JYVÄSKYLÄN YLIOPISTO
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Explainable Interactive Multiobjective Optimization: The What, The How, and Why You Should Care

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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.**

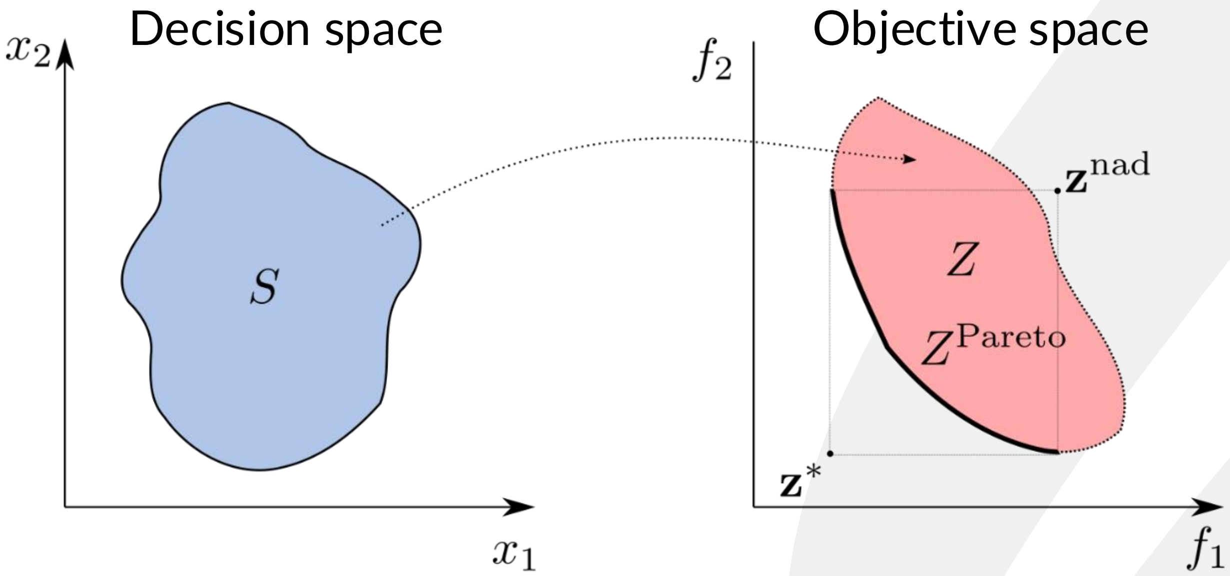
The multiobjective optimization problem

- Optimize simultaneously objective functions f_i $(i = 1, \ldots, k)$ 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** $(\boldsymbol{z}^*)$ **and nadir point** $\left(\boldsymbol{z}^{\boldsymbol{nad}}\right)$.
- Focus is on the Pareto front.

Problem definition

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

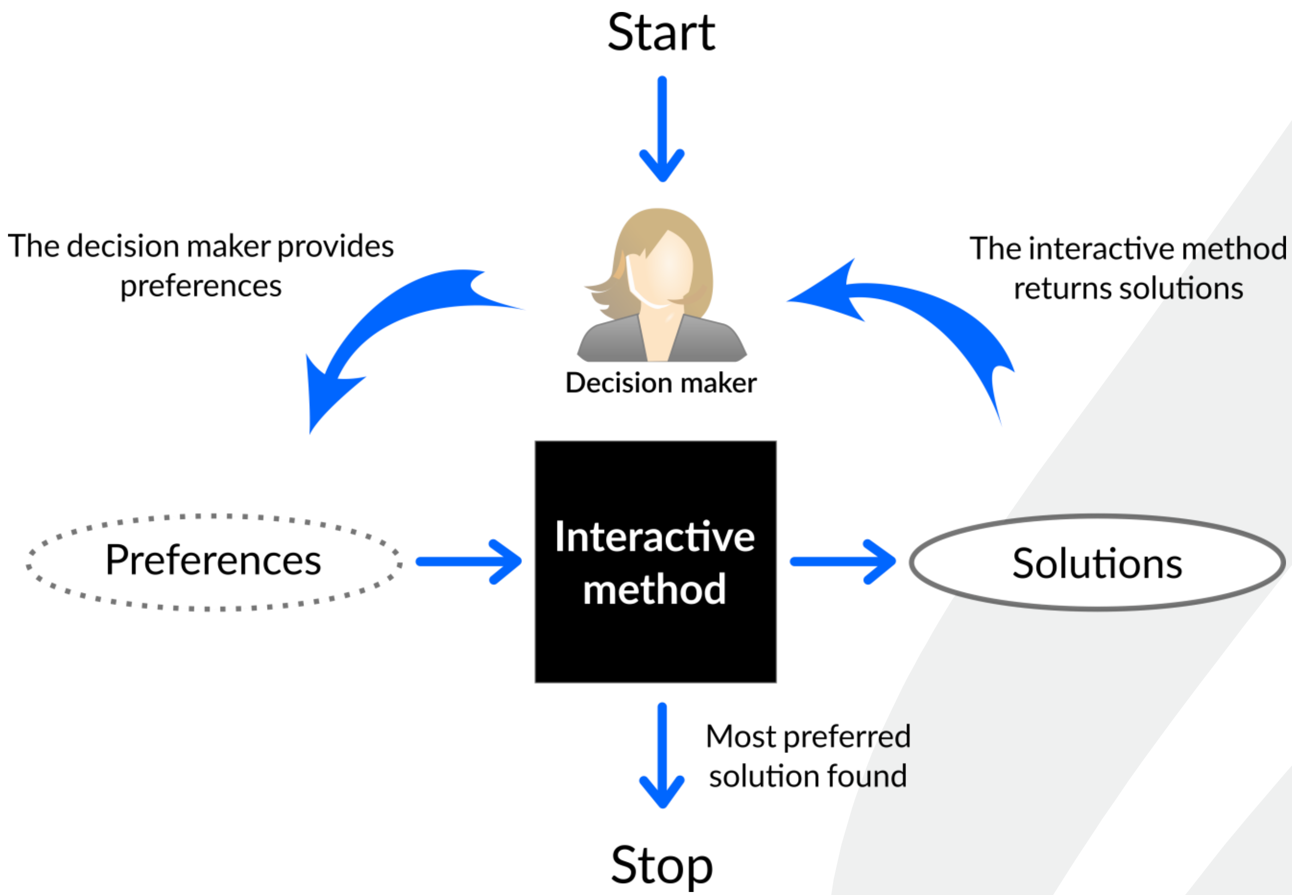
Central concepts



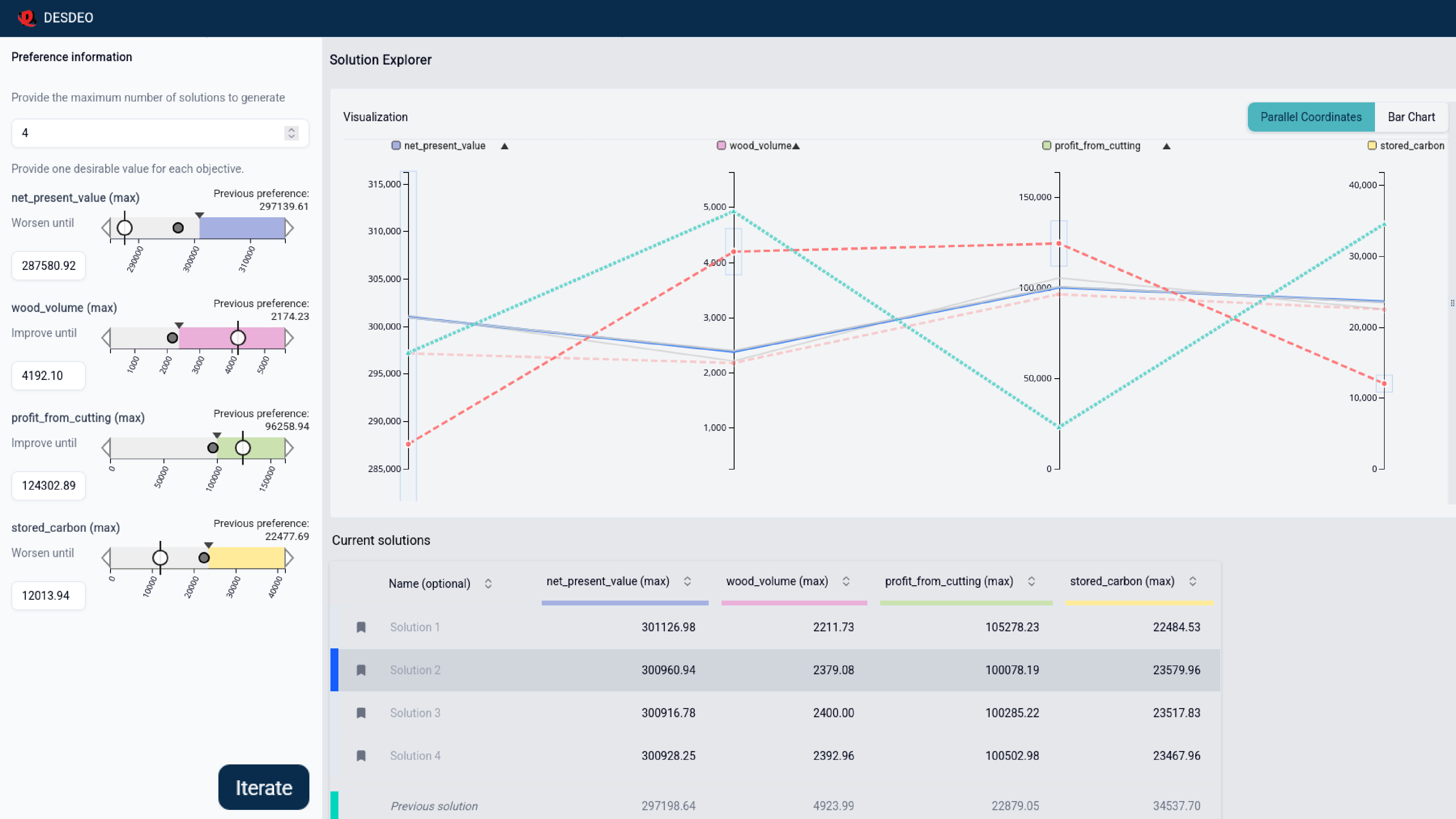
Miettinen, K. 1999. *Nonlinear multiobjective optimization*. Kluwer Academic Publishers.
Sawaragi, Y., Nakayama, H., & Tanino, T. 1985. *Theory of multiobjective optimization*. Academic Press, Inc.

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!**

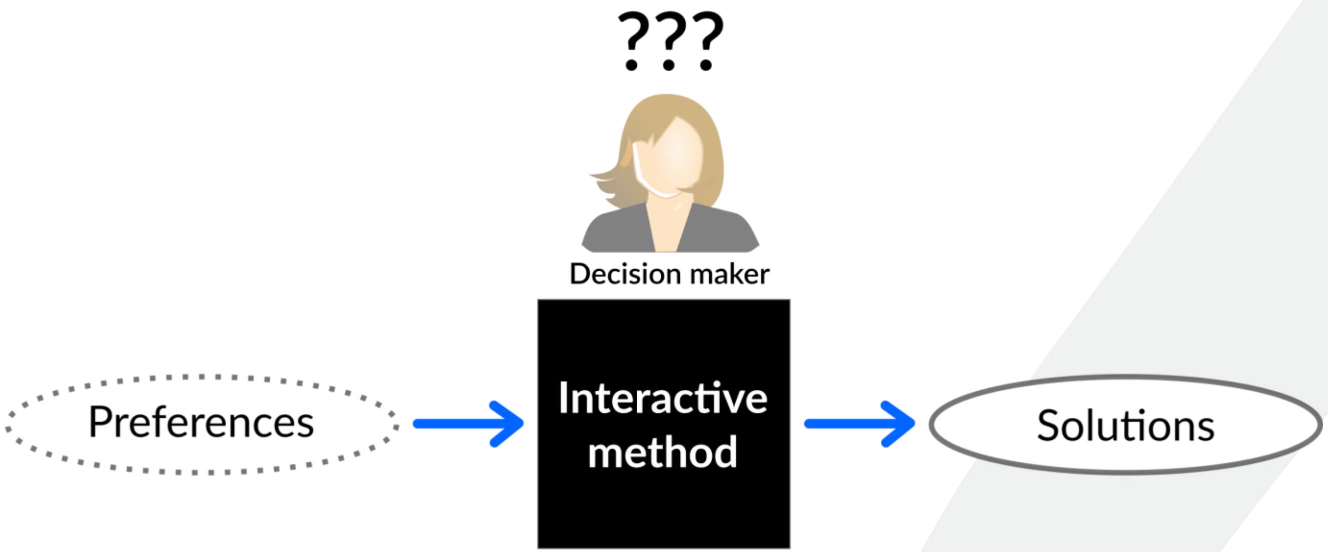


Branke, J., Deb, K., Miettinen, K., & Słowiński, R. (Eds.). 2008. *Multiobjective Optimization: Interactive and Evolutionary Approaches*. Springer.
Miettinen, K. 1999. *Nonlinear multiobjective optimization*. Kluwer Academic Publishers.


DESDEO
Preference information
Provide the maximum number of solutions to generate
4
Provide one desirable value for each objective.
net_present_value (max)
Previous preference: 297139.61
Worsen until
287580.92
290000
300000
310000
wood_volume (max)
Previous preference: 2174.23
Improve until
4192.10
1000
2000
3000
4000
5000
profit_from_cutting (max)
Previous preference: 96258.94
Improve until
124302.89
0
50000
100000
150000
stored_carbon (max)
Previous preference: 22477.69
Worsen until
12013.94
0
10000
20000
30000
40000
Iterate
Solution Explorer
Visualization
Parallel Coordinates
Bar Chart
net_present_value
wood_volume
profit_from_cutting
stored_carbon
315,000
310,000
305,000
300,000
295,000
290,000
285,000
5,000
4,000
3,000
2,000
1,000
150,000
100,000
50,000
0
40,000
30,000
20,000
10,000
0
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., Stefik, 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!

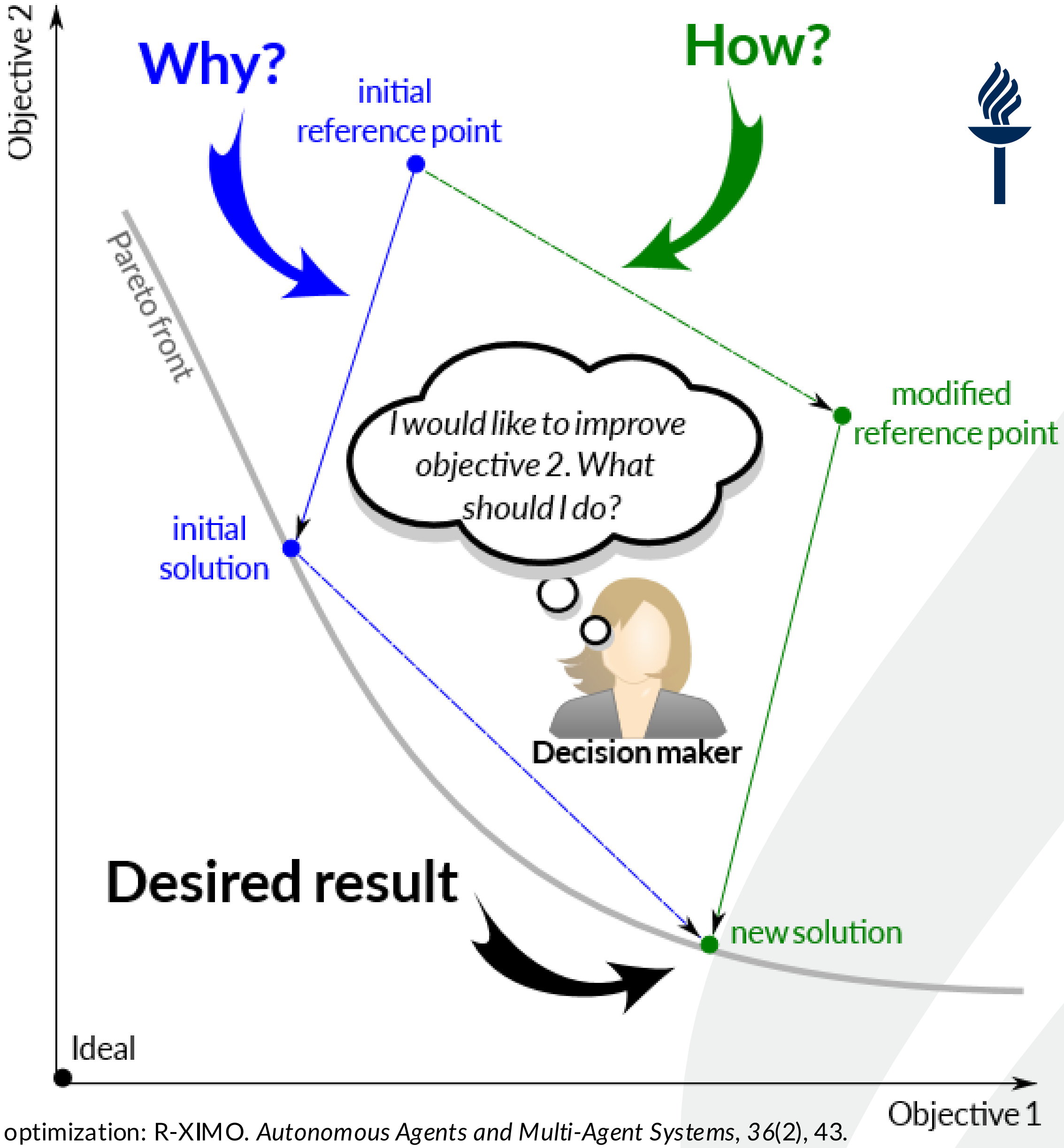
Supervised by Professor **Kaisa Miettinen** and Dr. **Bekir Afsar**

Composed of **four published articles**.

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?)

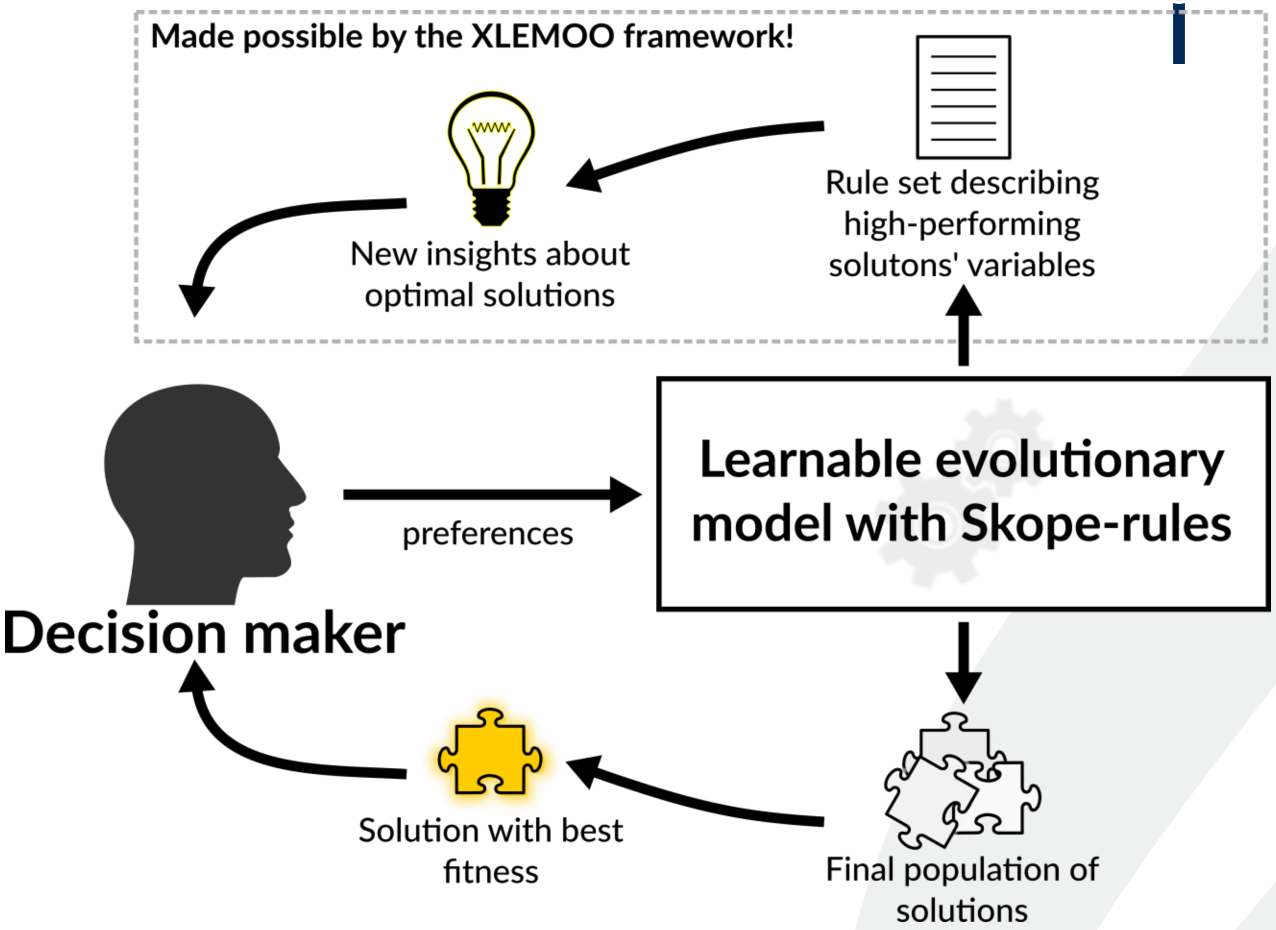
- Addresses the **lack of support when providing preferences** in reference point based interactive methods.
- Leverages SHAP values to build **explanations and suggestions on how to modify the reference point** (preferences) based on the wishes expressed by a decision maker.



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?)

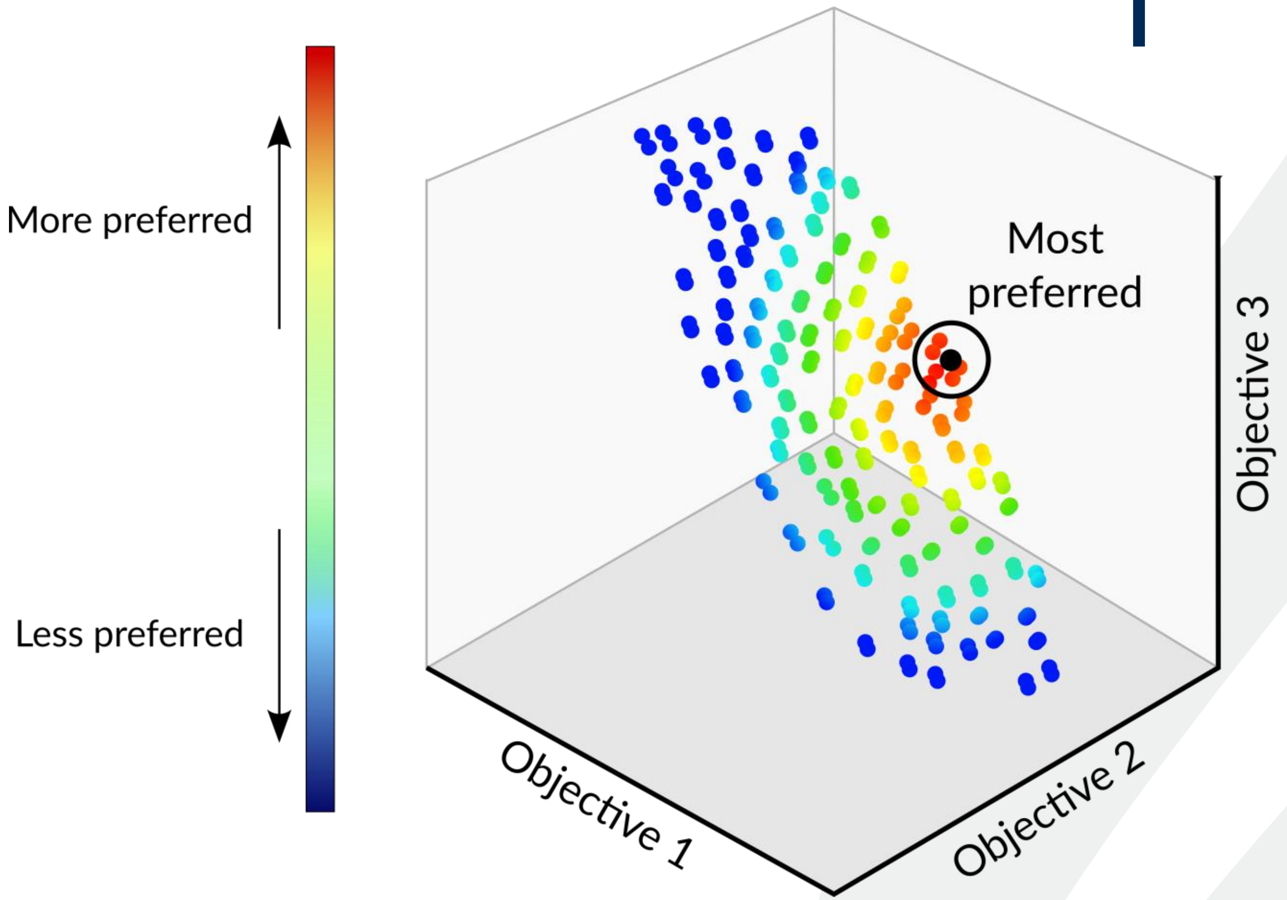
- Addresses the lack of **understanding decision makers can have in understanding what characterizes preferred solutions.**
- Combines the concept of **learnable evolutionary models** with an **interpretable rule-based machine learning model:** Skope rules.



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**.

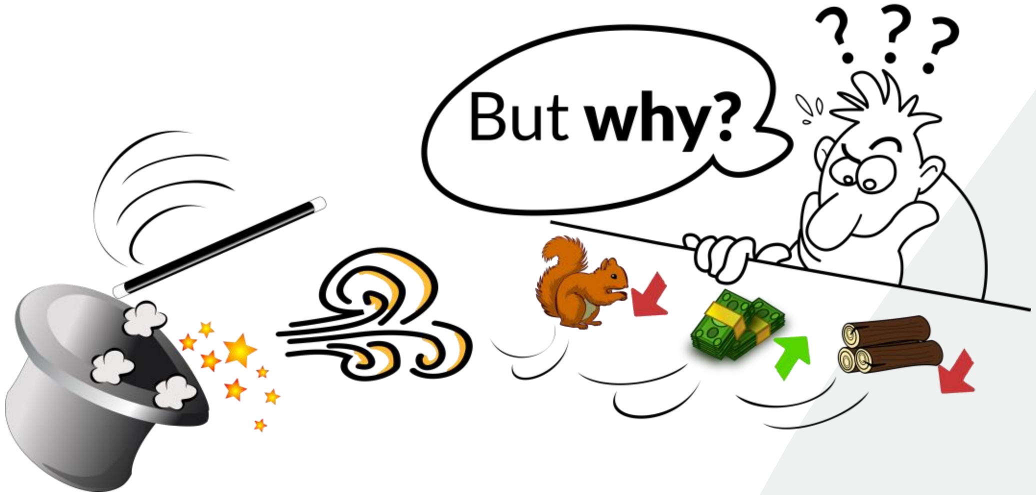
Misitano, G., Miettinen, K. 2025. *The Emerging Role of Explainability in Interactive Multiobjective Optimization: An Exploration of Current Approaches*. In: van Stein, N., Kononova, A.V. (eds) Explainable AI for Evolutionary Computation. Natural Computing Series. Springer.

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) at the University of Jyväskylä.