Explainability and its potential in interactive multiobjective optimization

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Overview

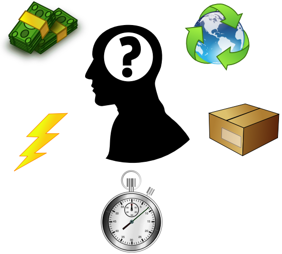
Motivation

Multiobjective optimization

- Real-life problems often consist of multiple conflicting objectives.
- These problems have many compromise, non-comparable solutions with various trade-offs.
- A domain expert, known as the decision maker, is needed to find the *best* solution.
- The decision maker can provide preferences, which are used to find the best solution.

Multiobjective optimization

- Multiobjective optimization methods support the decision maker in finding the best solution.
- The solution is then used in real-life decision-making.
- Often decision makers lack support in providing preferences.
- Can the decison maker *trust* the solution found? Can the solution be *justified* in any way?



Explainability and multiobjective optimization

- Could we make multiobjective optimization methods explainable?
- **Idea:** borrow exisiting techniques from explainable artificial intelligence (XAI).
- We will explore a new paradigm: explainable (interactive) multiobjectice optimization.

Explainable multiobjective optimization

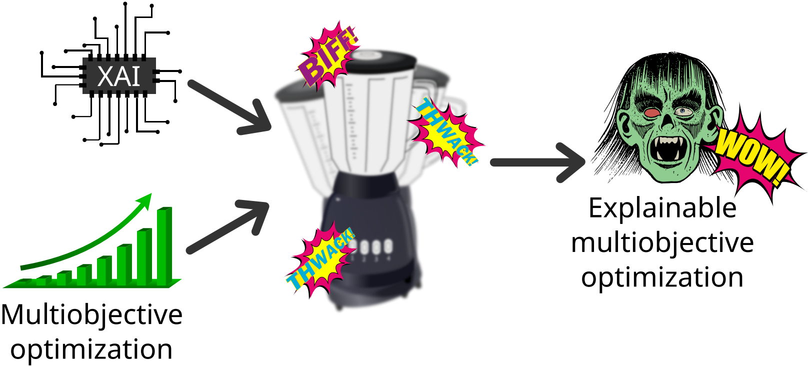


Figure: The main theme of this presentation and the main theme of my PhD.

Background

Multiobjective optimization problems

- A multiobjective optimization problem has many conflicting objectives, which are to be optimized simultaneously[1].

Multiobjective optimization problem

A multiobjective optimization problem can be defined as

$$\min F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x})), \quad (1)$$

where $f_1 \dots f_i$, $i \in [1, k]$ are objective functions and $\mathbf{x}$ is a decision variable vector. The vectors $\mathbf{x}$ can be subject to both **box-constraints** and **function constraints**. Feasible $\mathbf{x}$ belong to the *feasible variable space* S or $\mathbf{x} \in S$.

[1] Kaisa Miettinen. *Nonlinear multiobjective optimization*. Boston: Kluwer Academic Publishers, 1999.

Box-constraints

$$x_i^{\text{low}} <= x_i <= x_i^{\text{high}}, x_i \in \mathbf{x} \tag{2}$$

Function constraints

$$\begin{aligned} g(\mathbf{x}) - \delta_g &> 0 \\ h(\mathbf{x}) - \delta_h &= 0 \\ \delta_g, \delta_h &\in \mathrm{R} \end{aligned} \tag{3}$$

- In (2) x_i^{low} and x_i^{high} are the lower and higher limits for the ith element in $\mathbf{x}$, respectively.
- In (3) δ_g and δ_h are scalar values which should be exceeded or be exactly matched by $g(\mathbf{x})$ and $h(\mathbf{x})$, respectively.

More definitions

Pareto optimality

A solution $\mathbf{x}^* \in S$ is said to be Pareto optimal if, and only if, there does not exist any other solution $x \in S$ such that $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*) \, \forall i \in [1, k]$ and $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$ for at least some $i \in [1, k]$.

Objective vector

An objective vector $\mathbf{z}$ is the image of the solution $\mathbf{x} \in S$ such that $F(\mathbf{x}) = \mathbf{z}$. The set of objective vectors Z consists of all the images $\mathbf{z}$.

Pareto front

The Pareto front Z^{Pareto} consists of the images of all the Pareto optimal solutions. The set of Pareto optimal solutions is the Pareto optimal solution set.

More definitions

Ideal and nadir points

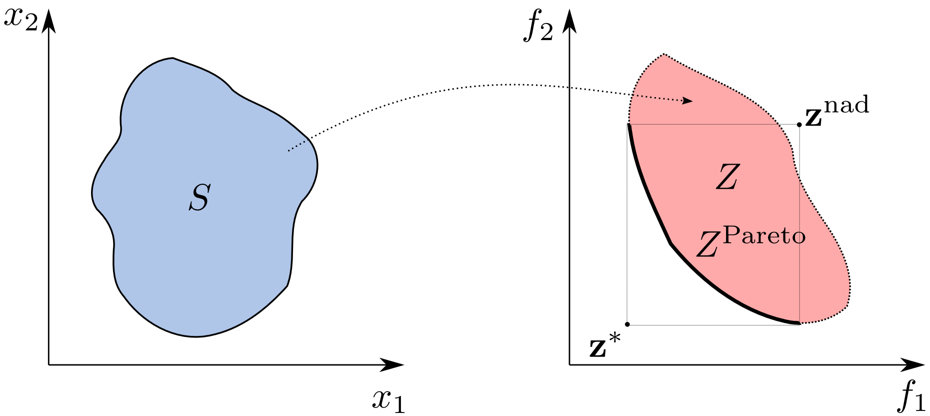
The ideal $\mathbf{z}^*$ and nadir $\mathbf{z}^{\text{nad}}$ points represent the best (lowest) and worst (highest) values of the objective function values on the Pareto front, respectively.

Reference point

A reference point $\bar{\mathbf{z}}$ is a vector of aspiration levels $\bar{z}_i, i = 1...k$. The reference point can be provided by a decision maker, in which case, the reference point represents the decision maker's preferences.

Important concepts graphically

$$\min_{\mathbf{x}\in S}\{f_1(\mathbf{x}), f_2(\mathbf{x})\}$$



Scalarization

- Multiobjective optimization problems can be scalarized using a scalarizing function $s : \mathrm{R}^k \to \mathrm{R}$.

Scalarized problem

$$\begin{aligned} \min \quad & s(\mathbf{F}(\mathbf{x}); \mathbf{p}) \\ \text{subject to} \quad & \mathbf{x} \in S, \end{aligned} \tag{4}$$

where **p** is a set of additional parameters given to the scalarizing function .

- Scalarizing functions usually have some desiderable properties, such as guaranteeing (weak) Pareto optimality of the solution found.

Scalarization

- Scalarizing function used in STOM[2]:

STOM

$$\text{STOM}(\mathbf{F};\bar{\mathbf{z}},\mathbf{z}^{**}) = \min_{\mathbf{x}\in S}\ \max_{i=1,\dots,k}\left[\frac{f_i(\mathbf{x}) - z_i^{**}}{\bar{z}_i - z_i^{**}}\right] + \rho\sum_{i=1}^{k}\frac{f_i(\mathbf{x})}{\bar{z}_i - z_i^{**}}, \tag{5}$$

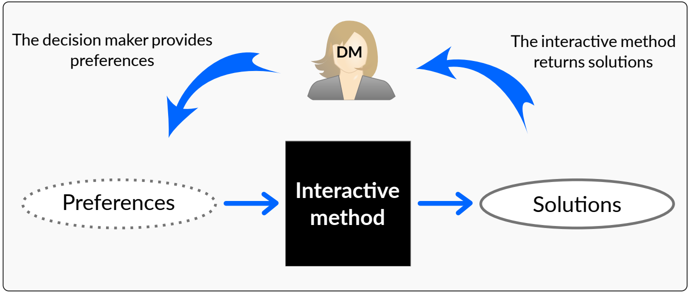
where $\mathbf{z}^{**} = (z_1^* - \delta, z_2^* - \delta, \dots, z_k^* - \delta)$ is an utopian point with $\delta \in \mathrm{R}^+$, and $\rho \in \mathrm{R}^+$.

- A reference point $\bar{\mathbf{z}}$ can be incorporated in scalarizing functions.
- More examples of scalarizing functions in[3].

[2] Hirotaka Nakayama. "Aspiration Level Approach to Interactive Multi-Objective Programming and Its Applications". In: *Advances in Multicriteria Analysis*. Ed. by Panos M. Pardalos, Yannis Siskos, and Constantin Zopounidis. Boston, MA: Springer, 1995, pp. 147–174. ISBN: 978-1-4757-2383-0. DOI: 10.1007/978-1-4757-2383-0_10.

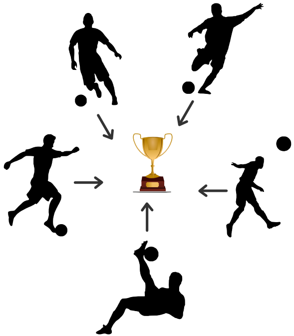
[3] Kaisa Miettinen and Marko M. Mäkelä. "On scalarizing functions in multiobjective optimization". In: *OR Spectrum* 24.2 (2002), pp. 193–213. DOI: 10.1007/s00291-001-0092-9.

- A decision maker (DM) iteratively provides preference information as a reference point.
    - New solution(s) are computed for the problem after each iteration.
- We focus on reference point based interactive methods.



Shapley values and SHAP

- Shapley values[4] is a game-theoretical concept.
- Shapley values are a way to quantify the contribution of each player to the payoff in an *n*-player game.



[4] Lloyd S Shapley. *17. A value for n-person games*. Santa Monica: RAND Corporation, 1951.

Shapley values and SHAP

- Shapley values have been used in the field of **explainable artificial intelligence**[5] to explain black-box machine learning models.
- Because of the nature how Shapley values are computed (remove player from game, compute partial payoff) makes them hard to be used with arbitrary machine learning models.
- Instead, we may rely on SHAP values[6], particularly kernel SHAP, which are computationally less expensive to compute than pure Shapley values.

[5] David Gunning et al. "XAI–Explainable artificial intelligence". In: *Science Robotics* 4.37 (2019). DOI: 10.1126/scirobotics.aay7120.

[6] Scott M Lundberg and Su-In Lee. "A Unified Approach to Interpreting Model Predictions". In: *Advances in Neural Information Processing Systems 30*. Ed. by I. Guyon et al. California: Curran Associates, Inc., 2017, pp. 4765–4774.

So?

"I am very confused Giovanni, what are you getting at?"

Explainable interactive multiobjective optimization

Explainable interactive multiobjective optimization

Could we somehow utilize SHAP values to probe interactive multiobjective optimization methods and get insight on how the preferences provided (the reference point) has affected the computes solution(s)?

YES!

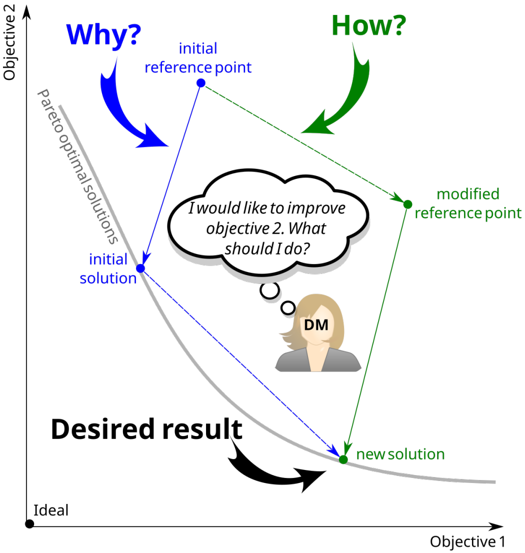
Explainable interactive multiobjective optimization

- A new method, R-XIMO, that can provide *explanations* on how reference points have affected computed solutions.
- From the explanations, we can derive *suggestions*.
- Suggestions to support the decision maker in providing new preferences in the next iteration.
- R-XIMO can be used with any multiobjective optimization method that takes as its input a reference point and computes a solution.

Explainable interactive multiobjective optimization

- A decision maker can express a wish to improve some objective function in a solution.
- A suggestion on how to modify the current reference point to achieve the desired improvement is provided.
- E.g., the decision maker wishes to improve objective 1, R-XIMO suggest that the decision maker should improve objective 1 in the reference point and impair objective 3.
    - We know this by computing SHAP values.

Explainable interactive multiobjective optimization



Explainable interactive multiobjective optimization

Decision maker: I would like to improve the first objective.

Example explanation:

Objective 1 was most improved in the solution by the second component and most impaired by the third component in the reference point.

Example suggestion:

Try improving the first[7] *component and impairing the third component in the reference point.*

[7] We always improve the component that matches the objective the decision maker wishes to improve.

Tests and results

Numerical experiment

- We utilized three reference point based interactive methods that consisted of minimizing different scalarizing functions (5).
- We tested R-XIMO with two real-life multiobjective optimization problems (3 and 5 objectives).
  - Check what happens if we follow the suggestion provided by R-XIMO fully, partly, or not at all, and see if we were successful in improving the desired objective and how much it improved.
  - We did the above many times and got statistical data.

Results of numerical experiment

Some key finding based on the numerical tests:

- It is best to follow the suggestion provided by R-XIMO.
- Even only partly following the suggestion had some value.
- R-XIMO seems to work just as well for different scalarizing functions.

Case study

- Piloted the suggestions and explanations generated by R-XIMO with a human decision maker.
- Problem in Finnish forest management with three objectives.
- The decision maker was a domain expert in the field of forest management.
- The decision maker solved the problem twice.

Case study results

- The suggestions were found to be useful by our human decision maker in the case study.
- The decision maker thought that R-XIMO supported them in reaching a satisfying solution in less iterations than without.
- However, the acutal explanations where too complicated and the decision maker did not want to read them.

Paper!

We have a paper conditionally accepted for publication in a special issue on multi-objective decision making in Autonomous Agents and Multi-Agent Systems.[8] Our paper is titled:

"R-XIMO: Towards Explainable Interactive Multiobjective Optimizaton"

[8] https://www.springer.com/journal/10458/updates/18060632

What next?

What next?

- With our work, we have taken an important step towards a new paradigm in (interactive) multiobjective optimization: **Explainable Interactive Multiobjective optimization** or **XIMO**.
- Took inspiration from what has been done in the field of explainable artificial intelligence
- Novel approaches tailored especially to multiobjective optimization probably needed.

Honorable mentions

- Explainability in multiobjective optimization is still very much in its incubation stage, but cracks in the shell have appeared outside our current work as well, especially in the context of evolutionary multiobjective optimization[9][10][11][12][13].

[9] Jinkun Wang et al. "Diversified recommendation incorporating item content information based on MOEA/D". In: *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE. 2016, pp. 688–696. DOI: 10.1109/HICSS.2016.91.

[10] Roykrong Sukkerd, Reid Simmons, and David Garlan. "Toward explainable multi-objective probabilistic planning". In: *2018 IEEE/ACM 4th International Workshop on Software Engineering for Smart Cyber-Physical Systems (SEsCPS)*. IEEE. 2018, pp. 19–25. DOI: 10.1145/3196478.3196488.

[11] Huixin Zhan and Yongcan Cao. "Relationship Explainable Multi-objective Optimization Via Vector Value Function Based Reinforcement Learning". In: *arXiv preprint arXiv:1910.01919* (2019).

[12] Giovanni Misitano. "Interactively Learning the Preferences of a Decision Maker in Multi-objective Optimization Utilizing Belief-rules". In: *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE. 2020, pp. 133–140. DOI: 10.1109/SSCI47803.2020.9308316.

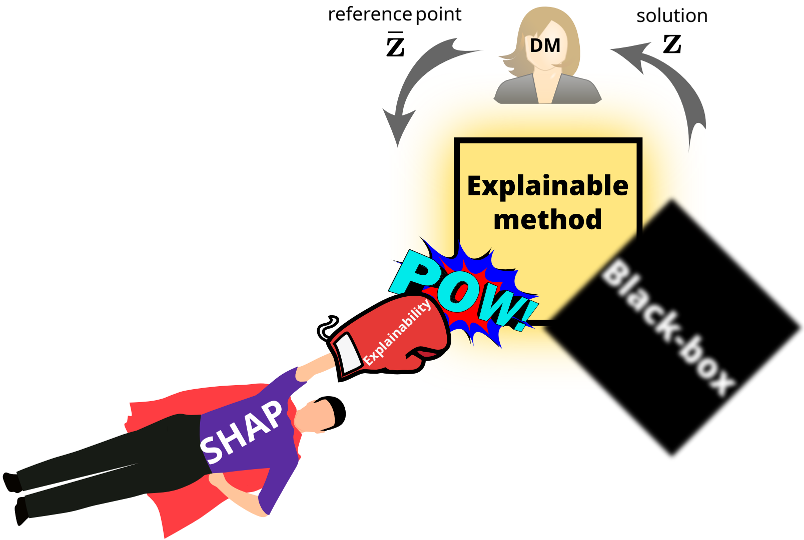
[13] Salvatore Corrente et al. "Explainable Interactive Evolutionary Multiobjective Optimization". In: *Available at SSRN 3792994* (2021).

Conclusions

Conclusions

- Explainability is an exciting and important concept to be studied in the context of and applied to multiobjective optimization.
- Makes life of decision makers easier.
- Very much an unexplored area still in the field of multiobjective optimization.
- New and wild ideas are needed!

Conclusions



Appendices

Aknowledgements

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Links and resources

- DESDEO framework[1][2]
- Multiobjective Optimization (research) Group[3]
- Follow me on LinkedIn[4]

[1] https://desdeo.it.jyu.fi

[2] G. Misitano et al. "DESDEO: The Modular and Open Source Framework for Interactive Multiobjective Optimization". In: *IEEE Access* 9 (2021), pp. 148277–148295. DOI: 10.1109/ACCESS.2021.3123825

[3] http://www.mit.jyu.fi/optgroup/

[4] https://linkedin.com/in/misitano

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