CSE 291 – AI Agents
1/21 Search for Planning in Simulations

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Basic components of a simulation

- S = set of all states
  - propositions that are true: you are in a house, door is open, knife in drawer
- A = set of all actions
  - take knife from drawer, walk through door
- T = transition matrix T: (S, A)→S
  - (you are in a house & door is open, walk through door) → you are outside

There are pre-conditions that need to be met to perform a certain action, and post-conditions that are true after

What’s in a PDDL task?

- Objects: Things in the world that interest us.
- Predicates: Properties of objects that we are interested in; can be true or false.
- Initial state: The state of the world that we start in.
- Goal specification: Things that we want to be true.
- Actions/Operators: Ways of changing the state of the world.

2 .pddl files, domain and problem

Slide credits for most PDDL stuff: Malte Helmert and Sheila McIllraith UofT.

You have a simulation, now what?

- You need to plan out a policy
- Sequence of actions to get from start state to goal state
- A *plan* gives you a way of getting said policy
  - Can be expressed as constraints on actions you can perform

How to get a plan?

- Search is a way of getting possible plans for a given spec

Search Terminology

- State Space Search - each state is a node on the search tree, go from there
- Planning Space Search – searching through space of possible plans or constraints on actions

- Satisficing – looking longer and longer for a good enough solution
- Optimal – looking for the best possible solution there is

Standard (but not necessary) Assumptions

- No environment stochasticity, exact post conditions always manifest once action is executed
- No agent stochasticity, actions are always executed as planned
- Think about ways not having these assumptions would complicate things in the methods we talk about here on out

Properties of Forward Search

- Sound: plans generated by the traces will guarantee a solution if executed
- Complete: if a solution exists, then at least one of the search’s traces will be a solution

Forward Search

- Some deterministic implementations of forward search:
  - breadth-first search
  - depth-first search
  - best-first search (e.g., A*)
  - greedy search
- Breadth-first and best-first search are sound and complete But they usually aren't practical, requiring too much memory
  - Memory requirement is exponential in the length of the solution
- In practice, more likely to use depth-first search or greedy search
  - Worst-case memory requirement is linear in the length of the solution
  - In general, sound but not complete
  - But classical planning has only finitely many states
  - Thus, can make depth-first search complete by doing loop-checking

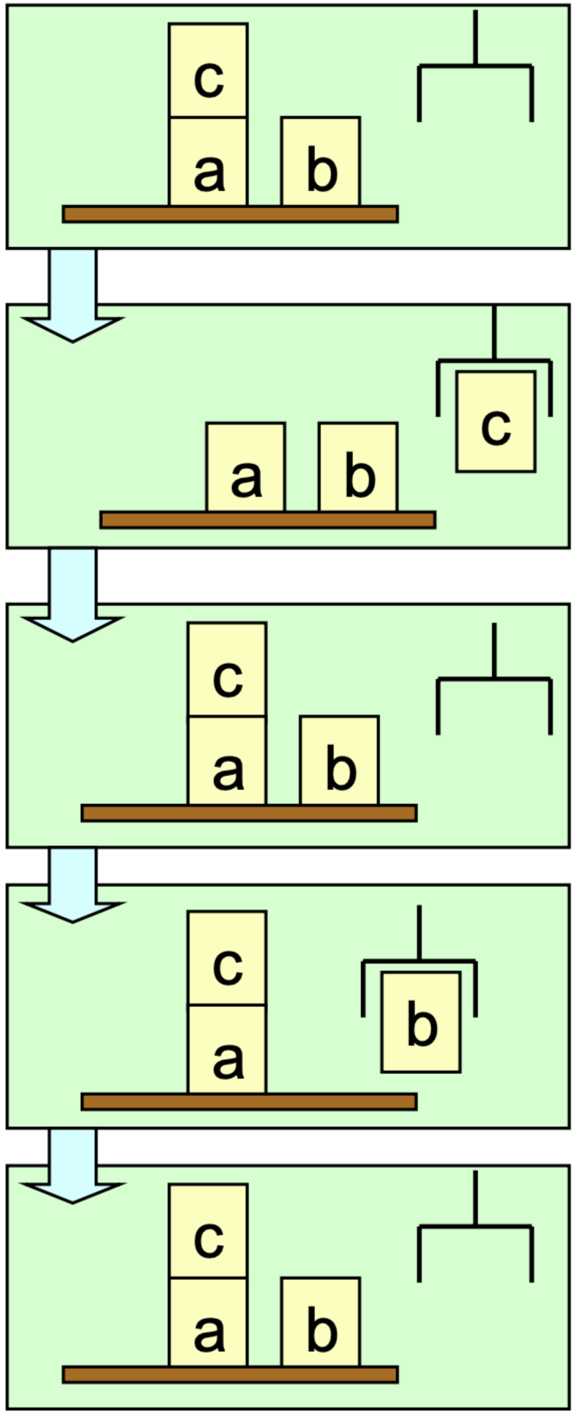
Forward Search Example – BlocksWorld

unstack(x,y)
Pre: on(x,y), clear(x), handempty
Eff: ~on(x,y), ~clear(x), ~handempty,
holding(x), clear(y)

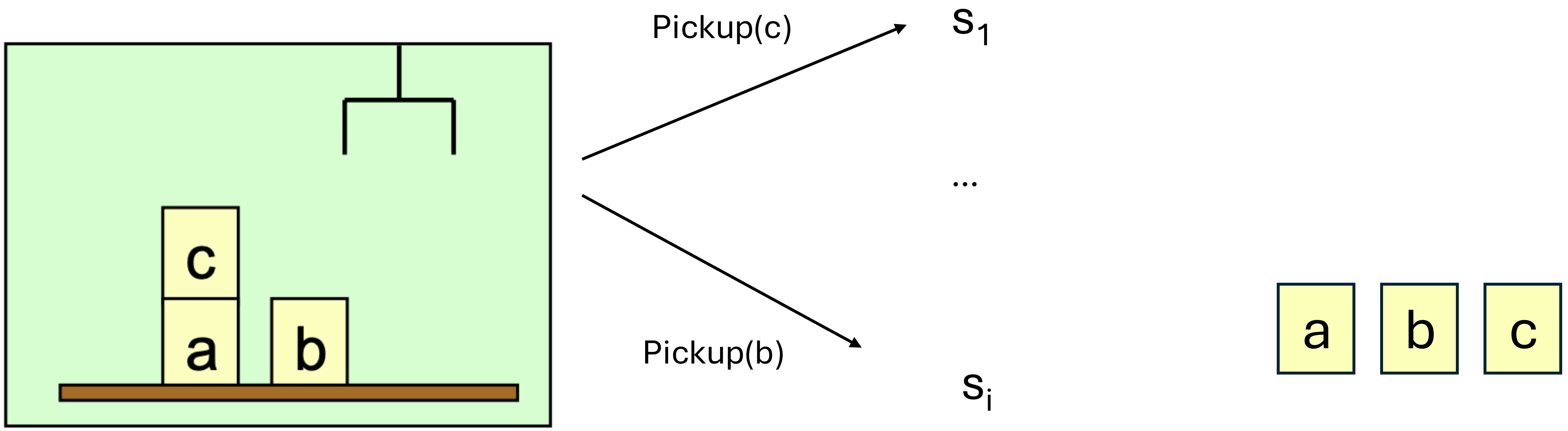
stack(x,y)
Pre: holding(x), clear(y)
Eff: ~holding(x), ~clear(y),
on(x,y), clear(x), handempty

pickup(x)
Pre: ontable(x), clear(x), handempty
Eff: ~ontable(x), ~clear(x), ~handempty, holding(x)

putdown(x)
Pre: holding(x)
Eff: ~holding(x), ontable(x), clear(x), handempty



Forward Search Example

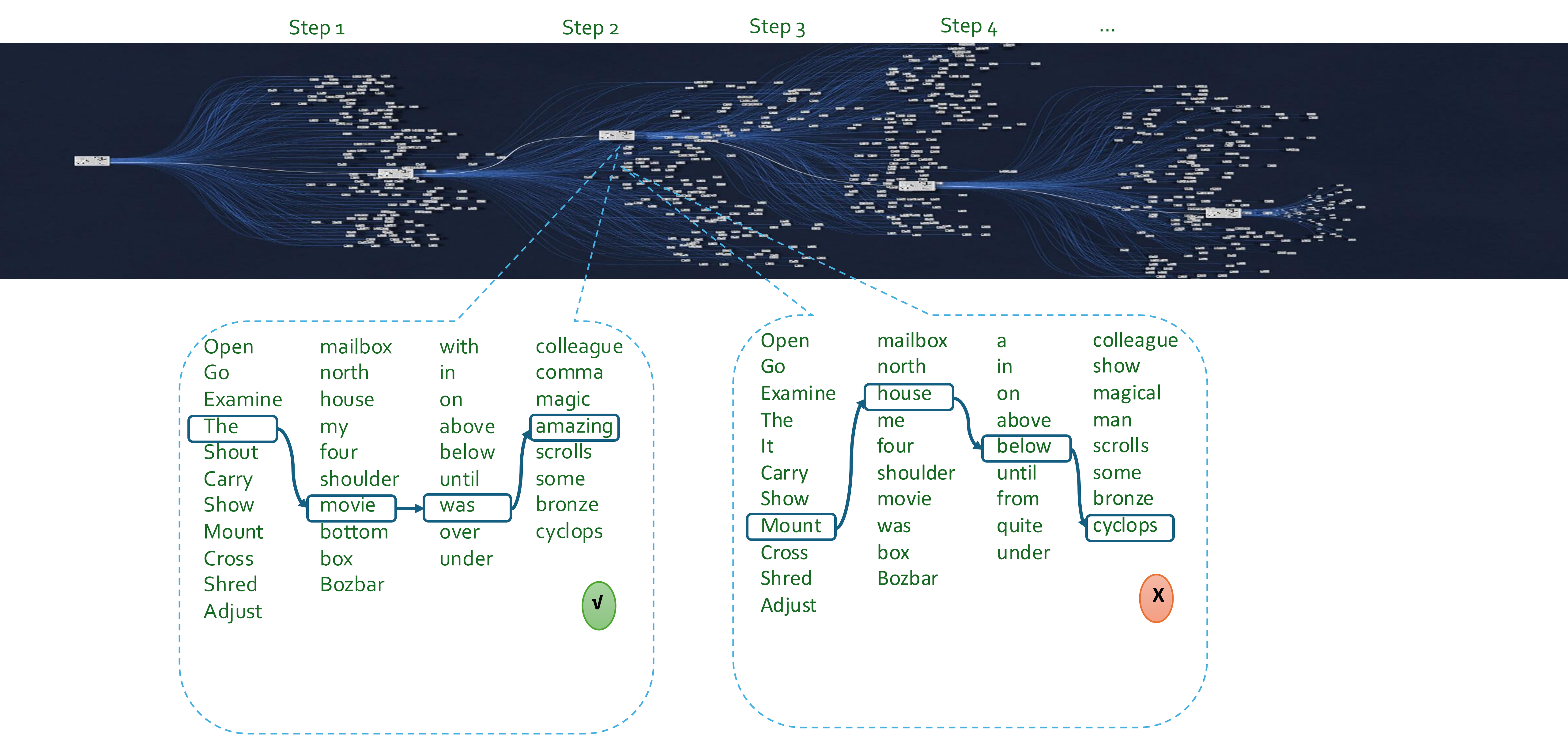


Initial state

Goal state

Forward Search Issues

- Branching factor - lots of possible states and actions, deterministic searches waste time trying a bunch of unnecessary stuff
- State and action spaces can blow up memory and compute costs



Imagine a controller with ~50000 buttons. How to scale language planning?

(Game of Go ~250, Chess ~35)

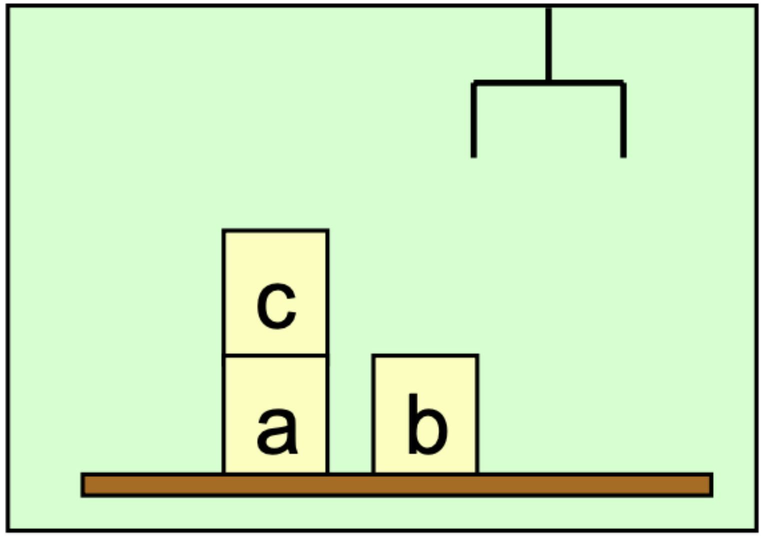
Backward Search

- For forward search, we started at the initial state and computed state transitions
  - new state = $T(s,a)$
- For backward search, we start at the goal and compute inverse state transitions
  - new set of subgoals = $T^{-1}(g,a)$
- To define $T^{-1}(g,a)$, must first define relevance: An action a is relevant for a goal g if
  - a makes at least one of g's literals true, $g \cap effects(a) \neq \emptyset$
  - a does not make any of g's literals false, $g^+ \cap effects^-(a) = \emptyset$ and $g^- \cap effects^+(a) = \emptyset$

Backward Search

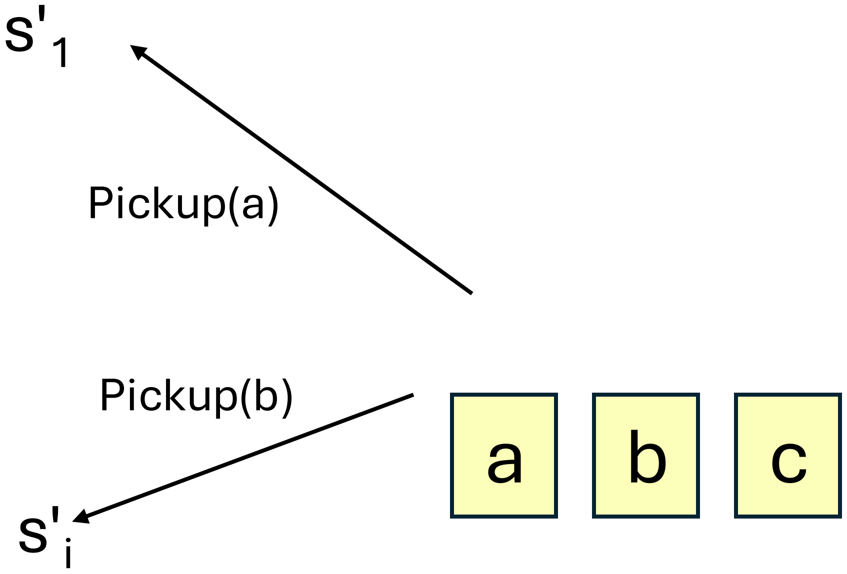
- To define $T^{-1}(g,a)$, must first define relevance: An action a is relevant for a goal g if
  - a makes at least one of g’s literals true, $g \cap \text{effects}(a) \neq \emptyset$
  - a does not make any of g’s literals false, $g^{+} \cap \text{effects}^{-}(a) = \emptyset$ and. $g^{-} \cap \text{effects}^{+}(a) = \emptyset$
  - If a is relevant for g, then $T^{-1}(g,a) = (g^{-} \text{effects}(a)) \cup \text{precond}(a)$
  - Otherwise, $T^{-1}(g,a)$ is undefined

Backward Search Example



Initial state

...



Goal state

Backward Search Issues

- Branching factor
  - an operator o that is relevant for g may have many instances a_1, a_2, …, a_n such that each a_i's input state might be unreachable from the initial state
- Goal states are actually described by constraints instead of exact list of propositions
- Generating predecessor states (inverting Transition matrix) is hard

Mitigations for Such Issues

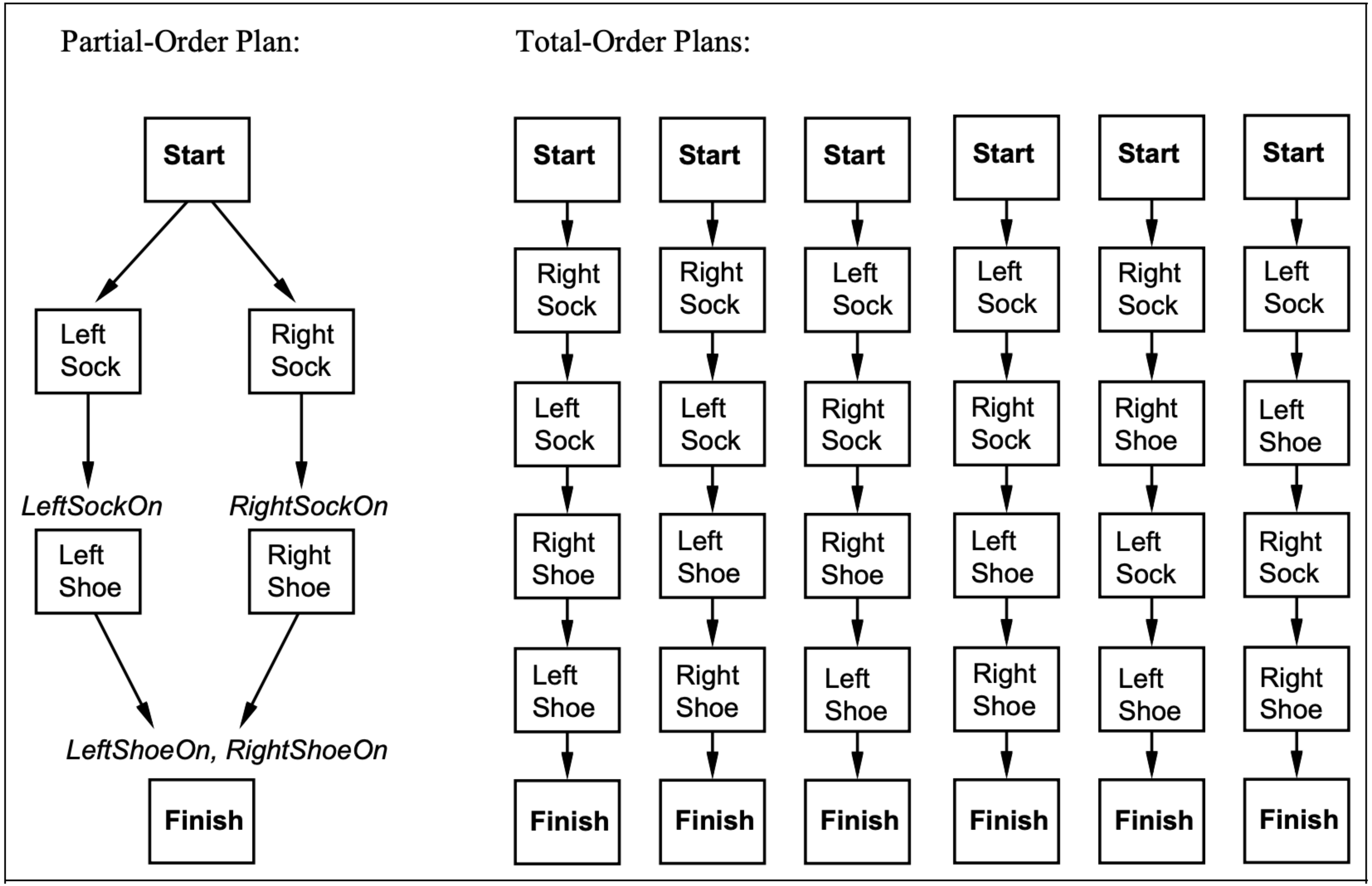
- Pruning state or action space … somehow

1. Just describe constraints that need to be satisfied
2. Find a heuristic to move effectively through state space

Total Order and Partial Order Plans

- Exact order of actions may not matter
- If you can break down problem into subproblems, partial planning may be easier → some actions and constraints on when they can be executed
- Partially ordered plans = planning space search (rather than state space search)

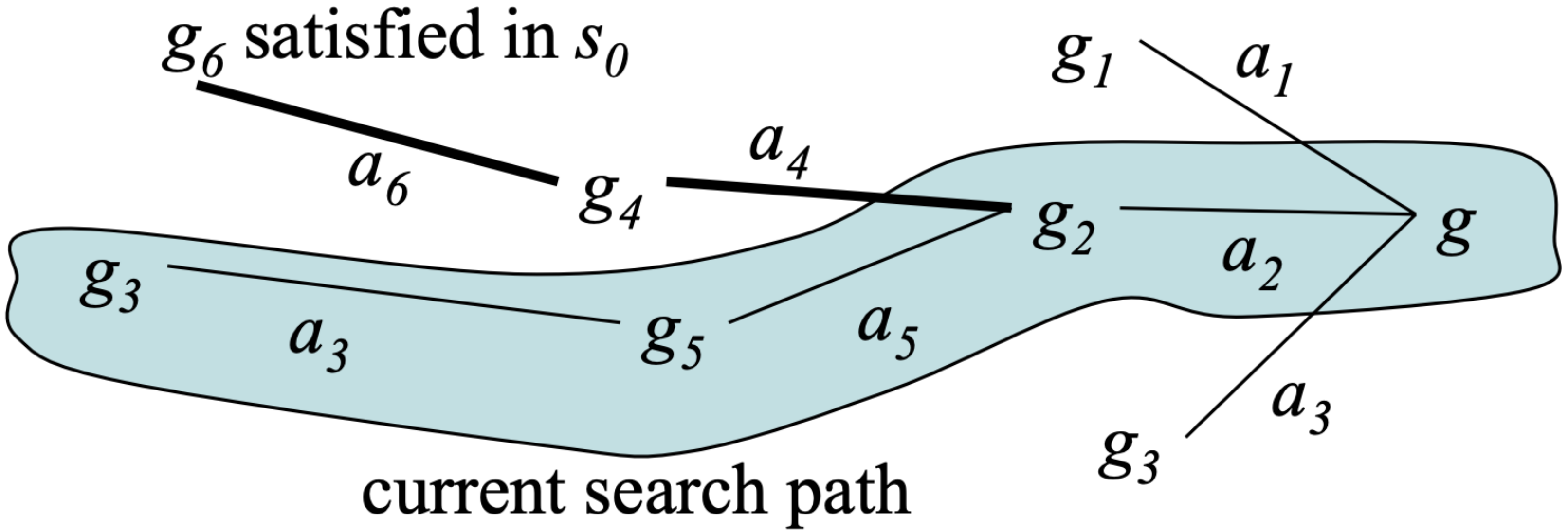
Total Order and Partial Order Plans



Heuristic Planning - STRIPS

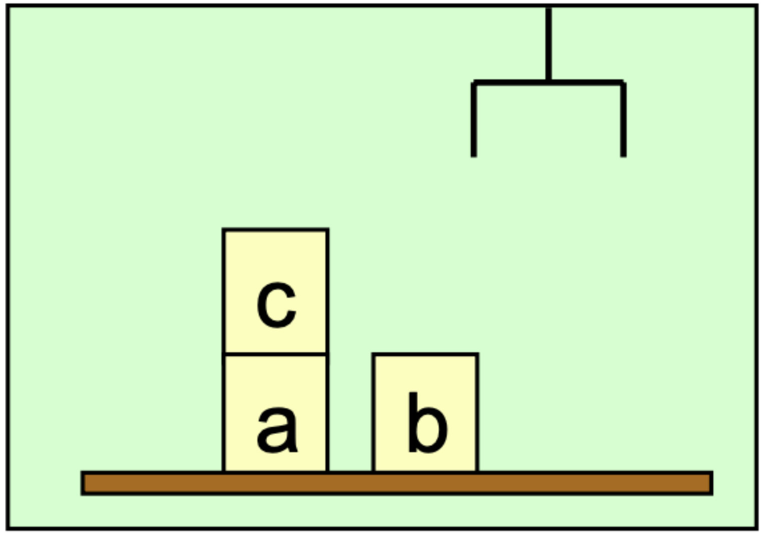
- One of the first planning algorithms (Shakey the robot)
- $\pi \leftarrow$ the empty plan
- do a modified backward search from g
  - ** each new subgoal is precond(a)
  - when you find an action that's executable in the current state, then go forward on the current search path as far as possible, executing actions and appending them to π
  - repeat until all goals are satisfied

Heuristic Planning - STRIPS

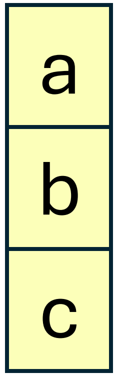


STRIPS Example

- Exercise, solve this like STRIPS would



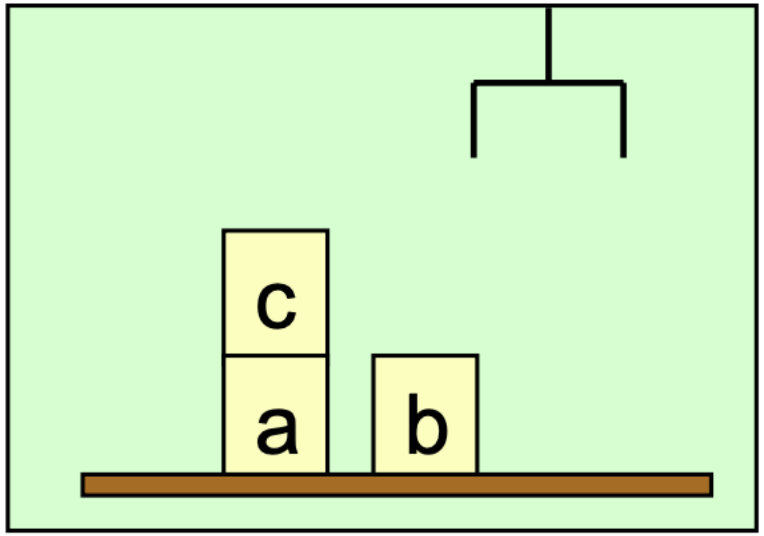
Initial state



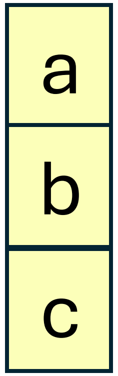
Goal state

Limitation of STRIPS

- Exercise, solve this like STRIPS would
  - Move a on top of b
  - Move b on top of c
  - Contradictory subgoals



Initial state



Goal state

Simulation Search

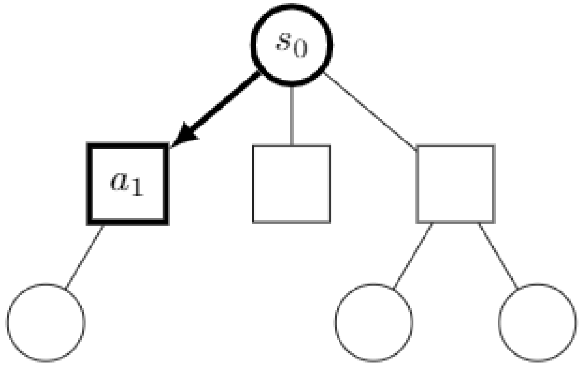
- Evolution of heuristic search, the model of the world is the heuristic that decides how the agent moves forward
- Use the simulation to build estimates of the "value" of being in a state – intuitively, if I am in a state what is the likelihood I will win

Monte Carlo Methods

- A set of methods that focus on learning better from simulated experiences collected by interacting with an environment
- When to use? You have a way of easily simulating an environment but it is too complex to solve deterministically with planning / search

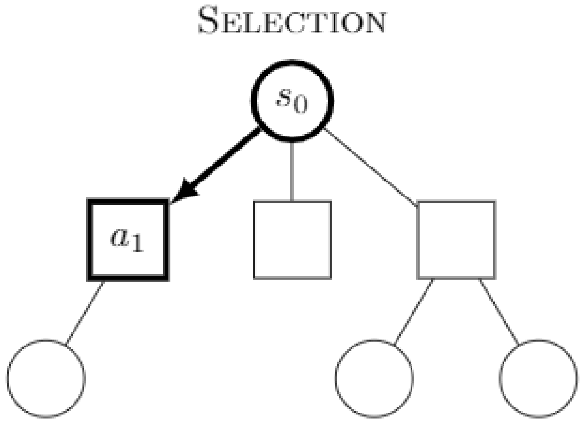
Monte Carlo Tree Search

- 4 phases of building out and simulating paths along a search tree
- Various forms of this used in everything from Alpha Zero to modern LLM inference
- For arbitrary problem with start state s_0 and actions a_i
- All states have attributes:
  - Total simulation reward Q(s) and
  - Total no. of visits N(s)



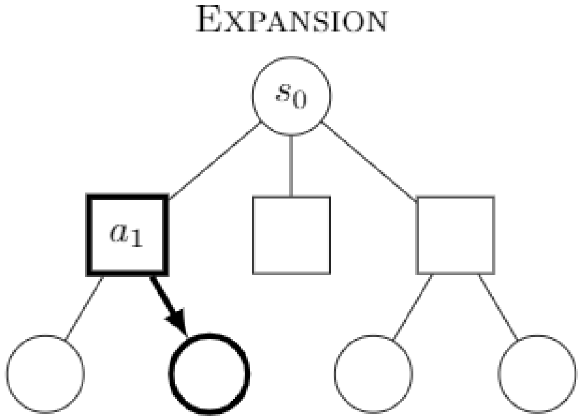
MCTS Part 1 - Selection

- From the current state, pick an action to perform
- For now, assume we pick randomly
- Update N(s) as you pick a new state



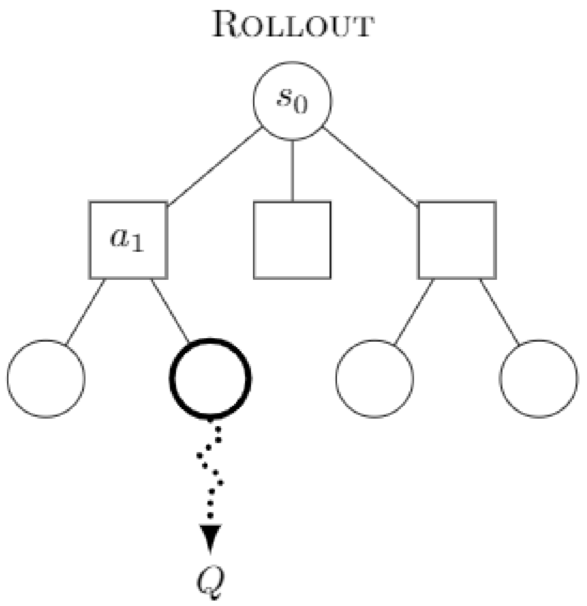
MCTS Part 2 - Expansion

- Execute transition
- If resultant state is a terminal state, observe result (reward)



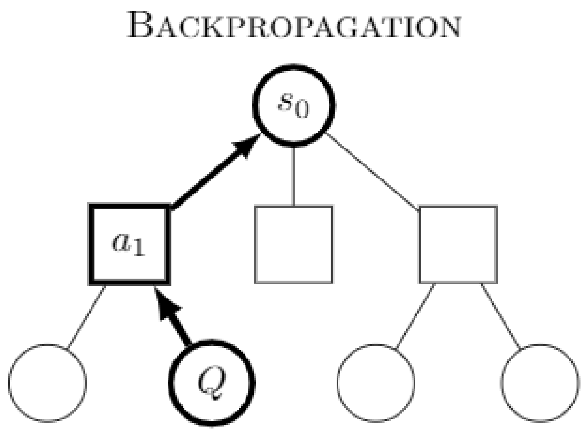
MCTS Part 3 – Simulation / Rollout

- If it isn't a terminal state, finish a playout until it is
- For now, we will "cheat" and directly use our simulation for this



MCTS Part 4 – Backpropogation

- Add the reward of the simulated path to all node scores, this gives you Q(s)



Improvements to MCTS Components

- Improvements are possible for each of the parts I talked about
- Think about that it would take to improve selection / expansion phases

Upper Confidence Trees (UCT)

- A way of improving the selection phase by treating selection as a multi-arm bandit problem: which possible action to select that maximizes the possible payout (reward) in the future

$$\mathrm{UCT}(v_i, v) = \frac{Q(v_i)}{N(v_i)} + c\sqrt{\frac{\ln N(v)}{N(v_i)}}$$

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Exploit

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Exploit Explore

Improvements to MCTS Components

- Improvements are possible for each of the parts I talked about
- Think about that it would take to improve selection / expansion phases
- Can you go further? How to improve the simulation phase?
- Can you add learning in here somehow?