Principles of AI Planning

14. Strong nondeterministic planning

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Strong planning

We will consider the simplest case of nondeterministic planning by restricting attention to strong plans.
Concepts
Recall the definition of strong plans:

**Definition (strong plan)**

Let $S$ be the set of states of a planning task $\Pi$. Then a strong plan for $\Pi$ 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 $s \in S_\pi$,
- $S_\pi(s_0) \subseteq S_\pi \cup S_*$ ($\pi$ is closed),
- $S_\pi(s') \cap S_* \neq \emptyset$ for all $s' \in S_\pi(s_0)$ ($\pi$ is proper), and
- there is no state $s' \in S_\pi(s_0)$ such that $s'$ is reachable from $s'$ following $\pi$ in a strictly positive number of steps ($\pi$ is acyclic).
Strong plans

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
Strong plans

(pick-up A B)

Algorithms
Strong plans

(pick-up A B)

(put-on A C)

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Concepts
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Strong plans

- (pick-up A B)
  - (pick-up-from-table A)
  - (put-on A C)
Images

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 $T$. 

$$img_o(T)$$
Images

Definition (image of a state)

\[ \text{img}_o(s) = \{ s' \in S | s \xrightarrow{o} s' \} = \text{app}_o(s) \]

Definition (image of a set of states)

\[ \text{img}_o(T) = \bigcup_{s \in T} \text{img}_o(s) \]
Weak preimages

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 $o$. 

$$wpreimg_o(T)$$
Weak preimages

**Definition (weak preimage of a state)**

\[ wpreimg_o(s') = \{ s \in S | s \xrightarrow{o} s' \} \]

**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 $o$. 

$$spreimg_o(T)$$

$T$
Strong preimages

Definition (strong preimage of a set of states)

\[ \text{spreimg}_o(T) = \{ s \in S \mid \exists s' \in T : s \xrightarrow{o} s' \land \text{img}_o(s) \subseteq T \} \]
Algorithms
Algorithms for strong planning

1. **Dynamic programming** (backward)
   Compute operator/distance/value for a state based on the operators/distances/values of its all successor states.
   - Zero actions needed for goal states.
   - 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**: Nondeterministically reached state

   Heuristic AND/OR search algorithms:
   AO*, Proof Number Search, . . .
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 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 $\pi(s) = o$, unless $\pi(s)$ was already assigned earlier.

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.
Backward distances

Example

distance to $G$

$\infty$ 3 2 1 0

$G$
Backward distances

**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 $O$:

\[
D_{0}^{bwd} := G
\]

\[
D_{i}^{bwd} := D_{i-1}^{bwd} \cup \bigcup_{o \in O} \text{spreimg}_{o}(D_{i-1}^{bwd}) \text{ for all } i \geq 1
\]
Definition (backward distance)

Let $G$ be a set of states and $O$ a set of operators, and let $D_0^{bwd}, D_1^{bwd}, \ldots$ 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 \( S_\star \).

**Extraction of a strong plan from distance sets**

1. Let \( S' \subseteq S \) be those states having a finite backward distance for \( G = S_\star \) 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 \( \text{img}_o(s) \subseteq D_{i-1}^{bwd} \). Hence \( o \) decreases the backward distance by at least one.

Then \( \pi \) 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?
Making the algorithm a logic-based algorithm

- 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).
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 $D_v = \{0, 1\}$. 
Breadth-first search with progression and state sets (deterministic case)

Progression breadth-first search

```python
def bfs-progression(V, I, O, γ):
    goal := formula-to-set(γ)
    reached := {I}
    loop:
        if reached ∩ goal ≠ ∅:
            return solution found
        new-reached := reached ∪ \bigcup_{o∈O} img_o(reached)
        if new-reached = reached:
            return no solution exists
        reached := new-reached
```

This can easily be transformed into a regression algorithm.
Breadth-first search with regression and state sets (deterministic case)

Regression breadth-first search

\[
\text{def } \text{bfs-regression}(V, I, O, \gamma):
\]
\[
\begin{align*}
\text{init} & := I \\
\text{reached} & := \text{formula-to-set}(\gamma) \\
\text{loop:} & \\
\quad & \text{if } \text{init} \in \text{reached}: \\
\quad & \hspace{1cm} \text{return } \text{solution found} \\
\quad & \hspace{1cm} \text{new-reached} := \text{reached} \cup \bigcup_{o \in O} \text{wpreimg}_o(\text{reached}) \\
\quad & \text{if } \text{new-reached} = \text{reached}: \\
\quad & \hspace{1cm} \text{return } \text{no solution exists} \\
\text{reached} & := \text{new-reached}
\end{align*}
\]

- This algorithm is very similar to the dynamic programming algorithm for the nondeterministic case!
Breadth-first search with regression and state sets (nondeterministic case)

Regression breadth-first search

```python
def bfs-regression(V, I, O, γ):
    init := I
    reached := formula-to-set(γ)
    loop:
        if init ∈ reached:
            return solution found
        new-reached := reached ∪ ∪_{o ∈ O} spreimg_0(reached)
        if new-reached = reached:
            return no solution exists
        reached := new-reached
```

- How do we define `spreimg` with logic (or BDD) operations?
Transition formula for nondeterministic operators

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

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 \( o = \langle \chi, e \rangle \)

\[
\tau_V(o) = \chi \land \bigwedge_{v \in V} ((EPC_v(e) \lor (v \land \neg EPC_{\neg v}(e))) \leftrightarrow v') \\
\land \bigwedge_{v \in V} \neg (EPC_v(e) \land EPC_{\neg v}(e))
\]

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

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

\[
\tau_V(o) = \chi \land \bigwedge_{a \in A} a' \land \bigwedge_{d \in D} \neg d' \land \bigwedge_{v \in V\setminus(A \cup D)} (v \leftrightarrow v')
\]
Transition formula for nondeterministic operators

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

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

Example

Let \( V = \{a, b\} \), \( V' = \{a', b'\} \), and \( o = \langle \neg a, \{a, a \land \neg b\} \rangle \). Then

\[
\tau_V(o) = \neg a \land \left( (a' \land (b \leftrightarrow b')) \lor (a' \land \neg b') \right).
\]
Computing strong preimages

Definition (substitution)

Let $\varphi, t_1, \ldots, t_n$ be propositional formulas and $v_1, \ldots, v_n$ atomic propositions.

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

**Definition (existential abstraction)**

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

$$
\exists v. \varphi := \varphi[\top/v] \lor \varphi[\bot/v] \\
\exists v_1 \ldots \exists v_n. \varphi := \exists v_1 \ldots \exists v_{n-1}. (\varphi[\top/v_n] \lor \varphi[\bot/v_n])
$$

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

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

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

**Strong preimages**

\[
spreimg_o(T) = \{ s \in S \mid \exists s' \in T : s \xrightarrow{o} s' \land img_o(s) \subseteq T \}
\]

\[
= \{ s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \land s' \in T) \land
\{ s' \in S \mid s \xrightarrow{o} s' \} \subseteq T \}
\]

\[
= \{ s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \land s' \in T) \land
(\forall s' \in S : s \xrightarrow{o} s' \Rightarrow (s' \in T)) \}
\]

\[
= \{ s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \land s' \in T) \land
(\neg \exists s' \in S : s \xrightarrow{o} s' \land s' \notin T) \}
\]
Computing strong preimages with boolean function operations

\[ \text{spreimg}_o(T) = \{ s \in S \mid (\exists s' \in S : s \xrightarrow{o} s' \land s' \in T) \land \neg(\exists s' \in S : s \xrightarrow{o} s' \land s' \notin T) \} \]

Strong preimages with boolean functions

For formula \( \varphi \) characterizing set \( T \) of strongly backward-reached states:

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

We can use this regression formula for efficient symbolic regression search. BDDs support all necessary operations (atomic propositions, \( \neg \), \( \land \), \( \lor \), substitution, \( \exists \), \ldots ).
Computing strong preimages with boolean function operations

Example

Let \( V = \{a, b\} \), \( V' = \{a', b'\} \), and

\[
o = \langle \lnot a, \{a, a \land \lnot b\} \rangle, \quad \text{i.e.,} \quad \tau_V(o) = \lnot a \land ((a' \land (b \leftrightarrow b')) \lor (a' \land \lnot b')).\]

Moreover, let \( \varphi = a \). Then

\[
spreimg_o(\varphi) = \exists a' \exists b'. \left( \lnot a \land ((a' \land (b \leftrightarrow b')) \lor (a' \land \lnot b')) \land a' \right)
\]

\[
\equiv \lnot a
\]
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*)
AND/OR search
AND/OR search
Progression Search

- 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.
AO* Search

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

Definition (solution graph)

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

1. $s_0 \in S'$,
2. for each $s' \in S' \setminus S_*$, 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
3. every directed path in $T'$ terminates at a goal state.
AO* Search

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, $\mathcal{T}_p$. 
AO* Search

Definition (partial solution graph)

A partial 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), $\mathcal{T}_p = \langle S_p, L, T_p \rangle$, 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 $\mathcal{T}_p$. 
AO* Search

**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 $T$, and let $T_p = \langle S_p, L, T_p \rangle$ be a partial solution graph. The **cost labeling** of $T_p$ is the solution to the following system of equations over the states $S_p$ of $T_p$:

$$f(s) = \begin{cases} 
0 & \text{if } s \text{ is a goal state} \\
h(s) & \text{if } s \text{ is an unexpanded non-goal} \\
1 + \max_{s \overset{o}{\rightarrow} s'} f(s') & \text{for the unique outgoing action } o \text{ of } s \text{ in } T_p, \text{ otherwise.}
\end{cases}$$

The cost of $T_p$ 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 $1 + \max_{s \overset{o}{\rightarrow} s'} f(s')$. 
AO* Search

Procedure ao-star

\[
\text{def } \text{ao-star}(\mathcal{T}): \\
\text{let } \mathcal{T}_e \text{ initially consist of the initial state } s_0. \\
\text{while } \mathcal{T}_p \text{ has unexpanded non-goal node:} \\
\quad \text{expand unexpanded non-goal node } s \text{ of } \mathcal{T}_p \\
\quad \text{add new successor states to } \mathcal{T}_e \\
\text{for all } \text{ new states } s' \text{ added to } \mathcal{T}_e: \\
\quad f(s') \leftarrow h(s') \\
\mathcal{Z} \leftarrow s \text{ and its ancestors in } \mathcal{T}_e \text{ along marked actions.} \\
\text{while } \mathcal{Z} \text{ is not empty:} \\
\quad \text{remove from } \mathcal{Z} \text{ a state } s \text{ w/o descendant in } \mathcal{Z}. \\
\quad f(s) \leftarrow \min_{o \text{ applicable in } s} (1 + \max_{s \xrightarrow{o} s'} f(s')). \\
\quad \text{mark the best outgoing action for } s \\
\quad \text{(this may implicitly change } \mathcal{T}_p). \\
\text{return } \text{an optimal solution graph.}
\]
Correctness (proof sketch)

- Solution graphs directly correspond to strong plans.
- Algorithm eventually terminates (finite number of possible node expansions).
- Acyclicity guarantees that extraction of $T_p$ and dynamic programming back-propagation of $f$ values always terminates.
- Marking makes sure that existing solutions are eventually marked.
AO* Search

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**.
AO* Search

Example
AO* Search

Example

10 → 3 → 4 → 8

10 → 3 → 2 → 3 → 8
AO* Search

Example
AO* Search

Example
AO* Search

Example

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Concepts
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Regression
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AO* Search

Example
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 heurstics we already know from classical planning (details omitted).
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.