Historical Developments in the Field of AI Planning and Search

The history of AI planning begins with the advent of the STRIPS system[1]. STRIPS came about as a result of needs in the fields of theorem proving and robotic problem solving, building upon the work by Green[2]. This new system established the idea of representing world models in first-order logic to execute the theorem proofs through use of search analysis, at the time referred to as “GPS-like”, which would later be expanded upon as planning graphs.

These planning graphs, first formalized by Blum and Furst's GraphPlan, were able to reduce the amount of search needed by use of constraints[3]. Through a combination of the problem’s constraints and cost based heuristics, the planning graph is able to obtain the shortest path available for a problem solution, if one exists. This was a large improvement in efficiency over the previous STRIPS system, executing in polynomial time with polynomial size. The constraints were implemented through the use of: 1) a leveled approach, alternating between a propositional state level and action level connected by edges that represent the relations between the two levels, and 2) restricting the states within each level by mutual exclusivity, where states are incompatible with each other over a variety of reasons.

GraphPlan was tested by comparison against the two most popular planning systems at the time, Prodigy and UCPOP. Though they were written in different languages, GraphPlan was able to achieve results dramatic enough to prove its usefulness over the two benchmarks, outperforming them by orders of magnitude as the Number of goals increased. In discussions about the results and the future of the field, the authors expressed concerns with the limitations of static actions and states removing the possibility of adaptability, which was also elluded to in the STRIPS research.

As of July 17, 2017, research has been published by the Google DeepMind research team that overcomes these limitations, when they introduce the notion of an “Imagination-based planner”(IBP) which can adaptively construct, evaluate, and execute plans[4]. This is accomplished by alternating between an “imagination” state in which the next decision is predicted, and a “world” state in which decisions are executed. Utilizing reinforcement learning, the algorithm uses the feedback from both states and is able to flexibly explore the action and state spaces, continuously attempting different combinations to reduce task loss and resource costs.

The model of IBP consists of: 1)A “manager” that determines which state to execute an action in, either world or imagination. 2)A “controller” that maps states to actions based on the manager’s decision. 3) The “imagination” which is a model of the world that maps current states and actions to exploratory consequent states and rewards. 4) The “memory” which aggregates the information from the sequence to deliver back to the manager. This cycle is repeated until an optimal solution is formed. For a discrete test, IBP was implemented to solve a maze task with multiple goal locations, which it succeeded in not only sufficient steps, but also resolved new goal positions not experienced by its training on the problem.

The discovery of this new method of planning opens many possibilities moving forward in the fields of problem solving and robotic control, perhaps as impactful as STRIPS was 40 years ago.

References

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3. Avrim L. Blum and Merrick L. Furst. Fast Planning Through Planning Graph Analysis. 1997.
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