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Recent developments in integrating explainability with interactive multiobjective optimization methods

Misitano, G., Afsar, B., and Miettinen, K.

MCDM Conference 2024, Hammamet, Tunisia

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Outline

- Motivation
- Background
- Connection between preferences and solutions
- Describing preferred solutions in a population-based method
- Other approaches
- Wrapping up
- Conclusions

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About me

Giovanni Misitano

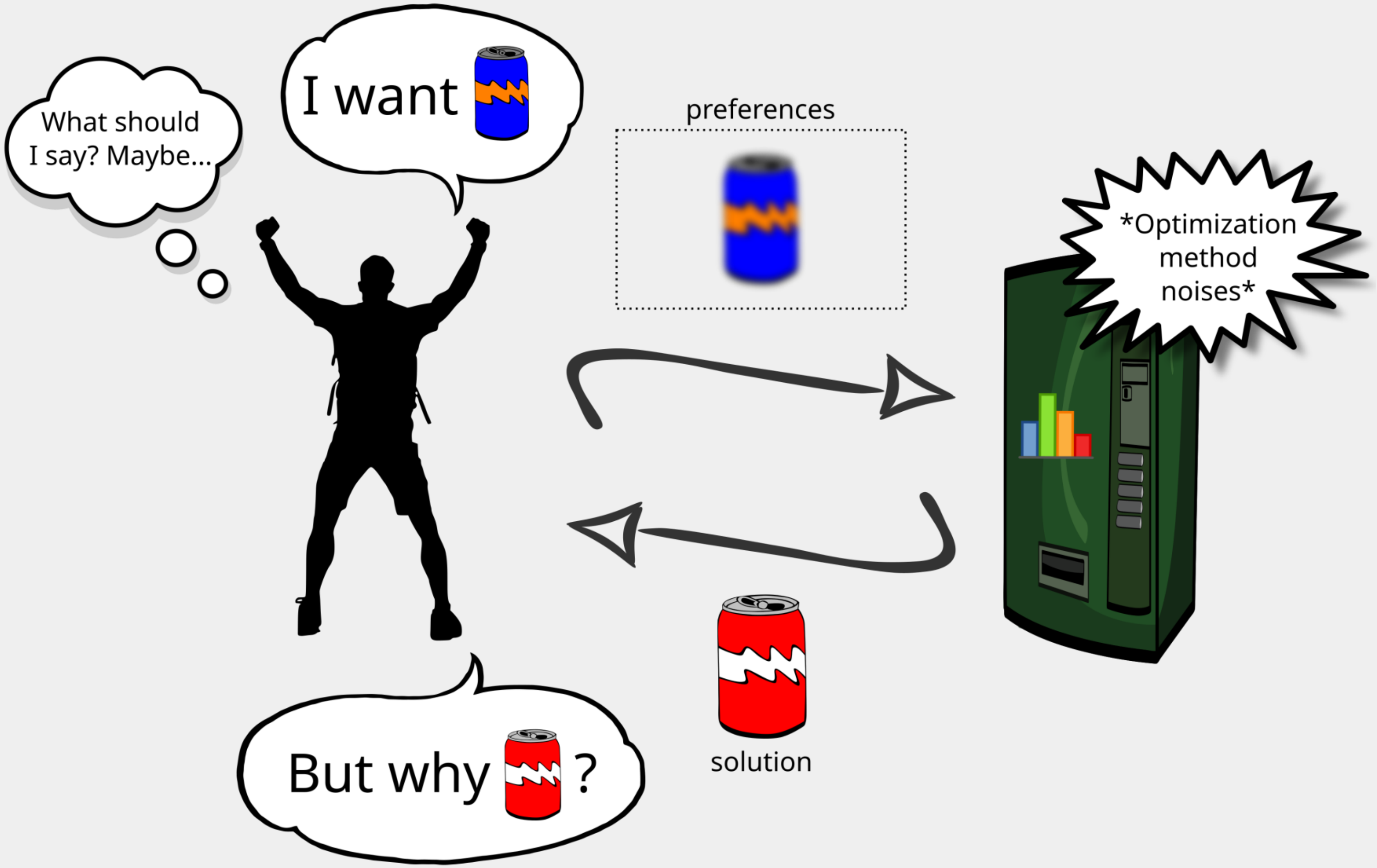
Almost a PhD (defended, but degree not granted yet)

- Doctoral researcher from the University of Jyväskylä.
- Working in the Multiobjective Optimization Group led by prof. Kaisa Miettinen.
- Defended my thesis titled **Enhancing the decision-support capabilities of interactive multiobjective optimization with explainability** on the 31st of May (last Friday!).
- Main research interest lies in the interface between decision makers and (interactive) multiobjective optimization methods.
- One of the main contributors and maintainers of the DESDEO software framework.

Motivation

- Multiobjective optimization methods are tools to support decision-making.
- These tools can help decision makers find solutions to problems with multiple conflicting objective functions and no clear single optimum.
- Because of the large amount of optimal solutions, preferences can be utilized in some methods to guide the optimization process.
- Especially in so-called interactive multiobjective optimization methods, the decision maker can iteratively explore the set of optimal solutions, which allows them to learn about the available solutions and the feasibility of their preferences.

But how clear is such a process to a decision maker?

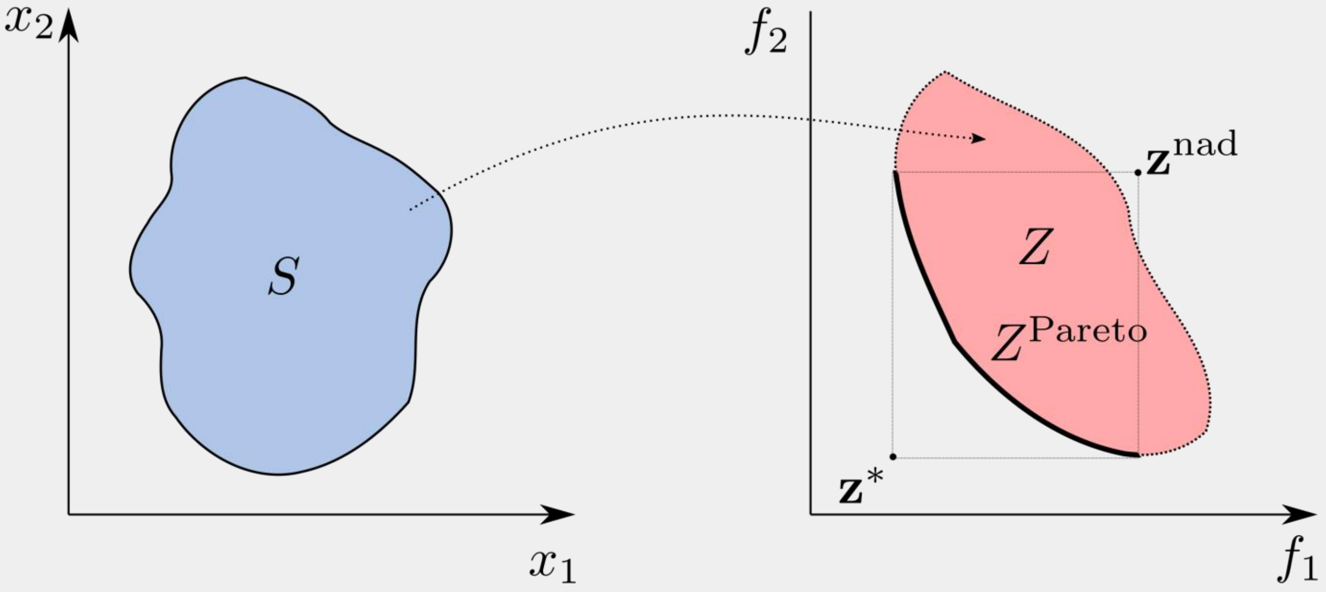


Background: concepts

Problem definition

$$\begin{aligned} \text{minimize} \quad & F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})) \\ \text{s.t.} \quad & \mathbf{x} \in S \end{aligned}$$

Central concepts



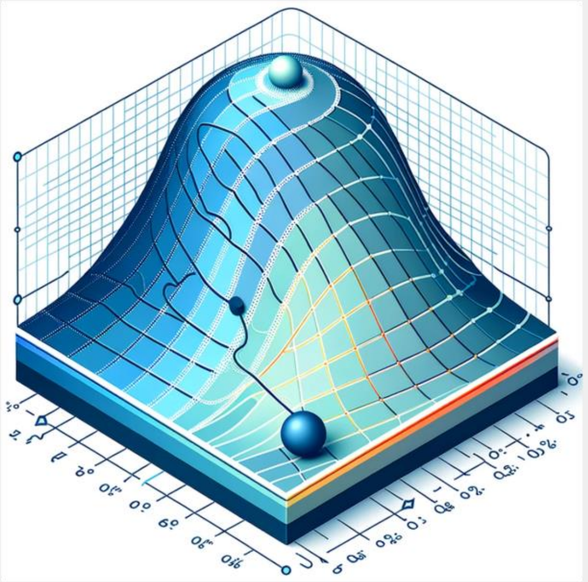
Miettinen, K. 1999. Nonlinear multiobjective optimization. Boston: Kluwer Academic Publishers.

Background: scalarization

Scalarization

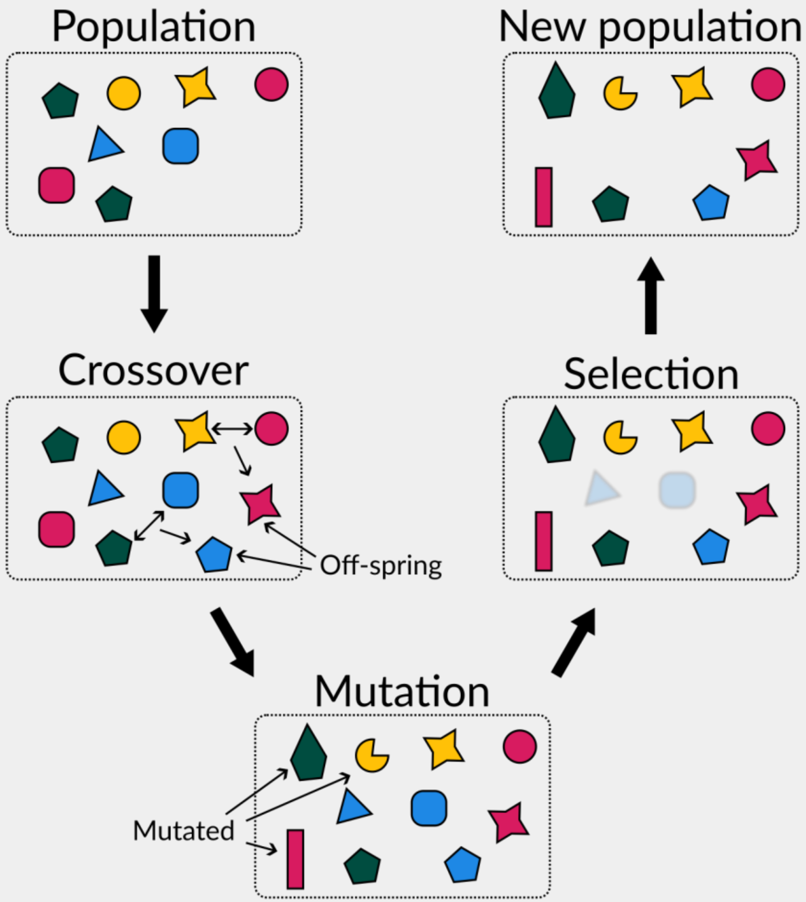
$$\max_{i=1,\ldots,k} \left[\frac{f_i(\mathbf{x}) - \bar{z}_i}{z_i^{\text{nad}} - (z_i^{\star} - \delta)} \right] + \rho \sum_{i=1}^{k} \frac{f_i(\mathbf{x})}{z_i^{\text{nad}} - (z_i^{\star} - \delta)}$$

Exact methods



Picture courtesy of ChatGPT.

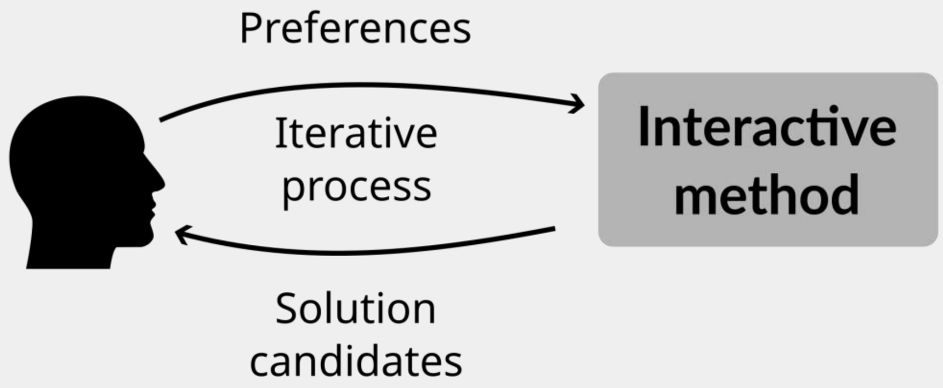
Background: evolutionary methods



Picture courtesy of ChatGPT.

Branke, J., Branke, J., Deb, K., Miettinen, K. & Slowiński, R. (Eds.) 2008. Multiob-ojective optimization: Interactive and evolutionary approaches. Springer.

Background: interactive methods



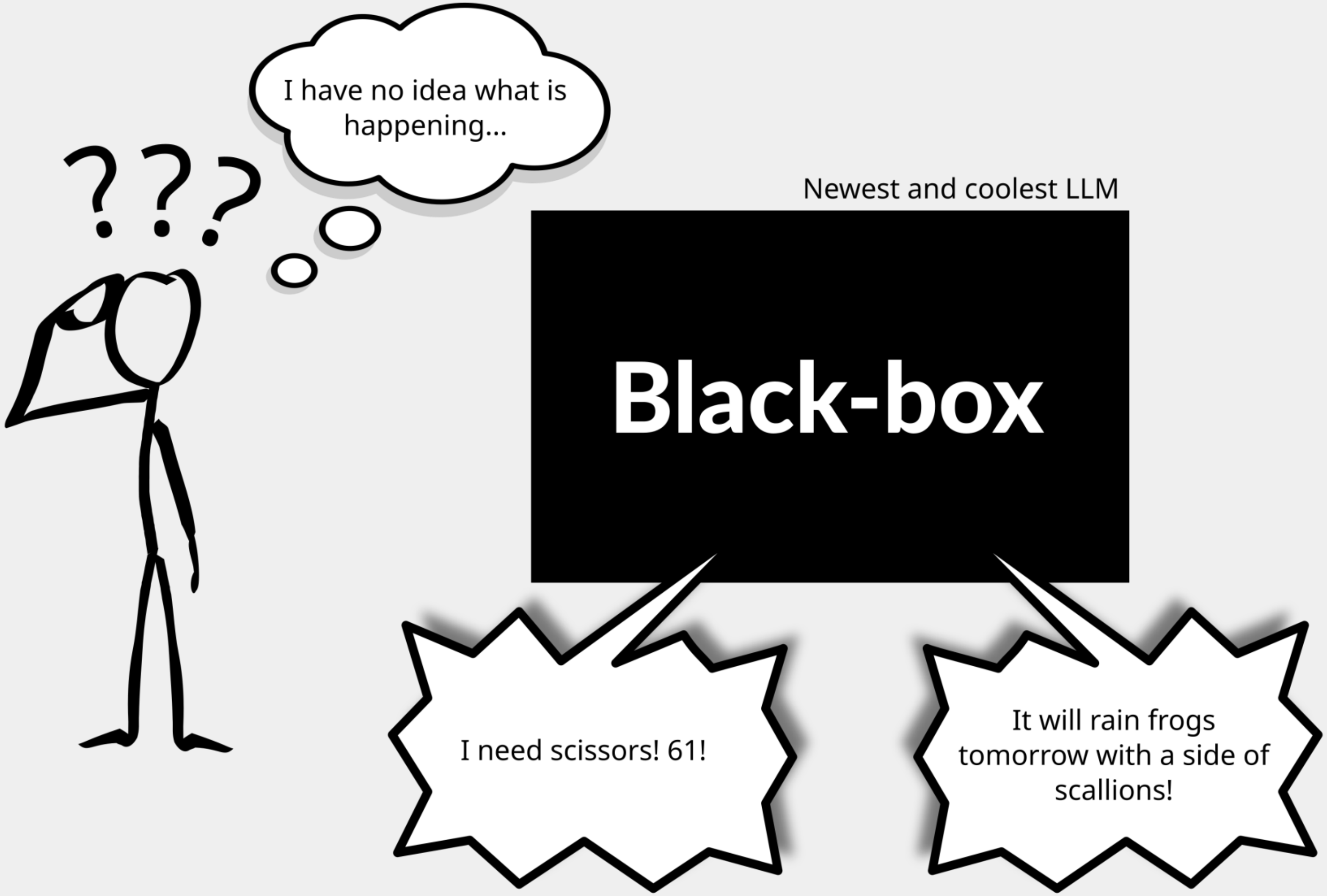
Exploration

Learning

Miettinen, K. 1999. Nonlinear multiobjective optimization. Boston: Kluwer Academic Publishers.

Branke, J., Branke, J., Deb, K., Miettinen, K. & Slowiński, R. (Eds.) 2008. Multiob-ojective optimization: Interactive and evolutionary approaches. Springer.

Background: explainable artificial intelligence



Kamath, U. & Liu, J. 2021. Explainable artificial intelligence: An introduction to interpretable machine learning. Springer.

Real-life example

You

what is alkumalja in english

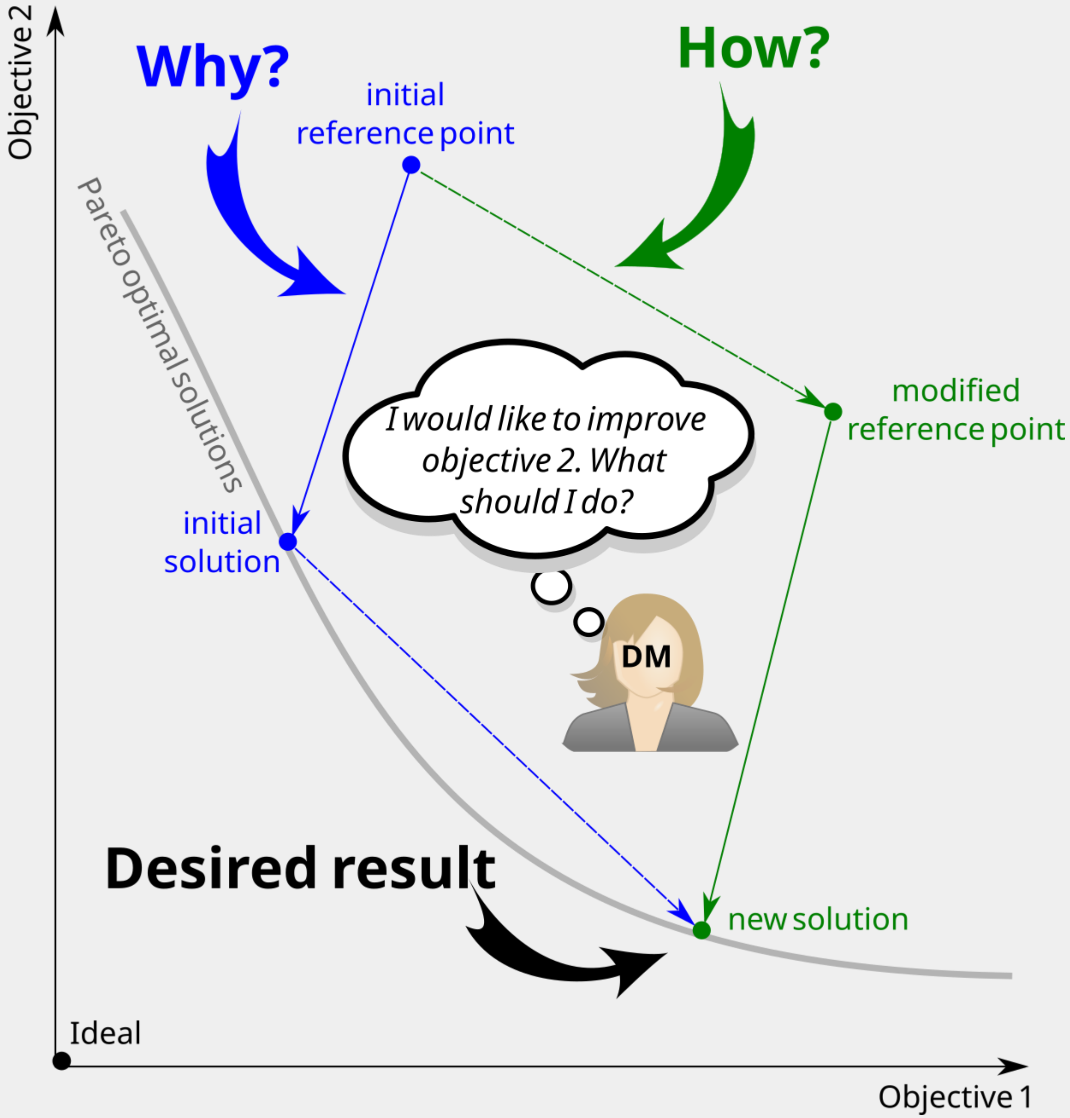
ChatGPT

"Alkumalja" is a Finnish word that translates to "starter battery" or "car battery" in English. It refers to the battery used to start a vehicle's engine.

"alkumalja" in Finnish means "opening toast"

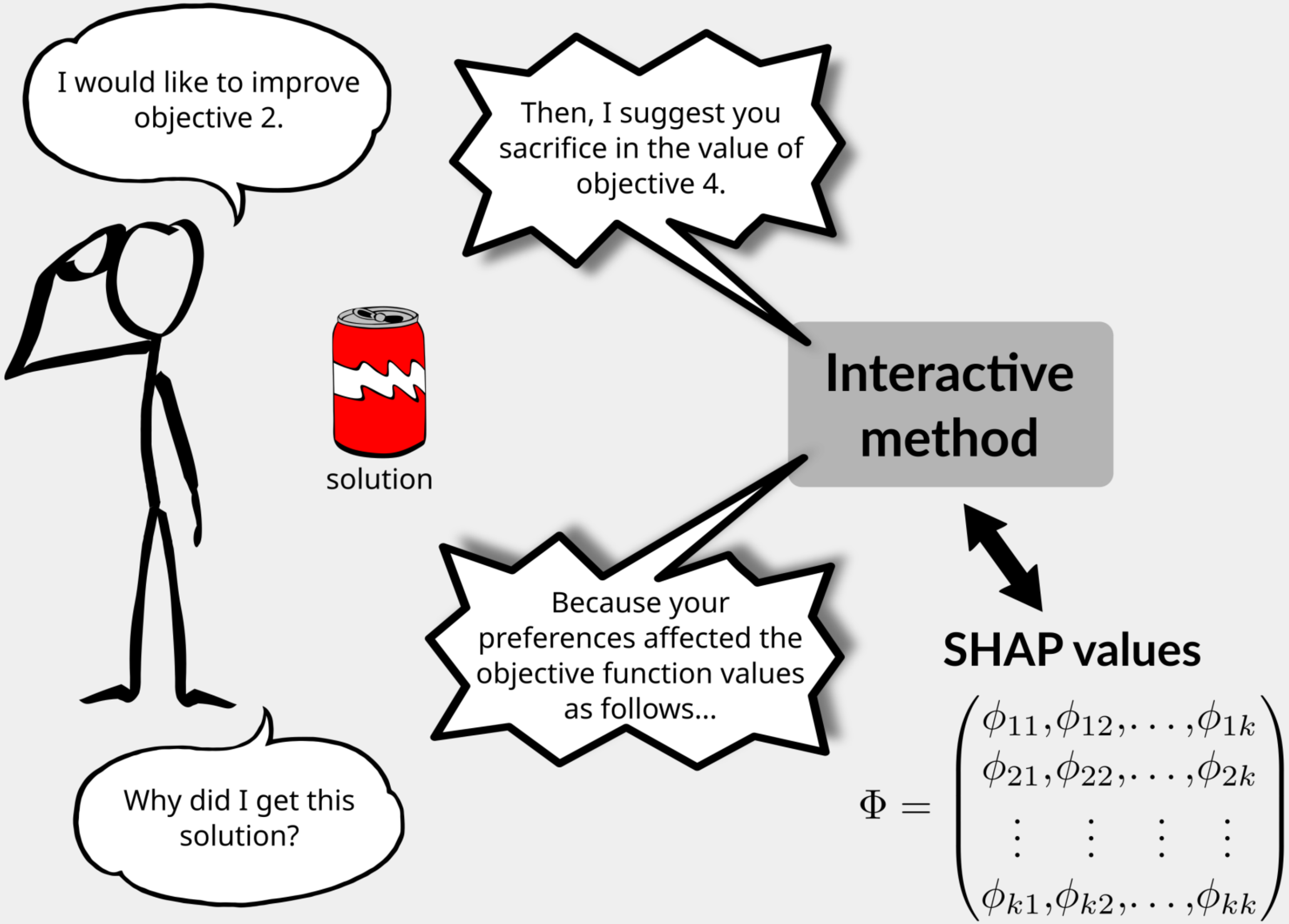
What about applying the concept of expainability to interactive multiobjective optimization?

Connection between preferences and solutions



Misitano, G., Afsar, B., Lárraga, G., & Miettinen, K. (2022). Towards explainable interactive multiobjective optimization: R-XIMO. *Autonomous Agents and Multi-Agent Systems*, *36*(2), 43.

Connection between preferences and solutions



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Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.

Autonomous Agents and Multi-Agent Systems (2022) 36:43
https://doi.org/10.1007/s10458-022-09577-3

Check for updates

Towards explainable interactive multiobjective optimization: R-XIMO

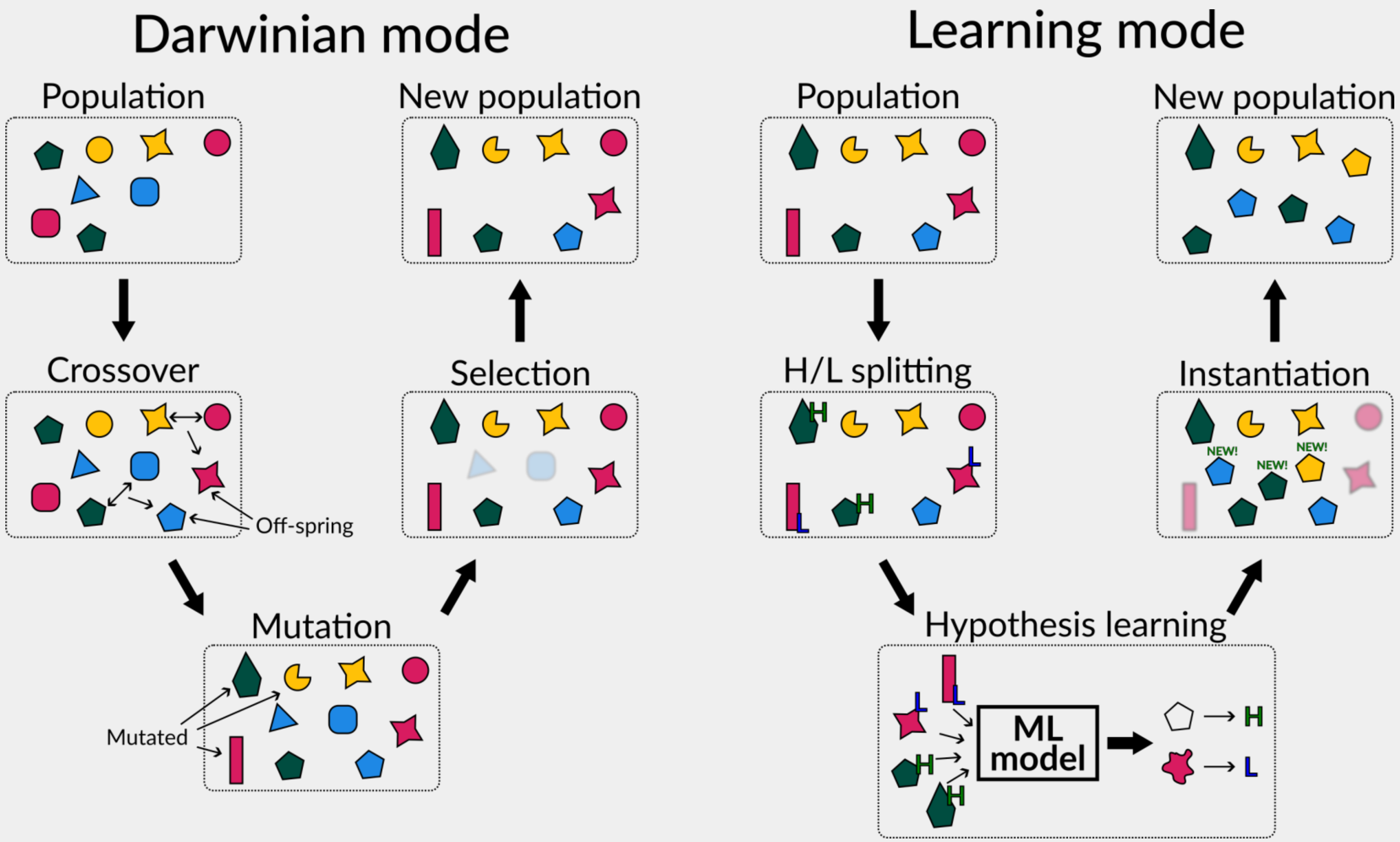
Giovanni Misitano[1] · Bekir Afsar[1] · Giomara Lárraga[1] · Kaisa Miettinen[1]

Accepted: 6 July 2022 / Published online: 13 August 2022

Abstract

In interactive multiobjective optimization methods, the preferences of a decision maker are incorporated in a solution process to find solutions of interest for problems with multiple conflicting objectives. Since multiple solutions exist for these problems with various trade-offs, preferences are crucial to identify the best solution(s). However, it is not necessarily clear to the decision maker how the preferences lead to particular solutions and, by introducing explanations to interactive multiobjective optimization methods, we promote a novel paradigm of *explainable interactive multiobjective optimization*. As a proof of concept, we introduce a new method, *R-XIMO*, which provides explanations to a decision maker for reference point based interactive methods. We utilize concepts of explainable artificial intelligence and SHAP (Shapley Additive exPlanations) values. R-XIMO allows

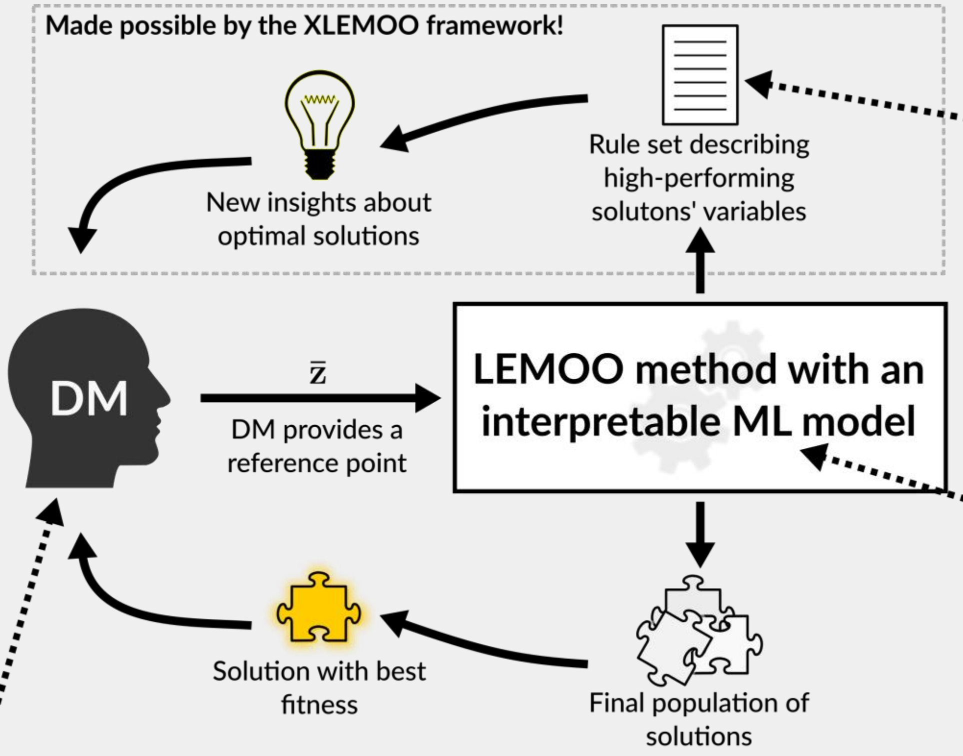
Describing preferred solutions in a population-based method



Misitano, G. (2024). Exploring the Explainable Aspects and Performance of a Learnable Evolutionary Multiobjective Optimization Method. *ACM Transactions on Evolutionary Learning*, *4*(1), 1-39.

Michalski, R. S. (2000). Learnable evolution model: Evolutionary processes guided by machine learning. Machine learning, 38, 9-40.

Describing preferred solutions in a population-based method



Described the variables of the solutions with the best fitness, e.g., the most preferred solutions

Skope-rules used

Can support technically inclined decision makers, e.g., engineers in design problems

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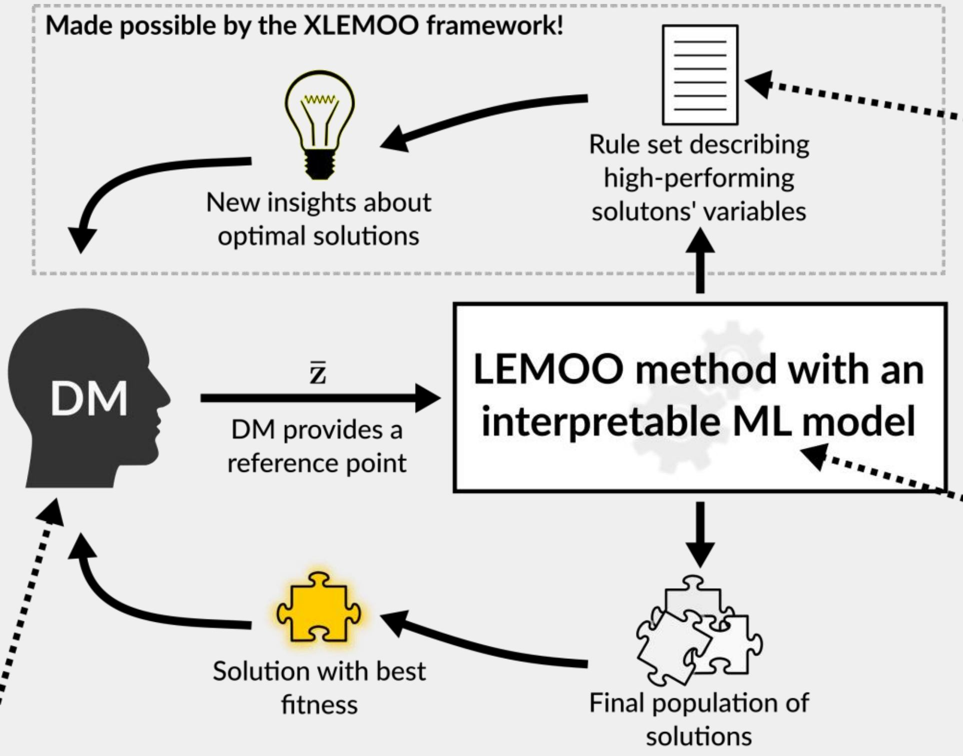
Describing preferred solutions in a population-based method



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Exploring the Explainable Aspects and Performance of a Learnable Evolutionary Multiobjective Optimization Method

GIOVANNI MISITANO, University of Jyväskylä, Finland

Multiobjective optimization problems have multiple conflicting objective functions to be optimized simultaneously. The solutions to these problems are known as Pareto optimal solutions, which are mathematically incomparable. Thus, a decision maker must be employed to provide preferences to find the most preferred solution. However, decision makers often lack support in providing preferences and insights in exploring the solutions available.

We explore the combination of learnable evolutionary models with interactive indicator-based evolutionary multiobjective optimization to create a learnable evolutionary multiobjective optimization method. Furthermore, we leverage interpretable machine learning to provide decision makers with potential insights about the problem being solved in the form of rule-based explanations. In fact, we show that a learnable evolutionary multiobjective optimization method can offer advantages in the search for solutions to a multiobjective optimization problem. We also provide an open source software framework for other researchers to implement and explore our ideas in their own works.

Our work is a step toward establishing a new paradigm in the field on multiobjective optimization: *explainable and learnable multiobjective optimization*. We take the first steps toward this new research direction and provide other researchers and practitioners with necessary tools and ideas to further contribute to this field.

4

Some other approaches to integrating explainability with interactive multiobjective optimization methods

- Shavarani, S. M., López-Ibáñez, M., Allmendinger, R., & Knowles, J. (2023). An Interactive Decision Tree-Based Evolutionary Multi-objective Algorithm. In M. Emmerich, A. Deutz, H. Wang, A. V. Kononova, B. Naujoks, K. Li, K. Miettinen, & I. Yevseyeva (Eds.), *Evolutionary Multi-Criterion Optimization* (Vol. 13970, pp. 620–634). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-27250-9_44

- Lin, P., Zhang, L., & Tiong, R. L. K. (2023). Multi-objective robust optimization for enhanced safety in large-diameter tunnel construction with interactive and explainable AI. *Reliability Engineering & System Safety*, *234*, 109172. https://doi.org/10.1016/j.ress.2023.109172

- Corrente, S., Greco, S., Matarazzo, B., & Słowiński, R. (2024). Explainable interactive evolutionary multiobjective optimization. *Omega*, *122*, 102925. https://doi.org/10.1016/j.omega.2023.102925

- Wang, J., Liu, Y., Sun, J., Jiang, Y., & Sun, C. (2016). Diversified Recommendation Incorporating Item Content Information Based on MOEA/D. *2016 49th Hawaii International Conference on System Sciences (HICSS)*, 688–696. https://doi.org/10.1109/HICSS.2016.91

- Zhan, H., & Cao, Y. (2019). *Relationship Explainable Multi-objective Optimization Via Vector Value Function Based Reinforcement Learning* (arXiv:1910.01919). arXiv. http://arxiv.org/abs/1910.01919

Wrapping up

- Integrating, or **enhancing**, interactive multiobjective optimization methods with explainability has many promising advantages.
- Explainability can aid the decision maker in providing preferences and understanding the connection between preferences and computed solutions.
- Explainability can help convey additional information about solutions, especially those that are close to the preferences of the decision maker.
- Explainability can make interactive methods more transparent tools, which is desirable from a decision-support perspective.
- There are many areas in multiobjective optimization where explainability can address different issues, and improve the decision-support capabilities of different methods.

To support your endeavors

- DESDEO has played an important supporting role in enabling the works discussed in this presentation.
- DESDEO is currently going through a complete overhaul, which will make it more usable and welcoming to wild new ideas, including explainability.

The Multiobjective Optimization Group

We regularly post about our activities on LinkedIn!

Misitano, G., Saini, B. S., Afsar, B., Shavazipour, B., & Miettinen, K. (2021). DESDEO: The modular and open source framework for interactive multiobjective optimization. *IEEE Access*, *9*, 148277-148295.

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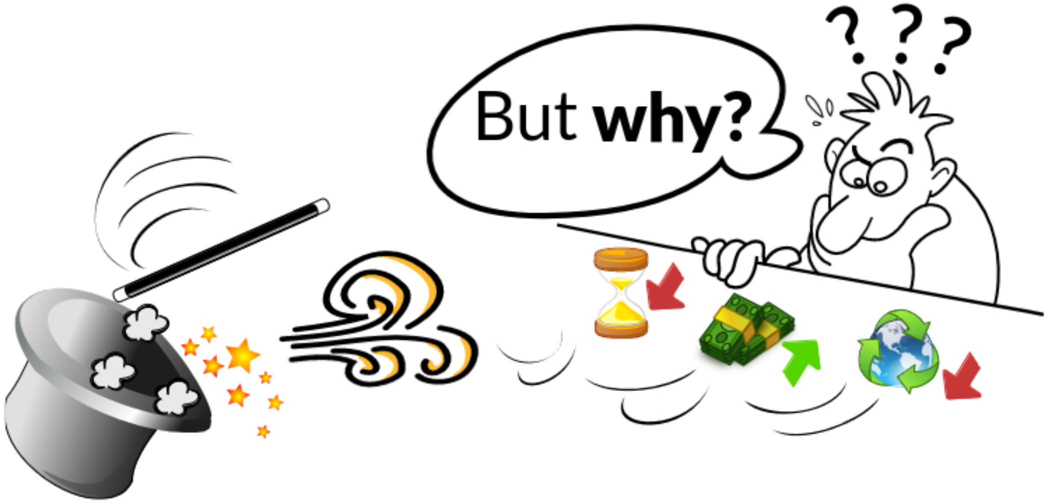
Giovanni Misitano

Enhancing the decision-support capabilities of interactive multiobjective optimization with explainability



Misitano, G. (2024). Enhancing the decision-support capabilities of interactive multiobjective optimization with explainability. *JYU Dissertations*.