Title

Machine Learning Assisted Evolutionary Multi- and Many-objective Optimization

Introduction to the topic

Evolutionary multi-objective optimization (EMO) are powerful optimization algorithms due to their ability to find and store multiple trade-off solutions in a single algorithmic execution. Also, over the past two decades, machine learning (ML) algorithms have demonstrated their ability to extract and capture the inherent relationships between the input and output of a system by processing available data. So far, research and applications in the EMO and ML domains have been to a great extent independent of each other. However, some recent studies have begun to use one to complement the other; particularly there has been a rise in research in the 'evolutionary machine learning' in which evolutionary computation methods are employed to benefit ML methods and applications. The scope for EMO-based enhancements in ML methods is also natural and intuitive, since ML methods usually have to cater to conflicting goals. For instance, feature selection seeks to minimize the number of features, while maximizing their quality; model selection is driven by the trade-off between model complexity and approximation/classification accuracy; and the generation of a diverse set of Pareto-optimal models is desired for constructing ensembles. In comparison, though the efforts toward ML-assisted EMO in the last two decades or so have only been sporadic, its immense potential is increasingly being recognized lately. This tutorial focuses on this latter aspect highlighting the use of ML methods in improving the performance of EMO algorithms and applications.

Outline of the tutorial

This tutorial will focus on how the Machine Learning (ML) techniques applied to the evolving solution sets offered by Evolutionary Multi- and Many-objective Optimization Algorithms (EMaOAs). EMaOAs can facilitate knowledge discovery and performance enhancement across different phases of, including, problem-modeling, optimal-search, and post-optimization decision-making. Beginning with the essential concepts in EMaO and ML domains, this tutorial will cover some representative studies endorsing the benefits of integrated use in these domains. It will highlight how ML intervention can facilitate: (i) better understanding of the problem-structure, (ii) dedicated operators to enhance the search efficacy of EMaOAs on convergence- and diversity-hard problems, and (iii) more efficient and customized decision-making. The presented approaches will be supported by exhaustive experimental results. Importantly, this tutorial will also emphasize the importance of not distorting the basic tenets of EMaOAs in pursuit of ML integration. A template to ensure the latter will be presented in light of ML-based risk-reward trade-off, exploration-exploitation balance, minimizing ad-hoc parameterization and avoiding extra solution evaluations. Notably, this tutorial will be interactive and will also include a walkthrough and execution of the python codes for the recently proposed ML-based operators to enhance EMaOA search efficacy. The tutorial will conclude with a number of pointers to future directions in ML-assisted Evolutionary Multi- and Many-objective Optimization, for those who are interested in the topic.

Syllabus:

1. Basic tenets of Evolutionary Multi- and Many-objective Optimization Algorithms (EMaOAs).
2. Basic tenets of Machine Learning (ML) techniques and synergy with EMaOAs.
3. Utility of ML intervention towards understanding the problem-structure better.
4. Dedicated ML-based operators for performance enhancement of EMaOAs, covering:
    a. Innovized operators (IP and IP2) for convergence enhancement (employing Artificial Neural Network (ANN) and Random Forests (RF)), with supporting results on convergence-hard test problems.
    b. Innovized operator (IP3) for diversity enhancement (employing k-Nearest Neighbors (kNN)), with supporting results on diversity-hard test problems.
    c. Unified Innovized operator (UIP) for simultaneous convergence and diversity enhancement (employing RF and kNN) with supporting results on both convergence and diversity-hard test problems.
    d. A template for Ml-assisted EMaAO: addressing the key considerations of ML-based risk-reward trade-off, exploration-exploitation balance, minimizing ad-hoc parameterization and avoiding extra solution evaluations
    e. A walkthrough and execution of codes implementing the above operators on test problems.
5. Utility of ML intervention towards more efficient and customized post-optimization decision-making.
6. Pointers to future directions in ML-assisted Evolutionary Multi- and Many-objective Optimization and brief discussion of EMaOA-assisted ML development.

Expected length of the tutorial (two, four or six hours)

Two hours

Level of the tutorial (introductory or advanced)

Introductory to advanced: the tutorial does not assume participants to have any deep knowledge in Evolutionary Multi- and Many-objective Optimization (EMaO) or Machine Learning (ML) domain.

Presenters:

1. **Name**: Kalyanmoy Deb
   Affiliation: Michigan State University
   Website: https://www.egr.msu.edu/~kdeb/
   Short Bio: Kalyanmoy Deb is University Distinguished Professor and Koenig Endowed Chair Professor at Department of Electrical and Computer Engineering in Michigan State University, USA. Prof. Deb's research interests are in evolutionary optimization and their application in multicriterion optimization, modeling, and machine learning. He has been a visiting professor at various universities across the world including University of Skövde in Sweden, Aalto University in Finland, Nanyang Technological University in Singapore, and IITs in India. He was awarded IEEE Evolutionary Computation Pioneer Award for his sustained work in EMO, Infosys Prize, TWAS Prize in Engineering Sciences, CajAstur

Mamdani Prize, Distinguished Alumni Award from IIT Kharagpur, Edgeworth-Pareto award, Bhatnagar Prize in Engineering Sciences, and Bessel Research award from Germany. He is a fellow of ACM, IEEE, ASME, and three Indian science and engineering academies. He has published over 580 research papers with Google Scholar citation of over 210,000 with h-index 142. He is on the editorial board of 10 major international journals. More information about his research contribution can be found from https://www.coin-lab.org.

2. **Name**: Dhish Kumar Saxena
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   https://www.iitr.ac.in/Departments/Mechanical%20and%20Industrial%20Engineering%20Department/People/Faculty/100603.html
   Short Bio: Dhish Kumar Saxena is a Professor in Department of Mechanical and Industrial Engineering, and Mehta family School of Data Science and Artificial Intelligence, Indian Institute of Technology Roorkee, Roorkee, India. From 2008 to 2012, he worked with Cranfield University, U.K., and Bath University, U.K.,. At a fundamental level, his research is centered around multi- and many-objective optimization, involving - development of evolutionary algorithms; performance enhancement of these algorithms through integration of machine learning techniques; termination criterion for these algorithms; and decision support based on objective and constrained reduction. At an applied level, his focus has been on demonstrating the utility of evolutionary computation and mathematical optimization on real world problems, including airline crew scheduling, engineering design, business-process, and multi-criterion decision making.

3. **Name**: Sukrit Mittal
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   Short Bio: Sukrit Mittal is a Senior Research Scientist with the AI & Digital Transformation Team at Franklin Templeton Investments. Currently, he is actively pursuing research in applying reinforcement learning and multi-objective optimization in the Fintech domain. He holds a Bachelor of Technology in Mechanical Engineering and a Doctorate in Optimization Algorithms from the Indian Institute of Technology Roorkee. Prior to his current engagement, he had been invited as a visiting researcher at Michigan State University. He has co-authored a book titled "Machine Learning Assisted Evolutionary Multi and Many objective Optimization", and several research papers in high-impact journals. He also holds a granted patent in his name.