Lecture 10: Planning and Acting in the Real World

CS 580 (001) - Spring 2018

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1. Outline of Today's Class

2. Classical Planning
   - Search vs. Planning
   - STRIPS Operators
   - Planning Domain Definition Language (PDDL)
   - Forward (Progression) Planning: (Valid) State-space Search
   - Backward (Regression) Planning: Relevant-states Search
   - Heuristics for Efficient Forward and Backward Planning
     - Planning Graph
   - Classical Planning Summary: Complexity, Top-Performers
   - STRIPS Planning Algorithm and the Sussman Anomaly
   - Partial-order Planning

3. Planning and Acting in the Real World
   - Assumptions Invalidated in the Real World
   - Planning that Scales: Hierarchical Task Network Planning
   - Conformant Planning
   - Contingent/Conditional Planning
   - Online Planning: Monitoring and Replacing

Planning is the process of computing several steps of a problem-solving procedure before executing any of them

This problem can be solved by search

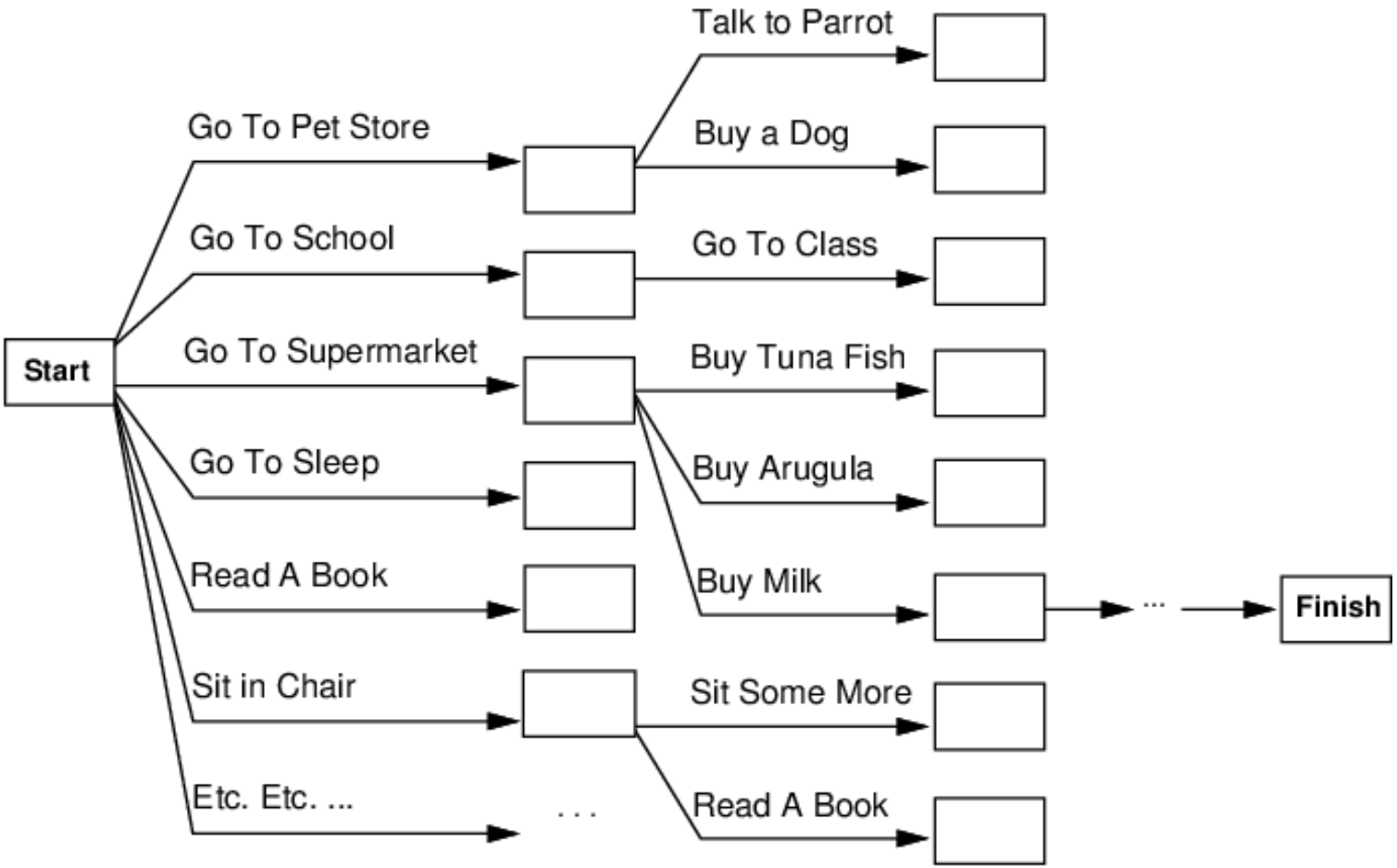
The main difference between search and planning is the representation of states

In **search**, states are represented as a single/atomic entity (which may be quite a complex object, but its internal structure is not used by the search algorithm)

In **planning**, states have structured/factored representations (collections of properties/attributes) which are used by the planning algorithm

Search vs. Planning (continued)

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

Planning systems do the following:

1) open up action and goal representation to allow selection

2) divide-and-conquer by subgoaling

3) 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

Classical Planning

- Atomic time: Each action is indivisible
- No concurrent actions allowed
- Deterministic actions: Result of each action is completely determined by the definition of the action, and there is no uncertainty in performing it in the world
- Agent is the sole cause of change in the world (environment is static and deterministic)
- Agent is omniscient – has complete knowledge of the state of the world (environment is fully-observable)
- **Closed World** assumption – everything known to be true in the world is included in a state description; what not listed is false

STRIPS operators

STRIPS planning language (Fikes and Nilsson, 1971)

Tidily arranged actions descriptions, restricted language

ACTION: $Buy(x)$
PRECONDITION: $At(p), Sells(p, x)$
EFFECT: $Have(x)$

[Note: this abstracts away many important details!]

Restricted language $\Longrightarrow$ efficient algorithm
Precondition: conjunction of **positive** literals
Effect: conjunction of literals

Complete set of STRIPS operators can be translated into set of successor-state axioms

PDDL

Planning Domain Definition Language

A bit more relaxed that STRIPS

Preconditions and goals can contain **negative** literals

Action: Buy(x)
Precondition: At(p), Sells(p, x)
Effect: Have(x)

is called an action schema

Planning Domain

States are sets of fluents (ground, function-less atoms)

Fluents which are not mentioned are false (this is the **closed world** assumption)

a $\in$ Actions(s) iff s $\models$Precond(a)
Result(s, a) = (s - Del(a)) $\cup$ Add(a)

where:
Del(a) is the list of literals which appear negatively in the effect of a
Add(a) is the list of positive literals in the effect of a

Example

Action: Buy(x)
Precondition: At(p), Sells(p, x), Have(Money)
Effect: Have(x), ¬Have(Money)

Del(Buy(Jaguar)) = Have(Money)
Add(Buy(Jaguar)) = Have(Jaguar)

If s = {At(JDealer), Sells(JDealer, Jaguar), Blue(Sky), Have(Money)}

Is Buy(Jaguar) ∈ Actions(s)? is it a valid action?
Yes: s ⊨Precond(a)

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Yes: s ⊨Precond(a) How?

Result(s, Buy(Jaguar)) = (s - Have(Money)) ∪ {Have(Jaguar)}
= {At(JDealer), Sells(JDealer, Jaguar), Blue(Sky), Have(Jaguar)}

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Planning Problem as a Search Problem

Planning problem = planning domain + initial state + goal

Goal is a conjunction of literals: Have(Jaguar) $\wedge \neg$ At(Jail)

Can solve planning problem using search

How?

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Can solve planning problem using search

How?

Forward Search or **Backward Search**

We mainly look at search as forward search: from initial to goal state

Nothing prevents us from searching from goal to initial state

Sometimes, branching factor makes searching backwards more reasonable

Motivating example: imagine trying to figure out how to get to some small place with few traffic connections from somewhere with a lot of traffic connections

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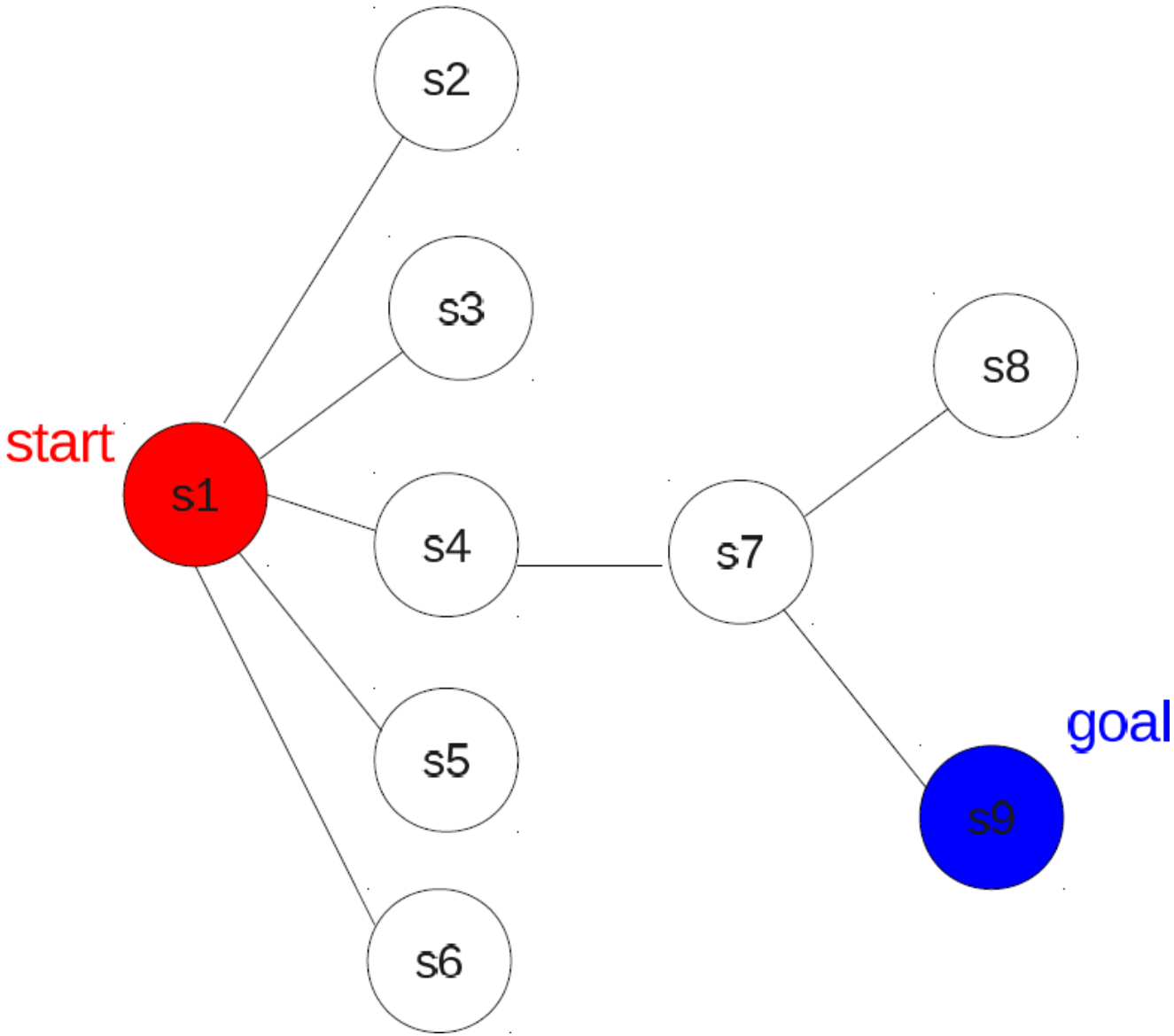
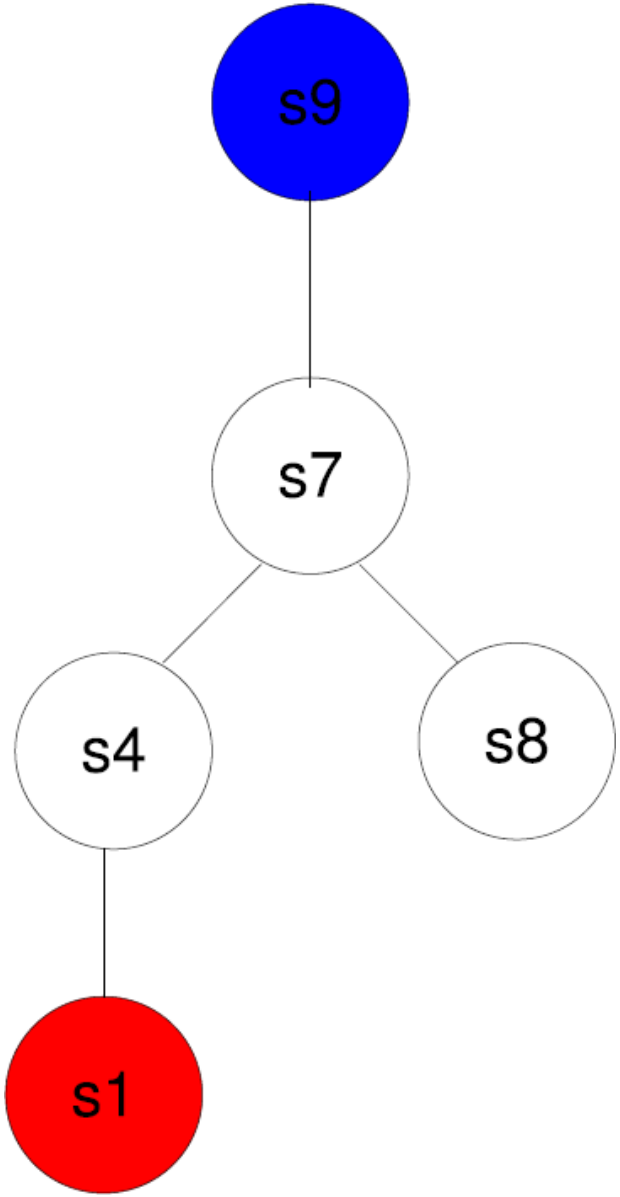
Example: Forward Search Tree



Example: Backward Search Tree



Backward Search

Can use any search method, BFS, DFS, IDS, Dijkstra, A*, etc.

If there are several goal states, search backwards from each in turn

Planning can use both forward and backward search (progression and regression planning)

Example of Forward/Progression Planning

Planning domain:

Predicates: At, Sells, Have

Two action schemas:

Action: Buy(x)
Precondition: At(p), Sells(p, x),Have(Money)
Effect: Have(x),¬Have(Money)

Action: Go(x, y)
Precondition: At(x)
Effect: At(y), ¬At(x)

Example of Forward/Progression Planning (continued)

Planning problem: planning domain above plus

Objects: Money, J (for Jaguar), Home, G (for garage)
Initial state: At(Home) $\wedge$ Have(Money) $\wedge$ Sells(G, J)
Goal state: Have(J)

Note: state descriptions are always ground (no variables).

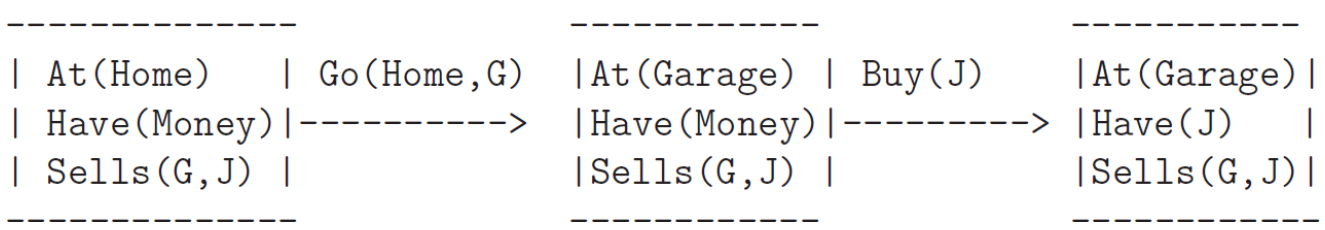
Goal description may have variables: At(x) $\wedge$ Have(y).

An atomic ground formula At(Home) is true iff it is in the state description.

A negation of a ground atom $\neg$At(G) is true iff the atom At(G) is not in the state description.

A property with a variable, such as At(x), is satisfied at a state if there is a way of substituting an object for x so that the resulting formula is true in the state.

Example of Forward/Progression Planning (continued)



Note:

At initial state:

Go(Home, Home) is applicable/valid and does not change the state

Buy(x) not available for any x (dont have Sells(Home, x))

At intermediate state:

Go(Garage, Home) and Go(Garage, Garage) both applicable/valid

Backward (Regression) Planning: Relevant-states Search

Also called relevant-states search

Start at the goal state(s) and do regression (go back)

To be precise, we start with a ground goal description g which describes a set of states (all those where Have(J) holds but Have(Money) may or may not hold, for example)

Example of Backward/Regression Planning

Given a goal description g and a ground action a, the regression from g over a gives a state description g':

g' = (g - Add(a)) $\cup$ {Precond(a)}

For example, if the goal is Have(J) and ground action is Buy(J):

g' = ({Have(J)} - {Have(J)}) $\cup$ { At(p), Sells(p, J), Have(Money)}
= {At(p), Sells(p, J), Have(Money)}

note that g' is partially uninstantiated (p is a free variable)

In this example, there is only one match for p, namely G(arage), but in general there may be several.

Backward/Regression Planning (continued)

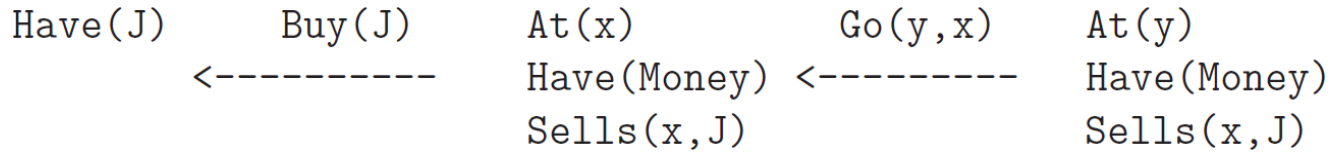
Which actions to regress over?

Relevant actions: have an effect which is in the set of goal elements and no effect which negates an element of the goal

For example, Buy(Jaguar) is a relevant action

In summary: backward planning searches backwards from g, remembering the actions and checking whether it reached an expression applicable to the initial state

Example of Backward/Regression Planning (continued)



Note:

goal state matches initial state with y/Home and x/G

intermediate state does not match initial state yet

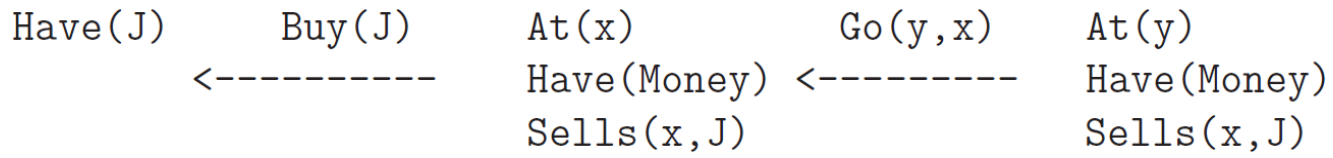
Let g = Have(Jaguar) $\wedge$ $\neg$At(Jail):

Buy(Jaguar) is a relevant action:
(has an effect which is in g and no effect which negates an element of g)

g' = ({Have(Jaguar), $\neg$At(Jail)} - {Have(Jaguar)}) $\cup$
{At(p), Sells(p, Jaguar), Have(Money)} =
{$\neg$At(Jail), At(p), Sells(p, Jaguar), Have(Money)}

If we had an extra action Steal(Jaguar), which also resulted in Have(Jaguar) but had an additional effect of At(Jail), Buy(Jaguar) would not be a relevant action

Example of Backward/Regression Planning (continued)



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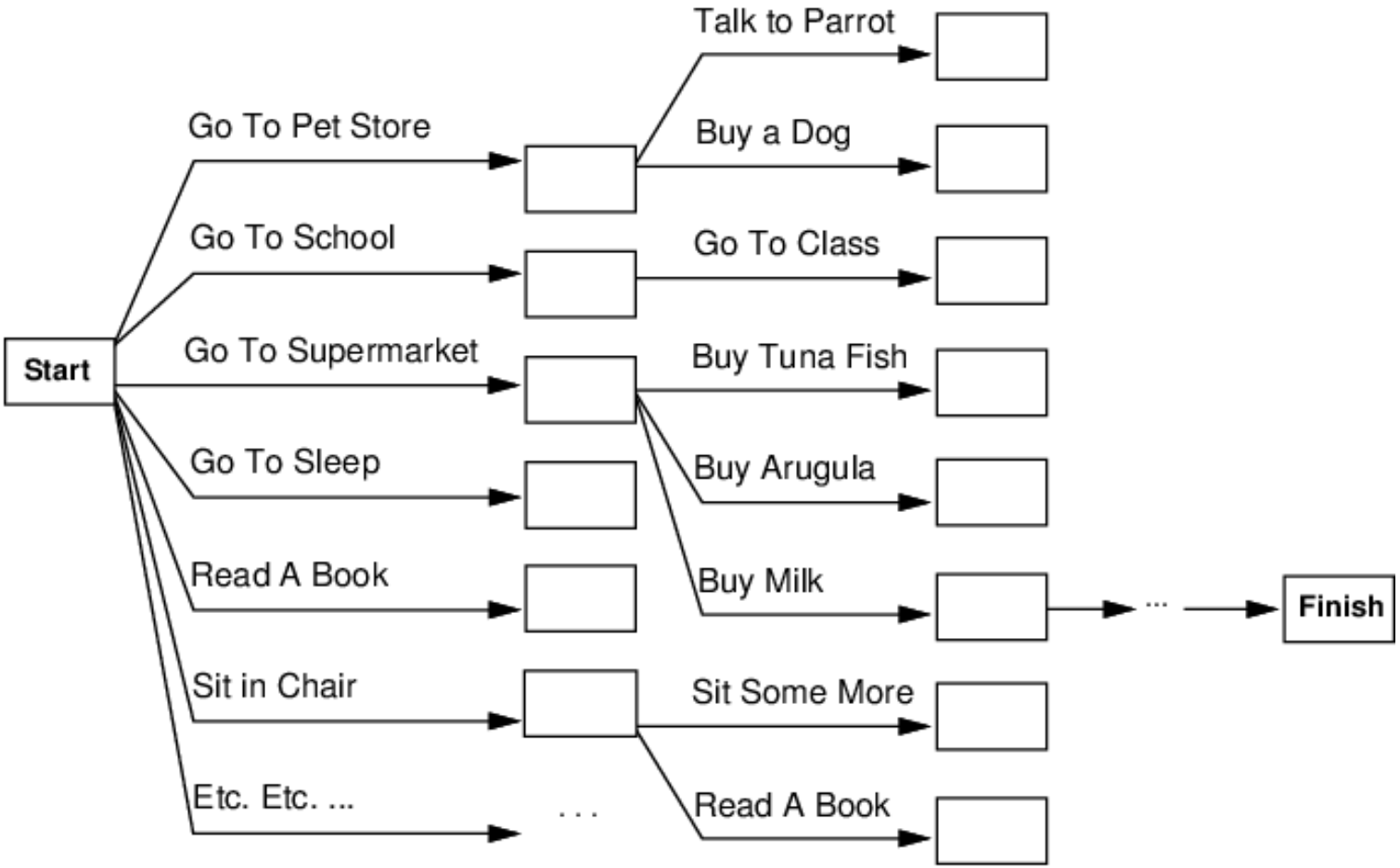
Forward vs. Backward Planning

If there are lots of actions, searching for a solution starting from the initial state looks hopeless



Heuristics to Tame Forward and Backward Planning

One can derive good heuristics (for A*) - two basic approaches to deriving heuristics:

1) relax the problem - effectively adding more edges to the graph
Strategies: remove (some) preconditions, ignore delete lists, etc.

Action: Slide(t, s1, s2)
Precond: On(t, s1) $\wedge$ Tile(t) $\wedge$ Blank(s2) $\wedge$ Adjacent(s1, s2)
Effect: On(t, s2) $\wedge$ Blank(s1) $\wedge$ $\neg$On(t, s1) $\wedge$ $\neg$Blank(s2)

removing preconditions Blank(s2) $\wedge$ Adjacent(s1, s2) $\Longrightarrow$ number-of-misplaced-tiles heuristic

removing Blank(s2) allows tiles to move to occupied places $\Longrightarrow$ Manhattan-distance heuristic

2) abstract the problem (group nodes together, make the search space smaller)

Backward planning considers a lot fewer actions/relevant states than forward search, but uses sets of states (g, g') - harder to come up with good heuristics:
planning graph can be used to derive better heuristics

Deriving Heuristics via Planning Graph

Planning graphs are also used as a source of heuristics (an estimate of how many steps it takes to reach the goal)

Planning graph is an approximation of a complete tree of all possible actions and their results

Organized into **levels**:

Level S0: initial state, consisting of nodes representing each fluent that holds in S0
Level A0: each ground action that might be applicable in S0
Then alternate Si and Ai

Si contains fluents which could hold at time i, (may be both P and $\neg$P)
literals may show up too early but never too late

Ai contains actions which could have their preconditions satisfied at i

Planning Domain and Problem Example

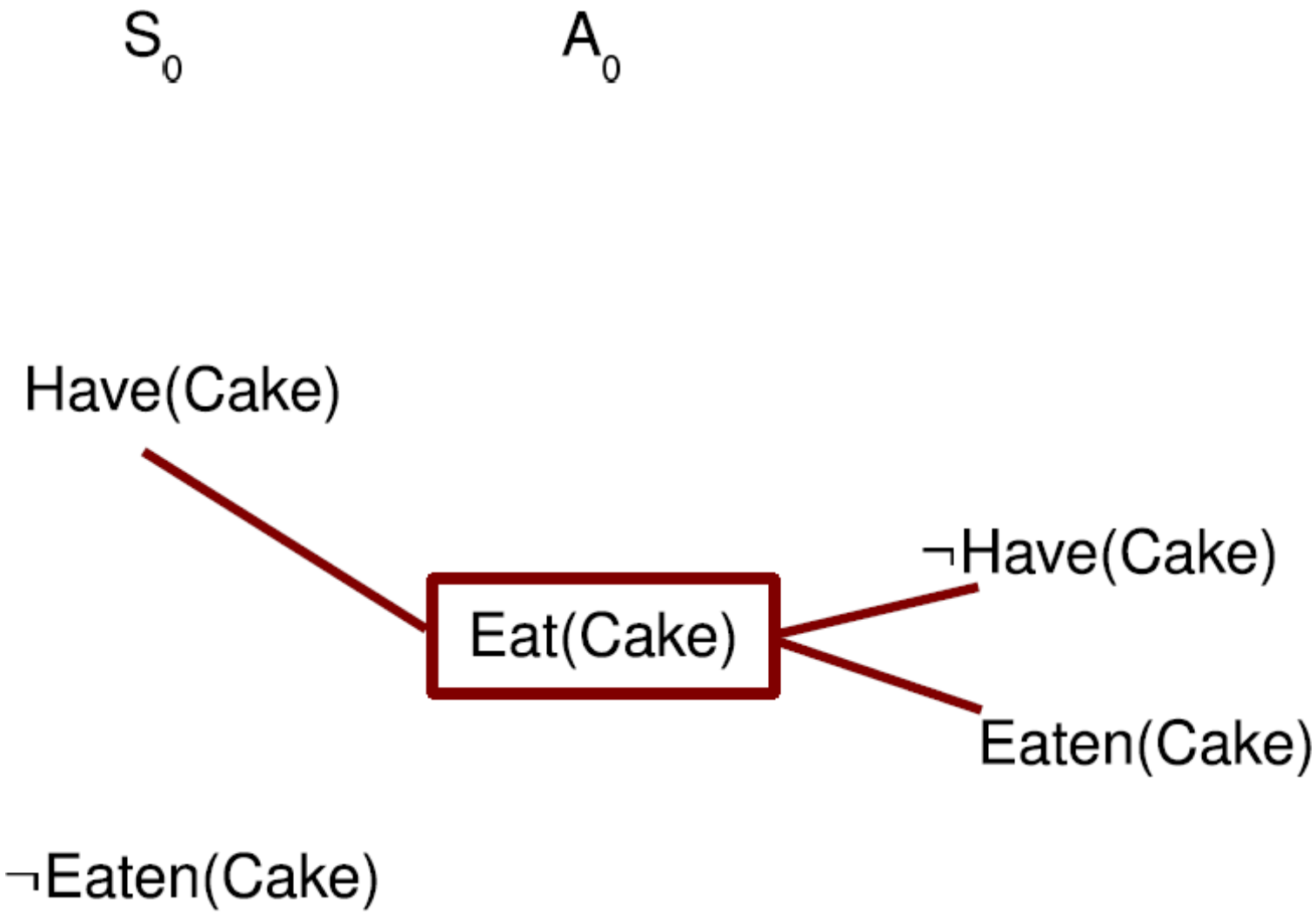
Initial state: Have(Cake)

Goal: Have(Cake) $\wedge$ Eaten(Cake)

Eat(Cake):
Precond: Have(Cake)
Effect: $\neg$Have(Cake) $\wedge$ Eaten(Cake)

Bake(Cake):
Precond: $\neg$Have(Cake)
Effect: Have(Cake)

Incomplete Planning Graph



Building a Planning Graph

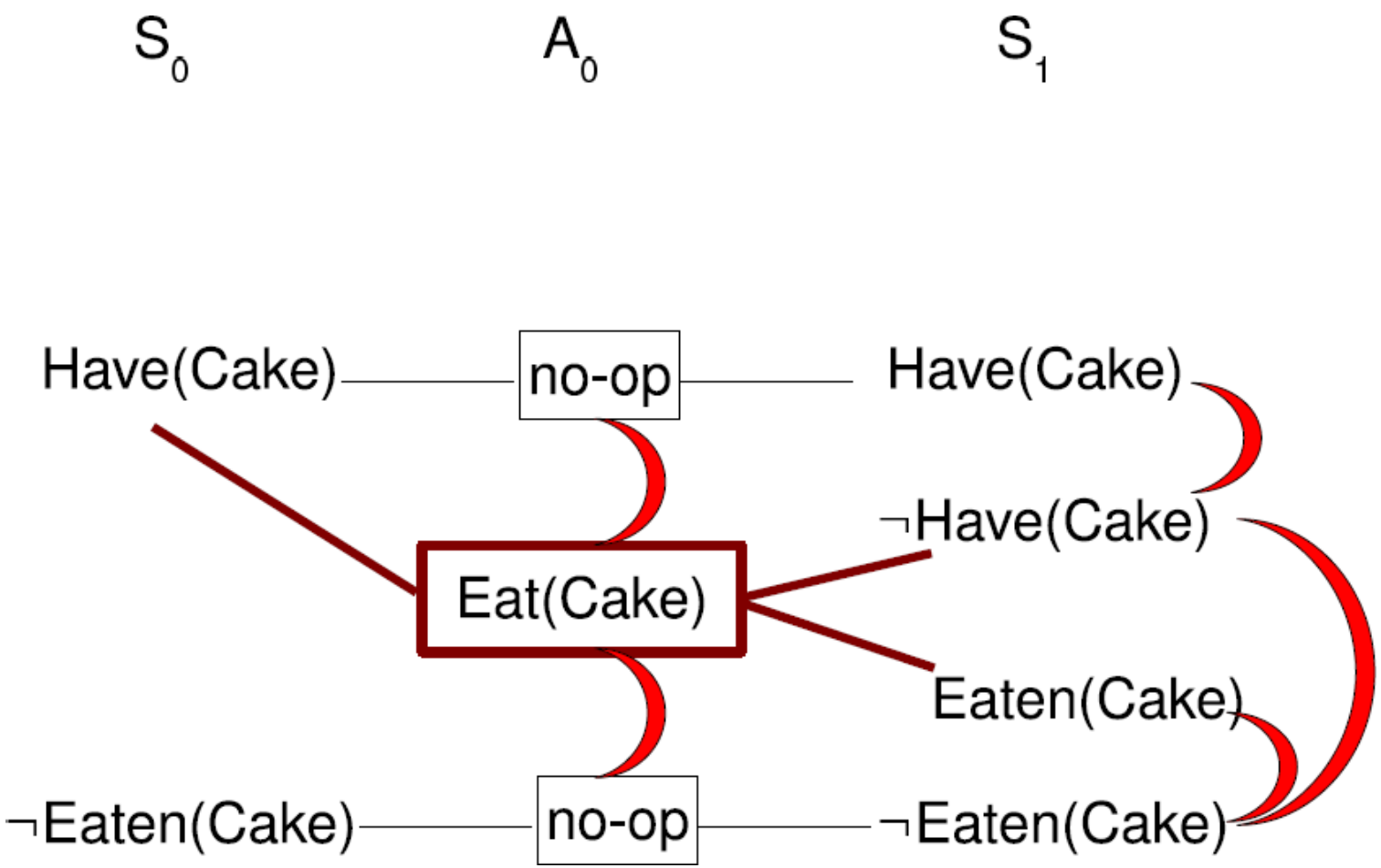
In addition to 'normal' action, persistence action or no-op (no operation): one for each fluent, preserves the fluents truth

Mutex or mutual exclusion links depicted by red semicircles mean that actions cannot occur together

Similarly there are mutex links between fluents

Build the graph until two consecutive levels are identical
    until the graph levels off

Incomplete Planning Graph (continued)



Mutex between Actions

Mutex relation holds between two actions at the same level if any of the following three conditions holds:

♢ Inconsistent effects: one action negates an effect of another

For example, Eat(Cake) and persistence for Have(Cake) have inconsistent effects (¬Have(Cake) and Have(Cake))

♢ Interference: one of the effects of one action is the negation of a precondition of the other

For example Eat(Cake) interferes with the persistence of Have(Cake) by negating its precondition

♢ Competing needs: one of the preconditions of one action is mutually exclusive with a precondition of the other

For example, Eat(Cake) has precondition Have(Cake) and Bake(Cake) has precondition of ¬Have(Cake).

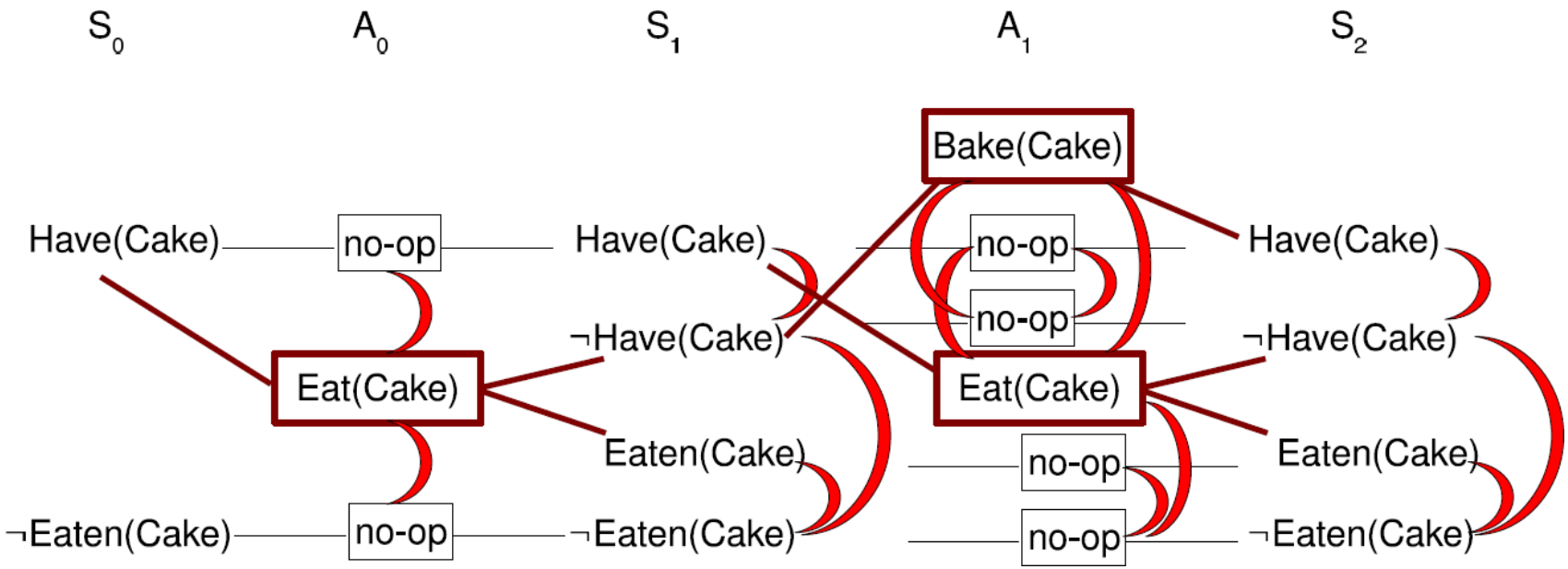
Mutex between Fluents

Mutex holds between fluents if:

♢ they are negations of each other, like Have(Cake) and ¬Have(Cake)

♢ each possible pair of actions that could achieve the two literals is mutually exclusive, for example Have(Cake) and Eaten(Cake) in S1 can only be achieved by persistence for Have(Cake) and by Eat(Cake) respectively.
(In S2 can use persistence for Eaten(Cake) and Bake(Cake) which are not mutex).

Complete Planning Graph (and Size)



Size: is polynomial in the size of the problem (unlike a complete search tree, which is exponential!)

If we have n literals and a actions:
each Si has no more than n nodes and n^2 mutex links,
each Ai has no more than a + n nodes (n because of no-ops), $(a + n)^2$ mutex links, and $2(an + n)$ precondition and effect links.

Hence, a graph with k levels has $O(k(a + n)^2)$ size.

Using Planning Graph for Heuristic Estimation

If some goal literal does not appear in the final level of the graph, the goal is not achievable

The cost of achieving any goal literal can be estimated by counting the number of levels before it appears

This heuristic never overestimates

It underestimates because planning graph allows application of actions (including incompatible actions) in parallel

Conjunctive goals:
max level heuristic: max level for any goal conjunct (admissible but inaccurate)

set level heuristic: which level they all occur on without mutex links (better, also admissible)

Planning with Planning Graph: GraphPlan

GraphPlan repeatedly adds a level to a planning graph with Expand-Graph

Once all the goals show up as non-mutex in the graph, calls Extract-Solution on the graph to search for a plan

If that fails, extracts another level

```
function GRAPHPLAN(problem) returns solution or failure
    graph ← INITIAL-PLANNING-GRAPH(problem)
    goals ← CONJUNCTS(problem.GOAL)
    loop do
        if goals all non-mutex in last level of graph then do
            solution ← EXTRACT-SOLUTION(graph,goals, NUMLEVELS(graph)
            if solution ≠ failure then return solution
            else if NO-SOLUTION-POSSIBLE(graph) then return failure
        graph ← EXPAND-GRAPH(graph,problem)
```

Solution can be then extracted via backward search

Search may still degenerate to exponential exploration, but heuristics exist

(Local) Fast Forward Search with Planning Graph: Fast Forward Search

Example of a planning system using planning graphs for heuristics

FF or FastForward system (Hoffman 2005)

Forward space searcher

Ignore-delete-lists heuristic estimated using planning graph

Uses hill-climbing search with this heuristic to find solution

When hits a plateau or local maximum uses iterative deepening to find a better state or gives up and restarts hill-climbing

Satisficing vs. Optimal (Classical) Planning

GraphPlan seeks optimal plan

SATPlan reduces planning problem to classical propositional SAT problem (section 10.4 in book)

SAT problem: is this propositional formula satisfiable? (is there an assignment that makes it true?)

Can only find plans of fixed maximal length

To use SATPlan, PDDL planning problem description needs first to be translated to a suitable form

Complexity of Classical Planning

PlanSAT is the question whether there exists any plan that solves a given planning problem

Bounded PlanSAT is the question whether there exists a plan of length k or less

PlanSAT is about satisficing (want any solution, not necessarily the cheapest or the shortest)

Bounded PlanSAT can be used to ask for the optimal solution

If in the PDDL language we do not allow functional symbols, both problems are decidable

Complexity of both problems is PSPACE (can be solved by a Turing machine which uses polynomial amount of space)

NP is a subset of PSPACE (PSPACE is even harder than NP)

Summary: Top-performing Planning Systems

Year	Track	Winning systems (approaches)
2008	Optimal	Gamer (symbolic bi-directional search)
2008	Satisficing	LAMA (fast forward search with FF heuristic)
2006	Optimal	SATPlan, MAXPlan (boolean satisfiability)
2006	Satisficing	SGPlan (forward search, partition into independent sub-problems)
2004	Optimal	SATPlan (boolean satisfiability)
2004	Satisficing	Fast Diagonally Forward (forward search with causal graph)
2002	Automated	LPG (local search, constraint satisfaction)
2002	Hand-coded	TLPLan (temporal action logic with control rules for forward search)
2000	Automated	FF (forward search)
2000	Hand-coded	TalPlanner (temporal action logic with control rules for forward search)
1998	Automated	IPP (planning graphs); HSP (forward search)

Classical planning algorithms typically do not scale well

Should subgoals be reached serially?

What about leveraging goal decomposition?

Does order matter?

Next: Partial-order Planning

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But first: an instructive exercise

Example Domain: the Blocks World

The domain consists of:

1. a table, a set of cubic blocks, and a robot arm

2. each block is either on the table or stacked on top of another block

3. the arm can pick up a block and move it to another position either on the table or on top of another block

4. the arm can only pick up one block at time, so it cannot pick up a block which has another block on top

A goal is a request to build one or more stacks of blocks specified in terms of which blocks are on top of which other blocks

State Descriptions

Blocks are represented by constants A,B,C . . . etc.

An additional constant Table represents the table

The following predicates are used to describe states:

On(b, x): block b is on x, where x is either another block or the table

Clear(x): there is a clear space on x to hold a block

Action Schemas

MOVE(b, x, y):
Precond: $\text{On}(b, x) \wedge \text{Clear}(b) \wedge \text{Clear}(y)$
Effect: $\text{On}(b, y) \wedge \text{Clear}(x) \wedge$
$\neg\text{On}(b, x) \wedge \neg\text{Clear}(y)$

MOVE-TO-TABLE(b, x):
Precond: $\text{On}(b, x) \wedge \text{Clear}(b)$
Effect: $\text{On}(b, \text{Table}) \wedge \text{Clear}(x) \wedge$
$\neg\text{On}(b, x)$

Problems with this Formalization

There is nothing to stop the planner using the 'wrong' operator to put a block on the table, i.e. MOVE(b, x, Table) rather than MOVE-TO-TABLE(b, x)

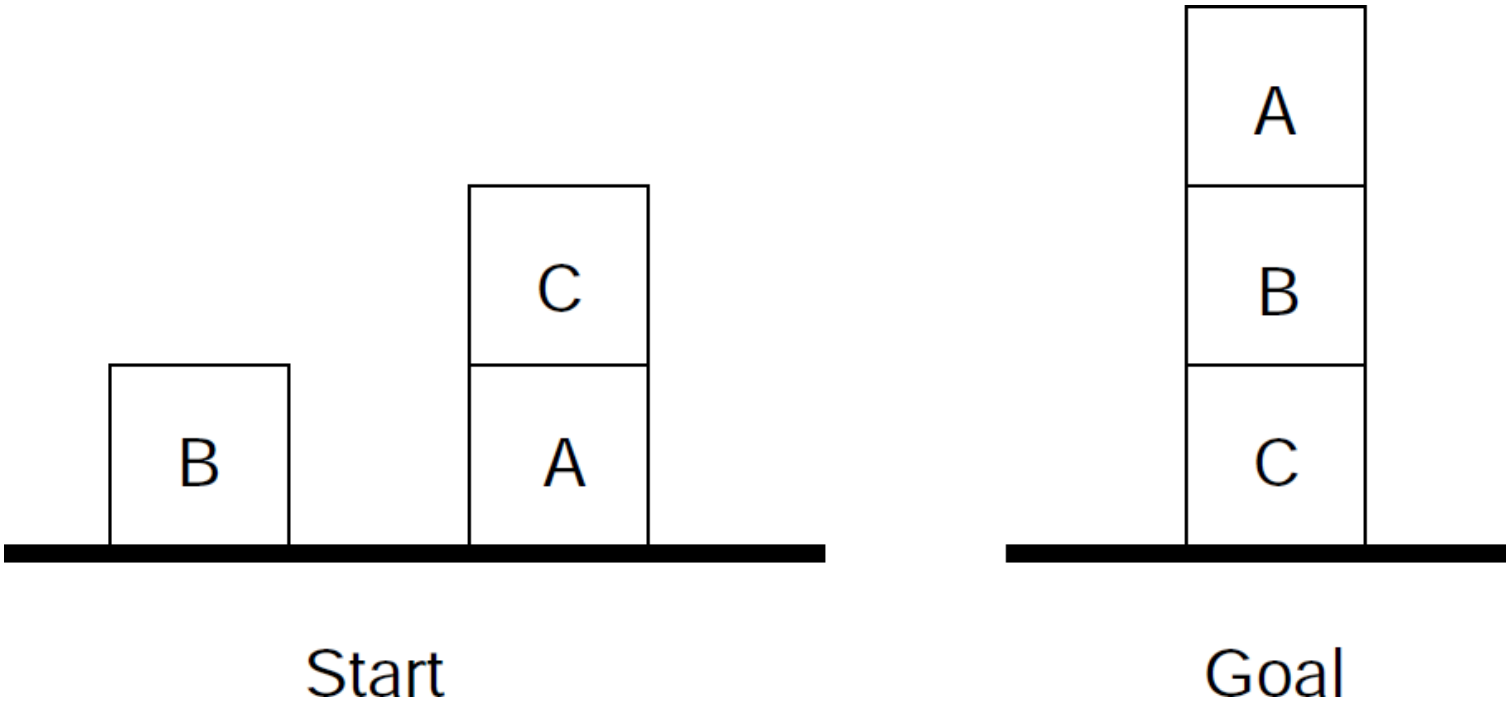
which results in a larger-than-necessary search space, and

Some of the operator applications, such as MOVE(B,C,C), which should do nothing, have inconsistent effects

To solve the first one, we could introduce predicate Block and make Block(x) and Block(y) preconditions of MOVE(x, y, z)

To solve the second we could add $\neg(y = z)$ as a precondition for MOVE(x, y, z)

Example Problem: Sussman Anomaly



Start Goal

Initial state:
On(C,A) $\wedge$ OnTable(A) $\wedge$ OnTable(B) $\wedge$ Clear(B) $\wedge$ Clear(C)

Goal state:
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

Goal Stack Planning

Goal Stack Planning: One of the earlier planning algorithms, used by STRIPS

Work backwards from the goal, looking for an operator which has one or more of the goal literals as one of its effects and then trying to satisfy the preconditions of the operator

The preconditions of the operator become subgoals that must be satisfied

Keep doing this until initial state is reached

Goal stack planning uses a stack to hold goals and actions to satisfy the goals, and a knowledge base to hold the current state, action schemas and domain axioms

Goal stack is like a node in a search tree

If there is a choice of action, create branches

Goal Stack Planning Pseudocode

Push the original goal on the stack.

Repeat until the stack is empty:

If stack top is a compound goal, push its unsatisfied subgoals on the stack.

If stack top is a single unsatisfied goal, replace it by an action that makes it satisfied and push the actions precondition on the stack.

If stack top is an action, pop it from the stack, execute it and change the knowledge base by the action's effects.

If stack top is a satisfied goal, pop it from the stack.

Goal Stack Planning Trace

(Below does pushing of subgoals at the same step as the compound goal.)
The order of subgoals is arbitrary; could have put On(B,C) on top

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

KB = {On(C,A), OnTable(A), OnTable(B), Clear(B), Clear(C)}

plan = [ ]

The top of the stack is a single unsatisfied goal. So push the action that would achieve it, and its preconditions.

Goal Stack Planning Trace (continued)

Clear(B)
Clear(A)
On(A, x)
Clear(A) $\wedge$ Clear(x)
MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {On(C,A),OnTable(A),OnTable(B),Clear(B),Clear(C)}

plan = [ ]

The top of the stack is a satisfied goal. We pop the stack.

Goal Stack Planning Trace (continued)

Clear(A)
On(A, x)
Clear(A) $\wedge$ Clear(x)
MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {On(C,A),OnTable(A),OnTable(B),Clear(B),Clear(C)}

plan = [ ]

The top of the stack is an unsatisfied goal. We push the action which would achieve it, and its preconditions.

Goal Stack Planning Trace (continued)

On(C, A)
Clear(C)
On(C, A) $\wedge$ Clear(C)
MOVE-TO-TABLE(C, A)
Clear(A)
On(A, x)
Clear(A) $\wedge$ Clear(x)
MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {On(C,A),OnTable(A),OnTable(B),Clear(B),Clear(C)}

plan = [ ]
The top of the stack is a satisfied goal. We pop the stack (three times).

Goal Stack Planning Trace (continued)

MOVE-TO-TABLE(C, A)
Clear(A)
On(A, x)
Clear(A) $\wedge$ Clear(x)
MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {On(C,A),OnTable(A),OnTable(B),Clear(B),Clear(C)}

plan = [ ]

The top of the stack is an action. We execute it, update the KB with its effects, and add it to the plan.

Goal Stack Planning Trace (continued)

Clear(A)
On(A, Table)
Clear(A) $\wedge$ Clear(x)
MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {OnTable(C),OnTable(A),OnTable(B),Clear(A),Clear(B),Clear(C)}
plan = [MOVE-TO-TABLE(C,A)]

The top of the stack is a satisfied goal. We pop the stack (thrice).

Goal Stack Planning Trace (continued)

MOVE(A, x, B)
On(A,B)
On(B,C)
OnTable(C)
On(A,B) $\wedge$ On(B,C) $\wedge$ OnTable(C)

KB = {OnTable(C),OnTable(A),OnTable(B),Clear(A),Clear(B),Clear(C)}

plan = [MOVE-TO-TABLE(C,A)]

The top of the stack is an action. We execute it, update the KB with its effects, and add it to the plan.

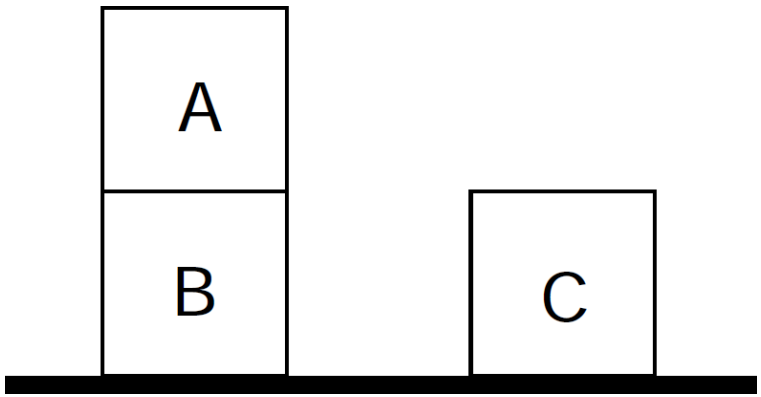
Goal Stack Planning Trace (continued)

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

KB = {On(A,B),OnTable(C),OnTable(B), Clear(A), Clear(C)}

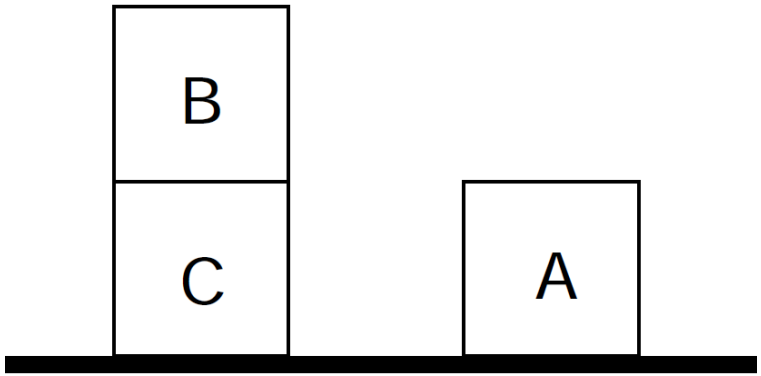
plan = [MOVE-TO-TABLE(C,A),MOVE(A, Table,B)]

the current state is:



Goal Stack Planning Trace (continued)

If we follow the same process for the On(B,C) goal, we end up in the state:



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

The remaining goal on the stack $On(A,B) \wedge On(B,C) \wedge OnTable(C)$ is not satisfied.

So On(A,B) will be pushed on the stack again!

Goal Stack Planning Trace (continued)

Now we finally can move A on top of B, but the resulting plan is redundant:

MOVE-TO-TABLE(C,A)
MOVE(A, Table,B)
MOVE-TO-TABLE(A,B)
MOVE(B, Table,C)
MOVE(A, Table,B)

There are techniques for 'fixing' inefficient plans (where something is done and then undone), but it is difficult in general (when it is not straight one after another)

Sussman Anomaly

It seemed to make sense to break up a conjunctive goal into subgoals and achieve them, separately, in some order

Sussman anomaly is instructive, because achieving one goal (On(A,B)) destroys preconditions of an action which is necessary to achieve the other goal (On(B,C)), namely Clear(B).

Such interaction between actions is called clobbering

This is addressed in partial order planning

Totally vs. Partially-ordered Plans

So far we produced a linear sequence of actions (totally ordered plan)

Often it does not matter in which order some of the actions are executed

For problems with independent subproblems, often easier to find a partially-ordered plan: a plan which is a set of actions and a set of constraints Before(ai, aj)

Partially ordered plans are created by a search through a space of plans (rather than the state space)

Partially Ordered Plans

Partially-ordered collection of steps with:
Start step has the initial state description as its effect
Finish step has the goal description as its precondition
Causal links from outcome of one step to precondition of another
Temporal ordering between pairs of steps

Open condition = precondition of a step not yet causally linked

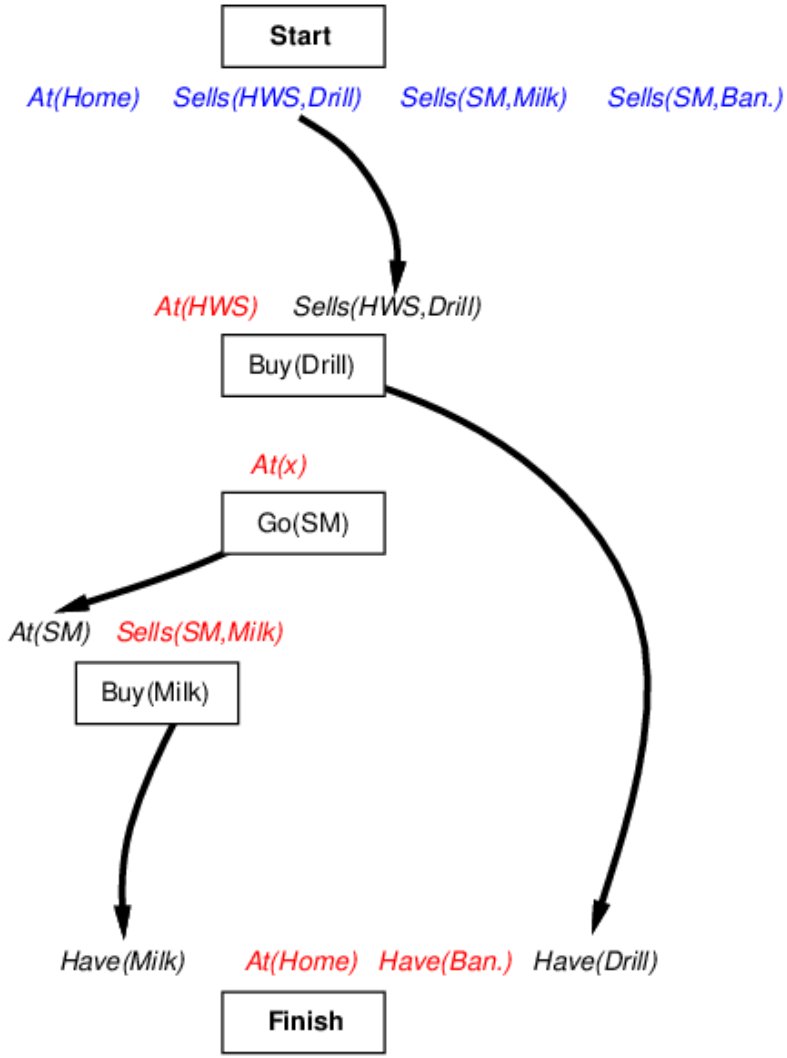
A plan is complete iff every precondition is achieved

A precondition is achieved iff it is the effect of an earlier step
and no possibly intervening step undoes it

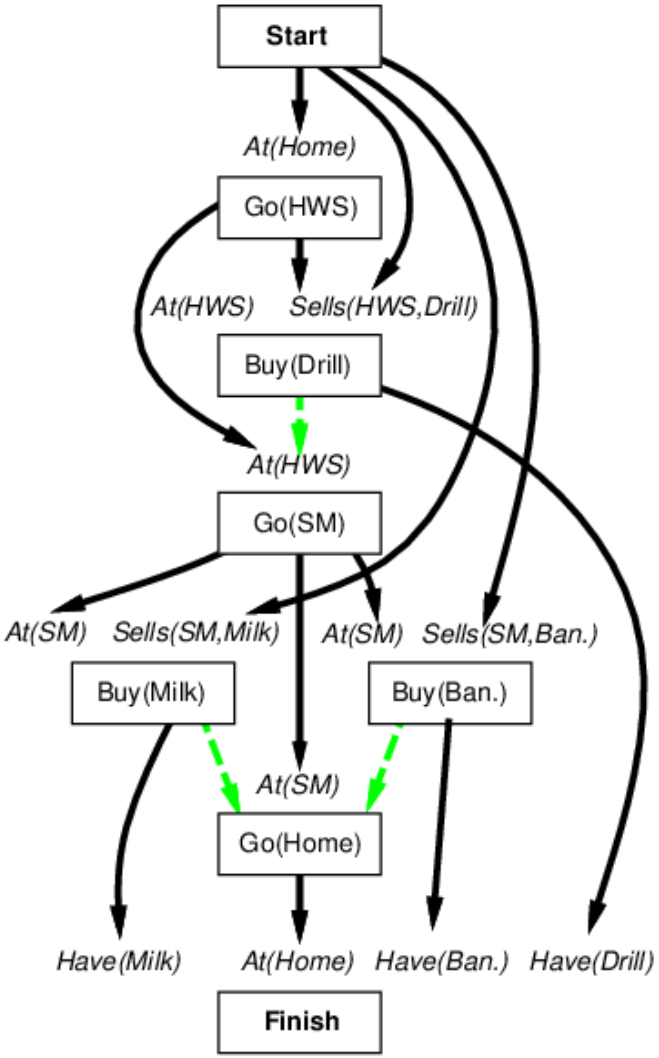
Example


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

Example


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

Example


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

Planning Process

Operators on partial plans:
add a link from an existing action to an open condition
add a step to fulfill an open condition
order one step wrt another to remove possible conflicts

Gradually move from incomplete/vague plans to complete, correct plans

Backtrack if an open condition is unachievable or
if a conflict is unresolvable

POP Algorithm Sketch

function POP(*initial*, *goal*, *operators*) **returns** *plan*

plan ← MAKE-MINIMAL-PLAN(*initial*, *goal*)
loop do
  if SOLUTION?(*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*) **returns** 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

procedure 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 ordering 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*)

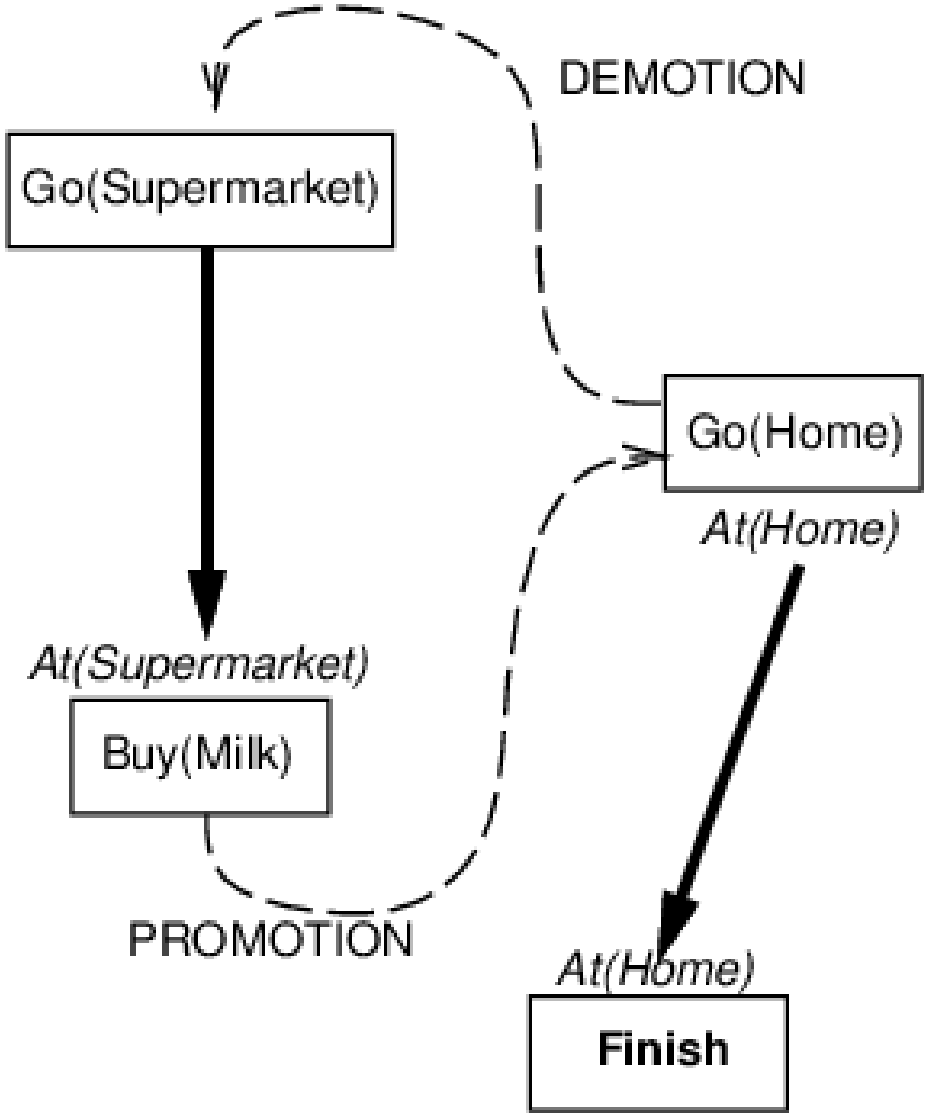
---

procedure RESOLVE-THREATS(*plan*)

for each S_{threat} that threatens a 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**
end

Clobbering and Promotion/Demotion

A clobberer is a potentially intervening step that destroys the condition achieved by a causal link. E.g., *Go*(*Home*) clobbers *At*(*Supermarket*):



Demotion: put before *Go*(*Supermarket*)

Promotion: put after *Buy*(*Milk*)

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

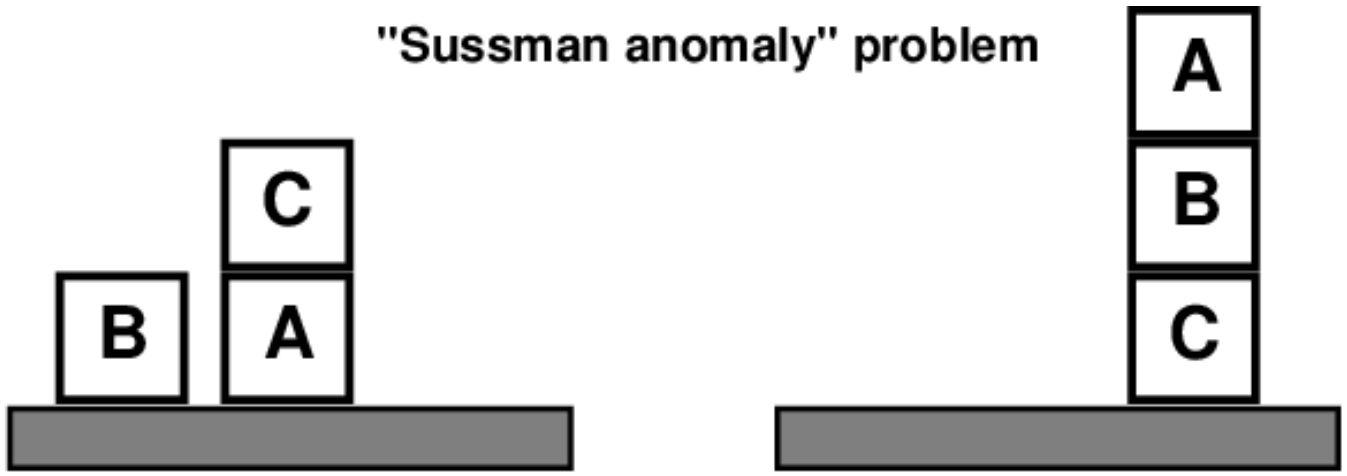
POP is sound, complete, and systematic (no repetition)

Extensions for disjunction, universals, negation, conditionals

Can be made efficient with good heuristics derived from problem description

Particularly good for problems with many loosely related subgoals

Example: Blocks World



Clear(x) On(x,z) Clear(y)

PutOn(x,y)

~On(x,z) ~Clear(y)
Clear(z) On(x,y)

Clear(x) On(x,z)

PutOnTable(x)

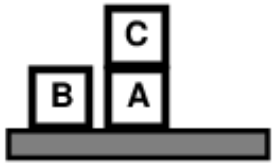
~On(x,z) Clear(z) On(x,Table)

+ several inequality constraints

Example Continued

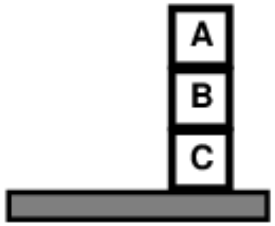
START

On(C,A) On(A,Table) Cl(B) On(B,Table) Cl(C)

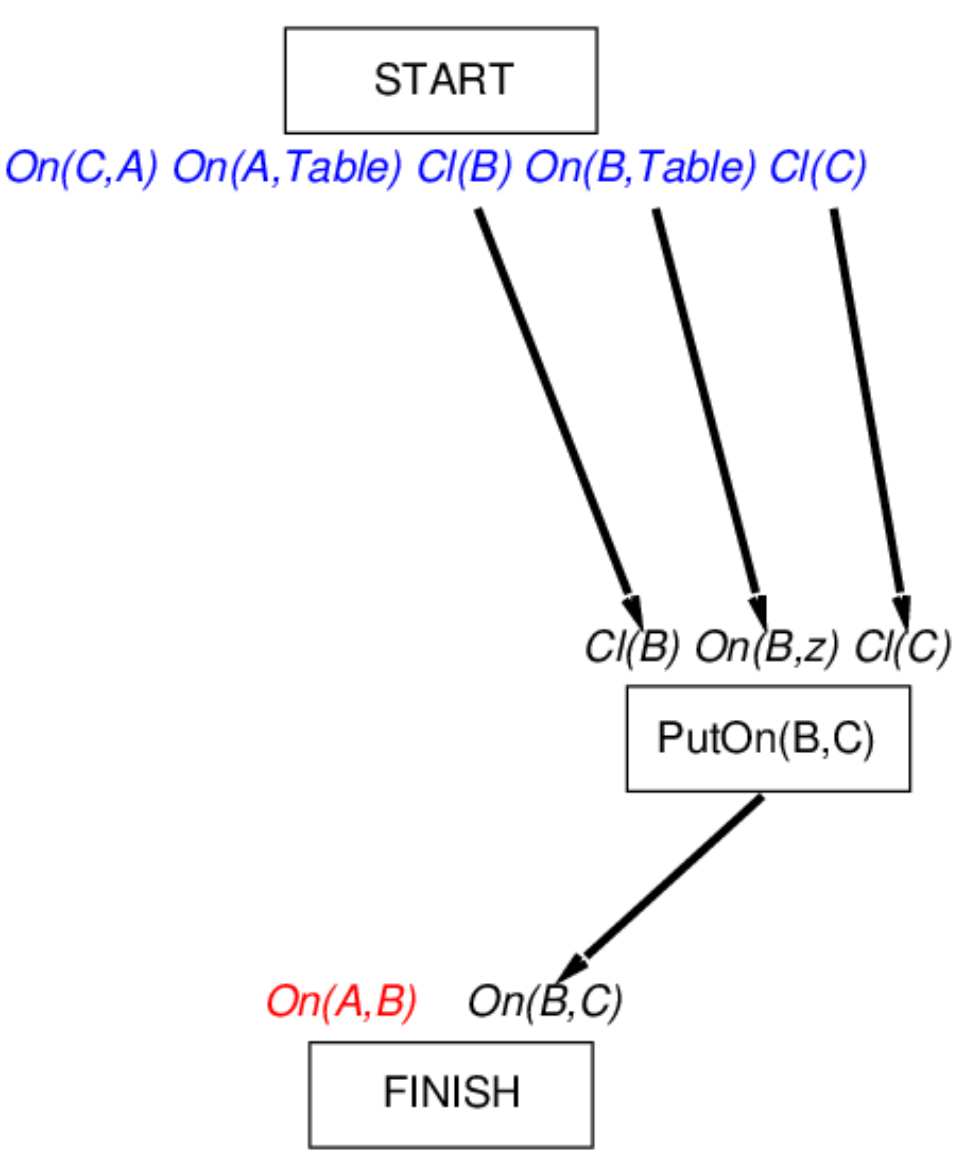


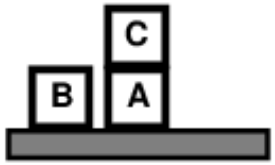
On(A,B) On(B,C)

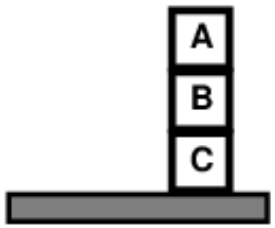
FINISH



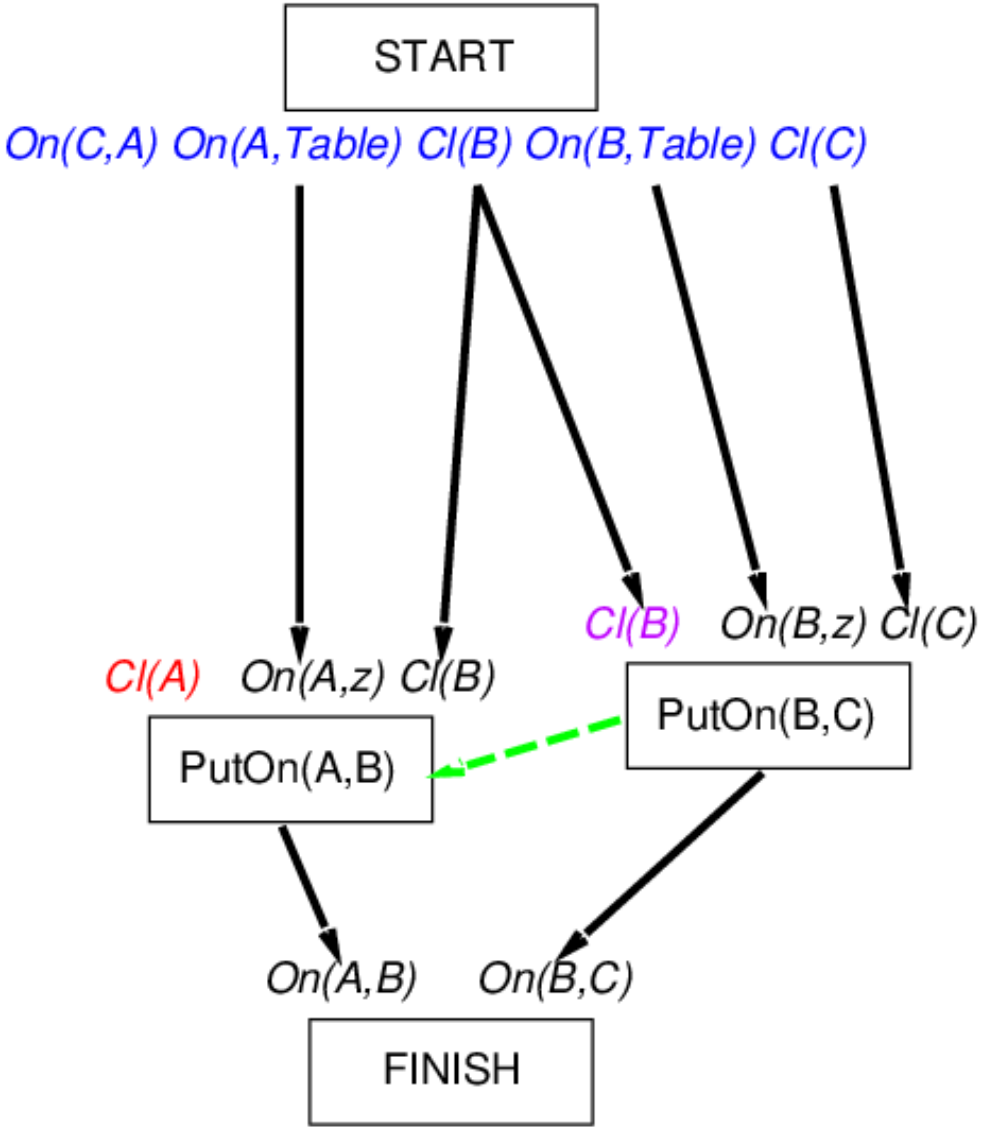
Example Continued

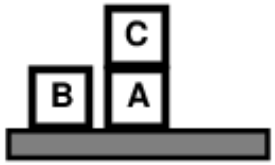




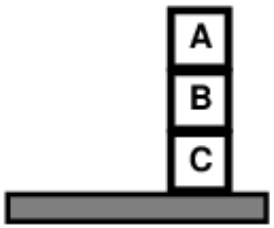


Example Continued

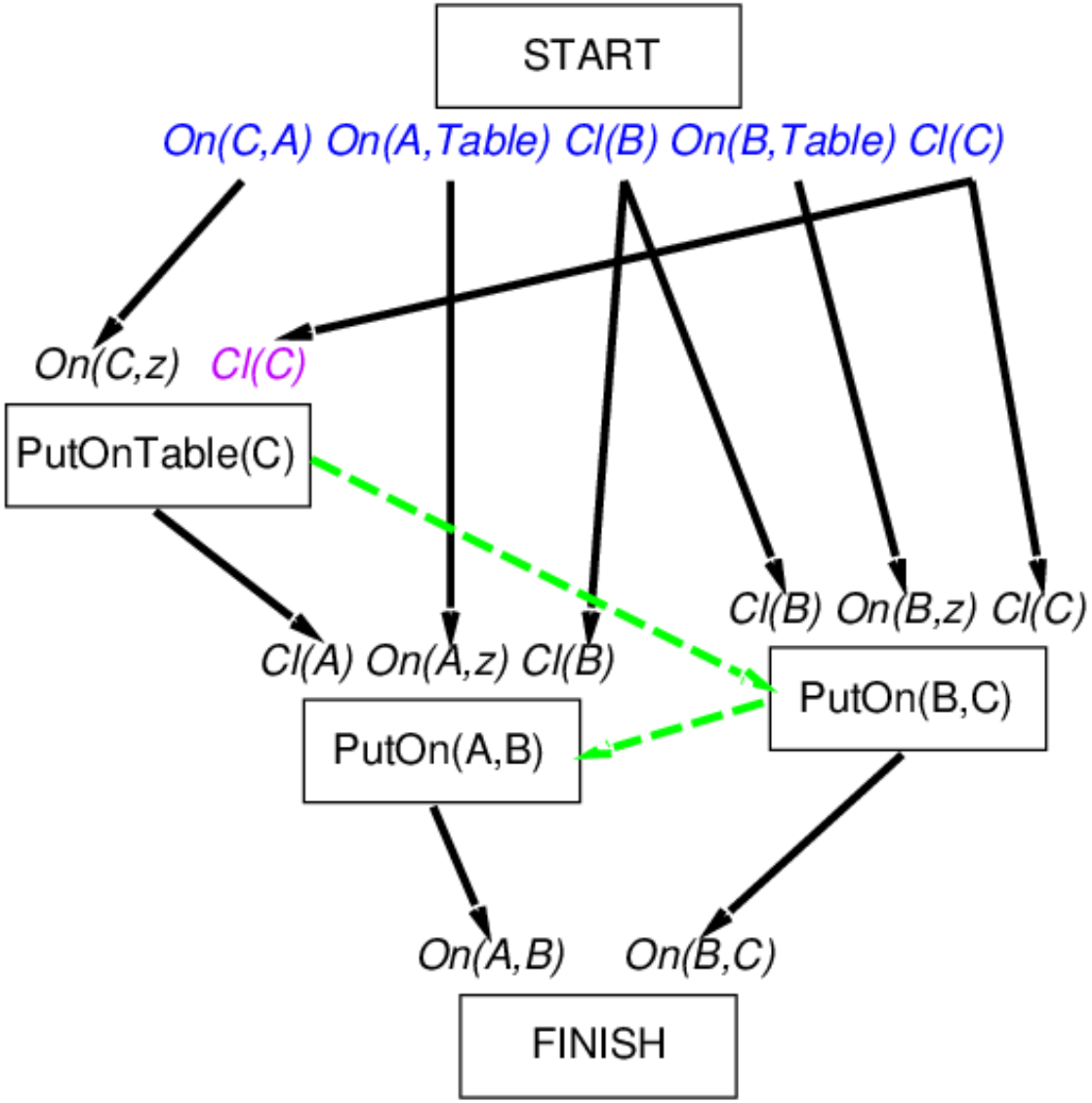


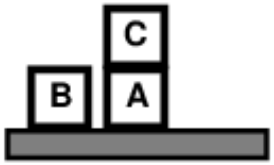


PutOn(A,B) clobbers Cl(B) => order after PutOn(B,C)



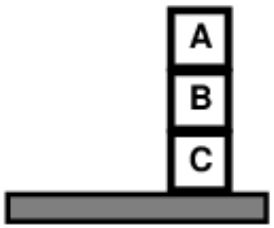
Example Continued





PutOn(A,B) clobbers Cl(B) => order after PutOn(B,C)

PutOn(B,C) clobbers Cl(C) => order after PutOnTable(C)



Planning in the Real World

Planning in the presence of limited resources:

Actions consume resources, time being one of them
Specialized scheduling algorithms or algorithms that integrate scheduling with planning address time

Semi-autonomous Planning:

Hierarchical task network planning (HTN) allows planning agent to incorporate advice from domain expert in the form of high-level actions (HLAs)

Assumptions of classic planning often violated in the real world:

Contingent plans allow agent to sense in a partially-observed environment
Online planning agent can address nondeterministic actions, exogeneous events, or incorrect models of the environment
Multiagent planning allows cooperation or competition with other agents in the environment

Markov decision processes and game theory allow agent to plan in stochastic environments

HTN Planning

Partial-order planning does not scale well in the real world

Some planning tasks involve millions of actions

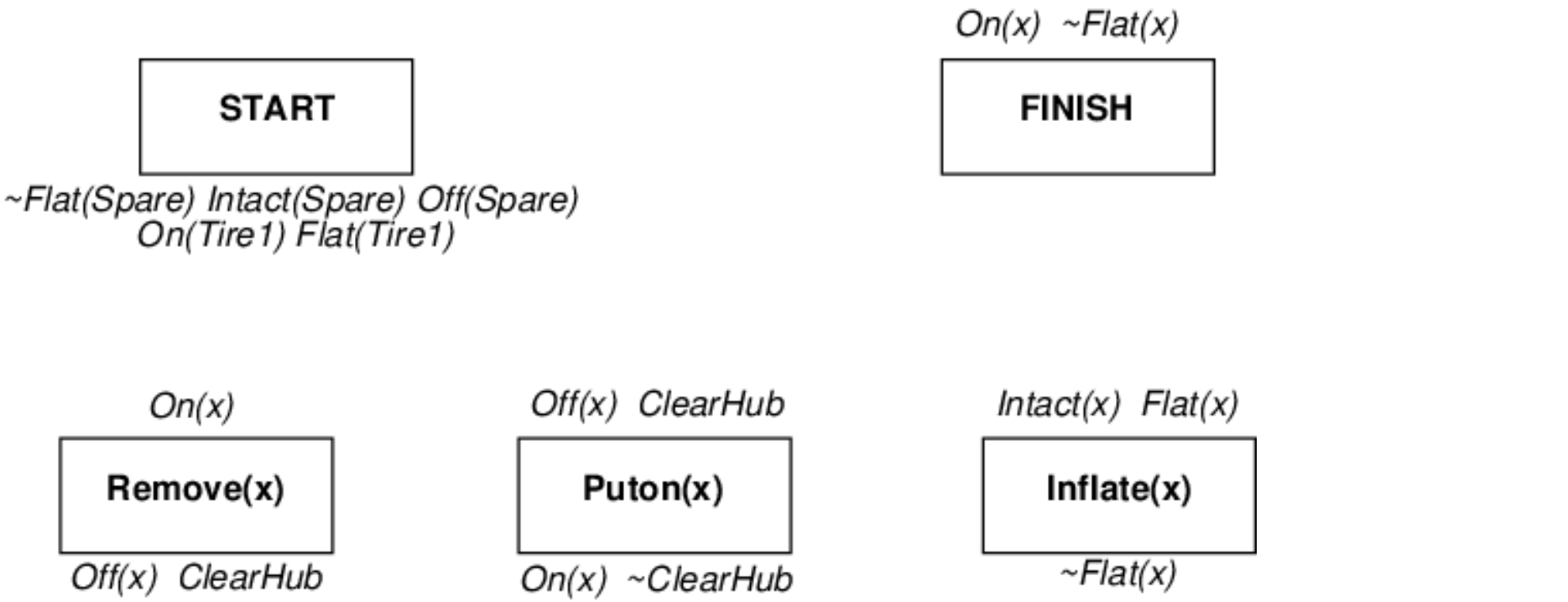
Example: planning to invade a country

There is, however, hierarchical structure that humans employ when putting together plans

HTN planning: plan at a higher level, then refine if necessary

Important concept: high-level actions (HLAs)

More in class, on the board


START
~Flat(Spare) Intact(Spare) Off(Spare)
On(Tire1) Flat(Tire1)
On(x) ~Flat(x)
FINISH
On(x)
Remove(x)
Off(x) ClearHub
Off(x) ClearHub
Puton(x)
On(x) ~ClearHub
Intact(x) Flat(x)
Inflate(x)
~Flat(x)

Things Go Wrong

Incomplete information

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

Incorrect information

Current state incorrect, e.g., spare NOT intact
Missing/incorrect postconditions in operators

Qualification problem:
can never finish listing all the required preconditions and possible conditional outcomes of actions

Solutions

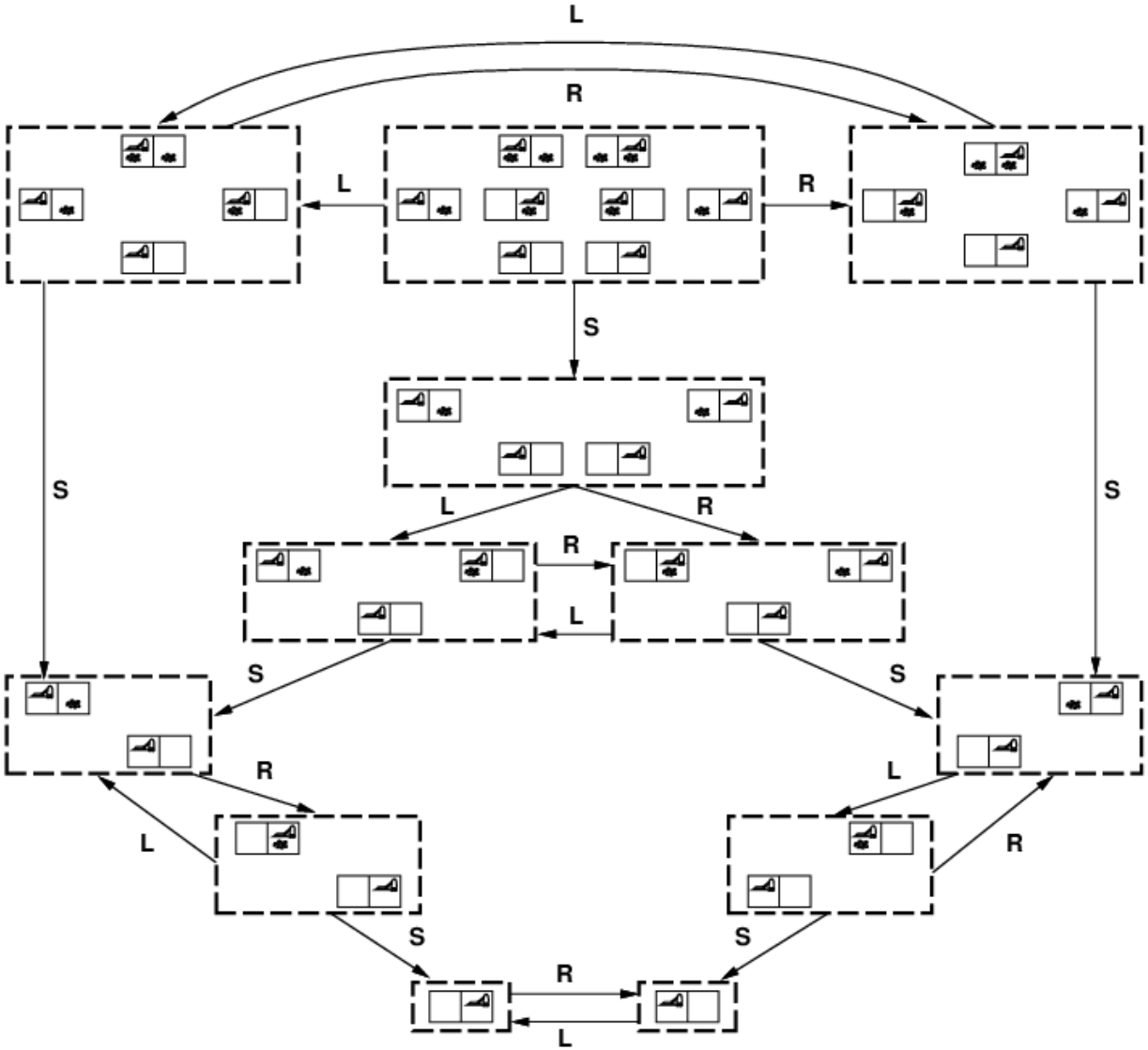
Conformant or sensorless planning
Devise a plan that works regardless of state or outcome
Such plans may not exist

Conditional planning
Plan to obtain information (**observation actions**)
Subplan for each contingency, e.g.,
[*Check*(*Tire*1), **if** *Intact*(*Tire*1) **then** *Inflate*(*Tire*1) **else** *CallAAA*
Expensive because it plans for many unlikely cases

Monitoring/Replanning
Assume normal states, outcomes
Check progress *during execution*, replan if necessary
Unanticipated outcomes may lead to failure (e.g., no AAA card)

(Really need a combination; plan for likely/serious eventualities,
deal with others when they arise, as they must eventually)

Search in space of belief states (sets of possible actual states)

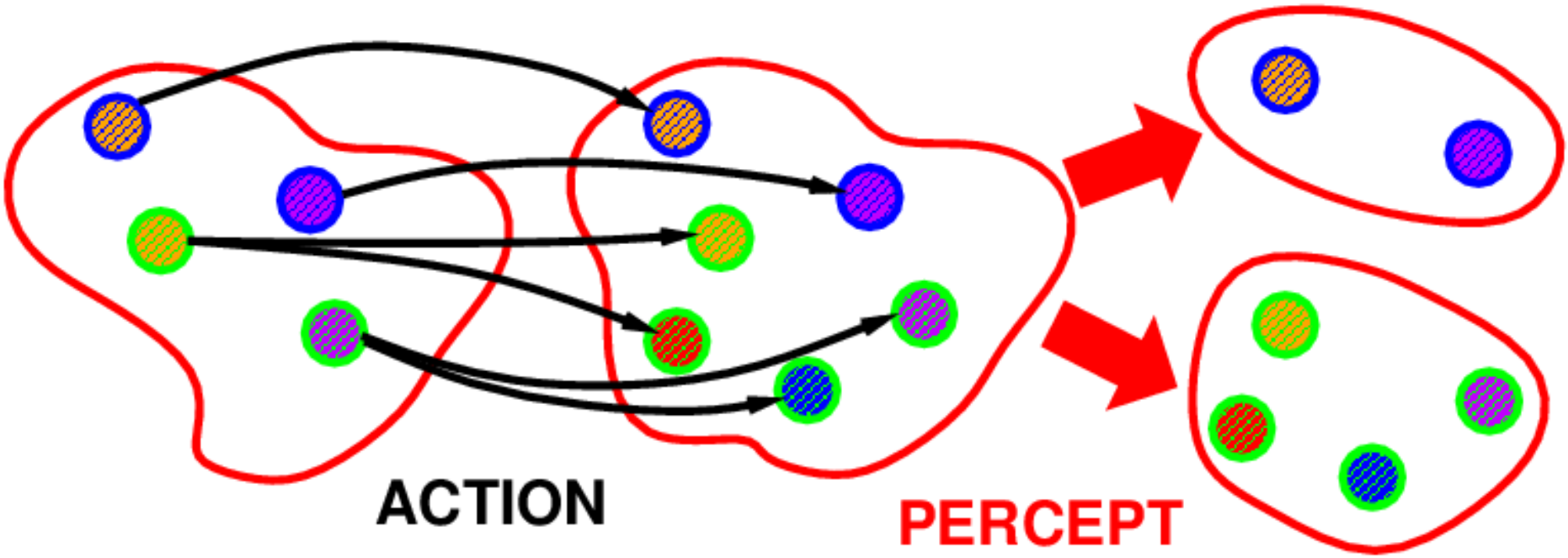


Conditional Planning

If the world is nondeterministic or partially observable

then percepts usually *provide information*,

i.e., *split up* the belief state



Conditional Planning (continued)

Conditional plans check (any consequence of KB +) percept
$[\ldots, \textbf{if } C \textbf{ then } \mathit{Plan}_A \textbf{ else } \mathit{Plan}_B, \ldots]$

Execution: check C against current KB, execute "then" or "else"

Need *some* plan for *every* possible percept
(Cf. game playing: *some* response for *every* opponent move)
(Cf. backward chaining: *some* rule such that *every* premise satisfied

AND–OR tree search (very similar to backward chaining algorithm)

AND-OR-GRAPH-SEARCH for Conditional Planning

function AND-OR-GRAPH-SEARCH(*problem*) **returns** a conditional plan, or failure

    OR-SEARCH(*problem*.INITIAL-STATE,*problem*,[])

---

function OR-SEARCH(*state*, *problem*, *path*) **returns** a conditional plan, or failure

    if *problem*.GOAL-TEST(*state*) **then return** the empty plan
    if *state* is on *path* **then return** failure
    for each *action* **in** *problem*.ACTIONS(*state*) **do**
        plan ← AND-SEARCH(RESULTS(*state*, *action*), *problem*,[*state* | *path*])
        if *plan* ≠ *failure* **then return** [*action* | *plan*]
    return *failure*

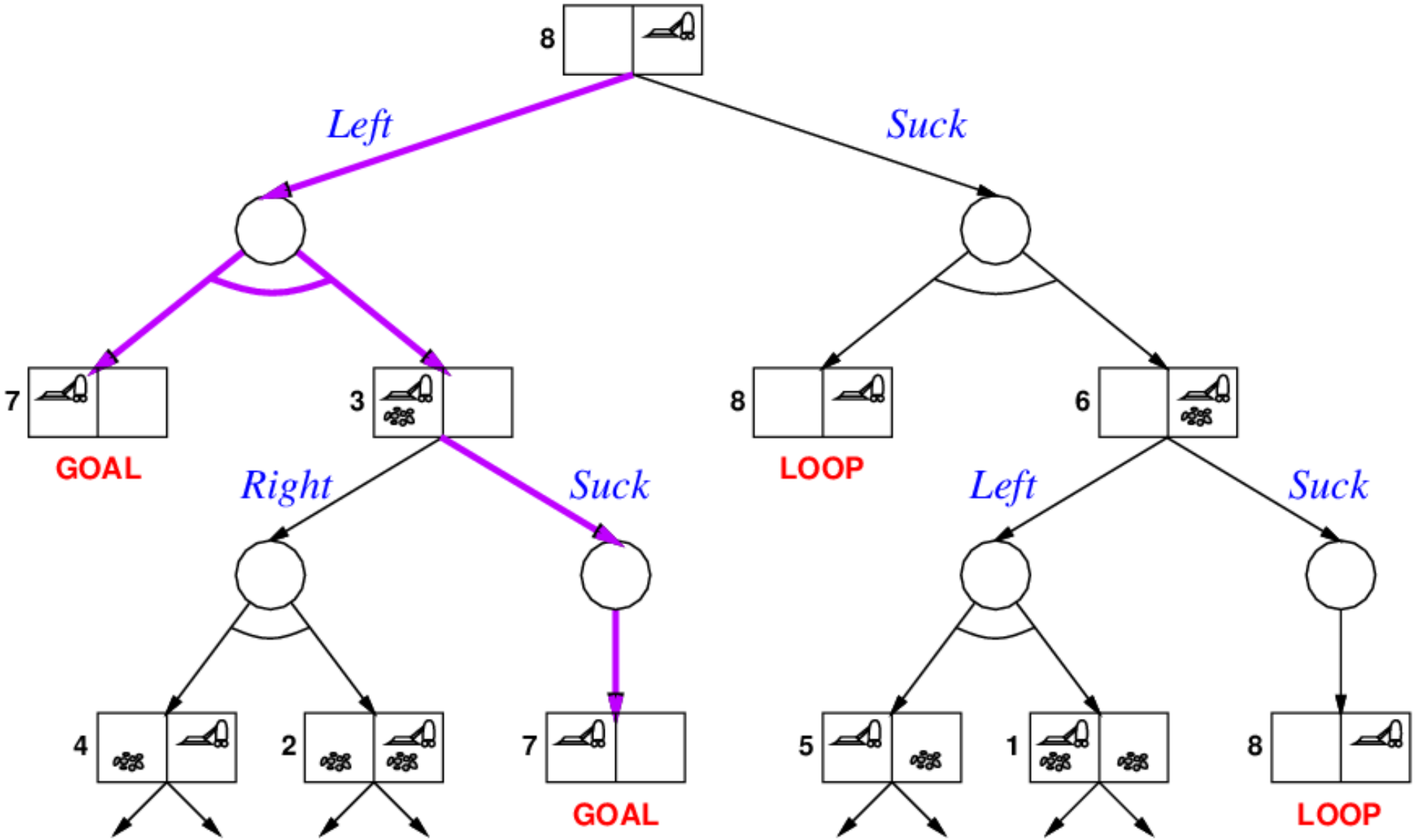
---

function AND-SEARCH(*states*, *problem*, *path*) **returns** a conditional plan, or failure

    for each s_i **in** *states* **do**
        $plan_i$ ← OR-SEARCH(s_i,*problem*, *path*)
        if *plan* = *failure* **then return** *failure*
    return [**if** s_1 **then** $plan_1$ **else if** s_2 **then** $plan_2$ **else** . . . **if** s_{n-1} **then** $plan_{n-1}$ **else** $plan_n$]

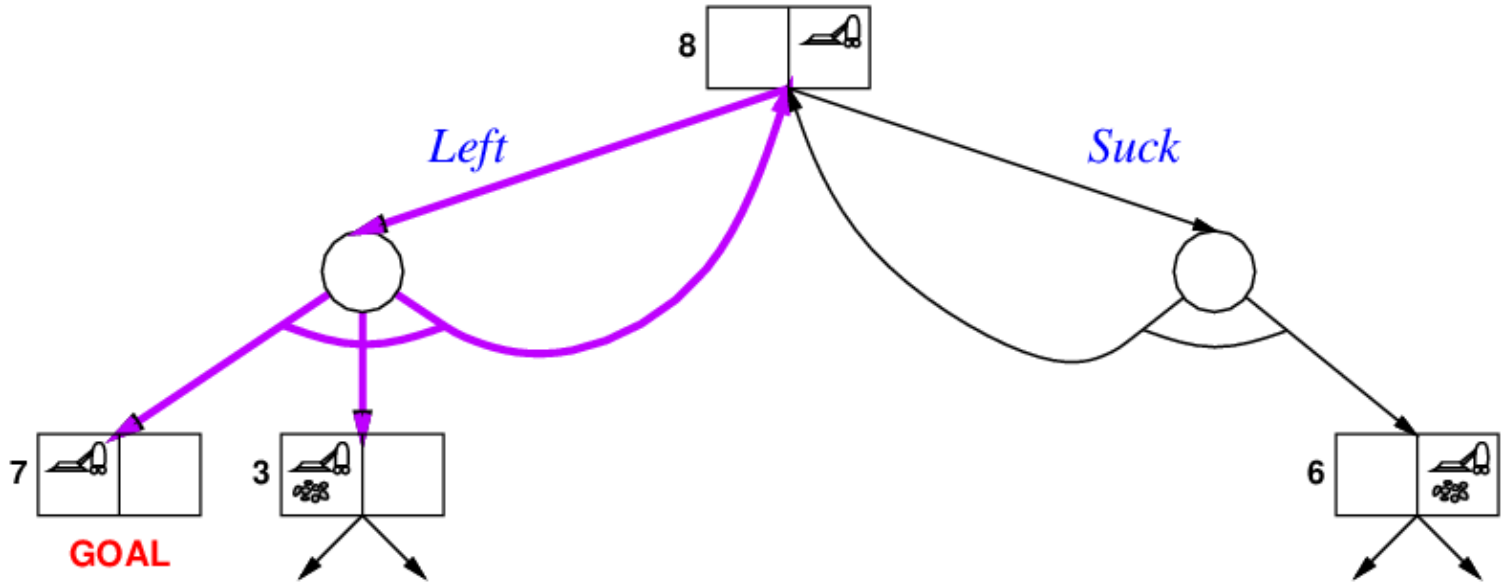
Nondeterministic Vacuum Cleaner

Double Murphy: sucking or arriving may dirty a clean square



Nondeterministic Vacuum Cleaner

Triple Murphy: also sometimes stays put instead of moving



$[L_1 : \ Left, \textbf{if } AtR \textbf{ then } L_1 \textbf{ else } [\textbf{if } CleanL \textbf{ then } [\,] \textbf{ else } Suck]]$

or $[\textbf{while } AtR \textbf{ do } [Left], \textbf{if } CleanL \textbf{ then } [\,] \textbf{ else } Suck]$

"Infinite loop" but will eventually work unless action always fails

Execution Monitoring - Replanning

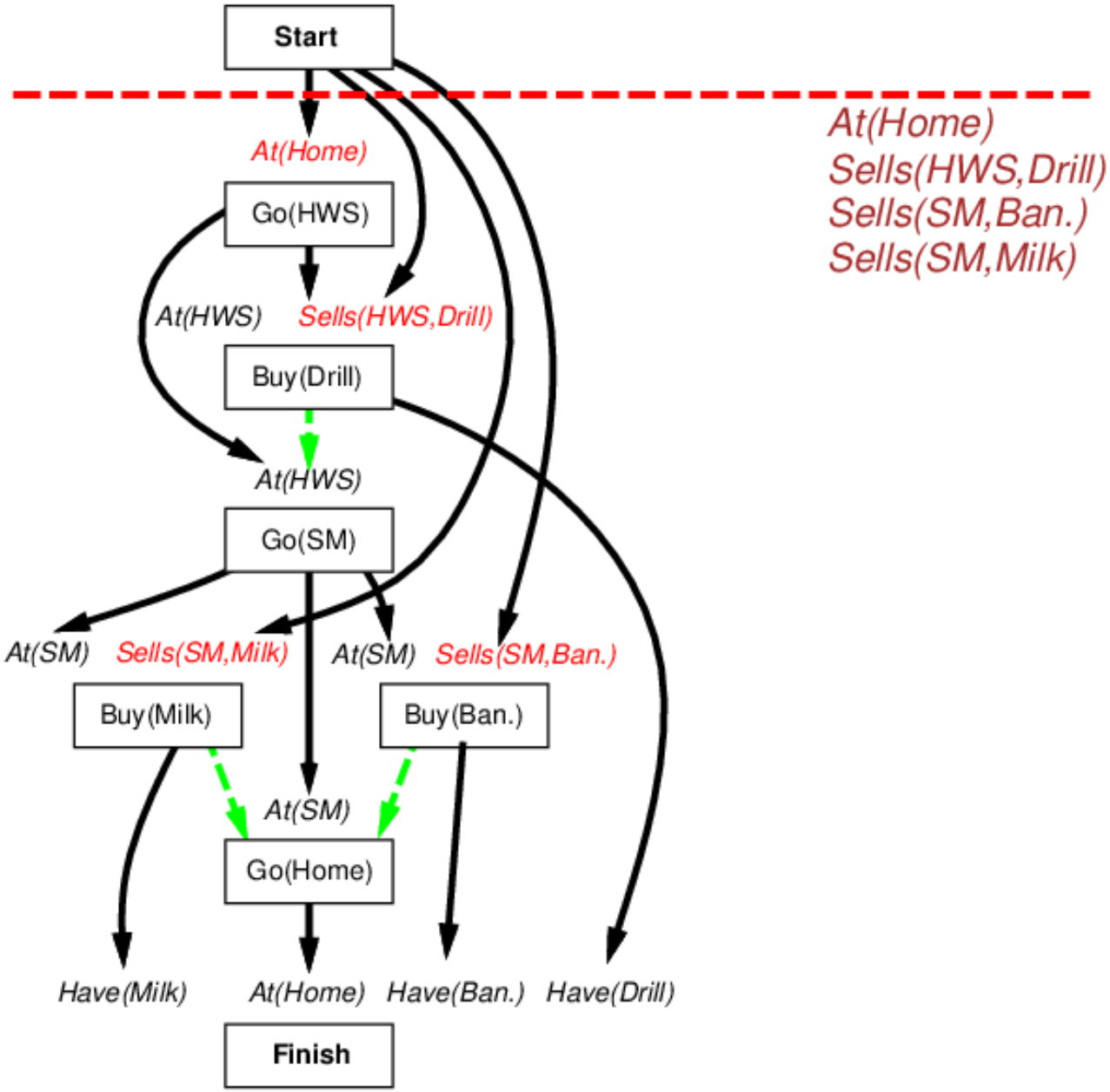
"Failure" = preconditions of *remaining plan* not met

Preconditions of remaining plan
= all preconditions of remaining steps not achieved by remaining steps
= all causal links *crossing* current time point

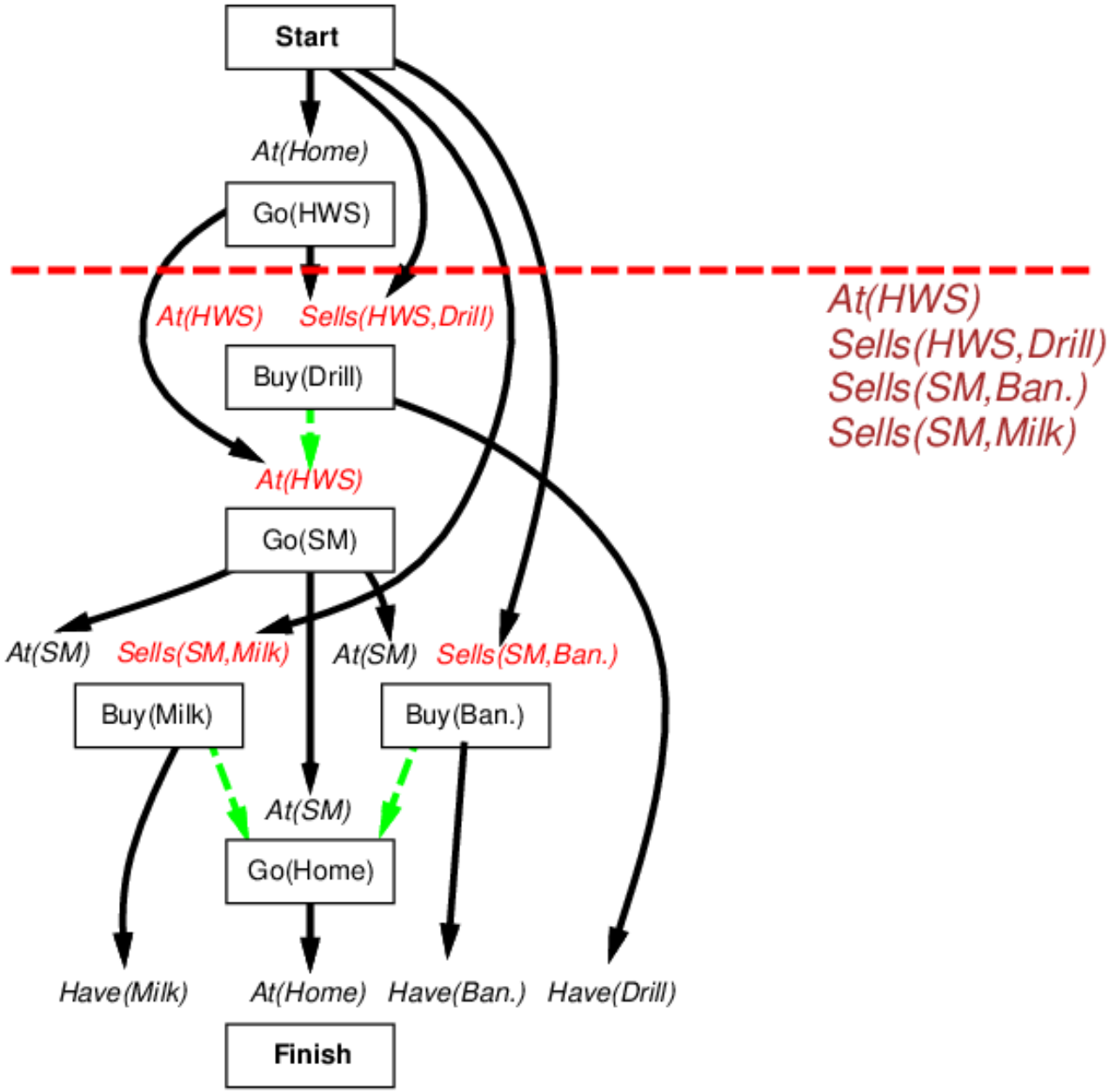
On failure, resume POP to achieve open conditions from current state

IPEM (Integrated Planning, Execution, and Monitoring):
keep updating *Start* to match current state
links from actions replaced by links from *Start* when done

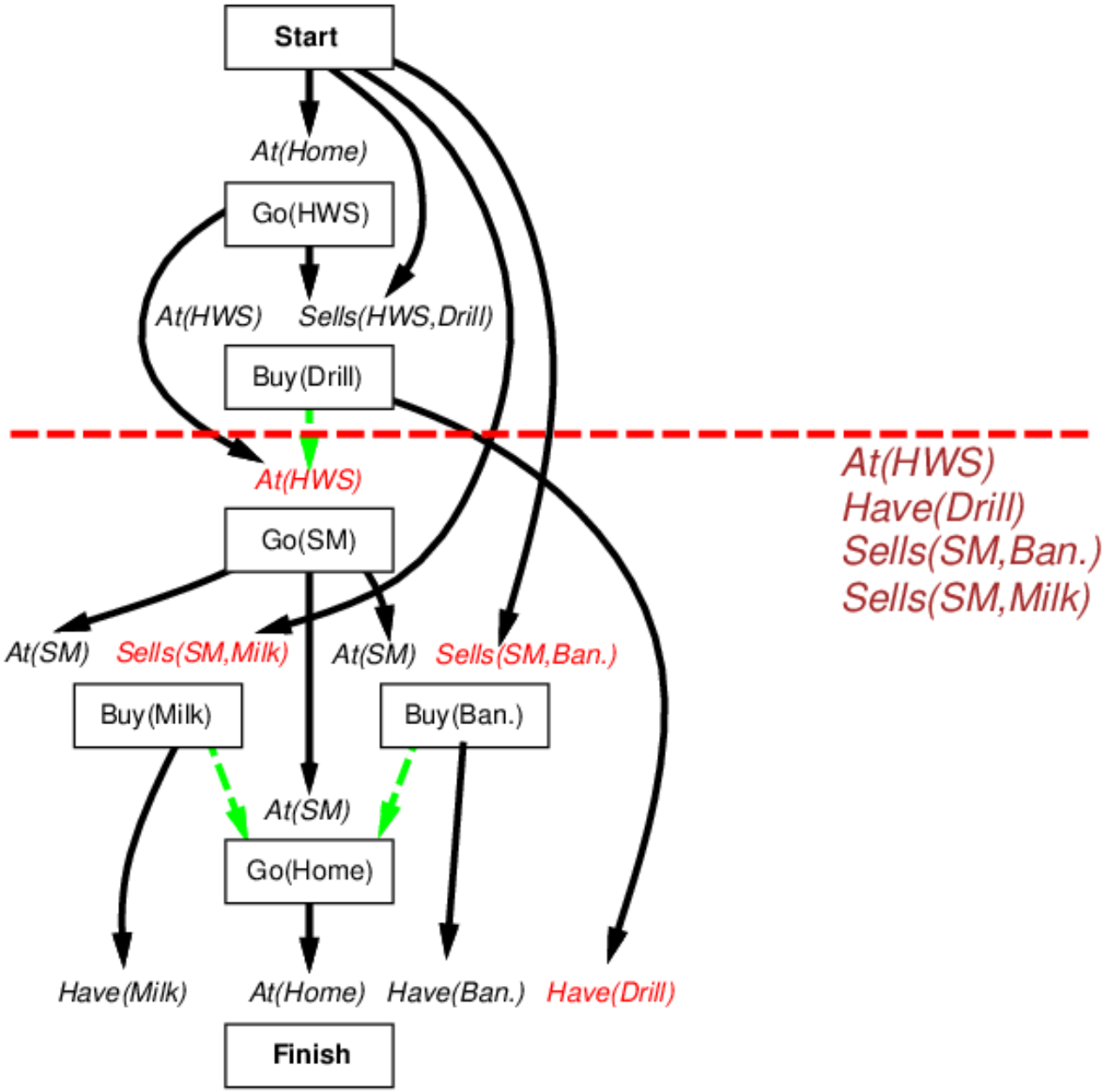
Example


Start
At(Home)
Sells(HWS,Drill)
Sells(SM,Ban.)
Sells(SM,Milk)
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

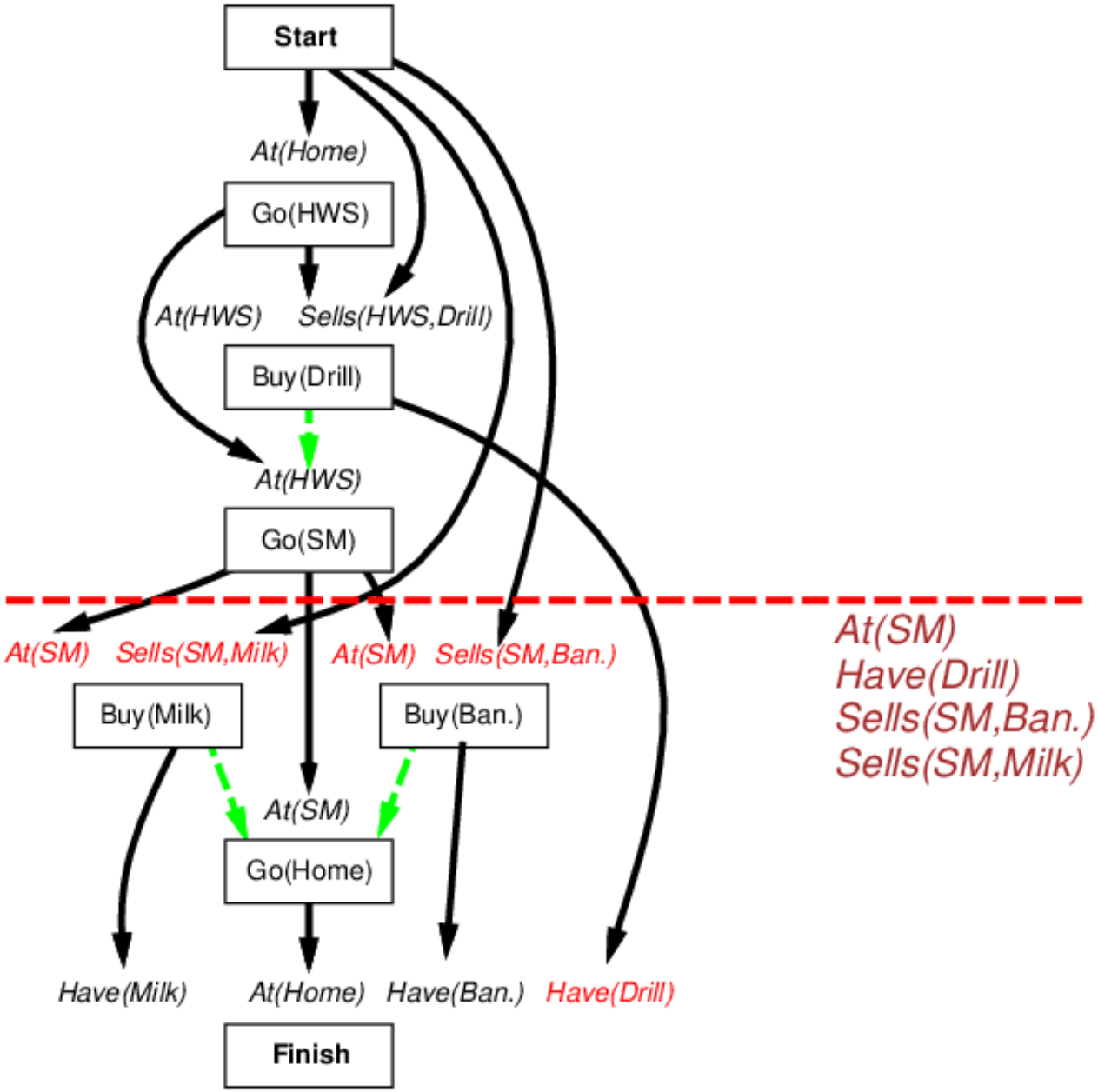
Example


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)
Sells(HWS,Drill)
Sells(SM,Ban.)
Sells(SM,Milk)

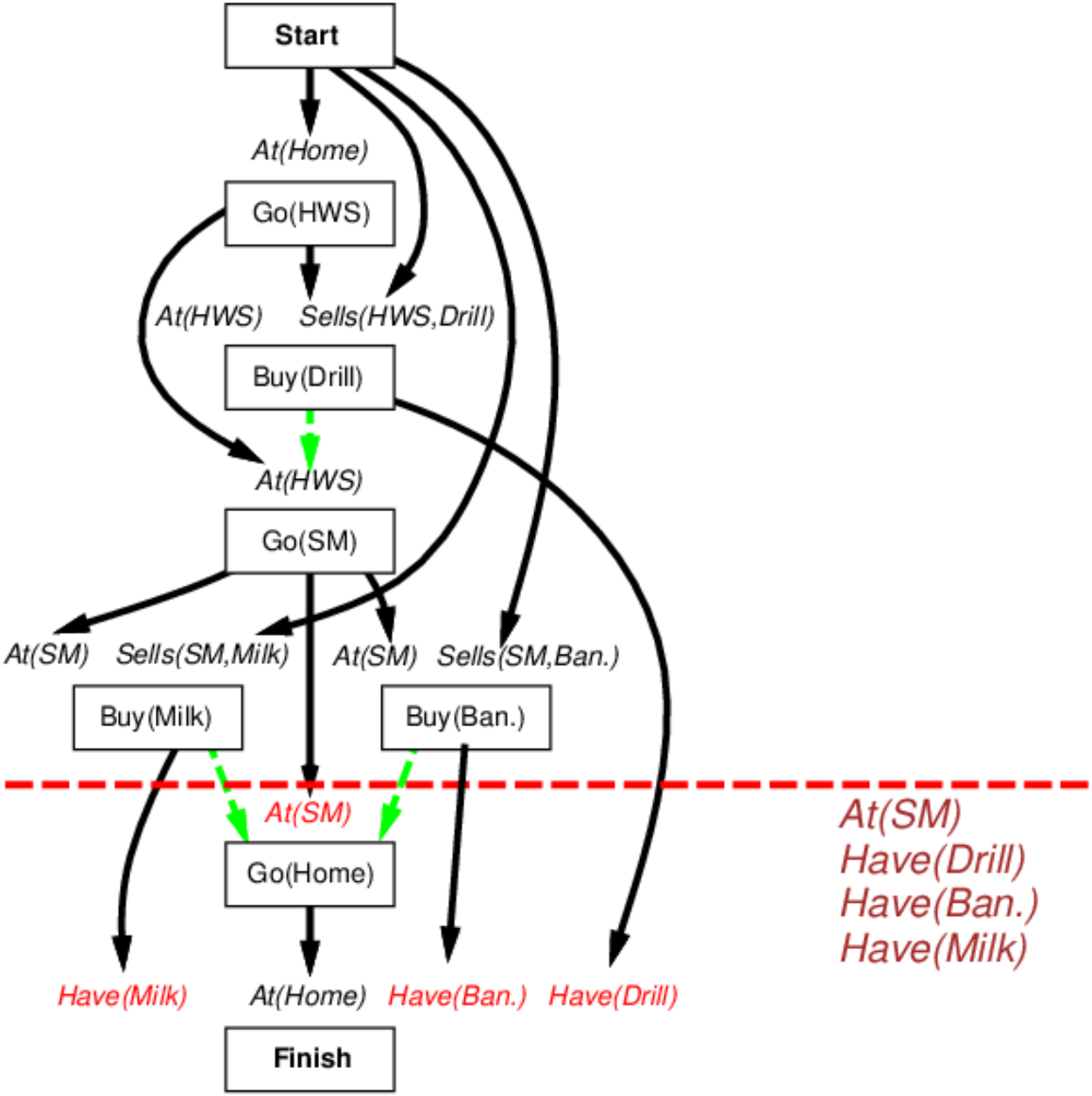
Example


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)

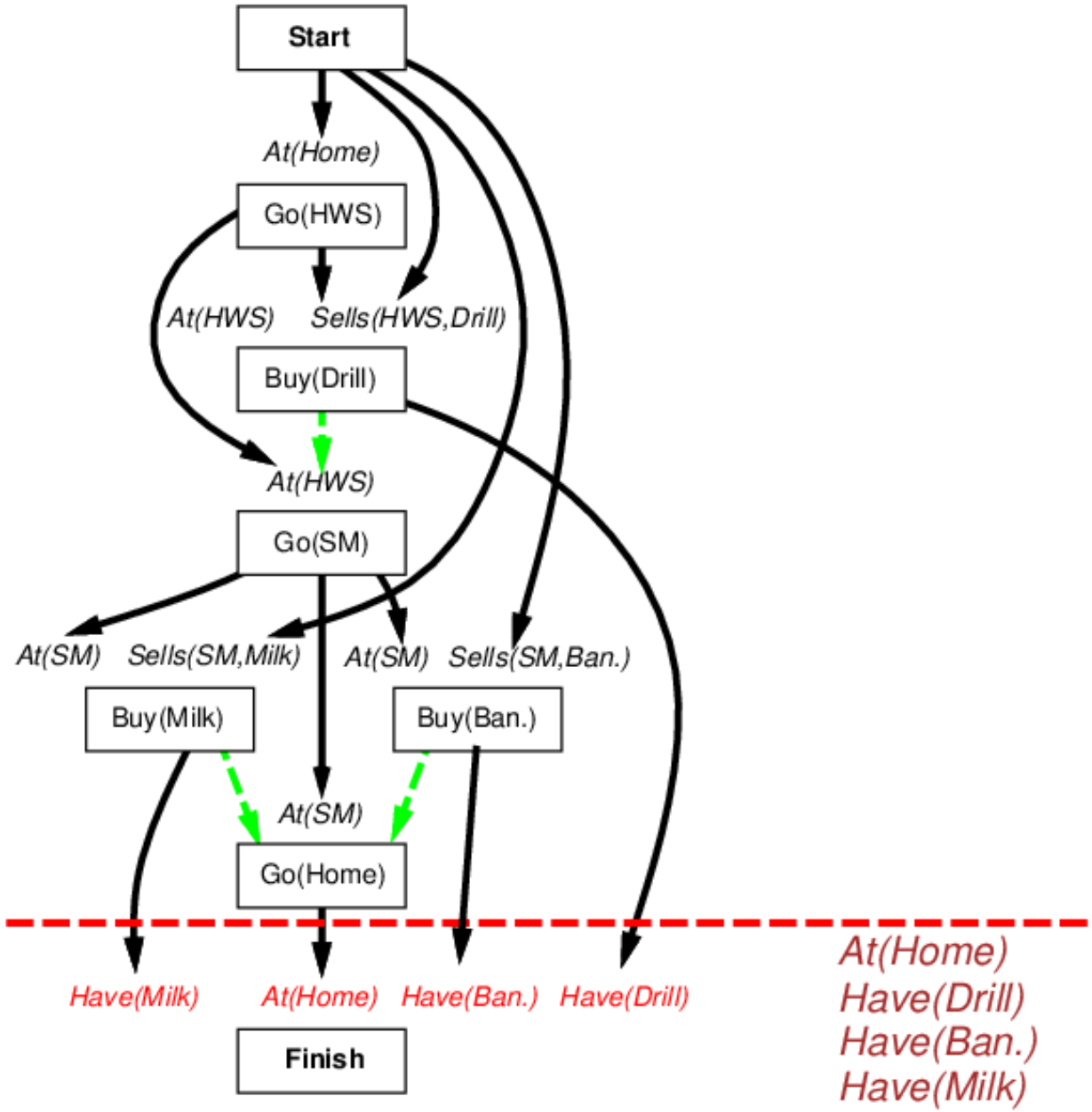
Example

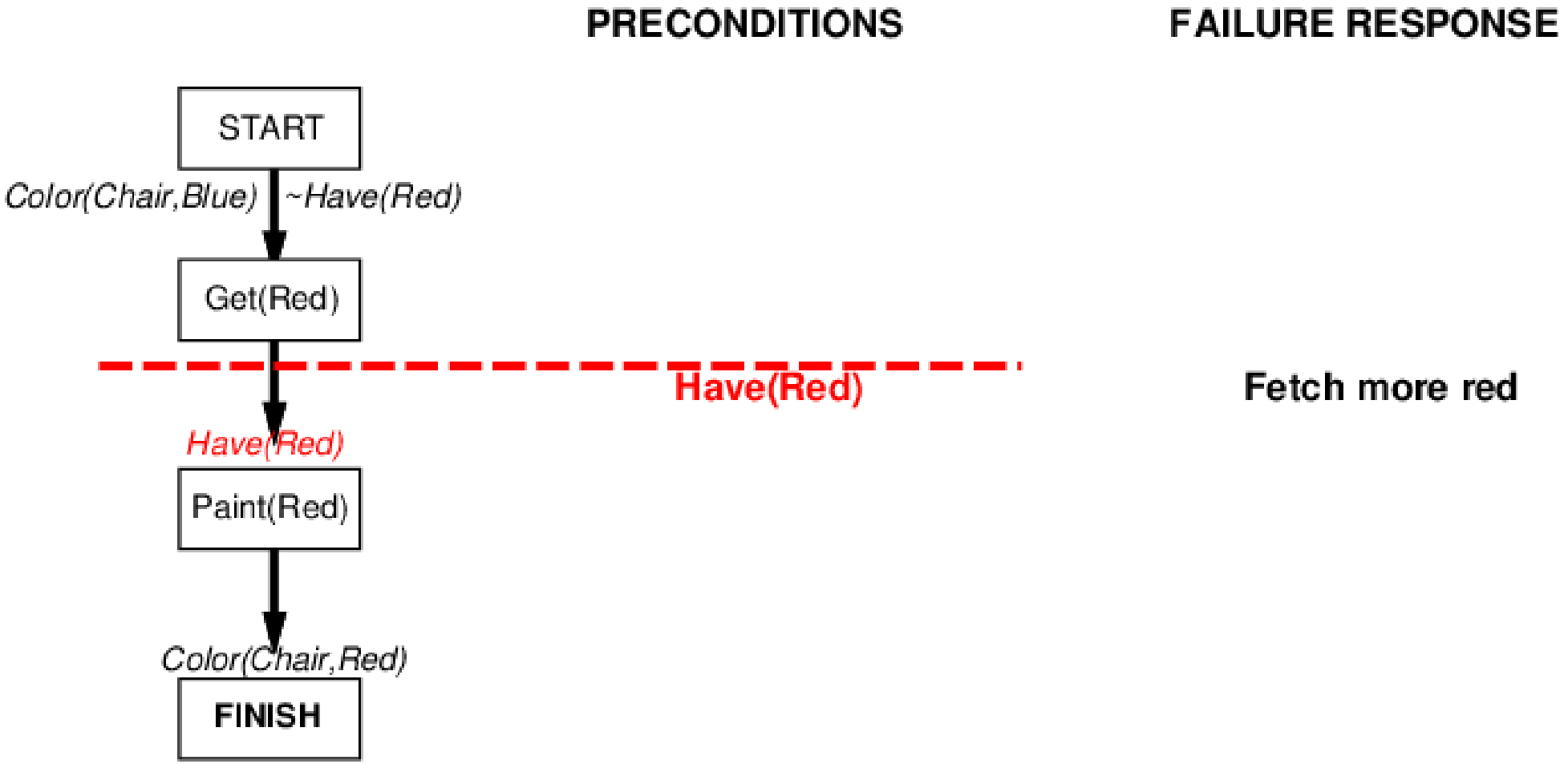

Start
At(Home)
Go(HWS)
At(HWS)
Sells(HWS,Drill)
Buy(Drill)
At(HWS)
Go(SM)
At(SM)
Sells(SM,Milk)
At(SM)
Sells(SM,Ban.)
Buy(Milk)
Buy(Ban.)
At(SM)
Go(Home)
Have(Milk)
At(Home)
Have(Ban.)
Have(Drill)
Finish
At(SM)
Have(Drill)
Sells(SM,Ban.)
Sells(SM,Milk)

Example

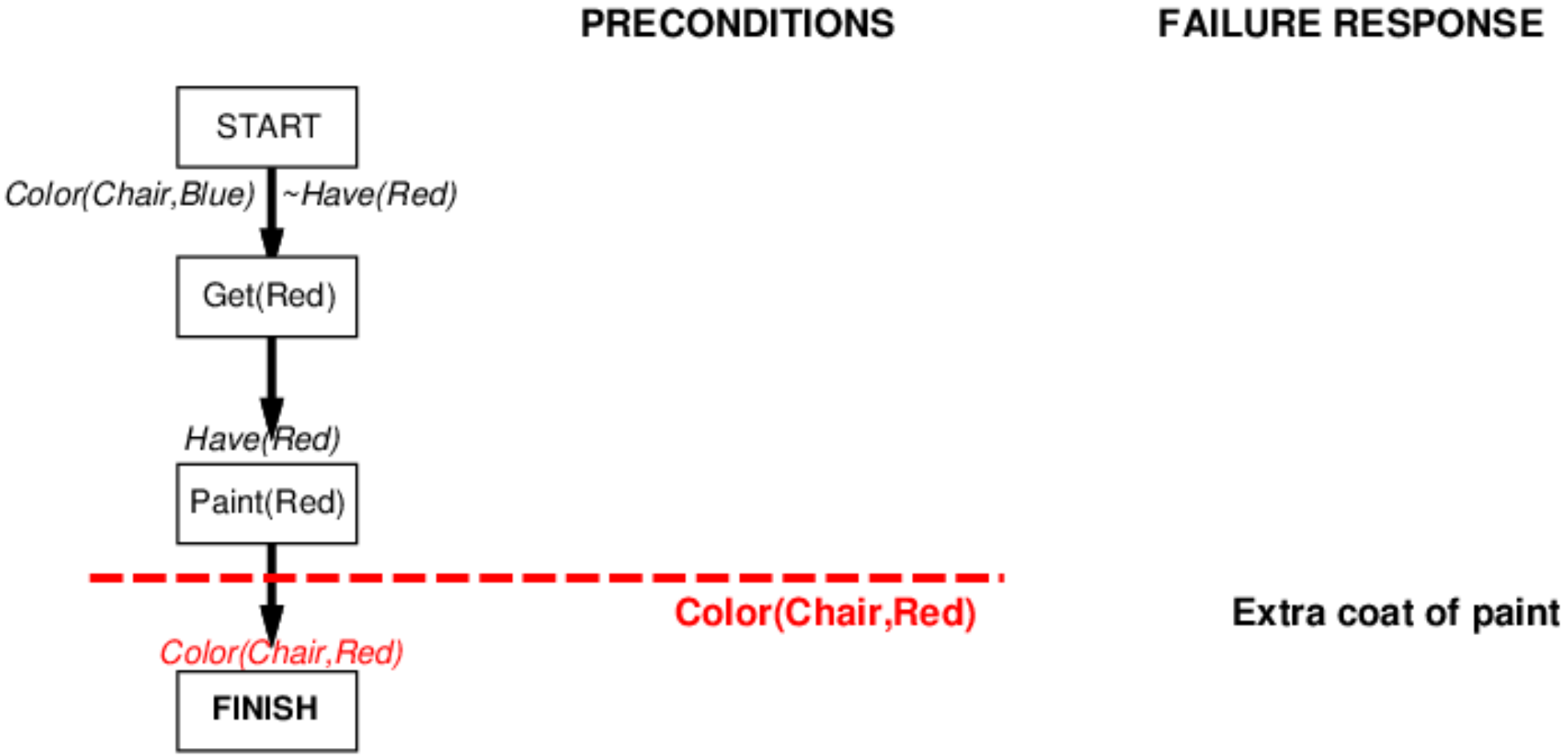

Start
At(Home)
Go(HWS)
At(HWS)
Sells(HWS,Drill)
Buy(Drill)
At(HWS)
Go(SM)
At(SM)
Sells(SM,Milk)
At(SM)
Sells(SM,Ban.)
Buy(Milk)
Buy(Ban.)
At(SM)
Go(Home)
Have(Milk)
At(Home)
Have(Ban.)
Have(Drill)
Finish
At(SM)
Have(Drill)
Have(Ban.)
Have(Milk)

Example


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)

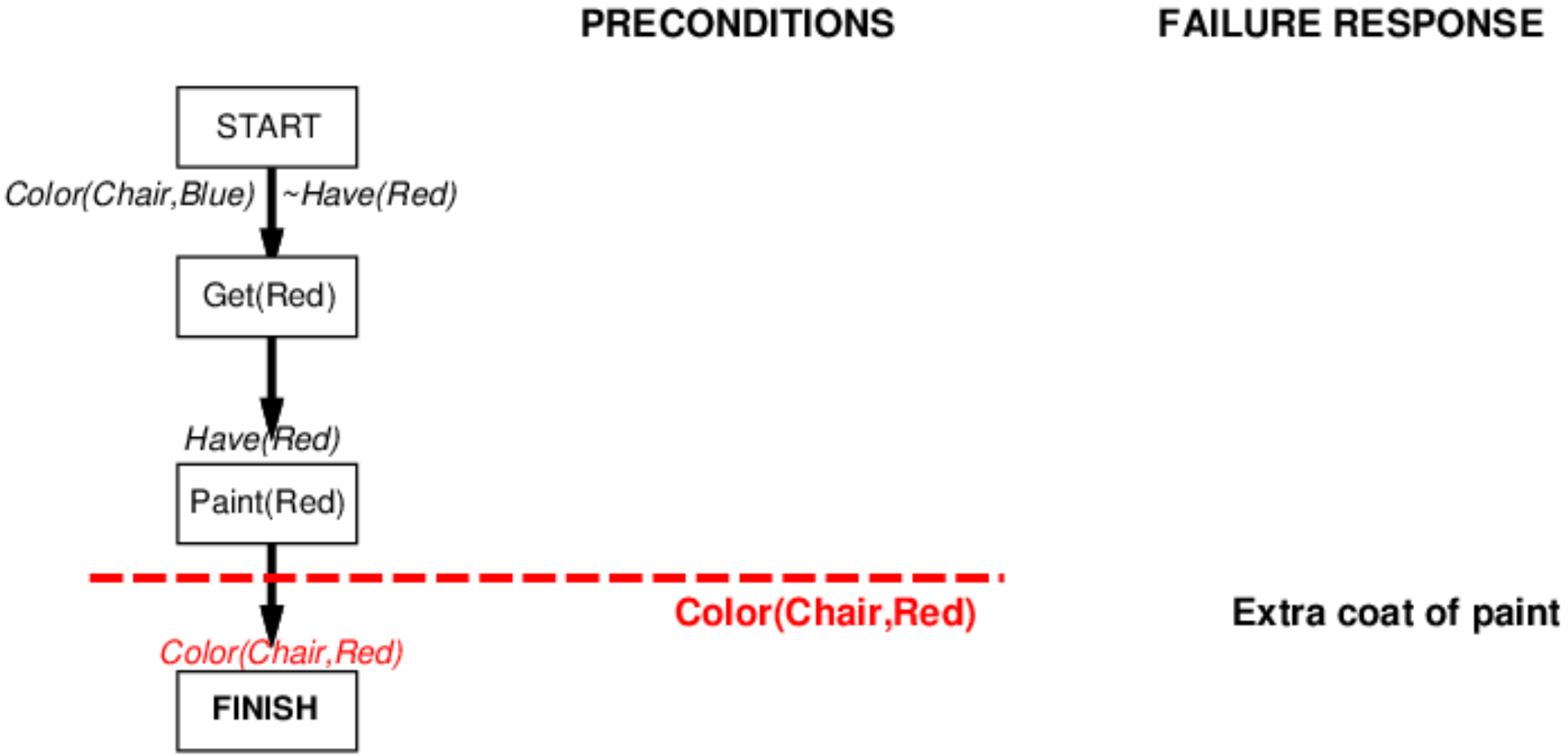

PRECONDITIONS
FAILURE RESPONSE
START
Color(Chair,Blue)
~Have(Red)
Get(Red)
Have(Red)
Fetch more red
Have(Red)
Paint(Red)
Color(Chair,Red)
FINISH

Emergent Behavior



"Loop until success" behavior *emerges* from interaction between monitor/replan agent design and uncooperative environment

Emergent Behavior



"Loop until success" behavior *emerges* from interaction between monitor/replan agent design and uncooperative environment