

Generalized Potential Heuristics for Classical Planning

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Generalized Planning

- ▶ Classical planners compute plans that work for a single instance.
- ▶ Generalized planning aims instead at policies that solve entire *classes of instances* that share an underlying structure.

Objective of this work

- ▶ Learn interpretable generalized policies from small instances.
- ▶ The target policies solve any instance in time linear in problem size.

Running Example: Blockworld



Description Logics for Planning (SOI with equality role-value-maps)

Primitive Concepts & Roles

- ▶ $ontable = \{\text{blue}, \text{green}\}$
- ▶ $on = \{\{\text{red}, \text{green}\}\}$
- ▶ $holding = \emptyset$
- ▶ $clear = \{\text{blue}, \text{red}\}$

Goal Concepts & Roles

- ▶ $on_G = \{\{\text{red}, \text{green}\}, \{\text{green}, \text{blue}\}\}$

Complex Concepts & Roles

- ▶ C_1 : Blocks that are correctly placed on the table
 $ontable_G \sqcap ontable = \emptyset$
- ▶ C_2 : Blocks that are placed on their target block
 $(\exists on_G. \top) \sqcap (on = on_G) = \{\text{red}\}$
- ▶ C_3 : Blocks with no target in the goal
 $\neg(ontable_G \sqcup \exists on_G. \top) = \{\text{blue}\}$
- ▶ C_4 : Blocks on object consistent with the goal
 $C_1 \sqcup C_2 \sqcup C_3 = \{\text{red}, \text{blue}\}$
- ▶ C_5 : Blocks where the block above is consistent with the goal
 $\forall on_G^{-1}. (on = on_G) = \{\text{red}, \text{green}\}$
- ▶ C_6 : Blocks that are well-placed
 $C_4 \sqcap \forall on^+. (C_4 \sqcap C_5) = \{\text{blue}\}$
- ▶ C_7 : Blocks held while their target block is clear and well-placed
 $holding \sqcap \exists on_G. (clear \sqcap C_6) = \emptyset$

Generalized Potential Heuristics

Generalized potential heuristics are linear combinations of first-order features well defined over all instances:

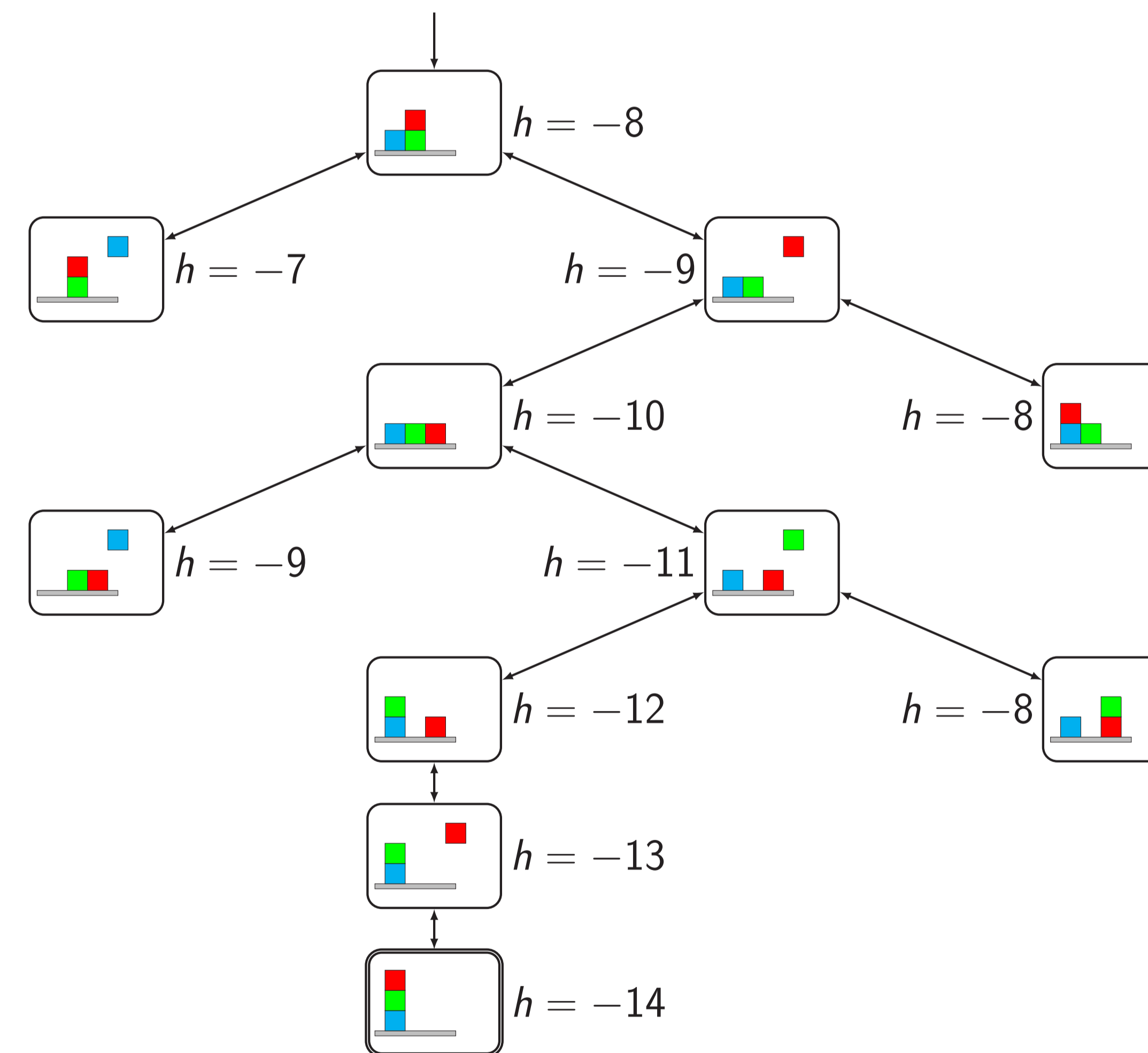
$$h(s) = \sum_{f \in \mathcal{F}} w_f f(s)$$

- ▶ Two types of *features*:
 - ▶ cardinality features $|C|$
 - ▶ distance features $dist(C, R, C')$
- ▶ Blockworld example:

$$h_{bw}(s) = -4|C_6| - |holding| - 2|ontable| - 2|C_7|$$

Good Heuristic Properties for Satisficing Greedy Search

- ▶ **descending**: all alive (reachable, solvable and non-goal) states have an improving successor.
- ▶ **dead-end avoiding**: all improving successors of alive states are solvable.



- ▶ **Key property**: Hill climbing with a descending, dead-end avoiding heuristic solves a problem in a *linear number of steps*.

Theoretical Results

We show that descending, dead-end avoiding generalized heuristics exist for a number of standard domains:

- ▶ Blockworld, Gripper, Spanner, Miconic, Logistics.

Learning a Generalized Heuristic from Examples

1. Fully expand a set of small instances
2. Generate a pool of features \mathcal{F}
3. Synthesize weights for a descending and dead-end avoiding heuristic using features from \mathcal{F}
→ if not possible: add features to \mathcal{F} and continue with (3)
4. Test on unseen instances
→ if not solved: add *refinement constraint* and continue with (3)

Synthesizing Weights

Synthesizing weights for fully expanded state spaces

MIP Model

$$\begin{aligned} \min_w \sum_{f \in \mathcal{F}} [w_f \neq 0] \mathcal{K}(f) \quad \text{subject to} \\ \bigvee_{s' \in \text{succ}(s)} h(s') + 1 \leq h(s) \quad \text{for } s \in \mathcal{S}_A \\ h(s') \geq h(s) \quad \text{for } (s, s') \in \mathcal{T}, s' \text{ unsolvable,} \end{aligned}$$

Search fails on unseen instance

- ▶ heuristic is either not descending or not dead-end avoiding

Refinement Constraint

$$\left(\bigvee_{i=0}^{n-1} h(s_i) \leq h(s_{i+1}) \right) \vee \left(\bigvee_{s' \in \text{succ}(s)} h(s') + 1 \leq h(s) \right)$$

Empirical Results

	Gripper	Miconic	Spanner	VisitAll
# of training instances	8	12	11	9
$ \mathcal{F} $	469	2105	904	330
Complexity of h	8 (18)	6 (14)	8 (20)	5 (8)
# of features in h	5	4	5	3
Total time	8h	32m	178s	87s
Total MIP time	7.4h	26m	6.8s	2.1s

Conclusions & Future Work

- ▶ We can learn interpretable, linear solving mechanisms that work for infinite classes of problems from small instances.
- ▶ First-order theorem proving could be used to prove deductively the correctness of the learned heuristics.