A Unified Framework for Alternating Offline Model Training and Policy Learning

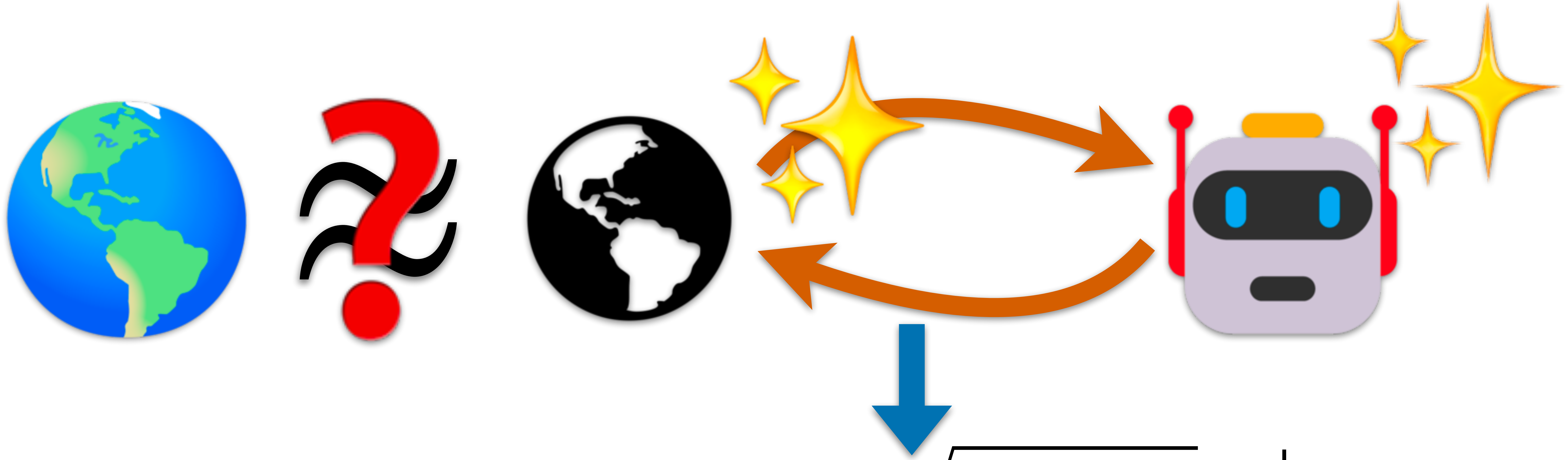
Shentao Yang[1], Shujian Zhang[1], Yihao Feng[2], Mingyuan Zhou[1]

[1]The University of Texas at Austin, [2]Salesforce Research

October, 2022

Proposed Method Sketch

- **Motivation**: model training = MLE ≠ improve policy = model usage.



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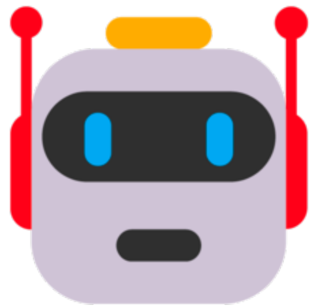
- Jointly train  and  to minimize an upper bound of the evaluation error.

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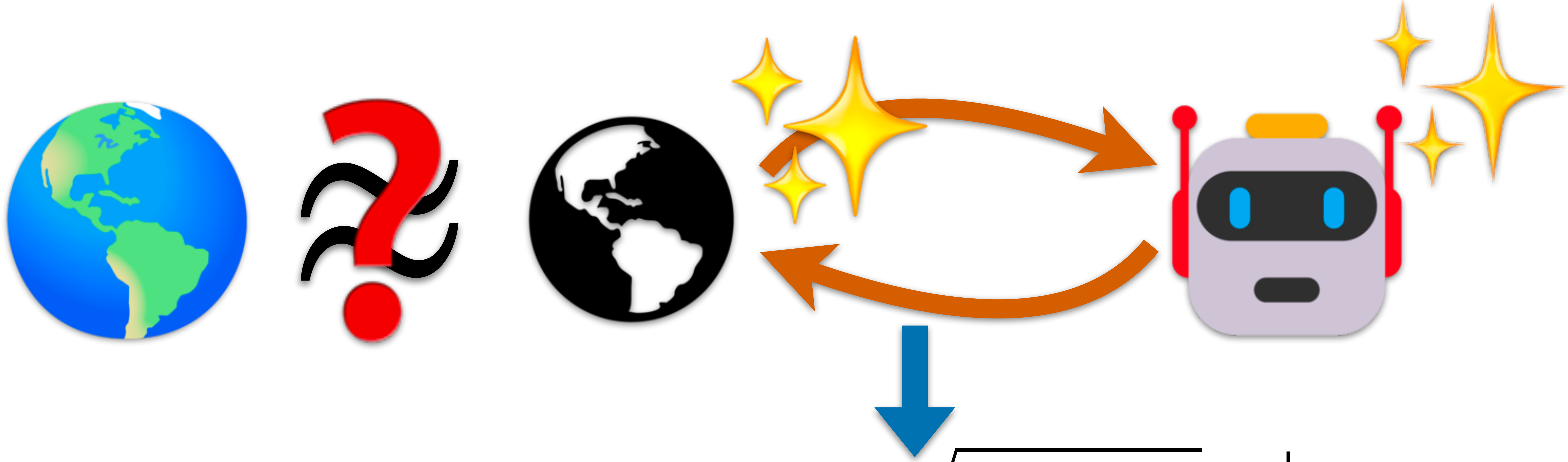

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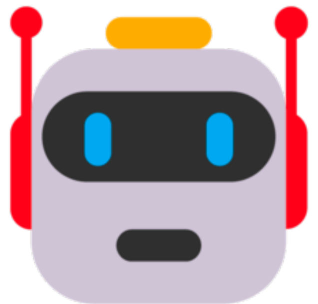
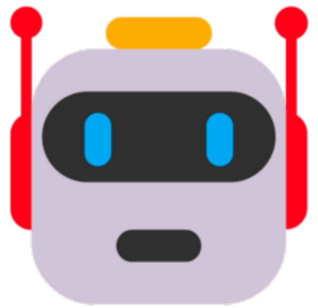
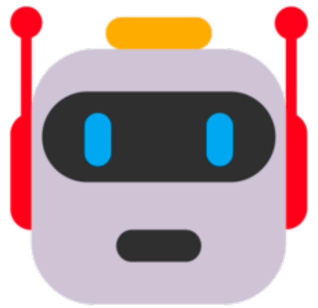
- Jointly train  and  to minimize an upper bound of the evaluation error.
  - Fixed ,  ≈  only on state-actions visited by .

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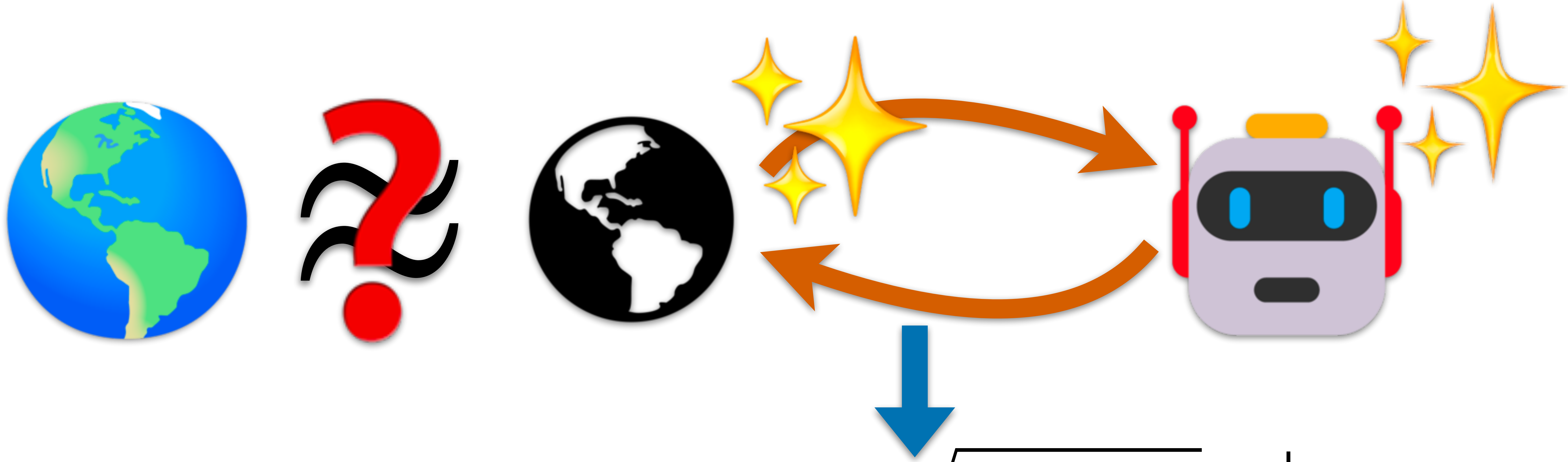

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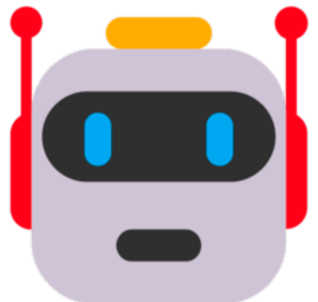
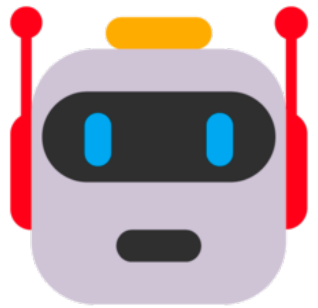
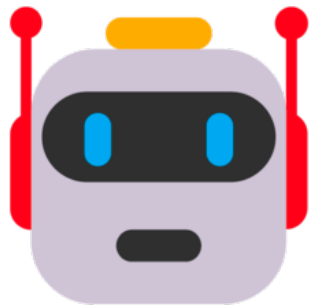
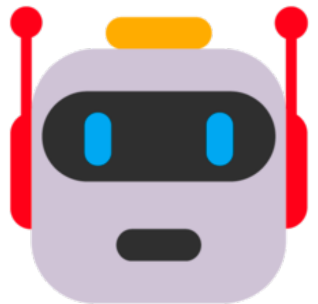
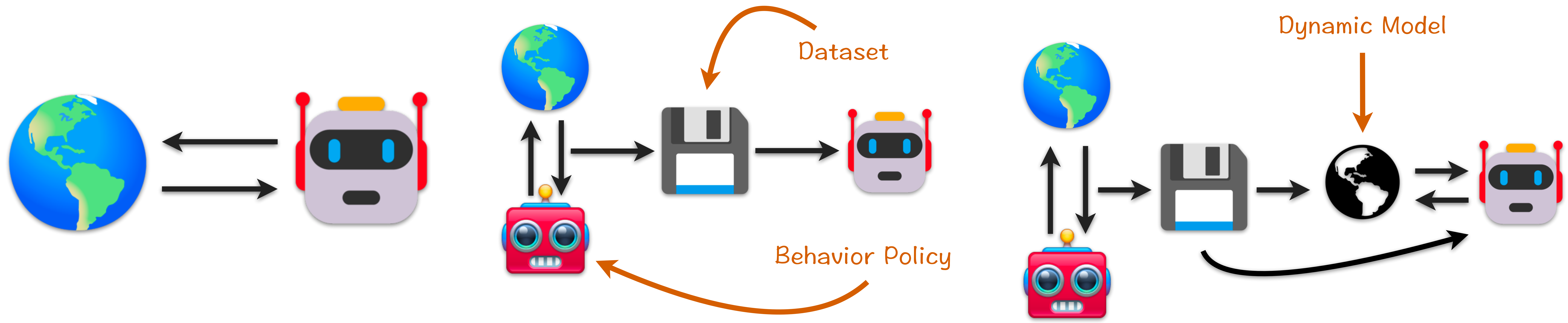
- Jointly train  and  to minimize an upper bound of the evaluation error.
  - Fixed ,  $\approx$  only on state-actions visited by .
  - Fixed , optimize  with a regularization based on .

Background

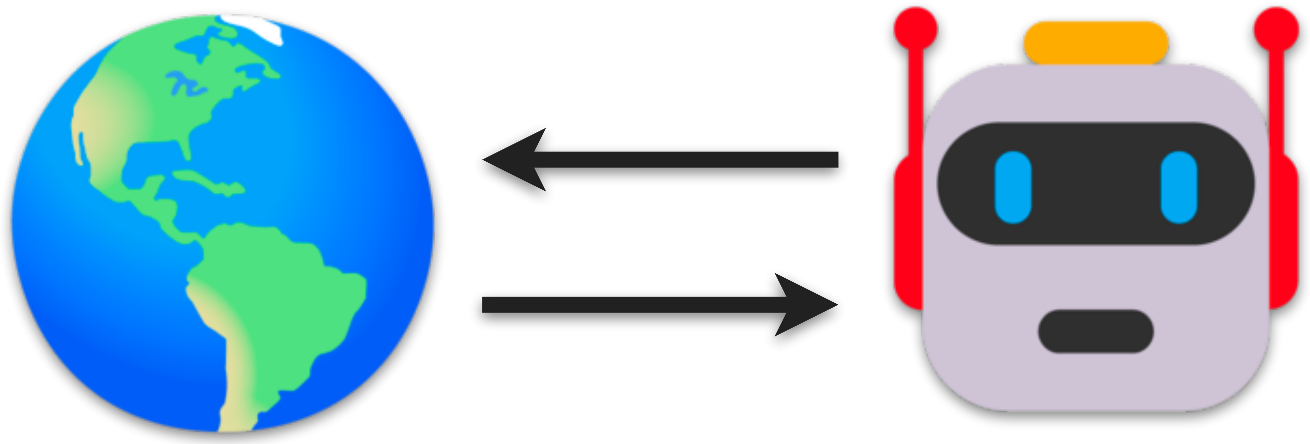
- Offline RL: learn policy from static datasets.



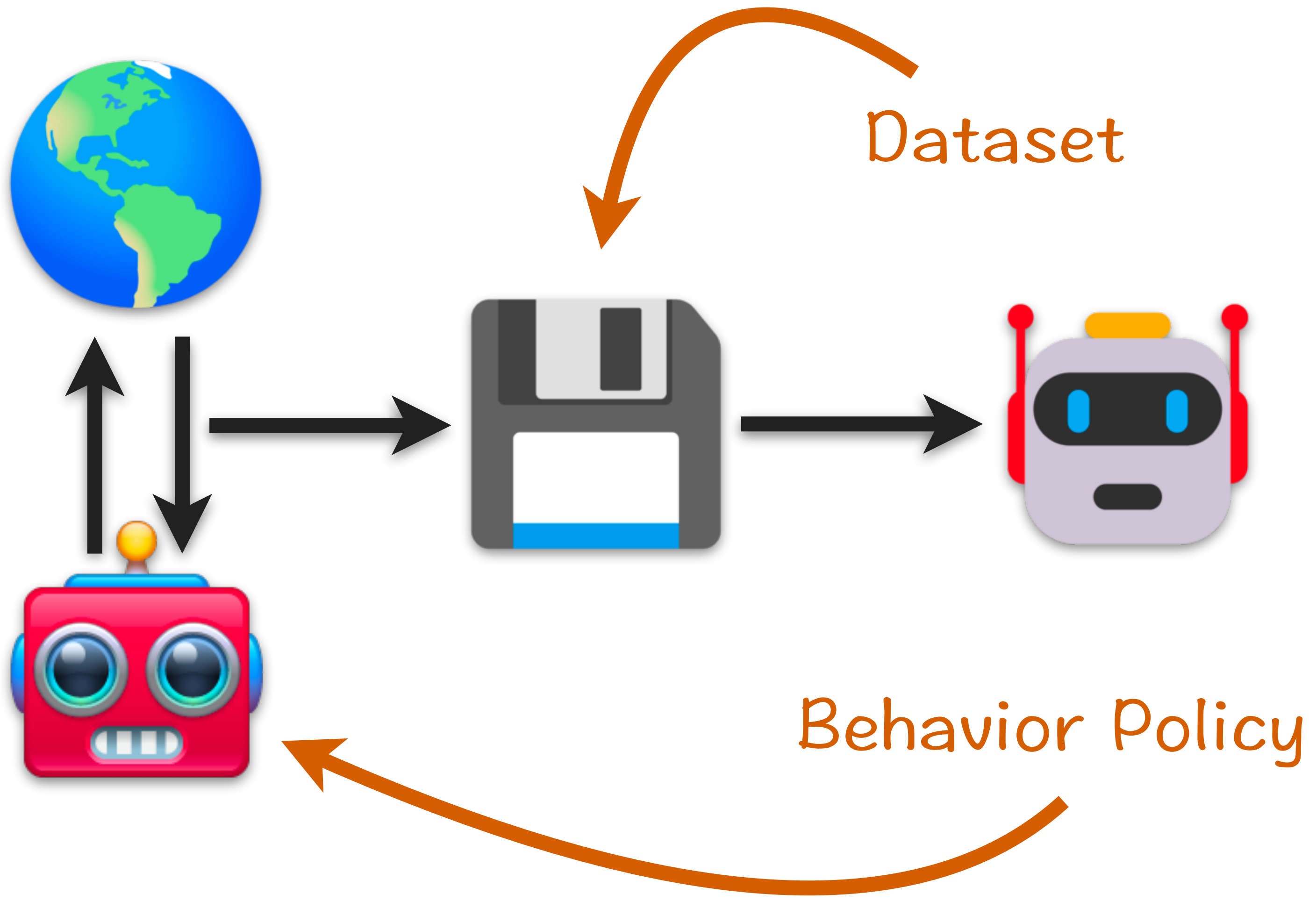
(a) Classical RL (b) Offline RL (c) Offline MBRL

Background

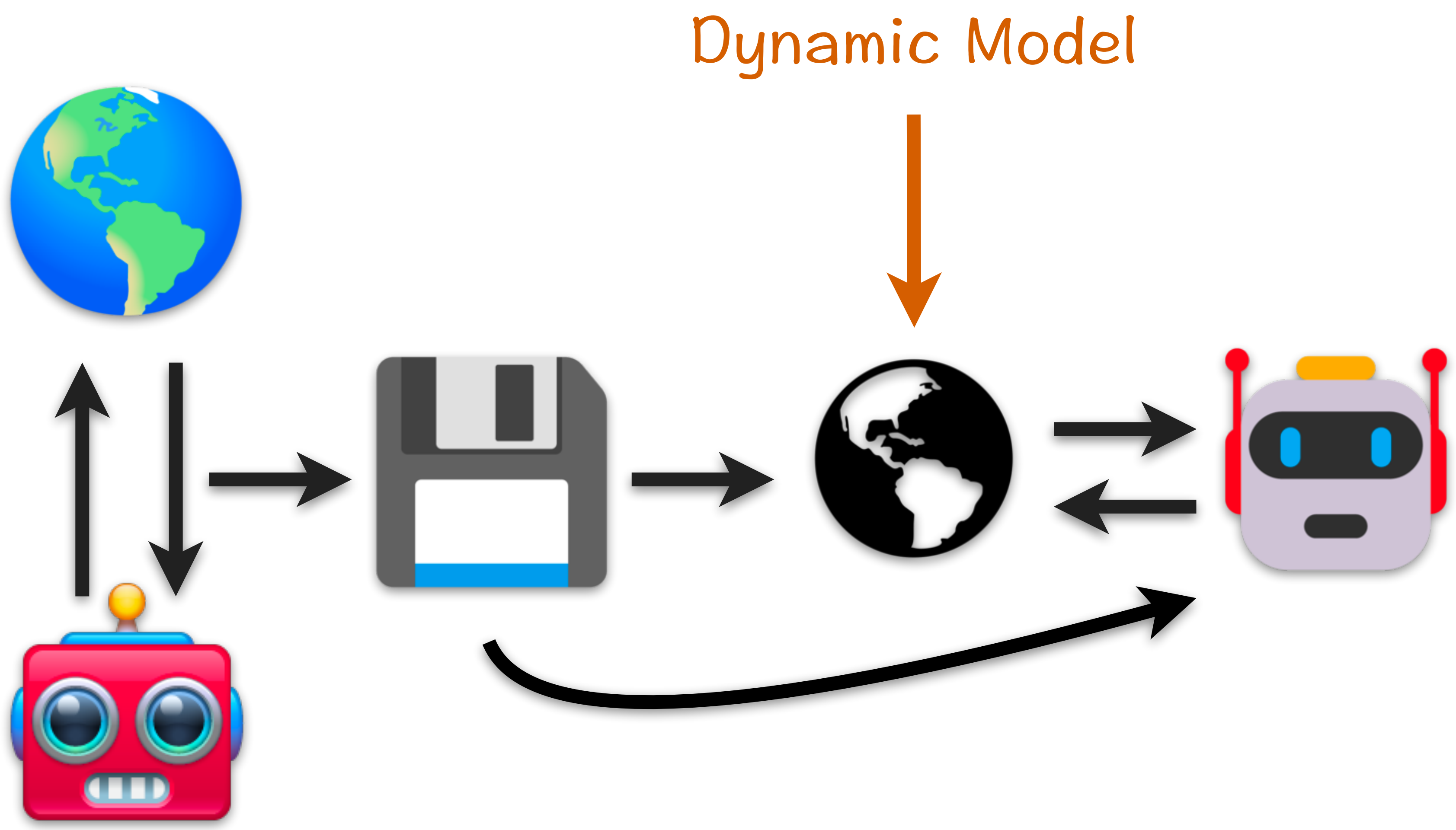
- Offline RL: learn policy from static datasets.
- Offline Model-Based RL (Offline MBRL): learn dynamic from static datasets.



(a) Classical RL



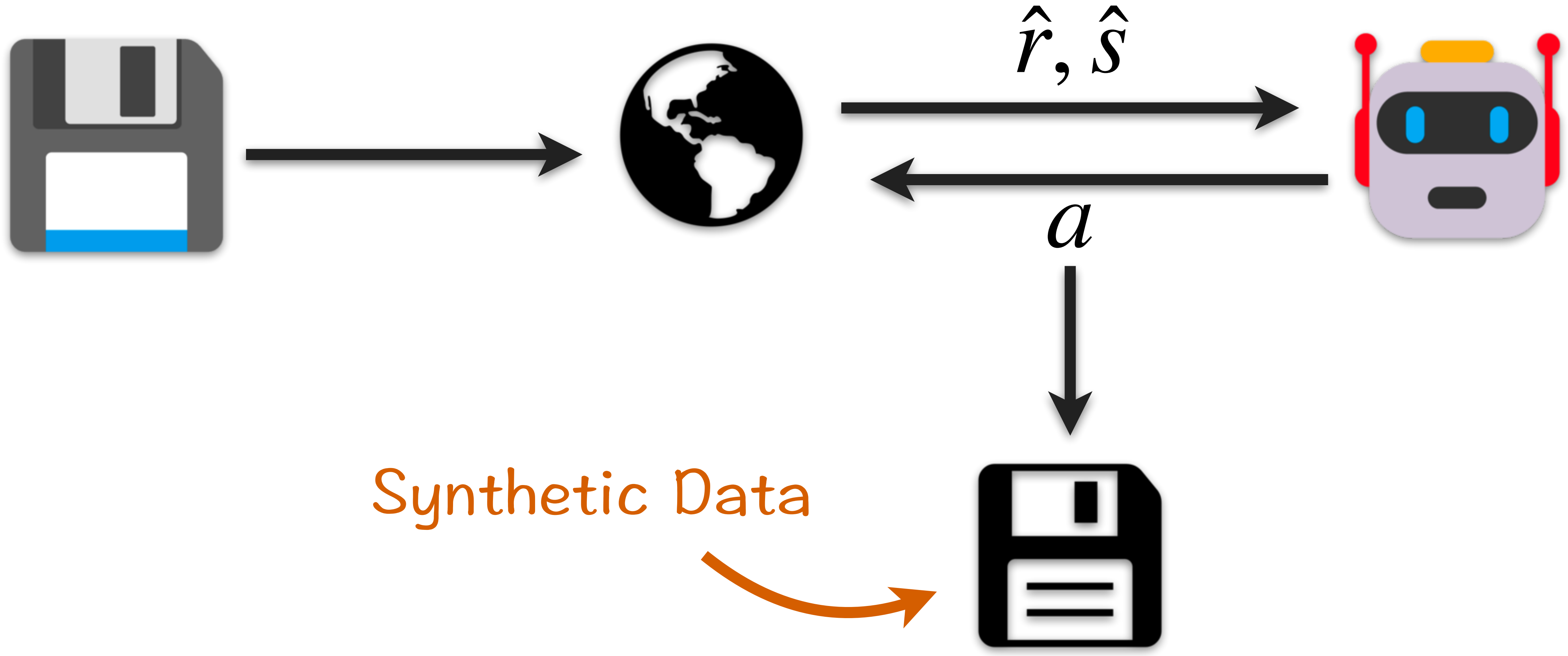
(b) Offline RL



(c) Offline MBRL

Background

- Benefits of offline MBRL



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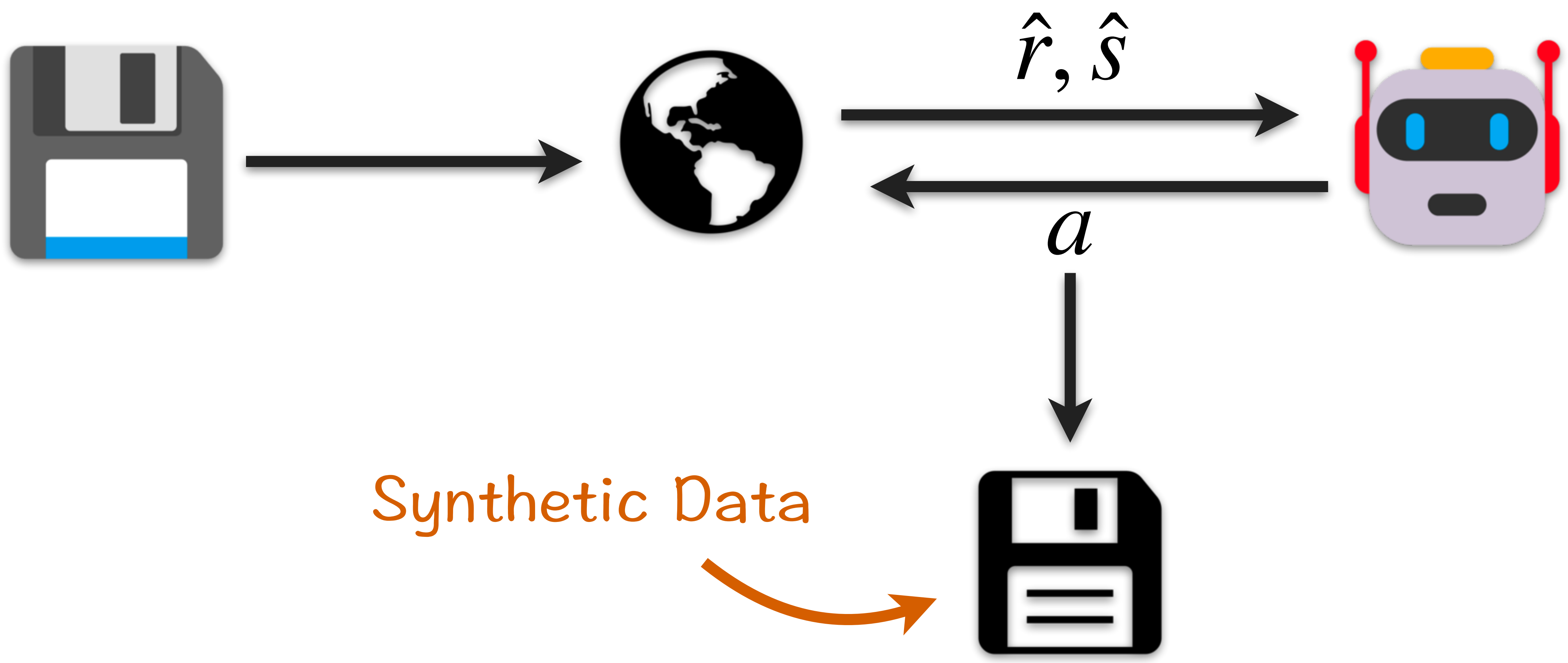
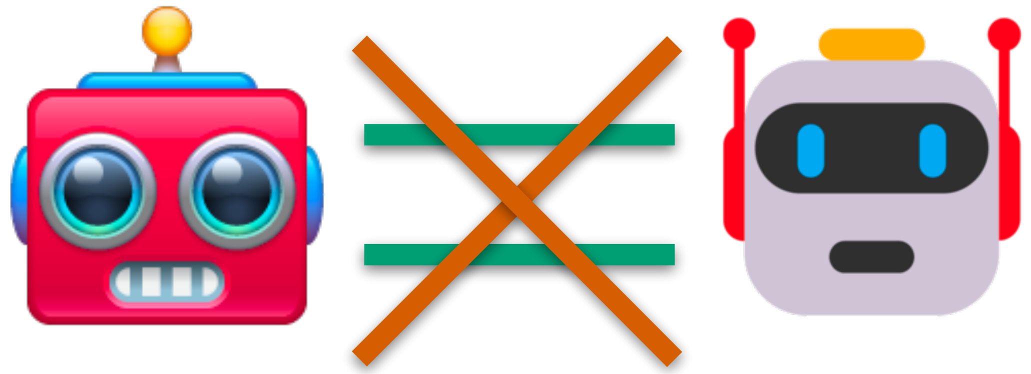


- Offline model-free RL
  - Only know reward and next state at state-actions within the dataset.
  - Off-policy issue  .

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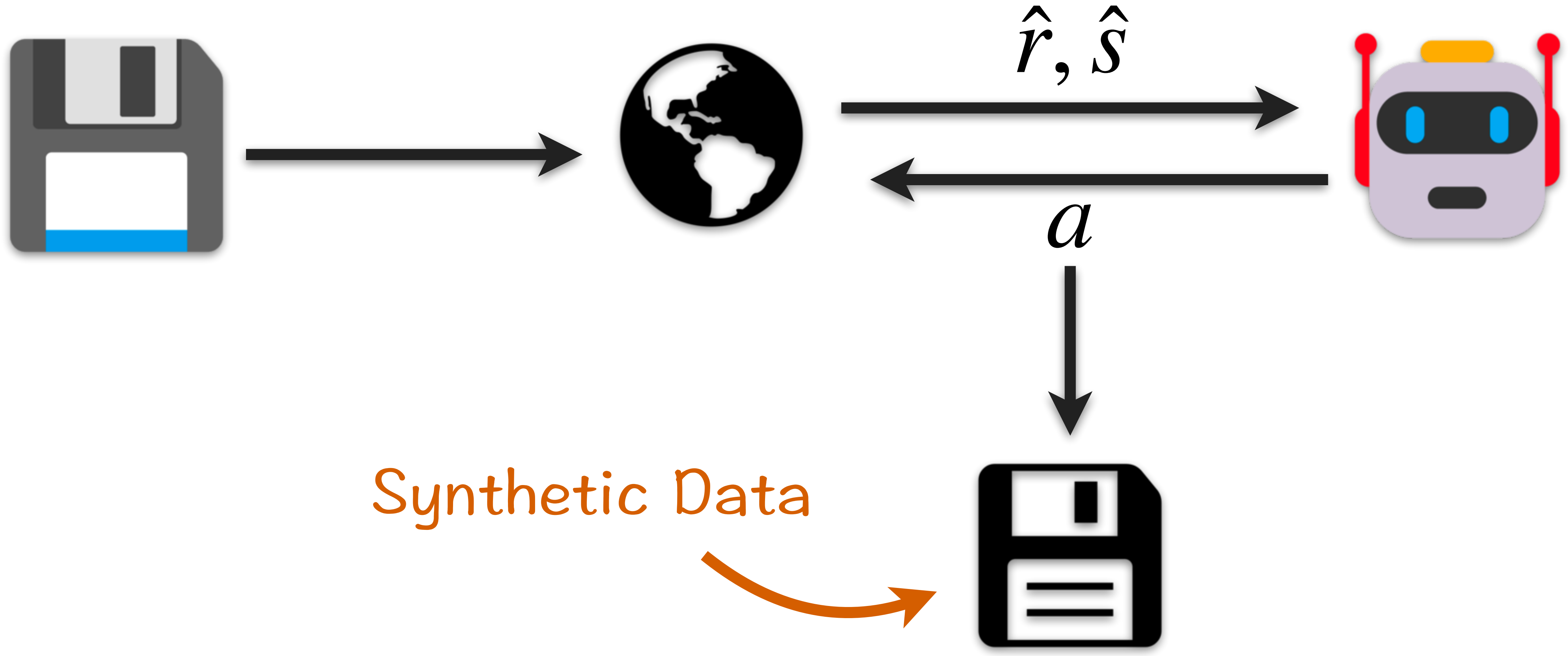

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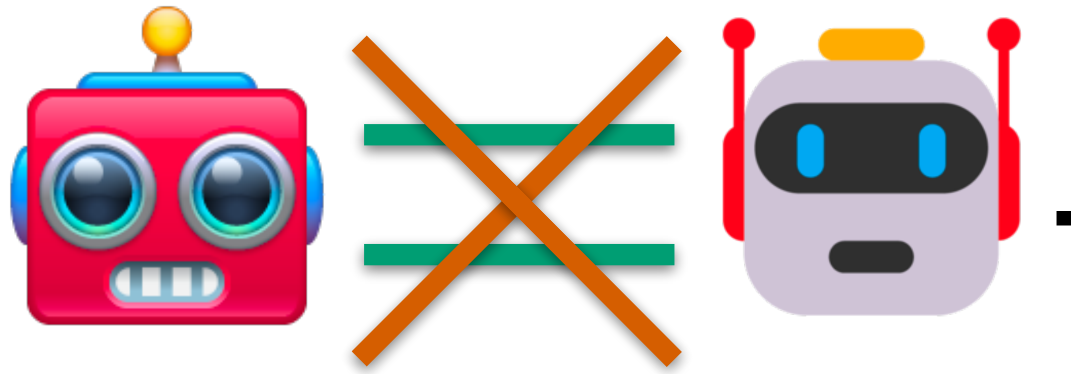
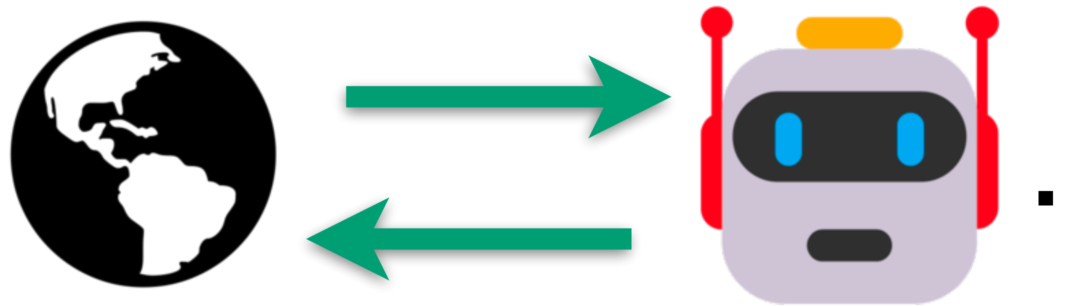
  - Off-policy issue 

- Offline model-based RL
  - Estimate reward and next state at new state-actions.
  - $\approx$ on-policy 

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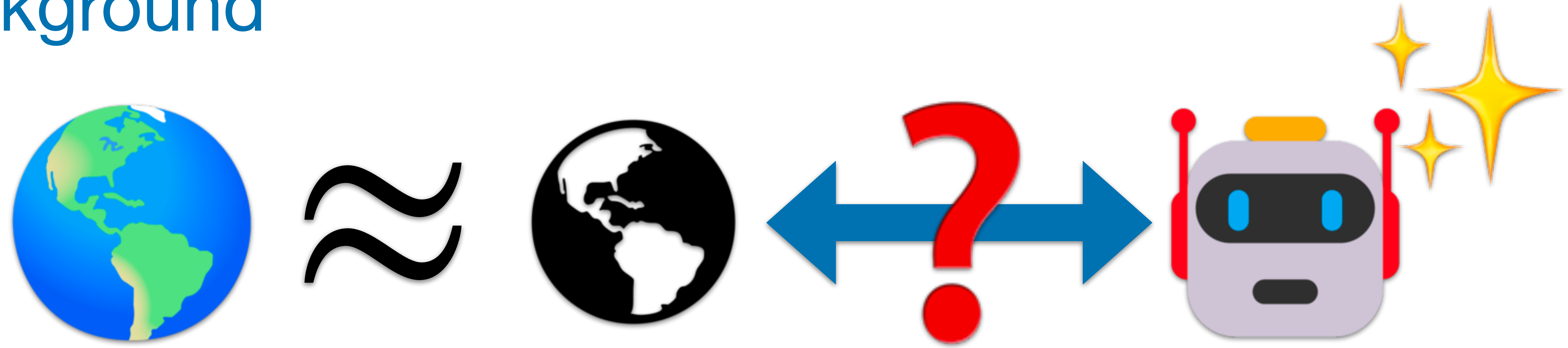

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    - Objective: MLE — “simply a mimic of the world.”
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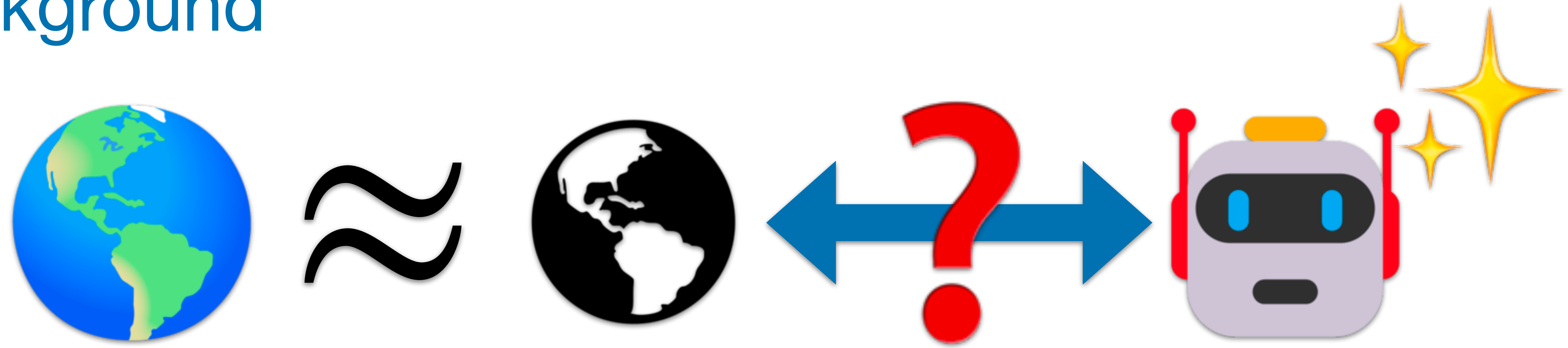

- Most offline MBRL: pre-train a fixed dynamic model on  .
    - Objective: MLE — “simply a mimic of the world.”
    - Usage: improve the policy.
- Objective mismatch: model training $\neq$ model usage.
    - Especially when  is limited and  is hard to learn.

Proposed Method: Bounding the Evaluation Error

- A tractable upper bound for the evaluation error

$$\left| J(\pi, P^*) - J(\pi, \widehat{P}) \right| \leq C \cdot \sqrt{D_\pi(P^*, \widehat{P})}, \quad \text{with}$$

$$D_\pi(P^*, \widehat{P}) \triangleq \mathbb{E}_{(s,a)\sim d^{P^*}_{\pi_b,\gamma}} \left[\omega(s,a)\,\mathrm{KL}\left(P^*(s' \mid s,a)\,\pi_b(a' \mid s') \,||\, \widehat{P}(s' \mid s,a)\,\pi(a' \mid s') \right) \right],$$

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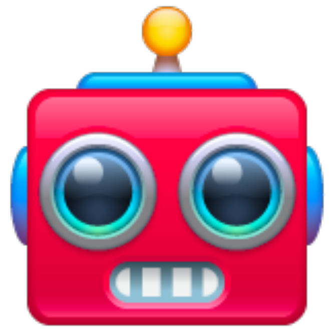
- π_b is the behavior policy  .

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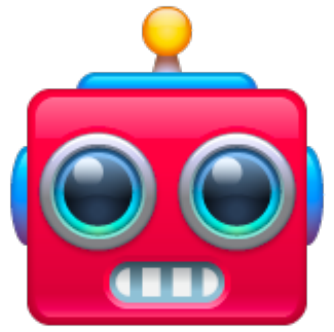
- π_b is the behavior policy  .
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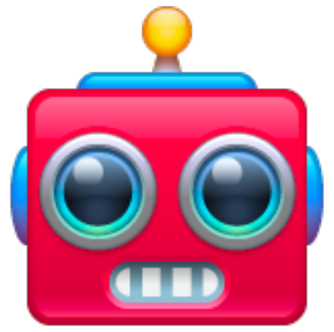
- π_b is the behavior policy  .
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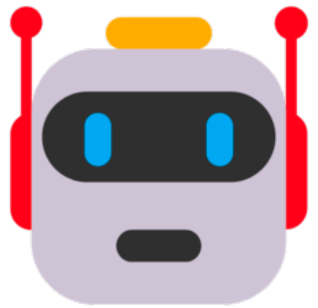
- $\omega(s,a) \triangleq \dfrac{d^{P^*}_{\pi,\gamma}(s,a)}{d^{P^*}_{\pi_b,\gamma}(s,a)}$ is the density ratio between  and visitation freq. of  .

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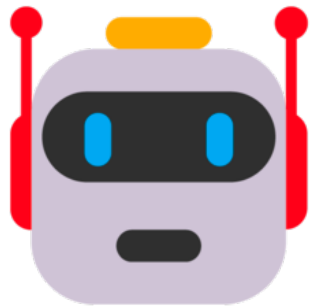
- Fix , we train the model  by

$$\ell(\widehat{P}) \triangleq -\mathbb{E}_{(s,a,s')\sim d^{P^*}_{\pi_b,\gamma}}\left[\omega(s,a)\log\left\{\widehat{P}(s' \mid s,a)\right\}\right] = D_\pi(P^*, \widehat{P}) - C', \quad \text{with } C' \text{ a constant to } \widehat{P}.$$

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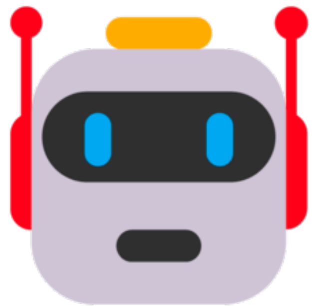
- Fix , we train the model  by

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- Given $\omega(s, a)$, a stable weighted MLE objective.

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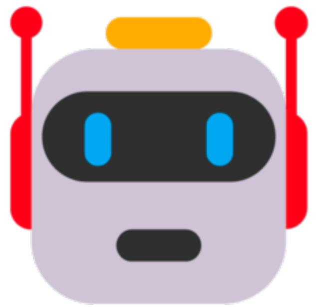
- A lower-bound of  performance: $J\left(\pi, \widehat{P}\right) - C \cdot \sqrt{D_\pi(P^*, \widehat{P}\,)}\,.$

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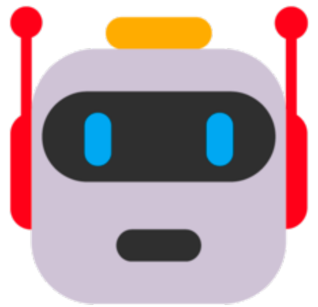
- A lower-bound of  performance: $J\left(\pi, \widehat{P}\right) - C \cdot \sqrt{D_\pi(P^*, \widehat{P})}\,.$
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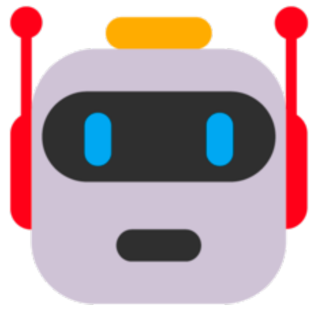
- A lower-bound of  performance: $J\left(\pi, \widehat{P}\right) - C \cdot \sqrt{D_\pi(P^*, \widehat{P})}$.
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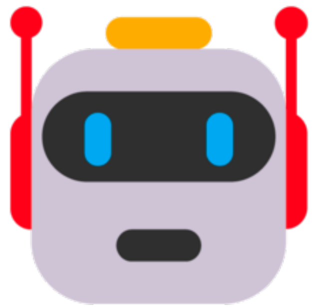
- A lower-bound of  performance: $J\left(\pi, \widehat{P}\right) - C \cdot \sqrt{D_\pi(P^*, \widehat{P})}$.
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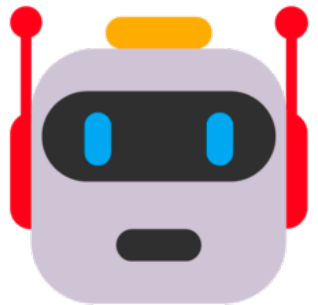
  - Stronger regularizer: regularizes  at both s and s'.

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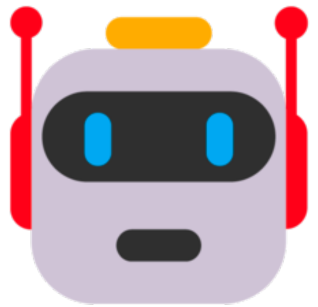
- A lower-bound of  performance: $J\left(\pi, \widehat{P}\right) - C \cdot \sqrt{D_\pi(P^*, \widehat{P})}$.
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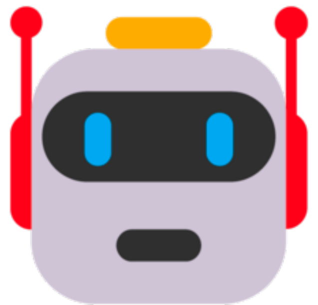
    - Stronger regularizer: regularizes  at both s and s'.
  - Changing KL-divergence to Jensen-Shannon divergence.

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- Based on the "forward" Bellman equation for $\omega(s,a)$ —not tractable 😭 !
  - Use Q-function as test function and $\sum_{(s',a')}$ on both sides.
    - Primal-dual relation between $\omega(s,a)$ and Q-function in OPE.

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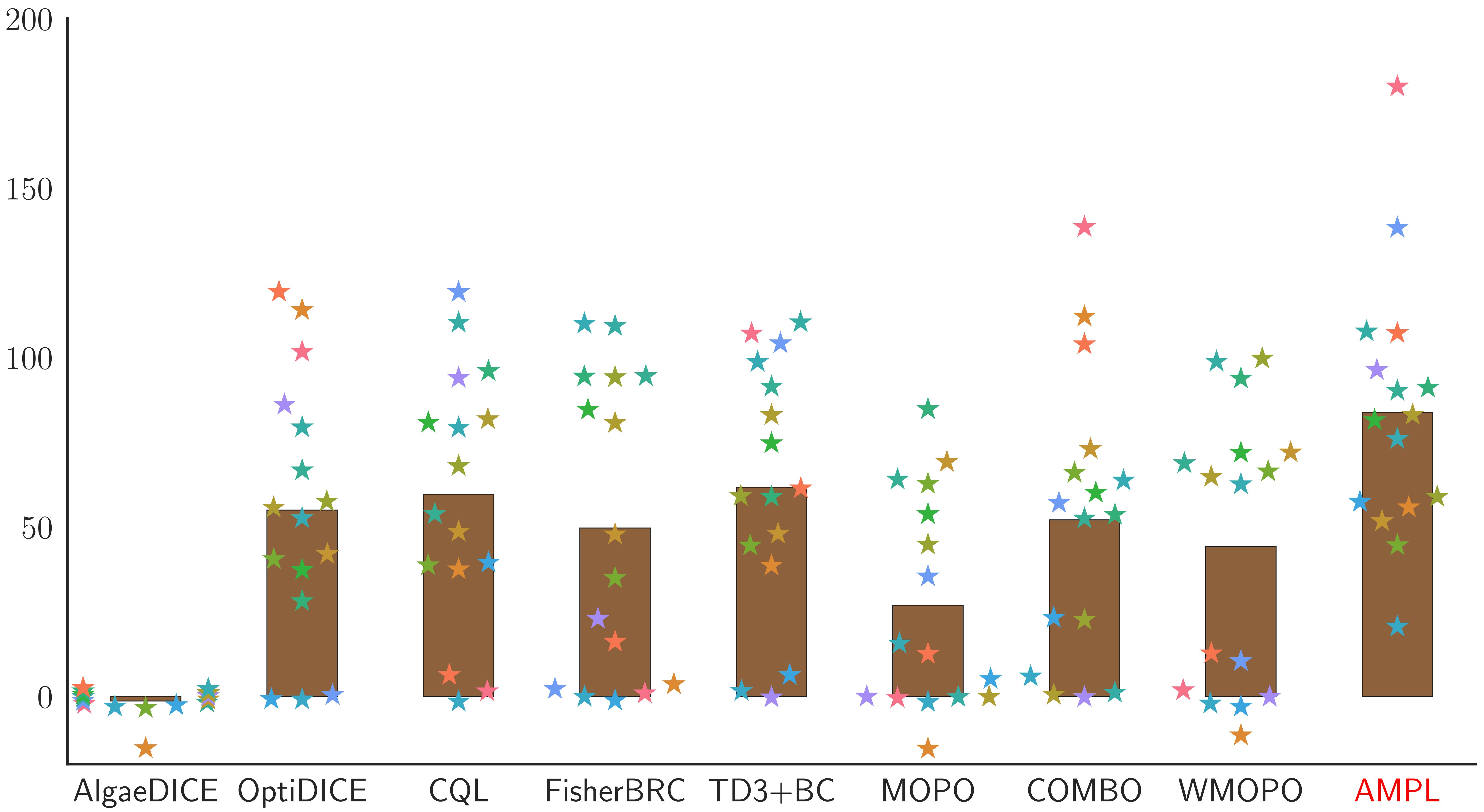
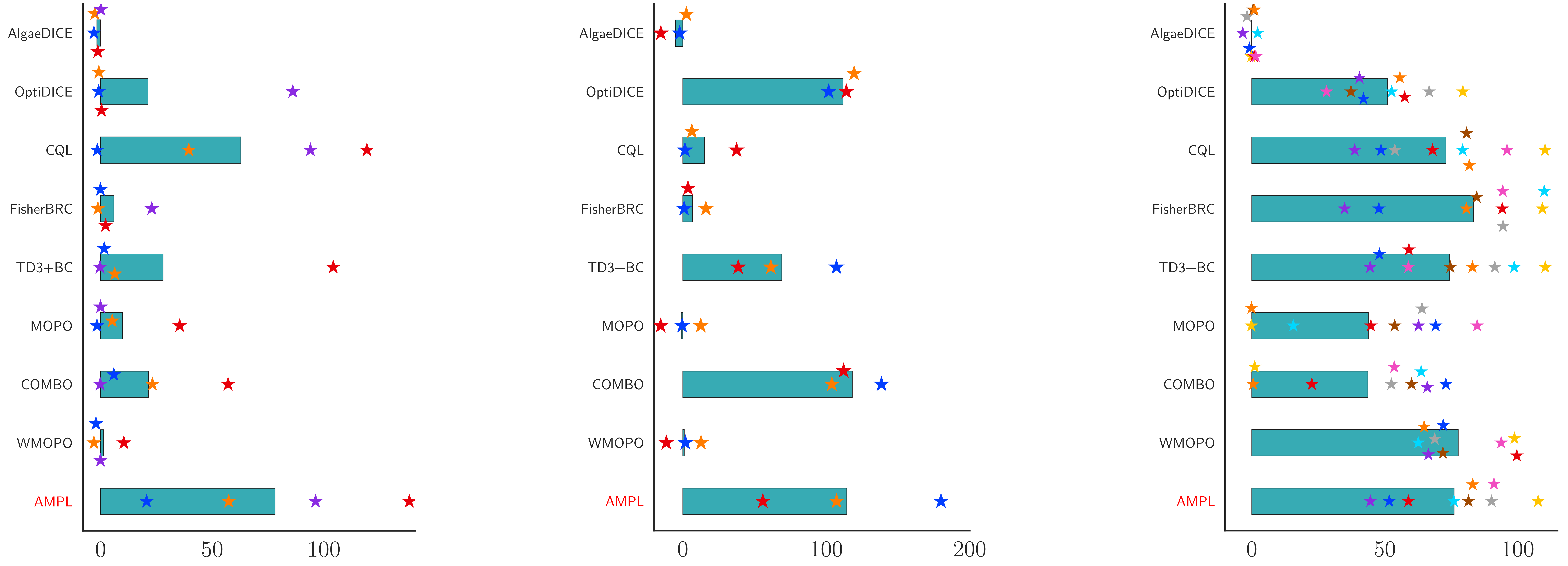
- Only requires samples from 💾 and the initial state-distribution.

Results: Main Method



- Our offline Alternating Model-Policy Learning (AMPL) performs well on D4RL tasks.

Results: Main Method



(a) Adroit (b) Maze2D (c) MuJoCo

- Learn well on the MuJoCo datasets.

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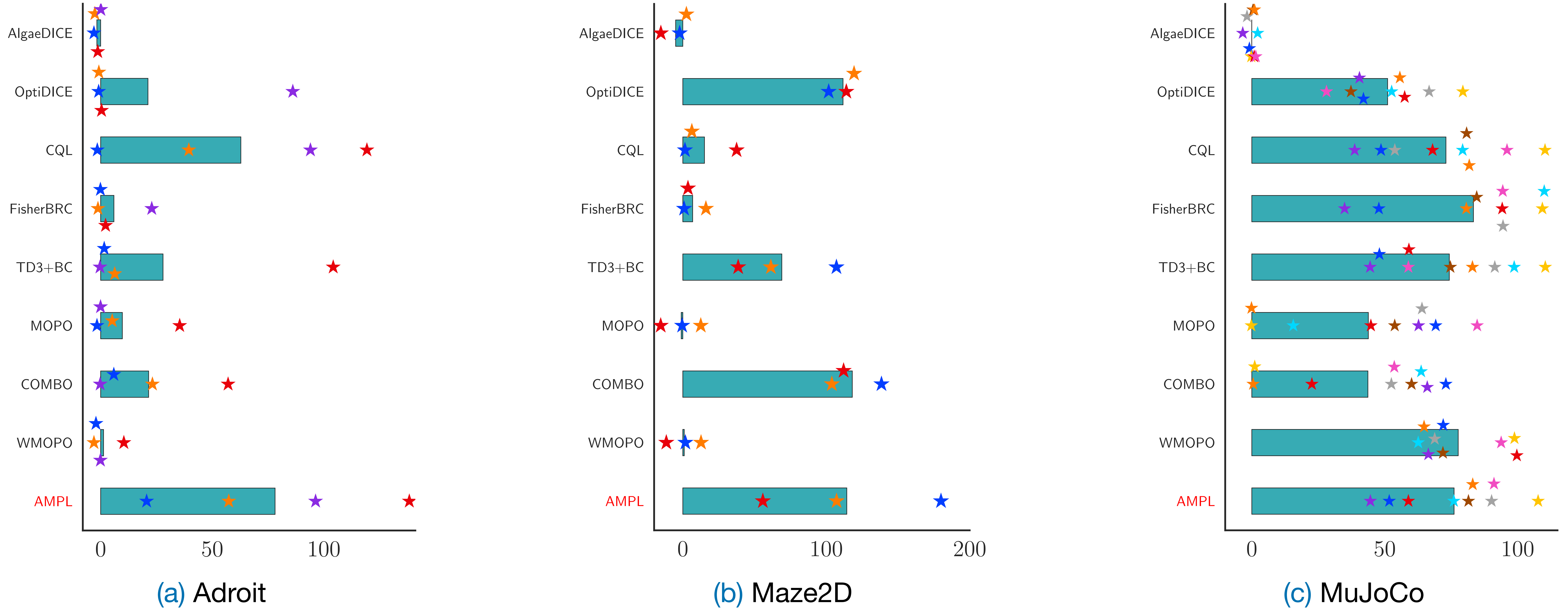
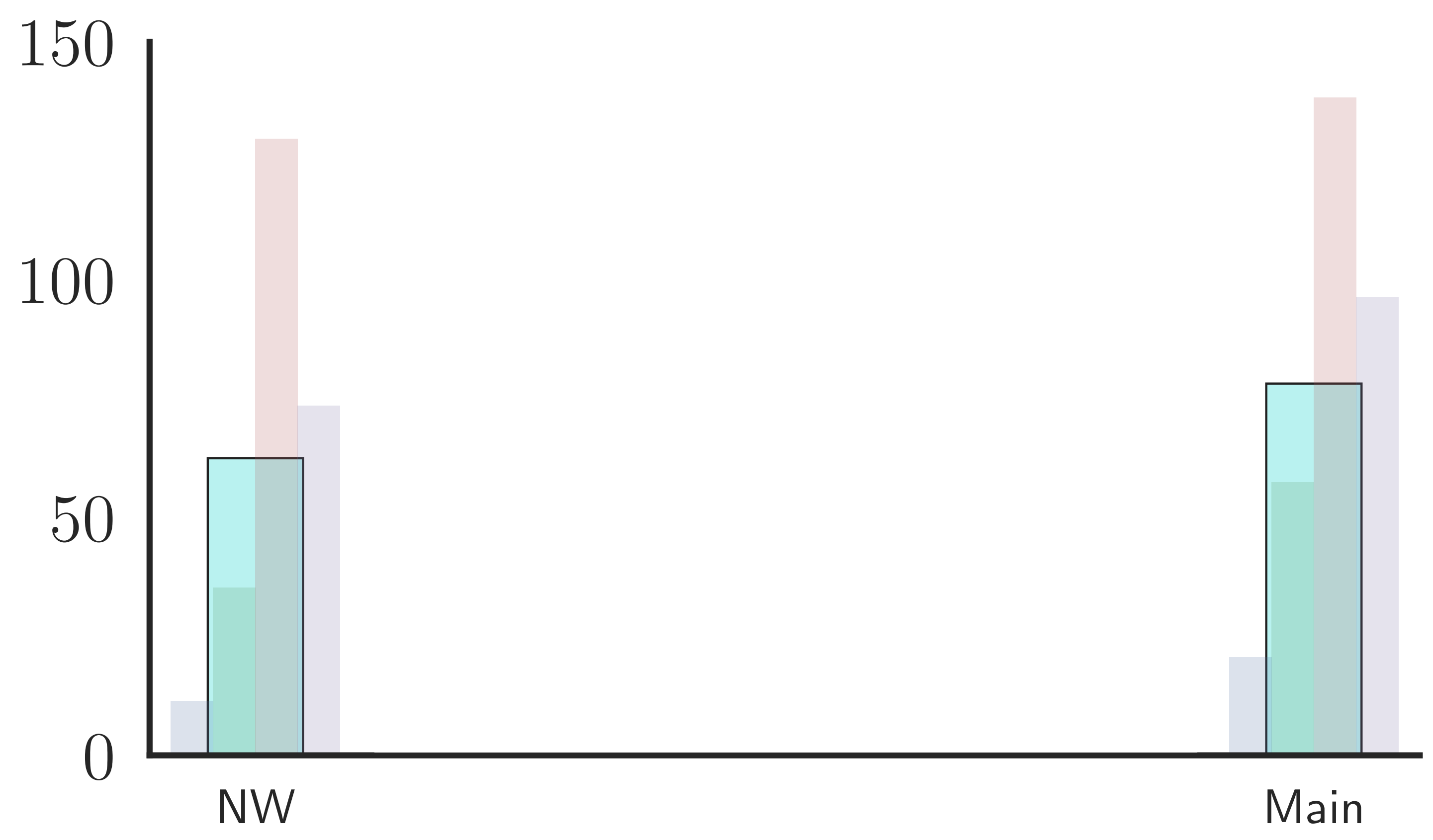


- Learn well on the MuJoCo datasets.

- Robust and good results on the challenging Adroit and Maze2D datasets.

Ablation Study I: Does weighted model (re)training help?



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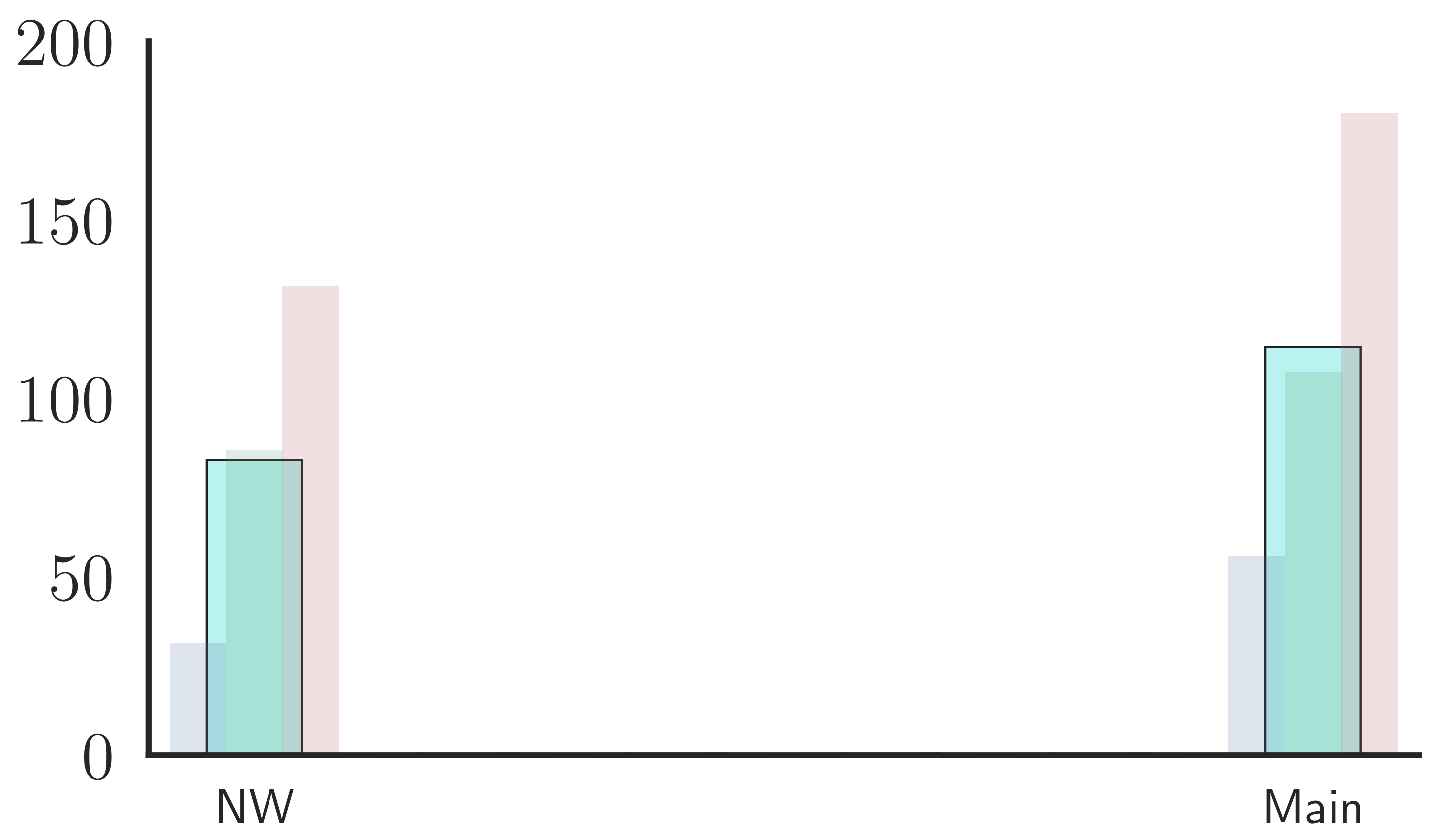
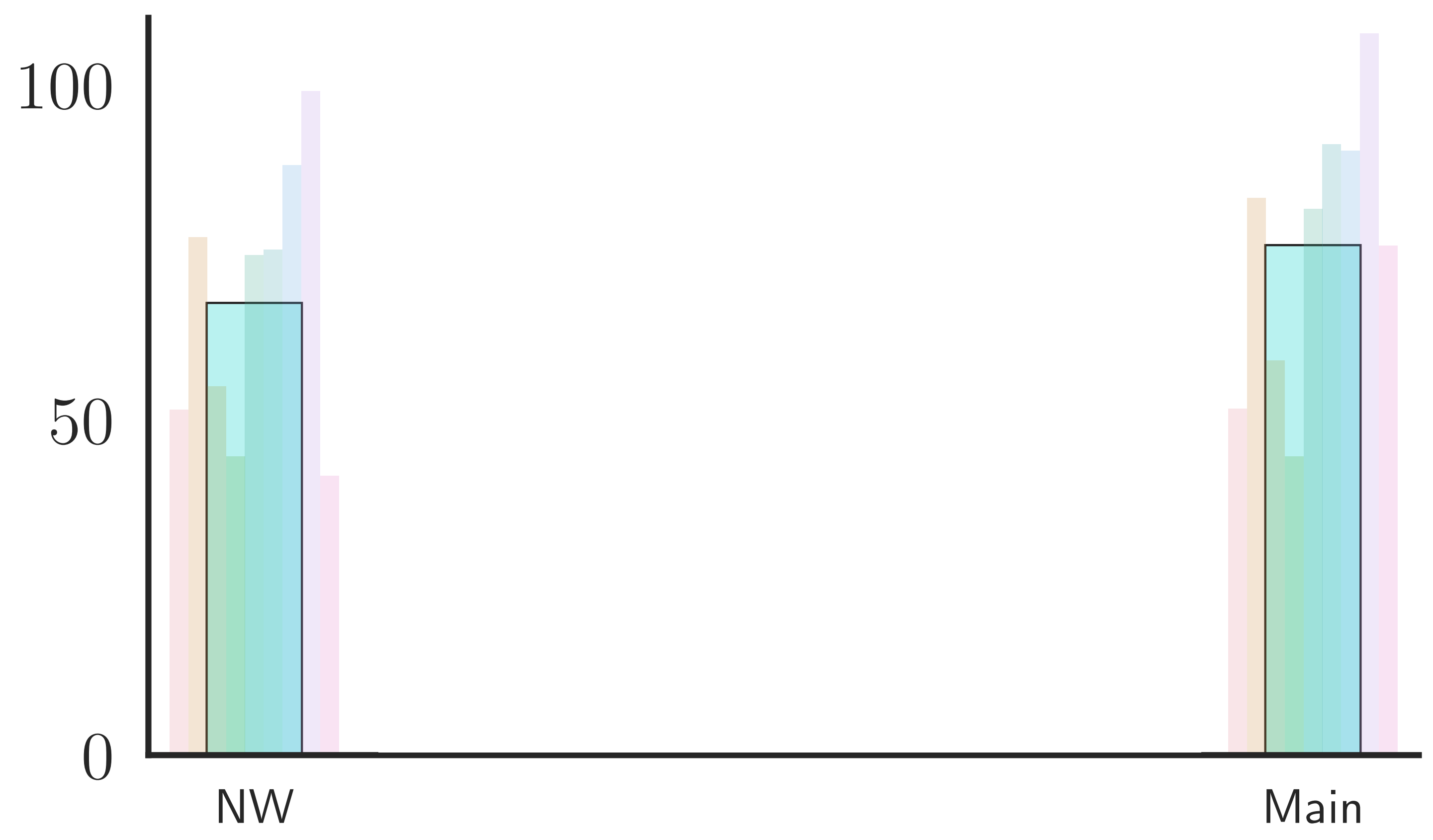


(b) Maze2D



(c) MuJoCo

- Variant: training  only at the beginning using MLE — No Weights (NW).

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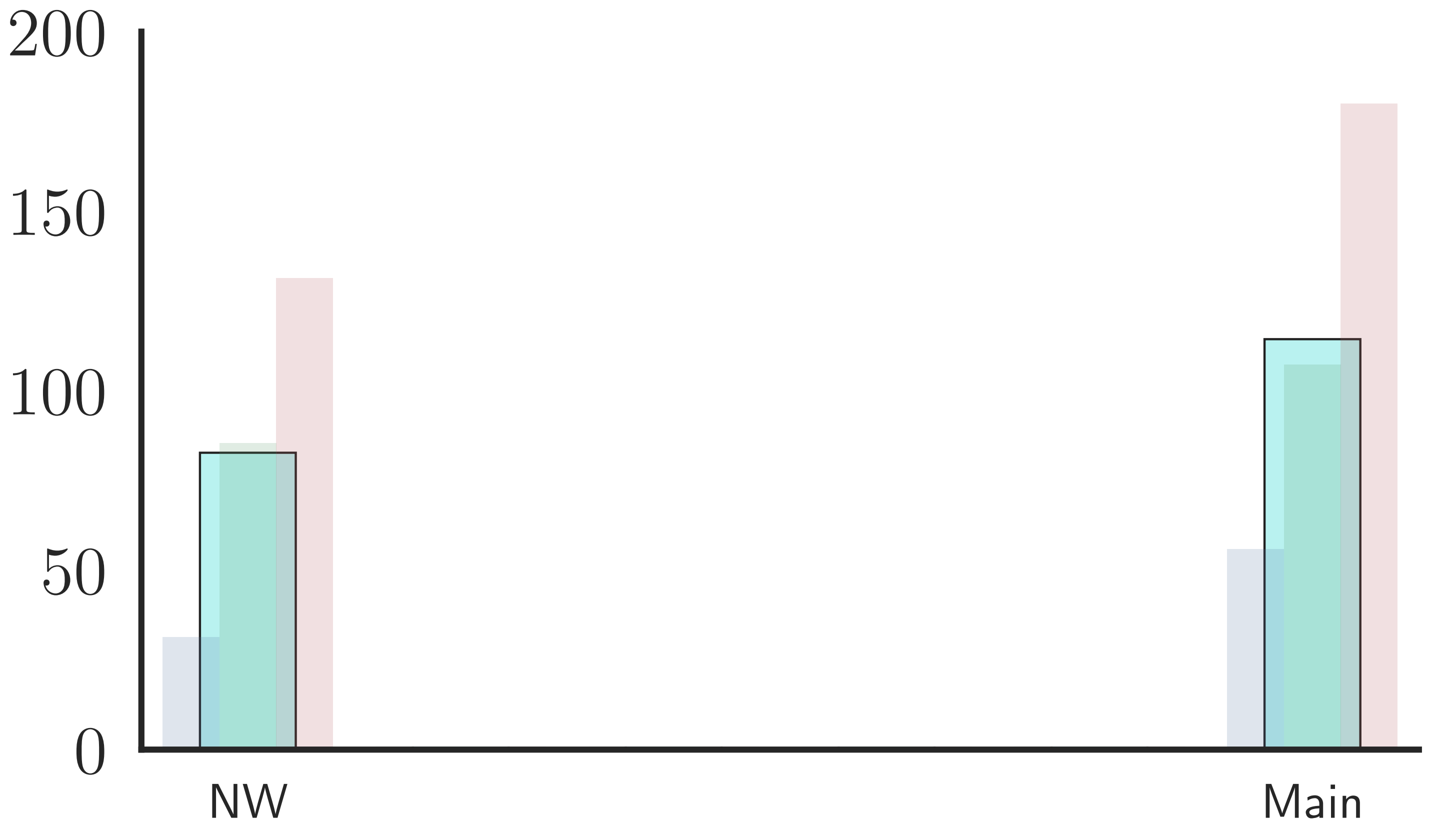


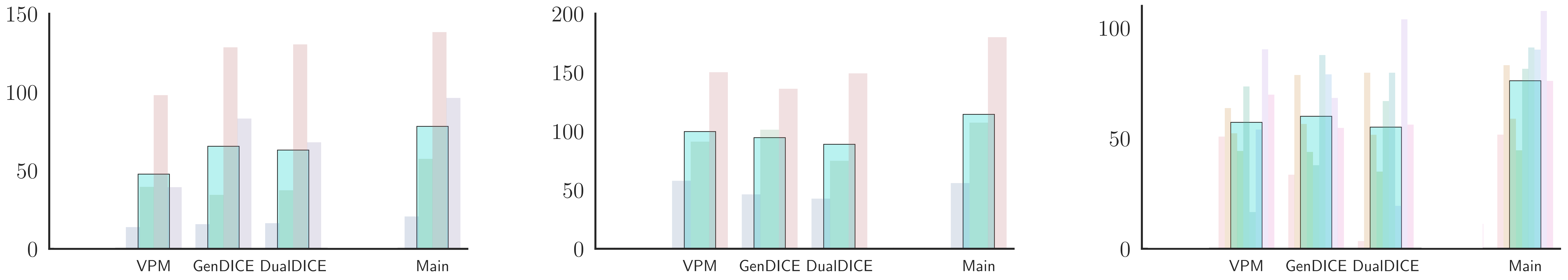
(b) Maze2D

(c) MuJoCo

- Variant: training  only at the beginning using MLE — No Weights (NW).

- On all three domains, the NW variant generally underperforms the main method.

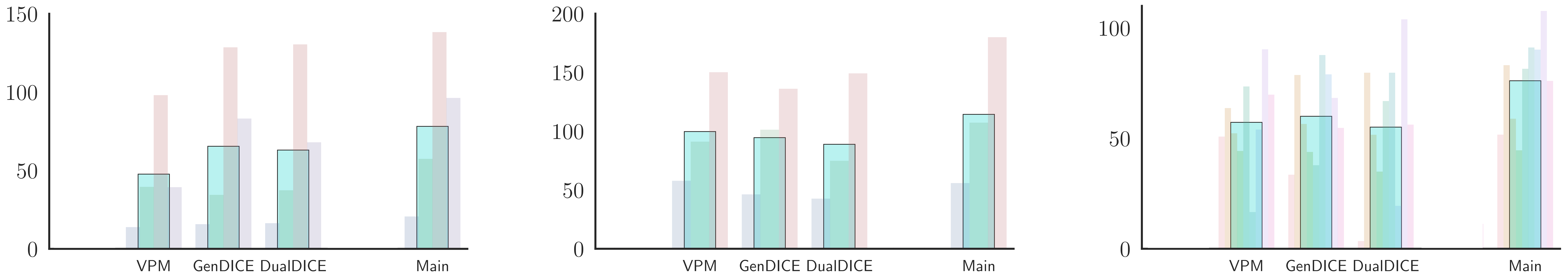
Ablation Study II: Other density-ratio estimation methods?



(a) Adroit (b) Maze2D (c) MuJoCo

- Variant: $\omega(s, a)$ is estimated by VPM, GenDICE, and DualDICE.

Ablation Study II: Other density-ratio estimation methods?

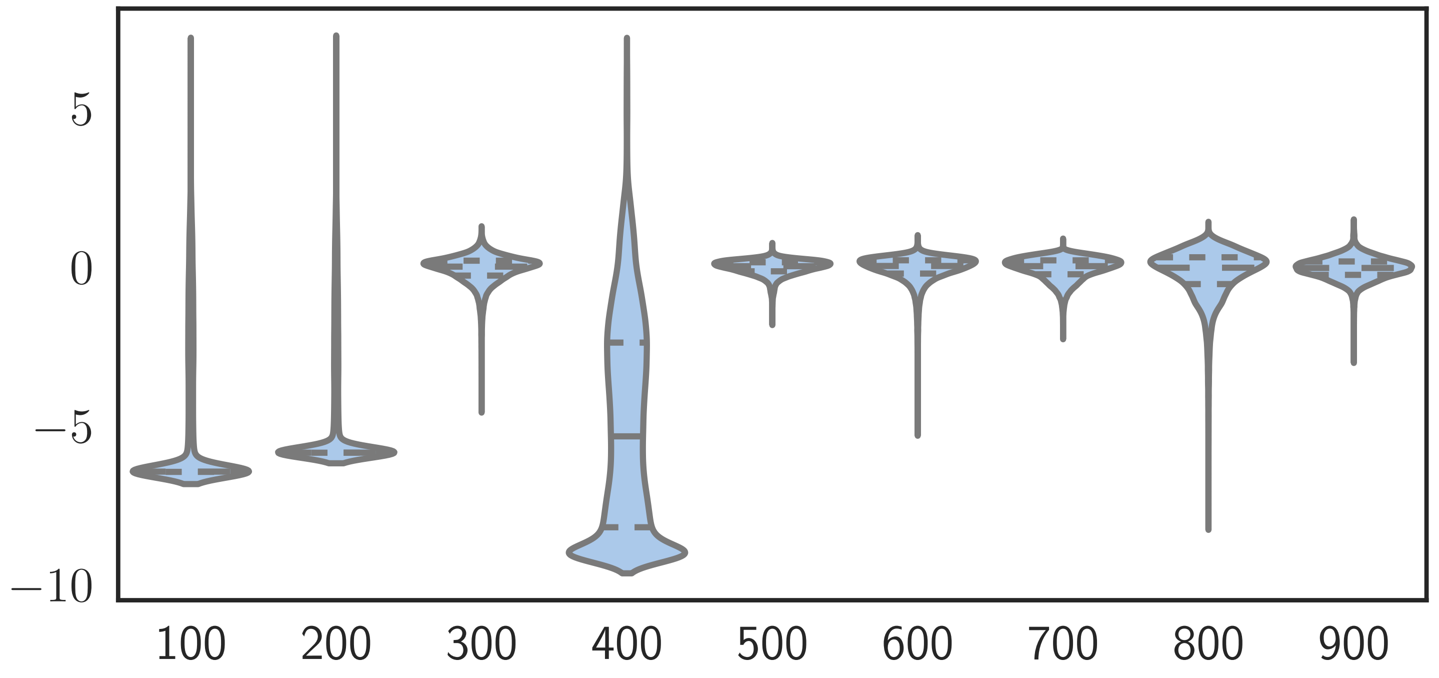


(a) Adroit (b) Maze2D (c) MuJoCo

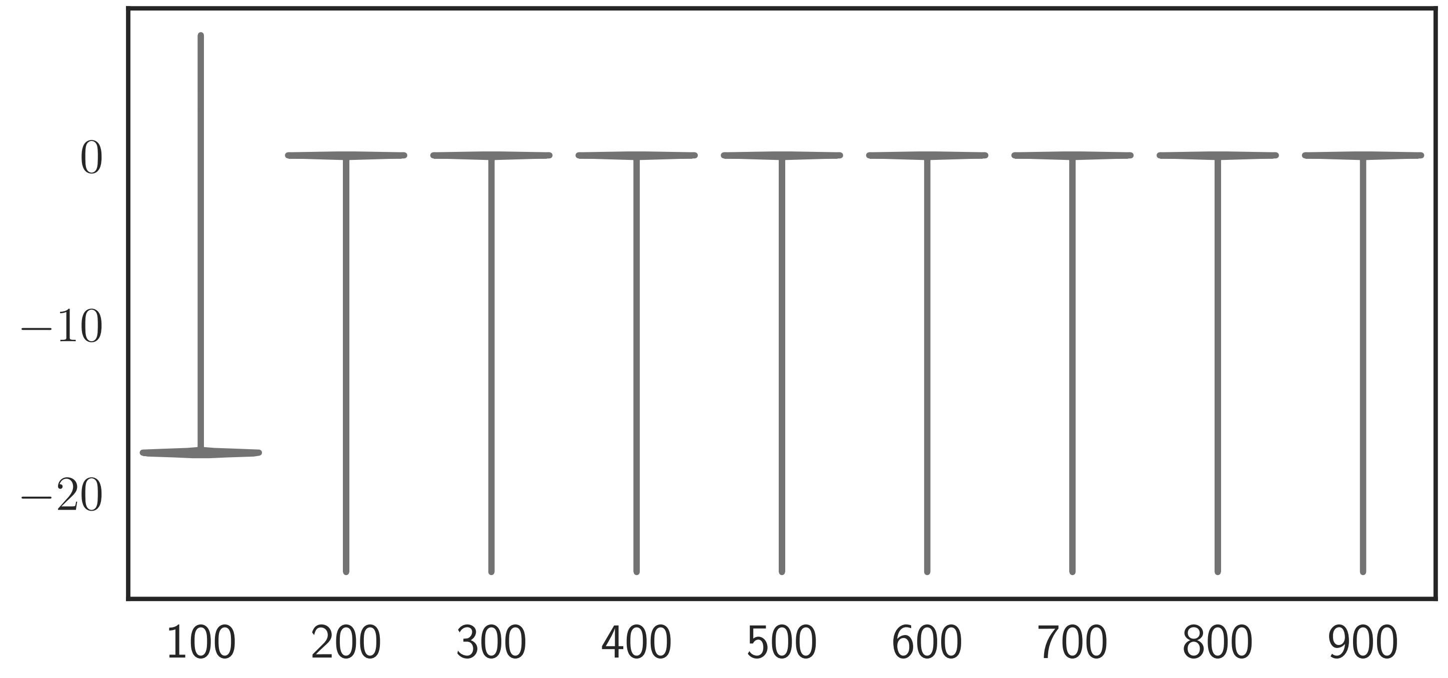
- Variant: $\omega(s, a)$ is estimated by VPM, GenDICE, and DualDICE.

- On all three domains, these three variants generally underperform our method.

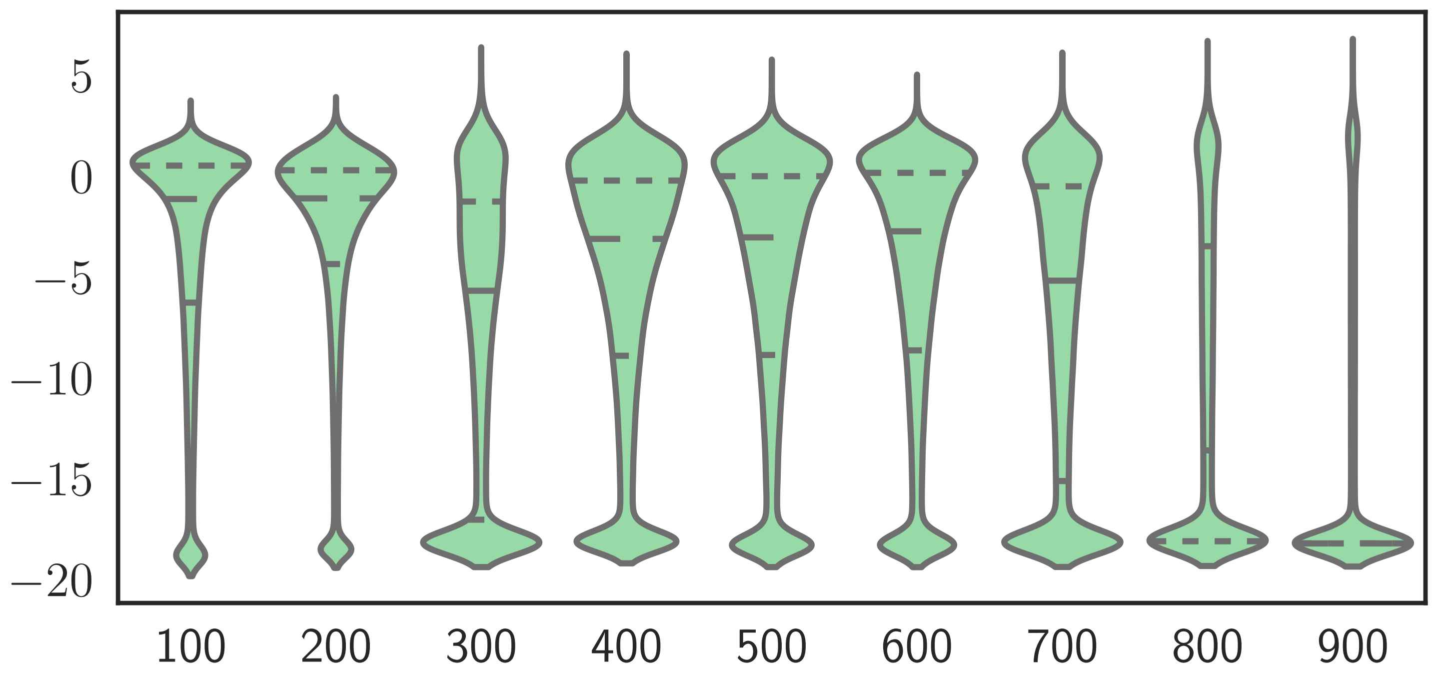
Ablation Study II: Other density-ratio estimation methods?



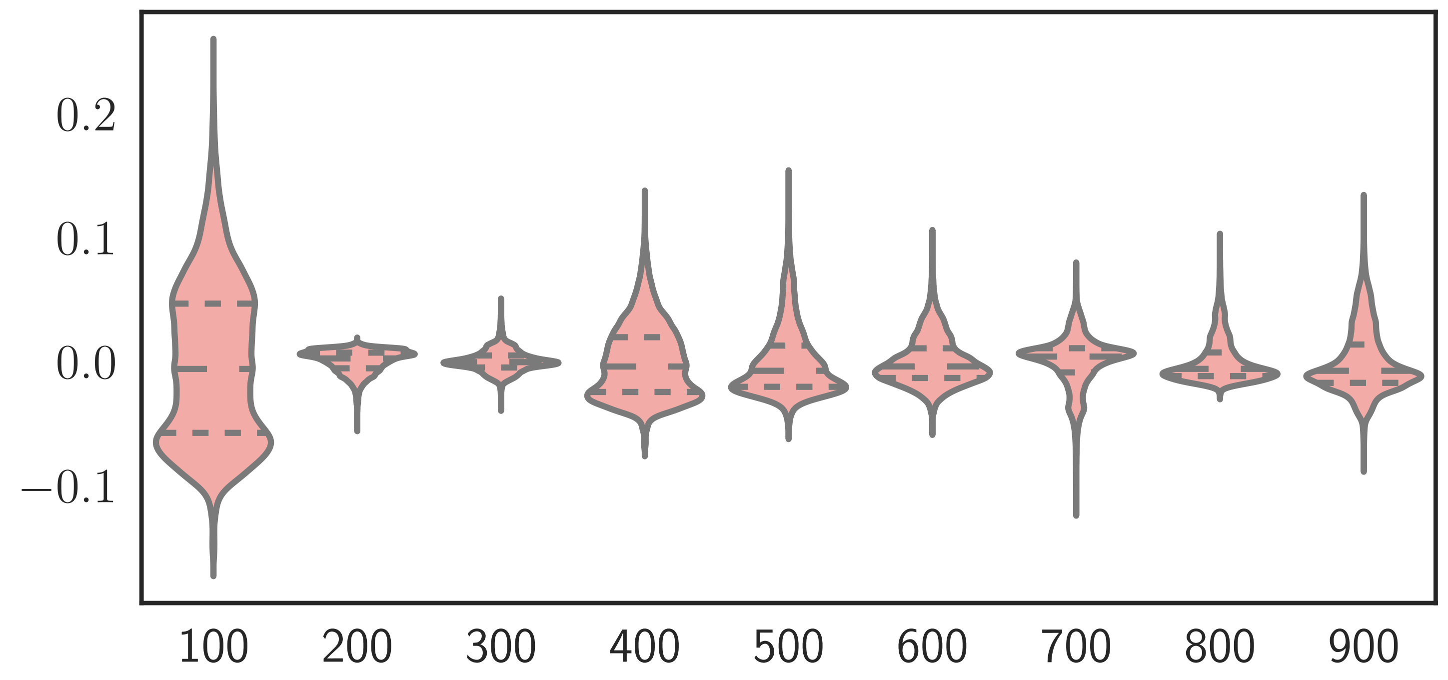
(a) VPM



(b) GenDICE



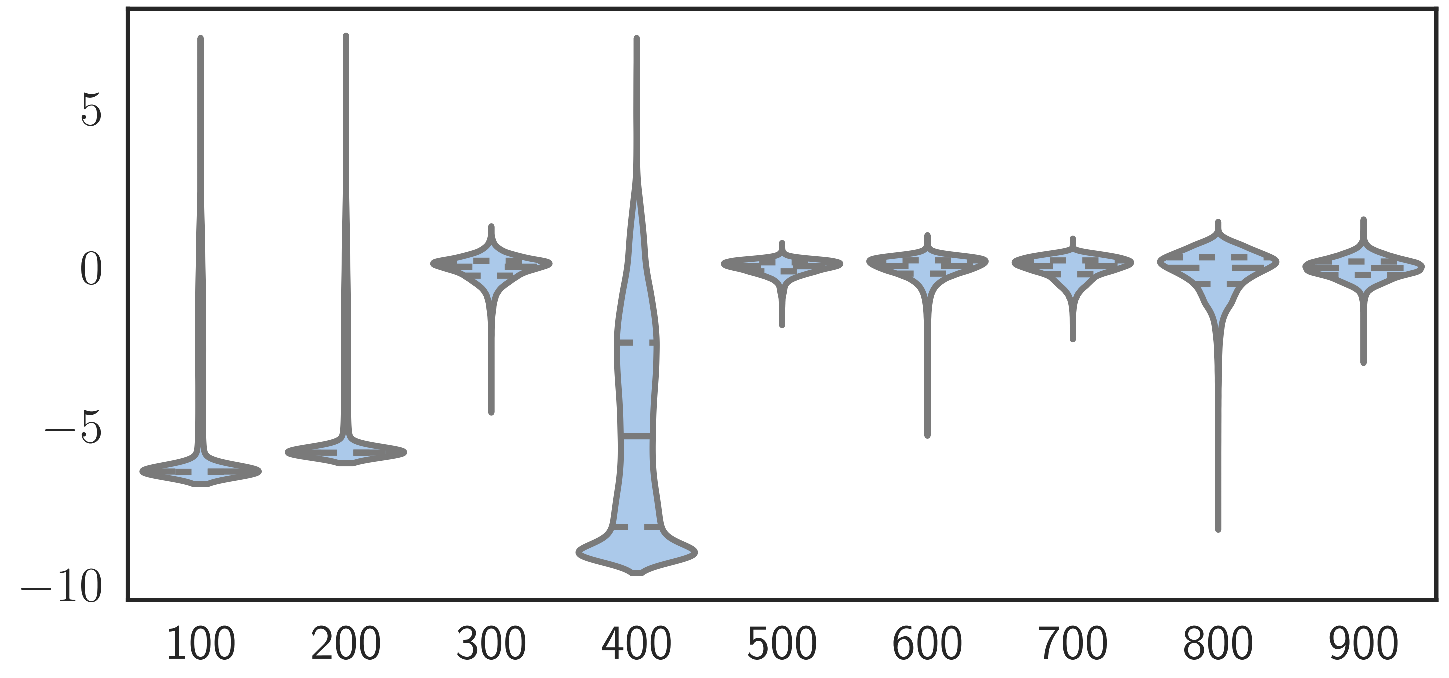
(c) DualDICE



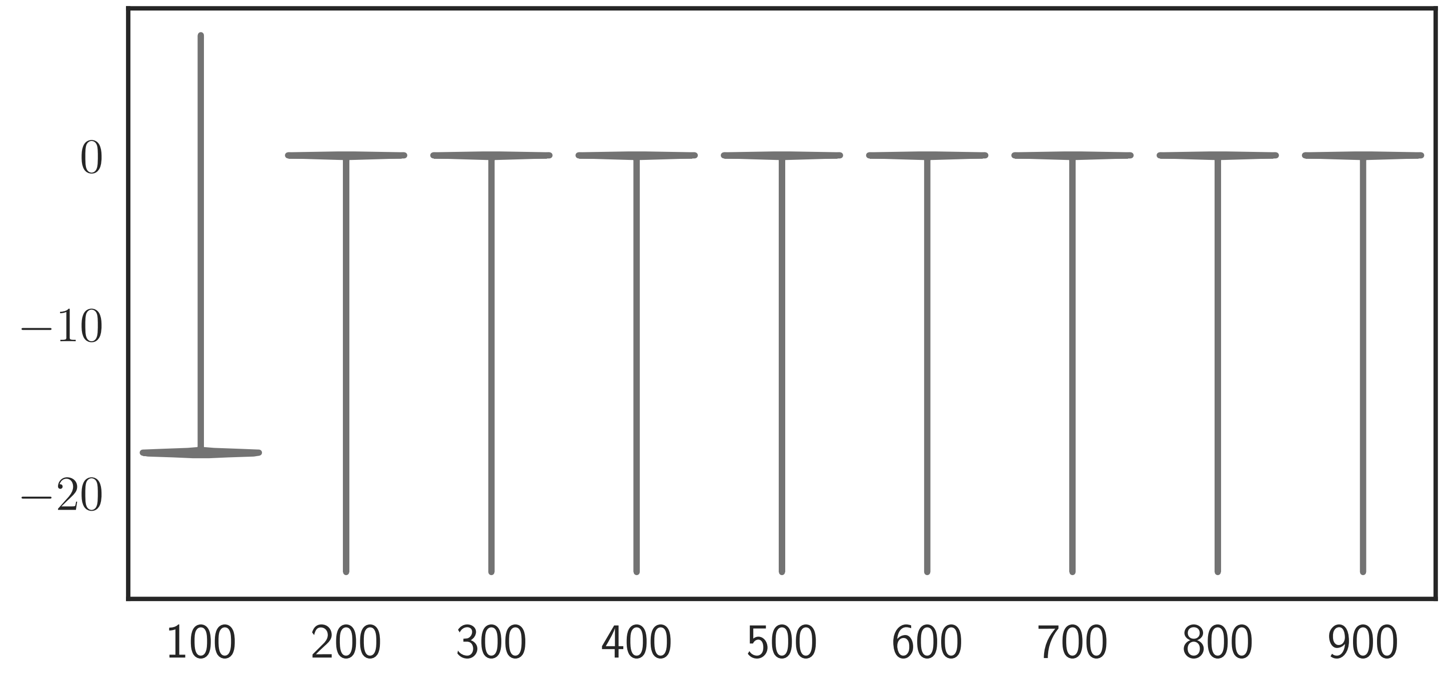
(d) Ours

- Distribution plot of $\log(\omega(s, a))$ during the training process, on “walker2d-medium-replay.”

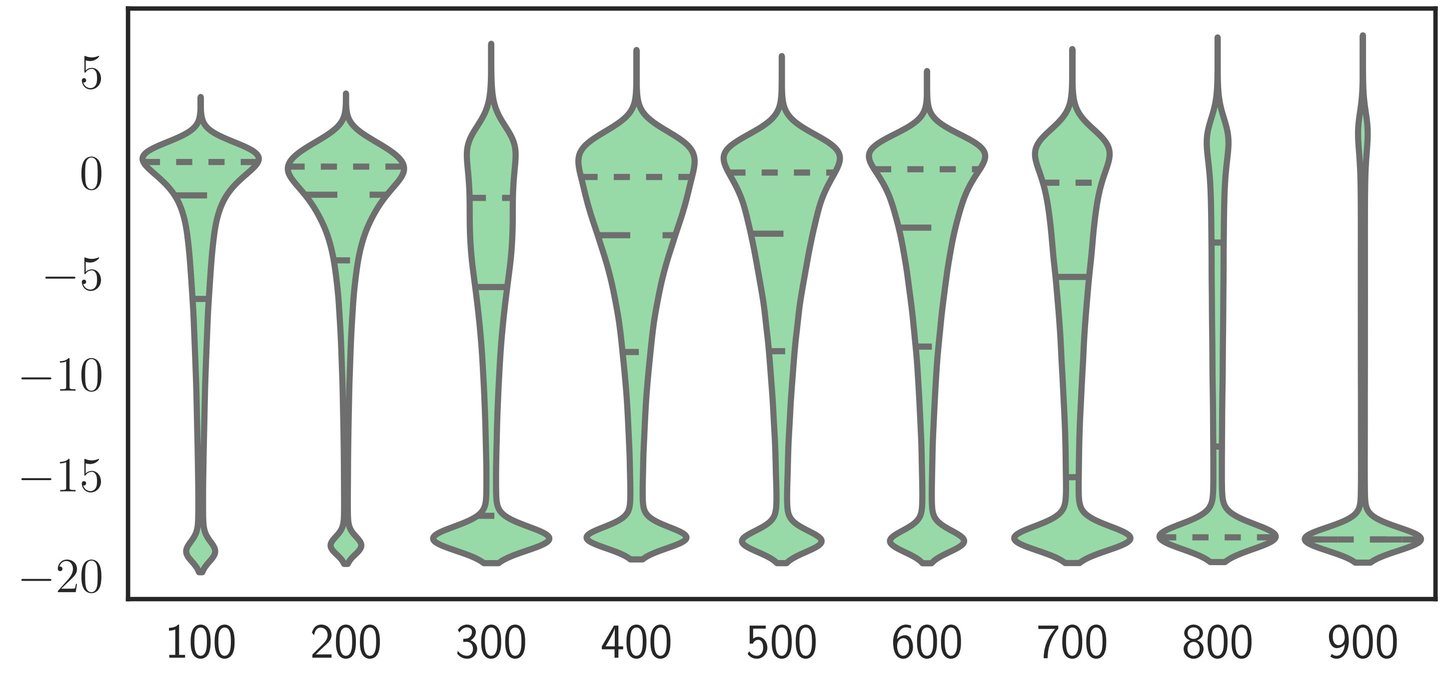
Ablation Study II: Other density-ratio estimation methods?



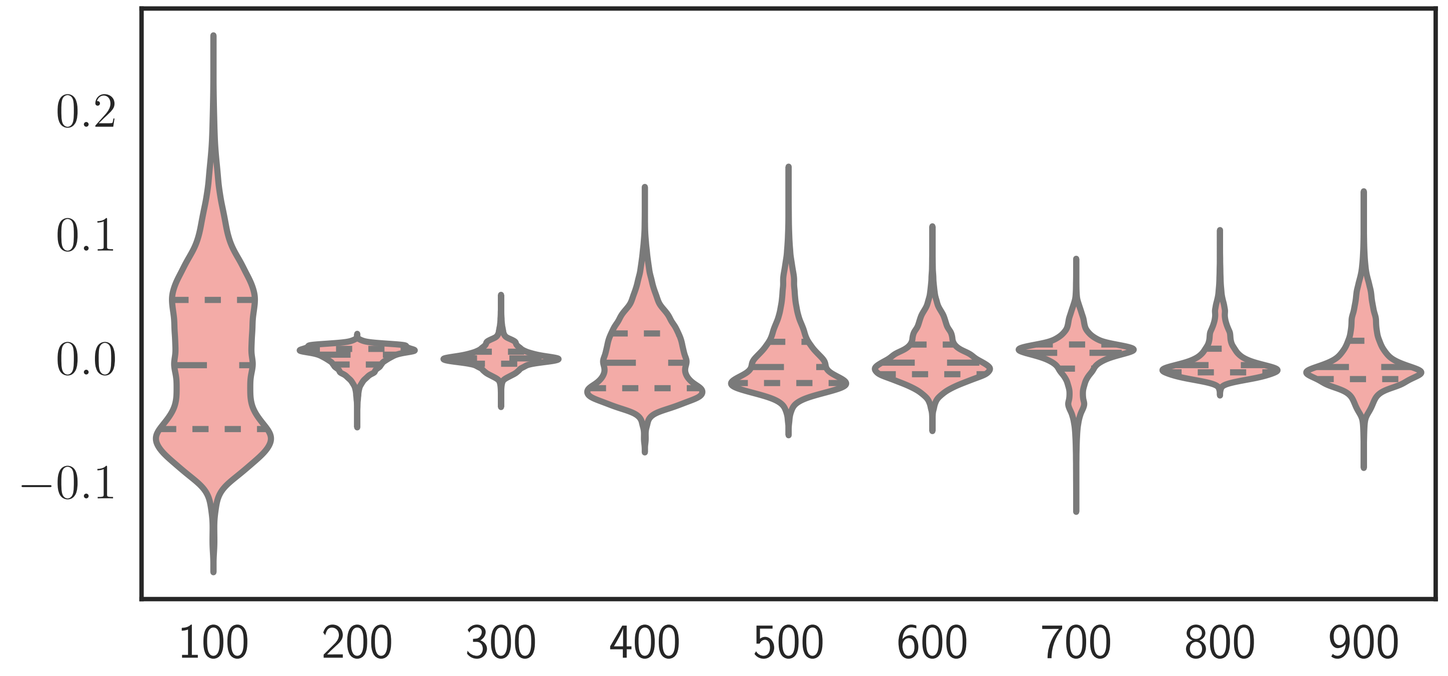
(a) VPM



(b) GenDICE



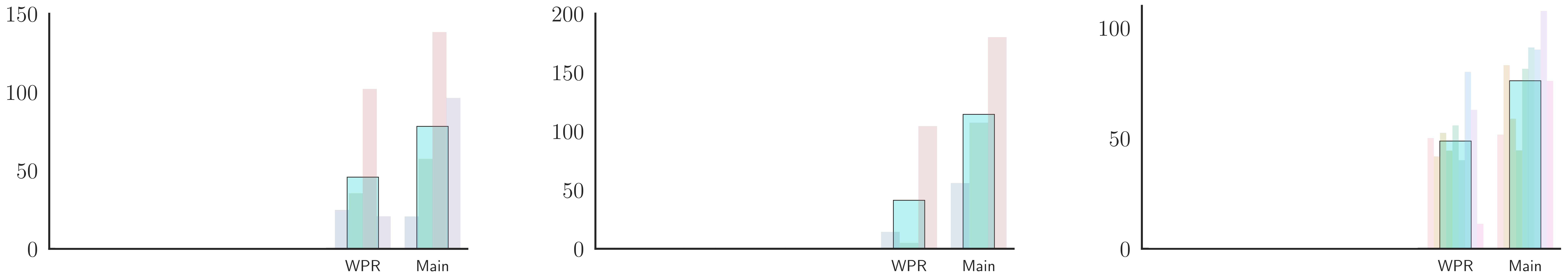
(c) DualDICE



(d) Ours

- Distribution plot of $\log(\omega(s, a))$ during the training process, on “walker2d-medium-replay.”
- Three alternatives can be unstable to provide good density-ratio for  training.

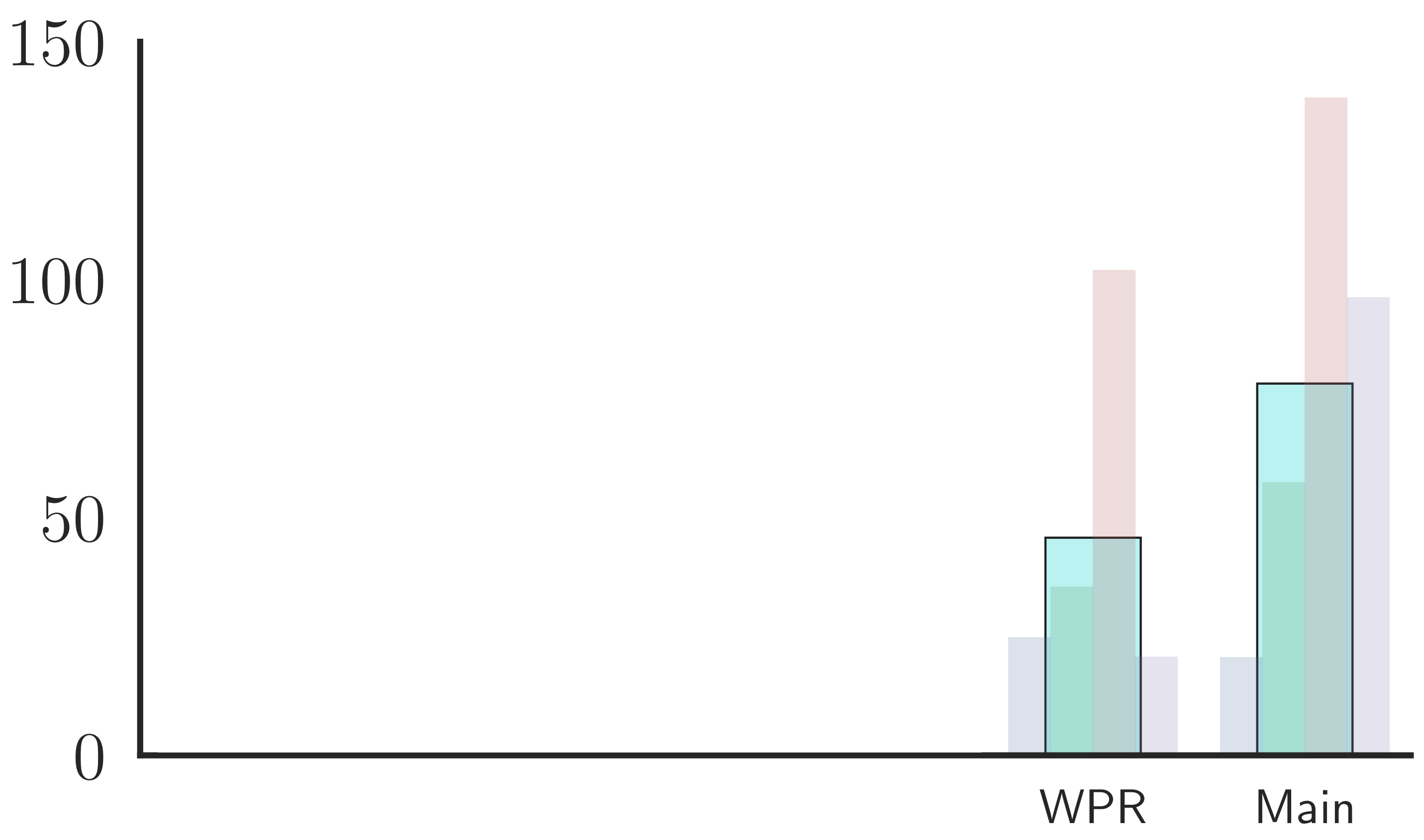
Ablation Study III: A weighted policy regularizer?



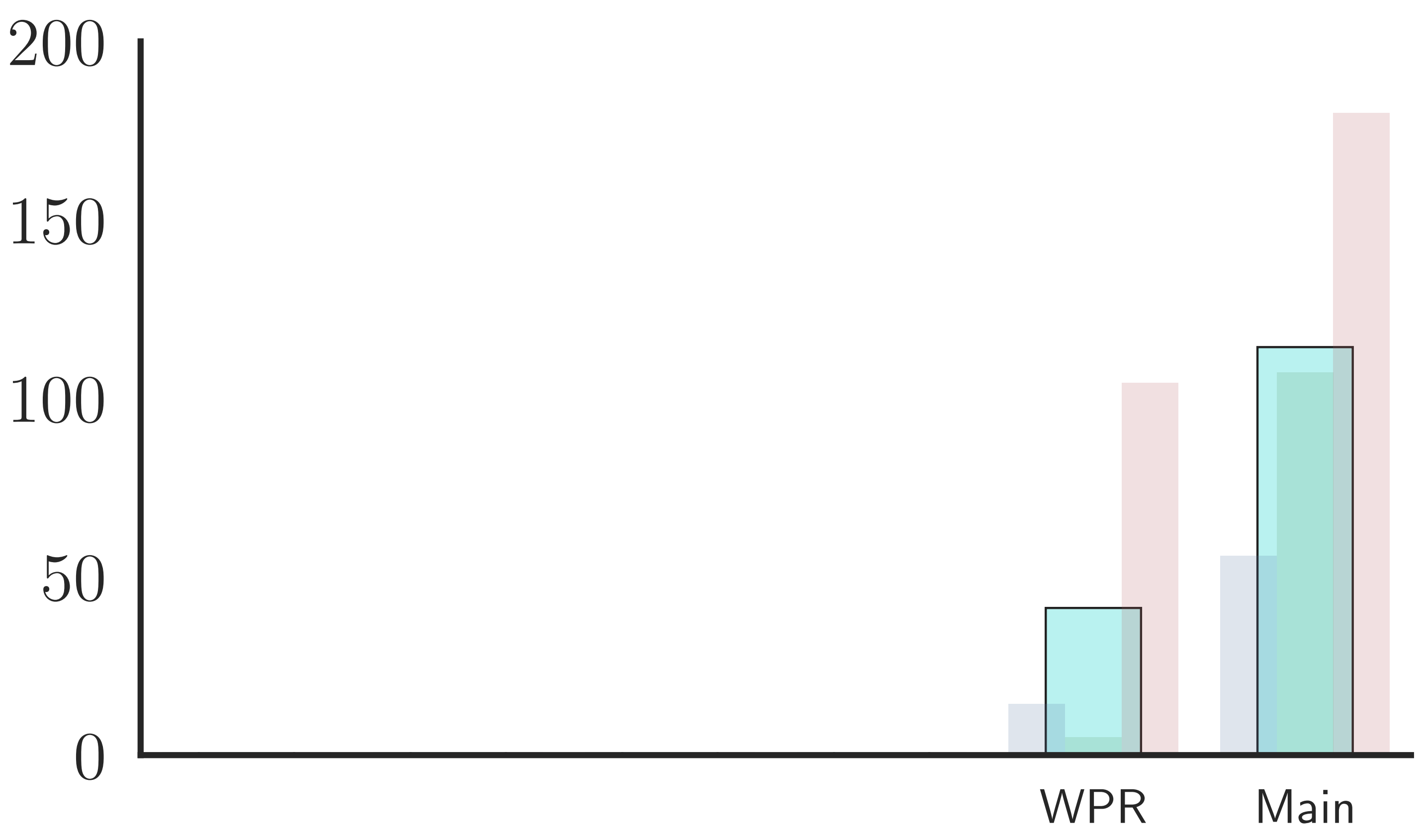
(a) Adroit (b) Maze2D (c) MuJoCo

- Variant: policy regularizer is weighted by the density ratio $\omega(s, a)$ (WPR).

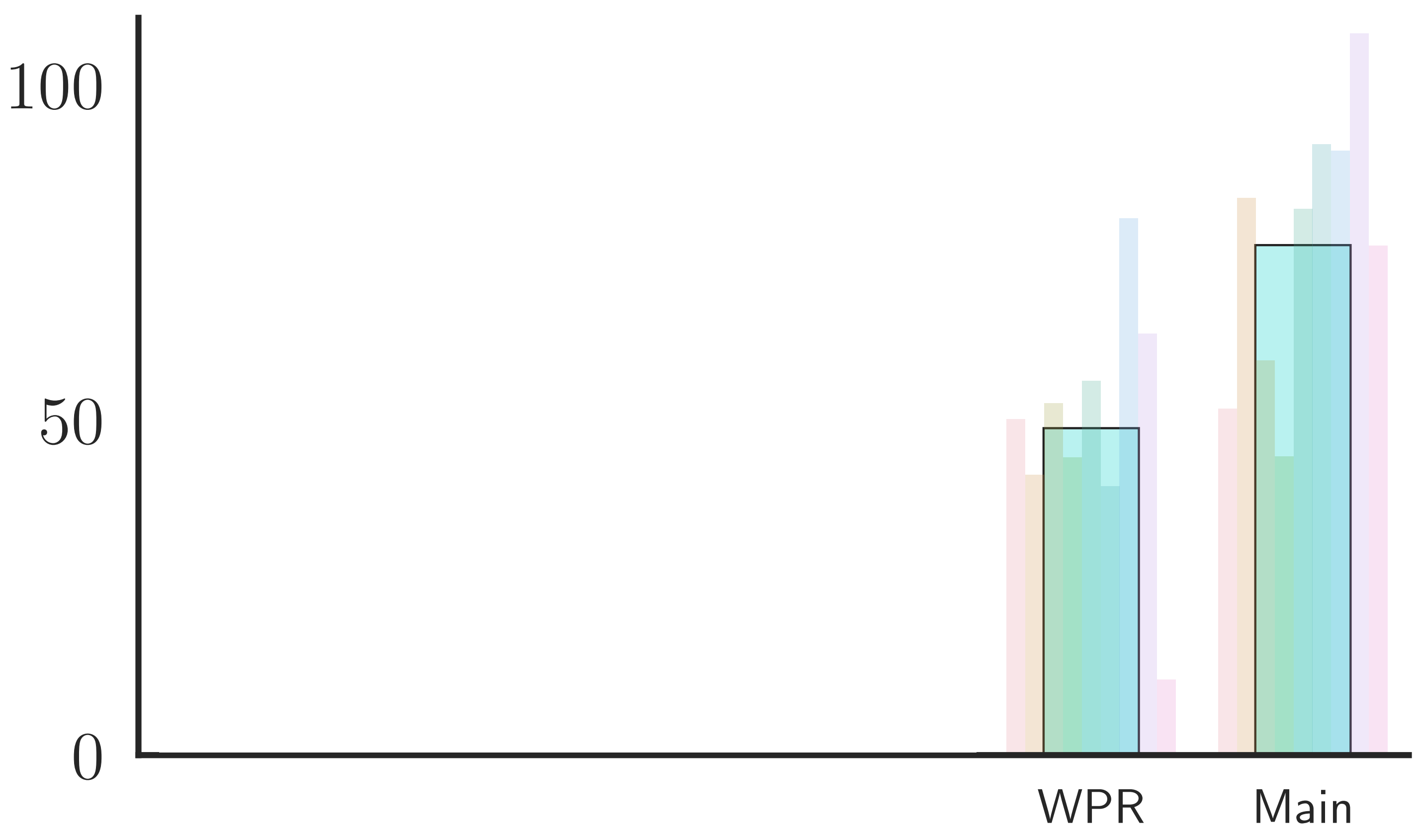
Ablation Study III: A weighted policy regularizer?



(a) Adroit



(b) Maze2D



(c) MuJoCo

- Variant: policy regularizer is weighted by the density ratio $\omega(s,a)$ (WPR).

- Additional instability in training $\Longrightarrow$ underperform!

Summary

- **Goal**: close the mismatched model objectives in offline MBRL.

- **Method**: offline Alternating Model-Policy Learning.

QR code for the full paper!

QR code for the GitHub Repo!