HARNESSING MIXED OFFLINE REINFORCEMENT LEARNING DATASETS VIA TRAJECTORY WEIGHTING

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ABSTRACT

Most offline reinforcement learning (RL) algorithms return a target policy maximizing a trade-off between (1) the expected performance gain over the behavior policy that collected the dataset, and (2) the risk stemming from the out-of-distributionness of the induced state-action occupancy. It follows that the performance of the target policy is strongly related to the performance of the behavior policy and, thus, the trajectory return distribution of the dataset. We show that in mixed datasets consisting of mostly low-return trajectories and minor high-return trajectories, state-of-the-art offline RL algorithms are overly restrained by low-return trajectories and fail to exploit high-performing trajectories to the fullest. To overcome this issue, we show that, in deterministic MDPs with stochastic initial states, the dataset sampling can be re-weighted to induce an artificial dataset whose behavior policy has a higher return. This re-weighted sampling strategy may be combined with any offline RL algorithm. We further analyze that the opportunity for performance improvement over the behavior policy correlates with the positive-sided variance of the returns of the trajectories in the dataset. We empirically show that while CQL, IQL, and TD3+BC achieve only a part of this potential policy improvement, these same algorithms combined with our reweighted sampling strategy fully exploit the dataset. Furthermore, we empirically demonstrate that, despite its theoretical limitation, the approach may still be efficient in stochastic environments.

1 INTRODUCTION

Offline reinforcement learning (RL) currently receives great attention because it allows one to optimize RL policies from logged data without direct interaction with the environment. This makes the RL training process safer and cheaper since collecting interaction data is high-risk, expensive, and time-consuming in the real world (e.g., robotics, and health care). Unfortunately, several papers have shown that near optimality of the offline RL task is intractable sample-efficiency-wise (Xiao et al., 2022; Chen & Jiang, 2019; Foster et al., 2022).

In contrast to near optimality, policy improvement over the behavior policy is an objective that is approximately realizable since the behavior policy may efficiently be cloned with supervised learning (Urbancic, 1994; Torabi et al., 2018). Thus, most practical offline RL algorithms incorporate a component ensuring, either formally or intuitively, that the returned policy improves over the behavior policy: pessimistic algorithms make sure that a lower bound on the target policy (i.e., a policy learned by offline RL algorithms) value improves over the value of the behavior policy (Petrik et al., 2016; Kumar et al., 2020b; Buckman et al., 2020), conservative algorithms regularize their policy search with respect to the behavior policy (Thomas, 2015; Laroche et al., 2019; Fujimoto et al., 2019), and one-step algorithms prevent the target policy value from propagating through bootstrapping (Brandfonbrener et al., 2021). These algorithms use the behavior policy as a stepping stone. As a consequence, their performance guarantees highly depend on the performance of the behavior policy.

Due to the dependency on behavior policy performance, these offline RL algorithms are susceptible to the return distribution of the trajectories in the dataset collected by a behavior policy. To illustrate this dependency, we will say that these algorithms are anchored to the behavior policy. Anchoring in a near-optimal dataset (i.e., expert) favors the performance of an algorithm, while anchoring in a low-performing dataset (e.g., novice) may hinder the target policy's performance. In realistic

scenarios, offline RL datasets might consist mostly of low-performing trajectories with few minor high-performing trajectories collected by a mixture of behavior policies, since curating high-performing trajectories is costly. It is thus desirable to avoid anchoring on low-performing behavior policies and exploit high-performing ones in mixed datasets. However, we show that state-of-the-art offline RL algorithms fail to exploit high-performing trajectories to their fullest. We analyze that the potential for policy improvement over the behavior policy is correlated with the positive-sided variance (PSV) of the trajectory returns in the dataset and advance that when the return PSV is high, the algorithmic anchoring may be limiting the performance of the returned policy.

In order to provide a better algorithmic anchoring, we propose to alter the behavior policy without collecting additional data. We start by proving that re-weighting the dataset during the training of an offline RL algorithm is equivalent to performing this training with another behavior policy. Furthermore, under the assumption that the environment is deterministic, by giving larger weights to high-return trajectories, we can control the implicit behavior policy to be high performing and therefore grant a cold start performance boost to the offline RL algorithm. While determinism is a strong assumption that we prove to be necessary with a minimal failure example, we show that the guarantees still hold when the initial state is stochastic by re-weighting with, instead of the trajectory return, a trajectory return advantage: $G(\tau_i) - V^\mu(s_{i,0})$, where $G(\tau_i)$ is the return obtained for trajectory i, $V^\mu(s_{i,0})$ is the expected return of following the behavior policy μ from the initial state $s_{i,0}$. Furthermore, we empirically observe that our strategy allows performance gains over their uniform sampling counterparts even in stochastic environments. We also note that determinism is required by several state-of-the-art offline RL algorithms (Schmidhuber, 2019; Srivastava et al., 2019; Kumar et al., 2019b; Chen et al., 2021; Furuta et al., 2021; Brandfonbrener et al., 2022).

Under the guidance of theoretical analysis, our principal contribution is two simple weighted sampling strategies: **Return-weighted (RW)** and **Advantage-weighted (AW)**. RW and AW re-weight trajectories using the Boltzmann distribution of trajectory returns and advantages, respectively. Our weighted sampling strategies are agnostic to the underlying offline RL algorithms and thus can be a drop-in replacement in any off-the-shelf offline RL algorithms, essentially at no extra computational cost. We evaluate our sampling strategies on three state-of-the-art offline RL algorithms, CQL, IQL, and TD3+BC (Kumar et al., 2020b; Kostrikov et al., 2022; Fujimoto & Gu, 2021), as well as behavior cloning, over 62 datasets in D4RL benchmarks (Fu et al., 2020). The experimental results reported in statistically robust metrics (Agarwal et al., 2021) demonstrate that both our sampling strategies significantly boost the performance of all considered offline RL algorithms in challenging mixed datasets with sparse rewarding trajectories, and perform at least on par with them on regular datasets with evenly distributed return distributions.

2 Preliminaries

We consider reinforcement learning (RL) problem in a Markov decision process (MDP) characterized by a tuple $(\mathcal{S}, \mathcal{A}, R, P, \rho_0)$, where $\mathcal{S}$ and $\mathcal{A}$ denote state and action spaces, respectively, $R : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is a reward function, $P : \mathcal{S} \times \mathcal{A} \to \Delta_{\mathcal{S}}$ is a state transition dynamics, and $\rho_0 : \Delta_{\mathcal{S}}$ is an initial state distribution, where $\Delta_{\mathcal{X}}$ denotes a simplex over set $\mathcal{X}$. An MDP starts from an initial state $s_0 \sim \rho_0$. At each timestep t, an agent perceives the state s_t, takes an action $a_t \sim \pi(.|s_t)$ where $\pi : \mathcal{S} \to \Delta_{\mathcal{A}}$ is the agent's policy, receives a reward $r_t = R(s_t, a_t)$, and transitions to a next state $s_{t+1} \sim P(s_{t+1}|s_t, a_t)$. The performance of a policy π is measured by the expected return $J(\pi)$ starting from initial states $s_0 \sim \rho_0$ shown as follows:

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{\infty} R(s_t, a_t) \;\middle|\; s_0 \sim \rho_0, a_t \sim \pi(.|s_t), s_{t+1} \sim P(.|s_t, a_t)\right]. \tag{1}$$

Given a dataset $\mathcal{D}$ collected by a behavior policy $\mu : \mathcal{S} \to \Delta_{\mathcal{A}}$, offline RL algorithms aim to learn a target policy π such that $J(\pi) \geq J(\mu)$ from a dataset $\mathcal{D}$ shown as follows:

$$\mathcal{D} = \left\{(s_{i,0}, a_{i,0}, r_{i,0}, \cdots s_{i,T_i}) \;\middle|\; \begin{array}{ll} s_{i,0} \sim \rho_0, & a_{i,t} \sim \mu(.|s_{i,t}), \\ r_{i,t} = R(s_{i,t}, a_{i,t}), & s_{i,t+1} \sim P(.|s_{i,t}, a_{i,t}) \end{array}\right\}, \tag{2}$$

where $\tau_i = (s_{i,0}, a_{i,0}, r_{i,0}, \cdots s_{i,T_i+1})$ denotes trajectory i in $\mathcal{D}$, (i, t) denotes timestep t in episode i, and T_i denotes the length of τ_i. Note that μ can be a mixture of multiple policies. For brevity, we omit the episode index i in the subscript of state and actions, unless necessary. Generically, offline

RL algorithms learn π based on actor-critic methods that train a Q-value function $Q : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ and π in parallel. The Q-value $Q(s, a)$ predicts the expected return of taking action a at state s and following π later; π maximizes the expected Q-value over $\mathcal{D}$. Q and π are trained through alternating between policy evaluation (Equation 3) and policy improvement (Equation 4) steps shown below:

$$Q \leftarrow \arg\min_{Q} \mathbb{E}\Big[\left(r_t + \gamma \mathbb{E}_{a' \sim \pi(.|s_{t+1})} \left[Q(s_{t+1}, a')\right] - Q(s_t, a_t)\right)^2 \;\Big|\; \text{Uni}(\mathcal{D}) \Big] \tag{3}$$

$$\pi \leftarrow \arg\max_{\pi} \mathbb{E}\Big[Q(s_t, a) \;\Big|\; \text{Uni}(\mathcal{D}), a \sim \pi(.|s_t) \Big], \tag{4}$$

where $\mathbb{E}[\,\cdot \mid \text{Uni}(\mathcal{D})]$ denotes an expectation over uniform sampling of transitions.

3 Problem formulation

Most offline RL algorithms are anchored to the behavior policy. This is beneficial when the dataset behavior policy is high-performing while detrimental when the behavior policy is low-performing. We consider mixed datasets consisting of mostly low-performing trajectories and a handful of high-performing trajectories. In such datasets, it is possible to exploit the rare high-performing trajectories, yet the anchoring restrains these algorithms from making sizable policy improvements over the behavior policy of the mixed dataset. We formally define the return positive-sided variance (RPSV) of a dataset in Section 3.1 and illustrate why the performance of offline RL algorithms could be limited on high-RPSV datasets in Section 3.2.

3.1 Positive-sided variance

Formally, we are concerned with a dataset $\mathcal{D} := \{\tau_0, \tau_1, \cdots \tau_{N-1}\}$ potentially collected by various behavior policies $\{\mu_0, \mu_1, \cdots \mu_{N-1}\}$ and constituted of empirical returns $\{G(\tau_0), G(\tau_1), \cdots G(\tau_{N-1})\}$, where τ_i is generated by μ_i, N is the number of trajectories, T_i denotes the length of τ_i, and $G(\tau_i) = \sum_{t=0}^{T_i - 1} r_{i,t}$. To study the distribution of return, we equip ourselves with a statistical quantity: the positive-sided variance (PSV) of a random variable X:

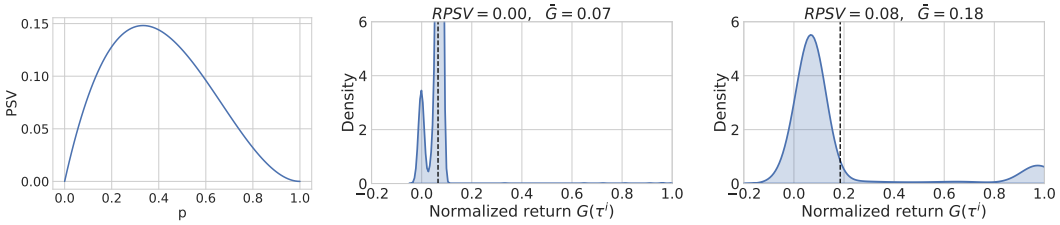
Definition 1 (Positive-sided variance)**.** *The positive-sided variance (PSV) of a random variable X is the second-order moment of the positive component of $X - \mathbb{E}[X]$:*

$$\mathbb{V}_+[X] \doteq \mathbb{E}\left[(X - \mathbb{E}[X])_+^2 \right] \quad \textit{with} \quad x_+ = \max\{x, 0\}. \tag{5}$$

We may symmetrically define the negative-sided variance $\mathbb{V}_-$ and notice that the variance is the sum of the two one-sided variances: $\mathbb{V}[X] = \mathbb{V}_+[X] + \mathbb{V}_-[X]$. The return PSV (RPSV) of $\mathcal{D}$ aims at capturing the positive dispersion of the distribution of the trajectory returns. An interesting question to ask is: *what distribution leads to high RPSV?* We simplify sampling trajectories collected by a novice and an expert as sampling from a Bernoulli distribution $\mathcal{B}$, and suppose that the novice policy always yields a 0 return, while the expert always yields a 1 return. Figure 1a visualizes $\mathbb{V}_+[\mathcal{B}(p)] = p(1-p)^2$, which is the Bernoulli distribution's PSV as a function of its parameter p, where p is the probability of choosing an expert trajectory. We see that maximal PSV is achieved for $p = \frac{1}{3}$. Both $p = 0$ (pure novice) and $p = 1$ (pure expert) leads to a zero PSV. This observation indicates that mixed datasets tend to have higher RPSV than a dataset collected by a single policy. We present the return distribution of datasets at varying RPSV in Figure 1. Low-RPSV datasets have their highest returns that remain close to the mean return, which limits the opportunity for policy improvement. In contrast, the return distribution of high-RPSV datasets disperses away from the mean toward the positive end.

3.2 Offline RL fails to utilize data in high-RPSV datasets

High-RPSV datasets (Figure 1c) have a handful of high-return trajectories, yet the anchoring of offline RL algorithms on behavior policy inhibits offline RL from utilizing these high-return data to their fullest. Predominating low-return trajectories in a high-RPSV dataset restrain offline RL algorithms from learning a non-trivial policy close to the best trajectories in $\mathcal{D}$ due to these algorithms' pessimistic and/or conservative nature. High RPSV implies that the average episodic return is far from the best return in $\mathcal{D}$ (see Figure 1c). The average episodic return reflects the performance $J(\mu)$



(a) Bernoulli distribution PSV (b) Low RPSV (c) High RPSV

Figure 1: **(a)** Bernoulli distribution PSV: $\mathbb{V}_+[\mathcal{B}(p)] = p(1-p)^2$. **(b-c)** The return distribution of datasets with (b) low and (c) high return positive-sided variance (RPSV) (Section 3.1) , where RPSV measures the positive contributions in the variance of trajectory returns in a dataset and $\bar{G}$ denotes the average episodic returns (dashed line) of the dataset. Intuitively, a high RPSV implies some trajectories have far higher returns than the average.

(formally justified in Section 4.1) of the behavior policy μ that collected $\mathcal{D}$, where μ is mixture of $\{\mu_0, \mu_1, \cdots \mu_{N-1}\}$ (Section 3.1).

Pessimistic algorithms (Petrik et al., 2016; Kumar et al., 2020b; Buckman et al., 2020) strive to guarantee the algorithm returns a π such that $J(\pi) \geq J(\mu)$, but this guarantee is loose when $J(\mu)$ is low. Conservative algorithms (Laroche et al., 2019; Fujimoto et al., 2019; Fujimoto & Gu, 2021; Kumar et al., 2019a) restrict π to behave closely to μ to prevent exploiting poorly estimated Q-values on *out-of-distribution* state-action pairs in actor-critic updates (*i.e.*, $(s_{t+1}, a') \notin \mathcal{D}$ in Equation 3), hence restricting $J(\pi)$ from deviating too much from $J(\mu)$. Similarly, one-step algorithms (Brandfonbrener et al., 2021; Kostrikov et al., 2022) that perform only a single step of policy improvement return a target policy subject to constraints that enforces π to be close to μ (Peters & Schaal, 2007; Peng et al., 2019). As a consequence, offline RL algorithms are restrained by $J(\mu)$ and fail to utilize high-return data far from $J(\mu)$ in high-RPSV datasets.

On the contrary, in low-RPSV datasets (Figure 1b), pessimistic, conservative, and one-step algorithms do not have this severe under-utilization issue since the return distribution concentrates around or below the average episodic return, and there are very few to no better trajectories to exploit. We will show, in Section 5.2, that no sampling strategy makes offline RL algorithms perform better in extremely low-RPSV datasets, while in high-RPSV datasets, our methods (Sections 4.2 and 4.3) outperform typical uniform sampling substantially.

4 Method

Section 3 explains why behavior policy anchoring prevents offline RL algorithms from exploiting high-RPSV datasets to their fullest. To overcome this issue, the question that needs to be answered is: *can we improve the performance of the behavior policy without collecting additional data?* To do so, we propose to implicitly alter it through a re-weighting of the transitions in the dataset. Indeed, we show that weighted sampling can emulate sampling transitions with a different behavior policy. We analyze the connection between weighted sampling and performance of the implicit behavior policy in Section 4.1, and then present two weighted sampling strategies in Sections 4.2 and 4.3.

4.1 Analysis

We start by showing how re-weighting the transitions in a dataset emulates sampling transitions generated by an implicit mixture behavior policy different from the one that collected the dataset. It is implicit because the policy is defined by the weights of transitions in the dataset. As suggested in Peng et al. (2019), sampling transitions from $\mathcal{D}$ defined in Section 3 is equivalent to sampling state-action pairs from a weighted joint state-action occupancy: $d_{\mathcal{W}}(s,a) = \sum_{i=0}^{N-1} w_i d_{\mu_i}(s)\mu_i(a|s)$, where w_i is the weight of trajectory i (each τ_i is collected by μ_i), $\mathcal{W} \doteq \{w_0, \cdots w_{N-1}\}$, and $d_{\mu_i}(s)$ denotes the unnormalized state occupancy measure (Laroche et al., 2022) in the rollout of μ_i. Tweaking weighting $\mathcal{W}$ effectively alters $d_{\mathcal{W}}$ and thus the transition distribution during sampling. As Peng et al. (2019) suggested, a weighting $\mathcal{W}$ also induces a weighted behavior policy:

$\mu_{\mathcal{W}}(a|s) = \frac{d_{\mathcal{W}}(s,a)}{\sum_{i=0}^{N-1} w_i d_{\mu_i}(s)}$. Uniform sampling $w_i = \frac{1}{N}$, $\forall w_i \in \mathcal{W}$ is equivalent to sampling from the joint state-action occupancy of the original mixture behavior policy μ that collected $\mathcal{D}$. To obtain a well-defined sampling distribution over transitions, we need to convert these trajectory weights w_i to transitions sample weights $w_{i,t}, \forall t \in [\![0, T_i - 1]\!]$:

$$w_{i,t} \doteq \frac{w_i}{\sum_{i=0}^{N-1} T_i w_i}, \qquad \sum_{i=0}^{N-1} \sum_{t=0}^{T_i-1} w_{i,t} = \sum_{i=0}^{N-1} T_i \frac{w_i}{\sum_{i=0}^{N-1} T_i w_i} = 1. \tag{6}$$

Thus, we formulate our goal as finding $\mathcal{W} \doteq \{w_i\}_{i \in [\![0,N-1]\!]} \in \Delta_N$ such that $J(\mu_{\mathcal{W}}) \geq J(\mu)$, where Δ_N denotes the simplex of size N. Naturally, we can write $J(\mu_{\mathcal{W}}) = \sum_{i=0}^{N-1} w_i J(\mu_i)$. The remaining question is then to estimate $J(\mu_i)$. The episodic return $G(\tau_i)$ can be treated as a sample of $J(\mu_i)$. As a result, we can concentrate $J(\mu_{\mathcal{W}})$ near the weighted sum of returns with a direct application of Hoeffding's inequality (Serfling, 1974):

$$\mathbb{P}\left[\left|J(\mu_{\mathcal{W}}) - \sum_{i=0}^{N-1} w_i G(\tau_i)\right| > \epsilon\right] \leq 2 \exp\left(\frac{2\epsilon^2}{G_{\top}^2 \sum_{i=0}^{N-1} w_i^2}\right), \tag{7}$$

where $G_{\top} \doteq G_{\text{MAX}} - G_{\text{MIN}}$ is the return interval amplitude (see Hoeffding's inequality). For completeness, the soundness of the method is proved for any policy and MDP with discount factor (Sutton & Barto, 2018) less than 1 in Appendix A.1. Equation 7 tells us that we have a consistent estimator for $J(\mu_{\mathcal{W}})$ as long as too much mass has not been assigned to a small set of trajectories.

Since our goal is to obtain a behavior policy with a higher performance, we would like to give high weights w_i to high performance μ_i. However, it is worth noting that setting w_i as a function of G_i could induce a bias in the estimator of $J(\mu_W)$ due to the stochasticity in the trajectory generation, stemming from ρ_0, P, and/or μ_i. In that case, Equation 7 concentration bound would not be valid anymore. To demonstrate and illustrate the bias, we provide a counterexample in Appendix A.2. The following section addresses this issue by making the strong assumption of determinism of the environment, and applying a trick to remove the stochasticity from the behavior policy μ_i. Section 4.3 then relaxes the requirement for ρ_0 to be deterministic by using the return advantage instead of the absolute return.

4.2 Return-weighting

In this section, we are making the strong assumption that the MDP is deterministic (i.e., the transition dynamics P and the initial state distribution ρ_0 is a Dirac delta distribution). This assumption allows us to obtain that $G(\tau_i) = J(\mu_i)$, where μ_i is the deterministic policy taking the actions in trajectory τ_i[1]. Since the performance of the target policy is anchored on the performance of a behavior policy, we find a weighting distribution $\mathcal{W}$ to maximize $J(\mu_{\mathcal{W}})$:

$$\max_{\mathcal{W} \in \Delta_N} \sum_{i=0}^{N-1} w_i G(\tau_i), \tag{8}$$

where w_i corresponds to the unnormalized weight assigned to each transition in episode i. However, the resulting solution is trivially assigning all the weights to the transitions in episode τ_i with maximum return. This trivial solution would indeed be optimal in the deterministic setting we consider but would fail otherwise. To prevent this from happening, we classically incorporate entropy regularization and turn Equation 8 into:

$$\max_{\mathcal{W} \in \Delta_N} \sum_{i=0}^{N-1} w_i G(\tau_i) - \alpha \sum_{i=0}^{N-1} w_i \log w_i, \tag{9}$$

where $\alpha \in \mathbb{R}^+$ is a temperature parameter that controls the strength of regularization. α interpolates the solution from a delta distribution ($\alpha \to 0$) to an uniform distribution ($\alpha \to \infty$). As the optimal solution to Equation 9 is a Boltzmann distribution of $G(\tau_i)$, the resulting weighting distribution $\mathcal{W}$ is:

$$w_i = \frac{\exp G(\tau_i)/\alpha}{\sum_{\tau_i \in \mathcal{D}} \exp G(\tau_i)/\alpha}. \tag{10}$$

[1]The formalization of μ_i is provided in Appendix A.1

The temperature parameter α (Equations 10 and 11) is a fixed hyperparameter. As the choice of α is dependent on the scale of episodic returns, which varies across environments, we normalize $G(\tau_i)$ using a max-min normalization: $G(\tau_i) \leftarrow \frac{G(\tau_i)-\min_j G(\tau_j)}{\max_j G(\tau_j)-\min_j G(\tau_j)}$.

4.3 Advantage-weighting

In this section, we allow the initial state distribution ρ_0 to be stochastic. The return-weighting strategy in Section 4.2 could be biased toward some trajectories starting from *lucky* initial states that yield higher returns than other initial states. Thus, we change the objective of Equation 9 to maximizing the weighted episodic advantage $\sum_{w_i \in \mathcal{W}} w_i A(\tau_i)$ with entropy regularization. $A(\tau_i)$ denotes the episodic advantage of τ_i and is defined as $A(\tau_i) = G(\tau_i) - \hat{V}^\mu(s_{i,0})$. $\hat{V}^\mu(s_{i,0})$ is the estimated expected return of following μ starting from $s_{i,0}$, using regression: $\hat{V}^\mu \leftarrow \arg\min_V \mathbb{E}\big[(G(\tau_i) - V(s_{i,0}))^2 \mid \text{Uni}(\mathcal{D})\big]$. Substituting $G(\tau_i)$ with $A(\tau_i)$ in Equation 9 and solving for $\mathcal{W}$, we obtain the following weighting distribution:

$$w_i = \frac{\exp A(\tau_i)/\alpha}{\sum_{\tau_i \in \mathcal{D}} \exp A(\tau_i)/\alpha}, \quad A(\tau_i) = G(\tau_i) - \hat{V}^\mu(s_{i,0}). \tag{11}$$

5 Experiments

Our experiments answer the following primary questions: (i) Do our weighted sampling strategies enable offline RL algorithms to exploit high-RPSV datasets to their fullest? (ii) Can our method also perform well in regular datasets? (iii) Is our method robust to stochasticity in an MDP?

5.1 Setup

Implementation. We implement our weighted-sampling strategy and baselines in the following offline RL algorithms: implicit Q-learning (IQL) (Kostrikov et al., 2022), conservative Q-learning (CQL) (Kumar et al., 2020b), TD3+BC (Fujimoto & Gu, 2021), and behavior cloning (BC). IQL, CQL, and TD3+BC were chosen to cover various approaches to Offline RL, including one-step, pessimistic, and conservative algorithms. Note that though BC is an imitation learning algorithm, we include it since BC clones the behavior policy, which is the object we directly alter, and BC is also a common baseline in offline RL research (Kumar et al., 2020b; Kostrikov et al., 2022). We compare our weighted sampling against uniform sampling (denoted as *Uniform*) and percentage filtering (Chen et al., 2021). Percentage filtering only uses episodes with top-$x\%$ returns for training and is denoted as *Top*-$x\%$. We consider percentage filtering as a baseline since it similarly increases the expected return of the behavior policy by discarding some data. In the following, we compare our method against *Top*-10% since 10% is the best configuration found in the hyperparameter search (Appendix A.7). Our return-weighted and advantage-weighted strategies are denoted as *RW* and *AW*, respectively, for which we use the same hyperparameter α in all the environments (see Appendix A.5).

Datasets and environments. We evaluate the performance of each algorithm+sampler variant (i.e., the combination of an offline RL algorithm and a sampling strategy) in MuJoCo locomotion environments of D4RL benchmarks (Fu et al., 2020) and stochastic classic control benchmarks. Each environment is regarded as an MDP and can have multiple datasets in a benchmark suite. The dataset choices are described in the respective sections of the experimental results. We evaluate our method in stochastic classic control to investigate if stochastic dynamics break our weighted sampling strategies. The implementation of stochastic dynamics is presented in Appendix A.4.

Evaluation metric. An algorithm+sampler variant is trained for one million batches of updates in five random seeds for each dataset and environment. Its performance is measured by the average normalized episodic return of running the trained policy over 20 episodes in the environment. As suggested in Fu et al. (2020), we normalize the performance using $(X - X_{Random})/(X_{Expert} - X_{Random})$ where X, X_{Random}, and X_{Expert} denote the performance of an algorithm-sampler variant, the random policy, and the expert one, respectively.

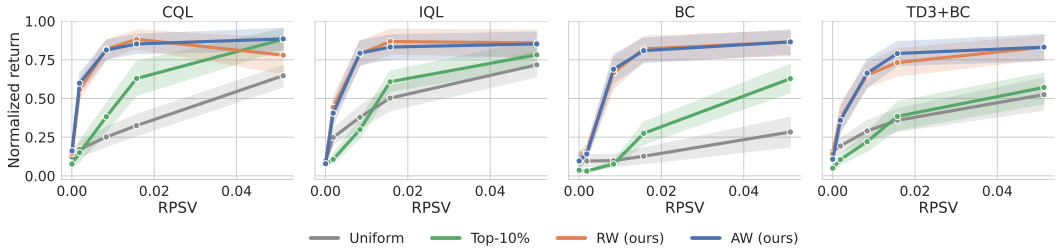


Figure 2: We test each sampling strategies in 32 mixed datasets and `random` dataset with four selected offline RL algorithms CQL (Kumar et al., 2020b), IQL (Kostrikov et al., 2022), BC, and TD3+BC (Fujimoto & Gu, 2021). Our *RW* and *AW* sampling strategies outperform uniform sampling and percentage filtering in all dataset PSV. x-axis denotes dataset normalized of RPSV; y-axis denotes the interquartile mean (IQM) (Agarwal et al., 2021) of normalized performance across environments and datasets at a certain RPSV. Section 5.2 details the return normalization.

5.2 Results in mixed datasets with varying RPSV

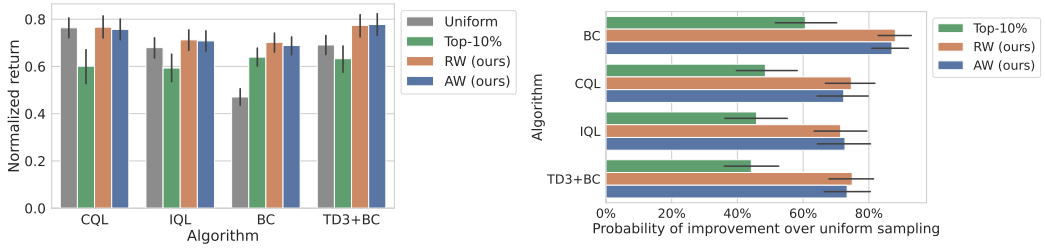
We test each algorithm+sampler variant in four MuJoCo locomotion environments and eight mixed and one non-mixed datasets for each environment. The mixed datasets are created by mixing $\sigma\%$ of either an `expert` or `medium` datasets (high-return) with $(1-\sigma\%)$ of a `random` dataset (low-return), for four ratios, $\sigma \in \{1, 5, 10, 50\}$. The `expert`, `medium`, and `random` datasets are generated by an expert policy, a policy with $1/3$ of the expert policy performance, and a random policy, respectively. We test all the variants in those 32 mixed datasets and `random` dataset, and report the RPSV of each dataset in Section A.3.

Figure 2 shows the mean normalized performance (y-axis) of each algorithm+sampler (color) variant at varying RPSV (x-axis). As the RPSV of the datasets span over a wide range, we aggregate the performance in the datasets with the same mixing ratio σ and take the average RPSV over the datasets as the coordinate on the x-axis. For the performance (y-axis), we report the interquartile mean (IQM) (also known as 25%-trimmed mean) since IQM is less susceptible to the outlier performance as suggested in Agarwal et al. (2021). Appendix A.6 details the evaluation protocol.

Figure 2 shows that for all the selected offline RL algorithms, our *RW* and *AW* strategies significantly outperform the baselines *Uniform* and *Top-10%* for all dataset RPSVs. *Uniform* fails to exploit to the fullest of the datasets when high-performing trajectories are sparse (i.e., low RPSV). *Top-10%* slightly improves the performance in moderate RPSV, yet fail to *Uniform* in low RPSVs. Overall, these results suggest that up-weighting high-return episodes in a high-RPSV dataset benefits performance while naively filtering out low-return episodes, as *Top-10%* does, does not consistently improve performance. Moreover, *AW* and *RW* do not show visible differences, likely because the initial state distribution is narrow in MuJoCo locomotion environments.

5.3 Results in regular datasets

To show that our method does not lose performance in non-mixed datasets, we also evaluate our method in the regular datasets of MuJoCo locomotion environments from the D4RL benchmark (Fu et al., 2020), without mixing `random` and `expert/medium`. Using the same evaluation metric as in Section 5.1, we report the results in 30 regular environments and datasets (including `random`) in Figure 3a. Our methods, *RW* and *AW*, both exhibit performance on par with the baselines in regular datasets, confirming that our method does not lose performance in regular datasets. Notably, we find that with our *RW* and *AW*, BC achieves competitive performance with other offline RL algorithms. The substantial improvement over uniform sampling in BC aligns with our analysis (Section 4.1) since the performance of BC solely depends on the performance of behavior policy and hence the average returns of sampled trajectories. Nonetheless, paired with *RW* and *AW*, offline RL algorithms (i.e., CQL, IQL, and TD3+BC) still outperform BC. This suggests that our weighted sampling strategies do not overshadow the advantage of offline RL over BC.



(a) (b)

Figure 3: **(a)** Performance in regular datasets. Our method matches the baselines, retaining the performance in regular datasets. **(b)** Probability of improvement over uniform sampling (Agarwal et al., 2021) in 32 mixed and 30 regular datasets. Our method has around 70% probability of improvement over uniform sampling, which is a statistically significant indicator (Agarwal et al., 2021) showing that our method mostly performs better than uniform sampling.

5.4 Overall improvements

In addition to average performance, the recent study by Agarwal et al. (2021) highlights the importance of measuring the robustness of an algorithm by its probability of improvement (PI). Since outliers could dominate the average performance, an algorithm with higher average performance could have an excessively higher return in a few environments while performing worse than the baselines in the majority of environments. Therefore, we evaluate our method in both regular and mixed datasets in D4RL using $PI(X > \textit{Uniform})$, which measures how likely algorithm X is to perform better than *Uniform*. The details can be found in Appendix A.6.1. Figure 3b presents $PI(\textit{RW} > \textit{Uniform})$, $PI(\textit{AW} > \textit{Uniform})$, and $PI(\textit{Top-10\%} > \textit{Uniform})$, showing that our method has the highest probabilities of improving over uniform sampling in all algorithms. This result indicates that our method is highly likely to improve over uniform sampling irrespective of dataset and environments in a trial. Notably, $PI(\textit{RW} > \textit{Uniform})$ and $PI(\textit{AW} > \textit{Uniform})$ are both greater than 50%, and hence statistically significant as suggested by Agarwal et al. (2021).

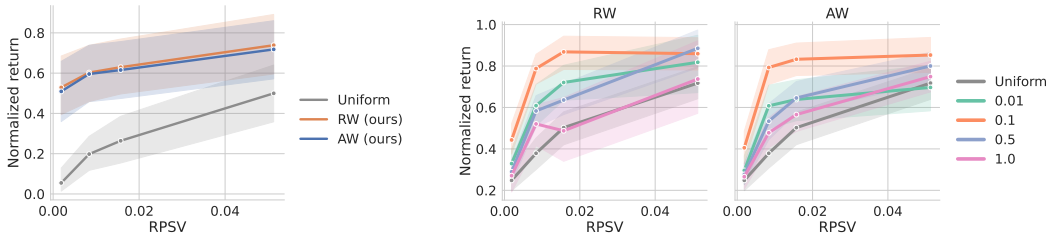
Note that $PI(\textit{RW} > \textit{Uniform}) = 70\%$ does not imply our method only beats uniform sampling in 70% of datasets and environments. PI takes the stochasticity resulting from random seeds into account, measuring the probability of improvements in a trial with a randomly selected seed, dataset, and environment. We also include the complete score table in Appendix A.9, where we see that in Tables 2, 3, 4, and 5, our AW and RW strategies all outperform uniform sampling in at least 80% of datasets.

5.5 Results in stochastic MDPs

As our weighted-sampling strategy theoretically requires a deterministic MDP, we investigate if stochastic dynamics (*i.e.*, stochastic state transitions) break our method by evaluating it in stochastic control environments. The details of their implementation can be found in Appendix A.4. We use the evaluation metric described in Section 5.1 and present the results in Figure 4a. Both of our methods still outperform uniform sampling in stochastic dynamics, suggesting that stochasticity does not break them. Note that we only report the results with CQL since IQL and TD3+BC are not compatible with the discrete action space used in stochastic classic control.

5.6 Sensitivity to temperature

The temperature α (Section 4) is an important hyperparameter of our method. We investigate how sensitive the choice of temperature algorithms is. Using the evaluation metric shown in Section 5.1, we compare the performance of *RW* and *AW* paired with IQL at varying temperature α in Figure 4b, where 0.1 is the temperature used in Sections 5.2, 5.3, and 5.5. Our methods outperform uniform sampling in a range of temperatures and hence are not overly sensitive to temperature. The full results in other offline algorithms are presented in Appendix A.8.



(a) (b)

Figure 4: **(a)** Performance in classic control tasks with stochastic dynamics. Our method still outperforms the baselines. **(b)** Performance of our method with varying temperature α (Sections 4.2 and 4.3), where color denotes α. Both *AW* and *RW* achieve higher returns than the baselines in a wide range of temperatures $[\![0.01, 1.0]\!]$, our methods are not overly sensitive to the choice of temperature.

6 Related Works

Our weighted sampling strategies and non-uniform experience replay in online RL aim to improve uniform sample selection. Prior works prioritize uncertain data (Schaul et al., 2015; Horgan et al., 2018; Lahire et al., 2021), attending on nearly on-policy samples (Sinha et al., 2022), or select samples by topological order Hong et al. (2022); Kumar et al. (2020a). However, these approaches do not take the performance of implicit behavioral policy induced by sampling into account and hence are unlikely to tackle the issue in mixed offline RL datasets.

Offline imitation learning (IL) (Kim et al., 2021; Ma et al., 2022; Xu et al., 2022) consider training an expert policy from a dataset that consists of a handful of expert data and plenty of random data. They train a model to discriminate if a transition is from an expert and learn a nearly expert policy from the discriminator's predictions. However, offline IL requires expert and random data to be separated while we neither assume separated datasets nor access to expert data. Also, we make use of the rewards from the dataset, and aim at policy improvement, while offline imitation learning is not concerned with rewards, but with mimicking (part of) the policy that was used to collect the data.

Mixed datasets with high RPSV are closely related to imbalanced datasets in supervised learning. Supervised learning approaches either over-sample minority classes (Cui et al., 2019; Cao et al., 2019; Dong et al., 2018) or sample data inversely proportional to the target value densities (Yang et al., 2021; Steininger et al., 2021). Other works (Chawla et al., 2002; García & Herrera, 2009) synthesize samples by interpolating data points nearby the minority data. In RL, on the other hand, over-sampling minority data (trajectories) can be harmful if the trajectory is low-return and does not cover high-performing policies' trajectories; in other words, naive application of over-sampling techniques from supervised learning can hurt in an RL setting as they are agnostic to the notion of return.

7 Conclusion

We show that state-of-the-art offline RL algorithms are overly constrained in mixed datasets with high RPSV and under-utilize the minority data. Our theoretical analysis proves that behavioral policy anchoring prevents offline RL algorithms from exploiting high-RPSV datasets to their fullest. To address this issue, we propose return- and advantage- weighted sampling strategies to re-weight trajectories in the dataset. The large-scale empirical evaluation in 62 datasets from D4RL shows that our method outperforms uniform sampling and percentage filtering in both mixed and regular datasets. Experiments in stochastic classic control show that stochasticity does not break our methods. Not only algorithmic contribution but also our work opens several promising future avenues on the practical side of RL. For example, our method enables offline RL to work on datasets consisting of mostly novice trajectories and minor skillful ones. Such datasets are more faithful in the real world than the synthetic ones curated in standard benchmarks.

REPRODUCIBILITY STATEMENT

We have included the implementation details in Appendix A.5.

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A APPENDIX

A.1 DETAILED ANALYSIS

We consider the definitions of a policy and a Markovian policy (Laroche et al., 2022):

Definition 2 (Policy)**.** *A policy π represents any function mapping its trajectory history $h_t = \langle s_0, a_0, r_0 \ldots, s_{t-1}, a_{t-1}, r_{t-1}, s_t \rangle$ to a distribution over actions $\pi(\cdot|h_t) \in \Delta_{\mathcal{A}}$, where $\Delta_{\mathcal{A}}$ denotes the simplex over $\mathcal{A}$. Let Π denote the space of policies, and Π_{D} the space of deterministic policies.*

Definition 3 (Markovian policy)**.** *Policy π is said to be Markovian if its action probabilities only depend on the current state s_t: $\pi(\cdot|h_t) = \pi(\cdot|s_t) \in \Delta_{\mathcal{A}}$. Otherwise, policy π is non-Markovian. We let Π_{M} denote the space of Markovian policies, and Π_{DM} the space of deterministic Markovian policies.*

We make no assumption on the behavior policy β, *i.e.* $\beta \in \Pi$. We notice that:

$$\mathcal{J}(\beta) = \mathbb{E}\left[R_\tau \,\middle|\, \tau \sim p_0, \beta, p\right] = \mathbb{E}\left[R_\tau \,\middle|\, \beta_\tau \sim \beta, \tau \sim p_0, \beta_\tau, p\right] = \mathbb{E}\left[\mathcal{J}(\beta_\tau) \,\middle|\, \beta_\tau \sim \beta\right]. \quad (12)$$

Equation 12 is a trick that has already been used in Peng et al. (2019). We go a bit further by constraining β_τ to be a deterministic policy sampled at the start of the episode, which may be programmatically interpreted as sampling the random seed used for the full trajectory. With a trajectory-wise reweighting $\mathcal{W}$, we obtain:

$$\mathcal{J}(\beta_{\mathcal{W}}) = \sum_{i=0}^{N-1} w_i \mathcal{J}(\beta_{\tau_i}). \quad (13)$$

Furthermore, Altman (1999) tell us that there exists a Markovian policy $\beta^{\text{M}}_{\mathcal{W}}$ with the same occupancy measure as $\beta_{\mathcal{W}}$ and the same performance when $\gamma < 1$ in MDPs with countable state space. Laroche et al. (2022) generalize this theorem to any MDP (including on uncountable state spaces) as long as $\gamma < 1$. Simão et al. (2020) prove in Theorem 3.2 Eq. (12) that, in finite MDPs, any Markovian behavior policy $\beta^{\text{M}}_{\mathcal{W}}$ can be cloned with policy $\hat{\beta}^{\text{M}}_{\mathcal{W}}$ from a dataset of N trajectory up to accuracy of $\frac{2r_\top}{1-\gamma}\sqrt{\frac{3|\mathcal{S}||\mathcal{A}|+4\log\frac{1}{\delta}}{2N^2\sum_{i=0}^{N-1} w_i^2}}$[2] with high probability $1-\delta$, where $2r_\top$ is the reward function amplitude.

A.2 EXAMPLE OF BIAS WITH WEIGHTS THAT DEPEND ON THE REALIZATION OF THE TRAJECTORY

We will consider a minimal example consisting of a stateless MDP (multi-arm bandit) and 2 actions $\mathcal{A} = \{a_1, a_2\}$. Action a_1 yields a deterministic reward of 0.6. Action a_2 Bernouilli distribution reward with parameter $p = 0.5$. In other words, a_2 is a coin flip: with 50% chance, no reward is received and with 50% chance, a maximal reward of 1. We collect a dataset containing some number of samples for each action. Now consider weights w_i such that:

$$w_i = \frac{\mathbb{1}[G(\tau_i) > 0.8]}{\sum_j \mathbb{1}[G(\tau_j) > 0.8]}. \quad (14)$$

Then,

$$\mathcal{J}(\mu_{\mathcal{W}}) = \sum_{i=0}^{N-1} w_i \mathcal{J}(\mu_i) = \mathcal{J}(\mu(a_2) = 1) = 0.5 \quad (15)$$

$$\sum_{i=0}^{N-1} w_i G(\tau_i) = \sum_{i=0}^{N-1} \frac{\mathbb{1}[G(\tau_i) > 0.8]}{\sum_j \mathbb{1}[G(\tau_j) > 0.8]} = 1, \quad (16)$$

showing a counter-example for the concentration bound proposed in equation 7.

A.3 DATASET RPSV

We list the PSV of each dataset in Table 1.

[2] We implicitly replace in the denominator their unweigthed term N with its weigthed version $N^2 \sum_{i=0}^{N-1} w_i^2$.

	RPSV
ant-expert-v2 ($\sigma = 0.01$)	0.002886
ant-expert-v2 ($\sigma = 0.05$)	0.013152
ant-expert-v2 ($\sigma = 0.1$)	0.026764
ant-expert-v2 ($\sigma = 0.5$)	0.151138
ant-expert-v2	0.015052
ant-full-replay-v2	0.096415
ant-medium-expert-v2	0.042611
ant-medium-replay-v2	0.038834
ant-medium-v2 ($\sigma = 0.01$)	0.001334
ant-medium-v2 ($\sigma = 0.05$)	0.006703
ant-medium-v2 ($\sigma = 0.1$)	0.013846
ant-medium-v2 ($\sigma = 0.5$)	0.075325
ant-medium-v2	0.020586
ant-random-v2	0.000092
antmaze-large-diverse-v0	0.015378
antmaze-large-play-v0	0.004538
antmaze-medium-diverse-v0	0.072896
antmaze-medium-play-v0	0.006583
antmaze-umaze-diverse-v0	0.029304
antmaze-umaze-v0	0.016956
halfcheetah-expert-v2 ($\sigma = 0.01$)	0.008236
halfcheetah-expert-v2 ($\sigma = 0.05$)	0.035784
halfcheetah-expert-v2 ($\sigma = 0.1$)	0.063523
halfcheetah-expert-v2 ($\sigma = 0.5$)	0.097583
halfcheetah-expert-v2	0.000130
halfcheetah-full-replay-v2	0.006521
halfcheetah-medium-expert-v2	0.028588
halfcheetah-medium-replay-v2	0.005747
halfcheetah-medium-v2 ($\sigma = 0.01$)	0.001771
halfcheetah-medium-v2 ($\sigma = 0.05$)	0.007604
halfcheetah-medium-v2 ($\sigma = 0.1$)	0.013685
halfcheetah-medium-v2 ($\sigma = 0.5$)	0.021007
halfcheetah-medium-v2	0.000110
halfcheetah-random-v2	0.000019
hopper-expert-v2 ($\sigma = 0.01$)	0.000318
hopper-expert-v2 ($\sigma = 0.05$)	0.001436
hopper-expert-v2 ($\sigma = 0.1$)	0.002948
hopper-expert-v2 ($\sigma = 0.5$)	0.024691
hopper-expert-v2	0.000771
hopper-full-replay-v2	0.041835
hopper-medium-expert-v2	0.064473
hopper-medium-replay-v2	0.018824
hopper-medium-v2 ($\sigma = 0.01$)	0.000129
hopper-medium-v2 ($\sigma = 0.05$)	0.000506
hopper-medium-v2 ($\sigma = 0.1$)	0.001055
hopper-medium-v2 ($\sigma = 0.5$)	0.008475
hopper-medium-v2	0.006648
hopper-random-v2	0.000025
walker2d-expert-v2 ($\sigma = 0.01$)	0.000264
walker2d-expert-v2 ($\sigma = 0.05$)	0.001261
walker2d-expert-v2 ($\sigma = 0.1$)	0.002601
walker2d-expert-v2 ($\sigma = 0.5$)	0.022037
walker2d-expert-v2	0.000030
walker2d-full-replay-v2	0.070379
walker2d-medium-expert-v2	0.027597
walker2d-medium-replay-v2	0.029698
walker2d-medium-v2 ($\sigma = 0.01$)	0.000128
walker2d-medium-v2 ($\sigma = 0.05$)	0.000559
walker2d-medium-v2 ($\sigma = 0.1$)	0.001233
walker2d-medium-v2 ($\sigma = 0.5$)	0.010165
walker2d-medium-v2	0.018411
walker2d-random-v2	0.000001

Table 1: RPSV calculated using normalized return.

A.4 STOCHASTIC CLASSIC CONTROL

We adapt `CartPole-v1`, `Acrobot-v1`, and `MountainCar-v0` in classic control environments in Open AI gym (Brockman et al., 2016). For each timestep, an agent's actions has 10% chance to be replaced with noisy action $a \sim \mathcal{A}$. As such, the transitions dynamics turns to be stochastic.

A.5 DETAILS OF IMPLEMENTATION

- **Temperature α.** For RW and AW, we use $\alpha = 0.1$ for IQL and TD3+BC, and $\alpha = 0.2$ for CQL.
- **Trajectory advantage.** We use linear regression to approximate V^μ. We make a training set $(s_{i,0}, G(\tau_i))\ \forall \tau_i \in \mathcal{D}$, and train a regression model on the training set.
- **Implementation.** We use the public codebase, `d3rlpy` (Takuma Seno, 2021). For each algorithm, we use the hyperparamters as it is.

A.6 DETAILS OF EVALUATION PROTOCOL

Performance logging. Given an environment E and a dataset D_E, for each trial (i.e., a random seed) we train each algorithm+sampler variant for one million batches using D_E and rollout the learned policy in the environment E for 20 episodes. The average return of the 20 episodes are booked as the performance of the trial.

Performance metric. Given a list of empirical returns of eacy trial $[g_1, g_2, \cdots]$, interquantile mean (IQM) (Agarwal et al., 2021) discards the bottom 25% and top 25% samples and calculate the mean.

A.6.1 PROBABILITY OF IMPROVEMENT

According to Agarwal et al. (2021), the probability of improvement in an environment m is defined as:

$$P(X_m \geq Y_m) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} S(x_{m,i}, y_{m,j}), \quad S(x_{m,i}, y_{m,j}) = \begin{cases} 1, x_{m,i} > y_{m,j} \\ \frac{1}{2}, x_{m,i} = y_{m,j} \\ 0, x_{m,i} < y_{m,j}, \end{cases}$$

where m denote an environment index, $x_{m,i}$ and $y_{m,j}$ denote the samples of mean of return in trials of algorithms X and Y, respectively. We report the average probability of improvements $\frac{1}{M}\sum_{m=0}^{M-1} P(X_m \geq Y_m)$ and its 95%-confidence interval using bootstrapping.

A.7 ADDITIONAL RESULTS OF PERCENTAGE FILTERING

Figure 5 presents the additional results at varying percentage for percentage filtering.

A.8 ADDITIONAL RESULTS OF TEMPERATURE SENSITIVITY

Figure 6 presents the full results at varying temperatures.

A.9 FULL RESULTS

We list the full benchmark results in Tables 2, 3, 4, and 5, where **bold** text denotes a score higher than *Uniform* and "*" sign indicates the maximum score in a dataset and environment (row).

Dataset	AW (ours)	RW (ours)	Top-10%	Uniform
ant-expert-v2 ($\sigma = 1$)	**0.31**	**0.31***	0.05	0.30
ant-medium-v2 ($\sigma = 1$)	**0.34**	**0.35***	0.06	0.31
halfcheetah-expert-v2 ($\sigma = 1$)	**0.02**	**0.03***	0.01	0.02
halfcheetah-medium-v2 ($\sigma = 1$)	**0.02**	**0.03***	0.02	0.02
hopper-expert-v2 ($\sigma = 1$)	**0.17***	**0.16**	0.03	0.04
hopper-medium-v2 ($\sigma = 1$)	**0.22**	**0.34***	0.04	0.04
walker2d-expert-v2 ($\sigma = 1$)	**0.02**	**0.02***	**0.01**	0.01
walker2d-medium-v2 ($\sigma = 1$)	**0.03**	**0.05***	**0.02**	0.01
ant-expert-v2 ($\sigma = 5$)	**1.01**	**1.08***	0.04	0.31
ant-medium-v2 ($\sigma = 5$)	**0.86***	**0.86**	0.10	0.31
halfcheetah-expert-v2 ($\sigma = 5$)	**0.14***	**0.11**	0.02	0.02
halfcheetah-medium-v2 ($\sigma = 5$)	**0.36***	**0.36**	**0.14**	0.02
hopper-expert-v2 ($\sigma = 5$)	**0.97***	**0.87**	**0.05**	0.04
hopper-medium-v2 ($\sigma = 5$)	**0.54***	**0.49**	**0.15**	0.05
walker2d-expert-v2 ($\sigma = 5$)	**1.03***	**1.01**	**0.01**	0.01
walker2d-medium-v2 ($\sigma = 5$)	**0.60***	**0.56**	**0.11**	0.02
ant-expert-v2 ($\sigma = 10$)	**1.19**	**1.19***	0.15	0.34
ant-medium-v2 ($\sigma = 10$)	**0.85**	**0.91***	0.27	0.45
halfcheetah-expert-v2 ($\sigma = 10$)	**0.68**	**0.76**	**0.77***	0.02
halfcheetah-medium-v2 ($\sigma = 10$)	**0.40**	**0.42**	**0.42***	0.02
hopper-expert-v2 ($\sigma = 10$)	**1.03**	**1.05***	**0.06**	0.05
hopper-medium-v2 ($\sigma = 10$)	**0.57***	**0.57**	**0.23**	0.05
walker2d-expert-v2 ($\sigma = 10$)	**1.08***	**1.06**	0.01	0.03
walker2d-medium-v2 ($\sigma = 10$)	**0.68***	**0.62**	**0.30**	0.06
ant-expert-v2 ($\sigma = 50$)	**1.24**	**1.21**	**1.26***	0.44
ant-medium-v2 ($\sigma = 50$)	**0.88**	**0.89***	**0.89**	0.73
halfcheetah-expert-v2 ($\sigma = 50$)	**0.92**	**0.92***	0.40	0.80
halfcheetah-medium-v2 ($\sigma = 50$)	**0.42***	**0.42**	**0.41**	0.10
hopper-expert-v2 ($\sigma = 50$)	**1.10***	**1.10**	**0.86**	0.04
hopper-medium-v2 ($\sigma = 50$)	**0.56**	**0.57***	**0.51**	0.03
walker2d-expert-v2 ($\sigma = 50$)	**1.08***	**1.08**	**0.25**	0.01
walker2d-medium-v2 ($\sigma = 50$)	**0.71**	**0.72***	**0.59**	0.10
ant-expert-v2	**1.25***	1.24	1.23	1.25
ant-full-replay-v2	**1.26**	**1.28***	**1.25**	1.18
ant-medium-expert-v2	**1.25**	**1.27***	**1.23**	1.17
ant-medium-replay-v2	**0.80***	**0.79**	0.66	0.67
ant-medium-v2	**0.86**	**0.88**	**0.93***	0.86
ant-random-v2	0.30	0.29	0.06	0.32*
antmaze-large-diverse-v0	**0.12**	**0.16***	0.00	0.00
antmaze-large-play-v0	**0.09**	**0.13***	0.00	0.00
antmaze-medium-diverse-v0	**0.10**	**0.29***	**0.01**	0.00
antmaze-medium-play-v0	**0.13**	**0.21***	**0.01**	0.00
antmaze-umaze-diverse-v0	**0.58**	**0.65***	0.51	0.54
antmaze-umaze-v0	**0.59**	**0.60**	**0.65***	0.49
halfcheetah-expert-v2	**0.92***	**0.92**	0.70	0.92
halfcheetah-full-replay-v2	**0.67**	**0.67***	**0.64**	0.62
halfcheetah-medium-expert-v2	**0.92**	**0.92***	**0.88**	0.58
halfcheetah-medium-replay-v2	**0.38**	**0.40***	0.31	0.34
halfcheetah-medium-v2	0.42	0.42	0.42	0.43*
halfcheetah-random-v2	0.02	0.02	0.02	0.02*
hopper-expert-v2	1.08	**1.11***	1.06	1.09
hopper-full-replay-v2	**0.98**	**1.01***	**0.93**	0.31
hopper-medium-expert-v2	**1.10**	**1.10***	**1.09**	0.53
hopper-medium-replay-v2	**0.72***	**0.67**	**0.63**	0.27
hopper-medium-v2	**0.56**	**0.54**	**0.58***	0.52
hopper-random-v2	**0.05***	**0.05**	**0.05**	0.04
walker2d-expert-v2	**1.09***	**1.08**	1.03	1.08
walker2d-full-replay-v2	**0.84**	**0.84**	**0.88***	0.27
walker2d-medium-expert-v2	**1.08**	**1.08***	**1.08**	0.97
walker2d-medium-replay-v2	**0.56**	**0.56***	**0.51**	0.19
walker2d-medium-v2	**0.70**	**0.71***	**0.70**	0.64
walker2d-random-v2	**0.01**	**0.01***	**0.01**	0.01
Num. win Uniform	58	58	39	-

Table 2: BC results

Dataset	AW (ours)	RW (ours)	Top-10%	Uniform
ant-expert-v2 ($\sigma = 1$)	**0.54***	**0.54**	0.06	0.25
ant-medium-v2 ($\sigma = 1$)	**0.82**	**0.82***	0.07	0.39
halfcheetah-expert-v2 ($\sigma = 1$)	0.03	**0.04***	0.03	0.03
halfcheetah-medium-v2 ($\sigma = 1$)	0.16	0.20	0.07	0.21*
hopper-expert-v2 ($\sigma = 1$)	**0.55***	**0.50**	0.11	0.12
hopper-medium-v2 ($\sigma = 1$)	0.39	0.50	0.30	0.53*
walker2d-expert-v2 ($\sigma = 1$)	**0.29***	**0.28**	0.10	0.12
walker2d-medium-v2 ($\sigma = 1$)	**0.46**	**0.48***	0.12	0.36
ant-expert-v2 ($\sigma = 5$)	**1.16**	**1.19***	0.12	0.60
ant-medium-v2 ($\sigma = 5$)	**0.88**	**0.91***	0.28	0.73
halfcheetah-expert-v2 ($\sigma = 5$)	**0.66**	**0.71***	0.04	0.04
halfcheetah-medium-v2 ($\sigma = 5$)	**0.43***	**0.41**	0.30	0.33
hopper-expert-v2 ($\sigma = 5$)	**1.02***	**0.87**	**0.18**	0.12
hopper-medium-v2 ($\sigma = 5$)	**0.53**	**0.56***	0.48	0.49
walker2d-expert-v2 ($\sigma = 5$)	**1.08**	**1.08***	**0.53**	0.25
walker2d-medium-v2 ($\sigma = 5$)	0.58	**0.61***	0.49	0.58
ant-expert-v2 ($\sigma = 10$)	**1.18**	**1.23***	0.40	0.74
ant-medium-v2 ($\sigma = 10$)	**0.87**	**0.90***	0.62	0.79
halfcheetah-expert-v2 ($\sigma = 10$)	**0.85**	**0.89***	**0.85**	0.08
halfcheetah-medium-v2 ($\sigma = 10$)	**0.45**	**0.45**	**0.45***	0.40
hopper-expert-v2 ($\sigma = 10$)	**1.00**	**1.01***	**0.36**	0.18
hopper-medium-v2 ($\sigma = 10$)	**0.55**	**0.60***	**0.54**	0.46
walker2d-expert-v2 ($\sigma = 10$)	**1.09***	**1.08**	**0.92**	0.66
walker2d-medium-v2 ($\sigma = 10$)	**0.67***	0.64	**0.66**	0.65
ant-expert-v2 ($\sigma = 50$)	**1.21**	**1.21**	**1.24***	1.07
ant-medium-v2 ($\sigma = 50$)	**0.92**	**0.94**	**0.96***	0.91
halfcheetah-expert-v2 ($\sigma = 50$)	**0.91**	**0.94***	**0.70**	0.50
halfcheetah-medium-v2 ($\sigma = 50$)	**0.47**	**0.47***	0.44	0.45
hopper-expert-v2 ($\sigma = 50$)	**1.06**	**1.07***	0.43	0.50
hopper-medium-v2 ($\sigma = 50$)	0.54	0.52	**0.62***	0.56
walker2d-expert-v2 ($\sigma = 50$)	**1.09***	**1.09**	1.08	1.08
walker2d-medium-v2 ($\sigma = 50$)	0.63	0.63	**0.71***	0.67
ant-expert-v2	**1.25**	**1.26**	**1.27***	1.13
ant-full-replay-v2	**1.29***	**1.27**	**1.25**	1.24
ant-medium-expert-v2	**1.23**	**1.32***	**1.28**	1.14
ant-medium-replay-v2	0.83	**0.86***	0.72	0.83
ant-medium-v2	0.97	0.98	0.88	0.99*
ant-random-v2	**0.14***	**0.14**	0.06	0.12
antmaze-large-diverse-v0	**0.40***	**0.24**	**0.04**	0.00
antmaze-large-play-v0	**0.18**	**0.33***	0.00	0.00
antmaze-medium-diverse-v0	**0.24**	**0.31***	0.02	0.05
antmaze-medium-play-v0	**0.41**	**0.43***	**0.03**	0.03
antmaze-umaze-diverse-v0	**0.54**	0.40	**0.61***	0.46
antmaze-umaze-v0	**0.87***	**0.86**	0.72	0.85
halfcheetah-expert-v2	**0.94***	**0.93**	0.74	0.93
halfcheetah-full-replay-v2	**0.75***	**0.75**	**0.71**	0.70
halfcheetah-medium-expert-v2	**0.94***	**0.93**	**0.89**	0.71
halfcheetah-medium-replay-v2	**0.44***	0.44	0.35	0.44
halfcheetah-medium-v2	**0.47**	**0.47***	0.45	0.47
halfcheetah-random-v2	0.07	0.07	0.04	0.12*
hopper-expert-v2	**1.00***	**0.96**	0.92	0.95
hopper-full-replay-v2	**0.97***	0.79	**0.97**	0.89
hopper-medium-expert-v2	**0.99**	**1.01**	**1.05***	0.59
hopper-medium-replay-v2	**0.84**	**0.86***	**0.85**	0.83
hopper-medium-v2	**0.57**	**0.57**	**0.65***	0.55
hopper-random-v2	0.06	0.07	0.08	0.09*
walker2d-expert-v2	**1.09***	**1.09**	**1.09**	1.09
walker2d-full-replay-v2	0.75	0.83	0.76	0.92*
walker2d-medium-expert-v2	**1.10***	**1.09**	**1.09**	1.06
walker2d-medium-replay-v2	0.47	0.37	0.51	0.69*
walker2d-medium-v2	0.69	0.66	0.65	0.75*
walker2d-random-v2	0.03	0.04	**0.11***	0.06
Num. win Uniform	48	47	29	-

Table 3: IQL results

Dataset	AW (ours)	RW (ours)	Top-10%	Uniform
ant-expert-v2 ($\sigma = 1$)	**0.80***	**0.74**	0.04	0.08
ant-medium-v2 ($\sigma = 1$)	**0.79**	**0.80***	0.06	0.14
halfcheetah-expert-v2 ($\sigma = 1$)	**0.39***	**0.38**	0.09	0.25
halfcheetah-medium-v2 ($\sigma = 1$)	**0.41**	**0.42***	0.26	0.40
hopper-expert-v2 ($\sigma = 1$)	**0.84***	**0.52**	**0.15**	0.09
hopper-medium-v2 ($\sigma = 1$)	**0.61***	**0.58**	**0.43**	0.30
walker2d-expert-v2 ($\sigma = 1$)	**0.57***	**0.54**	0.01	0.03
walker2d-medium-v2 ($\sigma = 1$)	**0.46**	**0.48***	**0.12**	0.03
ant-expert-v2 ($\sigma = 5$)	**1.06**	**1.06***	**0.35**	0.15
ant-medium-v2 ($\sigma = 5$)	**0.88**	**0.93***	**0.57**	0.50
halfcheetah-expert-v2 ($\sigma = 5$)	**0.67***	**0.66**	0.10	0.30
halfcheetah-medium-v2 ($\sigma = 5$)	**0.47***	0.47	0.44	0.47
hopper-expert-v2 ($\sigma = 5$)	**0.99***	**0.99**	**0.31**	0.10
hopper-medium-v2 ($\sigma = 5$)	**0.65**	**0.68***	**0.63**	0.43
walker2d-expert-v2 ($\sigma = 5$)	**1.06***	**1.02**	0.00	0.03
walker2d-medium-v2 ($\sigma = 5$)	**0.76***	**0.75**	**0.41**	0.04
ant-expert-v2 ($\sigma = 10$)	**1.11**	**1.16***	**0.93**	0.21
ant-medium-v2 ($\sigma = 10$)	**0.91**	**0.96***	**0.91**	0.57
halfcheetah-expert-v2 ($\sigma = 10$)	**0.76**	**0.76***	**0.74**	0.29
halfcheetah-medium-v2 ($\sigma = 10$)	**0.48**	**0.48***	0.47	0.48
hopper-expert-v2 ($\sigma = 10$)	**1.08***	**1.03**	**0.37**	0.14
hopper-medium-v2 ($\sigma = 10$)	**0.68**	**0.71**	**0.72***	0.62
walker2d-expert-v2 ($\sigma = 10$)	**1.02**	**1.09***	**0.12**	0.01
walker2d-medium-v2 ($\sigma = 10$)	**0.79***	**0.79**	**0.68**	0.24
ant-expert-v2 ($\sigma = 50$)	**1.26**	0.53	**1.27***	0.83
ant-medium-v2 ($\sigma = 50$)	**0.97**	**0.94**	**0.98***	0.82
halfcheetah-expert-v2 ($\sigma = 50$)	**0.80**	**0.86***	0.56	0.57
halfcheetah-medium-v2 ($\sigma = 50$)	0.49	0.49	0.47	0.49*
hopper-expert-v2 ($\sigma = 50$)	**1.02**	**1.04**	**1.04***	0.82
hopper-medium-v2 ($\sigma = 50$)	0.63	0.38	0.72	0.73*
walker2d-expert-v2 ($\sigma = 50$)	**1.09***	**1.08**	**0.96**	0.24
walker2d-medium-v2 ($\sigma = 50$)	**0.82**	**0.83***	**0.81**	0.81
ant-expert-v2	**1.27***	**1.27**	1.16	1.21
ant-full-replay-v2	**1.27**	**1.24**	**1.31***	1.22
ant-medium-expert-v2	**1.28***	**1.22**	**1.23**	1.17
ant-medium-replay-v2	**0.91**	**0.97***	0.83	0.90
ant-medium-v2	0.95	0.97	0.96	0.98*
ant-random-v2	0.08	0.08	0.06	0.11*
antmaze-large-diverse-v0	0.00	0.00	**0.08***	0.00
antmaze-large-play-v0	0.00	**0.01***	0.00	0.00
antmaze-medium-diverse-v0	0.00	**0.08***	0.00	0.00
antmaze-medium-play-v0	0.00	**0.03***	**0.01**	0.00
antmaze-umaze-diverse-v0	**0.22**	**0.10**	**0.23***	0.05
antmaze-umaze-v0	0.65	**0.71***	0.25	0.65
halfcheetah-expert-v2	**0.89***	**0.88**	0.77	0.79
halfcheetah-full-replay-v2	**0.79**	**0.79***	0.77	0.78
halfcheetah-medium-expert-v2	**0.84**	**0.85***	**0.70**	0.63
halfcheetah-medium-replay-v2	0.47	0.47	0.42	0.47*
halfcheetah-medium-v2	0.49	**0.49***	0.47	0.49
halfcheetah-random-v2	0.17	0.17	0.03	0.23*
hopper-expert-v2	1.05	1.03	1.01	1.05*
hopper-full-replay-v2	**1.03**	**1.07***	**1.01**	1.00
hopper-medium-expert-v2	0.91	**1.00**	**1.04***	0.99
hopper-medium-replay-v2	**0.99***	**0.99**	**0.96**	0.95
hopper-medium-v2	0.71	0.73	0.71	0.74*
hopper-random-v2	**0.27***	**0.24**	0.08	0.12
walker2d-expert-v2	**1.09**	**1.09***	1.09	1.09
walker2d-full-replay-v2	0.86	0.85	0.91	0.94*
walker2d-medium-expert-v2	**1.09**	**1.08**	**1.09***	1.08
walker2d-medium-replay-v2	**0.87***	**0.86**	0.71	0.84
walker2d-medium-v2	**0.83***	0.82	0.74	0.83
walker2d-random-v2	**0.14**	**0.14**	**0.17***	0.03
Num. win Uniform	50	50	33	-

Table 4: CQL results

Dataset	AW (ours)	RW (ours)	Top-10%	Uniform
ant-expert-v2 ($\sigma = 1$)	0.18	0.17	0.03	0.25*
ant-medium-v2 ($\sigma = 1$)	**0.48***	**0.46**	0.01	0.39
halfcheetah-expert-v2 ($\sigma = 1$)	0.04	0.04	**0.08***	0.04
halfcheetah-medium-v2 ($\sigma = 1$)	**0.21**	**0.18**	**0.31***	0.16
hopper-expert-v2 ($\sigma = 1$)	**0.57***	**0.52**	0.12	0.21
hopper-medium-v2 ($\sigma = 1$)	**0.53**	**0.54***	0.21	0.30
walker2d-expert-v2 ($\sigma = 1$)	**0.69**	**0.90***	0.03	0.05
walker2d-medium-v2 ($\sigma = 1$)	**0.18***	**0.17**	0.06	0.13
ant-expert-v2 ($\sigma = 5$)	**0.44***	**0.40**	0.08	0.32
ant-medium-v2 ($\sigma = 5$)	**0.99***	**0.81**	0.25	0.58
halfcheetah-expert-v2 ($\sigma = 5$)	**0.59**	**0.62***	0.08	0.14
halfcheetah-medium-v2 ($\sigma = 5$)	**0.47***	**0.47**	**0.45**	0.30
hopper-expert-v2 ($\sigma = 5$)	**0.97***	**0.88**	**0.44**	0.42
hopper-medium-v2 ($\sigma = 5$)	**0.55**	**0.55***	**0.42**	0.38
walker2d-expert-v2 ($\sigma = 5$)	**0.66**	**0.70***	0.02	0.13
walker2d-medium-v2 ($\sigma = 5$)	**0.64**	**0.78***	0.04	0.05
ant-expert-v2 ($\sigma = 10$)	**0.53***	0.46	0.16	0.46
ant-medium-v2 ($\sigma = 10$)	**1.09***	**1.05**	0.39	0.60
halfcheetah-expert-v2 ($\sigma = 10$)	**0.79**	**0.82***	**0.81**	0.31
halfcheetah-medium-v2 ($\sigma = 10$)	**0.48**	**0.47**	**0.48***	0.43
hopper-expert-v2 ($\sigma = 10$)	**1.02**	**1.05***	0.64	0.65
hopper-medium-v2 ($\sigma = 10$)	**0.57***	**0.57**	**0.53**	0.24
walker2d-expert-v2 ($\sigma = 10$)	**1.10***	**0.81**	0.03	0.08
walker2d-medium-v2 ($\sigma = 10$)	**0.76***	**0.62**	0.03	0.06
ant-expert-v2 ($\sigma = 50$)	0.48	**0.57***	0.47	0.51
ant-medium-v2 ($\sigma = 50$)	**1.11***	**1.06**	**1.00**	0.90
halfcheetah-expert-v2 ($\sigma = 50$)	**0.94**	**0.95***	0.69	0.80
halfcheetah-medium-v2 ($\sigma = 50$)	**0.48***	**0.48**	0.47	0.48
hopper-expert-v2 ($\sigma = 50$)	**1.11***	**1.10**	**1.01**	0.97
hopper-medium-v2 ($\sigma = 50$)	**0.62***	**0.60**	**0.52**	0.44
walker2d-expert-v2 ($\sigma = 50$)	**1.10***	**1.10**	0.07	0.08
walker2d-medium-v2 ($\sigma = 50$)	**0.80**	**0.81***	**0.34**	0.07
ant-expert-v2	**0.96**	**0.98***	**0.83**	0.55
ant-full-replay-v2	**1.34**	**1.38***	1.28	1.34
ant-medium-expert-v2	**1.13***	**1.12**	**0.95**	0.70
ant-medium-replay-v2	0.96	1.00	0.64	1.06*
ant-medium-v2	1.17	1.16	0.86	1.20*
ant-random-v2	0.22	0.36	-0.02	0.37*
antmaze-large-diverse-v0	0.00	**0.01**	**0.03***	0.00
antmaze-large-play-v0	0.00*	0.00*	0.00*	0.00*
antmaze-medium-diverse-v0	**0.10***	**0.05**	**0.07**	0.01
antmaze-medium-play-v0	**0.07***	**0.01**	**0.04**	0.00
antmaze-umaze-diverse-v0	**0.52***	0.26	0.17	0.47
antmaze-umaze-v0	0.50	0.72	0.51	0.79*
halfcheetah-expert-v2	**0.97***	**0.97**	0.84	0.95
halfcheetah-full-replay-v2	**0.78***	**0.77**	**0.76**	0.73
halfcheetah-medium-expert-v2	**0.97***	**0.96**	0.86	0.87
halfcheetah-medium-replay-v2	**0.44**	**0.45***	0.34	0.44
halfcheetah-medium-v2	**0.48***	0.48	0.48	0.48
halfcheetah-random-v2	0.11	**0.11**	**0.12***	0.11
hopper-expert-v2	1.05	1.10	1.06	1.11*
hopper-full-replay-v2	**1.04***	**1.03**	**1.02**	0.73
hopper-medium-expert-v2	**1.03**	**1.10***	**1.10**	0.96
hopper-medium-replay-v2	**0.93**	**0.95***	**0.85**	0.59
hopper-medium-v2	**0.62**	**0.62**	**0.64***	0.56
hopper-random-v2	0.07	0.07	0.08	0.10*
walker2d-expert-v2	**1.10***	**1.10**	1.10	1.10
walker2d-full-replay-v2	**0.96***	**0.96**	0.92	0.94
walker2d-medium-expert-v2	**1.10**	**1.10**	**1.10***	1.10
walker2d-medium-replay-v2	**0.80***	0.75	0.78	0.80
walker2d-medium-v2	0.80	0.81	0.67	0.82*
walker2d-random-v2	0.03	0.02	0.02	0.04*
Num. win Uniform	49	48	25	-

Table 5: TD3+BC results

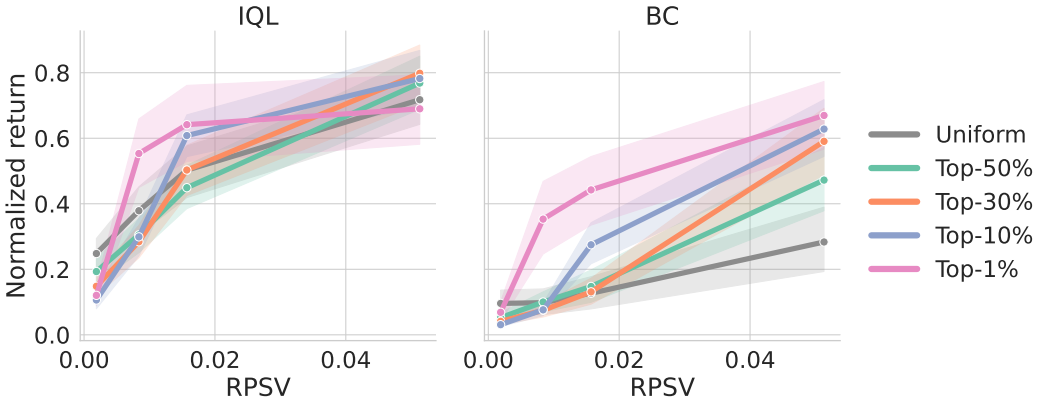

Figure 5: Performance of percentage-filtering sampling with varying percentages.

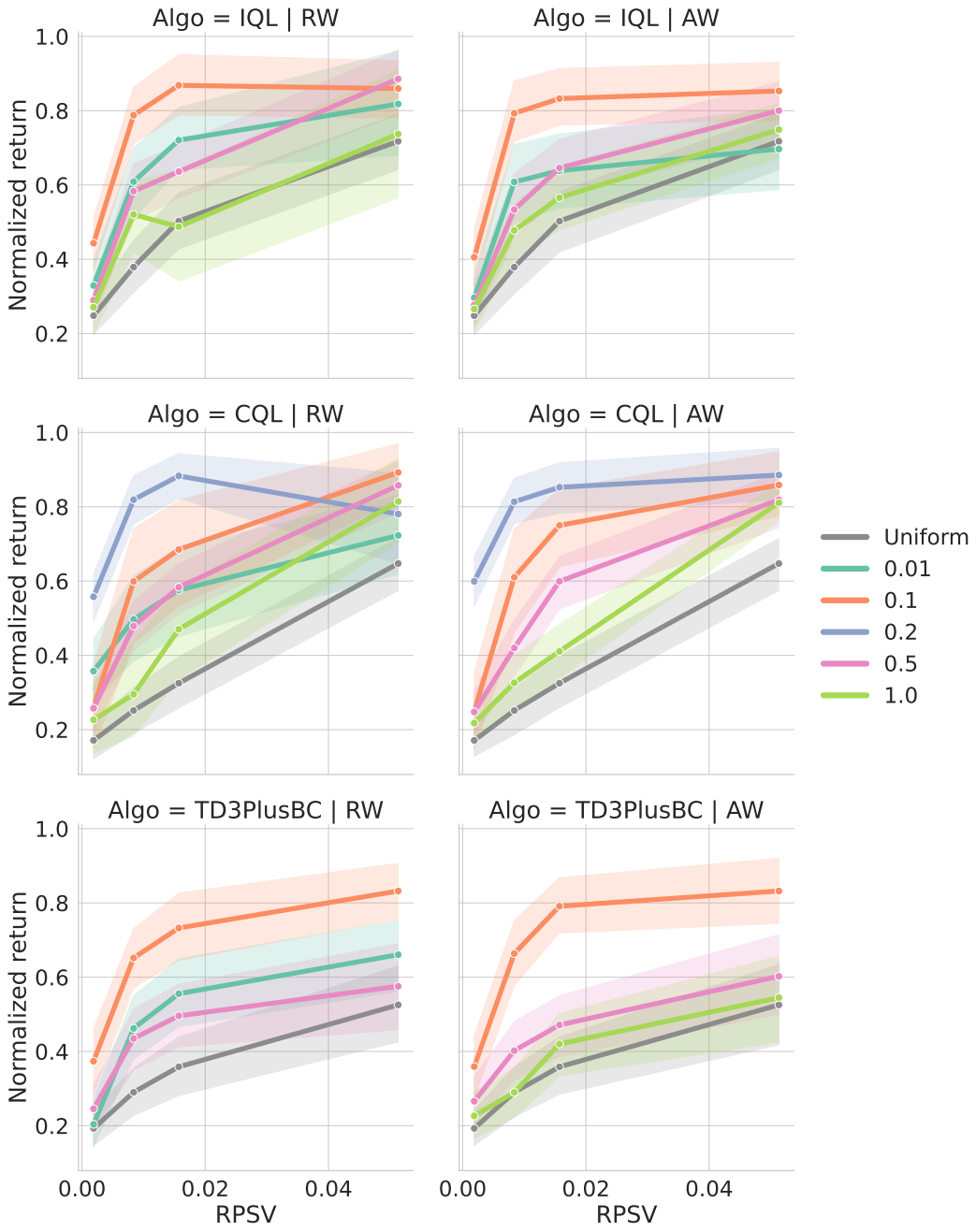

Figure 6: Performance at varying temperature.