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EDITORIAL

Special issue on evolutionary machine learning

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1. Introduction

We are delighted to present this special issue of The Knowledge Engineering Review on evolutionary machine learning. The field of evolutionary machine learning research has experienced a significant surge in interest in recent years. It is a fast-growing sub-field of research within machine learning that utilizes evolutionary methods to address machine learning problems, ranging from robot control to energy management. The aim of this special issue is to investigate open problems in the field of evolutionary machine learning.

Evolutionary machine learning combines the field of evolutionary computation with machine learning. Machine learning models often consist of many parameters that must be optimized. Selecting the optimum parameters for these models is often a complex and time-consuming problem. Evolutionary methods can be utilized to find suitable machine learning model parameters. There are multiple advantages of applying evolutionary methods to machine learning problems. The population-based nature of evolutionary algorithms means that candidate solutions can be evaluated in parallel. Methods such as genetic programming produce solutions that more easily interpreted by humans. Evolutionary methods can also be applied to problems where target outputs are not available, since evolutionary methods only require a fitness function.

2. Contents of the special issue

This special issue contains 4 papers, which were carefully selected out of over 20 initial manuscript submissions. All papers were rigorously peer reviewed before publication. These articles provide an overview of current research directions that are being explored by the evolutionary machine learning community.

In the first paper *Using Pareto simulated annealing to address algorithmic bias in machine learning* by Blanzeisky and Cunningham (2022), the authors utilize fairness within the learning objective to mitigate algorithmic bias and propose a multi-objective optimization strategy using pareto simulated annealing that considers both accuracy and bias. Blanzeisky and Cunningham evaluate their proposed algorithm using 4 classification datasets. The results reported demonstrate that the proposed multi-objective optimization strategy using pareto simulated annealing can reduce bias and maintain high accuracy.

The second paper *A scalable species-based genetic algorithm for reinforcement learning problems* by Seth *et al*. (2022) proposes a novel genetic algorithm (GA) variant called species-based GA (SP-GA) which utilizes a species-inspired weight initialization strategy and trains a population of deep neural

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networks, each estimating the Q-function for the RL problem. The authors' results on Atari 2600 games demonstrate that the performance of SP-GA is comparable with gradient-based algorithms like deep Q-network, asynchronous advantage actor critic and gradient-free algorithms like evolution strategy (ES) and simple GA while requiring far fewer hyperparameters to train. The algorithm also improved certain key performance indicators when applied to a remote electrical tilt optimization task in the telecommunication domain.

In the third paper *Merging pruning and neuroevolution: towards robust and efficient controllers for modular soft robots*, Nadizar *et al*. (2022) investigate the use of pruning to increase the robustness of evolved neural network controllers in modular soft robots. Pruning refers to the act of reducing the number of neurons or connections between neurons in neural networks with the aim of reducing the complexity of the neural network. The authors evolved three neural network controller architectures for biped and worm voxel-based soft robots (VSRs), and then analyzed the VSR behaviour. Their results indicate that pruning during evolution can increase robustness and maintain neural network controller effectiveness when compared to controllers evolved without pruning.

Finally, in the paper *Adversarial agent-learning for cybersecurity: a comparison of algorithms*, Shashkov *et al*. (2023) investigate methods for optimizing the adversarial behaviour of agents in cybersecurity simulations. The authors compare the performance of a variety of deep reinforcement learning (DRL), ES and Monte Carlo tree search methods. Their results show that when attackers are trained by DRL and ES algorithms, as well as when they are trained with both algorithms being used in alternation, they are able to effectively choose complex exploits that thwart a defence.

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