



JYVÄSKYLÄN YLIOPISTO  
UNIVERSITY OF JYVÄSKYLÄ

# The Role and Potential of Explainability in Interactive Multiobjective Optimization

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# Motivation



- The world is full of **problems** with multiple conflicting criteria.
- These **problems** can be modeled as **multiobjective optimization problems**.
  - E.g., minimize **time**, maximize **profit**, and minimize **negative environmental impact**.
- Multiobjective optimization problems have many (**uncountable number of**) optimal solutions.
- A **decision maker**, a **domain expert**, needs to select the **best and final solution**.
- But **decision makers lack support** in this process.
- In my thesis, I have explored ways to address this lack of process through the concept of **explainability**.



# The multiobjective optimization problem

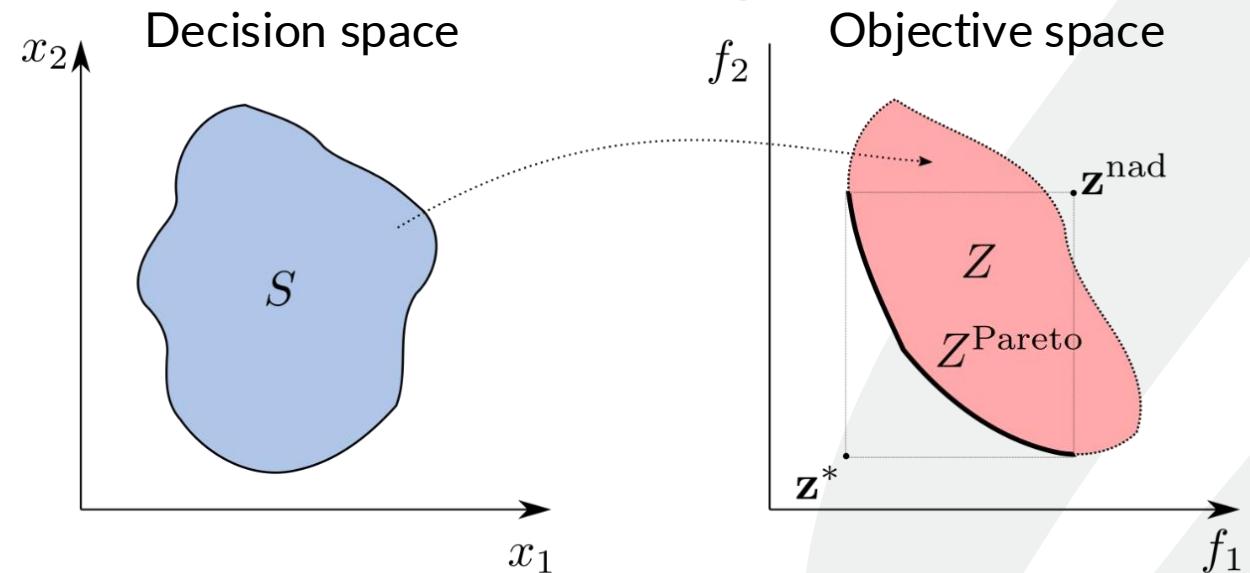


- Optimize simultaneously objective functions  $f_i$  ( $i = 1, \dots, k$ ) by finding solutions with feasible decision **variable values** (e.g.,  $x_1, x_2$ ).
- The feasible space  $S$  (and its image  $Z$ ) is defined by **constraints**.
- No single optima. Instead, a set of Pareto optimal solutions exist.
- The image of the optimal solutions, **the Pareto front** ( $Z^{Pareto}$ ), is characterized by the **ideal point** ( $z^*$ ) and **nadir point** ( $z^{nad}$ ).
- Focus is on the Pareto front.

## Problem definition

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

## Central concepts



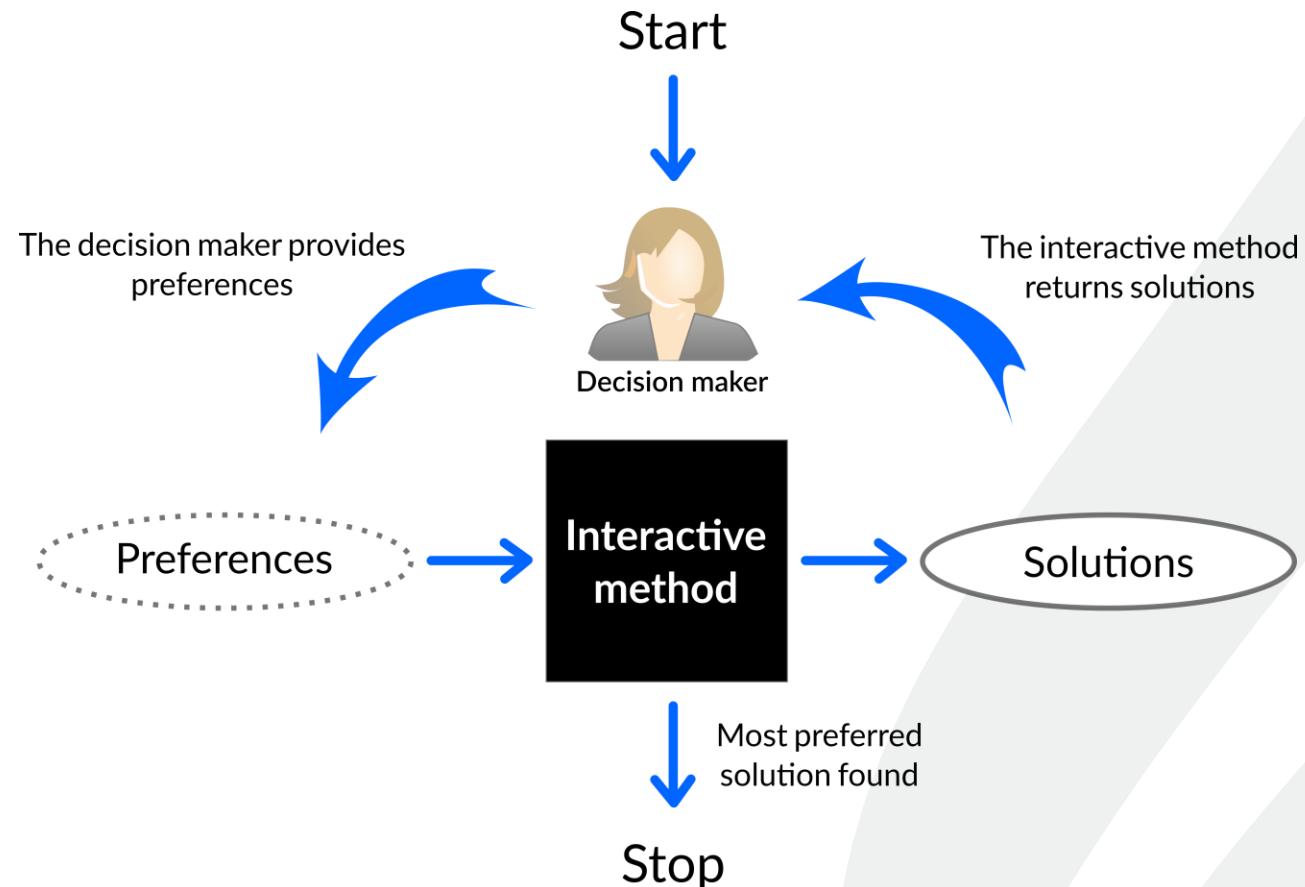
Miettinen, K. 1999. *Nonlinear multiobjective optimization*. Kluwer Academic Publishers.

Sawaragi, Y., Nakayama, H., & Tanino, T. 1985. *Theory of multiobjective optimization*. Academic Press, Inc.

# Multiobjective optimization methods



- Methods are needed to **find Pareto optimal solutions and support decision-making.**
- Decision makers provide **preference information**, which is used to find the best solution.
  - E.g.: a **reference point** consisting of **desirable objective function values**.
- Methods classified based on **when preferences are incorporated.**
  - A priori: before optimization
  - A posteriori: after optimization
  - **Interactive: during optimization**
- **Interactive methods support exploration and learning and save computational resources!**



Branke, J., Deb, K., Miettinen, K., & Słowiński, R. (Eds.). 2008. *Multiobjective Optimization: Interactive and Evolutionary Approaches*. Springer.  
Miettinen, K. 1999. *Nonlinear multiobjective optimization*. Kluwer Academic Publishers.

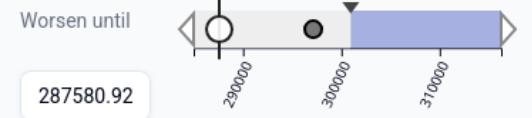
## Preference information

Provide the maximum number of solutions to generate

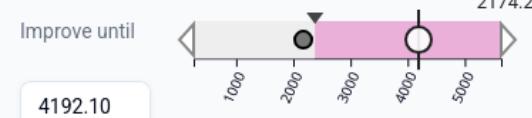
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Provide one desirable value for each objective.

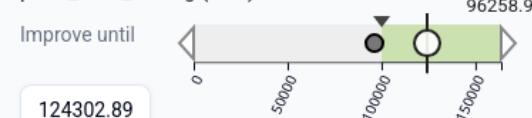
net\_present\_value (max)



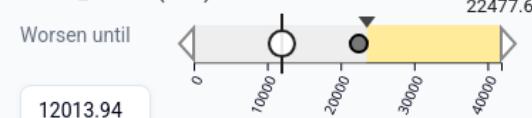
wood\_volume (max)



profit\_from\_cutting (max)



stored\_carbon (max)

**Iterate**

## Solution Explorer

## Visualization

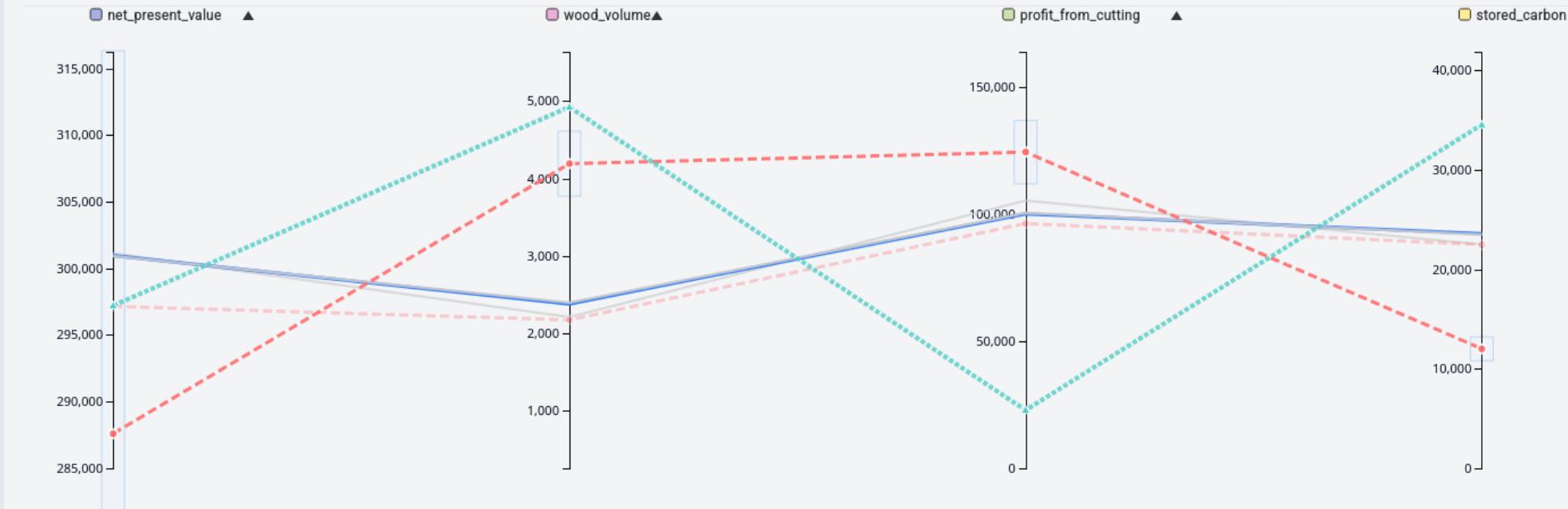
net\_present\_value

wood\_volume

profit\_from\_cutting

Parallel Coordinates

Bar Chart



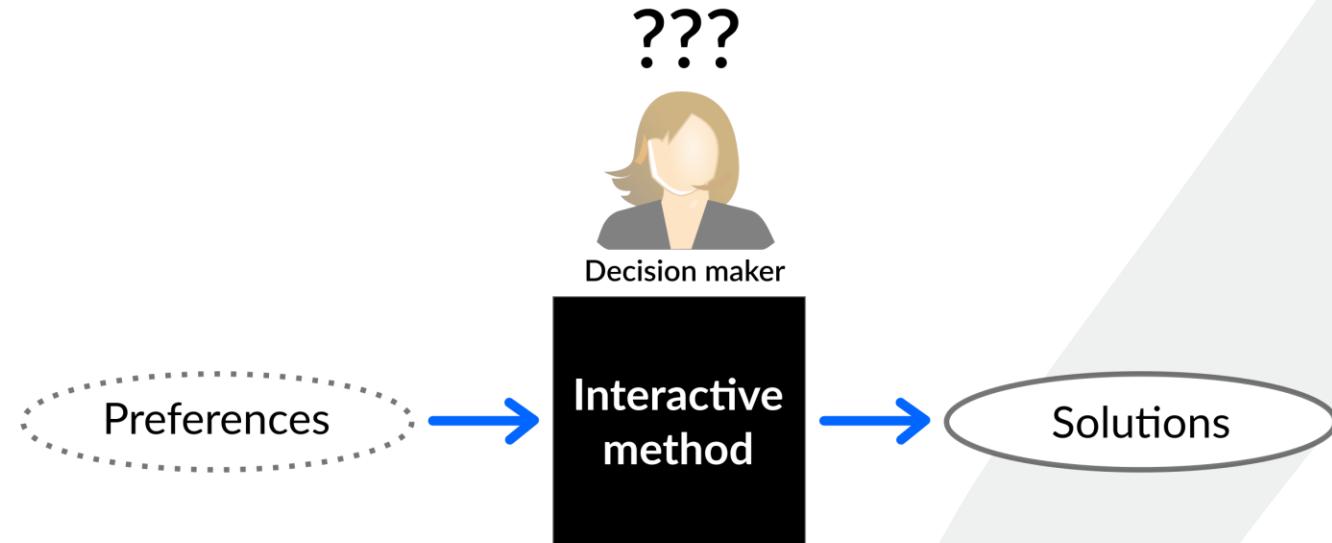
## Current solutions

Name (optional)	net_present_value (max)	wood_volume (max)	profit_from_cutting (max)	stored_carbon (max)
Solution 1	301126.98	2211.73	105278.23	22484.53
Solution 2	300960.94	2379.08	100078.19	23579.96
Solution 3	300916.78	2400.00	100285.22	23517.83
Solution 4	300928.25	2392.96	100502.98	23467.96
Previous solution	297198.64	4923.99	22879.05	34537.70

# Explainability



- Argument: **Interactive methods are opaque boxes** from the perspective of a decision maker.
- **Decision makers lack support** when utilizing interactive methods:
  - How to provide and modify preferences?
  - How to characterize the solutions found?
  - How are preferences modeled?
- Similar questions have been explored for machine learning models in the field of **explainable artificial intelligence** through the concept of **explainability**.



Brockhoff, D., Emmerich, M., Naujoks, B., & Purshouse, R. (Eds.). 2023. *Many-Criteria Optimization and Decision Analysis: State-of-the-Art, Present Challenges, and Future Perspectives*. Springer.

Gunning, D., Stefk, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. 2019. XAI—Explainable artificial intelligence. *Science robotics*, 4(37), eaay7120.

Kamath, U., & Liu, J. (2021). *Explainable Artificial Intelligence: An Introduction to Interpretable Machine Learning*. Springer.

# Central idea in my thesis: Explore and apply the concept of explainability in interactive methods to enhance their decision- support capabilities!

Supervised by Professor Kaisa Miettinen and Dr. Bekir Afsar

Composed of **four published articles**.

JYU DISSERTATIONS 794

Giovanni Misitano

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

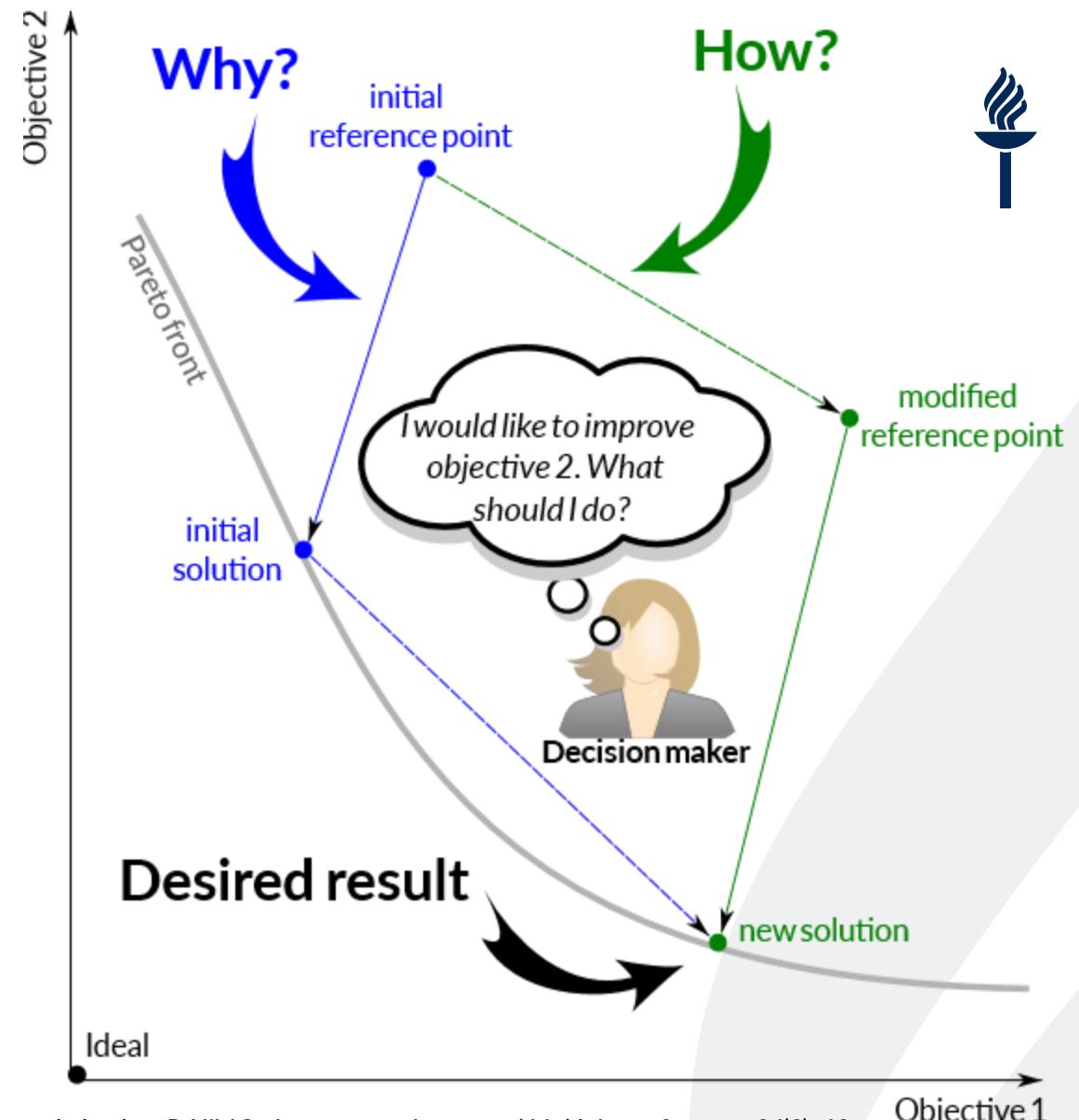


Misitano, G. 2024. *Enhancing the Decision-Support Capabilities of Interactive Multiobjective Optimization with Explainability*. PhD thesis, University of Jyväskylä.

# R-XIMO

(How to provide and modify preferences?)

- Addresses the **lack of support when providing preferences** in reference point based interactive methods.
- Leverages SHAP values to build **explanations and suggestions on how to modify the reference point** (preferences) based on the wishes expressed by a decision maker.



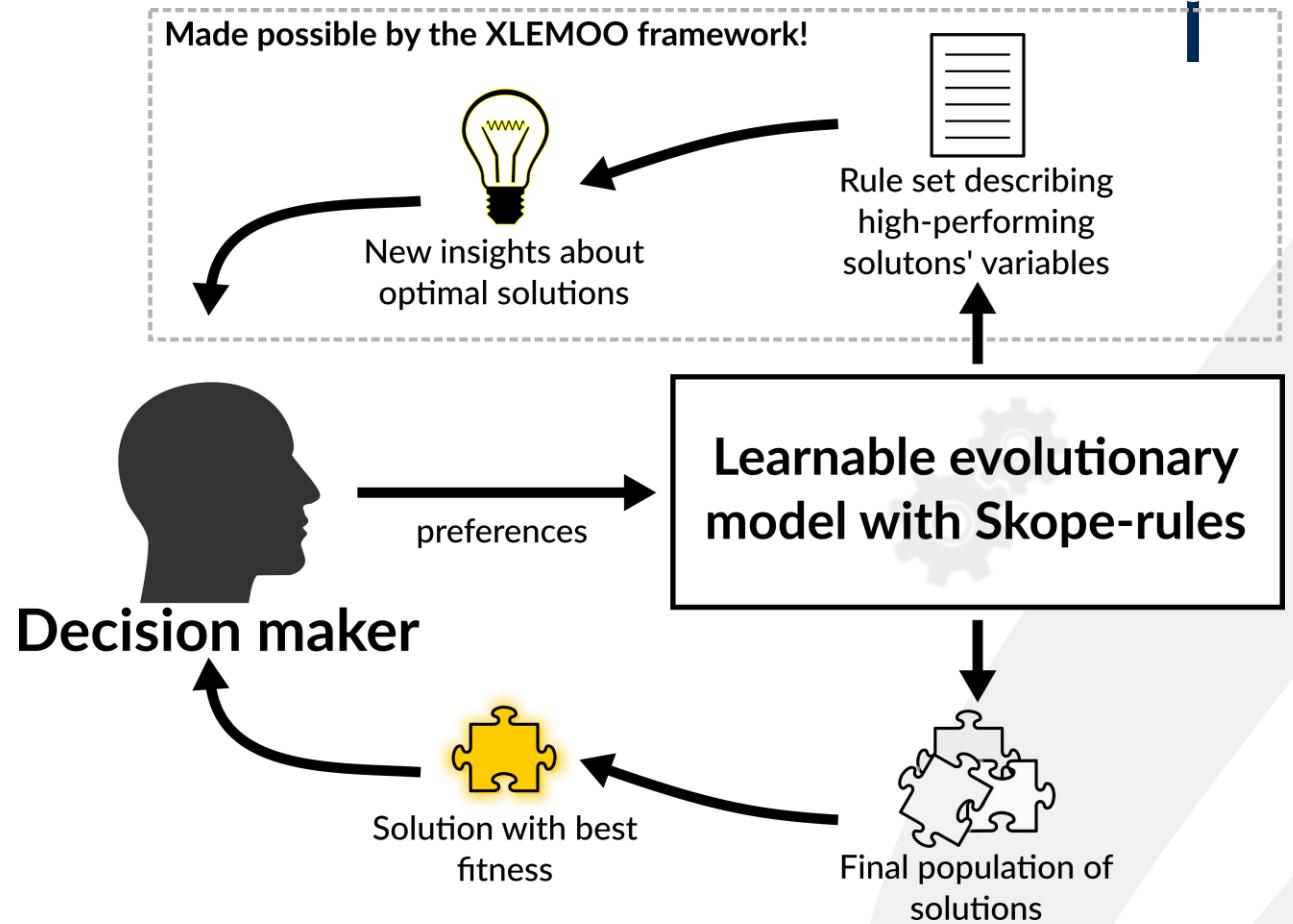
Misitano, G., Afsar, B., Lárraga, G., & Miettinen, K. 2022. Towards explainable interactive multiobjective optimization: R-XIMO. *Autonomous Agents and Multi-Agent Systems*, 36(2), 43.  
Lundberg, S. M., & Lee, S.-I. 2017. *A unified approach to interpreting model predictions*. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems 30* (pp. 4765–4774).

# XLEMOO

(How to characterize the solutions found?)



- Addresses the lack of **understanding** decision makers can have in understanding what characterizes preferred solutions.
- Combines the concept of **learnable evolutionary models** with an **interpretable rule-based machine learning model**: Skope rules.



Misitano, G. 2024. Exploring the explainable aspects and performance of a learnable evolutionary multiobjective optimization method. ACM Transactions on Evolutionary Learning and Optimization, 4(1), 1-39.  
Michalski, R. S. 2000. Learnable evolution Model: Evolutionary Processes Guided by Machine Learning. Machine Learning, 38, 9-40.

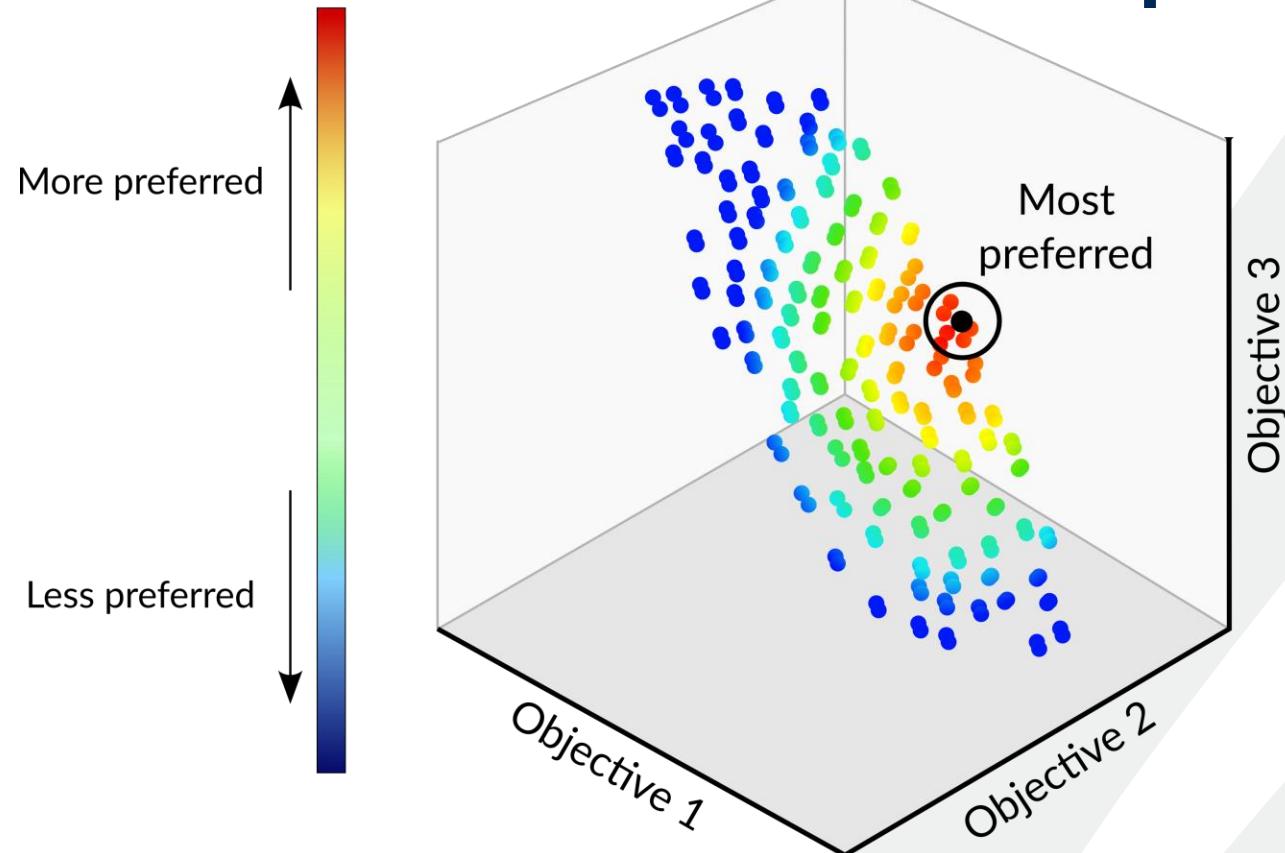
Nicolas Goix, Vighnesh Birodkar, Florian Gardin, Jean-Matthieu Schertzer, HOEBIN JEONG, manoj kumar, Alexandre Gramfort, Tim Staley, Tom Dupré la Tour, Boyuan Deng, C, Fabian Pedregosa, Lawrence Wu, Ariel Rokem, Kyle Jackson, & mrahim. 2020. scikit-learn-contrib/skope-rules v1.0.1 (v1.0.1). Zenodo. <https://doi.org/10.5281/zenodo.4316671>

# INFRINGER

(How are preferences modeled?)



- Attempts to build **explainable preference models** that a decision maker can understand and verify.
- Utilized **belief-rule based systems as the preference model**, which is learned during use of an interactive method.
- ...did not work well in terms of explainability but has a lot of potential in further studies.



Misitano, G. 2020. Interactively learning the preferences of a decision maker in multi-objective optimization utilizing belief-rules. In 2020 IEEE symposium series on computational intelligence (SSCI) (pp. 133-140). IEEE.

Yang, J. B., Liu, J., Wang, J., Sii, H. S., & Wang, H. W. 2006. Belief rule-base inference methodology using the evidential reasoning approach-RIMER. IEEE Transactions on systems, Man, and Cybernetics-part A: Systems and Humans, 36(2), 266-285.

# DESDEO: the open-source software framework



- Addresses the **lack of open-source implementation of interactive multiobjective optimization methods**.
- Allows researchers to **focus on novelty** and **enables publication of interactive methods as open-source software**.
- Thanks to DESDEO's **modular structure**:
  - R-XIMO: explanations easy to integrate into any reference point-based method.
  - XLEMOO: can be implemented as a custom evolutionary operator.
  - INFRINGER: preference model can be used in combination with a multitude of interactive methods.
- **Invaluable in applying and developing the methods included in my thesis**.

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.

# Conclusions



- My thesis paves the way towards a new research direction: **explainable interactive multiobjective optimization**.
- Many existing ideas are combined creating wholly new concepts. Truly standing on the shoulders of giants!
- Thinking from **the perspective of the decision maker** is very useful. Explainability is a nice vector for this!
- **Recently published book chapter.** State of the field and what others have been doing.
- The goal of this line of research is to provide **better decision-support tools to help decision makers solve challenging real-world problems**.

Misitano, G., Miettinen, K. 2025. *The Emerging Role of Explainability in Interactive Multiobjective Optimization: An Exploration of Current Approaches*. In: van Stein, N., Kononova, A.V. (eds) Explainable AI for Evolutionary Computation. Natural Computing Series. Springer.

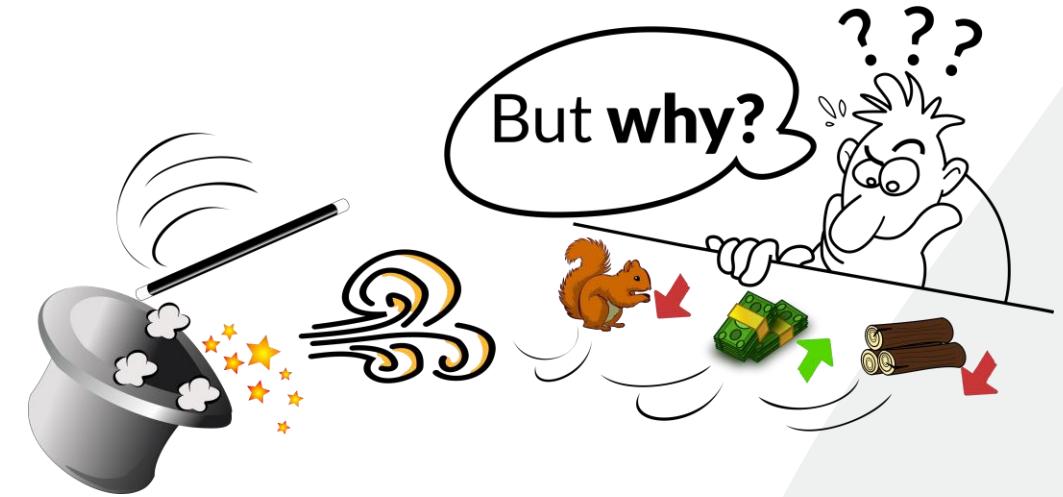
# Our research group



- Many ongoing research projects in our group building on the **ideas set in my thesis!**
- We strive to make our work **open source** and available to anybody via **DESDEO**.
- We pursue also many other research directions in our group as well. **We are always open to new collaborations!**



# Q&A + Resources



<https://linktr.ee/gialmisi>



Research Council of Finland

This work is part of the thematic research area Decision Analytics Utilizing Causal Models and Multiobjective Optimization (DEMO, [jyu.fi/demo](http://jyu.fi/demo)) at the University of Jyväskylä.