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February 3, 2018

Key Developments in the Field of AI Planning and Search

This short essay looks back about a decade and summarizes some of the recent developments in AI planning and search: Hierarchical task networks (HTN), goal reasoning, and the integration of reinforcement learning with planning. Classical planning domains have traditionally been the focus of automated planning research; however, recently the field has expanded to include probabilistic and other non-classical domains (Nau, 2007). While the restrictive assumptions of classical planning served a purpose, it appears domain-independent planning can be practically applied to only a limited number of problems. In part because real-world domains do not always have fully observable and static environments. Domain-configurable planners are one area of development that leverages details of the domain to optimize planning and search. HTN planning is different from classical planning generally due to its increased domain consideration.

Hierarchical representations can help simplify planning in many domains. For example, hierarchies of resources and tasks can be used to systematically manage domain operations like task decomposition and resource scheduling (Georgievski & Aiello, 2015). Interestingly, not all HTN planners are equally domain dependent. This inequality might explain the continued research in planning heuristics for HTN planning (viz., Bercher, Behnke, Höller, & Biundo, 2017). Heuristic functions can be employed to reduce the search space while providing optimal solutions. The value of admissible heuristics for HTC are multiplied when elements of planning, like task decomposition, are standard across domains.

An in-depth review of HTC surfaces real-world matters that motivate planning research. Temporal concerns appear in the form of task duration and resource scheduling, and dynamic environments appear in the form of unreliable information sources (e.g., Bercher et al., 2017). Dynamic environments demand an agent architecture that allows for a cycle of planning, acting, sensing. Real-world examples of highly dynamic environments include many robotics applications. Multi-agent environments, like those in which self-driving cars or other autonomous vehicles operate, present a uniquely challenging type of uncertainty.

In dynamic environments, better goals can become available during execution requiring goal reasoning on the fly. Agents capable of self-formulating goals might also be designed to handle execution-time anomalies rationally, propose alternative goals when attainment of the initial goal becomes impossible, or even balance competing needs related to present and future goals (Vattam, Klenk, and Molineaux, 2013). Architectures aimed at separating the concerns of goal management and planning have been used to build agents capable of goal reasoning. For example, *belief desire intention* (BDI) and *goal driven autonomy* (GDA) afford this separation.

Goal reasoning involves online planning to deal with changes as they happen. Goal reasoning is different from contingency planning in that many cases of contingency planning can be done offline. Teams working on autonomous underwater vehicles have employed goal reasoning to address dynamic, partial observability, and multi-agent environments in their domain (viz., Alterovitz, Koenig, & Likhachev, 2016). Their findings, from simulated marine missions, highlight the potential of goal-driven autonomy for robotic control. Their agent architecture includes a controller responsible for detecting discrepancies and generating an explanation. This development in the field will inform future work with similar computing constraints and uncertain environments. It also opens the door to research in the realm of learning and reactive planning.

In other work, researchers have used reinforcement learning to navigate partially-observable environments. Recently, Martínez, Alenya, Ribeiro, and Torras (2017) harnessed model-based reinforcement learning to aid in non-deterministic planning. They combined a *relational dynamic influence diagram language* (RDDL) based planner with a relational model learner to create a planning agent that could be trained. The research focused on exogenous effects and aimed to train a robot in clearing tableware. Remarkably, Martínez et al. were able to train the robot to coordinate with the wait staff and navigate timings of incoming tableware types.

The developments in AI planning and search discussed here represent a point in time. Just over ten years ago Nau (2007) characterized multi-agent and dynamic environments as areas for growth. Since then, planning and search have experienced continued interest in research and practice. Planning and search appear to be a vital component of AI engineering. Each of these developments integrates elements of the domain with the planning process and better prepares agents for uncertainty. These developments add to the body of knowledge in the AI planning field and offer new methods for continued advancement. This essay summarized only three recent developments in the field; although, there is no shortage or related research underway.

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