OFFLINE RL WITH RESOURCE CONSTRAINED ONLINE DEPLOYMENT

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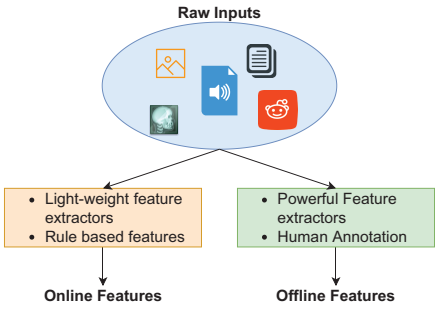
ABSTRACT

Offline reinforcement learning is used to train policies in scenarios where real-time access to the environment is expensive or impossible. As a natural consequence of these harsh conditions, an agent may lack the resources to fully observe the online environment before taking an action. We dub this situation the *resource-constrained* setting. This leads to situations where the offline dataset (available for training) can contain fully processed features (using powerful language models, image models, complex sensors, etc.) which are not available when actions are actually taken online. This disconnect leads to an interesting and unexplored problem in offline RL: **Is it possible to use a richly processed offline dataset to train a policy which has access to fewer features in the online environment?** In this work, we introduce and formalize this novel resource-constrained problem setting. We highlight the performance gap between policies trained using the full offline dataset and policies trained using limited features. We address this performance gap with a *policy transfer algorithm* which first trains a teacher agent using the offline dataset where features are fully available, and then transfers this knowledge to a student agent that only uses the resource-constrained features. To better capture the challenge of this setting, we propose a data collection procedure: Resource Constrained-Datasets for RL (RC-D4RL). We evaluate our transfer algorithm on RC-D4RL and the popular D4RL benchmarks and observe consistent improvement over the baseline (TD3+BC without transfer).

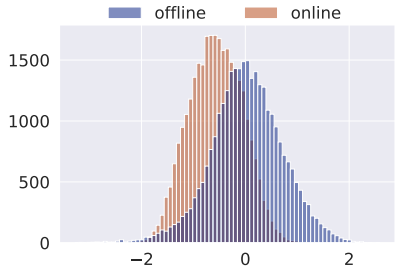
1 INTRODUCTION

There have been many recent successes in the field of Reinforcement Learning (Mnih et al., 2013; Lillicrap et al., 2015; Mnih et al., 2016; Silver et al., 2016; Henderson et al., 2018). In the online RL setting, an agent takes actions, observes the outcome from the environment, and updates its policy based on the outcome. This repeated access to the environment is not feasible in practical applications; it may be unsafe to interact with the actual environment, and a high-fidelity simulator may be costly to build. Instead of consuming interactions between the agent and the environment in real time, *offline RL*, consumes fixed training data which consist of recorded interactions between one (or more) agent(s) and the environment to train a policy (Levine et al., 2020). An agent with the trained policy is then deployed in the environment without further evaluation or modification. Notice that in offline RL, the deployed agent must consume data in the same format (i.e., having the same features) as in the training data. This is a crippling restriction in many large-scale applications, where, due to some combination of resource/system constraints, all of the features used for training cannot be observed by the agent during online operation. In this work, we lay the foundations for studying this *Resource-Constrained* setting. We then provide an algorithm that improves performance by transferring information from the full-featured offline training set to the deployed agent's policy acting on limited features. We first illustrate a few practical cases where resource-constrained settings emerge.

System Latency A deployed agent is often constrained by how much time it has to process the state of the environment and make a decision. For example, in a customer-facing web application, the customer will start to lose interest within a fraction of a second. Given this constraint, the agent may not be able to fully process more than a few measurements from the customer before making a decision. This is in contrast to the process of recording the training data for offline RL, where one



(a) Example of system constraints



(b) Histogram of rewards in online data collected by agents trained with online versus offline features

Figure 1: Illustrations of the resource-constrained setting

may take sufficient time to generate an abundance of features by post-processing high-dimensional measurements.

Power Constraints Consider a situation where an RL agent is being used in deep space probes or nano-satellites ((Deshmukh et al., 2018)). In this case an RL agent is trained on Earth with rich features and a large amount of sensory information. But when the agent is deployed and being used on these probes, the number of sensors is limited by power and space constraints. Similarly, consider a robot deployed in a real world environment. The limited compute power of the robot prevents it from using powerful feature extractors while making a decision. However, such powerful feature extractors can be used during the offline training of the robot (Fig 1a).

In the resource-constrained setting, one can simply ignore the offline features and only train the offline agent with the online features that are available during deployment. This strategy has the drawback of not utilizing all of the information available during training and can lead to a sub-optimal policy. To confirm this, we performed the following simple experiment. We consider an offline RL dataset for the OpenAI gym MuJoCo HalfCheetah-v2 environment and simulate the resource-constrained setting by removing a fixed set of randomly selected features during deployment (see Sections 5.1, 5.2 for more details). We train an offline RL algorithm, TD3+BC (Fujimoto & Gu, 2021) using only the online features and collect online data in the environment using the trained policy. We repeat this assuming all features available during deployment, train a TD3+BC agent using the same offline dataset with all features, and collect online data in the environment. We plot the histogram of rewards in the two datasets in Fig 1b. We observe that the agent trained only with online features obtains much smaller reward than the agent trained with offline features.

Traditionally, scenarios where the observability of the state of the system is limited are studied under the Partially Observable Markov Decision Process (POMDP) setting by assuming a belief over the observations (Åström, 1965). In contrast, we have an offline dataset (which records rich but not necessarily full state transitions) along with partially obscured (with respect to the offline dataset) observations online. Our goal is to leverage the offline dataset to reduce the performance gap caused by the introduction of resource constraints. Towards this, we propose a teacher-student *policy transfer* algorithm, wherein we first train an offline policy on the full-featured training dataset which then serves as a teacher while training a student policy that uses only online features. The transfer is performed by regularizing the behavior of the student policy to be closer to the teacher policy. Our main contributions are summarized below:

- We identify a key open challenge in offline RL: in the resource-constrained setting, datasets with rich features cannot be effectively utilized when only a limited number of features are observable during online operation.
- We propose a transfer algorithm (Algorithm 1) that trains an agent to efficiently leverage the offline dataset while only observing the limited features during deployment.
- We also highlight that when the behavior policy used by the data-collecting agent is trained using a limited number of features, the quality of the dataset suffers. We propose a data collection procedure (RC-D4RL) to simulate this effect. We evaluate our transfer algorithm on RC-D4RL

and the popular D4RL datasets for gym MuJoCo locomotion tasks and show significant gains over a state-of-the-art offline RL algorithm, TD3+BC (Fujimoto & Gu, 2021).

2 RESOURCE-CONSTRAINED ONLINE SYSTEMS

In the standard RL framework, we consider a Markov Decision Process (MDP) defined by the tuple $(\mathcal{S}, \mathcal{A}, R, P, \gamma)$ where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, $R : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function, $P : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$ is the transition function, $\Delta(\mathcal{S})$ denotes the set of all probability distributions over $\mathcal{S}$, and $\gamma \in (0, 1)$ is the discount factor. We consider the *discounted infinite horizon MDP* in this paper. We consider the continuous control setting and assume that both $\mathcal{S}$ and $\mathcal{A}$ are compact subsets of a real-valued vector space. The transition at time t, is given by the tuple $(s_t, a_t, R(s_t, a_t), s_{t+1})$. Each policy $\pi : \mathcal{S} \to \Delta(\mathcal{A})$, has a value function $Q^\pi : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ that estimates the expected discounted reward for taking action a in state s and uses the policy π after that. The goal of the agent is to learn the policy π that maximizes the expected discounted reward $\mathbb{E}_\pi[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)]$. In *online RL*, this problem is solved by interacting with the environment.

In *offline (or batch) RL* (Lange et al., 2012), instead of having access to the environment, the agent is provided with a finite dataset of trajectories or transitions denoted by $D = \{(s_i, a_i, r_i, s'_i)\}_{i=1}^N$. The data is collected by one or many behavior policies that induce a distribution μ on the space of $\mathcal{S} \times \mathcal{A}$. The goal of the agent is to learn a policy using the finite dataset to maximize the expected discounted reward when deployed in the environment.

In the *resource-constrained* setting, the agent does not have access to the full state space or features during deployment. Instead, the agent can only observe from $\widehat{\mathcal{S}}$ (another bounded subset of the real-valued vector space) that is different from $\mathcal{S}$. It is assumed that the space $\mathcal{S}$ is rich in information as compared to $\widehat{\mathcal{S}}$. For example, $\widehat{\mathcal{S}}$ might have fewer dimensions, or some entries may include extra noise (see Figure 1a). We will use *online/limited features*, to refer to observations from the online space $\widehat{\mathcal{S}}$, *offline/rich features* to refer to observations from the offline space $\mathcal{S}$, and *privileged information* to refer to the information present in the offline observations but not in online observations. We assume that both online features and offline features are available in offline data.

The goal of the agent is to use the offline data and train a policy $\pi : \widehat{\mathcal{S}} \to \Delta(\mathcal{A})$. The agent can use the offline features from $\mathcal{S}$ during training but is constrained to only use the online features from $\widehat{\mathcal{S}}$ while making a decision. A similar paradigm of Learning Under Privileged Information (LUPI) (Vapnik et al., 2015) has been studied under the supervised learning setting, where the privileged information is provided by a knowledgeable teacher.

3 RELATED WORK

Offline RL There has been an increasing interest in studying offline RL algorithms due to its practical advantages over online RL algorithms (Agarwal et al., 2020; Wu et al., 2021; Chen et al., 2021; Brandfonbrener et al., 2021). The general recipe for offline RL (in the model-free case) is as follows. There is a *policy evaluation (PE)* step that estimates the state-action value function Q and a *policy improvement (PI)* step that estimates the optimal policy with respect to the value function Q.

$$\begin{aligned} \text{PE:} \quad & \widehat{Q}^\pi_{k+1} \leftarrow \arg\min_{Q} \mathop{\mathbb{E}}_{\substack{(s,a)\sim\mu \\ s'\sim P(s,a)}} \left[\Big(Q(s,a) - \big(R(s,a) + \gamma \mathop{\mathbb{E}}_{a'\sim\pi_k(s')} [\widehat{Q}^\pi_k(s,a')] \big) \Big)^2 \right] \\ \text{PI:} \quad & \pi_{k+1} \leftarrow \arg\max_{\pi} \mathop{\mathbb{E}}_{\substack{s\sim\mu \\ a\sim\pi(s)}} [\widehat{Q}^\pi_{k+1}(s,a)] \end{aligned} \tag{1}$$

Offline RL algorithms typically suffer from overestimation of the value function as well as distribution shift between the offline data and on-policy data. Buckman et al. (2020) and Kumar et al. (2020) advocate a pessimistic approach to value function estimation to avoid over-estimation of rarely observed state-action pairs. To constrain the on-policy data to be closer to offline data, several techniques have been explored, such as restricting the actions inside the expectation in the evaluation step to be close to the actions observed in the dataset (Fujimoto et al., 2019), adding a regularization term during policy evaluation or iteration (Kostrikov et al., 2021), (Wu et al., 2019),(Guo et al.,

2020), adding a constraint of the form $\text{MMD}(\mu(\cdot|s), \pi(s))$ (Gretton et al., 2012; Blanchard et al., 2021; Deshmukh et al., 2019) on the policy (Kumar et al., 2019), using behavior cloning regularization (Fujimoto & Gu, 2021), adding an entropy term in the value function estimation (Wu et al., 2019), and model-based approaches that learn a pessimistic MDP Kidambi et al. (2020). A thorough review of these techniques is presented in an excellent tutorial by Levine et al. (2020).

To the best of our knowledge, there is no existing work that addresses the resource-constrained offline RL setting where there is a mismatch between the offline features and online features.

Knowledge Transfer *Knowledge transfer/distillation* is widely studied in various settings including vision, language, and RL domains (Gou et al., 2021; Wang & Yoon, 2021). In RL, under the *domain transfer* setting (Taylor & Stone, 2009; Liu et al., 2016), the teacher is trained on one domain/task and the student needs to perform on a different domain/task (Konidaris & Barto, 2006; Perkins et al., 1999; Torrey et al., 2005; Gupta et al., 2017). An offline RL algorithm for domain transfer has been proposed by Cang et al. (2021). *Policy distillation* is studied in the setting where the knowledge from a trained policy (teacher) is imparted to an untrained network (student) (Rusu et al., 2015; Czarnecki et al., 2019). This leads to several advantages such as model compression and the ability to learn from an ensemble of trained policies to improve performance (Zhu et al., 2020).

One distinguishing feature of the resource-constrained setting that differentiates it from other transfer settings is that the input features to the policy are different for the teacher and the student. In all existing approaches, the difference between teacher and student was either the network size (which is also present in our setting due to the difference in input features) or the dynamics (as in the domain transfer case). To the best of our knowledge, we are the first to study policy distillation in the offline RL framework under the resource-constrained setting.

Partially Observable MDP POMDP generalizes the MDP framework where the agent does not have access to the full features and only partially observes the state space (Åström, 1965; Kaelbling et al., 1998; Ortner et al., 2012). More recently, Rafailov et al. (2021) studied a model-based offline RL algorithm for image data under the POMDP setup. Our setting resembles this setup, but our agent also has access to the full privileged features in the offline dataset while training. This availability of the offline dataset with privileged information differentiates our setting and enables the student to inherit the knowledge from the rich space while only using the limited features during deployment.

4 Proposed Algorithm

We motivate the proposed algorithm by first providing a general approach to tackle the resource-constrained setting. In particular, we propose a teacher-student knowledge transfer model that distills the knowledge of the teacher policy to the student policy (Rusu et al., 2015; Czarnecki et al., 2019). This is a modeling choice; alternative types of knowledge transfer, such as transfer of the value function's knowledge, are also possible. (Czarnecki et al., 2019).

We first train a teacher network using the full offline dataset. Let us denote the policy output by the teacher network as $\pi_{\phi^{\texttt{teacher}}} : \mathcal{S} \to \Delta(\mathcal{A})$. The student network is denoted by $\pi_\phi : \widehat{\mathcal{S}} \to \Delta(\mathcal{A})$. The knowledge transfer is performed by using the pre-trained teacher network to compute a regularization term that is added to the objective (policy iteration):

$$\pi_{k+1} \leftarrow \arg\max_{\pi} \mathbb{E}\left[\widehat{Q}^{\pi}_{k+1}(\hat{s}, a) - \beta \mathcal{M}\Big(\pi_\phi(\hat{s}), \pi_{\phi^{\texttt{teacher}}}(s)\Big)\right]. \tag{2}$$

Here, $\mathcal{M}$ can be any divergence metric on the policy distributions. We can compute the terms $\pi_\phi(\hat{s})$ and $\pi_{\phi^{\texttt{teacher}}}(s)$ simultaneously since we assume that the offline dataset contains the offline features s and the corresponding online features $\hat{s}$. If the teacher and learned policy functions are deterministic, the divergence function can be the squared loss, and if they are stochastic, the divergence can be KL divergence, MMD (Maximum Mean Discrepancy), Wasserstein divergence, etc. This regularization term encourages the learnt policy to behave similarly to the teacher policy. An illustration of the proposed setup is given in Figure 7 in the appendix.

4.1 An instantiation of the Policy Transfer using TD3+BC

Background of TD3+BC We discuss a simple way to extend an existing offline RL algorithm to apply to the resource-constrained setting. TD3+BC (Fujimoto & Gu, 2021) is a recent offline RL

Algorithm 1 Policy Transfer with TD3+BC

Given: offline dataset D with full feature observations, the weights β_1, β_2 s.t. $\beta_1 + \beta_2 = 1$
Given: policy update frequency d; weighted average parameter τ, noise parameter $\bar{\sigma}$
Train an offline RL agent using TD3+BC which outputs the teacher model $\pi_{\phi^{\texttt{teacher}}}$
Initialize critic networks $Q_{\theta_1}, Q_{\theta_2}$ and an actor network π_ϕ
Initialize target networks $\theta_1^{'} \leftarrow \theta_1, \theta_2^{'} \leftarrow \theta_2, \phi^{'} \leftarrow \phi$.
for $t = 1, \cdots, T$ **do**
  Sample mini-batch of N transitions $(s, a, r, s') \in D$
  Online features for this transition is given as $(\hat{s}, a, r, \hat{s}')$
  $\tilde{a} \leftarrow \pi_{\phi'}(\hat{s}') + \min(\max(\epsilon, -c), c)$ where $\epsilon \sim \mathcal{N}(0, \tilde{\sigma})$
  $y \leftarrow r + \gamma \min_{i=1,2} Q_{\theta_i'}(\hat{s}', \tilde{a})$
  Update critics $\theta_i \leftarrow \arg\min_{\theta_i} \frac{1}{N} \sum_{i=1}^{N} \left(y - Q_{\theta_i}(\hat{s}, a)\right)^2$
  if t $\texttt{mod}$ d == 0 **then**
    Update ϕ by deterministic policy gradient optimizing the objective

$$\arg\max_{\phi} \frac{1}{N} \sum_{i=1}^{N} \left[\lambda Q_{\theta_1}(\hat{s}_i, \pi_\phi(s_i)) - \beta_1 \Big(\pi_\phi(\hat{s}_i) - a\Big)^2 - \beta_2 \Big(\pi_{\phi^{\texttt{teacher}}}(s_i) - \pi_\phi(\hat{s}_i)\Big)^2 \right] \quad (3)$$

    Update target networks:
      $\theta_i' \leftarrow \tau\theta_i + (1-\tau)\theta_i'$
      $\phi' \leftarrow \tau\phi + (1-\tau)\phi'$
  end if
end for

algorithm which shows that by adding an additional behavior cloning term to an existing online RL algorithm TD3 (Fujimoto et al., 2018) (that learns a deterministic policy), it is possible to attain state-of-the-art performance on the D4RL benchmark datasets (Fu et al., 2020). The policy evaluation step in TD3+BC is the same as TD3 where the minimum of two Q functions is used to reduce the over-estimation bias of the value function. In the policy iteration step, the behavior cloning term $(\pi_\phi(s) - a)^2$ regularizes the policy to take actions similar to the actions observed in the dataset. The policy iteration step is given by

$$\pi_{k+1} \leftarrow \arg\max_{\pi} \mathbb{E}\left[\lambda \widehat{Q}^{\pi}_{k+1}\big(s, \pi(s)\big) - \big(\pi_\phi(s) - a\big)^2\right]; \qquad \lambda = \frac{\alpha}{\frac{1}{N}\sum_{(s_i, a_i)} |Q(s_i, a_i)|},$$

where α is a hyper-parameter.

Proposed Algorithm We now propose our transfer algorithm that adopts TD3+BC to the resource-constrained setting. We add an additional regularization term during the policy iteration step, that tries to keep actions predicted by the trained policy close to the actions taken by the teacher policy. This knowledge can be imparted to the student policy through the regularization term below (see equation 3 for the full equation)

$$\overbrace{\beta_1 \Big(\pi_\phi(\hat{s}) - a\Big)^2}^{\text{Behavior Cloning}} - \overbrace{\beta_2 \Big(\pi_{\phi^{\texttt{teacher}}}(s) - \pi_\phi(\hat{s})\Big)^2}^{\text{Transfer}}.$$

We weigh the two terms with weights β_1, β_2. The transfer term is beneficial in learning because the teacher (trained using offline RL algorithm on full features) often predicts a better action than those available in the dataset (depending on the quality of the dataset) as observed in earlier offline RL works (Kumar et al., 2020). To keep all terms in equation 3 at comparable magnitudes, we add a constraint that $\beta_1 + \beta_2 = 1$. If $\beta_1 = 1$ and $\beta_2 = 0$, the proposed algorithm is equivalent to the TD3+BC algorithm. Algorithm 1 describes the complete steps.

5 Experimental Results

We designed our experimental analysis to answer the following questions.

- Does the proposed transfer algorithm outperform a baseline algorithm which is trained only on the limited online features? See Figures 2 and 3.
- How does the improvement offered by the transfer algorithm vary with the dataset difficulty? See Figures 4a and 5a.
- How does the improvement offered by the transfer algorithm vary with the number of offline features that are left out of the online setting? See Figures 4b and 5b.
- Since we are regularizing the student with the teacher's policy, we wish to study how important is the teacher's role in training the student. See Figure 6.

To answer these questions, we first discuss the resource-constrained setup used for the environments in Section 5.1. It is important to note that the data-collecting agent plays a vital role in determining the quality of the dataset (coverage of state-action pairs) and subsequently the performance of any offline RL algorithm. In the D4RL suite (Fu et al., 2020), datasets were collected using behavior policies of varying expertise to simulate the variation in data quality. Each of these behavior policies was trained online using the full feature set. Thus, these policies can use all of the information and explore the environment online. The quality of the offline dataset collected by these behavior policies is thus relatively high. Therefore, all offline RL algorithms trained using these datasets can perform better. In the resource-constrained setting, however, the behavior policy of the data-collecting agent does not have access to the full features online. The agent may only explore and navigate using the limited feature set during training. Using this behavior policy to collect data results in a relatively lower quality dataset. To account for this limitation, and to illustrate its effect on our algorithm's performance, we used two different methods to generate offline datasets.

- Offline RL datasets are collected by agents trained with limited features. We refer to these datasets as *RC-D4RL* (Resource-Constrained Datasets for RL). We use the OpenAI gym MuJoCo (Todorov et al., 2012) locomotion environments Hopper-v2, HalfCheetah-v2, and Walker2d-v2.
- Offline RL datasets are collected by agents trained using the full features. We use the D4RL-v0 datasets (Fu et al., 2020) of the MuJoCo locomotion environments.

5.1 Simulation of Resource-Constrained Setting

We simulate the resource-constrained setting by reducing the feature space available during the deployment of the agent. We do this by dropping a fixed set of features from the full features available. For instance, consider the MuJoCo environment Hopper-v2 where the original state space is 11 dimensional. We consider four scenarios where the online observable feature dimensions is reduced to 5, 7, 9 and 10 by randomly picking a subset of the features of the given dimension. For each of these scenarios, we consider 5 random seeds to simulate different features getting dropped in each seed. We summarize this setting for the three environments in Table 1.

Environment	Original Dim	Resource-Constrained Dim	Number of Seeds
Hopper	11	5, 7, 9, 10	5
HalfCheetah, Walker2d	17	9, 11, 13, 15	5

Table 1: Resource-Constrained Simulation using gym MuJoCo tasks

5.2 Dataset collection procedure: RC-D4RL

For the dataset collection using policies trained with limited features, we follow a similar protocol as the D4RL data collection procedure (Fu et al., 2020). In the D4RL benchmark suite, offline datasets with different difficulty levels are collected based on the exploration capacity of the data-collecting policy or behavior policy. The difficulty levels are denoted as medium-replay, medium, medium-expert and expert. For each combination (environment, difficulty, dimension, seed) in Table 1, we train an expert policy by training a TD3 (Fujimoto et al., 2018) algorithm for 1 million timesteps using the limited features, and using the base hyperparameters of the TD3 algorithm. We then train

Difficulty\Online Dim	5	7	9	10
medium-replay	47.4 ± 23.4	83.3 ± 41.0	186.0 ± 76.1	207.3 ± 45.5
medium	588.1 ± 351.5	754.4 ± 339.0	900.0 ± 285.5	1357.8 ± 423.6
medium-expert	660.6 ± 335.7	936.7 ± 395.1	1380.9 ± 473.1	1929.7 ± 469.3
expert	803.6 ± 320.0	1196.9 ± 402.8	2399.0 ± 744.9	3068.5 ± 617.1

Table 2: RC-D4RL Hopper dataset: Average reward per trajectory

the medium policy by training the TD3 algorithm until the agent reaches roughly half of the reward achieved by the expert policy for this combination. These policies are deployed in the simulator and the interactions are logged to generate the expert and medium datasets. Note that all the features are logged in the datasets. The medium-replay data comprises of the environment interactions recorded during the training of the medium policy. The medium-expert dataset is the concatenation of the medium and expert policies. Thus, we generate in total 240 [1] offline RL datasets. Note that we did not perform hyperparameter tuning to compute the expert data collection policy and only used the base hyperparameters used in the TD3 paper[2]. We can observe the variation in the quality of the datasets with the dimensionality of online features and the difficulty from Table 2. This reinforces the need to evaluate the proposed algorithm with the RC-D4RL datasets. A summary of the datasets for HalfCheetah and Walker2d environments is provided in Appendix A.2.

5.3 Training

We train a teacher agent using the full feature space in the dataset. We use the TD3+BC algorithm trained on the limited feature set as the baseline. Then we train the student agent using the trained teacher following Algorithm 1. We train the baseline and student for three random seeds.

Recent work (Fujimoto & Gu, 2021) highlighted the difficulty in comparing algorithmic contributions in Offline RL due to the high sensitivity of deep RL algorithms to implementation changes (Engstrom et al., 2019; Furuta et al., 2021). It is even more crucial in offline RL because hyperparameter tuning by interacting with the environment defies the purpose of offline RL, and tuning without environment access is not well understood (Paine et al., 2020). Therefore, to highlight our algorithmic contributions, we adopt the base hyperparameters of TD3+BC for the baseline and the proposed algorithm. In the proposed algorithm, we introduce two new hyperparameters β_1, β_2 that weigh the behavior cloning term and the transfer regularization terms respectively. We constrain them as $\beta_1 + \beta_2 = 1$. To illustrate the effect of the transfer, we consider two representative settings, (i) *Transfer (0.5, 0.5)* where $\beta_1 = \beta_2 = 0.5$ which gives equal weight to behavior cloning and transfer, (ii) *Transfer (0.0, 1.0)* where $\beta_1 = 0,\ \beta_2 = 1.0$ where only transfer is performed.

5.4 Evaluation

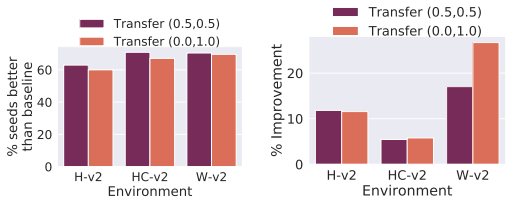
When reporting the performance of the algorithm, we assume online access to the gym MuJoCo simulator for evaluation. The agents are restricted to using the limited features (defined by the combination of the offline dataset used during training) to make a decision. Given a policy to evaluate, we perform 10 different rollouts using this simulator with random initial states and compute the mean of the cumulative rewards. We perform one round of evaluation of the policy (student or baseline) during training at a fixed frequency. We take the average value of the last 10 evaluation rounds during training and report the mean and the standard deviation of the score. Lastly, since we run multiple trials (for each configuration), we compute the mean and standard deviation of the results of the three random trials for the given configuration. In order to facilitate easier understanding and comparison of the results across datasets and environments, we adopt the normalized score computation[3] (Fu et al., 2020)

$$\text{normalized score} = 100 \times \frac{\text{score - score of random policy}}{\text{score of expert online policy - score of random policy}}.$$

[1] 3 environments x 4 dimensions x 5 seeds x 4 difficulty levels.

[2] The expert data collection policy affects the quality of all the 4 difficulties.

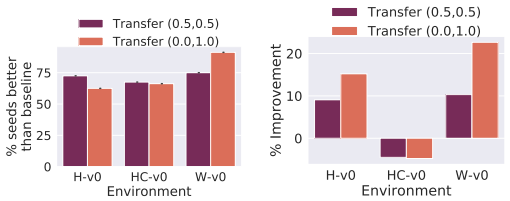
[3] Expert online policy is a fully trained online SAC policy (Haarnoja et al., 2018)



(a) % of succes over the baseline across all experiments.

(b) % improvement over the baseline score across all experiments.

Figure 2: Results on RC-D4RL datasets. [4]



(a) % of succes over the baseline across all experiments.

(b) % improvement over the baseline score across all experiments.

Figure 3: Results on D4RL datasets. [5]

5.5 Results and Discussion

From Figures 2 and 3, we can see that the proposed transfer algorithm significantly outperforms the baseline for both the RC-D4RL and D4RL datasets. In Figures 2a and 3a, we show the percentage of experiments (all the difficulties, dimensions, dataset seeds, algorithm seeds) where each of the proposed algorithms performs better than the baseline for each environment. We observe that the proposed algorithm performs similarly for both the datasets with the performance in D4RL being slightly better. In Figures 2b and 3b, we average the scores of all experiments for each environment and algorithm pair and compare the % improvement over the baseline. We observe that in Hopper and Walker2d datasets, the transfer algorithm achieves significant improvement over the baseline for both RC-D4RL and D4RL. For HalfCheetah, the transfer algorithm does not improve over the baseline in D4RL, whereas in RC-D4RL, the transfer algorithm outperforms the baseline. This could be because the RC-D4RL datasets have low quality interactions; the baseline performs even worse and therefore the transfer from teacher offers more scope of improvement over the baseline. We perform a thorough analysis of the results and summarize the findings below, focusing on the effect of difficulties of the datasets and different (limited) feature dimensions.

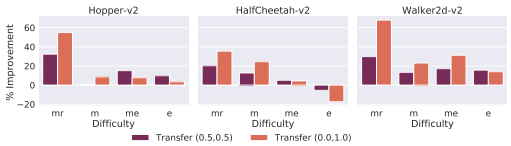
Dataset Difficulty From Figures 4a and 5a, we observe that majority of the performance gains have been observed for the medium or medium-replay datasets. The expert and medium-expert datasets consistently provided relatively lesser % improvement, and in some cases performed worse than the baseline. The trend is consistent across the different environments (although it is more significant for HalfCheetah-v2). With expert or medium-expert datasets, the coverage of the state-action product space is narrow but of good quality. When training with limited features, the trained policy can drift away from this distribution. Since the data distribution is narrow, it is difficult for the trained policy to distinguish between unsafe state-action pairs from the safe state-action pairs. Whereas for the datasets with poor quality (medium, medium-replay), the data distribution is wide. The regularization from the teacher is stronger and also the agent can better discriminate unsafe state-action pairs due to the good coverage of the data.

Reduced Feature Dimension From Figures 4b and 5b, we observe that the performance gains with the proposed algorithm follows an inverted "U" pattern. The highest gains with the transfer algorithm are observed when the reduced feature dimension is neither too small (very little information) nor too high (negligible loss of information). This trend is more predominant for the D4RL datasets.

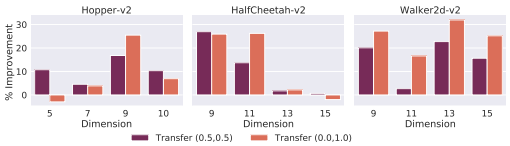
Closeness to teacher agent We represent the online distribution of the agent as the distribution of the state-action pairs visited by the agent during deployment. We use the maximum mean discrepancy (MMD) as a proxy to measure how far the online distributions of the baseline and transfer agents are with respect to the teacher agent. From Figure 6, we can observer that Transfer (0.0,1.0) agent is the closest to the teacher agent for all three cases. This is an expected behavior since the $\beta_2 = 1.0$ value gives all the weight to the regularization term with the teacher. Teacher (0.0,1.0) also performs the best in almost all cases while comparing the % improvement over the baseline. We also observe from Figures 11, 12, 13 (Appendix A.3) that in almost every case where the teacher outperforms the baseline, both the transfer algorithm variants outperformed the baseline.

[4] H-v2: Hopper-v2, HC-v2: HalfCheetah-v2, W-v2: Walker2d-v2

[5] H-v0: Hopper-v0, HC-v0: HalfCheetah-v0, W-v0: Walker2d-v0

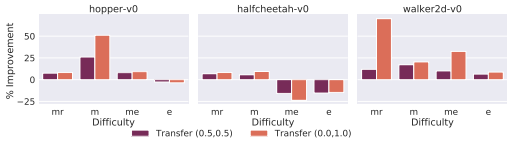


(a) % Improvement of the scores over the baseline, aggregated across the Dimensions. mr: medium-replay, m: medium, me: medium-expert, e: expert

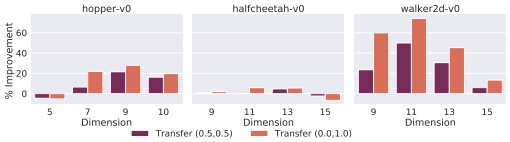


(b) % Improvement of the scores over the baseline, aggregated across the difficulties.

Figure 4: Results on RC-D4RL datasets.



(a) % Improvement of the scores over the baseline, aggregated across the Dimensions. mr: medium-replay, m: medium, me: medium-expert, e: expert



(b) % Improvement of the scores over the baseline, aggregated across the difficulties.

Figure 5: Results on D4RL datasets.

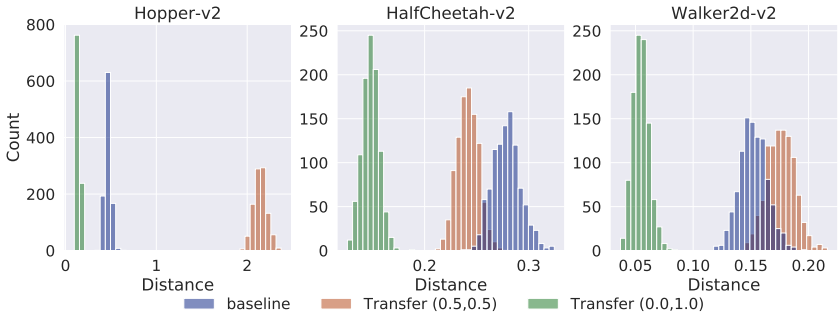


Figure 6: We use MMD to illustrate the distribution shift between the online distribution of the teacher and online distrbutions of the other agents.

6 Conclusion

In this work, we address an open challenge in Offline RL. In the resource-constrained setting that is motivated by real world applications, the features available during training offline may be different than the limited features available online during deployment. We highlighted a performance gap between offline RL agents trained using only the online features and agents trained using all the offline features. To bridge this gap, we proposed a student-teacher-based policy transfer algorithm. The proposed algorithm improves over the baseline significantly even when the dataset quality is lacking in the resource-constrained setting. The simplicity of the approach (with just one additional hyperparameter) makes it easy to extend it to other offline RL algorithms. It would be interesting to study the policy transfer with other divergence regularizations for stochastic policies in the future. Moreover, there are other knowledge transfer methods involving value function transfer, or a mixture of both value and policy transfer which we consider as future work. We hope that our resource-constrained framework and experimental results inspire more work on deployable RL algorithms.

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A EXPERIMENT DETAILS

We used the opensource implementation of TD3+BC available at TD3+BC for our experiments. We used the same network architectures, and all other hyperparameters in this implementation. We also normalized the offline RL dataset using the procedure described in Fujimoto & Gu (2021).

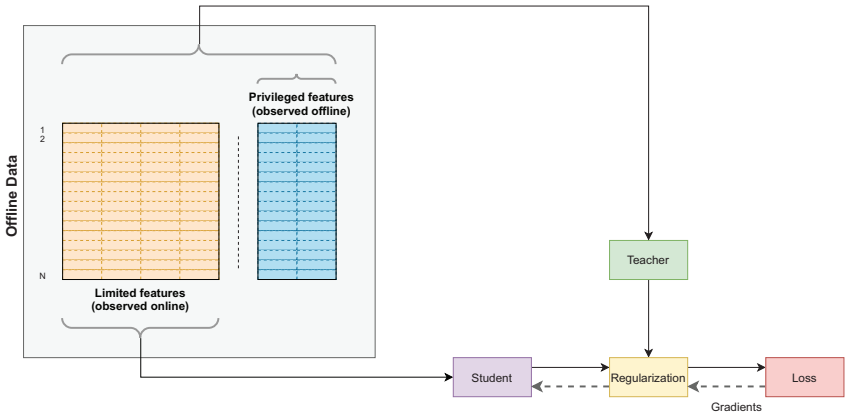
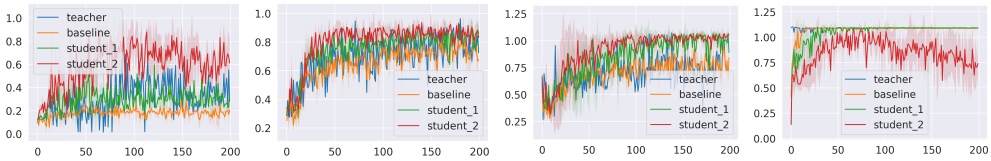


Figure 7: Illustration of the proposed method

A.1 LEARNING CURVES

Figures 8, 9, 10 depict the learning curves during training in the RC-D4RL experiments.

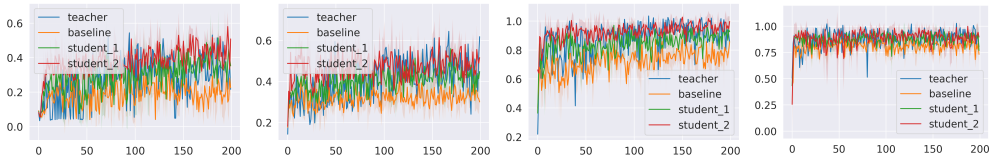


(a) medium-replay (b) medium (c) medium-expert (d) expert

Figure 8: Hopper

(a) medium-replay (b) medium (c) medium-expert (d) expert

Figure 9: HalfCheetah



(a) medium-replay (b) medium (c) medium-expert (d) expert

Figure 10: Walker2d

A.2 Dataset Summary

We present the summary of the RC-D4RL datasets.

Dataset	Reduced Dim: 5	7	9	10
medium-replay	47.4 ± 23.4	83.3 ± 41.0	186.0 ± 76.1	207.3 ± 45.5
medium	588.1 ± 351.5	754.4 ± 339.0	900.0 ± 285.5	1357.8 ± 423.6
medium-expert	660.6 ± 335.7	936.7 ± 395.1	1380.9 ± 473.1	1929.7 ± 469.3
expert	803.6 ± 320.0	1196.9 ± 402.8	2399.0 ± 744.9	3068.5 ± 617.1

Table 3: Hopper environment: Average reward per trajectory

Dataset	Reduced Dim: 9	11	13	15
medium-replay	-77.5 ± 140.9	-31.6 ± 141.2	183.7 ± 288.9	206.2 ± 276.5
medium	612.8 ± 321.5	838.3 ± 531.1	1389.1 ± 637.9	1786.6 ± 931.7
medium-expert	1013.2 ± 519.6	1450.2 ± 873.8	2471.6 ± 1073.3	3404.9 ± 1803.1
expert	1413.5 ± 724.8	2062.2 ± 1233.0	3554.1 ± 1528.2	5023.2 ± 2682.1

Table 4: HalfCheetah environment: Average reward per trajectory

Dataset	Reduced Dim: 9	11	13	15
medium-replay	19.8 ± 17.6	43.2 ± 65.2	175.2 ± 131.6	269.7 ± 73.2
medium	307.2 ± 106.2	446.8 ± 182.9	797.8 ± 208.4	1071.0 ± 188.5
medium-expert	424.1 ± 128.8	650.0 ± 273.4	1173.3 ± 367.4	1743.9 ± 341.4
expert	691.9 ± 302.2	1039.5 ± 507.4	1837.0 ± 735.4	3330.7 ± 685.7

Table 5: Walker2d environment: Average reward per trajectory

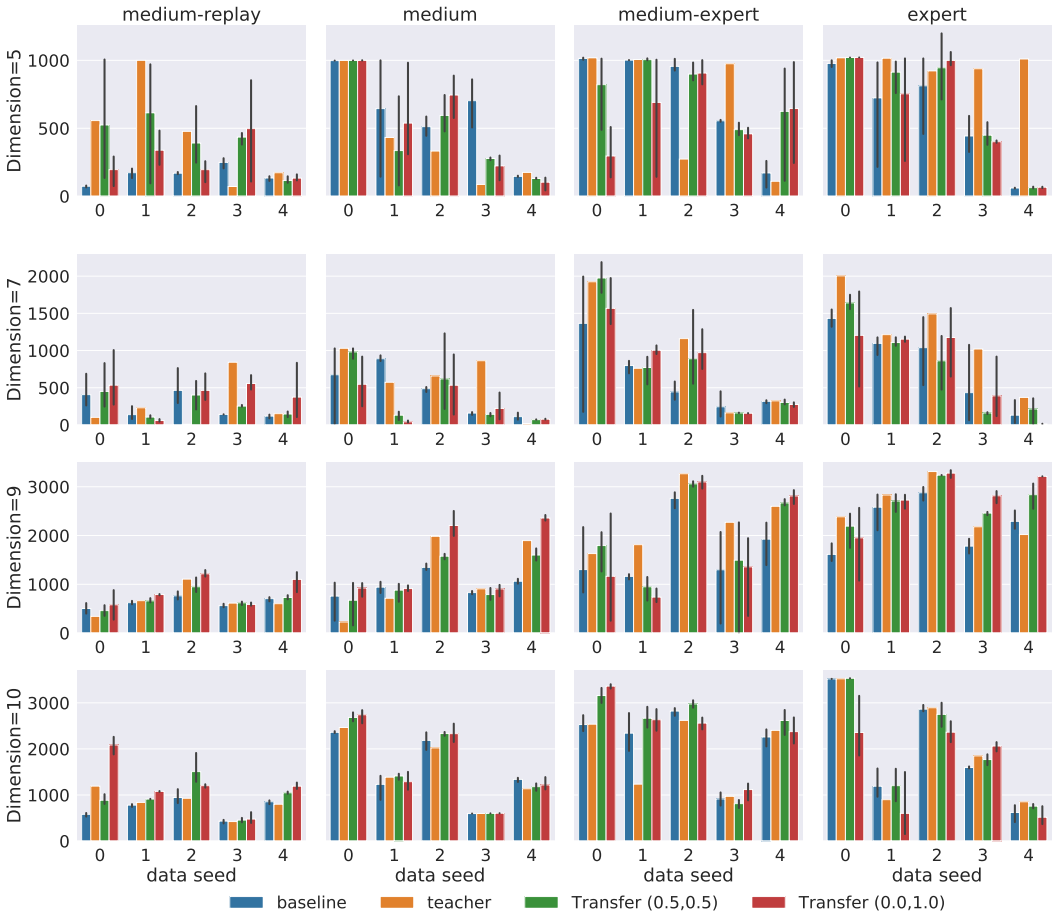


Figure 11: RC-D4RL Hopper-v2 experiments summary. We plot the mean of the rewards and the error bars represent the standard deviation across the 3 random seeds for a given dataset.

A.3 More Analysis

Figures 11, 12, 13 illustrate the results of our experiments with RC-D4RL datsets. We plot the mean normalized score and the error bars represent the standard deviation across the random seeds.

Tables 6, 7, 8 contain the results of the RC-D4RL experiments. 9, 10, 11 contain the results of the D4RL experiments. In both cases, we report the mean normalized score and the standard deviation.

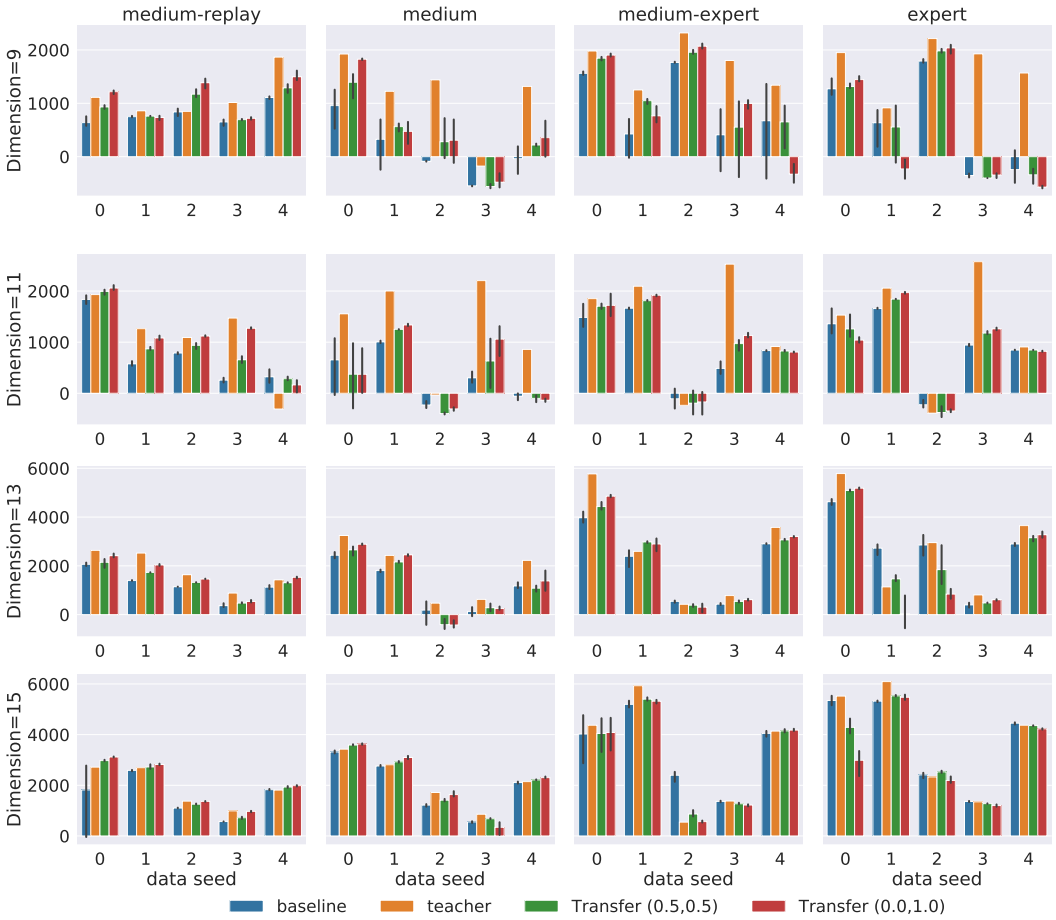


Figure 12: RC-D4RL HalfCheetah-v2 experiments summary. We plot the mean of the rewards and the error bars represent the standard deviation across the 3 random seeds for a given dataset.

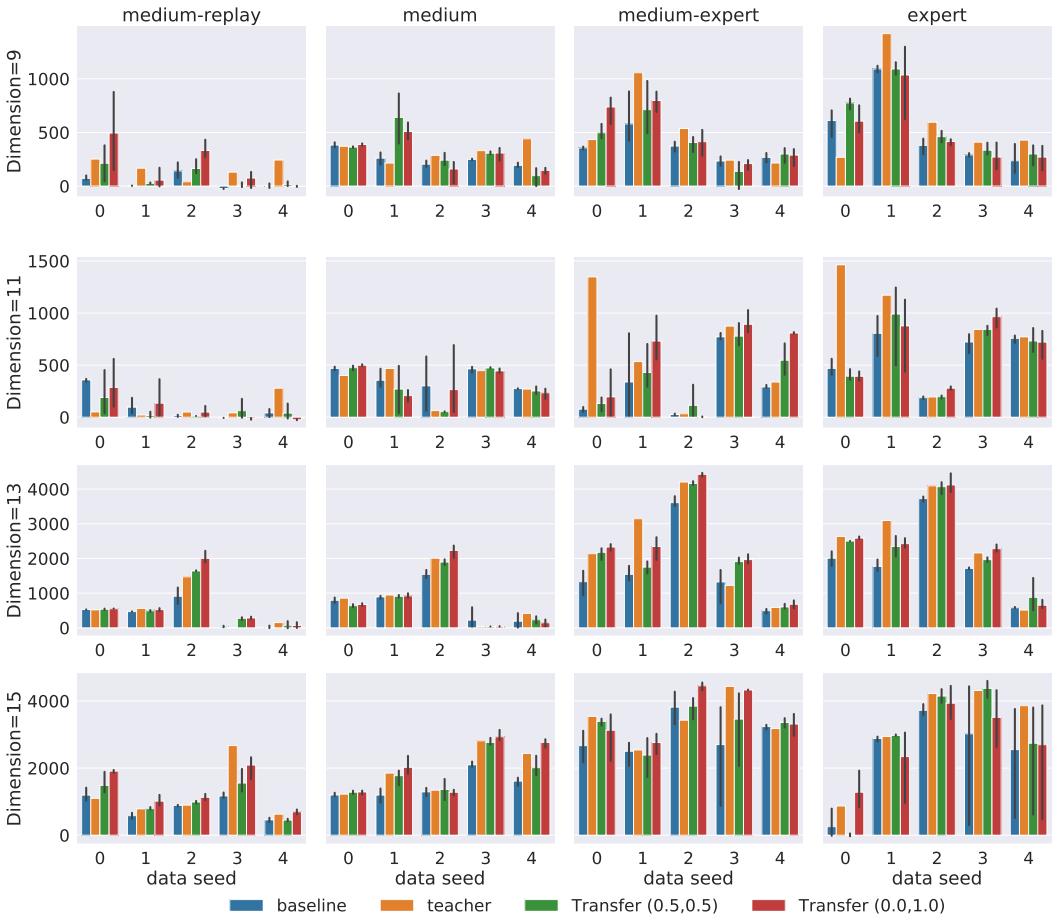


Figure 13: RC-D4RL Walker2d-v2 experiments summary. We plot the mean of the rewards and the error bars represent the standard deviation across the 3 random seeds for a given dataset.

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	5	5.5 ± 1.9	**13.4** ± 9.6	9.0 ± 6.4
	7	8.4 ± 6.4	9.0 ± 6.2	**12.9** ± 9.2
	9	20.0 ± 3.6	21.6 ± 5.6	**26.9** ± 9.5
	10	22.7 ± 6.3	30.2 ± 11.6	**37.7** ± 16.6
medium	5	**19.1** ± 10.5	15.0 ± 10.7	16.7 ± 11.6
	7	**14.9** ± 11.6	12.6 ± 13.0	9.4 ± 9.5
	9	31.0 ± 8.5	34.5 ± 14.2	**45.5** ± 21.8
	10	48.0 ± 21.1	**51.1** ± 24.4	50.9 ± 25.3
medium-expert	5	23.3 ± 10.6	**24.2** ± 8.6	19.0 ± 10.0
	7	20.1 ± 18.0	**25.8** ± 21.6	25.1 ± 17.3
	9	52.5 ± 24.6	**61.9** ± 29.4	57.0 ± 34.5
	10	67.4 ± 21.8	**75.8** ± 27.2	74.7 ± 23.8
expert	5	19.2 ± 12.1	**21.5** ± 12.2	20.5 ± 12.7
	7	**26.0** ± 17.5	25.1 ± 18.4	24.8 ± 19.0
	9	69.1 ± 16.3	83.2 ± 12.7	**86.6** ± 17.8
	10	60.8 ± 34.5	**62.2** ± 32.7	49.2 ± 29.6

Table 6: Results on RC-D4RL Hopper-v2 dataset

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	9	8.7 ± 1.5	10.1 ± 2.0	**11.2** ± 2.8
	11	8.3 ± 4.8	9.9 ± 4.8	**11.4** ± 5.0
	13	12.1 ± 4.6	13.5 ± 4.7	**15.1** ± 5.3
	15	15.0 ± 7.6	17.7 ± 7.1	**18.8** ± 6.9
medium	9	3.2 ± 4.7	5.3 ± 5.4	**6.3** ± 6.5
	11	5.0 ± 4.2	5.1 ± 5.4	**6.0** ± 5.6
	13	11.5 ± 7.7	11.6 ± 9.6	**12.8** ± 10.6
	15	18.3 ± 8.4	19.7 ± 8.7	**20.0** ± 9.7
medium-expert	9	10.0 ± 6.1	**12.0** ± 5.7	11.0 ± 7.3
	11	9.3 ± 5.5	10.5 ± 6.1	**11.0** ± 6.3
	13	18.8 ± 11.5	20.6 ± 13.1	**21.4** ± 14.2
	15	**29.7** ± 11.7	27.6 ± 14.9	27.0 ± 15.5
expert	9	**7.3** ± 7.2	**7.3** ± 8.0	6.0 ± 8.9
	11	9.6 ± 5.4	**9.9** ± 6.2	**9.9** ± 6.3
	13	**24.0** ± 11.4	21.6 ± 13.5	18.3 ± 16.4
	15	**32.7** ± 13.5	31.2 ± 12.6	28.2 ± 12.7

Table 7: Results on RC-D4RL HalfCheetah-v2 dataset

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	9	0.8 ± 1.5	1.8 ± 2.5	**4.1** ± 5.4
	11	**2.2** ± 3.1	1.4 ± 2.6	1.9 ± 3.7
	13	8.5 ± 7.8	13.0 ± 12.4	**14.9** ± 15.5
	15	18.7 ± 7.1	22.9 ± 10.3	**29.8** ± 12.6
medium	9	5.6 ± 1.6	**7.1** ± 4.6	6.5 ± 3.4
	11	**8.1** ± 3.0	6.6 ± 4.0	7.2 ± 4.1
	13	15.8 ± 11.7	16.2 ± 14.8	**17.5** ± 17.8
	15	32.2 ± 8.1	40.0 ± 12.8	**44.8** ± 16.2
medium-expert	9	7.9 ± 3.5	8.9 ± 5.1	**10.6** ± 5.7
	11	6.5 ± 6.9	8.7 ± 6.4	**11.4** ± 8.5
	13	36.1 ± 24.1	46.2 ± 26.1	**51.2** ± 27.4
	15	65.0 ± 18.3	71.6 ± 15.9	**78.3** ± 17.0
expert	9	11.3 ± 7.3	**12.9** ± 6.9	11.3 ± 7.3
	11	12.8 ± 5.6	13.7 ± 7.6	**14.1** ± 7.0
	13	42.7 ± 22.9	51.2 ± 23.7	**52.6** ± 25.0
	15	54.1 ± 36.3	**62.0** ± 38.4	59.9 ± 29.6

Table 8: Results on RC-D4RL Walker2d-v2 dataset

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	5	6.3 ± 3.3	8.0 ± 4.2	**8.2** ± 4.4
	7	14.7 ± 4.5	19.0 ± 4.9	**20.3** ± 6.9
	9	29.3 ± 3.0	30.6 ± 2.1	**30.9** ± 2.7
	10	31.5 ± 1.0	**32.3** ± 1.2	31.1 ± 0.7
medium	5	**10.6** ± 3.6	8.4 ± 2.3	6.5 ± 1.7
	7	29.6 ± 7.0	35.5 ± 19.1	**50.4** ± 30.7
	9	43.4 ± 12.7	73.0 ± 17.1	**88.6** ± 18.5
	10	66.9 ± 28.7	87.6 ± 18.3	**99.6** ± 0.5
medium-expert	5	6.6 ± 2.8	7.5 ± 3.4	**8.2** ± 3.0
	7	29.2 ± 15.4	35.5 ± 22.0	**43.0** ± 26.5
	9	85.6 ± 29.0	**104.6** ± 7.3	101.2 ± 5.3
	10	107.9 ± 3.3	**111.0** ± 1.3	109.0 ± 2.2
expert	5	**9.1** ± 2.2	7.4 ± 0.7	8.1 ± 1.6
	7	**46.9** ± 33.6	38.1 ± 37.6	33.1 ± 33.3
	9	**61.5** ± 50.6	58.9 ± 42.5	60.4 ± 39.7
	10	70.8 ± 55.5	91.0 ± 46.6	**92.0** ± 44.4

Table 9: Results on D4RL Hopper-v0 dataset

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	9	26.5 ± 5.8	29.4 ± 5.8	**30.0** ± 6.3
	11	33.1 ± 5.6	35.4 ± 4.5	**36.1** ± 4.4
	13	32.0 ± 8.9	**35.7** ± 6.8	35.6 ± 6.7
	15	38.9 ± 2.0	41.0 ± 1.2	**41.6** ± 1.3
medium	9	33.5 ± 4.1	35.6 ± 3.8	**37.3** ± 3.5
	11	36.1 ± 2.5	39.1 ± 0.9	**40.5** ± 1.2
	13	36.9 ± 2.0	39.3 ± 1.4	**40.8** ± 1.2
	15	40.2 ± 1.2	41.5 ± 1.0	**42.5** ± 0.7
medium-expert	9	**14.7** ± 8.6	13.1 ± 8.0	11.9 ± 5.9
	11	**21.4** ± 5.5	19.6 ± 4.9	18.7 ± 2.7
	13	**25.3** ± 14.9	25.3 ± 13.8	25.3 ± 14.8
	15	**40.8** ± 8.4	37.9 ± 12.9	31.1 ± 6.4
expert	9	6.2 ± 2.0	6.6 ± 2.8	**6.7** ± 2.9
	11	8.8 ± 6.5	9.1 ± 7.6	**12.8** ± 10.5
	13	24.5 ± 25.7	**25.0** ± 29.8	24.7 ± 28.8
	15	**59.4** ± 22.1	55.4 ± 25.0	52.8 ± 23.0

Table 10: Results on D4RL HalfCheetah-v0 dataset

Difficulty	Dimension	Baseline	Transfer (0.5,0.5)	Transfer (0.0,1.0)
medium-replay	9	2.3 ± 2.0	3.7 ± 4.7	**7.4** ± 3.6
	11	3.0 ± 4.4	5.2 ± 4.4	**8.3** ± 4.3
	13	6.9 ± 1.6	10.2 ± 3.4	**12.5** ± 3.5
	15	11.2 ± 2.7	10.0 ± 5.8	**16.0** ± 3.7
medium	9	8.8 ± 5.5	**11.5** ± 5.5	10.7 ± 4.2
	11	12.8 ± 6.0	**20.3** ± 8.9	17.1 ± 8.3
	13	25.9 ± 13.1	**37.0** ± 14.1	35.1 ± 20.4
	15	50.5 ± 12.8	57.9 ± 15.1	**67.3** ± 12.4
medium-expert	9	7.1 ± 4.1	10.1 ± 6.2	**15.4** ± 9.9
	11	15.8 ± 8.0	24.6 ± 5.1	**37.5** ± 20.7
	13	39.5 ± 17.4	50.6 ± 27.8	**67.4** ± 14.7
	15	89.1 ± 9.6	95.1 ± 14.7	**96.9** ± 10.4
expert	9	11.3 ± 8.3	11.1 ± 6.7	**13.8** ± 8.1
	11	21.9 ± 8.6	30.1 ± 10.5	**30.2** ± 13.3
	13	48.9 ± 27.3	60.4 ± 25.1	**61.1** ± 28.8
	15	93.4 ± 8.3	95.6 ± 9.1	**96.5** ± 7.8

Table 11: Results on D4RL Walker2d-v0 dataset