







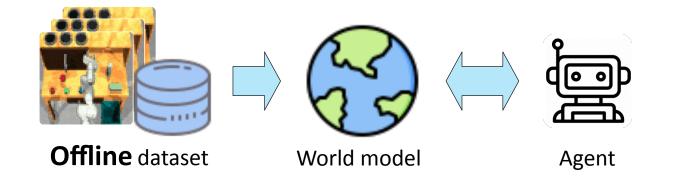
Making Offline RL Online: Collaborative World Models for Offline Visual Reinforcement Learning

Qi Wang*Junming Yang*Yunbo WangXin JinWenjun ZengXiaokang Yang

* Equal contribution Correspondence to: Yunbo Wang

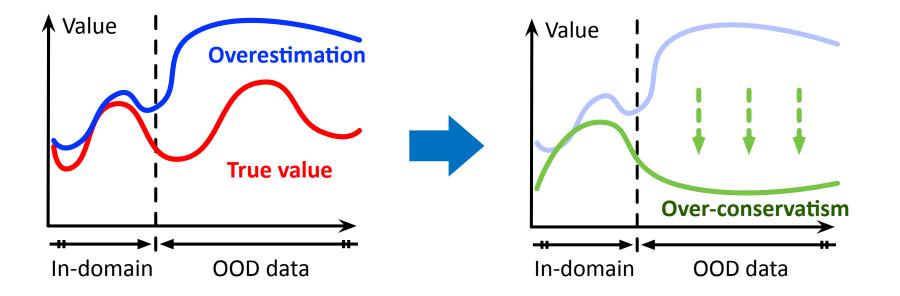


Model-based RL for offline visual control



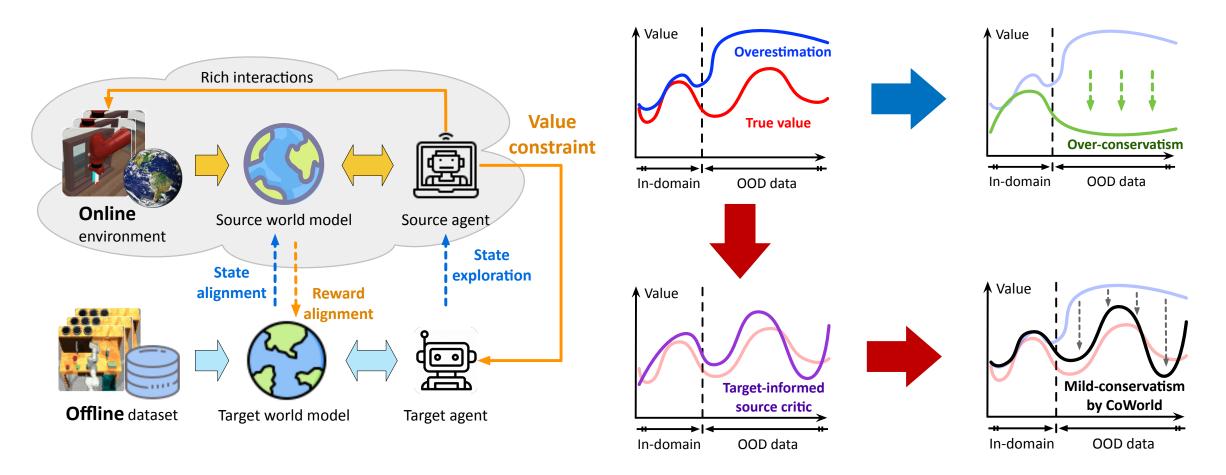
- Offline visual RL is a promising approach to learn an efficient control policy from visual observations, avoiding the need for high interaction costs with the physical world
- The benefits of using a world model for Offline RL are that the agent interacts with the model rather than directly with the dataset
- However, this approach cannot entirely solve the overestimation issue, as the world model may overfit the limited dataset, thereby introducing bias

How to tackle value overestimation?



- Typical offline RL methods often penalize estimated values beyond the offline data distribution, leading to value over-conservatism
- This penalization can suppress the agent's exploration in the world model --- Exploration that may sometimes be valuable and at other times should indeed be suppressed
- How can we differentiate between the two? Address each case accordingly?

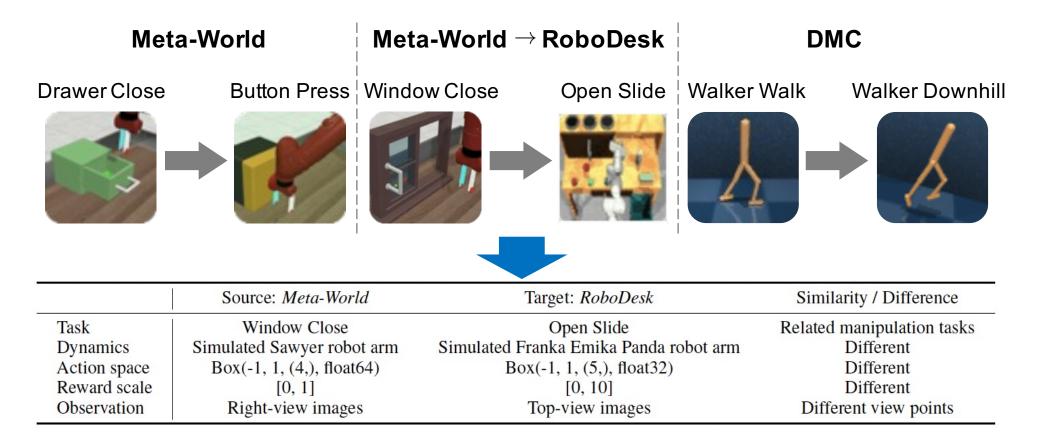
A New Thought: Online Simulator as a Behavior "Test Bed"



- CoWorld solves offline visual RL as an offline-online-offline transfer learning problem
- CoWorld leverages a target-informed source critic to provide mild constraints for target value estimation, without impeding state exploration with potential advantages

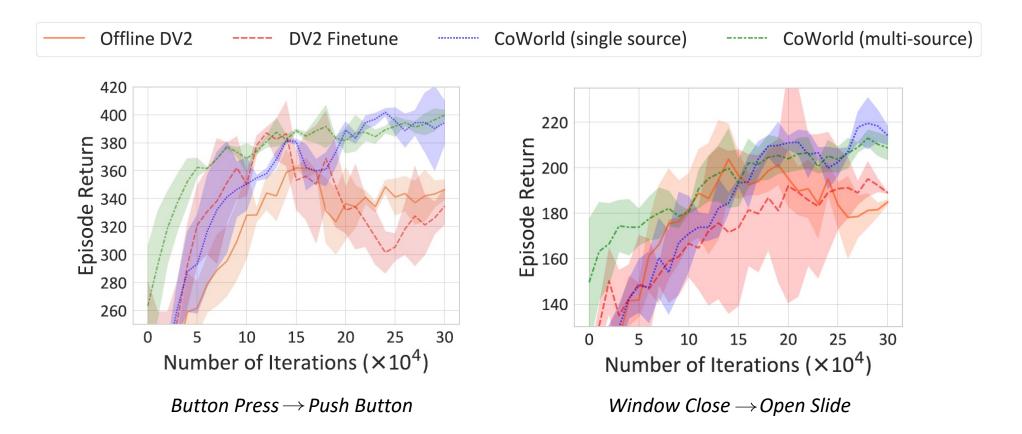
NeurIPS'24

Experimental Setups



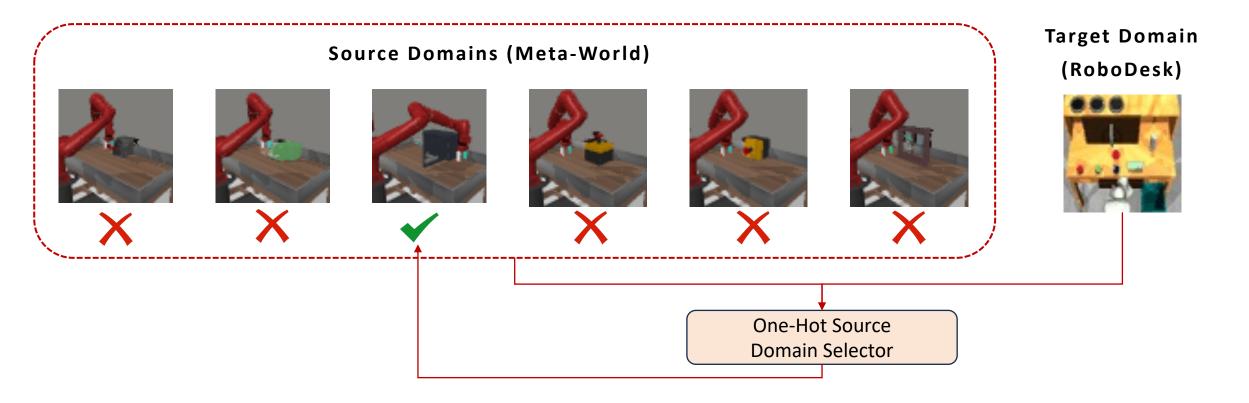
- Setup 1: Cross-Task experiments on Meta-World
- Setup 2: Cross-Environments experiments from *Meta-World* to *RoboDesk*
- Setup 3: Cross-Dynamics experiments on *DeepMind Control Suite* (DMC)

Results: Meta-World→RoboDesk



- CoWorld outperforms Offline DV2 and DV2 Finetune by large margins
- Directly fine-tuning the source world model in this cross-environment setup, does not result in significant improvements in the final performance

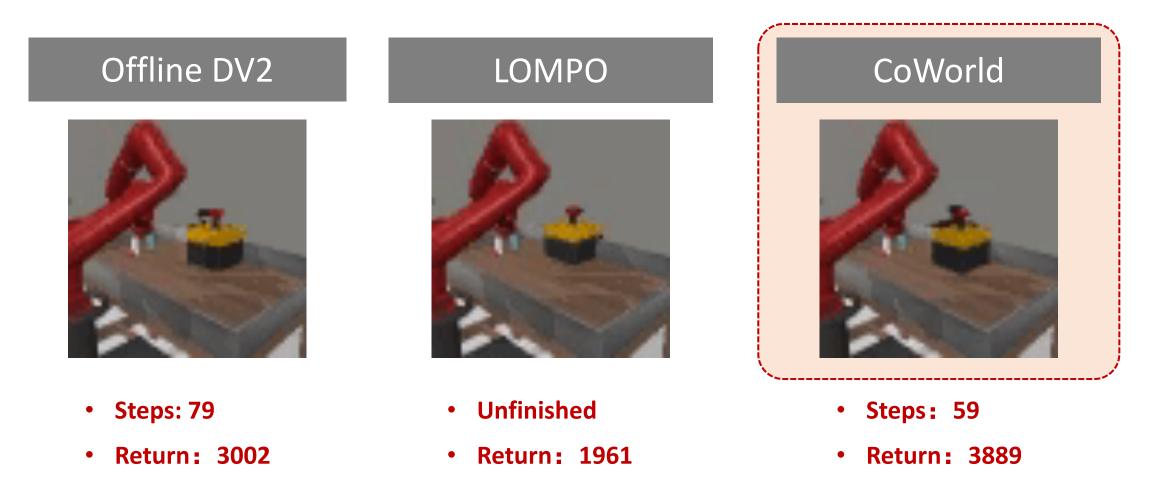
Results: Multi-Source CoWorld



• When there are notable distinctions between the source domain and target domain, multisource CoWorld can adaptively selects a useful source task

Results: Meta-World

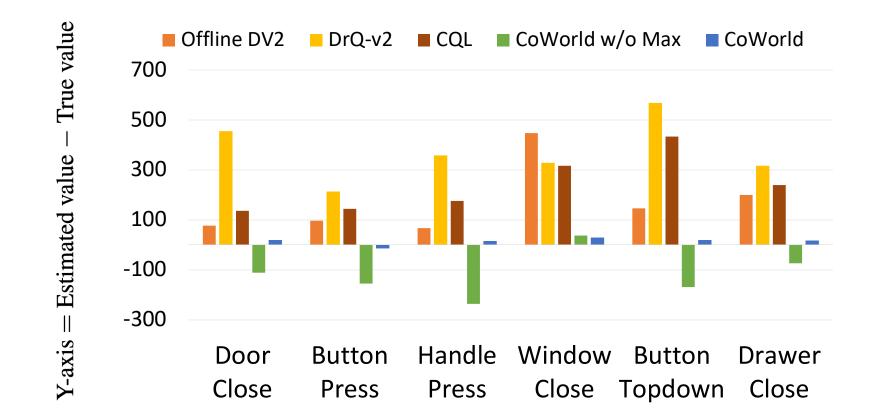
Model	$ BP \rightarrow DC^*$	$\text{DC} \rightarrow \text{BP}$	$BT {\rightarrow} WC$	$BP {\rightarrow} HP$	$WC \rightarrow DC$	$\mathrm{HP}{\rightarrow}\mathrm{BT}$	Avg.
OFFLINE DV2	2143±579	3142 ± 533	3921 ± 752	278 ± 128	$3899{\pm}679$	3002 ± 346	2730
LOMPO	2883±183	446 ± 458	2983 ± 569	2230 ± 223	2756 ± 331	1961 ± 287	1712
CoWorld	3967±312	3623±543	4521±367	4570±677	4845±14	3889±159	4241



NeurIPS'24

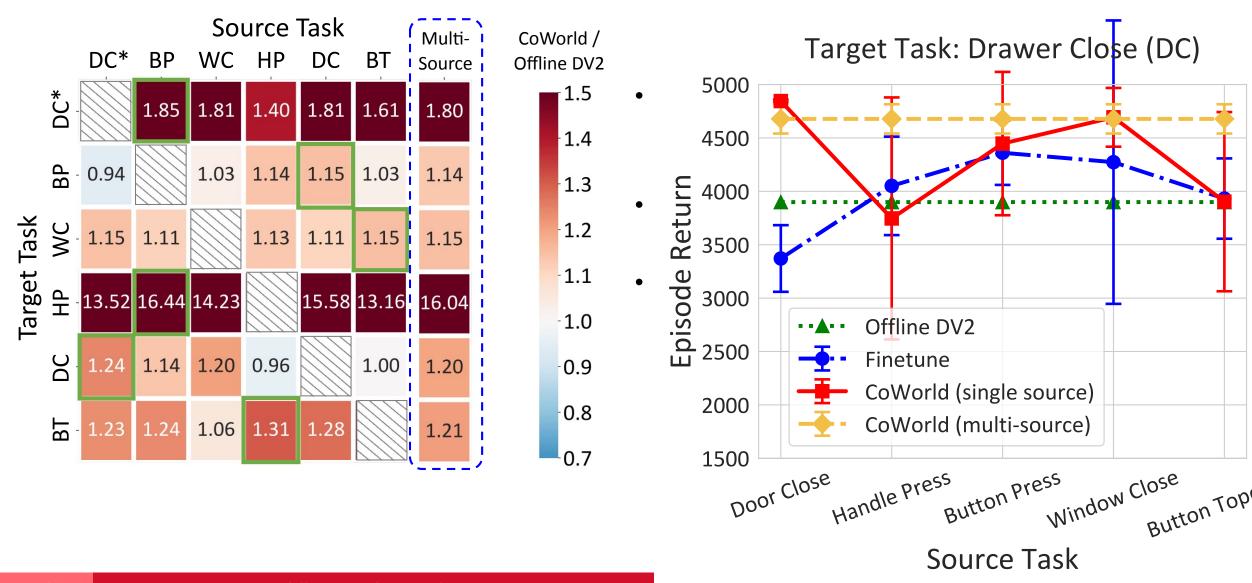
Making Offline RL Online: Collaborative World Models for Offline Visual Reinforcement Learning

Results: Meta-World



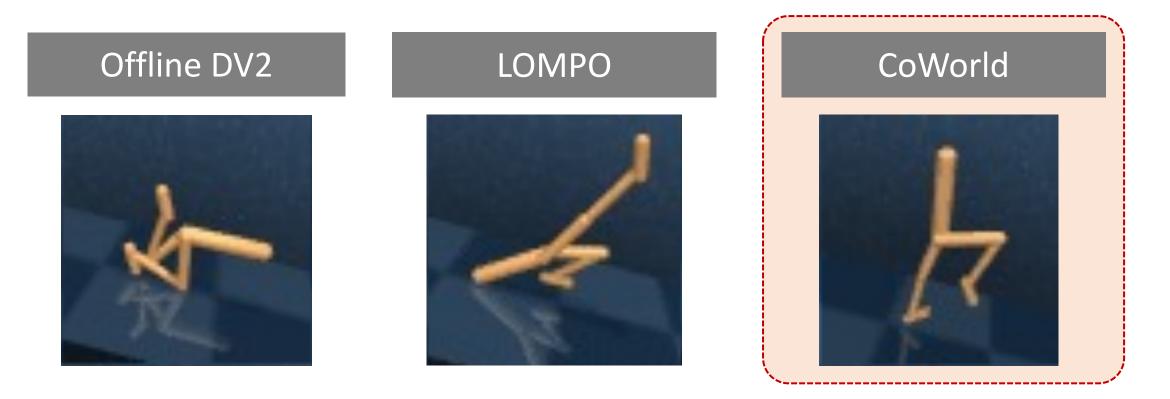
- Existing approaches often overestimate the value functions in the offline setup
- The values estimated by CoWorld are notably more accurate and more akin to the true values

Results: Meta-World



Results: DeepMind Control Suite

Model	$\mid WW \rightarrow WD$	$WW \to WU$	$WW \to WN$	$\text{CR} \rightarrow \text{CD}$	$CR \to CU$	$\text{CR} \rightarrow \text{CN}$	AVG.
OFFLINE DV2	435±22	139±4	214±4	243±7	3±1	51±4	181
LOMPO	462 ± 87	$260{\pm}21$	460±9	395 ± 52	$46{\pm}19$	$120{\pm}4$	291
CoWorld	629±9	407±141	426 ± 32	745±28	$225{\pm}20$	493±10	488



Making Offline RL Online: Collaborative World Models for Offline Visual Reinforcement Learning

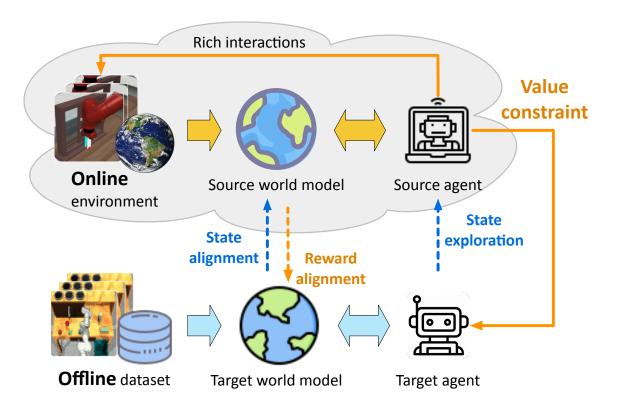
Method

Step 1: Offline-to-Online State Alignment

Step 2: Online-to-Offline Reward Alignment

Step 3: Min-Max Value Constraint

Please see our paper to find the technical details



Thanks!



https://qiwang067.github.io/coworld



Making Offline RL Online: Collaborative World Models for Offline Visual Reinforcement Learning