Efficient Design of the SHiP's Muon Shield

Through Machine Learning and High Performance Computing

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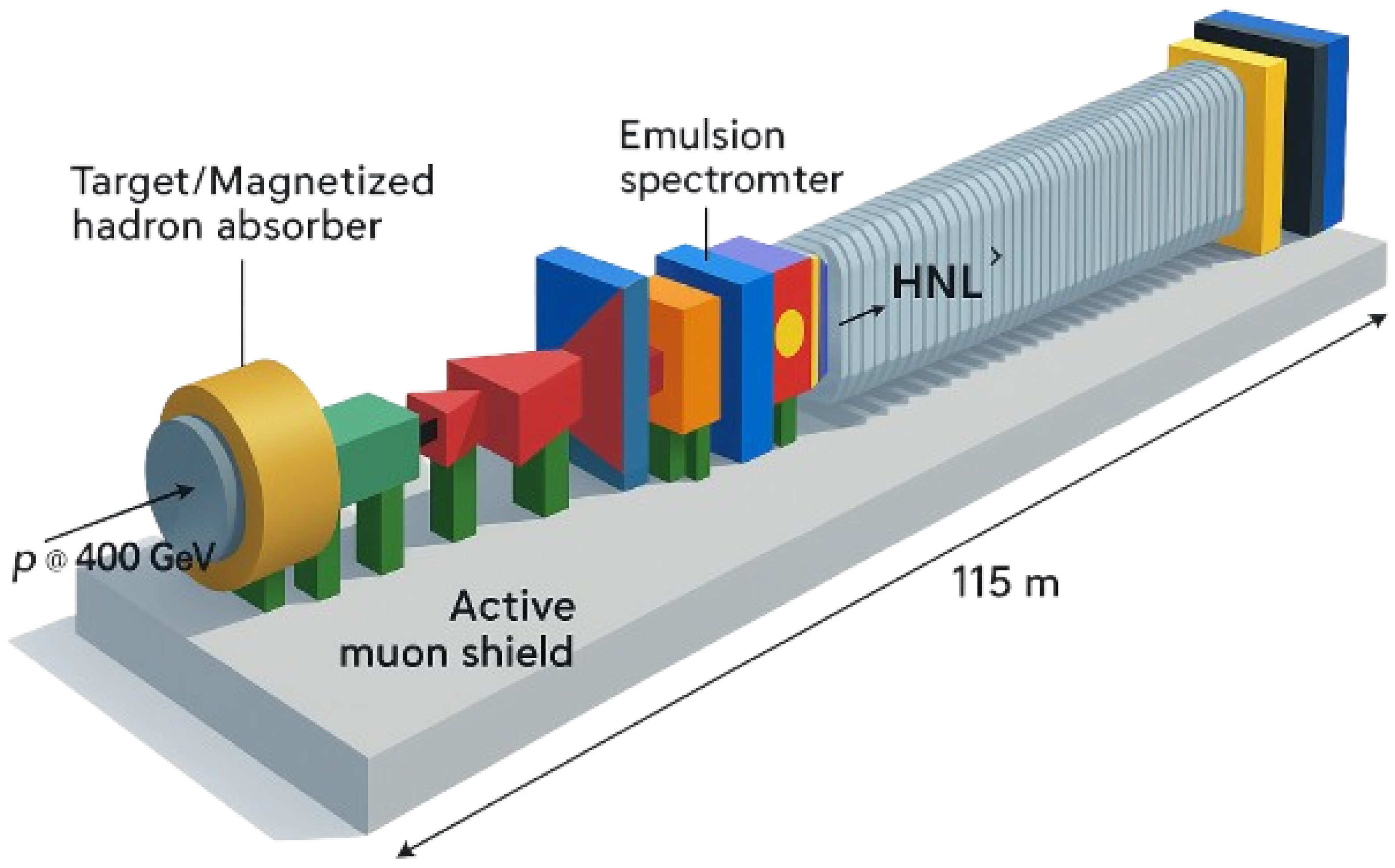
The SHiP's Muon Shield

The **Search for Hidden Particles (SHiP)** experiment at CERN aims to study weakly interacting particles beyond the Standard Model.

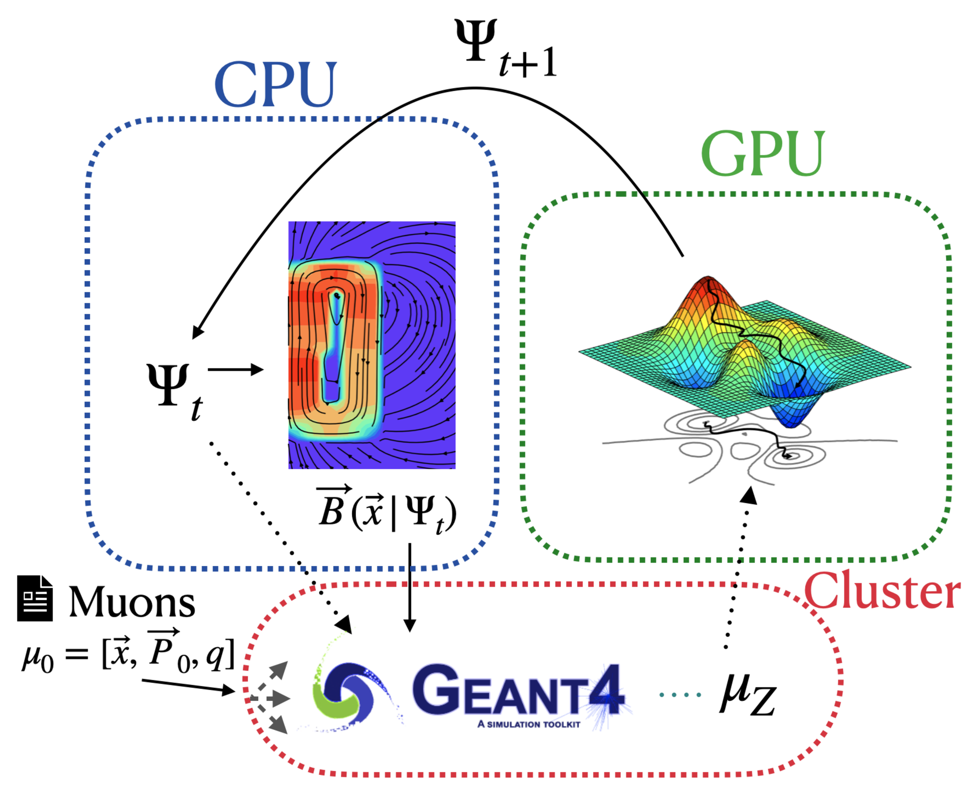
The **Muon Shield** is intended to reduce the **muon background flux**. Due to its critical role and **significant impact on overall costs**, optimizing the shield's design is both a challenging and essential task.

Challenges:

- **High dimensionality** and **complexity**
- **Expensive simulations**
- **Non-differentiability** and **stochasticity**



High Performance Computing

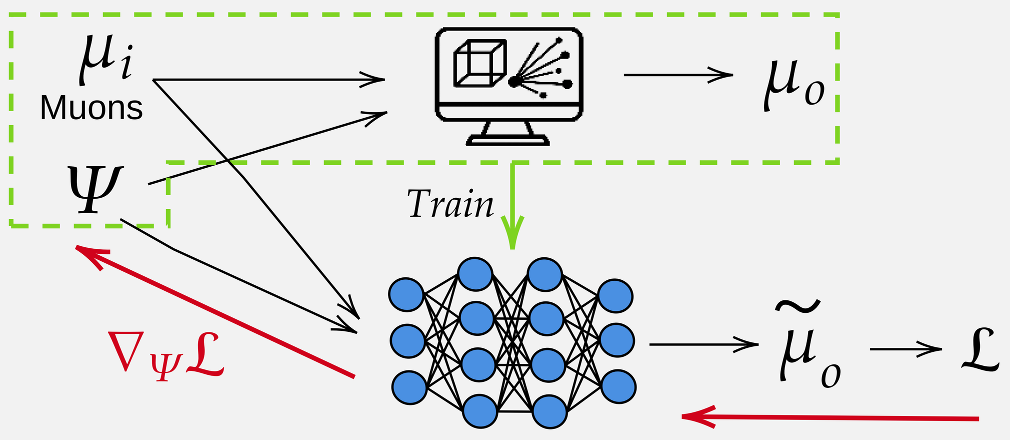


- Realistic simulations with **FEM + Geant4**
  - Magnetic field simulation on-the-fly
- High-performance **computing resources**
  - Parallelization using 1024 CPU cores
  - **GPU acceleration** for fast algorithms
- **Optimized algorithms** for time efficiency

Optimization with Machine Learning

Surrogate-Based Gradient Optimization

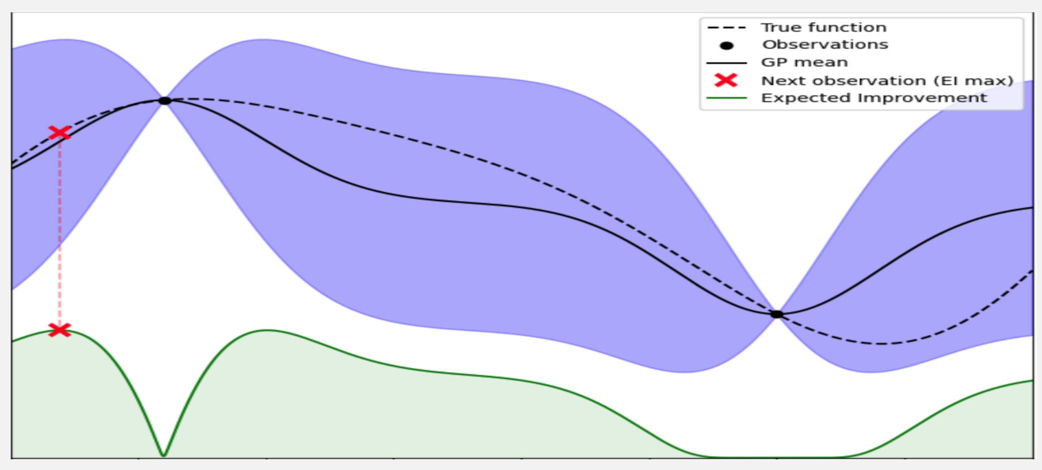
- Train **differentiable generative models** to surrogate the simulation.
- Perform **gradient-based optimization**



Limitation: Design space is limited to fixed **predefined layouts**.

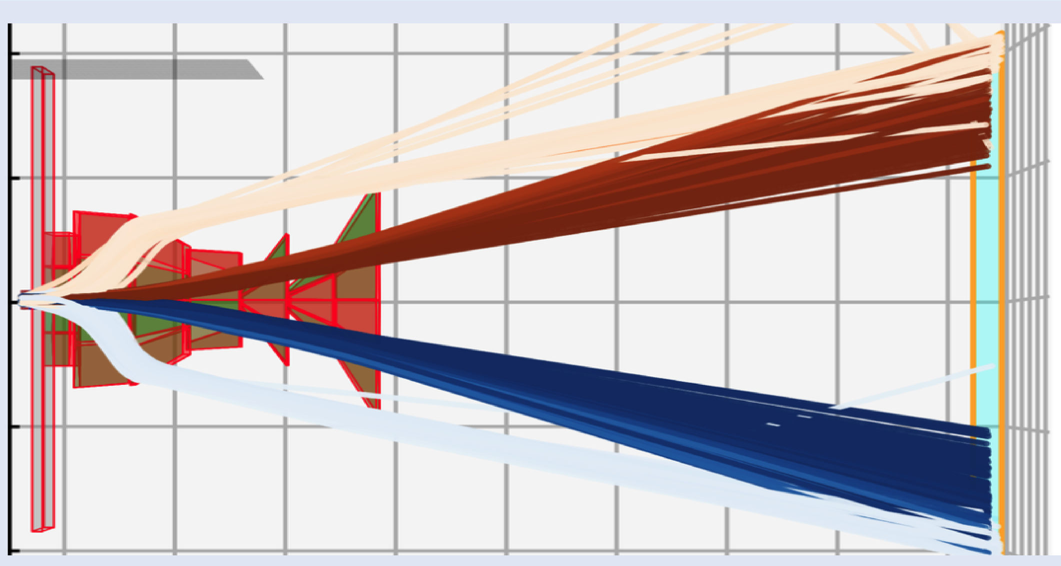
Bayesian Optimization with ML

- Model **predicts the performance** given parameters.
- Balances **exploration and exploitation**.



Key result: Hybrid global-local BO **outperforms** gradient-based optimization.

Results



- **Muon flux reduced** from $O(10^{10})$ to $O(10^4)$
- **Drastic speed-up**: from months to days
- Unprecedented inclusion of **engineering constraints**
- Incorporation of more **realistic simulations**
- Refined **cost estimation**

By leveraging **HPC** and **ML**, we **successfully addressed** the **Muon Shield Design** challenge at SHiP.

Reinforcement Learning Optimization and Design

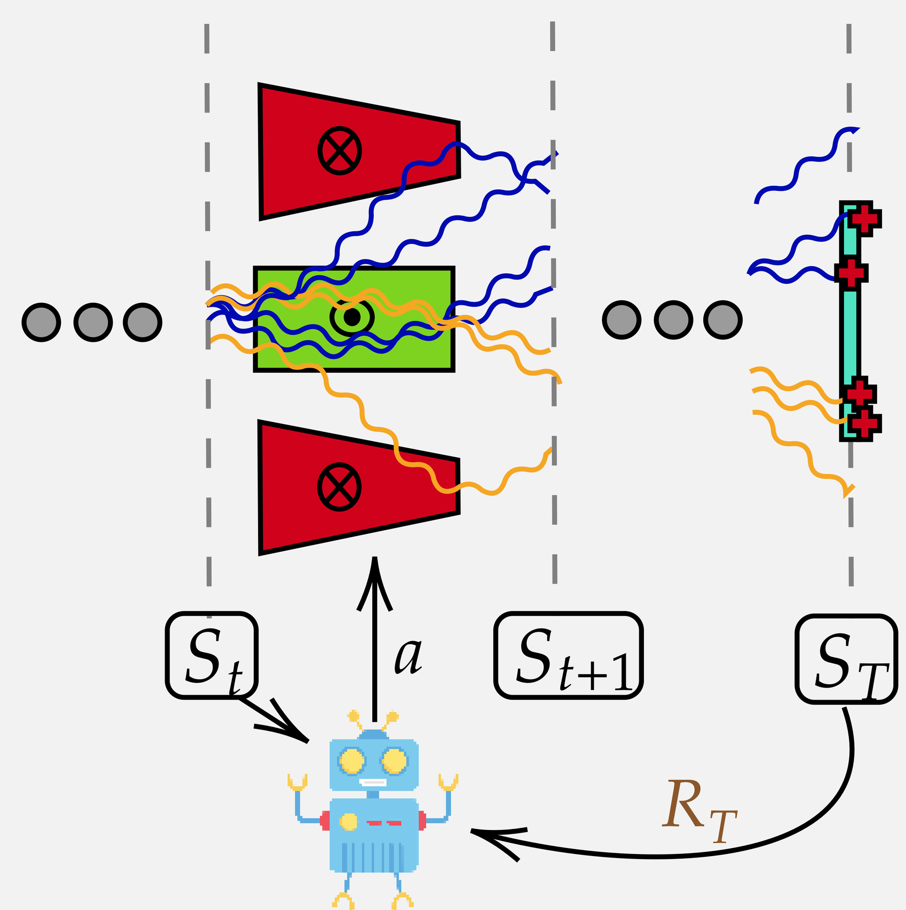
Our group aim to develop a novel **Reinforcement Learning** strategy that can dynamically design the muon shield.

Why use RL?

- Can handle **discrete decisions**: e.g. "place component A at position B"
- **Non-differentiable optimization**
- Ideal for **sequential tasks**
- Potential for **non-intuitive designs**

RL Framework:

- **State:** observed muon flux, veto system response, current layout
- **Action:** place or configure a shield component
- **Reward:** muon suppression score minus cost penalty



What's Next

- Apply **reinforcement learning** directly with simulation environments.
- **Joint optimization** with other subsystems.

References

[1] SHiP Collaboration. Ship experiment at the sps beam dump facility. *arXiv:2504.06692*, 2025.

[2] Shah Rukh Qasim, Patrick Owen, and Nicola Serra. Physics instrument design with reinforcement learning. *arXiv:2412.10237*, 2024.