Landmarks, Critical Paths and Abstractions: What's the Difference Anyway?

Extended Abstract

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We consider the problem of *domain-independent planning*, which for the reader not familiar with the planning literature can be briefly described as the problem of finding a path from an initial state to some goal state in a large, implicitly defined transition system. Domain-independent planning algorithms routinely solve problems of sizes far beyond the scope of classical graph search algorithms, in some cases exceeding 10^{100} reachable states.

More specifically, in this work we are interested in *optimal* planning, where rather than just producing any solution path (*plan*), we must guarantee that the generated plan is of minimal length. While optimal planners do not scale to problems of the same size as nonoptimal ones, they can solve many problem instances far beyond the reach of brute-force approaches like breadth-first search.

A common and successful algorithm in this setting is *heuristic search*, either in the space of world states reached through progression (forward search) or in the space of subgoals reached through regression (backward search). Apart from the choice of search algorithm such as A* [3] or IDA* [10], the main feature that distinguishes heuristic planners is their choice of *heuristic estimators*, which are functions that receive a state of the problem as an input and generate an estimate of the goal distance of that state as an output. Most current heuristic estimators are based on one of the following four ideas:

1. *delete relaxations*: e. g., h^+ [6], $h^{\max}$ [1], h^{add} [1], h^{FF} [6], h^{pmax} [11], h^{sa} [9]
2. *critical paths*: the h^m heuristic family [4]
3. *abstractions*: pattern databases [2], merge-and-shrink abstractions [5], and structural patterns [8]
4. *landmarks*: LAMA's h^{LM} [13], and the admissible landmark heuristics h^{L} and h^{LA} [7]

These four ideas have been developed in relative isolation: apart from Haslum and Geffner's result [4] that $h^{\max}$ is a special case of the h^m family ($h^{\max} = h^1$), we are not aware of any published formal connections between these approaches.

In this work, we prove further results that relate the quality of admissible (optimistic) heuristics from the above four families. Admissible heuristics have a clear notion of *dominance*: if $h(s) \geq h'(s)$ for all states s, then h is superior or equal to h' in terms of heuristic quality, with provable consequences for the performance of optimal search algorithms [12].

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We establish several such dominance results:

- Landmark heuristics dominate additive $h^{\max}$ heuristics.
- Additive $h^{\max}$ heuristics dominate landmark heuristics.
- Additive critical path heuristics with $m \geq 2$ strictly dominate landmark heuristics and additive $h^{\max}$ heuristics.
- Merge-and-shrink abstractions strictly dominate landmark heuristics and additive $h^{\max}$ heuristics.
- Pattern database abstractions are incomparable with landmark heuristics and additive $h^{\max}$ heuristics.

As a result of our dominance proofs, we also obtain a new admissible heuristic called the *landmark cut heuristic* $h^{\text{LM-cut}}$, which can alternatively be viewed as a landmark heuristic, a cost partitioning scheme for additive $h^{\max}$, or an approximation to the (intractable) optimal relaxation heuristic h^+. We experimentally demonstrate that $h^{\text{LM-cut}}$ gives excellent approximations to h^+ and compares favourably to other admissible heuristics in terms of accuracy. Moreover, we show that an optimal planner based on the landmark cut heuristic is highly competitive with the state of the art of optimal planning.

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