Chapter III
Reducing a Class of Machine Learning Algorithms to Logical Commonsense Reasoning Operations

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ABSTRACT

The purpose of this chapter is to demonstrate the possibility of transforming a large class of machine-learning algorithms into commonsense reasoning processes based on using well-known deduction and induction logical rules. The concept of a good classification (diagnostic) test for a given set of positive examples lies in the basis of our approach to the machine-learning problems. The task of inferring all good diagnostic tests is formulated as searching the best approximations of a given classification (a partitioning) on a given set of examples. The lattice theory is used as a mathematical language for constructing good classification tests. The algorithms of good tests inference are decomposed into subtasks and operations that are in accordance with main human commonsense reasoning rules.

INTRODUCTION

The development of a full online computer model for integrating deductive and inductive reasoning is of great interest in machine learning. The main tendency of integration is to combine, into a whole system, some already well-known models of learning (inductive reasoning) and deductive reasoning. For instance, the idea of combining inductive learning from examples with prior knowledge and default reasoning has been advanced in Giraud-Carrier and Martinez (1994).

Obviously, this way leads to a lot of difficulties in knowledge representation because deductive reasoning tasks are often expressed in the classical first-order logic language (FOL), but machine-learning tasks use a variant of simbolic-valued attribute language (AVL).

The principe of "aggregating" different models of human thinking for constructing intelligent computer systems leads to dividing the whole process into two separate modes: learning and execution or deductive reasoning. This division is used, for example, in Zakrevskij (1982, 1987; Zakrevskij & Vasylkova, 1997). This approach is based on using finite spaces of Boolean or multivalued attributes for modeling natural subject areas. It combines inductive inference used for extracting knowledge from data with deductive inference (the type of theorem proving) for solving pattern recognition problems. The inductive inference is reduced to looking for empty (forbidden) intervals of Boolean space of attributes describing a given set of positive examples. The deductive inference relates to the situation when an object is contemplated with known values of some attributes and unknown values of some others, including a goal attribute. The possible values of the latter ones are to be calculated on the base of implicative regularities in the Boolean space of attributes. In Zakrevskij (2001), the results of prolonged research conducted in that direction at the Institute of Engineering Cybernetics in Minsk are given.

The fundamental unified model for combining inductive reasoning with deductive reasoning is developed in the framework of inductive logic programming (ILP). ILP is a discipline that investigates the inductive construction of first-order clausal theories from examples and background knowledge. ILP has the same goal as machine learning, namely, to develop tools and techniques to induce hypotheses from examples and to obtain new knowledge from experience; but, the traditional theoretical basis of ILP is in the framework of first-order predicate calculus.

Inductive inference in ILP is based on inverting deductive inference rules; for example, inverting resolution (rules of absorption, identification, intraconstruction, and interconstruction), inverting implication (inductive inference under θ-subsumption).

There is a distinction between concept learning and program synthesis. Concept learning and classification problems, in general, are inherently object oriented. It is difficult to interpret concepts as subsets of domain examples in the frameworks of ILP. One of the ways to overcome this difficulty has been realized in a transformation approach: an ILP task is transformed into an equivalent learning task in different representation formalism. This approach is realized in LINUS (Lavraĉ & Džeroski, 1994; Lavraĉ, Gamberger, & Jovanoski, 1999), which is an ILP learner-inducing hypotheses in the form of constrained deductive hierarchical database (DHDB) clauses. The main idea of LINUS is to transform the problem of learning relational DHDB descriptions into the attribute-value learning task. This is achieved by the so-called DHDB interface. The interface transforms the training examples from the DHDB form into the form of attribute-value tuples. Some well-known attribute-value learners can then be used to induce "if-then" rules. Finally, the induced rules are transformed back into the form of DHDB clauses. The LINUS uses already-known algorithms, for example, the decision tree induction system ASSISTANT, and two rule induction systems: an ancestor of AQ15 named NEWGEM, and CN2.

A simple form of predicate invention through first-order feature construction is proposed by Lavraĉ and Flash (2000). The constructed features are used then for propositional learning.

Another way for combining ILP with an attribute-value learner has been developed in Lisi and Malerba (2004). In this work, a novel ILP setting is proposed. This setting adopts AL-log as a knowledge representation language. It allows a unified treatment of both the relational

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