# Imperial College London

## BAYESIAN OPTIMISATION OF THE SHIP MUON SHIELD

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#### **Overview of SHiP**



#### Two signatures:

1. Via decay to visible particles in hidden sector spectrometer

2. Via scattering in nuclear emulsion

 $\rightarrow$  Generic signatures predicted by many new physics models.

Crucial to have zero background

#### **Further information**

• Technical Proposal: [CERN-SPSC-2015-016]

#### Why optimise the muon shield?

- Active muon shield that has to reduce muon flux by at least 6 orders of magnitude
- kinematic range of muons up to  $p \sim 350 \,\mathrm{GeV}$
- kinematic range of muons up to  $p_T \sim 8 \,\mathrm{GeV}$

The muon shield is the critical component to optimise to maximise the experimental acceptance

### **Challenges of the optimisation**

- ~50 free parameters (lengths), each varying from cm to m
  Doubly statistically limited
  - Not enough simulation
  - Not enough computing power to use entire simulation for optimisation
- Underlying physics inherently stochastic
- Nearly identical configurations may have very different performance
   With a different random seed entirely different muons pass the shield

- Addendum to the Technical Proposal
   [CERN-SPSC-2015-040]
- Physics Proposal: [CERN-SPSC-2015-017]
- New papers on facility and optimisation this year!

#### Convergence



 $\rightarrow$  Evaluation of points very expensive, gradient information not available and can not be approximated

#### Bayesian optimisation for the SHiP muon shield

- $x_t^{+} = 0.1000$ 1.5True (unknown) • Observations  $\mu_{GP}(x)$ - -1.0 — u(x) CI 0.5 f(x) 0. -0.5 -1.0-1.5 \_\_\_\_\_ -2.0 -1.5 0.5 -1.0 -0.5 0.0 1.0 1.5 2.0 Х
- Two optimisers shown here: still evaluating different regression algorithms to determine which performs best
- Performance here is on the reduced muon sample: perform follow-up studies on the full dataset to confirm performance

#### Results



- Significant reduction in weight  $(\rightarrow cost)$
- Same performance with significantly reduced magnetic field

Configuration	length/m	weight/kt	reduced sample	full sample
baseline @1.8 T	34.60	1.72	27±5	70±15

- Bayesian optimisation does not scale well to so many dimensions
- Computing model imposes additional constraints.
- 1600 cores available at YANDEX  $\rightarrow$  Make up to 100 guesses at once (with 16 nodes parallelising every function evaluation)
- Use scikit-optimize implementation of Bayesian optimisation
- Use Gaussian processes and random forests as surrogate models
- Reduce muon sample by factor ~40 to speed up evaluation and even out coverage of phase space:
  - Currently manual data-driven method
  - Evaluating importance sampling and other options

new optimum @ 1.7 T 34.82 1.28 22±3 42±6

## Future work

- Close collaboration with engineers at MISIS to progress to a detailed engineering design using grainoriented steel
- Fully automate process, add additional constraints to loss function and improve the shield further!

#### Prototyping

Construct five different prototypes to test technologies in test beams at CERN:

• Different joints for grain oriented steel

Assembly of magnet elements