Augmentative Topology Agents For Open-ended Learning Supplementary Material

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APPENDIX I
ACTION DISTRIBUTION FIGURES

In Figure 1 we have added figures for the action distributions of each algorithm.

APPENDIX II
HYPERPARAMETER SETTINGS

This appendix is for hyperparameter settings which were used for ATEP and the baselines. Table I shows hyperparameters for ES in EPOET. Table II shows settings for NEAT in ATEP and Table III shows parameter configurations for CPPNs. General hyperparameters for reproduction are given in Table IV.

TABLE I: ES hyperparameter settings

Hyperparameter	**Setting**
ES Population	512
Weight update method	Adam
Initial learning rate	0.01
Decay factor of learning rate	0.9999
Initial noise standard deviation	0.1
Lower bound of noise standard deviation	0.01
Decay factor of noise standard deviation	0.999

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TABLE II: NEAT hyperparameter settings

Hyperparameter	**Setting**
Population size	1000
Crossover probability	0.3
Weight mutation (small) probability	0.85
Weight mutation (large) probability	0.15
Weight mutation (small) range	-0.1 - +0.1
Weight mutation (large) range	-1 - +1
Connection mutation probability	0.85
Node mutation probablity	0.15
Maximum stagnation	60
c_1	1.0
c_2	1.0
c_3	3.7
Delta threshold	3.0
Initial condition	full
Activation function	tanh
Number of inputs	24
Number of outputs	4

TABLE III: CPPN hyperparameter settings

Hyperparamer	**Setting**
Initial condition	full
Activation default	identity
Activation options	identity sin sigmoid square tanh
Aggregation default	sum
bias init stdev	0.1
bias init type	gaussian
bias max value	10.0
bias min value	-10.0
bias mutate power	0.1
bias mutate rate	0.75
num inputs	1
num outputs	1
response init mean	1.0
response init type	gaussian
response max value	10.0
response min value	-10.0
single structural mutation	True
structural mutation surer	default
weight init stdev	0.25
weight init type	gaussian
weight max value	10.0
weight min value	-10.0
weight mutate power	0.1
weight mutate rate	0.75

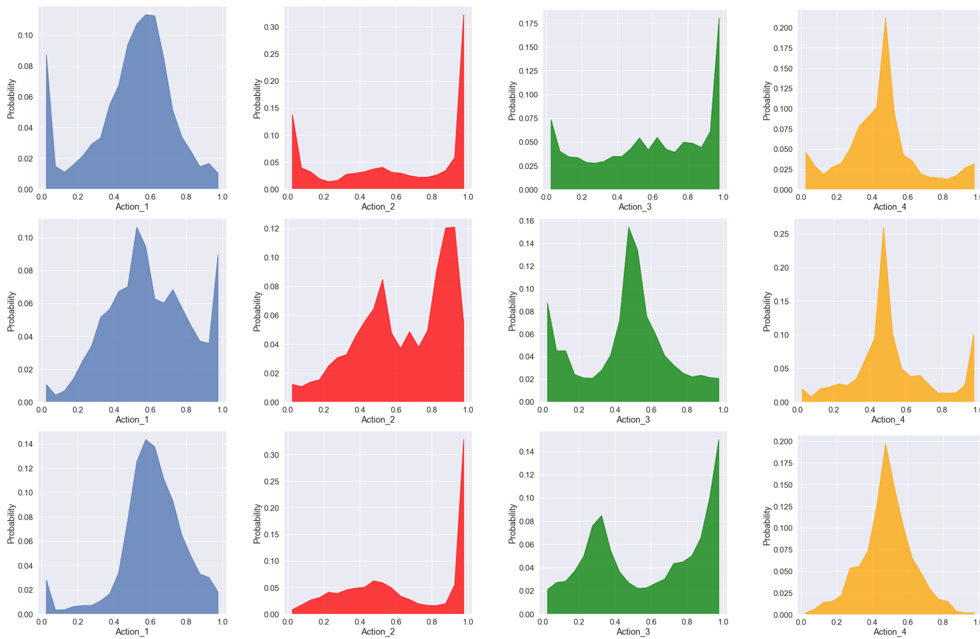

Fig. 1: Action Distributions for (top row) SBT-ATEP, (middle row) FBT-ATEP and (bottom row) EPOET40x40. Each column represents one specific dimension of the action array.

TABLE IV: EPOET general hyperparameter settings for ATEP

Hyperparameter	Setting
Reward threshold	200
Environment difficulty MC	25 - 340
Transfer check	25
Reproducibility check	150
Active environments	20

Algorithm 1: Species-Based Transfer

Input : Candidate population's best individual I_c. A function $find\_delta(.)$ that calculates delta score and $\delta_{threshold}$.
Let M = All environments - {Candidate environment}
foreach $m \in M$ **do**
    I_m = best individual of environment m
    δ_{ct} = find_delta(I_c, I_m) using Equation 1
    if $\delta_{ct} \leq \delta_{threshold}$ **then**
        delete target species
        Transfer candidate species to target population
    else
        Transfer is not possible
    end
end

Appendix III
Transfer Mechanisms

This appendix shows pseudocodes of Species-based and Fitness-based transfer mechanisms. Algorithms are shown in Algorithms 1 and 2, respectively. Algorithm 2, in particular, is very similar to the transfer algorithm described by Wang et al. [1].

Algorithm 2: Fitness-Based Transfer

Input : Candidate population's best individual I, a function *Score(.)* that calculates the maximum of the target agent's 5 most recent fitness scores.

Let M = All environments - {Candidate environment}

```
foreach m in M do
    Compute direct transfer I_D;
    if I_D > Score(m) then
        Compute fine-tuning transfer I_P;
        if I_P > Score(m) then
            Add m to T_candidates
        else
            Transfer not possible
        end
    else
        Transfer not possible
    end
end
Delete whole population of T_candidates
Transfer whole candidate population to T_candidates
```

References

[1] R. Wang, J. Lehman, A. Rawal, J. Zhi, Y. Li, J. Clune, and K. Stanley, "Enhanced POET: Open-ended reinforcement learning through unbounded invention of learning challenges and their solutions," in *International Conference on Machine Learning*, 2020, pp. 9940–9951.