

# Generalized Potential Heuristics for Classical Planning

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# Introduction

# Motivation

- Problems of a classical planning domain share a **common structure**
- **Generalized planning** tries to find a solution for a whole domain

## In this Work

- For some domains a solution that solves the whole domain can be described easily
- We try to **learn** these solutions **from small instances**

# Background

# Representing Progress with Heuristic Functions

## Descending & dead-end avoiding heuristics (Seipp et al., 2016)

- **descending:**  
all alive states have an improving successor
- **dead-end avoiding:**  
all improving successors of alive states are solvable

A state is *alive* if it is reachable, solvable and not a goal.

## Descending, dead-end avoiding heuristics

- guide greedy search to a goal
- use at most  $h(s_0) - h(s_g)$  steps
- encode a *measure of progress* (Parmar, 2002)

# Description Logics

## Description Logic *SOI* with Role Value Maps

- Primitive concepts
  - represent set of objects with some property
- Primitive roles
  - represent relation between objects

### Complex concepts

- $\perp, \top$
- $\neg C$
- $C_1 \sqcup C_2, C_1 \sqcap C_2$
- $\forall R.C, \exists R.C$
- $R_1 = R_2$
- $\{a_1, \dots, a_n\}$

### Complex roles

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

# Description Logic for Planning Domain

Description logic for a planning domain

- Interpretation for every state of any instance

Concepts and roles

- Primitive concept for each **unary predicate**
  - Example: *clear*
- Primitive role for each **binary predicate**
  - Example: *on*
- Primitive concepts and roles for **predicates in the goal**
  - Example:  $on_G$



# Generalized Potential Heuristics

# Generalized Potential Heuristics

## Definition (Generalized Potential Heuristic)

Linear combination of features well-defined over all instances:

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

- We use two types of features based on description logics:
  - **cardinality features**  $|C|$
  - **distance features** (see paper)

## Example: Clearing a Block

- Consider the subset of Blocksworld problems where the goal is to clear a given subset of blocks

### Descending and Dead-end Avoiding Generalized Potential Heuristic

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

- $C_1 \equiv \exists on^+.clear_G$ :  
“Set of blocks above some block that needs to be cleared”
- $C_2 \equiv holding$ :  
“Set of blocks being held”

# Existence of Descending and Dead-End Avoiding Heuristics

- We prove that descending, dead-end avoiding generalized heuristics **exist** for a number of standard domains:
    - Blocksworld
    - Gripper
    - Spanner
    - Miconic
    - Logistics
  - Greedy search **solves all instances in linear time**
- The challenge: can we obtain these heuristics automatically?

# Learning the Heuristic

# Learning the Heuristic

Overview of our inductive approach:

- 1 Fully expand small instances to generate training set  $\mathcal{S}$ .
- 2 Generate set of **generalized features**  $\mathcal{F}$  with all features under a certain syntactic complexity.
- 3 Compute **simplest potential heuristic** on  $\mathcal{F}$  that is descending and dead-end avoiding on states in  $\mathcal{S}$ .
  - If no such  $h$  exists, try with larger set  $\mathcal{F}$ .
  - If it does exist, test  $h$  on unseen instances.

# 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  $s$

$$h(s') \geq h(s)$$

for transitions  $(s, s')$   
where  $s$  is alive  
and  $s'$  is unsolvable

- Solutions map to heuristics that are descending and dead-end avoiding on all states in  $\mathcal{S}$ ...

# Computing the Weights

## Mixed Integer Linear Program

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

- Solutions map to heuristics that are descending and dead-end avoiding on all states in  $\mathcal{S}$ ...
- ... and have *minimum complexity*.



# Results

- Our approach **learns generalized heuristics** on standard domains such as Gripper, Miconic, Spanner, VisitAll.
- We have (manually) checked that they are descending and dead-end avoiding on **all instances** of the domain.
  - Exception VisitAll: No linear solution possible
- Steepest-ascent hill-climbing with these heuristics solves any instances of these domains in **linear time**.
- Other domains such as Blocksworld appear to need better feature exploration strategies.

# Conclusion

# Contributions

- General descending and dead-end avoiding heuristics **exist for several planning domains.**
- These **solve** any instance in **linear time.**
- We can **learn them automatically** from a suitable logical model and small instances.

## Discussion and Future Work

- The learned heuristic can be **easily interpreted**.
- The learned heuristic has **only inductive guarantees**, but
  - We have shown how it can be refined in an online fashion whenever it doesn't generalize correctly.
  - One could attempt to **prove the correctness** of the heuristic deductively with an **automatic theorem prover**.
- Better feature generation methods are necessary to scale up to more complex problems.

# Bonus Slides

## Example: unrestricted Blocksworld instances

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

- $C_1 : \text{ontable}_G \sqcap \text{ontable}$   
 Blocks that are correctly placed on the table
- $C_2 : (\exists \text{on}_G. \top) \sqcap (\text{on} = \text{on}_G)$   
 Blocks that are placed on their target block
- $C_3 : \neg(\text{ontable}_G \sqcup \exists \text{on}_G. \top)$   
 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
- $C_5 : \forall \text{on}_G^{-1}. (\text{on} = \text{on}_G)$   
 Blocks where the block above is consistent with the goal
- $C_6 : C_4 \sqcap \forall \text{on}^+. (C_4 \sqcap C_5)$   
 Blocks that are well-placed.
- $C_7 : \text{holding} \sqcap \exists \text{on}_G. (\text{clear} \sqcap C_6)$   
 Blocks held while their target block is clear and well-placed.

	<b>G</b>	<b>M</b>	<b>S</b>	<b>V</b>
# of training instances	8	12	11	9
# of iterations	2.0	2.7	1.0	1.7
$ \mathcal{F} $	469	2105	904	330
# of MIP variables	2017	7273	3381	1039
# of MIP constraints	2238	7331	3370	1190
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