

Poster #236:
Tue 6:30pm
@ Pacific Ballroom



A Framework for Bayesian Optimization in Embedded Subspaces

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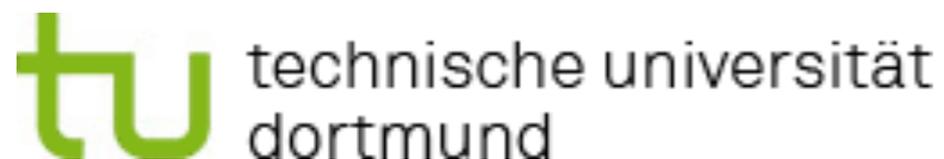
Amin Nayebi

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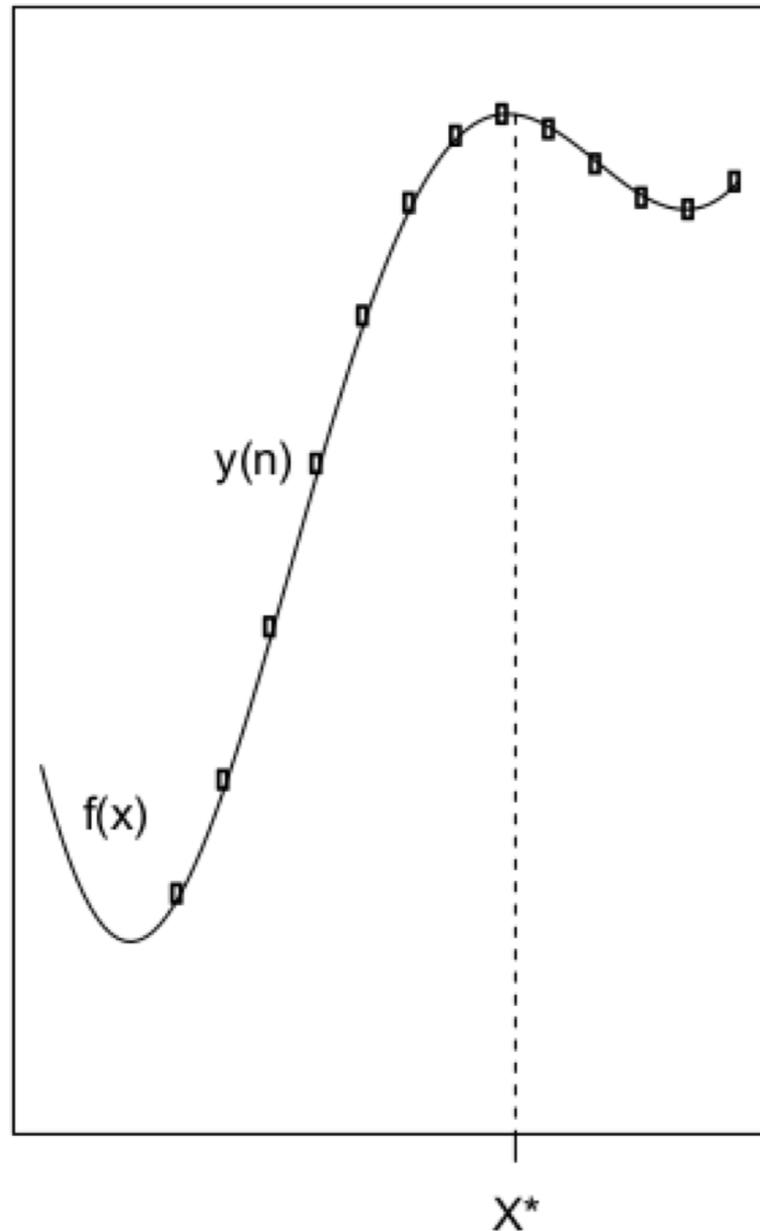
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ICML 2019



Bayesian Global Optimization of Expensive Functions



The Goal

Optimize an expensive-to-evaluate, black-box function $f(x)$ over a feasible region of parameter vectors x specified in D dimensions.

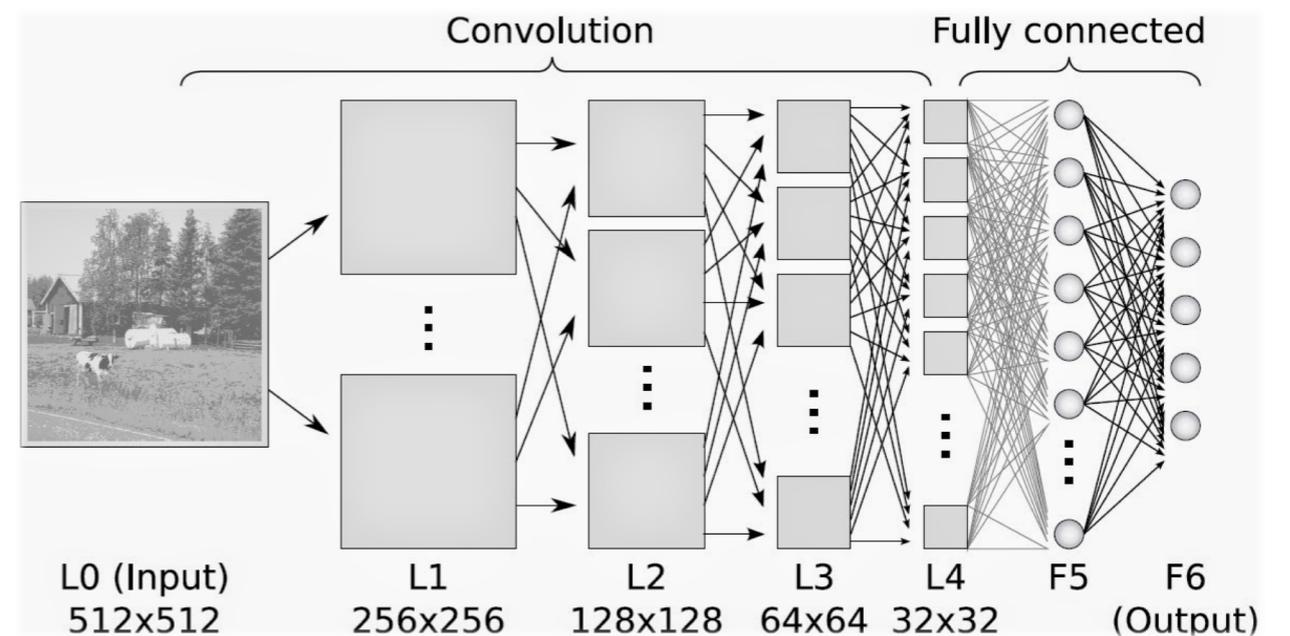
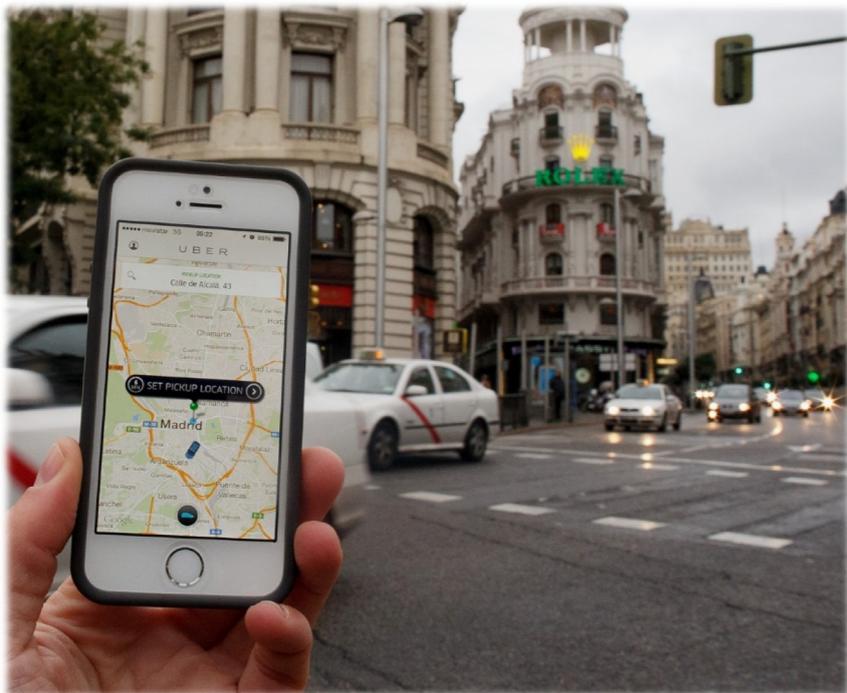
We can access for any x the value of $f(x)$ possibly with some noise, i.e., $f(x) + \epsilon$.

Typically: $D < 20$.

Here: D large, but $f(x)$ depends only on a d -dimensional active subspace.

Applications of high-dim. BO are ubiquitous

- Policy search in Reinforcement Learning
- Aerospace design
- Network architecture search
- Calibration of simulations to observed data
- Control of chemical processes
- Drug design



The HeSBO Framework for high-dimensional BO

Theorem: Active subspace embedding accurately preserves GP-prior (with constant probability)

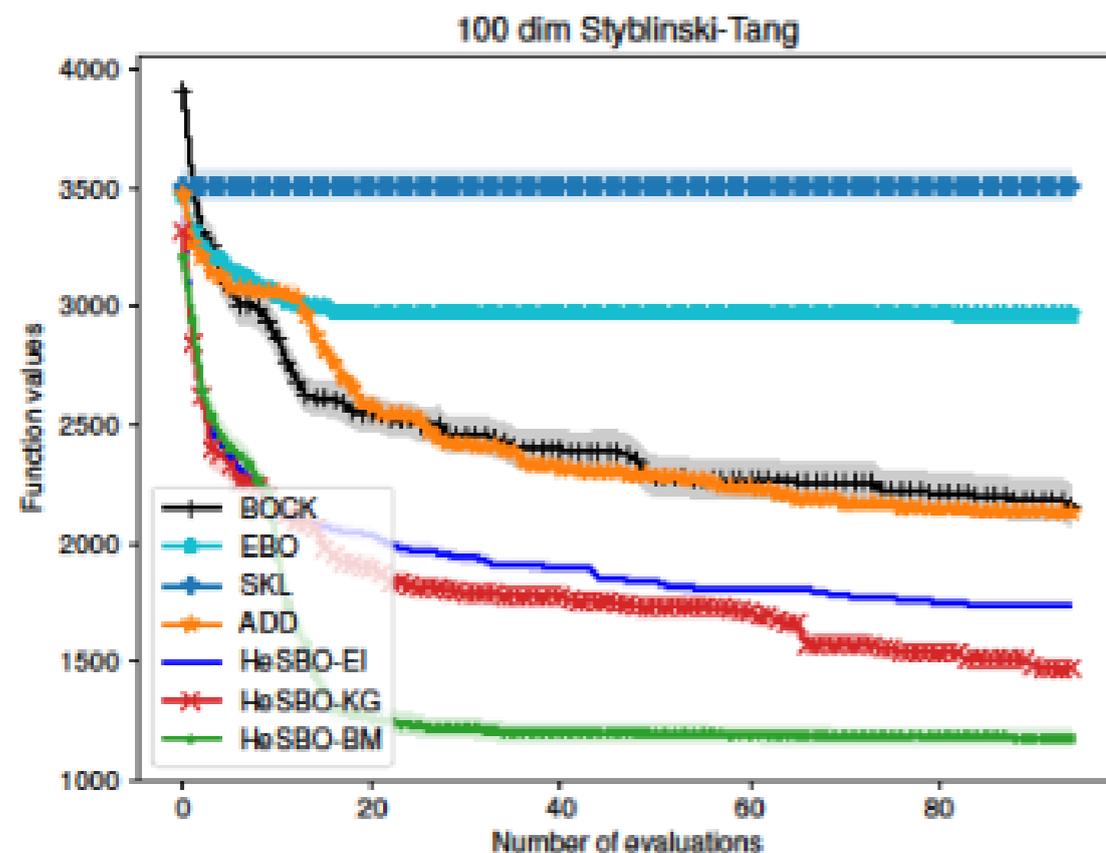
- For a variety of popular kernels: linear, polynomial, (squared) exponential, Matérn.
- The embedding can be combined with many GP-based BO algorithms, e.g., Knowledge Gradient (KG), BLOSSOM, Expected Improvement (EI).

Experiments demonstrate

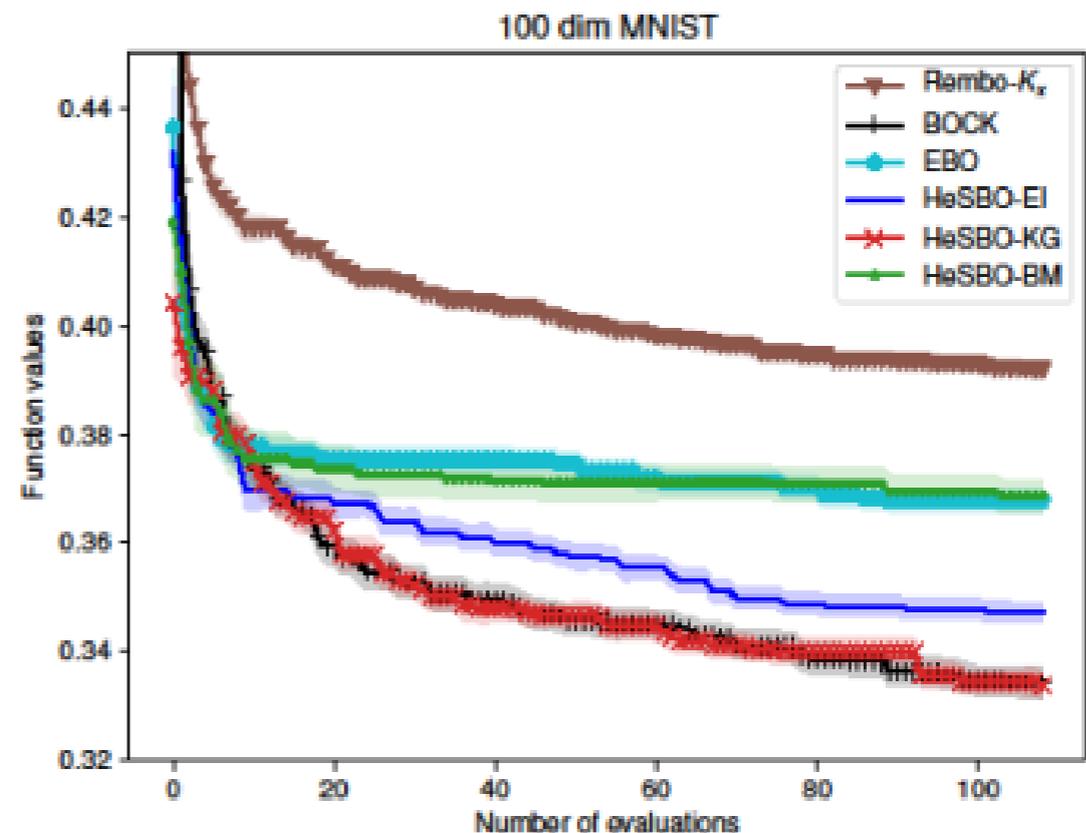
- Efficient and easy to code using hash functions.
- Robustness to ambient dimension D .
- Outperforms state-of-the-art: REMBO, BOCK, EBO, additive BO.

Visit us at the poster presentation!

Great performance even if subspace assumption not met, e.g., for
100-dim. Styblinski-Tang
Function



Neural Network Parameter Search
(Oh, Gavves, and Welling '18)



Visit <https://github.com/aminnayebi/HesBO>
for **HeSBO for KG, BLOSSOM, and EI.**

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