A Closer Look at Offline RL Agents

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Abstract

Despite recent advances in the field of Offline Reinforcement Learning (RL), less attention has been paid to understanding the behaviors of learned RL agents. As a result, there remain some gaps in our understandings, *i.e.*, why is one offline RL agent more performant than another? In this work, we first introduce a set of experiments to evaluate offline RL agents, focusing on three fundamental aspects: representations, value functions and policies. Counterintuitively, we show that a more performant offline RL agent can learn relatively *low-quality* representations and *inaccurate* value functions. Furthermore, we demonstrate that the proposed experiment setups can be effectively used to diagnose the bottleneck of offline RL agents. Inspired by the evaluation results, a novel offline RL algorithm is proposed by a simple modification of IQL and achieves SOTA performance. Finally, we investigate when a learned dynamics model is helpful to model-free offline RL agents, and introduce an uncertainty-based sample selection method to mitigate the problem of model noises. Code is available at: https://anonymous.4open.science/r/RIQL-BE73/.

1 Introduction

Offline Reinforcement Learning (RL), also known as batch RL, refers to the problem of learning effective control policies from a fixed offline dataset [39]. Due to the wide availability of logged-data and the increasing computing power, offline RL holds the promise for successful real-world applications [40]. For example, offline RL suits well for scenarios where collecting online data is time-consuming, dangerous or unethical, *i.e.*, robotics, self-driving cars and medical treatments [21]. While most off-policy RL algorithms are applicable in the offline setting, they usually suffer from the extrapolation error [18, 35, 11] due to out-of-distribution (OOD) samples. Different solutions have been proposed to mitigate this problem, *i.e.*, adding constraints [18, 50], behavior cloning (BC) [7, 57], learning a dynamics model [55, 28, 3], incorporating uncertainties [51], using ensembles [1], or learning pessimistic value functions [36, 5, 26].

Recently, offline RL algorithms have shown to be effective to solve various challenging tasks [46, 42]. However, most of these works mainly focus on designing new algorithms and less attention has been paid to understanding the behaviors of the learned offline RL agents. As a result, some basic questions are still poorly understood. For example:

- Why does one offline RL agent perform better than other baseline agents in a benchmark task, as illustrated in Fig 1?
- Does the more performant agent learn better representations or more accurate value functions?
- Which of the existing offline policy evaluation/improvement methods is more effective?
- When is a learned dynamics model helpful to a model-free offline RL agent?
- Given a learned dynamics model, how can we use the generated samples more efficiently?

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Baseline	Paradigm	Constraint Type	Speed	Disadvantage
TD3+BC [16]	Policy-regularized	Actor	✓	Fail in difficult tasks
CQL [36]	Pessimism	Critic	✗	Low computation efficiency
COMBO [54]	Model-based	Critic	✗	Sensitive to model noises
IQL [30]	Generalized BC	Both	✓	Need to tune parameter τ

Table 1: A brief summary of four SOTA offline RL baselines from different paradigms.

In spite of several potential intuitions, there is a lack of clear explanations for these questions. Such incomplete understanding impedes progress, as researchers fail to identify the full impact of algorithmic changes without extensive tuning [12]. Given the increasing number of newly proposed offline RL algorithms, we argue that it is time to benchmark current SOTA offline RL algorithms [15] and shed some lights on these fundamental questions. To this end, we empirically compare four SOTA offline RL baseline algorithms, as shown in Table 1, from different paradigms on the standard D4RL dataset [14].

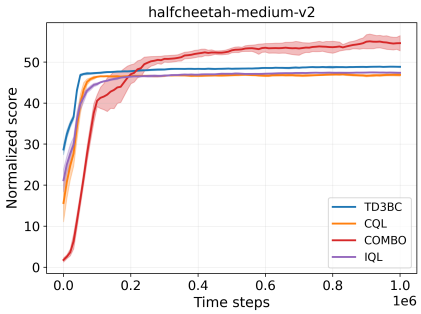

Figure 1: Why does the COMBO agent perform better than other baselines?

In this work, we design a comprehensive set of experiments to compare the *representations, value functions and policies* of offline RL agents in order to gain a deeper understanding of the behaviors of SOTA offline RL agents. We identify a surprising discovery that a more performant agent sometimes has *worse* representations and *inaccurate* value functions. This motivates us to take a closer look at the learned policies. Our empirical results show that a performant offline RL agent is usually able to select better sub-optimal actions while avoiding bad ones. Furthermore, we demonstrate that the proposed experiment setups can be used to evaluate the effectiveness of existing policy evaluation/improvement methods. As a case study, we introduce a variant of IQL [30] by relaxing the in-sample constraint for the policy improvement step, which achieves better performance. Moreover, we investigate when a learned dynamics model can help a model-free offline RL agent, and we propose an uncertainty-based sample selection method to mitigate the problem of model noises. Our contributions are as follows:

- We conduct extensive experiments, focusing on representations, value functions and policies, to compare different SOTA offline RL agents and explain some fundamental questions.
- We show the effectiveness of the proposed experiment setups in diagnosing the bottleneck of offline RL agents with a new variant of the IQL algorithm that achieves SOTA performance.
- We investigate when a learned dynamics model helps model-free offline RL agents, and we introduce an uncertainty-based sample selection method that is more robust to model noises.

2 Background

A Markov Decision Process (MDP) $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma \rangle$ [44] is specified by a state space $\mathcal{S}$, an action space $\mathcal{A}$, a transition kernel $\mathcal{P} : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$, a reward function $\mathcal{R} : \mathcal{S} \times A \to \mathbb{R}$, and a discount factor $\gamma \in [0, 1)$. The goal is to find a policy $\pi(a|s) : \mathcal{S} \to \Delta(\mathcal{A})$, which maps from state to distribution over actions, that maximizes the expected cumulative discounted reward $J(\pi) := \mathbb{E}_\pi[\sum_{t=0}^{\infty} \gamma^t r_t]$. The performance of the policy can be defined by the value functions $Q^\pi(s, a) := \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t r_t | s_0 = s, a_0 = a\right]$ and $V^\pi(s) := \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t r_t | s_0 = s\right]$, where $\mathbb{E}_\pi[\cdot]$ is the expected result when following the policy π.

In deep RL, Q-function is parameterized with a neural network $Q^\pi_\theta(s, a)$. Following prior works [20, 34, 32, 38], we denote the penultimate layer of the neural network as the learned *representation*, a d-dimensional mapping $\phi(s, a) : \mathcal{S} \times \mathcal{A} \to \mathbb{R}^d$. Such that the Q-function is linear in the representation $Q^\pi_\theta(s, a) = \theta^\top \phi(s, a)$, where $\theta \in \mathbb{R}^d$ is a vector of weights. If the state space $\mathcal{S}$ and action space $\mathcal{A}$ are finite, then the representation corresponds to a feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}| \cdot |\mathcal{A}| \times d}$, whose rows are the vector $\phi(s_i, a_i) \in \mathbb{R}^d$ for the i-th state-action pair (s_i, a_i).

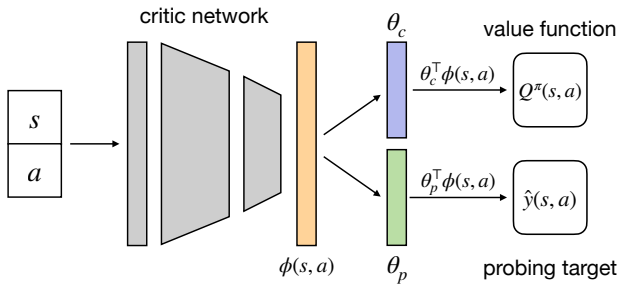

Figure 2: An illustration of the *representation probing* experiment.

Inductive Bias	Target	Probing Function
Transition Dynamics	reward r	$r = f_p(\phi(s,a))$
	next state s'	$s' = f_p(\phi(s,a))$
	inverse action a	$a = f_p(\psi(s), \psi(s'))$
Optimal Policy	optimal action a^*	$a^* = f_p(\psi(s))$
	optimal $Q^*(s,a)$	$Q^*(s,a) = f_p(\phi(s,a))$
	optimal $V^*(s)$	$V^*(s) = f_p(\psi(s))$

Table 2: Different probing targets.

In this work, we study the offline RL setting [40], where we aim to learn a policy $\pi(a|s)$ purely from a fixed offline dataset $\mathcal{D} = \{(s_i, a_i, s_i', r_i)\}$, generated from a behavior policy $\pi_\beta(a|s)$. Most of recent offline RL algorithms build on the *Approximate Dynamics Programming* (ADP) method [4] that learn the $Q_\theta^\pi(s,a)$ by minimizing temporal difference error:

$$L_{TD}(\mathcal{D}, \theta) = \mathbb{E}_{(s,a,r,s')\sim\mathcal{D}} \left[\left(r + \gamma \max_{a'} Q_{\hat{\theta}}^\pi(s', a') - Q_\theta^\pi(s,a)\right)^2 \right], \tag{1}$$

where $Q_{\hat{\theta}}^\pi(s,a)$ is the target network. A major challenge in offline RL is the issue of distributional shift between the learned policy $\pi(a|s)$ and the behavior policy $\pi_\beta(a|s)$. Specifically, the OOD actions a' can produce erroneously over-estimated target values for $Q_{\hat{\theta}}^\pi(s', a')$ in Eq 1. Therefore, many existing offline RL algorithms are motivated to constrain the learned policy to stay close to the behavior policy [50, 16], or penalize large over-estimated Q-values [36, 11]. We provide more extensive backgrounds in Appendix A.

3 Representation evaluation experiments

Inspired by the huge success achieved by representation learning in (un)supervised learning [6, 25, 45], it is natural to ask – does a more performant offline RL agent learn better representations? To answer this question, we first leverage the *representation probing* technique [2, 23, 37] to evaluate the learned representations of each baseline agent. Then we use some latest introduced *representation metrics* [34, 33, 38, 41] as proxies to evaluate the quality of the learned representations.

3.1 Representation probing experiment

For a state-action pair (s,a), we use the output of the penultimate layer of the critic network as the critic representation $\phi(s,a) \in \mathbb{R}^d$, as shown in Fig 2. We later train another linear model $f_p(\cdot)$ to predict a probing target, such as reward r, by linear regression $\hat{y}(s,a) = f_p(\phi(s,a)) = \theta_p^\top \phi(s,a)$. We evaluate the actor embedding $\psi(s) \in \mathbb{R}^d$ in a similar way. To validate whether the learned representations contain meaningful inductive biases [48, 53], we select two categories of probing targets (Table 2). We first use the next state, reward, and action to detect if the representations learned any semantics about the *transition dynamics*. We then directly use the optimal action and optimal value functions to check if the representations learned any information about the *optimal policy*.

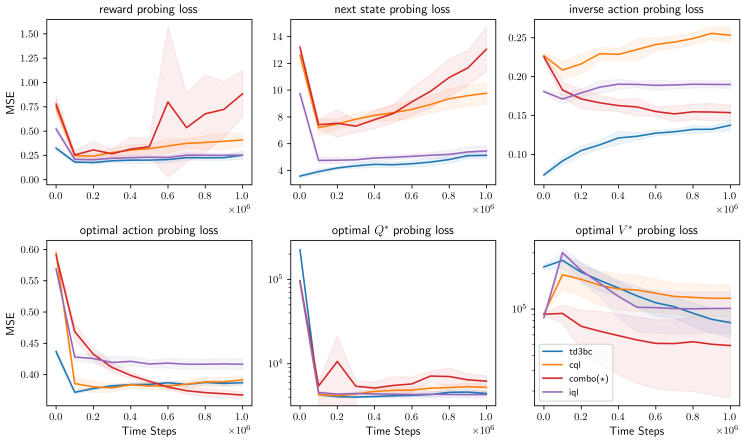

Figure 3: Representation probing experiment result on the *halfcheetah-medium-v2* environment. We label the most performant agent with a ($\star$) mark. Curves are averaged over 5 seeds.

	reward	next state	inverse action	optimal action	optimal Q^*	optimal V^*
#Env	0	0	3	5	4	4

Table 3: Number of environments that the most performant agent has the least probing loss.

In the experiment, an online TD3 agent [17] is used to approximate the optimal policy π^*. We use five checkpoints of the online agent (with different levels of performance) to collect 100K transitions as the probing dataset $\mathcal{D}_{probe}$. For each probing target, we use a 5-fold cross-validation on $\mathcal{D}_{probe}$ to train a linear regression model with Mean Squared Error (MSE) loss. The result of the probing experiment on *halfcheetah-medium-v2* environment is shown in Fig 3. Results on other environments are summarized in Appendix C.1. We also list the number of environments where the most performant offline RL agent has the least probing loss in Table 3.

We can observe that the most performant agent usually has worse probing results except for the *optimal action* experiment. These results indicate that the transition dynamics-based information is not that important for an offline RL agent to perform well in the selected benchmark tasks. Further, many baseline agents suffer from large MSE losses on the *optimal value functions* $Q^*(s, a)$ and $V^*(s)$ experiments, which highlights the difficulty to learn accurate value functions in such offline setting due to the limited data coverage and additional policy/value constraints. In addition, as long as the actor representation $\psi(s)$ preserves the ability to learn good actions (low optimal action probing loss), then the offline RL agent holds the potential to achieve good performance.

3.2 Representation metric experiment

We further utilize some recently proposed *metrics* [34, 33] as proxies to evaluate the quality of the learned representations. We start with the following definitions and more details are in Appendix A.2.

Definition 1 (Feature dot-product)**.** *Feature dot-product $\phi(s, a)^\top \phi(s', a')$ is the dot-product of two critic representations [34], where $s' \sim \mathcal{P}(\cdot|s, a)$ and $a' \sim \pi(\cdot|s')$ is the next state and next action.*

Definition 2 (Effective rank)**.** *Effective rank $\mathrm{srank}_\delta(\Phi) = \min\left\{k : \frac{\sum_{i=1}^k \sigma_i(\Phi)}{\sum_{i=1}^d \sigma_i(\Phi)} \geq 1 - \delta\right\}$ of a feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}|\cdot|\mathcal{A}| \times d}$ approximates the rank of Φ [33], where $\{\sigma_i(\Phi)\}$ are the singular values of Φ in the decreasing order ($\sigma_1 \geq \cdots \geq \sigma_d \geq 0$) and δ is a threshold parameter, i.e., 0.01.*

Definition 3 (Effective dimension)**.** *Effective dimension $d_{\text{eff}}(\Phi) = N \max_{i=1,\cdots,N} \|P_\Phi e_i\|_2^2$ of a feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}|\cdot|\mathcal{A}| \times d}$ measures the sparsity of the column space of Φ [38], where $N = |\mathcal{S}| \cdot |\mathcal{A}|$ and P_Φ is the orthogonal projector onto the column space of Φ.*

For the *feature dot-product* metric, we also compute the *cosine similarity* $\frac{\phi(s,a)^\top \phi(s',a')}{\|\phi(s,a)\|\|\phi(s',a')\|}$ to decouple the effect the representation norm. To compute the *effective rank*, we first compute the critic

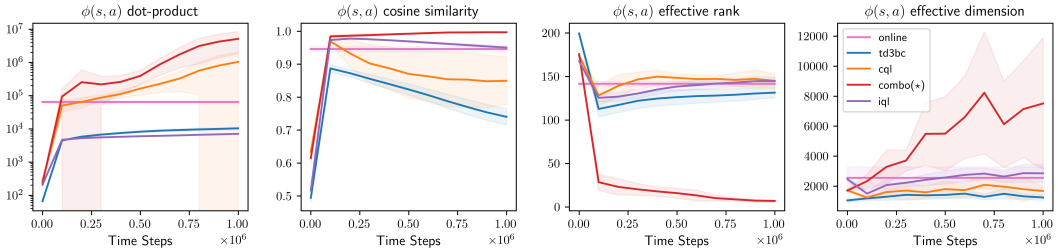

Figure 4: The best performing COMBO agent learns *low-quality* representations with large norms, in which $\phi(s, a)$ is very close to $\phi(s', a')$. Moreover, feature space collapses significantly.

representation $z_i = \phi(s_i, a_i)$ for each sample in the probing dataset $\mathcal{D}_{probe}$. Then we approximate the covariance matrix of Φ by $C(\Phi) = \frac{1}{|\mathcal{D}_{probe}|} \sum_i (z_i - \bar{z})(z_i - \bar{z})$, and use SVD on $C(\Phi)$ to compute the singular values $\{\sigma_i(\Phi)\}$ [27]. Unlike the original implementation of the *effective dimension* which used a fixed threshold to approximate the rank of Φ, we instead use the *effective rank* $\mathrm{srank}_\delta(\Phi)$. More details are discussed in Appendix C.2.

Fig 4 shows the experiment results on the *halfcheetah-medium-v2* environment. Results on other environments are summarized in Appendix C.2. We also add the result for the online TD3 agent for reference. We can observe that the most performant COMBO agent has most severe *feature co-adaptation* [34] (large feature dot-product) and *representation collapse* [33] (small effective rank) problems, which indicate it learned pretty "low quality" critic representations. In terms of these metrics alone, some baselines agents such as TD3+BC and IQL seem to learn similar or better critic representations than the *near-optimal* online agent. These results are consistent with our findings in the previous probing experiments, which indicate that a performant offline RL agent sometimes does not necessarily need high quality critic representations.

Observation 1. A performant offline RL agent sometimes learn low-quality representations.

4 Value ranking experiments

As described in the last section, a performant offline RL agent can learn low-quality representations. We therefore turn our focus to the value functions to investigate that – does a performant offline RL agent learn more accurate Q-functions? Since the pessimism-based offline RL algorithms adopt an additional penalty to learn lower-bounded Q-functions [36, 54], it could be inappropriate to measure the accuracy of Q-functions using metrics like MSE. Therefore, we design the following *value ranking experiments* that focus on the ability of Q-functions to rank actions. The motivation is simple – a "good" Q-function in offline RL can have large MSE loss, but it should be good at ranking actions, such that $Q^\pi(s, a_i) > Q^\pi(s, a_j)$ if $Q^*(s, a_i) > Q^*(s, a_j)$ where Q^* is the optimal Q-function.

In the experiment, we first use different behavior policies (four baseline agents and a near-optimal online agent) to interact with the environment to collect a validation set $\mathcal{D}_{value} = \{s_1, \cdots, s_N\}$. At each state s_i, we use each baseline agent to sample m different actions, *i.e.*, $\pi(\cdot|s_i) + \epsilon$ where ϵ is a Gaussian noise. Therefore, we have $M = 4m$ different actions $A_i = \{a_{i1}, \cdots, a_{iM}\}$ for each state. Then we use baseline agents to rank the M actions at state s_i, *i.e.*, $R^{\pi_j}(s_i) = \mathrm{sort}(Q^{\pi_j}(s_i, a_{i1}), \cdots, Q^{\pi_j}(s_i, a_{iM}))$ where Q^{π_j} is the learned Q-function of the j-th baseline agent. We use two metrics to evaluate the accuracy of the learned Q-functions: (1) Spearman's rank correlation coefficient (Rank IC) and (2) TopN accuracy. We approximate the optimal rank information using the online agent. Here, the larger rank IC/topN accuracy is, the more accurate is the $Q^\pi(s, a)$ at ranking actions. More details are described in Appendix D.

Experiment results are shown in Table 4 and Table 5. The most performant baseline agents in each environment are colored brown. We can observe that many best-performing agents have near-zero rank IC and lower TopN accuracy results. This indicates that the learned Q-functions are less capable of distinguishing good actions from the bad ones. Interestingly, such *inaccurate* Q-functions do not prevent the most performant agent to select sub-optimal actions to achieve good performances. Further, we can observe that the TD3+BC agent and IQL agent usually learn more accurate value

	TD3+BC	CQL	COMBO	IQL
halfcheetah-med-v2	**0.13 (0.01)**	-0.01 (0.01)	0.01 (0.02)	0.10 (0.02)
halfcheetah-med-rep-v2	**0.05 (0.01)**	0.02 (0.01)	0.02 (0.01)	0.02 (0.02)
halfcheetah-med-exp-v2	0.07 (0.04)	0.08 (0.04)	**0.09 (0.03)**	0.03 (0.02)
hopper-med-v2	0.07 (0.03)	0.02 (0.01)	0.05 (0.02)	**0.11 (0.03)**
hopper-med-rep-v2	0.07 (0.05)	0.08 (0.03)	**0.14 (0.04)**	0.13 (0.02)
hopper-med-exp-v2	0.09 (0.07)	0.11 (0.03)	**0.16 (0.03)**	0.04 (0.05)
walker2d-med-v2	0.02 (0.03)	-0.01 (0.01)	-0.01 (0.01)	**0.08 (0.03)**
walker2d-med-rep-v2	0.10 (0.02)	-0.04 (0.03)	-0.06 (0.05)	**0.10 (0.06)**
walker2d-med-exp-v2	0.10 (0.04)	0.09 (0.01)	0.05 (0.10)	**0.15 (0.04)**

Table 4: Rank IC measures the ability of Q-function to rank different actions. Results are averaged over 5 seeds.

	TD3+BC		CQL		COMBO		IQL	
	Top1 Acc	Top3 Acc	Top1 Acc	Top3 Acc	Top1 Acc	Top3 Acc	Top1 Acc	Top3 Acc
halfcheetah-med-v2	**8.72**	**27.60**	1.81	10.40	3.84	15.61	8.11	25.91
halfcheetah-med-rep-v2	**6.70**	**22.11**	2.86	13.53	3.67	15.43	5.92	20.20
halfcheetah-med-exp-v2	4.60	17.17	2.62	12.19	3.86	15.28	**5.84**	**20.59**
hopper-med-v2	13.20	32.08	1.52	6.92	4.67	14.48	**14.90**	**36.21**
hopper-med-rep-v2	9.70	27.39	4.51	15.05	8.33	25.63	**11.41**	**30.76**
hopper-med-exp-v2	12.43	30.57	2.77	10.41	7.11	21.19	**12.98**	**31.62**
walker2d-med-v2	7.10	23.56	1.64	9.99	1.77	10.36	**8.32**	**26.48**
walker2d-med-rep-v2	**8.93**	**28.07**	2.51	11.13	3.35	13.47	8.24	26.19
walker2d-med-exp-v2	6.50	23.38	1.10	8.72	1.93	13.47	**9.70**	**29.86**

Table 5: TopN accuracy measures the ability of Q-function to select the best action. Results are averaged over 5 seeds.

functions but achieves worse performance. This suggests that the *policy evaluation* method in TD3+BC and IQL might be more effective but the *policy improvement* method is limited. We provide more discussions in section 6.

Observation 2. A more performant offline RL sometimes learn less accurate Q-functions.

5 What does a performant policy look like?

In previous sections, we show that a performant offline RL agent sometimes learn relative *low-quality* representations and *inaccurate* value functions. In this section, we try to directly compare the learned policies in order to get a glimpse of "what does a performant offline RL policy look like". To this end, we first design a *policy ranking experiment* to measure *how well* does a performant offline RL policy work in practice. Then we check how often do the SOTA offline RL agents take OOD actions.

5.1 Policy ranking experiment

In this experiment, we first use a behavior policy to collect 30K transitions to create a test dataset $\mathcal{D}_{policy}$. At each state s_i, we use four baseline agents and a behavior cloning agent to select an action, respectively. Again, we use the online agent to approximate $Q^*(s, a)$ to rank the selected four actions. We use following two metrics to evaluate the policy π_j of the j-th baseline agent: (1) Average percentage of policy π_j that ranks the first/last (with largest/smallest Q^* value) across states. (2) Average MSE of the selected action w.r.t. the optimal action. More details are in Appendix E.1

Experiment results are shown in Table 6 and Table 7. We can observe that the learned policy of COMBO [54] agent is quite *extreme*, which both selects the most optimal and worst actions at the same time. In simple environments such as *halfcheetah* and *hopper*, such behavior helps to attain higher performance. However, in the more complex *walker* environment, the higher percentage of *bad* actions would lead to early termination and thus achieving lower scores. Moreover, as we can observe in Table 7 that the most performant offline RL agent usually have similar or larger MSE loss w.r.t. the optimal action a^*. This indicates that a performant policy is good at selecting better actions in different states, even though these sampled actions are still sub-optimal (with high MSE).

	TD3+BC		CQL		COMBO		IQL		BC	
	P_o	P_w	P_o	P_w	P_o	P_w	P_o	P_w	P_o	P_w
halfcheetah-med-v2	21.05	13.02	11.18	16.33	**41.10**	**32.86**	13.82	11.96	12.85	25.82
halfcheetah-med-rep-v2	21.89	16.72	14.45	17.40	**28.10**	**27.09**	19.42	20.16	16.15	18.63
halfcheetah-med-exp-v2	20.59	23.55	19.65	16.07	**26.57**	**27.50**	19.17	14.89	14.02	17.98
hopper-med-v2	16.84	19.98	17.23	17.63	**34.10**	**31.29**	21.20	16.35	10.63	14.74
hopper-med-rep-v2	12.76	19.52	23.25	18.68	**35.01**	**32.28**	16.13	16.40	12.86	13.12
hopper-med-exp-v2	15.23	20.22	15.98	20.55	**38.46**	**24.74**	15.44	21.18	14.89	13.32
walker2d-med-v2	21.79	19.81	19.68	19.92	**23.60**	**20.98**	22.61	18.08	12.32	21.21
walker2d-med-rep-v2	20.99	16.49	15.95	20.80	**26.77**	**32.55**	23.05	15.24	13.24	14.92
walker2d-med-exp-v2	25.58	15.64	12.66	20.70	**26.37**	**31.41**	23.74	13.09	11.65	19.16

Table 6: Percentage (%) of each agent that selects optimal action (P_o) and worst action (P_w). Results are averaged over 5 seeds.

	TD3+BC	CQL	COMBO	IQL	BC
halfcheetah-med-v2	8.31 (0.05)	8.41 (0.04)	**8.27 (0.06)**	8.30 (0.03)	8.45 (0.04)
halfcheetah-med-rep-v2	8.36 (0.03)	8.57 (0.03)	8.64 (0.08)	8.40 (0.04)	**8.35 (0.04)**
halfcheetah-med-exp-v2	6.96 (0.07)	7.03 (0.08)	7.16 (0.16)	**6.85 (0.07)**	7.11 (0.05)
hopper-med-v2	2.66 (0.01)	2.75 (0.04)	2.77 (0.02)	**2.61 (0.01)**	2.71 (0.01)
hopper-med-rep-v2	2.45 (0.10)	2.65 (0.10)	2.67 (0.05)	**2.38 (0.09)**	2.56 (0.08)
hopper-med-exp-v2	2.22 (0.04)	2.29 (0.06)	2.20 (0.07)	2.20 (0.03)	**2.20 (0.04)**
walker2d-med-v2	5.39 (0.02)	5.55 (0.03)	5.50 (0.02)	**5.38 (0.02)**	5.48 (0.02)
walker2d-med-rep-v2	**6.10 (0.07)**	6.61 (0.06)	6.66 (0.14)	6.14 (0.05)	6.34 (0.06)
walker2d-med-exp-v2	4.65 (0.07)	4.83 (0.08)	5.32 (1.06)	**4.61 (0.07)**	4.73 (0.06)

Table 7: MSE loss w.r.t. the optimal action. Results are averaged over 5 seeds.

Observation 3. A performant offline RL policy needs to strike a balance at selecting good actions while avoiding bad ones. Even though the selected actions are usually still sub-optimal.

5.2 OOD action experiment

Since existing offline RL algorithms usually attempt to minimize the negative effects caused by OOD samples. Therefore, we try to measure how often would the baseline agents take OOD actions. In the experiment, we utilize a learned dynamics model to predict whether a state-action pair (s, a) is OOD or not. The learned dynamics models is a probabilistic ensemble [8] as in COMBO [54], where each model $T_i(s'|s,a) = \mathcal{N}(\mu_{\theta_i}(s,a), \Sigma_{\theta_i}(s,a))$ outputs a Gaussian distribution with diagonal covariance parameterized by θ_i. We train the probabilistic ensemble using the D4RL dataset. We use the following metric to estimate how likely a state-action pair (s, a) is OOD: the uncertainty [55] estimated by the probabilistic ensemble $\sigma(s,a) = \max_{i=1,\cdots,N} \|\mu^i_\theta(s,a) - \frac{1}{N}\sum_{j=1}^N \mu^j_\theta(s,a)\|_2$.

In particular, we first compute $\sigma(s, a)$ on the original D4RL offline dataset, and then compute the $\sigma(s, a)$ on a dataset collected by the baseline agent. More details are described in Appendix E.2. We report the median of the estimated uncertainty in Table 8. As we can observe that the three model-free offline RL baselines usually learn conservative policies which mostly take high confidence actions with low $\sigma(s, a)$. On the other hand, the model-based baseline COMBO learns policies that sometimes take more risky actions with higher $\sigma(s, a)$. This confirms that taking risky actions in offline RL is a double-edged sword, which sometimes helps to learn from the OOD samples to avoid being too conservative and sometimes incurs the extrapolation error.

Observation 4. Taking OOD actions in offline RL could be a double-edged sword that sometimes helps to avoid being over-conservative but sometimes incurs the extrapolation error.

6 Case study: relaxed in-sample Q-learning (RIQL)

In this section, we conduct a case study to show that the proposed experiments can be used to compare the effectiveness of existing *policy evaluation/improvement* methods. We first briefly recap the four baseline algorithms as summarized in Table 9. Here we consider a parameterized Q-function $Q^\pi_\theta(s, a)$, policy $\pi_\phi(a|s)$ and loss weight parameters α, λ that we abuse in different baselines.

	Offline Data	TD3+BC	CQL	COMBO	IQL
halfcheetah-med-v2	10.09	7.96 (0.06)	8.11 (0.15)	**10.25 (0.71)**	7.96 (0.04)
halfcheetah-med-rep-v2	**23.96**	15.78 (0.66)	17.51 (0.88)	21.54 (1.18)	16.82 (0.34)
halfcheetah-med-exp-v2	11.03	10.74 (0.86)	9.17 (1.54)	**23.30 (12.62)**	8.50 (0.16)
hopper-med-v2	**2.19**	2.01 (0.02)	2.00 (0.01)	1.85 (0.08)	2.07 (0.03)
hopper-med-rep-v2	**5.13**	4.48 (1.27)	3.76 (0.34)	3.90 (0.84)	3.59 (0.28)
hopper-med-exp-v2	1.46	1.29 (0.05)	1.27 (0.02)	**1.52 (0.11)**	1.32 (0.08)
walker2d-med-v2	**14.01**	9.14 (0.22)	8.08 (0.19)	8.81 (0.99)	10.73 (0.49)
walker2d-med-rep-v2	**27.59**	14.21 (1.35)	13.03 (1.55)	14.80 (2.04)	16.09 (0.96)
walker2d-med-exp-v2	12.87	8.86 (0.38)	8.17 (0.06)	**75.93 (149.39)**	9.74 (1.37)

Table 8: The median of the estimated uncertainty $\sigma(s, a)$ in different tasks. Results are averaged over 5 seeds.

Baseline	Critic loss function	Actor loss functions
TD3+BC [16]	$L_{TD}(\mathcal{D}, \theta)$	$\lambda L_{TD3}(\mathcal{D}, \phi) + \mathcal{C}_{BC}(\mathcal{D}, \phi)$
CQL [36]	$L_{TD}(\mathcal{D}, \theta) + \alpha \mathcal{C}_{CQL}(\mathcal{D}, \theta)$	$L_{SAC}(\mathcal{D}, \theta, \phi)$
COMBO [54]	$L_{TD}(\mathcal{D}_{\widehat{\mathcal{M}}}, \theta) + \alpha \mathcal{C}_{CQL}(\mathcal{D}_{\widehat{\mathcal{M}}}, \theta)$	$L_{SAC}(\mathcal{D}_{\widehat{\mathcal{M}}}, \phi)$
IQL [30]	$L_{ER}(\mathcal{D}, \theta)$	$L_{AWR}(\mathcal{D}, \phi)$

Table 9: Different policy evaluation/improvement objectives.

Policy evaluation. TD3+BC [16] uses the default fitted Q-evaluation as in Eq 1. The only difference is that the $\max$ operator over next action a' is replaced by the policy $\pi_\phi(s')$:

$$L_{TD}(\mathcal{D}, \theta) = \mathbb{E}_{(s,a,r,s')\sim\mathcal{D}}\big[(r + \gamma Q^\pi_{\hat{\theta}}(s', \pi_\phi(s')) - Q^\pi_\theta(s, a))^2\big] \tag{2}$$

CQL [36] further adds a *conservative penalty* to push down large Q-values for OOD actions:

$$\mathcal{C}_{CQL}(\mathcal{D}, \theta) = \mathbb{E}_{s\sim\mathcal{D}}\big[\log \sum_a \exp(Q^\pi_\theta(s, a))\big] - \mathbb{E}_{(s,a)\sim\mathcal{D}}\big[Q^\pi_\theta(s, a)\big] \tag{3}$$

COMBO [54] extends CQL by using an augmented dataset $\mathcal{D}_{\widehat{\mathcal{M}}} = \mathcal{D} \cup \mathcal{D}_{model}$ for policy evaluation, where $\mathcal{D}_{model}$ is generated using the learned dynamics model. Unlike other three baselines, IQL [30] uses *expectile regression* (ER) for policy evaluation purely from in-sample data:

$$L_{ER}(\mathcal{D}, \theta) = \mathbb{E}_{(s,a,s',a')\sim\mathcal{D}}\big[L_2^\tau(r(s, a) + \gamma Q^\pi_{\hat{\theta}}(s', a') - Q^\pi_\theta(s, a))\big] \tag{4}$$

where $L_2^\tau(u) = |\tau - \mathbb{1}(u < 0)|u^2$ and $\tau \in (0, 1)$ is a hyperparameter.

Policy improvement. TD3+BC adds a simple behavior cloning loss $\mathcal{C}_{BC}(\phi) = \mathbb{E}[(\pi(s) - a)^2]$ to the original TD3 [17] actor loss $L_{TD3}(\phi) = -\mathbb{E}_{s\sim\mathcal{D}}[Q^\pi_\theta(s, \pi_\phi(s))]$. CQL and COMBO both use the default SAC [22] actor loss function $L_{SAC}(\phi) = \mathbb{E}_{(s,a)\sim\mathcal{D}}[\lambda \log(\pi_\phi(a|s)) - Q^\pi_\theta(s, \pi_\phi(a|s))]$. On the other hand, IQL uses the advantage-weighted regression (AWR) [43] to imitate high-quality in-sample actions $L_{AWR}(\phi) = \mathbb{E}_{(s,a)\sim\mathcal{D}}\big[\lambda \exp((Q_{\hat{\theta}}(s, a) - V_\psi(s))) \log \pi_\phi(a|s)\big]$, where $V_\psi(s)$ is a value function that only depends on state s.

Given these different policy evaluation/improvement methods, there is a lack of clear comparison to show which one is more effective in practice. Here, we try to show that the previously introduced experiment setups can be helpful tools to answer such questions. Recall the results in the Table 4 and Table 5, we can observe that IQL [30] usually achieves higher rank IC and larger topN accuracy, which suggests that the *expectile regression* based *policy evaluation* method in IQL is more capable to learn *accurate* value functions. However, IQL only achieves the best performance in one benchmark task. In addition, Table 8 indicates that IQL learns conservative policy that usually takes high confidence in-sample data. These results suggest that the AWR-based *policy-improvement* method is effective to avoid taking OOD actions but sometimes it is over-conservative which limits the performance. To validate this assumption, we introduce a simple variant of IQL, called *Relaxed In-sample Q-Learning* (RIQL), that replaces the original AWR-based actor loss with:

$$L_{RIQL}(\phi) = L_{SAC}(\phi) - \beta \mathbb{D}_{KL}(\pi_\beta, \pi_\phi) = L_{SAC}(\phi) - \beta \mathbb{E}_{(s,a)\sim\mathcal{D}}[\log \pi_\phi(a|s)]. \tag{5}$$

In short, we add a KL-divergence constraint to the original SAC actor loss, and we drop the $\mathbb{E}_{(s,a)\sim\mathcal{D}}[\log \pi_\beta(a|s)]$ term which is independent of actor parameter ϕ. The motivation is two-fold: (1) Unlike CQL and COMBO, the learned Q-functions in IQL are less discriminating w.r.t.

	TD3+BC	CQL	COMBO	IQL	RIQL
halfcheetah-med-v2	48.89 (0.15)	46.85 (0.22)	54.61 (1.48)	47.43 (0.07)	**55.93 (0.27)**
hopper-med-v2	60.19 (1.99)	61.18 (1.16)	**92.20 (5.04)**	64.64 (3.27)	91.58 (4.23)
walker2d-med-v2	**84.37 (0.55)**	81.21 (0.40)	81.93 (0.66)	80.28 (2.00)	80.85 (0.96)
halfcheetah-med-rep-v2	45.20 (0.30)	44.95 (0.45)	52.18 (0.43)	44.04 (0.71)	**52.39 (0.45)**
hopper-med-rep-v2	64.96 (7.26)	88.30 (4.21)	**96.53 (1.91)**	91.94 (14.94)	93.13 (7.46)
walker2d-med-rep-v2	77.24 (1.31)	77.68 (1.70)	62.05 (11.46)	73.53 (7.28)	**81.46 (4.72)**
halfcheetah-med-exp-v2	89.29 (5.07)	90.89 (0.44)	61.53 (9.76)	88.92 (1.34)	**92.91 (1.18)**
hopper-med-exp-v2	96.53 (4.97)	**105.19 (2.96)**	77.57 (16.57)	91.57 (27.03)	102.47 (5.49)
walker2d-med-exp-v2	**110.16 (0.18)**	104.61 (6.39)	84.98 (42.58)	107.68 (5.28)	108.34 (0.58)
Total	676.82	700.85	663.58	690.04	**759.05**

Table 10: RIQL achieves better performance than IQL in all benchmark tasks. Results are averaged over 5 seeds.

OOD samples. Thus, we need extra policy constraints to avoid taking too many OOD actions. (2) We want to use a less conservative actor loss to enable the policy learning from OOD actions. In addition, Eq 5 is similar to the actor loss in [11]. The difference is that we keep the entropy term which helps to prevent the learned policy from collapsing to a single point. Experiment results of RIQL is shown in Table 10 and more details are described in Appendix F. We can observe that RIQL outperforms IQL in all benchmark tasks, and it achieves higher total evaluation scores than other baseline agents. This result also validates our previous assumption that AWR-based policy improvement method is the bottleneck for IQL in some tasks which makes it over-conservative.

7 Uncertainty-based sample selection for model-based offline RL

In this section, we try to investigate when does a learned dynamics model is helpful to a model-free offline RL agent? In particular, we reuse the learned dynamics model in Section 5.2 to generate fake samples to train a model-free agent. For example, we introduce an MBRL variant of IQL/TD3+BC, named MIQL/MTD3+BC, which learns from the augmented dataset $\mathcal{D}_{\widehat{\mathcal{M}}} = \mathcal{D} \cup \mathcal{D}_{model}$ as in MOPO [55]. However, we find that such a naive MBRL agent (a simple combination of MOPO and model-free offline RL agents) usually performs worse than its model-free counterpart (Table 11) even though they are the same algorithm except for the training data. This result indicates that it is nontrivial to combine a learned dynamics model with model-free offline RL agents due to the model noises. COMBO [54] addresses this problem by adding a conservative penalty on the model-generated samples. Here, we introduce an *Uncertainty-based Sample Selection* (USS) method to filter fake samples with large model noises.

Since it is hard to measure model noises accurately, we adopt the model uncertainty $\sigma(s, a)$ defined in Section 5.2 as a proxy to approximate model noise. In addition, we maintain a dynamic *uncertainty threshold* δ_σ as follows $\delta_\sigma \leftarrow \eta\sigma^q_{batch}(s, a) + (1 - \eta)\delta_\sigma$, where $\sigma^q_{batch}(s, a)$ is the q-th quantile of the uncertainties in the sampled fake trajectories. We only add model-generated samples with an uncertainty lower than δ_σ to the model buffer which is later used to train the agent. More details are described in Appendix G. From Table 11, we can observe that the proposed USS trick usually helps to improve the performance of the MIQL/MTD3+BC agent. Moreover, USS is inferior to IQL/TD3+BC in some tasks which shows that it is still challenging to completely solve the model noise problem.

	IQL	MIQL	MIQL-USS	TD3+BC	MTD3+BC	MTD3+BC-USS
halfcheetah-med-v2	47.43 (0.07)	27.52 (7.69)	**53.85 (0.41)**	48.89 (0.15)	1.18 (1.61)	52.41 (0.39)
hopper-med-v2	64.64 (3.27)	8.89 (8.32)	**80.79 (15.21)**	60.19 (1.99)	46.07 (7.05)	67.74 (4.95)
walker2d-med-v2	80.28 (2.00)	43.44 (9.59)	77.21 (4.21)	84.37 (0.55)	**85.33 (0.95)**	84.80 (1.09)
halfcheetah-med-rep-v2	44.04 (0.71)	44.70 (3.20)	**48.49 (0.30)**	45.20 (0.30)	47.80 (0.70)	47.05 (0.41)
hopper-med-rep-v2	**91.94 (14.94)**	19.36 (3.18)	87.63 (6.90)	64.96 (7.26)	37.78 (8.71)	69.64 (8.93)
walker2d-med-rep-v2	73.53 (7.28)	59.41 (30.75)	85.83 (7.59)	77.24 (1.31)	85.02 (2.26)	**87.84 (2.57)**
halfcheetah-med-exp-v2	88.92 (1.34)	32.47 (4.81)	82.08 (4.54)	**89.29 (5.07)**	0.79 (1.36)	85.63 (2.77)
hopper-med-exp-v2	91.57 (27.03)	10.41 (8.66)	75.88 (41.26)	96.53 (4.97)	74.65 (20.27)	**96.81 (4.12)**
walker2d-med-exp-v2	107.68 (5.28)	87.96 (9.56)	108.25 (3.27)	110.16 (0.18)	110.37 (0.29)	**110.38 (0.41)**
Total	690.04	334.16	699.98	676.82	488.99	**702.29**

Table 11: USS is able to effectively mitigate the problem of model noises. Results are averaged over 5 seeds.

8 Conclusion

Besides the rapid development of novel offline RL algorithms, the behaviors of these offline RL agents have not been well studied. In this work, we take a closer look at SOTA offline RL agents. Specifically, we introduce a series of experiments to compare the learned representations, value functions and policies of four baseline agents. Surprisingly, we find that a performant agent sometimes has relatively low quality representations and inaccurate value functions. We also show that the proposed experiment setups can be used to compare the effectiveness of different policy evaluation/improvement methods by introducing a relaxed version of IQL that achieves SOTA performance. Lastly, we investigate when a learned dynamics model can help model-free offline RL agents, and we introduce an uncertainty-based sample selection method to mitigate the problem of model noises.

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Appendix

In the appendix, we first provide more background information and introduce some related works. Then we report the details of experiment setups and additional experiment results on all test environments. Lastly, we discuss the limitations and future directions of this work.

A Extended background material

Here, we provide a more extensive background review. Specifically, we present more discussions on offline reinforcement learning and representation learning for reinforcement learning.

A.1 Offline reinforcement learning

Offline reinforcement learning (RL) aims to learn effective control policies purely from fixed pre-collected datasets. Recent years have seen a surge of different offline RL methods. We crudely classify some latest works in the following categories.

Policy-regularized offline RL. The majority of the recent proposed offline RL algorithms share a similar idea – constraining the learned policy to stay close to the behavior policy. For example, BCQ [18] used a variational auto-encoder (VAE) to generate actions that are similar to samples in the offline dataset. KL-Control [24] and CDC [11] used KL divergence, BEAR [35] adopted maximum mean discrepancy (MMD) divergence, FBRC selected Fisher-divergence [31] as a regularizer in the loss function. On the other hand, BRAC[50] and BRAC+ [56] proposed general frameworks for the such policy-regularized approaches.

Pessimism-based offline RL. Another line of research focuses on attacking the over-estimation problem directly by using conservative penalties. CQL [36] proposed a penalty regularizer for out-of-distribution (OOD) samples, such that we can learn conservative Q-functions that lower-bounds its true value. In addition, Buckman et al. [5] proposed a general theoretical framework to unify some existing pessimism-based approaches. Recently, CDC [11] introduced a new regularizer that only penalizes high-valued samples selected by the actor.

Generalized behavior cloning (BC). Some other works resort to weighted behavior cloning, which reduces the RL problem to a supervised learning problem [10]. For example, AWR [43] and CRR

[49] used value-weighted regression to filter high-quality samples. BAIL [7] proposed upper-envelope to select good actions for later imitation learning. Recently, IQL [30] performed weighted behavioral cloning for policy extraction.

Model-based offline RL. One motivation for using Model-based RL (MBRL) in the offline setting is to increase the data coverage, where the batch RL agent can learn policies with OOD states [55, 29]. MOPO [55] and MoREL [29] measured the uncertainty of the model's prediction to formulate an uncertainty-penalized MDP. COMBO [54] combined CQL with a learned model by penalizing the samples generated by the learned model. MuZero Unplugged [47] directly used the learned model for policy and value improvement through planning.

Other types of offline RL. In addition to using uncertainty estimation under the MBRL framework, some recent model-free batch RL algorithms also adopt the uncertainty to mitigate the over-estimation error. UWAC [52] used dropout-uncertainty estimation to down-weight OOD samples loss. MSG [19] used an ensemble of independently-updated Q-functions for uncertainty estimation. Furthermore, REM [1] showed that standard off-policy RL methods can achieve good performance when the dataset is large and diverse.

A.2 Representation learning for reinforcement learning

Some recent works introduced different representation metrics as proxies to evaluate the quality of the learned representations of an RL agent [34, 33, 38, 41]. We provide a more detailed introduction to the following three metrics that we use in the experiments.

Definition 1 (Feature dot-product)**.** *Feature dot-product $\phi(s,a)^\top \phi(s',a')$ is the dot-product of two critic representations, where $s' \sim \mathcal{P}(\cdot|s,a)$ and $a' \sim \pi(\cdot|s')$ is the next state and next action.*

Definition 2 (Effective rank)**.** *Effective rank $\mathrm{srank}_\delta(\Phi) = \min\left\{k : \frac{\sum_{i=1}^k \sigma_i(\Phi)}{\sum_{i=1}^d \sigma_i(\Phi)} \geq 1-\delta\right\}$ of a feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}|\cdot|\mathcal{A}|\times d}$ approximates the rank of Φ [33], where $\{\sigma_i(\Phi)\}$ are the singular values of Φ in the decreasing order ($\sigma_1 \geq \cdots \geq \sigma_d \geq 0$) and δ is a threshold parameter, i.e.,* 0.01.

Definition 3 (Effective dimension)**.** *Effective dimension $d_{\text{eff}}(\Phi) = N \max_{i=1,\cdots,N} \|P_\Phi e_i\|_2^2$ of a feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}|\cdot|\mathcal{A}|\times d}$ measures the sparsity of the column space of Φ [38], where $N = |\mathcal{S}|\cdot|\mathcal{A}|$ and P_Φ is the orthogonal projector onto the column space of Φ.*

DR3 [34] introduced the *feature co-adaptation* phenomenon where the *feature dot-product* keeps increasing during the training of a deep Q-Network. In particular, DR3 provided a theoretical analysis to show that optimizing TD errors with SGD has an implicit "regularizer" that leads to the feature co-adaptation phenomenon which usually hurts the performance. Later, some related works [33, 38, 41] introduced the *representation collapse* phenomenon, where the rank of the feature space shrinks during the training step, which limits the learning capacity of an RL agent. In particular, Kumar et al. [33] pointed out that such representation collapse phenomenon is connected to the bootstrapping based update, and provided some theoretical explanations in the context of kernel regression and deep linear networks. On the other hand, Lan et al. [38] provided an informative bound on the generalization error w.r.t the *effective dimension* of state representations, and showed that a smaller *effective dimension* helps to improve the performance. To mitigate the problem of representation collapse, InFeR [41] presented a regularization term that forces the trained networks to regress to a random function of their initial output.

Another closely related work is ACL [53], which empirically investigated a number of representation auxiliary losses for RL agents. Moreover, Deng et al. [9] also explored the representation bottlenecks for deep neural networks. A major difference of this work and these related works is that we studied the detailed behaviors, including representations, value function and policies, of offline RL agents.

B Experiment details

In this section, we present more details about the dataset and the baseline algorithms.

B.1 Experiment setups

In the experiment, we evaluate all baseline agents on the standard D4RL benchmark [14]. In specific, we use the "-v2" dataset, which contains more metadata and fixes bugs in the "-v0" dataset [1], to train each baseline agent for 1M steps. In all experiments, we report the average result and standard deviation over 5 random seeds. We run all experiments on a workstation with GeForce GTX 3090 GPU and an Intel Core i9-12900KF CPU.

B.2 Baseline algorithms

We re-implement each baseline algorithm in JAX [13]. For TD3BC [16], CQL [36] and IQL [30], we use the default parameter settings as in the original implementations. Moreover, we find the default parameters in COMBO [54], which is originally trained on the "-v0" dataset, sometimes fail in the "-v2" dataset. Thus, we additionally tune the conservative parameter β for COMBO using the offline cross-validation scheme as described in the original paper [54].

For the software, we use the following versions:

- Python 3.9
- Jax 0.3.10
- Gym 0.23.1
- Mujoco 2.1.2
- mujoco-py 2.1.2.14
- d4rl 1.1

The running time for 1M steps for each baseline algorithm in the JAX version is usually faster than the original implementations [30] as summarized in Table 12:

	TD3BC	CQL	COMBO	IQL
Running time (min)	15	90	70	20

Table 12: Running time for 1M steps.

C Representation evaluation experiments

In this section, we provide more results of the representation experiments in different environments. In the experiment, we first train an online TD3 [17] agent for 2M steps to approximate the optimal policy $\pi^*(a|s)$ and optimal value functions $Q^*(s,a)$ and $V^*(s)$. For each probing target, we train a linear model for 200 epochs using the Adam optimizer with learning rate 3e-4. We adopt an early stopping strategy with patience of 10 epochs. We report the average result of a 5-fold cross-validation. The most performant baseline agents in each environment are brown, and the agent with the best probing experiment result is in **bold**.

C.1 Representation probing experiment results

In the experiment, the COMBO agent crashed in the *walker2d-medium-expert-v2* environment for one random seed (learned explosive $Q(s,a)$). In some probing experiments, the crashed COMBO agent diverges. We report the mean and standard deviation of the MSE loss over 5 random seeds.

From Table 13, Table 14 and Table 15, we can observe that the TD3BC agent usually has good probing experiment results (with the least probing loss), however, the TD3BC agent only achieves the best performance in 2 of the 9 environments. These results show that the transition dynamics-based side information is not that important for offline RL agents in the selected D4RL tasks. Intuitively, the most performant agent usually has small optimal a^* probing loss (Table 16). This indicates that as

[1] https://github.com/rail-berkeley/d4rl/wiki/Tasks

long as the actor representation $\psi(s)$ preserves the ability to learn good actions (low optimal action probing loss), then the offline RL agent holds the potential to achieve good performance. From Table 17 and Table 18, we can find that the probing loss w.r.t. the optimal value functions are usually very large. Such large probing loss highlights the difficulty to learn accurate value functions in the offline setting due to the limited data coverage and additional policy/value constraints.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	**0.25 (0.05)**	0.41 (0.07)	0.88 (0.27)	0.25 (0.02)
halfcheetah-med-rep-v2	**0.22 (0.01)**	0.40 (0.02)	0.27 (0.02)	0.29 (0.03)
halfcheetah-med-exp-v2	**0.22 (0.02)**	0.31 (0.05)	0.40 (0.08)	0.23 (0.00)
hopper-med-v2	**0.01 (0.00)**	0.07 (0.07)	0.05 (0.05)	0.01 (0.00)
hopper-med-rep-v2	**0.02 (0.01)**	0.02 (0.01)	0.13 (0.09)	0.03 (0.03)
hopper-med-exp-v2	0.01 (0.00)	0.04 (0.02)	0.07 (0.04)	**0.01 (0.00)**
walker2d-med-v2	0.16 (0.05)	0.20 (0.06)	0.28 (0.24)	**0.10 (0.04)**
walker2d-med-rep-v2	0.12 (0.03)	0.23 (0.11)	0.11 (0.05)	**0.09 (0.02)**
walker2d-med-exp-v2	0.16 (0.03)	0.18 (0.06)	NaN	**0.09 (0.04)**

Table 13: Reward probing experiment.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	**5.13 (0.29)**	9.76 (0.91)	13.05 (1.86)	5.45 (0.46)
halfcheetah-med-rep-v2	**4.56 (0.21)**	10.86 (0.21)	9.93 (0.65)	6.04 (0.37)
halfcheetah-med-exp-v2	**5.65 (0.27)**	8.98 (0.39)	11.14 (0.68)	6.10 (0.18)
hopper-med-v2	**0.11 (0.01)**	0.27 (0.05)	0.24 (0.06)	0.13 (0.03)
hopper-med-rep-v2	**0.17 (0.03)**	0.28 (0.06)	0.48 (0.13)	0.17 (0.03)
hopper-med-exp-v2	**0.11 (0.01)**	0.28 (0.04)	0.28 (0.07)	0.13 (0.03)
walker2d-med-v2	5.23 (0.45)	6.44 (1.01)	5.94 (3.08)	**4.45 (0.24)**
walker2d-med-rep-v2	4.61 (0.19)	6.62 (0.27)	6.29 (0.66)	**4.15 (0.30)**
walker2d-med-exp-v2	5.22 (0.26)	5.65 (0.12)	NaN	**4.40 (0.18)**

Table 14: Next state probing experiment.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	**0.14 (0.01)**	0.25 (0.01)	0.15 (0.01)	0.19 (0.01)
halfcheetah-med-rep-v2	**0.11 (0.00)**	0.27 (0.01)	0.27 (0.01)	0.20 (0.01)
halfcheetah-med-exp-v2	**0.14 (0.01)**	0.28 (0.01)	0.16 (0.01)	0.20 (0.01)
hopper-med-v2	0.10 (0.01)	0.18 (0.03)	**0.09 (0.01)**	0.13 (0.00)
hopper-med-rep-v2	**0.09 (0.01)**	0.21 (0.02)	0.23 (0.09)	0.13 (0.02)
hopper-med-exp-v2	0.10 (0.01)	0.18 (0.02)	**0.09 (0.00)**	0.12 (0.01)
walker2d-med-v2	**0.31 (0.00)**	0.37 (0.01)	0.31 (0.01)	0.34 (0.02)
walker2d-med-rep-v2	**0.30 (0.01)**	0.38 (0.02)	0.31 (0.01)	0.35 (0.01)
walker2d-med-exp-v2	**0.31 (0.01)**	0.36 (0.01)	6.47 (13.77)	0.34 (0.01)

Table 15: Inverse action probing experiment.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	0.39 (0.00)	0.39 (0.01)	**0.37 (0.01)**	0.42 (0.01)
halfcheetah-med-rep-v2	0.43 (0.01)	0.46 (0.00)	**0.39 (0.00)**	0.48 (0.01)
halfcheetah-med-exp-v2	**0.38 (0.01)**	0.40 (0.01)	0.39 (0.01)	0.44 (0.01)
hopper-med-v2	0.36 (0.03)	0.36 (0.04)	**0.32 (0.01)**	0.39 (0.04)
hopper-med-rep-v2	0.37 (0.04)	**0.36 (0.01)**	0.37 (0.04)	0.37 (0.04)
hopper-med-exp-v2	0.37 (0.01)	0.40 (0.08)	**0.32 (0.01)**	0.37 (0.04)
walker2d-med-v2	**0.34 (0.01)**	0.36 (0.02)	0.36 (0.01)	0.37 (0.01)
walker2d-med-rep-v2	0.35 (0.01)	0.39 (0.02)	**0.33 (0.01)**	0.41 (0.01)
walker2d-med-exp-v2	**0.34 (0.02)**	0.35 (0.02)	4.05 (8.27)	0.37 (0.02)

Table 16: Optimal action probing experiment.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	4.44 (0.31)	5.22 (0.61)	6.20 (1.13)	**4.30 (0.45)**
halfcheetah-med-rep-v2	5.22 (0.67)	7.65 (0.85)	**3.94 (0.12)**	5.16 (0.35)
halfcheetah-med-exp-v2	**4.16 (0.18)**	4.40 (0.21)	5.59 (1.01)	4.58 (0.20)
hopper-med-v2	**1.15 (0.24)**	1.49 (0.60)	1.55 (0.41)	1.21 (0.20)
hopper-med-rep-v2	0.75 (0.29)	1.10 (0.13)	**0.56 (0.15)**	1.25 (0.49)
hopper-med-exp-v2	**1.00 (0.12)**	1.20 (0.47)	1.45 (0.60)	1.43 (0.20)
walker2d-med-v2	**1.99 (0.34)**	2.38 (0.31)	2.59 (0.72)	2.05 (0.13)
walker2d-med-rep-v2	**2.67 (0.96)**	3.11 (0.68)	3.21 (0.78)	2.69 (0.53)
walker2d-med-exp-v2	**1.71 (0.07)**	2.42 (0.26)	NaN	2.04 (0.39)

Table 17: Optimal $Q^*(s, a)$ probing experiment: each number is divided by 1000.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	76.30 (22.05)	123.11 (42.42)	**48.73 (35.06)**	100.97 (43.36)
halfcheetah-med-rep-v2	109.73 (13.14)	95.85 (7.56)	**76.23 (9.11)**	153.07 (11.04)
halfcheetah-med-exp-v2	41.72 (13.59)	79.86 (26.85)	**23.90 (13.68)**	186.22 (20.99)
hopper-med-v2	2.76 (0.52)	5.82 (3.92)	**1.10 (0.29)**	3.38 (1.22)
hopper-med-rep-v2	**1.73 (0.50)**	1.93 (0.83)	2.13 (0.43)	2.30 (0.90)
hopper-med-exp-v2	1.78 (0.85)	4.79 (2.32)	**1.15 (0.13)**	1.90 (0.53)
walker2d-med-v2	3.36 (0.50)	3.33 (0.39)	**2.99 (0.44)**	4.35 (0.37)
walker2d-med-rep-v2	3.64 (0.12)	4.49 (0.71)	**2.27 (0.34)**	5.67 (0.25)
walker2d-med-exp-v2	**3.98 (0.56)**	4.09 (0.31)	4.80 (2.97)	4.27 (0.32)

Table 18: Optimal $V^*(s)$ probing experiment: each number is divided by 1000.

C.2 Representation metric experiment results

Before reporting the results for the representation metric experiment, we first give a brief discussion of the implementation of the *effective dimension*. As shown in the following code snippet (Algo 1), the original implementation of the *effective dimension* [2] uses a hard threshold (1e-5) to approximate the rank of the feature matrix. However, such a hard threshold is prone to over-estimate the rank when the norm of the representation is large, as we will see in Table 19 and Table 20. Therefore, we use a modified implementation which approximate the rank using a relative threshold (effective rank).

[2] Original implementation of the effective dimension.

Algorithm 1 A comparison of two implementations of effective dimension.

```
# matrix: sample representations (Nxd)
# thresh: a threshold to approximate the matrix rank

def calculate_effective_dim1(matrix, thresh=1e-5):
    """The original implementation"""
    num_rows, _ = matrix.shape

    # SVD
    u, s, _ = np.linalg.svd(matrix, full_matrices=False, compute_uv=True)

    # approximate matrix rank using a hard threshold
    rank = max(np.sum(s >= thresh), 1)

    # approximate the effective dimension
    u1 = u[:, :rank]
    projected_basis = np.matmul(u1, np.transpose(u1))
    norms = np.linalg.norm(projected_basis, axis=0, ord=2) ** 2
    eff_dim = num_rows * np.max(norms)
    return eff_dim


def calculate_effective_dim2(matrix, thresh=0.99):
    """A modified implementation"""
    num_rows, _ = matrix.shape

    # normalize the matrix
    normalized_matrix = matrix / np.linalg.norm(matrix, axis=-1, keepdims=True)

    # SVD
    u, s, _ = np.linalg.svd(normalized_matrix, full_matrices=False, compute_uv=True)

    # approximate matrix rank using a relative threshold (effective rank)
    cumsum_s = s.cumsum()
    threshold = cumsum_s[-1] * thresh
    rank = sum(cumsum_s <= threshold)

    # approximate the effective dimension
    u1 = u[:, :rank]
    projected_basis = np.matmul(u1, np.transpose(u1))
    norms = np.linalg.norm(projected_basis, axis=0, ord=2) ** 2
    eff_dim = num_rows * np.max(norms)
    return eff_dim
```

From Table 19, we can observe that the critic constraint in offline RL will make the *feature co-adaption* more severe. TD3BC agent does not use any critic constraint, and the consecutive state-action pairs are the least similar. On the other hand, the *feature co-adaptation* phenomenon is particularly severe when we adds a conservative penalty. Interestingly, such a large feature dot-product does not prevent the COMBO agent to achieve good performance in some offline RL tasks. In addition, combined results in Table 19 and Table 20, we can conclude that the increasing feature dot-product is mainly caused by the representation norm. These results also provide a hint for how the conservative penalty in CQL or COMBO works. As we can see that the representation norm $|\phi(s,a)|$ is usually large for a CQL or COMBO agent, then it learns a lower-bounded Q-values $Q_\theta(s,a) = \theta^\top \phi(s,a)$ by a small $|\theta|$ and (or) dissimilar vector direction of θ and $\phi(s,a)$.

From Table 21 and Table 22, we can observe that the COMBO agent ususally suffers from the *representation collapse* problem while its model-free counterpart CQL agent doesn't. This result indicates that the usage of a learned dynamics model would sometimes affect the learned critic representations. We leave a deeper investigation for future work.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	10.34 (0.86)	1036.34 (1179.43)	5115.07 (3688.67)	**7.06 (0.31)**
halfcheetah-med-rep-v2	**4.55 (0.41)**	81.10 (9.94)	229.43 (66.82)	7.11 (1.10)
halfcheetah-med-exp-v2	7.98 (0.26)	469.44 (57.80)	750.29 (495.01)	**6.67 (0.69)**
hopper-med-v2	8.43 (1.40)	56.37 (21.31)	335.85 (301.72)	**4.93 (0.31)**
hopper-med-rep-v2	**3.60 (0.58)**	44.93 (9.62)	2048.59 (1415.81)	4.82 (0.58)
hopper-med-exp-v2	6.81 (1.03)	62.69 (3.59)	1031.57 (671.65)	**4.86 (0.11)**
walker2d-med-v2	**5.80 (1.26)**	123.04 (61.53)	44.07 (11.08)	8.76 (0.86)
walker2d-med-rep-v2	**3.40 (0.34)**	93.49 (3.73)	144.16 (61.59)	5.90 (0.36)
walker2d-med-exp-v2	**7.01 (0.93)**	128.92 (12.80)	NaN	7.31 (0.37)

Table 19: Dot-product for $\phi(s, a)$: each value is divided by 1000.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	**0.74 (0.03)**	0.85 (0.08)	1.00 (0.00)	0.95 (0.01)
halfcheetah-med-rep-v2	**0.62 (0.03)**	0.77 (0.02)	0.94 (0.02)	0.86 (0.02)
halfcheetah-med-exp-v2	**0.74 (0.01)**	0.96 (0.01)	0.96 (0.02)	0.89 (0.01)
hopper-med-v2	**0.81 (0.03)**	0.99 (0.01)	1.00 (0.00)	1.00 (0.00)
hopper-med-rep-v2	**0.65 (0.05)**	0.99 (0.00)	1.00 (0.00)	1.00 (0.00)
hopper-med-exp-v2	**0.81 (0.04)**	0.99 (0.00)	0.99 (0.01)	1.00 (0.00)
walker2d-med-v2	**0.72 (0.05)**	0.95 (0.02)	0.99 (0.00)	0.97 (0.00)
walker2d-med-rep-v2	**0.65 (0.02)**	0.97 (0.00)	1.00 (0.00)	0.95 (0.00)
walker2d-med-exp-v2	**0.75 (0.03)**	0.99 (0.00)	0.99 (0.01)	0.98 (0.00)

Table 20: Cosine similarity for $\phi(s, a)$.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	131.40 (6.58)	**145.00 (9.51)**	6.80 (1.48)	144.60 (5.41)
halfcheetah-med-rep-v2	165.40 (0.89)	**174.00 (7.52)**	84.80 (10.28)	164.40 (3.51)
halfcheetah-med-exp-v2	131.00 (3.61)	129.20 (6.76)	73.60 (10.53)	**147.80 (4.15)**
hopper-med-v2	47.00 (4.00)	**110.40 (9.50)**	32.80 (11.10)	56.00 (4.74)
hopper-med-rep-v2	61.80 (4.44)	**93.60 (3.05)**	32.20 (6.14)	71.80 (4.02)
hopper-med-exp-v2	51.00 (4.74)	**110.40 (6.43)**	28.00 (9.75)	61.60 (7.99)
walker2d-med-v2	121.60 (5.98)	**155.60 (15.60)**	142.00 (7.18)	133.60 (1.67)
walker2d-med-rep-v2	168.00 (3.16)	**169.60 (5.18)**	49.00 (8.51)	162.00 (2.65)
walker2d-med-exp-v2	126.60 (1.67)	**151.60 (2.30)**	68.20 (37.77)	138.20 (3.63)

Table 21: Effective rank for $\phi(s, a)$.

	TD3BC	CQL	COMBO	IQL
halfcheetah-med-v2	**1238.21 (206.54)**	1671.35 (266.73)	7506.93 (4914.83)	2853.29 (662.05)
halfcheetah-med-rep-v2	**964.80 (74.90)**	3041.89 (1472.68)	6121.73 (2351.42)	1331.98 (50.85)
halfcheetah-med-exp-v2	**1694.37 (430.47)**	2340.58 (549.36)	4009.00 (933.79)	2199.08 (322.87)
hopper-med-v2	2994.54 (792.37)	**1991.76 (240.80)**	3493.77 (857.89)	3143.34 (524.72)
hopper-med-rep-v2	2853.40 (349.95)	2771.78 (619.28)	**1902.39 (347.89)**	2627.52 (567.50)
hopper-med-exp-v2	2745.54 (604.30)	**2240.43 (926.86)**	3906.44 (2240.04)	2672.30 (586.31)
walker2d-med-v2	**1854.38 (288.18)**	2460.55 (1292.07)	2588.08 (844.80)	1973.46 (396.32)
walker2d-med-rep-v2	1535.55 (82.77)	1558.29 (184.18)	11855.81 (1549.88)	**1478.16 (156.08)**
walker2d-med-exp-v2	1859.44 (378.47)	2610.34 (1587.02)	**1741.50 (989.31)**	1914.29 (142.38)

Table 22: Effective dimension for $\phi(s, a)$.

D Value ranking experiments

Fig **??** illustrates the pipeline of value ranking experiment. Firstly, we use a behavior policy π_β to interact with the environment to collect a set of states $\{s_1, \cdots, s_N\}$ as the test dataset. In particular, the behavior policy π_β is a mixture of four baseline offline RL agents and a near-optimal online agent. We use each agent to collect 50K transitions. Secondly, at each state s_i, we use each baseline agent to select $m = 5$ different actions $a' = \pi(\cdot|s_i) + \epsilon$, where ϵ_i is a Gaussian noise with $\mu = 0$ and $\sigma = 0.2$. Thirdly, we use each baseline agent to evaluate the Q-values of the collected state-action pairs. Lastly, we use the online agent to approximate the optimal agent to compute the Spearman's rank correlation coefficient (rank IC) and top-N accuracy.

Since this experiment only utilizes the learned Q-function of each baseline agent, therefore, we use the experiment result as a proxy to evaluate how *accurate* the learned Q-values are at ranking different actions. Moreover, the experiment result is also a useful evidence to show the effectiveness of different policy evaluation methods.

E Performant policy experiments

E.1 Policy ranking experiment

Fig **??** shows the pipeline of the policy ranking experiment. Similar to the previous value ranking experiment, we use the online agent to approximate optimal $Q^*(s, a)$ to rank the actions selected by each baseline agents. We use the following two metrics to evaluate the *goodness* of the learned policy: (1) Average percentage of policy π_j that rank the first/last (with largest/smallest Q^* value) across all states $\frac{1}{|\mathcal{D}_{policy}|}\sum_i \mathbb{1}\{\text{rank}(Q^*(\pi_j(s_i), s_i)) = 1\}$. (2) Average mean square error (MSE) loss of the selected action w.r.t. the optimal action $\frac{1}{|\mathcal{D}_{policy}|}\sum_t \|a_i^* - \pi_j(s_i)\|^2$.

E.2 OOD action experiments

To investigate how often do different offline RL agents take OOD actions, we first use each baseline agent to interact with the environment to collect 50K transitions. Then we use a probabilistic ensemble-based dynamics model [8] as in COMBO [54] to estimate the uncertainty [55] of each state-action pair as $\sigma(s, a) = \max_{i=1,\cdots,N} \|\mu_\theta^i(s, a) - \frac{1}{N}\sum_{j=1}^N \mu_\theta^j(s, a)\|_2$. In the experiment, we set the ensemble model number $N = 7$ as in COMBO. We report the average median and standard deviation of the uncertainty in the collection samples in Table 8.

F Relaxed in-sample Q-Learning (RIQL)

In RIQL, we attempt to make a minimal modification w.r.t. the IQL algorithm [30]. Since the motivation of RIQL is to relax the in-sample constraint for the policy improvement step in IQL, we therefore replace the *Advantage Weighted Regression* (AWR) loss function with the following:

$$L_\pi(\phi) = L_{SAC}(\phi) - \beta\mathbb{E}_{(s,a)\sim\mathcal{D}}[\log \pi_\phi(a|s)]$$

In short, we add a KL-divergence constraint to the SAC [22] actor loss. We determine the parameter $\beta = \{0.1, 0.25, 0.5, 1.0, 1.5\}$ using the offline cross-validation scheme as described in COMBO [54]. For the policy evaluation step, we follow the original expectile regression-based method to update the two value functions $Q_\theta(s, a)$ and $V_\psi(s)$:

$$L_Q(\theta) = \mathbb{E}_{(s,a,s')\sim\mathcal{D}}\left[(r(s, a) + \gamma V_\psi(s') - Q_\theta(s, a))^2\right]$$
$$L_V(\psi) = \mathbb{E}_{(s,a)\sim\mathcal{D}}[L_2^\tau(Q_{\hat{\theta}}(s, a) - V_\psi(s))]$$

where $Q_{\hat{\theta}}(s, a)$ is the target Q network, $L_2^\tau(u) = |\tau - \mathbb{1}(u < 0)|u^2$ and $\tau \in (0, 1)$ is a hyperparameter. The pseudocode of RIQL is described in Algo 2. In addition, Fig **??** shows the learning curves of RIQL where we report the average evaluation return over 5 random seeds and the standard deviation is in shadow.

Algorithm 2 Relaxed In-sample Q-Learning (RIQL)

Input: offline dataset $\mathcal{D}$.
Initialize parameters ψ, θ, $\hat{\theta}$, ϕ.
Policy evaluation with expectile regression:
for each gradient step **do**
  $\psi \leftarrow \psi - \lambda_V \nabla_\psi L_V(\psi)$
  $\theta \leftarrow \theta - \lambda_Q \nabla_\theta L_Q(\theta)$
  $\hat{\theta} \leftarrow (1-\alpha)\hat{\theta} + \alpha\theta$
end for
Policy improvement with KL constraint:
for each gradient step **do**
  $\phi \leftarrow \phi - \lambda_\pi \nabla_\phi L_\pi(\phi)$
end for

G Uncertainty-based Sample Selection (USS)

The proposed *Uncertainty-based Sample Selection* (USS) is a simple trick for model-based offline RL. Here we present a detailed pipeline to showcase how it can be implemented.

- We first learn a probabilistic ensemble-based dynamics model as in the COMBO using the offline dataset.
- For every $T = 1000$ step, we use the offline RL agent to rollout the model to generate 10K short trajectories (with horizon = 5).
- We then use the generated samples to update the dynamic uncertainty threshold $\delta_\sigma \leftarrow \eta\sigma^q_{batch}(s,a) + (1-\eta)\delta_\sigma$, where $\eta = 0.1$ and $\sigma^q_{batch}(s,a)$ is the median uncertainty of the sampled transitions. The δ_σ is initialized to be the median uncertainty of the transition samples in the first rollout. We only add samples with uncertainty lower than δ_σ to the extra model buffer $\mathcal{D}_{model}$.
- We train the agent using the augmented dataset $\mathcal{D} \cup \mathcal{D}_{model}$ where $\mathcal{D}$ is the original offline dataset.

H Limitations and future directions

In this work, we introduced a series of experiment setups to analyze the behaviors of offline reinforcement learning agents. Specifically, we focus on three fundamental aspects of an RL agent – learned representations, value functions, and policies. From the empirical experiment results, we discover some bottlenecks of current SOTA offline RL agents. As a case study, we introduced a variant of IQL agent, called RIQL, which uses a relaxed policy improvement method and achieves better performance. A major limitation of our work is that we need to use an online agent to approximate the optimal agent, which might be unavailable in many problems. In this work, we empirically show that some performant offline RL agents learned low-quality representations. Therefore, an interesting future direction is to investigate the effectiveness of the latest representation learning methods in offline RL. Another future direction is to extend the proposed experiment setups to the online setting.