# Course Logistics

- CS533: Intelligent Agents and Decision Making
  - M, W, F: 1:00—1:50
  - Instructor: Alan Fern (KEC2071)
  - Office hours: Th, F 10-11
  - Course website (link on instructor's home page) has
    - Lecture notes, Assignments, and HW Solutions
- The course will cover basics of AI planning with some advanced topics
  - Prepare you to formulate planning problems, apply algorithms, and read research papers on planning
- Homework:
  - Assigned and collected regularly
  - Not graded for correctness, but rather for "completion with good effort"
  - Must "complete with good effort" 90% of homework or a letter grade will be deducted from final grad
- Grade based on:
  - 20% Midterm exam (in class)
  - 30% Final exam (take home)
  - 30% Final Project (during last month)
  - 20% 2 mini-projects

# Course Outline

- Classical planning
  - Basic algorithmic paradigms
- Markov Decision Processes (MDPs)
  - Basic definitions and solution techniques
- Reinforcement learning
  - Basic algorithms
- Monte-Carlo Planning
  - Basic algorithms

# Homework 1

- Due January 12
- Download from course web-page

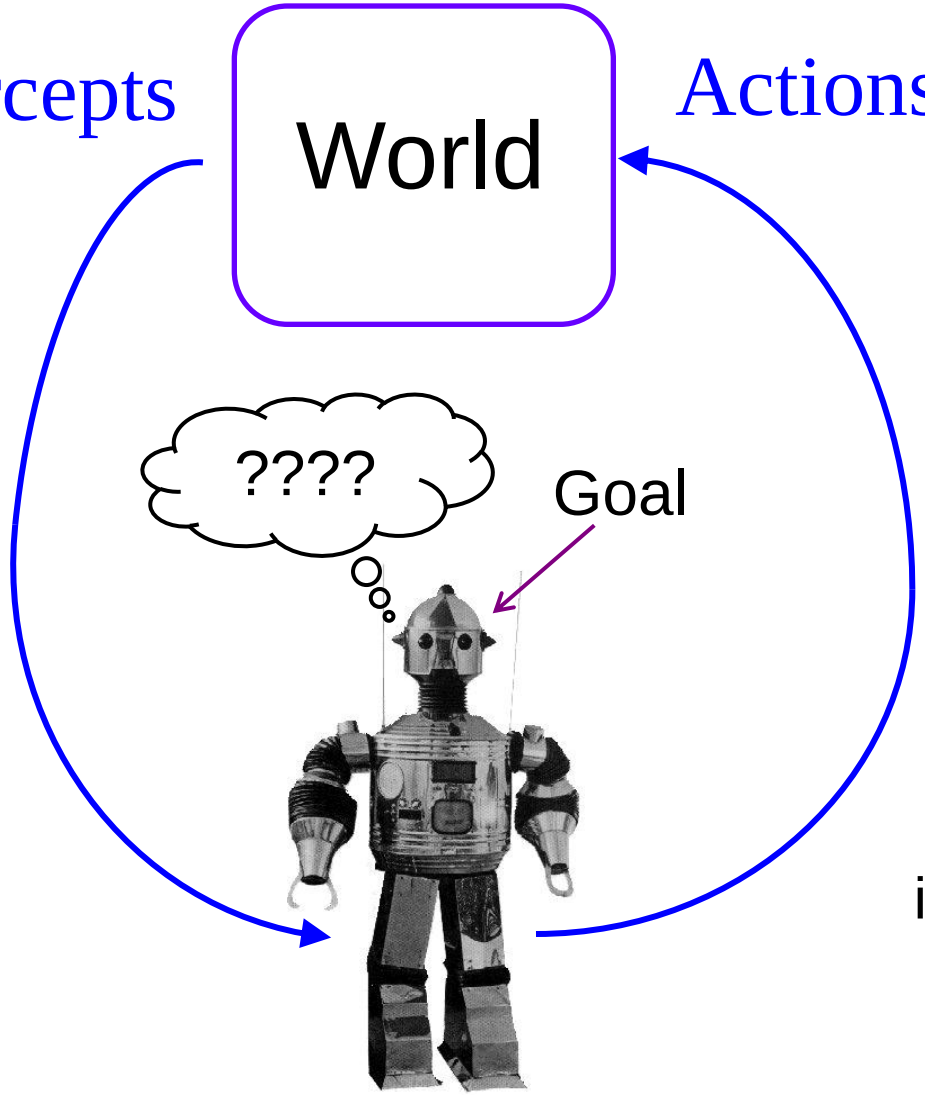
# Classical STRIPS Planning

Alan Fern *

- Classical planning assumptions
- STRIPS action language
- What is a planning problem?
  - complexity of planning

* Based in part on slides by Daniel Weld.

# AI Planning




perfect
vs.
noisy

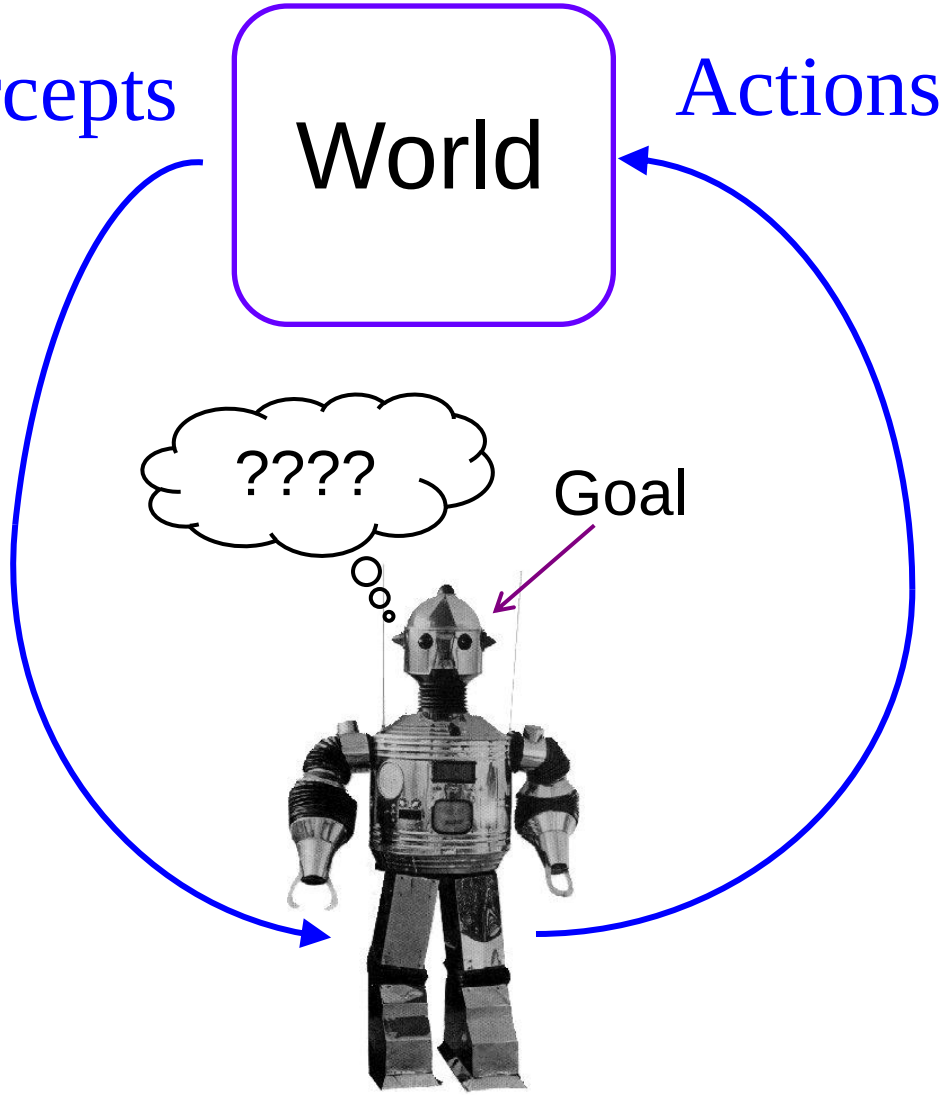
fully
observable
vs.
partially
observable

sole source
of change
vs.
other sources

deterministic
vs.
stochastic

instantaneous
vs.
durative

# Classical Planning Assumptions




perfect

fully observable

sole source of change

deterministic

instantaneous

# Why care about classical planning?

- Most advances seen first in classical planning
- Many stabilized environments ~satisfy classical assumptions (e.g. robotic crate mover)
  - It is possible to handle minor assumption violations through replanning and execution monitoring

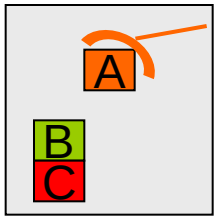
"This form of solution has the advantage of relying on widely-used (and often very efficient) classical planning technology" Boutilier, 2000

- Ideas from classical planning techniques often form the basis for developing non-classical planning techniques
  - E.g. recent work uses classical planners for probabilistic planning [Yoon et. al. 2008]

# Representing States

**World states** are represented as sets of facts.

We will also refer to facts as propositions.

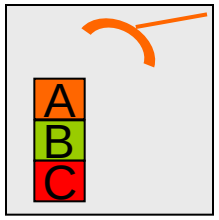



holding(A)
clear(B)
on(B,C)
onTable(C)

State 1

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

State 2




**Closed World Assumption (CWA):**

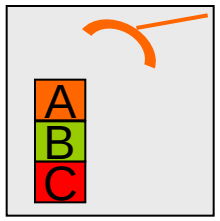
Fact not listed in a state are assumed to be false. Under CWA we are assuming the agent has full observability.

# Representing Goals

**Goals** are also represented as sets of facts.

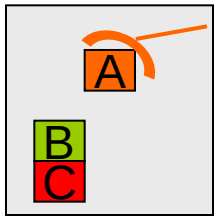
For example { on(A,B) } is a goal in the blocks world.

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

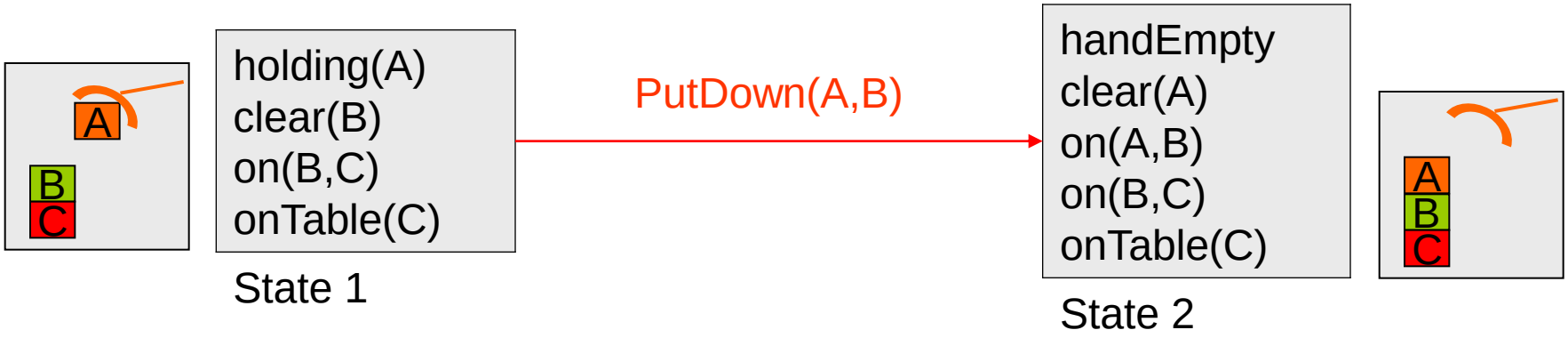



holding(A)
clear(B)
on(B,C)
onTable(C)

State 2

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

# Representing Action in STRIPS



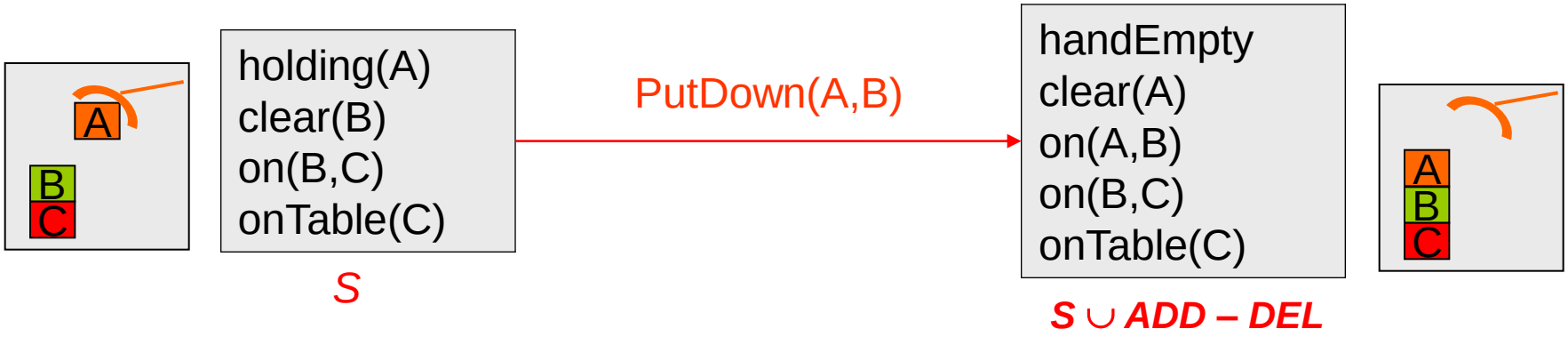

A STRIPS action definition specifies:

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):**

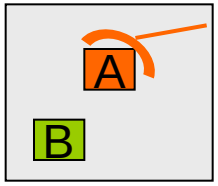
**PRE**: { holding(A), clear(B) }
**ADD**: { on(A,B), handEmpty, clear(A)}
**DEL**: { holding(A), clear(B) }

# 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) }

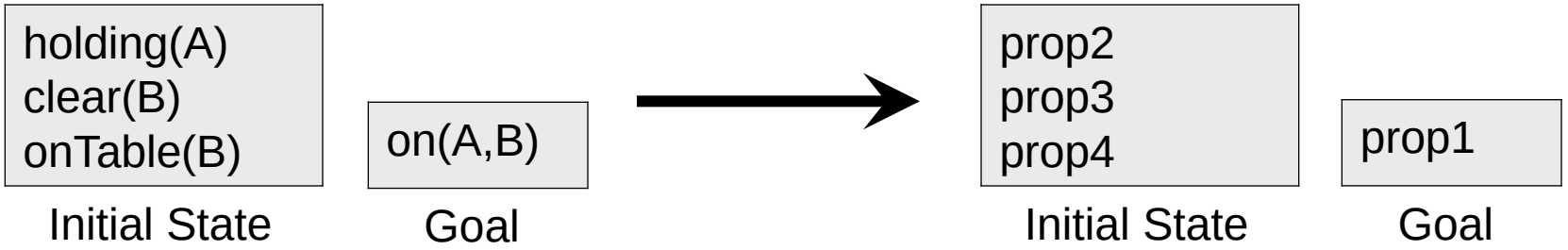
**PutDown(B,A):**

**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.



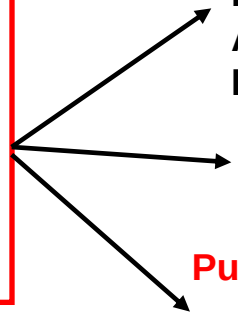
# STRIPS Action Schemas

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

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 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 by look at 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?

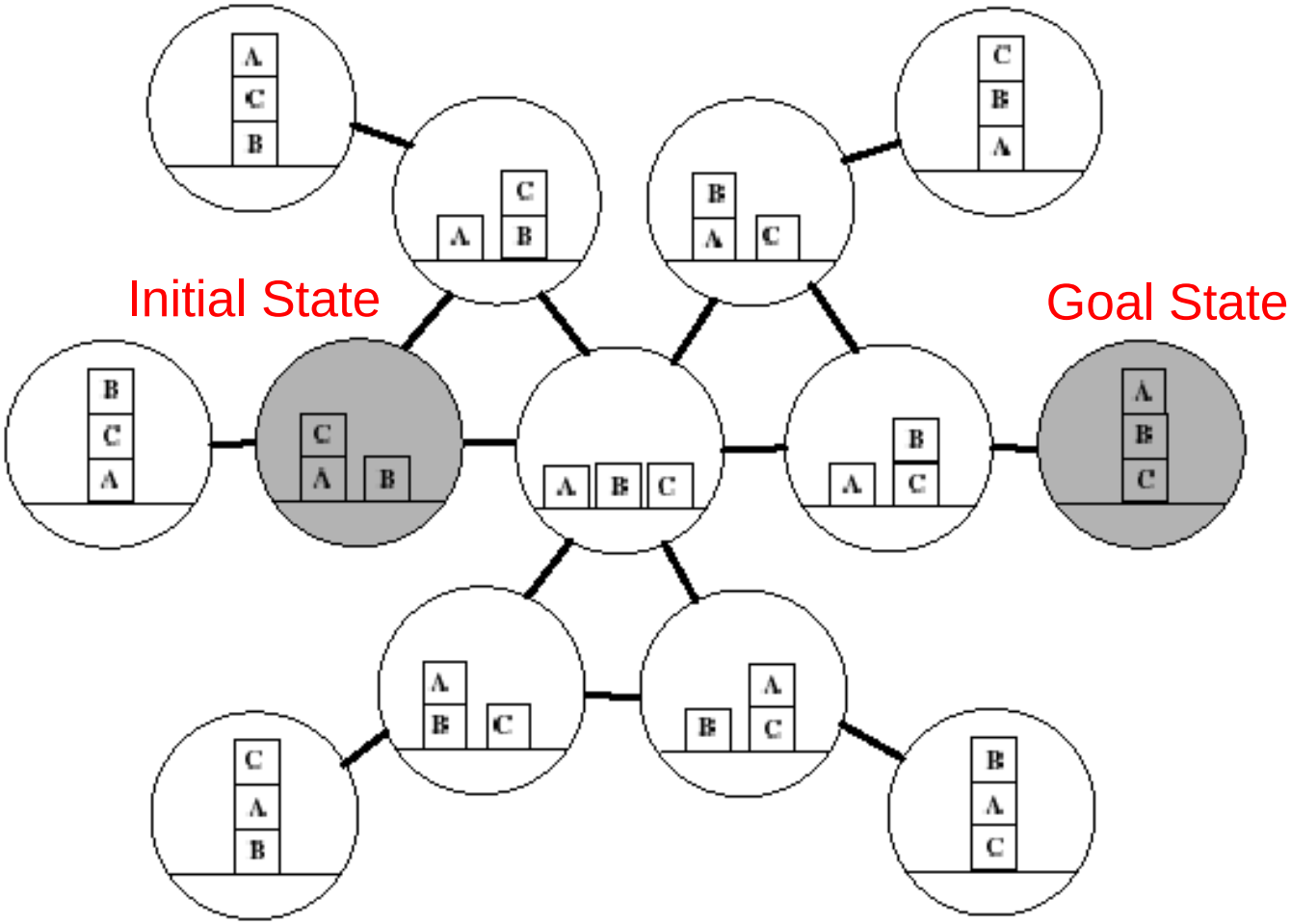
Is it a reasonable requirement?

# 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"

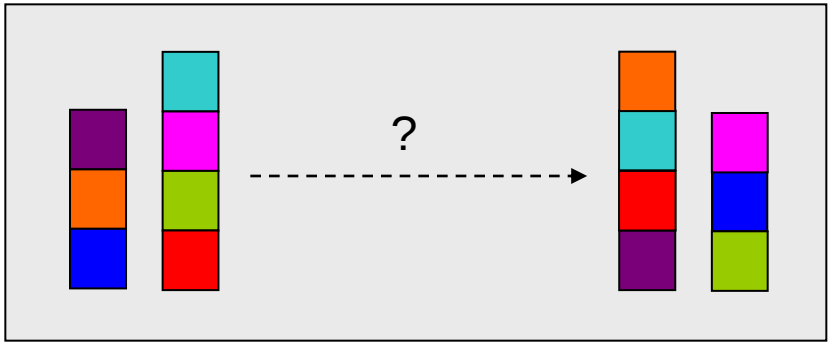
- PlanSAT is decidable.
  - Why?
- In general PlanSAT is PSPACE-complete!
  Just finding a plan is hard in the worst case.
  - even when actions limited to just 2 preconditions and 2 effects

**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.