Chapter 11
Planning

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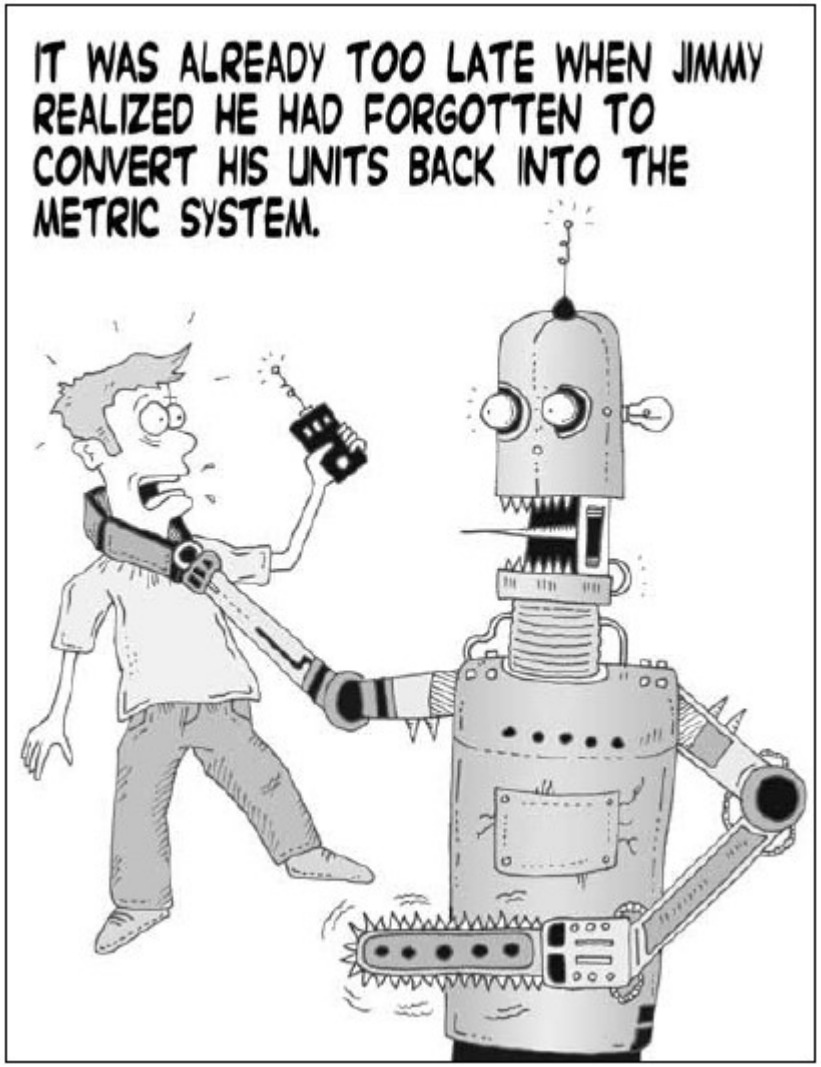


Real-World Problems

- Planning: the task of coming up with a sequence of actions that will achieve a goal
  - Search-based problem-solving agent
  - Logical planning agent
  - Complex/large scale problems?

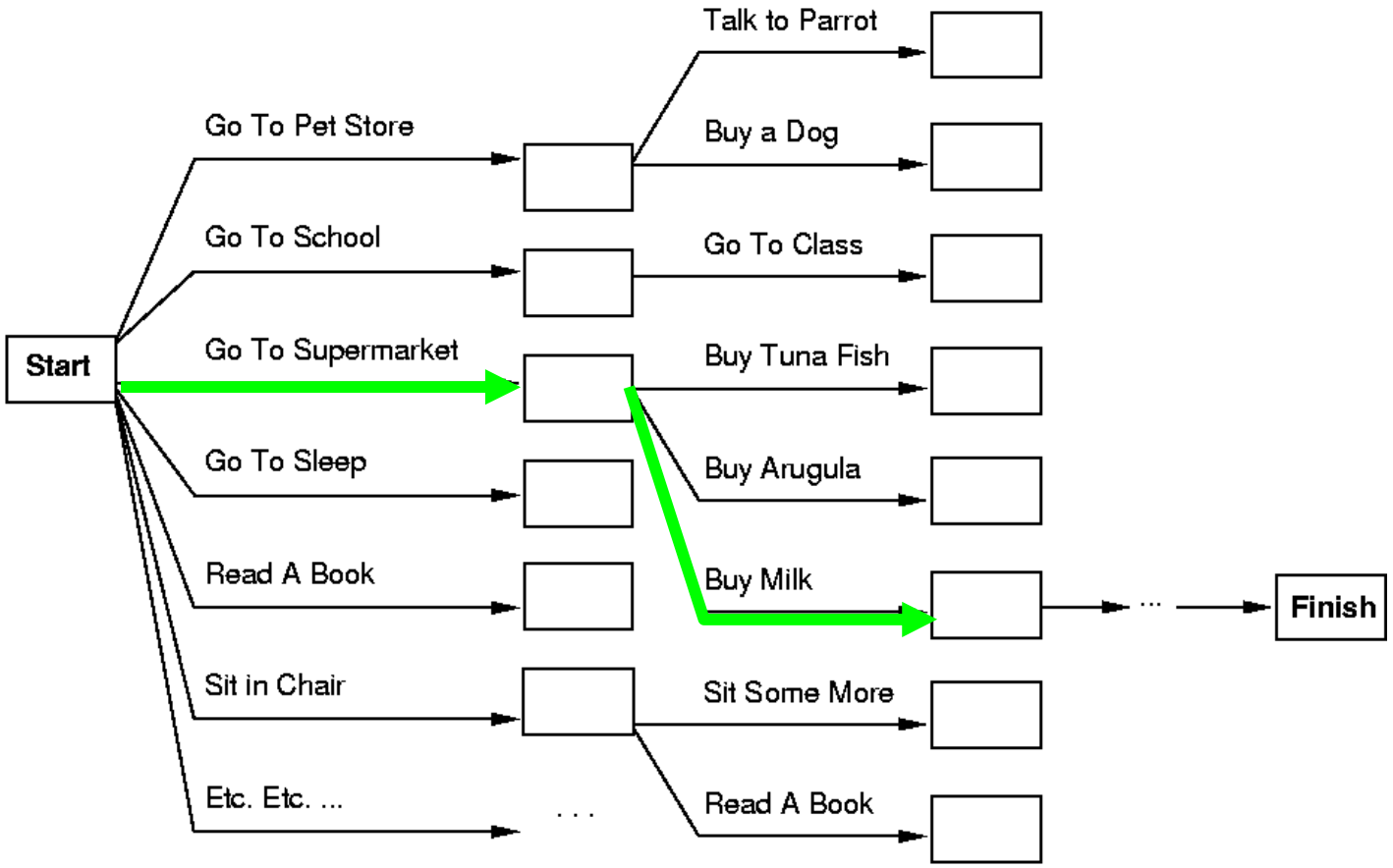
- For the discussion, we consider **classical planning environments** that are fully observable, deterministic, finite, static and discrete (in time, action, objects and effects)

Problems with Standard Search

- Overwhelmed by irrelevant actions
- Finding a good heuristic function is difficult
- Cannot take advantage of problem decomposition

Example

- Consider the task: get milk, bananas, and a cordless drill
  - Standard search algorithms seem to fail miserably
  - Why? Huge branching factor & heuristics



Problem Decomposition

- Perfectly decomposable problems are delicious but rare
  - Partial-order planner is based on the assumption that most real-world problems are **nearly decomposable**
  - Be careful, working on some subgoal may undo another subgoal

Planning vs. Problem Solving

- Planning agent is very similar to problem solving agent
  - Constructs plans to achieve goals, then executes them
- Planning agent is different from problem solving agent in:
  - Representation of goals, states, actions
  - Use of explicit, logical representations
  - Way it searches for solutions

Planning vs. Problem Solving

- Planning systems do the following:
  - divide-and-conquer
  - relax requirement for sequential construction of solutions

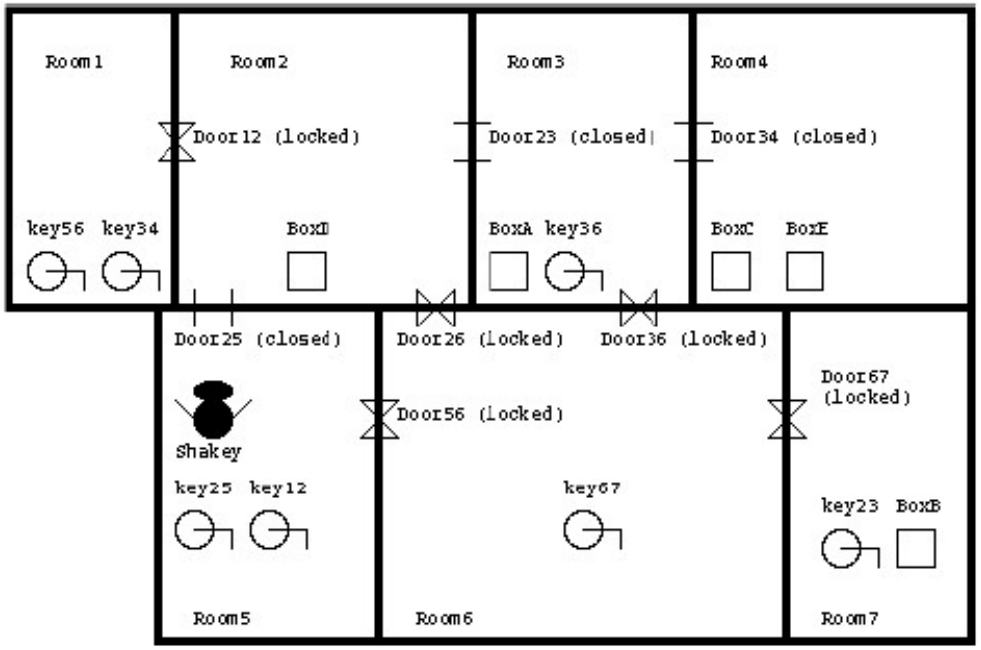
	Problem Sol.	**Planning**
States	data structures	logical sentences
Actions	code	preconditions/outcomes
Goal	code	logical sentences
Plan	sequence from s_0	constraints on actions

Famous Problem Solver Task: "Missionaries and Cannibals"

Planning-Based Approach to Robot Control

- Job of planner: generate a goal to achieve, and then construct a plan to achieve it from the current state

- Must define representations of:
  - Actions: generate successor state descriptions by defining preconditions and effects
  - States: data structure describing current situation
  - Goals: what is to be achieved
  - Plans: solution is a sequence of actions

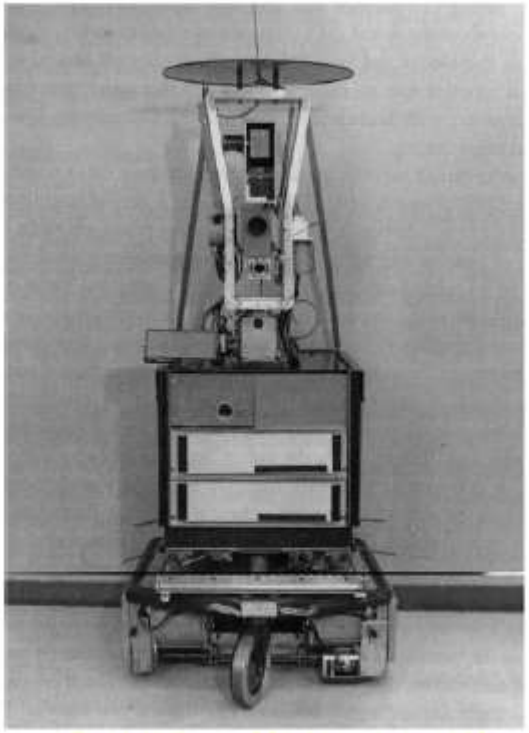


Many AI Planners in History

- Well-known AI Planners:
  - STRIPS (Fikes and Nilsson, 1971): theorem-proving system
  - ABSTRIPS (Sacerdoti, 1974): added hierarchy of abstractions
  - HACKER (Sussman, 1975): use library of procedures to plan
  - NOAH (Sacerdoti, 1975): problem decomposition and plan reordering

STRIPS-Based Approach to Robot Control

- Use first-order logic and theorem proving to plan strategies from start to goal
- STRIPS language:
  - "Classical" approach that most planners use
  - Lends itself to efficient planning algorithms
- Environment: office environment with specially colored and shaped objects
- STRIPS planner: developed for this system to determine the actions of the robot should take to achieve goals
- Cost of Shakey: $100, 000



Shakey (SRI), 1960's

STRIPS

- STRIPS (STanford Research Institute Problem Solver)
  - a restrictive way to express **states**, **actions** and **goals**, but leads to more efficiency

- States: conjunctions of ground, function-free, and positive literals, such as At(Home) ^ Have(Banana)
  - Closed-world assumption is used
- Goals: conjunctions of literals, may contain variables (existential), hence goal may represent more than one state
  - E.g. At(Home) ^ ¬ Have(Bananas)
  - E.g. At(x) ^ Sells(x, Bananas)
- Actions: preconditions that must hold before execution and the effects after execution

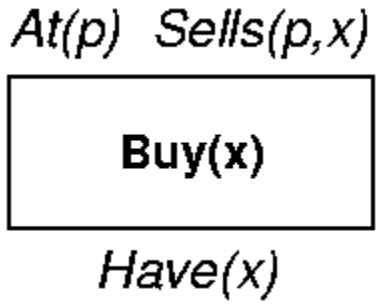
STRIPS Action Schema

- An action schema includes:
  - action name & parameter list (variables)
  - precondition: a conjunction of function-free positive literals. Any variables in it must also appear in parameter list
  - effect: a conjunction of function-free literals (positive or negative)
    - add-list: positive literals
    - delete-list: negative literals
- Example:

Action: Buy (x)

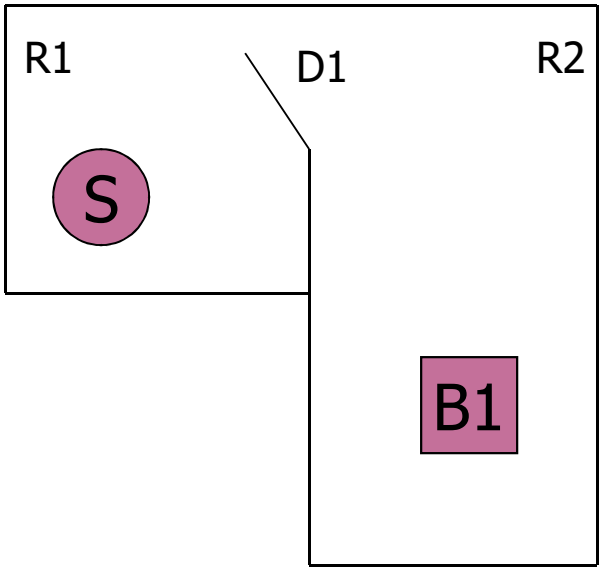
Precondition: At (p), Sells (p, x)

Effect: Have(x)



An Example of STRIPS World Model

- A world model is a set of facts
- The robot's knowledge can be represented by the following predicates:
  - INROOM(x, r), where x is a movable object, r is a room
  - NEXTTO(x, t)
  - STATUS(d, s), where d is a door, s means OPEN or CLOSED
  - CONNECTS(d, rx, ry)
- The world model in this figure can be represented with the above predicates, with the initial state and goal state

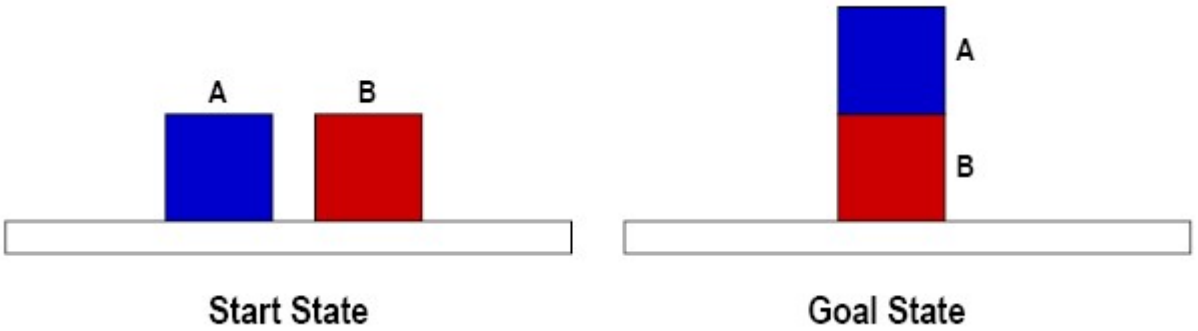


Shakey's STRIPS World

- Types of actions Shakey can make
  - Move from place to place:
    - GOTODOOR(S, dx):
      - PRECOND: INROOM(S, rk) ^ CONNECT(dx, rk, rm)
      - Effect:
        - add-list: NEXTTO(S, dx)
        - delete-list: null
    - GOTHRUDOOR(S, dx):
      - PRECOND: CONNECT(dx, rk, rm) ^ NEXTTO(S, dx) ^ STATUS(dx, OPEN) ^ INROOM(S, rk)
      - Effect:
        - add-list: INROOM(S, rm)
        - delete-list: INROOM(S, rk)

Simple Example of STRIPS-Style Planning

- Goal state: ON(A, B)
- Start state: ON(A, Table); ON(B, Table); EMPTYTOP(A); EMPTYTOP(B)
- Operators:
  - Move(x, y)
    - Preconditions: ?
    - Add-list: ?
    - Delete-list: ?



    - Preconditions: ON(x, Table); EMPTYTOP(y)
    - Add-list: ON(x, y)
    - Delete-list: EMPTYTOP(y); ON(x, Table)

Challenges of AI and Planning

- Closed world assumption: assumes that world model contains everything the robot needs to know: there can be no surprise

- Frame problem: how to represent real-world situations in a manner that is computationally tractable

Planning with State-Space Search

- Planning algorithms:
  - The most straightforward approach is to use state-space search
  - Forward state-space search (Progression)
  - Backward state-space search (Regression)

Problem Formulation for Progression

- Initial state:
  - Initial state of the planning problem
- Actions:
  - Applicable to the current state (actions' preconditions are satisfied)
- Goal test:
  - Whether the state satisfies the goal of the planning
- Step cost:
  - Each action is 1

Progression

- A plan is a sequence of STRIPS operators
- From initial state, search forward by selecting operators whose preconditions can be unified with literals in the state
- New state includes positive literals of effect; the negated literals of effect are deleted
- Search forward until goal unifies with resulting state
- This is state-space search using STRIPS operators

Regression

- A plan is a sequence of STRIPS operators
- The goal state must unify with at least one of the positive literals in the operator's effect
- Its preconditions must hold in the previous situation, and these become subgoals which might be satisfied by the initial conditions
- Perform backward chaining from goal
- Again, this is just state-space search using STRIPS operators

STRIPS Program To Control Shakey

- Work on board

Heuristics for State-Space Search

- How to find an admissible heuristic estimate?
  - Distance from a state to the goal?
  - Look at the effects of the actions and at the goals and guess how many actions are needed
  - NP-hard

- Relaxed problem
- Subgoal independence assumption:
  - The cost of solving a conjunction of subgoals is approximated by the sum of the costs of solving each subgoal independently

Relaxation Problem

- Idea: removing all preconditions from the actions
  - **Almost** implies that the number of steps required to solve a conjunction of goals is the number of unsatisfied goals
    - There may be two actions, each of which deletes the goal literal achieved by the other
    - Or, some action may achieve multiple goals
  - Combining relaxation with subgoal independence assumption → exact # of unsatisfied goals

Removing Negative Effects

- Generate a relaxed problem by removing negative effects:
  - Empty-delete-list heuristic
  - Quite accurate, but computing it involves running a simple planning algorithm

Extensions – ADL

- State: positive and negative literals
- Open world assumptions: unmentioned literals are unknown
- Effect: P ^ ¬ Q means add P and ¬ Q and delete ¬ P and Q
- Goal: quantified variables; conjunction and disjunction
- Effects: conditional effects
  - when P: E means E is an effect only if P is satisfied
- Equality predicate (x = y)
- Variables can have types (p: Plane)

Example: Air Cargo Transport

- Loading/unloading cargo onto/off planes and flying it from place to place.
- Actions: Load, Unload, and Fly
- States:
  - In(c, p): cargo c is inside plane p
  - At(x, a): object x (plane/cargo) at airport a

$$
\begin{aligned}
&Init(At(C_1, SFO) \land At(C_2, JFK) \land At(P_1, SFO) \land At(P_2, JFK) \\
&\quad \land Cargo(C_1) \land Cargo(C_2) \land Plane(P_1) \land Plane(P_2) \\
&\quad \land Airport(JFK) \land Airport(SFO)) \\
&Goal(At(C_1, JFK) \land At(C_2, SFO)) \\
&Action(Load(c, p, a), \\
&\quad \text{PRECOND}: At(c, a) \land At(p, a) \land Cargo(c) \land Plane(p) \land Airport(a) \\
&\quad \text{EFFECT}: \neg At(c, a) \land In(c, p)) \\
&Action(Unload(c, p, a), \\
&\quad \text{PRECOND}: In(c, p) \land At(p, a) \land Cargo(c) \land Plane(p) \land Airport(a) \\
&\quad \text{EFFECT}: At(c, a) \land \neg In(c, p)) \\
&Action(Fly(p, from, to), \\
&\quad \text{PRECOND}: At(p, from) \land Plane(p) \land Airport(from) \land Airport(to) \\
&\quad \text{EFFECT}: \neg At(p, from) \land At(p, to))
\end{aligned}
$$

Example: Spare Tire Problem

- Initial state: a flat tire on the axle and a good spare tire in the trunk
- Goal state: have a good spare tire properly mounted onto the car's axle

$$
\begin{aligned}
&Init(At(Flat, Axle) \wedge At(Spare, Trunk)) \\
&Goal(At(Spare, Axle)) \\
&Action(Remove(Spare, Trunk), \\
&\quad \text{PRECOND: } At(Spare, Trunk) \\
&\quad \text{EFFECT: } \neg At(Spare, Trunk) \wedge At(Spare, Ground)) \\
&Action(Remove(Flat, Axle), \\
&\quad \text{PRECOND: } At(Flat, Axle) \\
&\quad \text{EFFECT: } \neg At(Flat, Axle) \wedge At(Flat, Ground)) \\
&Action(PutOn(Spare, Axle), \\
&\quad \text{PRECOND: } At(Spare, Ground) \wedge \neg At(Flat, Axle) \\
&\quad \text{EFFECT: } \neg At(Spare, Ground) \wedge At(Spare, Axle)) \\
&Action(LeaveOvernight, \\
&\quad \text{PRECOND:} \\
&\quad \text{EFFECT: } \neg At(Spare, Ground) \wedge \neg At(Spare, Axle) \wedge \neg At(Spare, Trunk) \\
&\qquad \wedge \neg At(Flat, Ground) \wedge \neg At(Flat, Axle))
\end{aligned}
$$

Total-Order Planning

- Forward/backward state-space searches are forms of totally ordered plan search
  - explore only strictly linear sequences of actions directly connected to the start or goal
  - cannot take advantages of problem decomposition

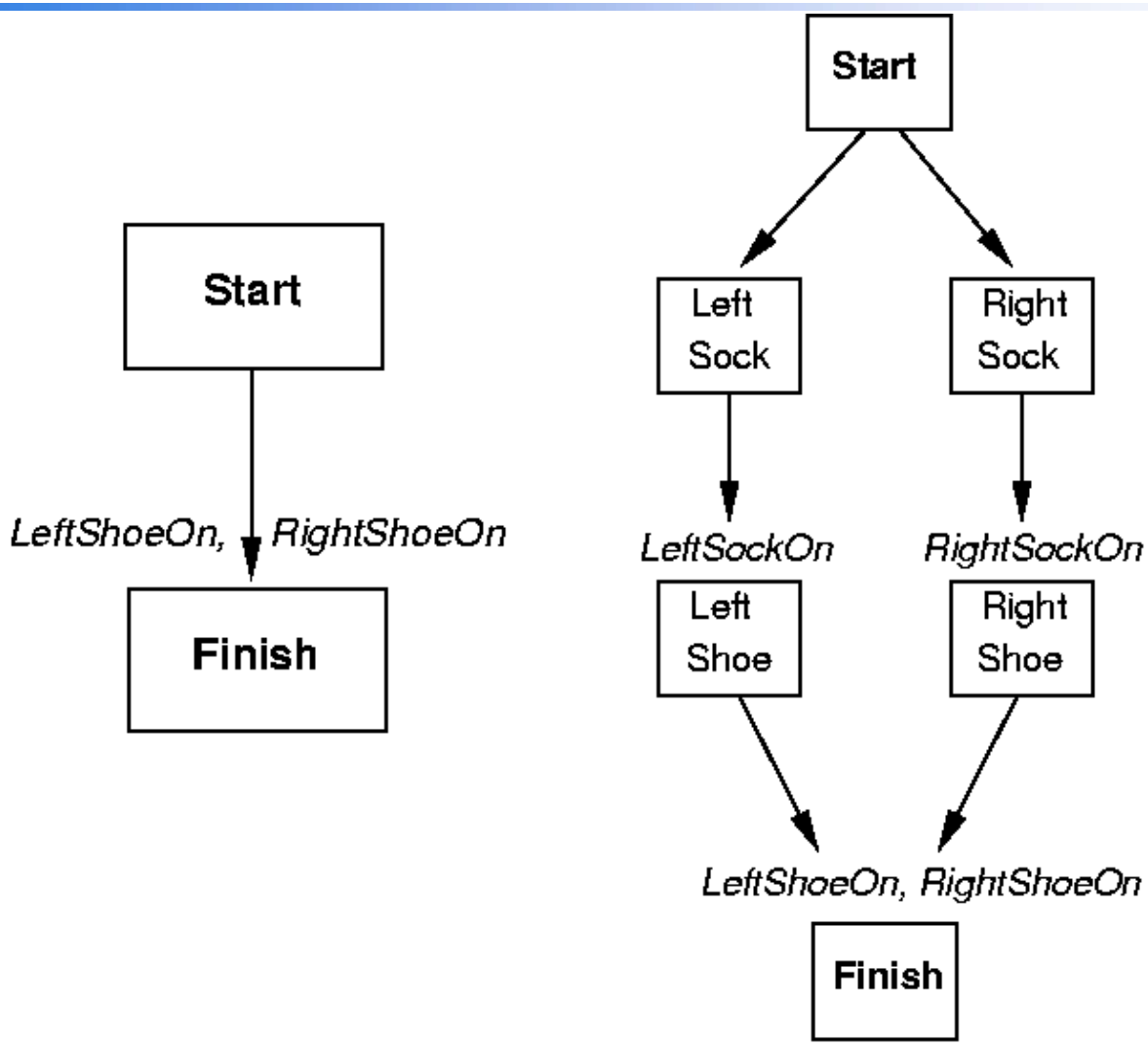
Partial-Order Planning

- Idea:
  - works on several subgoals independently
  - solves them with subplans
  - combines the subplans
  - flexibility in ordering the subplans
  - least commitment strategy:
    - delaying a choice during search
    - Example, leave actions unordered, unless they must be sequential

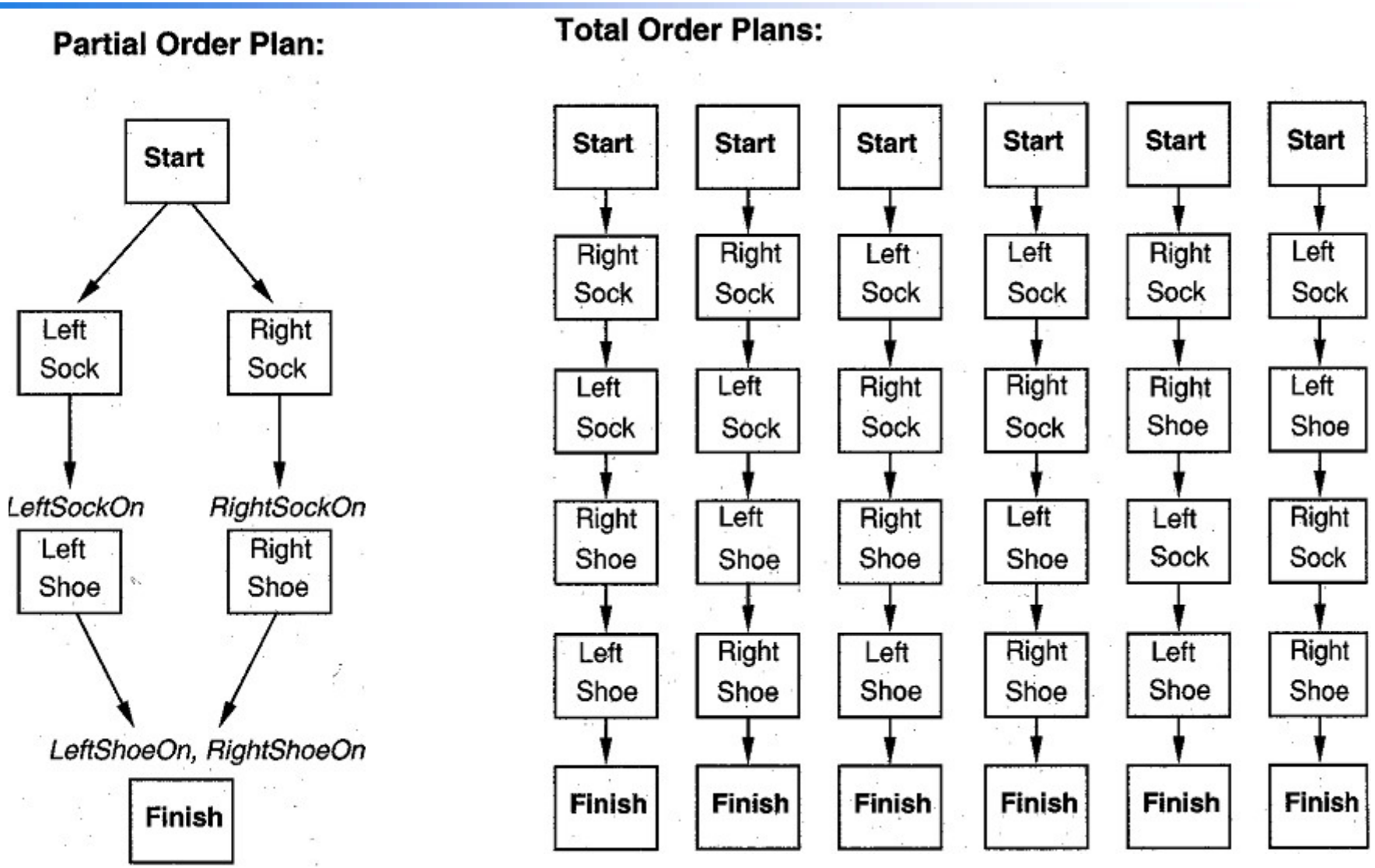
POP Example

- Putting on a pair of shoes:
  - Goal(RightShoeOn ^ LeftShoeOn)
  - Init()
  - Action: RightShoe
    - PRECOND: RightSockOn
    - EFFECT: RightShoeOn
  - Action: RightSock
    - PRECOND: None
    - EFFECT: RightSockOn
  - Action:LeftShoe
    - PRECOND: LeftSockOn
    - EFFECT: LeftShoeOn
  - Action: LeftSock
    - PRECOND: None
    - EFFECT: LeftSockOn

POP Example


Start
LeftShoeOn, RightShoeOn
Finish
Start
Left Sock
Right Sock
LeftSockOn
RightSockOn
Left Shoe
Right Shoe
LeftShoeOn, RightShoeOn
Finish

Partial Order Plan to Total Order Plan

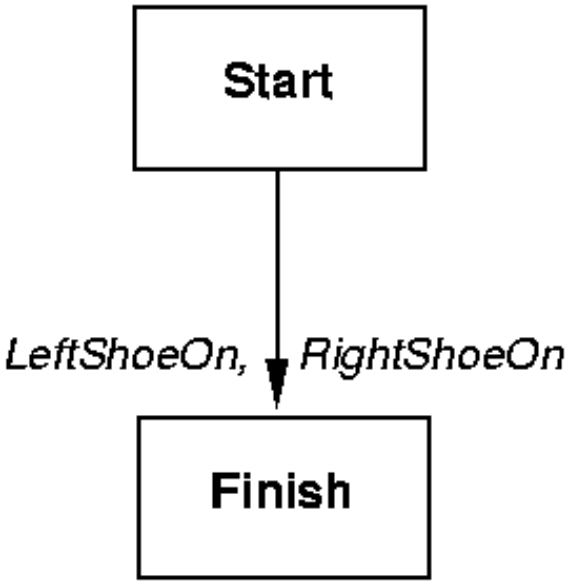


How to Define Partial Order Plan?

- A set of actions that make up the steps of the plan
- A set of ordering constraints: $A \prec B$
  - A before B
- A set of causal links: $A \xrightarrow{p} B$
  - A achieves p for B $RightSock \xrightarrow{RightSockOn} RightShoe$
  - May be conflicts if C has the effect of $\neg p$ and if C comes after A and before B
- A set of open preconditions:
  - a precondition is open if it is not achieved by some action in the plan

The Initial Plan

- Initial plan contains:
  - Start:
    - PRECOND: none
    - EFFECT: Add all propositions that are initially true
  - Finish:
    - PRECOND: Goal state
    - EFFECT: none
- Ordering constraints: $Start \prec Finish$
- Causal links: {}
- Open preconditions: {preconditions of Finish}



Next…

- Successor function
  - arbitrarily picks one open precondition *p* on an action *B* and generates a successor plan for every possible consistent way of choosing an action *A* that achieves *p*
  - Consistency:
    - Causal link $A \xrightarrow{p} B$ and the ordering constraint are added ($A \prec B \quad Start \prec A \quad A \prec Finish$)
    - Resolve conflict: add $B \prec C$ or $C \prec A$
- Goal test:
  - There are no open preconditions

Example: Final Plan

- The final plan has the following components:
  - **Actions**: {RightSock, RightShoe, LeftSock, LeftShoe, Start, Finish}
  - **Orderings**: {RightSock ‹ RightShoe, LeftSock ‹ LeftShoe}
  - **Open preconditions**: {}
  - **Links**:

$$RightSock \xrightarrow{RightSockOn} RightShoe$$

$$LeftSock \xrightarrow{LeftSockOn} LeftShoe$$

$$RightShoe \xrightarrow{RightShoeOn} Finish$$

$$LeftShoe \xrightarrow{LeftShoeOn} Finish$$

Example Algorithm for POP

- POP: A sound, complete partial order planner using STRIPS representation

```
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
```

where: * c is a precondition of a step S_{need}
* RESOLVE-THREATS: orders steps as needed to ensure intermediate steps don't undo preconditions needed by other steps

POP Example: Flat Tire

$Init(At(Flat, Axle) \wedge At(Spare, Trunk))$
$Goal(At(Spare, Axle))$
$Action(Remove(Spare, Trunk),$
PRECOND: $At(Spare, Trunk)$
EFFECT: $\neg At(Spare, Trunk) \wedge At(Spare, Ground))$
$Action(Remove(Flat, Axle),$
PRECOND: $At(Flat, Axle)$
EFFECT: $\neg At(Flat, Axle) \wedge At(Flat, Ground))$
$Action(PutOn(Spare, Axle),$
PRECOND: $At(Spare, Ground) \wedge \neg At(Flat, Axle)$
EFFECT: $\neg At(Spare, Ground) \wedge At(Spare, Axle))$
$Action(LeaveOvernight,$
PRECOND:
EFFECT: $\neg At(Spare, Ground) \wedge \neg At(Spare, Axle) \wedge \neg At(Spare, Trunk)$
$\wedge \neg At(Flat, Ground) \wedge \neg At(Flat, Axle))$

Strengths of POP

- The causal links lead to early pruning of portions of the search space because of irresolvable conflicts

- The solution is a partial-order plan
  - linearizations produce flexible plans

From Problem Solvers to Planners

- Key ideas:
  - "Open up" representation of states, goals, and actions
    - Use descriptions in a formal language – FOL
    - States/goals represented by sets of sentences
    - Actions represented by logical description of preconditions and effects
    - Enables planner to make direct connections between states and actions
  - Planner can add actions to plan whenever needed, rather than in strictly incremental fashion
    - No necessary connection between order of planning and order of execution
  - Most parts of the world are independent of most other parts of the world
    - Conjunctions can be separated and handled independently
    - Divide-and-conquer algorithms

Summary of Planning Problem

- Planning agents use look-ahead to find actions to contribute to goal achievement
- Planning agents differ from problem solvers in their use of more flexible representation of states, actions, goals, and plans
- The STRIPS language describes actions in terms of preconditions and effects
- Principle of least commitment is preferred
- POP is a sound and complete algorithm for planning using STRIPS representation

Exercise 1

- The monkey-and-bananas problem is faced by a monkey in a lab with some bananas hanging out of reach from the ceiling. A box is available that will enable the monkey to reach the bananas if he climbs on it.
- Initially the monkey is at A, bananas at B, the box at C. The monkey and box have height Low, but if the monkey climbs onto the box he will have height High, the same as the bananas.

Exercise 1 Cont'd

- Actions:
  - Go from one place to another
  - Push an object from one place to another
  - ClimbUp onto or ClimbDown from an object
  - Grasp or Ungrasp an object
  - The results of a Grasp is that the monkey holds the object if the monkey and object are in the same place at the same height.
- Questions
  - Write down the initial state description
  - Write down the goal state (monkey has banana at location D on the ground)
  - Write the six action schemas
  - Generate the plan

Exercise 2 & 3:

- Describe the differences and similarities between problem solving and planning.

- Explain why dropping negative effects from every action schema in a planning problem results in a relaxed problem.

Planning Domains

- Classical planning: fully observable, static, and deterministic; actions are correct and complete
- Incompleteness: partially observable, nondeterministic, or both
- Incorrectness: the world does not necessarily match my model of the world

Bounded/Unbounded Indeterminacy

- Bounded indeterminacy: actions have unpredictable effects, but the possible effects can be listed in the action description axioms

- Unbounded indeterminacy: the set of possible preconditions or effects either is unknown or is too large to be enumerated completely

Four Planning Methods For Handling Indeterminacy

- Sensorless planning: constructs sequential plans to be executed without perception
- Conditional planning (contingency planning): constructs a conditional plan with different branches for different contingencies that could happen
- Execution monitoring and replanning: uses preceding techniques to construct a plan, but it monitors the execution process and replan when necessary
- Continuous planning: a planner designed to persist over a lifetime

Example

- Scenario:
  - given an initial state with a chair, a table, and some cans of paint, with everything of unknown color, achieve the state where the chair and table have the same color
  - classical planning
  - sensorless planning
  - conditional planning
  - replanning

Planning With Partial Information

- We are familiar with: Deterministic, fully observable → single-state problem
  - agent knows exactly which state it will be in
  - solution is a sequence

- Deterministic, non-observable → multi-state problem
  - Also called sensorless problems (conformant problems)
  - agent may have no idea where it is
  - solution is a sequence

The Coloring Problem

- Initial state:
  - Object(Table) ^ Object(Chair) ^ Can(C1) ^ Can(C2) ^ InView(Table)
- Goal state:
  - Color(Chair, c) ^ Color (Table, c)
- Actions:
  - RemoveLid
  - Paint
  - LookAt

Sensorless Planning

- RemoveLid(Can1), Paint(Chair, Can1), Paint(Table, Can1)

Contingent planning

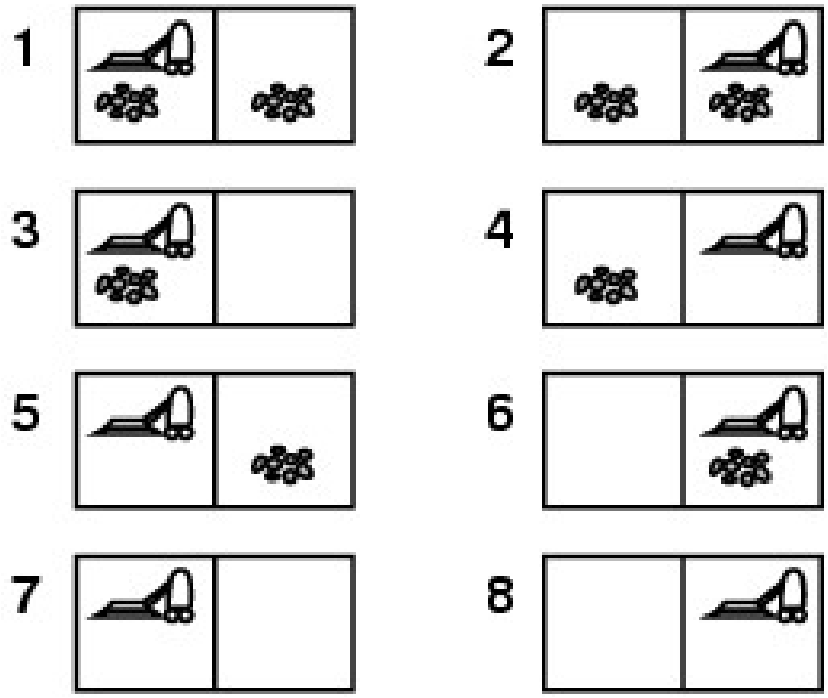
- LookAt(Table), LookAt(Chair)
- If Color(Table, c) ^ Color(Chair, c) then NoOp
- Else RemoveLid(Can1), LookAt(Can1), RemoveLid(Can2), LookAt(Can2)
- If Color(Table, c) ^ (Color(can, c), then Paint (Chair, can)
- If Color(Chair, c) ^ (Color(can, c), then Paint(Table, can)
- Else Paint(Chair, Can1), Paint(Table, Can1)

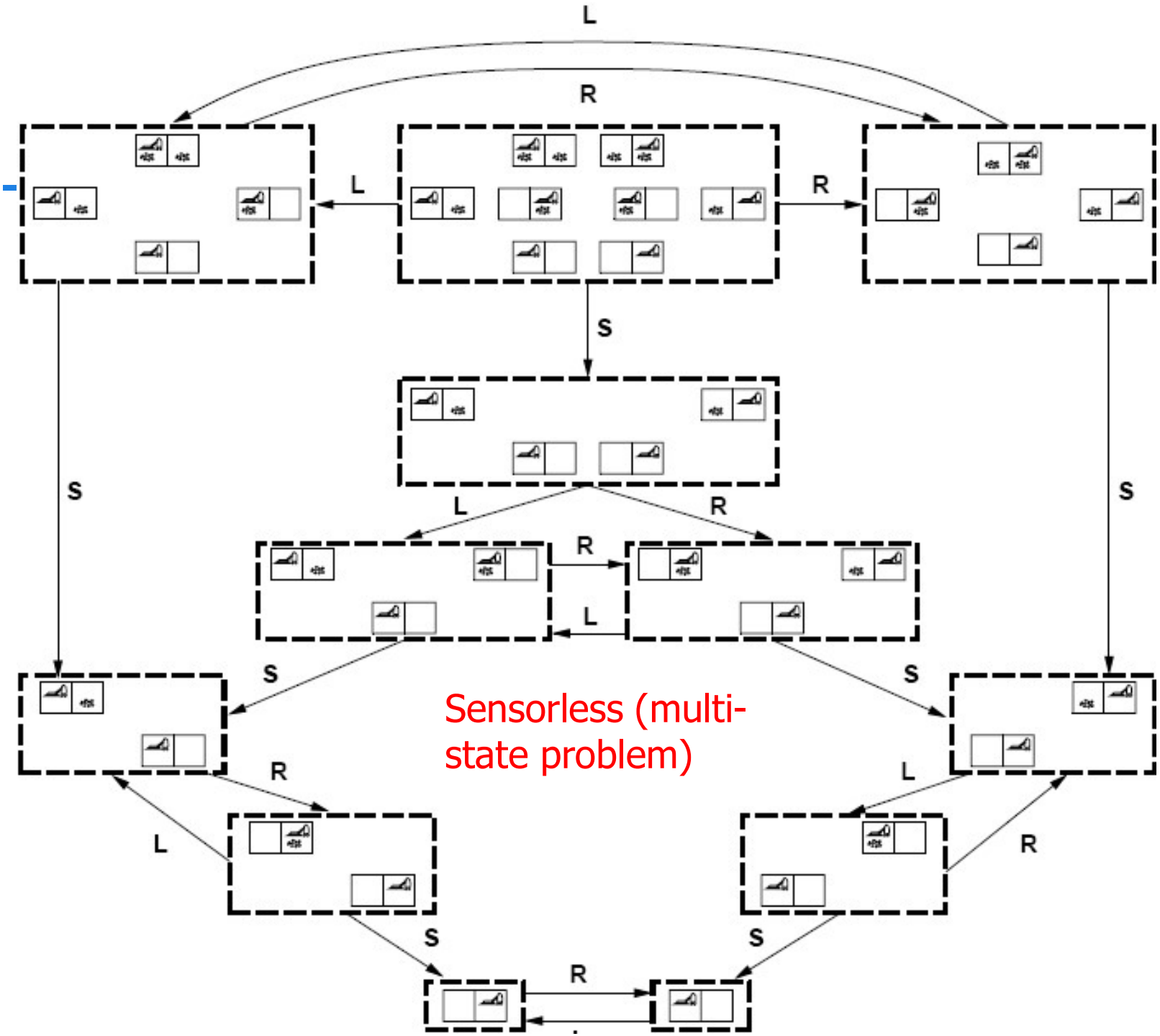
Replanning

- LookAt(Table), LookAt(Chair)
- If Color(Table, c) ^ Color(Chair, c) then NoOp
- Else RemoveLid(Can1), LookAt(Can1)
- If Color(Table, c) ^ Color(Can1, c) then Paint (Chair, Can1)
- Else replan

Example: Vacuum World

- Single-state, start in #5. Solution?
  - [Right, Suck]
- Multi-state, start in #[1, 2, …, 8]. Solution?
  - [Right, Suck, Left, Suck]





Sensorless (multi-state problem)

Conditional Planning in Fully Observable Environments

- Full observability means that the agent always knows the current state
- Non-deterministic, because the agent cannot predict the outcome of its actions
- The agent is able to check the state of the environment to decide what to do next
- Revisit our vacuum world example
  - Let AtL (AtR) be true if the agent is in the left (right) square
  - Let CleanL (CleanR) be true if the left (right) square is clean

Disjunctive, Conditional Effects

- To augment the STRIPS language to allow for nondeterminism, we allow actions to have **disjunctive effects** and **conditional effects**
- Conditional effect: $\text{when} < condition > : < effect >$

$$Action(Left, PRECOND: AtR,\ EFFECT: AtL \vee AtR)$$

$$Action(Suck, PRECOND:,\ EFFECT: (\text{when } AtL: CleanL) \wedge (\text{when } AtR: CleanR))$$

A vacuum cleaner that may dump dirt on the destination square when it moves, but only if that square is clean

$$Action(Left, PRECOND: AtR,\ EFFECT: AtL \vee (AtL \wedge \text{when } CleanL: \neg CleanL))$$

Conditional Plans

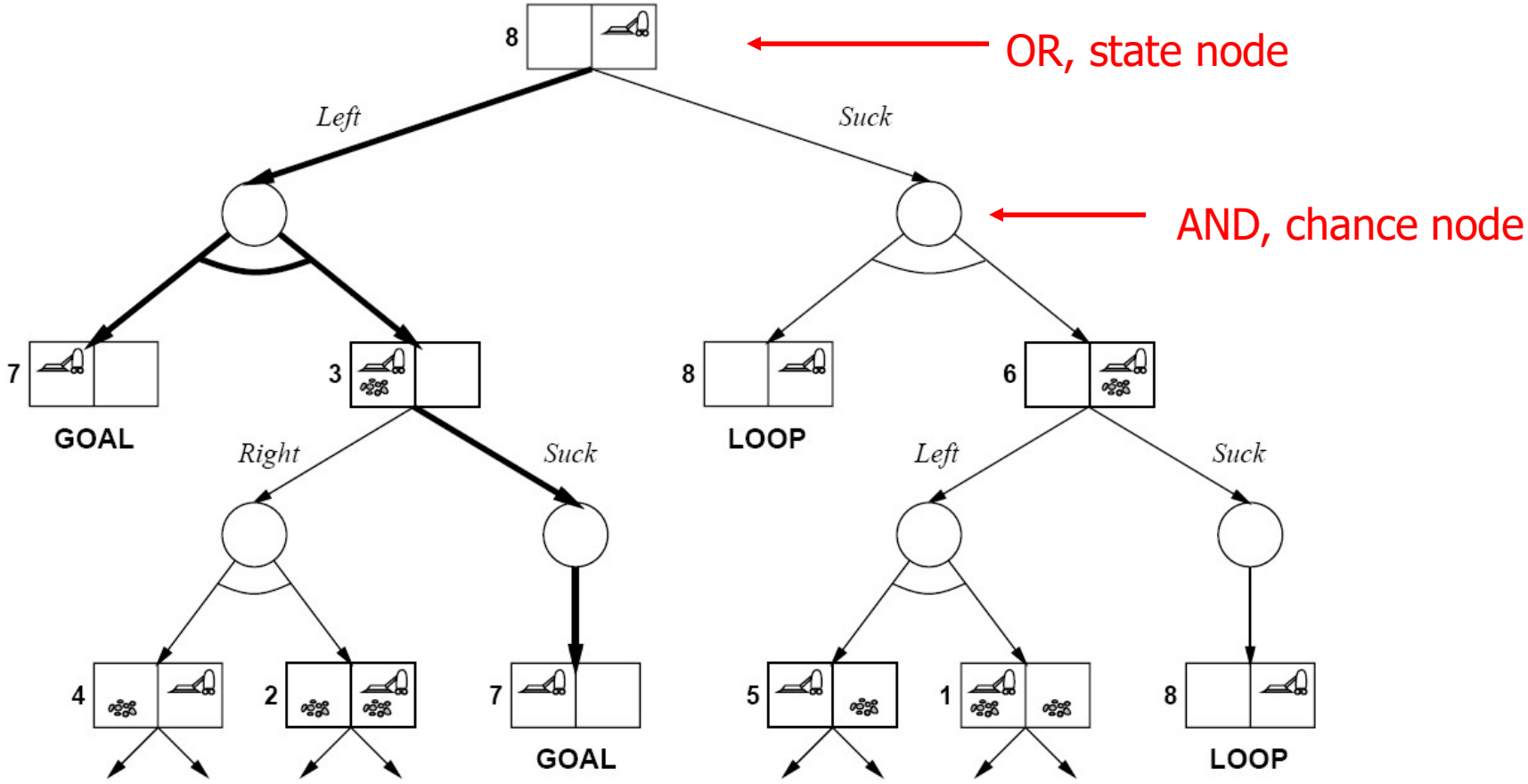
- To create conditional plans, we need conditional steps $\text{if } < test > \text{ then } plan\_A \text{ else } plan\_B$
  - For example $\text{if } AtL \wedge CleanL \text{ then } Right \text{ else } Suck$
  - By nesting conditional steps, plans become trees
  - In general, conditional plan should work *regardless of which action outcomes actually occur* -- games against nature

Consider the following vacuum cleaner:

The initial state has the robot in the right square of a clean world. The environment is fully observable. The goal state has the robot in the left square of a clean world.

It sometimes deposits dirt when it moves to a clean destination square and sometimes deposits dirt if Suck is applied to a clean square.

Example: Double-Murphy Cleaner



[Left, **if** CleanL **then** [] **else** Suck]

Solution

- A solution is a subtree that
  - has a goal node at every leaf
  - specifies one action at each of its "state" nodes
  - and includes every outcome branch at each its "chance" nodes

AND-OR Graph

- For conditional planning, we modify the minimax algorithm
  - MAX and MIN nodes become OR and AND nodes
    - the plan needs to take some action at every state, but must handle every outcome for the action it takes
  - The algorithm needs to return a conditional plan rather than just a single move
    - at an OR node, the plan is just the action selected
    - at an AND node, the plan is a nested series of if-then-else steps specifying subplans for each outcome

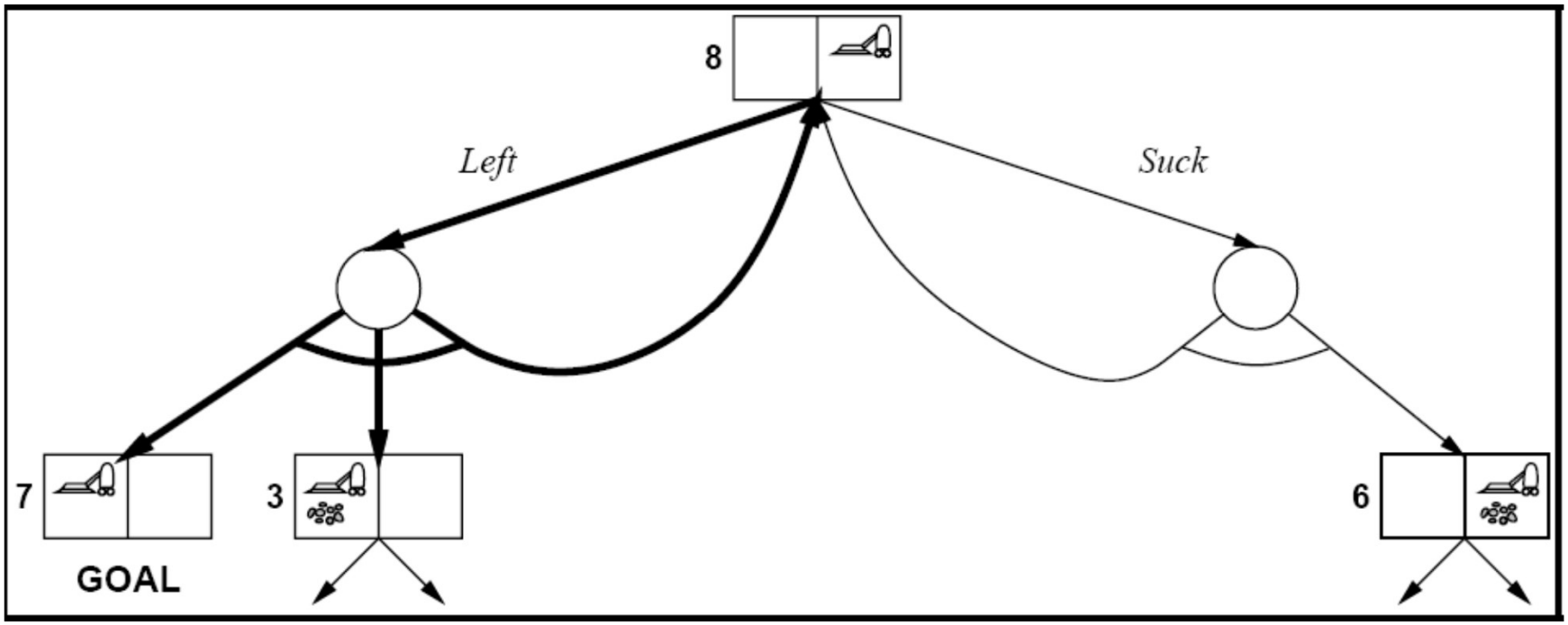
And-Or-Graph Search Algorithm

```
function AND-OR-GRAPH-SEARCH(problem) returns a conditional plan, or failure
  OR-SEARCH(INITIAL-STATE[problem], problem, [])

function OR-SEARCH(state, problem, path) returns a conditional plan, or failure
  if GOAL-TEST[problem](state) then return the empty plan
  if state is on path then return failure
  for each action, state_set in SUCCESSORS[problem](state) do
      plan ← AND-SEARCH(state_set, problem, [state | path])
      if plan ≠ failure then return [action | plan]
  return failure

function AND-SEARCH(state_set, problem, path) returns a conditional plan, or failure
  for each s_i in state_set 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]
```

The algorithm terminates in every finite state space, because every path must reach a goal, a dead end, or a repeated state. --- noncyclic solution

Example: Triple-Murphy

Vacuum cleaner sometimes fails to move when commanded



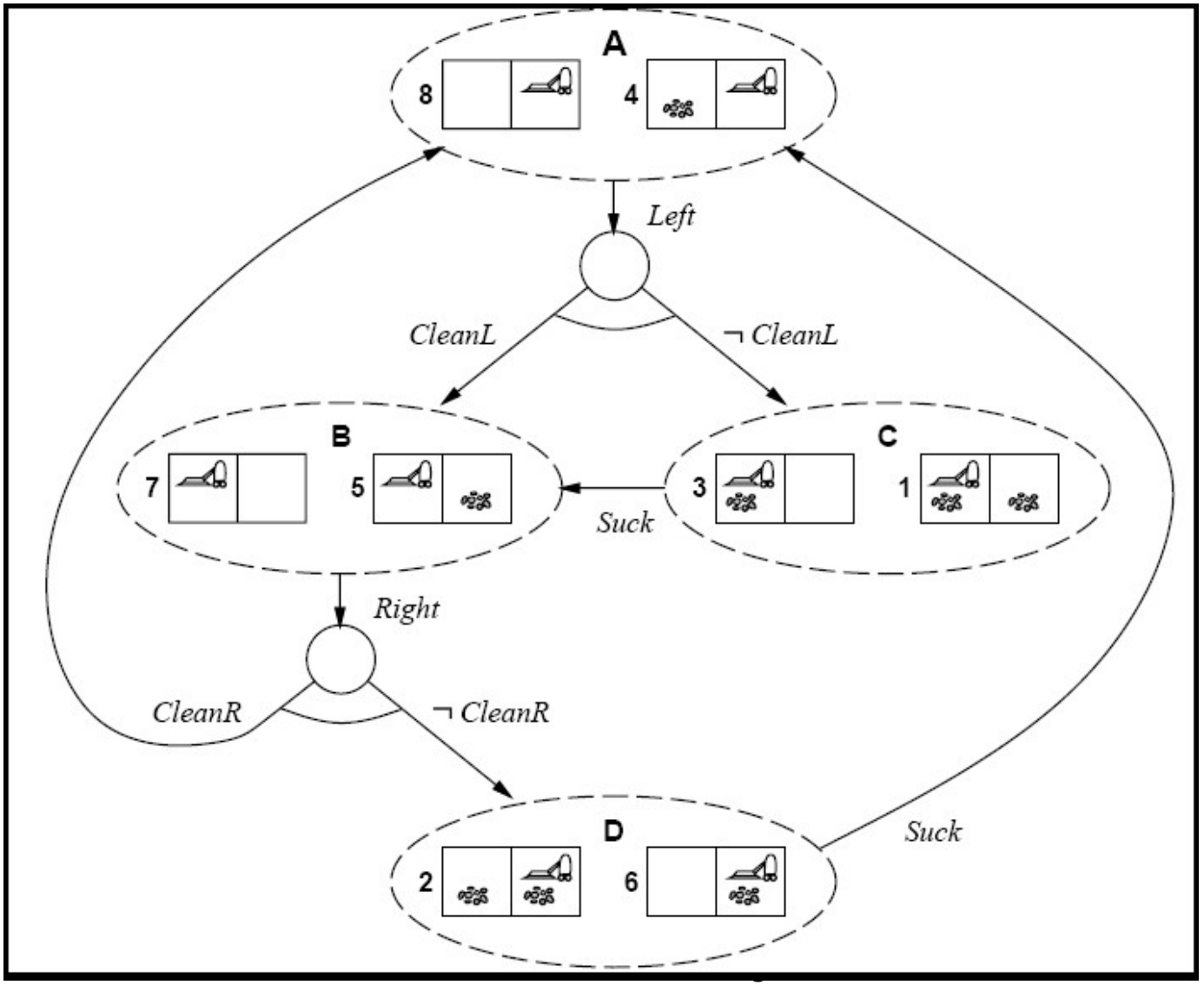
[L_1: Left, **if** AtR **then** L_1 **else if** CleanL **then** [] **else** Suck]

cyclic solution, less desirable than non-cyclic solution

Conditional Planning in Partially Observable Environments

- In real world, partial observability is more common
- The initial state belongs to a state set, which is also called belief state
- Assume a vacuum agent knows that is it in the right-hand square and that square is clean, but it cannot sense the dirt in other squares
- An alternate "double-murphy" world:
  - dirt can sometimes be left behind when the agent leaves a clean square

AND-OR Graph of Belief States



Belief States

- The agent's belief state is always fully observable
- Standard fully observable problem solving is just a special case in which every belief state is a singleton set containing one physical state
- Three basic choices for belief states:
  - Sets of full state descriptions $\{(AtR \wedge CleanR \wedge CleanL), (AtR \wedge CleanR \wedge \neg CleanL)\}$
    - Problems: large belief states
  - Logical sentences that capture exactly the set of possible worlds in the belief states – open world assumption $AtR \wedge CleanR$
    - Problems: requires general theorem proving among logically equivalent sentences
  - Knowledge propositions describing the agent's knowledge – closed world assumption
    - similar to the second approach

$$K(AtR) \wedge K(CleanR) \qquad \neg K(CleanL)$$
$$\neg K(\neg CleanL)$$

How Sensing Works?

- Automatic sensing:
  - at every time step the agent gets all the available percepts
- Active sensing:
  - the percepts are obtained only by executing specific sensory actions, such as *CheckDirt* and *CheckLocation*

Action Description Using Knowledge Propositions

- Suppose the agent moves Left in the alternate-double-Murphy world with automatic local dirt sensing: the agent might or might not leave dirt behind if the square is clean

$$Action(Left, PRECOND: AtR,$$
$$EFFECT: K(AtL) \wedge \neg K(AtR) \wedge$$
$$\text{when } CleanR: \neg K(CleanR) \wedge$$
$$\text{when } CleanL: K(CleanL) \wedge$$
$$\text{when } \neg CleanL: K(\neg CleanL))$$

Initial state: $K(AtR) \wedge K(CleanR)$

after move Left: $K(AtL) \wedge K(CleanL) \quad K(AtL) \wedge K(\neg CleanL)$

Active Sensing

- With active sensing, the agents get new percepts only by asking for them

$$
\begin{aligned}
&Action(CheckDirt, PRECOND:,\\
&\quad EFFECT: \text{when } AtL \wedge CleanL : K(CleanL) \wedge\\
&\qquad \text{when } AtL \wedge \neg CleanL : \neg K(CleanL) \wedge\\
&\qquad \text{when } AtR \wedge CleanR : K(CleanR) \wedge\\
&\qquad \text{when } AtR \wedge \neg CleanR : \neg K(CleanR))
\end{aligned}
$$

Left followed by *CheckDirt* in the active setting results in the same two belief states as *Left* did in the automatic sensing setting.

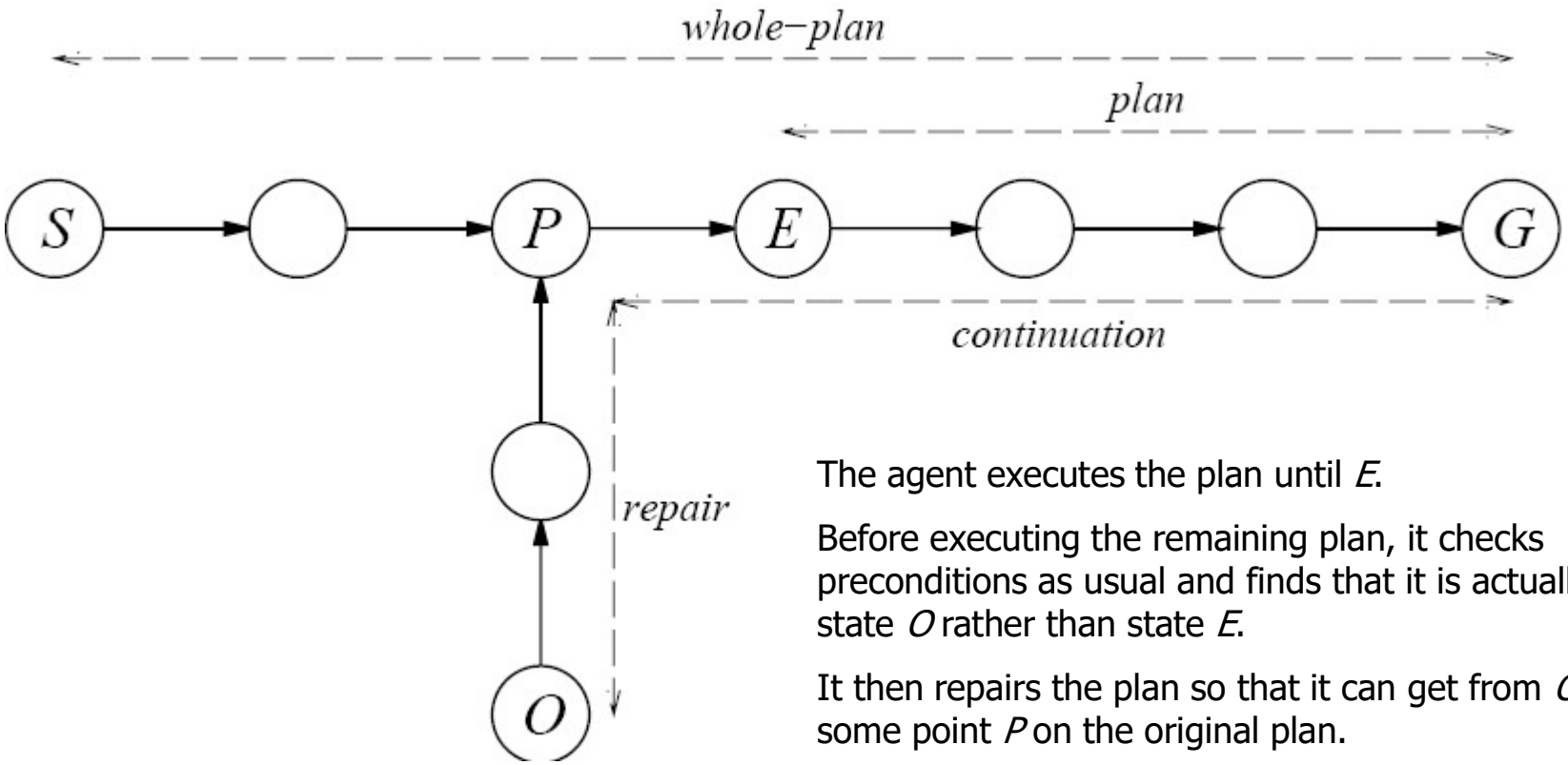
Execution Monitoring and Replanning

- An execution monitoring agent:
  - checks its percepts to see whether everything is going according to plan
    - action monitoring
    - plan monitoring, more efficient
- A replanning agent knows what to do when something unexpected happens
  - call a planner again to come up with a new plan to reach the goal
  - repair the old plan

A Monitoring and Replanning Agent

```
function REPLANNING-AGENT(percept) returns an action
  static: KB, a knowledge base (includes action descriptions)
          plan, a plan, initially []
          whole_plan, a plan, initially []
          goal, a goal

  TELL(KB, MAKE-PERCEPT-SENTENCE(percept, t))
  current ← STATE-DESCRIPTION(KB, t)
  if plan = [] then
      whole_plan ← plan ← PLANNER(current, goal, KB)
  if PRECONDITIONS(FIRST(plan)) not currently true in KB then
      candidates ← SORT(whole_plan, ordered by distance to current)
      find state s in candidates such that
            failure ≠ repair ← PLANNER(current, s, KB)
      continuation ← the tail of whole_plan starting at s
      whole_plan ← plan ← APPEND(repair, continuation)
  return POP(plan)
```

Visualize the Process



The agent executes the plan until *E*.

Before executing the remaining plan, it checks preconditions as usual and finds that it is actually in state *O* rather than state *E*.

It then repairs the plan so that it can get from *O* to some point *P* on the original plan.

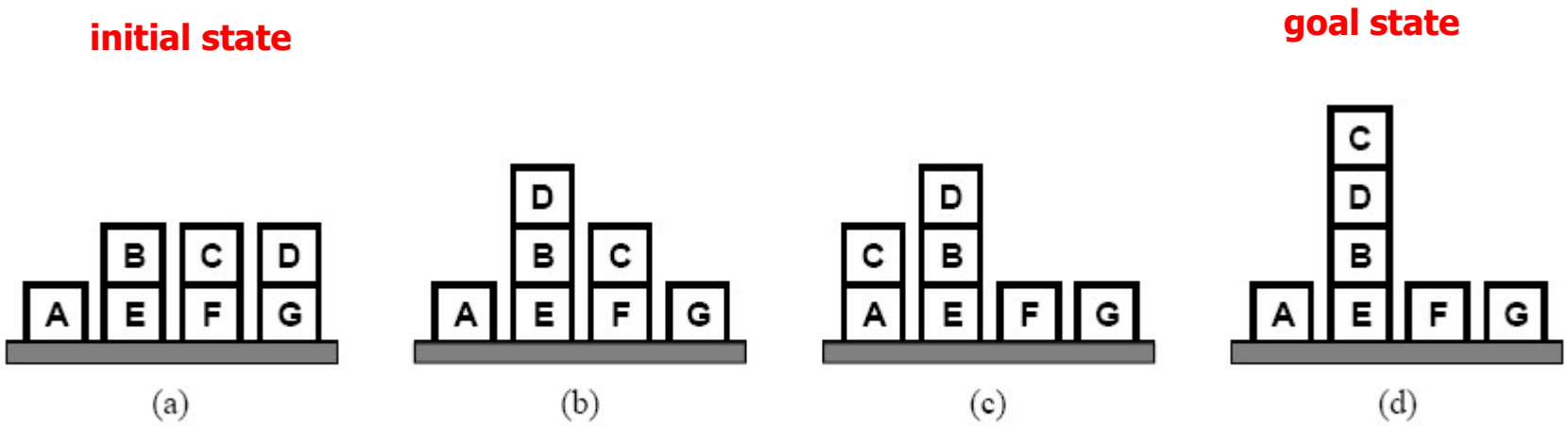
The new plan is the concatenation of **repair** and **continuation**.

Continuous Planning

- The agent lives through a series of goal formation, planning, and acting phases
- It has a cycle of "perceive, remove flaw, act"

```
function CONTINUOUS-POP-AGENT(percept) returns an action
  static: plan, a plan, initially with just Start, Finish

  action ← NoOp (the default)
  EFFECTS[Start] = UPDATE(EFFECTS[Start], percept)
  REMOVE-FLAW(plan)  // possibly updating action
  return action
```

Blocks World Example



The start state is (a).

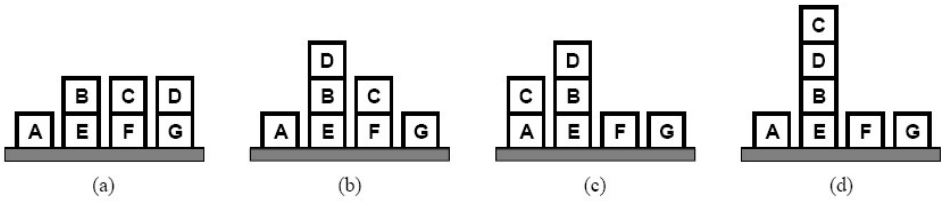
The goal state is On(C, D) ^ On(D, B).

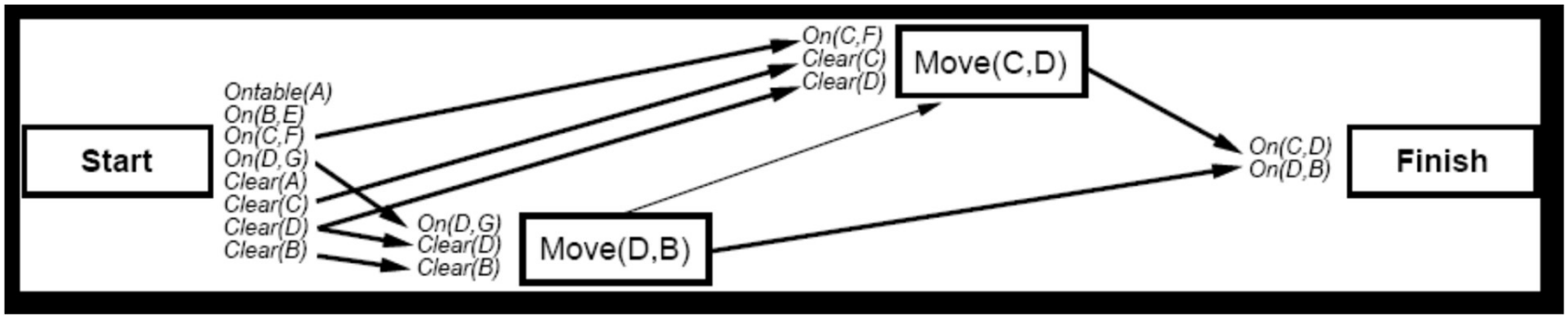
At (b), another agent has interfered, putting D on B.

At (c), the agent has executed Move(C, D) but has failed, dropping C on A instead.

It retries Move(C, D), reaching the goal state (d).

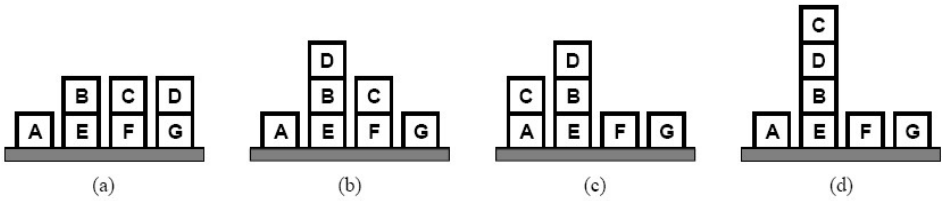
The Initial Plan

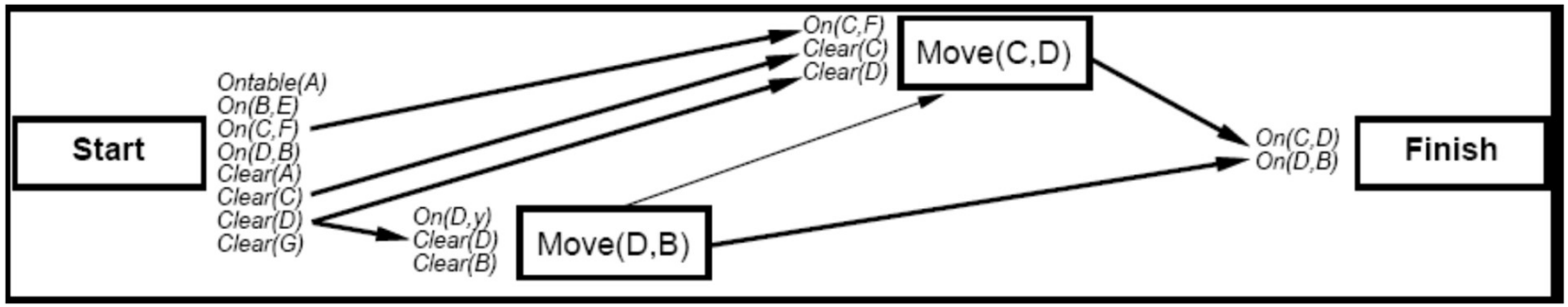




The initial plan is constructed by the continuous planning agent, just like other normal partial-order planner.

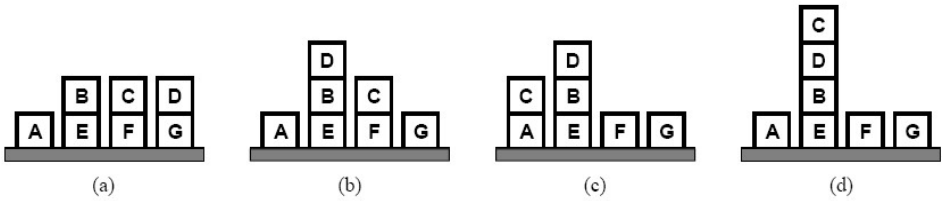
Continuous Planning

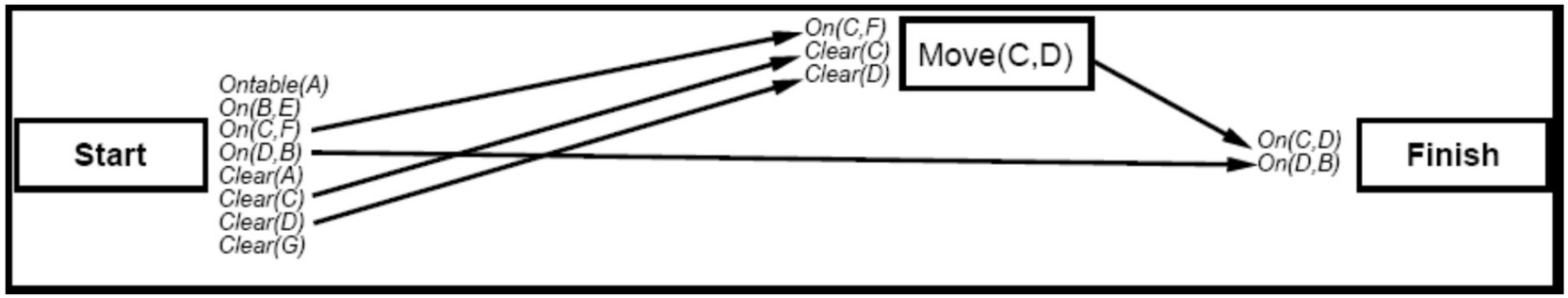




After someone else moves D onto B, the unsupported links supplying Clear(B) and On(D, G) are dropped, producing this plan.

Continuous Planning

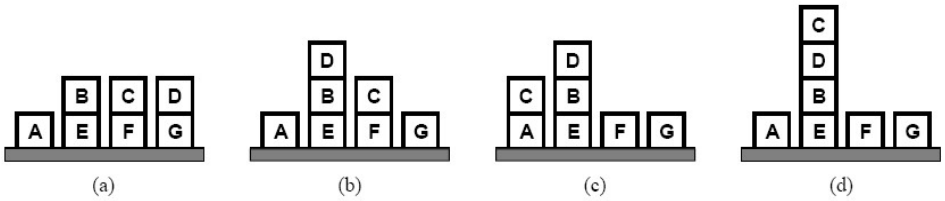




The link supplied by Move(D, B) has been replaced by one from Start, and the now-redundant step Move(D, B) has been dropped.

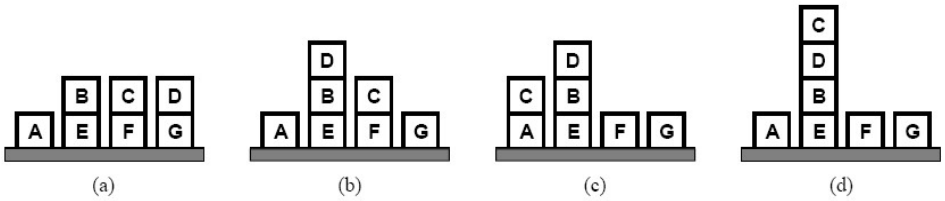
This process is called **extending a causal link** and is done whenever a condition can be supplied by an earlier instead of a later one without causing a new conflict.

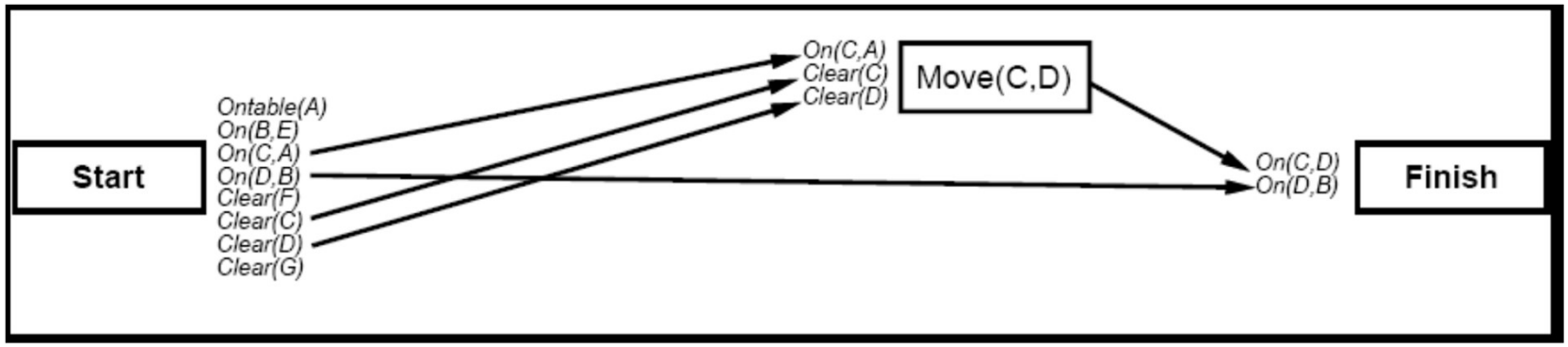
Continuous Planning



After Move(C, D) is executed and removed from the plan, the effects of the Start step reflect the fact that C ended up on A instead of the intended D. The goal precondition On(C, D) is still open.

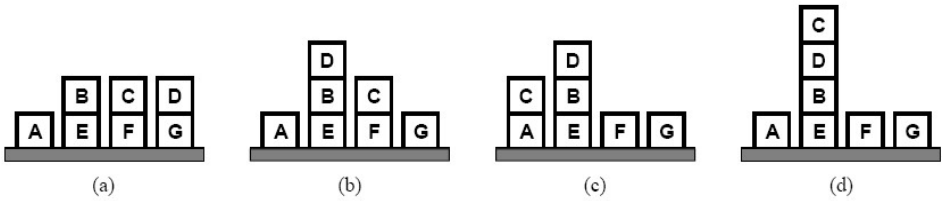
Continuous Planning

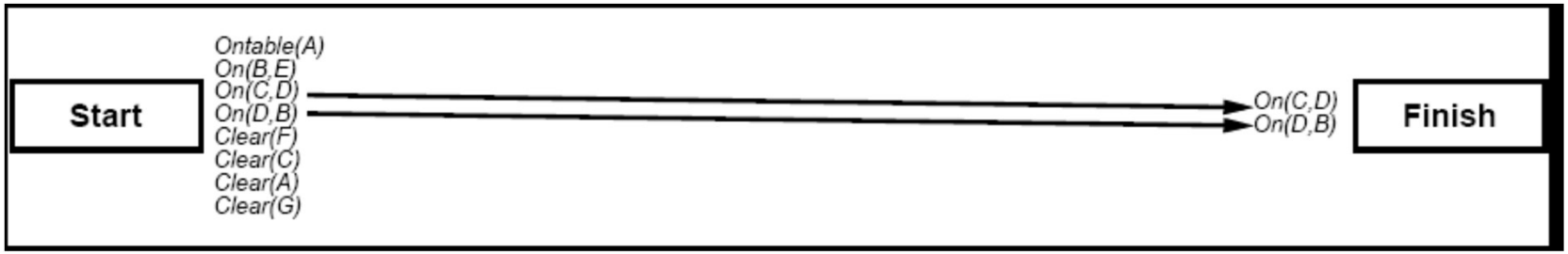




The open condition is resolved by adding Move(C, D) back in.

Reaching the Goal State





After Move(C, D) is executed and dropped from the plan, the remaining open condition On(C, D) is resolved by adding a causal link from the new Start step. The plan is now completed.

Summary of Planning

- Standard planning algorithms assume complete and correct information and deterministic, fully observable environments. Many domains violate this assumption.

- Conditional plans allow the agent to sense the world during execution to decide what branch of the plan to follow.
- Execution monitoring detects violations of preconditions for successful completion of the plan.
- A replanning agent uses execution monitoring and splices in repairs as needed.
- A continuous planning agent creates new goals as it goes and reacts in real time.