Lecture 11 — Planning

TDT4136: Introduction to Artificial Intelligence

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October 31, 2024

Outline

What is Planning?

Classical Planning

Find a sequence of actions to accomplish a goal in an environment that is:

- discrete
- deterministic
- static
- fully observable

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- deterministic
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In other words, what we have discussed before while studying **search**!

Why do we plan?

What is Planning?

- To address a new situation or problem

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- When the task is complex

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- When the task is complex
- when the environment imposes a high risk or cost!

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We *explicitly* plan when it is strictly necessary.

How do we do it?

What is Planning?

There are multiple ways to define a planning problem, and several ways of finding a valid plan.

How do we do it?

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So far, we have covered:

- Problem-solving by **searching**

How do we do it?

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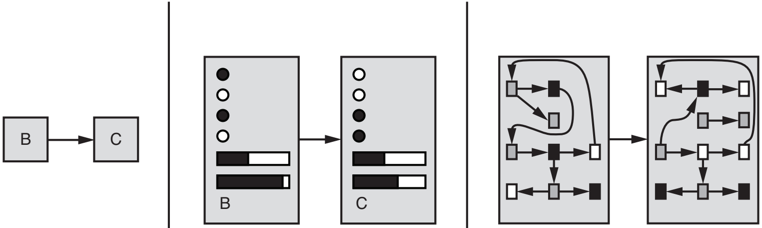
So far, we have covered:

- Problem-solving by **searching**
- **Logic** and **satisfiability**

Representing the world

Representing the world



(a) Atomic (b) Factored (b) Structured

The **state of the world** can be described in different ways.

An example: Wumpus World

Representing the world

- A **partially observable** world, with **sensors** and a limited set of actions
- We act rationally by updating **our belief** of the world
- The world is **stored as facts in a knowledge base** (a logical agent can solve this!)

`https://thiagodnf.github.io/wumpus-world-simulator/`

What happens when we move?

What happens when we move?

Time is important!

Dealing with time(steps)

Representing the world

- Some aspects of the world change from time to time. We call them **fluents**.

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  - There are extensions that can handle it, like **linear temporal** or **computational tree** logics!
- An agent’s actions can change aspects of the world (fluents) but not all
- The agent needs to keep track of fluents, and know what remains unchanged!

A snapshot of the world

Representing the world

Time 0

I am at *cellA*1 facing *east*, I feel a *breeze* and have 1 *arrow*.

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If we decide to move *Forward*, then in logic:

$$Location^0_{cellA1} \wedge FacingEast^0 \wedge Forward^0 \implies Location^1_{cellA2} \wedge \neg Location^1_{cellA1}$$

...and although the *arrows* and *breeze* percepts were not modelled, we would have 4 directions $\times T$ time steps $\times n^2$ locations.

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It is extremely expensive and inefficient!

Planning Domain Definition Language
PDDL

Instead, we can use **PDDL**, which uses actions with preconditions and **effects**:

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\begin{aligned}
&\mathit{Action}(\mathit{Move}(\mathit{who}, \mathit{from}, \mathit{to})\\
&\qquad \mathit{Precond} : \mathit{At}(\mathit{who}, \mathit{from}) \land \mathit{Adj}(\mathit{from}, \mathit{to}) \land \neg \mathit{Pit}(\mathit{to})\\
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- *Move* is the action being defined
- *who*, *from* and *to* are variables
- *Precond* describes the state of the world needed for the action *to occur*
- *Effect* describes the *resulting* state after acting

States in PDDL

PDDL

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As with search, we also need **starting** and **goal** states.

Example: Block world

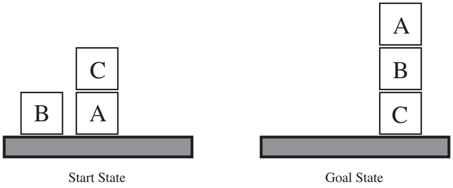
PDDL

Start State

Goal State

What would the **start and goal** states look like in **PDDL**?

Example: Block world



- **Start**: $On(A, Table), On(B, Table), On(C, A), Clear(B), Clear(C)$[1]
- **Goal**: $On(A, B), On(B, C)$

[1] Commas are a shorthand for *AND*s ($\wedge$) and semicolons for *OR*s ($\vee$)

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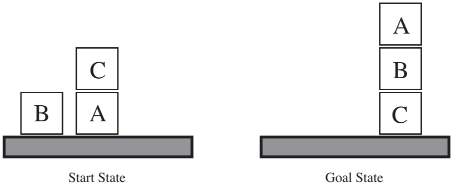

- **Start**: $On(A, Table), On(B, Table), On(C, A), Clear(B), Clear(C)$[1]
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What would the **actions** look like in **PDDL**?

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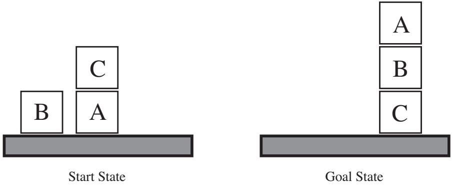

- **Start**: $On(A, Table), On(B, Table), On(C, A), Clear(B), Clear(C)$
- **Goal**: $On(A, B), On(B, C)$

$$Action(Move(block, x, y)$$
$$PRECOND : On(block, x), Clear(block), Clear(y), Block(block), Block(y)$$
$$EFFECT : On(block, y), Clear(x), \neg On(block, x), \neg Clear(y))$$

Notice how any variable in the **effect** must appear in the **precondition**!

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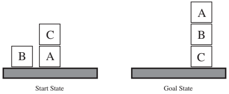

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&Action(MoveToTable(block, x) \\
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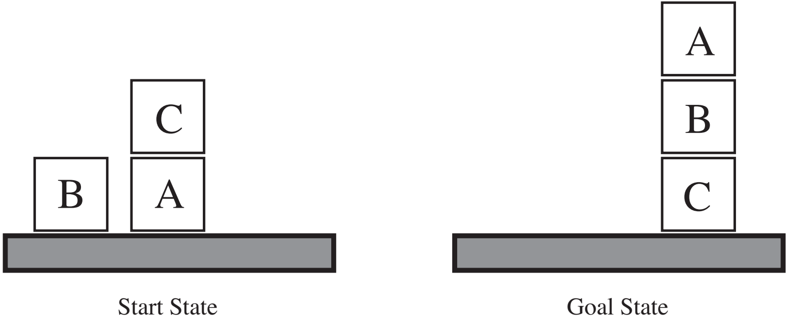
Example: Block world



Solution: [$MoveToTable(C, A)$, $Move(B, Table, C)$, $Move(A, Table, B)$]

Adding and deleting

PDDL

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At **each step** of the plan, the **state of the world** is **modified** depending on the **effect** of the action taken:

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These are known as the ADD and DEL lists, and allow us to calculate the state s at the next time step after taking action a:

$$s^{(t+1)} = (s^{(t)} \setminus DEL(a)) \cup ADD(a)$$

Designing actions

PDDL

There are some other things to consider.

- How would the system differentiate between $\mathit{MoveToTable}(\mathit{block}, x)$ and $\mathit{Move}(\mathit{block}, x, \mathit{Table})$?

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It is **not easy**!

How to plan?

There are several ways to come up with a feasible plan, and the **search space** might be different on each approach.

How to plan?

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- **State-space planning**: search through nodes representing states of the world. A plan is a **path** through the space
- **Plan-space planning**: search through partially instantiated operators and constraints—starts with a partial, *possibly incorrect* plan and then apply changes to correct it.
- **Heuristic planning**: search for a sequence of actions and evaluate your plan using an objective function.

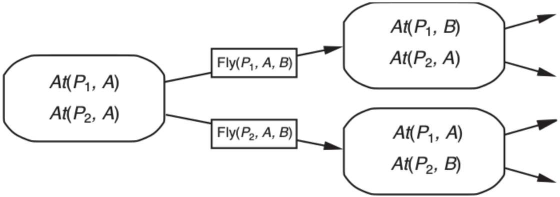
Algorithms for classical planning

How to plan?

- **Forward** (progression) search
- **Backward** (regression) search
- **Logical Inference**

Forward planning

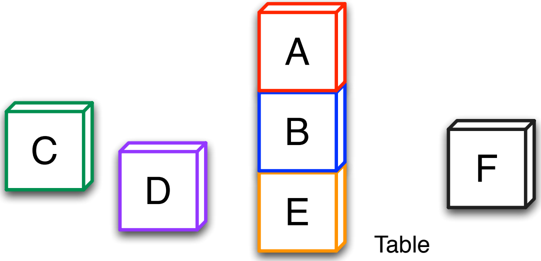
How to plan?



1. Determine all actions applicable
2. **Ground**[2] the actions by replacing any variable with constants
3. Choose an action to apply
4. Determine the new state of the world and update the knowledge based according to the action description
5. Repeat this process until the goal state is reached

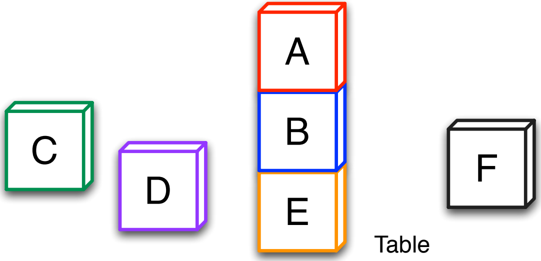
[2]Instantiate, if you will

Forward planning



What is your plan?

Forward planning



How many possible **first actions** are there?

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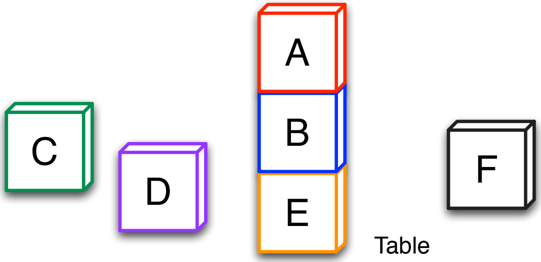

How many possible **first actions** are there?

How do we know which one is the *best* one?

Branching Factor
Forward Search

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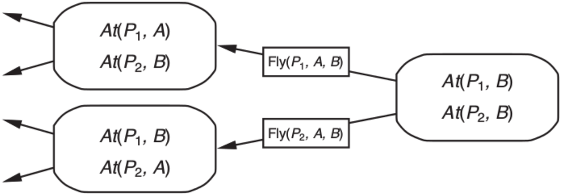
It needs a good (domain-specific) heuristic or pruning procedure!

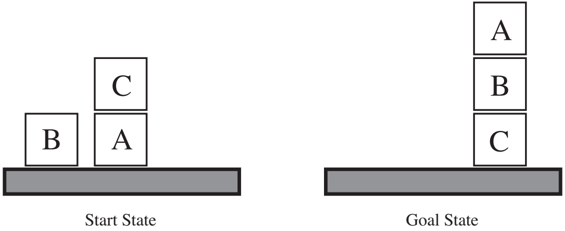
Backward search

How to plan?



1. Choose a **relevant** action that satisfies (*some*) goal propositions
2. Make a new goal by applying an action *a* **backwards**:
   - *DEL* satisfied conditions of goal
   - *ADD* preconditions of *a*
   - Keep unsolved goal propositions
3. Repeat until the goal is satisfied by the start state

Backward search



What are the **relevant actions** here?

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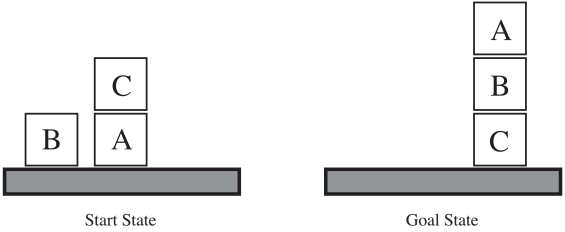

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  - It impacts the efficiency of the search
  - A wrong order can make the plan unfeasible

Sub-plans: Total and partial orders

How to plan

So far, we have only looked at algorithms that generate **complete** plans, with a **strict** order. However, there may exist **subplans**—sequence of actions that can be partially ordered.

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Think about it as when you put your socks and shoes on every morning:

- Which *sock* should go on first?
- Do you do the subsequence $sock_1 \rightarrow shoe_1$ like a lunatic or $sock_1 \rightarrow sock_2$ first?

If we had enough hands I guess we could do $sock_i \rightarrow shoe_i$ in **parallel**!

Heuristic Planning

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We need **heuristic** solutions!

General idea: relax
Heuristic Planning

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...or try a metaheuristic!

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Heuristic Planning

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- **Serialisable subplans**: achieving a subgoal (putting on $shoe_1$) does not interfere with other goals (putting on $shoe_2$)

Classical Planning vs IRL

Planning in Complex Environments

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Classical Planning vs IRL

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How do we plan when we encounter more complex environments?

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   - So we make a **sensorless plan**

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   - Then we need **online planning**

I cannot see

Sensorless planning

- I need to **make sure** that all **preconditions are met**
- I will then **carry out all operations** that will lead me to the goal

Example: paint a chair and a table with <u>the same</u> colour. How?

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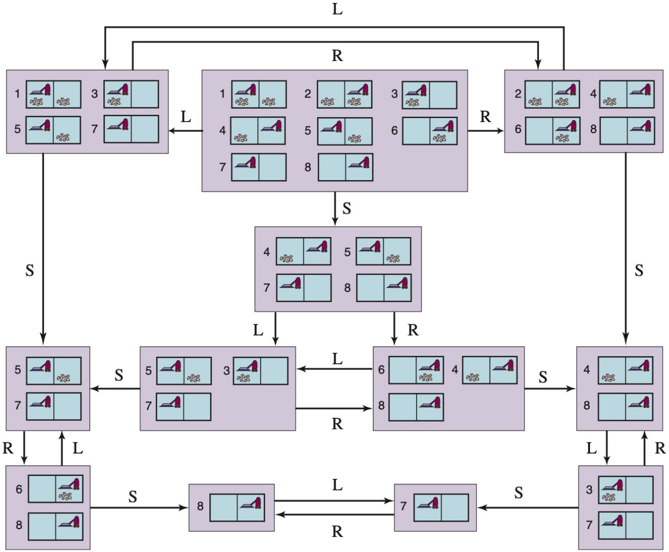
Example: paint a chair and a table with the same colour. How?

$$[RemoveLid(Can), Paint(Chair, Can), Paint(Table, Can)]$$

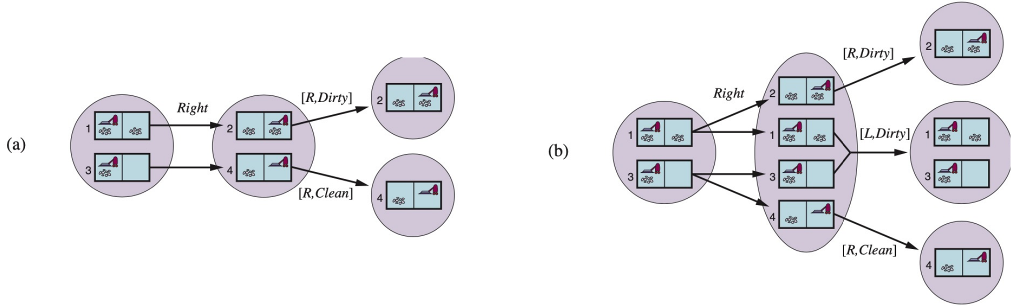
Recall

Belief space in sensorless planning



Recall

Belief space in non-deterministic world

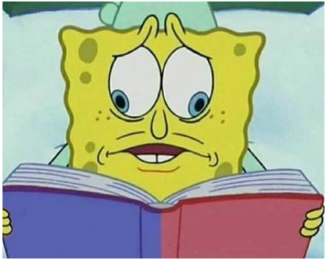


- The agent knows where it is and see the dirt (if any) on its spot
- The **transition model** becomes a **function** of a belief state, an action, and a **another** belief state
  - In case of nondeterminism (right), we do like Dr. Strange and consider possible outcomes on different universes. **How**?

I can see but I am not sure what will happen

Contingency planning

- I need to **make sure** to know where I am by **looking around**
- Then, and depending on where I am, I will **carry out** necessary operations **conditionally**



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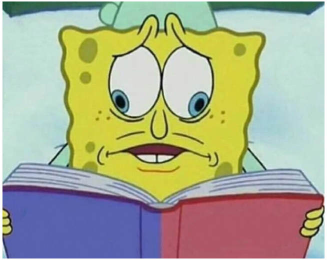

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$$\begin{aligned} & \mathit{FullPlan} = \\ & \qquad [\mathit{LookAt}(\mathit{Table}), \mathit{LookAt}(\mathit{Chair}), \\ & \qquad \textbf{if } \mathit{Color}(\mathit{Table}, c) \wedge \mathit{Color}(\mathit{Chair}, c), \textbf{then } \mathit{NoOP} \\ & \qquad \textbf{else } \mathit{ContingencyPlan}] \end{aligned}$$

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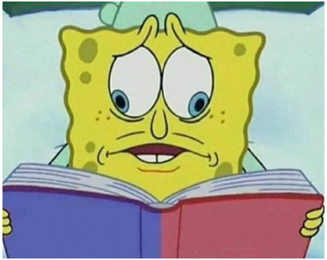

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\begin{aligned}
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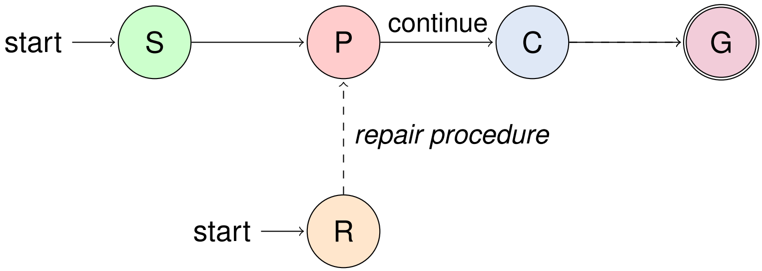
&\qquad \textbf{else}[Paint(Chair, Can), Paint(Table, Can)]]
\end{aligned}
$$

I need to keep an eye

Online planning

The world is **dynamic**, and it can change in unpredictable ways.

- **Action monitoring**: check that all **preconditions hold**
- **Plan monitoring**: check if the plan can **succeed** (or the goal is **satisfiable**)
- **Goal monitoring**: check if there is a *better* goal



The Job-shop Scheduling Problem

Figure 1

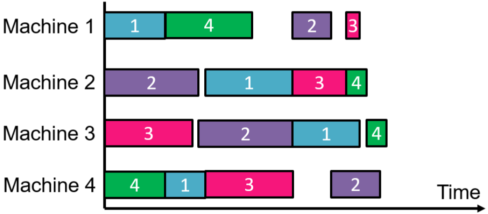


Figure 2

Machine	O1	O2	O3	O4
J1	1	4	2	3
J2	2	3	1	4
J3	3	4	2	1
J4	4	1	2	3

Table 1 Machine Sequence

Time	O1	O2	O3	O4
J1	3	2	4	3
J2	4	5	2	2
J3	4	4	3	1
J4	3	4	1	1

Table 2 Processing Time

Image from Ataç, 2023: Job Shop Scheduling Problem and Solution Algorithms

JSP: heuristic approach

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- Assign the **earliest** and **latest** possible start for each action

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In practice we use **metaheuristics**!