Principles of AI Planning

11. Planning as search: pattern database heuristics

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Pattern databases heuristics

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Summary

- The most commonly used abstraction heuristics in search and planning are pattern database (PDB) heuristics.
- PDB heuristics were originally introduced for the 15-puzzle (Culberson & Schaeffer, 1996) and for Rubik's cube (Korf, 1997).
- The first use for domain-independent planning is due to Edelkamp (2001).
- Since then, much research has focused on the theoretical properties of pattern databases, how to use pattern databases more effectively, how to find good patterns, etc.

Pattern database heuristics informally

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Pattern databases: informally

A pattern database heuristic for a planning task is an abstraction heuristic where

- some aspects of the task are represented in the abstraction with perfect precision, while
- all other aspects of the task are not represented at all.

Example (15-puzzle)

- Choose a subset T of tiles (the pattern).
- Faithfully represent the locations of T in the abstraction.
- Assume that all other tiles and the blank can be anywhere in the abstraction.

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Formally, pattern database heuristics are induced abstractions of a particular class of homomorphisms called projections.

Definition (projections)

Let Π be an FDR planning task with variable set V and state set S. Let $P \subseteq V$, and let S' be the set of states over P.

The projection $\pi_P : S \to S'$ is defined as $\pi_P(s) := s|_P$ (with $s|_P(v) := s(v)$ for all $v \in P$).

We call P the pattern of the projection π_P.

In other words, π_P maps two states s_1 and s_2 to the same abstract state iff they agree on all variables in P.

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Abstraction heuristics for projections are called pattern database (PDB) heuristics.

Definition (pattern database heuristic)

The abstraction heuristic induced by π_P is called a pattern database heuristic or PDB heuristic.
We write h^P as a short-hand for h^{π_P}.

Why are they called pattern database heuristics?

- Heuristic values for PDB heuristics are traditionally stored in a 1-dimensional table (array) called a pattern database (PDB). Hence the name "PDB heuristic".

Example: transition system
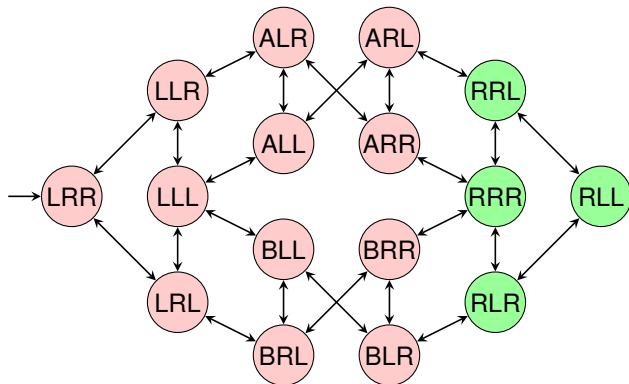
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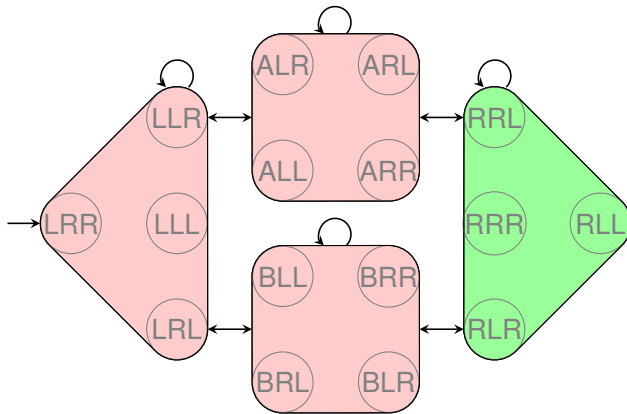
Logistics problem with one package, two trucks, two locations:

- state variable package: $\{L, R, A, B\}$
- state variable truck A: $\{L, R\}$
- state variable truck B: $\{L, R\}$

Example: projection

Abstraction induced by $\pi_{\{package\}}$:

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$$h^{\{package\}}(LRR) = 2$$

Example: projection (2)
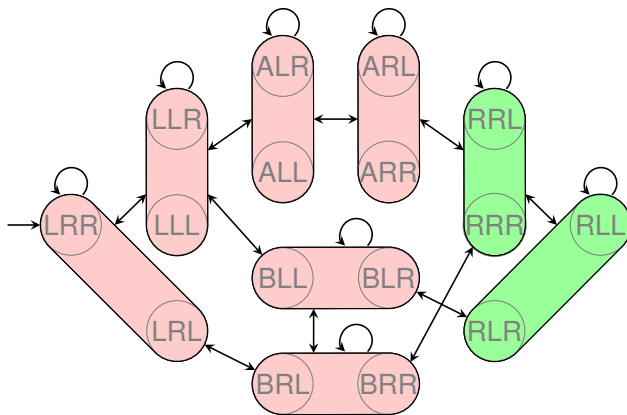
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Abstraction induced by $\pi_{\{\text{package},\text{truck A}\}}$:

$$h^{\{\text{package},\text{truck A}\}}(\text{LRR}) = 2$$

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In the rest of this chapter, we will discuss:

- how to **implement** PDB heuristics
- how to effectively make use of **multiple** PDB heuristics
- how to **find good patterns** for PDB heuristics

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Pattern database implementation

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Assume we are given a pattern P for a planning task Π.
How do we implement h^P?

1. In a precomputation step, we compute a graph representation for the abstraction $\mathcal{T}(\Pi)^{\pi_P}$ and compute the abstract goal distance for each abstract state.

2. During search, we use the precomputed abstract goal distances in a lookup step.

Precomputation step

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Let Π be a planning task and P a pattern.
Let $\mathcal{T} = \mathcal{T}(\Pi)$ and $\mathcal{T}' = \mathcal{T}^{\pi_P}$.

- We want to compute a graph representation of $\mathcal{T}'$.
- $\mathcal{T}'$ is defined through a homomorphism of $\mathcal{T}$.
    - For example, each concrete transition induces an abstract transition.
- However, we cannot compute $\mathcal{T}'$ by iterating over all transitions of $\mathcal{T}$.
    - This would take time $\Omega(\|\mathcal{T}\|)$.
    - This is prohibitively large (or else we could solve the task using breadth-first search or similar techniques).
- Hence, we need a way of computing $\mathcal{T}'$ in time which is polynomial only in $\|\Pi\|$ and $\|\mathcal{T}'\|$.

Syntactic projections

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Definition (syntactic projection)

Let $\Pi = \langle V, I, O, \gamma \rangle$ be an FDR planning task,
and let $P \subseteq V$ be a subset of its variables.
The syntactic projection $\Pi|_P$ of Π to P is the FDR planning task
$\langle P, I|_P, \{o|_P \mid o \in O\}, \gamma|_P \rangle$, where

- $\varphi|_P$ for formula φ is defined as the formula obtained from
  φ by replacing all atoms $(v = d)$ with $v \notin P$ by $\top$, and
- $o|_P$ for operator o is defined by replacing all formulas φ
  occurring in the precondition or effect conditions of o with
  $\varphi|_P$ and all atomic effects $(v := d)$ with $v \notin P$ with the
  empty effect $\top$.

Put simply, $\Pi|_P$ throws away all information not pertaining to
variables in P.

Trivially inapplicable operators

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Definition (trivially inapplicable operator)

An operator $\langle \chi, e \rangle$ of a SAS$^+$ task is called trivially inapplicable
if

- χ contains the atoms $(v = d)$ and $(v = d')$
  for some variable v and values $d \neq d'$, or
- e contains the effects $(v := d)$ and $(v := d')$
  for some variable v and values $d \neq d'$.

Notes:

- Trivially inapplicable operators are never applicable and
  can thus be safely omitted from the task.
- Trivially inapplicable operators can be detected in linear
  time.

Trivially unsolvable SAS⁺ tasks

Definition (trivially unsolvable SAS⁺ tasks)

A SAS⁺ task $\Pi = \langle V, I, O, \gamma \rangle$ is called trivially unsolvable if γ contains the atoms $(v = d)$ and $(v = d')$ for some variable v and values $d \neq d'$.

Notes:

- Trivially unsolvable SAS⁺ tasks have no goal states, and are hence unsolvable.
- Trivially unsolvable SAS⁺ tasks can be detected in linear time.

Equivalence theorem for syntactic projections

Theorem (syntactic projections vs. projections)

Let Π be a SAS$^+$ task that is not trivially unsolvable and has no trivially inapplicable operators, and let P be a pattern for Π. Then $\mathscr{T}(\Pi|_P) \overset{G}{\sim} \mathscr{T}(\Pi)^{\pi_P}$. $\square$

Note: The restrictions to SAS$^+$ tasks and to tasks without trivially inapplicable operators are necessary.

PDB computation

Using the equivalence theorem, we can compute pattern databases for (not trivially unsolvable) SAS⁺ tasks Π and patterns P:

Computing pattern databases

def compute-PDB(Π, P):

    Remove trivially inapplicable operators from Π.

    Compute $\Pi' := \Pi|_P$.

    Compute $\mathscr{T}' := \mathscr{T}(\Pi')$.

    Perform a backward breadth-first search from the goal
        states of $\mathscr{T}'$ to compute all abstract goal distances.

    PDB := a table containing all goal distances in $\mathscr{T}'$

    return PDB

The algorithm runs in polynomial time and space in terms of $\|\Pi\| + |PDB|$.

- Most practical implementations of PDB heuristics are limited to SAS⁺ tasks (or modest generalizations).
- One way to avoid the issues with general FDR tasks is to convert them to equivalent SAS⁺ tasks.
- However, most direct conversions can exponentially increase the task size in the worst case.

$\rightsquigarrow$ We will only consider SAS⁺ tasks in this chapter.

Lookup step: overview

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- During search, the PDB is the only piece of information necessary to represent h^P. (It is not necessary to store the abstract transition system itself at this point.)

- Hence, the space requirements for PDBs during search are linear in the number of abstract states S': there is one table entry for each abstract state.

- During search, $h^P(s)$ is computed by mapping $\pi_P(s)$ to a natural number in the range $\{0, \ldots, |S'| - 1\}$ using a perfect hash function, then looking up the table entry for that number.

Lookup step: algorithm

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Let $P = \{v_1, \ldots, v_k\}$ be the pattern.

- We assume that all variable domains are natural numbers counted from 0, i. e., $\mathscr{D}_v = \{0, 1, \ldots, |\mathscr{D}_v| - 1\}$.
- For all $i \in \{1, \ldots, k\}$, we precompute $N_i := \prod_{j=1}^{i-1} |\mathscr{D}(v_j)|$.

Then we can look up heuristic values as follows:

Computing pattern database heuristics

def PDB-heuristic(*s*):
    index := $\sum_{i=1}^{k} N_i s(v_i)$
    return *PDB*[*index*]

- This is a very fast operation: it can be performed in $O(k)$.
- For comparison, most relaxation heuristics need time $O(\|\Pi\|)$ per state.
- Cf. mixed-radix integer representation.

Lookup step: example

Abstraction induced by $\pi_{\{\text{package}, \text{truck A}\}}$:

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Lookup step: example (ctd.)

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- $P = \{v_1, v_2\}$ with v_1 = package, v_2 = truck A.
- $\mathscr{D}_{v_1} = \{L, R, A, B\} \approx \{0, 1, 2, 3\}$
- $\mathscr{D}_{v_2} = \{L, R\} \approx \{0, 1\}$

$\rightsquigarrow N_1 = \prod_{j=1}^{0} |\mathscr{D}_{v_j}| = 1$, $N_2 = \prod_{j=1}^{1} |\mathscr{D}_{v_j}| = 4$

$\rightsquigarrow index(s) = 1 \cdot s(\text{package}) + 4 \cdot s(\text{truck A})$

Pattern database:

abstract state	LL	RL	AL	BL	LR	RR	AR	BR
index	0	1	2	3	4	5	6	7
value	2	0	2	1	2	0	1	1

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Additive patterns for planning tasks

Pattern collections

- The space requirements for a pattern database grow exponentially with the number of state variables in the pattern.
- This places severe limits on the usefulness of single PDB heuristics h^P for larger planning task.
- To overcome this limitation, planners using pattern databases work with collections of multiple patterns.
- When using two patterns P_1 and P_2, it is always possible to use the maximum of h^{P_1} and h^{P_2} as an admissible and consistent heuristic estimate.
- However, when possible, it is much preferable to use the sum of h^{P_1} and h^{P_2} as a heuristic estimate, since $h^{P_1} + h^{P_2} \geq \max\{h^{P_1}, h^{P_2}\}$.

Criterion for additive patterns

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Theorem (additive pattern sets)

Let $P_1, \ldots, P_k$ be patterns for an FDR planning task Π.
If there exists no operator that has an effect on a variable
$v_i \in P_i$ and on a variable $v_j \in P_j$ for some $i \neq j$, then $\sum_{i=1}^{k} h^{P_i}$ is
an admissible and consistent heuristic for Π.

Proof.

If there exists no such operator, then no label of $\mathscr{T}(\Pi)$ affects
both $\mathscr{T}(\Pi)^{\pi_{P_i}}$ and $\mathscr{T}(\Pi)^{\pi_{P_j}}$ for $i \neq j$. By the theorem on affecting
transition labels, this means that any two projections π_{P_i} and
π_{P_j} are orthogonal. The claim follows with the theorem on
additivity for orthogonal abstraction mappings.

A pattern set $\{P_1, \ldots, P_k\}$ which satisfies the criterion of the
theorem is called an additive pattern set or additive set.

Finding additive pattern sets

The theorem on additive pattern sets gives us a simple criterion to decide which pattern heuristics can be admissibly added.

Given a pattern collection $\mathscr{C}$ (i.e., a set of patterns), we can use this information as follows:

1. Build the compatibility graph for $\mathscr{C}$.
   - Vertices correspond to patterns $P \in \mathscr{C}$.
   - There is an edge between two vertices iff no operator affects both incident patterns.

2. Compute all maximal cliques of the graph.
   These correspond to maximal additive subsets of $\mathscr{C}$.
   - Computing large cliques is an NP-hard problem, and a graph can have exponentially many maximal cliques.
   - However, there are output-polynomial algorithms for finding all maximal cliques (Tomita, Tanaka & Takahashi, 2004) which have led to good results in practice.

The canonical heuristic function

Definition (canonical heuristic function)

Let Π be an FDR planning task, and let $\mathscr{C}$ be a pattern collection for Π.

The canonical heuristic $h^{\mathscr{C}}$ for pattern collection $\mathscr{C}$ is defined as

$$h^{\mathscr{C}}(s) = \max_{\mathscr{D} \in \text{cliques}(\mathscr{C})} \sum_{P \in \mathscr{D}} h^{P}(s),$$

where $\text{cliques}(\mathscr{C})$ is the set of all maximal cliques in the compatibility graph for $\mathscr{C}$.

For all choices of $\mathscr{C}$, heuristic $h^{\mathscr{C}}$ is admissible and consistent.

How good is the canonical heuristic function?

- The canonical heuristic function is the best possible admissible heuristic we can derive from $\mathscr{C}$ using our additivity criterion.
- In theory, even better heuristic estimates can be obtained from projection heuristics using a more general additivity criterion based on an idea called cost partitioning.
  - Optimal polynomial cost partitioning algorithms exist (Katz & Domshlak, 2008a).

Canonical heuristic function: example

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Example

Consider a planning task with state variables $V = \{v_1, v_2, v_3\}$ and the pattern collection $\mathscr{C} = \{P_1, \ldots, P_4\}$ with $P_1 = \{v_1, v_2\}$, $P_2 = \{v_1\}$, $P_3 = \{v_2\}$ and $P_4 = \{v_3\}$.

There are operators affecting each individual variable, and the only operators affecting several variables affect v_1 and v_3.

What are the maximal cliques in the compatibility graph for $\mathscr{C}$?

Answer: $\{P_1\}$, $\{P_2, P_3\}$, $\{P_3, P_4\}$

What is the canonical heuristic function $h^{\mathscr{C}}$?

Answer: $h^{\mathscr{C}} = \max\{h^{P_1}, h^{P_2} + h^{P_3}, h^{P_3} + h^{P_4}\}$
$\qquad\quad = \max\{h^{\{v_1, v_2\}}, h^{\{v_1\}} + h^{\{v_2\}}, h^{\{v_2\}} + h^{\{v_3\}}\}$

Pattern selection

Pattern selection as an optimization problem

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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 candidate solutions
  (= pattern collections which fit into a given memory limit)

- Find: a best possible solution, 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) 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 evolutionary algorithm
- Haslum et al. (2007): using hill-climbing

⤳ we present the main ideas of the second approach here

Pattern selection as hill-climbing

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Reminder: Hill-climbing

σ := make-root-node(init())

forever:

    if is-goal(state(σ)):

        return extract-solution(σ)

    Σ' := { make-node(σ, o, s) | $\langle o, s \rangle \in$ succ(state(σ)) }

    σ := an element of Σ' minimizing h (random tie breaking)

Four questions to answer to use this for pattern selection:

1. init: What is the initial pattern collection?

2. is-goal: When do we terminate?

3. succ: Which collections are neighbours of the current collection?

4. h: How do we rank the quality of pattern collections?

Search space

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We first discuss the search space (init, is-goal, succ).

The basic idea is that we

- start from small patterns of only a single variable each,
- grow them by adding slightly larger patterns, and
- stop when heuristic quality no longer improves.

To motivate the precise definition of our search space, we need a little more theory.

Initial pattern collection

Theorem (non-goal patterns are trivial)

*Let Π be a SAS⁺ planning task that is not trivially unsolvable,
and let P be a pattern for Π such that no variable in P is
mentioned in the goal formula of Π.
Then $h^P(s) = 0$ for all states s.*

Proof.

All states in the abstraction are goal states.

This motivates our first answer:

1. What is the initial pattern collection?

The initial pattern collection is
$\{\{v\} \mid v$ is a state variable mentioned in the goal formula$\}$.

Termination criterion

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Our second question has a very simple answer:

2. When do we terminate?

We terminate as soon as the current pattern collection has no successors of better quality.

Note that this also covers the case where there are no successors at all because further growth of the current pattern collection would exceed a memory limit.

Search neighborhood: idea

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Our search neighbourhood is defined through incremental growth of the current pattern collection.

A successor is obtained by

- starting from the current pattern collection $\mathscr{C}$,
- choosing one of its patterns $P \in \mathscr{C}$ (without removing it from $\mathscr{C}$!),
- generating a new pattern by extending P with a single variable ($P' = P \cup \{v\}$), and
- adding P' to $\mathscr{C}$ to form the new pattern collection $\mathscr{C}'$

However, not all such collections $\mathscr{C}'$ are useful.

Causal graphs

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Definition (causal graph)

Let $\Pi = \langle V, I, O, \gamma \rangle$ be an FDR planning task.
The causal graph of Π, $CG(\Pi)$, is the directed graph with vertex set V and an arc from $u \in V$ to $v \in V$ iff $u \neq v$ and there exists an operator $o \in O$ such that:

- u appears anywhere in o (in precondition, effect conditions or atomic effects), and
- v is modified by an effect of o.

Idea: an arc $\langle u, v \rangle$ in the causal graph indicates that variable u is in some way relevant for modifying the value of v

Causally relevant variables

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Definition (causally relevant variables)

Let $\Pi = \langle V, I, O, \gamma \rangle$ be an FDR planning task and let $P \subseteq V$ be a pattern for Π.

We say that $v \in P$ is causally relevant for P if $CG(\Pi)$ contains a directed path from v to a variable $v' \in P$ that is mentioned in the goal formula γ.

Note: The definition implies that variables in P mentioned in the goal are always causally relevant for P.

Causally irrelevant variables are useless

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Theorem (causally irrelevant variables are useless)

Let $P \subseteq V$ be a pattern for an FDR planning task Π, and let $P' \subseteq P$ consist of all variables that are causally relevant for P. Then $h^{P'}(s) = h^P(s)$ for all states s. $\square$

Corollary: There is no point in growing a pattern by adding a variable that is causally irrelevant in the resulting pattern.

Causally connected patterns

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Definition (causally connected patterns)

Let $\Pi = \langle V, I, O, \gamma \rangle$ be an FDR planning task and let $P \subseteq V$ be a pattern for Π.

We say that P is causally connected if the subgraph of $CG(\Pi)$ induced by P is weakly connected (i. e., contains a path from every vertex to every other vertex, ignoring arc directions).

Disconnected patterns are decomposable

Theorem (causally disconnected patterns are decomposable)

Let $P \subseteq V$ be a pattern for a SAS$^+$ planning task Π that is not causally connected, and let P_1, P_2 be a partition of P into non-empty subsets such that $CG(\Pi)$ contains no arc between the two sets.
Then $h^{P_1}(s) + h^{P_2}(s) = h^P(s)$ for all states s. □

Corollary: There is no point in including a causally disconnected pattern in the collection. (Using its connected components instead requires less space and gives identical results.)

Search neighbourhood

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We can now put the pieces together to define our search neighbourhood, obtaining the third answer:

3. Which collections are neighbours of the current collection?

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

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

Search neighborhood (ctd.)

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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.

What is a good pattern collection?

- The last question we need to answer is how to rank the quality of pattern collections.

- This is perhaps the most critical point: without a good ranking criterion, pattern collections are chosen blindly.

The first search-based approach to pattern selection (Edelkamp, 2007) used the following strategy:

- only additive sets are used as pattern collections
    - no need for something like the canonical heuristic function

- the quality of a single pattern is estimated by its mean heuristic value (the higher, the better)

- the quality of a pattern collection is estimated by the sum of the individual pattern qualities

Discussion of the mean value approach

Pros of the approach:

- mean heuristic values are clearly correlated with search performance ⤳ the quality measure makes sense
- mean heuristic values are quite easy to calculate

Cons of the approach:

- cannot reasonably deal with infinite heuristic estimates
- difficult to generalize to pattern collections that are not fully additive
- there are better predictors for search performance than mean heuristic values

So what is a good pattern collection, again?

How can be come up with a better quality measure?

- We are chiefly interested in minimizing the number of node expansions for the canonical heuristic function during the actual search phase of the planner.
- There is theoretical work on predicting node expansions of heuristic search algorithms based on parameters of the heuristic (Korf, Reid & Edelkamp, 2001).

$\rightsquigarrow$ Try to estimate these parameters, then use their analysis.

Estimating heuristic quality in practice

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Summary

"I THINK YOU SHOULD BE MORE EXPLICIT HERE IN STEP TWO"

With some assumptions and simplifications, we reduce the problem of ranking the pattern collection quality to this:

Measuring degree of improvement

- Generate M states $s_1, \ldots, s_M$ through random walks in the search space from the initial state (according to certain parameters not discussed in detail).

- The degree of improvement of a pattern collection $\mathscr{C}'$ which is generated as a successor of collection $\mathscr{C}$ is the number of sample states s_i for which $h^{\mathscr{C}'}(s_i) > h^{\mathscr{C}}(s_i)$.

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

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- So we need to compute $h^{\mathscr{C}'}(s)$ for some states s and each candidate successor collection $\mathscr{C}'$.
- We have PDBs for all patterns in $\mathscr{C}$, but not for the new pattern $P' \in \mathscr{C}'$ (of the form $P \cup \{v\}$ for some $P \in \mathscr{C}$).
- If possible, we want to avoid computing the complete pattern database except for the best successor (where we will need it later anyway).

Idea:

- For SAS$^+$ tasks Π, $h^{P'}(s)$ is identical to the optimal solution length 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.

Summary

- Pattern database (PDB) heuristics are abstraction heuristics based on projection to a subset of variables.
- For SAS$^+$ tasks, they can easily be implemented via syntactic projections on the task representation.
- PDBs are lookup tables that store heuristic values, indexed by perfect hash values for projected states.
- PDB values can be looked up very fast, in time $O(k)$ for a projection to k variables.

Summary (ctd.)

- When faced with multiple PDB heuristics (a pattern collection), we want to admissibly add their values where possible, and maximize where addition is inadmissible.

- The canonical heuristic function is the best possible additive/maximizing combination for a given pattern collection given our additivity criterion.

- One way to automatically find a good pattern collection is by performing search in the space of pattern collections.