Logical settings for concept-learning*

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Abstract

Three different formalizations of concept-learning in logic (as well as some variants) are analyzed and related. It is shown that learning from interpretations reduces to learning from entailment, which in turn reduces to learning from satisfiability. The implications of this result for inductive logic programming and computational learning theory are then discussed, and guidelines for choosing a problem-setting are formulated.

Keywords: inductive logic programming, computational learning theory, concept-learning, logic.

1 Extended abstract

Various formalisations of concept-learning in logic have been proposed, e.g. learning from interpretations [Valiant, 1984; De Raedt and Džeroski, 1994; Angluin *et al.*, 1992], learning from entailment [Frazier and Pitt, 1993], and several inductive logic programming settings [Muggleton and De Raedt, 1994; De Raedt, 1996; Flach, 1992; Flach, 1995; Wrobel and Džeroski, 1995]. These formalizations differ in their representation of examples and the corresponding membership function or coverage notion, which determines whether an example is covered by a concept. At present, it is an open question as to what the relation among these different formalizations is. This question has been raised in different forms and in different contexts. Firstly, in computational learning theory, [Angluin, 1987; Frazier and Pitt, 1993; Angluin *et al.*, 1992] have wondered what the general relation is between learning from interpretations and learning from entailment, and which setting should be used for which type of learning problem. Secondly, in inductive logic programming it is unclear how systems such as FOIL [Quinlan, 1990] and Golem [Muggleton and Feng, 1990], which learn from entailment, relate to systems such as ICL [De Raedt and Van Laer, 1995] and Claudien [De Raedt and Dehaspe, 1997], which learn from interpretations. Furthermore, several variants have been proposed of these settings [Fensel *et al.*, 1995;

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Wrobel and Džeroski, 1995]. Thirdly, though computational learning theory and attribute-value learning techniques typically learn from interpretations, inductive logic programming has mainly addressed learning from entailment, which indicates that answers to the open question may also increase our understanding of the relation between inductive logic programming and attribute value learning. Fourthly, PAC-learning studies of inductive logic programming such as [Cohen and Page, 1995; De Raedt and Džeroski, 1994] have also left open the question as to whether learning from interpretations allows to PAC-learn classes of concepts that are not learnable from entailment.

The paper contributes answers to the open questions raised above. More specifically, it shows that learning from interpretations reduces to learning from entailment, which in turn reduces to learning from satisfiability. Learning from satisfiability is a more recent setting that generalizes the other settings. In this setting, examples and hypotheses are both full clausal theories.

The paper also shows that there exist propositional classes such as k-CNF that are PAC-learnable from interpretations, but that are not efficiently learnable from entailment or from satisfiability. The implications of this result for inductive logic programming, computational learning theory and attribute value learning are then analyzed. Furthermore, practical suggestions for choosing the right problem-setting are formulated.

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