

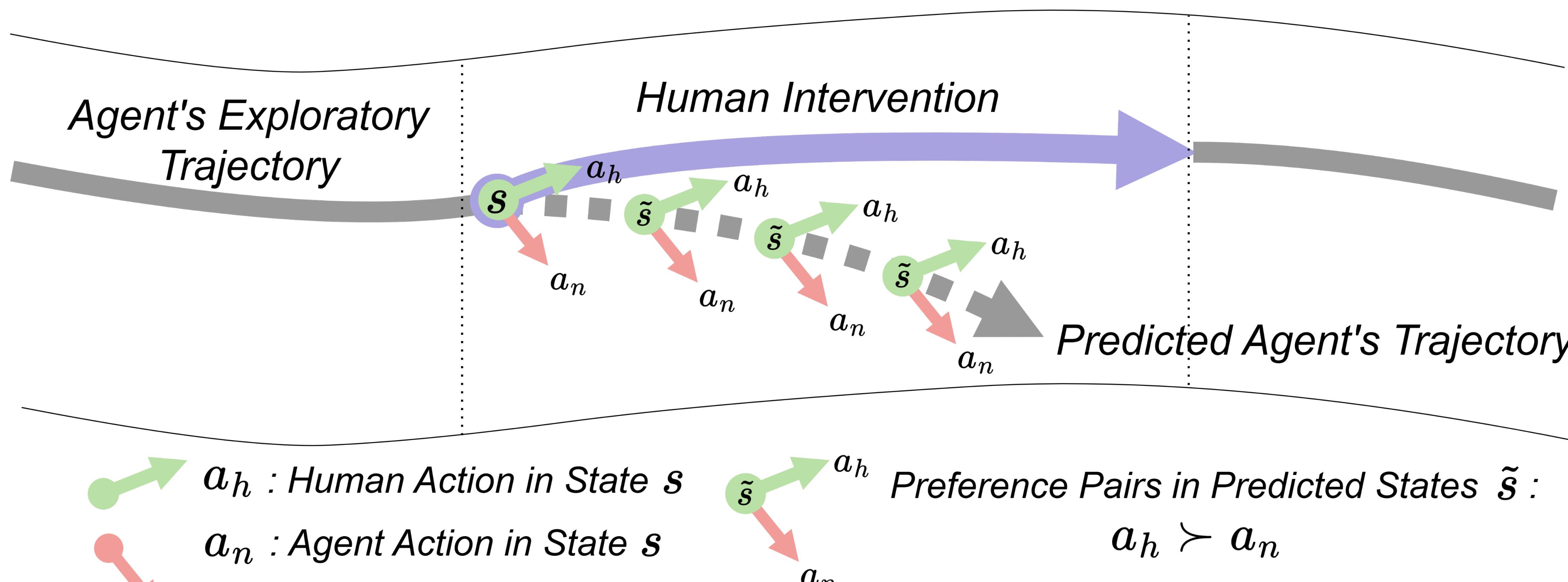


Predictive Preference Learning: Motivation

- Traditional IL: **1 Intervention = 1 BC Data**



- Our PPL: **1 Intervention = Multiple Preference Pairs**



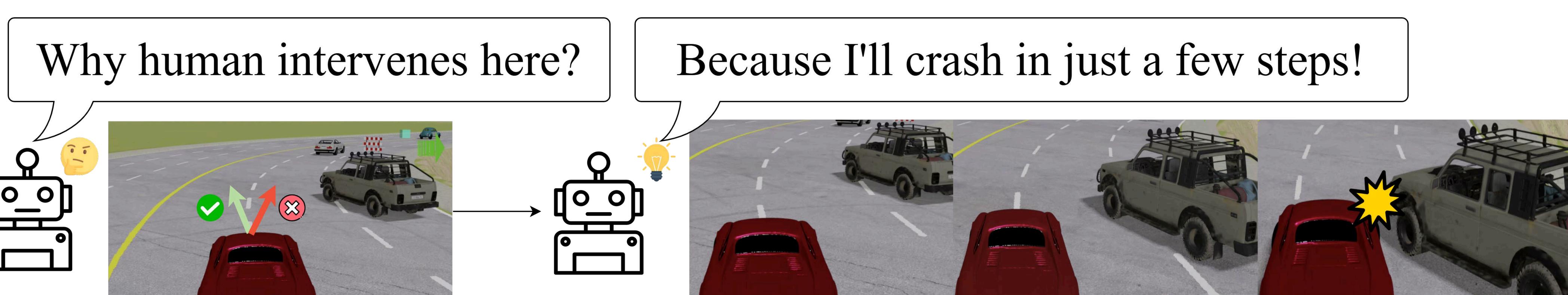
- Learn driving in **12 min** with only **2.9K** human data!



Key Idea: Online RLHF in Predicted Future States

- Incorporate human expertise in predicting future failures
- Construct multiple preference pairs for each intervention
- Online preference learning in future rollouts with DPO loss

1. Human Interventions Reveal Imminent Failures



2. Interventions Imply Preferences in Future Rollouts



3. DPO-Like Preference Loss Boosts Training Efficiency

Traditional IL: BC Loss

$$\mathcal{L}_{BC}(\pi) = - \mathbb{E}_{(s, a_+)} [\log \pi(a_+ | s)]$$

Ours: Contrastive Preference Loss

$$\mathcal{L}_{pref}(\pi) = \mathbb{E}_{(\tilde{s}, a^+, a^-)} \left[\log \sigma \left(\beta \log \frac{\pi(a^+ | \tilde{s})}{\pi(a^- | \tilde{s})} \right) \right]$$

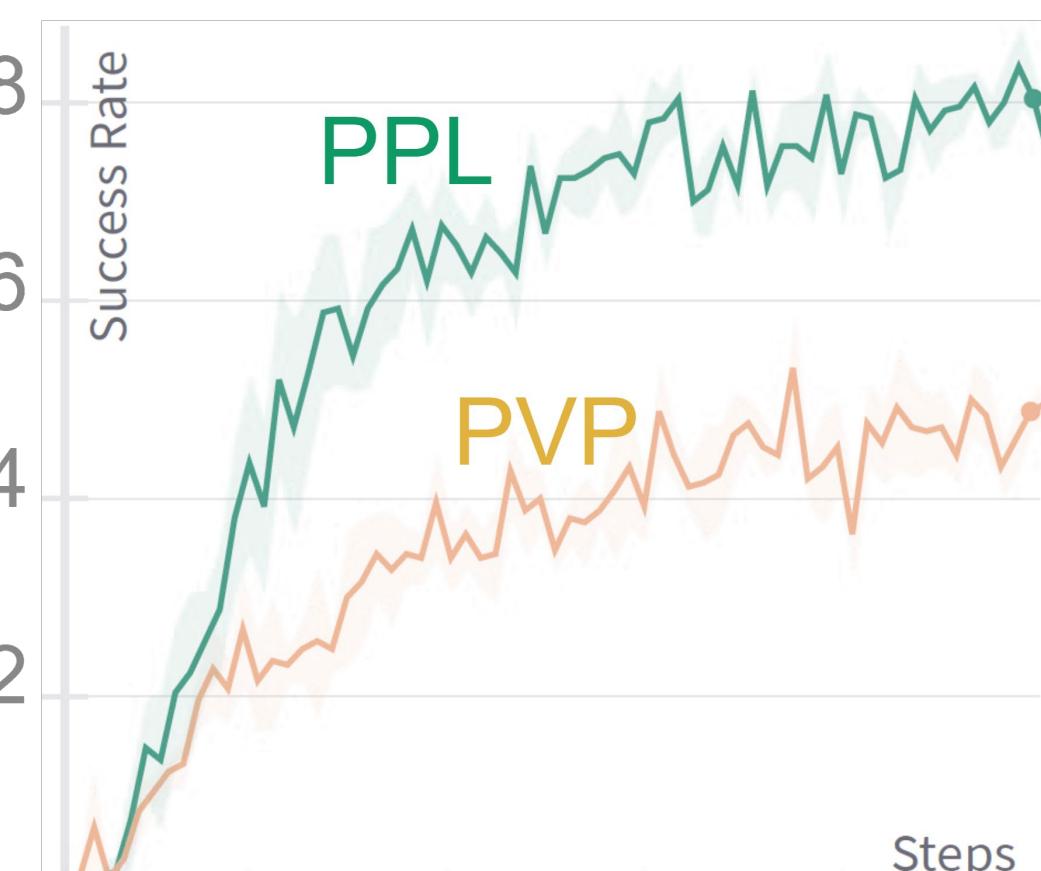
One intervention teaches multiple future states!

Real-Human Experiments: PPL Achieves **2X Sample Efficiency Improvement** Across Multiple Tasks

Driving



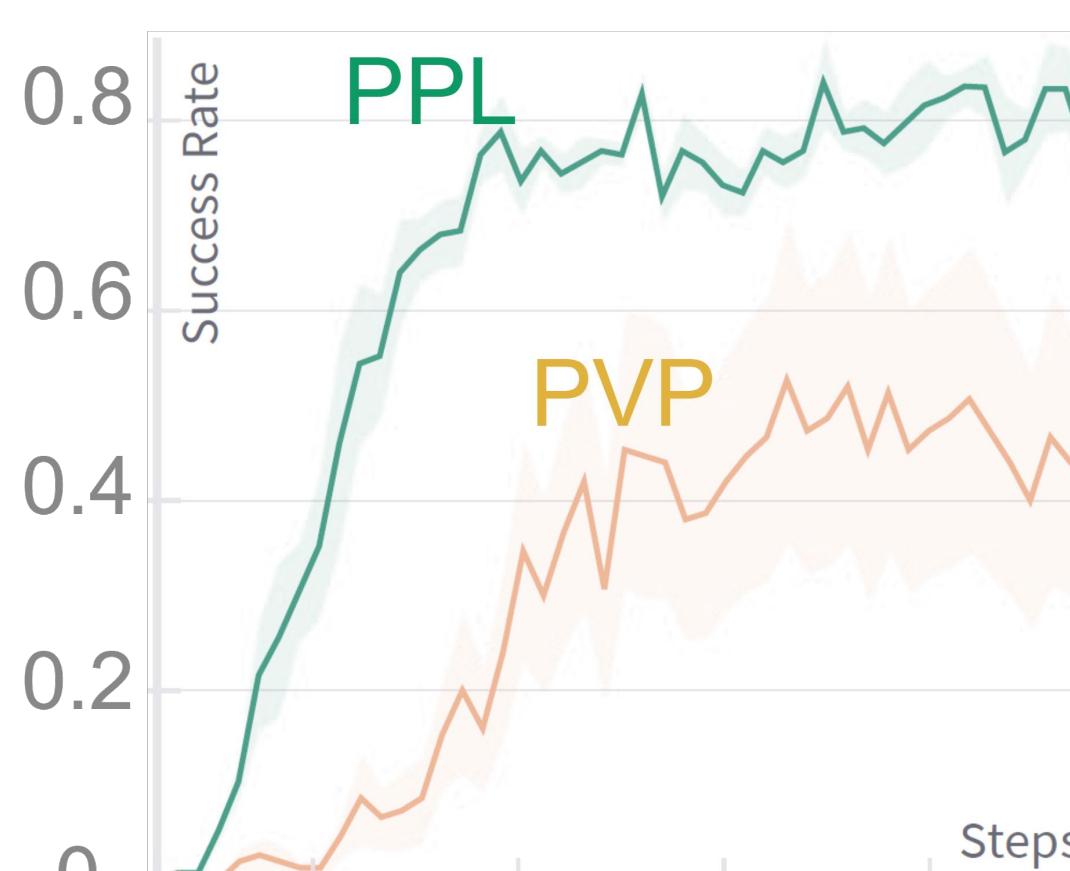
Test Success Rate



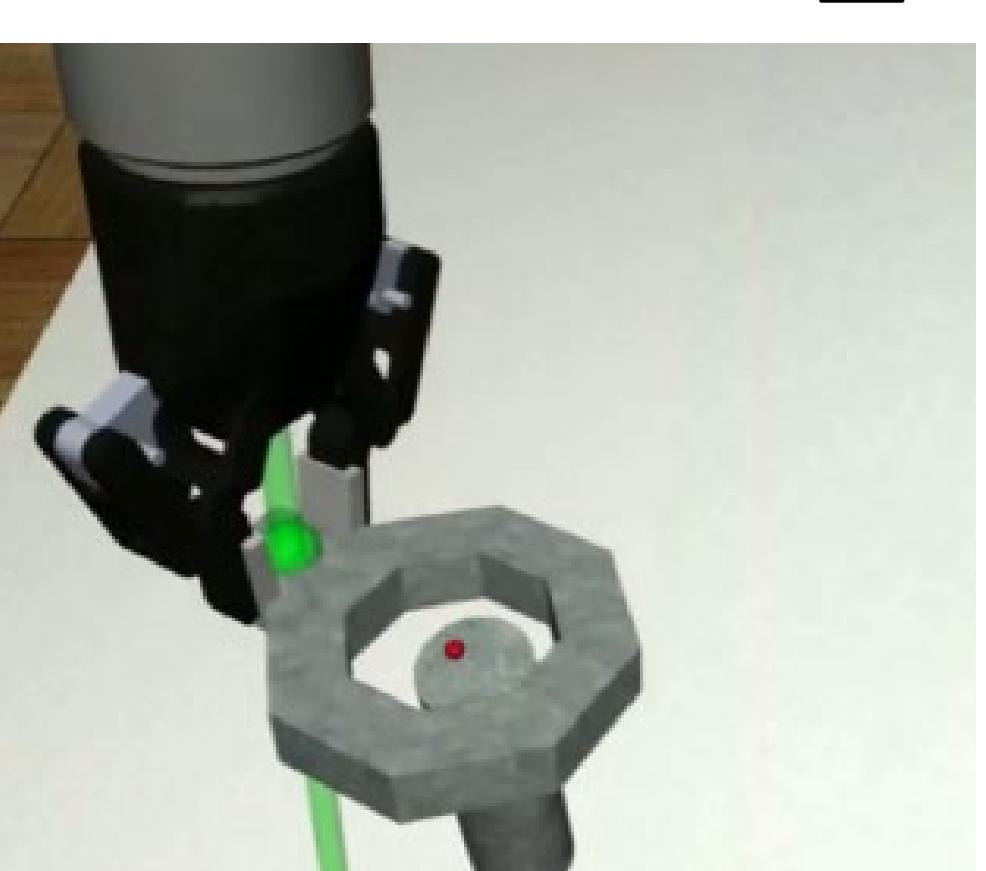
Wiping



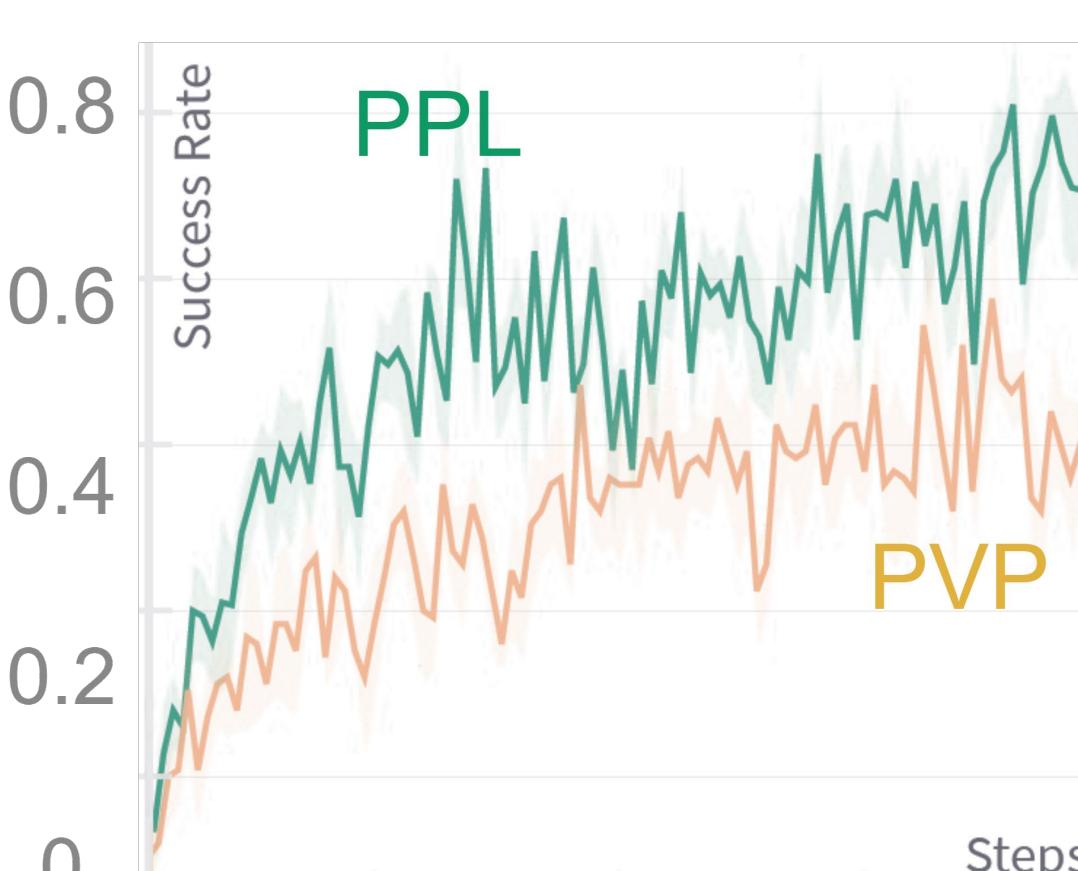
Test Success Rate



Peg Insertion



Test Success Rate



MetaDrive Statistics (10K Total Data)

Methods	Training	Testing		
		Human Data Usage	Success Rate	Episodic Return
Human Expert	-	0.95	349.2	0.98
PVP	4.9K	0.46	267.3	0.71
Thrifty-Dagger	3.2K	0.45	221.5	0.62
PPL (Ours)	2.9K	0.76	324.8	0.90