-based and fuzzy-rule-based systems; CREEK (Aamodt, 1991), which 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) also integrating 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) combining case-based and model-based 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), which integrates rule-based and case-based reasoning with intelligent information retrieval; A LA CARTE (Nakatani and Israel, 1993), which uses 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 to learn control knowledge by experience; and MMA (Plaza and Arcos, 1993) a reflective architecture capable of integrating different inference and learning methods. Finally, we should also mention an attempt to integrate Case-based and Inductive learning (Connolly et al. 1993, Banberger and Goos 1993, Manago et al. 1993, Armengol and Plaza 1994).

F4.3.4 Fuzzy CBR: Value Added to Conventional CBR

Fuzzy Logic (FL) techniques have proven to be very useful in addressing many of the open problems listed in section F4.3.3. FL can be used in case representation to provide a characterization of imprecise and uncertain information; in case retrieval to evaluate partial matches by means of fuzzy matching techniques (Dubois et al. 1988); and in case adaptation to modify the selected case by using the concept of gradual rules (Dubois and Prade 1992). More specifically, fuzzy logic can be used to enhance the following CBR functions:

- The case-base itself can be considered a fuzzy set since the cases it contains are not all simply *completely useful* or *not at all useful*, but rather their usefulness is a matter of degree (depending on the problem at hand) and this can be exploited by a fuzzy case-based reasoner.

- At the representation level, Fuzzy Logic allows us to represent cases whose attributes have imprecise values and in particular linguistic values (Plaza and Lopez de Mantaras, 1990, Bonissone and Ayub 1992, Lopez and Plaza 1993, Jaczynski and Trousse 1994).
- In order to retrieve appropriate cases, fuzzy prototypes, i.e. prototypes described by means of fuzzy terms, could be used. Additionally, viewing the description of a case as a tuple of attribute values, fuzzy logic provides a powerful weighted fuzzy pattern matching mechanism (Dubois et al. 1988) to compute the overall similarity between cases from partial similarities between the attributes describing the cases (Bonissone and Cheetham, 1998). Weighted fuzzy pattern matching allows us to take into account the relative level of importance of each attribute in the comparison process, thus limiting the penalty derived from the matching of cases that differ on rather unimportant attributes. Fuzzy logic can also be used to represent the degree of similarity between attribute values that are not precisely known. When the cases are imprecisely or incompletely described, their similarity measures can be described by lower and upper bounds, obtained from necessity and possibility measures, respectively (Dubois and Prade, 1995).
- Gradual rules of the general form *"the more similar two cases are with respect to some attribute(s) the more similar they possibly are with respect to another attribute that we want to infer"* were first developed within the framework of fuzzy logic and are the basis for many approximate reasoning applications. However, they can also be used in case adaptation, i.e. in adapting to the new case to solve, the values appearing in the known cases of the case base. Conditions can also include the assessment of difference between cases like for example in the rule "if two used cars are similar except for the mileage run, the difference between their prices will be a function of the mileage difference". For a fuzzy set-based formalization of case-based reasoning the interested reader is referred to (Dubois et al., 1997)

F4.3.5 A Brief Account of Fuzzy Case-based Reasoning Systems

In this section we will describe a representative sample of fuzzy techniques present in several important CBR systems. They all share the capability of using attributes with fuzzy values and a fuzzy pattern matcher for case retrieval.

F4.3.5.1 The ARC system

The memory organization of the ARC system (Plaza and Lopez de Mantaras 1990) is a hierarchy of classes and cases. Each class is represented by a fuzzy prototype which is a description of the features common to most of the cases belonging to the class. Furthermore, each class is linked to a set of sub-classes, a set of differentially indexed cases, and to cases that are near-misses. The memory organization is dynamic in the sense that classes can be modified or created after each reasoning step. The retrieval step consists in selecting first the most promising classes by means of a fuzzy pattern-matching algorithm based on common features. Next, cases are selected based on the similitudes and differences between the classes and the cases. Finally, near-misses are used to avoid repeating past failures. The certainties of the fuzzy prototypes and the matching degree are expressed by means of linguistic values.

F4.3.5.2 The BOLERO system

BOLERO (Lopez and Plaza 1993) is a system that integrates rule-based and case-based representations. The object level knowledge of BOLERO is represented by rules and the meta-knowledge are the solved instances of problems, conveniently organized in the memory of cases. Since these solved instances can contain uncertain and imprecise values, linguistic values represented by fuzzy sets are used. Moreover, the pattern matching algorithm at the retrieval step is adapted to deal with such linguistic values. An added-value of such hybrid system is the capability of learning meta-knowledge by experience. BOLERO has been successfully applied in a complex medical diagnosis problem using as object knowledge the rules for diagnosing pneumonias.

F4.3.5.3 The CAREFUL system

CAREFUL (Jaczynski and Trousse 1994) focuses on the first two steps of a case-based reasoner, i.e. the case and problem representation and the case retrieval. CAREFUL uses an object-oriented representation based on a hierarchy of fuzzy classes. The use of fuzzy logic allows to take into account the flexibility (imprecision, incompleteness, preferences) associated to the target description, the user requests, the case description and the retrieval process. As with the other systems, the fuzzy sets represent imprecise values of the attributes of the cases. Furthermore, in CAREFUL, fuzzy sets are also used to represent vague constraints on the problem description. The retrieval process proceeds in two steps. First the problem specification and case filtering step which guides the operator in specifying the problem and identifies potentially interesting cases, and second the selection step that chooses the nearest cases. The first step is based on an existing hierarchical fuzzy classification algorithm. The result of the first step is a set of potentially relevant cases that in the second step are compared with the problem description in order to select the nearest cases. To do so, each value of a problem attribute represents a fuzzy constraint and the process selects those cases that better satisfy these fuzzy constraints according to a weighted fuzzy pattern matching technique based on computing a possibility and a necessity degree.

F4.3.5.4 The CARS system

In CARS (Bonissone and Ayub 1992, 1994), cases and problems are also defined in an object-oriented environment. The representation of cases and problems is done by surface and abstract fuzzy attributes. The abstract attributes are computed using plausible inference rules. The most interesting aspect of CARS is the technique used in the selection of the nearest cases which uses a fuzzy similarity measure between attributes based on a fuzzy algebra. The obtained similarity, which is a fuzzy set, is compared, by means of a measure of inclusion, to reference fuzzy sets labelled NO-MATCH, PARTIAL-MATCH or COMPLETE-MATCH representing the matching degrees for each attribute. Finally, the matching degrees of each attribute are aggregated, taken into account their importance weight, using different combination methods.

F4.3.5.5 The FLORAN system

In FLORAN (Salotti 1992) the cases and problems are also represented within an object oriented environment where cases and problems are instances of classes whose slots can have fuzzy values. The classes of FLORAN are linked to dependency conexts i.e. objects that represent, for a given class, a specific goal, a list of relevant attributes, their importance and a set of fuzzy restrictions on the attributes. This is similar to the CAREFUL system except that the contexts in CAREFUL are hierarchically organized.

Like in the other systems, the retrieval step of FLORAN is divided into a filtering step and a selection step. In the filtering step, FLORAN first looks for the most compatible context and then gets its associated cases. In the selection step, the current problem is compared with each filtered case by means of a fuzzy pattern matching technique. The fuzzy pattern matcher takes into account a tolerance parameter associated with each context.

F4.3.6 Example of Fuzzy Case Based Reasoning

To better illustrate the value added by Fuzzy Logic to the Case Based Reasoning paradigm we will summarize an application of Fuzzy CBR to the problem of corporate Mergers & Acquisitions (M&A), with a specific focus on case indexing, matching, and its underlying similarity measure computation. For more details about this application the reader is referred to a description of the CARS system in (Bonissone, et al. 1994).

F4.3.6.1 Problem Description

The M&A area has many attributes which make it an ideal candidate domain for fuzzy CBR. M&A is a field where multiple agents, with different goals and viewpoints, attempt to plan strategies using incomplete, or uncertain information. In addition, M&A cases develop over time, allowing us to work on the problems of representing and reasoning about events in sequences.

Furthermore, the process of analyzing an M&A situation requires the use of case-based reasoning methods (e.g. in the area of anti-trust considerations), rule-based reasoning methods (e.g. in the area of strategy identification) or both (e.g. determining the price to offer for shares based on company worth derived from rules or derived from the price paid for the most similar previous offering). While many metrics can be used to judge the ultimate outcome of a takeover attempt, it is possible to have at least one crisp evaluation measure, that is, whether the takeover was ultimately successful or not.

F4.3.6.2 Organization of Case Memory

The case memory has been designed to represent cases consisting of the top-level goal(s) and information about the states and events. This information can be obtained from two basic sources: world observers and domain experts. *World observers* are capable of recording the *state* at any time, and of recognizing the execution of state changing *actions* in the world. Domain experts are capable of *interpreting/relating* these states and actions to the behaviors of an agent(s) attempting to achieve the top level goal(s) of the case.

The case memory is organized around two types of knowledge: *Conceptual Knowledge* and *Episodic Knowledge*.

F4.3.6.2.1 Conceptual Knowledge

Conceptual knowledge is the information about the objects, actions, and goals that are used in the cases. This knowledge, which represents an incomplete domain theory, provides the structure to represent cases and is used in case retrieval, case comparison, and solution adaptation. More formally, this knowledge is organized into three hierarchies: *Object hierarchy*, *Action hierarchy*, and *Goal hierarchy*.

These hierarchies are implicitly linked to each other and explicitly linked to the stored cases. For instance, objects from one hierarchy can be used as slot fillers or slot-type specifiers (implicit link); interpretations of a set of actions in a case can be linked to a node in the goal hierarchy (explicit link). These hierarchies are built by the domain expert. As more cases are stored in the case memory, these hierarchies are augmented with more knowledge.

F4.3.6.2.2 Episodic Knowledge

The cases in the Case Base are viewed as situation/solution pairs. Each situation is represented by the top-level goal(s) and the starting state. Each corresponding solution is represented by a network of *events* and a linear sequence of *states*. Events and states are related by explanatory information encoded as causal, temporal and membership links. Subsets of events are grouped into *interpretations* to facilitate their indexing, understanding, and re-use. A more detailed description of the structure of conceptual and episodic knowledge can be found in (Ayub, 1992, Bonissone, et al. 1994, Bonissone and Ayub 1994).

Partial membership values are used in the interpretation and causal links to represent the degree to which a case is an exemplary instance of a particular interpretation or a state change is the result of a given action. These values provide a partial ordering for structural similarity measures that are described in (Ayub 1992).

We will limit the scope of this section to the indexing of cases by means of abstract features and their use in the computation of similarity measures that can be aggregated hierarchically to rank and select the most similar cases.

F4.3.6.3 Case Indexing

To obtain an efficient and reliable case retrieval process, we need to represent and compare the cases in a robust and compact index space. For this purpose, the representation of the cases must be augmented by a mapping form surface to abstract features.

The surface features, usually obtained from a textual description of the case, provide factual information at a very low level of granularity. Typical surface features could be the company's assets, receivables, inventory, liabilities, outstanding shares, etc. In real world situations, financial analysts supplement that information using domain knowledge. Therefore we want to augment the case description with interpretations and judgments about the raider and target's financial conditions, the quality of the tender offer, and other subjective assessments usually provided by a financial analyst.

F4.3.6.3.1 Surface and Abstract Features

Following a step similar to the traditional pattern recognition process, we extracted this information and represented it in a more abstract, lower-dimensional space of *abstract* features. Unlike the typical pattern recognition process, however, our feature extraction was not of statistical or syntactic nature. Our mapping is based on approximate deduction from the surface features using plausible rules of inference. These rules encode the domain specific knowledge that will guide the case retrieval process.

For each abstract feature we have defined a termset of linguistic values. Each value is characterized by a label and its semantics. The semantics are represented by the membership distribution of a fuzzy set, defined on the unit interval, establishing a partial ordering among the labels.

As we will describe in the sequel, similarity measures, defined as the complement of metrics between fuzzy-sets, are evaluated for each abstract feature. Subset of these similarity measures are then aggregated to determine higher level similarity.

Categories and Abstract Features The companies in each case are represented along six categories: *Financial, Industry, Organizational, General, M&A, Relations with others.* One or more abstract features are derived for each category. To analyze a case along a certain category, only the abstract features for that category need to be derived.

For example, to analyze the category *Financial Condition (FC)*, we need to evaluate four abstract features: `Short-Term FC, Long-Term-FC, Coverage, Profitability`. In this example we will discuss in detail the computation of one of these abstract features, `Short-Term FC`.

The domain knowledge has been encoded into a PRIMO rule base (Aragones et al. , 1990), allowing us to generate abstract features such as `Short Term FC` from surface features such as `Receivable-Turnover`, `Cost of Goods Sold`, `Inventory Turnover`, `Current Assets`, `Current Liabilities`, etc.

The values of the abstract feature `Short-Term-FC` are linguistic values from a given termset, defining the relative strength of the target company financial conditions in the short term.

F4.3.6.4 Case Analysis

Each abstract feature is assigned a value and a degree of certainty. Values for features (abstract or surface), can be raw data or lexical terms (linguistic values representing fuzzy intervals) chosen from feature value term-sets provided in the Case Based Reasoner. The degree of certainty represents the extent to which the abstract features can be inferred from the surface features.

In our system there are five PRIMO plausible rules that can be used to determine the value of `Short-Term FC`. One of such rules is *Acid Ratio St Fc*, illustrated in Figure 1, which uses four surface features, `company assets, company liabilities, company inventory` and `industry acid ratio`, to determine the value of the retrieved company `Short-Term FC`. The same rule applied to the surface features of the target company will determine the target's `Short-Term FC`. This rule evaluation will be described in the following section. The comparison of the two abstract features that will determine the similarity value of `Target-Short-Term-Fc-Sim` will be described in the next one.

F4.3.6.4.1 Rule to Extract the Company Sort-Term FC

The PRIMO rule illustrated in Figure 1 consists of a *rule name, rule class, instantiation class, object variables, on-line documentation, context, antecedent, consequent*, and *rule strength.* These rule components are used for rule base design, rule instantiation control of inference, and rule evaluation.

Rule Base Design: *Rule name* and *rule class* are used to identify the rule and structure the rule base for the purposes of efficiency in inference and ease of debugging and knowledge engineering.

Rule Instantiation: Rules are written with object variables scoped by an implicit universal quantifier. While rule classes are design partitions of the rule base, *Instantiation classes* are instantiation partitions of the same rule base, i.e., they define the subsets of rules to be jointly instantiated when a new instance

```
(def-rule (acid-ratio-st-fc case-based                          ; RULE NAME
                            (resources)                         ; RULE CLASS
                            (company*industry-ratios)) ; INSTANTIATION CLASS
  (?company ?industry-ratios)                                   ; OBJECT-VARIABLES
  "short term financial condition using acid ratio"             ; ON-LINE DOCUMENTATION
  (lb-pass-threshold                                            ; CONTEXT
    (t3 (number-predicate (current-assets ?company))
        (number-predicate (current-liabilities ?company))
        (number-predicate (inventory ?company))
        (number-predicate (acid-ratio ?industry-ratios)))
    250)
  (acid-ratio-pred   (current-assets ?company)                  ; ANTECEDENT
                     (current-liabilities ?company)
                     (inventory ?company)
                     (acid-ratio ?industry-ratios))
  (((short-term-fc ?company)                                    ; CONCLUSION
    ((acid-ratio-cons   (current-assets ?company)
                        (current-liabilities ?company)
                        (inventory ?company)
                        (acid-ratio ?industry-ratios))
     (i::d3 *certain* *likely* :premise) :INTERSECT))))         ; RULE STRENGTH
```

Figure 1: PRIMO Rule Inferring the Company Short Term Financial Condition from its Acid Ratio

of an object occurs. *Object variables* are instantiated with the corresponding slot values of the new object instance. In our example, they are `?company` and `?industry-ratios`.

Inference Control: The *Context* is a pre-condition that must be satisfied before the antecedent of the rule is evaluated. Typically a context is a conjunctions of predicates on object-level variables (i.e., domain variables) or meta-level variables (i.e., processing resources and requirements). In our example they perform a type checking on the value of the predicates used in the antecedent (to guarantee that all numeric values are available).

Rule Evaluation: The *Antecedent* is a conjunction of fuzzy predicates on object-level variables, which in this example are the four surface features. The conjunction is implemented using T-norms (Bonissone 87). The result of the antecedent is the degree to which the conjunct of predicates have been satisfied. The output of the antecedent, in conjunction with the *Rule Strength* is used to determine the truth value of the *Rule Conclusion*. In our example we have one predicate `acid-ratio-pred`, which computes the acid ratio of the company as:

$$AcidRatio = \frac{CurrentAssets - Inventory}{CurrentLiabilities}$$

and normalizes it with respect to the industry average acid ratio. The resulting acid ratio percentage is used in the mapping, illustrated in Figure 2, to select the label that best describes the short term financial condition of the company, given the acid ratio average of its industry sector. The meaning of the label is represented as a parametrized fuzzy interval in the third column of Figure 2.

The parametric representation is used to describe the membership distribution of each term, N_i. Using this representation a fuzzy set of a universe of discourse U can be described as the four-tuple: (a, b, α, β). The universe U is unit interval (represented by an integer representation on the scale from 0 to 1000). The first two parameters (a, b) indicate the interval of the universe of discourse in which the membership value is 1.0; the third and fourth parameters (α, β) indicate the left and right *width* of the distribution. Linear functions are used to define the slopes. Let $N_i(x) : X \rightarrow [0, 1]$ be the membership function of the fuzzy set

N_i. The fuzzy set N_i can be represented as the four-tuple $(a_i, b_i, \alpha_i, \beta_i)$ where:

$$N_i(x) = \begin{cases} 0 & \text{if } x < (a_i - \alpha_i) \\ \frac{1}{\alpha_i}(x - a_i + \alpha_i) & \text{if } x \in [(a_i - \alpha_i), a_i] \\ 1 & \text{if } x \in [a_i, b_i] \\ \frac{1}{\beta_i}(b_i + \beta_i - x) & \text{if } x \in [b_i, (b_i + \beta_i)] \\ 0 & \text{if } x > (b_i + \beta_i) \end{cases}$$

In our implementation the intervals used in the mapping are actually fuzzy intervals. Therefore, the membership value of the acid ratio percentage is computed for each term in the termset. The term with the highest membership value is selected. The corresponding membership value describes the degree of confidence of this linguistic value assignment.

F4.3.6.4.2 Feature Value Comparisons

By analyzing both the probe and the retrieved case, a linguistic value's label is obtained for each of the abstract features. Each linguistic value's label has a meaning defined in its term set, as illustrated in Figure 2.

Having established the meaning of the labels used to define each abstract feature value, we will now discuss how the similarity measure for each abstract feature is determined. This is done by executing a two step procedure.

(1) Computation of Degree of Matching. The first step consists of computing the closeness of two linguistic values based on their semantics. Initially, the distance between the fuzzy set representations of the corresponding values is computed. For example, let us assume that the abstract feature `Target-Short-Term FC` has the value *VERY STRONG* in the probe and *STRONG* in the retrieved case. Their corresponding meanings are the fuzzy intervals (870 1000 20 0) and (730 830 30 20). The distance between their two corresponding fuzzy intervals is computed as the absolute value of their difference. This is done using fuzzy arithmetic operations that are closed under the four-tuple parametric representation (Bonissone, 1982, Bonissone and Decker, 1986). Specifically, given two fuzzy numbers $X = (a, b, \alpha, \beta)$ and $Y = (c, d, \gamma, \delta)$ we can define the difference

$$X - Y = (a - d, b - c, \alpha + \delta, \beta + \gamma)$$

In this example, the difference between *VERY-STRONG* and *STRONG* is (40 270 40 30). This distance is then transformed into a degree of matching by taking the complement with respect to the unit interval. Using the same formula for the difference, by representing the unit as (1000, 1000, 0 , 0) we have the degree of matching $1 - |X - Y| = (730, 960, 30, 40)$.

(2) Linguistic Approximation. The second step consists in selecting a label (chosen from one of the similarity term-sets provided) whose meaning is the closest to that of the computed degree of matching.

Acid Ratio Percentage Interval	*Term Label*	*Term Semantics*
[0,60]	*VERY-WEAK*	(0 130 0 20)
[60,80]	*WEAK*	(170 270 20 30)
[80,90]	*BELOW-AVERAGE*	(310 410 30 30)
[90,115]	*AVERAGE*	(450 550 30 30)
[115,140]	*ABOVE-AVERAGE*	(590 690 30 30)
[140,170]	*STRONG*	(730 830 30 20)
[170, ∞]	*VERY-STRONG*	(870 1000 20 0)

Figure 2: Mapping of Percentage Acid Ratio to Terms Labels and Semantics

Term Label	Term Meaning
NO-MATCH	(0 130 0 20)
ALMOST-NO-MATCH	(170 270 20 30)
LESS-THAN-PARTIAL-MATCH	(310 410 30 30)
PARTIAL-MATCH	(450 550 30 30)
MORE-THAN-PARTIAL-MATCH	(590 690 30 30)
ALMOST-COMPLETE-MATCH	(730 830 30 20)
COMPLETE-MATCH	(870 1000 20 0)

Figure 3: Termset For Partial Matching of Abstract Features

This semantic closeness is evaluated by a measure of set inclusion (Sanchez, 1979): $\frac{|P \cap D|}{|D|}$, where P is the similarity term, D is the result of complementing the set-distance, and | . | is the sigma-count or cardinality of the fuzzy set, which, in the continuous case, corresponds to the area under the membership function.

This measure of set inclusion, representing the degree of matching between the reference (P) and the data (D), is used as an associated certainty value for the label. The interested reader is referred to (Dubois and Prade, 1980, page 23-24) for a detailed study of measures of inclusions. A simple example of a seven term similarity termset is given by Figure 3.

In the case of our example, the degree of matching was the fuzzy number $(730, 960, 30, 40)$. By using the termset described in Figure 3, we can see that the term with the closest meaning $(730, 830, 30, 20)$ is *ALMOST-COMPLETE-MATCH*. The degree of confidence in this label selection is

$$\frac{|(730, 830, 30, 20) \cap (730, 960, 30, 40)|}{|(730, 960, 30, 40)|} = \frac{125}{265} = 0.47$$

From the same Figure 3 we could see that the term *COMPLETE-MATCH*, with its meaning described by (870 1000 20 0), would have a a degree of confidence of

$$\frac{|(870, 1000, 20, 0) \cap (730, 960, 30, 40)|}{|(730, 960, 30, 40)|} = \frac{120}{265} = 0.45$$

Therefore the term *ALMOST-COMPLETE-MATCH* was used as the value for the similarity measure for the abstract feature `Target-Short Term FC-SIM`.

F4.3.6.5 Similarity Measures

Similarities are defined at many levels: between individual abstract features, e.g. *Target-Short Term FC-SIM* (which is the similarity between the target financial conditions in the probe and the retrieved case); and between groups of abstract features, e.g. *Target-Target Similarity* (which is the overall similarity between the target company in the probe and in the case). These similarities are computed by the CBR similarity module. This module takes as input the cases returned by the retrieval system, the probe, and information relating to the needs of the reasoner. The retrieved cases and probe are augmented with a set of abstract features. Appropriate similarity measures are chosen and applied based on the needs of the reasoner (e.g., goal satisfaction or establishment of precedent), and the most similar cases are returned. They form the basis for the adaptation and the solution formulation.

F4.3.6.5.1 Combinations of Similarities

The similarity measure can be aggregated or chained (using the transitivity of similarity) according to well-defined operators called triangular norms. Triangular norms (T-norms) are the most general families of binary functions that satisfy the requirements of the conjunction operators. T-norms are two-place functions from [0,1]x[0,1] to [0,1] that are monotonic, commutative and associative. Their corresponding boundary conditions, i.e., the evaluation of the T-norms at the extremes of the [0,1] interval, satisfy the truth tables of the logical AND operator (Schweizer and Sklar, 1963, Schweizer and Sklar, 1983, Bonissone, 1987). Five uncertainty calculi based on the following five T- norms are used:

$$
\begin{aligned}
T_1(a,b) &= max(0, a+b-1) \\
T_{1.5}(a,b) &= (a^{0.5} + b^{0.5} - 1)^2 \quad \text{if } (a^{0.5} + b^{0.5}) \geq 1 \\
&= 0 \quad \text{otherwise} \\
T_2(a,b) &= ab \\
T_{2.5}(a,b) &= (a^{-1} + b^{-1} - 1)^{-1} \\
T_3(a,b) &= min(a,b)
\end{aligned}
$$

Their corresponding DeMorgan dual T-conorms, denoted by $S_i(a,b)$, are defined as

$$S_i(a,b) = 1 - T_i(1-a, 1-b)$$

These five calculi provide the user with an ability to choose the desired uncertainty calculus starting from the most conservative (T_1) to the most liberal (T_3).

The use of T-norms in aggregating and chaining certainty intervals during the extraction of abstract features is extended in this system to the aggregation of similarity measures.

This mechanism aggregates similarities by taking as input a list of similarities linguistic values to be combined, their associated meaning, and optional weights,[1] indicating the importance of the feature in the aggregation. This mechanism is based on three aggregation operators: *T-norms*, *T-conorms*, and *Linear combinations*. T-norms are used to discount low similarities. T-conorms are used to enhance high similarities. Linear combinations are used to average remaining similarities.

Tradeoffs First, this process normalizes the similarity values of various abstract features according to their relevance weights. Then the process penalizes bad matches, by applying a T-norm to the low similarity values, and rewards good matches, by applying a T-conorm to the high similarity values. Finally, the process considers compensatory tradeoffs. Since averaging operators, unlike T-norms and T-conorms, are not associative, we need to take the partial aggregations obtained from the T-norms and T-conorms, multiply them by the number (cardinality) of the aggregated values, and average them with the intermediate values of similarity.

The reader is referred to (Dubois and Prade, 1984) for a detailed study of aggregating operators.

A complete case study, illustrating the benefits of using fuzzy logic in Case-Based Reasoning can be found in (Bonissone and Cheetham, 1998), which appears in section G 15.1 of this Handbook .

[1] Weighted aggregations can be extended beyond the common convex sums used to perform weighted averages. In particular, they can be extended to T-norms and T-conorms. For example, let $\vec{X}$ and $\vec{W}$ be two *nth* dimensional vectors with elements in [0,1]. $x_i \in \vec{X}$ represents the similarity value of the *ith* abstract feature, while $w_I \in \vec{W}$ is its corresponding relevance weight. The weighted minimum WMIN($\vec{W}, \vec{X}$) is defined as

$$WMIN(\vec{W}, \vec{X}) = \bigwedge_{i=1}^{n} (w_i \rightarrow x_i) = \bigwedge_{i=1}^{n} max(1 - w_i, x_i)$$

Similarly, the weighted maximum WMAX($\vec{W}, \vec{X}$) is defined as

$$WMAX(\vec{W}, \vec{X}) = \bigvee_{i=1}^{n} min(w_i, x_i).$$

In our system we use linguistic values with fuzzy numbers semantics to represent similarity and weights. Therefore we have extended the above operations to fuzzy numbers in [0,1] using the four parameter representations and the formulae in reference (Bonissone and Decker, 1986).

F4.3.7 Conclusions

We have described Case-based Reasoning, a new paradigm in automated reasoning that solves new problems by identifying, retrieving, and adapting from a case library the most similar and relevant cases to the problem at hand. After reviewing CBR history and discussing CBR most important issues, we have focused on the Fuzzy Logic's value added to this new reasoning paradigm.

First, we described five fuzzy CBR systems, all using attributes with fuzzy values and a fuzzy pattern matcher for case retrieval. Then we analyzed one of them, CARS, discussing a method for using linguistic values with fuzzy semantics to index, match and retrieve cases from a Case Base. In CARS, the case description was augmented by abstract features derived from the cases surface features. Probe and cases were first compared along their abstract features, generating a linguistic value representing their corresponding similarity measure. By expressing the relevance of the various abstract features with weights, we were able to emphasize or de-emphasize their roles in the retrieval process.

These similarity measures could also be aggregated hierarchically, according to a semantic taxonomy, deriving *Target-Target, Raider-Raider* similarities, etc. The aggregation, based on T-norms, averaging operators, and T-conorms, generated a partial ordering on the retrieved cases, which was used for case selection and adaptation.

This methodology was tested in a system developed for the M&A application, which contains 70 PRIMO rules to extract 18 abstract features from 59 surface features and evaluate similarities for about 20 M&A cases. A more complete description of the CARS system can be found in (Bonissone et al. 1994).

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