The Challenge of Deep Models, Inference Structures, and Abstract Tasks

Abstract

The paper discusses methodological achievements which have been incorporated into second generation expert systems. The key ideas are (1) to incorporate more principled knowledge about the domain into a knowledge based system and to reason from these (first) principles, (2) to define the conceptual model explicitly, and (3) to do some abstraction. Abstraction is done on three levels: the factual knowledge level, the level of inference steps, and the task level. The challenges of these methods are discussed from the viewpoint of medical and technical applications.

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Introduction

The great rumor about expert systems started in the late 1970s. It was provoked by systems of great promise for medical diagnostic support and for interpretation, diagnosis and configuration in natural sciences areas and in technical domains. It resulted in a widespread application of expert system technology. The goal was to represent the skills of experienced domain experts in a knowledge based system (KBS) and make this knowledge available to less experienced users when solving daily problems. And the goal is still the same today.

Capturing the experience of experts focussed on his/her ability to find a quick solution to the problem. This resulted in building systems in a straightforward manner by representing associations between symptoms often seen and a diagnosis (e.g. for the diagnostic problem). Despite the success in several areas of application, a list of problems showed up:

While working well in the central area of expertise, the systems reach horrible conclusions on their knowledge boundaries. There is no graceful degradation of performance when coming to these boundaries, as we would expect from an expert. More seriously, the systems are not able to recognize their own boundaries.

Besides simple backward tracing of rule invocations there is no chance to provide meaningful and user-tailored explanations. This would require to explain the underlying principles how the problem at hand is solved.

Knowledge acquisition is the most pressing problem. In what is commonly called the Feigenbaum bottleneck: there is one knowledge engineer (the bottleneck) who filters all the expert's knowledge. The usual situation can be envisioned by having an expert telling the knowledge engineer some pieces of knowledge which come to his mind during a rather unstructured interview. The knowledge engineer has only a vague idea how these pieces of knowledge fit into the overall picture of the domain represented. As a result we are facing the problems of bad formalization, incorrect representation of knowledge, inconsistencies, and last but not least the open question of completeness.

A common cause of these problems is the lack of any understanding what the expert is really doing. The expert systems are representing surface knowledge only. The surface knowledge of the expert is transformed directly into a rule-based or frame-based form of representation. As a result, these systems do not have any idea about the underlying causes of the problem, the inherent structural relations and the tasks the expert is performing when solving the problem. They stay on the surface level.

Toward abstract knowledge structures, problem solv-

ing methods, task specifications

In the early 1980s several people stressed the importance of going away from the direct implementation of surface knowledge. Donald Michie pointed towards high-road programs incorporating structural information in the form of causal representations [Michie 1981]. Peter Hart identified several levels of representation, introducing the term deep knowledge. He put emphasis on the combination of surface and deep level systems in order to get fast performance and a good understanding of what is going on:

\In the near term, success of AI as viewed from the external world is most likely to come from the exploitation of surface systems, but long-term successes will come from continuing research on deep systems and from understanding the relation between deep and surface systems" [Hart 1982, p.15].

Allan Newell got one step further by introducing the knowledge level:

\Knowledge is to be characterized entirely functionally, in terms of what it does, not structurally, in terms of physical objects with particular properties and relations. This still leaves open the requirement for a physical structure for knowledge that can fill the functional role. In fact, that key role is never filled directly. Instead, it is filled only indirectly and approximately by symbol systems at the next lower level" [Newell 1982, p.105].

After nearly ten years of research we are able to see three methodological achievements:

1. An explicit representation of the application domain by incorporation of structural and functional knowledge into knowledge based systems. These systems are often called second generation expert systems or deep expert systems [Steels 1985].

2. A thorough description of the inference steps performed during problem solving. An abstract view of these inference steps gives us inference structures [Clancey 1985] and problem solving methods [McDermott 1988].

3. A specification of the tasks performed during problem solving. Whereas it is quite clear that the tasks differ from application to application, researchers try to find abstract task descriptions [Chandrasekaran 1986, 1987, 1988].

These three achievements are not to be seen as separating items, but rather as methods for knowledge-based systems operating on different levels. The integration of these levels can be seen in the KADS system [Hayward et al. 1987, Schreiber et al. 1988]. KADS is a system distinguishing knowledge at four different levels: (1) domain knowledge, describing concepts and elements of the domain and their interrelations; (2) the inference structure, describing inferences which can be made. The inference structure relates meta-classes. Meta-classes are an abstracted view of the domain knowledge by describing the role of

domain concepts; (3) the task knowledge specifies how the goals of the application can be achieved using the available inference steps; and (4) the strategic level, which should be able to control the execution of tasks by following specific strategies depending on the situation of the current case or problem. This strategic level is rather small when looking at existing KBS, but it reminds us of the possibility to follow different reasoning or problem-solving strategies. This will be definitely of importance in broad domains for future KBS.1

Leaving the strategic level aside for a moment, we get the componential framework of the layers: domain model, problem-solving methods, and task specification (see also [Steels 1990]). All three contribute essentially to the depth of a knowledge-based system by making explicit what are the knowledge structures of the domain, how do reasoning methods operate on these structures and what are the tasks performed during the problemsolving process.2

Key Ideas

Several key ideas which form the basis of these methodological developments are summarized in the following. References are with respect to applications in medical and in technical domains. This should enable us to contrast the biological field versus the technical field in the discussion.

Incorporating More Principled Knowledge About Domains

The first key idea is to incorporate more principled knowledge about the domain into the KBS. This can be done both by building a detailed model of the domain, and by following the principled ways of reasoning within the domain.

Representing more principled knowledge about the domain means (1) to bring a lot of structure into the model, often using the special form of taxonomies; and (2) to relate this structures. This relation can be done by linking the structures due to known causality. In this case we enter the area of causal modeling. The inference process follows the pathways of the causal net during problem solving. The causal net approach has its foundations in early medical (AIM-)systems (CASNET [Weiss et al. 1978], CADUCEUS [Pople 1982], ABEL [Patil et al. 1982]). It supports the trace of known pathophysiological relations. In addition, it is a convenient way to model the basic constituents of the medical domain: anatomy [Horn 1989], physiology, pathophysiology, etiology and nosology [Senyk et al. 1989], thus providing a basis for AIM-systems with the intent to cover broad areas of medical expertise.

1The `Oxford System of Medicine' - a decision support system designed for the use by General Practitioners - operates on the strategic level. It is able to modify medical strategies. Generic decision-making schemata are tailored to suit the needs of the tasks

to be performed during a consultation [Glowinski et al. 1989].
2A thorough discussion of factors being related to the depth of expert systems can be found in [Bylander 1987, Chandrasekaran et al. 1987, Klein and Finin 1987, Keravnou and Washbrook 1989, Steels 1988, Washbrook and Keravnou 1990].

A second form of relation is the functional relation. It describes the function or behavior of components by giving the function of its subcomponents. More and more detailed description levels can be reached using functional decomposition. This is of interest both for medical diagnosis and technical diagnosis [Steels 1989, Sticklen and Chandrasekaran 1989, Sticklen et al. 1989].

A third way of bringing more principled knowledge about the domain into the KBS is by describing the physiological structure of the system. This structure is used to simulate the behavior of the system. The simulation can be done either by using a model describing the physiological mechanisms in the form of qualitative relations (e.g. electrophysiology of the heart [Bratko et al. 1989, Hunter et al. 1989]) or by using a qualitative, constraint model like the QSIM approach [Kuipers 1986], which is mainly based on differential equations. Qualitative simulation is well suited to model flows (of liquids, pulses, information, etc.) both in the medical domain [Ironi et al. 1989] and the technical domain [Haag 1988]. The hard problem is how to make use of the simulation model for a diagnostic system. One possibility is to assume each component to be faulty which does not produce the expected behavior. The second is to explicitly define faults by introducing fault models. Model-based diagnosis currently concentrates on finding single or multiple device faults at hardware troubleshooting [Davis 1984, de Kleer and Williams 1987, Reiter 1987, de Kleer et al. 1990].

A detailed description of the structure and behavior of devices enables to use more principled methods of reasoning. That's what [Davis 1983] called reasoning from first principles. This works fine for technical domains as the correct or faulty behavior of devices is well defined. In the medical field `correct' behavior is often impossible to define exactly. The first principles approach is therefore limited to areas with well described physiological behavior, like renal physiology [Kunz 1983].

Defining the Conceptual Model Explicitly

The second key idea is the explicit definition of a conceptual model, which is clearly separated from the implementation. The conceptual model specifies the KBS at the knowledge level. The KADS approach provides interpretation models for creating a high-level functional specification of the problem solving process in the form of a conceptual model. The interpretation models are defined for many different inference methods. Similarly, Chandrasekaran's generic tasks are conceptual entities, which define a specific function at the knowledge level.

The conceptual model is an abstraction of the problem solving behavior of the domain experts. It is completely independant of the implementation of the KBS. In addition to the conceptual model, the KADS approach defines a design model, which is on the same level of abstraction as the conceptual model. It takes into account constraints from performance requirements, appearance of the system (e.g. user interfaces), and integration requirements with existing hardware and software systems. The design model is a specification of the KBS at a level, which [Steels 1990] calls the knowledge-use level. It should support direct implementation of the AI system.

Abstraction

Abstraction has a central role in designing KBS. Corresponding to the levels of a KBS previously mentioned, there are different forms of abstraction:

There is abstraction of factual knowledge. Knowledge is represented at different levels of abstraction supporting the inference steps to be performed at different levels of detail. An early example is the ABEL system [Patil 1981, Patil et al. 1982]. The importance of abstraction steps for diagnosis was also recognized early in the CA- DUCEUS system for internal medicine [Pople 1982] by introducing planning links associating manifestations with abstract involvement structures. The use of abstractions during diagnosis helps to focus the reasoning process. The resulting improvement of efficiency when applying abstractions on model based diagnosis has been shown by [Mozetic 1990]. But abstraction is not only of high importance to diagnosis. Planning has to look for ways to reuse solutions of one problem for a broad range of new problems. This can be achieved by building abstract plans [Tenenberg 1986].

From the viewpoint of reasoning steps, Pople's planning links form the basis of the inference step `match abstract solution'. That is the second step in the three step procedure: data abstraction { match abstract solution { refinement of solution. This procedure was found by [Clancey 1985] to be a fundamental abstract inference method when building the NEOMYCIN system. It is called `heuristic classification'. In the meantime several other abstract inference methods and problem solving classes have been identified (e.g. cover-and differentiate, propose-and-revise, hierarchical design). This is of high importance to knowledge acquisition. Using a repertoire of standard problem solving methods it is possible to instantiate the templates of these methods [Breuker et al. 1987, Marcus 1988], if the way an expert solves a problem matches one of the abstract problem solving methods. The templates guide the knowledge acquisition process by telling what to look for.

Comparable to the idea of abstract inference methods is the idea of abstract task structures: The generic task approach [Chandrasekaran 1986, 1987, 1988] has its focus on tasks like diagnosis, classification, or design. They are generic in the sense, that they will be instantiated to real tasks when confronted with a specific application. A generic task defines its function { the kind of problem it solves {, the knowledge structure and organization, and the control strategy to accomplish the function of the task. The focus is here on improvement of the knowledge acquisition process, too. Tools are provided for instantiating generic tasks: CSRL [Bylander et al. 1983], IDABLE [Sticklen 1983], DSPL [Brown and Chandrasekaran 1988]. If the application problem to solve is associated correctly with a generic task or a combination of tasks, the corresponding tool(s) will guide the knowledge acquisition process.

What can we expect?

Let us review the methodological achievements under the aspects of the limitations of first-generation expert systems:

Robustness vs. performance: The use of structural domain knowledge and the use of principled reasoning methods based on this fine-grained domain knowledge is the way to achieve robustness when solving uncommon problems. But deep models are very slow performing knowledge structures when applying principled ways of reasoning during problem solving. Their challenge is the ability to serve as a ground for automatic construction of surface models by use of machine learning techniques analyzing cases often seen. In combination we get a fast performing problem solver when confronted with common cases, which can fall back to its robust reasoning methods on complicated situations.

Explanability: The knowledge about the tasks and the inference steps the KBS is performing allows for explanations what is really going on. But not much focus has been put to explanation issues by the research community. In addition, explanations are expected to be user-tailored in the sense that they should take into account the level of experience of the user, the facts he/she already knows, and his/her intentions. This results in the need of an explicit user model. User modeling is a current area of AI research, but it will take some time until user models will guide the explanation (and reasoning) methods of expert systems in practice.

Knowledge acquisition support: The support tools using the specification of domain models, problem solving classes and abstract task descriptions give us a chance to build KBS in a more consistent and complete way by having a specification of the whole problem solving process. They provide a basis to keep the system expandable and maintainable during the whole lifecycle. But (unfortunately) the knowledge engineer is needed more than before. At moment direct knowledge transfer from the expert to the KBS is possible only for fixed domains with specific forms of representation (e.g., OPAL [Musen 1989]). Model-based knowledge acquisition [Shadbolt and Wielinga 1990] will hopefully guide the complex knowledge acquisition process in the form of an active and directive system in the future.

Of essential importance is the functional definition of the problem solver at a conceptual level. The specification of KBS at the knowledge level as instantiation of abstract knowledge structures may help us (1) to create understandable, expandable, and portable systems. We are not captured by the implementation details which often override the conceptual structures of the application. (2) It may give us new insights to domain models, problem solving classes and task structures, thus, enhancing our repertoire of methods.

Comparing the biological versus the technical domain we recognize the influence of medical applications not only to first-generation expert systems, but also to model-based architectures. The comparison of these two domains raises the question: Is there a unifying

perspective? I.e., are there completely domain-independent architectures? What speaks against is the fact that we have very different domains (medical vs. technical): analog systems with tolerances and correcting feed-back loops vs. digital systems with 0-1 behavior and errors effecting the whole system; partial models resulting from an incomplete understanding of biological processes vs.

complete technical models which are easy to describe formally; external (environmental) causes of errors vs. internal causes of errors (material problems); many different knowledge structures vs. complex reasoning processes operating on few knowledge types. This may be the reason why medical applications tend to focus on the extensive task of representing domain knowledge, whereas applications in the technical domains concentrate on finding efficient inference methods.

What speaks in favor of the unifying perspective is the fact that many medical applications formed the basis for more abstract methodologies, which have been used lateron in the technical domain: MYCIN ! EMYCIN, NEOMYCIN ! the inference method `heuristic classification', MDX/PATREC ! the generic task architecture. What seems to be identifyable are the same problem-solving methods and abstract domain concepts throughout very different domains. That makes abstract modeling a worthwhile thing to do. But at moment, we have only a very restricted view: (1) most systems have dealt with the problem of diagnosis, (2) the domains of application have been very restricted, and (3) we are at the early beginning of the usage of structure-based knowledge acquisition tools.

In conclusion, second-generation architectures are still in the research labs. They will have a hard time to find the way to daily practice. But they offer a lot of possibilities to overcome the limitations of currently widespread used KBS. We have a lot to expect and it seems very worthwhile to put efforts into these model-based architectures.

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