

Achievable Goals in Bayesian Multi-Objective Optimization

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We consider multi-objective optimization problems, $\min_{\mathbf{x} \in \mathbb{R}^d} (f_1(\mathbf{x}), \dots, f_m(\mathbf{x}))$, where the functions are expensive to evaluate. In such a context, Bayesian methods relying on Gaussian Processes (GP) [1], adapted to multi-objective problems [2] have allowed to approximate Pareto fronts in a limited number of iterations.

In the current work, we assume that the Pareto front center has already been attained (typically with the approach described in [3]) and that a computational budget remains. The goal is to uncover of a broader central part of the Pareto front: the intersection of it with some region to target, $\mathcal{I}_{\mathbf{R}}$ (see Fig. 1). $\mathcal{I}_{\mathbf{R}}$ has however to be defined carefully: choosing it too wide, i.e. too ambitious with regard to the remaining budget, will lead to a non converged approximation front. Conversely, a suboptimal diversity of Pareto optimal solutions will be obtained if choosing a too narrow area.

The GPs allow to forecast the future behavior of the algorithm: they are used in lieu of the true functions to anticipate which inputs/outputs will be obtained when targeting growing parts of the Pareto front. Virtual final Pareto fronts corresponding to a possible version of the approximation front at the depletion of the budget are produced for each $\mathcal{I}_{\mathbf{R}}$. A measure of uncertainty is defined and applied to all of them to determine the optimal improvement region $\mathcal{I}_{\mathbf{R}}^*$, balancing the size of the approximation front and the convergence to the Pareto front.

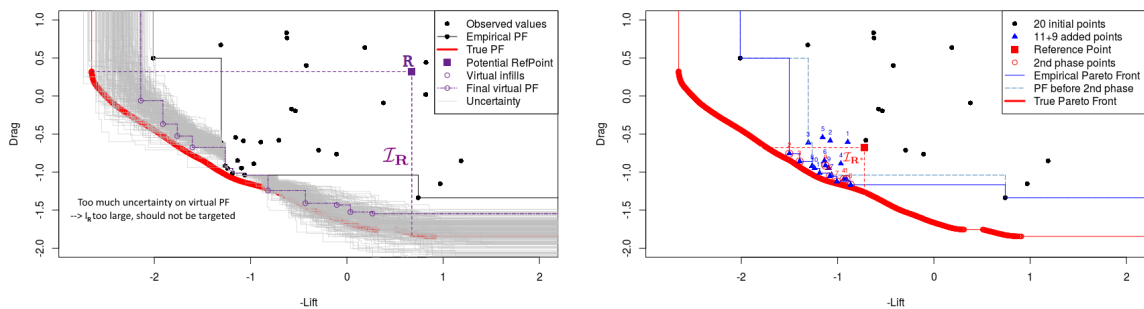


Figure 1: Left: virtual Pareto front (dashed, purple) obtained if targeting $\mathcal{I}_{\mathbf{R}}$ for the 9 remaining iterations. The uncertainty (grey) at the end of the optimization is forecasted to be too large because $\mathcal{I}_{\mathbf{R}}$ is too wide. The optimal improvement region $\mathcal{I}_{\mathbf{R}}^*$ is shown on the right. Good convergence is obtained in this region.

Références

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