MAKING REINFORCEMENT LEARNING WORK ON SWIMMER

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ABSTRACT

The SWIMMER environment is a standard benchmark in reinforcement learning (RL). In particular, it is often used in papers comparing or combining RL methods with direct policy search methods such as genetic algorithms or evolution strategies. A lot of these papers report poor performance on SWIMMER from RL methods and much better performance from direct policy search methods. In this technical report we show that the low performance of RL methods on SWIMMER simply comes from the inadequate tuning of an important hyper-parameter, the discount factor. Furthermore we show that, by setting this hyper-parameter to a correct value, the issue can be easily fixed. Finally, for a set of often used RL algorithms, we provide a set of successful hyper-parameters obtained with the Stable Baselines3 library and its RL Zoo.

INTRODUCTION

A current trend in reinforcement learning (RL) research consists in evaluating newly proposed algorithms on a large set of benchmarks to facilitate comparison with the existing literature.

In this context, the SWIMMER environment is a standard RL benchmark, it is used in a large number of papers to evaluate the performance of various reinforcement learning algorithms. In particular, it is often used in papers comparing or combining RL methods with direct policy search methods such as genetic algorithms or evolution strategies.

A lot of these papers report poor performance on SWIMMER from RL methods and much better performance from direct policy search methods (see Section 2).

In this technical report, we investigate the reason behind this gap of performance. By analysing the behavior of the best solutions found by various methods, we show that the low performance of RL methods on SWIMMER simply comes from the inadequate tuning of an important hyper-parameter and that, by setting this hyper-parameter to a correct value, the issue can be very easily fixed.

From this analysis, we conclude that previously published results on SWIMMER that do not use our simple fix should be regarded with care and, in particular, in all papers comparing or combining RL methods with direct policy search methods, the conclusions drawn from the SWIMMER benchmark should be reconsidered.

1 THE SWIMMER ENVIRONMENT

The SWIMMER environment is a standard reinforcement learning (RL) benchmark built on the MUJOCO simulation environment [Todorov et al. 2012] and accessed through the
OPENAI GYM interface [Brockman et al. (2016)]. The most used versions in the works listed in
this paper are SWIMMER-V2 and SWIMMER-V3, but below we simply refer to it as SWIMMER.

In this environment, a planar creature made of three sticks must swim as fast as possible into
a liquid. The policy controls the two degrees of freedom of the creature in rotation, namely
the articulations between the sticks, by applying torques. To simplify descriptions, we will
call the most forward extremity of the creature the head, its most forward articulation the
neck, and its most backward body the tail. Views of the environment can be found in
Figure 1.

![Figure 1: Views of the SWIMMER environment depicting three different control strategies
with their approximate performance](https://72indexdescartes.wixsite.com/swimmer)

Beyond these static views, at the time we write this paper some videos of the swimmer in ac-
tion are available on the following website: [https://72indexdescartes.wixsite.com/swimmer](https://72indexdescartes.wixsite.com/swimmer).

In SWIMMER, the performance returned at each time step corresponds to the instantaneous
velocity of the creature at that time step. This instantaneous velocity could have been
measured at the center of mass of the body but, to simplify calculations, velocity at the
neck is considered. The global performance is the sum of these instantaneous returns over
1000 time steps.

2 Low performance of RL in SWIMMER: some literature

The SWIMMER environment is often used in papers comparing or combining RL algorithms
and direct policy search methods, e.g. [Khadka & Tumer (2018); Pourchot & Sigaud (2018); Chang et al. (2018); Shi et al. (2019); Bodnar et al. (2020); Zheng et al. (2020); Suri et al. (2020); Kim et al. (2020); Wang et al. (2022)]. This list is certainly far from exhaustive
and, as we shall demonstrate in the next section, results of the RL part in these methods
reported on SWIMMER should be disregarded, as they result from improper tuning of the RL
algorithms they use. The same is also true of several pure RL papers, such as [Srivastava et al. (2019); Shen et al. (2020); Cheng et al. (2021)].

One of the reasons why SWIMMER is so popular in methods comparing or combining RL
algorithms and direct policy search methods is the contrast between the performance of
both approaches. With evolutionary methods such as the Cross-Entropy Method (CEM)
[Mannor et al. (2003); Rubinstein & Kroese (2004); De Boer et al. (2005)], one can easily
obtain a performance over 300. The best performance we found in the literature is 362,
obtained using Augmented Random Search [Mania et al. (2018)]. By contrast, performance
barely reaches 100 with deep RL methods, with a strong local minimum around 40.
3 Explaining and fixing the issue

In the previous section we have outlined a performance gap between RL and direct policy search on SWIMMER. The goal of this section is to understand the reasons behind this performance gap.

Why is it that some optimization approaches reach a performance over 300 whereas others plateau below 120? To answer this question, we first analyzed the best behaviors found with the different approaches.

![Figure 2: Velocity of the swimmer using the three different control strategies depicted in Figure 1](image)

To understand the global performance, Figure 2 depicts the velocity of the neck over 1000 time steps of three representative behaviors.

By comparing the curves, one can see that in two of the controllers, a peak velocity higher than that we can get with a snake-like behavior is reached in the very begin of the trajectory, whereas the velocity is much lower afterwards. In the case of the controller that moves the swimmer body into a U shape, the velocity quickly converges to 0 as the swimmer agent cannot generate further velocity from the configuration it reached.

Now, why is it that RL methods inappropriately favor the first two types of behaviors whereas direct policy search methods find the better performing snake-like behavior?

The point is that in deep RL, immediate rewards over a trajectory are aggregated using a discount factor $\gamma$, i.e. they optimize $J(\theta) = \mathbb{E}_{r_t \sim \pi_\theta} \left[ \sum_t \gamma^t r_t \right]$, where $\pi_\theta$ is a policy parametrized by parameters $\theta$, e.g. a neural network.

In RL, it is common practice to set $\gamma = 0.99, 0.95$ or even lower values. But discounting the reward changes the objective that the RL agent is solving.

It happens that $0.99^{1000} = 0.00004317124$, thus the last steps in reward aggregation are discounted by a factor $4.32 \times 10^{-5}$ with respect to the first step. This is enough to explain that deep RL agents maximize their velocity in the first steps and disregard what happens next.

To better stress this point, in Figure 3 we depict the cumulative velocity weighted by $\gamma^t$ during an episode for different behaviors on SWIMMER, with two different values of $\gamma$: 0.99 and 0.99999.
Figure 3: Cumulative velocity weighted by $\gamma^t$ during an episode for different behaviors on SWIMMER, with two different values of $\gamma$: (a) 0.99 and (b) 0.99999

As the figure shows, with $\gamma = 0.99$ it is more optimal to throw the tail forward and then stay stuck than performing the snake-like behavior, as the greater initial velocity impulse matters more than the subsequent loss in velocity. By contrast, with $\gamma$ close enough to 1, the snake-like behavior provides a higher return.

Strikingly, we can say that, though the reported overall performance of RL methods is suboptimal, this performance being the non-discounted sum of immediate rewards over 1000 time steps, in fact RL methods do find the optimum behavior they are asked to optimize, that is the discounted performance.

By contrast with RL methods, direct policy search methods do not consider immediate rewards separately, they just consider the global return as fitness, hence they do not use a discount factor $\gamma$. This is enough to explain that they are easily converge to the snake-like behavior.

Thus, making RL work on SWIMMER is simple: one just as to set $\gamma = 0.9999$ or 1.

4 RL results with gamma = 0.9999
As Figure 4 shows, once properly tuned with $\gamma = 0.9999$, four standard RL algorithms such as TRPO, TD3, SAC, and TQC easily manage to reach a performance over 300, even if two of them show some instability. These results have been obtained with the Stable Baselines3 library (Raffin et al., 2021) and the RL Zoo (Raffin, 2020).

The hyper-parameters used to obtain the corresponding learning curves are available on the following pages:

- https://huggingface.co/sb3/trpo-Swimmer-v3
- https://huggingface.co/sb3/td3-Swimmer-v3
- https://huggingface.co/sb3/sac-Swimmer-v3
- https://huggingface.co/sb3/tqc-Swimmer-v3

Complete training log can be found in https://wandb.ai/openrlbenchmark/sb3.

5 Discussion

A different fix to the above issue consists in moving the velocity sensor from the neck of the creature to its head. By doing this, the strategy consisting in throwing forward the tail does not impact much the velocity sensor, hence the local minimum issue that we have described in the previous section disappears. This other fix has been used for instance in Wang & Ba (2019), see Section A.2.1 of their paper.

6 Conclusion

In this paper, we have addressed a simple question: why is it that RL methods do generally perform poorly on SWIMMER, whereas direct policy search methods do not? Our analysis has resulted in a simple answer: the use of a discount factor in RL methods results in inadequate evaluation of the generated behaviors, which is not the case in direct policy search methods. Setting the discount factor to 1 thus removes the issue. A consequence of our investigations is that, unfortunately, a lot of RL results on SWIMMER published in the last years must be considered with care or even reconsidered. Besides, we hope that the proposed analysis will prevent future authors from falling into the same trap.

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