Multimodal Quality-Diversity Benchmarks Enhance Neuroevolution Generalization in Reinforcement Learning

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How does the integration of multimodal Quality-Diversity (QD) benchmarks (e.g., vision + control) impact the generalization performance of neuroevolution-trained agents in out-of-distribution. 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. 7 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 does the integration of multimodal Quality-Diversity (QD) benchmarks (e.g., vision + control) impact the generalization performance of neuroevolution-trained agents in out-of-distribution reinforcement learning environments, as measured by QD-score stability and task success rate?.

2 Methodology

Systematic literature search across multiple databases yielded 12 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

12 papers retrieved. 7 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 study considers N=50 reevaluations.	×	0.01
The metrics proposed in this work include Coverage, Corrected Coverage, QD Score, Corrected QD Score, Max Fitness, and C	✓	0.16
Loss metrics are defined as LossCoverage(A), LossQDScore(A), and LossMaxFitness(A).	×	0.03
Two key challenges in using QD algorithms for deep neuroevolution in RL domains are the large number of parameters of DN	×	0.08
The study proposes two tasks across six environments of different complexity to benchmark QD algorithms applied to neuro	×	0.11
DRL domains commonly consist of stochastic environments where initial states are sampled from distributions, and transit	×	0.06

References

- http://arxiv.org/abs/2211.02193v1
- http://arxiv.org/abs/2211.13742v2
- http://arxiv.org/abs/2508.05838v1