Machine Learning-based neutron reconstruction in the HGND at the BM@N experiment

V. Bocharnikov[1], M. Golubeva[2], F. Guber[2],
N. Karpushkin[2], S. Morozov[2], P. Parfenov[3,4],
F. Ratnikov[1], A. Shabanov[2], A. Zubankov[2]

[1]HSE University, [2]INR, Troitsk, [3]MEPhI, [4]JINR

7th International Conference on Particle Physics and Astrophysics, Moscow
25.10.2024

The work has been supported by the Russian Scientific Foundation grant №22-12-00132

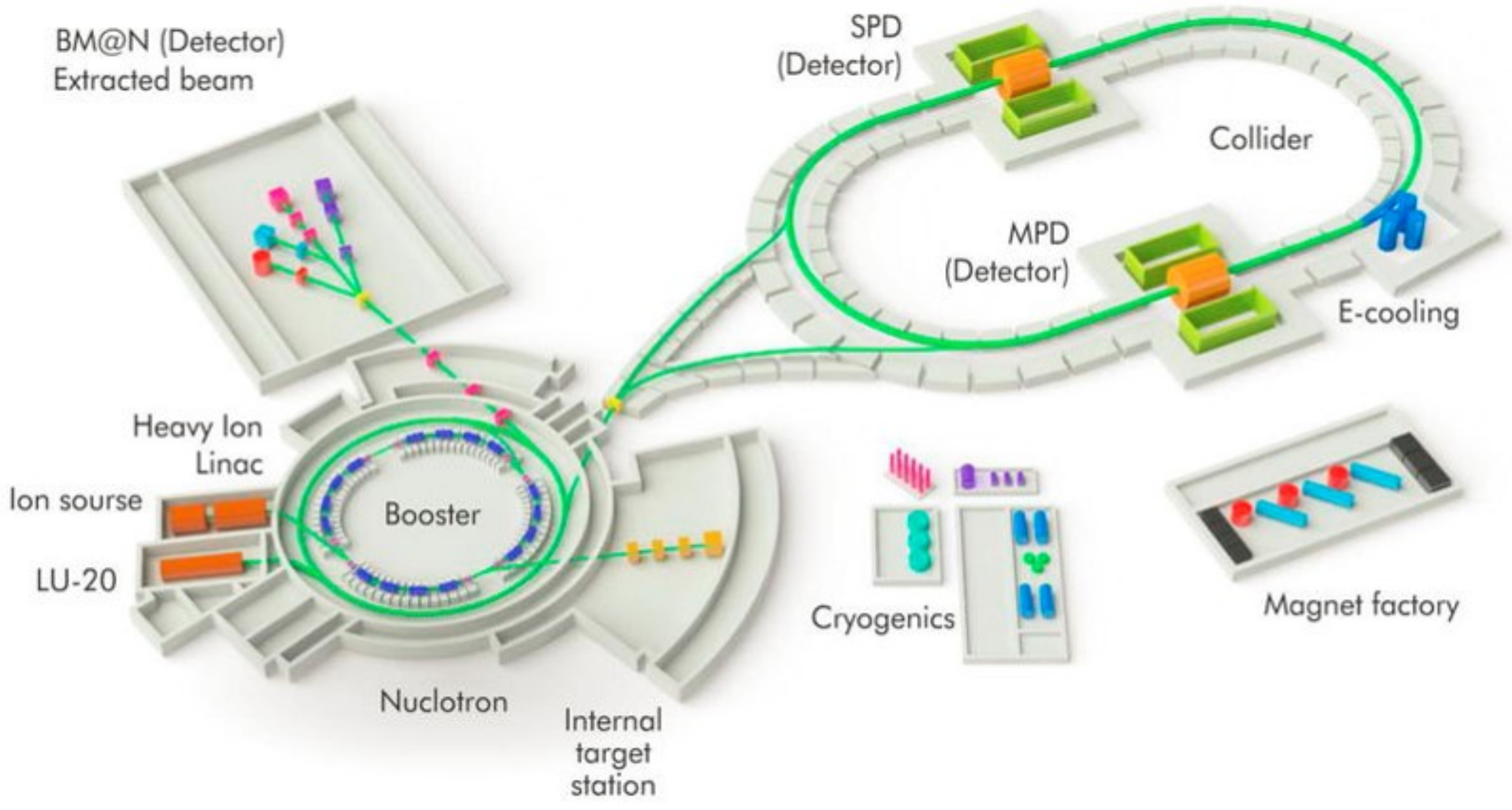
BM@N experiment

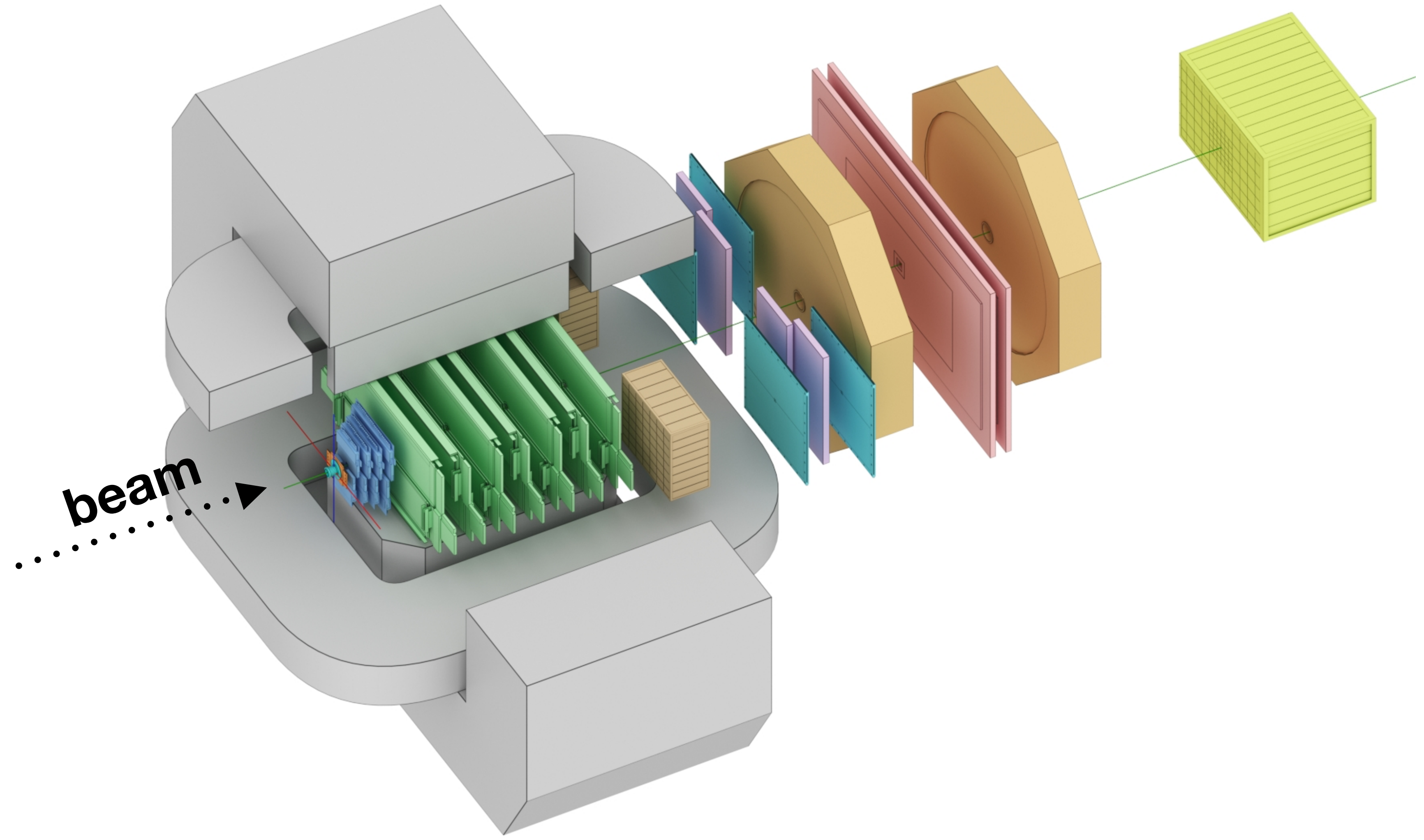
Studies of **B**aryonic **M**atter **at** the **N**uclotron (NICA, JINR Dubna)

- Heavy-Ion beam with energies up to 4A GeV interacts with fixed target

➡ investigate the equation-of-state (EOS) of **dense nuclear matter** which plays a central role for the dynamics of core collapse supernovae and for the stability of neutron stars.

- Azimuthal properties of produced particles - important tool for EOS studies
    - we focus on **neutron** flow and yields





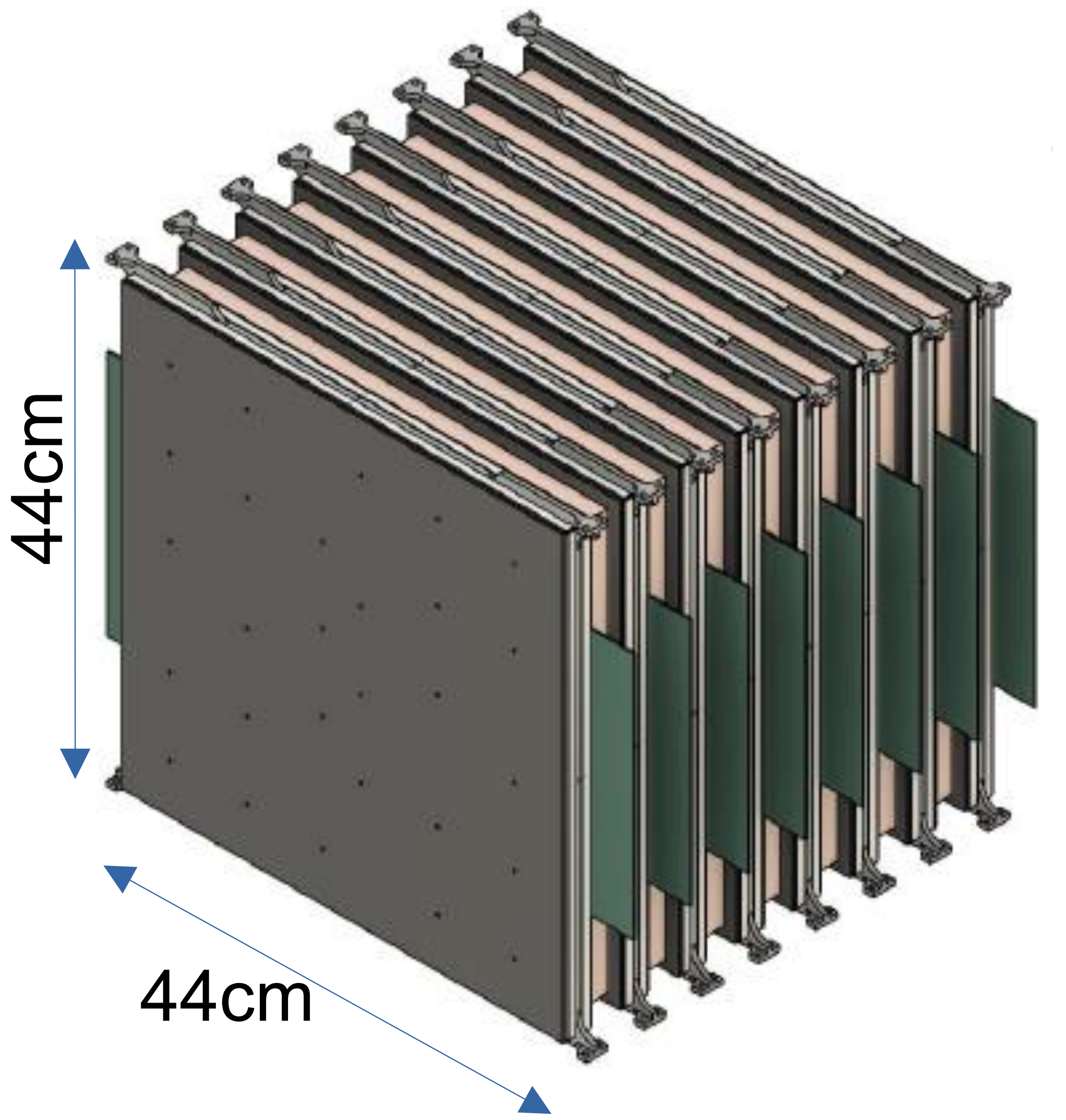
Motivation

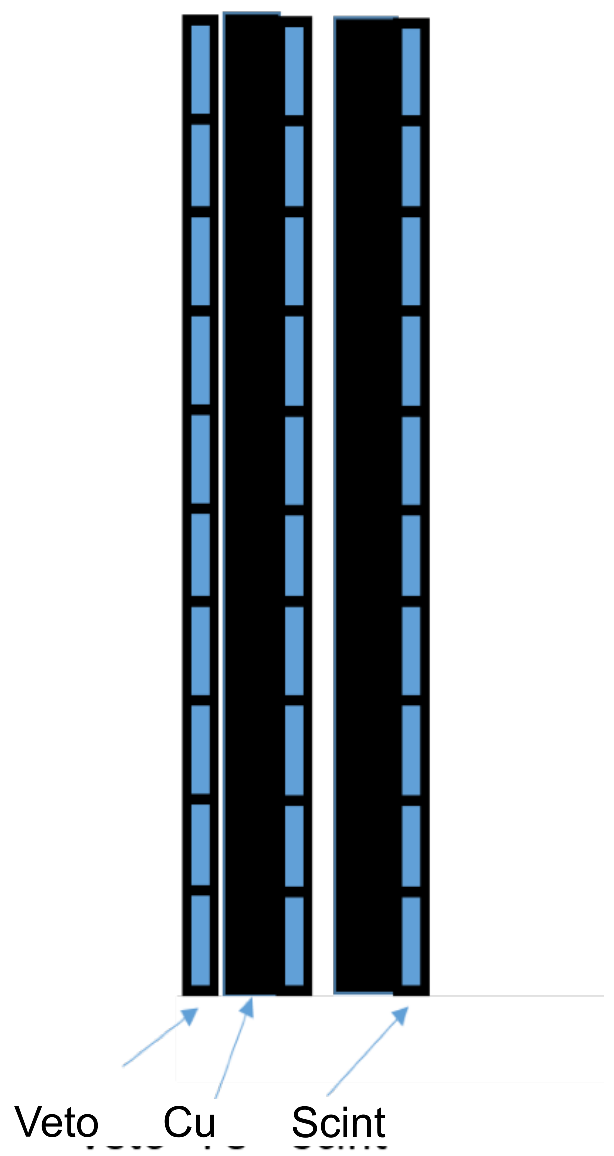
Measurements of neutron flow and yields require **reconstruction of neutrons**

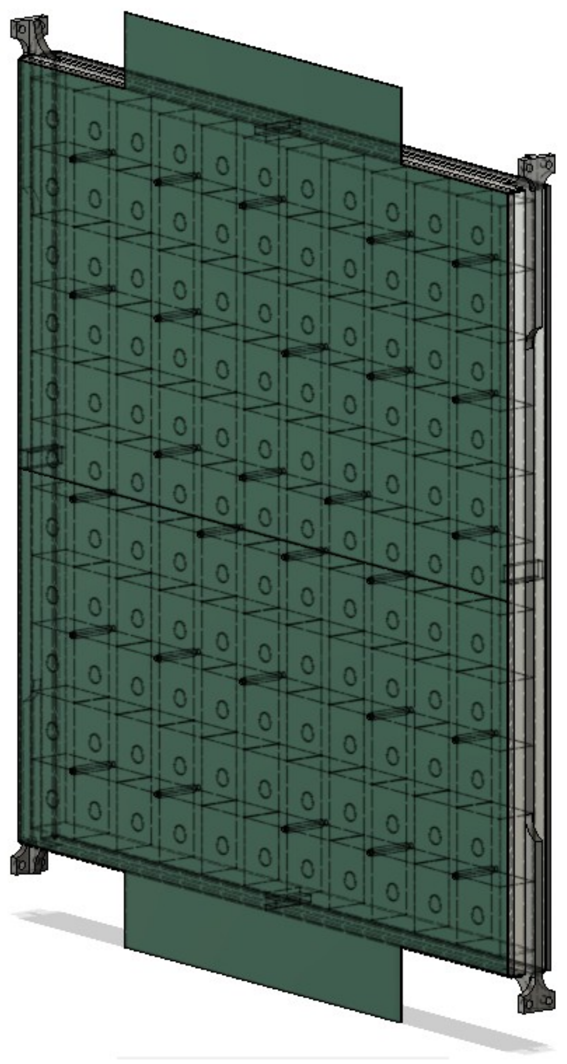
Neutron reconstruction task:

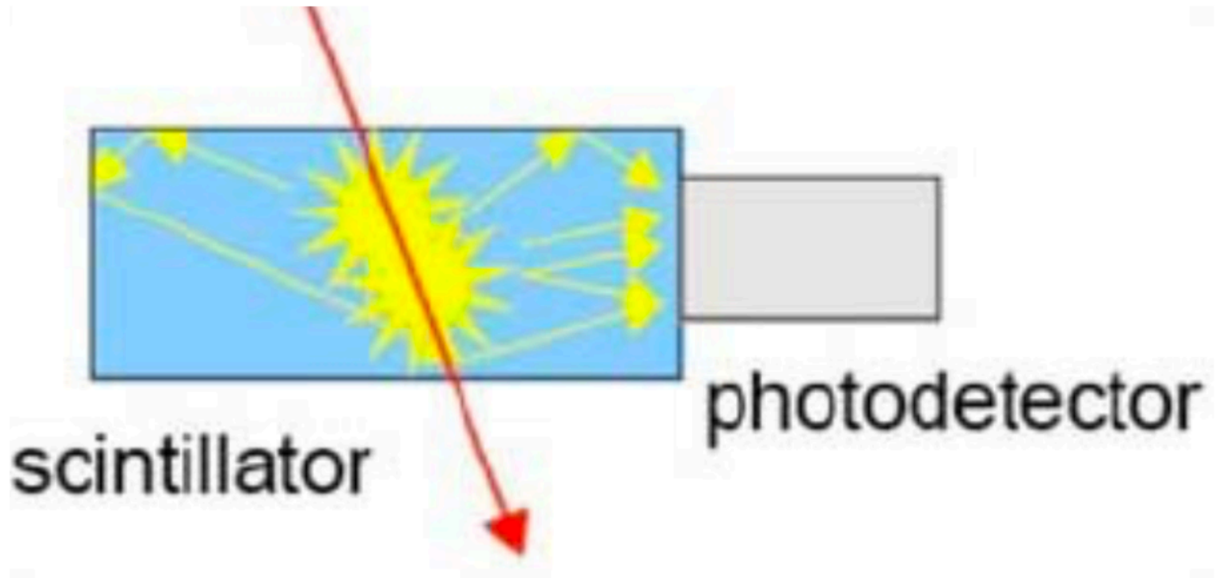
- **Identify neutrons** produced in reaction in presence of background
  ➡ use of **high granularity**
- Reconstruct neutron kinematics:
  - Kinetic energy — **time-of-flight** (ToF) method
- Multi-parameter task ⇒ may benefit from **ML-based methods**

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





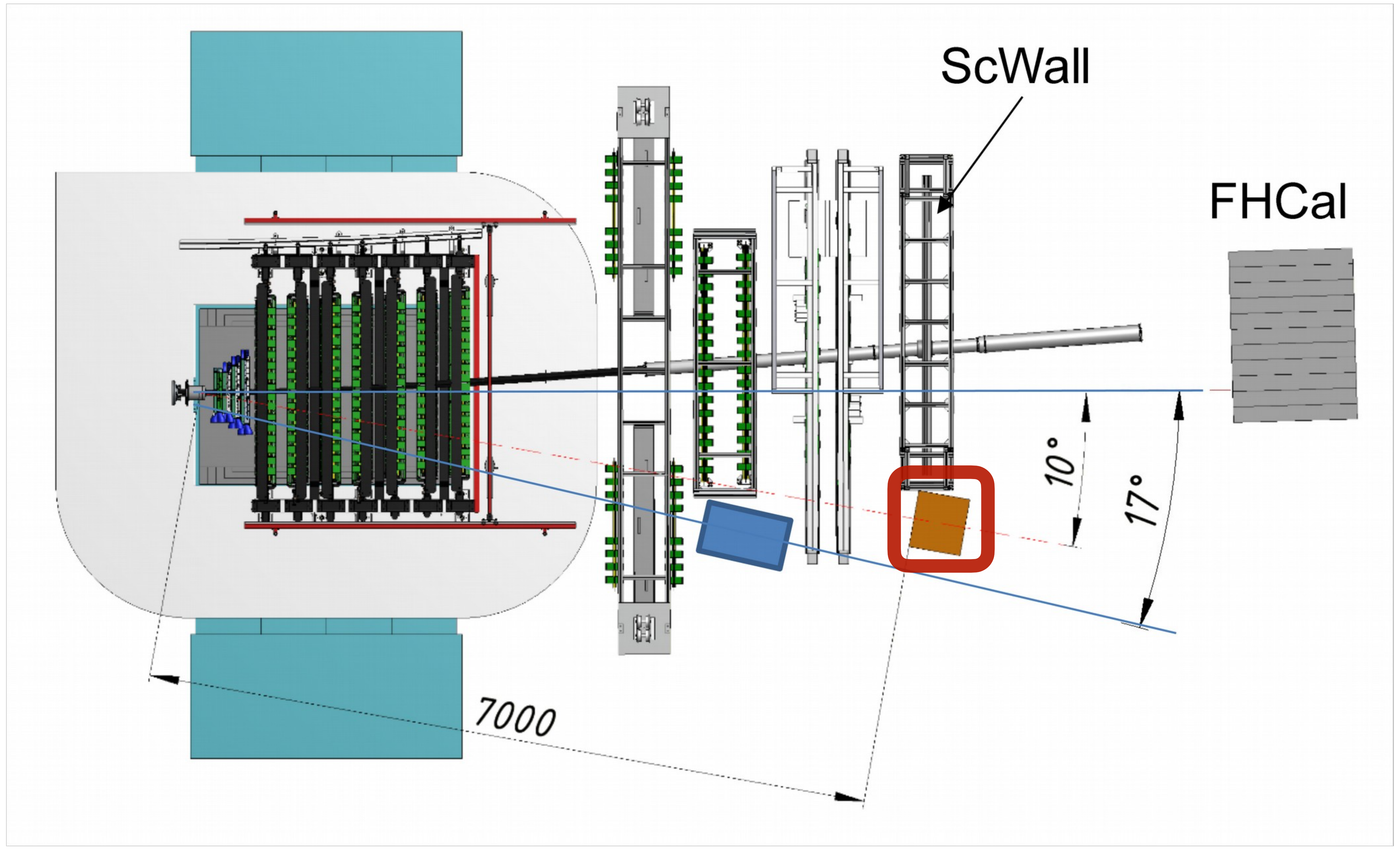


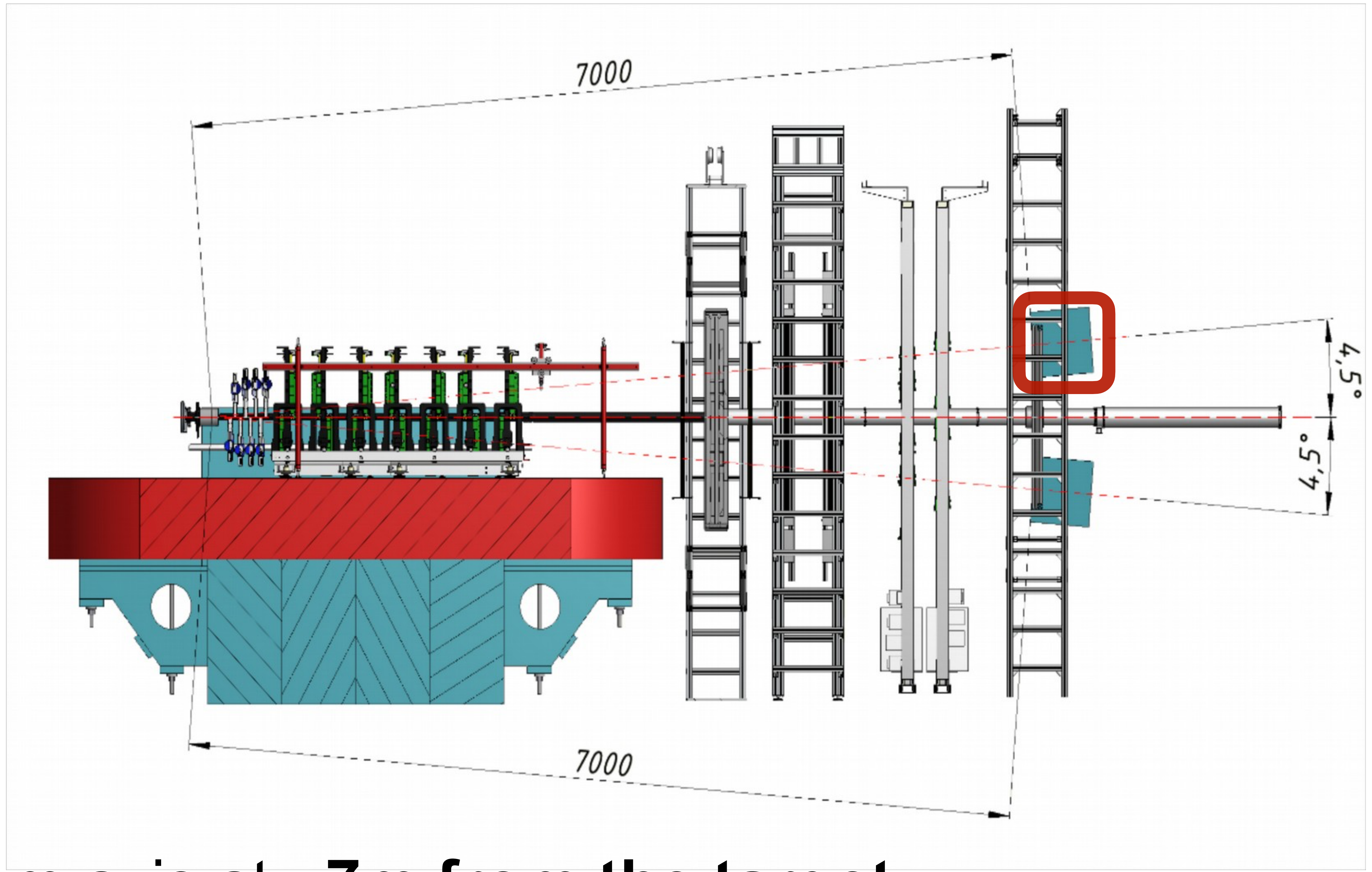


- (2x) 8 layers: *3cm Cu (absorber)* + *2.5cm Scintillator + 0.5cm PCB; 1st layer — 'veto' before absorber*
  ➡Total length: ~0.5m, **~1.5 λ_{in}**
  ➡ neutron detection efficiency ~60% @ 1 GeV
  - Transverse size: **44x44 cm^2**
  - *11x11 scintillator cell grid*

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

Configuration and Simulations





- HGND sub-detectors are located at **10º to the beam** axis at **~7m from the target**
- Monte-Carlo event simulations:
  - DCM-QGSM-SMM model + Geant4 v11.02 FTFP-BERT
  - **~0.5M events Bi+Bi @ 3 AGeV**
  - Only **top sub-detector** will be discussed further

Dataset

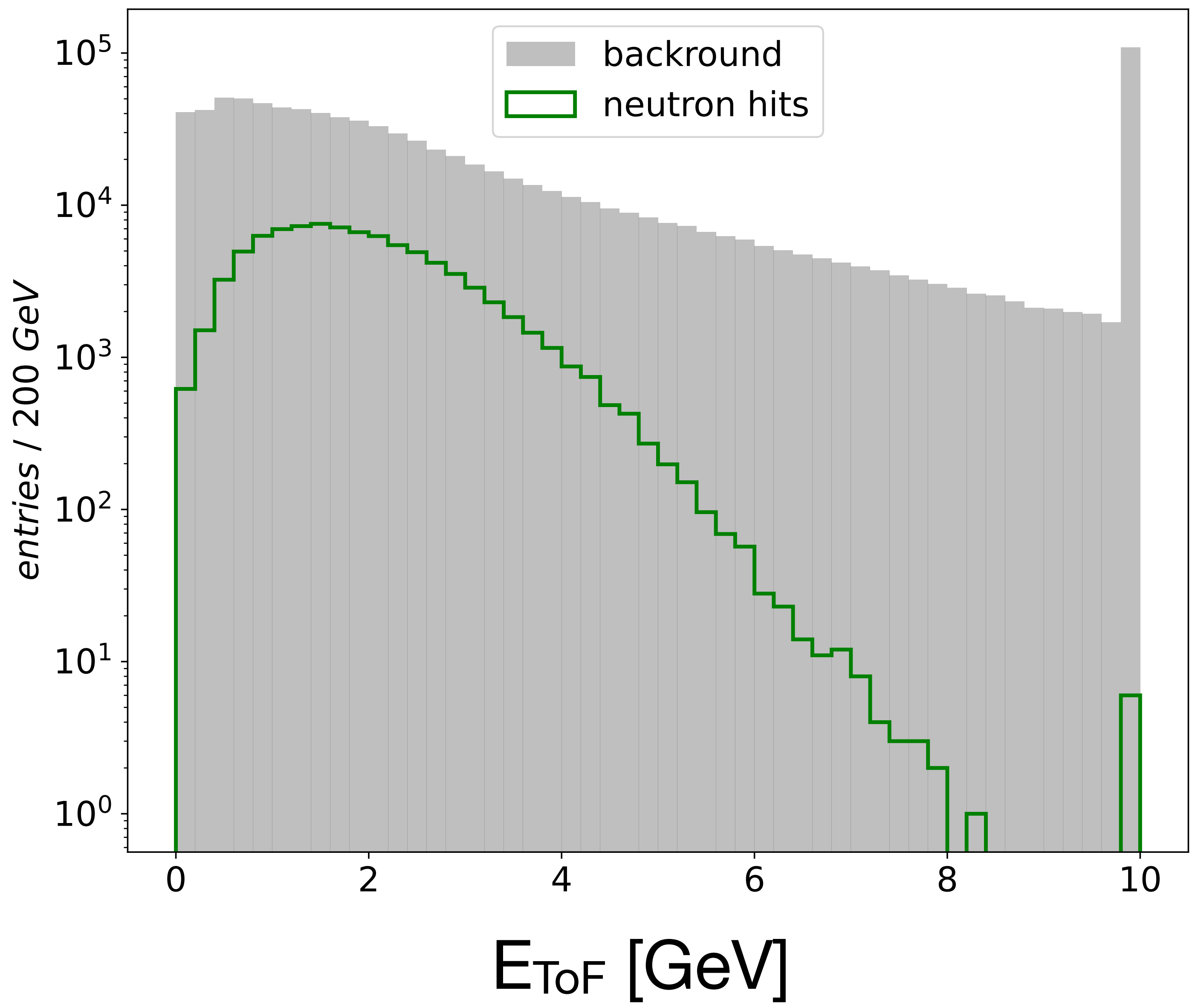
ToF energy for n^0 hypothesis:

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

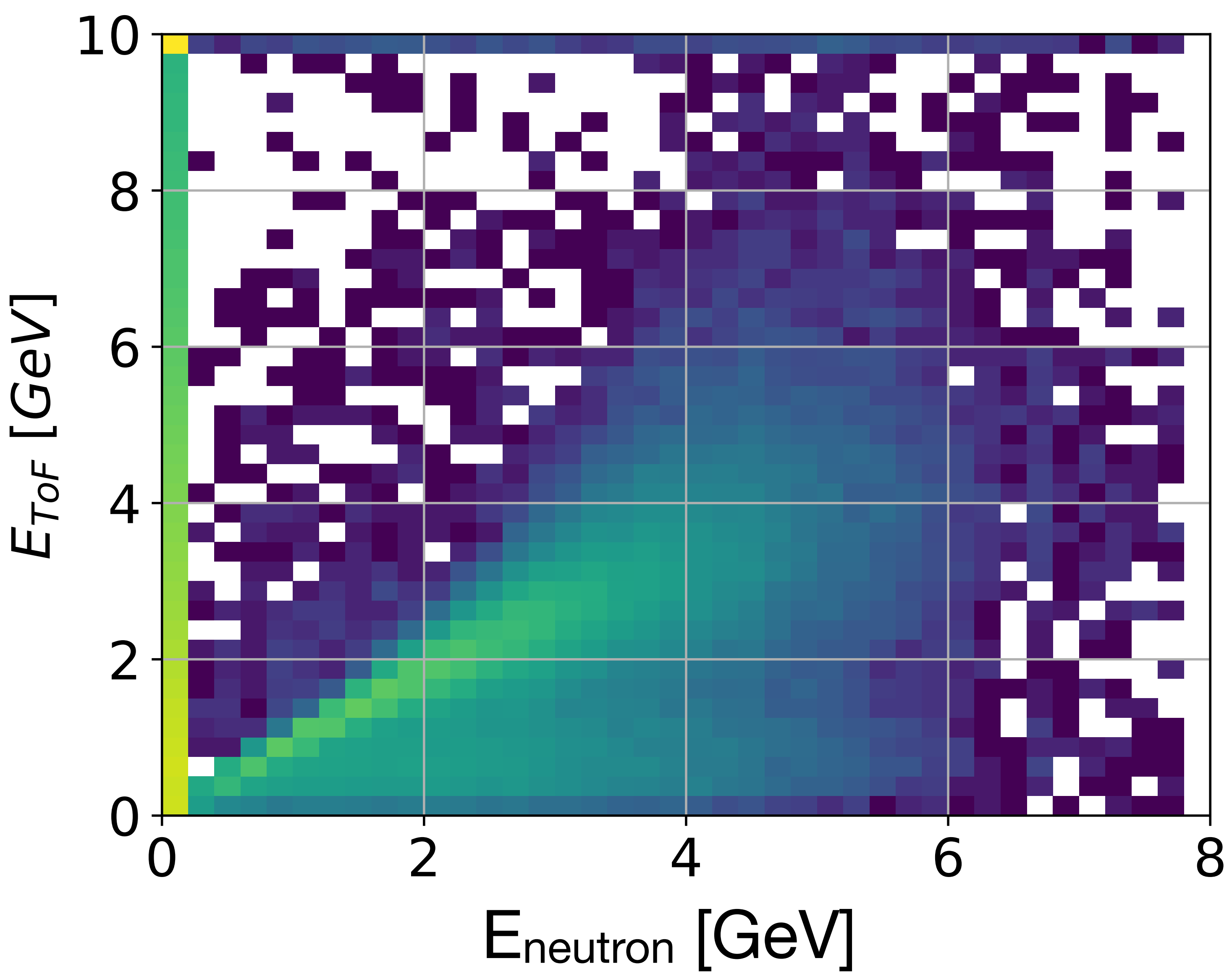
- $t_{hit}+\mathcal{N}(0,\sigma = 150ps) < 40ns$
- hits with E_{ToF}>10GeV are set to 10 GeV

- Each hit caused by a primary neutron is linked to corresponding MC particle
- Multiplicity counts require existence of 'Head' hit with $\delta(E_{ToF}) < 0.3$

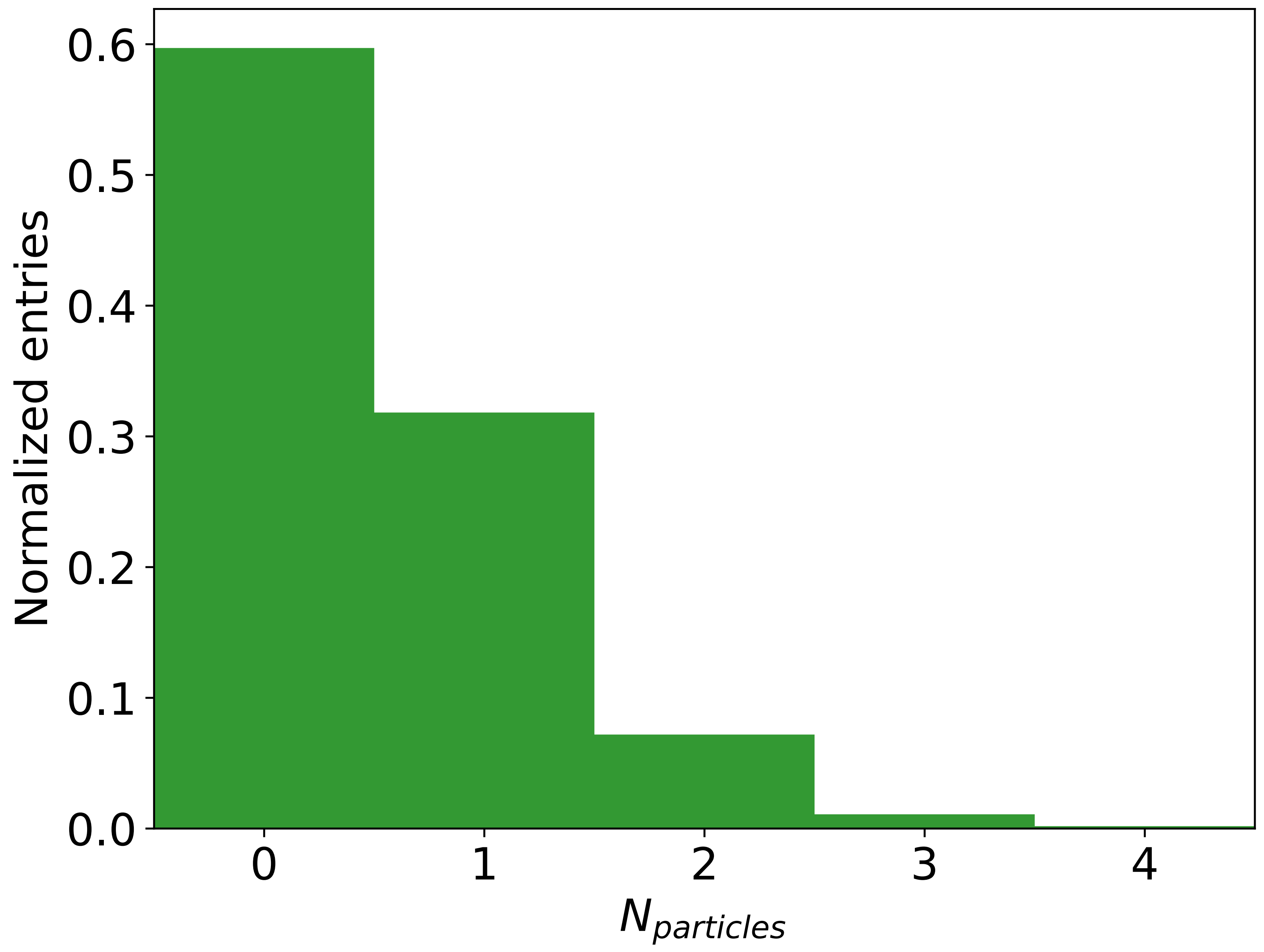
Hit E_{ToF} distribution



E_{ToF} vs MC truth correlation



Primary neutron multiplicity



Graph Neural Networks (GNN)

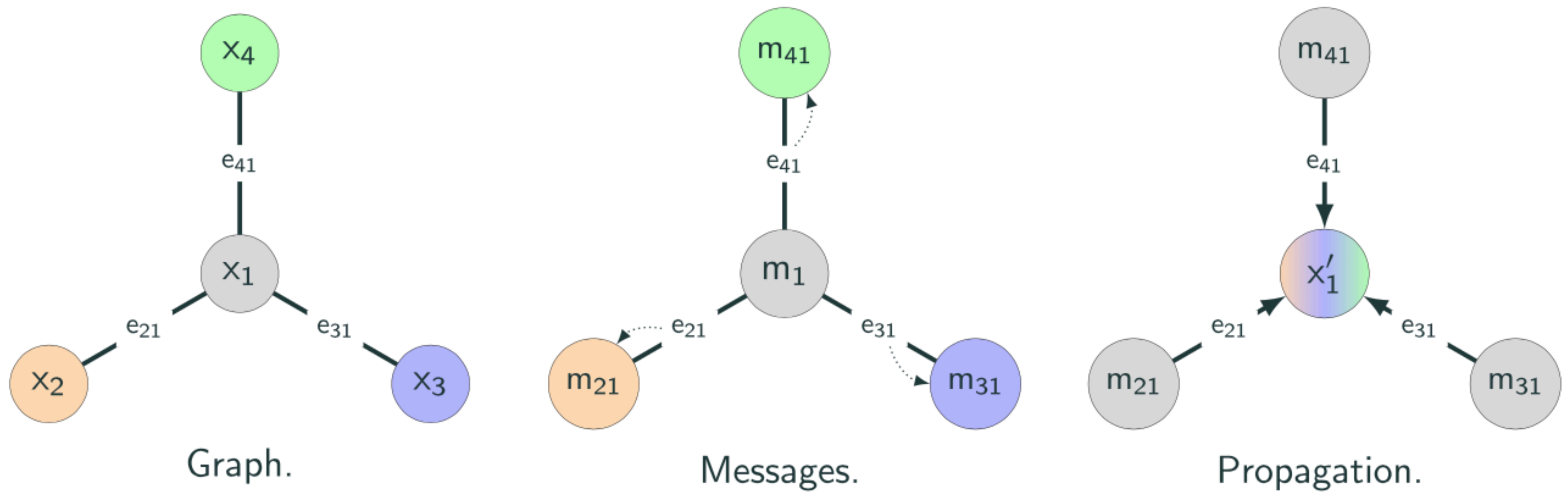
Why Graph Neural Networks:

- 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

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.

GNN Model

Graph construction:

- Nodes — hits. Observables per hit:
  - hit coordinates; Edep > 3 MeV ~ 0.5 MIP; E_{ToF}
  - additional global event node connected to each hit node
- **139004** graphs
- Constructed event graphs are split 50/50% to train and test procedure

Heterogenius GNN Model:

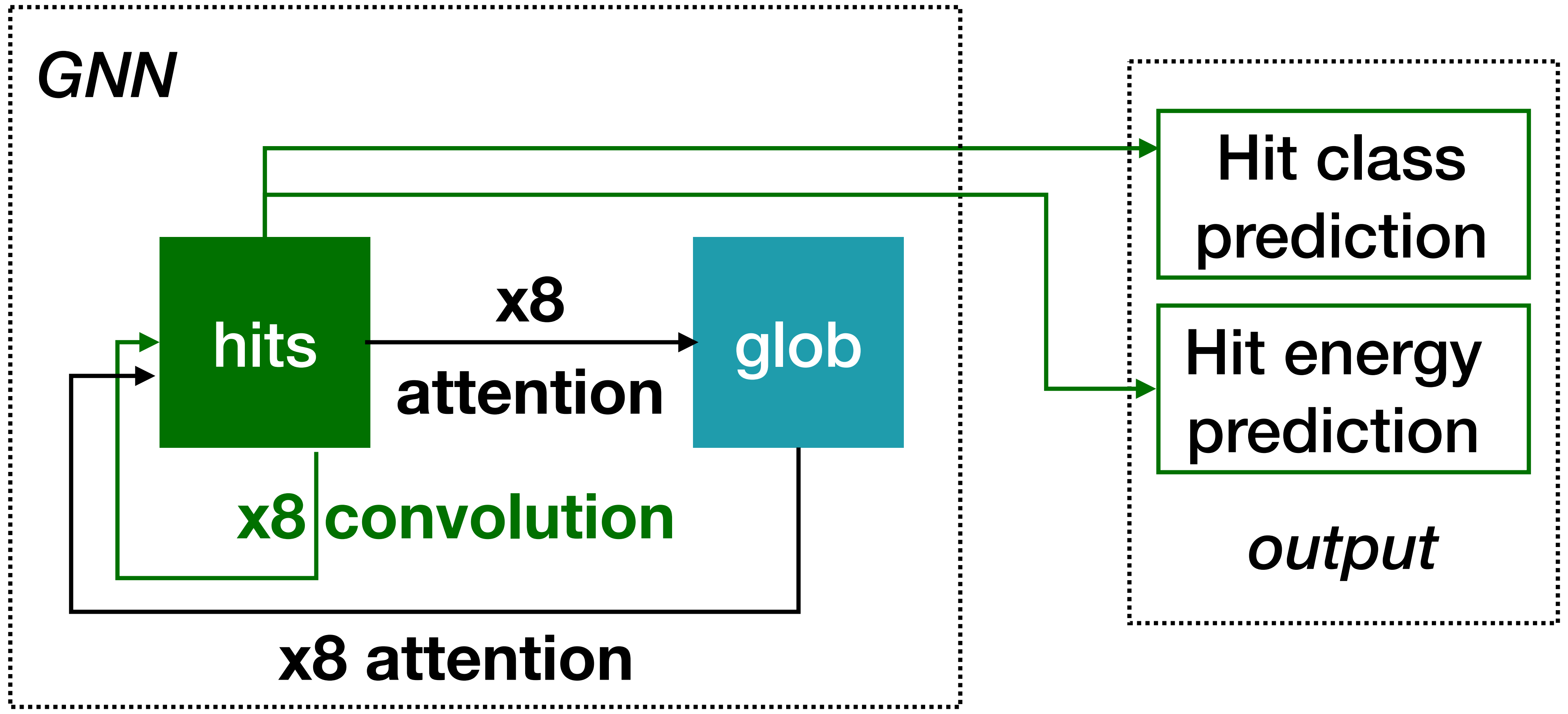
- Graph convolution layers between hit nodes. Hidden state size: 512
- Graph attention layers between hit and global node. Hidden state size: 512

PyTorch Geometric library

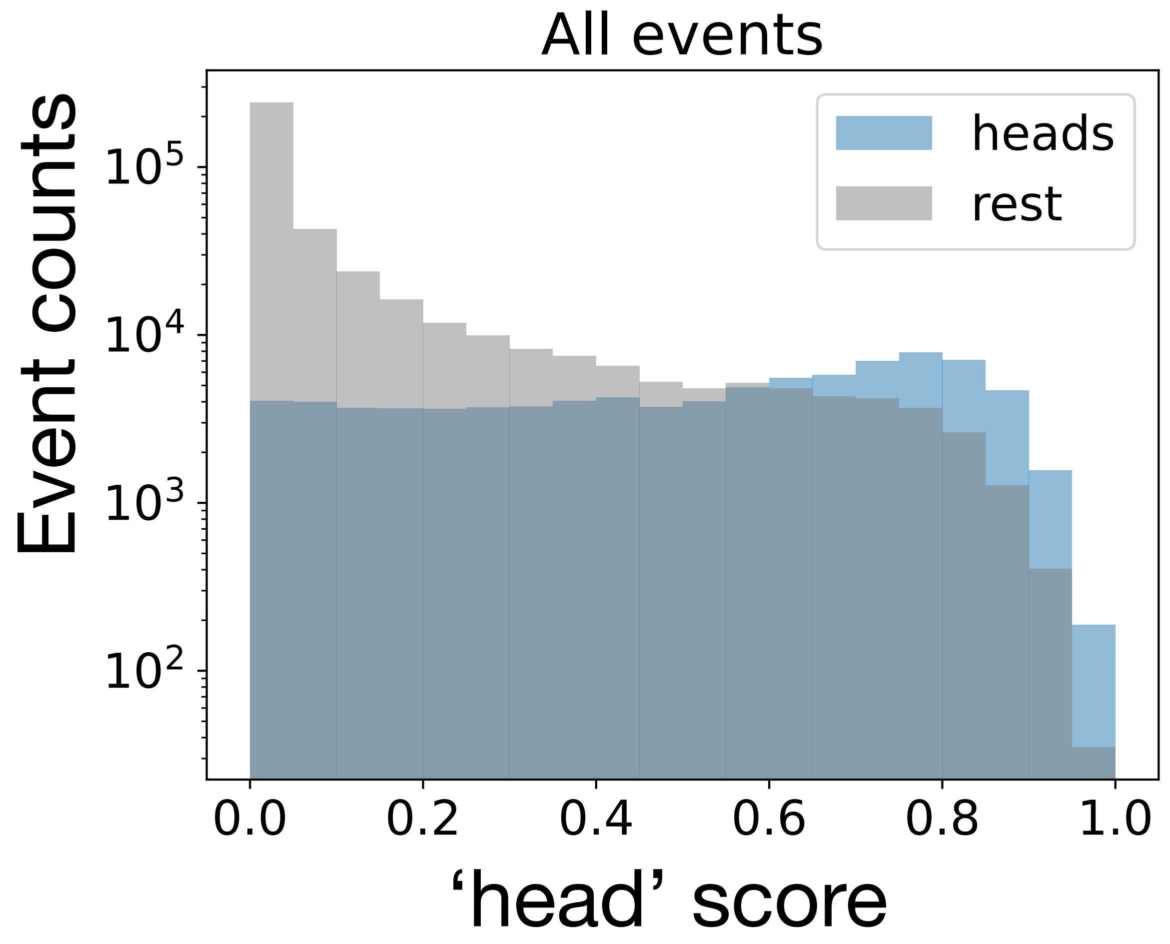
Output

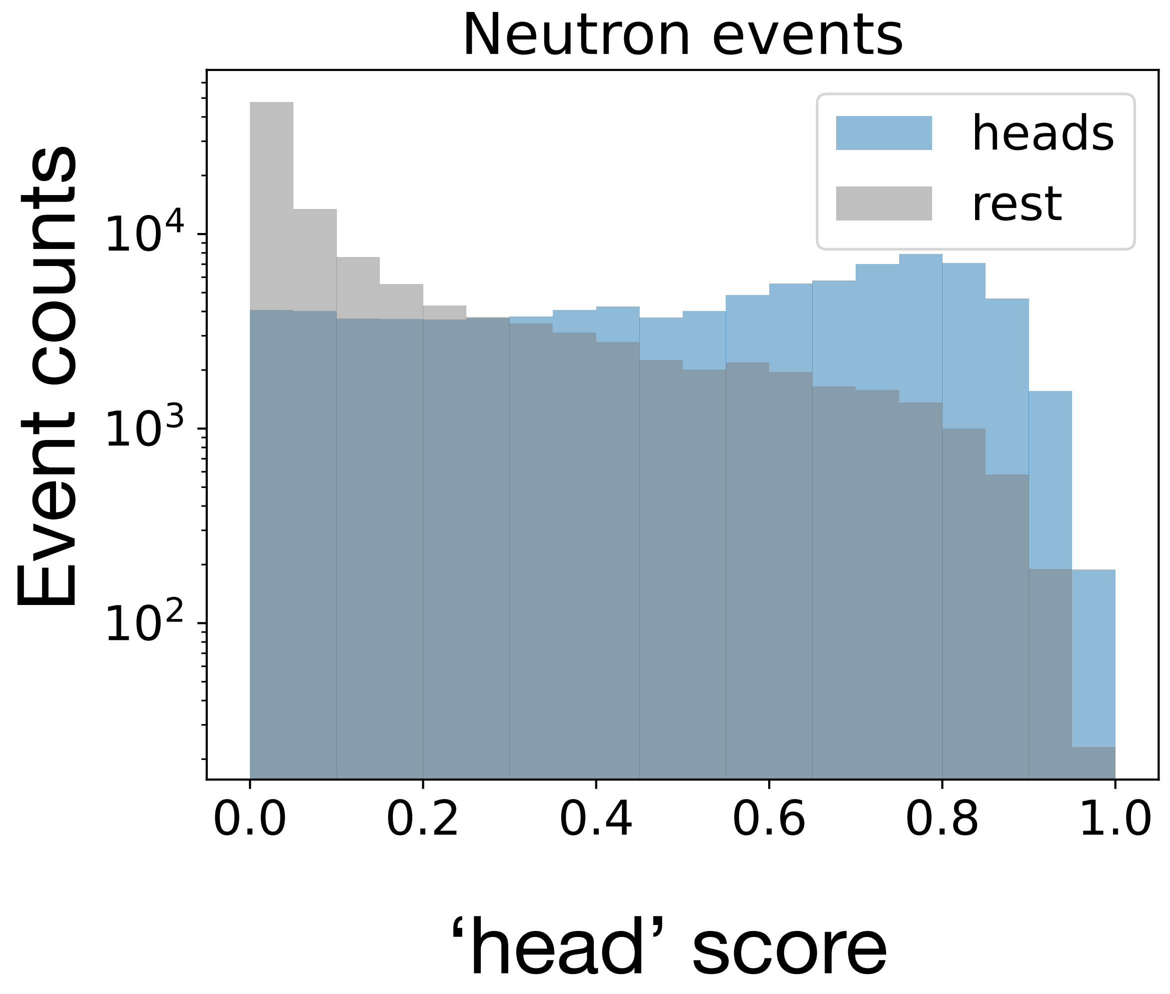
Training objective:

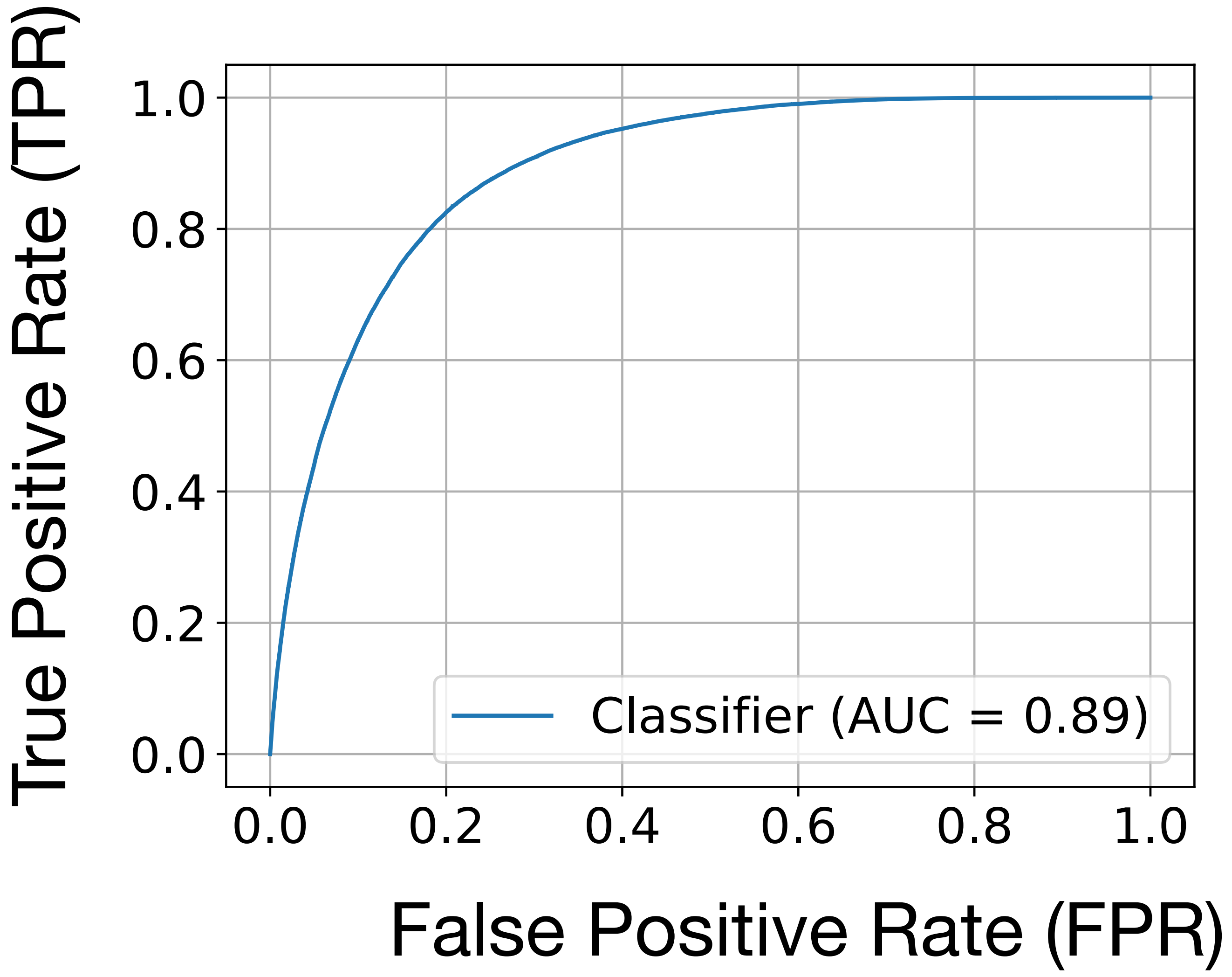
- Neutron 'head' class for each hit
  - Binary cross entropy loss function
- Neutron energy prediction for each hit to correct ToF
  - Mean squared error loss function
    - only on MC truth neutron hits



Neutron Head Prediction







$$TPR = \frac{TP}{TP + FN}$$

signal efficiency

$$FPR = \frac{FP}{TN + FP}$$

fake rate

		predicted	
		Positive	**Negative**
actual	**Positive**	TP	FN
	Negative	FP	TN

- Overall good hit classification performance
- Requires additional clustering algorithms to be used in neutron reconstruction

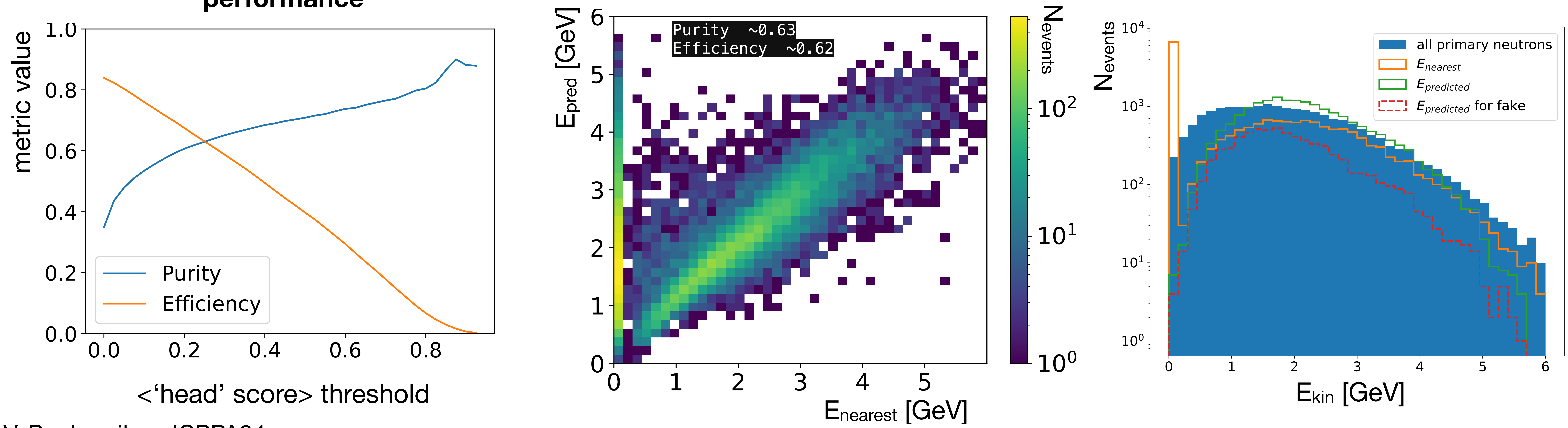
Simple Clustering Algorithm

- Gaussian Mixture clustering approach to find best neutron cluster per event
  - Variables: hit coordinates, E_{pred}, 'head' score — 5 dimentions
  - Up to 3 5D-gaussian components for each event select component with max(mean 'head' score)
  - $E_{nearest}$ — closest neutron energy to prediction (mean E_{pred} per cluster)

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

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

Single neutroneconstruction performance



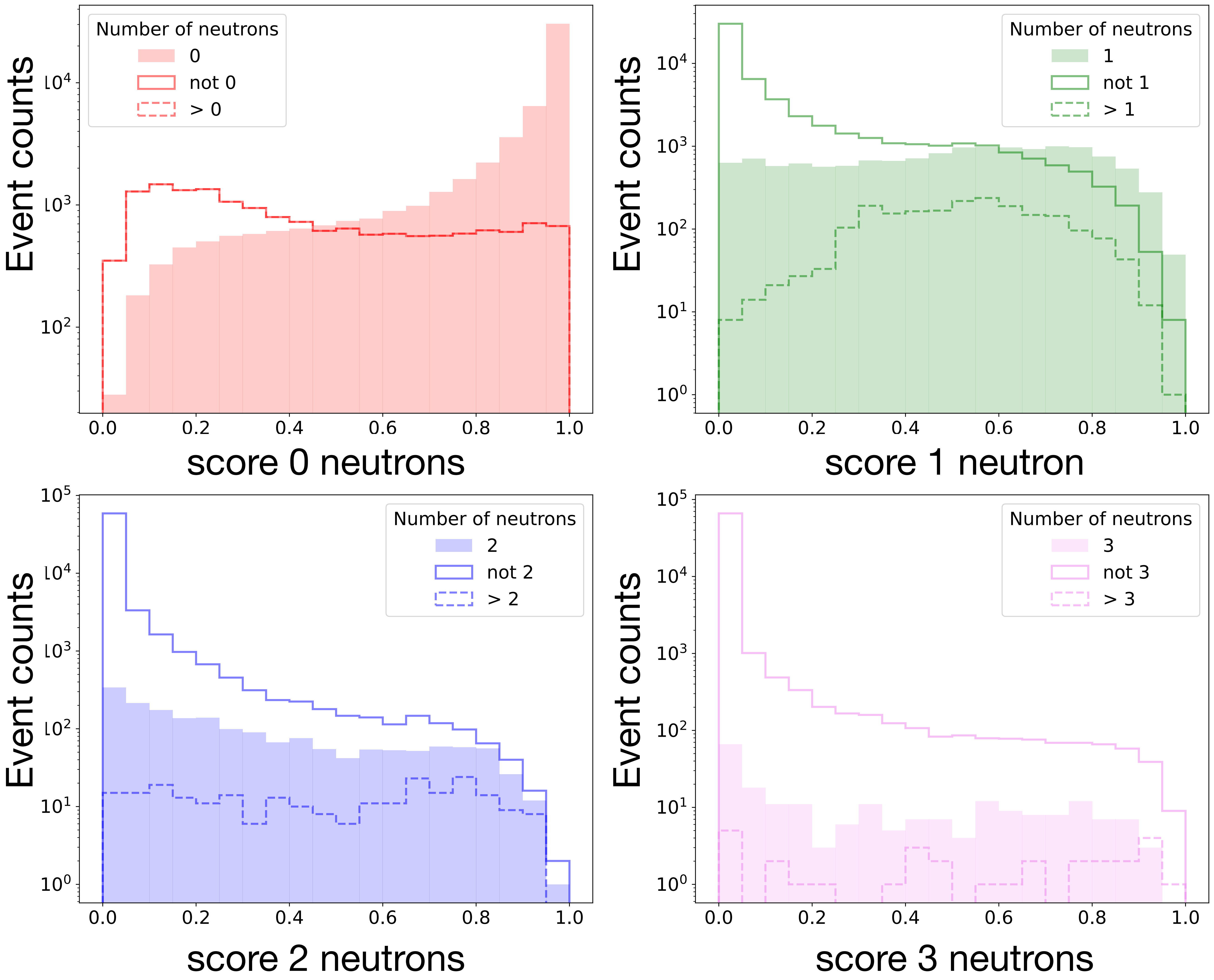
Summary and Outlook

- Machine learning approach for the neutron reconstruction in the HGND is presented and preliminary results are discussed.
  - Graph Neural Networks are used to capture local event structures
  - Single neutron reconstruction performance is estimated to have both purity and efficiency at the level of 60%

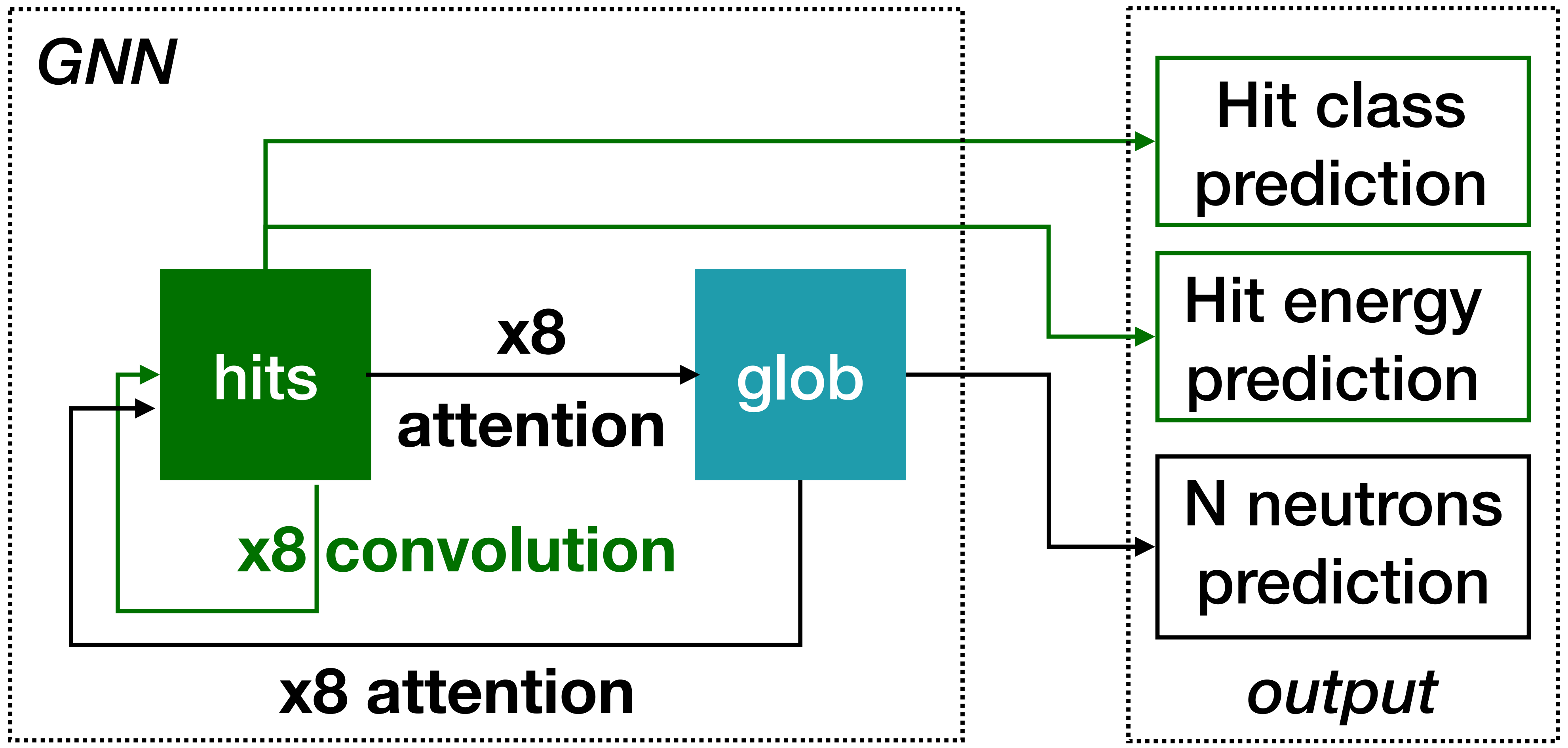
- Higher multiplicities to be addressed
- Estimation of neutron flow measurement performance is ongoing

Backup

Neutron Multiplicity Prediction

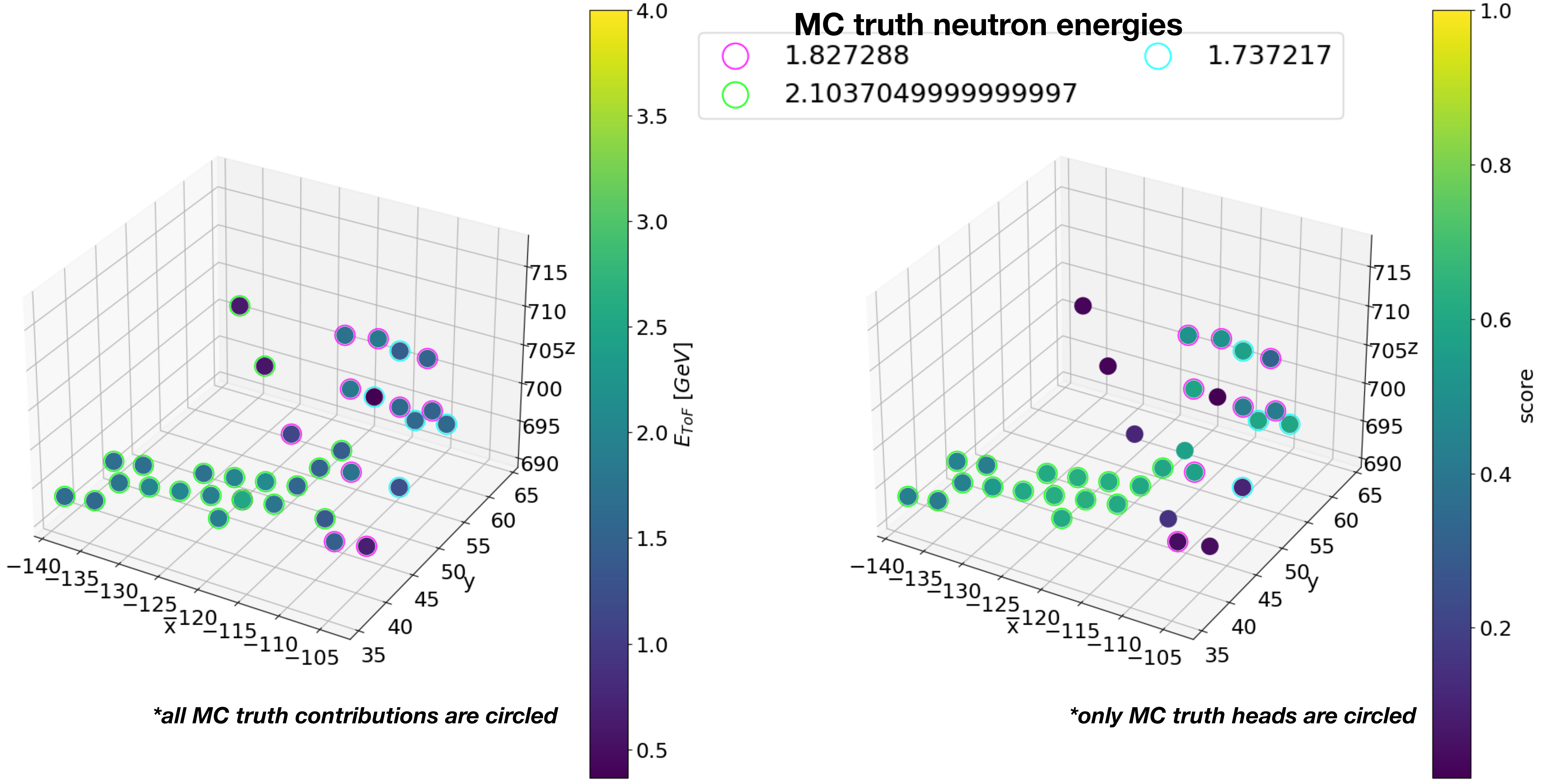


- Good separation of neutron events as a binary problem
- Higher multiplicities require more sophisticated algorithms
  - Multiplicity prediction -> unsupervised clustering



Reconstruction example

```
0 neutron score: 0.3053866344417157
1 neutron score: 0.669092359665289
2 neutron score: 0.1657184230945527
3 neutron score: 0.022741372617821658
1gm scores:  [0.45783916]
2gm scores:  [0.26996891 0.59203222]
3gm scores:  [0.34623281 0.59203222 0.21912647]
1 cluster prediction: [1.74045778]
2 cluster prediction: [1.48013984 1.92639919]
3 cluster prediction: [1.53982338 1.92639918 1.44035095]
```



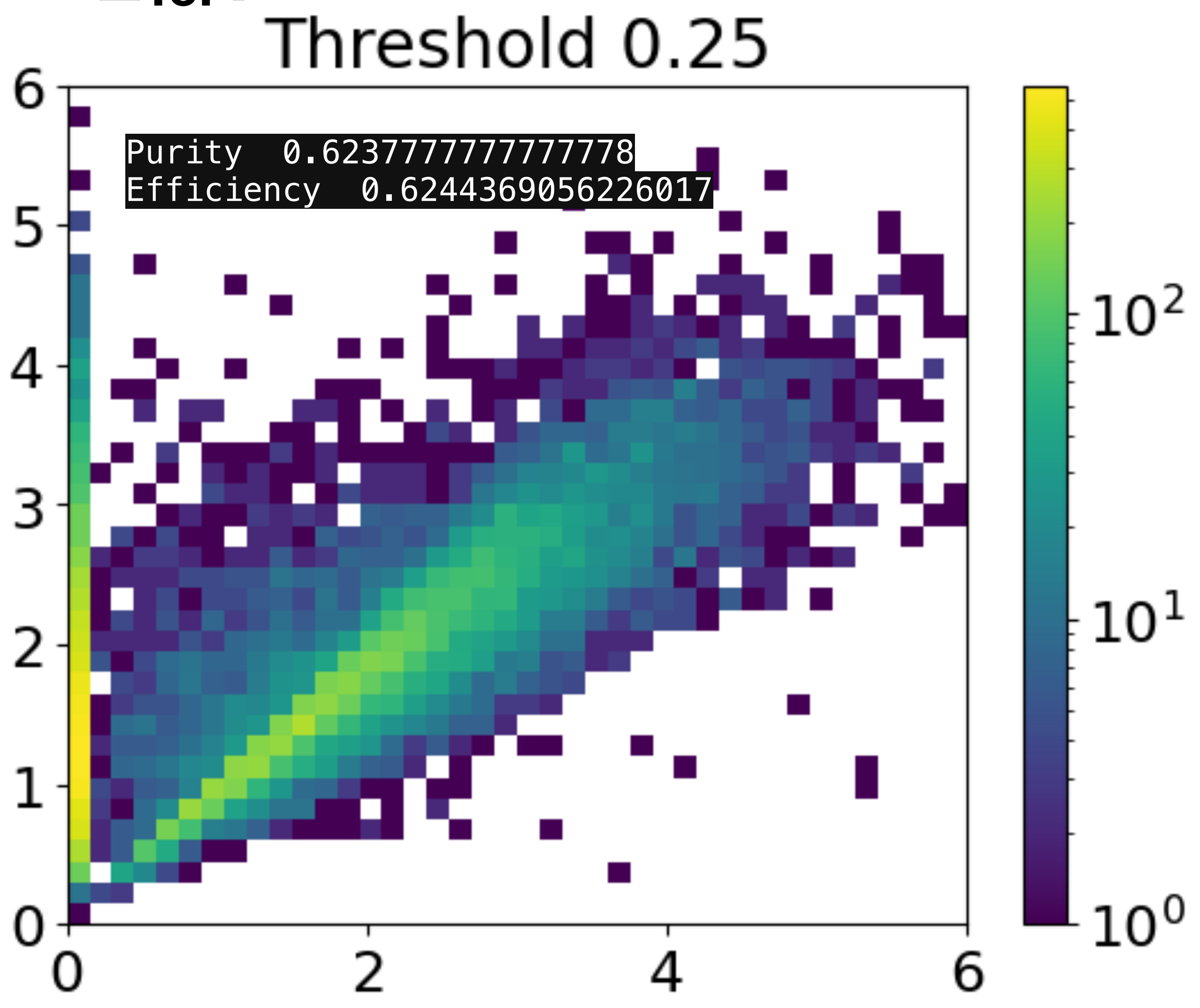
**all MC truth contributions are circled*

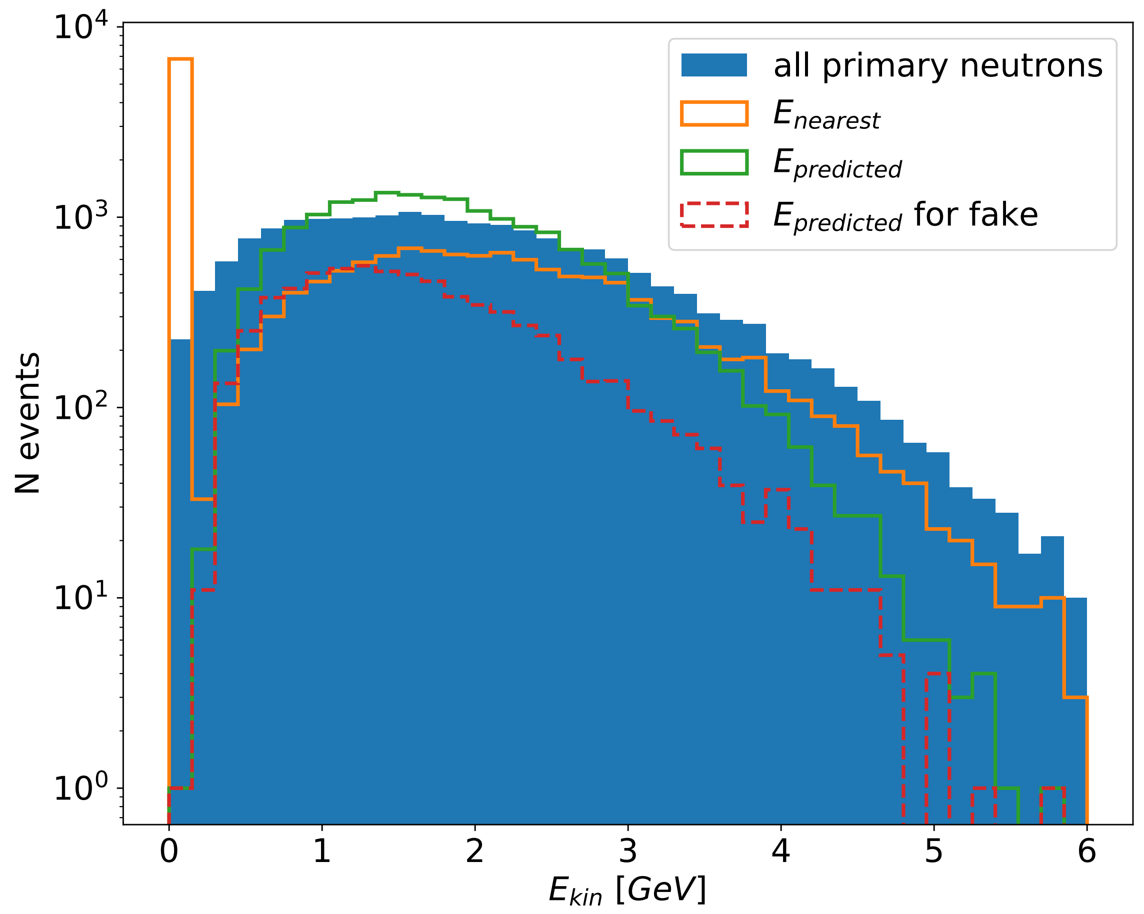
**only MC truth heads are circled*

- Delayed depositions have lower ‘head’ score
- Same neutron produce similar score for ‘heads’
- Gaussian Mixture approach potentially can be extended to reconstruct neutron with multiplicities > 1
- Combination with ‘classic’ cluster algorithm is foreseen

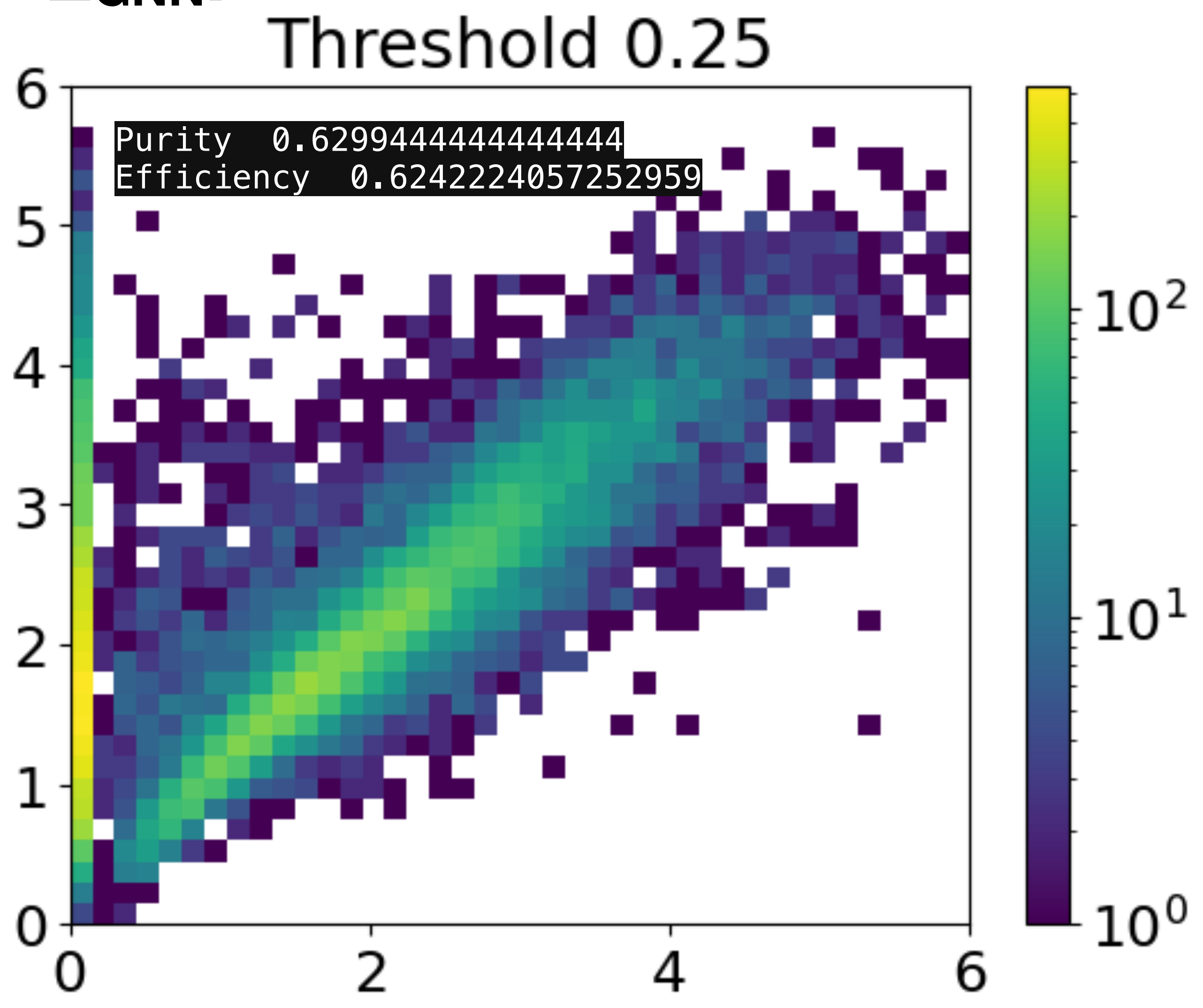
Energy correction

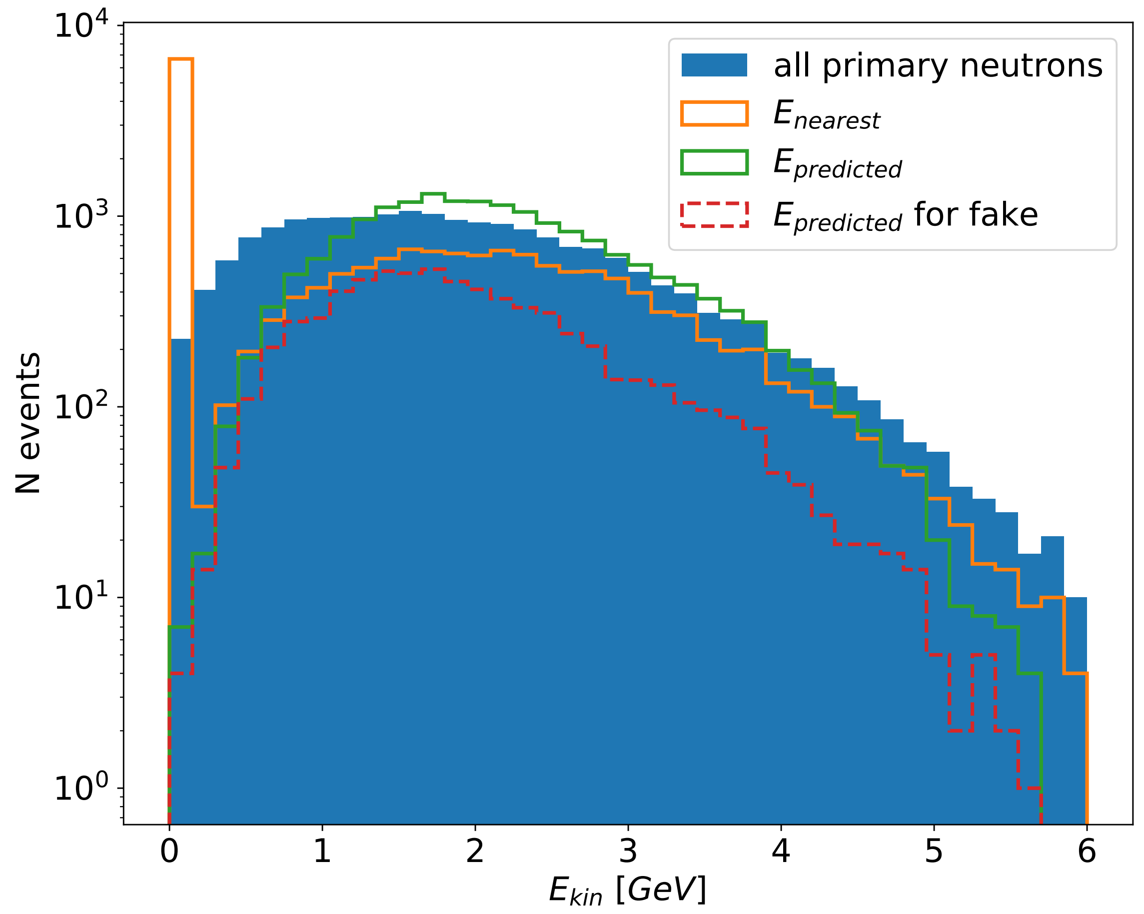
E_{ToF}:

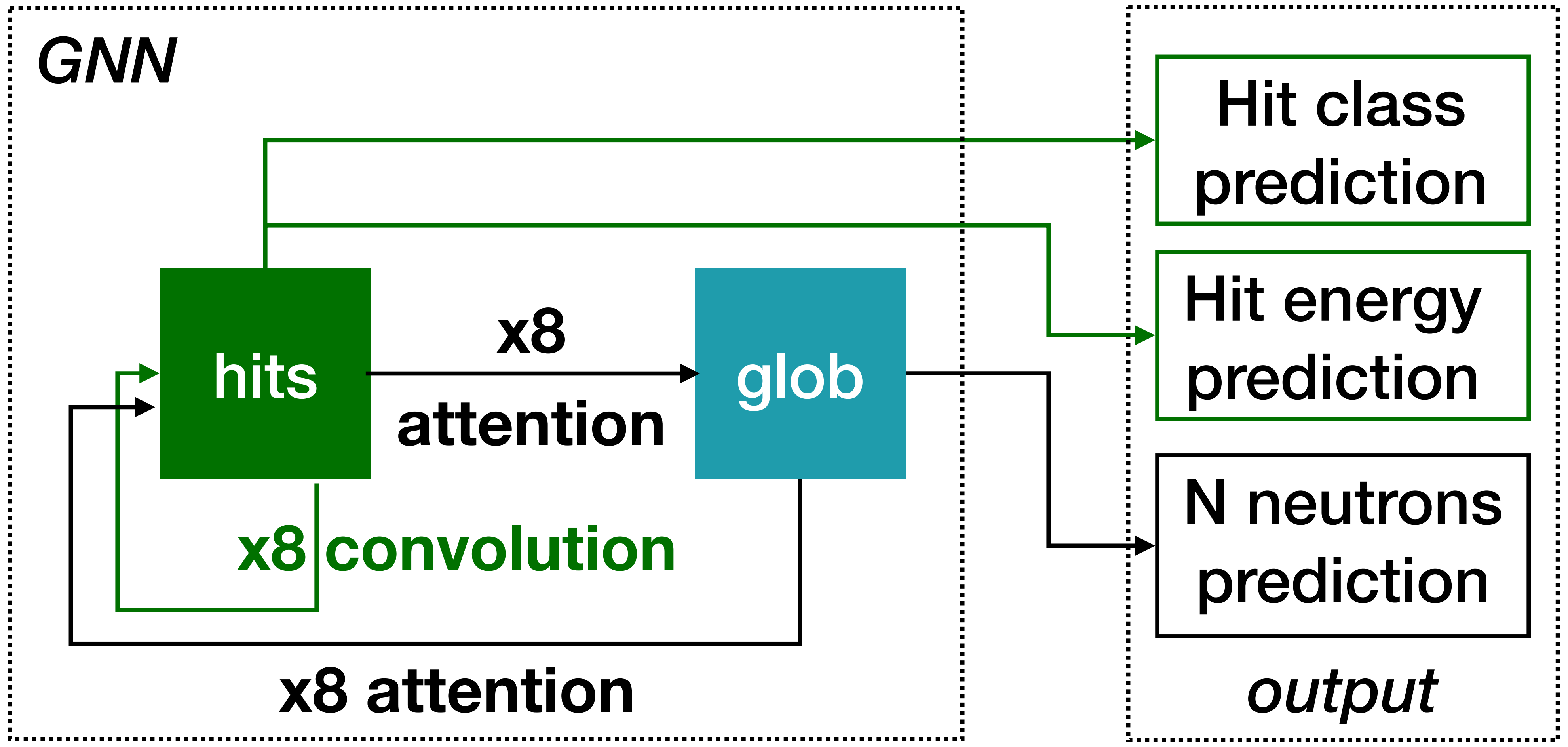




E_{GNN}:



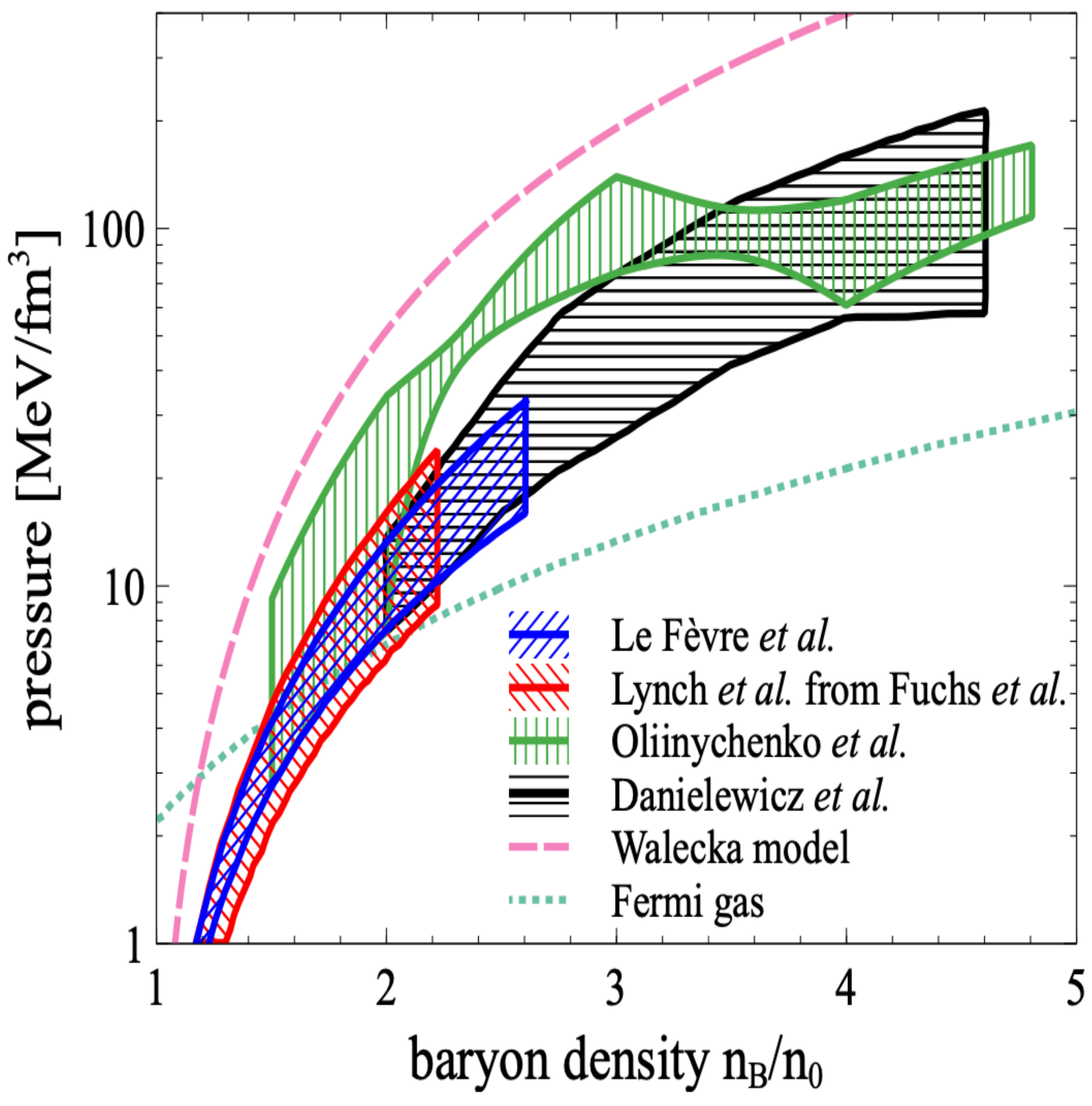




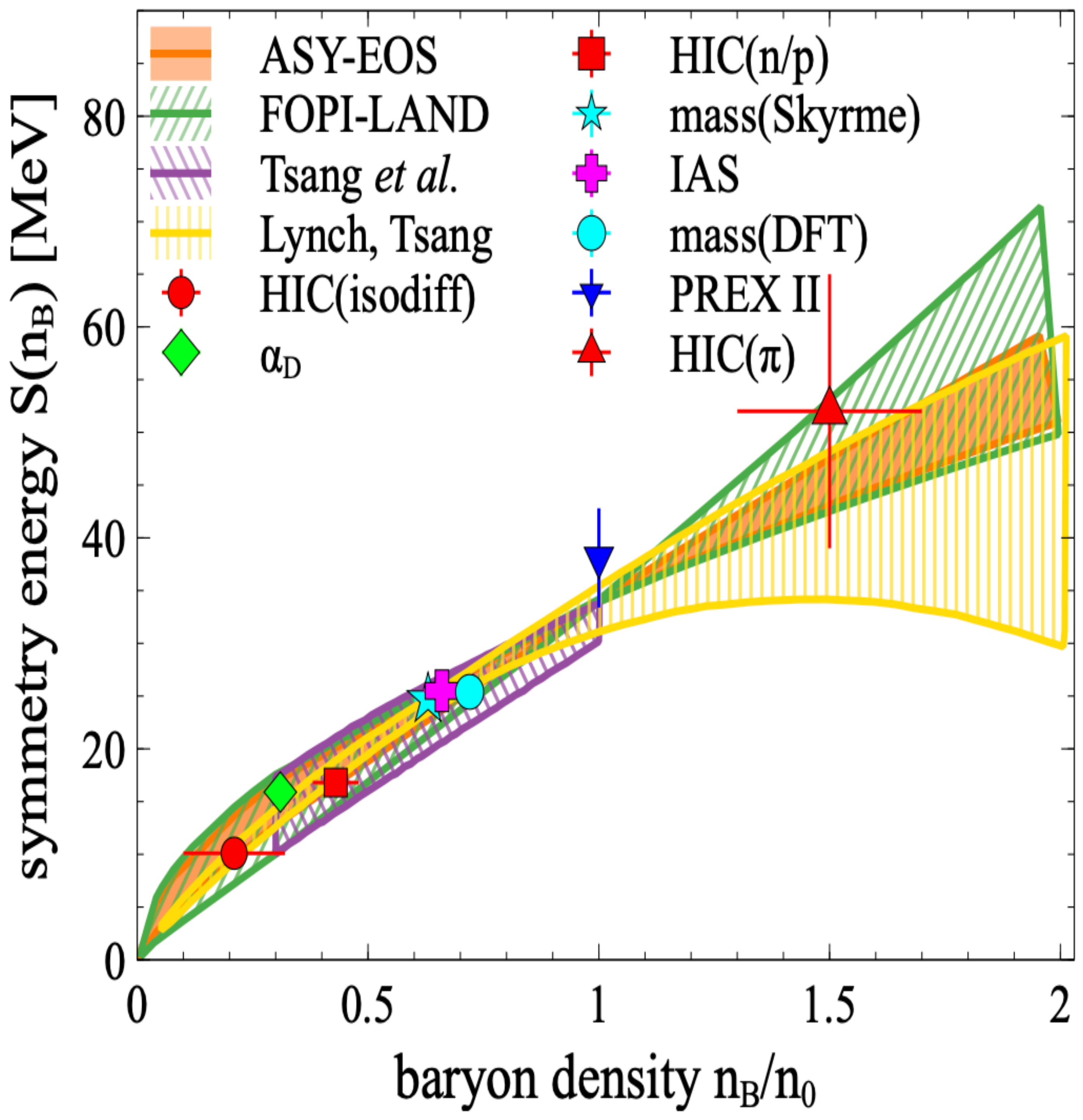
EOS for high baryon density matter

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

Anisotropic Flow Coefficients

Simplified estimation of coefficient measurement performance using classification-based neutron reconstruction in the HGND

- Data source: all primary neutrons from initial DCM-QGSM-SMM Bi+Bi @ 3 AGeV reaction
  - MC truth information
  - primary neutrons randomly sampled according to classifier efficiency
  - mixed with uniformly distributed $v_{1/2}$ as background (P_T and Y_{cm} are sampled from selected neutrons) according to classifier purity
- v_1 vs Y_{CM} selection criteria:
  - $E_{kin} > 0.4$ GeV
  - Impact parameter $\in (6, 9)$ fm
  - $P_T \in (1., 1.5)$ GeV
  - ➡ 279802 neutrons initially

v_1 amplitude increases with purity, stat. uncertainty is affected by event yield

v_1 vs rapidity distortion