Bayesian Techniques for Accelerator Characterization and Control

Ryan Roussel*, Auralee Edelen, Chris Mayes, *SLAC National Accelerator Laboratory*

Juan Pablo Gonzalez-Aguilera, Young Kee Kim, *University of Chicago*

AI/ML for Particle Accelerator, X-Ray Beamlines and Electron Microscopy

*rroussel@slac.stanford.edu

U.S. DEPARTMENT OF ENERGY | Stanford University

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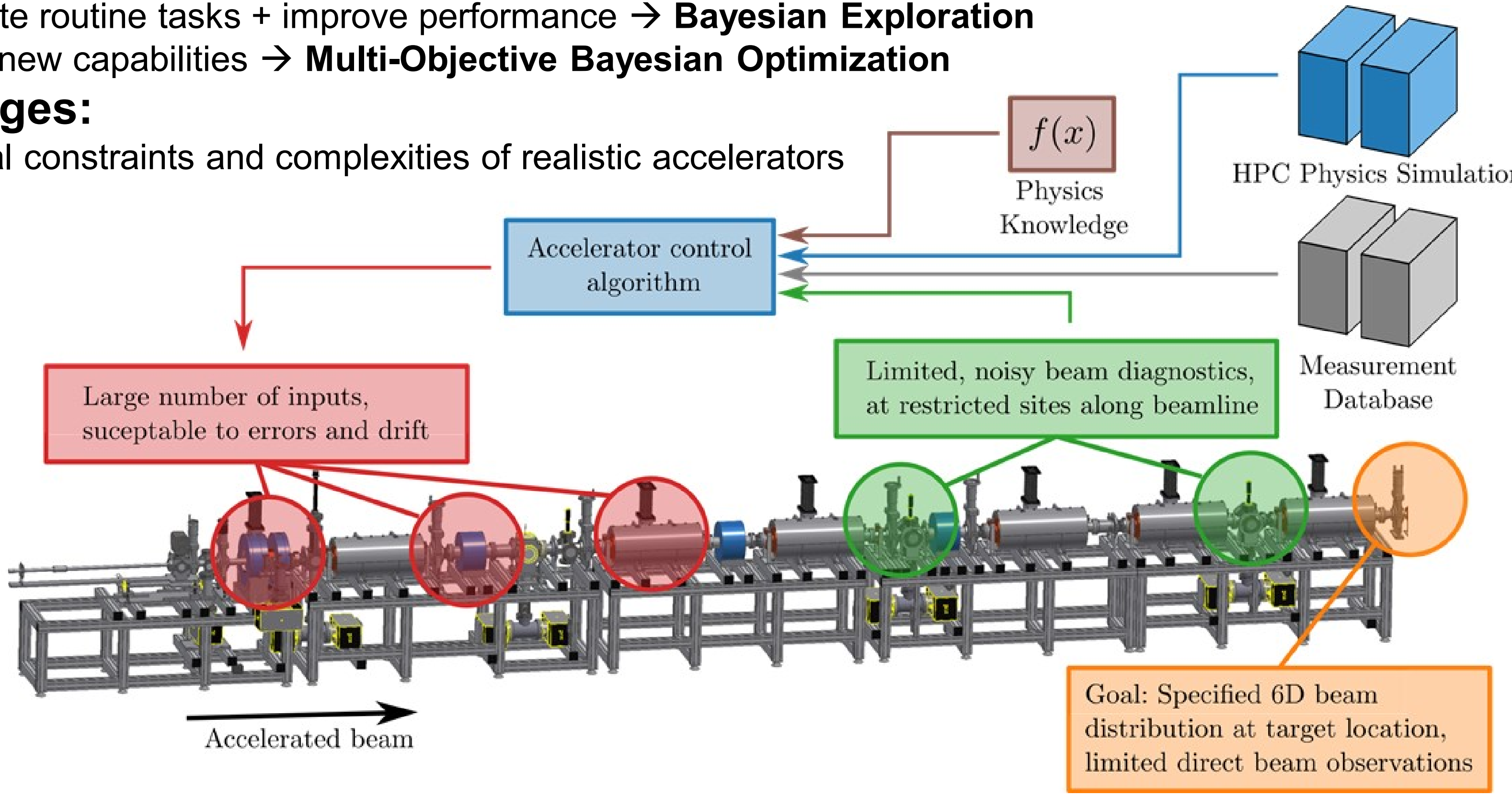
Bayesian Optimization Based Accelerator Control

Goals:

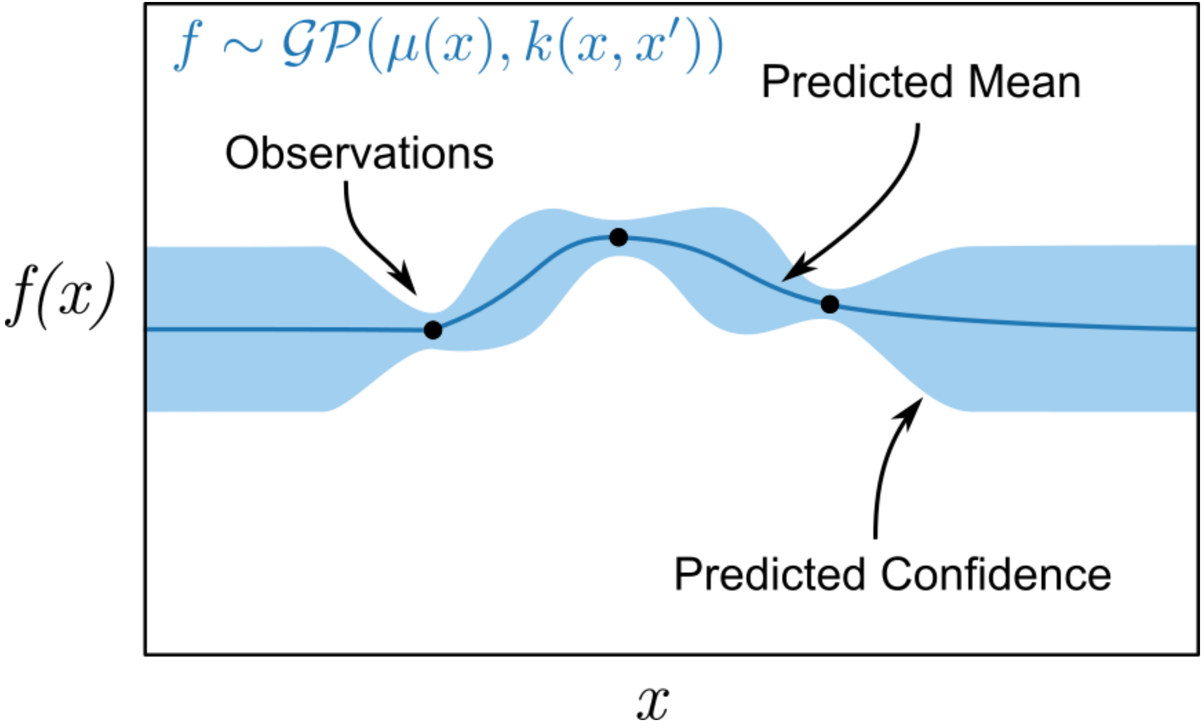
- Automate routine tasks + improve performance → **Bayesian Exploration**
- Enable new capabilities → **Multi-Objective Bayesian Optimization**

Challenges:

- Practical constraints and complexities of realistic accelerators

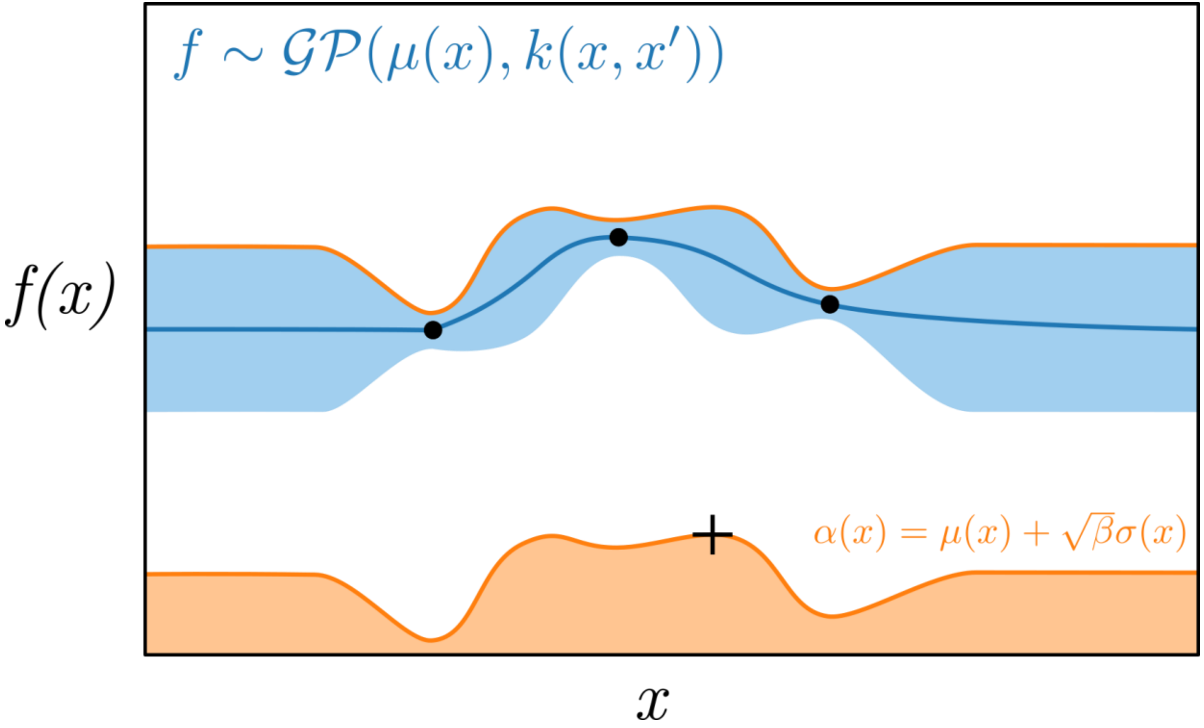


Gaussian Process Construction

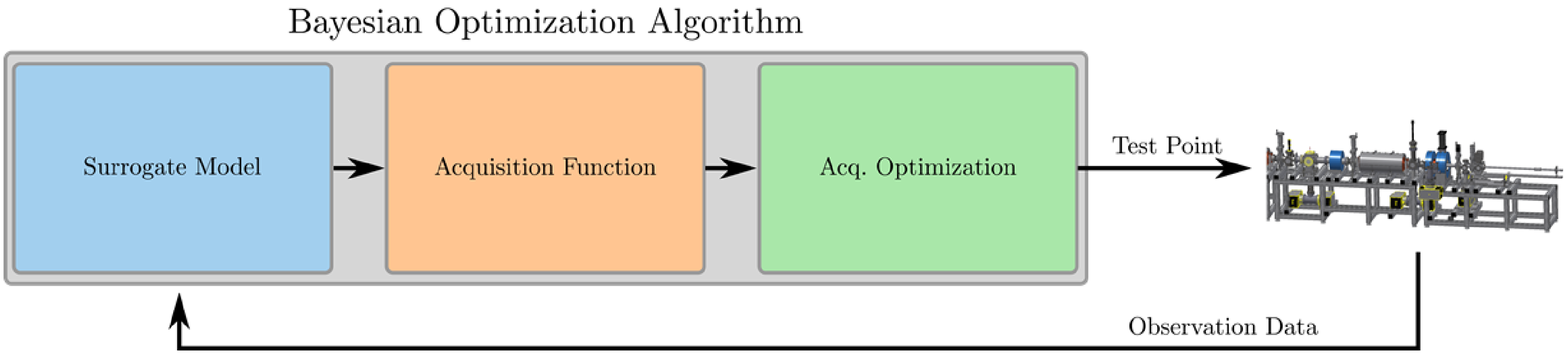


A **kernel** encodes high level functional behavior

Acquisition Function

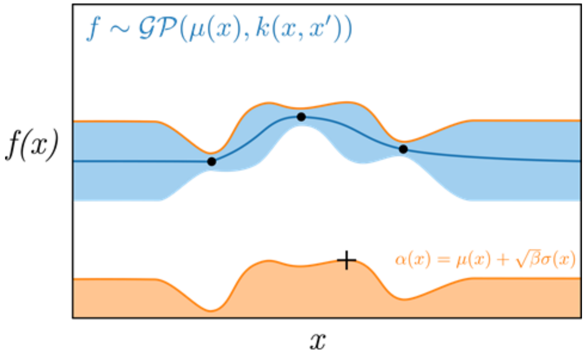


Bayesian Optimization Based Accelerator Control



Benefits:

- Specify trade-off between exploration and exploitation
- Inherently improves model accuracy in regions of interest
- Enables serial or parallelized optimization strategies



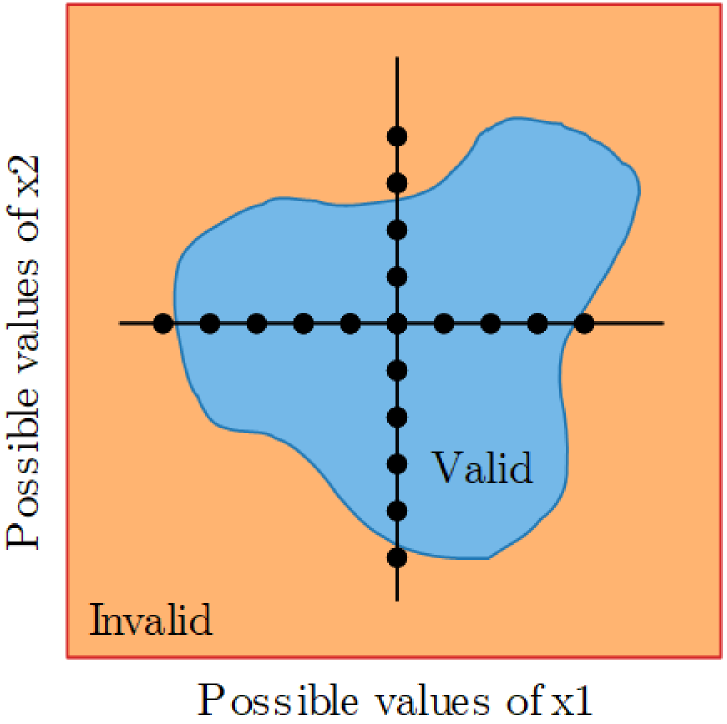
Characterizing functions with Bayesian Exploration

Favorite tool of the accelerator operator: **the 1D parameter scan**

- How quickly do we expect the beam response to change? -> **need to select a step size and the # of steps**
- What is the upper and lower bound of our parameter value? -> **usually dictated by whether the beam stays on the screen / fits on the screen**
- What should be the value of the other parameters? -> **usually, a historical running point**

What do we get from this effort? **The beam response when one parameter varies,** which hopefully generalizes when other parameters are varied?

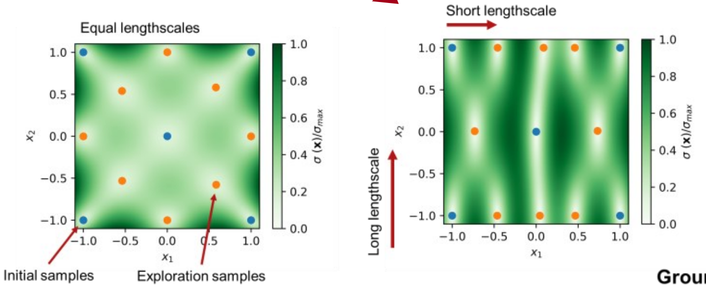
- **Works fine for a 1D system, but we exist in a many dimensional space!**



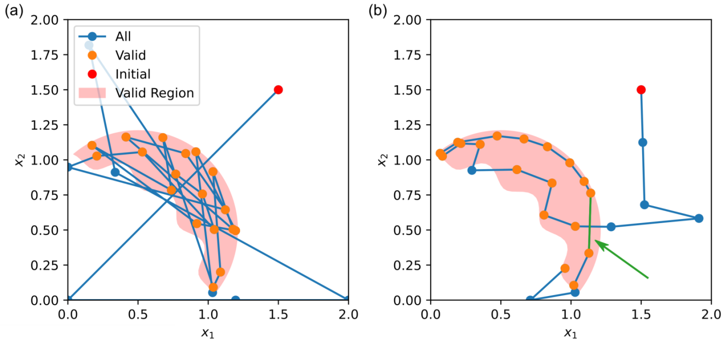
Bayesian Exploration

$$\alpha(\boldsymbol{x}) = \sigma(\boldsymbol{x}) \prod_{i=1}^{N} p_i(g_i(\boldsymbol{x}) \geq h_i)\, \Psi(\boldsymbol{x}, \boldsymbol{x_0})$$

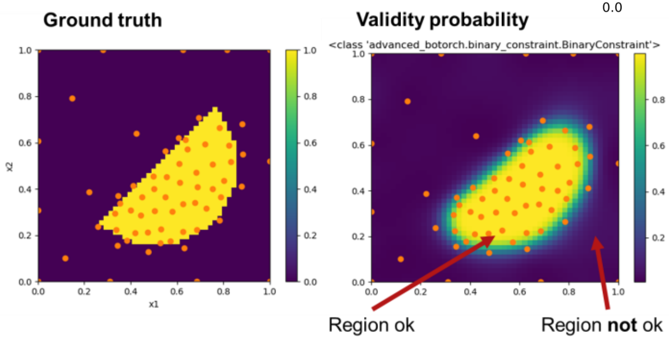
Adaptive sampling



Proximal biasing



Unknown constraints

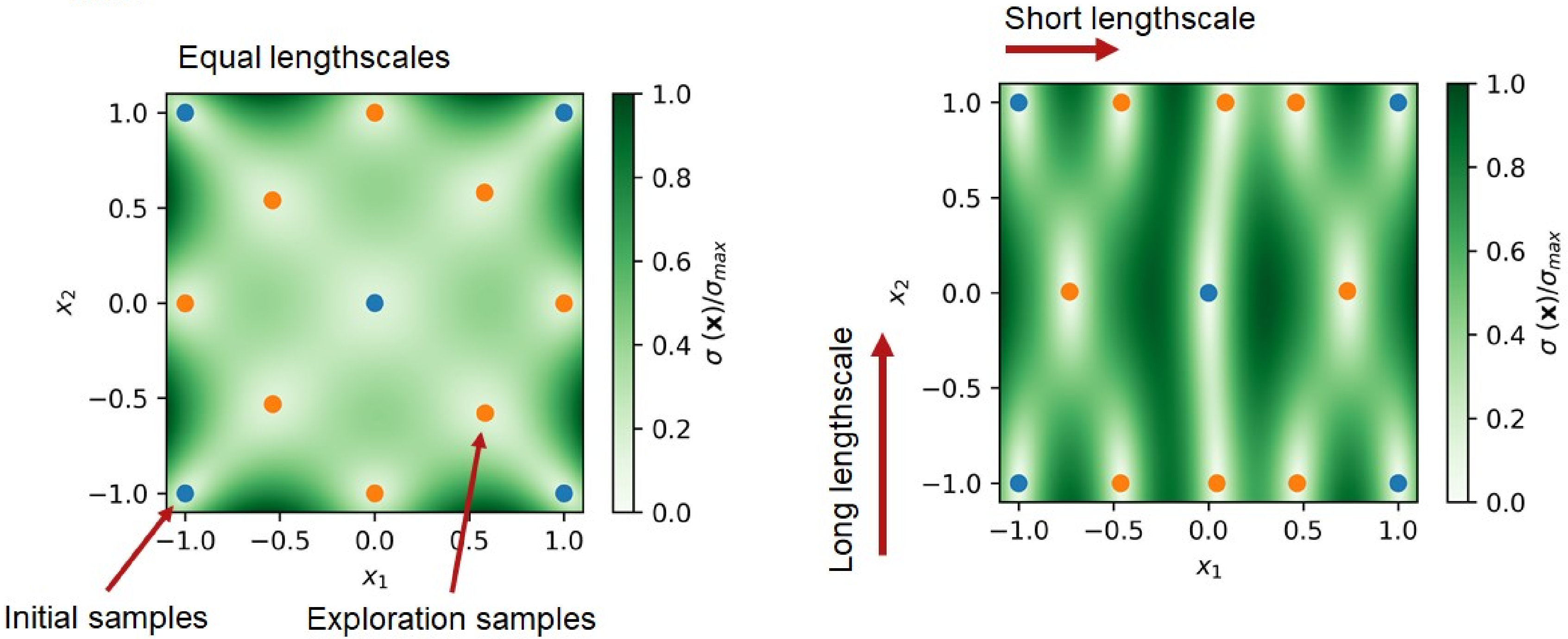


Roussel et. Al. *Nat. Comm.* **2021**

Learned Point Spacing

If the function changes more rapidly along one axis, sample more points along that axis!

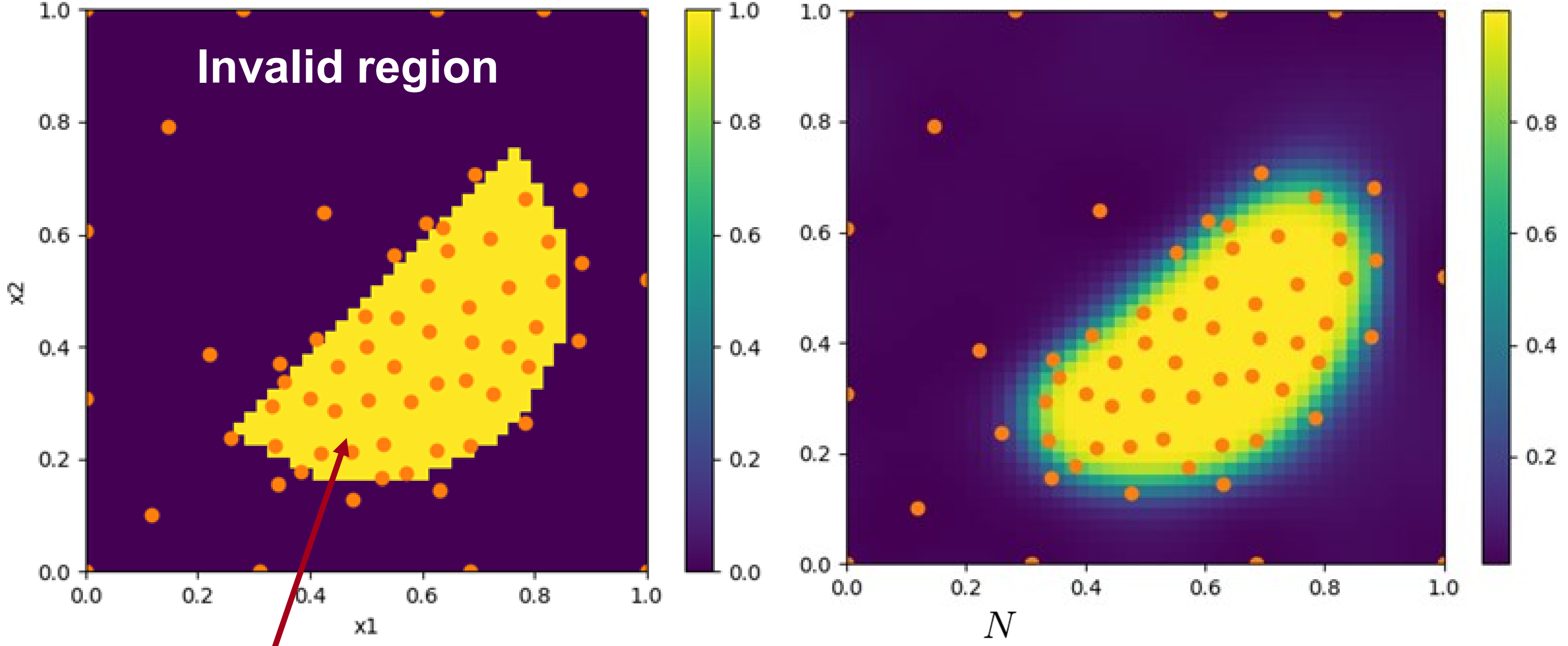
$$\alpha(x) = \sigma(x)$$



Adding Constraints

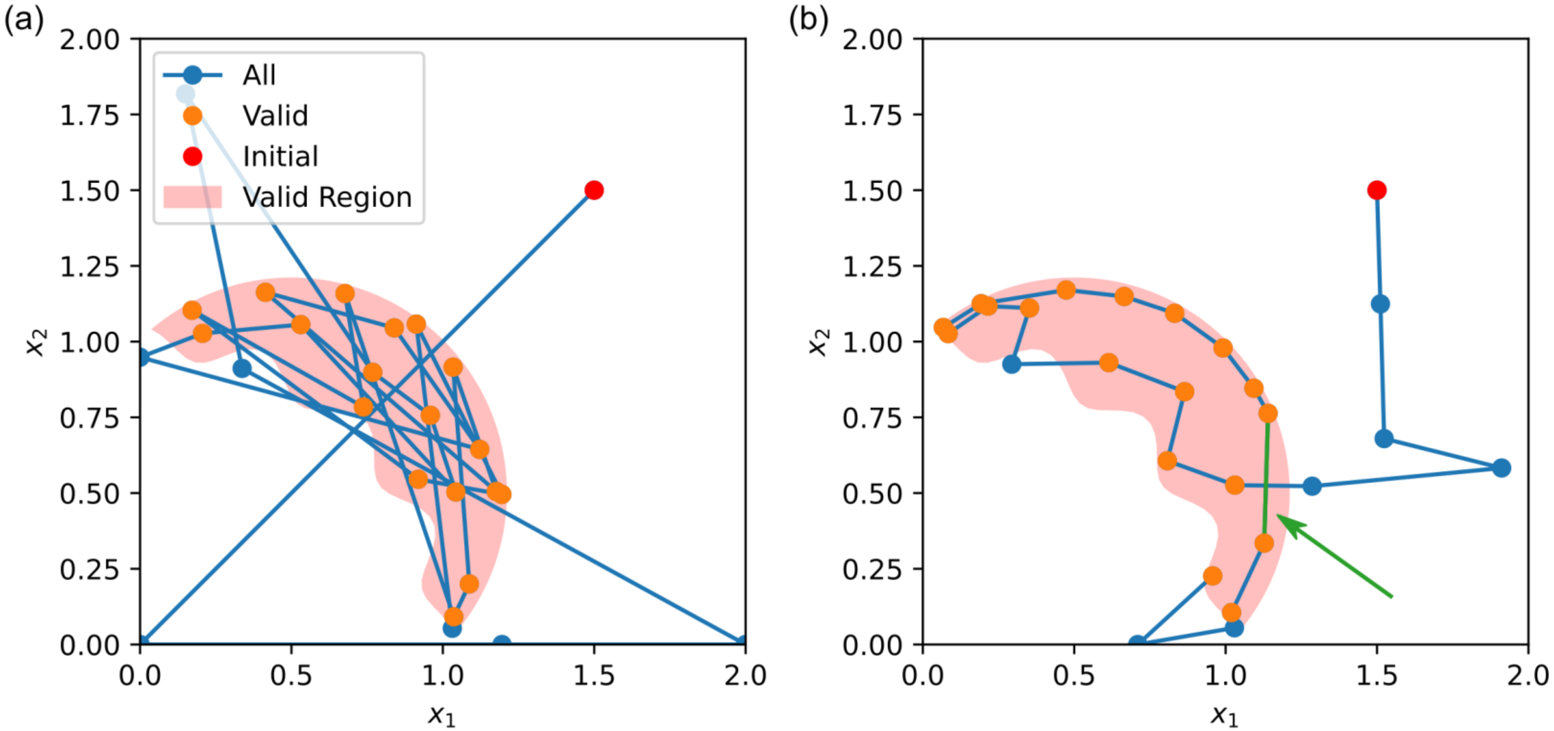
Ground truth

Prediction



$$\prod_{i=1}^{N} P_i[g_i(\mathbf{x}) \geq h_i]$$

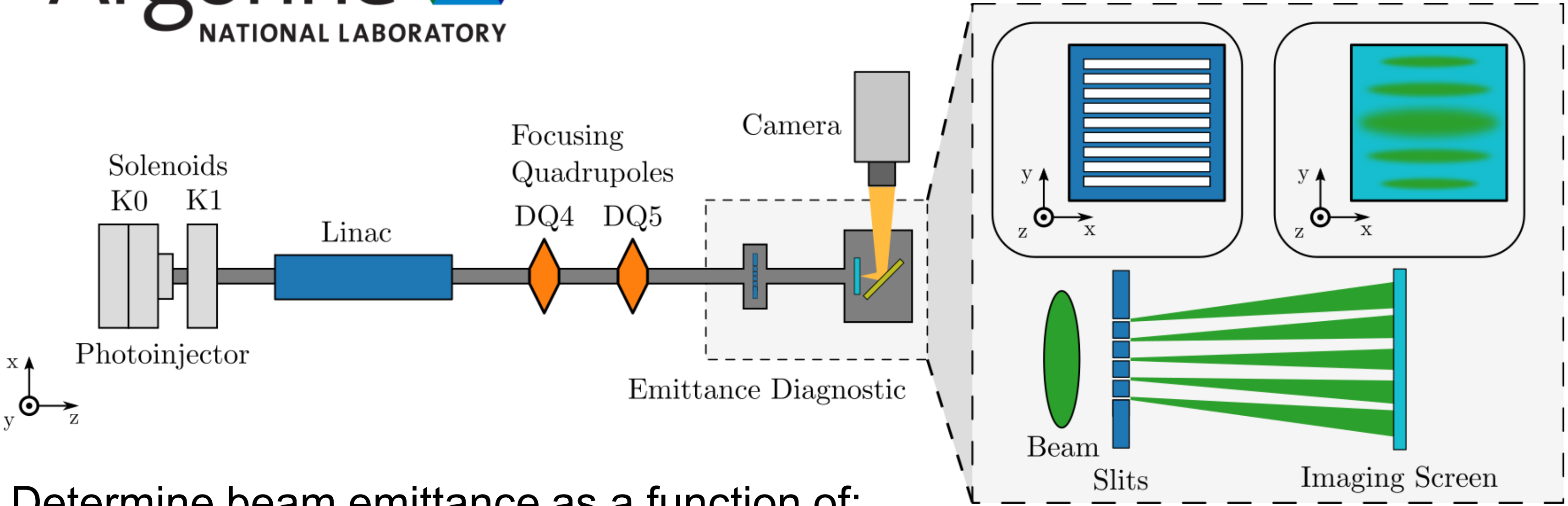
Proximal Biasing



Normal exploration

Biased exploration

Characterizing Photoinjector Emittance at AWA



Determine beam emittance as a function of:

- 2 solenoids
- 2 quadrupoles

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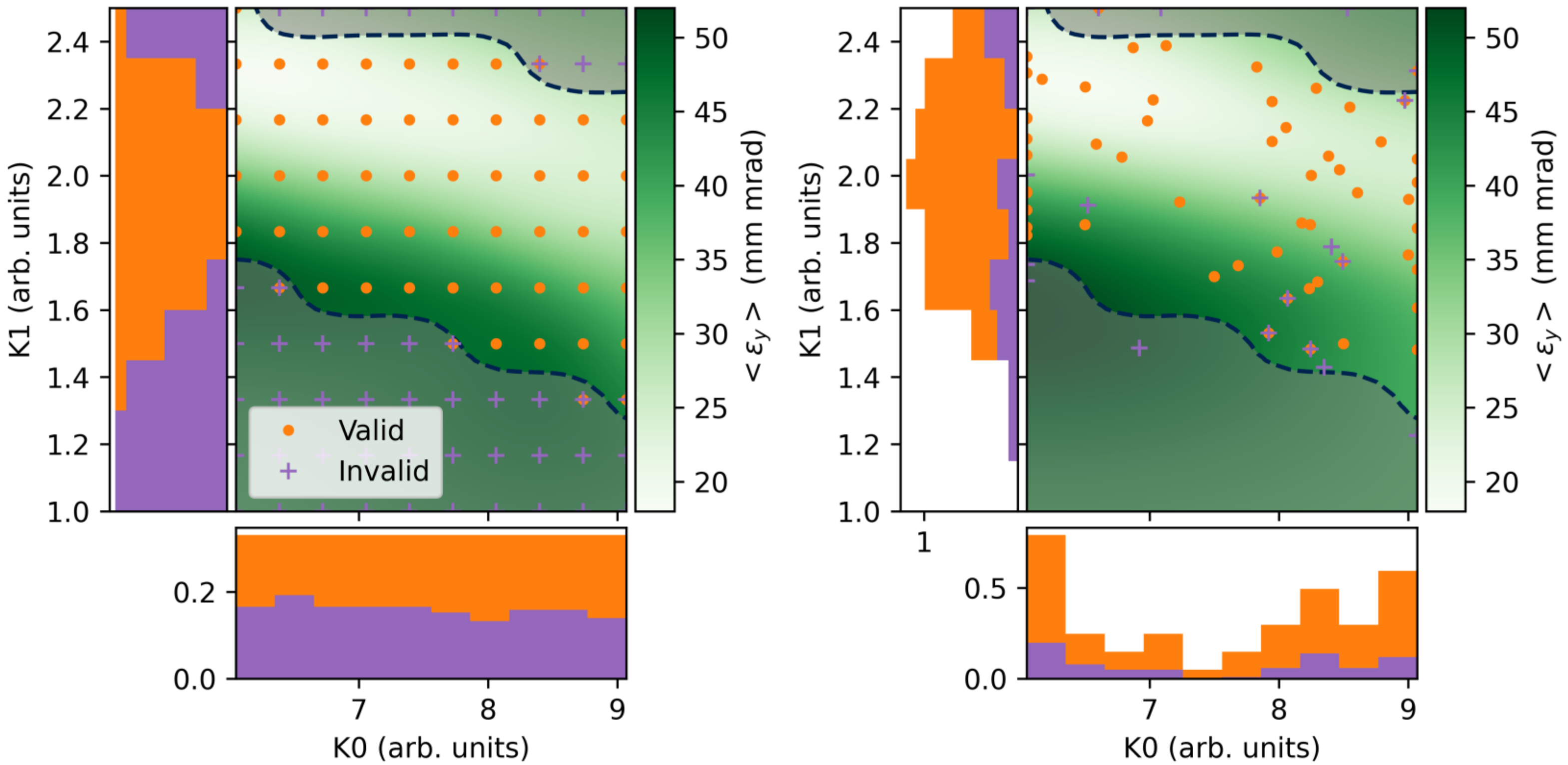
Characterizing Photoinjector Emittance at AWA



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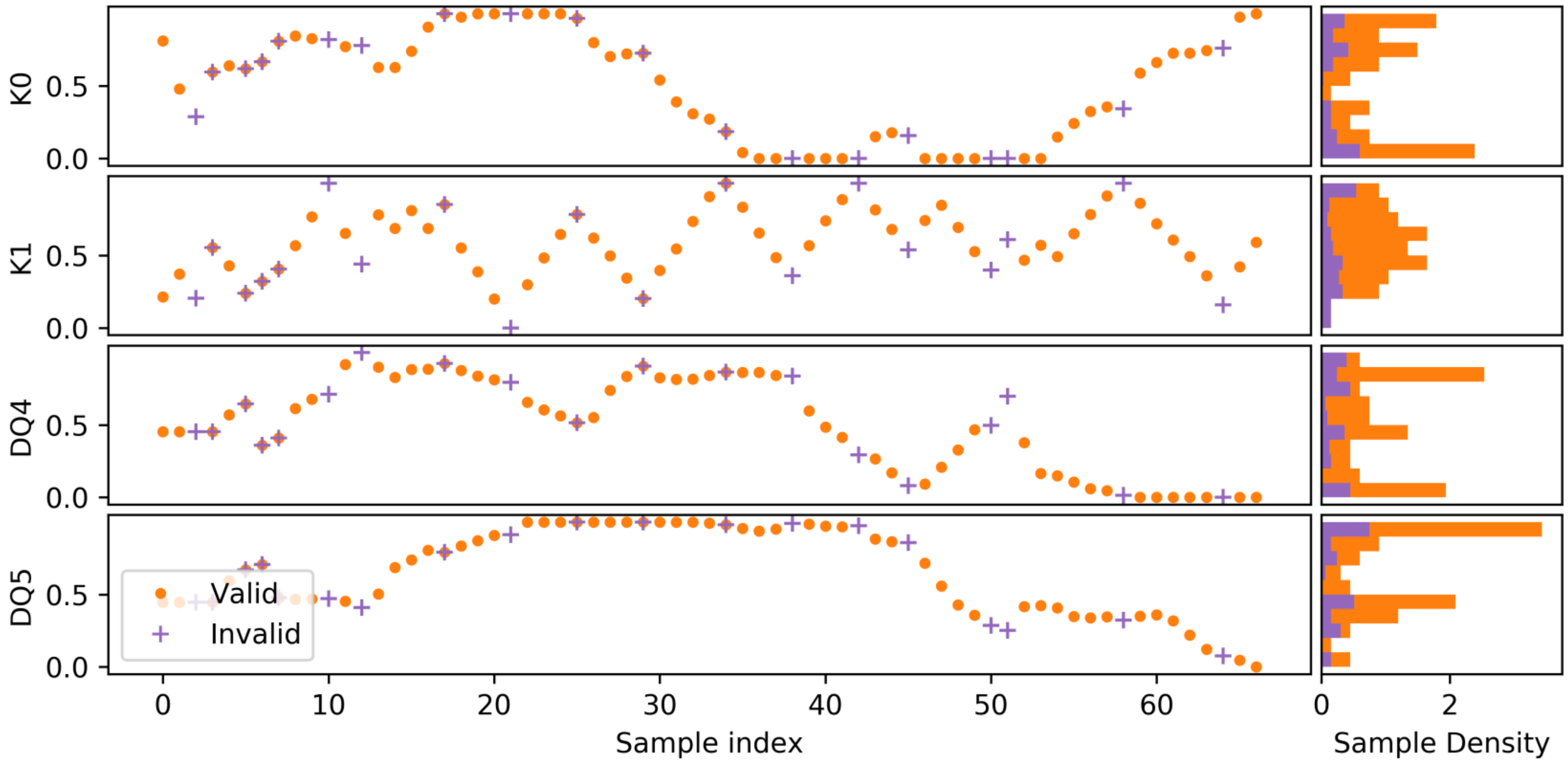
Characterizing Photoinjector Emittance at AWA



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Multi-Objective Bayesian Optimization

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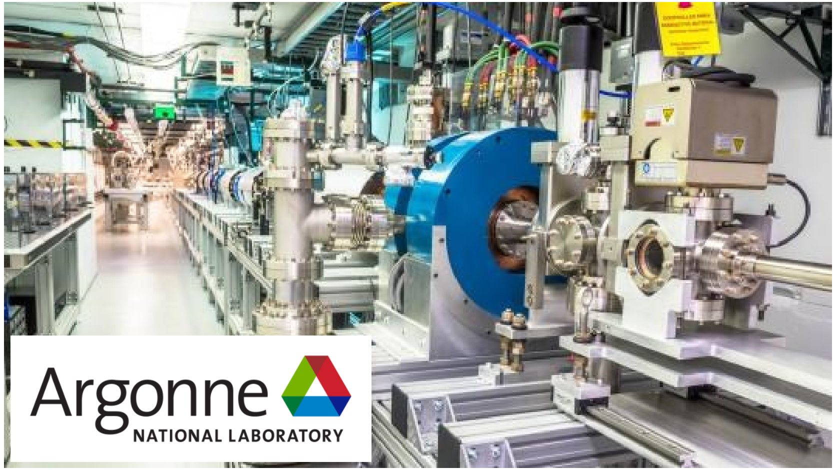
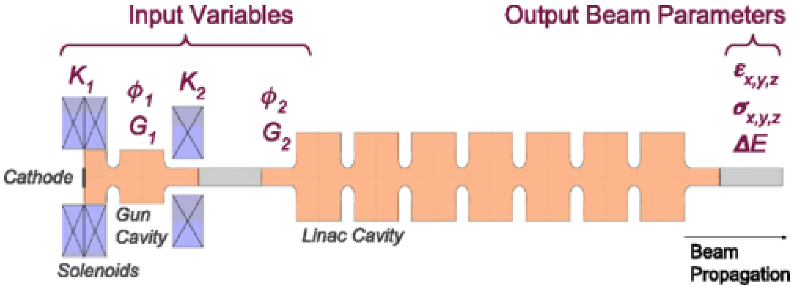
Multi-Objective Photoinjector Optimization





For online photoinjector optimization we wish to simultaneously:

- Minimize **emittances (3x)**
- Minimize **bunch sizes (3x)**
- Minimize **energy spread (1x)**

7 objectives

Tuning knobs:

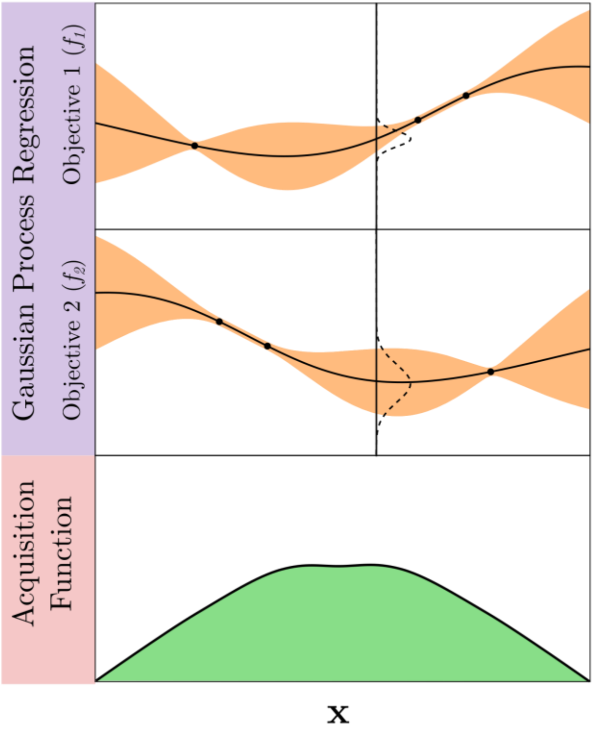
- Solenoid strengths **(2x)**
- RF Amplitudes **(2x)**
- RF Phases **(2x)**

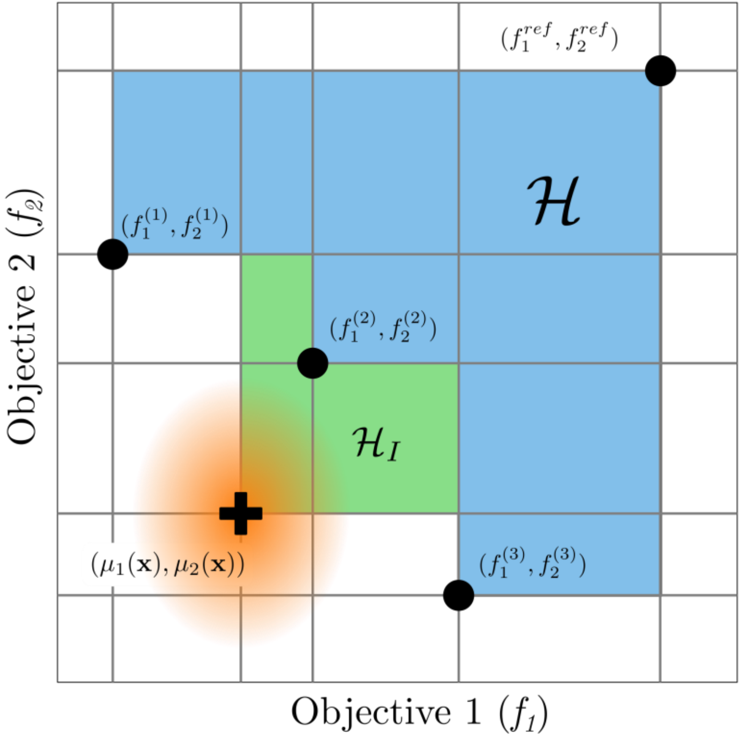
6 input parameters

Edelen, et al. PRAB **2020**

Expected Hypervolume Improvement

This allows us to find the Pareto front with a **small number** of measurements **in serial,** unlike genetic or swarm optimization methods





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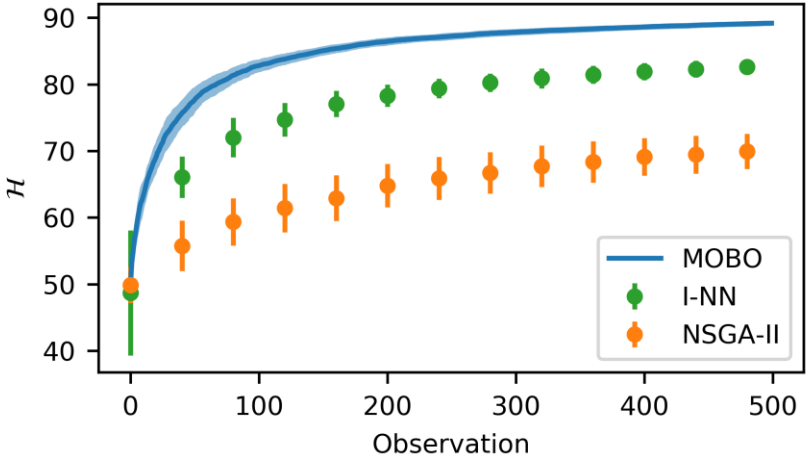
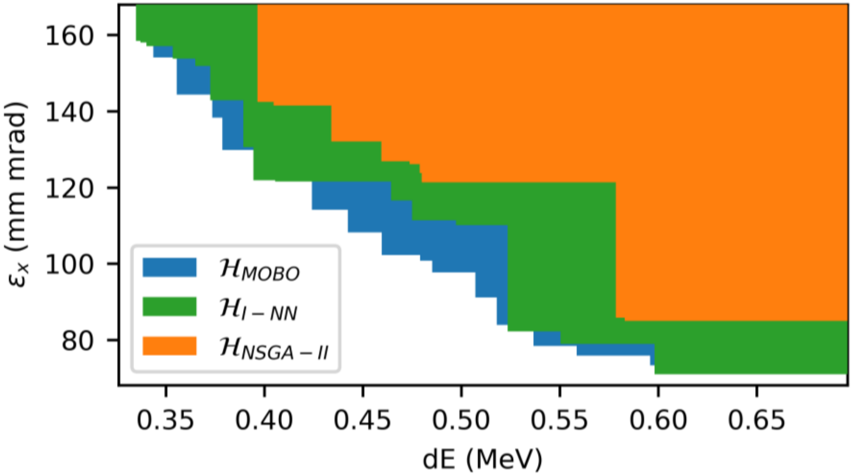
Simulated Photoinjector Optimization

SLAC





- 10 optimization runs
- 20 initial points each
- Peak hypervolume using < 500 observations (NSGA-II ~ 17.5k) factor of 35x speedup, tuned in < 45 mins!

Roussel et. Al. PRAB **2021**

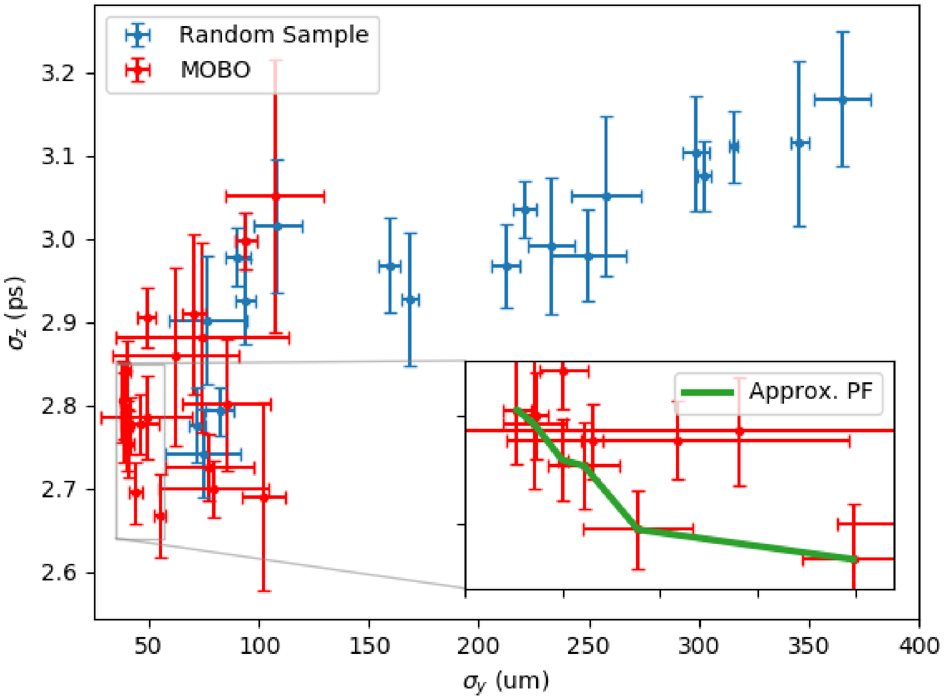
LCLS Photoinjector Optimization - Preliminary

Objectives:
- Minimize longitudinal bunch length
- Minimize vertical bunch size

Tuning variables:
- Solenoid strength
- Skew quad strength
- Normal quad strength

Used OTR screen + transverse deflecting cavity to measure bunch size

Started with random sampling of input space, then ran MOBO for 25 iterations



Xopt – Flexible Optimization in Python

Flexible implementation of advanced optimization algorithms in python

- Requires only a single python script to evaluate
- Available algorithms:
  - Bayesian exploration (*Nat. Comm.* **12**, 5612 (2021))
  - Multi-objective Bayesian optimization (*PRAB* **24**, 062801 (2021))
  - Multi-fidelity Bayesian optimization
  - Continuous NSGA
- Serial and parallel optimization using python threading, MPI etc.
- Used on HPC systems (NERSC)
- Used for real-time control at AWA

https://christophermayes.github.io/Xopt/

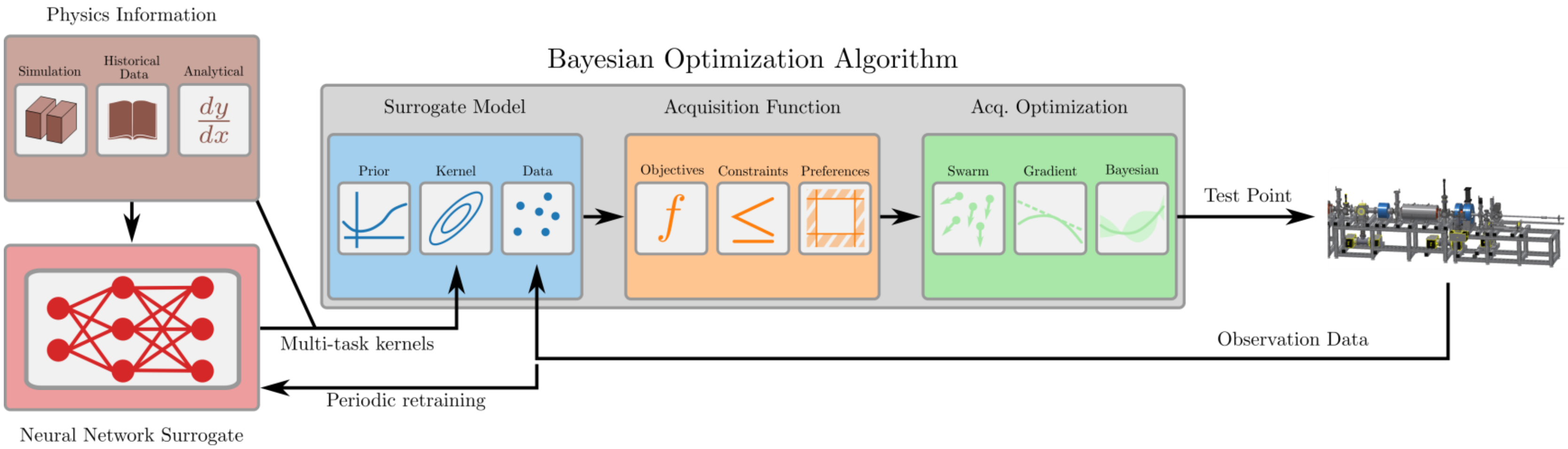
```yaml
xopt:
  output_path: null

algorithm:
  name: cnsga
  options:
    max_generations: 50
    population_size: 128
    crossover_probability: 0.9
    mutation_probability: 1.0
    selection: auto
    verbose: true
    population: null

simulation:
  name: test_TNK
  evaluate: xopt.tests.evaluators.TNK.evaluate_TNK

vocs:
  variables:
    x1: [0, 3.14159]
    x2: [0, 3.14159]
  objectives:
    y1: MINIMIZE
    y2: MINIMIZE
  constraints:
    c1: [GREATER_THAN, 0]
    c2: [LESS_THAN, 0.5]
  linked_variables:
    x9: x1
  constants:
    a: dummy_constant
```

Conclusion



Bayesian exploration and multi-objective Bayesian optimization represent steps towards a unified characterization and control system for accelerators