Classical STRIPS Planning

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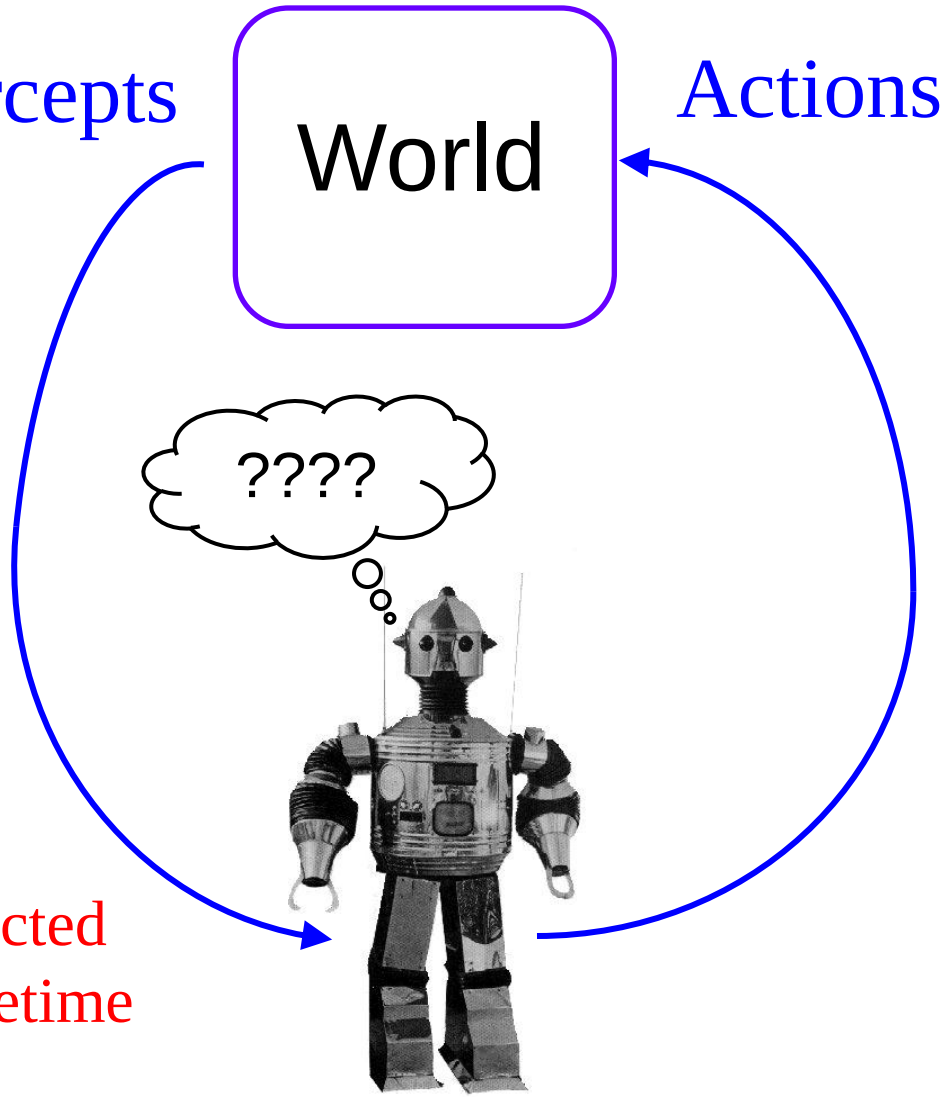
* Based in part on slides by Daniel Weld.

Stochastic/Probabilistic Planning: Markov Decision Process (MDP) Model



perfect

fully observable

sole source of change

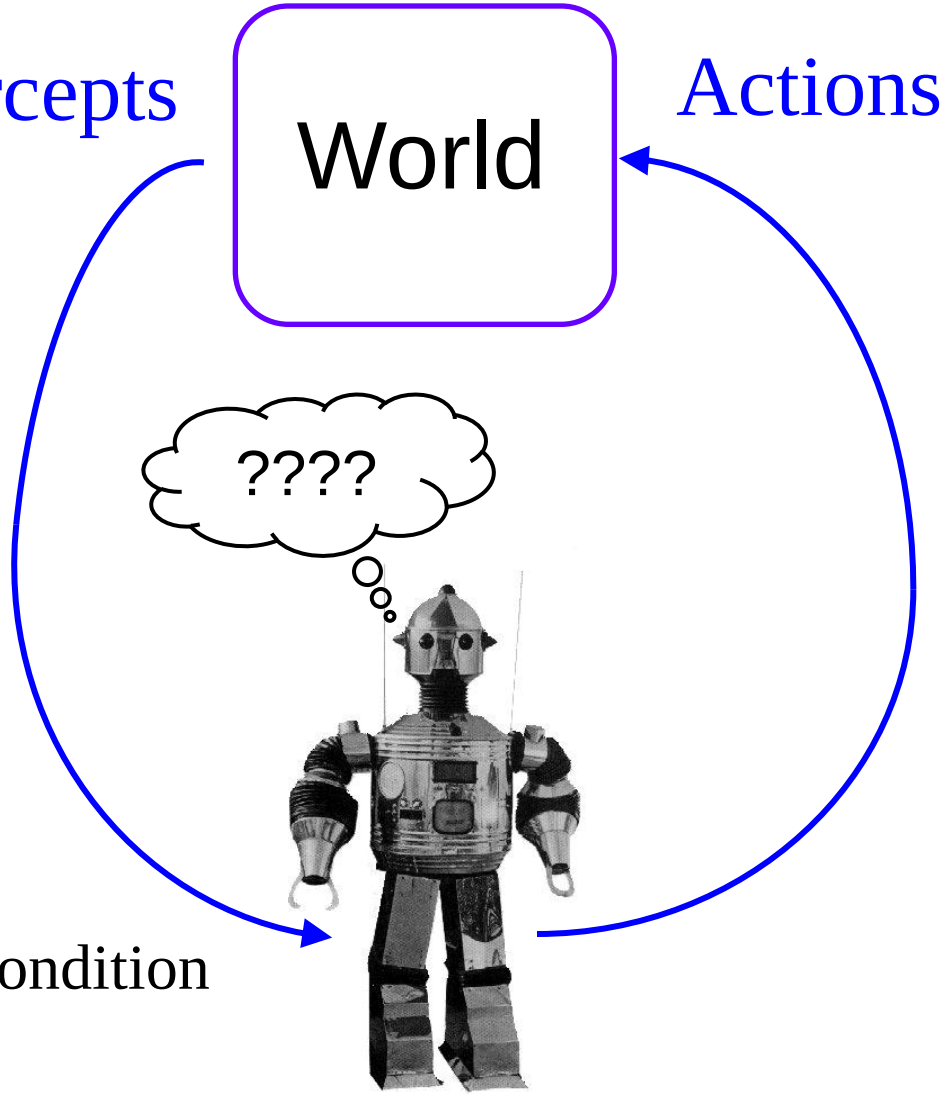
stochastic

instantaneous

Goal

maximize expected reward over lifetime

Classical Planning Assumptions



perfect

fully observable

sole source of change

deterministic

instantaneous

Goal

achieve goal condition

Why care about classical planning?

- Places an emphasis on analyzing the combinatorial structure of problems
  - Developed a many powerful ideas in this direction
  - MDP research has *mostly* ignored this type of analysis
- Classical planners tend scale much better to large state spaces by leveraging those ideas

- **Replanning:** many stabilized environments ~satisfy classical assumptions (e.g. robotic crate mover)
  - It is possible to handle minor assumption violations through replanning and execution monitoring
  - The world is often not so random and can be effectively thought about deterministically

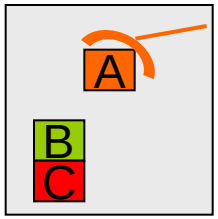
Why care about classical planning?

- Ideas from classical planning techniques often form the basis for developing non-classical planning techniques
  - Recent work uses classical planners as a component of probabilistic planning [Yoon et. al. 2008]
    (i.e. reducing probabilistic planning to classical planning)
  - Powerful domain analysis techniques from classical planning have been integrated into MDP planners

Representing States

World states are represented as sets of facts.

We will also refer to facts as propositions.

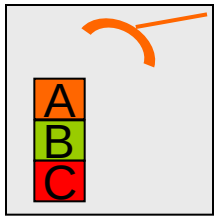


holding(A)
clear(B)
on(B,C)
onTable(C)

State 1

handEmpty
clear(A)
on(A,B)
on(B,C)
onTable(C)

State 2



Closed World Assumption (CWA):

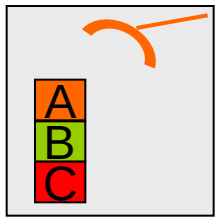
Fact not listed in a state are assumed to be false. Under CWA we are assuming the agent has full observability.

Representing Goals

Goals are also represented as sets of facts.

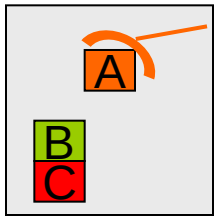
For example { on(A,B) } is a goal in the blocks world.

A **goal state** is any state that contains all the goal facts.



handEmpty
clear(A)
on(A,B)
on(B,C)
onTable(C)

State 1

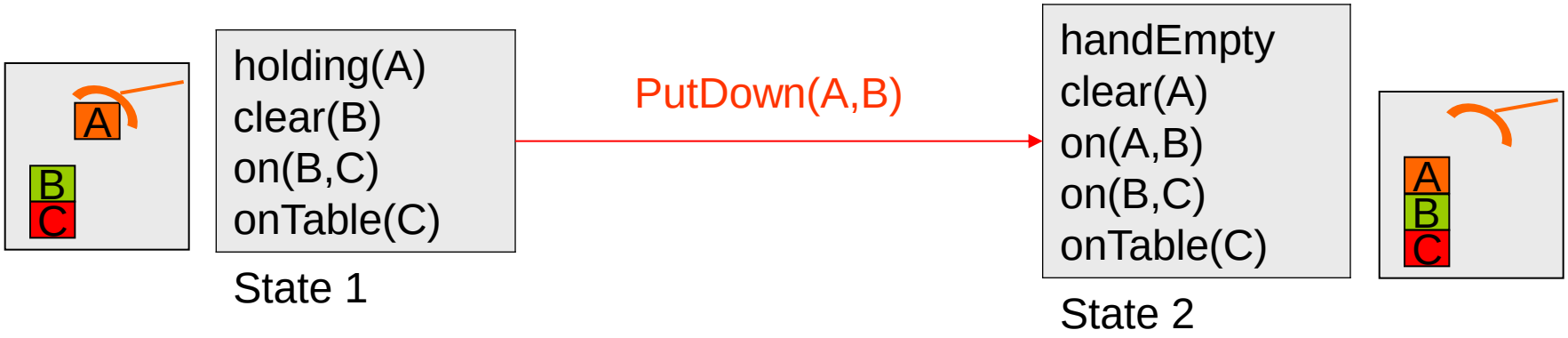


holding(A)
clear(B)
on(B,C)
onTable(C)

State 2

State 1 is a goal state for the goal { on(A,B) }.
State 2 is not a goal state for the goal { on(A,B) }.

Representing Action in STRIPS



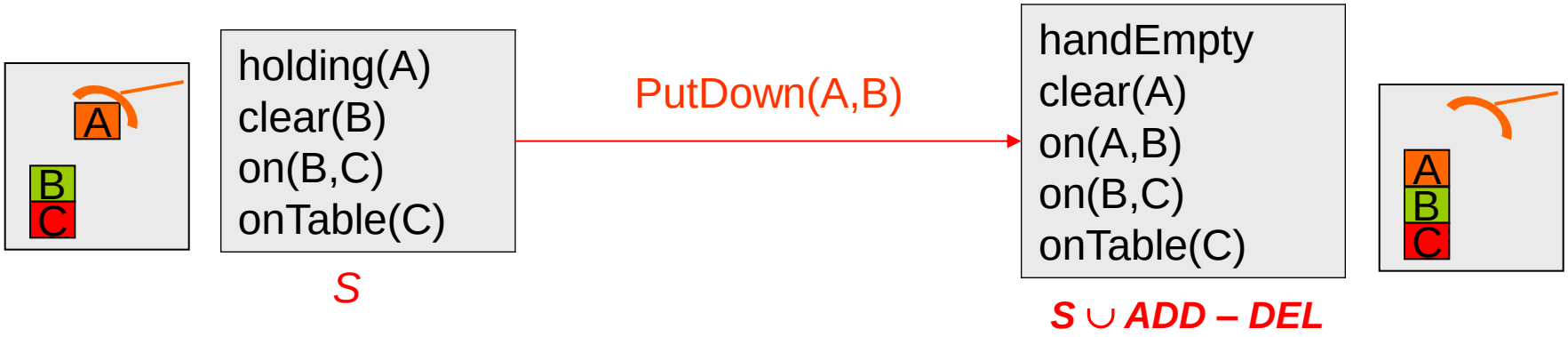
A STRIPS action definition specifies:

1) a set PRE of preconditions facts
2) a set ADD of add effect facts
3) a set DEL of delete effect facts

PutDown(A,B):

PRE: { holding(A), clear(B) }
ADD: { on(A,B), handEmpty, clear(A) }
DEL: { holding(A), clear(B) }

Semantics of STRIPS Actions



- A STRIPS action is **applicable** (or allowed) in a state when its preconditions are contained in the state.
- Taking an action in a state ***S*** results in a new state ***S ∪ ADD – DEL*** (i.e. add the add effects and remove the delete effects)

PutDown(A,B):

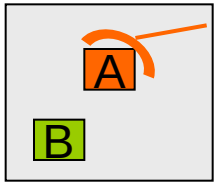
PRE: { holding(A), clear(B) }
ADD: { on(A,B), handEmpty, clear(A)}
DEL: { holding(A), clear(B) }

STRIPS Planning Problems

A **STRIPS planning problem** specifies:
1) an initial state *S*
2) a goal *G*
3) a set of STRIPS actions

Objective: find a "short" action sequence reaching a goal state, or report that the goal is unachievable

Example Problem:



holding(A)
clear(B)
onTable(B)

Initial State

on(A,B)

Goal

Solution: (PutDown(A,B))

PutDown(A,B):

PRE: { holding(A), clear(B) }
ADD: { on(A,B), handEmpty, clear(A)}
DEL: { holding(A), clear(B) }

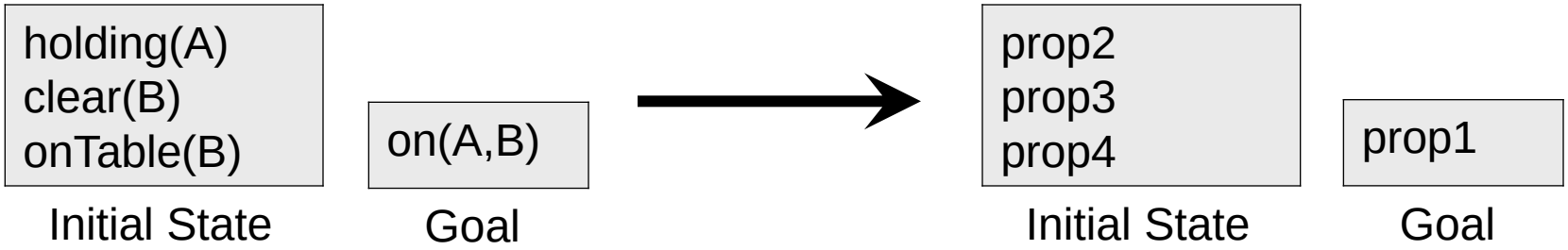
PutDown(B,A):

PRE: { holding(B), clear(A) }
ADD: { on(B,A), handEmpty, clear(B) }
DEL: { holding(B), clear(A) }

STRIPS Actions

Propositional Planners

- For clarity we have written propositions such as on(A,B) in terms of objects (e.g. A and B) and predicates (e.g. on).
- However, the planners we will consider ignore the internal structure of propositions such as on(A,B).
- Such planners are called **propositional planners** as opposed to first-order or relational planners
- Thus it will make no difference to the planner if we replace every occurrence of “on(A,B)” in a problem with “prop1” (and so on for other propositions)
- It feels wrong to ignore the existence of objects. But currently propositional planners are the state-of-the-art.



STRIPS Action Schemas

For convenience we typically specify problems via action schemas rather than writing out individual STRIPS actions.

Action Schema: (x and y are variables)

PutDown(x,y):

PRE: { holding(x), clear(y) }
ADD: { on(x,y), handEmpty, clear(x) }
DEL: { holding(x), clear(y) }

PutDown(B,A):

PRE: { holding(B), clear(A) }
ADD: { on(B,A), handEmpty, clear(B) }
DEL: { holding(B), clear(A) }

. . . .

PutDown(A,B):

PRE: { holding(A), clear(B) }
ADD: { on(A,B), handEmpty, clear(A) }
DEL: { holding(A), clear(B) }

- Each way of replacing variables with objects from the initial state and goal yields a "ground" STRIPS action.
- Given a set of schemas, an initial state, and a goal, propositional planners compile schemas into ground actions and then ignore the existence of objects thereafter.

STRIPS Versus PDDL

- Your book refers to the PDDL language for defining planning problems rather than STRIPS
- The Planning Domain Description Language (PDDL) was defined by planning researchers as a standard language for defining planning problems
  - Includes STRIPS as special case along with more advanced features
  - Some simple additional features include: type specification for objects, negated preconditions, conditional add/del effects
  - Some more advanced features include allowing numeric variables and durative actions
- Most planners you can download take PDDL as input
  - Majority only support the simple PDDL features (essentially STRIPS)
  - PDDL syntax is easy to learn from examples packaged with planners, but a definition of the STRIPS fragment can be found at:

http://eecs.oregonstate.edu/ipc-learn/documents/strips-pddl-subset.pdf

Properties of Planners

- A planner is **sound** if any action sequence it returns is a true solution
- A planner is **complete** if it outputs an action sequence or “no solution” for any input problem
- A planner is **optimal** if it always returns the shortest possible solution

Is optimality an important requirement?

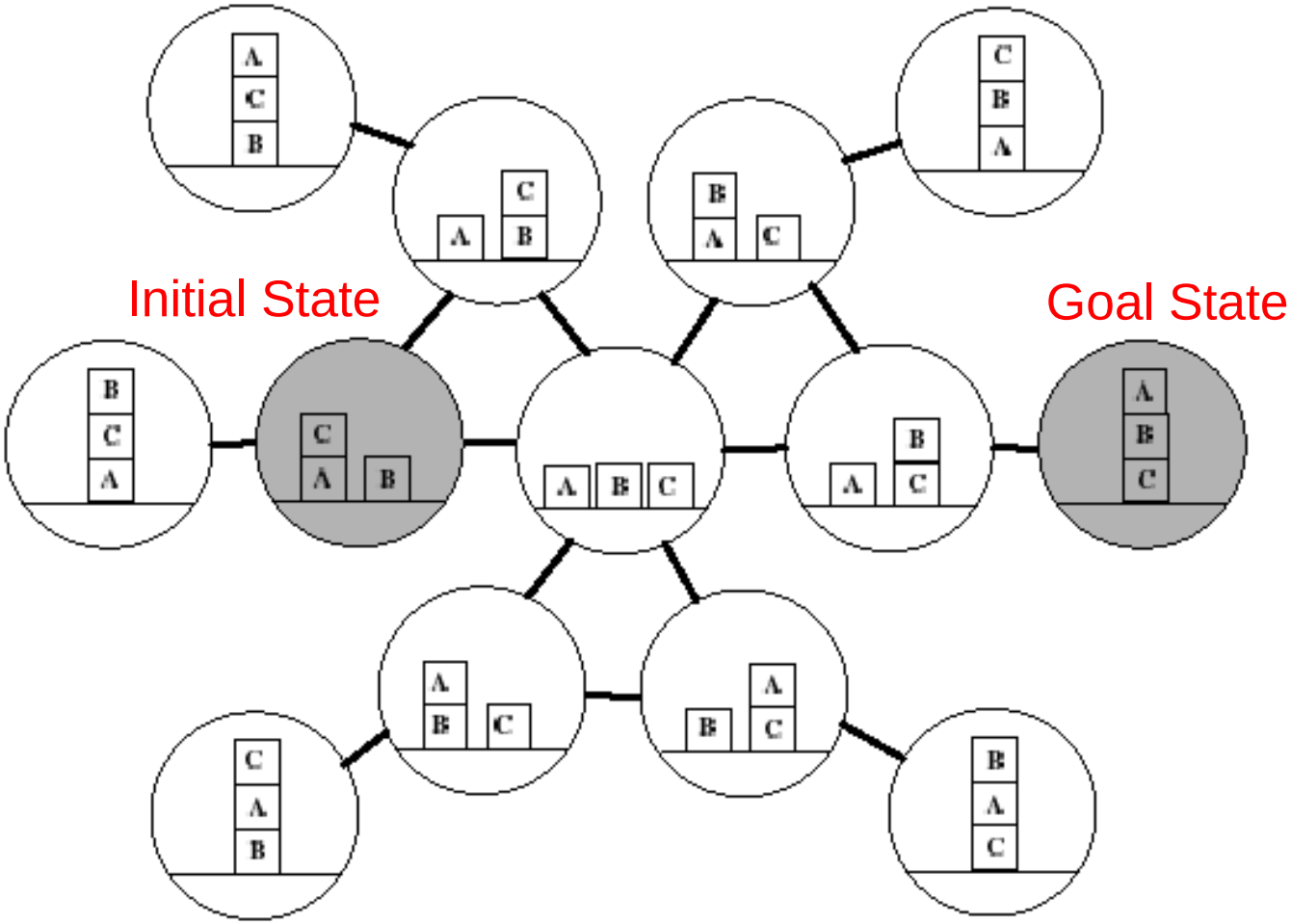
Is it a reasonable requirement?

Planning as Graph Search

- It is easy to view planning as a graph search problem
- Nodes/vertices = possible states
- Directed Arcs = STRIPS actions
- Solution: path from the initial state (i.e. vertex) to one state/vertices that satisfies the goal

Search Space: Blocks World

Graph is finite



Planning as Graph Search

- Planning is just finding a path in a graph
  - Why not just use standard graph algorithms for finding paths?
- **Answer:** graphs are exponentially large in the problem encoding size (i.e. size of STRIPS problems).
  - But, standard algorithms are poly-time in graph size
  - So standard algorithms would require exponential time
- Can we do better than this?

Complexity of STRIPS Planning

PlanSAT

Given: a STRIPS planning problem

Output: "yes" if problem is solvable, otherwise "no"

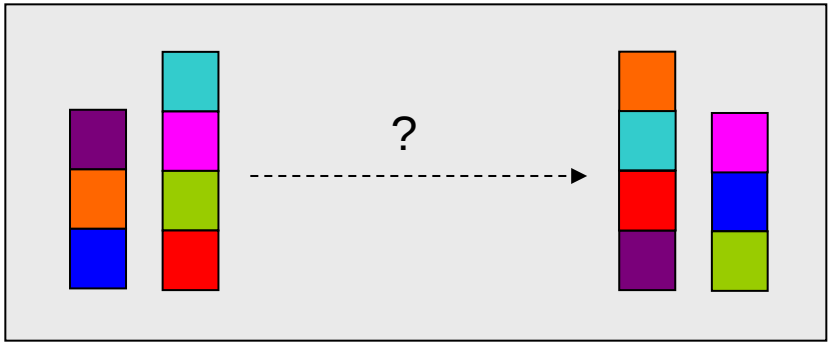
- PlanSAT is decidable.
  - Why?
- In general PlanSAT is PSPACE-complete!
  Just finding a plan is hard in the worst case.
  - even when actions limited to just 2 preconditions and 2 effects

Does this mean that we should give up on AI planning?

NOTE: PSPACE is set of all problems that are decidable in polynomial space.
PSPACE-complete is widely believed to strictly contain NP.

Satisficing vs. Optimality

- While just finding a plan is hard in the worst case, for many planning domains, finding a plan is easy.
- However finding optimal solutions can still be hard in those domains.
  - For example, optimal planning in the blocks world is NP-complete.
- In practice it is often sufficient to find “good” solutions “quickly” although they may not be optimal.
  - This is often referred to as the “satisficing” objective.
  - For example, producing approx. optimal blocks world solutions can be done in linear time. How?



Satisficing

- Still finding satisficing plans for arbitrary STRIPS problems is not easy.
  - Must still deal with the exponential size of the underlying state spaces
- Why might we be able to do better than generic graph algorithms?
- **Answer:** we have the compact and structured STRIPS description of problems
  - Try to leverage structure in these descriptions to intelligently search for solutions
- We will now consider several frameworks for doing this, in historical order.