Practical Black-box Optimization

Luigi Nardi

WASP-AI Assistant Professor Lund University

Researcher Stanford University

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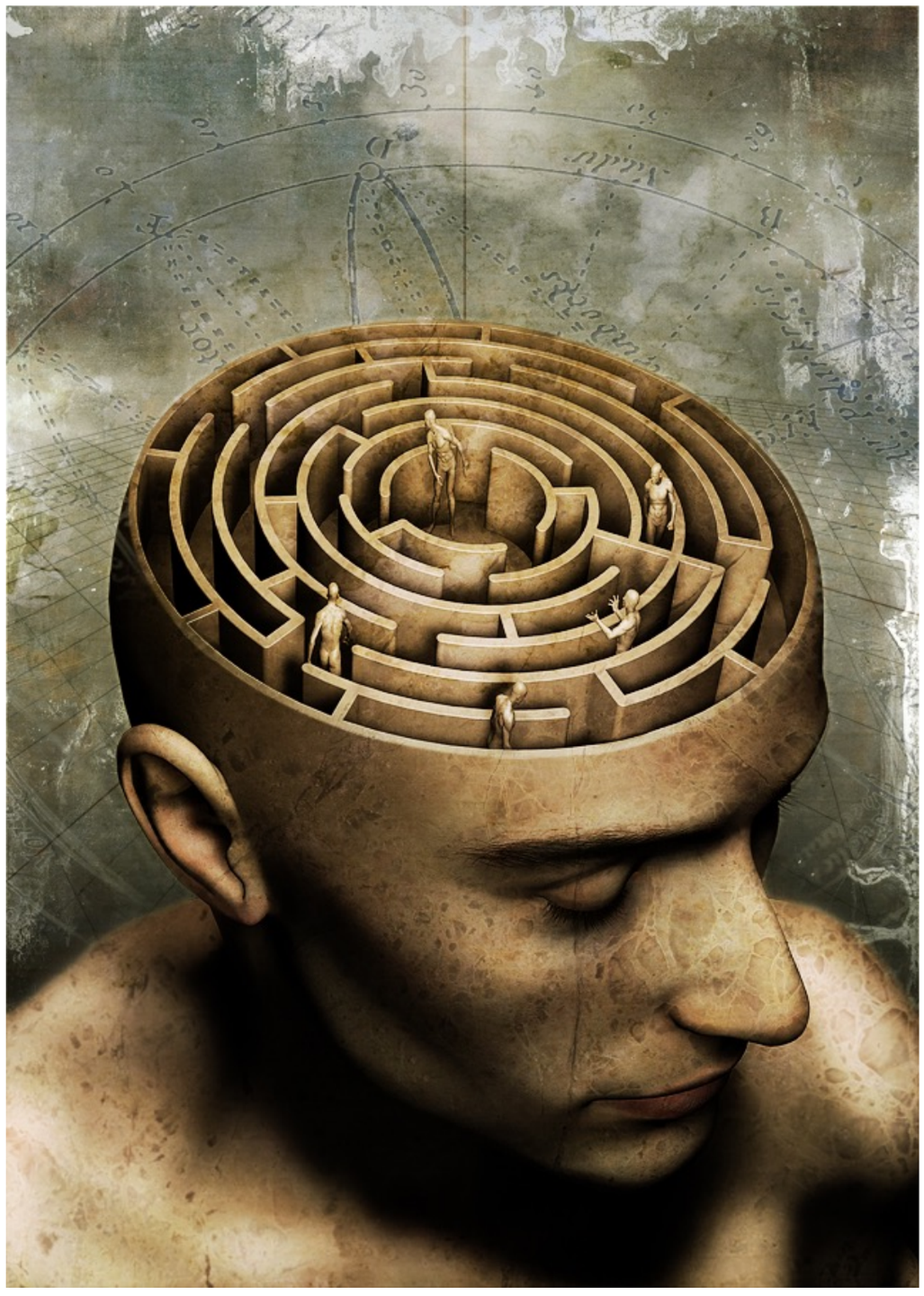
LUND UNIVERSITY

Main Papers Behind This Talk

1. Nardi, et al., "Practical Design Space Exploration", MASCOTS, 2019.
2. Koeplinger, et al., "Spatial: A Language and Compiler for Application Accelerators", PLDI, 2018.
3. Nardi, et al., "Algorithmic performance-accuracy trade-off in 3D vision applications using HyperMapper", iWAPT-IPDPS, 2017.
4. Saeedi, et al., "Application-oriented design space exploration for SLAM algorithms", ICRA, 2017.
5. Bodin, et al., "Integrating algorithmic parameters into benchmarking and design space exploration in 3D scene understanding", PACT, 2016.

Outline

1. **Black-box Optimization**
   - **Problem Setting**
   - **Motivation Examples**
   - **Taxonomy**
2. The HyperMapper Framework
   - Bayesian Optimization
   - Pareto and Hypervolume Indicator
   - Prior Distribution
3. Experimental Results
   - Hardware Design
   - Computer Vision
   - Databases



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3-parameters and 2-objective Pictorial

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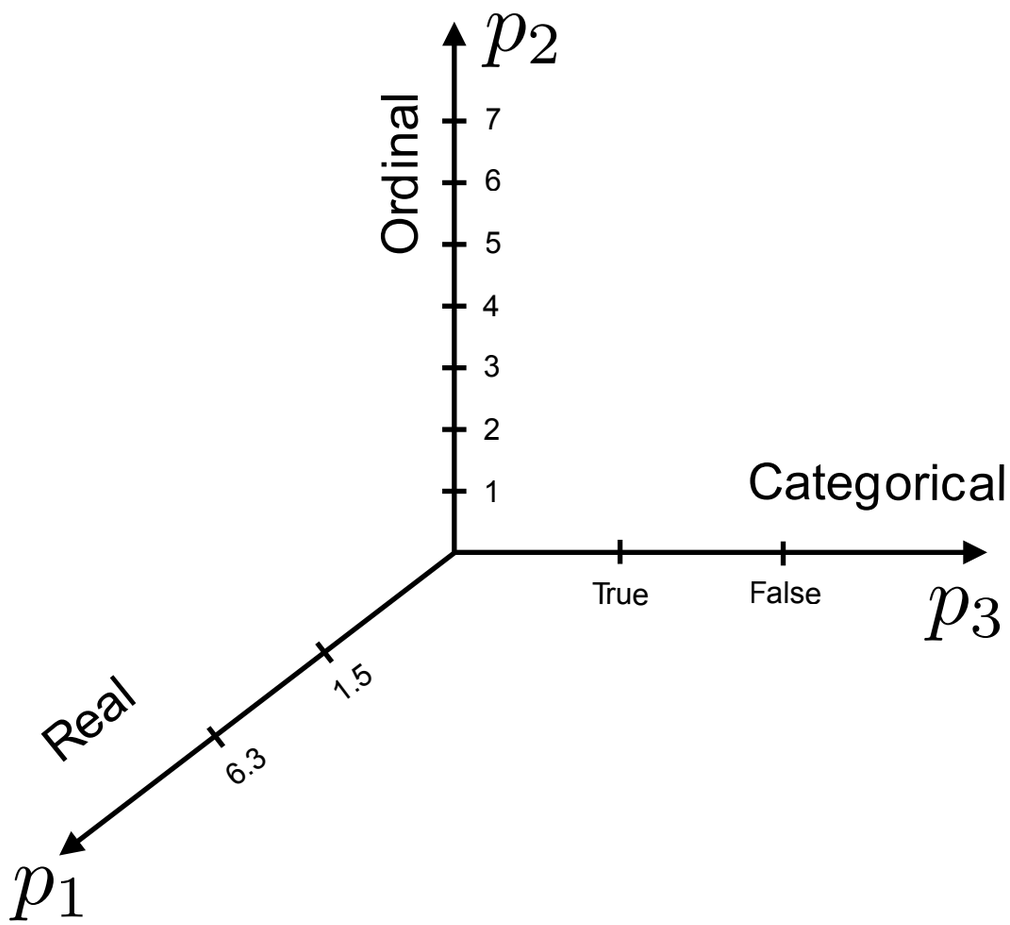

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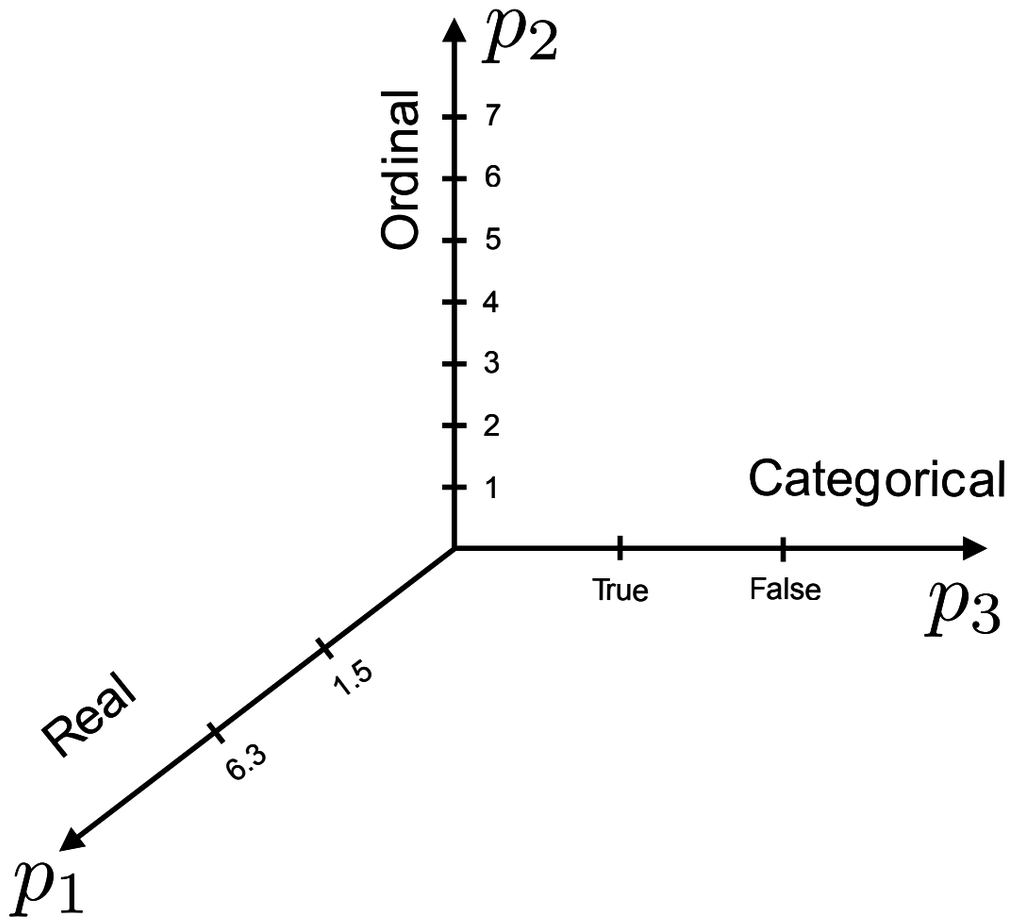

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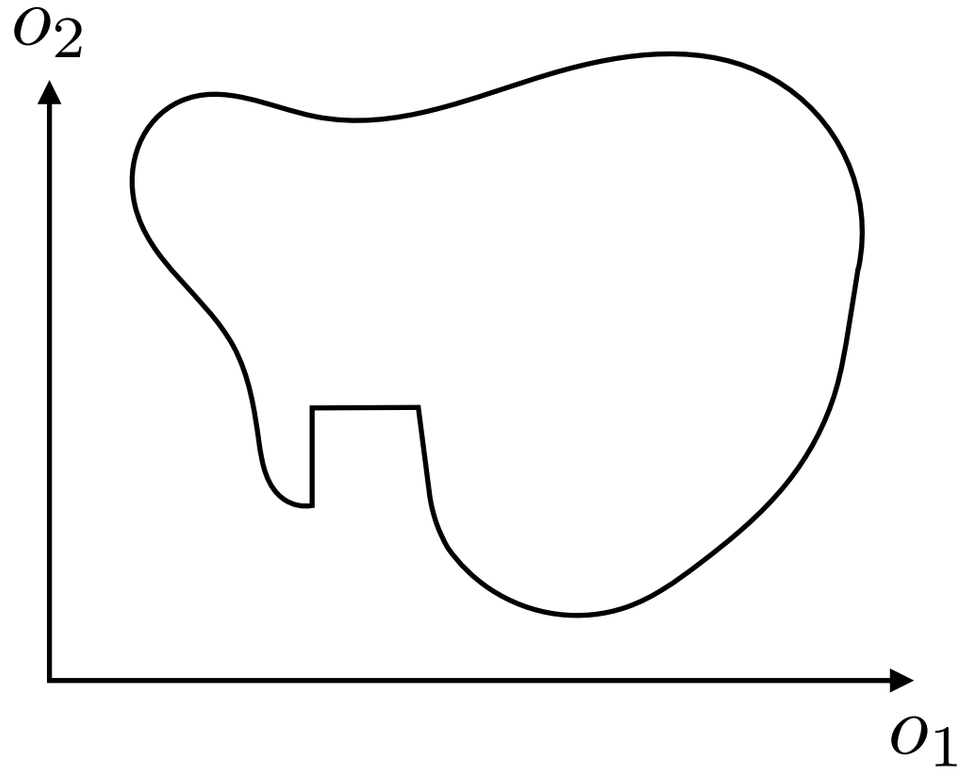

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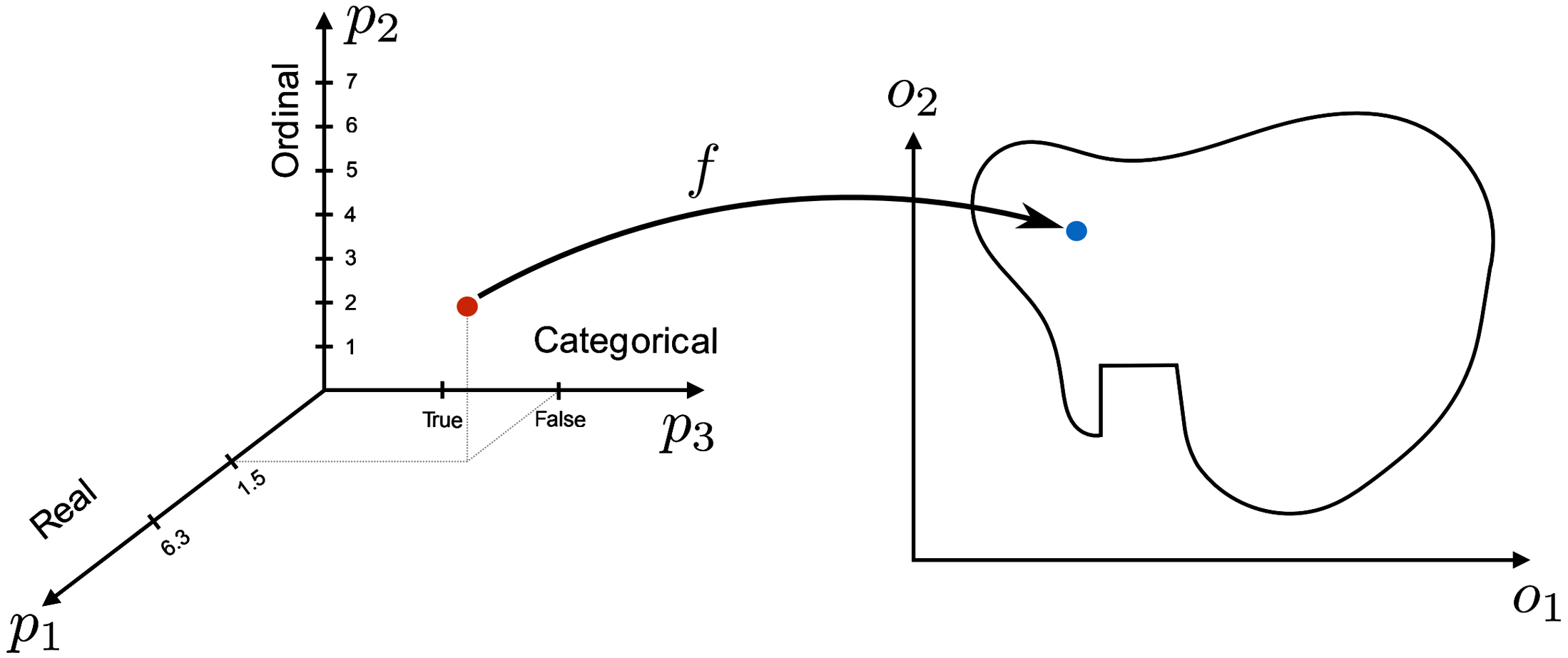

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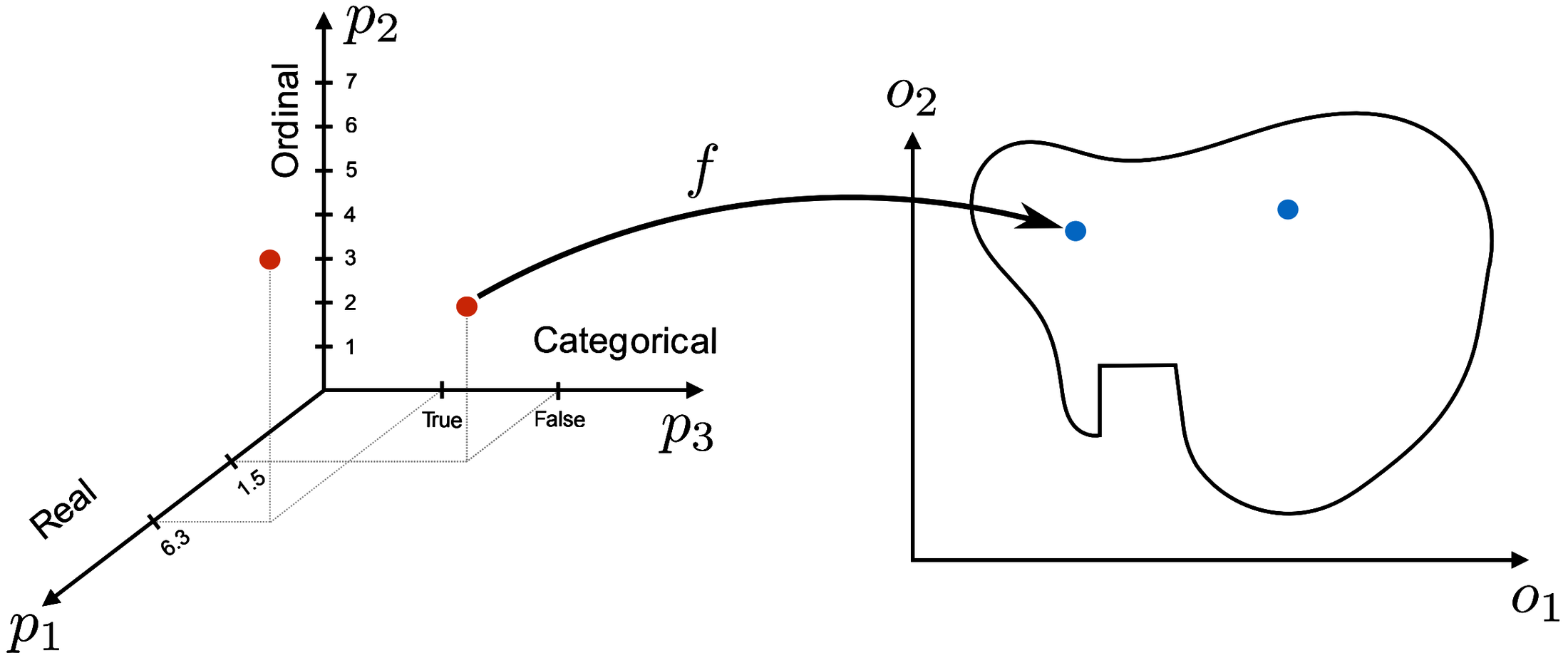

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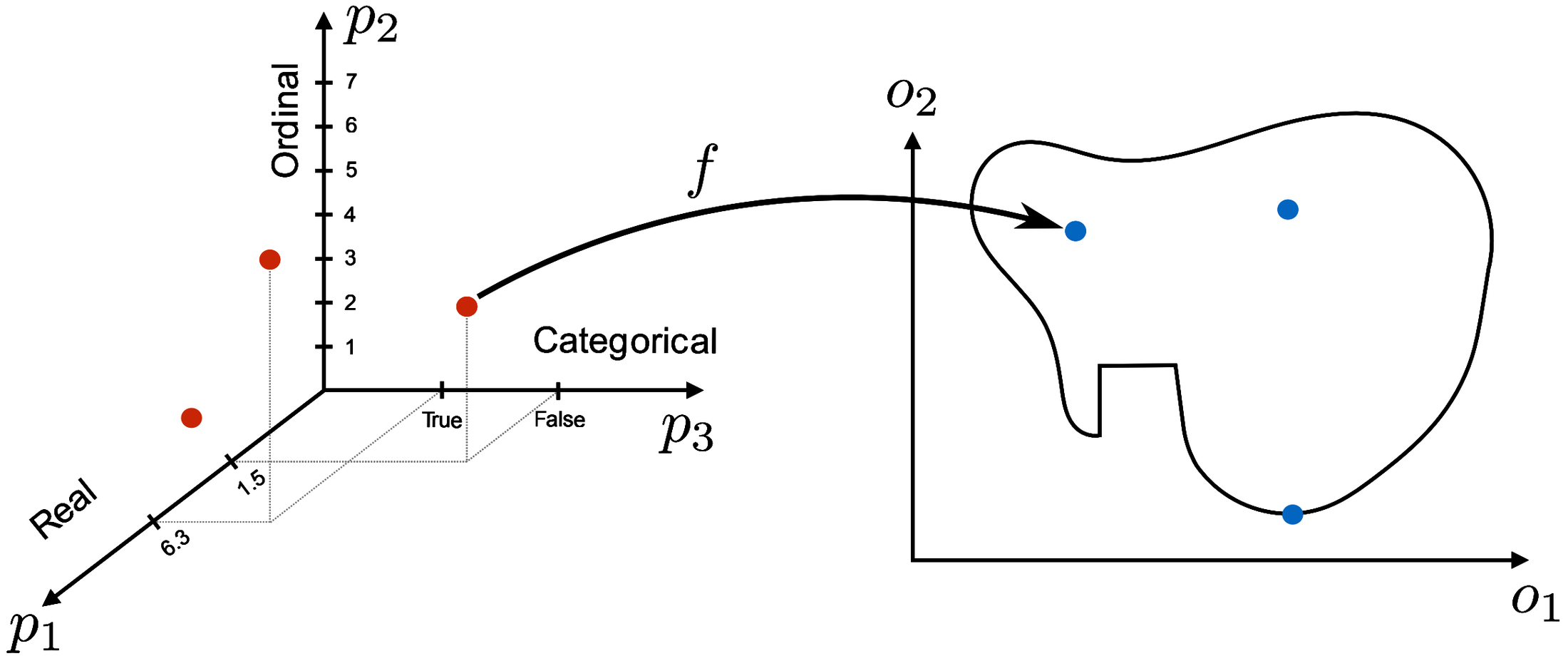

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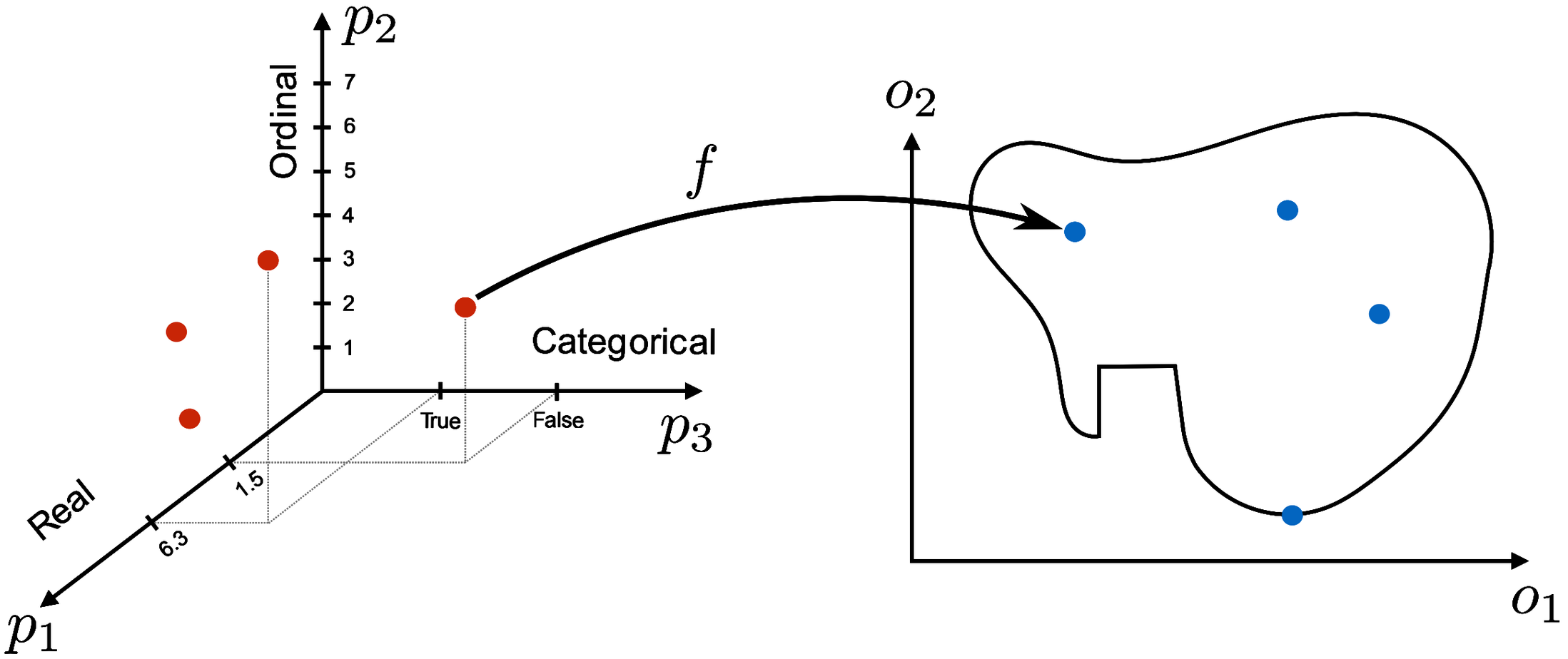

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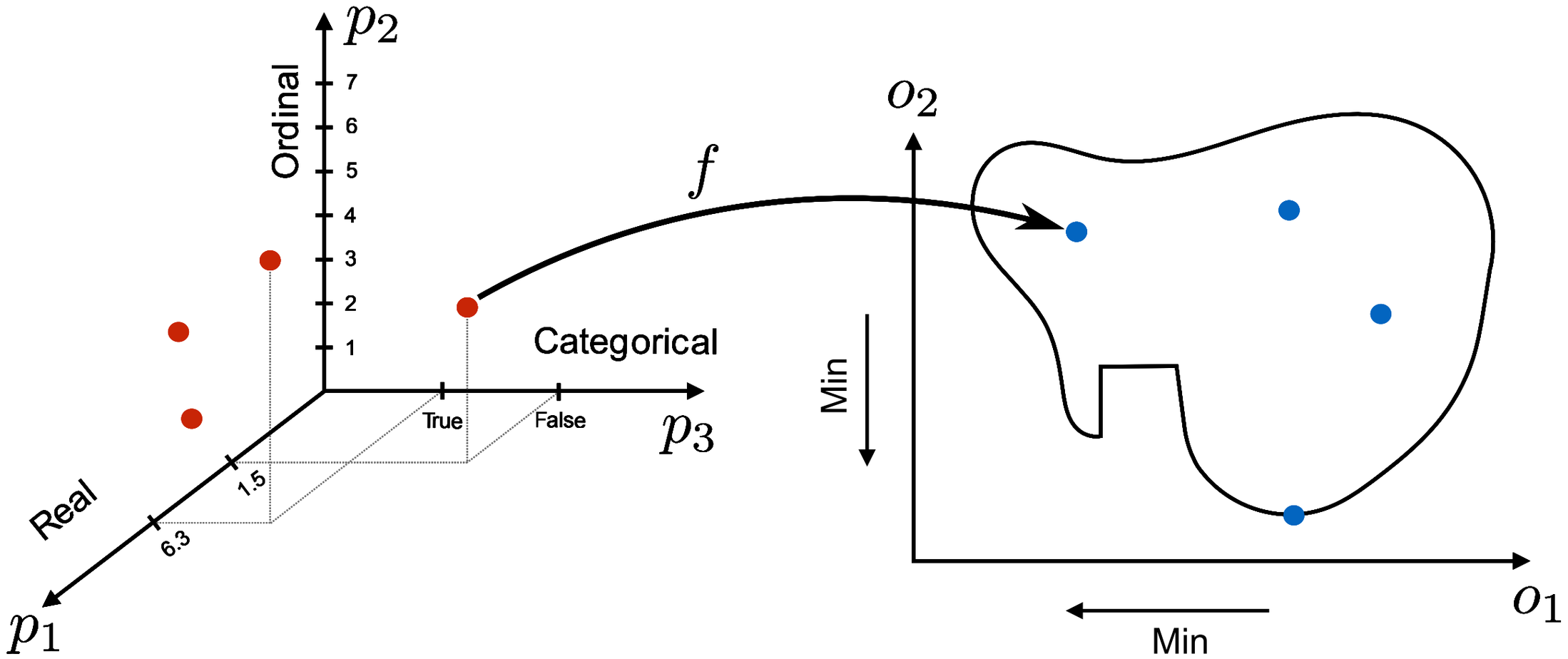

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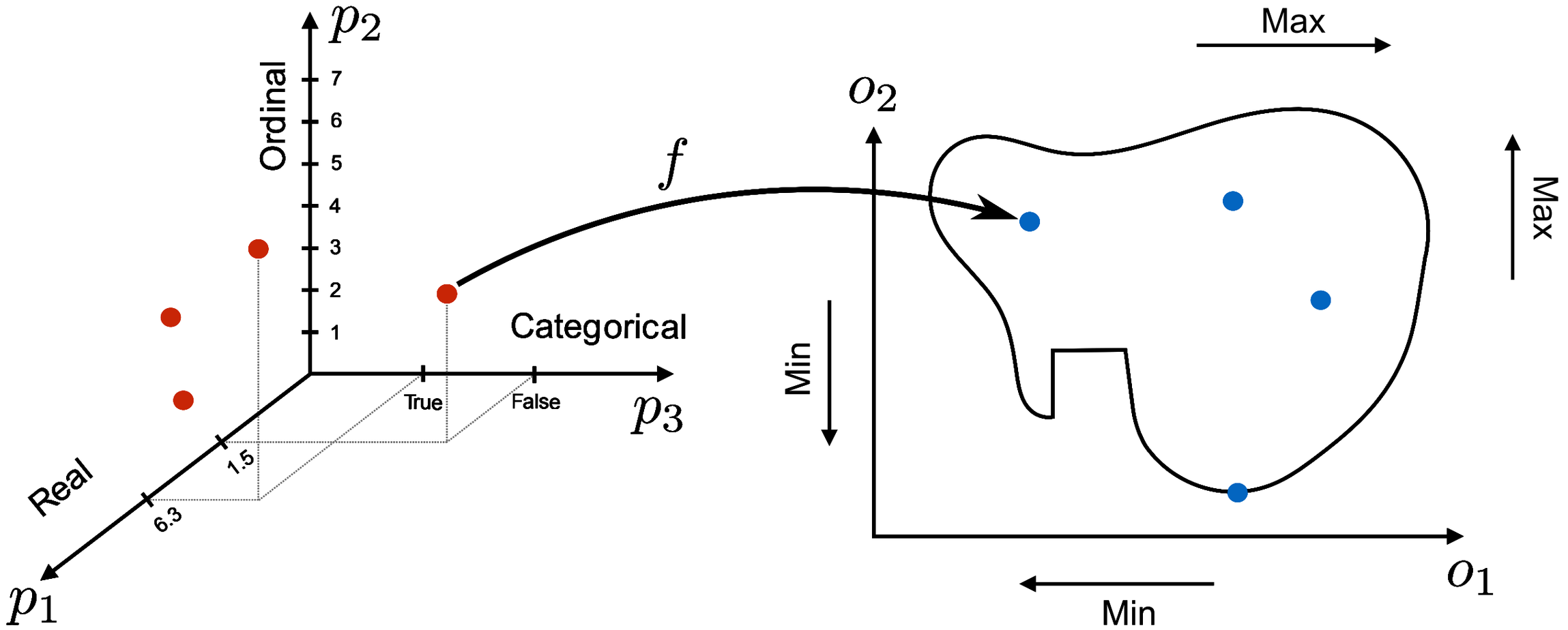

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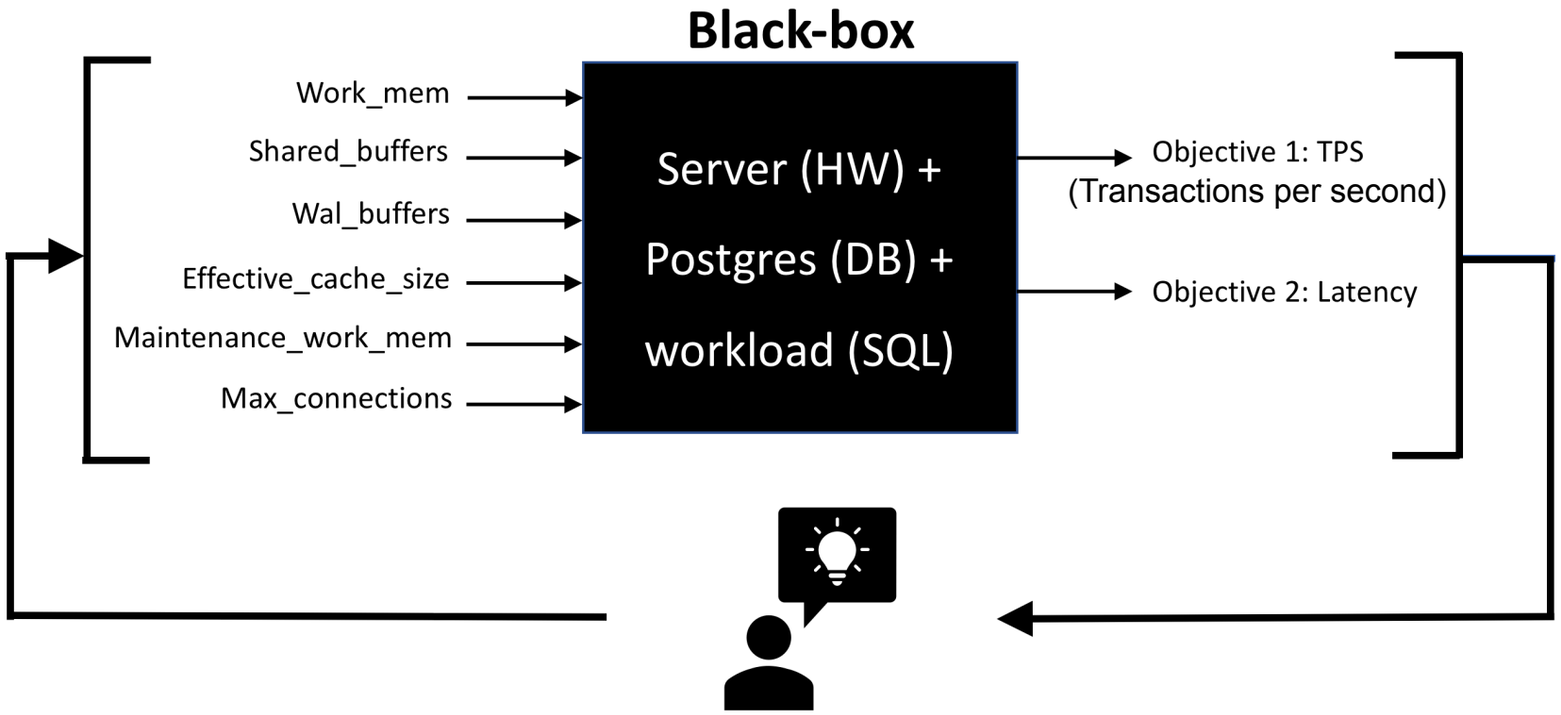
- Alternative approach: Bayesian Optimization (BO)

Example: PostgreSQL/Azure Autotuning



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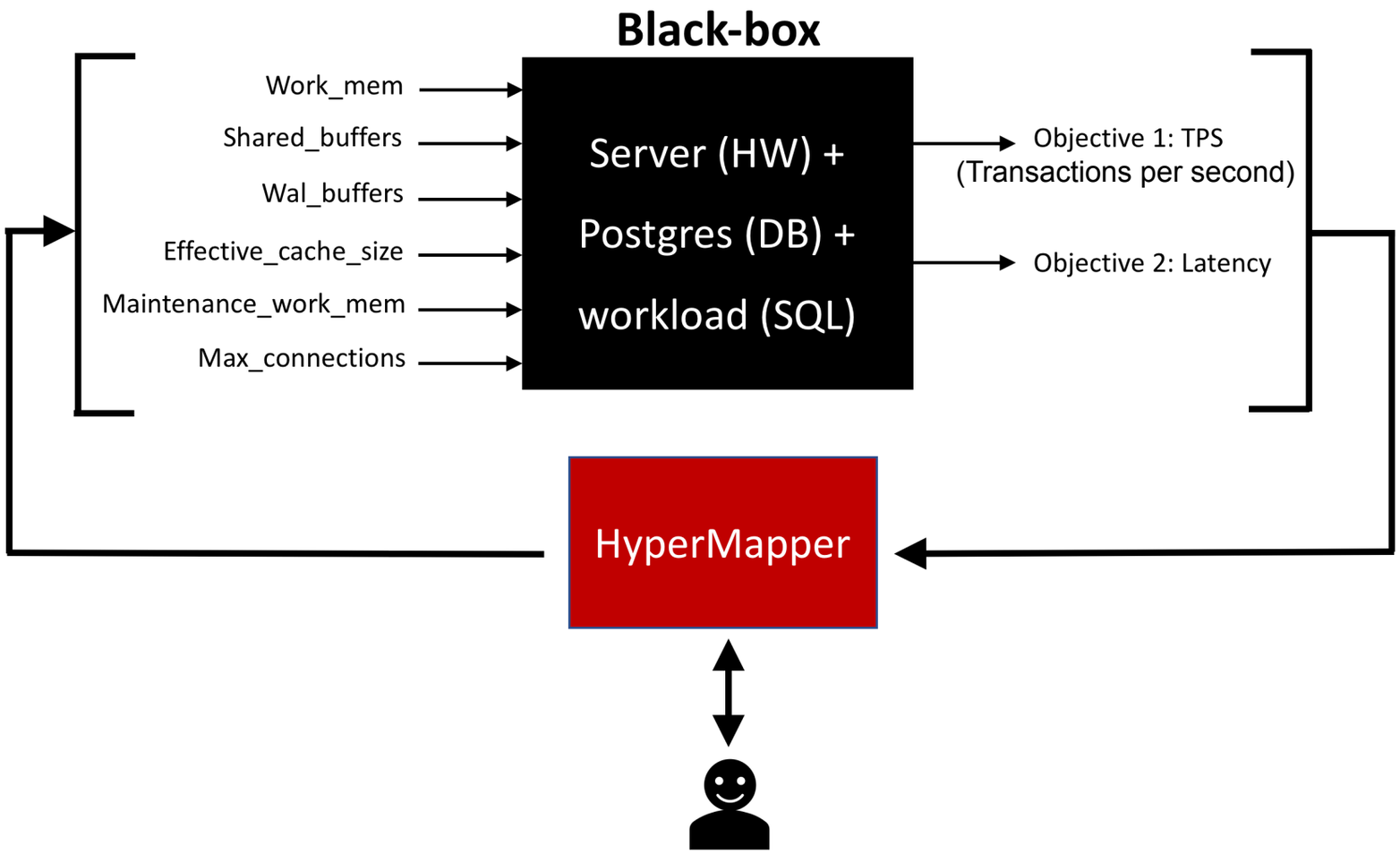

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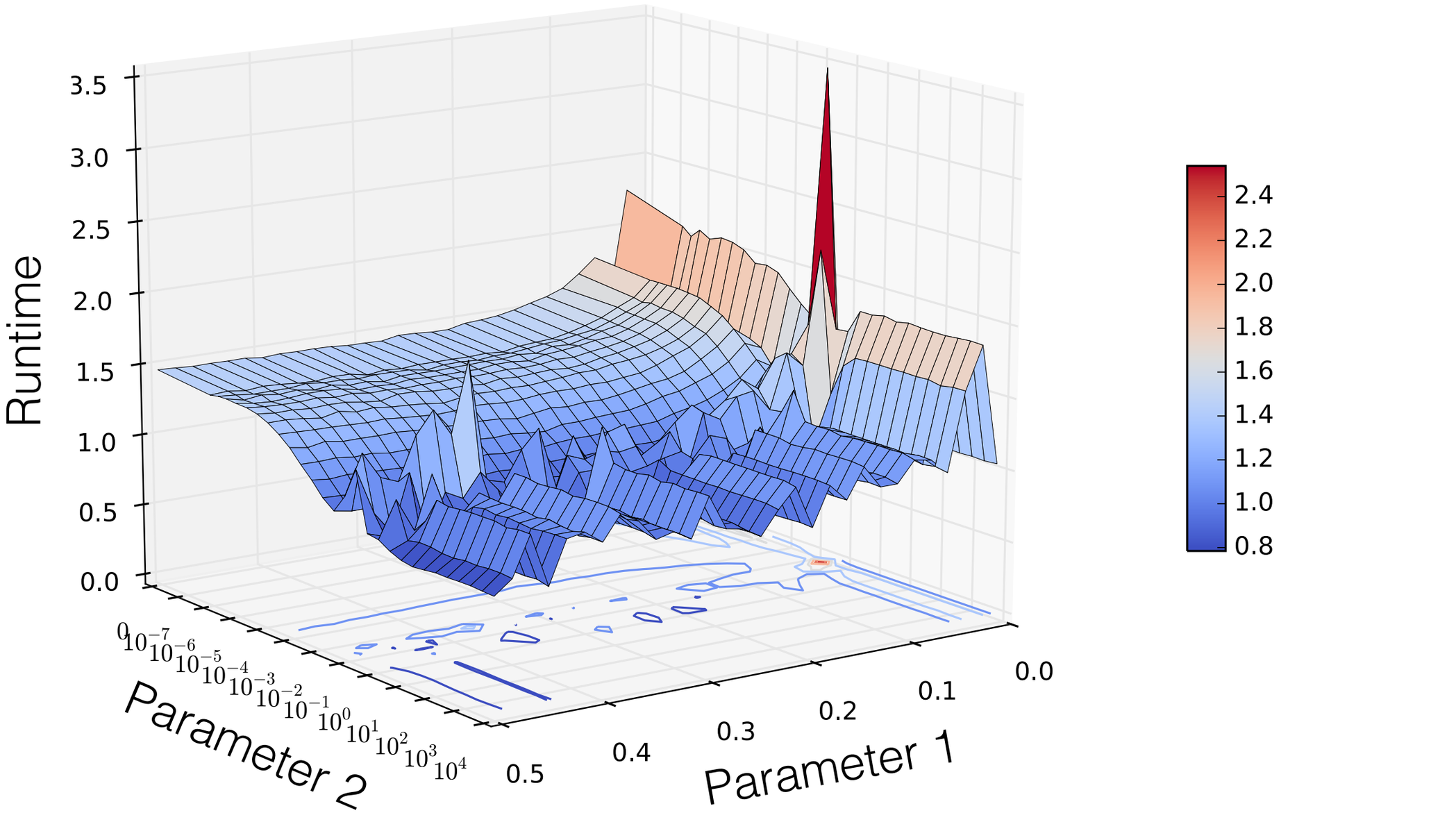
Motivation - Mono-objective



- Benchmark: SLAMBench 1.0 runtime response surface is: non-linear, multi-modal and non-smooth

Practical BBO: Important Features

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   - Example: trade-off accuracy and inference time
4. Unknown feasibility constraints (Constr.)
   - Example: black-box function crash; a design doesn't fit in the FPGA

BBO Tools Taxonomy

None of the tools available support all these BBO features

We introduce a new framework dubbed **HyperMapper**

Name	Multi	RIOC var.	Constr.	Prior
GpyOpt	✗	✗	✗	✗
OpenTuner	✗	✓	✗	✗
SURF	✗	✓	✗	✗
SMAC	✗	✓	✗	✗
Spearmint	✗	✗	✓	✗
Hyperopt	✗	✓	✗	✓
Hyperband	✗	✓	✗	✗
GPflowOpt	✓	✗	✓	✗
cBO	✗	✗	✓	✗
BOHB	✗	✓	✗	✗
HyperMapper	✓	✓	✓	✓

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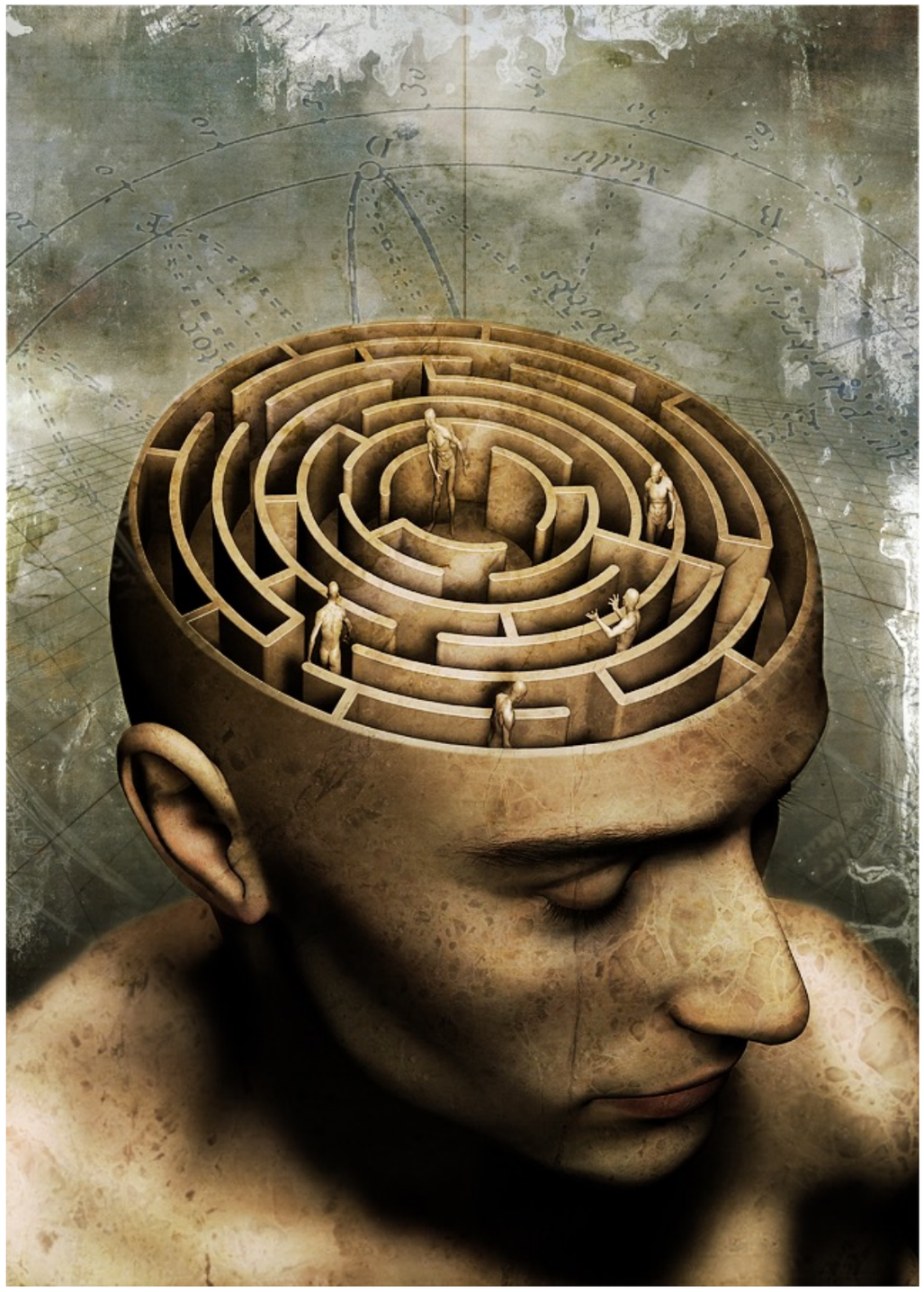

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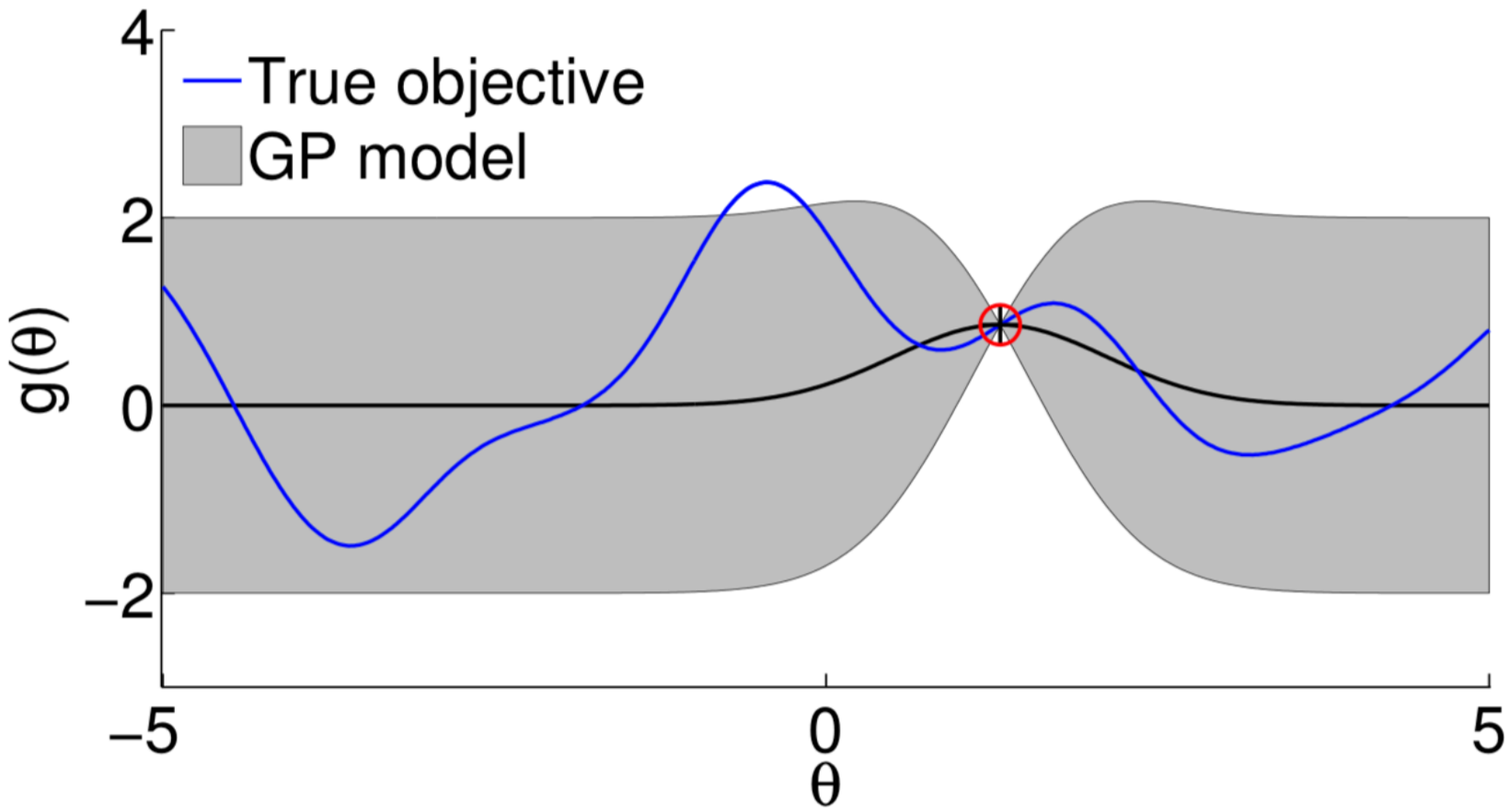
- Standard proxy: Gaussian process
  - But also: Random Forests, Tree Parzen Estimators, etc.

Bayesian Optimization: Illustration



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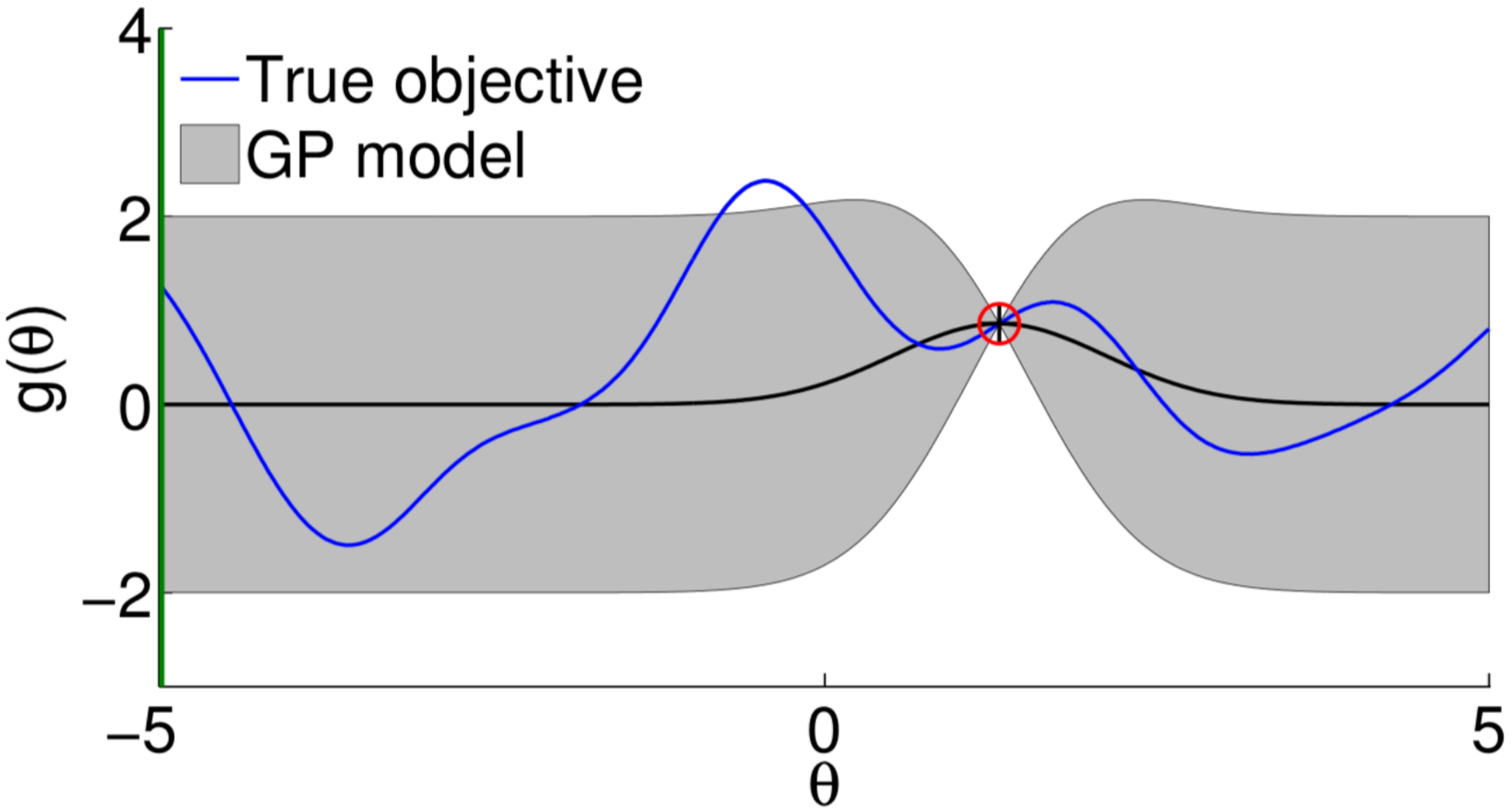

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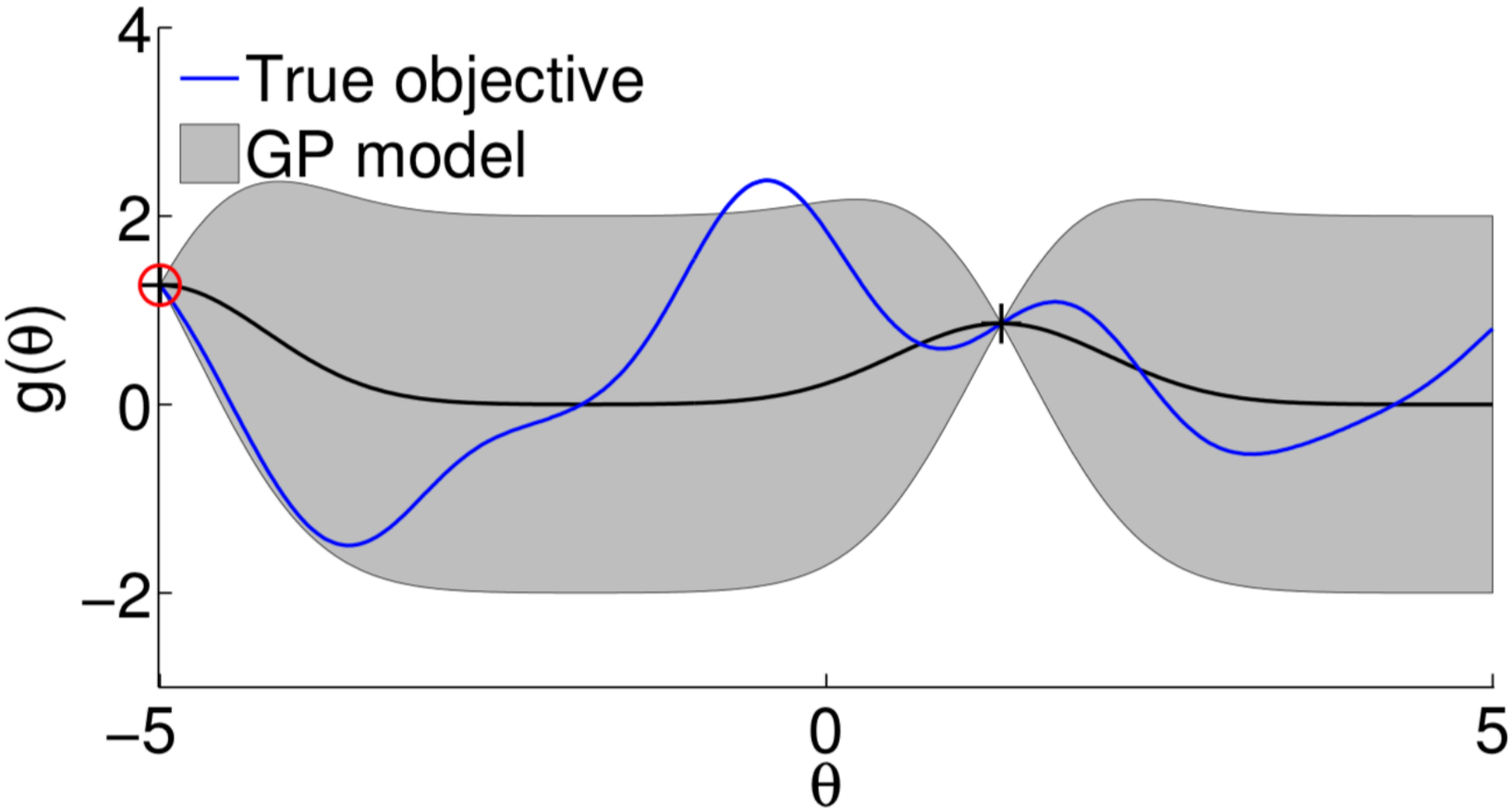

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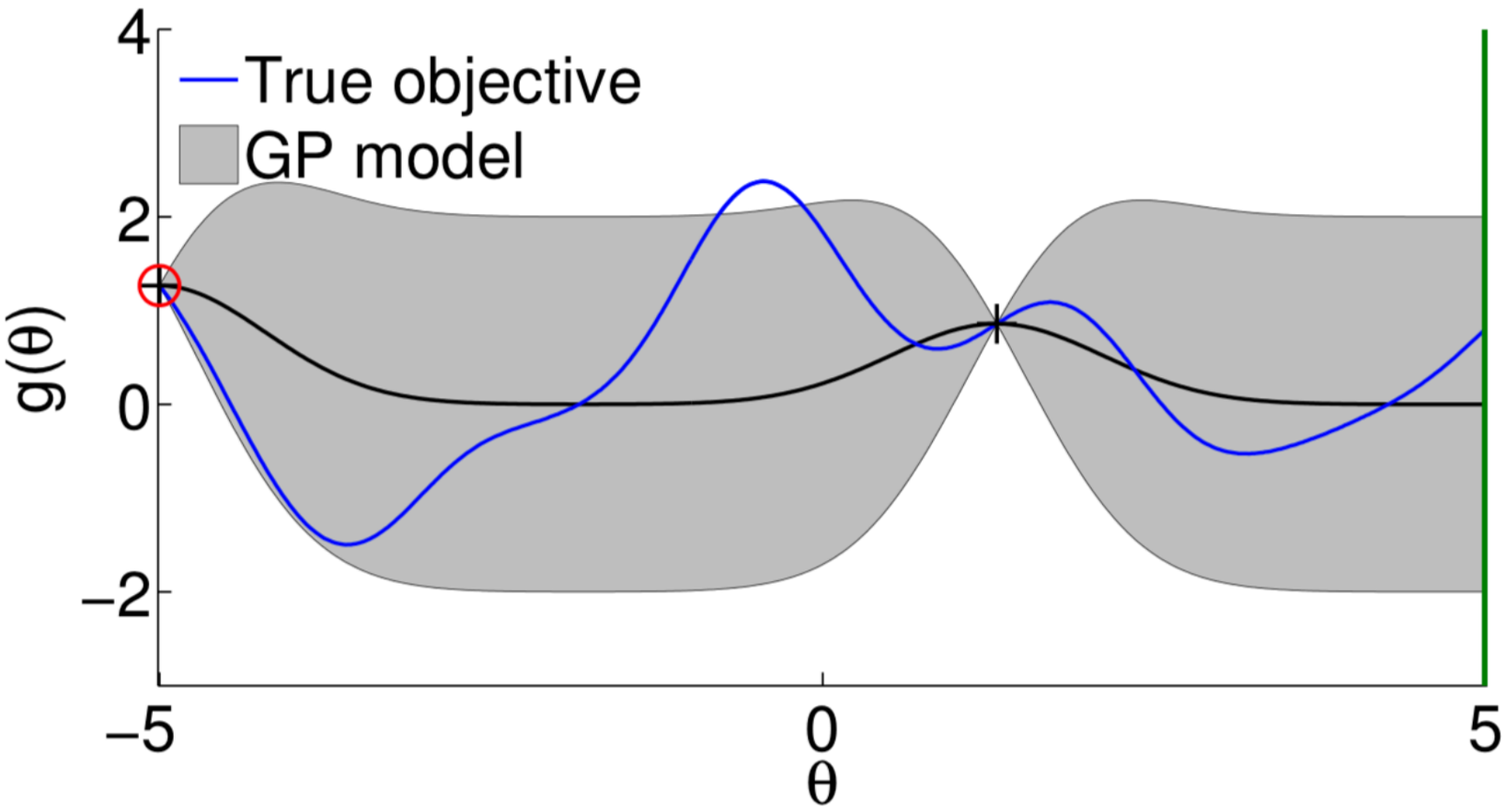

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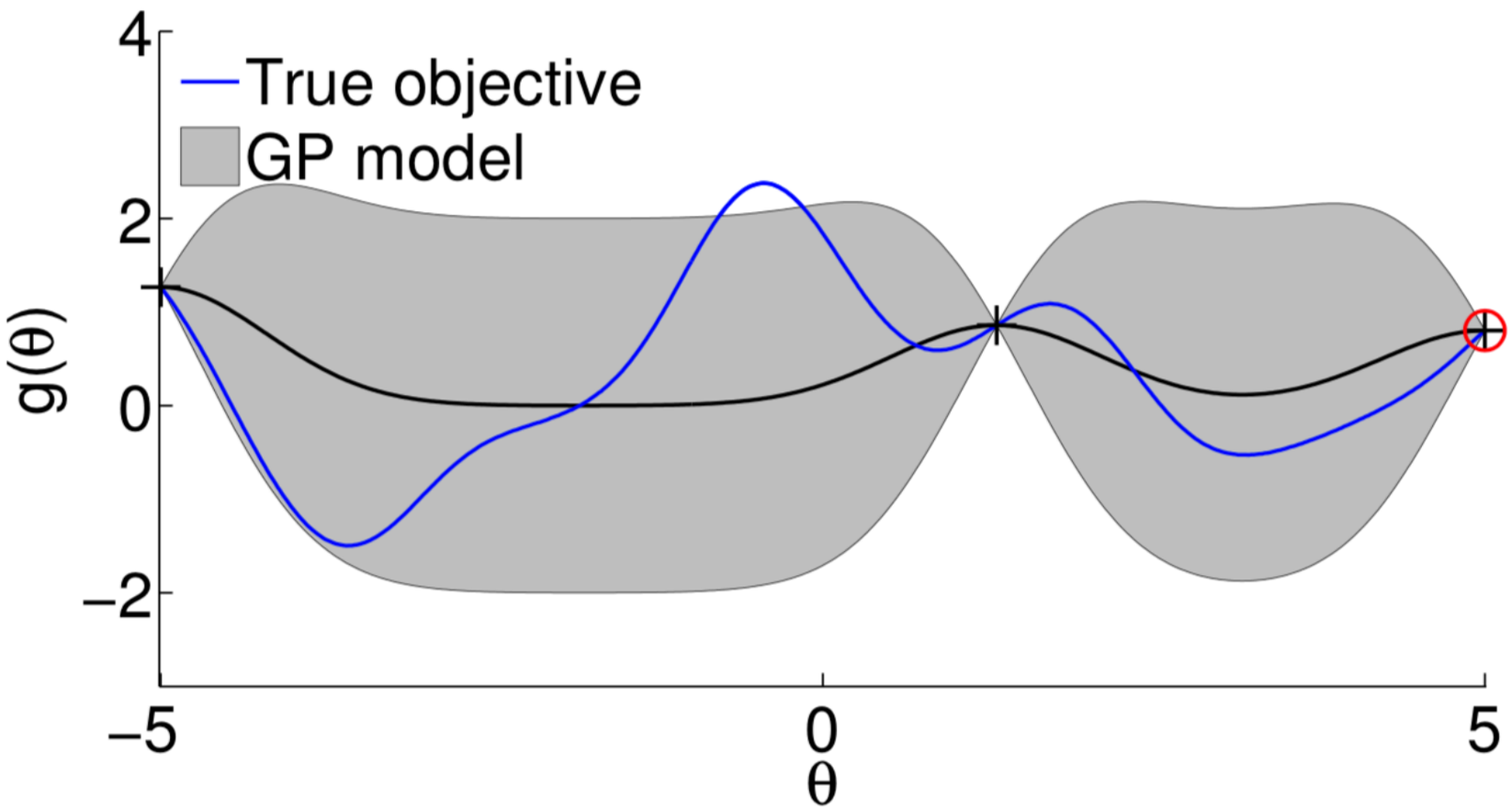

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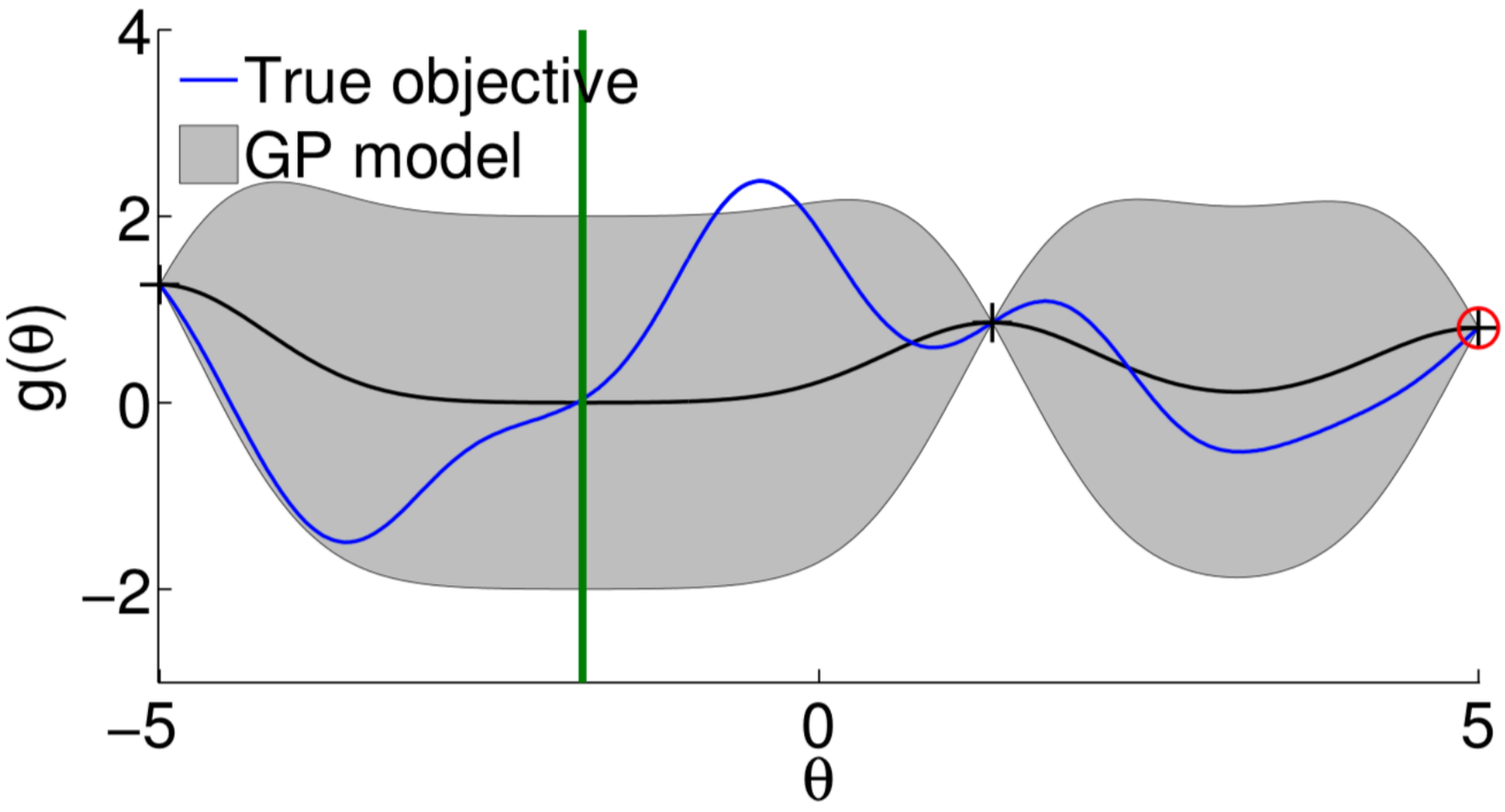

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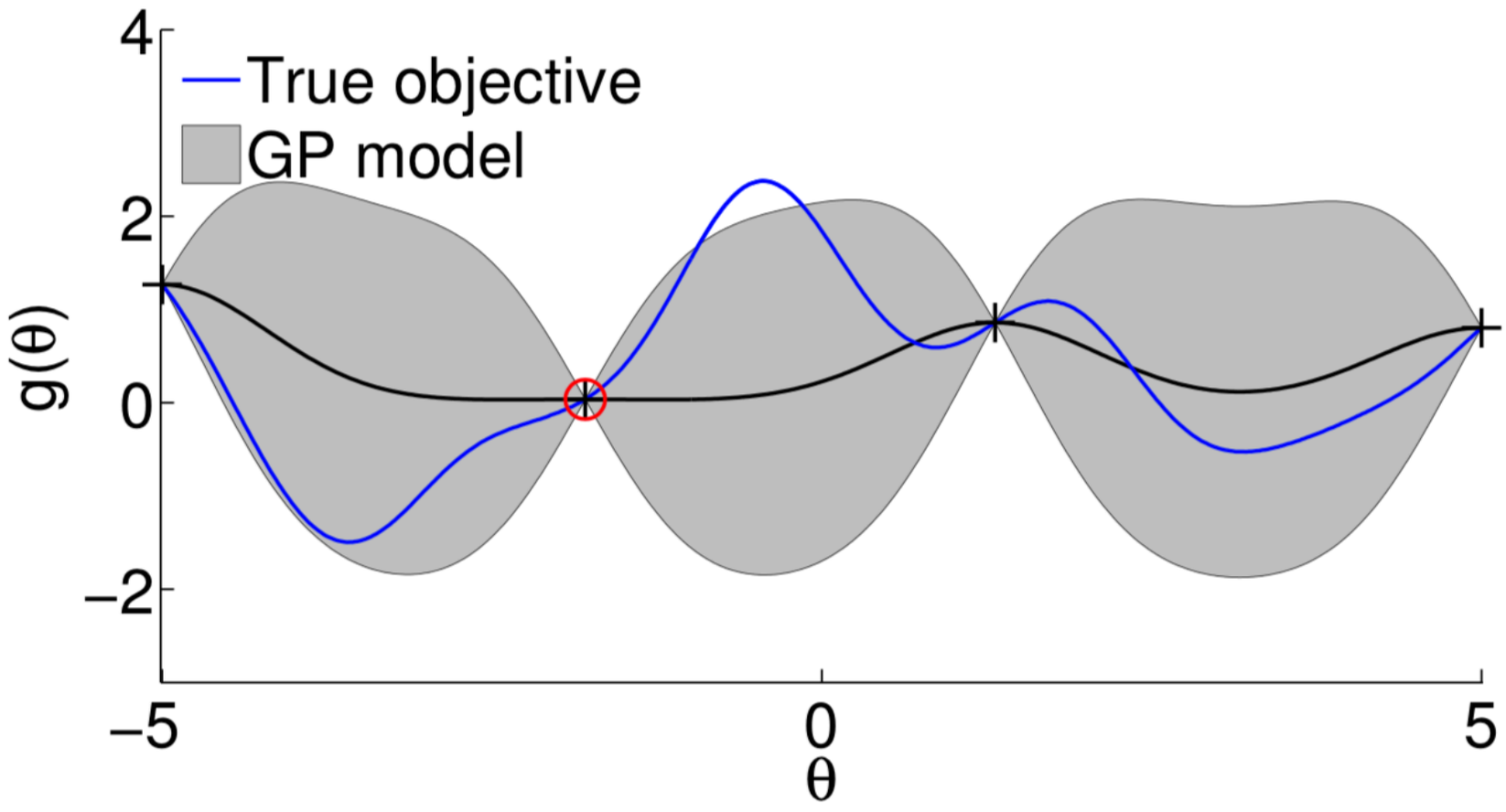

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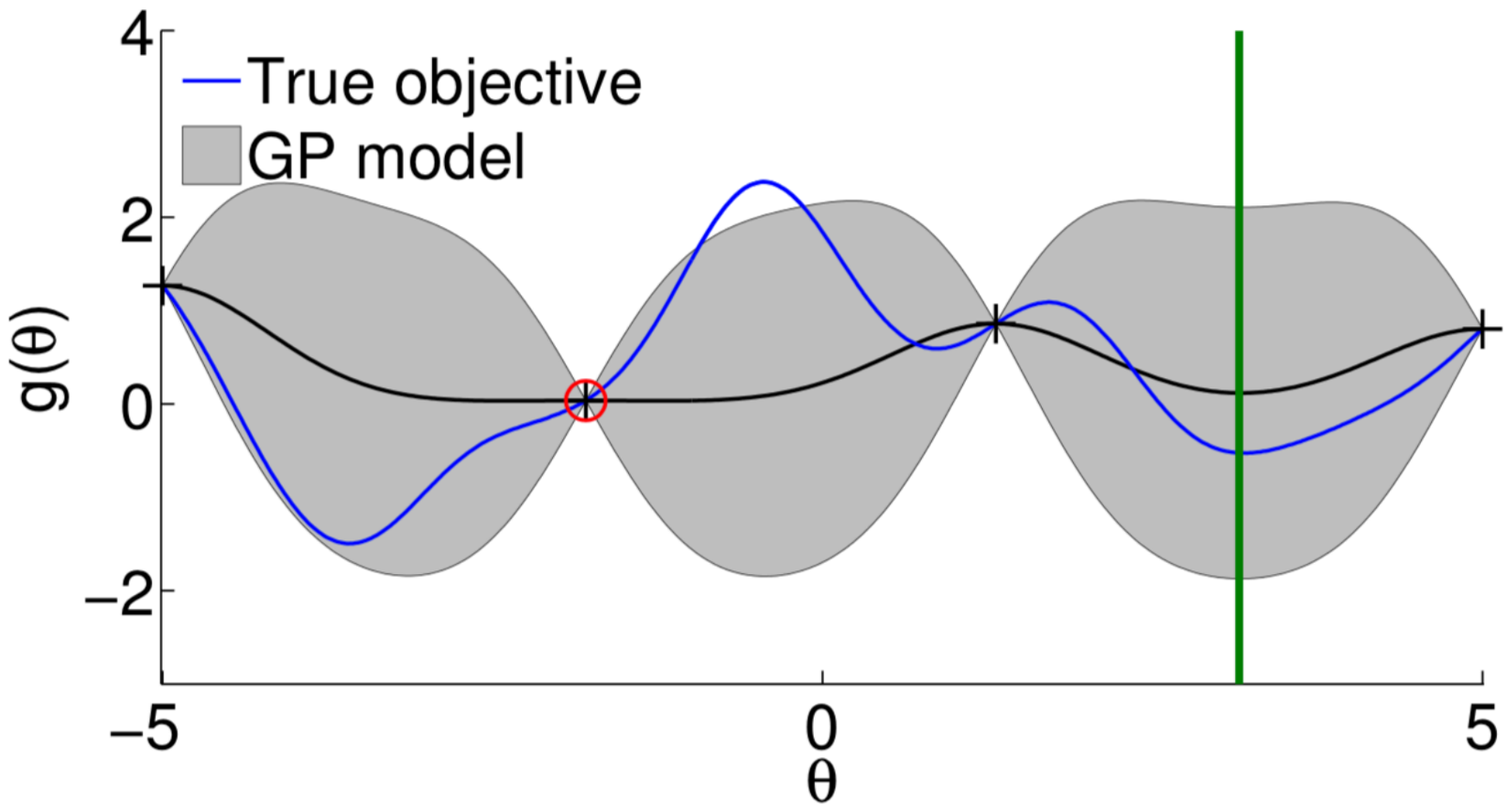

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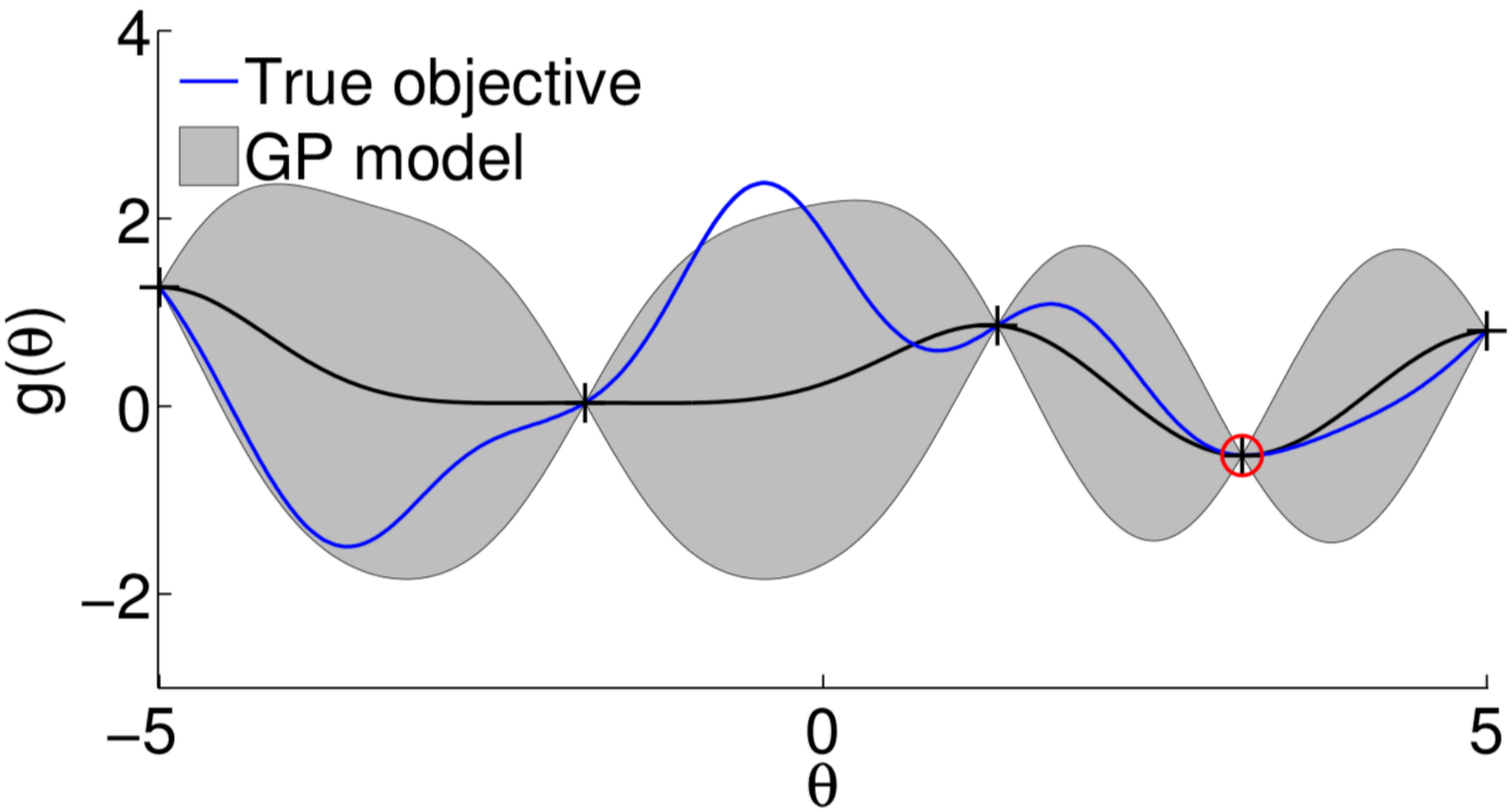

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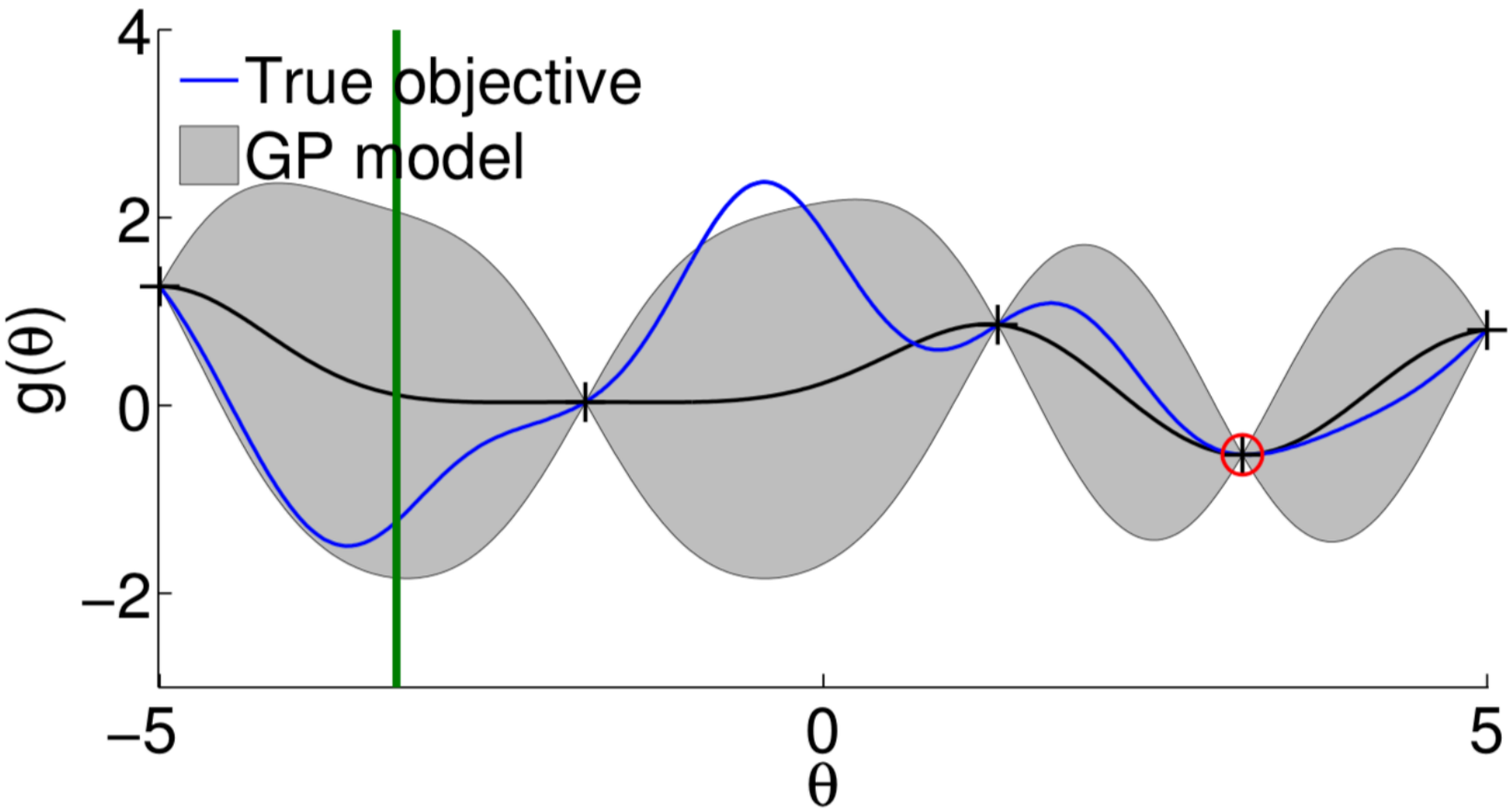

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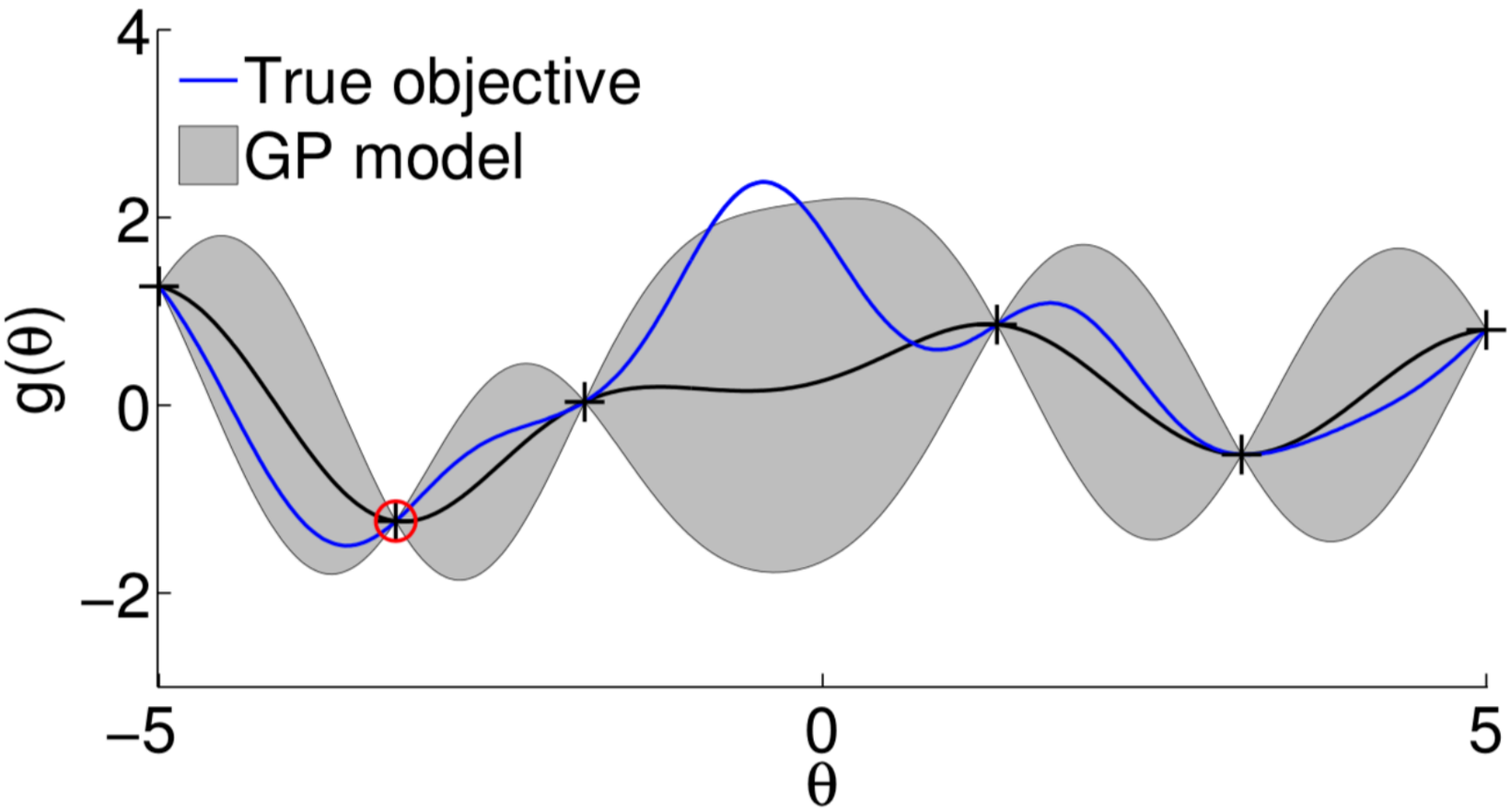

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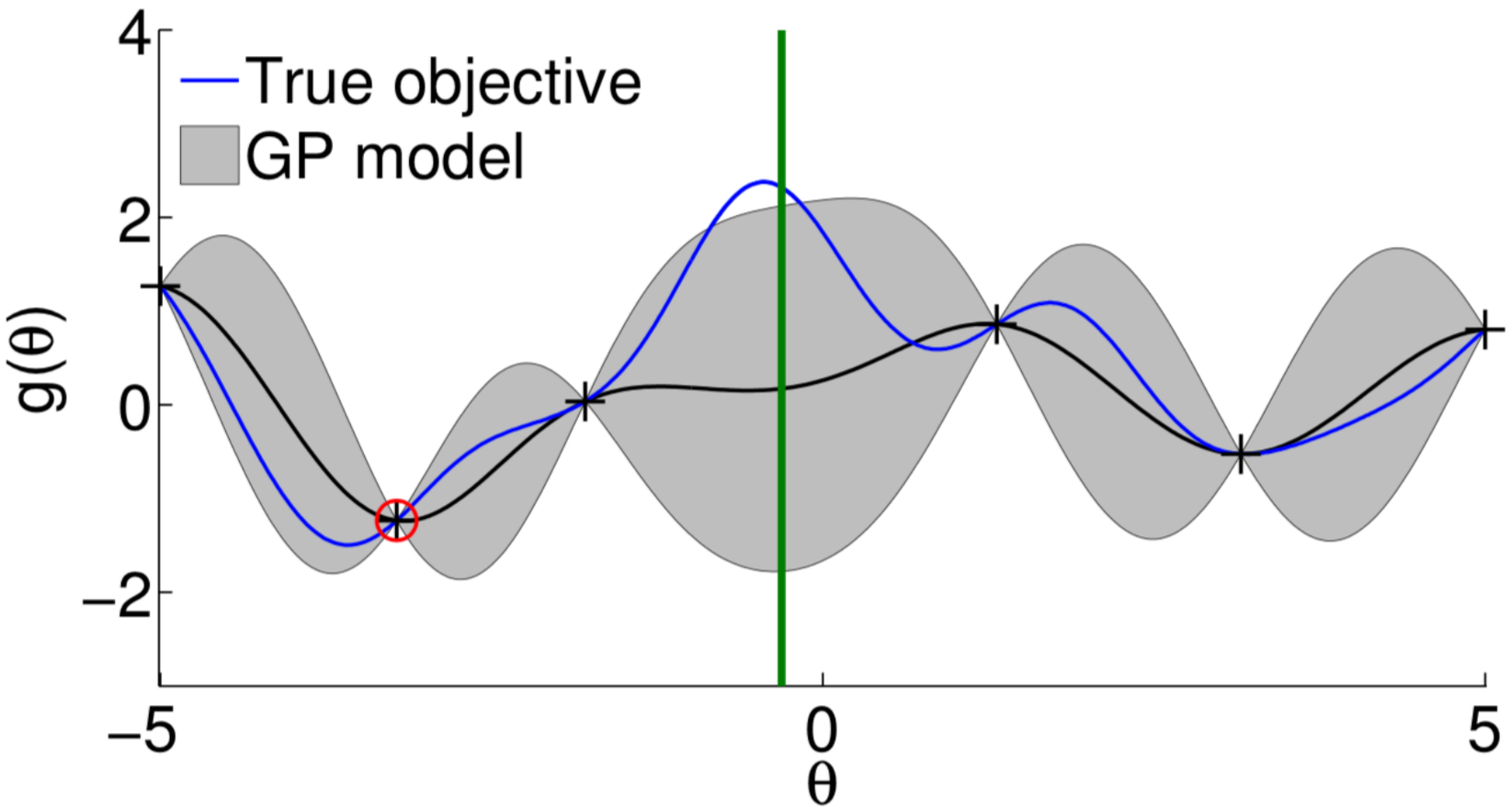

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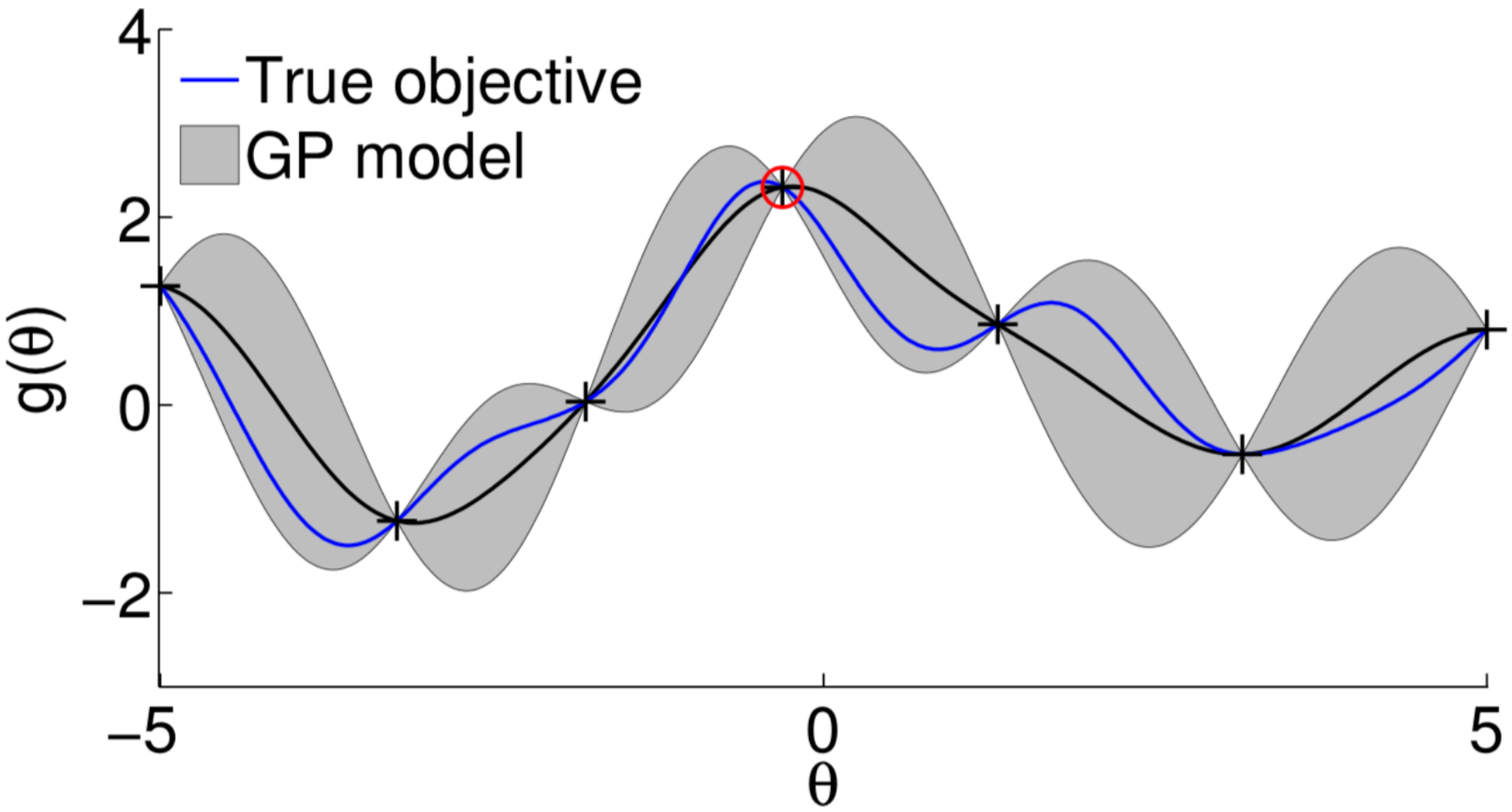

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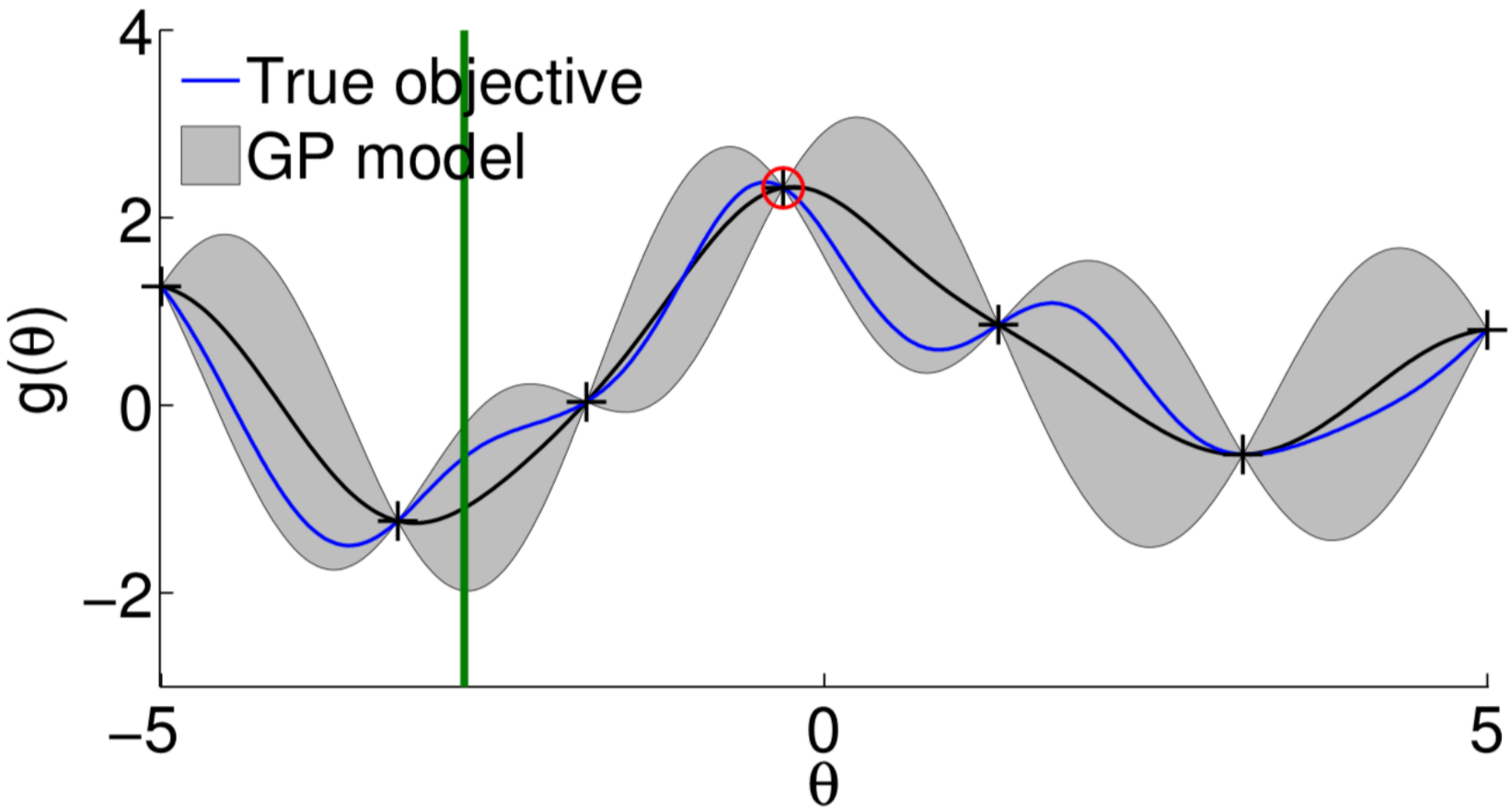

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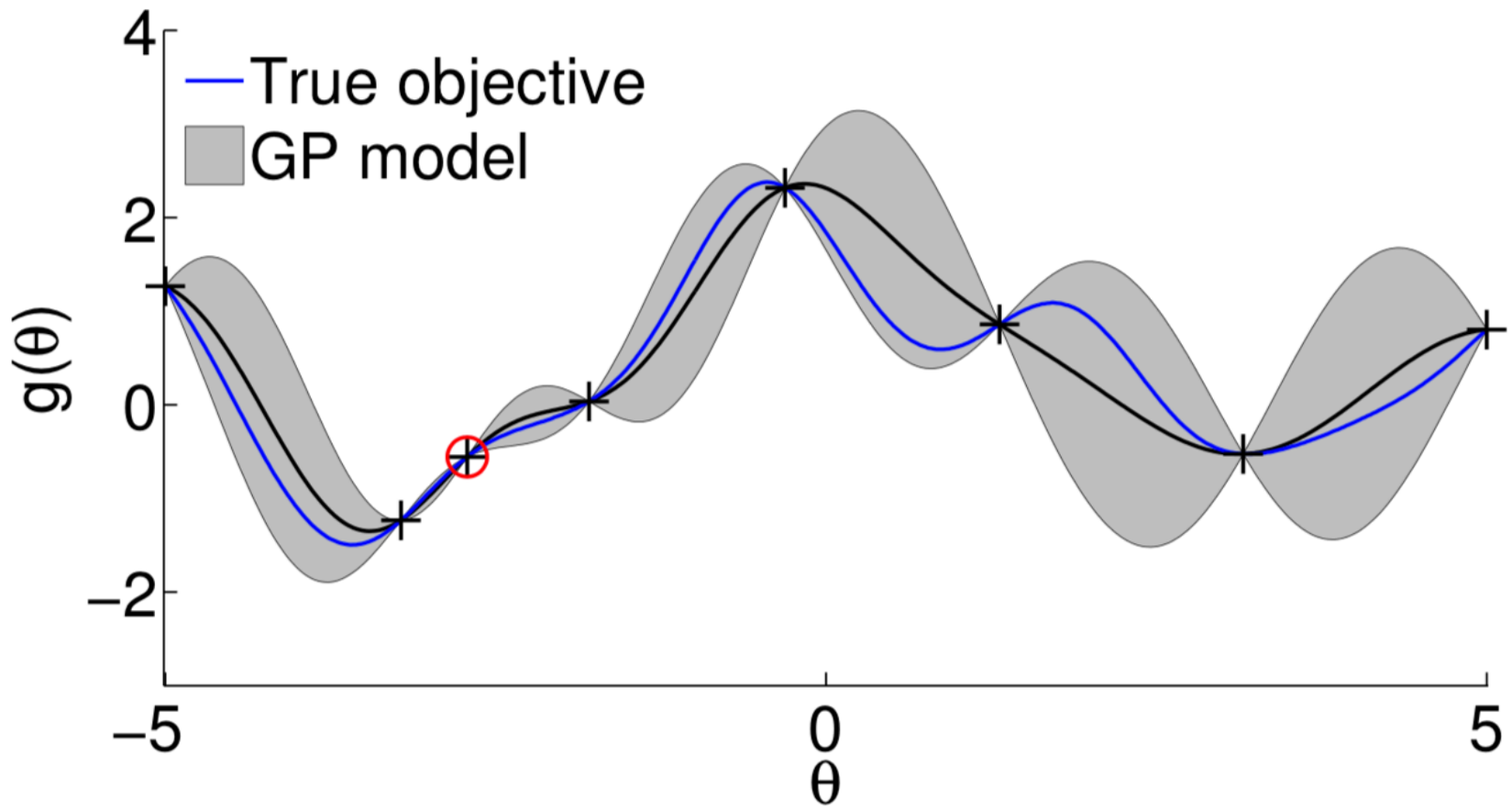

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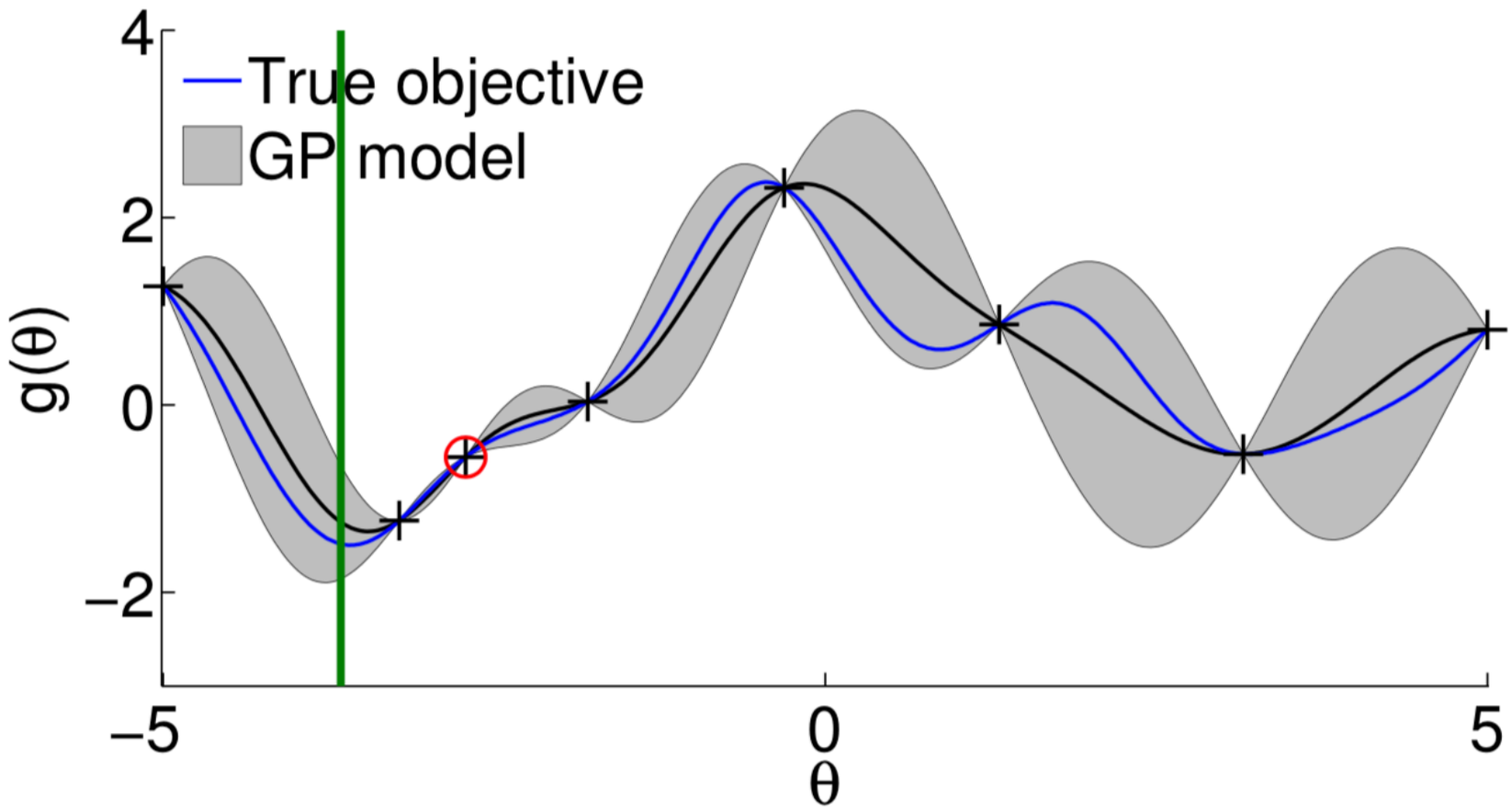

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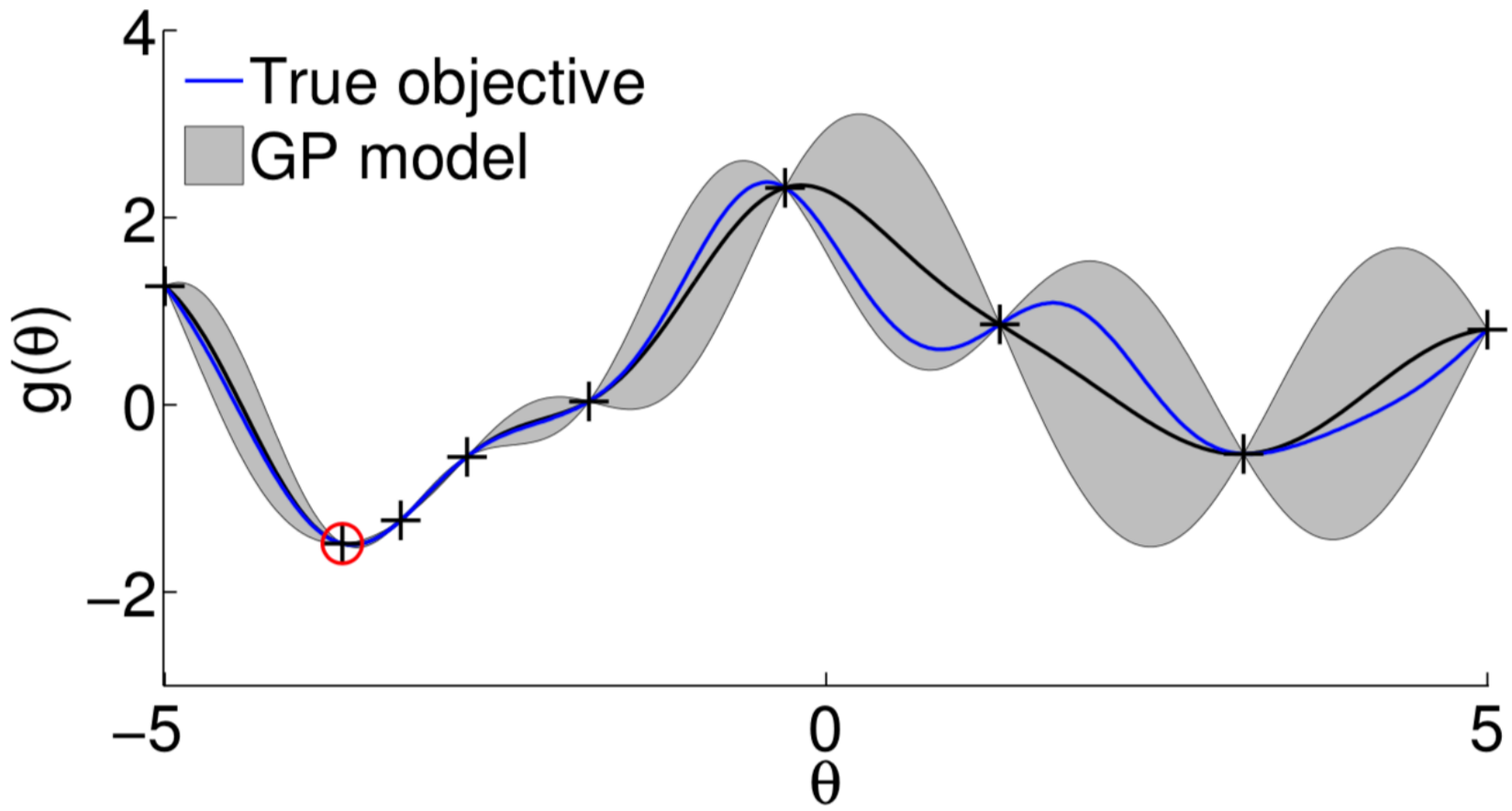

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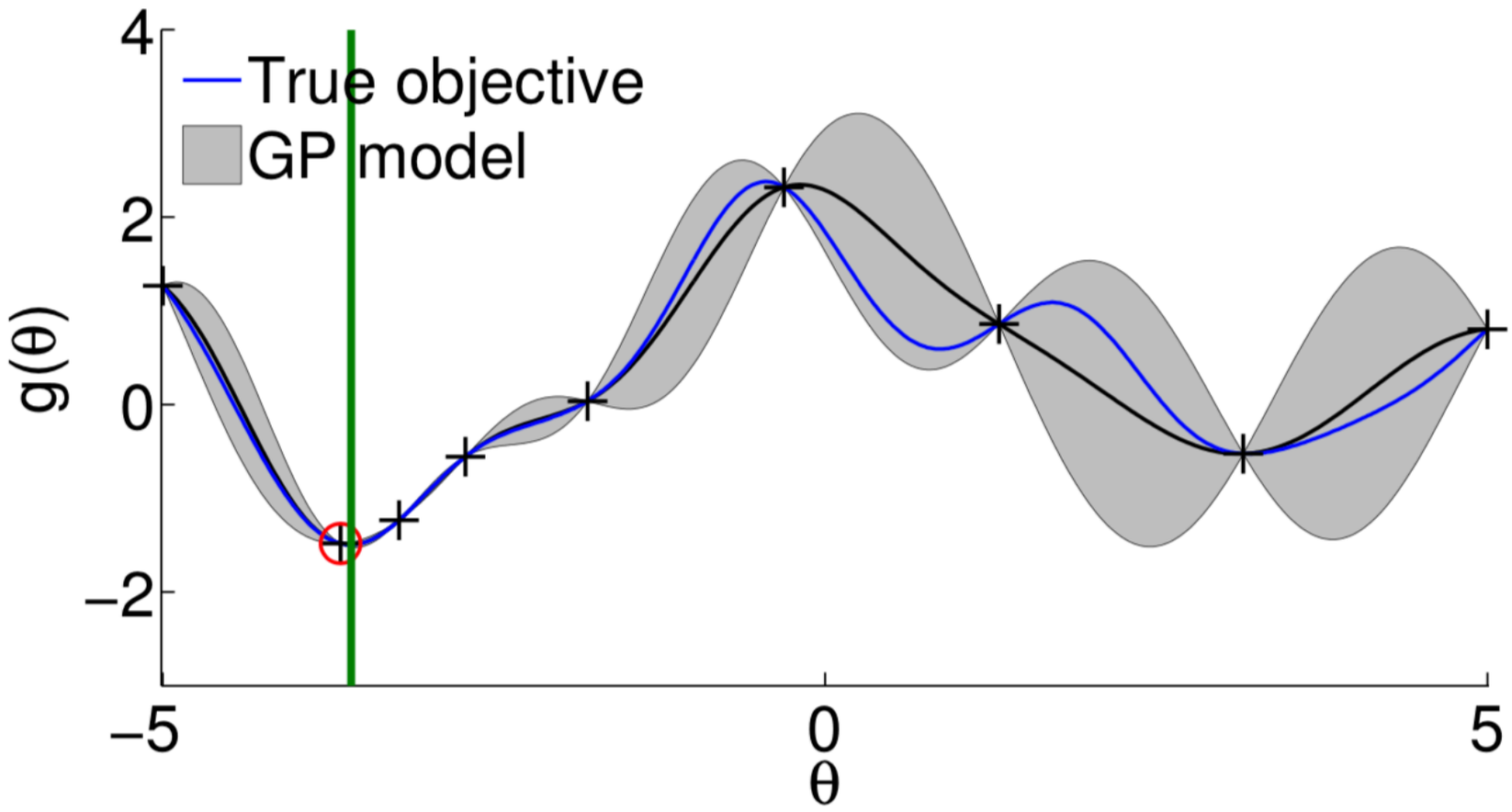

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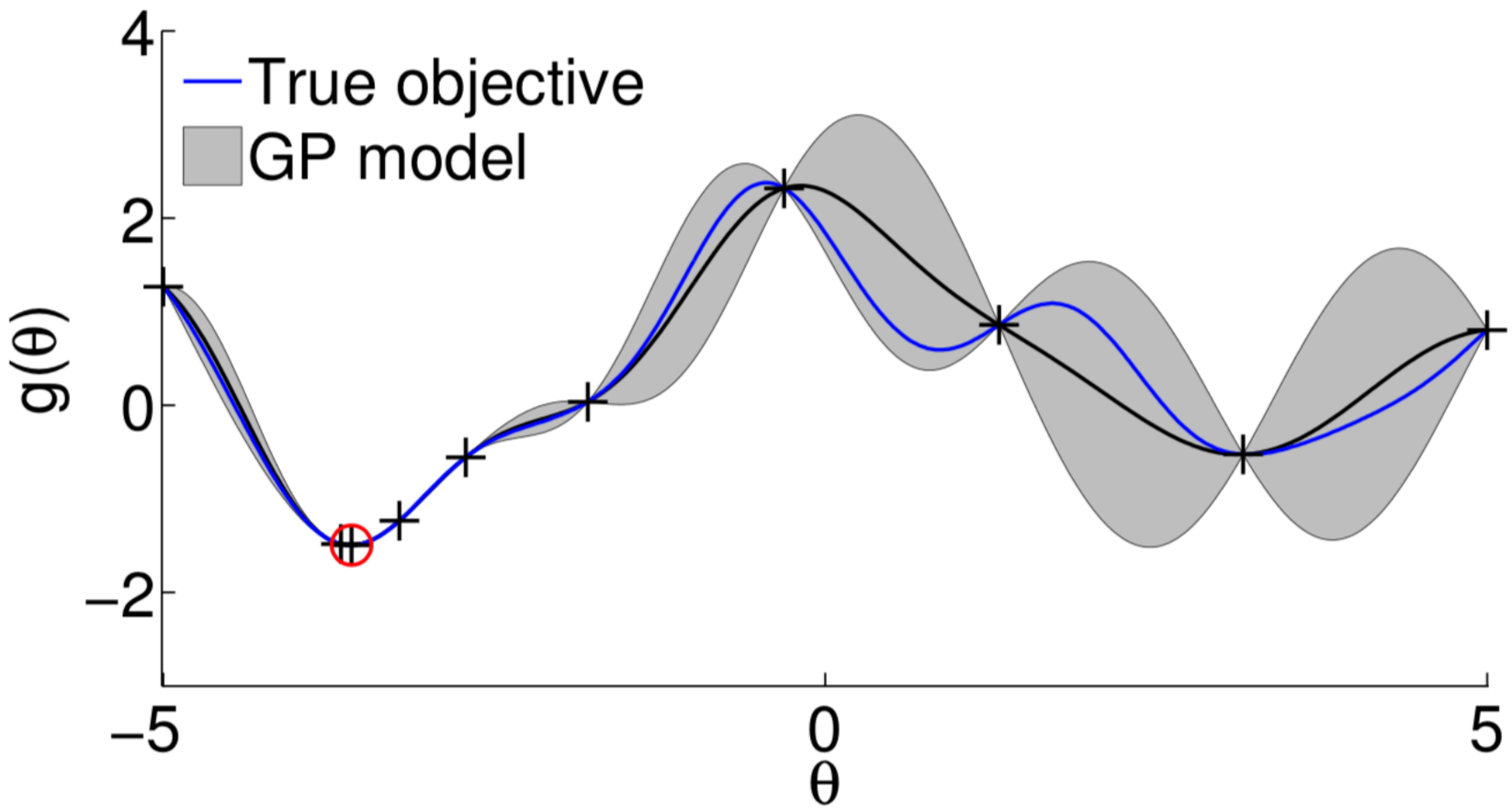

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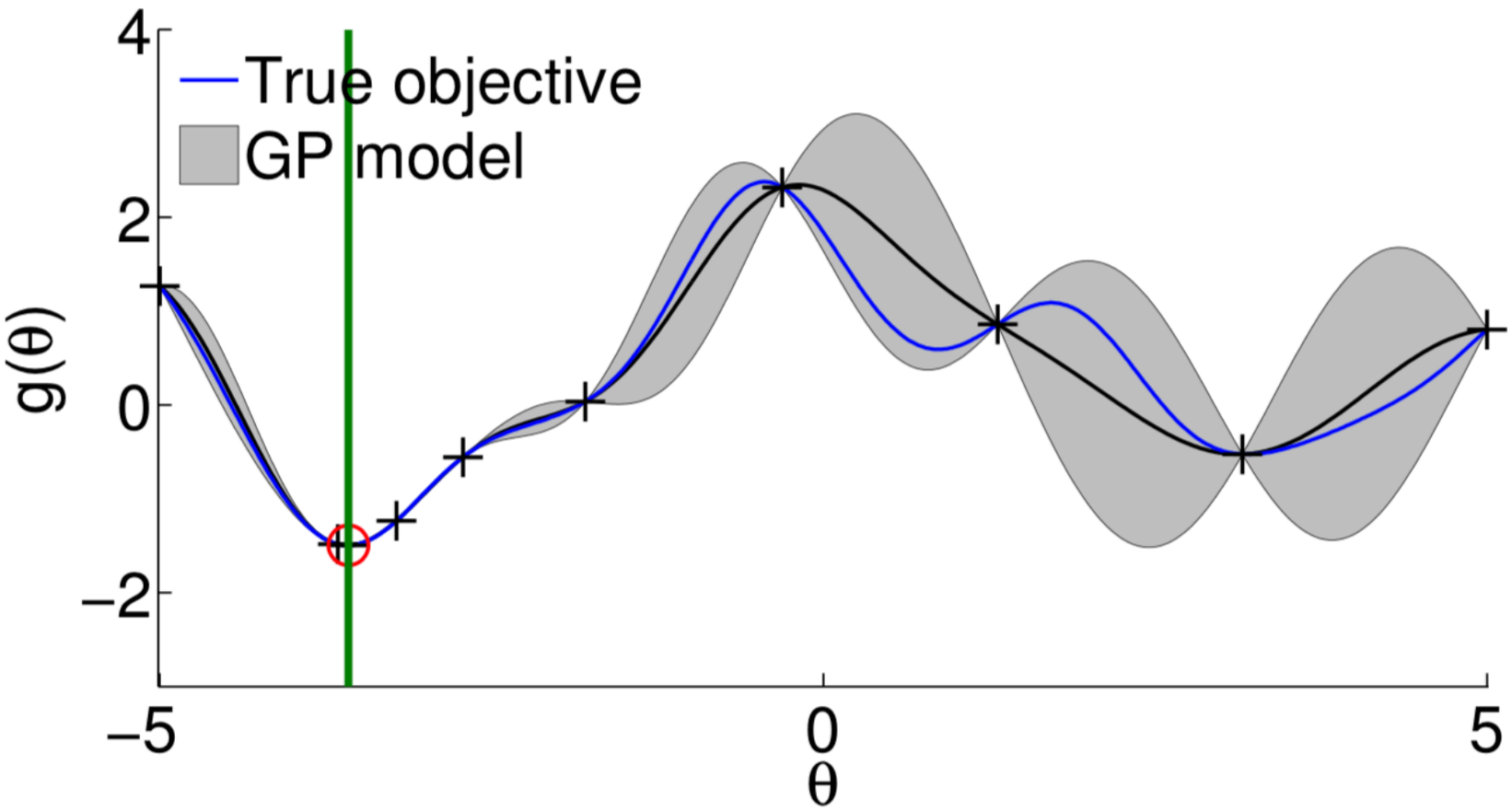

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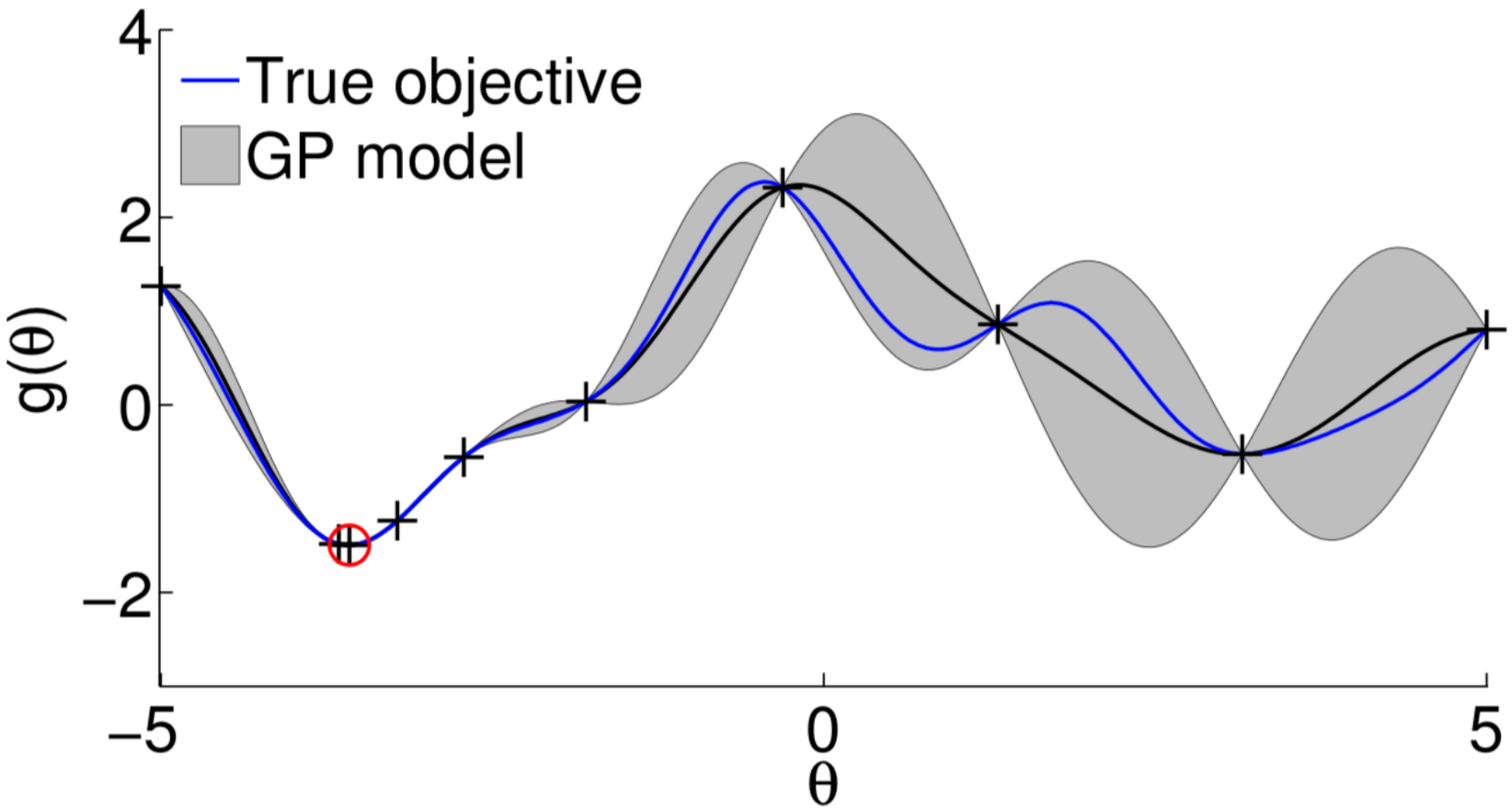
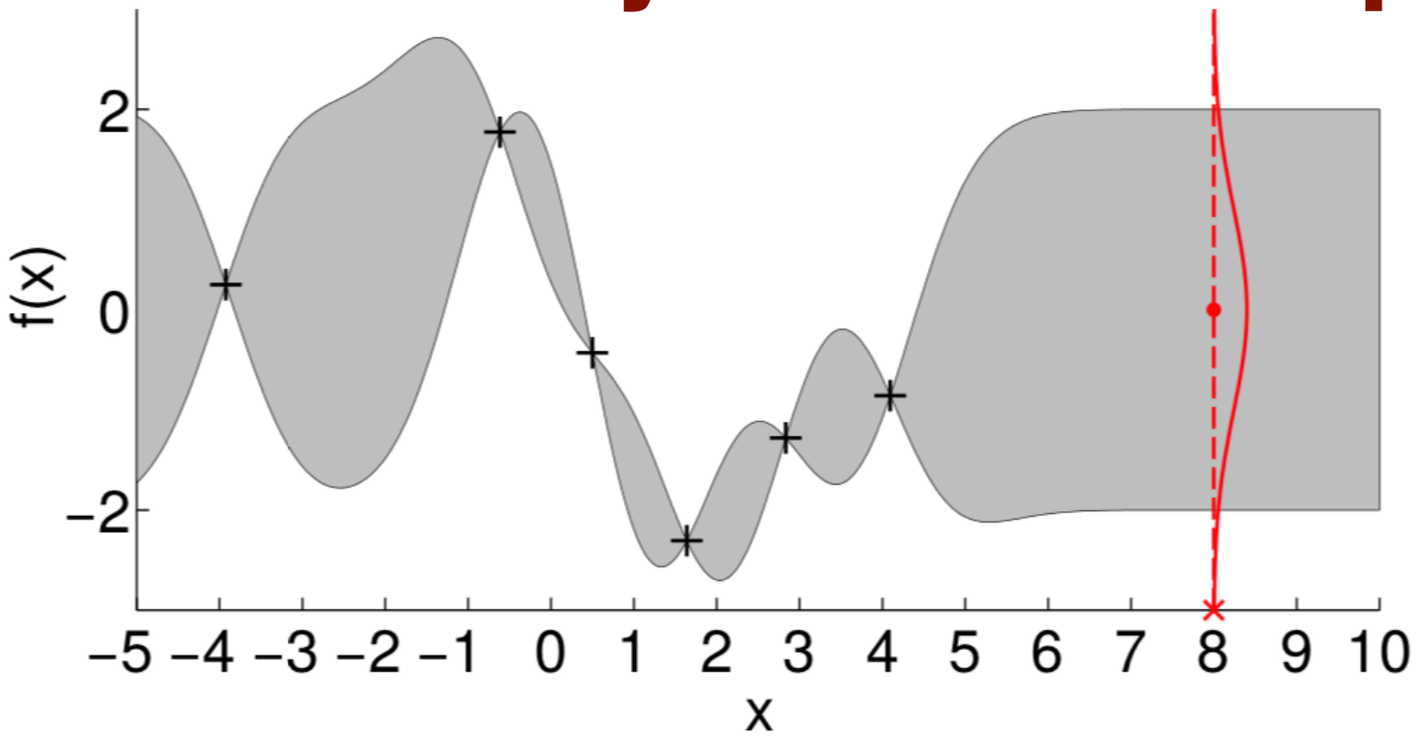
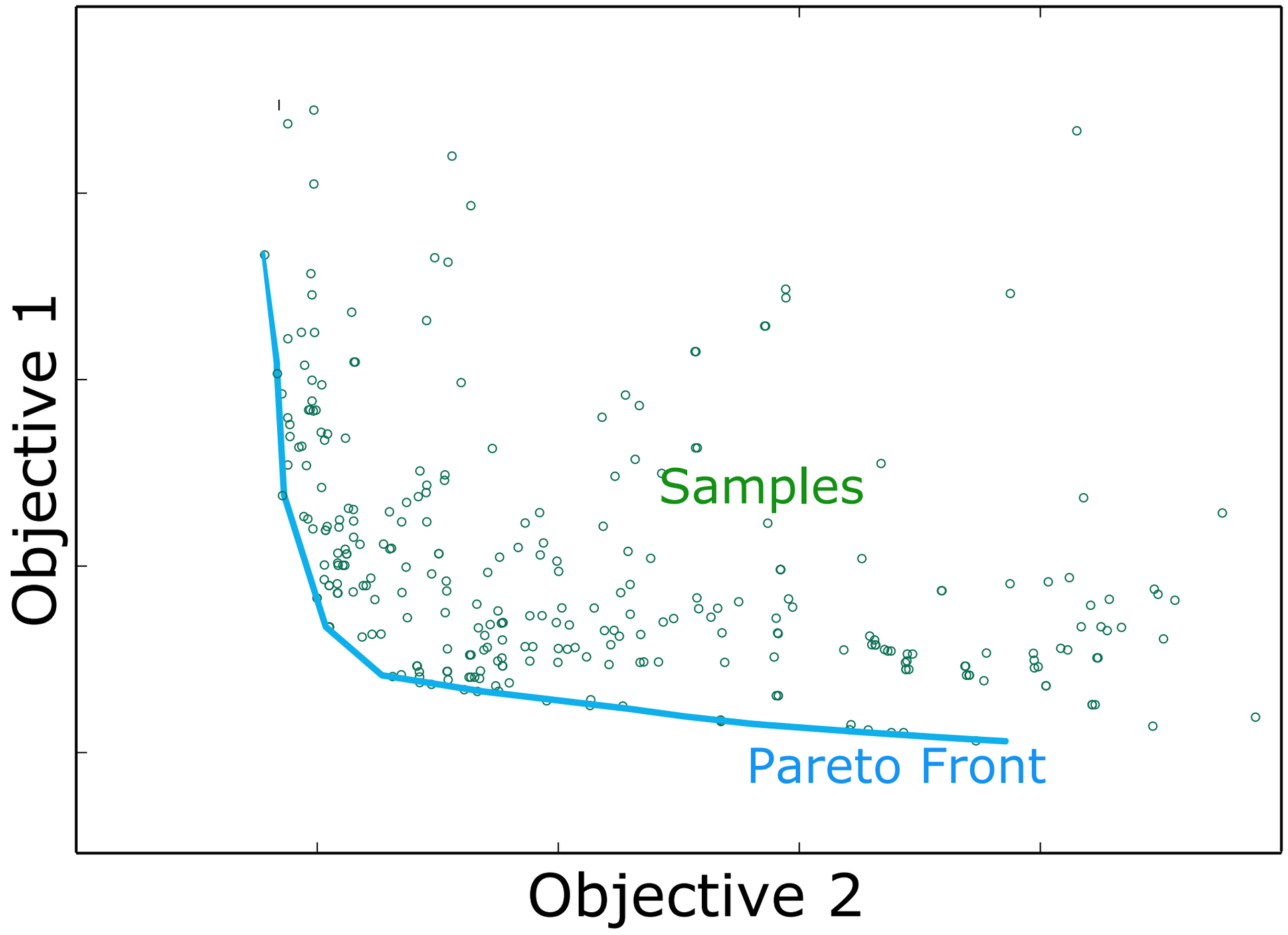


Using Uncertainty in Global Optimization



- Goal: choosing the next point to evaluate the true objective
- Find a good (global) optimum
  - Need to get out of local optima
  - Probabilistic model gives us means and variances
- Trade off exploration and exploitation
  - **Exploration**: seek places with high variance
  - **Exploitation**: seek places with low mean
- **Acquisition function** combines the two

Multi-Objective Goal: Pareto Front



Multi-objective Optimization

Random scalarizations [Paria et al.] adapted for:

- RIOC variables
- Acquisition functions

Given K objectives $f_1(\boldsymbol{x}), ..., f_K(\boldsymbol{x})$ and a weight distribution $\mathcal{L}$

defined as the simplex $\boldsymbol{\lambda} \in \mathbb{R}^K_+$, $||\boldsymbol{\lambda}||_1 = 1$, a random scalarization is

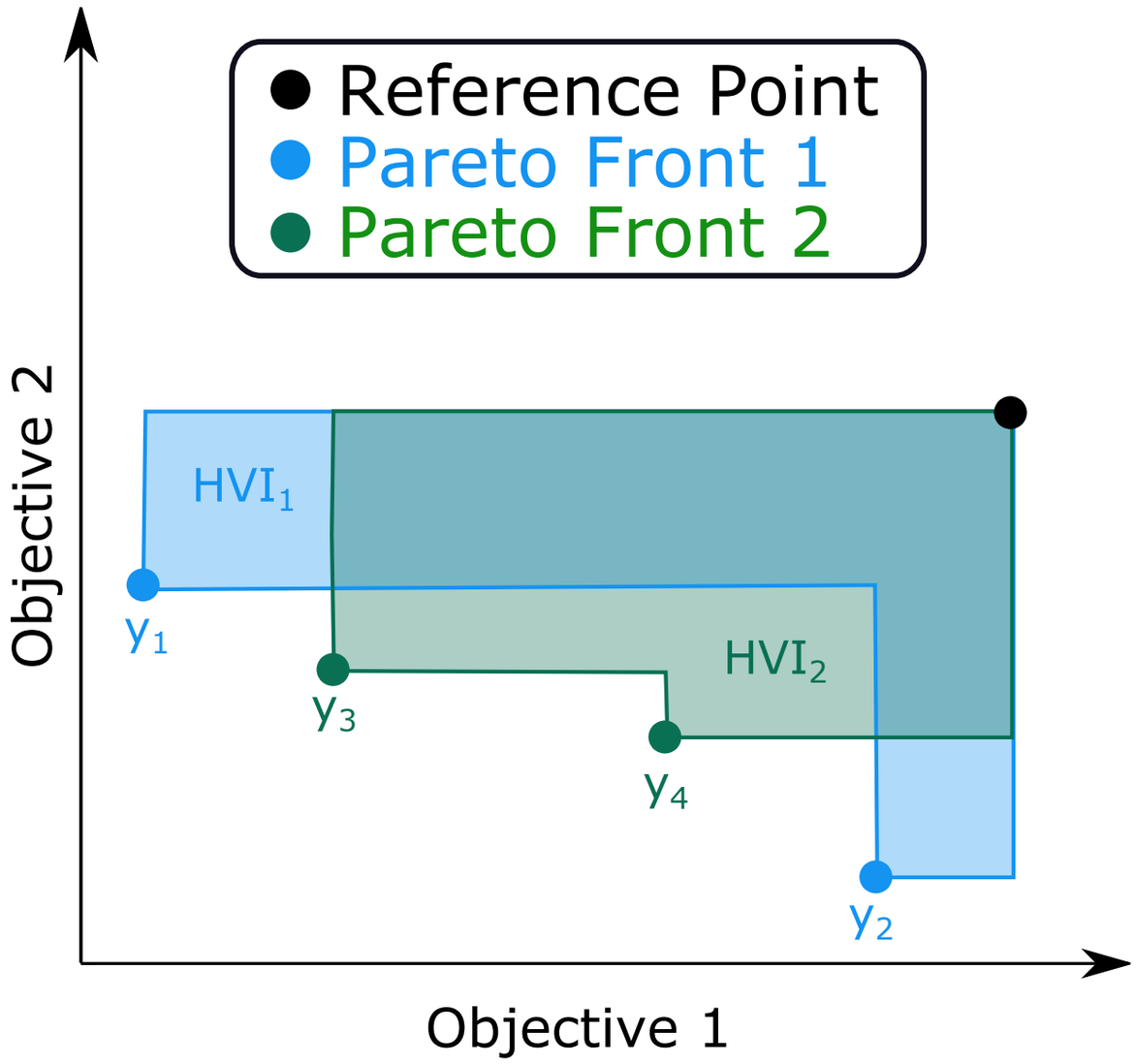
defined as $g(\boldsymbol{\lambda}, \boldsymbol{x})$ where $\boldsymbol{\lambda} \sim \mathcal{L}$

HyperMapper provides two scalarization functions:

linear and Tchebyshev

Linear scalarization: $g_{lin}(\boldsymbol{\lambda}, \boldsymbol{x}) = \sum_{k=1}^{K} \lambda_k f_k(\boldsymbol{x})$

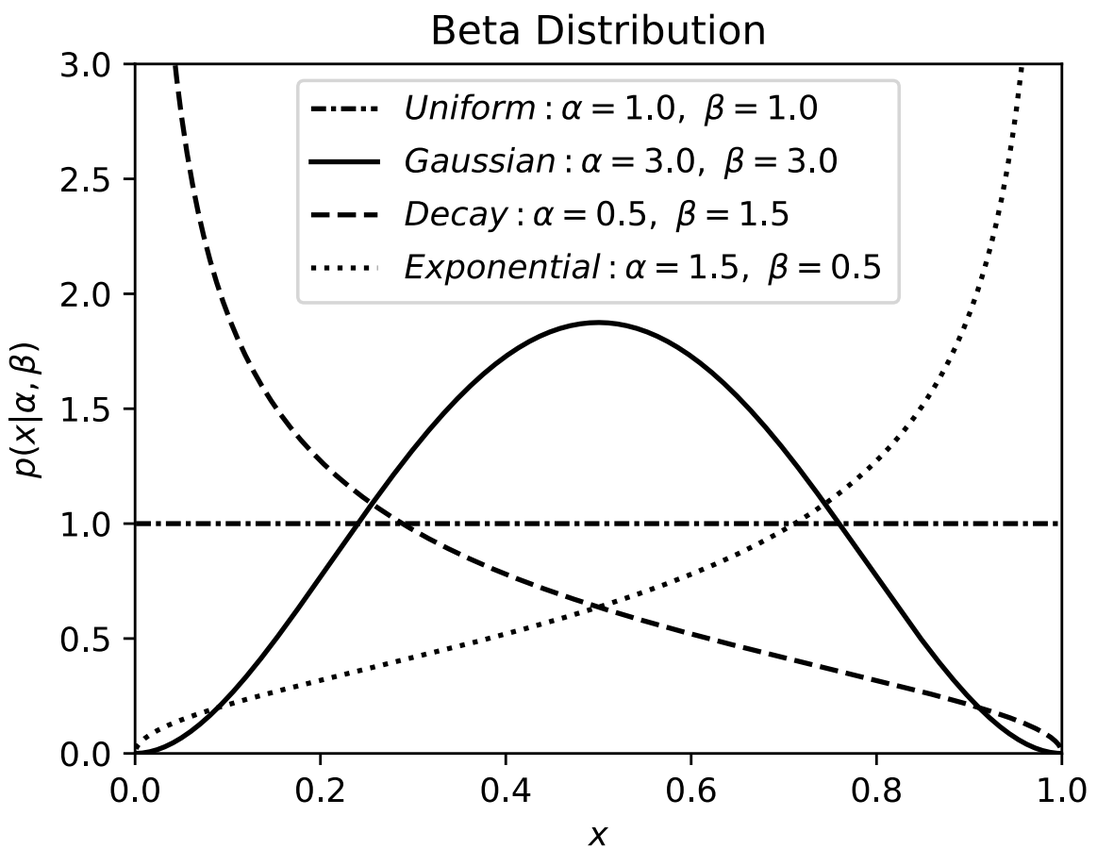
HyperVolume Indicator (HVI)



- Used to compare 2 Paretos
- HVI is a hypervolume
  - with respect to a reference
- It is always a scalar
  - even with multiple objectives
- The lower the better:
  HVI_{total} - HVI_i

Injecting Prior Knowledge

- Need a probability distribution that:
  1. Has a finite domain
  2. Can flexibly model shapes including:
     Bell-shape and J-shape
- Beta distribution - parameters alpha and beta
- In addition, need of a discrete distribution for categorical variables



PDF given by:

$$f(x|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

for $x \in [0,1]$ and $\alpha, \beta > 0$,

where Γ is the Gamma function

Probabilistic Model in HyperMapper

- Predicts an outcome given an input x

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- One surrogate model per objective
  - Random forests (RF) for regression

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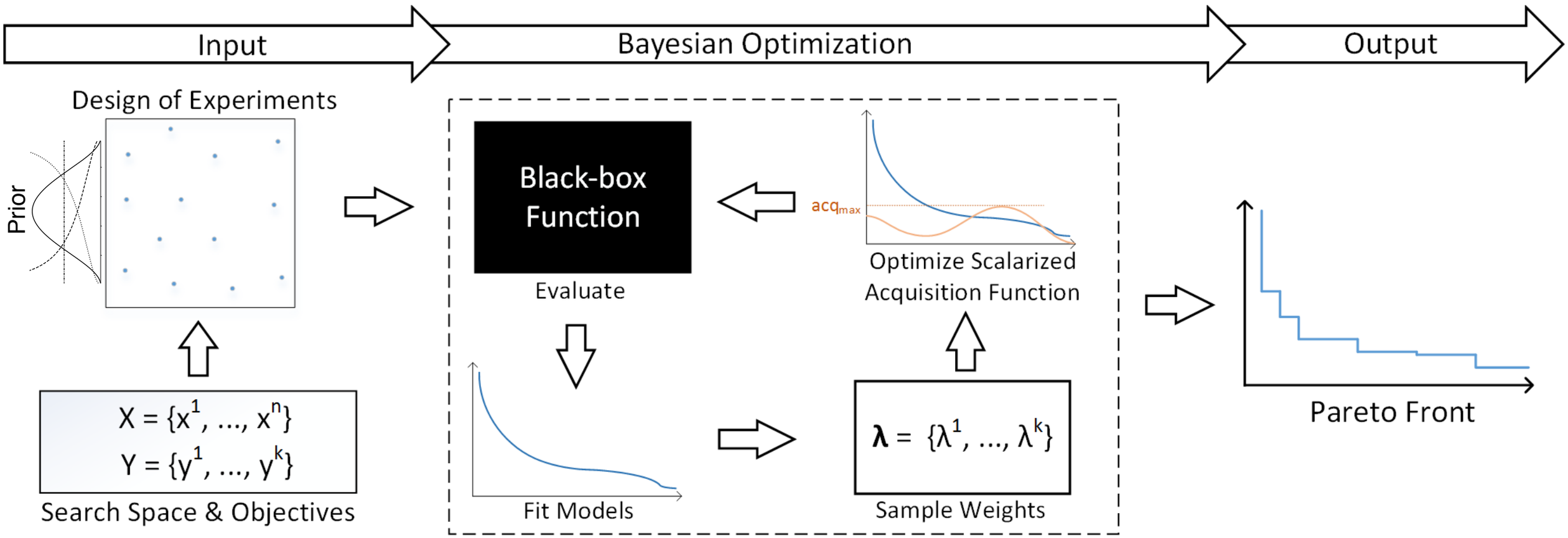
Probabilistic Model in HyperMapper

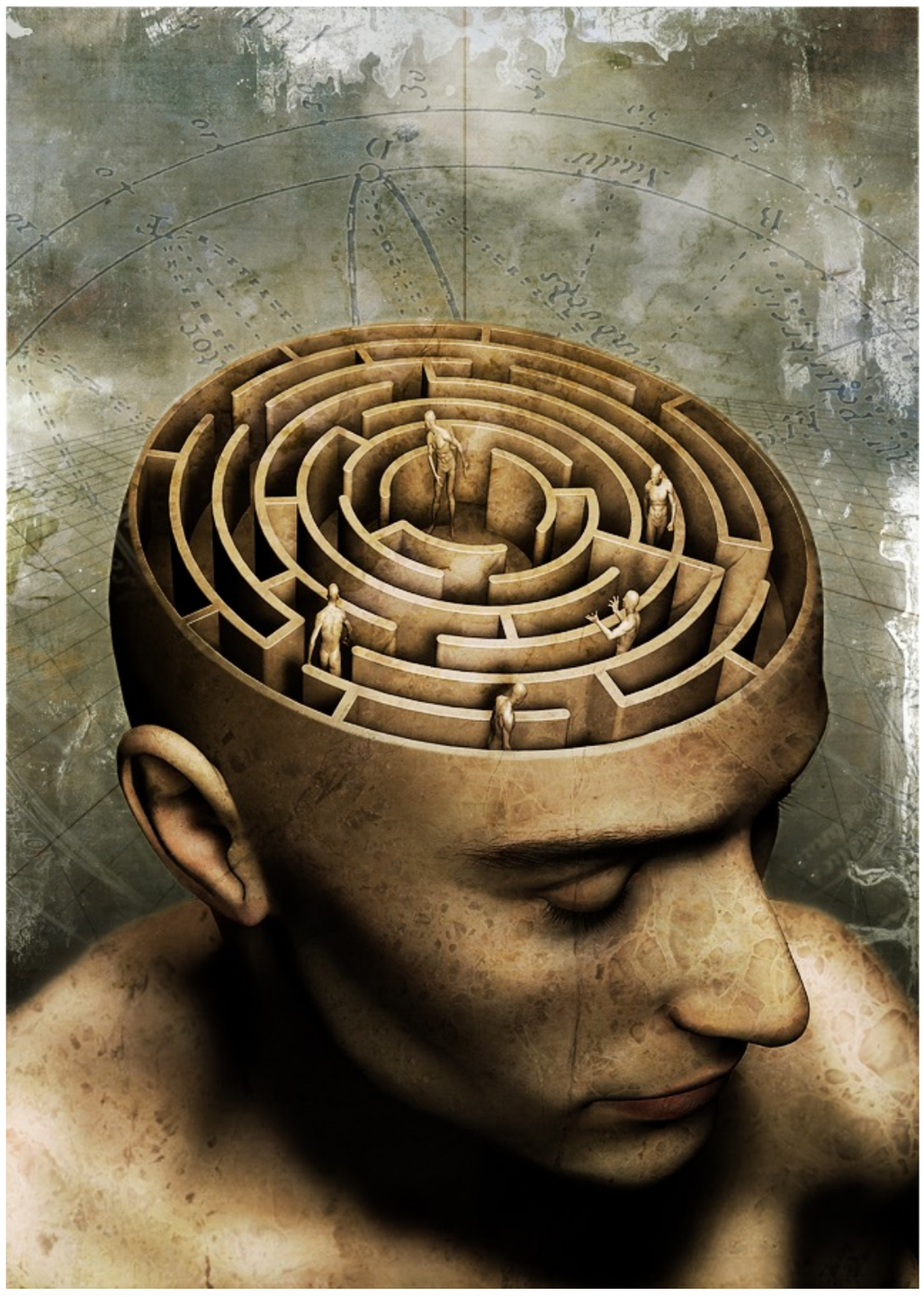
- Predicts an outcome given an input x
- One surrogate model per objective
  - Random forests (RF) for regression
- Intuition of why RF is a good model:
  - Good at non-linearity, multi-modality and non-smoothness
- The model has not to be perfect
  - Interested in optima not the best model
  - Coefficient of determination (R^2) is the wrong indicator of success

The HyperMapper Framework

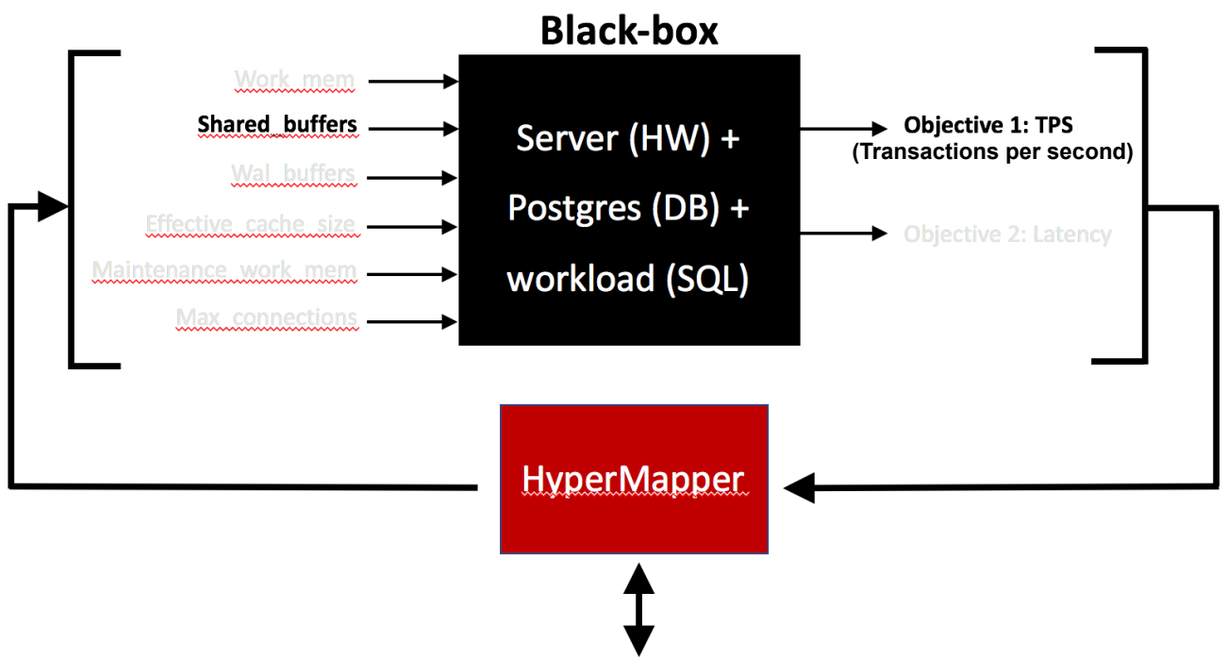


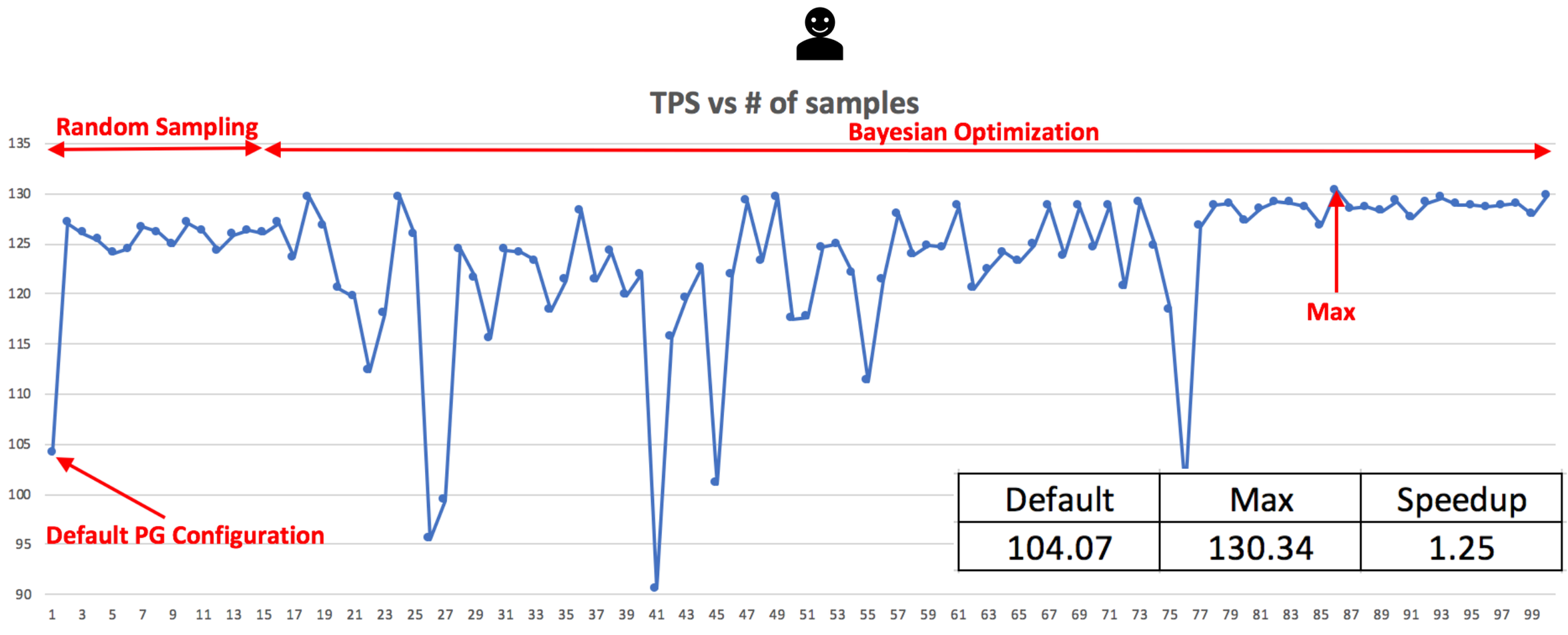
Outline

1. Black-box Optimization
   - Problem Setting
   - Motivation Examples
   - Taxonomy
2. The HyperMapper Framework
   - Bayesian Optimization
   - Pareto and Hypervolume Indicator
   - Prior Distribution
3. **Experimental Results**
   - **Hardware Design**
   - **Computer Vision**
   - **Databases**

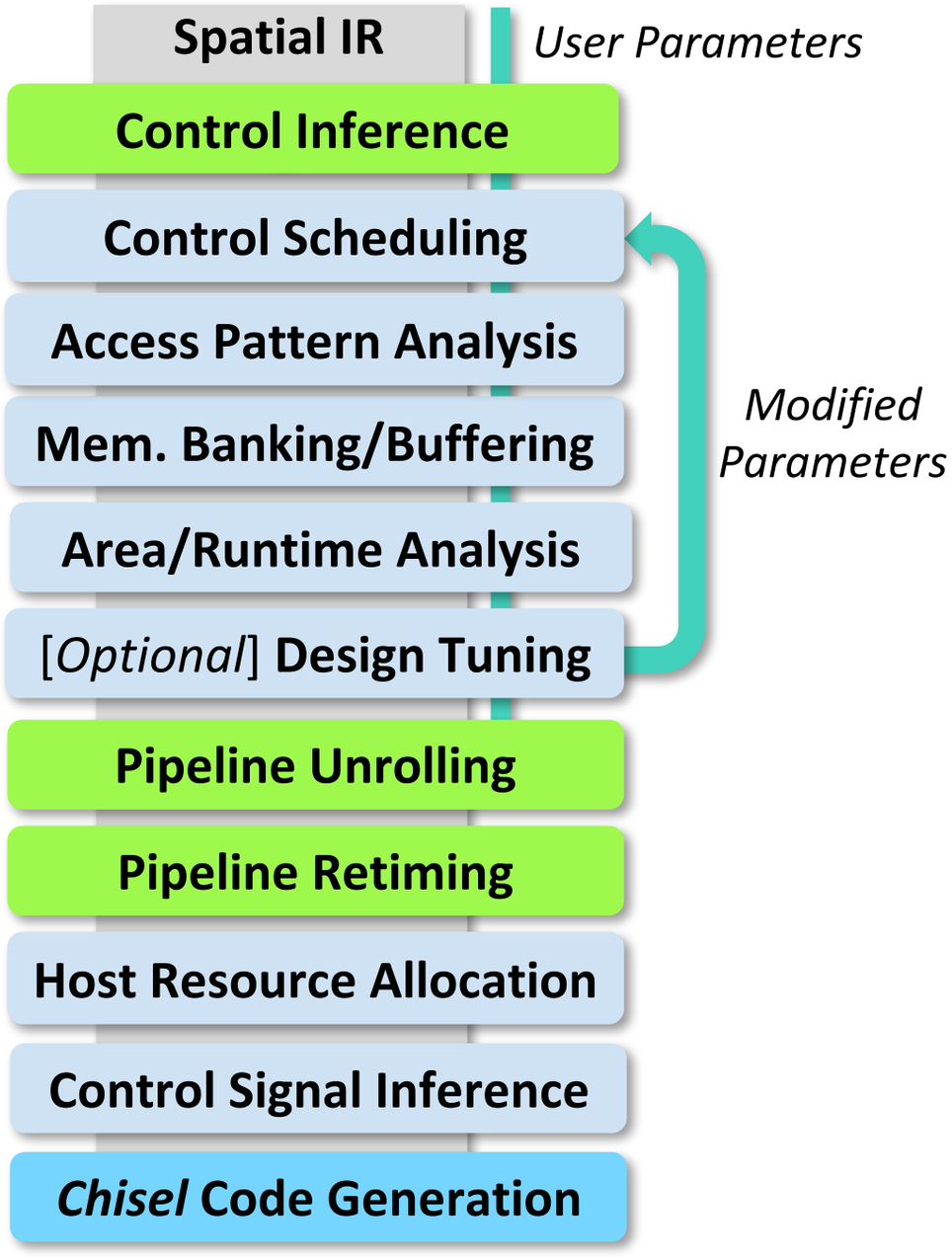


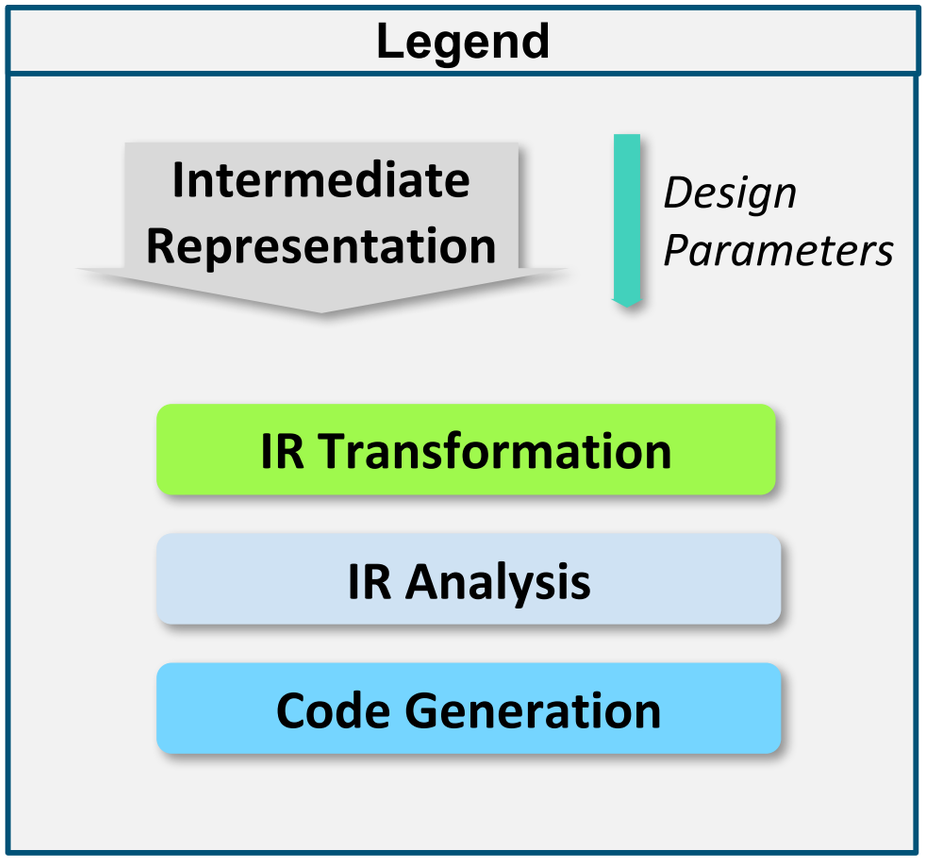
Application 1 - Microsoft Collaboration Preliminary Results on a Simple Scenario





Application 2: FPGA Design Space Exploration (Spatial Compiler)





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- On reconfigurable architectures FPGAs and CGRAs
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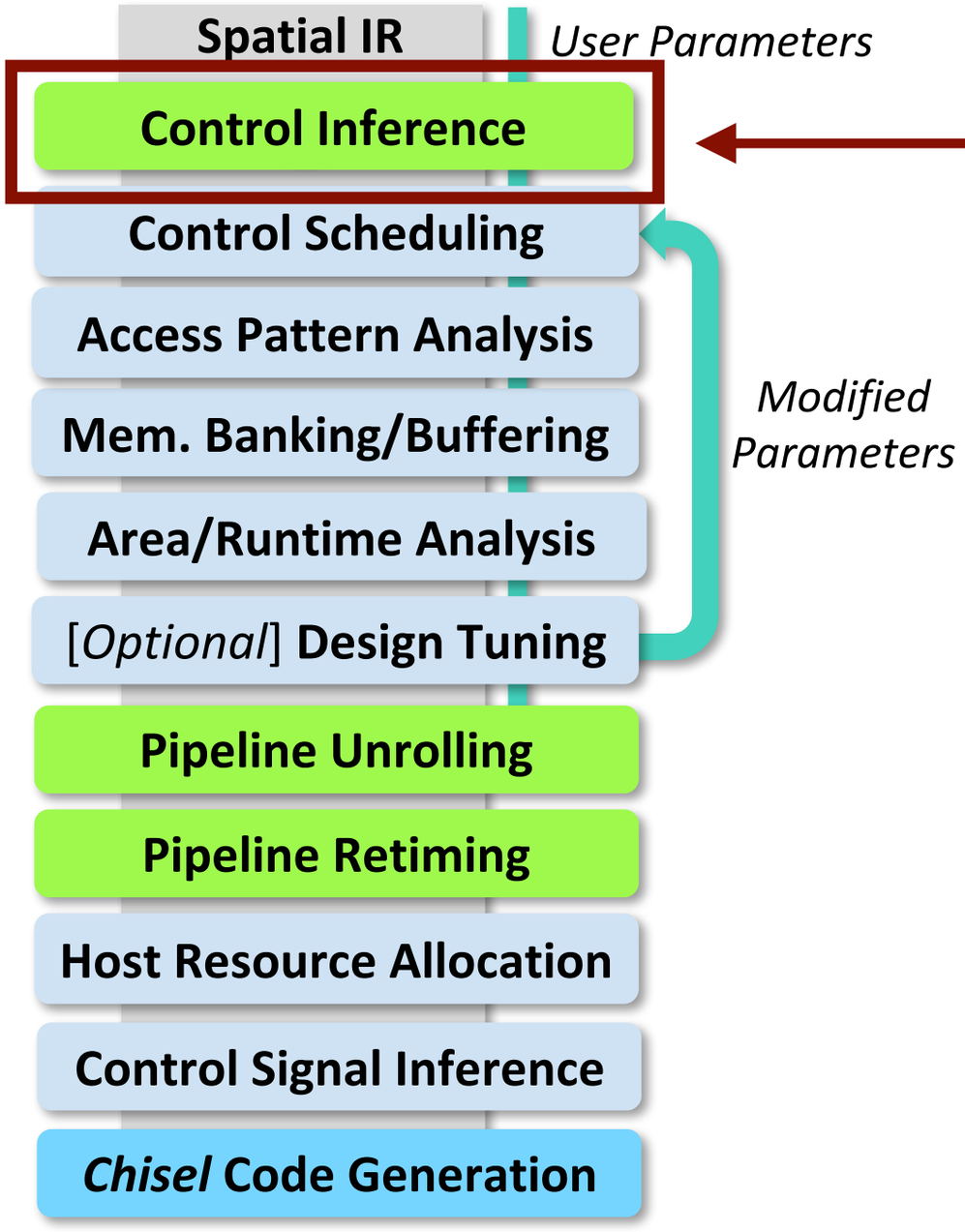
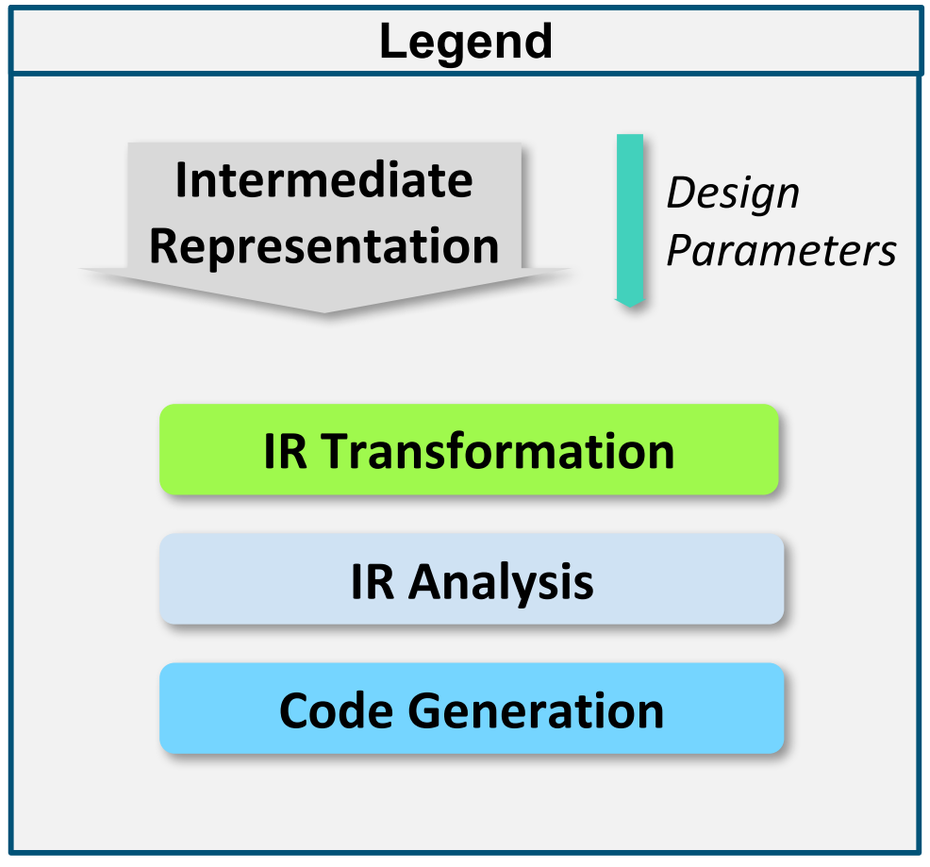


Performs basic hardware optimizations and estimates a domain for each design parameter



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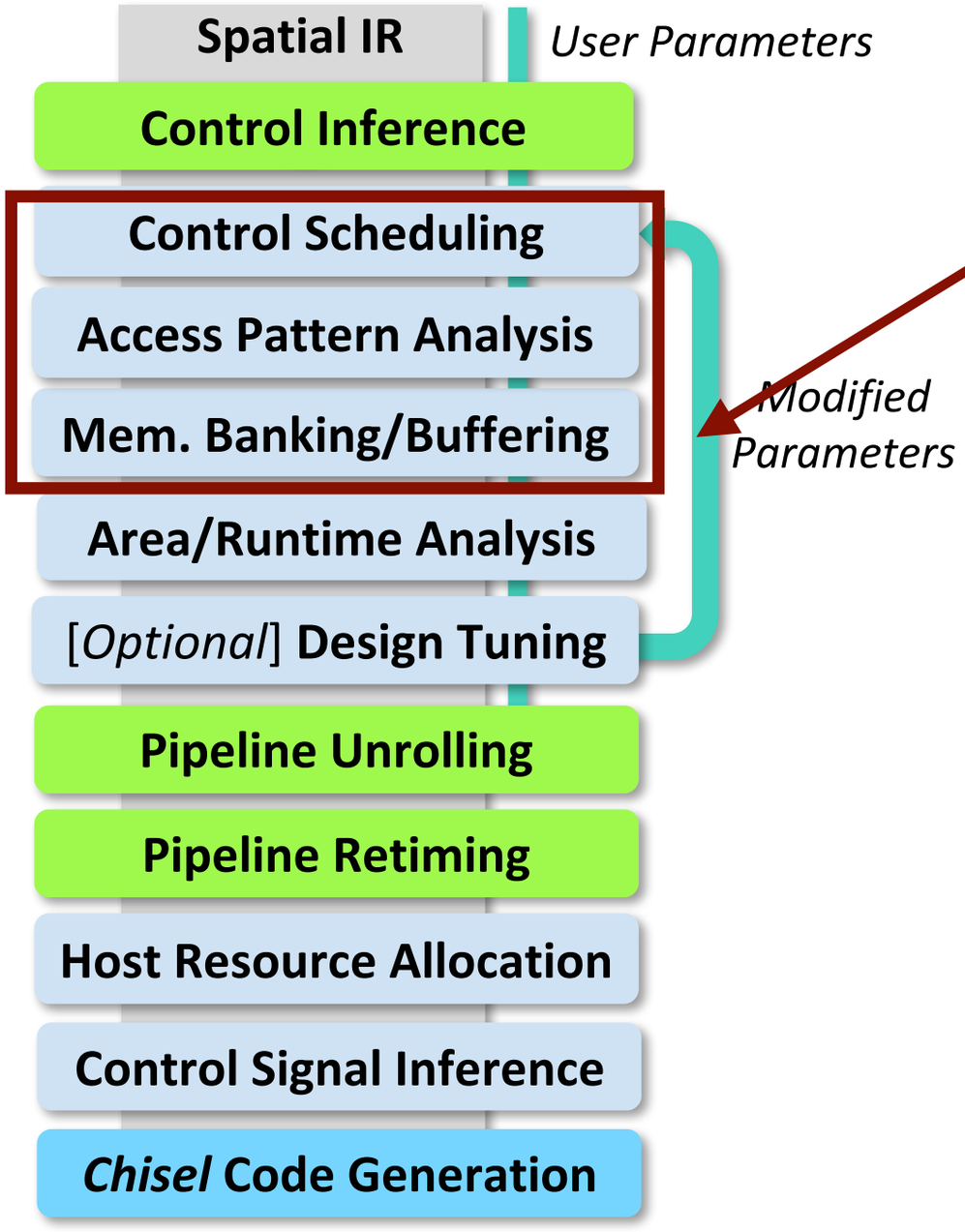
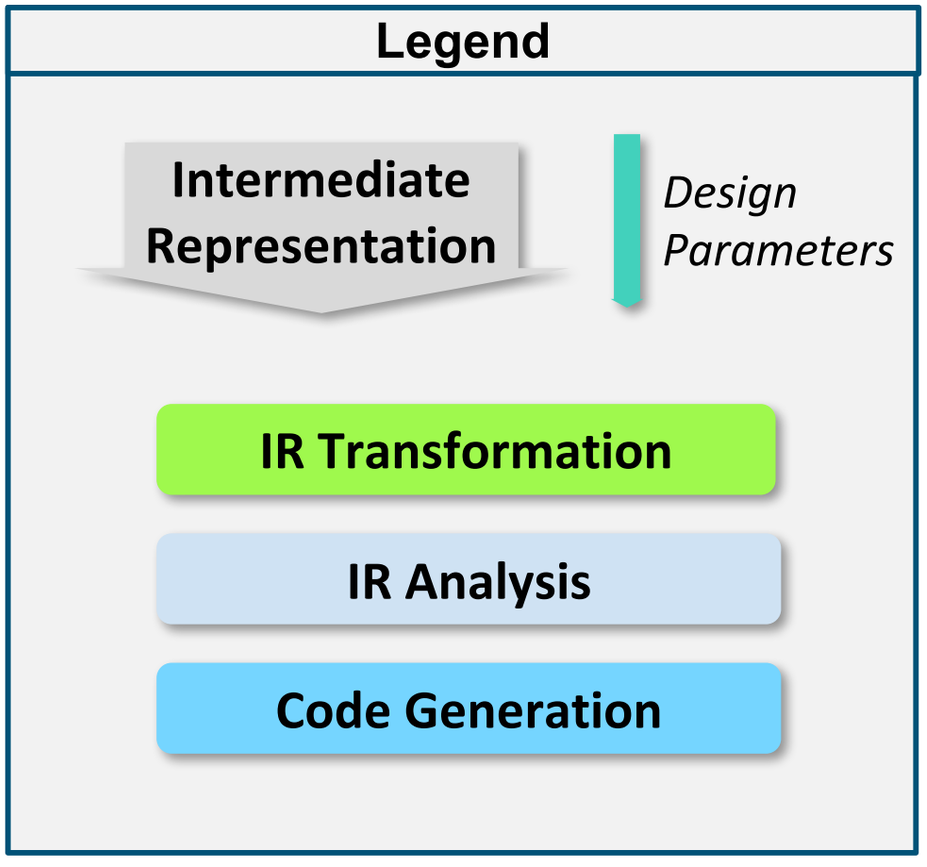


Computes loop pipeline schedules and on-chip memory layouts for some given value for each parameter



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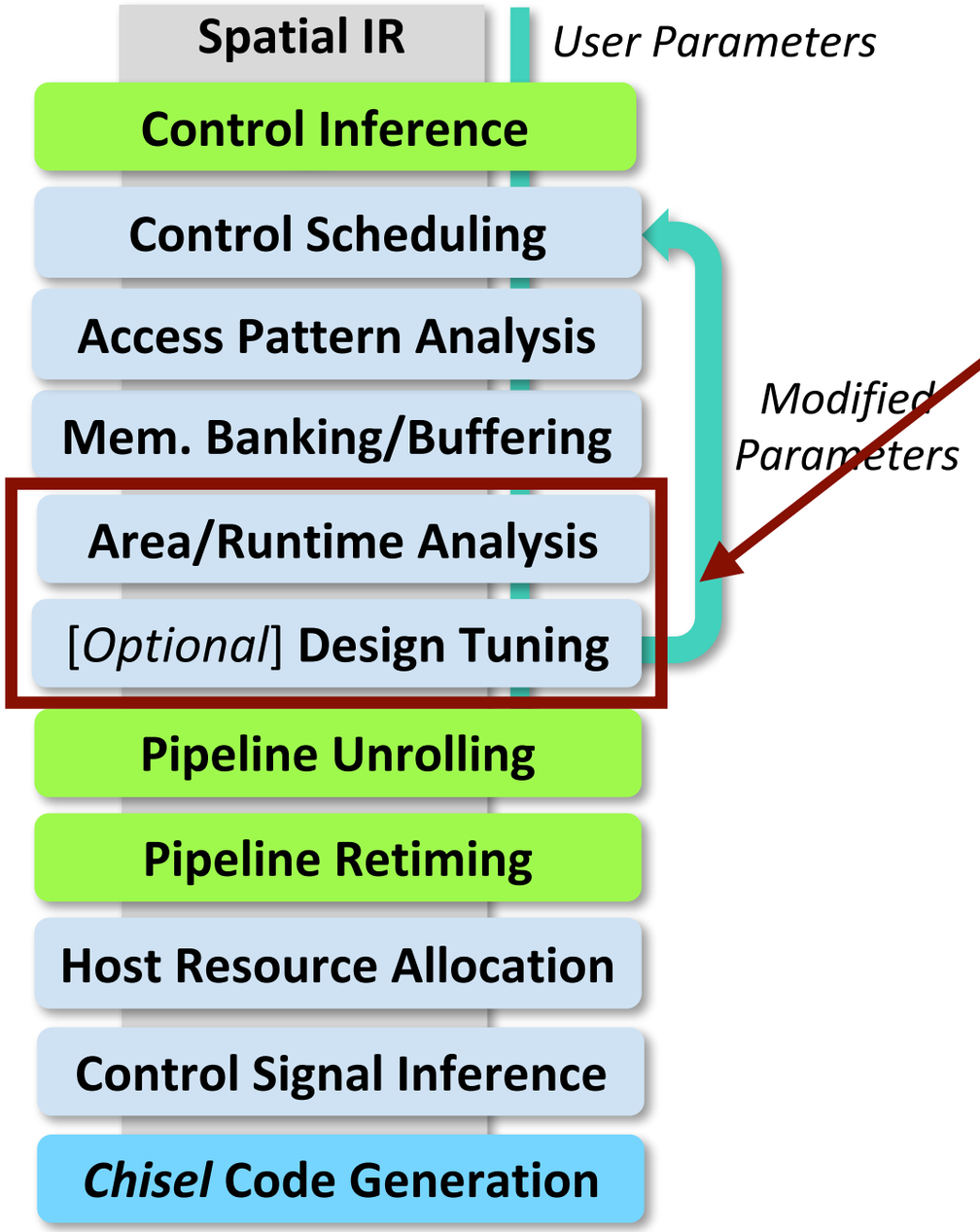
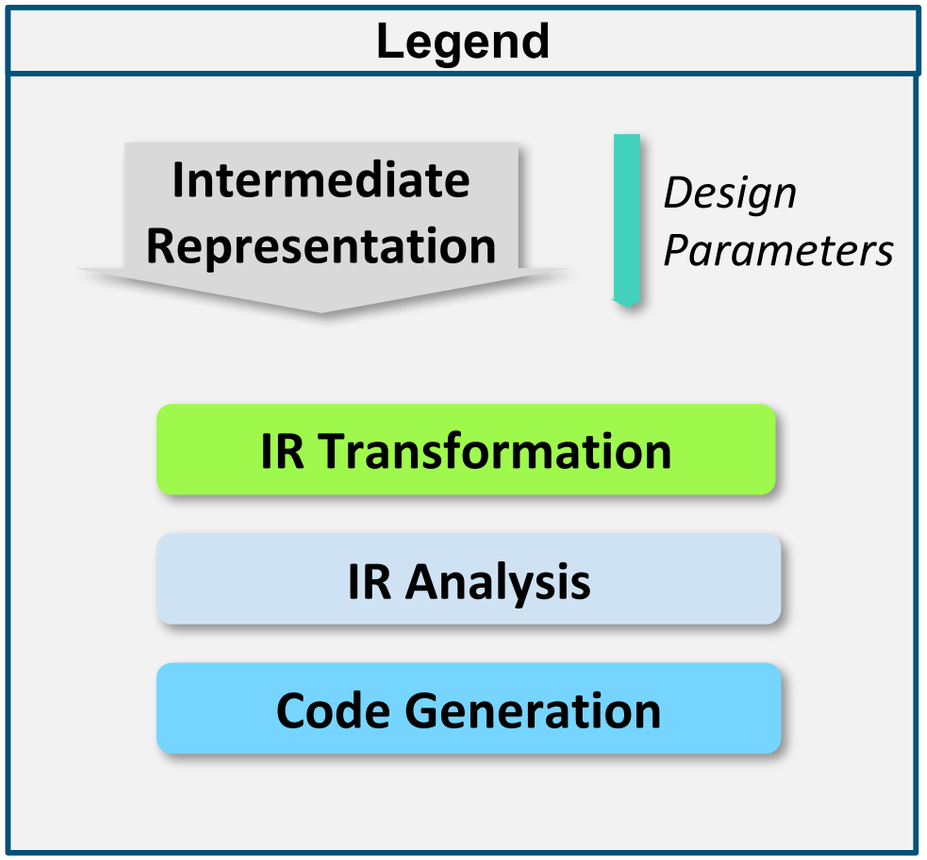


Estimates the amount of hardware resources and the runtime of the application



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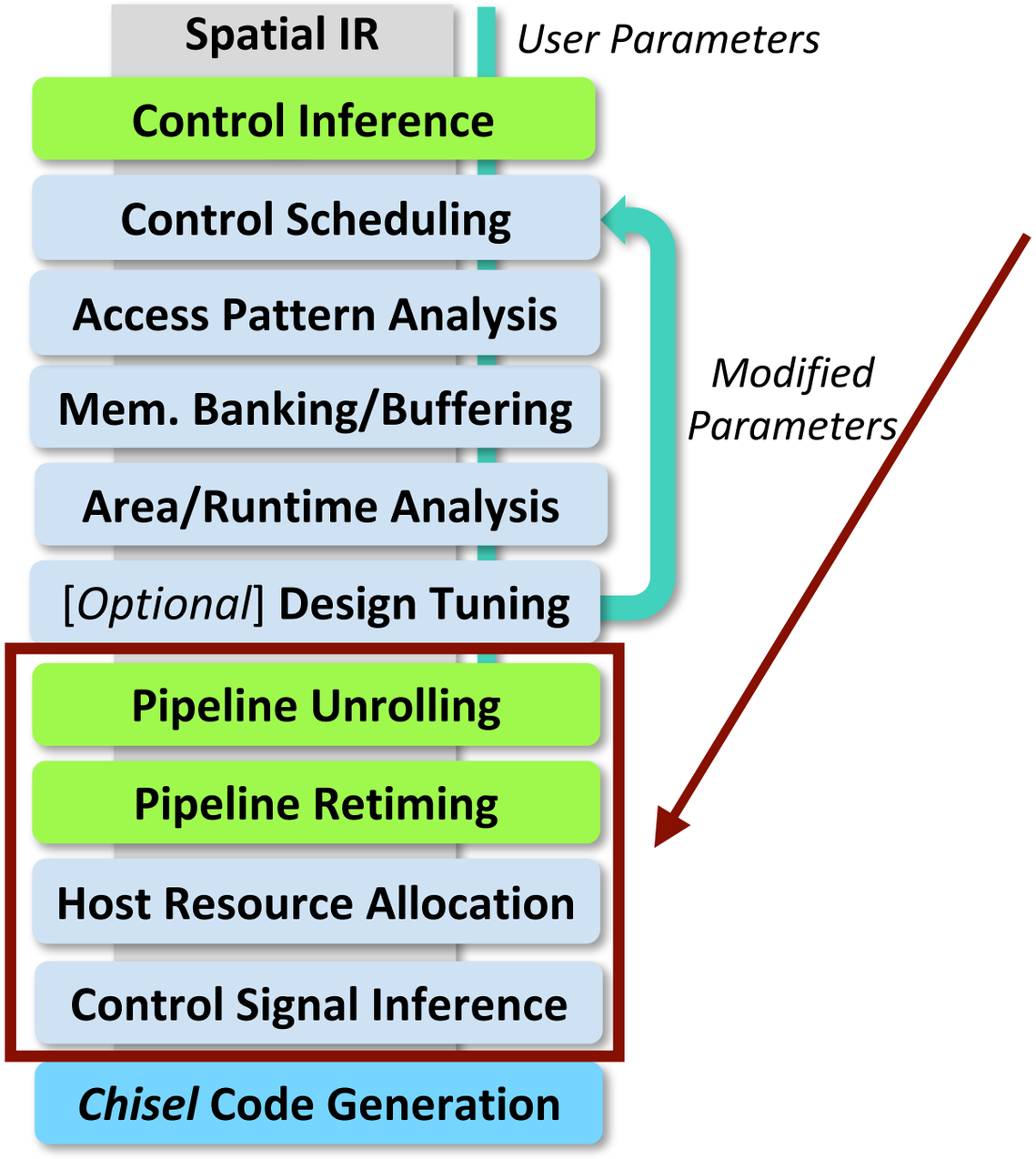
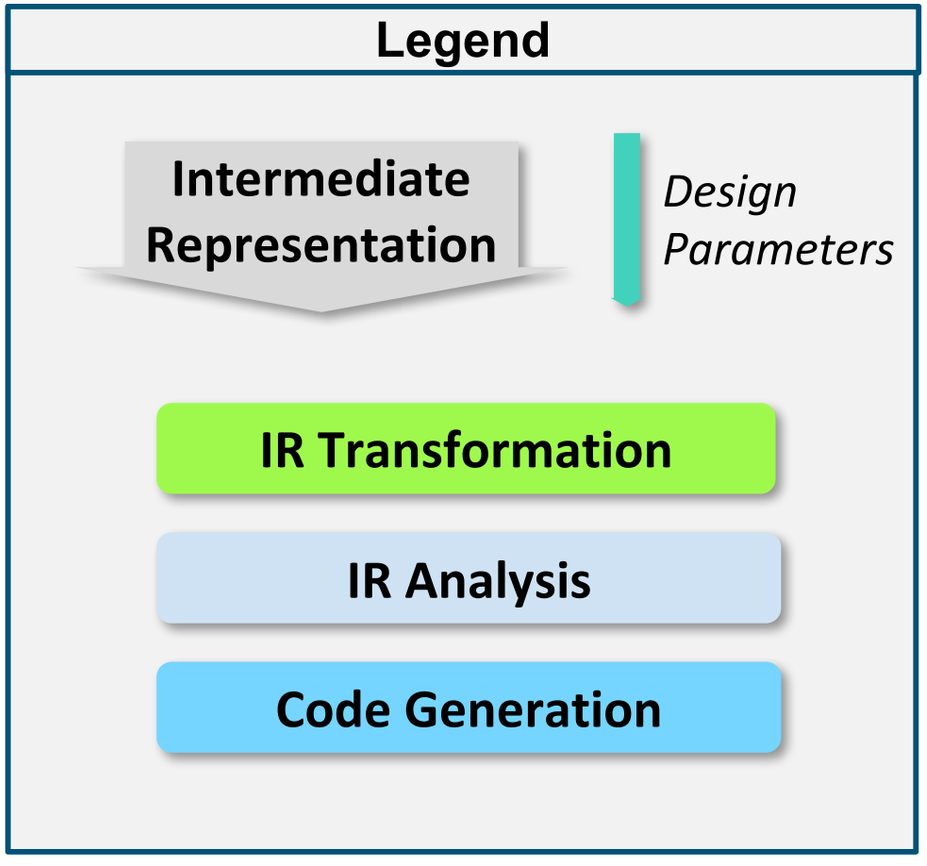


Unrolls loops, retimes pipelines, and performs on-chip memory layout.
The optimizations are computed based on the analyses of the previous phase



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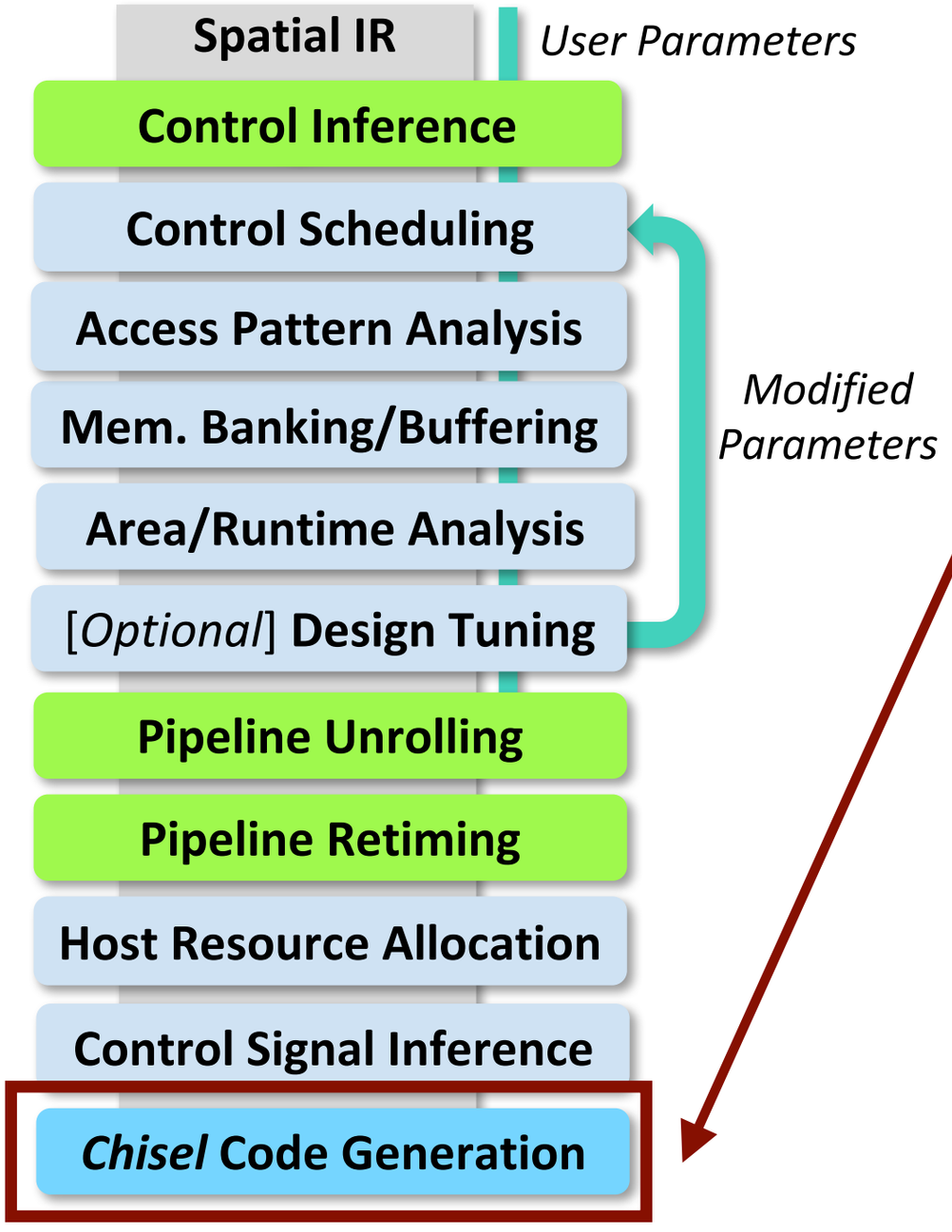
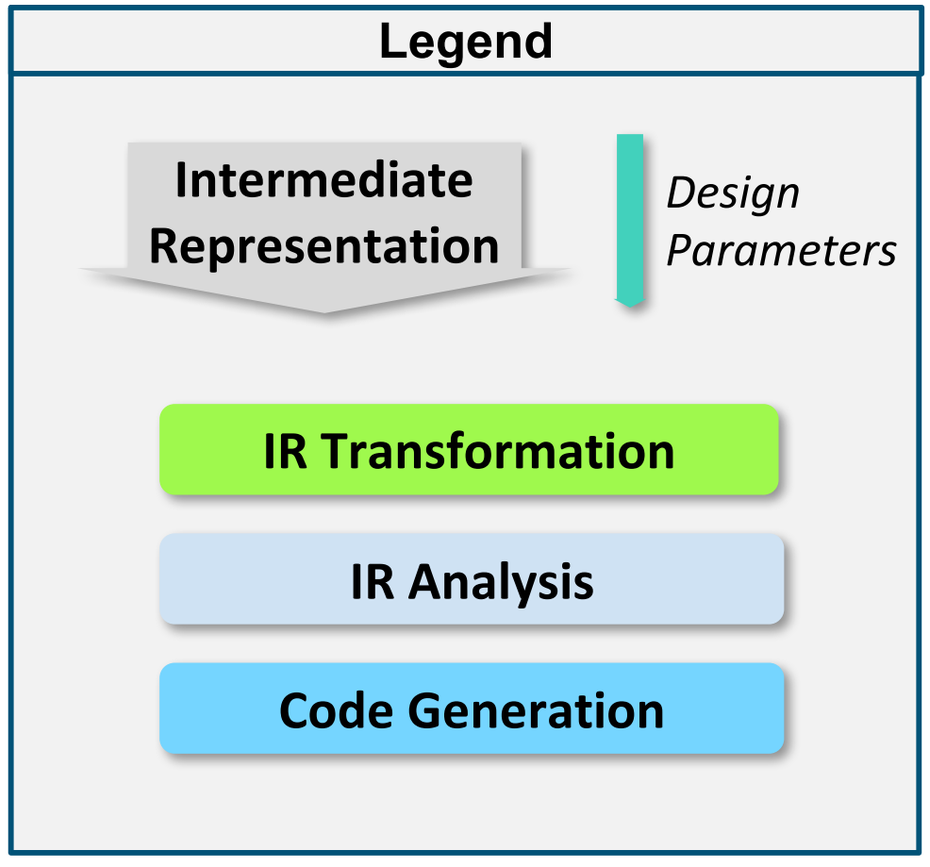


Generates a Chisel design which can be synthesized and run on the target FPGA



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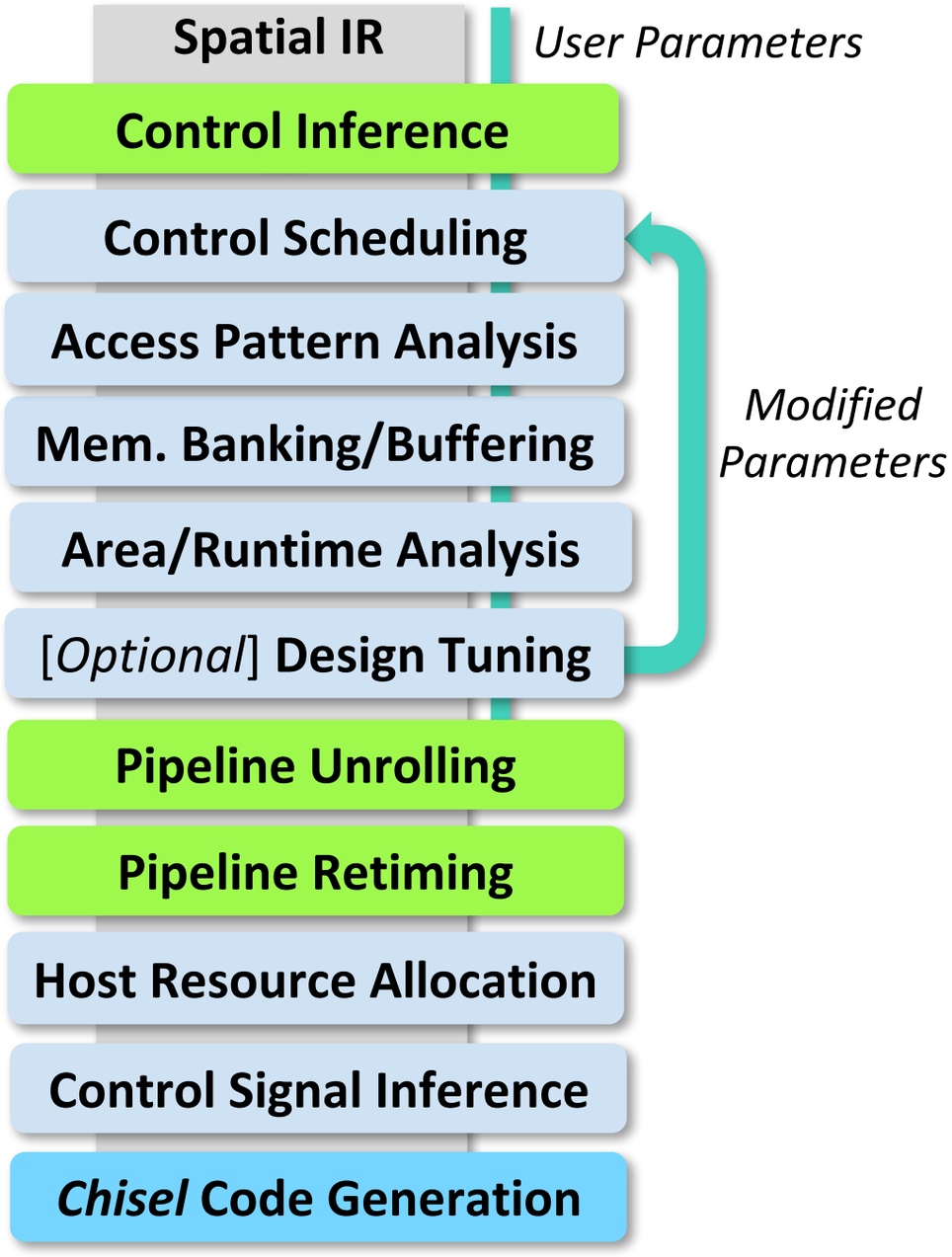

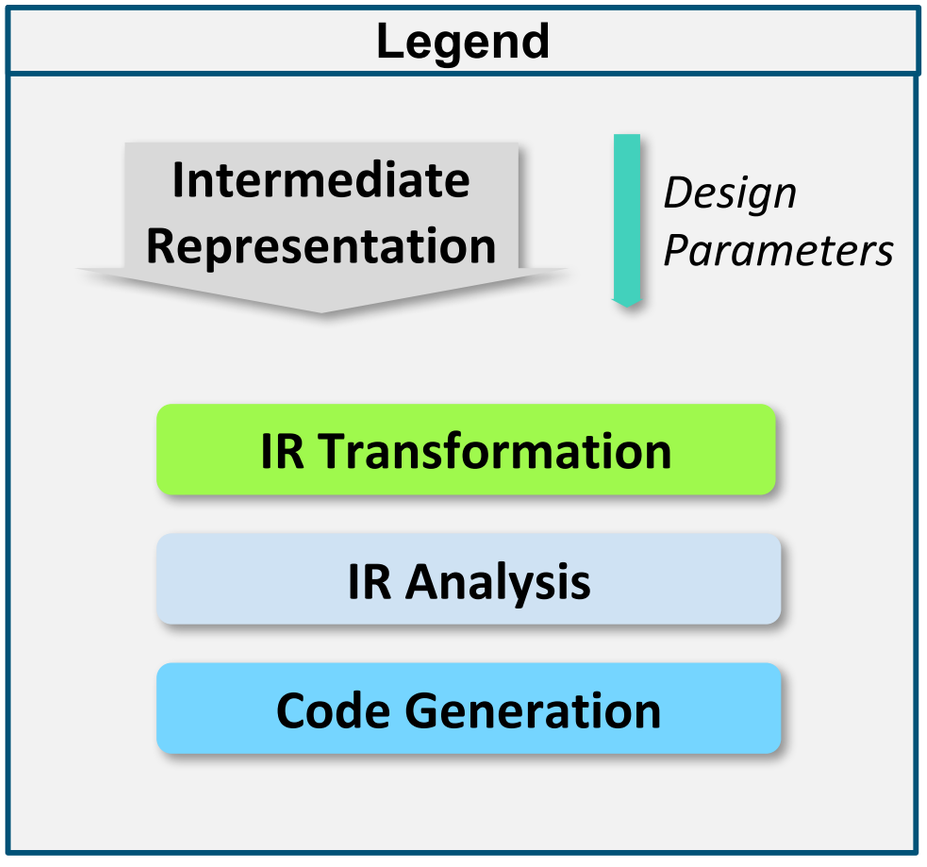

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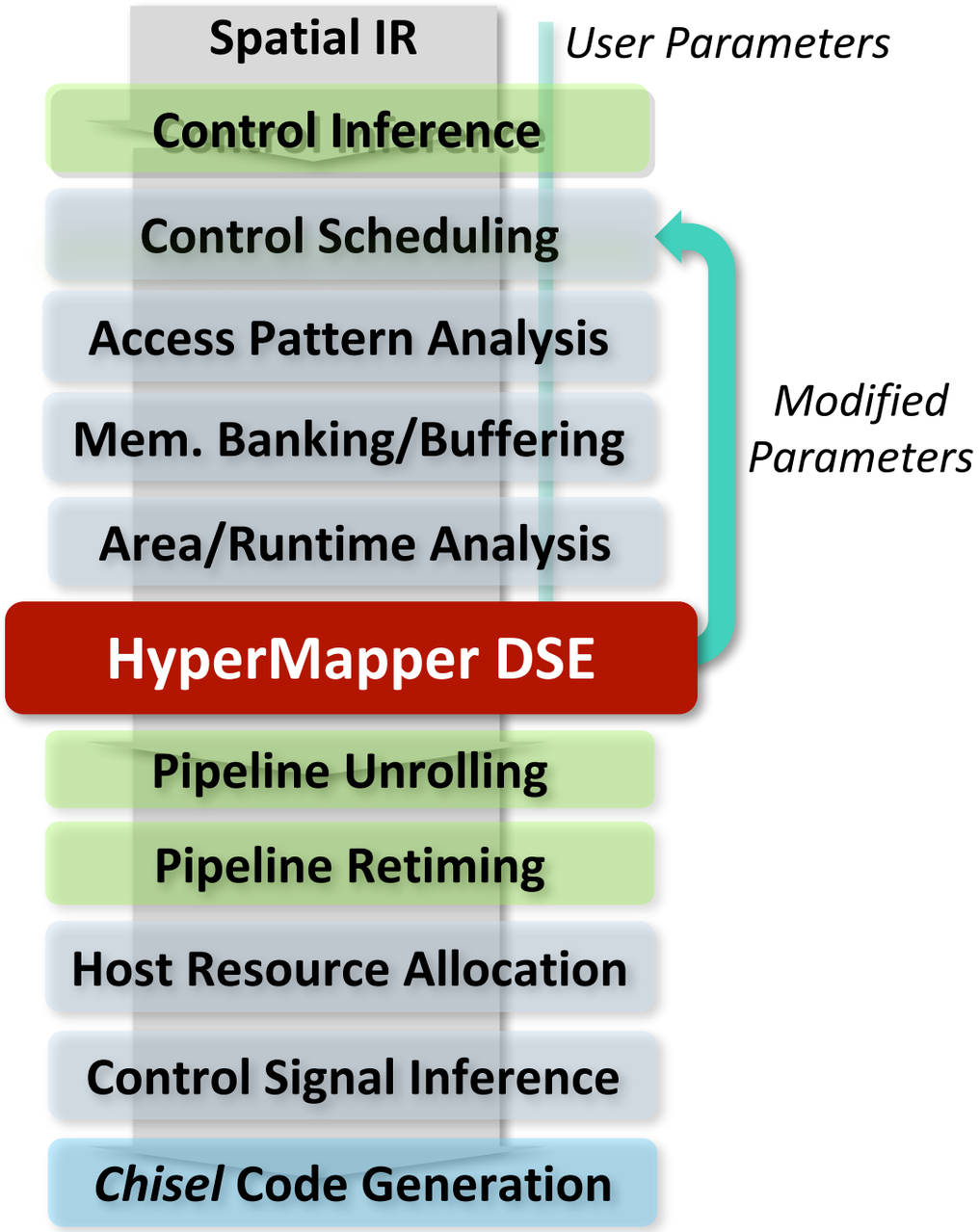

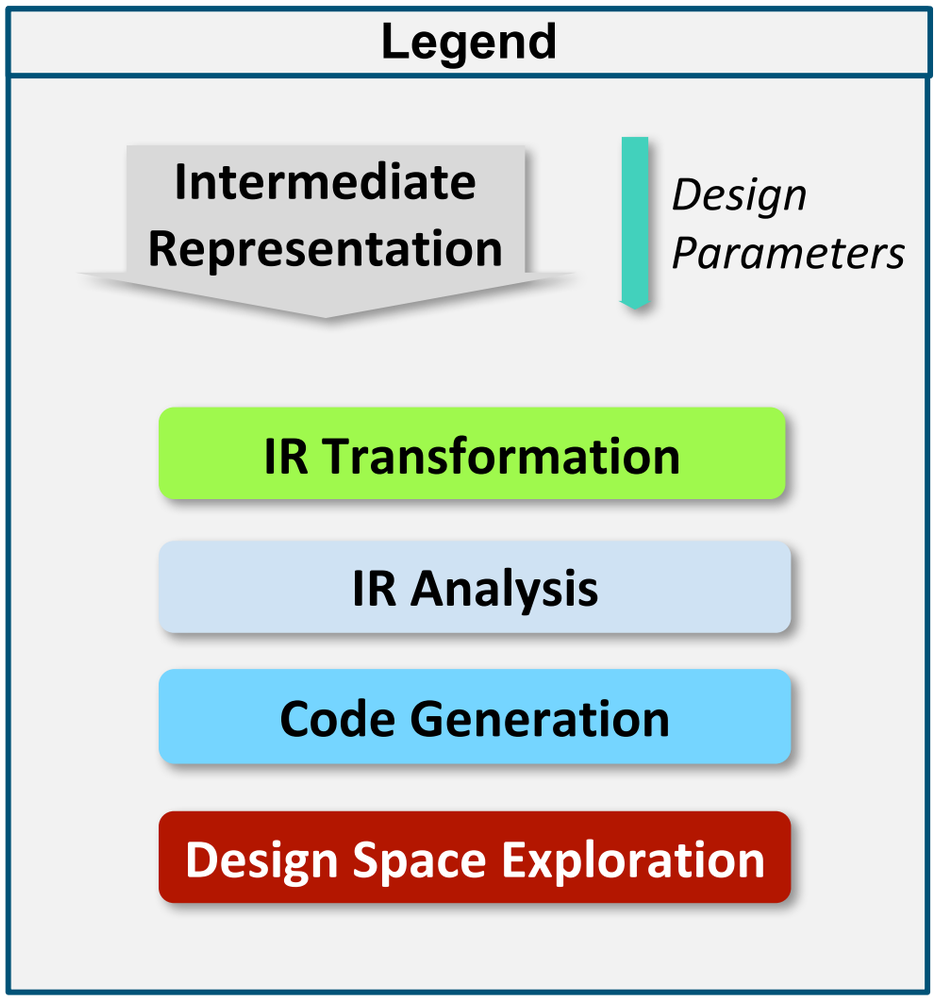

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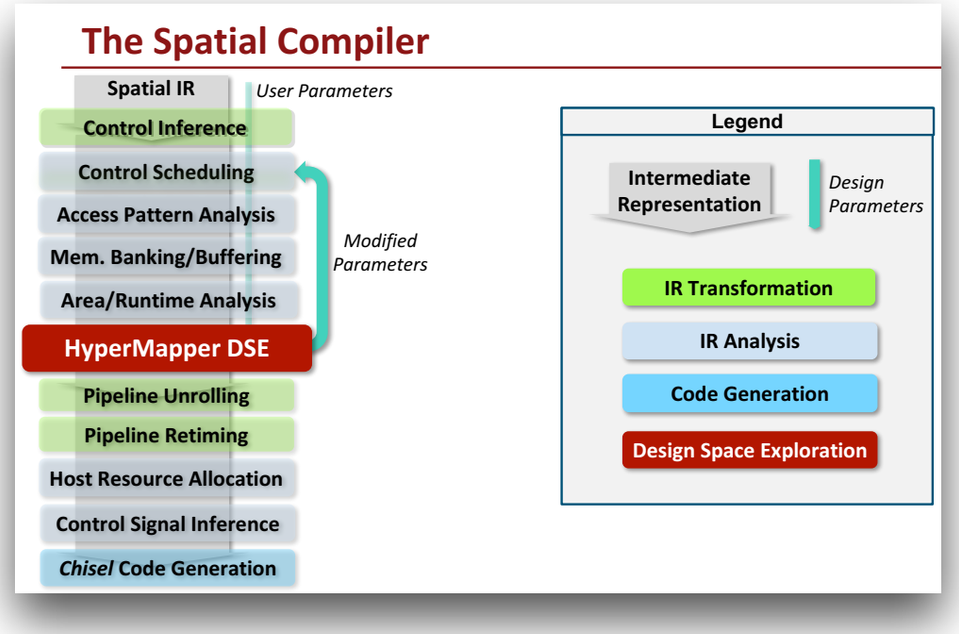


Benchmark	Variables	Space Size
BlackScholes	4	7.68×10^4
K-Means	6	1.04×10^6
OuterProduct	5	1.66×10^7
DotProduct	5	1.18×10^8
GEMM	7	2.62×10^8
TPC-H Q6	5	3.54×10^9
GDA	9	2.40×10^{11}

Input

Compiler automatically provides params:

- Tile size (ordinal)
- Inner and outer loop pipelining (ordinal)
- Meta-pipe (categorical)
- Unrolling factor (ordinal)
- Memory banking (ordinal)
- Parallelism (categorical)

Output

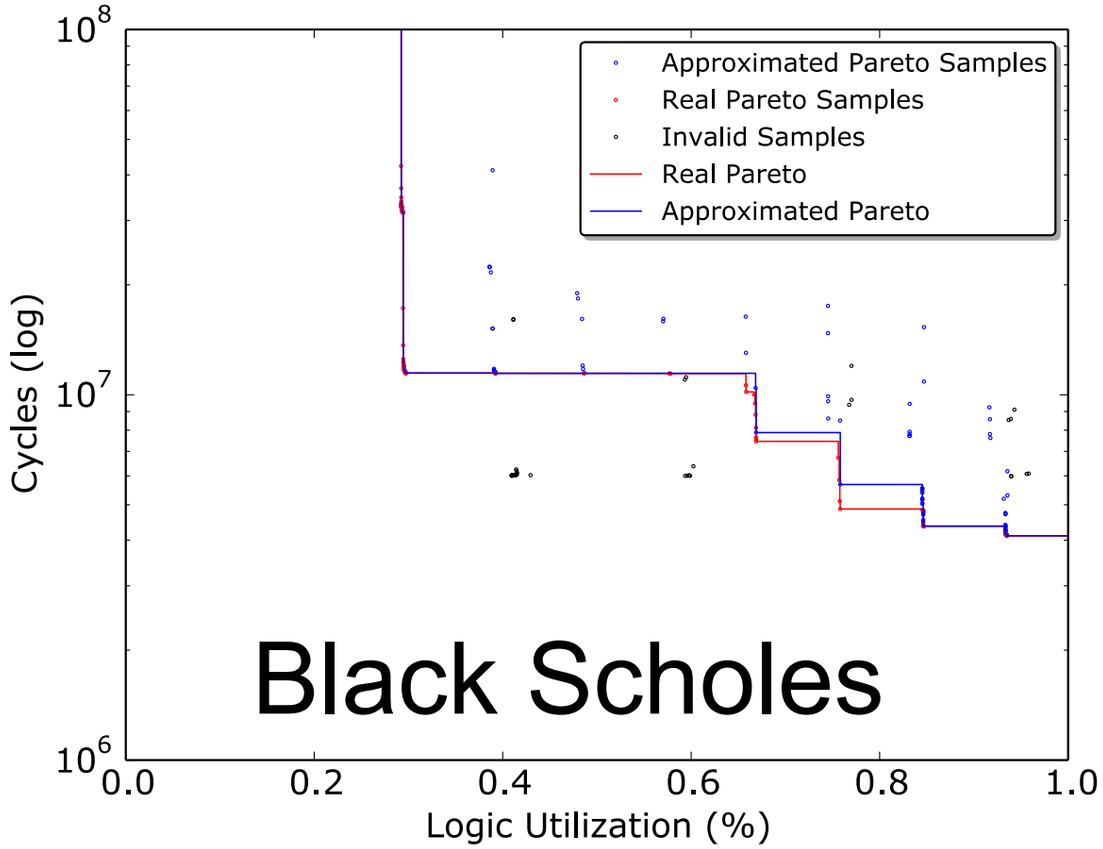
Two objectives:

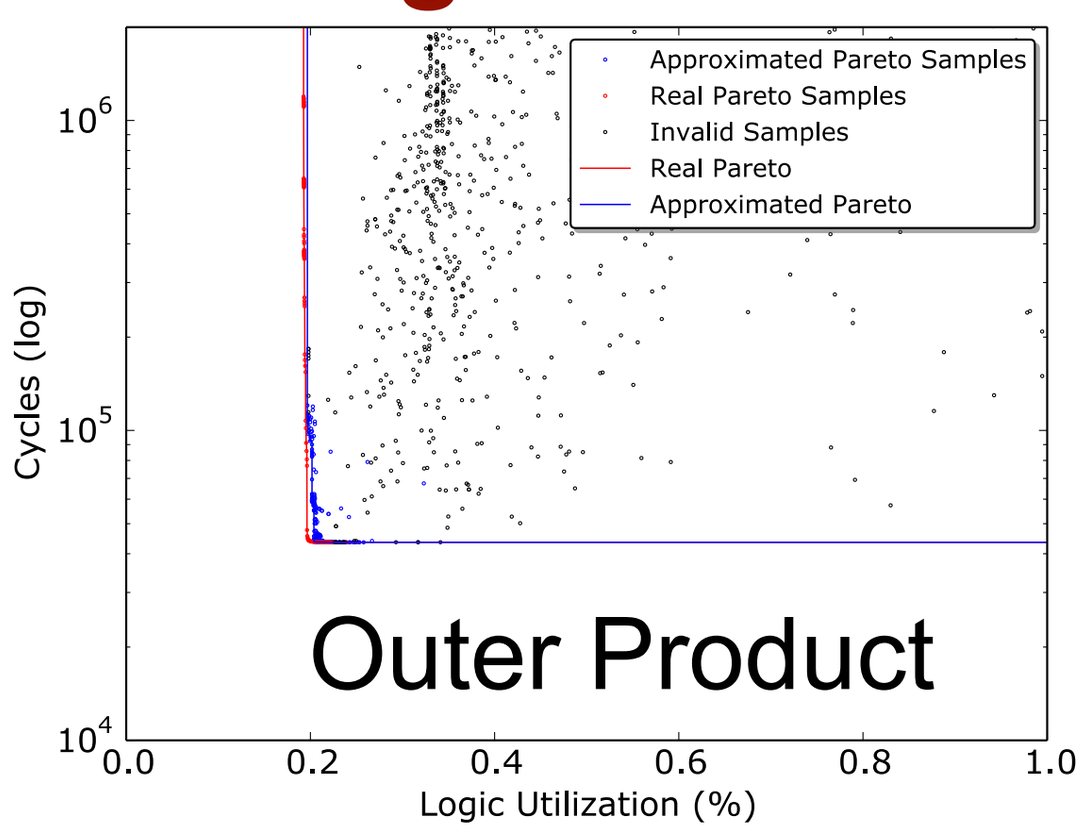
1. Minimize clock cycles (runtime)
2. Minimize FPGA logic utilization
   - For fitting multiple applications
   - Proxy for energy consumption

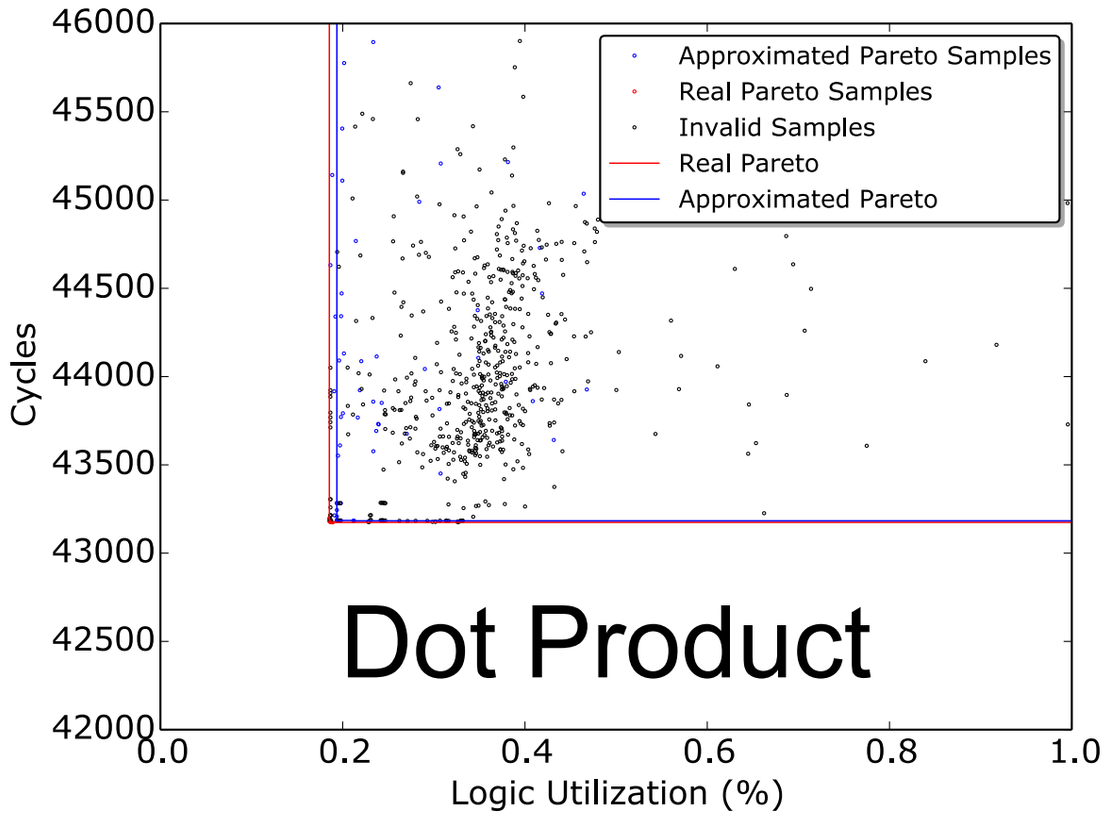
One constraint:

design must fit in the chip

Small benchmarks - Cycles/Logic Utilization



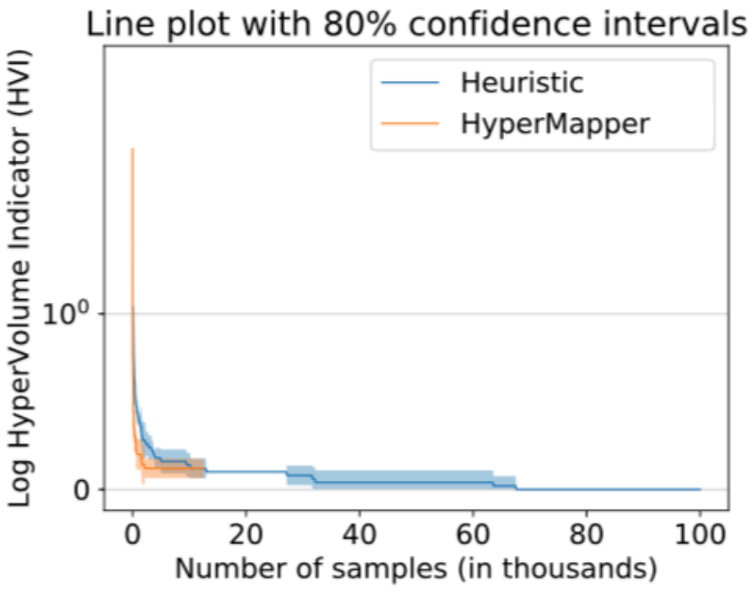




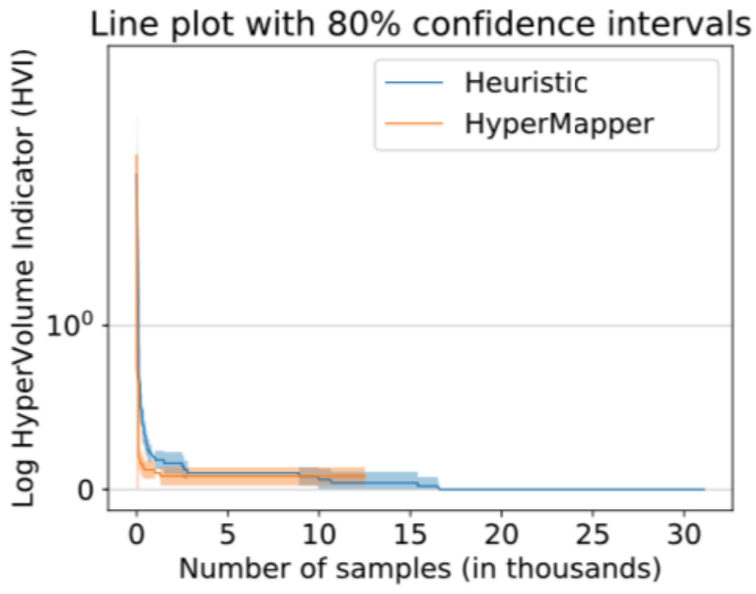
- 3 small benchmarks: compute real Pareto
- Real Pareto is exhaustive search
- Exhaustive: 6 to 12 hours on 16 cores
- Approximated Pareto is HyperMapper

HVI Cycles/Logic Utilization

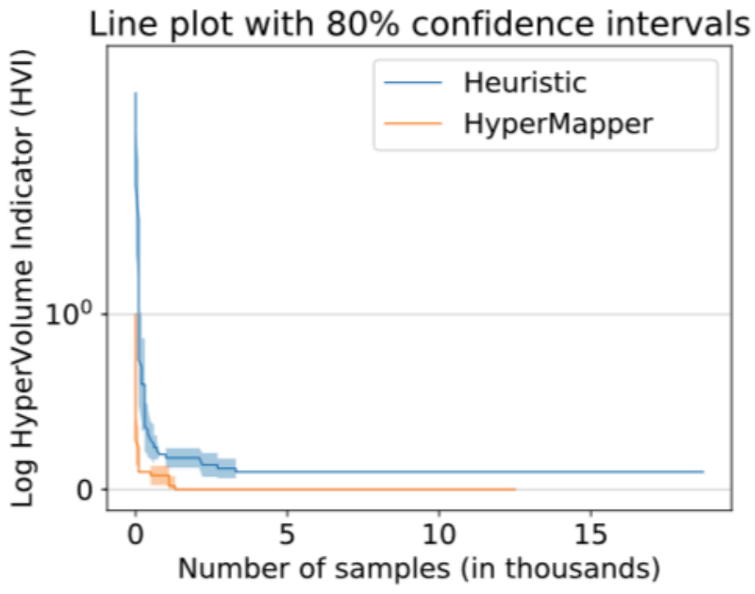
- Hypervolume indicator (HVI): scalar to compare Paretos
- Baseline is a pruning (based on heuristics) and 100K random sampling



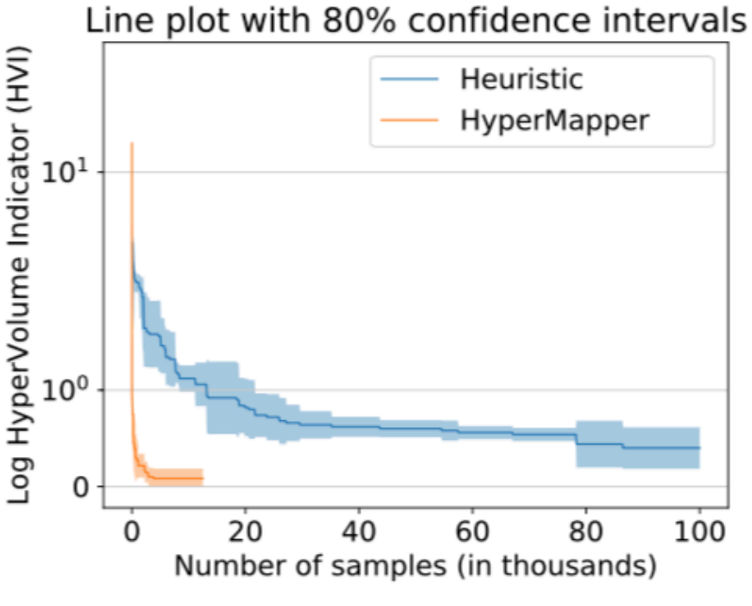
GEMM



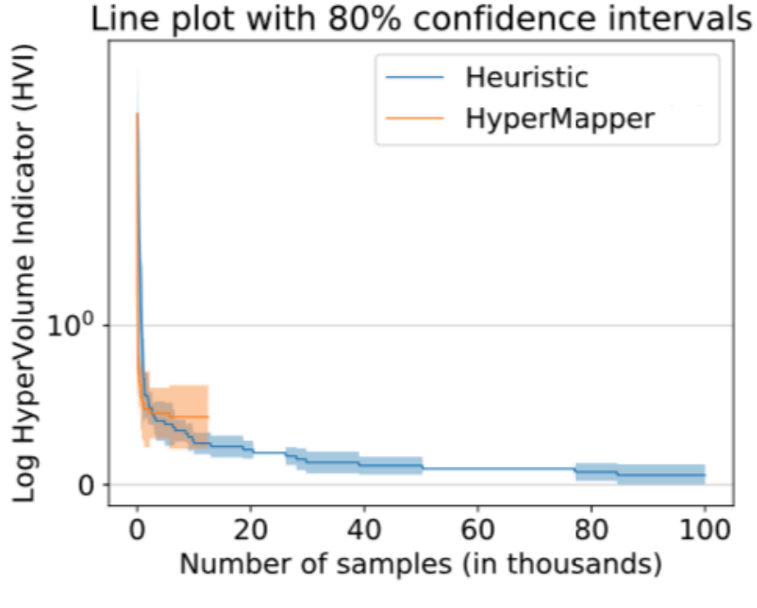
OuterProduct



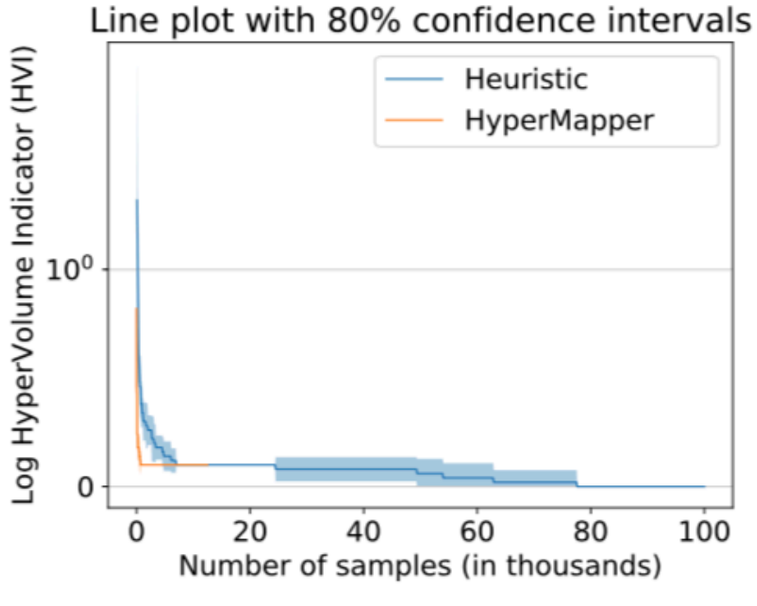
K-Means



GDA



T-PCH Q6



DotProduct

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Application 3:
Simultaneous Localization And Mapping Optimization

Build a coherent world representation and localize the camera in real-time

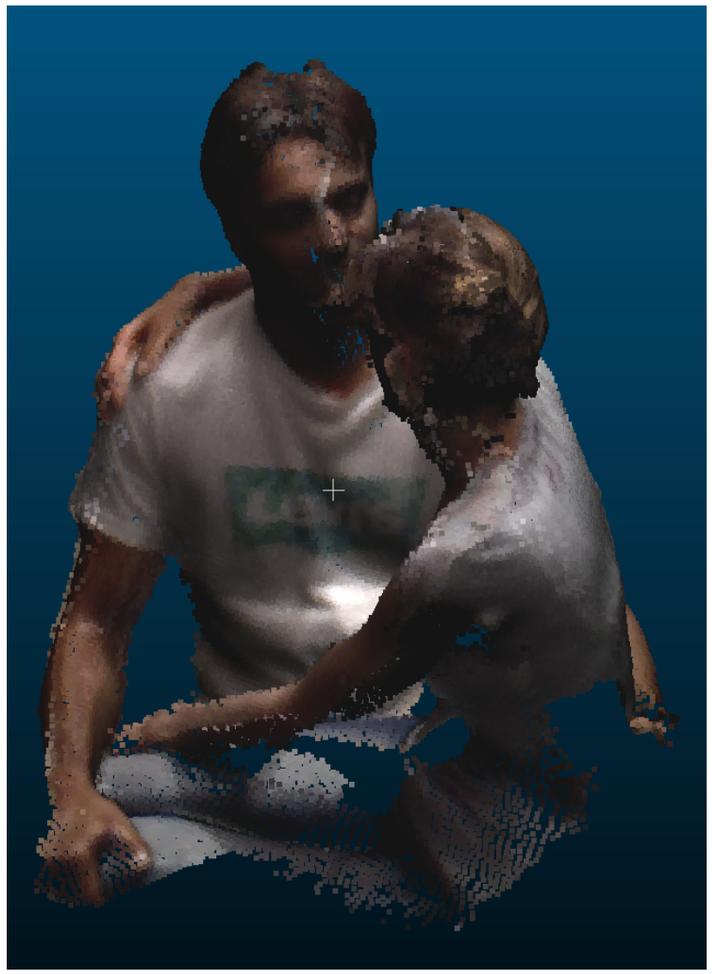
I will focus on two SLAM algorithms from SLAMBench:

- KinectFusion [Newcombe et al. ISMAR 2011]
- ElasticFusion [Whelan et al. RSS 2015]

Jesse Clayton (NVIDIA)
3D reconstruction

Applications, e.g.:

- Robotics
- Autonomous driving
- 3D printing
- Augmented reality
- Telepresence



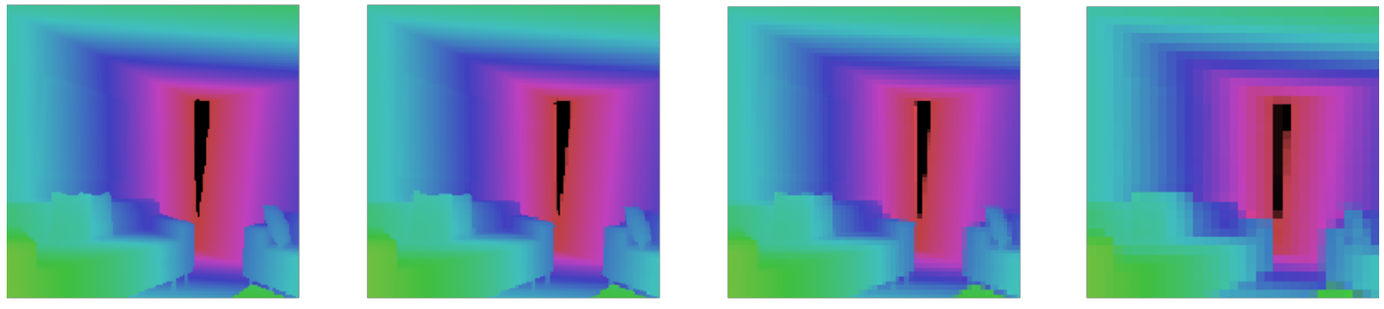
Daniele and Daniela
3D reconstruction

Pictures featured using ElasticFusion

Application 3: SLAM (KinectFusion) algorithmic features

Features	Ranges
Volume resolution	64x64x64, 128x128x128, 256x256x256, 512x512x512
μ distance	0 .. 0.5
Pyramid level iterations (3 levels)	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Image resolution (image ratio)	1, 2, 4, 8
Tracking rate	1, 2, 3, 4, 5
ICP threshold	10^{-6} .. 10^{2}
Integration rate	1 .. 30

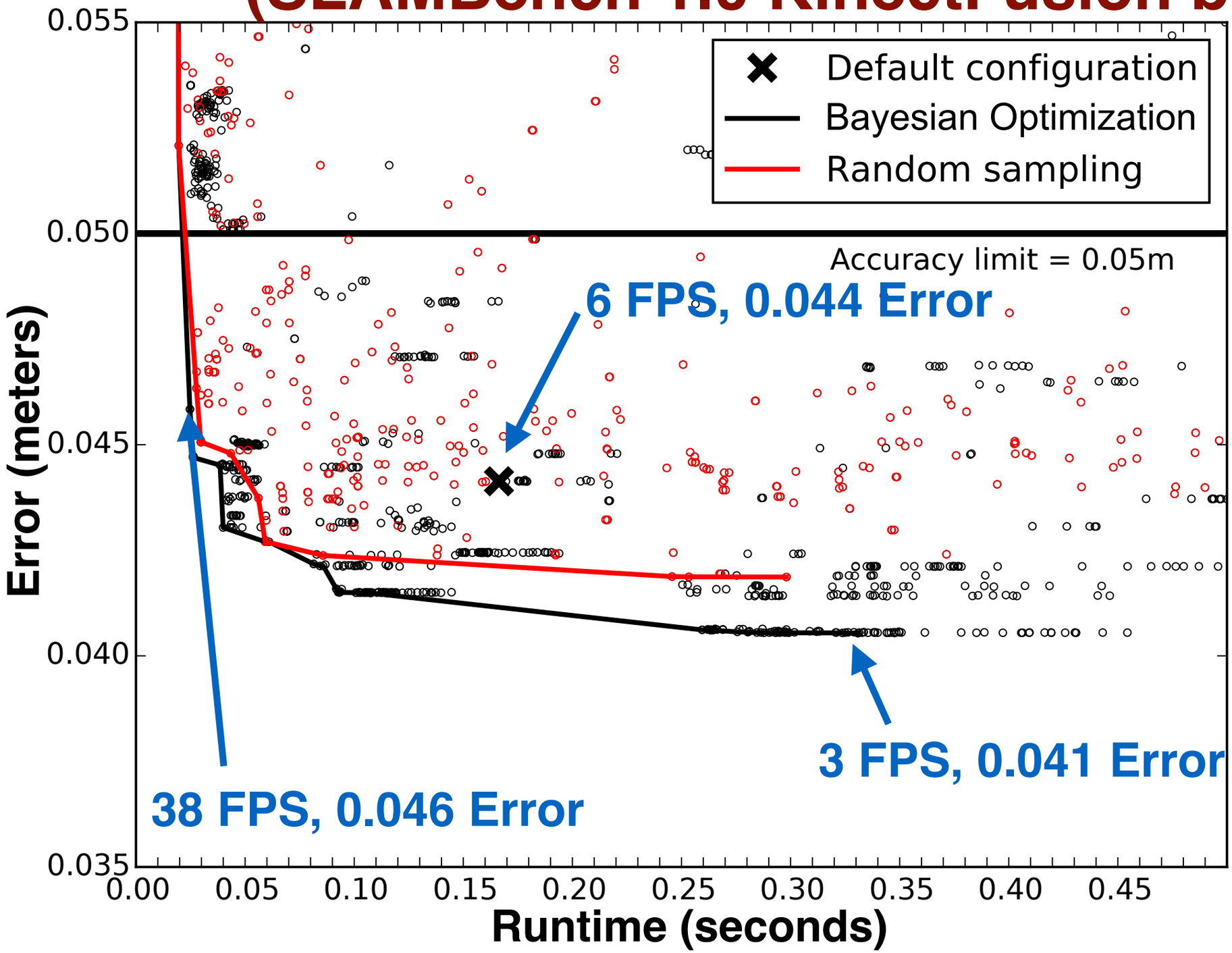
Image resolution (image ratio)

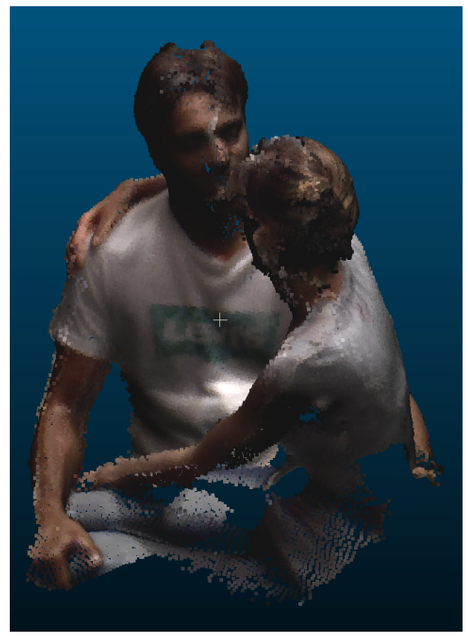


<u>Three objectives</u>:

1. Error
2. Runtime
3. Energy consumption

Example 3: Computer Vision Use Case
(SLAMBench 1.0 KinectFusion benchmark)

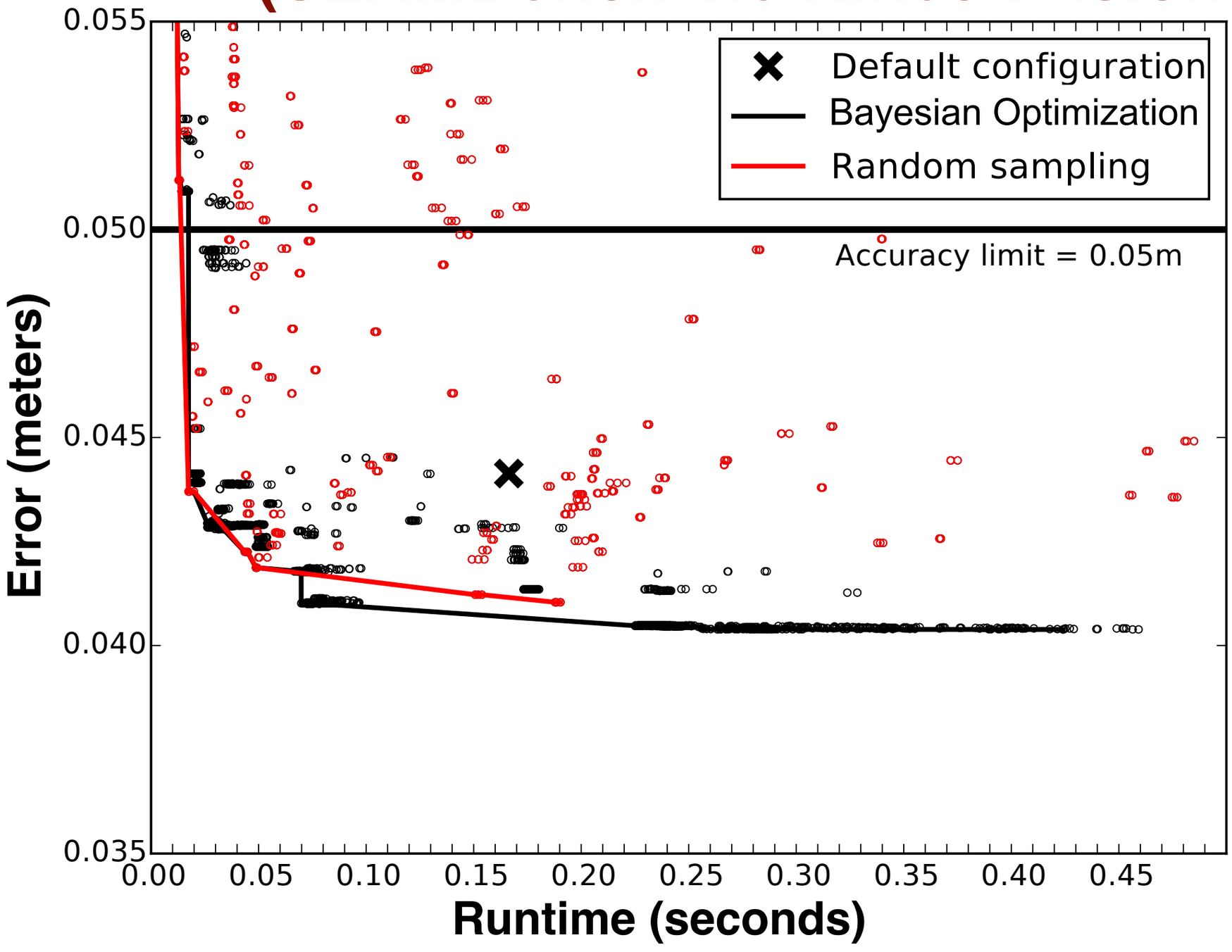




3D reconstruction

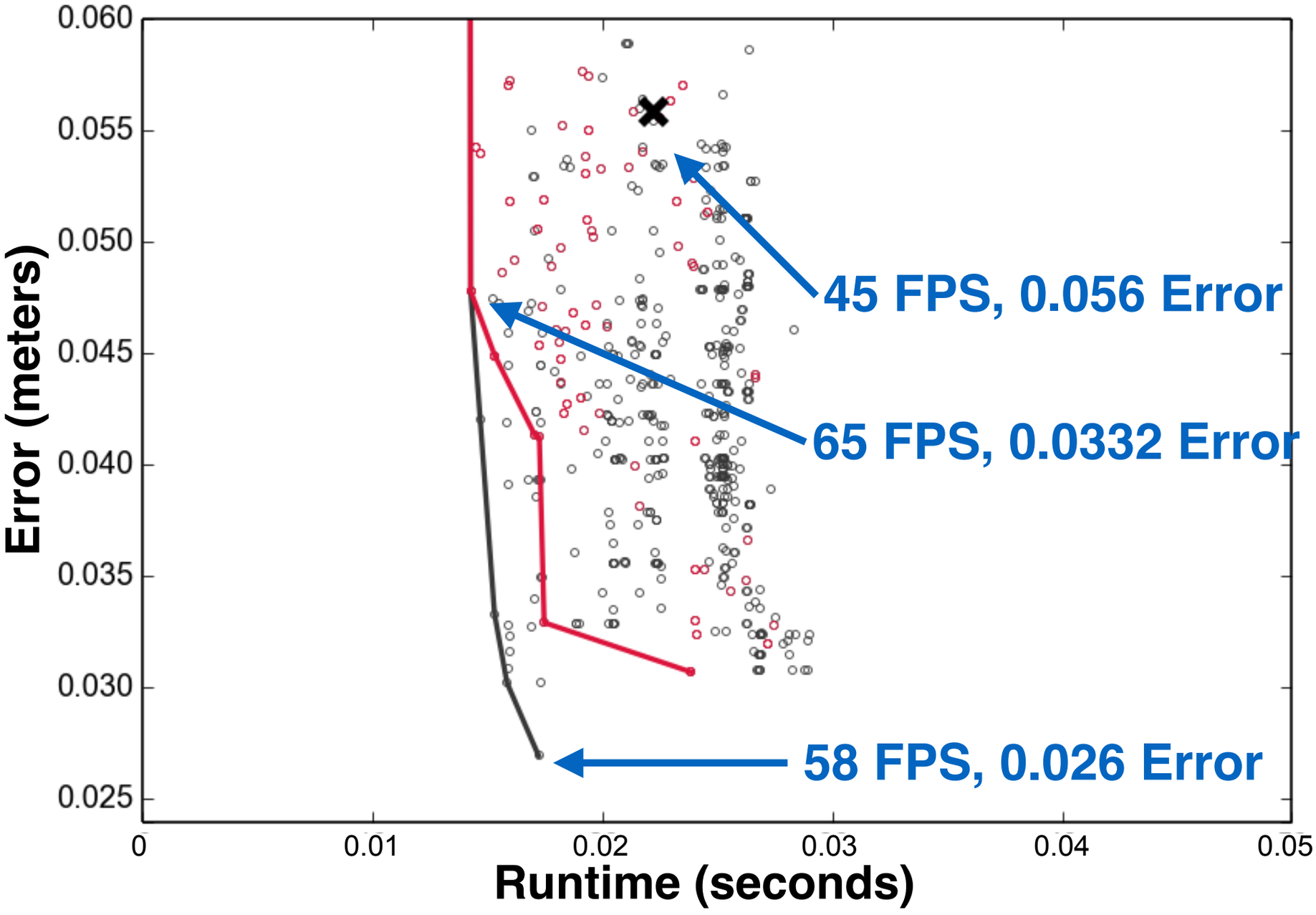
Machine	Type	CPU	CPU name	CPU cores	GPU	GPU name
Hardkernel **ODROID-XU3**	Embedded	ARM A15 + A7	Exynos 5422	4 + 4	ARM	Mali-T628

Example 3: Computer Vision Use Case
(SLAMBench 1.0 KinectFusion benchmark)



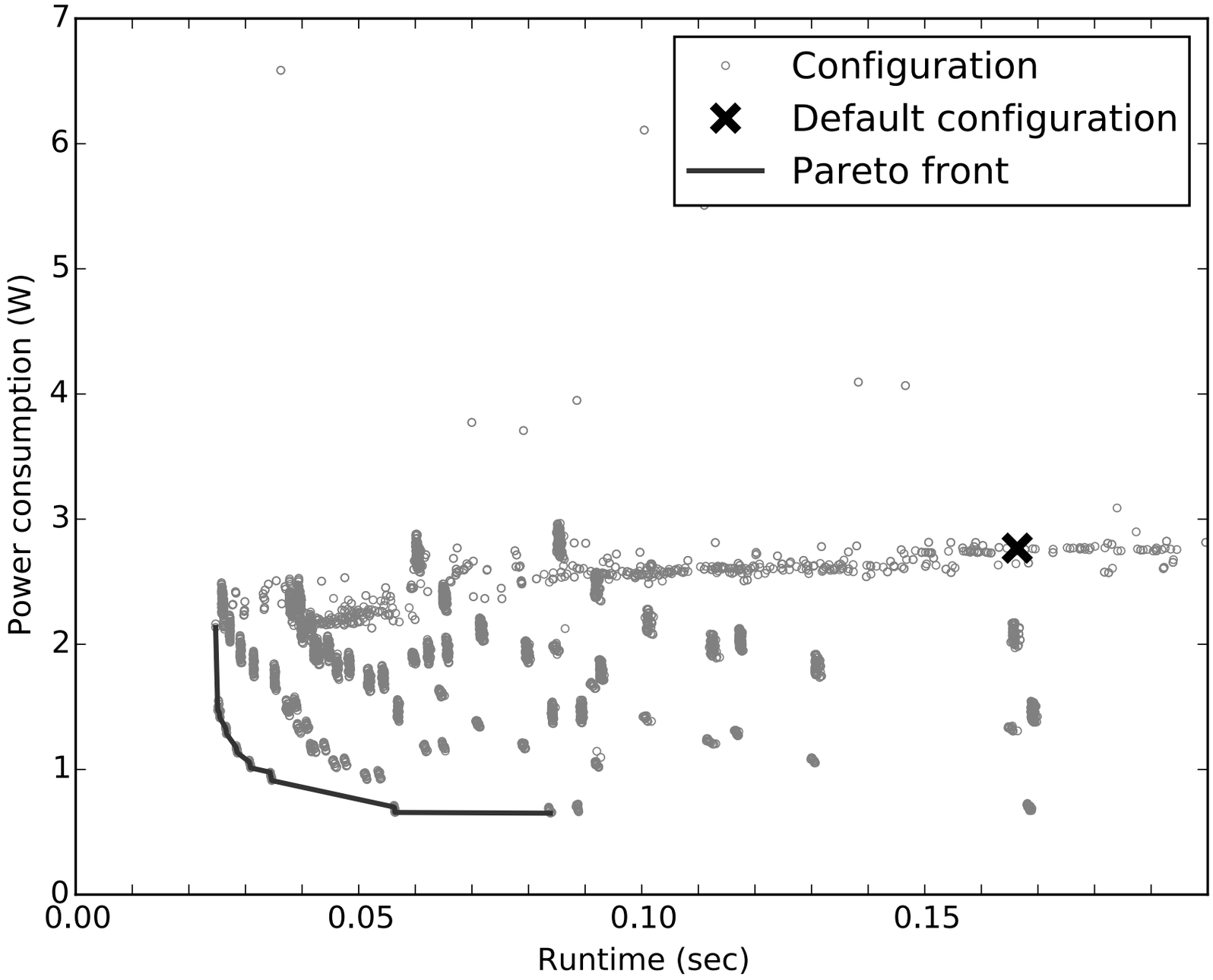
Machine	Type	CPU	CPU name	CPU cores	GPU	GPU name
ASUS **T200TA**	Detachable laptop	Intel Silvermont	Atom Z3795	4	Intel	HD Graphics

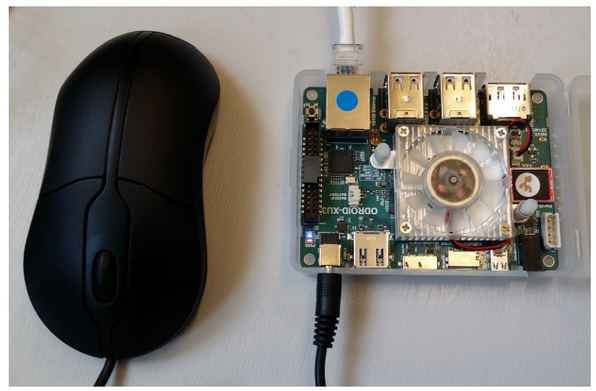
Example 3: Computer Vision Use Case
(SLAMBench 2.0 ElasticFusion benchmark)



Machine	Type	CPU	CPU name	CPU cores	GPU	GPU name
NVIDIA/Intel	Desktop	Intel Ivy Bridge	E5-1620	8	NVIDIA	GTX 780 Ti

Example 3: Computer Vision Use Case
(SLAMBench 1.0 KinectFusion benchmark)





Machine	Type	CPU	CPU name	CPU cores	GPU	GPU name
Hardkernel **ODROID-XU3**	Embedded	ARM A15 + A7	Exynos 5422	4 + 4	ARM	Mali-T628

Conclusion and Future Work

- Goal: HyperMapper is a multi-objective BBO framework
- Demonstrated on:
  hardware design, DBMS and CV applications
- Future:
  - Dynamic Black-box optimization
  - Use of prior knowledge in the multi-objective posterior
  - Asynchronous batch optimization
  - Transfer learning
  - Applications:
    - Microsoft PostgreSQL/Azure full scenario
    - Multi-fidelity in SLAM
    - Halide computer vision language

Research Team and Collaborators

- Work in collaboration with many people from academia and industry
- **We are hiring!** WASP-AI is funding positions for my research group:
  - 2 Ph.D. students (https://lu.varbi.com/en/what:job/jobID:280143/)
  - 2 Postdocs (https://lu.varbi.com/en/what:job/jobID:280619/)

Luigi Nardi, Ph.D.
WASP-AI Assistant Professor
in Machine Learning

Artur Luis
Ph.D. Student
UFMG

Info on HyperMapper

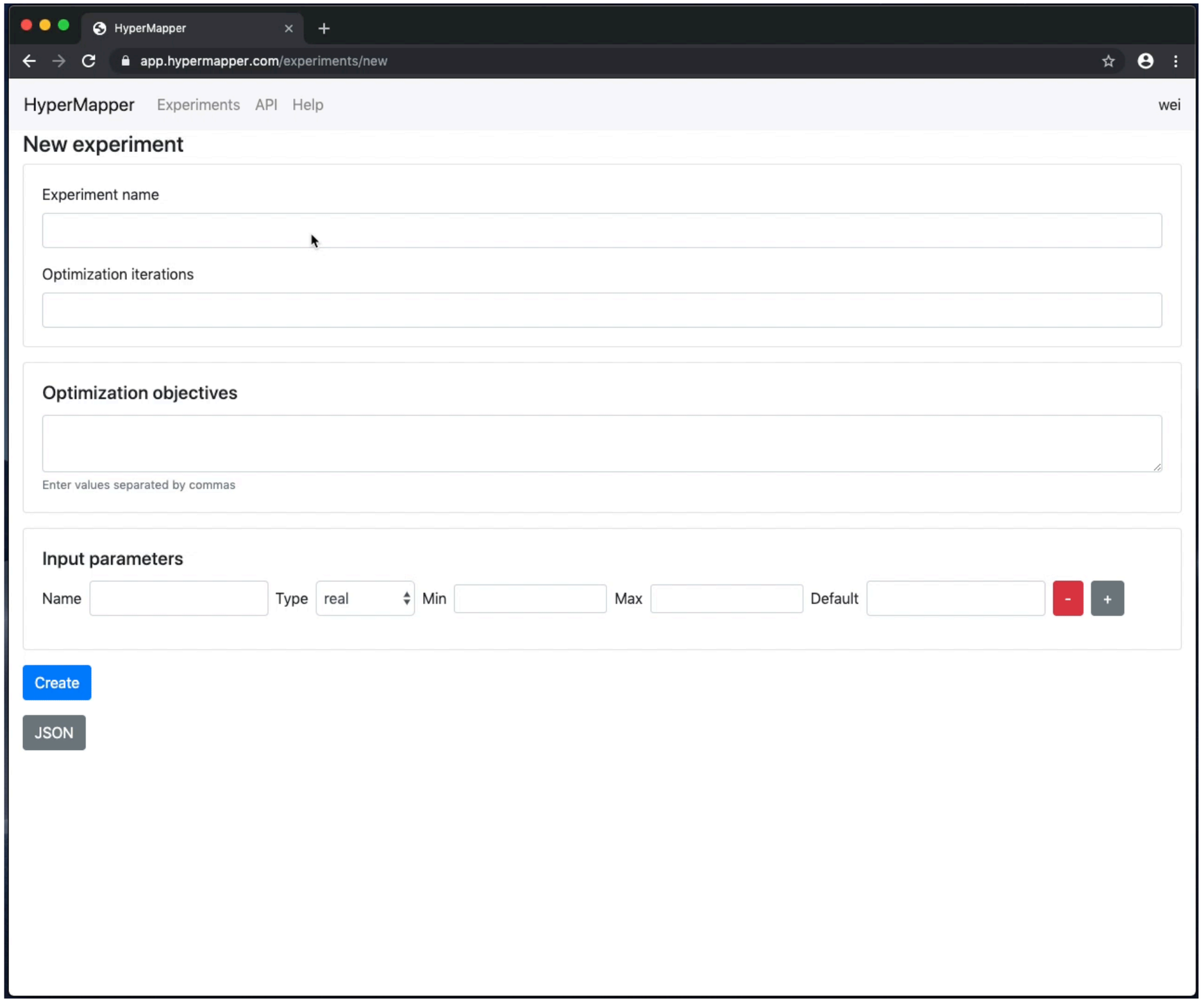
- Join HyperMapper on **Slack**: hypermapper.slack.com
- **Repo**: https://github.com/luinardi/hypermapper
- **Wiki**: https://github.com/luinardi/hypermapper/wiki
- HyperMapper **SaaS**: www.hypermapper.com

Adopters

Microsoft	Microsoft - Database Management Systems
teradata.	Teradata - Database Management Systems
Stanford University	Stanford University - Hardware Design
UC San Diego	UCSD - Spector Benchmarks (FPGAs)
TEXAS The University of Texas at Austin	UT Austin - Capri (Approximate Computing)
Imperial College London	ICL - Computer Vision and Robotics
	Etc.

Backup slides

HyperMapper SaaS



Demo HyperMapper

https://github.com/luinardi/hypermapper/wiki/Quick-Start-Guide