A Critical Literature Review Of
Case-Based Reasoning and Its Educational Applications

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ABSTRACT

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This critical literature review documents the shifts and variations in Case-Based Reasoning (CBR) terminology and reasoning models that have arisen in the past twenty years. Different versions of CBR theory, differences in terminology across these versions, and shifts in terminology within individual programs of theory development and research in CBR are identified. A framework for understanding the shifts and variations in CBR literature, and a framework for categorizing the variations in CBR cognitive science literature are proposed. Finally, educational applications of CBR are examined within the context and framework for understanding CBR I developed, and possible variations of these applications are explored.

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CHAPTER 1

INTRODUCTION

In my reading of the case-based reasoning (CBR) literature and my attempt to distinguish CBR from rule-based reasoning in people's cognitive processing, I have noted some problems: lack of clarity in terminology in the CBR literature, shifting senses of CBR in the field and related fields, even within one individual's research program. The meaning of the basic concept "case", for example, is inconsistent in the literature. The term "case" first appeared in Schank's *Dynamic Memory* (1982) as designating episodic knowledge units. Researchers in artificial intelligence soon extended the meaning of the term to encompass any kind of specific knowledge tied to specific situations, including events, heuristics, small rules, models, and units of structured information that could be useful for an expert system (e.g., Kolodner, 1993; Leake, Kinley & Wilson, 1997). However, researchers in cognitive psychology often do not recognize heuristics, small rules, and models as cases—although they do not appear to have a consensus regarding what cases are either. Some cognitive psychology researchers view cases as instances in a person's memory (e.g., Didierjean & Cauzinille-Marmeche, 1998), while some others include instances from other sources, such as examples found by a person in a textbook that do not reside in her memory, as cases as well (e.g., Vanlehn, 1999). There is no consensus on whether cases have to be actual experiences, or, in that sense, contain information that can be experienced. Researchers in education also refer to "cases" as different things in the literature. Much of the confusion comes directly from the confusion in the psychological CBR literature. Some education researchers interpret cases as actual, personal experiences gained from learning by doing (e.g., Schank, 1996);

some researchers believe there is not much difference between case-based reasoning and exemplar-based reasoning and use the terms interchangeably (e.g., Bareiss, 1989); and there is no agreement on whether heuristics and models from a source other than a person's memory could count as a case. Without a consensus or a clear definition of what cases are, case-based reasoning, and many other key terms are often used and referred to vaguely.

The ambiguity in CBR terminology makes it difficult to understand CBR theory and its relationship to other theories, as well as the extent to which these other theories and research conducted according to them lend support to CBR. Many educational and psychological issues have been connected to CBR, including models of memory, reasoning by analogy, learning from examples, problem-solving strategies and accounts of expertise. The risk for confusion in discussing the relationship of these topics to CBR is high, as there is no agreement on what is CBR, on which to base the discussion. In discussing the relationship of reasoning by analogy and CBR, for example, some researchers equate reasoning by analogy with CBR (e.g., Bhatta and Goel, 1997; Vanlehn, 1997), some researchers take CBR as a kind of reasoning by analogy (Kolodner, 1997), and some researchers claim that reasoning by analogy is one step of the CBR process (e.g., Leake, 1996). This situation is largely a result of inconsistency in the use and interpretation of CBR terminology, and the lack of documentation of various versions of CBR terminology commonly used.

In addition, the shifting senses of CBR challenges the rationale, terminology and precise design parameters of CBR applications, including some significant instructional applications and innovations that are widely used today, such as goal-based scenarios

(Schank, 1994), learning by design (Kolodner, 1997; Kolodner et al., 1998), case-based advisory systems (e.g., Ferguson et al., 1992) and knowledge-sharing systems (e.g., Kitano and Shimazu, 1995). The structure, content, goal, and educational approach of these applications and innovations might vary with the different versions of CBR. For example, in a case-based knowledge-sharing system, the issue of where and how heuristics and models should be documented, presented, and used, as well as the issue of how much emphasis the system should put on generalization, is largely affected by how CBR is interpreted by the designer of the system. It would be interesting for instructional designers and educational researchers to note how the design parameters or terminology of these applications might shift with the different versions of CBR.

In response to the situation outlined above, I will undertake a critical review of the CBR literature, analyze its relationship to related educational issues, and explore its educational implications and applications. I will document different versions of CBR theory, differences in terminology across these versions, and also shifts in terminology within individual programs of theory development and research in CBR. Then, I will explore educational and cognitive research under various themes that support and dispute CBR in order to discuss the validity of CBR, and analyze the relationship of CBR with those other bodies of research. Finally, I will examine the educational implications of CBR within the context and framework for understanding CBR I will have developed earlier in the thesis, and explore the possible variations of CBR educational applications.

CHAPTER 2

CASE-BASED REASONING

2.1. Overview

What is case-based reasoning (CBR)? What is the standard definition and what are the major shifts of the definition over time? What are the major variations in the CBR literature? In this section, I will present an overview of case-based reasoning and the major variations in response to these questions.

2.1.1. Standard Definition of Case-Based Reasoning

In the CBR community, there are two explanations of the term that are widely used and cited.

One is from Riesbeck's and Schank's (1989) *Inside Case-based reasoning*: "A case-based reasoner solves new problems by adapting solutions that were used to solve old problems". This description is a definition of a case-based reasoner rather than case-based reasoning, yet it presents the central concept of CBR, and thus has been cited quite often in the CBR community to describe CBR (e.g., Watson, 1995). We could adjust Riesbeck and Schank's statement to: Case-based reasoning means to solve new problems by adapting solutions that were used to solve old problems. Here, the term "solve a new problem" seems to be used in its broadest sense, incorporating all possible goal-based reasoning tasks that a reasoner might be involved in.

Another popular description of CBR comes from Kolodner's (1993) well-known CBR book:

> Case-based reasoning means reasoning based on previous cases or experiences. A case-based reasoner uses remembered cases to suggest a means of solving a new problem, to suggest how to adapt a solution that doesn't quite work, to warn of possible failures, to interpret a new situation, to critique a solution in progress, or to focus attention on some part of a situation or problem. (p.4)

This definition is different from Riesbeck's and Schank's description in that it extends the meaning of CBR to include all reasoning based on previous cases or experiences as CBR, both directly or indirectly. Thus, rules, patterns, models, or exceptional rules that a reasoner derived from experiences could all count as part of the case-based reasoning system, or even part of the cases. Likewise, once any of the above mentioned information is used by a reasoner, the reasoning process could be considered to be CBR.

2.1.2. Shifts of the Definition Over Time, and Variations in the Literature

The definition of case-based reasoning has gradually shifted in two directions, which correspond with the two different motivations for CBR research. The two primary motivations that drive CBR studies are: First, from cognitive science, the desire to model human reasoning and learning; second, from artificial intelligence, the pragmatic desire to develop technology to make AI systems more effective. Correspondingly, the two directions of CBR definitional shifts are: First, from cognitive science, the trend of imposing new limits to traditional CBR definitions in order to differentiate CBR from reasoning by analogy. Second, from artificial intelligence, the trend of making limits of traditional CBR definitions more flexible to incorporate elements that could enhance the performance of CBR expert systems.

In addition, CBR has been used in two ways along both directions. There is CBR in its typical sense, and CBR as a generic term. I will outline typical CBR in both cognitive science-oriented CBR studies and AI-oriented CBR studies in the following paragraphs, and then discuss what CBR in its general sense refers to.

First, in studies oriented towards using CBR to model human reasoning and learning, CBR in its typical sense is characterized by its focus on a) specific episodes rather than abstract knowledge and structural similarity (Leake, 1995), and b) near analogs rather than cross-domain analogs (Kolodner, 1997). This focus is brought about by the fact that CBR cognitive research was largely based on observations of people's reasoning process in solving real-life problems, and reasoning that uses nearly matching analogs of episodic memory units is employing the type of analogs used most extensively, easily, and successfully by people (Kolodner, 1997). In recent years, CBR in its typical sense has been further narrowed down. For example, Kolodner, who proposed one of the standard CBR definitions described in the last section, subsequently, confined her description of CBR to "analogical reasoning using near analogs... (that) is always done with a purpose" (Kolodner, 1997, p. 60). There have been efforts in the CBR community to integrate reasoning using domain knowledge (conceptual knowledge, rules, models, etc.) and various types of abstract reasoning with CBR in order to achieve a unified approach to reasoning. At the same time, the core CBR component is focused on reasoning tasks and processes of a smaller scope. The variations in the literature related to typical CBR in cognitive science mainly involve the following issues:

- knowledge representation in the CBR system and the role of generalized information in the system (e.g., Bareiss, 1989; Hammond, 1990; Kolodner, 1983; 1984; 1985; 1993; Porter, 1990; Riesbeck & Schank, 1989; Schank, 1982);
- whether the reuse of knowledge means reuse of knowledge in the same chunk size only (e.g., Didierjean & Cauzinille-Marmeche, 1998; Kolodner, 1996; Watson, 1995);
- the nature and scope of CBR (e.g., Bareiss, 1989; Schank, 1982; Kolodner, 1993; Porter, 1990).

In studies oriented towards building more effective AI expert systems, the different versions of CBR are mostly a variation of: "adapting big chunks of integrated information to solve new problems" (Aha & Ram, 1995). There are two characteristics that distinguish CBR from other similar approaches. First, a typical case-based reasoner is able to modify or adapt a retrieved solution when applied in a different problem-solving context. Second, a typical case is usually assumed to have a certain degree of richness of the information contained in it, and a certain complexity with respect to its internal organization. The term CBR in AI literature is used in a more flexible way and in a broader sense than the same term in cognitive science literature. Other than the above characteristics, the CBR framework and specific methodologies in AI engineering vary to a large extent depending on the goals of the case-based reasoners and other pragmatic concerns.

What CBR means in its typical sense in AI literature can be quite different from what it means in cognitive science literature. In AI, CBR is an approach that could be translated into various methods of building expert systems. But in cognitive science, CBR in its typical sense is considered a plausible model of cognition, and is thus more well-defined and narrowly-defined. Many expert systems that could be considered as employing a CBR approach from the AI CBR perspective would not be considered CBR models from the cognitive science CBR perspective. For example, large chunks of cases, such as an entire instructional design project, as well as small pieces of specific knowledge tied to specific situations, such as graphics, heuristics, rules, models, and patterns, could all be considered to be cases in AI CBR in its typical sense. In contrast, in cognitive science literature, cases are usually small episodic memory units that are not generalized. Another example of the differences between these two versions of CBR is: typical pragmatic CBR systems often integrate CBR with other available reasoning systems based on engineering concerns; thus, many of those integrated systems do not model human reasoning and are not accepted as CBR in cognitive science literature.

Besides the two versions of CBR described above, there are also CBR used as a generic term in AI, and CBR used as a generic term in cognitive science. In both AI and cognitive science, CBR in a general sense covers a wider scope of issues.

In the cognitive science literature, CBR as a generic term often refers to reasoning by analogy or reuse of contexualized information. In addition to reasoning based on near analogs and reasoning based on specific cases as addressed by the typical version CBR in cognitive science, the general version also covers cross-domain reasoning by analogy, schema-mediated reasoning by analogy, and structural mapping.

In the AI literature, CBR as a generic term refers to a new approach of building expert systems that differs from previous approaches which require reasoning from scratch with rules or models. That is, it covers all methods of building expert systems that reuse chunks of contexualized information. More specifically, CBR in its general sense is often used to refer to the following approaches similar to typical CBR: exemplar-based reasoning, instance-based reasoning, memory-based reasoning, case-based reasoning (in its typical sense), and analogy-based reasoning (Aamodt & Plaza, 1994). As can be seen from here, CBR in its typical sense in AI is one of the approaches covered by CBR used as a generic term in AI.

In summary, at the current stage, there are four general versions of CBR: CBR in its typical sense in cognitive science literature, CBR in its general sense in cognitive science literature, CBR in its typical sense in AI literature, and CBR in its general sense in AI literature. These four categories and corresponding trends are summarized in Table 2.1.

Table 2.1.

Major categories and trends of CBR

Category	Typical meaning	Trend
CBR in its typical sense in cognitive science literature	Reasoning based on specific experiences rather than schema. using mainly near analogs (within-domain analogy but not cross-domain analogy).	CBR is gradually narrowed down, addressing an increasingly limited scope of reasoning tasks.
CBR as a generic term in cognitive science literature	Reasoning by analogy, or reuse of contexualized information.	The line between CBR and reasoning by analogy is becoming blurred.
CBR in its typical sense in artificial intelligence literature	An approach to problem-solving by adapting big chunks of integrated information from previous experiences to solve new problems. (specific parameters very flexible)	CBR is gradually extended to address more reasoning tasks, especially by taking integrated approaches.
CBR as a generic term in artificial intelligence literature	Exemplar-based reasoning, instance-based reasoning, memory-based reasoning, case-based reasoning (in its typical sense), and analogy-based reasoning.	Various approaches are often integrated together on the basis of engineering considerations.

Besides the differences across these versions of CBR, there are also variations within each version around issues like case representation, knowledge structure, and where should knowledge be considered to reside (e.g., do cases residing outside the reasoner count as cases). The variations within general and typical CBR in AI mainly result from pragmatic and engineering considerations in building systems for different domains and different tasks. In those situations, flexibility in using the CBR approach is acceptable, and there seems to be little need for standardization. Therefore, I will not further discuss the variations within those versions of CBR. In cognitive science, however, it is desirable for researchers to have a more standardized version of CBR on which to base discussion of CBR and its relationship to other theories. It is especially important for us to categorize variations within the typical version of CBR in cognitive science because several educational applications and innovations are based on this version of CBR. These variations are closely related to how we should approach the design of these educational applications. It would be interesting to identify the differences among major CBR cognitive models, and examine these various models using empirical evidence from research in related fields. The rest of this chapter is an attempt to categorize the variations and confusions related to CBR cognitive models, followed by a discussion of how related theories support or oppose these models. At the end of this chapter is a discussion of the plausibility of each popular CBR cognitive model and the circumstances under which they are most plausible. In the next chapter, I will relate the discussions in this chapter to the popular educational applications of CBR.

2.2 CBR as a Cognitive Model

In this section, I will attempt to propose a framework for understanding popular variations of CBR as a cognitive model. First, I will describe the basic CBR cognitive model, then I will present the major variations, and finally, I will summarize and discuss the confusions in the literature, and propose a framework for categorizing and understanding the variations and confusions.

2.2.1. The Basic CBR Cognitive Model

Basically, from the CBR perspective, a *reasoner* is a being in the world that has goals (Schank, 1982). The being seeks to navigate its world in a way that can help it to successfully achieve its goals. It has experiences, some successful and some not as successful, some pleasant and some not so pleasant, that allow it to learn about its environment and ways of using that environment to achieve its goals. As it has experiences, it seeks to process its experiences in a way that allow it to achieve its goals more productively in the future. Therefore, in addition to storing its experiences, it is also engaged in interpreting these experiences to derive lessons that might be useful to its future, anticipating when those lessons might be useful, and labeling its experiences appropriately so that it will be able to recognize the applicability of an experience in a later situation. In addition, a case-based reasoner is also engaged in noticing the similarities and differences between similar situations and experiences so that it can draw conclusions about its world and notice the subtle differences that suggest when each of the lessons it has learned is most appropriately applicable. Essential to its learning is expectation failure – it needs to attempt to apply what it thinks is relevant and fail at that in order to notice subtleties it had not previously been aware of, it needs to have its assumptions about the world challenged in order to find out the bugs and holes in its knowledge.

In the CBR cognitive model, *cases* are experiences and interpretations of experiences. Cases have several subcomponents: the setting, the actors and their goals, a sequence of events, results, explanations linking results to goals, and the means of achieving the results and goals (Kolodner, 2000). The better the interpretations of each of these pieces, and the richer the explanations linking these pieces to each other, the more useful a case will be when it is remembered later. The explanations that tie pieces of a case together allow individuals to derive lessons from the case.

Cases reside in an individual's memory, and the set of cases in any individual's memory is referred to as her *case library*. Cases in an individual's case library might be derived from her own experiences or from the experiences of others.

The *indexes* and *indexing scheme* allow people to locate the right cases in their memory. People can find the right cases in their memories if they "indexed" them well when they entered the cases into the library, and if their indexing scheme is well-structured enough so that they can re-create an index for an appropriate case when trying to locate something in memory. If the reasoner cannot recognize a past experience as being applicable in a new situation, she will have no case to apply.

The primary CBR cognitive processes are retrieval, adaptation, problem-solving, and learning.

The *retrieval* process starts when one is faced with a new situation. At this time, one's memory searches for old cases in order to better solve the new problems. The retrieval process involves the searching and finding of one or more old cases that are analogous to the person's description of the new situation. If one's description of the new situation already matches these situations, the retrieval process may be a one-step search and find process. If not, the retrieval process may also involve re-interpretation, and re-representation of the situation in different or more specific terms, or from a different point of view. Such re-interpretation might be done incrementally, creating better and better descriptions of a situation on the basis of what is recalled or not recalled in earlier probes and its usefulness.

Once a case or cases are retrieved, they can be used in several ways to *solve a problem*. First, an old solution could be used to solve a new problem. Second, pieces of several old situations could be merged to create a new solution. Third, predictions could be made based on an old solution. Fourth, one or more old situations could be compared to and/or contrasted with the new situation to determine important issues to focus on; or what needs to be adapted, and so on (Kolodner, 1997). All these processes are called adaptation.

The next step is action that is based on inferences, which leads to results.

Learning takes place when the results are different than expected. Many things can be learned: for example, a new case, a new knowledge structure, new knowledge learned through explanation, a new way to index.

Although the primary processes and the underlying approach are the same, the various running CBR cognitive models are quite different. In the following sections, I will present the major CBR cognitive models one by one, and then summarize the confusions and variations.

2.2.2. Major Variations

2.2.2.1. Schank's Dynamic Memory Cognitive Model

The cognitive model proposed by *Dynamic Memory* (Schank, 1982) is the theoretical foundation of CBR research as well as the first CBR cognitive model. Dynamic Memory was first proposed by Schank as a model of episodic memory for understanding. The central idea of this model is that memory is dynamically changing as a result of its experiences. According to Schank (1982), our memories are flexible, open-ended systems that are constantly changing with the new things we encounter, the questions that arise in our minds as we encounter new things, and the way we answer these questions. We understand by trying to use what we already know to assimilate or accommodate new things we encounter. Understanding causes us to encounter old experiences and general knowledge structures as we process new information because we use expectations generated from what we already know to predict and understand the new information. If what we already know cannot explain the new experiences, or contradicts with the new experiences, we reflect on our past experiences and the memory structure we derived from them, and refine or/and reorganize our memory. Thus, there is an understanding and learning cycle in which remembering, understanding, experiencing, and learning can not be separated from each other. As long as we encounter new things, our memory will never be the same. In the following section, I will introduce the Dynamic Memory cognitive model as presented in Schank's *Dynamic Memory* published in 1982.

2.2.2.1.1. The original Dynamic Memory cognitive model

The knowledge representation in the Dynamic Memory cognitive model is basically a combination of generalizations and instances, with specific events (cases) at the bottom, attached to the higher-level generalizations (schema). Both cases and schema are organized in the same memory structures, both are indexed in the same ways, and both are accessed by the same retrieval processes. More specifically, Schank (1982) suggested a top-down hierarchical structure in which MOPs (terms defined below) hold scenes, scenes hold scripts, and both scenes and scripts hold events. There is another knowledge structure called TOPs, which is domain-independent, (unlike MOPs which are domain specific), and holds specific scenes, scripts or events that share similar goals and plans. According to Schank, within TOPs, the scenes and scripts have goals and plans for actions appropriate to the events that they represent. Schank's definition or explanation of these terms are:

> MOP: A MOP consists of a set of scenes directed toward the achievement of a goal. A MOP always has one major scene whose goal is the essence or purpose of the events organized by the MOP. (p.97)
>
> Scene: A memory structure that groups together actions with a shared goal, that occurred at the same time. It provides a sequence of general actions. Specific memories are stored in scenes, indexed with respect to how they differ from general actions in the scene. (p.95)
>
> Script: Scripts embody specific predictions connected to the more general scene that dominates them. (p.84)

> TOP: New structures that coordinate or emphasize the abstract significance of a combination of episodes. Structures that represent this abstract, domain-independent information...(p.111)... TOPs are goal based (p.114).

For example, according to Schank (1982), if a person went to the university clinic and waited in the waiting room, this episode would be an event, which could be organized in a script for "waiting in the university clinic waiting room". This script, in turn, could be a generalized knowledge structure attached to a more general scene for "waiting room". Finally, the waiting room scene could be one of the scenes that falls under the MOP for "professional office visit", along with other scenes such as "reception" and "professional office". We can see from here that the relationship between scripts and scenes is: Scenes are instantiated by scripts. Or, to put it another way, scripts are specific versions of scenes; scripts are abstracted from specific experiences whereas scenes are abstracted from specific scripts.

An example for TOPs that Schank (1982) provided is: If someone watching *West Side Story* is reminded of *Romeo and Juliet*, then this person probably has a TOP for "mutual pursuit of love against outside opposition which resulted in death of both lovers" or "faked death of one lover for the mutual pursuit of love resulted in suicide of her/his love, which in turn led to the suicide of herself/himself".

At an even higher level of abstraction in Dynamic Memory are universal MOPs (U-MOPs) and universal scenes (U-scenes) which carry no context information. Schank suggested several possible U-MOPs and U-scenes, such as UM-AGREEMENT, UM-PERFORMANCE, UM-FIX-PROBLEM, PRECONDITION U-scene, ENABLEMENT U-scene, PREPARATORY U-scene, etc. For example, UM-agreement is a possible U-

MOP that might be generalized from and linked to MOPs for diplomatic business negotiation, group collaboration, and so on. It contains decontexualized information about reaching agreements that are universal to all MOPs that involve this task. Schank (1982) claims that the U-MOPs and U-scenes make it possible for us to make generalizations and contrast general scenes. U-MOPs organize U-scenes, just like MOPs organize general scenes. U-scenes point to generalized scenes, which color them, just like generalized scenes point to scripts which color them. Any experience will be processed, in part, by episodic information attached to each of these structures and will affect each of the structures that helped in the processing.

In summary, the Dynamic Memory cognitive model takes a successive abstractions approach, proposing that episodic memory uses a sequence of structures in successive abstraction. It suggests that we reason from top-down, using generalizations such as scripts, scenes and MOPs when we dealing with new situations that are very familiar, and alternatively by referring to specific instances when these instances are unique and there is not yet a generalization for such experiences. In addition, it hypothesizes that our memory processes information in a parallel fashion; thus all structures are active at the same time, and they all guide processing and store memories. It also suggests that there are a variety of structures in memory, each abstracting out certain features of an event in such a way as to make that structure general enough to be of use in representing information from distinctly different events that are similar to the extent that they can share elements of the same structure. The higher level the structure responsible for processing, the greater its generality and hence the greater the possibility for learning across contexts.

This memory structure described above is actually one of redundant discrimination networks (Kolodner, 1993). A redundant discrimination network uses several different discrimination networks, each with a different ordering of questions, to organize information. Each discrimination network (Feigenbaum, 1963) is a hierarchical structure in which each internal node is a question that subdivides the set of items stored underneath. Each child node represents a different answer to the question posed by its parent, and each child node organizes the cases that have its answer. More important questions are placed higher in the hierarchy than less important ones. The networks are searched in parallel. If the answer to a question in one network is missing, search in that network is discontinued but continues in the other networks. Figure 2.1. illustrates a redundant discrimination network from CYRUS, one of the first CBR systems which implemented the Dynamic Memory cognitive model.

In this figure, triangles represent questions, and labels on arcs represent answers. Boxes are MOPs and sub-MOPs/lower-level MOPs (MOP*n* in the figure).

In terms of processes, the Dynamic Memory model suggests that remembering, understanding, experiencing, and learning is a cycle, and these processes cannot be separated from each other.

According to Schank, the key to successful reasoning is reminding, either it is finding a generalized knowledge structure or a specific event. When a new case description is given and the best matching is searched for, we would start searching from the highest level of our generalized knowledge structure. If a generalized knowledge structure (schema) that fits the situation is available, we would reason on the generalized level; if the available schema is not complete and points to specific cases for exceptional situations, we use both schema and cases to process the new information; if there is no schema available, we rely solely on cases to process the new information. Whatever form the knowledge we use to process new information takes, it should provide the best inferences.

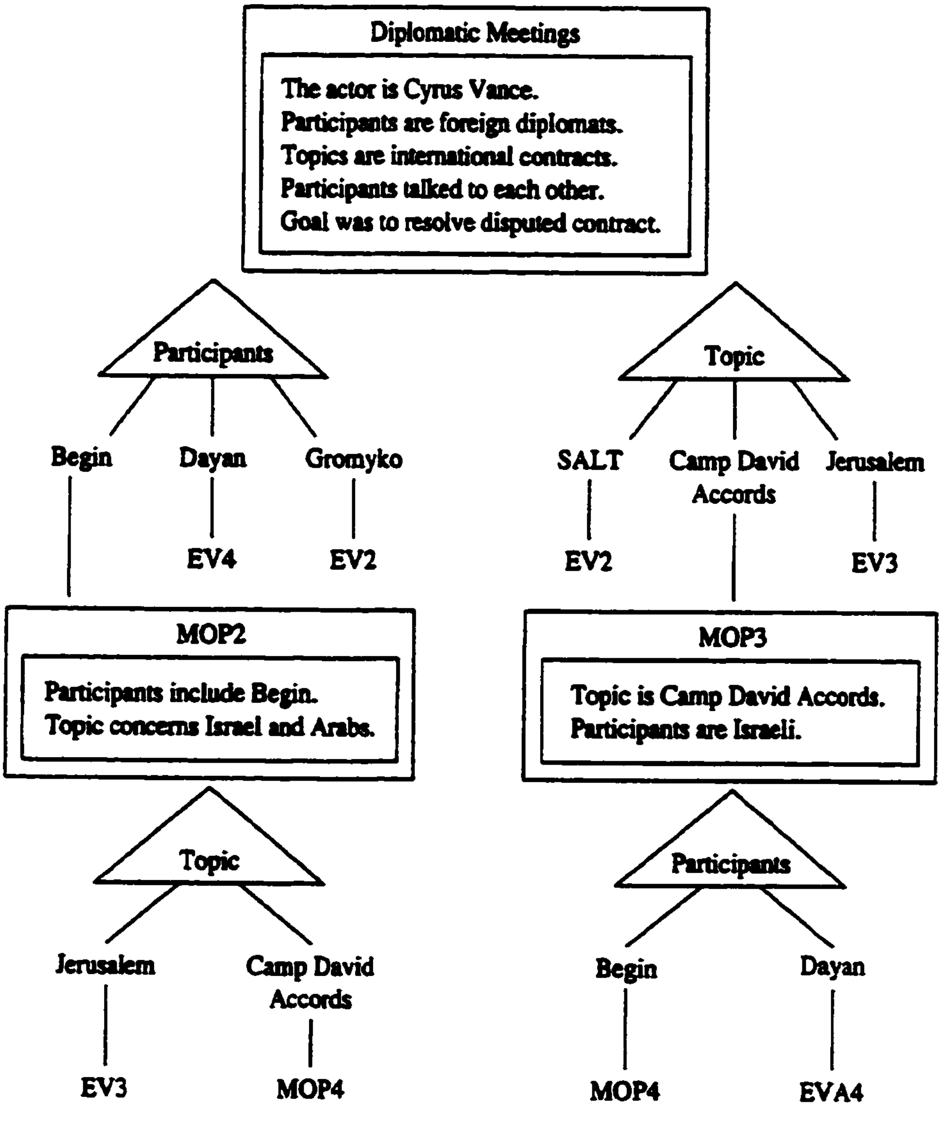

Figure 2.1. A redundant discrimination network from CYRUS based on Schank's Dynamic Memory cognitive CBR model (Kolodner, 1993, p305).

Schank (1982) proposed that the reminding process relies on the processing structures and indexing. The processing structures are the same as the storing structures; and the indices are part of the storing structures. According to him, knowledge structures and individual instances have indices that carry information concerning the category they are in and the way they differ from the category. Indexing is primarily the process of matching indices. Transfer takes place when two cases with different context information share similar higher-level generalizations as stored in the higher-level storing structures. Reasoning across contexts could also take place when we reason with structures other than MOPs, such as TOPs, U-MOPs or U-scenes, because only MOPs are context-based knowledge structures.

In the Dynamic Memory cognitive model, a new experience is categorized under the schema with the instances that are used to process it, and it is indexed according to how it differs from them. Thus, reminding makes it possible for us to remember because it provides information on where and how to store the new information. We invalidate, reorganize, and refine our memory by retrieving our knowledge and matching it with our new experiences. If our expectations and indices that were once useful cease to be useful or turn out to be mistaken, we experience expectation failures. Expectation failures drive us to refine our knowledge structures by adding new deviations or changing expectations. Or, if we experience several events that are similar to an instance in our memory that used to be unique, we would reorganize our memory by stopping to record that instance as a deviation, and creating a new generalized structure for these experiences.

As the first CBR cognitive model, and the CBR model that continues to influence cognitive CBR research for the longest time, the Dynamic Memory model gradually evolved with the development of cognitive CBR research, explaining new research findings, incorporating important new theoretical hypotheses, and extending its scope to address more reasoning issues.

2.2.2.1.2. The extension of the Dynamic Memory cognitive model

In the 1980's, the Dynamic Memory cognitive model added a new element in its theory on CBR processing by incorporating a new hypothesis on a process called "situation assessment" -- a process of sizing up a new situation and determining what the indexes for a similar case would be if it were in the case library. The issue of situation assessment was at first not addressed in the theory of Dynamic Memory. However, as Schank's student Kolodner worked on the development of computational models of Dynamic Memory, she discovered that this process is primary to successful case-based reasoning. Soon after this new element is added to the computational model of Dynamic Memory, Schank incorporated the situation assessment process as another primary step of the CBR process in his cognitive model.

Over the late 1980's, the Dynamic Memory cognitive model has been extended by CBR researchers to address issues of a larger scope. As introduced in the beginning of this section, the Dynamic Memory cognitive model was originally a model of episodic memory. Schank acknowledged at that time that there are many other types of information stored in our memory, which are not included as part of his cognitive model (Schank, 1982). But as CBR research flourished, researchers started to address issues in reasoning processes that involve other types of knowledge, such as reasoning in planning, design, problem-solving, interpretation, and many other fields in which people often use information stored in semantic memory. For example, from their perspective, the memory of experts in a certain domain are well-indexed large case libraries consisting of important success and failures cases in the domain. In these later CBR models based on Dynamic Memory, information that is usually considered to be part of the semantic memory are integrated into the cases and considered part of the Dynamic Memory system as well.

While it is still an issue whether those shifted interpretations of the Dynamic Memory model could count as new versions of Dynamic Memory, by the year 1995 it is clear that a new version of Dynamic Memory is formed, as Schank himself introduced an evolved Dynamic Memory model in discussing the application of CBR in education. Partly influenced by the trend of cognitive CBR research, and partly inspired by his research on case-based teaching in the early 1990's, Schank introduced an extended Dynamic Memory model to address both episodic and semantic memory.

In this new integrated Dynamic Memory cognitive model, Schank proposed that our memory system consists of four types of knowledge: cases (including indices and structure of cases), skills, strategies, and conceptual knowledge. The concept of "cases" is the same as proposed in the original Dynamic Memory cognitive model, while the concept of skills, strategies, and conceptual knowledge are new. I will briefly introduce each of these new concepts in the following paragraphs.

Skills, which we often consider part of our semantic memory as they are independent of specific experiences or contexts, are viewed by Schank as scripts in his new model.[1] Schank proposed that what we usually consider to be skills are actually

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[1] Scripts are also sometimes referred to as "microscripts" or "scriptlets" in Schank's publications (e.g., Schank, 1986; 1991; 1995; 1999), but Schank claimed that these terms are not really different in meaning (Schank, 1996).

scripts (such as addition) or packages of scripts (such as math, or biology). There are three broad classes of scripts: cognitive, physical, and perceptual. Cognitive scripts are knowledge about use, physical scripts are knowledge about operations, perceptual scripts are knowledge about observations. If we could say "John knows how to use X", X is a cognitive script, for example, to add, and to prove a theorem in plane geometry are cognitive scripts. If we could say "John knows how to operate an X", X is a physical script, for example, to dissect a frog, and to run a chemical experiment are physical scripts. If we could say "John knows how to recognize an X", X is a perceptual script, for example, to interpret chemical equations are perceptual scripts. While all three kind of scripts tend to be implicit in our memory, we tend to talk about cognitive scripts, but not physical or perceptual scripts. Schank further suggested that our scripts may change from one type to another over time. For example, as a skill becomes more automated, the cognitive script corresponding to it may change into a physical one. Although Schank claimed that his notion of "script" did not change over time, what he ended up referring to as scripts in his new publications seems to differ from the original definition quoted earlier in this section: "Scripts embody specific predictions connected to the more general scene that dominates them." Scripts, in the original Dynamic Memory cognitive model, are generalized but contexualized information that serve as "prototype stories" for sets of similar cases. However, scripts in the new model, corresponding to skills, often refer to decontexualized abstract knowledge processed at a high level in our memory hierarchy independent of the context in which they are first acquired. It appears that the term "script" shifted in the new Dynamic Memory model to include all procedural knowledge we have abstracted from cases.

"Strategies" is a new concept that Schank introduced into his new cognitive model. Strategies are domain-independent rules and heuristics that people invent while engaged in universal processes or generalize from particular cases. There are many kinds of strategies, some of the most common ones are communications strategies, human relations strategies, and reasoning strategies. Strategies are different from skills in that they are not executable procedures, but rather principles, rules, and heuristics that people accumulate with experience by trying to engage in processes. Schank suggested that strategies have all the characteristics of TOPs and indices, namely, they are domain-independent, generated or developed from particular cases and so on.

Schank also introduced conceptual knowledge, a type of knowledge conventionally considered not part of CBR systems, into his modified model. Conceptual knowledge is factual, declarative knowledge that is explicit in our memory. Unlike the first three types of knowledge, conceptual knowledge is not necessarily acquired from experience or generalized from cases. Schank (1995) suggests that we could acquire conceptual knowledge from many sources, but unless we are motivated to remember it or frequently retrieve it from our memory, it is unlikely for it to remain in our memory for long. Schank is most concerned with the type of knowledge that tends to remain long in our memory. Thus, in his new model, he focused on one type of conceptual knowledge, termed "explicit functional knowledge (EFK)". Explicit functional knowledge (EFK) is conceptual knowledge that people are genuinely interested in or use quite frequently. Schank suggested that EFK is of two basic types: physical and cognitive. If we need to know something in order to do something, we are talking about physical EFK. If we need to know something in order to know something else, we are talking about cognitive EFK.

Schank further proposed that the processes and structure of EFK are analogous to that of cases. Thus, this type of knowledge is also organized in hierarchies, reinforced by repeated use, and combines together to allow people to become adept at complex cognitive activities.

This new Dynamic Memory cognitive model proposed a new perspective on many forms of knowledge in human memory, but overall, it maintained the original processing structure. Although new types of knowledge are introduced in the new Dynamic Memory model, Schank did not specify how the integration of these four types of knowledge would be achieved in the memory system. Thus, although it has inspired much research on the application of CBR in the field of education, there has so far been few applications or computational models in AI CBR based on this model. Another factor that might contribute to the phenomena of limited AI CBR research on this model is probably the fact that much of the reasoning Schank addressed in his new model is not *case*-based reasoning. By integrating skills, strategies, and conceptual knowledge into his cognitive model, Schank extended his model to the degree that reasoning directly from cases to solve problems is a very limited portion of the reasoning that is carried out by his proposed memory system. Also, by claiming that we use cases directly when they are exceptions and generalized knowledge or structures when these types of knowledge exist in our memory system, Schank implied that reasoning directly from cases is only temporary as those exceptional cases tend to get generalized in the future and are jettisoned soon after. Although Schank claims that much of the other types of knowledge that we have are acquired through cases, his cognitive model seems to differ from typical

CBR models which base their reasoning primarily on cases, and process information largely at the case level.

2.2.2.1.2. CBR systems based on the Dynamic Memory cognitive model

So far, several computational CBR systems have been developed to implement the Dynamic Memory cognitive model. Among them are Lebowitz's IPP (1983a, 1983b) and Kolodner's CYRUS (1983; 1984; 1985), the forerunners of case-based reasoning programs. In addition, many case-based advising systems, such as the ASK systems (Ferguson et al, 1992, Schank et al, 1991) also uses the Dynamic Memory cognitive model. In such systems, the Dynamic Memory CBR model is not used as the computational model of the CBR system, but rather as the conceptual framework guiding the design of interaction between users and the CBR systems.

As the theoretical background of CBR, the Dynamic Memory model has profoundly influenced CBR cognitive research. Much CBR research, both cognitive and pragmatic, is based on Dynamic Memory's view about human memory and its claims about human reasoning. The Dynamic Memory model is also the basis of another popular CBR model, as will be described in the next section.

2.2.2.2. Kolodner's "knowledge-poor" CBR cognitive model

2.2.2.2.1. The original CBR cognitive model proposed by Kolodner

Kolodner started her research on CBR modeling using Schank's Dynamic Memory cognitive model. In the early 1980's, Kolodner's and Schank's CBR models are basically the same. But, as one of the most active CBR researchers, Kolodner soon formed her own CBR model (I will discuss the differences at the end of this section). Kolodner's CBR cognitive model is sometimes referred to as a "knowledge-poor" approach as it addresses reasoning issues in domains in which there is a lack of generalized rules and models to follow. Her CBR model values the concrete over the abstract (Kolodner, 1993), and she suggests that individuals think in terms of cases, which are interpretations of their experiences that are applied to new situations.

The case memory in Kolodner's model is a hierarchical structure of what is called generalized episodes (GEs) (Kolodner & Simpson, 1989). A generalized episode is more or less the equivalent of a MOP. It has the same structure as an episode, but describes a general type, not a specific experience. It is almost as specific as an episode, lacking only details. The basic idea is the same as the Dynamic Memory cognitive model here, that is, to organize specific cases which share similar properties under a more general structure. A GE contains three different types of objects: norms, indices, and cases. A norm is a feature common to all cases indexed under a GE. An index is a feature which discriminates among a GE's cases. It may point to a more specific GE, or directly to a case.

Cases in Kolodner's model are different than cases in the Dynamic Memory model. In fact, the size of cases in Kolodner's model corresponds with that of MOPs in Schank's model. Cases here are represented by a header that holds global information about the case and a set of causally connected subparts, called *snippets* (Kolodner, 1988). Snippets correspond with the concept of scenes in Dynamic Memory. Given the size of the cases, Kolodner proposed that cases could have subgoals. For cases that have subgoals, each snippet under the cases represents pursual of one reasoning subgoal or a set of subgoals. Each snippet contains information pertaining to pursuit of its goal(s), which includes the snippet's problem description, actions taken in pursuit of its goal, and pointers to related snippets. Snippets are independently indexed, just as the full cases are. Kolodner suggests that snippets are different than the scenes of MOPs because they have subgoals – Schank never discussed subgoals at all in proposing scenes as the components of MOPs (Kolodner, 1989).

The organizational structure of Kolodner's CBR model is one of redundant discrimination networks combined with shared feature networks (Kolodner, 1984, 1988). Redundant discrimination networks were introduced in the previous section as the memory structure of the Dynamic Memory model. Shared-feature networks are a hierarchical structure in which cases that share many features are clustered together. Each internal node of a shared-feature network holds features shared by the cases below it. Items without those features are stored in or below that node's siblings. Figure 2.2 illustrates a shared-feature network organizing mediation cases.

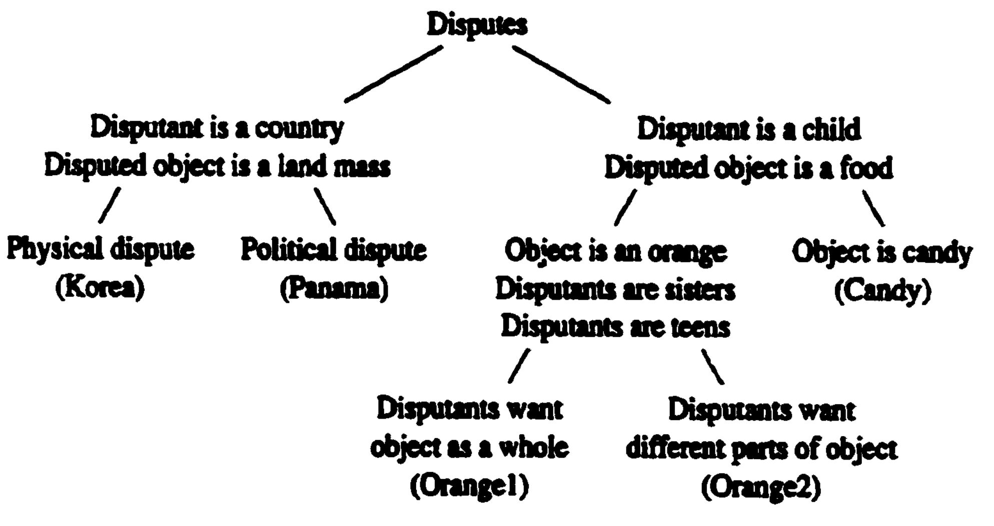

Figure 2.2. A shared-feature network (Kolodner, 1993, p297)

In Kolodner's CBR model, a node is either a generalized episode (containing the norms), an index name, index value or a case (Kolodner, 1993). Each index is a pair of index name and index value. It points from a GE to another GE or to a case. The indexing scheme is redundant, as described above, so there are multiple paths to a particular case or GE.

When a new case description is given and the best matching is searched for, Kolodner proposes that the input case structure will be pushed down the network structure, starting at the root (highest level of the hierarchy). The search procedure is similar to that of the Dynamic Memory model. When one or more features of the case matches one or more features of a GE, the case is further discriminated based on its remaining features. Eventually, the case with most features in common with the input case is found. During the process of storing a new case, when a feature of the new case matches a features of an existing case, a generalized episode (GE) is created. The two cases are then discriminated by indexing them under different indices below this generalized episode. If – during the storage of a case – two cases or two GEs end up under the same index, a new GE is automatically created. The retrieval process in Kolodner's model is carried out by finding the GE with most norms in common with the problem description and then traversing the indices under that GE so as to find the case which contains most of the additional problem features. Storing a new case is performed in the same way, with the additional process of dynamically creating generalized episodes, as described above.

2.2.2.2.2. How Kolodner's CBR cognitive model differs from the Dynamic Memory CBR model

Kolodner's CBR cognitive model is different from Schank's Dynamic Memory cognitive model in three major ways:

First, Kolodner's model extended the scope of reasoning beyond what Schank initially proposed in his Dynamic Memory model. She argued that it is plausible that the same retrieval processes and memory structures which support remindings in understanding also support tasks such as problem-solving, planning, and design (Kolodner, 1987). Thus, the nature of her CBR cognitive model is different from that of Dynamic Memory. So, also is the nature of "cases" different in her model. For example, in Kolodner's model, information such as rules, models, patterns and constraints, are often embedded in the CBR system and considered part of the cases, rather than stored at a higher level in the memory system as proposed by Schank (1982) in his Dynamic Memory model. Although Kolodner's CBR model also has hierarchies, she did not claim that the hierarchies in her CBR model are actually the Rule-Based Reasoning (RBR) or Model-Based Reasoning (MBR) systems of our memory, like Schank did (Schank, 1996), nor did she suggest that CBR and the other reasoning processes share certain portions of their organizational structures, as proposed by Schank in his new version of Dynamic Memory (Schank, 1996). Although Kolodner also proposed that hierarchical structures of abstract knowledge exist, she suggests that those that are abstracted in CBR systems are not necessarily the rules, models, or patterns. Instead, Kolodner proposed that RBR and MBR might be components of a larger memory system just like CBR, although CBR is the primary form of reasoning and cases are the primary generator of inferences. The other reasoning models closely interact with the case-based reasoning system by corresponding to parts of the cases and procedures of the CBR system such as indexing and adaptation.

Second, as described earlier in this section, the concept of cases in Kolodner's model differs from that of Schank's model. The grain size of cases in Schank's model is much smaller than those in Kolodner's model. In addition, cases in Kolodner's model are represented in a distributed way rather than a monolithic way. The cases in Kolodner's model are more structured, and the sub-parts of these cases could be directly retrieved to be used in solving new problems.

Third, Kolodner's model added new components to the CBR cognitive model that Dynamic Memory did not previously include. One is situation assessment, the process of analyzing a raw situation and elaborating it such that its description is in the same vocabulary as cases already in the case library. Basically, when we encounter a new situation and try to retrieve useful cases, we need to describe the new situation and the current reasoning goal in a way that makes it possible for us to retrieve useful old cases from memory. Situation assessment procedures allow us to determine what the indexes for the new situation would be if it were stored in the case library. This process was not addressed by the original Dynamic Memory cognitive model. Another component that Kolodner added is case subparts called snippets, which represent the pursual of case subgoals. Snippets and case representation in Kolodner's model have been described previously in this section. They are new in CBR because Schank did not discuss subgoals in cases or scenes when he first proposed the Dynamic Memory CBR model.

Fourth, the role of cases in the cognitive model is different in Kolodner's approach when compared with Schank's approach. Whereas Schank suggests that we mostly use generalized knowledge structures, or schema, in our reasoning unless the schema is incomplete or unavailable (Schank, 1982), Kolodner suggests that concrete information is always preferred in the reasoning process (Kolodner, 1993, 1995, 1997). Kolodner's model is more typically one of *case*-based reasoning as it puts more emphasis on reasoning at the case level, unlike Schank who suggests that we reason at all levels. Much of the information that is stored in the generalized structure in the Dynamic Memory model is considered to be stored in cases in Kolodner's model, and much of the processing that is done at the generalized level in Dynamic Memory is considered to be done at the case level in Kolodner's model. For example, while both models suggest that we use causal models to reason about cases, Kolodner suggests that the explanations are stored in cases as a result of interactions between the cases and the causal models, whereas Schank suggests that the explanations are stored as part of all knowledge structures and, as well, as an independent structure itself to organize cases in hierarchies. In addition, while both models acknowledge the importance of case structure in reasoning, especially cross-contextual reasoning, Kolodner suggests that cases are stored with a certain structure so that mapping can be done at the case level using mapping algorithms, whereas Schank suggests that it is the higher-level knowledge structures that make cross-contextual reasoning possible.

2.2.2.2.3. Shift of Kolodner's knowledge-poor CBR cognitive model

In the late 1990's, Kolodner's knowledge-poor CBR cognitive model shifted a bit to explain reasoning processes in knowledge-intensive domains. Kolodner (1996) proposed that by facilitating the explanation-generation process and the generalization process, case-based reasoning could support rule-based reasoning (RBR) and model-based reasoning (MBR). CBR as a cognitive model is integrated in a broader memory system by matching case components and generalizations drawn from cases with rules and models from other sub-systems of the broader memory system (Kolodner, 1996). Kolodner (1997) stated that, since CBR is one approach to reasoning by analogy which has a strong emphasis on the role of surface features, it could compliment RBR and MBR which focus on reasoning with abstract knowledge and deep features, and could also serve as the source from which rules and models in RBR and MBR are generated (Kolodner, 1997).

2.2.2.2.4. CBR systems based on Kolodner's knowledge-poor cognitive model

Kolodner's knowledge-poor CBR model has served as the basis of numerous CBR systems, including CASEY (Koton, 1988a; 1988b; 1989), CELIA (Redmond, 1989a; 1989b; 1989c; 1990a; 1990b; 1991; 1992), JULIA (Hinrichs, 1988; 1989;1992; Hinrichs & Kolodner, 1991), and MEDIATOR (Simpon, 1985; Kolodner & Simpson, 1988; 1989). CELIA, for example, acts as an apprentice mechanic. It models the memory and reasoning capabilities of a novice troubleshooter. CELIA solves problems by itself, and in addition, it learns by watching and listening to a teacher explain her reasoning about particular cases. As it listens to and understands the teacher, it integrates those experiences and what is learned from them with what it already knows. When experiments were run with CELIA (Redmond, 1992), it was found that the acquisition of cases was more useful in ensuring successful problem solving during early learning than for augmentation or refinement of domain or task knowledge. CELIA also suggests some minimal amount of knowledge that the student should have in order to make the most of their experiences. It also shows that it is better to present a variety of types of problems early on rather than concentrating on several very similar ones. As we shall see later (in the next chapter), experimental results from systems such as CELIA had a large impact on subsequent cognitive CBR research, and especially on research regarding the application of CBR in education.

Besides Schank's and Kolodner's CBR cognitive models, there is a third CBR model that has been quite popular in the field. This is Bareiss' and Porter's Category and Exemplar CBR model.

2.2.2.3. The Category and Exemplar Model

2.2.2.3.1. The Category and Exemplar model

Ray Bareiss and Bruce Porter (Bareiss, 1989, Porter, 1990) proposed a Category and Exemplar CBR model in the PROTOS system. The psychological and philosophical basis of this approach is the view that real-world, natural concepts should be defined extensionally. Different features are assigned different importance in describing a case's membership in a category. According to them, any attempt to generalize a set of cases should – if attempted at all – be done very cautiously. This fundamental view of concept representation forms the basis for this cognitive model, which distinguishes it from other CBR models.

In Bareiss and Porter's approach, the case memory is embedded in a network structure of categories, cases, and different kinds of connections. Categories are the extensional equivalent of concepts. Each category is represented by a set of retained cases. Cases in the Category and Exemplar model are called exemplars. They serve as exemplars of categories that people learn and models for interpreting new cases. The four kinds of connections between categories and cases are: reminding links, prototype links, difference links, and censor links. Reminding links associate features of cases with categories. Bareiss and Porter suggest that we use reminding links to make a guess at a category as the first step of our reminding process. Prototype links connect categories to items that most typify the category. Exemplars that are exceptional cases are not linked to the category by prototype links. Difference links, or indexes, record important differences between items (cases or categories). Difference links are recorded when near misses occurred in the reasoning process. They connect items to each other according to their differentiating features. Reminding links and difference links allow us to chose the best candidate from a category in the beginning of the reminding process, and they also allow us to proceed with our reminding process by moving from the first candidate item retrieved to other candidate items according to the differences between the candidate item and the new item identified by the match procedure. Censor links are learnt as a result of incorrect matches. We use them to rule out connections between items that might otherwise be made.

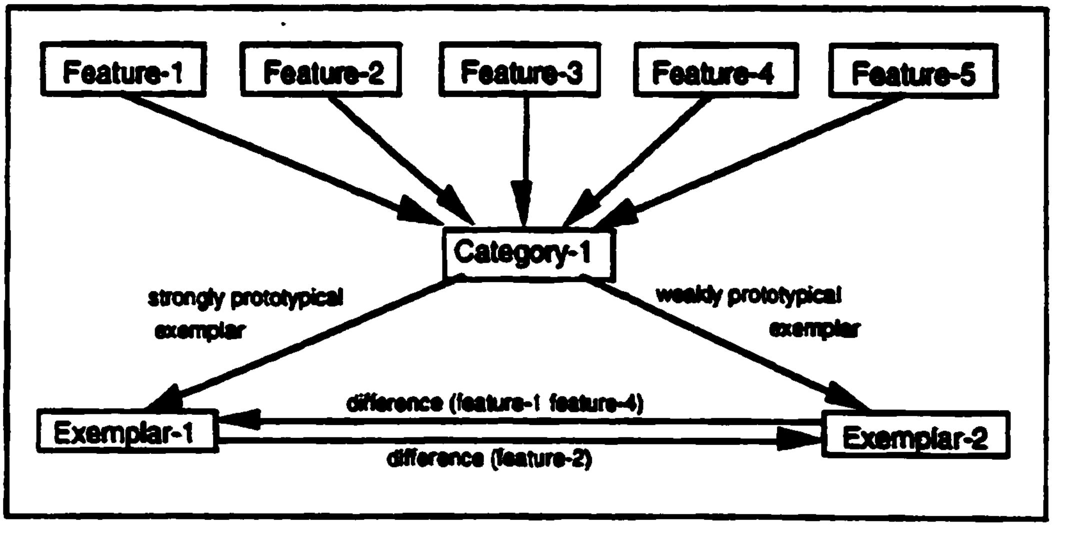

Figure 2.3. Structure of the Category and Exemplar model (Porter, 1990)

Within this memory organization, the categories are inter-linked within a semantic network, which also contains the features and intermediate states referred to by other terms. This network represents a background of general domain knowledge, which enables explanatory support to some of the CBR tasks. For example, a core mechanism of case matching is a method called "knowledge-based pattern matching" (Porter, 1990). Knowledge-based pattern matching means using domain knowledge within the category structure to construct explanations so as to relate the features of the new case to those of the exemplar. For example, if we have not seen a chair with four legs before, but know about chairs with a pedestal, when we see a four-legged chair, we might match the feature "four legs" of a new case to "pedestal" in exemplar X from the category "chair" based on the explanation "four legs is a specialization of 'seat support', which has another specialization 'pedestal'". This explanation based on domain knowledge suggests that the features are equivalent because they have the common generalization "seat support". Knowledge-based pattern matching is basically a search procedure. It searches for the strongest chain of known relations (also called chain of inferences) in the category structure, linking each feature of the exemplar to a feature of the new case. A chain of known relations is not a proof of equivalence, but rather the strongest argument that can be made, based on existing knowledge. Therefore, general domain knowledge is used to enable matching of features that are semantically similar.

2.2.2.3.2. How the Category and Exemplar model differ from Schank's and Kolodner's CBR models

Unlike Kolodner's model which is largely based on superficial, syntactical similarities among problem descriptors, the Category and Exemplar model attempts to retrieve cases based on features that have deeper, semantically-based similarities. In order to match cases based on semantic similarities and relative importance of features, an extensive body of general domain knowledge is needed to produce an explanation of why two cases match and how strong is the match. Thus, it is often referred to as the "knowledge-intensive" approach (e.g., Aamodt & Plaza, 1994), whereas Kolodner's research is referred to as a "knowledge-poor" approach.

The knowledge representation in the Category and Exemplar model is different from Schank's and Kolodner's CBR cognitive models not only because of its integration of case-based reasoning with domain knowledge, but also because of the way cases are organized and represented. Each case is considered to be the center of its *range of coverage* (Bareiss, 1989) within its category. The range of coverage is the range in which a case can closely match all cases in the region. This range is determined by the reasoner's domain knowledge. As the reasoner gains domain knowledge about the commonly occurring features of a category, her ability to use the knowledge to explain the equivalence of features improves. Since each case has its range of coverage, if a new case falls under the existing range of coverage, it would not be interesting enough to be retained in the memory system, because it could not teach us a new lesson. According to the Category and Exemplar model, only new cases that cannot be adequately explained by an existing case and those that we failed to predict correctly are retained in our memory. Otherwise, the new case will not retained in memory, but the prototypicality of the available case whose range of coverage the new case fell under will be increased to reflect the fact that it closely matched another instance of the category. Cases that have high prototypicality are also called "prototype cases". Unlike Schank's and Kolodner's

CBR models which place cases that are often encountered at a higher level of abstraction in the memory structure, the Category and Exemplar model proposes that prototype cases reside at the same level as the other cases in the memory system – although they are given priority in the retrieval process.

In addition, the Category and Exemplar model is unique in that each case is accompanied by explanations of why it is related to the category. Bareiss and Porter proposed that when rich explanations are generated, fewer exemplars are needed to learn a category because each exemplar will implicitly cover a wider range of featural variations. Explanations also enable effective learning of the case-category connections, which allow efficient access to the category structure.

2.2.2.3.3. CBR systems based on the Category and Exemplar cognitive model

The most faithful implementation of the Category and Exemplar model is PROTOS (Bareiss, 1989; Bareiss, Porter, and Murray 1989; Bareiss, Porter, and Weir, 1988; Porter, Bareiss, & Holte, 1990), PROTOS acts as an apprentice in diagnosing audiological disorders. Given a description of a situation or object, it classifies the situation or object by type. That is, given a description of the symptoms and test results of some patient, PROTOS determines which hearing disorder that patient has. When it misclassifies an item, its expert consultant steps in and informs PROTOS of its mistake and what knowledge it needed to classify the item correctly. Other CBR systems that are based on the Category and Exemplar model includes ORCA (Bareiss & Slator, 1991; 1992; Slator & Bareiss, 1992), and GREBE (Branting & Porter, 1991; Branting, 1991a; 1991b; 1991c; 1991d).

2.2.2.4. Other Variations

Besides the above three CBR cognitive models, there are also some other models that are quite different from them. Many of these models are the result of the trend to integrate the CBR method with other methods and representations of problem-solving, such as rule-induction or model-based reasoning. Another trend that led to the creation of some CBR models are efforts to model expert reasoning in specific domains. In fact, these efforts often yield integrated CBR models, as well. Those other CBR models, built to model reasoning in specific domains but using a purely CBR approach, are often limited in their scope—they could hardly be applied to domains in which a large component of the domain knowledge is other than case knowledge (Cunningham, 1993; Dupuy, 1988; Wendel, 1993). Therefore, in this section, I will focus instead on the new integrated CBR models that follow innovative approaches.

In the integrated CBR models, the cases, heuristic rules, and deep models are integrated into a unified knowledge structure. The main role of the general knowledge is to provide explanatory support to the case-based processes (Adamodt, 1993). Rules or deep models may also be used to solve problems on their own if the case-based method fails. The domain knowledge used in a CBR system is learnt from cases as well as other sources. In these CBR models, the overall architecture of the CBR system determines the interactions and control regime between the CBR method and other components. The majority of integrated CBR models are created with engineering considerations rather than from a cognitive science perspective. However, there are a few cognitive models available. For example, the modified Dynamic Memory CBR model and the Category and Exemplar CBR model can both be classified as integrated CBR cognitive models.

Other models that are approached from a cognitive perspective includes the QMC (Qualitative Modeling in CBR system) model, which integrates model knowledge with cases (Aarts & Rousu, 1997) based on Qualitative Process Theory (QPT) (Forbus, 1984); the MMA (Massive Memory Architecture) model (Plaza, 1993), which combine various CBR methods with rules and models; and the FABEL model (Sporl, 1995), which integrates case-based, schema-based and model-based reasoning.

QMC (Aarts & Rousu, 1997) integrates qualitative modeling (Forbus, 1984) with typical case-based reasoning. The qualitative modeling component of QMC represents processes, variables, and their relationships, called "influences". Processes are activities that may influence the state of a variable. For instance, when flying a plane, the process of *climbing* influences the variable *altitude*; the altitude of a plane will increase if the process is active. Variables are important features that moderate the end outcomes of a process. Processes and variables are linked by "influences". Not only are variables influenced by processes, processes may also be influenced by variables. For example, *fuel consumption* is influenced by the variable *friction*. In addition, variables can also be linked to one another by influences. For instance, *altitude* influences *friction*.

The qualitative model is integrated with case-based reasoning by mapping case components with qualitative model components. First, variables may directly correspond to case features. QMC distinguishes case features that are related to a situation (or input) and case features that reflect the outcome of the case. Those outcome case features are mapped to process variables. When the outcome features are directly related to case outcomes, or when domain knowledge indicates that they are important variables linking to the processes, those case features are directly mapped to corresponding variables in the qualitative model. However, not all outcome features can be directly linked to the outcome of the case, or easily matched to available domain knowledge. These kinds of case features cannot be directly mapped onto variables. Under such circumstances, the reasoner sometimes make assumptions about how certain variables in the qualitative model might influence such indirect outcome features. Those assumptions are stored as remarks attached to the variables, pointing to the outcome features that might be related to the variables. When a new case that has one of those indirect outcome features is encountered, the remarks will be activated, and the variable will be tried. Another way QMC integrates qualitative modeling with case-based reasoning is to map processes, operations and plans in cases to processes in the qualitative model. This kind of mapping relies on the appropriate definition of operations.

MMA is another integrated CBR approach. It is an integrated architecture for learning and problem-solving based on reuse of case experiences. A goal of MMA is understanding the relationship between learning and problem-solving and incorporating this understanding into a reflective or introspective framework. It seeks to model the reflection processes which allows the reasoning system to inspect its own past behavior in order to learn how to change its structure so as to improve its future performance. Case-based reasoning methods are implemented by retrieval methods (to retrieve past cases), a language of preferences (to select the best case) and a form of derivational analogy (to reuse the retrieved method in the context of the current problem). Learning in MMA is viewed as a form of introspective inference, where the reasoning is not about a domain but about the past behavior of the system and about ways to modify and improve this behavior. This view supports integration of case-based learning as well as other forms of learning from examples, like inductive methods, which are also integrated into the MMA and combined with CBR methods.

Another system that takes a similar approach to MMA is INRECA (Manago, 1993). These systems are closely related to the multistrategy learning systems (Michalski, 1992): the issues of integrating different problem-solving and learning methods are essential to them.

FABLE is an integrated CBR model based on the analysis of knowledge acquisition experiences in a building design domain. FABLE represents knowledge in the forms of cases, schemata, and generic models. Since it models reasoning in the domain of building design, cases in FABLE are arrangements of complex design objects. These design objects have concrete values like a type, a set of features, a location, etc., or a reference to other existing design objects. Schemata are step-wise abstractions from cases. Schemata can be instantiated and thus get specialized to cases. The constraints for the specialization usually emerge from the concrete situation and from the surrounding context. The models in FABEL define the scope of the assessment functions and serve as a framework for the adaptation functions.

These integrated approaches to CBR are examples rather than schools of integrated CBR research. In fact, there has been a plethora of research on integrated CBR models in recent years, especially in Europe. But so far, the only two popular integrated models are Schank's new Dynamic Memory model and Bariess's and Porter's Category and Exemplar model. This is probably due to the fact that most of the integrated CBR research has been done from an engineering standpoint.

In the next sections, I will summarize the confusions and lack of standardization in cognitive CBR research, and then propose a framework for understanding the major variations of CBR cognitive models.

2.2.3. Summary of Confusions and Lack of Standardization

The variations that led to confusions about CBR cognitive models mainly fall under five categories: 1) case content and representation; 2) organizational structure and knowledge representation in the CBR cognitive model; 3) the role of general domain knowledge in the CBR model; 4) processing and reasoning issues; 5) the scope of CBR.

First, although all CBR models focus on reasoning with cases, the nature of cases, and case representation varies from model to model. The typical definition of case is something like:

> A case is a contexualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner.
>
> (Kolodner, 1993, p.13)

This does not specify exactly what information should be represented in a case. Are cases small pieces of experience that represent one part of, or one facet of, a larger unit of experience, as described in Schank's Dynamic Memory model? Or are cases larger pieces of experiences that contains smaller sub-parts in them, as described in Kolodner's knowledge-poor CBR model? For example, if I went to a bookstore and accidentally found a map I was looking for, would that experience be one case in my memory composed of snippets "trip to the store", "browsing books", "found the map", "buying the map", and so on, or would that experience be broken down into cases such as "trip to the store", "found maps in the bookstore", and linked together by a "going to bookstore"

MOP? Are cases applied individually, or are they loosely connected sets of events that are reconstructed at retrieval time? These issues are still being debated in the field. Schank's model and Kolodner's model are representative to the two approaches to case representation (Alterman, 1989). Cases in Schank's model are called *monolithic cases*, and cases in Kolodner's model are called *distributed cases* (Alterman, 1989).

Second, as it is not clear what cases are and what the grain size of cases should be, it is also unclear how should the cases be organized in the CBR system. Knowledge representation proposed in CBR models range from very flat (as in the Category and Exemplar model, where cases that are encountered several times are stored at the same level with exceptional cases) to highly hierarchical (as in the Dynamic Memory model, where cases go through successive abstraction and turn into knowledge stored at higher levels). In structured models of CBR knowledge representation, it is also unclear on what bases are information generalized from cases, and what are the forms of the generalized knowledge in the memory structure. There are also several versions of memory organizational structure. Besides redundant discrimination networks (as in Dynamic Memory), redundant discrimination networks combined with shared-feature networks (as in Kolodner's model), semantic networks combined with Category and Exemplar (as in the Category and Exemplar model), and several other integrated approaches (as described in the "other variations" section), popular organizational structures also include shared-feature networks, discrimination networks, and prioritized discrimination networks (discrimination networks with priority given to important features). I will not describe these organizational structures in detail here, since a more detailed discussion of these organizational structures can be found in Kolodner's *Case-Based Reasoning* (1993).

Third, approaches to general knowledge in CBR cognitive models vary considerably. There are three types of generalized knowledge that are often considered part of the CBR system: general descriptions of particular kinds of situations, generalizations of the ways intentional and functional components of situations interact with each other, and adaptation methods. Besides these three types of knowledge, other forms of general knowledge, such as rules, models, and conceptual knowledge, are approached differently by various CBR models. Many researchers advocate integrated approaches in which CBR interacts with general knowledge in other sub-systems of our memory. QMC, MMA and FABEL are examples of this approach. Some other researchers view general knowledge, or a large portion of general knowledge, as part of the CBR system. For example, in Schank's moderated Dynamic Memory model, skills are equated with scripts in CBR and some rules are considered to be ossified cases (Schank, 1996); in the Category and Exemplar model, the semantic network is considered part of the CBR system. Some researchers who take a radical stance in this approach even claimed that "In a broad sense, everything is a case" (Riesbeck & Schank, 1989, P.11). So far, there is no consensus on exactly what role general knowledge plays in CBR, what types of general knowledge reside in CBR and where do they reside, or how does CBR interact with general knowledge in other systems.

Fourth, variations in these issues discussed above have resulted in variations in specific processing and reasoning issues. For example, although most CBR models acknowledge a top-down processing structure, there has been no consensus on whether cases are preferred over generalized knowledge, or are generalized knowledge preferred over cases. When we program our VCR after having done it for several times, for example, would we be reminded of a generalized knowledge structure (script, GE, etc.), or a specific previous experience of programming the VCR that is organized under that generalized structure, or a prototype experience that is an exemplar of our experiences of programming the VCR? If there is an appropriate generalized knowledge structure available, would we stop the retrieval process, or carry on until we retrieve a case? Is the structural mapping process done using higher-level knowledge structures, or is it done at the case level, or is it done by using both cases and general knowledge? Do we process information in a parallel fashion using knowledge at different generalization levels, or even from different memory sub-systems at the same time, or do we always process information using one type of knowledge? Those questions have generated much confusion about the case-based reasoning process, but so far, there has been no standardization on these issues.

Fifth, because of all those variations, it is unclear what is the scope of CBR as a cognitive model. Is it a unified approach to reasoning and memory or is it one of the sub-systems of a broader memory system? If CBR is a component of a larger memory system, when is it applied, and how does it interact with the other components? Under what circumstances are CBR extensively used so that we could use the CBR cognitive models to interpret phenomena or make predictions? Different CBR cognitive models approach these issues differently. For example, the moderated Dynamic Memory model and the Category and Exemplar model of CBR takes CBR as an unified model of cognition, while Koldoner's CBR model and some integrated approaches to CBR acknowledge that CBR is part of a larger memory system. In addition, each integrated model of CBR approaches CBR interaction with other systems differently. There has been, so far, no consensus in the field of CBR cognitive research on the scope of CBR.

Acknowledging these variations, I will present a framework for understanding the major variations of CBR cognitive models in the next section.

2.2.4. A Framework for Understanding the Major Variations of CBR Cognitive Models

Corresponding to the variations identified, I propose the following framework (presented in Table 2.2, pp. 49-50) to help us understand the variations and confusions in cognitive CBR literature. The major CBR cognitive models are analyzed and compared according to this framework, variations in the field that are not represented by the major models are presented under "other variations" along each dimension of the framework.

The five dimensions of variations in CBR cognitive models identified and discussed in the previous section could be used to form a framework for us to clarify the variations and confusions in cognitive CBR literature. Each major CBR model's approach to these five issues has been described in the sections dedicated respectively to each of those models. But in this section, in order to make these approaches more obvious for the framework I am proposing, and to make comparison across the major CBR cognitive models easier, I will summarize the main points of each CBR model's approach along each of the five dimensions, and present them in a table form (see Table 2.2). In Table 2.2, the major CBR cognitive models are analyzed and compared according to the framework I am proposing for understanding variations in cognitive CBR literature. Variations in the field that are not represented by the major models are presented under "other variations" along each dimension of the framework.

Table 2.2.

A Framework for Understanding the Major Variations of CBR Cognitive Models (Part I)

	Dynamic Memory (original)	Dynamic Memory (modified)	Kolodner's knowledge-poor CBR model	Category and Exemplar model	Other variations
Cases	Monolithic cases Flat case presentation	Monolithic cases Flat case presentation	Distributed cases Structured case presentation	Distributed cases Structured case presentation	N/A (No other variation from cognitive CBR literature)
Knowledge Representation	• Redundant discrimination networks • Highly-structured: U-MOP, U-Scene, TOP, MOP, scene, script, case • Successive abstraction based on surface features and deep structure	• Redundant discrimination networks • Highly-structured: U-MOP, U-Scene, TOP, MOP, scene, script/skill, case, strategy, conceptual knowledge • Successive abstraction based on surface features and deep structure	• Redundant discrimination networks combined with shared-feature networks • Structured: different levels of GE, case, snippet • Successive abstraction based mainly on surface features	• Organized in categories and ranked in order of prototypicality • Flat: semantic network, category, case (exemplar) • No direct generalization – generalization has to be based on domain knowledge	• Shared feature networks • Discrimination networks • Prioritized discrimination networks • Integrated structures
General domain knowledge	N/A (episodic memory system)	Partly reside in the higher-levels of the CBR system, partly reside in conceptual knowledge networks	Reside in all levels of the CBR system and linked to corresponding information stored in other memory systems	Reside in a semantic network interlinked with categories	Mapped from other systems to CBR components

Table 2.2.

A Framework for Understanding the Major Variations of CBR Cognitive Models (Part II)

	Dynamic Memory (original)	Dynamic Memory (modified)	Kolodner's knowledge-poor CBR model	Category and Exemplar model	Other variations
Reasoning	• Top-down process • May not reach the case level if appropriate generalized knowledge is available • Reasoning could be done at multiple levels	• Parallel top-down process (in both the CBR system and the conceptual knowledge network) • May not reach the case level if appropriate generalized knowledge is available • Reasoning could be done at multiple levels	• Top-down process • Always reach the case level if possible • Reasoning is usually done at the case level	• Top-down process combined with re-directing process • Always reach the case level if possible • Parallel reasoning mechanism using knowledge-based pattern matching	Integrated approaches, combining reasoning at the case level with reasoning using other memory systems, such as qualitative models, rule-based reasoning systems, model-based reasoning systems, conceptual knowledge network, etc..
Scope	• One component of a broader memory system • Episodic memory • Understanding	• Unified memory model • Cases used as exceptions and basis for generalizing abstract knowledge	• One component of a broader memory system • Reasoning in ill-defined domains	• Unified memory model • Cases used as prototypes or exceptions	Ranging from unified approaches to systems built for certain tasks or domains.

This framework outlines the variations and confusions in the field caused by the different hypotheses in different versions of CBR cognitive models. It would be interesting to discuss which of these CBR cognitive models are more plausible, or which claims from certain models are more plausible than claims from other models. But, so far, there seem to be no psychological experiment carried out to accomplish this, and therefore, no empirical evidence available to directly prove which propositions are right and which ones are wrong. In addition, each one of these models is well-formed to a degree that if stretched, it could provide explanations for tangential empirical evidence from related fields. Therefore, it is difficult to discuss which hypotheses or which models are "more true", or more supported, than others.

On a speculative note however, based on common sense, it seems to me that claims of CBR being one method of reasoning are more plausible than claims of certain CBR models being unified models of cognition (i.e., a cognitive model that underlies all human learning, reasoning, and performance.) More specifically, the moderated Dynamic Memory cognitive model and the Category and Exemplar model are claimed to be unified models of cognition, but it is hard for us to use these models to explain issues such as, e.g., those related to human emotions, why music therapy and art therapy have an impact on human behavior, etc.. It might be more reasonable if we limit our efforts to using CBR cognitive models to explain human cognition within task domains in which these models seem to be employed as the central way of learning and reasoning. For example, CBR cognitive models might be particularly useful in predicting and explaining reasoning in complex domains or dynamically changing domains in which there are no rules or models to comply; or domains in which there are many long lines of reasoning which are repeatedly used. In addition, people also seem to prefer cases as the initial source of information to learn or reason about a certain domain when they are new to it and do not have any general domain knowledge, such as principles or rules, to abide by.

CHAPTER 3. EDUCATIONAL APPLICATIONS OF CASE-BASED REASONING

3.1. Major Applications

Case-based reasoning has been applied to many instructional applications and innovations that are widely used today, such as goal-based scenarios (Schank, 1994), learning by design (Kolodner, 1997; Kolodner et al., 1998), case-based learning environments (Schank, 1990; Jonassen, 1996), knowledge-sharing systems (e.g., Kitano and Shimazu, 1995) and case-based advising systems. However, the structure, content, goal, and educational approach of these applications and innovations might vary with the different versions of CBR. In this chapter, I will first provide an overview of these CBR educational applications, introducing their design parameters, the CBR cognitive model they base their design on, and how the design of these applications links to the CBR model they use. Then, I will analyze how the design parameters or terminology of these applications might shift with the different versions of CBR.

3.1.1. Goal-Based Scenario

3.1.1.1. Overview of Goal-Based Scenario

Goal-based Scenario (Schank, Fano, Bell, & Jona, 1994) is a framework for learning environments developed by Roger Schank, one of the originators of CBR. The goal-based scenario (GBS) framework is created based on Schank's Dynamic Memory CBR cognitive model. The initial goal of the GBS research group was to create a case-based teaching environment that induces learners to acquire cases actively so that learners can have a large case library, just like the experts.

What Schank's group ended up creating as GBS is essentially a simulation environment in which learners assume a main role, which has associated with it a mission. Learners start the scenario with the goal to successfully accomplish this mission or task associated with their role(s) in the scenario. On the surface, GBS is quite similar to a typical gaming environment. What makes GBS a learning environment is: first, in order to achieve their goal(s) to pursue the mission successfully, the learners need to acquire particular skills and knowledge -- this is where and when the learning takes place; second, the learning environment also includes a set of resources that can help learners acquire the skills necessary to do so. The primary part of these resources is a CBR system with a case library of success and failure stories in the subject matter, well-indexed so that they could be presented to the learners at the right time, either when they just experienced an expectation failure or require support of a certain kind. The cases are often recorded in the form of video clips as experts telling war stories, and the search system is often presented as experts ready to answer learners' questions or to give them various forms of feedback.

By using these approaches, GBS presents an interesting situation for the learners to apply knowledge and skills and fail. Learners are motivated to explore, and when they fail, they are ready to hear a case, and be genuinely interested in the case presented. By encouraging expectation failures, GBS also allows both the system and the learners to detect what needs to be learnt, and which cases are relevant at a certain point. In addition, the use of CBR systems makes it possible for the system to make intelligent decisions about which case to present and not only when learners experience expectation failures, but also when they are curious about a certain topic and ask the system questions.

I will present a GBS learning environment, Sickle Cell Counselor (Bell & Bareiss, 1993), as an example to illustrate this framework. Sickle Cell Counselor is a GBS learning environment designed to help museum visitors gain a basic understanding of sickle cell disease. In this system, learners (i.e., museum visitors) are engaged in a mission of assisting couples who seek genetic counseling to learn more about the disease. Learners play the role of the counselor, the couples in the GBS come to the counselor and express (for various reasons) an urgent desire to learn more about the disease. With the goal of advising these couples based on their specific circumstances, learners embark on the mission performing a variety of activities related to the diagnosis of sickle cell disease. In the course of running these tasks, such as performing laboratory tests, calculating the probabilities of different outcomes, and advising clients about the results of their tests, learners learn about the various aspects of sickle cell disease. When the learners need support or feel they want extra information, they can consult the experts provided by the GBS environment. Sickle Cell Counselor presents four experts that can be reached at all times throughout the mission: a physician, a geneticist, a lab technician, and a guide. The physician and geneticist offer expert knowledge about sickle cell disease to users at appropriate times. The lab technician helps the learners with the mechanics of the blood lab. The guide serves as the voice of the tutor, offering help and suggestions regarding not only how to navigate through the program, but also what to look for and what to try next. Basically, learners take on the role of experts when they embark on the mission in this GBS framework, but because they are not actually experts in this domain and cannot finish the tasks on their own, they are motivated to learn more about the domain so as to finish the mission. They seek information from the experts in the system and gain knowledge in the process of finishing their tasks. By the time they have learnt enough from the system to successfully complete their mission, they would have gained enough knowledge about sickle cell disease from the GBS.

Having presented the basic framework of GBS, I will now introduce the structure and main components of GBS from an instructional design perspective. Overall, a GBS is made up of two main parts: the mission context and mission structure. Each of these two parts is in turn composed of two subparts, as illustrated in Figure 3.1.

The mission context deals with the development of the thematic aspects of the GBS. It is composed of the mission and the cover story. The mission is the overall goal of the GBS. The cover story is the premise under which the mission will be pursued. The mission specifies the goal the learners are trying to accomplish and sets the tone for the student's actions. The cover story defines more specifically the role the learner plays, the scenes where the action takes place, and provides other details that makes the GBS plausible and enticing to the student.

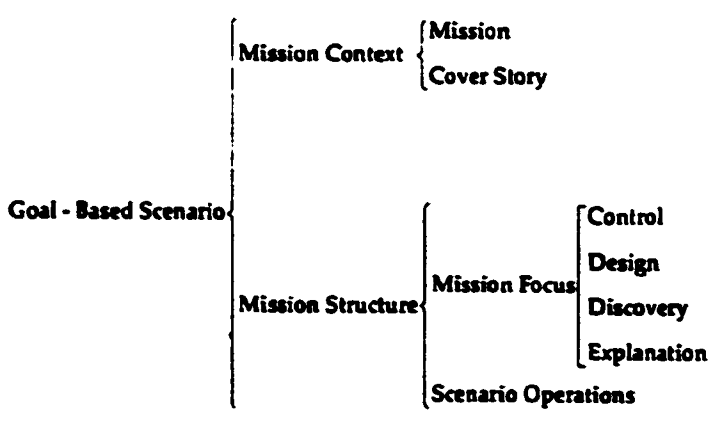

Figure 3.1. The structure of components in a goal-based scenario

The mission structure is the means by which the student will pursue a mission. In the real world, GBS missions can often be achieved by numerous plans, but in a GBS learning environment, only plans that require the execution of the skills intended to be taught by the GBS are supported. The mission structure specifies the plans to be supported in terms of the themes developed in the cover story.

Based on the mission structure of a GBS, the mission focus and scenario operations will be considered. The mission focus is the style of the activity in which the mission structure will be implemented. It provides the overall framework around which the rest of the GBS can be structured. There are four types of mission foci: control, design, discovery, and explanation. GBSs that have a control mission focus have the learner's principal activities centered around managing an organization, operating a complex system, controlling a mechanism, and so on. GBSs that have a design mission focus have the interactions centered around generative activities such as creating an artifact, specifying how a system should be organized, or specifying how a process should be executed, etc. If the mission focus of a GBS is explanation, the tasks of the GBS involve articulating an explanation explicitly through the design of an artifact. If the mission focus is discovery, the primary activities of the learner must be to infer the laws governing the microworld, notice opportunities to participate in activities or acquire resources, or discover how to deal successfully with the simulated agents that populate the microworld. In addition, a mission focus may include a combination of these approaches. The scenario operations are the actual activities the learner will be performing while engaged in a GBS. For example, activities such as answering a question, using a tool to shape part of an artifact, searching for a piece of information, and deciding between, alternatives are all scenario operations.

3.1.1.2. GBS and the Moderated Dynamic Memory Model

Underlying this GBS framework are three key components drawn from Schank's Dynamic Memory CBR model: 1) learning by doing: providing a realistic computer-mediated environment where learners can actively engage in the tasks; 2) learning from failure, whereby learners are deemed ready to acquire new knowledge when they encounter failure, so as to avoid similar mistakes in the future; and 3) learning from stories: use stories to present memorable ways to illustrate general principles while providing concrete details that learners can apply to different contexts (Schank, 1994).

These underlying components are drawn from Schank's Dynamic Memory CBR cognitive model. Although at the time the GBS framework was proposed, the new version of the Dynamic Memory CBR model was not yet published, many key concepts in the new model were used in the GBS framework. It appears that the moderated version of Dynamic Memory model and the GBS framework influenced the formation of each other. In the following paragraphs, I will use the moderated Dynamic Memory model to explain decisions made with regard to the design parameters of GBS.

The learning by doing component of GBS corresponds with the Dynamic Memory model in two ways. First, as described in the last chapter, learning, in Schank's cognitive model, is a bottom-up process of successive abstraction. The Dynamic Memory model asserts that people learn by acquiring cases and generalizing higher-level abstract structures from cases. Learning by doing is the most natural way to accumulate cases and facilitate generalization. In addition, Schank claims that skills, one of the four types of knowledge in our memory system (cases, skills, strategies, and conceptual knowledge), can only be learnt by doing. Therefore, the only way for learners to acquire all types of knowledge is to let them learn by doing. Second, the Dynamic Memory CBR model suggests that cases learnt by doing are more concrete and memorable, because they contain more detailed information for us to create indices from. Schank (1995) claimed that cases from other people's stories are distilled every time they are re-told, risking the chance of losing critical details or missing important information. If we learn by doing, we will have more indexes for a case, and it is more likely for us to access the case in the future. Every time we access a case for reuse, it is reinforced in our memory. Thus, cases learnt by doing are more likely to be remembered for a long time. Furthermore, the richness of cases acquired by doing something enable us to better detect nuances so as to make sound generalizations and/or assist future decision-making. Thus, cases learnt by doing tend to be more useful in future reasoning than cases acquired from other people's experience.

Learning from failure is a new concept that Schank proposed on the basis of the Dynamic Memory CBR model (Schank, 1982). As described in the last chapter, in Schank's CBR cognitive model, expectation failures are one of the major components of the indexing system. All exceptional memory units are indexed in the Dynamic Memory system by indices generated from people's expectation failures. Thus, it is important for the reasoner to experience expectation failure in order to obtain a well-indexed CBR system. Furthermore, Schank suggested in his cognitive model that expectation failures make the memory system unstable and leave the reasoner eager to find explanations. That is, people are motivated to learn more when they realize that they do not know enough about a certain topic. Therefore, expectation failures can serve as a source of intrinsic motivation for people to learn. Schank also suggested that it is advantageous for learners to learn by doing and learn from failures because it is easier for them to detect small holes and bugs in their knowledge this way. More cases are retrieved and tested when the reasoner is actively involved in the reasoning process, and when a problem is detected, more cases will be invalidated or reinterpreted.

Learning from stories is also a core underlying component of GBS. It serves as the case-based teaching part of the GBS system. Schank views learning as the accumulation and indexing of cases, and thinking as the finding and consideration of an old case to use for decision-making about a new case (Schank, 1996). Thus, one of the main objectives of GBS is to support learners' acquisition of cases on an as-needed basis. Cases are presented in the form of stories. These stories contain information that help learners understand a situation, the solution that was derived, why it was derived, what happened as a result, as well as the explanations that tie those pieces together, just as in the way cases would be recorded in an expert CBR system.

Another lesson that the learning from stories component drew from the Dynamic Memory cognitive model is to support learners accumulating both cases about success and cases about failures. Research based on the Dynamic Memory model shows that it is important for a CBR system to have both success and failure cases in order for it to be able to predict potential problems and generate efficient strategies (Kolodner, 1984). In a GBS, stories about success are valuable for the advice they give about how to proceed or what strategies to use, stories about failures provide advice about what to avoid or issues to focus on, and the combination of success and failure stories provide learners the basis for making predictions, generating indices, and inventing strategies. Finally, stories in GBS are indexed in ways that anticipate their use, making it possible for the GBS system to find cases that provide adequate scaffolding.

These underlying notions, when applied to each aspect of the design structure, are specified into a set of design criteria for the four main components of GBS (Schank et al. 1994). These design criteria are presented in Table 3.1. pp. 62-63. Some of them are not directly drawn from the CBR model *per se*, but are rather pragmatic concerns about linking the main components together and building a powerful learning environment. But the other ones, such as empowerment, flexible achievement, frequent practice opportunities, and responsiveness, directly correspond to the principles drawn from the Dynamic Memory cognitive model. For example, the Dynamic Memory model suggests that good reasoning is partly a result of being able to retrieve the right case or the right generalized knowledge structure at the right time. Indexing and generalization is key to this process. Useful indices and generalizations are created when the reasoner has enough cases to make decisions about, e.g., which features are important, when would the case (and/or similar cases) be applicable, and what are the aspects to focus on in similar cases. Corresponding to these claims of the Dynamic Memory model, the frequent practice opportunities criteria of the GBS framework emphasize giving learners opportunities to practice their target skills in a wide variety of contexts, so as to support generalization and indexing based on important features; and the empowerment criterion reinforces this approach by focusing on helping the learners realize the applicability of the cases and generalized knowledge they have acquired. These GBS design criteria that are derived from the Dynamic Memory cognitive model are bolded in Table 3.1.

I will analyze these design criteria in more detail and discuss possible ways these criteria might shift if the application were based on other CBR models, as well as new components that could be added to the GBS framework, later in the analysis section of this chapter. But before that, I will first present two other popular applications of CBR.

Table 3.1.

Design Criteria of GBS Design Components (Part I)

GBS component	Design criteria	Definition of design criteria
Every component	Thematic coherence	The process of achieving the mission must be thematically consistent with the goal itself.
	Realism/ richness	**The GBS must be realistic and rich enough to provide varied opportunities for learning the target skills. Not only must opportunities for the acquisition of the target skills arise, but they must arise in a realistic and varied enough way to render the skills useful to the student.**
	Control/ empowerment	Students should be put in control. They should feel responsible for the completion of the task.
	Challenge consistency	The various components of the GBS should promote a consistent degree of difficulty. They must ensure that an environment presents neither insurmountable obstacles nor trivial and distracting subtasks.
	Responsiveness	**The GBS components must convey the right feedback in a manner that is useful, timely, and understandable to the student. Students should be able to observe the causal effects of their operations.**
	Pedagogical support	The proposed scenario should be compatible with and supports the acquisition of target skills. The target skills must make sense in the context of the proposed scenario. Ample opportunities must arise for the use of the skills.
	Pedagogical goal resources	The strategies and materials used to assist the student must be carefully chosen to match both the skills being taught and the premise of the GBS.
Mission	Goal distinction	The goal should be clear, plausible, and consistent with the cover story. Progress towards the goal as well as its accomplishment should be obvious to the student.
	Goal motivation	Much of the motivation to work through the GBS will come from the desire to complete the mission. The mission should be a goal that the students already have, or one that there is reason to believe the students will enthusiastically adopt.
	Target skill dependence	Completion of the mission should require mastery of the target skills and knowledge.
	Flexible achievement	**A mission should be selected that can be achieved many different ways, yet for which no single solution is guaranteed to work every time.**
	Task consistency	The overall focus of the student's activities should be suggested by the mission and cover story. Possible mission focuses include explanation, control, discovery, and design.

Table 3.1.

Design Criteria of GBS Design Components (Part II)

GBS component	Design criteria	Definition of design criteria
Mission focus	Student investment	The mission focus should promote a student's sense of personal investment in the mission.
	Progress emphasis	Pedagogical goals should depend principally on the progress of trying to complete the mission.
	Artifact dependence	The "artifact" of the mission focus, be it a design, an explanation, or otherwise, should reflect the student's understanding of the domain and embody a solution to the problem at hand. The properties of the artifact and its performance within the cover story should reflect the strengths and weaknesses of the solution.
	Role coherence	The cover story should provide a desirable role for the student within a plausible, exciting, and accessible story.
Cover story	**Target skill density**	**The cover story should be designed to lead to situations that maximized the need to apply the target skills and minimize the need for others.**
	Frequent practice opportunities	**Advancing the cover story should require minimal time and effort relative to that spent on acquiring target skills and knowledge. The cover story should provide situations that allow the target skills to be practiced in an wide variety of contexts.**
	Integrated support	Additional assistance required by students should be provided using materials consistent with the cover story when possible.
Scenario operations	Expressivity	Students should be provided with a sufficient number of operations to allow them to pursue the mission as they see fit. The operations available should include those that can lead to a failure in achieving the mission.
	Causal consistency	Operations and their outcomes should be consistent with the cover story and mission.
	Peripheral support	**The student should be relieved of operations that are not central to the pedagogical goals of the GBS.**

3.1.2. Learning By Design

3.1.2.1. Overview of Learning by Design

Learning by design (Kolodner et al. 1997) is a CBR approach to learning science concepts and skills proposed by Kolodner and her students. The learning by design (LBD) framework uses design challenges (science projects) as the learning context, and a series of reflection tools and classroom rituals as ways of facilitating reflection. LBD is different from goal-based scenarios (GBSs) in that it involves designing and building on top of tasks such as decision-making, testing, and explaining, which are typical GBS tasks. In addition, unlike GBSs that have a mission structure and a set of possible paths for learners to follow, LBD encourages learners to create their own solutions and explore. It allows learners to experiment and play around, rather than restricting them to set paths which allow no turning back, like GBSs do. Furthermore, LBD gives reflection and generalization a central role. It advocates explicit reflections and articulations – a process emphasized but not directly facilitated in GBS.

The two major components of LBD learning environments are a) the design challenge, and b) the reflection tools and classroom rituals.

Design challenges in LBD are centered on the design and construction of working devices or working models that illustrate physical phenomena or that measure phenomena. Design challenges provide opportunities for learners to engage in and learn complex cognitive, social, practical, and communication skills. For example, students design parachutes (made from coffee filters) to learn about air resistance, gravity, and their relationship; they design miniature vehicles and their propulsion systems to learn about forces, motion, and Newton's laws; and they design ways of managing the erosion on barrier islands to learn about erosion, water currents, and the relationship between people and the environment.

Reflection tools in LBD include: tools to support the recording of design experiences, tools to prompt explanation of design decisions and design experiences, tools to support generalization and the formation of useful cases in memory, and tools that present appropriate experts' cases to learners (Kolodner, 2000). The system of classroom rituals that compliments the reflection tools includes activities that help learners relate past experiences to present situations (*messing about*), activities that help them anticipate what they need to learn more about (*whiteboarding*), and activities that support learners to share their ideas with one another (*gallery walks* and *pinups*) (Kolodner, 2000).

Tools to support the recording of design experiences are either paper-based or computer-based. They works like journals or design logs, helping learners to keep track of their design experiences so that they can remember what they did and draw lessons from their experiences.

Tools to prompt explanation of design decisions and design experiences encourage learners to link their experiences with causal models and rules. Learners engage in group activities articulating and explaining their decisions and experiences. They get to actively reflect upon their experiences, explain their decisions in a clear and coherent manner, get feedback from others, and re-examine their decisions and experiences based on the feedback they received.

Tools to support generalization and the formation of useful cases in memory prompt students to extract and articulate the content and skills they are learning from their experiences and write them up as stories to share with other students. These tools help learners to focus on the important aspects of their experiences, to distinguish core content, skills, and rules or models learnt from other experiences that are less important. The story write-up process also helps learners to view their experiences in a more structured way. In order to summarize their experiences and write them up as stories, learners need to structure their experiences in a way that only the most important aspects and the key variables will be present.

Tools that present appropriate experts' cases to learners retrieve useful cases written by experts from the case library based on learners' needs. These tools also help learners to extract the science and advice that can help them with their design challenge from those cases presented.

The *messing about* classroom ritual is basically guided play done in small groups, helping learners to make connections between a design challenge and what they already know (Kolodner, 2000). For example, playing with toy cars and seeing which can go over hills and which cannot, gets learners thinking about what it takes to get a vehicle over a hill and the different ways they have made things move.

The *whiteboarding* classroom ritual follows messing about. It is a whole-class activity in which learners articulate together what they discovered during messing about and generate ideas about how to proceed and which learning issues to pursue (Kolodner, 2000).

The *gallery walks* and *pinups* classroom rituals give small groups of students the opportunity to share their plans with the whole class and hear other students' ideas (Kolodner, 2000). Pin-ups and gallery walks require students to articulate what they are doing well enough for others to understand; they also provide students with ideas to build on in moving forward, a venue for getting feedback on their articulations, for asking for advice and getting suggestions, and for vicarious experience applying the concepts and skills they are learning.

3.1.2.1. LBD and Kolodner's Knowledge-Poor CBR Model

In order to better understand the links between the above-described LBD design features and Kolodner's CBR model, I will first present here Kolodner's claims of CBR's implications in learning, which serve as the conceptual framework of the LBD approach. Based on her claims, I will then proceed to analyze the connections between the features of LBD and Kolodner's CBR cognitive model.

According to Kolodner (1997), CBR suggests five important facilitators for learning effectively from hands-on activities: 1) having the kinds of experiences that afford learning what needs to be learned; 2) interpreting those experiences so as to recognize what can be learned from them, drawing connections between their parts so as to transform them into useful cases, and extracting lessons that might be applied elsewhere; 3) anticipating their usefulness so as to be able to develop indices for these cases that will allow their applicability to be recognized in the future; 4) experiencing failure of an individual's conceptions to work as expected, explaining those failures, and trying again (iteration); and 5) learning to use cases effectively to reason.

The use of design challenges in LBD corresponds with the notion of a) providing learners the kinds of experiences that afford learning what needs to be learnt, and b) providing learners the opportunities to experience expectation failures, and prompting learners to explain those failures and try again.

First, CBR emphasizes the importance of accumulating concrete experiences from learning by doing and learning from failure (as discussed in the last section with the GBS approach). It also suggests that expectation failures from the learning by doing approach provides learners intrinsic motivation to learn more. Design challenges is a learning by doing approach to learning science which provides abundant opportunities to learn from failure. In addition, CBR suggests that the right kinds of experiences for learners should be those that afford concrete, authentic, and timely feedback so that learners have the opportunity to confront their conceptions and identify what they still need to learn (Kolodner, 2000). This kind of feedback helps learners to generate explanations for their experiences, to recognize what can be learned from them, to create useful indices and connections to other experiences, and to extract lessons that might be applied elsewhere. Designing, building, and testing working devices provides this kind of concrete, authentic, and timely feedback.

Second, according to Kolodner (1998), CBR suggests that it takes several encounters with a concept or skill to learn it well. The first encounter allows the learner to build an impoverished picture of the concept or skill. Later encounters, in which that impoverished pictures is applied and fails to work as expected, let a learner know that her knowledge base is incomplete or incorrect, prompting the engaged learner to want to revise her knowledge, cases, or indexing so that it works better. In addition, based on her CBR cognitive model, Kolodner (1998) claims that encounters that cover the range of applicability of the concept or skill allow the learner to see its varied uses, and the other concepts or skills to which it is related. So, the opportunity to encounter a concept of skill repeatedly, in a variety of contexts, will lead learners to move iteratively toward better and better development of the skills and concepts they are learning. Design challenges provides opportunities to learn the target skills and concepts in a range of situations and under a variety of conditions. They encourage learners to try to solve a problem or achieve a challenge, use the impasses and failures of expectation to show what needs to be learned, investigate to learn more, and try again.

To summarize, design challenges help learners acquire the right experiences, as the construction and trial of real devices gives them the motivation to want to learn, the opportunity to discover what they need to learn, the opportunity to experience uses of science, and the opportunity to test their conceptions and discover the bugs and holes in their knowledge.

The reflection tools and classroom rituals, on the other hand, seem to correspond to the following principles suggested by CBR: a) help learners to explain their experiences so that they can recognize what can be learned from them, draw connections between their parts to make them useful cases, and extract lessons that might be applied elsewhere; b) help learners construct useful indices for these experiences so as to be able to use them later; and c) help learners learn how to use cases effectively to reason and form good "intellectual habits" in doing case-based reasoning.

The reflection tools and classroom rituals are combined with each other to explicitly address these principles. Tools to support recording of experiences help learners to keep track of "raw data" on every aspect of their experiences so that it is less likely for learners to forget important aspects of their experiences. The information recorded in them supports the use of the other tools and classroom rituals. Tools to prompt explanation of design decisions and design experiences directly aim at the principles: a) "help learners to explain their experiences" and c) "help learners learn how to use cases effectively to reason". Tools to support generalization and the formation of useful cases in memory, on the other hand, directly correspond to all three principles mentioned above. The classroom rituals, messing about, whiteboarding, gallery walks, and pinups are complimentary to the reflection tools. They correspond to all three principles mentioned above, as well, helping learners to identify what they need to learn, derive well-articulated cases from their experiences and insert them into their own memories, and prompting them to engage in active explanation, reflection, and articulation processes.

The LBD framework will be further discussed in the analysis section, where the design features of this framework will be analyzed from the perspectives of other major CBR cognitive models. In the next section, I will present some CBR educational applications that apply CBR pragmatic models.

3.1.3. Case-Based Advisory Systems and Knowledge-Sharing Systems

Unlike GBS and LBD, which derive their conceptual framework and design principles from CBR cognitive models but are not actual CBR systems, there are also some other CBR educational applications that directly use pragmatic CBR models to attack educational issues. *Case-based advisory systems*, an interactive model of CBR systems, is typical of this approach. *Case-based knowledge-sharing systems* are a variation of the case-based advisory systems, extended to accommodate user collaboration, user creation and editing of cases. In this section, I will introduce the framework of case-based advisory systems first. Then, I will discuss the framework of case-based knowledge-sharing systems on the basis of what is added in this new extended approach to case-based advisory systems.

3.1.3.1. Case-Based Advisory Systems

Case-based advisory systems are also often called *case-based aiding systems*. They use interactive CBR engineering models to support human reasoning. I will briefly provide a background of interactive CBR here. Pragmatic CBR systems could be divided into two categories: automated CBR systems, and interactive CBR systems. Automated CBR systems solve problems without human intervention. Most of the CBR systems that implement CBR cognitive models, for example, are automated CBR systems. Interactive CBR systems, on the other hand, work with people to solve problems. Some interactive CBR systems require human support for their reasoning tasks. For example, some CBR systems need people to help with their adaptation, decision-making, or evaluation in order to successfully complete their tasks. Some interactive CBR systems, on the other hand, are designed to support human reasoning. For example, some such systems act as case retrievers, providing cases to a user who employs the cases to reason, while some provide other forms of support, such as help with adaptation or help with evaluation. The degree of automation in interactive CBR systems varies. But no matter what degree of automation is used, those interactive CBR systems designed to support human reasoning are usually case-based advisory systems.

Case-based advisory system provide users the opportunity to learn on the job. The more automated ones can act like an expert looking over the shoulder of the user, providing timely support on an as-needed bases. The simpler ones use their case libraries to augment the memory of a user solving a problem, and perhaps provide other forms of support as well. With the support of case-based advisory systems, the users can make decisions on things such as which cases could be used, which adaptations to apply, and which potential problems to address. In the following section, I will discuss in more detail how case-based advisory system support the reasoning and learning or their users.

3.1.3.1. 1. Ways in which case-based advisory systems support user reasoning and learning

Case-based advisory systems typically support users in three ways: inform users of potentially useful cases, provide adaptation support, and provide evaluation support.

First, case-based advisory systems can augment the user's memory. The case library of a case-based advisory system is usually built to cover the range of reasoning tasks the system will be responsible for supporting, and cover the range of well-known solutions and well-known mistakes (Kolodner, 1993). When users are trying to understand and assess situations, such representative sets of cases allow them to interpret or understand a situation in the context of other similar situations. Those similar situations can not only point out to users what to focus on and what outcomes might arise, but also allow them to argue and justify the pros and cons of interpreting a situation in a certain way. It is especially helpful when users are interpreting open-ended and ill-defined concepts. In the process of problem-solving, similar cases retrieved from the case-based advisory systems' case library allow users to a) propose solutions to problems quickly, avoiding the time necessary to derive those answers from scratch; b) propose solutions in domains that they do not completely understand; c) be aware of the potential for problems that have occurred in the past and take actions to avoid repeating past mistakes; and d) focus their reasoning on important parts of a problem. In addition, the variety of cases included in the case-based advisory systems exposes users to multiple situations, multiple decisions, and multiple perspectives. This multiplicity helps to build awareness of knowing what skills to apply and when to apply them. A beneficial side effect of using the case-based advisory systems to augment users' memory is that users could acquire a representative set of cases for their own case libraries (memories) in the process of using the systems to support their reasoning.

Second, the case-based advisory systems can support the adaptation process of reasoners by suggesting adaptation strategies, applicable conditions of adaptation strategies, and past adaptation processes which could be usefully recorded as part of the cases in their case libraries. Some case-based advisory systems which integrate CBR method with semantic networks or other reasoning methods such as rule-based reasoning or model-based reasoning can also provide users with relevant domain knowledge to support their adaptation. Adaptation support from case-based advisory systems can help users identify what to change, find out what available adaptation or repair strategies there are and what are their conditions, determine what appropriate strategies are and, in the case when several appropriate strategies suggest different adaptations, can help users to choose among several appropriate strategies.

Third, case-based advisory systems can also help users with evaluation by showing them the factors that should be considered during evaluation and clustering cases to make comparison easy. This could be done by a) retrieving and presenting cases which have similar situations and similar solutions to the ones the users are evaluating, and b) suggesting what factors should the users focus on when they are comparing and contrasting new situations and their solutions to old ones in order to determine if an old outcome can apply to a new situation. The outcome of the old situations can be projected on the new ones, allowing the outcome of the new solutions to be predicted. When different old cases can be used to predict different outcomes, the factors suggested by case-based advisory systems can also help the users to do argumentation, i.e., to determine which of the old cases are indeed similar enough to the new one for the projection to make sense. This process has the potential to help the users in several ways. First, it can point out what the potential problems with a proposed solution are, pointing the way toward repairing solutions appropriately. Second, it can point out what might be changed to make a good solution better. Third, scenarios used during critiquing can serve as justifications for whatever solution is decided upon. Fourth, it can help the users realize what is important to pay attention to in future problem solving.

Because of the fact that case-based advisory systems have the potential to support not only reasoning but also learning in so many ways, some case-based advisory systems have been built especially for instructional purposes. In the following section, I will briefly describe a popular series of case-based advisory training systems – the ASK systems (Ferguson et al., 1992).

3.1.3.1. 2. The ASK systems

The ASK systems (Ferguson et al., 1992) are hypermedia case-based advisory systems designed to simulate a conversation between a novice (the user) and an expert (the system). This series of systems (e.g., ASK-Tom, ASK-Michael, Advise the president, Trans-ASK, Engines of Education) are basically CBR systems which consistently predict what a user might be interested in, and accordingly, retrieve cases for her to choose from.

A user starts using an ASK system by first "zooming" from the top level structure of a domain to a specific case. This could be done by identifying an area of interest, then choosing a theme from that area of interest, and subsequently choosing a case of interest from that theme. Afterwards, the users start the "browsing" process in which they go from case to case in a manner similar to conversing with an expert. A user starts browsing with the first case she chooses at the end of the zooming process. The case summary and follow-up questions related to that case will be presented in a case screen, and the user can either a) choose to view the full case, or b) choose to follow up a question to go to another case screen. If she choose to view the full case, a story in the form of a short video will be presented. When the user finishes viewing or reading the first case, she will be brought back to the case screen. Then, she could follow the links to another case screen and repeat the cycle.

I will use ASK-Tom (Ferguson et al., 1992) as an example to illustrate the approach. ASK-Tom teaches novice bank consultants in Anderson Consulting about trust bank consulting. When ASK-Tom is started, it displays the big picture diagram of trust bank consulting (see Figure 3.2.), which presents several topic areas. Clicking on the nodes or links in this big picture diagram causes the screen to display either a more specific big-picture diagram, describing, for example, the temporal layout of a typical consulting engagement at a trust bank (Figure 3.3.), or else a screen showing a set of themes and stories that they organize (Figure 3.4.). Big-picture diagram screens always ultimately lead to a theme screen, like the one shown in Figure 3.4. When the users reach the theme screen, they will find, under each theme, several listings representing individual stories that correspond to various aspects of the theme. Once a choice is made, the system presents the story screen of the story chosen (see Figure 3.5.). The clip named in the center of the screen is a link to the video clip of the main story. The questions linked to the main story are questions that the users might ask in a conversation with the expert following their previous conversation. These questions are predicted by the CBR system using a conversation model. Choosing one question linked to the current story brings the user to another story screen (Figure 3.6), and the cycle repeats itself. The overall the structure of an ASK system can be illustrated in a diagram of ASK-Tom's structure, as shown in Figure 3.7.

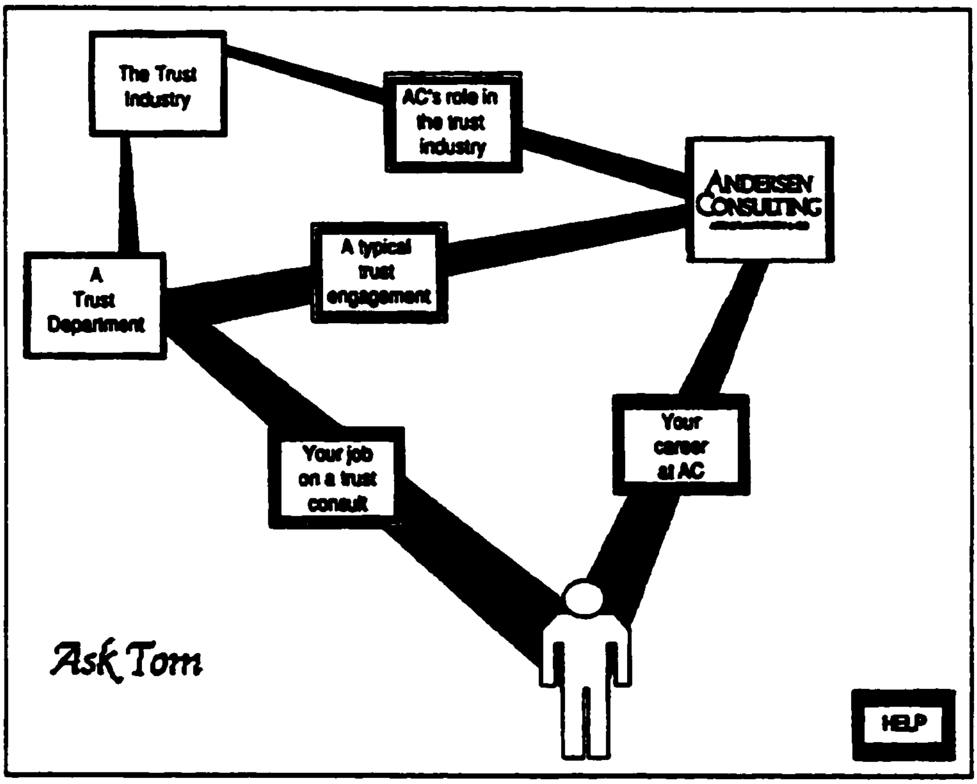

Figure 3.2. The big picture diagram displayed on the first screen of ASK-Tom (Ferguson et al., 1992)

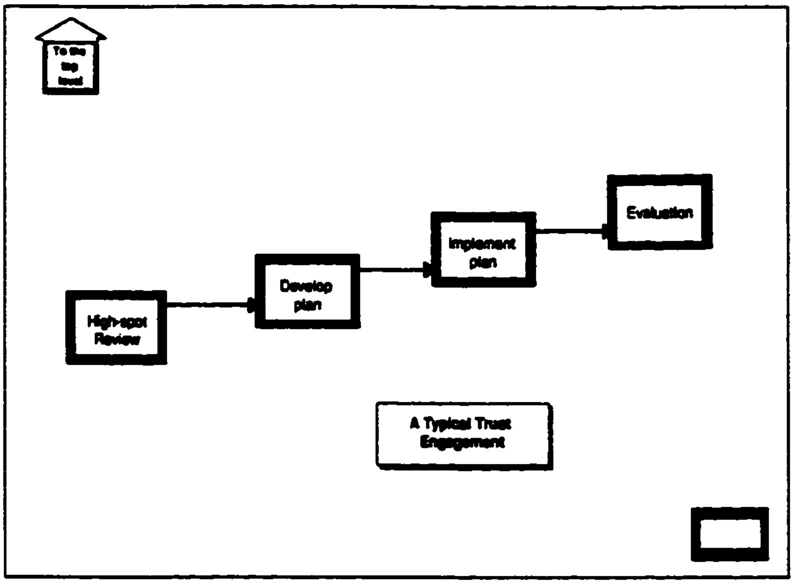

Figure 3.3. A sub-level big picture diagram in ASK-Tom reached from the screen in Figure 3.2. (Ferguson et al., 1992)

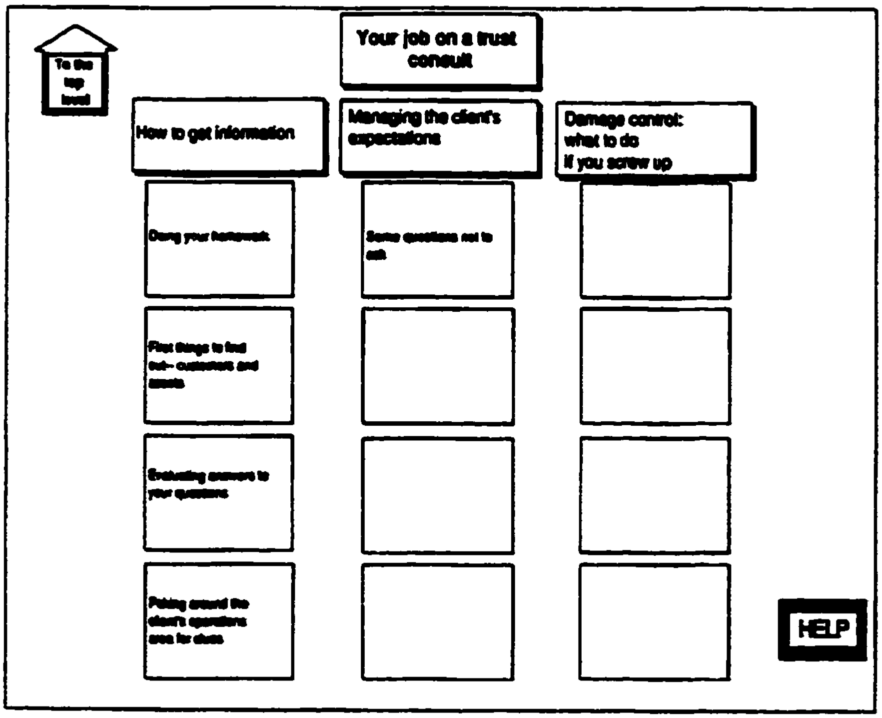

Figure 3.4. A theme screen in ASK-Tom reached from the screen in Figure 3.2. (Ferguson et al., 1992)

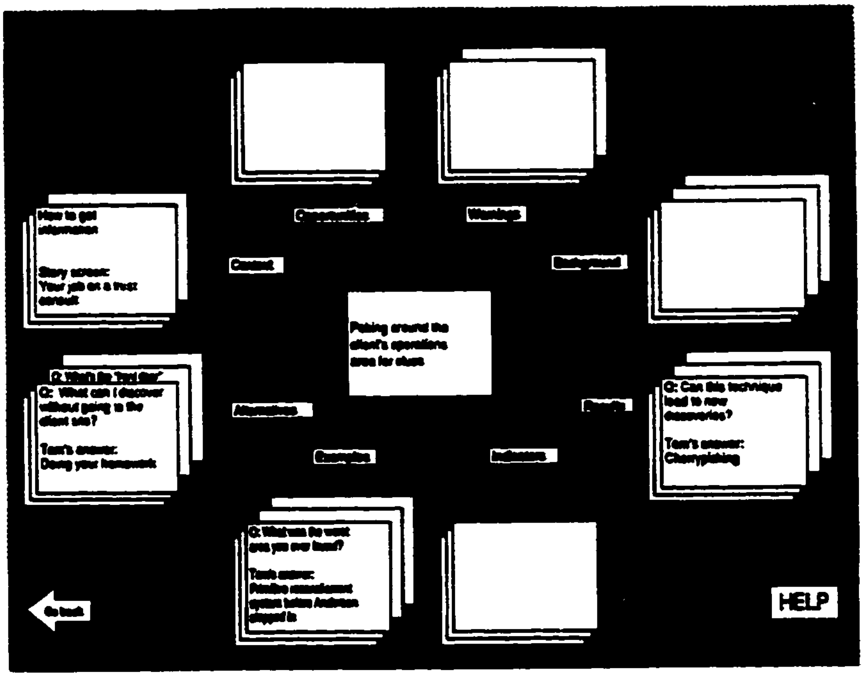

Figure 3.5. A story screen in ASK-Tom reached from the screen in Figure 3.3. (Ferguson et al., 1992)

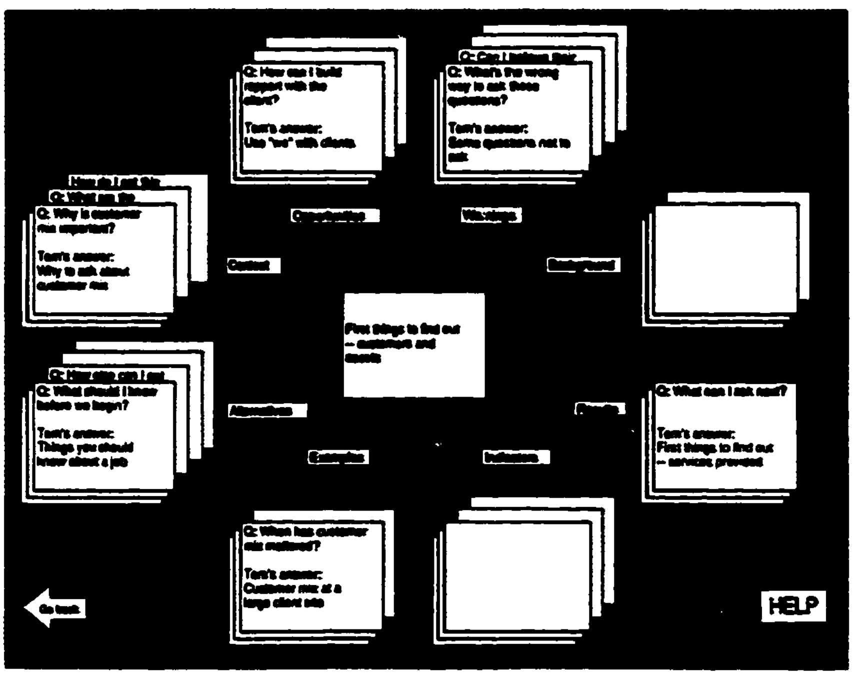

Figure 3.6. A story screen in ASK-Tom reached from the screen in Figure 3.4. (Ferguson et al., 1992)

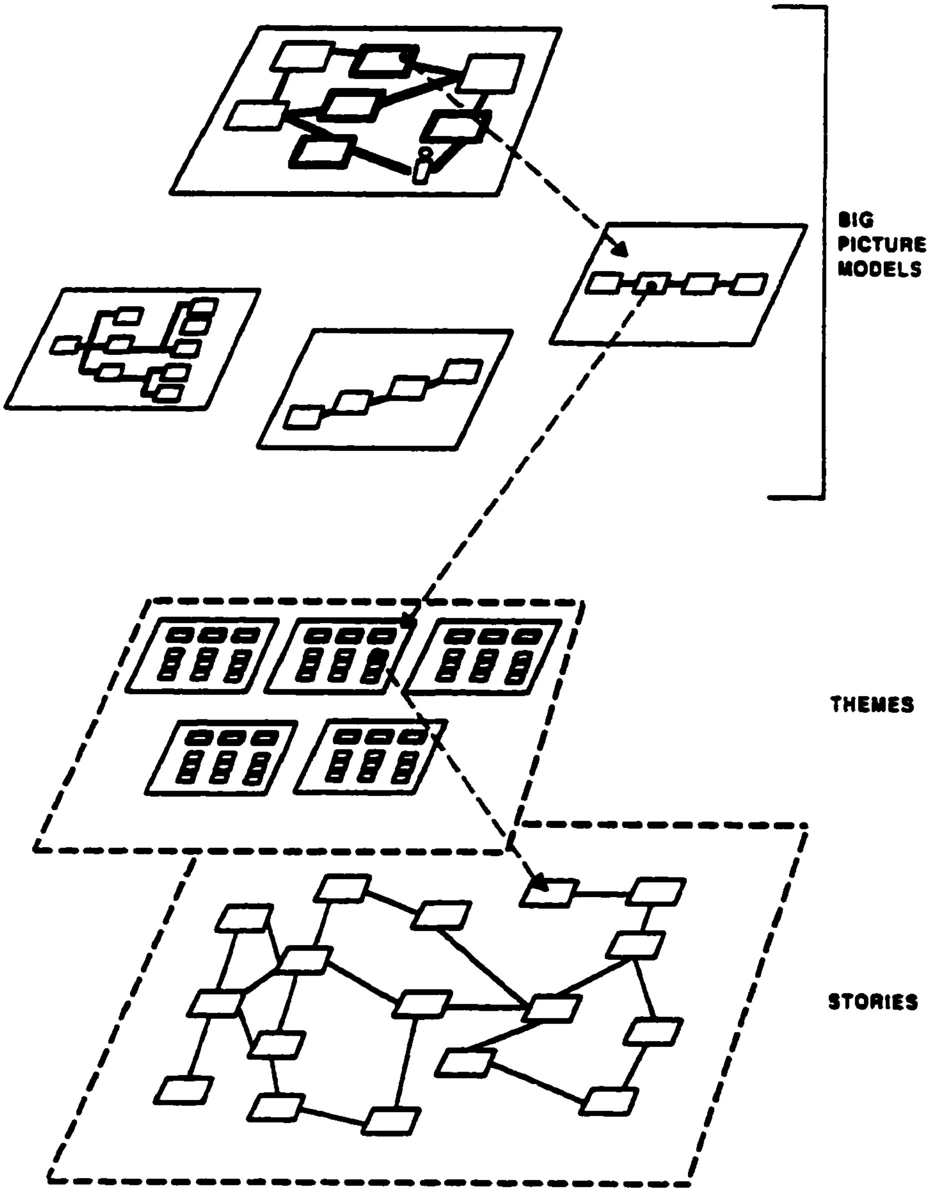

Figure 3.7. An overview of the ASK-Tom system (Ferguson et al., 1992)

The tree of all big-picture models in the system forms a conceptual map of the domain, organized around its most important agents, relationships, and processes. These big-picture models not only mediate the users' choices of areas of interest, but also help the learners understand the structure of the domain, and prompt them to see individual cases as illustrations of general principles. By using case-based reasoning algorithms, these case-based advisory systems are able to provide users with a coherent model of the subject matter. This coherent model, in turn, enables the users to assimilate the answers to their questions in a way that they can then use those answers to solve problems.

It should also be noted here that the ASK systems use a story-telling approach to instruction implied by the Dynamic Memory cognitive model. The ASK systems are designed with the assumptions that expertise can be represented as a large, diverse bank of cases organized by a knowledge structure similar to the structure of the subject domain, and that novices could learn to become experts in a certain domain by becoming familiar with the expert's case library.

The ASK system as described above is an example of the case-based advisory systems. In the next section, I will introduce another type of instructional CBR system -- the case-based knowledge-sharing systems.

3.1.3.2. Case-Based Knowledge-Sharing Systems

Case-based knowledge sharing systems are case-based advisory systems extended to both augment users' memory and be augmented by users' memory. Users' experiences of reasoning with the support of case-based knowledge sharing systems are selectively collected to be recorded as new cases for the systems' case libraries. Such CBR systems are usually used to serve as corporate memory. A case-based knowledge-sharing system starts with a representative case library, and is constantly augmented by new cases to update and perfect its case library. The basic idea is to gradually build up a system that could act as a large-scale case-based reasoner which consists of the case-based knowledge-sharing system itself and all users of the system. This large-scale case-based reasoner would solve problems by 1) assessing the problem situation on the users' side using the case library of the system; 2) retrieving similar cases from the case library either by the system automatically or through special requests from users; 3) interpreting the current case using past experiences and adapting available cases to solve new problems, usually done by the users with the support of the system; and 4) evaluating the solution and recording useful lessons learnt as new cases, which is done by the users but recorded into the system. The valuable experiences of all reasoners who use the system would be incorporated into the large case-based reasoner's memory. In turn, this "memory of the community" would use the collective experiences and expertise of the system and the entire user community to support the reasoning of each reasoner.

In addition to all benefits offered by case-based advisory systems, a case-based knowledge-sharing system also offers a forum for building and sharing the wisdom and insights derived from diverse sources. They encourage users to contribute their expertise through cases to a community of users within an organization, thereby enabling best practices of the community to be dissemniated quickly. Since contributions from all users can not only serve as a source of information, but also serve as a source of inspiration and criticism, the collective experiences of members in the community can generate ideas that no individual would have developed alone, which leads to higher quality reasoning and more learning gains. In time, this will also result in a higher-quality case library in the case-based knowledge-sharing system.

Another feature that is often included in case-based knowledge-sharing systems, but not case-based advisory systems, is the collaboration tools. The collaborations tools allow users to discuss certain cases or reasoning tasks, to annotate cases in the system, and to provide other forms of support to one another complimentary to the kinds of support the system provides. The communications which carry these "other forms of support" are sometimes also recorded in the knowledge-sharing system for later reference.

In the following section, I will analyze the major educational applications of CBR, and discuss the possible shifts and variations of their design parameters.

3.2. Analysis

As discussed in the last chapter, there are several versions of CBR. The CBR educational applications presented use different versions to serve as their conceptual framework. How would the design of these applications shift with the variations of CBR models? In this section, I will analyze the design of these CBR applications and discuss what are the possible ways that the design of these applications would change, and especially what possible improvements to these applications could other CBR models suggest.

3.2.1. Analysis of Goal-Based Scenario

The goal-based scenario framework is built upon Schank's moderated Dynamic Memory CBR cognitive model. This version of CBR suggests that learning is the acquisition of cases, skills, strategies, and conceptual knowledge. It implies an approach to learning which emphasizes learning by doing, learning from failure, and learning from stories. The design parameters of the GBS approach have been introduced in the overview section. In this analysis section, I will focus on the design parameters that are derived specifically from the Dynamic Memory CBR cognitive model rather than those that are derived from the basic CBR model. The presentation of each design parameter or group of design parameters that are based on a certain aspect of the Dynamic Memory CBR model will be followed by a discussion of how would the design parameter(s) shift if other CBR cognitive models were used as the underlying conceptual framework. The analysis of each design parameter or group of design parameters is presented under a separate sub-heading.

3.2.1.1. GBS's Top-Down Approach to Design

First, the moderated Dynamic Memory CBR model implies that a learning environment should revolve around the target knowledge and skills that it aims to teach by helping learners accumulate the kind of cases that can lead to the acquisition of that knowledge and generalization of those skills. That is, the design of a learning environment should take a top-down approach, starting with the higher-level knowledge (skills and strategies) to focus on, then going down to the bottom level to choose specific cases that would facilitate the generalization of the higher-level knowledge, and finally incorporating the conceptual knowledge to be taught into those cases. The cases chosen should be ones that are directly linked to at least one of the target skills, and the set of cases should be diverse in context and include both success and failure cases.

Correspondingly, in the design of GBS, the structure (mission structure) and content (scenario operations, mission, mission focus, cover story) of the learning environment is determined by the target knowledge and skills. Experiences that do not directly contribute to the generalization of target skills are minimized (the *target skill density* design criteria and *peripheral support* design criteria, see page 64). Experiences that directly contribute to the abstraction of target skills are not only maximized, but also designed to be diverse in context, and to include both experiences of success and experiences of failure (the *frequent practice opportunities* design criteria, see page 64, and the *realism/richness* design criteria, see page 63). Strategies and conceptual knowledge are presented either as part of a scenario, or as part of the experts' stories which are presented to learners when they experience expectation failures. Frequent opportunities are provided for learners to practice the strategies they learnt and reuse the conceptual knowledge they acquired.

The other CBR cognitive models, i.e., Kolodner's knowledge-poor CBR cognitive model, the Category and Exemplar CBR cognitive model, and the integrated CBR cognitive models, would suggest a slightly different approach. While the Dynamic Memory cognitive model focuses on generalization based on the accumulation of cases, the other versions of CBR cognitive models do not propose that generalizations from cases are more important than concrete cases themselves in a reasoning system. In Kolodner's CBR cognitive model, for example, generalizations are important mainly because they allow efficient retrieval of cases. But when it comes to reasoning, concrete cases are always preferred over generalized information. Therefore, according to her CBR model, helping learners acquire the right kind of experiences (a representative and reliable set of cases), interpret them the right way, and retain the important parts of those experiences, and helping learners to learn how to reason from cases effectively, should be the main objective of a learning environment. Supporting the generalization of skills and strategies, while also considered important in Kolodner's CBR cognitive model, is not suggested to be the ultimate goal of a learning environment.

In addition, Kolodner's CBR cognitive model, the case of the Category and Exemplar model, and many of the integrated CBR models, do not consider skills and strategies as part of the CBR knowledge structure that has to be generalized from cases. These systems propose that skills and strategies might reside in systems separate from the CBR system but closely matched to information in the CBR system. As cases and those forms of knowledge may not reside in the same system, there is no need for a strictly "top-down" approach to the design of a learning environment. According to these models, the generalization process does not have to be central in learning because abstract knowledge does not have to be personally generalized by the learners. For example, learners could acquire general knowledge, such as a rule like Newton's First Law, by generating explanations to link abstract knowledge and examples to illustrate that piece of abstract knowledge, rather than accumulating a number of cases so as to be able to generate that rule. In fact, the Category and Exemplar model, as well as several integrated CBR models, imply that the learning of a certain domain could best be achieved by learning domain knowledge directly, acquiring cases either by doing or from examples, and generating explanations between domain knowledge and specific cases. I will discuss this point in more detail in the following section.

3.2.1.2. Learning by Doing without Prior Acquisition of General Domain Knowledge

As mentioned earlier, according to the Dynamic Memory CBR model, learning is a bottom-up process. That is, the accumulation of cases is considered the basis of all subsequent types of learning. Therefore, according to Schank (1995), learning by doing does not require prior learning of "background knowledge", and should happen before any other types of learning. Therefore, general domain knowledge, strategies and skills should not be introduced before learners start to learn by doing.

The GBS framework uses exactly this approach. Learners engage in a mission immediately after they start using a GBS; no other forms of knowledge are introduced prior to the accumulation of cases through learning by doing.

This approach is contrary to what the Category and Exemplar model proposes. According to the Category and Exemplar model, general domain knowledge not only helps learners to interpret their experiences more efficiently and effectively, but also makes their experiences more useful because the range of coverage of cases is determined by the available domain knowledge. Therefore, presenting some domain knowledge to learners before they start to learn by doing is a recommended way to structure instruction. Studies conducted on a computational model of Kolodner's CBR model (CELIA) also suggest that acquiring some background knowledge before learning by doing can help learners make the most of the cases they acquire (Redmond, 1992). As mentioned earlier, the other versions of CBR models suggest that learning could be achieved by a combination of direct learning (presentation of skills, strategies and conceptual knowledge), learning from examples, learning by doing, learning from explanations, learning through reflection, and so on.

If GBS were based on these alternative CBR cognitive models, some presentation of target knowledge and skills might be added in the beginning of a GBS. For example, there could be a "modeling" session before the mission starts, in which an expert models the use of the target skills and strategies, and presents a minimal amount of conceptual knowledge to learners as background information.

3.2.1.3. Focus on Lower Levels of the Knowledge Structure

Although the moderated Dynamic Memory CBR model is a unified model of memory, it focuses on the lower levels of the knowledge structure, such as cases, scripts (skills) and MOPs. That is, it mainly addresses issues related to reasoning that is either directly based on cases, or based on a general knowledge structure that could be directly abstracted from cases. The moderated Dynamic Memory CBR model does not specifically discuss how exactly do we reason with highly abstracted knowledge such as

U-MOPs or U-Scenes proposed in the original Dynamic Memory cognitive model, or how the overall knowledge representation of a reasoner affects her reasoning given the same set of cases in the case library. Schank's focus on specific experiences and abstractions of those experiences at a lower level (less abstracted level) resulted in a GBS framework with few features to help learners structure their knowledge representation, link their experiences with general domain knowledge, or engage in abstract thinking. For example, the GBS framework does not include features to present domain knowledge representation to learners or ask learners to compare their knowledge structure with that of an expert. Neither does GBS have features to encourage learners to explain their experiences with general principles or domain knowledge. Feedback in GBS is provided to learners in the form of experts' war stories, which are not clearly structured and focus on specific experiences rather than higher-level abstract knowledge.

The Category and Exemplar CBR model and many integrated CBR models which combine CBR and rule-based reasoning (RBR) or model-based reasoning (MBR) approach this issue differently. In these models, using a causal representation is thought to add significant explanatory and predictive capabilities to the reasoner. A coherent knowledge model, and rich explanation links between case knowledge and abstract knowledge or domain knowledge are considered key in learning. Therefore, these models suggest that learners should be aware of the knowledge structure of a domain (when applicable), actively engage in explaining their experiences with abstract domain knowledge or by applying domain knowledge in their reasoning, and get feedback in a form that facilitates the linking between cases and abstract domain knowledge.

If GBS were to be built based on the Category and Exemplar model, or CBR models which integrates CBR with RBR or MBR, features such as an advanced organizer or concept map might be added; reflection tools and self-explanation tools might be incorporated; tasks which require complex abstract thinking might be presented to the learner, and work space as well as system feedback might be provided at the same time to facilitate abstract reasoning. In addition, the experts' stories might highlight abstract knowledge, and feedback that specifically features abstract domain knowledge or domain knowledge structure might also be included in the framework.

3.2.2. Analysis of Learning By Design

Learning By Design (LBD) has Kolodner's knowledge-poor CBR model as its underlying conceptual framework. Kolodner's CBR cognitive model suggests five important facilitators for learning: 1) having the kinds of experiences that afford learning what needs to be learned; 2) interpreting those experiences so as to recognize what can be learned from them, drawing connections between their parts so as to transform them into useful cases, and extracting lessons that might be applied elsewhere; 3) anticipating their usefulness so as to be able to develop indices for these cases that will allow their applicability to be recognized in the future; 4) experiencing failure of an individual's conceptions to work as expected, explaining those failures, and trying again (iteration); and 5) learning to use cases effectively to reason. These facilitators correspond to design parameters in the design challenge, reflection tools, and classroom rituals of the LBD framework, as have been discussed in the section "LBD and Kolodner's Knowledge-Poor CBR Model" (p.77). The following discussion focuses on analyzing LBD design parameters that are derived specifically from Kolodner's CBR model instead of from the basic CBR model. Possible shifts and variations of these parameters they would result if they were based on other CBR cognitive models will be discussed. The analysis of LBD design parameters suggested by each specific aspect of Kolodner's CBR model are presented under a separate sub-heading.

3.2.2.1. Focus on the acquisition of high-quality cases

First, Kolodner's CBR cognitive model focuses on reasoning directly based on cases and thus implies an instructional approach in which the acquisition of high-quality cases is key. The design of the LBD framework applies this notion by using design challenges, software tools and classroom rituals which help learners acquire rich, concrete cases. Design challenges provide learners a context in which they need to be constantly exploring and experimenting. Software tools and classroom rituals are designed in a way to prompt learners to record their experiences, articulate their experiences, reflect on their experiences and generate rich explanations. In addition, the reflection tools in the LBD framework help learners to structure their cases and remember the important aspects of them by asking learners to record their experiences in a structured way and by providing guidelines to help learners to realize on what aspects of their experiences should they focus. On the other hand, since Kolodner's CBR cognitive model emphasizes the acquisition of cases rather than the acquisition of general episodes (GEs), she did not specifically address the issue of designing cases tightly around target knowledge and skills so as to avoid tasks that do not directly contribute to the acquisition of certain generalized knowledge. For example, in LBD, learners may spend a large amount of time in the process of building the objects they designed before they can test them. Much of this building process may not be directly related to the target knowledge and skills, but the LBD framework encourages learners to spend time exploring and experimenting with it. The LBD framework does not incorporate features to minimize this kind of task so as to maximize tasks that directly contribute to the acquisition of target knowledge and skills.

This approach is very different from the approach suggested by Schank's Dynamic Memory cognitive model. As has been discussed earlier with the analysis of the GBS framework, the Dynamic Memory cognitive model implies that learners' time should always be spent on tasks that will help them generalize target knowledge and skills. Peripheral support, pedagogical support, and target skill density are some of the design criteria or elements of that framework.

If the LBD framework were based on Schank's Dynamic Memory cognitive model, learning by doing activities that do not directly lead to the acquisition of target knowledge and skills would be limited. Peripheral support might be provided to relieve learners of operations that are not central to the pedagogical goals of the LBD curriculum unit. Reflection tools might include features to help students reduce the time spent on writing or typing. Classroom rituals might be designed in a way which allow learners to spend more time on articulating and explaining their own project and less on listening to others and providing feedback on other learners' projects.

3.2.2.2. Mapping of case knowledge to general domain knowledge

Kolodner's CBR cognitive model views general domain knowledge as knowledge which resides in memory systems other than CBR but is closely matched to information in the CBR system. Therefore, according to her CBR model, not only would generalization from cases help learners acquire general domain knowledge, but explanations to link cases with general domain knowledge will also facilitate this type of learning. The LBD framework implements this concept by incorporating a series of reflection tools and classroom rituals to promote explicit reflection, explanation, and articulation. These LBD components are designed in a way to encourage learners to use knowledge from their semantic memory (e.g., science concepts, rules, models) to interpret, explain and reflect upon knowledge in their CBR system.

This approach to learning is again quite different from that of the Dynamic Memory cognitive model, as the latter puts less emphasis on the matching of general domain knowledge with specific cases. If the Dynamic Memory cognitive model were used as the underlying conceptual framework of LBD, reflection tools and classroom rituals might be more centered on generalizing deep structure out of specific cases rather than linking generalized knowledge with cases. In addition, the reflection tools and classroom rituals would have a less important role in the LBD framework.

The Category and Exemplar CBR model also proposes that knowledge residing in cases and knowledge structures generalized from cases (categories) are mapped to general domain knowledge, and suggests that rich explanation promotes learning. But the Category and Exemplar model has a concept that is not included in Kolodner's model and not addressed in the LBD framework: range of coverage. If LBD were designed based on the Category and Exemplar model, learners would be encouraged to discuss topics such as: in what kind of situations would their cases be useful; when would the general domain knowledge they learnt be applicable; and, how to use their general domain knowledge to determine what new situations are similar to situations they have experienced before.

3.2.2.3. Learn to reason with cases effectively

One unique aspect addressed by Kolodner's CBR cognitive model is that people's ability to reason with cases varies. Certain ways of structuring cases and organizing the case library, and certain ways of using cases are suggested to enable some reasoners to reason more efficiently and effectively than others. Kolodner proposed that lessons learnt from AI CBR research on how to build effective CBR cognitive models can be applied in education to teach people how to do case-based reasoning better. For example, some people are biased in their reasoning because they assume an answer from a previous case is right without justifying it with regard to the new case. Helping these people learn how to justify case-based suggestions and how to make justification or evaluation a part of their intellectual habit for case-based reasoning tasks will enable them to make more thoughtful decisions in the future. In the LBD framework, guidelines are provided in reflection tools to help learners focus on the important aspects of their experiences; distinguish core content, skills, rules and models from less important parts of their experiences; and store the important aspects of their experiences in a structured manner. Guidelines for helping learners select the most useful indices are included as part of the reflection tools and classroom rituals. Learners are acquainted with every step of the case-based reasoning cycle, as well as how to perform each step of the process. In addition, activities are incorporated to support learners construct a memory system with case-based knowledge tightly interlinked with semantic memory units. These design features help learners to be aware of how to do case-based reasoning, and through practice, help learners to form good habits for reasoning with cases.

The other CBR models are not as concerned with this issue, and do not propose specific features to help learners in this aspect.

3.2.3. Analysis of Case-Based Advisory Systems and Knowledge-Sharing Systems

Case-based advisory systems and knowledge-sharing systems are different from GBS and LBD, not only because they are CBR systems, but also because the majority of them are designed to be job aids rather than educational systems. Most of them are built with engineering and economic concerns, and do not follow any CBR cognitive model strictly. Factors such as the nature of the subject matter, the target audience, and the resources available, often determine what the framework of a specific case-based advisory system or case-based knowledge-sharing system would be.

Therefore, in this section, I will not discuss how the design parameters of these systems might change, as there are no standardized system frameworks. Instead, I will present a few features that various CBR cognitive models might suggest the case-based advisory systems and knowledge-sharing systems to include. Some of these features have been discussed earlier in the analysis of GBS and LBD.

3.2.3.1. Present cases as well as overall knowledge representation

As mentioned in the previous discussion, Kolodner's CBR model, the Category and Exemplar model, and some integrated CBR models suggest that there are semantic networks of general domain knowledge in people's memory. These CBR models acknowledge the fact that overall knowledge representation of a person's semantic networks could affect her reasoning capacity. Therefore, these CBR models might suggest the case-based advisory systems and knowledge-sharing systems should make the overall knowledge representation of the subject domain available to the users. If the CBR systems themselves are structured according to the structure of the subject domain, for example, it might be beneficial to make the structure of the CBR system and indices of cases available to users. In addition, tables, figures, concept maps, and other means of helping users understand the field better would also be desirable to be included in the systems.

3.2.3.2. Make explicit important features, deep structure, and rules, models or strategies used

Kolodner's CBR cognitive model suggests that making important features, deep structure, and rules, models or strategies explicit to users helps them to focus on the important factors and make more thoughtful decisions. Her model implies that case-based advisory systems should present cases in such a manner to their users, and in the case of case-based knowledge-sharing systems, in addition to presenting cases in such a way, those systems should also have features to help users input their experiences into the system in a similar structured manner.

Schank's moderated Dynamic Memory CBR model also implies that presenting cases in such a structured way would facilitate reasoning because it helps users to create a more effective indexing scheme. In addition, the Dynamic Memory CBR model suggests that it is desirable to present strategies in the context of cases, because a) strategies could only be acquired from cases, and b) after the users acquire strategies from those cases, their overall reasoning capability will be enhanced, and they would be better prepared to reason effectively and efficiently.

3.2.3.3. Explain cases with generalized domain knowledge

The Category and Exemplar model and several integrated CBR models emphasize rich explanatory links between case knowledge and generalized domain knowledge. It proposes that cases, when explained with generalized domain knowledge, are easier to retrieve, easier to adapt, more predictive, and more memorable. Therefore, it suggests that case-based advisory systems and knowledge-sharing systems should include explanations which refer to generalized domain knowledge in their cases, and case-based knowledge-sharing systems, in particular, should include features or guidelines to encourage users to explain their experiences with generalized domain knowledge whenever possible.

3.2.3.4. Avoid reasoning bias by presenting exceptions

If the case-based advisory systems and knowledge-sharing systems use the above-mentioned approach (explain cases with generalized domain knowledge), the Dynamic Memory cognitive model would suggest that exceptions to the generalized knowledge should also be made available to users. The Category and Exemplar model also suggests that information should be provided to users to help them be aware of similar situations in which the generalized domain knowledge would apply.

3.2.3.5. Support effective CBR

Finally, as discussed in the analysis of the LBD framework, Kolodner's CBR model suggests that support should be provided to help users employ the cases effectively. Support in the form of guidelines, hints, procedures to follow, reflection tools, and so on could be incorporated into the case-based advisory systems and knowledge-sharing systems.

3.2.4. Summary of Analysis

To summarize the analysis of goal-based scenarios, learning by design, case-based advisory systems and knowledge-sharing systems, possible shifts of design parameters in the major CBR educational applications are summarized in table 3.2 through 3.4. In Table 3.2. and Table 3.3., original design parameters of the CBR educational applications (i.e., GBS and LBD) are summarized and presented in the first column. To the right of each group of these original design parameters, possible variations corresponding to these parameters are briefly described under the alternative CBR cognitive models which suggest these modifications. Therefore, within the column of each CBR cognitive model, we can find that model's unique approach to the design of GBS or LBD. In Table 3.4, design parameters of case-based advisory systems and knowledge-sharing systems suggested by various CBR cognitive models are reviewed in brief under each of the models. These three tables could be used as a set of guidelines for designing CBR educational applications.

Table. 3.2. Possible variations of design parameters in GBS

Original GBS design parameters based on the moderated Dynamic Memory cognitive model	Possible variations of GBS design parameters suggested by other CBR cognitive models		
	Kolodner's CBR model	Category and Exemplar model	Other integrated approaches
The top-down approach to designing learning environments	Focus on the acquisition of high-quality cases rather than generalization of target knowledge and skills	Target skills and knowledge does not have to be generalized from the CBR system. They could be learnt in an integrated way.	
Encouraging learning by doing without prior acquisition of general domain knowledge	Help learners acquire some background knowledge before they start to learn by doing.		
Focus on lower levels of the knowledge structure	Use RBR and MBR to provide feedback or explain expert's stories when applicable.	Present overall knowledge representation to learners. Provide or facilitate the generation of rich explanations linking cases with higher-level abstract knowledge.	

Table. 3.3. Possible variations of design parameters in LBD

Original LBD design parameters based on Kolodner's knowledge-poor CBR cognitive model	Possible variations of GBS design parameters suggested by other CBR cognitive models		
	The Dynamic Memory CBR model	Category and Exemplar model	Integrated approaches
Focus on the acquisition of high-quality cases rather than generalization of target knowledge and skills	Top-down approach; minimize learners' time spent on tasks that do not directly lead to the generalization of target skills and knowledge.		
Emphasis on mapping of case knowledge to general domain knowledge	Emphasis on generalization instead of mapping	Enhance this approach by adding features to help learners reflect on the *range of coverage* of their cases	
Support for learning to reason with cases effectively.	[other CBR cognitive models do not address this issue]		

Table. 3.4. Design parameters of case-based advisory systems and knowledge-sharing systems suggested by various CBR cognitive models

Design Parameters suggested by: The Dynamic Memory cognitive model	Kolodner's CBR cognitive model	Category and Exemplar model	Integrated approaches
	Present cases as well as overall knowledge representation		
Present cases in a structured way so as to support indexing; present strategies in the context of cases.	Make explicit important features, deep structure, and rules, models, or strategies used		
		Present and facilitate the generation of rich explanatory links between case knowledge and generalized domain knowledge.	
If generalized knowledge is presented, help users be aware of exceptions.			
	Provide support to help users employ the cases effectively		

It should be noted here that these CBR approaches to building instructional environments may not be applicable to all target domains. Cases are only useful to learners if they can understand these cases enough to distinguish surface features from structural features. In domains in which a learner would need to use a lot of general knowledge in order to perform, a CBR learning-by-doing approach, such as GBS, may not be the best way to structure learning. For example, when medical students are learning to perform medical diagnosis, they need a large amount of background knowledge about the conditions, symptoms, underlying physiology, incidence for different populations, and so on. A GBS framework which suggest learners to learn by doing without acquiring background knowledge would not be appropriate in this situation. The LBD approach, on the other hand, is best suited for situations in which students in a community of learners have a lot of time to learn certain rules and concepts in domains where rules and models can be easily manipulated. When learners are learning under time constraints, when collaboration and getting feedback is difficult, or when they are learning subjects that can not be designed and tested, such as literature, it is difficult to implement the LBD approach. As for the case-based advisory systems and knowledge-sharing systems: it is only worth building these systems when we are trying to assist reasoning tasks that involve long lines or reasoning, or reasoning in ill-defined domains. Otherwise, a simple database might suffice. In addition, CBR approaches to learning are often not aimed at helping learners acquire factual knowledge or hone high-level abstract reasoning skills in well-defined domains. In situations in which we are trying to teach or provide information about simple facts, or trying to provide learners opportunities to practice higher-level abstract reasoning skills in well-defined domains, other instructional approaches might be more suitable.

Chapter 4

SUMMARY AND CONCLUSION

Case-based reasoning (CBR) has been an active area of research for the past two decades. It was initially proposed and implemented as a cognitive model by artificial intelligence researchers, and then applied as a model for building expert systems. Since the early 1990's, several popular educational applications and innovations have been developed based on lessons learnt from CBR research, and many educational theories have been linked to the CBR cognitive model. However, due to the lack of standardization in the CBR literature, the variations and shifts in CBR terminology and reasoning models have caused much confusion.

In response to this situation, in this thesis I have reviewed the CBR literature and identified major versions of CBR in the field, and trend shifts in the CBR research over time. In doing so I have proposed there are currently four versions of case-based reasoning: CBR in its typical sense in cognitive science literature, CBR in its general sense in cognitive science literature, CBR in its typical sense in artificial intelligence literature, and CBR in its general sense in artificial intelligence literature. These four versions are the result of a) two types of interest motivating CBR research, and b) two ways of using the terminology. The two different motivations for CBR research are: the desire to model human reasoning and learning in the cognitive science CBR community, and the desire to develop technology to make AI systems function more effectively in the artificial intelligence CBR community. In both types of CBR research, the term CBR has been used in two ways: there is CBR in its typical sense, and CBR as a generic term.

Recall that table 2.2. summarized these four versions and the trends in CBR research corresponding to each version.

Besides the differences across these versions of CBR, there are also variations within each version around issues such as case representations, knowledge structure, and where should knowledge be considered to reside. This thesis focused on the shifts and variations in the CBR cognitive model, and proposed a framework for clarifying and understanding these differences (see Table 2.2, pp. 49-50). This framework is developed by identifying major versions of CBR cognitive models, analyzing their shifts when applicable, and comparing and contrasting these different versions with one another. The major CBR cognitive models are: Schank's Dynamic Memory cognitive model (Schank, 1982), Kolodner's "knowledge-poor" CBR cognitive model (Kolodner, 1993), Bareiss and Porter's Category and Exemplar CBR cognitive model (Bareiss, 1989, Porter, 1990), and various integrated approaches (e.g., Aarts & Rousu, 1997; Plaza, 1993; Sporl, 1995). The variations that led to confusions about CBR cognitive models are summarized into five categories: case content and representation, organizational structure and knowledge representation in the CBR cognitive model; the role of general domain knowledge in the CBR model, processing and reasoning issues, and the scope of CBR. The framework for understanding major variations of CBR cognitive models corresponds to the variations identified, and presents the approach of each popular version of the CBR cognitive model along each of the five dimensions of variation.

Finally, major CBR educational applications -- Goal-Based Scenario (GBS), Learning By Design (LBD), and case-based advisory systems and knowledge-sharing systems -- were introduced and analyzed based on their ties to the CBR cognitive models they derive from, and how their design parameters would change were they based on other cognitive models. The goal-based scenario framework is based on Schank's moderated Dynamic Memory cognitive model. Its design parameters that are based specifically on this CBR model are: a) the top-down approach to designing learning environments; b) encouraging learning by doing without prior acquisition of general domain knowledge; and c) the focus on lower levels of the knowledge structure rather than the overall or higher-level knowledge structure. These parameters are challenged by alternative CBR cognitive models. Possible variations are shown in table 3.2.

Learning by design is based on Kolodner's knowledge-poor CBR model. LBD design parameters that are suggested by unique aspects of this CBR model include: a) its focus on the acquisition of high-quality cases rather than generalization of target knowledge and skills; b) emphasis on mapping of case knowledge to general domain knowledge, and; c) support for learning to reason with cases effectively. Possible variations of these design parameters are summarized in table 3.3.

Case-based advisory systems and knowledge-sharing systems are usually not strictly based on any particular CBR cognitive model. But there are a few features that various CBR cognitive models might suggest these systems should include (see table 3.4.).

By clarifying CBR terminology, identifying major categories and trends in CBR research, and proposing a framework for understanding the variations of CBR and CBR cognitive models, this thesis provides researchers in CBR and CBR-related fields a means to better understand literature on or related to CBR, as well as a basis for discussing CBR and related issues in the future. Researchers could use the framework outlined in this thesis to determine which version of CBR a certain piece of research refers to, and make judgments on the discussion or research findings on that basis. They could also clarify which version of CBR are they using in their research, so that potential confusion and misunderstanding could be avoided.

This thesis also suggests areas in which further research and discussions are needed in order to standarize the terminologies and clear up confusions in the field. Efforts to test the different hypotheses in major CBR cognitive models are desired, and further standarization of CBR in cognitive science is needed. These types of research will not only help us to discard false hypotheses and thereby reduce the variations in the field, but also suggest which approaches to designing CBR educational applications would be most appropriate.

Finally, the discussion of common design parameters in CBR educational applications and the possible shifts of those design parameters in this thesis could serve as guidelines for instructional designers. It provides them a fresh perspective of looking at goal-based scenarios, learning by design, case-based advisory systems, and case-based knowledge-sharing systems. With the aid of the analysis in this thesis, instructional designers could make more well-informed decisions about how to approach a certain CBR educational application based on from whence the design parameters of the framework for that application are derived, what are the alternative approaches and what are their sources, as well as when to use that particular application.

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