CSC2542
State-Space Planning

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Acknowledgements

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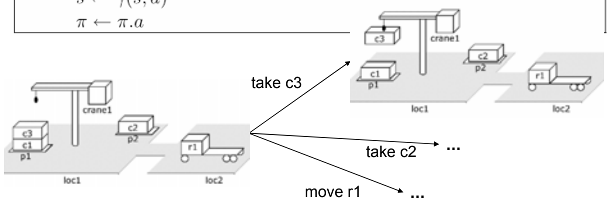
Motivation

- Nearly all planning procedures are search procedures
- Different planning procedures have different search spaces
  Two examples:
    - State-space planning
    - Plan-space planning
- *State-space planning*
  - Each node represents a state of the world
  - A plan is a path through the space
- *Plan-space planning*
  - Each node is a set of partially-instantiated operators, plus some constraints
  - Impose more and more constraints, until we get a plan

Outline

- State-space planning
  - Forward search
  - Backward search
  - Lifting
  - STRIPS
  - Block-stacking

Forward-search(O, s_0, g)
- $s \leftarrow s_0$
- $\pi \leftarrow$ the empty plan
- loop
  - if s satisfies g then return π
  - $E \leftarrow \{a | a$ is a ground instance an operator in O, and $\text{precond}(a)$ is true in $s\}$
  - if $E = \emptyset$ then return failure
  - nondeterministically choose an action $a \in E$
  - $s \leftarrow \gamma(s, a)$
  - $\pi \leftarrow \pi.a$

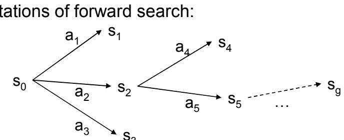


Properties

- Forward-search is *sound*
  - for any plan returned by any of its nondeterministic traces, this plan is guaranteed to be a solution
- Forward-search also is *complete*
  - if a solution exists then at least one of Forward-search's nondeterministic traces will return a solution.

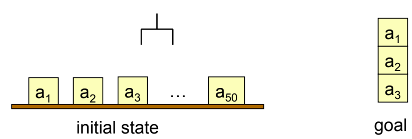
Deterministic Implementations

- Some deterministic implementations of forward search:
  - breadth-first search
  - depth-first search
  - best-first search (e.g., A*)
  - greedy search



- Breadth-first and best-first search are sound and complete
  - But they usually aren't practical, requiring too much memory
  - Memory requirement is exponential in the length of the solution
- In practice, more likely to use depth-first search or greedy search
  - Worst-case memory requirement is linear in the length of the solution
  - In general, sound but not complete
    - But classical planning has only finitely many states
    - Thus, can make depth-first search complete by doing loop-checking

Branching Factor of Forward Search



- Forward search can have a very large branching factor
  - Can have many applicable actions that don't progress toward goal
- Why this is bad:
  - Deterministic implementations can waste time trying lots of irrelevant actions
- **Need a good heuristic function and/or pruning procedure**
  (This will be a focus of later discussion)

Backward Search

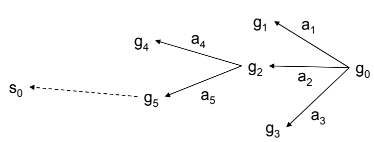
- For forward search, we started at the initial state and computed state transitions
  - new state = $\gamma(s,a)$
- For backward search, we start at the goal and compute inverse state transitions
  - new set of subgoals = $\gamma^{-1}(g,a)$
- To define $\gamma^{-1}(g,a)$, must first define *relevance*:
  - An action *a* is relevant for a goal *g* if
    - *a* makes at least one of *g*'s literals true
      - $g \cap \text{effects}(a) \neq \emptyset$
    - *a* does not make any of *g*'s literals false
      - $g^+ \cap \text{effects}^-(a) = \emptyset$ and $g^- \cap \text{effects}^+(a) = \emptyset$

Inverse State Transitions

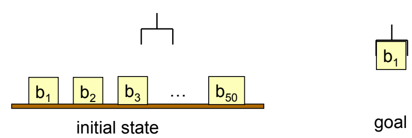
- If *a* is relevant for *g*, then
  - $\gamma^{-1}(g,a) = (g - \text{effects}(a)) \cup \text{precond}(a)$
- Otherwise $\gamma^{-1}(g,a)$ is undefined

- Example: suppose that
  - *g* = {on(b1,b2), on(b2,b3)}
  - *a* = stack(b1,b2)
- What is $\gamma^{-1}(g,a)$?


```
Backward-search(O, s0, g)
  π ← the empty plan
  loop
    if s0 satisfies g then return π
    A ← {a|a is a ground instance of an operator in O
          and γ^{-1}(g, a) is defined}
    if A = ∅ then return failure
    nondeterministically choose an action a ∈ A
    π ← a.π
    g ← γ^{-1}(g, a)
```



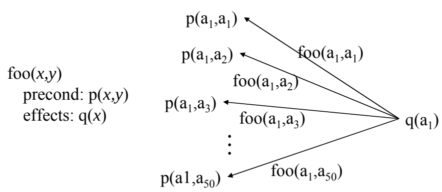
Efficiency of Backward Search



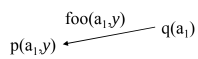
- Backward search can *also* have a very large branching factor
  - E.g., an operator *o* that is relevant for *g* may have many ground instances $a_1, a_2, \ldots, a_n$ such that each a_i's input state might be unreachable from the initial state

- As before, deterministic implementations can waste lots of time trying all of them

Lifting



- Can reduce the branching factor of backward search if we *partially* instantiate the operators
  - this is called *lifting*



Lifted Backward Search

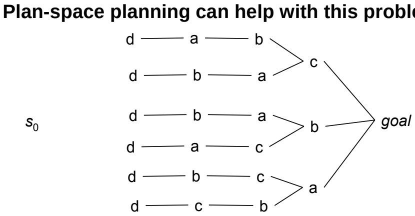
- Basic Idea: Delay grounding of operators until necessary in order to bind variables with those required to realize goal or subgoal
- More complicated than Backward-search
  - Must keep track of what substitutions were performed
- But it has a much smaller branching factor

Lifted Backward Search

Lifted-backward-search(O, s_0, g)
  $\pi \leftarrow$ the empty plan
  loop
    if s_0 satisfies g then return π
    $A \leftarrow \{(o,\theta) | o$ is a standardization of an operator in O,
        θ is an mgu for an atom of g and an atom of $\mathrm{effects}^+(o)$,
        and $\gamma^{-1}(\theta(g), \theta(o))$ is defined$\}$
    if $A = \emptyset$ then return failure
    nondeterministically choose a pair $(o, \theta) \in A$
    $\pi \leftarrow$ the concatenation of $\theta(o)$ and $\theta(\pi)$
    $g \leftarrow \gamma^{-1}(\theta(g), \theta(o))$

The Search Space is Still Too Large

- Lifted-backward-search generates a smaller search space than Backward-search, but it still can be quite large
  - Suppose actions *a*, *b*, and *c* are independent, action *d* must precede all of them, and there's no path from s_0 to *d*'s input state
  - We'll try all possible orderings of *a*, *b*, and *c* before realizing there is no solution
  - **Plan-space planning can help with this problem**



Pruning the Search Space

Pruning the search space can really help.

Two techniques we will discuss:

- Sound pruning using branch-and-bound heuristic search
- Domain customization that prunes actions and states

For now, just two examples:

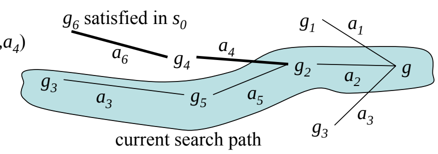
- STRIPS
- Block stacking

STRIPS

- One of the first planning algorithms (Shakey the robot)
- π ← the empty plan
- do a modified backward search from *g*
  - ** each new subgoal is precond(*a*) (instead of $\gamma^{-1}(s,a)$)
  - when you find an action that's executable in the current state, then go forward on the current search path as far as possible, executing actions and appending them to π
  - repeat until all goals are satisfied

$\pi = \langle a_6, a_4 \rangle$

$s = \gamma(\gamma(s_0, a_6), a_4)$



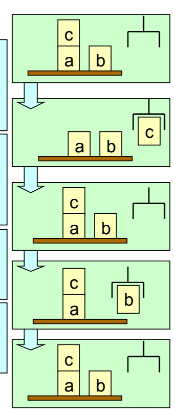
Quick Review of Blocks World

unstack(x,y)
Pre: on(x,y), clear(x), handempty
Eff: ~on(x,y), ~clear(x), ~handempty, holding(x), clear(y)

stack(x,y)
Pre: holding(x), clear(y)
Eff: ~holding(x), ~clear(y), on(x,y), clear(x), handempty

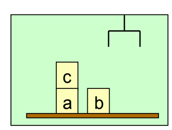
pickup(x)
Pre: ontable(x), clear(x), handempty
Eff: ~ontable(x), ~clear(x), ~handempty, holding(x)

putdown(x)
Pre: holding(x)
Eff: ~holding(x), ontable(x), clear(x), handempty

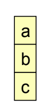


Limitations of STRIPS

Example 1. The Sussman Anomaly



Initial state



goal

- On this problem, STRIPS cannot produce an irredundant solution.
  - Try it and see. Start with the goal {on(b,c), on(a,b)}.

Example 2. Register Assignment Problem

- State-variable formulation:

  Initial state: {value(r1)=3, value(r2)=5, value(r3)=0}

  Goal: {value(r1)=5, value(r2)=3}

  Operator: assign(r,v,r',v')
  precond: value(r)=v, value(r')=v'
  effects: value(r)=v'

- STRIPS cannot solve this problem at all

How to Handle Problems like These?

Several ways:

- Do something other than state-space search
  - e.g., Chapters 5–8
- Use forward or backward state-space search, with *domain-specific* knowledge to prune the search space
  - Can solve both problems quite easily this way
  - Example: block stacking using forward search

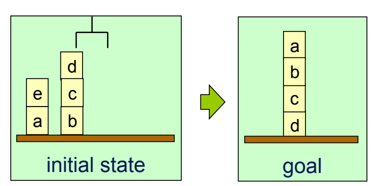
Domain-Specific Knowledge

- A blocks-world planning problem $P = (O, s_0, g)$ is solvable if s_0 and g satisfy some simple consistency conditions
  - g should not mention any blocks not mentioned in s_0
  - a block cannot be on two other blocks at once
  - etc.
    - Can check these in time O(n log n)
- If P is solvable, can easily construct a solution of length O($2m$), where m is the number of blocks
  - Move all blocks to the table, then build up stacks from the bottom
    - Can do this in time O(n)
- With additional domain-specific knowledge can do even better …

Additional Domain-Specific Knowledge

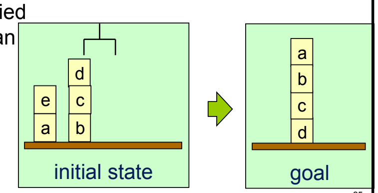
A block x needs to be moved if any of the following is true:

- s contains ontable(x) and g contains on(x,y) - see a below
- s contains on(x,y) and g contains ontable(x) - see d below
- s contains on(x,y) and g contains on(x,z) for some $y \neq z$ - see c below
- s contains on(x,y) and y needs to be moved - see e below



Domain-Specific Algorithm

loop
  if there is a clear block *x* such that
      x needs to be moved **and**
      x can be moved to a place where it won't need to be moved
    then move *x* to that place
  else if there is a clear block *x* such that *x* needs to be moved
    then move *x* to the table
  else if the goal is satisfied
    then return the plan
  else return failure
repeat



Easily Solves the Sussman Anomaly

loop
  if there is a clear block *x* such that
      x needs to be moved **and**
      x can be moved to a place where it won't need to be moved
    then move *x* to that place
  else if there is a clear block *x* such that
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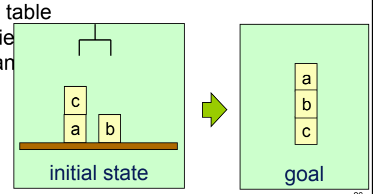

Properties

The block-stacking algorithm:

- Sound, complete, guaranteed to terminate
- Runs in time $O(n^3)$
  - Can be modified to run in time $O(n)$
- Often finds optimal (shortest) solutions
- But sometimes only near-optimal