Behavioral Descriptor Designs and Robustness in Neuroevolution for Unseen Environments

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How do different behavioral descriptor designs in multimodal QD benchmarks influence the robustness of neuroevolution-trained agents when transferred to unseen environments, as evaluated by coverage. We present a Quality-Diversity benchmark suite for Deep Neuroevolution in Reinforcement Learning domains for robot control. The suite includes the definition of tasks, environments, behavioral descriptors, and fitness. 9 claims were extracted from source literature; 2 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Benchmarking Quality-Diversity Algorithms on Neuroevolution for Reinforcement Learning. Research question: How do different behavioral descriptor designs in multimodal QD benchmarks influence the robustness of neuroevolution-trained agents when transferred to unseen environments, as evaluated by coverage and maximum fitness retention?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.2/10.

3 Results

14 papers retrieved. 9 claims extracted; 2 independently verified. Quality review score: 5.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The source code is available online at https://github.com/adaptive-intelligent-robotics/QDax	✓	0.31
The paper was published in Gecco '22, July 09–13, 2022, Boston	×	0.01
The paper has a DOI of 10.1145/1122445.1122456	×	0.01
The paper considers N=50 for reevaluations	×	0.01
The paper compares MAP-Elites, CVT-MAP-Elites, and Random Search on the Ant-omnidirectional task	×	0.01
The paper proposes metrics: Coverage, Corrected Coverage, QD Score, Corrected QD Score, Max Fitness, Corrected Max Fitne	✓	0.18
The paper proposes loss metrics: LossCoverage, LossQDScore, and LossMaxFitness	×	0.02
The paper identifies two key challenges in using QD algorithms for deep neuroevolution in RL domains: large number of pa	×	0.09
The paper summarizes two tasks across six environments of different complexity for benchmarking QD algorithms applied to	×	0.11

References

- http://arxiv.org/abs/2211.02193v1
- http://arxiv.org/abs/2506.00739v4
- http://arxiv.org/abs/2503.19334v1