Experimentation-Driven Operator Learning

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Expert-provided operator descriptions are expensive, incomplete, and incorrect. Given the assumptions of noise-free information and an completely-observable state, OBSERVER can autonomously learn and refines new operators through observation and practice (Wang 1995). WISER, our learning system, relaxes these assumptions and learns operator preconditions through experimentation utilizing imperfect expert-provided knowledge. Our decision-theoretic formula calculates a probably best state S' for experimentation based on the imperfect knowledge. When a robotic action is executed successfully for the first time in a state S, the corresponding operator's initial preconditions are learned as *parameterized S*. We empirically show the number of training examples required to learn the initial preconditions as a function of the amount of injected error. The learned preconditions contain all the necessary positive literals, but no negative literals.

Unless given a rule like *arm-empty* $\rightarrow \neg$*holding(X)*, a robot may believe a state, {(arm-empty), (holding *box)*}, to be possible due to unavoidable perceptual alias. The plan execution in this state is unreliable. To make a planner robust in a noisy state, WISER learns constraining negative preconditions by interconnecting two types of logic systems used in planning systems. The state representation uses two-value logic plus the Closed-World Assumption and the operator representation uses three-value logic. Let L represent all the predicates known to WISER and P the predicates true in S. By CWA, N, the predicates not true in S, is defined as $\{L - P\}$. WISER induces preconditions from $S^* = \{P \cup \neg N\}$, which prevent inconsistent actions in a noisy state.

Let the instantiated operators, iop_i and iop_j, be obtained from an operator *op* by instantiating each parameter of *op* to the same object respectively except that one parameter is instantiated to different objects of the same type, say a for iop_i and b for iop_j. iop_j is obtained by substituting b for a. In any state S, if the preconditions for iop_i and iop_j are both satisfied (or not satisfied) and their respective actions have the same (parameterized) effects on S, the two objects a and b are called *homogeneous* in terms of *op*. For example, if both *box1* and *box2* can be picked up by an agent, they are homogeneous to the PICKUP operator. Homogeneous objects of a type form an equivalence relation, partitioning the type into subtypes. If an object of a subtype is tested for the operator, no additional object of the subtype needs to be tested further.

WISER adopts the *abstract domain assumption* that every object in a type belongs to one and only one subtype. Therefore, we can experiment with an operator using only one object of a type for a parameter. This assumption drastically reduces the size of the search space. The abstraction of objects is inevitable in a real domain. The resulting representation is, however, inherently incomplete. The robot must be able to adjust its initial definitions, learned under the *abstract domain assumption*, in complex environments composed of heterogeneous objects by decomposing a type into many subtypes. The traditional approach, where a human-provided fixed type hierarchy is given, cannot handle this problem.

We handle this type classification problem using C4.5. Some unobservable predicates, such as *carriable(X)*, are used in classifying a type into subtypes. An object is described as a vector of observable features. The robot initially learns overly-general preconditions by assuming that every object of a box type is *carriable*. Experimentation acts as an environmental feedback and produces positive and negative training examples for [*carriable*] subtype of the box type. C4.5 selects the features to distinguish between positive and negative examples. The unobservable functional concept is represented by structural descriptions consisting of observable features, satisfying the operational criterion. We empirically demonstrate the learner's ability to generate more accurate definitions with each learning iteration.

References

Wang, X. 1995. Learning by observation and practice: An incremental approach for planning operator acquisition. In *Proceedings of the 12th International Conference on Machine Learning.*