

Fundamentals of Artificial Intelligence

Chapter 04: **Beyond Classical Search**

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https://disi.unitn.it/rseba/DIDATTICA/fai_2023/

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M.S. Course “Artificial Intelligence Systems”, academic year 2024-2025

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Generalities

- So far we address a single category of problems:
 - 1 observable,
 - 2 deterministic,
 - 3 with known environment,
 - 4 s.t. the solution is a sequence of actions.
- What happens when these assumptions are relaxed?
- In order we will:
 - release condition 4 \implies local search
 - release condition 2 \implies search with non-deterministic actions
 - release condition 1 \implies search with no observability or with partial observability
 - release condition 3 \implies online search

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 - General Ideas
 - Hill-Climbing
 - Simulated Annealing
 - Local Beam Search & Genetic Algorithms
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General Ideas

- Search techniques: **systematic exploration of search space**
 - solution to problem: **the path to the goal state**
 - ex: **8-puzzle**
- With many problems, **the path to goal is irrelevant**
 - **goals expressed as conditions, not as explicit list of goal states**
 - solution to problem: only **the goal state** itself
 - ex: **N-queens**
 - many important applications:
integrated-circuit design, factory-floor layout, job-shop scheduling, automatic programming, telecommunications network optimization, vehicle routing, portfolio management...
- The state space is a set of “complete” configurations
 - **decision problems**: find goal configuration satisfying constraints/rules (ex: N-queens)
 - **optimization problems**: find **optimal** configurations
(ex: Travelling Salesperson Problem TSP)
- If so, we can use **iterative-improvement algorithms** (in particular **local search algorithms**):
 - **keep a single “current” state, try to improve it**

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Local Search

- Idea: use single current state and move to “neighbouring” states
 - operate using a single current node
 - the paths followed by the search are not retained
- Two key advantages:
 - use very little memory (usually constant)
 - can often find reasonable solutions in large or infinite (continuous) state spaces, for which systematic algorithms are unsuitable
- Also useful for pure optimization problems
 - find the best state according to an objective function
 - often do not fit the “standard” search model of previous chapter
 - ex: Darwinian survival of the fittest: metaphor for optimization, but no “goal test” and no “path cost”
- A complete local search algorithm: guaranteed to always find a solution (if exists)
- A optimal local search algorithm: guaranteed to always find a maximum/minimum solution
 - maximization and minimization dual (switch sign)

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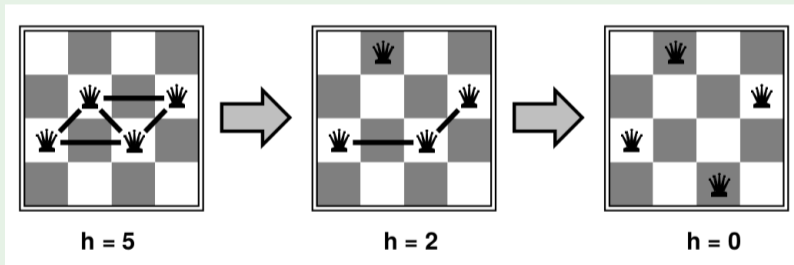
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Local Search Example: N-Queens

- One queen per column (incremental representation)
- Cost (h): # of queen pairs on the same row, column, or diagonal
- Goal: $h=0$
- Step: move a queen vertically to reduce number of conflicts

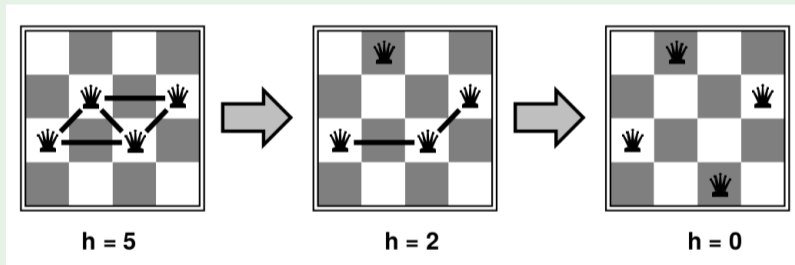


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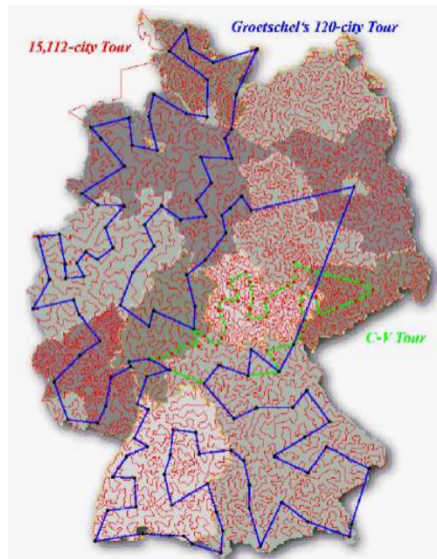
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Optimization Local Search Example: TSP

Travelling Salesperson Problem (TSP)

Given an undirected graph, with n nodes and each arc associated with a positive value, find the Hamiltonian tour with the minimum total cost.

Very hard for classic search!

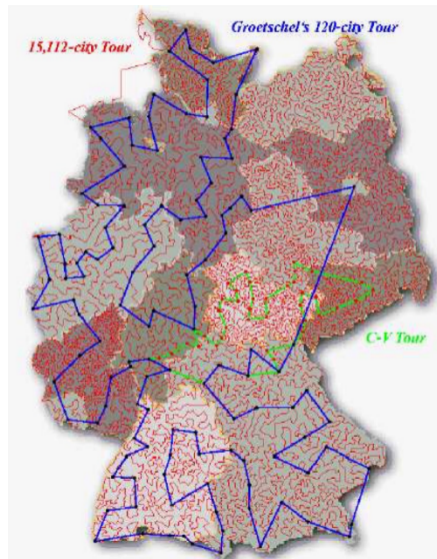


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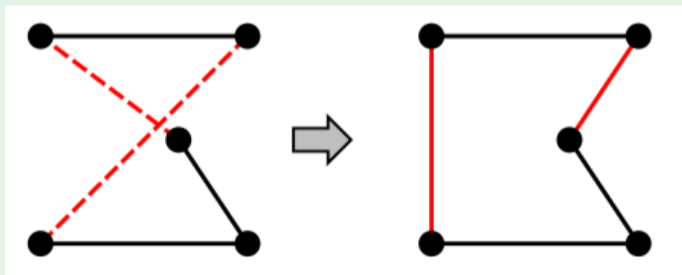
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Optimization Local Search Example: TSP

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- Cost (h): total cycle length
- Start with any complete tour
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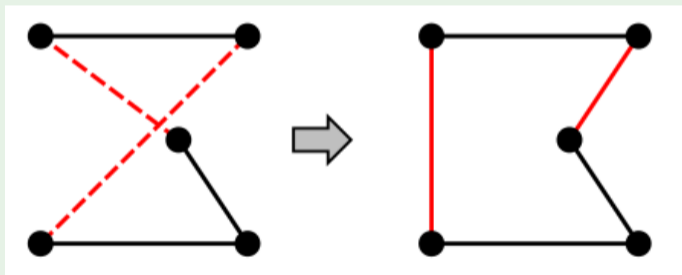


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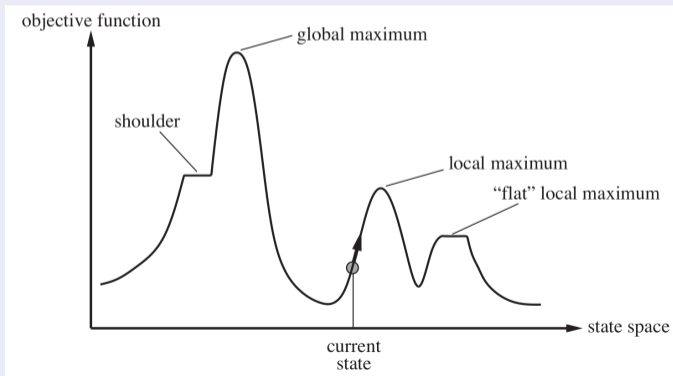
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Local Search: State-Space Landscape

State-space landscape (Maximization)

- Local search algorithms **explore state-space landscape**
 - state space n-dimensional (and typically discrete)
 - move to “nearby” states (**neighbours**)
- **NP-Hard problems may have exponentially-many local optima**



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Hill-Climbing Search (aka Greedy Local Search)

Hill-Climbing

- Very-basic local search algorithm
- Idea: **a move is performed only if the solution it produces is better than the current solution**
 - (steepest-ascent version): **selects the neighbour with best score improvement**
(select randomly among best neighbours if ≥ 1)
 - does not look ahead of immediate neighbors of the current state
 - **stops as soon as it finds a (possibly local) minimum**
- Several variants (Stochastic H.C., Random-Restart H.C., ...)
- Often used as part of more complex local-search algorithms

function HILL-CLIMBING(*problem*) **returns** a state that is a local maximum

current \leftarrow MAKE-NODE(*problem*.INITIAL-STATE)

loop do

neighbor \leftarrow a highest-valued successor of *current*

if *neighbor*.VALUE \leq *current*.VALUE **then return** *current*.STATE

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8-queen puzzle (minimization)

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 - Cost (h): # of queen pairs on the same row, column, or diagonal
 - Goal: $h=0$

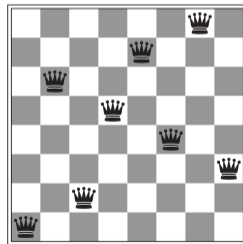
- Two scenarios ((a) \implies (b) in 5 steps) :

(a) 8-queens state with heuristic cost estimate $h = 17$ (12d, 5h)

(b) local minimum: $h=1$, but all neighbours have higher costs

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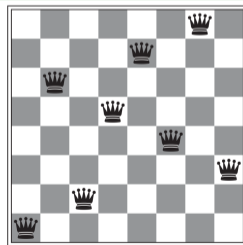
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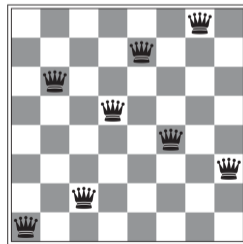
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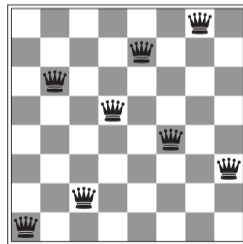
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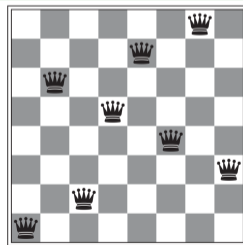
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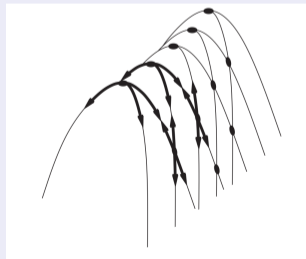
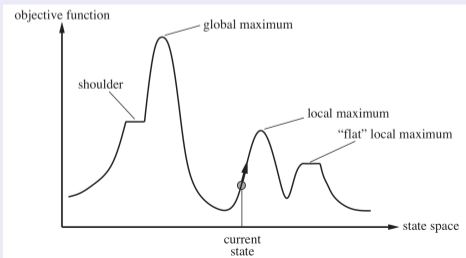
Hill-Climbing Search: Drawbacks

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 - Ex: **with 8-queens, gets stuck 86% of the time**, fast when succeed

note: converges very fast till (local) minima or plateaux
- Possible idea: **allow 0-progress moves** (aka **sideways moves**)
 - pros: may allow getting out of shoulders
 - cons: may cause infinite loops with flat local optima

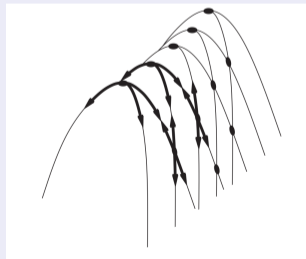
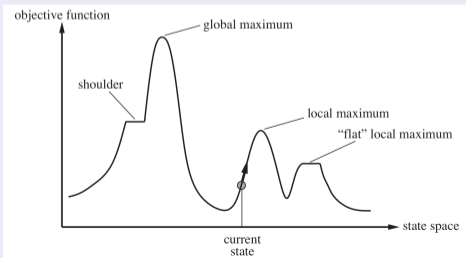
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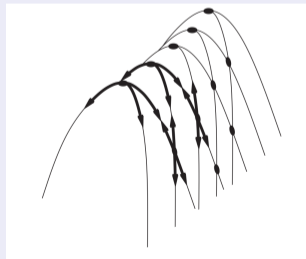
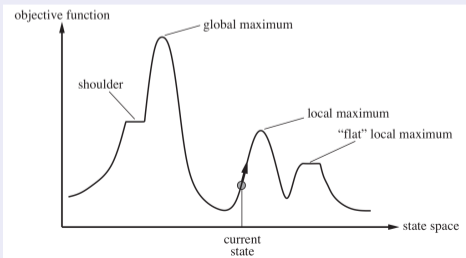
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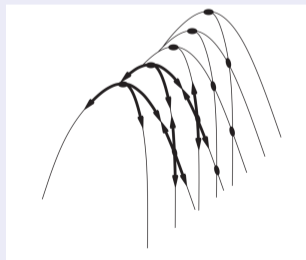
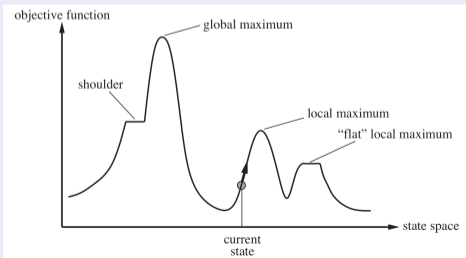
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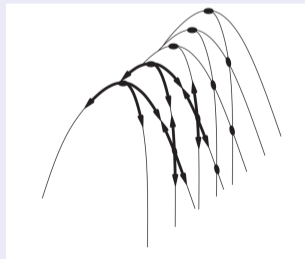
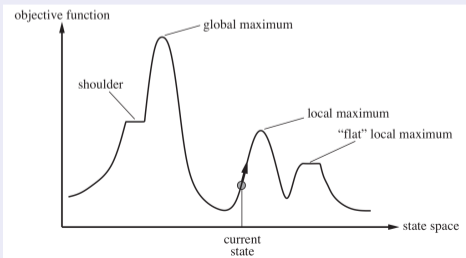
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Hill-Climbing Search: Drawbacks

- **Incomplete**: gets stuck in **local optima**, **flat local optima** & **shoulders** (aka **plateaux**), **ridges** (sequences of local optima)
 - Ex: **with 8-queens**, gets stuck **86% of the time**, fast when succeednote: converges very fast till (local) minima or plateaux
- Possible idea: **allow 0-progress moves** (aka **sideways moves**)
 - pros: **may allow getting out of shoulders**
 - cons: **may cause infinite loops with flat local optima**⇒ set a limit to consecutive sideways moves (e.g. 100)
 - Ex: **with 8-queens**, pass from **14% to 94% success**, slower



Hill-climbing: Variations

- **Stochastic hill-climbing**
 - random selection among the uphill moves
 - selection probability can vary with the steepness of uphill move
 - sometimes slower, but often finds better solutions
- **First-choice hill-climbing**
 - generates successors randomly until a better one is found
 - good when there are large amounts of successors
- **Random-restart hill-climbing**
 - conducts a series of hill-climbing searches from randomly generated initial states
 - tries to avoid getting stuck in local maxima

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- 2 Search with Nondeterministic Actions
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Simulated Annealing

- Inspired to statistical-mechanics analysis of metallurgical annealing (Boltzmann's state distributions)
- Idea: **Escape local maxima by allowing "bad" moves...**
 - "bad move": move toward states with worse value
 - typically pick a move taken at random ("random walk")
- ... **but gradually decrease their size and frequency.**
 - sideways moves progressively less likely
- Analogy: get a ball into the deepest crevice in a bumpy surface
 - initially shaking hard ("high temperature")
 - progressively shaking less hard ("decrease the temperature")

Widely used in large-scale optimization tasks (e.g. VLSI layout problems, factory scheduling,...)

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Simulated Annealing [cont.]

Simulated Annealing (maximization)

- A “temperature” parameter T slowly decreases with steps (“schedule”)
- The probability of picking a “bad move”:
 - decreases exponentially with the “badness” of the move $|\Delta E|$
 - decreases as the “temperature” T goes down
- If schedule lowers T slowly enough, then the algorithm will find a global optimum with probability approaching 1

function SIMULATED-ANNEALING(*problem*, *schedule*) **returns** a solution state

inputs: *problem*, a problem

schedule, a mapping from time to “temperature”

current \leftarrow MAKE-NODE(*problem*.INITIAL-STATE)

for $t = 1$ **to** ∞ **do**

$T \leftarrow$ *schedule*(t)

if $T = 0$ **then return** *current*

next \leftarrow a randomly selected successor of *current*

$\Delta E \leftarrow$ *next*.VALUE – *current*.VALUE

if $\Delta E > 0$ **then** *current* \leftarrow *next*

else *current* \leftarrow *next* only with probability $e^{\Delta E/T}$

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Local Beam Search

Local Beam Search

Idea: **keep track of k states instead of one**

- Initially: k random states
- Step:
 - 1 determine all successors of k states
 - 2 if any of successors is goal \implies finished
 - 3 **else select k best from successors**
- Different from k searches run in parallel:
 - searches that find good states recruit other searches to join them
 \implies information is shared among k search threads
- Lack of diversity: **quite often, all k states end up in the same local hill**

\implies **Stochastic Local Beam**: choose k successors randomly,
with probability proportional to state success.

Resembles natural selection with asexual reproduction:

the successors (offspring) of a state (organism) populate the next generation according to its value (fitness), with a random component.

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- Variant of local beam search: **successor states generated by combining two parent states** (rather than one single state)
 - States represented as strings over a finite alphabet (e.g. $\{0, 1\}$)
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- Step:
 - parent states are rated according to a fitness function
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 - for each parent pair
- Ends when some state is fit enough (or timeout)
- **Many algorithm variants available**

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function GENETIC-ALGORITHM(*population*, FITNESS-FN) **returns** an individual

inputs: *population*, a set of individuals

FITNESS-FN, a function that measures the fitness of an individual

repeat

new_population \leftarrow empty set

for $i = 1$ **to** SIZE(*population*) **do**

$x \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

$y \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

child \leftarrow REPRODUCE(x , y)

if (small random probability) **then** *child* \leftarrow MUTATE(*child*)

add *child* to *new_population*

population \leftarrow *new_population*

until some individual is fit enough, or enough time has elapsed

return the best individual in *population*, according to FITNESS-FN

function REPRODUCE(x , y) **returns** an individual

inputs: x , y , parent individuals

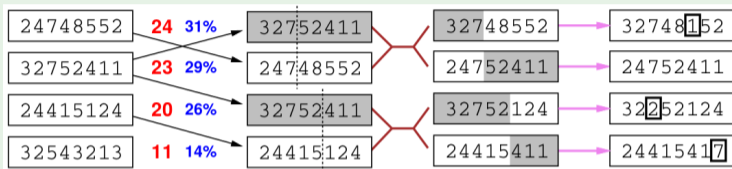
$n \leftarrow$ LENGTH(x); $c \leftarrow$ random number from 1 to n

return APPEND(SUBSTRING(x , 1, c), SUBSTRING(y , $c + 1$, n))

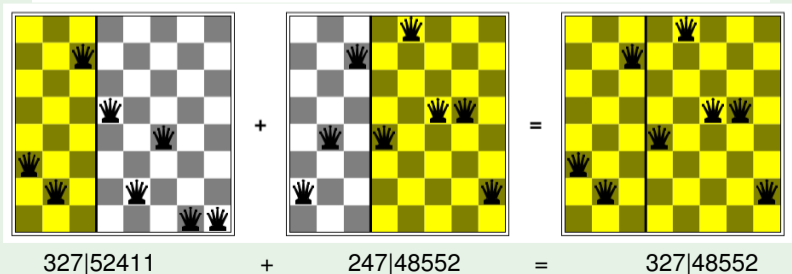
Genetic Algorithms: Example

Example: 8-Queens

$state[i]$: (upward) position of the queen in i th column



Fitness Selection Pairs Cross-Over Mutation



Genetic Algorithms: Intuitions, Pros & Cons

Intuitions

- **Selection** drives the population toward high fitness
- **Crossover** combines good parts from good solutions (but it might achieve the opposite effect)
- **Mutation** introduces diversity

Pros & Cons

- Pros:
 - extremely simple
 - general purpose
 - tractable theoretical models
- Cons:
 - not completely understood
 - good coding is crucial (e.g., Gray codes for numbers)
 - too simple genetic operators

Widespread impact on optimization problems, i.e. circuit layout and job-shop scheduling

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Recall: Generalities

- So far we address a single category of problems:
 - 1 observable,
 - 2 deterministic,
 - 3 with known environment,
 - 4 s.t. the solution is a sequence of actions.
- What happens when these assumptions are relaxed?
- In order we will:
 - release condition 4 \implies local search
 - release condition 2 \implies search with non-deterministic actions
 - release condition 1 \implies search with no observability or with partial observability
 - release condition 3 \implies online search

Generalities (cont.)

- Assumptions so far (see ch. 2 and 3):

- the environment is deterministic
- the environment is fully observable
- the agent knows the effects of each action

⇒ The agent does not need perception:

- can calculate which state results from **any sequence of actions**
- always knows which state it is in
- If one of the above does not hold, then **percepts are useful**
 - the future percepts cannot be determined in advance
 - the agent's future actions will depend on future percepts
- Solution: not a sequence but a **contingency plan** (aka **conditional plan, strategy**)
 - specifies the actions **depending on what percepts are received**
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Example: The Erratic Vacuum Cleaner

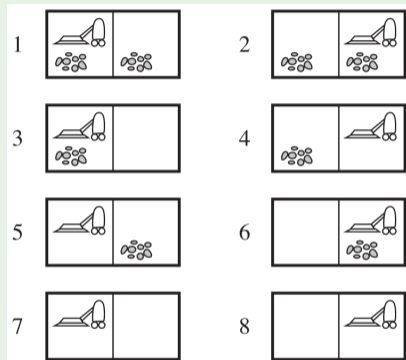
Erratic Vacuum-Cleaner Example

- actions: Left, Right, Suck
- goal: A and B cleaned (states 7, 8)
- if environment is observable, deterministic, and completely known \implies solvable by search algos
- ex: if initially in 1, then [suck,right,suck] leads to 8: [1,5,6,8]

- Nondeterministic version (erratic vacuum cleaner):

- if dirty square: cleans the square, sometimes cleans also the other square. Ex: $1 \xrightarrow{\text{suck}} \{5, 7\}$
- if clean square: sometimes deposits dirt on the carpet

Ex: $5 \xrightarrow{\text{suck}} \{1, 5\}$

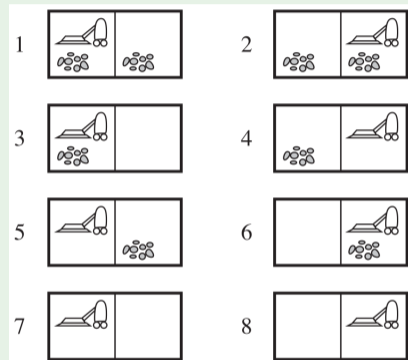


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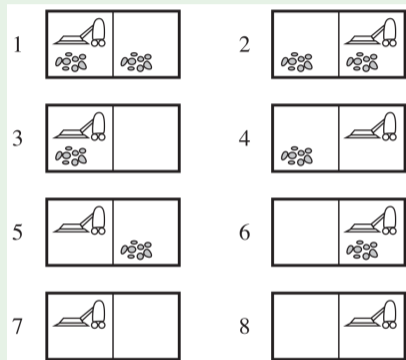
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Searching with Nondeterministic Actions

Generalized notion of transition model

- $RESULTS(s,A)$ returns a set of possible outcomes states
 - Ex: $RESULTS(1,SUCK) = \{5, 7\}$, $RESULTS(5,SUCK) = \{1, 5\}$, ...
- A solution is a contingency plan (aka conditional plan, strategy)
 - contains nested conditions on future percepts (if-then-else, case-switch, ...)
 - Ex: from state 1 we can act the following contingency plan:
[SUCK, IF STATE = 5 THEN [RIGHT, SUCK] ELSE []]
- Can cause loops (see later)

Remark

In practice, we don't reason on states, rather on state variable values:
[Suck; if B.Dirty then [Right, Suck] else []]

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 - Ex: RESULTS(1,SUCK)={5,7}, RESULTS(5,SUCK)={1,5}, ...
- A solution is a contingency plan (aka conditional plan, strategy)
 - contains nested conditions on future percepts (if-then-else, case-switch, ...)
 - Ex: from state 1 we can act the following contingency plan:
[SUCK, IF STATE = 5 THEN [RIGHT, SUCK] ELSE []]
- Can cause loops (see later)

Remark

In practice, we don't reason on states, rather on state variable values:
[Suck; if B.Dirty then [Right, Suck] else []]

Searching with Nondeterministic Actions [cont.]

And-Or Search Trees

- In a **deterministic environment**, we branch on **agent's choices**
 - ⇒ **OR nodes**, hence **OR search trees**
 - **OR nodes correspond to states**
- In a **nondeterministic environment**, we branch also on (environment's choice of) **outcome for each action**
 - the agent has to handle all such outcomes
 - ⇒ **AND nodes**, hence **AND-OR search trees**
 - **AND nodes correspond to actions**
 - leaf nodes are goal, dead-end or loop OR nodes
- A **solution** for an AND-OR search problem is a subtree s.t.:
 - has a goal node at every leaf
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OR tree: AND-OR tree with 1 outcome each AND node (determinism)

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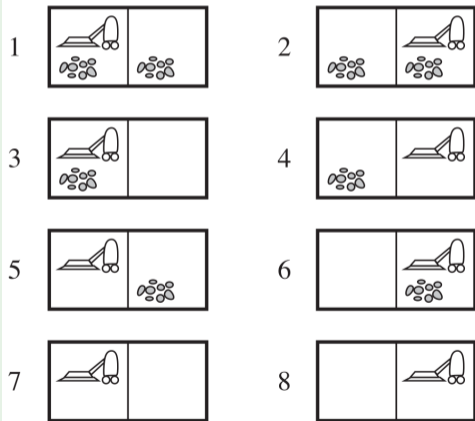
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And-Or Search Trees: Example

(Part of) And-Or Search Tree for Erratic Vacuum Cleaner Example.

Problem: Init: 1, Goal: 7,8.

Solution: [SUCK, IF STATE = 5 THEN [RIGHT, SUCK] ELSE []] (solid arcs)

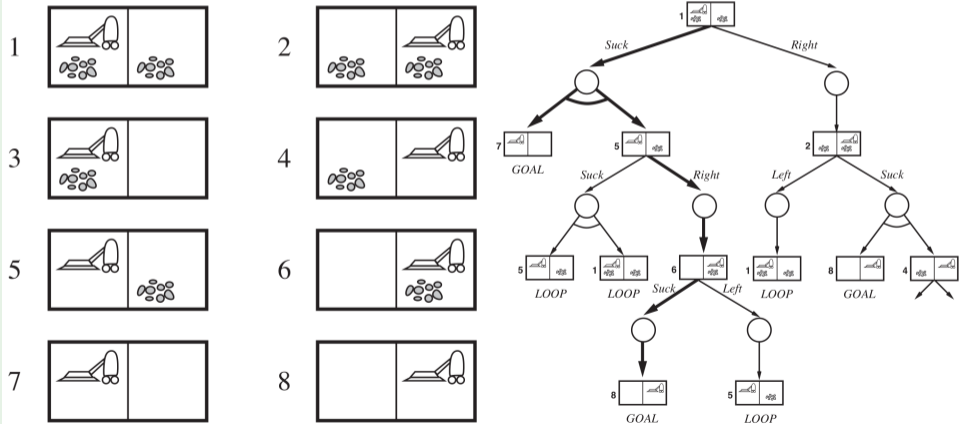


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AND-OR Search

Recursive Depth-First (Tree-based) AND-OR Search

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

function OR-SEARCH(*state*, *problem*, *path*) **returns** a conditional plan, or failure
if *problem*.GOAL-TEST(*state*) **then return** the empty plan
if *state* is on *path* **then return failure** // CYCLE DETECTION
for each *action* **in** *problem*.ACTIONS(*state*) **do**
 plan ← AND-SEARCH(RESULTS(*state*, *action*), *problem*, [*state* | *path*])
 if *plan* ≠ *failure* **then return** [*action* | *plan*]
return failure

function AND-SEARCH(*states*, *problem*, *path*) **returns** a conditional plan, or failure
for each s_i **in** *states* **do**
 plan_i ← OR-SEARCH(s_i , *problem*, *path*)
 if *plan_i* = *failure* **then return failure**
return [**if** s_1 **then** *plan₁* **else if** s_2 **then** *plan₂* **else** ... **if** s_{n-1} **then** *plan_{n-1}* **else** *plan_n*]

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Note: nested if-then-else can be rewritten as case-switch

AND-OR Search [cont.]

Recursive Depth-First (Tree-based) AND-OR Search

- Cycles: if the current state already occurs in the path \implies failure
 - cycle detection like with ordinary DFS
 - does not mean “no solution”
 - means “if there is a non-cyclic solution, then it must be reachable from the earlier incarnation of the current state”
 \implies the new incarnation can be discharged

\implies Complete (if state space finite): every path must reach a goal, a dead-end or loop state

- Can be augmented with “explored” data structure for avoiding redundant branches (graph-based search)
- Implicitly Depth-First, but can also be explored by breadth-first or best-first method
 - e.g. A* variant for AND-OR search available (see AIMA book)

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AND-OR Search: Cyclic Solutions

- Some problems have no acyclic solutions
- A **cyclic plan** may be considered a **cyclic solution** provided that:
 - every leaf is a goal state (loop states not considered leaves), and
 - a leaf is reachable from every point in the plan
- Can be expressed by means of introducing
 - labels, and backward goto's to labels
 - loop syntax (e.g., while-do)

⇒ Executing a cyclic solution eventually reaches a goal,
provided that each outcome of a nondeterministic action eventually occurs

- Is this assumption reasonable?
- Yes, provided we distinguish:
(nondeterministic, observable) ≠ (deterministic, partially-observable)
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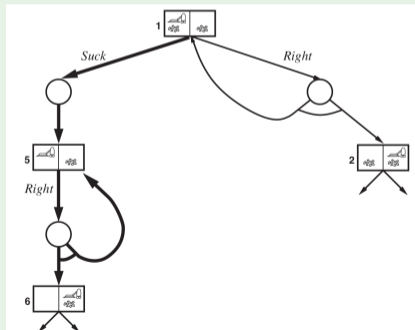
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Cyclic Solution: Example

Example: Slippery Vacuum Cleaner

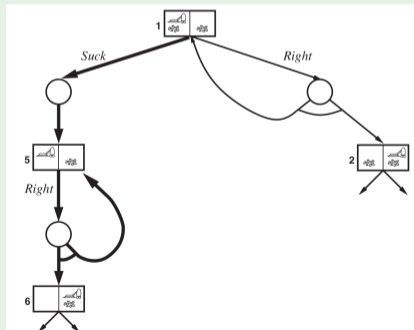
- Movement actions may fail: e.g., $Results(1, Right) = \{1, 2\}$
- A cyclic solution
- Use labels: [Suck, L1 : Right, if State = 5 then L1 else Suck]
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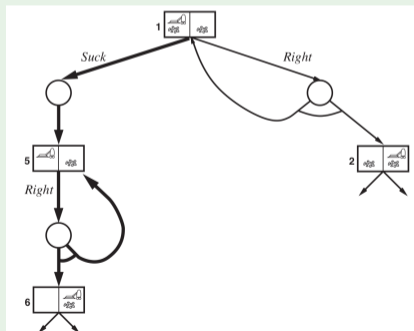


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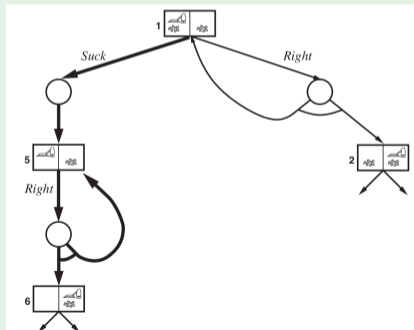


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Recall: Generalities

- So far we address a single category of problems:
 - 1 observable,
 - 2 deterministic,
 - 3 with known environment,
 - 4 s.t. the solution is a sequence of actions.
- What happens when these assumptions are relaxed?
- In order we will:
 - release condition 4 \implies local search
 - release condition 2 \implies search with non-deterministic actions
 - release condition 1 \implies search with no observability or with partial observability
 - release condition 3 \implies online search

Generalities

Partial Observability

- **Partial observability:** percepts do not capture the whole state
 - partial state corresponds to **a set of possible physical states**
- If the agent is in one of several possible physical states, then an action may lead to one of several possible outcomes, **even if the environment is deterministic**

Belief States

- **Belief state:** the agent's current belief about the possible physical states it might be in, given the previous sequence of actions and percepts
- Example: a robot in a hallway with two doors (one of them is open, but does not know in which one) and a goal in the other physical state the agent is in
 - If the robot opens the door in state 1, or in state 2, then it does not know in which one the goal is
 - If the robot opens the door in state 1, then the goal is in state 1
 - If the robot opens the door in state 2, then the goal is in state 2
- 2^n possible belief states out of n possible physical states!

In practice, the agent reasons in terms of **partial states**, rather than a of **sets of states**.

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 - ex: $\{1, 2\}$: the agent is either in state 1 or in state 2 (but it does not know in which one)
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Search with No Observation (aka Sensorless Search or Conformant Search)

- Idea: To solve sensorless problems, **the agent searches in the space of belief states** rather than in that of physical states
 - **fully observable**, because the agent knows its own belief space
 - **solutions are always sequences of actions** (no contingency plan), because percepts are always empty and thus predictable
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Search with No Observation: Example

Example: Sensorless Vacuum Cleaner

- the vacuum cleaner knows the geography of its world, but it **doesn't know its location or the distribution of dirt**

- initial state: {1, 2, 3, 4, 5, 6, 7, 8}
- after action RIGHT, state is {2, 4, 6, 8}
- after action sequence [RIGHT,SUCK], state is {4, 8}
- after action sequence [RIGHT,SUCK,LEFT], state is {3, 7}
- after action sequence [RIGHT,SUCK,LEFT,SUCK], state is {7}

- In practice, the information on the state is made progressively less partial by the actions:

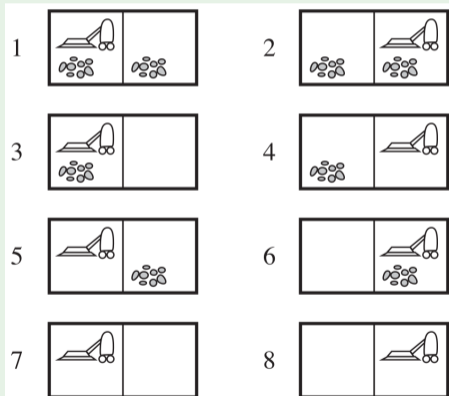
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{2,4,6,8}

{?, (? , ?)}

RIGHT

{B, (? , ?)}



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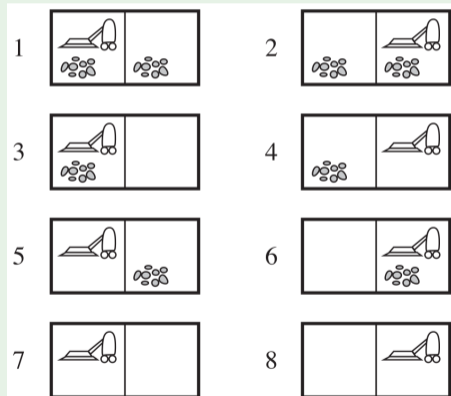
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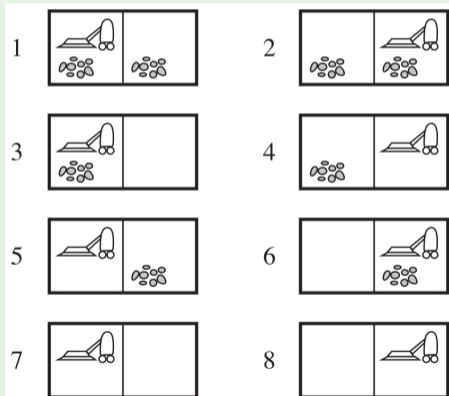
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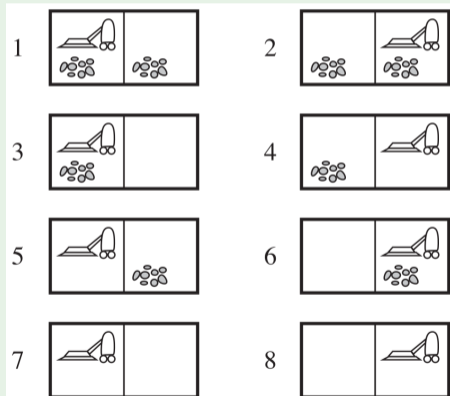
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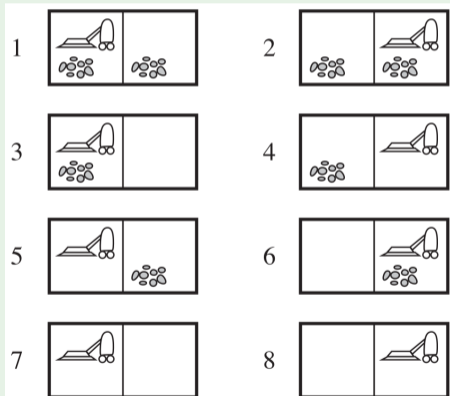
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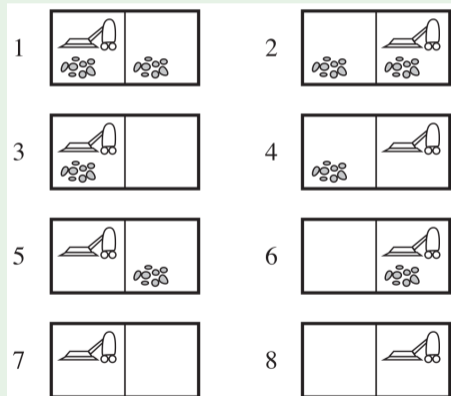
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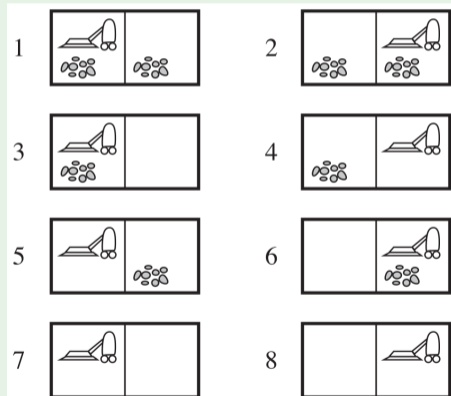
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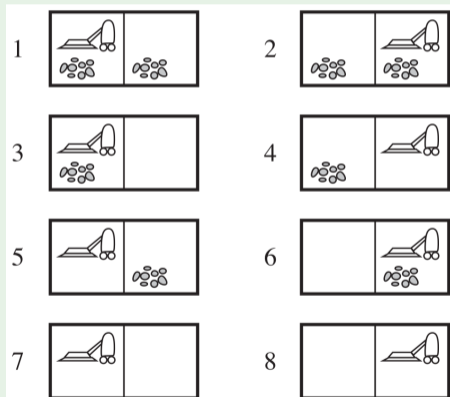
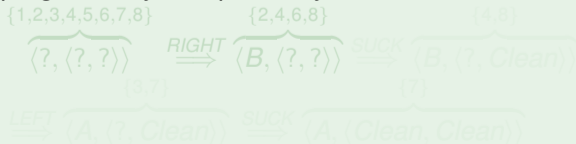
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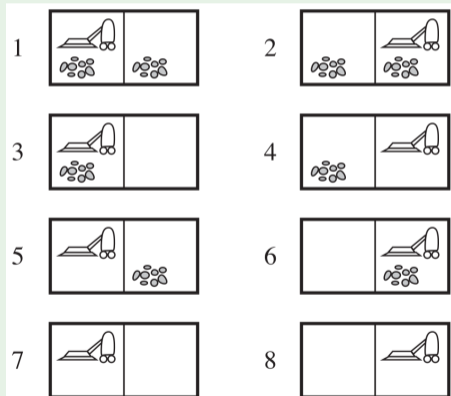
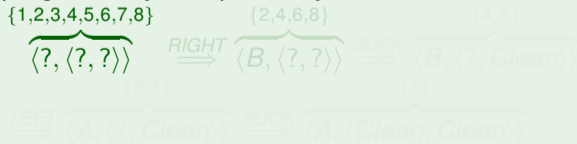
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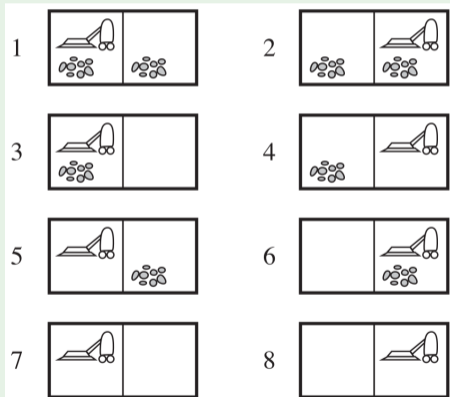
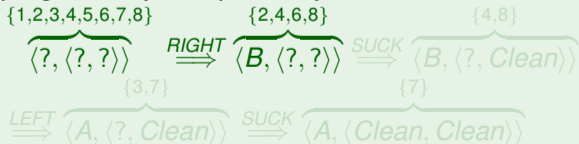
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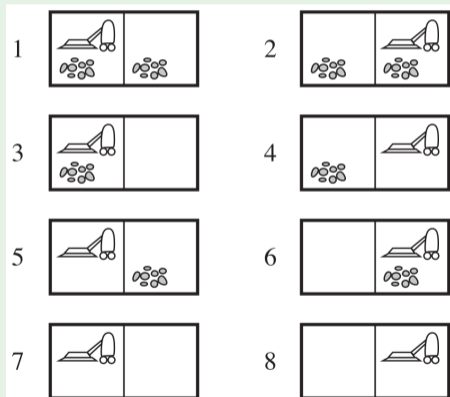


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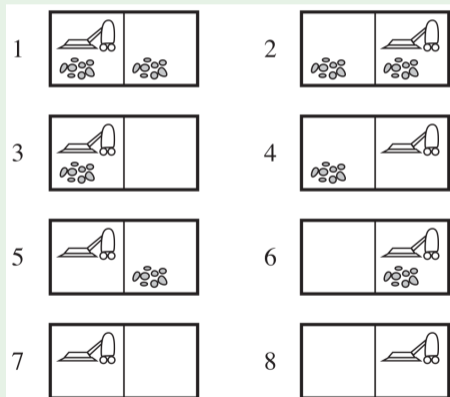


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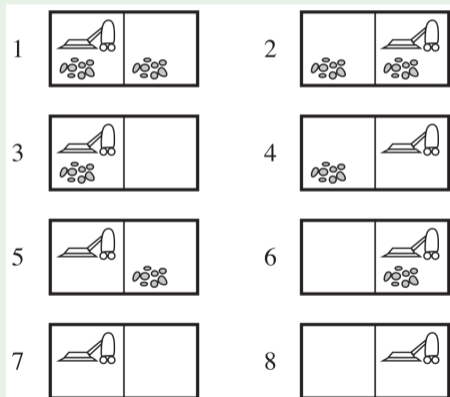


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Belief-State Problem Formulation

Let $Actions_P()$, $Result_P()$, $GoalTest_P()$, $StepCost_P()$ refer to physical System P :

- **Belief states**: subsets of physical states
 - If P has N states, then the sensorless problem has up to 2^N states
- **Initial state**: typically the set of all physical states in P
- **Actions**: (assumption: illegal actions have no effects)
 - $Actions(b) \stackrel{\text{def}}{=} \bigcup_{s \in b} Actions_P(s)$ (i.e., must consider all possible actions in all possible states)
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 - for deterministic actions: $b' = Result(b, a) \stackrel{\text{def}}{=} \{s' \mid s' = Result_P(s, a) \text{ and } s \in b\}$
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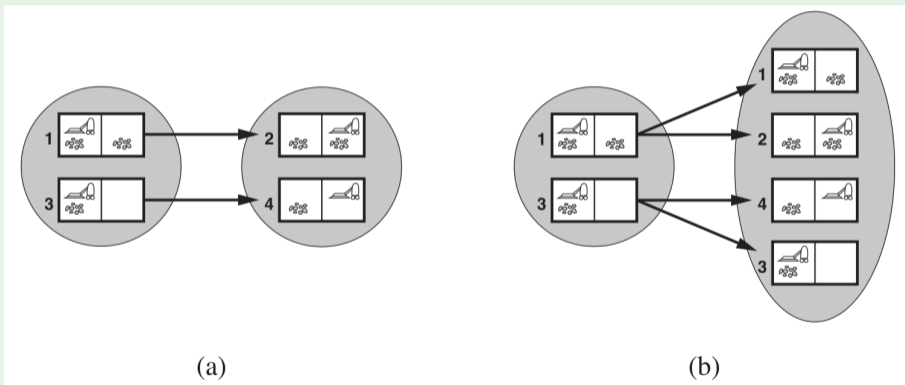
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Belief-State Problem Formulation [cont.]

Example: Sensorless Vacuum Cleaner, plain and slippery versions

Prediction: $Result(\{1, 3\}, Right)$, deterministic (a) and nondeterministic action (b)

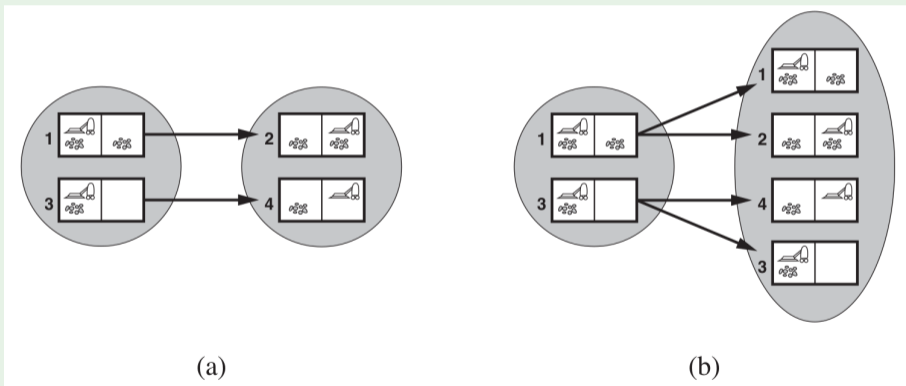


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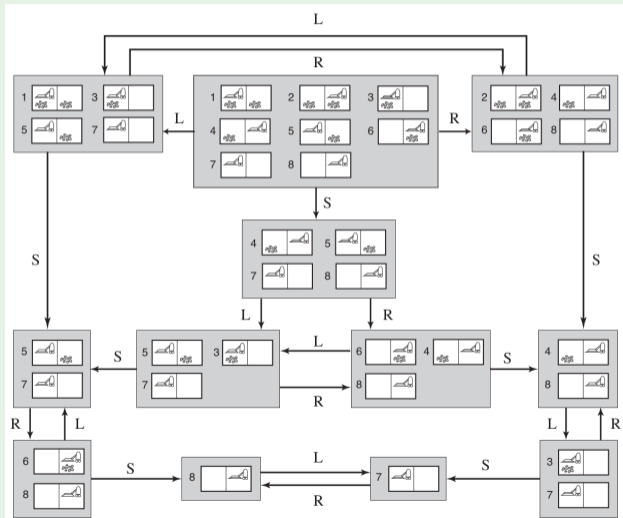


(© S. Russell & P. Norwig, AIMA)

Belief-State Problem Formulation [cont.]

Example: Sensorless Vacuum Cleaner: Belief State Space

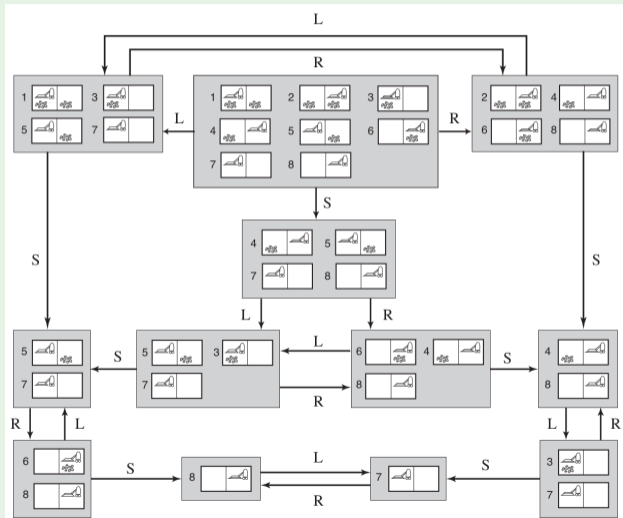
(self-loops are omitted)



Belief-State Problem Formulation [cont.]

Example: Sensorless Vacuum Cleaner: Belief State Space

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Exercises

Draw the Belief State Space in case of:

- Erratic vacuum cleaner
- Slippery vacuum cleaner

Belief-State Problem Formulation [cont.]

Remarks

- if $b \subseteq b'$, then $Result(b, a) \subseteq Result(b', a)$ (b more informative than b')
- If a is deterministic, then $|Result(b, a)| \leq |b|$
- The agent might achieve the goal earlier than $Goal/Test(b)$ holds, but it does not know it (because he knows it only when all states in the belief state are goal states)

Properties

- An action sequence is a solution for b iff it leads b to a goal
- If an action sequence is a solution for a belief state b , then it is also a solution for any belief state b' s.t. $b' \subseteq b$
 - if $b \xrightarrow{a_1} \dots \xrightarrow{a_n} g$, then $b' \xrightarrow{a_1} \dots \xrightarrow{a_n} g$

We can apply to the Belief-State space any search algorithm.

- if a solution for b has been found, then any $b' \subseteq b$ is solvable
- if $b' \subseteq b$ has already been generated and discarded, then we can discard a path reaching a belief state b

⇒ Dramatically improves efficiency

Belief-State Problem Formulation [cont.]

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We can apply to the Belief-State space any search algorithm.

- if a solution for b has been found, then any $b' \subseteq b$ is solvable
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⇒ Dramatically improves efficiency

Belief-State Problem Formulation [cont.]

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Outline

- 1 Local Search and Optimization
 - General Ideas
 - Hill-Climbing
 - Simulated Annealing
 - Local Beam Search & Genetic Algorithms
- 2 Search with Nondeterministic Actions
- 3 Search with Partial or No Observations (Deterministic/Nondeterministic Actions)**
 - Search with No Observations
 - Search with Partial Observations**
- 4 Online Search (aka Exploration)

Search with Observations

Perception and Belief-State Problem Formulation

- $Percept(s)$ returns the percept received in state s
(if sensing is nondeterministic, a function $Percepts(s)$ returns a **set of possible percepts**)
 - ex: **local-sensing vacuum cleaner**, can perceive dirty/clean only on the current position:
 $Percept(1) = [A, Dirty]$
 - with **fully observable problems**: $Percept(s) = s, \forall s$
 - with **sensorless problems**: $Percept(s) = null, \forall s$
- **Partial observations**: many states can produce the same percept
 - ex: $Percept(1) = Percept(3) = [A, Dirty]$
 - ⇒ $Percepts(s)$ may correspond to many different candidate states
- $Actions()$, $StepCost()$, $GoalTest()$: as with sensorless case

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Transition Model with (Partial) Perceptions

The Prediction-Observation-Update process

- Three steps:

- 1 Prediction (same as for sensorless): predict the belief state after action a

$$\hat{b} = \text{Predict}(b, a) \stackrel{\text{def}}{=} \text{Result}_{(\text{sensorless})}(b, a) = \{s' \mid s' = \text{Result}_P(s, a) \text{ and } s \in b\}$$

- 2 Observation prediction: determines the set of percepts that could be observed in the predicted belief state: $\text{PossiblePercepts}(\hat{b}) \stackrel{\text{def}}{=} \{o \mid o = \text{Percept}(s) \text{ and } s \in \hat{b}\}$

- 3 Update: for each percept o , determine the belief state b_o , i.e., the subset of states in \hat{b} that could have produced the percept o :

- $b_o = \text{Update}(\hat{b}, o) \stackrel{\text{def}}{=} \{s \mid s \in \hat{b} \text{ and } o = \text{Percept}(s)\}$

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 \Rightarrow each next possible percepts o is used to partition \hat{b} into a smaller belief state b_o

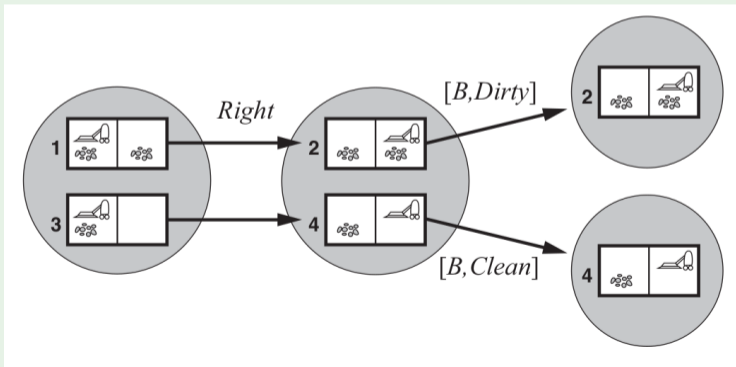
\Rightarrow **Non-deterministic** belief-state problem

- due to the inability to predict exactly the next percept

Transition Model with Perceptions: Example

Deterministic actions: Local-sensing vacuum cleaner

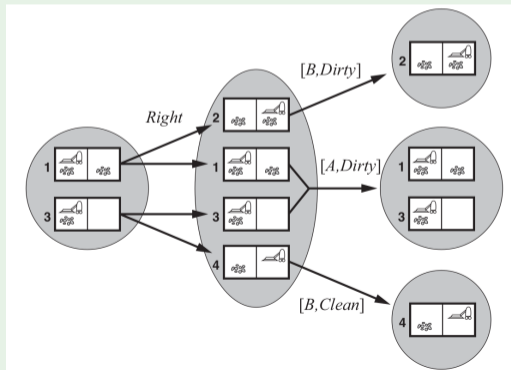
- $\hat{b} = \text{Predict}(\{1, 3\}, \text{Right}) = \{2, 4\}$
- $\text{PossiblePercepts}(\hat{b}) = \{[B, \text{Dirty}], [B, \text{Clean}]\}$
- $\text{Result}(\{1, 3\}, \text{Right}) = \{\{2\}, \{4\}\}$



Transition Model with Perceptions: Example

Nondeterministic actions: Slippery local-sensing vacuum cleaner

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Solving Partially-Observable Problems

- Formulation as a **nondeterministic belief-state search problem**
 - non-determinism due to different possible percepts

⇒ The AND-OR search algorithms can be applied

⇒ The solution is a conditional plan

Solution for initial percept [A, Dirty] (deterministic): [Suck, Right, if Bstate = {6} then Suck else []]

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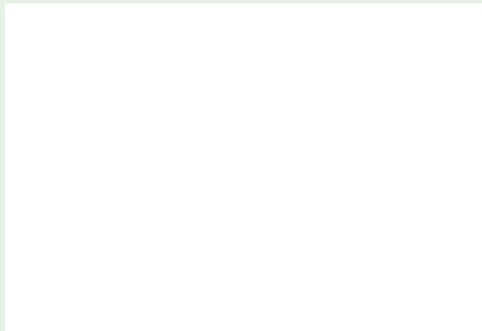
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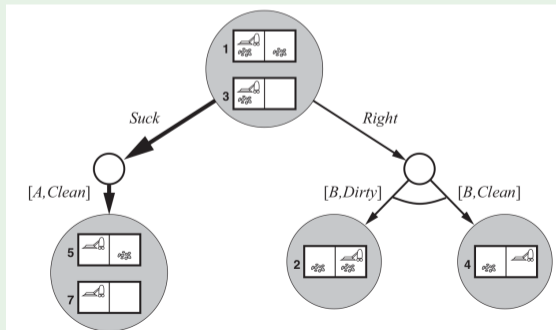
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An Agent for Partially-Observable Environments

- Agent quite similar to the simple problem-solving agent [Ch.3]:
 - formulates a problem (as a belief-state search)
 - calls a search algorithm (an AND-OR-GRAPH one)
 - executes the solution
- Two main differences:
 - the solution is a conditional plan, not an action sequence
 - in step (3) the agent needs to maintain its belief state as it performs actions and receives percepts (aka monitoring, filtering, state estimation)
- State estimation resembles the prediction-observation-update process:
 - simpler, because the percept o is given by the environment
⇒ no need to calculate it
 - given b , a and o : $b' = Update(Predict(b, a), o)$

Remark

The computation has to happen as fast as percepts are coming in
⇒ in some complex applications, compute approximate belief states

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Example: Belief-State Maintenance

Example: Kindergarden Vacuum-Cleaner

- local sensing \implies partially observable
- any square may become dirty at any time unless the agent is actively cleaning it at that moment
 \implies nondeterministic

● Ex: $Update(\overbrace{Predict(\{1, 3\}, Suck)}^{\{5,7\}}, [A, Clean]) = \{5, 7\}$

● Ex: $Update(\overbrace{Predict(\{5, 7\}, Right)}^{\{2,4,6,8\}}, [B, Dirty]) = \{2, 6\}$

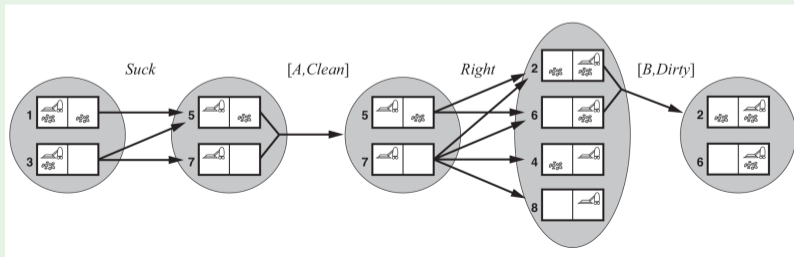
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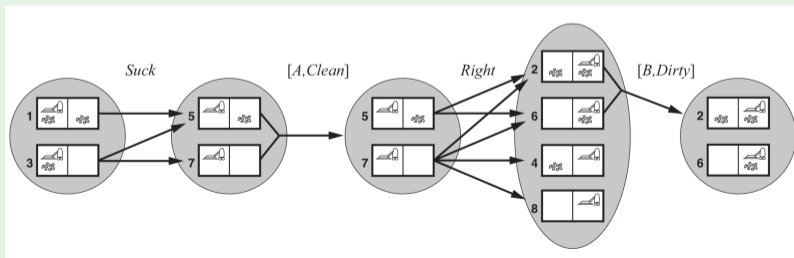
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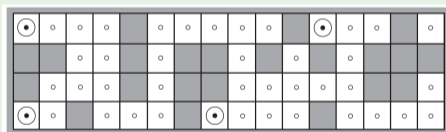
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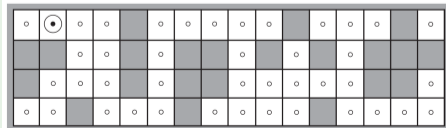


Example:

- Knows the map, senses walls in the four directions (NESW)
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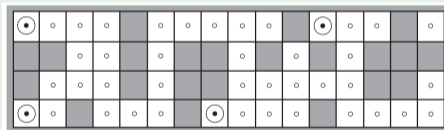
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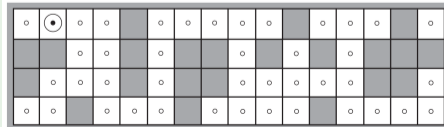
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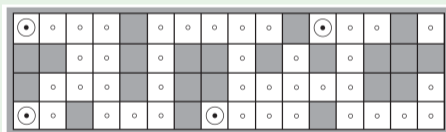
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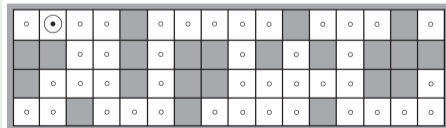
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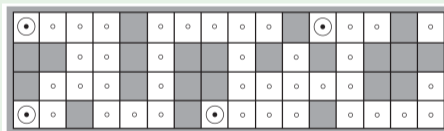
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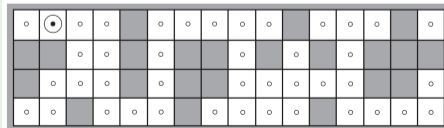
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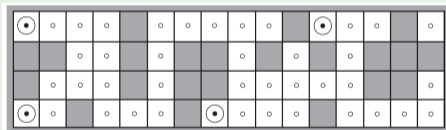
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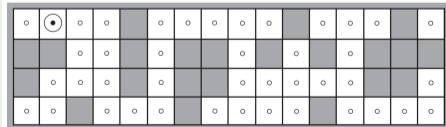
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Outline

- 1 Local Search and Optimization
 - General Ideas
 - Hill-Climbing
 - Simulated Annealing
 - Local Beam Search & Genetic Algorithms
- 2 Search with Nondeterministic Actions
- 3 Search with Partial or No Observations (Deterministic/Nondeterministic Actions)
 - Search with No Observations
 - Search with Partial Observations
- 4 Online Search (aka Exploration)

Recall: Generalities

- So far we address a single category of problems:
 - 1 observable,
 - 2 deterministic,
 - 3 with known environment,
 - 4 s.t. the solution is a sequence of actions.
- What happens when these assumptions are relaxed?
- In order we will:
 - release condition 4 \implies local search
 - release condition 2 \implies search with non-deterministic actions
 - release condition 1 \implies search with no observability or with partial observability
 - release condition 3 \implies online search

Generalities

Online vs. offline search

- So far: **Offline search**
 - it computes a complete solutions before executing it
- **Online search**: agent interleaves computation and action
 - it takes an action,
 - then it observes the environment and computes the next action
 - (repeat)
- Necessary in **dynamic domains** or **unknown domains**
 - cannot know the states and consequences of actions
 - faces an **exploration problem**: must use actions as experiments in order to learn enough
 - ex: a robot placed in a new building \implies must explore it to build a map for getting from A to B
 - ex: newborn baby \implies acts to learn the outcome of his/her actions
- Useful in **nondeterministic domains**
 - prevents search blowup

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- Assumption: a **deterministic and fully observable environment**
- The agent knows only
 - $Actions(s)$, which returns the list of actions allowed in s
 - the **step-cost function** $c(s, a, s')$ (cannot be used until s' is known)
 - $GoalTest(s)$
- Remark: **The agent cannot determine $Result(s, a)$**
 - except by actually being in s and doing a
- The agent knows an **admissible heuristic function** $h(s)$, that estimates the distance from the current state to a goal state
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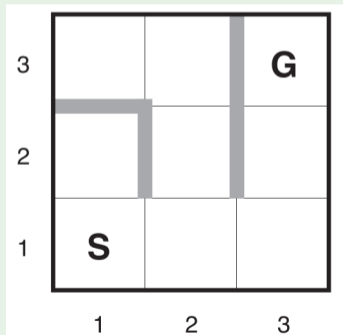
Working Hypotheses

- Assumption: **a deterministic and fully observable environment**
- The agent knows only
 - *Actions*(s), which returns the list of actions allowed in s
 - the **step-cost function** $c(s, a, s')$ (cannot be used until s' is known)
 - *GoalTest*(s)
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Online Search: Example

Example: a simple maze problem

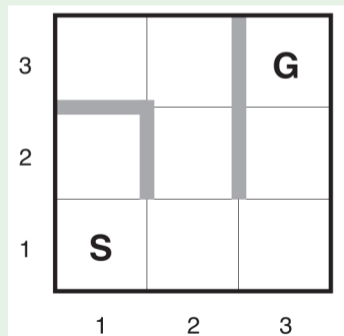
- the agent does not know that going Up from (1,1) leads to (1,2)
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- the agent might know the location of the goal
- it may be able to use the Manhattan-distance heuristic



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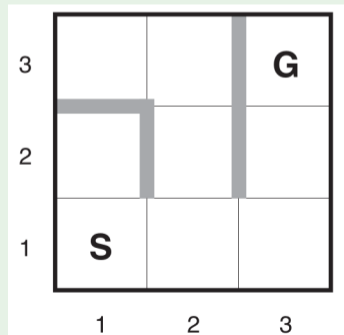
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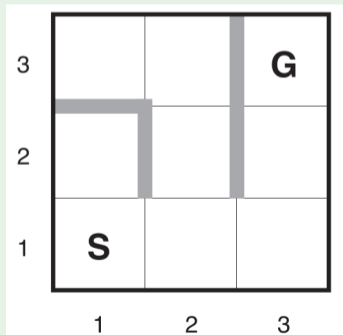
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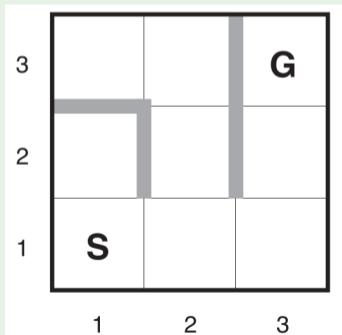
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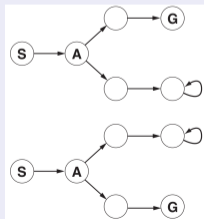
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Online Search: Deadends

Inevitability of Deadends

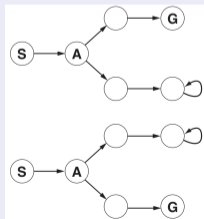
- Online search may face deadends (e.g., with **irreversible actions**)
- **No algorithm can avoid dead ends in all state spaces**
- **Adversary argument**: for each algo, an adversary can construct the state space while the agent explores it
 - If states S and A visit. What next?
 - ⇒ if algo goes right, adversary builds (top), otherwise builds (bot)
 - ⇒ adversary builds a deadend
- Assumption the state space is **safely explorable**: some goal state is reachable from every **reachable state** (ex: reversible actions)



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Online Search Agents

Online Search Agents: Basic Ideas

- Idea: The agent creates & maintains a map of the environment ($result[s, a]$)
 - map is updated based on percept input after every action
 - map is used to decide next action
- Difference wrt. offline algorithms (ex A^* , BFS)
 - Can only expand the node it is physically in
 - Needs to backtrack physically

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 - DFS: go back to the state from which the agent most recently entered the current state
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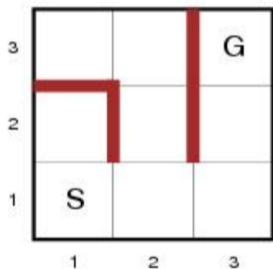
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Online DFS Search Agents

function ONLINE-DFS-AGENT(*problem*, s') **returns** an action
 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

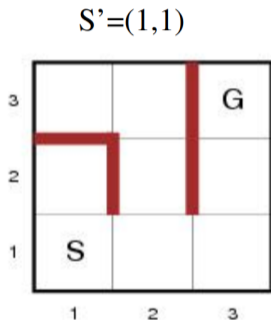
if $problem.IS\text{-}GOAL(s')$ **then return** $stop$
if s' is a new state (not in $untried$) **then** $untried[s'] \leftarrow problem.ACTIONS(s')$
if s is not null **then** // if neither initial nor result of backtracking
 $result[s, a] \leftarrow s'$
 add s to the front of $unbacktracked[s']$
if $untried[s']$ is empty **then** //backtrack // $results[s',b]$ exists because $untried[s']$ is empty
 if $unbacktracked[s']$ is empty **then return** $stop$ // added in 4th ed. AIMA
 $a \leftarrow$ an action b such that $result[s', b] = POP(unbacktracked[s'])$ $s' \leftarrow null$
 else $a \leftarrow POP(untried[s'])$ // all actions in $actions(s')$ have been tried
 $s \leftarrow s'$
return a

Online DFS: Example



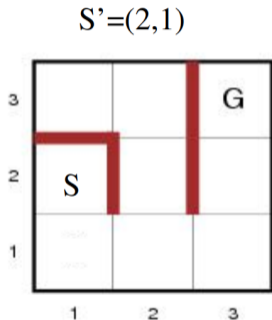
- Assume maze problem on 3x3 grid.
- $s' = (1,1)$ is initial state
- Result, untried, unbacktracked, ... are empty
- S,a are also empty

Online DFS: Example



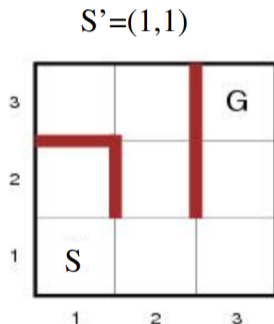
- GOAL-TEST((1,1))?
 - **S not = G thus false**
- (1,1) a new state?
 - **True**
 - **ACTIONS((1,1)) -> untried[(1,1)]**
 - {RIGHT,UP}
- s is null?
 - **True (initially)**
- untried[(1,1)] empty?
 - **False**
- POP(untried[(1,1)])->a
 - **A=UP**
- s = (1,1)
- Return a

Online DFS: Example



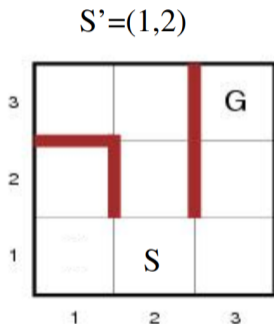
- GOAL-TEST((2,1))?
 - **S not = G thus false**
- (2,1) a new state?
 - **True**
 - **ACTION((2,1)) -> untried[(2,1)]**
 - {DOWN}
- s is null?
 - **false (s=(1,1))**
 - **result[UP,(1,1)] <- (2,1)**
 - **unbacktracked[(2,1)]={(1,1)}**
- untried[(2,1)] empty?
 - **False**
- A=DOWN, s=(2,1) return A

Online DFS: Example



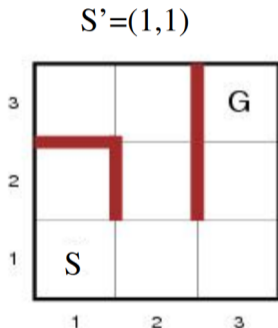
- GOAL-TEST((1,1))?
 - **S not = G thus false**
- (1,1) a new state?
 - **false**
- s is null?
 - **false (s=(2,1))**
 - **result[DOWN,(2,1)] ← (1,1)**
 - **unbacktracked[(1,1)]={(2,1)}**
- untried[(1,1)] empty?
 - **False**
- A=RIGHT, s=(1,1) return A

Online DFS: Example



- GOAL-TEST((1,2))?
 - **S not = G thus false**
- (1,2) a new state?
 - **True,**
untried[(1,2)]={RIGHT,UP,LEFT}
- s is null?
 - **false (s=(1,1))**
 - **result[RIGHT,(1,1)] <- (1,2)**
 - **unbacktracked[(1,2)]={(1,1)}**
- untried[(1,2)] empty?
 - **False**
- A=LEFT, s=(1,2) return A

Online DFS: Example



- GOAL-TEST($(1,1)$)?
 - **S not = G thus false**
- $(1,1)$ a new state?
 - **false**
- s is null?
 - **false (s=(1,2))**
 - **result[LEFT,(1,2)] <- (1,1)**
 - **unbacktracked[(1,1)]={ (1,2),(2,1) }**
- untried[(1,1)] empty?
 - **True**
 - **unbacktracked[(1,1)] empty?**
False
- $A=b$ for b in result[b,(1,1)]=(1,2)
 - **B=RIGHT**
- $A=RIGHT$, $s=(1,1)$...

Online Search Agents

Online Search Agents: Facts

- Works only if actions are always reversible
- Worst case: each link $\langle s, a, s' \rangle$ is visited twice
 - one as exploration ($a \in \text{untried}[s]$)
 - one as backtracking ($a \in \text{unbacktracked}[s]$)
- An agent can go on a long walk even if it is close to the solution
 - an online iterative deepening approach solves this problem

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Online Local Search

- **Hill Climbing** natural candidate for online search
 - locality of search
 - only one state is stored
 - unfortunately, stuck in local minima
 - **random restarts** not possible
- Possible solution: **Random Walk**
 - selects randomly one available actions from the current state
 - preference can be given to actions that have not yet been tried
 - **eventually finds a goal or complete its exploration** if space is finite
 - unfortunately, **very slow**

Random Walk: example

- random walk takes exponentially many steps to find a goal (backward progress is twice as likely as forward progress)

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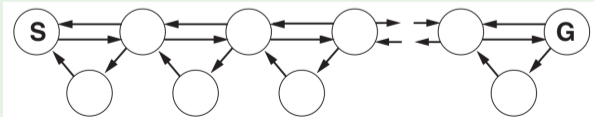
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(© S. Russell & P. Norwig, AIMA)

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$LRTA^*$: General ideas

- Better possible solution: **add memory to hill climbing**
 - Idea: store a “current best estimate” $H(s)$ of the cost to reach the goal from each state that has been visited
 - initially $h(s)$
 - updated as the agent gains experience in the state space
- (recall that $h(s)$ is in general “too optimistic”)

⇒ Learning Real-Time A^* ($LRTA^*$)

- builds a map of the environment in the $result[s,a]$ table
 - chooses the “apparently best” move a according to current $H()$
 - updates the cost estimate $H(s)$ for the state s it has just left, using the cost estimate of the target state s'
 - $H(s) := c(s, a, s') + H(s')$
 - “optimism under uncertainty”: untried actions in s are assumed to lead immediately to the goal with the least possible cost $h(s)$
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An $LRTA^*$ agent is guaranteed to find a goal in any finite, safely explorable environment.

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function $LRTA^*$ -AGENT(s') **returns** an action

inputs: s' , a percept that identifies the current state

persistent: $result$, a table, indexed by state and action, initially empty

H , a table of cost estimates indexed by state, initially empty

s , a , the previous state and action, initially null

if GOAL-TEST(s') **then return** $stop$

if s' is a new state (not in H) **then** $H[s'] \leftarrow h(s')$

if s is not null

$result[s, a] \leftarrow s'$

$H[s] \leftarrow \min_{b \in \text{ACTIONS}(s)} LRTA^*\text{-COST}(s, b, result[s, b], H)$

$a \leftarrow$ an action b in $\text{ACTIONS}(s')$ that minimizes $LRTA^*\text{-COST}(s', b, result[s', b], H)$

$s \leftarrow s'$

return a

function $LRTA^*\text{-COST}(s, a, s', H)$ **returns** a cost estimate

if s' is undefined **then return** $h(s)$

else return $c(s, a, s') + H[s']$

Example: *LRTA**

Five iterations of *LRTA** on a one-dimensional state space

- states labeled with current $H(s)$, arcs labeled with step cost
- shaded state marks the location of the agent,
- updated cost estimates at each iteration are circled

