Lean Evolutionary Reinforcement Learning by Multitasking with Importance Sampling

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Abstract—Studies have shown evolution strategies (ES) to be a promising approach for reinforcement learning (RL) with deep neural networks. However, the issue of high sample complexity persists in applications of ES to deep RL. In this paper, we address the shortcoming of today’s methods via a novel neuroevolutionary multitasking (NuEMT) algorithm, designed to transfer information from a set of auxiliary tasks (of short episode length) to the target (full length) RL task at hand. The artificially generated auxiliary tasks allow an agent to update and quickly evaluate policies on shorter time horizons. The evolved skills are then transferred to guide the longer and harder task towards an optimal policy. We demonstrate that the NuEMT algorithm achieves data-lean evolutionary RL, reducing expensive agent-environment interaction data requirements. Our key algorithmic contribution in this setting is to introduce, for the first time, a multitask information transfer mechanism based on the statistical importance sampling technique. In addition, an adaptive resource allocation strategy is utilized to assign computational resources to auxiliary tasks based on their gleaned usefulness. Experiments on a range of continuous control tasks from the OpenAI Gym confirm that our proposed algorithm is efficient compared to recent ES baselines.

Index Terms—Reinforcement learning; evolutionary strategies; evolutionary multitasking; importance sampling

I. INTRODUCTION

In reinforcement learning (RL), agents learn how to interact with dynamic and uncertain environments by taking actions that maximize expected rewards. To this end, many popular RL algorithms, such as TRPO [1], DDPG [2], D4PG [3], DQN [4], among others, are based on the Markov decision process (MDP) formalism and the concept of value functions. Algorithms belonging to this class have achieved notable success in applications such as locomotion tasks [1, 5], strategy board games (e.g., surpassing the level of the world champion in GO [6]) and playing Atari from pixels [1, 4, 5].

Advances in RL have however shed light on evolution strategies (ES) as a viable alternative for handling continuous control tasks [7], or even playing Atari games with pixel inputs [8]. Being a derivative-free optimization approach, ES attempts to directly search for an optimal policy mapping the states of an environment to the best course of action, with the objective of maximizing the agent’s cumulative rewards. This type of approach falls under the umbrella of neuroevolution when the underlying policy is parameterized by the weights of a neural network [9]. The simplicity of implementation (obviating the need to propagate derivatives through the computation graph), better exploration capacity, and inherently parallelizable nature of population-based search makes ES a worthwhile option for RL, especially when given access to modern distributed computer systems.

Despite the simplicity, surprising levels of performance achievable, and scalability of ES—delivering linear speedup in the number of CPU cores available—the high sample complexity of such black-box optimization methods leaves much to be desired. Even though ES can make good use of parallel resources, the need for vast amounts of agent-environment interaction data to evaluate populations of candidate policies can become prohibitively resource-intensive. Moreover, each data sample generated in a standard ES is utilized just for a single search update, hence indicating a wastage of costly and useful information. The issue of lowering sample complexity has thus attracted significant research interest lately, with various methods proposed for making effective use of data in the search for optimal policies [10, 11]. One promising approach in this regard is that of experience transfer [12]. The motivation derives from an analogy to humans who, instead of solving problems from scratch, learn to adapt and reuse experiential priors. Likewise, it is deemed that RL agents may also learn more efficiently by building on data/experiences drawn from related tasks. Algorithmic realizations of this concept have been explored beyond the realms of RL as well, for teaching machines transferable skills in diverse areas of learning [13] and optimization [14].

Tapping on experience transfers in the context of deep RL, Fuku et al. [15] proposed the idea of progressive episode lengths (PEL) with canonical ES [16]. PEL comprises a set of artificially generated auxiliary tasks that are distinguished by the ascending order of their episode lengths. The tasks are then tackled sequentially, with the search for each task seeded by good solutions found for its predecessor. This procedure naturally leads to the reuse of experiential priors from related (short time horizon) tasks, with the hope of speeding up learning on longer and harder tasks. However, the direct seeding of solutions could cause harmful negative transfers. Evolved skills may overspecialize to an auxiliary task, thus not generalizing well to the target (full length) task at hand. As an illustration, imagine a hypothetical agent to be trained to run the 26.2 mile marathon where available energy is
to be strategically conserved. If such an agent first specializes on shorter 100-metre sprints, then the burst in speed would be energy sapping, leaving little in the tank for the full marathon.

In this paper, we thus re-examine the idea of experience transfer through the lens of evolutionary multitasking (EMT) [17]. Our aim is to achieve lean evolutionary RL by effectively exploiting transferable skills while guarding against threats of negative transfer. Minimizing the wastage of computational resources on auxiliary tasks that are not useful to the target is a key consideration. To this end, we propose a new EMT algorithm that builds on a particular variant of ES (popularly known as OpenAI-ES [8]) with demonstrated efficacy for direct neural network policy search. We refer to our resulting neuroevolutionary multitasking algorithm as NuEMT for short. The crucial distinction from [15] is that, instead of processing tasks sequentially, NuEMT combines all auxiliary (short episode length) tasks together with the target in a single multitask formulation. This not only supports sample efficiency by learning from relevant experiential priors, but also enables online neutralization of those tasks whose evolved skills do not transfer well to the target agent.

Since the inception of EMT, a range of techniques using nested probability mixture models (that capture the distribution of jointly evolving populations) have been proposed to adapt the quantity and frequency of inter-task information transfers [18, 19]; applications can be found in [20, 21]. However, it is observed that the repeated building of mixture models at prespecified “transfer intervals” can become expensive in itself, bringing an additional layer of internal algorithmic complexity into the search. To overcome this bottleneck, we equip NuEMT with a novel yet simple multitask information transfer mechanism based on the theory of importance sampling [22]. Stochastic gradient estimates with cross-task solution sampling is made possible under this approach, enabling fast mixture model updates without the need to continually rebuild the model from the ground up. What is more, stochastic updates of the mixture coefficients yield the evolving relevance of the auxiliary tasks. Hence, the coefficient values are used to allocate more computational resources to those tasks that are gleaned to be useful, while neutralizing those that are not.

In summary, the main contributions of this paper, spanning the problem setup and the proposed algorithm, are threefold:

- An EMT formulation with experience transfers for data-lean evolutionary RL is presented.
- A NuEMT algorithm with importance sampling for inter-task information transfers is crafted.
- An online resource allocation strategy is embedded in NuEMT to minimize wastage of computational resources on those tasks that are unaligned with the target.

A series of experimental studies on benchmarks from the OpenAI Gym showcase the effectiveness of our contributions. The remainder of this paper is organized as follows. Section II contains a brief overview of related work in the literature. Section III contains the preliminaries of ES, EMT, and importance sampling. Section IV describes the generation of auxiliary tasks in RL and presents the NuEMT algorithm. In Section V, we test the algorithm and compare its performance against recent ES baselines. We conclude the paper with directions for future research in Section VI.

II. RELATED WORK

There is growing interest in neuroevolutionary algorithms for direct policy search in RL. One of the most notable works in this regard is that by Salimans et al. [8], which established ES as a viable alternative for deep RL. Their experiments revealed the advantages of ES in terms of better exploration capacity (compared to a policy gradient method TRPO [1]) and the ease of scaling to thousands of parallel workers. (This variant of ES has since come to be known as OpenAI-ES in the literature [23, 24], and will be referred to as such hereinafter.) However, even though the run time of a population-based ES can be greatly reduced by distributing workloads on modern distributed computer systems, the high sample complexity (requiring vast amounts of interaction data for policy updates) remains a computational bottleneck.

Earlier works in ES also evinced its potential applicability for direct policy search. In particular, Igel [7] successfully demonstrated the application of the CMA-ES [25] for RL. Two variable metric methods for solving RL tasks, namely, the natural actor critic algorithm [26] and the CMA-ES, were compared and contrasted in [27]. The results showed CMA-ES to be more robust to the selection of hyper-parameters, while being competitive in terms of learning speed.

More recently, significant research effort has been invested towards lowering the sample complexity of ES by introducing better search directions, effective utilization of historical data, and exploration techniques such as novelty search [28]. Choromanski et al. [29] showed that random orthogonal and Quasi Monte Carlo finite difference directions could be more effective for parameter exploration than the random Gaussian directions in [8]. Liu et al. [30] proposed to improve sample efficiency by reducing the variance of the stochastic gradient estimator of the vanilla ES in high-dimensional optimization. This was done by sampling search directions from a hybrid probabilistic distribution characterized by a gradient subspace—defined by recent historical estimated gradients—and its orthogonal complement. In [10], efficient use of sampled data was sought by a novel iterative procedure that optimizes a surrogate objective function. A monotonic improvement guarantee for such procedure was theoretically proven. Further, Conti et al. [31] hybridized novelty search with ES to enhance policy space exploration, thus encouraging RL agents to exhibit different behaviors that reduce the danger of being stuck indefinitely (and hence wastefully) in local optima of deceptive reward functions.

Neuroevolution with genetic algorithms (GAs)—that differ from ES mainly in that they employ crossover operators—has also shown promising results in tuning the parameters of deep neural network policies. Such et al. [32] investigated the use of a simple GA on deep RL benchmarks and discovered that GA can compete with popular RL algorithms such as A3C [33], DQN, and the OpenAI-ES. GAs also possess the same scalability advantage as ES, that can drastically speedup run time if distributed computing resources are available.
Gangwani and Peng [11] introduced a new GA with imitation learning for policy crossovers in state space, producing offspring policies that effectively mimic their best parent in generating similar state visitation distributions. This idea was shown to lessen catastrophic performance drops stemming from naive GA crossovers in parameter space—which tend to destroy the hierarchical relationship of the networks.

In this paper, we propose an alternative approach to lean evolutionary RL that reduces expensive agent-environment interaction data requirements. Our method exploits the temporal structure of RL with auxiliary tasks of progressive episode lengths. Differently from [15], our algorithm integrates ES with the notion of experience transfers by means of evolutionary multitasking. Preliminaries of these algorithmic components are discussed next.

III. PRELIMINARIES

In this section, we first present the general problem statement for direct policy search in RL. The OpenAI-ES [8], which is the base algorithm for NuEMT, is described. The basics of EMT and its probabilistic formulation are presented next. The section ends with a brief overview of importance sampling for probabilistic inference.

A. DIRECT POLICY SEARCH

In RL, the goal is to find a policy, i.e., a state-action mapping function, that maximizes cumulative rewards over time of an agent operating in a dynamic and uncertain environment. The policy determines how the agent interacts with the environment so as to receive highest returns. The problem can be cast as one of policy parameter optimization as:

$$\max_{\theta \in \mathbb{R}^n} F(\pi_\theta),$$

(1)

where objective function $F$ is the total returns provided by an environment under policy $\pi_\theta$, parameterized by $\theta$.

There are several methods for solving the maximization problem in Eq. (1), such as policy iteration [34], policy gradients [35], or derivative-free optimization [36]. In this work, we focus on derivative-free ES for training neural network policies ($\theta$ thus represents the weights of the network), where $F$ is treated largely as a black-box.

B. ES FOR DIRECT POLICY SEARCH

Consider the OpenAI-ES [8]. The algorithm is based on adding isotropic Gaussian noise of fixed covariance $\sigma^2I$ to a mean vector $\tilde{\theta}$, transforming Eq. (1) to the following maximization of the expected reward (averaged over the induced probability distribution in parameter space):

$$\max_{\theta \sim \mathcal{N}(\tilde{\theta}, \sigma^2I)} \mathbb{E}_{\theta \sim \mathcal{N}(\tilde{\theta}, \sigma^2I)}[F(\pi_\theta)].$$

(2)

This Gaussian-blurred version of the objective function helps to remove non-smoothness introduced by the environment, hence enabling $\tilde{\theta}$ to be effectively updated by the following expected reward gradient (derived by the ‘log-likelihood trick’):

$$\nabla_{\tilde{\theta}} \mathbb{E}_{\theta \sim \mathcal{N}(\tilde{\theta}, \sigma^2I)}[F(\pi_\theta)] = \frac{1}{\sigma^2} \mathbb{E}_\theta[F(\pi_\theta)(\theta - \tilde{\theta})].$$

(3)

In practice, the gradient is approximated via the Monte Carlo method. A fixed number of samples—equivalent to the population size $N$ of the ES algorithm—are drawn from $\mathcal{N}(\tilde{\theta}, \sigma^2I)$ to compute stochastic gradient estimates of the policy update in every iteration. A pseudocode of the OpenAI-ES is shown in Algorithm 1. The algorithm first perturbs parameter vector $\theta$ by sampling $\epsilon_i$’s from a multivariate normal distribution $\mathcal{N}(0, I)$; see steps 3 and 4. The perturbed parameter values $\theta_i = \tilde{\theta} + \sigma \epsilon_i$ are then evaluated by running an episode in the environment with the corresponding policy. The results ($F_i$’s) obtained from these episodes approximate the gradient in Eq. (3) as $\frac{1}{N \sigma^2} \sum_{i=1}^{N} F_i * (\theta_i - \tilde{\theta})$, which is then used to update the mean $\theta$. The above repeats until a terminal condition (e.g., function evaluation budget) is met.

Algorithm 1 Pseudocode of the OpenAI-ES

**Input:** $\alpha$: step size, $\sigma$: noise standard deviation, $\tilde{\theta}_0$: initial policy parameters, $N$: population size

1: Set $t = 0$
2: repeat
3: Sample $\epsilon_1, \epsilon_2, \ldots, \epsilon_N \sim \mathcal{N}(0, I)$
4: Let $\theta_i = \tilde{\theta}_t + \sigma \epsilon_i$
5: Collect $n$ returns, $F_i = F(\pi_{\theta_i})$, $\forall i \leq N$
6: Update $\tilde{\theta}_{t+1} \leftarrow \tilde{\theta}_t + \frac{\alpha}{N \sigma^2} \sum_{i=1}^{N} F_i * (\theta_i - \tilde{\theta}_t)$
7: Set $t = t + 1$
8: until termination condition is met

A parallel implementation of the OpenAI-ES was discussed in [8] where evaluations were handled independently among distributed workers. The main novelty there was that the algorithm made use of shared random seeds, reducing the bandwidth required for communication between the workers. Such implementations can greatly reduce run time, making ES comparable with other hardware-accelerated approaches such as the training of deep RL agents with GPUs.

C. BASICS OF EVOLUTIONARY MULTITASKING

The motivation behind EMT is to enhance evolutionary search by the exchange and reuse of evolved skills between jointly optimized tasks. This idea can be applied to boost convergence rates in a difficult target task by solving it in tandem with a group of related auxiliary tasks that are simpler and/or of lower computational cost. Viable applications of this kind with EMT have been shown in the literature [20, 37, 38]. Specifically, the auxiliary tasks serve as informative proxies that quickly guide the target optimization process towards promising regions of the search/parameter space, by the adaptive transfer of discovered solutions.

Let us consider a scenario with $K$ optimization tasks solved simultaneously. Suppose, without loss of generality, each task $T_i$, $\forall i \in \{1, 2, \ldots, K\}$, to be a maximization problem instance with search space $\Theta_i$ and objective function $F_i : \Theta_i \to \mathbb{R}$. Each task may be subject to additional equality and/or inequality constraints. In this setting, the goal of a multitask optimization algorithm is to find in a single run a set of optimal solutions $\{\theta^*_1, \theta^*_2, \ldots, \theta^*_K\} = \arg \max \{F_1(\theta), F_2(\theta), \ldots, F_K(\theta)\}$, such that $\theta^*_i \in \Theta_i$ and satisfies all constraints of $T_i$, $\forall i$. 
In many instances of EMT, tasks are defined in search spaces bearing the same phenotypic meaning [39], i.e., \( \Theta_1 = \Theta_2 = \ldots = \Theta_K \), while their objective functions \( F_1, F_2, \ldots, F_K \) may differ. (This is also true in the present paper, since tasks are defined in a common space of RL policy parameters.) In such cases, we symbolize the single unified space, encompassing all task-specific search spaces, simply as \( \Theta \). The unified space provides a shared pathway for distinct but possibly related tasks to exchange mutually beneficial information. For instance, the direct transfer of elite solutions between tasks with correlated objective functions could lead to the rapid discovery of performant solutions. Substantial speedups can thus be achieved in comparison to conventional methods that re-explore search spaces from scratch.

In this paper, we consider a special case of EMT where we are primarily interested in solving a target task denoted hereinafter by \( T_k \). The remaining \( T_1, T_2, \ldots, T_{K-1} \) act as auxiliary tasks catalyzing the evolutionary search.

### D. A Probabilistic View of Evolutionary Multitasking

Let the target optimization task \( T_k \) be:

\[
\max_{\theta \in \Theta_k} F_K(\theta)
\]

(4)

Through the lens of probabilistic model-based search [40], the statement of Eq. (4) is expressed akin to Eq. (2) as:

\[
T_K : \max_{p_K(\theta)} \int_{\Theta_k} F_K(\theta) p_K(\theta) d\theta
\]

(5)

where \( p_K(\theta) \) is the underlying probability distribution of a population of candidate solutions evolved for \( T_k \).

In the EMT setting, the probabilistic models \( p_1(\theta), p_2(\theta), \ldots, p_{K-1}(\theta) \) pertaining to \( T_1, T_2, \ldots, T_{K-1} \), respectively, are accessible to \( T_k \) whilst being jointly solved in the unified space \( \Theta \). These models are viewed as succinct computational representations of the skills evolved for the different tasks. Hence, we seek to exploit these building-blocks of additional information to accelerate the target search. To that end, we generalize Eq. (5) via a mixture model formulation to depict the population distribution in \( T_k \). This gives,

\[
T_K : \max_{w_{K,1}, \ldots, w_{K,K}} \int_{\Theta} F_K(\theta) \sum_{i=1}^K w_{K,i} \cdot p_i(\theta) d\theta,
\]

(6)

where \( w_{K,i} \geq 0 \), \( w_{K,K} > 0 \) and \( \sum_{i=1}^K w_{K,i} = 1 \). Eq. (6) is the fundamental equation underpinning our proposed NuEMT algorithm (to be fully developed in Section IV). Note, when we set \( w_{K,K} = 1 \) and \( w_{K,i} \neq 0 \) for all \( i \neq K \), indicating zero inter-task information transfers, the mixture model collapses to \( p_K(\theta) \) and we fall back to the original formulation of Eq. (5).

Leveraging mixture models to cross-sample solutions between tasks is one way to actualize skills transfer in EMT. In particular, mixture coefficient \( w_{K,i} \) prescribes the probability of generating candidate solutions for \( T_k \) by sampling from the population distribution model \( p_i(\theta) \) of task \( T_i \). Hence, for any pair of strongly correlated tasks \( (T_k, T_i) \), a high value of the coefficient \( w_{K,i} \) (i.e., close to 1) could induce increased positive transfers. Conversely, for a pair of uncorrelated tasks \( (T_k, T_j) \), a low value of the coefficient \( w_{K,j} \) (i.e., close to 0) curbs the threat of negative transfers. In other words, the mixture coefficients serve as similarity/correlation measures mandating the extent of inter-task information transfers. The values of the coefficients must therefore be appropriately gleaned during the course of EMT for effective multitasking.

### E. Probabilistic Inference by Importance Sampling

Importance sampling is a general statistical technique for inferring properties of a nominal probability distribution \( p(\theta) \), given samples drawn from a different distribution \( q(\theta) \). The technique is widely used for variance reduction in Monte Carlo methods where \( q(\theta) \) takes the form of a biasing distribution from which samples \( (\theta's) \) are drawn; an instructive review on the subject can be found in [22], and applications in RL can be referred to [41]. In this paper, we shall utilize importance sampling in a unique manner to induce information transfers between tasks in the parameter space of EMT.

Let \( \mathbb{E}_{p_i(\theta)}[F_i(\theta)] \) be the expectation of \( F_i(\theta) \) under the nominal distribution \( p_i(\theta) \) in the parameter space \( \Theta_i \subset \mathbb{R}^n \). If the biasing distribution \( q_i(\theta) \) is also defined in \( \mathbb{R}^n \) such that \( \text{supp}(p_i) \subset \text{supp}(q_i) \), where \( \text{supp}(p_i) = \{ \theta : p_i(\theta) > 0 \} \), then the expectation \( \mathbb{E}_{p_i(\theta)}[F_i(\theta)] \) can be reformulated as:

\[
\mathbb{E}_{p_i(\theta)}[F_i(\theta)] = \int_{\Theta_i} F_i(\theta) p_i(\theta) d\theta = \int_{\Theta_i} \frac{F_i(\theta) p_i(\theta)}{q_i(\theta)} q_i(\theta) d\theta
\]

(7)

Here, the multiplicative adjustment to \( F_i(\theta) \) given by importance weights \( p_i(\theta)/q_i(\theta) \) compensates for sampling from a different distribution \( q_i(\theta) \) whilst inferring properties of the nominal distribution \( p_i(\theta) \). In the context of EMT (as presented in Section III-D), Eq. (7) points to a technique for updating the probabilistic model \( p_K(\theta) \) of a target task (see Eq. (5)) using solution samples that originate from a different probability distribution (namely, the mixture model in Eq. (6)); hence, leading to the transfer of information through cross-sampling. This new insight lies at the core of the proposed NuEMT algorithm, which is developed in the next section.

### IV. NuEMT with Importance Sampling

In this section, we first describe the creation of auxiliary tasks to catalyze policy search in the main target task at hand. Next, we describe the NuEMT algorithm with importance sampling to facilitate skills transfer. An adaptive resource allocation strategy is proposed to dynamically adjust computational resources to each constituent task in NuEMT.

#### A. Construction of Auxiliary Tasks

Skills can be seen as the culmination of a continuous learning process, accumulating and building on experiences gained from every long or short training session. Bringing this perspective to RL, it is conjectured that the transfer of skills
acquired from simpler tasks (of shorter episode lengths) could help solve longer and harder tasks more effectively.

In this paper, we realize the aforementioned idea for the first time in a multitask setting. To guide the policy search of the target task \( T_K \)—of maximum episode length ‘\( H \)’—we construct a set of auxiliary tasks, \( T_1, T_2, \ldots, T_{K-1} \), with shorter episodes of progressive lengths to be solved jointly with \( T_K \). The design of the NuEMT algorithm is such that solutions encoding skills evolved in tasks with shorter episodes are progressively transferred to those that are longer and harder. A visualization of the idea is provided in Figure 1, where there are a total of \( K = 3 \) tasks, i.e., two auxiliary tasks and one main task. We standardize the episode length of the auxiliary tasks according to their indices, i.e., the \( i \)th auxiliary task has an episode length of \( \frac{1}{K} \cdot H \).

![Fig. 1: Two auxiliary tasks with shorter episodes of varying lengths are constructed to assist the main target task. The skills that are quickly evolved in shorter episodes are progressively transferred to longer and harder tasks (e.g., with more obstacles).](image)

Given this setup, the probabilistic formulation for \( T_i \) can be written in terms of a mixture model (similarly to Eq. (6)) as:

\[
\max_{p_i(\theta), w_{i,1}, \ldots, w_{i,i}} \mathbb{E}_{q_i(\theta)}[F_i(\pi_\theta)] = \int \mathcal{F}_i(\pi_\theta^*) \, q_i(\theta) \, d\theta, \tag{8}
\]

where \( p_i(\theta) \) is the \( i \)th task-specific probabilistic model, and \( q_i(\theta) = \sum_{j \leq i} w_{i,j} \cdot p_j(\theta) \) represents the integrated mixture model of \( T_i \). Note that when \( i = 1 \), the mixture reduces as \( q_1(\theta) = p_1(\theta) \). Hence, no knowledge transfer occurs to \( T_1 \) (i.e., the task with shortest episode length).

B. Naive Stochastic Gradient Estimates

From Section III-B, recall the use of an isotropic multivariate Gaussian (of fixed covariance), parameterized by its mean, as the search distribution in the OpenAI-ES. Accordingly, for task \( T_i \) we may define \( p_i(\theta) = \mathcal{N}(\theta_i, \sigma^2 I) \). The gradient \( \nabla_{\theta_i} \) of the objective function in Eq. (8) is:

\[
\nabla_{\theta_i} \mathbb{E}[F_i(\pi_\theta)] = \nabla_{\theta_i} \int \mathcal{F}_i(\pi_\theta^*) \, q_i(\theta) \, d\theta = w_{i,i} \int \mathcal{F}_i(\pi_\theta^*) \, p_i(\theta) \, [\nabla_{\theta_i} \log p_i(\theta)] \, d\theta, \tag{9}
\]

where the second statement comes from the log-likelihood trick. Eq. (9) yields the following Monte Carlo approximation:

\[
\nabla_{\theta_i} \mathbb{E}[F_i(\pi_\theta)] \approx \frac{1}{N_i} w_{i,i} \sum_{k=1}^{N_i} F_i(\pi_{\theta_k})(\theta_k - \theta_i). \tag{10}
\]

Here, \( \theta_k \sim p_i(\theta) \) and \( N_i \) is the total samples (i.e., population size) assigned to task \( T_i \). As per Eq. (10), it is clear that solutions sampled from probabilistic models of tasks \( T_{j \neq i} \) would not directly exert any influence on the stochastic gradient updates of \( p_i(\theta) \). In other words, skills transfer between tasks is non-existent in this naive approach. Therefore, a modification to the gradient estimation is needed for inter-task communication to be established. This is achieved via the importance sampling technique, as disclosed next.

C. Importance Sampling for Skills Transfer

Note that the mixture model \( q_i(\theta) \) in Eq. (8) includes the task-specific model \( p_i(\theta) \) as one of its components. Moreover, since \( w_{i,i} > 0 \), the condition \( \text{supp}(p_i) \subseteq \text{supp}(q_i) \) for importance sampling (see Section III-E) is theoretically satisfied. Thus, we can effectively estimate expectations under \( p_i(\theta) \)—as in Eq. (9)—by using samples from the mixture model \( q_i(\theta) \) instead. Accordingly, rewriting \( p_i(\theta) \) as \( \frac{q_i(\theta)}{q_i(\theta)} p_i(\theta) \) and plugging this into Eq. (9), we get:

\[
\nabla_{\theta_i} \mathbb{E}[F_i(\pi_\theta)] = w_{i,i} \int \mathcal{F}_i(\pi_\theta^*) \, \frac{p_i(\theta)}{q_i(\theta)} \, [\nabla_{\theta_i} \log q_i(\theta)] \, q_i(\theta) \, d\theta
\]

\[
\approx w_{i,i} N_i \sigma^2 \sum_{k=1}^{N_i} \int_{\text{supp}(p_\theta)} \frac{p_i(\theta)}{q_i(\theta)} \, p_i(\theta_k) \, \sum_{l=1}^i w_{i,l} \cdot p_l(\theta_k) \, (\theta_k - \theta_i), \tag{11}
\]

where \( \theta_k \sim q_i(\theta) \). As a result of the reformulation, solutions sampled from all components \( p_{j \leq i}(\theta) \) of the mixture model \( q_i(\theta) \) shall directly influence stochastic gradient updates of the search distribution parameter \( \theta_i \) of \( T_i \). Hence, through importance sampling, the desired transfer of solutions encoding evolved skills is facilitated from tasks of shorter episode lengths to those that are longer and harder.

In addition to \( \theta_i \), the mixture coefficients of \( q_i(\theta) \) are also updated during the search process. Applying importance sampling once again, the gradient estimate with respect to \( w_{i,j} \) \((j \leq i)\) can be obtained as:

\[
\frac{\partial \mathbb{E}[F_i(\pi_\theta)]}{\partial w_{i,j}} = \frac{\partial}{\partial w_{i,j}} \int \mathcal{F}_i(\pi_\theta^*) \, q_i(\theta) \, d\theta
\]

\[
= \int_{\text{supp}(p_\theta)} \mathcal{F}_i(\pi_\theta) \, p_j(\theta) \, d\theta
\]

\[
= \int_{\text{supp}(p_\theta)} \mathcal{F}_i(\pi_\theta) \, \frac{p_j(\theta)}{q_i(\theta)} \, q_i(\theta) \, d\theta
\]

\[
\approx \frac{1}{N_i} \sum_{k=1}^{N_i} \mathcal{F}_i(\pi_{\theta_k}) \, \frac{p_j(\theta_k)}{q_i(\theta_k)} \, \sum_{l=1}^i w_{i,l} \cdot p_l(\theta_k). \tag{12}
\]

D. Derived NuEMT Update Equations

In order to make the methodology robust and invariant to outliers in a population, a rank-based fitness shaping function defined by utility values \( u_i \) as replacements to the actual returns \( F_i \) is considered for gradient estimations [42]:

\[
u_{i,k} = \frac{\max(0, \log(\frac{N_i}{2} + 1) - \log k)}{\sum_{n=1}^{N_i} \max(0, \log(\frac{N_i}{2} + 1) - \log n)}, \tag{13}
\]
where \( u_{i,k} \) is the utility of the \( k \)th sample in a sorted population list, i.e., \( F_i(\pi_{\theta_0}) \geq F_i(\pi_{\theta_2}) \geq \ldots \geq F_i(\pi_{\theta_k}) \), in the population of \( T_i \).

In practice, as the gap between \( \tilde{\theta}_i \) and \( \hat{\theta}_i \) (for any \( j < i \)) increases, the importance weight \( q_i(\theta_j) \) in Eq. (11), for \( \theta_k \sim p_j(\theta) \), rapidly approaches zero due to distribution sparsity in even moderately high dimensional parameter spaces. For large distances, the importance weights thus suppress the influence of cross-sampled solutions on the update of \( \tilde{\theta}_i \). To resolve this issue, we adopt a projection technique introduced in [43]; accordingly, solutions \( \theta_k \sim p_j(\theta) \) that lie outside Mahalanobis distance \( r \) from \( p_i(\theta) \) are mapped back to a distance \( r \) (set to 1 in all experiments) while maintaining the same directional bias. A mapped solution, \( \theta_k \), is defined as:

\[
\theta_k' = \begin{cases} 
\tilde{\theta}_i + (\theta_k - \tilde{\theta}_i) \cdot \min \left(1, \frac{r}{\|\theta_k - \tilde{\theta}_i\|} \right) & \text{if } \theta_k \neq p_i(\theta) \\
\theta_k & \text{otherwise},
\end{cases}
\]

(14)

where \( \alpha \) is the learning stepsize for \( \tilde{\theta}_i \).

For the update of the mixture coefficients, the constraints \( \sum_{j \leq i} w_{i,j} = 1 \) and \( w_{i,j} \geq 0 \) must be satisfied. Thus, an additional step projecting the gradient approximation of Eq. (12) to the constraint plane is needed. Denoting the normal vector to the plane as \( \vec{a} = [1, \ldots, 1] \), and the gradient estimate as \( \vec{b} = [\frac{\partial F_i(\pi_{\theta})}{\partial w_{i,1}}, \frac{\partial F_i(\pi_{\theta})}{\partial w_{i,2}}, \ldots, \frac{\partial F_i(\pi_{\theta})}{\partial w_{i,N_i}}] \), the scaled projection of the gradient on the plane takes the form:

\[
\text{proj}_C(\vec{b}) = \beta \cdot (\vec{b} - \vec{a} \cdot \frac{\vec{b}}{\vec{a} \cdot \vec{a}}),
\]

(16)

where \( \beta \) is the learning stepsize for the mixture coefficients. Then, the final update equation for \( w_i = [w_{i,1}, w_{i,2}, \ldots, w_{i,N_i}] \) takes the following form:

\[
w_i \leftarrow w_i + \lambda \cdot \text{proj}_C(\vec{b}),
\]

(17)

where \( \lambda \) is an additional scaling factor ensuring nonnegativity.

### E. Adaptive Resource Allocation Strategy

Since a high mixture coefficient \( w_{K,j} \) suggests strong correlation between \( T_K \) and \( T_j \), the simpler auxiliary task \( T_j \) could serve as an effective substitute for the main target task \( T_K \) to advance quickly in its search. Hence, more resources could be allocated to \( T_j \) to boost its search effort while simultaneously transferring learnt skills over to \( T_K \) at a fraction of the computational cost. Such a resource allocation strategy has been demonstrated to work well in the past in the context of EMT for evolutionary machine learning [20]. With that in mind, we incorporate an adaptive resource allocation strategy into NuEMT as well, assigning resources to the shorter and simpler tasks as:

\[
N_j = N_{\text{total}} \cdot w_{K,j}
\]

(18)

where \( N_{\text{total}} \) is the total amount of resources (i.e., population size), and \( N_j \) is the resources allocated to \( T_j \). This arrangement reduces resource wastage, since an auxiliary task unaligned with the target will get a small or zero population size.

#### Algorithm 2: Pseudocode of the NuEMT algorithm

**Input:** \( N_{\text{total}} \): population size, \( K \): number of tasks, \( \sigma \): noise standard deviation, \( \alpha \): stepsize, \( \beta \): mixture stepsize, \( H \): full time horizon, \( T = \{T_1, T_2, \ldots, T_K\} \): set of tasks

1. Set mixture weight \( w_{i,j} = 1/i, \forall j \leq i \) for \( T_i \), \( \forall i \)
2. Set population size \( N_i = w_{K,i} \cdot N_{\text{total}} \) for \( T_i \), \( \forall i \)
3. Set \( H_i = \frac{1}{\sigma} \cdot H, \forall i \leq K \)
4. Set \( \tilde{\theta}_i = 0 \in \mathbb{R}^n \) for \( T_i \), \( \forall i \)
5. repeat
   6. for each \( T_i \in T \) do
      7. Set \( q_i(\theta) = \sum_{j \leq i} w_{i,j} \cdot p_j(\theta) \), where \( p_j(\theta) = N(\bar{\theta}_j, \sigma^2 1) \)
      8. Sample \( \theta_1, \theta_2, \ldots, \theta_{N_i} \sim q_i(\theta) \)
      9. Collect \( N_i \) based on episode length \( H_i \):
         \[
         F_{i,k} = F_i(\pi_{\theta_k}), \forall k \neq N_i
         \]
      10. Sort \( F_{i,k} \) in descending order of fitness, and apply rank-based fitness shap:
         \[
         u_{i,1} \geq \ldots \geq u_{i,N_i} \leftarrow F_{i,1} \geq \ldots \geq F_{i,N_i}
         \]
      11. Project solutions not sampled from \( p_i(\theta) \):
         \[
         \theta_k' = \begin{cases} 
\tilde{\theta}_i + (\theta_k - \tilde{\theta}_i) \cdot \min \left(1, \frac{r}{\|\theta_k - \tilde{\theta}_i\|} \right) & \text{if } \theta_k \neq p_i(\theta) \\
\theta_k & \text{otherwise},
\end{cases}
\]
      12. Calculate gradient estimates for \( \theta_i \) and \( w_{i,j} \):
      13. Perform update step:
      14. end for
5. until termination condition is met

#### F. Summarizing NuEMT for RL

Piecing together the derived update equations, we herein summarize the NuEMT algorithm for RL. Our methodology incorporates mixture modelling as a means of inter-task relationship capture, to control the extent of skills transfer between tasks. The auxiliary tasks \( T_i \), for \( i = 1, 2, \ldots, K - 1 \), are designed to run episodes of the same environment as the main
task $T_K$, but with shorter episode lengths, i.e., $\frac{1}{K} \times H$. A pseudocode of the overall procedure is given in Algorithm 2.

At initialization, all coefficients of the mixture model pertaining to any task $T_i$ are set equal, i.e., $w_{i,j} = 1/i$ for $j = 1, 2, \ldots, i$. An equal population size of $N_i = \frac{N_{\text{total}}}{K}$ is allocated to each task. In each iteration, every task samples solutions, $\theta_1, \theta_2, \ldots, \theta_N$, from its mixture model $q_i(\theta)$. Each $\theta_k$ parameterizes a policy $\pi_{\theta_k}$, and $F_i(\pi_{\theta_k})$ represents the total reward received from an episode run with length $H_i = \frac{1}{K} \times H$. The $N_i$ reward values received are then used for parameter updates as formulated in Eq. (15) and Eq. (17). Subsequently, the coefficients $w_{i,K}$ from the main task’s mixture model $q_K(\theta)$ are used to determine the population size to be allocated to each of the auxiliary tasks in the next iteration. This process continues until a terminal condition is met.

In our implementation, we find it useful to perform state normalization [36] as it enables different state components to have a fair share of influence during training. A similar normalization approach known as virtual batch normalization is also used by OpenAI-ES [8]. In addition, weight decay is added as a form of regularization to prevent parameters of the policy network from exploding. Lastly, we adopt mirror sampling [44] as a variance reduction technique.

It is worth noting that when we compare NuEMT with a conventional neuroevolutionary algorithm, the computational cost of NuEMT (per iteration) will be lower given the same $N_{\text{total}}$. This is because each of the $K$ tasks is assigned $\frac{N_{\text{total}}}{K}$ solutions to start with, and, assuming the computational cost of evaluating a solution for $T_i$ to be $C_i$, the total cost will be $\sum_i C_i \cdot \frac{N_{\text{total}}}{K} < N_{\text{total}} \cdot C_K$ since $C_1 < C_2 < \ldots < C_K$. This is especially crucial for RL problems that may be dealing with extremely long episodes in large-scale simulations.

V. EXPERIMENTAL STUDIES

In this section, we present a set of experiments on continuous control tasks from the OpenAI Gym [45] (see Figures 2 and 3) to showcase the efficiency of the NuEMT algorithm.

A. Experimental Configuration

In our experiments, we compare against the OpenAI-ES [8] and the recently proposed PEL framework [15]. Our implementation of the latter uses the OpenAI-ES as the base optimizer, and is referred to as PEL for the rest of the section. The comparison with the OpenAI-ES allows us to investigate the sample efficiency of our multitask algorithm alongside its single-task counterpart. Similarly, the comparison between sequential transfer (PEL) and multitask transfer (NuEMT) helps us to understand the differences in performance between the two approaches across a variety of environments. This is especially important since we are interested in observing how the limitations of sequential transfers can be averted by multitasking. Recall, the notion of sequential transfer may degrade or stagnate performance if poor or overspecialized solutions are propagated from the simpler to the harder tasks.

The experimental setups are configured as follows. The maximal episode length of the main target task in NuEMT is equal to that of the final task in the PEL baseline; this is equal to the episode length of the single-task in the OpenAI-ES. The number of tasks in NuEMT and PEL are kept the same, for fairness of comparison. For instance, let us assume that there are 3 tasks in NuEMT and PEL, and the full episode length is 1200 timesteps. In the case of NuEMT, the first and second auxiliary tasks will have episode lengths of 400 and 800 timesteps, respectively, while the target task will have maximal episode length of 1200 timesteps. Similarly, for PEL, the episode scheduler is configured as follows. The first task will have an episode length of 400 timesteps, followed by 800 timesteps for the second task, and 1200 timesteps for the last task. In contrast, the single-task OpenAI-ES will have a constant episode length of 1200 timesteps for evaluating all policy parameters generated during its evolutionary run.

A single run of an algorithm ends when the total number of agent-environment interaction timesteps performed (summed across all tasks in PEL and NuEMT) exceeds a predefined termination condition. This termination condition also determines manual settings of the time scheduler of PEL, i.e., the number of agent-environment interactions performed in a given task before moving on to the next. In our implementation, we take the total timesteps for each task in PEL to be uniform (obtained by dividing the termination condition by $K$). Note, we use total timesteps instead of the actual wall-clock time used in [15].

The total population size $N_{\text{total}}$ for all algorithms is the same. In NuEMT, a minimum population size of $N_{\text{total}} / K$ is imposed for the main target task along with the adaptive resource allocation strategy, to prevent its population from collapsing—as an exceedingly small population may lead to brittle performance with high variance. For PEL, the population size remains the same for all tasks. The compared algorithms train policies with identical architectures, namely,
multilayer perceptrons with 2 hidden layers of 64 nodes and tanh activation functions.

For our implementation, we apply the same parallelization approach in [36] using the Python library Ray [46]. All experiments are performed on a single machine with 12-core/24-thread CPU. Each worker holds unique random seeds for sampling noise in the shared noise table as well as initialising the OpenAI Gym environment.

B. Results on Advanced Physics Simulation MuJoCo Tasks

Here, we compare NuEMT against the baseline algorithms on a variety of MuJoCo tasks. We selected 6 of the popular simulations commonly used in the RL literature, as depicted in Figure 2. For the Humanoid-v2 tasks, we find that the survival bonus from the reward function encourages policies that make the MuJoCo models stand at the same spot until maximum episode length is reached [36], resulting in getting stuck in a local optima of the policy space. To resolve this issue, we minus off the survival bonus (score of 5) from the reward function at each timestep during training. Table I presents the details of our experiments for each MuJoCo tasks. Our experiment also conducted each simulation for a total of 20 independent trials. In every trial, different random seeds are assigned to each worker and the Gym environment.

The results shown in Table II are the mean and standard deviation of the total rewards achieved by all the algorithms at different timesteps. The convergence trends of each algorithm are also shown in Figure 4. We see from Table II that NuEMT outperforms the comparative algorithms at different timesteps for most of the control tasks. Comparing NuEMT with OpenAI-ES, the former is found to offer significant speedup. Note, the main difference between the two algorithms is the transfer of evolved skills in NuEMT. Moreover, the multitask strategy of NuEMT enables accelerated convergence on 5 out of the 6 Mujoco tasks compared to the sequential PEL. The convergence plots in Figure 4 reveal a similar story. This is especially clear when we observe convergence behaviours at the initial stages of evolution, where the proposed algorithm rapidly attains higher rewards (on the main task) than the baseline algorithms. Note, on Swimmer-v2, PEL fails to outperform the OpenAI-ES. In contrast, the convergence trends of NuEMT consistently provides strong evidence of its ability to achieve lean evolutionary RL (measured in terms of the amount of agent-environment interaction data needed).

C. Results on Box2d Simulators

Here, we selected BipedalWalker as a representative in the Box2D simulator from OpenAI Gym. In the BipedalWalker experiment, the robot gets up to 300 plus points when it reaches the far end and 100 points are deducted if the robot falls. We have adjusted the length of the legs (depicted in Figure 3) such that each continuous control task will have different stability issues to overcome while traversing the terrain. Table III shows the number of tasks, episode length, number of timesteps (termination condition) and other implementation details for our experiments. For each simulation, a total of 20 independent trials is conducted. Similar to the MuJoCo experiments, unique random seeds are assigned to each worker and the Gym environment in every trial.

Table IV shows the mean and standard deviations of the total rewards at different timesteps. As seen from the results, NuEMT outperforms the comparative algorithms at most timesteps in all three simulation. Comparing NuEMT with the base optimizer, OpenAI-ES, the former is found to be significantly more data-lean. This improvement is a consequence of inter-task skills transfer, which is the fundamental algorithmic distinction between NuEMT and OpenAI-ES. The superior sample efficiency is achieved by tapping on useful information from simpler tasks (of shorter agent-environment interaction episodes) to quickly achieve better performance on the longer and harder task at hand.

While the PEL baseline performs slightly better than NuEMT on the 0.5x leg length BipedalWalker-v3 simulation, it struggles to perform consistently in the other two simulations that pose increasing difficulty in maintaining balance due to longer leg lengths. In contrast, the NuEMT methodology maintains sample efficient performance in all three experiments, vastly outperforming competitors on 1.0x and 1.5x leg length.

D. Analysing Effects of Mixture Coefficient Learning

It is worth understanding how our algorithm would perform with and without mixture coefficient learning. To this end, we perform two sets of experiments on HalfCheetah-v2 and Hopper-v2, two of the MuJoCo simulations. One experiment is performed with our mixture coefficient learning and subsequent mixture coefficient update, while the other experiment is performed with a fixed set of mixture coefficients that does not change over iterations. The number of auxiliary tasks is set to 1, as per the configuration in earlier results. The mean performance between the two sets of experiment is shown in Figure 5. We see that mixture coefficient learning in Eq. (17) is able to uplift the performance of the fixed weight variant by up to 23% at the end of the training curve. This provides an interesting outlook of how mixture coefficients can directly affect the gradient estimate for $\hat{\theta}$ (see Eq. (15)), driving search towards good solutions by self-adapting the sampling between different search distribution models.

E. Analysing Effects of the Number of Auxiliary Tasks

Here, we investigate how the number of auxiliary tasks in NuEMT affects its performance. We ran several experiments...
### TABLE I
DETAILS OF THE MuJoCo TASKS

| Simulation      | Algorithm | No. of Tasks | Episode Length | Termination Condition (No. of Timesteps) | Population Size | Learning Parameters |
|-----------------|-----------|--------------|----------------|-----------------------------------------|-----------------|---------------------|
| HalfCheetah-v2  | NuEMT     | 2            | \(T_1: 500, \ T_2: 1000\) | 5,000,000                               | 64              | \(\alpha = 0.05, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.05\)   |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |
| Swimmer-v2      | NuEMT     | 2            | \(T_1: 500, \ T_2: 1000\) | 5,000,000                               | 64              | \(\alpha = 0.05, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.05\)   |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |
| Hopper-v2       | NuEMT     | 2            | \(T_1: 500, \ T_2: 1000\) | 16,000,000                              | 64              | \(\alpha = 0.05, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.05\)   |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |
| Ant-v2          | NuEMT     | 2            | \(T_1: 500, \ T_2: 1000\) | 9,000,000                               | 128             | \(\alpha = 0.05, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.05\)   |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |
| Walker2d-v2     | NuEMT     | 2            | \(T_1: 500, \ T_2: 1000\) | 50,000,000                              | 96              | \(\alpha = 0.05, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.05\)   |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |
| Humanoid-v2     | NuEMT     | 4            | \(T_1: 250, \ T_2: 500, \ T_3: 750, \ T_4: 1000\) | 40,000,000                              | 480             | \(\alpha = 0.1, \beta = 0.05\) |
|                 | PEL       |              |                |                                         |                 | \(\alpha = 0.1\)    |
|                 | OpenAI-ES |              | 1000           |                                         |                 |                     |

### TABLE II
COMPARISON OF THE MEAN PERFORMANCE AND STANDARD DEVIATION ACROSS MuJoCo TASKS AND COMPARATIVE ALGORITHMS. RESULTS IN BOLD INDICATE BEST MEAN PERFORMANCE.

| Simulation      | No. of Timesteps | NuEMT Mean ± Std | OpenAI-ES Mean ± Std | PEL Mean ± Std |
|-----------------|------------------|-------------------|----------------------|----------------|
| HalfCheetah-v2  | 2,500,000        | 3241.65 ± 780.85  | 2278.48 ± 237.24    | 1610.29 ± 243.84 |
|                 | 5,000,000        | 4291.73 ± 822.79  | 3217.82 ± 469.71    | 3572.97 ± 541.49 |
| Swimmer-v2      | 2,500,000        | 334.82 ± 33.45    | 109.29 ± 83.05      | 67.79 ± 38.22   |
|                 | 5,000,000        | 359.54 ± 13.50    | 199.07 ± 141.60     | 188.81 ± 115.43 |
| Hopper-v2       | 8,000,000        | 2157.65 ± 1015.59 | 1178.39 ± 34.01     | 1265.63 ± 332.43 |
|                 | 16,000,000       | 3003.78 ± 895.22  | 1304.84 ± 664.29    | 3223.41 ± 543.70 |
| Ant-v2          | 4,500,000        | 2057.33 ± 118.22  | 1127.06 ± 35.54     | 833.76 ± 56.51  |
|                 | 9,000,000        | 2513.13 ± 186.28  | 1615.80 ± 81.69     | 2131.40 ± 213.71 |
| Walker2d-v2     | 25,000,000       | 4176.12 ± 415.54  | 1604.66 ± 664.29    | 1644.01 ± 363.12 |
|                 | 50,000,000       | 4746.42 ± 477.50  | 1604.66 ± 669.72    | 4739.50 ± 955.66 |
| Humanoid-v2*    | 10,000,000       | 169.56 ± 62.46    | 44.89 ± 1.55        | 44.89 ± 1.55    |
|                 | 20,000,000       | 241.08 ± 91.81    | 59.99 ± 8.37        | 59.99 ± 8.37    |
|                 | 30,000,000       | 297.27 ± 107.08   | 94.20 ± 20.86       | 94.20 ± 20.86   |
|                 | 40,000,000       | 345.29 ± 108.80   | 136.92 ± 53.06      | 136.92 ± 53.06  |

*Survival bonus is removed at every timestep. Moreover, OpenAI-ES and PEL perform identically since none of the OpenAI-ES’s agents survive beyond the configured episode length for PEL throughout the training.

With different numbers of auxiliary tasks in the BipedalWalker-v3 simulation. The Bipedalwalker-v3 simulation used has the default leg length. For the experimental settings, each experiment consists of 20 independent trials with 20 different seeds. The population size is set to be 128 candidate solutions. The learning rates \(\alpha, \beta\) for parameter \(\theta\) and mixture coefficient \(w\) are fixed as 0.05 and 0.05, respectively. Our goal is to analyse the effect of increasing the number of tasks given a fixed population size. Averaged results are shown in Figure 6.

From Figure 6, we see that NuEMT with 3 auxiliary tasks performs the best among the 5 line plots, followed by NuEMT with 4 auxiliary tasks, NuEMT with 2 auxiliary tasks, NuEMT with 1 auxiliary task, and finally NuEMT with no auxiliary task (which reduces to the OpenAI-ES). While having more auxiliary tasks could provide more information to the target, the total population size must also grow to allow the search on shorter episode lengths to generate useful transferrable skills. Hence, with a fixed population size of 128 solutions, NuEMT.
TABLE III
DETAILS OF THE BOX2D SIMULATORS

| Simulation            | Algorithm | No. of Tasks | Episode Length | Termination Condition (No. of Timesteps) | Population Size | Learning Parameters |
|-----------------------|-----------|--------------|----------------|------------------------------------------|-----------------|---------------------|
| BipedalWalker-v3 (0.5x Leg Length**) | NuEMT PEL | 4            | $T_1$: 400, $T_2$: 800, $T_3$: 1200, $T_4$: 1600 | 70,000,000          | 128              | $\alpha = 0.05, \beta = 0.05$ |
|                       | OpenAI-ES | 1            | 1600           |                                          |                 | $\alpha = 0.05$     |
| BipedalWalker-v3 (1.0x Leg Length**) | NuEMT PEL | 4            | $T_1$: 400, $T_2$: 800, $T_3$: 1200, $T_4$: 1600 | 80,000,000          | 128              | $\alpha = 0.05, \beta = 0.05$ |
|                       | OpenAI-ES | 1            | 1600           |                                          |                 | $\alpha = 0.05$     |
| BipedalWalker-v3 (1.5x Leg Length**) | NuEMT PEL | 4            | $T_1$: 400, $T_2$: 800, $T_3$: 1200, $T_4$: 1600 | 90,000,000          | 128              | $\alpha = 0.05, \beta = 0.05$ |
|                       | OpenAI-ES | 1            | 1600           |                                          |                 | $\alpha = 0.05$     |

**Bipedal walkers with varying leg lengths are shown in Figure 3.

TABLE IV
COMPARISON OF THE MEAN PERFORMANCE AND STANDARD DEVIATION ACROSS BOX2D TASKS AND COMPARATIVE ALGORITHMS. RESULTS IN BOLD INDICATE BEST MEAN PERFORMANCE.

| Simulation            | No. of Timesteps | NuEMT          | OpenAI-ES       | PEL          |
|-----------------------|------------------|----------------|-----------------|--------------|
|                       |                  | Mean ± Std     | Mean ± Std      | Mean ± Std   |
| BipedalWalker-v3 (0.5x Leg Length) | 17,500,000 | 282.92 ± 38.13 | 58.81 ± 89.33  | 67.27 ± 23.20 |
|                       | 35,000,000 | 295.55 ± 19.09 | 100.70 ± 120.17 | 206.39 ± 51.93 |
|                       | 52,500,000 | 296.13 ± 14.34 | 123.03 ± 126.98 | 302.68 ± 40.02 |
|                       | 70,000,000 | 295.11 ± 12.91 | 181.70 ± 118.19 | 331.06 ± 13.60 |
| BipedalWalker-v3 (1.0x Leg Length) | 20,000,000 | 233.17 ± 74.27 | 5.18 ± 3.37    | 8.61 ± 0.66  |
|                       | 40,000,000 | 262.94 ± 73.06 | 6.47 ± 2.45    | 11.31 ± 8.91 |
|                       | 60,000,000 | 290.61 ± 19.22 | 7.85 ± 3.24    | 13.92 ± 12.29 |
|                       | 80,000,000 | 297.38 ± 15.47 | 8.15 ± 3.64    | 44.64 ± 80.10 |
| BipedalWalker-v3 (1.5x Leg Length) | 22,500,000 | 27.72 ± 66.12  | 10.09 ± 4.67   | 13.34 ± 0.17 |
|                       | 45,000,000 | 80.43 ± 115.70 | 11.35 ± 4.53   | 13.03 ± 0.36 |
|                       | 67,500,000 | 133.33 ± 128.44 | 12.46 ± 0.415 | 12.83 ± 0.53 |
|                       | 90,000,000 | 152.28 ± 127.35 | 12.79 ± 0.52  | 12.68 ± 0.57 |

VI. CONCLUSION

In this paper, we explored the application of evolutionary multitasking as a novel means to achieve data-lean evolutionary RL. Our proposed neuroevolutionary multitasking (NuEMT) algorithm is based on the idea of harnessing useful information (transferrable skills) from auxiliary tasks with shorter episode lengths, to quickly optimize a neural network policy for the target task at hand. The uniqueness of NuEMT lies in utilizing the statistical importance sampling technique as the information transfer mechanism within the base optimizer, OpenAI-ES, without having to modify its other search operators. The multitasking trick is shown to provide enhanced sample efficiency, attaining higher cumulative rewards with lesser agent-environment interactions.

In our experiments, a variety of continuous control environments from the OpenAI Gym were considered. The results unveiled significant advantages of multitasking over the single-task OpenAI-ES as well as a sequential transfer-based ES (which made use of the same auxiliary tasks). Multitasking overcomes the threat faced by sequential transfer in those cases where solutions evolved for shorter episodes do not propagate well to longer and harder tasks in the future. Our results thus mark a major step forward in confirming the viability of evolutionary algorithms as simple, scalable and sample efficient alternatives for deep RL.

For the next step in this line of research, we plan to extend the general idea of leveraging simpler tasks to improve learning on complex problems beyond the realms of RL. Other machine learning sub-fields, such as neural architecture search, may also benefit greatly from the potential to jointly evolve multiple tasks, producing diverse models specialized to different datasets and/or different hardware constraints in a single evolutionary run.

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Fig. 5: Comparison of performance trends of NuEMT with learnt mixture coefficients and NuEMT with fixed mixture coefficients.

Fig. 6: Comparison of the mean performance trends achieved using different numbers of auxiliary tasks on the BipedalWalker-v3 simulation. The total population size is 128 candidate solutions. The term ‘auxiliary tasks’ is abbreviated as AT in the legend.
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