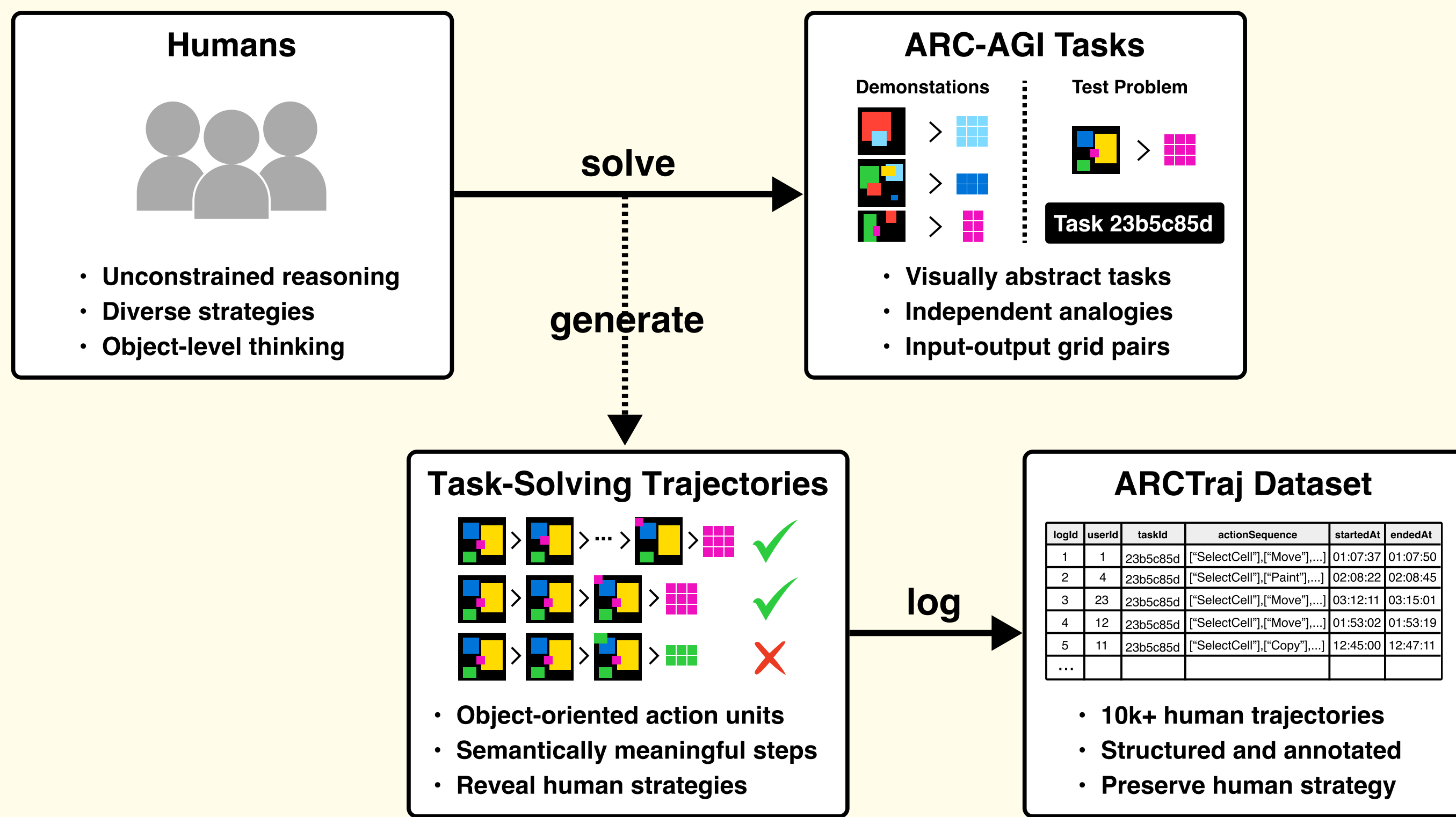


TL;DR Human actions may deviate, but intentions can still be *inferred*.

ARCTraj: More Than Action Logs

ARC Tasks + Human Solution → ARCTraj



$\tau := (s_0, a_0, s_1, \dots, a_{l-1}, s_l) \in \text{ARCTraj}$

- τ is a sequence of states and actions
- τ is logged from humans solving ARC tasks
- Rich supervision, but intentions not explicit in τ

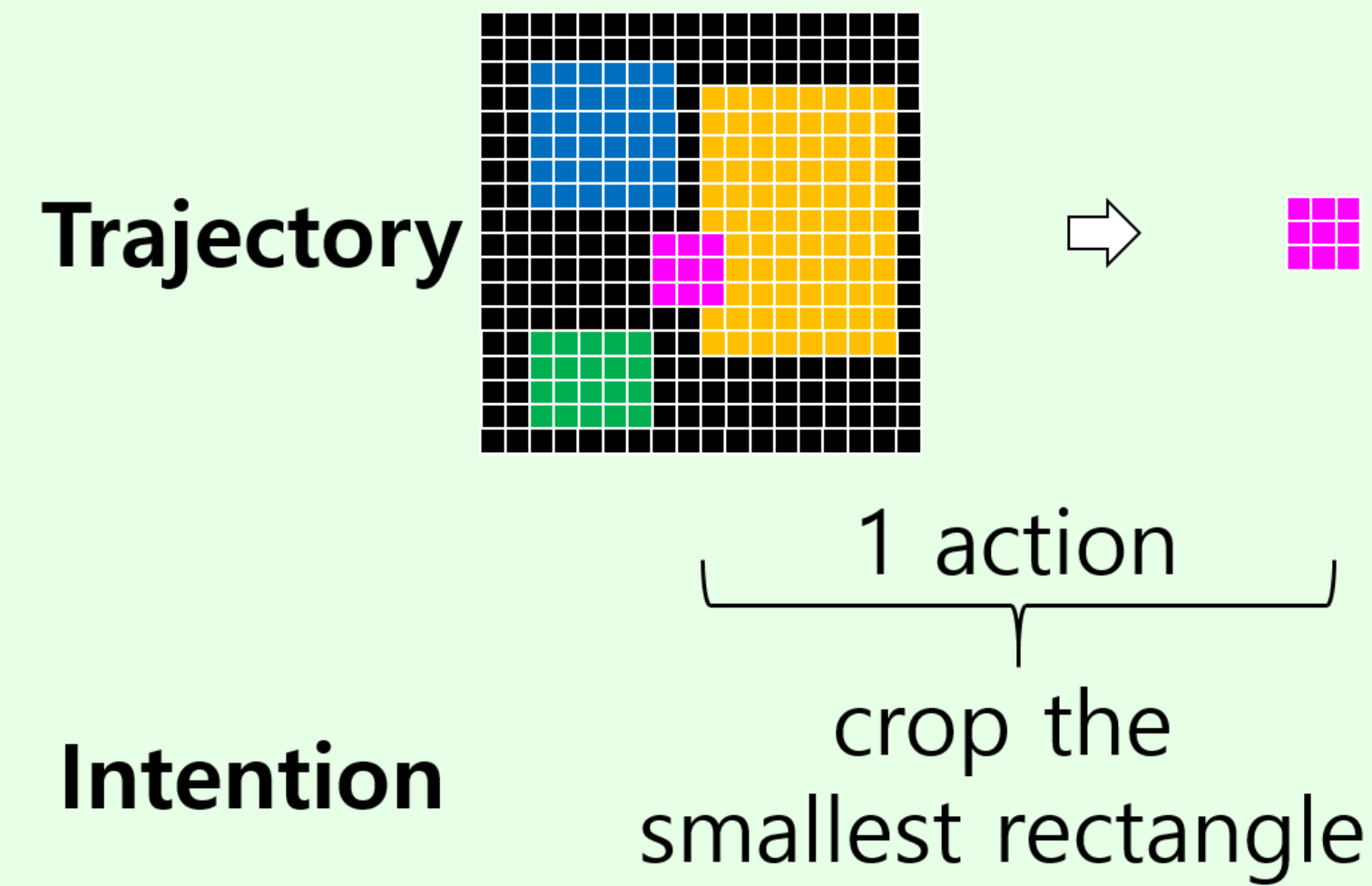
Why Intention Estimation Matter

→ Actions → (Diverge)
 → Intentions → (Stable)

- Inconsistent actions may reflect consistent goals
- Inferring intent patterns aids understanding

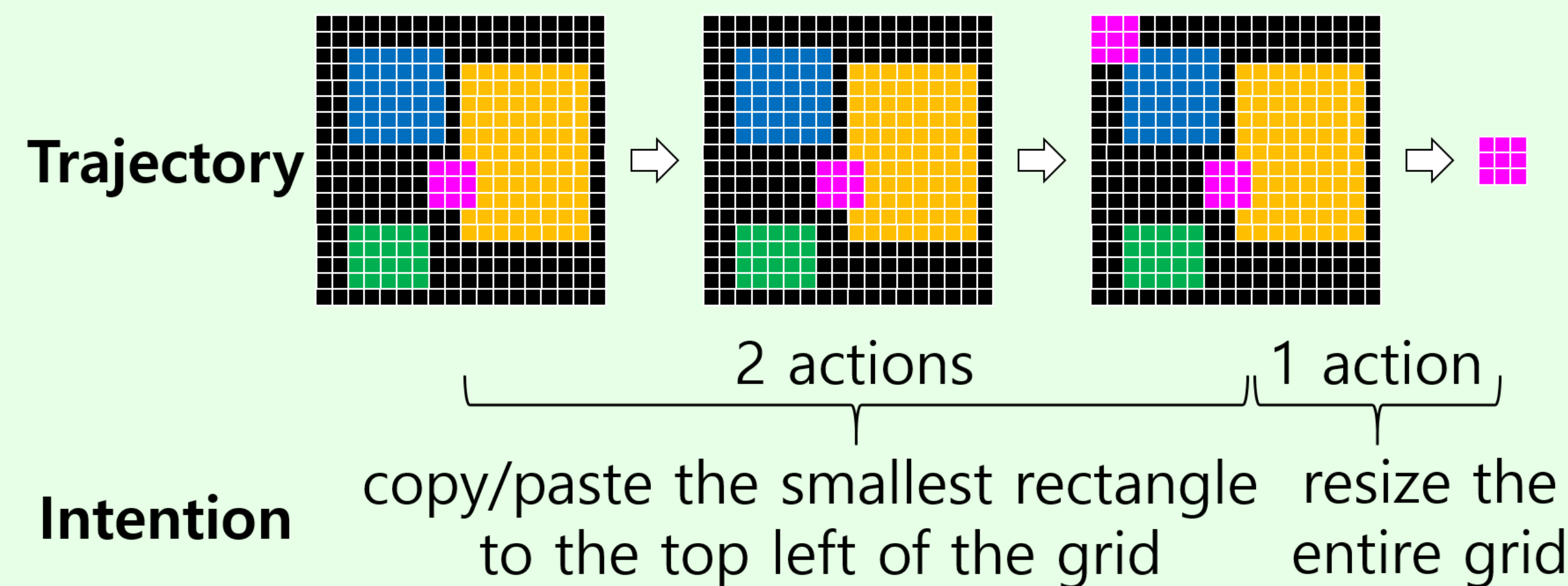
Observed Actions \nrightarrow User Intentions

Intention \equiv Action

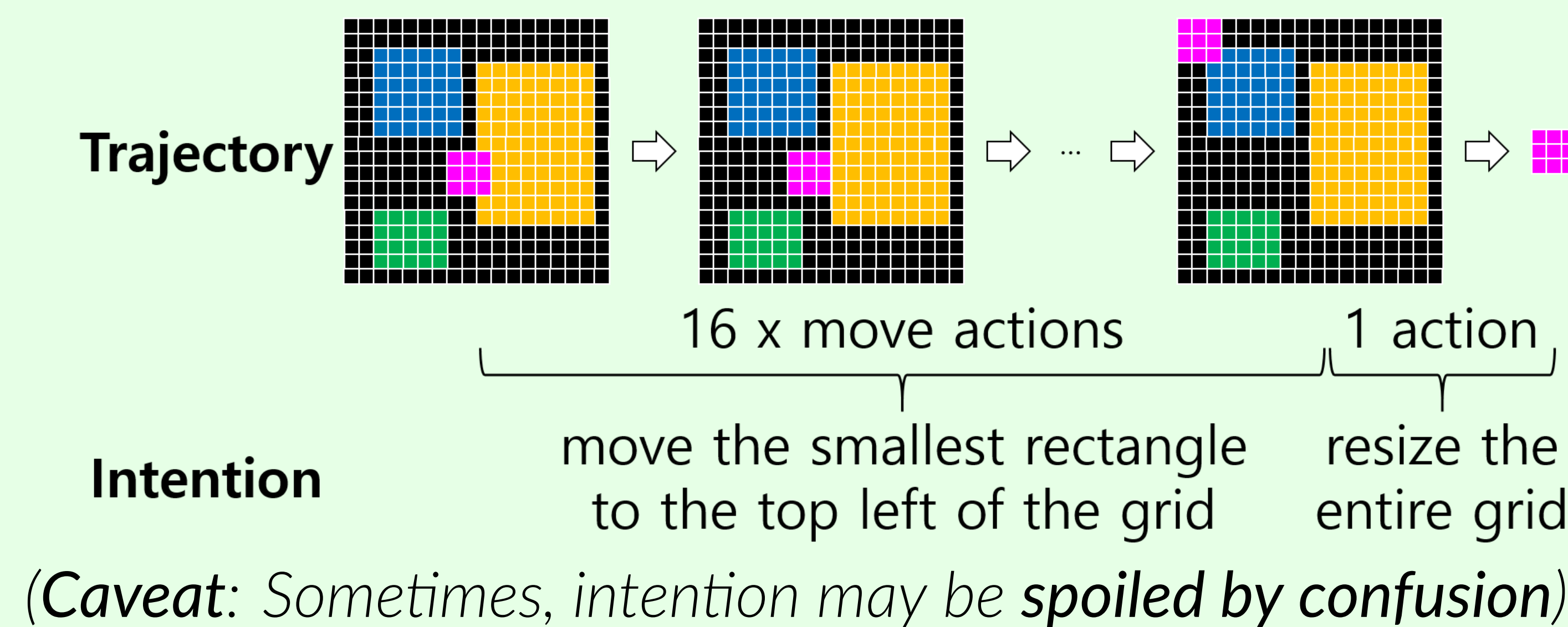


Intention \equiv Action Sequence

Case 1: Tool Limitation



Case 2: User Unfamiliarity

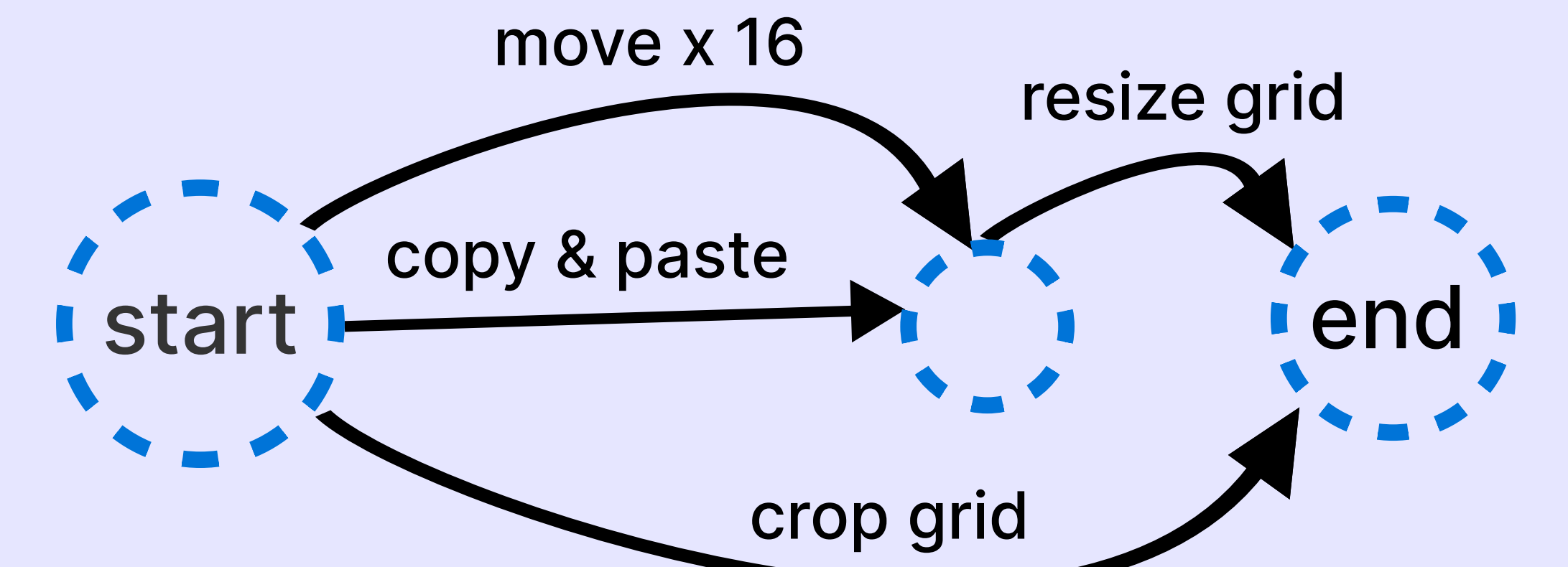


Same Intention, Diverging Paths

$\tau_i \neq \tau_j$, but possibly $\mathcal{I}(\tau_i) = \mathcal{I}(\tau_j)$
 (An intention can be represented through various trajectories)

Inferring Intentions from ARCTraj

Step 1: Extracting Popular States (\mathcal{P})



- \mathcal{P} are extracted intra-task by frequency

Step 2: Segmenting Trajectories (τ)

$$\tau \rightarrow \tau_1 \circ \tau_2 \circ \dots \circ \tau_n$$

where $\tau_i = (s_i^{\text{in}}, \dots, s_i^{\text{out}})$, $s_i^{\text{in}}, s_i^{\text{out}} \in \mathcal{P}$

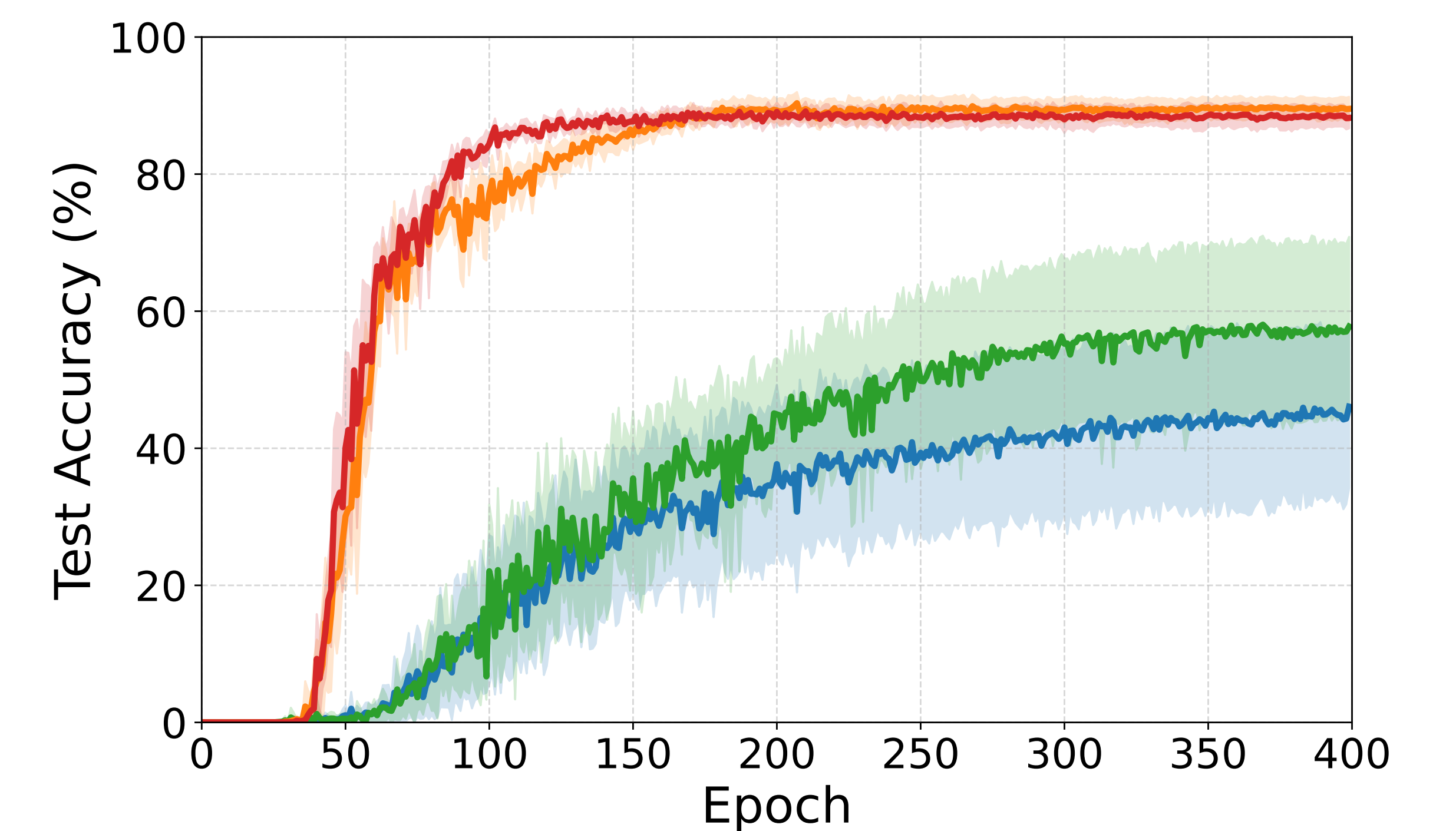
- Each τ is split into segments (τ_i)
- Splits occur at popular state pairs ($s_i^{\text{in}}, s_i^{\text{out}}$)

Step 3: Representing Intention ($\mathcal{I}(\tau_i)$)

$$\mathcal{I}(\tau_i) := (s_i^{\text{in}}, s_i^{\text{out}})$$

- Segment is interpreted as a distinct intent transition

Effect of Intention-Guided Learning



- Faster convergence (● > ●), Better accuracy (● > ●)
- Human intent improves both efficiency & generalization