GenPO: Generative Diffusion Models Meet On-Policy Reinforcement Learning

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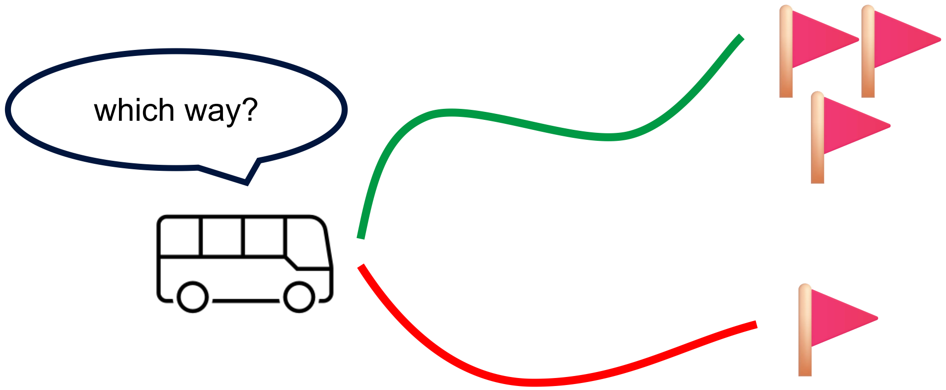
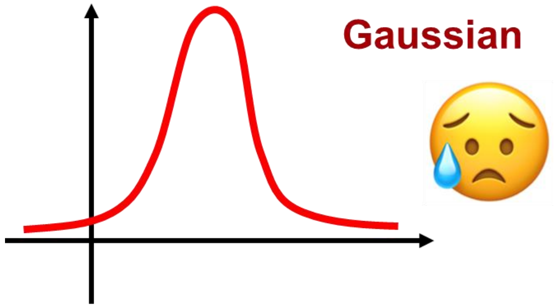
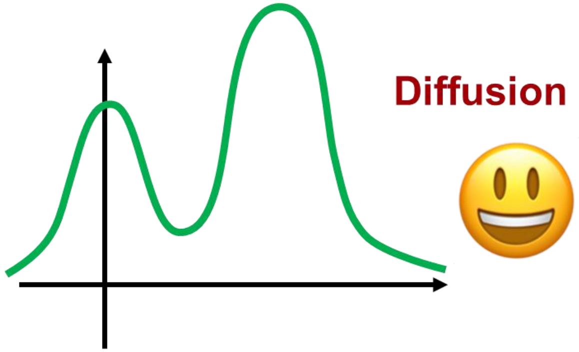
Background: Diffusion in Online RL

1. **Exploration capability** of Gaussian policy or deterministic policy is limited

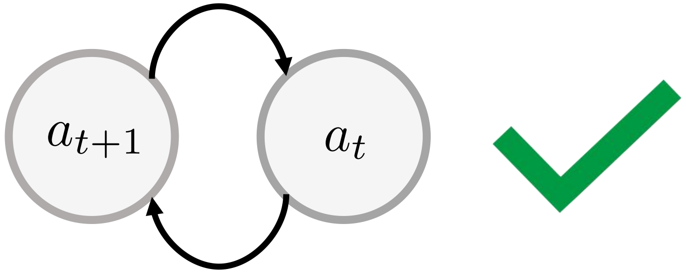
2. **Expressiveness and multimodality** of diffusion avoid policy falling into the local optimality







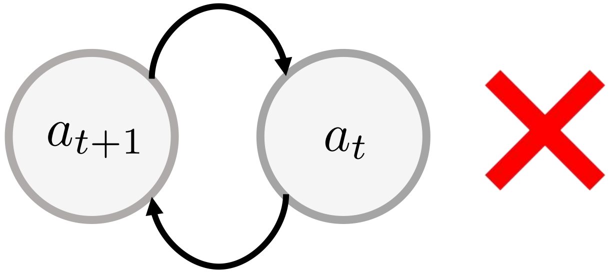
Background: Diffusion in Online RL



Existing diffusion-based RL methods are almost all **off-policy**,
and cannot benefit from the large-scale parallel simulator!

Background: Diffusion in Online RL

Existing on-policy RL methods (**PPO, TRPO**)



Existing on-policy RL methods cannot benefit from the multimodality and powerful exploration capability of **diffusion model**!

Background: Diffusion in Online RL

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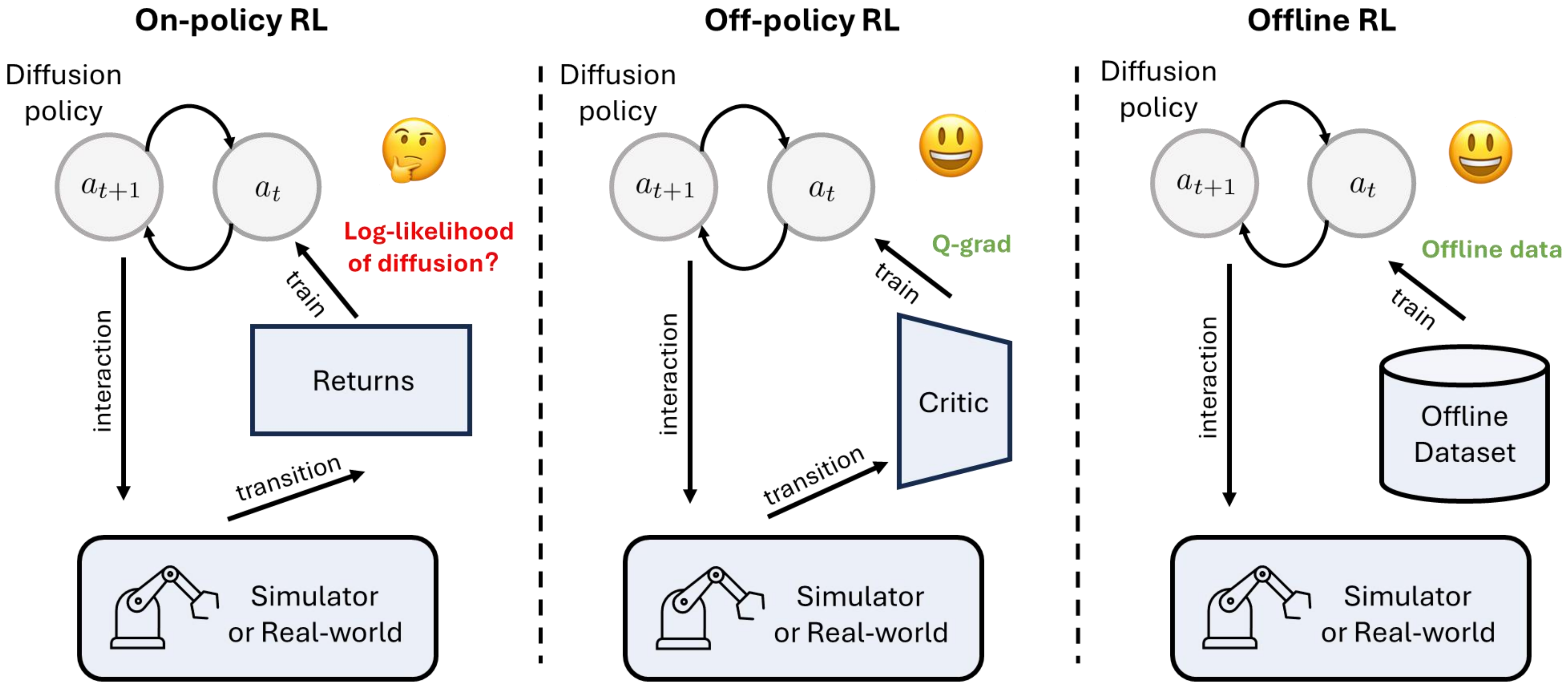

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Solution: GenPO

How can we train diffusion policy in an on-policy RL paradigm?

Calculate the **log-likelihood** of the diffusion model?

But the log-likelihood of the diffusion model is **not available**.

What if make the denoising procedure **invertible** and calculate the log-likelihood via **change of variables**?

Solution: GenPO

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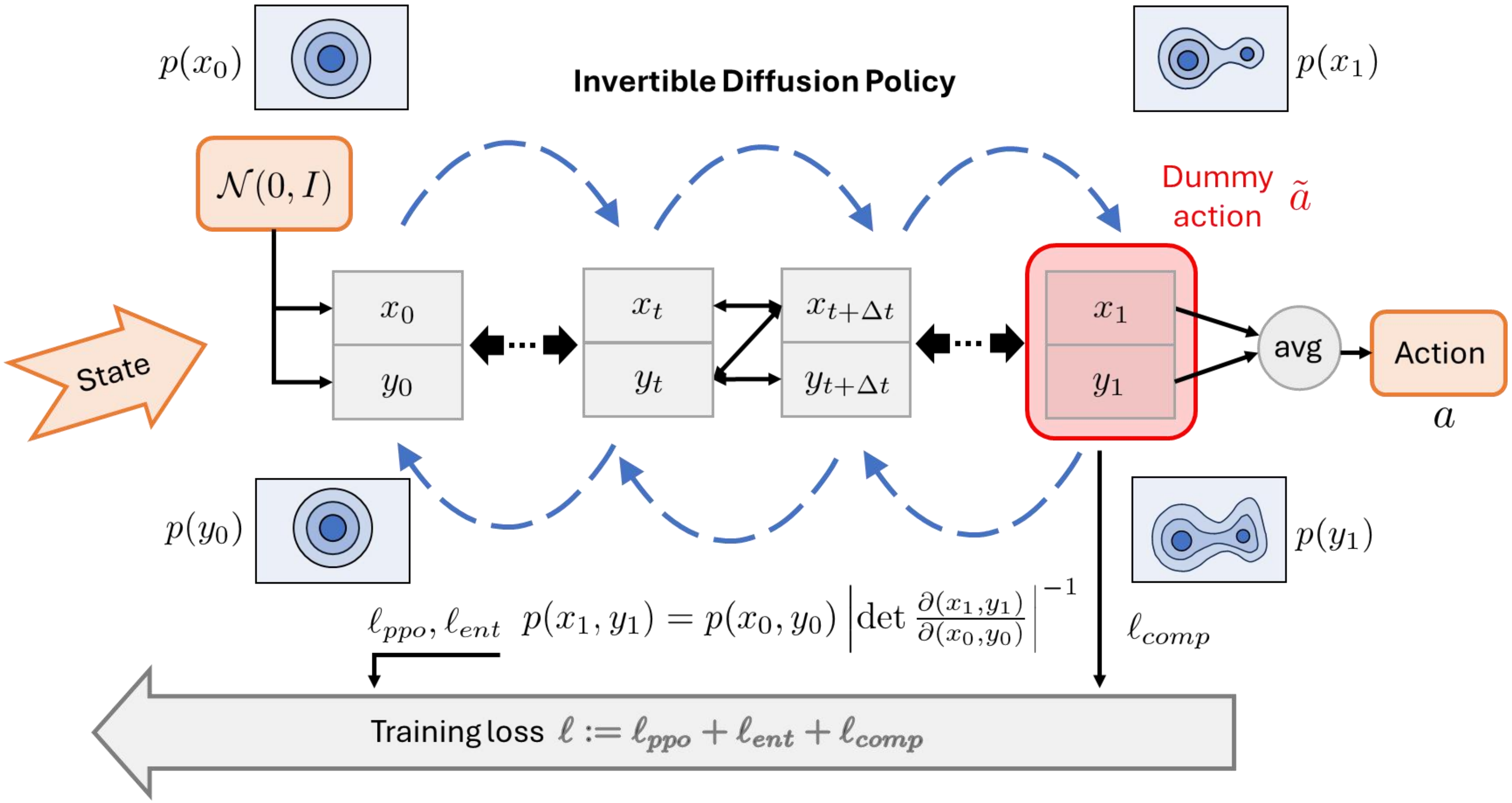
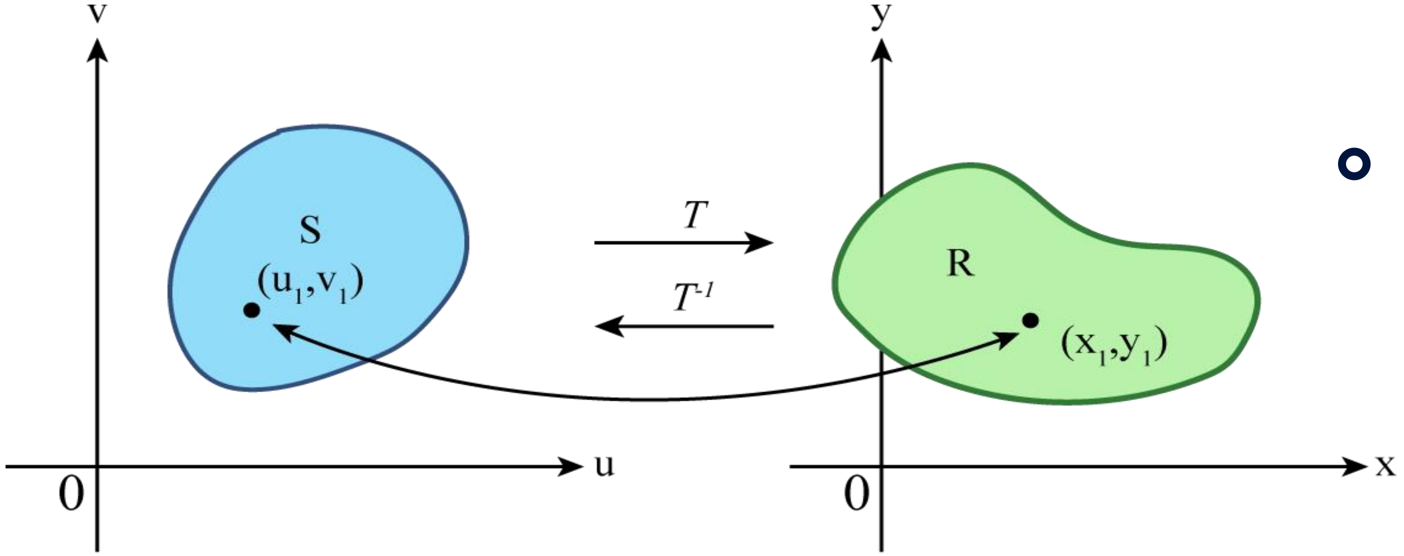
Motivated by these two ideas, we design an invertible diffusion policy and propose GenPO.



Change of Variables

Let $f : \mathbb{R}^n \to \mathbb{R}^n$ is an invertible and smooth mapping. If we have the random variable $X \sim q(x)$ and the random variable $Y = f(X)$ transformed by function f , the distribution of Y is $p(y) = q(x) \left| \det \frac{\partial f}{\partial x} \right|^{-1}$.

Log-likelihood



How to further make the diffusion model invertible?

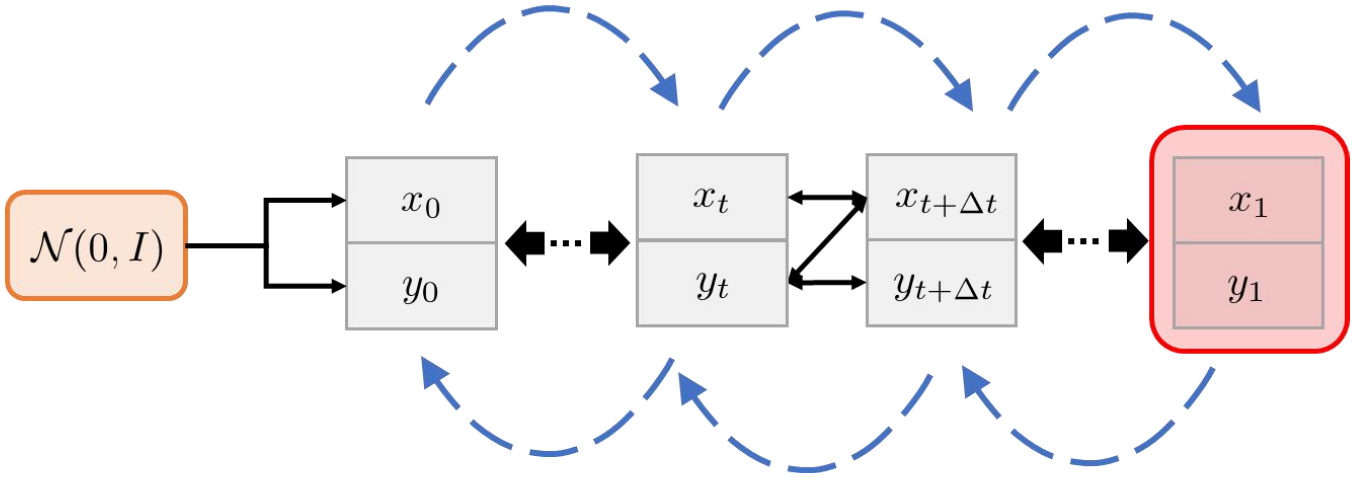
Exact Diffusion Inversion

Classical diffusion models (e.g., DDPM/DDIM) are not invertible due to discretization:

$$\text{Reverse:}\quad x_{t-1} = \sqrt{\alpha_{t-1}}\,\frac{x_t - \sqrt{1-\alpha_t \boldsymbol{\epsilon}_\theta(x_t,t)}}{\sqrt{\alpha_t}} + \sqrt{1-\alpha_{t-1}}\,\boldsymbol{\epsilon}_\theta(x_t,t)$$

$$\text{Forward:}\quad x_t = \frac{x_{t-1} - b_t \boldsymbol{\epsilon}_\theta(x_t,t)}{a_t} \approx \frac{x_{t-1} - b_t \boldsymbol{\epsilon}_\theta(x_{t-1},t)}{a_t}.$$

Motivated by [1], we design an invertible diffusion model:



Invertible diffusion with doubled noise vectors

[1] Wallace B, Gokul A, Naik N. Edict: Exact diffusion inversion via coupled transformations[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023: 22532-22541.

Exact Diffusion Inversion

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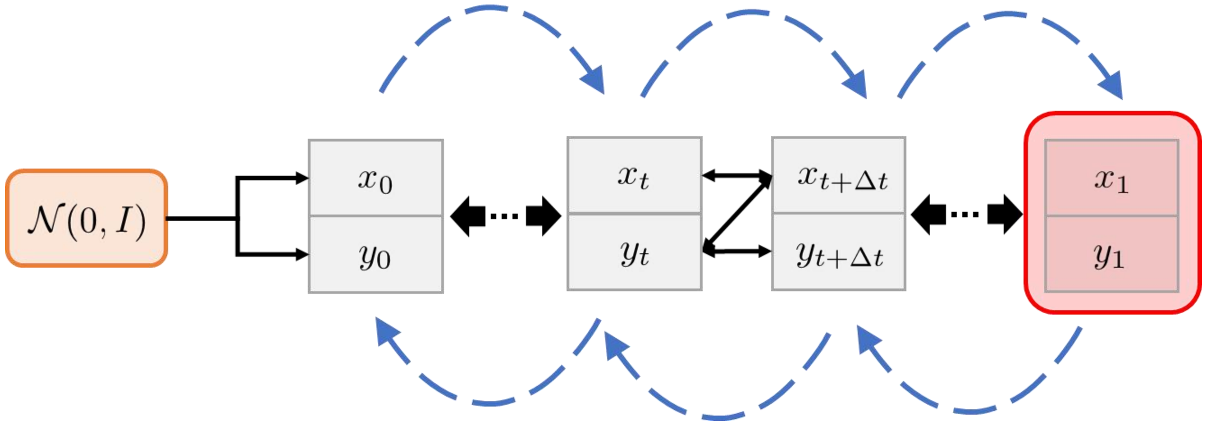

Invertible diffusion with doubled noise vectors

Use x or y as the final action? Or the concatenation of them?

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Doubled Dummy Action

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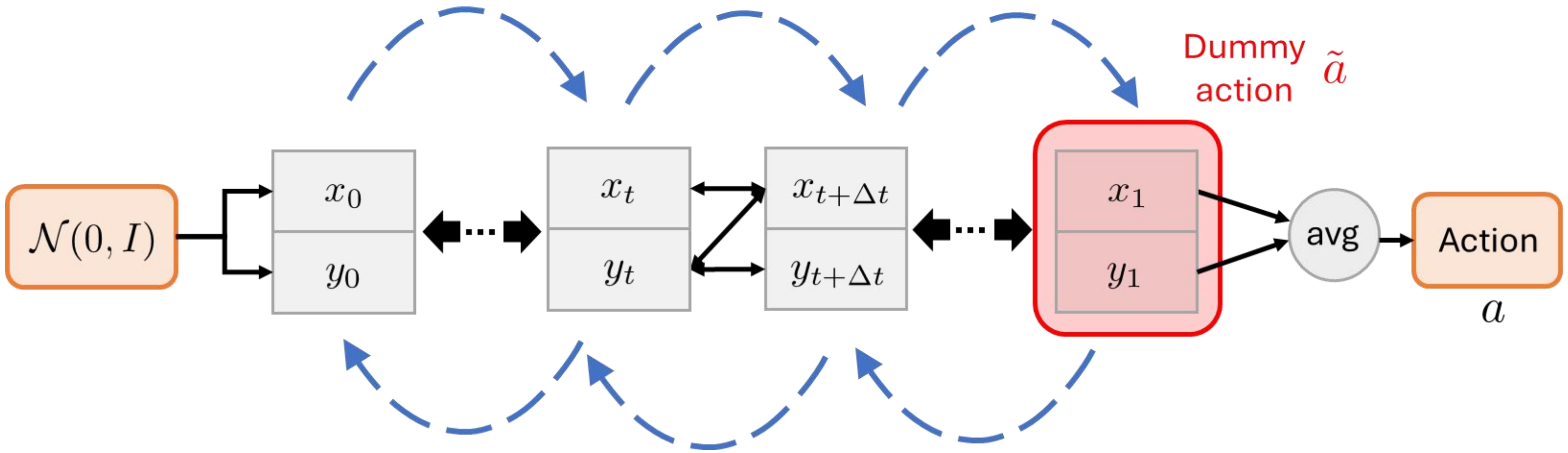

1. Number of actions may be odd
2. Double the action space of the actual problem for optimization
3. Use the average of the two parts of doubled actions as the final action
4. Mixing trick for the consistency of x and y

Unmixing: $\tilde{y}_{t+\Delta t} = \frac{y_{t+\Delta t} - (1-p)x_{t+\Delta t}}{p}$ $\quad \tilde{x}_{t+\Delta t} = \frac{x_{t+\Delta t} - (1-p)\tilde{y}_{t+\Delta t}}{p}$

Forward: $y_t = \tilde{y}_{t+\Delta t} - v_\theta(\tilde{x}_{t+\Delta t}, t)\Delta t,$ $\quad x_t = \tilde{x}_{t+\Delta t} - v_\theta(y_t, t)\Delta t$

Reverse: $\tilde{x}_{t+\Delta t} = x_t + v_\theta(y_t, t)\Delta t,$ $\quad \tilde{y}_{t+\Delta t} = y_t + v_\theta(\tilde{x}_{t+\Delta t}, t)\Delta t$

Mixing: $x_{t+\Delta t} = p \cdot \tilde{x}_{t+\Delta t} + (1-p) \cdot \tilde{y}_{t+\Delta t},$ $\quad y_{t+\Delta t} = p \cdot \tilde{y}_{t+\Delta t} + (1-p) \cdot x_{t+\Delta t}$

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Compression Loss

$$\mathcal{L}(\theta) := \mathcal{L}^{PPO} + \lambda\mathcal{L}^{ENT} + \nu\mathbb{E}_{x_1, y_1 \sim \pi_\theta}\left[(x_1 - y_1)^2\right].$$

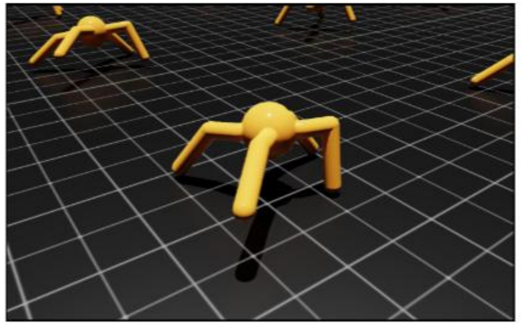
$$\mathcal{L}^{ENT}(\pi_\theta) := \mathbb{E}_{s, \tilde{a} \sim \pi_\theta}\left[\log\left(\pi_\theta(\tilde{a} \mid s)\right)\right].$$

$$\mathcal{L}^{\text{PPO}}(\theta) := \mathbb{E}_{(s_t, \tilde{a}_t) \sim \pi_{\theta_{\text{old}}}}\left[\min\left(\frac{\pi_\theta(\tilde{a}_t \mid s_t)}{\pi_{\theta_{old}}(\tilde{a}_t \mid s_t)}\hat{A}_t,\ \text{clip}(\frac{\pi_\theta(\tilde{a}_t \mid s_t)}{\pi_{\theta_{old}}(\tilde{a}_t \mid s_t)}, 1 - \epsilon, 1 + \epsilon)\hat{A}_t\right)\right].$$

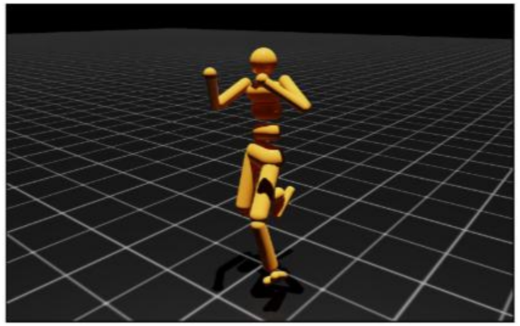
1. Since GenPO can access the log-likelihood of diffusion model, we directly calculate the RL loss and entropy of diffusion policy

2. To avoid **unnecessary exploration** in the doubled action space, we also propose the compression loss to further maintain the consistency of x and y

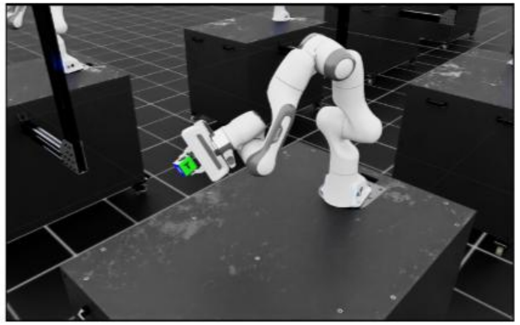
IsaacLab Benchmarks



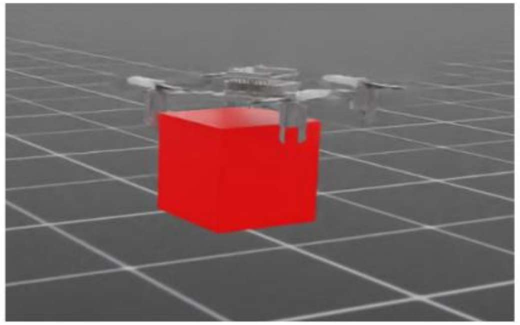
(a) Ant



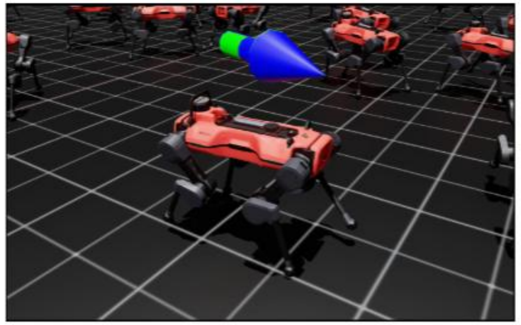
(b) Humanoid



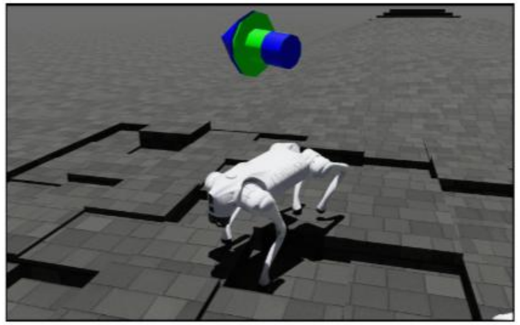
(c) Franka Arm



(d) Quadcopter

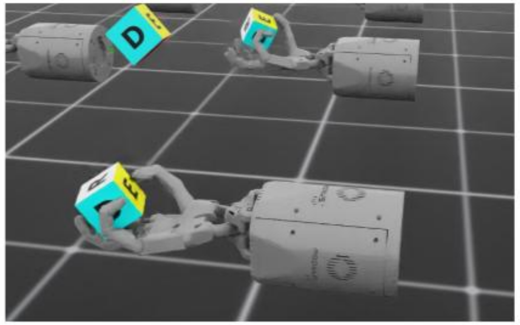


(e) Anymal-D



(f) Unitree-Go2

(g) Unitree-H1



(h) Shadow Hand

Results

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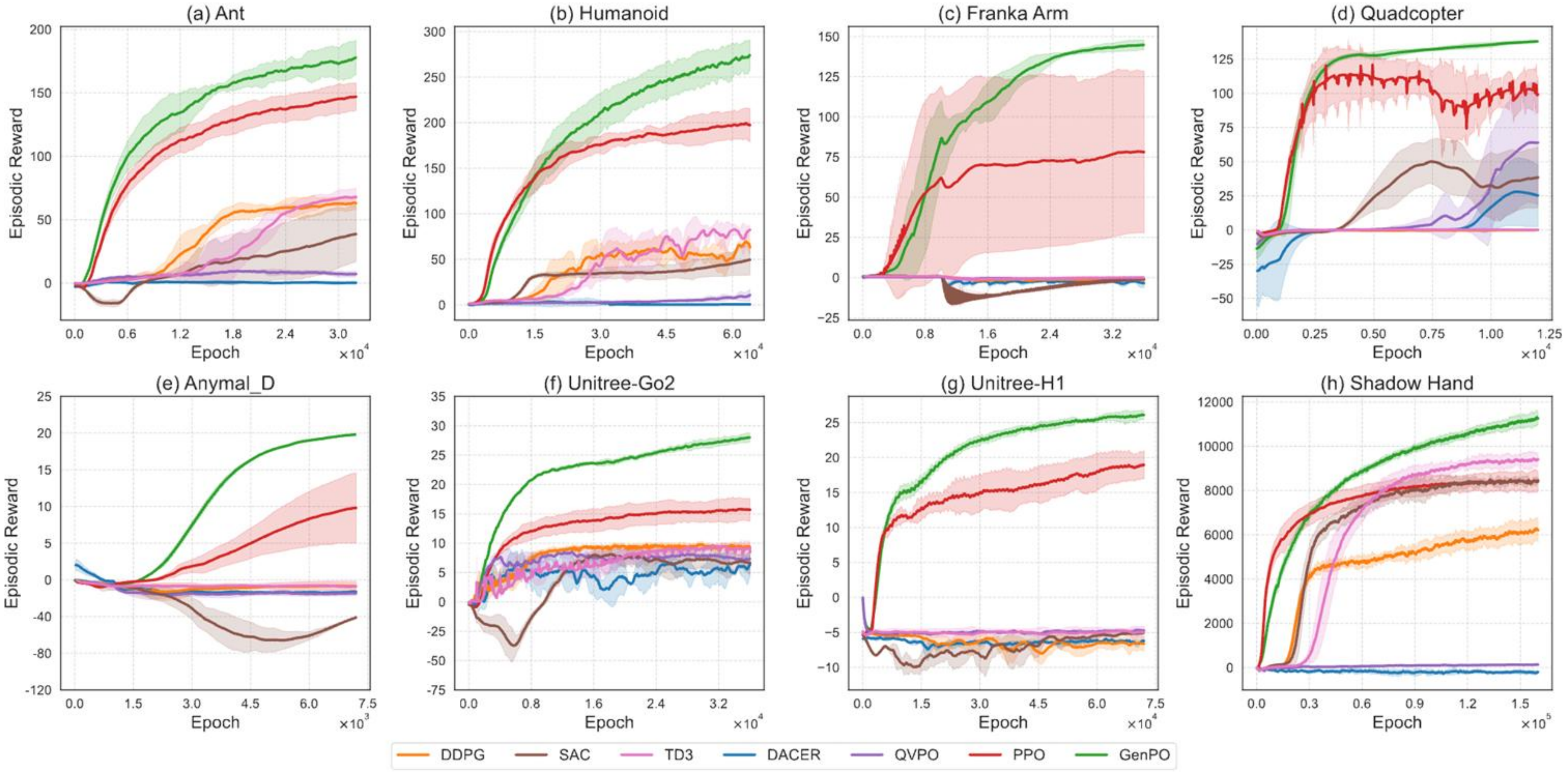

Performance in IsaacLab