Import Historical Developments in the Field of AI Planning and Search

Machine Learning: Automated Planning

Automated Planners (AP) require an accurate description of the planning task. These descriptions include a model of the actions that can be carried out in the environment, a specification of the state of the environment and the goals to achieve. In the real world, the execution of an action may result in numerous outcomes, the knowledge of the state of the environment may be partial and the goals may not be completely defined. Generating exact definitions of the planning tasks in advance is unfeasible for most real-world problems.

For hard domains, automated planner can exploit the domain-specific control knowledge to improve their performance in terms of both speed and quality of the solutions. However, deriving manual definition of control knowledge is quite difficult and requires expertise in that domain.

Machine Learning (ML) technique can be used to design learning based planners. ML can be used to (1) learning planning action models and (2) learning search control. Traditionally, most planners separate the definition of the action models from the definition of search control knowledge to allow the planner the use of different representations. There are cases, however, where this division between models and control knowledge is unclear like, for example, macro actions that can be placed in both categories. Using ML techniques such as Reinforcement Learning (RL), the agent interacts with its environment to automatically learn an action-value function of the environment. This action-value function combines information from both the search control and action model to solve a particular task. This area is still under research and learning track was opened at ICKEPS in 2008 to find ML based solution to the challenges of AP.

Empirical Model Learning: boosting optimization through machine learning

One of the biggest challenges in the design of decision support and optimization tools for complex, real-world, systems is coming up with a good combinatorial model. The traditional way to craft a combinatorial model is through interaction with domain experts: this approach provides model components (objective functions, constraints), but with limited accuracy guarantees. Often enough, accurate predictive models (e.g. simulators) can be devised, but they are too complex or too slow to be employed in combinatorial optimization.

Empirical Model Learning (EML) methodology relies on Machine Learning for obtaining decision model components that link decision variables and observables, using data either extracted from a predictive model or harvested from a real system.

EML uses two learning methods - Artificial Neural Networks and Decision Trees, and it encapsulate the learned model in a number of optimization techniques, namely Local Search, Constraint Programming, Mixed Integer Non-Linear Programming and SAT Modulo Theories.

Policy Recognition: Abstract Hidden Markov Model

Abstract Hidden Markov Model (AHMM) is a proposed stochastic model used to recognize an agent's behaviour in dynamic, noisy, uncertain domains, and across multiple levels of abstraction. Proposed plan recognition framework based on the AHMM as the plan execution model. The hybrid inference for AHMM can take advantage of the independence properties inherent in a model of plan execution, leading to an algorithm for online probabilistic plan recognition that scales well with the number of levels in the plan hierarchy. This illustrates that while stochastic models for plan execution can be complex, they exhibit special structures which, if exploited, can lead to efficient plan recognition algorithms.

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