

Automated planning is a branch of AI that deals with the creation of strategies or action sequences that can typically be executed by intelligent agents like autonomous robots and unmanned vehicles. Given a description of the possible initial states of the world, a description of the desired goals, and a description of a set of possible actions, the planning problem is to synthesise a plan that is guaranteed to generate a state which contains the desired goals when applied to any of the initial states. In known environments with available models, the complexity of planning arises from the multidimensional nature of the environments and the need for optimisation based on various heuristics. In dynamically unknown environments, the strategy often needs to be revised on the fly leading to even greater complexity. This paper deals with three advancements made in this field and their impact on the field of AI.

Till 1995, research on AI planning had concentrated on the so-called non-linear or partial-order planning algorithms (see for example [\[McAllester and Rosenblitt, 1991\]](#)). In 1995, [Blum and Furst](#) introduced the Graphplan algorithm which had two characteristics that separated it from earlier ones:

1. it finds plans of a fixed length (that is incrementally increased until a plan is found). Doing plan search in this way has several benefits. First, shortest plans (in terms of points of time) are found. Second, the descriptions of both the initial and the goal states can be used for effectively inferring fluent values at different time points, thereby reducing exhaustive search.
2. it uses reachability information for pruning the search tree. Using invariants, formulae that are true in the initial state and are preserved by the application of every operator, and consequently they are true in all states that are reachable from the initial state, a set of states reachable from the initial state can be characterised and thus all other possibilities can be pruned, reducing the search space considerably.

These differences brought the performance of Graphplan to a level not seen in connection with earlier planners.

However, the impact and success of Graphplan wasn't limited merely to performance. It inspired researchers to look at techniques outside the traditional AI planning toolbox. In 1996 Kautz and Selman demonstrated that a general purpose satisfiability algorithm can in many cases outperform Graphplan and other algorithms specifically designed for AI planning. By translating the descriptions of the goal and the initial states as well as the conditions are into propositional logic, a satisfiability algorithm can be applied to find solutions. [Kautz and Selman](#) were able to show that for solving hard problems from several challenging domains, their of approach outperformed some of the best specialized planning algorithms by orders of magnitude. These results challenged the common assumptions in AI that planning required specialized search techniques and that planning is an inherently systematic process.

However, the problem with two approaches above is that in problems of the size that could be practically solved then, the advantages of reduction in the search tree size were outweighed by the additional polynomial time computation that led to sufficient reduction in the depth or branching factor to be beneficial. Thus, in 2001, [Bonet and Geffner's HSP planners](#), showed that the use of plain forward or backward chaining, has very good performance on many benchmark problems, and increased interest in heuristic search as a planning technique.

References:

1. [Automated planning and scheduling](#), from Wikipedia, the free encyclopedia
2. [Systematic Nonlinear Planning](#), by McAllister and Rosenblit
3. [Fast Planning Through Planning Graph Analysis](#), by Blum and Furst
4. [Pushing the envelope: Planning, Propositional Logic and Stochastic Search](#), by Kautz and Selman
5. [Planning as heuristic search](#), by Bonet and Geffner