SAMPLE-EFFICIENT AUTOMATED DEEP REINFORCEMENT LEARNING

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ABSTRACT

Despite significant progress in challenging problems across various domains, applying state-of-the-art deep reinforcement learning (RL) algorithms remains challenging due to their sensitivity to the choice of hyperparameters. This sensitivity can partly be attributed to the non-stationarity of the RL problem, potentially requiring different hyperparameter settings at different stages of the learning process. Additionally, in the RL setting, hyperparameter optimization (HPO) requires a large number of environment interactions, hindering the transfer of the successes in RL to real-world applications. In this work, we tackle the issues of sample-efficient and dynamic HPO in RL. We propose a population-based automated RL (AutoRL) framework to meta-optimize arbitrary off-policy RL algorithms. In this framework, we optimize the hyperparameters, including architecture hyperparameters while simultaneously training the agent. By sharing the collected experience across the population, we substantially increase the sample efficiency of the meta-optimization. We demonstrate the capabilities of our sample-efficient AutoRL approach in a case study with the popular TD3 algorithm in the MuJoCo benchmark suite, where we reduce the number of environment interactions needed for meta-optimization by up to an order of magnitude compared to population-based training.

1 INTRODUCTION

Deep reinforcement learning (RL) algorithms are often sensitive to the choice of internal hyperparameters (Jaderberg et al., 2017; Mahmood et al., 2018), and the hyperparameters of the neural network architecture (Islam et al., 2017; Henderson et al., 2018), hindering them from being applied out-of-the-box to new environments. Tuning hyperparameters of RL algorithms can quickly become very expensive, both in terms of high computational costs and a large number of required environment interactions. Especially in real-world applications is sample efficiency crucial (Lee et al., 2019).

While hyperparameter optimization (HPO) (Snoek et al., 2012; Feurer & Hutter, 2019) approaches can be sample-efficient in the meta-optimization search space, they usually treat the algorithm under optimization as a black-box, which in the setting of RL requires full training runs every time a configuration is evaluated. This leads to a suboptimal sample-efficiency in terms of interactions in the environment. Another pitfall for HPO is that the non-stationarity of the RL problem. Hyperparameter settings that are optimal at the beginning of the learning phase can become unfavorable or even harmful in later stages (François-Lavet et al., 2015). This issue can be addressed through dynamic configuration, either through self adaptation (Tokic & Palm, 2011; François-Lavet et al., 2015; Tokic, 2010) or through external adaptation as in population-based training (PBT) (Jaderberg et al., 2017). While current dynamic configuration approaches can handle the non-stationarity of the hyperparameter settings, they substantially increase the number of environment interactions.

In this work, we introduce a simple meta-optimization framework for Sample-Efficient Automated RL (SEARL) to tackle both issues: sample-inefficient HPO and the need for dynamic configuration. The foundation of our approach is a joint optimization of the model and its hyperparameters using an evolutionary approach. This allows our approach to discover a schedule of hyperparameter
configurations rather than a single static configuration. Our approach uses evolvable neural networks to keep trained network parameters while being able to adapt their architecture.

The usage of a shared replay memory across the whole population reduces the total amount of required environment interactions drastically. This allows the RL agents to learn better policies with fewer environment interactions, making it possible to perform AutoRL at practically the same cost as learning the policy for a single configuration. Simultaneously, SEARL preserves the benefits of dynamic configuration present in population-based approaches, enabling an adaptive online hyperparameter optimization. We emphasize that our approach is simple to use and allows efficient AutoRL for any off-policy deep RL algorithm.

In a case study, including an extensive ablation analysis, we demonstrate the benefits of our approach and each of its components. We increase the sample-efficiency of the meta-optimization by a factor of up to ten compared to random search and PBT, when optimizing the popular TD3 algorithm (Fujimoto et al., 2018) in the MuJoCo benchmark suite (Todorov et al., 2012). Specifically, our contributions are:

- We expose the actual cost that is required for the tuning of RL agent hyperparameters and propose an evaluation to compare AutoRL systems on a fair footing.
- We drastically reduce the cost of hyperparameter tuning for off-policy RL agents by facilitating experience sharing, allowing joint tuning of algorithm and architecture hyperparameters without substantial overhead in terms of environment interactions.
- We perform a dynamic adaption of hyperparameters, including online architecture changes, thereby discovering effective configuration schedules.
- We demonstrate the benefits of SEARL in a case study, reducing the number of environment interactions by up to an order of magnitude.

2 RELATED WORK

**ERL/PDERL/CERL:** The recent work ERL (Khadka & Tumer, 2018) and successors PDERL (Bodnar et al., 2019) and CERL (Khadka et al., 2019) combine Actor-Critic RL algorithms with genetic algorithms to evolve a small population of agents. This line of work mutates policies to increase the diversity of collected sample trajectories. The experience is stored in a shared replay memory and used to train an Actor-Critic learner with fixed network architectures using DDPG/TD3 while periodically adding the trained actor to a separate population of evolved actors. CERL extends this approach by using a whole population of learners with varying discount rates. In the present work, like ERL/PDERL/CERL, we also benefit from a diverse set of mutated actors collecting experience in a shared replay memory. However, ERL/PDERL/CERL aims to increase the performance of a single configuration, while our work automatically finds an effective configuration and simultaneously trains the agent.

**ApeX/IMPALA:** Resource utilization in the RL setting can be improved by using multiple actors in a distributed setup and decoupling the learner from the actor. Horgan et al. (2018) extend a prioritized replay memory to a distributed setting (Ape-X) to scale experience collection for a replay memory used by a single trainer. In IMPALA (Espeholt et al., 2018), multiple rollout actors asynchronously send their collected trajectories to a central learner through a queue. To correct for the policy lag, this distributed setup introduces, IMPALA leverages the proposed V-trace algorithm for the central learner. These works aim at collecting large amounts of experience to benefit the learner, but they do not explore the space of hyperparameter configurations. In contrast, the presented work aims to reduce the number of environment interactions to perform efficient AutoRL.

**AutoRL:** Within the framework of AutoRL, the joint hyperparameter optimization and architecture search problem is addressed as a two-stage optimization problem in Chiang et al. (2019), first shaping the reward function and optimizing for the network architecture afterward. Similarly, Runge et al. (2019) propose to jointly optimize algorithm hyperparameters and network architectures by searching over the joint space. Faust et al. (2019) uses an evolutionary approach to optimize a parametrized reward function based on which fixed network topologies are trained using standard RL algorithms, treating the RL algorithm together with a sampled reward function as a black-box optimizer. Here, we do not use parametrized reward functions, but instead, directly optimize for the environment reward. However, the main difference to this line of work is sample efficiency: While they train and
evaluate thousands of configurations from scratch, we can dynamically adapt the architecture and RL-algorithm hyperparameters online, thereby drastically reducing the total amount of environment interactions required for the algorithm to achieve good performance on a given task.

**HOOF:** Paul et al. (2019) proposes sample-efficient online hyperparameter tuning for policy gradient methods by greedily maximizing the value of a set of candidate policies at each iteration. However, they demonstrate that conditioning the value function on key hyperparameters is imperative for the success of their method. This setting makes it difficult to also optimize the architecture on the fly, which can be integrated more naturally in the evolutionary approach presented here. In contrast to our work, they perform HPO for on-policy algorithms which do not seem to achieve comparable performance on continuous control tasks while requiring more environment interactions. Further, they do not consider dynamic configuration and architecture optimizations.

**Population-Based Training (PBT):** PBT is a widely used dynamic and asynchronous optimization algorithm introduced by Jaderberg et al. (2017). This approach adapts a population of different hyperparameter settings online and in parallel during training, while periodically replacing inferior members of the population with more promising members. Similarly to SEARL, PBT can jointly optimize the RL agent and its hyperparameters online, making it the most closely related work. In contrast to SEARL, PBT does not optimize the architecture and, more importantly, does not share experience within the population.

3 **SAMPLE-EFFICIENT AUTO RL**

We propose a Sample-Efficient framework for Automated Reinforcement Learning (SEARL) based on an evolutionary algorithm, extended with gradient-based training and a shared experience replay. In the following, we discuss the foundations of the framework. Then, we give an overview of the proposed AutoRL framework and a detailed description of each individual component.

3.1 **BACKGROUND**

**Evolvable neural network:** There is an extensive history of using evolutionary algorithms to design neural networks, referred to as Neuroevolution (Florea et al., 2008; Stanley et al., 2019). While some approaches only optimize the network weights (Such et al., 2017), others optimize the architecture and weights jointly (Zhang, 1993; Stanley & Miikkulainen, 2002; Stanley et al., 2009). To evolve the neural network, its architecture is encoded, e.g., with the number of layers and the nodes per layer (Miikkulainen et al., 2019). When adding a new node to a layer, the existing parameters are copied, and only the newly added parameters are initialized with a small magnitude. This is a common technique to preserve already trained network parameters (Wei et al., 2016; Miikkulainen et al., 2019).

**Shared experience replay:** Replaying collected experiences (Lin, 1992) to smooth the training distribution over many past rollouts has been introduced to deep RL in Mnih et al. (2013). The experience replay acts as a store for experience collected by one or more worker agents interacting with the environment. Deep RL algorithms can sample from this storage to calculate gradient-based updates for the neural networks. It has been used and extended in various flavors, often to make use of diverse or in parallel collected experience (Horgan et al., 2018; Khadka & Tumer, 2018; Bodnar et al., 2019; Khadka et al., 2019).

3.2 **FRAMEWORK**

Our proposed SEARL framework represents a population-based approach to online architecture evolution and hyperparameter adaption. Each individual in our population represents a deep reinforcement learning agent consisting of a policy and value network and the RL training algorithm hyperparameters, including the network architecture encodings. The training and meta-optimization of these individuals take place in an evolutionary loop that consists of five basic phases (initialization, evaluation, selection, mutation, and training) as shown in Figure 1. During one epoch of this evolutionary loop, all properties of an individual can be subject to change through different mutations and training operators. This happens independently for each individual and can be processed in parallel.
One novel feature of our approach is that the rollouts of each individual are not only used for evaluation and selection purposes but also serve as experience for off-policy RL training of all agents and are stored in a shared replay memory. The newly updated weights of an agent during training are not only used in the evaluation phase to decide the performance of its current setup. Instead, we found it crucial to preserve the gradient-based training updates to the agent for the next generation. This approach is often referred to as Lamarckian evolution (Ross, 1999). In the following, we describe the different phases of our evolutionary loop in detail; we refer the reader to Appendix B for detailed pseudocode of the algorithm.

**Initialization:** SEARL uses a population, \( \text{pop} \), of \( N \) individuals, each consisting of an RL agent, \( A_i \), and its hyperparameter settings, \( \Theta_i \). Based on that, we can represent \( \text{pop}_g \) at each generation \( g \) as follows:

\[
\text{pop}_g = (\{A_1, \Theta_1\}_g, \{A_2, \Theta_2\}_g, ..., \{A_N, \Theta_N\}_g)
\]

The initialization of an individual’s hyperparameter setting \( \Theta_i \) is composed of architecture hyperparameters like the number of layers or layer size and algorithm hyperparameters like the learning rate. To arrive at a minimum viable neural network size, we start with a reasonably small neural network architecture and enable the growth by the use of mutation operators, which can either add additional nodes to a given layer or add a new layer altogether. Other hyperparameters could either be sampled from a predefined range or set to some initial value, as it is subsequently adapted in the evolutionary loop.

**Evaluation:** After initialization and after each training phase, we evaluate each individual in the population by using the RL agent, \( A_i \), for at least one episode or a minimum number of steps in the environment. This ensures a minimum amount of new experience from each agent and helps to keep the stored trajectories in the shared replay memory diverse. The evaluation can be performed in parallel since each agent acts independently. For the selection, we use the mean episodic reward as fitness value \( f_i \).

**Selection:** We make use of tournament selection with elitism (Miller et al., 1995) for each prospective slot in the new generation of the population. For each tournament, \( k \) individuals are randomly chosen from the current population \( \text{pop}_g \), and the individual with the largest fitness value \( f_i \) is selected for the slot. We repeat this tournament \( N \) times to fill all slots. The size \( k \) allows us to control how greedily the selection mechanism picks candidates for the new population. We reserve one spot in the new population for the best-performing individual of the current population, thus preserving it across generations.

**Mutation:** To explore the space of network weights and hyperparameters, we use different single-parent mutation operators. For each individual, we apply one of the following mutation operators uniformly at random: (1) Gaussian mutation of network weights, (2) change of activation function, (3) change of the network size, (4) change of algorithm hyperparameters, or (5) no operation. For a more detailed description, we refer the reader to Appendix A.

**Training:** Using each individual’s current hyperparameter setting, we perform an RL training by sampling from the shared replay memory. Each individual is trained for as many steps as frames have been generated in the evaluation phase. Optionally, one could reduce the training time by using only a fraction \( j \) of the accumulated steps.

Since the neural network size could be subject to mutation between two training phases, the target network of the RL algorithm must be adapted too. Furthermore, the optimizer parameters connected to individual network weights, as, e.g., used in the Adam optimizer (Kingma & Ba, 2015), cannot
remain the same across generations. We address these two issues by creating a new target network and re-initializing the optimizer at the beginning of each training phase. Our experiments show that this re-creation and re-initialization does not harm the performance of the considered RL algorithm and sometimes even improves the performance. Please find more details in Appendix C. Similar to the evaluation phase, the training can be performed in parallel since every individual is trained independently.

**Shared experience replay:** A shared experience replay memory collects trajectories from all evaluations and provides a diverse set of samples for each individual agent during the training phase. This helps to improve training speed and reduces the potential of over-fitting. Using a prioritized replay memory (Schaul et al., 2015) has not proven beneficial in our preliminary experiments. We attribute this to the complexity to compute priority values, which need to be applicable for all agents in the population at the same time. However, we identify using a shared experience replay as the leading cause of improved sample efficiency.

### 4 Case study: Meta-optimization of TD3

To demonstrate the capabilities and benefits of SEARL, we jointly optimize the algorithm and architecture hyperparameters of the Twin Delayed Deep Deterministic Policy Gradient (TD3) (Fujimoto et al., 2018). TD3 was demonstrated to significantly improve upon the Deep Deterministic Policy Gradient algorithm (DDPG) (Lillicrap et al., 2015) and can be regarded as a representative of the state of the art in off-policy continuous control among methods such as Soft Actor-Critic (SAC) (Haarnoja et al., 2018). Due to the generality of our framework, other off-policy RL algorithms, like SAC, could also be optimized using SEARL. We evaluate our approach on the challenging and widely used MuJoCo continuous control benchmark suite (Todorov et al., 2012).

All meta-algorithms are tasked with optimizing network architecture, activations, and learning rates of the actor and the critic. We evaluated all methods on the following five MuJoCo environments: HalfCheetah, Walker2D, Ant, Hopper, and Reacher.

#### 4.1 Baselines

Since there is no directly comparable approach for efficient AutoRL (see Section 2), we compare SEARL to a random search and PBT modified for architecture adaption. As RL is sensitive to the choice of hyperparameters, the design of the configuration space matters. In order to allow for a fair comparison, we keep the search spaces for all methods similar, see Appendix D.

**Random search:** Random search makes no assumptions on the algorithm and is a widely used baseline for HPO (Feurer & Hutter, 2019). We sample 20 random configurations and train TD3 with each configuration and without any online architecture or hyperparameters changes for 1M frames. We choose the search space to lie within a reasonable range based on commonly reported hyperparameter values (Fujimoto et al., 2018); for more details, please refer to Appendix D. We select the configuration that resulted in the best training performance and evaluate it with 10 different random seeds to obtain its validation performance.

**Modified Population-based training:** To fairly compare PBT with our proposed approach, we modify PBT to be able to adapt the architecture of the networks. The partially trained networks are reused by copying their values to new weight matrices. If the network size is extended, new weights are initialized randomly, as in SEARL. If the size of the network is reduced, the weight matrix is cropped. Following Jaderberg et al. (2017), we initialize the population by sampling from the configuration space uniformly at random, see Appendix D. We train and evaluate each agent for 10 000 steps in the environment per generation and use a population of size 20. We want to emphasize that we compare SEARL to this modified version of PBT, not the original version, for it does not allow for architecture changes.

#### 4.2 SEARL for TD3

We opted to start all individuals within the population from the same configuration. In an ablation study testing random initialization, we found no benefit of the more diverse starting population; please find details in Appendix E.
Figure 2: Performance comparison of SEARL, modified PBT, and random search with regards to the required total steps in the environment. Random search and modified PBT require an order of magnitude more steps in the environment to reach the same reward as SEARL. The blue line depicts SEARL, the green line of modified PBT, and the red line of RS. All approaches evaluated over 10 random seeds. The x-axis shows the required environment interactions to achieve performance. Dashed lines are performances of the different seeds and the shaded area of the standard deviation.

Since we evolve actor and critic networks over time, we start with a one-layer ANN with 128 hidden nodes, which represents the lower bound of the search space defined in Appendix D. For the remaining hyperparameters, we chose a commonly used configuration consisting of ReLU activation and an initial learning rate of 0.001. Similar to the PBT baseline, we used 20 workers, but we run our algorithm only for 2 million environment interactions to keep the computational budget in a reasonable range. Please find details in Appendix F.

We evaluate on one episode or at least 250 steps in the environment. This results in at least 5,000 new environment interactions stored in the shared replay memory. To select a new population, we use a tournament size of $k = 3$. We apply all mutation operators, as described in Section 3.2. For details about the mutation we refer the reader to Appendix A and to Appendix F for a table of all configuration values. After mutation, we train the individuals for $j = 0.5$ times the sum of environment interactions of the whole population during evaluation in this generation.

4.3 Fair evaluation protocol for AutoRL methods

Standard evaluation of RL agents commonly shows the achieved cumulative reward in an episode after having interacted with the environment for $N$ steps. It is common practice to only report the best configuration’s rewards found by an offline or online meta-optimization algorithm. However, this hides the much larger number of environment interactions needed to find this well-performing configuration. In contrast, we strongly believe that the interaction counter should start ticking immediately as we tackle a new task/environment. Such a fair reporting of meta-optimization could also increase the comparability of approaches (Feurer & Hutter, 2019).

As there is no convention on how to display the performance of meta-learning while taking into account the total amount of environment interactions as described above, we opt for the following simple presentation: When reporting the meta-optimization effort, every environment interaction used for the meta-optimization process should be counted when reporting the performance at any given time. In the case of offline meta-optimization efforts as in random search trials, this translates to multiplying the number of interactions of the best configuration’s performance curve by the number of trials used to arrive at this configuration.
This form of reporting meta-optimization effort shows that a framework that makes efficient use of all generated experience, e.g., through a shared replay memory as proposed in SEARL, can use individual samples much more effectively. A single agent should then be able to learn much more efficiently since it can make use of the additional samples during training. This gained efficiency of the individual learning agents can be used to compensate the overhead (in terms of environment interactions) introduced by the meta-algorithm to tune the hyperparameters for the learning agents.

4.4 Results & discussion

Comparison to modified PBT and random search: In Figure 2, we compare the mean performance of SEARL to a modified version of PBT and random search when training the TD3 agent and tuning its algorithm and architecture hyperparameters. We report the results following the evaluation outlined in 4.3. SEARL outperforms modified PBT in three out of five experiments and performs on par on the two others. In comparison to random search, SEARL is on par in three environments, better in one and only struggling on Reacher. Furthermore, we often see a smaller standard deviation, which could indicate that SEARL is robust to random seeds. Most importantly, we see a significant gain in the sample efficiency of our approach.

While the main goal of using shared replay data is to make more efficient use of environment interactions across the population, we want to stress that individuals within the population don’t get to use single experience samples more often during training compared with the modified PBT setup. On the contrary: As presented, the individuals in SEARL only train on half of the collected samples. Therefore, the substantial increase in sample efficiency for meta-optimization is not merely due to the fact that individual experience samples get re-used more often during the training phase.

Also, Figure 2 shows that SEARL matches or surpasses the performance of modified PBT and random search with up to ten times fewer environment interactions. This suggests that SEARL is a promising candidate for automated RL on real-world problems.

Performance in the search space: In Figure 3, we evaluate the single-run performance of SEARL in the search space of TD3 random search. We plot the mean performance over 10 random seeds for a single SEARL run and 10 sampled TD3 configurations. We observe that SEARL matches the performance of the favorable part of the search space even within the same number of environment steps as a single TD3 run, again only struggling on Reacher. This indicates that SEARL evolves...
effective configuration schedules during training, even when starting with a population consisting of a single hyperparameter setting using a small one-layer neural network architecture.

**Dynamic configuration:** We show exemplary hyperparameter schedules discovered by SEARL on the HalfCheetah task in Figure 4. In the first 500,000 environment interactions SEARL quite quickly increases the network size of the TD3 agents to values which are more in line with commonly reported network architectures used for strong results on MuJoCo’s HalfCheetah task. Afterward, the architecture size is increased more slowly, before it saturates after approximately 1M environment interactions. This shows that SEARL can adapt the network architecture starting from a rather small network size, but also prevents further increases in size once the network capacity is sufficient. The learning rates shown in the lower part of Figure 4 for both the actor and the critic networks are slowly decreasing over time. Similar schedules can be observed on other benchmarks; for more details, we refer to Appendix G.

**Ablation studies:** To determine how the individual parts of our proposed method influence performance, we ran an ablation study, which is shown in Figure 5. The ablation study clearly shows that disabling shared experience replay harms the performance most across all tasks. However, the advantage of other SEARL features seems to be task-dependent. While some benefit strongly from architecture adaption, others benefit more from additional parameter mutation. For further details and plots for all tasks, we refer the reader to Appendix I. To test the generality of SEARL, we performed another ablation study, which can be found in Appendix I. This shows better or on-par performance on four out of five environments compared with a held-out tuned TD3 configuration, demonstrating the generalization capabilities of SEARL across different environments.

**SEARL for on-policy deep RL:** The meta-optimization of on-policy algorithms using SEARL would most likely not show the same benefits in sample-efficiency due to the high impact of the shared experience replay. Nonetheless, we expect that the dynamic configuration of the algorithm and network architecture hyperparameters would still have a positive impact on these types of algorithms. Another option would be to incorporate the choice of the deep RL algorithm being optimized as an additional hyperparameter for each individual, thus allowing multiple RL algorithms to be optimized within the same framework.

**Computational effort:** SEARL requires less compute to optimize an agent than a random search or PBT. This has two reasons: (A) As shown in Figure 2, SEARL requires up to 10 times fewer environment interactions. (B) SEARL evolves a neural network starting with a small network size, which reduces the compute at the beginning of the meta-optimization. Even though all compared methods can run in parallel, random search and PBT can run asynchronously, while SEARL has an evolutionary loop that requires synchronicity, at least in our current implementation.
5 CONCLUSION

Tuning reinforcement learning algorithms is an expensive endeavor, and approaches to automating the tuning of hyperparameters have so far neglected this cost by only reporting the performance of the final best-found agent. To capture the truly required cost for tuning RL agents, we propose a fair evaluation of meta-optimization in reinforcement learning.

For RL agents to become a viable approach to real-world applications, their training and meta-optimization should be achieved in an affordable amount of environment steps. To address this need, we propose a sample-efficient AutoRL framework with which we can efficiently and robustly train any off-policy algorithm while jointly tuning the algorithm and architecture hyperparameters of the training agent, discovering effective configuration schedules.

We demonstrated the effectiveness of our framework by meta-optimizing TD3 in the MuJoCo benchmark suite, requiring up to an order of magnitude fewer interactions in the environment compared to random search and PBT. We showed that this improvement can be attributed mainly to the use of shared experiences while training our agents. This improvement in sample efficiency allows us to essentially perform AutoRL almost for free. SEARL required nearly the same amount of environment interactions while training our agents and find strong hyperparameter configurations at the same time.

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APPENDIX

A  MUTATION OPERATORS

For each individual, we select one of the following operators uniformly at random:

**Gaussian Mutation:** This operator adds Gaussian noise to a subset of the RL agent’s neural network weights. The additive noise is only added to the actor network in a similar fashion, as described in [Khadka & Tumer (2018)] Algorithm 3, using the same hyperparameters.

**Activation Function:** For each network independently, a new activation function for the hidden layers is chosen randomly from a pre-defined set with equal probability. The set contains the activation functions (relu, elu, tanh) excluding the current used activation function.

**Network Size:** This operator changes the network size, either by adding a new layer with a probability of 20% or new nodes with a probability of 80%. When adding a new layer, the last hidden layer will be copied and its weights are re-initialized. This leaves the features learned in the earlier layers unchanged by the mutation operator. When adding new nodes, we first select one of the existing hidden layers at random and add either 16, 32 or 64 additional nodes to the layer. The existing weight matrix stays the same and the additional part of the weight matrix is initialized.

**Hyperparameter Perturbations:** This operator adapts the hyperparameters of the training algorithm online. We make use of hyperparameter changes as proposed in PBT [Jaderberg et al. (2017)]. For the TD3 case study, we only change the learning rates of the actor and critic network. To this end, we randomly decide to increase or decrease the learning rate by multiplying the current rate by a factor of 0.8 or 1.2.

**No-Operator:** No change is applied to the individual. This option allows more training updates with existing settings.
Algorithm 1: SEARL algorithm

**Input:** population size $N$, number of generations $G$, training fraction $j$

1. Initialize replay memory $\mathcal{R}$
2. Initialize start population $\text{pop}_0 = (\{A_1, \Theta_1\}_0, \{A_2, \Theta_2\}_0, ..., \{A_N, \Theta_N\}_0)$

3. **for** $g = 1$ **to** $G$ **do**
4. 
5. 
6. 
7. 

   /\* Evaluation of previous population */

   **foreach** $\{A_i, \Theta_i\}_{g-1} \in \text{pop}_{g-1}$ **do**
7. 
8. 
9. 
10. 
11. 
12. 

   /\* Tournament selection with elitism */

   best $\leftarrow$ SELECTBESTINDIVIDUAL($\text{pop}_{g-1}, \mathcal{F}_g$)
14. 
15. 
16. 
17. 
18. 
19. 

   /\* Mutation of tournament selection */

   **foreach** $\{A_i, \Theta_i\} \in \text{pop}^{selected}$ **do**
20. 
21. 
22. 

   /\* RL-Training steps */

   **foreach** $\{A_i, \Theta_i\} \in \text{pop}^{mutated}$ **do**
24. 
25. 
26. 
27. 
28. 
29. 

Due to the changing network architecture in the mutation phase of SEARL, each training phase requires a change of the value target network, as well as a re-initialization of the optimizers used during training. To deal with this, SEARL copies the individual’s current value network after the mutation phase and makes use of this copy as the frozen value target network for the training phase. SEARL also re-initializes the optimizers to deal with the changing network architectures. We analyze the performance impact of this \textit{target network re-creation and re-initialization} by simulating the effects in the context of the TD3 algorithm in the MuJoCo suite. To this end, we re-create the target network and re-initialize the optimizer after every episode in the environment. We note that in the original TD3 setting, the target network is updated using soft updates. The target re-creation case we analyze corresponds to a hard update of the target network. The results of the described experiments are shown in Figure 6, where each curve represents the mean performance of 20 TD3 runs with different random seeds and the shaded area represents the standard deviation. We observe that, perhaps surprisingly, re-creation and re-initialization do not seem to hurt performance and even improve performance in 2 out of 5 environments.

![Figure 6](image_url)

**Figure 6:** The impact of value network target re-creation and optimizer re-initialization after each episode in the TD3 algorithm. The default configuration uses a soft target update and only initializes the optimizer once in the begin of the training. The plots show the mean performance over 20 random seeds on the MuJoCo suite and the shaded area represents the standard deviation.
D Hyperparameter Search Spaces

The search space for the hyperparameter is inspired by the PBT-UNREAL experiments and can be found in Table 1. We choose the initial hyperparameter space for PBT smaller than random search since PBT is able to increase or decrease parameters during the optimization.

| Parameter | PBT | Random Search |
|-----------|-----|---------------|
| learning rate | $\{5 \times 10^{-3}, 10^{-5}\}$ | |
| activation | relu, tanh, elu | |
| layers | $\{1, 2\}$ | $\{1, 2, 3\}$ |
| units | $(128, 384)$ | $(64, 500)$ |

Table 1: Considered hyperparameter search spaces. The random search space is slightly larger since the configurations are fixed whereas PBT is able to explore network sizes.
E  RANDOM HYPERPARAMETER INITIALIZATION IN SEARL

We hypothesize that a more diverse starting population coming from random initialization of each individual might help in finding well performing configurations faster. In this ablation study we initialize the SEARL population with the same search space as in PBT (Appendix D). Figure 7 shows the mean performance of 10 runs with different random seeds. The shaded area represents the standard deviation. We observe that using a more diverse starting population does not provide substantial benefits in any environment. But in cases where less task-specific information is available, we show that using a random initialization does not seem to harm performance significantly.

Figure 7: The mean performance over 10 random seeds of SEARL using the default configuration for hyperparameter initialization (blue line) compared with random initialization (orange) over 2M environment steps. The shaded area represents the standard deviation.
### F SEARL Configuration

Table 2 shows the configuration of SEARL for the TD3 case study.

| Parameter                                | Value          |
|------------------------------------------|----------------|
| Max. frames in environment               | 2 000 000      |
| Replay memory size                       | 1 000 000      |
| Min. frames per evaluation               | 250            |
| Population size                          | 20             |
| Selection tournament size                | 3              |
| New layer probability                    | 20%            |
| New nodes probability                    | 80%            |
| Parameter noise standard deviation       | 0.1            |
| Training batch size                      | 100            |
| Fraction of eval frames for training     | 0.5            |
| Default learning rate                    | 0.001          |
| Optimizer                                | Adam           |
| TD3 Gamma                                | 0.99           |
| TD3 Tau                                  | 0.005          |
| TD3 policy noise                         | 0.2            |
| TD3 noise clip                           | 0.5            |
| TD3 update frequency                     | 2              |
| Default activation function              | relu           |
| Start network size                       | [128]          |

Table 2: The configuration of SEARL in the TD3 case study.
G  Change of Hyperparameters Over Time

To generate more insights about the online hyperparameter adaption, we visualize a set of hyperparameters over the course of a SEARL optimization run. We show the sum of hidden nodes, as well as the learning rates of both the actor and the critic for all individuals in the population in Figure 8. While for runs in environments like HalfCheetah and Ant the learning rate seems to decrease over time for most individuals, in the other environments the learning rate seems to stay more constant. This suggests that no single learning rate schedule seems to be optimal for all environments, thus showing the need for online hyperparameter adaptation. In terms of total network size, we also observe that different environments require different network sizes in order to achieve strong performance. This is in line with previous findings, e.g. in [Henderson et al.] (2018).

Figure 8: Change of the total network size (as the sum of hidden nodes in all layers, orange) and the learning rates (actor learning rate in red, critic in blue) over time. A plot contains all population individuals configurations over 2M steps for one SEARL run.
H ABLATION STUDY OF SEARL FEATURES

In this ablation study we independently remove the features of SEARL to gain insights about their impact on the performance. For the ablation experiment without architecture evolution, TD3’s default architecture with two hidden layers, with hidden layer size of $[400, 300]$, is used. The mean performance over five runs and its standard deviation in the MuJoCo suite is shown in Figure 9. From these ablation experiments it is clear that removing the shared replay memory greatly reduces the performance. The different environments benefit differently from the different SEARL features. For example, removing the architecture in HalfCheetah leads to a drop in performance while its beneficial in Walker2D but the hyper-parameter adaptations exert the opposite behaviour. So, the impact of removing other SEARL features individually does not show a clear picture across all environments and suggests that a variety of features helps to adapt RL to the environments characteristics.

![Figure 9: Comparison of performance impact when removing different SEARL features individually. All results show mean performance across five different random seeds. The standard deviation is shown as shaded areas.](image)
I ABLATION STUDY OF SEARL COMPARED TO TD3 HELD-OUT OPTIMIZATION

We test the generality of SEARL against a held-out tuned TD3 configuration. Therefore, we tune TD3 hyperparameters in the artificial setting of four similar environments with 2M interactions in total to find the hyperparameter setting that is best on average across these four environments and evaluate on the held-out environment for 2M steps. We compare this leave-one-environment-out performance to a single fixed hyperparameter configuration for SEARL across all environments running for 2M environment interactions to demonstrate that SEARL is capable of robust joint HPO and training of a learning agent. As shown in Figure 10, SEARL outperforms the TD3-tuned hyperparameter setting in three environments, performs on par in “Walker2d” and slightly worse in “Reacher”. These results demonstrate the generalization capabilities of SEARL across different environments.

Figure 10: Comparison the performance of SEARL against a held-out tuned TD3 configuration, tuned with the same budget of a SEARL run (2M environment interactions) and evaluated over 2M steps. All results show mean performance across 10 different random seeds. The standard deviation is shown as shaded areas.