

Bayesian Optimization for Min Max Optimization

Dorina Weichert & Alexander Kister

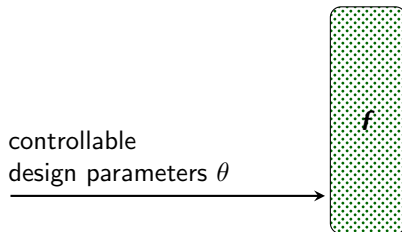
firstname.lastname@iais.fraunhofer.de

Fraunhofer Institute for Intelligent Analysis and Information Systems



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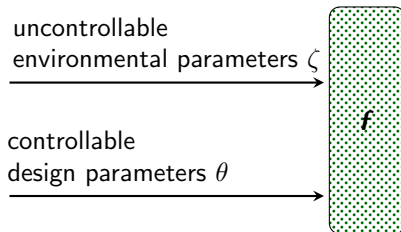
In the lab, engineers search for the optimal controllable design parameters.



Therefore, they have to solve:

$$\min_{\theta \in \Theta} f(\theta). \quad (1)$$

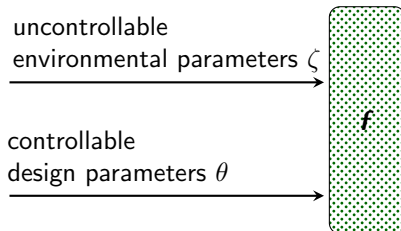
In real life, engineers have to consider the worst-case uncontrollable environmental conditions when designing a product.



Therefore, they have to solve:

$$\min_{\theta \in \Theta} \max_{\zeta \in Z} f(\theta, \zeta). \quad (2)$$

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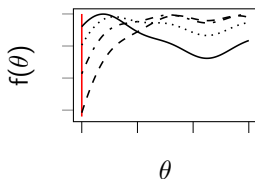
$$\min_{\theta \in \Theta} \max_{\zeta \in Z} f(\theta, \zeta). \quad (3)$$

As function evaluations are costly and there exists enough prior knowledge to construct a surrogate model using a Gaussian Process, we can use Bayesian Optimization [1].

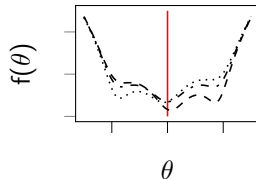
The work on Bayesian Optimization for Min Max Optimization adapts the following acquisition functions:

Our work	Recent approaches
Entropy Search [2] Knowledge Gradient [5]	Expected Improvement [3], [4] GP-UCB [6]–[8]
return candidates that increase the information about the optimum	return candidates that potentially are the optimum

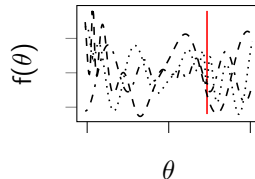
Our test problems:



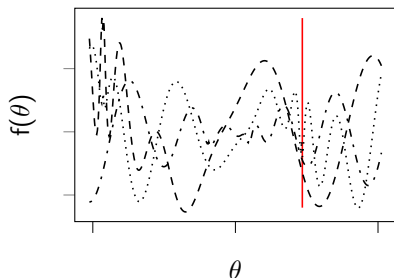
(a) branin*



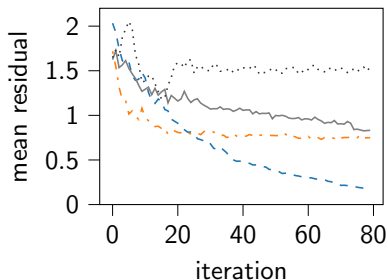
(b) six-hump camel*



(c) eggholder*



(a) eggholder*



(b) mean residuals

Figure 3: Eggholder* problem and corresponding results.

- : Entropy Search, -o-: Knowledge Gradient,
- : Thompson Sampling, ···: GP-UCB

Thank you.

Thank you.

Feel free to contact us: dorina.weichert@iais.fraunhofer.de
alexander.kister@iais.fraunhofer.de

Have a look into our work on
<https://github.com/fraunhofer-iais/MinMaxOpt>

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