Guest Editorial Special Issue on Multiobjective Evolutionary Optimization in Machine Learning

WE ARE very pleased to introduce this special issue on multiobjective evolutionary optimization for machine learning (MOML). Optimization is at the heart of many machine-learning techniques. However, there is still room to exploit optimization in machine learning. Every machine-learning technique has hyperparameters that can be tuned using evolutionary computation and optimization, considering normally multiple criteria, such as bias, variance, complexity, and fairness in model selection. Multiobjective evolutionary optimization can help meet these criteria for optimizing machine-learning models. Some of the existing approaches address these multiple criteria by transforming the problem into a single-objective optimization problem. However, multiobjective optimization models are able to outperform single-objective ones in contributing to multiple intended objectives (criteria). In recent years, evolutionary computation has been shown to be the premier method for solving multiobjective optimization problems (MOPs), producing both optimal and diverse solutions beyond the capabilities of other heuristics. This is particularly true for very large solution spaces, which is the case in real-world machine-learning problems with many features.

Multiobjective evolutionary optimization can be used to address different machine-learning challenges. In feature selection, it can help by minimizing the amount of bias and minimizing the number of predictors. In learning from incomplete data, it provides an opportunity to impute missing values and develop classification/prediction models at the same time. In semi-supervised clustering, it can recognize the patterns that not only have similar characteristics but are informative toward the labels. It can select the best training set in terms of maximizing the classification accuracy and minimizing the reduction rate. In imbalance learning, it can generate synthetic instances for minority classes that are similar to minority instances, cover diversely the minority space, maintain the data distribution, and improve the performance of the classifiers. It can also develop a new classifier that minimizes the misclassification errors for all classes (or important classes) rather than the total misclassification errors to avoid being biased toward the majority class. Multiobjective evolutionary optimization can develop versatile machine-learning models that address several challenges simultaneously.

We received 22 submissions, from which eight great papers that address the above issues were accepted. First, Li et al. [A1] focused on investigating an interactive evolutionary multitasking algorithm (EMA) toward solutions of interest (SOI) for decision makers, a research issue at the intersection of EMA and multicriteria decision making. Within an interactive preference-based general framework, progressive learning with a learning-to-rank neural network is devised, which can be plugged in any EMA, thus benefits potentially a wider literature. Further work on interactive EMA may also contribute to enhanced interpretability in black-box optimization.

Jiao et al. [A2] addressed a new MOP in feature selection for building classifiers with multiple data streams, where the asynchronous concept drift occurs over time in a nonstationary environment. The MOP thus concerns minimizing the differences while seeking the most important key feature subset shared between data streams. The devised multiobjective algorithm may contribute to addressing highly challenging expensive problems in potentially more real-world applications where data are collected from multiple sources.

In [A3] by Xue et al., the neural architecture search (NAS) problem of generating deep neural networks (DNNs) is defined as a multiobjective evolutionary algorithm with a probability stack, minimizing computational cost and optimizing precision. The problem is concerned as to evolving diverse blocks, which can be stacked into the final networks. The search space is block based, where a queue of blocks learned with probability selectors is evolved by NSGA-II to accelerate the search. Benchmark problems are solved with significantly reduced computational costs.

Zhou et al. [A4] proposed a problem-specific local feature selection (LFS) through an MOP to consider different aspects in a classification problem and improve the classification performance. The proposed MOP, which is called region purity-based LFS (RP-LFS), introduces a new region purity objective function on top of two other objective functions, namely, the proportion of the selected features and region-based distance metric. Optimal solutions to minimize three objective functions are found through proposing an improved version of NSGA-III. The experimental results validate the effectiveness of RP-LFS in terms of classification accuracy and a reduced feature subset.

Li et al.'s paper [A5] focuses on evolutionary multitasking for high-dimensional feature selection problems. In their algorithm, multiple filtering methods are first adopted to

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generate several diversified low-dimensional feature selection tasks. After that, a modified competitive swarm optimizer is proposed for solving these tasks and transferring useful knowledge among them to accelerate the solution of the original high-dimensional feature selection task. Extensive empirical analyses show that the developed algorithm obtains better feature subsets in comparison with other feature selection methods.

Garza-Fabre et al. [A6] tackled the challenge of clustering multiview data, to identify the most appropriate grouping of entities that can be described from multiple perspectives, by proposing an evolutionary multiobjective optimization model. The proposed evolutionary algorithm optimizes multiple objective functions simultaneously to provide tradeoffs amongst data views. It also automatically determines the number of clusters and selects a single solution from the Pareto front. The experiments are conducted on protein structures for bioinformatics applications and a diversified set of synthetic problems. The proposed algorithm discovers high-quality and robust partitions.

Jiang et al. [A7] used multiobjective optimization to generate efficient queries for adversarial examples used in defensive DNNs. The key difference to other related work is the focus on defensive DNNs. This means that the attack methods need to achieve high values for three objectives: 1) attack effectiveness; 2) attack evasiveness; and 3) attack coverage. This insight leads to the multiobjective problem that needs to be solved. Specific reproduction functions are used to preserve the well-designed attacks and ideas from particle swarm optimization are used to speed up the process. Experiments demonstrate that the number of successful attacks increases by 55.58% while obtaining a 70.92% reduction in terms of query cost.

Finally, Zhang et al.'s paper [A8] looks at the very topical subject of fairness and unfairness in multiobjective evolutionary optimization for ensembles. The paper starts by observing that there are many measures of fairness, some of which conflict with each other and/or with an optimization objective such as accuracy. Thus, a multiobjective approach is considered more efficient at looking at this issue than traditional optimization approaches. The idea is to construct ensemble learners that balance the various measures. Experimental results on 3- and 9-objective functions show that the proposed algorithm can strike a good balance between objectives. An important finding is that the proposed model is robust against different fairness metrics, not overfitting to a specific fairness measure. This means that the proposed algorithm should be useful to researchers in a wide number of other applications.

As Guest Editors of this special issue, we would like to thank the Editor-in-Chief, Prof. Carlos A. Coello Coello, and his editorial assistant Gregorio Toscano for their support of our special issue. We also would like to express our sincere appreciation to the many referees for their constructive comments. We believe that this special issue will provide important insights for advancing the theory, methodology, and practical application of MOML in the future and hope the readers of IEEE TEVC enjoy it as much as we did!

Appendix: Related Articles

[A1] K. Li, G. Lai, and X. Yao, "Interactive evolutionary multi-objective optimization via learning-to-rank," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 749–763, Aug. 2023.

[A2] B. Jiao, Y. Guo, S. Yang, J. Pu, and D. Gong, "Reduced-space multistream classification based on multi-objective evolutionary optimization," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 764–777, Aug. 2023.

[A3] Y. Xue, C. Chen, and A. Slowik, "Neural architecture search based on a multi-objective evolutionary algorithm with probability stack," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 778–786, Aug. 2023.

[A4] Y. Zhou, Y. Qiu, and S. Kwong, "Region purity-based local feature selection: A multi-objective perspective," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 787–801, Aug. 2023.

[A5] L. Li, M. Xuan, Q. Lin, M. Jiang, Z. Ming, and K. C. Tan, "An evolutionary multitasking algorithm with multiple filtering for high-dimensional feature selection," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 802–816, Aug. 2023.

[A6] M. Garza-Fabre, J. Handl, and A. José-García, "Evolutionary multi-objective clustering over multiple conflicting data views," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 817–831, Aug. 2023.

[A7] W. Jiang, S. You, J. Zhan, X. Wang, H. Lei, and D. Adhikari, "Query-efficient generation of adversarial examples for defensive DNNs via multi-objective optimization," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 832–847, Aug. 2023.

[A8] Q. Zhang, J. Liu, Z. Zhang, J. Wen, B. Mao, and X. Yao, "Mitigating unfairness via evolutionary multi-objective ensemble learning," *IEEE Trans. Evol. Comput.*, vol. 27, no. 4, pp. 848–862, Aug. 2023.

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Dr. Charkhgard has been an Editorial Advisory Board Member of *Computers & Operations Research* since 2019. He was also the Lead Co-Chair of the 2022 INFORMS Computing Society Conference with the theme of "Optimization and Machine Learning Nexus."