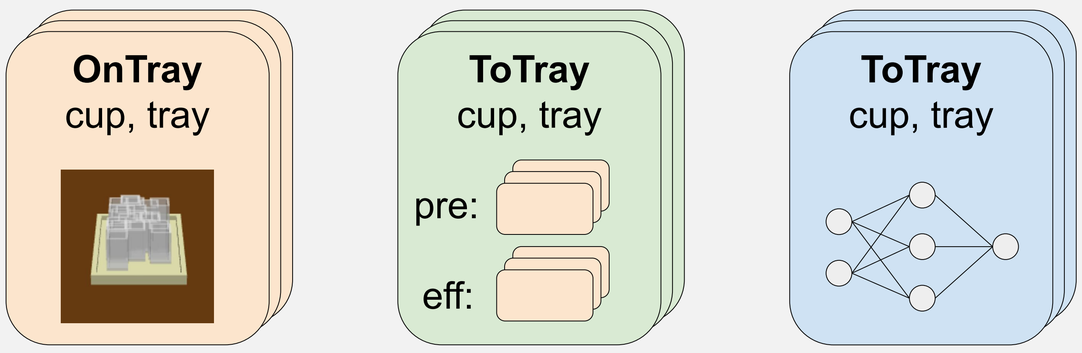
Neuro-Symbolic Imitation Learning:
Discovering Symbolic Abstractions for Skill Learning

Website

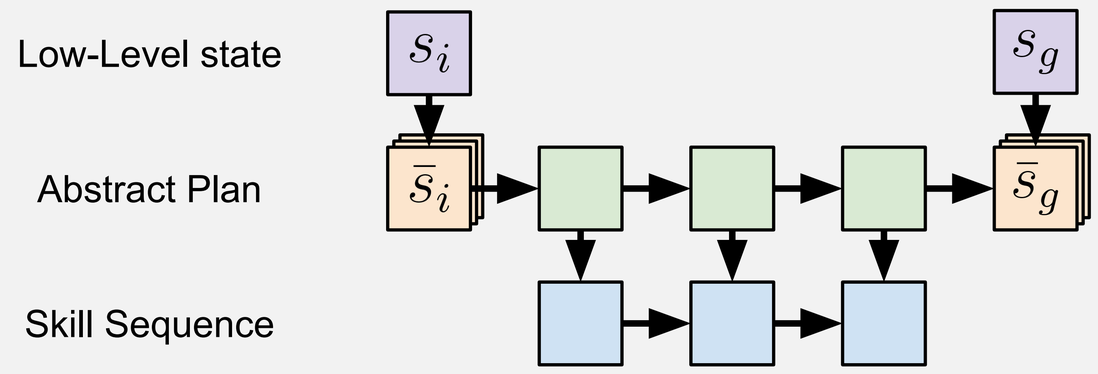
Most imitation learning approaches are limited to learning isolated skills. However, to apply robots in our everyday life, they must not only learn individual skills but also how to sequence them to solve multi-step tasks. To address this, we **propose a neuro-symbolic imitation learning framework** that **learns a symbolic representation** for abstract planning and **neural skills** for refining abstract plans into actionable commands.

Components



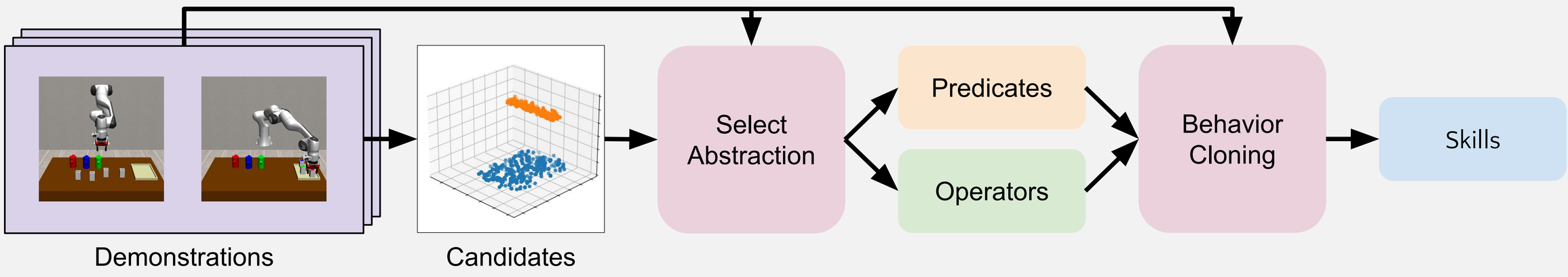
Predicates abstract the state-space, **operators** define an abstract transition model and **skills** execute abstract plans.

Execution



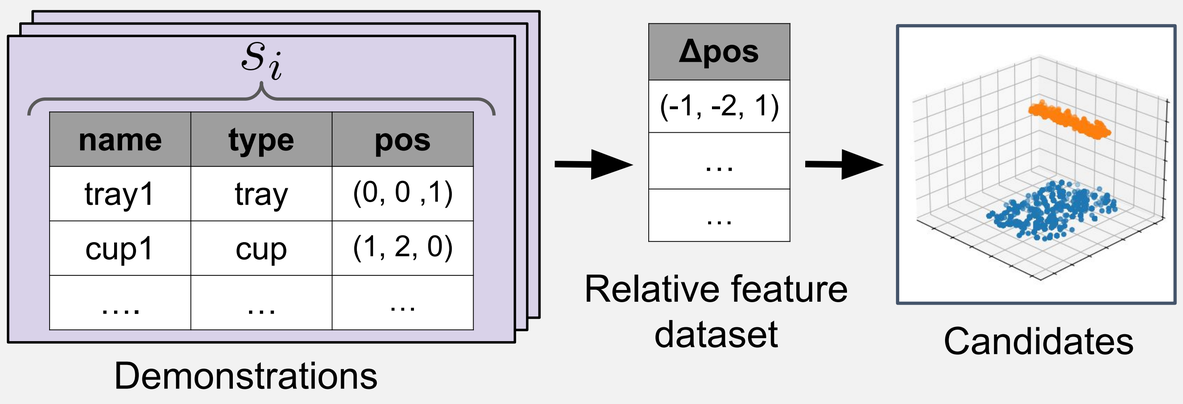
We first compute an **abstract plan** using classical planning algorithms. Subsequently, we execute the corresponding **skill sequence**.

Overview



We first **learn** a **symbolic representation** from **task demonstrations**. Following we utilize these symbols to learn **skills** using **behavior cloning**.

Candidate Generation



We generate **candidate predicates** by **clustering relative features** observed in the demonstrations.

Select Abstraction

Maximize the number of segments.

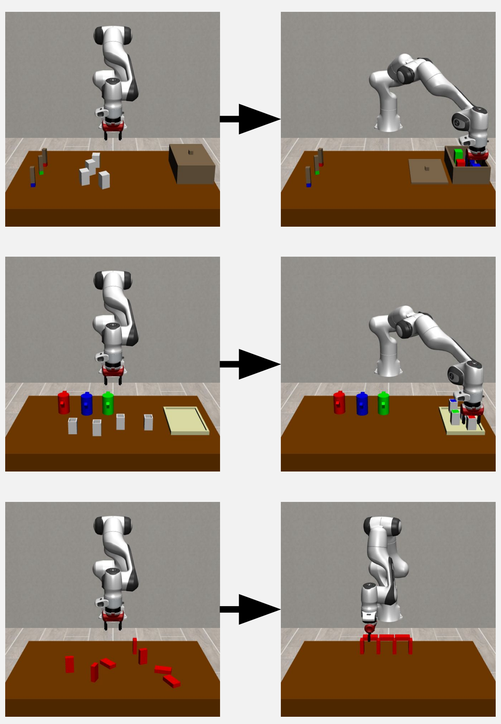
Minimize the number of operators.

$$\max_{\mathcal{P} \subset \mathcal{C}} \sum_{\boldsymbol{\tau} \in \mathcal{D}} |\psi(\mathcal{P}, \boldsymbol{\tau})| - \alpha |\Sigma(\mathcal{P}, \mathcal{D})|$$

$$\text{s.t. } |\psi(\mathcal{P}, \boldsymbol{\tau})| = |\text{plan}(\mathcal{P}, \Sigma, \boldsymbol{\tau}_0, \boldsymbol{\tau}_N)| \; \forall \boldsymbol{\tau} \in \mathcal{D} \quad ,$$

Assumption: Abstract plans in the demonstrations are optimal.

Tasks

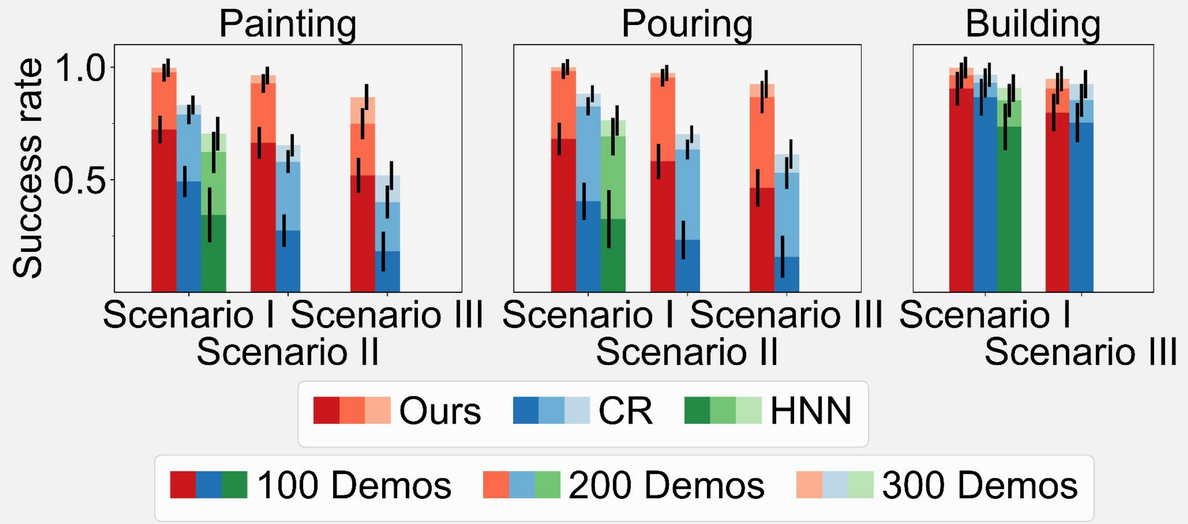


Painting: The robot's task is to paint the blocks and subsequently place them into the box.

Pouring: The robot's task is to pour tea into the cups and afterwards place them on the tray.

Building: The robot's task is to construct a bridge by assembling the building blocks.

Results



Scenario I: unseen initial poses
Scenario II: I + unseen goals
Scenario III: I + II + more objects

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