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# INTRODUCTION TO AI STRIPS PLANNING

.. and Applications to Video-games!

# Course overview

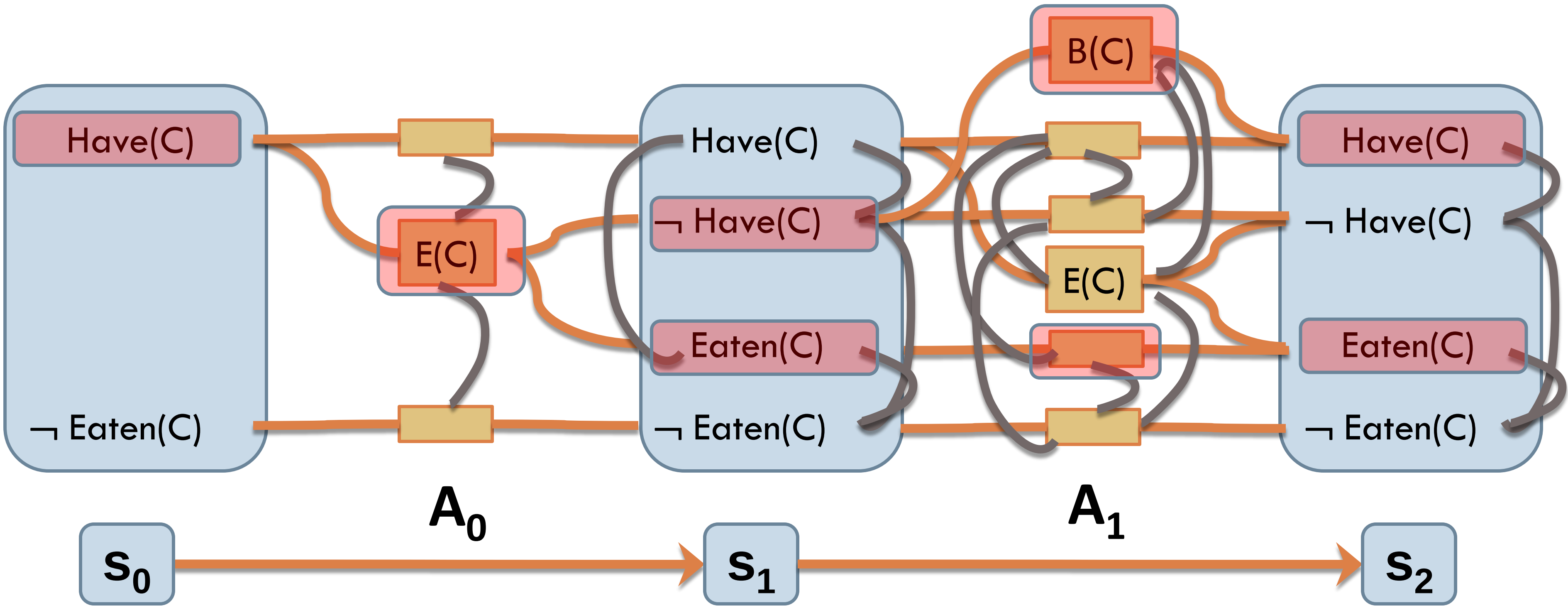


- Lecture 1: Game-inspired competitions for AI research, AI decision making for non-player characters in games
- Lecture 2: STRIPS planning, state-space search
- Lecture 3: Planning Domain Definition Language (PDDL), using an award winning planner to solve Sokoban
- Lecture 4: Planning graphs, **domain independent heuristics for STRIPS planning**
- Lecture 5: Employing STRIPS planning in games: SimpleFPS, iThinkUnity3D, SmartWorkersRTS
- Lecture 6: Planning beyond STRIPS

# Planning graphs



- Planning graph



# Planning graphs



- Planning graph
  - Special **data structure**
  - Easy to compute: **polynomial complexity!**
  - Can be used by the **GRAPHPLAN** algorithm to **search for a solution** (following similar reasoning as in the example)
  - Can be used as a **guideline for heuristic functions** for progressive planning that are more accurate than the ones we sketched in Lecture 1

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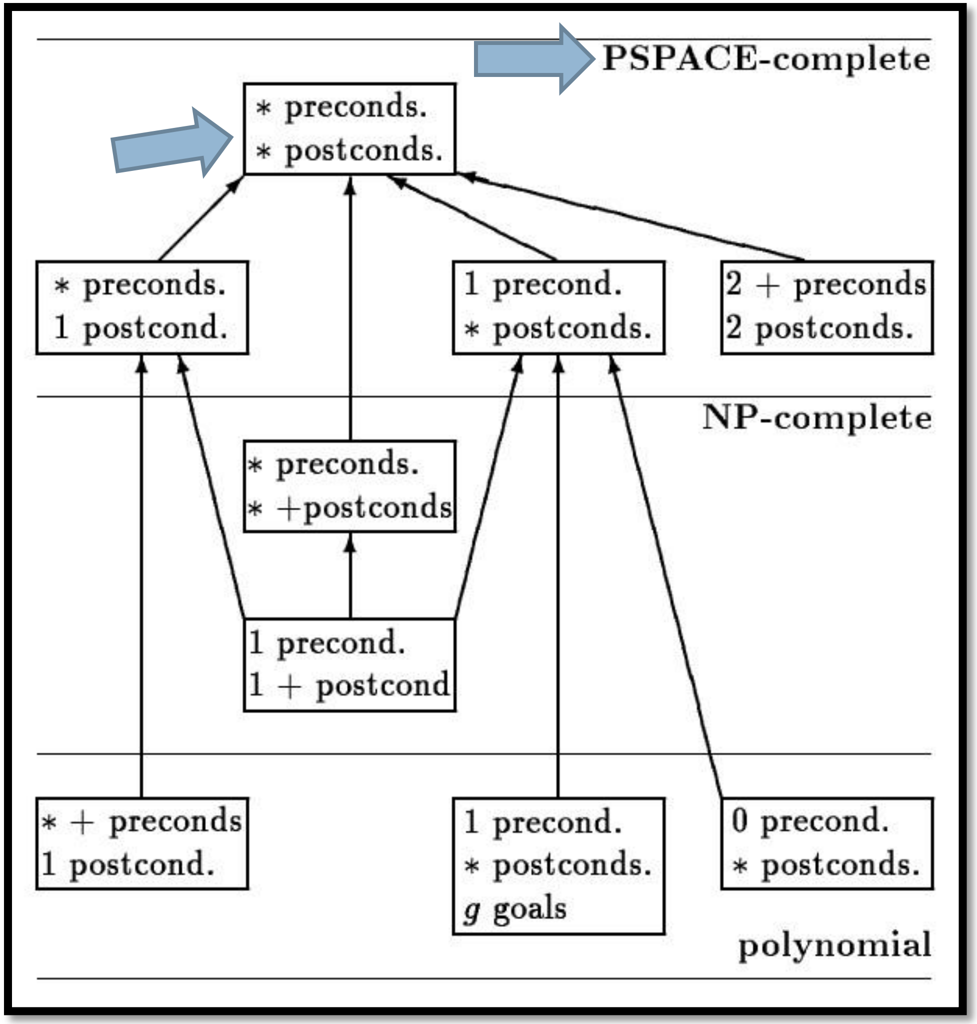
# Planning graphs



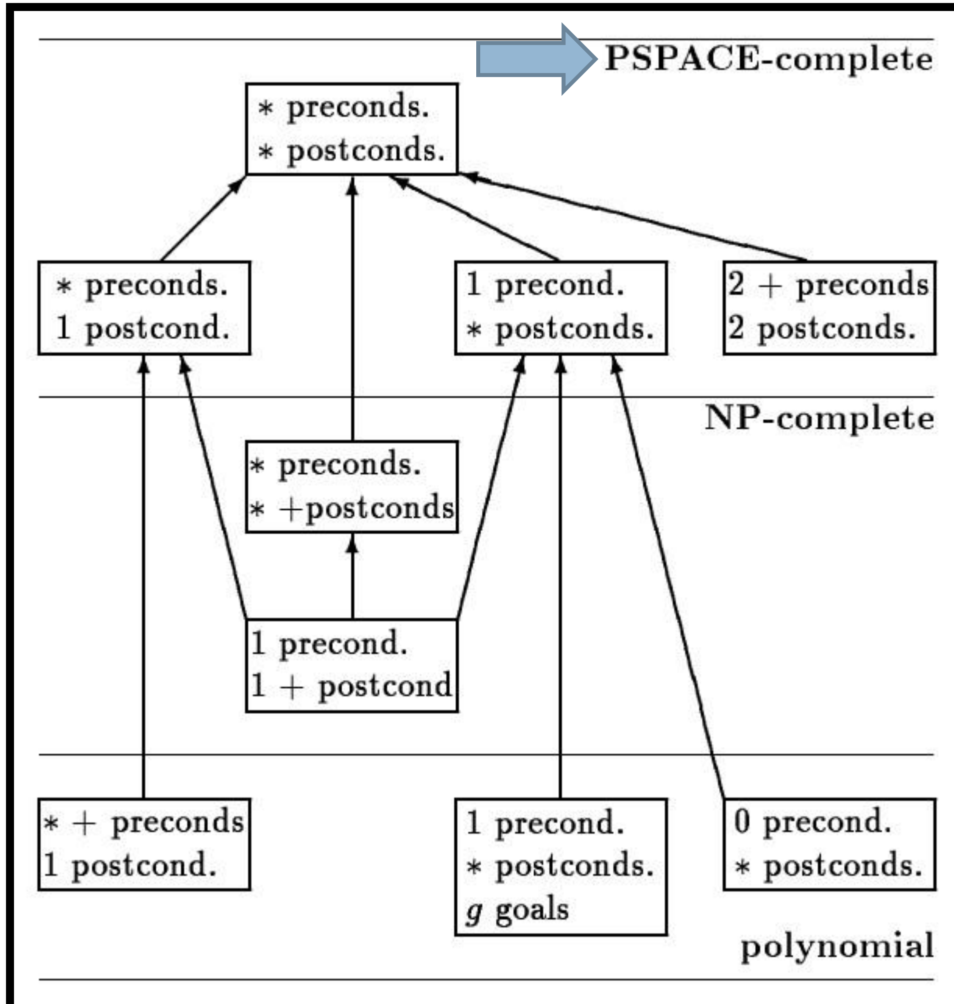
- Planning graph
  - Computing the graph has **polynomial** complexity
- STRIPS planning
  - Finding a solution is **PSPACE-complete**
- **Where's the complexity hiding?**



# Planning graphs



- Planning graph
  - Computing the graph has **polynomial** complexity
  - Finding a solution using the graph is NP-complete, while we may also need to extend the graph a finite number of times… → PSPACE



# Planning graphs

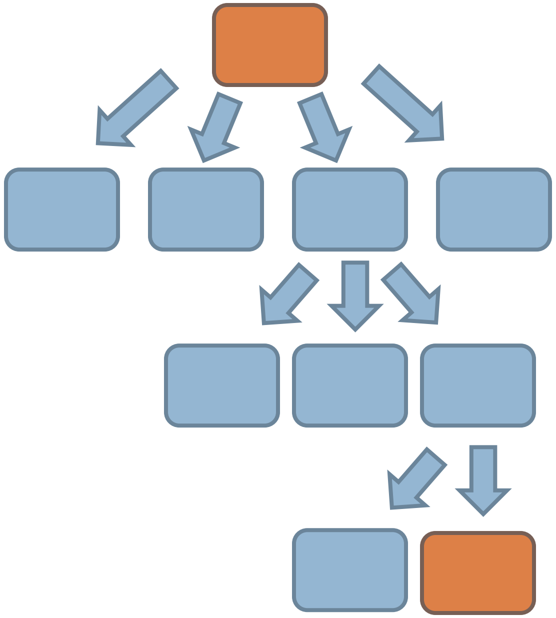


- Planning graph
  - Special **data structure**
  - Easy to compute: **polynomial complexity!**
  - Can be used by the **GRAPHPLAN** algorithm to **search for a solution** (following similar reasoning as in the example)
  - Can be used as a **guideline for heuristic functions** for progressive planning that are more accurate than the ones we sketched in Lecture 2

# Planning graphs



- Start from the initial state
- Check if the current state satisfies the goal
- Compute applicable actions to the current state
- Compute the successor states
- Pick ~~one~~ **the most promising** of the successor states as the current state
- Repeat until a solution is found or the state space is exhausted



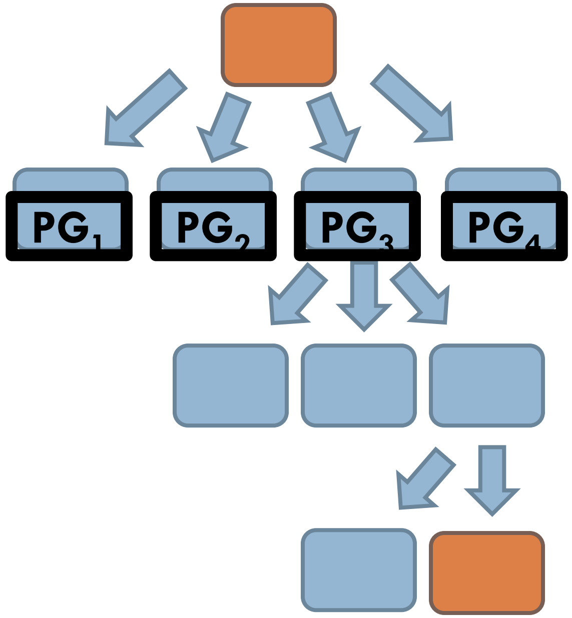
# Planning graphs



- Start from the initial state
- Check if the current state satisfies the goal
- Compute applicable actions to the current state

Compute a planning graph for each successor state to estimate goal distance

- Repeat until a solution is found or the state space is exhausted



# Planning graphs



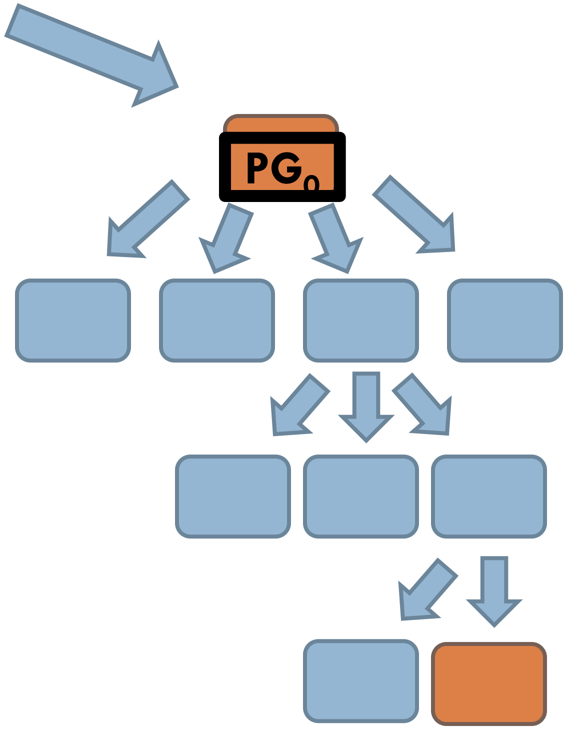
- Heuristic functions based on planning graphs
  - **Level cost:** the level where a literal appears in the graph for the first time
    - Note: A literal that does not appear in the final level of the graph cannot be achieved by any plan!
  - **Max-level**: the max of the level cost for each sub-goal
  - **Sum-level**: the sum of the level cost for each sub-goal
  - **Set-level**: the first level that all sub-goals appear together without mutexes

# Planning graphs



As an example let's see the heuristics for the planning graph from the initial state

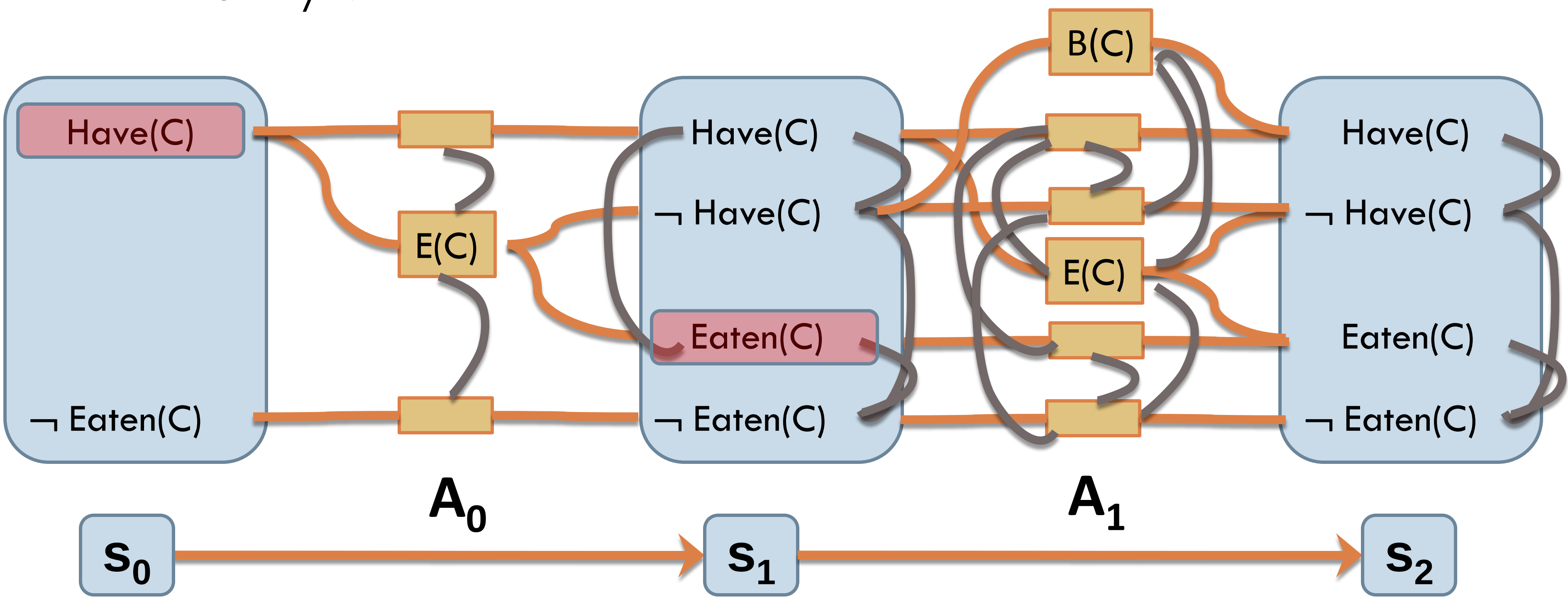
- Compute applicable actions to the current state
- Compute the successor states
- Pick ~~one~~ **the most promising** of the successor states as the current state
- Repeat until a solution is found or the state space is exhausted



# Planning graphs



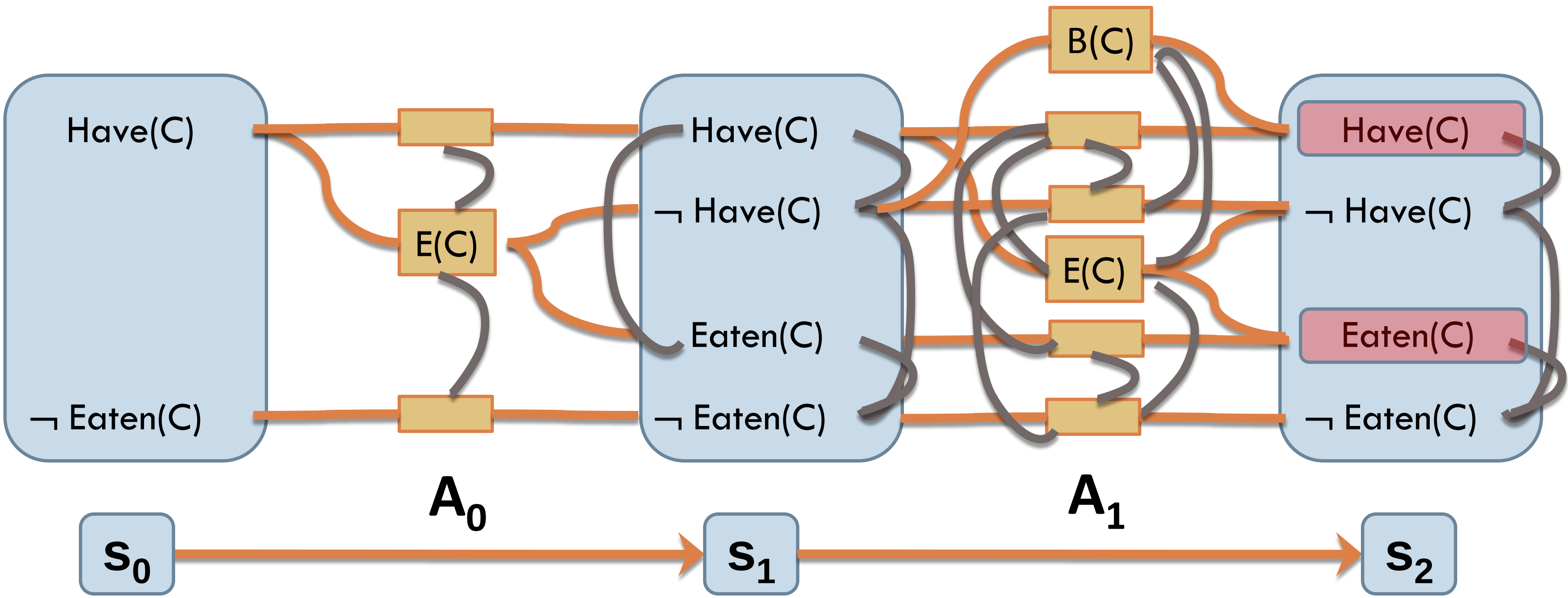
- Level cost for sub-goal Have(C) = 0
- Level cost for sub-goal Eaten(C) = 1
- Sum/Max-level heuristic = 1



# Planning graphs



- Level cost for sub-goal Have(C) = 0
- Level cost for sub-goal Eaten(C) = 1
- Set-level heuristic = 2



# Planning graphs



- Heuristic functions based on planning graphs
  - As building the planning graph is relatively cheap (polynomial) we can build one for every state we want to evaluate and use Sum/Max/Set-level to estimate the distance to the goal
  - As long as the heuristic provides good estimates, the time spent to calculate the planning graphs pays off because it helps us bypass big parts of the search space

# Planning graphs



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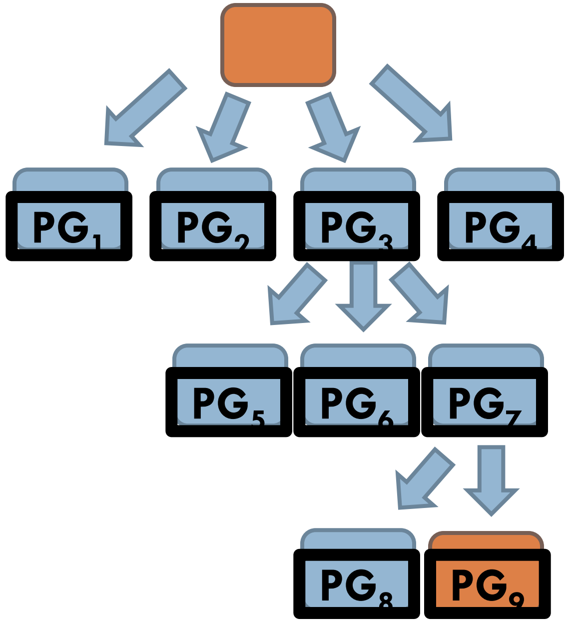


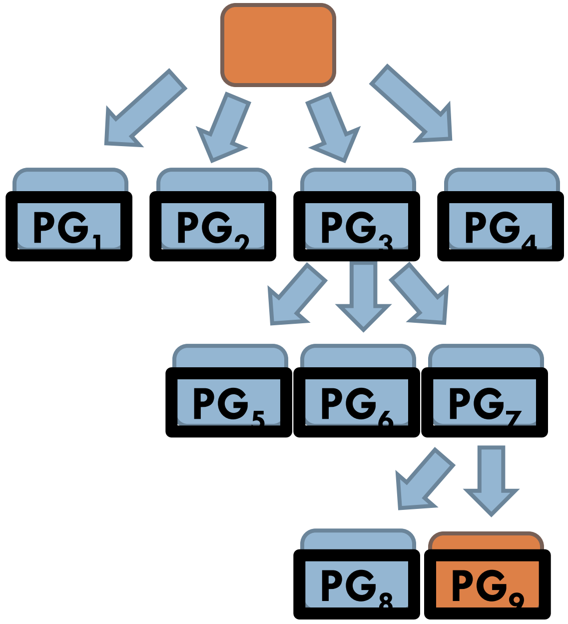
# Planning graphs



- Start from the initial state
- Check if the current state satisfies the goal
- Compute applicable actions to the current state

Here: computing 9 PGs may have helped search a state-space of 1000s of nodes

- Repeat until a solution is found or the state space is exhausted



# Relaxed planning task



- Let's look closer now to one idea we discussed briefly in Lecture 2
- Same as we did with planning graphs, but instead **solve** a **relaxed (i.e., simpler) planning task** in order to estimate the goal distance
- Relaxation: Assume an **empty list of preconditions**

# Relaxed planning task



- Start from the initial state
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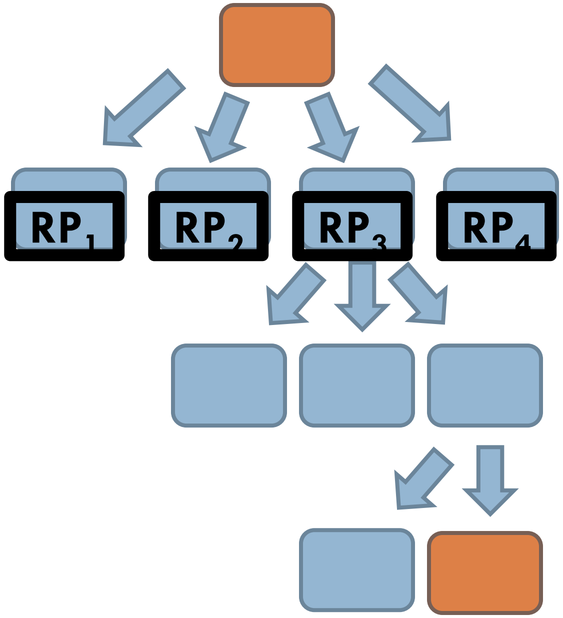
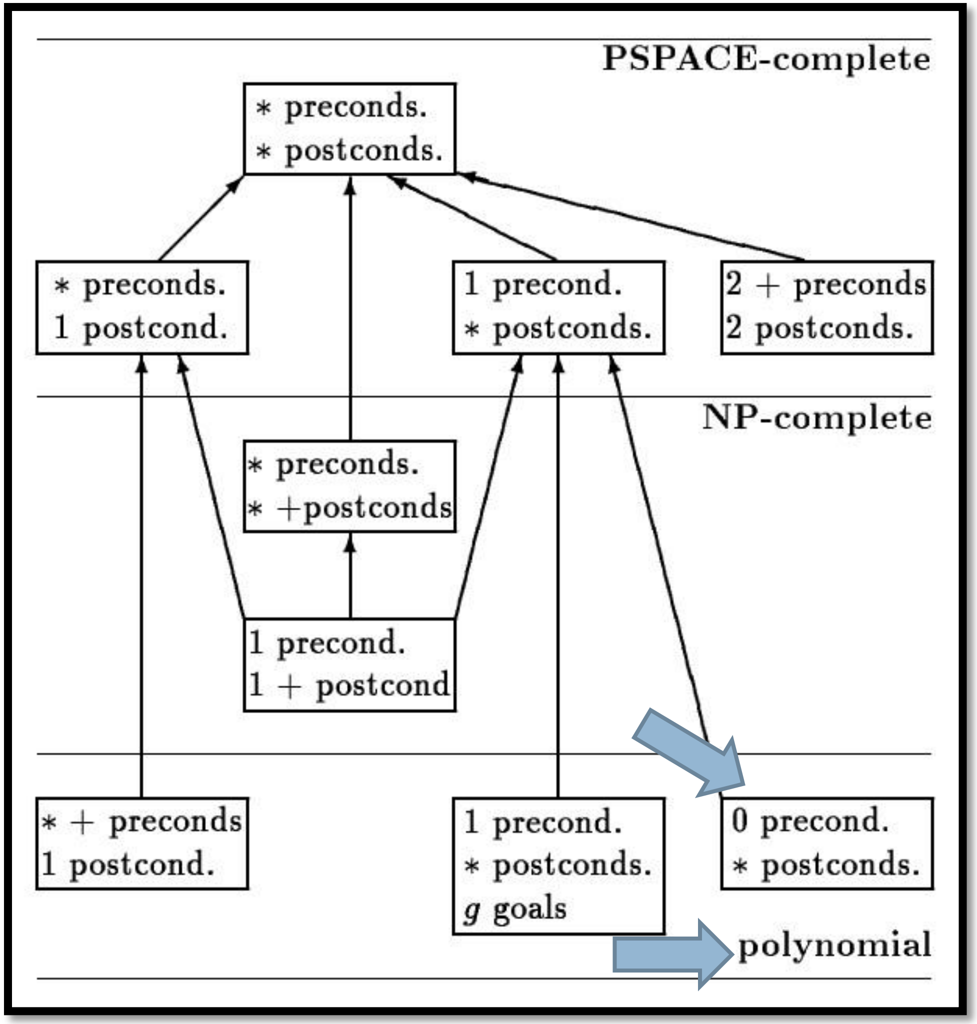


# Relaxed planning task



- Planning graph
  - Computing the graph has **polynomial** complexity
- Empty list of preconditions
  - Finding a solution to the relaxed planning task is **polynomial**
  - OK, but not very informative



# Relaxed planning task



- Empty list of preconditions
  - Initial state
  - Goal

  - Without preconditions you can move each block to the desired position in one step: push(block, from, to, dir)
  - From every state the goal is at most three actions away

# Relaxed planning task



- Let’s look closer now to one idea we discussed briefly in Lecture 1
- Same as we did with planning graphs, but instead **solve** a **relaxed (i.e., simpler) planning task** in order to estimate the goal distance
- Relaxation: Assume an **empty list of negative effects**

# Relaxed planning task



- Start from the initial state
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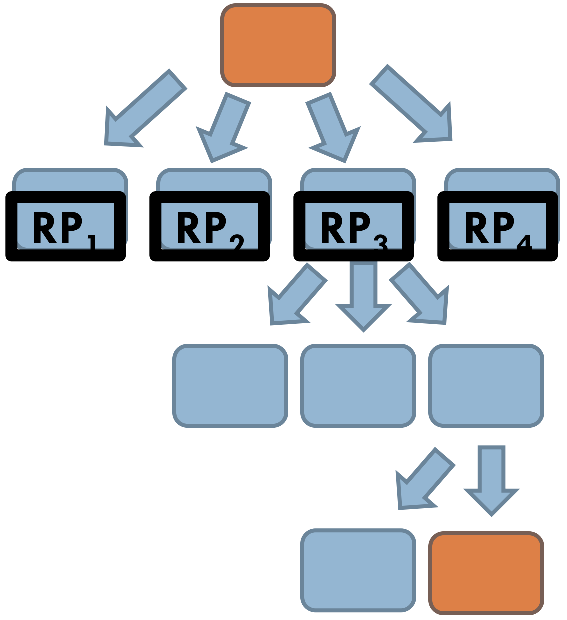
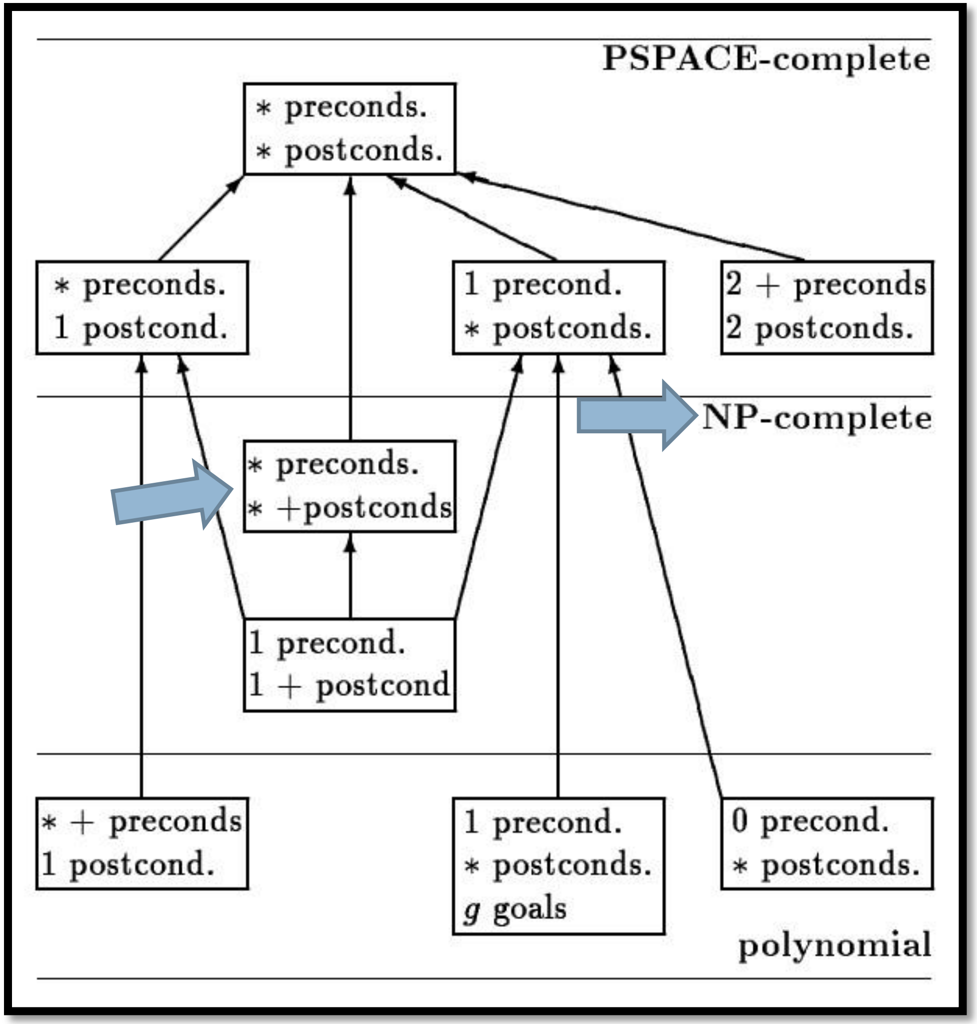


# Relaxed planning task



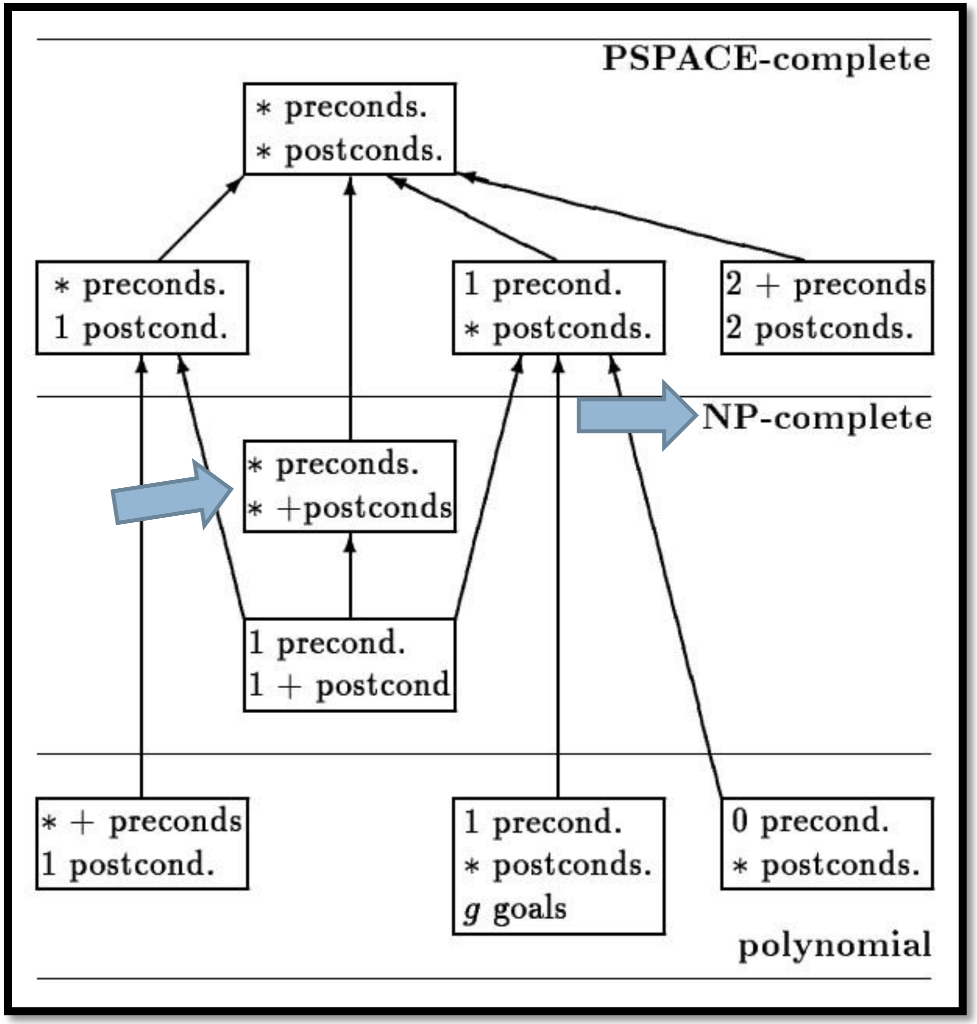
- Planning graph
  - Computing the graph has **polynomial** complexity
- Empty list of negative effects
  - Finding a solution to the relaxed planning task is **NP-complete**
- It's not helping…



# Relaxed planning task



- Planning graph
  - Computing the graph has **polynomial** complexity
- Empty list of negative effects
  - Finding a solution to the relaxed planning task is **NP-complete**
- **We can estimate it!**



# Relaxed planning task: $h_{add}$, $h_{max}$

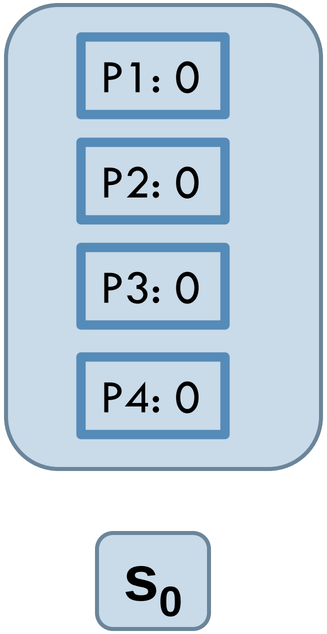


- Build a graph that approximates the cost of achieving literal **p** from state **s** [Bonet, Geffner 2001]
  - Initialize the graph with literals in **s** having cost 0
  - For every action **a** such that **p** is a **positive effect**, add **p** and set the cost of **p** by combining the cost of achieving the preconditions of **a**
  - Build the graph iteratively keeping the minimum cost when a literal **p** re-appears
  - The way the cost is combined for two literals defines the heuristic: $h_{add}$, $h_{max}$

# Relaxed planning task: $h_{add}$, $h_{max}$



- Initialize the graph with literals in s having cost 0



# Relaxed planning task: $h_{add}$, $h_{max}$



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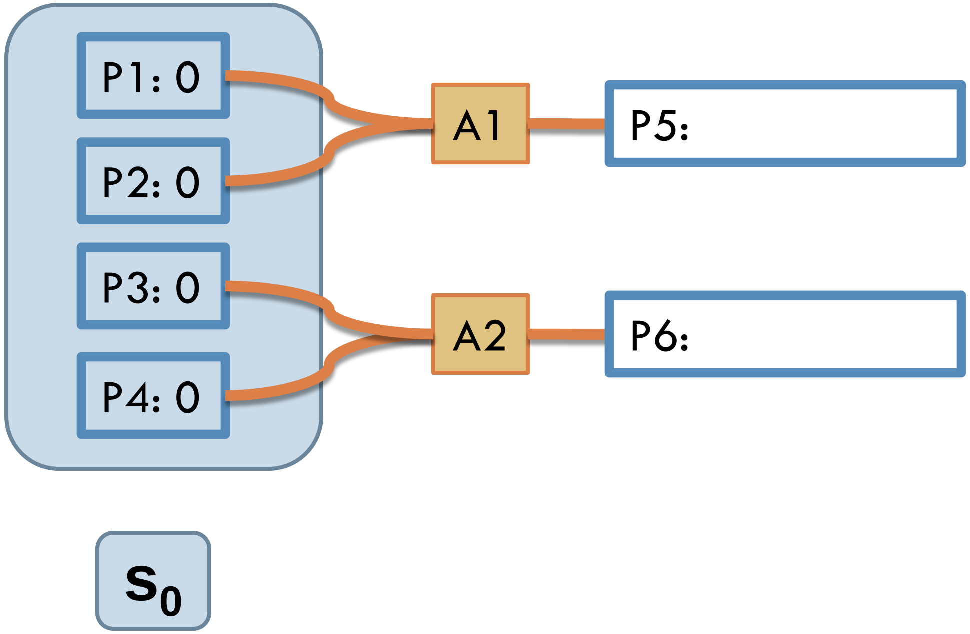

# Relaxed planning task: $h_{add}$, $h_{max}$



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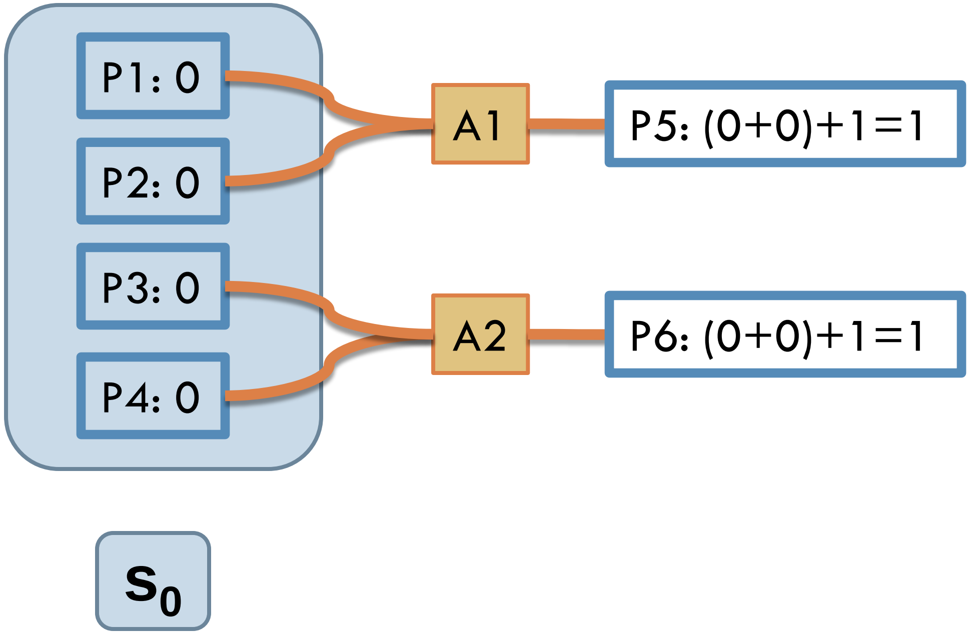


Additive heuristic $h_{add}$: sum the cost of preconditions +1

# Relaxed planning task: $h_{add}$, $h_{max}$



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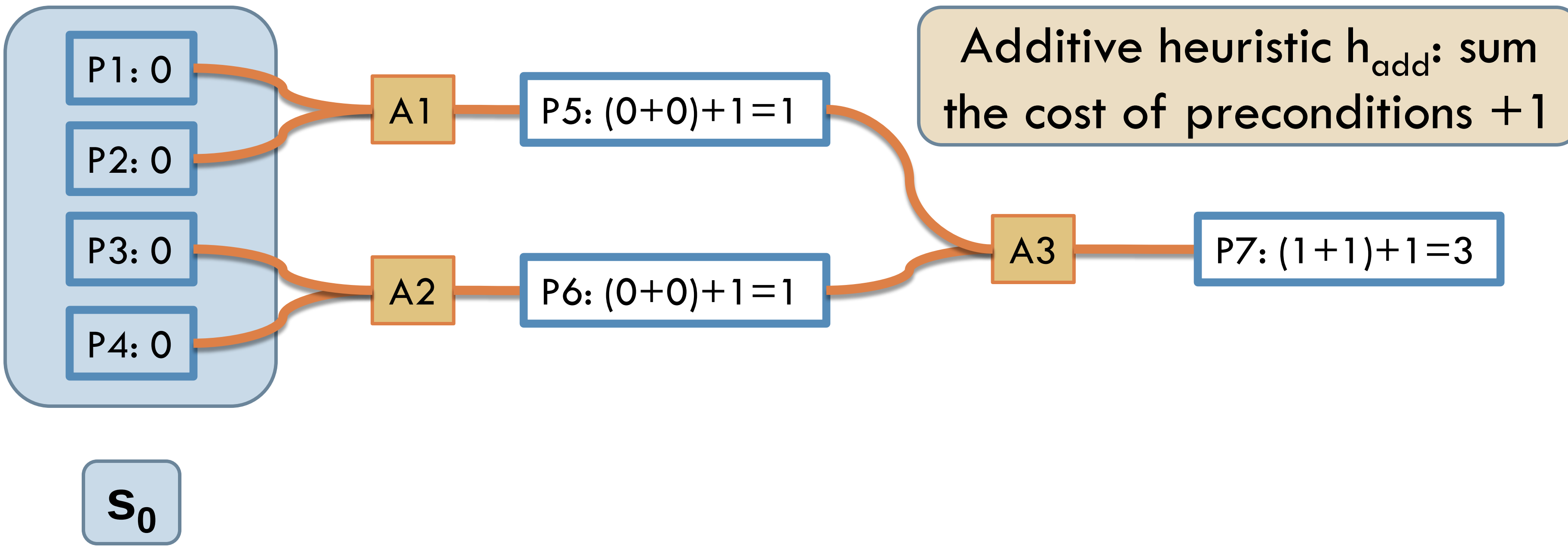
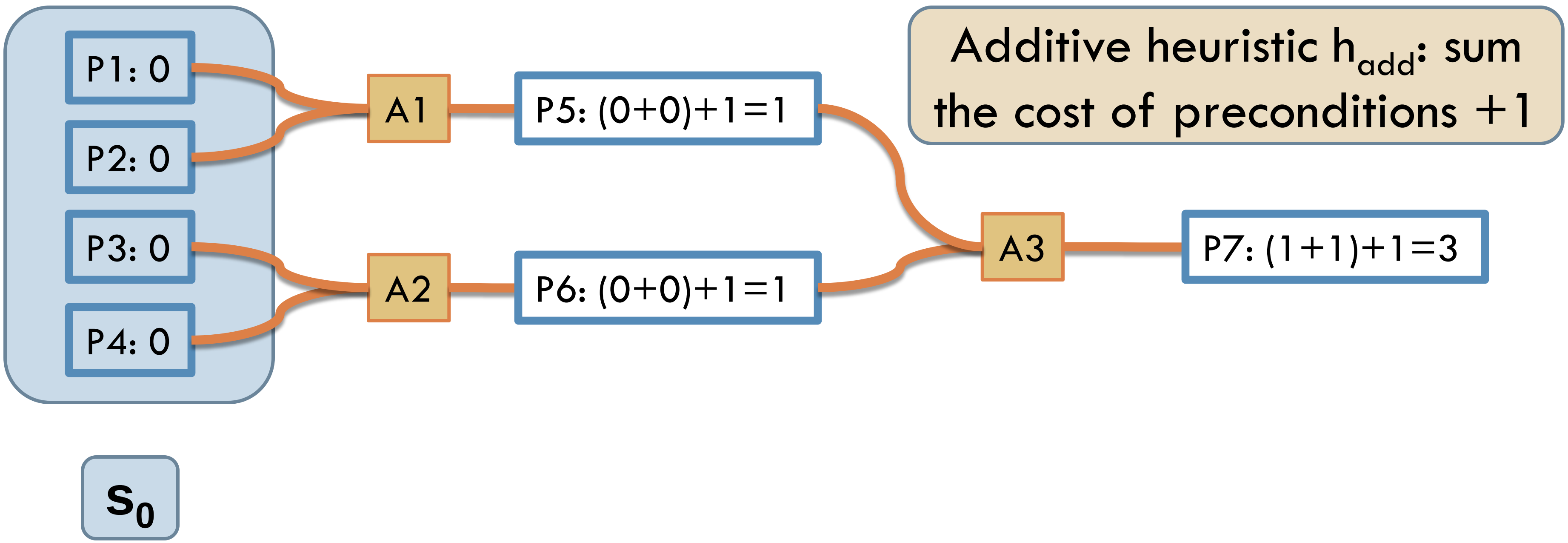


# Relaxed planning task: $h_{add}$, $h_{max}$



- Build the graph iteratively keeping the minimum cost when a literal **p** re-appears
  - (similar to planning graphs, stop when no changes arise)



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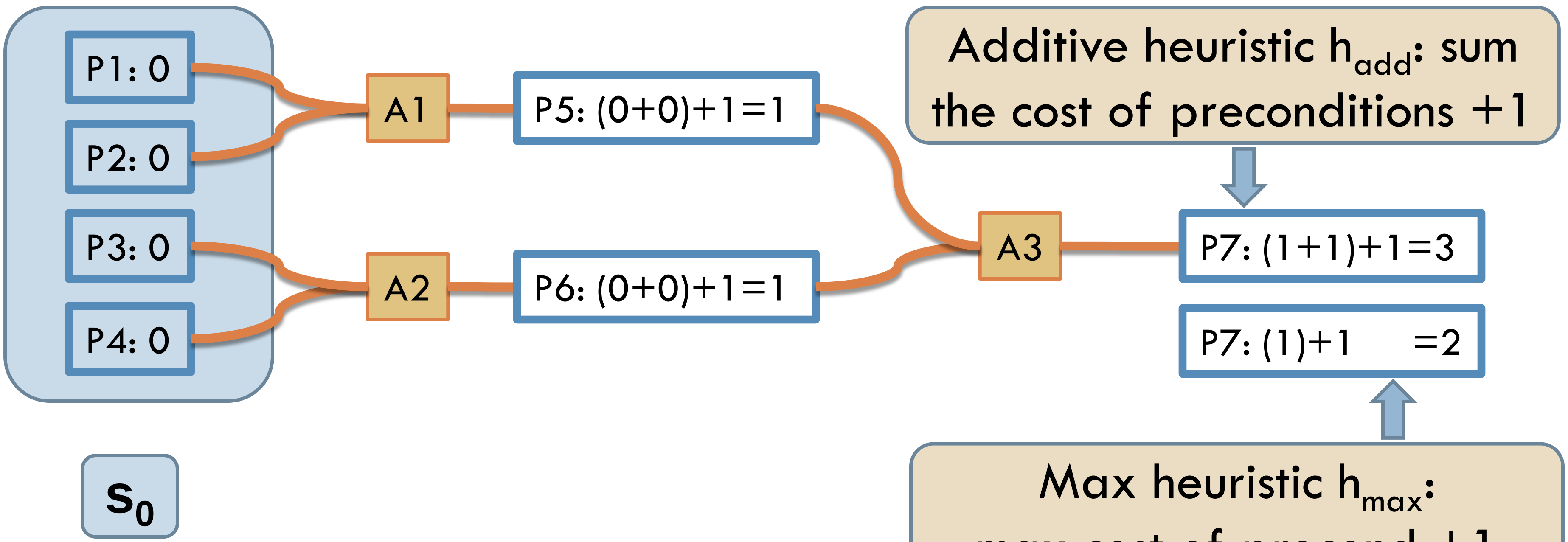
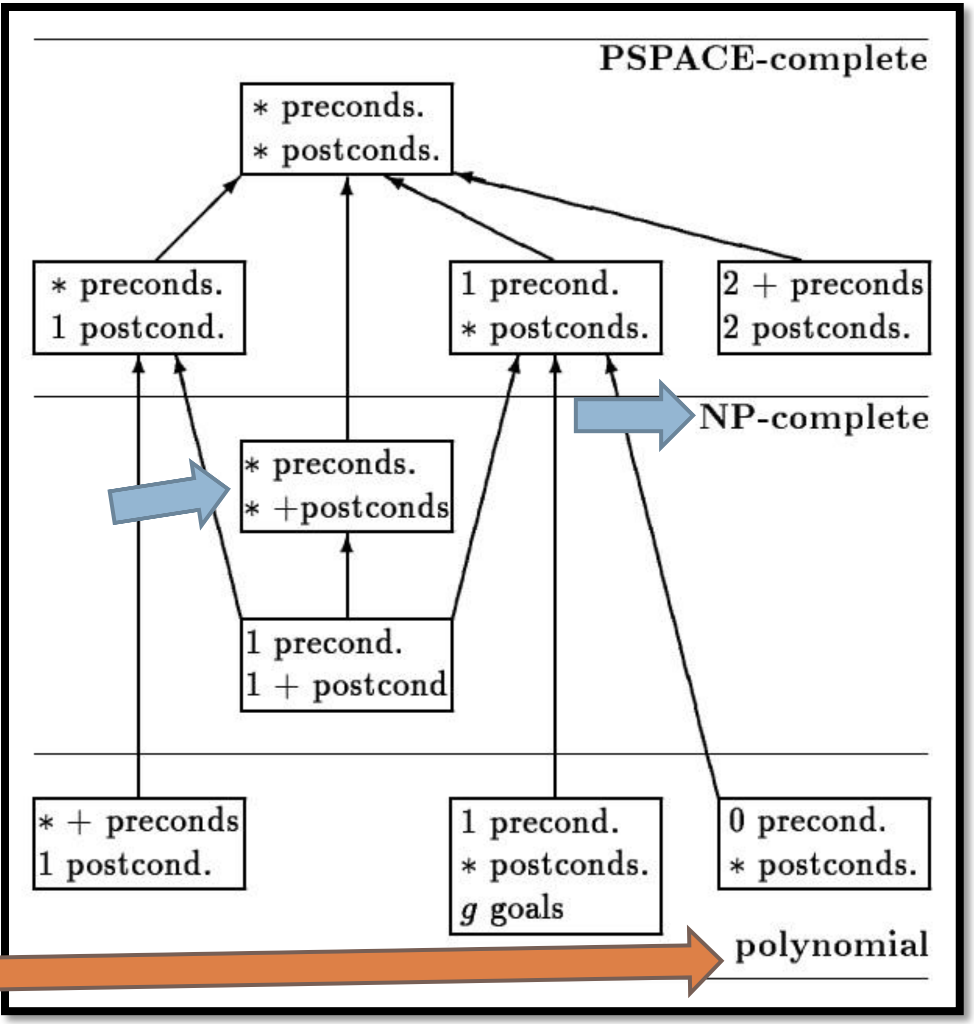


# Relaxed planning task: $h_{add}$, $h_{max}$



- Planning graph
  - Computing the graph has **polynomial** complexity
- Empty list of negative effects
  - Finding a solution to the relaxed planning task is **NP-complete**
- We can estimate it!



# Relaxed planning task: $h_{add}$, $h_{max}$



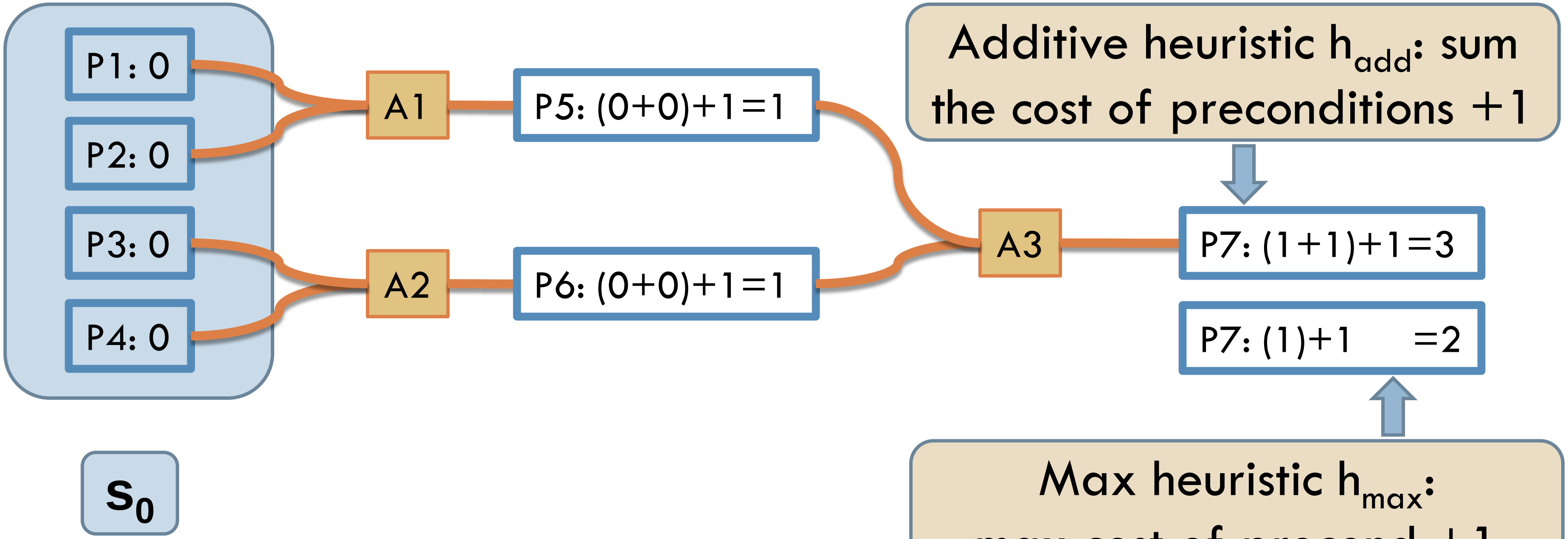
- Additive heuristic $h_{add}$: sum the cost of preconditions
- Max heuristic $h_{max}$: max cost of preconditions

- **Observation 1:** These heuristics assume goal independence, therefore miss useful information

# Relaxed planning task: $h_{add}$, $h_{max}$



- Note: literals appear at most once in this graph; the iteration in which they appear is a lower-bound of the estimated cost



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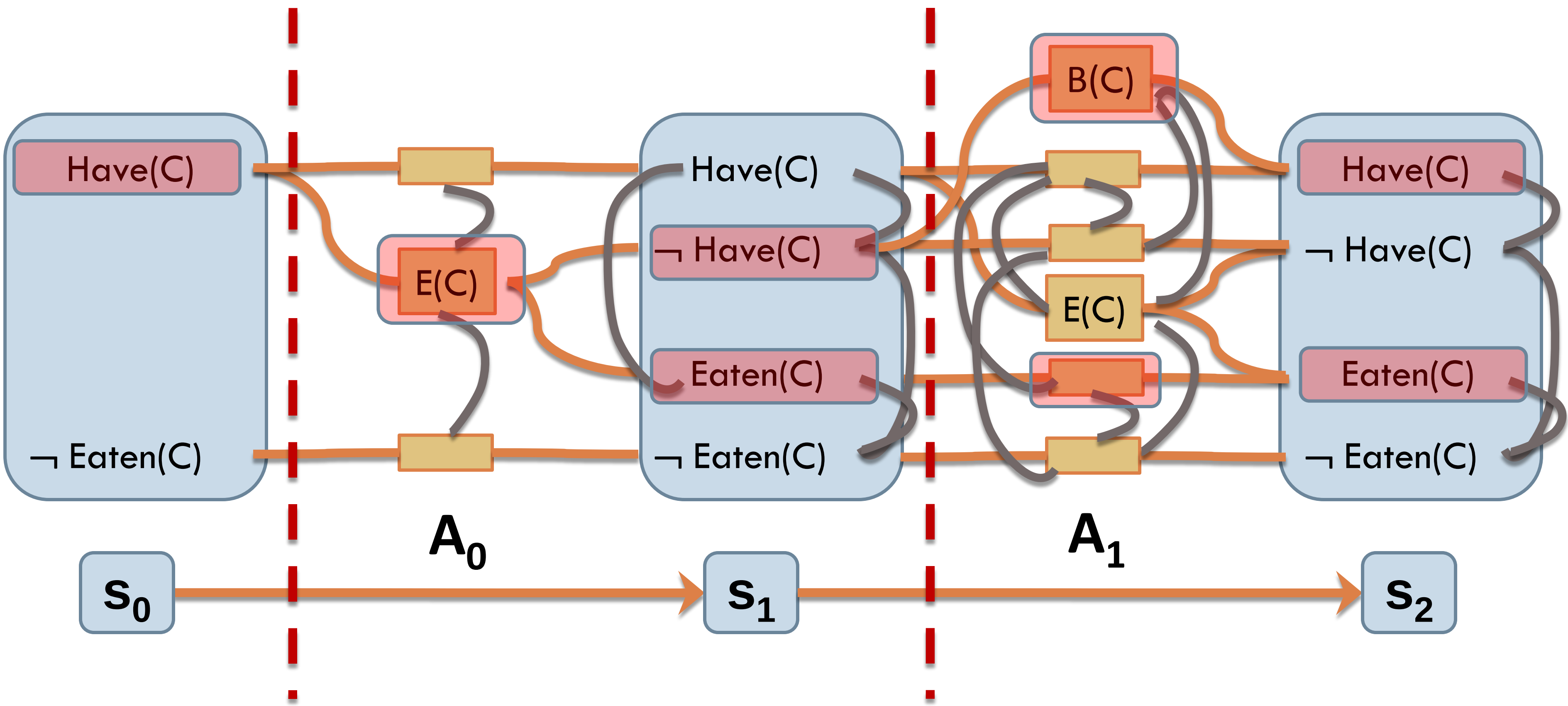
- **Observation 2:** Planning graphs keep track of how actions interact, and look like the graphs we examined

# Planning graphs



- Note: literals are structured in increasingly larger layers which also keep track of how actions interact



# Relaxed planning task: $h_{add}$, $h_{max}$



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- **Observation 2:** Planning graphs keep track of how actions interact, and look like the graphs we examined

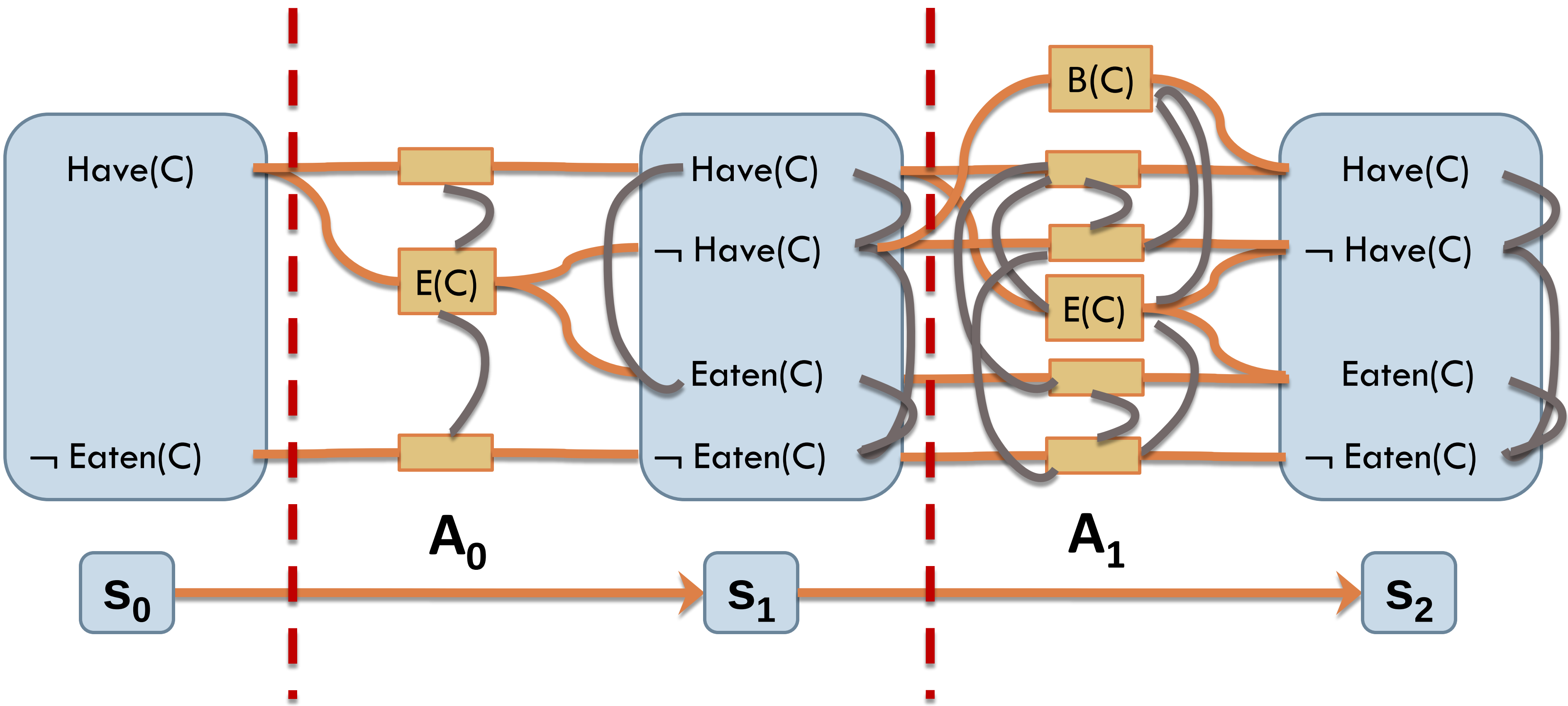
- **FF Heuristic: Let's apply the empty delete list relaxation to planning graphs!**

[Hoffmann, Nebel 2001]

# Relaxed planning task: FF



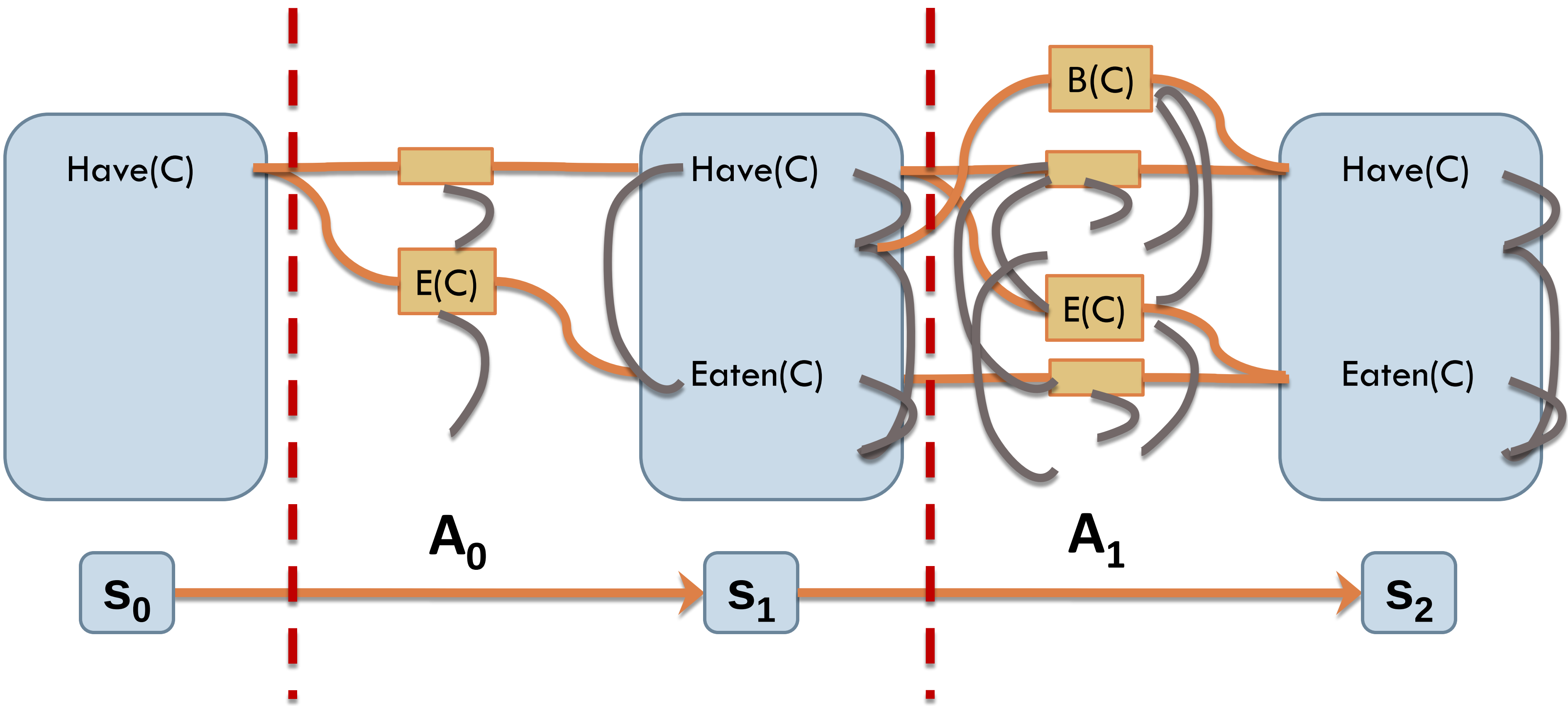
- Assume an empty list of negative effects



# Relaxed planning task: FF



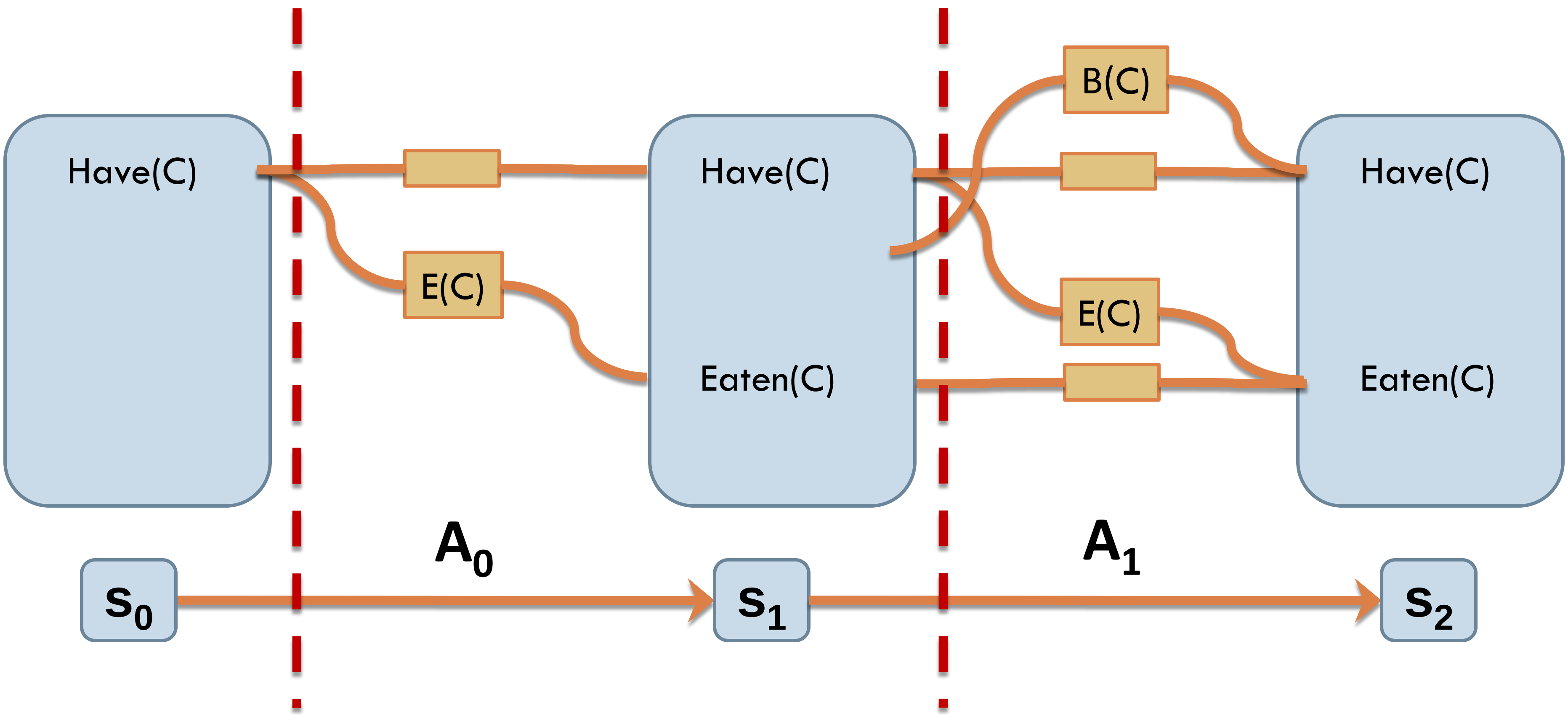
- Assume an empty list of negative effects
- No negative literals



# Relaxed planning task: FF



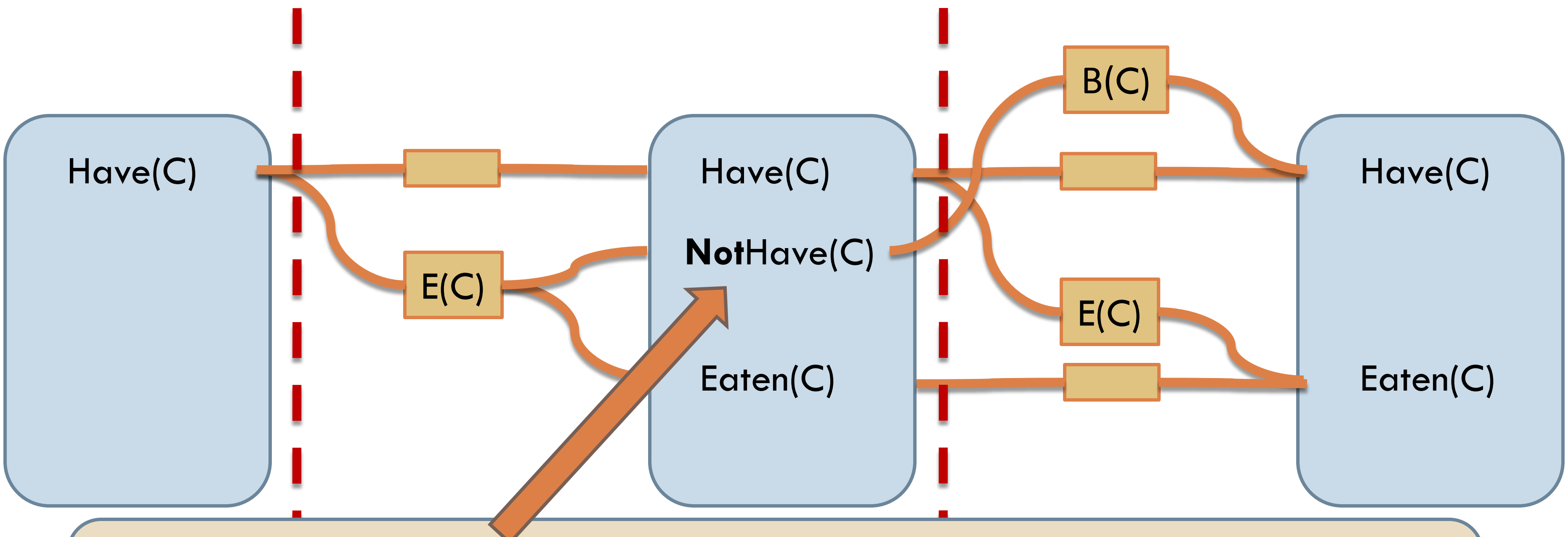
- Assume an empty list of negative effects
- No negative literals → No mutual constraints



# Relaxed planning task: FF



- Extracting a solution has **polynomial** complexity: pick actions for each sub-goal in a single sweep

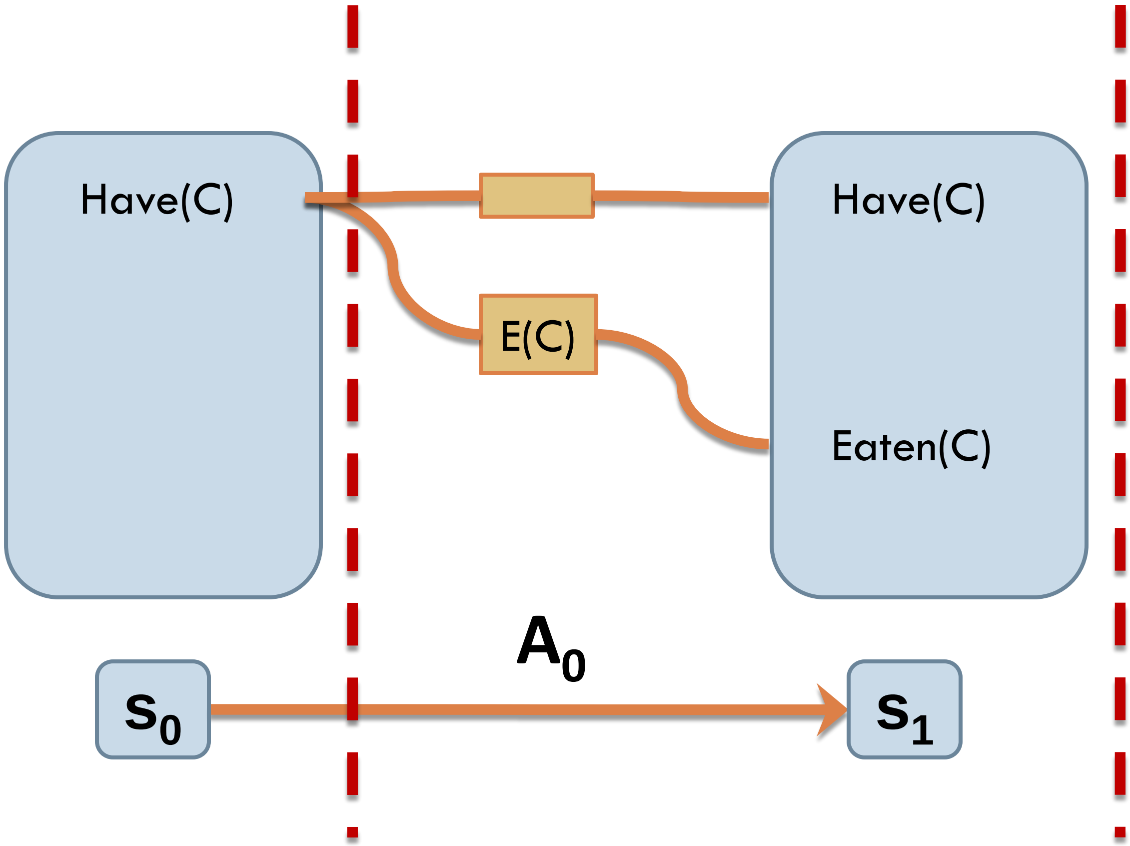



Note: this is actually not a very good example because we have used negative preconditions (did anybody notice? :-)

# Relaxed planning task: FF



- Extracting a solution has **polynomial** complexity: pick actions for each sub-goal in a single sweep




In any case, here we would have stopped at $\mathbf{s_1}$ where we first reach the goal

# Relaxed planning task: $h_{add}$, $h_{max}$, FF, $h^2$



- Additive heuristic $h_{add}$:
  sum the cost of preconditions

- Max heuristic $h_{max}$:
  max cost of preconditions

- FF heuristic:
  exploit positive interaction

**Still one of the best heuristics!**

- $h^2$ heuristic:
  same idea like $h_{max}$ but keep track of **pairs** of literals

# Relaxed planning task: $h_{add}$, $h_{max}$, FF, $h^2$



- Additive heuristic $h_{add}$:
  sum the cost of preconditions +1

  **Not** admissible

- Max heuristic $h_{max}$:
  max cost of preconditions +1

  Admissible

- FF heuristic:
  exploit positive interaction

  **Not** admissible

- $h^2$ heuristic:
  same idea like $h_{max}$ but keep track of **pairs** of literals

  Admissible

# Relaxed planning task: $h_{add}$, $h_{max}$, FF, $h^2$



- Let's see again the performance of the Fast-downward planner in the Sokoban planning problem we examined in Lecture 3

# Using PDDL planners: Sokoban

- search/downward --search "astar(blind())" <output

```
Plan length: 30 step(s).
Plan cost: 30
Initial state h value: 1
Expanded 1372 state(s).
Reopened 0 state(s).
Evaluated 1435 state(s).
Evaluations: 1435
Generated 3560 state(s).
Dead ends: 0 state(s).
Expanded until last jump: 1356 state(s).
Reopened until last jump: 0 state(s).
Evaluated until last jump: 1415 state(s).
Generated until last jump: 3521 state(s).
Search space hash size: 1435
Search space hash bucket count: 1543
Search time: 0s
Total time: 0s
Peak memory: 3036 KB
```

# Using PDDL planners: Sokoban



- search/downward --search "astar(goalcount())"

```
Plan length: 30 step(s).
Plan cost: 30
Initial state h value: 1.
Expanded 1298 state(s).
Reopened 0 state(s).
Evaluated 1365 state(s).
Evaluations: 1365
Generated 3370 state(s).
Dead ends: 0 state(s).
Expanded until last jump: 1295 state(s).
Reopened until last jump: 0 state(s).
Evaluated until last jump: 1361 state(s).
Generated until last jump: 3365 state(s).
Search space hash size: 1365
Search space hash bucket count: 1543
Search time: 0s
Total time: 0s
Peak memory: 3040 KB
```

# Using PDDL planners: Sokoban



- search/downward --search "astar(hmax())" <output

```
Plan length: 30 step(s).
Plan cost: 30
Initial state h value: 5.
Expanded 139 state(s).
Reopened 0 state(s).
Evaluated 176 state(s).
Evaluations: 176
Generated 364 state(s).
Dead ends: 21 state(s).
Expanded until last jump: 133 state(s).
Reopened until last jump: 0 state(s).
Evaluated until last jump: 166 state(s).
Generated until last jump: 351 state(s).
Search space hash size: 176
Search space hash bucket count: 193
Search time: 0s
Total time: 0s
Peak memory: 3052 KB
```

# Using PDDL planners: Sokoban



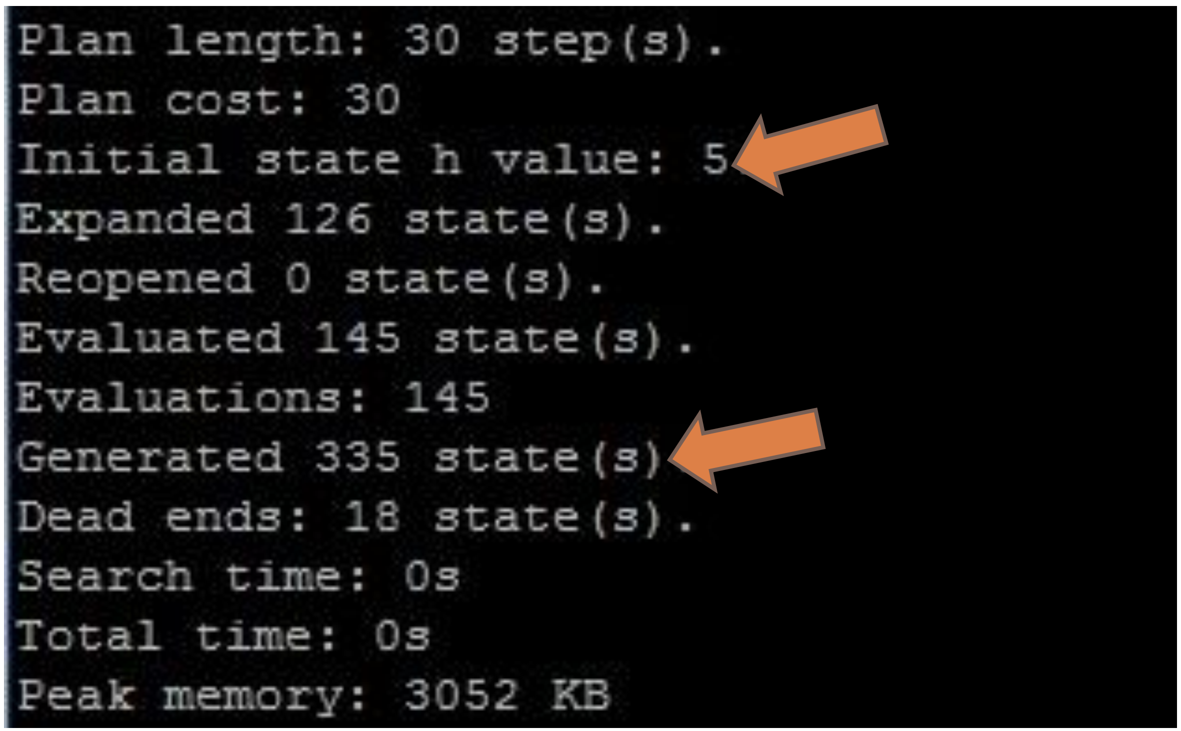
- search/downward --search "astar(add())" <output

```
Plan length: 30 step(s).
Plan cost: 30
Initial state h value: 9
Expanded 93 state(s).
Reopened 0 state(s).
Evaluated 142 state(s).
Evaluations: 142
Generated 253 state(s).
Dead ends: 18 state(s).
Expanded until last jump: 72 state(s).
Reopened until last jump: 0 state(s).
Evaluated until last jump: 103 state(s).
Generated until last jump: 198 state(s).
Search space hash size: 142
Search space hash bucket count: 193
Search time: 0s
Total time: 0s
Peak memory: 3052 KB
```

# Using PDDL planners: Sokoban



- search/downward --search "lazy_greedy(ff())" <output



```
Plan length: 30 step(s).
Plan cost: 30
Initial state h value: 5
Expanded 126 state(s).
Reopened 0 state(s).
Evaluated 145 state(s).
Evaluations: 145
Generated 335 state(s)
Dead ends: 18 state(s).
Search time: 0s
Total time: 0s
Peak memory: 3052 KB
```

# Next lecture



- Lecture 1: Game-inspired competitions for AI research, AI decision making for non-player characters in games
- Lecture 2: STRIPS planning, state-space search
- Lecture 3: Planning Domain Definition Language (PDDL), using an award winning planner to solve Sokoban
- Lecture 4: Planning graphs, domain independent heuristics for STRIPS planning
- Lecture 5: Employing STRIPS planning in games: SimpleFPS, iThinkUnity3D, SmartWorkersRTS
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# Bibliography



- References

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