Generalized Potential Heuristics for Classical Planning

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Generalized Potential Heuristics
In this Work

- **Context**: classical planning using heuristic search
- Some domains can be solved in **linear time**
- **Hill-climbing** + heuristic leading direct to the goal
- We want to **learn** these heuristics automatically
Definition (Generalized Potential Heuristic)

Linear combination of features well-defined over all tasks:

\[ h(s) = \sum_{f \in \mathcal{F}} w(f) \cdot f(s) \]
Description Logics for Planning

**Primitive Concepts & Roles**

- \(ontable = \{\square, \triangledown\}\)
- \(on = \{(\blacksquare, \triangledown)\}\)
- \(holding = \emptyset\)
- \(clear = \{\square, \blacksquare\}\)
- \(clear_G = \{\triangledown\}\)
Description Logic

Description Logic $\mathcal{SOL}$ with Role Value Maps

Complex concepts
- $\bot, \top$
- $\neg C$
- $C_1 \sqcup C_2, C_1 \sqcap C_2$
- $\forall R.C, \exists R.C$
- $R_1 = R_2$
- $\{a_1, \ldots, a_n\}$

Complex roles
- $R^{-1}$
- $R^+$
- $R_1 \circ R_2$

Complex Concepts & Roles
- “Set of blocks above some block that needs to be cleared”
- $\exists on^+.clear_G = \{\blacksquare\}$
Example: Clearing a Block

Generalized Potential Heuristic for Blocksworld

Blocksworld tasks where the goal is to clear a set of blocks

\[ h(s) = 2 \cdot |C_1| + |C_2| \]

- \( C_1 \equiv \exists \mathit{on}^+.\mathit{clear}_G \): “Set of blocks above some block that needs to be cleared”
- \( C_2 \equiv \mathit{holding} \): “Set of blocks being held”
We prove that generalized heuristics leading directly to a goal state exist for a number of standard domains:

- Blocksworld
- Gripper
- Spanner
- Logistics
- ...

Greedy search solves any task in time $O(|\text{Objects}|)$
We prove that generalized heuristics leading directly to a goal state exist for a number of standard domains:

- Blocksworld
- Gripper
- Spanner
- Logistics
- ...

Greedy search solves any task in time $O(|\text{Objects}|)$

Can we obtain these heuristics automatically?
Learning the Heuristic
Overview of our inductive approach:

1. Fully expand small tasks to generate training set $S$. 
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1. Fully expand small tasks to generate training set $S$.
2. Generate set of generalized features $\mathcal{F}$ with all features under a certain syntactic complexity.
3. Compute simplest potential heuristic on $\mathcal{F}$ leading states from $S$ directly to the goal.
   - If no such $h$ exists, augment $\mathcal{F}$.
   - If it does exist, test $h$ on unseen tasks.
Computing the Weights

Mixed Integer Linear Program

\[
\min_w \sum_{f \in \mathcal{F}} [w_f \neq 0] \mathcal{K}(f)
\]
subject to
\[
\bigvee_{s' \in \text{succ}(s)} h(s') + 1 \leq h(s)
\]
for alive states \(s\)
\[
\]
\[
\]
for transitions \((s, s')\)
\[
\]
where \(s\) is alive
\[
\]
and \(s'\) is unsolvable
Results

- **Learn**: Generalized heuristics on standard domains
  - Gripper, Miconic, Spanner, VisitAll.
- **Prove**: Heuristics generalize all possible tasks.
  - Except VisitAll: No linear solution possible
- **Solve**: Steepest-ascent hill-climbing in linear time.
- In some domains, such heuristics exist but we cannot scale.
Conclusion
Contributions

- Generalized descending and dead-end avoiding heuristics exist for several planning domains.
- Heuristics learned can be interpreted.
- Solve any task in linear time.
- We can learn them automatically from a suitable logical model and small tasks.
  - Heuristic refinement procedure in the paper
Bonus Slides
### Semantics – Examples

#### Concepts:

\[(\exists R.C)^M = \{a \mid \exists b : (a, b) \in R^M \land b \in C^M\}\],

\[(R = R')^M = \{a \mid \forall b : (a, b) \in R^M \iff (a, b) \in R'^M\}\].

#### Roles:

\[(R^{-1})^M = \{(b, a) \mid (a, b) \in R^M\}\],

\[(R \circ R')^M = \{(a, c) \mid \exists b : (a, b) \in R^M \land (b, c) \in R'^M\}\].
Example: unrestricted Blocksworld tasks

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

- **$C_1$:** $ontable_G \sqcap ontable$
  Blocks that are correctly placed on the table

- **$C_2$:** $(\exists on_G. \top) \sqcap (on = on_G)$
  Blocks that are placed on their target block

- **$C_3$:** $\neg(ontable_G \sqcup \exists on_G. \top)$
  Blocks that are not mentioned in the goal

- **$C_4$:** $C_1 \sqcup C_2 \sqcup C_3$
  Blocks where block (or table) below is consistent with the goal

- **$C_5$:** $\forall on_G^{-1}.(on = on_G)$
  Blocks where the block above is consistent with the goal

- **$C_6$:** $C_4 \sqcap \forall on^+. (C_4 \sqcap C_5)$
  Blocks that are well-placed.

- **$C_7$:** $holding \sqcap \exists on_G.(clear \sqcap C_6)$
  Blocks held while their target block is clear and well-placed.
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<th></th>
<th>G</th>
<th>M</th>
<th>S</th>
<th>V</th>
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<td>12</td>
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<td>9</td>
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<td>1.7</td>
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<td>Complexity of $h$</td>
<td>8 (18)</td>
<td>6 (14)</td>
<td>8 (20)</td>
<td>5 (8)</td>
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<tr>
<td># of features in $h$</td>
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<td>4</td>
<td>5</td>
<td>3</td>
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<td>Total time</td>
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<td>32m</td>
<td>178s</td>
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<tr>
<td>Total MIP time</td>
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<td>26m</td>
<td>6.8s</td>
<td>2.1s</td>
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