SEVEN HARD PROBLEMS IN SYMBOLIC BACKGROUND KNOWLEDGE ACQUISITION

Yves Kodratoff
CNRS & Université Paris Sud, LRI, Bldg 490, 91405 Orsay, France
George Mason University, AI Center, Fairfax, Virginia 22030, USA

ABSTRACT

By using a special characterization of machine learning algorithms, we first define what is background knowledge, as opposed to case-based, strategic, and explanatory types of knowledge. We oppose also the symbolic to the numeric view of background knowledge. We discuss then what we see as the seven most difficult topics in background knowledge acquisition, namely the detection of implicit implications, first order logic knowledge representation and acquiring "Skolem" functions, uncertain knowledge, weak knowledge, time management and fusion of several sources of knowledge, knowledge for vision, certification of knowledge.

1 INTRODUCTION

In this paper we shall speak of knowledge acquisition in a general sense, that encompasses both automatic knowledge acquisition as in machine learning (ML), and working by interviews with the field experts, as in the sub-field of artificial intelligence (AI) which is called knowledge acquisition. Actually, we shall focus our attention on a specific type of knowledge, called background knowledge (BK), be it acquired automatically or through interviews.

1.1 Background knowledge

We define BK as follows. The knowledge learned concerns a given domain containing a given set of objects. For instance, the domain of cars contains, say, some of the cars existing in a particular area. This domain is described by a set of descriptors. For instance, the make, color, shape, position, maximum_speed etc. of the set of cars under study. The values of the descriptors give the state in which a particular object is to be found. For instance, for the particular object "my_car", one has make = Peugeot, color = beige, etc. These descriptors show relationships among them, characterizing the particular field under study. These relationships are theorems that hold within this field. For instance, since there are no Peugeot cars of yellow color, one of these theorems can be written as \( \forall x [\text{peugeot}(x) \implies \neg \text{yellow}(x)] \). As an other example, in the area of data bases, one calls "integrity constraint" such a relation that must hold among the values of the descriptors. Besides, as an important feature not insisted upon enough in the literature, the descriptors show an inheritance structure, by which some of them are recognized as being of greater degree of generality than others. It may happen, but this is not compulsory, that this inheritance structure follows the structure of the descriptors. For instance, the descriptor color may be seen has being the parent of its values: beige, red etc. Each de-
scriptor is usually (in non-trivial cases) part of several of such inheritance structure. For instance, color can be also the parent of "primary color" and secondary color", or of "light color" and dark color" etc. We call BK the set of all descriptors, their values, and of the relations among the descriptors. The existence of such structures may seem innocuous enough at first sight. Actually, we have shown in (Kodratoff, 1990) that some classical paradoxes of induction, namely Hempel's "black crows" and Goodman's "grue emeralds" are nonexistent when the knowledge is so structured. Since we are here concerned with the acquisition of new knowledge which cannot but be an inductive process, it is important for us to define the knowledge we deal with in such a way that induction is not an absurd behavior.

Let us compare BK to other kinds of knowledge by using a characterization of ML algorithms that has been progressively set up in our research group, of which several approximations have already been published (Ganascia and Helft, 1988; Kodratoff, 1989; Bisson and Lauble, 1989; Bratko and Kodratoff, 1989; Morik, Rouveirol and Sims, 1989).

This characterization relies on the assumption that there exist four kinds of knowledge, BK, strategic knowledge, examples (or case-based knowledge), and strategic knowledge. To each of them are associated four kinds of processes that generate and/or control them. BK is generated by the so-called learning algorithms, strategic knowledge is generated by a control and test algorithm, cases are generated by an example generator, and causal knowledge is specific to the field expert. Each learning system can then be described by the flow of information between the four kinds of knowledge and the four kinds of processes. Figure one, below, shows the application of this scheme to the description of the functioning of KATE, a ML software developed by the company INTELLISOFT, which combines the power of information compression, as in Quinlan's ID3 (Quinlan, 1983), and the knowledge representation of object-oriented languages. We can now attempt making the definition of BK more precise by singling out its differences with the other kinds of knowledge. Cases are descriptions of instantiated examples illustrating concepts or behaviors of interest to the user, causal knowledge explains the relations between these concepts or behaviors, or attributes a causal label to some of the implications\(^1\). Therefore, these two kinds of knowledge are very strongly user dependent. This is why we tend to believe that knowledge acquisition from field experts should concentrate on these domains, as we have been doing with our system DISCIPLE (Kodratoff and Tecuci, 1987; Tecuci and Kodratoff, 1990). Strategic knowledge is any kind of knowledge that says how BK must be used in order to optimize a given criterion. In most cases, strategic knowledge consists of an ordering of operators (or of descriptors in the case of symbolic learning), telling which should be used when some given conditions are met. The automation of the acquisition of strategic knowledge is certainly the most common among existing systems. Let us cite here five examples.

ID3 (Quinlan, 1983) optimizes the compression of information in order to generate an ordering on the use of the descriptors. AQ (on the symbolic side, see Michalski (1983, 1984)) and cluster analysis algorithms (on the numeric side, see for instance (Benzecri et al., 1973)) optimize a distance measure in order to select clusters of "closely related" descriptors. Recently, a large emphasis has been given to neural networks that optimize the back-propagation of coefficients in order to attribute coefficients to sites in the network.

\(^1\) We are aware that logicians attribute a causal value to any implication. We disagree with this point of view, thus following the now classical Explanation-Based Learning view (Mitchell et al., 1986; DeJong and Mooney, 1986) that an implication has to link operational predicates in order to be explanatory.