Learning Goal-Decomposition Rules using Exercises*

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Teaching problem-solving through exercises is a widely used pedagogic technique. A human teacher selects certain problems and orders them according to their level of difficulty to form a sequence of exercises. A student starts by solving simple problems first; then, attempts harder problems applying the knowledge gained from solving the earlier problems; and then still harder problems, and so on.

Machine learning of problem solving using exercises, apart from following this pedagogic tradition, offers a compromise between supervised speedup learning and unsupervised speedup learning. Supervised speedup learning, although more efficient than the latter, places the burden of providing the solutions to the training problems on the teacher—mostly a human. Unsupervised speedup learning, in contrast, expects the learner to solve the training problems, while unburdening the teacher. However, this is computationally hard for the learner for it lacks control knowledge and, hence, its only recourse is brute-force search. In exercises approach, teacher has the task of providing an exercise set—a sequence of problems ordered by difficulty. The learner has to solve the exercise problems using the bootstrapping method akin to the above-described method followed by a human student.

Previously, Natarajan (1989) used exercises approach in speedup learning for learning control rules represented in the form of tree patterns. In this work, we use exercises approach for learning first-order recursive goal-decomposition rules (d-rules). A d-rule is a 3-tuple $\langle g, c, sg \rangle$ that decomposes a goal g into a sequence of subgoals sg, provided the condition c holds.

The input to the system is a sequence of exercises ordered according to their difficulty levels. The difficulty levels correspond to goal-subgoal hierarchies except in the case of recursion—where the number of recursive calls is also used to set the difficulty level of a goal.

This approach follows two main steps: For each exercise, (1) exercise-solver solves the exercise by searching in the space of operators and previously learned d-rules, and outputs the solution (the plan) and the subgoals used; and (2) first-order inductive learner forms a hypothesis d-rule using the initial state as the d-rule

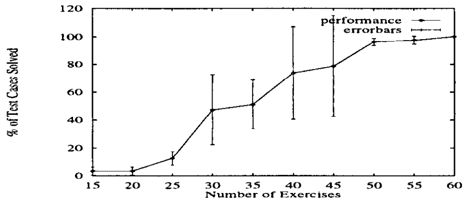

Figure 1: Performance of the learner in ATC

condition and the subgoals as the d-rule subgoals, and generalizes by finding the least general generalization (LGG) of this hypothesis with previously formed similar hypotheses. As a means to limit the size of LGGs, membership queries are needed. However, the exercises approach lends well to the use of testing in lieu of membership queries: to check whether a hypothesis d-rule is correct, the learner generates problems that saitisfy the condition of the hypothesis and tests to see whether the problems could be solved using the subgoals dictated by the hypothesis d-rule.

We have implemented this approach and successfully demonstrated it in two domains: (1) A variant of STRIPS world, with recursive d-rules; and (2) Kanfer-Ackerman air-traffic control (ATC) task. Figure 1 shows the amount of training vs. the performance on test cases, for the ATC task.

Exercises approach can be seen from reinforcement learning point of view as learning policies hierarchically: learn to solve simplest tasks first, and then using the learned policies for these, explore and learn to solve progressively harder tasks. In this way, the exploration is made more directed and efficient by structuring the tasks hierarchically.

For the full-paper version of this abstract, see (Reddy and Tadepalli 1997).

References

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