



DISCOVERING AND LEARNING PREFERRED OPERATORS FOR CLASSICAL PLANNING WITH NEURAL NETWORKS

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1. Introdução
2. Planning
3. Next

Planning has the goal of finding a **sequence of actions** from a **initial state** that satisfy the **goal condition**.

Example: *Classical* Planning

environment:

- **static** vs. dynamic
- **deterministic** vs. non-deterministic vs. stochastic
- **fully observable** vs. partially observable vs. not observable
- **discrete** vs. continuous
- **single-agent** vs. multi-agent

problem solving method:

- problem-specific vs. **general** vs. learning

Definition 1 (A planning problem in STRIPS). $\Pi = \langle F, O, I, G \rangle$
where

- F is a set of boolean variables (*facts*),
- O is a set of *operators* or actions over F , where $\langle \text{Pre}(o), \text{Add}(o), \text{Del}(o) \rangle \subseteq F$,
- $I \subseteq F$ is the *initial state*, and
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Finally, $\pi = a_0, a_1, \dots, a_n$ is called a *plan* for Π where a_i is an applicable action.

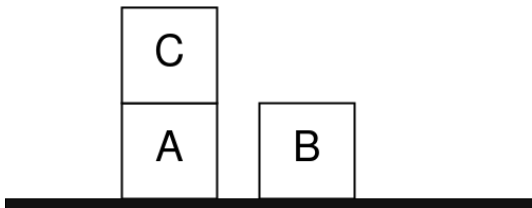


Figura: A task of the Blocksworld domain.

Example: Blocksworld

$$\Pi = \langle F, O, I, G \rangle$$

- $F = \{\text{on}(a,b), \text{on}(a,c), \text{on}(b,a), \text{on}(b,c), \text{on}(c,a), \text{on}(c,b), \text{on-table}(a), \text{on-table}(b), \text{on-table}(c), \text{clear}(a), \text{clear}(b), \text{clear}(c)\}$
- $O = \{\text{move}(a,b,c), \text{move}(a,c,b), \text{move}(b,a,c), \text{move}(b,c,a), \text{move}(c,a,b), \text{move}(c,b,a), \text{to-table}(a,b), \text{to-table}(a,c), \text{to-table}(b,a), \text{to-table}(b,c), \text{to-table}(c,a), \text{to-table}(c,b), \text{from-table}(a,b), \text{from-table}(a,c), \text{from-table}(b,a), \text{from-table}(b,c), \text{from-table}(c,a), \text{from-table}(c,b)\}$
- $I = \{\text{on}(c,a), \text{on-table}(a), \text{on-table}(b), \text{clear}(c), \text{clear}(b)\}$
- $G = \{\text{on}(a,b), \text{on}(b,c)\}$

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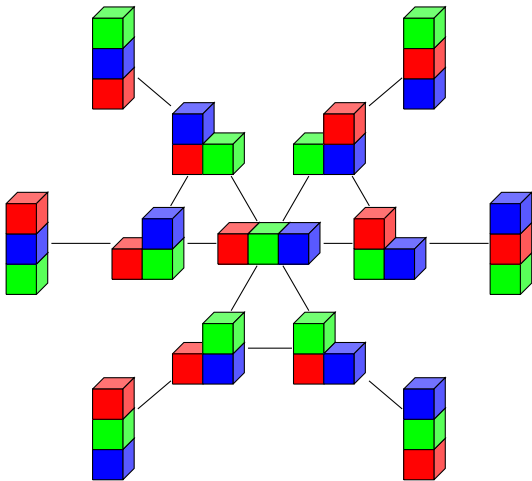
- *move*: move a block from one block to another.
 - $\text{Pre}(\text{move}(a,b,c)) = \{\text{on}(a,b), \text{clear}(a), \text{clear}(c)\}$
 - $\text{Add}(\text{move}(a,b,c)) = \{\text{on}(a,c), \text{clear}(b)\}$
 - $\text{Del}(\text{move}(a,b,c)) = \{\text{on}(a,b), \text{clear}(c)\}$
 - From the initial state, is this action applicable?
- *to-table*: move a block from a block to the table.
- *from-table*: move a block from the table to a block.

2

PLANNING

STATE SPACE OF BLOCKSWORLD WITH 3 BLOCKS

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PREFERRED OPERATORS



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 - Etc.
- We have answers to these questions and, to the best of our knowledge, the **best coverage results with a learned heuristic in a model-free setting.**