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Enhancing the Decision-Support Capabilities of Interactive Multiobjective Optimization with Explainability

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Why This Thesis?

- Real-life decisions involve balancing conflicting criteria, modeled as multiobjective optimization (MOO) problems.
- Many powerful methods exist, but they remain underutilized outside academia.
- Decision makers need more than optimal solutions. They need to understand and trust the optimization and solution process.
- **This thesis explores how the concept of explainability can address these, and other, gaps.**

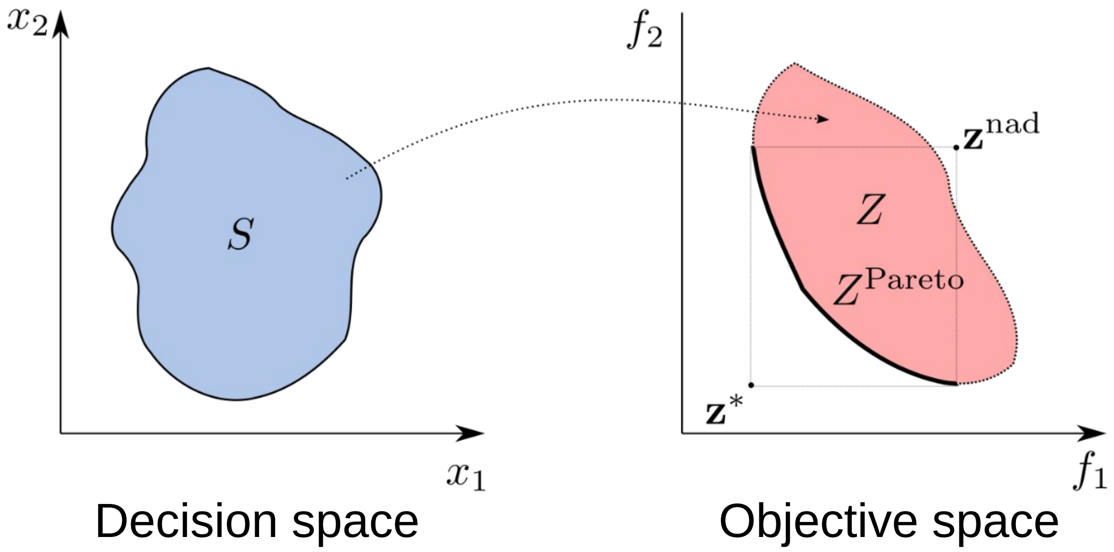
The Multiobjective Optimization Problem

- Optimize simultaneously k >= 2 conflicting objective functions by finding feasible decision variable values.
- No single optimum: a set of Pareto optimal solutions exists, forming the Pareto front.
- Front is bound by the ideal point (z*, best values) and nadir point (z^nad, worst values).
- A **decision maker**, a domain expert, is needed to identify the most preferred solution.

Problem definition

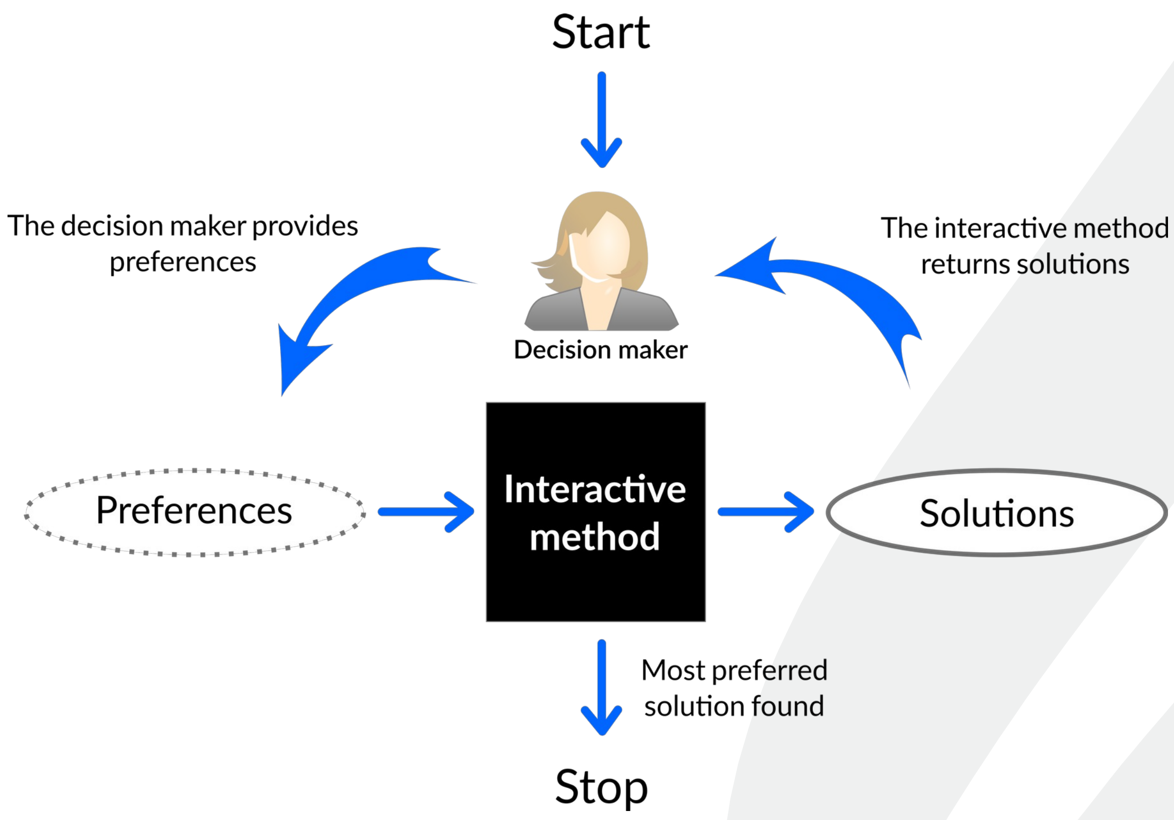
$$\begin{aligned} \text{minimize} \quad & F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})) \\ \text{s.t.} \quad & \mathbf{x} \in S \end{aligned}$$

Central concepts



Interactive Methods: The Right Paradigm

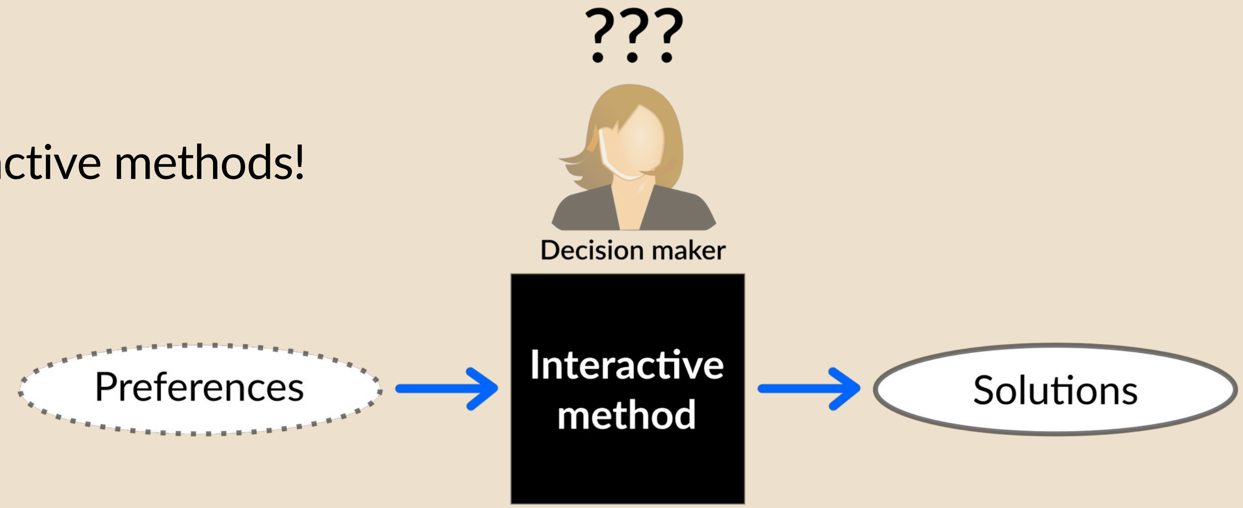
- A priori: preferences before optimization. DM may lack knowledge about available solutions.
- A posteriori: preferences after optimization. Cognitively overwhelming, wastes computation.
- **Interactive: preferences during optimization. DM iteratively provides preferences, sees solutions, learns, and adjusts.**
- Interactive methods support exploration and learning while saving computational resources.



Miettinen, K. (1999). Nonlinear Multiobjective Optimization. Kluwer Academic Publishers.

The Problem: Interactive Methods Are Opaque

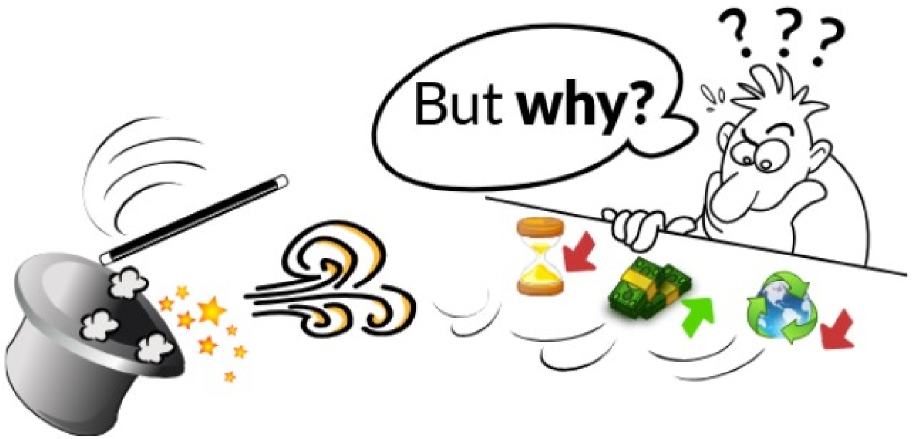
- From the **DM's perspective**, interactive methods are black boxes: preferences in, solutions out. But how and why?
- **Q1: How should I provide and modify my preferences?**
- **Q2: What characterizes the solutions I am seeing?**
- **Q3: How are my preferences being modeled?**
- Decision makers lack support when operating interactive methods!



Belton, V., Branke, J., Eskelinen, P., Greco, S., Molina, J., Ruiz, F., & Słowiński, R. (2008). Interactive multiobjective optimization from a learning perspective. In J. Branke, K. Deb, K. Miettinen, & R. Słowiński (Eds.), Multiobjective optimization: Interactive and evolutionary approaches (pp. 405–433). Springer.

The Central Idea: Explainability

- Explainable AI (XAI) has tackled similar black-box challenges for machine learning models.
- Ad hoc approaches: explain any model by observing inputs and outputs (e.g., SHAP values).
- Inherently interpretable models: self-descriptive models such as rule-based models.
- **Key insight: treat interactive MOO methods as black boxes and apply the same ideas.**
- **Thesis contribution: lay the groundwork for explainable interactive multiobjective optimization.**



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

Four Articles, Three Methods, One Framework

Each method addresses one of the three open questions (Q1-3) using a different explainability approach.

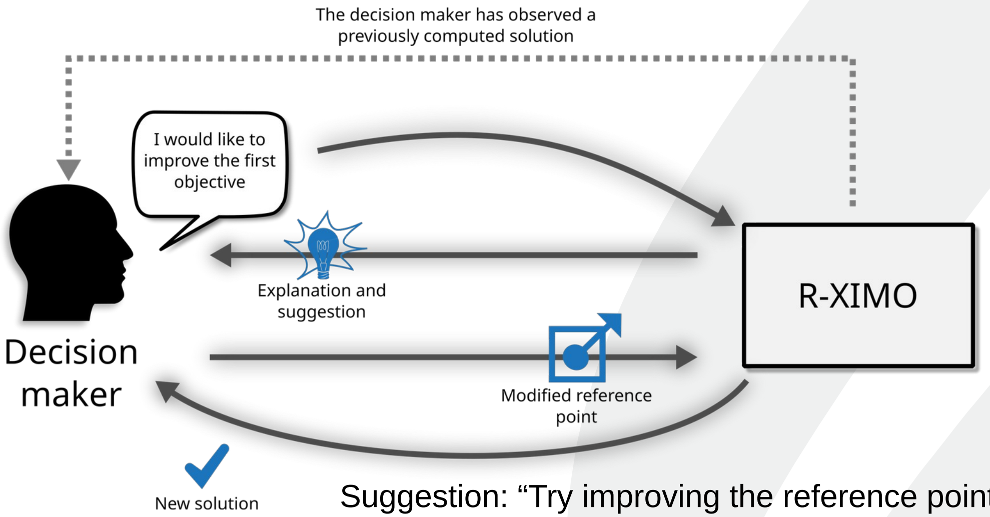
R-XIMO: Explaining Preferences to Solutions

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.

- **Q1: How to provide and modify preferences in reference point based interactive methods?**
- Treat the interactive method as a black box. Use SHAP values to explain how each aspiration level affected each objective.
- Generate actionable suggestions: identify the best objective to trade off for improving a desired one.
- Validated numerically and in a case study with DM in Finnish forestry management: suggestions helped reach preferred solutions in fewer iterations.

$$\text{SHAP values} = \begin{pmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1k} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k1} & \phi_{k2} & \cdots & \phi_{kk} \end{pmatrix}$$

Each element represent the average effect of of each aspiration level in the reference point to the objective function values in a solution.



Suggestion: "Try improving the reference point component of the first objective and impairing the component of the third objective."

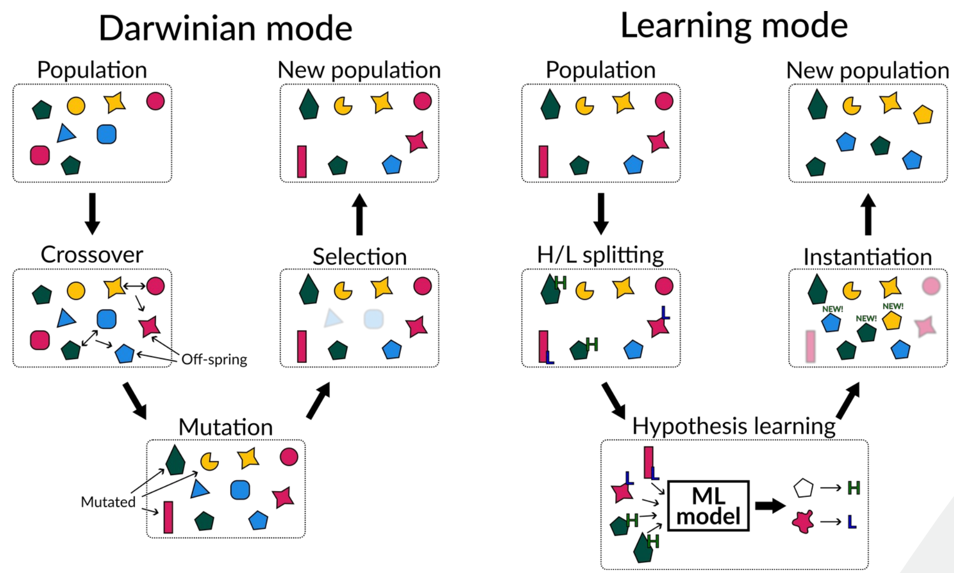
Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.

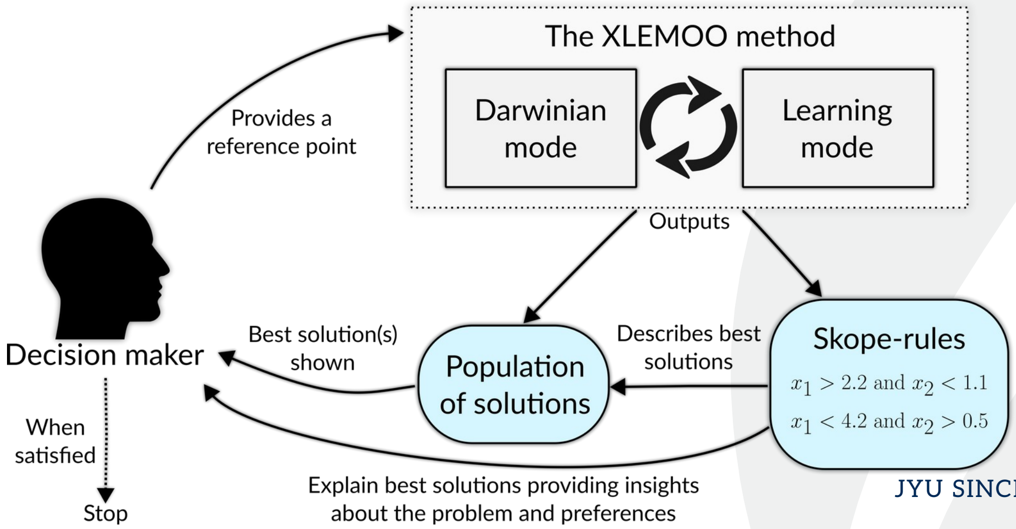
XLEMOO: Explaining Solution Characteristics

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.

- **Q2: What characterizes the solutions near the decision maker's preferences?**
- Combine evolutionary methods with interpretable machine learning (skope-rules) based on learnable evolutionary models.
- IF-THEN rules describe decision variable ranges for high-performing solutions near the reference point.
- Learning mode boosts search performance of the evolutionary method.
- Showcase: rules revealed which design variables matter most; prompted questioning the problem formulation.

Michalski, R. S. (2000). Learnable evolution model: Evolutionary processes guided by machine learning. Machine learning, 38(1), 9-40.

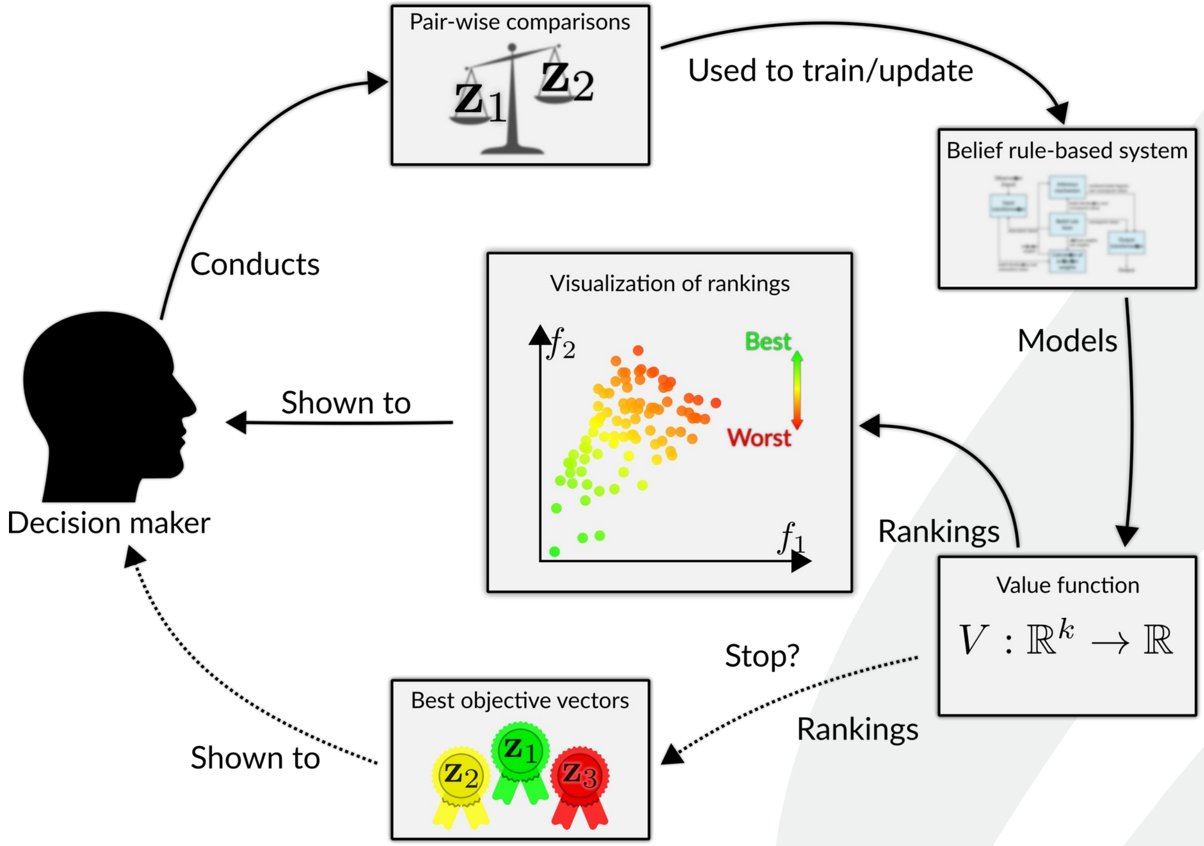




INFRINGER: Toward Explainable Preference Models

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.

- **Q3: How are the decision maker's preferences modeled?**
- Learn a value function using belief rule-based systems via pairwise comparisons.
- Case study: DM felt rankings were gradually converging to match their preferences.
- Honest assessment: the model was too complex (27 rules) to be directly explainable.
- **Key lesson: an inherently explainable model is not automatically explainable. Complexity matters.**

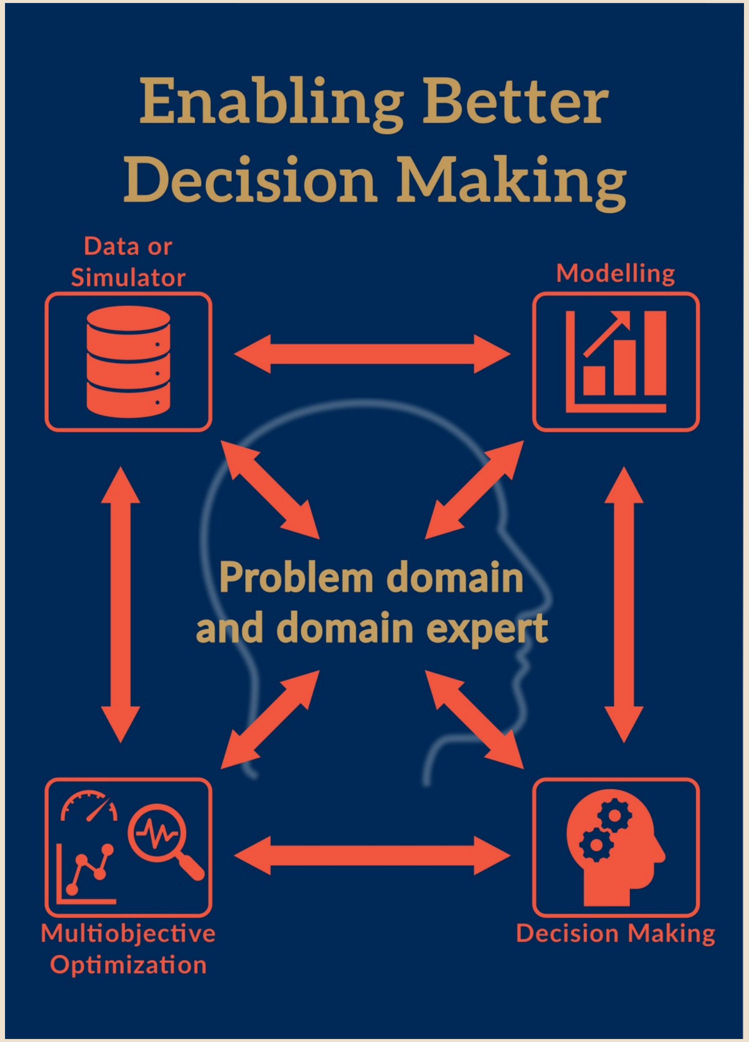


Yang, J.-B., Liu, J., Wang, J., Sii, H.-S., & Wang, H.-W. (2006). Belief rule-base inference methodology using the evidential reasoning approach — RIMER. IEEE Transactions on Systems, Man, and Cybernetics — Part A, 36(2), 266–285.

DESDEO: The Enabling Infrastructure

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.

- Open-source Python framework for interactive MOO. Unique: both MCDM and evolutionary interactive methods.
- Enables hybridizing methods, switching mid-process, reusing components for new methods.
- Offers the foundation to build decision support tools, which take the whole big picture into account.
- **The lack of method implementations in our field is alarming. Open source should be the norm.**
- The framework was overhauled about a year ago into ‘DESDEO 2’.



Central Findings of the Dissertation

- **Explainability can aid decision makers find their most preferred solution in different ways.**
  - R-XIMO: support in providing preferences. XLEMOO: understanding solution characteristics. INFRINGER: learning about preferences.
- **Incorporating explainability has potential in improving the decision support capabilities of interactive methods.**
  - R-XIMO: It can, confirmed by DM. XLEMOO and INFRINGER: promising but needs further validation.
- **Explainability could improve justifiability.**
  - All methods provide grounds for DMs to justify preference changes and audit the optimization process.

Impact: Why This Dissertation?

- **Establishes the field of explainable interactive multiobjective optimization.**
- First systematic application of XAI to interactive MOO: three new methods spanning scalarization-based, evolutionary, and preference modeling.
- All methods and code published as open-source. DESDEO is the only open-source framework for interactive MOO.
- Already inspiring follow-up: further studies, ongoing doctoral research, funded projects, book chapter.
- Others exploring this avenue as well (e.g., recall the keynote on Monday)!

Bekir, A., Lárraga, G., & Miettinen, K. (2025, March). Can LIME Make Interactive Multiobjective Optimization Methods Explainable?. In 2025 IEEE Symposium on Trustworthy, Explainable and Responsible Computational Intelligence (CITREx) (pp. 1-7). IEEE.

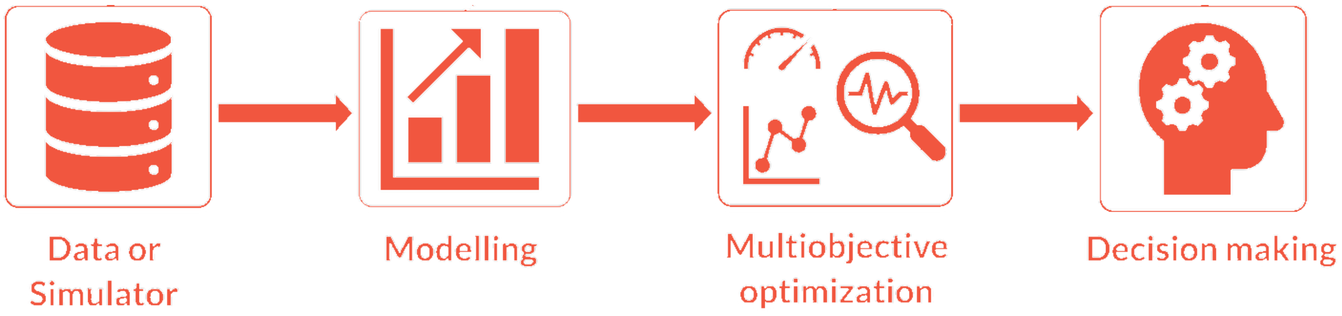
Misitano, G., & Miettinen, K. (2025). The Emerging Role of Explainability in Interactive Multiobjective Optimization: An Exploration of Current Approaches. In Explainable AI for Evolutionary Computation (pp. 149-174). Springer.

Corrente, S., Greco, S., Matarazzo, B., & Słowiński, R. (2024). Explainable interactive evolutionary multiobjective optimization. Omega, 122, 102925.

Osika, Z., Salazar, J. Z., Roijers, D. M., Oliehoek, F. A., & Murukannaiah, P. K. (2023, August). What lies beyond the pareto front? a survey on decision-support methods for multi-objective optimization. In Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (pp. 6741-6749).

Future Research Directions

- **Communication:** text is limited. Specialized visualizations needed for conveying explanations to DMs.
- **Broader coverage:** apply explainability to NAUTILUS, NIMBUS, navigation methods. Explore, e.g., counterfactual explanations.
- **Human studies:** rigorous experiments to measure actual benefits of explanations.
- **Theory:** leverage mathematical properties unique to MOO problems to enhance explainability.



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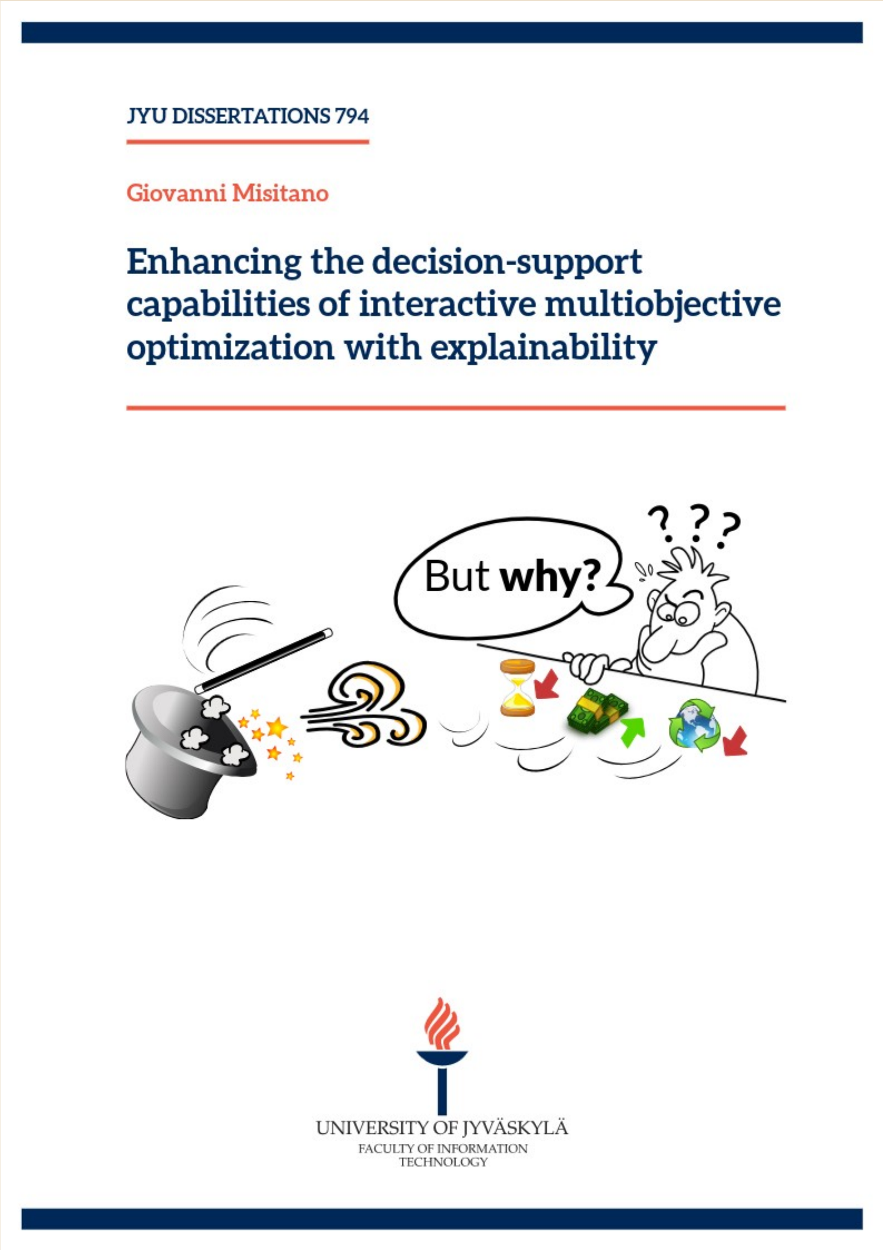
Concluding Take-Aways

- Multiobjective optimization is not just mathematics.
- We need to be multidisciplinary.
- Open-source is not optional.
- Explainability is the perfect excuse to explore what lies beyond just the Pareto front.



Acknowledgements, Resources, Q&A

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Thesis, articles, DESDEO, and more, behind the link below!

https://linktr.ee/gialmisi

Research Council of Finland

SUOMALAINEN TIEDEAKATEMIA
FINNISH ACADEMY OF SCIENCE AND LETTERS

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