

Imperial College
London



SLAC



Black-Box Optimization with Local Generative Surrogates (L-GSO)

RealML workshop, ICML 2020

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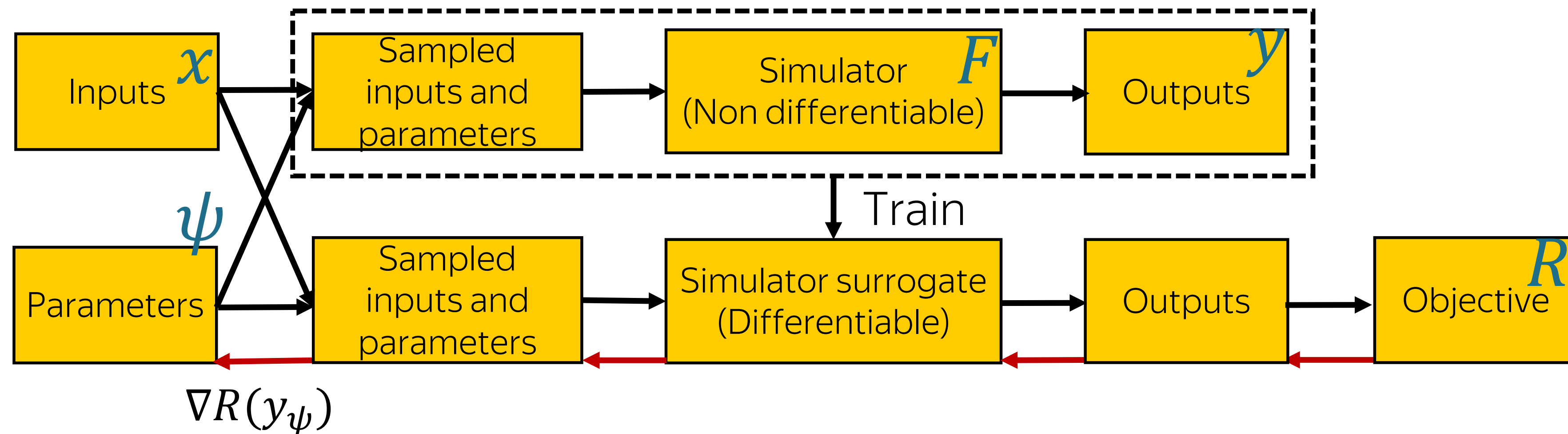
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Problem statement

TL;DR: We approximate a stochastic black-box function with generative neural networks to enable gradient based optimisation

Intractable

$$\operatorname{argmin}_{\psi} E_y [R(y_{\psi})] = \int R(y) p(y|x; \psi) q(x) dx dy \approx \sum_x R(F(x, \psi))$$

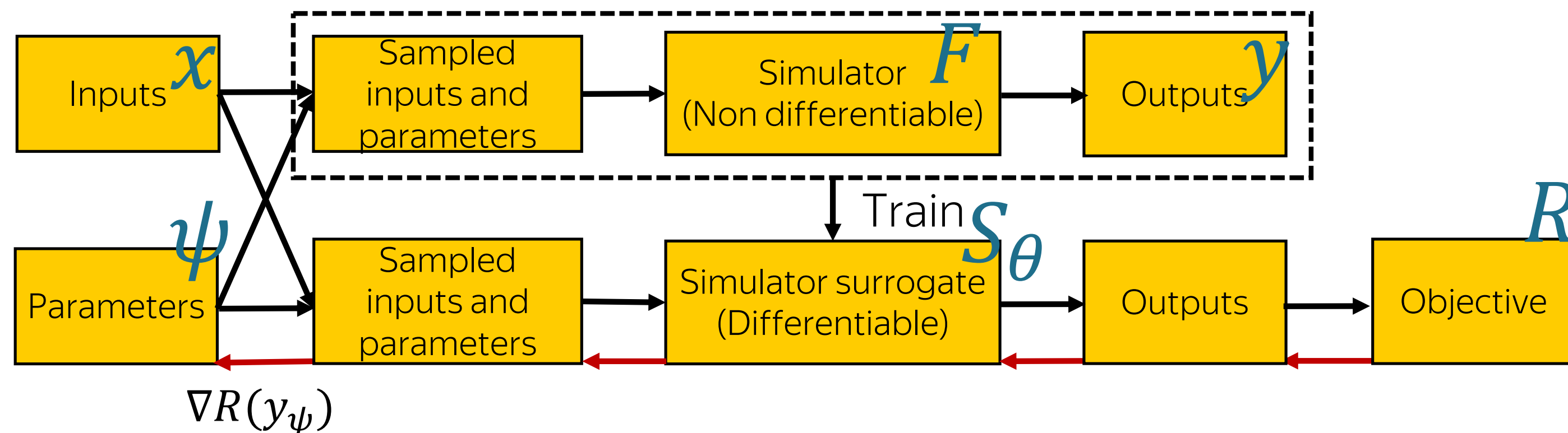
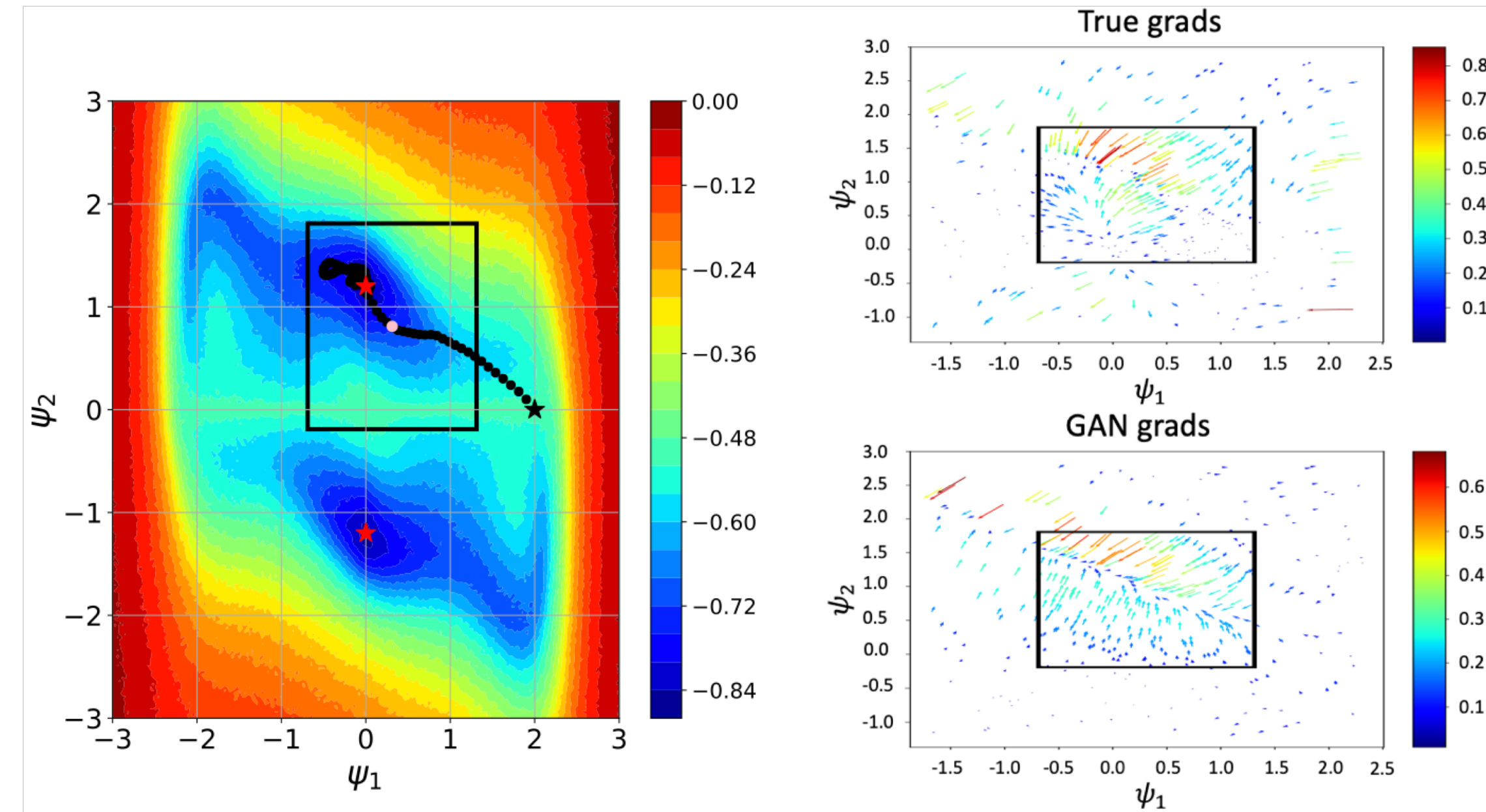


Our Method (L-GSO)

Approximate:
$$\nabla_{\psi} E_y [R(y_{\psi})] \approx \sum_x \nabla_{\psi} R(S_{\theta}(z, x, \psi))$$

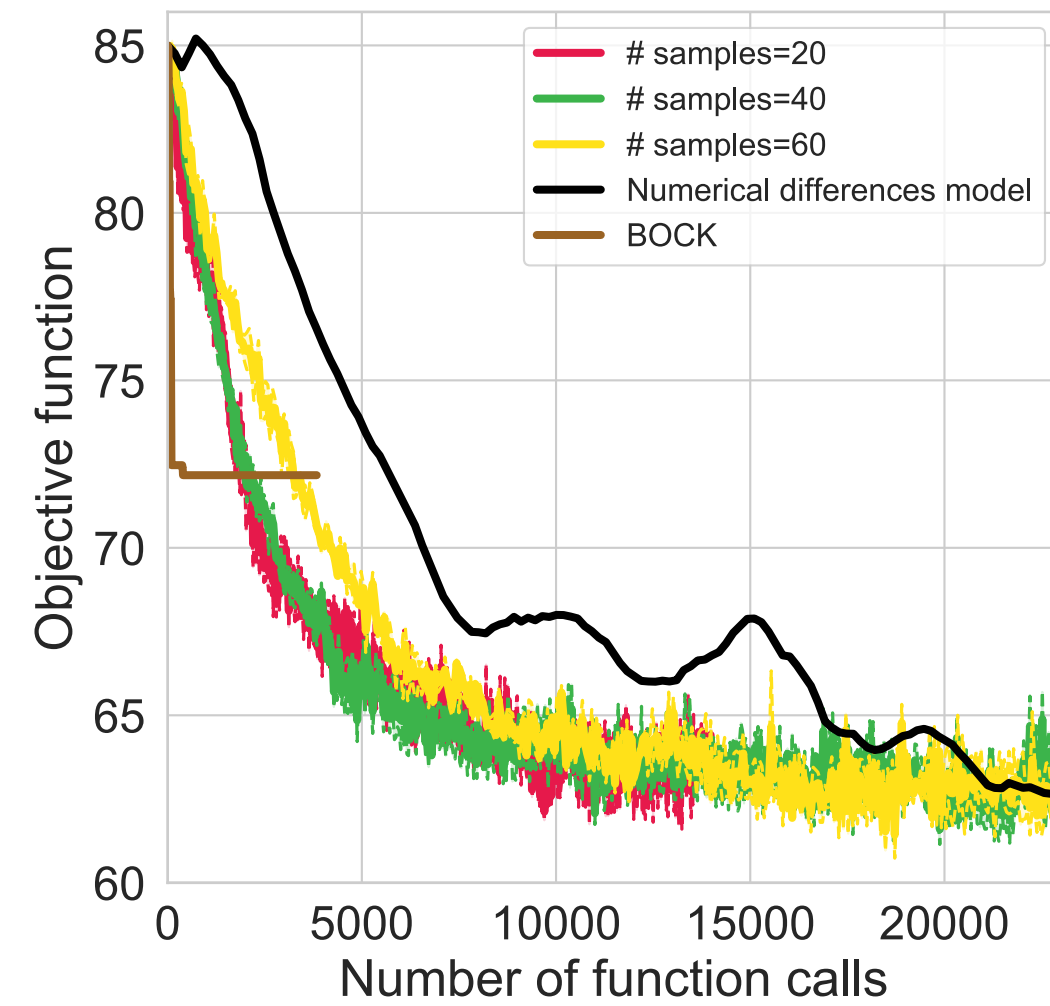
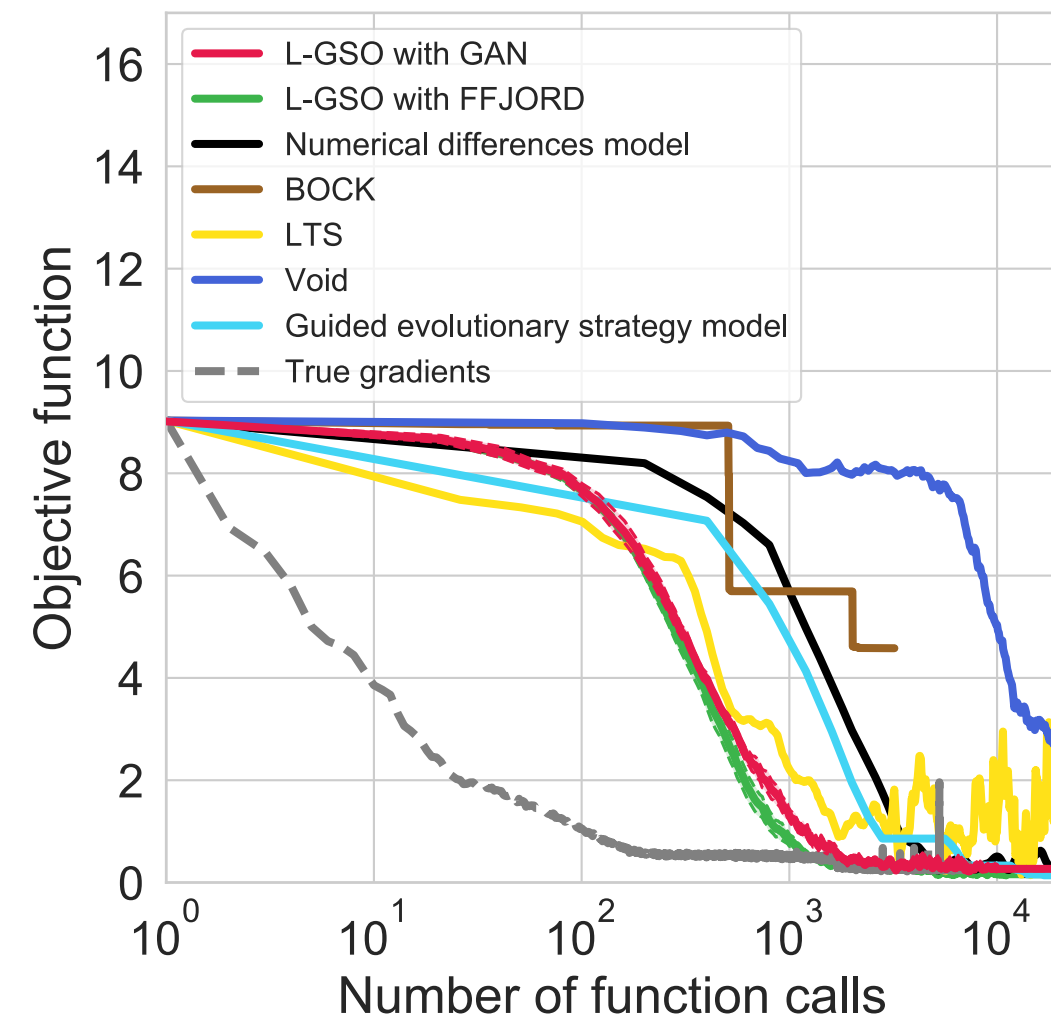
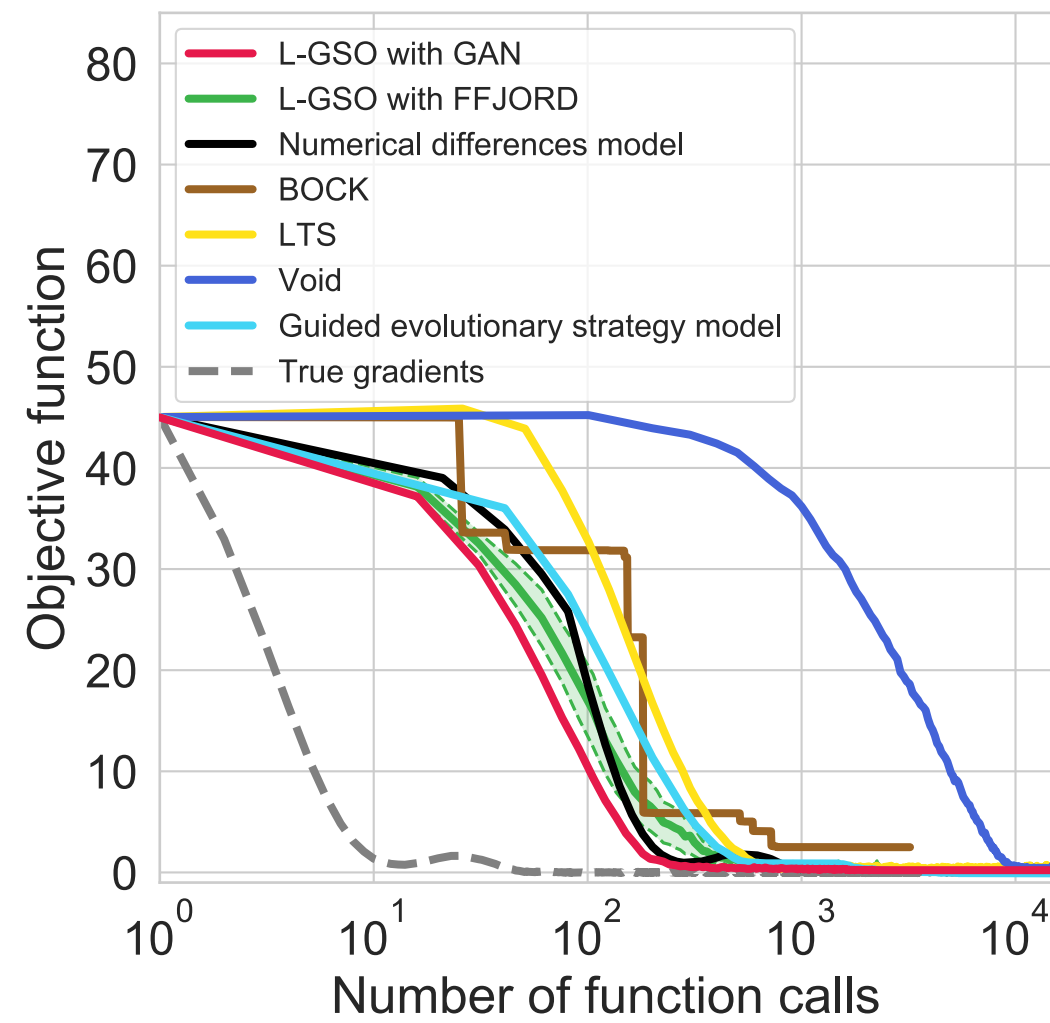
S_{θ} is a Deep Generative model (GAN, FFJORD, etc)

To fight "curse of dimensionality": We train surrogate in a local neighbourhood of parameter space and perform optimisation step

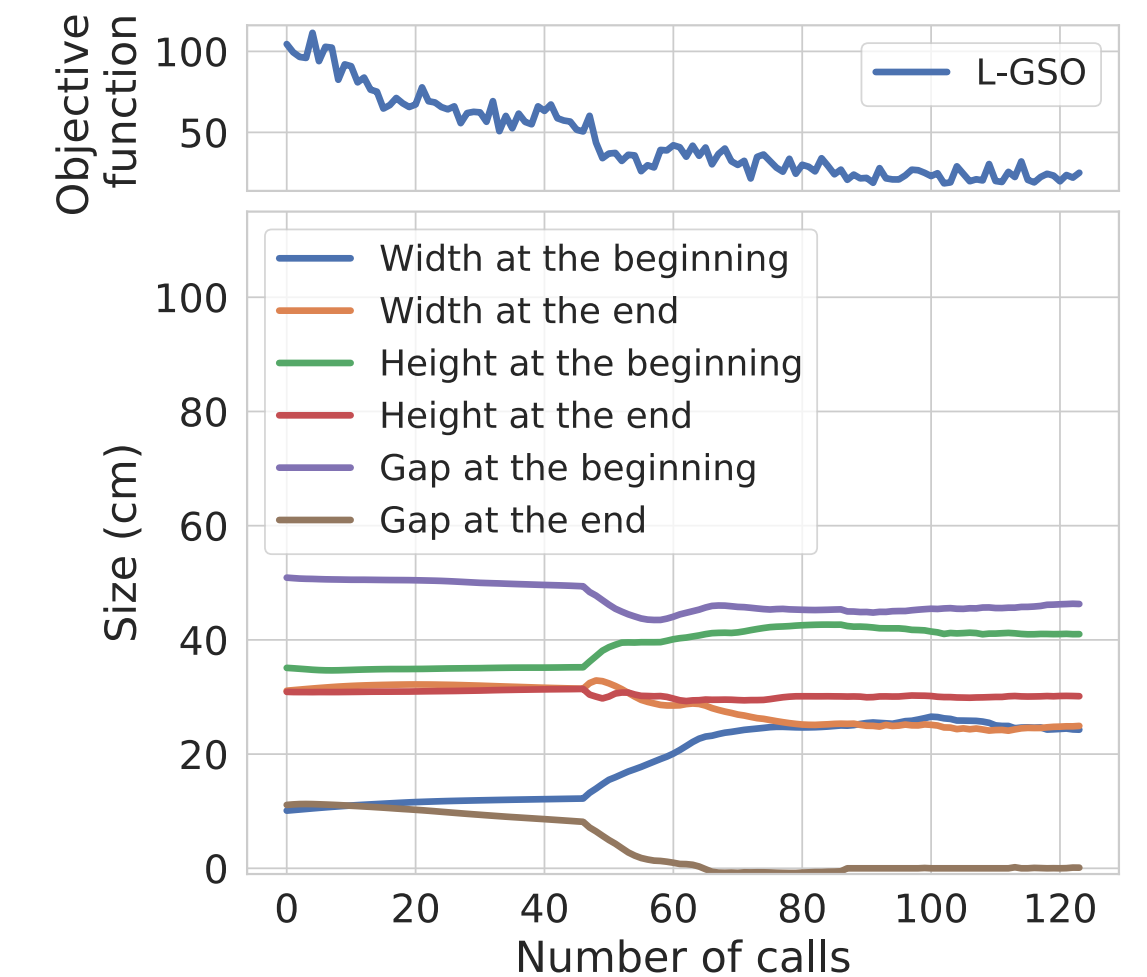


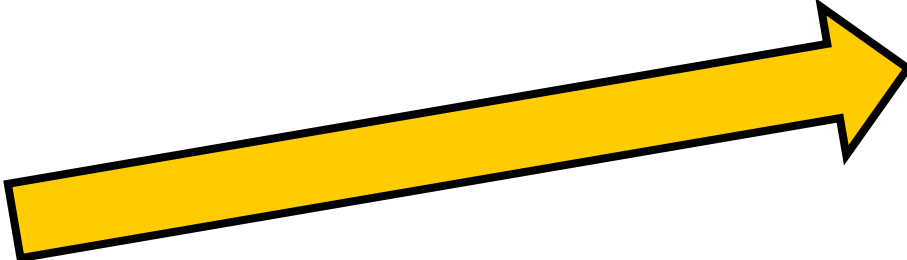
Results

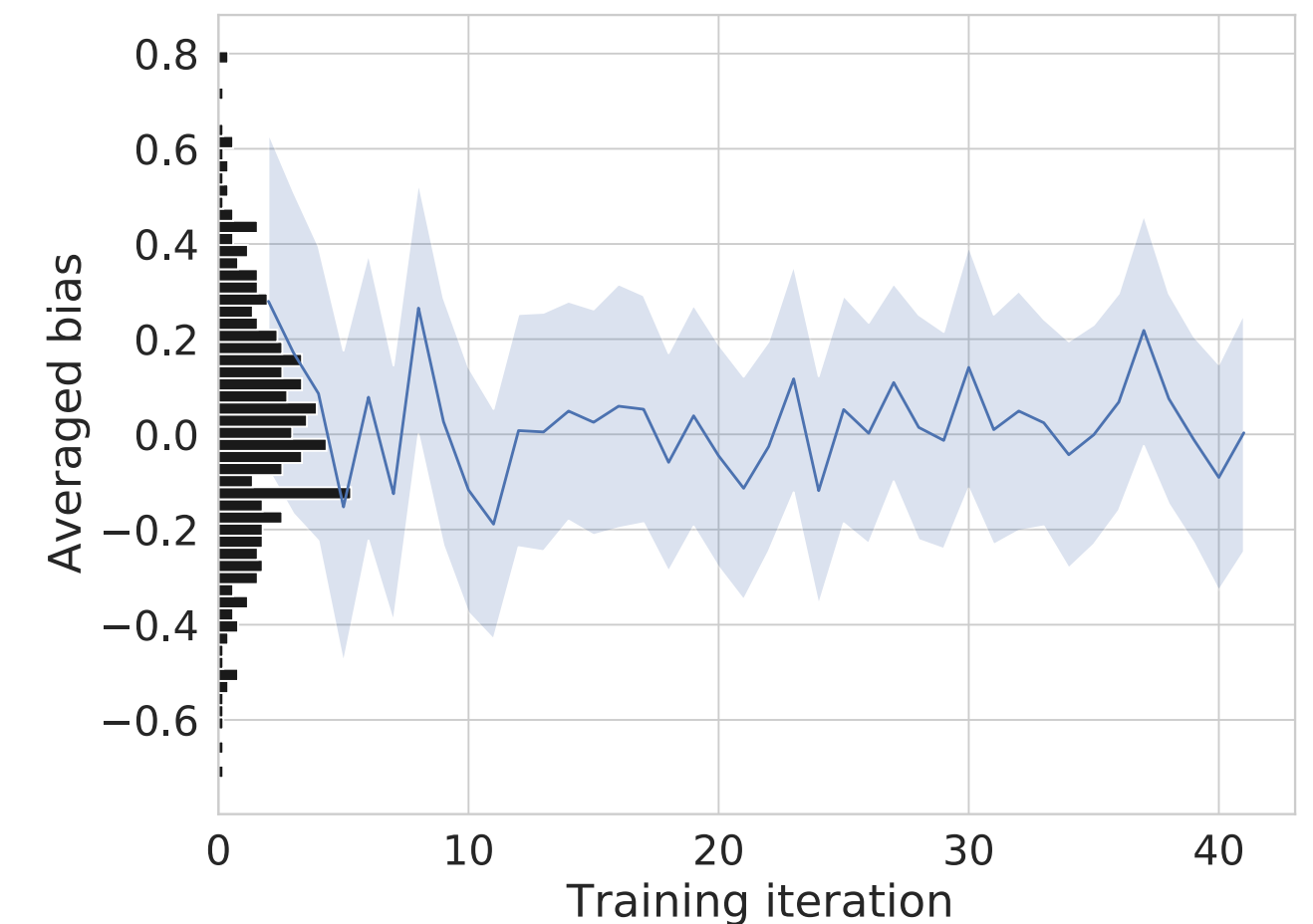
Toy problems: Rosenbrock function, Degenerate Rosenbrock, Neural Network weights optimisation



Optimisation in 42 dimensional space of physics simulator



- Our algorithm is comparable with all baselines and outperforms **REINFORCE- and evolutionary-based** algorithms in speed of convergence
- Our algorithm outperforms **all** algorithms in high-dimensional setting when parameters are constrained to a **lower dimension manifold**
- We do not observe bias in gradients 



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