An Evolution Strategy with Progressive Episode Lengths for Playing Games

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Abstract

Recently, Evolution Strategies (ES) have been successfully applied to solve problems commonly addressed by reinforcement learning (RL). Due to the simplicity of ES approaches, their runtime is often dominated by the RL-task at hand (e.g., playing a game). In this work, we introduce Progressive Episode Lengths (PEL) as a new technique and incorporate it with ES. The main objective is to allow the agent to play short and easy tasks with limited lengths, and then use the gained knowledge to further solve long and hard tasks with progressive lengths. Hence allowing the agent to perform many function evaluations and find a good solution for short time horizons before adapting the strategy to tackle larger time horizons. We evaluated PEL on a subset of Atari games from OpenAI Gym, showing that it can substantially improve the optimization speed, stability and final score of canonical ES. Specifically, we show average improvements of 80% (32%) after 2 hours (10 hours) compared to canonical ES.

1 Introduction

In reinforcement learning (RL), an agent learns how to solve a given task by interacting with its environment. Recent advances using deep policy networks have successfully addressed problems previously considered to be unsolvable, including surpassing the level of a world champion Go Player [Silver *et al.*, 2017] and playing well a large collection of Atari games [Mnih *et al.*, 2015].

Recently, evolution strategy (ES) showed surprisingly good performance as an alternative approach to deep RL-algorithms for playing Atari games [Salimans *et al.*, 2017; Conti *et al.*, 2018; Chrabaszcz *et al.*, 2018]. The ES directly optimizes the weights of deep policy networks encoding a mapping from states to actions. Thus, an ES approach for RL consists of optimizing a population of policies in the spaces of potentially millions of network weights. The advantages of ES compared to gradient-based optimizers are that (i) ES is a gradient-free black-box approach which is able to optimize non-differentiable functions and more importantly, (ii) ES can be efficiently parallelized resulting in short optimization time compared to sequential optimizers and many deep RL-algorithms [Salimans *et al.*, 2017].

Whereas the advantages of ES are intriguing, ES has some drawbacks similarly to the ones observed in RL. Although ES uses parallel resources efficiently, ES still has to evaluate many episodes and thus needs a lot of CPU time, e.g., Chrabaszcz *et al.* [2018] used $4\,000$ CPU hours for a single ES run. Nevertheless, ES approaches are often trapped in local optima shown by better policies found by RL-approaches or even random search on some games [Such *et al.*, 2017].

In this work, we aim to advance the state-of-the-art of ES for RL-problems and propose a new algorithm, evaluated on Atari games from OpenAI. The contributions of this work are:

1. We introduce a novel technique which we dub Progressive Episode Lengths (PEL) and show how to incorporate it into canonical ES [Rechenberg, 1973; Chrabaszcz *et al.*, 2018]. The underlying idea is to allow an agent to play short and easy tasks first, and then use the gained knowledge to further solve longer and harder tasks, similar as in transfer learning and curriculum learning.
2. We demonstrate the use of different time and episode schedulers in PEL, controlling the maximal episode length for a given time frame.
3. On a set of OpenAI Gym games, we show that ES is often able to learn a policy on short episodes and transfer this policy to longer episodes.
4. We study the empirical performance of PEL approach with different time schedulers and show that after 2 (10) hours of training, the agent is able to play the game with an average improvement of 80% (32%) compared to the use of canonical ES without PEL.

2 Related Work

The foundation of ES approaches are built upon the early work of Rechenberg [1973]. In recent years, ES has been proposed as an alternative approach to RL algorithms. Salimans *et al.* [2017] showed that using a natural ES [Wierstra *et al.*, 2014] can achieve comparable results in a few hours compared to sequential RL methods (e.g., [Mnih *et al.*, 2015; Schulman *et al.*, 2017]). Following Salimans's work, Chrabaszcz *et al.* [2018] showed that an even simpler canonical ES can achieve better results.

Conti *et al.* [2018] proposed a method that improves the exploration of ES by introducing novelty seeking. This technique tries to avoid local optima and induce exploration by completely ignoring the reward function and selecting agents which perform new behaviors. The results show that the proposed algorithm can learn to play Atari games and solve MuJoCo 3D humanoid tasks even when completely ignoring the reward input. LaPorte *et al.* [2015] proposed an adaptive parent population method in ES, aiming to adapt the parent population size which maximizes the final results.

ES approaches are applied in various disciplines and have been incorporated in various fields in machine learning. Cuccu *et al.* [2018] incorporated an ES approach with compact state representation. Using vector quantization and sparse coding, the used neural network containing only 6 to 18 neurons is capable of playing Atari games. Miller *et al.* [1989] used ES to design neural networks, leading to a modern ES for neural architecture search (e.g., [Real *et al.*, 2017]) and neuroevolution for playing games [Risi and Togelius, 2017]. Furthermore, Alvernaz and Togelius [2017] and Poulsen *et al.* [2017] combined gradient-based RL-approaches and ES-based approaches.

Our work is also related to the recent trend of multi-fidelity Bayesian Optimization, in particular for hyperparameter optimization, e.g., multi-task Bayesian Optimization [Swersky *et al.*, 2013], successive halving as a bandit strategy [Karnin *et al.*, 2013] and a combination of both [Falkner *et al.*, 2018]. Similarly, we also try to approximate the learning task by cheaper fidelities (here the episode length) and invest only a fraction of the overall optimization budget on the full expensive learning task.

Furthermore, our work is closely related to curriculum learning [Bengio *et al.*, 2009; Jiang *et al.*, 2015], since we also organize experiences in a meaningful order which gradually introduces more concepts and more complex concepts. In contrast to curriculum learning for RL (e.g. [Narvekar, 2017]), we do not divide the main task into sub tasks, but we rather use the fact that shorter episodes naturally contain less (and less complex) concepts; we also demonstrate that the knowledge learned from such short episodes does indeed transfer to longer episodes.

3 Background

In this section, we present canonical ES for playing Atari games [Chrabaszcz *et al.*, 2018] as prototypical algorithm where progressive episode lengths (PEL) can be applied to.

3.1 Canonical Evolution Strategy

Following the work of Salimans *et al.* [2017], Chrabaszcz *et al.* [2018] presented a simple ES algorithm dubbed *canonical evolution strategy* which achieved comparable results for playing Atari games as the more complex variant by Salimans et al. The algorithm is shown in Algorithm 1. Slightly adapting the original algorithm to the need of progressive episode lengths, we assume that an initial policy θ_0 (representing the policy network weights) is an argument of the algorithm; in the simplest case, θ_0 is randomly sampled. Then an optimization loop (Line 4) is started in which the initialized policy is

Algorithm 1: Canonical Evolution Strategy

Input:
θ_0 - Initial policy vector parameters
T - time budget
E - max length for each episode
λ - Population size
μ - Parent population size
σ - Mutation step-size
$F(\theta)$ - Fitness function for policy evaluation

1 **for** $j \in \{1 \dots \mu\}$ **do**
2 $\quad w_j = \frac{log(\mu+0.5)-log(j)}{\sum_{k=1}^{\mu} log(\mu+0.5)-log(k)}$
3 **end**
4 **for** $t = 0, 1, \dots, T$ **do**
5 $\quad$ **for** $i = 1, 2, \dots, \lambda$ **do**
6 $\quad\quad \epsilon_i \sim \mathcal{N}(0, I)$
7 $\quad\quad s_i \leftarrow F_E(\theta_t + \sigma \cdot \epsilon_i)$
8 $\quad$ **end**
9 $\quad$ Sort $(\epsilon_1, \dots, \epsilon_\lambda)$ according to s in ascending order
10 $\quad$ Update policy: $\theta_{t+1} \leftarrow \theta_t + \sigma \cdot \sum_{j=1}^{\mu} w_j \cdot \epsilon_j$
11 **end**

Output: Return best found policy θ_t

mutated in a similar fashion to the one done by the natural evolution approach, where random noise $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$ is added to its parameters vector $(\theta_t + \sigma \cdot \epsilon)$ for a fixed given step size σ (Lines 6 and 7). The performance of the newly mutated policy $(\theta_t + \sigma \cdot \epsilon_i)$ is then evaluated by a fitness function $(F(\theta_t + \sigma \cdot \epsilon_i))$ (Line 7), representing the cumulative reward of an entire episode. The entire population of new agents is then ranked and sorted in an ascending order based on their evaluation scores s_i (Line 9). Finally, the current policy θ_t is updated using the update step by computing the weighted mean of the top μ policies denoted as $\sum_{j=1}^{\mu} w_j \cdot \epsilon_j$ (Line 10) where w is a vector of predefined weights (Lines 1 and 2) such that better ranked policies have a larger impact on the updated policy θ_{t+1}. This new policy is then forwarded to the next generation from which a new optimization loop is started. The whole optimization process is repeated iteratively to improve the policy performance over time.

3.2 Network Architecture

The policy network represented as θ in Algorithm 1 is based on the architecture proposed by Mnih *et al.* [2015]. For our approach, we strictly follow the slightly modified architecture proposed by Chrabaszcz *et al.* [2018], as shown in Figure 1. The number of parameters in each layer which represent the batch norm and kernel parameters are shown on top. The activation function is changed from ReLU to ELU as proposed by Clevert *et al.* [2016] and a virtual batch normalization layer is added as done by Salimans *et al.* [2016]. Virtual batch normalization is a variant of batch normalization, where instead of using mini-batches to compute the normalization statistics, a reference batch is collected at the beginning of the optimization and is fixed for the entire optimization process. The reference batch is collected by playing an Atari game with randomized actions and saving the current states

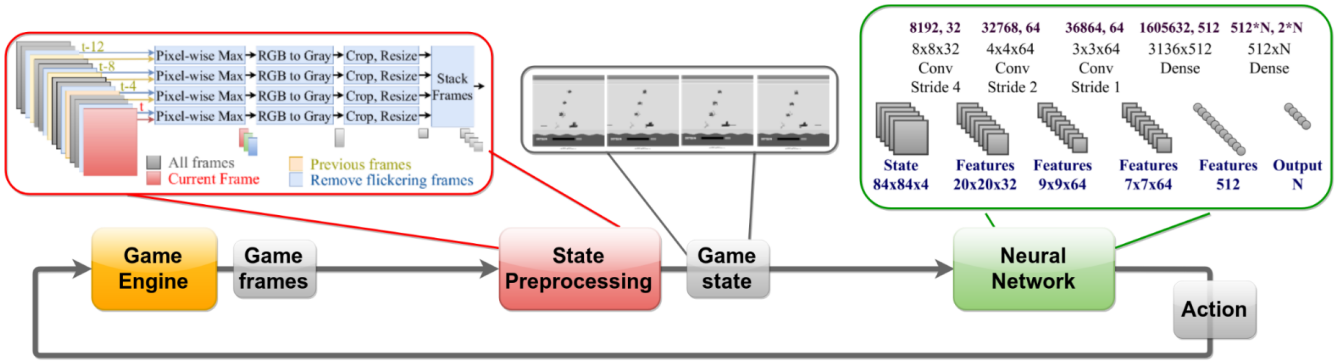

Figure 1: Playing Atari games using Deep Neural Networks following Chrabaszcz et al.

with a probability of 1% until 128 samples are collected. The policy vector weights of the network which consists of 1.7M parameters are initialized by sampling from a normal distribution $\mathcal{N}(\mu = 0, \sigma = 0.05)$.

The input data given by the Atari Gym environment is an image with pixel size of 210x160 and 3 color channels. Following the pre-preprocessing procedure proposed by Mnih *et al.* [2013], the image is resized and stacked into 4 consecutive frames resulting in an image tensor of size 84x84x4. In order to speed up the policy evaluation step in Algorithm 1, every 4th frame is collected instead of collecting over each frame.

4 Evolution Strategy with Progressive Episode Lengths

In this section, we introduce *Progressive Episode Lengths*, discuss its components and show how we incorporate it into canonical ES.

4.1 Problems of Canonical ES

Although Chrabaszcz *et al.* [2018] showed that ES can perform quite well quantitatively, i.e., reaching a good score, the learned policies are quite poor from a qualitative perspective of humans. For example, in the game of *Pong*, a trained agent might score quite well, but fails to hit even easy balls reliably, an easy task for human players. The same observation applies to other Atari games as well in which the agent follows a good strategy to maximize its main scores, but fails to solve easy tasks and to play in a natural way. This leads to a brittle performance and high variance.

4.2 PEL: Progressive Episode Lengths

Inspired by the human strategy to first learn short and easy tasks, before learning the hard tasks, we propose to use progressive episode lengths (PEL), i.e., first train an agent to play short episodes and then based on the experience gained on these short episodes, train an agent on longer episodes.

The PEL approach is based on incremental learning, where an agent utilizes the capabilities obtained in limited games to an entire episodic run. The goal of this approach is to achieve more stable and faster optimization process by focusing on simpler and shorter tasks first. When integrating it with canonical ES, the latter is able to optimize by only playing a portion of a game, transferring the abilities obtained in a short game to a longer one. For example in the game of *Pong*, by solely learning to hit the ball, the algorithm could learn to play an entire game.

Algorithm 2: ES-based Progressive Episode Length

Input:
E - Episode Scheduler
T - Time Scheduler
N - Maximal number of iterations

1 Initialize a policy from normal distribution $\theta_0 \sim \mathcal{N}$;
2 **for** $n \in \{1, \ldots, N\}$ **do**
3 Set episode length according to $E(n-1)$;
4 Set time limit according to $T(n-1)$;
/* Perform ES as in Algorithm 1 */
5 $\theta_n \leftarrow \text{ES}(\theta_{n-1}, T(n-1), E(n-1))$;
6 **end**

Output: θ_N

Another important advantage of the proposed PEL is that the ES approach can evaluate more policies by playing shorter games and thus, it can potentially make progress much faster. This applies in particular to tasks in RL, since the most time-consuming step is often the evaluation of policies and not the ES-update of the policies. For the case of Atari games, these games typically last until the player loses all its in-game lives, which can take quite some time in certain games even if only a simple policy is applied. Therefore, limited episode lengths for evaluating more policies can speed up the optimization process substantially.

We formalized the idea of PEL in Algorithm 2. The input to PEL are two components: (i) the time scheduler T and (ii) the episode scheduler E (both discussed in the next subsections) and a maximal number of iterations (or another budget for running PEL). First we initialize the policy randomly (Line 1). In each iteration n, we update the maximal episode length using E (Line 3) and the time limit using T (Line 4) depending on $n-1$ to run ES given an initial policy θ_{n-1} (Line 5). The further improved policy θ_n returned by ES is used in the next iteration with potentially larger budgets.

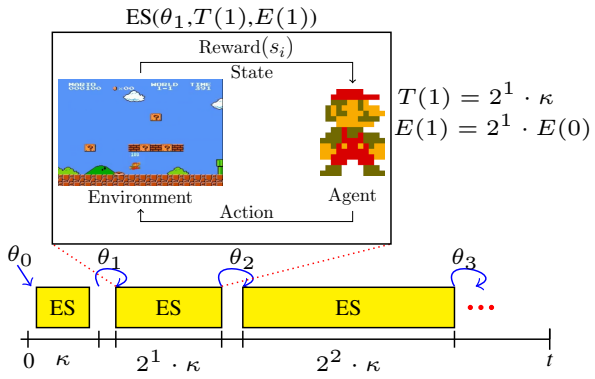

Figure 2: A framework of ES-based limited episode's length

4.3 Episode Scheduler

One of the main components of PEL is the episode scheduler to determine how many steps an episode should have at most. Partially following the idea of successive halving by Karnin *et al.* [2013], we propose a simple, yet effective episode scheduler that doubles the maximal episode length in each step, i.e., $E(n) = 2^n \cdot E(0)$.

In preliminary experiments, we observed that in practice an important design decision is how to initialize the episode scheduler with $E(0)$—similar to the important minimal budget in successive halving and approaches build upon it [Li *et al.*, 2017; Falkner *et al.*, 2018]. For playing Atari games, we found that using the expected number of steps in playing random games is a good first estimate for $E(0)$. However, on some games even more aggressive strategies can be beneficial such that we initialize $E(0)$ by the expected number of steps in playing random games divided by a constant; we used 2 in our experiments.[1] To approximate the expectation, we used Monte-Carlo roll-outs.

4.4 Time Scheduler

The second main component of PEL is the time scheduler $T(n)$ defining how long to run ES given a limited episode length $E(n)$. We propose two simple but yet effective schedulers. The first scheduler simply uses the time uniformly, i.e., $T(n)$ is constant (in our experiments, we used 1 hour). The second schedule is again motivated by successive halving [Karnin *et al.*, 2013] such that we double the time budget in each iteration, i.e., $T(n) = 2^n \cdot \kappa$ for some user-defined κ (20 min in our experiments). Using the second scheduler combined with our proposed episode scheduler, PEL will spend half of its overall optimization budget on the maximal episode length. Therefore, even if our heuristic assumption of learning on short games how to play long games should not hold, PEL will still focus on long games for most of its optimization budget.

4.5 An Example for PEL on Evolution Strategies

Figure 2 illustrates an instance of PEL where we double the episode length and the time frame simultaneously. To play a game for a total time budget t, runs of ES with different limited episodes are carried out. For each of these maximal episode lengths, the canonical ES is performed for a time limit defined by the time scheduler. For example in Figure 2, in the second iteration, $n = 2$, the ES algorithm starts its optimization loop from the policy θ_1 which is passed from the first iteration. The ES evaluates episodes with at most $E(1)$ actions, which is twice as much as in the previous iteration. Furthermore, the ES algorithm itself runs for at most $T(1)$ (e.g., seconds or generations). The improved policy θ_2 is then passed to the third run of ES.

[1] We show all further empirical results in an online appendix.

5 Experiments

In this section, we will address the following research questions:

Q1 How does PEL compare to the canonical ES by Chrabaszcz *et al.* [2018] for playing Atari games?

Q2 How well do the proposed time schedulers perform?

Q3 Is it possible to learn well-performing policies for long games by training only on short games?

5.1 Experimental Setup

To evaluate the performance of our proposed algorithm, we used a set of Atari games [Chrabaszcz *et al.*, 2018] from OpenAI Gym [Brockman *et al.*, 2016] and used the parallelization technique introduced by Salimans *et al.* [2017] that reduces the communication needed between workers. Each run used 400 CPUs on a high-performance cluster equipped with Intel Xeon E5-2630v4 processors and 128GB RAM.

We evaluated two time schedulers:

T_c $\rightarrow$ The time limit is set to a constant of 1 hour, $T_c(n) = 1$

T_d $\rightarrow$ The time limit is set to 20 minutes and doubled in each iteration, $T_d(n) = 20 \cdot 2^n$.

Both versions use a doubling scheme to increase the maximal episode length. To compare PEL against canonical ES, we computed the relative improvement on each game and aggregated it by using a geometric mean. In our comparison, we used the same parametric setup for both PEL and canonical ES which is presented in Table 1. In order to estimate the initial episode length $E(0)$ for PEL, we played each game multiple times using random actions and then divided by 2 the average number of actions until the episodes ended. To evaluate an approach, we ran five independent repetitions and evaluated the top found policy for 30 times. We report the mean evaluation scores of each of the five runs for both PEL (with T_d and T_c) in comparison with canonical ES.[2]

5.2 Q1: Comparison against Canonical ES

Table 2 shows our results for the two time schedulers T_c and T_d and compare them to canonical ES. After 2 hours of training, the PEL approach with both schedulers outperformed the

[2] We note that the code of Salimans *et al.* [2017] is not publicly available and Salimans *et al.* [2017] reported only a single run of their ES approach such that their performance estimate is potentially very noisy and not comparable with our results.

Variable	Symbol	Value
Population size	λ	800
Parent population size	μ	50
Mutation step size	σ	0.01

Table 1: Hyperparameters used in all ES variants (same as used by Chrabaszcz et al).

canonical ES in 5 and 6 games out of 9 and improved the scores by 49% and 80% on average, respectively. This shows the effectiveness of using the proposed PEL approach to improve the performance of canonical ES by optimizing different episode lengths, and utilizing the best-so-far policy of the previous iteration to improve further. After 10 hours, both schedulers are better than canonical ES in 7 out of 9 games, with an average improvement of 28% and 32% respectively. We conjecture that by running canonical ES for a longer time, the effect of PEL evaluating more policies decreases in comparison, such that the average improvement drops. On the other hand, PEL increases the episode lengths more often by running for 10 hours such that the PEL is more robust in this setting. (Please note that PEL with T_c increased the episode length only once within 2 hours).

Figure 4 shows that PEL optimized for more iterations than canonical ES on most games, shown by the red line (canonical ES) which ends earlier than the green line (PEL with T_d) and the blue line (PEL with T_c). On the game of *Phoenix*, it is obvious that this led to much better scores. However, on *Enduro* all approaches performed nearly the same amount of iterations; nevertheless, PEL achieved higher scores and had a much smaller variance across our repeated experiments (shown by a smaller shaded area).

Playing the game *SpaceInvaders*, PEL performed worse than canonical ES. In this specific game, the agent trained by PEL has never seen a major event in the game after optimizing for 2 hours: the arrival of the mothership which provides many points by shooting it. Therefore, PEL struggled to learn shooting the mothership reliably and obtained smaller scores on average.

5.3 Q2: Comparison of Time Schedulers

Comparing both schedulers, T_d performed better in 6 out of 9 games both after 2 and 10 hours. The average improvement of T_d after 2 hours is much higher than T_c's, but it is quite similar after 10 hours. To study the performance of both approaches over time in more detail, Figure 3 shows the performance of the best-so-far found policy evaluated on the full game lengths at each time point. T_d performed particularly well after the first 5 hours and benefited from running longer games later on more than T_c. We draw a similar conclusion from studying the performance over the number of iterations (i.e., updates of the population), as shown in Figure 4.

5.4 Q3: Learning on Short Games

In order to verify whether an agent can learn a reasonable policy on short games, we studied the performance of PEL with T_c after 2 hours. At this point, PEL has not seen the full game, as shown in Figure 5 by the vertical lines. Nevertheless, PEL was able to find policies that played well on these short games (until the vertical line), but which are also able to perform well if we let them continue playing the games (after the vertical line). This verifies that the policies found by ES generalize to longer games and therefore, PEL is an efficient approach on these games.

6 Discussion and Future Work

We introduced a new approach dubbed Progressive Episode Lengths (PEL) and integrated it with (canonical) ES. The main idea of PEL is to divide the time budget into differently limited time slots, and perform ES for each to firstly focus on solving simple tasks (e.g., shorter games). We then use the policies found on these short games to warm start ES to run on harder tasks (e.g., longer games) which leads to better results. We evaluated the performance of PEL on a set of Atari games from OpenAI Gym, and the results demonstrate that the proposed approach is able to provide better results compared to canonical ES, which always evaluated on full games.

The PEL approach has several assumptions: (i) We can find a well-performing policy on short games that generalizes well to longer games. We showed that this holds for many Atari games. For other tasks with sparse rewards or substantially delayed rewards, our approach has some limitations and will likely not perform well if the agent needs to play for a long time to get some rewards. Nevertheless, the PEL approach will not entirely fail in such tasks but it will lead to a slowdown such that the agent is still able to learn well. In the future, we will study whether this also holds for other RL-tasks such as MuJoCo. (ii) We initialize our minimal episode length by playing random games. For games with a survival component, this often provides a reasonable starting point. However, preliminary results already indicate that for some Atari games a more aggressive strategy and for some others a less aggressive strategy will perform better. For RL-tasks with no natural episode lengths and for tasks where shorter episodes increase the difficulty, this heuristic will fail. Therefore, future work will include finding a more reliable heuristic to initialize episode lengths, and to start the evolution from different game fragments instead of playing the game from the beginning all the time.

Another direction for future work is to include a self-adapting scheduler such that the maximum number of allowed actions can be increased or decreased based on a potentially learned heuristic. Also, ES in its current form explores its environment by injecting random noise to its policy vector. Introducing a guided exploration by estimating the direction of a more rewarding space can improve the optimization process. Overall, we believe that integrating PEL into deep reinforcement learning algorithms is a promising direction and can lead to new advances in the state of the art.

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Game	2H			10H		
	Can. ES	**PEL-ES$_{T_c}$**	**PEL-ES$_{T_d}$**	**Can. ES**	**PEL-ES$_{T_c}$**	**PEL-ES$_{T_d}$**
Alien	1962	**3673.4**	3108.2	4063	**5763.6**	5509.6
BankHeist	41.6	214.2	**229.8**	192.4	**341.8**	269.4
BeamRider	**743**	718	734.8	1259	1107.6	**1744.2**
Breakout	16.4	10	**44.8**	64.6	110.4	**120.2**
Enduro	55.6	82.4	**88**	78.6	106	**108.6**
Phoenix	1011.6	**3330.8**	2872.6	2203.2	3821.6	**3888.2**
Pong	4.8	9.6	**14.4**	11	14.2	**15.2**
Seaquest	**1263**	1008.2	797.2	1914.2	**2123.6**	1755
SpaceInvaders	**960.8**	790	930	**2030.6**	1448	1610.6
Average Improvement		49%	**80%**		28%	**32%**

Table 2: Mean evaluation scores for PEL-ES approach with two different time limits compared to canonical ES. Each entry in the table is the mean score over 5 optimization runs in which 30 evaluations runs are performed for each. The average improvement is computed in comparison with canonical ES. Bold values indicate the highest mean scores.

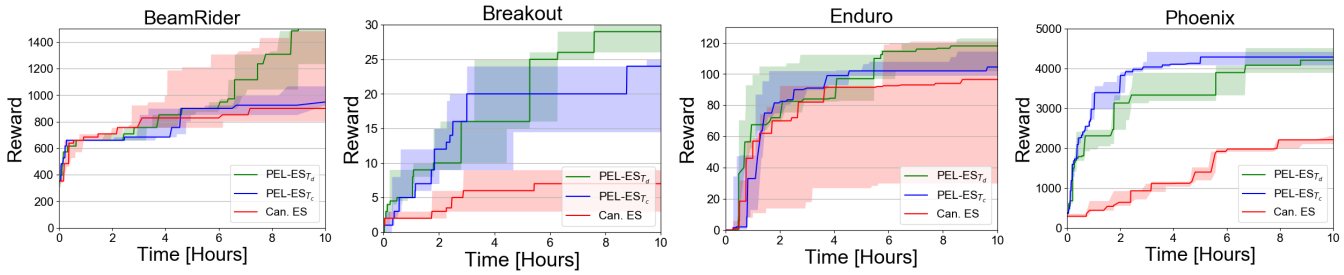

Figure 3: Score over time for PEL (blue T_c and green T_d) and canonical ES (red). Each line is the median score of 5 optimization runs and the shaded areas show the 25% and 75% percentiles of these runs.

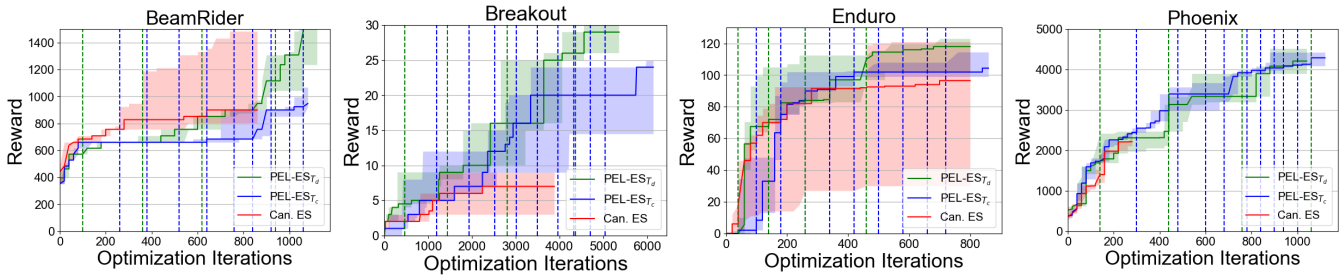

Figure 4: Score over time for PEL (T_c and T_d) and canonical ES. Each line is the median score of 5 optimization runs and the shaded areas show the 25% and 75% percentiles of these runs. The vertical lines show the points after which the maximal episode lengths were increased.

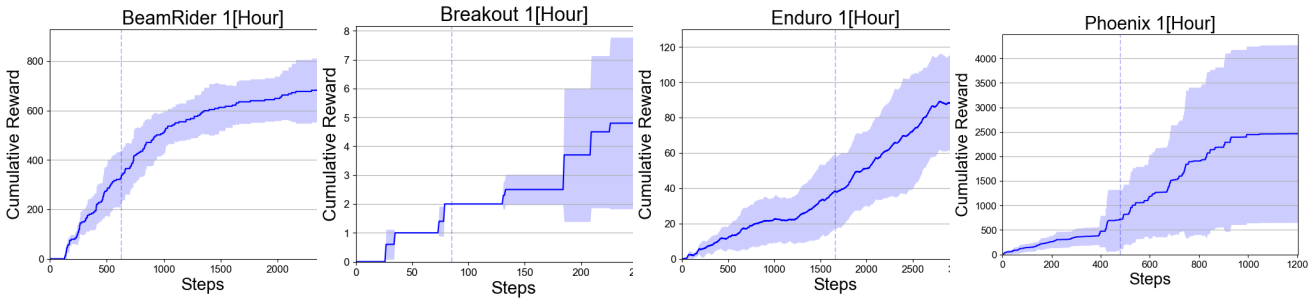

Figure 5: Mean of cumulative reward for 30 evaluation runs for PEL with T_c with 2 hours time budget. The red dashed line indicates the maximal number of actions observed by PEL.

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Appendix

Game	Number of steps
Alien	$\sim$650
BankHeist	$\sim$550
BeamRider	$\sim$1400
Breakout	$\sim$150
Enduro	$\sim$3200
Phoenix	$\sim$1200
Pong	$\sim$950
Seaquest	$\sim$500
SpaceInvaders	$\sim$700

Table 1: Number of average steps taken until the end of an episode in different Atari games with randomized actions.

Game	2H			10H		
	Can. ES	**PEL-ES$_{T_c}$**	**PEL-ES$_{T_d}$**	**Can. ES**	**PEL-ES$_{T_c}$**	**PEL-ES$_{T_d}$**
Alien	1283 ± 992	4681 ± 48	3565 ± 1787	3926 ± 666	4750 ± 35	6601 ± 293
	2070 ± 747	3380 ± 1090	3213 ± 1361	6373 ± 17	4411 ± 706	4874 ± 1947
	3363 ± 1206	5569 ± 746	3035 ± 1297	4581 ± 1215	6447 ± 1988	5419 ± 2456
	900 ± 673	1994 ± 1194	3701 ± 37	1372 ± 1126	5675 ± 744	6673 ± 767
	2194 ± 561	2743 ± 1625	2027 ± 1455	4063 ± 1409	7535 ± 1659	3981 ± 2894
Mean score	1962	**3673.4**	3108.2	4063	**5763.6**	5509.6
BankHeist	0 ± 0	200 ± 0	213 ± 5	110 ± 0	600 ± 0	239 ± 5
	54 ± 48	300 ± 0	230 ± 0	194 ± 17	321 ± 19	230 ± 0
	84 ± 12	130 ± 1	193 ± 4	231 ± 2	167 ± 14	299 ± 3
	11 ± 6	271 ± 16	200 ± 1	237 ± 69	360 ± 0	200 ± 1
	59 ± 5	170 ± 0	313 ± 40	190 ± 0	261 ± 33	379 ± 29
Mean score	41.6	214.2	**229.8**	192.4	**341.8**	269.4
BeamRider	752 ± 318	783 ± 210	701 ± 194	1975 ± 1141	1078 ± 483	858 ± 208
	748 ± 164	750 ± 143	736 ± 246	908 ± 235	1758 ± 1130	1946 ± 1081
	748 ± 144	663 ± 221	694 ± 426	778 ± 218	793 ± 215	1370 ± 806
	697 ± 243	687 ± 171	806 ± 229	1825 ± 974	932 ± 276	2001 ± 1206
	770 ± 168	707 ± 169	737 ± 187	809 ± 176	977 ± 272	2546 ± 1498
Mean score	**743**	718	734.8	1259	1107.6	**1744.2**
Breakout	19 ± 21	11 ± 8	11 ± 8	77 ± 94	195 ± 194	95 ± 114
	14 ± 17	5 ± 4	107 ± 130	25 ± 26	13 ± 13	139 ± 192
	21 ± 21	14 ± 10	12 ± 12	117 ± 142	184 ± 199	167 ± 178
	12 ± 13	6 ± 4	9 ± 5	15 ± 16	16 ± 11	28 ± 25
	16 ± 15	14 ± 10	85 ± 125	89 ± 117	144 ± 185	172 ± 178
Mean score	16.4	10	**44.8**	64.6	110.4	**120.2**
Enduro	15 ± 9	55 ± 17	115 ± 19	29 ± 12	97 ± 22	122 ± 18
	104 ± 18	80 ± 24	74 ± 29	120 ± 23	92 ± 21	122 ± 19
	78 ± 19	110 ± 24	107 ± 17	97 ± 23	127 ± 26	118 ± 20
	7 ± 10	70 ± 30	74 ± 23	25 ± 12	102 ± 21	93 ± 22
	74 ± 24	97 ± 17	70 ± 24	122 ± 21	112 ± 15	88 ± 18
Mean score	55.6	82.4	**88**	78.6	106	**108.6**
Phoenix	849 ± 766	3019 ± 1547	2917 ± 1462	1798 ± 1248	3019 ± 1547	3543 ± 1369
	940 ± 799	2909 ± 1379	3223 ± 1501	2551 ± 1203	4348 ± 1338	4998 ± 1160
	1373 ± 1307	3268 ± 1204	2603 ± 1672	1970 ± 1015	3929 ± 1030	3943 ± 1419
	1046 ± 747	3729 ± 1435	3021 ± 1127	2154 ± 1150	3929 ± 1296	3294 ± 1483
	850 ± 595	3729 ± 902	2599 ± 1500	2543 ± 1470	3883 ± 1006	3663 ± 1503
Mean score	1011.6	**3330.8**	2872.6	2203.2	3821.6	**3888.2**
Pong	7 ± 18	9 ± 17	6 ± 19	14 ± 15	18 ± 10	9 ± 18
	0 ± 0	21 ± 0	7 ± 19	0 ± 0	21 ± 0	8 ± 19
	7 ± 16	1 ± 20	20 ± 0	21 ± 0	1 ± 20	20 ± 0
	7 ± 19	10 ± 15	21 ± 0	12 ± 13	10 ± 15	21 ± 0
	3 ± 20	7 ± 19	18 ± 2	8 ± 19	21 ± 0	18 ± 2
Mean score	4.8	9.6	**14.4**	11	14.2	**15.2**
Seaquest	1327 ± 384	1911 ± 157	578 ± 85	2090 ± 368	4126 ± 81	1715 ± 8
	1137 ± 25	866 ± 236	850 ± 190	1200 ± 0	1076 ± 576	1486 ± 198
	1490 ± 147	621 ± 171	615 ± 31	3128 ± 920	1434 ± 156	2098 ± 1232
	1172 ± 21	833 ± 242	1060 ± 137	1896 ± 32	1429 ± 490	1807 ± 37
	1189 ± 9	810 ± 104	883 ± 428	1257 ± 30	2553 ± 59	1669 ± 124
Mean score	**1263**	1008.2	797.2	1914.2	**2123.6**	1755
SpaceInvaders	776 ± 232	748 ± 384	1018 ± 372	2226 ± 97	1515 ± 1044	1468 ± 1245
	828 ± 72	749 ± 87	1031 ± 167	1346 ± 328	1531 ± 1389	1770 ± 922
	1159 ± 236	1092 ± 78	864 ± 292	2227 ± 166	1568 ± 726	1534 ± 945
	903 ± 252	665 ± 125	870 ± 355	2335 ± 0	1296 ± 602	1493 ± 1073
	1138 ± 417	660 ± 60	867 ± 92	2019 ± 401	1330 ± 927	1788 ± 121
Mean score	**960.8**	790	930	**2030.6**	1448	1610.6
Average Improvement		49%	80%		28%	32%

Table 2: A comparison of mean evaluation scores for PEL-ES approach with two different time limits and canonical ES. Five independent runs are performed and each entry in the table is the mean score over 30 evaluation runs. The average improvement is computed in comparison with canonical ES. Bold values indicate the highest mean scores

Game	**Can. ES**	**PEL-ES**$_{T_c}$ $R = 2$	**PEL-ES**$_{T_c}$ $R = 4$	**PEL-ES**$_{T_c}$ $R = 8$
Alien	1345 ± 857 2215 ± 636 3649 ± 1595	4665 ± 56 3951 ± 1087 5668 ± 737	2717 ± 665 2606 ± 198 1766 ± 738	1624 ± 667 2941 ± 1235 3443 ± 741
Mean score	2403	**4761**	2366	2669
BankHeist	0 ± 0 38 ± 36 87 ± 9	200 ± 0 300 ± 0 130 ± 0	413 ± 14 130 ± 0 399 ± 38	300 ± 0 70 ± 0 250 ± 0
Mean score	42	210	**314**	206
BeamRider	818 ± 218 730 ± 220 741 ± 98	818 ± 261 759 ± 202 819 ± 346	728 ± 275 731 ± 212 784 ± 215	660 ± 165 794 ± 281 686 ± 152
Mean score	768	**798**	747	713
Breakout	26 ± 21 18 ± 18 22 ± 22	15 ± 11 6 ± 4 17 ± 6	15 ± 4 9 ± 8 9 ± 3	7 ± 4 5 ± 3 68 ± 3
Mean score	**22**	13	10	6
Enduro	18 ± 11 107 ± 23 80 ± 31	69 ± 27 79 ± 28 118 ± 19	38 ± 36 103 ± 11 45 ± 24	57 ± 38 23 ± 6 13 ± 8
Mean score	68	**89**	62	31
Phoenix	836 ± 603 979 ± 726 1207 ± 1327	3262 ± 1063 3621 ± 1364 3862 ± 644	4927 ± 463 3273 ± 1406 3606 ± 1038	3004 ± 1879 3318 ± 2378 1806 ± 480
Mean score	1007	3582	**3935**	2709
Pong	2 ± 19 0 ± 0 8 ± 18	16 ± 12 21 ± 0 4 ± 20	17 ± 21 21 ± 0 21 ± 0	21 ± 0 21 ± 0 21 ± 0
Mean score	3	14	19	**21**
Seaquest	1444 ± 306 1144 ± 24 1420 ± 177	2005 ± 139 858 ± 168 622 ± 64	466 ± 45 584 ± 12 610 ± 73	482 ± 101 512 ± 93 584 ± 63
Mean score	**1336**	1161	533	526
SpaceInvaders	782 ± 201 846 ± 45 1133 ± 201	728 ± 521 758 ± 91 1097 ± 74	681 ± 282 933 ± 620 523 ± 201	524 ± 44 541 ± 170 406 ± 260
Mean score	**920**	861	732	490

Table 3: Compare the LEL approach with different step-limitation division constants ($R = [2, 4, 8]$) against the Canonical Evolutionary Strategy after 5 hours of optimization. Each entry is the top mean score of 10 policy runs.

Game	**Can. ES**	**PEL-ES**$_{T_c}$ $R = 2$	**PEL-ES**$_{T_c}$ $R = 4$	**PEL-ES**$_{T_c}$ $R = 8$
Alien	3958 ± 932 6371 ± 20 5025 ± 358	4758 ± 38 4436 ± 438 7290 ± 2438	5931 ± 2585 2894 ± 591 2895 ± 220	2849 ± 1883 4398 ± 3251 4700 ± 220
Mean score	5118	**5495**	3906	3982
BankHeist	110 ± 0 200 ± 0 232 ± 4	600 ± 0 324 ± 17 168 ± 14	413 ± 14 130 ± 0 424 ± 52	300 ± 0 90 ± 0 250 ± 0
Mean score	180	**364**	322	213
BeamRider	2168 ± 1162 962 ± 237 858 ± 208	1536 ± 1259 1593 ± 771 824 ± 163	886 ± 198 1002 ± 307 891 ± 306	732 ± 246 862 ± 212 813 ± 254
Mean score	**1329**	1317	926	802
Breakout	115 ± 94 35 ± 28 161 ± 105	234 ± 190 15 ± 12 207 ± 205	205 ± 167 195 ± 192 249 ± 163	196 ± 188 210 ± 206 56 ± 66
Mean score	103	152	**216**	150
Enduro	30 ± 14 129 ± 9 93 ± 16	96 ± 15 101 ± 23 126 ± 21	120 ± 22 121 ± 14 121 ± 19	104 ± 19 127 ± 13 56 ± 35
Mean score	84	108	**120**	95
Phoenix	1882 ± 1361 1804 ± 935 1951 ± 1136	3953 ± 1051 4669 ± 1111 3964 ± 859	5100 ± 964 4410 ± 1542 3752 ± 2005	3883 ± 2399 3986 ± 1923 3900 ± 2776
Mean score	1879	4195	**4420**	3923
Pong	13 ± 16 0 ± 0 21 ± 0	21 ± 19 21 ± 0 8 ± 0	21 ± 0 21 ± 0 21 ± 0	21 ± 0 21 ± 0 21 ± 0
Mean score	11	17	**21**	**21**
Seaquest	2100 ± 262 1200 ± 0 2712 ± 820	4087 ± 63 1216 ± 623 1434 ± 48	1168 ± 18 1636 ± 23 1744 ± 19	1784 ± 264 1204 ± 39 904 ± 332
Mean score	2004	**2245**	1516	1297
SpaceInvaders	2228 ± 154 1468 ± 332 2218 ± 190	1629 ± 996 1536 ± 1369 1604 ± 1182	1268 ± 701 1749 ± 938 1363 ± 952	1567 ± 606 1439 ± 884 1191 ± 1089
Mean score	**1971**	1589	1460	1399

Table 4: Compare the LEL approach with different step-limitation division constants ($R = [2, 4, 8]$) against the Canonical Evolutionary Strategy after 5 hours of optimization. Each entry is the top mean score of 10 policy runs.