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Towards Explainable Interactive Multiobjective Optimization: R-XIMO

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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 (often an 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.
- **The R-XIMO method proposed in our paper begins to address this lack of support.**

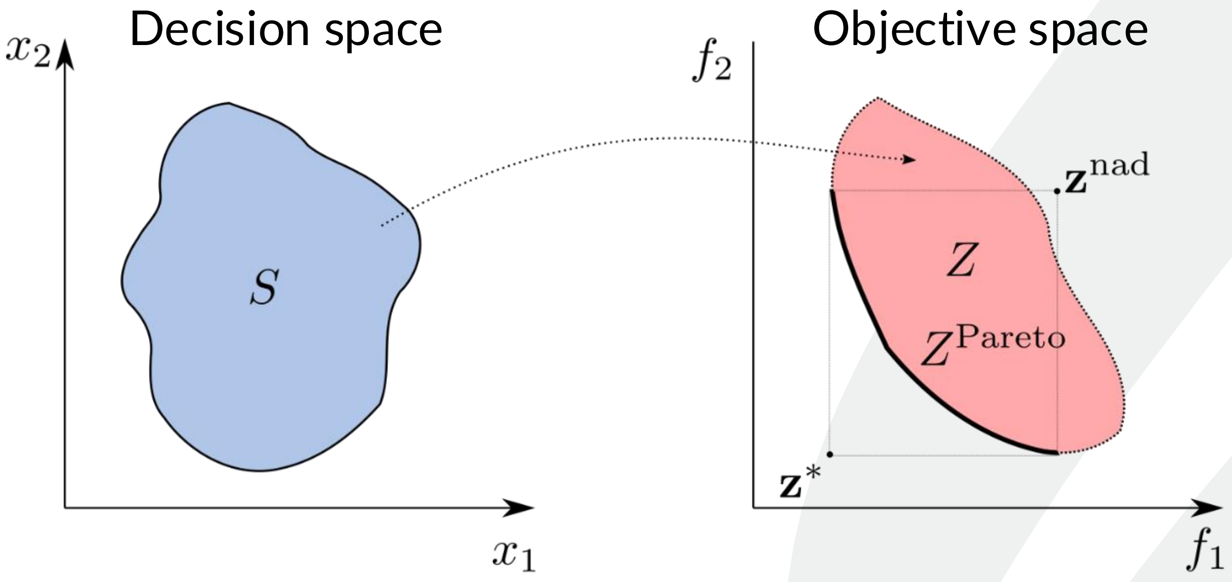
The multiobjective optimization problem

- 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** ($\boldsymbol{z}^*$) **and nadir point** $\left(\boldsymbol{z}^{nad}\right)$.
- Focus is on the Pareto front.

Problem definition

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

Central concepts



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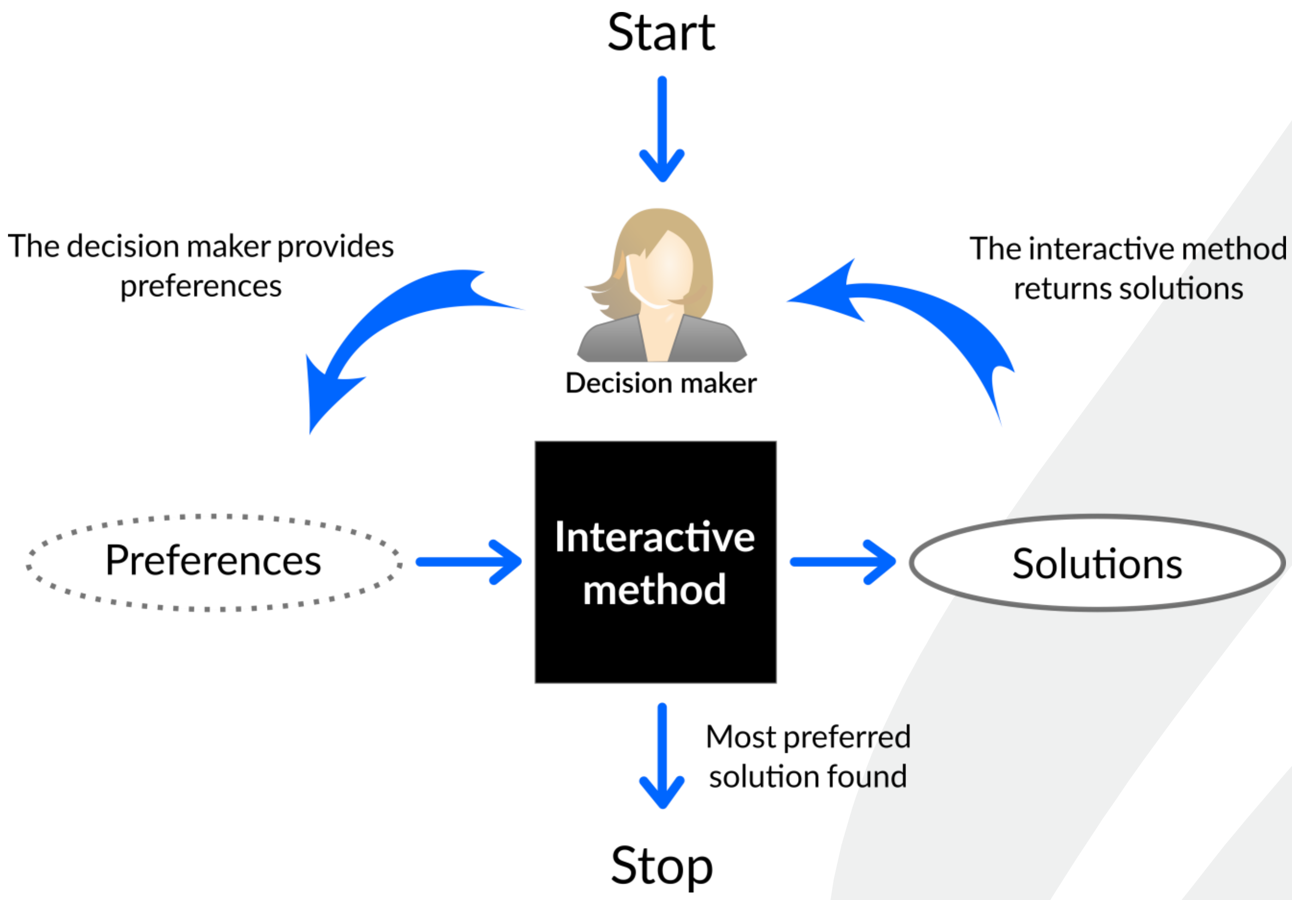
Multiobjective optimization methods

- 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

wood_volume (max)

Previous preference: 2174.23

Improve until

4192.10

profit_from_cutting (max)

Previous preference: 96258.94

Improve until

124302.89

stored_carbon (max)

Previous preference: 22477.69

Worsen until

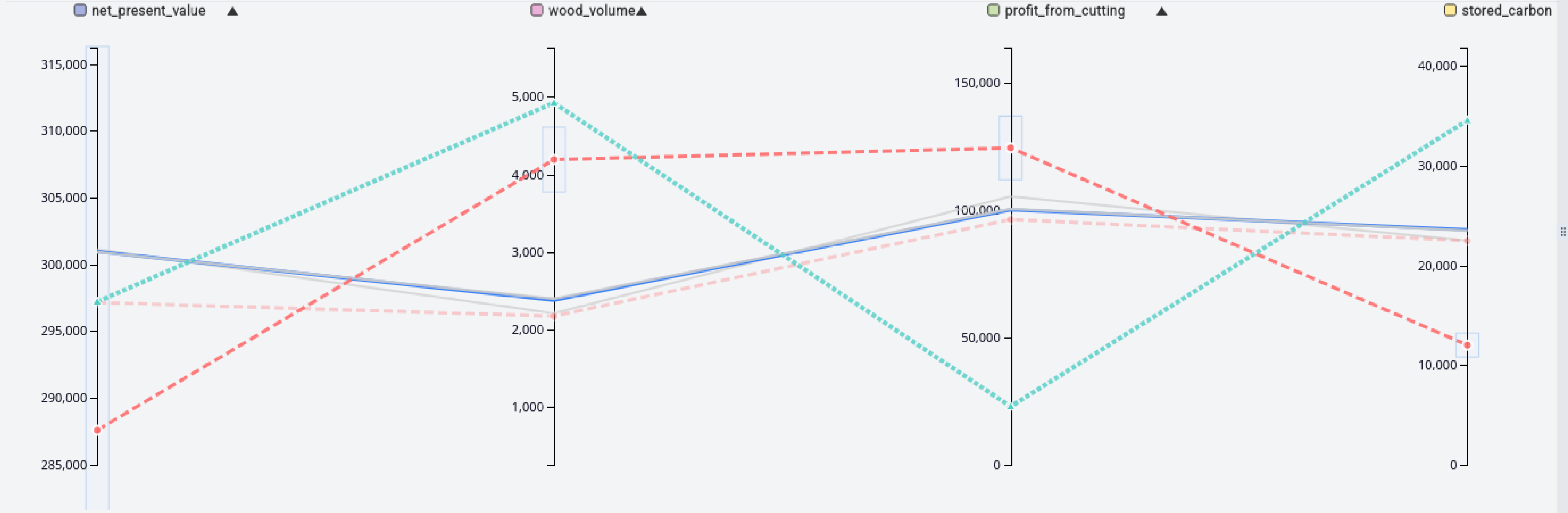
12013.94

Iterate

Solution Explorer

Visualization

Parallel Coordinates | Bar Chart

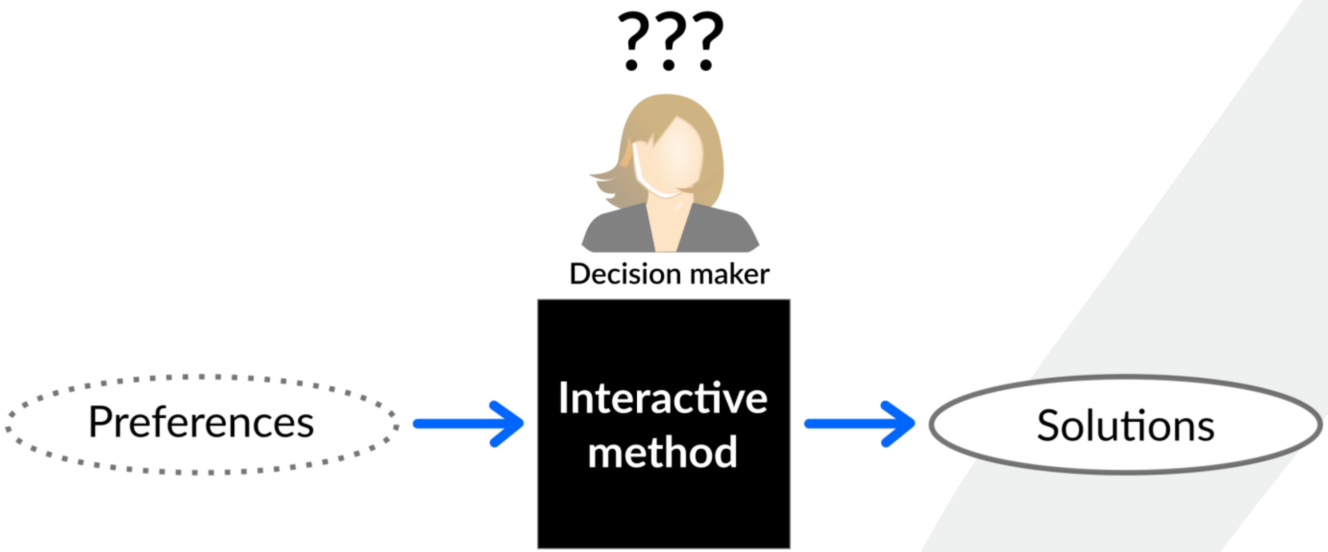


Current solutions

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

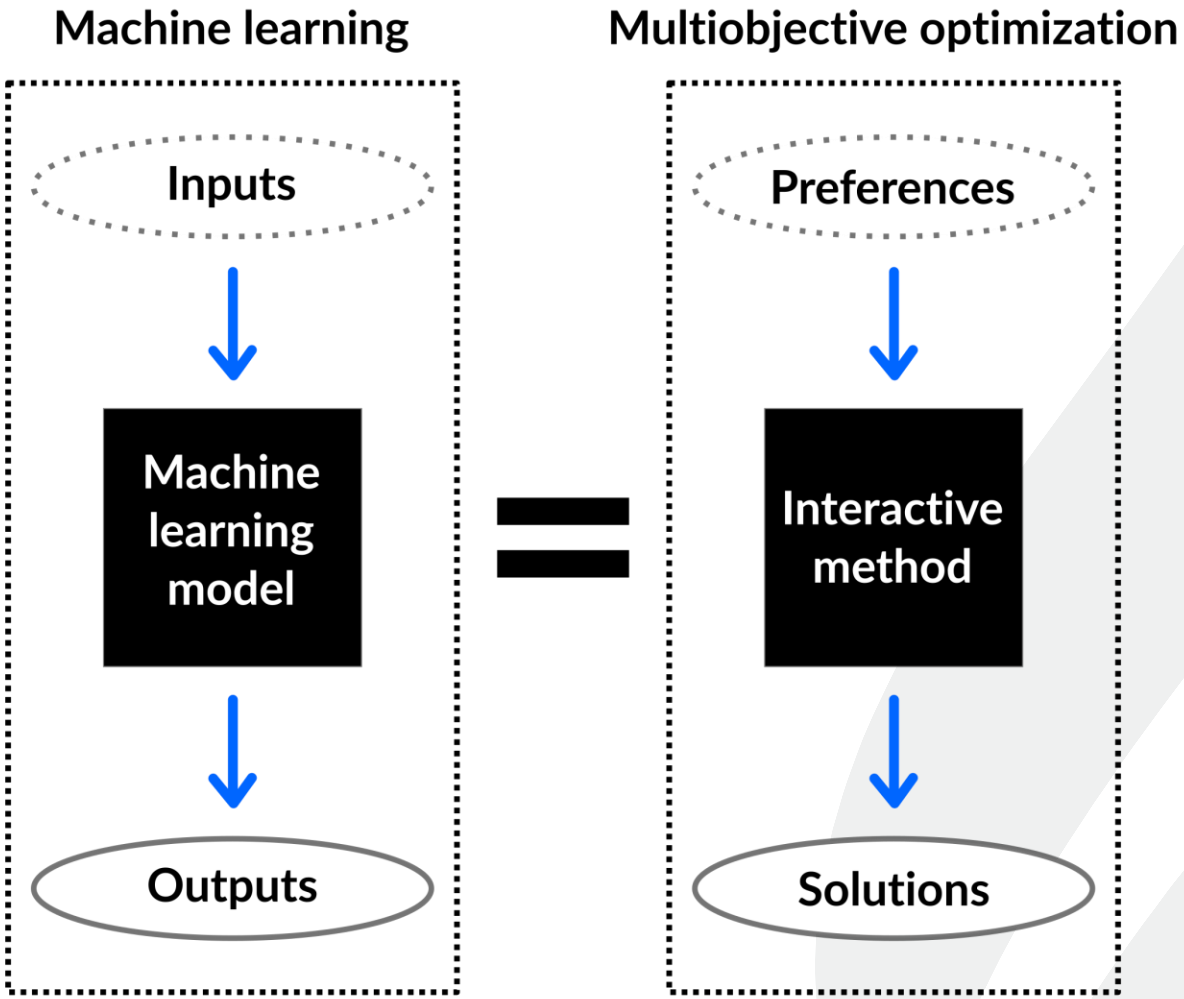
- Argument: **Interactive methods are opaque boxes from the perspective of a decision maker**.
- **Decision makers lack support** when utilizing interactive methods:
  - E.g., **how do my preferences affect the solutions found?**
- **Machine learning models are often also opaque boxes**, which is an issue addressed 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.

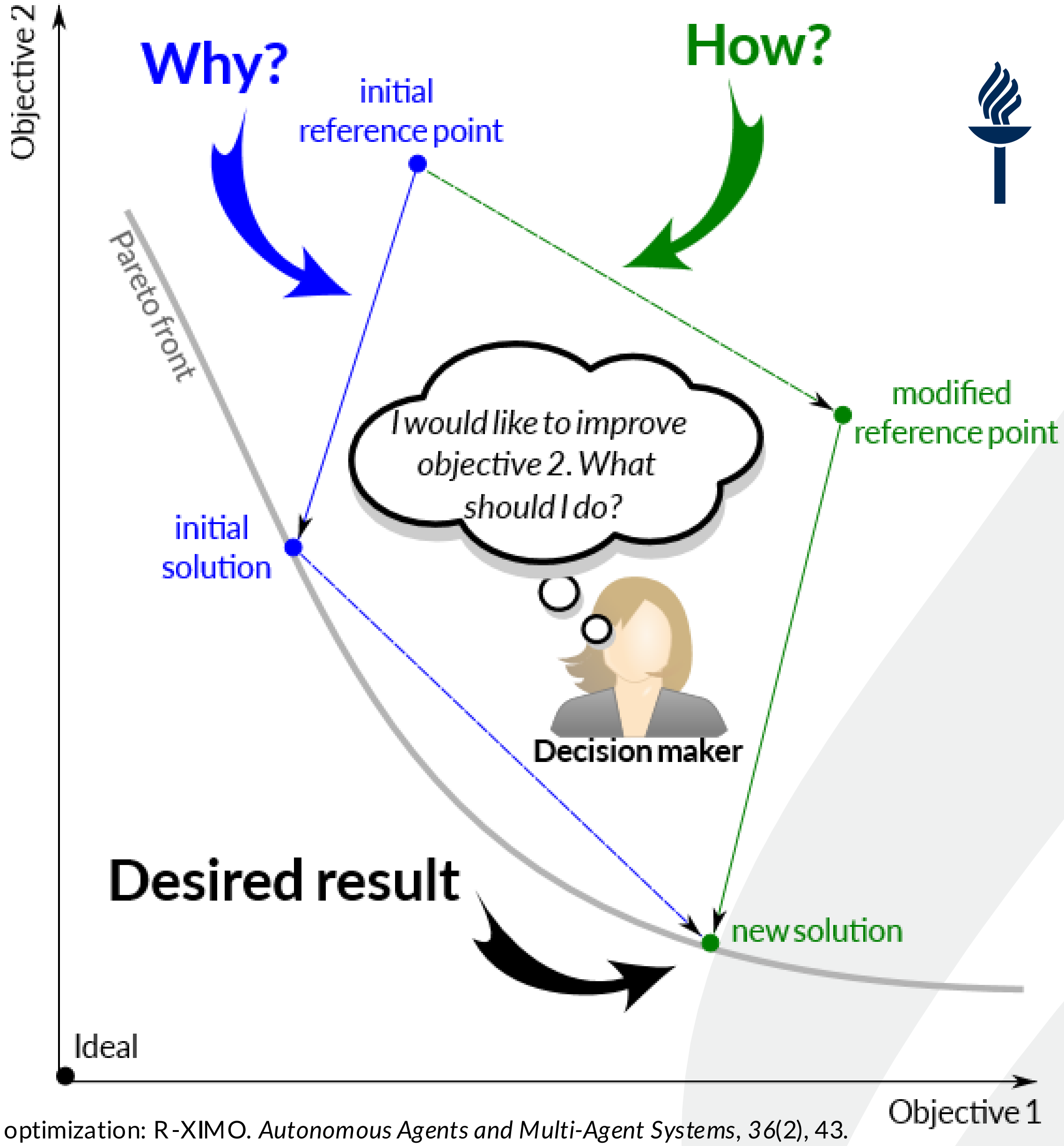
The key-idea in our work

- **Existing methods for explainability** in explainable artificial intelligence could be applied to interactive methods as well!
- **The fundamental problem is the same**: to understand the results of an opaque box based on its inputs.
- But rather than trying to de-bias a machine learning model, or similar, we can take advantage of the explanations to modify the inputs so that we can find a more desirable output for the decision maker. **This is the key difference.**



The R-XIMO method

- 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.



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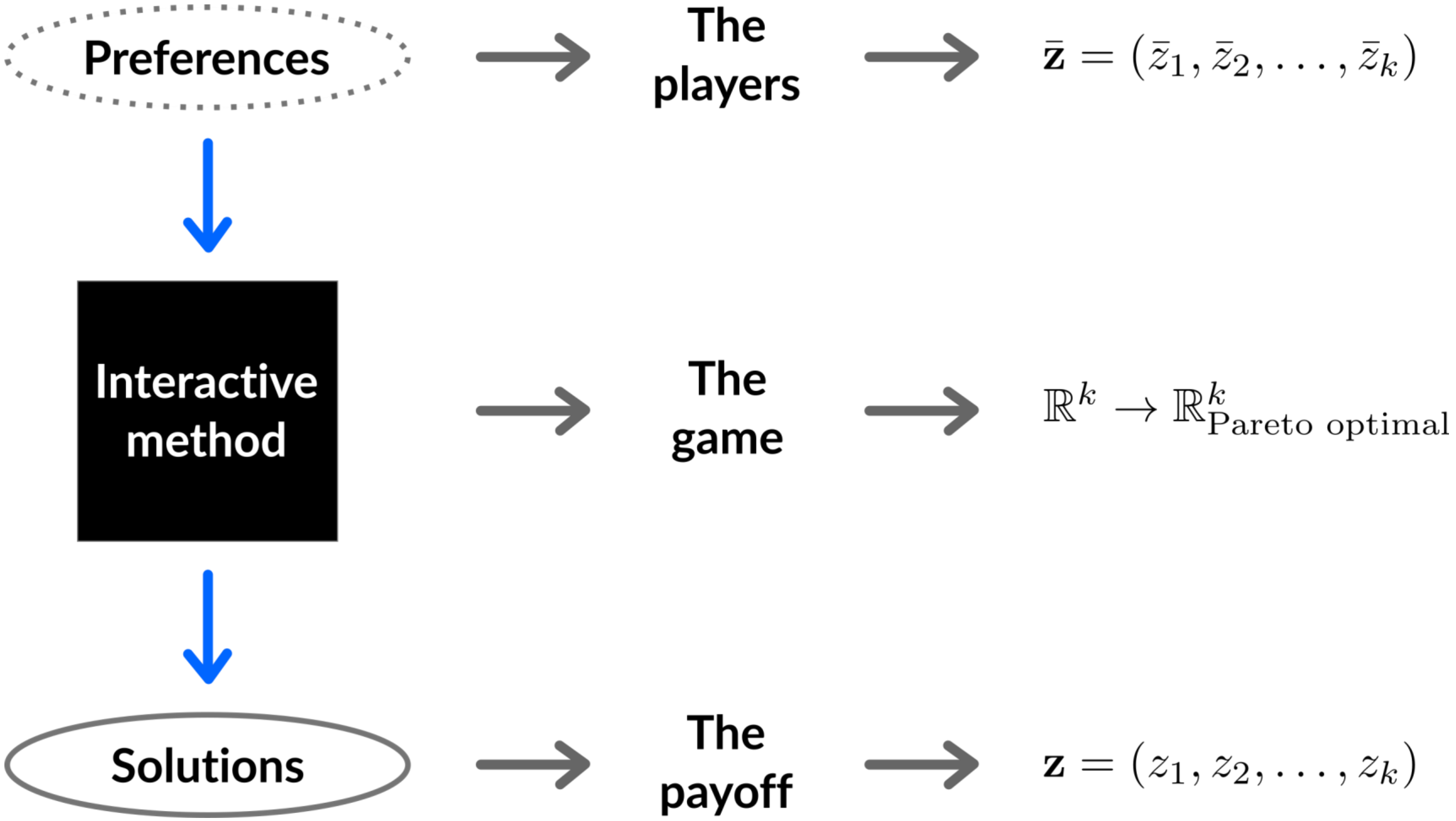
Lundberg, S. M., & Lee, S.-I. 2017. *A unified approach to interpreting model predictions*. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), Advances in Neural Information Processing Systems 30 (pp. 4765–4774).

SHAP values

- Based on **Shapley values,** an idea originally developed in the field of **game theory.**
- Considers an ***n*-player game** and **quantifies the contribution of each player** to the payoff.
- Applied to machine learning:
  - the **model** plays the role of **the n-player game**;
  - **inputs** play the role of the **players**; and
  - **outputs** play the role of the **payoff**.
- SHAP values is a **computationally efficient framework to approximate** Shapley values.

Shapley, L. S. 1953. A value for N-person games. Contributions to the Theory of Games 2 (28), 307–317.
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).

In case of R-XIMO



Utilizing SHAP values in R-XIMO

- Computing the SHAP values for **a specific input (a reference point)** results in a **matrix consisting of SHAP values**:

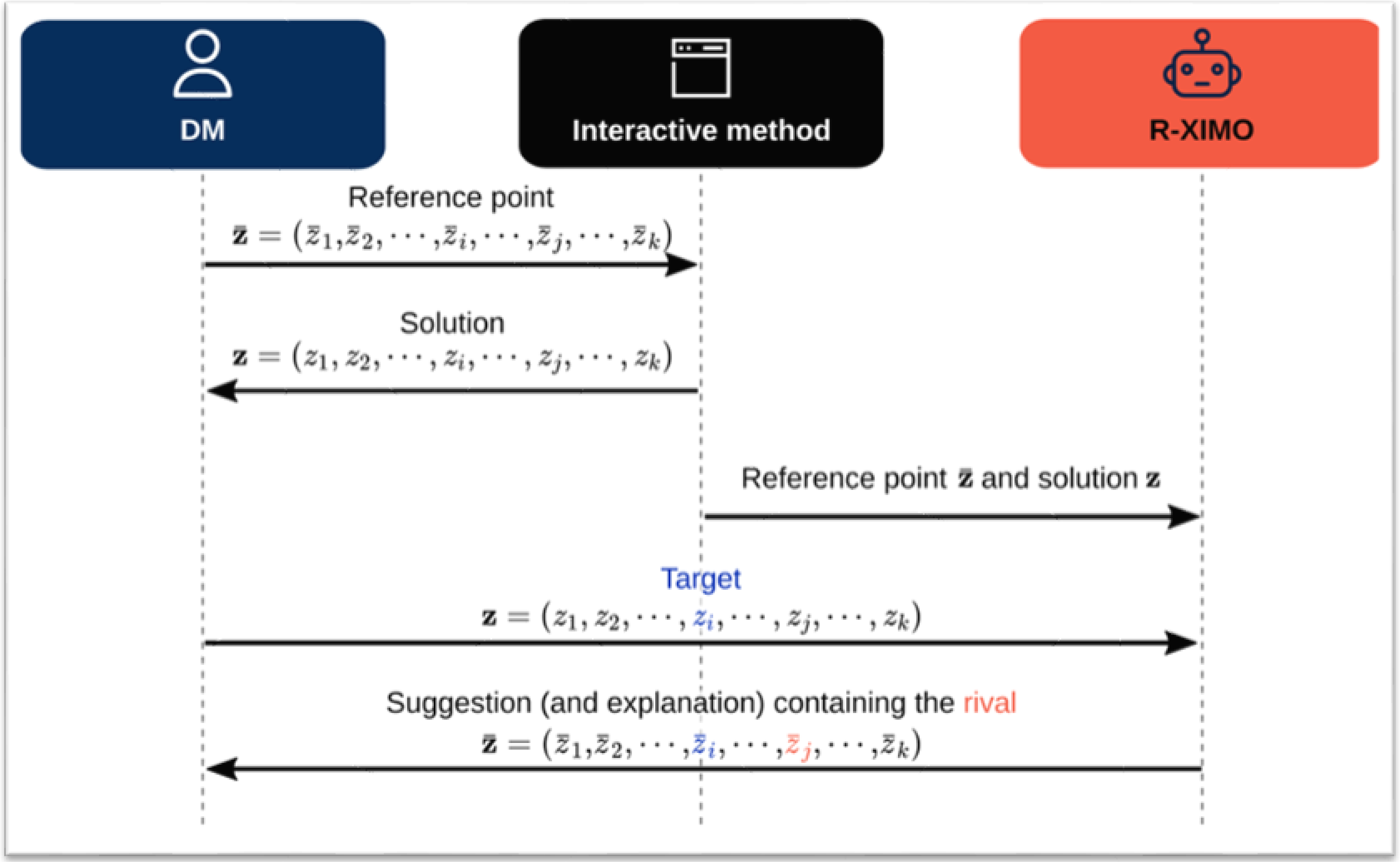
$$\Phi = \begin{pmatrix} \phi_{11}, & \phi_{12}, & \dots, & \phi_{1k} \\ \phi_{21}, & \phi_{22}, & \dots, & \phi_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ \phi_{k1}, & \phi_{k2}, & \dots, & \phi_{kk} \end{pmatrix}$$

- A **component ϕ_{ij} then expresses the average effect** of the j^{th} component in the reference point to the i^{th} component in the solution:
  - a **positive value** means an **increasing average effect**;
  - a **negative value** means a **decreasing average effect**; and
  - a **zero value** means **no effect** on average.

Utilizing SHAP values in R-XIMO

- Once the SHAP values have been computed for a reference point, the **decision maker can express which objective function they would like to improve** in the next iteration.
  - This objective functions is designed as the **target**.
- Utilizing the SHAP values, we can identify the component in **the reference point which had the greatest impairing effect on the target.**
  - The respective objective function is then designed as the **rival**.
- We may then **suggest to the decision maker to consider a trade-off between the target and the rival** when formulating the next reference point.
- **The SHAP values can also themselves be used to build explanations** on how, on average, the reference point has affected the solutions computed in each iteration of the interactive method.

Utilizing SHAP values



Tests and case study

- The R-XIMO method was **tested statistically** and **applied to a case study** in Finnish forestry management.
- Although SHAP values convey average effect, the statistical **tests show that the suggestions clearly work most of the time** for the tested problems and methods.
- The case study was really encouraging as **the decision maker felt the suggestions to be helpful** but did not find the general explanations derived from SHAP values to be much of use (too verbose!).

Future directions

- Consider interactive methods based on **other types of preference information** than the reference point.
- Consider **more than just one target/rival**.
- Can we produce **better explanations**? How? How to convey them best?
- Can **we improve the accuracy of the suggestions/explanations**?
- How to better **convey the suggestions**? (paper in works on how to visualize these!)
- How to **integrate into a decision-support system**? (paper in the works on how to implement the idea in a multi-agent system!)
- How to **measure the usefulness and impact** of explanations/suggestions in multiobjective optimization in general?
- Much more…

Conclusions

- The R-XIMO method was developed to address **the lack of support decision makers can face when providing preference information** in reference point –based interactive multiobjective optimization methods.
- Addresses **real needs decision makers face** when utilizing interactive methods.
- A simple, novel, and powerful example, on **how ideas from other fields** of research can be adapted and utilized in new ways in multiobjective optimization.
- The R-XIMO method **is an important step in establishing the emerging field of explainable multiobjective optimization**.
- The work has sparked **further research interest and applications to support real-life decision-making**, which can lead to a better quality in the decisions decision makers make.
- The R-XIMO method is **available as open-source software** in the DESDEO framework.

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). Singapore: Springer Nature Singapore.
Corrente, S., Greco, S., Matarazzo, B., & Słowiński, R. 2024. Explainable interactive evolutionary multiobjective optimization. *Omega*, *122*, 102925.
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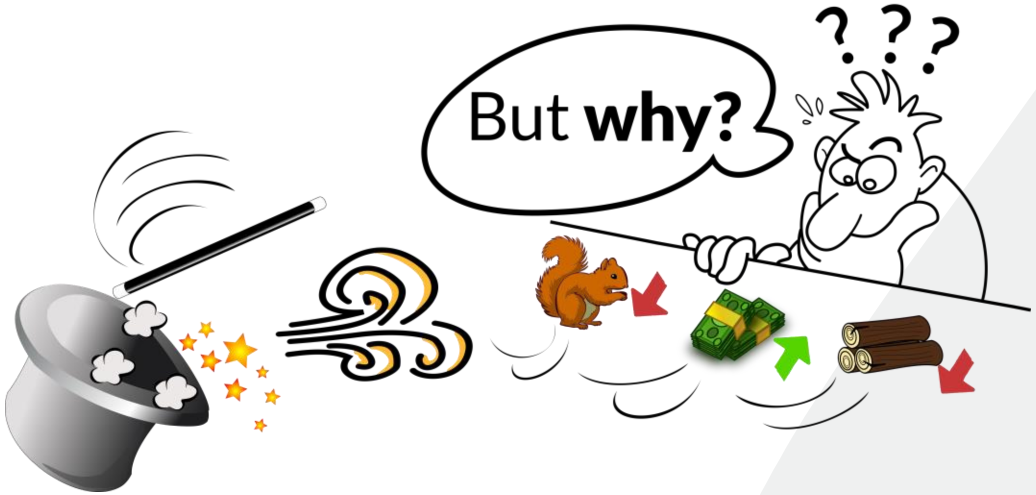
Q&A + Resources

https://linktr.ee/gialmisi



Research Council of Finland

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