Artificial Intelligence 1
Winter Semester 2024/25

– Lecture Notes –
Part IV: Planning and Acting

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This document contains Part IV of the course notes for the course "Artificial Intelligence 1" held at FAU Erlangen-Nürnberg in the Winter Semesters 2016/17 ff. This part covers the AI subfield of "planning", i.e. search-based problem solving with a structured representation language for environment state and actions — in planning, the focus is on the latter.

We first introduce the framework of planning (structured representation languages for problems and actions) and then present algorithms and complexity results. Finally, we lift some of the simplifying assumptions – deterministic, fully observable environments – we made in the previous parts of the course. Other parts of the lecture notes can be found at `http://kwarc.info/teaching/AI/notes-*.pdf`.

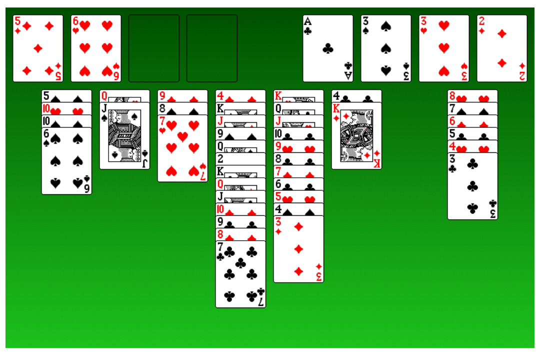
Contents

Chapter 17

Planning I: Framework

Reminder: Classical Search Problems

▷ **Example 17.0.1 (Solitaire as a Search Problem).**



- ▹ States: Card positions (e.g. position_Jspades=Qhearts).
- ▹ Actions: Card moves (e.g. move_Jspades_Qhearts_freecell4).
- ▹ Initial state: Start configuration.
- ▹ Goal states: All cards "home".
- ▹ Solutions: Card moves solving this game.

Planning

▷ **Ambition:** Write one program that can solve all classical search problems.

▷ **Idea:** For CSP, going from "state/action-level search" to "problem-description level search" did the trick.

▷ **Definition 17.0.2.** Let Π be a search problem (see ??)

- ▹ The blackbox description of Π is an API providing functionality allowing to construct the state space: $\text{InitialState}()$, $\text{GoalTest}(s)$, ...

  - ▷ "Specifying the problem" $\widehat{=}$ programming the API.
- ▷ The declarative description of Π comes in a problem description language. This allows to implement the API, and much more.
  - ▷ "Specifying the problem" $\widehat{=}$ writing a problem description.
- ▷ Here, "problem description language" $\widehat{=}$ planning language. (up next)
- ▷ **But Wait:** Didn't we do this already in the last chapter with logics? (For the Wumpus?)

17.1 Logic-Based Planning

Before we go into the planning framework and its particular methods, let us see what we would do with the methods from ?? if we were to develop a "logic-based language" for describing states and actions. We will use the Wumpus world from ?? as a running example.

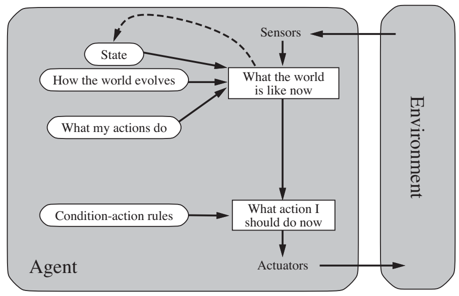
Fluents: Time-Dependent Knowledge in Planning

- ▷ **Recall from ??:** We can represent the Wumpus rules in logical systems. (propositional/first-order/ALC)
  - ▷ Use inference systems to deduce new world knowledge from percepts and actions.
- ▷ **Problem:** Representing (changing) percepts immediately leads to contradictions!
- ▷ **Example 17.1.1.** If the agent moves and a cell with a draft at (a perceived breeze) is followed by one without.
- ▷ **Obvious Idea:** Make representations of percepts time-dependent
- ▷ **Example 17.1.2.** D^t for $t \in \mathbb{N}$ for PL^0 and $\mathrm{draft}(t)$ in PL^1 and $\mathrm{PL}^{\mathrm{nq}}$.
- ▷ **Definition 17.1.3.** We use the word fluent to refer an aspect of the world that changes, all others we call atemporal.

Let us recall the agent-based setting we were using for the inference procedures from ??. We will elaborate this further in this section.

Recap: Logic-Based Agents

- ▷ **Recall:** A model-based agent uses inference to model the environment, percepts, and actions.



function KB−AGENT ($percept$) **returns** an action
  persistent: KB, a knowledge base
    t, a counter, initially 0, indicating time
  TELL(KB, MAKE−PERCEPT−SENTENCE($percept$,t))
  $action$:= ASK(KB, MAKE−ACTION−QUERY(t))
  TELL(KB, MAKE−ACTION−SENTENCE($action$,t))
  $t := t+1$
  return $action$

- **Still Unspecified:** (up next)
  - MAKE−PERCEPT−SENTENCE: the effects of percepts.
  - MAKE−ACTION−QUERY: what is the best next action?
  - MAKE−ACTION−SENTENCE: the effects of that action.

In particular, we will look at the effect of time/change. (neglected so far)

Now that we have the notion of fluents to represent the percepts at a given time point, let us try to model how they influence the agent's world model.

Fluents: Modeling the Agent's Sensors

- **Idea:** Relate percept fluents to atemporal cell attributes.
- **Example 17.1.4.** E.g., if the agent perceives a draft at at time t, when it is in cell $[x, y]$, then there must be a breeze there:

$$\forall t, x, y.\mathrm{Ag@}(t, x, y) \Rightarrow (\mathrm{draft}(t) \Leftrightarrow \mathrm{breeze}(x, y))$$

- Axioms like these model the agent's sensors – here that they are totally reliable: there is a breeze, iff the agent feels a draft at.
- **Definition 17.1.5.** We call fluents that describe the agent's sensors sensor axioms.
- **Problem:** Where do fluents like $\mathrm{Ag@}(t, x, y)$ come from?

You may have noticed that for the sensor axioms we have only used first-order logic. There is a general story to tell here: If we have finite domains (as we do in the Wumpus cave) we can always "compile first-order logic into propositional logic"; if domains are infinite, we usually cannot.

We will develop this here before we go on with the Wumpus models.

Digression: Fluents and Finite Temporal Domains

- **Observation:** Fluents like $\forall t,x,y.\mathrm{Ag@}(t,x,y) \Rightarrow (\mathrm{draft}(t) \Leftrightarrow \mathrm{breeze}(x,y))$ from ?? are best represented in first-order logic. In PL^0 and $\mathrm{PL}^{\mathrm{nq}}$ we would have to use concrete instances like $\mathrm{Ag@}(7,2,1) \Rightarrow (\mathrm{draft}(7) \Leftrightarrow \mathrm{breeze}(2,1))$ for all suitable t, x, and y.
- **Problem:** Unless we restrict ourselves to finite domains and an end time t_{end} we have infinitely many axioms. Even then, formalization in PL^0 and $\mathrm{PL}^{\mathrm{nq}}$ is very tedious.
- **Solution:** Formalize in first-order logic and then compile down:
  1. enumerate ranges of bound variables, instantiate body, ($\rightsquigarrow \mathrm{PL}^{\mathrm{nq}}$)
  2. translate $\mathrm{PL}^{\mathrm{nq}}$ atoms to propositional variables. ($\rightsquigarrow \mathrm{PL}^0$)
- **In Practice:** The choice of domain, end time, and logic is up to agent designer, weighing expressivity vs. efficiency of inference.
- WLOG: We will use PL^1 in the following. (easier to read)

We now continue to our logic-based agent models: Now we focus on effect axioms to model the effects of an agent's actions.

Fluents: Effect Axioms for the Transition Model

- **Problem:** Where do fluents like $\mathrm{Ag@}(t,x,y)$ come from?
- **Thus:** We also need fluents to keep track of the agent's actions. (The transition model of the underlying search problem).
- **Idea:** We also use fluents for the representation of actions.
- **Example 17.1.6.** The action of "going forward" at time t is captured by the fluent $\mathrm{forw}(t)$.
- **Definition 17.1.7.** Effect axioms describe how the environment changes under an agent's actions.
- **Example 17.1.8.** If the agent is in cell $[1,1]$ facing east at time 0 and goes forward, she is in cell $[2,1]$ and no longer in $[1,1]$:

  $$\mathrm{Ag@}(0,1,1) \wedge \mathrm{faceeast}(0) \wedge \mathrm{forw}(0) \Rightarrow \mathrm{Ag@}(1,2,1) \wedge \neg\mathrm{Ag@}(1,1,1)$$

  Generally: (barring exceptions for domain border cells)

  $$\forall t,x,y.\mathrm{Ag@}(t,x,y) \wedge \mathrm{faceeast}(t) \wedge \mathrm{forw}(t) \Rightarrow \mathrm{Ag@}(t+1,x+1,y) \wedge \neg\mathrm{Ag@}(t+1,x,y)$$

  This compiles down to $16 \cdot t_{\mathrm{end}}$ $\mathrm{PL}^{\mathrm{nq}}/\mathrm{PL}^0$ axioms.

Unfortunately, the percept fluents, sensor axioms, and effect axioms are not enough, as we will show in ??. We will see that this is a more general problem – the famous frame problem that needs to be considered whenever we deal with change in environments.

Frames and Frame Axioms

- **Problem:** Effect axioms are not enough.
- **Example 17.1.9.** Say that the agent has an arrow at time 0, and then moves forward at into $[2, 1]$, perceives a glitter, and knows that the Wumpus is ahead.

  To evaluate the action $\text{shoot}(1)$ the corresponding effect axiom needs to know $\text{havarrow}(1)$, but cannot prove it from $\text{havarrow}(0)$.

  Problem: The information of having an arrow has been lost in the move forward.
- **Definition 17.1.10.** The frame problem describes that for a representation of actions we need to formalize their effects on the aspects they change, but also their non-effect on the static frame of reference.
- **Partial Solution:** (there are many many more; some better)

  Frame axioms formalize that particular fluents are invariant under a given action.
- **Problem:** For an agent with n actions and an environment with m fluents, we need $\mathcal{O}(nm)$ frame axioms.

  Representing and reasoning with them easily drowns out the sensor and transition models.

We conclude our discussion with a relatively complete implementation of a logic-based Wumpus agent, building on the schema from slide 552.

A Hybrid Agent for the Wumpus World

- **Example 17.1.11 (A Hybrid Agent).** This agent uses
  - logic inference for sensor and transition modeling,
  - special code and A^* for action selection & route planning.

```
function HYBRID−WUMPUS−AGENT(percept) returns an action
   inputs: percept, a list, [stench,breeze,glitter,bump,scream]
   persistent: KB, a knowledge base, initially the atemporal
                        "wumpus physics"
                  t, a counter, initially 0, indicating time
                  plan, an action sequence, initially empty
  TELL(KB, MAKE−PERCEPT−SENTENCE(percept,t))
```

then some special code for action selection, and then (up next)

```
  action := POP(plan)
  TELL(KB, MAKE−ACTION−SENTENCE(action,t))
  t := t + 1
  return action
```

So far, not much new over our original version.

Now look at the "special code" we have promised.

A Hybrid Agent: Custom Action Selection

▷ **Example 17.1.12 (A Hybrid Agent (continued)).** So that we can plan the best strategy:

```
TELL(KB, the temporal "physics" sentences for time t)
safe := {[x,y] | ASK(KB,OK(t,x,y))=T}
if ASK(KB,glitter(t)) = T then
    plan := [grab] + PLAN−ROUTE(current,{[1,1]},safe) + [exit]
if plan is empty then
    unvisited := {[x,y] | ASK(KB,Ag@(t′,x,y))=F} for all t′ ≤ t
    plan := PLAN−ROUTE(current,unvisited ∪ safe,safe)
if plan is empty and ASK(KB,havarrow(t)) = T then
    possible_wumpus := {x,y | [x,y]}ASK(KB,¬wumpus(t,x,y)) = F
    plan := PLAN−SHOT(current,possible_wumpus,safe)
if plan is empty then // no choice but to take a risk
    not_unsafe := {[x,y] | ASK(KB,¬OK(t,x,y)) = F}
    plan := PLAN−ROUTE(current,unvisited ∪ not_unsafe,safe)
if plan is empty then
    plan := PLAN−ROUTE(current,{[1,1]},safe) + [exit]
```

Note that OK wumpus, and glitter are fluents, since the Wumpus might have died or the gold might have been grabbed.

And finally the route planning part of the code. This is essentially just A^* search.

A Hybrid Agent: Custom Action Selection

▷ **Example 17.1.13 (Action Selection).** And the code for PLAN−ROUTE (PLAN−SHOT similar)

```
function PLAN−ROUTE(curr,goals,allowed) returns an action sequence
  inputs: curr, the agent's current position
          goals, a set of squares;
                 try to plan a route to one of them
          allowed, a set of squares that can form part of the route
  problem := ROUTE−PROBLEM(curr,goals,allowed)
  return A*(problem)
```

▷ **Evaluation:** Even though this works for the Wumpus world, it is not the "universal, logic-based problem solver" we dreamed of!

▷ Planning tries to solve this with another representation of actions. (up next)

17.2 Planning: Introduction

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26892`.

How does a planning language describe a problem?

- **Definition 17.2.1.** A planning language is a way of describing the components of a search problem via formulae of a logical system. In particular the
  - states (vs. blackbox: data structures). (E.g.: predicate $Eq(.,.)$.)
  - initial state I (vs. data structures). (E.g.: $Eq(x,1)$.)
  - goal states G (vs. a goal test). (E.g.: $Eq(x,2)$.)
  - set A of actions in terms of preconditions and effects (vs. functions returning applicable actions and successor states). (E.g.: "increment x: pre $Eq(x,1)$, iff $Eq(x \wedge 2) \wedge \neg Eq(x,1)$".)

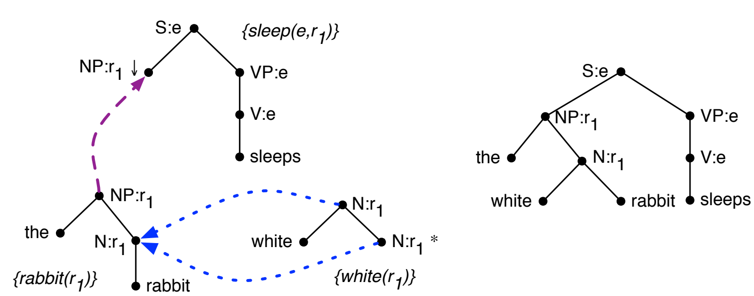
  A logical description of all of these is called a planning task.
- **Definition 17.2.2.** Solution (plan) $\widehat{=}$ sequence of actions from $\mathcal{A}$, transforming $\mathcal{I}$ into a state that satisfies $\mathcal{G}$. (E.g.: "increment x".)

  The process of finding a plan given a planning task is called planning.

Planning Language Overview

- **Disclaimer:** Planning languages go way beyond classical search problems. There are variants for inaccessible, stochastic, dynamic, continuous, and multi-agent settings.
- We focus on classical search for simplicity (and practical relevance).
- For a comprehensive overview, see [GNT04].

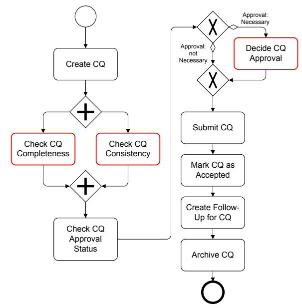
Application: Natural Language Generation



- **Input**: Tree-adjoining grammar, intended meaning.
- **Output**: Sentence expressing that meaning.

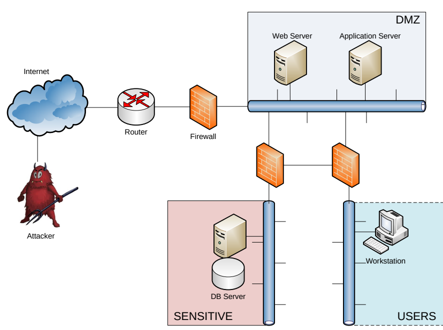
Application: Business Process Templates at SAP

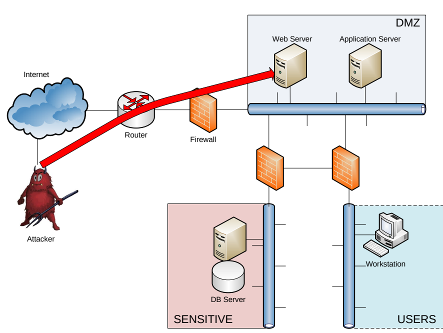
Action name	precondition	effect
Check CQ Completeness	CQ.archiving:notArchived	CQ.completeness:complete OR CQ.completeness:notComplete
Check CQ Consistency	CQ.archiving:notArchived	CQ.consistency:consistent OR CQ.consistency:notConsistent
Check CQ Approval Status	CQ.archiving:notArchived AND CQ.approval:notChecked AND CQ.completeness:complete AND CQ.consistency:consistent	CQ.approval:necessary OR CQ.approval:notNecessary
Decide CQ Approval	CQ.archiving:notArchived AND CQ.approval:necessary	CQ.approval:granted OR CQ.approval:notGranted
Submit CQ	CQ.archiving:notArchived AND (CQ.approval:notNecessary OR CQ.approval:granted)	CQ.submission:submitted
Mark CQ as Accepted	CQ.archiving:notArchived AND CQ.submission:submitted	CQ.acceptance:accepted
Create Follow-Up for CQ	CQ.archiving:notArchived AND CQ.acceptance:accepted	CQ.followUp:documentCreated
Archive CQ	CQ.archiving:notArchived	CQ.archiving:archived

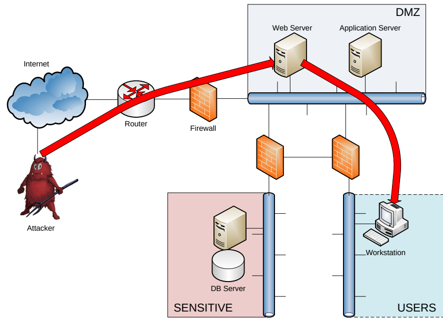


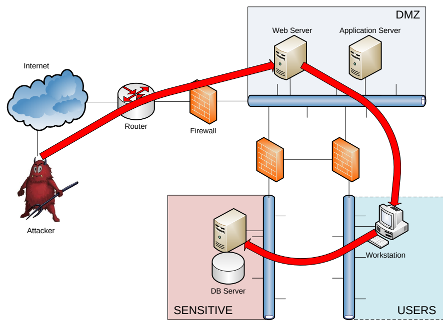
- ▷ **Input**: model of behavior of activities on business objects, process endpoint.
- ▷ **Output**: Process template leading to this point.

Application: Automatic Hacking









- ▷ **Input**: Network configuration, location of sensible data.
- ▷ **Output**: Sequence of exploits giving access to that data.

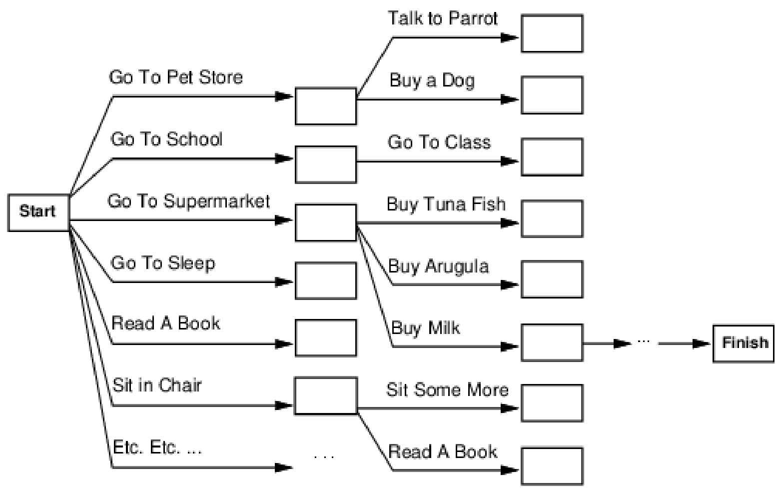
Reminder: General Problem Solving, Pros and Cons

- ▷ **Powerful:** In some applications, generality is absolutely necessary. (E.g. SAP)
- ▷ **Quick:** Rapid prototyping: 10s lines of problem description vs. 1000s lines of C++ code. (E.g. language generation)
- ▷ **Flexible:** Adapt/maintain *the description*. (E.g. network security)
- ▷ **Intelligent:** Determines automatically how to solve a complex problem efficiently! (The ultimate goal, no?!)
- ▷ **Efficiency loss:** Without any domain-specific knowledge about chess, you don't beat Kasparov . . .
  - ▷ Trade-off between "automatic and general" vs. "manual work but efficient".
- ▷ **Research Question:** How to make fully automatic algorithms efficient?

Search vs. planning

▷ Consider the task *get milk, bananas, and a cordless drill*.

▷ Standard search algorithms seem to fail miserably:



After-the-fact heuristic/goal test inadequate

Search vs. planning (cont.)

▷ Planning systems do the following:

1. open up action and goal representation to allow selection
2. divide-and-conquer by subgoaling

▷ relax requirement for sequential construction of solutions

	Search	Planning
States	`Lisp` data structures	Logical sentences
Actions	`Lisp` code	Preconditions/outcomes
Goal	`Lisp` code	Logical sentence (conjunction)
Plan	Sequence from S_0	Constraints on actions

Reminder: Greedy Best-First Search and A^*

▷ **Recall:** Our heuristic search algorithms (duplicate pruning omitted for simplicity)

```
function Greedy_Best−First_Search (problem)
  returns a solution, or failure
```

n := node with n.state=problem.InitialState
$frontier$:= priority queue ordered by ascending h, initially $[n]$
loop do
  if Empty?($frontier$) **then return** failure
  n := Pop($frontier$)
  if problem.GoalTest(n.state) **then return** Solution(n)
  for each action a **in** problem.Actions(n.state) **do**
    n' := ChildNode(problem,n,a)
    Insert(n', $h(n')$, $frontier$)

For A^*

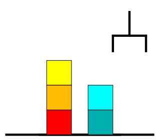
- order $frontier$ by $g + h$ instead of h (line 4)
- insert $g(n') + h(n')$ instead of $h(n')$ to $frontier$ (last line)

▷ Is greedy best-first search optimal? No ⇝ satisficing planning.

▷ Is A^* optimal? Yes, but only if h is admissible ⇝ optimal planning, **with such** h.

ps. "Making Fully Automatic Algorithms Efficient"

▷ **Example 17.2.3.**



- n blocks, 1 hand.
- A single action either takes a block with the hand or puts a block we're holding onto some other block/the table.

blocks	states	blocks	states
1	1	9	4596553
2	3	10	58941091
3	13	11	824073141
4	73	12	12470162233
5	501	13	202976401213
6	4051	14	3535017524403
7	37633	15	65573803186921
8	394353	16	1290434218669921

▷ **Observation 17.2.4.** *State spaces typically are huge even for simple problems.*

▷ **In other words:** Even solving "simple problems" automatically (without help from a human) requires a form of intelligence.

▷ With blind search, even the largest super computer in the world won't scale beyond 20 blocks!

Algorithmic Problems in Planning

▷ **Definition 17.2.5.** We speak of satisficing planning if

Input: A planning task Π.
Output: A plan for Π, or "unsolvable" if no plan for Π exists.
and of optimal planning if
Input: A planning task Π.
Output: An optimal plan for Π, or "unsolvable" if no plan for Π exists.

▷ The techniques successful for either one of these are almost disjoint. And satisficing planning is *much* more efficient in practice.

▷ **Definition 17.2.6.** Programs solving these problems are called (optimal) planner, planning system, or planning tool.

Our Agenda for This Topic

▷ **Now:** Background, planning languages, complexity.

- ▷ Sets up the framework. Computational complexity is essential to distinguish different algorithmic problems, and for the design of heuristic functions. (see next)

▷ **Next:** How to automatically generate a heuristic function, given planning language input?

- ▷ Focussing on heuristic search as the solution method, this is the main question that needs to be answered.

Our Agenda for This Chapter

1. **The History of Planning**: How did this come about?
   - ▷ Gives you some background, and motivates our choice to focus on heuristic search.
2. **The STRIPS Planning Formalism**: Which concrete planning formalism will we be using?
   - ▷ Lays the framework we'll be looking at.
3. **The PDDL Language**: What do the input files for off-the-shelf planning software look like?
   - ▷ So you can actually play around with such software. (Exercises!)
4. **Planning Complexity**: How complex is planning?
   - ▷ The price of generality is complexity, and here's what that "price" is, exactly.

17.3 The History of Planning

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26894`.

Planning History: In the Beginning ...

- **In the beginning: Man invented Robots:**
  - "Planning" as in "the making of plans by an autonomous robot".
  - Shakey the Robot (Full video here)
- **In a little more detail:**
  - [NS63] introduced *general problem solving*.
  - *... not much happened (well not much we still speak of today) ...*
  - 1966-72, Stanford Research Institute developed a robot named "Shakey".
  - They needed a "planning" component taking decisions.
  - They took inspiration from general problem solving and theorem proving, and called the resulting algorithm STRIPS.

History of Planning Algorithms

- **Compilation into Logics/Theorem Proving:**
  - e.g. $\exists s_0, a, s_1.at(A, s_0) \wedge execute(s_0, a, s_1) \wedge at(B, s_1)$
  - **Popular when**: Stone Age – 1990.
  - **Approach**: *From planning task description, generate PL1 formula φ that is satisfiable iff there exists a plan; use a theorem prover on φ.*
  - **Keywords/cites**: Situation calculus, frame problem, ...
- Partial order planning
  - e.g. $open = \{at(B)\}$; apply $move(A, B)$; $\leadsto open = \{at(A)\} \ldots$
  - **Popular when**: 1990 – 1995.
  - **Approach**: *Starting at goal, extend partially ordered set of actions by inserting achievers for open sub-goals, or by adding ordering constraints to avoid conflicts.*
  - **Keywords/cites**: **UCPOP** [PW92], causal links, flaw selection strategies, ...

History of Planning Algorithms, ctd.

- GraphPlan
  - e.g. $F_0 = at(A); A_0 = \{move(A, B)\}; F_1 = \{at(B)\}$;
    mutex $A_0 = \{move(A, B), move(A, C)\}$.

- **Popular when**: 1995 – 2000.
- **Approach**: *In a forward phase, build a layered "planning graph" whose "time steps" capture which pairs of action can achieve which pairs of facts; in a backward phase, search this graph starting at goals and excluding options proved to not be feasible.*
- **Keywords/cites**: [BF95; BF97; Koe+97], action/fact mutexes, step-optimal plans, ...

▷ **Planning as SAT:**

- SAT variables $at(A)_0$, $at(B)_0$, $move(A,B)_0$, $move(A,C)_0$, $at(A)_1$, $at(B)_1$; clauses to encode transition behavior e.g. $at(B)_1{}^F \vee move(A,B)_0{}^T$; unit clauses to encode initial state $at(A)_0{}^T$, $at(B)_0{}^T$; unit clauses to encode goal $at(B)_1{}^T$.
- **Popular when**: 1996 – today.
- **Approach**: *From planning task description, generate propositional CNF formula φ_k that is satisfiable iff there exists a plan with k steps; use a SAT solver on φ_k, for different values of k.*
- **Keywords/cites**: [KS92; KS98; RHN06; Rin10], SAT encoding schemes, Black-Box, ...

History of Planning Algorithms, ctd.

▷ **Planning as Heuristic Search:**

- init $at(A)$; apply $move(A,B)$; generates state $at(B)$; ...
- **Popular when**: 1999 – today.
- **Approach**: Devise a method $\mathcal{R}$ to simplify ("relax") any planning task Π; given Π, solve $\mathcal{R}(\Pi)$ to generate a heuristic function h for informed search.
- **Keywords/cites**: [BG99; HG00; BG01; HN01; Ede01; GSS03; Hel06; HHH07; HG08; KD09; HD09; RW10; NHH11; KHH12a; KHH12b; KHD13; DHK15], critical path heuristics, ignoring delete lists, relaxed plans, landmark heuristics, abstractions, partial delete relaxation, ...

The International Planning Competition (IPC)

▷ **Definition 17.3.1.** The International Planning Competition (IPC) is an event for benchmarking planners (http://ipc.icapsconference.org/)

- **How**: Run competing planners on a set of benchmarks.
- **When**: Runs every two years since 2000, annually since 2014.
- **What**: Optimal track vs. satisficing track; others: uncertainty, learning, ...

▷ **Prerequisite/Result:**

▷ Standard representation language: PDDL [McD+98; FL03; HE05; Ger+09]

▷ Problem Corpus: ≈ 50 **domains**, $\gg 1000$ **instances**, 74 (!!) planners in 2011

International Planning Competition

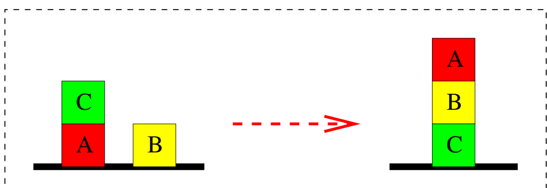
▷ **Question:** If planners x and y compete in IPC'YY, and x wins, is x "better than" y?

▷ **Answer:** reserved for the plenary sessions $\rightsquigarrow$ be there!

▷ **Generally:** reserved for the plenary sessions $\rightsquigarrow$ be there!

Planning History, p.s.: Planning is Non-Trivial!

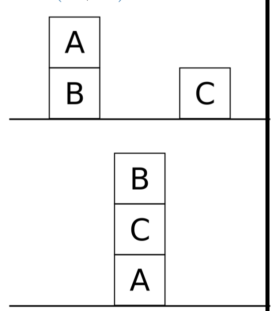
▷ **Example 17.3.2.** The Sussman anomaly is a simple blocksworld planning problem:



Simple planners that split the goal into subgoals $\mathrm{on}(A,B)$ and $\mathrm{on}(B,C)$ fail:

▷ If we pursue $\mathrm{on}(A,B)$ by unstacking C, and moving A onto B, we achieve the first subgoal, but cannot achieve the second without undoing the first.

▷ If we pursue $\mathrm{on}(B,C)$ by moving B onto C, we achieve the second subgoal, but cannot achieve the first without undoing the second.



17.4 The STRIPS Planning Formalism

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26896`.

STRIPS Planning

▷ **Definition 17.4.1.** STRIPS $=$ Stanford Research Institute Problem Solver.

STRIPS is the simplest possible (reasonably expressive) logics based planning language.

- ▷ STRIPS has only propositional variables as atomic formulae.
- ▷ Its preconditions/effects/goals are as canonical as imaginable:
  - ▷ Preconditions, goals: conjunctions of atoms.
  - ▷ Effects: conjunctions of literals
- ▷ We use the common special-case notation for this simple formalism.
- ▷ I'll outline some extensions beyond STRIPS later on, when we discuss PDDL.
- ▷ **Historical note:** STRIPS [FN71] was originally a planner (cf. Shakey), whose language actually wasn't quite that simple.

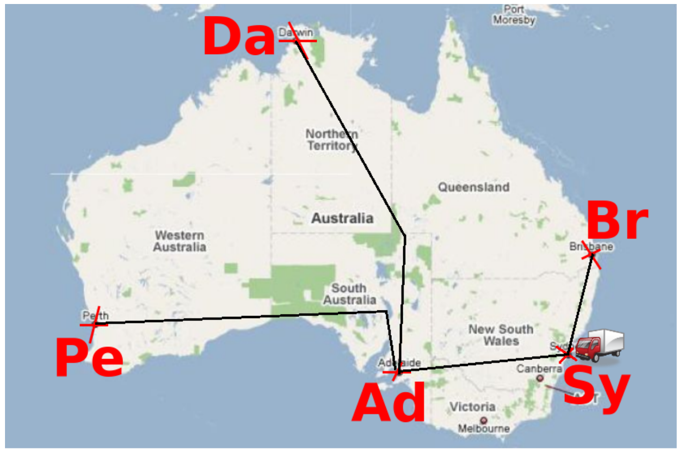
STRIPS Planning: Syntax

- ▷ **Definition 17.4.2.** A STRIPS task is a quadruple $\langle P, A, I, G\rangle$ where:
  - ▷ P is a finite set of facts: atomic proposition in PL^0 or $\mathrm{PL}^{\mathrm{nq}}$.
  - ▷ A is a finite set of actions; each $a \in A$ is a triple $a = \langle \mathrm{pre}_a, \mathrm{add}_a, \mathrm{del}_a\rangle$ of subsets of P referred to as the action's preconditions, add list, and delete list respectively; we require that $\mathrm{add}_a \cap \mathrm{del}_a = \emptyset$.
  - ▷ $I \subseteq P$ is the initial state.
  - ▷ $G \subseteq P$ is the goal state.

  We will often give each action $a \in A$ a name (a string), and identify a with that name.
- ▷ **Note:** We assume, for simplicity, that every action has cost 1. (Unit costs, cf. ??)

"TSP" in Australia

- ▷ **Example 17.4.3 (Salesman Travelling in Australia).**



Strictly speaking, this is not actually a **TSP** problem instance; simplified/adapted for illustration.

STRIPS Encoding of "TSP"

▷ **Example 17.4.4 (continuing).**

- ▷ Facts P: $\{\mathrm{at}(x), \mathrm{vis}(x) \mid x \in \{\mathrm{Sy}, \mathrm{Ad}, \mathrm{Br}, \mathrm{Pe}, \mathrm{Da}\}\}$.
- ▷ Initial state I: $\{\mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
- ▷ Goal state G:$\{\mathrm{at}(\mathrm{Sy})\} \cup \{\mathrm{vis}(x) \mid x \in \{\mathrm{Sy}, \mathrm{Ad}, \mathrm{Br}, \mathrm{Pe}, \mathrm{Da}\}\}$.
- ▷ Actions $a \in A$: $\mathrm{drv}(x, y)$ where x and y have a road.
  Preconditions pre_a: $\{\mathrm{at}(x)\}$.
  Add list add_a: $\{\mathrm{at}(y), \mathrm{vis}(y)\}$.
  Delete list del_a: $\{\mathrm{at}(x)\}$.
- ▷ Plan: $\langle \mathrm{drv}(\mathrm{Sy}, \mathrm{Br}), \mathrm{drv}(\mathrm{Br}, \mathrm{Sy}), \mathrm{drv}(\mathrm{Sy}, \mathrm{Ad}), \mathrm{drv}(\mathrm{Ad}, \mathrm{Pe}), \mathrm{drv}(\mathrm{Pe}, \mathrm{Ad}), \ldots$
  $\ldots, \mathrm{drv}(\mathrm{Ad}, \mathrm{Da}), \mathrm{drv}(\mathrm{Da}, \mathrm{Ad}), \mathrm{drv}(\mathrm{Ad}, \mathrm{Sy})\rangle$

STRIPS Planning: Semantics

▷ **Idea:** We define a plan for a STRIPS task Π as a solution to an induced search problem Θ_Π. (save work by reduction)

▷ **Definition 17.4.5.** Let $\Pi := \langle P, A, I, G\rangle$ be a STRIPS task. The search problem induced by Π is $\Theta_\Pi = \langle S_P, A, T, I, S_G\rangle$ where:

- ▷ The states (also world state) $S_P := \mathcal{P}(P)$ are the subsets of P.
- ▷ A is just Π's action. (so we can define plans easily)
- ▷ The transition model T_A is $\{s \xrightarrow{a} \mathrm{apply}(s, a) \,|\, \mathrm{pre}_a \subseteq s\}$.
  If $\mathrm{pre}_a \subseteq s$, then $a \in A$ is applicable in s and $\mathrm{apply}(s, a) := (s \cup \mathrm{add}_a)\backslash\mathrm{del}_a$.
  If $\mathrm{pre}_a \not\subseteq s$, then $\mathrm{apply}(s, a)$ is undefined.
- ▷ I is Π's initial state.
- ▷ The goal states $S_G = \{s \in S_P \,|\, G \subseteq s\}$ are those that satisfy Π's goal state.

An (optimal) plan for Π is an (optimal) solution for Θ_Π, i.e., a path from s to some $s' \in S_G$. Π is solvable if a plan for Π exists.

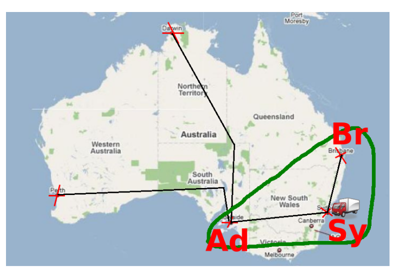
▷ **Definition 17.4.6.** For a plan $a = \langle a_1, \ldots, a_n\rangle$, we define

$$\mathrm{apply}(s, a) := \mathrm{apply}(\ldots \mathrm{apply}(\mathrm{apply}(s, a_1), a_2) \ldots, a_n)$$

if each a_i is applicable in the respective state; else, $\mathrm{apply}(s, a)$ is undefined.

STRIPS Encoding of Simplified TSP

▷ **Example 17.4.7 (Simplified traveling salesman problem in Australia).**

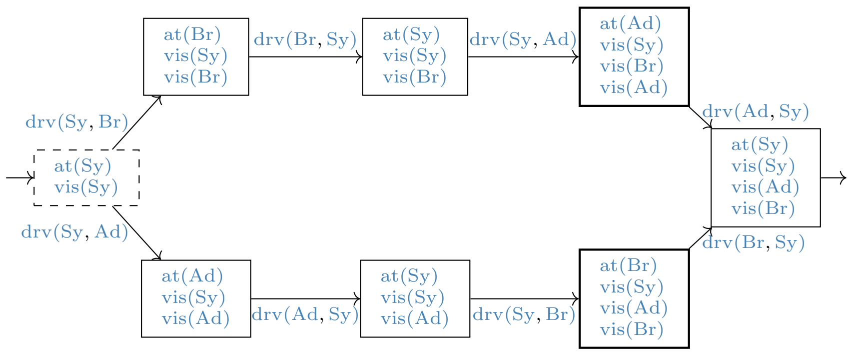


Let TSP_ be the STRIPS task, $\langle P, A, I, G\rangle$, where

- ▷ Facts P: $\{\mathrm{at}(x), \mathrm{vis}(x) \,|\, x \in \{\mathrm{Sy}, \mathrm{Ad}, \mathrm{Br}\}\}$.
- ▷ Initial state state I: $\{\mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
- ▷ Goal state G: $\{\mathrm{vis}(x) \,|\, x \in \{\mathrm{Sy}, \mathrm{Ad}, \mathrm{Br}\}\}$ (note: $\mathrm{noat}(\mathrm{Sy})$)
- ▷ Actions A: $a \in A$: $\mathrm{drv}(x, y)$ where x y have a road.
  - ▷ preconditions pre_a: $\{\mathrm{at}(x)\}$.
  - ▷ add list add_a: $\{\mathrm{at}(y), \mathrm{vis}(y)\}$.
  - ▷ delete list del_a: $\{\mathrm{at}(x)\}$.

Questionaire: State Space of TSP_{-}

▷ The state space of the search problem $\Theta_{\mathrm{TSP}_{-}}$ induced by TSP_{-} from ?? is



▷ **Question:** Are there any plans for TSP_{-} in this graph?

▷ **Answer:** Yes, two – plans for TSP_{-} are solutions for $\Theta_{\mathrm{TSP}_{-}}$, dashed node $\widehat{=}\ I$, thick nodes $\widehat{=}\ G$:

- ▹ $\mathrm{drv}(\mathrm{Sy},\mathrm{Br}), \mathrm{drv}(\mathrm{Br},\mathrm{Sy}), \mathrm{drv}(\mathrm{Sy},\mathrm{Ad})$ (upper path)
- ▹ $\mathrm{drv}(\mathrm{Sy},\mathrm{Ad}), \mathrm{drv}(\mathrm{Ad},\mathrm{Sy}), \mathrm{drv}(\mathrm{Sy},\mathrm{Br})$. (lower path)

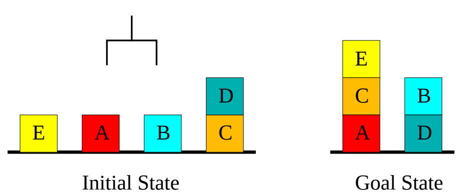
▷ **Question:** Is the graph above actually the state space induced by ?

▷ **Answer:** No, only the part reachable from I. The state space of $\Theta_{\mathrm{TSP}_{-}}$ also includes e.g. the states $\{\mathrm{vis}(\mathrm{Sy})\}$ and $\{\mathrm{at}(\mathrm{Sy}), \mathrm{at}(\mathrm{Br})\}$.

The Blocksworld

▷ **Definition 17.4.8.** The blocks world is a simple planning domain: a set of wooden blocks of various shapes and colors sit on a table. The goal is to build one or more vertical stacks of blocks. Only one block may be moved at a time: it may either be placed on the table or placed atop another block.

▷ **Example 17.4.9.**



- ▹ Facts: $\mathrm{on}(x,y)$, $\mathrm{onTable}(x)$, $\mathrm{clear}(x)$, $\mathrm{holding}(x)$, $\mathrm{armEmpty}$.
- ▹ initial state: $\{\mathrm{onTable}(E), \mathrm{clear}(E), \ldots, \mathrm{onTable}(C), \mathrm{on}(D,C), \mathrm{clear}(D), \mathrm{armEmpty}\}$.
- ▹ Goal state: $\{\mathrm{on}(E,C), \mathrm{on}(C,A), \mathrm{on}(B,D)\}$.
- ▹ Actions: $\mathrm{stack}(x,y)$, $\mathrm{unstack}(x,y)$, $\mathrm{putdown}(x)$, $\mathrm{pickup}(x)$.
- ▹ $\mathrm{stack}(x,y)$?

pre : $\{\text{holding}(x), \text{clear}(y)\}$
add : $\{\text{on}(x, y), \text{armEmpty}, clear x\}$
del : $\{\text{holding}(x), \text{clear}(y)\}$.

STRIPS for the Blocksworld

- **Question:** Which are correct encodings (ones that are part of some correct overall model) of the STRIPS Blocksworld $\text{pickup}(x)$ action schema?

(A)	$\{\text{onTable}(x), \text{clear}(x), \text{armEmpty}\}$ $\{\text{holding}(x)\}$ $\{\text{onTable}(x)\}$	(B)	$\{\text{onTable}(x), \text{clear}(x), \text{armEmpty}\}$ $\{\text{holding}(x)\}$ $\{\text{armEmpty}\}$
(C)	$\{\text{onTable}(x), \text{clear}(x), \text{armEmpty}\}$ $\{\text{holding}(x)\}$ $\{\text{onTable}(x), \text{armEmpty}, \text{clear}(x)\}$	(D)	$\{\text{onTable}(x), \text{clear}(x), \text{armEmpty}\}$ $\{\text{holding}(x)\}$ $\{\text{onTable}(x), \text{armEmpty}\}$

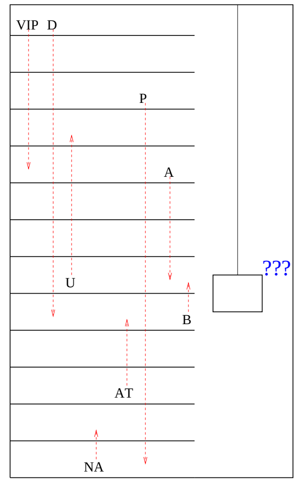
  Recall: an actions a represented by a tuple $\langle \text{pre}_a, \text{add}_a, \text{del}_a \rangle$ of lists of facts.

- **Hint:** The only differences between them are the delete lists
- **Answer:** reserved for the plenary sessions $\rightsquigarrow$ be there!

The next example for a planning task is not obvious at first sight, but has been quite influential, showing that many industry problems can be specified declaratively by formalizing the domain and the particular planning tasks in PDDL and then using off-the-shelf planners to solve them. [KS00] reports that this has significantly reduced labor costs and increased maintainability of the implementation.

Miconic-10: A Real-World Example

- **Example 17.4.10.** Elevator control as a planning problem; details at [KS00]
  Specify mobility needs before boarding, let a planner schedule/otimize trips



- ▷ VIP: Served first.
- ▷ D: Lift may only go *down* when inside; similar for U.
- ▷ NA: Never-alone
- ▷ AT: Attendant.
- ▷ A, B: Never together in the same elevator
- ▷ P: Normal passenger

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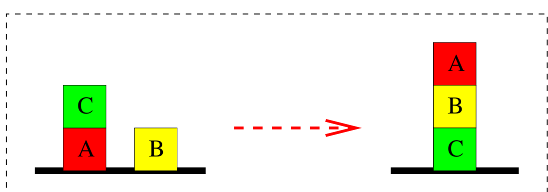
17.5 Partial Order Planning

In this section we introduce a new and different planning algorithm: partial order planning that works on several subgoals independently without having to specify in which order they will be pursued and later combines them into a global plan. **A Video Nugget** covering this section can be found at `https://fau.tv/clip/id/28843`.

To fortify our intuitions about partial order planning let us have another look at the Sussman anomaly, where pursuing two subgoals independently and then reconciling them is a prerequisite.

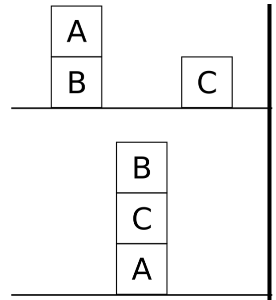
Planning History, p.s.: Planning is Non-Trivial!

▷ **Example 17.5.1.** The Sussman anomaly is a simple blocksworld planning problem:



Simple planners that split the goal into subgoals $\mathrm{on}(A, B)$ and $\mathrm{on}(B, C)$ fail:

- If we pursue $\text{on}(A, B)$ by unstacking C, and moving A onto B, we achieve the first subgoal, but cannot achieve the second without undoing the first.
- If we pursue $\text{on}(B, C)$ by moving B onto C, we achieve the second subgoal, but cannot achieve the first without undoing the second.



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Before we go into the details, let us try to understand the main ideas of partial order planning.

Partial Order Planning

- **Definition 17.5.2.** Any algorithm that can place two actions into a plan without specifying which comes first is called as partial order planning.
- **Ideas** for partial order planning:
  - Organize the planning steps in a DAG that supports multiple paths from initial to goal state
    - nodes (steps) are labeled with actions (actions can occur multiply)
    - edges with propositions added by source and presupposed by target

    acyclicity of the graph induces a partial ordering on steps.
  - additional temporal constraints resolve subgoal interactions and induce a linear order.
- **Advantages** of partial order planning:
  - problems can be decomposed $\leadsto$ can work well with non-cooperative environments.
  - efficient by least-commitment strategy
  - causal links (edges) pinpoint unworkable subplans early.

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We now make the ideas discussed above concrete by giving a mathematical formulation. It is advantageous to cast a partially ordered plan as a labeled DAG rather than a partial ordering since it draws the attention to the difference between actions and steps.

Partially Ordered Plans

- **Definition 17.5.3.** Let $\langle P, A, I, G\rangle$ be a STRIPS task, then a partially ordered plan $\mathcal{P} = \langle V, E\rangle$ is a labeled DAG, where the nodes in V (called steps) are labeled with actions from A, or are a
  - start step, which has label "effect" I, or a
  - finish step, which has label "precondition" G.

Every edge $(S,T) \in E$ is either labeled by:

- A non-empty set $p \subseteq P$ of facts that are effects of the action of S and the preconditions of that of T. We call such a labeled edge a causal link and write it $S \xrightarrow{p} T$.
- $\prec$, then call it a temporal constraint and write it as $S \prec T$.

An open condition is a precondition of a step not yet causally linked.

- **Definition 17.5.4.** Let Π be a partially ordered plan, then we call a step U possibly intervening in a causal link $S \xrightarrow{p} T$, iff $\Pi \cup \{S \prec U, U \prec T\}$ is acyclic.
- **Definition 17.5.5.** A precondition is achieved iff it is the effect of an earlier step and no possibly intervening step undoes it.
- **Definition 17.5.6.** A partially ordered plan Π is called complete iff every precondition is achieved.
- **Definition 17.5.7.** Partial order planning is the process of computing complete and acyclic partially ordered plans for a given planning task.

A Notation for STRIPS Actions

- **Definition 17.5.8 (Notation).** In diagrams, we often write STRIPS actions into boxes with preconditions above and effects below.
- **Example 17.5.9.**
  - Actions: $Buy(x)$
  - Preconditions: $At(p)$, $Sells(p,x)$
  - Effects: $Have(x)$

$$\begin{array}{c} At(p)\ Sells(p,x) \\ \boxed{Buy(x)} \\ Have(x) \end{array}$$

- **Notation:** A causal link $S \xrightarrow{p} T$ can also be denoted by a direct arrow between the effects p of S and the preconditions p of T in the STRIPS action notation above.

  Show temporal constraints as dashed arrows.

Planning Process

- **Definition 17.5.10.** Partial order planning is search in the space of partial plans via the following operations:
  - add link from an existing action to an open precondition,
  - add step (an action with links to other steps) to fulfil an open precondition,
  - order one step wrt. another (by adding temporal constraints) to remove possible conflicts.

▷ **Idea:** Gradually move from incomplete/vague plans to complete, correct plans. backtrack if an open condition is unachievable or if a conflict is unresolvable.

Example: Shopping for Bananas, Milk, and a Cordless Drill

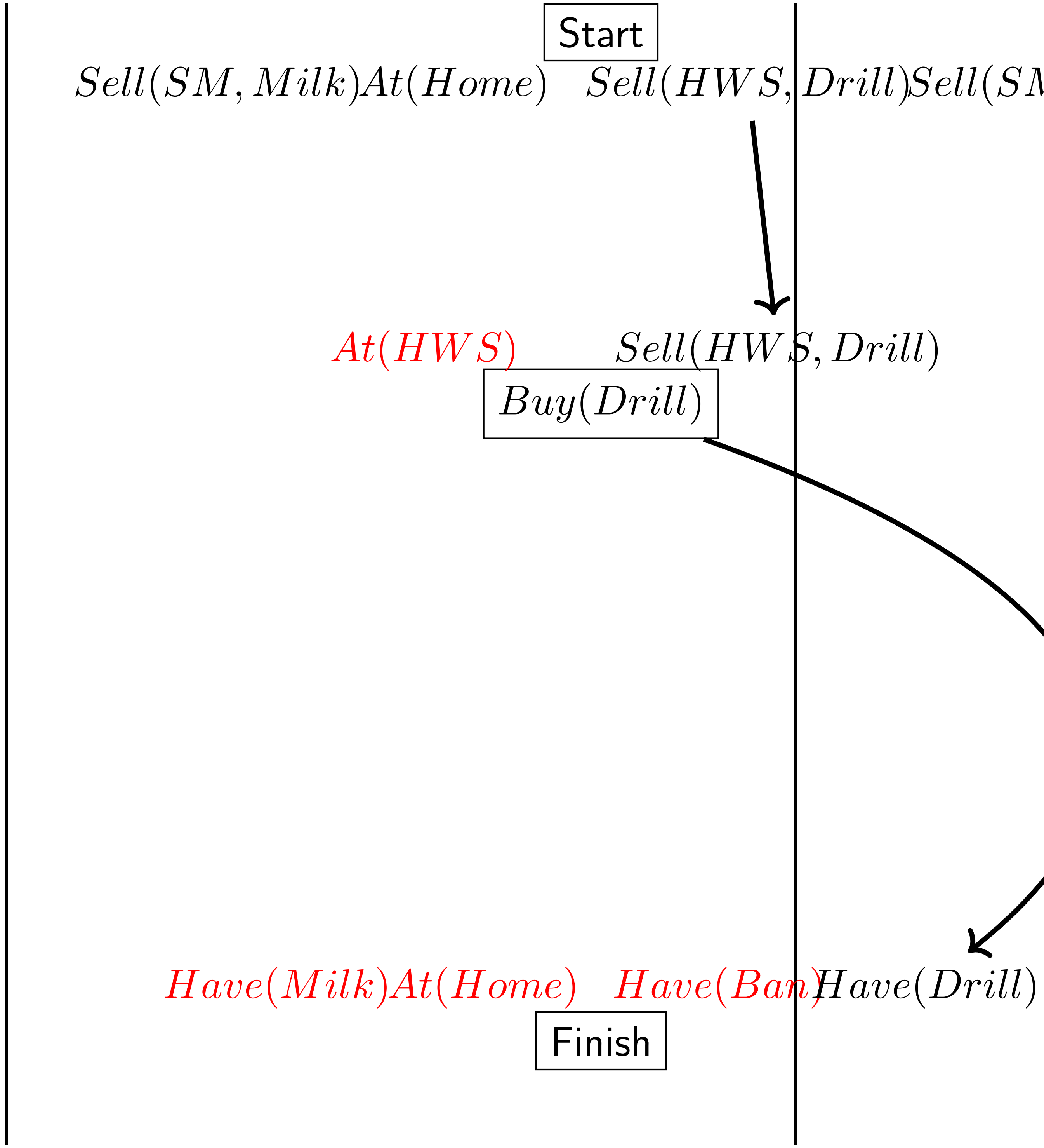
▷ **Example 17.5.11.**

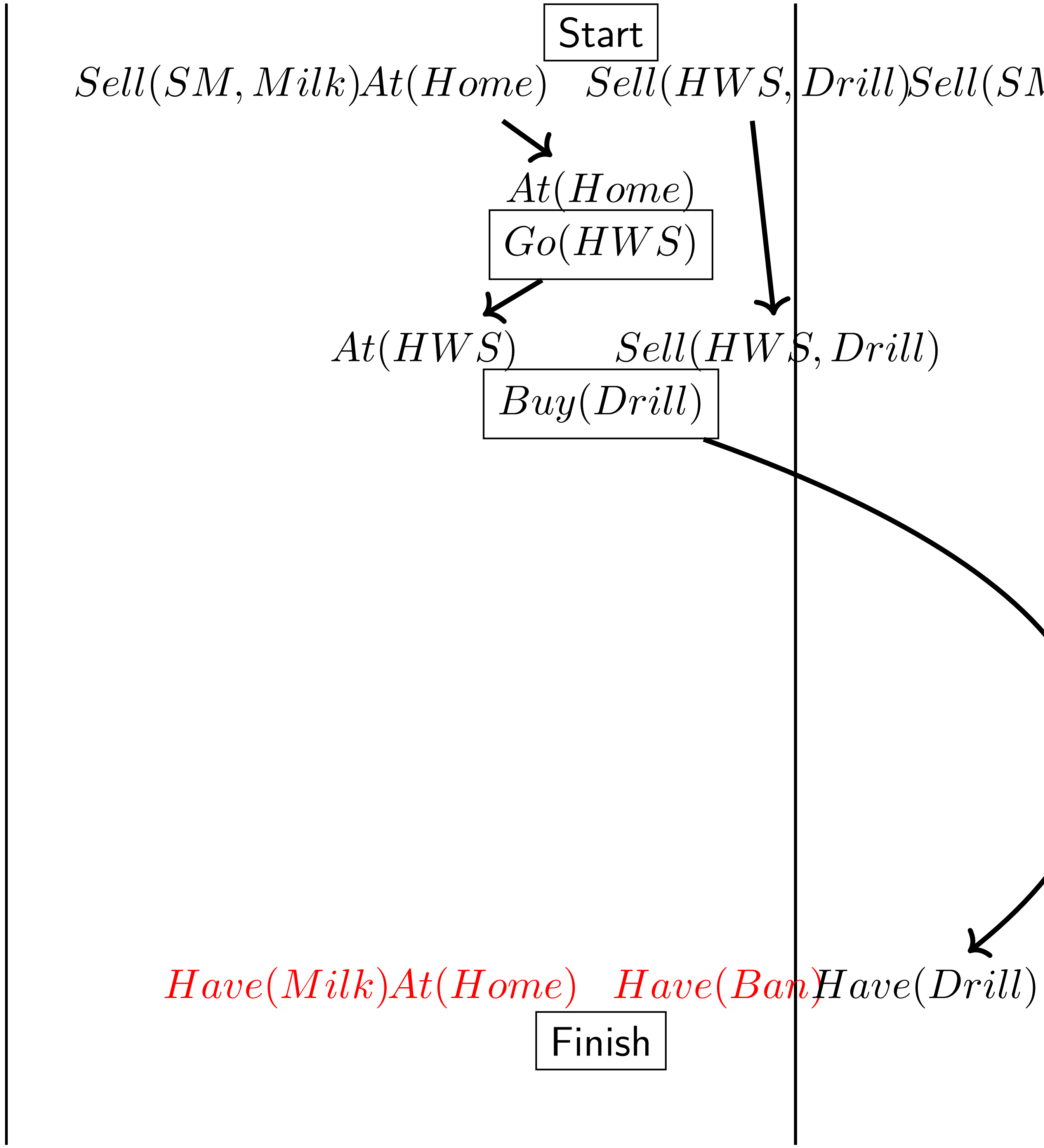
Start

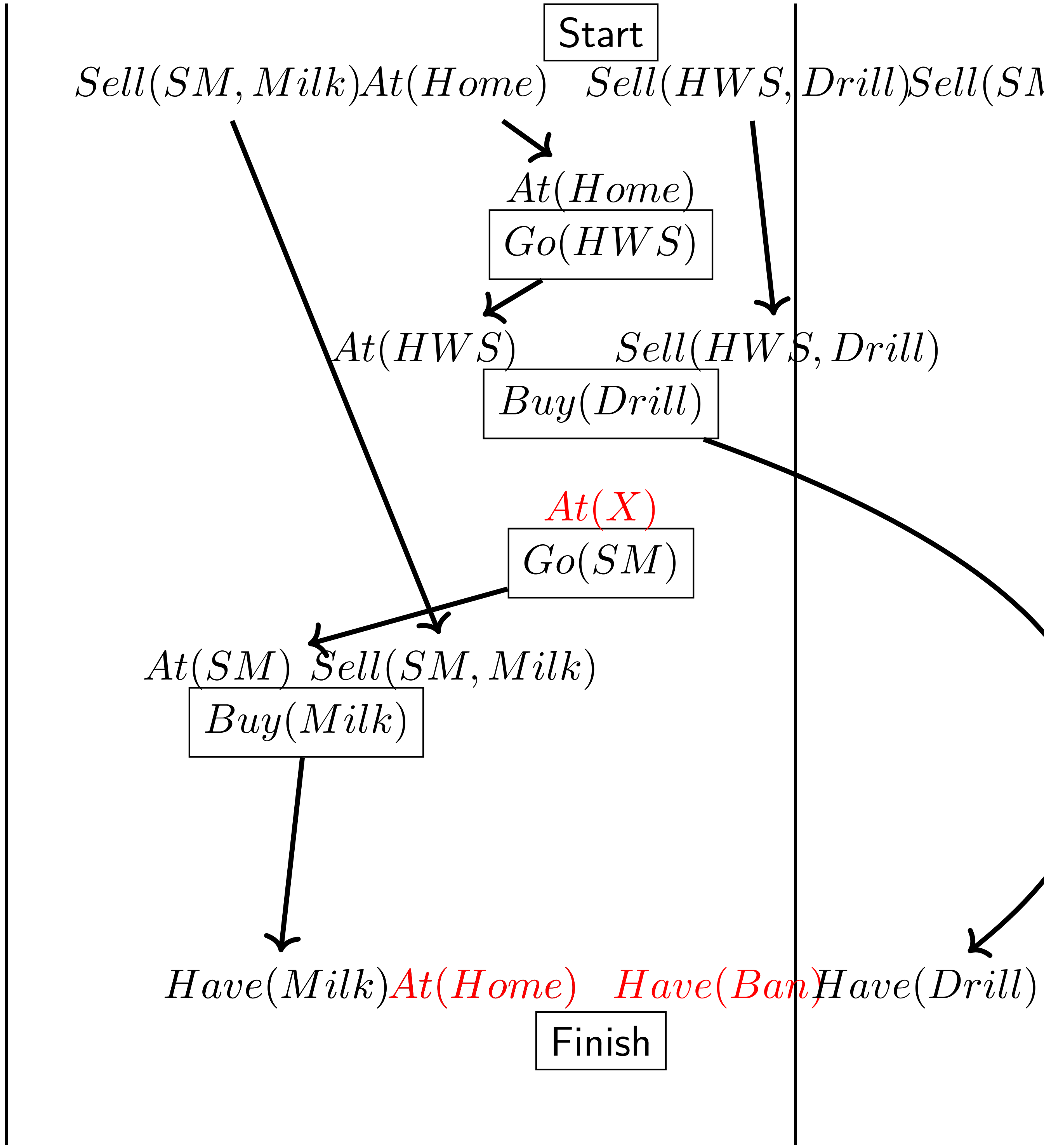
$Sell(SM, Milk) At(Home) \quad Sell(HWS, Drill) Sell(SM$

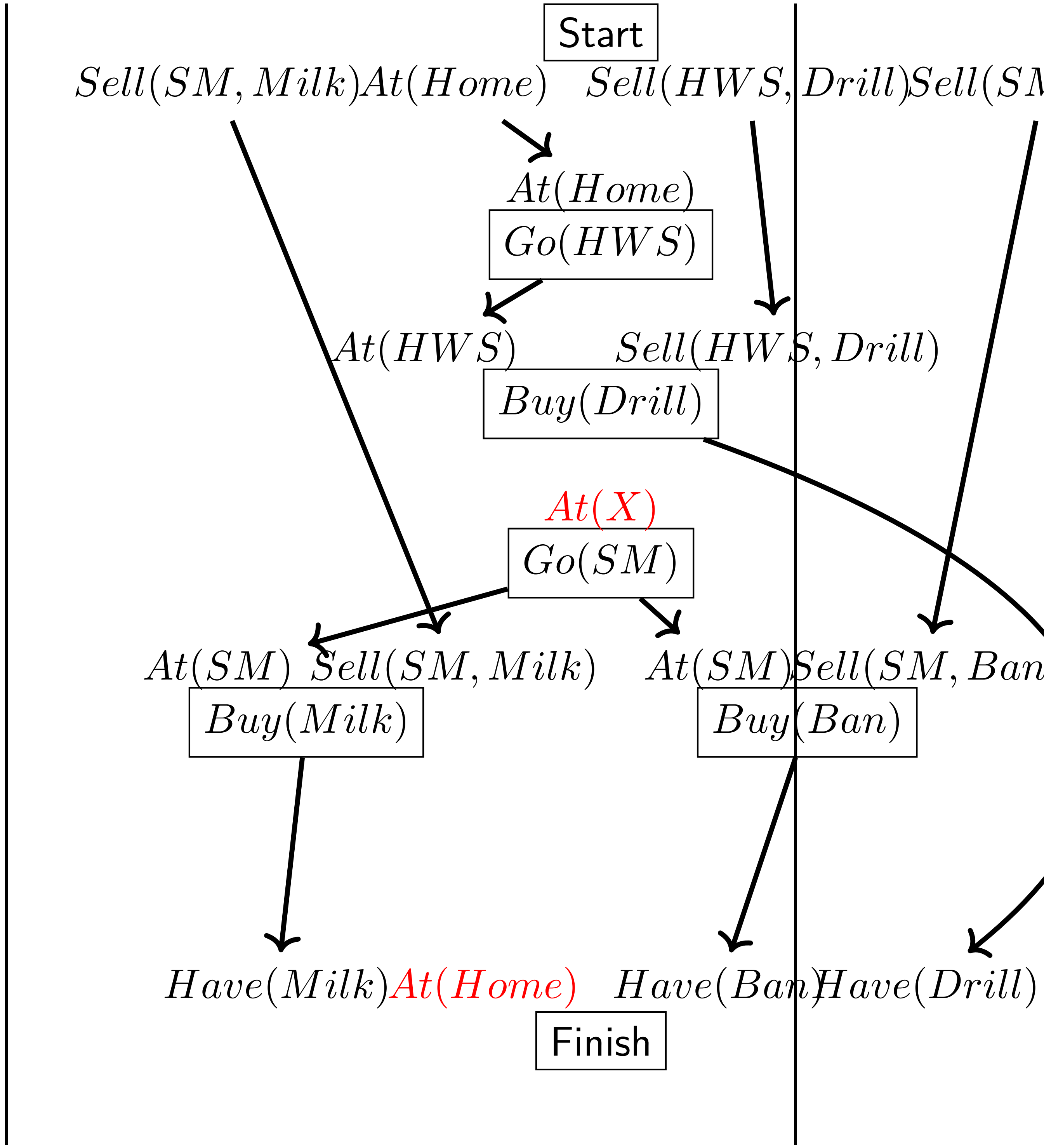
$Have(Milk) At(Home) \quad Have(Ban) Have(Drill)$

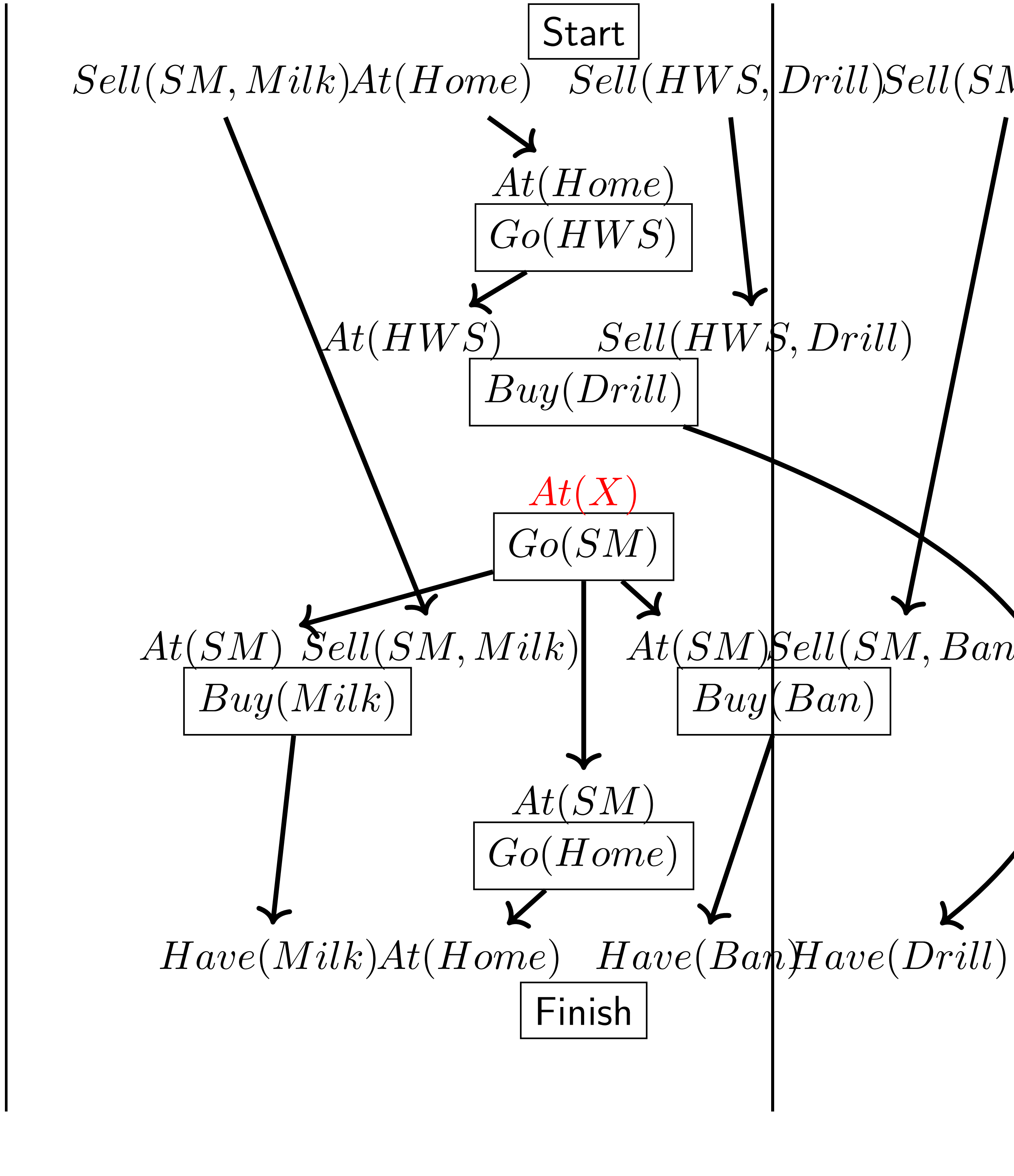
Finish


Start
Sell(SM, Milk)
At(Home)
Sell(HWS, Drill)
At(HWS)
Sell(HWS, Drill)
Buy(Drill)
Have(Milk)
At(Home)
Have(Drill)
Finish

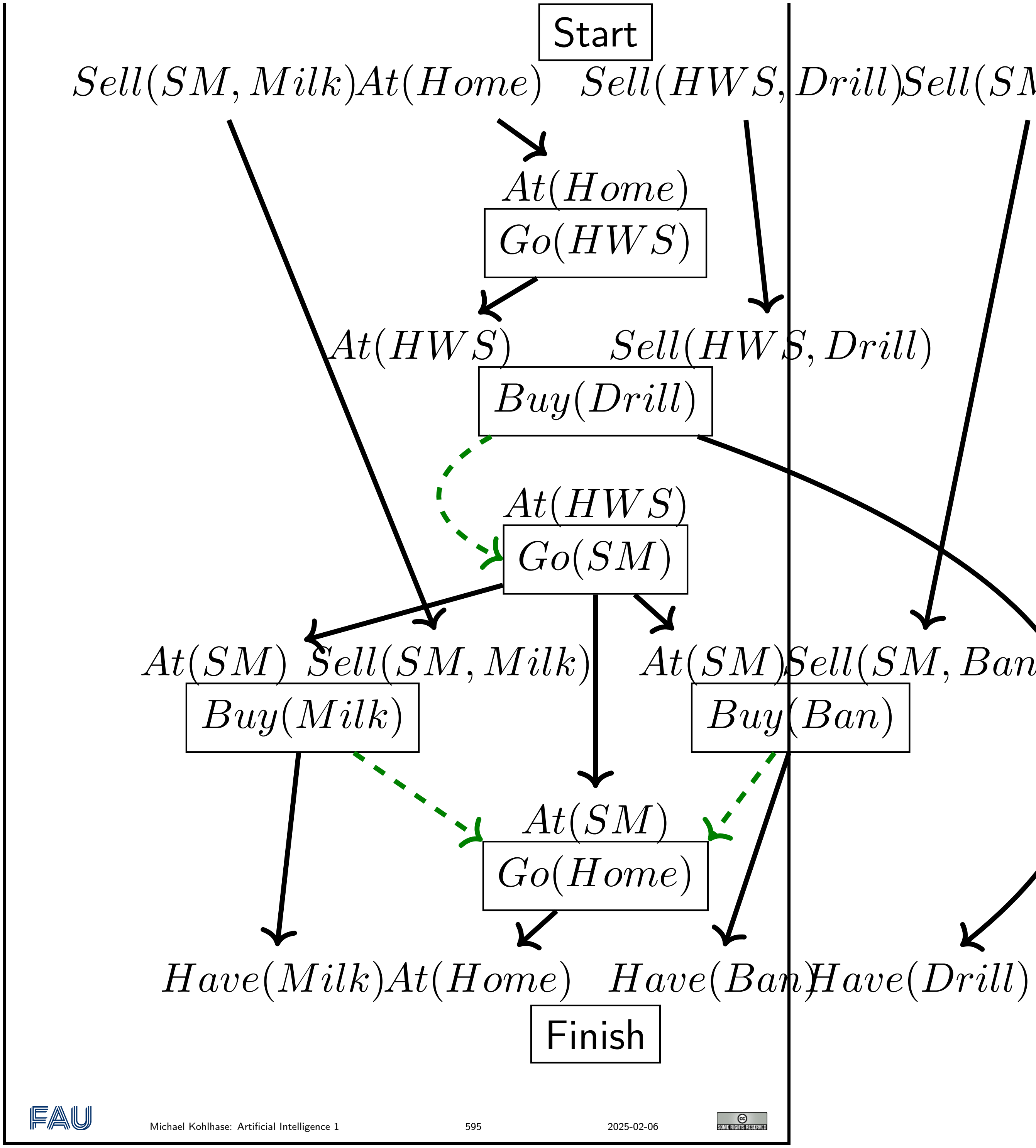

Start
Sell(SM, Milk)At(Home)
Sell(HWS, Drill)Sell(SM
At(Home)
Go(HWS)
At(HWS)
Sell(HWS, Drill)
Buy(Drill)
Have(Milk)At(Home)
Have(Ban)Have(Drill)
Finish


Start
Sell(SM, Milk) At(Home) Sell(HWS, Drill) Sell(SM
At(Home)
Go(HWS)
At(HWS) Sell(HWS, Drill)
Buy(Drill)
At(X)
Go(SM)
At(SM) Sell(SM, Milk)
Buy(Milk)
Have(Milk) At(Home) Have(Ban) Have(Drill)
Finish


Start
Sell(SM, Milk)At(Home) Sell(HWS, Drill)Sell(SM
At(Home)
Go(HWS)
At(HWS) Sell(HWS, Drill)
Buy(Drill)
At(X)
Go(SM)
At(SM) Sell(SM, Milk) At(SM)Sell(SM, Ban
Buy(Milk) Buy(Ban)
Have(Milk)At(Home) Have(Ban)Have(Drill)
Finish



Start
Sell(SM, Milk)
At(Home)
Sell(HWS, Drill)
At(Home)
Go(HWS)
At(HWS)
Sell(HWS, Drill)
Buy(Drill)
At(X)
Go(SM)
At(SM)
Sell(SM, Milk)
Buy(Milk)
At(SM)
Buy(Ban)
At(SM)
Go(Home)
Have(Milk)
At(Home)
Have(Drill)
Finish



Here we show a successful search for a partially ordered plan. We start out by initializing the plan by with the respective start and finish steps. Then we consecutively add steps to fulfill the open preconditions – marked in red – starting with those of the finish step.

In the end we add three temporal constraints that complete the partially ordered plan. The search process for the links and steps is relatively plausible and standard in this example, but we do not have any idea where the temporal constraints should systematically come from. We look at this next.

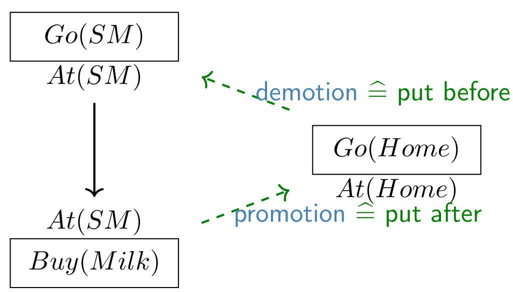
Clobbering and Promotion/Demotion

▷ **Definition 17.5.12.** In a partially ordered plan, a step C clobbers a causal link $L := S \xrightarrow{p} T$, iff it destroys the condition p achieved by L.

▷ **Definition 17.5.13.** If C clobbers $S \xrightarrow{p} T$ in a partially ordered plan Π, then we can solve the induced conflict by

- ▷ demotion: add a temporal constraint $C \prec S$ to Π, or
- ▷ promotion: add $T \prec C$ to Π.

▷ **Example 17.5.14.** $Go(Home)$ clobbers $At(Supermarket)$:



POP algorithm sketch

▷ **Definition 17.5.15.** The POP algorithm for constructing complete partially ordered plans:

```
function POP (initial, goal, operators) : plan
    plan:= Make−Minimal−Plan(initial, goal)
    loop do
        if Solution?(goal,plan) then return plan
        S_need, c := Select−Subgoal(plan)
        Choose−Operator(plan, operators, S_need,c)
        Resolve−Threats(plan)
    end

function Select−Subgoal (plan, S_need, c)
    pick a plan step S_need from Steps(plan)
        with a precondition c that has not been achieved
    return S_need, c
```


POP algorithm contd.

▷ **Definition 17.5.16.** The missing parts for the POP algorithm.

function Choose—Operator (plan, operators, S_{need}, c)
  choose a step S_{add} from operators or Steps(plan) that has c as an effect
  if there is no such step **then fail**
  add the causal—link $S_{add} \xrightarrow{c} S_{need}$ **to** Links(plan)
  add the temporal—constraint $S_{add} \prec S_{need}$ **to** Orderings(plan)
  if S_{add} is a newly added \step from operators **then**
    add S_{add} **to** Steps(plan)
    add $Start \prec S_{add} \prec Finish$ **to** Orderings(plan)

function Resolve—Threats (plan)
  for each S_{threat} that threatens a causal—link $S_i \xrightarrow{c} S_j$ **in** Links(plan) **do**
    choose either
      demotion: Add $S_{threat} \prec S_i$ **to** Orderings(plan)
      promotion: Add $S_j \prec S_{threat}$ **to** Orderings(plan)
    if not Consistent(plan) **then fail**

Properties of POP

▷ Nondeterministic algorithm: backtracks at choice points on failure:

- ▷ choice of S_{add} to achieve S_{need},
- ▷ choice of demotion or promotion for clobberer,
- ▷ selection of S_{need} is irrevocable.

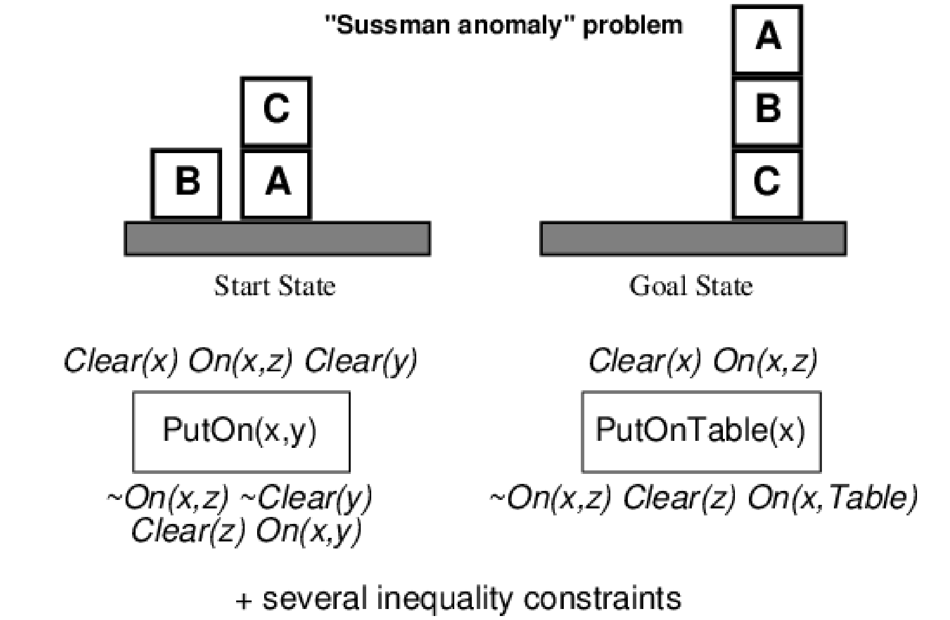
▷ **Observation 17.5.17.** *POP is sound, complete, and systematic i.e. no repetition*

▷ There are extensions for disjunction, universals, negation, conditionals.

▷ It can be made efficient with good heuristics derived from problem description.

▷ Particularly good for problems with many loosely related subgoals.

Example: Solving the Sussman Anomaly



Example: Solving the Sussman Anomaly (contd.)

▷ **Example 17.5.18.** Solving the Sussman anomaly

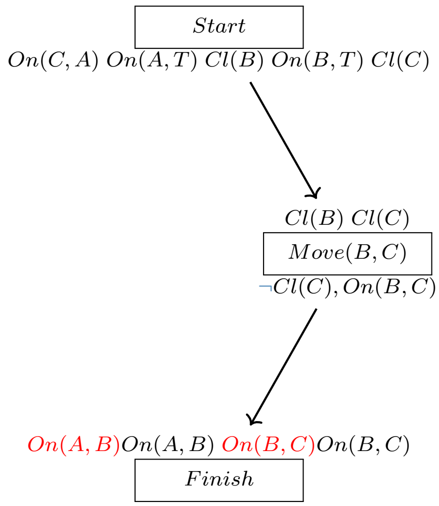
$\boxed{Start}$

$On(C,A)\ On(A,T)\ Cl(B)\ On(B,T)\ Cl(C)$

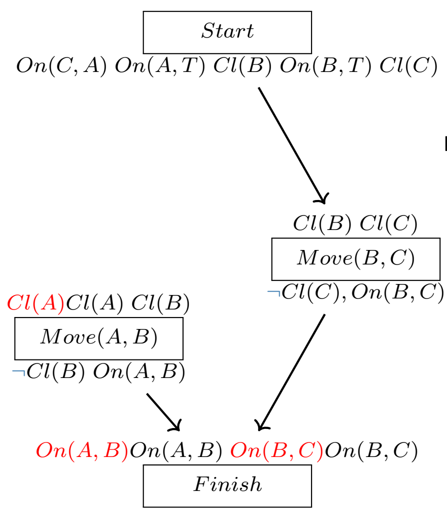
Initializing the partial order plan with with Start and Finish.

$On(A,B) On(A,B)\ On(B,C) On(B,C)$

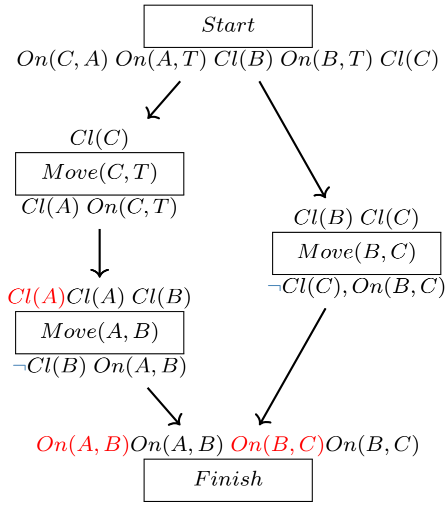
$\boxed{Finish}$



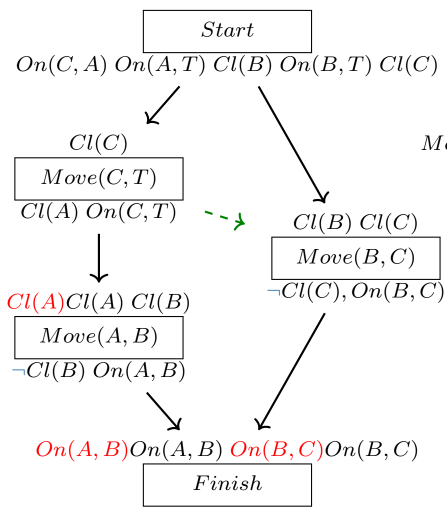
Refining for the subgoal $On(B,C)$.



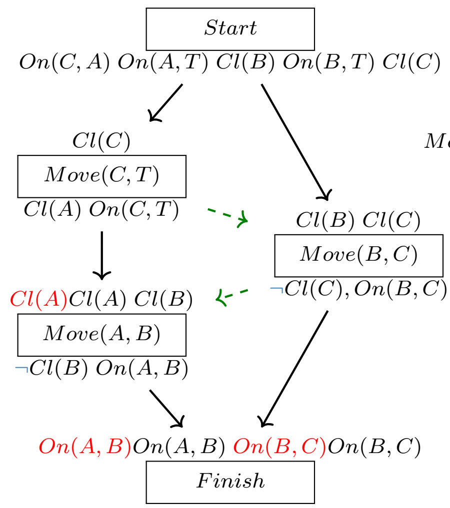
Refining for the subgoal $ON(A,C)$.



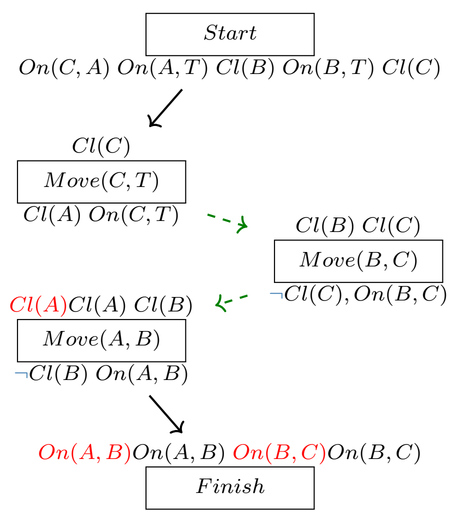
Refining for the subgoal $Cl(A)$.



$Move(A, B)$ clobbers $Cl(B) \rightsquigarrow$ demote.



$Move(B,C)$ clobbers $Cl(C)$ $\leadsto$ demote.



A totally ordered plan.

17.6 The PDDL Language

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26897`.

PDDL: Planning Domain Description Language

- ▷ **Definition 17.6.1.** The Planning Domain Description Language (PDDL) is a standardized representation language for planning benchmarks in various extensions of the STRIPS formalism.
- ▷ **Definition 17.6.2.** PDDL is not a propositional language

- ▷ Representation is lifted, using object variables to be instantiated from a finite set of objects. (Similar to predicate logic)
- ▷ Action schemas parameterized by objects.
- ▷ Predicates to be instantiated with objects.

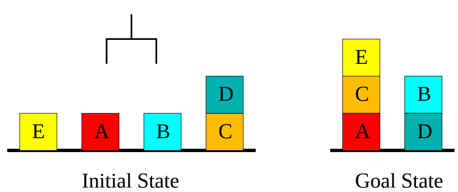
▷ **Definition 17.6.3.** A PDDL planning task comes in two pieces

- ▷ The problem file gives the objects, the initial state, and the goal state.
- ▷ The domain file gives the predicates and the actions.

History and Versions:

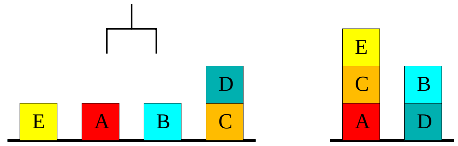
- Used in the International Planning Competition (IPC).
- 1998: PDDL [McD+98].
- 2000: "PDDL subset for the 2000 competition" [Bac00].
- 2002: PDDL2.1, Levels 1-3 [FL03].
- 2004: PDDL2.2 [HE05].
- 2006: PDDL3 [Ger+09].

The Blocksworld in PDDL: Domain File




```
(define (domain blocksworld)
  (:predicates (clear ?x) (holding ?x) (on ?x ?y)
               (on−table ?x) (arm−empty))
  (:action stack
   :parameters (?x ?y)
   :precondition (and (clear ?y) (holding ?x))
   :effect (and (arm−empty) (on ?x ?y)
               (not (clear ?y)) (not (holding ?x))))
  . . .)
```


The Blocksworld in PDDL: Problem File



Initial State   Goal State

```
(define (problem bw−abcde)
  (:domain blocksworld)
  (:objects a b c d e)
  (:init (on−table a) (clear a)
    (on−table b) (clear b)
    (on−table e) (clear e)
    (on−table c) (on d c) (clear d)
    (arm−empty))
  (:goal (and (on e c) (on c a) (on b d))))
```


Miconic-ADL "Stop" Action Schema in PDDL

```
(:action stop
 :parameters (?f − floor)
 :precondition (and (lift−at ?f)
  (imply
   (exists
    (?p − conflict−A)
    (or (and (not (served ?p))
             (origin ?p ?f))
        (and (boarded ?p)
             (not (destin ?p ?f)))))
   (forall
    (?q − conflict−B)
    (and (or (destin ?q ?f)
             (not (boarded ?q)))
         (or (served ?q)
             (not (origin ?q ?f))))))
  (imply (exists
          (?p − conflict−B)
          (or (and (not (served ?p))
                   (origin ?p ?f))
              (and (boarded ?p)
                   (not (destin ?p ?f)))))
         (forall
          (?q − conflict−A)
          (and (or (destin ?q ?f)
                   (not (boarded ?q)))
               (or (served ?q)
                   (not (origin ?q ?f))))))
  (imply
   (exists
    (?p − never−alone)
    (or (and (origin ?p ?f)
             (not (served ?p)))
        (and (boarded ?p)
             (not (destin ?p ?f)))))
   (exists
    (?q − attendant)
    (or (and (boarded ?q)
             (not (destin ?q ?f)))
        (and (not (served ?q))
             (origin ?q ?f)))))
  (forall
   (?p − going−nonstop)
   (imply (boarded ?p) (destin ?p ?f)))
  (or (forall
       (?p − vip) (served ?p))
      (exists
       (?p − vip)
       (or (origin ?p ?f) (destin ?p ?f))))
  (forall
   (?p − passenger)
   (imply
    (no−access ?p ?f) (not (boarded ?p)))))
 )
```


Planning Domain Description Language

▷ **Question:** What is PDDL good for?

(A) Nothing.

(B) Free beer.

(C) Those AI planning guys.

(D) Being lazy at work.

▷ **Answer:** reserved for the plenary sessions ⇝ be there!

17.7 Conclusion

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26900`.

Summary

▷ General problem solving attempts to develop solvers that perform well across a large class of problems.

▷ Planning, as considered here, is a form of general problem solving dedicated to the class of classical search problems. (Actually, we also address inaccessible, stochastic, dynamic, continuous, and multi-agent settings.)

▷ Heuristic search planning has dominated the International Planning Competition (IPC). We focus on it here.

▷ STRIPS is the simplest possible, while reasonably expressive, language for our purposes. It uses Boolean variables (facts), and defines actions in terms of precondition, add list, and delete list.

▷ PDDL is the de-facto standard language for describing planning problems.

▷ Plan existence (bounded or not) is **PSPACE**-complete to decide for STRIPS. If we bound plans polynomially, we get down to **NP**-completeness.

Suggested Reading:

- Chapters 10: *Classical Planning* and 11: *Planning and Acting in the Real World* in [RN09].
  - Although the book is named "*A Modern Approach*", the planning section was written long before the IPC was even dreamt of, before PDDL was conceived, and several years before heuristic search hit the scene. As such, what we have right now is the attempt of two outsiders trying in vain to catch up with the dramatic changes in planning since 1995.
  - Chapter 10 is Ok as a background read. Some issues are, imho, misrepresented, and it's far from being an up-to-date account. But it's Ok to get some additional intuitions in words different from my own.
  - Chapter 11 is useful in our context here because we don't cover any of it. If you're interested in extended/alternative planning paradigms, do read it.
- A good source for modern information (some of which we covered in the course) is Jörg Hoffmann's *Everything You Always Wanted to Know About Planning (But Were Afraid to Ask)* [Hof11] which is available online at `http://fai.cs.uni-saarland.de/hoffmann/papers/ki11.pdf`

Chapter 18

Planning II: Algorithms

18.1 Introduction

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26901`.

Reminder: Our Agenda for This Topic

- ▷ **??**: Background, planning languages, complexity.
  - ▷ Sets up the framework. computational complexity is essential to distinguish different algorithmic problems, and for the design of heuristic functions.
- ▷ **This Chapter:** How to automatically generate a heuristic function, given planning language input?
  - ▷ Focussing on heuristic search as the solution method, this is the main question that needs to be answered.

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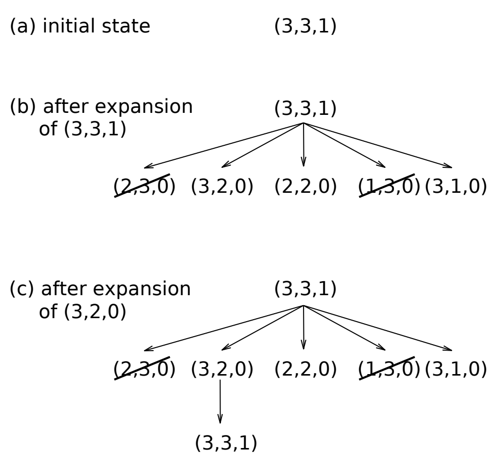
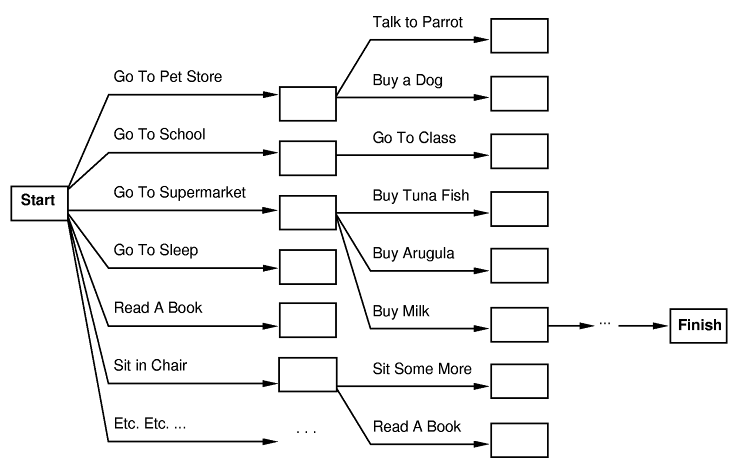
Reminder: Search

- ▷ Starting at initial state, produce all successor states step by step:



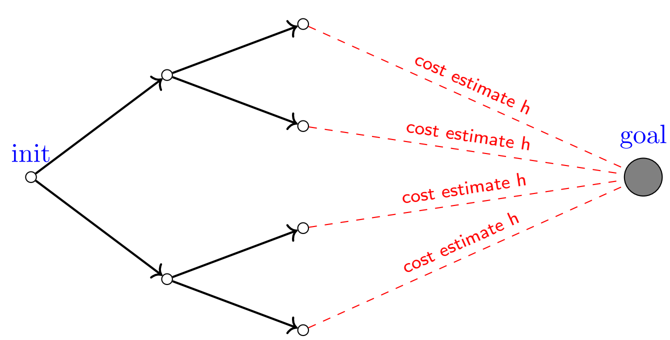
In planning, this is referred to as forward search, or forward state-space search.

Search in the State Space?



▷ Use heuristic function to guide the search towards the goal!

Reminder: Informed Search



▷ Heuristic function h estimates the cost of an optimal path from a state s to the goal state; search prefers to expand states s with small $h(s)$.

▷ Live Demo vs. Breadth-First Search:

`http://qiao.github.io/PathFinding.js/visual/`

Reminder: Heuristic Functions

- **Definition 18.1.1.** Let Π be a STRIPS task with states S. A heuristic function, short heuristic, for Π is a function $h\colon S \to \mathbb{N} \cup \{\infty\}$ so that $h(s) = 0$ whenever s is a goal state.
- Exactly like our definition from ??. Except, because we assume unit costs here, we use $\mathbb{N}$ instead of $\mathbb{R}^+$.
- **Definition 18.1.2.** Let Π be a STRIPS task with states S. The perfect heuristic h^* assigns every $s \in S$ the length of a shortest path from s to a goal state, or ∞ if no such path exists. A heuristic h for Π is admissible if, for all $s \in S$, we have $h(s) \leq h^*(s)$.
- Exactly like our definition from ??, except for path *length* instead of path *cost* (cf. above).
- In all cases, we attempt to approximate $h^*(s)$, the length of an optimal plan for s. Some algorithms guarantee to lower bound $h^*(s)$.

Our (Refined) Agenda for This Chapter

- **How to Relax:** How to relax a problem?
  - Basic principle for generating heuristic functions.
- **The Delete Relaxation:** How to relax a planning problem?
  - The delete relaxation is the most successful method for the *automatic* generation of heuristic functions. It is a key ingredient to almost all IPC winners of the last decade. It relaxes STRIPS tasks by ignoring the delete lists.
- **The h^+ Heuristic:** What is the resulting heuristic function?
  - h^+ is the "ideal" delete relaxation heuristic.
- **Approximating h^+:** How to actually compute a heuristic?
  - Turns out that, in practice, we must approximate h^+.

18.2 How to Relax in Planning

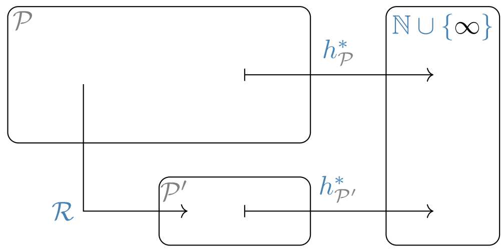
A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26902`.
We will now instantiate our general knowledge about heuristic search to the planning domain. As always, the main problem is to find good heuristics. We will follow the intuitions of our discussion in ?? and consider full solutions to relaxed problems as a source for heuristics.

How to Relax

▷ **Recall:** We introduced the concept of a relaxed search problem (allow cheating) to derive heuristics from them.

▷ **Observation:** This can be generalized to arbitrary problem solving.

▷ **Definition 18.2.1 (The General Case).**



1. You have a class $\mathcal{P}$ of problems, whose perfect heuristic $h^*_{\mathcal{P}}$ you wish to estimate.
2. You define a class $\mathcal{P}'$ of *simpler problems*, whose perfect heuristic $h^*_{\mathcal{P}'}$ can be used to estimate $h^*_{\mathcal{P}}$.
3. You define a transformation – the relaxation mapping $\mathcal{R}$ – that maps instances $\Pi \in \mathcal{P}$ into instances $\Pi' \in \mathcal{P}'$.
4. Given $\Pi \in \mathcal{P}$, you let $\Pi' := \mathcal{R}(\Pi)$, and estimate $h^*{}_{\mathcal{P}}(\Pi)$ by $h^*{}_{\mathcal{P}'}(\Pi')$.

▷ **Definition 18.2.2.** For planning tasks, we speak of relaxed planning.

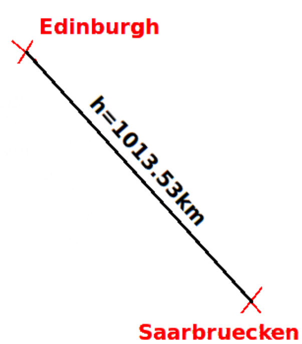
Reminder: Heuristic Functions from Relaxed Problems

▷ Problem Π: Find a route from Saarbrücken to Edinburgh.

Reminder: Heuristic Functions from Relaxed Problems

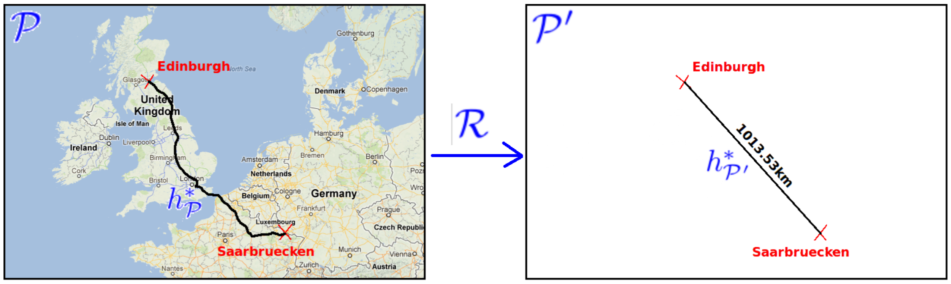
▷ Relaxed Problem Π': Throw away the map.

Reminder: Heuristic Functions from Relaxed Problems



▷ Heuristic function h: Straight line distance.

Relaxation in Route-Finding



- ▷ **Problem class** $\mathcal{P}$: Route finding.
- ▷ **Perfect heuristic** $h^*_{\mathcal{P}}$ **for** $\mathcal{P}$: Length of a shortest route.
- ▷ **Simpler problem class** $\mathcal{P}'$: Route finding on an empty map.
- ▷ **Perfect heuristic** $h^*_{\mathcal{P}'}$ **for** $\mathcal{P}'$: Straight-line distance.
- ▷ **Transformation** $\mathcal{R}$: Throw away the map.

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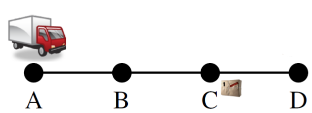
How to Relax in Planning? (A Reminder!)

▷ **Example 18.2.3 (Logistics).**



- ▷ facts P: $\{\text{truck}(x) \mid x \in \{A, B, C, D\}\} \cup \{\text{pack}(x) \mid x \in \{A, B, C, D, T\}\}$.
- ▷ initial state I: $\{\text{truck}(A), \text{pack}(C)\}$.
- ▷ goal state G: $\{\text{truck}(A), \text{pack}(D)\}$.
- ▷ actions A: (Notated as "precondition $\Rightarrow$ adds, $\neg$ deletes")
  - ▷ $\text{drive}(x, y)$, where x and y have a road: "$\text{truck}(x) \Rightarrow \text{truck}(y), \neg\text{truck}(x)$".
  - ▷ $\text{load}(x)$: "$\text{truck}(x), \text{pack}(x) \Rightarrow \text{pack}(T), \neg\text{pack}(x)$".
  - ▷ $\text{unload}(x)$: "$\text{truck}(x), \text{pack}(T) \Rightarrow \text{pack}(x), \neg\text{pack}(T)$".

▷ **Example 18.2.4 ("Only-Adds" Relaxation).** Drop the preconditions and deletes.

- ▷ "$\text{drive}(x, y)$: $\Rightarrow \text{truck}(y)$";
- ▷ "$\text{load}(x)$: $\Rightarrow \text{pack}(T)$";
- ▷ "$\text{unload}(x)$: $\Rightarrow \text{pack}(x)$".

▷ Heuristics value for I is?

▷ $h^{\mathcal{R}}(I) = 1$: A plan for the relaxed task is $\langle \text{unload}(D) \rangle$.

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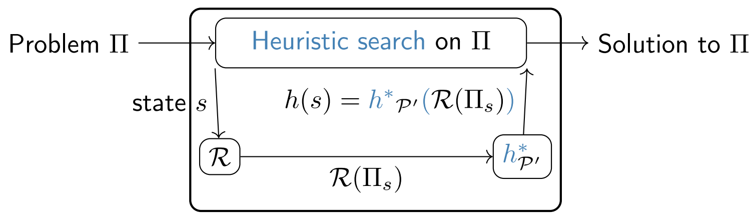
We will start with a very simple relaxation, which could be termed "positive thinking": we do not consider preconditions of actions and leave out the delete lists as well.

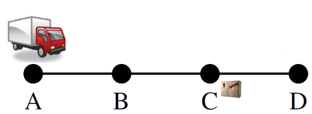
How to Relax During Search: Overview

- **Attention:** Search uses the real (un-relaxed) Π. The relaxation is applied (e.g., in Only-Adds, the simplified actions are used) **only within the call to** $h(s)$**!!!**



- Here, Π_s is Π with initial state replaced by s, i.e., $\Pi := \langle P, A, I, G\rangle$ changed to $\Pi^s := \langle P, A, \{s\}, G\rangle$: The task of finding a plan for search state s.
- A common student error is to instead apply the relaxation once to the whole problem, then doing the whole search "within the relaxation".
- The next slide illustrates the correct search process in detail.

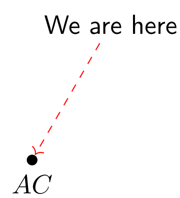
How to Relax During Search: Only-Adds

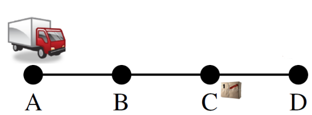


Real problem:

- Initial state I: AC; goal G: AD.
- Actions A: pre, add, del.
- $drXY, loX, ulX$.

Greedy best-first search: (tie-breaking: alphabetic)

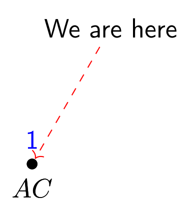


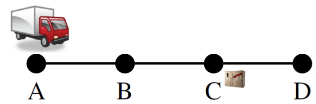


Relaxed problem:

- State s: AC; goal G: AD.
- Actions A: add.
- $h^{\mathcal{R}}(s) = 1$: $\langle ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

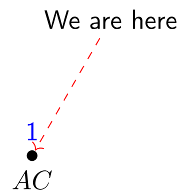


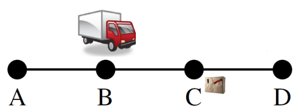


Relaxed problem:

- ▷ State s: AC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s)$ =1: $\langle ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

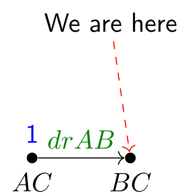


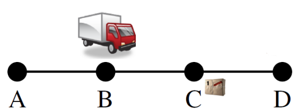


Real problem:

- ▷ State s: BC; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ $AC \xrightarrow{drAB} BC$.

Greedy best-first search: (tie-breaking: alphabetic)

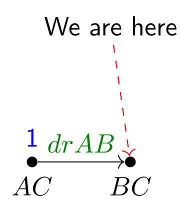


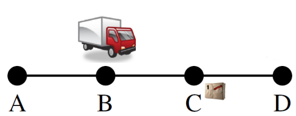


Relaxed problem:

- ▷ State s: BC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s)$ =2: $\langle drBA, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

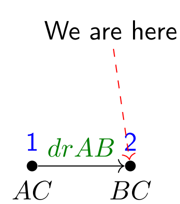


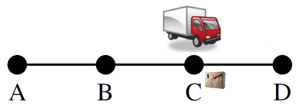


Relaxed problem:

- ▷ State s: BC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s)$ =2: $\langle drBA, ulD \rangle$.

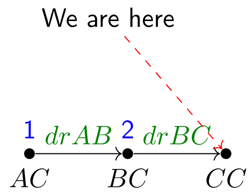
Greedy best-first search: (tie-breaking: alphabetic)

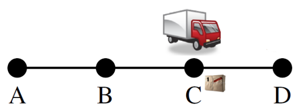




Real problem:
- ▷ State s: CC; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ $BC \xrightarrow{drBC} CC$.

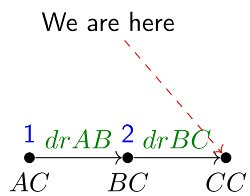
Greedy best-first search: (tie-breaking: alphabetic)

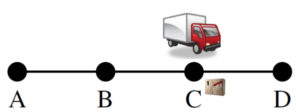




Relaxed problem:
- ▷ State s: CC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD \rangle$.

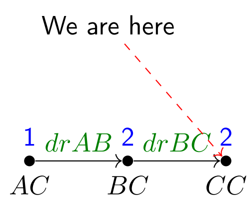
Greedy best-first search: (tie-breaking: alphabetic)

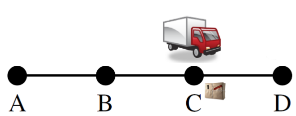




Relaxed problem:
- ▷ State s: CC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD \rangle$.

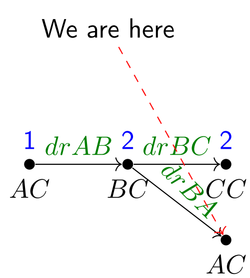
Greedy best-first search: (tie-breaking: alphabetic)

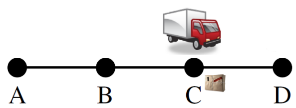




Real problem:
- ▷ State s: AC; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ $BC \xrightarrow{drBA} AC$.

Greedy best-first search: (tie-breaking: alphabetic)

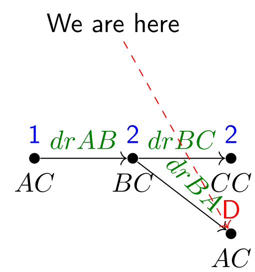


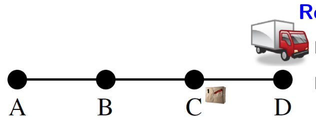


Real problem:

- ▷ State s: AC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Duplicate state, prune.

Greedy best-first search: (tie-breaking: alphabetic)

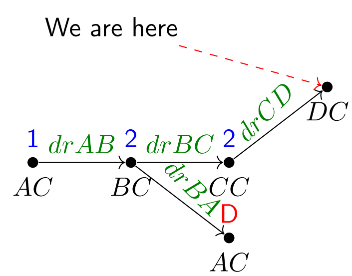


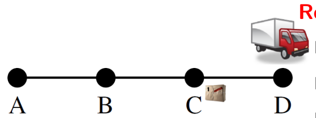


Real problem:

- ▷ State s: DC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ $CC \xrightarrow{drCD} DC$.

Greedy best-first search: (tie-breaking: alphabetic)

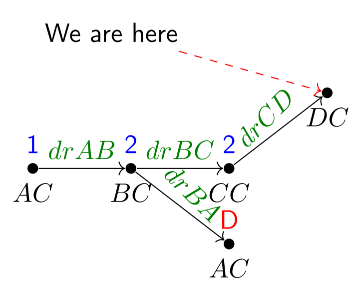


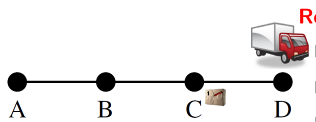


Relaxed problem:

- ▷ State s: DC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

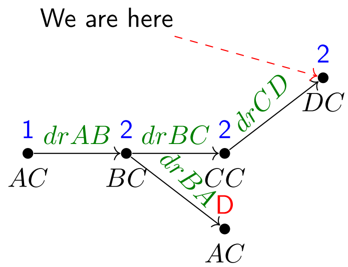




Relaxed problem:

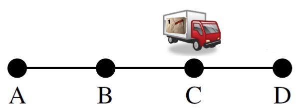
- ▷ State s: DC; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

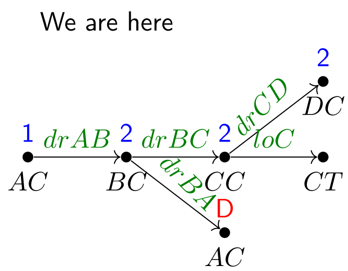


Real problem:

- ▷ State s: CT; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ $CC \xrightarrow{loC} CT$.

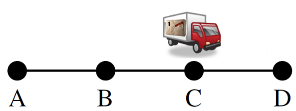


Greedy best-first search: (tie-breaking: alphabetic)

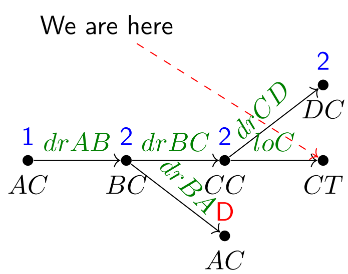


Relaxed problem:

- ▷ State s: CT; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD \rangle$.

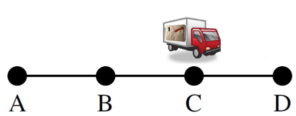


Greedy best-first search: (tie-breaking: alphabetic)

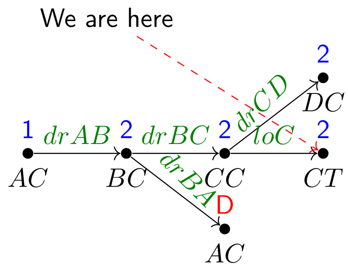


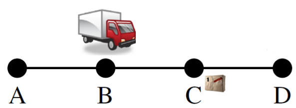
Relaxed problem:

- ▷ State s: CT; goal G: AD.
- ▷ Actions A: add.
- ▷ $h^{\mathcal{R}}(s) = 2$: $\langle drBA, ulD \rangle$.



Greedy best-first search: (tie-breaking: alphabetic)

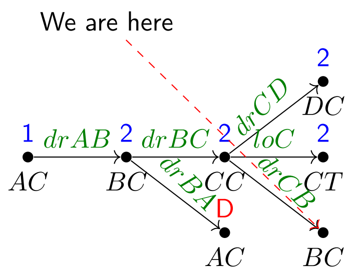


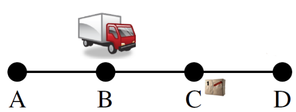


Real problem:

- ▷ State s: BC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ $CC \xrightarrow{drCB} BC$.

Greedy best-first search: (tie-breaking: alphabetic)

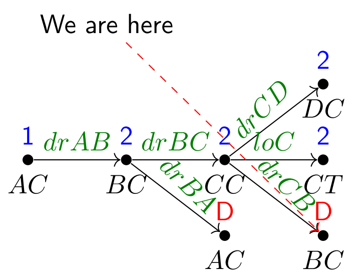


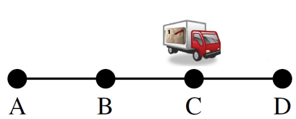


Real problem:

- ▷ State s: BC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Duplicate state, prune.

Greedy best-first search: (tie-breaking: alphabetic)

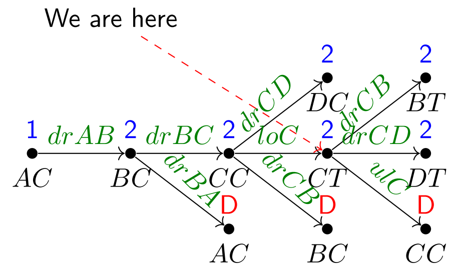


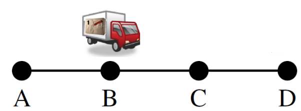


Real problem:

- ▷ State s: CT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: BT, DT, CC.

Greedy best-first search: (tie-breaking: alphabetic)

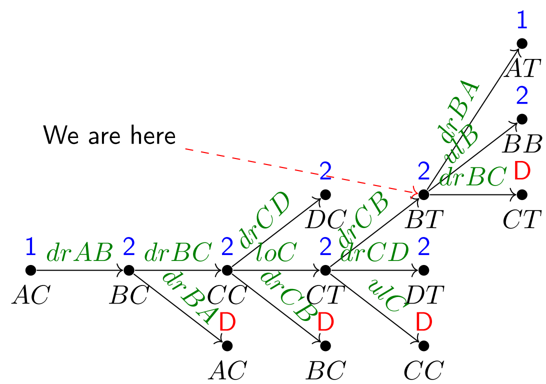


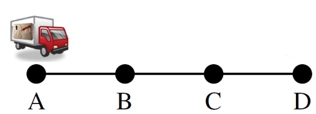


Real problem:

- ▷ State s: BT; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ Successors: AT, BB, CT.

Greedy best-first search: (tie-breaking: alphabetic)

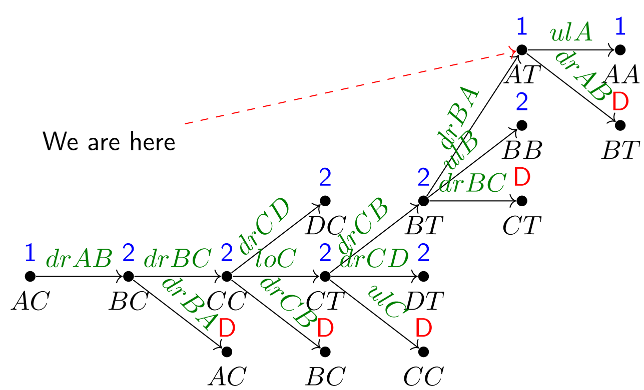


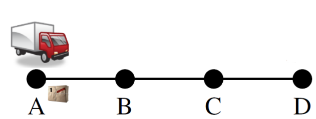


Real problem:

- ▷ State s: AT; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ Successors: AA, BT.

Greedy best-first search: (tie-breaking: alphabetic)

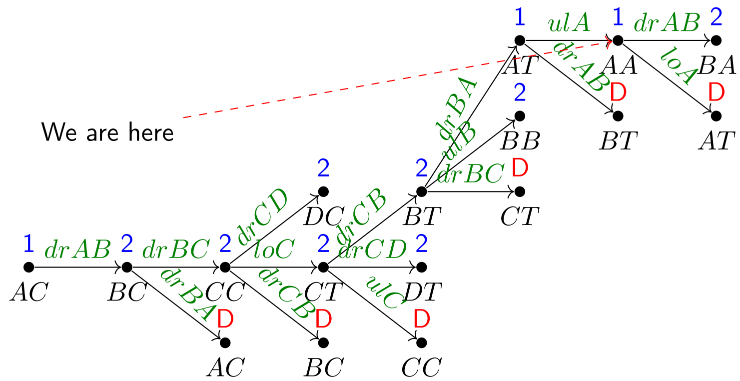


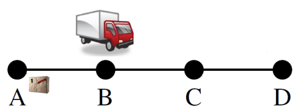


Real problem:

- ▷ State s: AA; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ Successors: BA, AT.

Greedy best-first search: (tie-breaking: alphabetic)

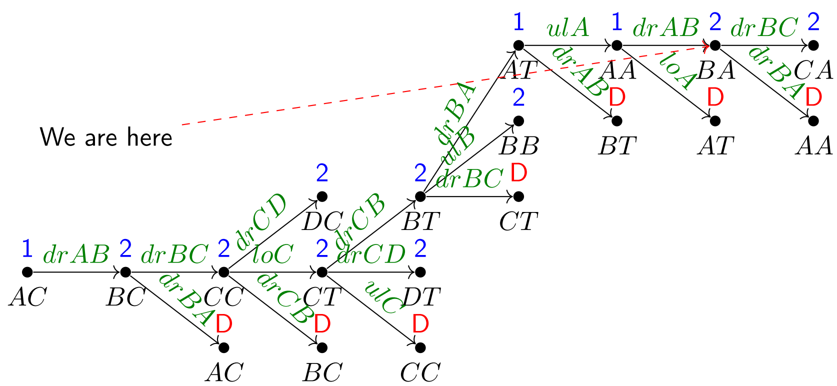


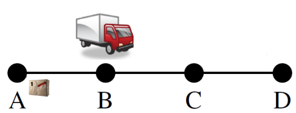


Real problem:

- ▷ State s: BA; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: CA, AA.

Greedy best-first search: (tie-breaking: alphabetic)

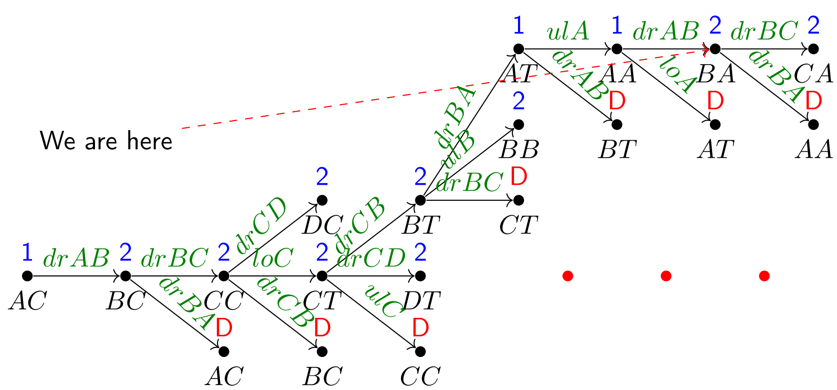




Real problem:

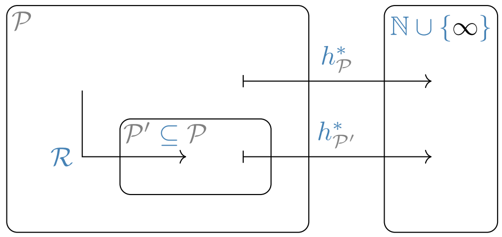
- ▷ State s: BA; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: CA, AA.

Greedy best-first search: (tie-breaking: alphabetic)



Only-Adds is a "Native" Relaxation

▷ **Definition 18.2.5 (Native Relaxations).** Confusing special case where $\mathcal{P}' \subseteq \mathcal{P}$.



- **Problem class $\mathcal{P}$**: STRIPS tasks.
- **Perfect heuristic $h^*_{\mathcal{P}}$ for $\mathcal{P}$**: Length h^* of a shortest plan.
- **Transformation $\mathcal{R}$:** Drop the preconditions and delete lists.
- **Simpler problem class $\mathcal{P}'$** is a special case of $\mathcal{P}$, $\mathcal{P}' \subseteq \mathcal{P}$: STRIPS tasks with empty preconditions and delete lists.
- Perfect heuristic for $\mathcal{P}'$: Shortest plan for only-adds STRIPS task.

18.3 The Delete Relaxation

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26903`.
We turn to a more realistic relaxation, where we only disregard the delete list.

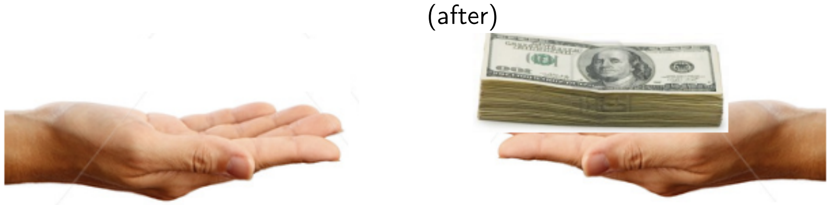
How the Delete Relaxation Changes the World (I)

▷ Relaxation mapping $\mathcal{R}$ saying that:

"When the world changes, its previous state remains true as well."

Real world: (before)

Real world: (after)



Relaxed world: (before)

Relaxed world: (after)

How the Delete Relaxation Changes the World (II)

- ▷ Relaxation mapping $\mathcal{R}$ saying that:

Real world: (before)

Real world: (after)

Relaxed world: (before)

Relaxed world: (after)

How the Delete Relaxation Changes the World (III)

▷ Relaxation mapping $\mathcal{R}$ saying that:

Real world:

Relaxed world:

The Delete Relaxation

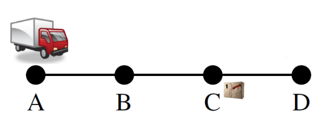
▷ **Definition 18.3.1 (Delete Relaxation).** Let $\Pi := \langle P, A, I, G \rangle$ be a STRIPS task. The delete relaxation of Π is the task $\Pi^+ = \langle P, A^+, I, G \rangle$ where $A^+ := \{a^+ \mid a \in A\}$ with $\mathrm{pre}_{a^+} := \mathrm{pre}_a$, $\mathrm{add}_{a^+} := \mathrm{add}_a$, and $\mathrm{del}_{a^+} := \emptyset$.

- ▷ In other words, the class of simpler problems $\mathcal{P}'$ is the set of all STRIPS tasks with empty delete lists, and the relaxation mapping $\mathcal{R}$ drops the delete lists.
- ▷ **Definition 18.3.2 (Relaxed Plan).** Let $\Pi := \langle P, A, I, G\rangle$ be a STRIPS task, and let s be a state. A relaxed plan for s is a plan for $\langle P, A, s, G\rangle^{+}$. A relaxed plan for I is called a relaxed plan for Π.
- ▷ A relaxed plan for s is an action sequence that solves s when pretending that all delete lists are empty.
- ▷ Also called delete-relaxed plan: "relaxation" is often used to mean delete relaxation by default.

A Relaxed Plan for "TSP" in Australia

1. **Initial state:** $\{\mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
2. $\mathrm{drv}(\mathrm{Sy}, \mathrm{Br})^{+}$: $\{\mathrm{at}(\mathrm{Br}), \mathrm{vis}(\mathrm{Br}), \mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
3. $\mathrm{drv}(\mathrm{Sy}, \mathrm{Ad})^{+}$: $\{\mathrm{at}(\mathrm{Ad}), \mathrm{vis}(\mathrm{Ad}), \mathrm{at}(\mathrm{Br}), \mathrm{vis}(\mathrm{Br}), \mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
4. $\mathrm{drv}(\mathrm{Ad}, \mathrm{Pe})^{+}$: $\{\mathrm{at}(\mathrm{Pe}), \mathrm{vis}(\mathrm{Pe}), \mathrm{at}(\mathrm{Ad}), \mathrm{vis}(\mathrm{Ad}), \mathrm{at}(\mathrm{Br}), \mathrm{vis}(\mathrm{Br}), \mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.
5. $\mathrm{drv}(\mathrm{Ad}, \mathrm{Da})^{+}$: $\{\mathrm{at}(\mathrm{Da}), \mathrm{vis}(\mathrm{Da}), \mathrm{at}(\mathrm{Pe}), \mathrm{vis}(\mathrm{Pe}), \mathrm{at}(\mathrm{Ad}), \mathrm{vis}(\mathrm{Ad}), \mathrm{at}(\mathrm{Br}), \mathrm{vis}(\mathrm{Br}), \mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$.

A Relaxed Plan for "Logistics"



- ▷ Facts P: $\{\mathrm{truck}(x) \mid x \in \{A, B, C, D\}\} \cup \{\mathrm{pack}(x) \mid x \in \{A, B, C, D, T\}\}$.
- ▷ Initial state I: $\{\mathrm{truck}(A), \mathrm{pack}(C)\}$.
- ▷ Goal G: $\{\mathrm{truck}(A), \mathrm{pack}(D)\}$.
- ▷ Relaxed actions A^{+}: (Notated as "precondition $\Rightarrow$ adds")
  - ▷ $\mathrm{drive}(x, y)^{+}$: "$\mathrm{truck}(x) \Rightarrow \mathrm{truck}(y)$".

- $\text{load}(x)^+$: "$\text{truck}(x), \text{pack}(x) \Rightarrow \text{pack}(T)$".
- $\text{unload}(x)^+$: "$\text{truck}(x), \text{pack}(T) \Rightarrow \text{pack}(x)$".

Relaxed plan:

$$\langle \text{drive}(A,B)^+, \text{drive}(B,C)^+, \text{load}(C)^+, \text{drive}(C,D)^+, \text{unload}(D)^+ \rangle$$

▷ We don't need to drive the truck back, because "it is still at A".

$\mathbf{PlanEx}^+$

▷ **Definition 18.3.3 (Relaxed Plan Existence Problem).** By $\mathbf{PlanEx}^+$, we denote the problem of deciding, given a STRIPS task $\Pi := \langle P, A, I, G \rangle$, whether or not there exists a relaxed plan for Π.

▷ This is easier than $\mathbf{PlanEx}$ for general STRIPS!

▷ $\mathbf{PlanEx}^+$ is in $\mathbf{P}$.

▷ *Proof:* The following algorithm decides $\mathbf{PlanEx}^+$

1.

   var $F := I$
   while $G \not\subseteq F$ **do**
   $\quad F' := F \cup \bigcup_{a \in A : \text{pre}_a \subseteq F} \text{add}_a$
   $\quad$**if** $F' = F$ **then return** "unsolvable" endif $\qquad (*)$
   $\quad F := F'$
   endwhile
   return "solvable"

2. The algorithm terminates after at most $|P|$ iterations, and thus runs in polynomial time.
3. Correctness: See slide 632

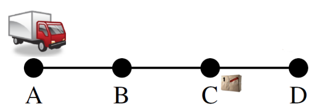
Deciding $\mathbf{PlanEx}^+$ in "TSP" in Australia

Iterations on F:

1. $\{\mathrm{at}(\mathrm{Sy}), \mathrm{vis}(\mathrm{Sy})\}$
2. $\cup$ $\{\mathrm{at}(\mathrm{Ad}), \mathrm{vis}(\mathrm{Ad}), \mathrm{at}(\mathrm{Br}), \mathrm{vis}(\mathrm{Br})\}$
3. $\cup$ $\{\mathrm{at}(\mathrm{Da}), \mathrm{vis}(\mathrm{Da}), \mathrm{at}(\mathrm{Pe}), \mathrm{vis}(\mathrm{Pe})\}$

Deciding PlanEx^+ in "Logistics"

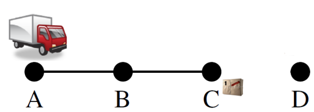
▷ **Example 18.3.4 (The solvable Case).**



Iterations on F:

1. $\{\mathrm{truck}(A), \mathrm{pack}(C)\}$
2. $\cup\{\mathrm{truck}(B)\}$
3. $\cup\{\mathrm{truck}(C)\}$
4. $\cup\{\mathrm{truck}(D), \mathrm{pack}(T)\}$
5. $\cup\{\mathrm{pack}(A), \mathrm{pack}(B), \mathrm{pack}(D)\}$

▷ **Example 18.3.5 (The unsolvable Case).**



Iterations on F:

1. $\{\mathrm{truck}(A), \mathrm{pack}(C)\}$
2. $\cup\{\mathrm{truck}(B)\}$
3. $\cup\{\mathrm{truck}(C)\}$
4. $\cup\{\mathrm{pack}(T)\}$
5. $\cup\{\mathrm{pack}(A), \mathrm{pack}(B)\}$
6. $\cup\emptyset$

PlanEx^+ Algorithm: Proof

Proof: To show: The algorithm returns "solvable" iff there is a relaxed plan for Π.

1. Denote by F_i the content of F after the ith iteration of the while-loop,
2. All $a \in A_0$ are applicable in I, all $a \in A_1$ are applicable in $\mathrm{apply}(I, A_0^+)$, and so forth.
3. Thus $F_i = \mathrm{apply}(I, \langle A_0^+, \ldots, A_{i-1}^+\rangle)$. (Within each A_j^+, we can sequence the actions in any order.)
4. Direction "$\Rightarrow$" *If "solvable" is returned after iteration n then $G \subseteq F_n = \mathrm{apply}(I, \langle A_0^+, \ldots, A_{n-1}^+\rangle)$ so $\langle A_0^+, \ldots, A_{n-1}^+\rangle$ can be sequenced to a relaxed plan which shows the claim.*
5. Direction "$\Leftarrow$"
   5.1. Let $\langle a_0^+, \ldots, a_{n-1}^+\rangle$ be a relaxed plan, hence $G \subseteq \mathrm{apply}(I, \langle a_0^+, \ldots, a_{n-1}^+\rangle)$.
   5.2. Assume, for the moment, that we drop line (*) from the algorithm. It is then

easy to see that $a_i \in A_i$ and $\text{apply}(I, \langle a_0^+, \ldots, a_{i-1}^+ \rangle) \subseteq F_i$, for all i.

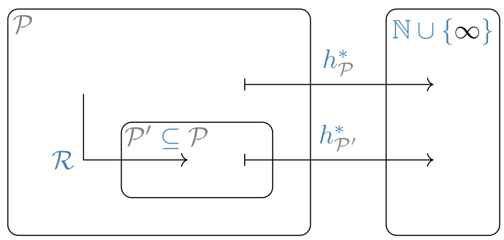
5.3. We get $G \subseteq \text{apply}(I, \langle a_0^+, \ldots, a_{n-1}^+ \rangle) \subseteq F_n$, and the algorithm returns "solvable" as desired.

5.4. Assume to the contrary of the claim that, in an iteration $i < n$, (*) fires. Then $G \not\subseteq F$ and $F = F'$. But, with $F = F'$, $F = F_j$ for all $j > i$, and we get $G \not\subseteq F_n$ in contradiction.

18.4 The h^+Heuristic

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26905`.

Hold on a Sec – Where are we?



- $\mathcal{P}$: STRIPS tasks; $h^*_{\mathcal{P}}$: Length h^* of a shortest plan.
- $\mathcal{P}' \subseteq \mathcal{P}$: STRIPS tasks with empty delete lists.
- $\mathcal{R}$: Drop the delete lists.
- Heuristic function: Length of a shortest relaxed plan ($h^* \circ \mathcal{R}$).
- **PlanEx$^+$** is not actually what we're looking for. **PlanEx$^+$** $\widehat{=}$ relaxed plan *existence*; we want relaxed plan *length* $h^* \circ \mathcal{R}$.

h^+: The Ideal Delete Relaxation Heuristic

- **Definition 18.4.1 (Optimal Relaxed Plan).** Let $\langle P, A, I, G \rangle$ be a STRIPS task, and let s be a state. A optimal relaxed plan for s is an optimal plan for $\langle P, A, \{s\}, G \rangle^+$.
- Same as slide 626, just adding the word "optimal".
- Here's what we're looking for:
- **Definition 18.4.2.** Let $\Pi := \langle P, A, I, G \rangle$ be a STRIPS task with states S. The ideal delete relaxation heuristic h^+ for Π is the function $h^+ : S \to \mathbb{N} \cup \{\infty\}$ where $h^+(s)$ is the length of an optimal relaxed plan for s if a relaxed plan for s exists, and $h^+(s) = \infty$ otherwise.
- In other words, $h^+ = h^* \circ \mathcal{R}$, cf. previous slide.

h^+ is Admissible

▷ **Lemma 18.4.3.** *Let $\Pi := \langle P, A, I, G\rangle$ be a STRIPS task, and let s be a state. If $\langle a_1, \ldots, a_n\rangle$ is a plan for $\Pi_s := \langle P, A, \{s\}, G\rangle$, then $\langle a_1^+, \ldots, a_n^+\rangle$ is a plan for Π^+.*

▷ *Proof sketch:* Show by induction over $0 \leq i \leq n$ that $\mathrm{apply}(s, \langle a_1, \ldots, a_i\rangle) \subseteq \mathrm{apply}(s, \langle a_1^+, \ldots, a_i^+\rangle)$.

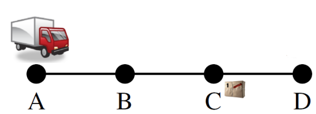
▷ If we ignore deletes, the states along the plan can only get bigger.

▷ **Theorem 18.4.4.** *h^+ is Admissible.*

▷ *Proof:*

1. Let $\Pi := \langle P, A, I, G\rangle$ be a STRIPS task with states P, and let $s \in P$.
2. $h^+(s)$ is defined as optimal plan length in Π_s^+.
3. With the lemma above, any plan for Π also constitutes a plan for Π_s^+.
4. Thus optimal plan length in Π_s^+ can only be shorter than that in $\Pi_s i$, and the claim follows.

How to Relax During Search: Ignoring Deletes



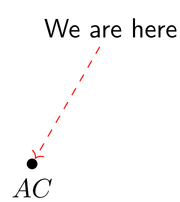
Real problem:

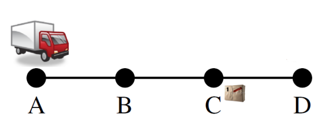
▷ Initial state I: AC; goal G: AD.

▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.

▷ $drXY, loX, ulX$.

Greedy best-first search: (tie-breaking: alphabetic)





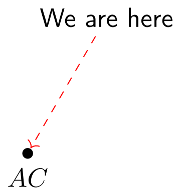
Relaxed problem:

▷ State s: AC; goal G: AD.

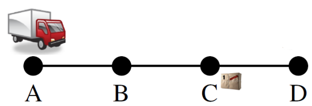
▷ Actions A: $\mathrm{pre}, \mathrm{add}$.

▷ $h^+(s)$ =5: e.g. $\langle drAB, drBC, drCD, loC, ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

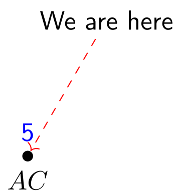


Relaxed problem:

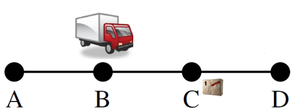


- State s: AC; goal G: AD.
- Actions A: $\mathrm{pre}, \mathrm{add}$.
- $h^+(s)$ =5: e.g. $\langle drAB, drBC, drCD, loC, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

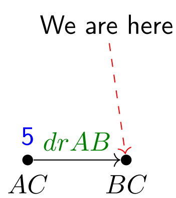


Real problem:

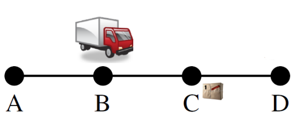


- State s: BC; goal G: AD.
- Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- $AC \xrightarrow{drAB} BC$.

Greedy best-first search: (tie-breaking: alphabetic)



Relaxed problem:



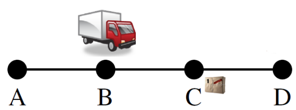
- State s: BC; goal G: AD.
- Actions A: $\mathrm{pre}, \mathrm{add}$.
- $h^+(s)$ =5: e.g. $\langle drBA, drBC, drCD, loC, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here

$$AC \xrightarrow{5\ drAB} BC$$

Relaxed problem:



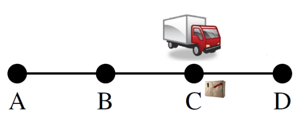
- ▷ State s: BC; goal G: AD.
- ▷ Actions A: pre, add.
- ▷ $h^+(s)$ =5: e.g. $\langle drBA, drBC, drCD, loC, ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here

$$AC \xrightarrow{5\ drAB} BC\ 5$$

Real problem:



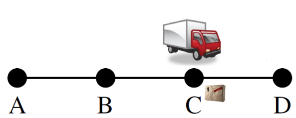
- ▷ State s: CC; goal G: AD.
- ▷ Actions A: $\text{pre}, \text{add}, \text{del}$.
- ▷ $BC \xrightarrow{drBC} CC$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here

$$AC \xrightarrow{5\ drAB} BC \xrightarrow{5\ drBC} CC$$

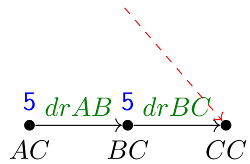
Relaxed problem:



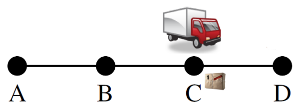
- ▷ State s: CC; goal G: AD.
- ▷ Actions A: pre, add.
- ▷ $h^+(s)$ =5: e.g. $\langle drCB, drBA, drCD, loC, ulD\rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here



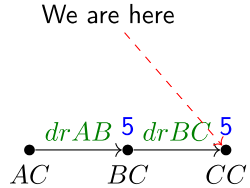
Relaxed problem:



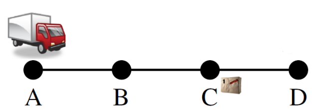
- State s: CC; goal G: AD.
- Actions A: pre, add.
- $h^+(s)$ =5: e.g. $\langle drCB, drBA, drCD, loC, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here



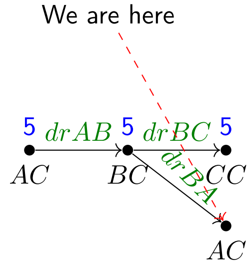
Real problem:



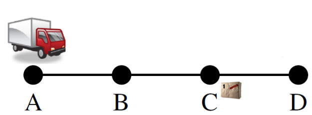
- State s: AC; goal G: AD.
- Actions A: pre, add, del.
- $BC \xrightarrow{drBA} AC$.

Greedy best-first search: (tie-breaking: alphabetic)

We are here

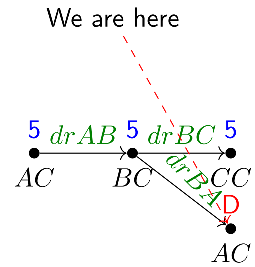


Real problem:

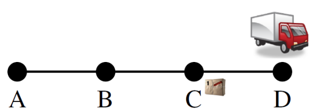


- State s: AC; goal G: AD.
- Actions A: pre, add, del.
- Duplicate state, prune.

Greedy best-first search: (tie-breaking: alphabetic)

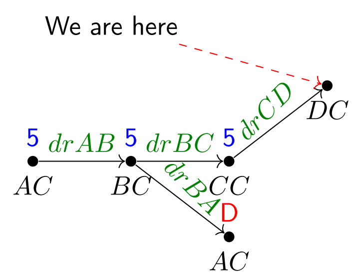


Real problem:

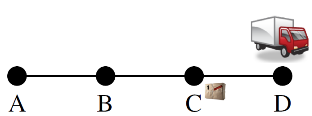


- ▷ State s: DC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ $CC \xrightarrow{drCD} DC$.

Greedy best-first search: (tie-breaking: alphabetic)

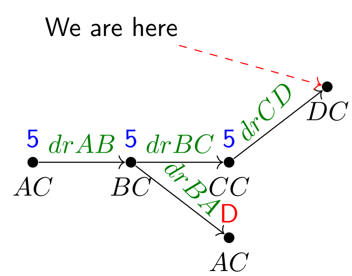


Relaxed problem:

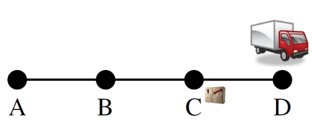


- ▷ State s: DC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}$.
- ▷ $h^+(s)$ $=5$: e.g. $\langle drDC, drCB, drBA, loC, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

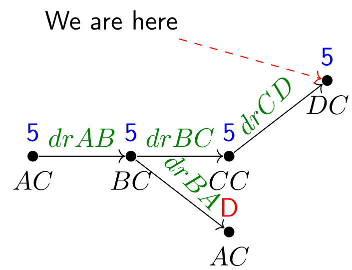


Relaxed problem:

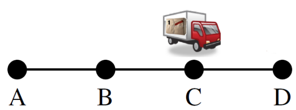


- ▷ State s: DC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}$.
- ▷ $h^+(s)$ $=5$: e.g. $\langle drDC, drCB, drBA, loC, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

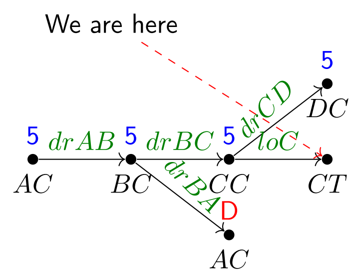


Real problem:

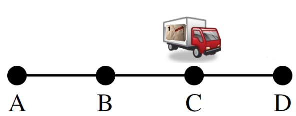


- ▷ State s: CT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ $CC \xrightarrow{loC} CT$.

Greedy best-first search: (tie-breaking: alphabetic)

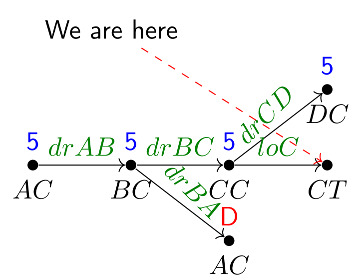


Relaxed problem:

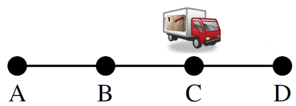


- ▷ State s: CT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}$.
- ▷ $h^+(s)$ =4: e.g. $\langle drCB, drBA, drCD, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

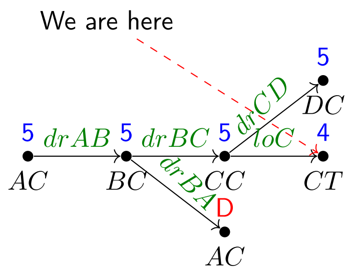


Relaxed problem:

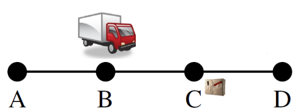


- ▷ State s: CT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}$.
- ▷ $h^+(s)$ =4: e.g. $\langle drCB, drBA, drCD, ulD \rangle$.

Greedy best-first search: (tie-breaking: alphabetic)

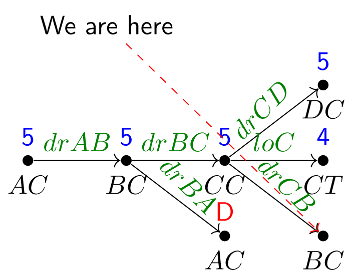


Real problem:

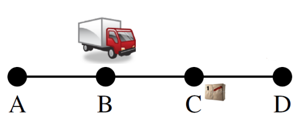


- ▷ State s: BC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ $CC \xrightarrow{drCB} BC$.

Greedy best-first search: (tie-breaking: alphabetic)

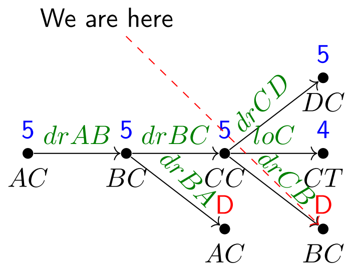


Real problem:

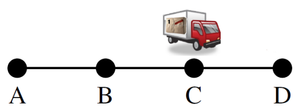


- ▷ State s: BC; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Duplicate state, prune.

Greedy best-first search: (tie-breaking: alphabetic)

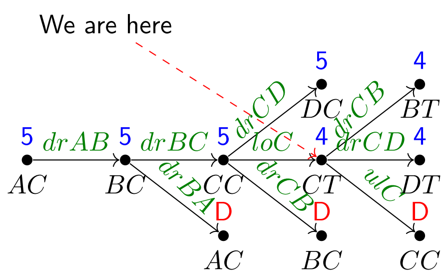


Real problem:

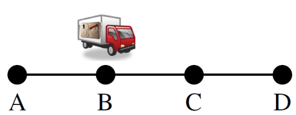


- ▷ State s: CT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: BT, DT, CC.

Greedy best-first search: (tie-breaking: alphabetic)

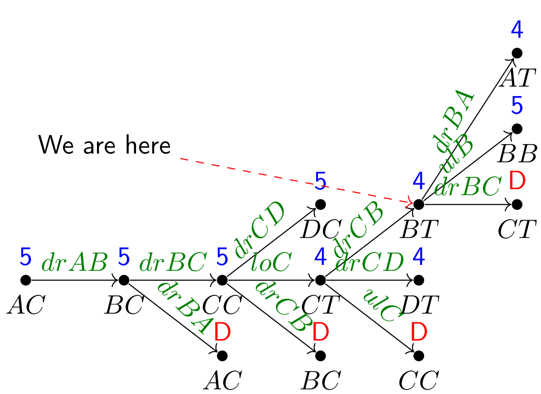


Real problem:

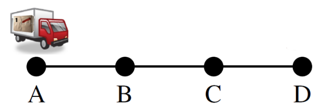


- ▷ State s: BT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: AT, BB, CT.

Greedy best-first search: (tie-breaking: alphabetic)

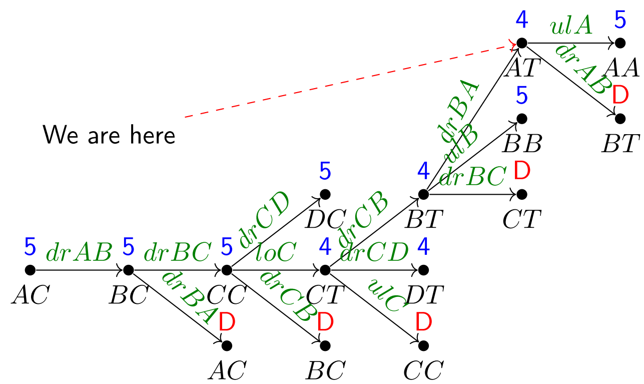


Real problem:

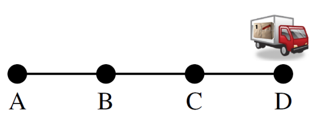


- ▷ State s: AT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: AA, BT.

Greedy best-first search: (tie-breaking: alphabetic)

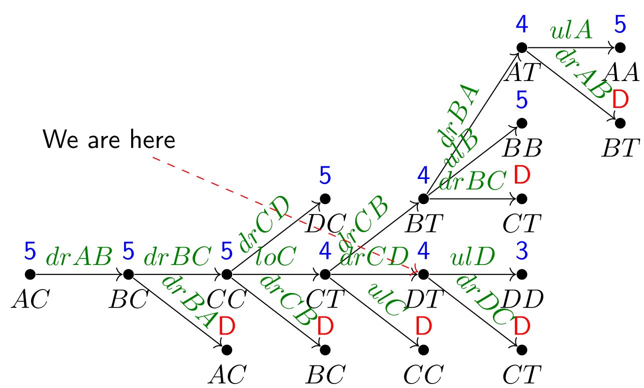


Real problem:

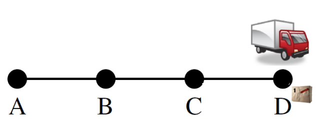


- ▷ State s: DT; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: DD, CT.

Greedy best-first search: (tie-breaking: alphabetic)

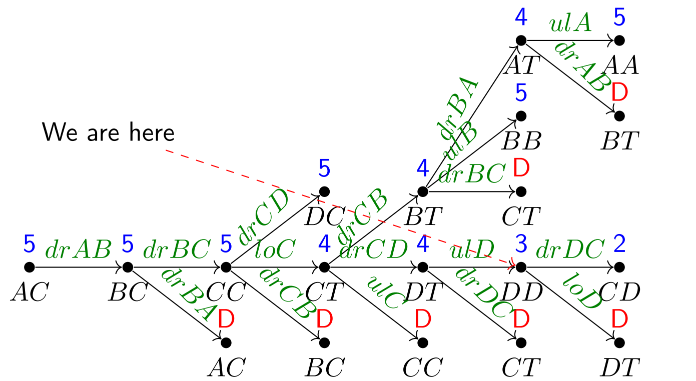


Real problem:

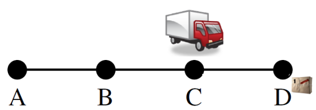


- ▷ State s: DD; goal G: AD.
- ▷ Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- ▷ Successors: CD, DT.

Greedy best-first search: (tie-breaking: alphabetic)

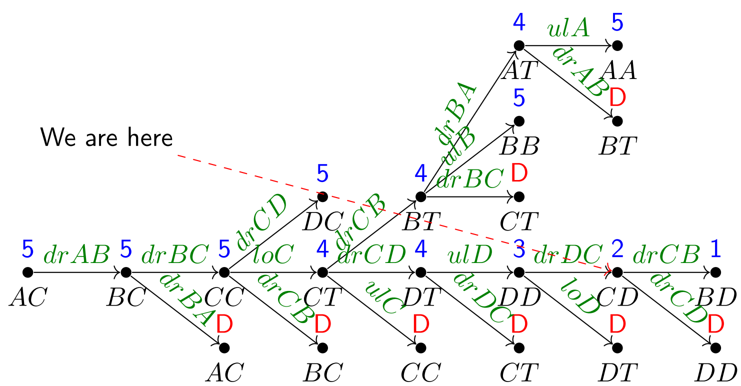


Real problem:

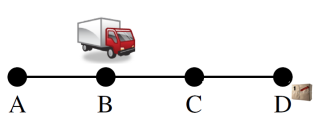


- ▷ State s: CD; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ Successors: BD, DD.

Greedy best-first search: (tie-breaking: alphabetic)

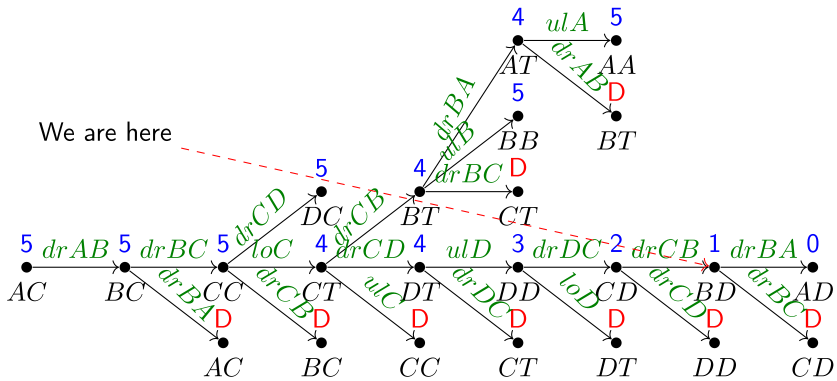


Real problem:

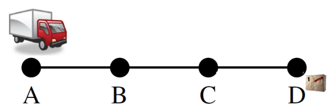


- ▷ State s: BD; goal G: AD.
- ▷ Actions A: pre, add, del.
- ▷ Successors: AD, CD.

Greedy best-first search: (tie-breaking: alphabetic)

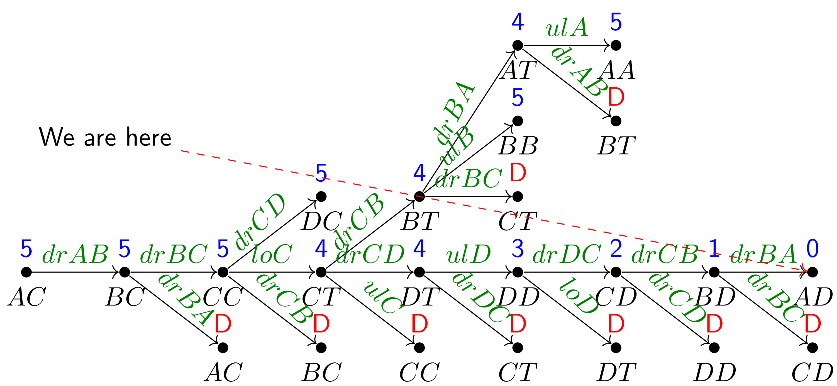


Real problem:



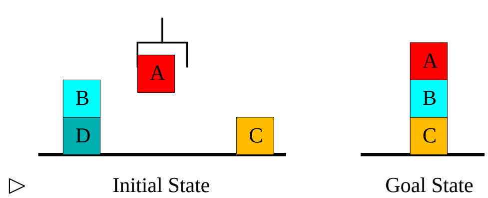
- State s: AD; goal G: AD.
- Actions A: $\mathrm{pre}, \mathrm{add}, \mathrm{del}$.
- Goal state!

Greedy best-first search: (tie-breaking: alphabetic)



Of course there are also bad cases. Here is one.

h^+ in the Blocksworld



- **Optimal plan**: $\langle \mathrm{putdown}(A), \mathrm{unstack}(B,D), \mathrm{stack}(B,C), \mathrm{pickup}(A), \mathrm{stack}(A,B) \rangle$.
- **Optimal relaxed plan**: $\langle \mathrm{stack}(A,B), \mathrm{unstack}(B,D), \mathrm{stack}(B,C) \rangle$.
- **Observation:** What can we say about the "search space surface" at the initial state here?

▷ The initial state lies on a local minimum under h^+, together with the successor state s where we stacked A onto B. All direct other neighbors of these two states have a strictly higher h^+ value.

18.5 Conclusion

A Video Nugget covering this section can be found at https://fau.tv/clip/id/26906.

Summary

▷ Heuristic search on classical search problems relies on a function h mapping states s to an estimate $h(s)$ of their goal state distance. Such functions h are derived by solving relaxed problems.

▷ In planning, the relaxed problems are generated and solved automatically. There are four known families of suitable relaxation methods: *abstractions*, *landmarks*, *critical paths*, and *ignoring deletes* (aka delete relaxation).

▷ The delete relaxation consists in dropping the deletes from STRIPS tasks. A relaxed plan is a plan for such a relaxed task. $h^+(s)$ is the length of an optimal relaxed plan for state s. h^+ is **NP**-hard to compute.

▷ h^{FF} approximates h^+ by computing some, not necessarily optimal, relaxed plan. That is done by a forward pass (building a *relaxed planning graph*), followed by a backward pass (*extracting a relaxed plan*).

Topics We Didn't Cover Here

▷ **Abstractions, Landmarks, Critical-Path Heuristics, Cost Partitions, Compilability between Heuristic Functions, Planning Competitions:**

▷ **Tractable fragments:** Planning sub-classes that can be solved in polynomial time. Often identified by properties of the "causal graph" and "domain transition graphs".

▷ **Planning as SAT:** Compile length-k bounded plan existence into satisfiability of a CNF formula φ. Extensive literature on how to obtain small φ, how to schedule different values of k, how to modify the underlying SAT solver.

▷ **Compilations:** Formal framework for determining whether planning formalism X is (or is not) at least as expressive as planning formalism Y.

▷ **Admissible pruning/decomposition methods:** Partial-order reduction, symmetry reduction, simulation-based dominance pruning, factored planning, decoupled search.

▷ **Hand-tailored planning:** Automatic planning is the extreme case where the computer is given no domain knowledge other than "physics". We can instead allow the user to provide search control knowledge, trading off modeling effort against search performance.

▷ **Numeric planning**, **temporal planning**, **planning under uncertainty** . . .

Suggested Reading (RN: Same As Previous Chapter):

- Chapters 10: *Classical Planning* and 11: *Planning and Acting in the Real World* in [RN09].
  - Although the book is named "*A Modern Approach*", the planning section was written long before the IPC was even dreamt of, before PDDL was conceived, and several years before heuristic search hit the scene. As such, what we have right now is the attempt of two outsiders trying in vain to catch up with the dramatic changes in planning since 1995.
  - Chapter 10 is Ok as a background read. Some issues are, imho, misrepresented, and it's far from being an up-to-date account. But it's Ok to get some additional intuitions in words different from my own.
  - Chapter 11 is useful in our context here because we don't cover any of it. If you're interested in extended/alternative planning paradigms, do read it.
- A good source for modern information (some of which we covered in the course) is Jörg Hoffmann's *Everything You Always Wanted to Know About Planning (But Were Afraid to Ask)* [Hof11] which is available online at `http://fai.cs.uni-saarland.de/hoffmann/papers/ki11.pdf`

Chapter 19

Searching, Planning, and Acting in the Real World

Outline

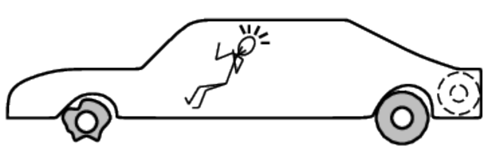
- ▷ **So Far:** we made idealizing/simplifying assumptions:
  The environment is fully observable and deterministic.
- ▷ **Outline:** In this chapter we will lift some of them
  - ▷ The real world (things go wrong)
  - ▷ Agents and Belief States
  - ▷ Conditional planning
  - ▷ Monitoring and replanning
- ▷ **Note:** The considerations in this chapter apply to both search and planning.

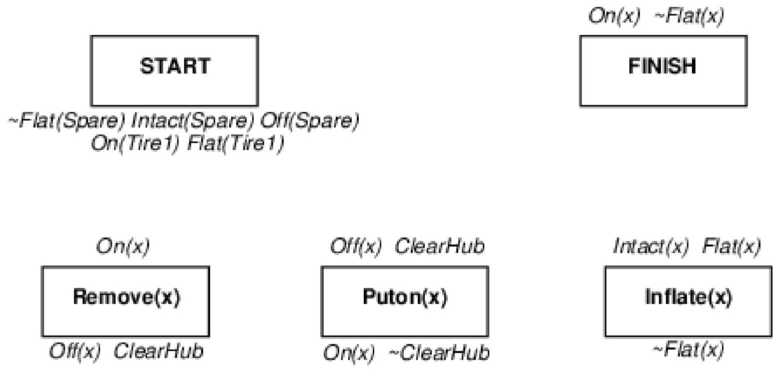
19.1 Introduction

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/26908`.

The real world

- ▷ **Example 19.1.1.** We have a flat tire – what to do?





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Generally: Things go wrong (in the real world)

▷ **Example 19.1.2 (Incomplete Information).**

- ▹ Unknown preconditions, e.g., $Intact(Spare)$?
- ▹ Disjunctive effects, e.g., $Inflate(x)$ causes $Inflated(x) \vee SlowHiss(x) \vee Burst(x) \vee BrokenPump \vee \ldots$

▷ **Example 19.1.3 (Incorrect Information).**

- ▹ Current state incorrect, e.g., spare NOT intact
- ▹ Missing/incorrect effects in actions.

▷ **Definition 19.1.4.** The qualification problem in planning is that we can never finish listing all the required preconditions and possible conditional effects of actions.

▷ **Root Cause:** The environment is partially observable and/or non-deterministic.

▷ **Technical Problem:** We cannot know the "current state of the world", but search/-planning algorithms are based on this assumption.

▷ **Idea:** Adapt search/planning algorithms to work with "sets of possible states".

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What can we do if things (can) go wrong?

▷ **One Solution:** Sensorless planning: plans that work regardless of state/outcome.

▷ **Problem:** Such plans may not exist! (but they often do in practice)

▷ **Another Solution:** Conditional plans:

- ▹ Plan to obtain information, (observation actions)
- ▹ Subplan for each contingency.

▷ **Example 19.1.5 (A conditional Plan).** (AAA $\widehat{=}$ ADAC)
$[Check(T1), \text{if } Intact(T1) \text{ then } Inflate(T1) \text{ else } CallAAA \text{ fi}]$

▷ **Problem:** Expensive because it plans for many unlikely cases.

▷ **Still another Solution:** Execution monitoring/replanning

- ▷ Assume normal states/outcomes, check progress *during execution*, replan if necessary.

▷ **Problem:** Unanticipated outcomes may lead to failure. (e.g., no AAA card)

▷ **Observation 19.1.6.** *We really need a combination; plan for likely/serious eventualities, deal with others when they arise, as they must eventually.*

19.2 The Furniture Coloring Example

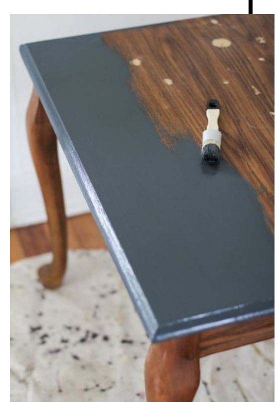
A Video Nugget covering this section can be found at `https://fau.tv/clip/id/29180`.
We now introduce a planning example that shows off the various features.

The Furniture-Coloring Example: Specification

▷ **Example 19.2.1 (Coloring Furniture).**

Paint a chair and a table in matching colors.

- ▷ The initial state is:
  - ▷ we have two cans of paint of unknown color,
  - ▷ the color of the furniture is unknown as well,
  - ▷ only the table is in the agent's field of view.
- ▷ Actions:
  - ▷ remove lid from can
  - ▷ paint object with paint from open can.



We formalize the example in PDDL for simplicity. Note that the :percept scheme is not part of the official PDDL, but fits in well with the design.

The Furniture-Coloring Example: PDDL

▷ **Example 19.2.2 (Formalization in PDDL).**

- ▷ The PDDL domain file is as expected (actions below)

```
(define (domain furniture−coloring)
  (:predicates (object ?x) (can ?x) (inview ?x) (color ?x ?y))
  ...)
```

- The PDDL problem file has a "free" variable ?c for the (undetermined) joint color.

```
(define (problem tc−coloring)
  (:domain furniture−objects)
  (:objects table chair c1 c2)
  (:init (object table) (object chair) (can c1) (can c2) (inview table))
  (:goal (color chair ?c) (color table ?c)))
```

- Two action schemata: *remove can lid to open* and *paint with open can*

```
(:action remove−lid
         :parameters (?x)
         :precondition (can ?x)
         :effect (open can))
(:action paint
         :parameters (?x ?y)
         :precondition (and (object ?x) (can ?y) (color ?y ?c) (open ?y))
         :effect (color ?x ?c))
```

has a universal variable ?c for the paint action ⇝ we cannot just give paint a color argument in a partially observable environment.

- **Sensorless Plan**: Open one can, paint chair and table in its color.
- **Note**: Contingent planning can create better plans, but needs perception
- Two percept schemata: *color of an object* and *color in a can*

```
(:percept color
          :parameters (?x ?c)
          :precondition (and (object ?x) (inview ?x)))
(:percept can−color
          :parameters (?x ?c)
          :precondition (and (can ?x) (inview ?x) (open ?x)))
```

To perceive the color of an object, it must be in view, a can must also be open. **Note**: In a fully observable world, the percepts would not have preconditions.

- An action schema: *look at an object* that causes it to come into view.

```
(:action lookat
         :parameters (?x)
         :precond: (and (inview ?y) and (notequal ?x ?y))
         :effect (and (inview ?x) (not (inview ?y))))
```

- **Contingent Plan**:
  1. look at furniture to determine color, if same ⇝ done.
  2. else, look at open and look at paint in cans
  3. if paint in one can is the same as an object, paint the other with this color
  4. else paint both in any color

19.3 Searching/Planning with Non-Deterministic Actions

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/29181`.

Conditional Plans

- **Definition 19.3.1.** Conditional plans extend the possible actions in plans by conditional steps that execute sub plans conditionally whether $K + P \models C$, where $K + P$ is the current knowledge base + the percepts.
- **Definition 19.3.2.** Conditional plans can contain
  - conditional step: $[\ldots, \mathrm{if}\ C\ \mathrm{then}\ Plan_A\ \mathrm{else}\ Plan_B\ \mathrm{fi}, \ldots]$,
  - while step: $[\ldots, \mathrm{while}\ C\ \mathrm{do}\ Plan\ \mathrm{done}, \ldots]$, and
  - the empty plan $\emptyset$ to make modeling easier.
- **Definition 19.3.3.** If the possible percepts are limited to determining the current state in a conditional plan, then we speak of a contingency plan.
- **Note:** Need *some plan* for *every possible percept*! Compare to

  game playing: *some response* for *every opponent* move.

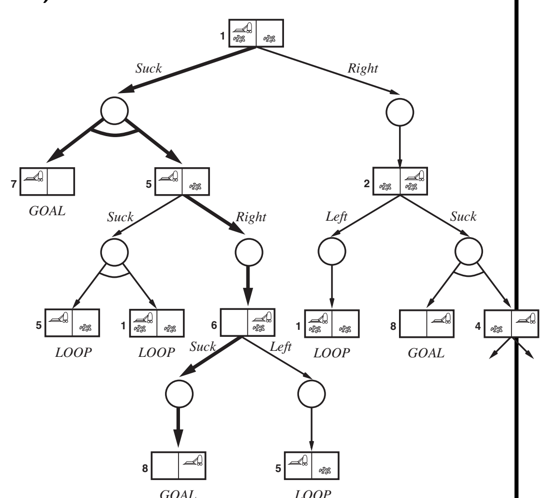
  backchaining: *some rule* such that *every premise* satisfied.
- **Idea:** Use an AND–OR tree search (very similar to backward chaining algorithm)

Contingency Planning: The Erratic Vacuum Cleaner

- **Example 19.3.4 (Erratic vacuum world).**

A variant *suck* action: if square is

- *dirty*: clean the square, sometimes remove dirt in adjacent square.
- *clean*: sometimes deposits dirt on the carpet.



Solution: $[suck, \mathrm{if}\ State = 5\ \mathrm{then}\ [right, suck]\ \mathrm{else}\ []\ \mathrm{fi}]$

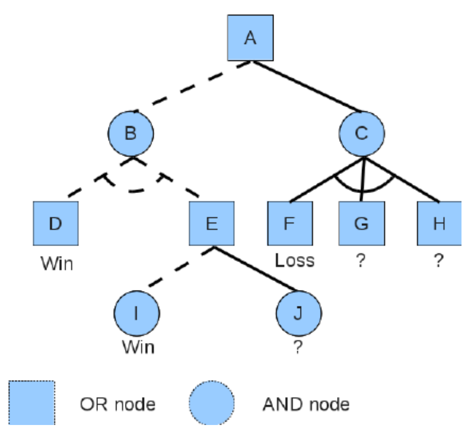
Conditional AND-OR Search (Data Structure)

- **Idea:** Use AND-OR trees as data structures for representing problems (or goals) that can be reduced to to conjunctions and disjunctions of subproblems (or subgoals).
- **Definition 19.3.5.** An AND-OR graph is a is a graph whose non-terminal nodes are partitioned into AND nodes and OR nodes. A valuation of an AND-OR graph T is an assignment of T or F to the nodes of T. A valuation of the terminal nodes of T can be extended by all nodes recursively: Assign T to an
  - OR node, iff at least one of its children is T.
  - AND node, iff all of its children are T.

  A solution for T is a valuation that assigns T to the initial nodes of T.
- **Idea:** A planning task with non deterministic actions generates a AND-OR graph T. A solution that assigns T to a terminal node, iff it is a goal node. Corresponds to a conditional plan.

Conditional AND-OR Search (Example)

- **Definition 19.3.6.** An AND-OR tree is a AND-OR graph that is also a tree.
  Notation: AND nodes are written with arcs connecting the child edges.
- **Example 19.3.7 (An AND-OR-tree).**



Conditional AND-OR Search (Algorithm)

- **Definition 19.3.8.** AND-OR search is an algorithm for searching AND–OR graphs generated by nondeterministic environments.

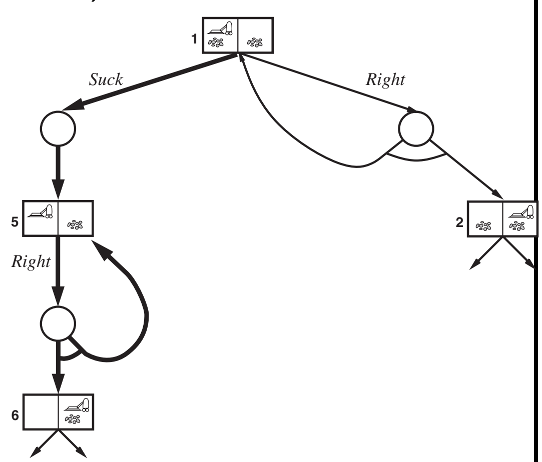
function AND/OR−GRAPH−SEARCH($prob$) **returns** a conditional plan, or **fail**
  OR−SEARCH($prob$.INITIAL−STATE, $prob$, [])
function OR−SEARCH($state$,$prob$,$path$) **returns** a conditional plan, or **fail**

  if $prob$.GOAL−TEST($state$) **then return** the empty plan
  if $state$ is on $path$ **then return fail**
  for each $action$ **in** $prob$.ACTIONS($state$) **do**
    $plan$:= AND−SEARCH(RESULTS($state$,$action$),$prob$,[$state$ | $path$])
    if $plan \neq$ **fail then return** [$action$ | $plan$]
  return fail
function AND−SEARCH($states$,$prob$,$path$) **returns** a conditional plan, or **fail**
  for each s_i **in** $states$ **do**
    p_i := OR−SEARCH(s_i,$prob$,$path$)
    if p_i = **fail then return fail**
    return [**if** s_1 **then** p_1 **else if** s_2 **then** p_2 **else** ... **if** s_{n-1} **then** p_{n-1} **else** p_n]

- ▷ **Cycle Handling:** If a state has been seen before $\leadsto$ **fail**
  - ▷ **fail** does not mean *there is no solution*, but
  - ▷ *if there is a non-cyclic solution, then it is reachable by an earlier incarnation*!

The Slippery Vacuum Cleaner (try, try, try, ...try again)

- ▷ **Example 19.3.9 (Slippery Vacuum World).**



Moving sometimes fails
$\leadsto$ AND-OR graph

Two possible solutions (depending on what our plan language allows)

- ▷ $[L_1: \; left, \text{if } AtR \text{ then } L_1 \text{ else } [\text{if } CleanL \text{ then } \emptyset \text{ else } suck \text{ fi}] \text{ fi}]$ or
- ▷ $[\text{while } AtR \text{ do } [left] \text{ done}, \text{if } CleanL \text{ then } \emptyset \text{ else } suck \text{ fi}]$

- ▷ We have an infinite loop but plan eventually works unless action always fails.

19.4 Agent Architectures based on Belief States

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/29182`.
We are now ready to proceed to environments which can only partially observed and where actions are non deterministic. Both sources of uncertainty conspire to allow us only partial knowledge about the world, so that we can only optimize "expected utility" instead of "actual utility" of our actions.

World Models for Uncertainty

- **Problem:** We do not know with certainty what state the world is in!
- **Idea:** Just keep track of all the possible states it could be in.
- **Definition 19.4.1.** A model-based agent has a world model consisting of
  - a belief state that has information about the possible states the world may be in, and
  - a sensor model that updates the belief state based on sensor information
  - a transition model that updates the belief state based on actions.
- **Idea:** The agent environment determines what the world model can be.
- In a fully observable, deterministic environment,
  - we can observe the initial state and subsequent states are given by the actions alone.
  - thus the belief state is a singleton (we call its member the world state) and the transition model is a function from states and actions to states: a transition function.

That is exactly what we have been doing until now: we have been studying methods that build on descriptions of the "actual" world, and have been concentrating on the progression from atomic to factored and ultimately structured representations. Tellingly, we spoke of "world states" instead of "belief states"; we have now justified this practice in the brave new belief-based world models by the (re-) definition of "world states" above. To fortify our intuitions, let us recap from a belief-state-model perspective.

World Models by Agent Type in AI-1

- **Search-based Agents:** In a fully observable, deterministic environment
  - goal-based agent with world state $\widehat{=}$ "current state"
  - no inference. (goal $\widehat{=}$ goal state from search problem)
- **CSP-based Agents:** In a fully observable, deterministic environment
  - goal-based agent withworld state $\widehat{=}$ constraint network,
  - inference $\widehat{=}$ constraint propagation. (goal $\widehat{=}$ satisfying assignment)
- **Logic-based Agents:** In a fully observable, deterministic environment
  - model-based agent with world state $\widehat{=}$ logical formula
  - inference $\widehat{=}$ e.g. DPLL or resolution.
- **Planning Agents:** In a fully observable, deterministic, environment
  - goal-based agent with world state $\widehat{=}$ PL0, transition model $\widehat{=}$ STRIPS,
  - inference $\widehat{=}$ state/plan space search. (goal: complete plan/execution)

Let us now see what happens when we lift the restrictions of total observability and determinism.

World Models for Complex Environments

- In a fully observable, but stochastic environment,
  - the belief state must deal with a set of possible states.
  - $\leadsto$ generalize the transition function to a transition relation.
- **Note:** This even applies to online problem solving, where we can just perceive the state. (e.g. when we want to optimize utility)
- In a deterministic, but partially observable environment,
  - the belief state must deal with a set of possible states.
  - we can use transition functions.
  - We need a sensor model, which predicts the influence of percepts on the belief state – during update.
- In a stochastic, partially observable environment,
  - mix the ideas from the last two. (sensor model + transition relation)

Preview: New World Models (Belief) $\leadsto$ new Agent Types

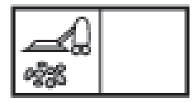
- **Probabilistic Agents:** In a partially observable environment
  - belief state $\widehat{=}$ Bayesian networks,
  - inference $\widehat{=}$ probabilistic inference.
- **Decision-Theoretic Agents:** In a partially observable, stochastic environment
  - belief state + transition model $\widehat{=}$ decision networks,
  - inference $\widehat{=}$ maximizing expected utility.
- We will study them in detail in the coming semester.

19.5 Searching/Planning without Observations

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/29183`.

Conformant/Sensorless Planning

- **Definition 19.5.1.** Conformant or sensorless planning tries to find plans that work without any sensing. (not even the initial state)



▷ **Example 19.5.2 (Sensorless Vacuum Cleaner World).**

States	integer dirt and robot locations
Actions	$left, right, suck, noOp$
Goal states	$notdirty?$

▷ **Observation 19.5.3.** *In a sensorless world we do not know the initial state. (or any state after)*

▷ **Observation 19.5.4.** *Sensorless planning must search in the space of belief states (sets of possible actual states).*

▷ **Example 19.5.5 (Searching the Belief State Space).**

- ▹ Start in $\{1, 2, 3, 4, 5, 6, 7, 8\}$
- ▹ Solution: $[right, suck, left, suck]$

$$\begin{array}{ll} right & \to \{2,4,6,8\} \\ suck & \to \{4,8\} \\ left & \to \{3,7\} \\ suck & \to \{7\} \end{array}$$

Search in the Belief State Space: Let's Do the Math

▷ **Recap:** We describe an search problem $\Pi := \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{I}, \mathcal{G} \rangle$ via its states $\mathcal{S}$, actions $\mathcal{A}$, and transition model $\mathcal{T} : \mathcal{A} \times \mathcal{S} \to \mathcal{P}(\mathcal{A})$, goal states $\mathcal{G}$, and initial state $\mathcal{I}$.

▷ **Problem:** What is the corresponding sensorless problem?

▷ **Let' think:** Let $\Pi := \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{I}, \mathcal{G} \rangle$ be a (physical) problem

- ▹ States $\mathcal{S}^b$: The belief states are the $2^{|\mathcal{S}|}$ subsets of $\mathcal{S}$.
- ▹ The initial state $\mathcal{I}^b$ is just $\mathcal{S}$ (no information)
- ▹ Goal states $\mathcal{G}^b := \{S \in \mathcal{S}^b \mid S \subseteq \mathcal{G}\}$ (all possible states must be physical goal states)
- ▹ Actions $\mathcal{A}^b$: we just take $\mathcal{A}$. (that's the point!)
- ▹ Transition model $\mathcal{T}^b : \mathcal{A}^b \times \mathcal{S}^b \to \mathcal{P}(\mathcal{A}^b)$: i.e. what is $\mathcal{T}^b(a, S)$ for $a \in \mathcal{A}$ and $S \subseteq \mathcal{S}$? This is slightly tricky as a need not be applicable to all $s \in S$.
  1. if actions are harmless to the environment, take $\mathcal{T}^b(a, S) := \bigcup_{s \in S} \mathcal{T}(a, s)$.
  2. if not, better take $\mathcal{T}^b(a, S) := \bigcap_{s \in S} \mathcal{T}(a, s)$. (the safe bet)

▷ **Observation 19.5.6.** *In belief-state space the problem is always fully observable!*

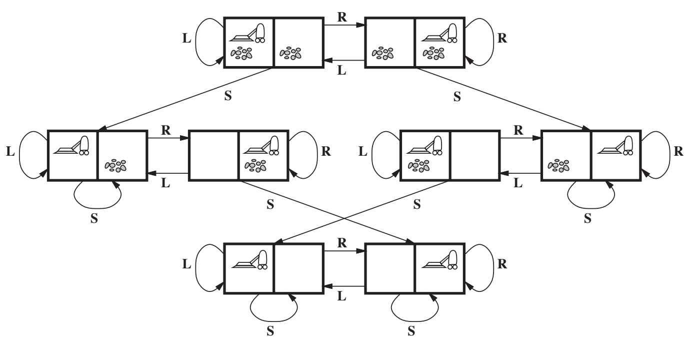
Let us see if we can understand the options for $\mathcal{T}^b(a, S)$ a bit better. The first question is when we want an action a to be applicable to a belief state $S \subseteq \mathcal{S}$, i.e. when should $\mathcal{T}^b(a, S)$ be non-empty.

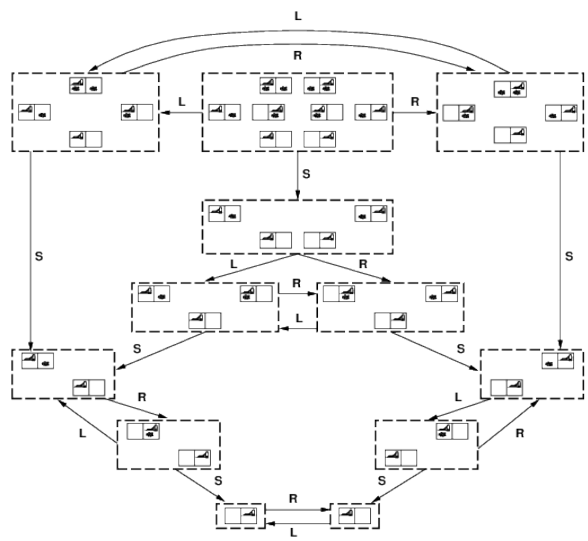
In the first case, a^b would be applicable iff a is applicable to some $s \in S$, in the second case if a is applicable to all $s \in S$. So we only want to choose the first case if actions are harmless.

The second question we ask ourselves is what should be the results of applying a to $S \subseteq \mathcal{S}$?, again, if actions are harmless, we can just collect the results, otherwise, we need to make sure that all members of the result a^b are reached for all possible states in S.

State Space vs. Belief State Space

▷ **Example 19.5.7 (State/Belief State Space in the Vacuum World).** In the vacuum world all actions are always applicable (1./2. equal)





Evaluating Conformant Planning

▷ **Upshot:** We can build belief-space problem formulations automatically,

- ▷ but they are exponentially bigger in theory, in practice they are often similar;
- ▷ e.g. 12 reachable belief states out of $2^8 = 256$ for vacuum example.

▷ **Problem:** Belief states are HUGE; e.g. initial belief state for the 10×10 vacuum world contains $100 \cdot 2^{100} \approx 10^{32}$ physical states

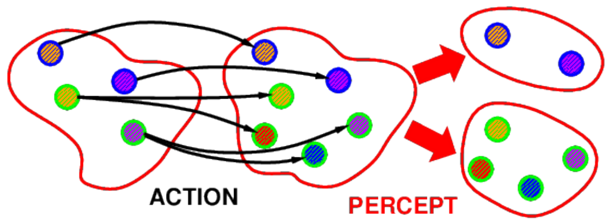
- **Idea:** Use planning techniques: compact descriptions for
  - belief states; e.g. *all* for initial state or *not leftmost column* after $left$.
  - actions as belief state to belief state operations.
- **This actually works:** Therefore we talk about conformant planning!

19.6 Searching/Planning with Observation

A Video Nugget covering this section can be found at https://fau.tv/clip/id/29184.

Conditional planning (Motivation)

- **Note:** So far, we have never used the agent's sensors.
  - In ??, since the environment was observable and deterministic we could just use offline planning.
  - In ?? because we chose to.
- **Note:** If the world is nondeterministic or partially observable then percepts usually provide information, i.e., split up the belief state



- **Idea:** This can systematically be used in search/planning via belief-state search, but we need to rethink/specialize the Transition model.

A Transition Model for Belief-State Search

- We extend the ideas from slide 657 to include partial observability.
- **Definition 19.6.1.** Given a (physical) search problem $\Pi := \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{I}, \mathcal{G} \rangle$, we define the belief state search problem induced by Π to be $\langle \mathcal{P}(\mathcal{S}), \mathcal{A}, \mathcal{T}^b, \mathcal{S}, \{S \in \mathcal{S}^b \mid S \subseteq \mathcal{G}\} \rangle$, where the transition model $\mathcal{T}^b$ is constructed in three stages:
  - The prediction stage: given a belief state b and an action a we define $\widehat{b} := \mathrm{PRED}(b, a)$ for some function $\mathrm{PRED}\colon \mathcal{P}(\mathcal{S}) \times \mathcal{A} \to \mathcal{P}(\mathcal{S})$.
  - The observation prediction stage determines the set of possible percepts that could be observed in the predicted belief state: $\mathrm{PossPERC}(\widehat{b}) = \{\mathrm{PERC}(s) \mid s \in$

$\widehat{b}\}$.

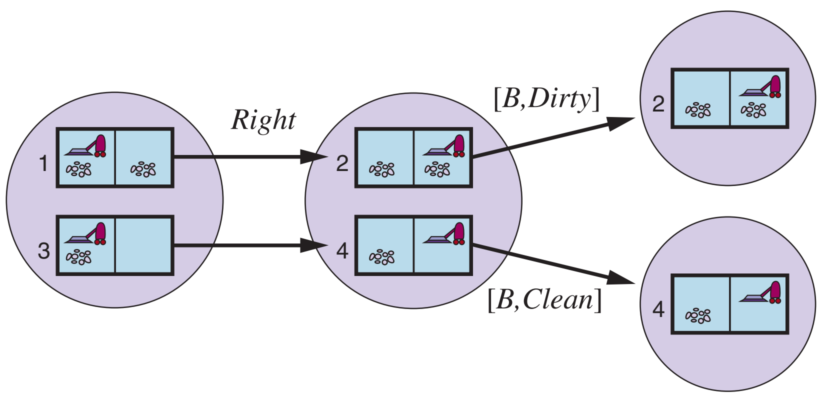
- ▷ The update stage determines, for each possible percept, the resulting belief state: $\mathrm{UPDATE}(\widehat{b}, o) := \{s \mid o = \mathrm{PERC}(s) \text{ and } s \in \widehat{b}\}$

The functions PRED and PERC are the main parameters of this model. We define $\mathrm{RESULT}(b, a) := \{\mathrm{UPDATE}(\mathrm{PRED}(b, a), o) \mid \mathrm{PossPERC}(\mathrm{PRED}(b, a))\}$

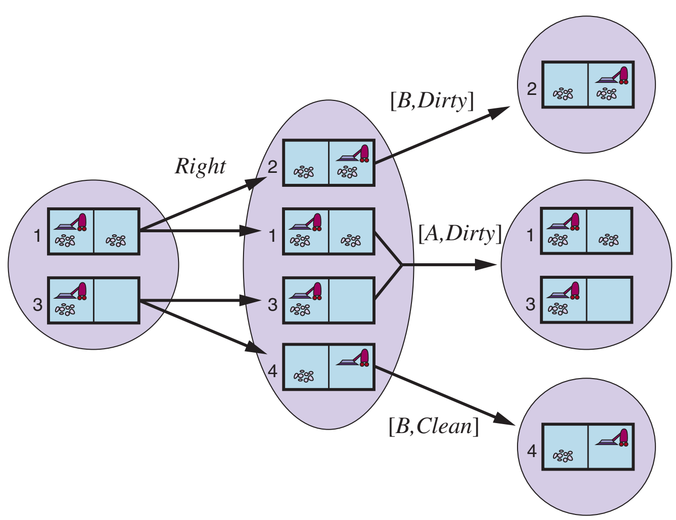
- ▷ **Observation 19.6.2.** *We always have* $\mathrm{UPDATE}(\widehat{b}, o) \subseteq \widehat{b}$.
- ▷ **Observation 19.6.3.** *If sensing is deterministic, belief states for different possible percepts are disjoint, forming a partition of the original predicted belief state.*

Example: Local Sensing Vacuum Worlds

- ▷ **Example 19.6.4 (Transitions in the Vacuum World).** Deterministic World:



The action $Right$ is deterministic, sensing disambiguates to singletons Slippery World:



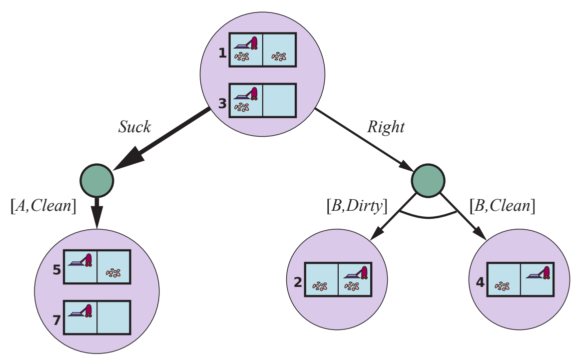
The action $Right$ is non-deterministic, sensing disambiguates somewhat

Belief-State Search with Percepts

▷ **Observation:** The belief-state transition model induces an AND-OR graph.

▷ **Idea:** Use AND-OR search in non deterministic environments.

▷ **Example 19.6.5.** AND-OR graph for initial percept $[A, Dirty]$.



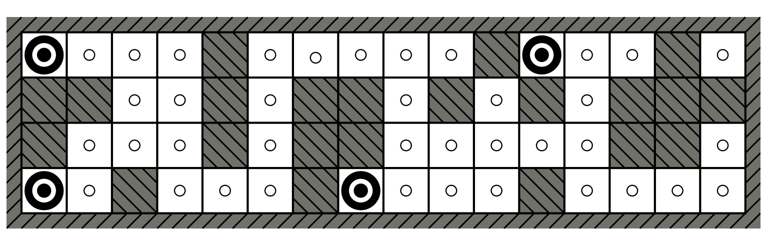
Solution: $[Suck, Right, \text{if } Bstate = \{6\} \text{ then } Suck \text{ else } [] \text{ fi}]$

▷ **Note:** Belief-state-problem ⇝ conditional step tests on belief-state percept (plan would not be executable in a partially observable environment otherwise)

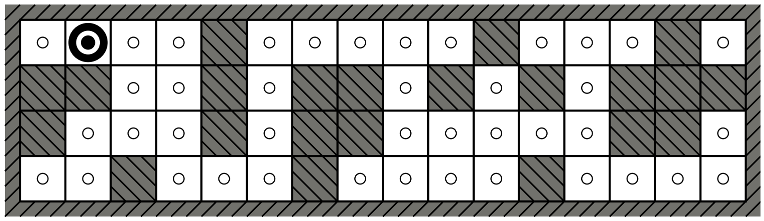
Example: Agent Localization

▷ **Example 19.6.6.** An agent inhabits a maze of which it has an accurate map. It has four sensors that can (reliably) detect walls. The $Move$ action is non-deterministic, moving the agent randomly into one of the adjacent squares.

1. Initial belief state ⇝ $\widehat{b}_1$ all possible locations.
2. Initial percept: NWS (walls north, west, and south) ⇝ $\widehat{b}_2 = \text{UPDATE}(\widehat{b}_1, NWS)$



3. Agent executes $Move$ ⇝ $\widehat{b}_3 = \text{PRED}(\widehat{b}_2, Move) =$ *one step away from these*.
4. Next percept: NS ⇝ $\widehat{b}_4 = \text{UPDATE}(\widehat{b}_3, NS)$



All in all, $\widehat{b}_4 = \mathrm{UPDATE}(\mathrm{PRED}(\mathrm{UPDATE}(\widehat{b}_1, NWS), Move), NS)$ localizes the agent.

▷ **Observation:** PRED enlarges the belief state, while UPDATE shrinks it again.

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Contingent Planning

▷ **Definition 19.6.7.** The generation of plan with conditional branching based on percepts is called contingent planning, solutions are called contingent plans.

▷ Appropriate for partially observable or non-deterministic environments.

▷ **Example 19.6.8.** Continuing ??.
One of the possible contingent plan is

```
((lookat table) (lookat chair)
  (if (and (color table c) (color chair c)) (noop)
    ((removelid c1) (lookat c1) (removelid c2) (lookat c2)
     (if (and (color table c) (color can c)) ((paint chair can))
       (if (and (color chair c) (color can c)) ((paint table can))
         ((paint chair c1) (paint table c1)))))))
```

▷ **Note:** Variables in this plan are existential; e.g. in

- ▷ line 2: If there is come joint color c of the table and chair $\rightsquigarrow$ done.
- ▷ line 4/5: Condition can be satisfied by $[c_1/can]$ or $[c_2/can]$ $\rightsquigarrow$ instantiate accordingly.

▷ **Definition 19.6.9.** During plan execution the agent maintains the belief state b, chooses the branch depending on whether $b \models c$ for the condition c.

▷ **Note:** The planner must make sure $b \models c$ can always be decided.

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Contingent Planning: Calculating the Belief State

▷ **Problem:** How do we compute the belief state?

▷ **Recall:** Given a belief state b, the new belief state $\widehat{b}$ is computed based on prediction with the action a and the refinement with the percept p.

▷ **Here:**

Given an action a and percepts $p = p_1 \wedge \ldots \wedge p_n$, we have

- $\widehat{b} = b \backslash \mathrm{del}_a \cup \mathrm{add}_a$ (as for the sensorless agent)
- If $n = 1$ and (:percept p_1 :precondition c) is the only percept axiom, also add p and c to $\widehat{b}$. (add c as otherwise p impossible)
- If $n > 1$ and (:percept p_i :precondition c_i) are the percept axioms, also add p and $c_1 \vee \ldots \vee c_n$ to $\widehat{b}$. (belief state no longer conjunction of literals ☹)

▷ **Idea:** Given such a mechanism for generating (exact or approximate) updated belief states, we can generate contingent plans with an extension of AND-OR search over belief states.

▷ **Extension:** This also works for non-deterministic actions: we extend the representation of effects to disjunctions.

AI-1 Survey on ALeA

▷ Online survey evaluating ALeA until 28.02.25 24:00 (Feb last)

▷ Works on all common devices (mobile phone, notebook, etc.)

▷ Is in English; takes about 10 - 20 min
depending on proficiency in english and using ALeA

▷ Questions about how ALeA is used, what it is like usig ALeA, and questions about demography

▷ Token is generated at the end of the survey (SAVE THIS CODE!)

- Completed survey count as a successfull prepquiz in AI1!
- Look for Quiz 15 in the usual place (single question)
- just submit the token to get full points
- The token can also be used to exercise the rights of the GDPR.

▷ Survey has no timelimit and is free, anonymous, can be paused and continued later on and can be cancelled.

Find the Survey Here

https:
//ddi-survey.cs.fau.de/limesurvey/index.php/667123?lang=en

This URL will also be posted on the forum tonight.

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19.7 Online Search

A Video Nugget covering this section can be found at https://fau.tv/clip/id/29185.

Online Search and Replanning

- ▷ **Note:** So far we have concentrated on offline problem solving, where the agent only acts (plan execution) after search/planning terminates.
- ▷ **Recall:** In online problem solving an agent interleaves computation and action: it computes one action at a time based on incoming perceptions.
- ▷ Online problem solving is helpful in
  - ▷ dynamic or semidynamic environments. (long computation times can be harmful)
  - ▷ stochastic environments. (solve contingencies only when they arise)
- ▷ Online problem solving is necessary in unknown environments $\rightsquigarrow$ exploration problem.

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Online Search Problems

- ▷ **Observation:** Online problem solving even makes sense in deterministic, fully observable environments.
- ▷ **Definition 19.7.1.** A online search problem consists of a set S of states, and

- ▷ a function $\mathrm{Actions}(s)$ that returns a list of actions allowed in state s.
- ▷ the step cost function c, where $c(s,a,s')$ is the cost of executing action a in state s with outcome s'. (cost unknown before executing a)
- ▷ a goal test $\mathrm{Goal\ Test}$.

▷ **Note:** We can only determine $\mathrm{RESULT}(s,a)$ by being in s and executing a.

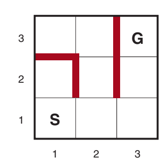
▷ **Definition 19.7.2.** The competitive ratio of an online problem solving agent is the quotient of

- ▷ offline performance, i.e. cost of optimal solutions with full information and
- ▷ online performance, i.e. the actual cost induced by online problem solving.

Online Search Problems (Example)

▷ **Example 19.7.3 (A simple maze problem).**
The agent starts at S and must reach G but knows nothing of the environment. In particular not that

- ▷ $\mathrm{Up}(1,1)$ results in $(1,2)$ and
- ▷ $\mathrm{Down}(1,1)$ results in $(1,1)$ (i.e. back)



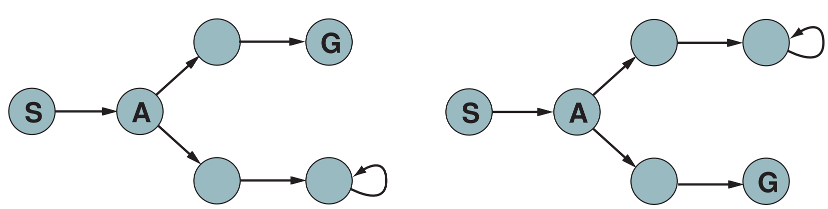
Online Search Obstacles (Dead Ends)

▷ **Definition 19.7.4.** We call a state a dead end, iff no state is reachable from it by an action. An action that leads to a dead end is called irreversible.

▷ **Note:** With irreversible actions the competitive ratio can be infinite.

▷ **Observation 19.7.5.** *No online algorithm can avoid dead ends in all state spaces.*

▷ **Example 19.7.6.** Two state spaces that lead an online agent into dead ends:

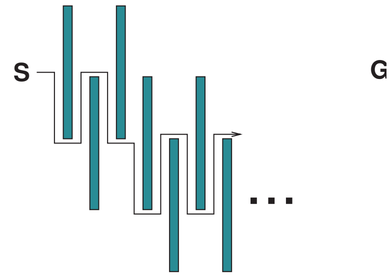


Any agent will fail in at least one of the spaces.

▷ **Definition 19.7.7.** We call ?? an adversary argument.

▷ **Example 19.7.8.** Forcing an online agent into an arbitrarily inefficient route:

Whichever choice the agent makes the adversary can block with a long, thin wall



- **Observation:** Dead ends are a real problem for robots: ramps, stairs, cliffs, ...
- **Definition 19.7.9.** A state space is called safely explorable, iff a goal state is reachable from every reachable state.
- We will always assume this in the following.

Online Search Agents

- **Observation:** Online and offline search algorithms differ considerably:
  - For an offline agent, the environment is visible a priori.
  - An online agent builds a "map" of the environment from percepts in visited states.

  Therefore, e.g. A^* can expand any node in the fringe, but an online agent must go there to explore it.
- **Intuition:** It seems best to expand nodes in "local order" to avoid spurious travel.
- **Idea:** Depth first search seems a good fit. (must only travel for backtracking)

Online DFS Search Agent

- **Definition 19.7.10.** The online depth first search algorithm:

function ONLINE−DFS−AGENT(s') **returns** an action
  inputs: s', a percept that identifies the current state
  persistent: $result$, a table mapping (s,a) **to** s', initially empty
    $untried$, a table mapping s **to** a list of untried actions
    $unbacktracked$, a table mapping s **to** a list backtracks not tried
    s, a, the previous state and action, initially null
  if $\mathrm{Goal\ Test}(s')$ **then return** stop
  if $s' \notin untried$ **then** $untried[s'] := \mathrm{Actions}(s')$
  if s is not null **then**
    $result[s,a] := s'$
    add s **to** the front of $unbacktracked[s']$
  if $untried[s']$ is empty **then**

if $unbacktracked[s']$ is empty **then return** stop
else $a :=$ an action b such that $result[s', b] = pop(unbacktracked[s'])$
else $a := pop(untried[s'])$
$s := s'$
return a

▷ **Note:** $result$ is the "environment map" constructed as the agent explores.

19.8 Replanning and Execution Monitoring

A Video Nugget covering this section can be found at `https://fau.tv/clip/id/29186`.

Replanning (Ideas)

▷ **Idea:** We can turn a planner P into an online problem solver by adding an action $\mathrm{RePlan}(g)$ without preconditions that re-starts P in the current state with goal g.

▷ **Observation:** Replanning induces a tradeoff between pre-planning and re-planning.

▷ **Example 19.8.1.** The plan $[\mathrm{RePlan}(g)]$ is a (trivially) complete plan for any goal g. (not helpful)

▷ **Example 19.8.2.** A plan with sub-plans for every contingency (e.g. what to do if a meteor strikes) may be too costly/large. (wasted effort)

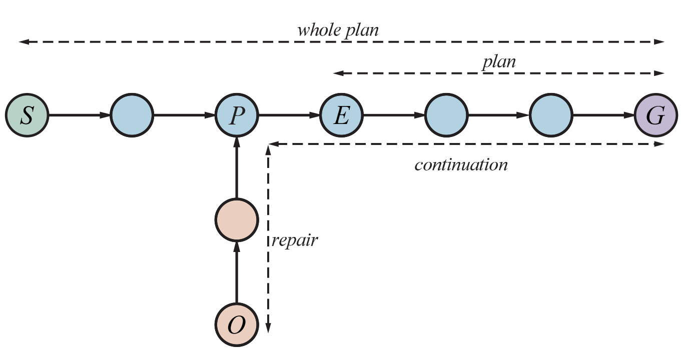
▷ **Example 19.8.3.** But when a tire blows while driving into the desert, we want to have water pre-planned. (due diligence against catastrophies)

▷ **Observation:** In stochastic or partially observable environments we also need some form of execution monitoring to determine the need for replanning (plan repair).

Replanning for Plan Repair

▷ **Generally:** Replanning when the agent's model of the world is incorrect.

▷ **Example 19.8.4 (Plan Repair by Replanning).** Given a plan from S to G.



- ▷ The agent executes $wholeplan$ step by step, monitoring the rest ($plan$).
- ▷ After a few steps the agent expects to be in E, but observes state O.
- ▷ Replanning: by calling the planner recursively
  - ▷ find state P in $wholeplan$ and a plan $repair$ from O to P. (P may be G)
  - ▷ minimize the cost of $repair + continuation$

Factors in World Model Failure ⇝ Monitoring

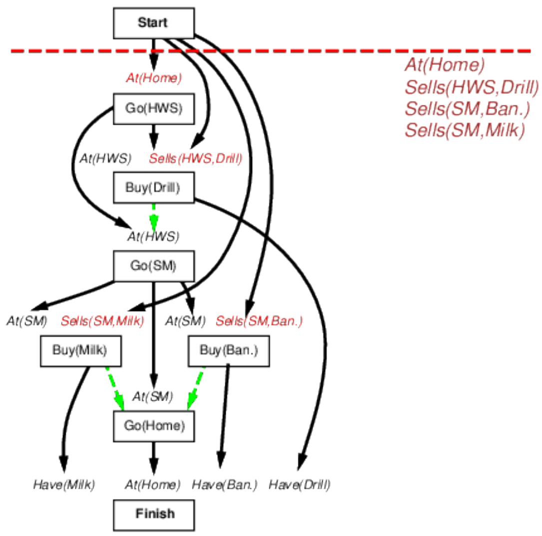
- ▷ **Generally:** The agent's world model can be incorrect, because
  - ▷ an action has a missing precondition (need a screwdriver for remove—lid)
  - ▷ an action misses an effect (painting a table gets paint on the floor)
  - ▷ it is missing a state variable (amount of paint in a can: no paint ⇝ no color)
  - ▷ no provisions for exogenous events (someone knocks over a paint can)
- ▷ **Observation:** Without a way for monitoring for these, planning is very brittle.
- ▷ **Definition 19.8.5.** There are three levels of execution monitoring: before executing an action
  - ▷ action monitoring checks whether all preconditions still hold.
  - ▷ plan monitoring checks that the remaining plan will still succeed.
  - ▷ goal monitoring checks whether there is a better set of goals it could try to achieve.
- ▷ **Note:** ?? was a case of action monitoring leading to replanning.

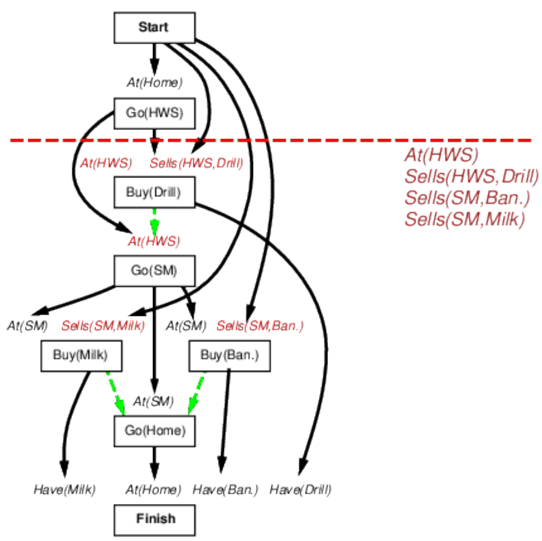
Integrated Execution Monitoring and Planning

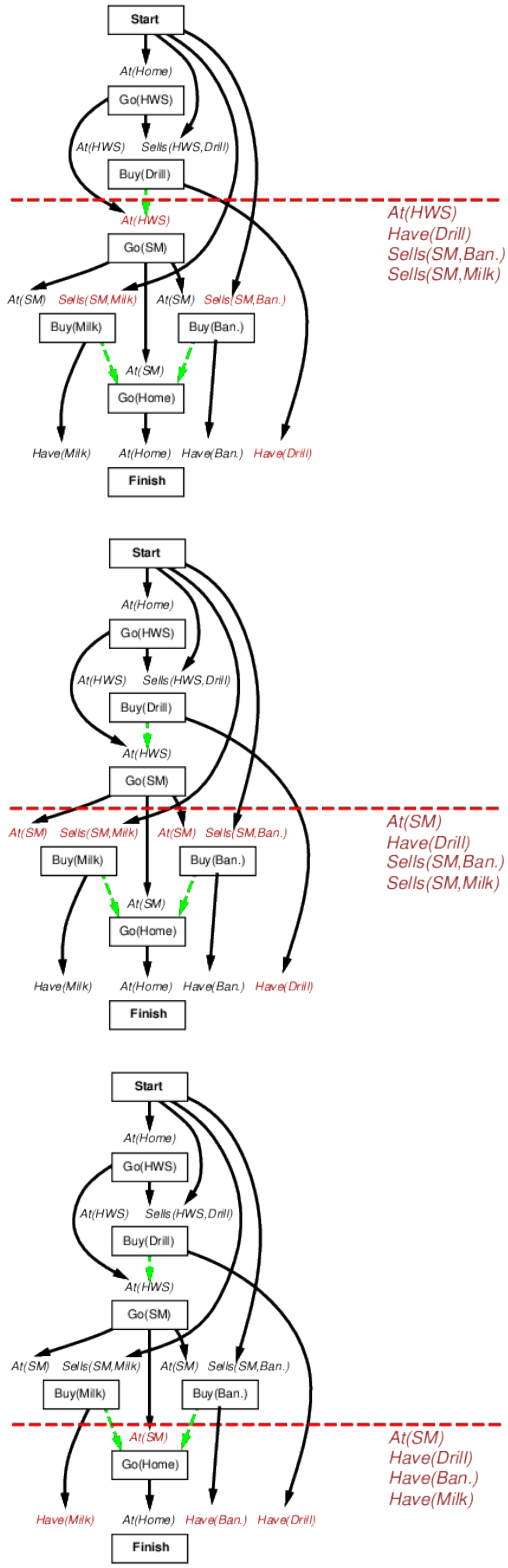
- ▷ **Problem:** Need to upgrade planing data structures by bookkeeping for execution monitoring.
- ▷ **Observation:** With their causal links, partially ordered plans already have most of the infrastructure for action monitoring:
  Preconditions of remaining plan
  $\hat{=}$ all preconditions of remaining steps not achieved by remaining steps
  $\hat{=}$ all causal link "crossing current time point"
- ▷ **Idea:** On failure, resume planning (e.g. by POP) to achieve open conditions from current state.
- ▷ **Definition 19.8.6.** IPEM (Integrated Planning, Execution, and Monitoring):
  - ▷ keep updating $Start$ to match current state
  - ▷ links from actions replaced by links from $Start$ when done

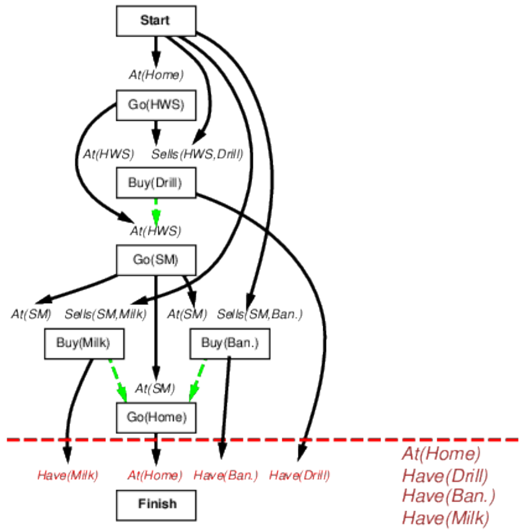
Execution Monitoring Example

▷ **Example 19.8.7 (Shopping for a drill, milk, and bananas).** Start/end at home, drill sold by hardware store, milk/bananas by supermarket.






Start
At(Home)
Go(HWS)
At(HWS)
Sells(HWS,Drill)
Buy(Drill)
At(HWS)
Go(SM)
At(SM)
Sells(SM,Milk)
At(SM)
Sells(SM,Ban.)
Buy(Milk)
Buy(Ban.)
At(SM)
Go(Home)
Have(Milk)
At(Home)
Have(Ban.)
Have(Drill)
Finish
At(HWS)
Have(Drill)
Sells(SM,Ban.)
Sells(SM,Milk)
At(SM)
Have(Drill)
Sells(SM,Ban.)
Sells(SM,Milk)
At(SM)
Have(Drill)
Have(Ban.)
Have(Milk)


Start
At(Home)
Go(HWS)
At(HWS)
Sells(HWS,Drill)
Buy(Drill)
At(HWS)
Go(SM)
At(SM)
Sells(SM,Milk)
At(SM)
Sells(SM,Ban.)
Buy(Milk)
Buy(Ban.)
At(SM)
Go(Home)
Have(Milk)
At(Home)
Have(Ban.)
Have(Drill)
Finish
At(Home)
Have(Drill)
Have(Ban.)
Have(Milk)

Chapter 20

What did we learn in AI 1?

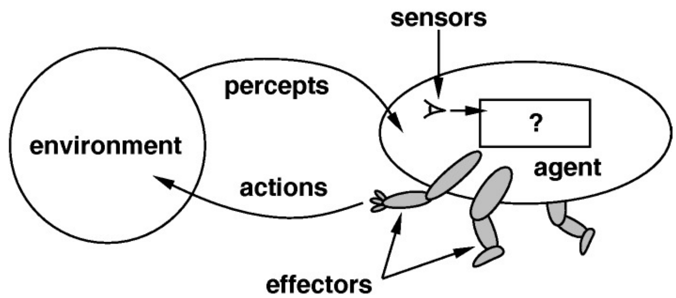
A Video Nugget covering this chapter can be found at `https://fau.tv/clip/id/26916`.

Topics of AI-1 (Winter Semester)

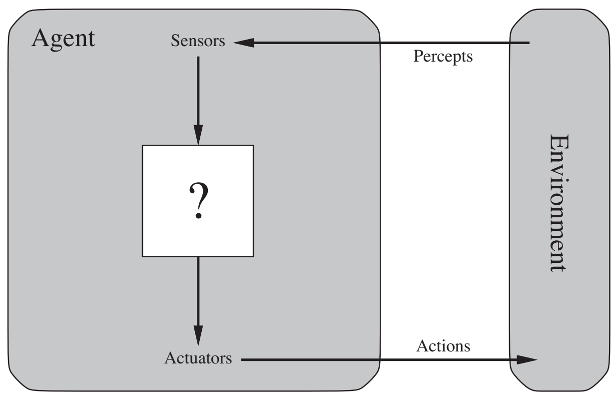
- Getting Started
  - What is Artificial Intelligence? (situating ourselves)
  - Logic programming in Prolog (An influential paradigm)
  - Intelligent Agents (a unifying framework)
- Problem Solving
  - Problem Solving and search (Black Box World States and Actions)
  - Adversarial search (Game playing) (A nice application of search)
  - constraint satisfaction problems (Factored World States)
- Knowledge and Reasoning
  - Formal Logic as the mathematics of Meaning
  - Propositional logic and satisfiability (Atomic Propositions)
  - First-order logic and theorem proving (Quantification)
  - Logic programming (Logic + Search$\rightsquigarrow$ Programming)
  - Description logics and semantic web
- Planning
  - Planning Frameworks
  - Planning Algorithms
  - Planning and Acting in the real world

Rational Agents as an Evaluation Framework for AI

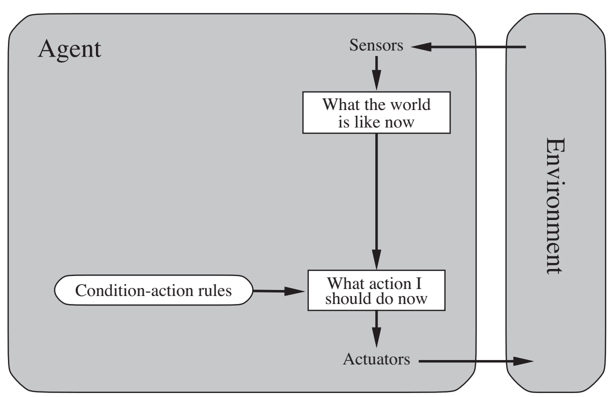
- Agents interact with the environment



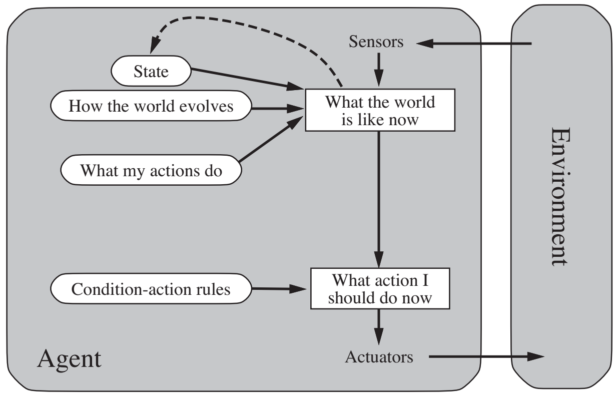
General agent schema



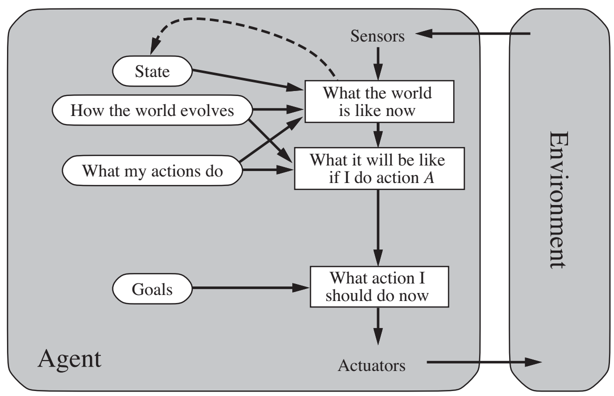
Simple Reflex Agents



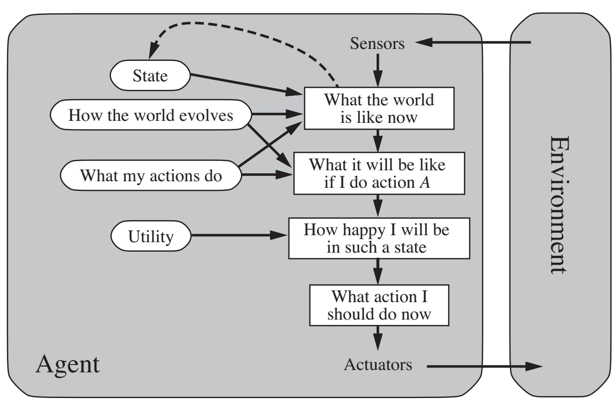
Reflex Agents with State



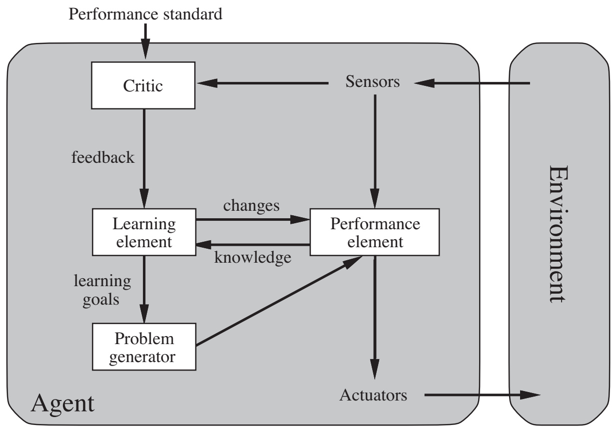
Goal-Based Agents



Utility-Based Agent



Learning Agents



Rational Agent

- **Idea:** Try to design agents that are successful (do the right thing)
- **Definition 20.0.1.** An agent is called rational, if it chooses whichever action maximizes the expected value of the performance measure given the percept sequence to date. This is called the MEU principle.
- **Note:** A rational agent need not be perfect
  - only needs to maximize expected value (rational $\neq$ omniscient)
    - need not predict e.g. very unlikely but catastrophic events in the future
  - percepts may not supply all relevant information (Rational $\neq$ clairvoyant)
    - if we cannot perceive things we do not need to react to them.
    - but we may need to try to find out about hidden dangers (exploration)
  - action outcomes may not be as expected (rational $\neq$ successful)
    - but we may need to take action to ensure that they do (more often) (learning)
- Rational $\leadsto$ exploration, learning, autonomy

Symbolic AI: Adding Knowledge to Algorithms

- Problem Solving (Black Box States, Transitions, Heuristics)
  - **Framework**: Problem Solving and Search (basic tree/graph walking)
  - **Variant**: Game playing (Adversarial search) (minimax + $\alpha\beta$-Pruning)
- Constraint Satisfaction Problems (heuristic search over partial assignments)
  - States as partial variable assignments, transitions as assignment

- ▷ Heuristics informed by current restrictions, constraint graph
- ▷ Inference as constraint propagation (transferring possible values across arcs)

▷ Describing world states by formal language (and drawing inferences)

- ▷ Propositional logic and DPLL (deciding entailment efficiently)
- ▷ First-order logic and ATP (reasoning about infinite domains)
- ▷ **Digression**: Logic programming (logic + search)
- ▷ Description logics as moderately expressive, but decidable logics

▷ Planning: Problem Solving using white-box world/action descriptions

- ▷ **Framework**: describing world states in logic as sets of propositions and actions by preconditions and add/delete lists
- ▷ **Algorithms**: e.g heuristic search by problem relaxations

Topics of AI-2 (Summer Semester)

▷ Uncertain Knowledge and Reasoning

- ▷ Uncertainty
- ▷ Probabilistic reasoning
- ▷ Making Decisions in Episodic Environments
- ▷ Problem Solving in Sequential Environments

▷ Foundations of machine learning

- ▷ Learning from Observations
- ▷ Knowledge in Learning
- ▷ Statistical Learning Methods

▷ Communication (If there is time)

- ▷ Natural Language Processing
- ▷ Natural Language for Communication

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