

Planning and Optimization

D5. Pattern Databases: Pattern Selection

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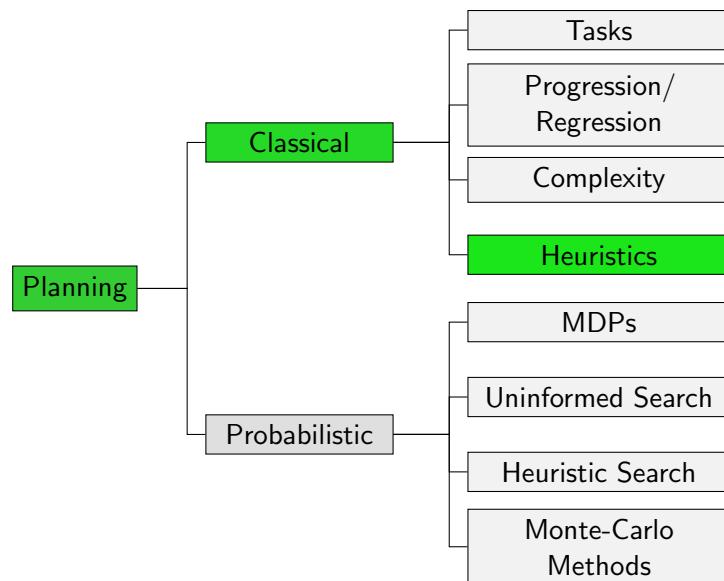
D5.1 Pattern Selection as Local Search

D5.2 Search Neighbourhood

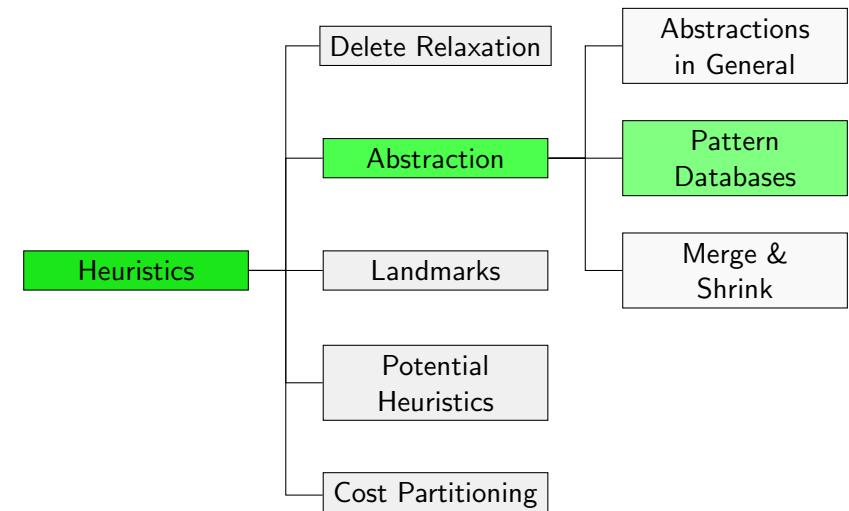
D5.3 Literature

D5.4 Summary

Content of this Course



Content of this Course: Heuristics



D5.1 Pattern Selection as Local Search

Pattern Selection as Local Search

How to solve this optimization problem?

- ▶ For problems of interesting size, we cannot hope to find (and prove optimal) a **globally optimal** pattern collection.
 - ▶ **Question:** How many candidates are there?
- ▶ Instead, we try to find **good** solutions by **local search**.

Two approaches from the literature:

- ▶ Edelkamp (2007): using an **evolutionary algorithm**
- ▶ Haslum et al. (2007): using **hill-climbing**

~~ in the following: main ideas of the second approach

Pattern Selection as an Optimization Problem

Only one question remains to be answered now in order to apply PDBs to planning tasks in practice:

How do we automatically find a good pattern collection?

The Idea

Pattern selection can be cast as an **optimization problem**:

- ▶ **Given:** a set of **candidates**
(= pattern collections which fit into a given memory limit)
- ▶ **Find:** a **best possible** candidate, or an approximation
(= pattern collection with high heuristic quality)

Pattern Selection as Local Search

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Pattern Selection as Hill-Climbing

Reminder: Hill Climbing

current := an **initial candidate**

loop forever:

```
next := a neighbour of current with maximum quality
if quality(next)  $\leq$  quality(current):
  return current
current := next
```

more on hill climbing:

~~ Chapters 20–21 of the **Foundations of Artificial Intelligence** course at <https://dmi.unibas.ch/de/studium/computer-science-informatik/fs18/lecture-foundations-of-artificial-intelligence/>

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Three questions to answer to use this for pattern selection:

- ① **initial candidate:** What is the initial pattern collection?
- ② **neighbourhood:** Which pattern collections are considered next starting from a given collection?
- ③ **quality:** How do we evaluate the quality of pattern collections?

D5.2 Search Neighbourhood

Search Neighbourhood: Basic Idea

The basic idea is that we

- ▶ start from **small patterns** with only a single variable,
- ▶ grow them by **adding slightly larger patterns**
- ▶ and prefer moving to pattern collections that **improve** the heuristic value of **many states**.

Initial Pattern Collection

1. Initial Candidate

The initial pattern collection is

$\{\{v\} \mid v \text{ is a state variable mentioned in the goal formula}\}$.

Motivation:

- ▶ patterns with one variable are the simplest possible ones and hence a natural starting point
- ▶ non-goal patterns are trivial (\rightsquigarrow Chapter D4), so would be useless

Which Pattern Collections to Consider Next

From this initial pattern collection, we **incrementally grow** larger pattern collections to obtain an improved heuristic.

2. Neighbourhood

The neighbours of \mathcal{C} are all pattern collections $\mathcal{C} \cup \{P'\}$ where

- ▶ $P' = P \cup \{v\}$ for some $P \in \mathcal{C}$,
- ▶ $P' \notin \mathcal{C}$,
- ▶ all variables of P' are causally relevant for P' ,
- ▶ P' is causally connected, and
- ▶ all pattern databases in $\mathcal{C} \cup \{P'\}$ can be represented within some prespecified space limit.

- ~~ add **one pattern** with **one additional variable** at a time
- ~~ use criteria for **redundant** patterns (~~ Chapter D4) to avoid neighbours that cannot improve the heuristic

Checking Causal Relevance and Connectivity

Remark: For causal relevance and connectivity, there is a sufficient and necessary criterion which is easy to check:

- ▶ v is a predecessor of some $u \in P$ in the causal graph, **or**
- ▶ v is a successor of some $u \in P$ in the causal graph and is mentioned in the goal formula.

Evaluating the Quality of Pattern Collections

- ▶ The last question we need to answer is how to evaluate the **quality** of pattern collections.
- ▶ This is perhaps the most critical point: without a good evaluation criterion, pattern collections are chosen blindly.

Approaches for Evaluating Heuristic Quality

Three approaches have been suggested:

- ▶ estimating the **mean heuristic value** of the resulting heuristic (Edelkamp, 2007)
- ▶ estimating **search effort** under the resulting heuristic using a model for predicting search effort (Haslum et al., 2007)
- ▶ **sampling** states in the state space and counting **how many** of them have **improved** heuristic values compared to the current pattern collection (Haslum et al., 2007)

The last approach is most commonly used and has been shown to work well experimentally.

Heuristic Quality by Improved Sample States

3. Quality

- ▶ Generate M states s_1, \dots, s_M through random walks in the state space from the initial state (according to certain parameters not discussed in detail).
- ▶ The **degree of improvement** of a pattern collection \mathcal{C}' which is generated as a successor of collection \mathcal{C} is the **number of sample states** s_i for which $h^{\mathcal{C}'}(s_i) > h^{\mathcal{C}}(s_i)$.
- ▶ Use the degree of improvement as the **quality measure** for \mathcal{C}' .

Computing $h^{\mathcal{C}'}(s)$

- ▶ So we need to compute $h^{\mathcal{C}'}(s)$ for some states s and each candidate successor collection \mathcal{C}' .
- ▶ We have PDBs for all patterns in \mathcal{C} , but not for the new pattern $P' \in \mathcal{C}'$ (of the form $P \cup \{v\}$ for some $P \in \mathcal{C}$).
- ▶ If possible, we want to avoid fully computing all PDBs for all neighbours.

Idea:

- ▶ For SAS⁺ tasks Π , $h^{P'}(s)$ is identical to the **optimal solution cost for the syntactic projection $\Pi|_{P'}$** .
- ▶ We can use **any optimal planning algorithm** for this.
- ▶ In particular, we can use **A*** search using h^P as a heuristic.

D5.3 Literature

References (1)

References on planning with pattern databases:

- ▶ **Stefan Edelkamp.**
Planning with Pattern Databases.
Proc. ECP 2001, pp. 13–24, 2001.
First paper on planning with pattern databases.
- ▶ **Stefan Edelkamp.**
Symbolic Pattern Databases in Heuristic Search Planning.
Proc. AIPS 2002, pp. 274–283, 2002.
Uses BDDs to store pattern databases more compactly.

References (2)

References on planning with pattern databases:

 **Patrik Haslum, Blai Bonet and Héctor Geffner.**

New Admissible Heuristics for Domain-Independent Planning.
Proc. AAAI 2005, pp. 1164–1168, 2005.

Introduces **constrained PDBs**.

First pattern **selection methods** based on **heuristic quality**.

References (3)

References on planning with pattern databases:

 **Stefan Edelkamp.**

Automated Creation of Pattern Database Search Heuristics.
Proc. MoChArt 2006, pp. 121–135, 2007.

First **search-based** pattern selection method.



Patrik Haslum, Adi Botea, Malte Helmert, Blai Bonet and Sven Koenig.

Domain-Independent Construction of Pattern Database Heuristics for Cost-Optimal Planning.

Proc. AAAI 2007, pp. 1007–1012, 2007.

Introduces **canonical heuristic** for pattern collections.

Search-based pattern selection based on **Korf, Reid & Edelkamp's theory** for search effort estimation.

D5.4 Summary

Summary

- ▶ One way to **automatically find a good pattern collection** is by **searching** in the space of **pattern collections**.
- ▶ One such approach uses **hill-climbing** search
 - ▶ **starting** from **single-variable** patterns
 - ▶ **adding** patterns with **one additional variable** at a time
 - ▶ **evaluating** patterns by the number of **improved sample states**
- ▶ By exploiting what we know about **redundant** patterns, the hill-climbing search space can be reduced significantly.