A Study of Generalization in Offline Reinforcement Learning

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Abstract

Despite the recent progress in offline reinforcement learning (RL) algorithms, these methods are still trained and tested on the same environment. In this paper, we perform an in-depth study of the generalization abilities of offline RL algorithms, showing that they struggle to generalize to new environments. We also introduce the first benchmark for evaluating generalization in offline learning, collecting datasets of varying sizes and skill-levels from Procgen (2D video games) and WebShop (e-commerce websites). The datasets contain trajectories for a limited number of game levels or natural language instructions and at test time, the agent has to generalize to new levels or instructions. Our experiments reveal that existing offline learning algorithms perform significantly worse than online RL on both train and test environments. Behavioral cloning is a strong baseline, typically outperforming offline RL aprpoac and sequence modeling approaches when trained on data from multiple environments and tested on new ones. Finally, we find that increasing the diversity of the data, rather than its size, improves generalization for all algorithms. Our study demonstrates the limited generalization of current offline learning algorithms highlighting the need for more research in this area.

1 Introduction

Offline Reinforcement Learning (RL) [77] has demonstrated significant potential in application domains where online data collection can be expensive or dangerous, such as healthcare [81], education [110], robotics [109], or autonomous driving [60, 96]. The abillity to generalize to new scenarios is crucial for the safe deployment of these methods particularly in such high-stakes domains. However, the generalization capabilities of offline RL algorithms to new environments (with different initial states, transition functions, or reward functions) remains underexplored. A key reason for this is that existing offline RL datasets predominantly focus on singleton environments where all trajectories are from the same environment (such as playing an Atari game or making a humanoid walk), thereby limiting the evaluation of generalization. This paper aims to investigate the generalization performance of offline learning algorithms (including behavioral cloning, sequence modeling [17], and state-of-the-art offline RL [34, 35, 65, 63] approaches) by assessing them on two different scenarios: (1) *unseen levels* in the case of Procgen [22] and (2) *unseen instructions* in the case of WebShop [123]. Our results show that none of the benchmarked offline learning methods, i.e. BCQ [34], CQL [65], IQL [64], BCT and, DT [17] are able to generalize as well as behavioral cloning (BC) and emphasize the need to develop offline learning methods with better generalization capabilities.

In this work, we first introduce a collection of offline RL datasets of different sizes and skill-levels from the Procgen [22] and WebShop [123] to facilitate a comprehensive evaluation of the generalization capabilities of offline learning algorithms. The Procgen benchmark consists of 16 procedurally generated 2D video games which differ in their visual appearances, layouts, dynamics, and reward functions. Since the levels are procedurally generated, generalization to new levels can be

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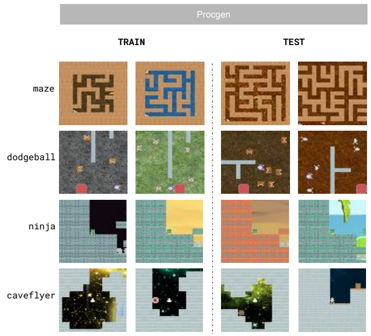


(a)

Train Instructions

Instruction 1: i am looking for yuanl 2 pcs stainless steel tongue scraper to clear out the white, coated layer on your tongue or maintain better oral hygiene, this effective tongue scraper for adults and kids, and price lower than 40.00 dollars

Instruction 2: i'm looking for an easy to use electric foot grinder in blue, and price lower than 50.00 dollars

Instruction 3: i'm looking for a 4-tier shelving unit and tv stand that is espresso and classic black color. also, it should have engineered wood, and price lower than 90.00 dollars

Test Instructions

Instruction 1: i am looking for a high power sound column subwoofer, that uses bluetooth and is also a 3d surround sound system, and price lower than 660.00 dollars

Instruction 2: i would like to buy a 14 inch rose gold throw pillow cover for my living room, and price lower than 50.00 dollars

Instruction 3: i'm trying to find white bluetooth speakers that are not only water resistant but also come with stereo sound, and price lower than 50.00 dollars

(b)

Figure 1: (a) Sample screenshots from the train and test environments of four Procgen games. (b) Sample instructions (item descriptions) from the train and test set of human demonstrations from WebShop. Red and blue highlight the type and attributes of the desired item, respectively.

assessed in this benchmark. We create a number of Procgen datasets that aim to test an agent's ability of *solving new levels* i.e., with the same reward function but different initial states and dynamics.

Webshop is a simulated e-commerce website environment with more than 1 million real-world products. Given a text instruction describing the desired product, the agent needs to navigate multiple types of webpages and issue different actions to find, customize, and purchase an item. We create a number of WebShop datasets both by using the human demonstrations provided and by generating suboptimal trajectories, which aim to test an agent's ability of *following new instructions* i.e., with the same dynamics but different initial states and reward functions. Figure 1 shows some sample observations from Procgen and trajectories from WebShop.

We then benchmark a variety of widely-used offline learning algorithms, allowing us to verify the generalization of these algorithms and establish baselines for future research. On the expert and suboptimal datasets from Procgen (Section 5.1), all offline learning methods underperform online RL at test time, with BC outperforming many of the offline RL and sequence modeling approaches. On WebShop's human demonstrations dataset (Section 5.6), BC again outperforms offline RL baselines in terms of both final score and success rate. We also study the generalization of these algorithms as the diversity (Section 5.4) and size (Section 5.5) of the training data increases, observing that an increase in data diversity significantly improves generalization while increasing the size of training data does not. These findings not only provide insights into the strengths and weaknesses of existing algorithms but also emphasize the necessity for more research on understanding and improving generalization in offline learning. We hope our datasets, baselines, and proposed evaluation protocols will lower the barrier for future research in this area.

2 Background

This work studies the effectiveness of offline learning algorithms in *contextual Markov decision processes* [CMDPs; 41]. A CMDP is defined as a tuple $\mathcal{M} = (\mathcal{C}, \mathcal{S}, \mathcal{A}, \mathcal{M}(\mathrm{c}))$, where $\mathcal{C}$ is the set of contexts, $\mathcal{S}$ is the set of states, $\mathcal{A}$ is the set of actions and $\mathcal{M}$ is a function that maps a specific context $\mathrm{c} \in \mathcal{C}$ to a Markov decision process [115, MDP] $\mathcal{M}(\mathrm{c}) = (\mathcal{S}, \mathcal{A}, \mathcal{T}^{\mathrm{c}}, \mathcal{R}^{\mathrm{c}}, \rho^{\mathrm{c}})$, where $\mathcal{T}^{\mathrm{c}} : \mathcal{S} \times \mathcal{A} \times \mathcal{C} \to \mathcal{S}$ is the contextual transition function, $\mathcal{R}^{\mathrm{c}} : \mathcal{S} \times \mathcal{C} \to \mathbb{R}$ is the contextual reward function, and ρ^{c} is the initial state distribution conditioned on the context. Given a CMDP, reinforcement learning (RL) seeks to maximize the value of the agent's policy π defined as $\mathbb{E}\left[\sum_{t=0}^{T} r_t \gamma^t\right]$, where r_t is the reward at time t and T is the time horizon.

Note that $\mathrm{c} \in \mathcal{C}$ is not observable. The space of contexts $\mathcal{C}$ will be split into a training set $\mathcal{C}_{train}$, a validation set $\mathcal{C}_{val}$, and a test set $\mathcal{C}_{test}$. For Procgen, we use $|\mathcal{C}_{train}| = 200$, $|\mathcal{C}_{val}| = 50$, and $|\mathcal{C}_{test}| = 100$, as followed by [22, 100, 54], while for WebShop we use $|\mathcal{C}_{train}| = 398$, $|\mathcal{C}_{val}| = 54$, and $|\mathcal{C}_{test}| = 500$ instructions, unless otherwise noted [123]. The training contexts are used for generating the datasets, the validation ones are used for performing hyperparameter sweeps and model selection, and the test sets are used to evaluate the agents via online interactions with the environment. In the case of Procgen, the context c corresponding to an instance of the environment (or level) an $\mathcal{M}(c)$ determines the initial state and transition function. In the case of Webshop, the context c corresponding to an instance of the environment (or instruction) $\mathcal{M}(c)$ determines the initial state and reward function.

In this paper, the agents *learn from an offline dataset* $\mathcal{D}$ which contains trajectories generated by a behavior policy π_B by interacting with the training contexts. This policy can have different degrees of expertise (e.g., expert or suboptimal), hence the offline learning algorithms must learn to extract meaningful behaviors using this static dataset without access to any online interactions with the environment. Since the dataset is fixed, it typically does not cover the entire state-action distribution of the environment. Because of this, offline RL algorithms can suffer from distributional shift and hence, they must employ techniques that enable them to generalize to new states at test time [77] or prevent sampling actions which are out-of-distribution [65, 34, 64].

3 Experimental Setup

3.1 Datasets

We collect the following datasets as part of our offline learning benchmark: (1) Procgen expert dataset with 1M transitions, (2) Procgen suboptimal dataset with 1M transitions, (3) Procgen expert dataset with 10M transitions, (4) Procgen mixed suboptimal-expert dataset with 25M transitions, (5) WebShop human dataset with 452 trajectories, (6) WebShop suboptimal datasets with 100, 1K, 1.5K, 5K, and 10K trajectories

More specifically, we collect data from 200 different Procgen levels for offline training, validate the hyperparameters on the another 50 levels, and evaluate the agents' online performance on the remaining levels, i.e. level_seed $\in [250, \infty)$.

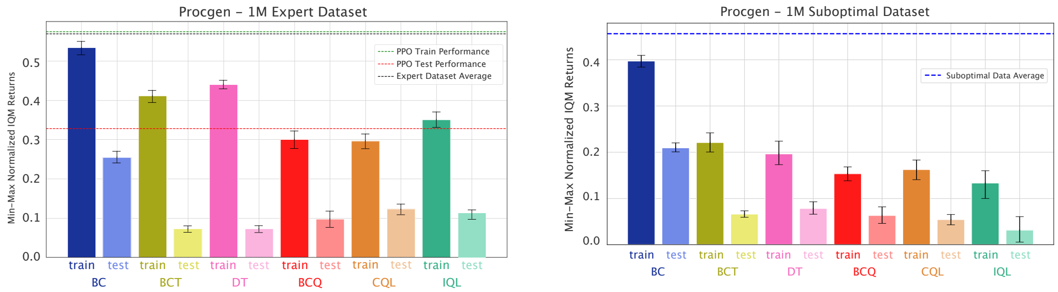
For more details on the process for collecting these datasets and their reward distributions, see Appendix F. We also explain the architecture used for the underlying policy in Appendix G.2.1.

3.2 Baselines

For the Procgen datasets, we evaluate 7 methods which are competitive on other offline learning benchmarks [69, 31, 2, 1] and frequently used in the literature [31, 39, 97]:

4 Methods Used

- **Behavioral Cloning (BC)** is trained to predict the actions corresponding to all states in the dataset, via cross-entropy loss. This baseline is parameterized by either a ResNet [46] (in the case of Procgen) or a BERT [24] (in the case of WebShop), takes as input the current state and outputs a probability distribution over all possible actions.
- **Batch Constrained Q-Learning (BCQ) [35]** restricts the agent's action space to actions that appear in the dataset for a given state, in an effort to reduce distributional drift which is one of the main challenges in offline RL.
- **Conservative Q-Learning (CQL) [65]** regularizes the Q-values by adding an auxiliary loss to the standard Bellman error objective, in an effort to alleviate the common problem of value overestimation in off-policy RL.
- **Implicit Q-Learning (IQL) [64]:** uses expectile regression to estimate the value of the best action in a given state, in order to prevent evaluating out-of-distribution actions.
- **Behavioral Cloning Transformer (BCT) [17]** is a transformer-based version of BC, where the agent's policy is parameterized by a causal transformer with a context containing all previous (state, action) pairs in the episode. The agent has to predict the next action given the current state and episode history.
- **Decision Transformer (DT) [17]** is similar to BCT but in addition to the state and action tokens, the context also contains the return-to-go at each step. The agent has to predict the action and the current return-to-go given state and episode history. At test time, DT is conditioned on the maximum possible return-to-go for that particular game.



(a) Expert

(b) Suboptimal

Figure 2: **Performance on Procgen.** Train and test min-max normalized returns aggregated across all 16 Procgen games, when trained on (a) expert and (b) suboptimal demonstrations. Each method was evaluated online across 100 episodes on levels sampled uniformly from the test set. The IQM aggregate metric is computed over 5 model seeds, with the error bars representing upper (75th) and lower (25th) interval estimates. For both datasets, BC outperforms all offline RL and sequence modelling approaches on both train and test environments. All offline learning methods lag behind online RL on both train and test.

For the WebShop datasets, we evaluate BC, CQL and BCQ. We cannot evaluate existing transformer-based approaches such as DT or BCT due to their limited context lengths of the underlying causal transformer.. Many WebShop states have 512 tokens, so we typically cannot fit multiple (state, action) pairs in the transformer's context. Similarly for IQL, it is not straightforward to implement the loss function since in WebShop, the action space differs for each state so the size of the action space is not fixed. Since these algorithms cannot be applied to WebShop without significant changes, they are out-of-scope for this paper.

Evaluation Metrics For Procgen, we report the mean and standard deviation across 5 model seeds for each game, as well as the inter-quartile mean (IQM) [4] and mean normalized return averaged across all 16 games. We follow Agarwal et al. [2] which showed that IQM is a more robust metric than the mean or median when reporting aggregate performance across multiple tasks, especially for a small number of runs per task. For WebShop, we follow the recommended procedure in Yao et al. [123] and report the average scores and success rates on a set of train and test instructions.

5 Experimental Results

5.1 Generalization to New Environments using Expert Data

Figure 2a shows the IQM performance [4] of baselines averaged across all 16 Procgen games when trained using the 1M expert dataset, normalized using the min-max scores provided in [22]. We follow Agarwal et al. [2] which showed that IQM is a more robust metric than the mean or median when reporting aggregate performance across multiple tasks, especially for a small number of runs per task. As we can see, *BC outperforms all other sequence modeling or offline RL methods by a significant margin on both train and test levels.* This is in line with prior work which also shows that BC can outperform offline RL algorithms when trained on expert trajectories [77]. Sequence modeling approaches like DT and BCT perform better than offline RL methods on the training environments, but similarly or slightly worse on the test environments. The gap between BC and DT or BCT is small for training, but large for test. This indicates that, *relative to standard BC, transformer-based policies like DT or BCT, may struggle more with generalization to new scenarios, even if they are just as good on the training environments.* For per-game performance, refer to Figure 18 and Table 5 in Appendix M.

Generalization to New Environments (Expert Dataset)

Existing offline RL and sequence modeling approaches struggle to generalize to new environments when trained on expert demonstrations, performing worse at test time than online RL methods trained on the same environments. Behavioral cloning is a competitive approach, outperforming all other offline learning baselines on both train and test.

5.2 Generalization to New Environments using Mixed Expert-Suboptimal Data

In the previous section, we observed that offline RL methods struggle to generalize to new environments when trained on expert demonstrations. Prior works [11, 65, 64] on singleton environments (where agents are trained and tested on the same environment) show that state-of-the-art offline RL methods typically outperform BC when trained on suboptimal demonstrations. In this section, we investigate whether this finding holds when agents are trained an tested on different environments.

For this, we create a mixed, expert-suboptimal dataset by uniformly mixing data from the expert PPO checkpoint and another checkpoint whose performance was 50% that of the expert. Therefore, these datasets have average episodic returns of about 3/4th those of the expert datasets.

Contrary to prior results on singleton environments, Figure 2b shows that even with suboptimal data, BC outperforms other offline learning baselines on test levels. However, all methods have a similar generalization gap (Figure 24 from Appendix M), suggesting that their generalization abilities are similar. This result indicates that BC can train better on diverse datasets containing trajectories from different environments relative to other offline learning approaches, even if these demonstrations are subotpimal. In Procgen and other CMDPs, it is common for methods with better training performance to also have better test performance since learning to solve all the training tasks is non-trivial and existing algorithms are typically underfitting rather than overfitting. Hence, in such settings the challenges lie both in optimization and generalization [55].

IQL, which achieved state-of-the-art on other singleton environments [64], struggles to train well on data from multiple levels and also fails to generalize to new levels at test time. Thus, it appears that training on more diverse datasets with demonstrations from different environments and generalizing to new ones poses a significant challenge to offline RL and sequence modeling approaches, despite their effectiveness when trained on more homogenous datasets from a single environment. However, this finding is not necessarily surprising since these offline learning methods have been developed on singleton environments and haven't been evaluated on unseen environments (different from the training ones). Hence, we believe the community should focus more on the setting we propose here (testing agents in different environments than the ones used to collect training data) in order to improve the robustness of these algorithms and make them better suited for real-world applications where agents are likely to encounter new scenarios at test time.

Generalization to New Environments (Suboptimal Data)

Behavioral cloning outperforms state-of-the-art offline RL and sequence modeling methods on both train and test environments when learning from suboptimal data. All offline learning methods struggle to generalize well to new environments when trained on suboptimal demonstrations.

5.3 Training and Testing on a Single Environment

In the previous section, we found that, when trained on data form multiple environments and tested on new ones, BC outperforms offline RL algorithms. However, prior work showed that offline RL methods typically outperform BC when trained on suboptimal data from a single environment an tested on the same environment [65, 66, 11]. At the same time, BC has been shown to outperform offline RL when trained on expert data from a single environment. Here, we aim to verify whether these observations hold in Procgen in order to confirm the correctness of our implementations.

Therefore, in this section, we show the results when training and testing agents on expert and suboptimal data from a single level. We conduct this experiment across two different datasets with either expert or suboptimal demonstrations, two different game levels with seeds 40 and 1, and all 16 Procgen games. We collect 100,000 expert trajectories in both of these levels by rolling out the final PPO checkpoint, and 100,000 suboptimal trajectories in both of these levels by uniformly sampling out the transitions from two checkpoints, the final one and another checkpoint whose performance is 50% that of the final checkpoint, similar to what we did in the previous section.

Figure 3 shows the performance of these baselines when trained on the expert and suboptimal datasets from level 40. In Appendix I, we report aggregate performance on the expert and suboptimal datasets, as well as per-game performance on both datasets on all 16 games. Figure 3 (top) shows the results when training on the expert dataset, where most offline learning methods perform about as well as PPO, with many of these algorithms achieving the maximum score possible (see Coinrun, Leaper, Ninja, Maze, Miner in Figure 11 from Appendix I).Figure 3 (bottom) shows the results when training on the suboptimal dataset, where on dodgeball, miner, and starpilot games (in expert dataset too) offline RL methods are either comparably to or better than BC thus, which is in line with prior work. However, there are a few exceptions where BC outperforms offline RL methods, namely on Chaser, Heist and Plunder. On Heist and Plunder, sequence modelling is comparable to BC. Overall, on expert dataset, except Chaser, on all other 15 games offline RL and sequence modelling methods are comparable or better than BC. On suboptimal dataset, however, in addition to Chaser, these methods do not perform as well as BC on Heist and Maze as well but on remaining 13 games offline learning is either greater than or equal to BC. For Chaser, we think the underlying environment dynamics favour imitation learning more than other methods as similar conclusion is seen in another single level dataset (collected from level seed 1) in Figures 12 and 13. However, note that in level seed 1, offline learning is as well as BC in Heist and Maze too. We report the results on level 1 in Appendix I. These results are consistent with the broader literature which shows that offline RL generally performs comparable to, or in some case, better than BC when trained and tested on suboptimal demonstrations from the same environment. However, as shown in previous sections, this finding does not hold true when these algorithms are trained and tested on multiple different environments. In such settings, BC tends to outperform other offline learning methods as shown here.

Training and Testing on a Single Environment

All offline learning algorithms perform well when trained and tested in the same environment but struggle to learn and generalize when trained on multiple environments and tested on new ones. When trained and tested on the same environment using expert data, behavioral cloning performs best, as expected. When using suboptimal data, offline RL performs comparable to or better than behavioral cloning on most games, which is in line with prior work.

5.4 The Effect of Data Diversity on Generalization

To investigate the role of data diversity on the generalization capabilities of offline learning algorithms, we conduct an experiment to analyze how the performance of each offline learning algorithm scales with the number of training levels while keeping the dataset size fixed to 1M transitions. We run these experiments on Procgen. We consider 200, 400, 800, 1k, 10k and 100k training levels. For each game, we train PPO policies for 25M steps on the corresponding number of levels. We then use the final PPO checkpoints (after 25M training steps) to collect a total of 1M transitions (from the corresponding levels) and train each offline learning algorithm on these datasets (using the same hyperparameters for all datasets). To evaluate these policies, we follow the procedure outlined in Section G.2.1. More specifically, for each dataset we randomly sample 100 test levels from $[n, \infty)$

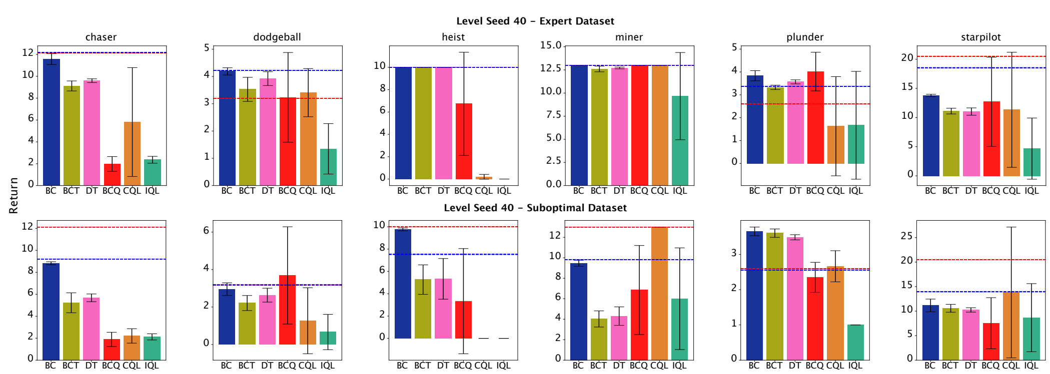
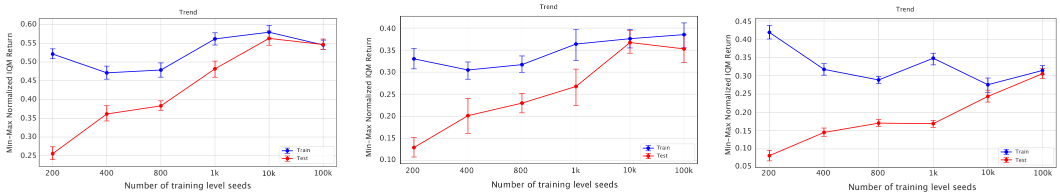


Figure 3: Performance of each baseline across selected Procgen games when **trained and tested on the same level using expert and suboptimal dataset**. Blue line represents the dataset average and red line represents the performance of our expert PPO checkpoint on this level. Here we report performance on selected levels: Chaser, Dodgeball, Heist, Miner, Plunder and Starpilot. For all games, refer to Figures 10 and 11 in Appendix I.



(a) BC (b) BCQ (c) DT

Figure 4: **The Effect of Data Diversity on Performance.** Train and test performance of offline learning algorithms for varying number of training levels in the 1M expert datasets, aggregated across all Procgen games. The plot shows the IQM and error bars represent the 75-th and 25th percentiles computed over 3 model seeds. While the training performance doesn't change much with the number of training levels, the test performance increases (and generalization gap decreases) with the diversity of the dataset.

where $n \in [250, 450, 850, 1050, 10050, 100050]$, respectively, and evaluate the models via online interactions with these levels. In each case, the levels from $[n-51, n-1]$ are used for evaluation and the remaining ones from $[0, n-51]$ are used for training. Since we use a fixed number of transitions for all datasets, the number of levels is a proxy for the dataset diversity. Figure 4 shows that:

The Effect of Data Diversity on Generalization

Increasing the diversity of the dataset by, for example, increasing the number of training environments while keeping the size of the dataset fixed, leads to significant improvements in generalization to new environments.

This finding suggests that in order to train better-generalizing agents using offline data, we should create diverse datasets covering a broad range of experiences.

Note that the results presented here use 50 levels for validation for each run. We also experiment with a proportional number of validation levels (with respect to the number of training levels) in Appendix K and find that it leads to the same conclusion.

5.5 The Effect of Data Size on Generalization

In other domains of machine learning, it is well-established that dataset size can play a pivotal role in model performance and generalization [66, 59]. While the significance of the data diversity has been underscored in the previous section, the impact of the dataset size remains an open question. In this section, we investigate how generalization correlates with the dataset size when the diversity and quality of the dataset is fixed. For this, we scale the training datasets, both expert and suboptimal, in Procgen by progressively increasing the dataset size from 1 million to 5 million and subsequently to 10 million transitions. Throughout this scaling process, we keep all other hyperparameters same as well as the number of training levels constant at 200.

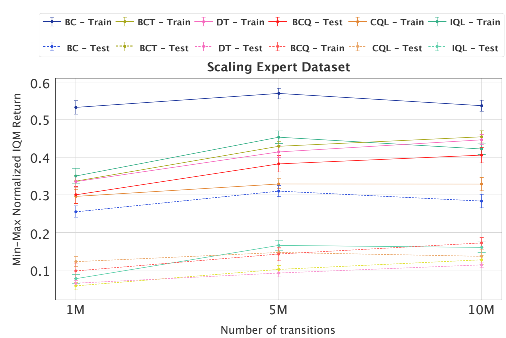


Figure 5: **The Effect of Data Size on Performance (Expert)**. Train and test min-max normalized IQM scores for all offline learning algorithms as the size of the dataset is increased from 1 to 10 million transitions aggregated across 5 random trials. Scaling the dataset size while keeping the number of training levels fixed (to 200) leads to a slight increase in both train and test returns, but the generalization gap remains about the same.

Expert Dataset As can be seen in Figure 5, across four offline learning algorithms, there is only a slight increase in both train and test performance as a consequence of increasing the dataset size. However, note that the generalization gap remains almost constant. This indicates that increasing the diversity of the dataset (while maintaining its total size) can lead to a bigger generalization improvement than increasing the size of the dataset (while maintaining its diversity) (see Figure 4).

Suboptimal Dataset Here we use the entire training log of the behavioral policy (PPO) (Appendix H) and use a subset of interactions made by that agent as our offline dataset (see seed 1 in Figure 9) which has 25M transitions in total. *This approach of using the training trajectory of the behavioural policy and sampling mixed data out of it is also consistent with the previous literature ([2], [39], [65], [31]).* We then uniformly sample episodes from the dataset such that we get a mixed, suboptimal-expert training dataset in Procgen and the dataset size has almost 1 million, 5 million as well as 10 million transitions. Throughout this scaling process, we keep all other hyperparameters same as well as the number of training levels constant at 200. From Figure 6, it is evident that all the algorithms exhibit poor train and test performance, even with 10M transitions. In contrast with prior work showing that offline RL approaches learn well and even outperform BC when trained on suboptimal data, our experiments show that they still struggle when trained on data from multiple environments and tested on new ones, irrespective of the quality of the demonstrations (i.e., whether they are expert of suboptimal).

The Effect of Data Size on Generalization

Increasing the dataset size alone without increasing its diversity by, for example, increasing the number of transitions without also increasing the number of training environments, doesn't lead to significant generalization improvements.

5.6 Generalization to New Instructions using Human Demonstrations

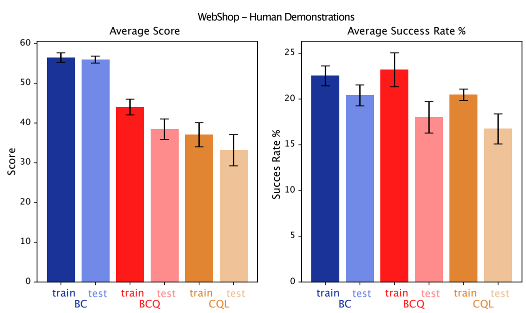
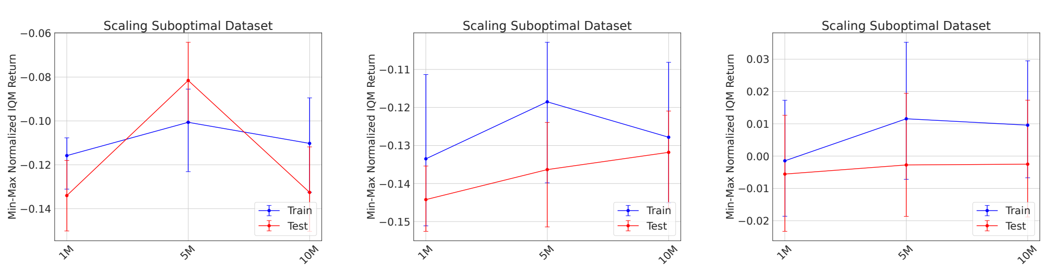


Figure 7: **Performance on WebShop.** Scores and success rates (%) for BC, BCQ, and CQL when trained on a dataset of human demonstrations from WebShop. Results were calculated by taking an average across 500 instructions (item descriptions) for both train and test. The mean and standard deviation were computed across 3 model seeds.

Here we aim to asses a different type of generalization, namely generalization to unseen initial state and reward functions. Moreover, we also want to test if our conclusions hold in more challenging and realistic domains, hence we benchmark three algorithms, BC, CQL and BCQ, on a challenging benchmark, WebShop. Figure 7 shows the train and test scores (where average score = average reward $*10$) and the success rate (i.e., % of rollouts which achieve the maximum reward of 10). While the average score measures how closely an agent policy is able to follow the given instruction, the success rate determines how correct the actions taken are. As per the results, BC on average gets a higher score but its success rate is lower than BCQ indicating that there are many instances where BC might click the buy" button on a product which it feels is closely related to the specified product, but on the other hand, BCQ will not do so and will click buy only when it is fully confident about the product. Following a similar evaluation procedure



(a) BC (b) BCQ (c) DT

Figure 6: **The Effect of Data Size on Performance (Suboptimal)**. Train and test min-max normalized IQM scores for BC, BCQ, and DT as the size of the suboptimal dataset ia increased from 1 to 10 million transitions. All algorithms have poor train and test performance (even when using 10M transitions). While the train performance slightly increases with the dataset size, the test performance does not vary much.

as in [123], for each of our pre-trained models, we roll out the policy on the entire test set of goals (i.e. $\in [0, 500)$) and the first 500 goals from the train set (i.e $\in [1500, 2000)$). For each offline learning algorithm, we compute the mean and standard deviation of the average train and test scores and success rates using 3 model seeds.

As Figure 7 shows, on the human demonstration dataset, BC achieves a higher score than CQL and BCQ, on both train and test instructions from the human dataset. Note that the difference between train and test scores in BC is not very large. However, if trained for longer, all of these methods obtain much better training performance but their test performance starts decreasing, suggesting that they are prone to overfitting. During training, BCQ has a slightly higher success rate than BC and CQL. At test time, however, BC achieves the highest success rate, thus making BC a better-performing baseline in this domain.

5.7 Generalization to New Instructions using Suboptimal Demonstrations in WebShop

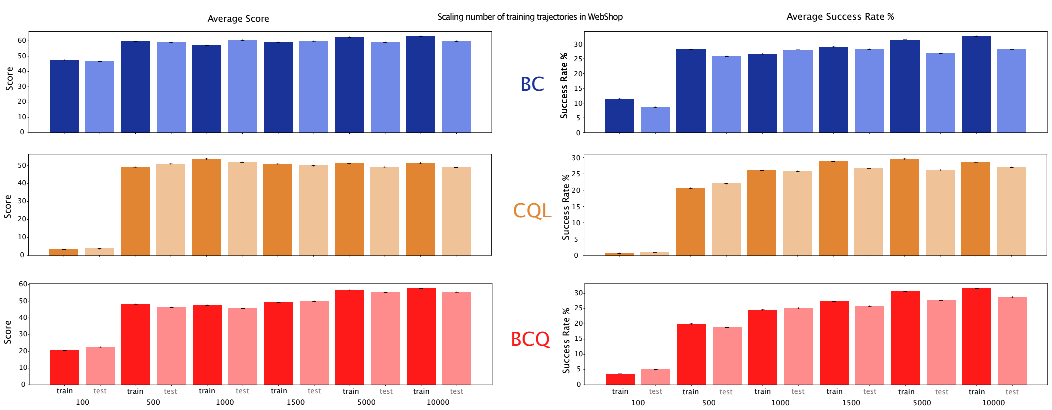


Figure 8: Score and success rate of each baseline on the WebShop environment when trained on various sizes of datasets. Once the dataset consists of 500 episodes, the performance increases significantly, however, beyond that the change in performance is not much.

Here we train BC, CQL and BCQ on dataset collected using a pre-trained behavioral cloning policy (see Appendix F.2) to test the effect of scaling the number of episodes (and hence the variety of goal instructions) on the performance of these baselines. Figure 8 shows that in all three baseline, the train and test performance significantly increases once the dataset has atleast 500 episodes. After that point, while there is not much increase in the scores in train and test levels, there is slight increasing trend in the success rates for BCQ and CQL.

Overall, similar to Procgen, BC outperforms both BCQ and CQL on all datasets, thus highlighting the need for more research in this area

6 Related Work

Generalization in RL A large body of work has emphasized the challenges of training online RL agents that can generalize to new transition and reward functions [102, 83, 58, 92, 127, 130, 90, 20, 21, 57, 70, 38, 16, 8, 10, 37, 61, 5, 26, 82]. A number of different RL environments have recently been created to support research on the generalization abilities of RL agents [56, 71, 106, 30, 6]. However, all of these simulators focus on benchmarking online rather than offline learning algorithms and don't have associated datasets. A natural way to alleviate overfitting is to apply widely-used regularization techniques such as implicit regularization [112], dropout [50], batch normalization [29], or data augmentation [126, 75, 74, 101, 121, 124, 43, 44, 62]. Another family of methods aims to learn better state representations via bisimulation metrics [129, 128, 3], information bottlenecks [50, 27], attention mechanisms [15], contrastive learning [85], adversarial learning [105, 32, 98], or decoupling representation learning from decision making [113, 111]. Other approaches use uncertainty-driven exploration [55], policy-value decoupling [100], information-theoretic approaches [16, 84], non-stationarity reduction [49, 91], curriculum learning [52, 117, 53, 93], planning [7], forward-backward representations [119], or diverse policies [68]. Note that all these works consider the online rather than offline RL setting. More similar to our work, Mazoure et al. [85] train an offline RL agent using contrastive learning based on generalized value functions, showing that it generalizes better than other baselines in some cases. However, they don't focus on creating offline RL benchmarks for generalization across both transition and reward functions, and they don't compare offline RL algorithms with other competitive approaches based on sequence modeling or transformer policies.

Offline RL Benchmarks For many real-world applications such as education, healthcare, autonomous driving, or robotic manipulation, learning from offline datasets is essential due to safety concerns and time constraints [23, 14, 79, 114, 118, 48, 94, 51]. Recently, there has been a growing interest in developing better offline RL methods [77, 96, 64, 34, 35, 2, 89, 33, 73, 104, 125, 12, 122, 131, 19] which aim to learn offline from fixed datasets without online interactions with the environment. With it, a number of offline RL datasets have been created [31, 97, 39, 13, 133, 103, 69]. However, all these datasets contain trajectories collected from a single environment instance. In contrast, our collected datasets aim to evaluate an agent's ability to generalize to environment instances after being trained purely offline on a dataset of trajectories from similar yet distinct environment instances. A number of large-scale datasets of human replays have also been released for StarCraft [120], Dota [9], MineRL [40], and MineDojo [28]. However, training models on these datasets requires massive computational resources, which makes them unfeasible for academic or independent researchers. More similar to ours, [42] introduces a large-scale offline RL dataset of trajectories from the popular game of NetHack [72] consisting of 3 billion state-action-score transitions from 100,000 bot trajectories. Here too, BC outperforms offline RL when trained on multiple environments and the algorithms need to generalize to do well at test time. However, this dataset requires significant resources to train highly performant agents, only considers generalization across different transition functions and not across different reward functions, and does not allow for a clear split between train and test scenarios. In contrast, one can train competitive agents on our datasets in just a few hours, making it a more accessible benchmark for generalization in offline RL that should enable fast iteration on research ideas.

7 Conclusion

In this paper, we conduct a comprehensive study on the generalization capabilities of some of the most widely-used offline learning methods. Our experiments show that offline learning algorithms (including state-of-the-art offline RL, behavioral cloning, and sequence modeling approaches) generalize worse) to new environments than online RL methods (like PPO. Moreover, our paper is first to introduce a benchmark for evaluating the generalization of offline learning algorithms. The absence of such a benchmark has historically limited our understanding of these algorithms' real-world applicability, so our work strives to bridge this gap. To achieve this, we release a collection of offline learning datasets containing trajectories from Procgen and WebShop. Our results suggest that existing offline learning algorithms developed without generalization in mind are not enough to tackle these challenges, which are crucial in order to make them feasible for real-world applications. We observe that increasing dataset diversity can lead to significant improvements in generalization even without increasing the size of the dataset. Contrary to prior work on offline RL in singleton environments, we find that their generalization doesn't significantly improve with the size of the dataset without also enhancing its diversity. Hence, we believe more work is needed to develop offline learning algorithms that can perform well on new scenarios at test time.

One promising avenue for future research is to combine offline RL methods with techniques that improve generalization in online RL such as data augmentation [74, 101, 124], regularization [112, 50, 29], representation learning [129, 128, 3, 85], or other approaches focused on data collection, sampling, or optimization [52, 99, 55]. It is also possible that entirely new approaches that take into account the particularities of this problem setting will need to be developed in order to tackle the challenge of generalization in offline learning. As mentioned in the paper, sequence modeling approaches that rely on transformer-based policies cannot be directly applied to more complex environments like WebShop due to their limited context lengths. Thus, we expect these methods will benefit from future advances in transformer architectures that can handle longer inputs. We hope our study and benchmark can enable faster iteration on research ideas towards developing more general agents that can learn robust behaviors from offline datasets.

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A Appendix

We will be open-osurcing our codebase and datasets upon acceptance. The code repository consists of two separate folders: 1. Procgen and 2. WebShop. Each of these sub-repositories have a well-documented README.md with all the necessary steps needed to reproduce the experimental results in this paper to implement and train other offline learning models, or to generate other datasets and use them.

License We will be releaseing the codebase and the datasets under a CC-by-NC license.

B Limitations and Future Work

In this section, we discuss some potential limitations of our work and suggest future research avenues. First, our main datasets in Procgen have 1 million transitions. Contrasting this with many offline RL datasets like Atari [2] where the dataset consists of the entire training trajectory from the behaviour policy, the dataset size could have been inflated to 25M (since in Procgen, PPO uses 25M evironment steps to reach convergence). We believe this is a good step. However, training offline learning methods on such large datasets requires multi-GPU parallelism and significant computational resources, especially when using sequence modelling approaches. Thus, we opted for a more lightweight dataset which can enable a broad community of researchers to make progress on these problems without requiring extensive computational resources. Future work could explore the possibility of leveraging larger datasets, while seeking more efficient computational strategies.

We also note that all of our datasets have a discrete action space. Lately, numerous offline RL algorithms [45, 36], have been developed exclusively for continuous action spaces. Adapting their loss function to discrete action space is a non-trivial task, so we leave it to future work to address this conversion problem which should extend the applicability of these algorithms.

Our datasets from the WebShop environment did not explore cross-product (i.e. training on selected instructions having some categories of products and testing on never-seen-before categories) generalization, an aspect that could be a fascinating direction for subsequent studies. The ability of models to generalize across diverse products could prove extremely useful in web-navigation environments. It is also worth considering the latest improvements like [18, 88], that make transformer models better at handling longer context length in situations like WebShop. This could help deal with the problem of long inputs in the state space. This might allow us to use sequential decision-making like the Decision Transformers that require multiple steps of observations in one context.

Lastly, Offline RL algorithms have a quadratic error bound on the horizon since there is no control over the data-generating policy and it may require evaluating out-of-distribution states [77]. However, this theoretical observation has only been empirically validated on singleton environments. The goal of our study is to empirically evaluate offline RL algorithms on new environments rather than provide a theoretical explanation. Our results are in line with the theoretical results demonstrating that offline RL algorithms struggle with generalization but only in theory but also in practice. We hope this will inspire future work that aims to overcome these limitations, as well as a theory of why existing offline RL algorithms struggle to generalize to new environments (which better models our setting and would be an extension of prior work on this topic).

C Broader Impact

This paper proposes datasets for evaluating generalization of behaviors learned offline via behavioral cloning, offline reinforcement learning, and other approaches. We also evaluate state-of-the-art methods on this benchmark, concluding that more work is needed to train agents that generalize to new scenarios after learning solely from offline data. On the one hand, improving the generalization of offline learning methods can be important for developing more robust and reliable autonomous agents that take reasonable actions even in states that they haven't encountered during training, which are likely to be common once such agents are deployed in real-world applications. On the other hand, deploying autonomous agents for high-stakes applications can have negative consequences, so additional safety precautions should be taken when considering deployment in the real-world. Since our results are based on simulated environments for video games and e-commerce like Procgen and

WebShop, which are somewhat simplified compared to real-world settings, we do not foresee any direct negative impact on society.

D Extended Related Work

Multi-task RL Recently, significant attention has been directed towards the large-scale multi-task offline RL and meta RL settings. Notably, pioneering multi-task approaches such as those outlined in Kumar et al. [67], Lee et al. [76], Taiga et al. [116] have showcased their efficacy in harnessing extensive multi-task datasets based on Atari Agarwal et al. [2]. However, these settings are different from the problem we consider our this paper. To elaborate, Lee et al. [76] pre-trains the model on select Atari games, followed by subsequent fine-tuning on the remaining ones. Similarly, a lot of meta RL works [80, 95, 132, 25, 86] also try to tackle this problem but require some finetuning at test time. In contrast, our benchmark centers around the evaluation of zero-shot generalization which is a more challenging setting with wider applicability in the real-world. Similarly, the works presented in Kumar et al. [65] and Taiga et al. [116] delve into the realm of inter-game generalization in Atari, employing a training dataset comprising of approximately 40 games. Our focus, in contrast, resides in scrutinizing intra-game inter-level generalization within the Procgen framework. It is worth highlighting that our dataset architecture prioritizes memory efficiency, allowing for seamless execution by the academic community without necessitating access to a large number of GPUs, a requirement which, regrettably, constrained the feasibility of the approaches proposed in [65] and [116] that heavily relies on many TPUs. This emphasis on accessible resources aligns with our intent to facilitate broader engagement and reproducibility in this research area.

E Discussion

In this section, we discuss a few points that we believe are the reasons why BC generalizes better than offline RL, even in the presence of suboptimal data. We believe the reason offline RL methods fall behind BC is that they adopt a risk-averse approach, avoiding actions not encountered during training. This becomes a limitation when agents are tested in new environments, as they are likely to default to suboptimal policies due to unfamiliar states. On the other hand, BC, unbounded by these constraints, utilizes its learned representations to select the best action by identifying the most similar training state to the current test state. If BC effectively learns state representations, it could generalize well in new environments. Regarding why offline learning methods are outperformed by online RL, we think that the advantage of online RL comes from its ability to gather and learn from a broader range of states through its own data collection, as opposed to the fixed dataset in BC and offline RL [2]. This exposure to a variety of states enables better learning of representations and decision-making in new scenarios. Our experiments in Section 5.4 demonstrate that training with more varied data significantly enhances offline learning methods' generalization. However, as indicated in Section 5.2, merely using data from multiple PPO checkpoints (i.e. in the case of suboptimal dataset) is not sufficient. This data, being sparsely sampled, doesn't cover the entire state space. Understanding how training dynamics affect data diversity is an area worth exploring in future research.

F Dataset Details

F.1 Procgen

Environment Procgen [22] is an online RL benchmark that serves to assess generalization in 16 different 2D video games. Procgen makes use of procedural content generation in order to generate a new level (corresponding to a particular seed) when the episode is reset. This way an unlimited number of varying levels can be generated for each game, each level having different dynamics, layouts, and visual appearances (such as background colors and patterns, or number and location of various items and moving entities), but the same reward function. This makes Procgen a good benchmark for testing an agent's ability to generalize to *new environment instances (levels) with unseen initial states and transition functions but the same reward function*.

A single transition in Procgen comprises of an observation (represented by an RGB image of shape 64x64x3), a discrete action (the maximum action space is 15), a scalar reward (which can be dense or sparse depending on the game), and a boolean value indicating whether the episode has ended.

Table 1: **Procgen 1M Dataset Average Return:** This table shows the average return of each game's dataset collected by different model seeds of the expert PPO policy, as well as the suboptimal dataset.

Game	Suboptimal	Expert			
	Seed 1	**Mixed**	**Seed 0**	**Seed 1**	**Seed 2**
Bigfish	10.61	9.57	12.03	14.01	6.69
Bossfight	6.05	8.31	8.32	8.10	8.62
Caveflyer	4.95	7.23	6.74	6.97	7.79
Chaser	5.32	6.50	5.95	6.68	6.93
Climber	6.37	8.58	8.30	8.53	8.59
Coinrun	7.16	9.42	9.23	9.64	9.33
Dodgeball	3.50	5.46	5.97	4.61	6.26
Fruitbot	22.36	29.21	29.97	29.81	29.15
Heist	5.96	7.85	7.84	7.97	7.26
Jumper	6.88	8.55	8.53	8.47	8.50
Leaper	2.03	2.68	2.68	2.71	2.72
Maze	6.83	9.35	9.44	9.22	9.33
Miner	9.40	12.68	12.78	12.46	12.74
Ninja	6.01	8.07	7.85	8.05	8.00
Plunder	4.15	5.26	5.34	5.53	5.05
Starpilot	20.93	27.23	26.75	27.69	29.34

Offline Data Collection Each level of a Procgen game is procedurally generated by specifying the $level\_seed$ which is a non-negative integer. We use levels $[0, 200)$ for collecting trajectories and offline training, levels $[200, 250)$ for hyperparameter tuning and model selection, and levels $[250, \infty)$ for online evaluation of the agent's performance.

To generate the offline learning datasets based on Procgen, for each game, we train 3 PPO [107] policies (with random seeds 0, 1, and 2) using the best hyperparameters found in [100] for 25M steps on the easy version of the game. We save model checkpoints once every 50 epochs (from a total of 1525 epochs). We then use these checkpoints to collect trajectories for constructing an *expert dataset* and a *suboptimal dataset*.

To create the *expert dataset*, we roll out the final checkpoint from a single pretrained PPO model, also referred to as the expert policy, in the training levels (i.e., allow it to interact online with the environment) and store 1 million $\{state, action, reward, terminated\}$ transitions for each Procgen game. Figures 20 and 21 show the number of episodes and transitions per level respectively. As can be seen, there can be variation in the number of transitions across the 16 games since some games have shorter episodes than others.

To create the *suboptimal datasets*, we evenly combine data from both the expert PPO checkpoint and another checkpoint that achieves 50% of the expert's performance. Consequently, these datasets showcase average episodic returns that are approximately 75% of those seen in the expert datasets. Table 1 shows the average return per dataset collected by different PPO model seeds for 1M transition steps. Since we ran our experiments on the 1M expert dataset collected from Seed 1, we also collected a suboptimal dataset using PPO's checkpoints from this model seed only. Figures 22 and 23 show the number of episodes per level and total number of transitions per level for each game in Procgen from the 1M *suboptimal* dataset (seed 1) which was used for all experiments in Section 5.2.

Data Storage For each episode, we store all the corresponding $\{state, action, reward, terminal\}$ transitions. Each trajectory is then stored as a single $.npz$ file, with the name of $timestamp\_index\_length\_level\_return$. This naming convention allows for analyzing and working with trajectories filtered by level or return.

F.2 WebShop

Environment WebShop [123] is a text-based web-navigation environment, built to assess the natural language instruction following and sequential decision making capabilities of language-based agents. In this environment, there are two types of tasks: search and choice. For the search task, the agent has to learn to generate relevant keywords based on a description of the desired product in order to increase the likelihood of getting a good product match within the search results. For the choice task, the agent needs to look through the search page and each item's individual page to select, customize, and buy the item that matches all the attributes mentioned in the instruction. Since the scope of our study is to assess the sequential decision making capabilities of offline agents, we limit our study to only the choice task. For the search task, we use a pre-trained BART model [78] used in [123] to generate a search query at test time and then continue rolling out our pre-trained policies.

Offline Data Collection For WebShop, we collect two types of offline learning datasets based on: (i) the *human demonstration dataset* provided by the authors which allows us to create a fixed size dataset of high quality (since the human demonstrations can be considered a gold standard), and (ii) the *imitation learning (IL) policy* pre-trained on these human demonstrations which allows us to create multiple datasets of varying sizes in order to study how performance scales with the dataset size and diversity. We also collect environment rewards for 452 out of 1571 human demonstrations provided by simulating the trajectories via the gym environment provided in WebShop's source code[2]. The initial state of this environment is determined by a random selection of 10 English letters. So we call the reset function repeatedly until the environment generates an instruction which is in the dataset. We then execute the actions of the episode from the dataset, and verify that the states returned by the environment per each step are the same as those in the dataset (except the last state, as the dataset doesn't store the *confirmation* state once an episode is completed). The rewards were collected on the fly and we stored them under the key "rewards" together with "states", "actions", etc. This way, we were able to collect 452 trajectories with their corresponding per-step rewards (out of 1571 in the human dataset) from the WebShop environment. Following the original paper, we represent observations using only the text modality. In the human dataset, we have 452 episodes, wherein the train split has 398 episodes, 3.7k transitions and an average reward of 7.54, and the evaluation split has has 54 episodes, 406 transitions and an average reward of 8. We also use the final IL checkpoint provided by the authors of WebShop to collect datasets of different sizes, i.e. $\in 100, 1000, 1500, 5000, 10000$ episodes, where in all of these datasets the average reward is 5.8-5.9. In this case, a larger dataset also has a greater diversity of environment instances specified by different natural language instructions (or item descriptions).

Data Storage Following Yao et al. [123], we store all episodes in a single $.json$ file.

G Hyperparameters

G.1 Behaviour Policy

Procgen We use PPO [108] as the behaviour policy for collecting datasets in the Procgen environment. The architecture consists of a ResNet [47] which encodes the 64x64 RGB images into a linear embedding, which is then processed by two parallel fully-connected layers, one for the actor and one for the critic with hidden dimension of 256. The policy is trained for 25M environment steps and checkpoints are saved regularly throughout this process. All of the hyperparameters are same as the one used in [100] and [22].

WebShop We use the pre-trained IL checkpoint provided on the GitHub repository of WebShop[3]. This policy consists of a 110M parameter BERT model for encoding the current states and a list of available actions, and outputs log probabilities over the available actions.

G.2 Model Training

Here we list down the set of hyperparameters used in each offline learning algorithm separately. Moreover, all offline RL baselines (i.e. BCQ, CQL and IQL), plus BC, had the same encoder size and type, which was a ResNet in the case of Procgen, and a BERT encoder in the case of WebShop. All of our experiments were run on a single NVIDIA V100 32GB GPU on the internal cluster, with varying training times and memory requirements.

[2] `https://github.com/princeton-nlp/WebShop`
[3] `https://github.com/WebShop/baseline-models`

Algorithm	Hyperparameter	1M Expert	1M Suboptimal	25M Mixed	10M Expert
BC	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Batch Size	256	256	256	256
BCT	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Batch Size	512	512	512	512
	Context Length	30	5	5	5
	Eval Return Multiplier	0	0	0	0
DT	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Batch Size	512	512	512	512
	Context Length	10	5	5	5
	Eval Return Multiplier	5	5	5	5
BCQ	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Batch Size	256	256	512	256
	Target model Weight Update	Direct copy	Polyak	Direct copy	Direct copy
	τ	-	0.5	-	-
	Target update frequency	1000	-	1000	1000
	Threshold	0.5	0.5	0.5	0.5
CQL	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Batch Size	256	256	256	256
	Target model Weight Update	Direct copy	Polyak	Direct copy	Direct copy
	τ	-	0.99	-	-
	Target update frequency	1000	-	1000	1000
	Alpha	4.0	4.0	4.0	4.0
IQL	Learning Rate	0.0005	0.0005	0.0005	0.0005
	Target model Weight Update	Direct copy	Polyak	Direct copy	Direct copy
	Batch Size	512	256	512	512
	τ	-	0.005	-	-
	Target update frequency	100	-	1000	100
	Temperature	3.0	3.0	3.0	3.0
	Expectile	0.8	0.8	0.8	0.8

Table 2: List of hyperparameters used in Procgen experiments

G.2.1 Procgen

Hyperparameters For BC, we performed a sweep over the batch size $\in \{64, 128, 256, 512\}$ transitions and learning rate $\in \{5e-3, 1e-4, 5e-4, 6e-5\}$. For BCQ, CQL, and IQL, which use a DQN-style training setup (i.e., they have a base model and a frozen target model) [87], in addition to the hyperparameters mentioned for BC, we swept over whether to use polyak moving average or directly copy weights, in the latter case, the target model update frequency $\in \{1, 100, 1000\}$ and in the former case, the polyak moving average constant $\tau \in \{0.005, 0.5, 0.99\}$. For BCQ, we also swept over the threshold value for action selection $\in \{0.3, 0.5, 0.7\}$. For CQL, we swept over the CQL loss coefficient, which we refer to as cql_alpha in our codebase, $\in \{0.5, 1.0, 4.0, 8.0\}$. Finally, for IQL, we sweep over the temperature $\in \{3.0, 7.0, 10.0\}$ and the expectile weight $\in \{0.7, 0.8, 0.9\}$.

For sequence modelling algorithms, DT and BCT, we sweep over the learning rate and batch size mentioned above, as well as the context length size $\in \{5, 10, 30, 50\}$. For DT, we also sweep over the return-to-go (rtg) multiplier $\in \{1, 5\}$. We follow similar approach in [17] to set the maximum return-to-go at inference time by finding the maximum return in the training dataset for a particular game and then multiplying by either 1 or 5 depending on the rtg multiplier value. We also use the default value of 0.1 for dropout in DT and BCT from [17].

We run 3 random trials per each configuration and select the best hyperparameter by looking at the min-max normalized mean train and validation results, averaged across all 16 games. Train results are calculated by rolling out the final checkpoint of the policy 100 times on training level and likewise for validation results, the policy is rolled out 100 times by randomly sampling one level at a time out of 50 validation levels. During our initial experiments we noticed that many of these algorithms overfitted quickly (within 10-20 epochs) on the training dataset. Therefore, to save training time and prevent overfitting, we employ early stopping by calculating the validation return after every epoch and stopping the training process if the validation return does not improve in the last 10 epochs. However, in Section 5.5, where the dataset size was either 5M or 10M transitions, we used fixed 3 epochs only.

Table 2 list the final hyperparameters for BC, BCQ, BCT, DT, CQL and IQL for 1M expert and suboptimal dataset, 10M expert dataset as well as for the single level experiments (except for IQL, which uses polyak averaging in single-level experiments). Since the 25M mixed suboptimal-expert dataset, which was used in Section 5.2, has a very different distribution than our synthetically created 1M suboptimal dataset (which had 75% returns of experts'), we ran a hyperparameter sweep on this dataset by uniformly sampling 1M transitions and following a similar procedure as above. We performed a similar sweep for the 10M expert dataset experiment as well. The best hyperparameters for this dataset are also listed in Table 2.

G.2.2 WebShop

Hyperparameters For BC, we performed a sweep over the batch size $\in \{1, 4, 8\}$ and learning rate $\in \{2e-5, 2e-4, 2e-3\}$. For BCQ and CQL, we swept over the target model update frequency $\in \{100, 1000\}$. For BCQ, we also swept over the threshold value for action selection $\in \{0.1, 0.5, 0.9\}$ and for CQL α, we swept over $\{4.0, 7.0\}$.

For the scaling experiment in Appendix 5.7, the sweep for BCQ threshold was even wider $\in \{0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$ with rest of the hyperparameters being the same from the best hyperparameter selected above.

We run 1 trial for each combination of hyperparameters and select the best performing one by rolling out the agent on all validation goal levels ($goal\_idx = (500, 1500)$) and on the first 500 train goal levels ($goal\_idx = (500, 1500)$). Final hyperparameters are listed in Tables 3 for BC, CQL and BCQ.

Algorithm	Hyperparameter	Human Demonstrations	IL Trajectories
BC	Learning Rate	0.00005	0.00005
	Batch Size	1	1
BCQ	Learning Rate	0.00005	0.00005
	Batch Size	1	1
	τ	0.005	0.005
	Target update frequency	100	1000
	Threshold	0.5	0.9
CQL	Learning Rate	0.00005	0.00005
	Batch Size	1	1
	τ	0.005	0.005
	Target update frequency	1000	100
	Alpha	7.0	4.0

Table 3: List of hyperparameters used in WebShop experiments

H Online Dataset Collection

To collect datasets for each of the 16 games within Procgen, we employed the Proximal Policy Optimization (PPO) algorithm [108] using the setup outlined in Raileanu and Fergus [100]. Specifically, our PPO training involved training the policy for 25 million environment steps, utilizing a set of 200 training levels. The hyperparameters are detailed in Table 4 which were shared across all 16 games.

To provide an overview of the policy's performance, Figure 9 depicts the training returns across each game for the entire 25 million environment steps for all 3 model seeds. Our expert dataset, which

Table 4: Table summarizing the hyperparameters used for PPO in Procgen

Hyperparameter	Value
γ	0.999
λ_{GAE}	0.95
PPO rollout length	256
PPO epochs	3
PPO minibatches per epoch	8
PPO clip range	0.2
PPO number of workers	1
Number of envs per worker	64
Adam learning rate	5e-4
Adam ϵ	1e-5
PPO max gradient norm	0.5
PPO value clipping	no
return normalization	yes
value loss coefficient	0.5
entropy bonus	0.01

is obtained online, is derived from the final checkpoint of this training procedure. Furthermore, we curated a suboptimal dataset by selecting a checkpoint having performance at 50% of the expert's level. The achieved returns for these checkpoints in each game are listed in Table 1.

For the WebShop game, we employed a pre-trained Imitation Learning (IL) checkpoint provided by [123] to collect training trajectories by rolling out the policy in the online environment. This particular checkpoint achieves a score of 59.9 (which corresponds to a mean reward of 5.99) and success rate 29.1% in the test set.

I Training and Testing on Single Level in Procgen

Here we show the results when training agents on expert and suboptimal transitions from level_seed=1 and testing online only on that level. Figures 14c and 12 show the performance of all baselines after training and testing on expert dataset from level 1, demonstrating that not just BC, but other offline RL baselines can learn well when trained on high-return demonstrations from singleton environments. Note that offline RL methods still seem to struggle more on some of the games, even when trained on demonstrations from a single level. Also note that here even the final checkpoint of PPO struggles in some games (achieving 0 reward), and we therefore report performance on level_seed=40 in Figures 14b, 10 and 11. Figure 14d and Figure 13 show the performance of these baselines when trained on suboptimal dataset in level_seed=1. Here, in 9 out of 16 games, Offline RL performs comparable or even better (in Bigfish, Fruitbot, Heist, Jumper) compared to BC and sequence modelling.

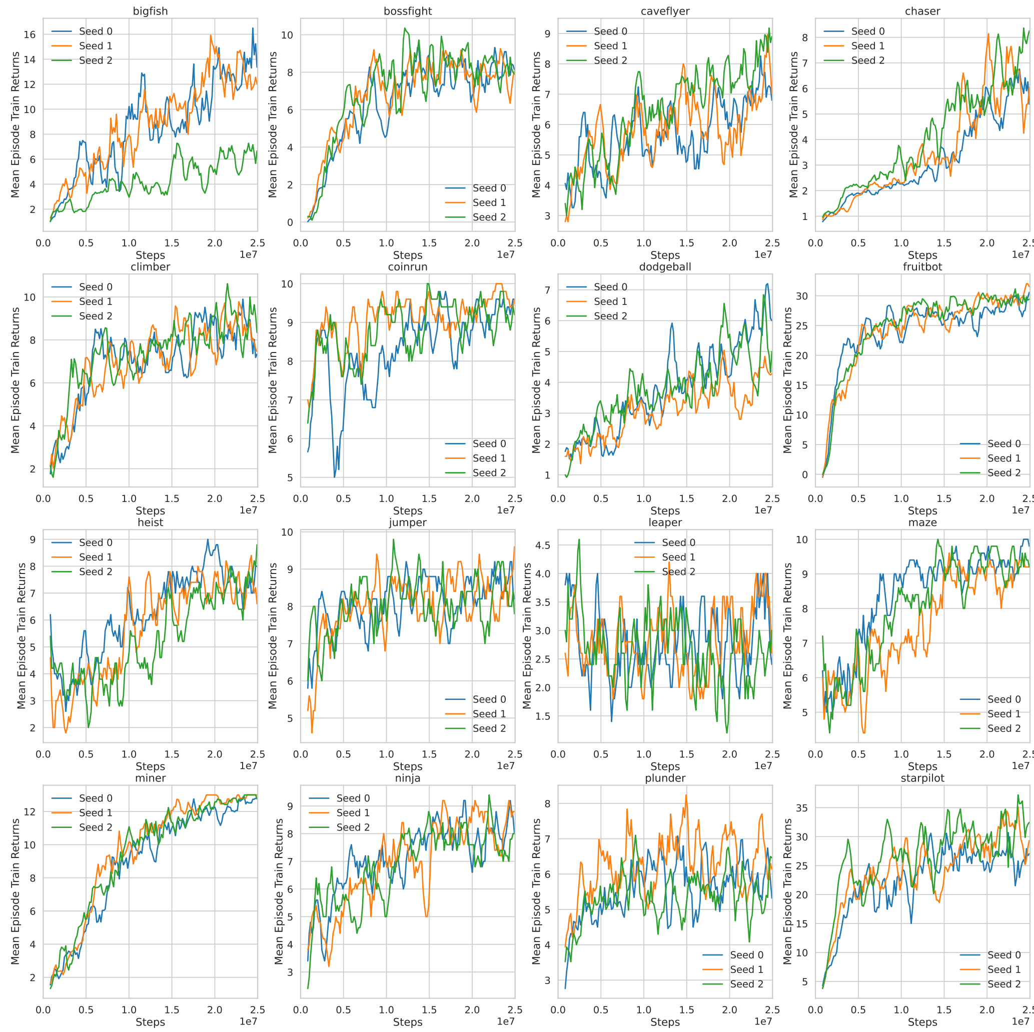


Figure 9: Training Returns for the Procgen data collecting behavioral policy PPO.

J Effect of Data Diversity on Generalization: More Results

Here we perform the same experiment from Section 5.4 on the remaining offline learning algorithms: BCT, CQL and IQL. Figure 15 shows similar trend here as well, i.e. on increasing the number of training levels in the dataset while keeping the dataset size fixed leads to lower generalization gap.

K Scaling number of validation levels in Procgen

In this section, we compare the use of a limited set of 50 validation levels in Section 4. We contrast this approach with a similar proportion of levels used for training. Specifically, if $[0, n)$ levels are allocated for training, then $[n, n + (0.1 * n))$ levels are reserved for validation. As illustrated in Figure 16, a notable trend emerges among all offline learning algorithms, indicating a robust correlation between the two aforementioned approaches. To maintain methodological consistency with our broader array of experiments presented in this paper, we advocate for the adoption of a consistent practice for this benchmark. Specifically, we suggest that researchers consider employing a level range of $[n, n + 50)$ exclusively for validation purposes.

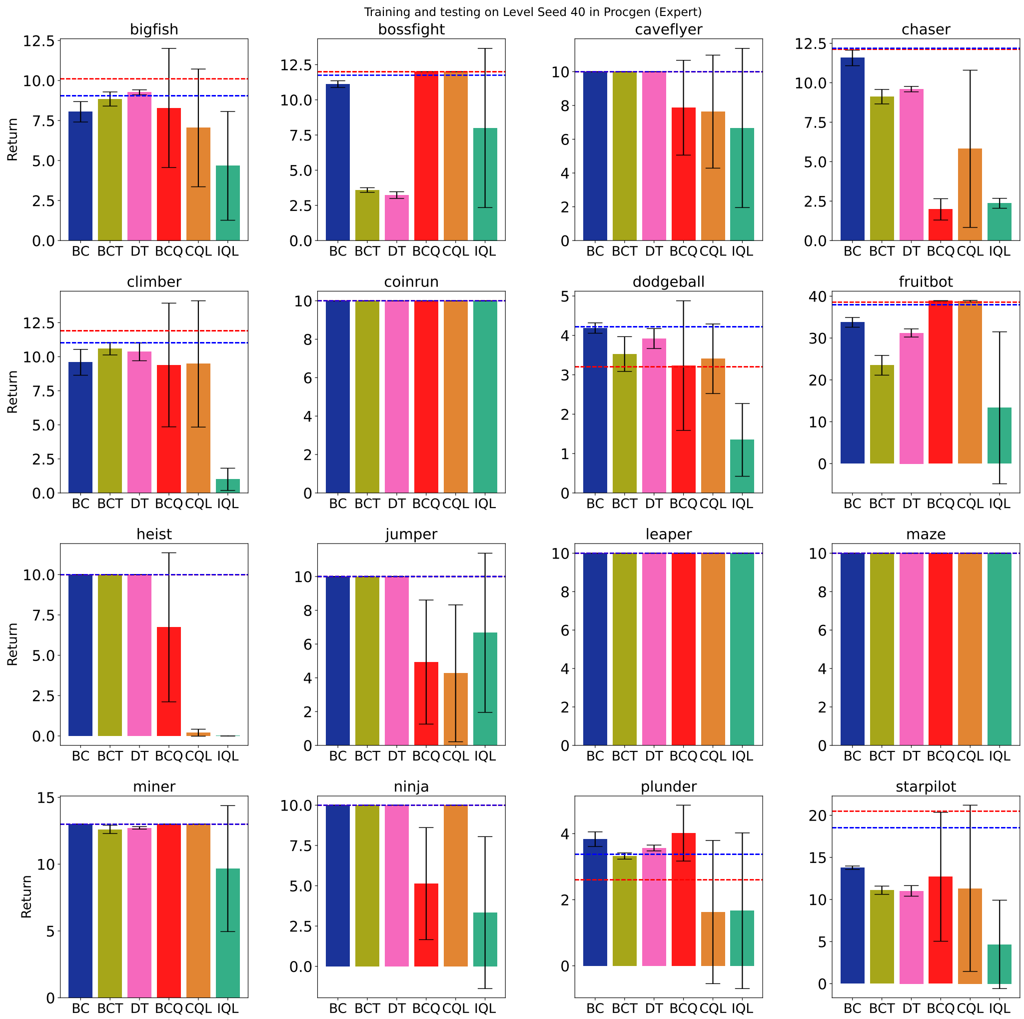


Figure 10: Performance of each baseline on level 40 in each Procgen game when **trained and tested on the same level using expert dataset**. Blue line represents the dataset average and red line represents the performance of our expert PPO checkpoint on this level.

L Effect of Suboptimal Data Size on Generalization: More Results

In this section, we perform the same experiment of scaling offline learning algorithms on the 25M mixed dataset from Section 5.5 on the remaining offline learning algorithms: BCT, CQL and IQL. We observe similar findings in Figure 17, i.e. all three methods have poor train and test aggregate performance and contrary to prior works, in our setup when we sample and train offline learning algorithms on a subset of episodes from the training log of the behavioral policy, the resulting offline learning policy does not generalize at all and does not even perform well on the 200 training levels as well.

M Per-game scores in Procgen

Figure 18 shows the performance of these baselines on each individual game when trained using 1M expert dataset. On the left, we compare the training returns which were calculated by averaging over 100 episodes by randomly sampling levels from the training set. The red line shows the average return of the trajectories in the training dataset. For most games, at least some of these methods match the average performance of the training data. Among the different approaches, BC is the most

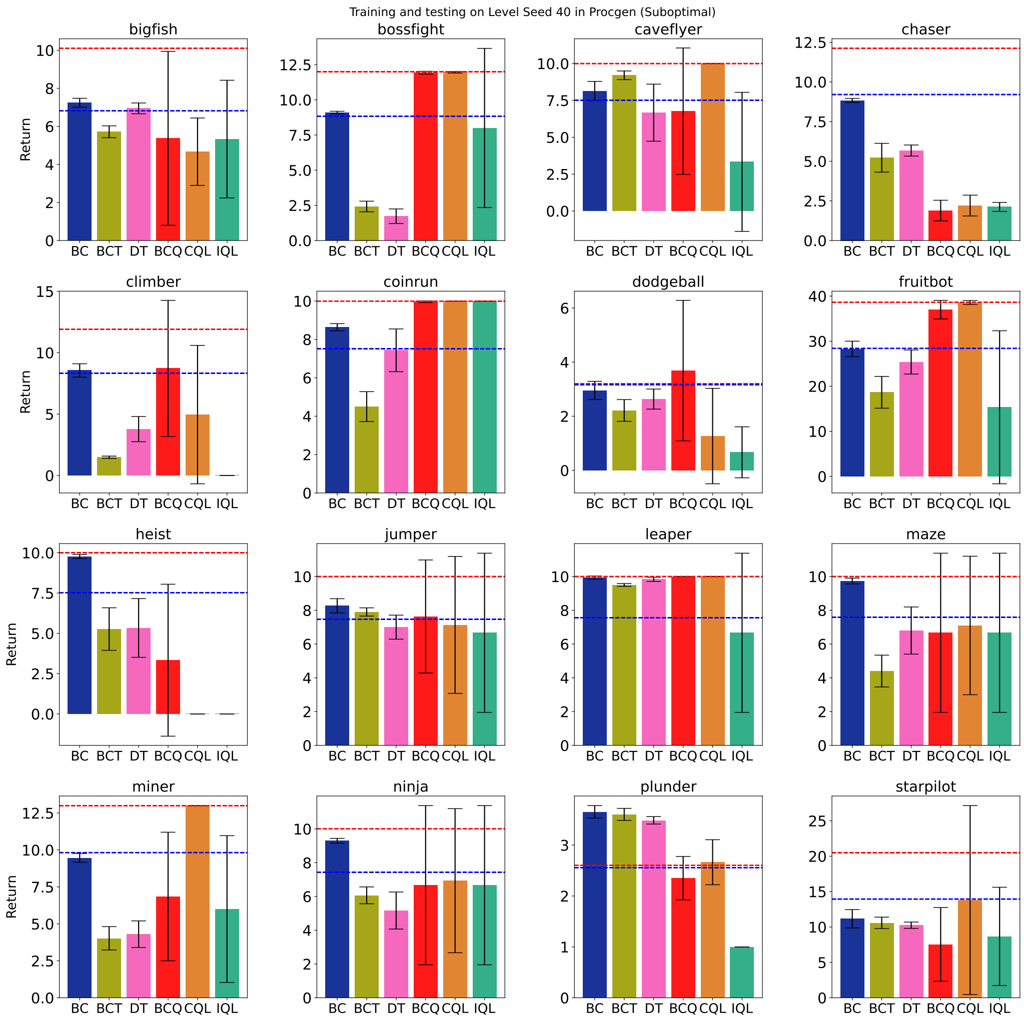


Figure 11: Performance of each baseline on level 40 in each Procgen game when **trained and tested on the same level using suboptimal dataset**. Blue line represents the dataset average and red line represents the performance of our expert PPO checkpoint on this level.

robust, while the offline RL and sequence modeling approaches fail to do well on some of the games. On the right, we compare the test returns which were calculated by averaging over 100 episodes by randomly sampling levels from the test set. The blue line shows the average performance of the final PPO checkpoint across 100 randomly sampled test levels.

Generalization to New Environments (Expert)

In most cases, BC performs similarly or better than the offline RL and sequence modeling approaches on test levels. However, *all the offline learning methods (state-of-the-art offline RL, behavioral cloning, and sequence modeling approaches) perform worse on average than the online RL method (PPO) on unseen environments*. For more than half of the games, offline RL methods cannot reach PPO's test performance. All sequence modelling and offline RL methods fail to generalize on the game of Miner, which is one of the most stochastic games in Procgen.

Tables 5, 6, 7 and 8 show the train and test performances of each offline learning algorithm in 16 Procgen games for both types of offline data regimes, 1M expert and 1M suboptimal respec-

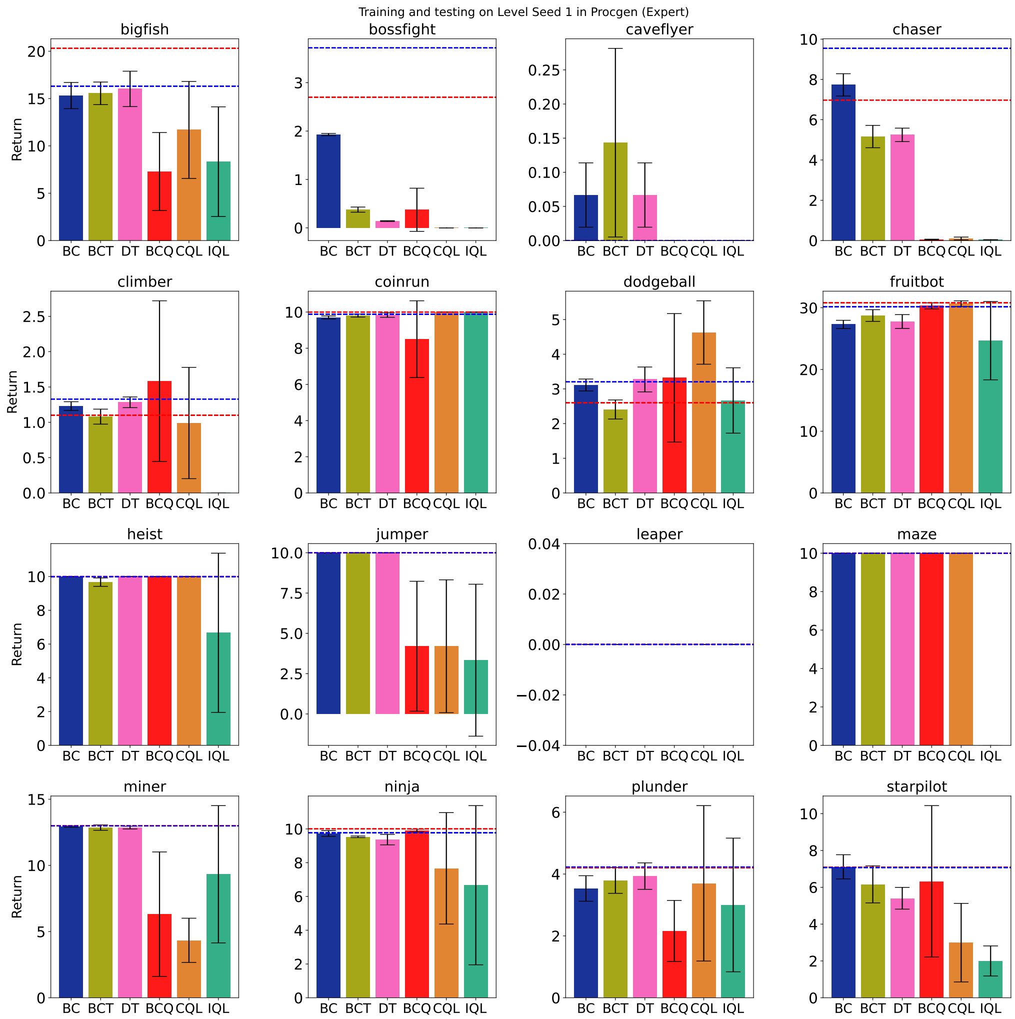


Figure 12: Performance of each baseline on level 1 in each Procgen game when **trained and tested on the same level using expert dataset**. Blue line represents the dataset average and red line represents the performance of our expert PPO checkpoint on this level.

tively. Moreover, we also plot the generalization gap for each algorithm in every game for better understanding of how well they learn from training levels and perform zero-shot on testing levels in Figures 19, 24 and 25.

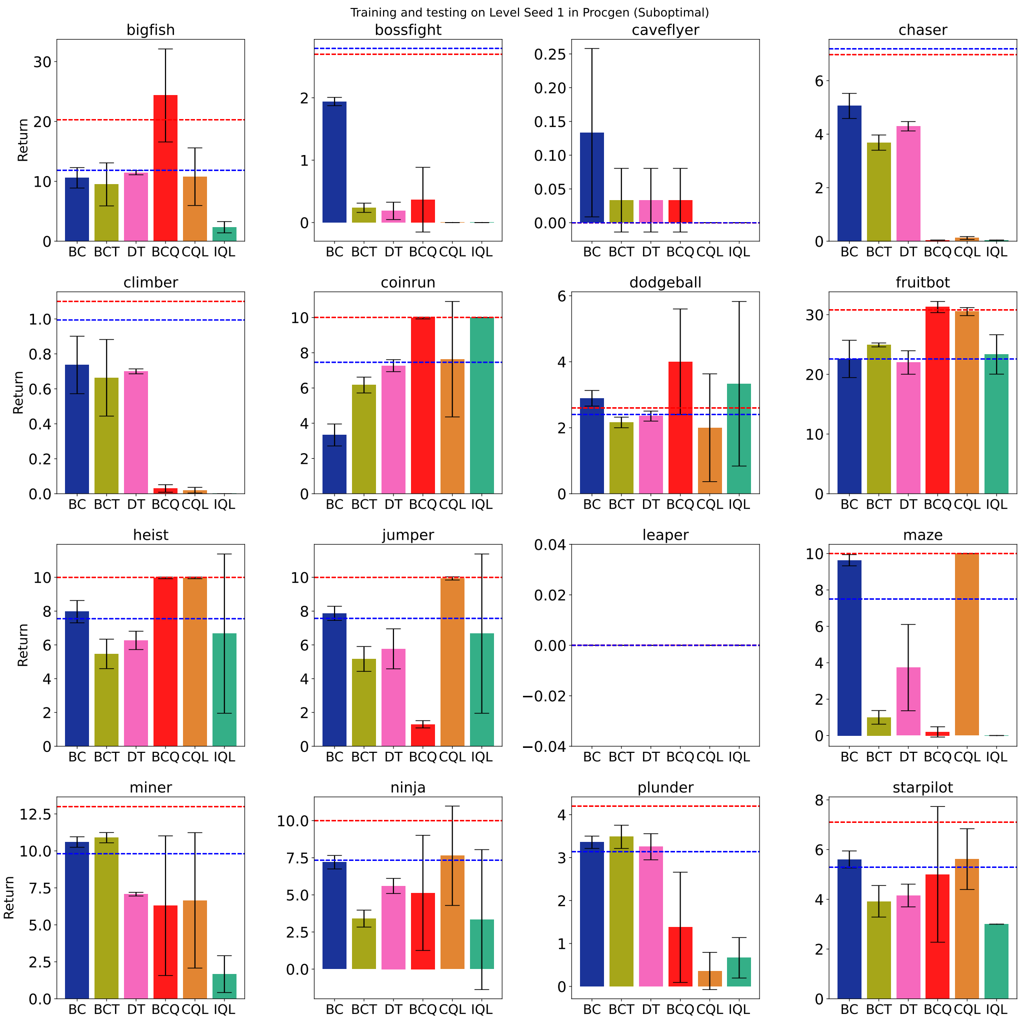


Figure 13: Performance of each baseline on level 1 in each Procgen game when **trained and tested on the same level using suboptimal dataset**. Blue line represents the dataset average and red line represents the performance of our expert PPO checkpoint on this level.

Environment	BC	BCT	DT	BCQ	CQL	IQL
bigfish	$\mathbf{10.94 \pm 0.75}$	9.99 ± 0.64	10.35 ± 0.69	6.23 ± 1.02	9.02 ± 1.37	8.19 ± 0.54
bossfight	7.16 ± 0.35	1.11 ± 0.15	1.01 ± 0.18	7.4 ± 0.36	$\mathbf{8.57 \pm 0.32}$	8.45 ± 0.36
caveflyer	$\mathbf{6.84 \pm 0.25}$	6.06 ± 0.15	6.56 ± 0.2	2.57 ± 0.39	2.65 ± 0.23	4.55 ± 0.31
chaser	$\mathbf{5.6 \pm 0.12}$	2.67 ± 0.23	2.98 ± 0.19	4.37 ± 0.56	3.94 ± 0.52	3.68 ± 0.13
climber	8.27 ± 0.22	$\mathbf{8.35 \pm 0.27}$	7.98 ± 0.27	2.19 ± 0.27	1.89 ± 0.17	5.22 ± 0.26
coinrun	$\mathbf{9.48 \pm 0.14}$	9.32 ± 0.06	9.42 ± 0.06	8.28 ± 0.18	8.58 ± 0.29	8.52 ± 0.26
dodgeball	$\mathbf{4.01 \pm 0.24}$	3.43 ± 0.06	3.9 ± 0.23	1.55 ± 0.15	1.7 ± 0.14	2.74 ± 0.25
fruitbot	27.35 ± 0.98	23.36 ± 0.34	23.5 ± 0.38	14.68 ± 1.29	19.42 ± 1.21	$\mathbf{27.51 \pm 0.51}$
heist	$\mathbf{7.78 \pm 0.26}$	7.0 ± 0.22	7.32 ± 0.12	3.96 ± 0.5	3.74 ± 0.31	5.02 ± 0.42
jumper	8.2 ± 0.06	$\mathbf{8.74 \pm 0.1}$	8.54 ± 0.13	7.14 ± 0.15	7.68 ± 0.16	7.8 ± 0.26
leaper	2.78 ± 0.18	2.34 ± 0.12	2.96 ± 0.2	2.54 ± 0.08	2.42 ± 0.23	$\mathbf{3.08 \pm 0.15}$
maze	$\mathbf{9.0 \pm 0.14}$	8.08 ± 0.2	8.74 ± 0.16	7.78 ± 0.22	7.34 ± 0.14	7.48 ± 0.13
miner	$\mathbf{12.36 \pm 0.14}$	11.1 ± 0.23	11.42 ± 0.2	8.3 ± 0.33	6.98 ± 0.23	8.48 ± 0.34
ninja	7.44 ± 0.33	7.62 ± 0.2	$\mathbf{7.72 \pm 0.12}$	5.76 ± 0.33	5.92 ± 0.2	5.7 ± 0.35
plunder	5.26 ± 0.22	5.53 ± 0.12	$\mathbf{5.57 \pm 0.07}$	4.47 ± 0.56	4.78 ± 0.36	4.56 ± 0.17
starpilot	20.91 ± 0.51	14.39 ± 0.53	14.39 ± 0.59	25.94 ± 1.68	$\mathbf{26.36 \pm 1.02}$	24.11 ± 0.64

Table 5: Mean and Standard Deviation for the **train performances** of each offline learning algorithm averaged over 5 random seeds when trained on **1M Expert Dataset in Procgen**.

Environment	BC	BCT	DT	BCQ	CQL	IQL
bigfish	4.38 ± 0.38	2.18 ± 0.13	2.37 ± 0.16	3.57 ± 0.34	4.1 ± 0.37	$\mathbf{4.85 \pm 0.52}$
bossfight	5.87 ± 0.26	0.35 ± 0.11	0.52 ± 0.08	6.53 ± 0.33	$\mathbf{8.13 \pm 0.13}$	7.62 ± 0.33
caveflyer	$\mathbf{4.92 \pm 0.28}$	3.85 ± 0.17	3.48 ± 0.35	2.15 ± 0.26	2.12 ± 0.28	3.43 ± 0.22
chaser	$\mathbf{4.62 \pm 0.36}$	1.69 ± 0.08	1.86 ± 0.04	4.05 ± 0.65	4.39 ± 0.31	3.17 ± 0.17
climber	$\mathbf{4.91 \pm 0.22}$	3.49 ± 0.12	3.58 ± 0.21	0.87 ± 0.12	0.98 ± 0.06	2.33 ± 0.33
coinrun	$\mathbf{8.26 \pm 0.19}$	7.66 ± 0.33	8.08 ± 0.22	7.02 ± 0.15	7.22 ± 0.17	7.74 ± 0.21
dodgeball	$\mathbf{0.98 \pm 0.07}$	0.89 ± 0.07	0.84 ± 0.04	0.76 ± 0.09	0.85 ± 0.07	0.93 ± 0.12
fruitbot	21.18 ± 0.62	13.93 ± 0.75	13.56 ± 0.73	11.54 ± 2.12	16.99 ± 1.55	$\mathbf{25.22 \pm 0.94}$
heist	$\mathbf{2.42 \pm 0.14}$	1.9 ± 0.16	1.78 ± 0.09	0.48 ± 0.14	0.44 ± 0.12	0.58 ± 0.26
jumper	$\mathbf{5.68 \pm 0.18}$	4.54 ± 0.18	5.6 ± 0.23	4.14 ± 0.22	4.26 ± 0.22	4.06 ± 0.21
leaper	$\mathbf{2.84 \pm 0.07}$	2.56 ± 0.21	2.36 ± 0.18	2.48 ± 0.09	2.82 ± 0.28	2.44 ± 0.21
maze	$\mathbf{4.46 \pm 0.16}$	4.26 ± 0.25	3.88 ± 0.31	2.48 ± 0.11	3.04 ± 0.11	2.68 ± 0.31
miner	$\mathbf{7.85 \pm 0.32}$	1.53 ± 0.06	1.47 ± 0.08	1.46 ± 0.32	2.21 ± 0.24	1.66 ± 0.17
ninja	$\mathbf{5.88 \pm 0.3}$	5.8 ± 0.07	5.74 ± 0.22	4.52 ± 0.44	4.36 ± 0.25	4.38 ± 0.12
plunder	$\mathbf{4.94 \pm 0.13}$	4.65 ± 0.12	4.7 ± 0.24	3.66 ± 0.29	3.84 ± 0.23	4.03 ± 0.14
starpilot	17.69 ± 0.59	10.9 ± 0.49	10.72 ± 0.32	22.21 ± 0.7	22.42 ± 0.39	$\mathbf{22.88 \pm 0.59}$

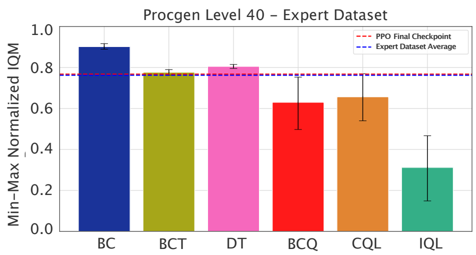
Table 6: Mean and Standard Deviation for the **test performances** of each offline learning algorithm averaged over 5 random seeds when trained on **1M Expert Dataset in Procgen**.

Environment	BC	BCT	DT	BCQ	IQL	CQL
bigfish	7.81 ± 0.91	7.83 ± 1.19	7.47 ± 0.59	7.53 ± 1.02	$\mathbf{8.03 \pm 1.04}$	6.53 ± 0.77
bossfight	5.53 ± 0.22	0.71 ± 0.1	0.63 ± 0.07	7.24 ± 0.58	7.73 ± 0.1	$\mathbf{7.96 \pm 0.44}$
caveflyer	5.06 ± 0.44	$\mathbf{5.14 \pm 0.06}$	4.34 ± 0.31	3.79 ± 0.67	2.68 ± 0.44	3.68 ± 0.67
chaser	$\mathbf{4.05 \pm 0.21}$	2.37 ± 0.19	2.35 ± 0.11	1.74 ± 0.35	1.42 ± 0.63	2.76 ± 0.5
climber	$\mathbf{6.94 \pm 0.35}$	4.9 ± 0.34	4.99 ± 0.12	2.0 ± 0.21	1.15 ± 0.77	2.98 ± 0.99
coinrun	7.9 ± 0.47	$\mathbf{8.5 \pm 0.06}$	8.37 ± 0.35	7.73 ± 0.35	6.67 ± 0.73	7.73 ± 0.2
dodgeball	$\mathbf{3.03 \pm 0.05}$	$\mathbf{3.03 \pm 0.41}$	2.95 ± 0.44	2.0 ± 0.13	2.7 ± 0.06	2.15 ± 0.15
fruitbot	21.97 ± 1.12	16.53 ± 0.93	15.38 ± 1.09	25.36 ± 0.29	$\mathbf{26.89 \pm 0.28}$	26.06 ± 0.6
heist	$\mathbf{6.43 \pm 0.34}$	4.83 ± 0.5	4.43 ± 0.23	2.47 ± 0.12	1.67 ± 0.42	1.6 ± 0.17
jumper	$\mathbf{7.53 \pm 0.23}$	6.43 ± 0.37	6.93 ± 0.34	6.83 ± 0.48	6.93 ± 0.2	6.87 ± 0.27
leaper	$\mathbf{3.1 \pm 0.15}$	2.87 ± 0.28	2.73 ± 0.27	2.47 ± 0.09	2.33 ± 0.68	2.77 ± 0.03
maze	$\mathbf{7.8 \pm 0.26}$	5.8 ± 0.2	5.9 ± 0.65	4.73 ± 0.17	4.53 ± 0.48	3.77 ± 0.03
miner	$\mathbf{9.49 \pm 0.33}$	5.77 ± 0.69	4.87 ± 0.34	3.56 ± 0.24	4.05 ± 0.67	2.36 ± 0.41
ninja	6.2 ± 0.1	$\mathbf{6.7 \pm 0.17}$	6.4 ± 0.15	5.0 ± 0.12	3.83 ± 0.77	4.97 ± 0.32
plunder	$\mathbf{5.81 \pm 0.21}$	5.41 ± 0.17	4.9 ± 0.37	4.18 ± 0.23	4.34 ± 0.48	3.93 ± 0.15
starpilot	21.92 ± 0.35	13.64 ± 0.12	12.34 ± 0.57	22.66 ± 2.14	$\mathbf{22.8 \pm 0.84}$	21.57 ± 2.17

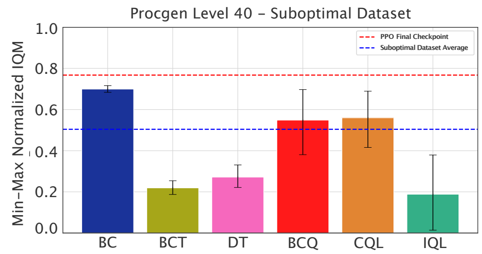
Table 7: Mean and Standard Deviation for the train performances of each offline learning algorithm averaged over 5 random seeds when trained on **1M Suboptimal Dataset in Procgen**. See Appendix 5.2 for more details.

Environment	BC	BCT	DT	BCQ	IQL	CQL
bigfish	2.89 ± 0.15	2.09 ± 0.08	2.23 ± 0.15	4.13 ± 0.52	$\mathbf{4.14 \pm 0.54}$	3.64 ± 0.36
bossfight	5.13 ± 0.14	0.37 ± 0.18	0.58 ± 0.16	6.69 ± 0.57	7.12 ± 0.43	$\mathbf{7.91 \pm 0.35}$
caveflyer	$\mathbf{4.05 \pm 0.24}$	3.1 ± 0.41	3.43 ± 0.5	2.42 ± 1.08	1.66 ± 0.67	1.97 ± 0.41
chaser	$\mathbf{3.43 \pm 0.22}$	1.95 ± 0.05	1.86 ± 0.07	1.44 ± 0.2	1.41 ± 0.6	2.58 ± 0.12
climber	$\mathbf{4.64 \pm 0.29}$	3.18 ± 0.21	2.93 ± 0.42	0.73 ± 0.25	0.57 ± 0.35	0.94 ± 0.14
coinrun	$\mathbf{7.77 \pm 0.24}$	7.47 ± 0.07	7.5 ± 0.21	6.63 ± 0.12	6.0 ± 0.36	7.17 ± 0.41
dodgeball	$\mathbf{1.19 \pm 0.14}$	1.13 ± 0.05	0.94 ± 0.09	0.55 ± 0.16	0.87 ± 0.11	0.67 ± 0.01
fruitbot	18.84 ± 0.7	11.39 ± 0.61	11.35 ± 1.39	22.76 ± 1.44	22.0 ± 0.43	$\mathbf{24.46 \pm 0.52}$
heist	$\mathbf{2.37 \pm 0.3}$	2.0 ± 0.17	1.97 ± 0.07	0.53 ± 0.15	0.27 ± 0.03	0.5 ± 0.06
jumper	$\mathbf{4.63 \pm 0.47}$	4.27 ± 0.43	4.53 ± 0.3	2.8 ± 0.15	3.0 ± 0.5	2.9 ± 0.17
leaper	2.6 ± 0.25	2.5 ± 0.06	$\mathbf{2.7 \pm 0.35}$	2.43 ± 0.29	2.27 ± 0.53	2.43 ± 0.26
maze	4.77 ± 0.32	4.77 ± 0.19	$\mathbf{5.5 \pm 0.06}$	1.93 ± 0.13	2.1 ± 0.15	1.97 ± 0.18
miner	$\mathbf{6.56 \pm 0.09}$	1.28 ± 0.11	1.28 ± 0.08	0.51 ± 0.15	0.8 ± 0.1	0.43 ± 0.08
ninja	$\mathbf{5.23 \pm 0.12}$	5.37 ± 0.38	5.1 ± 0.36	4.67 ± 0.43	3.23 ± 0.81	3.77 ± 0.26
plunder	$\mathbf{4.59 \pm 0.16}$	4.53 ± 0.16	4.3 ± 0.17	3.39 ± 0.28	3.86 ± 0.25	3.76 ± 0.26
starpilot	17.93 ± 0.32	11.64 ± 0.71	10.69 ± 0.23	$\mathbf{21.86 \pm 2.07}$	19.64 ± 1.79	20.11 ± 0.43

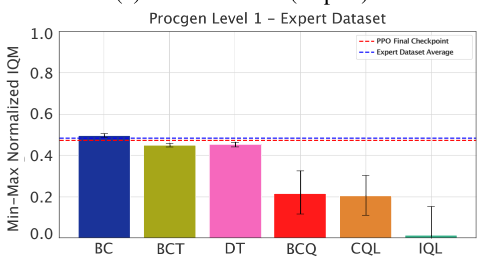
Table 8: Mean and Standard Deviation for the test performances of each offline learning algorithm averaged over 5 random seeds when trained on **1M Suboptimal Dataset in Procgen**. See Appendix 5.2 for more details.



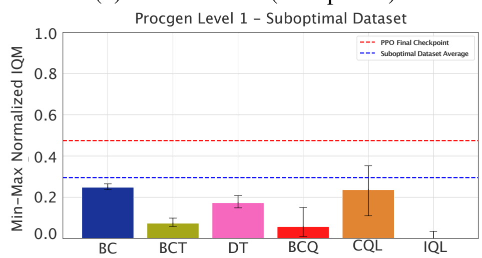
(a) Level Seed 40 (Expert)



(b) Level Seed 40 (Suboptimal)

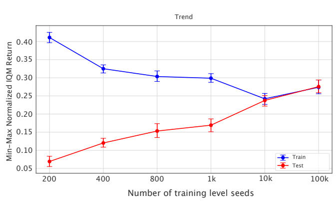


(c) Level Seed 1 (Expert)

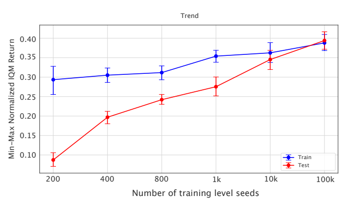


(d) Level Seed 1 (Suboptimal)

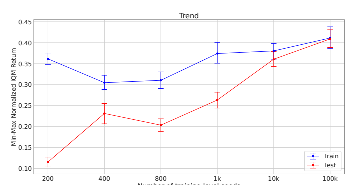
Figure 14: Aggregated performance of each baseline across all Procgen games when **trained and tested on the same level using suboptimal or expert dataset**. Blue line represents the performance of our expert PPO checkpoint on this level seed.



(a) BCT

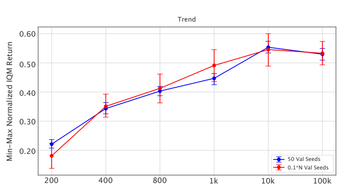


(b) CQL

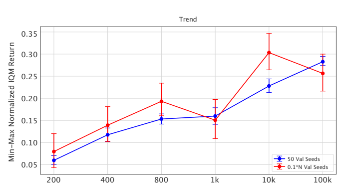


(c) IQL

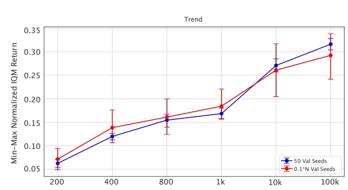
Figure 15: **The Effect of Data Diversity on Performance of BCT, CQL & IQL.** Train and test performance for varying number of training levels in the 1M expert datasets, aggregated across all Procgen games. The plot shows the IQM and error bars represent the 75-th and 25th percentiles computed over 3 model seeds. While the training performance does not change much with the number of training levels, the test performance increases (and generalization gap decreases) with the diversity of the dataset.



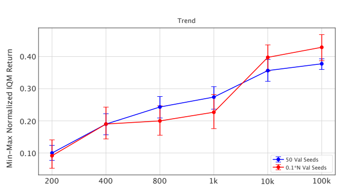
(a) BC



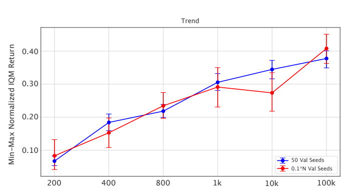
(b) BCT



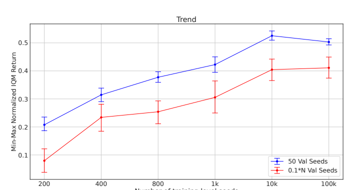
(c) DT



(d) BCQ

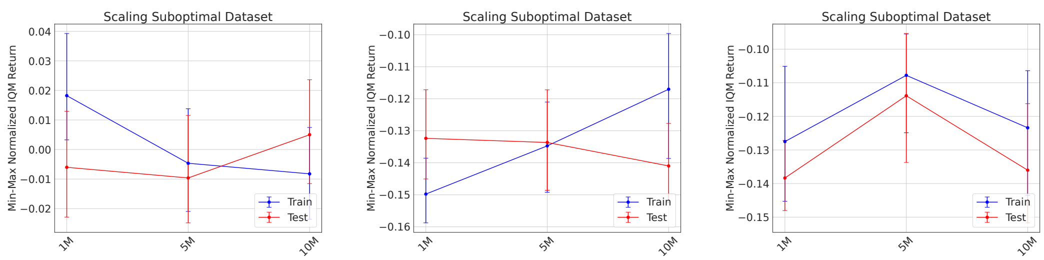


(e) CQL



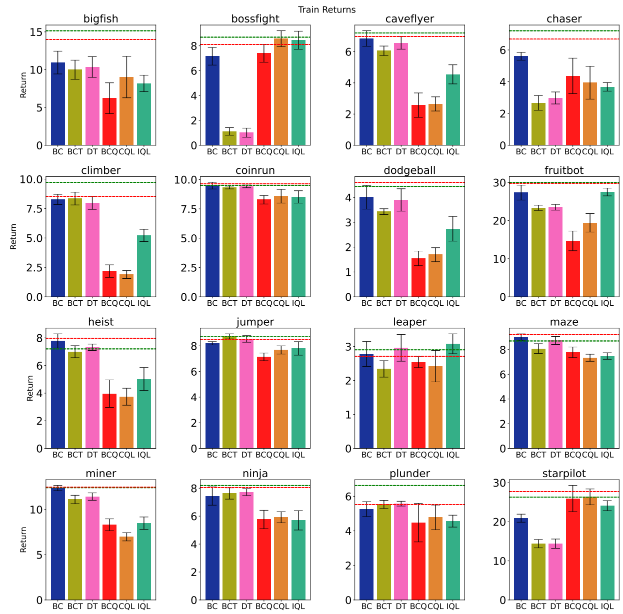
(f) IQL

Figure 16: Comparing the use of 50 validation levels vs. validation levels proportional to the number of training levels.

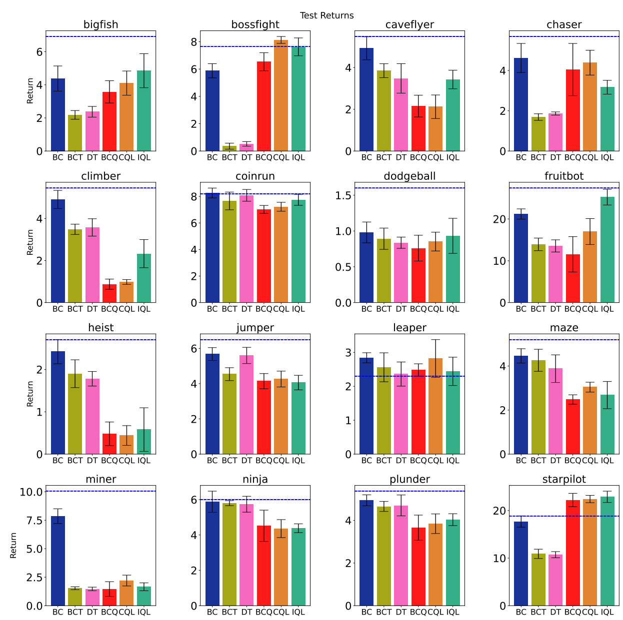


(a) BCT (b) CQL (c) IQL

Figure 17: **Scaling suboptimal dataset in Procgen**. This plot shows the train and test min-max normalized IQM scores for all offline learning algorithms as the quantity of suboptimal offline dataset in increased from 1 million transitions to 10 million transitions. As can be seen, all algorithms have very poor train and test performance (even when using 10M transitions) and at a very granular level, the train performance generally increases, but test performance does not change much.

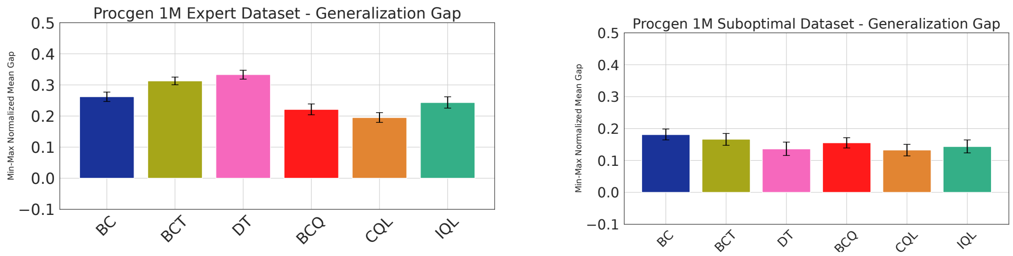


(a) Train



(b) Test

Figure 18: **Per-Game Procgen Results on the 1M Expert Dataset.** Average episode return for each method on train (left) and test (right) levels for each Procgen game. The mean and standard deviation are computed across 5 model seeds. The red line shows the average return of the trajectories in the training dataset. The green line shows PPO's average train return, while the blue line shows PPO's average test return, where both were computed over 100 randomly sampled train and test levels, respectively. Most of the methods match the average performance of the training data. However, many of them fail to reach PPO's performance at test time. In most cases, BC is competitive or better than the offline RL and sequence modeling approaches. For numerical comparison, refer to Table 5 in Appendix.



(a) 1M Expert Dataset

(b) 1M Suboptimal Dataset

Figure 19: Min-max normalized mean **Generalization Gap** plots for offline learning algorithms trained using 1M expert and suboptimal dataset in Procgen respectively.

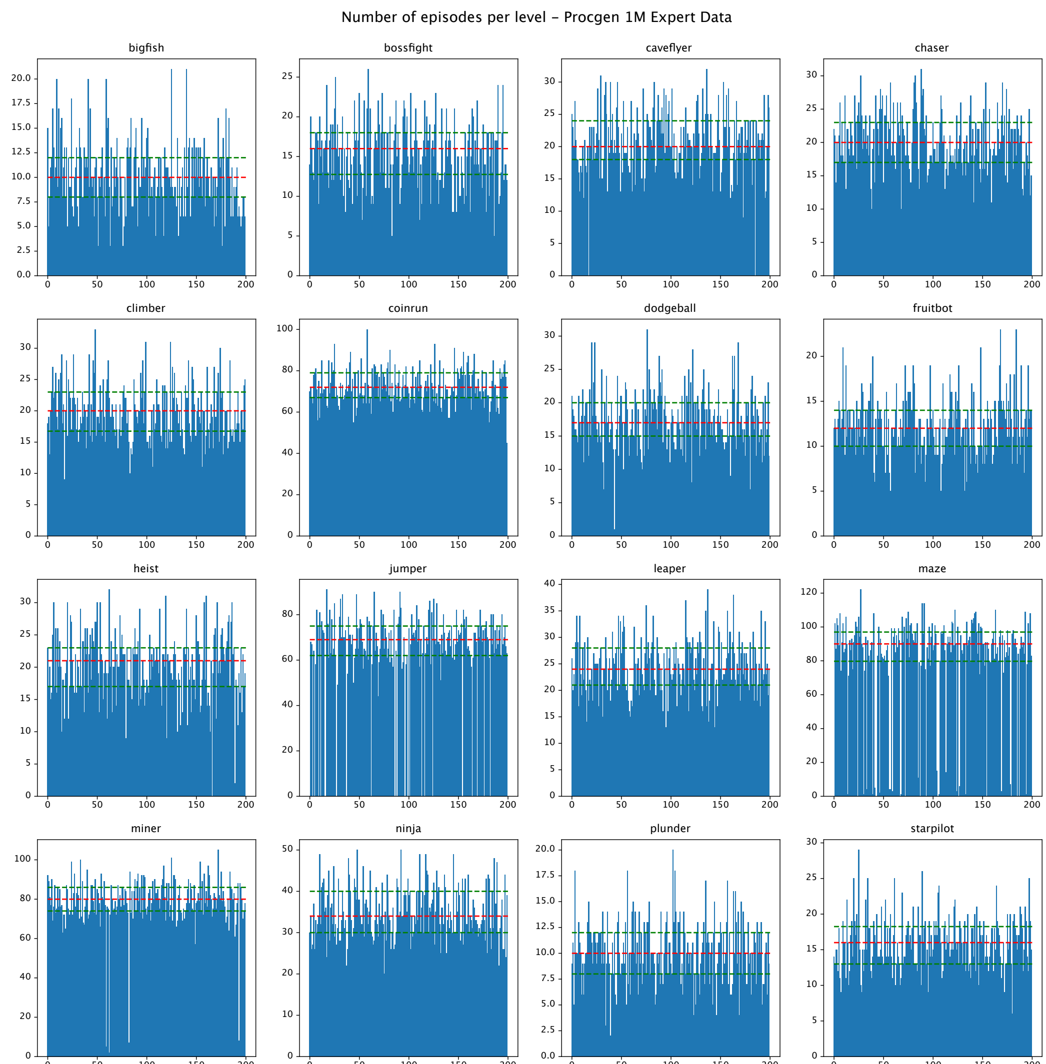


Figure 20: Number of episodes per level from the training set for each environment in the 1M expert dataset from Procgen. Red line represents the median. Lower and upper green lines represent the 25th and 75th percentile of the values respectively.

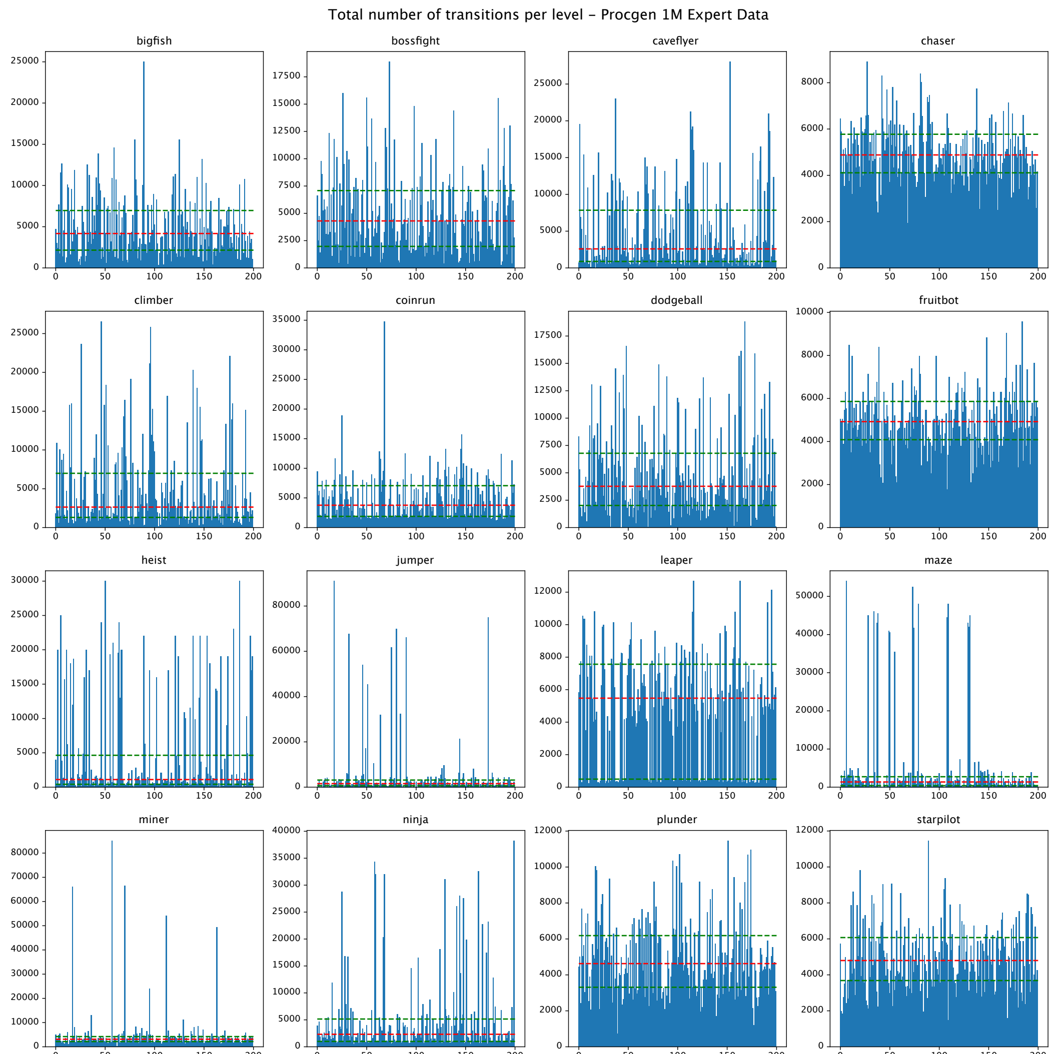


Figure 21: Total number of transitions per level from the training set for each environment in the 1M expert dataset from Procgen. Red line represents the median. Lower and upper green lines represent the 25th and 75th percentile of the values respectively.

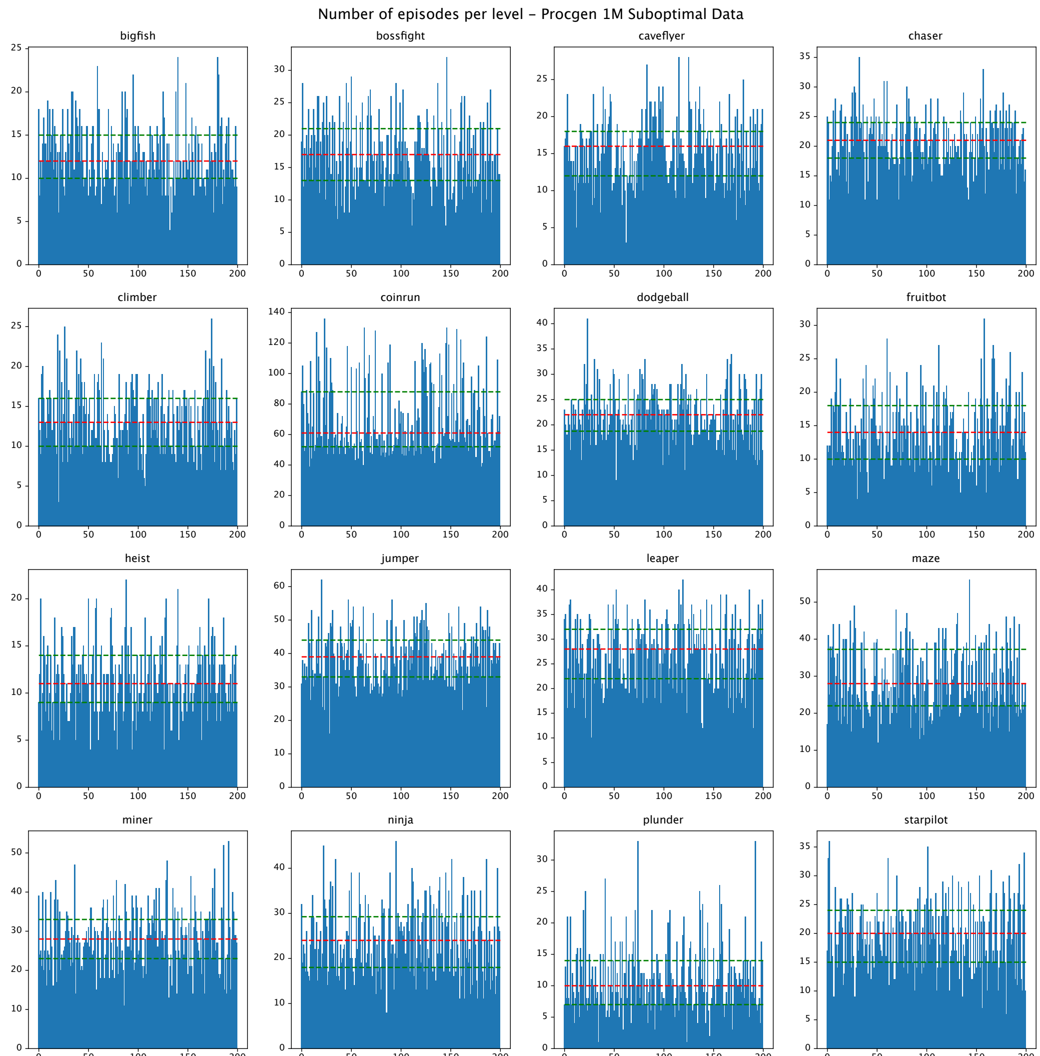


Figure 22: Number of episodes per level from the training set for each environment in the 1M suboptimal dataset from Procgen. Red line represents the median. Lower and upper green lines represent the 25th and 75th percentile of the values respectively.

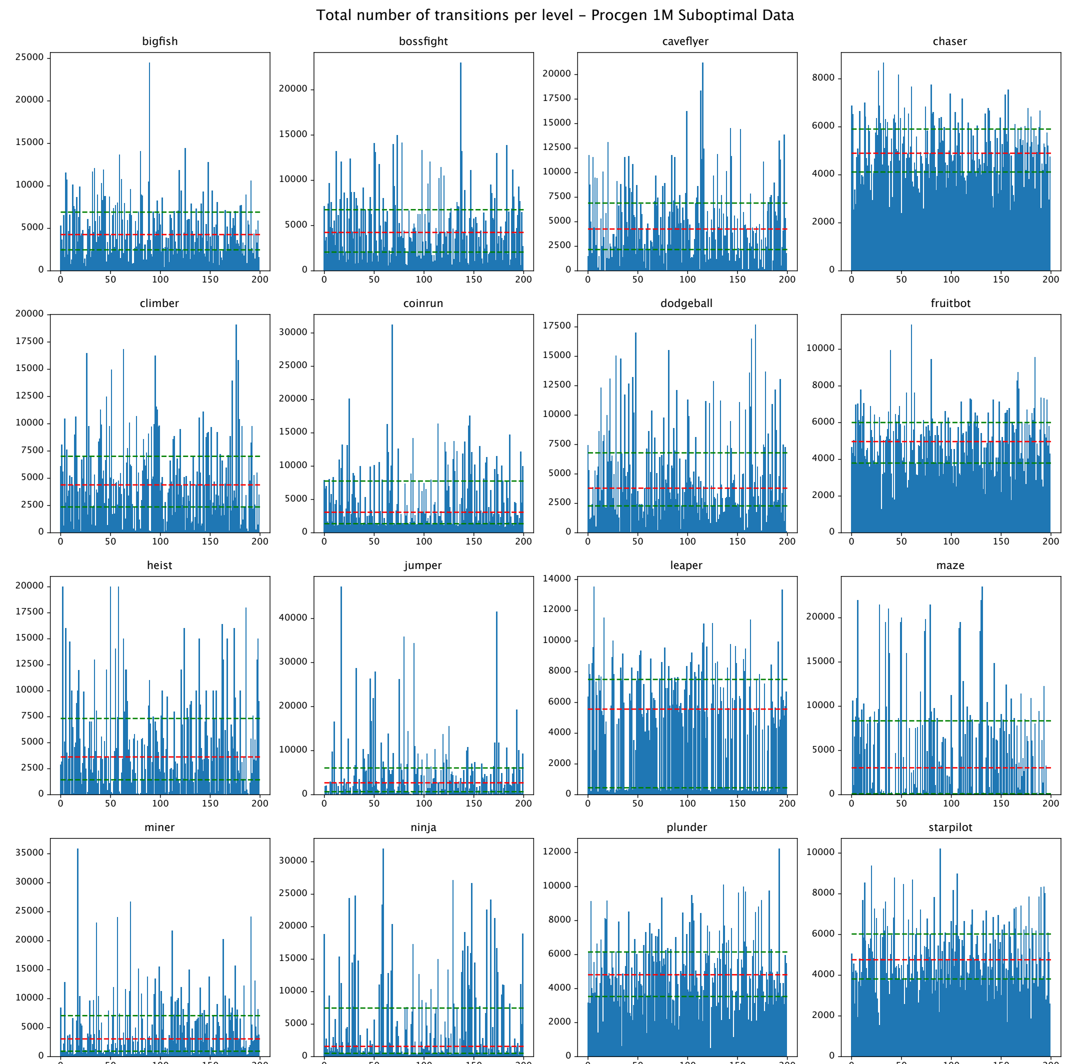


Figure 23: Total number of transitions per level from the training set for each environment in the 1M suboptimal dataset from Procgen. Red line represents the median. Lower and upper green lines represent the 25th and 75th percentile of the values respectively.

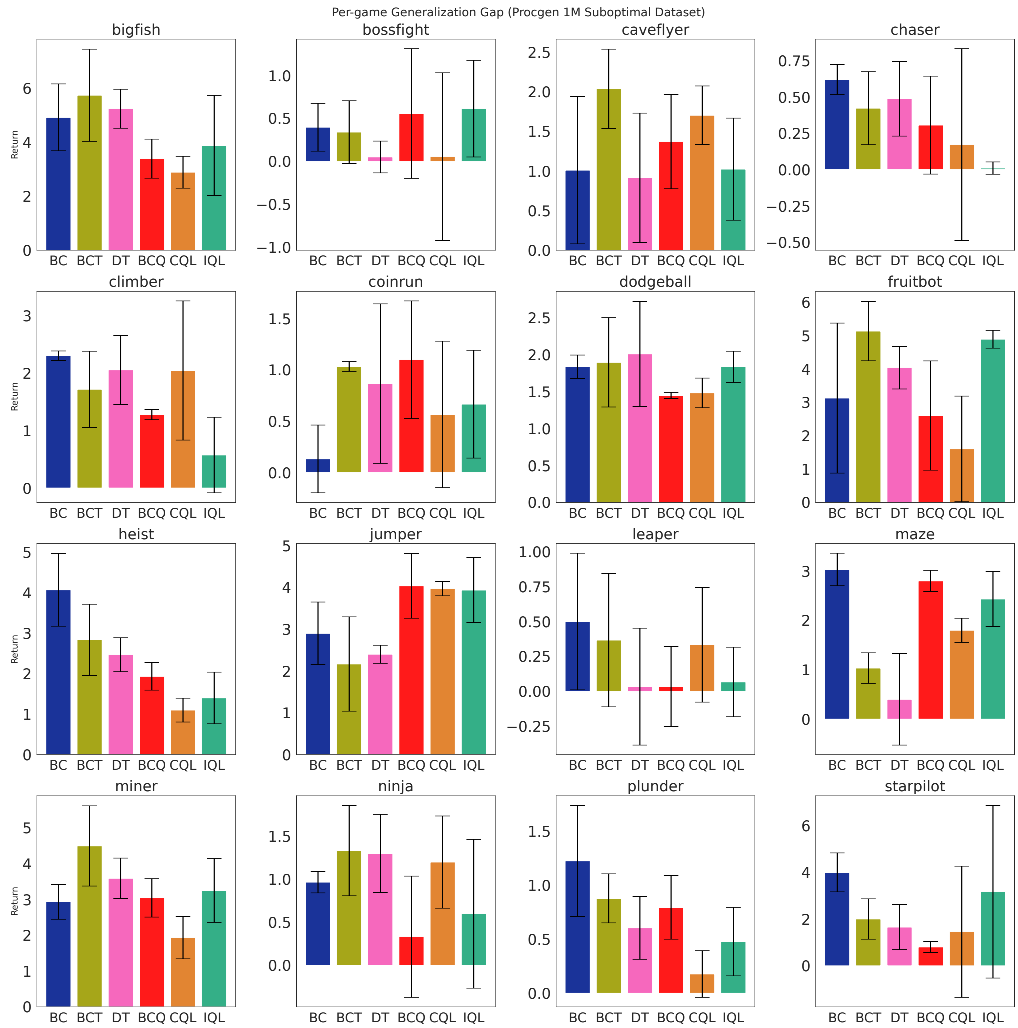


Figure 24: Mean and standard deviation of Per-game Generalization Gap for every offline learning algorithm in Procgen when trained using 1M suboptimal data. Every algorithm is run for 5 random trials.

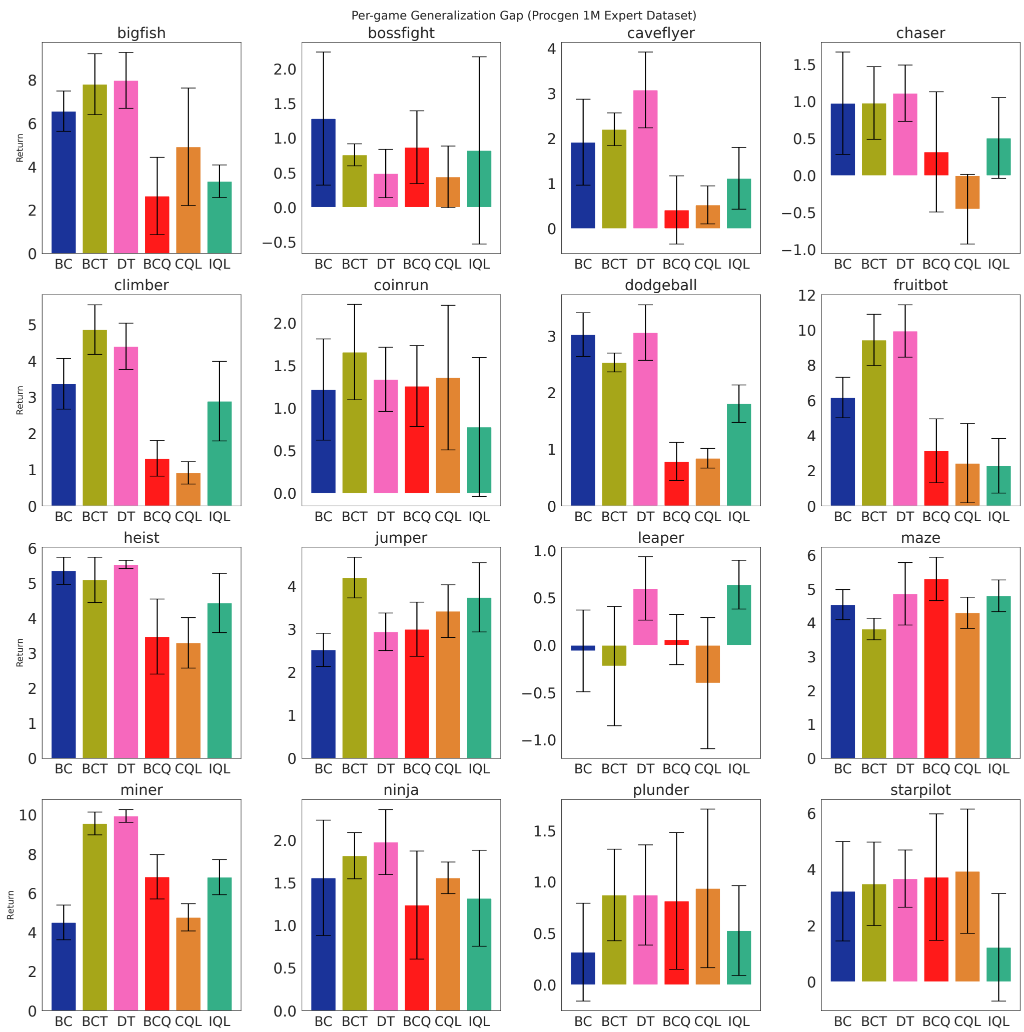


Figure 25: Mean and standard deviation of Per-game Generalization Gap for every offline learning algorithm in Procgen when trained using 1M expert data. Every algorithm is run for 5 random trials.