CS 5/7320
Artificial Intelligence

Search with Uncertainty

AIMA Chapters 4.3-4.5

Slides by Michael Hahsler
with figures from the AIMA textbook

Types of uncertainty we consider for now*

Nondeterministic Actions: Outcome of an action in a state is uncertain.

No observations: Sensorless problem

Partially observable environments: The agent does not know in what state it is.

Unknown environments: Online search

* we will quantify uncertainty with probabilities later.

Consequence of Uncertainty

- **Remember**: The solution for the known maze was a fixed **sequence of actions** from start to goal.

- **With uncertainty**: Solution is not a precomputed sequence, but a

  conditional plan (a strategy or policy)

  that depends on percepts.

Nondeterministic Actions

Nondeterministic Actions

Outcome of actions in the environment is nondeterministic = **transition model need to describe uncertainty**

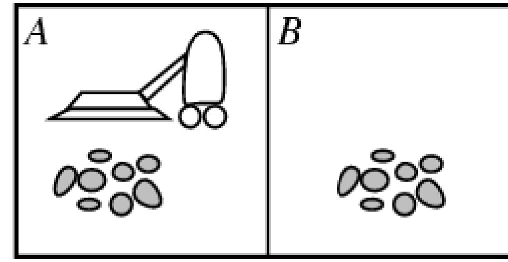
Example transition:

$$Results(s_1, a) = \{s_2, s_4, s_5\}$$

i.e., action a in s_1 can lead to one of several states.

The set of possible states $\mathrm{b} = \{s_2, s_4, s_5\}$ is called a **belief state** of the agent.

Example: Erratic Vacuum World

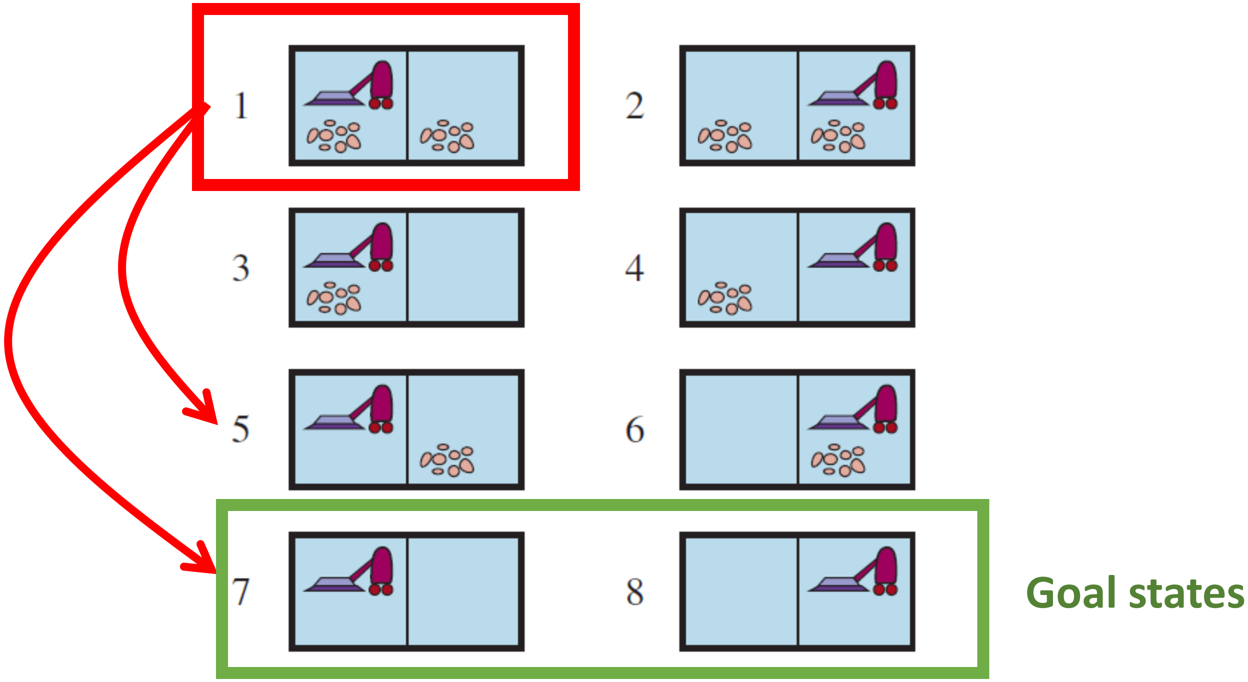


Regular vacuum world, but the action ‘**suck**’ is more powerful and nondeterministic:

a) **On a dirty square**: cleans the square and sometimes cleans dirt on adjacent squares as well.
b) **On a clean square**: sometimes deposits some dirt on the square.

Example: Erratic Vacuum World

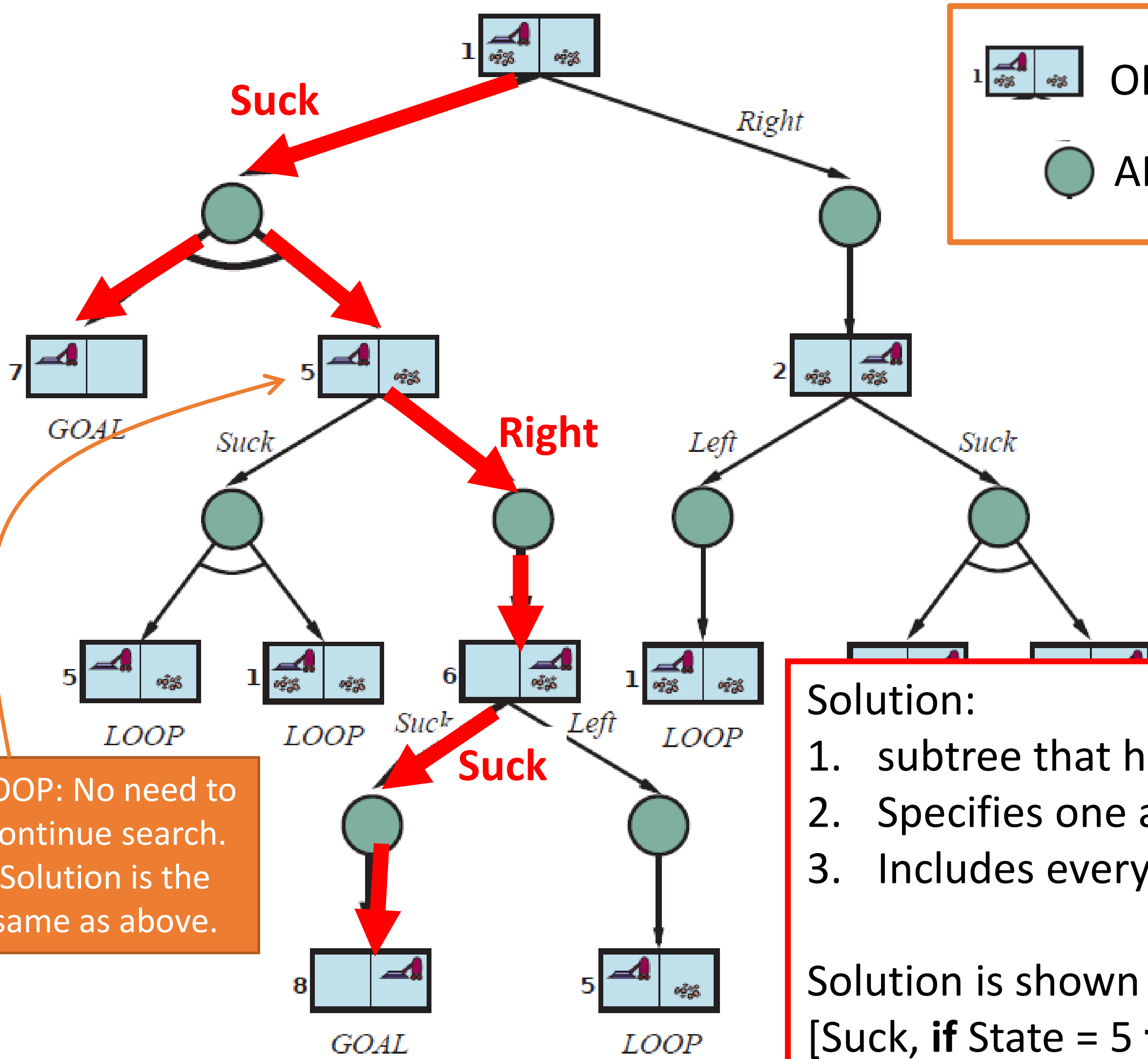
$Results(1, Suck) = \{5, 7\}$



We need a conditional plan

[Suck, **if** State = 5 **then** [Right, Suck] **else** []]

AND-OR Search Tree



OR node (choose action)

AND node (possible outcomes)

LOOP: No need to continue search. Solution is the same as above.

Solution:

1. subtree that has only GOAL leaf nodes
2. Specifies one action at each OR node (state)
3. Includes every outcome of AND nodes

Solution is shown with **bold** arrows:

[Suck, **if** State = 5 **then** [Right, Suck] **else** []]

AND-OR Recursive DFS Algorithm

= nested If-then-else statements

function AND-OR-SEARCH(*problem*) **returns** a conditional plan, or *failure*
  return OR-SEARCH(*problem*, *problem*.INITIAL, [ ])

path is only maintained for cycle checking!

function OR-SEARCH(*problem*, *state*, *path*) **returns** *a conditional plan, or failure*
  if *problem*.IS-GOAL(*state*) **then return** the empty plan
  if IS-CYCLE(*path*) **then return** *failure* // don't follow loops using path.
  for each *action* **in** *problem*.ACTIONS(*state*) **do** // try all possible actions
    plan ← AND-SEARCH(*problem*, RESULTS(*state*, *action*), [*state*] + *path*])
    if *plan* ≠ *failure* **then return** [*action*] + *plan*]
  return *failure*

function AND-SEARCH(*problem*, *states*, *path*) **returns** *a conditional plan, or failure*
  for each s_i **in** *states* **do** // try all possible outcomes, none can fail!
    $plan_i \leftarrow$ OR-SEARCH(*problem*, s_i, *path*) // (= belief state)
    if $plan_i$ = *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** $plan_n$]

BFS and A* search can also be used to search an AND-OR tree.

Search with no Observations

No Observations

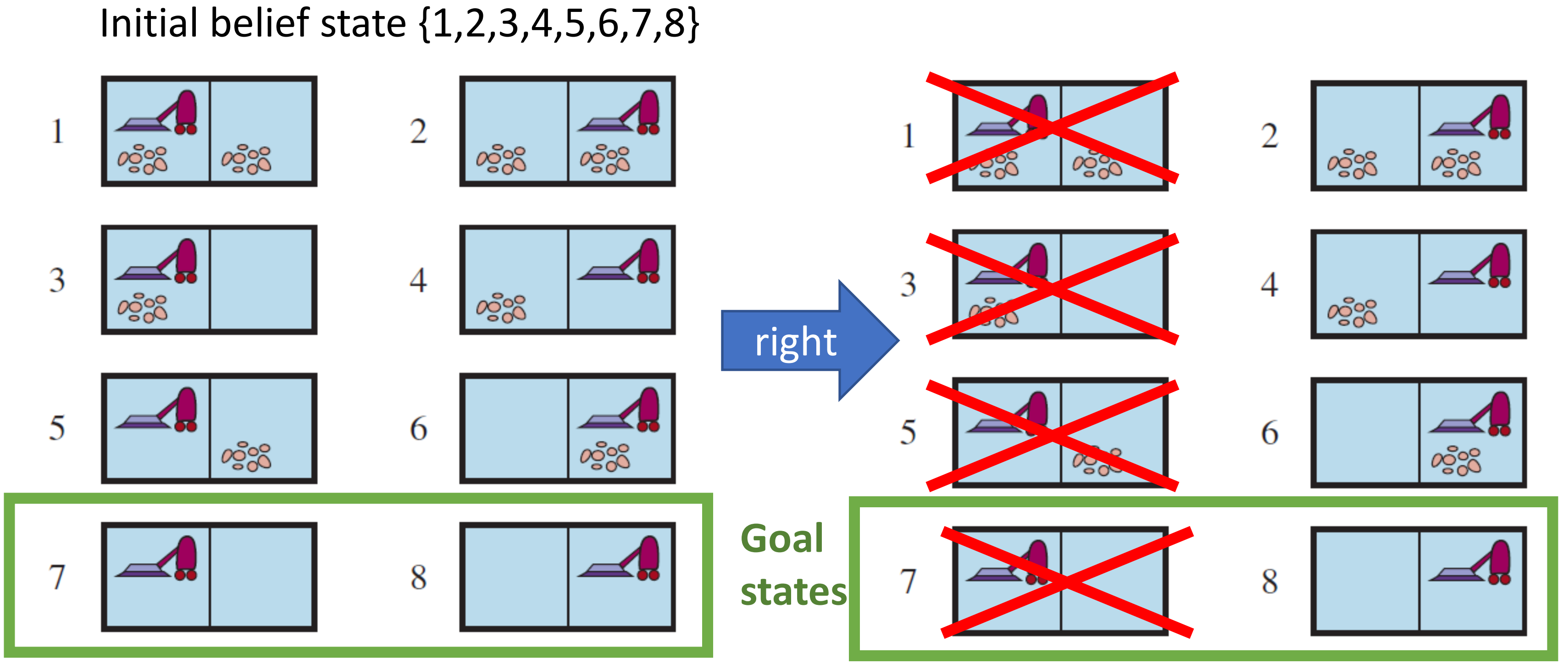
- Sensorless problem = conformant problem

- **Example**: Doctor prescribes a broad-band antibiotic instead of performing time-consuming blood work for a more specific antibiotic. This saves time and money.

- **Basic idea**: Find a solution (a sequence of actions) that works from any state.

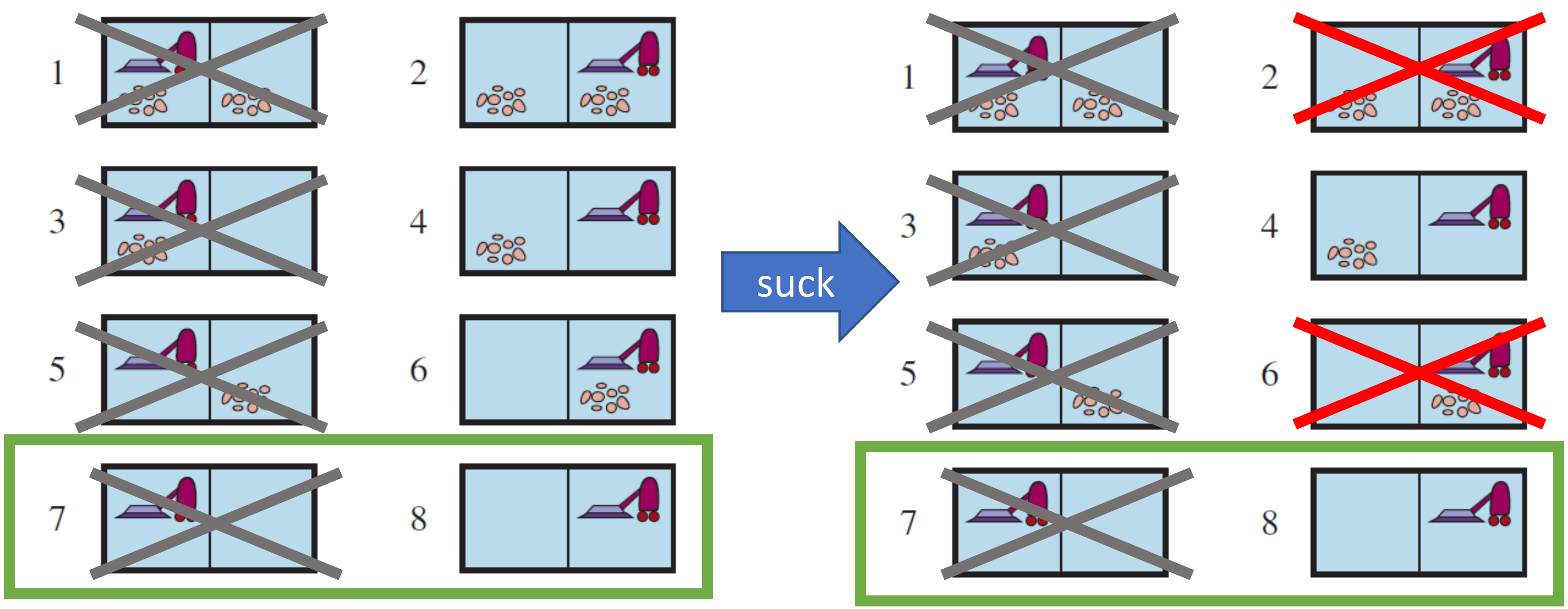
Actions to Coerce the World into States

- Actions can reduce the number of possible states.
- **Example**: Deterministic vacuum world. Agent does not know its position and the dirt distribution.



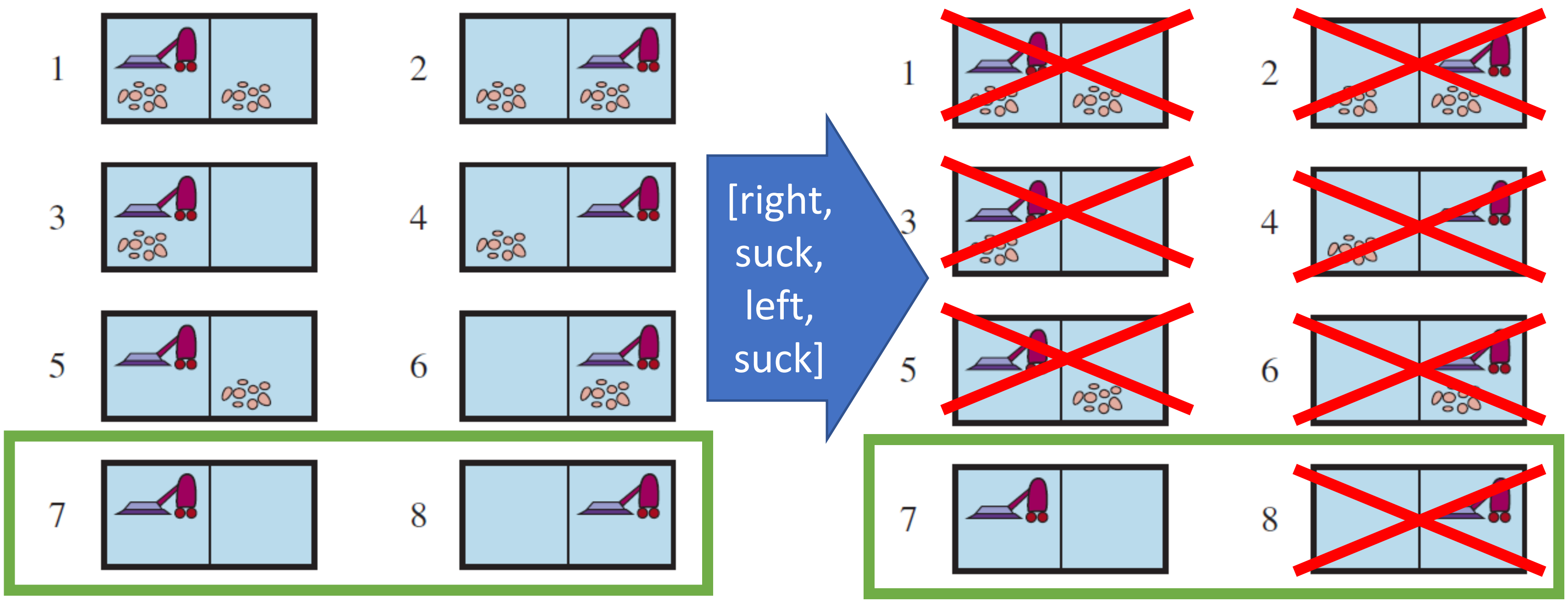
Actions to Coerce the World into States

- Actions can reduce the number of possible states.
- **Example**: Deterministic vacuum world. Agent does not know its position and the dirt distribution.



Actions to Coerce the World into States

- The action sequence [right, suck, left, suck] coerces the world into the goal state 7.
- This works from any initial state and there is no need for a conditional plan!



Find the Solution Sequence

Note: State space size makes this impractical for larger problems!

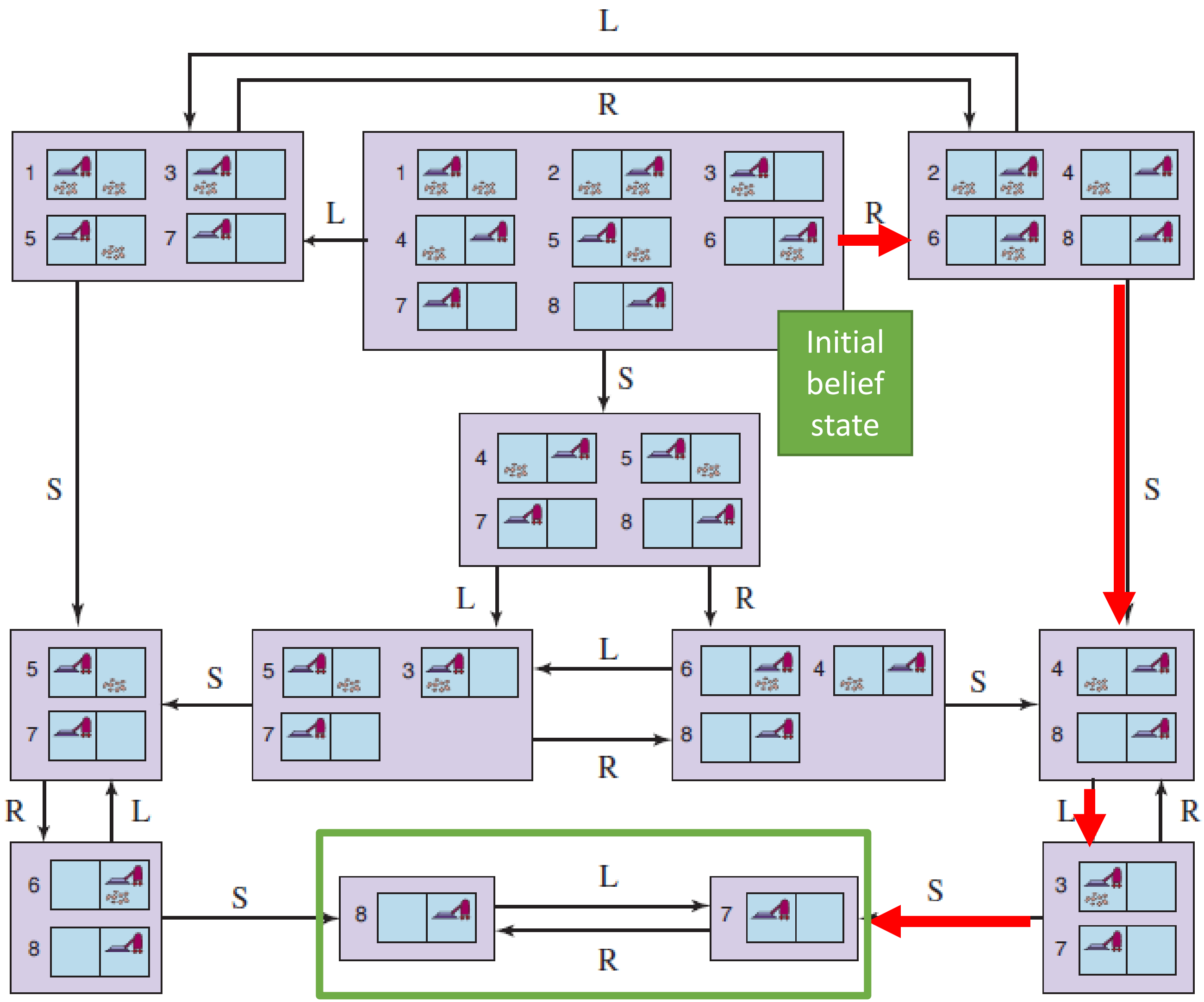
Use regular search (DFS, BFS, A*) for the problem:

- **States**: All belief states (=powerset $\mathcal{P}_s$ of states of size 2^N for N states)
- **Initial state:** Often the belief state consisting of all states.
- **Actions:** Actions of a belief state are the union of the possible actions for all the states it contains.
- **Transition model:** $b' = Results(b, a) = \{s' : s' = Result(s, a) \text{ } and \text{ } s \in b\}$
- **Goal test:** Are all states in the belief state goal states?
- **Simplifying property:** If a belief state (e.g., $b_1 = \{1,2,3,4,5\}$) is solvable (i.e., there is a sequence of actions that coerce all states to only goal states), then belief states that are subsets (e.g., $b_2 = \{2,5\}$) are also solved using the same action sequence. Used to prune the search tree.

Other approach:

- **Incremental belief-state search**. Generate a solution that works for one state and check if it also works for all other states.

Reachable belief-state space for the deterministic, sensorless vacuum world



Solution Sequence: [right, suck, left, suck]

Size of the belief state space:

$$\mathcal{P}_s = 2^N = 2^8 = 256$$

Only as small fraction is reachable.

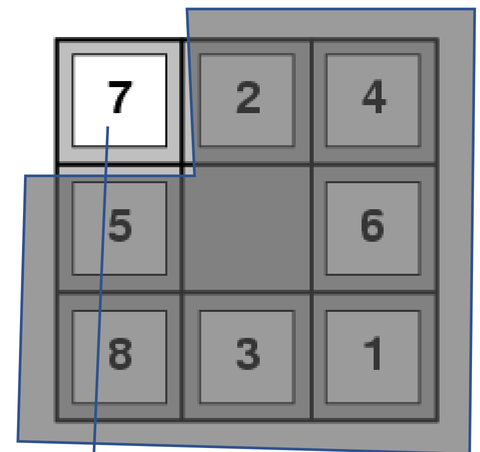
Partially Observable Environments

Percepts

- Many problems cannot be solved efficiently without sensing (e.g., 8-puzzle).
- We need to be able to at least see one square.

Percept function: $Percept(s)$

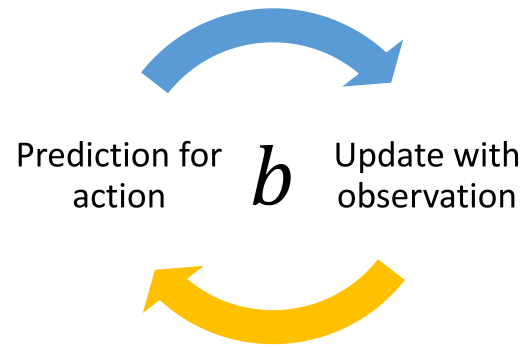
- **Fully observable**: $Percept(s) = s$
- **Sensorless**: $Percept(s) = null$
- **Partially observable**: $Percept(s) = o$



$Percept(s) = Tile7$

Problem: Many states can produce the same percept!

Prediction and Update



Assume we have a belief state b (i.e., the set of states we could be in)

Prediction: Compute new belief state that results from action a.

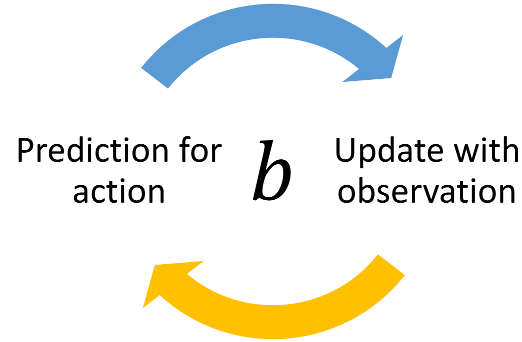
$$\hat{b} = Predict(b, a)$$

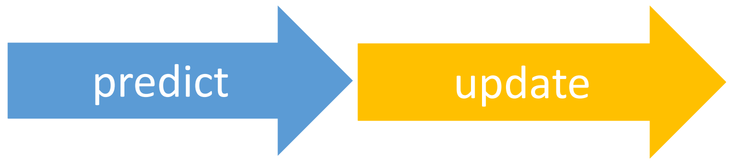
Update: Filter states that are consistent with new observation o.

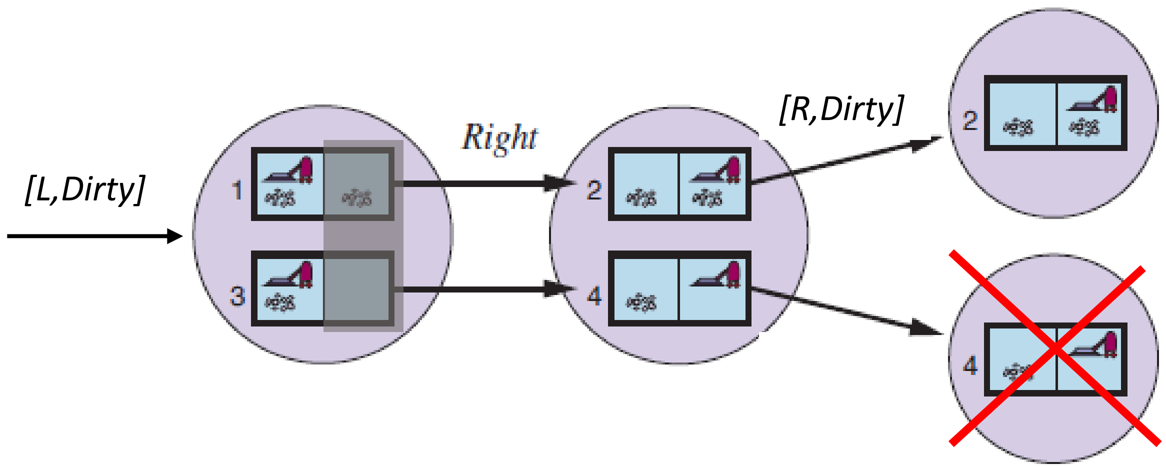
$$b_o = Update(\hat{b}, o) = \{s : o = Percept(s) \text{ and } s \in \hat{b}\}$$

Both steps in one: $b \leftarrow Update(Predict(b, a), o)$

Example: Deterministic local sensing vacuum world





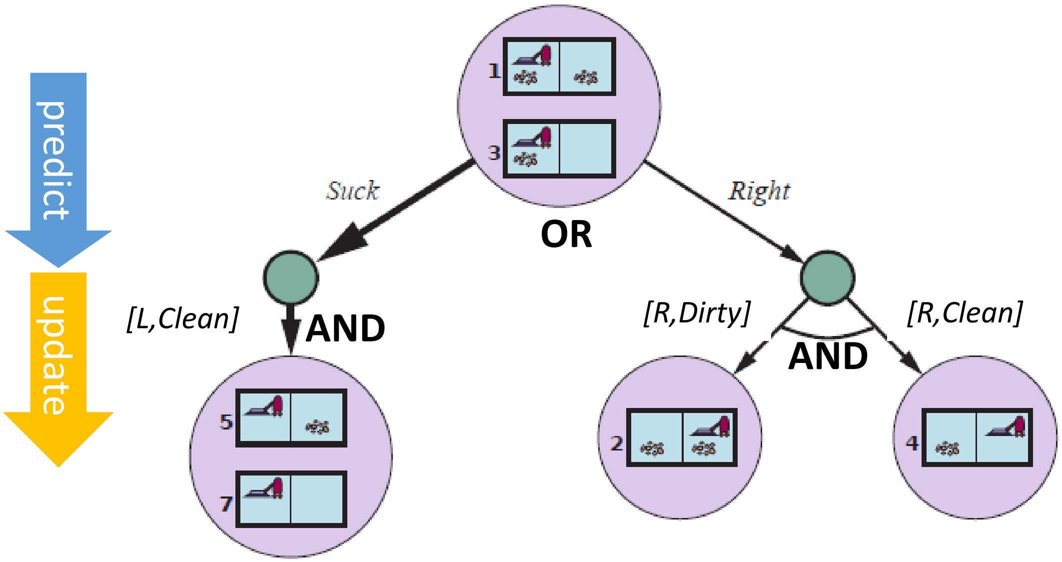


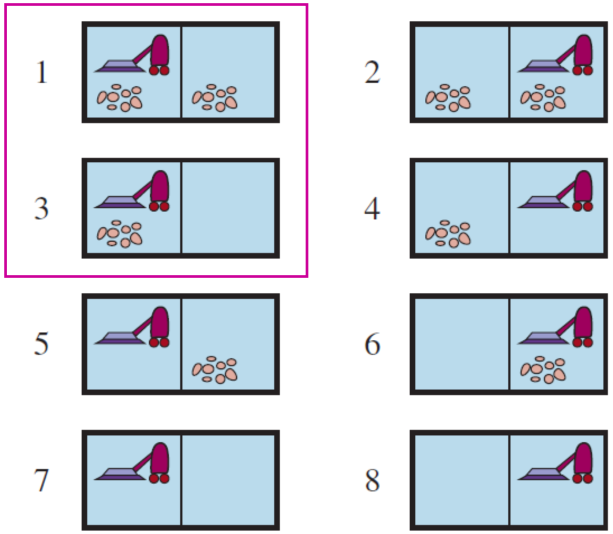
$$b \leftarrow Update(Predict(b, a), o)$$

$$Update(Predict(\{1,3\}, Right), [R.Dirty]) = \{2\}$$

Solving Partially Observable Problems

Use an AND-OR tree to create a conditional plan

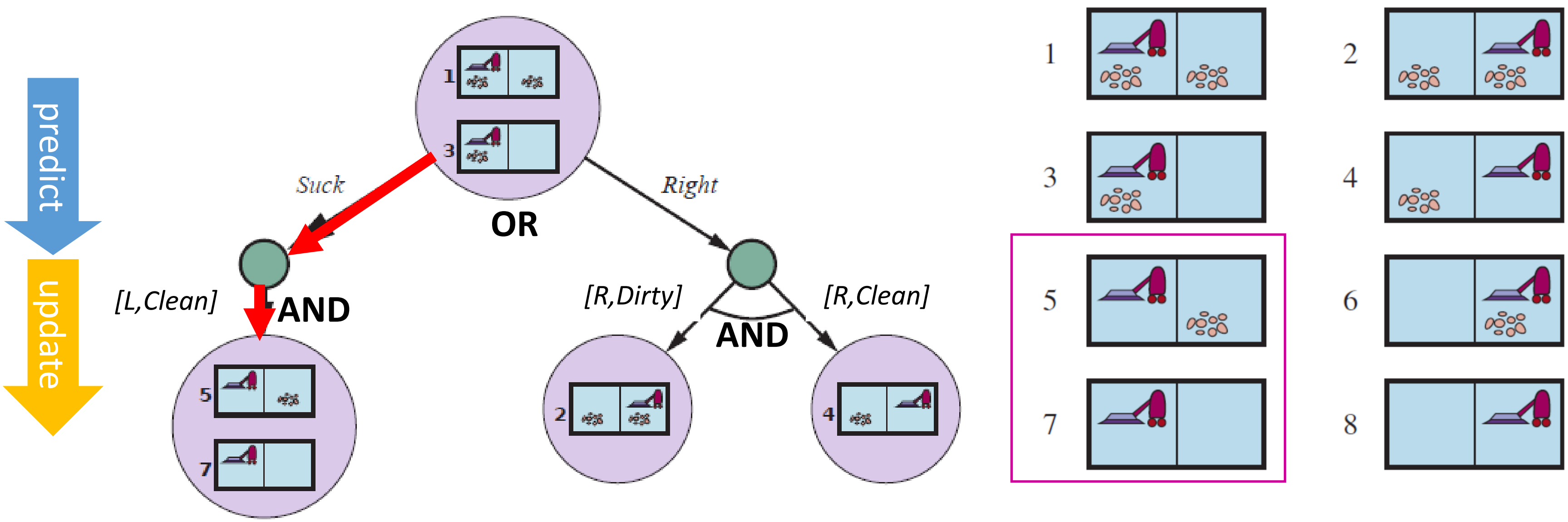




Solution: *[Suck, Right,* **if** *b = {6}* **then** *Suck* **else** *[]]*

Solving Partially Observable Problems

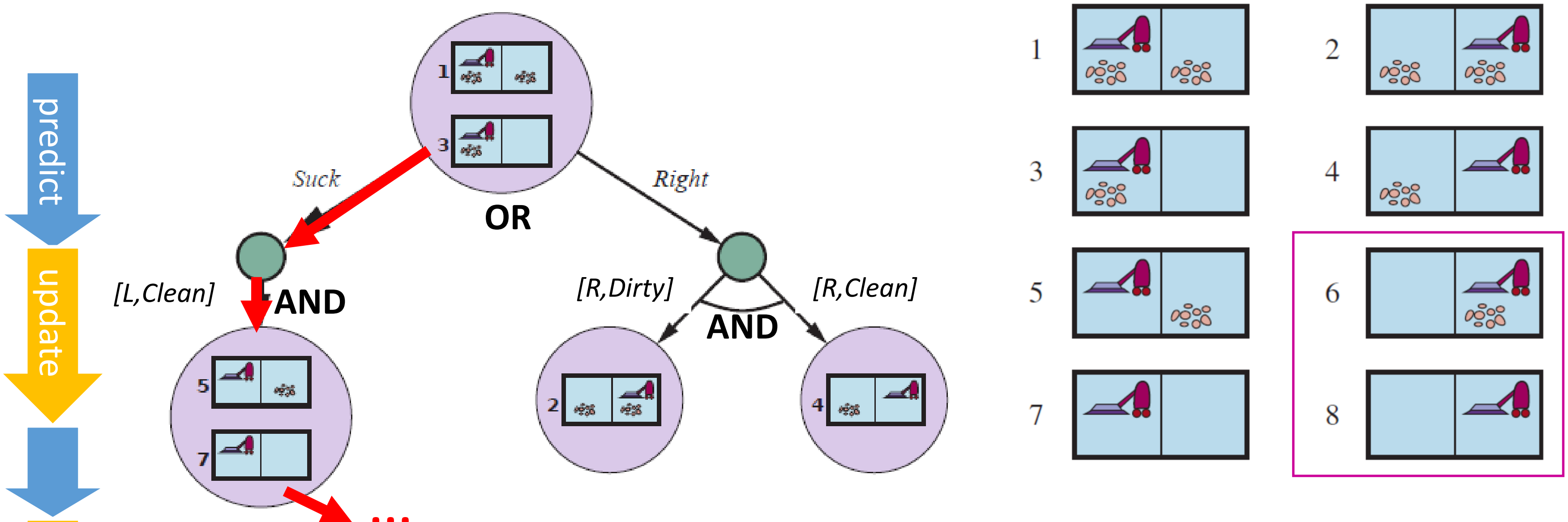
Use an AND-OR tree to create a conditional plan



Solution: *[Suck, Right,* **if** *b = {6}* **then** *Suck* **else** *[]]*

Solving Partially Observable Problems

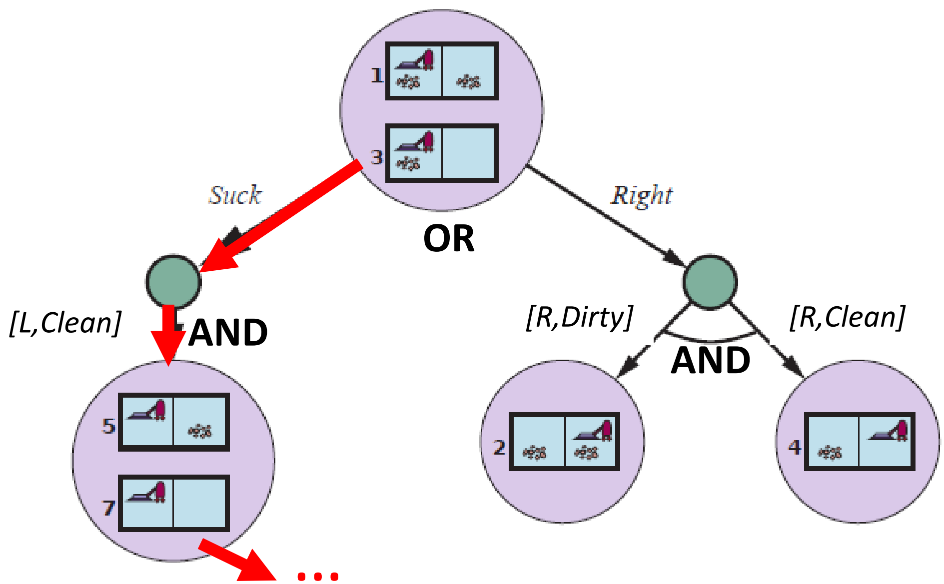
Use an AND-OR tree to create a conditional plan

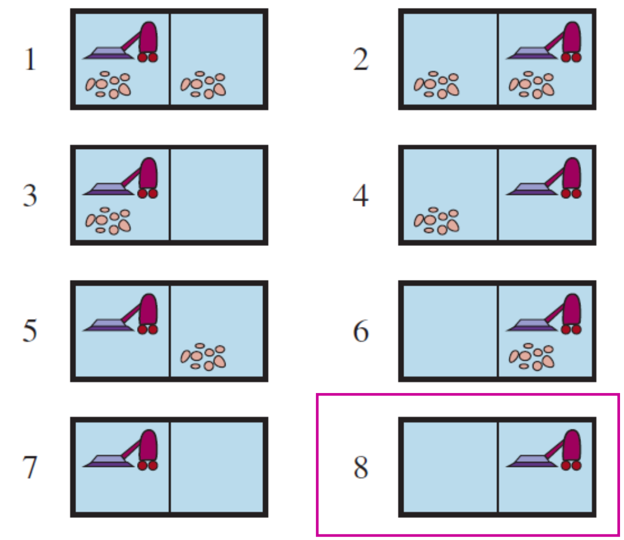


Solution: *[Suck, Right,* **if** *b = {6}* **then** *Suck* **else** *[]]*

Solving Partially Observable Problems

Use an AND-OR tree to create a conditional plan





Solution: *[Suck, Right, if b = {6} then Suck else []]*

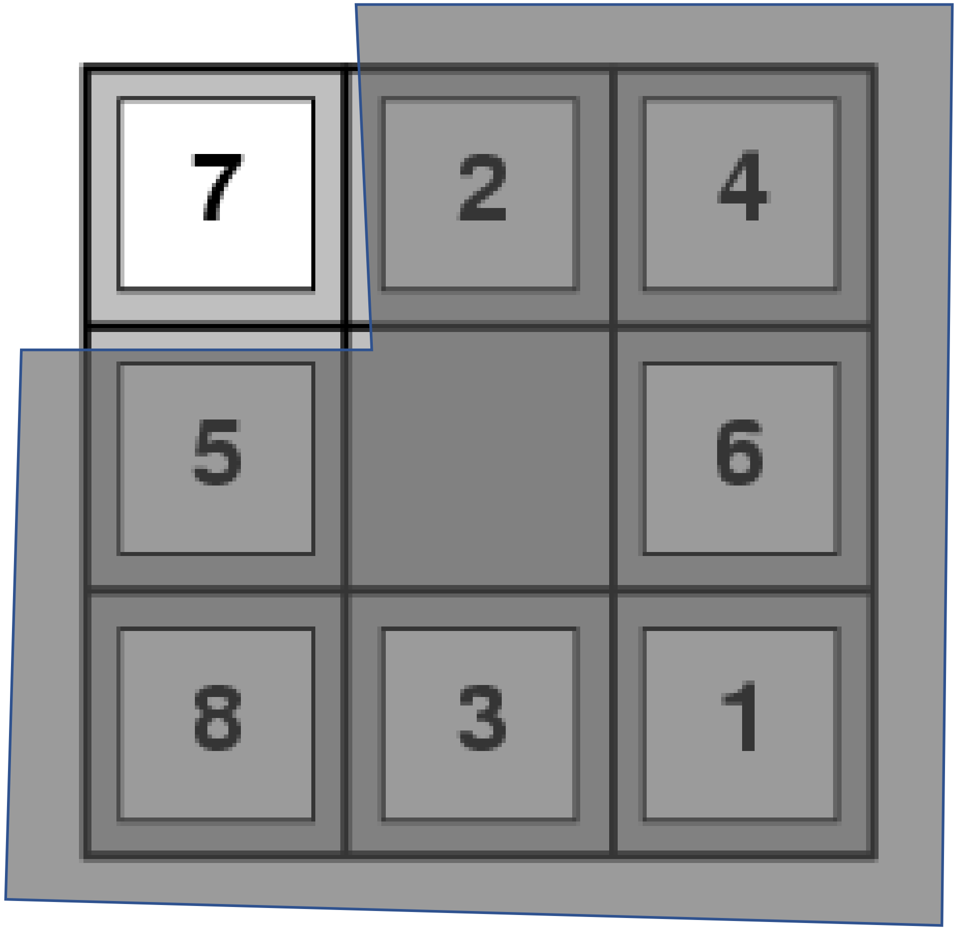
Note: Belief states that are subsets can be used for pruning!

State Estimation and Approximate Belief States

- Agents choose an **action** and then receive an **observation** from the environment.
- The agent keep track of its belief state using the following update:

$$b \leftarrow Update(Predict(b, a), o)$$

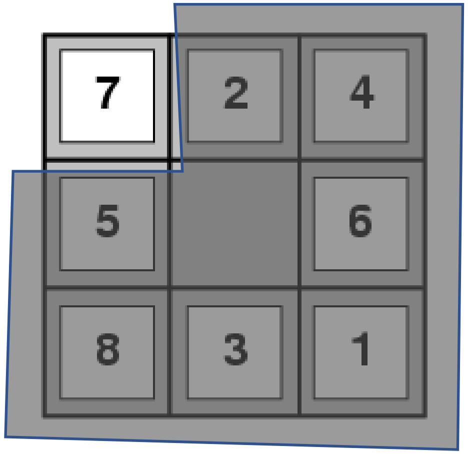
- This process is often called
  - **monitoring**,
  - **filtering**, or
  - **state estimation**.
- The agent needs to be able to update its belief state following observations in **real time**! For many practical application, there is only time to compute an **approximate belief state!** These approximate methods are outside the scope of this introductory course.



Case Study

Partially
Observable
8-Puzzle

Partially Observable 8-Puzzle



- How do we solve this problem? What are the main steps?

- Give a problem description for each step.
  - States:
  - Initial state:
  - Actions:
  - Transition model:
  - Goal test:
  - Percept function:

- What algorithms can be used?

Unknown Environment

Online Search

Online Search

- **Recall offline search**: Create plan using the state space as a model before taking any action. The plan can be a sequence of actions or a conditional plan (for all possible observations).

- **Online search** explores the real world one action at a time. Prediction is replaced by “act” and update by “observe.”

- Useful for
  - **Real-time problems**: When offline computation takes too long and there is a penalty for sitting around and thinking.
  - **Nondeterministic domain**: Deal with what actually happens.
  - **Unknown environment**: The agent needs to explore to map an unknown area (state space).
    The map is the transition model $f : S \times A \to S$

Issues With Online Search

- **Knowledge**: What does the agent know about the outcome of actions? E.g., does go north and then south lead to the same location?
- **Safely explorable state space/world**: There are **no irreversible actions** that cannot be undone (e.g., traps, cliffs). At least the agent does not execute these actions.

- Expanding nodes in **local order** is more efficient:

  Depth-first search with back tracking

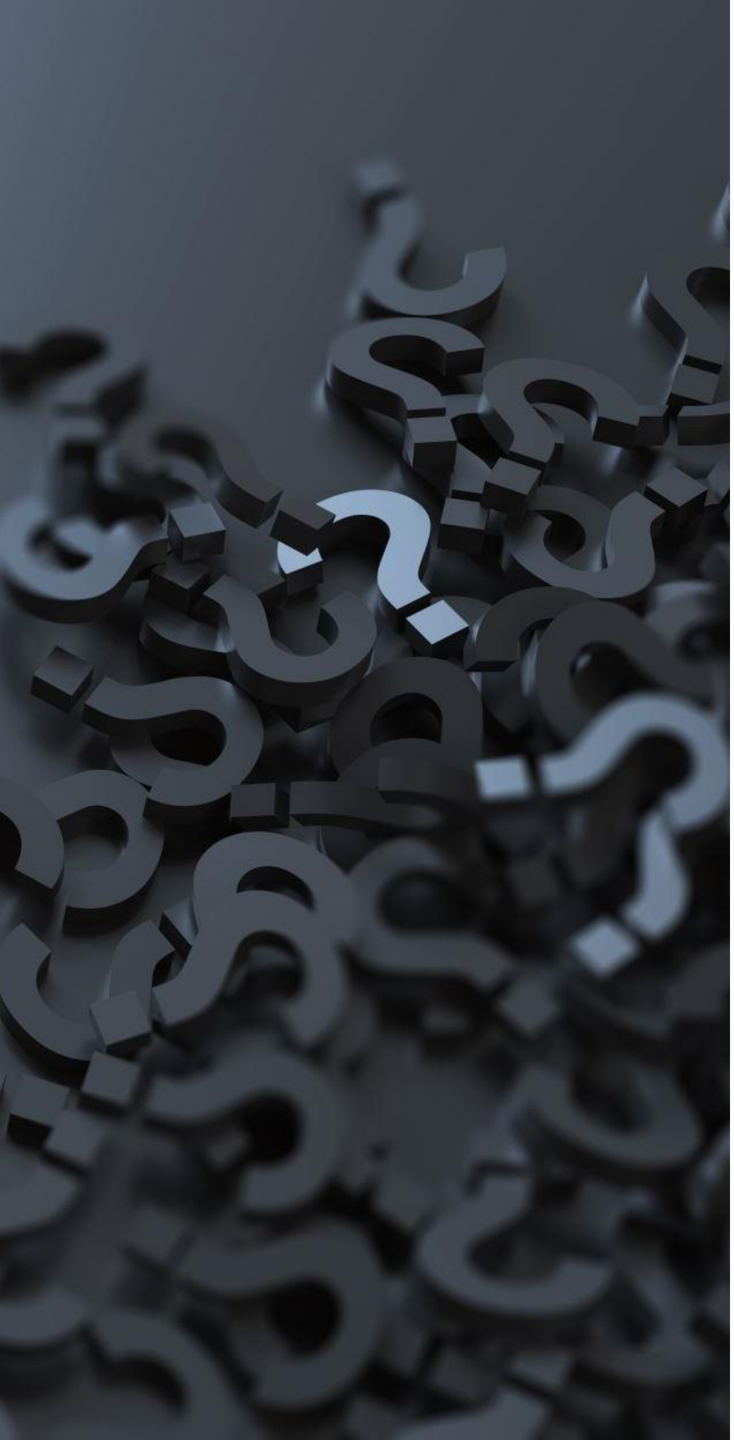
DFS Online Search Algorithm

Environment is deterministic and completely observable ($percept(s) = s'$ after action a), but the transition model (function $result$) is unknown.
This algorithm builds the map $result$ by trying all actions and backtracks when all actions in a state have been explored.

function ONLINE-DFS-AGENT($problem$, s') **returns** an action
    persistent: s, a, the previous state and action, initially null
        $result$, a table mapping (s, a) to s', initially empty
        $untried$, a table mapping s to a list of untried actions
        $unbacktracked$, a table mapping s to a list of states never backtracked to

Learns results and uses it for backtracking

if $problem$.IS-GOAL(s') **then return** $stop$
if s' is a new state (not in $untried$) **then** $untried[s'] \leftarrow problem$.ACTIONS($s'$)
if s is not null **then**
    $result[s, a] \leftarrow s'$
    add s to the front of $unbacktracked[s']$ // unbacktraced leaves a "breadcrumb trail"
if $untried[s']$ is empty **then**
    if $unbacktracked[s']$ is empty **then return** $stop$
    else $a \leftarrow$ an action b such that $result[s', b] =$ POP($unbacktracked[s']$)
else $a \leftarrow$ POP($untried[s']$)
$s \leftarrow s'$
return a



Important concepts that you should be able to explain and use now…

- Difference between the solution types:
  - a fixed actions sequence, and
  - a conditional plan (also called strategy or policy).
- What are belief states?
- How actions can be used to coerce the world into states.
- State estimation with repeated predict and update steps.
- The use of AND-OR trees.