Automatic Data Augmentation for Generalization in Deep Reinforcement Learning

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Abstract

Deep reinforcement learning (RL) agents often fail to generalize to unseen scenarios, even when they are trained on many instances of semantically similar environments. Data augmentation has recently been shown to improve the sample efficiency and generalization of RL agents. However, different tasks tend to benefit from different kinds of data augmentation. In this paper, we compare three approaches for automatically finding an appropriate augmentation. These are combined with two novel regularization terms for the policy and value function, required to make the use of data augmentation theoretically sound for certain actor-critic algorithms. We evaluate our methods on the Procgen benchmark which consists of 16 procedurally-generated environments and show that it improves test performance by $\approx 40\%$ relative to standard RL algorithms. Our agent outperforms other baselines specifically designed to improve generalization in RL. In addition, we show that our agent learns policies and representations that are more robust to changes in the environment that do not affect the agent, such as the background. Our implementation is available at https://github.com/rraileanu/auto-drac.

1 Introduction

Generalization remains one of the key challenges of deep reinforcement learning (RL). A series of recent studies show that RL agents fail to generalize to new environments, even when they are trained on a large set of diverse yet semantically similar ones \cite{17, 19, 59, 11, 12, 50}. This indicates that current RL methods memorize specific trajectories rather than learning transferable skills. Generalization in RL can be split into different categories, such as generalization across different visual inputs (with the same semantics) \cite{11, 19, 37}, dynamics \cite{42}, or other environment structures \cite{3, 55, 12}. In this paper, we focus on generalization with respect to both visual and layout changes in the environment.

To improve generalization in RL, several strategies have been proposed, such as the use of regularization \cite{17, 59, 11, 25}, data augmentation \cite{11, 37, 54}, or representation learning \cite{25, 37}. Here, we particularly focus on the use of data augmentation, which has proven effective on a wide range of supervised and unsupervised learning tasks \cite{35, 48, 10, 8, 33}. Recent results have shown that the use of transformations common in the supervised learning paradigm (such as cutout, color-jitter, or random shifts) can also be beneficial in RL \cite{11, 37, 52, 34}. However, as was noted by Kostrikov et al. \cite{32}, there are important differences between supervised and reinforcement learning that prevent a straightforward adoption of data augmentation in RL.
In this paper, we show that a naive application of data augmentation can lead to both theoretical and practical problems with standard RL algorithms (such as unprincipled objective estimates and poor performance). As a solution, we propose Data-regularized Actor-Critic or DrAC, a new algorithm that enables the use of data augmentation with actor-critic algorithms in a theoretically sound way. Specifically, we introduce two regularization terms which constrain the agent’s policy and value function to be invariant to various state transformations. Empirically, this method allows the agent to learn useful behaviors (that outperform standard RL methods) in settings in which a naive use of data augmentation completely fails or converges to a sub-optimal policy. While we use Proximal Policy Optimization (PPO [46]) to describe our approach and validate it empirically, our method can be easily adapted to any actor-critic algorithm with a discrete stochastic policy such as A3C [41], TRPO [45], ACER [56], SAC [21], or IMPALA [15].

The current use of data augmentation in RL relies on expert knowledge to pick an appropriate augmentation [37, 32] or separately evaluates a large number of transformations to find the best one [11, 34]. In this paper, we propose three methods for automatically finding a good augmentation for a given task. The first two automatically find an effective augmentation from a fixed set, using either a variant of the upper confidence bound (UCB [1]) algorithm (UCB-DrAC), or meta-learning [55] (RL2-DrAC). The third method directly meta-learns the weights of a convolutional network, without access to predefined transformations (Meta-DrAC). Figure 1 gives an overview of UCB-DrAC.

We evaluate our method on the Procgen generalization benchmark [12], which consists of 16 procedurally-generated environments with visual observations. Our results show that UCB-DrAC is the most effective for automatically finding an augmentation, and is comparable or better than using DrAC with the best augmentation from a given set. UCB-DrAC also outperforms baselines specifically designed to improve generalization in RL [25, 37, 34] on both train and test. In addition, we show that our agent learns policies and representations that are more robust to changes in the environment which are inconsequential for the agent (such as the background theme).

To summarize, our work makes the following contributions: (i) we introduce a principled way of using data augmentation with actor-critic algorithms, (ii) we propose a practical approach for automatically selecting an effective augmentation in RL settings, and (iii) we show that the use of data augmentation leads to policies and representations that better capture task invariances.

## 2 Background

We consider a standard reinforcement learning (RL) framework where an agent interacts with an environment in discrete time steps. This can be formalized as a finite-horizon Markov decision process (MDP) [5] defined by the tuple $(S, A, T, R, \gamma)$, where $S$ is the space of states and each state is a single RGB image. $A$ is the action space, $T$ is the transition function, $R : S \times A \rightarrow \mathbb{R}$ is the reward function and $\gamma$ is the discount factor. We aim to find a policy that maximizes the cumulative discounted return $\mathbb{E}[\sum_{t=1}^{\infty} \gamma^t R_t]$. In this work, we probe the generalization of RL agents using procedurally-generated environments. At the beginning of each episode, a new level is generated so that its state space and transition function depend on the level’s seed. Following the setup from [12], agents are trained on a fixed set of 200 levels (using integer seeds from 1 to 200) and tested on all other levels (procedurally-generated using any integer $> 200$ that can be represented by a computer).

**Proximal Policy Optimization** (PPO [46]) is an actor-critic algorithm that learns a policy $\pi_\theta$ and a value function $V_\phi$ with the goal of finding an optimal policy for a given MDP. PPO alternates between sampling data through interaction with the environment and maximizing a clipped surrogate objective function $J_{\text{PPO}}$ using stochastic gradient ascent. Please see Appendix [A] for a full description of
PPO. One component of the PPO objective is the policy gradient term $J_{PG}$, which is estimated using importance sampling:

$$J_{PG}(\theta) = \sum_{a \in A} \pi_\theta(a|s) \hat{A}_{\theta,old}(s,a) = \mathbb{E}_{a \sim \pi_{\theta,old}} \left[ \frac{\pi_\theta(a|s)}{\pi_{\theta,old}(a|s)} \hat{A}_{\theta,old}(s,a) \right], \quad (1)$$

where $\hat{A}(\cdot)$ is an estimate of the advantage function, $\pi_{\theta,old}$ is the behavior policy used to collect trajectories (i.e. that generates the training distribution of states and actions), and $\pi_\theta$ is the policy we want to optimize (i.e. that generates the true distribution of states and actions).

### 3 Automatic Data Augmentation for RL

#### 3.1 Data Augmentation in RL

Image augmentation has been successfully applied in computer vision for improving generalization on object classification tasks [43, 9, 8, 33]. However, as noted by Kostrikov et al. [32], these tasks are invariant to certain image transformations such as rotations or flips. In contrast, RL tasks are not always invariant to such augmentations [32]. For example, if your observation is flipped the signal to the agent. While data augmentation has been previously used in RL settings without other algorithmic changes [11, 34], we argue that this approach is not theoretically sound.

If transformations are naively applied to (some of) the observations in PPO’s buffer, as done in Laskin et al. [34], the PPO objective changes and equation (1) is replaced by

$$J_{PG}(\theta) \equiv \sum_{a \in A} \pi_\theta(a|s) \hat{A}_{\theta,old}(s,a) = \mathbb{E}_{a \sim \pi_{\theta,old}} \left[ \frac{\pi_\theta(a|fs)}{\pi_{\theta,old}(a|s)} \hat{A}_{\theta,old}(s,a) \right], \quad (2)$$

where $f : S \times H \to S$ is the image transformation. However, the right hand side of the above equation is not a sound estimate of the left hand side because $\pi_\theta(a|fs) \neq \pi_\theta(a|s)$, since nothing constrains $\pi_\theta(a|fs)$ to be close to $\pi_\theta(a|s)$. Moreover, one can define certain transformations $f(\cdot)$ that result in an arbitrarily large ratio $\pi_\theta(a|fs)/\pi_\theta(a|s)$.

Figure 2 shows examples where a naive use of data augmentation prevents PPO from learning a good policy in practice, suggesting that this is not just a theoretical issue. In the following section, we propose an algorithmic change that enables the use of data augmentation with actor-critic algorithms in a principled way.

#### 3.2 Policy and Value Function Regularization

Inspired by the recent work of Kostrikov et al. [32], we propose two novel regularization terms for the policy and value functions that enable the proper use of data augmentation for actor-critic RL algorithms. Our algorithmic contribution differs from that of [32] in that it constrains both the actor and the critic, as opposed to only regularizing the critic.

Following [32], we define an optimality-invariant state transformation $f : S \times H \to S$ as a mapping that preserves both the agent’s policy $\pi$ and its value function $V$ such that $V(s) = V(fs, \nu)$ and $\pi(a|s) = \pi(a|fs, \nu)$, $\forall s \in S, \nu \in H$, where $\nu$ are the parameters of $f(\cdot)$, drawn from the set of all possible parameters $H$.

To ensure that the policy and value functions are invariant to these transformation of the input state, we propose an additional loss term for regularizing the policy,

$$G_\pi = KL[\pi_\theta(a|fs, \nu) | \pi(a|s)], \quad (3)$$

as well as an extra loss term for regularizing the value function,

$$G_V = (V_\theta(fs, \nu) - V(s))^2. \quad (4)$$

Thus, our data-regularized actor-critic method, or DrAC, maximizes the following objective:

$$J_{DrAC} = J_{PPO} - \alpha_r(G_\pi + G_V) \quad (5)$$
where $\alpha_r$ is the weight of the regularization term. To improve stability, we only backpropagate gradients through $\pi(a|f(s))$ and $V(f(s))$ in equations (3) and (4), respectively.

The use of $G_\pi$ and $G_V$ ensures that the agent’s policy and value function are invariant to the transformations induced by various augmentations. Particular transformations can be used to impose certain inductive biases relevant for the task (e.g. invariance with respect to colors or textures). In addition, $G_\pi$ and $G_V$ can be added to the objective of any actor-critic algorithm with a discrete stochastic policy (e.g. A3C [41], TRPO [45], SAC [21], IMPALA [15]) without any other changes.

Note that when using DrAC, as opposed to [34], we still use the correct importance sampling estimate of the left hand side objective in equation (1) (instead of a wrong estimate as in equation (2)). This is because the transformed observations $f(s)$ are only used to compute the regularization losses $G_\pi$ and $G_V$, and thus are not used for the main PPO objective. Without these extra terms, the only way to use data augmentation is as explained in Section 3.1 which leads to inaccurate estimates of the PPO objective. Hence, DrAC benefits from the regularizing effect of using data augmentation, while mitigating the adverse effects it has on the RL objective.

### 3.3 Automatic Data Augmentation

Since different tasks benefit from different kinds of data augmentation, we would like to design a method that can automatically find an effective augmentation for any given task. Such a technique would significantly reduce the computational requirements for applying data augmentation in RL. More specifically, it can decrease the computational resources needed by a factor of $N$, where $N$ is the number of augmentations a researcher wants to evaluate. In this section, we describe three approaches for doing this. In all of them, the augmentation learner is trained at the same time as the agent learns to solve the task using DrAC. Hence, the distribution of rewards varies significantly as the agent improves, making the problem highly nonstationary.

#### Upper Confidence Bound

The problem of selecting a data augmentation from a given set can be formulated as a multi-armed bandit problem, where the action space is the set of available transformations $\mathcal{F} = \{f_1, \ldots, f_n\}$. A popular algorithm for multi-armed bandit problems is the Upper Confidence Bound or UCB [1], which selects actions according to the following policy:

$$f_t = \text{argmax}_{f \in \mathcal{F}} \left[ Q(f) + c \sqrt{\frac{\log(t)}{N(f)}} \right] \quad (6)$$

where $N(f)$ is the number of times transformation $f$ has been selected before time step $t$ and $c$ is UCB’s exploration coefficient. Before the $t$-th DrAC update, we use equation (6) to select an augmentation $f$. Then, we use equation (5) to update the agent’s policy and value function. We also update the counter: $N(f) = N(f) + 1$. Next, we collect rollouts with the new policy and update the $Q$-function: $Q(f) = \frac{1}{K} \sum_{i=t-K}^{t} R(f_t = f)$, which is computed as a sliding window average of the past $K$ mean returns obtained by the agent after being updated using augmentation $f$. We refer to this algorithm as UCB-DrAC. Note that UCB-DrAC’s estimate of $Q(f)$ differs from that of a typical UCB algorithm which uses rewards from the entire history. However, the choice of estimating $Q(f)$ using only more recent rewards is crucial due to the nonstationarity of the problem.

#### Meta-Learning the Selection of an Augmentation

Alternatively, the problem of selecting a data augmentation from a given set can be formulated as a meta-learning problem. Here, we consider a meta-learner like the one proposed by [55], which is an actor-critic architecture parameterized by an LSTM [24] that takes as inputs the previous reward and action (i.e. augmentation). Before each DrAC update, the meta-learner selects an augmentation, which is then used to update the agent using equation (5). Then, we collect rollouts using the new policy and update the meta-learner using the mean return of these trajectories. We refer to this approach as RL2-DrAC.

#### Meta-Learning the Weights of the Augmentation

Another approach for automatically finding an appropriate augmentation is to directly learn the weights of a certain transformation rather than selecting an augmentation from a given set. In this work, we focus on meta-learning the weights of a convolutional network which can be applied to the observations to obtain a perturbed image (with the same dimensions as the original observation). We meta-learn the weights of this network using an approach similar to the one proposed by [13], which we implement using the higher library [20]. For each agent update, we also perform a meta-update of the transformation function by splitting PPO’s buffer into training and validation sets. We refer to this approach as Meta-DrAC.
4 Experiments

In this section, we evaluate our methods on the Procgen benchmark \[12\] which consists of 16 procedurally-generated games (see Appendix, Figure 5). Procgen has a number of attributes that make it a good testbed for generalization in RL: (i) it has a diverse set of games in a similar spirit to the ALE benchmark \[5\], (ii) each of these games has procedurally-generated levels which present agents with meaningful generalization challenges, (iii) agents have to learn motor control directly from images, and (iv) it has a clear protocol for testing generalization. All Procgen environments use a discrete 15 dimensional action space and produce $64 \times 64 \times 3$ RGB observations. We use Procgen’s easy setup, so for each game, agents are trained on 200 levels and tested on a virtually infinite number of levels. We use PPO \[46\] as a base for all our methods. Further details of our experimental setup along with a full list of hyperparameters can be found in Appendix C. See https://sites.google.com/view/ucb-drac for videos of the agent at different training stages.

Data Augmentation. In our experiments, we use a set of eight transformations: crop, grayscale, cutout, cutout-color, flip, rotate, random convolution and color-jitter \[33, 13\]. We use RAD’s \[34\] implementation of these transformations, except for crop, in which we pad the image with 12 (boundary) pixels on each side and select random crops of $64 \times 64$. We found this implementation of crop to be significantly better on Procgen than the one in \[34\], and thus it can be considered an empirical upper bound of RAD in this case. For simplicity, we will refer to our implementation as RAD throughout this section. DrAC uses the same set of transformations as RAD, but is trained with additional regularization losses for the actor and the critic, as described in Section 3.2.

Automatic Selection of Data Augmentation. We compare three different approaches for automatically selecting an appropriate data augmentation for each task: UCB-DrAC which uses UCB \[1\] to select an augmentation from a given set, RL2-DrAC which uses $RL^2$ \[55\] to do this, and Meta-DrAC which meta-learns \[18\] the weights of a convolutional network using higher \[20\].

Ablations. Rand-DrAC uses a uniform distribution to select an augmentation each time. Crop-DrAC uses crop for all games (which is the best augmentation for half of the Procgen games). UCB-RAD combines UCB with RAD (i.e. it does not use the regularization terms).

Baselines. We also compare UCB-DrAC with Rand-FM \[37\] and IBAC-SNI \[25\], two methods specifically designed for improving generalization in RL, which were evaluated on CoinRun, one of the Procgen games. Rand-FM uses a random convolutional network to perturb the inputs with a regularization loss in feature space, while IBAC-SNI uses an information bottleneck with selective noise injection. For both of them, we use the open sourced implementations released by the authors.

Evaluation Metrics. For each method and each game, we normalize the final score (averaged over 5 seeds) using the corresponding PPO score. We report the mean and median scores aggregated over all 16 Procgen environments (Table 1). For a per-game breakdown, see Tables 4 and 5 in the Appendix.

4.1 Generalization Ability

Table 1 shows train and test performance on Procgen. UCB-DrAC significantly outperforms standard RL (PPO) and other baselines designed to improve generalization in RL (Rand-FM and IBAC-SNI). Regularizing the policy and value function leads to improvements over merely using data augmentation, and thus the performance of DrAC is better than that of RAD (both using the best augmentation for each game). See Figures 6 and 7 in the Appendix for results with all augmentations. Our experiments show that the most effective way of automatically finding an augmentation is UCB-DrAC. As expected, meta-learning the weights of a transformation function parameterized by a CNN using Meta-DrAC performs reasonably well on the games in which the random convolution augmentation helps. But overall, Meta-DrAC and RL2-DrAC are worse than UCB-DrAC. In addition, UCB is generally more stable, easier to implement, and requires less fine-tuning compared to meta-learning algorithms. See Figures 8 and 9 in the Appendix for a comparison of these three approaches on each game. Moreover, automatically selecting the augmentation from a given set using UCB-DrAC performs just as well or even better than a method that uses the best augmentation for each task throughout the entire training process. UCB-DrAC also achieves higher returns than an ablation that uses a uniform distribution to select an augmentation each time, Rand-DrAC. Similarly, UCB-DrAC is better than Crop-DrAC, which uses crop for all the games (which is the best augmentation for half of the Procgen games as shown in Tables 6 and 7 in the Appendix).
Table 1: Train and test performance for the Procgen benchmark (aggregated over all 16 tasks, 5 seeds). (a) compares PPO with two baselines specifically designed to improve generalization in RL and shows that they do not significantly help. (b) compares using the best augmentation from our set with and without regularization, corresponding to DrAC and RAD respectively, and shows that regularization improves performance on both train and test. (c) compares different approaches for automatically finding an augmentation for each task, namely using UCB or RL\textsuperscript{2} for selecting the best transformation from a given set, or meta-learning the weights of a convolutional network (Meta-DrAC). (d) shows additional ablations: Rand-DrAC selects an augmentation using a uniform distribution, Crop-DrAC uses image crops for all tasks, and UCB-RAD is an ablation that does not use the regularization losses. UCB-DrAC performs best on both train and test, and achieves a return comparable with or better than DrAC (which uses the best augmentation).

| Method               | Train Median | Test Median | Train Mean | Test Mean |
|----------------------|--------------|-------------|------------|-----------|
| (a) PPO              | 100.0        | 100.0       | 100.0      | 100.0     |
| Rand-FM              | 91.83        | 87.26       | 90.16      | 75.5      |
| IBAC-SNI             | 91.60        | 102.28      | 77.87      | 84.73     |
| (b) DrAC (Best)      | 109.0        | 116.2       | 117.0      | 137.4     |
| RAD (Best)           | 102.0        | 109.7       | 112.2      | 134.6     |
| (c) UCB-DrAC (Ours)  | 100.3        | 116.2       | 115.3      | 139.2     |
| RL2-DrAC             | 99.1         | 97.7        | 108.0      | 105.2     |
| Meta-DrAC            | 79.7         | 79.3        | 85.3       | 86.0      |
| (d) Rand-DrAC        | 101.0        | 100.3       | 101.2      | 103.3     |
| Crop-DrAC            | 98.7         | 113.3       | 112.6      | 129.8     |
| UCB-RAD              | 93.1         | 104.2       | 103.1      | 126.9     |

4.2 Regularization Effect

In Section 3.1, we argued that additional regularization terms are needed in order to make the use of data augmentation in RL theoretically sound. However, one might wonder if this problem actually appears in practice. Thus, we empirically investigate the effect of regularizing the policy and value function. For this purpose, we compare the performance of RAD and DrAC with grayscale and random convolution augmentations on Chaser, Miner, and StarPilot. Figure 2 shows that not regularizing the policy and value function with respect to the transformations used can lead to drastically worse performance than vanilla RL methods, further emphasizing the importance of these loss terms. In contrast, using the regularization terms as part of the RL objective (as DrAC does) results in an agent that is comparable or, in some cases, significantly better than PPO.

4.3 Automatic Augmentation

Our experiments indicate there is not a single augmentation that works best across all Procgen games (see Tables 6 and 7 in the Appendix), which is consistent with the observations of [34]. Moreover, our intuitions regarding the best transformation for each game might be misleading. For example, at a first sight, Climber appears to be somewhat similar to CoinRun or Jumper, but the augmentation that performs best on Climber is color-jitter, while for CoinRun and Jumper is random-conv (see Tables 6 and 7). In contrast, Miner looks like a very different game from CoinRun or Jumper, but they all have the same best performing augmentation, namely random-conv. These observations further underline the need for a method that can automatically find the right augmentation for each task.

Table 1 along with Figures 8 and 9 in the Appendix compare different approaches for automatically finding an augmentation, showing that using a simple multi-armed bandit algorithm like UCB performs best and reaches the asymptotic performance obtained when the most effective transformation for each game is used throughout the entire training process. Figure 3 illustrates an example of UCB’s policy during training on Ninja and Dodgeball, showing that it converges to always selecting the most effective augmentation (i.e. color-jitter for Ninja and crop for Dodgeball).

Figure 4 in the Appendix illustrates how UCB’s behavior varies with its exploration coefficient.
To further investigate the generalization ability of RL agents, we analyze whether their learned policies and hidden representations are invariant to changes in their observations which are inconsequential for acting in the environment or solving the task.

We first measure the Jensen-Shannon divergence (JSD) between the agent’s policy for an observation and a modified version of that observation with a different background theme (i.e., color and pattern). We chose to report the JSD because it is also a lower bound for the joint empirical risk across train and test, as proven by [27]. The background theme is randomly selected from the set of backgrounds available for all other Procgen tasks, except for the one used to train the agent. Thus, the agent has never seen the second observation during training. Note that the modified observation has the same semantics as the original one (with respect to maximizing reward), so we would expect the agent to have the same policy in both cases. However, some of the backgrounds are not uniform and can contain objects such as trees or planets which can be misled for objects the agent can interact with. As seen in Table 2, UCB-DrAC finds the most effective augmentation from the given set and reaches the performance of DrAC. Our methods improve both train and test performance.

### 4.4 Robustness Analysis

To quantitatively evaluate the quality of the learned hidden representation, we use the cycle-consistency metric proposed in [2] and used in [27]. See Appendix B for more details about this metric. Table 2 reports the percentage of input observations in the seen environment that are cycle-consistent with trajectories in modified unseen environments, which have a different background but the same layout (and thus are semantically identical with the seen level). UCB-DrAC has higher cycle-consistency than PPO, suggesting that it learns representations that are more invariant to changes in the observations that do not affect the agent and are not relevant for solving the task.
Table 2: JSD and Cycle-Consistency (%) (aggregated across all Procgen tasks) for PPO and UCB-DrAC, measured between observations that vary only in their background themes (i.e. colors and patterns that do not interact with the agent). UCB-DrAC learns more robust policies and representations that are more invariant to changes in the observation that are irrelevant for the task.

| Method    | JSD (Mean, Median) | Cycle-Consistency (2-way Mean, Median) | Cycle-Consistency (3-way Mean, Median) |
|-----------|--------------------|----------------------------------------|----------------------------------------|
| PPO       | 0.25, 0.23         | 20.50, 18.70                           | 12.70, 5.60                            |
| UCB-DrAC  | 0.16, 0.15         | 27.70, 24.80                           | 17.30, 10.30                           |

5 Related Work

Generalization in Deep RL. A recent body of work has pointed out the problem of overfitting in deep RL [44, 29, 39, 42, 59, 60, 11, 12, 54, 57, 43]. A promising approach to prevent overfitting in RL is to apply regularization techniques originally developed for supervised learning such as dropout [52] or batch normalization [28]. Farebrother et al. [17] and Cobbe et al. [11] show that such regularization methods can improve the generalization ability of RL agents in Atari [39] and CoinRun [11], respectively. Similarly, Igl et al. [25] use selective noise injection with a variational information bottleneck to mitigate overfitting in RL. More recently, Lee et al. [37] regularize the agent’s representation with respect to random convolutional transformations. Concurrently, Sonar et al. [49] learn invariant policies, while Zhang et al. [59] learn invariant representations using bisimulation and Igl et al. [26] reduce non-stationary using policy distillation. More similar to our work is that of Laskin et al. [34] who use a set of image augmentations to add perturbed observations to the training buffer of an RL agent. However, as we show in this work, naively applying data augmentation in RL, as done in [11, 34, 51], can lead to both theoretical and practical issues. Our algorithmic contributions alleviate these problems while still benefiting from the use of data augmentation.

Data Augmentation has been extensively used in computer vision for both supervised [4, 9, 10, 33, 35, 36, 48] and self-supervised [14, 40] learning. More recent work uses data augmentation for contrastive learning, leading to state-of-the-art results on downstream tasks [58, 7, 23, 22]. Domain randomization can also be considered a type of data augmentation, which has proven useful for transferring RL policies from simulation to the real world [53]. However, domain randomization requires access to a physics simulator, which is not always available. Recently, a few papers propose the use of data augmentation in RL [11, 32, 34, 37, 51], but all of them use a fixed (set of) augmentation(s) rather than automatically finding the most effective one. The most similar work to ours is that of [32], which proposes to regularize the Q-function in Soft Actor-Critic (SAC) [21] using random shifts of the input image. Our work differs from theirs in that it uses multiple transformations, regularizes both the actor and the critic, and focuses on the problem of generalization rather than sample efficiency. While there is a body of work on the automatic use of data augmentation [16, 38, 47], these approaches were designed for supervised learning and, as we explain here, cannot be applied to RL without further algorithmic changes.

6 Discussion

In this work, we propose UCB-DrAC, a method for automatically finding an effective data augmentation for RL tasks. Our approach enables the principled use of data augmentation with actor-critic algorithms by regularizing the policy and value functions with respect to state transformations. We show that UCB-DrAC avoids the theoretical and empirical pitfalls typical in naive applications of data augmentation in RL. Our approach improves training performance by ~ 16% and test performance by ~ 40% on the Procgen benchmark, relative to standard RL methods such as PPO [46]. UCB-DrAC outperforms, on both train and test environments, several methods specifically designed to aid generalization in RL [23, 37, 34]. In addition, our agent learns policies and representations that are more robust to variations in the environment that do not relevant for solving the task, such as backgrounds. A promising avenue for future research is the development of more sophisticated techniques that meta-learn the parameters of a transformation using a more expressive class of functions that captures a wider range of inductive biases.
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A PPO

Proximal Policy Optimization (PPO) \[^{46}\] is an actor-critic RL algorithm that learns a policy \(\pi_\theta\) and a value function \(V_\theta\) with the goal of finding an optimal policy for a given MDP. PPO alternates between sampling data through interaction with the environment and optimizing an objective function using stochastic gradient ascent. At each iteration, PPO maximizes the following objective:

\[
J_{\text{PPO}} = J_\pi - \alpha_1 J_V + \alpha_2 S_{\pi_\theta},
\]

where \(\alpha_1, \alpha_2\) are weights for the different loss terms, \(S_{\pi_\theta}\) is the entropy bonus for aiding exploration, \(J_V\) is the value function loss defined as

\[
J_V = (V_\theta(s) - V_t^{\text{target}})^2.
\]

The policy objective term \(J_\pi\) is based on the policy gradient objective which can be estimated using importance sampling in off-policy settings (i.e. when the policy used for collecting data is different from the policy we want to optimize):

\[
J_{\text{PG}}(\theta) = \sum_{a \in A} \pi_\theta(a|s) \hat{A}_{\theta_{old}}(s, a) = \mathbb{E}_{a \sim \pi_{\theta_{old}}} \left[ \frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)} \hat{A}_{\theta_{old}}(s, a) \right],
\]

where \(\hat{A}(\cdot)\) is an estimate of the advantage function, \(\theta_{old}\) are the policy parameters before the update, \(\pi_{\theta_{old}}\) is the behavior policy used to collect trajectories (i.e. that generates the training distribution of states and actions), and \(\pi_\theta\) is the policy we want to optimize (i.e. that generates the true distribution of states and actions).

This objective can also be written as

\[
J_{\text{PG}}(\theta) = \mathbb{E}_{a \sim \pi_{\theta_{old}}} \left[ r(\theta) \hat{A}_{\theta_{old}}(s, a) \right],
\]

where

\[
r_\theta = \frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)}
\]

is the importance weight for estimating the advantage function.

PPO is inspired by TRPO \[^{45}\], which constrains the update so that the policy does not change too much in one step. This significantly improves training stability and leads to better results than vanilla policy gradient algorithms. TRPO achieves this by minimizing the KL divergence between the old (i.e. before an update) and the new (i.e. after an update) policy. PPO implements the constraint in a simpler way by using a clipped surrogate objective instead of the more complicated TRPO objective. More specifically, PPO imposes the constraint by forcing \(r(\theta)\) to stay within a small interval around 1, precisely \([1 - \epsilon, 1 + \epsilon]\), where \(\epsilon\) is a hyperparameter. The policy objective term from equation (7) becomes

\[
J_\pi = \mathbb{E}_{\pi} \min \left( r_\theta \hat{A}, \text{clip} (r_\theta, 1 - \epsilon, 1 + \epsilon) \hat{A} \right),
\]

where \(\hat{A} = \hat{A}_{\theta_{old}}(s, a)\) for brevity. The function clip\((r(\theta), 1 - \epsilon, 1 + \epsilon)\) clips the ratio to be no more than \(1 + \epsilon\) and no less than \(1 - \epsilon\). The objective function of PPO takes the minimum one between the original value and the clipped version so that agents are discouraged from increasing the policy update to extremes for better rewards.

Note that the use of the Adam optimizer \[^{30}\] allows loss components of different magnitudes so we can use \(G_\pi\) and \(G_V\) from equations (3) and (4) to be used as part of the DrAC objective in equation (5) with the same loss coefficient \(\alpha_r\). This alleviates the burden of hyperparameter search and means that DrAC only introduces a single extra parameter \(\alpha_r\).

B Cycle-Consistency

Here is a description of the cycle-consistency metric proposed by Aytar et al. \[^{2}\] and also used in Lee et al. \[^{37}\] for analyzing the learned representations of RL agents. Given two trajectories \(V\) and \(U\), \(v_i \in V\) first locates its nearest neighbor in the other trajectory \(u_j = \arg \min_{u \in U} \|h(v_i) - h(u)\|^2\), where \(h(\cdot)\) denotes the output of the penultimate layer of trained agents. Then, the nearest neighbor
of $u_j \in V$ is located, i.e., $v_k = \arg\min_{v \in V} \| h(u_j) - h(u_j) \|_2$, and $v_i$ is defined as cycle-consistent if $|i - k| \leq 1$, i.e., it can return to the original point. Note that this cycle-consistency implies that two trajectories are accurately aligned in the hidden space. Similar to [21], we also evaluate the three-way cycle-consistency by measuring whether $v_i$ remains cycle-consistent along both paths, $V \rightarrow U \rightarrow J \rightarrow V$ and $V \rightarrow J \rightarrow U \rightarrow V$, where $J$ is the third trajectory.

### C Hyperparameters

We use [31]'s implementation of PPO [46], on top of which all our methods are build. The agent is parameterized by the ResNet architecture from [15] which was used to obtain the best results in [12]. Unless otherwise noted, we use the best hyperparameters found in [12] for the easy mode of Procgen (i.e. same experimental setup as the one used here), namely:

| Hyperparameter | Value |
|----------------|-------|
| $\gamma$      | 0.999 |
| $\lambda$     | 0.95  |
| # timesteps per rollout | 256 |
| # epochs per rollout | 3 |
| # minibatches per epoch | 8 |
| entropy bonus | 0.01  |
| clip range    | 0.2   |
| reward normalization | yes |
| learning rate | 5e-4  |
| # workers     | 1     |
| # environments per worker | 64 |
| # total timesteps | 25M |
| optimizer     | Adam  |
| LSTM          | no    |
| frame stack   | no    |
| $\alpha_r$    | 0.1   |
| $c$           | 0.1   |
| $K$           | 10    |

For DrAC, we did a grid search for the regularization coefficient $\alpha_r \in [0.0001, 0.01, 0.05, 0.1, 0.5, 1.0]$ used in equation (5) and found that the best value is $\alpha_r = 0.1$, which was used to produce all the results in this paper.

For UCB-DrAC, we did grid searches for the exploration coefficient $c \in [0.0, 0.1, 0.5, 1.0, 5.0]$ and the size of the sliding window used to compute the Q-values $K \in [10, 50, 100]$. We found that the best values are $c = 0.1$ and $K = 10$, which were used to obtain the results shown here.

For Meta-DrAC, the convolutional network whose weights we meta-learn consists of a single convolutional layer with 3 input and 3 output channels, kernel size 3, stride 1 and 0 padding. At each epoch, we perform one meta-update where we unroll the inner optimizer using the training set and compute the meta-test return on the validation set.

For Rand-FM [37] we use the recommended hyperparameters in the authors’ released implementation, which were the best ones found on CoinRun [11], one of the Procgen games used for evaluation in [11].

For IBAC-SNI [25] we also use the authors’ open sourced implementation. We use the parameters corresponding to IBAC-SNI $\lambda = .5$. We use weight regularization with $l_2 = .0001$, data augmentation turned on, and a value of $\beta = .0001$ which turns on the variational information bottleneck, and selective noise injection turned on. This corresponds to the best version of this approach, as found by the authors after evaluating it on CoinRun [11]. While IBAC-SNI outperforms the other methods on
maze-like games such as heist, maze, and miner, it is still significantly worse than our approach on the entire Procgen benchmark.

For both baselines, Rand-FM and IBAC-SNI, we use the same experimental setup for training and testing as the one used for our methods. Hence, we train them for 25M frames on the easy mode of each Procgen game, using (the same) 200 levels for training and the rest for testing.

We use the Adam [30] optimizer for all our experiments. Note that by using Adam, we do not need separate coefficients for the policy and value regularization terms (since Adam rescales gradients for each loss component accordingly).

D Analysis of UCB’s Behavior

In Figure 3, we show the behavior of UCB during training, along with train and test performance on the respective environments. In the case of Ninja, UCB converges to always selecting the best augmentation only after 15M training steps. This is because the augmentations have similar effects on the agent early in training, so it takes longer to find the best augmentation from the given set. In contrast, on Dodgeball, UCB finds the most effective augmentation much earlier in training because there is a significant difference between the effect of various augmentations. Early discovery of an effective augmentation leads to significant improvements over PPO, for both train and test environments.

Another important factor is the exploration coefficient used by UCB (see equation 6) to balance the exploration and exploitation of different augmentations. Figure 4 compares UCB’s behavior for different values of the exploration coefficient. Note that if the coefficient is 0, UCB always selects the augmentation with the largest Q-value. This can sometimes lead to UCB converging on a suboptimal augmentation due to the lack of exploration. However, if the exploration term of equation 6 is too large relative to the differences in the Q-values among various augmentations, UCB might take too long to converge. In our experiments, we found that an exploration coefficient of 0.1 results in a good exploration-exploitation balance and works well across all Procgen games.
E Breakdown of Procgen Scores

Figure 5: Screenshots of multiple procedurally-generated levels from five Procgen environments: Maze, Climber, Plunder, Ninja, and BossFight (from left to right).

Table 4: Procgen scores on train levels after training on 25M environment steps.

| Game    | PPO | Rand + FM | IBAC-SNI | DrAC (Best) | RAD (Best) | UCB-DrAC (Ours) | RL2-DrAC | Meta-DrAC |
|---------|-----|-----------|----------|-------------|------------|-----------------|----------|-----------|
| BigFish | 8.98| 5.97      | 19.02    | 12.99       | 15.81      | 13.24           | 12.48    | 5.59      |
| StarPilot| 29.46| 26.2      | 26.5     | 32.47       | 35.68      | 34.08           | 30.55    | 25.73     |
| FruitBot| 29.12| 29.21     | 29.5     | 29.8        | 29         | 29.57           | 27.72    | 23.55     |
| BossFight| 8.31 | 5.58      | 7.75     | 8.15        | 8.15       | 8.35            | 8.24     | 6.26      |
| Ninja   | 7.45 | 7.1       | 8.06     | 8.83        | 8.13       | 8.55            | 7.9      | 5.85      |
| Plunder | 6.11 | 5.38      | 5.88     | 9.21        | 8.55       | 10.5            | 6.6      | 5.55      |
| CaveFlyer| 6.82 | 6.44      | 6.08     | 8.18        | 8.88       | 5.7             | 6.2      | 5.28      |
| CoinRun | 9.39 | 9.69      | 9.56     | 9.63        | 9.12       | 9.41            | 9.03     | 8.97      |
| Jumper  | 8.31 | 8.84      | 8.41     | 8.96        | 8.67       | 8.16            | 8.43     | 7.95      |
| Chaser  | 4.44 | 2.78      | 3.02     | 7.14        | 6.45       | 7.38            | 4.78     | 3.19      |
| Climber | 8.36 | 7.46      | 6.96     | 9.69        | 6.94       | 8.13            | 7.89     | 6.77      |
| Dodgeball| 4.24 | 4.21      | 9.36     | 6.94        | 4.95       | 8.13            | 6.14     | 3.46      |
| Heist   | 7.12 | 4.7       | 5.42     | 6.72        | 5.52       | 6.75            | 5.51     | 4.87      |
| Leaper  | 5.44 | 2.55      | 2.92     | 5.1         | 4.55       | 5.12            | 2.88     | 3.58      |
| Maze    | 9.13 | 8.12      | 7.5      | 6.47        | 7.93       | 8.59            | 6.88     | 7.61      |
| Miner   | 11.93| 11.57     | 8.35     | 12.51       | 10.27      | 11.8            | 11.08    | 8.63      |
Table 5: Procgen scores on test levels after training on 25M environment steps.

| Game      | PPO  | Rand + FM | IBAC-SNI | DrAC (Best) | RAD (Best) | UCB-DrAC | RL2-DrAC | Meta-DrAC |
|-----------|------|-----------|----------|-------------|------------|----------|----------|-----------|
| BigFish   | 3.59 | 0.505     | 0.32     | 8.54        | 12.2       | 9.7      | 5.65     | 2.29      |
| StarPilot | 24.9 | 8.41      | 4.9      | 29.11       | 33.33      | 30.53    | 27.43    | 23.48     |
| FruitBot  | 26.53| 24.32     | 24.4     | 27.71       | 25.23      | 28       | 29.16    | 22.15     |
| BossFight | 7.64 | 1.51      | 0.13     | 7.85        | 7.57       | 8.23     | 7.19     | 5.74      |
| Ninja     | 6    | 5.96      | 9.17     | 7.02        | 6.79       | 6.54     | 6.28     | 5.11      |
| Plunder   | 5.13 | 2.89      | 2.01     | 7.79        | 8.03       | 8.59     | 5.42     | 5.02      |
| CaveFlyer | 5.01 | 5.21      | 7.86     | 6.44        | 7.78       | 5.09     | 4.44     | 4.57      |
| CoinRun   | 8.56 | 9.16      | 9.46     | 8.78        | 8.54       | 8.58     | 8.61     | 8.31      |
| Jumper    | 5.89 | 5.23      | 3.46     | 6.3         | 6.23       | 6.34     | 6.37     | 5.96      |
| Chaser    | 3.73 | 1.36      | 1.14     | 5.81        | 5.73       | 6.52     | 4.06     | 2.85      |
| Climber   | 5.71 | 5.15      | 3.17     | 7.02        | 5.37       | 6.38     | 6.28     | 5.07      |
| Dodgeball | 1.66 | 0.39      | 1.25     | 4.28        | 2.83       | 4.44     | 2.81     | 1.37      |
| Heist     | 2.5  | 2.29      | 9.71     | 3.98        | 3.93       | 3.82     | 2.47     | 2.17      |
| Leaper    | 4.99 | 6.00      | 6.91     | 5.17        | 4.2        | 4.95     | 3.03     | 3.37      |
| Maze      | 5.6  | 7.87      | 10.00    | 6.47        | 6.23       | 6.32     | 5.56     | 5.31      |
| Miner     | 8.42 | 7.59      | 7.87     | 9.7         | 7.08       | 9.85     | 8.63     | 6.6       |
Data Augmentation

Figure 6: Train performance of DrAC with different augmentations.

Table 6: Best augmentation type for each game, as evaluated on the test environments.

| Game      | BigFish | StarPilot | FruitBot | BossFight | Ninja | Plunder | CaveFlyer | CoinRun |
|-----------|---------|-----------|----------|-----------|-------|---------|-----------|---------|
| Best Augmentation | crop    | crop      | crop     | flip      | color-jitter | crop | rotate | random-conv |

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Figure 7: Test performance of DrAC with different augmentations.

Table 7: Best augmentation type for each game, as evaluated on the test environments.

| Game     | Jumper | Chaser | Climber | Dodgeball | Heist | Leaper | Maze | Miner |
|----------|--------|--------|---------|-----------|-------|--------|------|-------|
| Best Augmentation | random-conv | crop   | color-jitter | crop     | crop  | crop   | crop | color-jitter |
Figure 8: Train performance of various approaches that automatically select an augmentation, namely UCB-DrAC, RL2-DrAC, and Meta-DrAC.
Figure 9: Test performance of various approaches that automatically select an augmentation, namely UCB-DrAC, RL2-DrAC, and Meta-DrAC.