Scalable Combinatorial Bayesian **Optimization with Tractable Models**

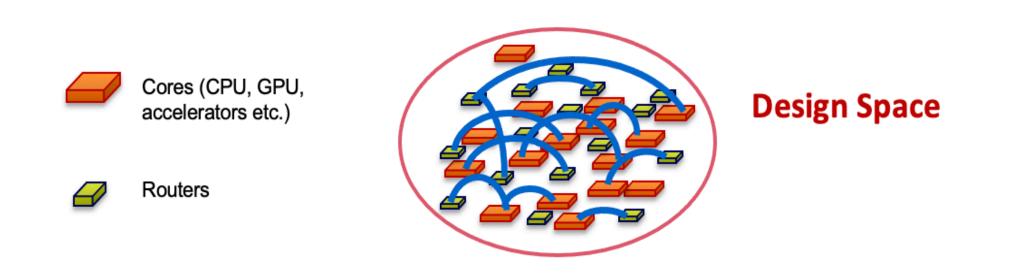
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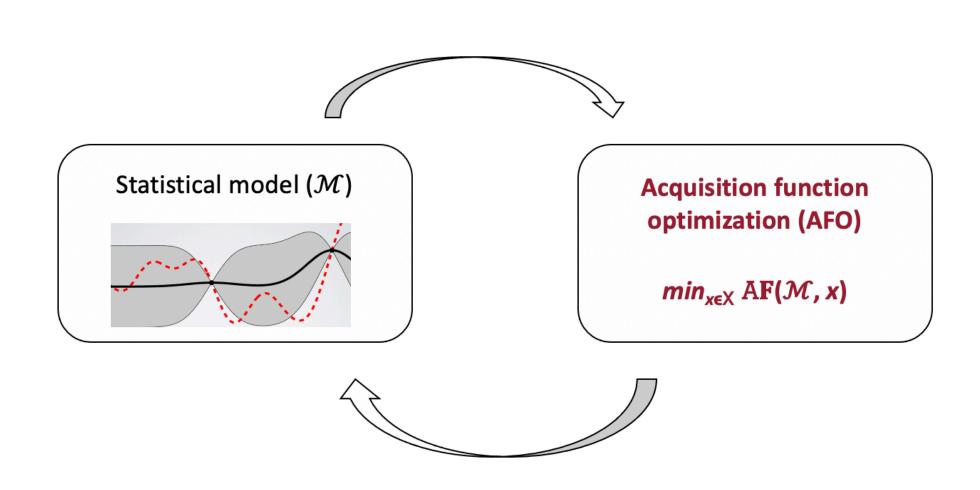
Introduction

- > Problem: Optimize expensive black-box functions over combinatorial spaces (e.g. sets, sequences, graphs)
- Many applications in science and engineering. For example, multi-core chip design, materials design etc.



> Goal: find a structure that optimizes a black-box function by *minimizing the* number of function evaluations

Bayesian Optimization Framework



Balancing challenge: > Key tradeoff between Statistical model and Acquisition function optimization

Parametrized Submodular Relaxation

> Statistical model (Baptista R. And Poloczek M.)

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$$f_{\alpha}(x) = \alpha_0 + \sum_j \alpha_j x_j + \sum_{i,j>i} \alpha_{ij} x_i x_j$$
; $x \in \{0,1\}^n$

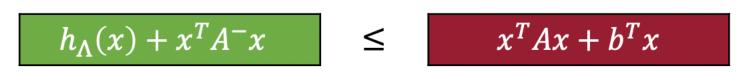
- > Acquisition function : Thompson Sampling
- > Acquisition function optimization (AFO)

$$\min_{\substack{x \in \{0,1\}^n \\ x \in \{0,1\}^n}} f_{\alpha_t}(x)$$

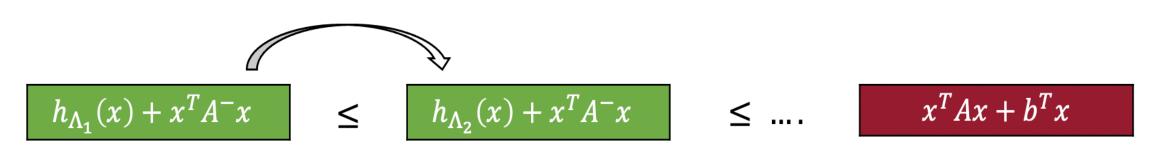
$$\min_{\substack{x \in \{0,1\}^n \\ x \in \{0,1\}^n}} x^T A x + b^T x$$

Binary quadratic programming (BQP) problem

> Construct a Λ-parametrized submodular of the BQP objective



- Relaxation solvable via scalable & efficient minimum graph cut algorithms
- Optimize the relaxation over Λ

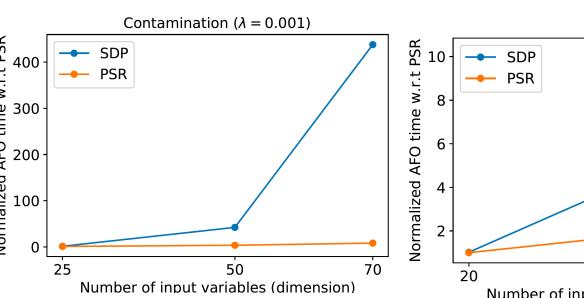


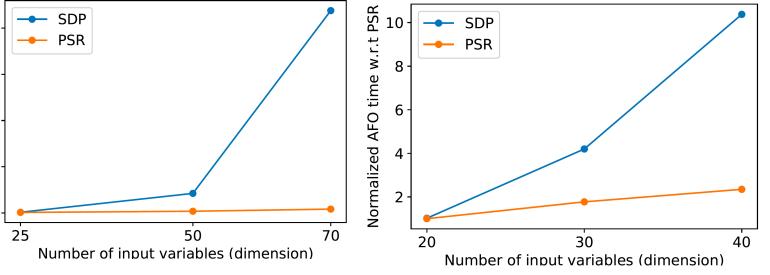
> Inspired by work on prescriptive price optimization (Ito S. and Fujimaki R.)

Experimental Results

Scalability

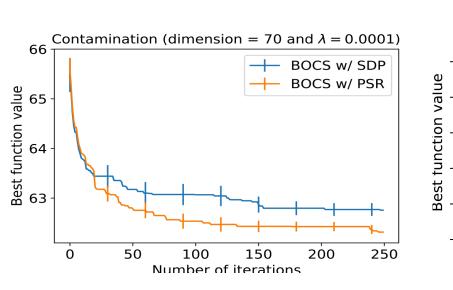
- PSR scales better than SDP

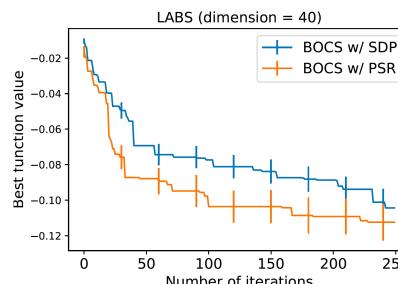




Overall BO performance

PSR finds better AFO solutions





References

Baptista, R. & Poloczek, M.. (2018). Bayesian optimization of combinatorial structures. Proceedings of the 35th International Conference on Machine Learning, in PMLR 80:462-471

Ito, S., & Fujimaki, R. (2016). Large-scale price optimization via network flow. In Advances in Neural Information Processing Systems (pp. 3855-3863).

