Abstract

Title of Dissertation: Case-based Planning with a High-Performance Parallel Memory

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Case-based planning (CBP) systems, like other case-based reasoning systems, can take advantage of previous planning experience by reusing stored cases (plans) in similar situations in the future. Advantages of CBP include speedup over planning from scratch and the ability to function with limited causal domain knowledge. "Traditional" CBP systems with the latter advantage typically cannot produce plans from scratch because they lack the more powerful adaptation mechanisms of generative planning systems. These "reuse-only" CBP systems rely on retrieving a plan from the casebase that is close to a solution plan. This requires large casebases with good coverage of the problem space and the ability to encode and match cases at fine levels of detail.

Many such CBP systems, however, have fallen short of these requirements. They support only small, pre-indexed casebases. Pre-indexing constrains retrieval, as does the use of less expressive feature-based case representation schemes. The encoding and matching of detailed structural relationships in cases is not possible in such systems. These systems often adapt a single plan to the target problem using methods that are ad hoc or heuristic.

CAPER is a novel, domain-independent, case-based planning system with improvements over traditional reuse-only CBP systems from its use of techniques that exploit a high-performance parallel memory of cases. CAPER takes a memory-intensive approach by making frequent use of memory during all phases of planning and by using large casebases, which can be automatically seeded. Because the parallel retrieval mechanisms scale to real-world sized casebases of thousands of plans, memory does not have to be pre-indexed and

thus retrieval is more flexible. Detailed queries can be used to match cases, which are stored using an expressive, graph-structured case representation scheme.

Plan adaptation in CAPER borrows techniques from generative planning, such as the use of plan validations, which capture dependencies in a plan, and plan composition. These techniques are incorporated into a reuse-only CBP framework for a more principled approach to adaptation than in many reuse-only CBP systems. CAPER can also use its flexible retrieval mechanisms and case representations to retrieve patch or substitute plans from memory.

Case-based Planning with a High-Performance Parallel Memory

by

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Chapter 1

Introduction

Artificial intelligence systems require much knowledge to understand the world and solve problems in it. This knowledge can be built into to an A.I. system by humans or learned by the system over the course of its operation. The former approach is useful when a large body of knowledge exists and can be encoded into a form that the A.I. system can use. The latter approach is useful when the available knowledge is impoverished, and thus the A.I. system must gather knowledge on its own. It will have to understand a new situation or solve a new problem in terms of its current knowledge. A new experience can be remembered as a *case*, an encoded description of the situation/problem and its interpretation/solution. When a similar situation is encountered in the future, the system can apply knowledge from its *casebase*, a persistent collection of cases. Reasoning using cases is called *case-based reasoning* (CBR) and has been investigated by A.I. researchers over the past fifteen years (Kolodner, 1993).

CBR is a kind of analogical reasoning. In *analogical reasoning*, knowledge from one problem or situation is applied to understand a problem or situation via an analogy. An *analogy* is a comparison between two *analogues* — two things, two models (e.g., an atom and a solar system), two events, (e.g., the Vietnam and Korean wars), or two problems (e.g., preparing a beef and broccoli stir-fry dish and a chicken and snow peas stir-fry dish). Often one analogue is a novel problem or situation that the reasoner is trying to solve or understand in terms of a more familiar problem (or situation) recalled by the reasoner. The novel problem/situation is termed the *target* analogue, and the familiar problem/situation is termed the *source* analogue. In CBR, the analogues are cases.

Cognitive scientists have long studied analogical reasoning in humans and have even constructed some computational models (e.g., (Holyoak and Thagard, 1995; Falkenhainer *et al.*, 1990; Falkenhainer *et al.*, 1990)). As will be discussed in Section 8.3.2, this work provides a framework for conceptualizing the CBR process. The technique of CBR itself was inspired by psychological studies of human memory (see Section 8.3.1). The synergy between cognitive science and CBR continues in the work described in this thesis, the CAPER system. Though CAPER is not a model of cognition, several aspects of its design were inspired by work in cognitive science, as will be discussed in Sections 4.6.5 and 9.1.3.

CBR systems have been built for many different tasks and domains including several successful commercial "expert" systems (Kolodner, 1993). It has been well-established that human experts reason using cases in a variety of domains such as law or medicine (e.g.,(Boshuizen and Schmidt, 1992)). These fields have huge repositories of knowledge in the form of cases, and new cases are interpreted in terms of old ones. A casebase can serve as a repository of expertise in an organization — a kind of institutional collective memory which does not fade or retire.[1] Novices can access this knowledge during training or when no expert is available. A person cannot possibly remember every case in a casebase of thousands of cases, particularly when there are no obvious similarities between the cases. Although they solve problems without human intervention, CBR systems can also complement the recall limitations of people by presenting relevant cases to support their decision making.

CBR systems are often easier to build than rule-based systems (Kolodner, 1993)[p. 94]. Human experts may be better able to articulate their expertise in terms of specific cases, rather than in terms of general rules. If a system is to explain its reasoning to a person, a list of cases used by the system may be more informative than a list of rules used or statistical calculations performed. Cases may also be used to complement rules in a system (e.g., (Rissland and Skalak, 1991; Kettler and Darden, 1993; Sanders, 1994)).

1.1 Planning

Many real-world problems involve planning of some kind. Planning problems range in scope from planning the day's errands to planning for military force deployment. Over the past thirty years, research in A.I. planning has focused on the development of general-purpose planning techniques applicable to *domains* such as manufacturing, transport logistics, robot navigation, etc. A *planning problem* consists of an initial world state and the set of goals to achieve. The purpose of planning is to generate a plan, a sequence of actions that achieves a set of goals when executed.[2]

A.I. planning systems have used many techniques (Allen *et al.*, 1990). This dissertation focuses on the technique of *case-based planning* (CBP), a kind of case-based reasoning first used in the CHEF system (Hammond, 1986)). A CBP solves a new *target* problem by retrieving a case — a previously solved problem and its plan — from the casebase and adapting the *source* plan to solve the target problem, possibly with the aid of feedback from plan execution. The newly generated plan is then added to the casebase for later reuse.

A.I. researchers have focused on *domain-independent* techniques, those designed to be applicable for multiple planning domains. A planning system embodying these techniques is configured for a particular domain by supplying it with *domain knowledge* in some encoded form. The assumption is that reconfiguration of the planner requires less effort than building

[1]The term "memory" will be used in this document to refer to either a knowledge base (KB) of a computer program or to human memory. It will *not* be used to mean physical computer memory (RAM, disk, etc.).

[2]This conception of planning as a sequence of actions that transforms an initial state into a goal state is the "classical" one. More recent research on reactive AI planning systems in dynamic environments has suggested alternate conceptions of planning.