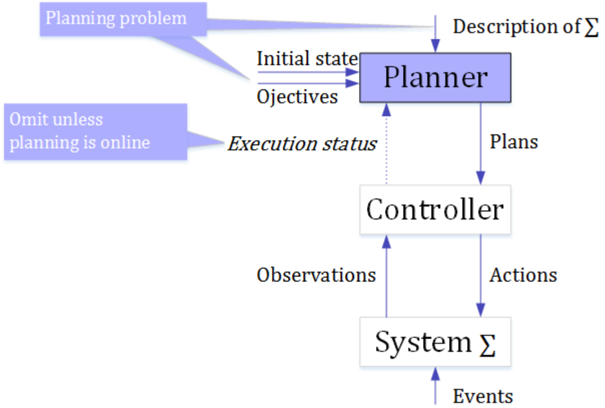
Intelligent Agents
State-Space Planning

Ute Schmid

Cognitive Systems, Applied Computer Science, Bamberg University

last change: 15. Juni 2015

Today: The Planner



Computing A Sequence of Actions

- Previous lecture: How to transform a state into a successor state by applying an action ($\gamma(s, a) = s'$)
- Today: Compute a plan – a sequence of action applications to transform an initial state into a state fulfilling all objectives (goals)

Motivation

- Nearly all planning procedures are search procedures
- Different planning procedures have different search spaces
    - Two examples:

⇒ *State-space planning*

- Each node represents a state of the world
    - A plan is a path through the space

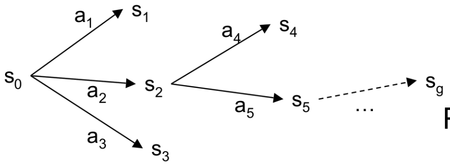
⇒ *Plan-space planning*

- Each node is a set of partially-instantiated operators, plus some constraints
    - Impose more and more constraints, until we get a plan

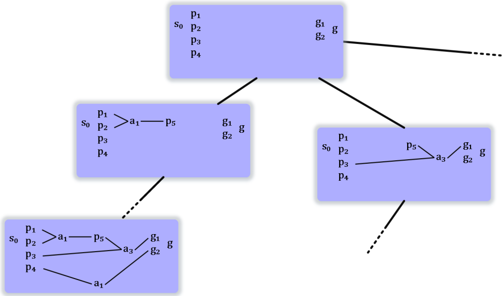
Dana Nau: Lecture slides for *Automated Planning*

Motivation

State-Space-Planning



Plan-Space-Planning



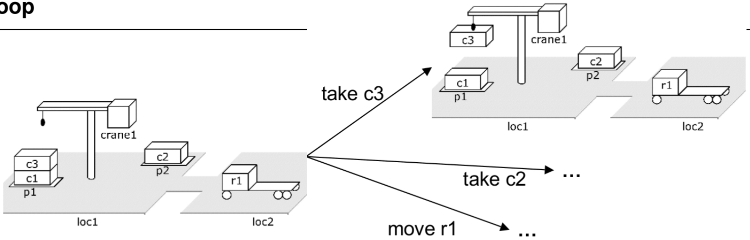
Outlook

- Forward Search
- Backward Search
  - Inverse State Transition
  - Lifting
- Soundness, Completeness, Efficiency
- Strips
- Incompleteness of Linear Planning
  - Sussman Anomaly
- Domain Specific Knowledge

Forward-Search

Algorithm 1 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 of an operator in O, and precond(a) is true in $s\}$
  if $E = \emptyset$ then return failure
  non-deterministically choose any action $a \in E$
  $s \leftarrow \gamma(s, a)$
  $\pi \leftarrow \pi.a$
end loop



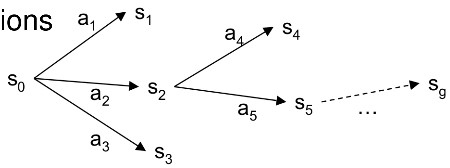
Dana Nau: Lecture slides for *Automated Planning*

Properties

- Forward-search is *sound*
  - for any plan returned by any of its non-deterministic 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 non-deterministic traces will return a solution.
- **Remarks on non-determinism:**
  - In Algorithm 1 and further algorithms, no strategy for selecting an action is fixed.
  - Non-deterministic selection as an abstract concept guarantees that the "right" actions can be selected and in consequence that a plan can be found if one exists.
  - In practice, a deterministic action selection strategy has to be implemented. This strategy might be incomplete.

Deterministic Implementations

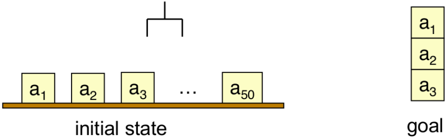
- Some deterministic implementations of forward search:
  - breadth-first search
  - depth-first search
  - best-first search (e.g., A*)
  - greedy search



- Breadth-first and best-first search are sound and complete
  - But they usually aren't practical because they require 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

Dana Nau: Lecture slides for *Automated Planning*

Branching Factor of Forward Search



- Forward search can have a very large branching factor
  - E.g., 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
  - See section 4.5 (Domain-Specific State-Space Planning)

    in Ghallab, Malik, Dana Nau, and Paolo Traverso. Automated planning: theory & practice. Elsevier, 2004.
  - and lecture on Heuristic Search Planning

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 sub-goals $= \gamma^{-1}(g, a)$
- To define $\gamma^{-1}(g, a)$, must first define *relevance*:
  - An action *a* is relevant for a goal *g* if
    - $\Rightarrow$ *a* makes at least one of *g*'s literals true
      - $\rightsquigarrow g \cap \mathit{effects}(a) \neq \emptyset$
    - $\Rightarrow$ *a* does not make any of *g*'s literals false
      - $\rightsquigarrow g^+ \cap \mathit{effects}^-(a) \neq \emptyset$ and $g^- \cap \mathit{effects}^+(a) = \emptyset$

Inverse State Transitions

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

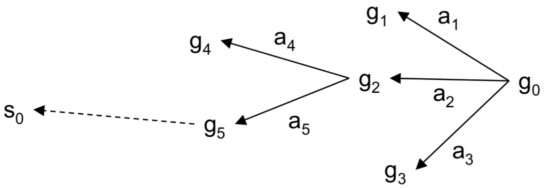
- Example: suppose that
  $g = \{$on(b1,b2), on(b2,b3)$\}$
  a = stack(b1,b2)
- What is $\gamma^{-1}(g, a)$?

Dana Nau: Lecture slides for *Automated Planning*

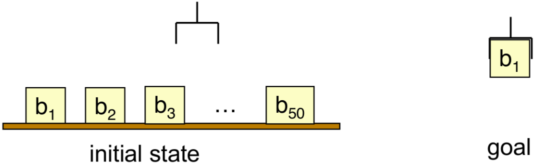
Backward-Search

Algorithm 2 Backward-search(O, s_0, g)

$\pi \leftarrow$ the empty plan
loop
  if s_0 satisfies g then return π
  $A \leftarrow \{a | a$ is a ground instance of an operator in O and $\gamma^{-1}(g, a)$ is defined$\}$
  if $A = \emptyset$ then return failure
  non-deterministically choose any action $a \in A$
  $\pi \leftarrow a.\pi$
  $g \leftarrow \gamma^{-1}(g, a)$
end loop



Efficiency of Backward Search

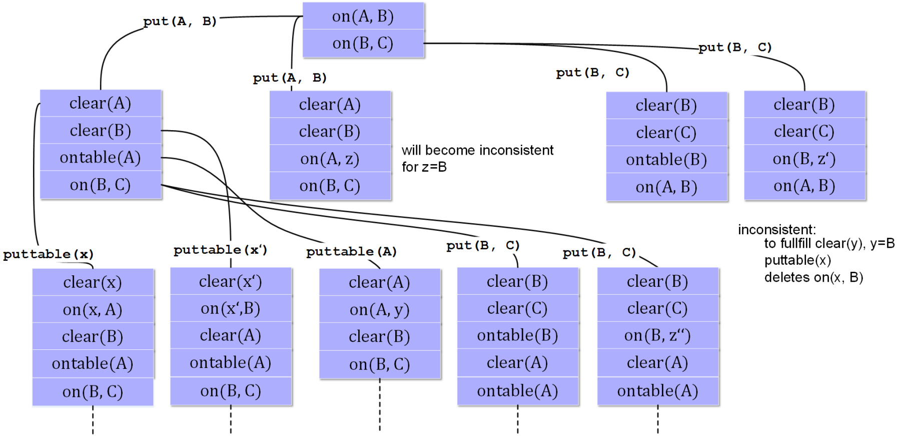


- Backward search can *also* have a very large branching factor
  - E.g., an operator o that is relevant for g may have many ground instances $a_1, a_2, \ldots, a_n$ such that each a_i's input state might be unreachable from the initial state
- As before, deterministic implementations can waste lots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

Remarks on Backward Planning

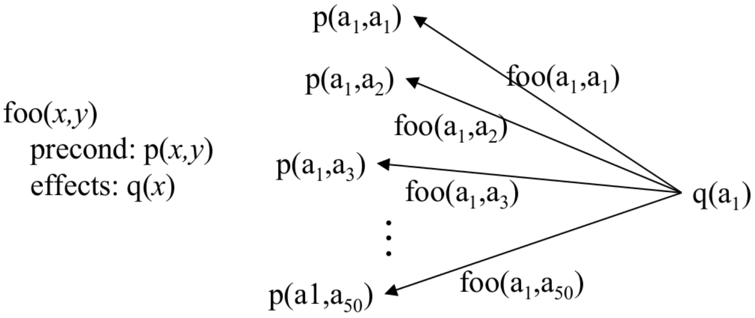
- Forward search also called *progression* planning
- Backwards search also called *regression* planning
- Problem with backwards planning:
  inconsistent states can be produced (see blocksworld example)
- Compare Graphplan strategy:
  build a Planning Graph by forwards search (polynomial effort) and extract the plan from the graph backwards (exponential effort, as usual for planning)

Backward Planning cont.

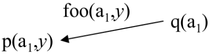


Axiom: $\forall x, y \; on(x, y) \rightarrow \neg clear(y)$

Lifting



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



Lifted Backward Search

- More complicated than Backward-search
  - Have to keep track of what substitutions were performed
- But it has a much smaller branching factor
- mgu = most general unifier (see later), e.g. for $foo(x, y)$, substitution $\theta = \{x \leftarrow a_1\}$ results in equality between all effects of $foo(a1, y)$ and goal $q(a_1)$

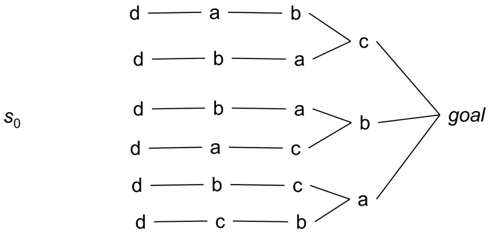
Algorithm 3 Lifted-backward-search(O, s_0, g)

$\pi \leftarrow$ 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 $effects^+(o)$,
    and $\gamma^{-1}(\theta(g), \theta(o))$ is defined $\}$
  if $A = \emptyset$ then return failure
  non-deterministically choose a pair $(o, \theta) \in A$
  $\pi \leftarrow$ the concatenation of $\theta(o)$ and $\theta(\pi)$
  $g \leftarrow \gamma^{-1}\theta(g), \theta(o))$
end loop

The Search Space is Still Too Large

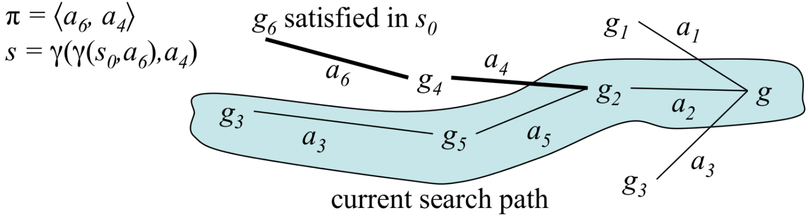
- Lifted-backward-search generates a smaller search space than Backward-search, but it still can be quite large
  - Suppose actions *a, b*, and *c* are independent, action *d* must precede all of them, and there's no path from s_0 to *d*'s input state
  - We'll try all possible orderings of *a, b,* and *c* before realizing there is no solution
  - More about this in Chapter 5 (Plan-Space Planning)

in Ghallab, Malik, Dana Nau, and Paolo Traverso. Automated planning: theory & practice. Elsevier, 2004.



STRIPS

- $\pi \leftarrow$ the empty plan
- do a modified backward search from g
  - instead of $\gamma^{-1}(s, a)$, each new set of sub-goals is just precond(a)
  - whenever 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



STRIPS

- by Fikes & Nilsson (1971),
  "**St**anford **R**esearch **I**nstitute **P**roblem **S**olver"
- classical example:
  moving boxes between rooms ("Strips World")
- Originally:
  representation formalism (relying on CWA) and planning algorithm
  today:
  "STRIPS planning" refers to classical representation without extensions and not to a specific algorithm
- STRIPS algorithm:
  a linear (and therefore incomplete) approach
- compare to:
  General Problem Solver (GPS), a cognitively motivated problem solving algorithm which is also linear and therefore incomplete

STRIPS Algorithm

- Backward-search with a kind of hill climbing strategy
- In each recursive call only such sub-goals are relevant which are preconditions of the last operator added
- Consequence:
  considerable reduction of branching, but resulting in incompleteness
- Linear planning:
  organizing sub-goals in a stack
- Non-linear planning:
  organizing sub-goals in a set, interleaving of goals

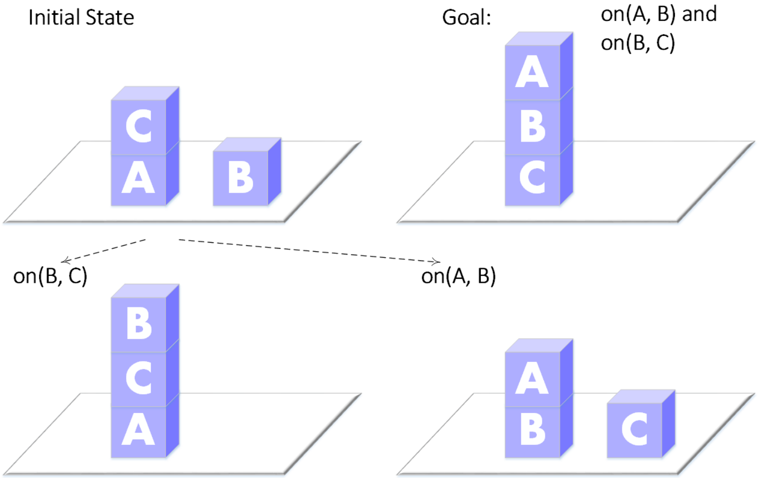
STRIPS Algorithm

Algorithm 4 STRIPS (O, s, g)

```
π ← empty plan
loop
    if s satisfies g then
        return π
    end if
    A ← {a|a is a ground instance of an operator in O, and a is relevant for g}
    if A = ∅ then
        return failure
    end if
    non-deterministically choose any action a ∈ A
    π' ← STRIPS(O, s, precond(a))
    if π' = failure then
        return failure                ;;if we get here, then π' achieves precond(a) from s
    end if
    s ← γ(s, π')                      ;;s now satisfies precond(a)
    s ← γ(s, a)
    π ← π.π'.a
end loop
```

Incompleteness of Linear Planning

The Sussman Anomaly



Sussman Anomaly

Linear planning corresponds to dealing with goals organized in a stack:

[on(A, B), on(B, C)]

try to satisfy goal *on(A, B)*
- solve sub-goals *[clear(A), clear(B)]* [1]
- all sub-goals hold after *puttable(C)*
- apply *put(A, B)*

goal *on(A, B)* is reached

try to satisfy goal *on(B, C)*.

[1] We ignore the additional subgoal *ontable(A)* rsp. *on(A, z)* here.

Interleaving of Goals

- Non-linear planning allows that a sequence of planning steps dealing with one goal is interrupted to deal with another goal.
- For the Sussman Anomaly, that means that after block *C* is put on the table pursuing goal *on(A, B)*, the planner switches to the goal *on(B, C)*.
- Non-linear planning corresponds to dealing with goals organized in a set.
- The correct sequence of goals might not be found immediately without backtracking.

Interleaving of Goals cont.

{on(A, B), on(B, C)}

try to satisfy goal *on(A, B)*

{clear(A), clear(B), on(A, B), on(B, C)}

clear(A) and *clear(B)* hold after *puttable(C)*

try to satisfy goal *on(B, C)*

apply *put(B, C)*

try to satisfy goal *on(A, B)*

apply *put(A, B)*.

Rocket Domain

(Veloso)

- Objects:
  n boxes, Positions (Earth, Moon), one Rocket
- Operators:
  load/unload a box, move the Rocket
  (oneway: only from earth to moon, no way back!)
- Linear planning:
  to reach the goal, that Box1 is on the Moon, load it, shoot the Rocket, unload it, now no other Box can be transported!

The 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

Dana Nau: Lecture slides for *Automated Planning*

Use of Domain Specific Knowledge

- The Sussman Anomaly can also be handled by the usage of domain-specific knowledge

  By Ghallab, Malik, Dana Nau, and Paolo Traverso. Automated planning: theory & practice. Elsevier, 2004.

- Example: block stacking using forward search

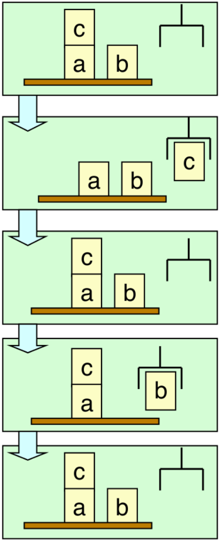
Quick Review of Blocks World

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

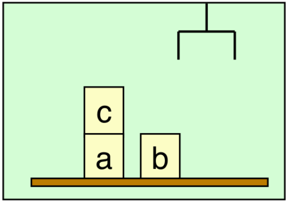
pickup(x)
Pre: ontable(x), clear(x), handempty
Eff: ~ontable(x), ~clear(x), ~handempty, holding(x)

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

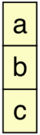


Dana Nau: Lecture slides for *Automated Planning*

The Sussman Anomaly



Initial state



goal

- On this problem, STRIPS can't produce an irredundant solution
  - Try it and see

Dana Nau: Lecture slides for *Automated Planning*

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.

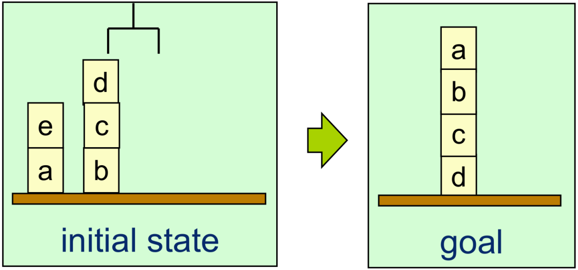
    $\Rightarrow$ Can check these in time $O(n \log n)$
- If P is solvable, can easily construct a solution of length $O(2m)$, where m is the number of blocks
  - Move all blocks to the table, then build up stacks from the bottom

    $\Rightarrow$ Can do this in time $O(n)$
- With additional domain-specific knowledge can do even better ...

Dana Nau: Lecture slides for *Automated Planning*

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 $y \neq z$
    - $\Rightarrow$ see **c** below
  - *s* contains **on(x,y)** and *y* needs to be moved - see **e** below



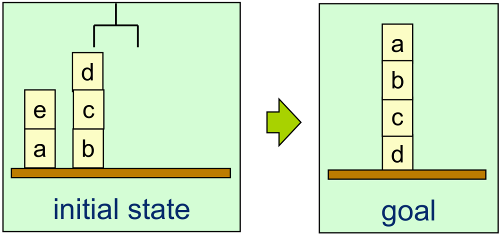
Dana Nau: Lecture slides for *Automated Planning*

Domain-Specific Algorithm

loop

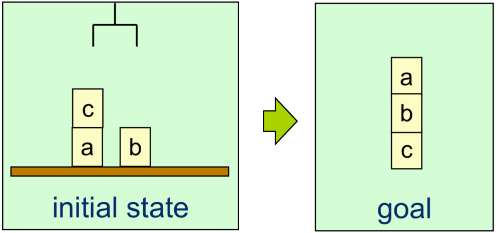
if there is a clear block *x* such that
x needs to be moved **and**
x can be moved to a place where it won't need to be moved
then move *x* to that place
else if there is a clear block *x* such that
x needs to be moved
then move *x* to the table
else if the goal is satisfied
then return the plan
else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



Dana Nau: Lecture slides for *Automated Planning*

Properties

- The block-stacking algorithm:
  - Sound, complete, guaranteed to terminate
  - Runs in time $O(n^3)$

    $\Rightarrow$ Can be modified to run in time $O(n)$
  - Often finds optimal (shortest) solutions
  - But sometimes only near-optimal (Exercise 4.22 in the book)

    $\Rightarrow$ *PLAN LENGTH* for the blocks world is NP- complete

Dana Nau: Lecture slides for *Automated Planning*

Specific vs. General Approaches

- In general, it is more useful to have a general purpose approach, such as a domain-independent planner
- However, if there is knowledge available for a domain, it should not be ignored; but used to make the general approach more informed and thereby ususally more efficient
- One possibility to exploit knowledge in a more general way, is to combine planning and machine learning

  U. Schmid & E. Kitzelmann, Inductive Rule Learning on the Knowledge Level, *Cognitive Systems Research, 12(3)*, 237-248, 2011.

  Applying the inductive programming system IGOR2 to learn Tower building from solution examples.

Learning A Solution Strategy for BlocksWorld

Tower (9 examples of towers with up to four blocks, 1.2 sec)
(10 corresponding examples for Clear and IsTower as BK)

```
Tower(O, S) = S   if IsTower(O, S)
Tower(O, S) = put(O, Sub1(O, S),
             Clear(O, Clear(Sub1(O, S),
                   Tower(Sub1(O, S), S))))   if not(IsTower(O, S))

Sub1(s(O), S) = O .
```

Summary

- Planning is search
- Basic search techniques are forward (from initial state to a state fulfilling the goals) and backward (from the goals to the initial state)
- For backward search an inverse state-transition operator has to be defined
- Algorithms need to be sound and complete, furthermore, efficiency should be considered (branching factor during search!)
- A classical planning algorithm is Strips
- Strips is incomplete as demonstrated with the Sussman Anomaly
- Incompleteness can be overcome by defining domain specific algorithms