

Principles of AI Planning

15. Strong nondeterministic planning

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In this chapter, we will consider the simplest case of nondeterministic planning by restricting attention to **strong plans**.



Concepts

Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary



Recall the definition of strong plans:

Definition (strong plan)

Let S be the set of states of a planning task Π . Then a **strong plan** for Π is a function $\pi : S_\pi \rightarrow O$ for some subset $S_\pi \subseteq S$ such that

- $\pi(s)$ is applicable in s for all $s \in S_\pi$,
- $S_\pi(s_0) \subseteq S_\pi \cup S_\star$ (π is closed),
- $S_\pi(s') \cap S_\star \neq \emptyset$ for all $s' \in S_\pi(s_0)$ (π is proper), and
- there is no state $s' \in S_\pi(s_0)$ such that s' is reachable from s' following π in a strictly positive number of steps (π is acyclic).

Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary



Concepts

Strong plans

Images

Weak preimages

Strong preimages

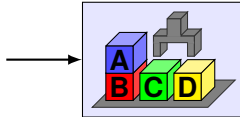
Algorithms

Summary

Execution of a strong plan

- 1 Determine the current state s .
- 2 If s is a goal state then terminate.
- 3 Execute action $\pi(s)$.
- 4 Repeat from first step.

Strong plans



Concepts

Strong plans

Images

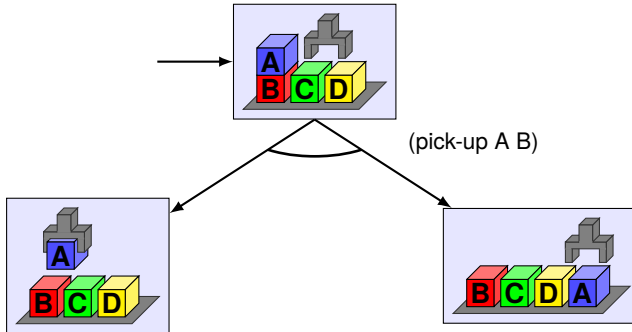
Weak preimages

Strong preimages

Algorithms

Summary

Strong plans



Concepts

Strong plans

Images

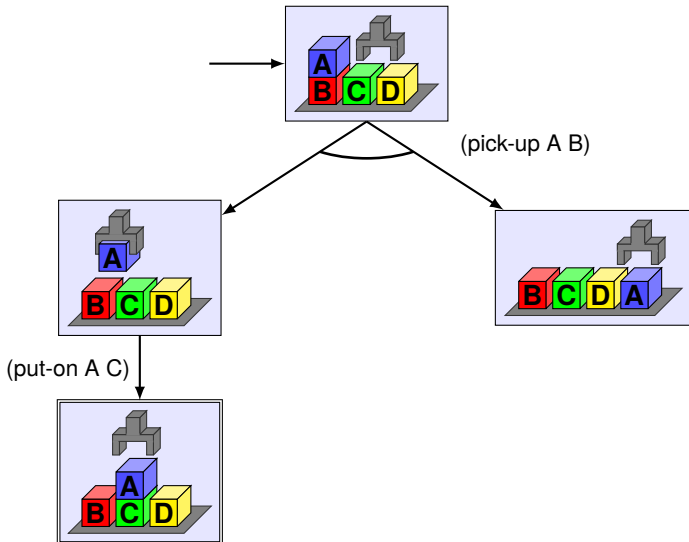
Weak preimages

Strong preimages

Algorithms

Summary

Strong plans



Concepts

Strong plans

Images

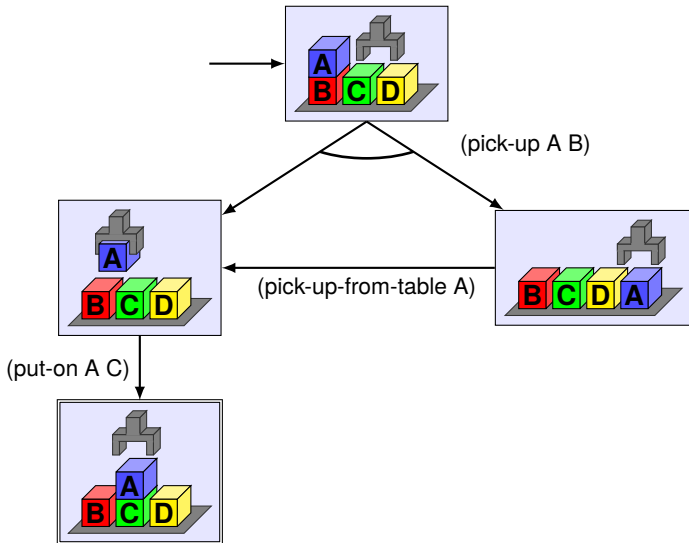
Weak preimages

Strong preimages

Algorithms

Summary

Strong plans



Concepts

Strong plans

Images

Weak preimages

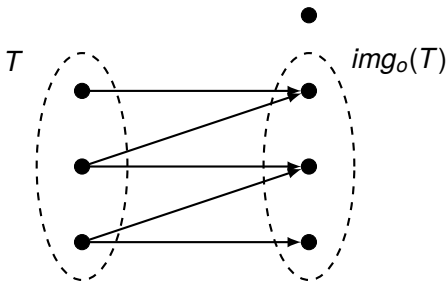
Strong preimages

Algorithms

Summary

Image

The **image** of a set T of states with respect to an operator o is the set of those states that can be reached by executing o in a state in T .



Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary



Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary

Definition (image of a state)

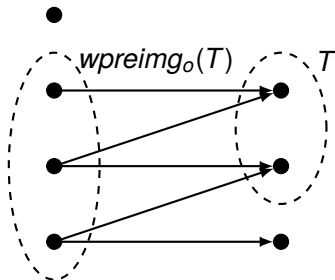
$$img_o(s) = \{s' \in S \mid s \xrightarrow{o} s'\} = app_o(s)$$

Definition (image of a set of states)

$$img_o(T) = \bigcup_{s \in T} img_o(s)$$

Weak preimage

The **weak preimage** of a set T of states with respect to an operator o is the set of those states from which a state in T can be reached by executing o .



Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary



Concepts

Strong plans
Images

Weak preimages
Strong preimages

Algorithms

Summary

Definition (weak preimage of a state)

$$wpreimg_o(s') = \{s \in S \mid s \xrightarrow{o} s'\}$$

Definition (weak preimage of a set of states)

$$wpreimg_o(T) = \bigcup_{s \in T} wpreimg_o(s).$$

Strong preimage

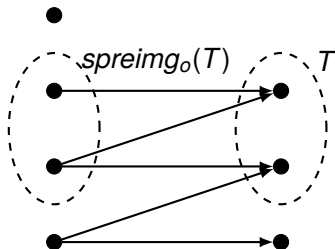
The **strong preimage** of a set T of states with respect to an operator o is the set of those states from which a state in T is always reached when executing o .

Concepts

- Strong plans
- Images
- Weak preimages
- Strong preimages

Algorithms

Summary





Concepts

Strong plans

Images

Weak preimages

Strong preimages

Algorithms

Summary

Definition (strong preimage of a set of states)

$$spreimg_o(T) = \{s \in S \mid \exists s' \in T : s \xrightarrow{o} s' \wedge img_o(s) \subseteq T\}$$



Algorithms

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



1 Dynamic programming (backward)

Compute operator/distance/value for a state based on the operators/distances/values of its all successor states.

- 1 Zero actions needed for goal states.
- 2 If states with i actions to goals are known, states with $\leq i + 1$ actions to goals can be easily identified.

Automatic reuse of plan suffixes already found.

2 Heuristic search (forward)

Strong planning can be viewed as AND/OR graph search.

OR nodes: Choice between operators

AND nodes: Choice between effects

Heuristic AND/OR search algorithms:

AO*, Proof Number Search, ...

Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary



Planning by dynamic programming

If for all successors of state s with respect to operator o a plan exists, assign operator o to s .

- **Base case $i = 0$:** In goal states there is nothing to do.
- **Inductive case $i \geq 1$:** If $\pi(s)$ is still undefined and there is $o \in O$ such that for all $s' \in \text{img}_o(s)$, the state s' is a goal state or $\pi(s')$ was assigned in an earlier iteration, then assign $\pi(s) = o$.

Backward distances

If s is assigned a value on iteration $i \geq 1$, then the **backward distance** of s is i . The dynamic programming algorithm essentially computes the **backward distances** of states.

Concepts

Algorithms

Regression

Efficient
implementation of
regression
Progression

Summary

Example

distance to G

∞

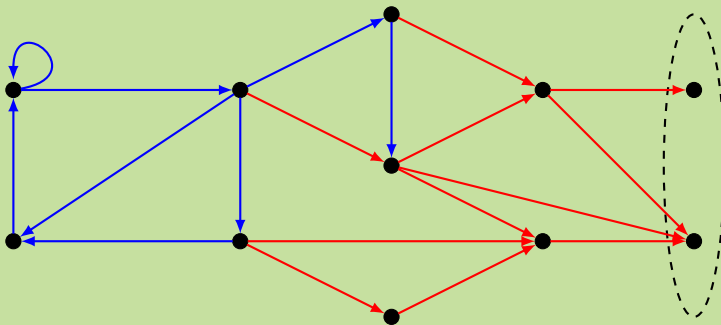
3

2

1

0

G



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Definition (backward distance sets)

Let G be a set of states and O a set of operators.

The **backward distance sets** D_i^{bwd} for G and O consist of those states for which there is a guarantee of reaching a state in G with at most i operator applications using operators in O :

$$D_0^{bwd} := G$$

$$D_i^{bwd} := D_{i-1}^{bwd} \cup \bigcup_{o \in O} \text{spreimg}_o(D_{i-1}^{bwd}) \text{ for all } i \geq 1$$

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Concepts

Algorithms

Regression

Efficient
implementation of
regression
Progression

Summary

Definition (backward distance)

Let G be a set of states and O a set of operators, and let $D_0^{bwd}, D_1^{bwd}, \dots$ be the backward distance sets for G and O . Then the **backward distance** of a state s for G and O is

$$\delta_G^{bwd}(s) = \min\{i \in \mathbb{N} \mid s \in D_i^{bwd}\}$$

(where $\min \emptyset = \infty$).

Strong plans based on distances



Let $\Pi = \langle V, I, O, \gamma \rangle$ be a nondeterministic planning task with state set S and goal states S_* .

Extraction of a strong plan from distance sets

- 1 Let $S' \subseteq S$ be those states having a finite backward distance for $G = S_*$ and O .
- 2 Let $s \in S'$ be a state with distance $i = \delta_G^{bwd}(s) \geq 1$.
- 3 Assign to $\pi(s)$ any operator $o \in O$ such that $img_o(s) \subseteq D_{i-1}^{bwd}$. Hence o decreases the backward distance by at least one.

Then π is a strong plan for \mathcal{T} iff $I \in S'$.

Question: What is the **worst-case** runtime of the algorithm?

Question: What is the **best-case** runtime of the algorithm if most states have a finite backward distance?

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



- An algorithm that represents the states **explicitly** stops being feasible at about 10^8 or 10^9 states.
- For planning with bigger transition systems **structural properties** of the transition system have to be taken advantage of.
- As before, representing state sets as **propositional formulae** (or **BDDs**) often allows taking advantage of the structural properties: a formula (or BDD) that represents a set of states or a transition relation that has certain regularities may be very small in comparison to the set or relation.
- In the following, we will present an algorithm using a boolean-formula representation (without going into the details of how to implement it using BDDs).

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Remark: The following algorithm assumes a propositional representation of the state space as opposed to a finite-domain representation. We have already seen how to translate an FDR encoding into a propositional encoding in Chapter 9 (cf. definition of the “induced propositional planning task”).

Therefore, for the rest of the present section, we will assume without loss of generality that all $v \in V$ are propositional variables with domain $\mathcal{D}_v = \{0, 1\}$.

Breadth-first search with progression and state sets (deterministic case)



Progression breadth-first search

```
def bfs-progression( $V, I, O, \gamma$ ):  
     $goal := formula-to-set(\gamma)$   
     $reached := \{I\}$   
    loop:  
        if  $reached \cap goal \neq \emptyset$ :  
            return solution found  
         $new-reached := reached \cup \bigcup_{o \in O} img_o(reached)$   
        if  $new-reached = reached$ :  
            return no solution exists  
         $reached := new-reached$ 
```

↪ This can easily be transformed into a **regression** algorithm.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Regression breadth-first search

def bfs-regression(V, I, O, γ):

init := I

reached := *formula-to-set*(γ)

loop:

if *init* \in *reached*:

return solution found

new-reached := *reached* $\cup \cup_{o \in O} wpreim_{o}(reached)$

if *new-reached* = *reached*:

return no solution exists

reached := *new-reached*

- This algorithm is very similar to the dynamic programming algorithm for the nondeterministic case!

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Breadth-first search with regression and state sets (strong nondeterministic case)



Regression breadth-first search

def bfs-regression(V, I, O, γ):

init := I

reached := *formula-to-set*(γ)

loop:

if *init* \in *reached*:

return solution found

new-reached := *reached* \cup $\bigcup_{o \in O} spreimg_o(\textit{reached})$

if *new-reached* = *reached*:

return no solution exists

reached := *new-reached*

- How do we define *spreimg* with logic (or BDD) operations?

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Transition formula for nondeterministic operators



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Let V be the set of state variables and $V' := \{v' \mid v \in V\}$ a set of primed copies of the variables in V . Intuition:

- Variables in V describe the **current state** s .
- Variables in V' describe the **next state** s' .

We would like to define a formula $\tau_V(o)$ that describes the transitions labeled with o between states s (over V) and s' (over V') in terms of V and V' .

Transition formula for nondeterministic operators



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

The formula $\tau_V(o)$ must express

- the conditions for **applicability** of o ,
- how o **changes** state variables, and
- which state variables o **does not change**.

A significant difficulty lies in the third requirement because **different variables** may be affected depending on nondeterministic choices.

Transition formula for nondeterministic operators



$\tau_V(o)$ for deterministic operators $o = \langle \chi, e \rangle$

$$\begin{aligned} \tau_V(o) = & \chi \wedge \bigwedge_{v \in V} ((EPC_V(e) \vee (v \wedge \neg EPC_{\neg v}(e))) \leftrightarrow v') \\ & \wedge \bigwedge_{v \in V} \neg(EPC_V(e) \wedge EPC_{\neg v}(e)) \end{aligned}$$

Assume that $e = \bigwedge_{a \in A} a \wedge \bigwedge_{d \in D} \neg d$ for $A = \{a_1, \dots, a_k\}$ and $D = \{d_1, \dots, d_l\}$ with $A \cap D = \emptyset$. Then this becomes simpler.

$\tau_V(o)$ for STRIPS operators $o = \langle \chi, \bigwedge_{a \in A} a \wedge \bigwedge_{d \in D} \neg d \rangle$

$$\tau_V(o) = \chi \wedge \bigwedge_{a \in A} a' \wedge \bigwedge_{d \in D} \neg d' \wedge \bigwedge_{v \in V \setminus (A \cup D)} (v \leftrightarrow v')$$

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Transition formula for nondeterministic operators



For nondeterministic operators $o = \langle \chi, \{e_1, \dots, e_n\} \rangle$ with corresponding add and delete lists A_i and D_i of e_i such that $A_i \cap D_i = \emptyset$, $i = 1, \dots, n$, we get:

$\tau_V(o)$ for nondeterministic operators $o = \langle \chi, \{e_1, \dots, e_n\} \rangle$

$$\tau_V(o) = \chi \wedge \bigvee_{i=1}^n \left(\bigwedge_{a \in A_i} a' \wedge \bigwedge_{d \in D_i} \neg d' \wedge \bigwedge_{v \in V \setminus (A_i \cup D_i)} (v \leftrightarrow v') \right)$$

Example

Let $V = \{a, b\}$, $V' = \{a', b'\}$, and $o = \langle \neg a, \{a, a \wedge \neg b\} \rangle$. Then

$$\tau_V(o) = \neg a \wedge \left((a' \wedge (b \leftrightarrow b')) \vee (a' \wedge \neg b') \right).$$

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Definition (substitution)

Let φ, t_1, \dots, t_n be propositional formulas and v_1, \dots, v_n atomic propositions.

We denote the formula obtained from φ by simultaneous replacement of all variables v_i by the corresponding formulas t_i , $i = 1, \dots, n$, by $\varphi[t_1, \dots, t_n/v_1, \dots, v_n]$.

Definition (existential abstraction)

Let φ be a propositional formula and v_1, \dots, v_n be atomic propositions. Then the **existential abstraction** of φ wrt. v_1, \dots, v_n is recursively defined as follows:

$$\exists v. \varphi := \varphi[\top/v] \vee \varphi[\perp/v]$$

$$\exists v_1 \dots \exists v_n. \varphi := \exists v_1 \dots \exists v_{n-1}. (\varphi[\top/v_n] \vee \varphi[\perp/v_n])$$

For a set of variables $V = \{v_1, \dots, v_n\}$ we use the abbreviation

$$\exists V. \varphi := \exists v_1 \dots \exists v_n. \varphi.$$

Note: Even with intermediate formula simplifications this can lead to an exponential blowup. BDDs can be useful here.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Strong preimages

$$\begin{aligned} \text{spreimg}_o(T) &= \{s \in S \mid \exists s' \in T : s \xrightarrow{o} s' \wedge \text{img}_o(s) \subseteq T\} \\ &= \{s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \wedge s' \in T) \wedge \\ &\quad \{s' \in S \mid s \xrightarrow{o} s'\} \subseteq T\} \\ &= \{s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \wedge s' \in T) \wedge \\ &\quad (\forall s' \in S : s \xrightarrow{o} s' \Rightarrow s' \in T)\} \\ &= \{s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \wedge s' \in T) \wedge \\ &\quad (\neg \exists s' \in S : s \xrightarrow{o} s' \wedge \neg(s' \in T))\} \end{aligned}$$

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Computing strong preimages with boolean function operations



$$\text{spreimg}_o(T) = \{s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \wedge s' \in T) \wedge (\neg \exists s' \in S : s \xrightarrow{o} s' \wedge \neg(s' \in T))\}$$

Strong preimages with boolean functions

For formula φ characterizing set T of strongly backward-reached states:

$$\text{spreimg}_o(\varphi) = (\exists V'. (\tau_V(o) \wedge \varphi[v'_1, \dots, v'_n / v_1, \dots, v_n])) \wedge (\neg \exists V'. (\tau_V(o) \wedge \neg \varphi[v'_1, \dots, v'_n / v_1, \dots, v_n]))$$

We can use this regression formula for efficient **symbolic** regression search. BDDs support all necessary operations (atomic propositions, \neg , \wedge , \vee , substitution, \exists , ...).

Computing strong preimages with boolean function operations



Example

Let $V = \{a, b\}$, $V' = \{a', b'\}$, and

$$o = \langle \neg a, \{a, a \wedge \neg b\} \rangle, \quad \text{i.e.,}$$

$$\tau_V(o) = \neg a \wedge \left((a' \wedge (b \leftrightarrow b')) \vee (a' \wedge \neg b') \right).$$

Moreover, let $\varphi = a$. Then

$$\begin{aligned} \text{spreimg}_o(\varphi) &= \exists a' \exists b'. \left(\neg a \wedge \left((a' \wedge (b \leftrightarrow b')) \vee (a' \wedge \neg b') \right) \wedge a' \right) \wedge \\ &\quad \neg \exists a' \exists b'. \left(\neg a \wedge \left((a' \wedge (b \leftrightarrow b')) \vee (a' \wedge \neg b') \right) \wedge \neg a' \right) \\ &\equiv \neg a \end{aligned}$$

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



- We saw a generalization of **regression search** to strong planning.
- However, this search is **uninformed** (breadth-first search).
- Is there an **analogue to A* search** for strong planning?
- Yes: **AO* search**
 - **Progression** search (like A*)
 - Guided by a **heuristic** (like A*)
 - Guaranteed **optimality** (under certain conditions, like A*)

Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

AND/OR search



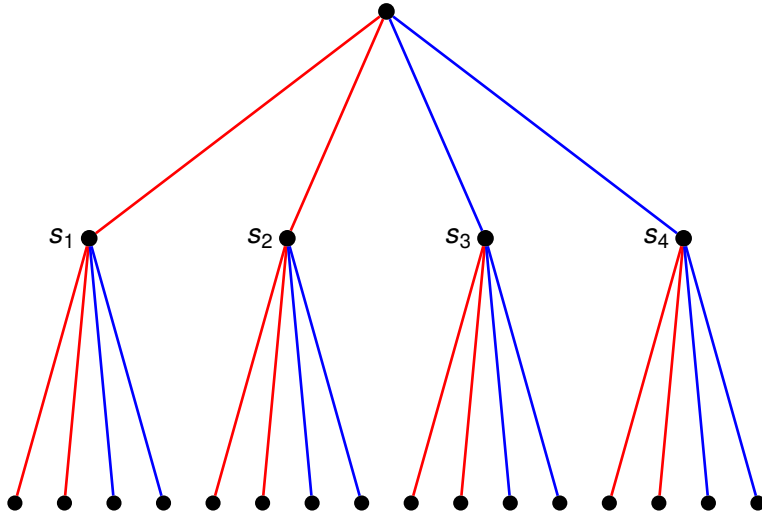
Concepts

Algorithms

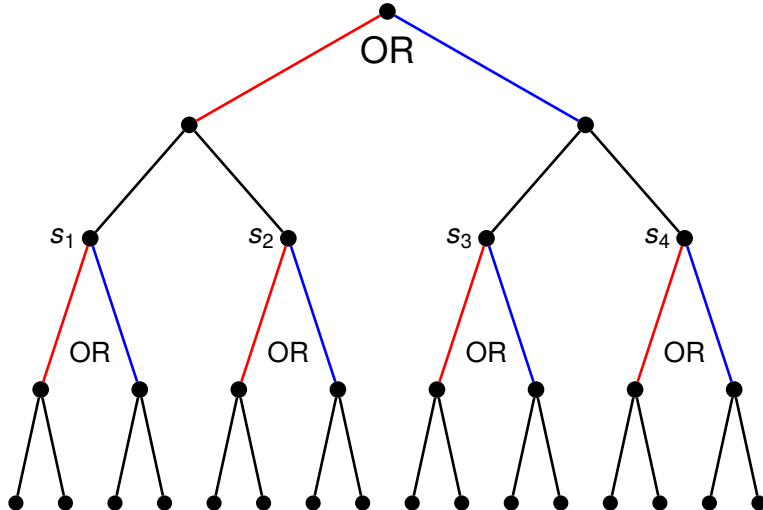
Regression
Efficient
implementation of
regression

Progression

Summary



AND/OR search



Concepts

Algorithms

- Regression
- Efficient implementation of regression
- Progression

Summary



- We describe AO* on a graph representation **without intermediate nodes**, i.e., as in the first figure.
- There are different variants of AO*, depending on whether the graph that is being searched is an AND/OR **tree**, an AND/OR **DAG**, or a general, possibly **cyclic**, AND/OR graph.
- The graphs we want to search, $\mathcal{T}(\Pi)$, are in general cyclic.
- However, AO* becomes a bit more involved when dealing with cycles, so we only discuss AO* under the assumption of acyclicity and leave the generalization to cyclic state spaces as an exercise.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



- The search is over $\mathcal{T}(\Pi)$.
- For ease of presentation, we do not distinguish between states of $\mathcal{T}(\Pi)$ and search nodes.
- Also, for ease of presentation, we do not handle the case that no strong plan exists.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Definition (solution graph)

A **solution graph** for a nondeterministic transition system $\mathcal{T} = \langle S, L, T, s_0, S_\star \rangle$ is an acyclic subgraph of \mathcal{T} (viewed as a graph), $\mathcal{T}' = \langle S', L, T' \rangle$, such that

- $s_0 \in S'$,
- for each $s' \in S' \setminus S_\star$, there is exactly one label $l \in L$ s.t.
 - T' contains at least one outgoing transition from s' labeled with l ,
 - T' contains all outgoing transitions from s' labeled with l (and S' contains the states reached via such transitions),
 - T' contains no outgoing transitions from s' labeled with any $\tilde{l} \neq l$, and
- every directed path in \mathcal{T}' terminates at a goal state.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary

Conceptually, there are three graphs/transition systems:

- The induced transitions system $\mathcal{T} = \mathcal{T}(\Pi)$, which only exists as a mathematical object, but is in general not made explicit completely during AO* search,
- The current portion of \mathcal{T} explicitly represented by the search algorithm, \mathcal{T}_e , and
- The current portion of \mathcal{T}_e considered by the algorithm as the cheapest/best current **partial solution graph**, \mathcal{T}_p .

Definition (partial solution graph)

A **partial solution graph** for a nondeterministic transition system $\mathcal{T} = \langle S, L, T, s_0, S_* \rangle$ is an acyclic subgraph of \mathcal{T} (viewed as a graph), $\mathcal{T}_p = \langle S_p, L, T_p \rangle$, s.t.

- $s_0 \in S_p$,
- for each $s' \in S_p$ **that is not an unexpanded leaf node in \mathcal{T}_p** there is exactly one label $l \in L$ such that
 - T_p contains at least one outgoing transition from s' labeled with l ,
 - T_p contains all outgoing transitions from s' labeled with l (and S_p contains the states reached via such transitions),
 - T_p contains no outgoing transitions from s' labeled with any $\tilde{l} \neq l$, and
- every directed path in \mathcal{T}_p terminates at a **goal state or an unexpanded leaf node in \mathcal{T}_p** .

Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary



Definition (cost of a partial solution graph)

Let $h : S \rightarrow \mathbb{N} \cup \{\infty\}$ be a heuristic function for the state space S of \mathcal{T} , and let $\mathcal{T}_\rho = \langle S_\rho, L, T_\rho \rangle$ be a partial solution graph. The **cost labeling** of \mathcal{T}_ρ is the solution to the following system of equations over the states S_ρ of \mathcal{T}_ρ :

$$f(s) = \begin{cases} 0 & \text{if } s \text{ is a goal state} \\ h(s) & \text{if } s \text{ is an unexpanded non-goal} \\ 1 + \max_{s \xrightarrow{o} s'} f(s') & \text{for the unique outgoing action} \\ & o \text{ of } s \text{ in } \mathcal{T}_\rho, \text{ otherwise.} \end{cases}$$

The cost of \mathcal{T}_ρ is the cost labeling of its root.

AO* search keeps track of a **cheapest** partial solution graph by **marking** for each expanded state s an outgoing action o **minimizing** $1 + \max_{s \xrightarrow{o} s'} f(s')$.

Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Procedure ao-star

def ao-star(\mathcal{T}):

let \mathcal{T}_e initially consist of the initial state s_0 .

while \mathcal{T}_p has unexpanded non-goal node:

expand unexpanded non-goal node s of \mathcal{T}_p

add new successor states to \mathcal{T}_e

for all new states s' added to \mathcal{T}_e :

$$f(s') \leftarrow h(s')$$

$Z \leftarrow s$ and its ancestors in \mathcal{T}_e along marked actions.

while Z is not empty:

remove from Z a state s w/o descendant in Z .

$$f(s) \leftarrow \min_{o \text{ applicable in } s} (1 + \max_{s \xrightarrow{o} s'} f(s')).$$

mark the best outgoing action for s

(this may implicitly change \mathcal{T}_p).

return an optimal solution graph.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Correctness (proof sketch)

- Solution graphs directly correspond to strong plans.
- Algorithm eventually terminates (finite number of possible node expansions).
- Acyclicity guarantees that extraction of \mathcal{T}_p and dynamic programming back-propagation of f values always terminates.
- Marking makes sure that existing solutions are eventually marked.

Concepts

Algorithms

Regression

Efficient
implementation of
regression

Progression

Summary



Details

- Pseudocode omits **bookkeeping of solved states** (can improve performance).
- **Choice of unexpanded non-goal node of best partial solution graph is unspecified.**
 - Correctness/optimality not affected.
 - One possibility: choose node with lowest cost estimate.
 - Alternative: expand several nodes simultaneously.
- Algorithm can be extended to deal with **cycles in the AND/OR graph.**

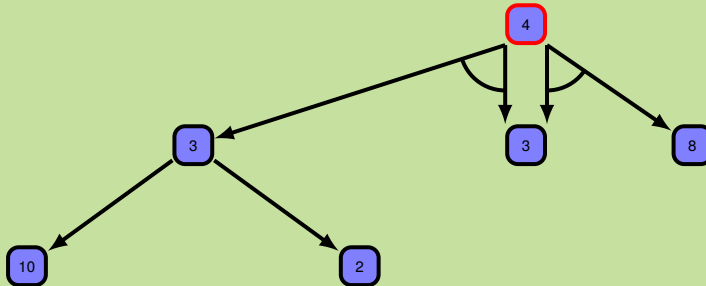
Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Example



Concepts

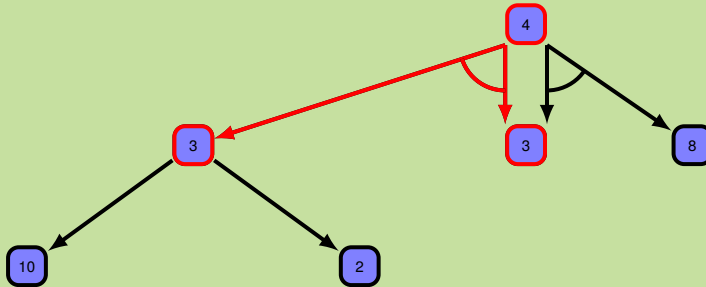
Algorithms

Regression
Efficient
implementation of
regression

Progression

Summary

Example



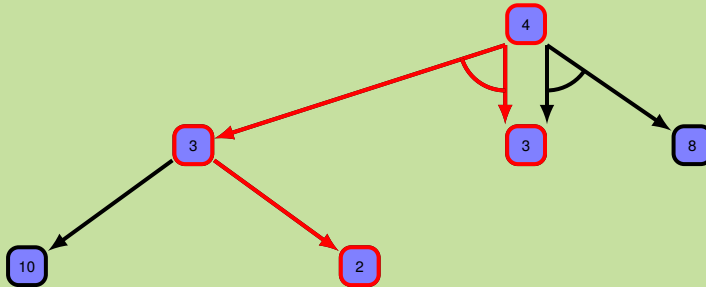
Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Example



Concepts

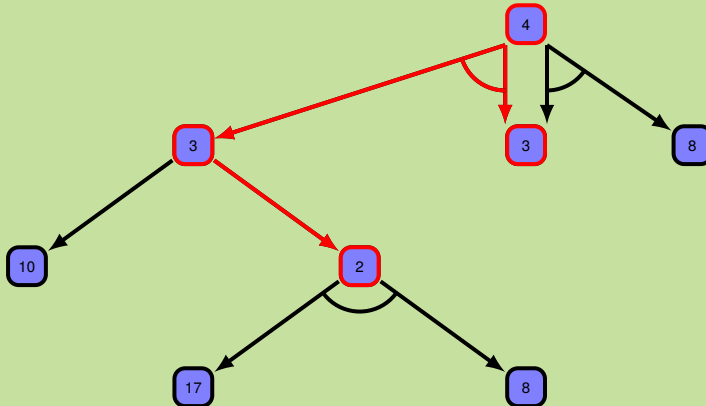
Algorithms

Regression
Efficient
implementation of
regression

Progression

Summary

Example



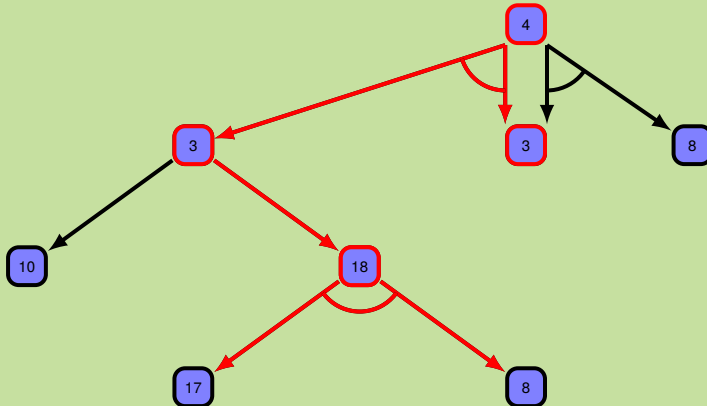
Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Example



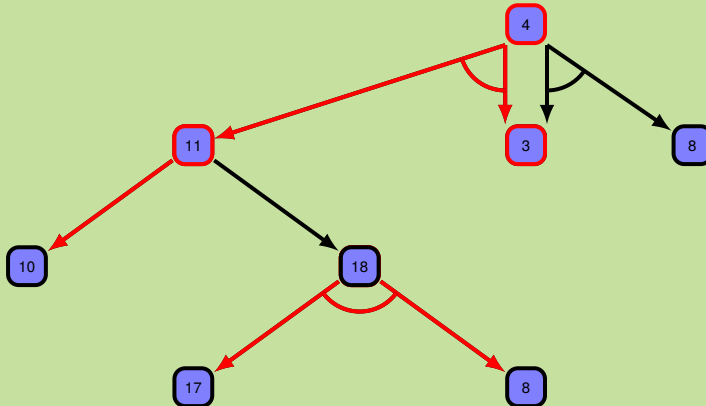
Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Example



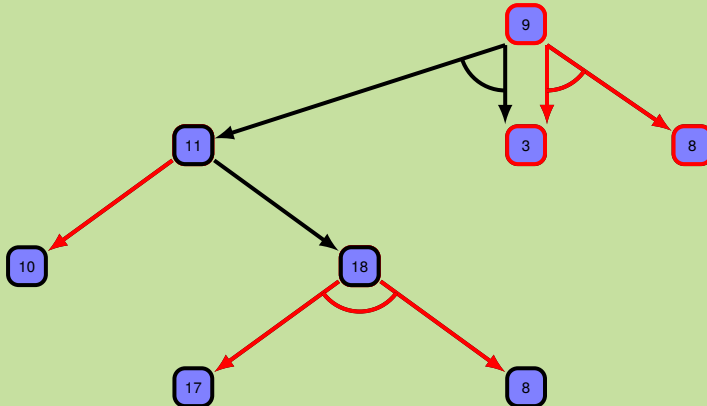
Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary

Example



Concepts

Algorithms

Regression
Efficient
implementation of
regression

Progression

Summary



Heuristic Evaluation Function

- **Desireable**: **informative, domain-independent heuristic** to initialize cost estimates.
- Heuristic should **estimate (strong) goal distances**.
- Heuristic does **not necessarily** have to be **admissible** (unless we seek optimal solutions).
- We can adapt many heuristics we already know from classical planning (details omitted).

Concepts

Algorithms

Regression
Efficient
implementation of
regression
Progression

Summary



Summary



- We have considered the special case of nondeterministic planning where
 - planning tasks are **fully observable** and
 - we are interested in **strong plans**.
- We have introduced important concepts also relevant to other variants of nondeterministic planning such as
 - **images** and
 - **weak and strong preimages**.
- We have discussed some basic classes of algorithms:
 - **backward induction** by dynamic programming, and
 - **forward search** in AND/OR graphs.