Revising First-Order Logic Theories from Examples Through Stochastic Local Search

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Abstract. First-Order Theory Revision from Examples is the process of improving user-defined or automatically generated First-Order Logic (FOL) theories, given a set of examples. So far, the usefulness of Theory Revision systems has been limited by the cost of searching the huge search spaces they generate. This is a general difficulty when learning FOL theories but recent work showed that Stochastic Local Search (SLS) techniques may be effective, at least when learning FOL theories from scratch. Motivated by these results, we propose novel SLS based search strategies for First-Order Theory Revision from Examples. Experimental results show that introducing stochastic search significantly speeds up the runtime performance and improve accuracy.

1 Introduction

A variety of Inductive Logic Programming systems have been developed to automatically learn First-Order Logic (FOL) theories [11], [4], with good results on a number of important applications [13,12], [3]. Most such systems are designed to learn theories from scratch, given a set of examples and a fixed body of prior knowledge, the background knowledge. There has been relatively less work on the problem of repairing incorrect or incomplete theories. One example of theories that could be repaired or improved are theories that had been elicited from a domain expert, and thus may include useful information, but on the other hand may be incomplete, and/or rely on incorrect assumptions, or even be inconsistent. A second common example is the case where new examples are not well explained by the original theory. In such cases standard ILP systems would take one of the two following positions: they could either discard the initial theory, or consider it as part of background knowledge which can not be modified.

Since the task of knowledge acquisition is difficult and time-consuming, and since the original theory may contain valuable prior information, one would like to take advantage of the original theory as a start point to the learning process.
Ideally, this should accelerate learning time and result in more accurate theories. Theory refinement systems have been proposed towards this goal [15,7]. Such systems assume the initial theory is approximately correct. If so, then only some points in the theory prevent it from correctly modeling the dataset. The idea is therefore to search for such points in the theory and revise them instead of using an algorithm that learns a whole new theory from scratch. Note that these revision algorithms can be seen as a generalization of learning from scratch, as performed by most ILP systems. However, in contrast to most ILP systems, theory revision algorithms do not apply cover removal, where clauses that explain uncovered examples are searched sequentially. Instead, theory revision algorithms perform search in the space of whole theories. Arguably, cover removal frequently generate unnecessarily long hypothesis with too many clauses.

Theory revision systems operate by searching for revision points, that is, the points which explain faults in the theory, and then proposing revisions to such points, through applying at each point a number of matching revision operators. Therefore, theory revision can be seen as a search process, and very much as most ILP algorithms, revising logic programs may need to search a very large search space and therefore may incur big time and storage requirements. Search space grows quickly with the size of the knowledge base. We would also expect for search to be harder if the theory has more faults. Last, theory revision systems are particularly ambitious in that they tackle whole theories, which is known to be a hard problem [1].

One possible way of alleviating the huge requirements of searching in theory revision algorithms is to take advantage of clever search strategies such as stochastic local search (SLS). Such methods have been successfully applied to solve difficult combinatorial propositional problems [8,10,9] and recently they have also been applied to learn theories from scratch in ILP systems [5,14], substantially improving the efficiency of both domains. Motivated by these works and by the increased combinatorial explosion of searching in entire theories, we investigate the relevance of applying SLS in a theory revision algorithm. To do so, we develop algorithms that performs stochastic local search, when proposing revisions and when searching for a revision to be implemented. Such stochastic theory revision approach is compared to a theory revision algorithm that performs only greedy hill-climbing search and to a state-of-art ILP system.

The outline of the paper is as follows. Some preliminary knowledge concerning SLS and theory revision are reviewed in sections 2 and 3, respectively. The algorithms developed to revise FOL theories from examples through SLS are devised in section 4. Experimental results are presented in section 5, followed by conclusions and future work in section 6.

2 Stochastic Search

Stochastic Search algorithms are a family of search algorithms that strongly rely on randomized decisions while searching for solutions. Stochastic Local search