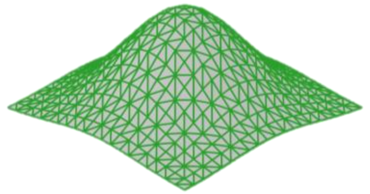
How best to exploit a process model and probability distribution of its parameters to design maximally informative experiments for parameter estimation?

THE CHALLENGE

Parameter uncertainty may cause inaccurate predictions of information content thus suboptimal experiments



$$y = f(x, \theta)$$

Parameter Uncertainty

Process Model

$$\xi^* := \begin{Bmatrix} x_1 & \dots & x_{N_c} \\ p_1 & \dots & p_{N_c} \end{Bmatrix}$$

$$\max_{\xi} \phi(\mathbf{M}(\xi))$$

Optimal Campaign

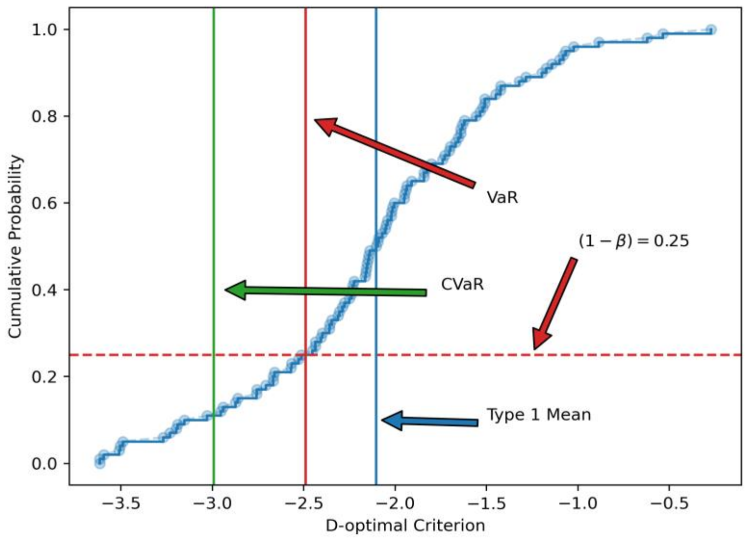
Experimental Design

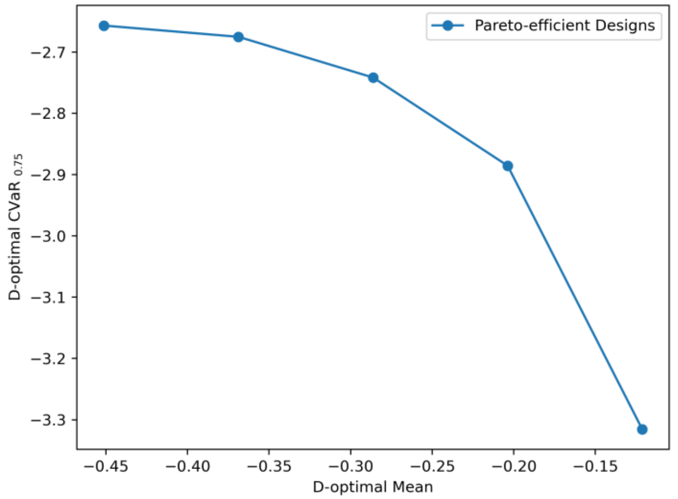
How to improve over existing methods?

METHODOLOGY

Bi-objective Framework

Use **conditional value at risk** as an **additional objective** to the **mean** of the predicted information content





Main Outcome

A family of Pareto-efficient campaigns with maximal predicted mean for a given conditional value at risk suitable for experimenters to pick

CONCLUSIONS

Varying conclusions, depending on case:

Existence of Goldilocks Campaign

Discovered existence of **Goldilocks campaign**

~5 units improvement in conditional value at risk

~1 unit loss in mean

(Relative to the “standard” maximal mean design)

A Unique Pareto-efficient Campaign

In another case we found a unique campaign, optimal **independent** of one’s **attitude** towards uncertainty

Tractable Solution Technique

Tractable for a case adapted from an industrial study with a **dynamic 10-parameter** reaction model, solved within **a day** of computational time