Lecture 3
A^* Search and Search in Complex Environments

TDT4136: Introduction to Artificial Intelligence

Xavier F. C. Sánchez Díaz

Department of Computer Science
Faculty of Information Technology and Electrical Engineering
Norwegian University of Science and Technology

September 1, 2025

Outline

Recap on Uninformed Search

- Uninformed search strategies systematically navigate the search space blindly—not questioning where the goal may be in the space.
- The search space is often very large.

Recap on Uninformed Search

- Uninformed search strategies systematically navigate the search space blindly—not questioning where the goal may be in the space.

- The search space is often very large.

- We can be smarter about it using a heuristic (guess estimate)
- We covered (Greedy) Best First, where you pick the option with the best estimate
- We also covered A^*, which uses both the cost and the estimate

Friendly reminder

Things to look out for

Implementation details vary a lot, and can be tricky!

- Is the algorithm checking for redundant paths (**graph search**) or not (**tree search**)?
- Is the goal check performed **early** (when a node is *generated*) or **late** (when a node is *expanded*)?
- Is the algorithm **storing** all **reached states**, or **reconstructing the path** from a chain of parent nodes?

Read the book!

To become familiar with the algorithms and their implementations details, you should read the book. These slides are not a replacement for the book; they are a summary of the most important points.

Cheatsheet

Things to look out for

Most of the search strategies we cover in this course use the same algorithm to search.[1]
It is just `Best-First-Search` with different functions to decide which element will be popped out of the priority queue:

Depth-First Search

$$f(n) = -\text{depth}(n)$$

Uniform-Cost Search (Dijkstra)

$$f(n) = g(n)$$

Greedy Best-First Search

$$f(n) = h(n)$$

A* Search

$$f(n) = g(n) + h(n)$$

[1] Except for BFS that has a separate algorithm.

A^* search

Informed search strategies

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A^* search

Informed search strategies

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A^* search

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where

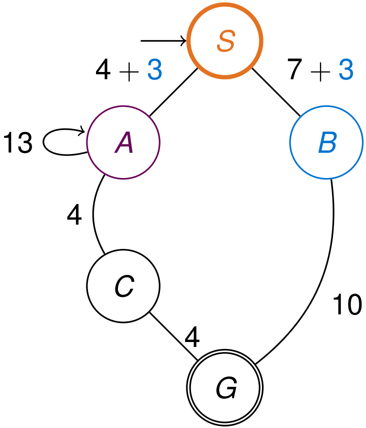
- $g(n)$ is the cost we have paid so far to reach n
- $h(n)$ is the estimated cost of the node (to the goal)
- $f(n)$ is then the estimated cost of the cheapest solution through n to the goal

A^* search

Informed search strategies

With the following estimated distances to the goal:

- $h(A) = 3$
- $h(B) = 3$
- $h(C) = 3$
- $h(G) = 0$



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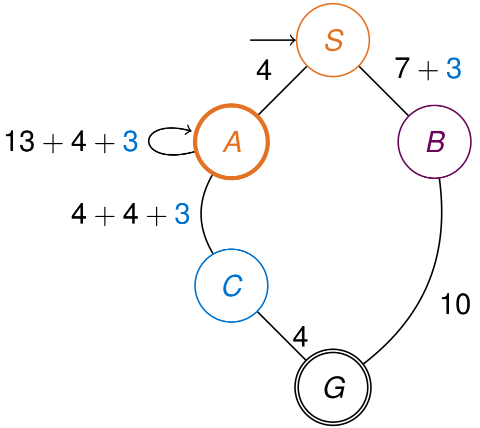

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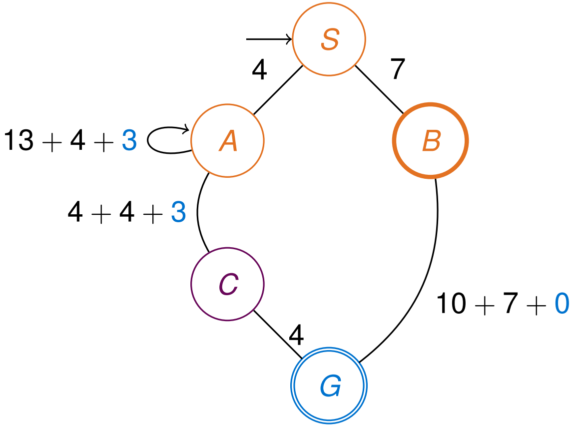

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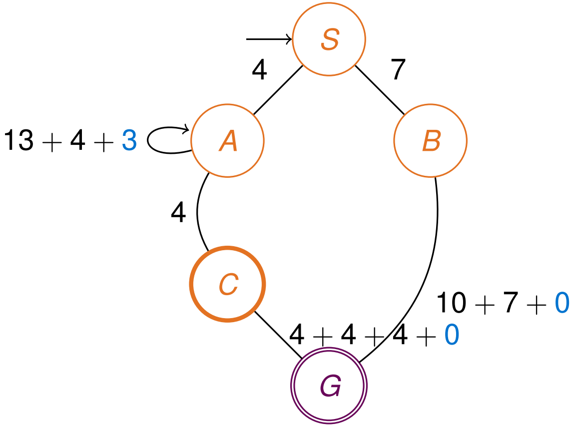

A^* search

Informed search strategies

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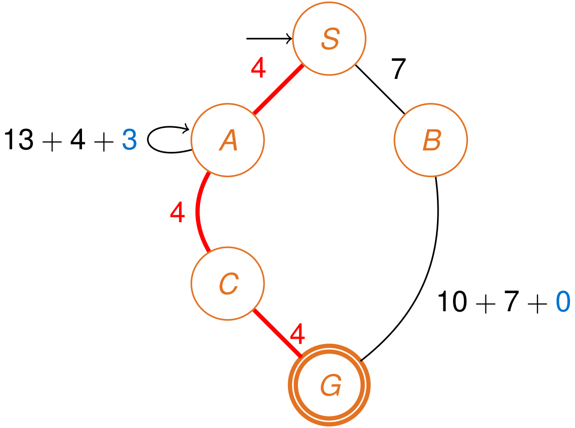

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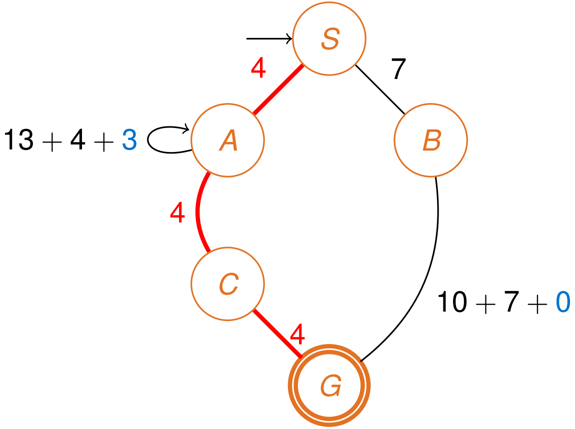
- It is **complete** for positive costs, within a finite state space and an existing solution.



A^* search

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- We have found the goal!
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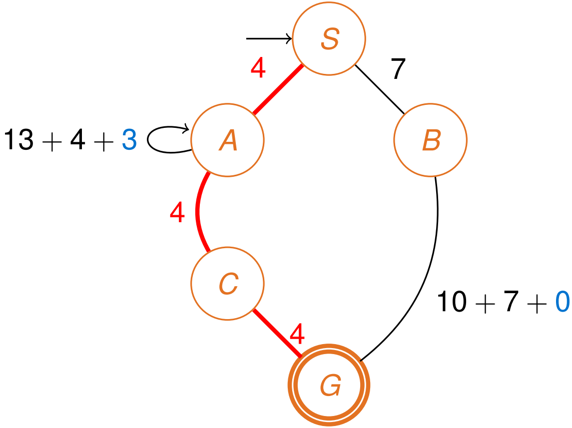
- It is **cost-optimal** if **certain conditions are met**



A^* optimality

More on A^*

A^* is **cost-optimal** if **certain conditions are met.** What are these conditions?

[2] They usually are.

A^* optimality

More on A^*

A^* is **cost-optimal** if **certain conditions are met.** What are these conditions?

- Arc costs need to be positive[2]
- The heuristic function needs to be **admissible** and non-negative.

[2] They usually are.

Admissibility

More on A^*

Admissibility of h

We say a heuristic h is **admissible** if it **never overestimates** the cost from a node to the goal node.

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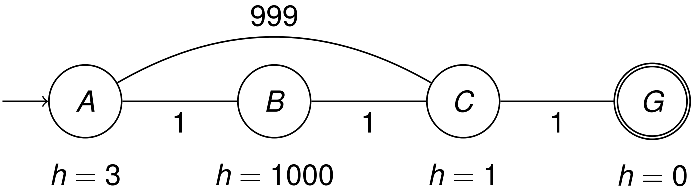
An admissible heuristic is *optimistic!*

A crazy example

More on A^*



A crazy example

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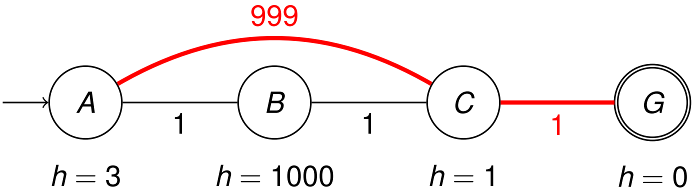

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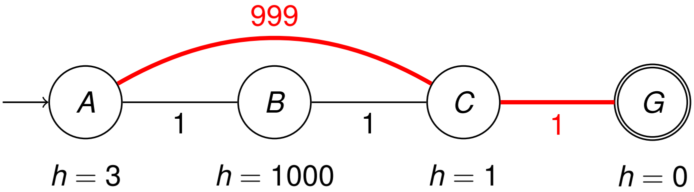

We would not choose the optimal path due to $h(B)$ being overestimated of the actual cost!

Consistency

More on A^*

Another important (and even stronger) property of a heuristic h is **consistency**.

Consistency of h

A heuristic h is **consistent** if for every node n and all of its successors n' generated by an action a, we have

$$h(n) \leq c(n, a, n') + h(n')$$

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In other words, the estimate of a node should be less or equal than the the estimate of a descendant plus the cost of reaching there.

Consistency: an example

More on A^*

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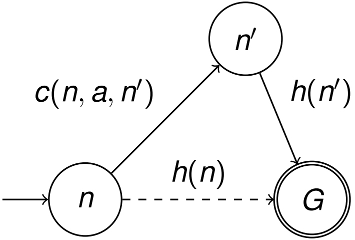
$$h(n) \leq c(n, a, n') + h(n')$$

- A triangle inequality helps picturing it!
- Moving through $h(n)$ **has** to be cheaper than going to G via the successor n'
- This **must** be true for every successor n' of n
  - Think of an euclidean grid



Consistency and admissibility

More on A^*

Why is this important?

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  - That means that $f(n)$ is non-decreasing along any path

Optimality and efficiency

More on A^*

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- Beam search – limit size of *frontier* to k-best candidates
- Iterative deepening A^* – gradually increase the f-cost *cutoff*.
- Memory-bounded A^* – expand until memory is ful, and then drop the worst candidate from *frontier*

A generalised heuristic search

More on A^*

Generalised heuristic search

$$f(n) = g(n) + w \cdot h(n)$$

where w is a *weight* defining how important the heuristic $h(n)$ is.

In most other applications, we usually have w_1 and w_2, one for $g(n)$ and one for $h(n)$. The book uses only w for $h(n)$.

A generalised heuristic search

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Of course you can set w to something else, depending for example if there is *uncertainty* on your heuristic (but this then becomes a whole other course :^))

Building heuristics

More on A^*

How far are we from solving this sliding puzzle?

- $h_1(n)$ will be the number of misplaced tiles
- $h_2(n)$ will be the **total** Manhatttan distance[a]

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Remember that each configuration is a state!

Other ideas for building heuristics

More on A^*

- Consider relaxations of the problem
- Consider creating the heuristic by looking **backwards from the goal**.
- Consider dividing into subproblems!
  - For example, instead of solving the whole sliding puzzle at once, consider getting in place four tiles only
  - Then store all these solutions in a DB. Create an admissible heuristic for this subproblem
  - Combine the subproblems to choose the best heuristic

The process of choosing the appropriate representation, data structures and heuristics for a problem is known as **modelling** and is crucial for AI developers and researchers!

Dominance: comparing heuristics

More on A^*

Which of the heuristics is better?

Dominance: comparing heuristics

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Admissible heuristics can be compared by looking at their values.

Heuristic Domination

An admissible heuristic h_2 it is said to **dominate** another admissible heuristic h_1 if **for every** node n, $h_2(n) \geq h_1(n)$.
This will reflect in A^* expanding fewer nodes on h_2, and thus finding an optimal solution, faster.

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A generalisation of this would then be

$$h_{best}(n) = \max(h_a(n), h_b(n), \dots)$$

Section 3

Search in Complex Environments

Searching in complex environments

- Both informed and uninformed searching strategies are designed to explore search spaces systematically
- They keep one or more paths in memory, and record which alternatives have been explored at each point along the path
- The path to that goal constitutes a solution
- But in most problems in the real world, the path to a solution might be **irrelevant**

Searching in complex environments

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- The path to that goal constitutes a solution
- But in most problems in the real world, the path to a solution might be **irrelevant**

If we only care about finding a solution, then there are better ways to search the space!

Local Search

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[3] as in most real world applications

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- It eases up on the completeness and optimality in the interest of improving time and space complexity[3]
- Local Search algorithms use “little” memory (usually a constant amount)
- They can often find reasonable solutions in very large (or infinite) state spaces

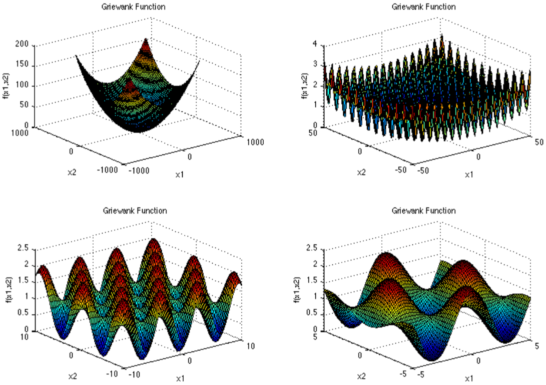
[3] as in most real world applications

The search landscape

Search in complex environments

Usually, the **state space** is referred to as the **search space**. We can **visualise** this space by looking at the heuristic function!

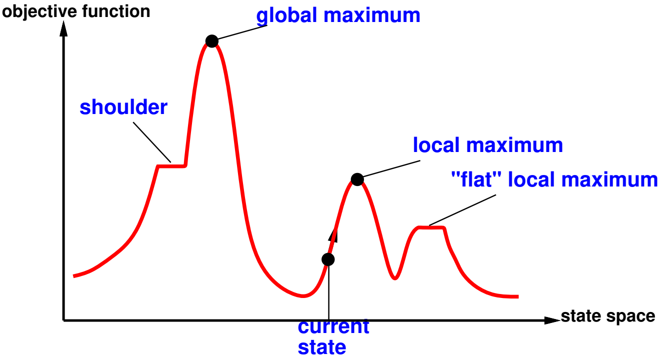
$$f(x) = \sum_{i=1}^{d} \frac{x^2}{4000} - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$



The Griewank function. Image from Surjanovic & Bingham
https://www.sfu.ca/~ssurjano/griewank.html

The search landscape

Search in complex environments

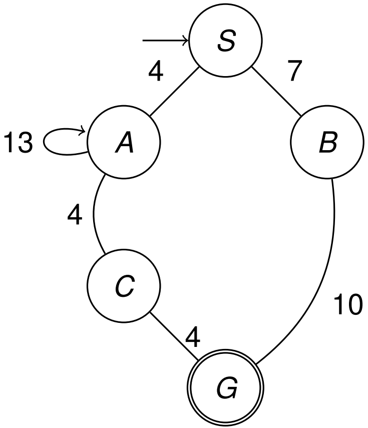


- Each point in the landscape represents a state in the search space and has “an elevation” (its $h(n)$)
- If the elevation corresponds to an objective function, then the aim is to find the highest peak (or **maximum**)
- If the elevation corresponds to a cost function, then we look for the lowest valley (or **minimum**)

The search landscape

Search in complex environments

Recall our search problems.



- A is a neighbour of S, C and itself because those are the states than can be reached from A.
- The **neighbourhood** of A is then $\{A, C, S\}$.
- This concept of neighbourhood is very important for **local search**, as we decide *where to move next* by looking around us!

Section 4

Local Search Algorithms

As the last time with algorithms, please check the full details on the book!

Hill climbing and gradient descent

Local search algorithms

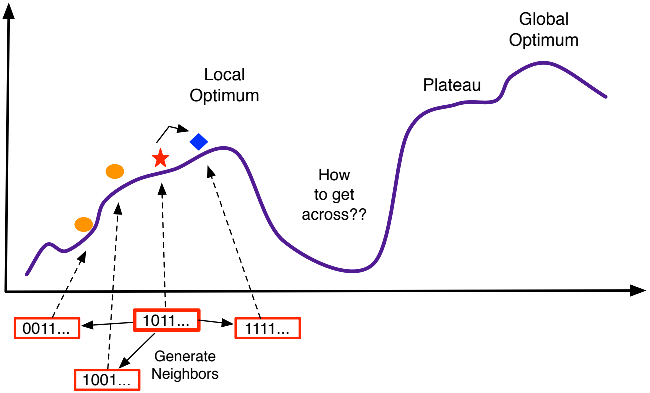
Idea: Go to the best spot you see now.

Hill climbing and gradient descent

Local search algorithms

Idea: Go to the best spot you see now.

- Assume you are doing **maximisation**
- You then want to **climb** the tallest peak
- This is called **hill-climbing**!



If you are **minimising** instead, then the procedure is called **gradient descent** as we want to move towards the direction where the difference in “height” is largest.

How to get across?

Both **hill-climbing** and **gradient descent** get stuck in **local optima**. How do we get out of this mess?

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  - This is the key to the **simulated annealing** algorithm
- Idea 3: Search multiple paths in batches

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  - Either via *long* jumps when you are not doing very good
  - Or doing *short* hops when you are in a promising state (you do not want to miss it)

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Genetic Algorithms

Local search algorithms

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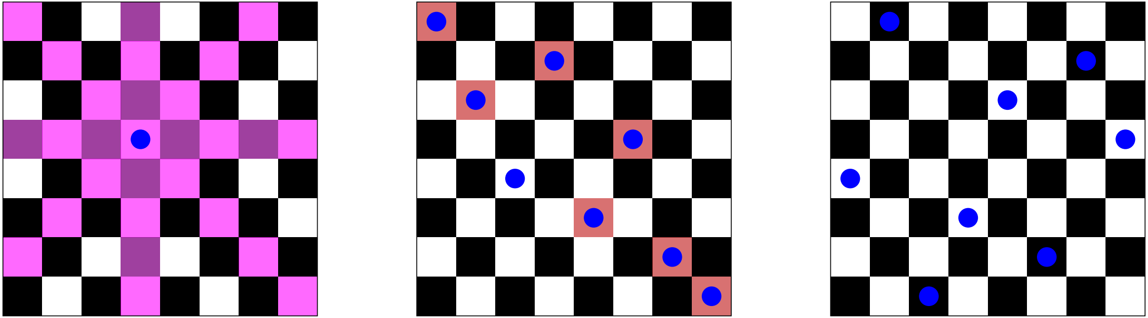
This process will be repeated until a solution has been found, or until enough *generations* have been replaced.

We have a whole course on evolutionary computation methods during the spring semester: IT3708 Bio-Inspired AI!

The 8-queens problem

Place 8 queens in a chess board such that no queen checks each other.



(a) Queen constraints (b) Generated conflicts (c) Possible solution

Figure: The 8-queens problem. 1a shows the constraints (in pink) imposed by the placement of a single queen piece (in blue). 1b highlights the conflicts arising from a possible configuration of the board. 1c illustrates one possible solution with no conflicts.

See a worked example in `https://ntnu-ai-lab.github.io/EvoLP.jl/stable/tuto/8_queens.html`

Section 5

Nondeterministic and partially observable environments

Searching with Nondeterminism

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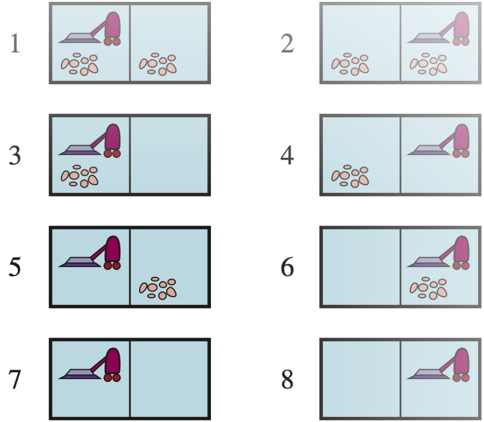
- So far, we have assumed that actions are deterministic
  - That our intended action will **always** yield the result we expect
- In the real-world, things do not always go as expected
- To account for different possible outcomes, we need to come up with a contingency plan instead of a single path of actions

Example: The Erratic Vacuum World

Searching with Nondeterminism



- Nondeterministic *suck* action: $suck(s_1) = \{s_5, s_7\}$

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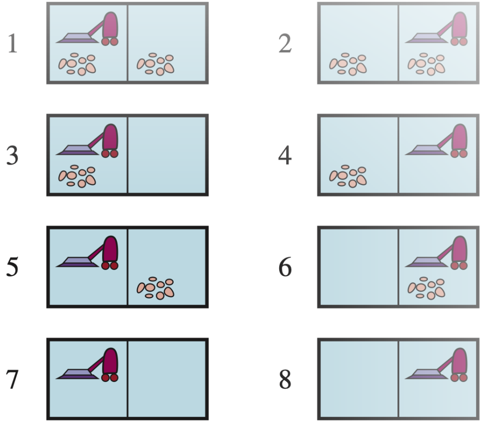

- Nondeterministic *suck* action:
  $suck(s_1) = \{s_5, s_7\}$
  - which means both states s_5 and s_7 are possible outcomes of executing a *suck* action on state s_1

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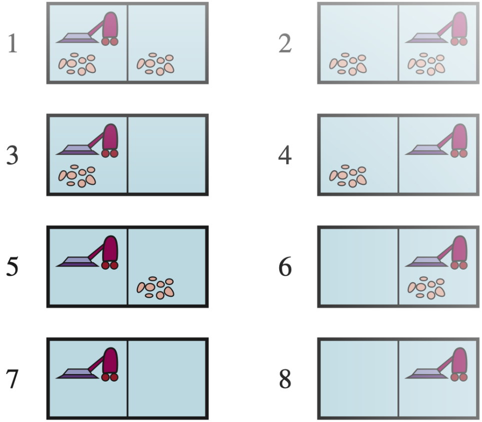

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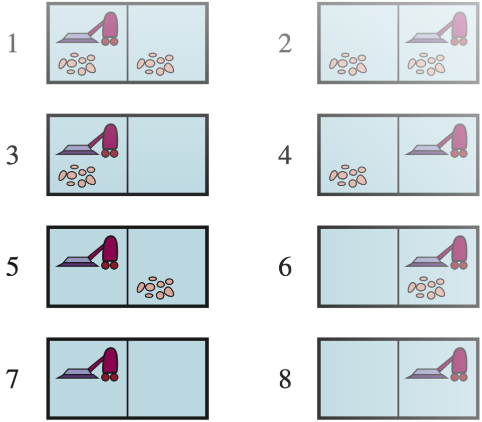

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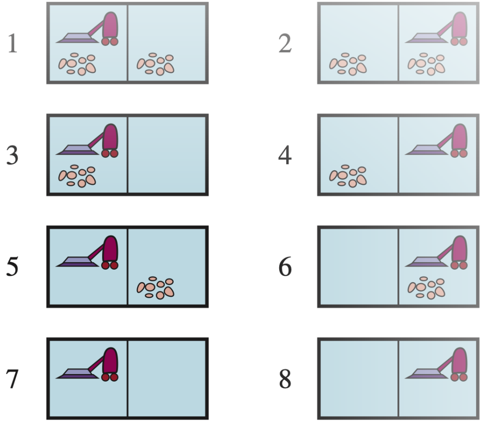

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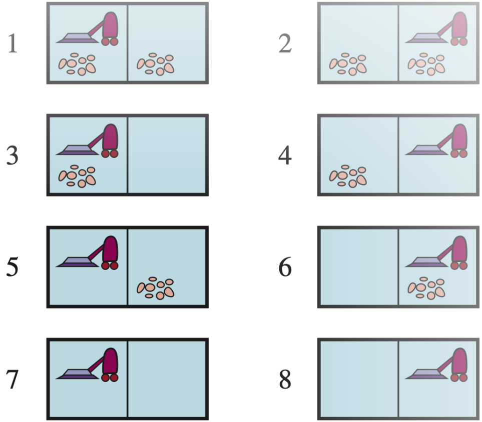

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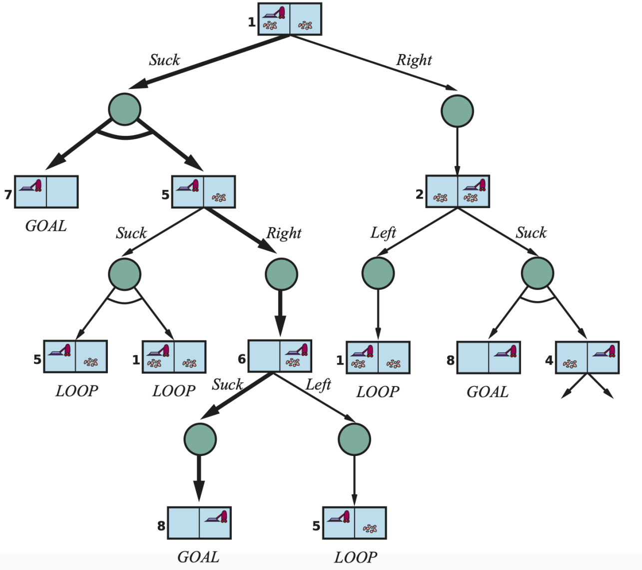
Nondeterminism can happen with other actions like *moveRight*! See the *slippery vacuum world* in the book!

AND-OR search trees

Searching with Nondeterminism

One way to handle these, is to consider *compound nodes*, made up of the possible states after a given action

- **OR** nodes represent actions
- **AND** nodes represent outcomes
- Since it is a **tree**, we can **search** in it
  - This is called **AND-OR search**
  - It is recursive, with a base case of either failure or an empty plan



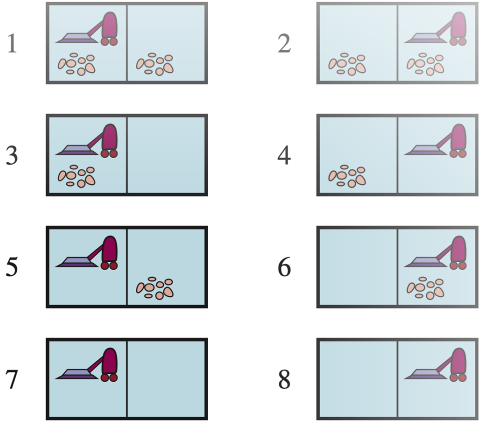
Searching in Partially Observable Environments

- So far, we have assumed that the agent knows exactly the state of its environment
- In reality, an agent receives partial (and possibly noisy) observations
- Therefore, the state can only be *estimated* through a “belief”

Sensorless deterministic vacuum world

Searching in partially observable environments

- $Result(\{1,2,3,4,5,6,7,8\}, moveRight) = \{2,4,6,8\}$



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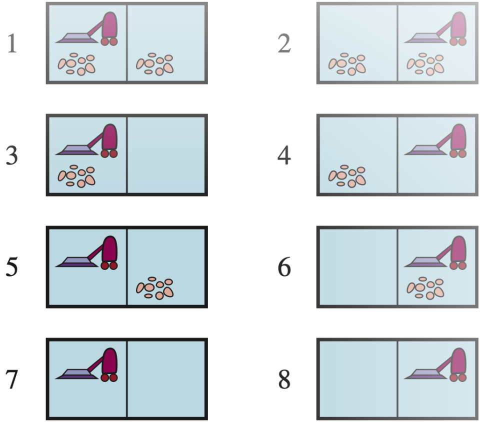

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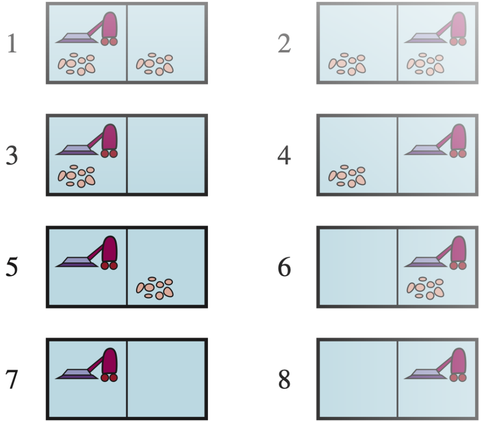

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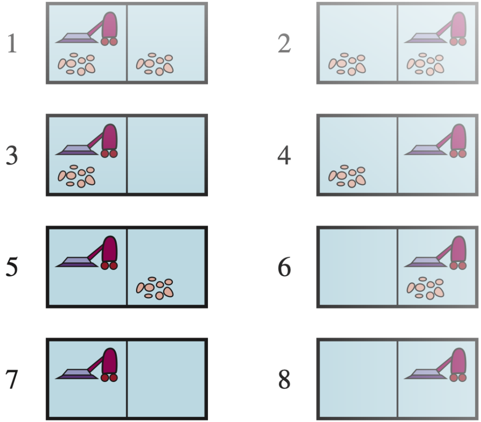

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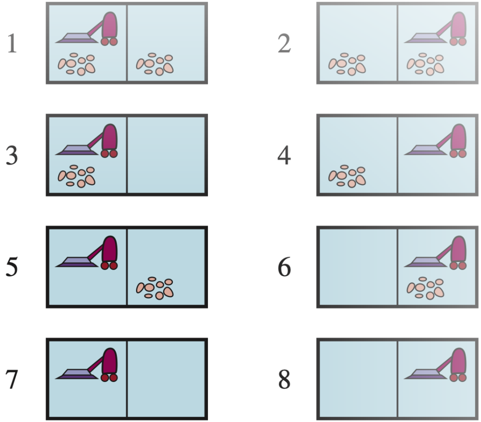

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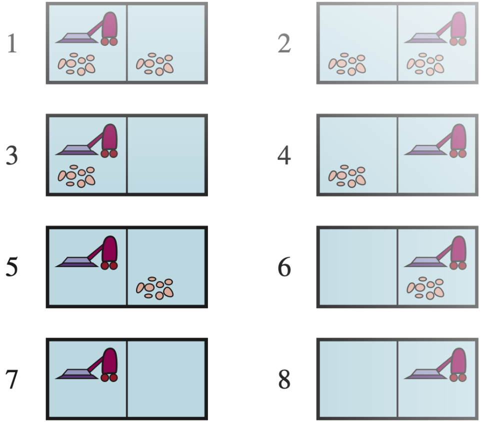
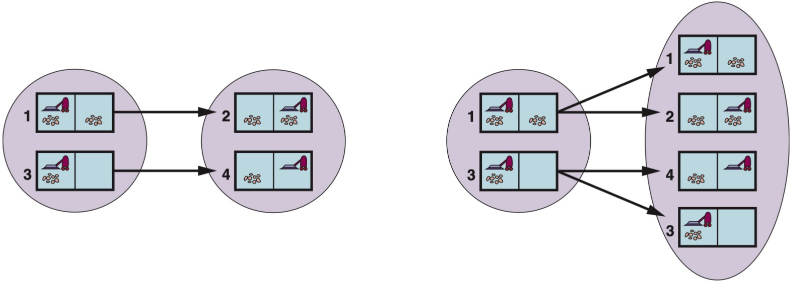


Think of 5D-chess: you solve the problem on multiple paths at the same time!

Predicting the next state with sensorless agents

Searching in partially observable environments

We are, in a way, making compound nodes with multiple outcomes in, where some of our actions lead to specific environment settings inside those belief states.



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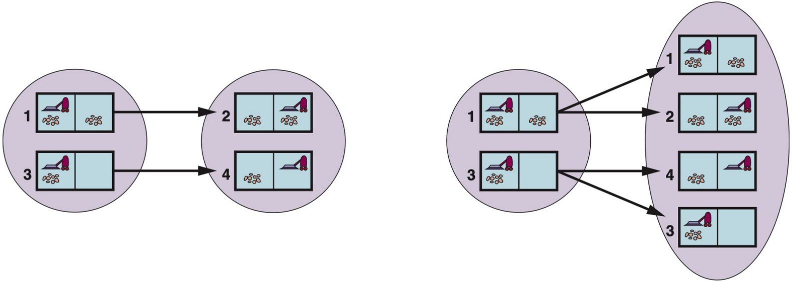
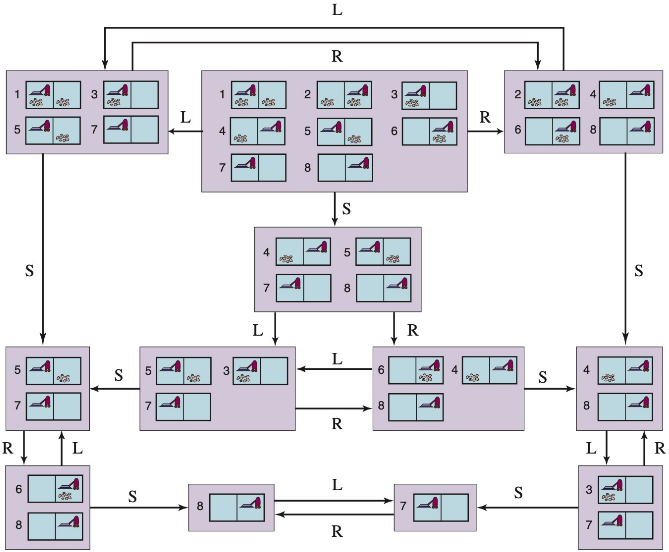


Of course it can be **both** nondeterministic and partially observable!

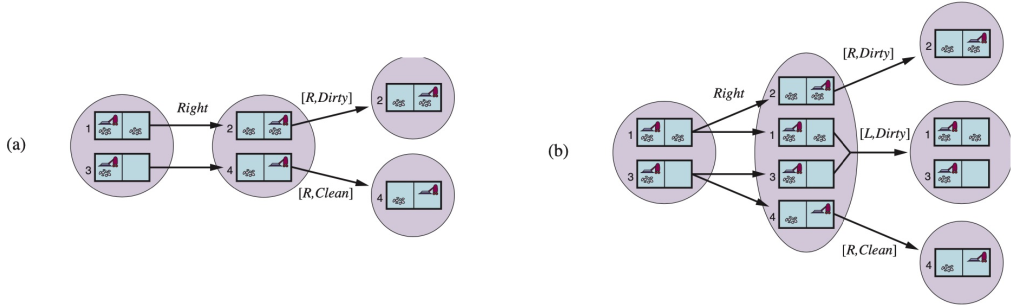
Searching through the belief space in deterministic environments

If we have a deterministic setting, we can use an ordinary search algorithm.



Searching through the belief space in partially observable environments

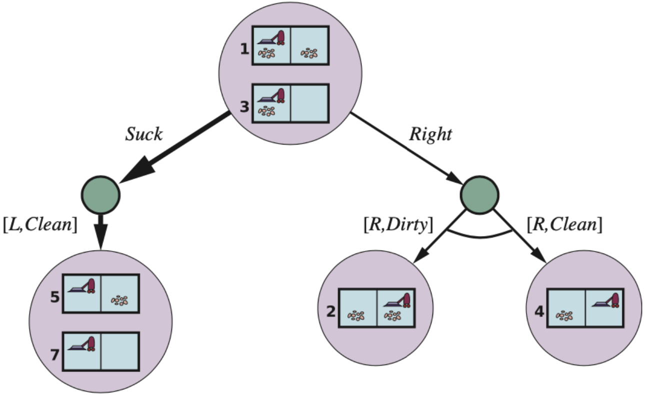
With sensors



- The agent knows where it is and see the dirt (if any) on its spot
- The **transition model** becomes a **function** of a belief state, an action, and a **another** belief state
  - In case of nondeterminism (right), we do like Dr. Strange and consider possible outcomes on different universes. **How**?

Seaching through the belief space in partially observable environments

With sensors, in a nondeterministic world



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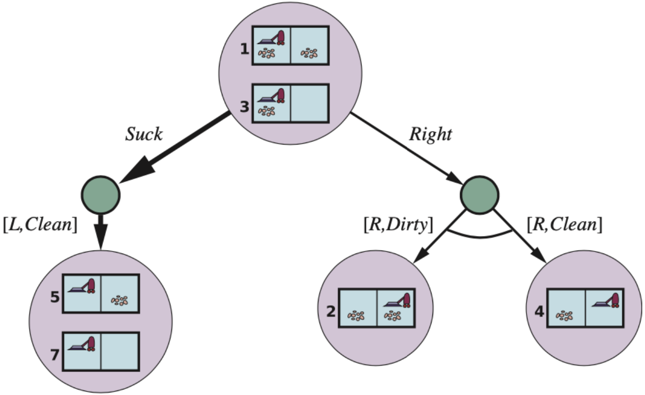

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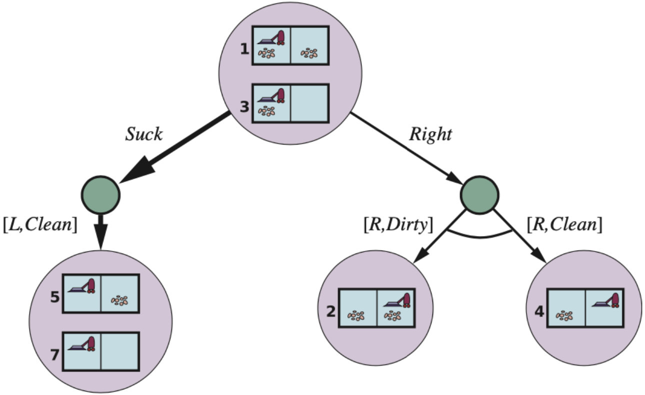

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- The solution is a conditional **plan**