ML-based neutron reconstruction in the HGND

14th BM@N Collaboration Meeting, JINR

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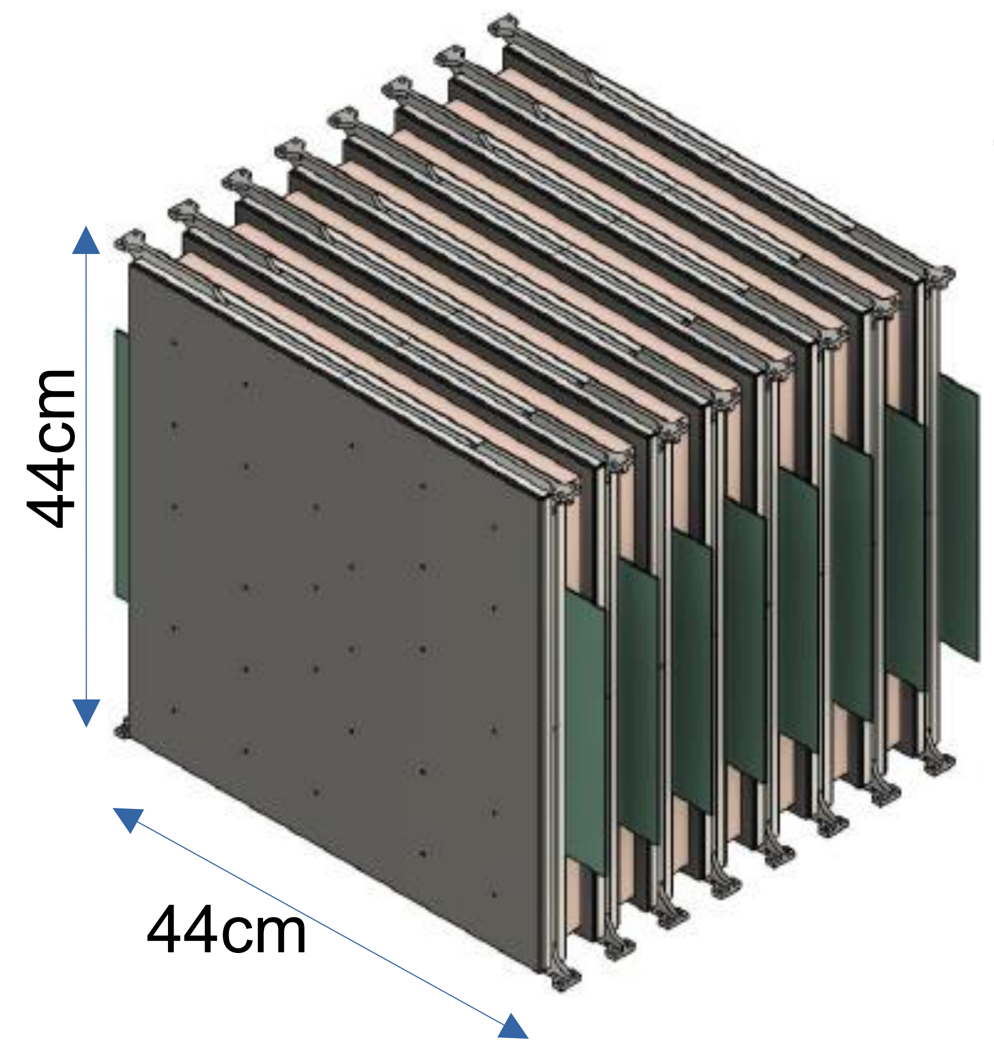
on behalf of the HGND group

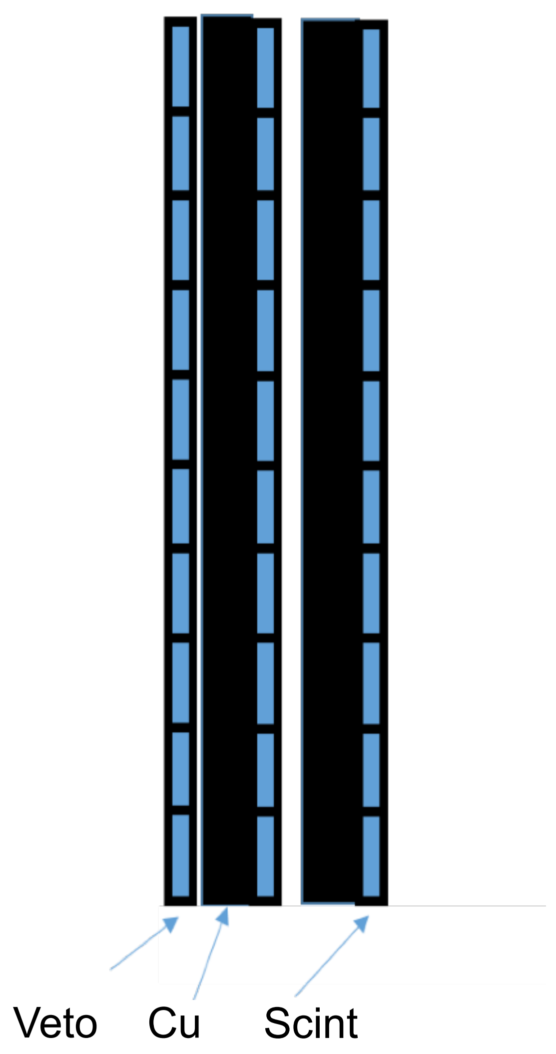
14.05.2025

LAMBDA • HSE

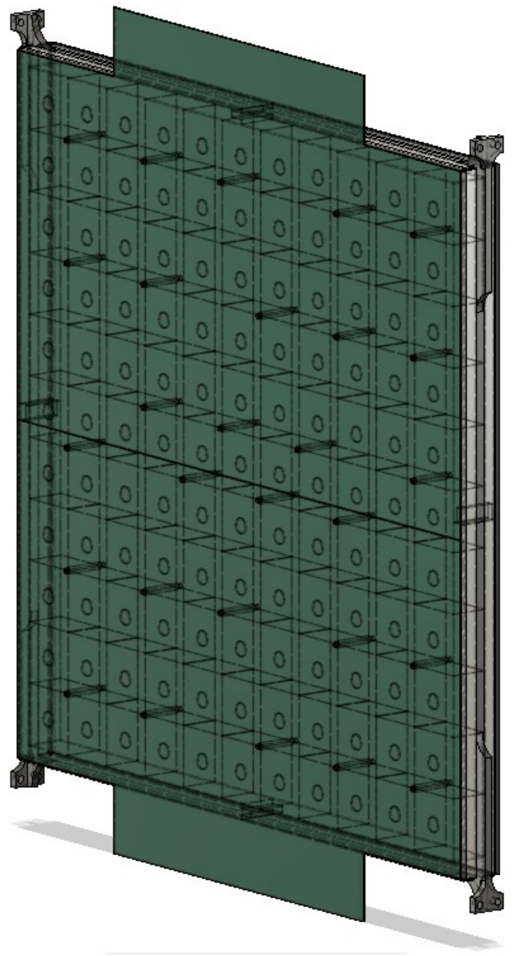
Highly granular time-of-flight neutron detector (HGND)

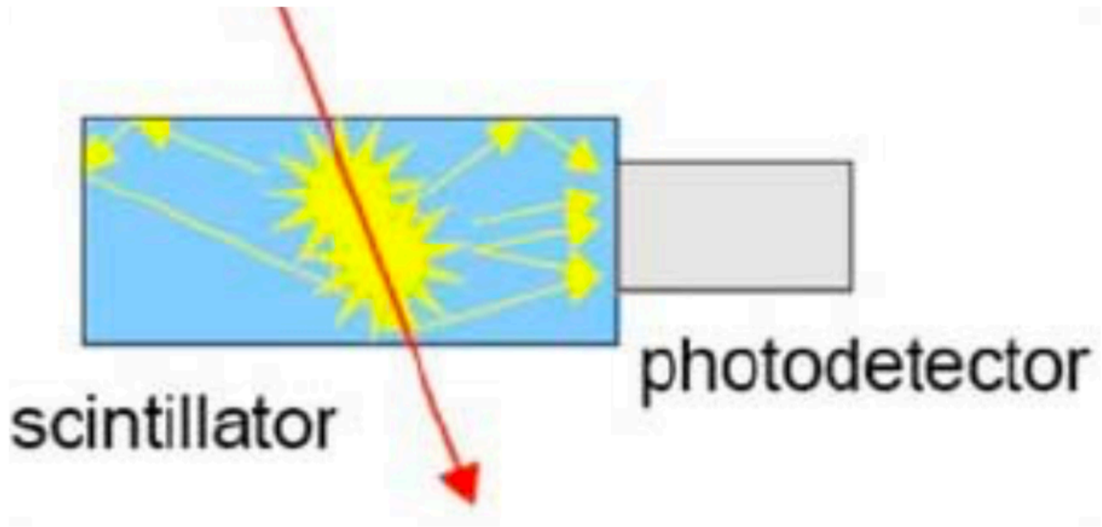


Longitudinal structure



Active layer

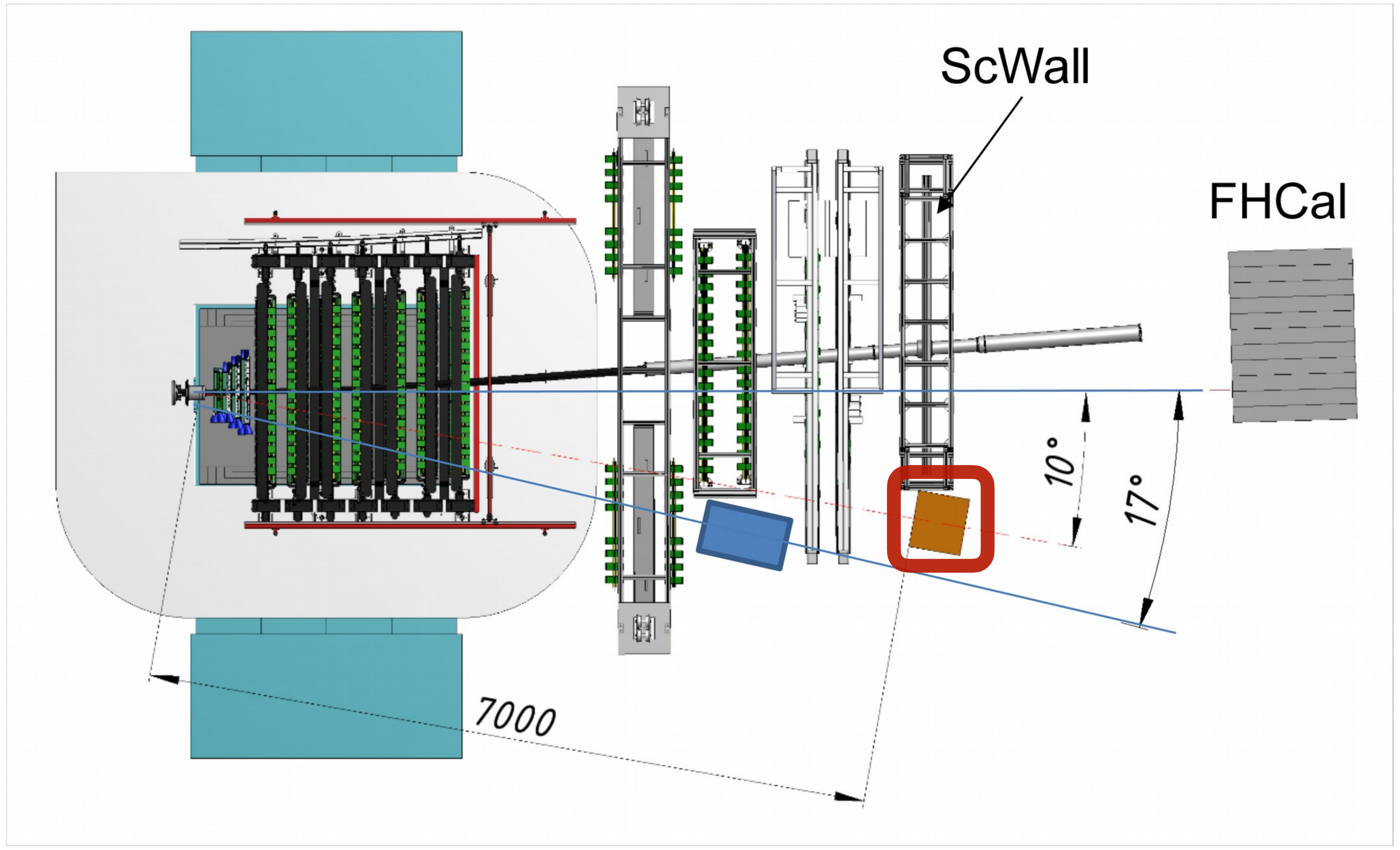


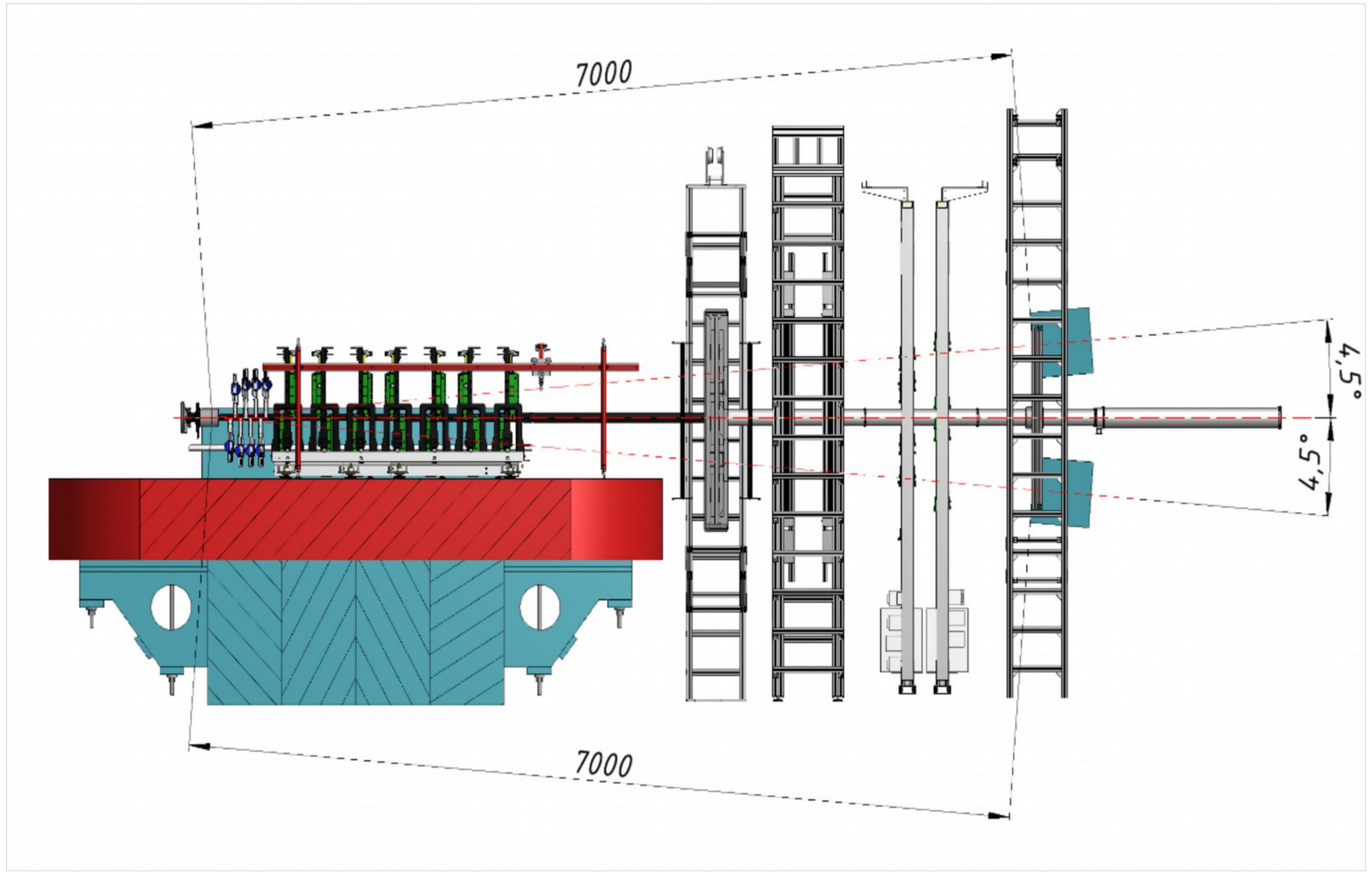


- (2x) 8 layers: *3cm Cu (absorber)* + *2.5cm Scintillator + 0.5cm PCB; 1st layer — 'veto' before absorber*
  ➡Total length: ~0.5m, **~1.5 λ_{in}**
  ➡ neutron detection efficiency ~60% @ 1 GeV
  - Transverse size: **44x44 cm²**
  - *11x11 scintillator cell grid*

- scintillator cells:
  - size: 4x4x2.5 cm^3,
  - **total number of cells: 968 (x2)**
  - individual readout by SiPM
  - expected time resolution per cell: ~150 ps

Detector Setup and Simulations





- HGND sub-detectors are located at **10º to the beam** axis at **~7m from the target**
- Monte-Carlo event simulations:
  - **3 AGeV Bi+Bi** DCM-QGSM-SMM model + Geant4 v11.2.0 QGSP_BERT
  - **~1M events**

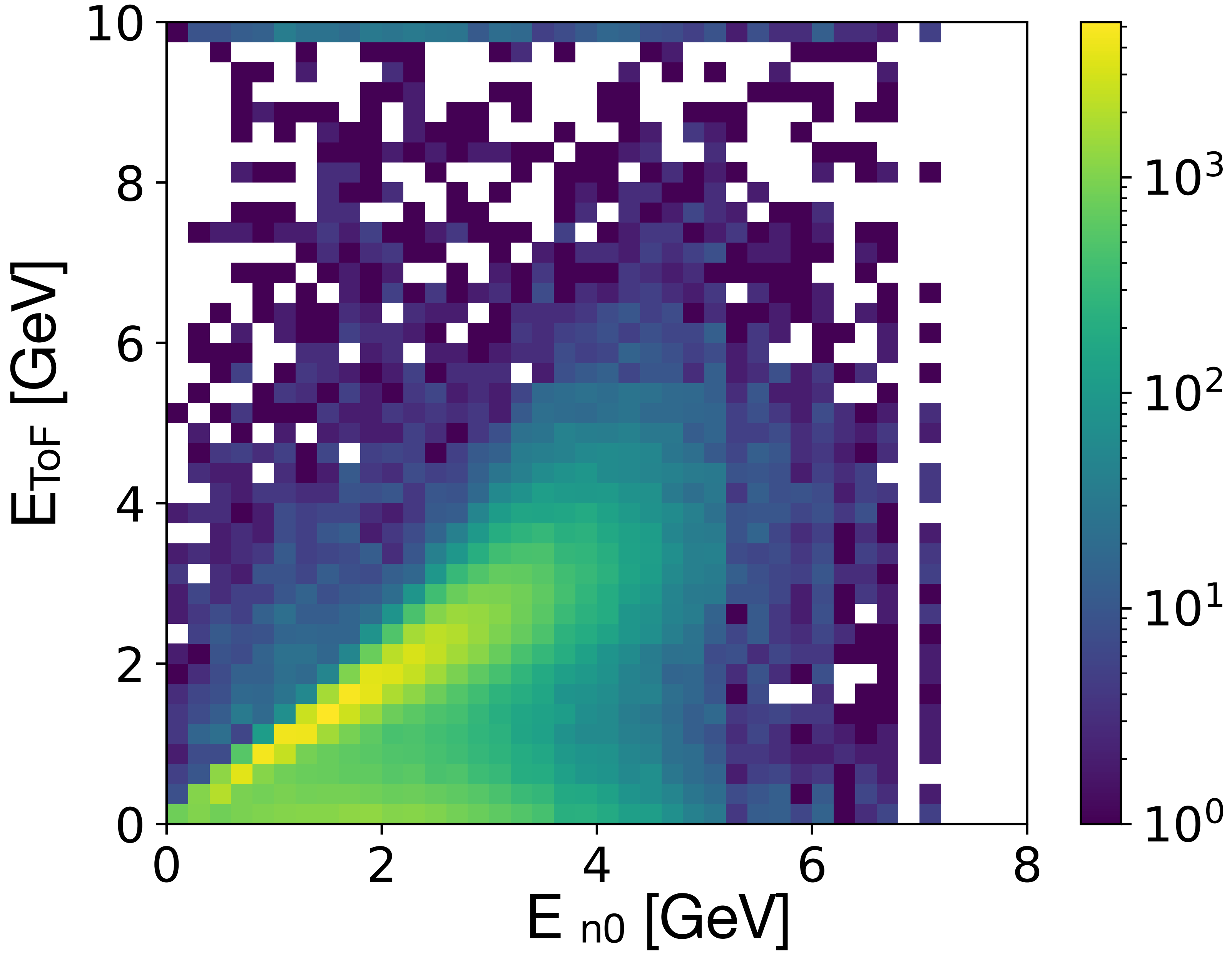
Hit Level Information

- E_{dep} > 3 MeV ~ 0.5 MIP
- **ToF energy** for *n^0* hypothesis:

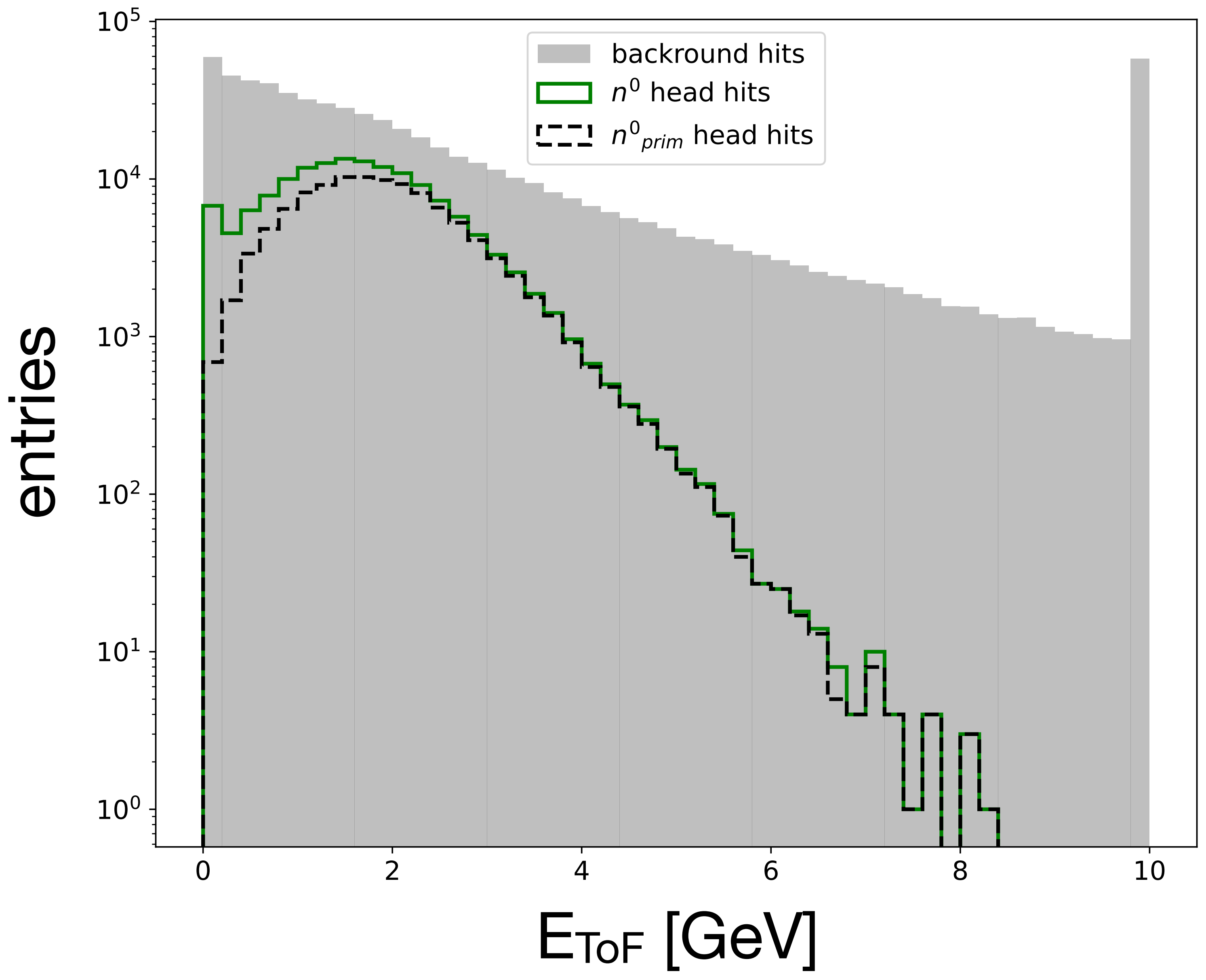
$$E_{ToF} = m_n\left(\frac{1}{\sqrt{1-\beta^2}} - 1\right)$$

  - $t_{hit}+\mathcal{N}(0,\sigma = 150\text{ps})$
  - hits with E_{ToF}>10GeV are set to 10 GeV
- Each hit is linked with corresponding surface MC particle
- Prompt neutron deposition selected by $\delta(E_{ToF}) < 0.35$
  - other hits - background
- Primary neutrons are selected by MotherID=-1

ToF energy for primary neutron hits



Hit E_{ToF} distributions

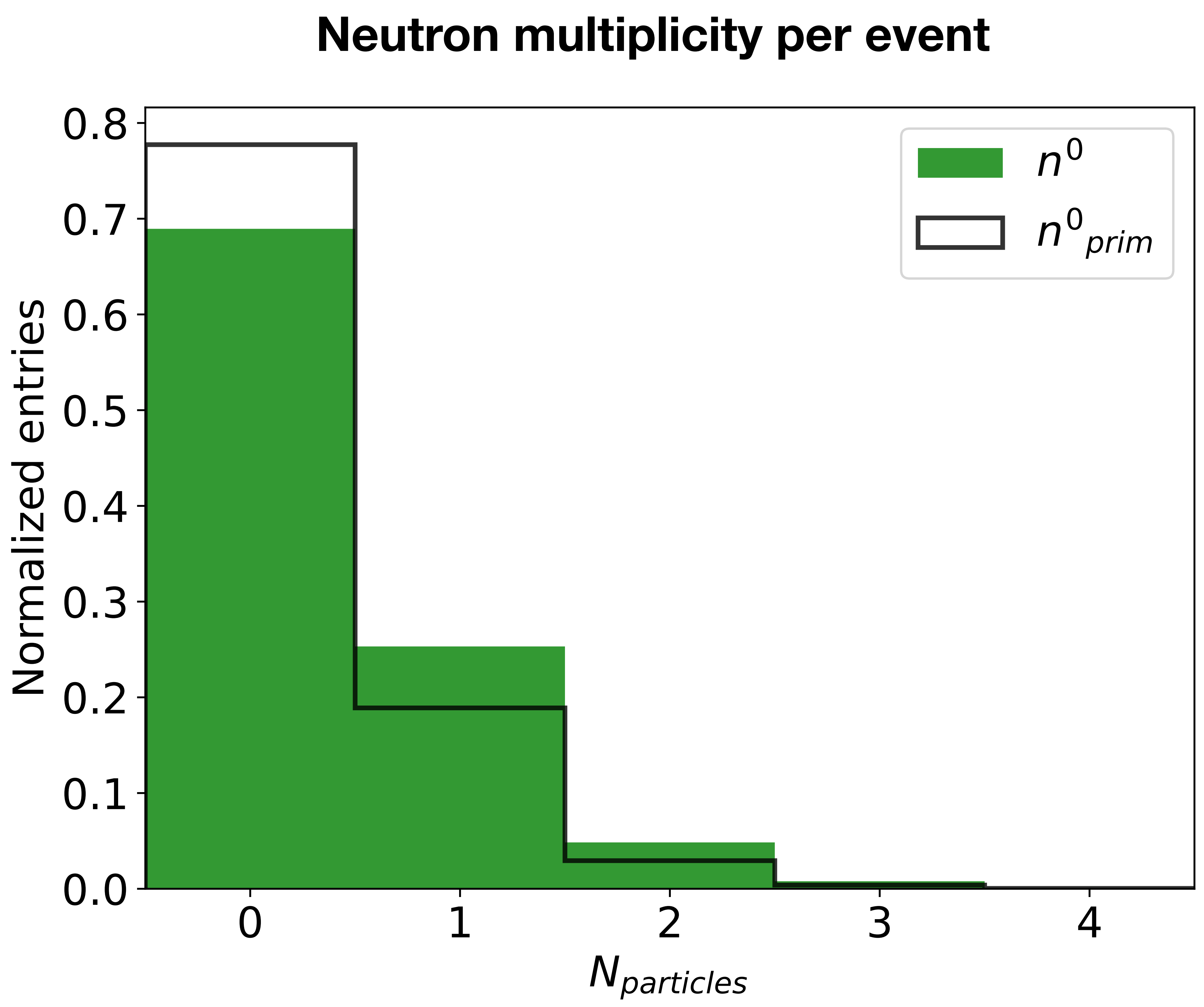


- Underestimation - neutron shower development
- Overestimation - background contributions in the same hits

  ➡More precise labelling is under development

Neutron Multiplicity

- Multiplicity counts require
  - existence of prompt hit with $\delta(E_{ToF}) < 0.35$
  - $E_{n0} > 0.1$ GeV
- Distributions normalised to number of events with energy deposition
  ➡Neutron detection efficiency is not discussed
- Reconstruction algorithm has to deal with neutron multiplicities > 1



Graph Neural Networks (GNN)

Why Graph Neural Networks:

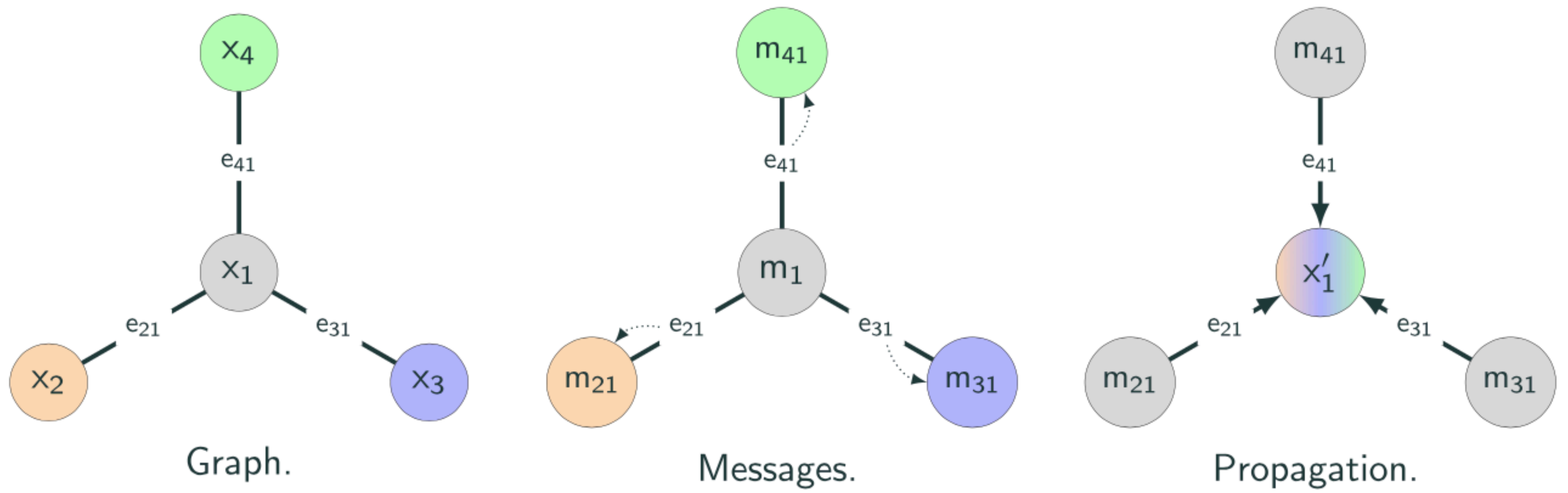
- Natural vector event representation
  - Detector cell hits as graph nodes
- Easily applied to sparse data with variable input size
  - Typically we have signal only in small fraction of sensors
- Captures event structures
- Increasing number of successful implementations in HEP

HEPML-LivingReview

Message passing architecture

Key idea:

- Edges propagate information between nodes in a trainable manner to encode local graph structures
- Node embeddings are then aggregated to a problem-specific value, e.g.:
  - Graph/hit class “probability” — signal/background
  - Target value — neutron energy



J. Gilmer *et al.*, “Neural message passing for quantum chemistry,” 2017.

Graph Construction

- **Nodes — hits.** Observables per hit:
  - hit coordinates: layer, row, column
  - E_{dep} > 3 MeV ~ 0.5 MIP
  - hit time + $\mathcal{N}(0,\sigma = 150\text{ps})$
  - E_{ToF}
- **Edges**
  - Predefined clustering:
    - radius graph. **R = 3.6 cells**
    - time window **1 ns**
    - cluster — isolated subgraph

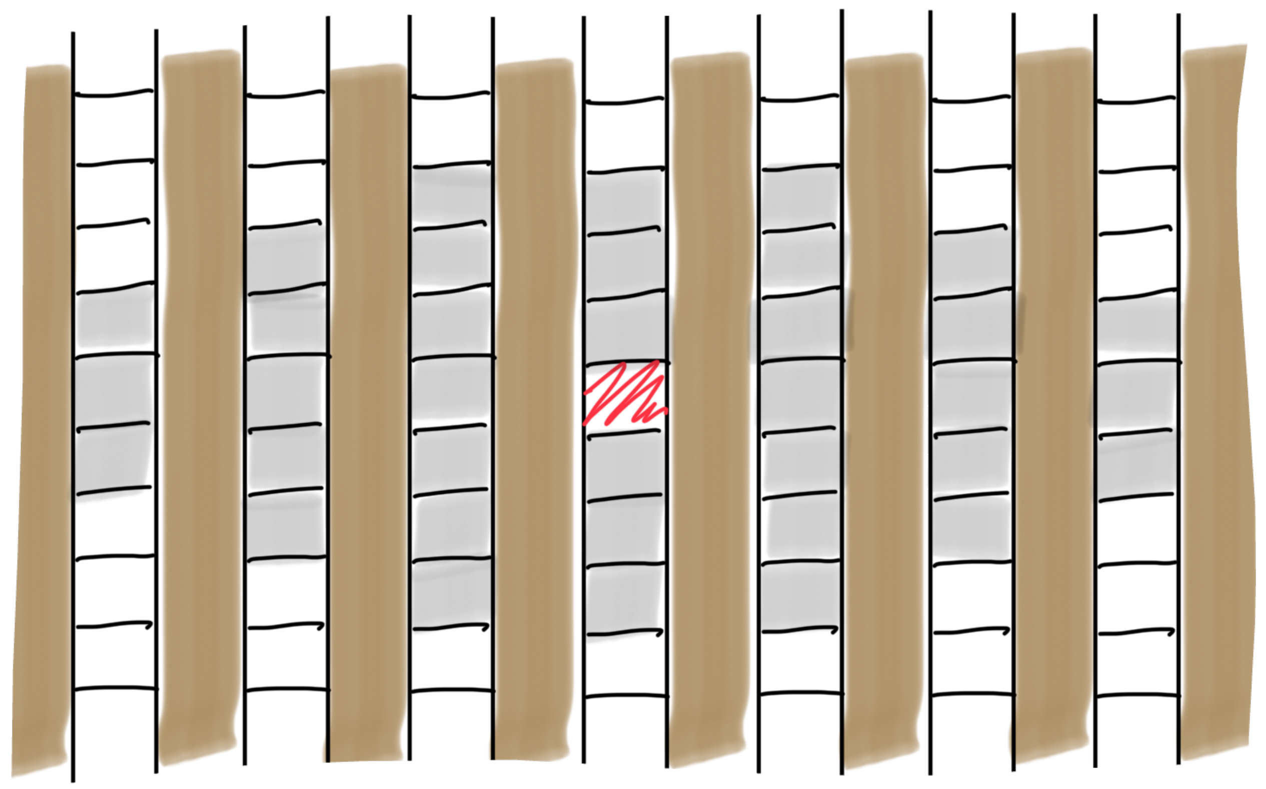
Labeling for further training

- Cluster level:
  - **Signal** cluster contains at least 1 **prompt neutron** hit
  - **Energy** of fastest neutron with prompt hit in a cluster
- Node level (additional):
  - Prompt neutron deposition
  - Connection between same MC particles

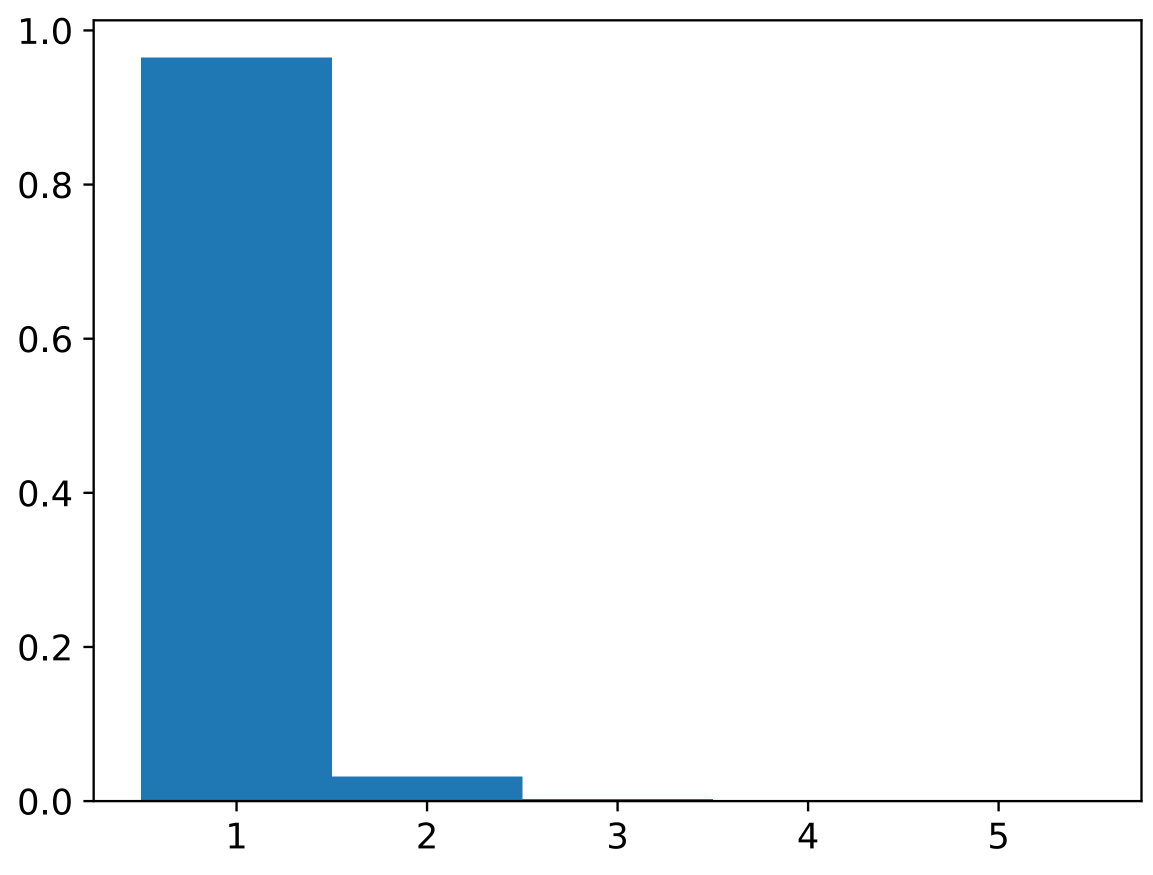
Clustering

- Soft spatial rule.
  - search radius **R = 3.6 cells**
- ~strict temporal rule
  - time window **1 ns**

➡ first guess parameters, to be optimised, included in GNN

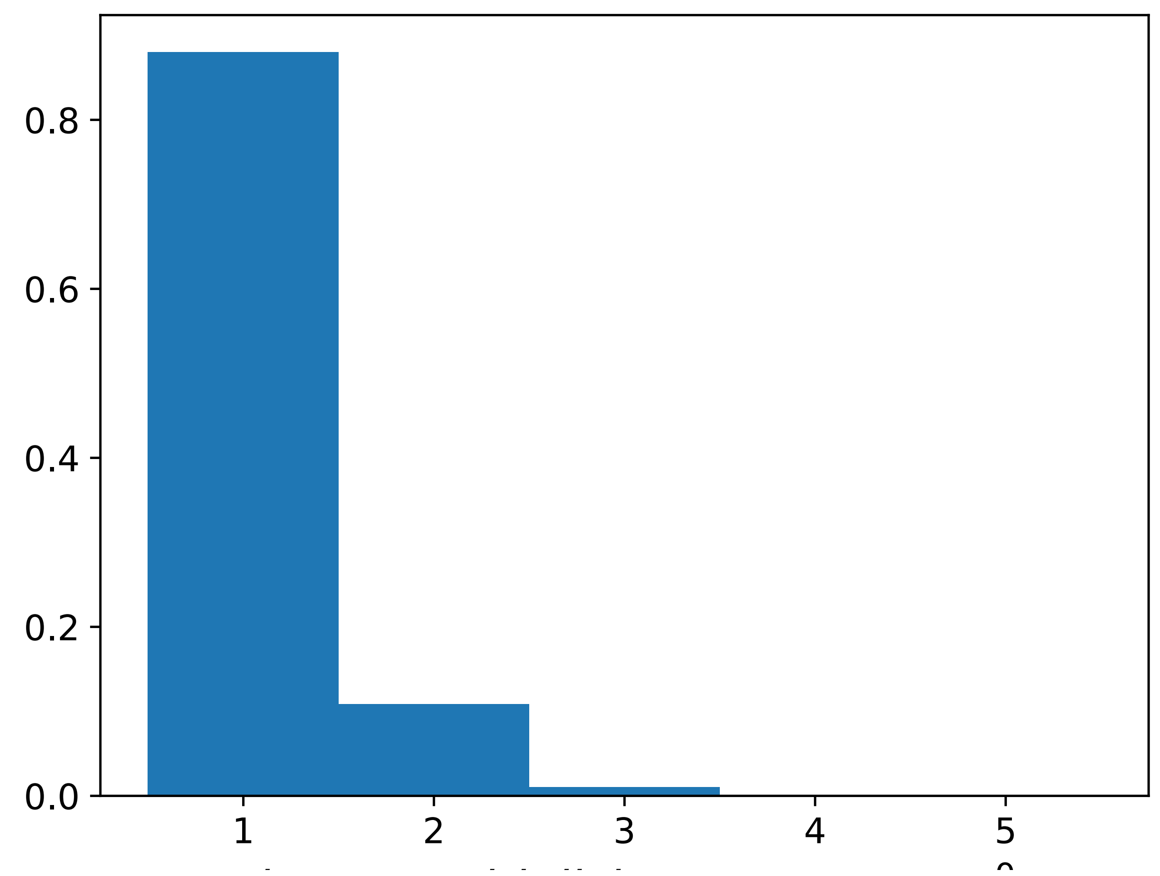


Prompt n⁰ multiplicity per signal cluster



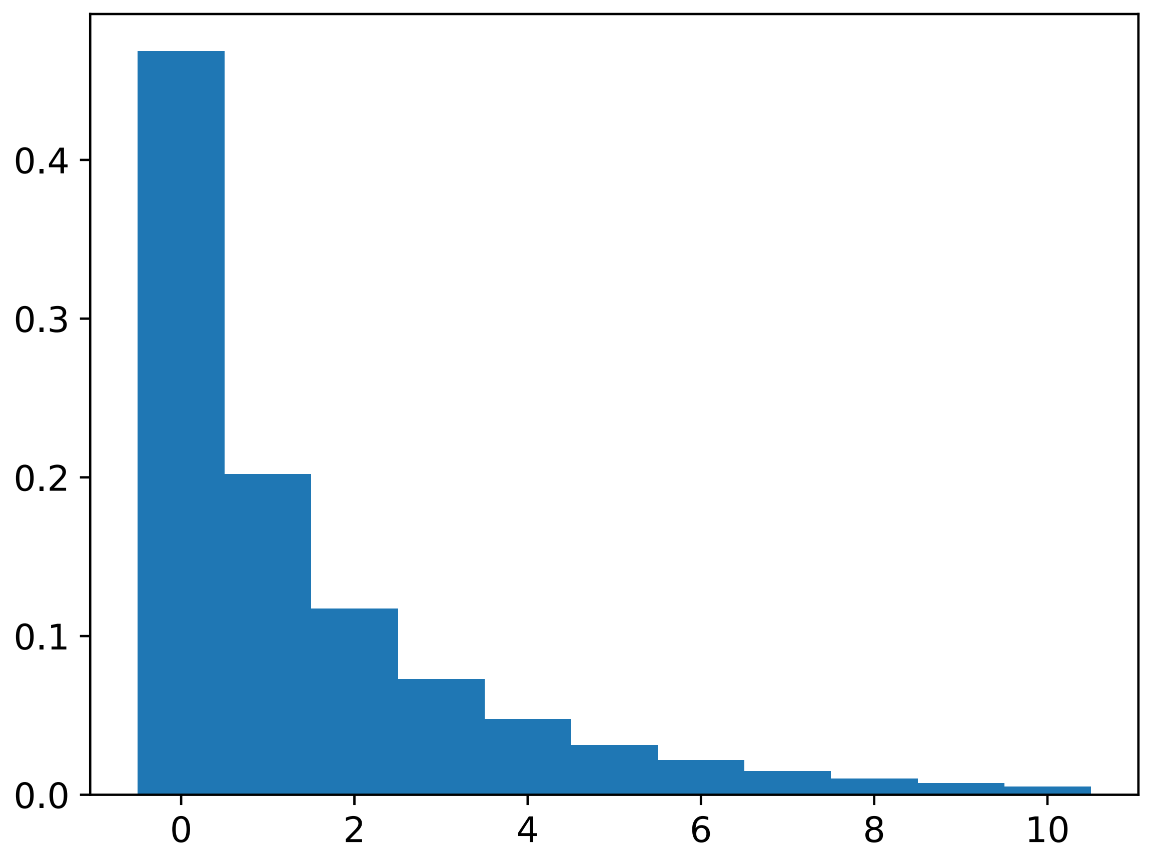
- isolation >95%

Cluster multiplicity per prompt n⁰



- prompt n⁰ splits in secondary clusters at level of <13%

Background multiplicity per signal cluster



- significant background contribution => make use of ML

GNN Model

Training objective

- **Cluster** level:
  - predict **neutron class** score
  - reconstruct expected **neutron energy**

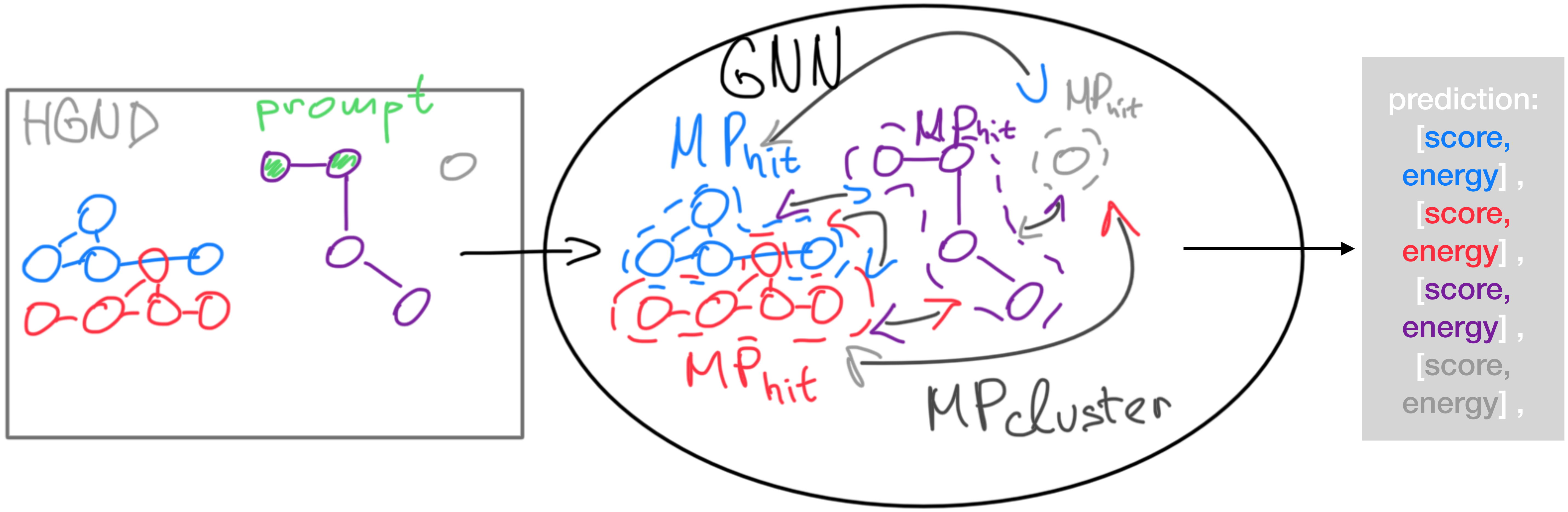
Loss function

- Binary Cross Entropy for classification
- Mean Squared Error for energy regression

$$Loss = BCE_{cluster} + MSE_{cluster}$$

GNN architecture

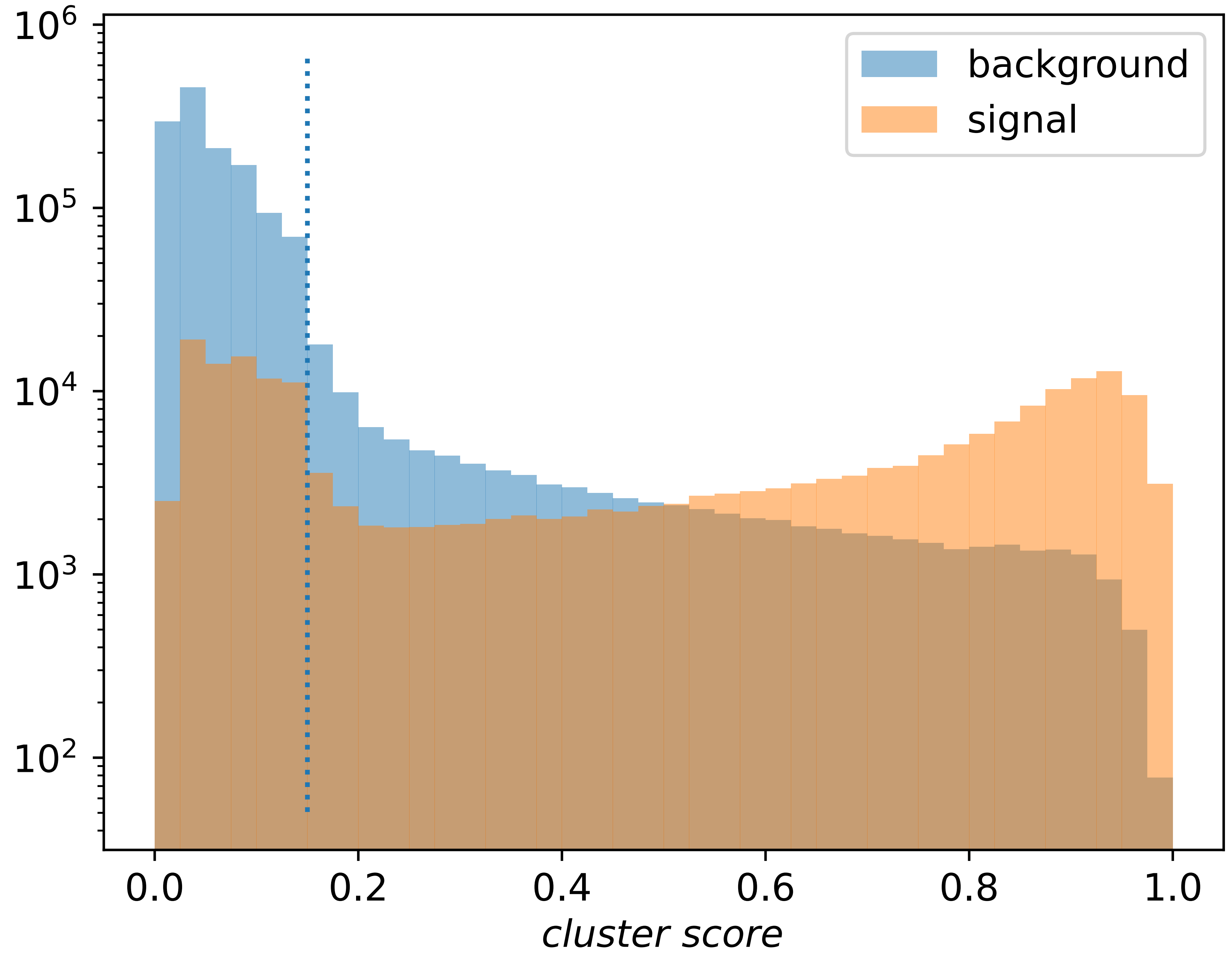
- *MP_{hit}*. Message passing layers *hit -> hit* within clusters
- Average pooling layer to aggregate *hit nodes -> cluster* node
- *$MP_{cluster}$*. Message passing layers. *cluster -> cluster*
- Cluster output**: class score, predicted energy**



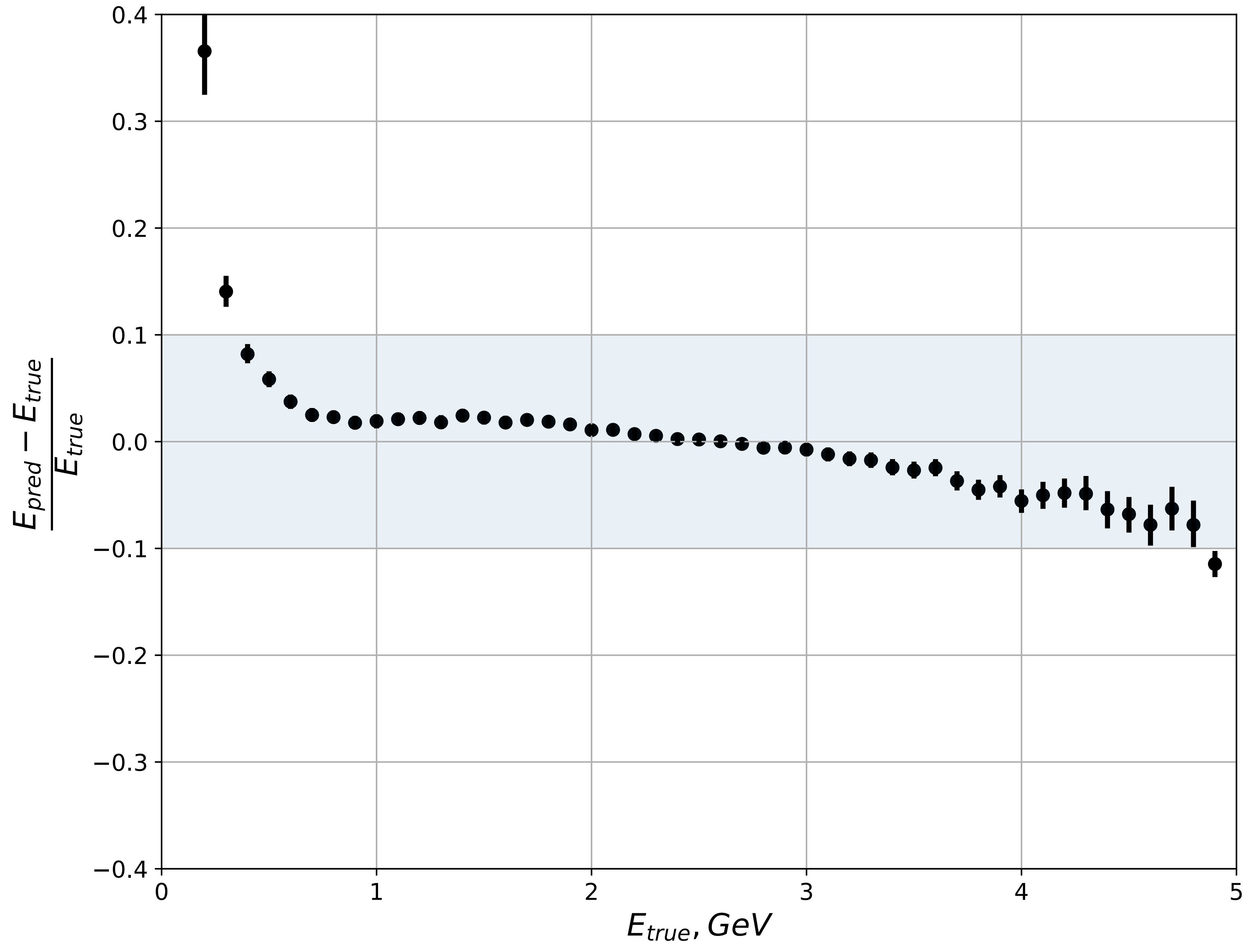
PyTorch Geometric library

Cluster Reconstruction Performance

Classifier output



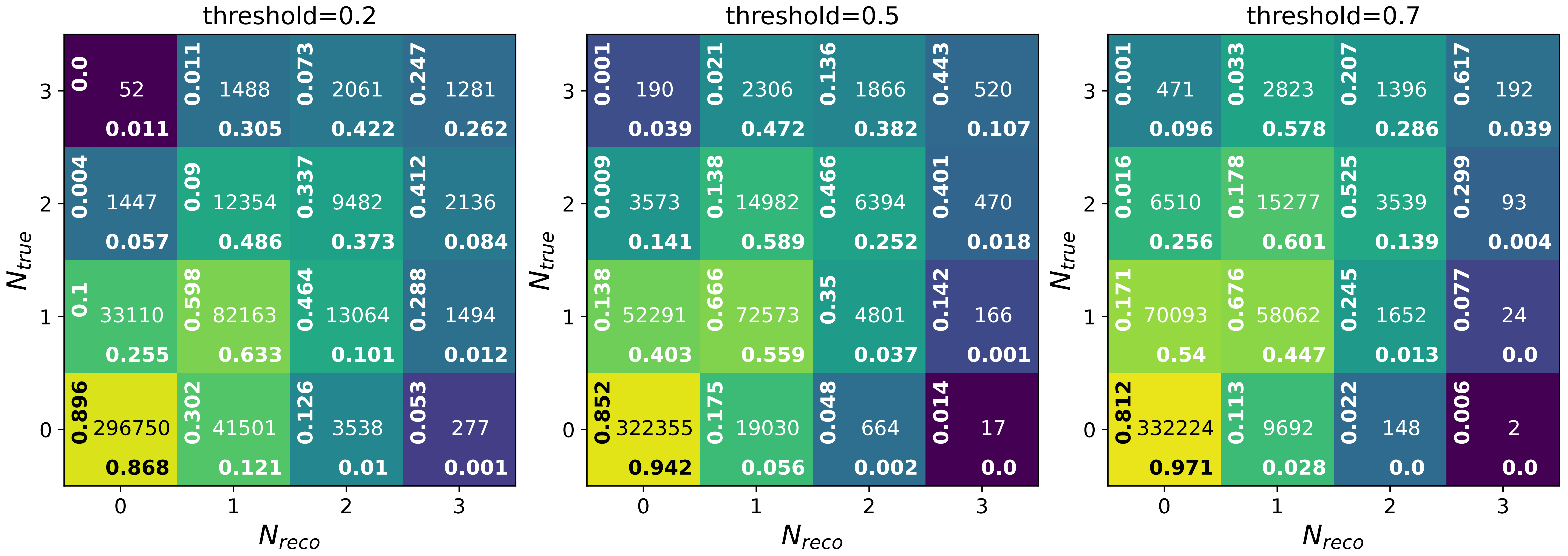
**Energy reconstruction for signal clusters.
Threshold = 0.15**



- Overall good cluster classification performance
- Bump at score ≈0.1 is caused by a technical issue for single hit clusters (more details in backup slides)
- Energy resolution ≈15%. Linearity within 10% for the most part of energy spectrum

Multiplicity Reconstruction

- Test dataset
  - 540565 events
- Selection:
  - E_{true} > 0.1 GeV
  - E_{reco} > 0.1 GeV
- 4 multiplicity classes:
  - [0, 1, 2, 3 and more]
- 3 cluster score thresholds:
  - [0.2, 0.5, 0.7]



- horizontal normalisation is related to efficiency
  - efficiency decreases for higher true multiplicities and higher score threshold
- vertical normalisation is related to purity
  - high score threshold allows to separate up to 3 ‘good’ neutron clusters

Event Level Performance

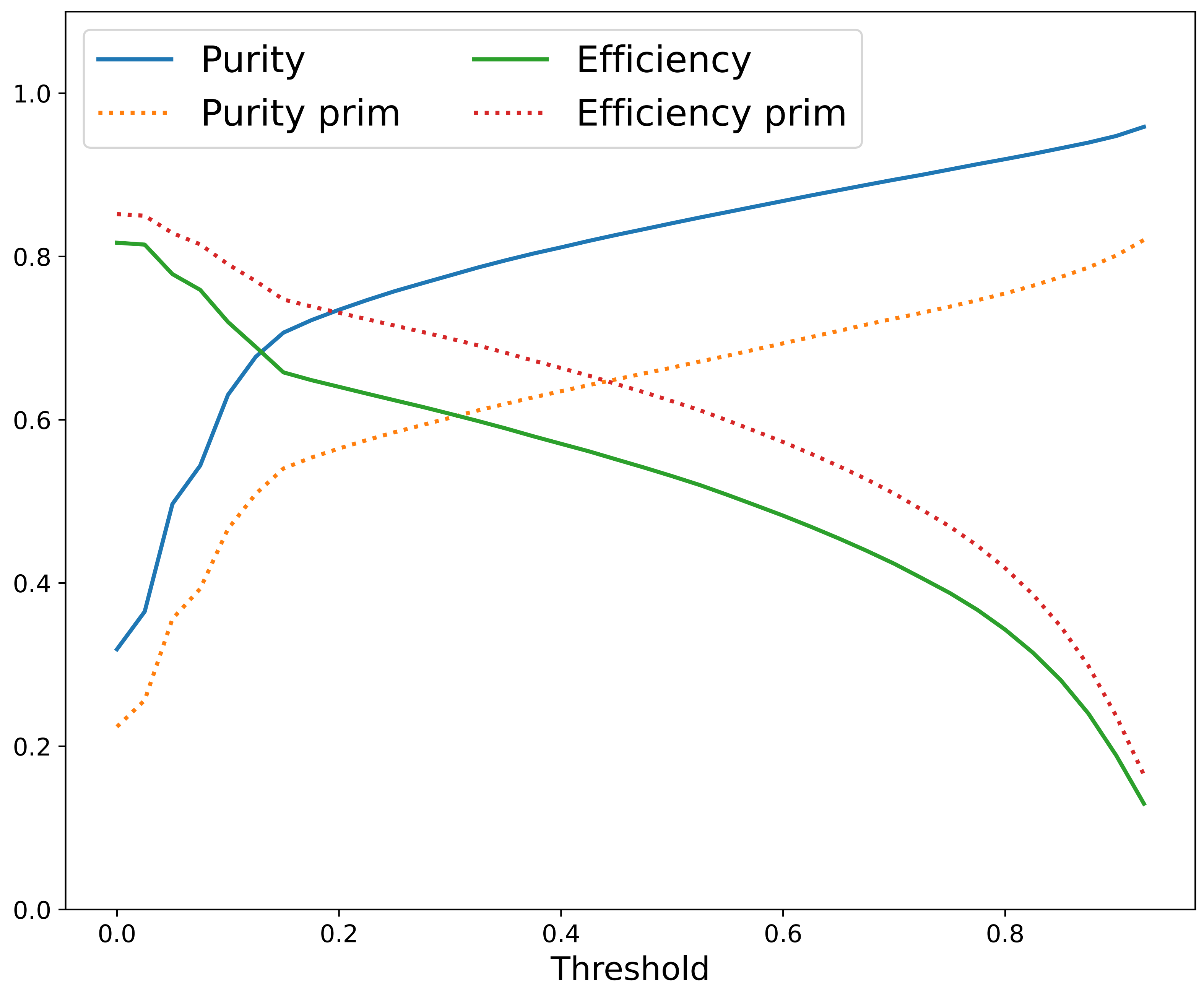
Single neutron reconstruction approach:

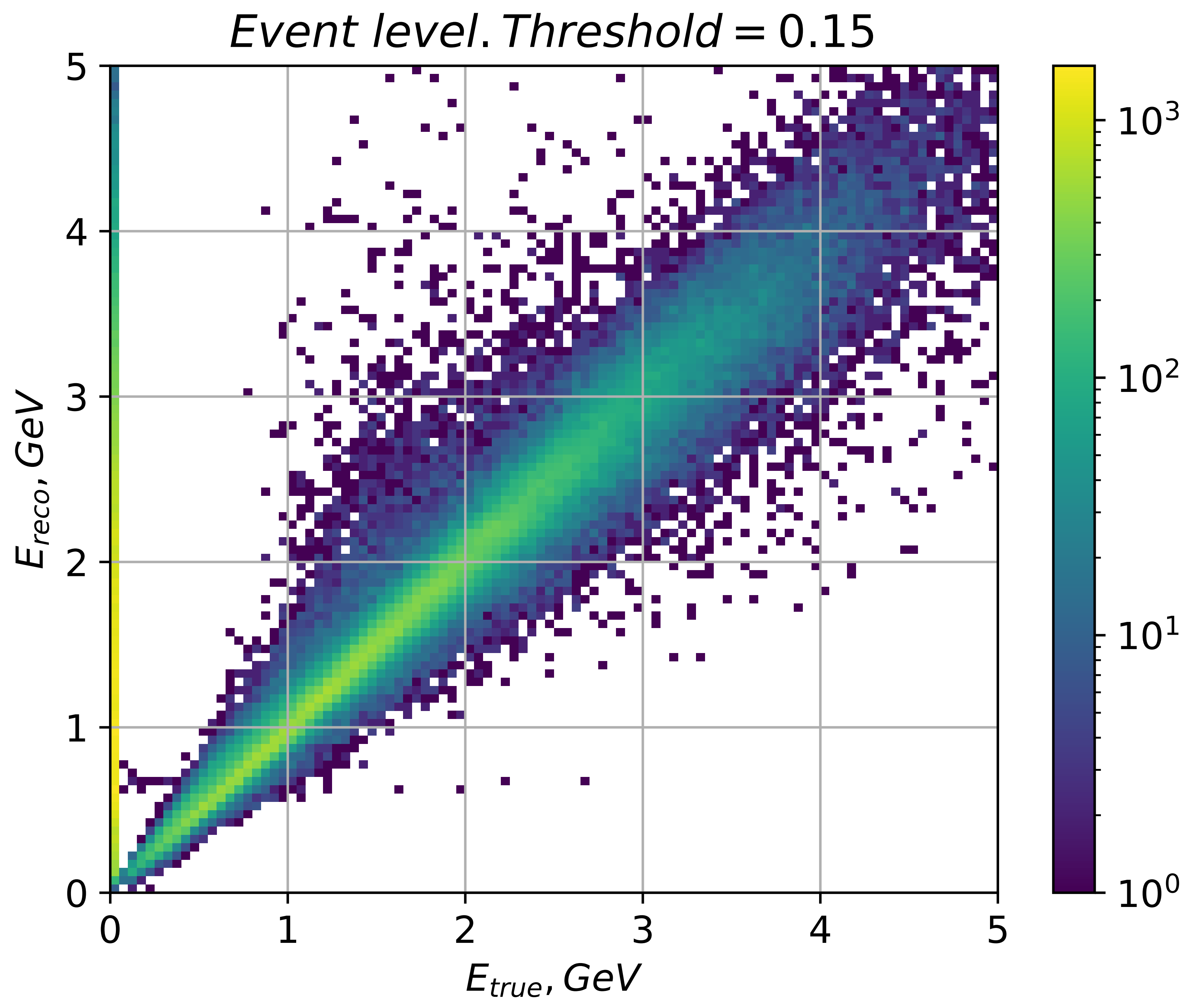
- Select best cluster in event by cluster score
- Varying threshold for event score and calculate neutron reconstruction efficiency and purity

Event classification performance vs score threshold

$$Purity = \frac{N_{reco\ true}}{N_{reco\ all}}$$

$$Efficiency = \frac{N_{reco\ true}}{N_{neutrons}}$$

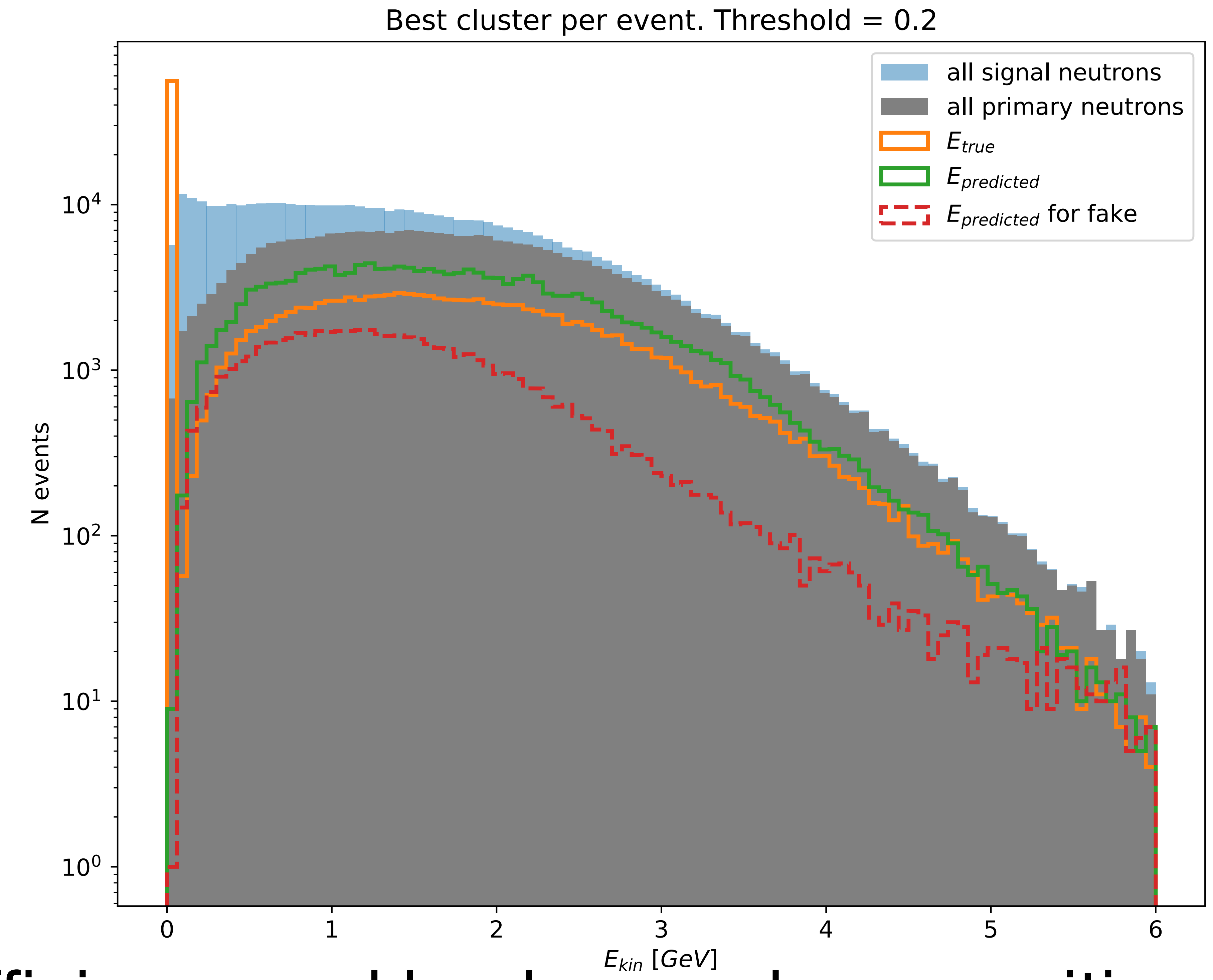


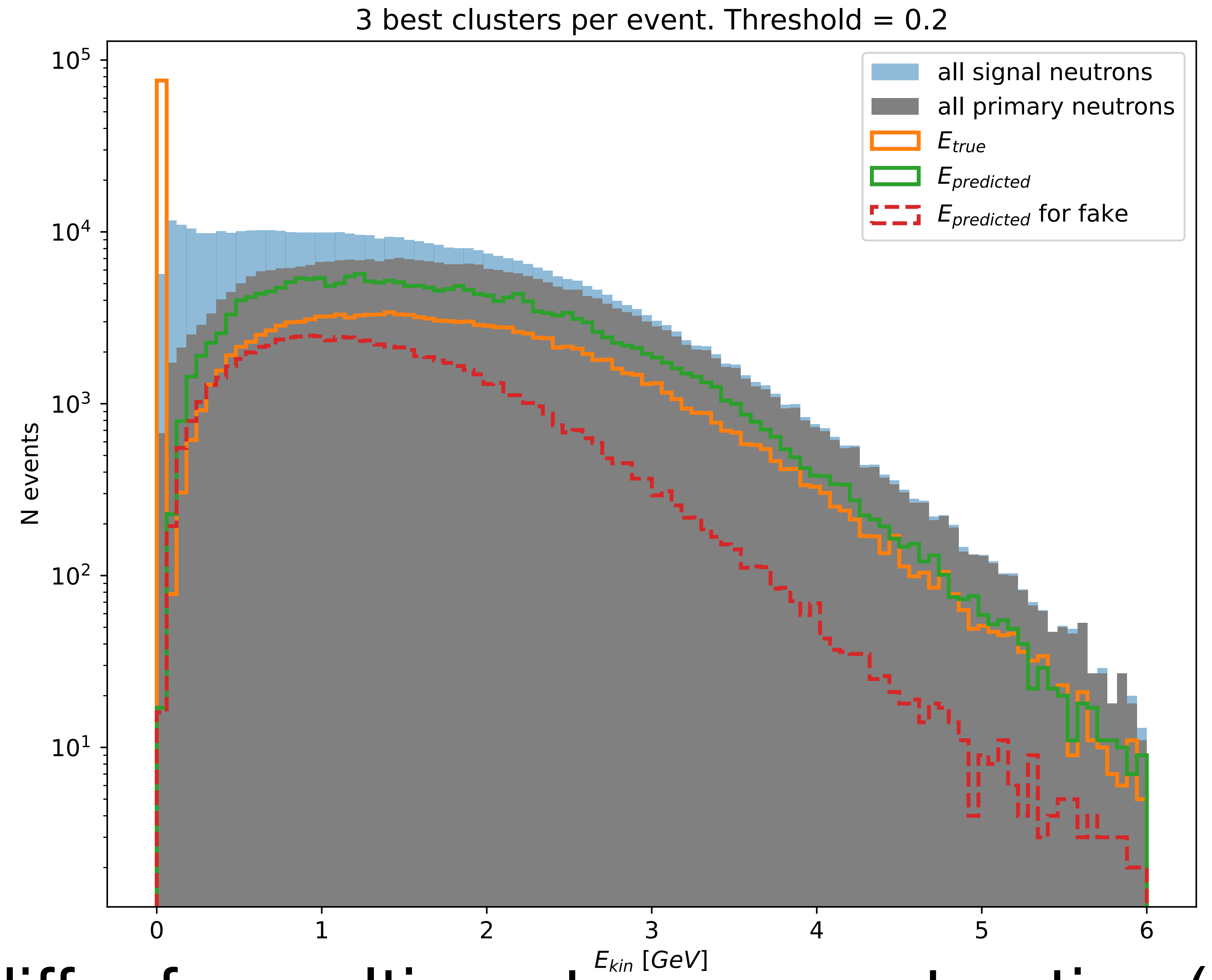


- Minimum working point is ~0.2 cluster score threshold

Neutron Energy Spectra

Example of resulting neutron energy spectra at fixed score threshold





- Efficiency and background composition slightly differ for multi-neutron reconstruction (more examples in backup slides)
  - Possible neutron double counting to be corrected for multi-neutron reconstruction
- Optimal reconstruction scenario will be optimised on end-to-end physics performance simulation

Summary & Outlook

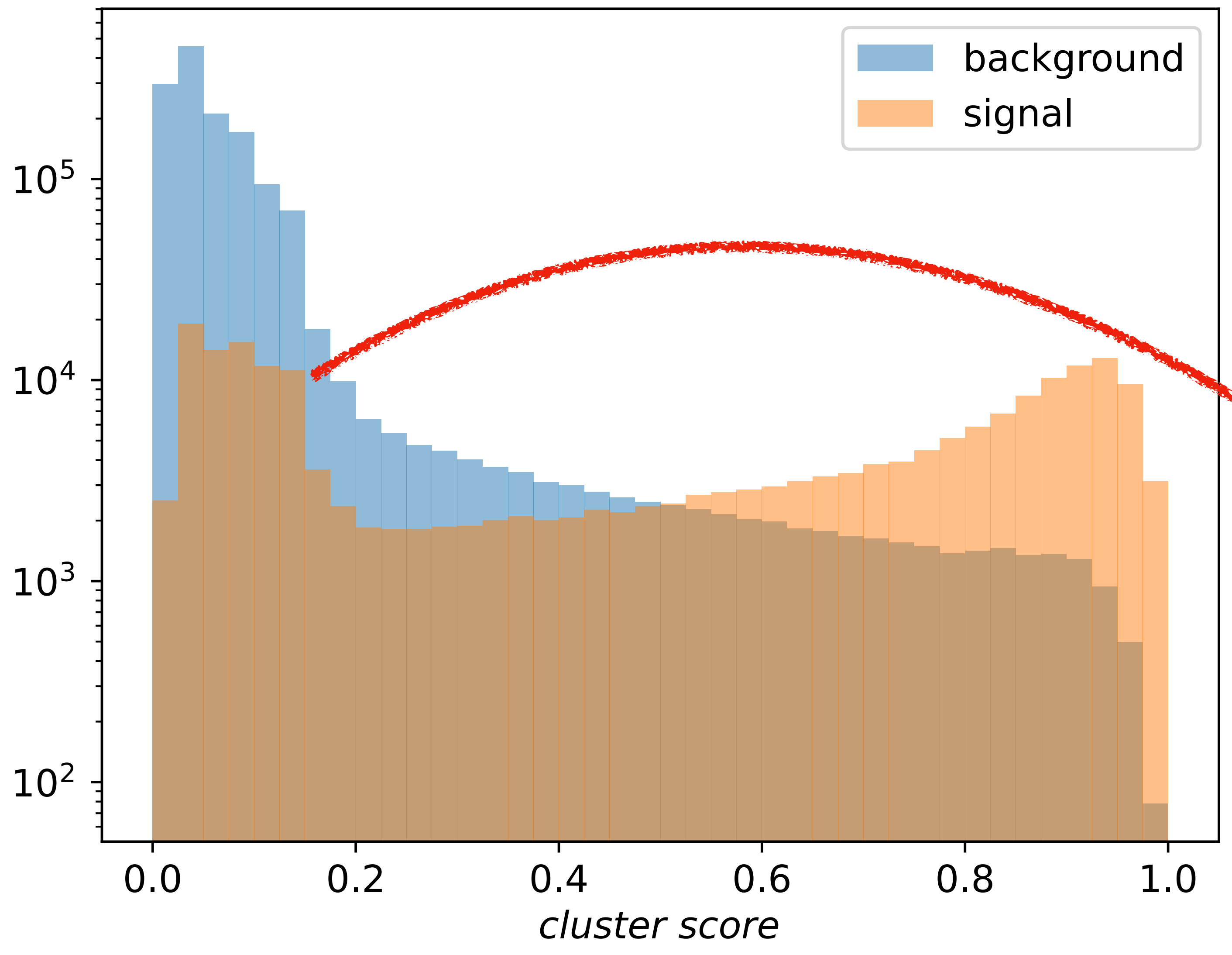
- Status of the Graph Neural Network-based neutron reconstruction algorithm in the HGND is presented
- Neutron multiplicities >1 are addressed by applying pre-defined clustering
  - Promising results have been achieved

- GNN model is under development
  - Implementation of cluster recombination in the model architecture
  - Implementation of differentiable clustering instead of rule-based
- Detailed study of background contributions is ongoing

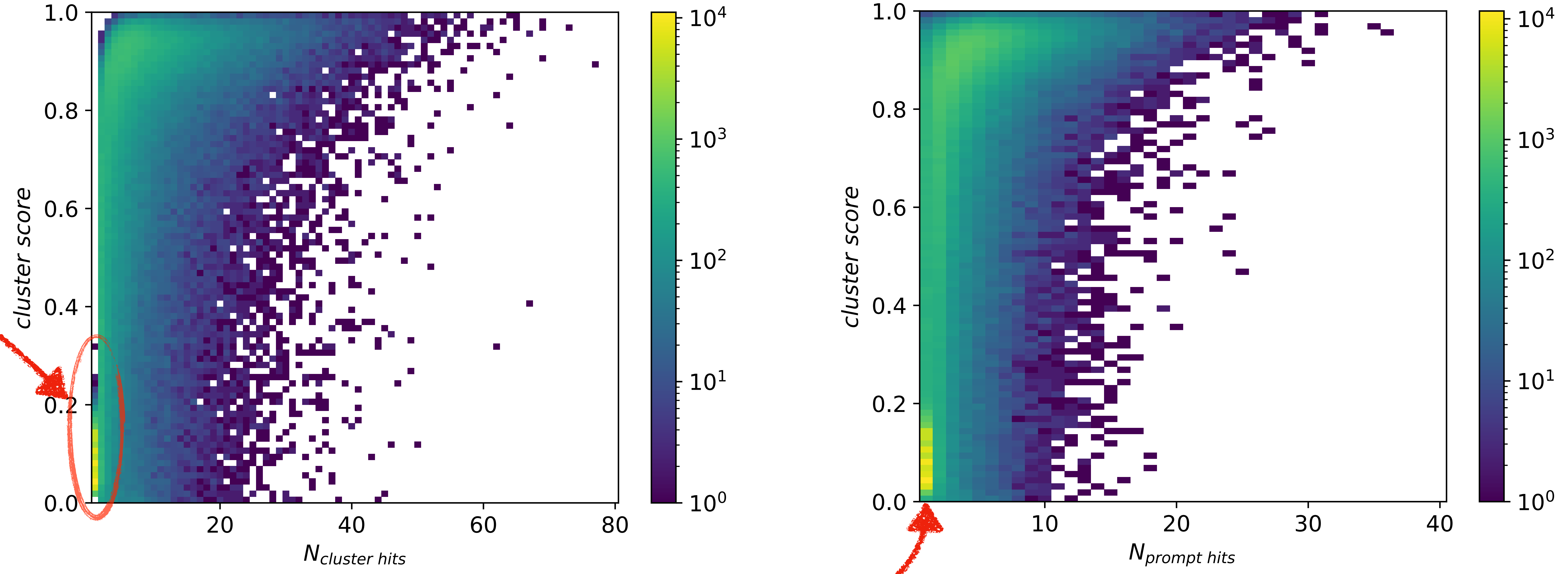
- Final physics performance and optimal reconstruction procedure will be defined using parametrised simulations

Backup

Cluster Reconstruction Performance

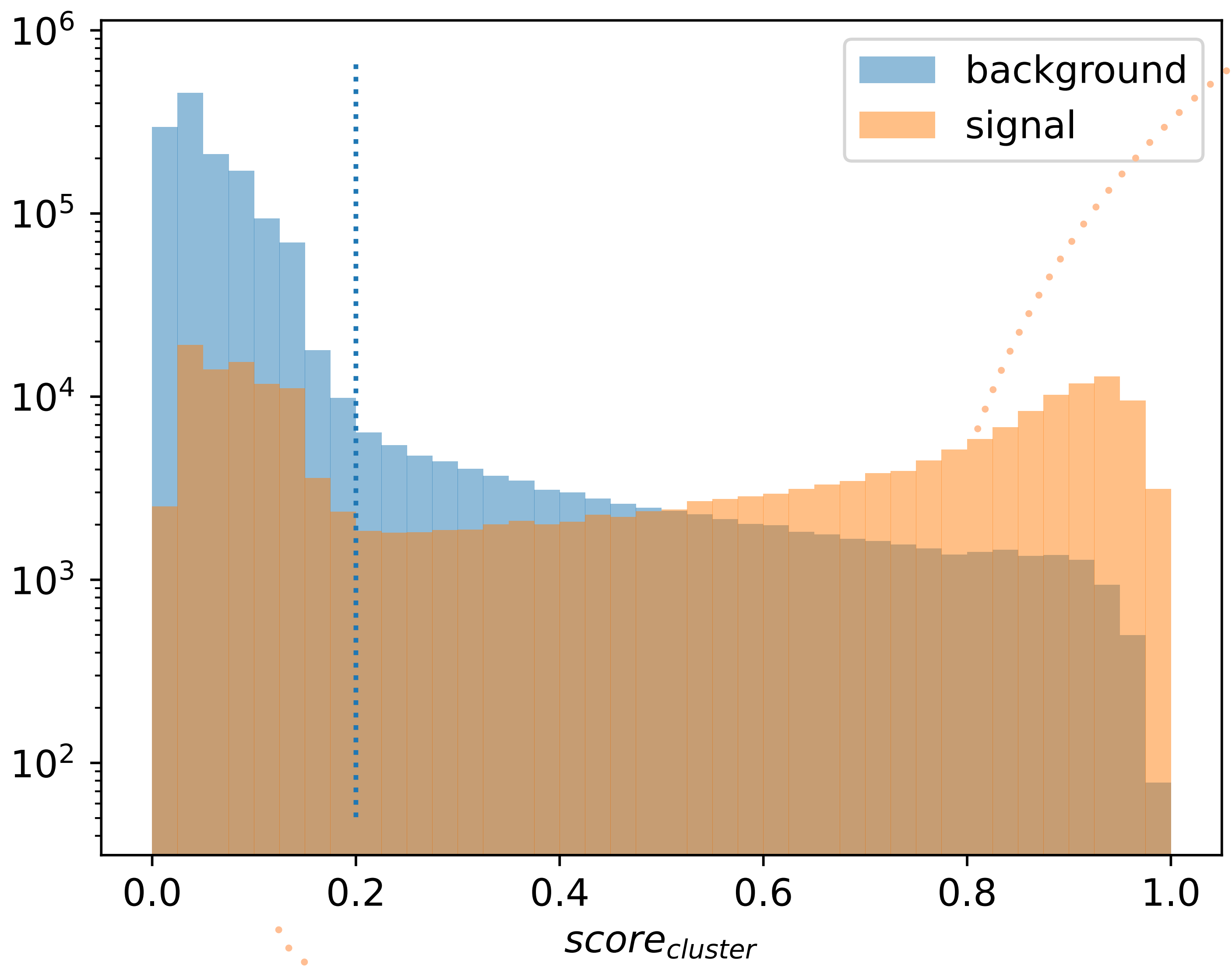


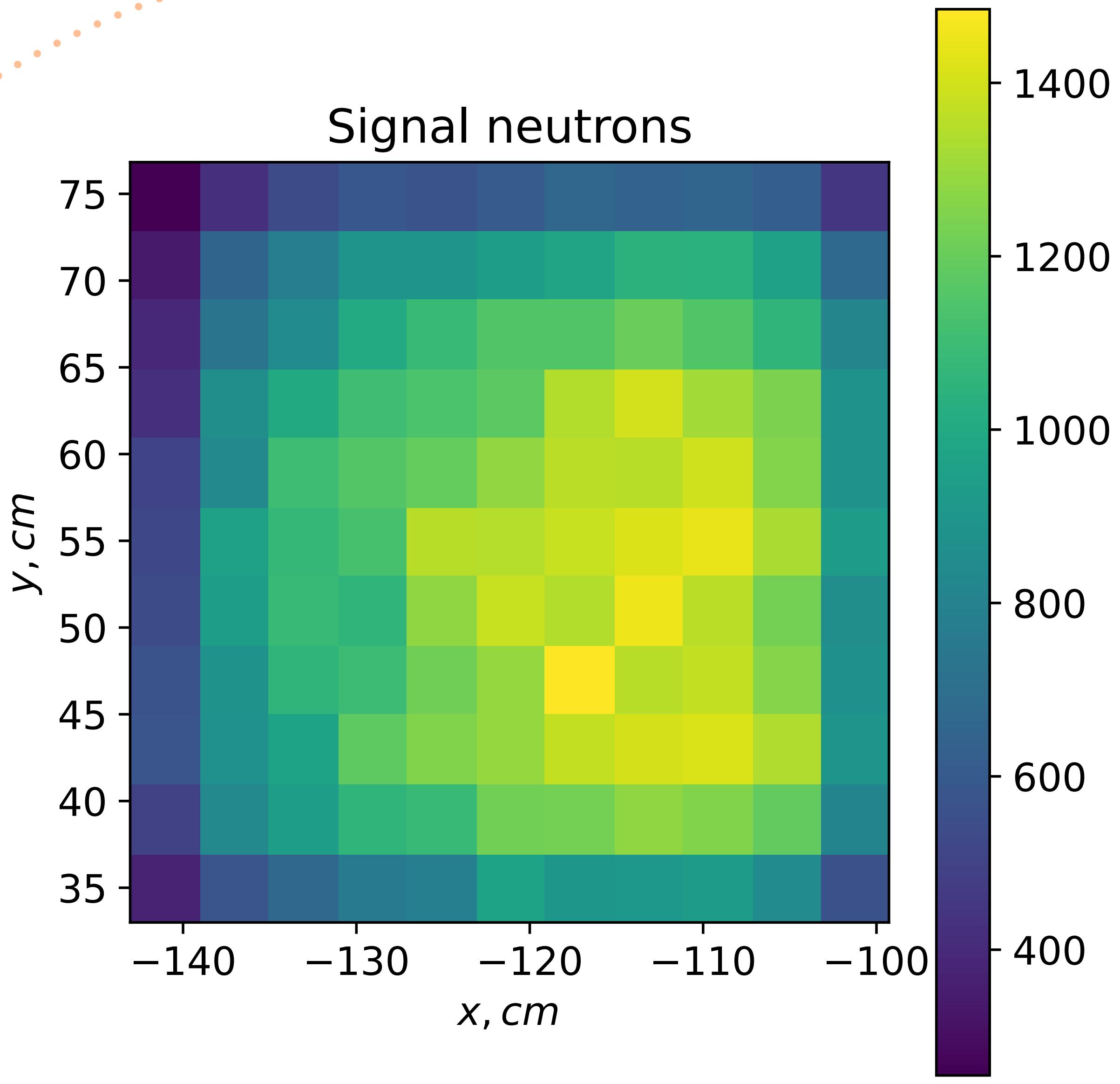
signal clusters



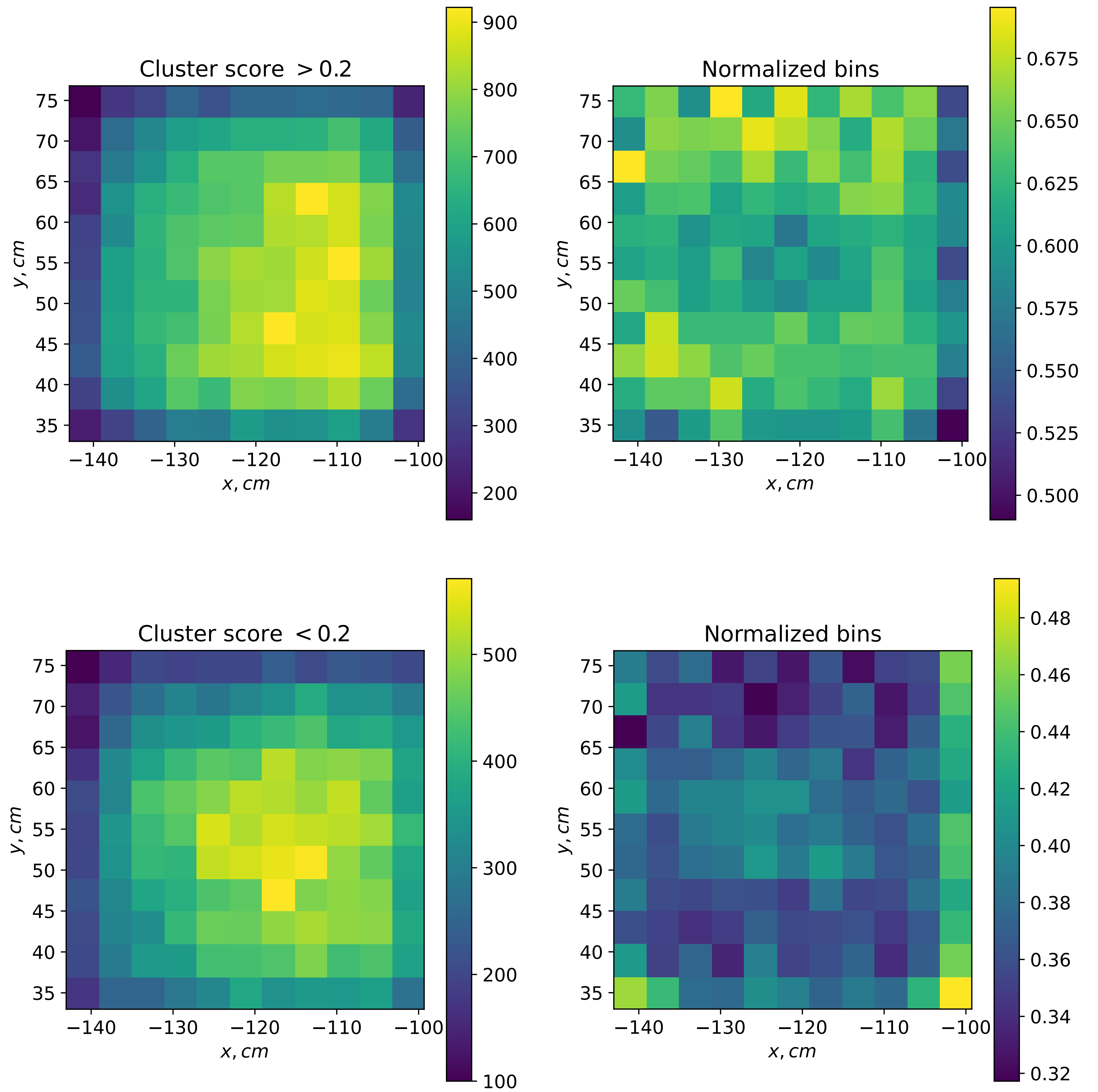
- Bump at score ≈0.1 corresponds to single node clusters
- GNN model is able to reconstruct clusters with a single prompt n0 hit for clusters with at least 2 nodes
- graph construction is done without self-loops => single node subgraphs participate in message passing in a fishy way
  - ➡ solution will be to test self-loops or other connections

Cluster Reconstruction Performance





Signal neutrons passing top front wall



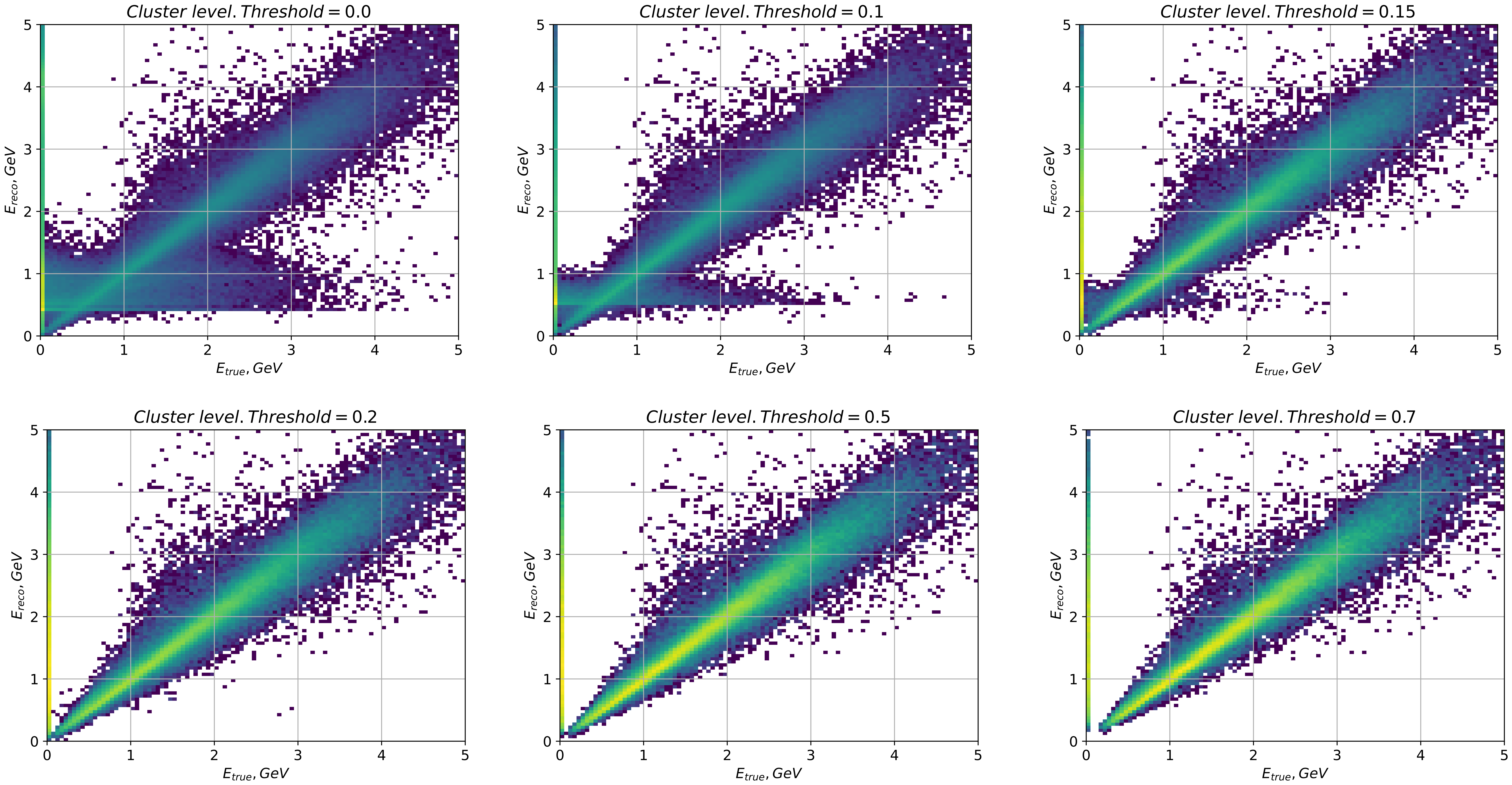
- Low score signal clusters have a notable corespondency to a beam-pipe-side neutrons

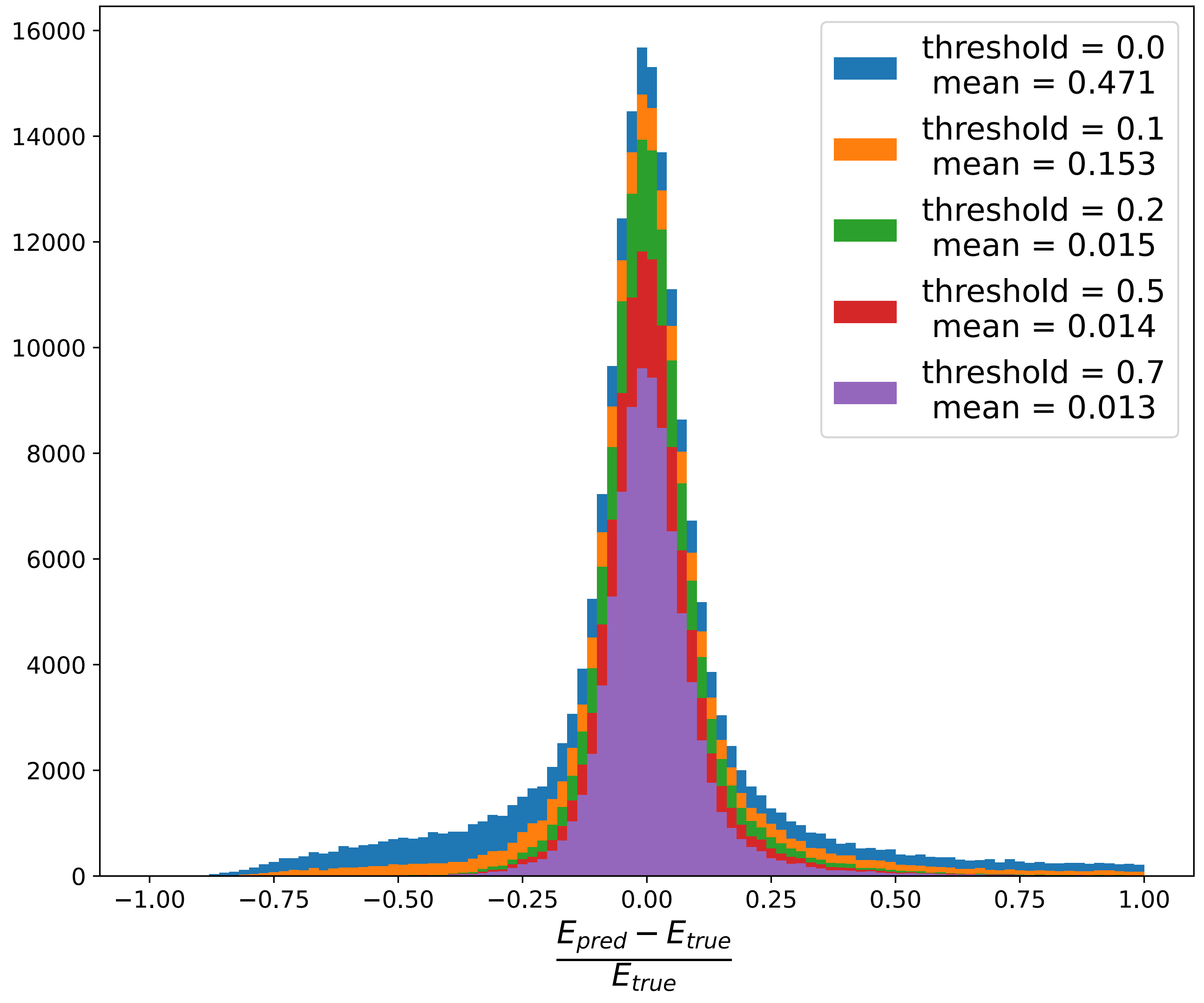
Multiplicity Reconstruction

‘0’ vs ‘1’ vs ‘2’ vs ‘3 and more’

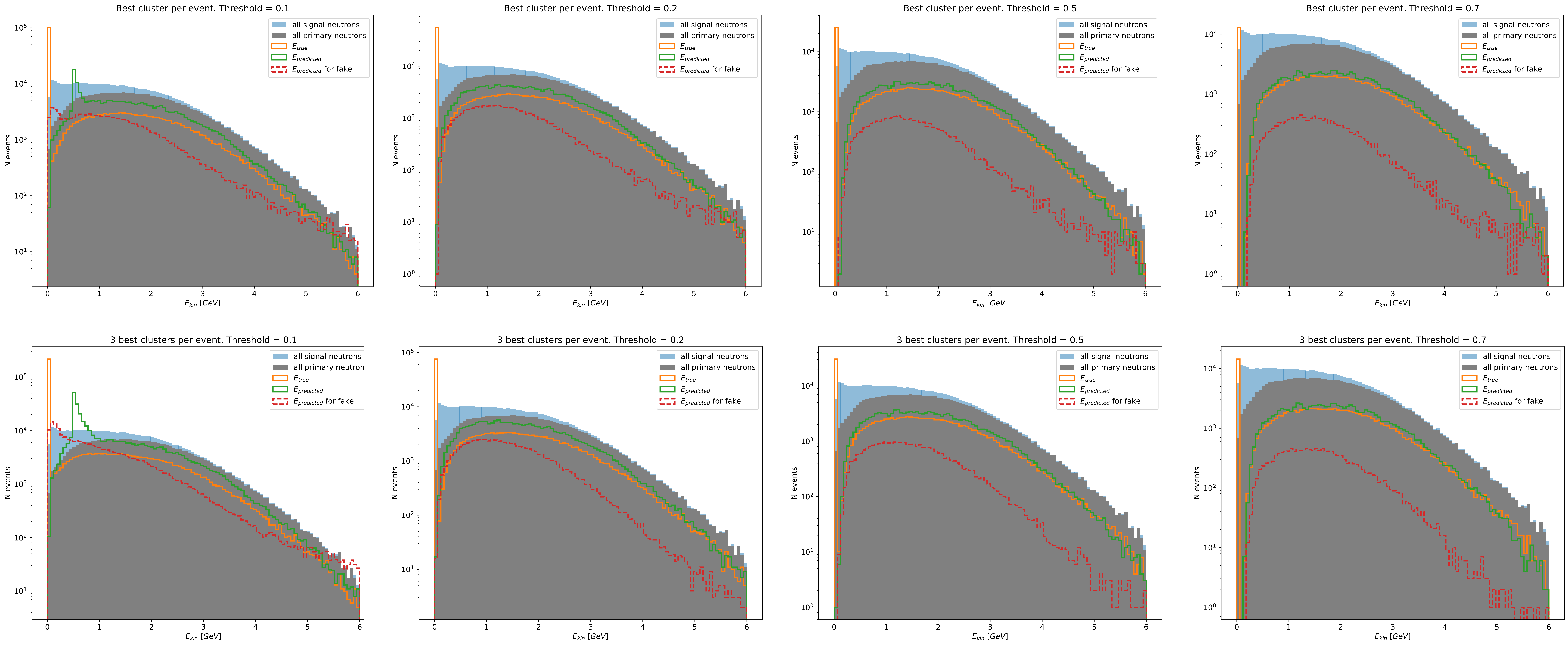
‘0’ vs ‘1’ vs ‘2 and more’

Energy Reconstruction





Spectra Reconstruction



GNN Model

Training objective

- **Cluster** level:
  - predict **neutron class** score
  - reconstruct expected **neutron energy**
- Node level (*additional*):
  - ‘prompt’ neutron deposition class score
  - Edge class score connecting same MC particles within clusters

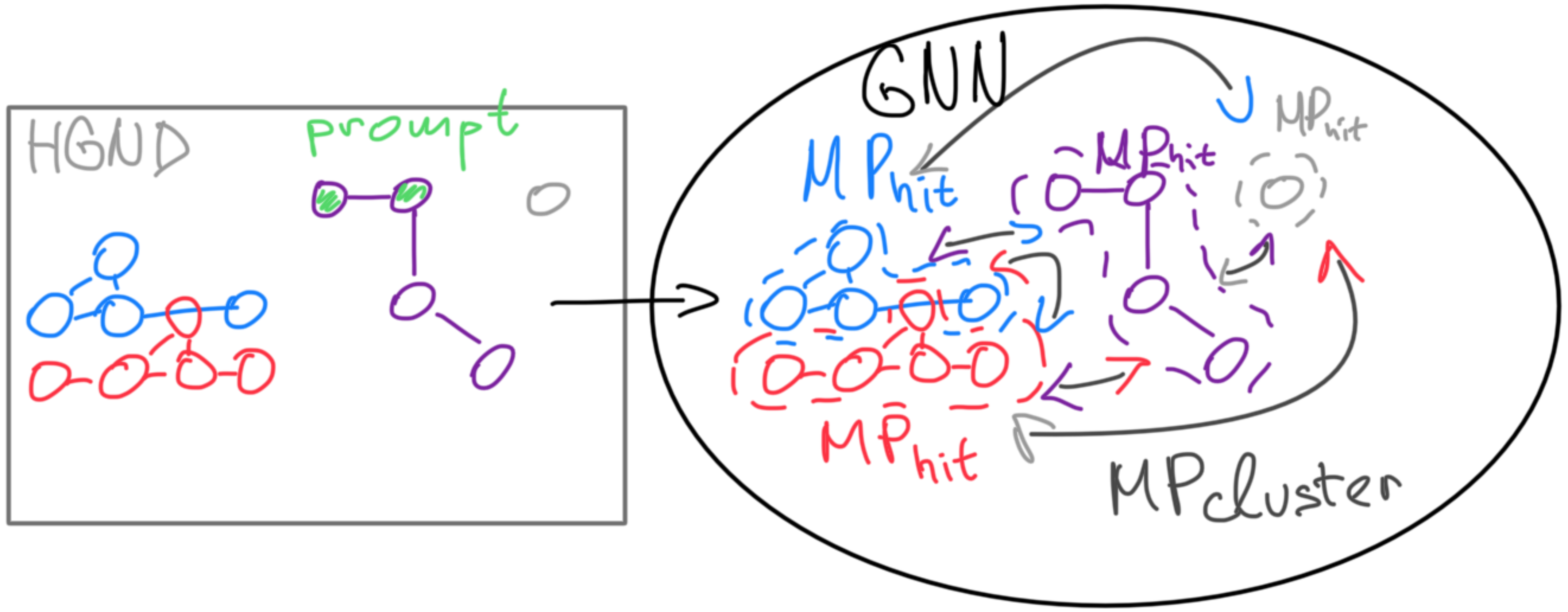
Loss function

- Binary Cross Entropy for classification
- Mean Squared Error for regression

$$Loss = BCE_{cluster} + MSE_{cluster} + (BCE_{hit} + BCE_{edge})$$

GNN architecture

- *MP_{hit}*. Message passing layers *hit -> hit* within clusters
- Average pooling layer to aggregate *hit nodes -> cluster* node
- $MP_{cluster}$. Message passing layers. *cluster -> cluster*
- Cluster output: class score, predicted energy
- Additional outputs: node class score, edge class score

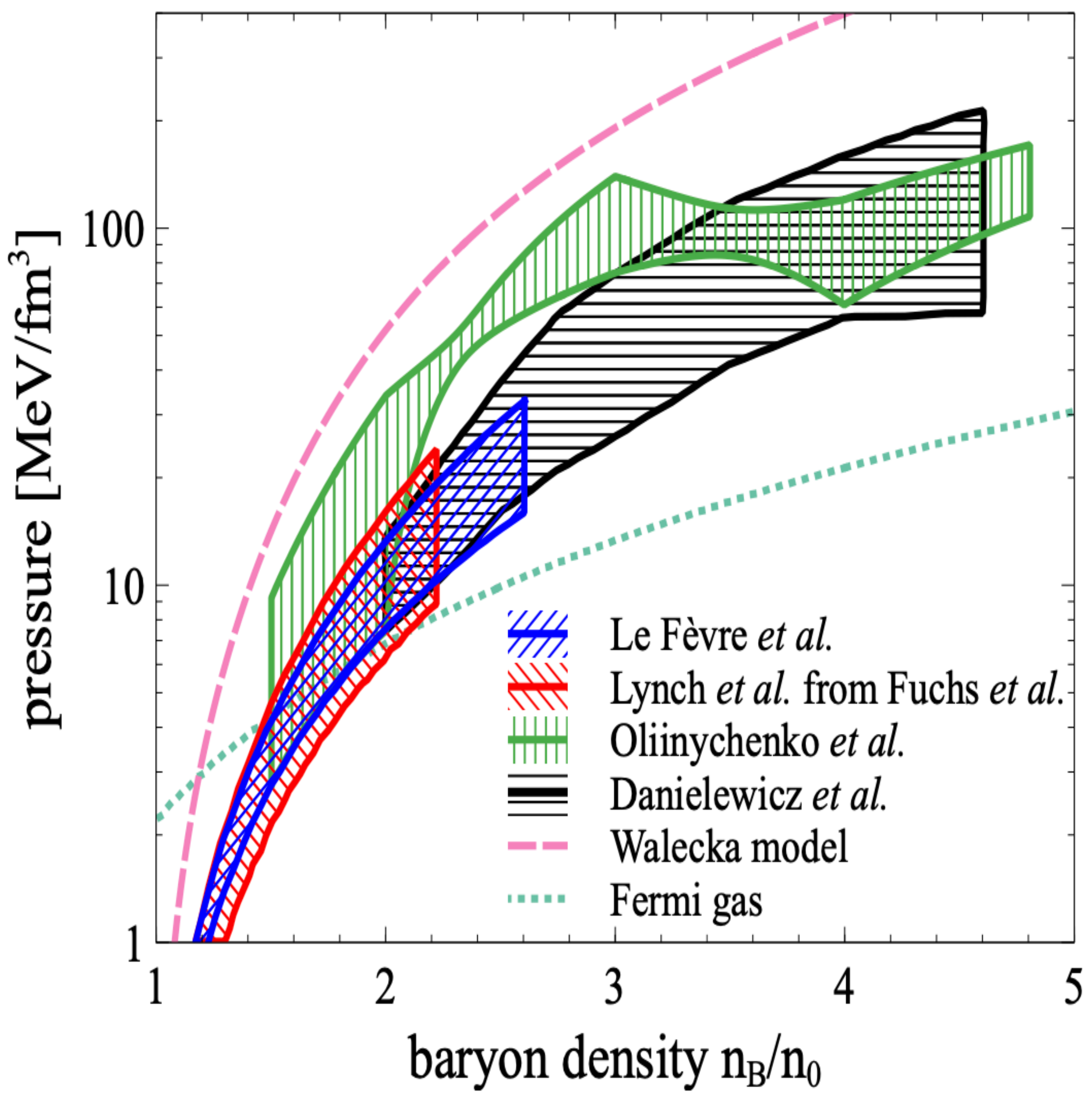


PyTorch Geometric library

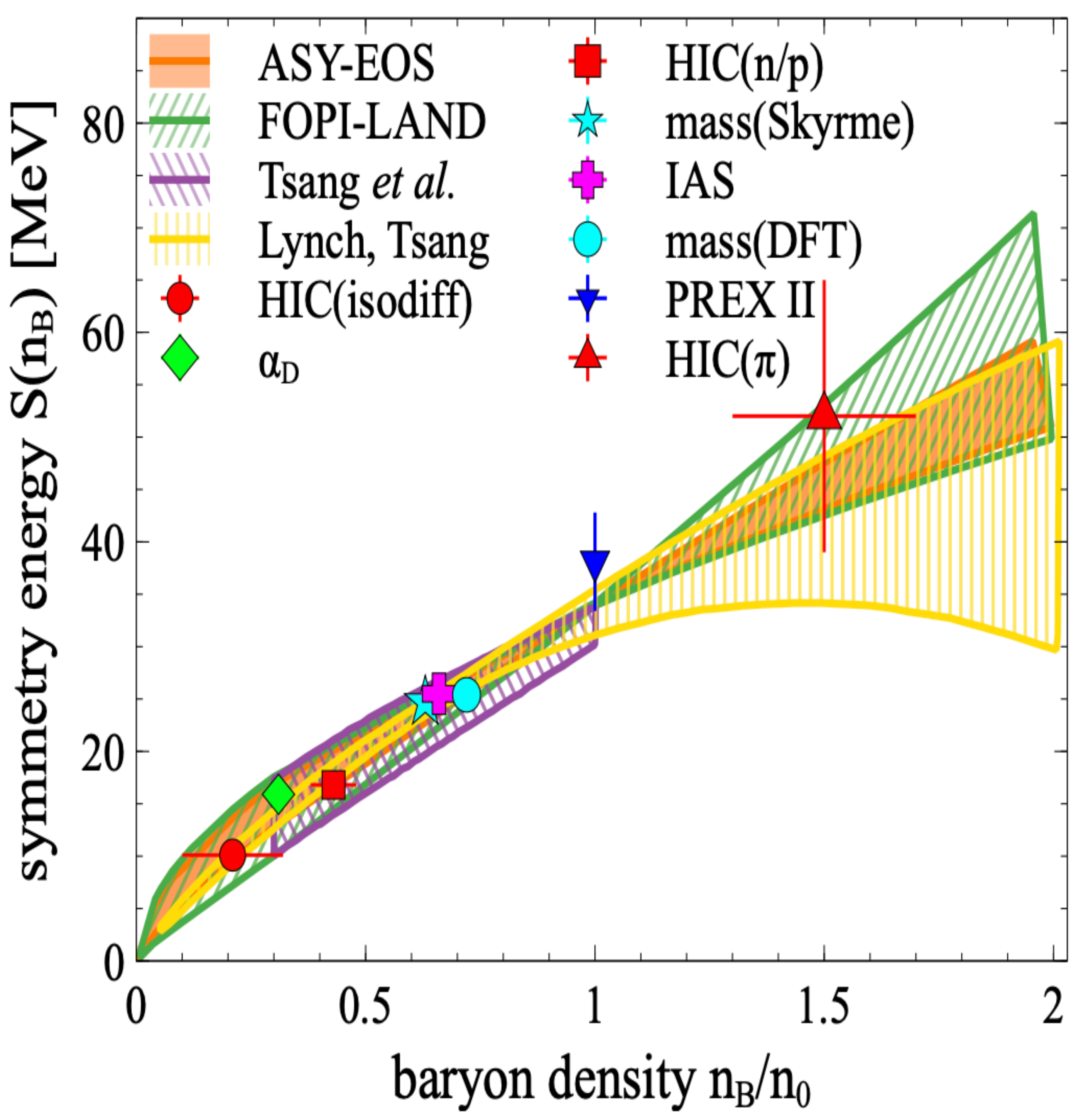
EOS for high baryon density matter

The binding energy per nucleon: $$E_A(\rho,\delta) = E_A(\rho,0) + E_{sym}(\rho)\delta^2 + O(\delta^4)$$

Symmetric matter



Symmetry energy



$\delta = (\rho_n - \rho_p)/\rho$ **- Isospin asymmetry**

- **Neutron flow** measurements are essential to further constrain symmetry energy
- Sensitive observables:

Anisotropy flow coefficients:

$$\frac{dN}{d\phi} \propto 1 + 2\sum_{n=1} v_n \cos[n(\phi - \Psi_{RP})], \quad v_n = \langle \cos[n(\phi - \Psi_{RP})] \rangle$$

A. Sorensen et. al., Prog.Part.Nucl.Phys. 134 (2024) 104080