On Learning and Logic*

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A brief survey is given of learning theory in a logic framework, concluding with some topics for further research. The idea of learning using logic is traced back to Turing's 1951 radio address [15]. An early seminal result is that clauses have a least general generalization [18]. Another important concept is inverse resolution [16]. As the most common formalism is logic programs, the area is often referred to as inductive logic programming, with yearly ILP conferences since 1991.

Positive learnability results include an equivalence and membership query algorithm for CLASSIC, a version of description logic [4], a PAC algorithm obtained with the product homomorphism method [10], and an algorithm for first-order Horn formulas [12], which also uses queries but has an efficient implementation using examples only [2]. Each algorithm is based on some kind of product of structures. Positive and negative PAC-learnability results for ILP are surveyed in [3]. The notion of a certificate of exclusion from a concept class, characterizing query complexity [8, 9], could be of interest outside of learning theory as well. A certificate size upper bound for monadic second order logic over trees, implying a theoretically efficient, though not practical, learning algorithm, is given in [7].

The integration of both learning and reasoning, and of logical and probabilistic approaches is important for the development of intelligent systems [13, 5, 19]. Another related objective is to provide agents with commonsense reasoning capability. It stands to reason that such agents should be able to learn. A point of entry into this many-faceted problem area is belief revision, the study of how to revise a knowledge base if new information is received that may be inconsistent with what is known. Here one usually begins with postulates required of a rational revision process, such as the AGM postulates [1], aimed at formalizing the requirement of minimal change. There are representation results, constructions (akin to learning algorithms) and connections to probabilistic reasoning. It seems to be a challenging general question whether successful learning and rational revision can be combined. Sofar, this has been considered mostly in inductive inference [11, 14], but it is also discussed in machine learning ([20] and recently [17]). The efficient revision of theories with queries is studied in [6].

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