

Principles of AI Planning

7. Planning as search: relaxed planning tasks

Bernhard Nebel and Robert Mattmüller

Albert-Ludwigs-Universität Freiburg

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Obtaining
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Relaxed
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Summary

How to obtain a heuristic

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Obtaining
heuristics

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heuristic
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planning tasks

Summary

A simple heuristic for deterministic planning

STRIPS (Fikes & Nilsson, 1971) used the number of state variables that differ in current state s and a STRIPS goal $a_1 \wedge \dots \wedge a_n$:

$$h(s) := |\{i \in \{1, \dots, n\} \mid s \neq a_i\}|.$$

Intuition: more true goal literals \rightsquigarrow closer to the goal

\rightsquigarrow **STRIPS heuristic (a.k.a. goal-count heuristic)** (properties?)

Note: From now on, for convenience we usually write heuristics as functions of states (as above), not nodes.

Node heuristic h' is defined from state heuristic h as $h'(\sigma) := h(\text{state}(\sigma))$.

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Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

Criticism of the STRIPS heuristic

What is wrong with the STRIPS heuristic?

- quite **uninformative**:
the range of heuristic values in a given task is small;
typically, most successors have the same estimate
 - very sensitive to **reformulation**:
can easily transform any planning task into an equivalent one where $h(s) = 1$ for all non-goal states (how?)
 - ignores almost all **problem structure**:
heuristic value does not depend on the set of operators!
- ↪ need a better, principled way of coming up with heuristics

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Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

Coming up with heuristics in a principled way

General procedure for obtaining a heuristic

Solve an easier version of the problem.

Two common methods:

- **relaxation**: consider **less constrained** version of the problem
- **abstraction**: consider **smaller** version of real problem

Both have been very successfully applied in planning.

We consider both in this course, beginning with **relaxation**.

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Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

Relaxing a problem

How do we relax a problem?

Example (Route planning for a road network)

The road network is formalized as a weighted graph over points in the Euclidean plane. The weight of an edge is the **road distance** between two locations.

A relaxation **drops constraints** of the original problem.

Example (Relaxation for route planning)

Use the **Euclidean distance** $\sqrt{|x_1 - x_2|^2 + |y_1 - y_2|^2}$ as a heuristic for the road distance between $\langle x_1, y_1 \rangle$ and $\langle x_2, y_2 \rangle$. This is a **lower bound** on the road distance (\rightsquigarrow admissible).

\rightsquigarrow We drop the constraint of having to travel on roads.

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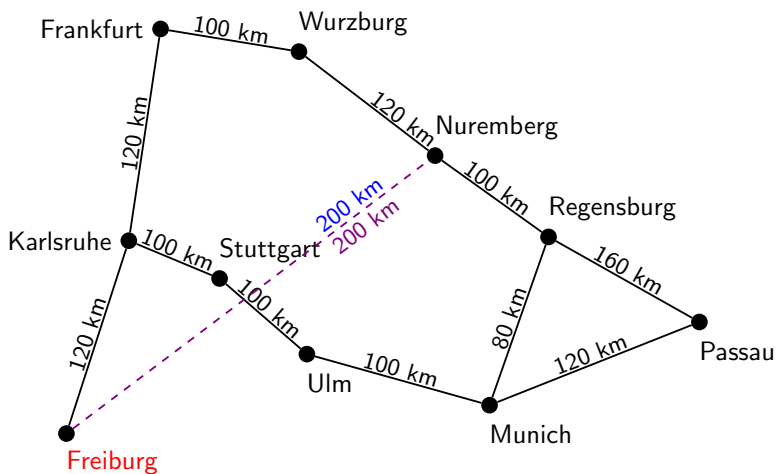
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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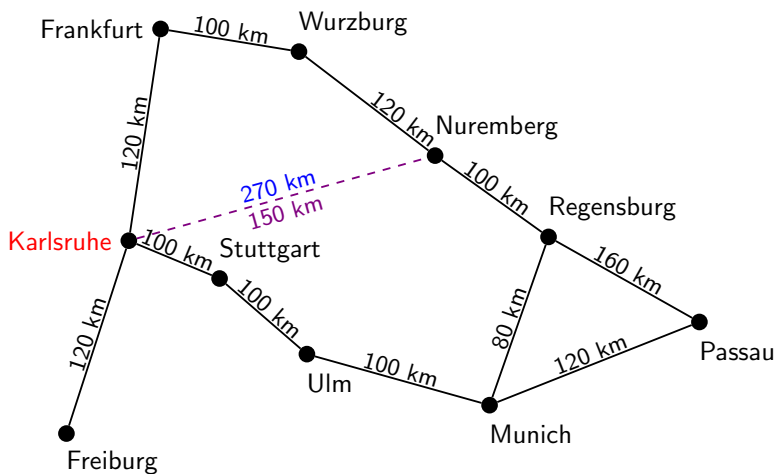
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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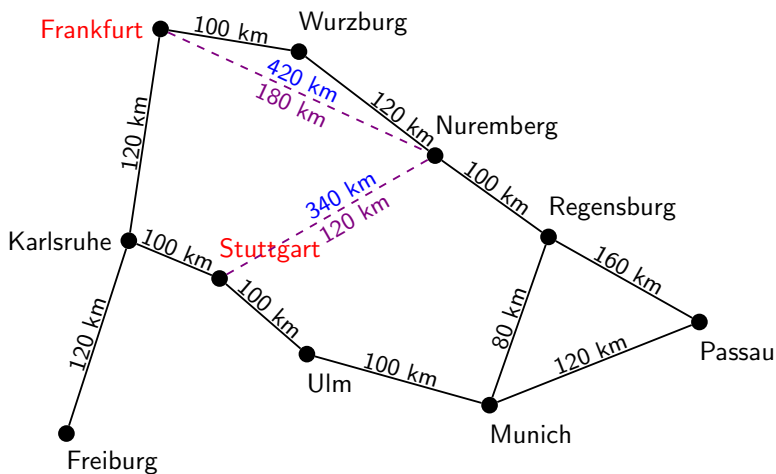
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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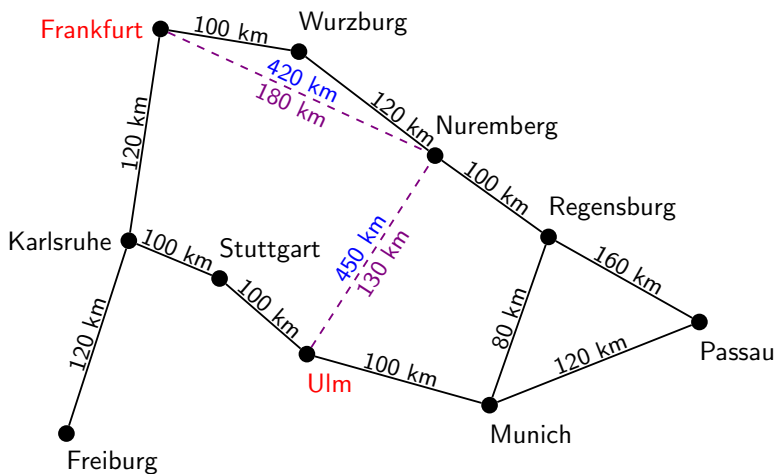
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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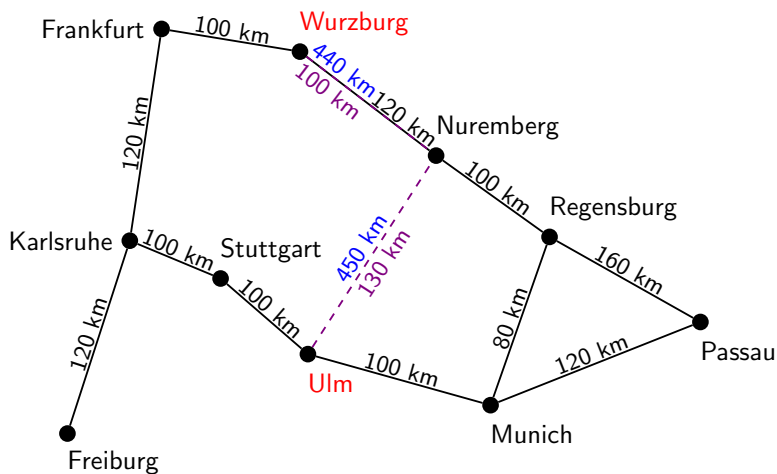
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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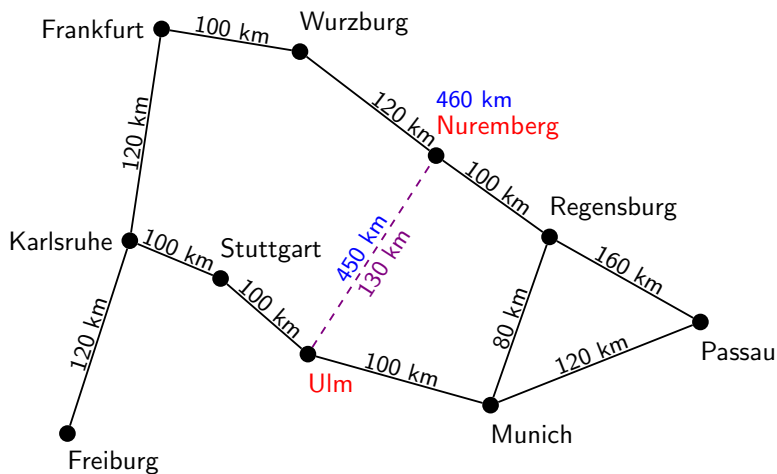
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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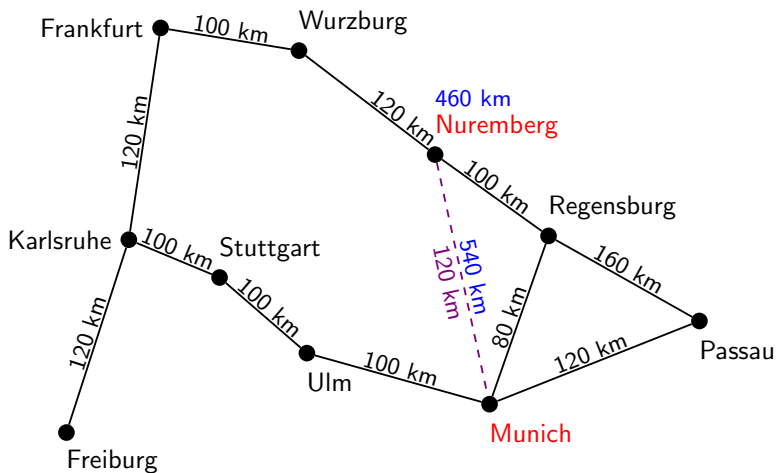
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



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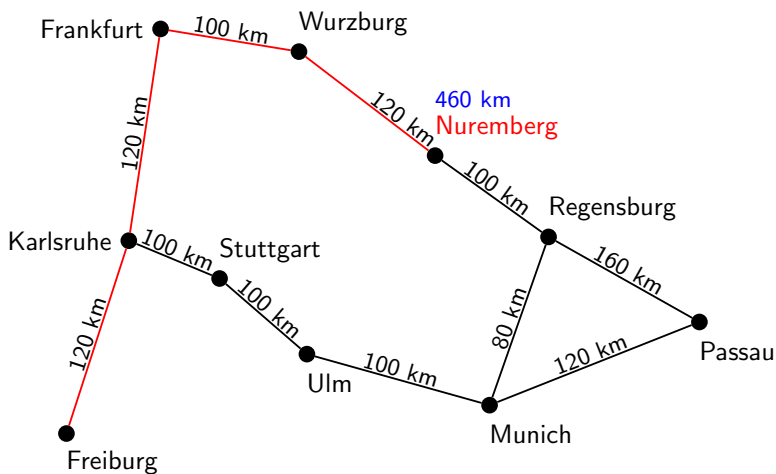
Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

A* using the Euclidean distance heuristic



AI Planning

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R. Mattmüller

Obtaining
heuristics

STRIPS
heuristic
Relaxation and
abstraction

Relaxed
planning tasks

Summary

Relaxed planning tasks

AI Planning

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Obtaining
heuristics

**Relaxed
planning tasks**

Definition
The relaxation
lemma
Greedy algorithm
Optimality
Discussion

Summary

Relaxed planning tasks: idea

In **positive normal form** (remember?), good and bad effects are easy to distinguish:

- Effects that make state variables true are good (**add effects**).
- Effects that make state variables false are bad (**delete effects**).

Idea for the heuristic: Ignore all delete effects.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Relaxed planning tasks

Definition (relaxation of operators)

The **relaxation** o^+ of an operator $o = \langle \chi, e \rangle$ in positive normal form is the operator which is obtained by replacing all negative effects $\neg a$ within e by the do-nothing effect \top .

Definition (relaxation of planning tasks)

The **relaxation** Π^+ of a planning task $\Pi = \langle A, I, O, \gamma \rangle$ in positive normal form is the planning task $\Pi^+ := \langle A, I, \{o^+ \mid o \in O\}, \gamma \rangle$.

Definition (relaxation of operator sequences)

The **relaxation** of an operator sequence $\pi = o_1 \dots o_n$ is the operator sequence $\pi^+ := o_1^+ \dots o_n^+$.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Relaxed planning tasks: terminology

- Planning tasks in positive normal form without delete effects are called **relaxed planning tasks**.
- Plans for relaxed planning tasks are called **relaxed plans**.
- If Π is a planning task in positive normal form and π^+ is a plan for Π^+ , then π^+ is called a **relaxed plan for Π** .

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Dominating states

The **on-set** $on(s)$ of a state s is the set of true state variables in s , i.e. $on(s) = s^{-1}(\{1\})$.

A state s' **dominates** another state s iff $on(s) \subseteq on(s')$.

Lemma (domination)

Let s and s' be valuations of a set of propositional variables A and let χ be a propositional formula over A which does not contain negation symbols.

If $s \models \chi$ and s' dominates s , then $s' \models \chi$.

Proof.

Proof by induction over the structure of χ .

- Base case $\chi = \top$: then $s' \models \top$.
- Base case $\chi = \perp$: then $s \not\models \perp$.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Dominating states (ctd.)

Proof (ctd.)

- Base case $\chi = a \in A$: assume $s \models a$ and $on(s) \subseteq on(s')$. With $a \in on(s)$ we get $a \in on(s')$, hence $s' \models a$.
- Inductive case $\chi = \chi_1 \wedge \chi_2$: by induction hypothesis, our claim holds for the proper subformulas χ_1 and χ_2 of χ .

$$\begin{aligned} s \models \chi &\iff s \models \chi_1 \wedge \chi_2 \\ &\iff s \models \chi_1 \text{ and } s \models \chi_2 \\ \text{I.H. (twice)} &\implies s' \models \chi_1 \text{ and } s' \models \chi_2 \\ &\iff s' \models \chi_1 \wedge \chi_2 \\ &\iff s' \models \chi. \end{aligned}$$

- Inductive case $\chi = \chi_1 \vee \chi_2$: Analogous.



The relaxation lemma

For the rest of this chapter, we assume that all planning tasks are in positive normal form.

Lemma (relaxation)

Let s be a state, let s' be a state that dominates s , and let π be an operator sequence which is applicable in s . Then π^+ is applicable in s' and $app_{\pi^+}(s')$ dominates $app_{\pi}(s)$. Moreover, if π leads to a goal state from s , then π^+ leads to a goal state from s' .

Proof.

The “moreover” part follows from the rest by the domination lemma. Prove the rest by induction over the length of π .

Base case: $\pi = \epsilon$

$app_{\pi^+}(s') = s'$ dominates $app_{\pi}(s) = s$ by assumption.

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B. Nebel,
R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

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AI Planning

B. Nebel,
R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

The relaxation lemma (ctd.)

Proof (ctd.)

Inductive case: $\pi = o_1 \dots o_{n+1}$

By the induction hypothesis, $o_1^+ \dots o_n^+$ is applicable in s' , and $t' = \text{app}_{o_1^+ \dots o_n^+}(s')$ dominates $t = \text{app}_{o_1 \dots o_n}(s)$.

Let $o := o_{n+1} = \langle \chi, e \rangle$ and $o^+ = \langle \chi, e^+ \rangle$. By assumption, o is applicable in t , and thus $t \models \chi$. By the domination lemma, we get $t' \models \chi$ and hence o^+ is applicable in t' . Therefore, π^+ is applicable in s' .

Because o is in positive normal form, all effect conditions satisfied by t are also satisfied by t' (by the domination lemma). Therefore, $([e]_t \cap A) \subseteq [e^+]_{t'}$ (where A is the set of state variables, or positive literals).

We get $\text{on}(\text{app}_\pi(s)) \subseteq \text{on}(t) \cup ([e]_t \cap A) \subseteq \text{on}(t') \cup [e^+]_{t'} = \text{on}(\text{app}_{\pi^+}(s'))$, and thus $\text{app}_{\pi^+}(s')$ dominates $\text{app}_\pi(s)$. \square

AI Planning

B. Nebel,
R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

**The relaxation
lemma**

Greedy algorithm

Optimality

Discussion

Summary

The relaxation lemma (ctd.)

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AI Planning

B. Nebel,
R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

The relaxation lemma (ctd.)

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AI Planning

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R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

The relaxation lemma (ctd.)

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AI Planning

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R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Consequences of the relaxation lemma

Corollary (relaxation leads to dominance and preserves plans)

*Let π be an operator sequence which is applicable in state s .
Then π^+ is applicable in s and $app_{\pi^+}(s)$ dominates $app_{\pi}(s)$.
If π is a plan for Π , then π^+ is a plan for Π^+ .*

Proof.

Apply relaxation lemma with $s' = s$. □

- ↪ Relaxations of plans are relaxed plans.
- ↪ Relaxations are no harder to solve than the original task.
- ↪ Optimal relaxed plans are never longer than optimal plans for original tasks.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Consequences of the relaxation lemma (ctd.)

Corollary (relaxation preserves dominance)

Let s be a state, let s' be a state that dominates s , and let π^+ be a relaxed operator sequence applicable in s . Then π^+ is applicable in s' and $\text{app}_{\pi^+}(s')$ dominates $\text{app}_{\pi^+}(s)$.

Proof.

Apply relaxation lemma with π^+ for π , noting that $(\pi^+)^+ = \pi^+$. □

- ↪ If there is a relaxed plan starting from state s , the same plan can be used starting from a dominating state s' .
- ↪ Making a transition to a dominating state never hurts in relaxed planning tasks.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

**The relaxation
lemma**

Greedy algorithm

Optimality

Discussion

Summary

Monotonicity of relaxed planning tasks

We need one final property before we can provide an algorithm for solving relaxed planning tasks.

Lemma (monotonicity)

Let $o^+ = \langle \chi, e^+ \rangle$ be a relaxed operator and let s be a state in which o^+ is applicable.

Then $app_{o^+}(s)$ dominates s .

Proof.

Since relaxed operators only have positive effects, we have $on(s) \subseteq on(s) \cup [e^+]_s = on(app_{o^+}(s))$. □

↪ Together with our previous results, this means that making a transition in a relaxed planning task **never** hurts.

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Greedy algorithm for relaxed planning tasks

The relaxation and monotonicity lemmas suggest the following algorithm for solving relaxed planning tasks:

Greedy planning algorithm for $\langle A, I, O^+, \gamma \rangle$

$s := I$

$\pi^+ := \epsilon$

forever:

if $s \models \gamma$:

return π^+

else if there is an operator $o^+ \in O^+$ applicable in s

 with $app_{o^+}(s) \neq s$:

 Append such an operator o^+ to π^+ .

$s := app_{o^+}(s)$

else:

return unsolvable

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Correctness of the greedy algorithm

The algorithm is **sound**:

- If it returns a plan, this is indeed a correct solution.
- If it returns “unsolvable”, the task is indeed unsolvable
 - Upon termination, there clearly is no relaxed plan from s .
 - By iterated application of the monotonicity lemma, s dominates I .
 - By the relaxation lemma, there is no solution from I .

What about **completeness** (termination) and **runtime**?

- Each iteration of the loop adds at least one atom to $on(s)$.
- This guarantees termination after at most $|A|$ iterations.
- Thus, the algorithm can clearly be implemented to run in polynomial time.
 - A good implementation runs in $O(\|II\|)$.

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Obtaining
heuristics

Relaxed
planning tasks

Definition
The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Using the greedy algorithm as a heuristic

We can apply the greedy algorithm within heuristic search:

- In a search node σ , solve the relaxation of the planning task with $state(\sigma)$ as the initial state.
- Set $h(\sigma)$ to the length of the generated relaxed plan.

Is this an **admissible** heuristic?

- Yes if the relaxed plans are **optimal** (due to the plan preservation corollary).
- However, usually they are not, because our greedy planning algorithm is very poor.

(What about safety? Goal-awareness? Consistency?)

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

The set cover problem

To obtain an admissible heuristic, we need to generate optimal relaxed plans. Can we do this efficiently?

This question is related to the following problem:

Problem (set cover)

Given: a finite set U , a collection of subsets $C = \{C_1, \dots, C_n\}$ with $C_i \subseteq U$ for all $i \in \{1, \dots, n\}$, and a natural number K .

Question: Does there exist a set cover of size at most K , i. e., a subcollection $S = \{S_1, \dots, S_m\} \subseteq C$ with $S_1 \cup \dots \cup S_m = U$ and $m \leq K$?

The following is a classical result from complexity theory:

Theorem (Karp 1972)

The set cover problem is NP-complete.

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Obtaining
heuristics

Relaxed
planning tasks

Definition
The relaxation
lemma
Greedy algorithm
Optimality
Discussion

Summary

Hardness of optimal relaxed planning

Theorem (optimal relaxed planning is hard)

The problem of deciding whether a given relaxed planning task has a plan of length at most K is NP-complete.

Proof.

For **membership in NP**, guess a plan and verify. It is sufficient to check plans of length at most $|A|$, so this can be done in nondeterministic polynomial time.

For **hardness**, we reduce from the set cover problem.

AI Planning

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Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Hardness of optimal relaxed planning (ctd.)

Proof (ctd.)

Given a set cover instance $\langle U, C, K \rangle$, we generate the following relaxed planning task $\Pi^+ = \langle A, I, O^+, \gamma \rangle$:

- $A = U$
- $I = \{a \mapsto 0 \mid a \in A\}$
- $O^+ = \{\langle \top, \bigwedge_{a \in C_i} a \rangle \mid C_i \in C\}$
- $\gamma = \bigwedge_{a \in U} a$

If S is a set cover, the corresponding operators form a plan. Conversely, each plan induces a set cover by taking the subsets corresponding to the operators. Clearly, there exists a plan of length at most K iff there exists a set cover of size K .

Moreover, Π^+ can be generated from the set cover instance in polynomial time, so this is a polynomial reduction. \square

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R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation
lemma

Greedy algorithm

Optimality

Discussion

Summary

Using relaxations in practice

How can we use relaxations for heuristic planning in practice?

Different possibilities:

- Implement an **optimal planner** for relaxed planning tasks and use its solution lengths as an estimate, even though it is NP-hard.
↪ **h^+ heuristic**
- Do not actually solve the relaxed planning task, but compute an estimate of its difficulty in a different way.
↪ **h_{\max} heuristic, h_{add} heuristic, $h_{\text{LM-cut}}$ heuristic**
- Compute a solution for relaxed planning tasks which is not necessarily optimal, but “reasonable”.
↪ **h_{FF} heuristic**

AI Planning

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R. Mattmüller

Obtaining
heuristics

Relaxed
planning tasks

Definition

The relaxation

lemma

Greedy algorithm

Optimality

Discussion

Summary

Summary

- Two general methods for coming up with heuristics:
 - **relaxation**: solve a **less constrained** problem
 - **abstraction**: solve a **small** problem
- Here, we consider the **delete relaxation**, which requires tasks in positive normal form and ignores delete effects.
- Delete-relaxed tasks have a **domination** property: it is always beneficial to make more fluents true.
- They also have a **monotonicity** property: applying operators leads to dominating states.
- Because of these two properties, **finding some relaxed plan** greedily is **easy** (polynomial).
- For an informative heuristic, we would ideally want to find **optimal relaxed plans**. This is **NP-complete**.

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Obtaining
heuristics

Relaxed
planning tasks

Summary