Studies on detector optimisation through end-to-end surrogate models including discrete parameters

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The usual chain









Our simulation is fantastic



A particle being stopped in dense material

- High fidelity simulation of particles interacting with matter
- Carefully validated
- Validity also spans orders of magnitude
- Not* differentiable

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http://arxiv.org/abs/2108.02803



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A few quantities

Many pixels, detector elements, hits







Complexity of the Problem

A few quantities



arXiv:1909.09193









Make Wider Steps?









Make Wider Steps?







Make Wider Steps?







The type of approach















- Complex showers
- So far designs relatively simple
- Good place to invest in systematic gradient-based optimisation

Calorimeters



Detect (sensors) Absorb/stop

Much cheaper





The simulation and reconstruction

double p = /* diff'able */; if(rng->flat()

 E_t





E_t : e.g. single value

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 E_p/E_t : approx. Gaussian distribution (narrow = better)







A diffusion model as a surrogate



https://scholar.harvard.edu/binxuw/classes/machine-learning-scratch/materials/foundation-diffusion-generative-models





Adding conditioning



- (O(100)) in principle slow
- Very low-dimensional problem
- Fast enough and very easy to









Single particles Full Geant4 Simulation (Photons and hadrons) Layer material* E = [1,20] GeV • Layer thicknesses

- Conditioned on θ , E_t

A pipeline

	Recon- struction	Analysis
(θ)	Simple DNN reconstruction • Has access to θ	Objective: $L = \frac{(E_p - E_t)^2}{E_t}$

Simple diffusion model (DNN) • One input (noise) and one final output (E)

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Training









- Input normalisations are kept fixed after first training iteration
- Reconstruction and diffusion models are *refined* on the new data, not trained from scratch
 - Transfer-learning significantly reduces the amount of simulation resources needed *

Optimisation







- Photons: 1-20 GeV, uniform
- Absorber Pb: 1cm
- Active PbWO4 : 1cm
- Constraint: depth of 25 cm



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Sanity check









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It works





A look at discrete parameters: Material



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The problem with discrete parameters



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Generative models have trouble modelling this

Polystyrene







• We can use the strong tendency of DNNs to "interpolate everything" to effectively model (gradients on) discrete parameters

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The output as a function of the discrete parameter

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Polystyrene







Cost in objective function



• Implement also the material cost into the objective function using a smoother dependence







- 3 x (absorber + sensor)
- Different particles (electromagnetic and hadronic)
- Short showers
- Deep showers
- All with energies between 1 and 20 GeV
- Material cost <50k CHF
- Length <180 cm
- Start with a <u>horrible</u> configuration
- e.g. no photon will actually reach the first sensor

Does it work?









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Does it work?



























An end-to-end surrogate avoids creating a differentiable model for the complex, high dimensional intermediate detector-level state

It smoothes out non-differentiable operations in the simulation (and reconstruction)

In the (simplified) setting of calorimeters, it seems to work well

The dependence on discrete parameters can be modelled in an effective manner

More detailed studies ongoing - stay tuned

I have omitted many physics and technical details - please feel free to ask

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Summary



