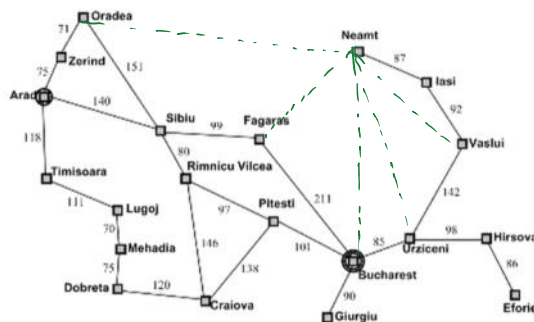


Relaxation

Method for automatically constructing heuristics in planning models

→ Relaxation means to simplify the problem, and take the solution to the simpler problem as the heuristic estimate for the solution to the actual problem.

Relaxation in Route-Finding



How to derive straight-line distance by relaxation?

- Problem \mathcal{P} : Route finding.
- Simpler problem \mathcal{P}' : Route finding for birds.
- Perfect heuristic h'^* for \mathcal{P}' : Straight-line distance.
- Transformation r : Pretend you're a bird.
Change connections to fully connected graph

Definition (Relaxation). Let $h^* : \mathcal{P} \mapsto \mathbb{R}_0^+ \cup \{\infty\}$ be a function. A *relaxation* of h^* is a triple $\mathcal{R} = (\mathcal{P}', r, h'^*)$ where \mathcal{P}' is an arbitrary set, and $r : \mathcal{P} \mapsto \mathcal{P}'$ and $h'^* : \mathcal{P}' \mapsto \mathbb{R}_0^+ \cup \{\infty\}$ are functions so that, for all $\Pi \in \mathcal{P}$, the *relaxation heuristic* $h^{\mathcal{R}}(\Pi) := h'^*(r(\Pi))$ satisfies $h^{\mathcal{R}}(\Pi) \leq h^*(\Pi)$. The relaxation is:

- *native* if $\mathcal{P}' \subseteq \mathcal{P}$ and $h'^* = h^*$; *Simplified Problem can be constructed in the original problem*
- *efficiently constructible* if there exists a polynomial-time algorithm that, given $\Pi \in \mathcal{P}$, computes $r(\Pi)$; *Simplification is not expensive*
- *efficiently computable* if there exists a polynomial-time algorithm that, given $\Pi' \in \mathcal{P}'$, computes $h'^*(\Pi')$. *Calculating heuristic is not expensive*

Reminder:

- You have a problem, \mathcal{P} , whose perfect heuristic h^* you wish to estimate.
- You define a simpler problem, \mathcal{P}' , whose perfect heuristic h'^* can be used to (admissibly!) estimate h^* .
- You define a transformation, r , from \mathcal{P} into \mathcal{P}' .
- Given $\Pi \in \mathcal{P}$, you estimate $h^*(\Pi)$ by $h'^*(r(\Pi))$.

Relaxation in Route-Finding: Properties



Relaxation $\mathcal{R} = (\mathcal{P}', r, h'^*)$: Pretend you're a bird.

- **Native?** No: Birds don't do route-finding. (Well, it's equivalent to trivial maps with direct routes between everywhere.)
- **Efficiently constructible?** Yes (pretend you're a bird).
- **Efficiently computable?** Yes (measure straight-line distance).

"Goal-Counting" Relaxation in Australia: Properties



- **Propositions** P : $at(x)$ for $x \in \{Sy, Ad, Br, Pe, Da\}$; $v(x)$ for $x \in \{Sy, Ad, Br, Pe, Da\}$.
- **Actions** $a \in A$: $drive(x, y)$ where x, y have a road; $pre_a = \{at(x)\}$, $add_a = \{at(y), v(y)\}$, $del_a = \{at(x)\}$.
- **Initial state** I : $at(Sy), v(Sy)$.
- **Goal** G : $at(Sy), v(x)$ for all x .

Relaxation $\mathcal{R} = (\mathcal{P}', r, h'^*)$: Remove preconditions and deletes, then use h^* .

- **Native?** Yes. Empty pre and del lists. Still STRIPS Problem
- **Efficiently constructible?** Yes. Remove pre and del
- **Efficiently computable?** Generally no, if multiple goals can be reached with single actions then NP-HARD

What shall we do with the relaxation?

Approximate h^* using goal counting

Delete Relaxation

For STRIPS problems: drop delete lists

Π^+ : Delete relaxed STRIPS planning task

h^+ : Optimal Delete relaxation Heuristic

s^+ : State in Π^+

- Anything that becomes true in Π^+ stays true
- h^+ always admissible, but hard to compute

State Dominance

s_1 dominates s_2 if $s_2 \subset s_1$

- All True facts in S_2 are present in S_1

Greedy Relaxed Planning for Π_s^+

```

 $s^+ := s; \bar{a}^+ := \langle \rangle$ 
while  $G \not\subseteq s^+$  do: While not in goal
  if  $\exists a \in A$  s.t.  $pre_a \subseteq s^+$  and  $appl(s^+, a^+) \neq s^+$  then
    select one such  $a$  Apply an action satisfied by Preconditions
     $s^+ := appl(s^+, a^+); \bar{a}^+ := \bar{a}^+ \circ \langle a^+ \rangle$  that adds new facts
  else return " $\Pi_s^+$  is unsolvable" endif if no new facts can be added
  then return unsolvable
endwhile
return  $\bar{a}^+$ 

```

- Safe
- goal aware
- non admissible

Approximations to h^+ for multiple objectives

h^{add} : calculate cost of achieving each individual objective in relaxed problem, and sum the total cost

h^{max} : return cost of achieving most expensive objective in relaxed problem.

$$h^{max} \leq h^+ \leq h^* \quad \text{admissible}$$

$$h^{add} \geq h^+ \quad \text{may not be admissible}$$

Bellman-Ford

Bellman-Ford variant computing h^{add} for state s

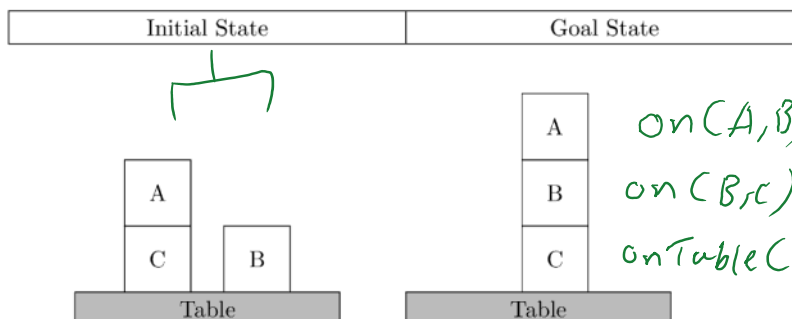
```

new table  $T_0^{add}(g)$ , for  $g \in F$ 
For all  $g \in F$ :  $T_0^{add}(g) := \begin{cases} 0 & g \in s \\ \infty & \text{otherwise} \end{cases}$ 
fn  $c_i(g) := \begin{cases} T_i^{add}(g) & |g| = 1 \\ \sum_{g' \in g} T_i^{add}(g') & |g| > 1 \end{cases}$ 
fn  $f_i(g) := \min[c_i(g), \min_{a \in A, g \in add_a} c(a) + c_i(pre_a)]$ 
do forever:
  new table  $T_{i+1}^{add}(g)$ , for  $g \in F$ 
  For all  $g \in F$ :  $T_{i+1}^{add}(g) := f_i(g)$ 
  if  $T_{i+1}^{add} = T_i^{add}$  then stop endif
   $i := i + 1$ 
enddo

```

Add column for every predicate
 Set True facts to 0 and ∞ otherwise
 Until convergence:
 Apply every possible action that adds new facts / decreases value of a fact
 Value of fact = Action cost + sum of values for preconditions on prev line
 (for h^{max} : Value = Action cost + max Precondition value)

→ Basically the same algorithm works for h^{max} , just change \sum for max
 HAVE TO WAIT UNTIL CONVERGENCE!! because values can update in later iterations



h^add table																				
i	clear(a)	clear(b)	clear(c)	handempty()	holding(a)	holding(b)	holding(c)	on(a, a)	on(a, b)	on(a, c)	on(b, a)	on(b, b)	on(b, c)	on(c, a)	on(c, b)	on(c, c)	ontable(a)	ontable(b)	ontable(c)	
0	0	0	0	inf	0	inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	0	0	0
1	0	0	0	1	0	1	1	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	0	0	0
2	0	0	0	1	0	1	1	2	2	2	0	2	2	3	inf	inf	inf	2	0	0
3	0	0	0	1	0	1	1	2	2	2	0	2	2	3	3	3	4	2	0	0
4	0	0	0	1	0	1	1	2	2	2	0	2	2	3	3	3	4	2	0	0
h^add	5																			
h^max table																				
i	clear(a)	clear(b)	clear(c)	handempty()	holding(a)	holding(b)	holding(c)	on(a, a)	on(a, b)	on(a, c)	on(b, a)	on(b, b)	on(b, c)	on(c, a)	on(c, b)	on(c, c)	ontable(a)	ontable(b)	ontable(c)	
0	0	0	0	inf	0	inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	0	0	0
1	0	0	0	1	0	1	1	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	0	0	0
2	0	0	0	1	0	1	1	2	2	2	0	2	2	2	inf	inf	inf	2	0	0
3	0	0	0	1	0	1	1	2	2	2	0	2	2	2	3	3	3	2	0	0
4	0	0	0	1	0	1	1	2	2	2	0	2	2	2	3	3	3	2	0	0
h^max	2																			