Berkeley UNIVERSITY OF CALIFORNIA

Jean-Baptiste Bouvier, Kanghyun Ryu, Kartik Nagpal, Qiayuan Liao, Koushil Sreenath, and Negar Mehr

DDAT: Diffusion Policies Enforcing Dynamically Admissible Robot Trajectories

Introduction

Trajectories generated by diffusion models are inherently **stochastic** and cannot satisfy the equations of motion of a robot.

- We use *autoregressive projections* to make trajectories feasible.
- We *interleave* these projections through the denoising iterations.

Background

Previous works either:
- only consider fully-actuated systems;
- replan every few timesteps;
- project the trajectory after inference;
- plan action sequences.

Most diffusion works do not enforce robot dynamics and generate infeasible trajectories.

Problem Formulation

Given:

State $s_t \in \mathcal{S}$ → **Black-box dynamics** $s_{t+1} = f(s_t, a_t)$ → $s_{t+1} \in \mathcal{S}$

Action $a_t \in \mathcal{A}$ → **Black-box dynamics**

Dataset of trajectories $\mathcal{D} = \{\tau_1, \dots, \tau_N\}$

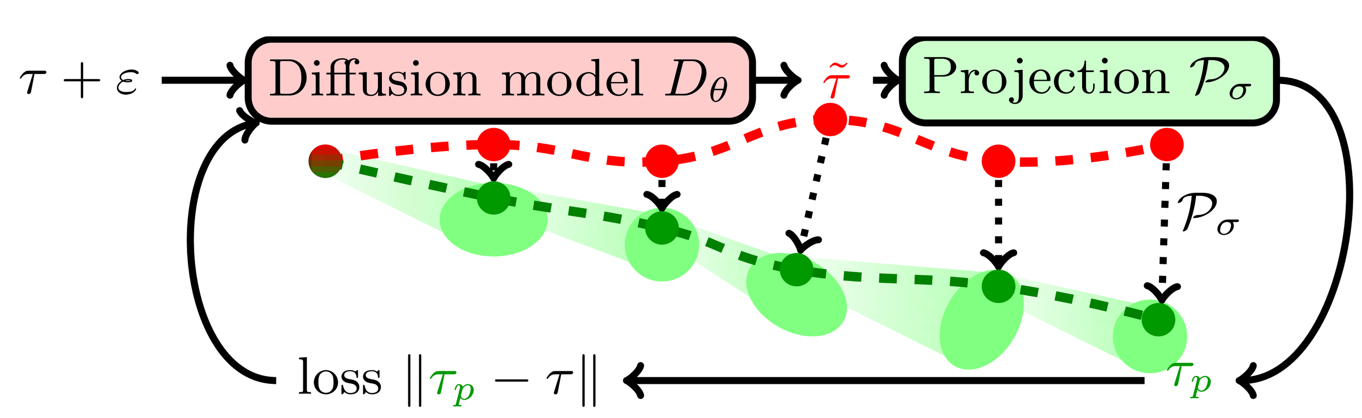
Train:

$s_0 \in \mathcal{S}$ → **Diffusion model D_θ** → $(\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_T) \in \mathcal{S}$, $(\tilde{a}_0, \tilde{a}_1, \dots, \tilde{a}_{T-1}) \in \mathcal{A}$

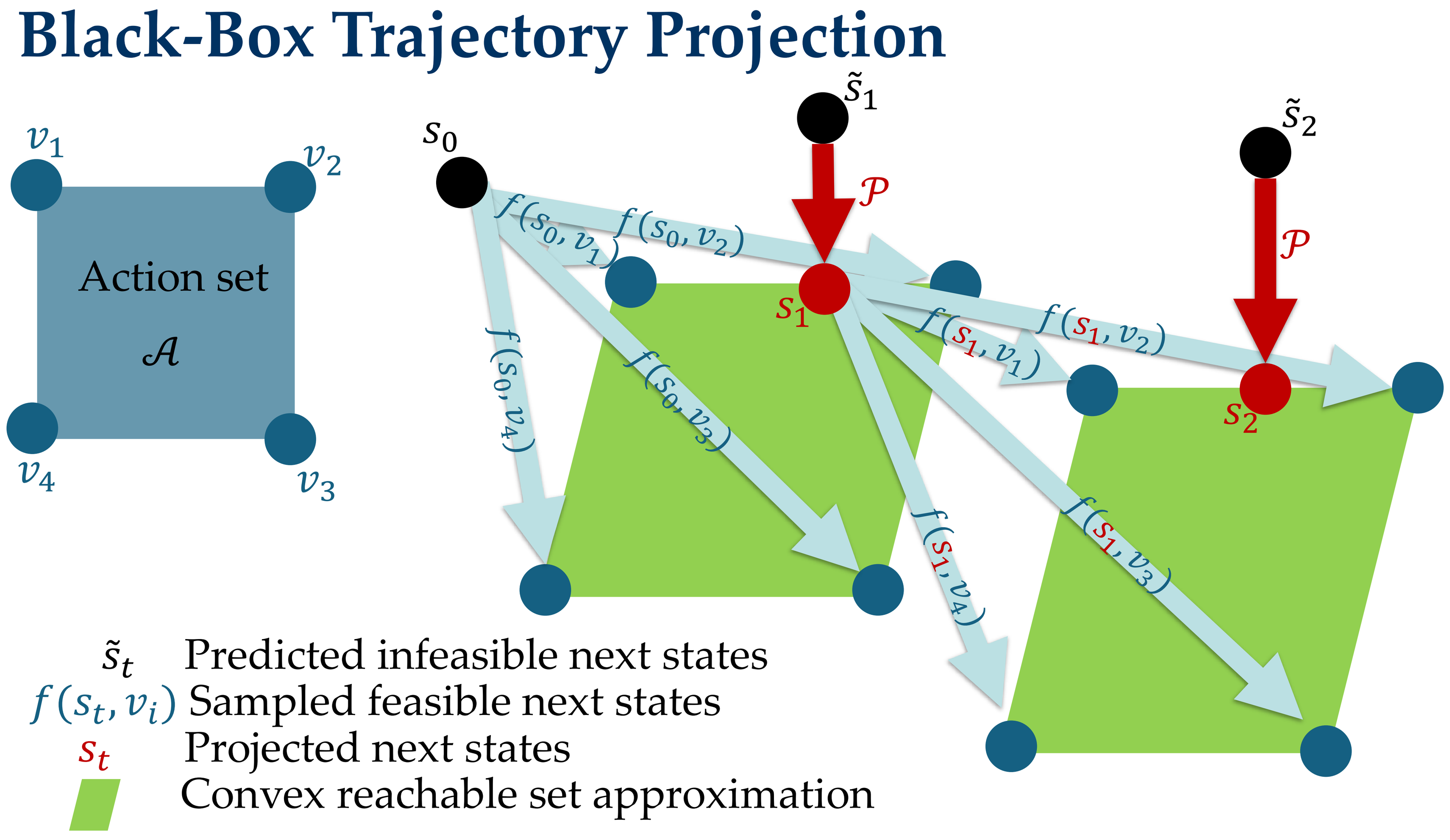
Such that:

$$\tilde{s}_{t+1} \in \mathcal{R}(\tilde{s}_t) = \{f(\tilde{s}_t, a) \text{ for all } a \in \mathcal{A}\} \quad \text{or} \quad \tilde{s}_{t+1} = f(\tilde{s}_t, \tilde{a}_t)$$

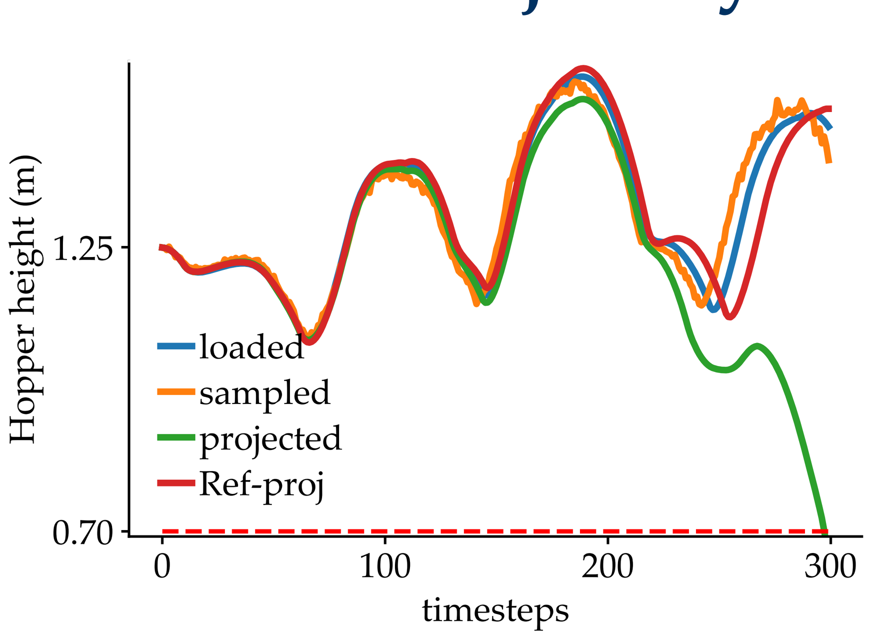
Our Approach: *DDAT*



Black-Box Trajectory Projection



Reference Trajectory Projection



Greedy projections tend to diverge

Use a reference to guide projections

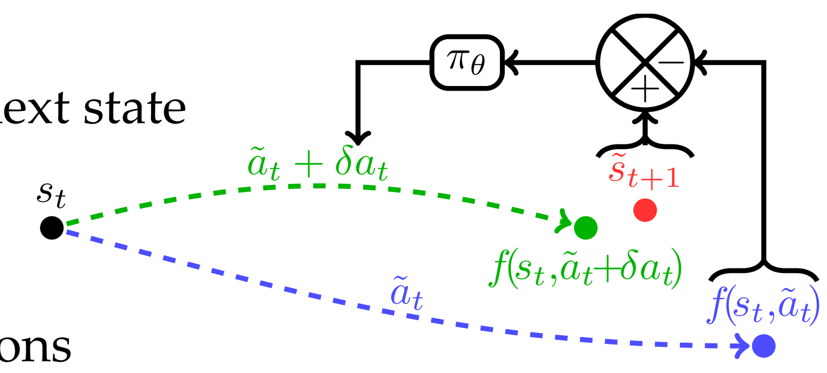
Reference generated by diffusion

Better long-horizon performance

Projections Leveraging Action Prediction

Predicted action can give a reachable next state

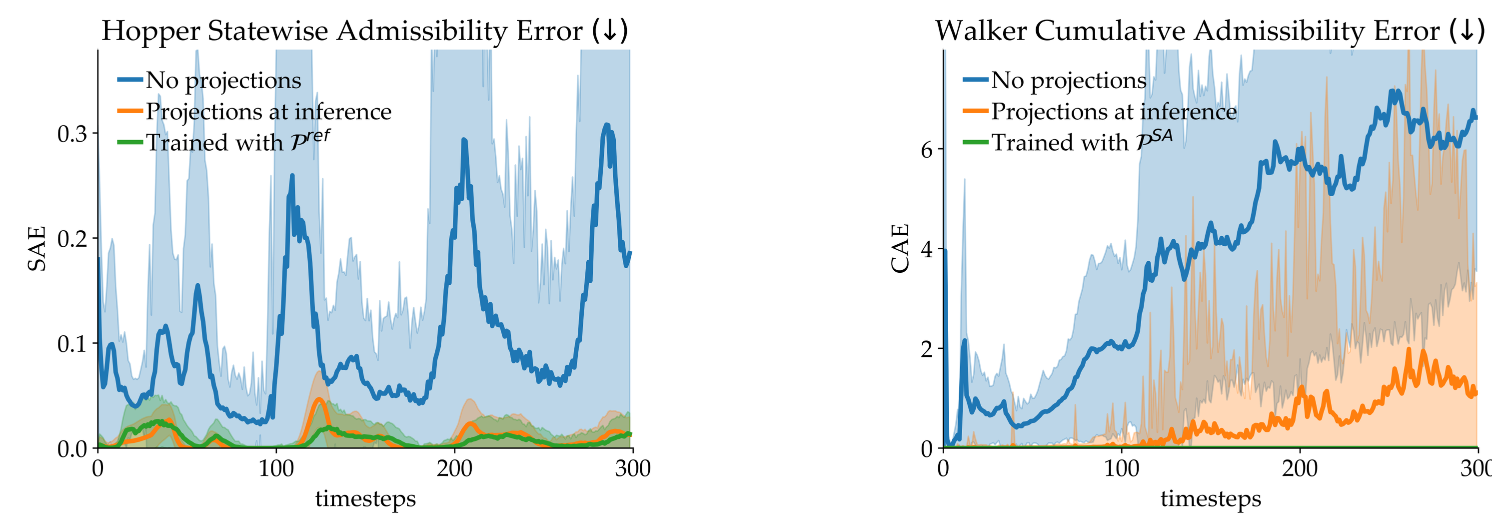
$$\mathcal{P}^A(s_t, \tilde{s}_{t+1}) \coloneqq f(s_t, \tilde{a}_t)$$



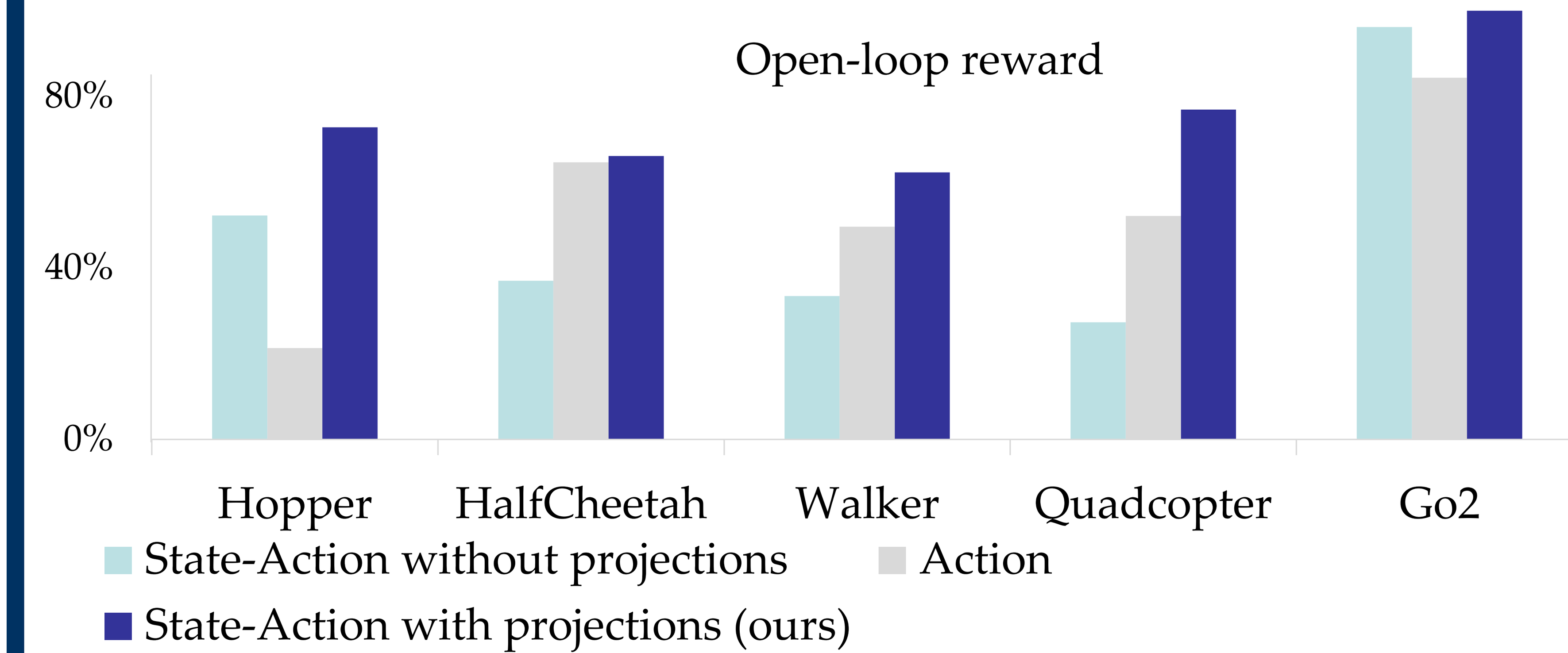
Predicted action can guide the projections

$$\mathcal{P}^{SA}(s_t, \tilde{s}_{t+1}) \coloneqq f(s_t, \tilde{a}_t + \delta a_t) \quad \text{with} \quad \delta a_t = \pi_\theta\big(\tilde{s}_{t+1} - f(s_t, \tilde{a}_t)\big)$$

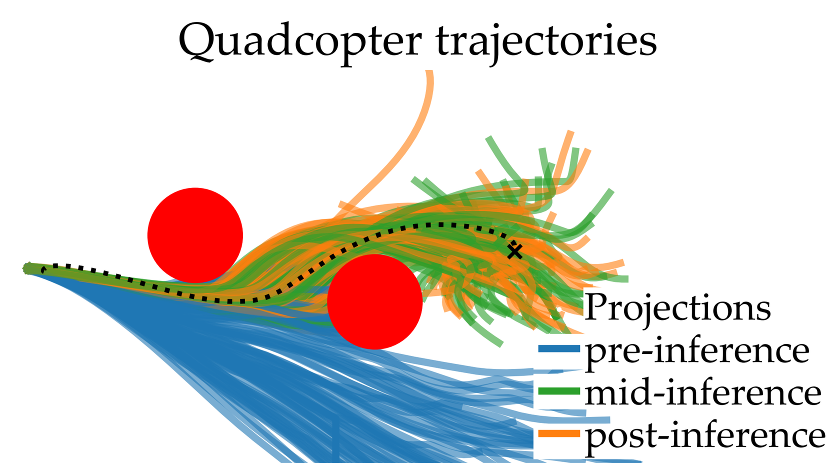
Projections Improve Feasibility

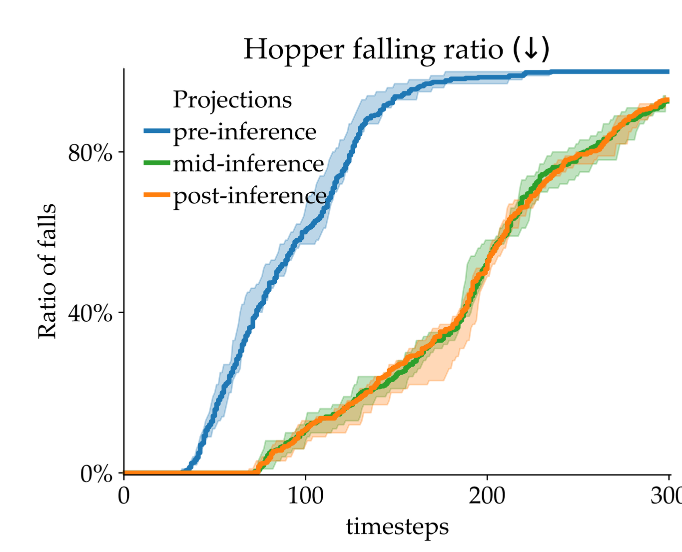


Projections Improve Quality



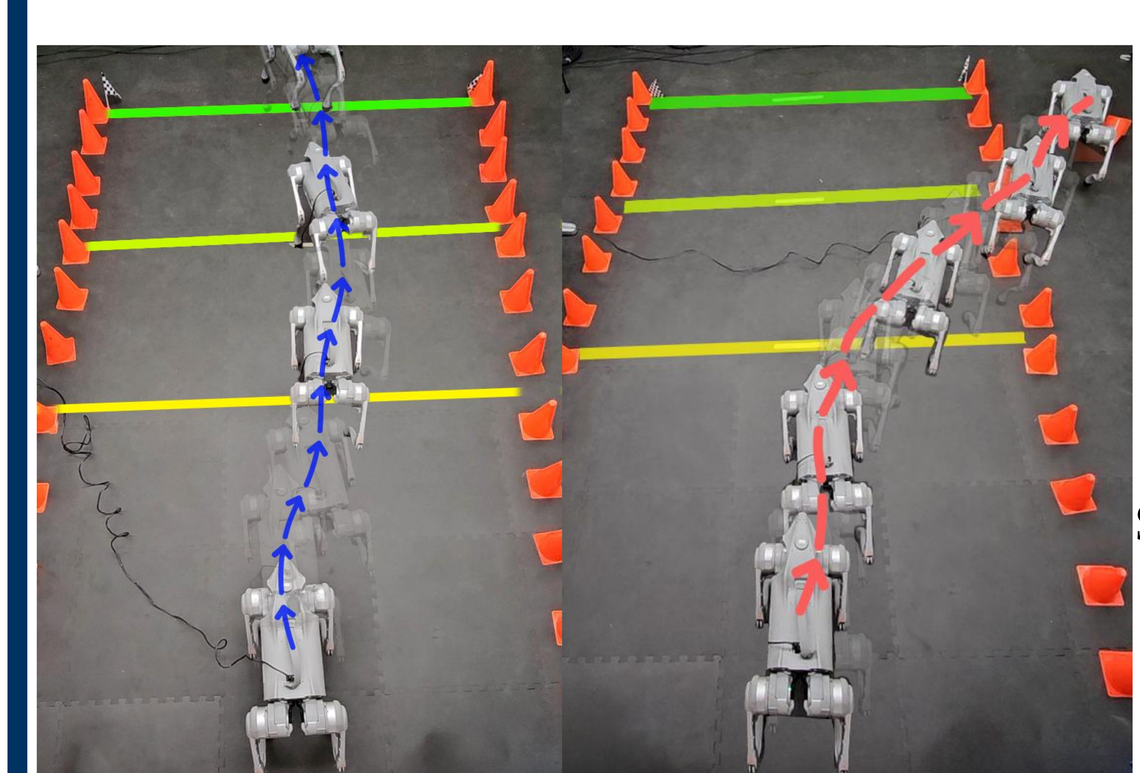
Projection Scheduling

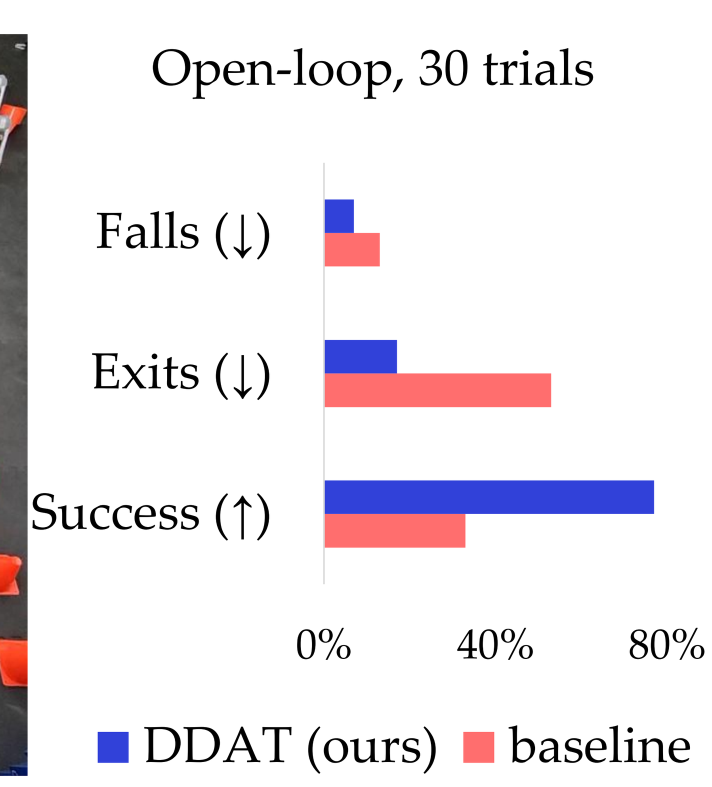




Projections at high noise level (—) reduce quality of trajectories.

Zero-Shot Hardware Deployment





Key Points

Projections improve the quality of diffusion planning.

With higher quality samples, we can wait longer before replanning.

Sponsored by Google BAIR

https://iconlab.negarmehr.com/DDAT