Evolving Generalizable Actor-Critic Algorithms

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Abstract

Deploying Reinforcement Learning (RL) agents in the real world requires designing and tuning algorithms for problem-specific objectives such as performance, robustness, or stability. These objectives can frequently change, which will then necessitate further painstaking design and tuning. This paper presents MetaPG, an evolutionary method for designing new loss functions for actor-critic RL algorithms that optimize for different objectives. In particular, we focus on the objectives of final performance in training regime, policy robustness to unseen environment configurations, and training curve stability over random seeds. We initialize our algorithm population from Soft Actor-Critic (SAC) and optimize for these objectives over a set of continuous control tasks from the Real-World RL Benchmark Suite. We find that our method evolves algorithms that, using a single environment during evolution, improve upon SAC’s performance and generalizability by 3% and 17%, respectively, and reduce instability up to 65% in that same environment. Then, we scale up to more complex environments from the Brax physics simulator and replicate conditions that can be encountered in practical settings (such as different friction coefficients). MetaPG evolves algorithms that can obtain 9% better policy robustness within the same meta-training environment without loss of performance and robustness when doing cross-domain evaluations in other Brax environments. Lastly, we analyze the structure of the best algorithms in the population and interpret the specific elements that help the algorithm optimize for a certain objective, such as regularizing the critic loss.

1 Introduction

Many Reinforcement Learning (RL) practitioners working on real-world problems, besides aiming for strong performance, look for stable RL algorithms with good generalization that can be deployed with minimal human intervention. Deployed policies should perform well according to specific standards set in the training environment but at the same time should generalize to unseen scenarios with zero-shot learning. In addition, since policies are re-trained many times during the development process, RL algorithms should be stable, i.e., the training curve should be consistent across independent runs of the algorithm. Examples from domain-specific research (e.g., robotics [1], energy systems [2], fluid dynamics [3]) demonstrate the impact of this triad. When optimizing for these three objectives at the same time is not possible, domain experts make decisions over their preferences, which might change over time as the agent operates in the real world. Even for state-of-the-art RL algorithms, these challenges are considerably adverse in the context of real scenarios, either by themselves or in combination [4]. Prior work generally prioritizes optimizing for one objective over the rest, obviating the multi-preference perspective many real-world environments intrinsically require.

State-of-the-art RL algorithms, such as D4PG [5] or DMPO [6], fall short when policies face real-world challenges such as generalization to environment configurations not seen during training
Warm start RL algorithm (e.g., SAC)

RL algorithms are represented as graphs with typed inputs and outputs

Population of K evolved RL algorithms with two fitness scores each

Fitness scores RL algorithm 1
Fitness scores RL algorithm 2
Fitness scores RL algorithm K

Fitness scores are computed based on returns after training using the evolved algorithms to learn a policy

Fitness scores are encoded two RL objectives. (a) The method starts by taking a warm-start RL algorithm with its loss function represented in the form of a directed acyclic graph. MetaPG consists of a meta evolution process that, after initializing algorithms to the warm-start, discovers a population of new algorithms. (b) Each evolved algorithm is evaluated by training an agent following the algorithm encoded by it, and then computing two fitness scores based on the training outcome. (c) After evolution, all RL algorithms can be represented in the fitness space and a Pareto-optimal set of algorithms can be identified. (d) Identifying which graph substructures change across the algorithms in the Pareto set allows to see which operations favor specific RL objectives. MetaPG can be scaled to more than two RL objectives.

Figure 1: MetaPG overview, example with two fitness scores encoding two RL objectives. (a) The method starts by taking a warm-start RL algorithm with its loss function represented in the form of a directed acyclic graph. MetaPG consists of a meta evolution process that, after initializing algorithms to the warm-start, discovers a population of new algorithms. (b) Each evolved graph is evaluated by training an agent following the algorithm encoded by it, and then computing two fitness scores based on the training outcome. (c) After evolution, all RL algorithms can be represented in the fitness space and a Pareto-optimal set of algorithms can be identified. (d) Identifying which graph substructures change across the algorithms in the Pareto set allows to see which operations favor specific RL objectives. MetaPG can be scaled to more than two RL objectives.

| 1 | 2 | 3 | 4 |
|---|---|---|---|
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(e.g., physical parameters of the environment are different) [4]. The impact is worse when multiple challenges are combined in one experiment [4]. While policy goodness is generally measured by average training return, domain-specific practitioners also value other objectives such as policy robustness to environmental perturbations and therefore, depending on the context, are willing to prioritize it and trade it for training performance [7]. This preference might shift due to multiple factors outside of the practitioner’s control [8]. In addition, stability is a well-known problem for RL [9]; and RL algorithms are seldom ranked according to this property. As current RL algorithm design tends to be different from this multi-preference setup, there is little knowledge on how to prioritize more than one goal at the same time and balance the tradeoffs.

Previous work propose multiple solutions to address individual goals [10, 11], the majority of them follow human-driven design processes. When we want to optimize for multiple objectives and our preferences vary, this poses two problems: 1) the costs of human-driven design might become prohibitively expensive when trying to optimize more than one RL objective or re-design is frequently required; and 2) it is unclear whether designing an all-purpose RL algorithm that works across domains is possible in these contexts. We argue multi-preference RL builds the case for automating algorithm design and speeding up the process of RL algorithm discovery. Automated Machine Learning or AutoML [12] has proven to be a successful tool for Supervised Learning problems [13–16], and it has been recently applied in the context of RL for automating loss function search [17–20].

This paper proposes MetaPG (see Figure 1), a method that evolves a population of continuous action actor-critic algorithms [21], identified by their loss functions; loss functions are represented as directed acyclic graphs, using multiple fitness scores encoding independent RL objectives that are taken into account by means of the multi-objective ranking algorithm NSGA-II [22]. Compared to manual design, this strategy allows us to explore the algorithm space more efficiently by automating search operations. MetaPG finds algorithm improvement directions that jointly optimize the objectives.

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In this work we use the term algorithm and loss function interchangeably.
considered until it obtains a Pareto-optimal set of loss functions that maximizes fitness with respect
to each objective, approximating the underlying tradeoff among them.

To evaluate MetaPG, we carry out multi-objective experiments using, first, the Real-World RL
environment suite [4], which provides benchmarks for generalization under physical perturbations;
and second, the Ant and Humanoid environments from the Brax physical simulator [23]. We warm-
start the evolution with a graph-based representation of Soft Actor-Critic (SAC) [24], and demonstrate
that our method is able to evolve a Pareto-optimal set of actor-critic algorithms that improve SAC’s
performance and generalizability by 3% and 17%, respectively, and reduce instability up to 65%. We
use a single environment class during evolution (e.g., Cartpole) and evaluate the improvements in
that same class. Then, using the same warm-starting procedure in the Brax environments, we find
algorithms that, after hyperparameter-tuning, outperform SAC by 12%, 9%, and 24% in performance,
generalizability, and stability, respectively. Furthermore, we observe that algorithms evolved in
Ant show minimal performance and generalizability loss when transferred to Humanoid and vice
versa. Their metrics in the new environment are comparable to SAC’s after hyperparameter-tuning.
Finally, since loss functions are represented as graphs, by comparing the structure of loss functions in
different points of the fitness space, we can offer an interpretation of which substructures influence
the observed fitnesses for the environments considered. For instance, we find MetaPG evolves loss
functions that remove the entropy term in SAC to trade performance for generalizability.

In summary, this paper makes three main empirical contributions. The first contribution is a method
that combines multi-objective evolution with a search language representing actor-critic algorithms
as graphs, which can discover new loss functions over a set of different objectives. The second
contribution consists of our encoding of stability, training performance, and policy generalization
over environment perturbations as a specific set of objectives to optimize. The last contribution
is a dataset of Pareto-optimal actor-critic loss functions which outperform baselines like SAC on
multiple objectives. This dataset can hopefully be further analyzed to understand how algorithmic
changes affect the tradeoff between these different objectives.

We believe this paper would be of interest to the broader RL community, as it highlights an important
aspect of designing RL algorithms for practical applications: the balancing of different preferences
over multiple objectives that together pose bottlenecks for deployment. Our findings can benefit
AutoML research; as automating RL still remains a complex research problem, our work provides
a new method aligned with practical goals and insights on interpretable loss function optimization.
Lastly, this work also interests domain-specific practitioners; it provides a way of encoding their—
possibly multiple—problem needs and picking the algorithm whose tradeoffs align better with the
practical goals. The latter might not always be possible with current all-purpose RL algorithms.

2 Related Work

RL with multiple reward signals Certain environments intrinsically provide multiple reward
signals in the form of different benefits and/or costs. Number of techniques handle those scenarios:
reducing all reward signals into a single scalar [25], combining in the distribution space individual
policies trained for each signal [26], training one policy per preference over rewards [27, 28], or meta
learning to automate reward search [29, 30]. Our work does not focus on accounting for multiple
reward signals. Instead, it focuses on RL algorithms that, in addition to optimizing for a cumulative
reward, also optimize for the stability and generalization objectives, objectives desired in many
real-world applications.

Optimizing for real-world RL objectives A large body of works identifies various application-
specific RL objectives [4, 1, 31, 32]. For example, specific algorithms address individual objectives
(e.g., Offline RL [33], safe RL [34], generalization [11]). However, multi-objective optimization
for combinations of these objectives is seldom a goal in the literature, despite practitioners valuing
combining them or establishing different sets of preferences. We frame our method as a multi-
objective optimization of RL objectives (in our case performance, generalizability, and stability), in
which relevant goals are simultaneously encoded.

Optimizing RL components Automated RL or AutoRL seeks to meta learn RL components [35],
such as RL algorithms [17, 36, 18, 20], their hyperparameters [37–39], policy/neural network [40, 41].

The dataset can be found at: https://github.com/authors2022/dataset
or the environment [42–46]. This work evolves RL algorithms and leaves other elements of the RL problem out of the scope. We focus on the RL algorithm given its interaction with all elements in a RL problem: states, actions, rewards, and the policy.

**Evolutionary AutoML**  Neuro-evolution introduced evolutionary methods in the context of AutoML [47, 48], including neural network architecture search [49, 50, 15]. In the RL context evolution searched for policy gradients [51] and value iteration losses [17]. Our work is also related to the field of genetic programming, in which the goal is to discover computer code [52, 53, 17]. In this work we use a multi-objective evolutionary method to discover new RL algorithms, specifically actor-critic algorithms [21], represented as graphs that do not have meta parameters to be learned.

**Learning RL algorithms**  Loss functions play a central role in RL algorithms and are traditionally designed by human experts. Recently, several lines of work propose to view RL loss functions as tunable objects that can be optimized automatically [35]. One popular approach is to use neural loss functions whose parameters are optimized via meta-gradient [36, 20, 18, 19]. An alternative is to use symbolic representations of loss functions and formulate the problem as optimizing over a combinatorial space. One example is [54], which represents extrinsic rewards as a graph and optimizes it by cleverly pruning a search space. Learning value-based RL loss functions was first proposed in [17], and was applied to solving discrete action problems. In contrast, MetaPG focuses on continuous control problems and searches for symbolic loss functions of actor-critic algorithms.

## 3 Methods

We represent actor-critic loss functions (policy loss and critic loss) as directed acyclic graphs and use an evolutionary algorithm to evolve a population of graphs, which are ranked based on their fitness scores. The population is seeded or warm-started with known algorithms such as SAC and undergoes mutations over time. Each graph’s fitnesses are measured by training from scratch an RL agent with the corresponding loss function and encode three objectives: performance, generalizability, and stability. We use the multi-objective evolutionary algorithm NSGA-II [22] to jointly optimize all objectives until growing a Pareto-optimal set of graphs. Algorithm 1 in Appendix B summarizes the process. Section 3.1 provides RL algorithm graph representation details. Then, the main logic of MetaPG is contained in the evaluation routine, which computes fitness scores (Section 3.2) and employs several techniques to speed up the evolution and evaluation processes (Section 3.3). See Appendix B for further implementation details.

### 3.1 RL algorithm representation

MetaPG encodes loss functions as graphs consisting of typed nodes sufficient to represent a wide class of actor-critic algorithms. Compared to the prior value-based RL evolutionary search [17], MetaPG search space greatly expands on it and adds types to manage the search complexity. As a representative example, Appendix D presents the encoding for SAC that we use in this paper. In our experiments we limit the number of nodes per graph to 60 and 80, which supposes searching over a space of approximately $10^{300}$ and $10^{400}$ graphs, respectively (see Appendix A). Nodes in the graph encode loss function inputs, operations, and loss function outputs. The inputs include elements from experience tuples, constants such as the discount factor $\gamma$, a policy network $\pi$, and multiple critic networks $Q_i$. Operation nodes support intermediate algorithm instructions such as basic arithmetic or array and neural network operations. Then, the outputs of the graphs correspond to the policy and critic losses. The gradient descent minimization process takes these outputs and computes their gradient with respect to the respective network parameters. In Appendix A we provide a full description of the search language and nodes considered. MetaPG’s search language supports both on-policy and off-policy algorithms; however, in this paper we focus on off-policy algorithms given their better sample efficiency.

### 3.2 Fitness scores

This work focuses on optimizing single-task performance, zero-shot generalizability, and stability across independent runs with different random seeds. To compute the fitness scores we rely on a set of environments $\mathcal{E}$, which comprises multiple instances of the same environment class, including a training instance $E_{train} \in \mathcal{E}$. For example, $\mathcal{E}$ is the set of all RWRL Cartpole environments with
different pole lengths (0.1 meters to 3.0 meters in 0.1 intervals), and \( E_{train} \) corresponds to an instance with a specific pole length (1.0 meters). Using \( E_{train} \) to train a policy \( \pi \), the performance score \( f_{perf} \) is the average evaluation return on the training environment configuration:

\[
f_{perf} = \frac{1}{N_{eval}} \sum_{n=1}^{N_{eval}} G(\pi, E_{train}),
\]

where \( G \) corresponds to the normalized episode return given a policy and an environment instance, and \( N_{eval} \) is the number of evaluation episodes. The generalizability score \( f_{gen} \) is in turn computed as the average evaluation return of the policy trained on \( E_{train} \) over the whole range of environment configurations. We emphasize that the policy is trained on a single environment configuration (for example 1.0 meter pole length) and then is evaluated in a zero-shot fashion to new unseen environment configurations:

\[
f_{gen} = \frac{1}{|E|N_{eval}} \sum_{E \in E} \sum_{n=1}^{N_{eval}} G(\pi, E)
\]

Finally, stability entails getting consistent training curves across independent runs of the algorithm, mitigating the effect of stochastic elements. In that sense, stability is needed across objectives, as performance and generalizability should be consistent too. To that end, we leverage multiple random seeds; let \( f \) be a score (performance or generalizability), we measure \( f \) multiple times by running the RL training loop using \( N \) seeds. Then, we define stability-adjusted score as:

\[
\hat{f} = \mu(\{ f_n \}_{n=1}^{N}) - \kappa \cdot \sigma(\{ f_n \}_{n=1}^{N})
\]

where \( f_n \) denotes the score for seed \( n \); \( \mu \) and \( \sigma \) are the mean and standard deviation across the \( N \) seeds, respectively; and \( \kappa \) is a penalization coefficient. The final fitness of a graph is the tuple \((\hat{f}_{perf}, \hat{f}_{gen})\).

### 3.3 Evolution details

**Mutation** The population is initialized with a provided RL algorithm as a warm-start; all individuals are copies of this algorithm’s graph at the beginning. Once the population is initialized, individuals undergo mutations that change the structure of their respective graphs. Specifically, mutations consist of either replacing one or more nodes in the graph or switching the connections for one edge. The specific number of nodes that are affected by mutation is randomly sampled for each different individual; see Appendix B for more details.

**Operation consistency** To prevent introducing corrupted child graphs into the population, MetaPG checks operation consistency, i.e., for each operation, it makes sure the shapes of the input tensors are valid and compatible, and computes the shape of the output tensor. These shapes and checks are propagated along the computation graph.

**Hashing** To avoid repeated evaluations, MetaPG hashes [53] all graphs in the population. Once the method produces a child graph and proves its consistency, it computes a hash value and, in case of cache hit, reuses the fitness score from the older individual in the population. In our case, we not only want to make sure that we do not evaluate the same graph twice, but also identify graphs that are different in form but identical in function. To that end, before hashing we prune all graphs so that only nodes that contribute to the output are taken into account. Then, we look at the gradients of the output losses with respect to the input parameters and use their concatenation as the hash value. In this process we use a fixed set of synthetic inputs.

**Hurdle evaluations** We carry out evaluations for different individuals in the population in parallel, while evaluating across seeds for one algorithm is done sequentially. To prevent spending too many resources on algorithms that are likely to yield bad policies, MetaPG uses a simple hurdle environment [17] and a number of hurdle seeds. We first evaluate the algorithm on the hurdle environment for each hurdle seed, and only proceed with more complex and computationally and expensive environments if the resulting policy performs above a certain threshold on the hurdle environment.

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5 More precisely, should be \( E \in E \) except \( E_{train} \). In practice, we find this makes no significant difference in the metric because the number of test configurations is normally around 30.
4 Results

This section aims to answer the following questions: 1) Is MetaPG capable of evolving algorithms that improve upon the three objectives in different practical settings? 2) How well do discovered algorithms do in environments different from those used to evolve them? 3) Can we derive an explanation of what influences the scores of specific algorithms by looking at their graph structure?

We divide the experiments into meta training, meta validation, and meta testing phases. Each MetaPG run begins with the evolution process described in the previous section; this corresponds to the meta training phase, in which a specific set of seeds $S_{\text{train}}$ is used. After this phase, we obtain the population of algorithms, each with a pair of meta training fitness scores. Since the evolution process is non-deterministic, we run each experiment multiple times without configuration changes and aggregate all resulting populations into one single bigger population. Then, to avoid selecting algorithms that overfit to the set of seeds $S_{\text{train}}$, we reevaluate all algorithms in the population with a different set of seeds $S_{\text{valid}}$; this corresponds to the meta validation phase, which provides updated fitness scores for all algorithms. Finally, to assess the fitness of specific algorithms when deployed in different environments, we use a third set of seeds $S_{\text{test}}$ that provides realistic fitness scores in the new environments; this corresponds to the meta testing phase. In our analyses of the results, we focus on the set of meta-validated algorithms and then meta-test some of them.

4.1 Training setup

**Training environments** We use as training environments: Cartpole and Walker from the RWRL Environment Suite [4], Gym Pendulum, and Ant and Humanoid from the Brax physics simulator [23]. We define different instances of these environments by varying the pole length in Cartpole, the thigh length in Walker, the pendulum length and mass in Pendulum, and, to mimic a practical setting, the mass, friction coefficient, and torque in Ant and Humanoid. See Appendix C for the specifics.

**Meta training details** The population and maximum graph size consist of 100 individuals and 80 nodes in the Brax environments, respectively, and 1,000 individuals and 60 nodes in the rest of the environments. All are initialized using SAC as a warm-start (see Appendix D). For RL algorithm evaluation, we use 10 different seeds $S_{\text{train}}$ and fix the number of evaluation episodes $N_{\text{eval}}$ to 20. In the case of Brax, since training takes longer, we use 4 different seeds but increase $N_{\text{eval}}$ to 32. We meta-train using 100 TPU 1x1 v2 chips for 4 days in the case of Brax environments ($\sim$200K and $\sim$50K evaluated graphs in Ant and Humanoid, respectively), and using 1,000 CPUs for 10 days in the rest of environments ($\sim$100K evaluated graphs per experiment). In all cases we normalize the fitness scores to the range [0, 1]. We set $\kappa = 1$ in (3). Additional details are in Appendix B.

**Meta validation details** During meta validation, we use a set of 10 seeds $S_{\text{valid}}$, disjoint with respect to $S_{\text{train}}$. In the case of Brax environments, we use 4 meta validation seeds. Same applies during meta testing. In each case, we use a number of seeds that achieve a good balance between preventing overfitting and having affordable evaluation time. The value of $N_{\text{eval}}$ during meta validation and meta testing matches the one used in meta training.

**Hyperparameter tuning** We use the same fixed hyperparameters during all meta training. Algorithms are also meta validated using the same hyperparameters. In the case of Brax environments, we do hyperparameter-tune the algorithms during meta validation; additional details can be found in Appendix F. We also hyperparameter-tune all baselines we compare our evolved algorithms against.

**RL Training details** The architecture of the policies corresponds to two-layer MLPs with 256 units each. Additional training details are presented in Appendix E.

4.2 Optimizing performance, generalizability, and stability in RWRL Environment Suite

We apply MetaPG to RWRL Cartpole and compare the evolved algorithms in the meta-validated Pareto-optimal set with the warm-start SAC and ACME SAC [55] (Figure 2a). When running ACME SAC we first do hyperparameter tuning and pick the two configurations that lead to the best performance and the best generalizability (ACME SAC HPT Perf and ACME SAC HPT Gen, respectively). In Table 1, we show numeric scores with standard errors. The results show that, by mutating the graphs, MetaPG discovers RL algorithms that improve upon the warm start’s and ACME SAC’s performance and generalizability in the same environment we used during evolution.
(a) Stability-adjusted fitness scores (computed using Equation 3) for algorithms in the Pareto-optimal set.

(b) Average return and standard deviation across seeds when evaluating trained policies in multiple RWRL Cartpole instances with different pole lengths (Training configuration is 1.0, see Appendix C).

Figure 2: Evolution results (meta validation across 10 different seeds) alongside the warm-start algorithm (SAC), and the hyperparameter-tuned ACME SAC when using the RWRL Cartpole environment for training. We show the Pareto-optimal set of algorithms that results after merging the 10 populations corresponding to the 10 repeats of the experiment. The best performer and best generalizer correspond to the algorithms with the highest stability-adjusted performance and generalizability scores, respectively, according to Equations 1, 2, and 3.

Table 1: Average performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for three algorithms in the Pareto-optimal set and SAC when using RWRL Cartpole as a training environment. We compute these metrics across 10 seeds.

| RL Algorithm          | Avg. Perf. score \((f_{perf})\) | Avg. Gen. score \((f_{gen})\) |
|-----------------------|---------------------------------|------------------------------|
| Pareto point 1: Best performer | 0.871 ± 0.003 | 0.475 ± 0.016 |
| Pareto point 6       | 0.854 ± 0.002 | 0.531 ± 0.017 |
| Pareto point 10: Best generalizer | 0.770 ± 0.014 | 0.570 ± 0.019 |
| warm-start SAC       | 0.845 ± 0.009 | 0.487 ± 0.027 |
| ACME SAC HPT Perf    | 0.865 ± 0.001 | 0.372 ± 0.060 |
| ACME SAC HPT Gen     | 0.845 ± 0.012 | 0.518 ± 0.040 |

Compared to the warm-start, the best performer achieves a 3% improvement in the performance score, the best generalizer achieves a 17% increase in the generalizability score, and the selected algorithm in the Pareto-optimal set (Pareto point 6) achieves a 1% and a 9% increase in both performance and generalizability, respectively. Then, in terms of the stability objective, evolved algorithms achieve between 33% and 65% reduction in the standard deviation of the results and therefore improve in that dimension as well. We repeat the same experiments in RWRL Walker and Gym Pendulum and observe that MetaPG also discovers a Pareto-optimal set of algorithms that outperform SAC in both environments. These results, as well as additional information on the stability of the algorithms, are in Appendix F.

Figure 2b compares how the best performer and the best generalizer behave in different instances of the environment in which we change the pole length (all instances form the environment set \(E\) used during evolution). We follow the same procedure as described in [4]. The best performer achieves better return in the training configuration than the warm-start’s. The best generalizer in turn achieves a lower return but it trades it for higher returns in configurations outside of the training regime, being better at zero-shot generalization. The same behavior holds when using RWRL Walker and Gym Pendulum as training environments (see Appendix F).

4.3 Transferring evolved algorithms between Brax environments

Figure 3 shows the behaviour of evolved algorithms when meta-tested in Brax Ant, using an evaluation consisting of perturbations encountered in many practical settings (changes in friction coefficient, mass, and torque, see Appendix C). We first evolve algorithms independently in both Ant and Humanoid, then, for each case, select the algorithm with the best meta-training performance \(\hat{f}_{perf}\) (in this case we focus on only one of the evolved algorithms since there is strong correlation between both metrics; the best performer and best generalizer are close, sometimes even encode the same
algorithm), then meta-validate it with different hyperparameter sets (see Appendix F), and select the hyperparameter set that leads to the best generalizability. We then fix the hyperparameters and re-evaluate using the meta-testing seeds. We compare algorithms evolved in Ant and Humanoid with hyperparameter-tuned SAC.

These results highlight that, with proper hyperparameter tuning, an algorithm evolved by MetaPG in Brax Ant performs and generalizes better than a hyperparameter-tuned SAC baseline. Specifically, we observe a 12% improvement in performance and 9% improvement in generalizability. We also obtain a 24% reduction in instability. In addition, we observe that an algorithm initially evolved using Brax Humanoid and meta-validated in Ant transfers reasonably well to Ant during meta testing, achieving minimal loss of performance compared to hyperparameter-tuned SAC (6% less performance and 4% less generalizability compared to SAC). A similar result is obtained when Brax Humanoid environment serves as the meta testing environment (see Appendix F).

4.4 Analyzing the evolved RL algorithms

Next, we analyze evolved algorithms from our experiments on RWRL Cartpole. We pick the best meta-validated performer and generalizer, both evolved from the warm-start SAC (see Appendix D). The policy loss $L_\pi$ and critic losses $L_{Q_i}$ (one for each of the identical critic networks $Q_i$ considered, see Appendix A) observed from the graph structure for the best performer are the following:

$$L_{\text{perf} \pi} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim D} \left[ \log(\min(\pi(\tilde{a}_{t+1}|s_{t+1}), \gamma)) - \min_i Q_i(s_t, \tilde{a}_t) \right]$$  (4)

$$L_{\text{perf} Q_i} = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ (r_t + \gamma (Q_{\text{targ}_i}(s_{t+1}, \tilde{a}_{t+1}) - Q_i(s_t, a_t))^2 \right]$$  (5)

where $\tilde{a}_t \sim \pi(\cdot|s_t)$, $\tilde{a}_{t+1} \sim \pi(\cdot|s_{t+1})$, and $D$ is an experience dataset extracted from the replay buffer. Likewise, the loss equations for the best generalizer are:

$$L_{\text{gen} \pi} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim D} \left[ \log \pi(\tilde{a}_t|s_t) - \min_i Q_i(s_{t+1}, \tilde{a}_t) \right]$$  (6)

$$L_{\text{gen} Q_i} = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ \text{atan} \left( (r_t + \gamma (\min_i Q_{\text{targ}_i}(s_t, \tilde{a}_t) - \log \pi(\tilde{a}_t|s_t)) - Q_i(s_t, a_t))^2 \right) \right]$$  (7)

While both algorithms resemble the warm-start SAC (see Appendix D), we observe that the best performer does not include the entropy term in the critic loss while the best generalizer does (i.e., they correspond to setting $\alpha$ to 0 and 1 in the original SAC algorithm [24], respectively). This aligns with the hypothesis that, since ignoring the entropy pushes the agent to exploit more and explore less, the policy of the best performer overfits better to the training configuration compared to SAC. In contrast, the best generalizer is able to explore more. Figure 4a validates the latter observation showing a higher entropy for the best generalizer’s actor compared to the warm-start’s.

The use of arctangent in the critic loss of the best generalizer is also noticeable as, supported by Figure 4b, we observe this operation serves as a way of clipping the loss, which makes gradients...
smaller and thus prevents the policy’s parameters from changing too abruptly. In our experiments, we fix the number of training episodes as a compromise between achievable returns and evaluation runtimes. Clipping the loss has then an early-stopping effect compared to the baseline and results in a policy less overfitted, which benefits generalization. In Appendix F, we show both extended results that ignore the fix budget requirement and the equations for the best evolved algorithms in the remaining environments.

4.5 Discussion

Computational cost We acknowledge running MetaPG involves a non-negligible upfront computational cost. However, we believe this cost can be amortized by reusing the evolved algorithms; this is something that is aligned with the economy of scale AutoML approaches look for [56]. First, the cost is amortized by generating a Pareto-optimal set of loss functions from which practitioners can choose a specific point based on the desired performance vs. generalizability preference. A single-objective approach would require running MetaPG every time this preference changes. In addition, the achieved cross-domain generalization provides an additional perspective on amortizing the cost; we can reuse the algorithms across different domains and environments.

Improving evolution The Pareto-optimal set observed in Figure 2 combines 10 separate runs of evolution, since each individual run could converge to a different local optimum. We leave it to future work to improve the robustness of a single search experiment.

Potential value of interpolation between algorithms Our analyses have constantly focused on two extreme points from the Pareto-optimal sets (best performer and best generalizer). It is possible to interpolate between these two points to form an ensemble loss function. Such loss function may give additional flexibility for practitioners when designing an RL system by encoding complex design choices into an interpolation across objectives.

Cross-domain performance We have carried out cross-domain evaluation for Brax experiments and run additional experiments on the RWRL suite (see Appendix F). We have observed that, while evolved algorithms transfer reasonably well (especially best performers), sometimes they do not perform better than SAC in the new environments without hyperparameter tuning first, and that might not be enough in a small set of cases. This suggests that a direction of future work is to improve the transferrability of the evolved algorithms. At the same time, it poses an interesting research question of determining whether MetaPG is better suited to find “super algorithms” for specific environments or a new generation of all-purpose algorithms.

5 Conclusion

We presented MetaPG, a method that evolves actor-critic RL loss functions to optimize multiple RL objectives simultaneously and applied it to discovering algorithms that perform well, achieve zero-shot generalization across different environment configurations, and are stable; a triad of objectives with real-world implications. The experiments in RWRL Cartpole, RWRL Walker, and Gym Pendulum demonstrated that MetaPG discovered algorithms that, when using one environment
during evolution and then meta-validating in that same environment, outperform SAC, achieving a 3% and 17% improvement in performance and generalizability, respectively, and a reduction of 33% to 65% in instability. Experiments on Brax Ant and Brax Humanoid proved evolution is successful in more complex environments, achieving a 12% and 9% increase in performance and generalizability, respectively. We also observed that, when transferring evolved algorithms to environments different from those used during evolution, the loss of performance and generalizability in the new environment is minimal and is comparable to SAC. Finally, we have analyzed the evolved loss functions and linked specific elements in their structure to fitness results, such as the removal of the entropy term to benefit performance.

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JGL and AF conceived the project. AF assembled the team. JGL initiated research ideas, ran experiments and analysis. ER, AF, JT advised on evolutionary algorithms, reinforcement learning, and real-world applications, respectively. ER built the evolutionary infrastructure, with contributions from YM and AP. JGL developed the search space, with contributions from YM, JD, AP, and JT. JGL wrote the paper.

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A Search space details

In this section we present the details of the search space; we divide the nodes into input, output, and operation nodes. Output nodes correspond to losses computed by the algorithm, whose gradient with respect to the algorithm inputs is then computed in a training loop. In this paper we do steepest gradient descent to update network parameters; given the search space complexity, we leave incorporating other gradient descent strategies into the search space out of its scope. However, other strategies such as natural gradient or conjugate gradient could be incorporated, as they do gradient transformations and are agnostic to loss functions.

In the training process, agents then learn the policy by means of experience tuples coming from a replay buffer. MetaPG admits both continuous and discrete action spaces; specific nodes in the graphs —e.g., the networks— are adapted to work with the corresponding space.

During the evolution process, we fix a maximum number of nodes, which consists of the aforementioned input and output nodes, and several operation nodes. The majority of operation nodes treat input elements as tensors with variable shapes in order to maximize graph flexibility. Each node possesses a certain number of input and output edges, which are determined by the specific operation this node carries out. For example, a node that takes in two tensors and multiplies them element-wise has two input edges and a single output edge.

A.1 List of nodes

A complete list of the nodes considered follows:

Input nodes We only encode canonical RL elements as inputs:
- Policy network $\pi$
- Two critic networks, $Q_1$ and $Q_2$, and two target critic networks, $Q_{\text{targ}1}$ and $Q_{\text{targ}2}$
- Batch of states $s_t$ and next states $s_{t+1}$
- Batch of actions $a_t$
- Batch of rewards $r_t$
- Discount factor $\gamma$

Output nodes The output of these nodes is used as loss function to compute gradient descent on:
- Policy loss $L_\pi$
- Critic loss $L_{Q_i}$

Operation nodes These nodes operate generally on tensors and can broadcast operations when input sizes do not match:
- Addition: add two, three, or four tensors
- Multiplication: compute element-wise product of two or three tensors
- Subtract two tensors
- Divide two tensors and add constant $\epsilon$ to the denominator
- Neural network operations: Action distribution from state, stopping gradient computation
- Operations with action distributions: Sample, Log-probability
- Mean, sum, and standard deviation over last axis of array or over entire array
- Cumulative sum, cumulative sum with discount
- Squared difference
- Multiply by a constant: -1, 0.1, 0.01, 0.5, 2.0
- Minimum and maximum over last axis of a tensor
- Minimum and maximum element-wise between two tensors
- Other general operations: clamp, absolute value, square, logarithm, exponential
- Trigonometry functions
A.2 Size of the search space

To get an upper bound of the size of the search space in terms of the number of possible graphs (not all of them valid), we consider the \((k+1)\)-th node in the graph of size \(K\) nodes. This node can correspond to one of the \(N\) different operation nodes. Assuming that this node has two inputs, there are \(\binom{k}{2}\) possibilities of connecting to previous nodes in the graph. Therefore, we have a total of \(\frac{1}{2}Nk(k-1)\) possible combinations for the \((k+1)\)-th node. Then, an upper bound of the total number of possible graphs is

\[
\left(\frac{NK(K-1)}{2}\right)^K
\]  

(8)

With \(N = 33\) and \(K = 60\) we obtain approximately \(10^{286}\) graphs. This number increases to \(10^{401}\) if \(K = 80\) instead.

B Additional implementation details

Multi-objective evolution Algorithm 1 details the evolution process for MetaPG, in which Offspring and RankAndSelect are NSGA-II subroutines [22]. We do 10 independent repeats of MetaPG when evolving on RWRL Cartpole, RWRL Walker, and Gym Pendulum; 5 repeats when evolving on Brax Ant; and 3 repeats for Brax Humanoid.

| Algorithm 1 MetaPG Overview |
|-----------------------------|
| **Input:** Training environments \(E\) |
| **Initialize:** Initialize population \(P_0\) of loss function graphs (random initialization or bootstrap with an algorithm such as SAC). |
| 1: for \(L\) in \(P_0\) do \(L.score\) ← Eval\((L,E)\) |
| 2: end for |
| 3: \(Q_0\) ← Offspring\((P_0)\) ▷ NSGA-II |
| 4: for \(L\) in \(Q_0\) do \(L.score\) ← Eval\((L,E)\) |
| 5: end for |
| 6: for \(t = 1\) to \(G\) do |
| 7: \(R\) ← \(P_{t-1}\) \(\bigcup\) \(Q_{t-1}\) |
| 8: \(P_t\) ← RankAndSelect\((R)\) ▷ NSGA-II |
| 9: \(Q_t\) ← Offspring\((P_t)\) ▷ NSGA-II |
| 10: for \(L\) in \(Q_t\) do \(L.score\) ← Eval\((L,E)\) |
| 11: end for |
| 12: end for |
| 13: **Output:** Pareto-front of all loss function graphs. |

Warm-starting Algorithms are initialized using the warm-start SAC graph (see Appendix D), which consists of 33 nodes. Additional operation nodes are added to each individual until reaching the maximum amount of 60 nodes.

Mutation During mutation, there is a 50% chance an individual undergoes node mutation and a 50% chance it undergoes edge mutation. During node mutation, there is a 50% chance of replacing one node, a 25% chance of replacing 2 nodes, a 12.5% chance of replacing 4 nodes, and a 6.25% chance of replacing 8 and 16 nodes, respectively. During edge mutation, only one edge in the graph is replaced.

Hashing In the hashing process we use a fixed set of synthetic inputs with a batch size of 16.

Encoding multiple objectives MetaPG keeps the population to a fixed size during evolution. To decide which individuals should be removed in the process, the method makes use of different fitness scores that encode each of the RL objectives considered. These scores are not combined but treated separately in a multi-objective fashion. This means that, after evaluating a graph \(i\), it will have fitness
scores \( \{f_{i,1}, f_{i,2}, \ldots, f_{i,F}\} \), where \( F \) is the number of objectives considered. Then, when comparing two graphs \( i \) and \( j \), we say \( i \) has higher fitness than \( j \) iff \( f_{i,k} \geq f_{j,k} \), \( \forall k \), with at least one fitness score \( k' \) such that \( f_{i,k'} > f_{j,k'} \). In this case we also say graph \( i \) Pareto-dominates graph \( j \). If neither \( i \) Pareto-dominates \( j \) nor vice versa, we say both graphs are Pareto-optimal.

The process of removing individuals from the population follows the NSGA-II algorithm [22] which, assuming a maximum population size of \( P_{\text{max}} \) individuals:

1. From a set of \( P \) individuals, with \( |P| > P_{\text{max}} \), it computes the set \( P_{\text{opt}} \) of Pareto-optimal fittest graphs. None of the graphs in \( P_{\text{opt}} \) is Pareto-dominated by any other graph in the population and, if a graph \( i \) in \( P \) is Pareto-dominated by at least one other graph, then \( i \) does not belong to the Pareto-optimal set.
2. If \( |P_{\text{opt}}| \geq P_{\text{max}} \), the graphs are ranked based on their crowding distance in the fitness space. This favors individuals that are further apart from other individuals in the fitness space. The fittest \( P_{\text{max}} \) individuals of the Pareto-optimal set \( P_{\text{opt}} \) are kept in the population.
3. Otherwise, if \( |P_{\text{opt}}| < P_{\text{max}} \), the set \( P_{\text{opt}} \) is kept in the population and the process is repeated taking \( P \leftarrow P \setminus P_{\text{opt}} \) and \( P_{\text{max}} \leftarrow P_{\text{max}} - |P_{\text{opt}}| \).

**Computational cost vs. performance**

Figure 5 shows the evolution of the best fitness in the population with respect to the total number of graphs evolved in the case of RWRL Cartpole; 10 independent runs of the same experiment are shown. It can be observed that the largest jumps in stability-adjusted performance and generalizability occur in the first 10% and 25% of individual evaluations, respectively. The stochastic nature of an individual experiment can lead to different outcomes with shorter or longer distances between fitness jumps. We find that aggregating populations—after meta training— from 10 different experiments is a good way of countering such stochasticity.

![Figure 5: Evolution curves of the best fitness in the population with respect to the total number of evaluated individuals. Figures show 10 identical runs of the evolution experiment using RWRL Cartpole.](image)

#### C Environment Configurations

In this work we use multiple environments for our experiments: Cartpole and Walker from the RWRL Environment Suite [4], Gym Pendulum, and Ant and Humanoid from the Brax physics simulator [23]. In Table 2 we list the training configuration used for each and the parameters that we use to assess the generalizability of the policies. The parameters that are not listed are fixed to the default values for the environment in question.

In the case of Gym Pendulum and the Brax environments, we have more than one perturbation parameter; the generalizability score is computed by first sweeping through the perturbation values for one, taking the average \( f_{\text{gen}} \), repeating the same process for the others to compute \( f_{\text{gen}_2}, \ldots, f_{\text{gen}_P} \), and then computing the average of both to get the final score, i.e., \( f_{\text{gen}} = (f_{\text{gen}_1} + \ldots + f_{\text{gen}_P}) / P \), where \( P \) is the total number of different parameters that are perturbed.

For the parameters that undergo perturbations, we select the specific value used in the training configuration based on the following criteria: in the case of the RWRL Environment Suite, we pick
the training value used in [4], which corresponds to the default value as described in each benchmark; in the case of Gym Pendulum, we pick the default values given by the environment as training configuration; in the case of Brax, we follow the rationale of selecting training configurations that represent a baseline scenario (i.e., no mass variations, normal friction, and normal torque).

D warm-start SAC

We present the version of Soft Actor-Critic (SAC) [24] used in this work as the warm-start algorithm to initialize the population. We first present the equations for the policy loss $L_{\pi}^{WS}$ and critic loss $L_{Q_i}^{WS}$.

Table 2: Environment parameters and perturbations.

| Environment parameter                  | Value                             |
|----------------------------------------|-----------------------------------|
| **Rollout length**                     | 2,000                             |
| Min. return                            | -2,000                            |
| Max. return                            | 0                                 |
| Training episodes                      | 100                               |
| Perturbation parameter 1 (PP1)         | Pendulum mass                     |
| PP1 Default value                      | 1.0                               |
| PP1 Generalizability values            | 1.0, 2.0, 4.0, 10.0               |
| Perturbation parameter 2 (PP2)         | Pendulum length                   |
| PP2 Default value                      | 1.0                               |
| PP2 Generalizability values            | 1.0, 2.0, 4.0, 5.0, 7.5, 10.0      |
| **Brax environments**                 |                                   |
| Rollout length                         | 1,000                             |
| Min. return                            | 0                                 |
| Max. return                            | 1,000                             |
| Training episodes                      | 150                               |
| Perturbation parameter 1 (PP1)         | Mass coefficient                  |
| PP1 Default value                      | 1.0                               |
| PP1 Generalizability values            | 0.8 to 1.2 in steps of 0.05       |
| Perturbation parameter 2 (PP2)         | Friction coefficient              |
| PP2 Default value                      | 1.0                               |
| PP2 Generalizability values            | 0.3 to 1.0 in steps of 0.05       |
| Perturbation parameter 3 (PP3)         | Torque multiplier                 |
| PP3 Default value                      | 1.0                               |
| PP3 Generalizability values            | 0.5 to 1.0 in steps of 0.05       |
| Perturbation parameter 4 (PP4)         | Combined parameters PP1, PP2, and PP3 |
| PP4 Default value                      | 1.0 for each                      |
| PP4 Generalizability values            | Grid search over individual generalizability values |
\begin{align}
L_{\pi}^{WS} &= \mathbb{E}_{(s_t, a_t) \sim D} \left[ \log \pi(\tilde{a}_t|s_t) - \min_i Q_i(s_t, \tilde{a}_t) \right] \\
L_{Q_i}^{WS} &= \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ \left( r_t + \gamma \left( \min_i Q_{\text{targ}}(s_{t+1}, \tilde{a}_{t+1}) - \log \pi(\tilde{a}_{t+1}|s_{t+1}) \right) - Q_i(s_t, a_t) \right)^2 \right]
\end{align}

where $\tilde{a}_t \sim \pi(\cdot|s_t)$, $\tilde{a}_{t+1} \sim \pi(\cdot|s_{t+1})$, and $D$ is a dataset from the replay buffer. Then, in Figure 6 we represent these two equations that define the SAC algorithm in the form of a graph with typed input and outputs. MetaPG then modifies these graphs following the procedure described in Section 3.

Figure 6: Soft Actor-Critic (SAC) algorithm represented as a graph to initialize the population as a warm-start algorithm.

E Additional RL training details

An individual encoding a RL algorithm in the form of a graph is evaluated by training an agent using such algorithm. We use an implementation based on an ACME agent [55] for the RWRL and Gym environments, and an implementation based on the Brax physics simulator [23] for the Brax environments. The configuration of the training setup are shown in Table 3 for RWRL and Gym environments, and in Table 4 for the Brax environments.

F Additional results

In this section we present the additional results of the paper. We first introduce the remaining figures for RWRL Cartpole, then outline evolution results for RWRL Walker and Gym Pendulum, then show how different algorithms in the population for all three environments compare in terms of stability, then provide results for the Brax environments, then provide the equations of the evolved algorithms, and finally provide more details on other metrics of evolved algorithms.
Table 3: RL Training setup for the RWRL and Gym environments.

| Parameter                        | Value                                    |
|----------------------------------|------------------------------------------|
| Discount factor $\gamma$        | 0.99                                     |
| Batch size                       | 64 (RWRL Cartpole and Gym Pendulum)      |
|                                 | 128 (RWRL Walker)                        |
| Learning rate                    | $3 \cdot 10^{-4}$                        |
| Target smoothing coeff. $\tau$   | 0.005                                    |
| Replay buffer size               | 1,000,000                                |
| Min. num. samples in the buffer  | 10,000                                   |
| Gradient updates per learning step n step | 1                                      |
| Reward scale                     | 5.0                                      |
| Actor network                    | MLP (256, 256)                           |
| Actor activation function        | ReLU                                     |
| Tanh on output of actor network  | Yes                                      |
| Critic networks                  | MLP (256, 256)                           |
| Critic activation function       | ReLU                                     |

Table 4: RL Training setup for the Brax environments.

| Parameter                        | Value                                    |
|----------------------------------|------------------------------------------|
| Discount factor $\gamma$        | 0.95                                     |
| Batch size                       | 128                                      |
| Learning rate                    | $6 \cdot 10^{-4}$                        |
| Target smoothing coeff. $\tau$   | 0.005                                    |
| Replay buffer size               | 1,000,000                                |
| Min. num. samples in the buffer  | 1,000                                    |
| Gradient updates per learning step n step | 64                                      |
| Reward scale                     | 10.0                                     |
| Number of parallel environments  | 128                                      |
| Actor network                    | MLP (256, 256)                           |
| Actor activation function        | ReLU                                     |
| Tanh on output of actor network  | Yes                                      |
| Critic networks                  | MLP (256, 256)                           |
| Critic activation function       | ReLU                                     |

F.1 Evolution results for RWRL Cartpole

Figure 7 shows the resulting population when running evolution using the RWRL Cartpole environment [4] and Table 5 shows the average fitness scores ($\pm$ standard error of the mean) for each algorithm in the Pareto-optimal set. Figure 8 shows the performance of the evolved algorithms across different environment configurations, it updates Figure 2b by introducing PPO [57] in the comparison. We found that PPO was not well-suited for the continuous control tasks explored in this work.

F.2 Evolution results for RWRL Walker

We present evolution results when running MetaPG with RWRL Walker as the training environment. In Figures 9 and 10 we show the resulting population and the performance across environment configurations for the best performer and the best generalizer in the Pareto-optimal set, respectively. Exact numbers for each algorithm in the Pareto-optimal set can be found in Table 6. This table also shows the scores of the warm-start and ACME SAC. As covered in Appendix F.10, we do not hyperparameter-tune the warm-start before the experiments. As a result, the warm-start might perform poorly, as is the case in this environment. We can observe MetaPG is able to increase the fitness of the evolved algorithms during the evolution process.
Figure 7: Meta training and meta validation stability-adjusted fitness scores (computed using Equation 3 across 10 seeds) for each RL algorithm in the population alongside the warm-start (SAC) and ACME SAC when using the RWRL Cartpole environment for training. We show the meta validated Pareto-optimal set of algorithms that results after merging the 10 populations corresponding to the 10 repeats of the experiment.

Figure 8: Average and standard deviation across seeds of the meta validation performance when training on a single configuration of RWRL Cartpole and evaluating on multiple unseen ones. We compare the best performer, the best generalizer, the warm start SAC, and we also add two hyperparameter-tuned PPO runs, one tuned for performance and the other for generalizability (see Appendix F.10 for hyperparameter tuning details). The pole length changes across environment configurations and a length of 1.0 is used as training configuration.

F.3 Evolution results for Gym Pendulum

We present evolution results when running MetaPG with Gym Pendulum as the training environment. In Figures 11 and 12 we show the resulting population and the performance across environment configurations for the best performer and the best generalizer in the Pareto-optimal set, respectively. In the case of Pendulum, the generalizability fitness score is computed across the perturbation of two different parameters: the pendulum mass and the pendulum length. These parameters are changed separately, as opposed to varying both the mass and length of the pendulum in the same run. Exact numbers can be found in Table 7, in which an average improvement over the warm-start of 1% in performance and 16% in generalizability is achieved.

F.4 Stability analyses for RWRL Cartpole, RWRL Walker, and Gym Pendulum

We present the stability results, which are accounted for by penalizing the standard deviation across seeds, following Equation 3. For each environment considered in this work, we select a subset of the meta validated graphs that covers all the explored fitness space and, in Figure 13, show the average and standard deviation of each fitness score. Algorithms in the Pareto-optimal set and those closer
Table 5: Average meta-validated performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for the 10 algorithms in the Pareto-optimal set and SAC when using RWRL Cartpole as a training environment. We compute these metrics across 10 seeds.

| RL Algorithm          | Avg. Perf. score \(f_{\text{perf}}\) | Avg. Gen. score \(f_{\text{gen}}\) |
|-----------------------|---------------------------------------|-----------------------------------|
| Pareto 1: Best performer | 0.871 ± 0.003                        | 0.475 ± 0.016                    |
| Pareto 2              | 0.857 ± 0.001                        | 0.513 ± 0.025                    |
| Pareto 3              | 0.857 ± 0.002                        | 0.514 ± 0.025                    |
| Pareto 4              | 0.856 ± 0.002                        | 0.517 ± 0.024                    |
| Pareto 5              | 0.855 ± 0.002                        | 0.520 ± 0.023                    |
| Pareto 6              | 0.854 ± 0.002                        | 0.531 ± 0.017                    |
| Pareto 7              | 0.798 ± 0.010                        | 0.540 ± 0.016                    |
| Pareto 8              | 0.794 ± 0.010                        | 0.546 ± 0.018                    |
| Pareto 9              | 0.783 ± 0.007                        | 0.579 ± 0.026                    |
| Pareto 10: Best generalizer | 0.770 ± 0.014                        | 0.570 ± 0.019                    |
| Warm-start SAC         | 0.845 ± 0.009                        | 0.487 ± 0.027                    |
| ACME SAC HPT Perf     | 0.865 ± 0.001                        | 0.372 ± 0.060                    |
| ACME SAC HPT Gen      | 0.845 ± 0.012                        | 0.518 ± 0.040                    |

Figure 9: Meta training and meta validation stability-adjusted fitness scores (computed using Equation 3 across 10 seeds) for each RL algorithm in the population alongside the warm-start (SAC) and ACME SAC when using the RWRL Walker environment for training. We show the meta validated Pareto-optimal set of algorithms that results after merging the 10 populations corresponding to the 10 repeats of the experiment.

Figure 10: Average and standard deviation across seeds of the meta validation performance of the best performer, the best generalizer, and the warm-start (SAC) when training on a single configuration of RWRL Walker and evaluating on multiple unseen ones. The thigh length changes across environment configurations and a length of 0.225 is used as training configuration.

to it present lower variability, showing MetaPG is also successful in improving the stability of RL algorithms.
Table 6: Average meta-validated performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for the 7 algorithms in the Pareto-optimal set and SAC when using RWRL Walker as a training environment. We compute these metrics across 10 seeds.

| RL Algorithm       | Avg. Perf. score (\(f_{\text{perf}}\)) | Avg. Gen. score (\(f_{\text{gen}}\)) |
|--------------------|----------------------------------------|--------------------------------------|
| Pareto 1: Best performer | 0.963 ± 0.002                          | 0.544 ± 0.018                        |
| Pareto 2           | 0.962 ± 0.003                          | 0.536 ± 0.012                        |
| Pareto 3           | 0.960 ± 0.002                          | 0.542 ± 0.015                        |
| Pareto 4           | 0.959 ± 0.003                          | 0.541 ± 0.013                        |
| Pareto 5           | 0.960 ± 0.005                          | 0.541 ± 0.009                        |
| Pareto 6           | 0.954 ± 0.003                          | 0.555 ± 0.009                        |
| Pareto 7: Best generalizer | 0.955 ± 0.005                          | 0.569 ± 0.015                        |
| warm-start SAC      | 0.028 ± 0.002                          | 0.033 ± 0.001                        |
| ACME SAC HPT Perf  | 0.968 ± 0.003                          | 0.444 ± 0.014                        |
| ACME SAC HPT Gen   | 0.926 ± 0.008                          | 0.510 ± 0.012                        |

Figure 11: Meta training and meta validation stability-adjusted fitness scores (computed using Equation 3 across 10 seeds) for each RL algorithm in the population alongside the warm-start (SAC) and ACME SAC when using the Gym Pendulum environment for training. We show the meta validated Pareto-optimal set of algorithms that results after merging the 10 populations corresponding to the 10 repeats of the experiment.

Figure 12: Average and standard deviation across seeds of the meta validation performance of the best performer, the best generalizer, and the warm-start (SAC) when training on a single configuration of Gym Pendulum and evaluating on multiple unseen ones. The pendulum mass and the pendulum length independently change across environment configurations (we change one at a time). The training configurations use a pendulum mass and a pendulum length of 1.0 and 1.0, respectively.

F.5 Evolution results for Brax Ant

Table 8 shows the meta testing fitness scores of the best performer algorithms obtained after running evolution on Brax Ant and Brax Humanoid, respectively. We compare those against the hyperparameter-tuned warm-start SAC and observe an improvement of 12% and 9% in performance and generalizability, respectively, and up to a 24% reduction in instability. We observe that, after
Table 7: Average meta-validated performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for the 8 algorithms in the Pareto-optimal set and SAC when using Gym Pendulum as a training environment. We compute these metrics across 10 seeds.

| RL Algorithm       | Avg. Perf. score ($f_{perf}$) | Avg. Gen. score ($f_{gen}$) |
|--------------------|-------------------------------|-----------------------------|
| Pareto 1: Best performer | 0.887 ± 0.010             | 0.360 ± 0.011               |
| Pareto 2           | 0.885 ± 0.009                 | 0.381 ± 0.017               |
| Pareto 3           | 0.887 ± 0.010                 | 0.391 ± 0.014               |
| Pareto 4           | 0.887 ± 0.011                 | 0.392 ± 0.013               |
| Pareto 5           | 0.887 ± 0.011                 | 0.393 ± 0.007               |
| Pareto 6           | 0.886 ± 0.010                 | 0.433 ± 0.018               |
| Pareto 7           | 0.886 ± 0.011                 | 0.437 ± 0.019               |
| Pareto 8: Best generalizer | 0.868 ± 0.034             | 0.445 ± 0.021               |
| warm-start SAC     | 0.879 ± 0.022                 | 0.383 ± 0.015               |
| ACME SAC HPT Perf  | 0.880 ± 0.014                 | 0.392 ± 0.012               |
| ACME SAC HPT Gen   | 0.879 ± 0.014                 | 0.400 ± 0.009               |

Figure 13: From a subset of the meta validated graphs, for each of them, we show the average fitness scores surrounded by an ellipse with semiaxes representing the standard deviation across seeds for each fitness score.

cross-domain transfer, the algorithm evolved in Brax Humanoid achieves comparable scores to SAC. We follow the hyperparameter tuning procedure explained in Appendix F.11.

Table 8: Average meta-tested performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for algorithms first evolved in Brax Ant and Brax Humanoid, and then evaluated on Brax Ant on a different set of seeds. We compare these scores against the hyperparameter-tuned warm start SAC. We compute these metrics across 4 seeds.

| RL Algorithm       | Avg. Perf. score ($f_{perf}$) | Avg. Gen. score ($f_{gen}$) |
|--------------------|-------------------------------|-----------------------------|
| Ant performer      | 0.770 ± 0.041                 | 0.627 ± 0.035               |
| Humanoid performer | 0.643 ± 0.117                 | 0.553 ± 0.086               |
| warm-start SAC     | 0.685 ± 0.053                 | 0.573 ± 0.036               |

F.6 Evolution results for Brax Humanoid

Figure 14 shows the behaviour of evolved algorithms when meta-tested in Brax Humanoid, using an evaluation consisting of perturbations encountered in many practical settings (changes in friction coefficient, mass, and torque), as outlined in Appendix C. We first evolve algorithms independently in both Humanoid and Ant, then, for each case, select the algorithm with the best performance $\tilde{f}_{perf}$ (in this case we focus on only one of the evolved algorithms since there is strong correlation between both metrics; the best performer and best generalizer are close, sometimes even encode the same algorithm), then meta-validate it with different hyperparameter sets (see Appendix F.11), and select the hyperparameter set that leads to the best generalizability. We then fix the hyperparameters and re-evaluate using the meta-testing seeds. We compare algorithms evolved in Ant and Humanoid with hyperparameter-tuned SAC.
Figure 14: Average return and standard deviation across random seeds when evaluating evolved algorithms and SAC baseline in multiple Brax Humanoid instances with different friction coefficients, mass coefficients, and torque multipliers. We compare, after hyperparameter tuning, algorithms evolved in Brax Humanoid, Brax Ant (to assess cross-domain transfer), and the SAC baseline used as warm-start. In all cases 1.0 is used as training configuration.

The numerical results of this analysis are found in Table 9. We observe that, while the evolved algorithm achieves better generalizability and a clear reduction in instability (up to 40%), the evolved algorithm performs worse than SAC when meta testing. In this case the algorithms are hyperparameter-tuned for generalizability, hence the higher score. Note we evolved less graphs in the specific case of Humanoid (50K compared to 200K evolved graphs for Brax Ant), as training a policy in Humanoid is more costly. We expect these results to improve if more algorithms are evolved in the population. Then, as in the case where we used Brax Ant as evaluation environment, we achieve a good cross-domain fitness compared to SAC, but the scores are lower. In this case, however, the algorithm evolved in Brax Ant shows more stability than SAC when both are evaluated in Humanoid.

| RL Algorithm            | Avg. Perf. score ($L_{perf}$) | Avg. Gen. score ($L_{gen}$) |
|-------------------------|-------------------------------|----------------------------|
| Ant performer           | 0.440 ± 0.066                 | 0.420 ± 0.036              |
| Humanoid performer      | 0.474 ± 0.083                 | 0.462 ± 0.042              |
| warm-start SAC          | 0.514 ± 0.104                 | 0.450 ± 0.070              |

Table 9: Average meta-tested performance and generalizability scores (Equations 1 and 2, respectively) ± standard error of the mean for algorithms first evolved in Brax Ant and Brax Humanoid, and then evaluated on Brax Humanoid on a different set of seeds. We compare these scores against the hyperparameter-tuned warm start SAC. We compute these metrics across 4 seeds.

F.7 Best performer and best generalizer for RWRL Walker and Gym Pendulum

We present the loss equations for both the best performer and best generalizer when using RWRL Walker and Gym Pendulum as training environments. First, the best performer for RWRL Walker:

\[ L_{perf}^{\pi} = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}} \left[ r_t + \gamma \left( \min_i Q_{\text{targ},i}(s_{t+1}, \tilde{a}_{t+1}) - \text{atan}(\gamma/Q(s_t, a_t)) \right) - Q(s_t, a_t) \right] \]

(11)

\[ L_{perf}^{Q_i} = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}} \left[ (r_t + \gamma \left( \min_i Q_{\text{targ},i}(s_{t+1}, \tilde{a}_{t+1}) - \text{atan}(\gamma/Q_i(s_t, a_t)) \right) - Q_i(s_t, a_t))^2 \right] \]

(12)

In all cases, \( \tilde{a}_t \sim \pi(\cdot|s_t), \tilde{a}_{t+1} \sim \pi(\cdot|s_{t+1}) \), and \( \mathcal{D} \) is a dataset of experience tuples from the replay buffer. Next, the best generalizer for RWRL Walker:

\[ L_{gen}^{\pi} = \mathbb{E}_{(s_t, a_t, s_{t+1}) \sim \mathcal{D}} \left[ \frac{0.2 \cdot \log \pi(\tilde{a}_{t+1}|s_{t+1})}{Q_i(s_{t+1}, \tilde{a}_{t+1}) - 0.1 \cdot \log \pi(\tilde{a}_{t+1}|s_{t+1})} - \min_i Q_i(s_t, \tilde{a}_{t+1}) \right] \]

(13)

\[ L_{gen}^{Q_i} = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}} \left[ (r_t + \gamma (Q_i(s_{t+1}, \tilde{a}_{t+1}) - 0.1 \cdot \log \pi(\tilde{a}_{t+1}|s_{t+1})) - Q_i(s_t, a_t))^2 \right] \]

(14)
Now we present the best performer for Gym Pendulum:

\[ L_{\pi}^{perf} = E_{(s_t, a_t) \sim D} \left[ 2 \cdot \text{atan}(\log(\pi(\tilde{a}_t|s_t))) - \min_i Q_i(s_t, \tilde{a}_t) \right] \] (15)

\[ L_{Q_i}^{perf} = E_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ (r_t + \gamma Q_i(s_{t+1}, \tilde{a}_t) - \log(\pi(\tilde{a}_t|s_t))) - Q_i(s_t, a_t))^2 \right] \] (16)

Finally, the equations for the best generalizer when using Gym Pendulum are:

\[ L_{\pi}^{gen} = E_{(s_t, a_t) \sim D} \left[ \log(\pi(\tilde{a}_t|s_t)) - \min_i Q_i(s_t, \tilde{a}_t) \right] \] (17)

\[ L_{Q_i}^{gen} = E_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ (r_t + \gamma (Q_{targ_i}(s_{t+1}, \tilde{a}_t) - \log(\pi(\tilde{a}_t|s_t))) - Q_i(s_t, a_t))^2 \right] \] (18)

### F.8 Best performer for Brax Ant and Brax Humanoid

We present the loss equations (policy loss and critic loss) for the best performer algorithms evolved in Brax Ant and Brax Humanoid; we focus on these two algorithms in the analyses of this paper. The loss functions for the best performer for Brax Ant are:

\[ L_{\pi}^{perf} = E_{(s_t, a_t) \sim D} \left[ \log(\pi(\tilde{a}_t+1|s_{t+1})) - \min_i Q_i(s_t, a_t) \right] \] (19)

\[ L_{Q_i}^{perf} = E_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ \left( r_t + \gamma \left( \min_i Q_{targ_i}(s_t, \tilde{a}_t) - \gamma \right) - Q_i(s_t, a_t) \right)^2 \cdot C_1 \right] \] (20)

where

\[ C_1 = r_t + \gamma \cdot \left( \min_i Q_i(s_{t+1}, \tilde{a}_{t+1}) - \gamma \right) \] (21)

In all cases, \( \tilde{a}_{t+1} \sim \pi(\cdot|s_{t+1}) \) and \( D \) is a dataset of experience tuples from the replay buffer. Then, the equations for the best performer evolved in Brax Humanoid are:

\[ L_{\pi}^{perf} = E_{(s_t, a_t) \sim D} \left[ \log(\pi(\tilde{a}_t+1|s_{t+1})) - \min_i Q_i(s_t, a_t) \right] \] (22)

\[ L_{Q_i}^{perf} = E_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[ (C_2 - Q_i(s_t, a_t))^2 \cdot C_2 \right] \] (23)

where

\[ C_2 = r_t + \gamma \left( \min_i Q_{targ_i}(s_t, \tilde{a}_{t+1}) - \log(\pi(\tilde{a}_{t+1}|s_{t+1})) \right) \] (24)

### F.9 Additional analysis on evolved algorithms for RWRL Cartpole

Figure 15 shows the entropy and norm of the gradients of the actor for the RWRL Cartpole best generalizer. We also show these same metrics for the warm-start algorithm. This is an extension of Figure 4; in both cases, we let the agents train for more episodes than those in the experimental setup. We see that ignoring this fixed number of training episodes and letting run for longer makes this type of metrics converge to similar values across algorithms. We acknowledge that training until convergence is usually preferred; however, in certain applications the number of training episodes might be a constraint, so we find MetaPG’s ability to exploit this kind of constraints beneficial in those setups.

### F.10 Hyperparameter tuning for transfer and benchmark for RWRL and Gym

In our experiments with the RWRL Environment suite and Gym Pendulum, once an evolution experiment is over and the evolved algorithms are meta-validated, we compare them against: 1) ACME SAC [55], and 2) other RL algorithms that have been evolved in a different environment. To that end, for each ACME benchmark and evolved algorithm transfer, we tune the hyperparameters of the algorithms. Since we consider two fitness scores in this work (performance and generalizability), we select the two hyperparameter configurations that lead to the best performance and best generalizability scores, respectively. We denote these two configurations as the best performer and best generalizer, respectively. To that end, we do a grid search across the sets of hyperparameters listed in Table 10.

This process is only carried out once the evolution is over; the warm-start algorithm is not hyperparameter-tuned before evolution.
(a) Average entropy of the policy during training for RWRL Cartpole.

(b) Average gradient norm of the actor loss during training for RWRL Cartpole.

Figure 15: Analysis of the entropy and gradient norm of the actor when evaluating the best generalizer from RWRL Cartpole in comparison to the warm-start.

Table 10: Hyperparameter values considered during the tuning process.

| Hyperparameter                  | Values                  |
|---------------------------------|-------------------------|
| Discount factor $\gamma$       | 0.9, 0.99, 0.999        |
| Batch size                      | 32, 64, 128             |
| Learning rate                   | $1 \cdot 10^{-4}, 3 \cdot 10^{-4}, 1 \cdot 10^{-3}$ |
| Target smoothing coeff. $\tau$ | 0.005, 0.01, 0.05       |
| Reward scale                    | 0.1, 1.0, 5.0, 10.0     |

F.11 Hyperparameter tuning for transfer and benchmark for Brax

In our experiments in Brax Ant and Brax Humanoid, given they are more costly environments, we do not meta validate all algorithms in the population. Instead, we choose the best algorithms during meta training and directly meta test them with additional hyperparameter tuning. To that end, we do a grid search across the hyperparameters listed in Table 11 and select the configuration that maximizes the score we are interested in for each case, as described in the previous section.

Table 11: Hyperparameter values considered during the tuning process.

| Hyperparameter                               | Values                  |
|----------------------------------------------|-------------------------|
| Discount factor $\gamma$                    | 0.95, 0.99, 0.999       |
| Batch size                                   | 128, 256, 512           |
| Learning rate                                | $1 \cdot 10^{-4}, 6 \cdot 10^{-4}, 1 \cdot 10^{-3}$ |
| Gradient updates per learning step           | 32, 64, 128             |
| Reward scale                                 | 0.1, 1.0, 10.0, 100.0   |

F.12 Transferring algorithms evolved in RWRL and Gym

We present the results of carrying out transfer experiments in which we take the best performer and best generalizer obtained after evolving in a specific environment and test them in the other two environments considered in this work. To that end, we follow the hyperparameter tuning procedure described above and therefore, for each different RL algorithm, we obtain the hyperparameter configurations that lead to the best performance and best generalizability, respectively. For example, taking the best performer from RWRL Walker (Walker Perf.) and testing it on RWRL Cartpole leads to two sets of fitness scores (best performer and best generalizer). The transfer results for RWRL Cartpole, RWRL Walker, and Gym Pendulum can be observed in Tables 12, 13, and 14, respectively.
Table 12: Transfer results (average fitness ± standard error of the mean) on RWRL Cartpole. The row highlighted in gray corresponds to the results of the evolution experiment in RWRL Cartpole. The rest correspond to the best performance and best generalizability configurations that result from doing hyperparameter tuning to the best performer and best generalizer evolved in different environments.

| Evaluation and tuning environment: RWRL Cartpole | Best performance | Best generalizability |
|-----------------------------------------------|------------------|-----------------------|
| RL Algorithm | $f_{\text{perf}}$ | $f_{\text{gen}}$ | $f_{\text{perf}}$ | $f_{\text{gen}}$ |
| Cartpole     | 0.871 ± 0.003   | 0.475 ± 0.016       | 0.770 ± 0.014   | 0.570 ± 0.019   |
| Walker Perf. | 0.849 ± 0.010   | 0.444 ± 0.041       | 0.826 ± 0.024   | 0.456 ± 0.041   |
| Walker Gen.  | 0.670 ± 0.094   | 0.374 ± 0.039       | 0.670 ± 0.094   | 0.374 ± 0.039   |
| Pendulum Perf.| 0.857 ± 0.001   | 0.502 ± 0.024       | 0.851 ± 0.005   | 0.535 ± 0.012   |
| Pendulum Gen.| 0.829 ± 0.025   | 0.489 ± 0.051       | 0.766 ± 0.079   | 0.509 ± 0.040   |
| ACME SAC     | 0.865 ± 0.001   | 0.372 ± 0.060       | 0.845 ± 0.012   | 0.518 ± 0.040   |

Table 13: Transfer results (average fitness ± standard error of the mean) on RWRL Walker. The row highlighted in gray corresponds to the results of the evolution experiment in RWRL Walker. The rest correspond to the best performance and best generalizability configurations that result from doing hyperparameter tuning to the best performer and best generalizer evolved in different environments.

| Evaluation and tuning environment: RWRL Walker | Best performance | Best generalizability |
|-----------------------------------------------|------------------|-----------------------|
| RL Algorithm | $f_{\text{perf}}$ | $f_{\text{gen}}$ | $f_{\text{perf}}$ | $f_{\text{gen}}$ |
| Cartpole Perf.| 0.959 ± 0.004   | 0.502 ± 0.025       | 0.958 ± 0.006   | 0.533 ± 0.012   |
| Cartpole Gen.| 0.031 ± 0.002   | 0.032 ± 0.001       | 0.027 ± 0.003   | 0.035 ± 0.001   |
| Walker       | 0.963 ± 0.002   | 0.544 ± 0.018       | 0.955 ± 0.005   | 0.569 ± 0.015   |
| Pendulum Perf.| 0.611 ± 0.145   | 0.296 ± 0.066       | 0.611 ± 0.145   | 0.296 ± 0.066   |
| Pendulum Gen.| 0.929 ± 0.024   | 0.510 ± 0.045       | 0.927 ± 0.024   | 0.518 ± 0.035   |
| ACME SAC     | 0.968 ± 0.003   | 0.444 ± 0.014       | 0.926 ± 0.008   | 0.510 ± 0.012   |

Table 14: Transfer results (average fitness ± standard error of the mean) on Gym Pendulum. The row highlighted in gray corresponds to the results of the evolution experiment in Gym Pendulum. The rest correspond to the best performance and best generalizability configurations that result from doing hyperparameter tuning to the best performer and best generalizer evolved in different environments.

| Evaluation and tuning environment: Gym Pendulum | Best performance | Best generalizability |
|-----------------------------------------------|------------------|-----------------------|
| RL Algorithm | $f_{\text{perf}}$ | $f_{\text{gen}}$ | $f_{\text{perf}}$ | $f_{\text{gen}}$ |
| Cartpole Perf.| 0.875 ± 0.013   | 0.352 ± 0.023       | 0.874 ± 0.017   | 0.364 ± 0.015   |
| Cartpole Gen.| 0.843 ± 0.022   | 0.337 ± 0.014       | 0.843 ± 0.022   | 0.337 ± 0.014   |
| Walker Perf. | 0.873 ± 0.013   | 0.342 ± 0.018       | 0.843 ± 0.030   | 0.395 ± 0.020   |
| Walker Gen.  | 0.864 ± 0.015   | 0.349 ± 0.030       | 0.754 ± 0.075   | 0.401 ± 0.013   |
| Pendulum     | 0.888 ± 0.010   | 0.360 ± 0.011       | 0.868 ± 0.034   | 0.445 ± 0.021   |
| ACME SAC     | 0.879 ± 0.014   | 0.392 ± 0.012       | 0.879 ± 0.014   | 0.400 ± 0.009   |