



Diffusion Rewards Guided Adversarial Imitation Learning

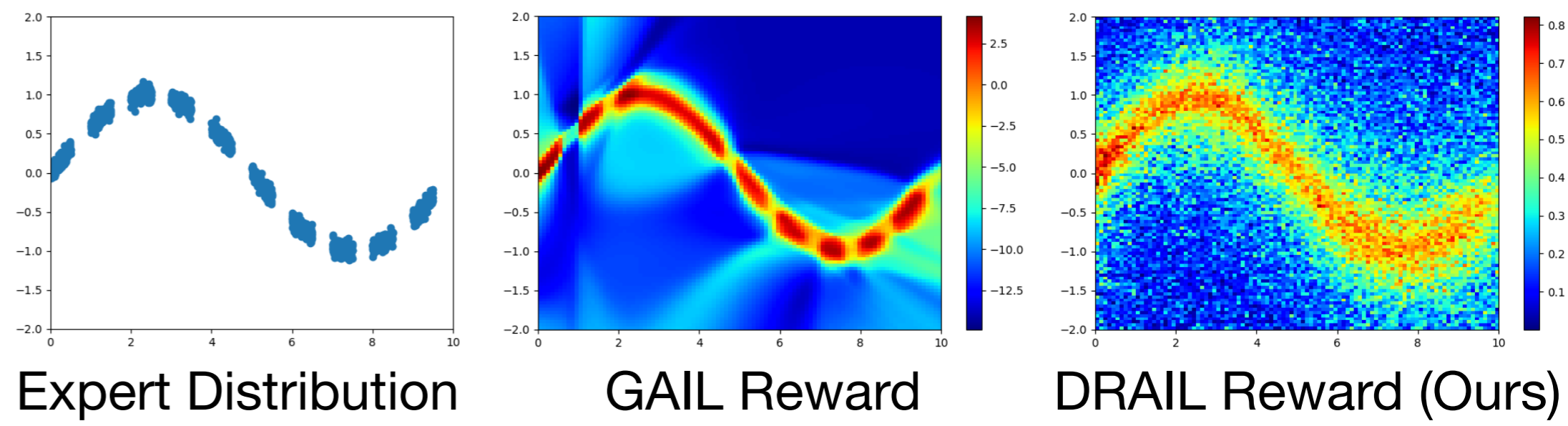
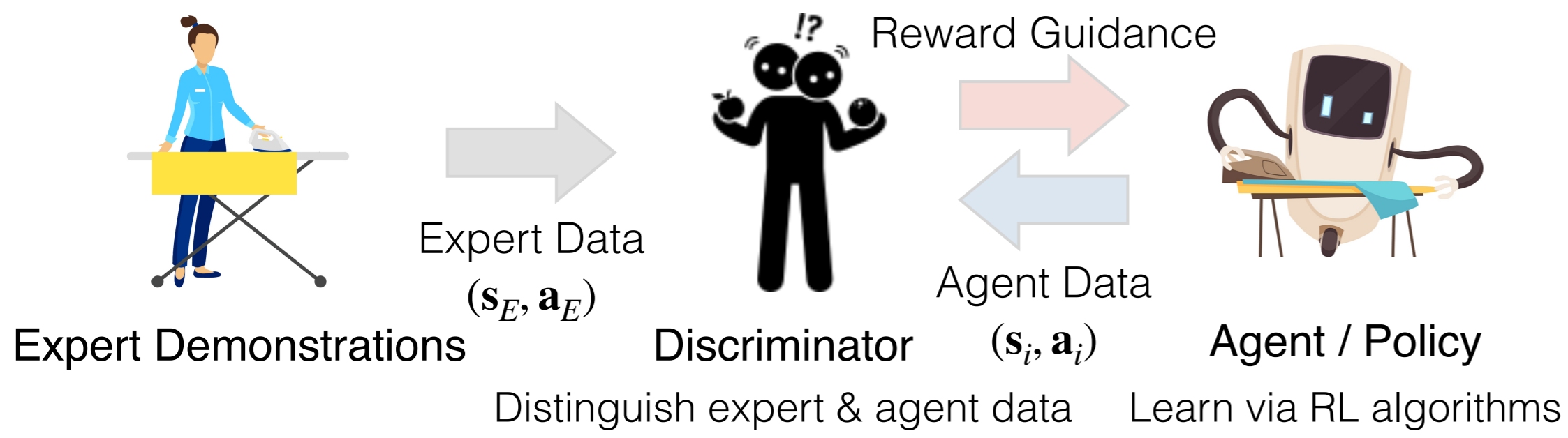


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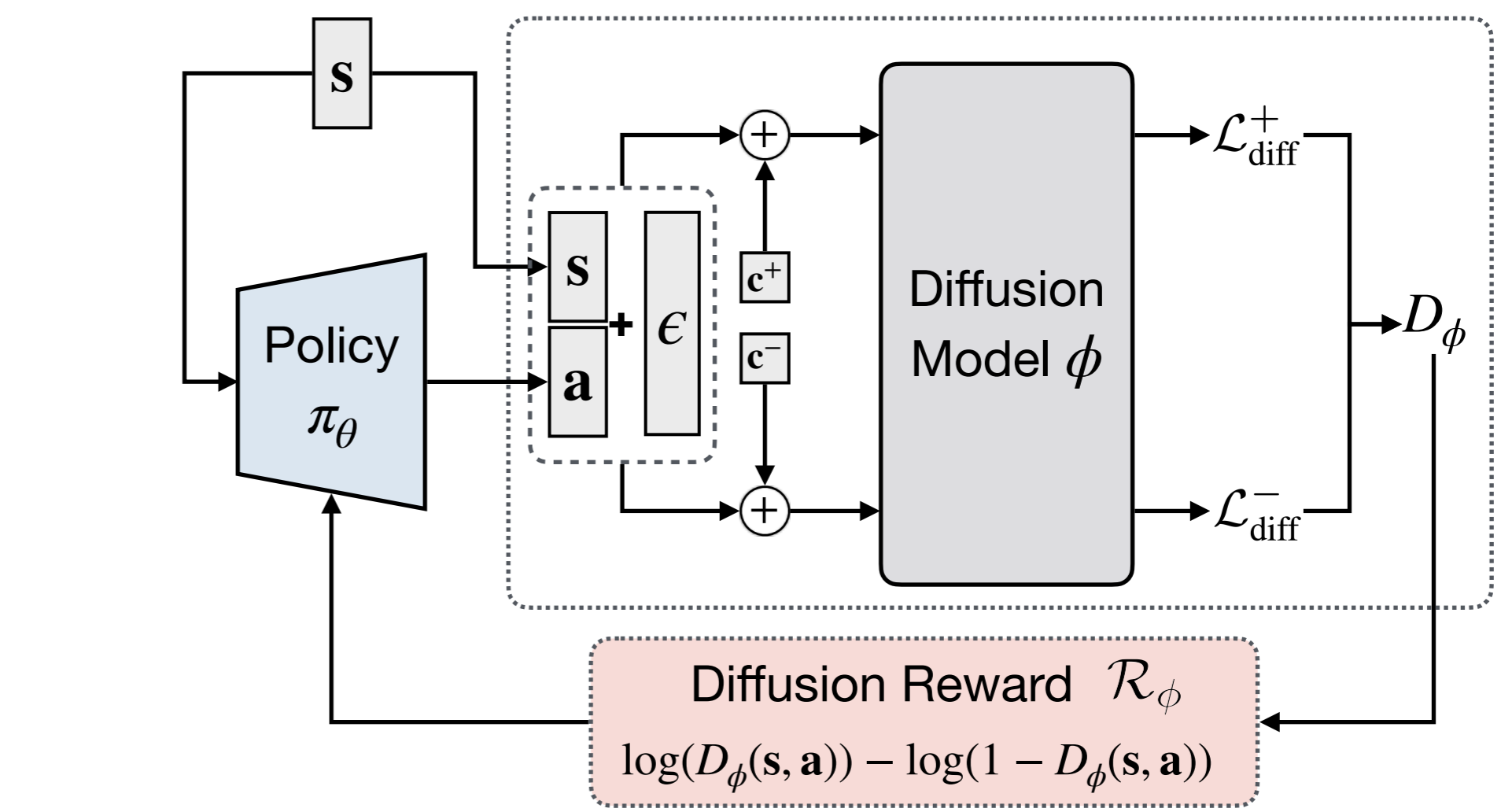
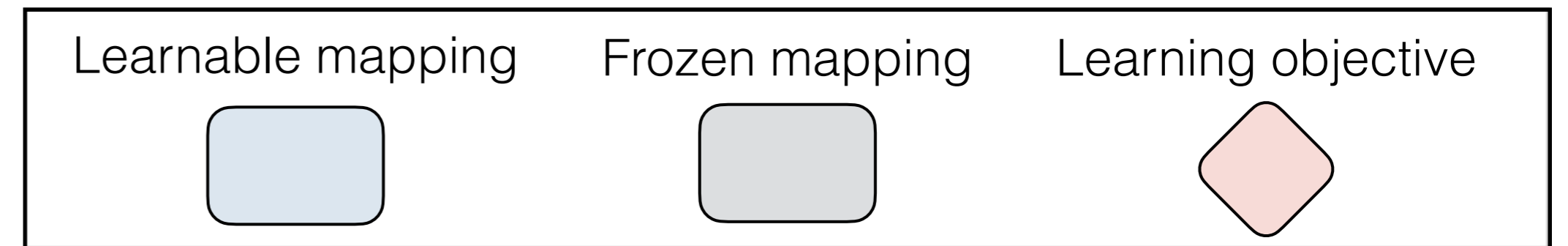
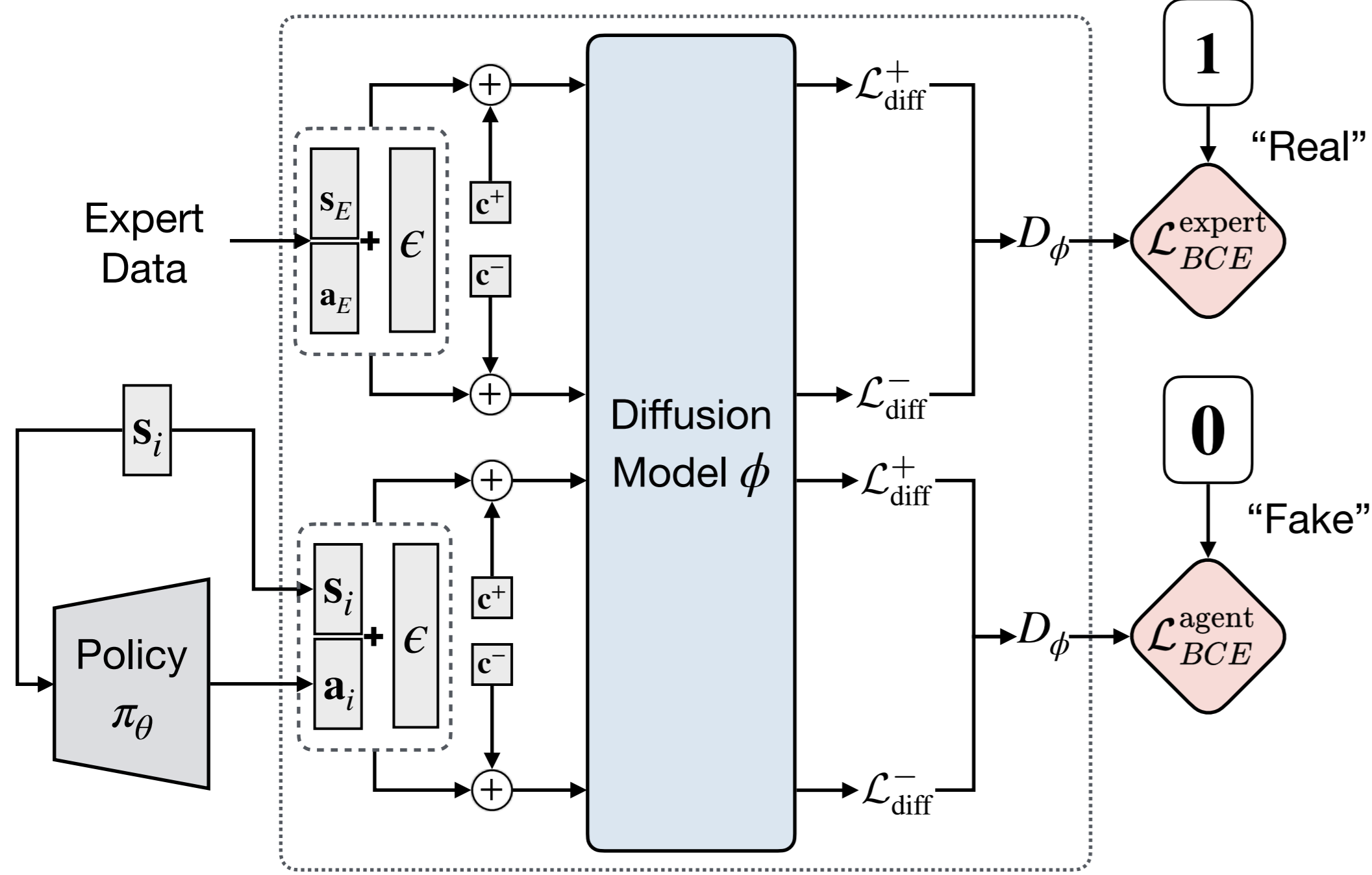
Adversarial Imitation Learning

Reward Function Visualization



Diffusion Rewards Guided Adversarial Imitation Learning (DRAIL)

Diffusion Discriminative Classifier



(a) Learning Diffusion Discriminative Classifier

(b) Learning Policy with Diffusion Rewards

Diffusion discriminative classifier learns to distinguish expert data (s_E, a_E) from agent data (s_i, a_i) using a diffusion model ϕ by denoising expert and agent state-action pairs concatenated with a real/expert label c^+ or a fake/agent label c^- .

Policy π_θ learns to maximize the diffusion reward computed based on the output of the diffusion discriminative classifier D_ϕ that takes the state-action pairs from the policy as input.

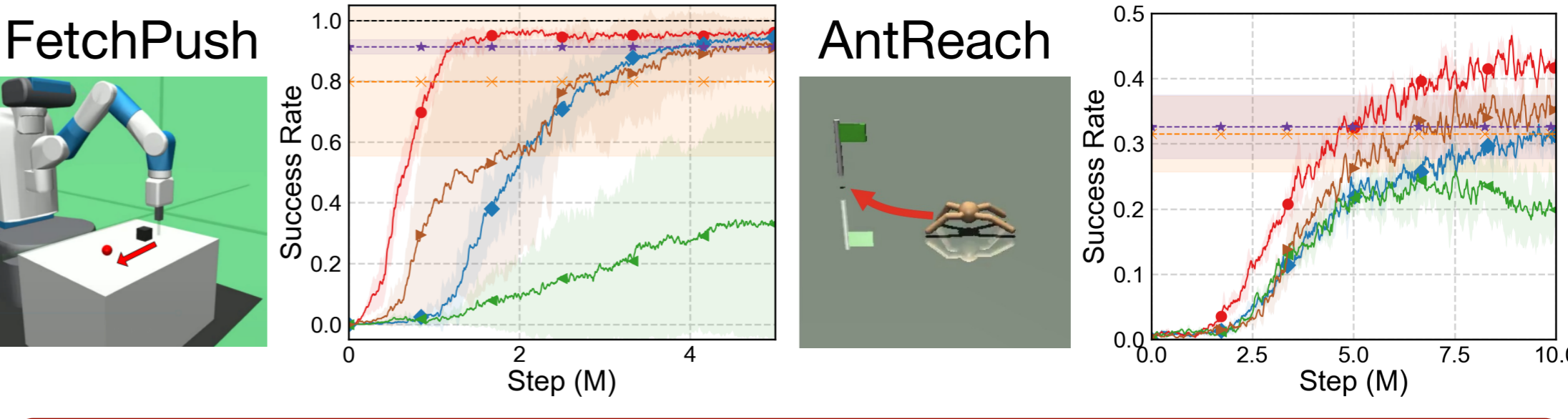
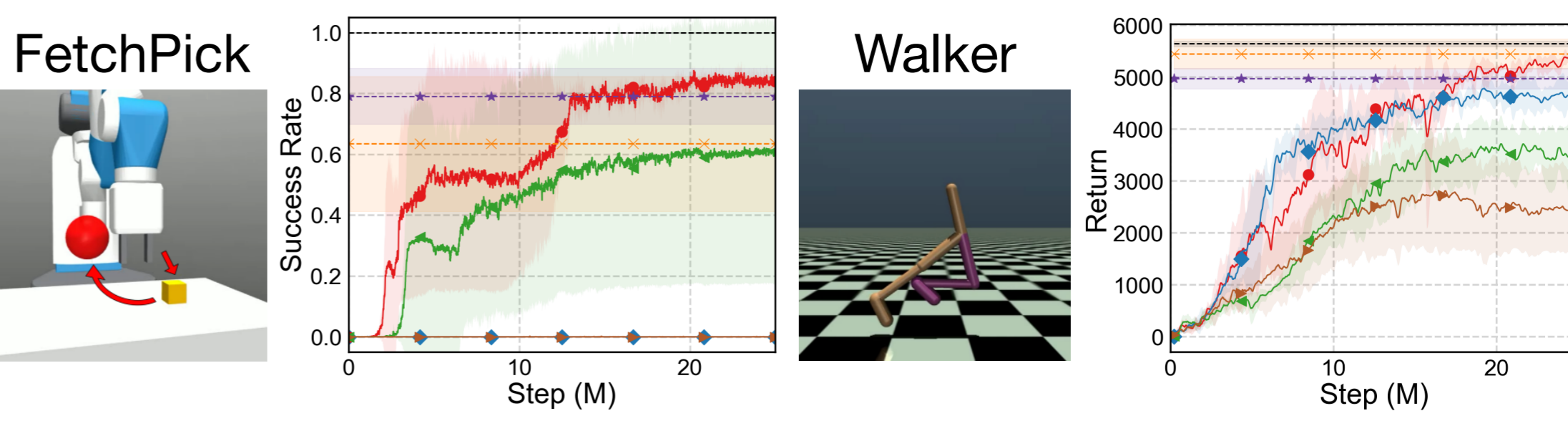
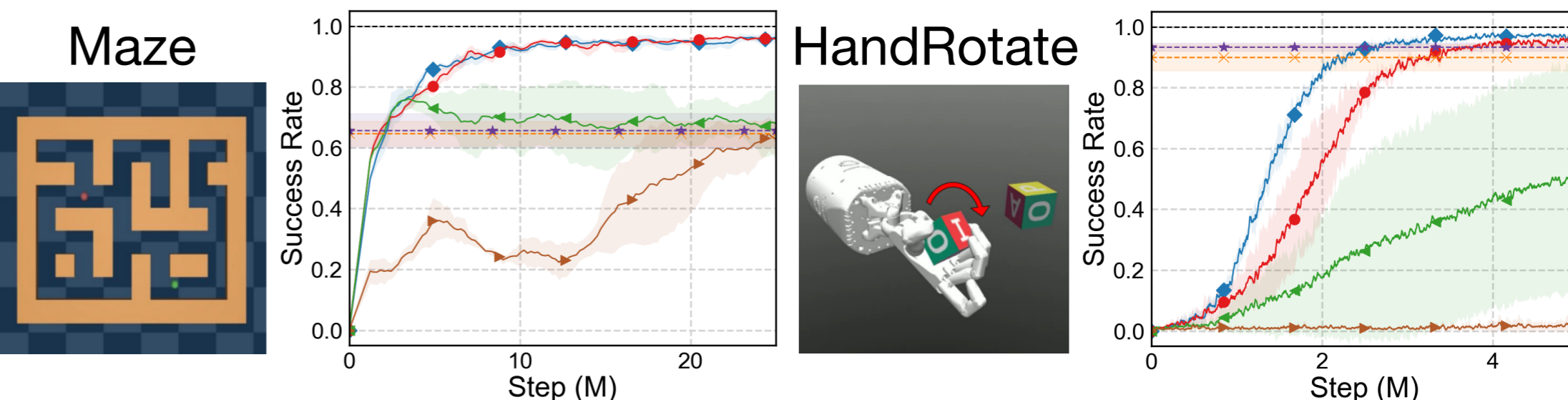
- Diffusion Loss $\mathcal{L}_{diff}(s, a, c) = \mathbb{E}_{t \sim T} [\|\hat{\epsilon}_\phi(s, a, \epsilon, t|c) - \epsilon\|^2]$

- "Realness" of (s, a) $D_\phi(s, a) = \frac{e^{-\mathcal{L}_{diff}(s, a, c^+)}}{e^{-\mathcal{L}_{diff}(s, a, c^+)} + e^{-\mathcal{L}_{diff}(s, a, c^-)}}$

- Diffusion Reward $\mathcal{R}_\phi(s, a) = \log(D_\phi(s, a)) - \log(1 - D_\phi(s, a))$

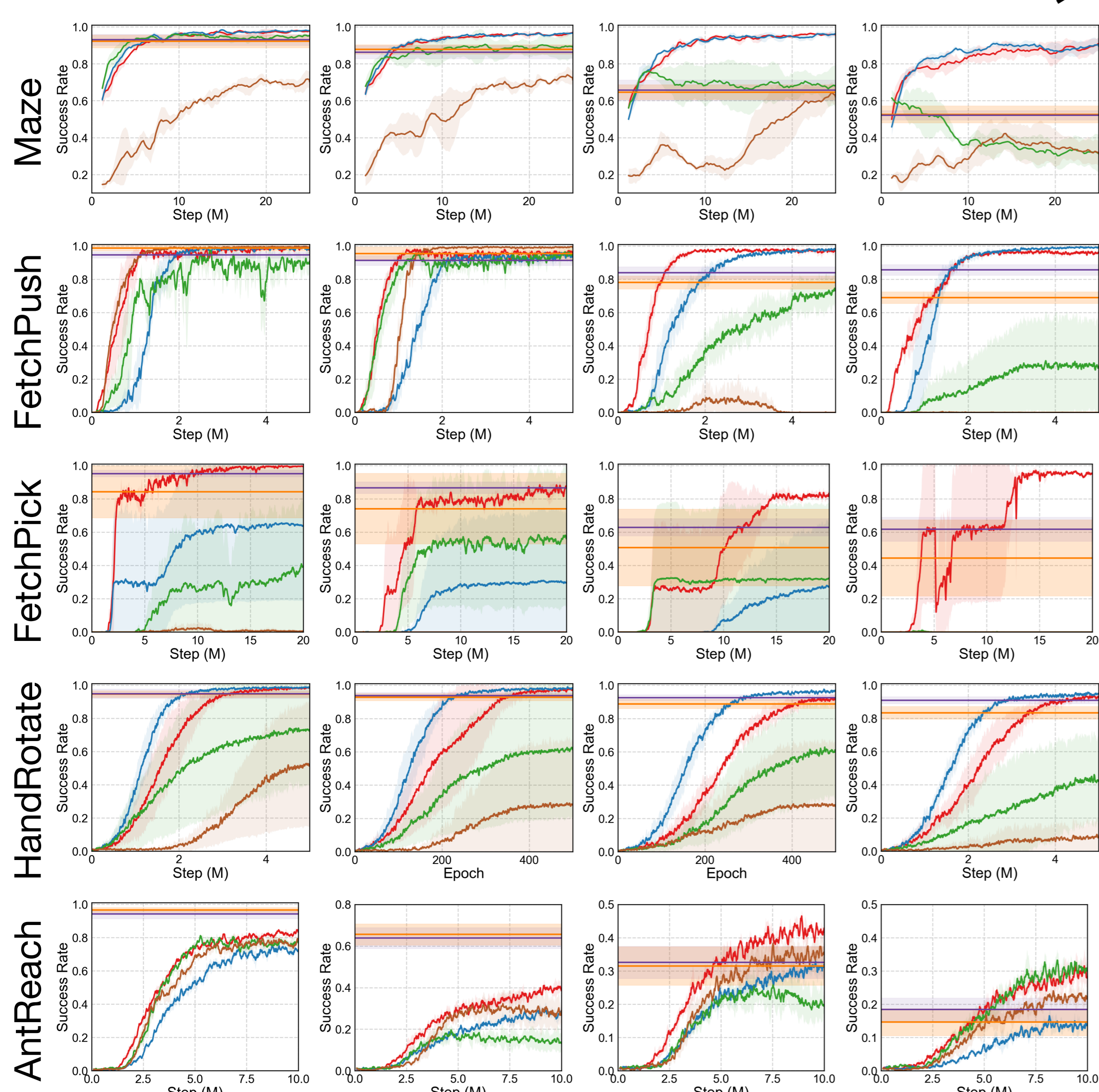
Sample Efficiency

Legend: BC (orange), Diffusion Policy (purple), GAIL (green), WAIL (brown), DRAIL-UN (blue), DRAIL (Ours) (red).



Generalizability

Generalizing to more novel states/goals/tasks is required →



Data Efficiency

