Simple and Fast Strong Cyclic Planning for Fully-Observable Nondeterministic Planning Problems

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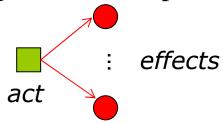
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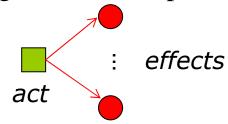
- To solve strong cyclic planning problems from a Fully-Observable Nondeterministic planning domain
- A planning problem is a triple $\langle s_0, g, \Sigma \rangle$, where s_0 is the initial state, g is the goal condition, and Σ is the planning domain

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v Formally, a nondeterministic domain

is a 4-tuple
$$\Sigma = (P, S, A, \gamma)$$

- p P is a finite set of propositions;
- $_{p}$ $S \subseteq 2^{p}$ is a finite set of states in the system;
- p A is a finite set of actions; and
- $\gamma: S \times A \rightarrow 2^S$ is the state-transition function

 To solve strong cyclic planning problems from a Fully-Observable Nondeterministic planning domain

- To solve strong cyclic planning problems from a Fully-Observable Nondeterministic planning domain
- Full observabilityThe states of the world are fully observable

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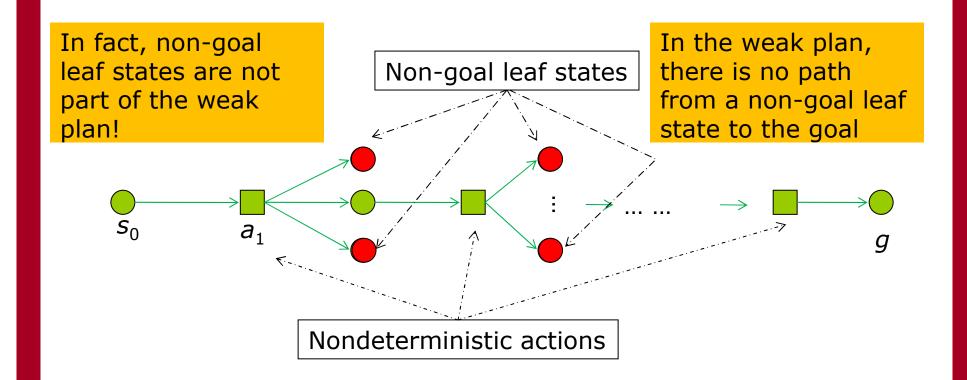
v Strong cyclic planning

refers to a particular type of solutions to nondeterministic problems

different from so-called weak planning

Weak Planning Solutions

Solutions where there is a chance to achieve the goal



Strong Cyclic Planning Solutions

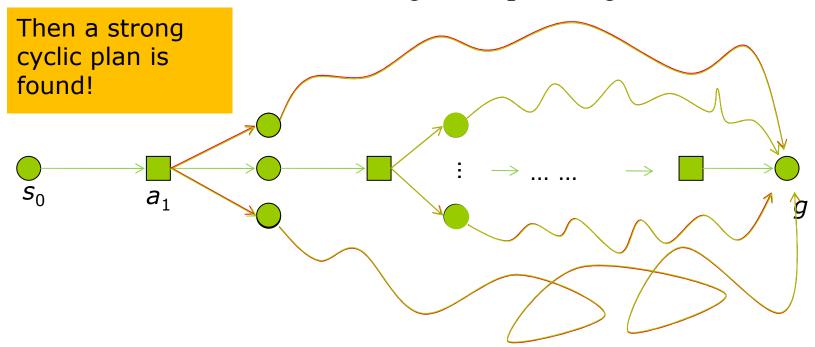
Prescribe actions for all possible non-goal leaf states

Find a path for each non-goal leaf state to the goal state

May loop indefinitely

But contain no dead-ends

More difficult than finding weak planning solutions



Representing a Plan

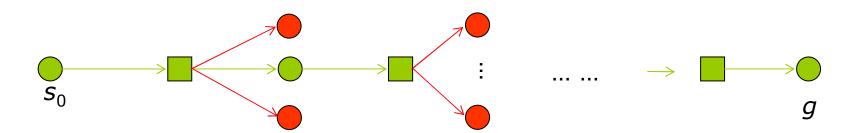
- Regardless of whether a plan is weak or strong cyclic, we can represent it as a policy π a partial function mapping states to actions
- More formally, policy $\pi: S_{\pi} \to A$ consists of state action pairs (s, a) such that $\pi(s) = a$ defines which action to take under state s

How to Generate a Strong Cyclic Plan

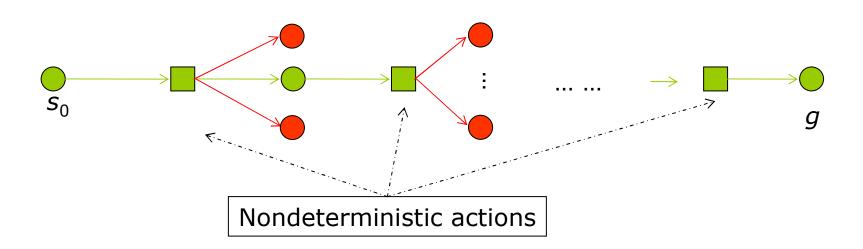
v Given a planning problem with initial state *s*₀ and goal state *g*, we employ a 3-step Basic algorithm motivated by work in Incremental contingency planning [Dearden *et al*, 2003], FF-replan [Yoon, Fern, and Givan, 2007], and NDP [Kuter *et al.*, 2008]

Find a **path** (i.e., weak plan) from s_0 to g using a classic planner

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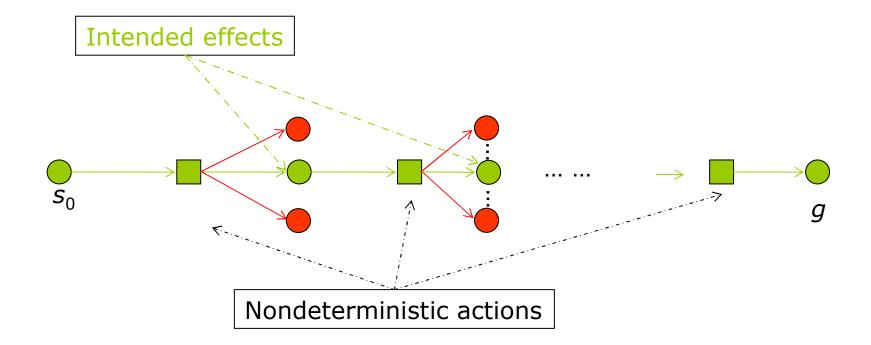


Find a **path** (i.e., weak plan) from s_0 to g using a classic planner



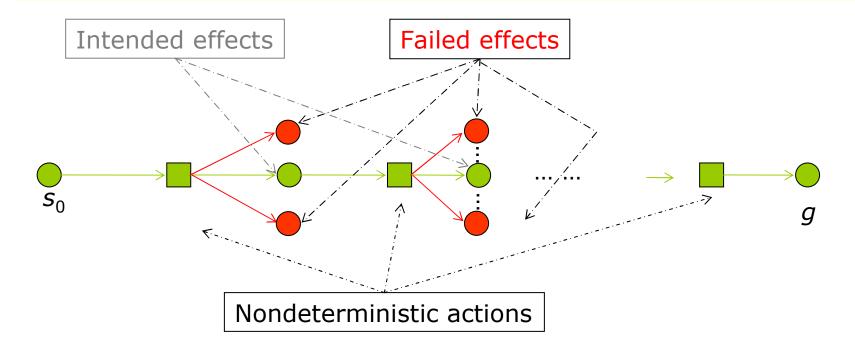
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Given a nondeterministic action, the effect included in the weak plan is its **Intended Effect**



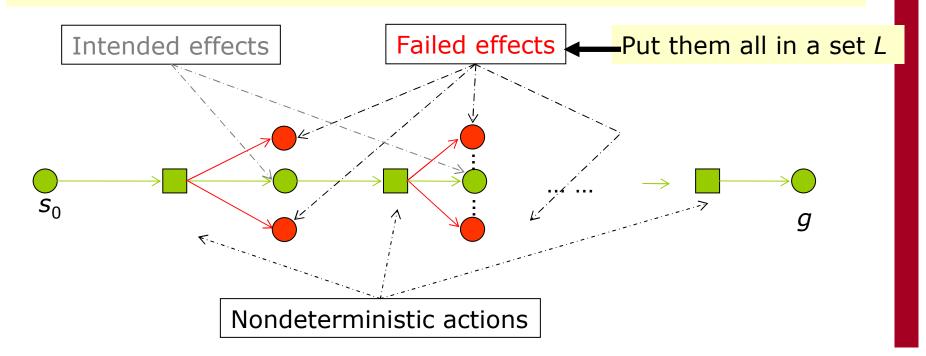
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Given a nondeterministic action, the effect included in the weak plan is its **Intended Effect** the effects not included in the weak plan are its **Failed Effects**



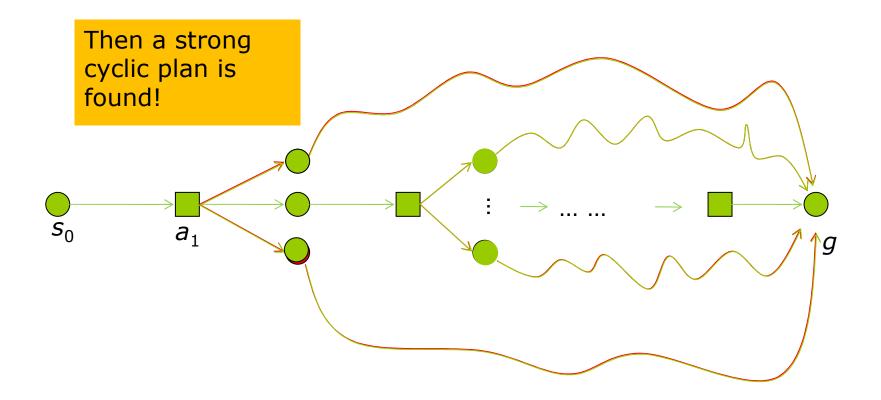
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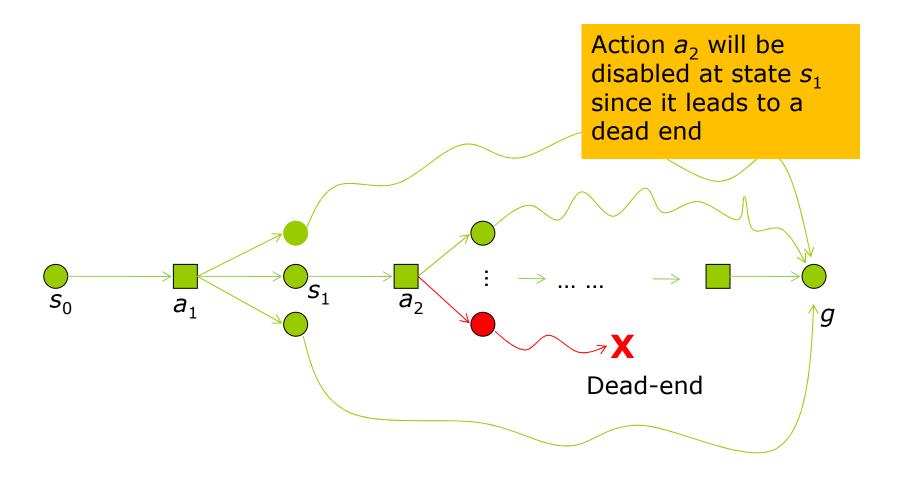


 ∇ For every failed effect e, find a path from e to g.

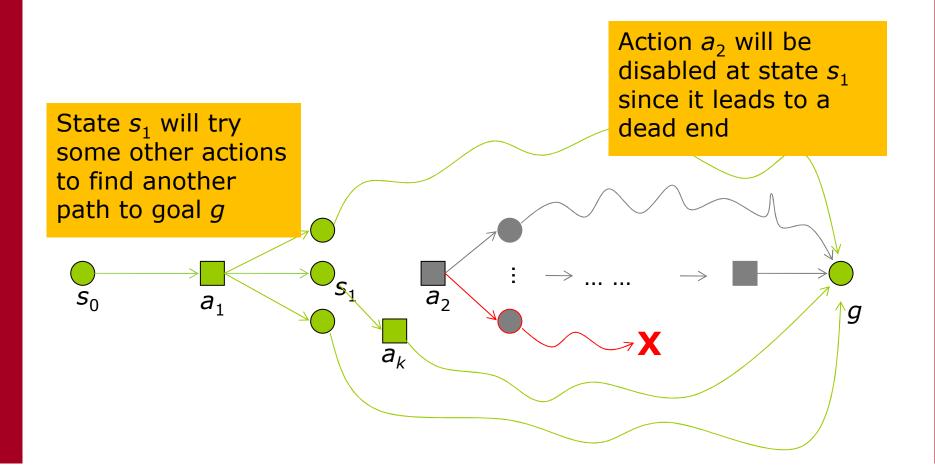
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But sometimes we may encounter a dead end. In this case, we need to backtrack

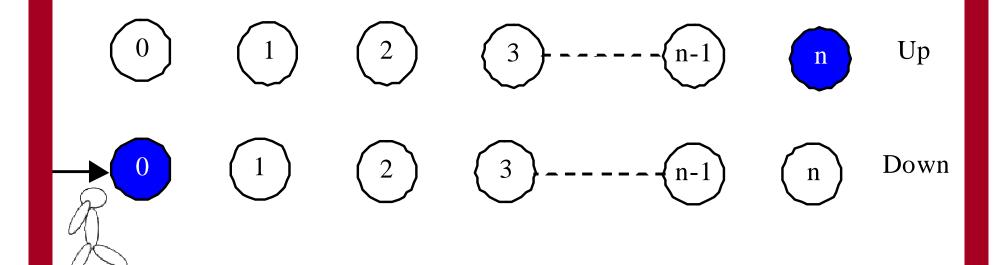


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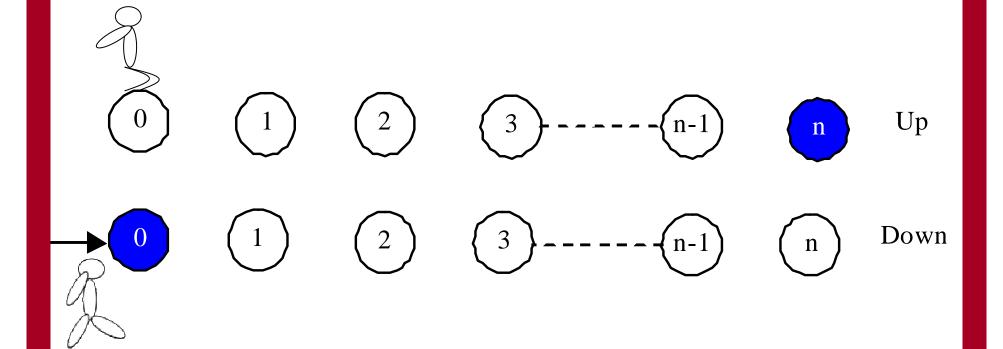
Basic Algorithm: Application to Beam Domain

- v A set of **positions** in one of two levels: *up* or *down*
- **Goal:** have the agent move from $down_0$ to up_n
- Three possible actions can be used to move around



Action 1: Climb

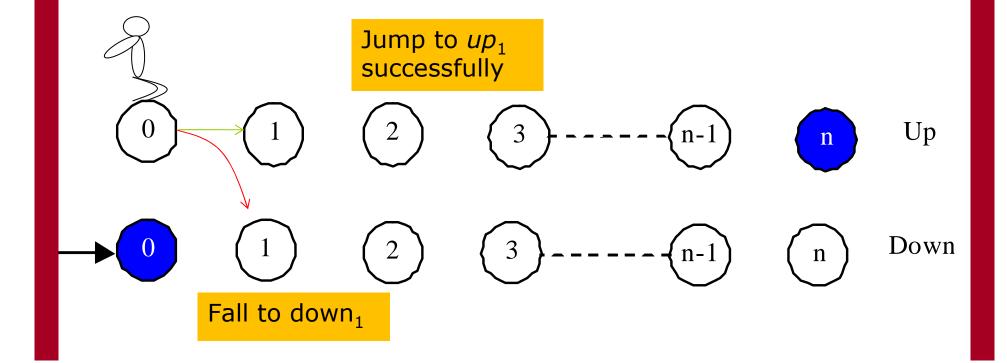
Climb is deterministic
it moves the agent from down₀ to up₀.
can only be applied to down₀



Action 2: Jump

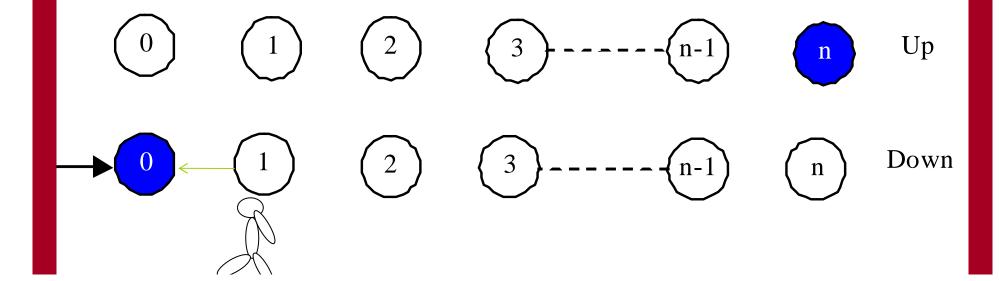
v Jump is nondeterministic

can be applied only to a position in the upper level if successful, agent moves to up position to its right if unsuccessful, agent moves to down position to its right



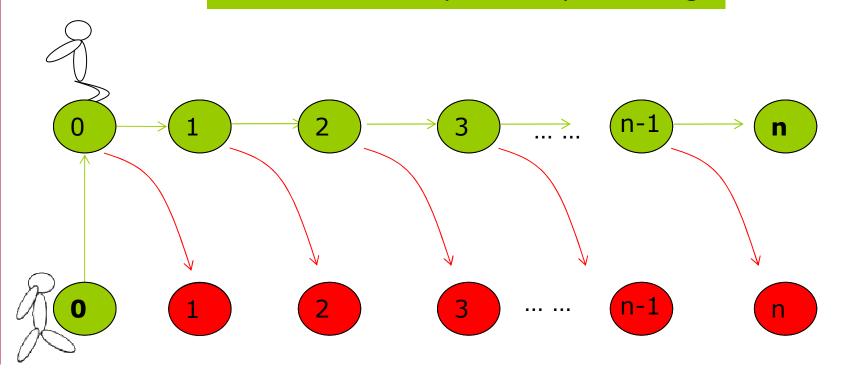
Action 3: Moveback

Moveback is deterministic
can be applied only to a position in the lower level
moves agent one step to the left

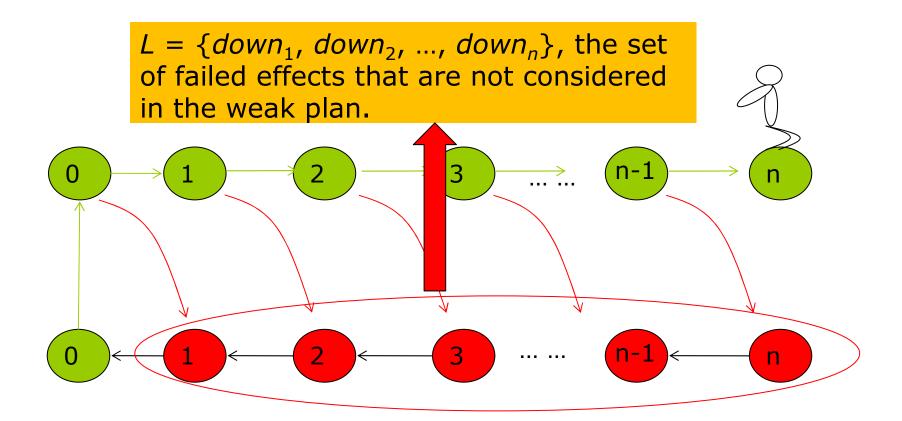


- v Initially, $L = \{down_0\}$
- v **Step 1**: Find a path from $down_0$ to up_n

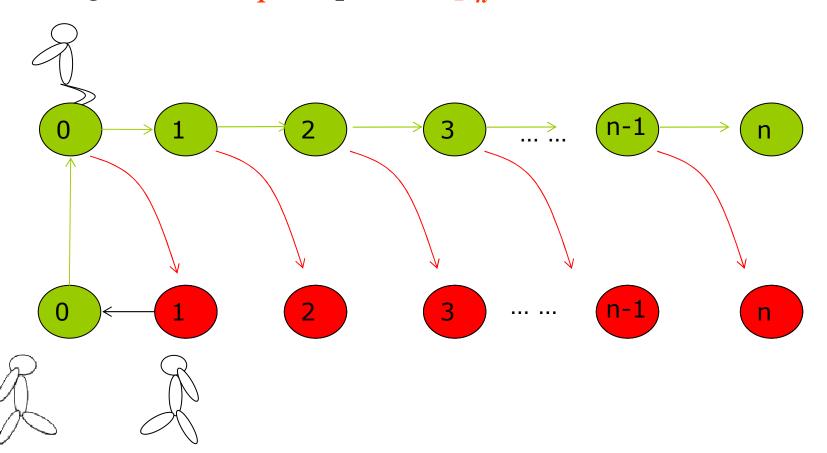
This is a weak plan because it does not consider the possibility of falling!



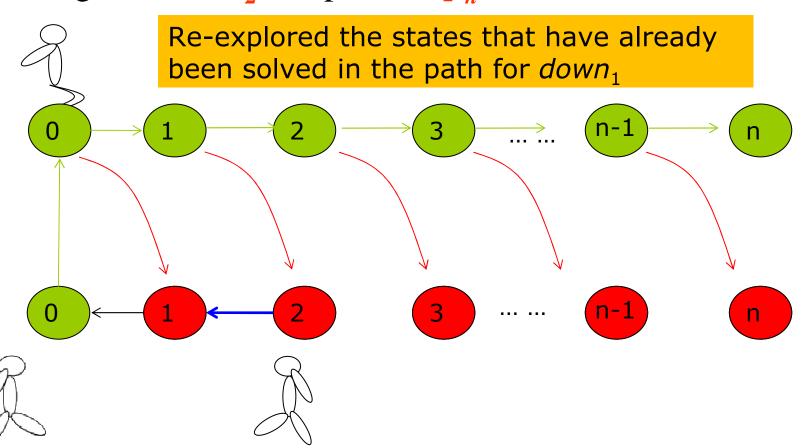
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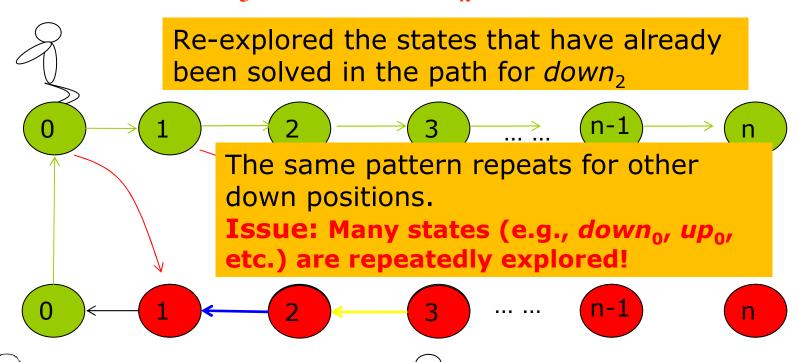
- $V L = \{down_1, down_2, ..., down_n\}$
- **Step 2**: Find a path from **each** position in L to up_n .
- v E.g., for $down_1$, the path to up_n is:



- $V L = \{down_1, down_2, ..., down_n\}$
- **Step 2**: Find a path from **each** position in L to up_n .
- v E.g., for $down_2$, the path to up_n is:



- $V L = \{down_1, down_2, ..., down_n\}$
- **Step 2**: Find a path from **each** position in *L* to up_n .
- v E.g., for $down_3$, the path to up_n is:



So ...

The basic algorithm can be **inefficient** many states can be repeatedly explored

v Goal

improve the Basic algorithm w.r.t. planning efficiency and plan size by proposing two extensions

Extension 1: Goal Alternative

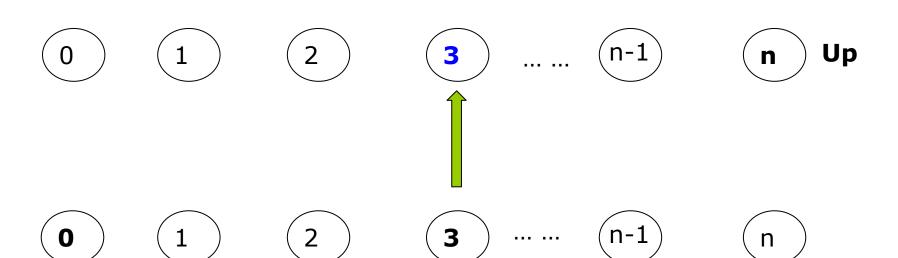
Observation

The Basic algorithm attempts to find a path from each failed effect to goal state *g*, which can be far away

- With goal alternative, we attempt to find a path from each failed effect to an alternative goal
 - an alternative goal is presumably closer to the associated failed effect than the overall goal *g*
 - p could improve planning efficiency and reduce plan size each failed effect has its own alternative goal
 - p i.e., an alternative goal is associated with a failed effect
 - p we use the corresponding intended effect as alternative goal

 \mathbf{v} For each failed effect $down_i$

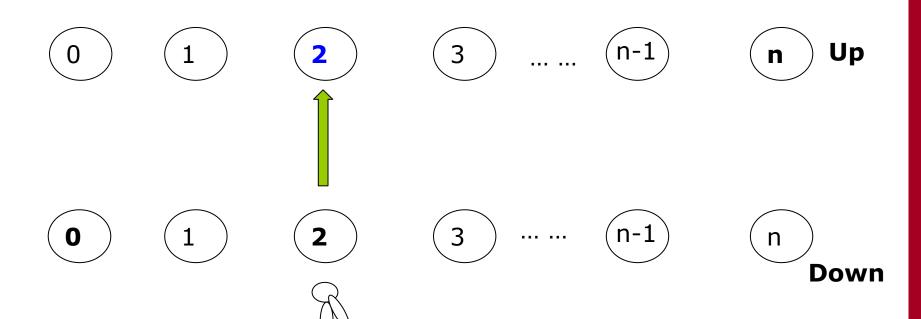
instead of using up_n as the search goal, we use the intended effect up_i of action $Jump(up_{i-1}, up_i)$ as the search goal



Down

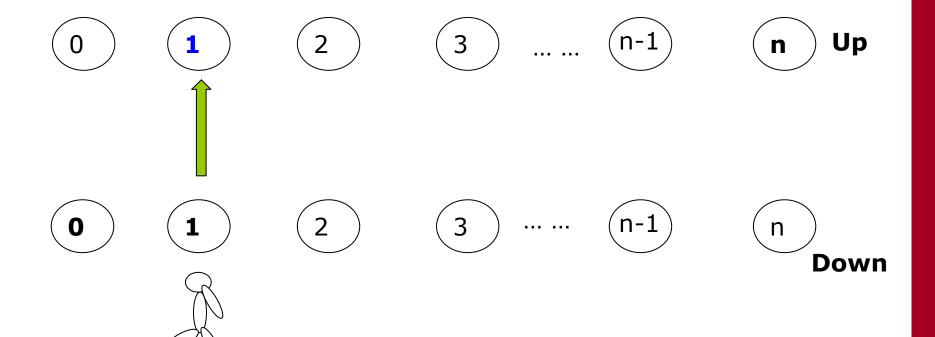
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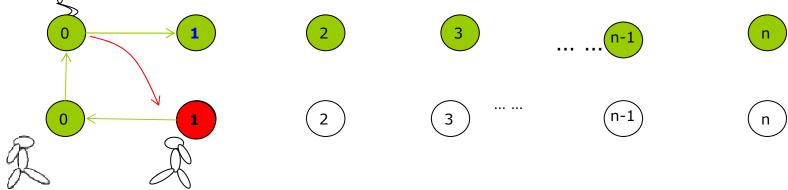
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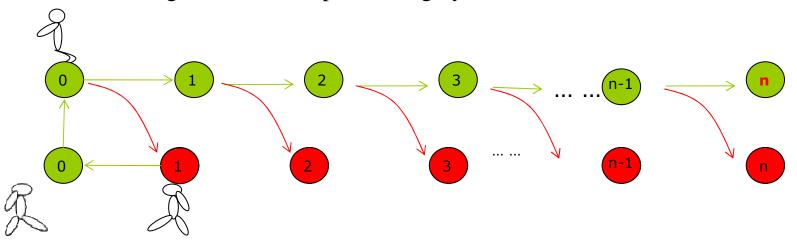
 ∇ For failed effect $down_1$,





If we use the **ultimate goal** up_n as the search goal

S The generated weak plan is lengthy



Goal Alternative: A Caveat

- V It is possible that a path cannot be established between a failed effect and its alternative goal
- If this happens, we resort to establishing a path from the failed effect to the original goal g

Why is Goal Alternative correct?

- By definition, an intended effect \hat{s} is included in some path wp to goal g, while a failed effect s is ignored in wp
- Since we have already found a path from \hat{s} to g, if we can find a path from s to \hat{s} , then the path from s to \hat{s} can be the solution to $\langle s, g, \Sigma \rangle$
- Hence, much effort is saved by avoiding the search from \hat{s} to g.

Extension 2: State Reuse

Observation

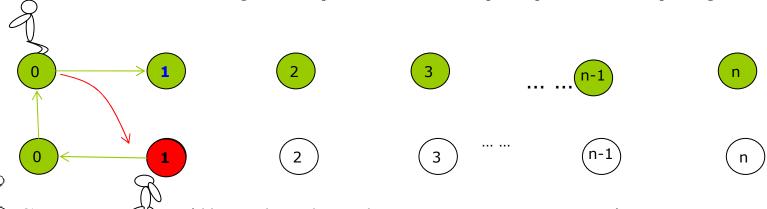
Even if a state is solved (i.e., a path has been found from *s* to the goal *g*), the Basic algorithm still attempts to solve it every time it is encountered

State reuse aims to improve planning efficiency by not re-solving a state

When searching for a weak plan, if a solved state is encountered, the search stops

State Reuse: Example

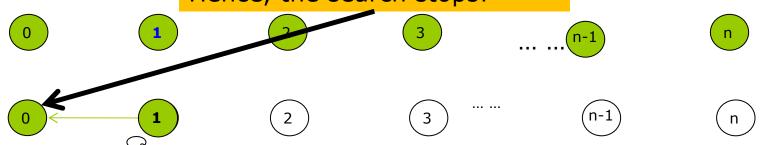
For failed effect $down_1$, goal alternative generates the plan Moveback $(down_1, down_0)$; Climb $(down_0, up_0)$; Jump (up_0, up_1)



State reuse will make the plan even more concise

Moveback(down₁, down₂)

Reached a solved state down₀. Hence, the search stops!



Note that ...

State reuse and goal alternative can be applied independently of each other

In particular, goal alternative does NOT rely on state reuse to improve planning efficiency

v In our poster

we use the blocksworld example to show that goal alternative plays a more critical role than state reuse

Evaluation

V All problem instances belong to the benchmark domains of the IPC2008 FOND track

Blocksworld, Forest, Faults, and First-responders

v Goal

compare FIP, our planner that implements the Basic algorithm with the two extensions, against two state-of-the-art planners, MBP and Gamer

give each planner 1200 seconds to solve each problem instance

Evaluation 1: Problem Coverage

Domain	Gamer	MBP	FIP
blocksworld (30)	10	1	30
faults (55)	38	16	55
first-responders (100)	21	11	75
forest(90)	7	0	7
Total (275)	76	28	167

FIP solves more problems than Gamer and MBP within the time limit

Evaluation 2: Efficiency

Problem	Gamer		MBP	Basic		FIP	
	t	S	t	t	S	t	S
bw-1	38.748	10	3556.517	0.011	12	0.007	8

v Comparing with the Basic Algorithm

FIP is on average more than 8 times faster than Basic

As the problem complexity increases, FIP could be more than 100 times faster than Basic

FIP's plans are 3.4 times smaller than Basic on average

faults-8-8	1106.105	325	 0.101	514	0.007	26
faulte 0 0	930 272	511	0.217	Q/1Q	0.007	20

v Comparing with MBP and Gamer

FIP is on average more than three orders of magnitude faster

FIP's plans are 2.8 times smaller than Gamer's

TOT COL 2 /	0.122	77	0.007	77	0.000	77
forest-2-8	0.638	56	 0.007	56	0.008	56
forest-2-9	0.607	42	 0.006	42	0.007	42
forest-2-10	0.927	44	 0.007	44	0.008	44

Evaluation 3: Which of the two extensions makes a more critical contribution?

bw-12

faults

FIP-SR-only: extends Basic with state reuse only

FIP-GA-only: extends Basic with goal alternative only

On average, FIP-GA-only runs more than 5 times faster than FIP-SR-only

FIP-GA-only creates plans that are 3.4 times smaller than FIP-SR-only.

Problem	FII	FIP		R-only	FIP-GA-only		
	t	S	t	S	t	S	
bw-1	0.007	8	0.010	12	0.007	8	
bw-2	0.006	7	0.008	10	0.005	7	
bw-3	0.008	10	0.008	10	0.010	10	
bw-4	0.011	14	0.012	16	0.013	14	
bw-5	0.010	12	0.014	12	0.013	12	
bw-6	0.009	10	0.010	10	0.011	10	
bw-7	0.010	17	0.016	22	0.015	17	

So, goal alternative plays a more crucial role than state reuse in improving faults planning efficiency and faults reducing plan size!

rauro						
faults-10-7	0.007	32	0.960	2140	0.008	32
faults-10-10	0.009	32	1.101	2050	0.009	32
f-r-1-8	0.002	10	0.003	10	0.003	10
f-r-2-3	0.003	11	0.003	11	0.003	11
f-r-4-2	0.003	6	0.003	6	0.003	6
f-r-6-2	0.003	7	0.003	7	0.003	7
forest-2-5	0.008	56	0.007	56	0.009	56
forest-2-6	0.008	50	0.007	50	0.009	50
forest-2-7	0.008	44	0.007	44	0.009	44
forest-2-8	0.008	56	0.007	56	0.009	56
forest-2-9	0.007	42	0.006	42	0.008	42
forest-2-10	0.008	44	0.006	44	0.009	44

Summary

- Proposed two extensions to the Basic strong cyclic planning algorithm, goal alternative and state reuse
- FIP significantly outperforms state-of-the-art planners in terms of problem coverage, efficiency, and solution size.