AI Classical and Non-deterministic Planning: Model-based Autonomous Behavior

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Part I

Non-deterministic Planning

Part 1: Non-deterministic Planning

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Planning Models: Vanilla Model for Classical AI Planning

- finite and discrete state space S
- a **known initial state** $s_0 \in S$
- a set $S_G \subseteq S$ of goal states
- actions $A(s) \subseteq A$ applicable in each $s \in S$
- a **deterministic transition function** $s' = f(a, s)$ for $a \in A(s)$
- positive **action costs** $c(a, s)$

A **solution**/**plan** is seq. of applicable actions $\pi = a_0, \ldots, a_n$ that maps s_0 into S_G.

Plan is **optimal** if it minimizes the **sum of action costs**.

ℹ️ Different **models** obtained by **relaxing** assumptions in **bold**.

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Planning with non-deterministic actions

What if an action may yield different effect outcomes?

- **Slipery floor:** you may slip and fall (and maybe hurt yourself).
- **Slipery blocksworld:**
  if you stack or unstack a block, it may fall down to the table.
- **Dice rolling:** if you roll a die, it may yield different outcomes: 1,2,3,4,5 or 6.
- **Robot operation:** when using the gripper, it may succeed or fail to pick an object (and may need to retry).

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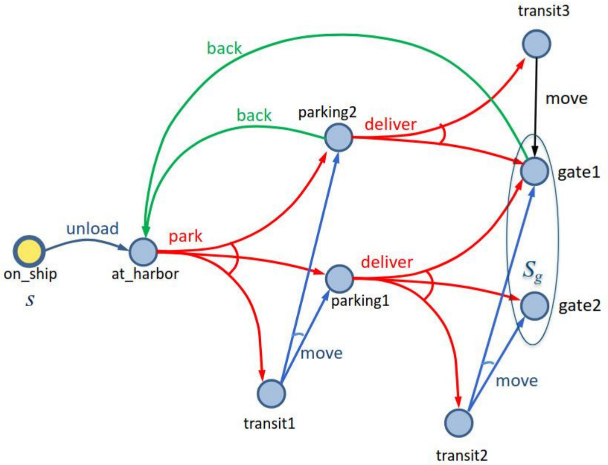
- **Robot operation:** when using the gripper, it may succeed or fail to pick an object (and may need to retry).
- **Finding parking:** when visiting a block you may or may not find parking space (if not, keep going around the block).
- **Walking on beam:** if you do a step on a beam, you may advance or fall down.
- **Walking on corridor:** if you do a step you may or may not be at the end of the corridor.

Example: Harbor Management FOND Problem

Very simple harbor management domain:

1. Unload a single item from a ship.
2. Park the item in a storage facility.
3. Deliver it to gates (to be loaded into tracks).

Storage and gates may be unavailable, but we can always wait and move containers around.



(Example 11.1 in *Acting, Planning, and Learning* Ghallab, Nau, Traverso 2025)

Planning with Markov Decision Processes

Goal MDPs are **fully observable, probabilistic** state models:

1. a state space S
2. initial state $s_0 \in S$
3. a set $G \subseteq S$ of goal states
4. actions $A(s) \subseteq A$ applicable in each state $s \in S$
5. **transition probabilities** $P_a(s' \mid s)$ for $s \in S$ and $a \in A(s)$ ☜
6. action costs $c(a, s) > 0$

- **Solutions** are **functions (called "policies")** mapping states into actions; $\pi : S \mapsto A$
  - $\pi(s)$ *states what action to do in state* s
- **Optimal** solutions minimize **expected cost** to goal.
- **Reward-based** MDPs involve **rewards** instead of costs, and **discount factor** $\gamma \in [0, 1)$ in place of goals. They underlie theory of RL. 😉

FOND Planning: Fully-observable Non-Deterministic Planning

A **FOND state model** is like the "logical" counterpart of Goal MDPs:

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4. actions $A(s) \subseteq A$ applicable in each state $s \in S$
5. **non-det state transition function** F: successors $s' \in F(a, s)$, $s \in S$, $a \in A(s)$ ☜
6. action costs $c(a, s) = 1$

- **Main change** from Classical Planning: $F(a, s)$ maps to set of possible states (not to one unique state).
  - Nature decides what next state is reached after action a is applied in state s — non-determinism.
  - ... but agent will observe the state reached after a is applied.

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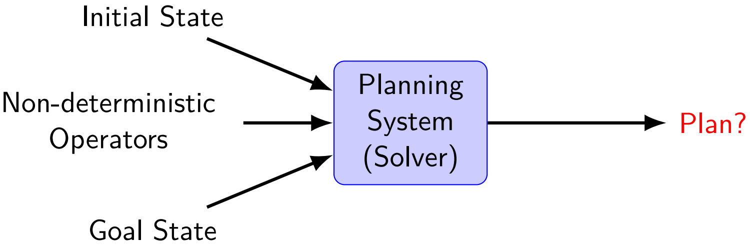
- **Main change** from MDPs: possible transitions $s \in F(a, s)$ not weighted by probabilities.

Fully Observable Non-Deterministic Planning (FOND)



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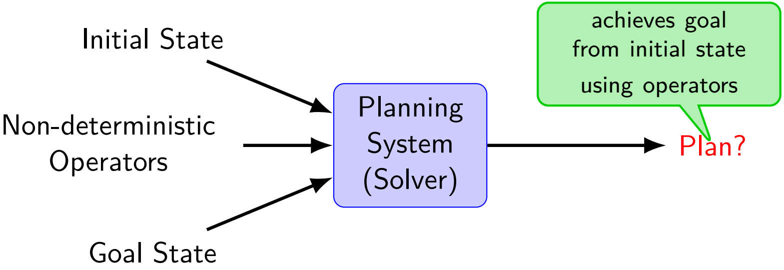

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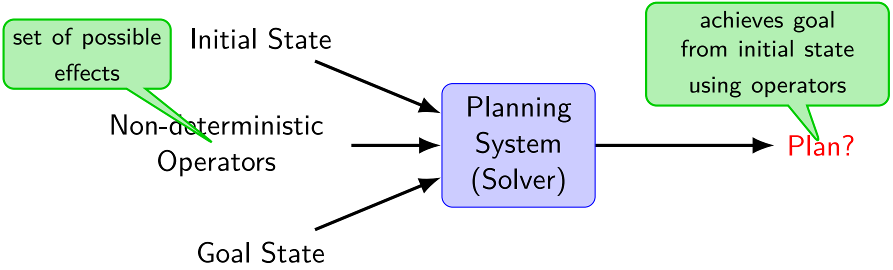
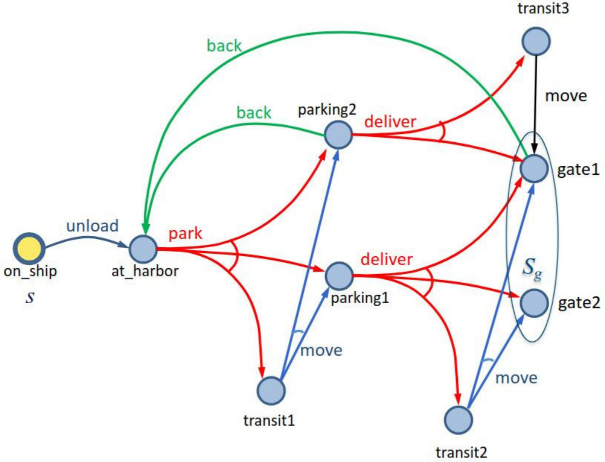


Example: Does it have a solution?

- Is it possible to always deliver the containers to the gates?
- If so, what is the sequence of actions?



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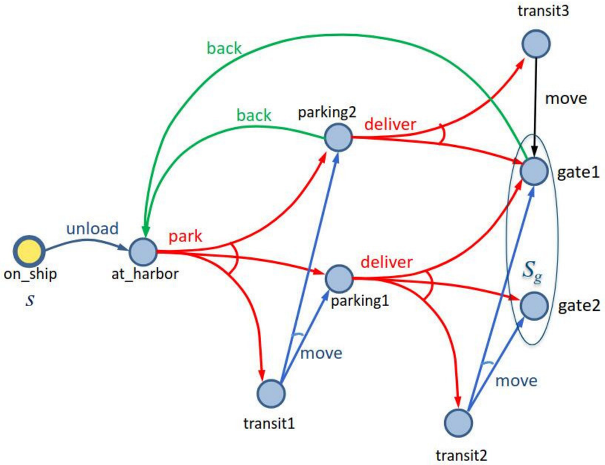

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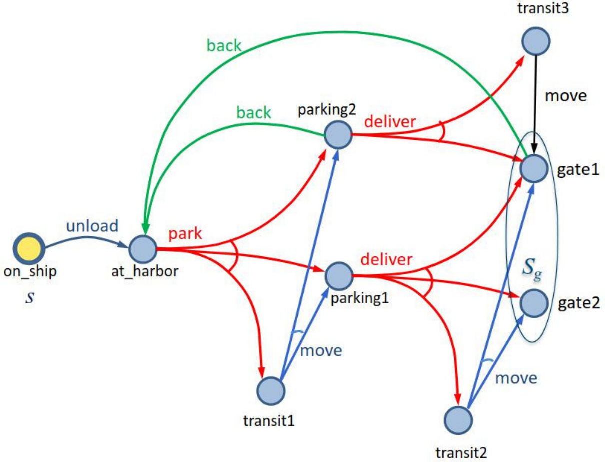

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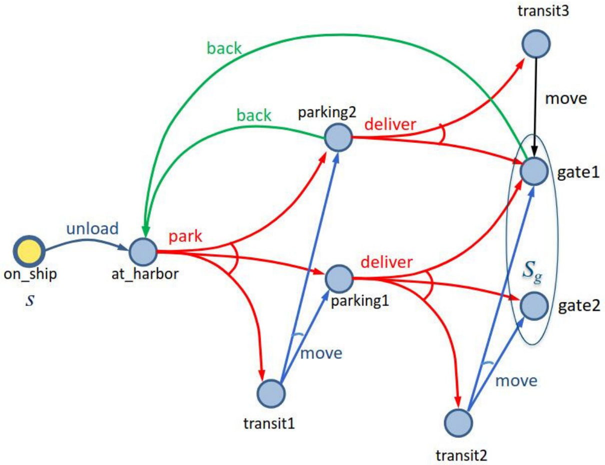

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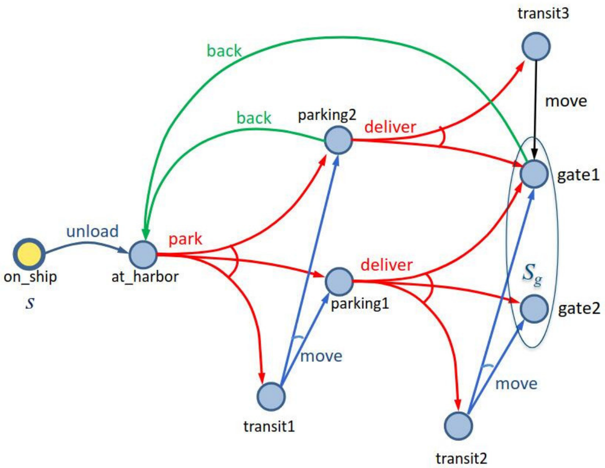
🤔 Is there a "good" policy π?



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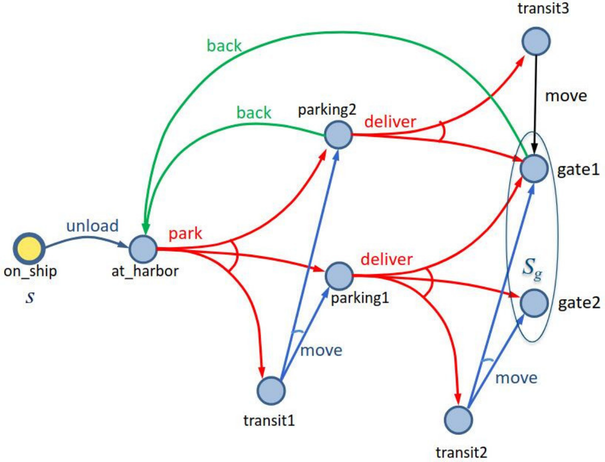
Example: Does π_1 solve the task?

Policy π_1

S	$\pi_1(s)$
on_ship	unload
at_harbor	park
parking1	deliver
parking2	back
transit1	move
transit2	move
transit3	move



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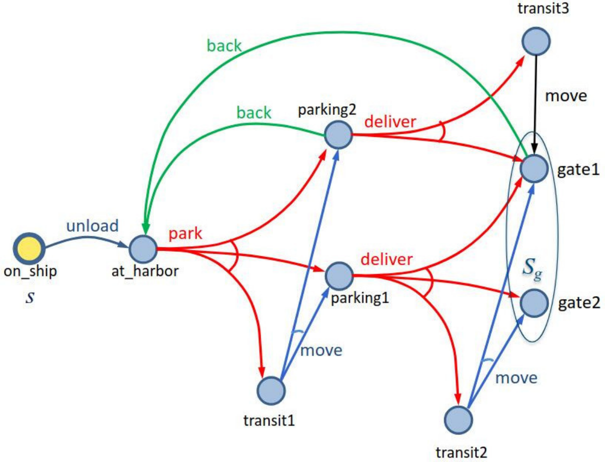

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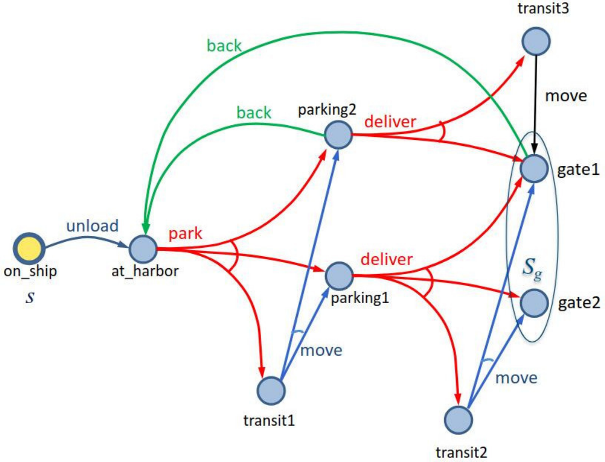

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Example: What about π_2?

Policy π_2

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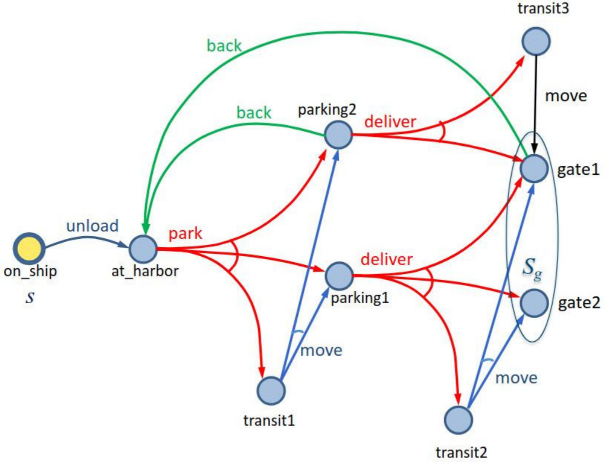

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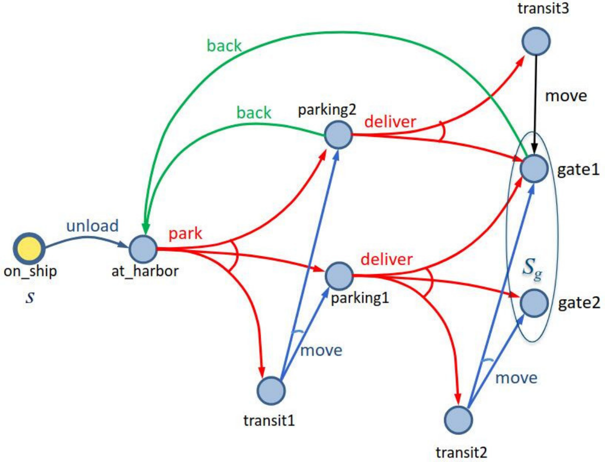

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Example: Which one is better?

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Policy π_4

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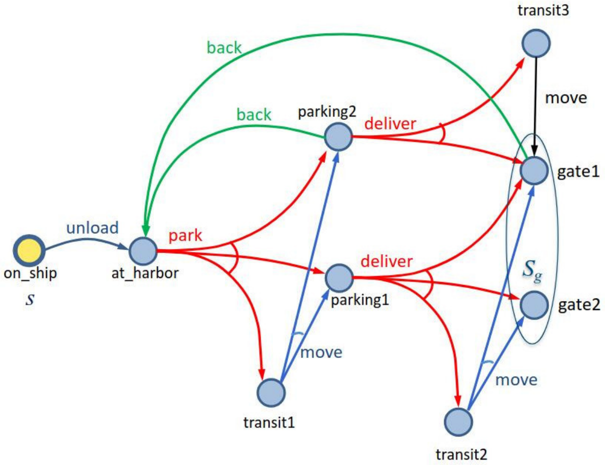

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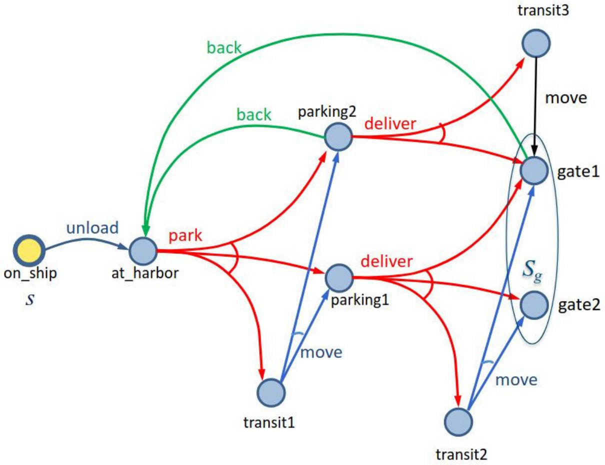

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Example: What if transit1 is a dead-end?

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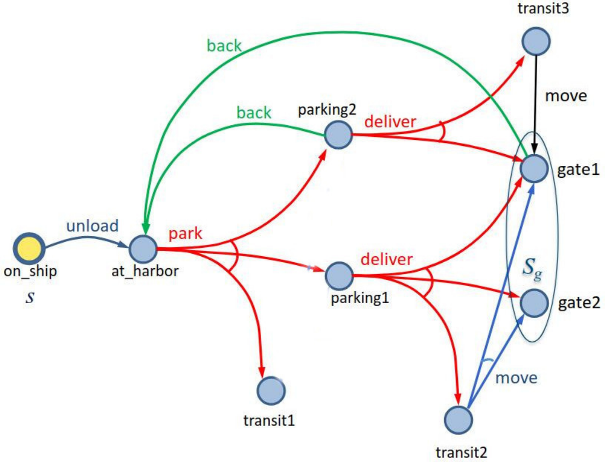

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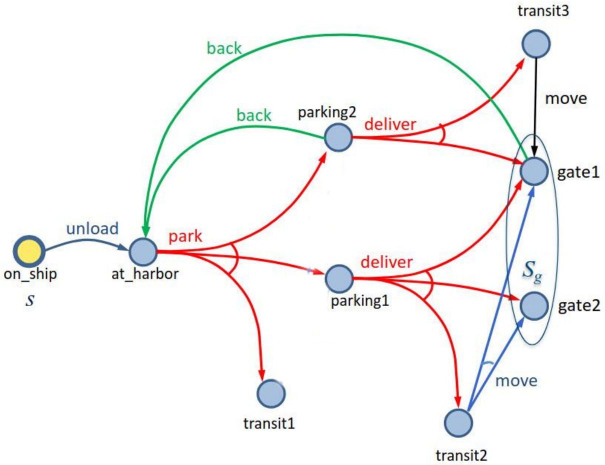
But could π_2 succeed (sometimes)? 🤔



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Example: What if parking2 is not connected to gates?

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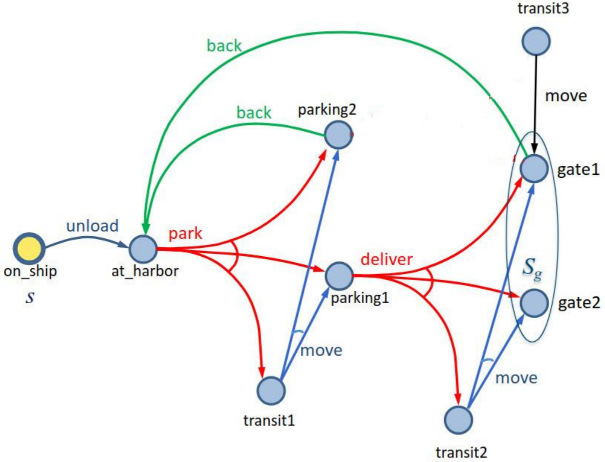

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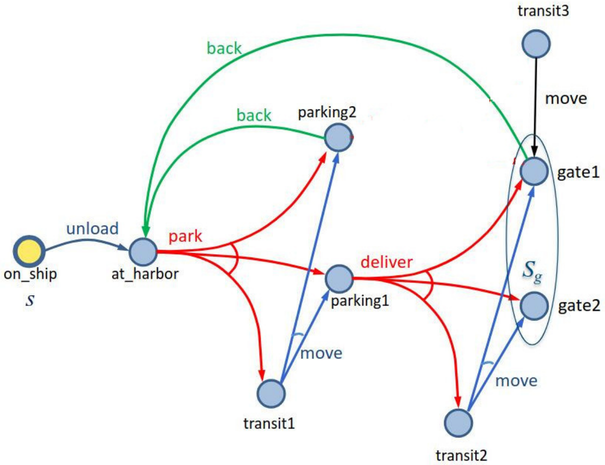
Storage parking1 may never be available!



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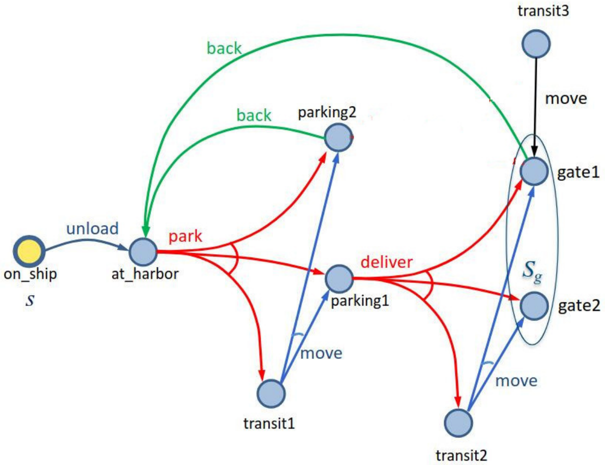
But, what if we know parking1 would eventually becomes available? 🤔



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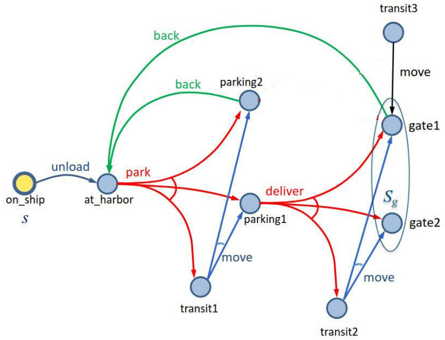
So, some lessons...

- Classical plans as sequences of actions are **not enough** to solve FOND problems.
- We need to use a **policy** that maps states into actions.
  - *More like "programs" with conditionals and loops!*
- Some (bad) policies are better than others.
- Some policies ***may* achieve** the goal, but not always.
- Some policies will achieve the goal *if* environment is **not too adversarial** — not unfair.



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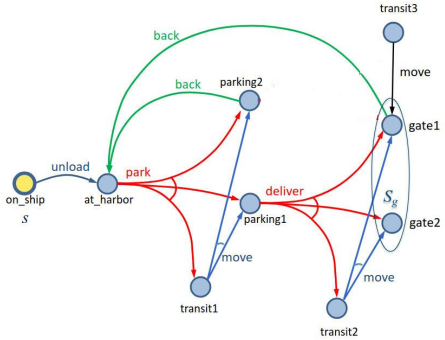
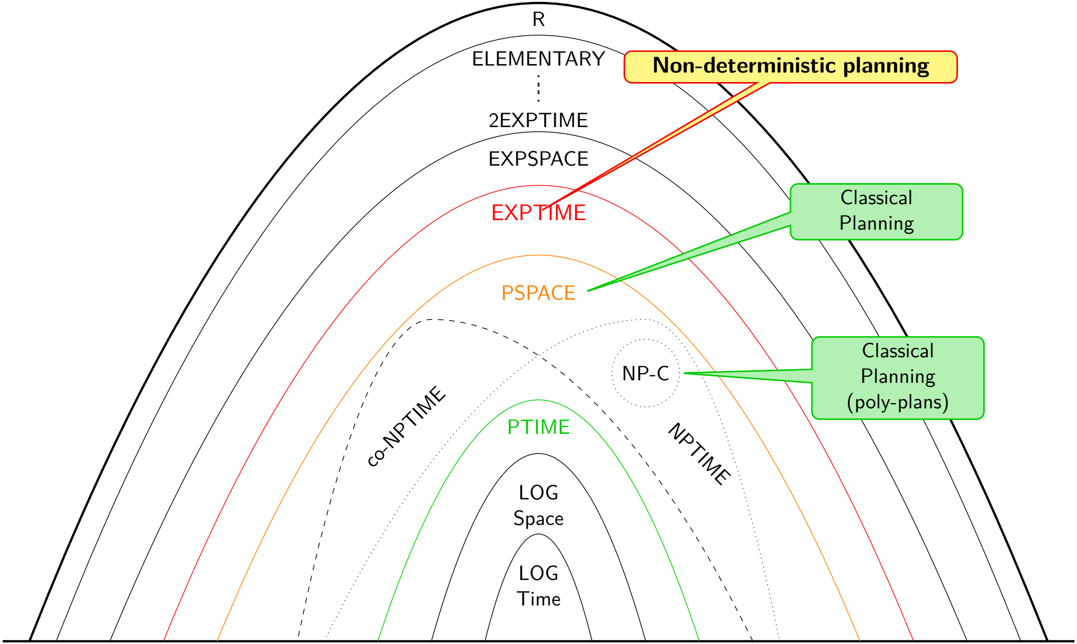
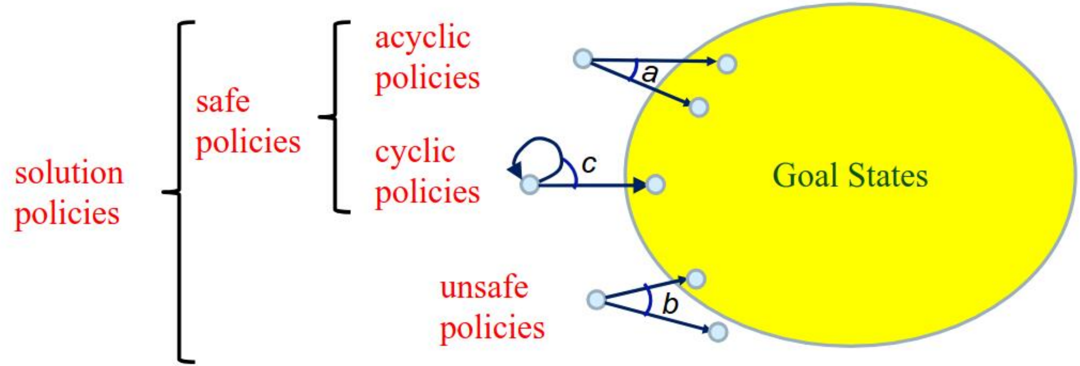


This seems way more complex planning! 😟

Planning is hard!



Kinds of Solution Policies



Acting, Planning, and Learning Ghallab, Nau, Traverso 2025

Part 1: Non-deterministic Planning

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FOND Planning: Solution Concepts

Running policy π from state s yields trajectories runs:

- π-**trajectories** $s_0, \ldots, s_n$, such that $s_{i+1} \in F(a_i, s_i)$, $a_i = \pi(s_i)$, for $i \in [0, n-1]$.
- π-trajectory **maximal** if 1) s_n is goal state, 2) $\pi(s_n) = \bot$, or 3) $n = \infty$ (π is infinite)

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3. π is **strong cyclic solution** if for each state s reachable from s_0 with a π-trajectory, there is a π-trajectory from s to goal.

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   - Always a *possibility* to reach the goal.

FOND Planning: Solution Concepts

Running policy π from state s yields trajectories runs:

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- π-trajectory **maximal** if 1) s_n is goal state, 2) $\pi(s_n) = \bot$, or 3) $n = \infty$ (π is infinite)

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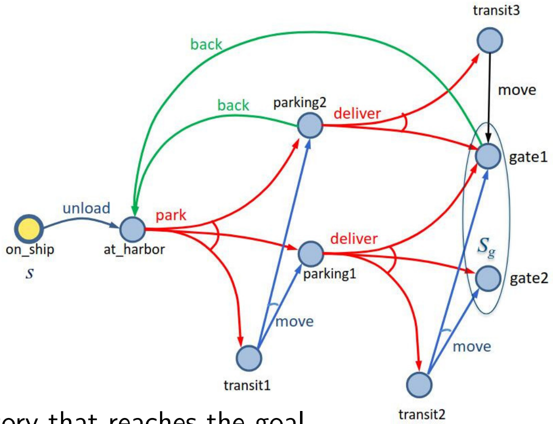
   - Goal will be achieved if environment is not "adversarial"
   - Plans may have conditionals & loops!

Weak Plans

S	$\pi_1(s)$
on_ship	unload
at_harbor	park
parking1	deliver
parking2	back
transit2	move
transit3	move



- ✓ Policy π is a weak plan as there is a trajectory that reaches the goal.
  - *{on_ship}, {at_harbor}, {parking1}, {gate1}*
- ✖ But π is *not* a strong plan.
  - *{on_ship}, {at_harbor}, {parking2}, {at_harbor}, {parking2}, {at_harbor}, ...*

What about strong cyclic?

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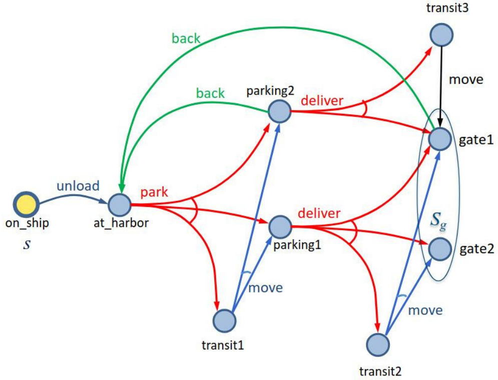

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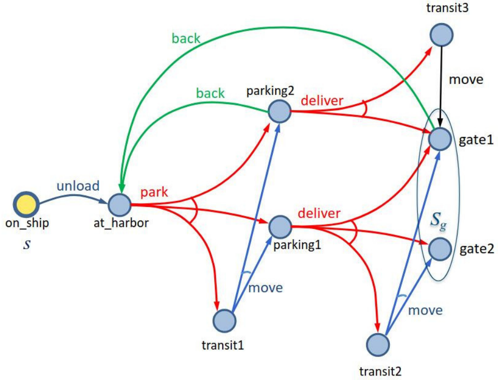

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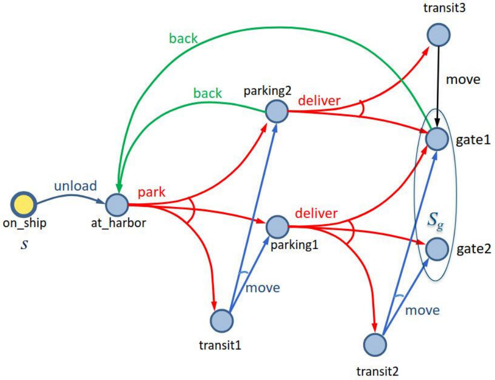

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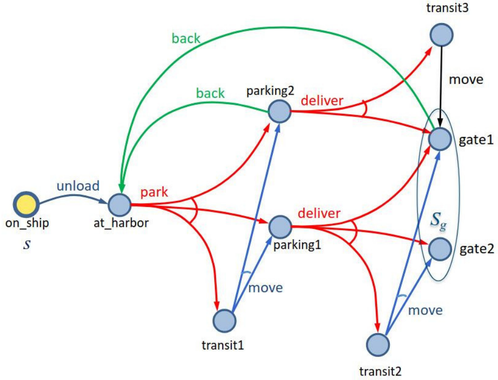

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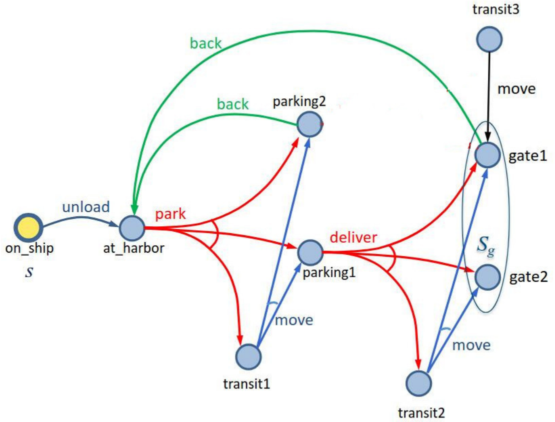
- **Yes!**, policy never "loses" the possibility to get the goal 👍
- But, it may **loop** "forever" in some states.
- We can make π strong by changing it to $\pi_1(\text{parking2}) = \text{deliver}$.

Strong cyclic policies: when do they work?

❓ Is there a strong plan?



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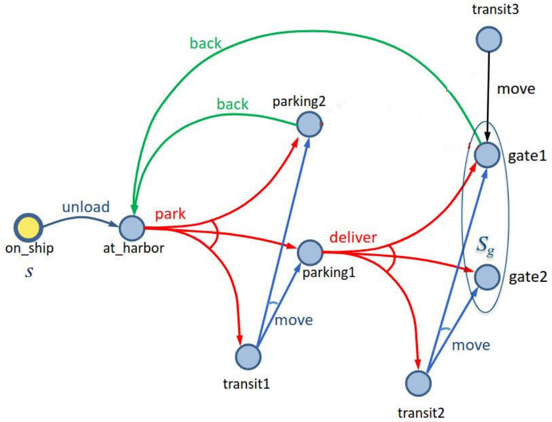

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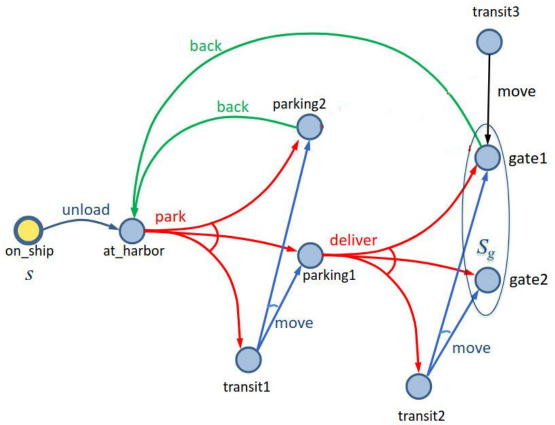

❓ **When will this policy reach the goal?**

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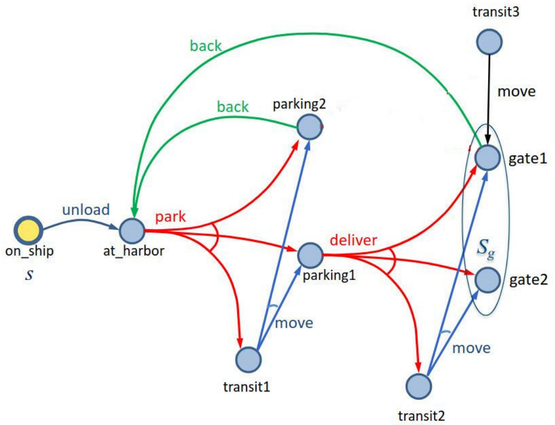

❓ **When will this policy reach the goal?**

When executed in "**fair**" environments!

Fairness Environments

A trajectory σ is an **unfair** execution of π if a state s appears infinitely often in σ but some outcome state $s' \in F(\pi(a), s)$ only appears a finite number of times in σ.

Non-determinism behavior under fairness assumption

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❓ What type of environments?

- Where each effect listed has indeed **non-zero probability**.
- **Re-trying** is an effective strategy.
  - rolling a die until it shows a 6.
  - driving around the block until a parking space is available.
  - pour into cup until full.

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Recap: Solution plans for FOND planning

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Question

How can we compute these plans with loops? How to compute strong-cyclic plans policies?

Part 1: Non-deterministic Planning

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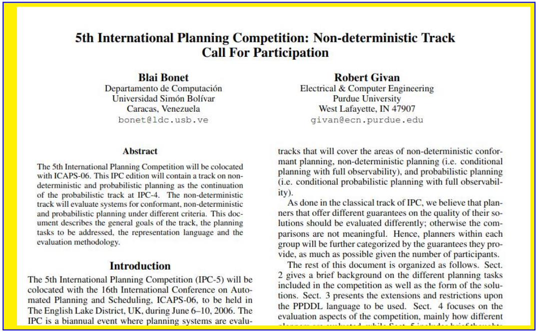
Non-determinism in PDDL

- Non-deterministic effects added to PDDL for the 5th IPC in 2006.
- Action effect can have a **one-of** effect:

```
(oneof e1 e2 ... en)
```

- To support uncertainty track in IPC-5.



5th International Planning Competition: Non-deterministic Track Call For Participation

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Abstract

The 5th International Planning Competition will be colocated with ICAPS-06. This IPC edition will contain a track on non-deterministic and probabilistic planning as the continuation of the probabilistic track at IPC-4. The non-deterministic track will evaluate systems for conformant, non-deterministic and probabilistic planning under different criteria. This document describes the general goals of the track, the planning tasks to be addressed, the representation language and the evaluation methodology.

Introduction

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tracks that will cover the areas of non-deterministic conformant planning, non-deterministic planning (i.e. conditional planning with full observability), and probabilistic planning (i.e. conditional probabilistic planning with full observability).

As done in the classical track of IPC, we believe that planners that offer different guarantees on the quality of their solutions should be evaluated differently; otherwise the comparisons are not meaningful. Hence, planners within each group will be further categorized by the guarantees they provide, as much as possible given the number of participants.

The rest of this document is organized as follows. Sect. 2 gives a brief background on the different planning tasks included in the competition as well as the form of the solutions. Sect. 3 presents the extensions and restrictions upon the PPDDL language to be used. Sect. 4 focuses on the evaluation aspects of the competition, mainly how different

```
(:action unstack
    :parameters (?b1 ?b2 - block)
    :precondition (and (not (= ?b1 ?b2)) (emptyhand) (clear ?b1) (on ?b1 ?b2))
    :effect (oneof
      (and (holding ?b1) (clear ?b2) (not (emptyhand)) (not (clear ?b1)) (not (on ?b1 ?b2)))
      (and (clear ?b2) (on-table ?b1) (not (on ?b1 ?b2)))))
            ;; second effect: fail to grab; ?b1 ends on table
```

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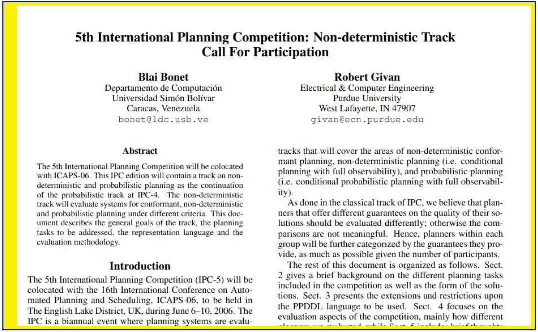
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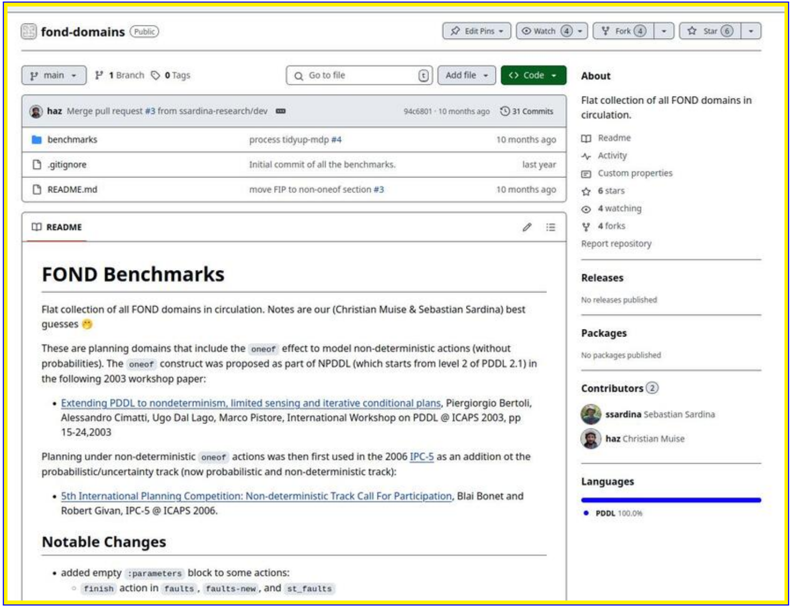
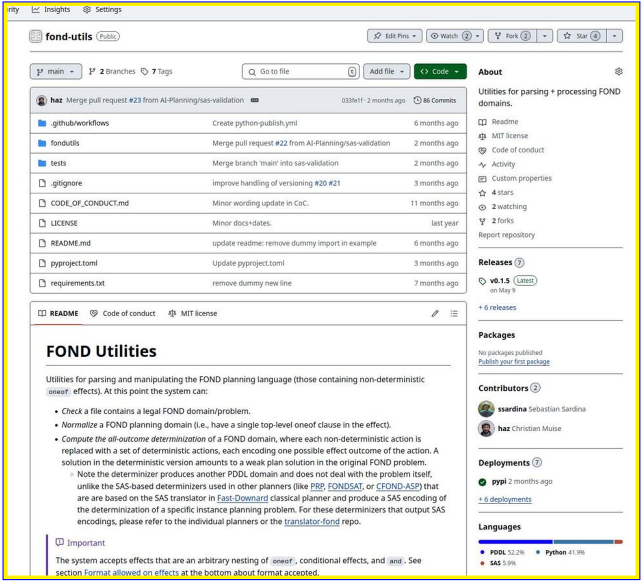
```
(:action pick-up-from-table
    :parameters (?b - block)
    :precondition (and (emptyhand) (clear ?b) (on-table ?b))
    :effect (oneof
        (and)    ;; no effect - things stay the same!
        (and (holding ?b) (not (emptyhand)) (not (on-table ?b)))))
```

AI-Planning/fond-domains @ GH: Benchmark for FOND



https://github.com/AI-Planning/fond-domains

AI-Planning/fond-utils @ GH: Utilities for FOND



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FOND Planning using Classical Planners

✅ One of the most effective ways to solve FOND planning problems is to use **classical planners**! Weird...? 😕

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They all use a **deterministic relaxation** of the FOND problem:

All-outcome determinization

Deterministic relaxation P_D of FOND P obtained by substituing **non-det** actions a with effects $\{e_1, \ldots, e_n\}$ by **deterministic** actions $a^1, \ldots, a^n$, where a^i's effect is e_i, for $i \in [1, n]$.

- P_D is a deterministic classical planning problem.
- Under reasonable assumptions, P_D is polynomially larger than P.
- There are tools to do the determinization: https://github.com/AI-Planning/fond-utils

Week and Online Solutions for FOND Planning

⚙️ **Weak (open loop) solution** for P

From any **classical plan** ρ for P_D:

- If ρ generates trajectory $s_0, \ldots, s_N$ in P_D, set $\pi(s_i) = a$ if $\rho_i \in a$.
- Run π and hope for the best! 🤞

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Reach goal by interacting with FOND "system" that returns **observation** $s' \in F(a, s)$:

1. From **current state** s, initially s_0, compute **plan** $\rho = \rho_1, \ldots, \rho_N$ for $P_D[s]$.
2. Execute **prefix** $a_1, \ldots, a_i$ for $\rho_i \in a_i$ until state s_i **observed** is goal or **different** than state s'_i **predicted** in P_D.
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☀️ **Properties:** If **no dead-end states** reachable in P, under mild assumptions, goal state eventually reached. Else, method is **incomplete**.

PRP: Strong Cyclic Policies using Classical Planners

More powerful off-line method, can compute **strong cyclic policies**:

PRP: Planning for Relevant Policies (Muise, McIllraith, Beck ICAPS'12)

1. Run **simulated on-line** method not just from s_0 but from every possible sucessor s' of a (simulated) **observed** state s; i.e., $s' \in F(a,s)$ for a executed in s.
2. If state $s' \in F(a,s)$ is reached from which **no classical plan** for $P_D(s)$; **remove** a from $A(s)$, and **start all over again**.
3. Keep policy to $\pi(s) = a$ where deterministic version a_i is head of **shortest classical prefix** found from s to goal.

Properties:

- Method is **sound and complete**: returns strong cyclic policy if one exists. 👍
- More **scalable** than other methods as it uses **classical planners**.
- Can be made more efficient by **generalizing plans** using **regression**.
- Struggles if there are many "risky" nondeterminism leading to dead-ends.

Regression to Generalize Policies

Consider the following situation:

1. Goal is $G = \{g\}$.
2. Classical plan $\rho = a_1, \ldots, a_n$ optimally achieves G from state s_0 in P_D.
3. So, ρ yields trajectory $s_0, s_1, \ldots, s_n$ in P_D such that $g \in s_n$.
   - *The last action of ρ has $g \in \text{Add}(a_n)$ — a_n achieves the goal.*
4. The precondition of a_n is $\text{Pre}(a_n) = \{p, q\}$.
   - *Clearly, $p, q \in s_{n-1}$ – a_n's precondition hold just before the goal.*

So, we can set our FOND policy to $\pi(s_{n-1}) = a_n$.

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3. So, ρ yields trajectory $s_0, s_1, \ldots, s_n$ in P_D such that $g \in s_n$.
   - *The last action of ρ has $g \in$* Add(a_n) — *a_n achieves the goal.*
4. The precondition of a_n is Pre$(a_n) = \{p, q\}$.
   - *Clearly, $p, q \in s_{n-1}$ – a_n's precondition hold just before the goal.*

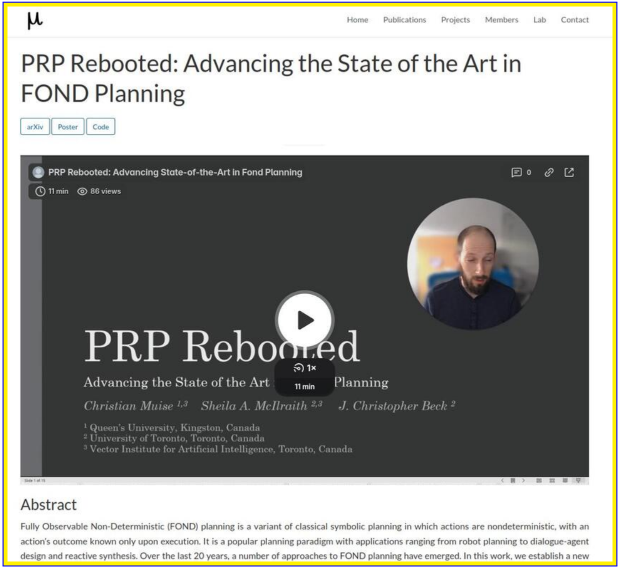
So, we can set our FOND policy to $\pi(s_{n-1}) = a_n$. **Is that the best we can do?** 🤔

What about any other state s' such that $p, q \in s'$? **Can we also set $\pi(s') = a_n$?** 🤔
YES! — $\{p, q\}$ is the *regression* of goal w.r.t. action a_n

Question

If Add$(a_{n-1}) = \{p\}$ and Pre$(a_{n-1}) = \{w\}$, what states s' can we set $\pi(s') = a_{n-1}$?

PRP Rebooted: AAAI'24



https://mulab.ai/project/pr2/

Shortcomings of Classical Planners for FOND

PRP scales wellas it uses **classical planners** + **regression**. However:

- Codebase is highly **sophisticated**; thousands of lines.
- Uses a lot of **tricks**: regression, dead-end detection, regression, loop closing, strong-cyclic check, etc.
- Struggle from "risky nondeterminism", where previous search choices need to be thrown and restarted.
  - *non-deterministic actions whose other effects will eventually lead to dead-ends.*
- May output very large policies — no guarantees of "compactness".
- Unable to handle **mixed fairness** environments.
  - *some actions are fair, others are unfair.*

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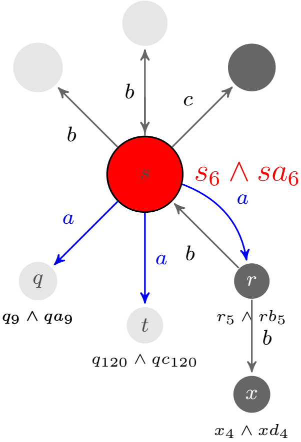
? What can we do about these issues? Can we get a simpler, declarative solver for FOND?

Recall Theory $C(P, n)$ for Classical Problem $P = \langle F, A, I, G \rangle$

- **Init:** p_0 for $p \in I$, $\neg q_0$ for $q \in F$ and $q \notin I$
- **Goal:** p_n for $p \in G$
- **Actions:** For $i = 0, 1, \ldots, n-1$, and each action $a \in A$
  - $a_i \supset p_i$ for $p \in Prec(a)$
  - $a_i \supset p_{i+1}$ for each $p \in Add(a)$
  - $a_i \supset \neg p_{i+1}$ for each $p \in Del(a)$
- **Persistence:** For $i = 0, \ldots, n-1$, and each atom $p \in F$, where $O(p^+)$ and $O(p^-)$ stand for the actions that add and delete p resp.
  - $p_i \wedge \bigwedge_{a \in O(p^-)} \neg a_i \supset p_{i+1}$
  - $\neg p_i \wedge \bigwedge_{a \in O(p^+)} \neg a_i \supset \neg p_{i+1}$
- **Seriality:** For each $i = 0, \ldots, n-1$, if $a \neq a'$, $\neg(a_i \wedge a'_i)$

Strong Cyclic Planning as SAT

💡 **Key idea:** label each state with action and distance to goal.



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  - **Variables** of SAT encoding (i is not time index!)
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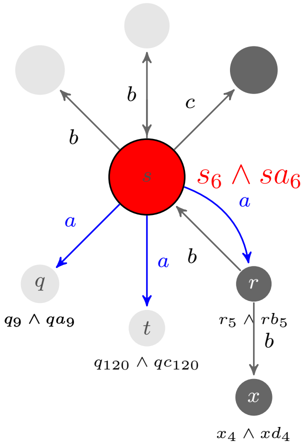

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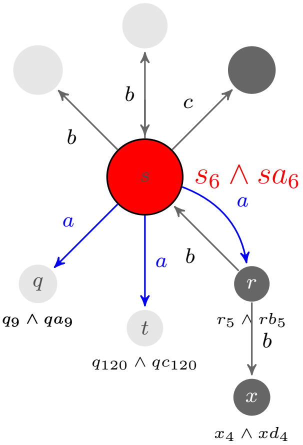

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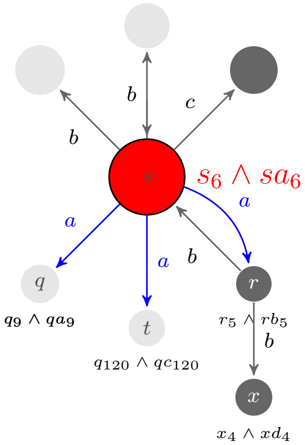

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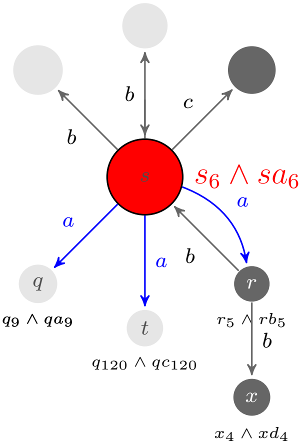

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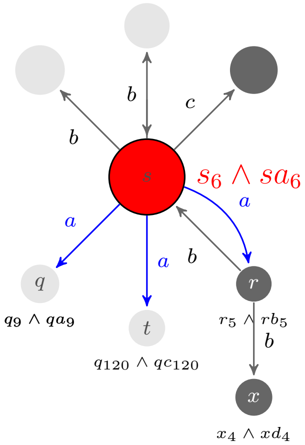

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  7. $sa_{max} \supset s'_{max}$; if $\pi(s) = a$, all $s' \in f(a,s)$, must reach goal
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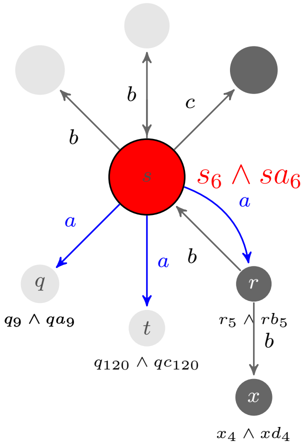

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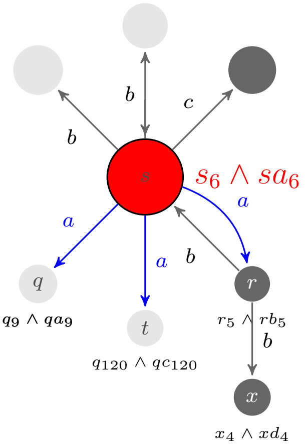


Theorem

1. *Model M has a **strong-cyclic policy** π iff $C(M)$ is satisfiable.*
2. *If σ satisfies $C(M)$, $\pi(s) = a$ for sa_{max} true in σ is a **strong-cyclic policy** that solves M*

Too large encoding: Towards Compact Polocies

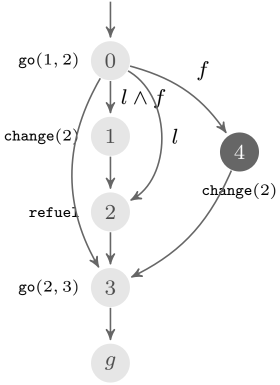
- Encodings are **exhaustive**, all states s represented! ✖
- (Geffner & Geffner 2018) proposed an encoding in SAT computing **compact policies**.
  - *of course, not in worst case*
- Can also be adjusted to compute **strong policies**.
- Can also handle **dual FOND**: fair and unfair actions!
- (Yadav & Sardina 2023): alternative encoding in a Answer Set Programming (ASP):
  - More compact — exploits ASP first-order language.
  - More readable — uses a more declarative style.
  - Integrates regression ideas from PRP.
  - Exploits ASP technology.

Compact Controllers via ASP (Yadav & Sardina 2023)

💡 **Key idea:** devise a finite state controller with n states - (Geffner & Geffner 2018)

Encoding in ASP for FOND problem $P = \langle A, I, G \rangle$:

- `atom(P)`: for each predicate `P` $\in A$.
- `action(A)`: for each action `A` $\in A$. In addition, to define an action's precondition and effects we use the following terms:
  - `prec(A, P)`: atom `P` is in precondition of action `A`.
  - `effect(A, E)`: associates an action with its `E`-th effect (one per oneoff effect).
  - `add(A, E, P)`: `E`-th effect of action `A` adds atom `P`.
  - `del(A, E, P)`: `E`-th effect of action `A` deletes atom `P`.
- `init(P)`: predicate `P` $\in I$ is true in the initial state.
- `goal(P)`: predicate `P` $\in G$ is in the goal condition.



Define Controllers States and Transitions

Solver to decide:

1. `policy(S, A)`: action `A` executed in controller state `S`.
2. `next(S1, E, S2)`: `S2` is the next controler state if the `E`-th effect of prescribed action in `S1` ocurrs.

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```
state(0..k).  % states of the controller
{policy(S, A): action(A)} = 1:- state(S), S != k.
{next(S1, E, S2): state(S2)} = 1 :- policy(S1, A), effect(A, E).
```

1. Defines controller $k+1$ states. State k is goal state.
2. Select one action per controller state (except goal state k).
3. Defines a transition for each action's effect to a next controller state.

Define Controllers States and Transitions

```
1 holds(S, P) :- policy(S, A), prec(A, P).
2 holds(S1, P) :-
3    next(S1, E, S2), holds(S2, P), policy(S1, A), not add(A, E, P).
4 -holds(S2, P) :- next(S1, E, S2), policy(S1, A), del(A, E, P).
5 -holds(0, P) :- atom(P), not init(P).
6 holds(k, P) :- goal(P).
```

1. Preconditions must hold where action is prescribed.
2.
3. Regression: `P` must have been true in the previous controller state.
4. Progression: `P` must be false next if action deleted it.
5. Initial state negative atoms.
6. What must be true at goal controller state `k`

Define Solution Concept: Strong Cyclic

```
reachableG(S):- state(S), S = k.
reachableG(S):- next(S, _, S1), reachableG(S1).
:- not reachableG(S), state(S).
```

1. Goal controller state is reachable from itself.
2. Transitive clousure: Any (previous) controller state connected to a controller state that reaches the goal state, also reaches the controller goal state.
3. **Constraint:** No controller state does not reach the goal state.

Full FOND-ASP Code

```
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:- not reachableG(S), state(S).
```

If a model is returned, controller defined in predicates `policy/2` and `next/3`.

Experimental Results vs. PRP and FOND-SAT

☀ Better in risky non-determinism domains — first five. PRP better in the rest.

Recap SAT/ASP for FOND Planning

- Declarative elegant solver for FOND planning problems via SAT or ASP.
- Compact controllers: finite state controller with $k+1$ states.
- Increase the size when no solution found, and repeat.
- Faster than classical planning based approaches in domains with meaningful non-determinism ("risky").
- Can incorporate domain control knowledge (e.g., "do not executre a after b").
- Still struggles with large domains with "easy" non-determinism.

Part 1: Non-deterministic Planning

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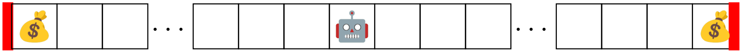
Can the robot get the money?

Consider an robot in a corridor:



- Robot can move $left$ or $right$ (up to the walls). Unknown size of steps, but ≥ 1
- A price is at some of the end of the corridor.
- Robot doesn't know its cell, but can sense if there is a wall on left/right after moving.

❓ **Can the robot get the money? How to model the setting?**

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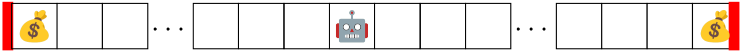

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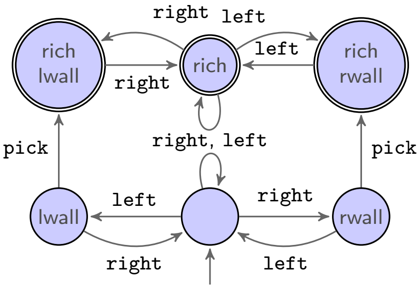
Can the robot get the money? How to model the setting?

```
(define (domain tile)
  (:predicates (leftWall) (rightWall))
  (:action right
        :parameters ()
        :precondition (not rightWall)
        :effect (oneof () (rightWall)))
  (:action left
        :parameters ()
        :precondition (not leftWall)
        :effect (oneof () (leftWall)))
  (:action pick
        :parameters ()
        :precondition (or leftWall rightWall)
        :effect (rich)))
```



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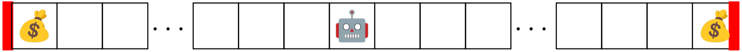
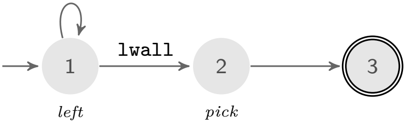
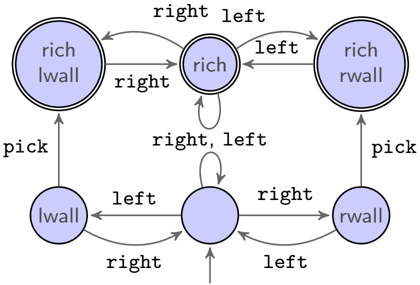


Would this controller work?





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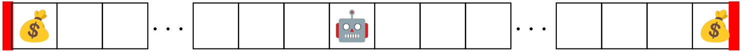
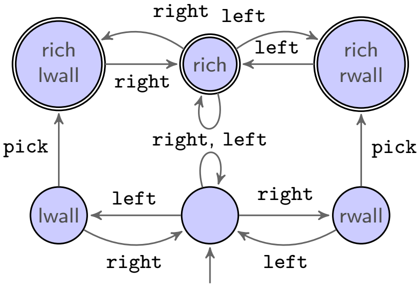
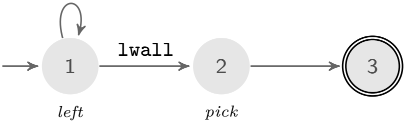




❓ Would this controller work? YES!



Strong-cyclic policy: Retrying *left* works!

Can the robot get the money?

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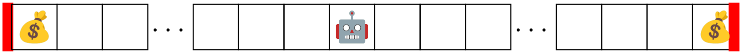

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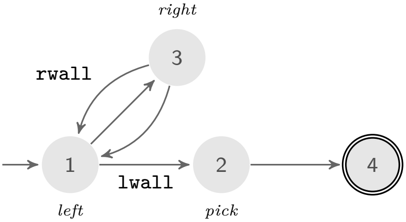

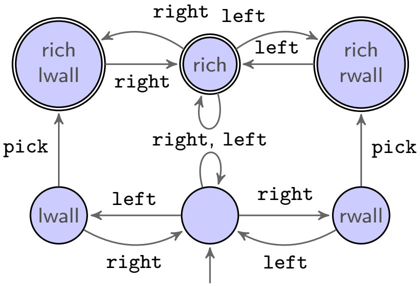

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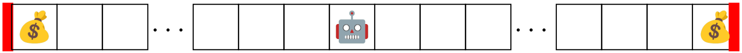

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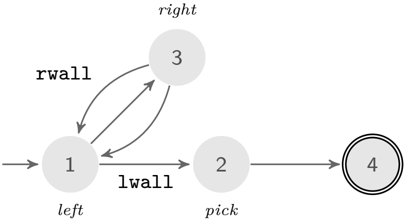

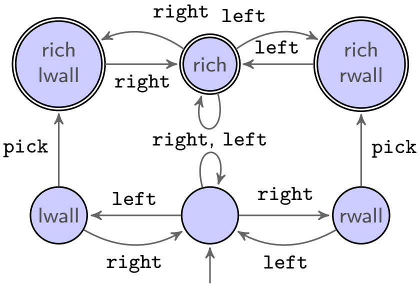

How come? It is also a **strong-cyclic policy!**
States where rich true are always reachable..
left action done infinitely many times in initial state

Conditional Fairness (Rodriguez et al. 2021)

- Standard fairness assumption is **not enough**:
  - trying *left* is not sufficient!
  - must not move *right* while trying... 😉
- We need conditional fairness: *left* is fair as long as *right* is not executed.
  - *Same for right: fair provided left is not executed.*
- Standard FOND planners cannot handle this: they assume that **all actions are fair**.
- (Rodriguez et al. 2021)'s FOND$^+$ in ASP can handle:
  - Strong-cyclic policies with conditional fairness.
  - Mixed fairness: some actions are fair, others not.


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FOND Planning with Explicit Fairness Assumptions

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Abstract

We consider the problem of reaching a propositional goal condition in fully-observable non-deterministic (FOND) planning under a general class of fairness assumptions that are given explicitly. The fairness assumptions are of the form A/B and say that state trajectories that contain infinite occurrences of an action a from A in a state s and finite occurrence of actions from B, must also contain infinite occurrences of action a in s followed by each one of its possible outcomes. The infinite trajectories that violate this condition are deemed as *unfair*, and the solutions are policies for which *all the fair trajectories reach a goal state.* We show that strong and strong-cyclic FOND planning, as well as QNP planning, a planning model introduced recently for generalized planning, are all special cases of FOND planning with fairness assumptions of this form which can also be combined. FOND$^+$ planning, as this form of planning is called, combines the syntax of FOND planning with some of the versatility of LTL for expressing fairness constraints. A sound and complete FOND$^+$ planner is implemented by reducing FOND$^+$ planning to answer set programs, and its performance is evaluated in comparison with FOND and QNP planners, and LTL synthesis tools. Two other FOND$^+$ planners are introduced as well which are more scalable but are not complete.

(Best Paper Award ICAPS'21)

FOND$^+$

Let's generalize FOND:

FOND$^+$ Problem

A FOND$^+$ problem $P_c = \langle P, C \rangle$ is a FOND problem P extended with a set C of **(conditional) fairness assumptions** of the form A_i/B_i, $i = 1, \ldots, n$ and where each A_i is a set of **non-deterministic actions** in P, and each B_i is a set of actions in P disjoint from A_i.

Meaning of $A/B \in C$: If a state trajectory contains infinite occurrences of actions $a \in A$ in a state s, and *finite* occurrences of actions from B, then s must be immediately followed by each $s' \in F(\pi(s), s)$ an infinite number of times.

- ✏ *if $left$ is executed infinitely many times in s, but $right$ is executed, say, 10 times, then eventually we will see the left wall.*

FOND Solutions as FOND$^+$ Solutions

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Theorem

The ***strong-cyclic solutions*** *of a FOND problem P are the solutions of the FOND$^+$ problem $P_c = \langle P, \{A/\emptyset\} \rangle$, where A is the set of all the non-deterministic actions in P.*

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Theorem

The ***strong solutions*** *of a FOND problem P are the solutions of the FOND$^+$ problem $P_c = \langle P, \emptyset \rangle$.*

FOND$^+$-ASP: An ASP-based Planner

```
% policy, edges, and connectedness
{ pi(S,A) : ACTION(A) } = 1 :- STATE(S), not GOAL(S).
successor(S,T) :- pi(S,A), TRANSITION(S,A,T).

connected(S,T) :- successor(S,T).
connected(S,T) :- connected(S,X), successor(X,T), S != X.

blocked(S,T) :- STATE(S), STATE(T), not connected(S,T).
blocked(S,T) :- connected(S,T), terminate(S).
blocked(S,T) :- connected(S,T), terminate(T).
blocked(S,T) :- connected(S,T),
                blocked(X,T) : successor(S,X), connected(X,T).

fair(S) :- pi(S,A), ASET(I,A), blocked(X,S) : pi(X,B), BSET(I,B), not blocked(S,X).

% terminating states
terminate(S) :- GOAL(S).
terminate(S) :- fair(S), successor(S,T), terminate(T).
terminate(S) :- not fair(S), successor(S,_), terminate(T) : successor(S,T).

% reachable states must terminate
:- reachable(S), not terminate(S).
reachable(S) :- INITIAL(S).
reachable(S) :- reachable(X), not GOAL(X), successor(X,S).
```

```
STATE(S)
INITIAL(S)
GOAL(S)
ACTION(A)
TRANSITION(S,A,T)
ASET(A,I)
BSET(B,I)
```

just 24 lines!

figs/fondplus.lp

FOND$^+$-ASP: Graphical Intuition...

figure of a transition system, with two states looping, the first selects action A and the second B. draw successors of each..

FOND^{+}-ASP: Solution Policy

```
1  % policy, edges, and connectedness
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5  % reachable states must terminate
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2 Select an action per domain state.

3 Edges are transitions of the action selected.

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2 Select an action per domain state.

3 Edges are transitions of the action selected.

6 **Constraint:** every reachable state via the policy needs to eventually terminate.

7-8 Define reachable states via the policy.

FOND^{+}-ASP: State Termination

Defines when a state will eventually lead to termination and not get “sucked” in a loop..

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```

2 If the state is a goal state.

3 If state will *behave **fairly*** (wrt effects of prescribed action) and one successor state will terminate.

4 If state may *not* behave **fairly**, and all successors will terminate.

FOND$^+$-ASP: Fairness

```
1   connected(S,T) :- successor(S,T).
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4   % terminating states
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9
10  fair(S) :- pi(S,A), ASET(I,A),
11             blocked(X,S) : pi(X,B), BSET(I,B), not blocked(S,X).
```

1-2 States connected by the policy.

4-7 Every path from `S` to `T` will terminate somewhere.

10 Fair if any loop that includes actions in a fairness pair A/B (e.g., $left$ and $right$), will terminate somewhere else.

FOND$^+$-ASP: Strong Cyclic

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*The **strong-cyclic solutions** of a FOND problem P are the solutions of the FOND$^+$ problem $P_c = \langle P, \{A/\emptyset\}\rangle$, where A is the set of all the non-deterministic actions in P.*

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always false

Line 3 always applies!

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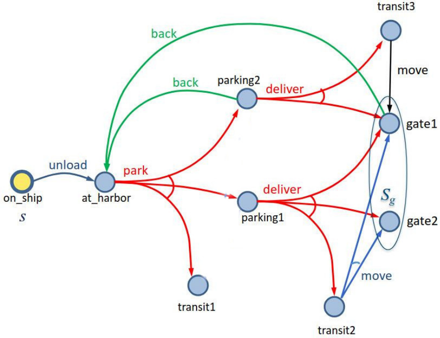
Discussion

- We tested FOND$^+$-ASP experimentally:
  - Only planner that can solve FOND+ problems!
  - Performs better than FOND-SAT and LTL synthesis tool STRIX.
  - PRP scales up better for FOND tasks.
  - **Limitation:** state space grounding.



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  - *Just add* `oneof` *in effects!*
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  - Complexity up to EXPTIME-complete.
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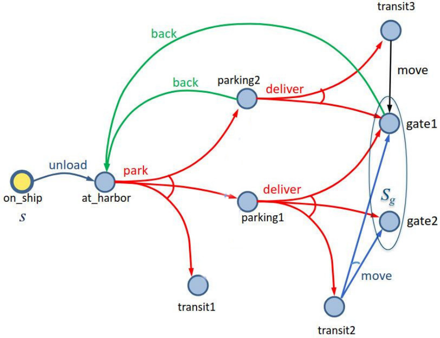
  - Can model scenarios with "re-tries"
  - Can deal with adversarial domains.



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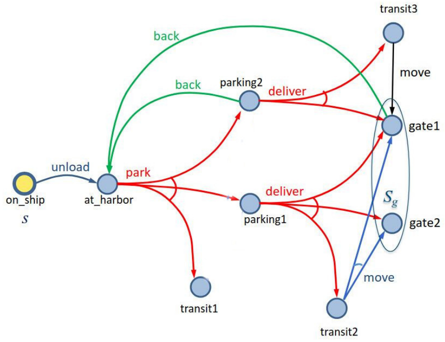

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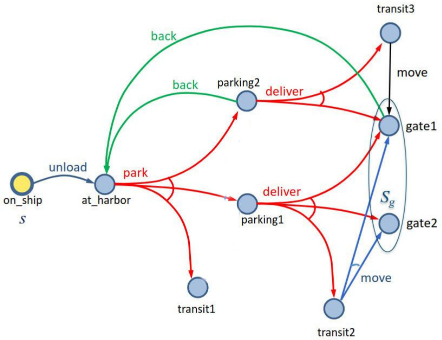
Qualitative Numeric Planning (QNP)



Que vimos? 👀

1. **Busqueda** as a general problem solving method:
   - Representación: state model (a graph!).
   - Uninformed methods: BrFS, DFS, IDS, UCS.
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   - Model-based approach to autonomous behavior.
   - Languages: STRIP and PDDL.
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   - Planning graphs.
3. **FOND Planning**: Non-determinism
   - Non-deterministic state models (no probabilities!)
   - PDDL with `one-of` effects + Policies.
   - Solution concepts: weak, strong, strong-cyclic.
   - Fairness assumption on environment.
   - Computing policies.

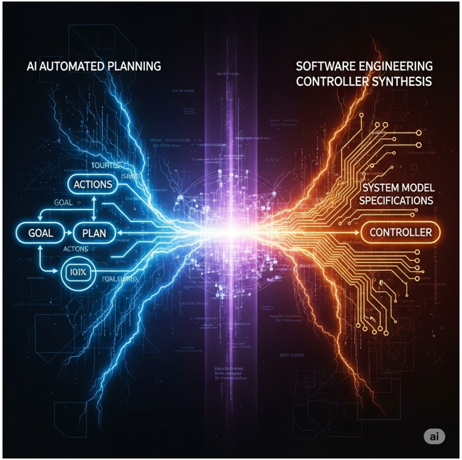
AI Planning and Control Synthesis in SE 🤝

- What if we want to plan for **more complex goals**?
  ➠ **Elevator controller:** every passenger floor requests needs to be *eventually* fulfilled, but **never** have more than 10 passengers on board.

- **Event-driven systems**: some events cannot be planned/controlled (e.g., user aborts transaction)

- **Infinite behavior:** continuous operation, never stop.
  ➠ What are the goals if we never finish? Infinite games vs. finite games

- **Compositional planning/synthesis**: software components described separately
  ➠ Plan on different PDDLs and the combine.



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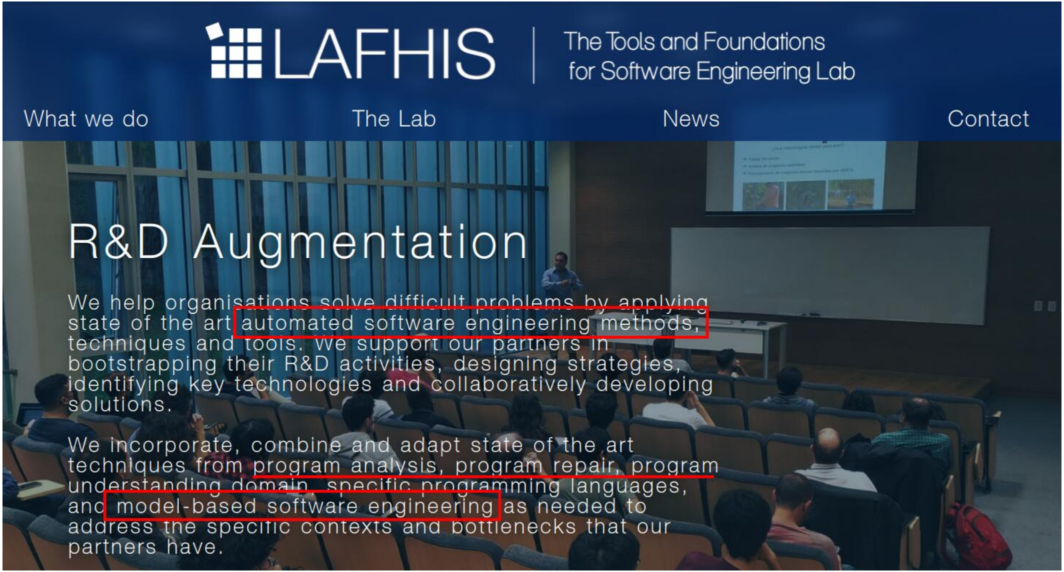

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R&D Augmentation

We help organisations solve difficult problems by applying state of the art automated software engineering methods, techniques and tools. We support our partners in bootstrapping their R&D activities, designing strategies, identifying key technologies and collaboratively developing solutions.

We incorporate, combine and adapt state of the art techniques from program analysis, program repair, program understanding domain, specific programming languages, and model-based software engineering as needed to address the specific contexts and bottlenecks that our partners have.

Contact sebastian.sardina@rmit.edu.au - https://ssardina.github.io/