AI-driven detector design for the EIC

Benjamin Nachman

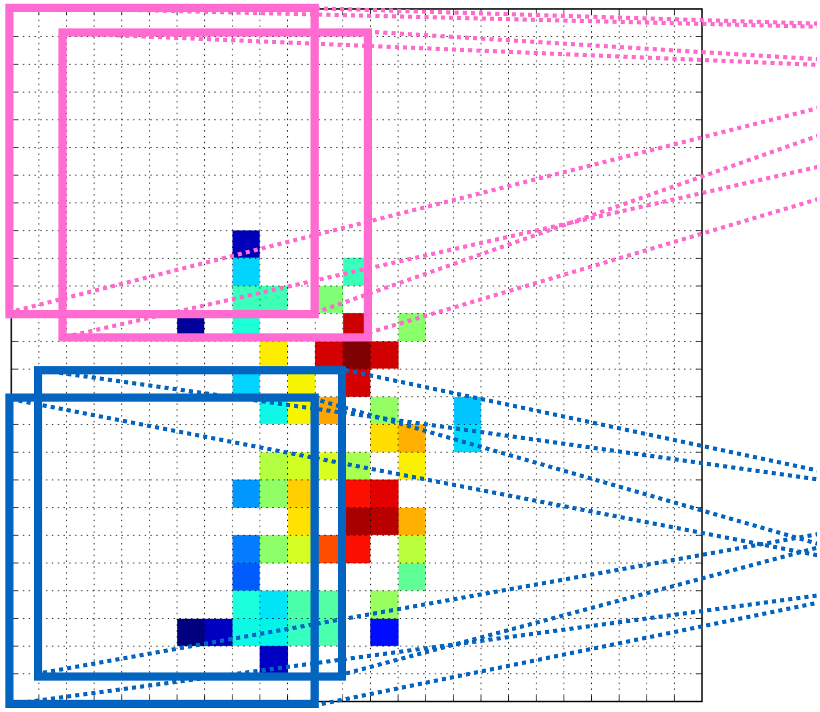
Lawrence Berkeley National Laboratory

bpnachman.com

bpnachman@lbl.gov

@bpnachman

bnachman



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Oct. 10, 2022

Overview

Detector Model

parameters of interest θ

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Goal: find best θ given a metric(s).

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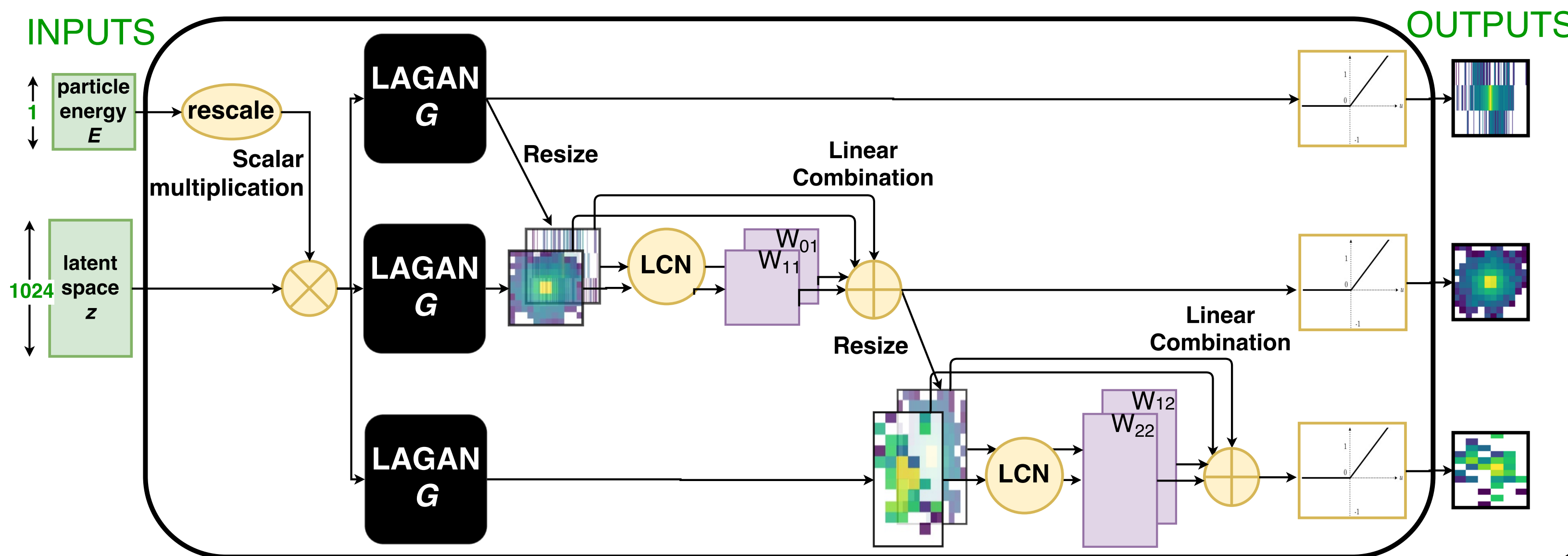
Today: can we use ML to (1) interpolate in the high-dimensional space, (2) define optimal metrics, and (3) find the best values of θ.

Outline



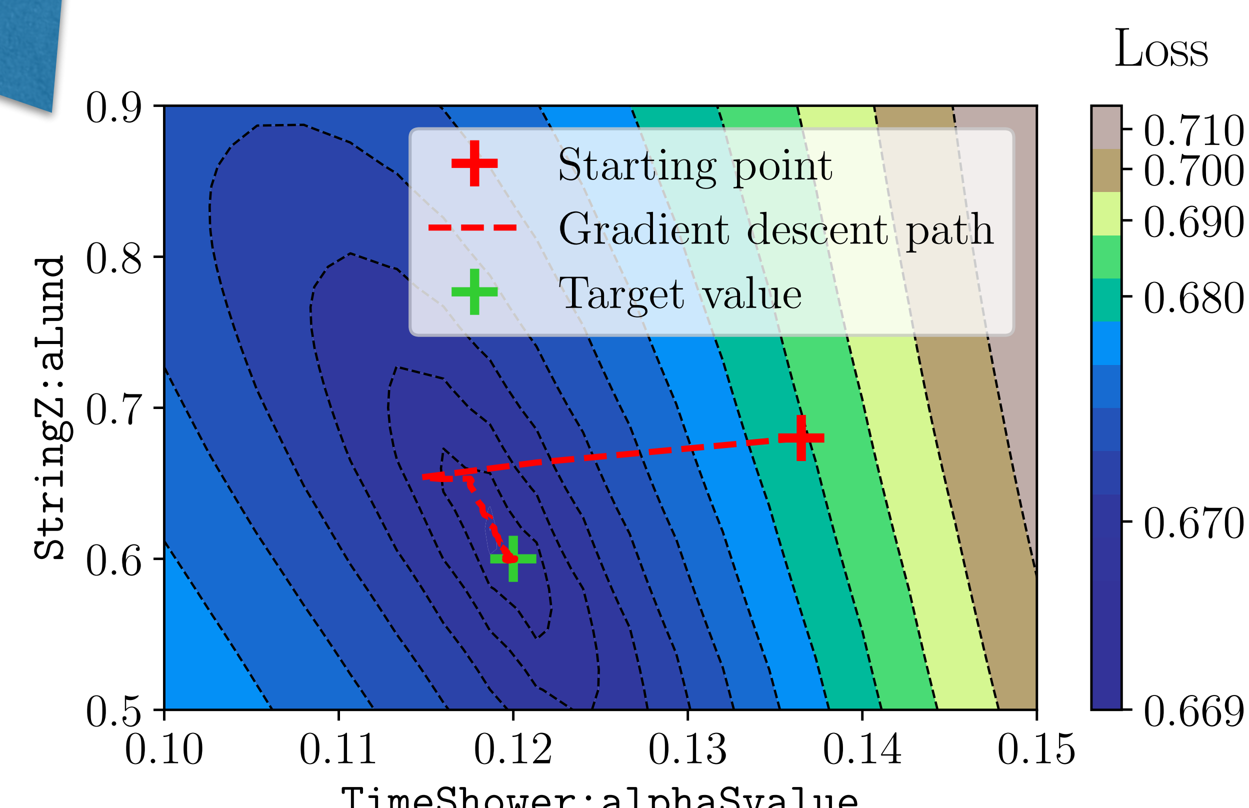
Detector Modeling

Surrogate Model
Differentiable Simulation

For free: GPU-enabled fast sim.

ML-based Optimization

Gradient-based
Gradient-free



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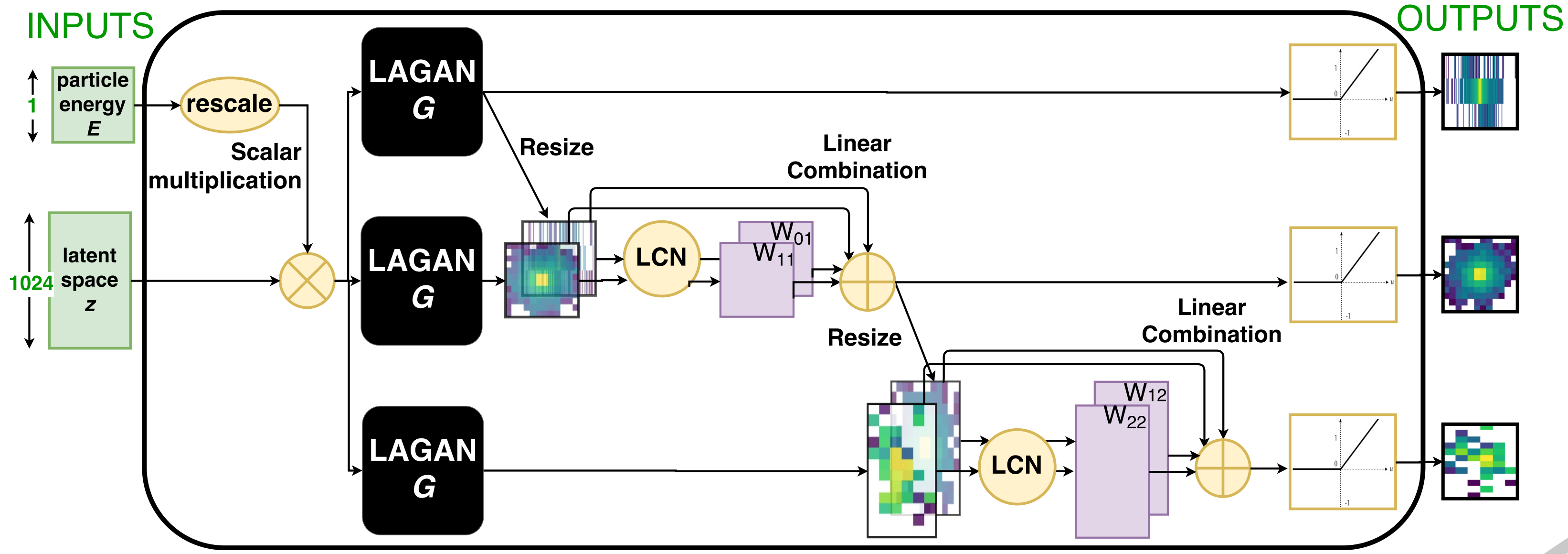

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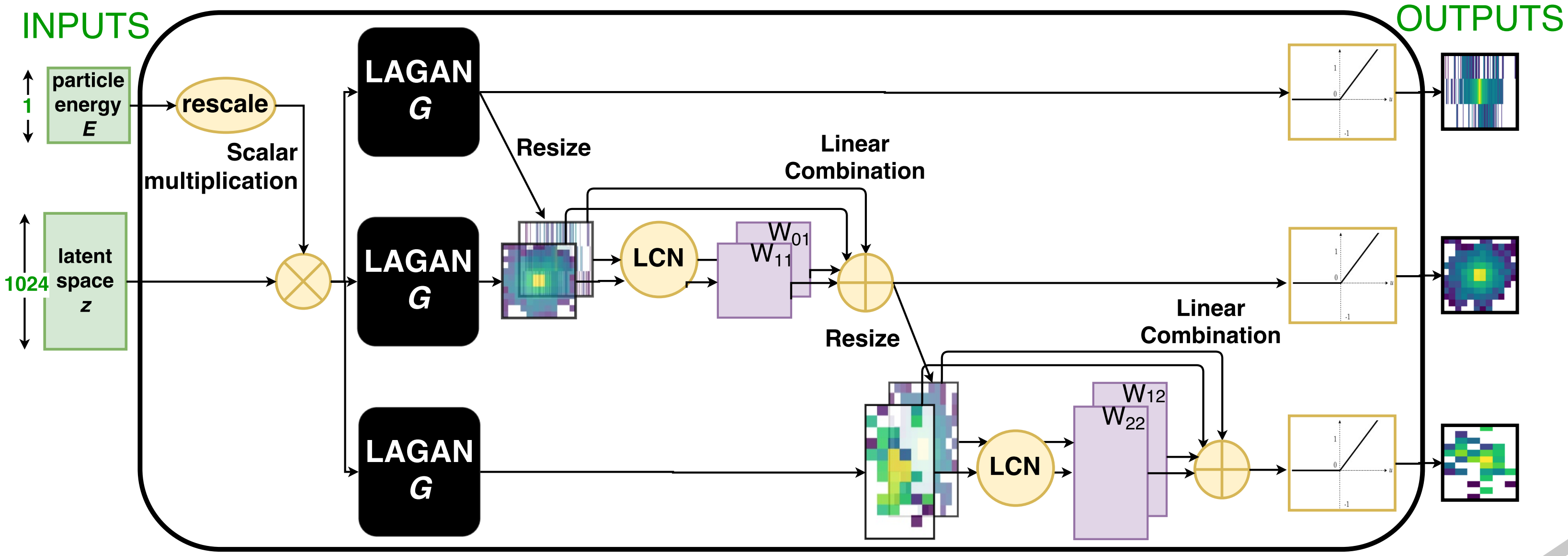

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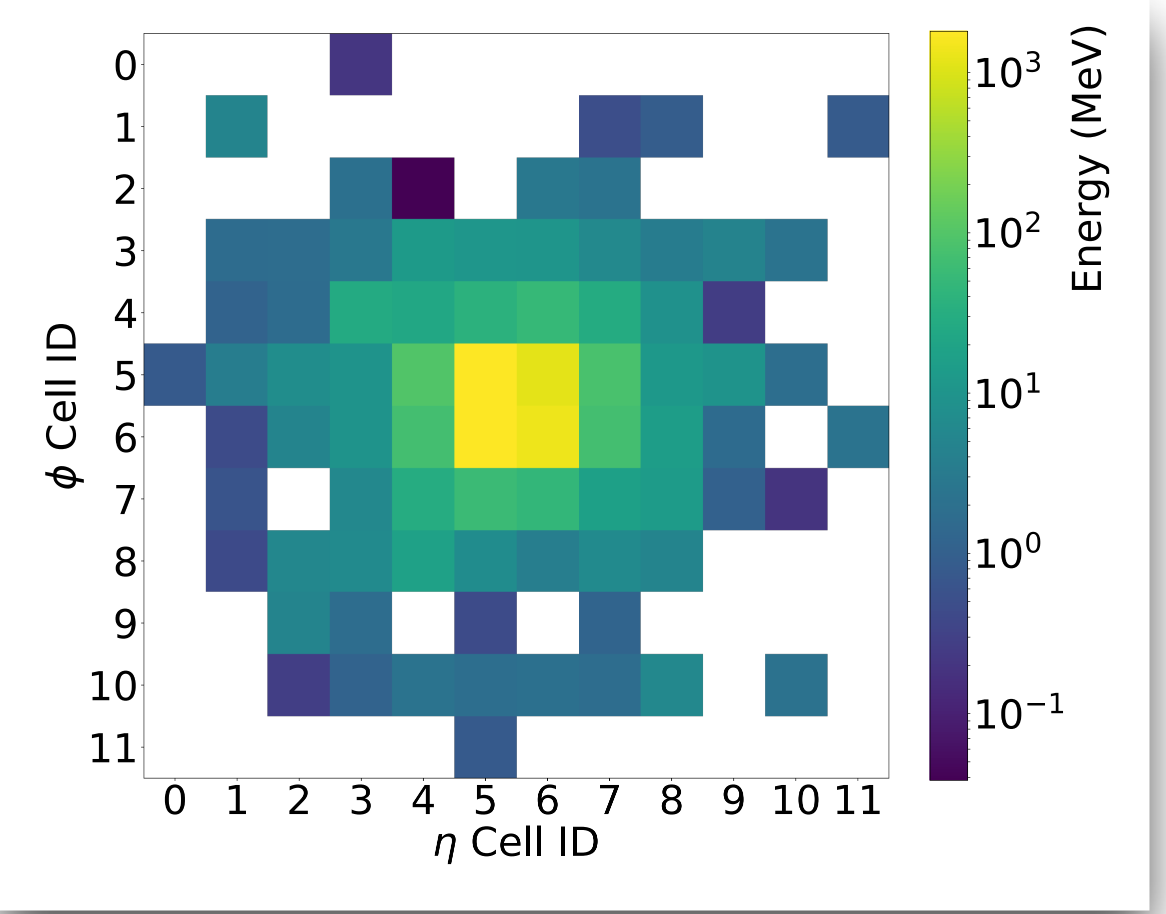
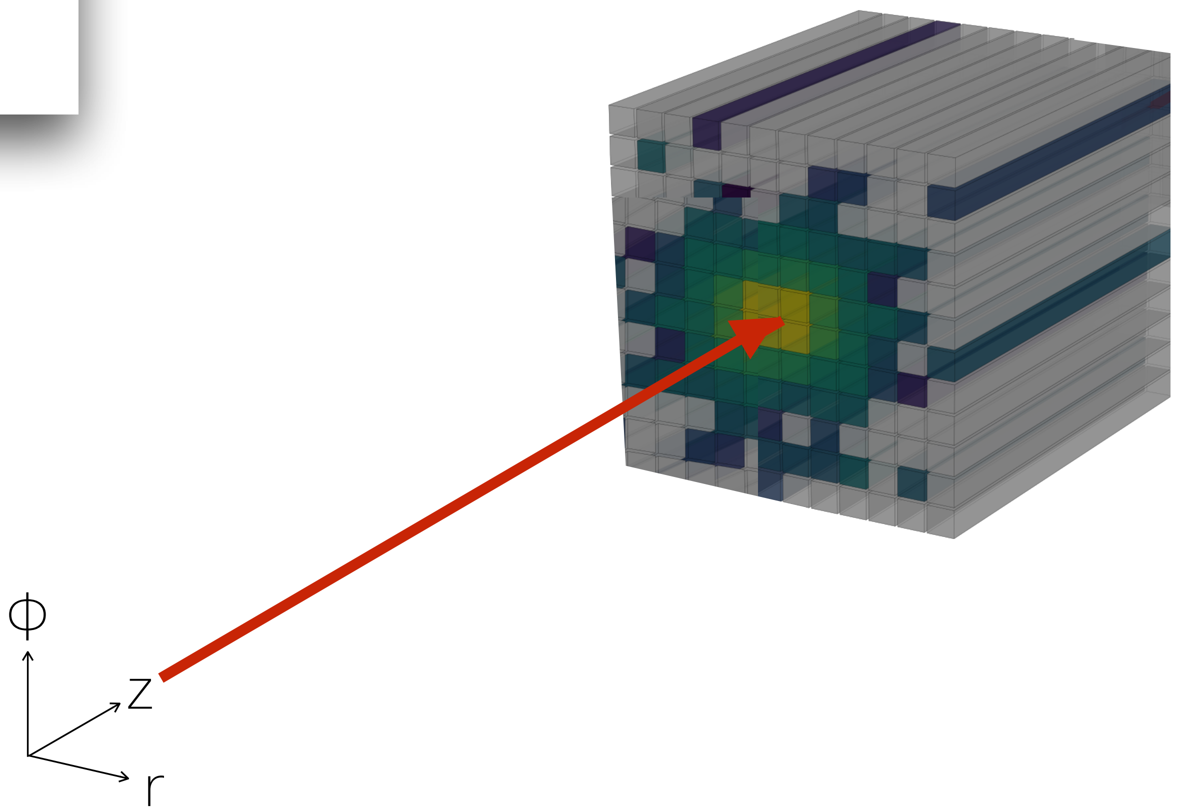
Surrogate Models with ML



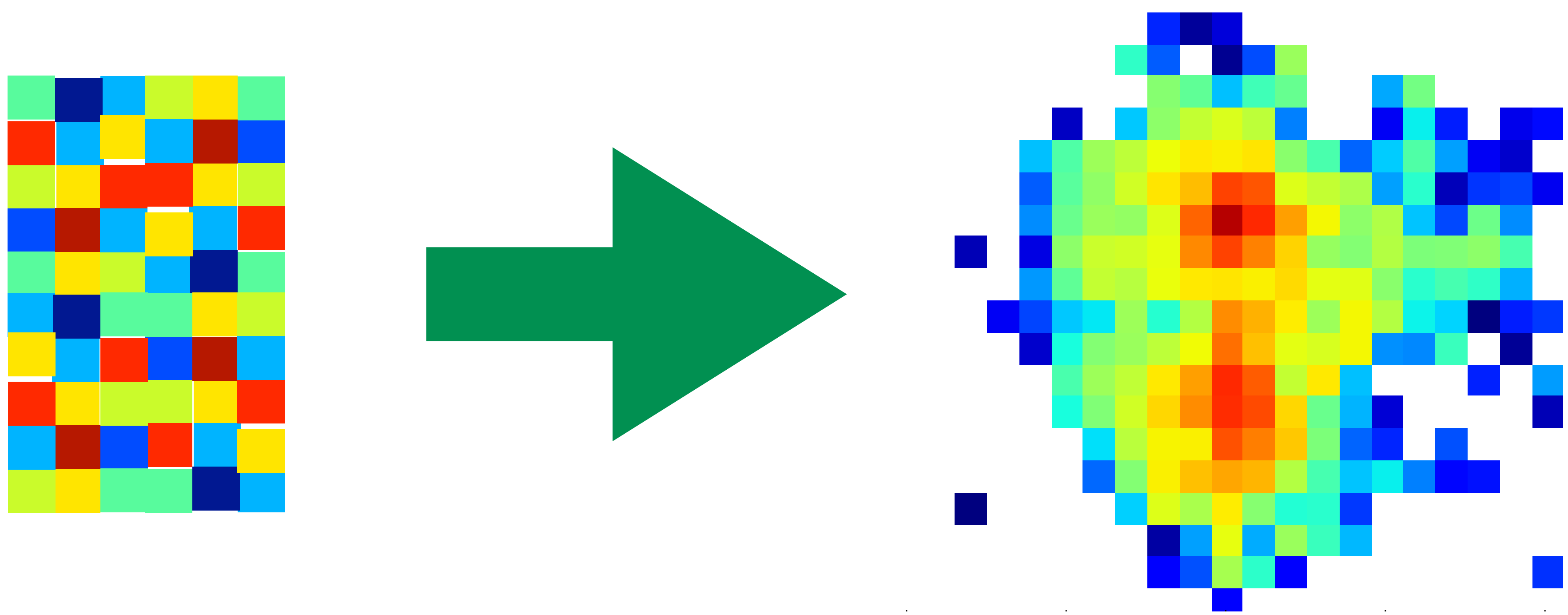
Can we train a neural network to emulate the detector simulation?



Grayscale images: Pixel intensity = energy deposited

Introduction: generative models

A **generator** is nothing other than a function that maps random numbers to structure.



Deep generative models: the map is a deep neural network.

Tools

GANs

Generative Adversarial Networks

Score-based

NFs

Normalizing Flows

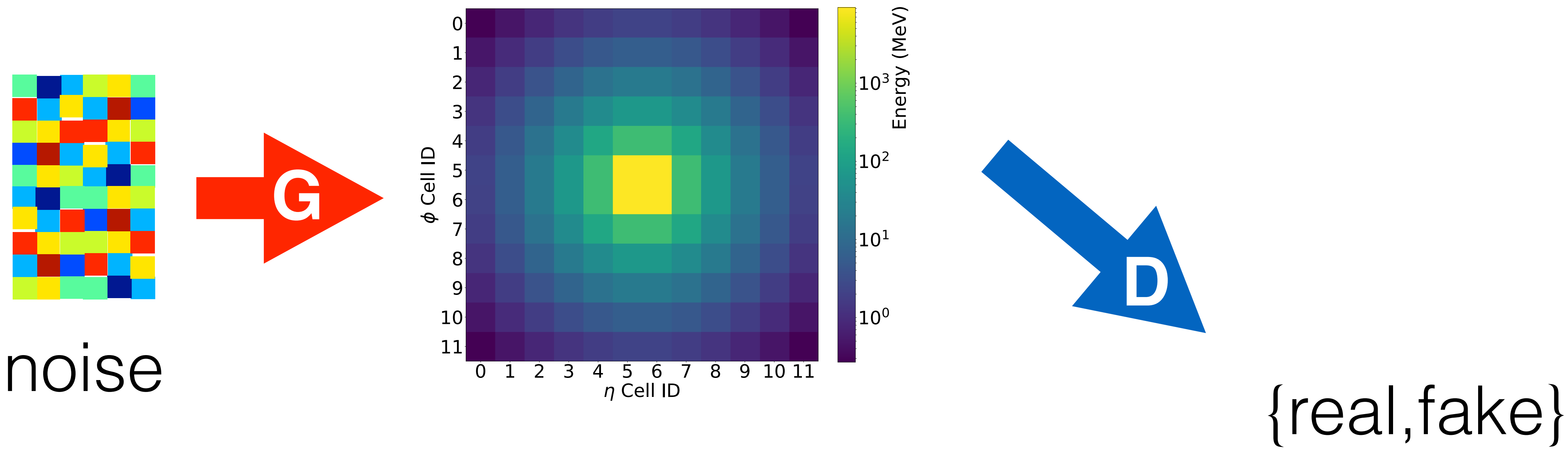
VAEs

Variational Autoencoders

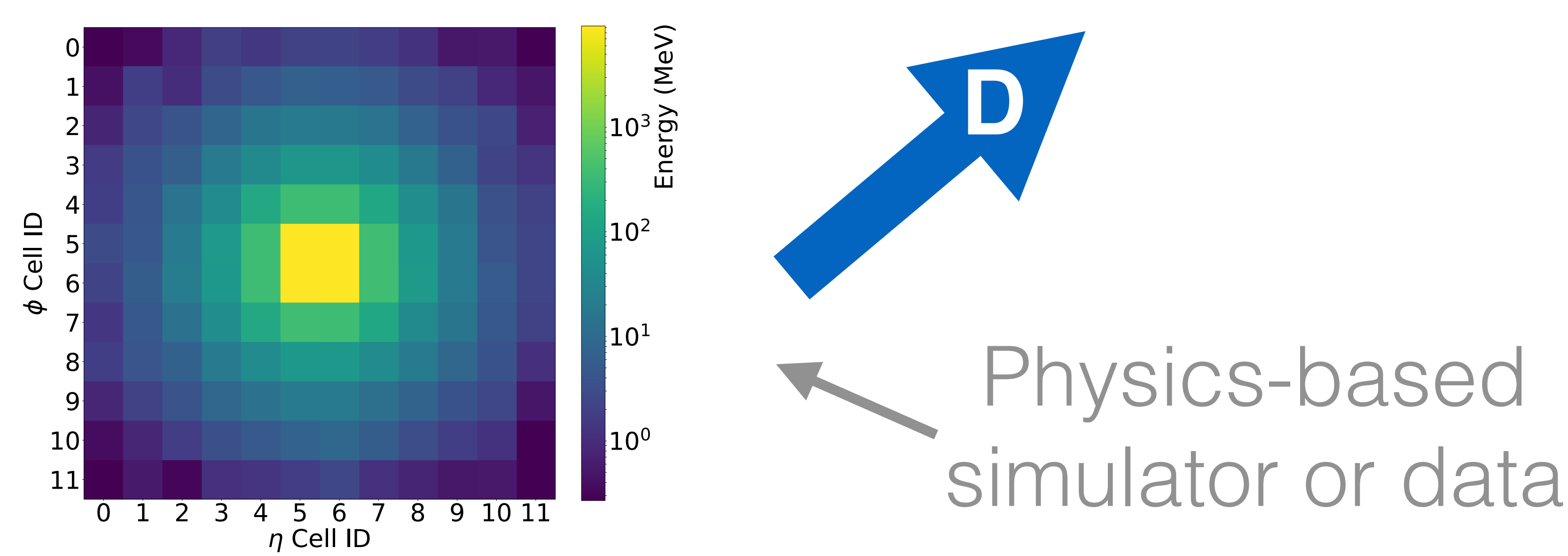
Deep generative models: the map is a deep neural network.

Introduction: GANs

Generative Adversarial Networks (GANs):
A two-network game where one ***maps noise to structure*** *and one* ***classifies images as fake or real****.*

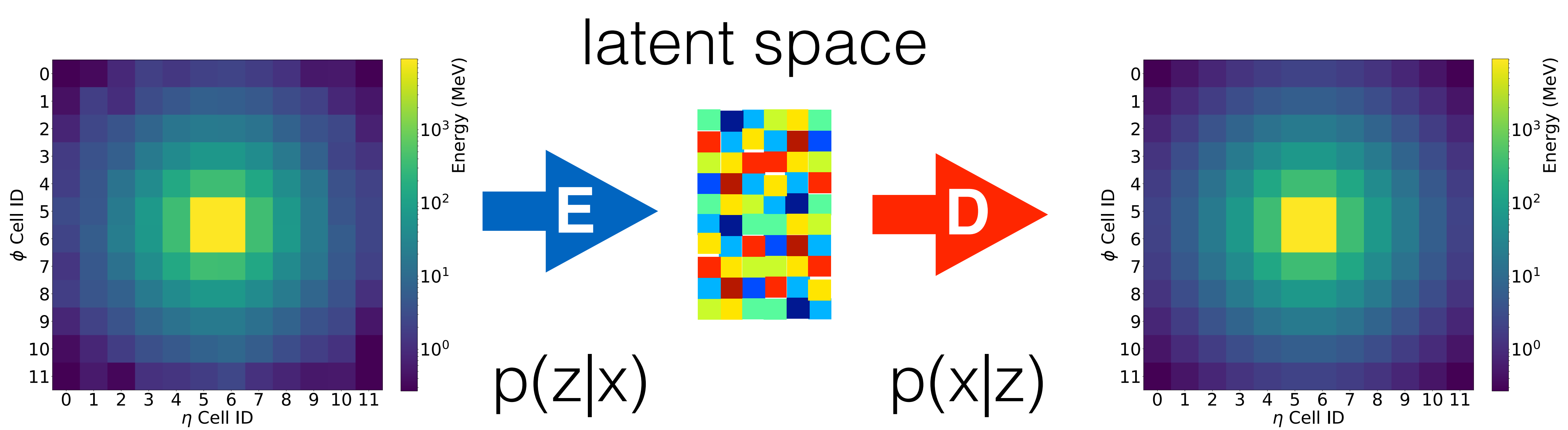


When **D** is maximally confused, **G** will be a good generator



Introduction: VAEs

Variational Autoencoders (VAEs):
A pair of networks that embed the data into a latent space with a given prior and decode back to the data space.



Physics-based simulator or data

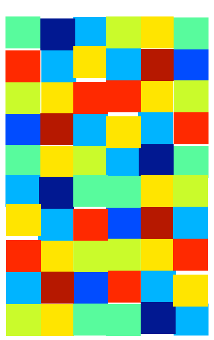
Probabilistic ***encoder***

Probabilistic ***decoder***

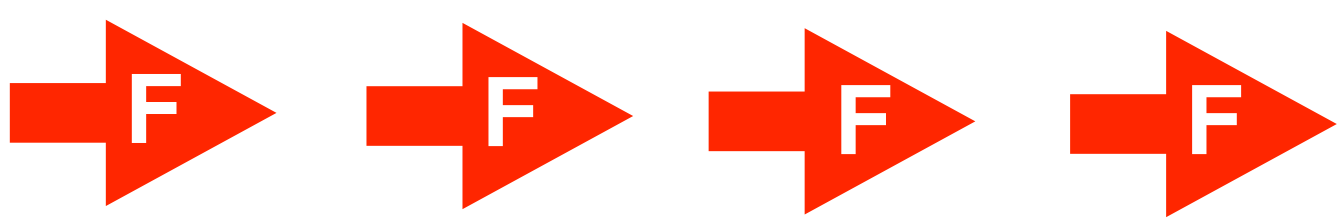
Introduction: NFs

Normalizing Flows (NFs):
A series of invertible transformations mapping a known density into the data density.

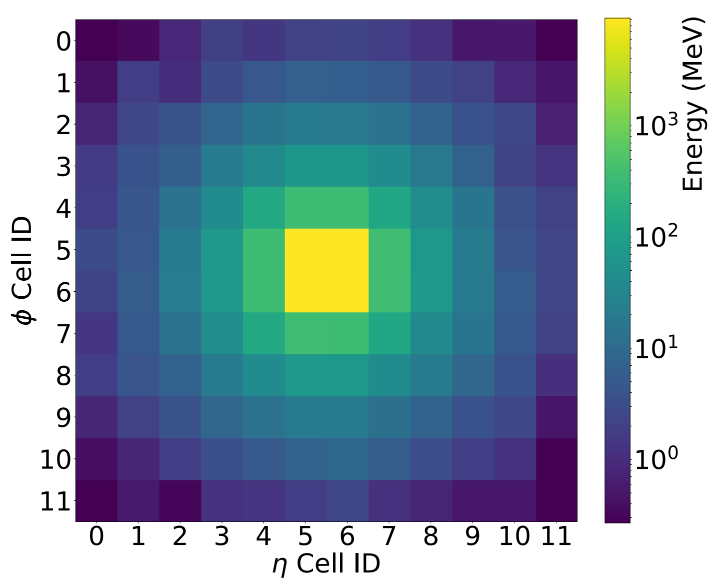
Optimize via maximum likelihood



latent space



Invertible transformations with tractable Jacobians



p(z)

$$p(x) = p(z)\, |dF^{-1}/dx|$$

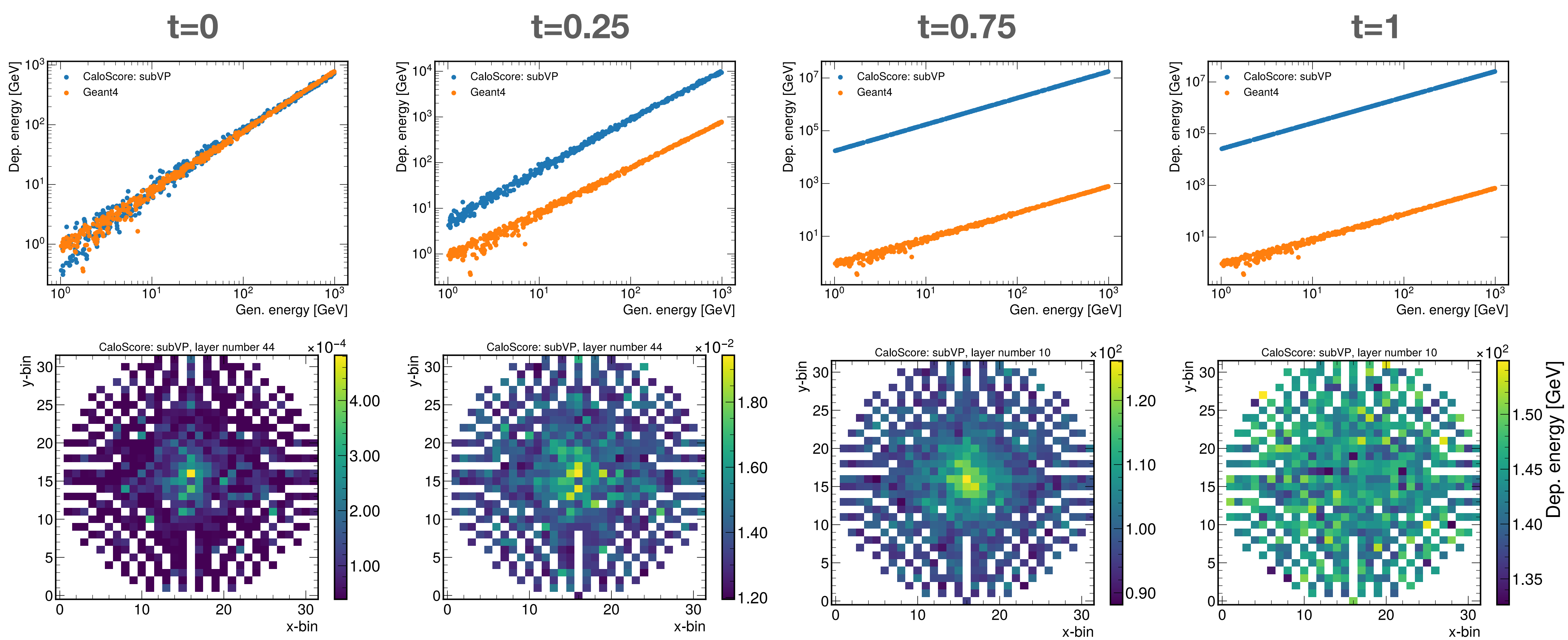
p(x)

Introduction: Score-based

Score-based

Learn the gradient of the density instead of the probability density itself.

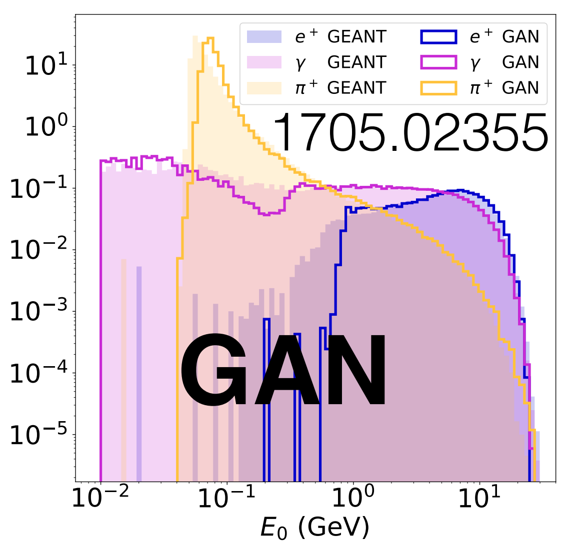
Forward diffusion (training)

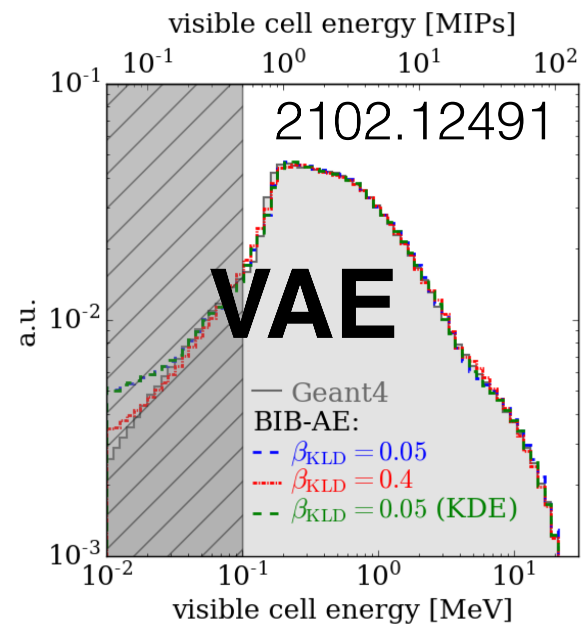


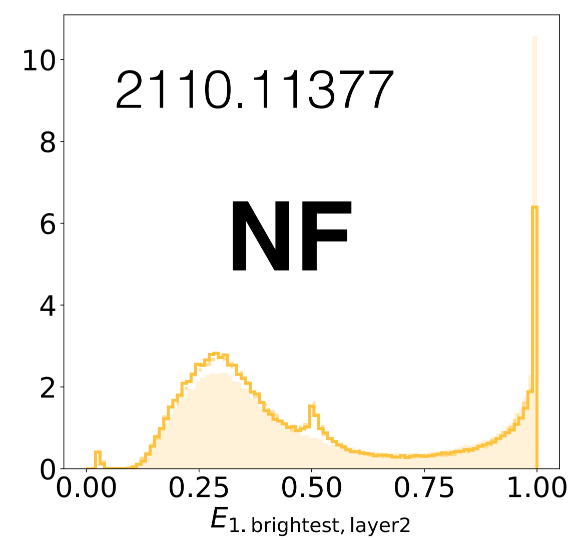
Reverse-time diffusion (data generation)

From 2206.11898

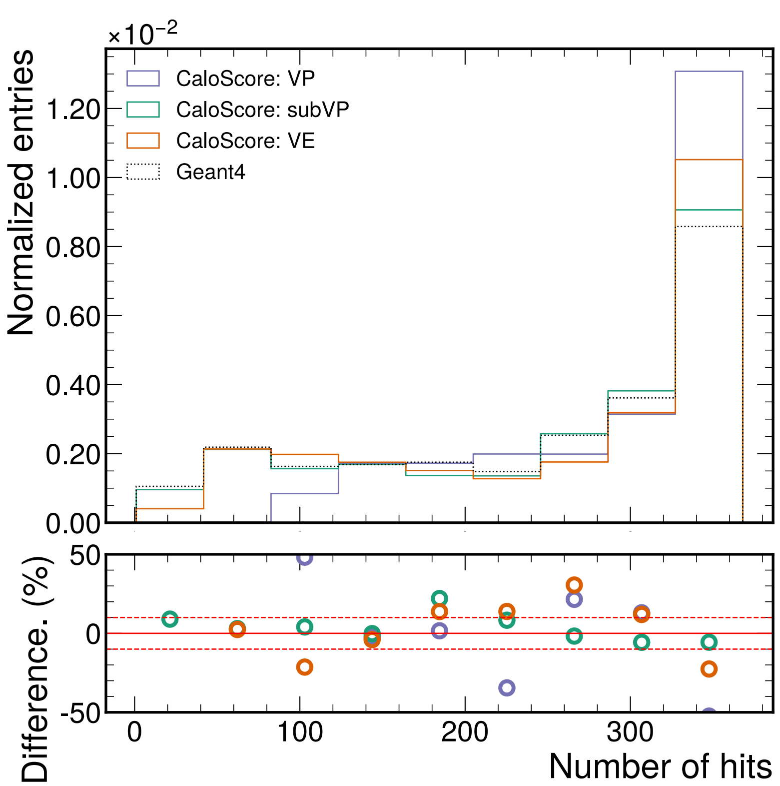
Calorimeter ML Surrogate Models

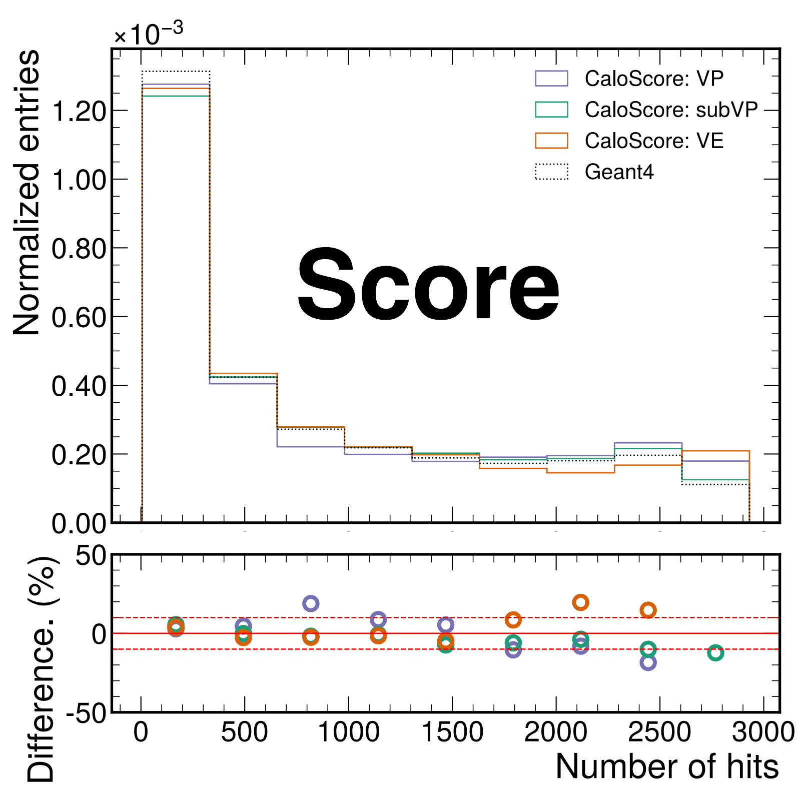


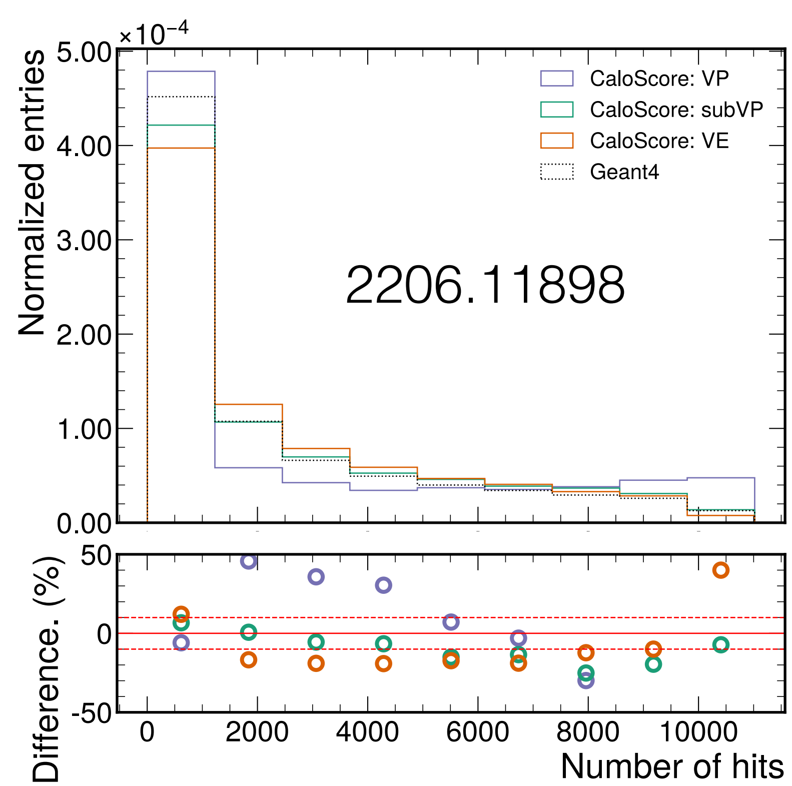




Many papers on this subject - see the living review for all

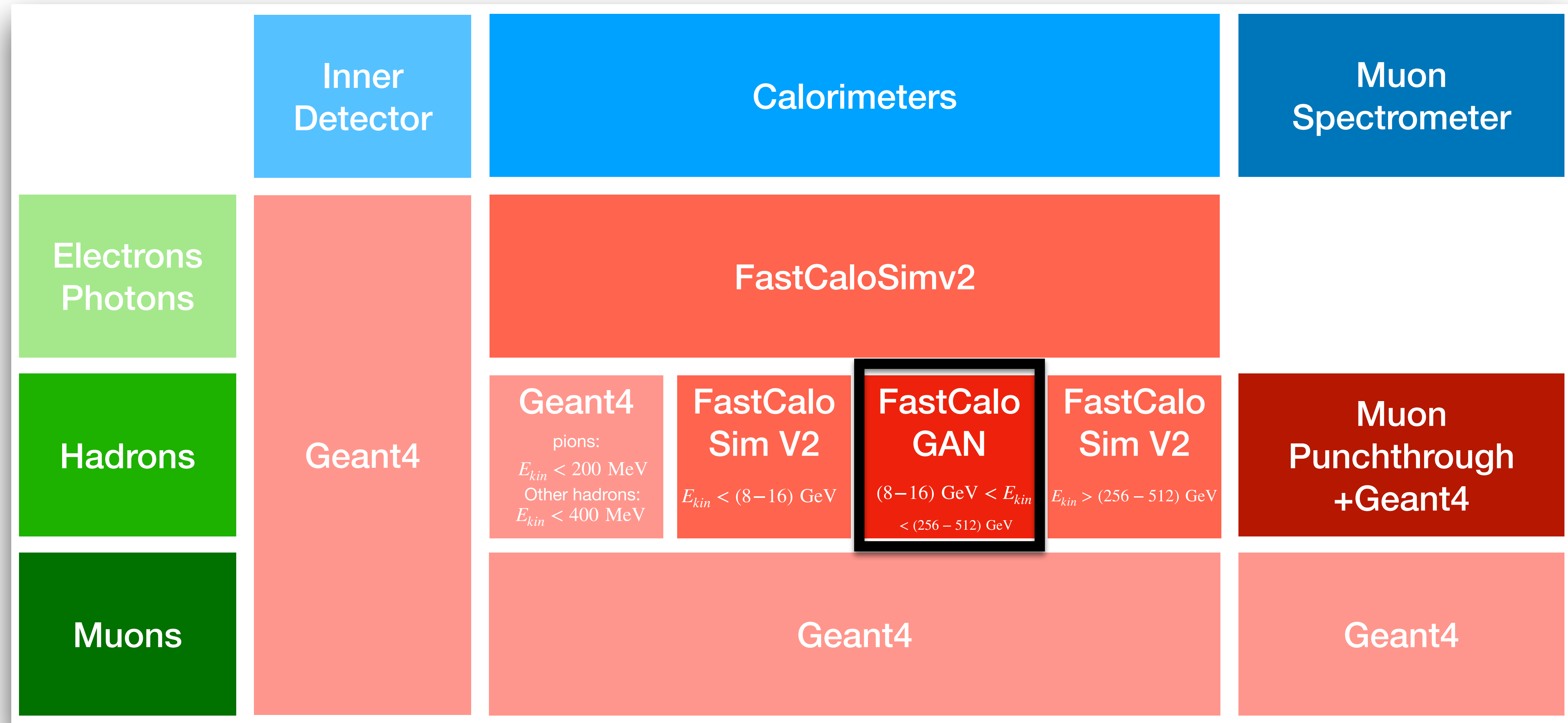






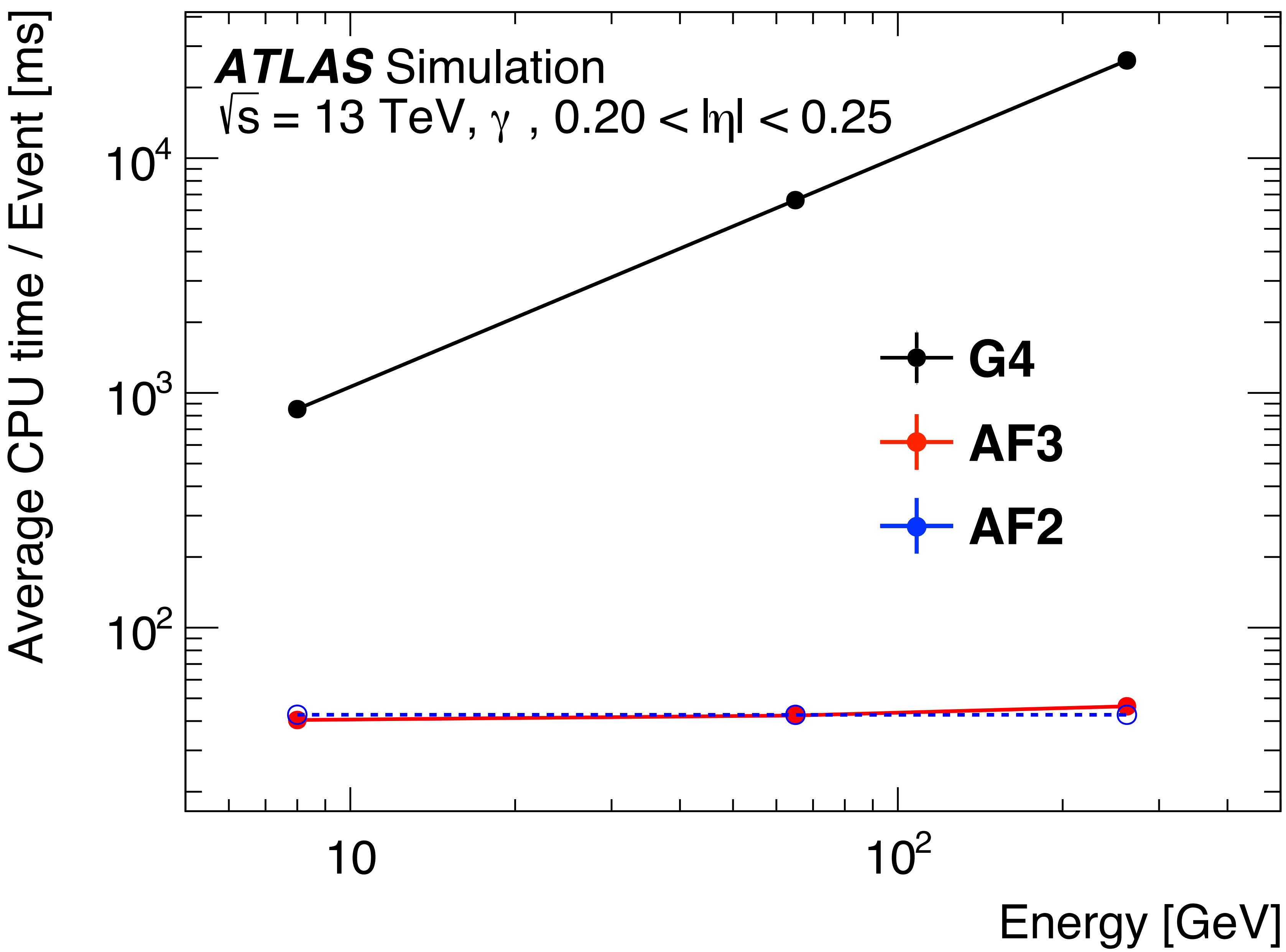
See also https://calochallenge.github.io/homepage/

Integration into real detector sim.



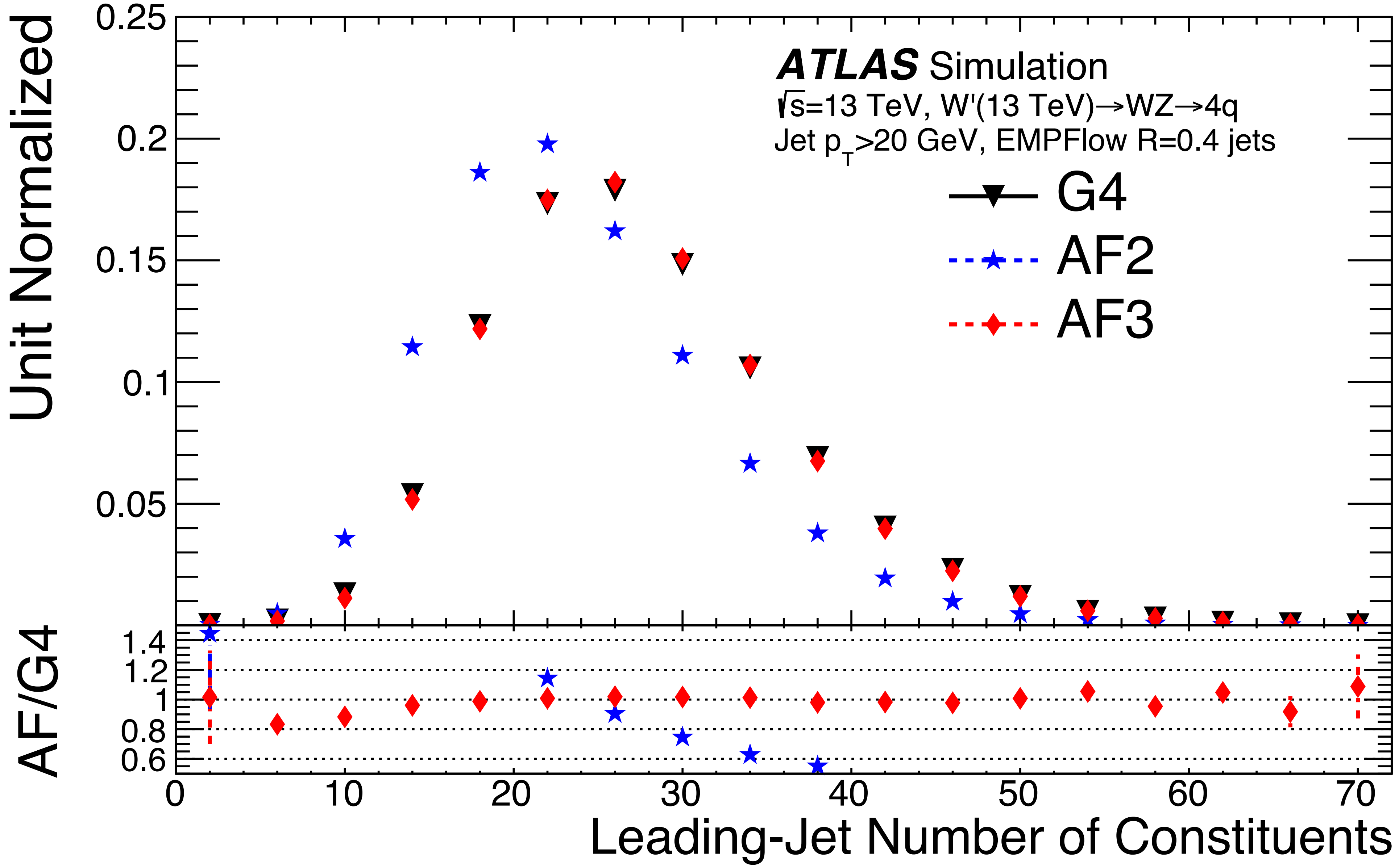
The ATLAS Collaboration fast simulation (AF3) now includes a GAN at intermediate energies for pions

Integration into real detector sim.



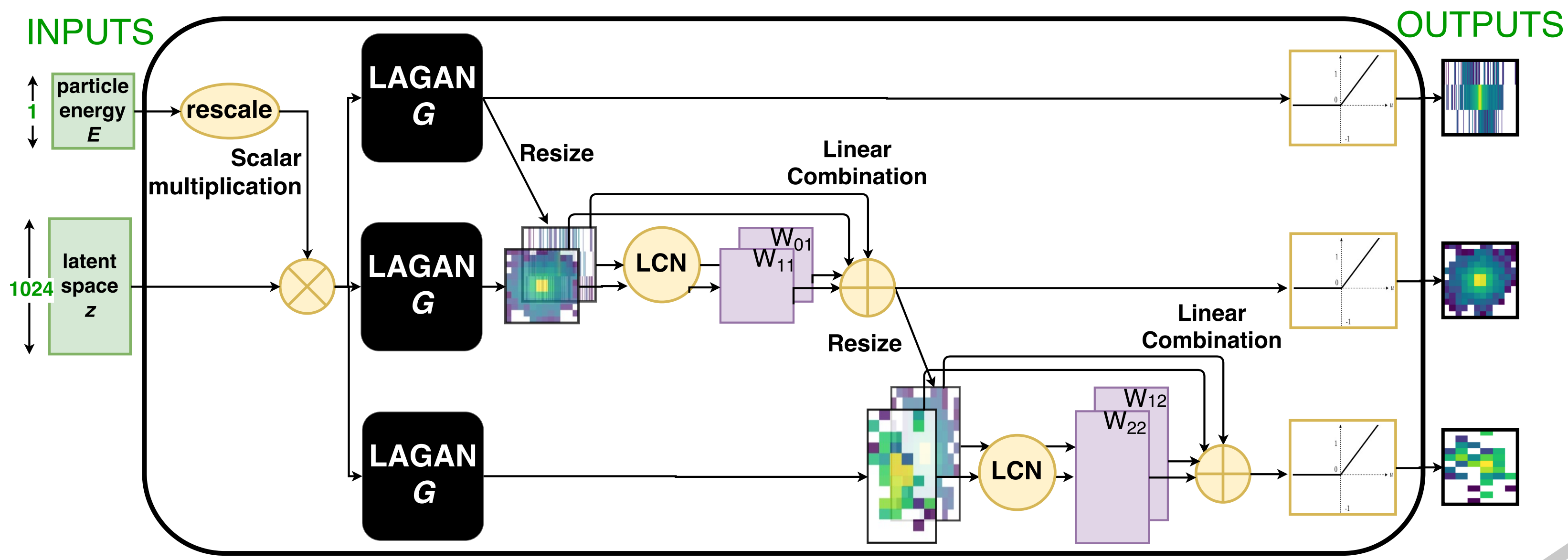
As expected, the fast sim. timing is independent of energy, while Geant4 requires more time for higher energy.

Integration into real detector sim.



The new fast simulation (**AF3**) significantly improves jet substructure with respect to the older one (**AF2**).

Outline



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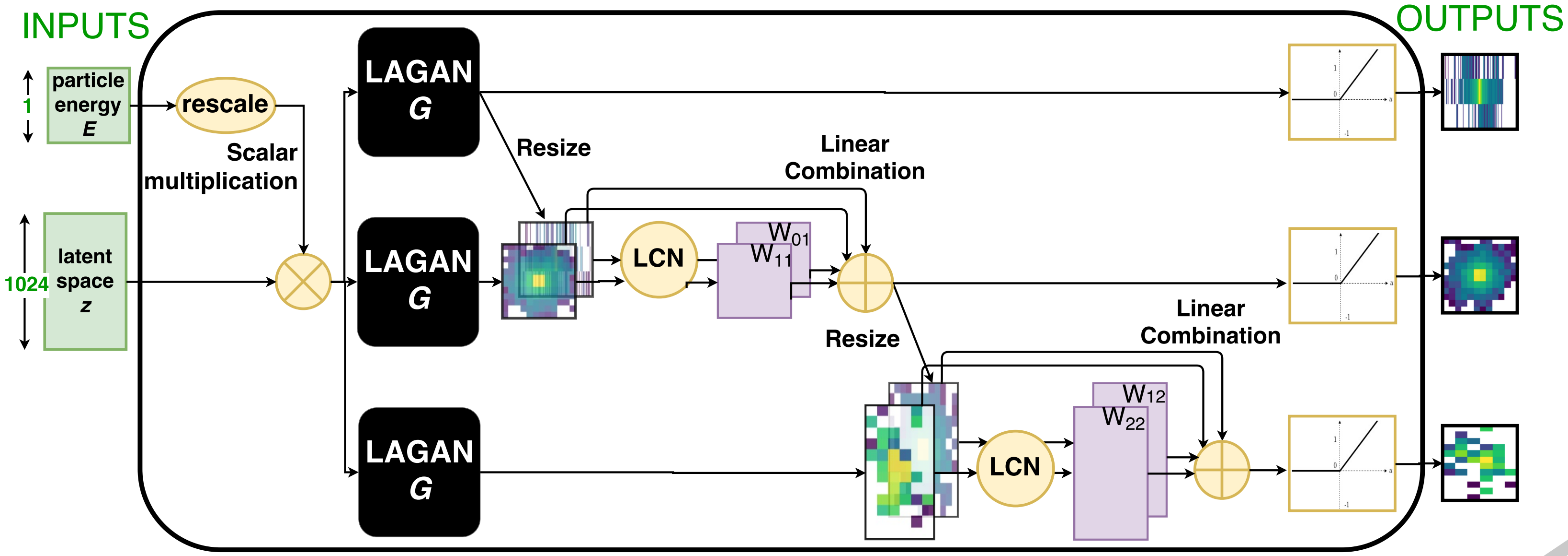

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Removed randomness from simulator

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Z = np.random.uniform(0,1)
x = sigma*Phiinv(z)+mu
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(**`Phiinv`** = inverse Gaussian CDF)

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We can then do:

$$\text{sim}(\mu_0 + \epsilon) \approx \text{sim}(\mu_0) + \frac{\partial \text{sim}}{\partial \mu}\epsilon$$

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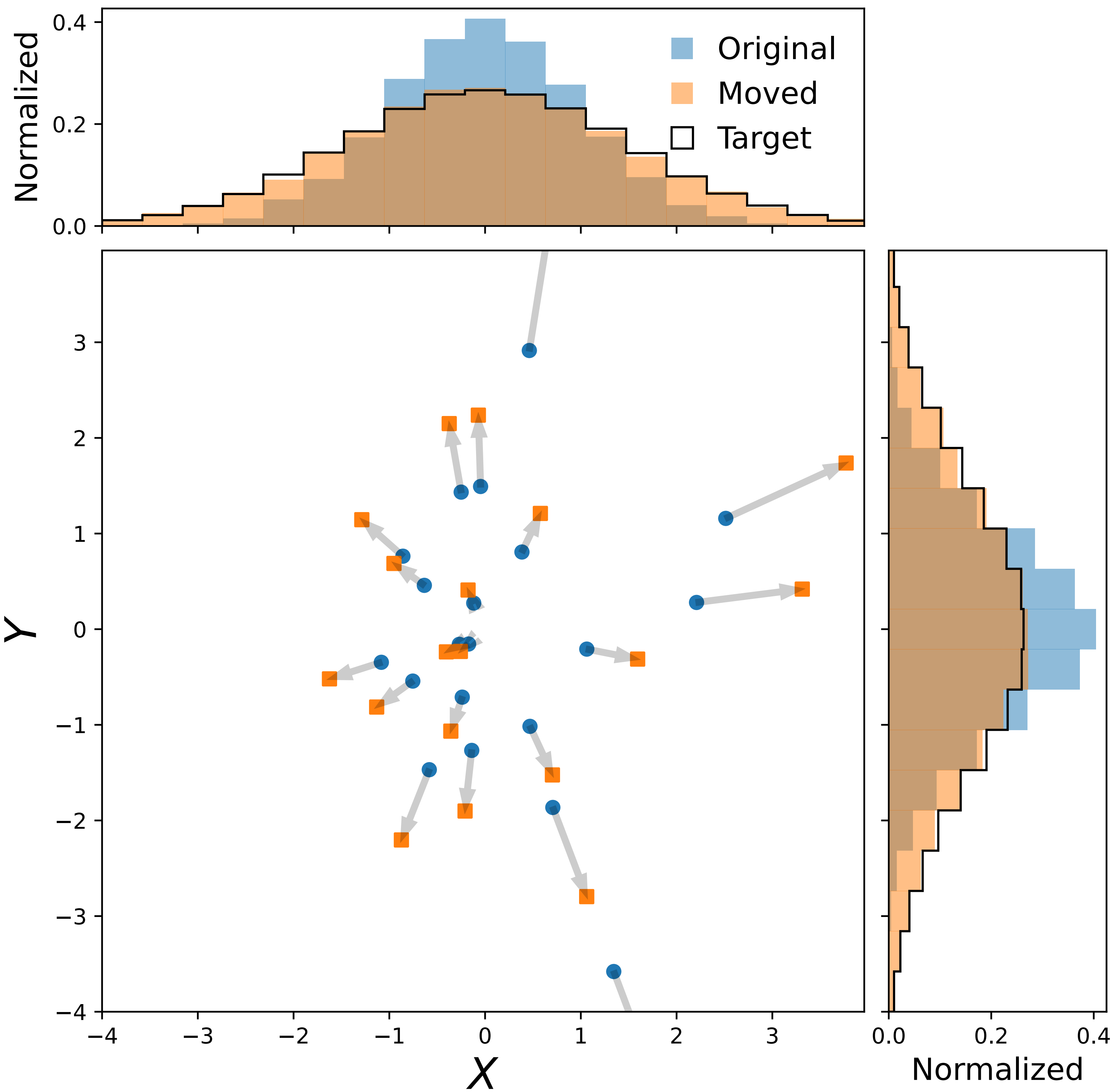

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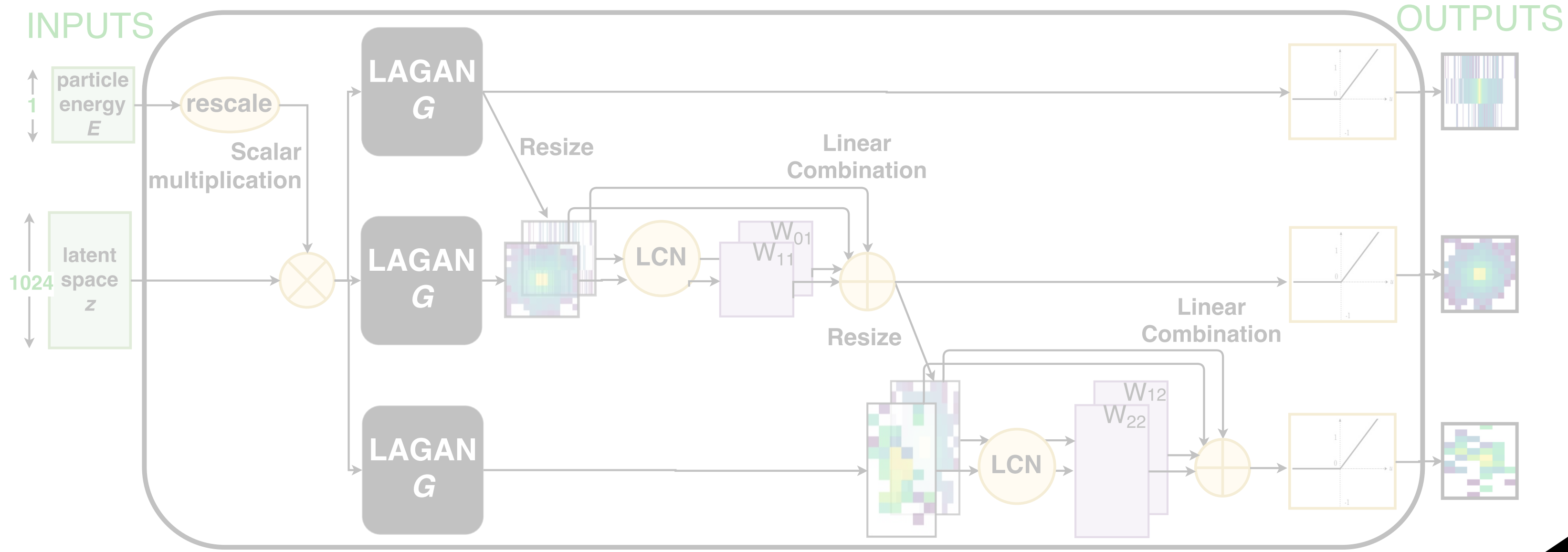
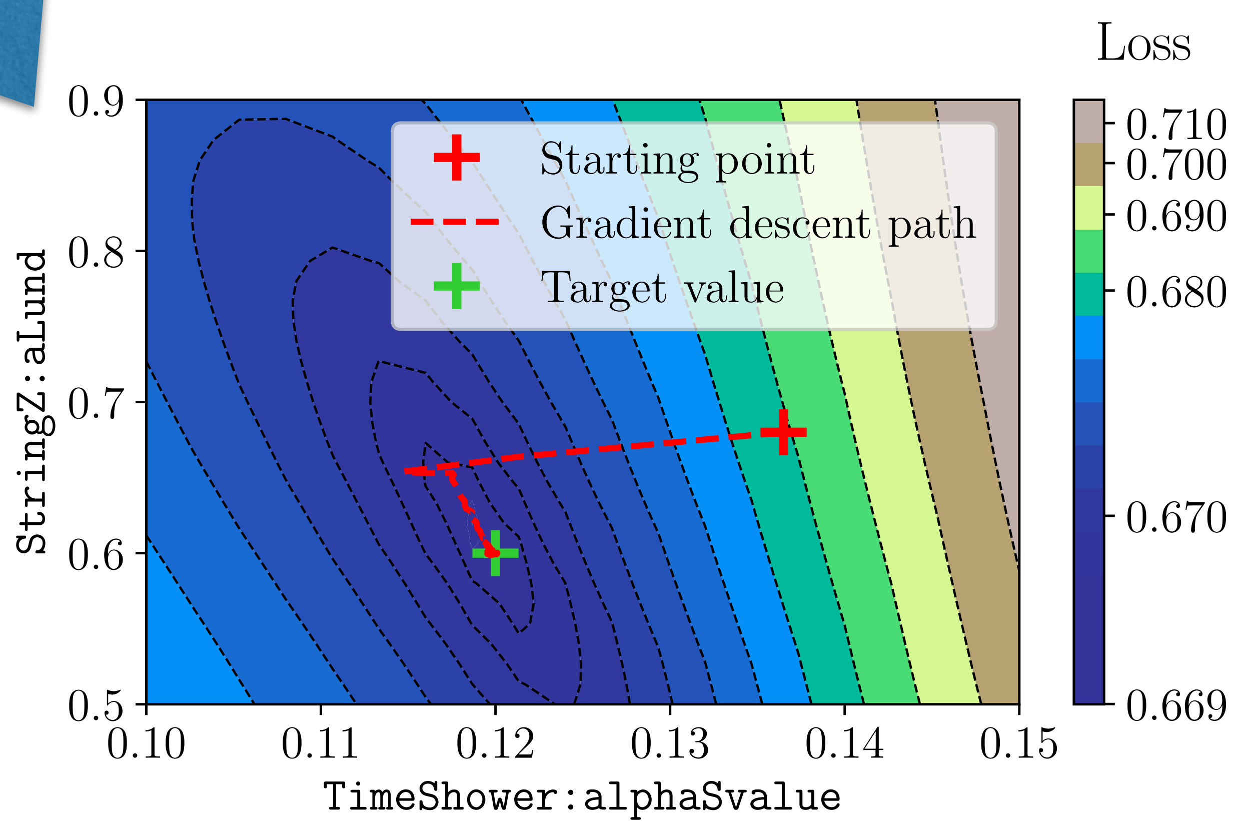


Detector Modeling

ML-based Optimization



Example

Here, instead of emulating $p(x \mid \theta)$ directly, we learn $\dfrac{p(x \mid \theta)}{p(x \mid \theta_0)}$

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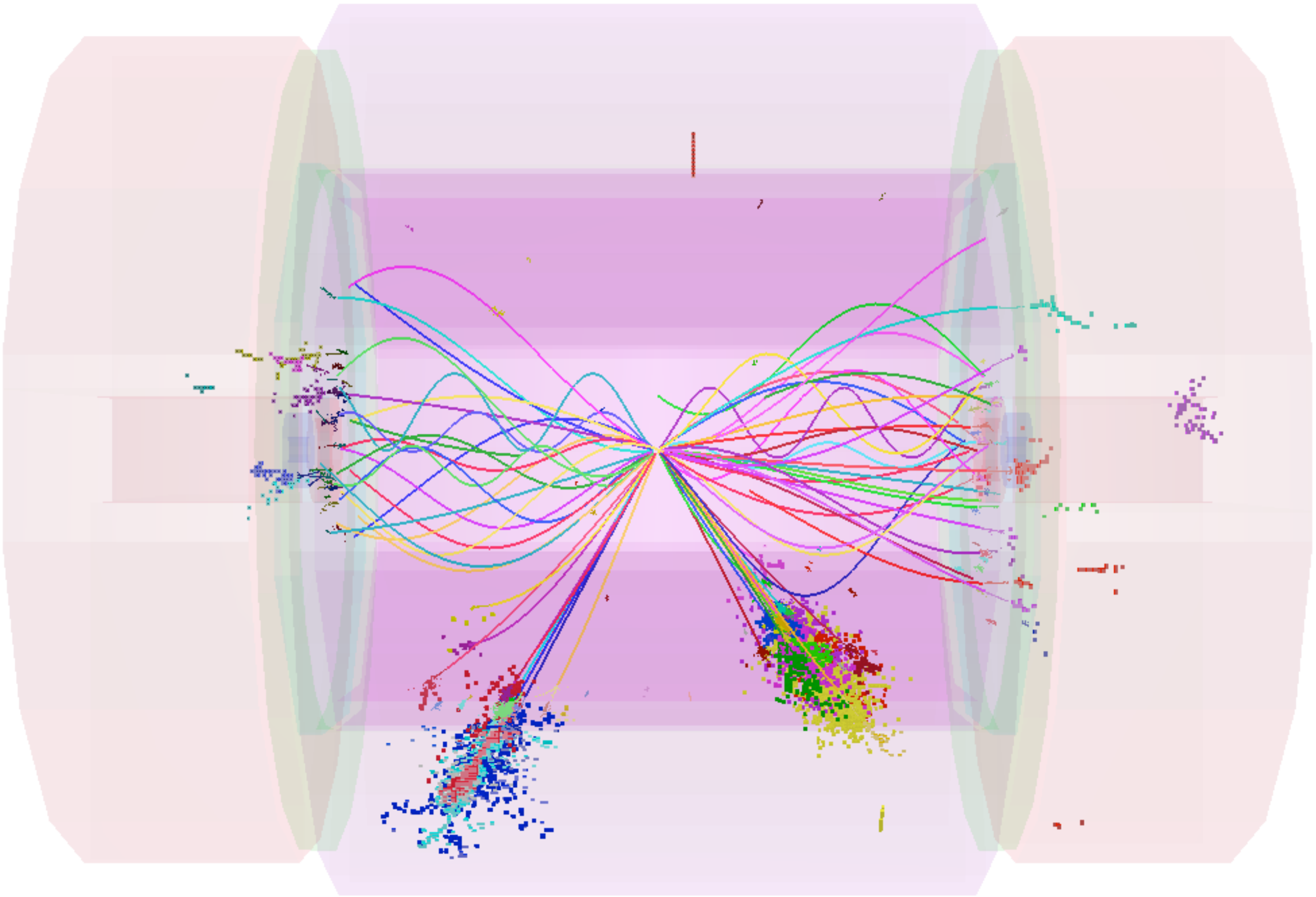

Benefit: easy to integrate complex data structure (symmetries, etc.)

Downside: large weights when θ is far from θ_0

Image: Linear Collider Detector Project

Example

Step 1: Differentiable Surrogate Model

$$f(x,\theta) = \underset{f'}{\mathrm{argmax}} \sum_{i\in\boldsymbol{\theta_0}} \log f'(x_i,\theta) + \sum_{i\in\boldsymbol{\theta}} \log(1 - f'(x_i,\theta))$$

See also 1805.00020

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Step 2: Gradient-based optimization

$$\theta^* = \underset{\theta'}{\mathrm{argmax}} \sum_{i \in \boldsymbol{\theta_0}} \log f(x_i,\theta') + \sum_{i \in \boldsymbol{\theta_1}} \log(1 - f(x_i,\theta'))$$

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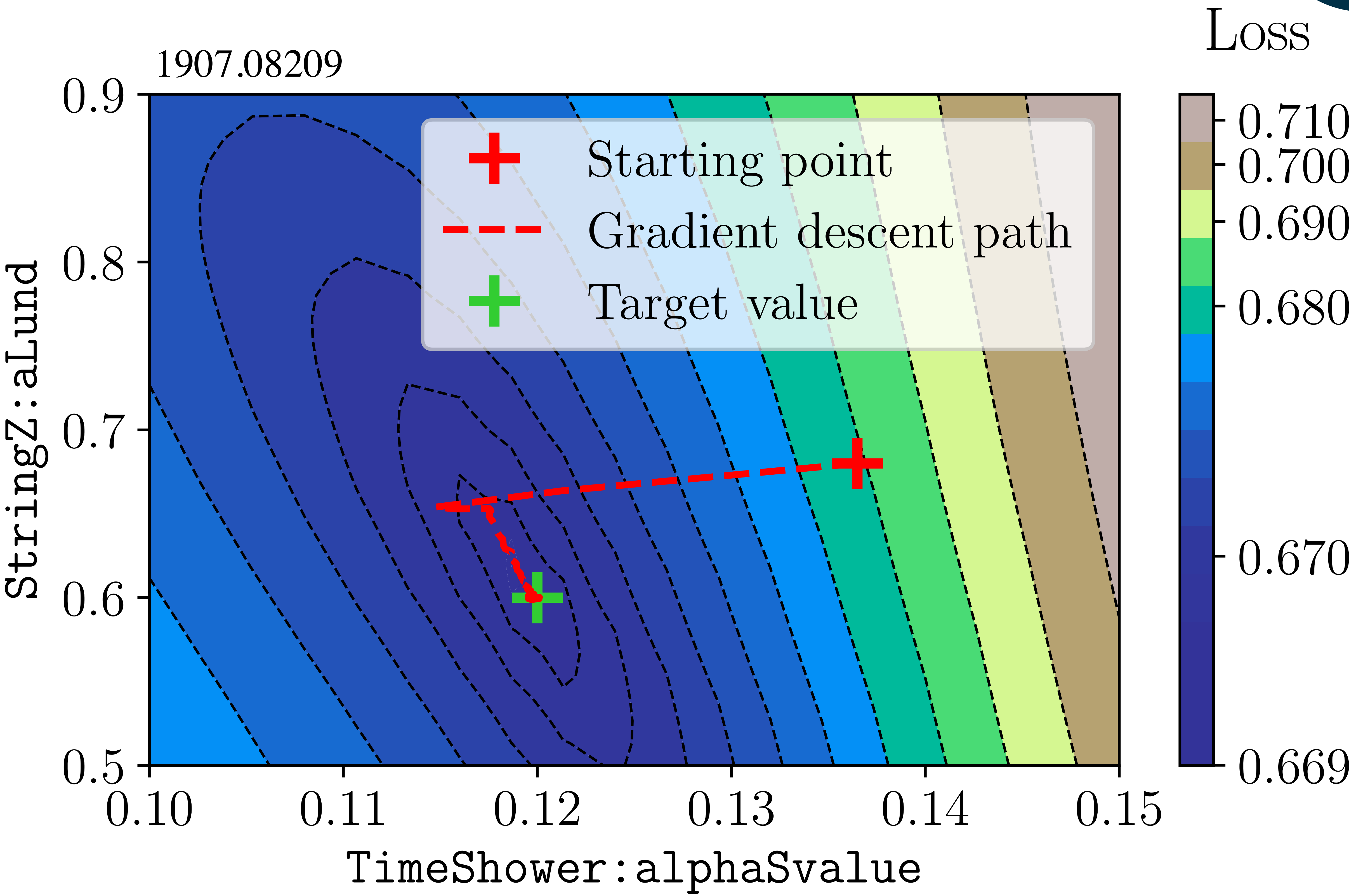
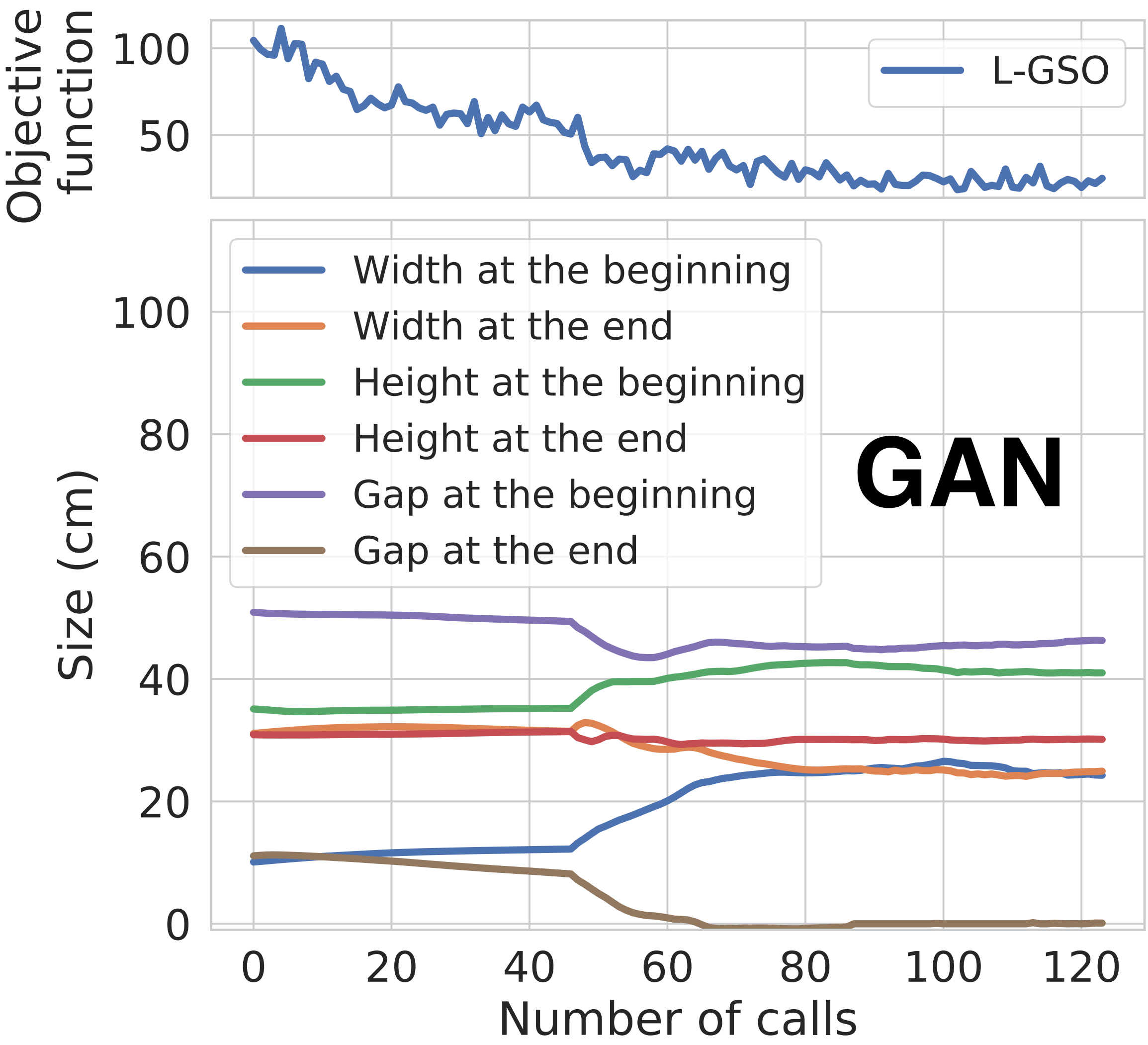
Example


1907.08209
Loss
Starting point
Gradient descent path
Target value
0.710
0.700
0.690
0.680
0.670
0.669
0.9
0.8
0.7
0.6
0.5
StringZ:aLund
0.10
0.11
0.12
0.13
0.14
0.15
TimeShower:alphaSvalue

Other examples

Example: Optimizing the active muon shield of the SHIP experiment (proposed fixed-target @ CERN SPS)

2002.04632



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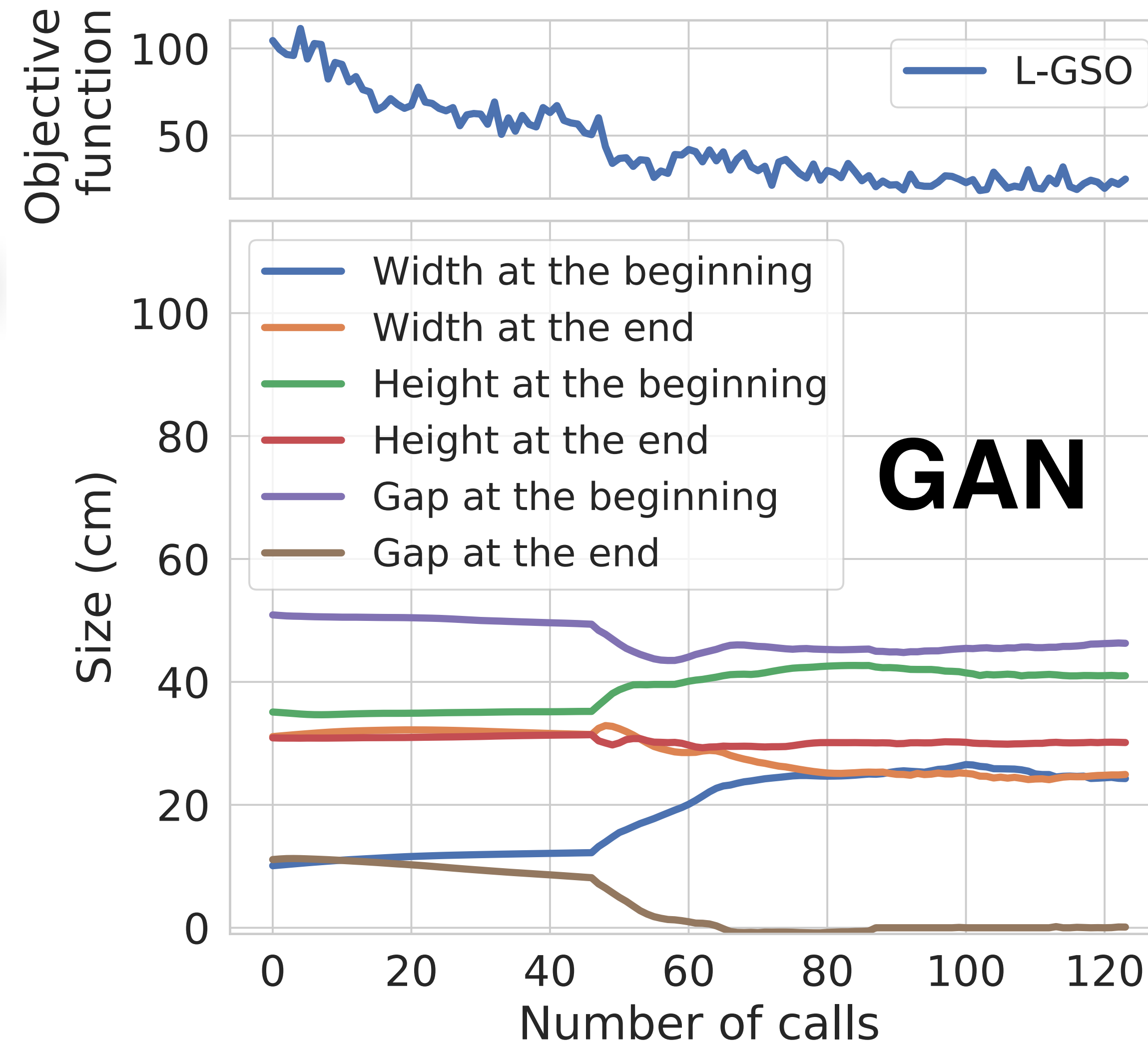
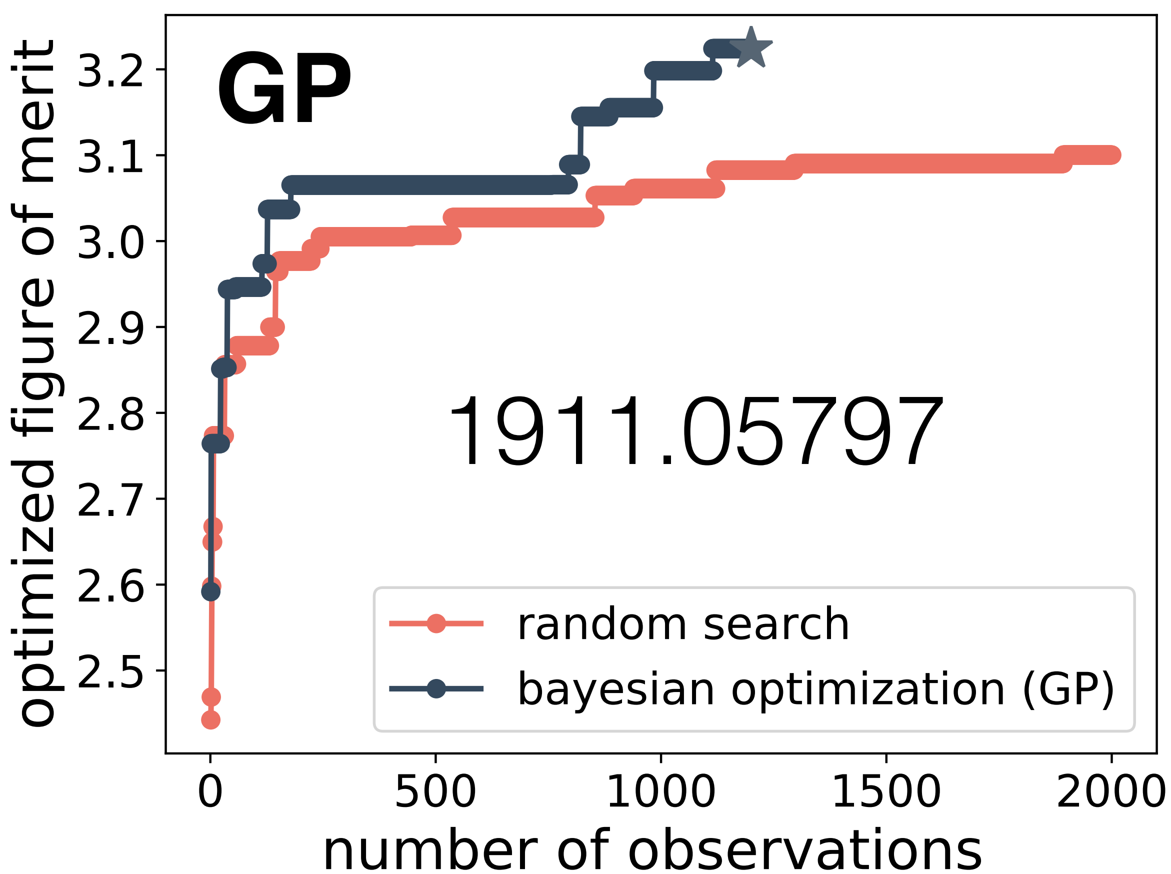




RICH detector @ EIC

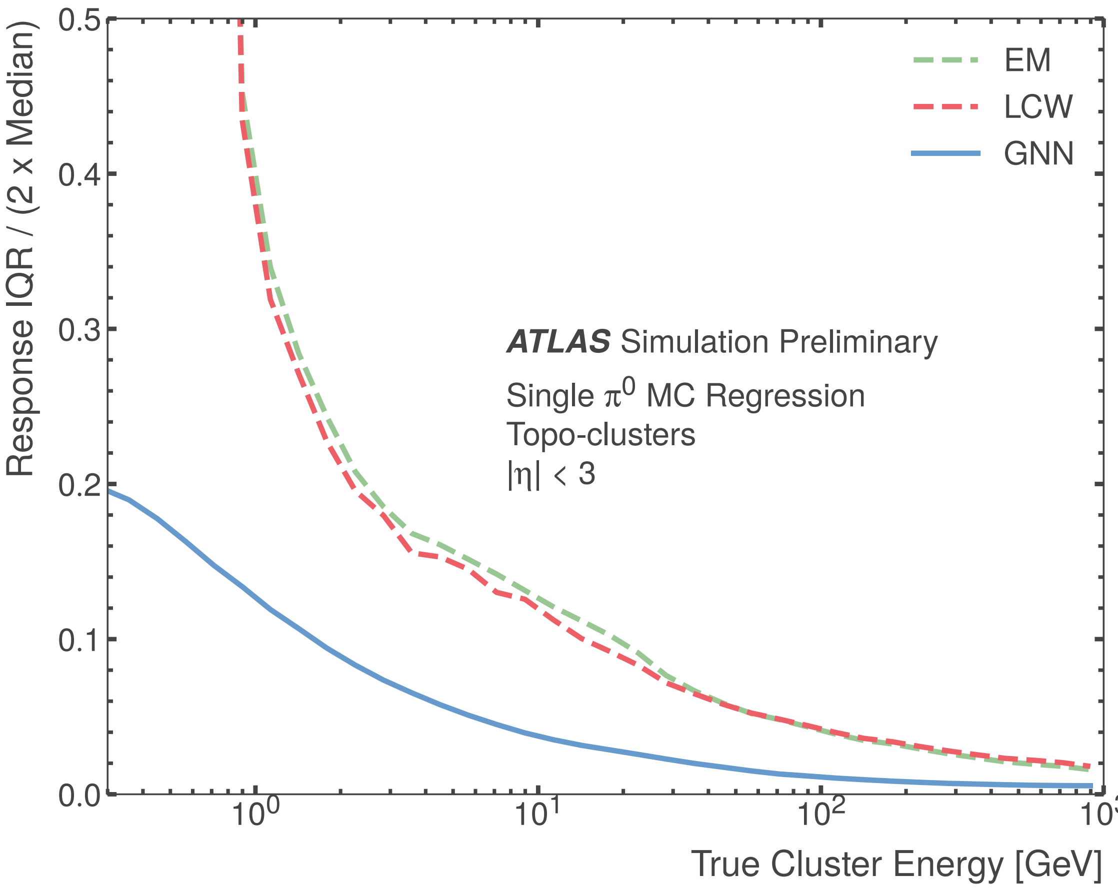
(perhaps you will hear more about this in other talks this week!)

Remark about Objective Functions

Today: can we use ML to (1) interpolate in the high-dimensional space, (2) define optimal metrics, and (3) find the best values of θ.

Remark about Objective Functions

If doing gradient-based optimization, the target also needs to be differentiable. For example, target could be resolution of some reconstructed object. This could itself be a neural network!



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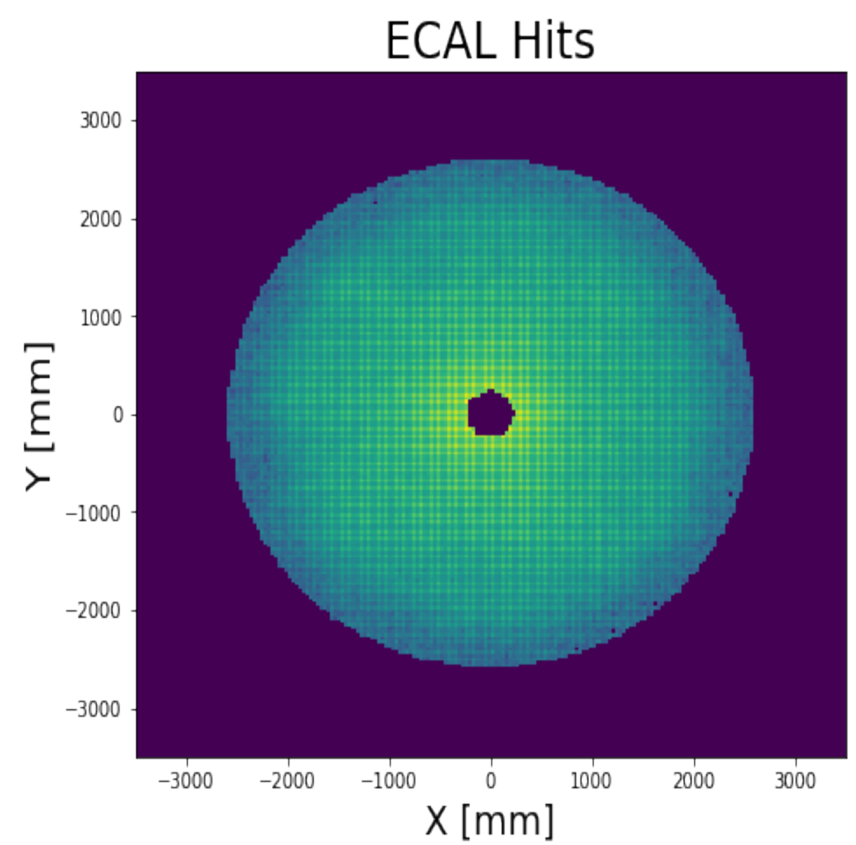
Outlook

The EIC detector(s) may the first large-scale detectors optimized with machine learning.

On our side, we are looking into the calorimeter system(s). I am excited to hear about other efforts as well!



Plot from Fernando Torales Acosta

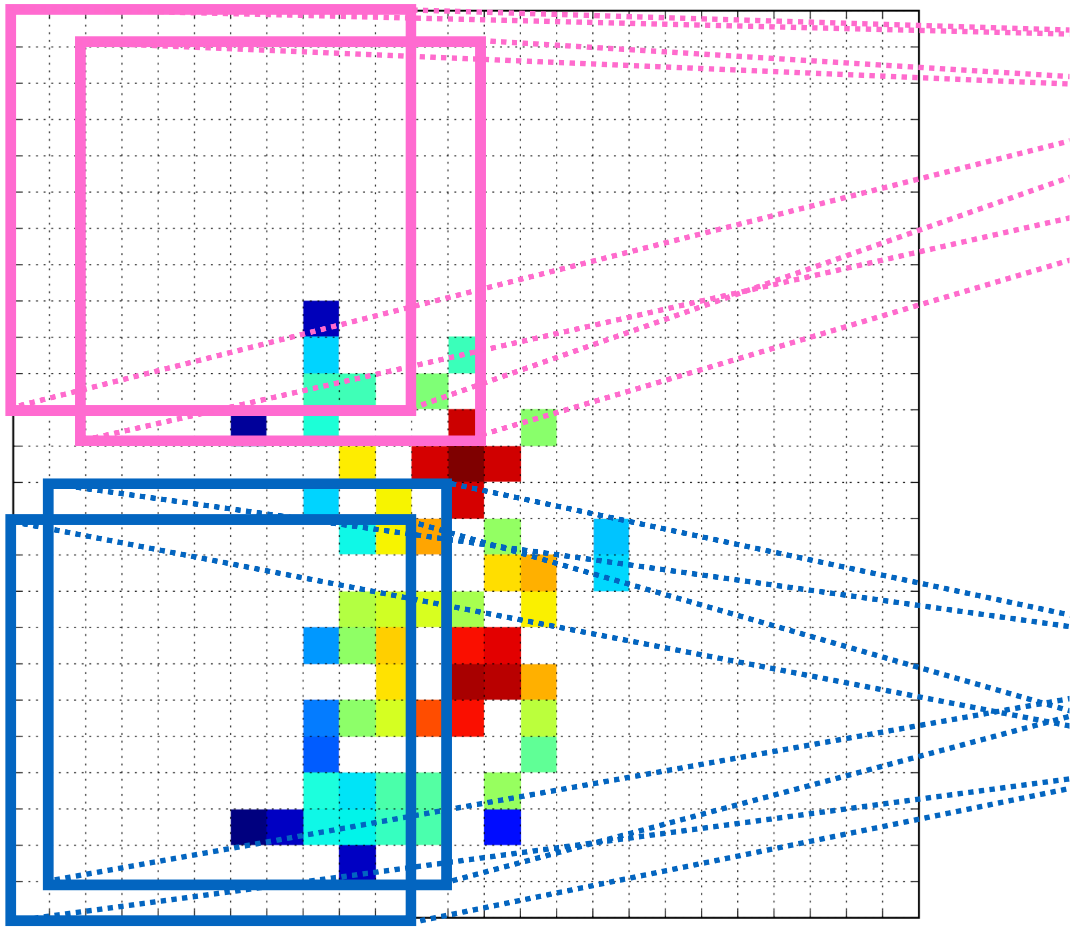
Miguel Arratia and co.

Aaron Angerami and co.

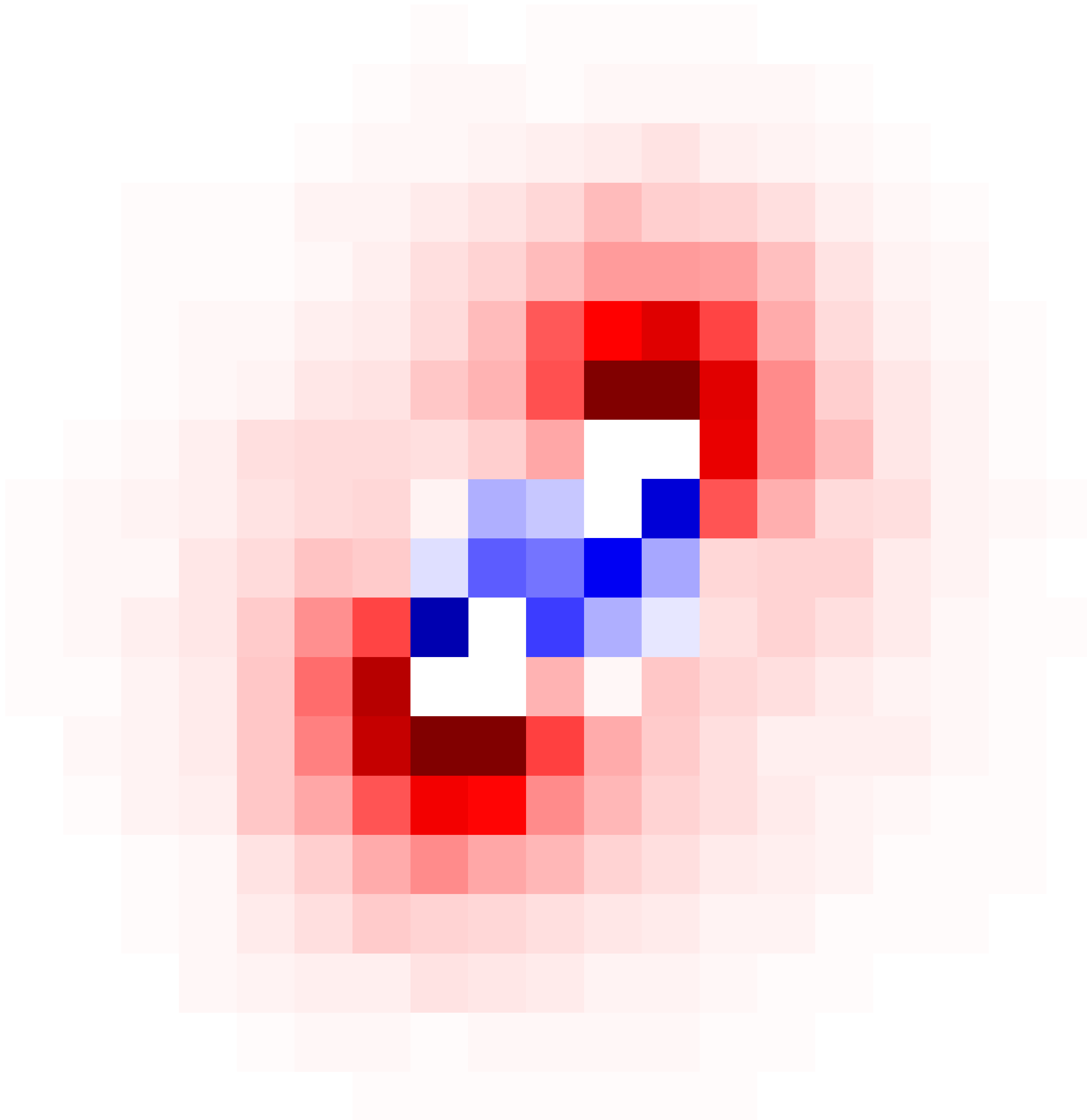
Conclusions

AI/ML can do more than improve data analysis!

We can use these tools to optimize our detectors - a qualitatively new application of ML!



This is an exiting time to be working on this topic - let's use the best tools to get the best physics out of the EIC!



Fin.