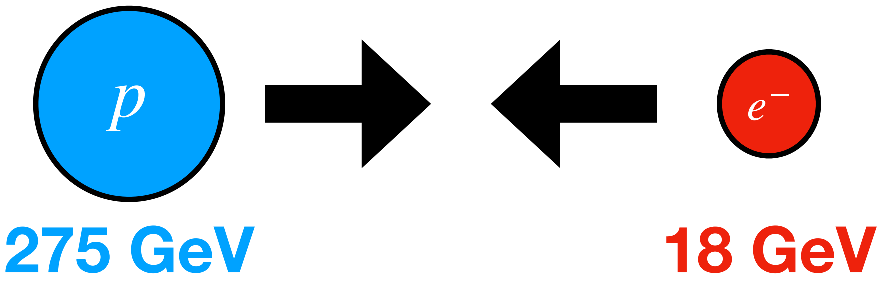
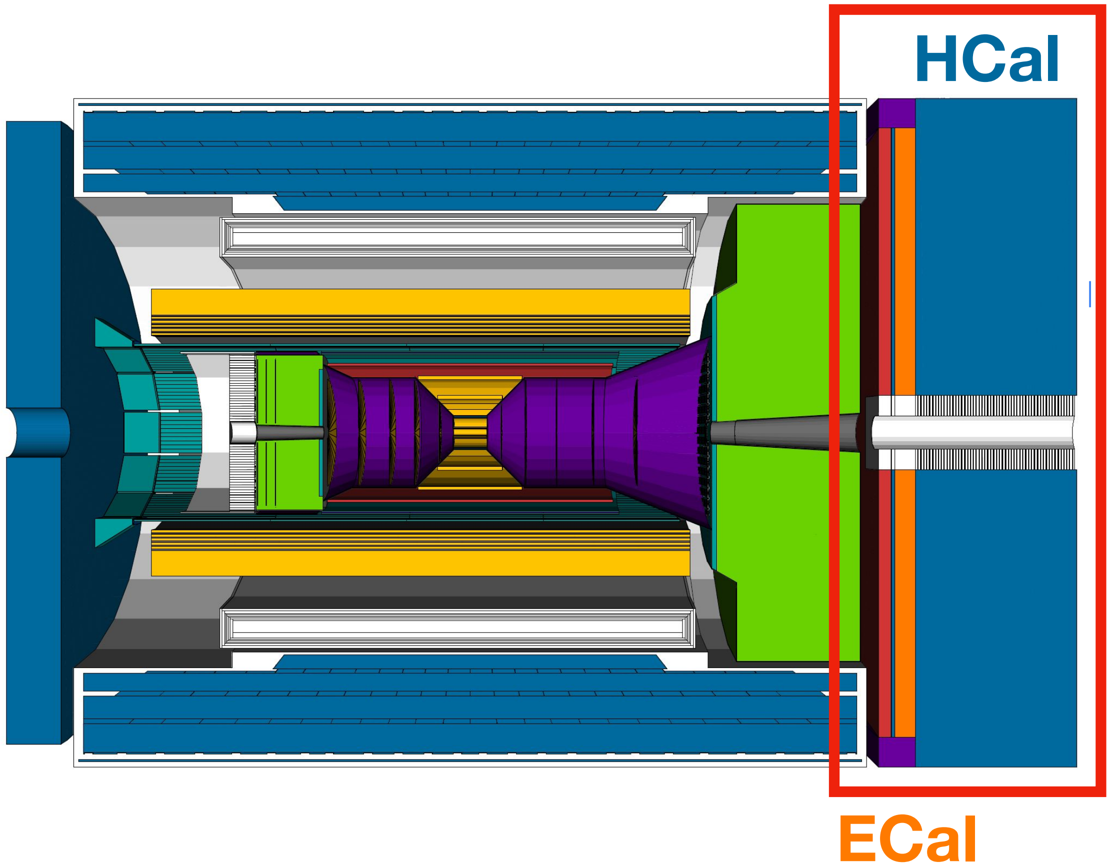
Software Compensation with GNN
+
Impact of longitudinal segmentation

Goal:
best experimental design suited for the best detector reconstruction

Forward Hadronic Calorimeter

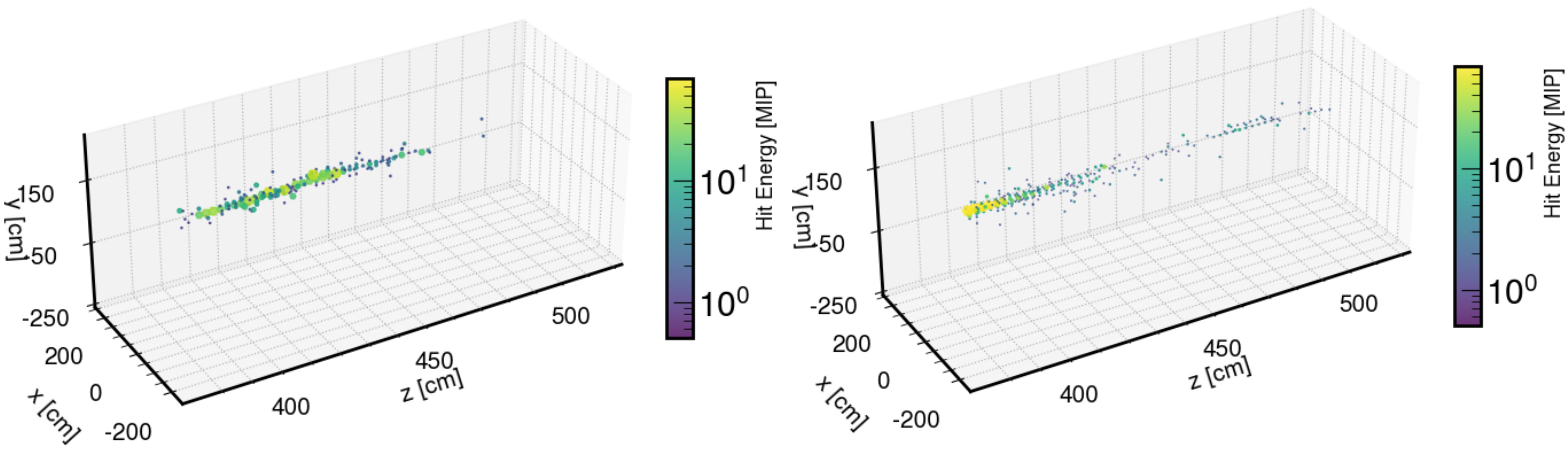




- The incoming proton/ion has a significantly larger kinetic energy than the incoming electron.
- If we want to measure *jets*, we need a granular, forward calorimeter
  - Forward region, $1.2 < \eta < 3.5$
- Deep Sets and GNNs for pion energy regression
- Software Compensation
- G4 geometry modeled *approximately* after *ePIC*

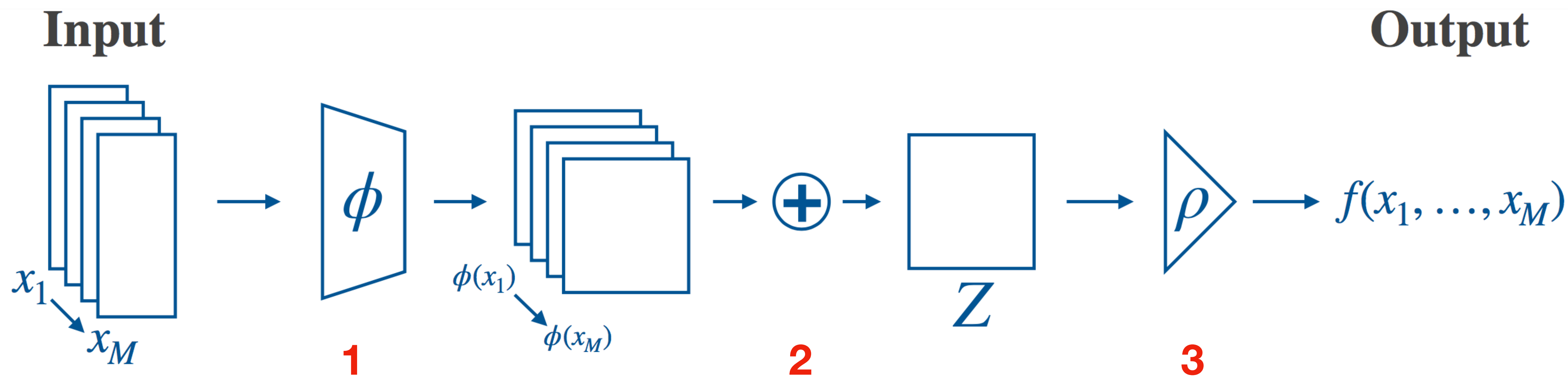
Figure Courtesy ePIC

Detector Simulation and Reconstruction

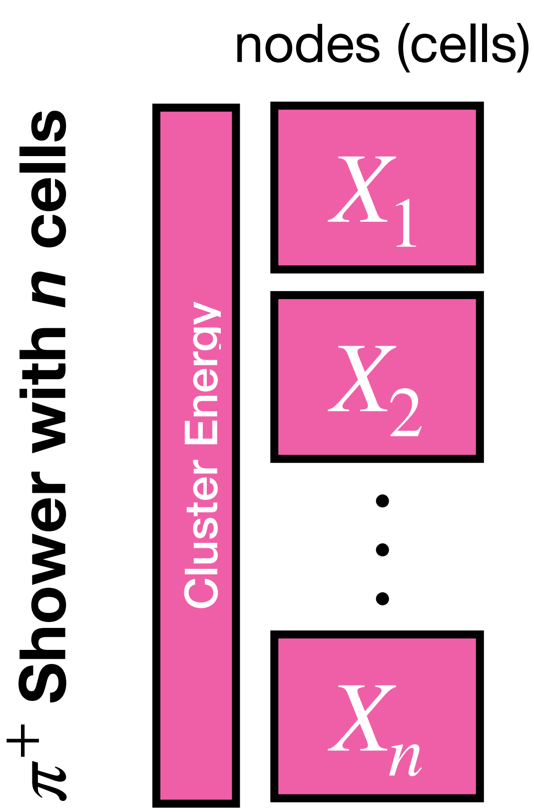


- Geant4 Simulation of single π^+ showers$1 < P_{\mathrm{Gen.}} < 125\ \mathrm{GeV}/c$
- $\mathcal{O}100 - 1000$ Cell Hits per shower, ***point clouds***
- Establish a model to predict $P_{\mathrm{Gen.}}$ given cell information
- ML for *Software Compensation* and *Energy Reconstruction*
- **Optimal reconstruction scheme is non-trivial in a complex system**

Deep Sets



$X \in \mathbb{R}^M \longrightarrow \mathbb{R}^{NxM} \longrightarrow \mathbb{R}^N \longrightarrow \mathbb{R}$



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

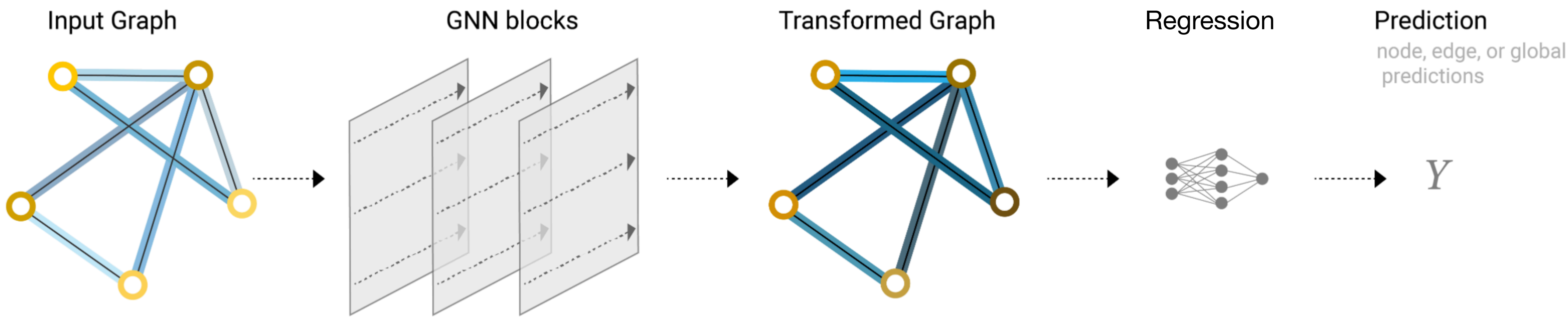
1. **Latent**
2. **Aggregation**
3. **Final Output**

Goal:

π^+ Energy Regression

Model uses energy and position information for energy regression

Graph Neural Network



- For each node in the graph, *gather* all the neighboring node embeddings (*messages*)
- *Aggregate* all messages via an aggregate function
- All pooled messages are passed through an *update function*, usually a learned neural network

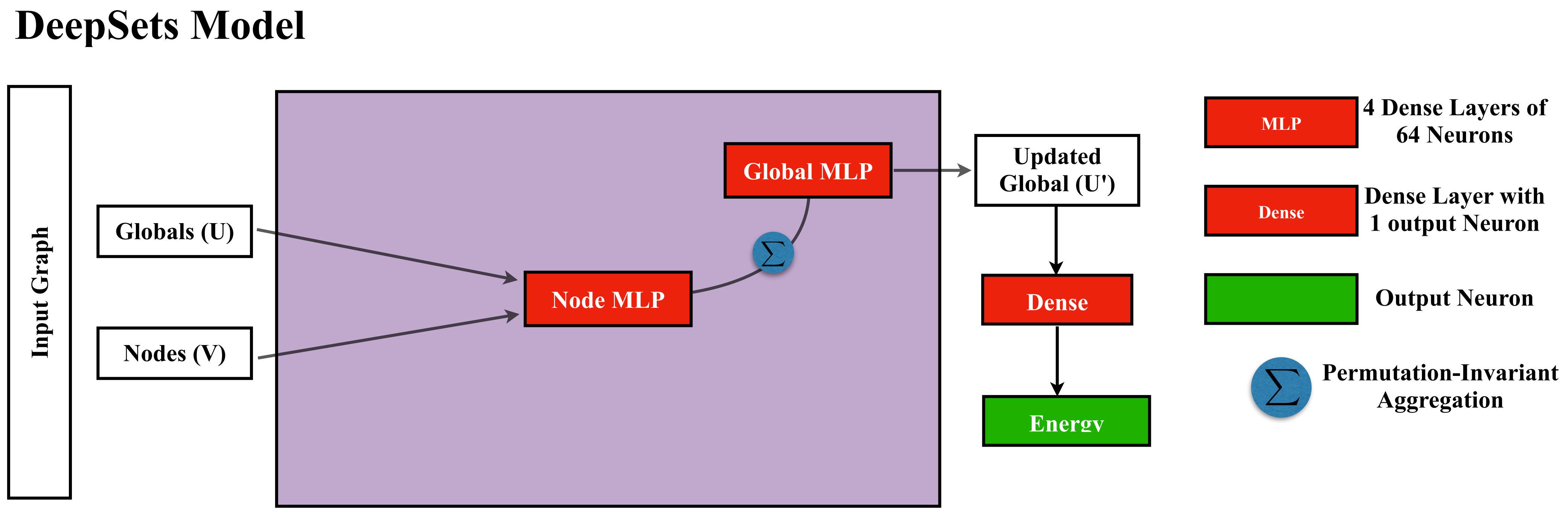
V Vertex (or node) attributes
e.g., node identity, number of neighbors

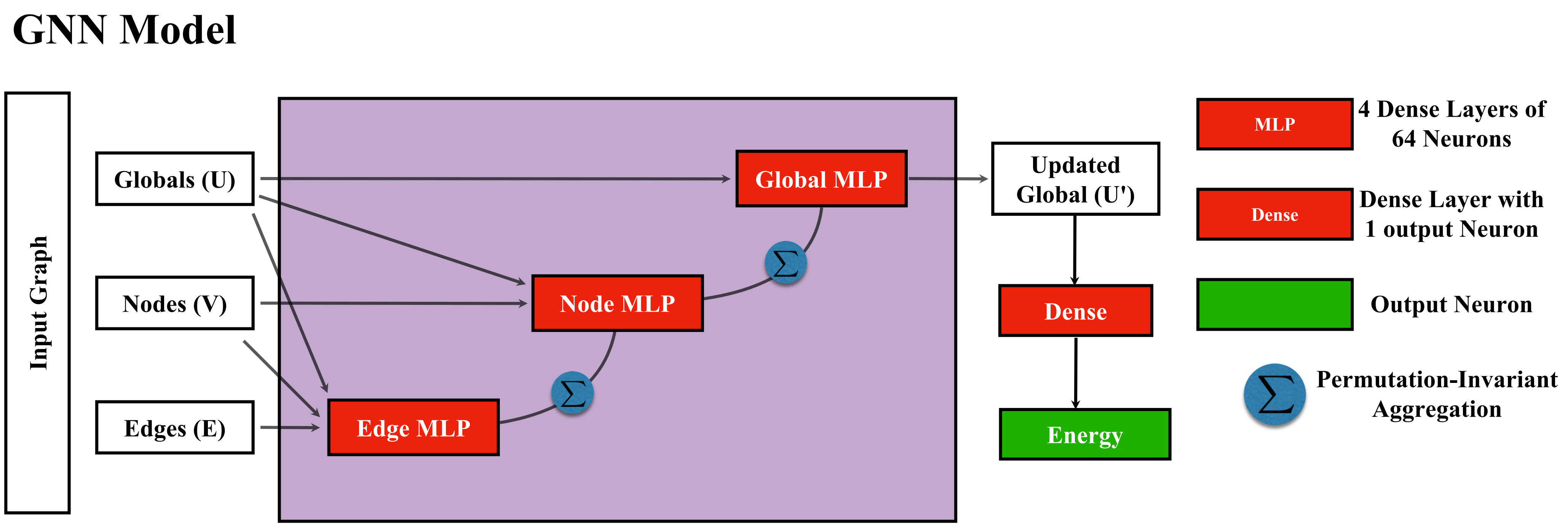
E Edge (or link) attributes and directions
e.g., edge identity, edge weight

U Global (or master node) attributes
e.g., number of nodes, longest path

Using k-nearest neighbors

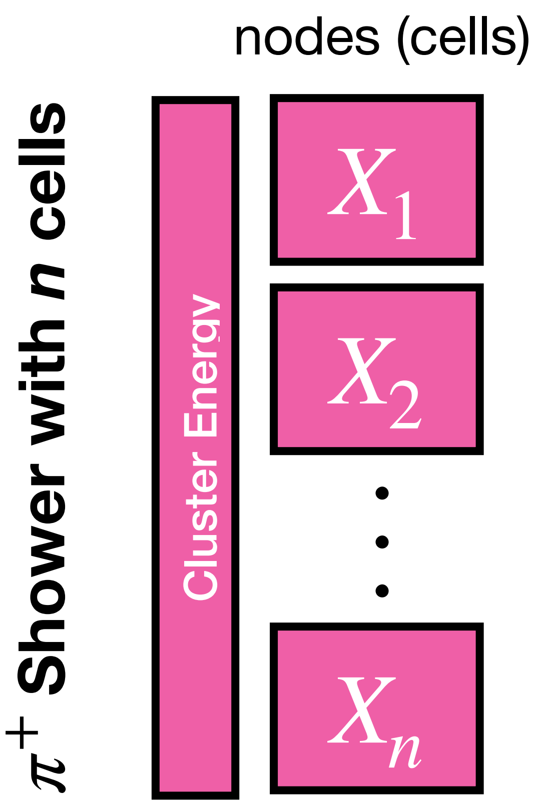
Obligatory Model Schematics





- In *theory,* DS can learn *everything* a GNN can
- We encode geometric information *directly* in the GNN

Varying the Input Features

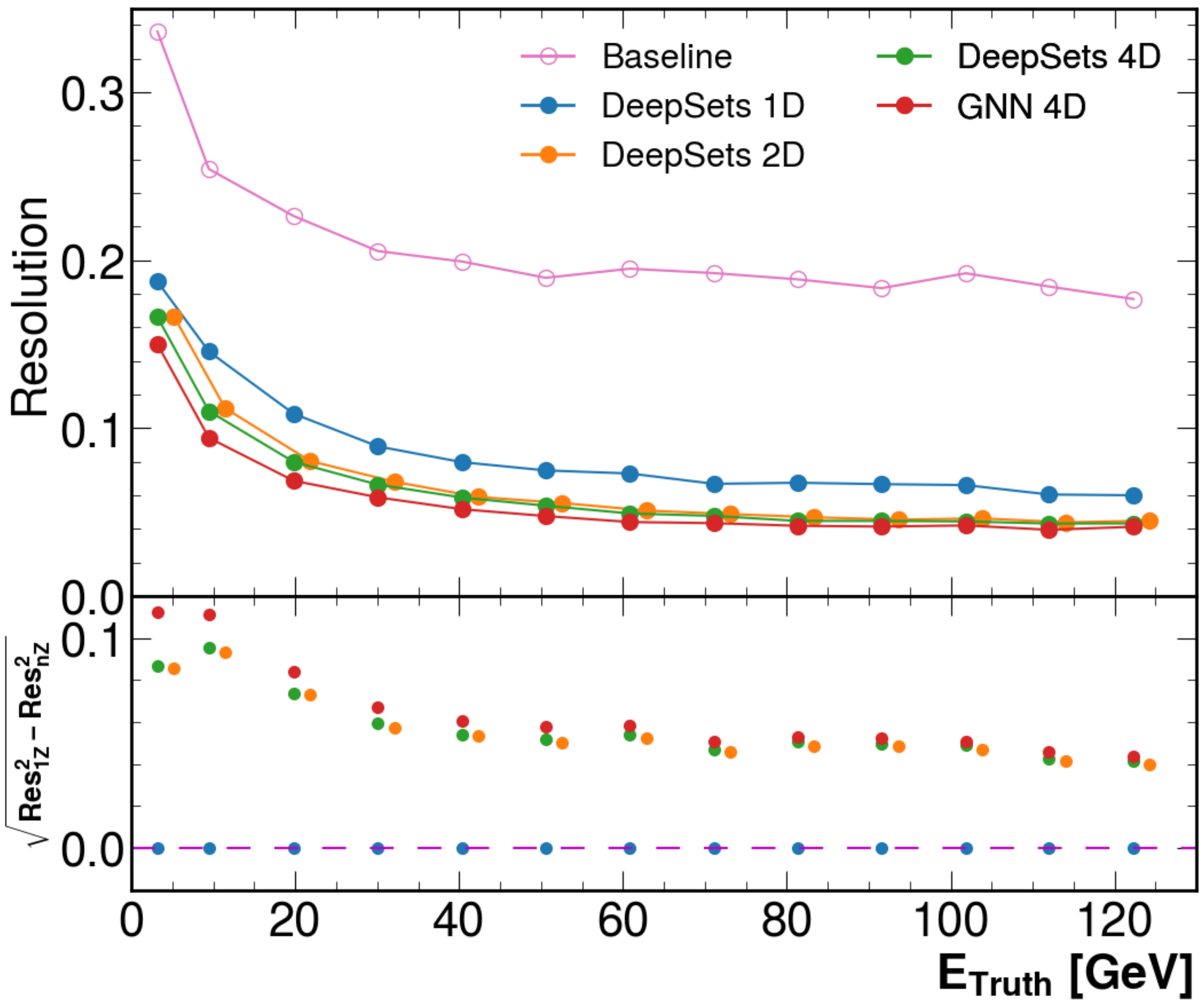


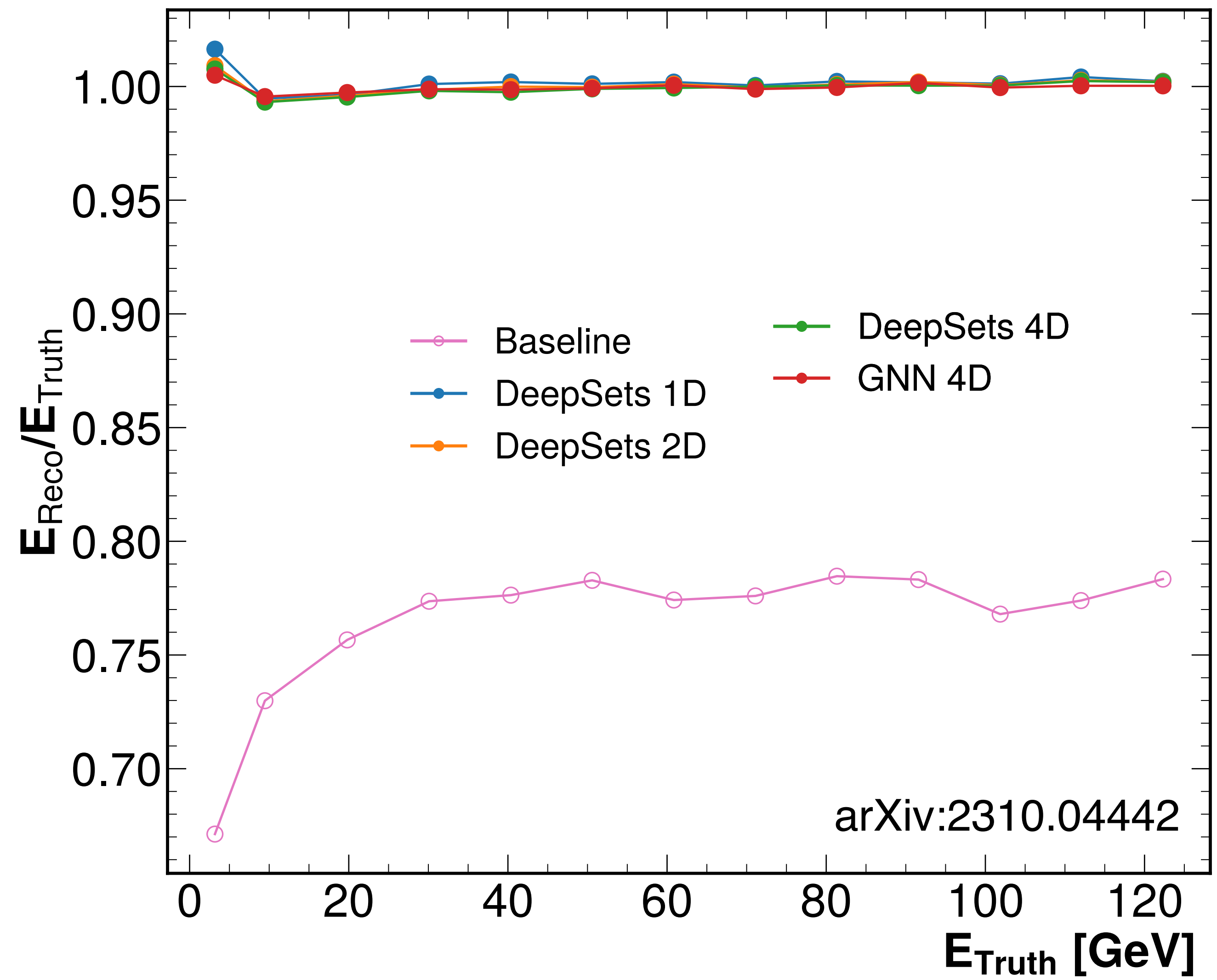
$$X_i = \left\{ \begin{matrix} E \\ X \\ Y \\ Z \end{matrix} \right\} \in \mathbb{R}^4$$

Want understand what information is most relevant for the Energy Reconstruction and ML-based software reconstruction

We train Deepsets models on E, E+Z, E+XYZ (1D, 2D, 4D)

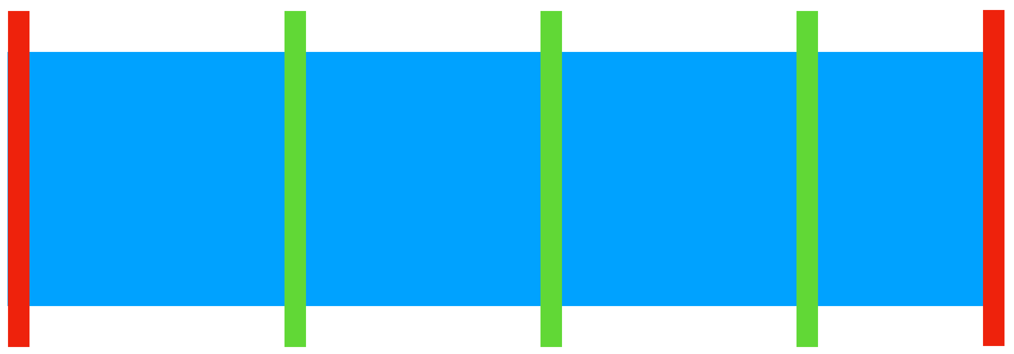
Energy Regression: Feature Dimension

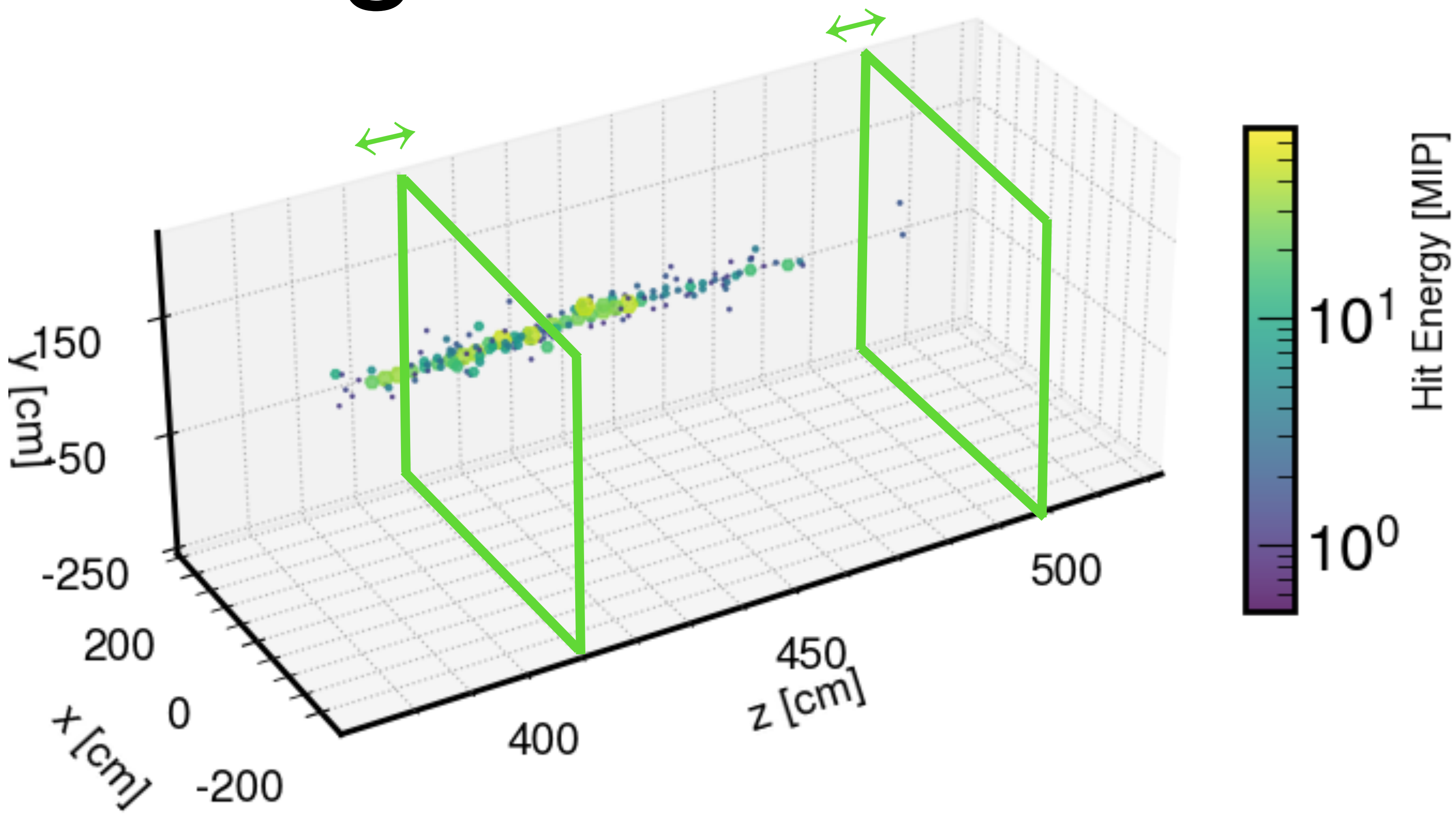




- Biggest improvement after the inclusion Z information
- GNN Performs Best! (2D →4D less impactful)
- Less sensitive to fluctuations of the EM fraction of the shower
- Energy scale within 2% of truth (1% after 10 GeV)
  - *Effective Software Compensation!*

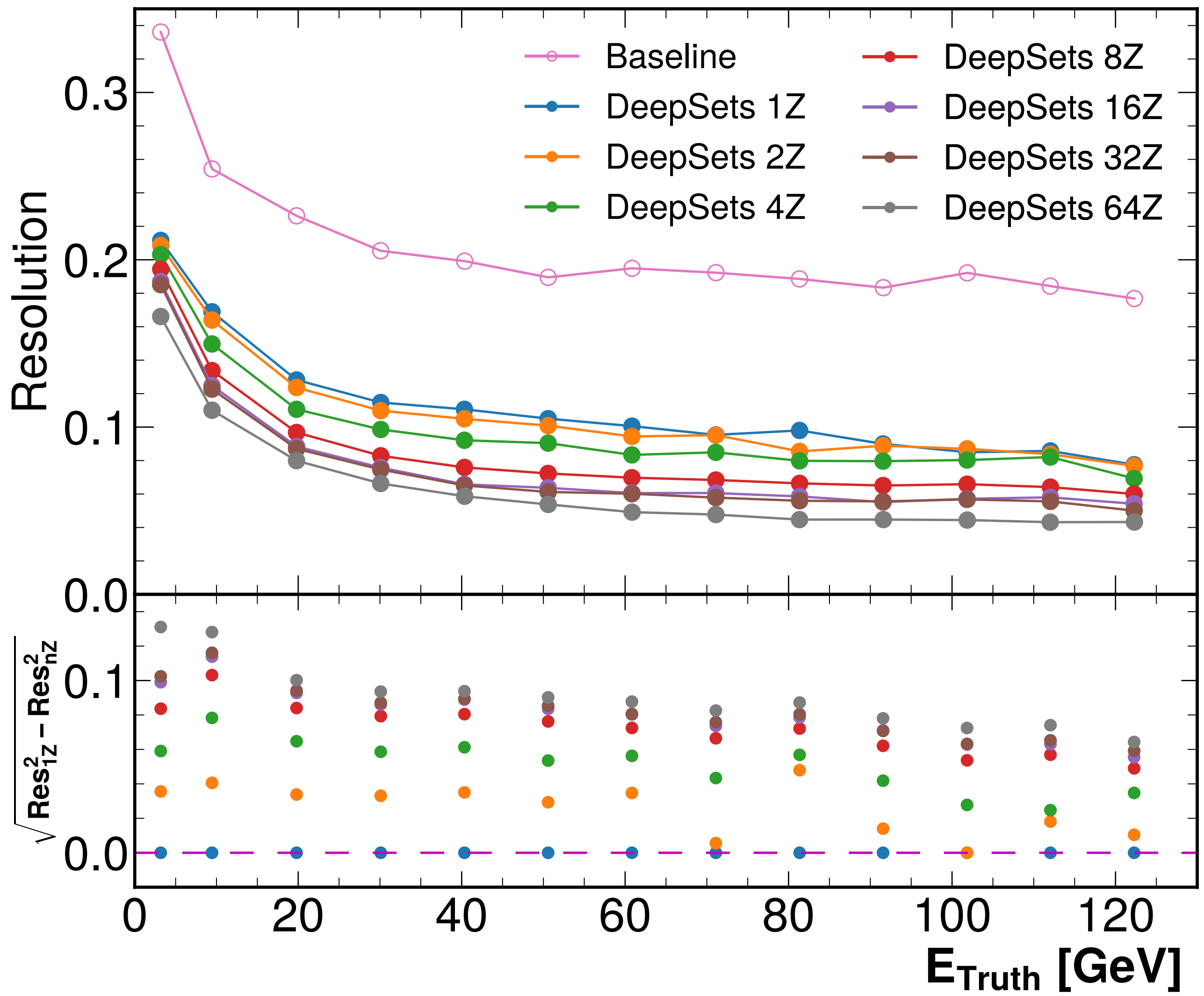
Data Processing for Models

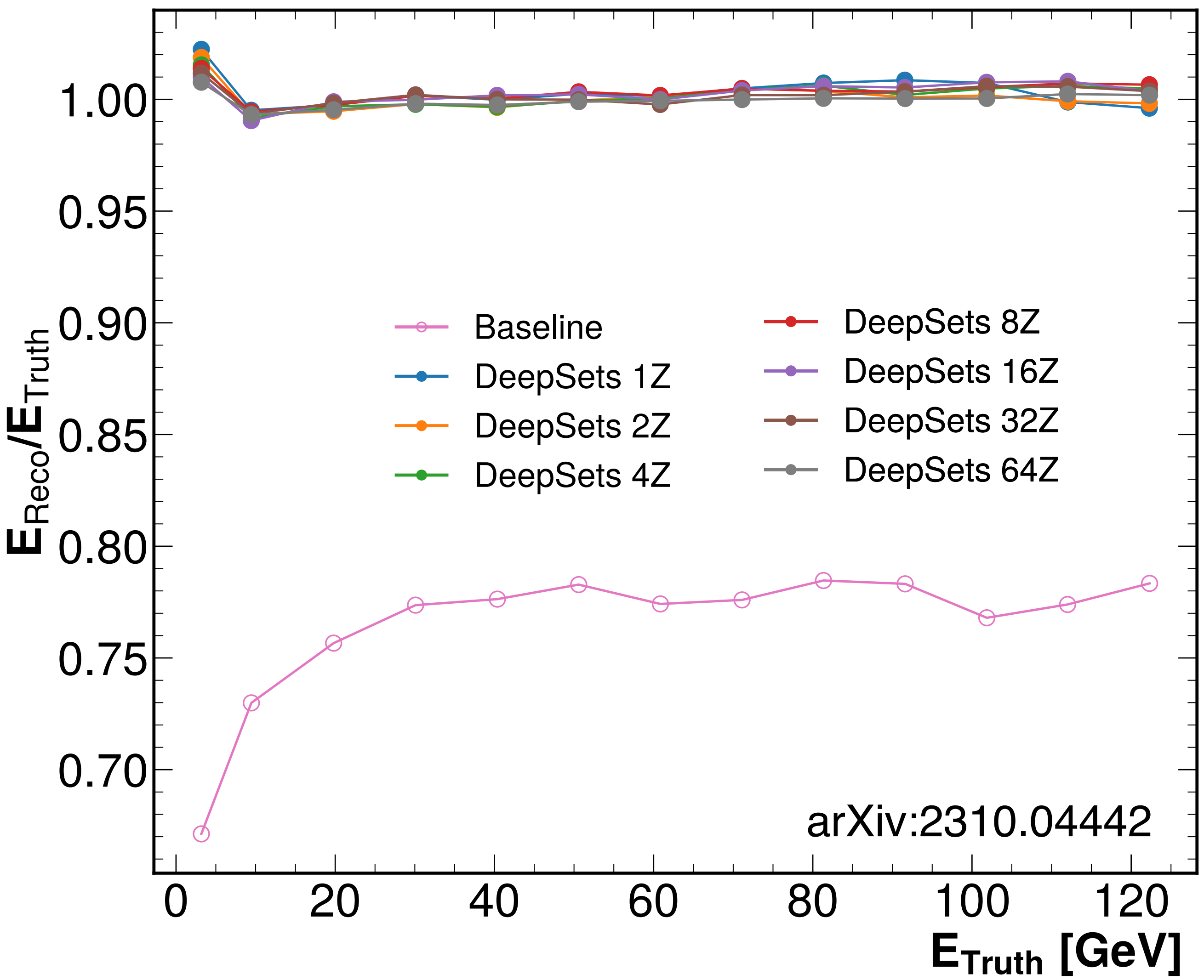




- Full point-cloud readout is *unrealistic* for final detector
- Segment the calorimeter N=1-64 layers
- Run regression, identifying optimal longitudinal configuration

Energy Regression: Number of Layers





- 1-Layer configuration w/ Deepsets outperforms baseline
- Intuitive increase in performance as N_z increases
- Software compensation does incredibly well

Conclusions and Outlooks

https://arxiv.org/abs/2310.04442

- ML extremely effective method for software compensation

- Every Resolution most effected by longitudinal information. Less sensitive to transverse segmentation

- Point Clouds for Generative Models:
  - https://arxiv.org/abs/2307.04780

- Next Step: Model conditioned directly on detector configuration

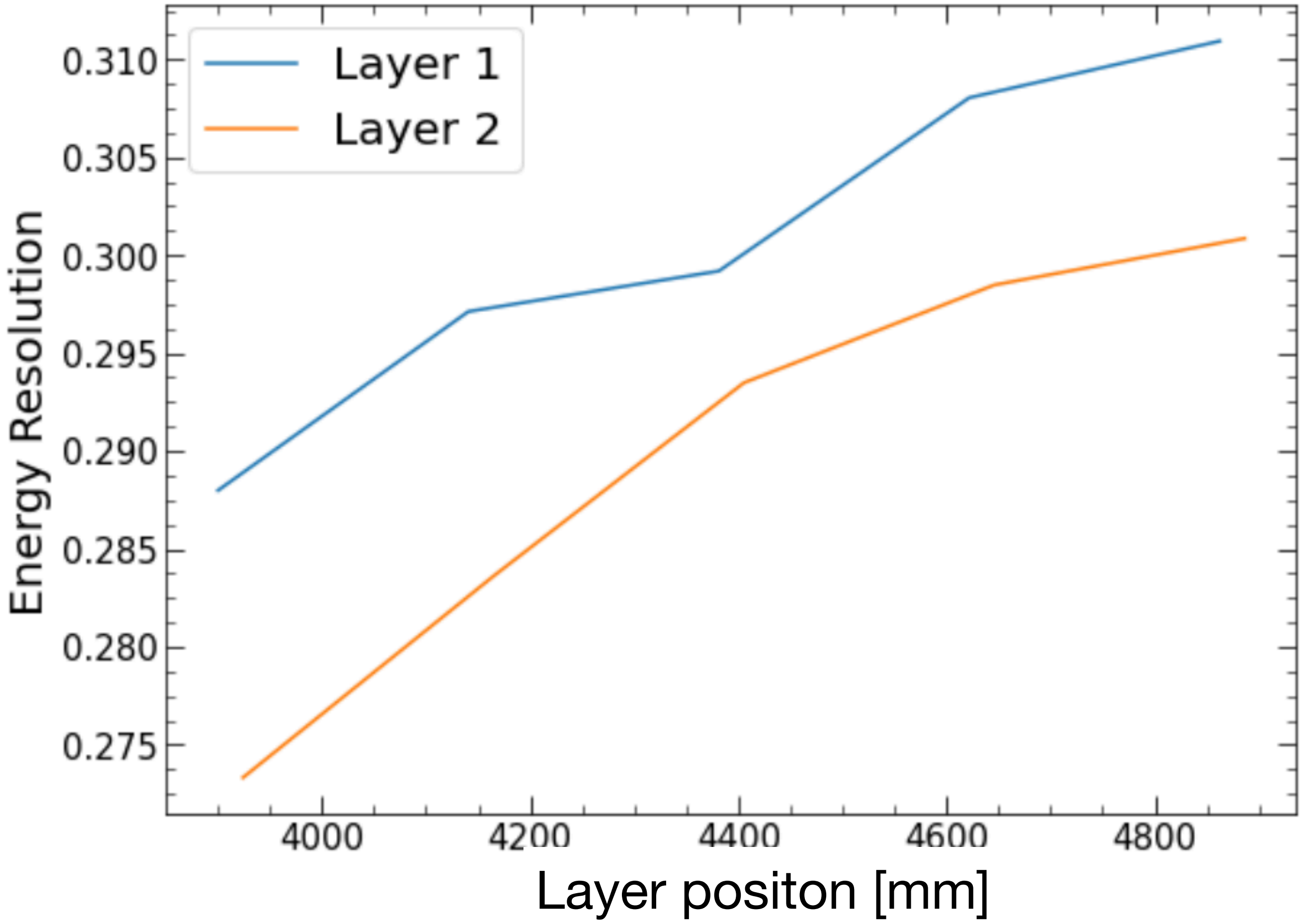
$$\sigma_E = f(z_1,\ z_2, \vec{x})$$

END… END

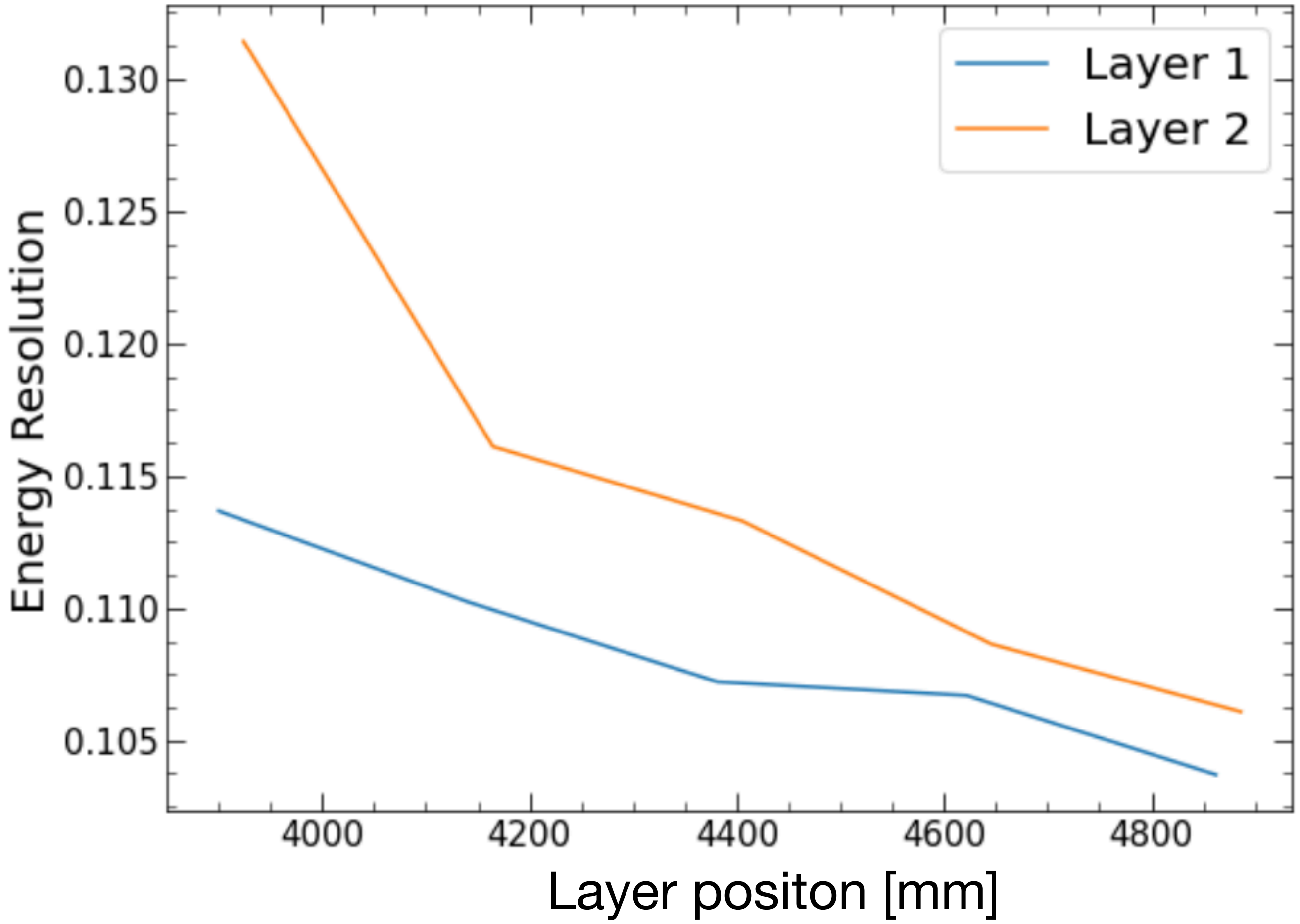
Backup

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

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

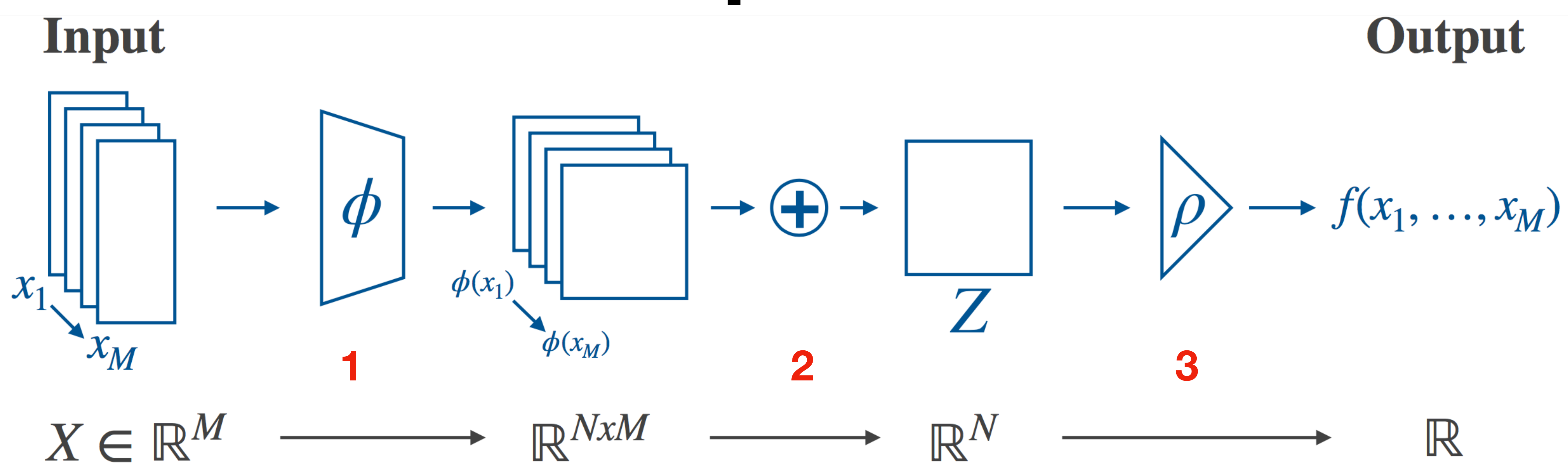


$P_{\text{Gen.}} > 50.0$ GeV/c



We have a differentiable function for energy resolution

Deep Sets



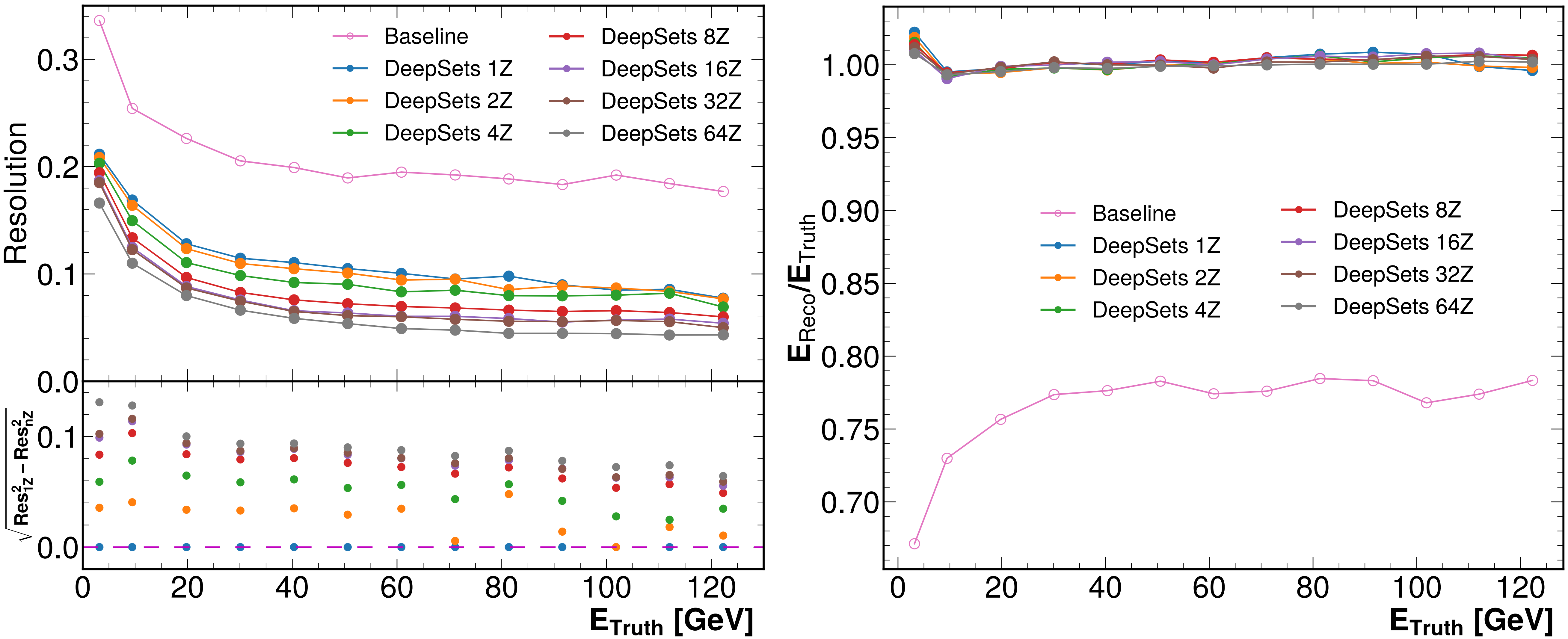
1. Transform inputs into some latent space
2. Destroy the ordering information in the latent space (+, μ)
3. Transform from the latent space to the final output

<u>Permutation Invariant</u>
Works well with point clouds
A GNN without edges

<u>arXiv: 1703.06114</u>

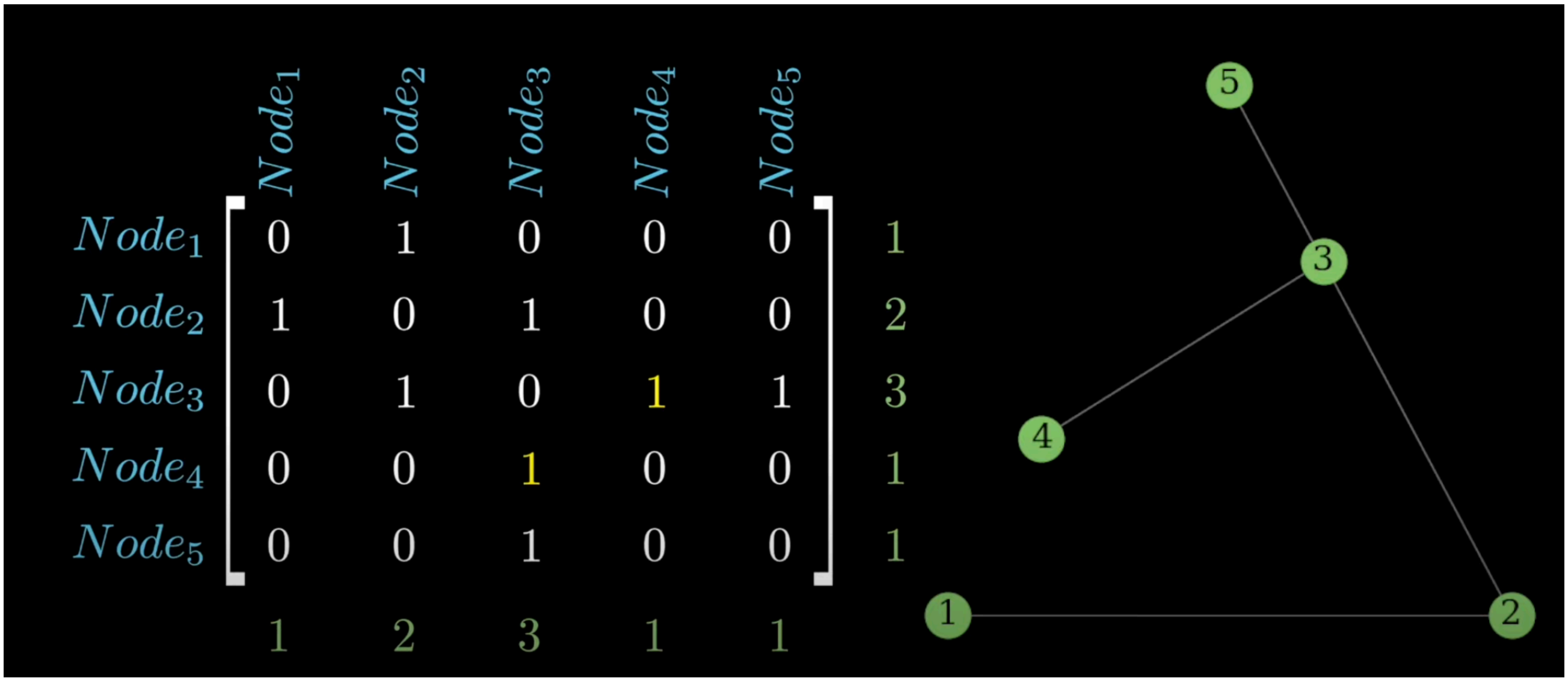
<u>arXiv:1810.05165</u>

Energy Regression Results



- Geant4 Simulation of single π^+ showers
- Condition model on position of longitudinal segmentation

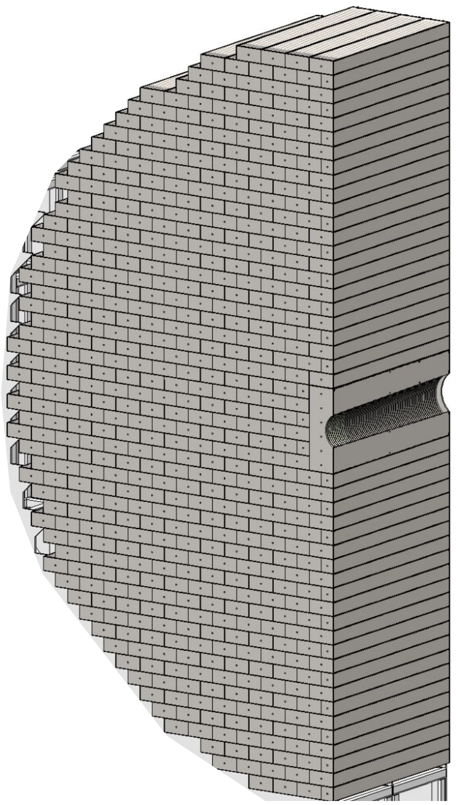
Adjacency Matrix



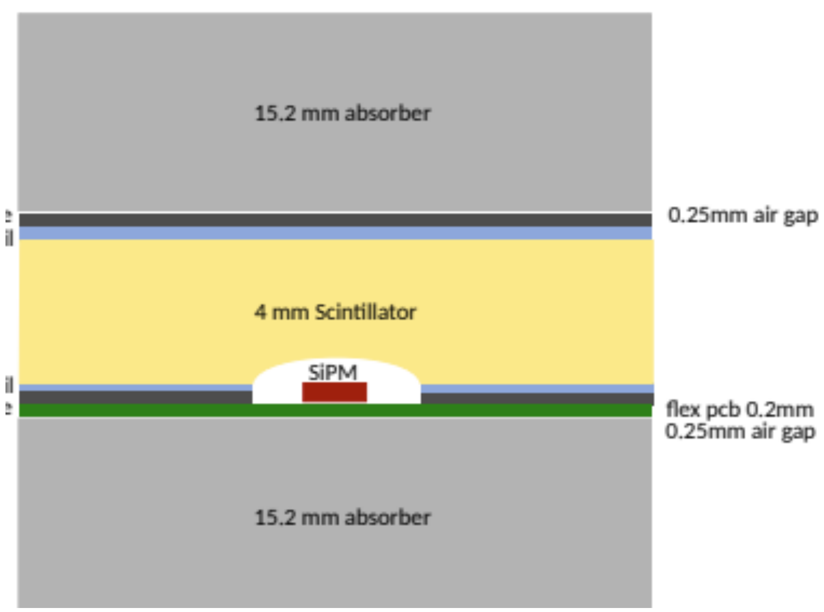
Simple Example of Adjacency Matrix for GNN

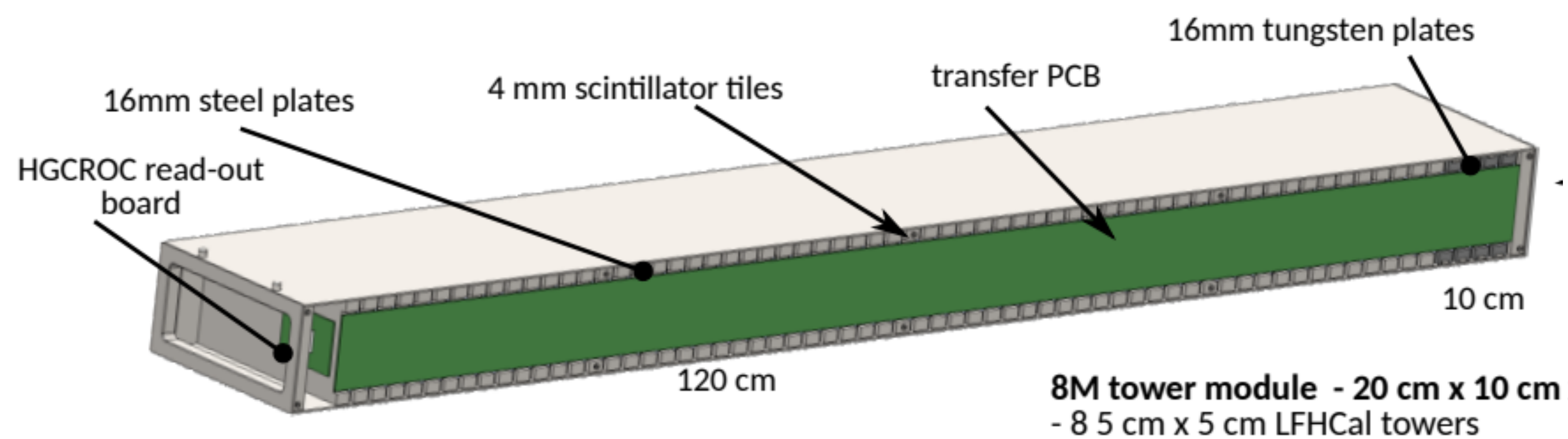
In our case, we use Keras K-Nearest neighbors algorithm in cartesian coordinates

Forward HCal



- High-granularity iron-scintillator calorimeter
- Forward region, 1.2 < η < 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

Observable Motivation

1. Probes soft gluon radiation $S(g)$
   - Soft gluon radiation can be the primary contribution to asymmetry for certain kinematics
   - Asymmetry is Perturbative, test pQCD calculations

2. May represent a vital reference for other signals, in particular TMD PDF measurements
   - Large interest in Lepton-Jet Correlations to probe TMDs
   - In TMD factorization framework, one can factorize contributions from transverse momentum dependent (TMD) PDFs and Soft gluon radiation

3. Observable is sensitive to gluon saturation phenomena, potentially measurable at the EIC

$\langle \cos(n\phi) \rangle$ for n = 1, 2, 3