Conditional Energy Regression

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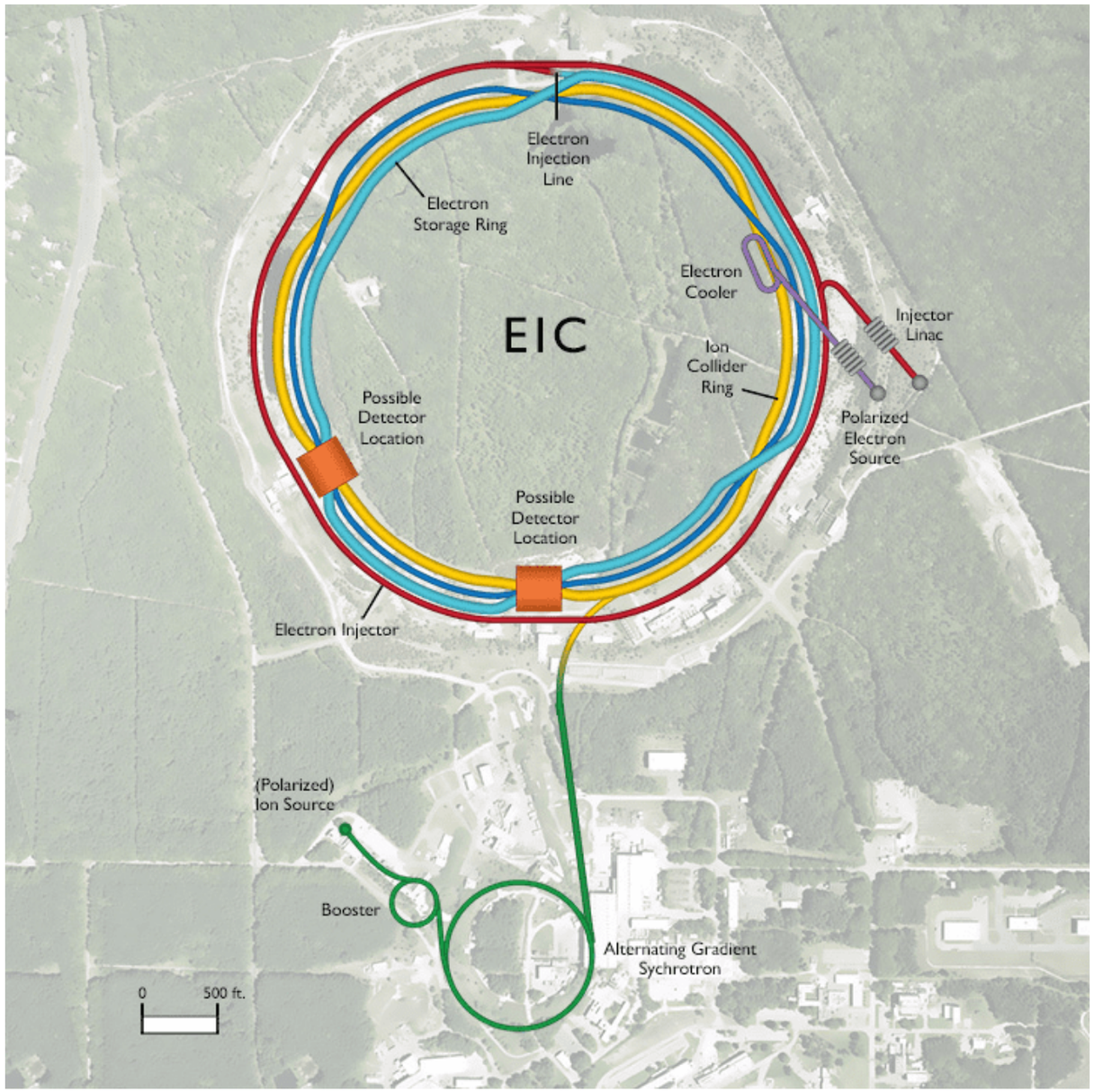
A High Level Overview

- Obtain dependable, highly performant energy reconstruction scheme

- Use the optimal energy reconstruction to design the detector

- **To do this, we aim to make the reconstruction itself differentiable in the detector configuration.**

Electron Ion Collider



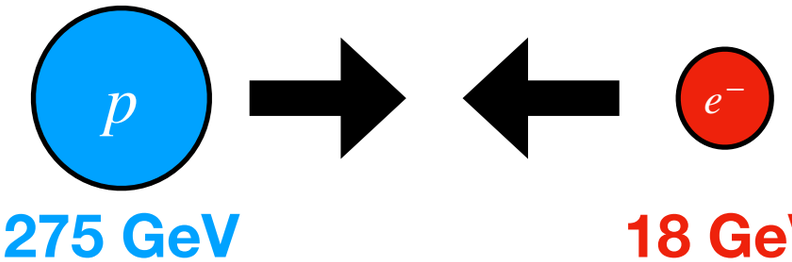
- Collide Electron and Protons + Ions
  - 18 GeV Electrons
  - 275 GeV Protons/Ions
  - $\sqrt{s} = 89$ GeV

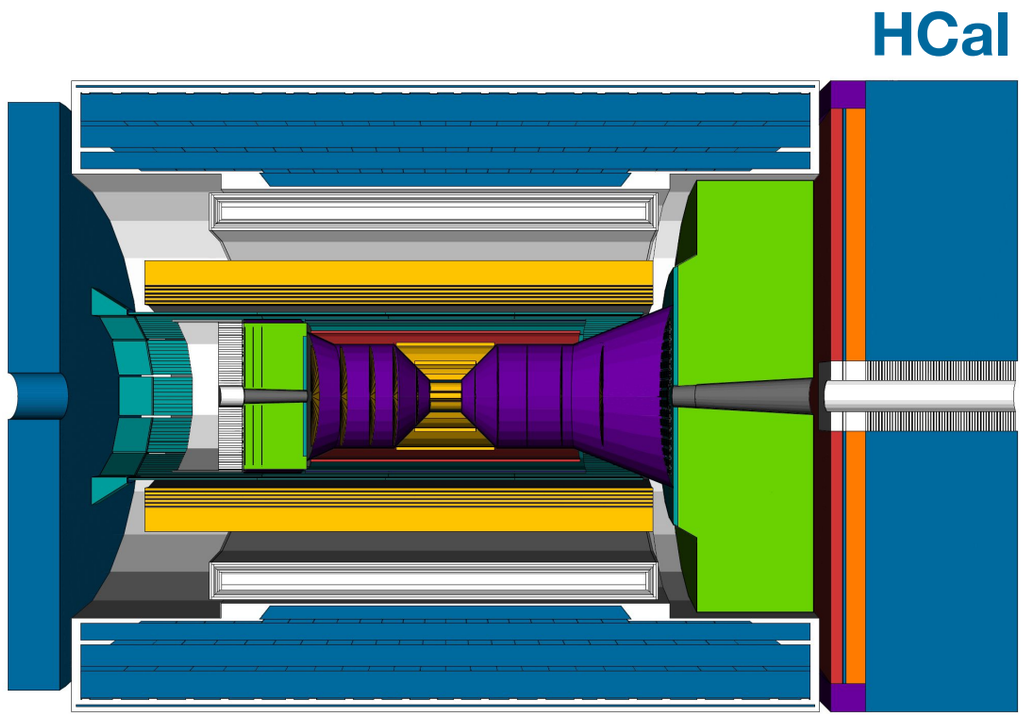
- To be built an Brookhaven national lab, Long Island

- Provide access to regions in the nucleon/nuclei where their structure is dominated by gluons

Many detectors are still at the design stage

Forward Hadronic Calorimeter

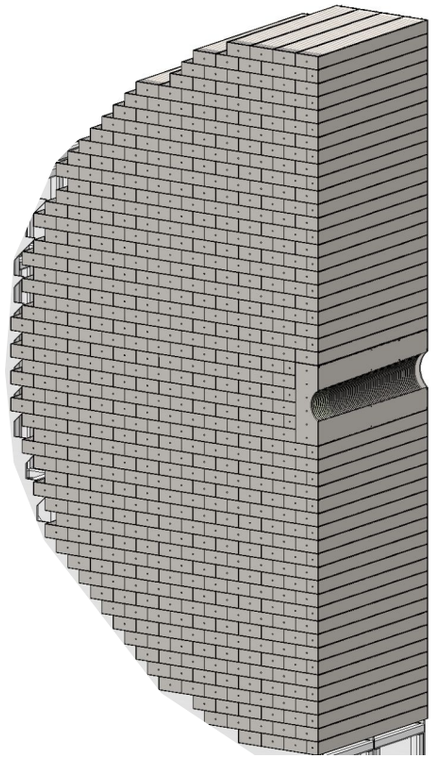




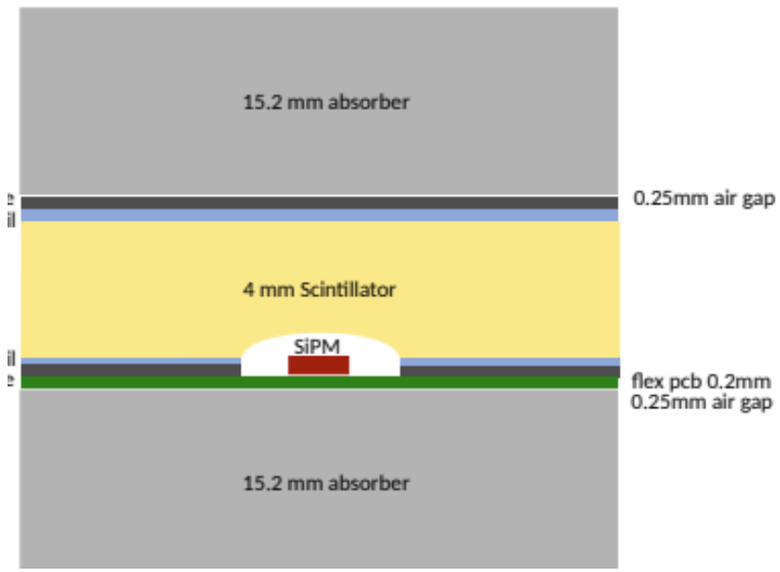
- The incoming proton/ion has a significantly larger kinetic energy than the incoming electron.
- Most of the hadrons are emitted in the same direction as the hadron beam (“forward” direction)
- If we want to measure *jets*, we need a granular, forward calorimeter

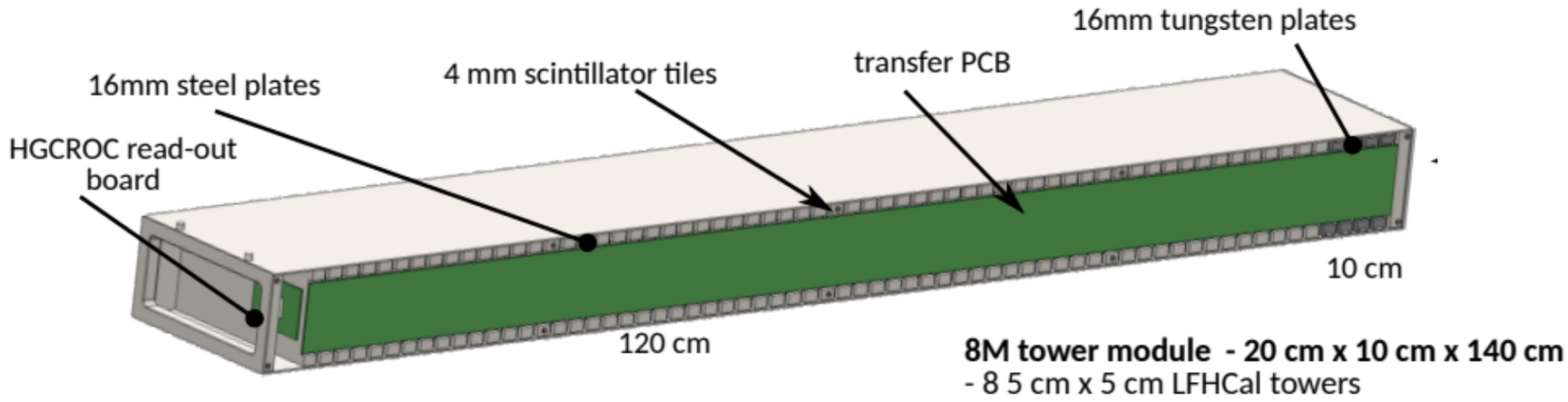
Figure Courtesy ePIC

Forward HCal



- High-granularity iron-scintillator calorimeter
- Forward region, $1.2 < \eta < 3.5$
- Sampling calorimeter comprised of 0.3 cm scintillator tiles sandwiched between 2.0 cm steel plates

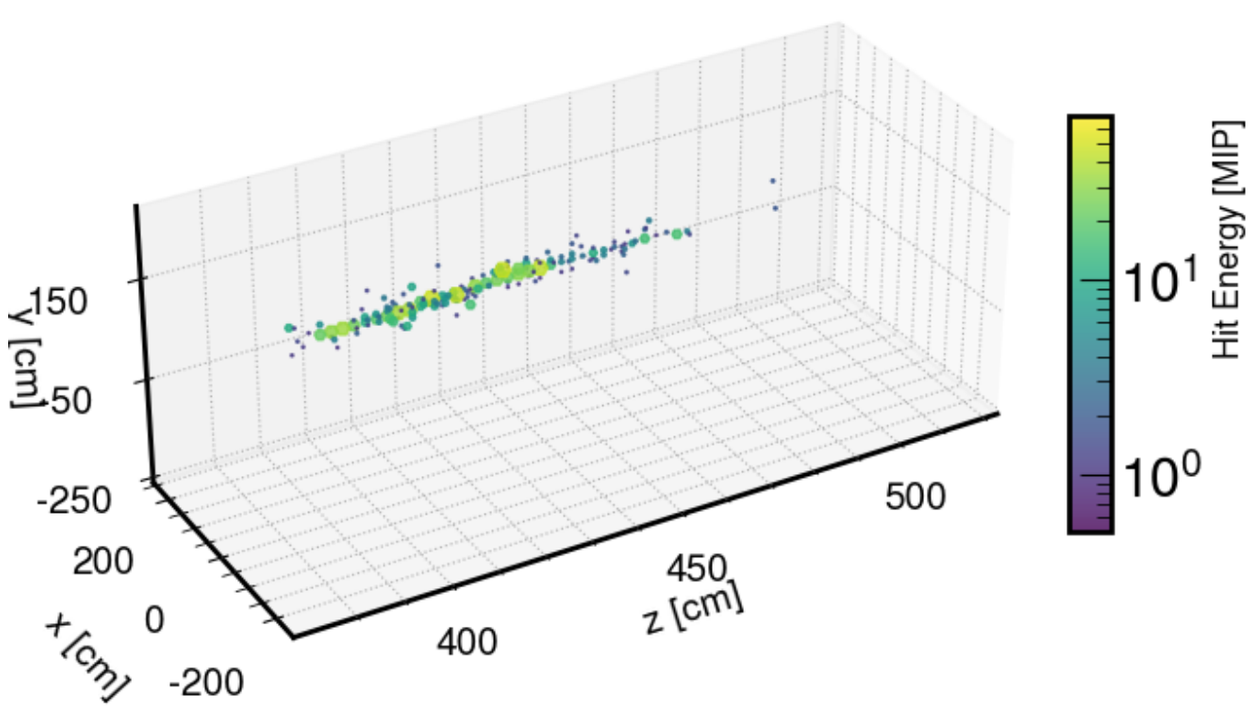


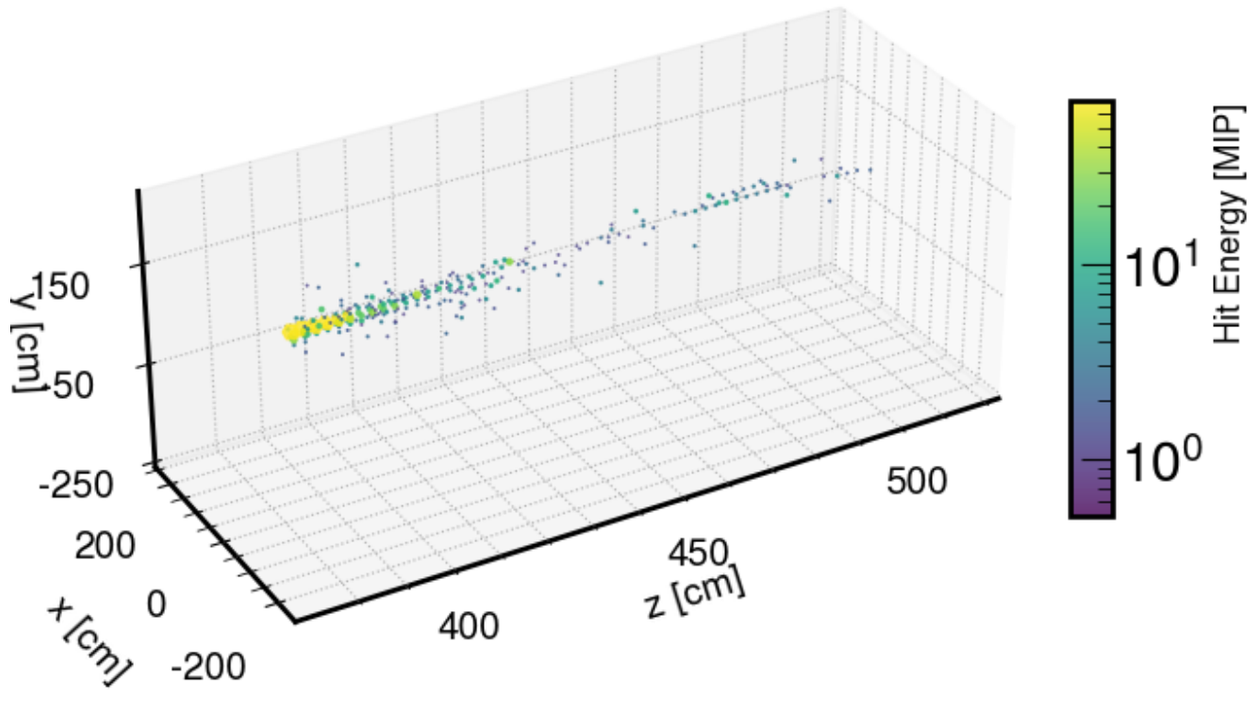


8M tower module - 20 cm x 10 cm x 140 cm
- 8 5 cm x 5 cm LFHCal towers

Figure Courtesy ePIC

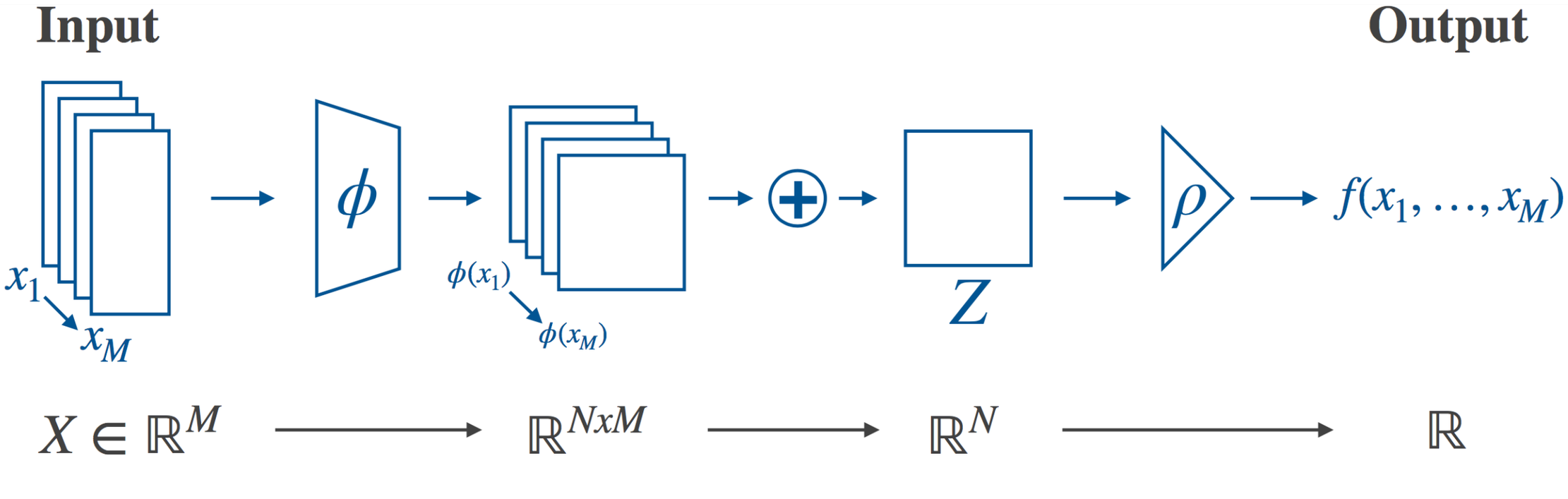
Detector Simulation and Reconstruction





- Geant4 Simulation of single π^+ showers
- Standalone DD4Hep sim. of detector similar to ePIC HCAL
- $1 < P_{\text{Gen.}} < 125\ \text{GeV}/c$
- $\mathcal{O}100 - 1000$ Cell Hits per shower, ***point clouds***
- Establish a model to predict $P_{\text{Gen.}}$ given cell information
- Condition model on position of longitudinal segmentation

Deep Sets



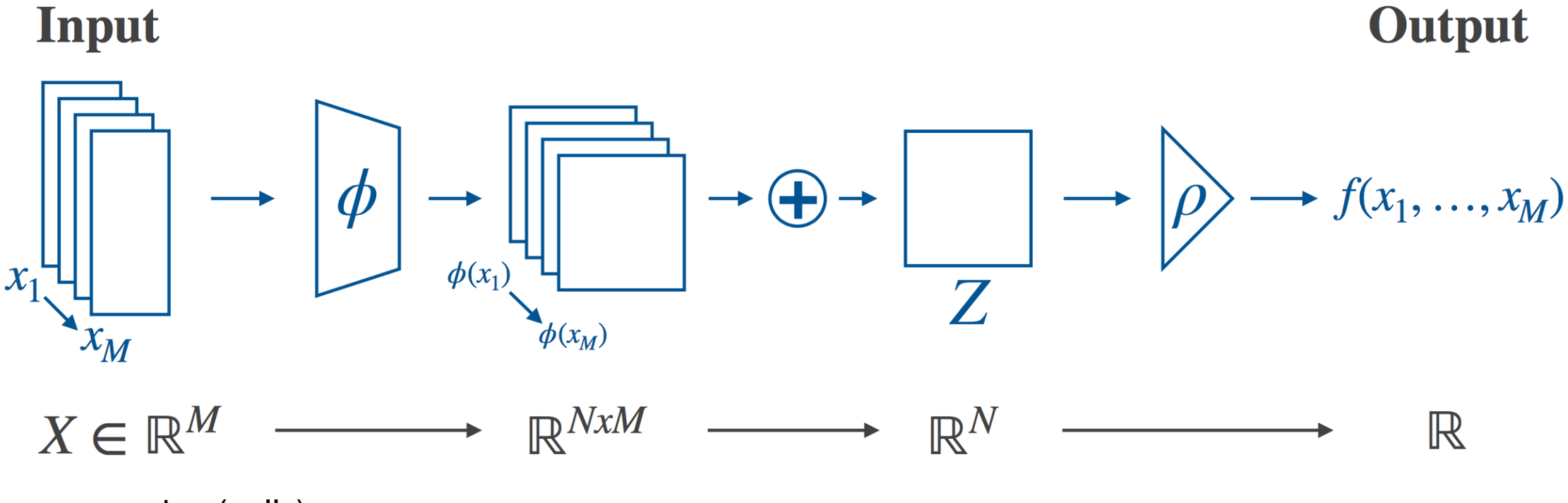
1. Transform inputs into some latent space
2. Destroy the ordering information in the latent space (+, μ)
3. Transform from the latent space to the final output

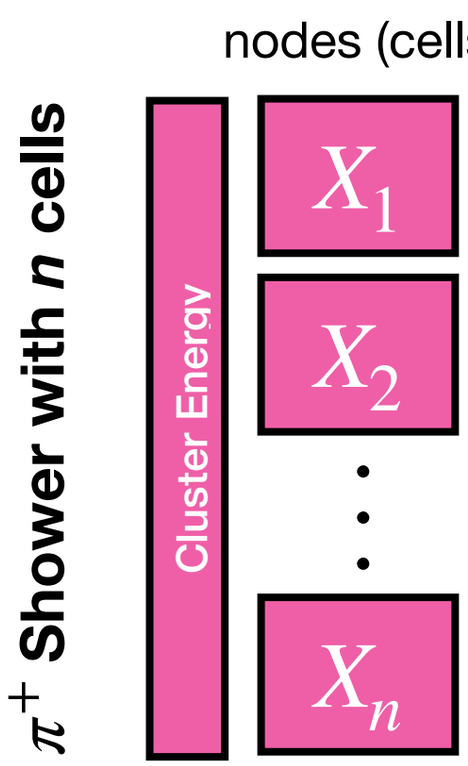
Permutation Invariant
Works well with point clouds
A GNN without edges

arXiv: 1703.06114

arXiv:1810.05165

Deep Sets



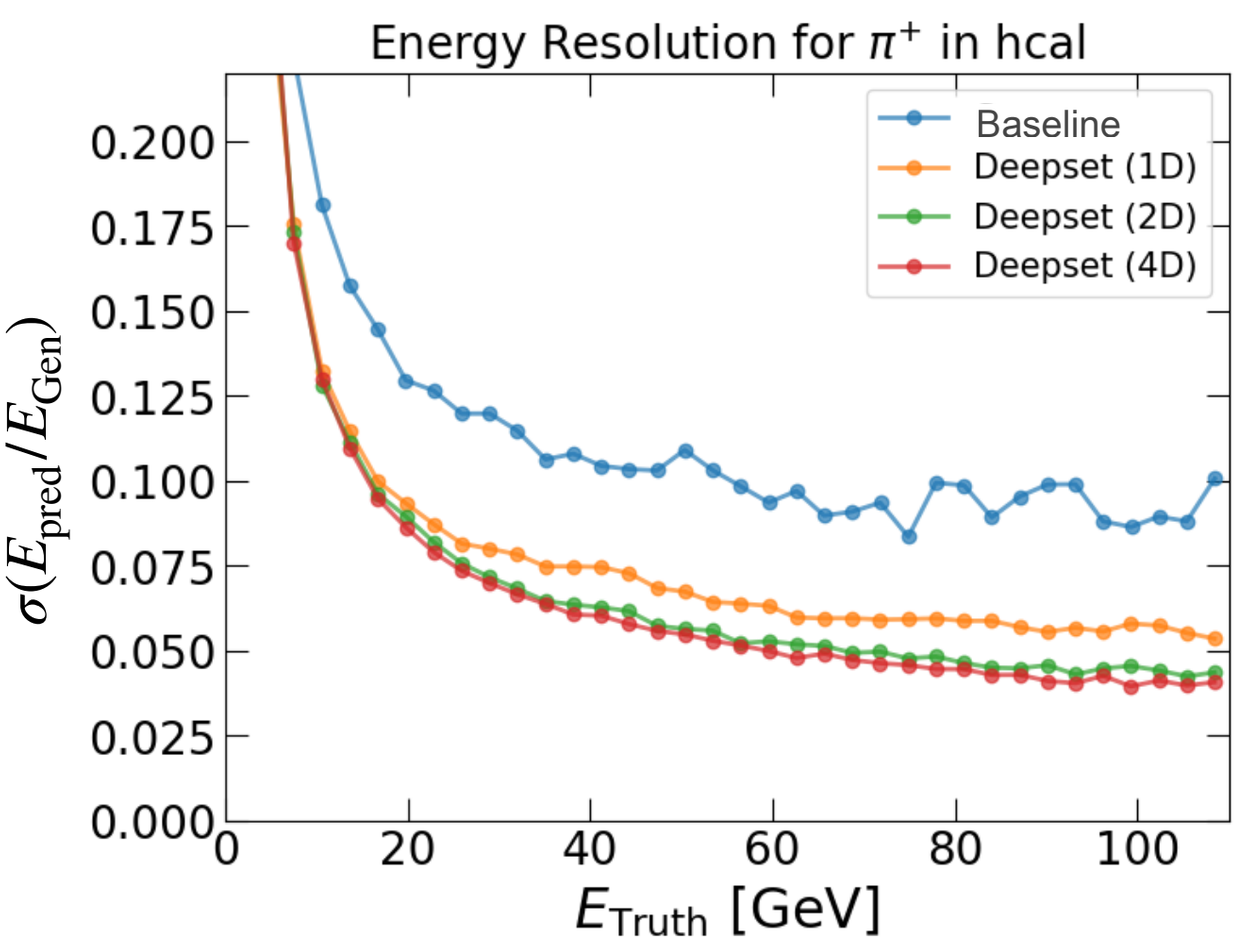


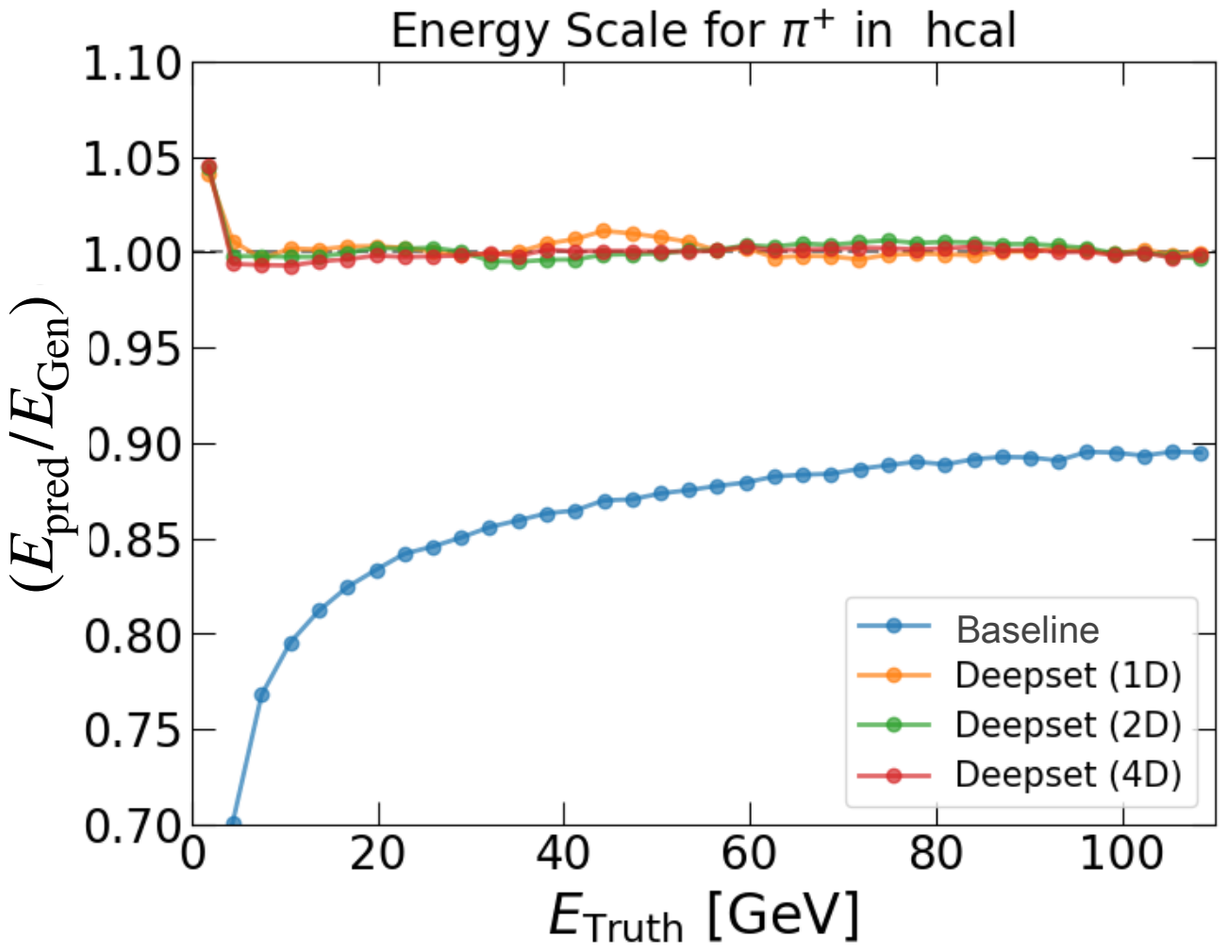
$$X_i = \left\{ \begin{matrix} \mathbf{E} \\ \mathbf{X} \\ \mathbf{Y} \\ \mathbf{Z} \end{matrix} \right\} \in \mathbb{R}^4$$

Goal:
π^+ Energy Regression

Model uses energy and position information for energy regression

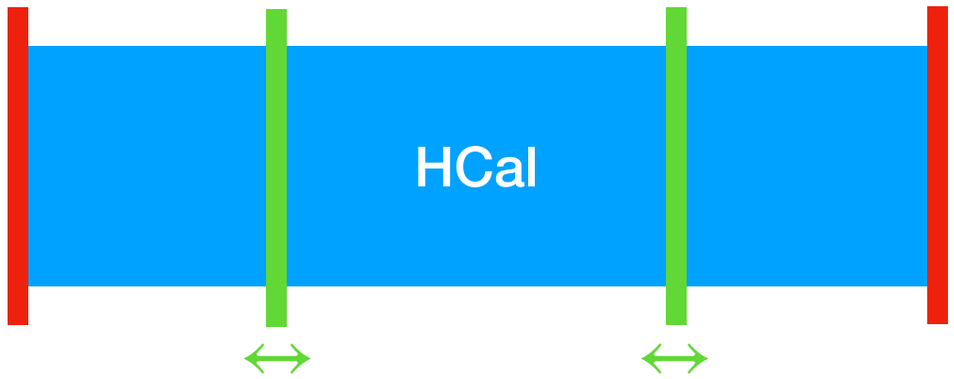
Energy Regression Results

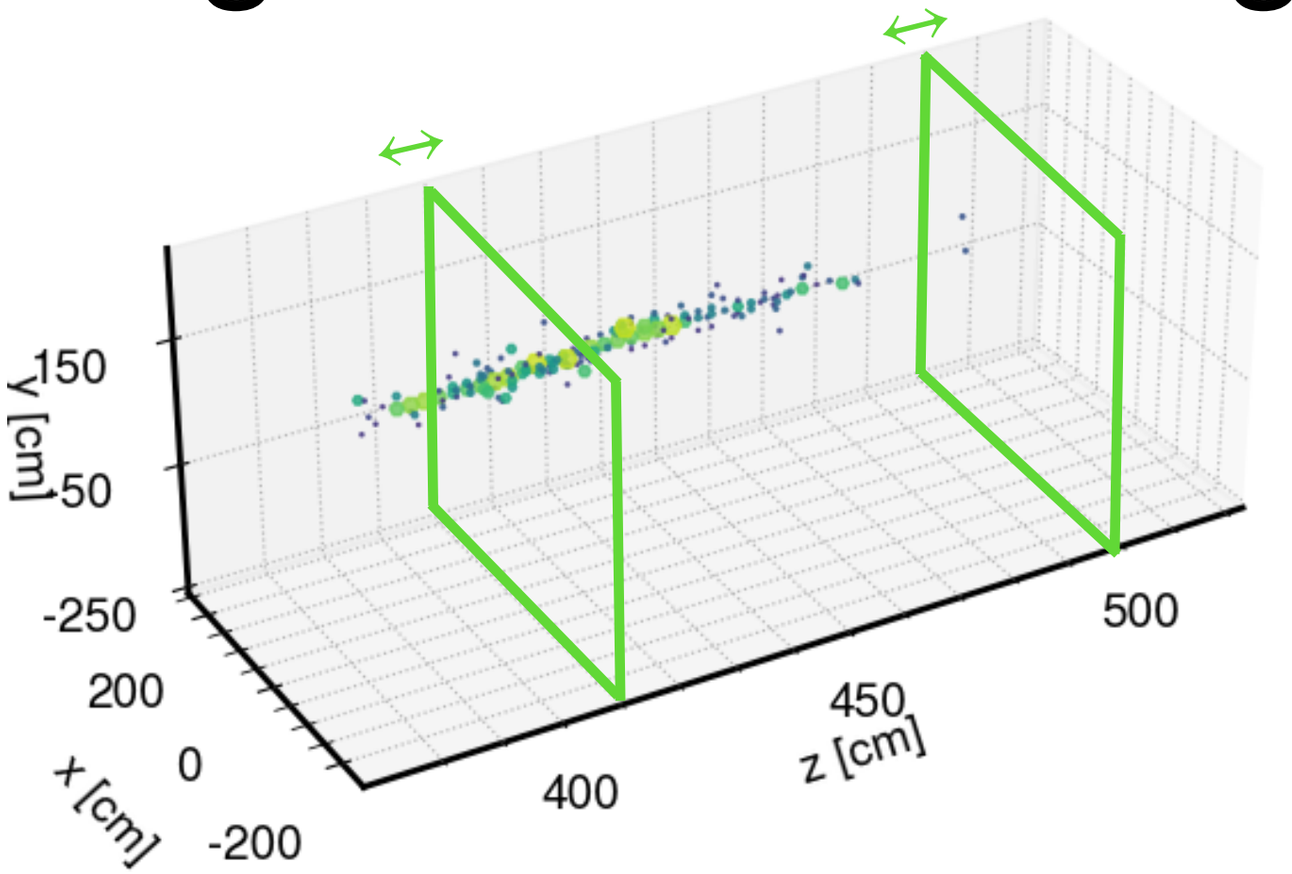




Energy resolution well below baseline clusterer
Energy scale within 1% of truth for almost all energies
Cell Position information improves resolution
Overall, very dependable energy reconstruction model

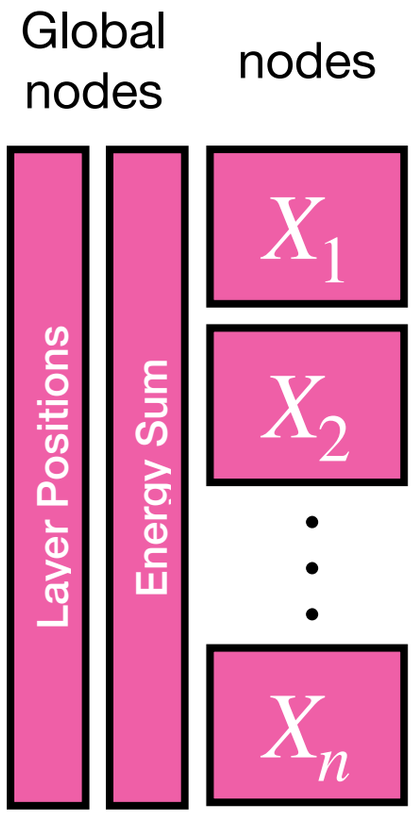
Data Processing for Conditioning





- Each point is a ***local node*** with information x_i
- The group of points making up the shower can be assigned values called ***global nodes***
  - Sum of all cell energies in the event
  - position of longitudinal boundaries
- For every event, 5 random configurations of layers are created

Conditioning on Longitudinal Segmentation

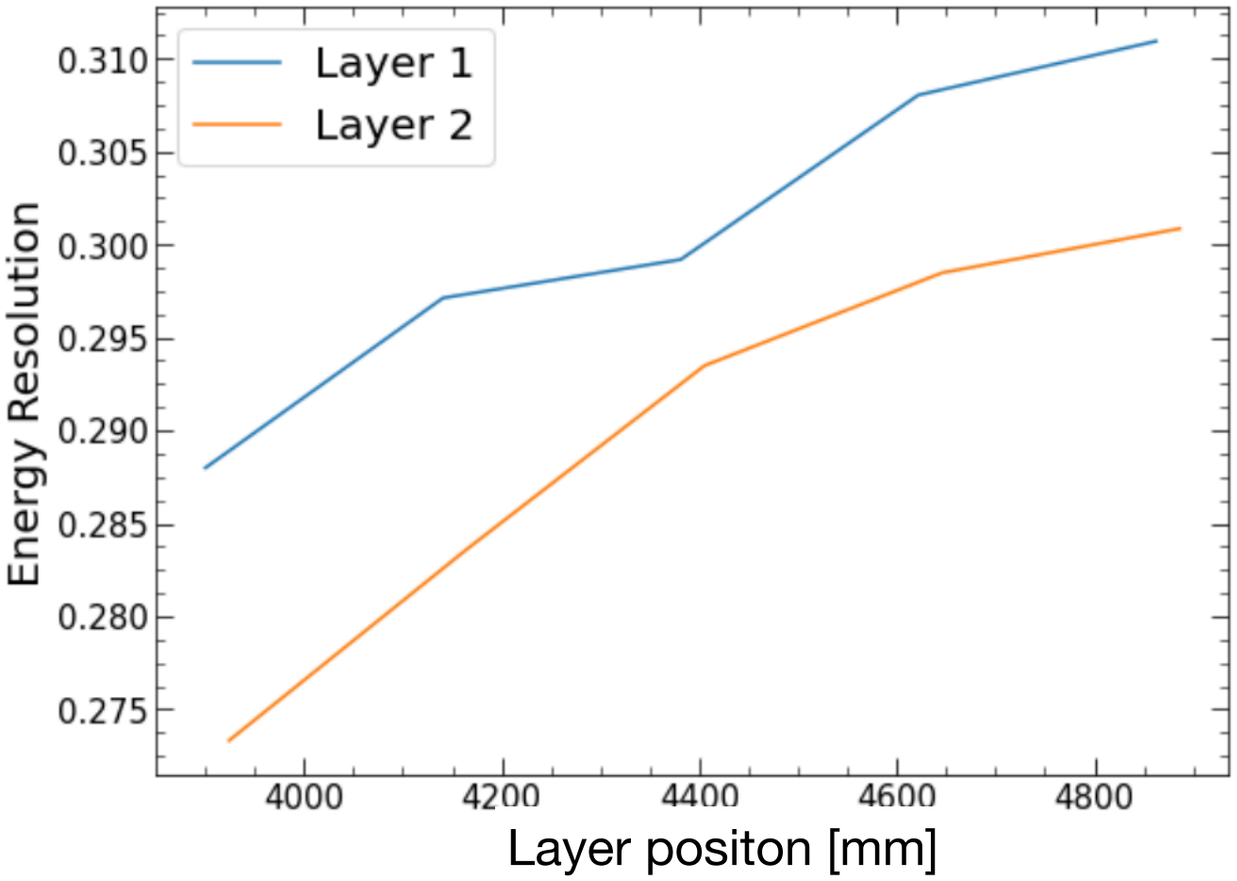


$$X_i = \left\{ \begin{matrix} \mathbf{E} \\ \mathbf{z} \end{matrix} \right\} \in \mathbb{R}^2$$

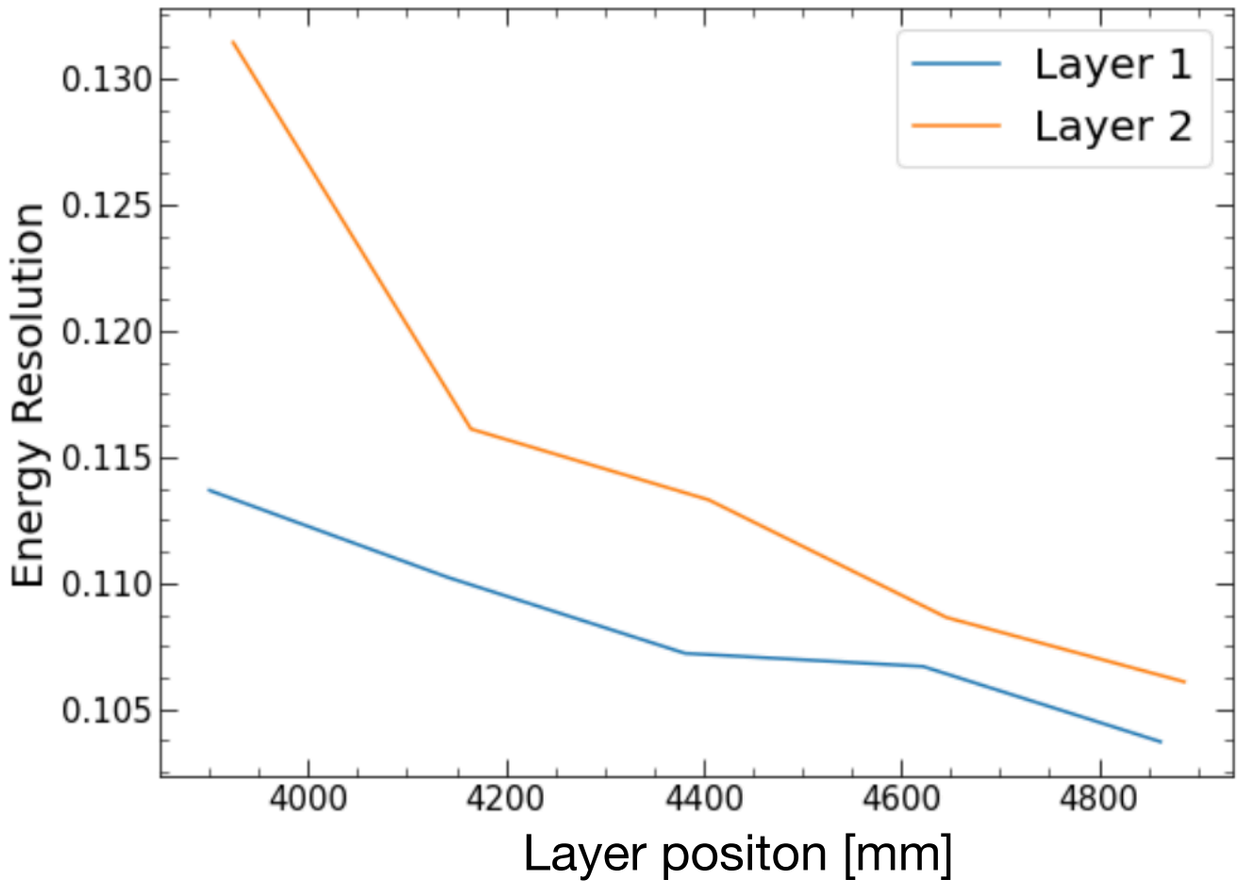
The position of middle two layers are added as global features
Reduce the local node features (for now)
For each event, 5 random configurations are used
110 unique configurations, 2.4M Events

$$\sigma_E = f(z_1,\ z_2, \vec{x})$$

$P_{\text{Gen.}} < 10.0$ GeV/c



$P_{\text{Gen.}} > 50.0$ GeV/c



$$\sigma_E = \sigma(E_{\text{pred}}/E_{\text{Gen}})$$

We have a differentiable function for energy resolution conditioned on detector parameters

Conclusions and Next Steps

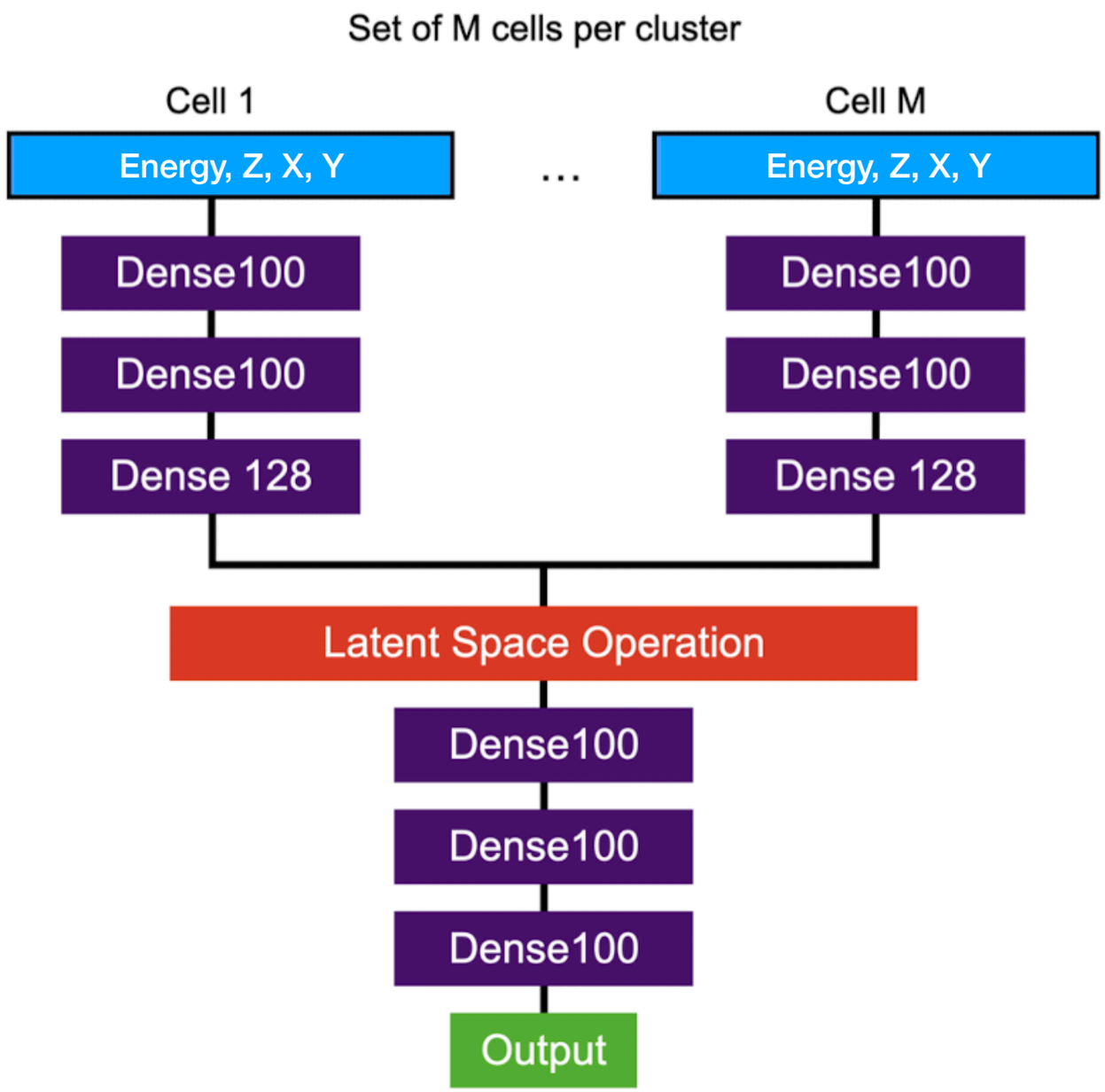
- We have our first energy regression conditioned on detector parameters

$$\sigma_E = f(z_1,\ z_2, \vec{x})$$

- Compare gradients standard tools: *auto_diff* on $\sigma_E = f(z_1,\ z_2, \vec{x})$
- Explore conditioning with additional layers
- Re-condition with higher dimensional data

Extra Slides

Deep Sets Architecture

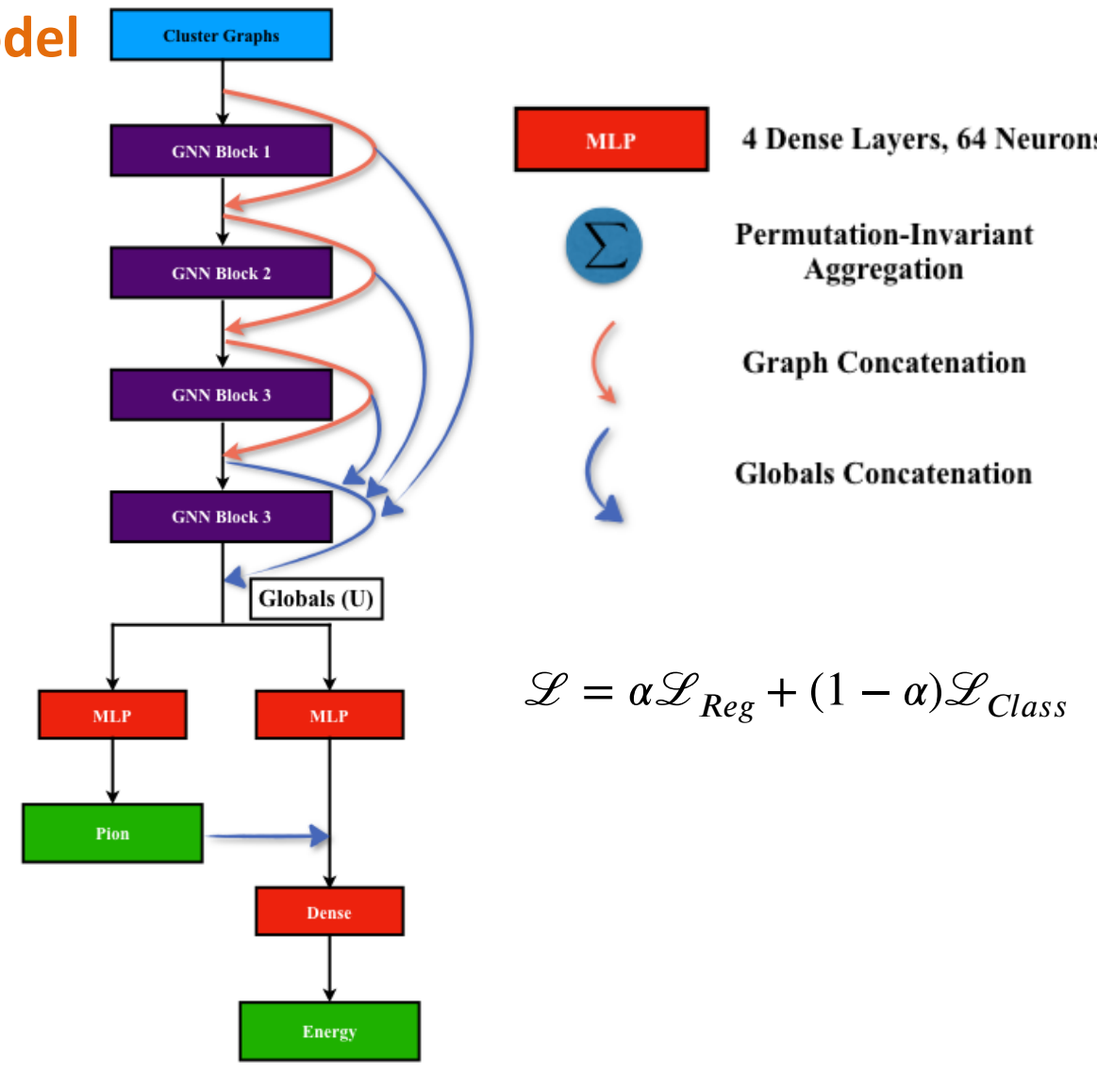


GNN Model

- Graph Nets library by DeepMind
  - Highly customizable graph blocks
  - Lightweight
  - Not actively developed or widely used

FullGNN Block

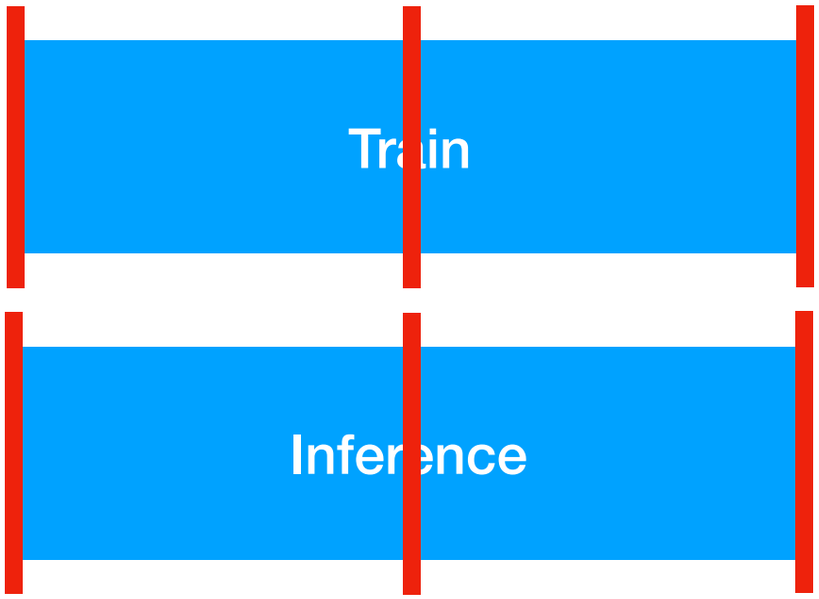
Model



$$\mathscr{L} = \alpha \mathscr{L}_{Reg} + (1-\alpha)\mathscr{L}_{Class}$$

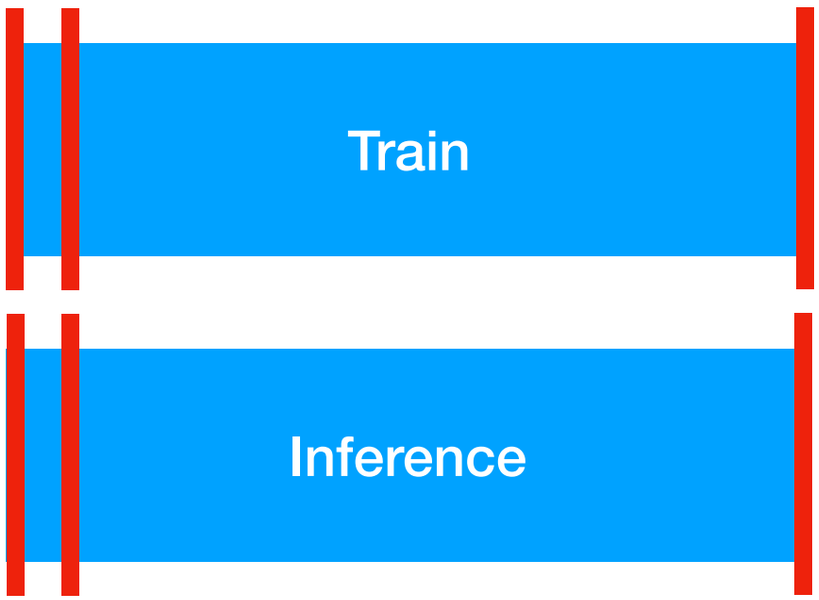
Overall Scale of effect

MSE = 0.030856214

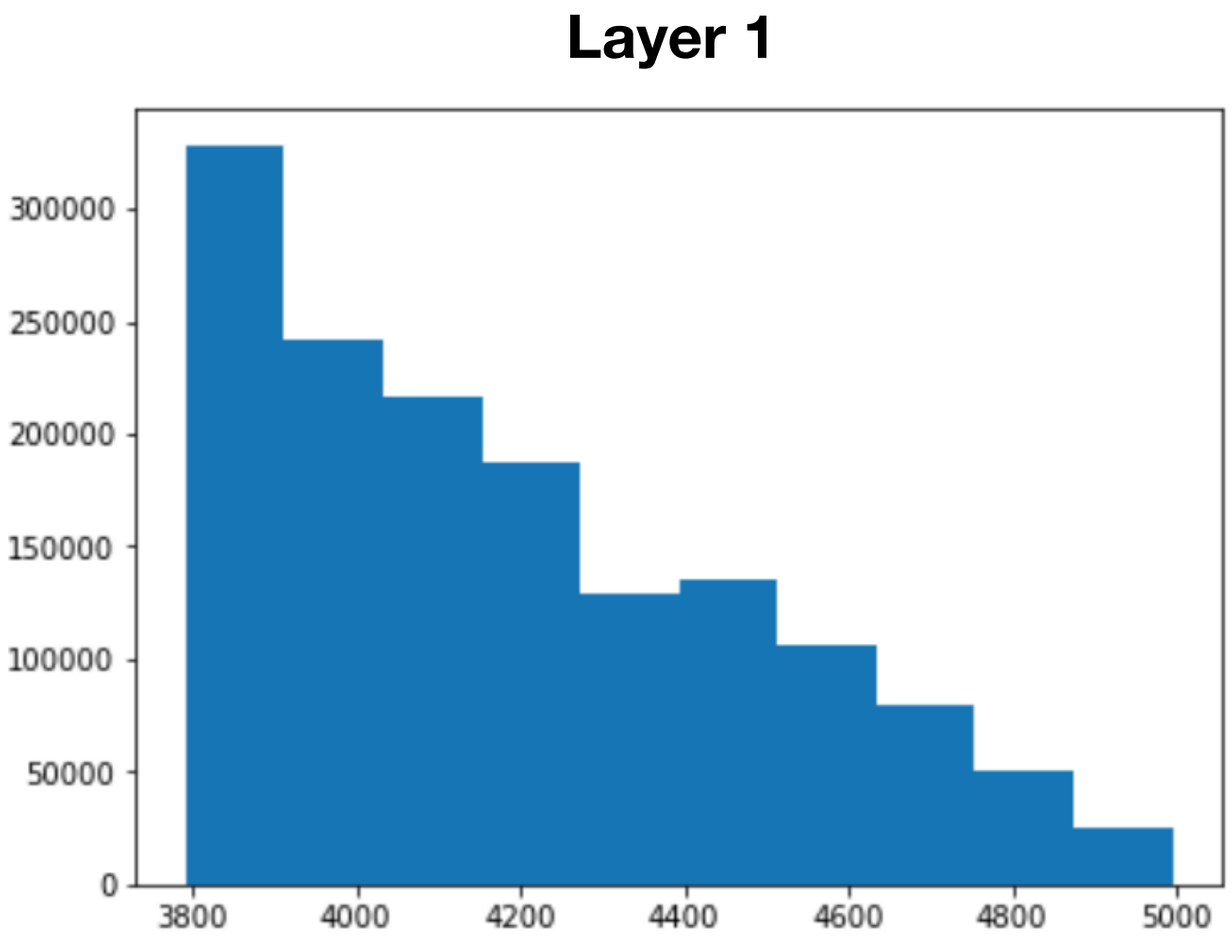


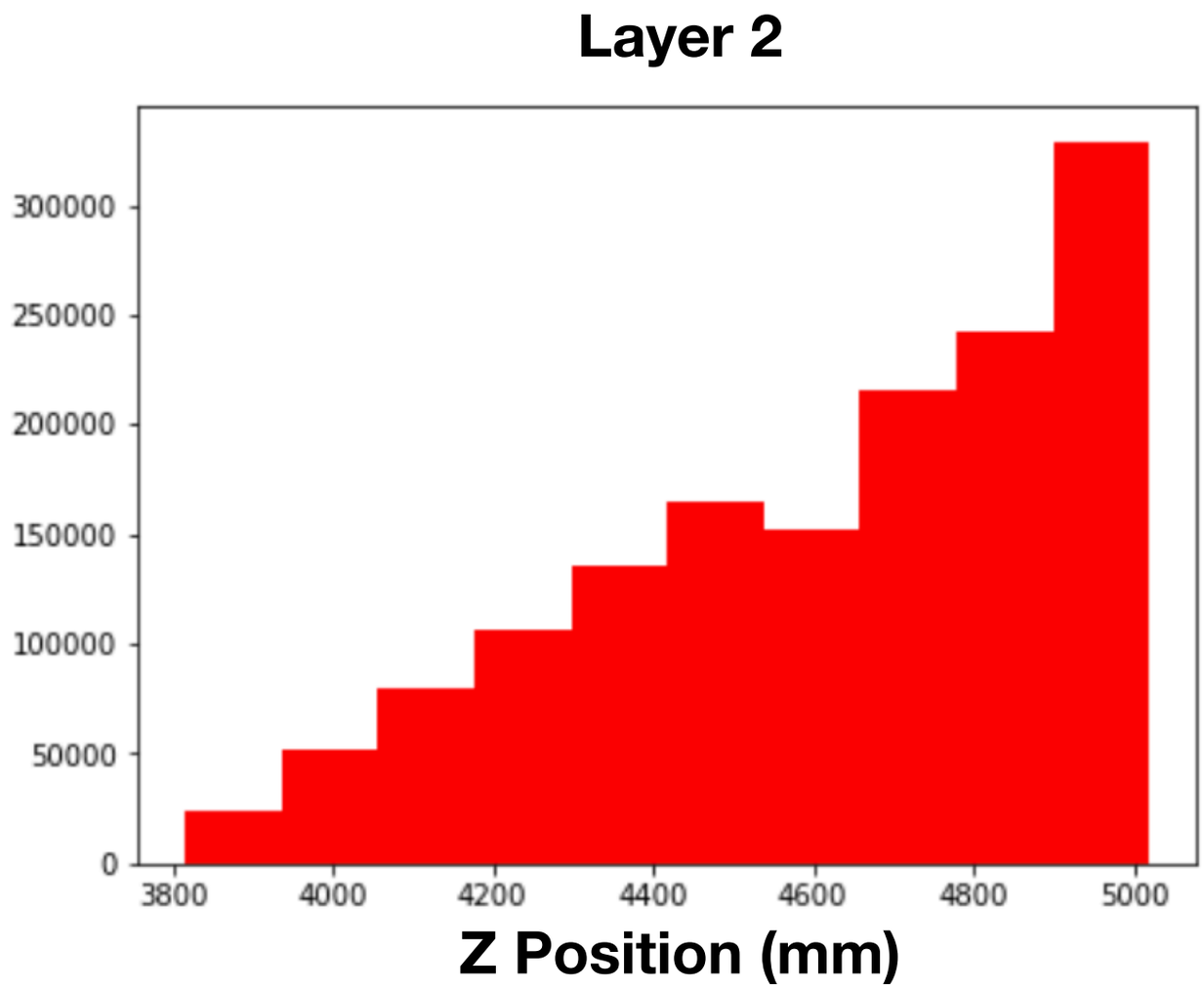
ΔMSE 0.003

MSE = 0.033682253

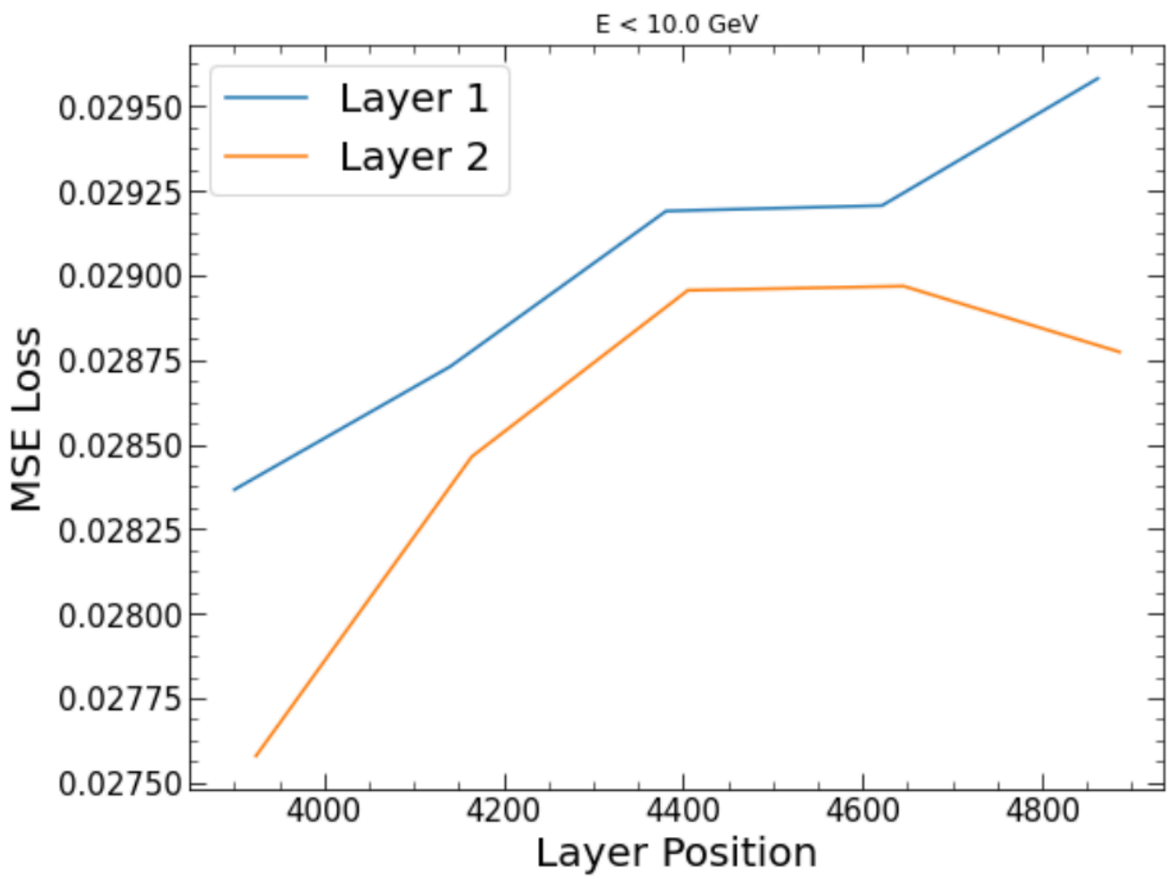


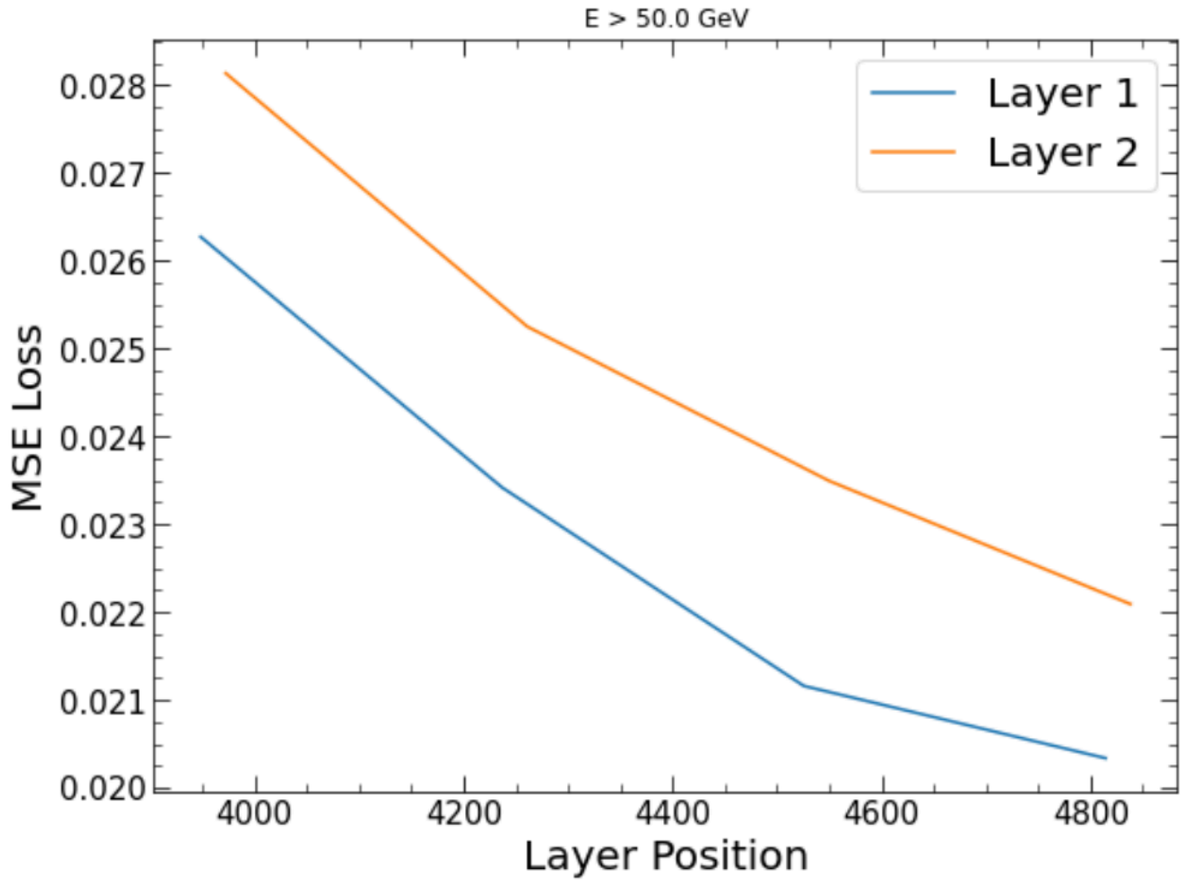
Longitudinal Segmentation





MSE plots





Model provides $\mathrm{MSE} = f(z_1,\ z_2, \vec{x})$

MSE Loss Plot

$1.0 < P_{\text{Gen.}} < 125.0$ GeV/c