Toward A.I.-Assisted Design of Experiments

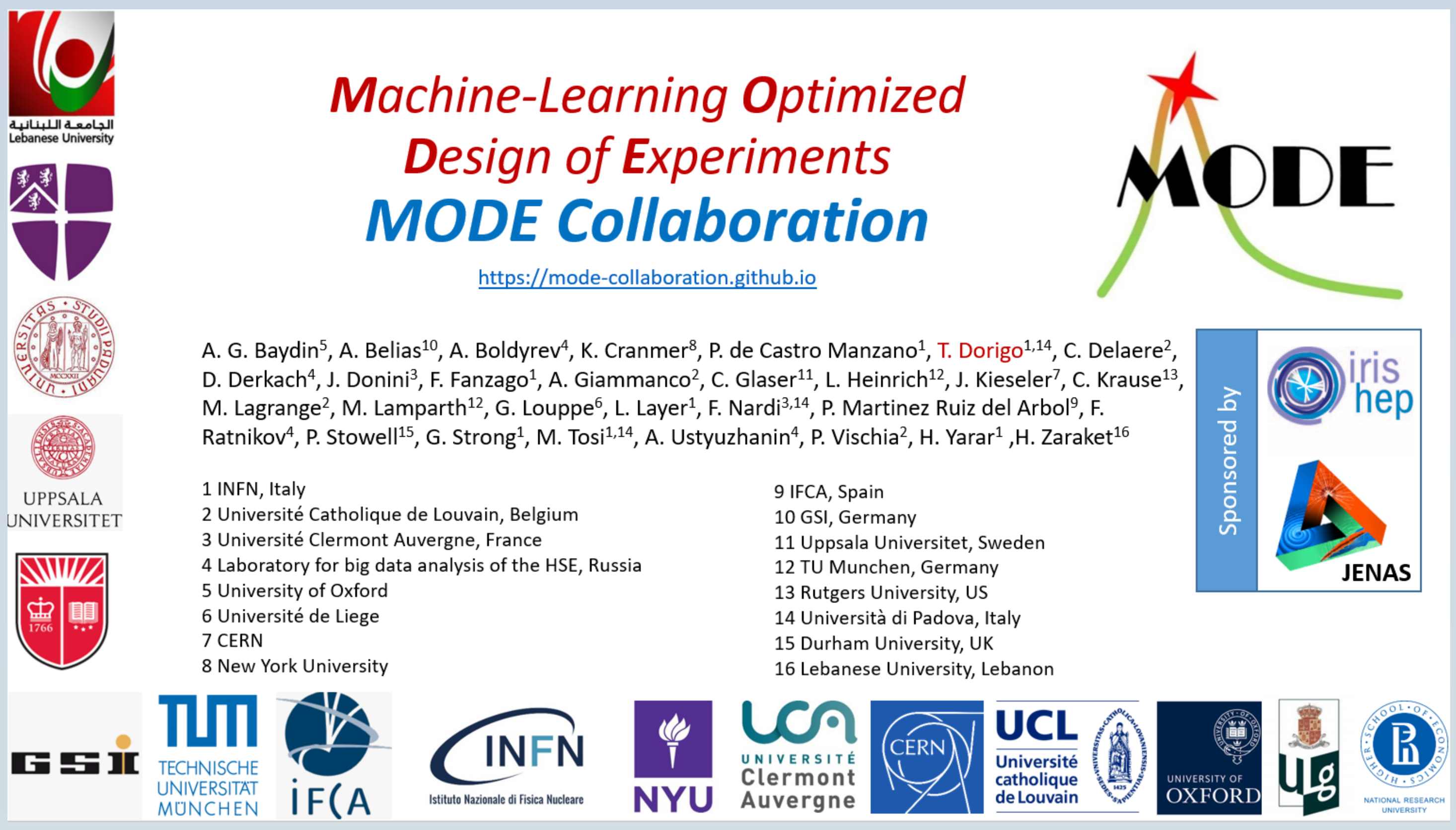
Tommaso Dorigo (INFN, Sezione di Padova) for the **MODE Collaboration**

MOTIVATION

In 2012 we discovered the Higgs boson with machine learning tools. That marked a paradigm shift in data analysis procedures and performance.

A similar paradigm shift is offered today by Artificial Intelligence methods allowing for the end-to-end optimization of our instruments:

Differentiable Programming (**DP**).



MODE [3] aims to pave the way to the full optimization of our future instruments.

By solving problems of moderate complexity, we are building a modular software library, gradually empowering the study of harder use cases [4].

Detector design in HEP traditionally leverages robustness-driven paradigms

- «*Track first, destroy later*»;
- focus on redundancy, ensuring intercalibration;
- symmetrical layouts

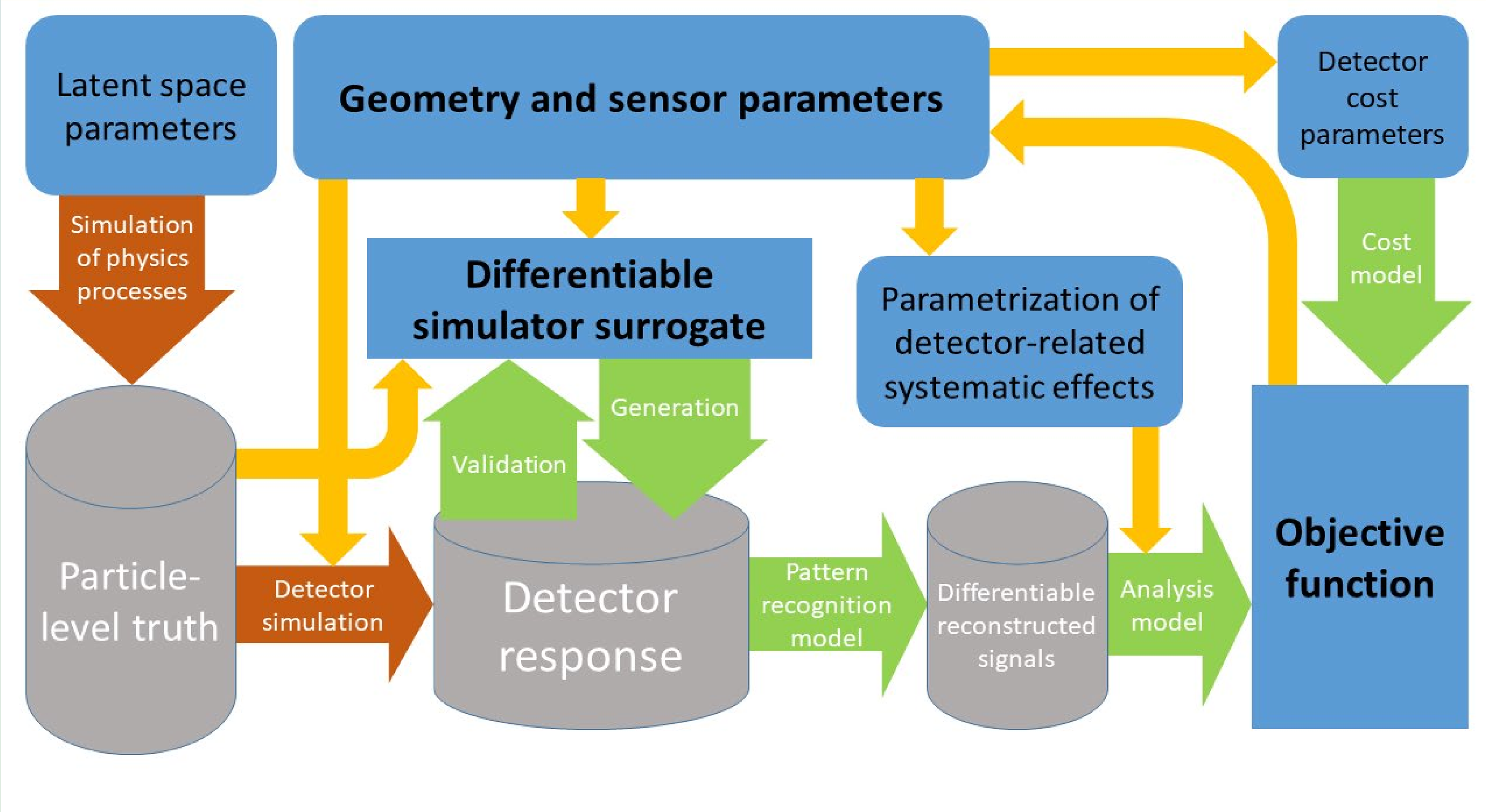
→ Great, but not meant to optimize performance!

DP-based **models** describing all parts of an experiment, from sensor geometry to inference extraction, **enable a continuous mapping of the performance**, probing the result of design choices in high-dimensional spaces which we cannot explore with discrete sampling.

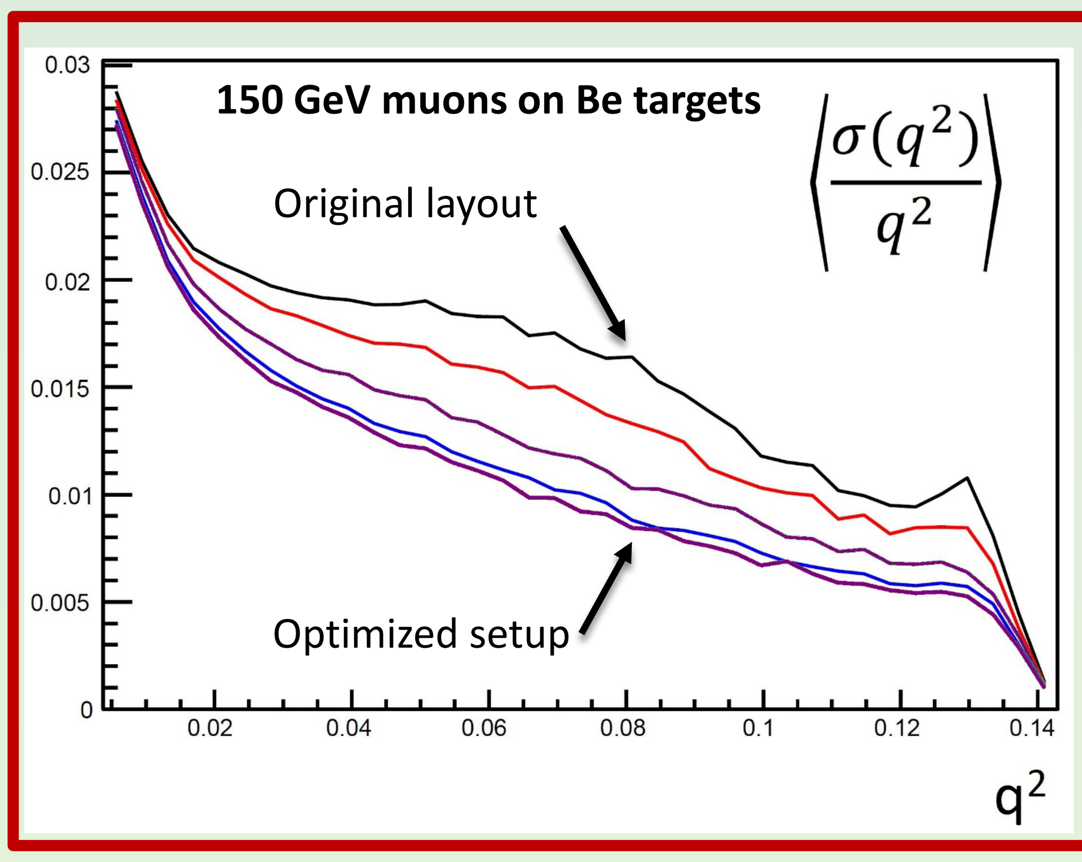
These models may allow the discovery of human-impervious, innovative solutions, with LARGE potential gains. E.g., see below:

What is differentiable programming?

DP is the technology under the hood of **deep learning methods**, enabling automatic calculation of derivatives. Using the chain rule of differential calculus we may compute how parameter variations affect the loss function of a NN, or the global utility of an optimization task.



Left: Encoding all system elements within a pipeline allows for the back-propagation of gradients of the objective function, and a full scanning of the parameter space of design options.



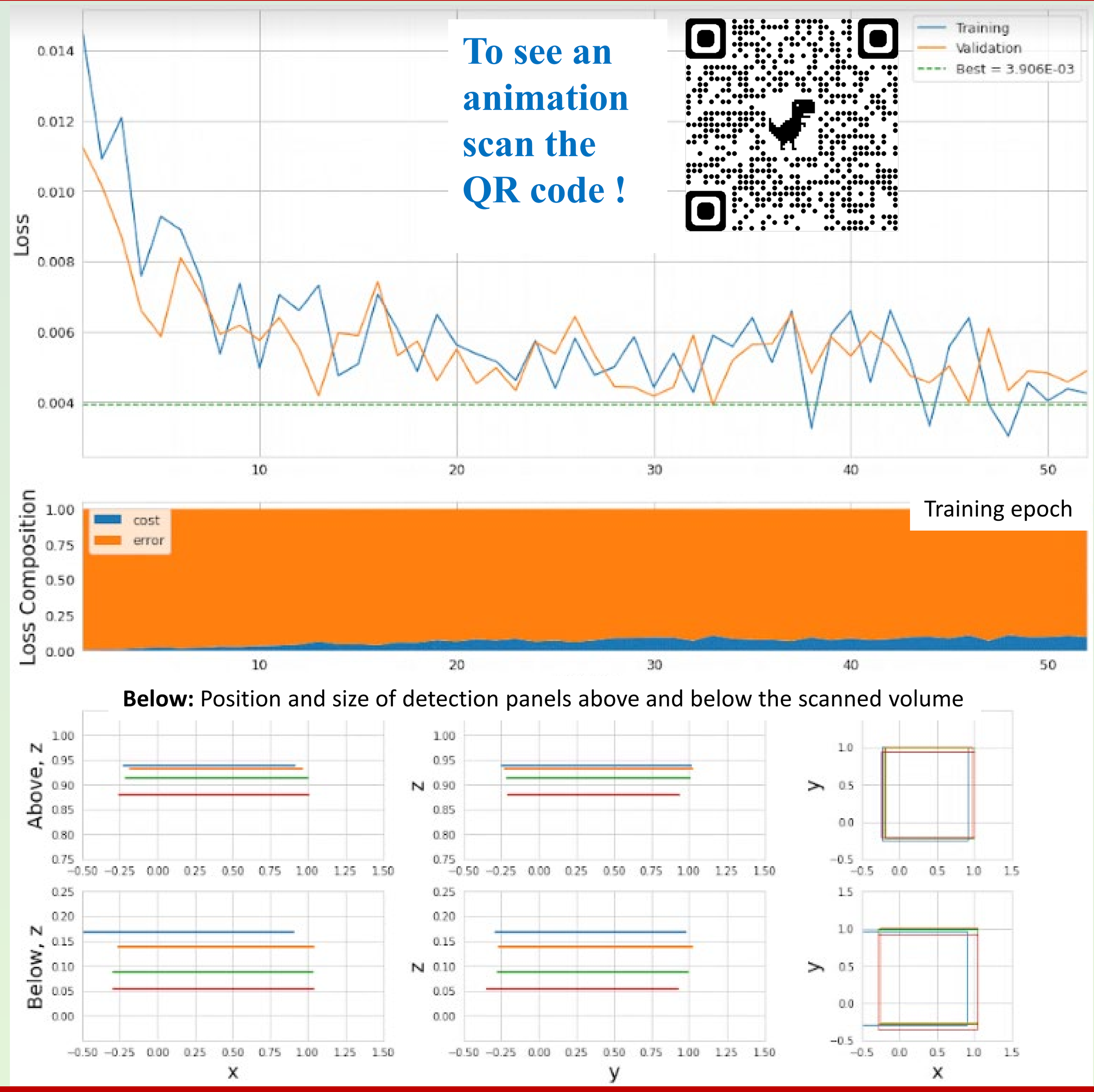
Left: The optimization of the **MUonE** experiment identified a modified layout of its tracker, offering **factor of 2** improvement in the relevant figure of merit (relative resolution in q^2 of high-energy scatterings) with respect to original design **[1]**.

Similarly, a **factor of 2** reduction in muon flux in **SHIP** by magnet optimization was shown in **[2]**.

Right: Proof of optimization of a **muon tomography detector**.

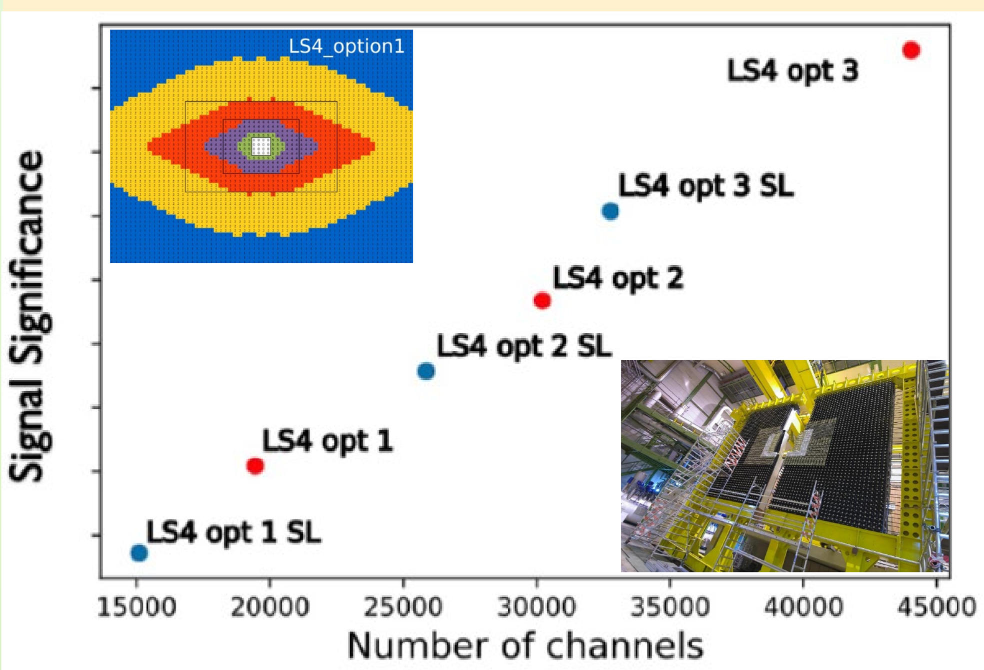
DP software finds optimal geometry of detection panels given cost, constraints, and specified objective (e.g., power of detection of specific materials).

Case shown: detection of U blocks in scrap metal within container.

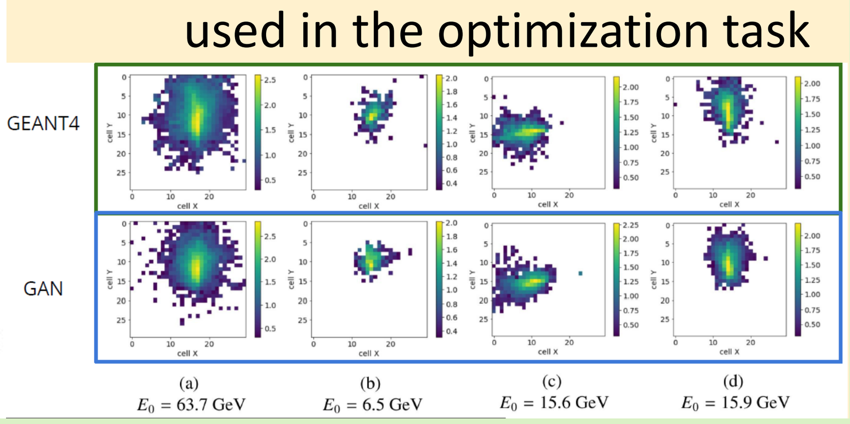


Generative models for particle interactions can be used to model non-differentiable stochastic processes:

Below, left: Upgrade of **LHCb EM calorimeter**. Optimized significance to $B_s \to J/\psi\ \pi^0$ signal is shown given number of channels **[4]**. Insets show baseline PMT layout



Below, right: simulation of EM showers produced by GEANT4 are well reproduced by a generative adversarial network model, then used in the optimization task



Use cases currently studied include:

- Muon tomography detectors (see **above**)
- EM calorimeter for **μ collider** detector (in progress)
- Upgrade of **LHCb** EM calorimeter (see **left**)
- Hybrid hadron calorimetry (in progress)
- **SWGO** Cherenkov array optimization (starting)

References

[1] T. Dorigo, "*Geometry Optimization of a Muon-Electron Scattering Detector*", Physics Open 4 (2020) 100022.
[2] S. Shirobokov et al., NeurIPS 34 (2020), arXiv:2002.04632 [cs.LG].
[3] See https://mode-collaboration.github.io .
[4] T. Dorigo et al., arXiv:2203.13818 [physics.ins-det] (2020).