CS 5/7320
Artificial Intelligence

Search with Uncertainty

AIMA Chapters 4.3-4.5

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with figures from the AIMA textbook

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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.

Exploration:
Unknown environments and 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 typically not a precomputed sequence, but a

  conditional plan (a strategy or policy)

  that depends on percepts.

Nondeterministic Actions

Nondeterministic Actions

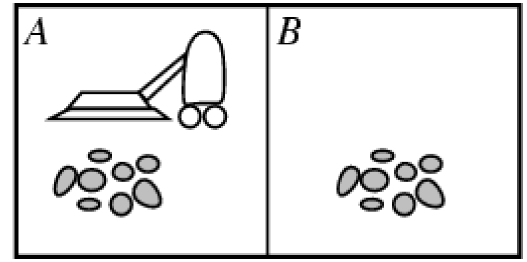
Outcome of actions in the environment is nondeterministic = **transition model need to describe uncertainty**

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.

Example: Erratic Vacuum World

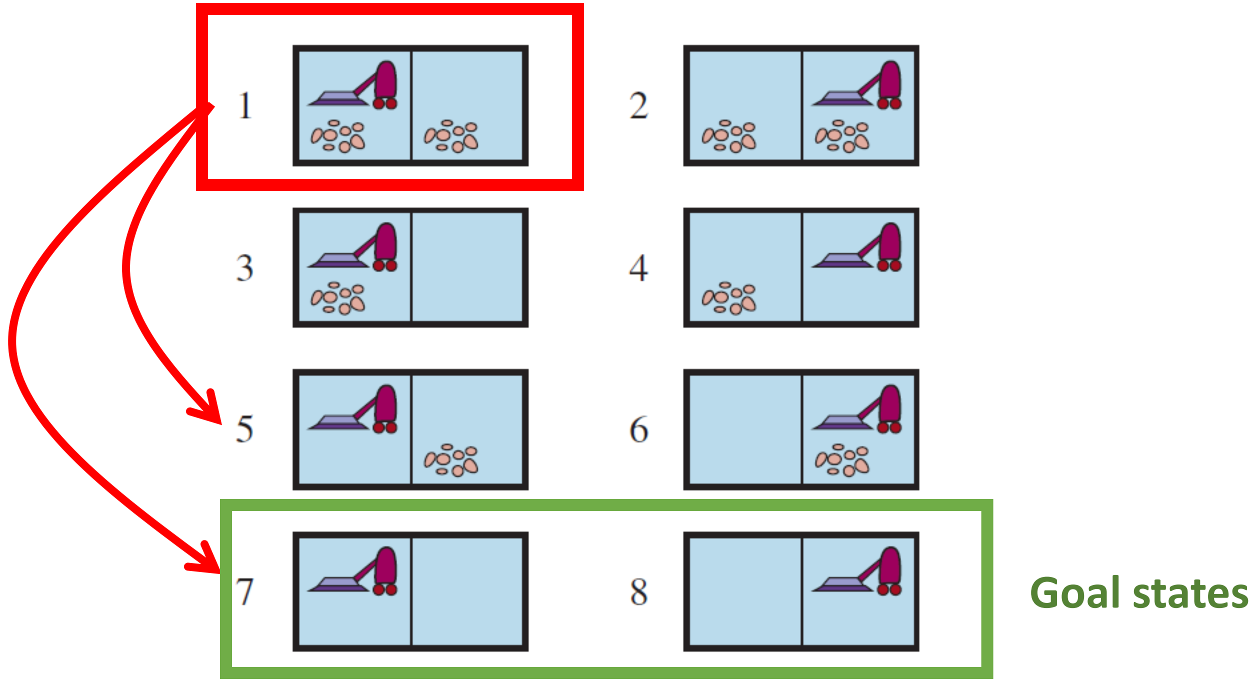


Regular fully-observable vacuum world, but the action '**suck**' is more powerful and **nondeterministic**:

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

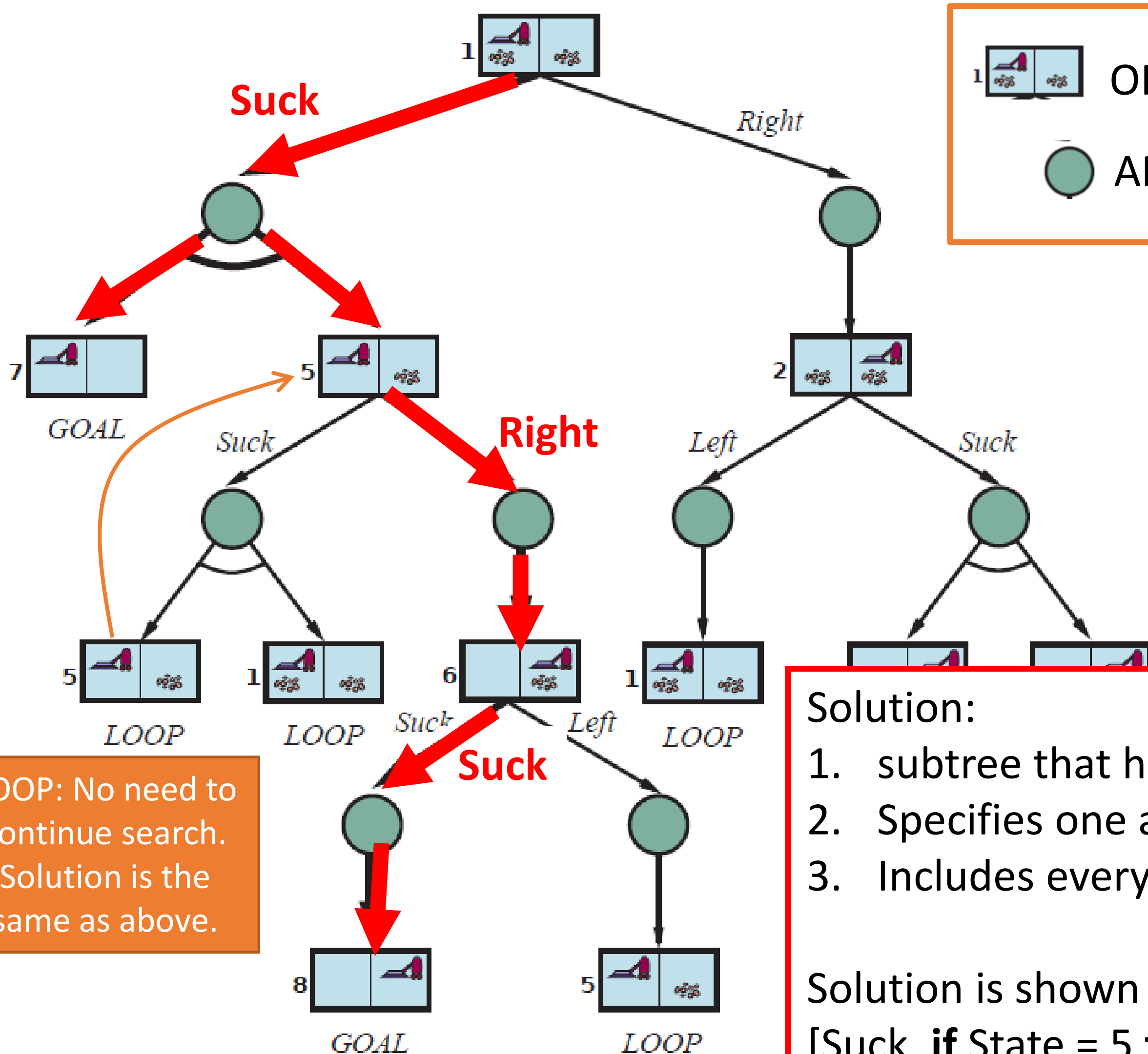
$Results(1, Suck) = \{5, 7\}$



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 ← 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]
```

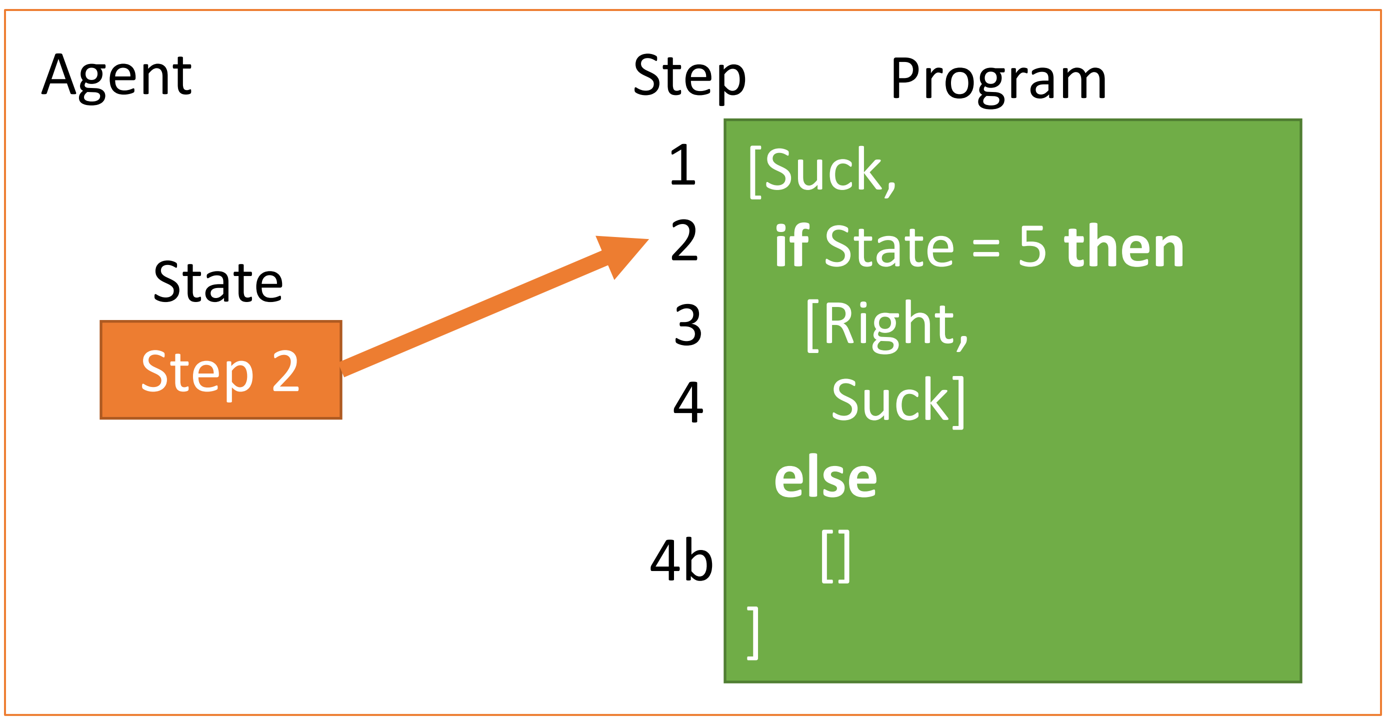
Notes:

- The DFS search tree is implicitly created using the call stack.
- DFS is **not optimal**! BFS and A* search can be used to find the optimal solution.

Use of Conditional Plans

- The conditional plan can be used in a **model-based reflex agent**.

Example: After the initial action “suck”



Search with no Observations

Using Actions to Coerce the World into Known States

No Observations

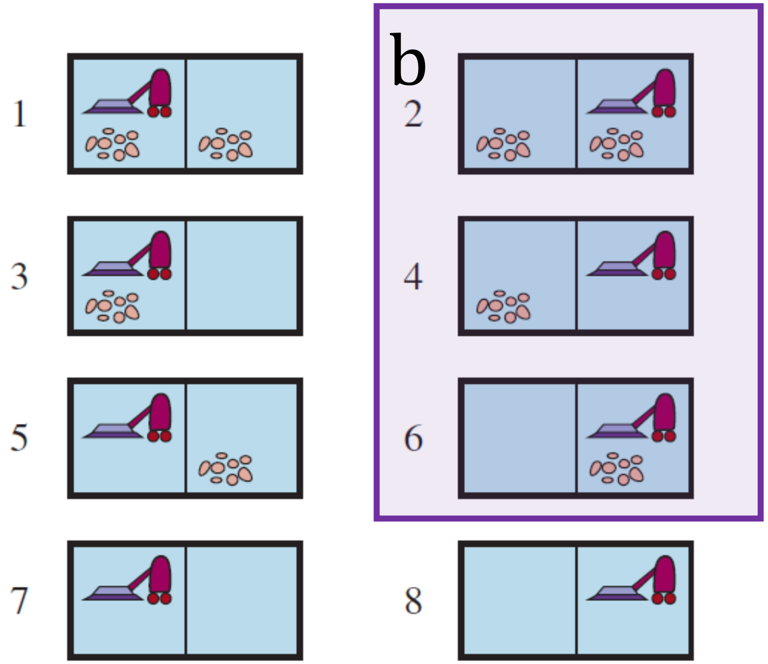
- Sensorless problem = conformant problem

- **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** and then just blindly execute it (called open loop system).

Belief State

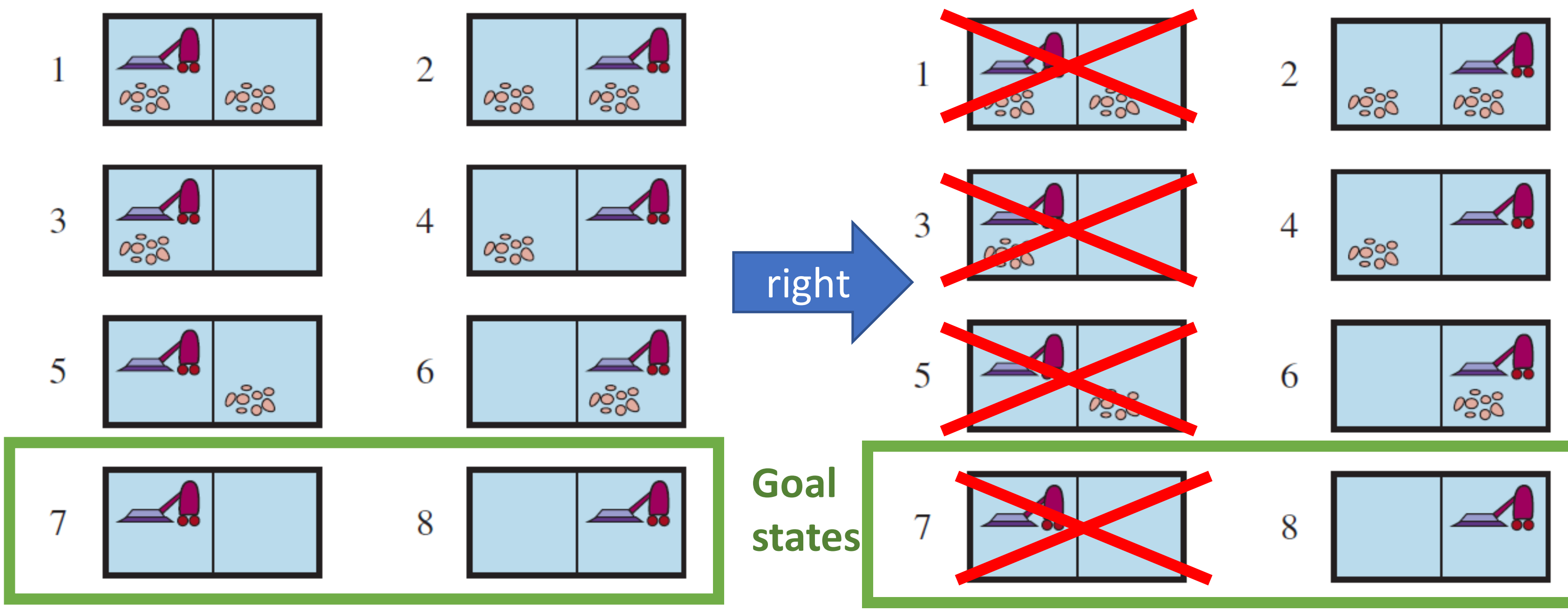
- The set of possible states that the agent could be in is called a **belief state** of the agent.
- The agent does not know in which he is exactly in.
- Example: $\mathrm{b} = \{s_2, s_4, s_6\}$



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.

Initial belief state {1,2,3,4,5,6,7,8}



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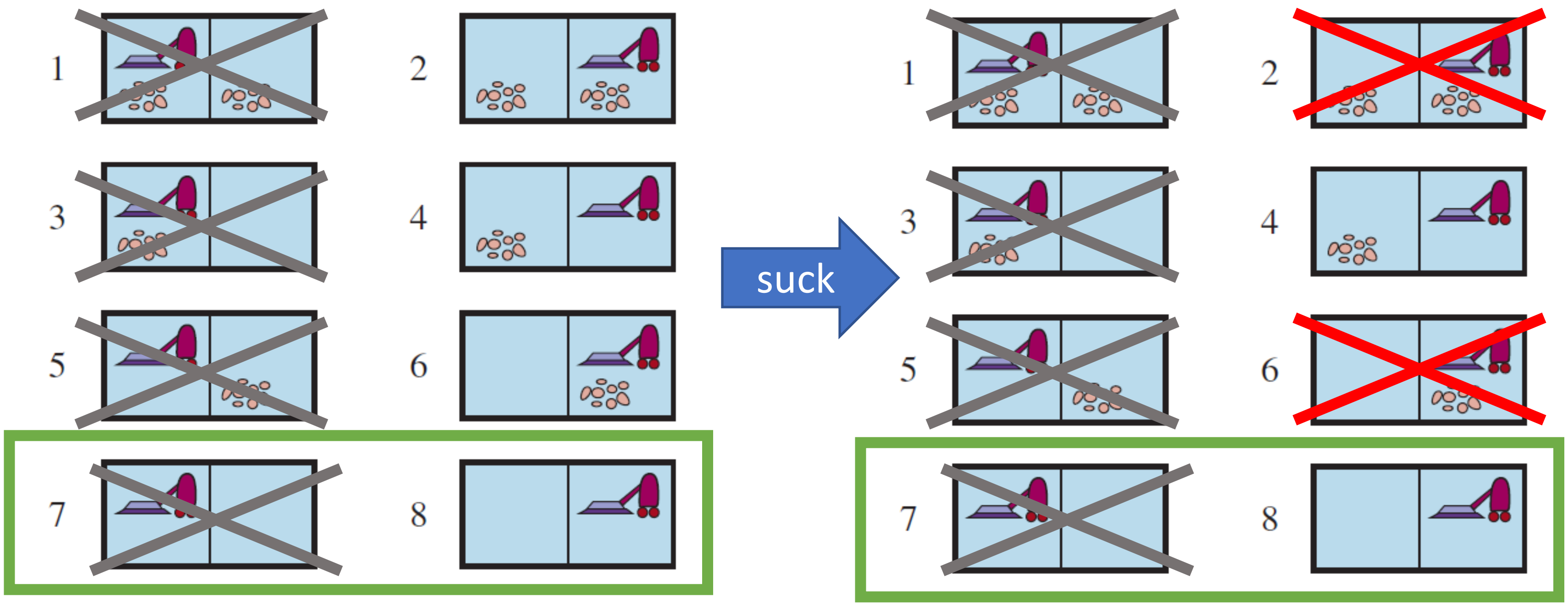
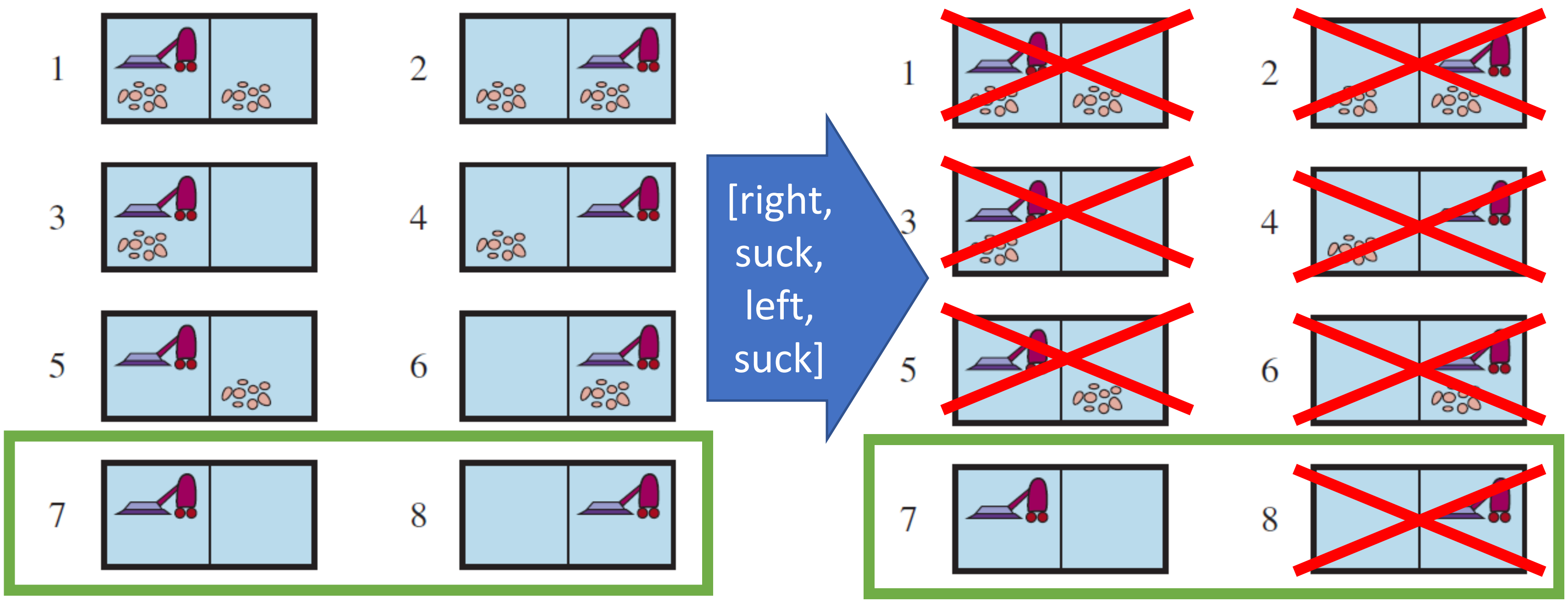
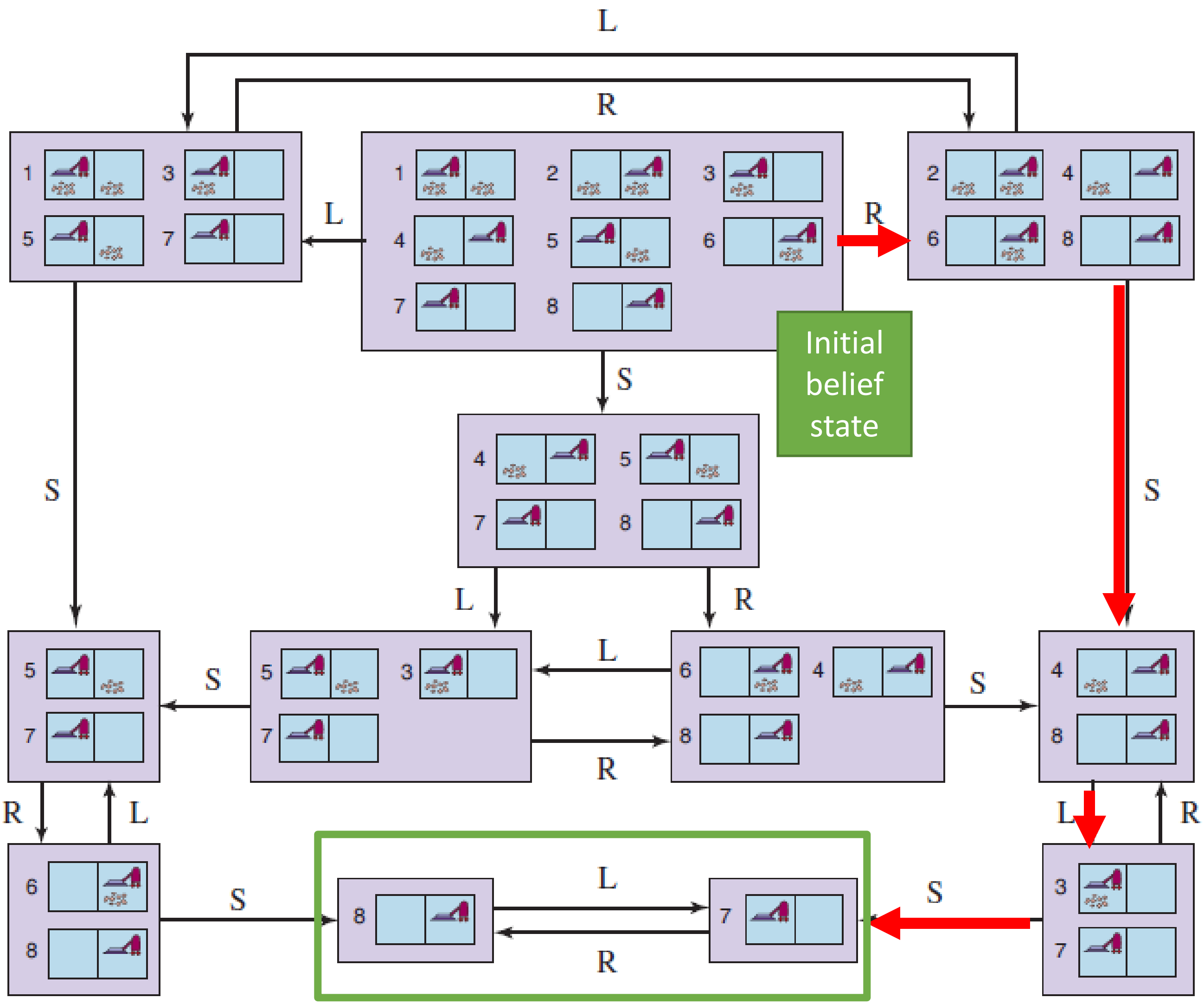


Actions to Coerce the World into States

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



Example: The reachable belief-state space for the deterministic, sensorless vacuum world



Size of the belief state space:

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

Only as small fraction is reachable.

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

Finding a Solution Sequence

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

Formulate as a regular search and solve with DFS, BFS or A*:

- **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. This is similar to local search.

Partially Observable Environments

Using Observations to
Learn About the State

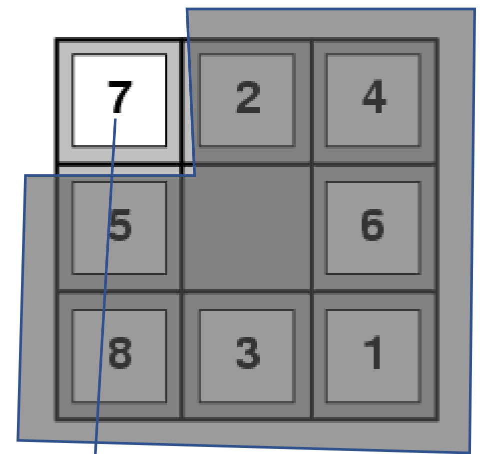
Percepts and Observability

- 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: $Percept(s)$

s is the state

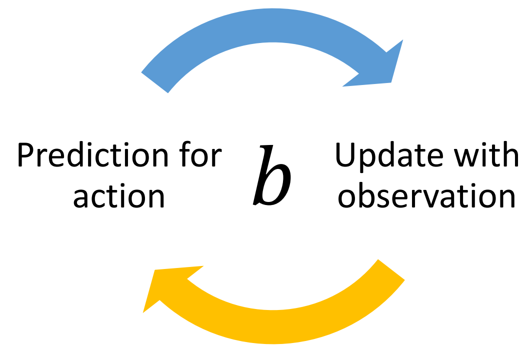
- **Fully observable**: $Percept(s) = s$
- **Sensorless**: $Percept(s) = null$
- **Partially observable**: $Percept(s) = o$



$Percept(s) = Tile7$

Problem: Many states can produce the same percept!

Use Observations to Learn About the State



Agents choose an action and then receive an observation.
Idea: Observations can be used to learn about the agent's state.

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

Prediction for action: Choose an action a and compute a new belief state that results from the action.

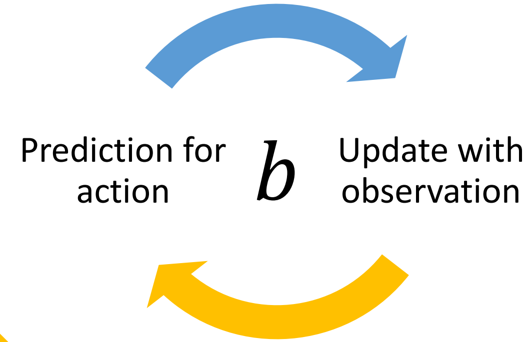
$$\hat{b} = Predict(b, a) = \bigcup_{s \in b} Predict(s, a)$$

Update with observation: You receive an observation o and only keep states that are consistent with the new observation.

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

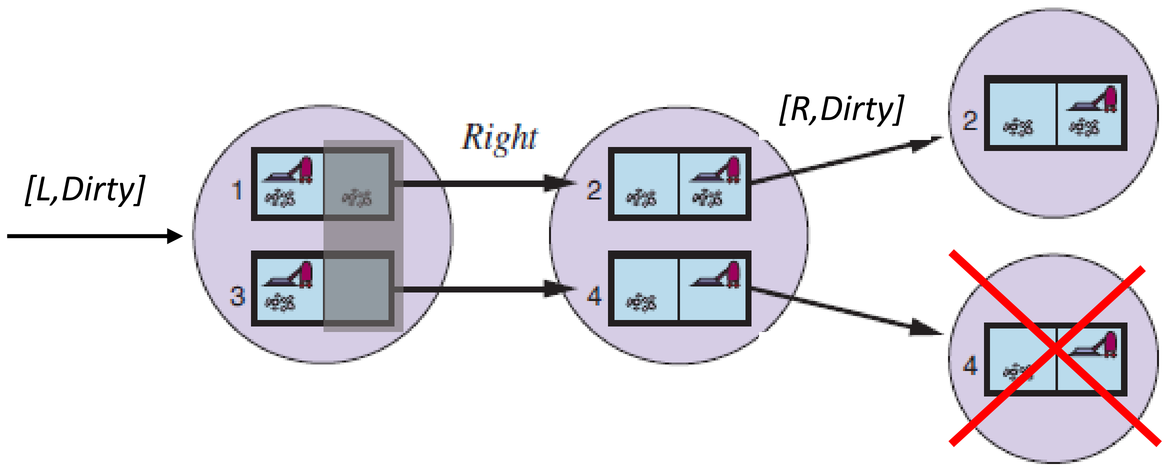
Both steps in one: $b \leftarrow Update(Predict(b, a), o)$

Example: Deterministic local sensing vacuum world



Predict for actions

Update with observation

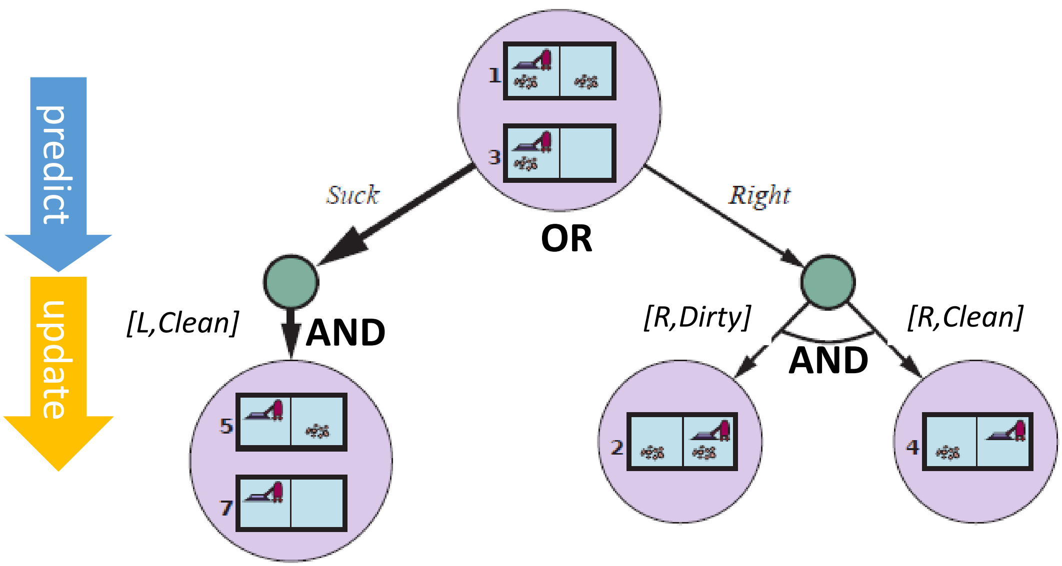


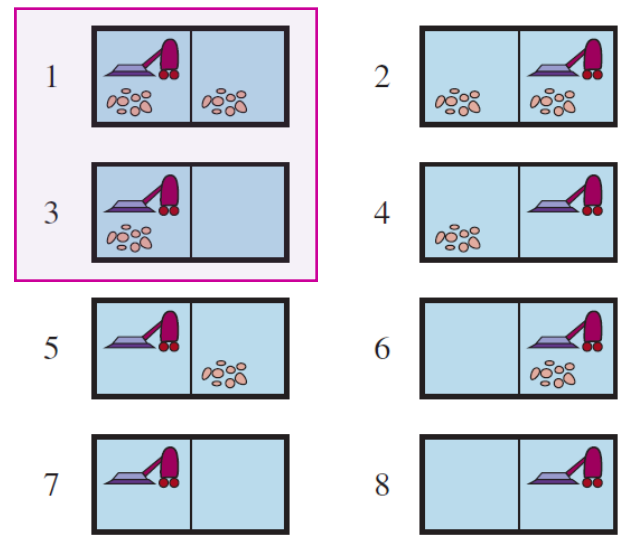
$$b \leftarrow Update(Predict(\ b\ ,\ \ a\ ),\ \ o\ \ )$$

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

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

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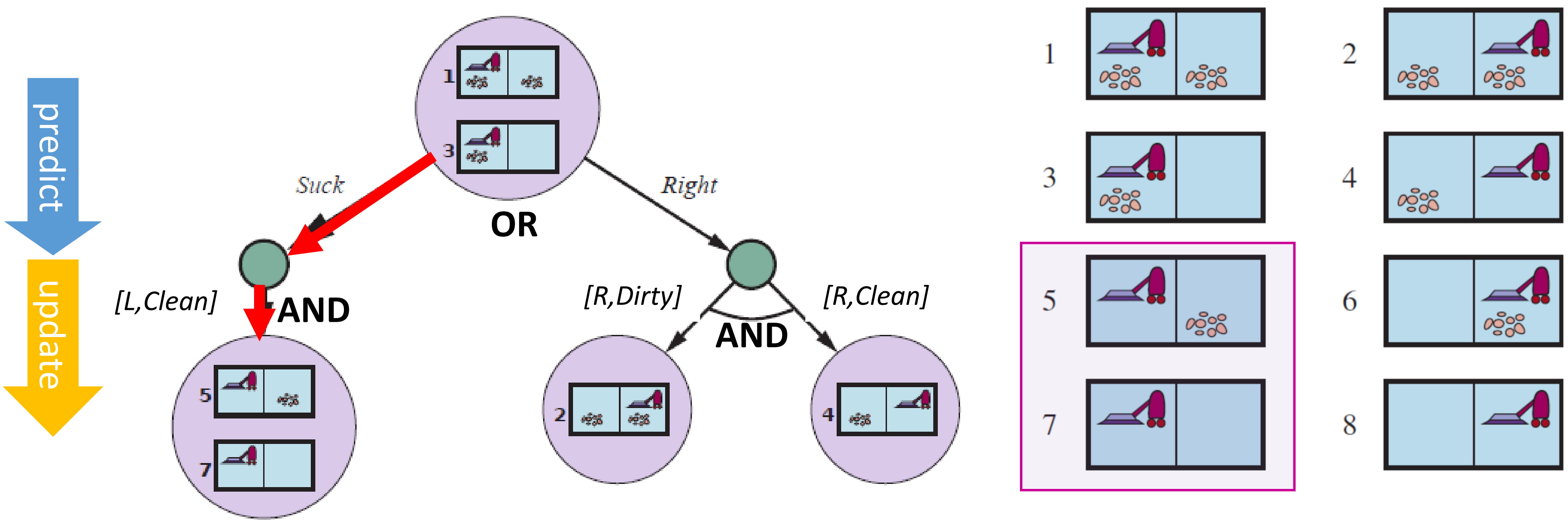

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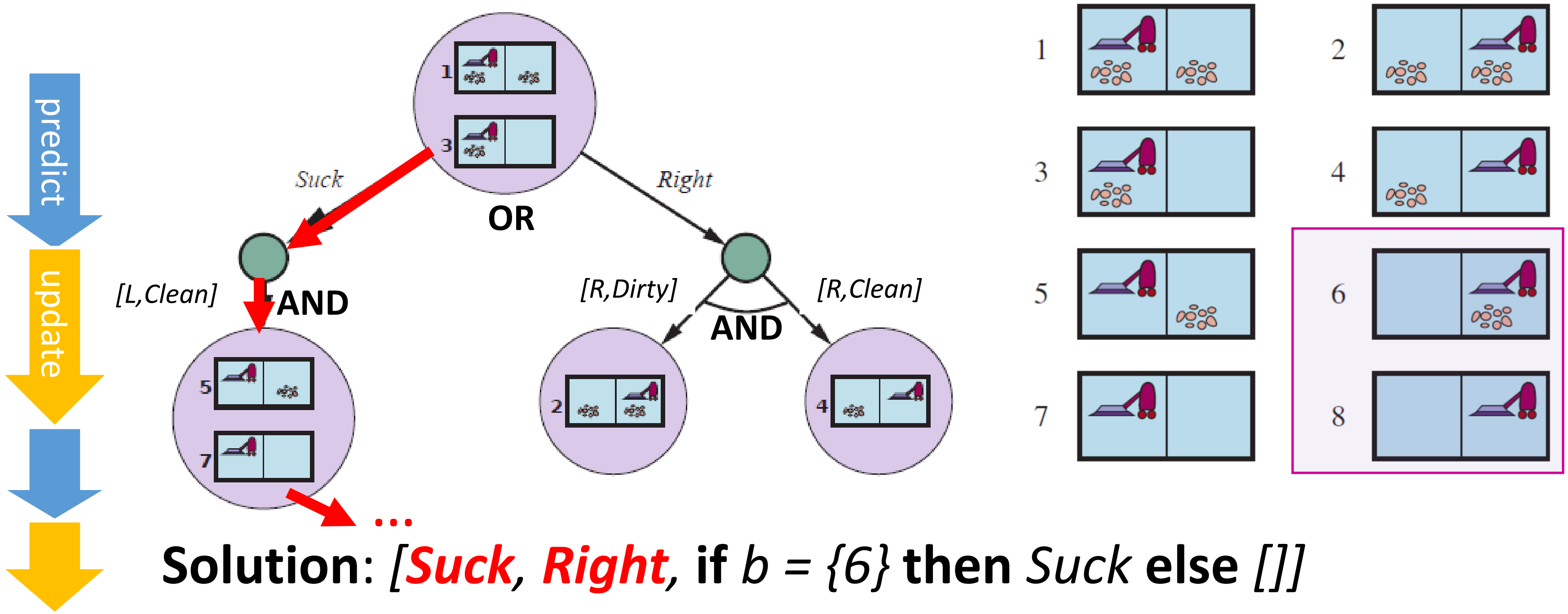

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Solving Partially Observable Problems

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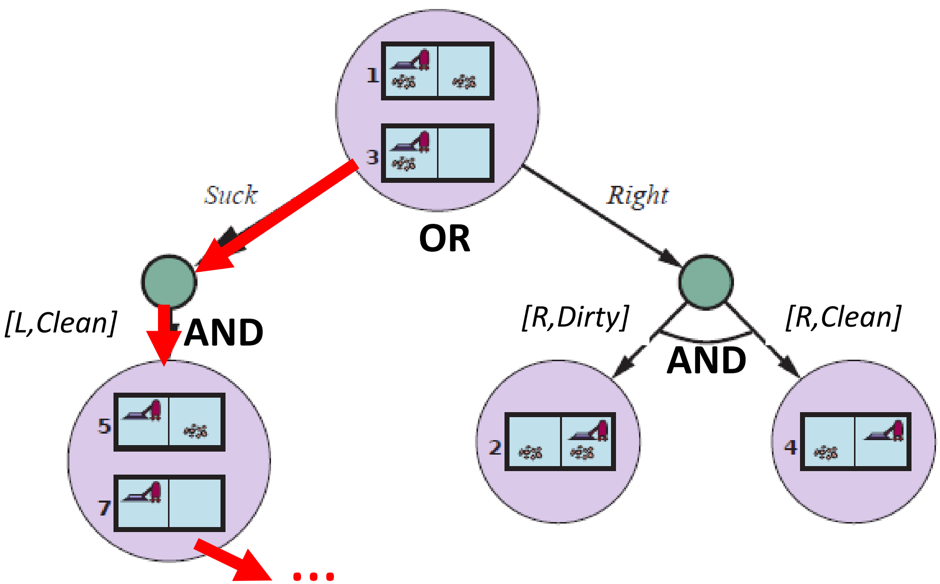
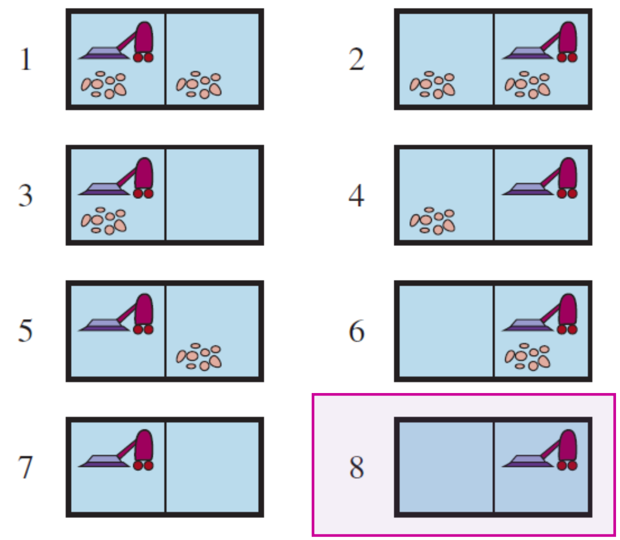




Solution: *[Suck, Right, if b = {6} then Suck else []]*

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

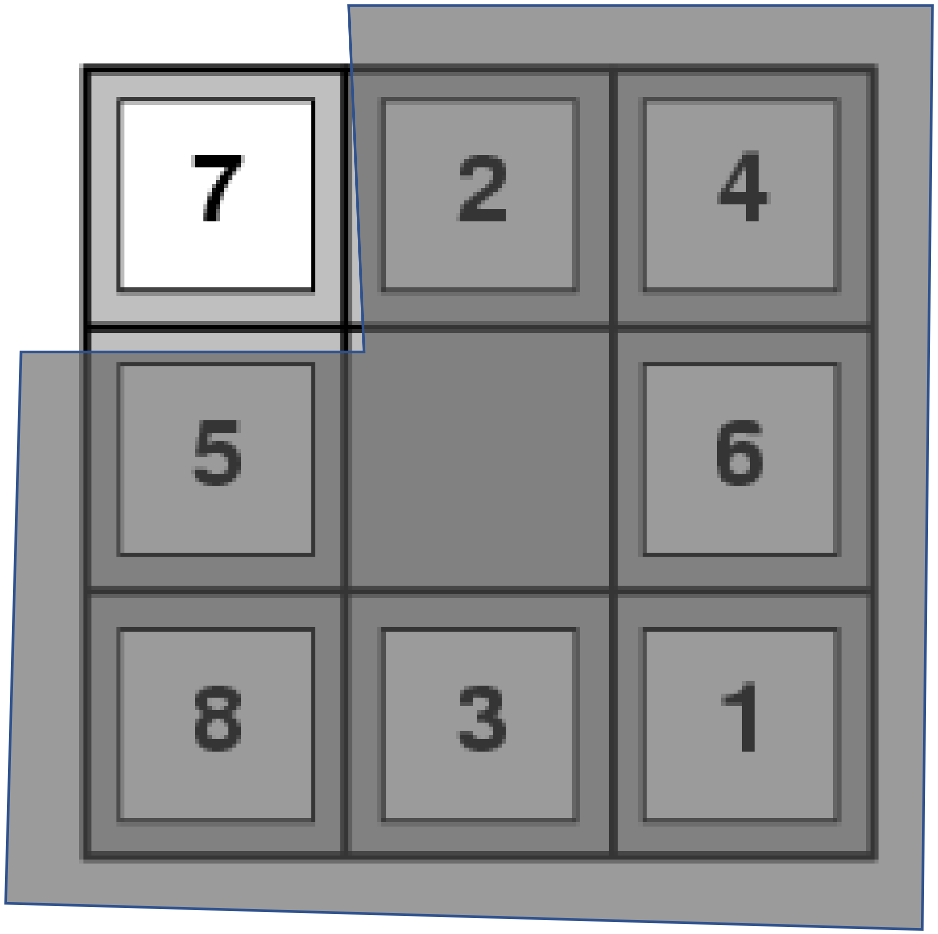
State Estimation and Approximate Belief States

- 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**.

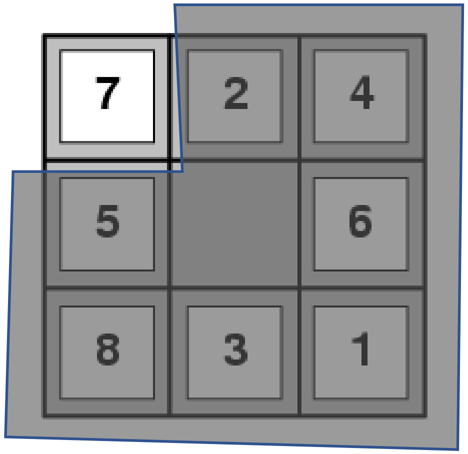
- The agent needs to be able to update its belief state following observations in **real time**! For many practical application, there is only time to compute an **approximate belief state!** These approximate methods are outside the scope of this introductory course.



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?

Exploration

Unknown Environment and 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 instead of planning for everything!
  - **Unknown environment**: The agent needs to explore to map an unknown area (state space) and/or what actions do.
    The map is the transition model $f : S \times A \to S$

Design Considerations for Online Search

- **Knowledge**: What does the agent already 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.

- **Exploration order**: Expanding nodes in **local order** is more efficient if you have to execute the actions to get observations: Depth-first search with backtracking

Online Search: Agent Program for Unknown Transition model

Environment is deterministic and completely observable ($percept(s) = s$) but the transition model (function $result$) and the state space are unknown.

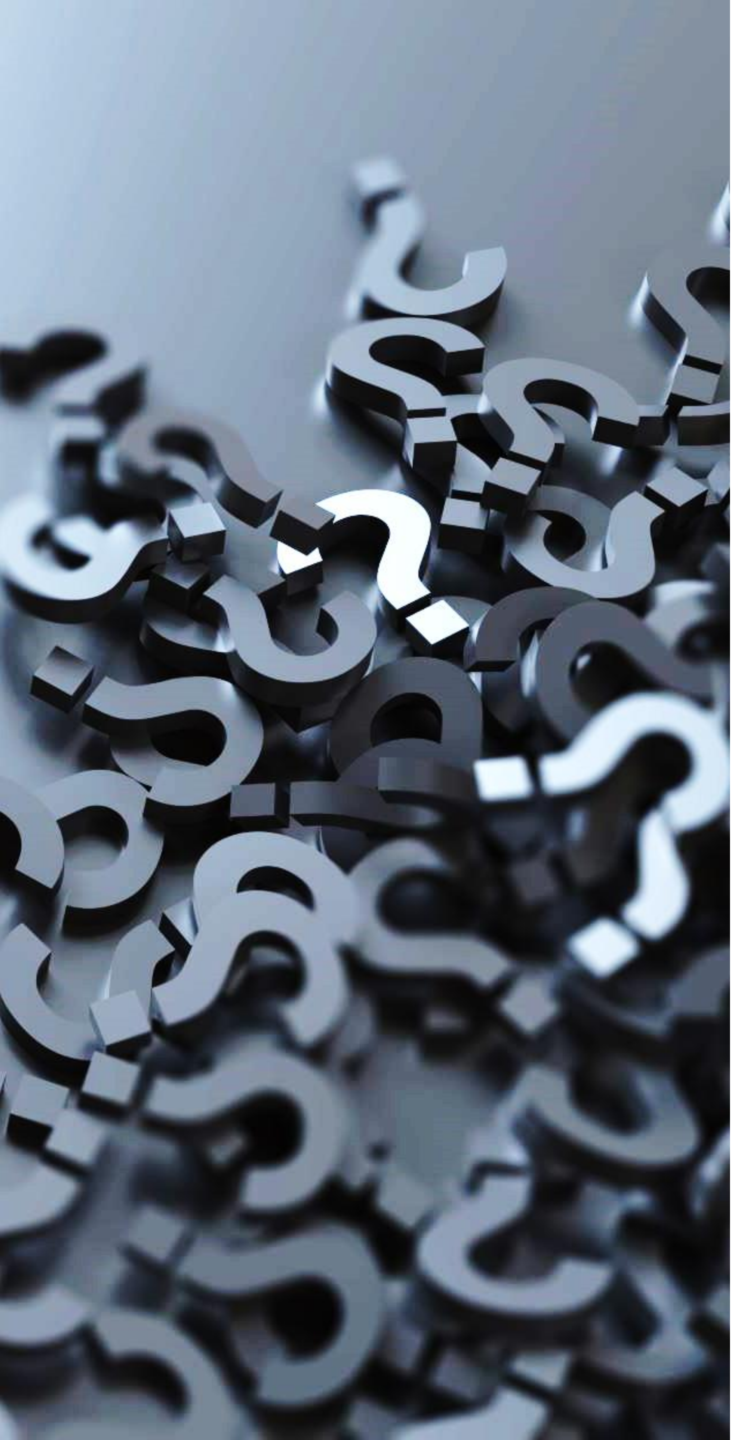
Approach: The algorithm builds the map $result(s, a) \rightarrow s'$ by trying all actions and backtracks when all actions in a state have been explored.

Learns results

Untried and unbacktracked are the "frontier"

```
function ONLINE-DFS-AGENT(problem, s') returns an action
               s, a, the previous state and action, initially null
  persistent:  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

  if problem.IS-GOAL(s') then return stop
  if s' is a new state (not in untried) then untried[s'] ← problem.ACTIONS(s')
  if s is not null then
      result[s, a] ← s'
      add s to the front of unbacktracked[s']
  if untried[s'] is empty then
      if unbacktracked[s'] is empty then return stop
      else a ← an action b such that result[s', b] = POP(unbacktracked[s'])
  else a ← POP(untried[s'])
  s ← 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.
- How observations can be used to learn about the state: State estimation with repeated predict and update steps.
- The use of AND-OR trees.