Planning and Optimization

E8. Pattern Databases: Pattern Selection

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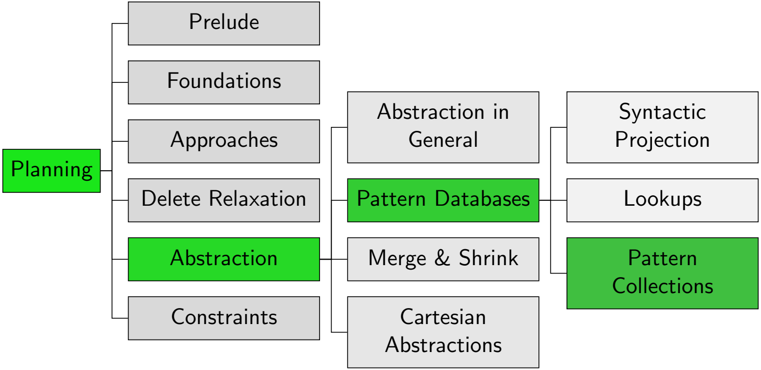
Content of the Course



E8.1 Pattern Selection as Local Search

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

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

$\rightsquigarrow$ in the following: main ideas of the second approach

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:

$\rightsquigarrow$ Foundations of Artificial Intelligence course FS 2025, Ch. C1–C2

Pattern Selection as Hill-Climbing

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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?

E8.2 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
$\{\{v\} \mid v$ 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 E7), 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.

$\rightsquigarrow$ add one pattern with one additional variable at a time

$\rightsquigarrow$ use criteria for redundant patterns ($\rightsquigarrow$ Chapter E7) 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; Franco et al., 2017)
- 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.

E8.3 Literature

References (1)

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

References (4)

References on planning with pattern databases:

Santiago Franco, Álvaro Torralba, Levi H. S. Lelis and Mike Barley.
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Improved version of Edelkamp's pattern collection selection approach evaluating pattern collections based on a prediction of A* search effort.

E8.4 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.