Image Augmentation Is All You Need:
Regularizing Deep Reinforcement Learning
from Pixels

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Abstract

We propose a simple data augmentation technique that can be applied to standard model-free reinforcement learning algorithms, enabling robust learning directly from pixels without the need for auxiliary losses or pre-training. The approach leverages input perturbations commonly used in computer vision tasks to regularize the value function. Existing model-free approaches, such as Soft Actor-Critic (SAC) [20], are not able to train deep networks effectively from image pixels. However, the addition of our augmentation method dramatically improves SAC’s performance, enabling it to reach state-of-the-art performance on the DeepMind control suite, surpassing model-based [21, 31, 22] methods and recently proposed contrastive learning [42]. Our approach can be combined with any model-free reinforcement learning algorithm, requiring only minor modifications. An implementation can be found at https://sites.google.com/view/data-regularized-q.

1 Introduction

Sample-efficient deep reinforcement learning (RL) algorithms capable of directly training from image pixels would open up many real-world applications in control and robotics. However, simultaneously training a convolutional encoder alongside a policy network is challenging when given limited environment interaction, strong correlation between samples and a typically sparse reward signal. Naive attempts to use a large capacity encoder result in severe over-fitting (see Figure 1a) and smaller encoders produce impoverished representations that limit task performance.

Limited supervision is a common problem across AI and a number of approaches are adopted: (i) pre-training with self-supervised learning (SSL), followed by standard supervised learning; (ii) supervised learning with an additional auxiliary loss and (iii) supervised learning with data augmentation. SSL approaches are highly effective in the large data regime, e.g. in domains such as vision [7, 23] and NLP [12, 13] where large (unlabeled) datasets are readily available. However, in RL this is not the case: an off-policy RL agent is trained on a replay buffer that grows as the agent interacts with the environment. But in a sample efficient regime the buffer may only hold $10^4$–$10^5$ transitions from a few hundred trajectories, limiting the effectiveness of SSL methods.

A wide range of auxiliary loss functions have been proposed to augment supervised objectives, e.g. weight regularization, noise injection [25], or some form of online SSL objective. In RL,
Figure 1: The performance of SAC [20] trained from pixels on the DeepMind Control suite using image encoder networks of different capacity (network architectures taken from recent RL algorithms, with parameter count indicated). (a): unmodified SAC. Task performance can be seen to get worse as the capacity of the encoder increases, indicating over-fitting. For Walker Walk (right), all architectures provide mediocre performance, demonstrating the inability of SAC to train directly from pixels on harder problems. (b): SAC combined with image augmentation in the form of random shifts. The task performance is now similar for all architectures, regardless of their capacity. Furthermore, there is a clear performance improvement relative to (a), particularly for the more challenging Walker Walk task.

The paper makes the following contributions: (i) we demonstrate how image augmentation, a popular regularization technique in computer vision, can be applied in the context of model-free off-policy RL. (ii) Combined with vanilla SAC [20] and using hyper-parameters fixed across all tasks, the approach obtains state-of-the-art performance on the DeepMind control suite [43]. (iii) It is thus the first effective approach able to train directly from pixels without the need for unsupervised auxiliary losses or a world model. (iv) Systematic exploration shows the method to be robust to the exact choice of hyper-parameters. (v) We also provide a PyTorch implementation of the approach combined with SAC.

2 Background

Reinforcement Learning from Images We formulate image-based control as a finite-horizon partially observable Markov decision process (POMDP) [6][27], instantiated by an episodic environment with discrete time step $t \in [1, T]$, where $T$ is fixed. An POMDP can be described as...
the tuple \((O, A, p, r, \gamma)\), where \(O\) is the high-dimensional observation space (image pixels), \(A\) is the action space, the transition dynamics \(p = Pr(o_t|o_{<t}, a_t)\) capture the probability distribution over the next observation \(o_t\) given the history of previous observations \(o_{<t}\) and current action \(a_t\), \(r : O \times A \rightarrow \mathbb{R}\) is the reward function that maps the current observation and action to a reward \(r_t = r(o_{<t}, a_t)\), and \(\gamma \in [0, 1)\) is a discount factor. Per common practice \([37]\), throughout the paper the POMDP is converted into an MPD \([6]\) by stacking three consecutive image observations into a state \(s_t = \{o_t, o_{t-1}, o_{t-2}\}\). For simplicity we redefine the transition dynamics \(p = Pr(s_t'|s_t, a_t)\) and the reward function \(r_t = r(s_t, a_t)\) to operate on \(s_t, s_t'\) and \(a_t\). We thus aim to find a policy \(\pi(a_t|s_t)\) that maximizes the cumulative discounted return \(E_{\pi} \sum_{t=1}^{T} \gamma^t r_t(a_t \sim \pi(\cdot|s_t), s_t' \sim p(\cdot|s_t, a_t), s_1 \sim p(\cdot))\).

**Soft Actor-Critic** The Soft Actor-Critic (SAC) \([20]\) learns a state-action value function \(Q_\theta\), stochastic policy \(\pi_\theta\) and a temperature \(\alpha\) to find an optimal policy for an MPD \((S, A, p, r, \gamma)\) by optimizing a \(\gamma\)-discounted maximum-entropy objective \([51]\). \(\theta\) is used generically to denote the parameters updated through training in each part of the model. The actor policy \(\pi_\theta(a_t|s_t)\) is a parametric tanh-Gaussian that given \(s_t\) samples \(a_t = \text{tanh}(\mu_\theta(s_t) + \sigma_\theta(s_t) \epsilon)\), where \(\epsilon \sim \mathcal{N}(0, 1)\) and \(\mu_\theta\) and \(\sigma_\theta\) are parametric mean and standard deviation.

The policy evaluation step learns the critic \(Q_\theta(s_t, a_t)\) network by optimizing a single-step of the soft Bellman residual

\[
J_Q(D) = \mathbb{E}_{(s_t,a_t,s_t') \sim D}[(Q_\theta(s_t, a_t) - y_t)^2]
\]

\[y_t = r(s_t, a_t) + \gamma Q_\theta'(s_t', a'_t) - \alpha \log \pi_\theta(a'_t|s'_t),\]

where \(D\) is a replay buffer of transitions, \(\theta'\) is an exponential moving average of the weights as done in \([33]\). SAC uses clipped double-Q learning \([45][13]\), which we omit from our notation for simplicity but employ in practice.

The policy improvement step then fits the actor policy \(\pi_\theta(a_t|s_t)\) network by optimizing the objective

\[
J_\pi(D) = \mathbb{E}_{s_t \sim D} [D_{KL}(\pi_\theta(\cdot|s_t)||\exp{\frac{1}{\alpha} Q_\theta(s_t, \cdot)})].
\]

Finally, the temperature \(\alpha\) is learned with the loss

\[
J_\alpha(D) = \mathbb{E}_{a_t \sim \pi_\theta(\cdot|s_t)} [-\alpha \log \pi_\theta(a_t|s_t) - \alpha \tilde{H}],
\]

where \(\tilde{H} \in \mathbb{R}\) is the target entropy hyper-parameter that the policy tries to match, which in practice is usually set to \(\tilde{H} = -|A|\).

### 3 Sample Efficient Reinforcement Learning from Pixels

This work focuses on the data-efficient regime, seeking to optimize performance given limited environment interaction. However, with images as input a convnet encoder must be trained in conjunction with the policy network. In Figure 1a we show a motivating experiment that demonstrates over-fitting to be a significant issue in this scenario. Using three tasks from the DeepMind control suite \([43]\), SAC \([20]\) is trained with the same policy network architecture but using different image encoder architectures, taken from the following RL approaches: NatureDQN \([37]\), Dreamer \([21]\), Impala \([15]\), SAC-AE \([49]\) (also used in CURL\([42]\)), and D4PG \([4]\)). The encoders vary significantly in their capacity, with parameter counts ranging from 220k to 2.4M. The curves show that performance decreases as parameter count increases, a clear indication of over-fitting.

#### 3.1 Image Augmentation with Random Shifts

A range of successful image augmentation techniques to counter over-fitting have been developed in computer vision \([8][9][40][29][1]\). These apply transformations to the input image for which the task labels are invariant, e.g. for object recognition tasks, image flips and rotations do not alter the semantic label. However, tasks in RL differ significantly from those in vision and in many cases the reward would not be preserved by these transformations. We therefore limit our choice of
augmentation to simple random shifts of the image. This technique is commonly used to help with overfitting on small images from MNIST\cite{LeCun:98} and CIFAR10\cite{Krizhevsky:09}.

Figure 1b shows the results of this augmentation applied during SAC training. The images from the DeepMind control suite are $84 \times 84$. We pad each side by 4 pixels (by repeating boundary pixels) and then select a random $84 \times 84$ crop, yielding the original image shifted by $\pm 4$ pixels. This procedure is repeated every time an image is sampled from the replay buffer. The plots show overfitting is greatly reduced, closing the performance gap between the encoder architectures. Surprisingly, these random shifts alone enable SAC to achieve competitive absolute performance, without the need for auxiliary losses.

3.2 Optimality Invariant Image Transformations

While the image augmentation described above is effective, it does not fully exploit the MDP structure inherent in RL tasks. We now introduce a general framework for regularizing the value function through transformations of the input state. For a given task, we define an optimality invariant state transformation $f : S \times T \rightarrow S$ as a mapping that preserves the $Q$-values

$$Q(s, a) = Q(f(s, \nu), a)$$

for all $s \in S$, $a \in A$ and $\nu \in T$.

where $\nu$ are the parameters of $f(\cdot)$, drawn from the set of all possible parameters $T$. One example of such transformations are the random image translations successfully applied in the previous section.

For every state, the transformations allow the generation of several surrogate states with the same $Q$-values, thus providing a mechanism to reduce the variance of $Q$-function estimation. In particular, for an arbitrary distribution of states $\mu(\cdot)$ and policy $\pi$, instead of using a single sample $s^* \sim \mu(\cdot)$, $a^* \sim \pi(\cdot|s^*)$ estimation of the following expectation

$$\mathbb{E}_{s \sim \mu(\cdot)}[Q(s, a)] \approx Q(s^*, a^*)$$

we can instead generate $K$ samples via random transformations and obtain an estimate with lower variance

$$\mathbb{E}_{s \sim \mu(\cdot)}[Q(s, a)] \approx \frac{1}{K} \sum_{k=1}^{K} Q(f(s^*, \nu_k), a_k)$$

where $\nu_k \in T$ and $a_k \sim \pi(\cdot|f(s^*, \nu_k))$.

This suggests two distinct ways to regularize $Q$-function. First, we use the data augmentation to compute the target values for every transition tuple $(s_i, a_i, r_i, s'_i)$

$$y_i = r_i + \gamma \frac{1}{K} \sum_{k=1}^{K} Q_\theta(f(s'_i, \nu_{i,k}'), a'_{i,k})$$

where $\nu'_{i,k} \in T$ corresponds to a transformation parameter of $s'_i$. Then the Q-function is updated using these targets through an SGD update using $\lambda_\theta$ learning rate

$$\theta \leftarrow \theta - \lambda_\theta \nabla_{\theta} \frac{1}{N} \sum_{i=1}^{N} (Q_\theta(f(s_i, \nu_i), a_i) - y_i)^2.$$  \hfill (2)

In tandem, we note that the same target from Equation (1) can be used for different augmentations of $s_i$, resulting in the second regularization approach

$$\theta \leftarrow \theta - \lambda_\theta \nabla_{\theta} \frac{1}{NM} \sum_{i=1}^{N,M} (Q_\theta(f(s_{i,m}, \nu_{i,m}), a_i) - y_i)^2.$$  \hfill (3)

When both regularization methods are used, $\nu_{i,m}$ and $\nu'_{i,k}$ are drawn independently. Algorithm 1 details how they are incorporated into a generic pixel-based off-policy actor-critic algorithm.
3.3 Our Method: DrQ

Our approach, DrQ, is the union of the three separate regularization mechanisms introduced above: (i) transformations of the input image (Section 3.1, orange in Algorithm 1); (ii) averaging the Q target over K image transformations (Equation (1), green in Algorithm 1) and (iii) averaging the Q function itself over M image transformations (Equation (3) blue in Algorithm 1). For the experiments in this paper, we pair DrQ with SAC [20], a popular model-free algorithm for control in continuous action spaces. We select image shifts as the class of image transformations, with ν = ±1, as explained in Section 3.1. For target Q and Q augmentation we use K = 2 and M = 2 respectively. Figure 2 shows DrQ and ablated versions, demonstrating clear gains over unaugmented SAC.

![Figure 2: Different combinations of our three regularization approaches on tasks from [43] using SAC. Black: standard SAC. Blue: SAC augmented with Image shifts, corresponding to Algorithm 1 with K = 1, M = 1. Red: Image + Target Q with K = 2, M = 1. Purple: Our approach, DrQ, comprising SAC with Image + Target Q + Q augmentations, using K = 2, M = 2. All three regularization methods independently provide beneficial gains over unaugmented SAC.]

Algorithm 1 DrQ: Data regularized Q applied to a generic off-policy actor critic algorithm.

**Black:** unmodified off-policy actor-critic.

**Orange:** image transformation.

**Green:** target Q augmentation.

**Blue:** Q augmentation.

**Hyperparameters:** Total number of environment steps T, mini-batch size N, learning rate λθ, target network update rate τ, image transformation f, number of target Q augmentations K, number of Q augmentations M.

```plaintext
for each timestep t = 1..T do
    a_t ~ π(·|s_t)
    s_t′ ~ p(·|s_t, a_t)
    D ← D ∪ (s_t, a_t, r(s_t, a_t), s_t′)
    UPDATECRITIC(D)  ▷ Standard actor update
    UPDATEACTOR(D)  ▷ Update the critic
end for

procedure UPDATECRITIC(D)
    \{(s_i, a_i, r_i, s_i')\}_{i=1}^N \sim D
    \{\nu_{i,k}'\}_{i,k} \sim \mathcal{U}(T), i = 1..N, k = 1..K  ▷ Sample parameters of target augmentations
    for each i = 1..N do
        a_i' ~ π(·|s_i')  or  a_i,k' ~ π(·| f(s_i', ν_{i,k}'))  \( k = 1..K \)
        \hat{Q}_i = Q_\theta(s_i, a_i')  or  \hat{Q}_i = \frac{1}{K} \sum_{k=1}^K Q_\theta(f(s_i', \nu_{i,k}'), a_i,k')
        y_i ← r(s_i, a_i) + γ \hat{Q}_i
    end for
    J_q(θ) = \frac{1}{N} \sum_{i=1}^N (Q_\theta(s_i, a_i) - y_i)^2  or  J_q(θ) = \frac{1}{NM} \sum_{i,m=1}^{N,M} (Q_\theta(f(s_i, \nu_{i,m}), a_i) - y_i)^2
    θ ← θ - λ_θ \nabla J_q(θ)  ▷ Update the critic
    θ' ← (1 - τ)θ' + τθ  ▷ Update the critic target
end procedure
```
4 Experiments

In this section we evaluate our algorithm (DrQ) on the two commonly used benchmarks based on the DeepMind control suite \[43\], namely the PlaNet \[22\] and Dreamer \[21\] setups. Throughout these experiments all hyper-parameters of the algorithm are kept fixed: the actor and critic neural networks are trained using the Adam optimizer \[28\] with default parameters and a mini-batch size of 512. For SAC, the soft target update rate \(\tau\) is 0.01, initial temperature is 0.1, and target network and the actor updates are made every 2 critic updates (as in \[49\]). We use the image encoder architecture from SAC-AE \[49\] and follow their training procedure. The full set of parameters can be found in Appendix A. Following \[24\], the models are trained using 10 different seeds; for every seed the mean episode returns are computed every 10000 true environment steps, averaging over 10 episodes. All figures plot the mean performance over the 10 seeds, together with \(\pm 1\) standard deviation shading.

We compare our DrQ approach to leading model-free and model-based approaches: PlaNet \[22\], SAC-AE \[49\], SLAC \[31\], CURL \[42\] and Dreamer \[21\]. The comparisons use the results provided by the authors of the corresponding papers.

4.1 PlaNet Benchmark

The PlaNet benchmark \[22\] consists of six challenging control tasks from \[43\] with different traits. The benchmark specifies a different action-repeat hyper-parameter for each of the six tasks \[22\]. Following common practice \[22, 31, 49, 37\], we report the performance using true environment steps, thus are invariant to the action-repeat hyper-parameter. Aside from action-repeat, all other hyper-parameters of our algorithm are fixed across the six tasks, using the values previously detailed. Figure 3 compares DrQ to PlaNet \[22\], SAC-AE \[49\], CURL \[42\], SLAC \[31\], and an upper bound performance provided by SAC \[20\] that directly learns from internal states. We use the version of SLAC that performs one gradient update per an environment step to ensure a fair comparison to other approaches. DrQ achieves state-of-the-art performance on this benchmark on all the tasks, despite being much simpler than other methods. Furthermore, since DrQ does not learn a model \[22, 31\] or any auxiliary tasks \[42\], the wall clock time also compares favorably to the other methods. In Table 1 we also compare performance given at a fixed number of environment interactions (e.g. 100k and 500k).

4.2 Dreamer Benchmark

A more extensive benchmark was introduced in Dreamer \[21\], featuring a diverse set of tasks from the DeepMind control suite. Tasks involving sparse reward were excluded (e.g. Acrobat and Quadruped) since they require modification of SAC to incorporate multi-step returns \[4\], which is beyond the scope of this work. We evaluate on the remaining 15 tasks, fixing the action-repeat hyper-parameter to 2, as in Dreamer.

We compare DrQ to Dreamer \[21\] and the upper-bound performance of SAC \[20\] from states \[4\]. Again, we keep all the hyper-parameters of our algorithm fixed across all the tasks. In Figure 4 DrQ demonstrates the state-of-the-art results by collectively outperforming Dreamer \[21\], although Dreamer is superior on three of the 15 tasks (Walker Run, Cartpole Swingup Sparse and Pendulum Swingup). On many tasks DrQ approaches the upper-bound performance of SAC \[20\] trained directly on states.

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2 This means the number of training observations is a fraction of the environment steps (e.g. an episode of 1000 steps with action-repeat 4 results in 250 training observations).

3 In contrast to prior work, CURL \[42\] plots returns as a function of modified environment steps, i.e. true environment steps divided by the action-repeat hyper-parameter. This has the effect of increasing the reported sample-efficiency by a factor proportional to action repeat. For a fair comparison, we plot the CURL curves based on unmodified environment steps, following the convention used by all other methods.

4 No other publicly reported results are available for the other methods due to the recency of the Dreamer \[21\] benchmark.
Figure 3: The PlaNet benchmark. Our algorithm (DrQ) outperforms the other methods and demonstrates the state-of-the-art performance. Furthermore, on several tasks DrQ is able to match the upper-bound performance of SAC trained directly on internal state, rather than images. Finally, our algorithm not only shows improved sample-efficiency relative to other approaches, but is also faster in terms of wall clock time.

| 500k step scores | DrQ (Ours) | CURL | PlaNet | SAC-AE | SLAC | SAC State |
|-------------------|------------|------|--------|--------|------|-----------|
| Finger Spin       | 938±103    | 874±151 | 418±382 | 914±107 | 771±203 | 927±43    |
| Cartpole Swingup  | 868±10     | 861±30  | 464±50  | 730±152 | -     | 870±7     |
| Reacher Easy      | 942±71     | 904±94  | 351±483 | 601±135 | -     | 975±5     |
| Cheetah Run       | 660±96     | 500±91  | 321±104 | 544±50  | 629±74 | 772±60    |
| Walker Walk       | 921±45     | 681±68  | 293±114 | 858±82  | 865±97 | 964±8     |
| Ball In Cup Catch | 963±49     | 958±13  | 352±467 | 810±121 | 959±4  | 979±6     |

| 100k step scores |
|-------------------|
| Finger Spin       | 901±104    | 779±108 | 95±164  | 747±130 | 680±130 | 672±76    |
| Cartpole Swingup  | 759±92     | 592±170 | 303±71  | 276±38  | -     | 812±45    |
| Reacher Easy      | 601±213    | 517±113 | 140±256 | 225±164 | -     | 919±123   |
| Cheetah Run       | 344±67     | 307±48  | 165±123 | 240±38  | 391±47* | 228±95    |
| Walker Walk       | 612±164    | 323±43  | 125±57  | 395±58  | 428±74 | 604±517   |
| Ball In Cup Catch | 913±53     | 772±241 | 198±442 | 338±196 | 607±173| 957±26    |

Table 1: The PlaNet benchmark at 100k and 500k environment steps. Our method (DrQ) outperforms other approaches in both the data-efficient (100k) and asymptotic performance (500k) regimes.

*: SLAC uses 100k exploration steps which are not counted in the reported values. By contrast, DrQ only uses 1000 exploration steps which are included in the overall step count.

5 Robustness Investigation

To demonstrate the robustness of our approach [24], we perform a comprehensive study on the effect of different hyper-parameter choices on performance. A review of prior work [22, 21, 31, 42] shows consistent values for discount \( \gamma = 0.99 \) and target update rate \( \tau = 0.01 \) parameters, but variability on network architectures, mini-batch sizes, learning rates. Since our method is based on SAC [20], we also check whether the initial value of the temperature is important, as it plays a crucial role in the initial phase of exploration. We omit search over network architectures since Figure 1b shows our method to be robust to the exact choice. We thus focus on three hyper-parameters: mini-batch size, learning rate, and initial temperature.

Due to computational demands, experiments are restricted to a subset of tasks from [43]. Walker Walk (Figure 5a), Cartpole Swingup (Figure 5b), and Finger Spin (Figure 5c). These were selected...
to be diverse, requiring different behaviors including locomotion and goal reaching. A grid search is performed over mini-batch sizes \( \{128, 256, 512\} \), learning rates \( \{0.0001, 0.0005, 0.001, 0.005\} \), and initial temperatures \( \{0.005, 0.01, 0.05, 0.1\} \). We follow the experimental setup from Section 4 except that only 3 seeds are used due to the computation limitations, but since variance is low the results should be representative.
Figure 5: A robustness study of our algorithm (DrQ) to changes in mini-batch size, learning rate, and initial temperature hyper-parameters on three different tasks from [43]. Each row corresponds to a different mini-batch size. The low variance of the curves and heat-maps shows DrQ to be generally robust to exact hyper-parameter settings.
Figure 5 shows performance curves for each configuration as well as a heat map over the mean performance of the final evaluation episodes, similar to [36]. Our method demonstrates good stability and is largely invariant to the studied hyper-parameters. We emphasize that for simplicity the experiments in Section 4 use the default learning rate of Adam [28] (0.001), even though it is not always optimal.

6 Related Work

Computer Vision Data augmentation via image transformations has been used to improve generalization since the inception of convolutional networks [5, 40, 30, 9, 8]. Following AlexNet [29], they have become a standard part of training pipelines. For object classification tasks, the transformations are selected to avoid changing the semantic category, i.e. translations, scales, color shifts, etc. Perturbed versions of input examples are used to expand the training set and no adjustment to the training algorithm is needed. While a similar set of transformations are potentially applicable to control tasks, the RL context does require modifications to be made to the underlying algorithm.

Data augmentation methods have also been used in the context of self-supervised learning. [14] use per-exemplar perturbations in a unsupervised classification framework. More recently, a several approaches [7, 23, 35] have used invariance to imposed image transformations in contrastive learning schemes, producing state-of-the-art results on downstream recognition tasks. By contrast, our scheme addresses control tasks, utilizing different types of invariance.

Regularization in RL Some early attempts to learn RL function approximators used 2 regulariza-
tion of the Q [16, 48] function. Another approach is entropy regularization [51, 20, 38, 47], where causal entropy is added to the rewards, making the Q-function smoother and facilitating optimization [2]. Prior work has explored regularization of the neural network approximator in deep RL, e.g. using dropout [17] and cutout [11] techniques. See [34] for a comprehensive evaluation of different network regularization methods. In contrast, our approach directly regularizes the Q-function in a data-driven way that incorporates knowledge of task invariances, as opposed to generic priors.

Generalization between Tasks and Domains A range of datasets have been introduced with the explicit aim of improving generalization in RL through deliberate variation of the scene colors/textures/backgrounds/viewpoints. These include Robot Learning in Homes [19], Meta-World [50], the ProcGen benchmark [10]. There are also domain randomization techniques [44, 41] which synthetically apply similar variations, but assume control of the data generation procedure, in contrast to our method. Furthermore, these works address generalization between domains (e.g. synthetic-to-real or different game levels), whereas our work focuses on a single domain and task.

Continuous Control from Pixels There are a variety of methods addressing the sample-efficiency of RL algorithms that directly learn from pixels. The most prominent approaches for this can be classified into two groups, model-based and model-free methods. The model-based methods attempt to learn the system dynamics in order to acquire a compact latent representation of high-dimensional observations to later perform policy search [22, 31, 21]. In contrast, the model-free methods either learn the latent representation indirectly by optimizing the RL objective [4, 1] or by employing auxiliary losses that provide additional supervision [49, 42]. Our approach is complementary to these methods and can be combined with them to improve performance.

7 Conclusion

We have introduced a simple regularization technique that significantly improves the performance of Soft-Actor-Critic trained directly from image pixels on standard continuous control tasks. Our method is easy to implement and adds a negligible computational burden. We compared our method to state-of-the-art approaches and demonstrated that it outperforms them on the majority of tasks. Furthermore, we demonstrate the method to be robust to the choice of hyper-parameters. Feature research can likely demonstrate that the method is general and does not depend on the choice of the base RL algorithm.
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Appendix

A Hyper Parameters and Setup

A.1 Actor and Critic Networks

We employ clipped double Q-learning \cite{7, 18} for the critic, where each Q-function is parametrized as a 3-layer MLP with ReLU activations after each layer except of the last. The actor is also a 3-layer MLP with ReLUs that outputs mean and covariance for the diagonal Gaussian that represents the policy. The hidden dimension is set to 1024 for both the critic and actor.

A.2 Encoder Network

We employ an encoder architecture from \cite{49}. This encoder consists of four convolutional layers with $3 \times 3$ kernels and 32 channels. The ReLU activation is applied after each conv layer. We use stride to 1 everywhere, except of the first conv layer, which has stride 2. The output of the convnet is fed into a single fully-connected layer normalized by LayerNorm \cite{3}. Finally, we apply $\tanh$ nonlinearity to the 50 dimensional output of the fully-connected layer. We initialize the weight matrix of fully-connected and convolutional layers with the orthogonal initialization \cite{39} and set the bias to be zero.

The actor and critic networks both have separate encoders, although we share the weights of the conv layers between them. Furthermore, only the critic optimizer is allowed to update these weights (e.g. we stop the gradients from the actor before they propagate to the shared conv layers).

A.3 Training and Evaluation Setup

Our agent first collects 1000 seed observations using a random policy. The further training observations are collected by sampling actions from the current policy. We perform one training update every time we receive a new observation. In cases where we use action repeat, the number of training observations is only a fraction of the environment steps (e.g. a 1000 steps episode at action repeat 4 will only result into 250 training observations). We evaluate our agent every 10000 true environment steps by computing the average episode return over 10 evaluation episodes. During evaluation we take the mean policy action instead of sampling.

A.4 PlaNet and Dreamer Benchmarks

We consider two evaluation setups that were introduced in PlaNet \cite{22} and Dreamer \cite{21}, both using tasks from the DeepMind control suite \cite{43}. The PlaNet benchmark consists of six tasks of various traits. Importantly, the benchmark proposed to use a different action repeat hyper-parameter for each task, which we summarize in Table 2.

The Dreamer benchmark considers an extended set of tasks, which makes it more difficult than the PlaNet setup. Additionally, this benchmark requires to use the same set of hyper-parameters for each task, including action repeat (set to 2), which further increases the difficulty.

| Task name               | Action repeat |
|-------------------------|---------------|
| Cartpole Swingup        | 8             |
| Reacher Easy            | 4             |
| Cheetah Run             | 4             |
| Finger Spin             | 2             |
| Ball In Cup Catch       | 4             |
| Walker Walk             | 2             |

Table 2: The action repeat hyper-parameter used for each task in the PlaNet benchmark.
A.5 Pixels Preprocessing

We construct an observational input as an 3-stack of consecutive frames \([37]\), where each frame is a RGB rendering of size \(84 \times 84\) from the 0th camera. We then divide each pixel by \(255\) to scale it down to \([0, 1]\) range.

A.6 Other Hyper Parameters

We also provide a comprehensive overview of all the remaining hyper parameters in Table 3.

| Parameter name                        | Value        |
|---------------------------------------|--------------|
| Replay buffer capacity                | 1000000      |
| Seed steps                            | 1000         |
| Batch size                            | 512          |
| Discount \(\gamma\)                   | 0.99         |
| Optimizer                             | Adam         |
| Learning rate                         | \(10^{-3}\)  |
| Critic target update frequency        | 2            |
| Critic Q-function soft-update rate \(\tau\) | 0.01        |
| Actor update frequency                | 2            |
| Actor log stddev bounds               | \([-10, 2]\) |
| Init temperature                      | 0.1          |

Table 3: A complete overview of used hyper parameters.
B Improved Data-Efficient Reinforcement Learning from Pixels

Our method allows to generate many various transformations from a training observation due to the data augmentation strategy. Thus, we further investigate whether performing more training updates per an environment step can lead to even better sample-efficiency. Following [46] we compare a single update with a mini-batch of 512 transitions with 4 updates with 4 different mini-batches of size 128 samples each. Performing more updates per an environment step leads to even worse over-fitting on some tasks without data augmentation (see Figure 6a), while our method DrQ, that takes advantage of data augmentation, demonstrates improved sample-efficiency (see Figure 6b).

Figure 6: In the data-efficient regime, where we measure performance at 100k environment steps, DrQ is able to enhance its efficiency by performing more training iterations per an environment step. This is because DrQ allows to generate various transformations for a training observation.