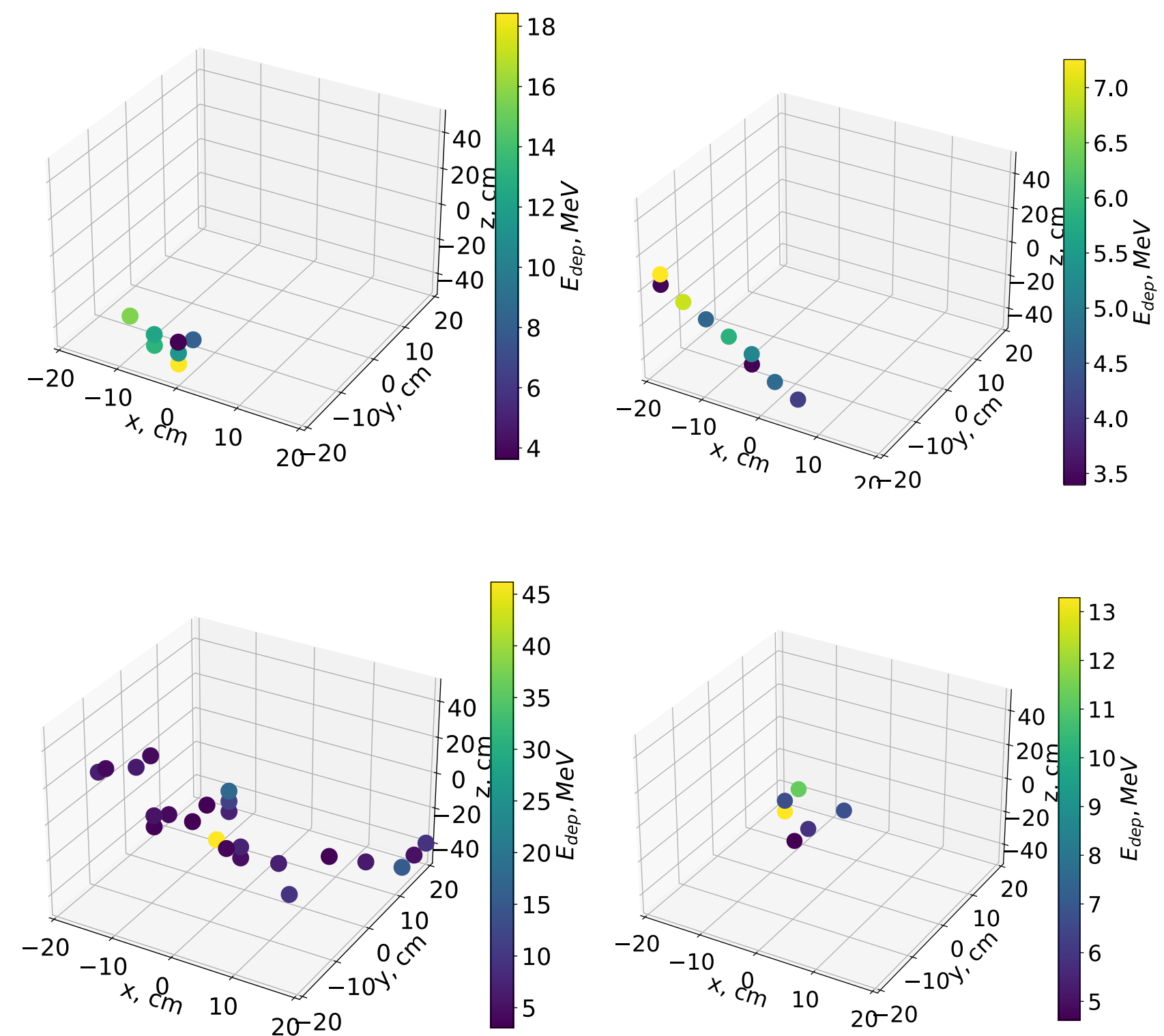


Performance study of the neutron reconstruction using HGN detector at the BM@N experiment

V. Bocharnikov¹, D. Derkach¹, F. Ratnikov¹,
M. Golubeva², F. Guber², S. Morozov²,
P. Parfenov^{2,3}

¹HSE University, ²INR, Troitsk, ³MEPhI

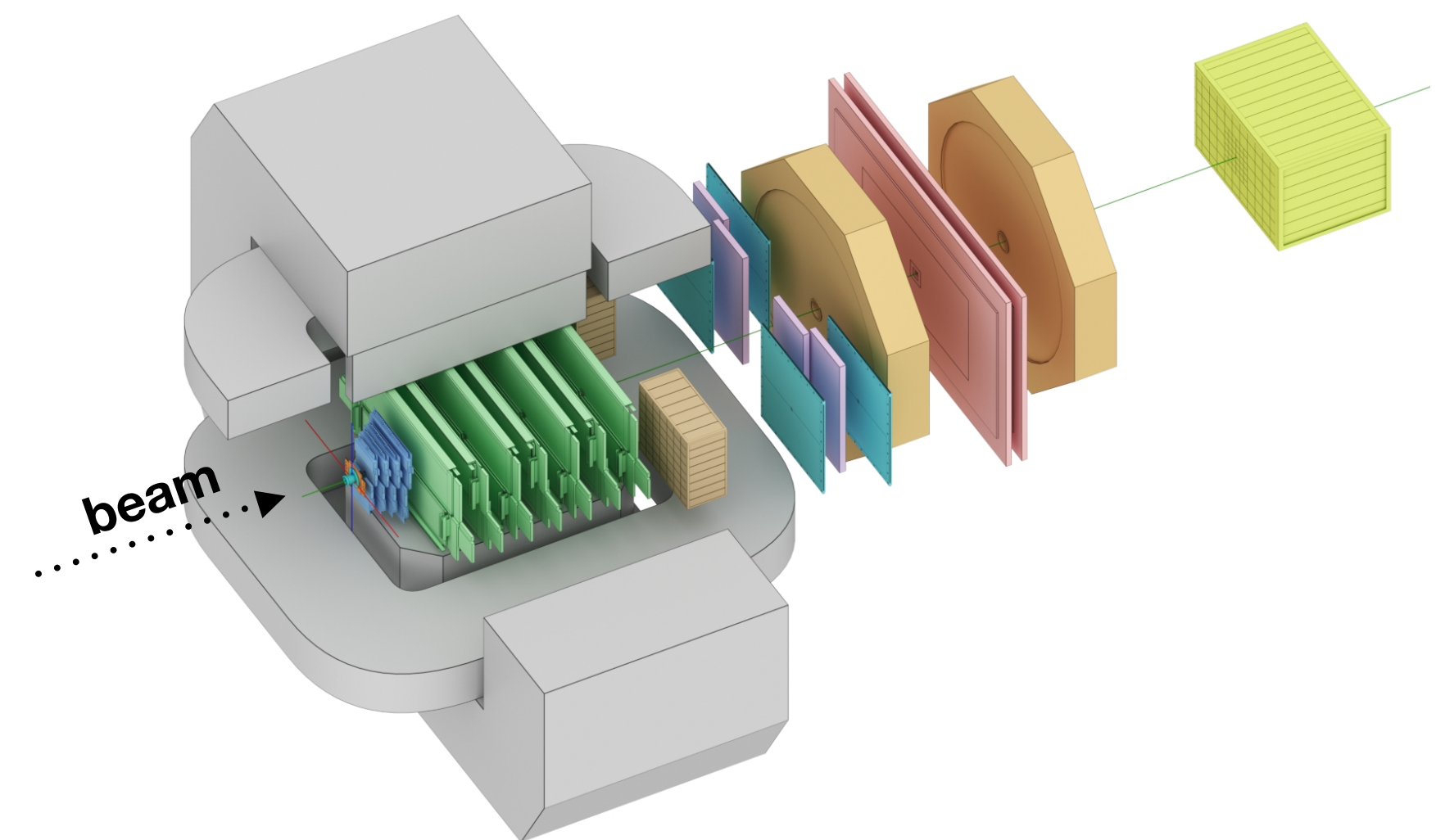
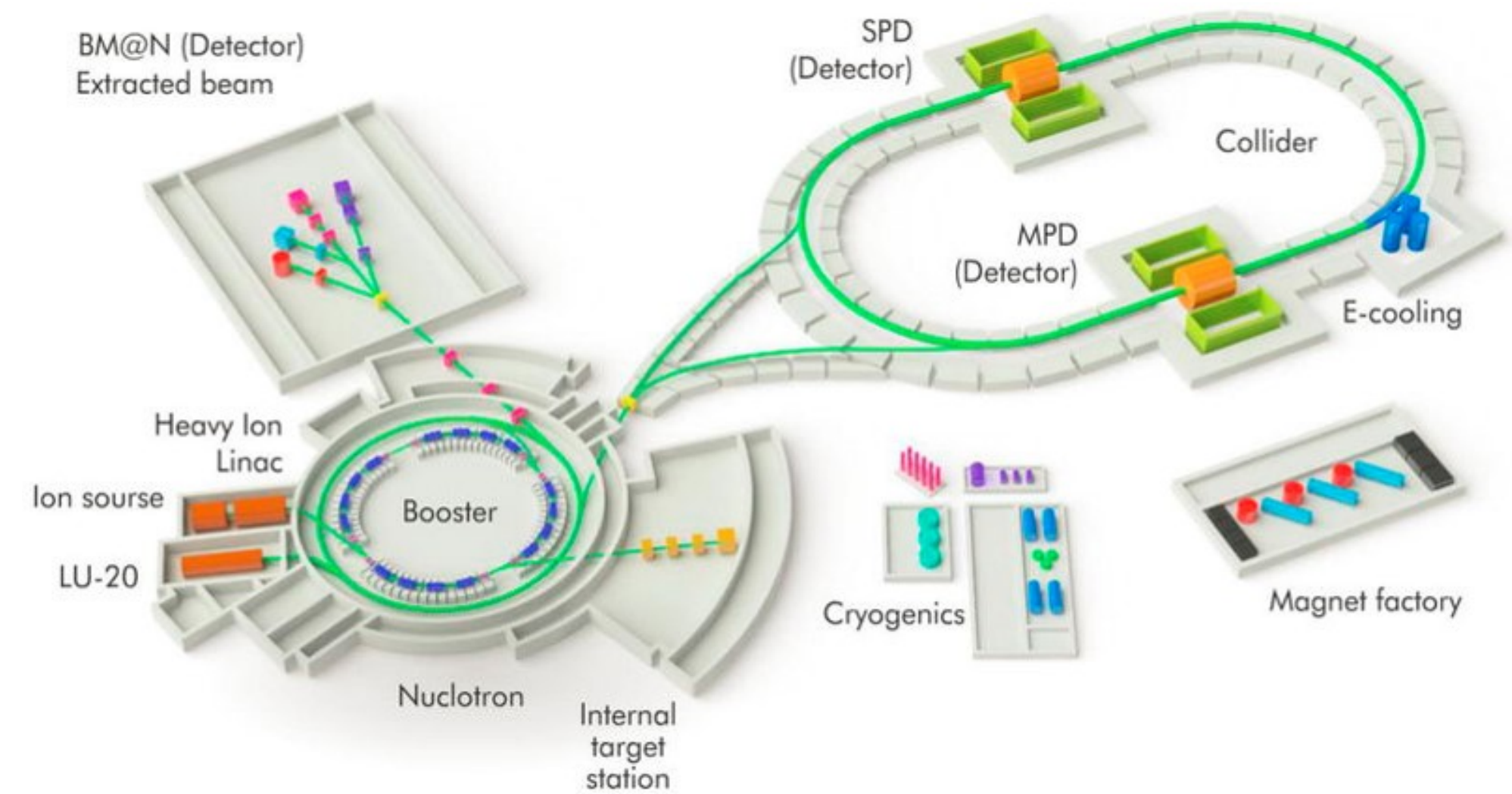
ISHEPP-2023, Dubna
19.09.2023



BM@N experiment

Studies of **Baryonic Matter at the Nuclotron** (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.

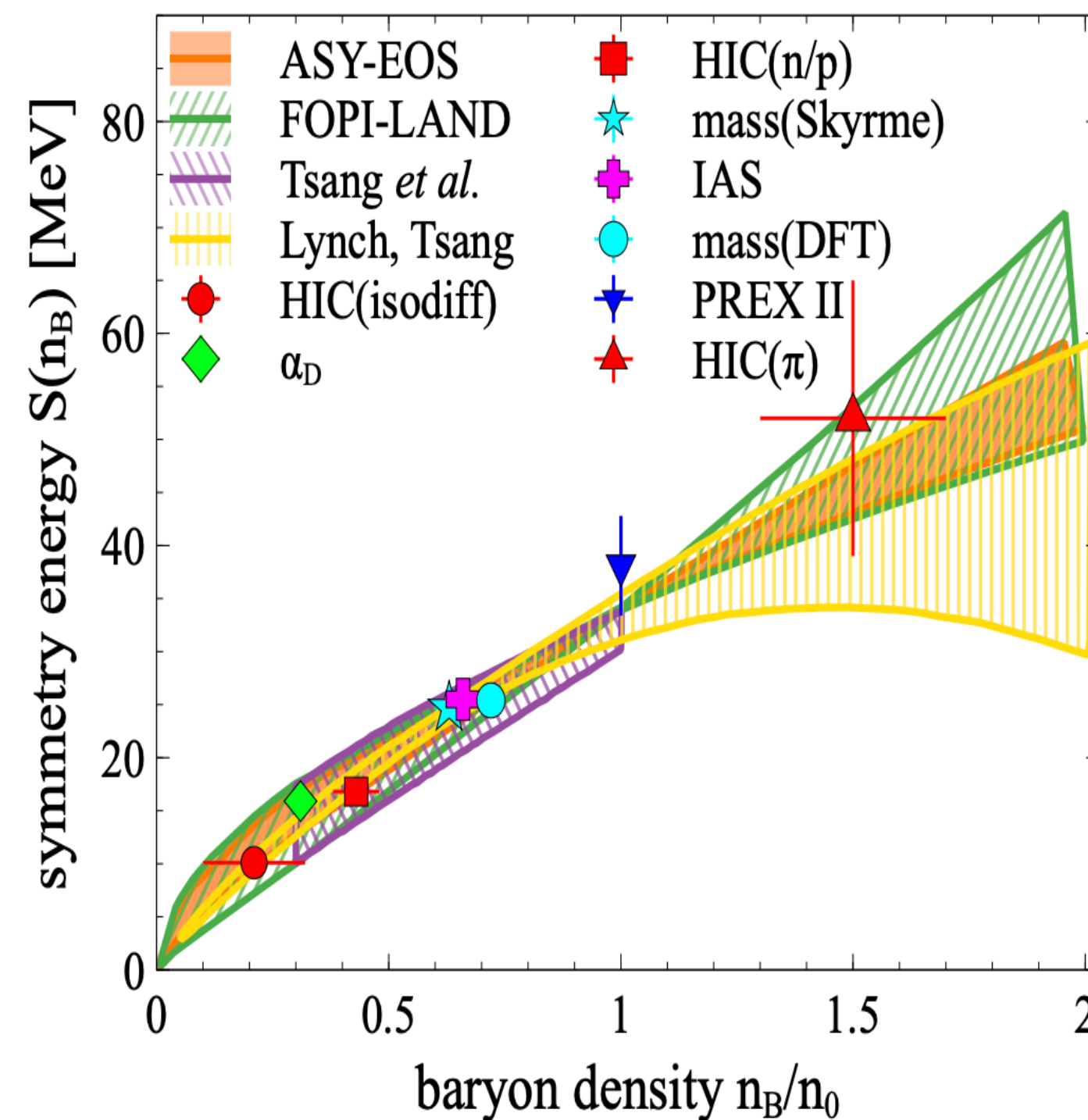
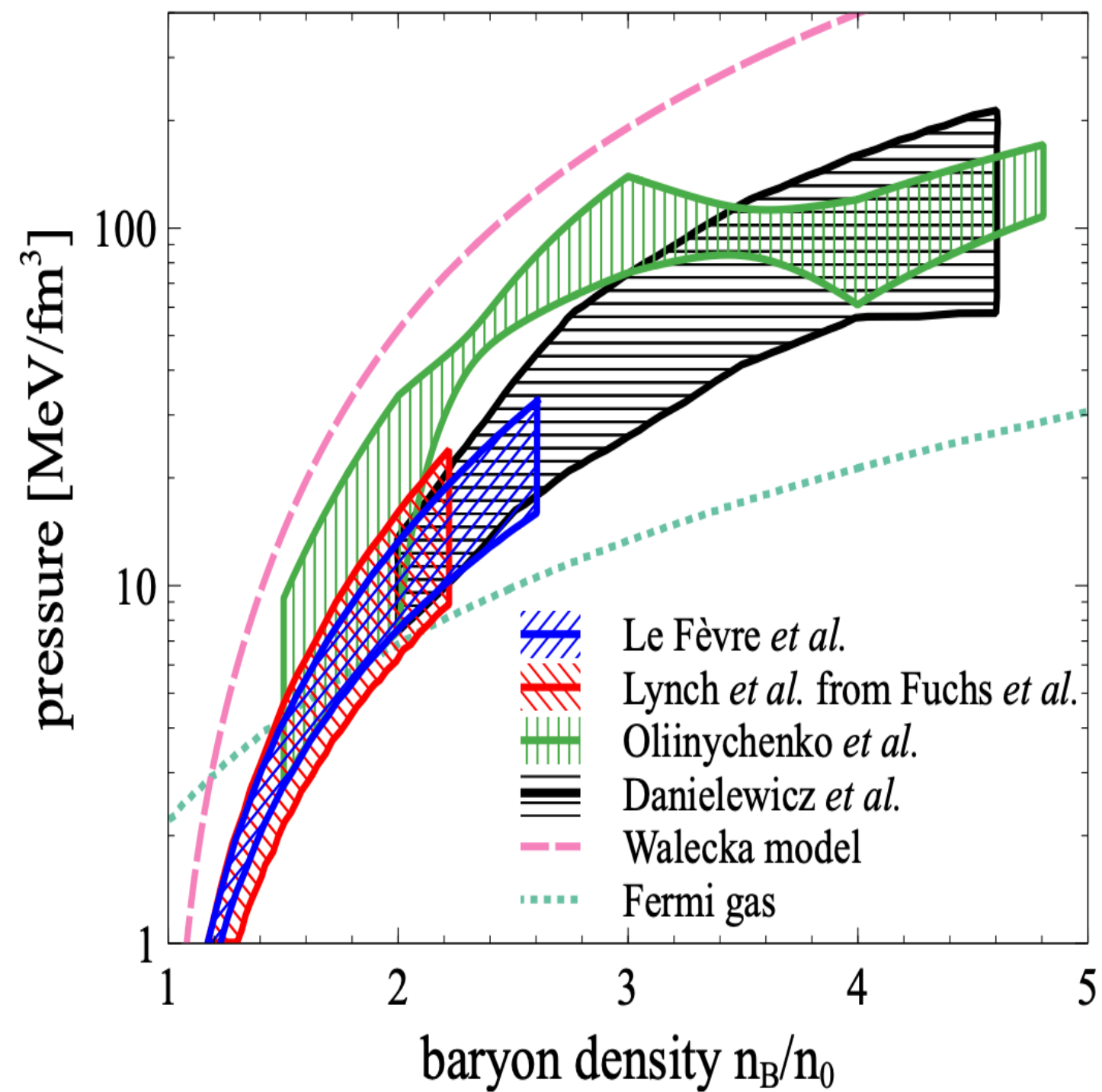


EOS for high baryon density matter

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

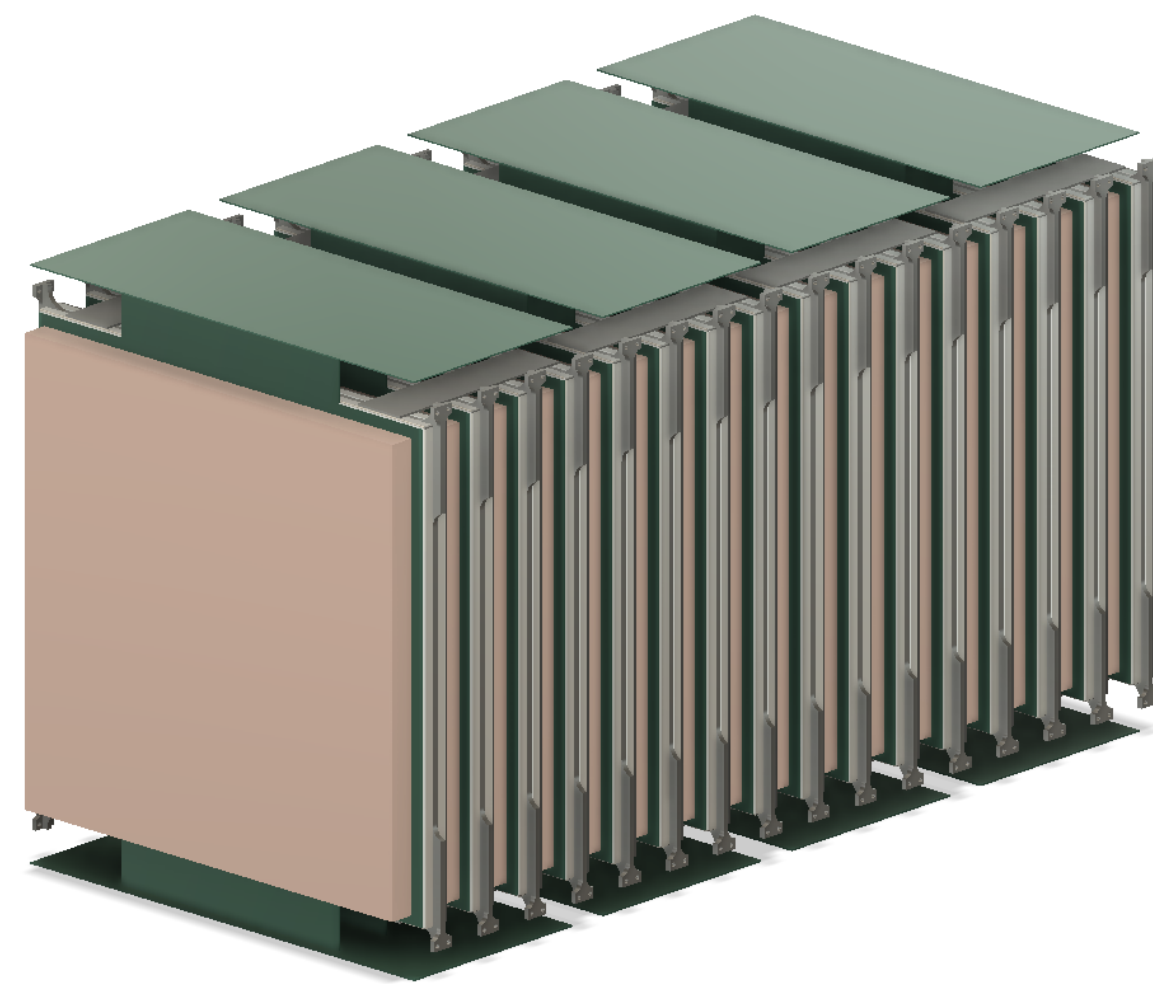
- **Neutron flow** measurements are essential to further constrain symmetry energy
- Sensitive observables:

Anisotropy flow coefficients:

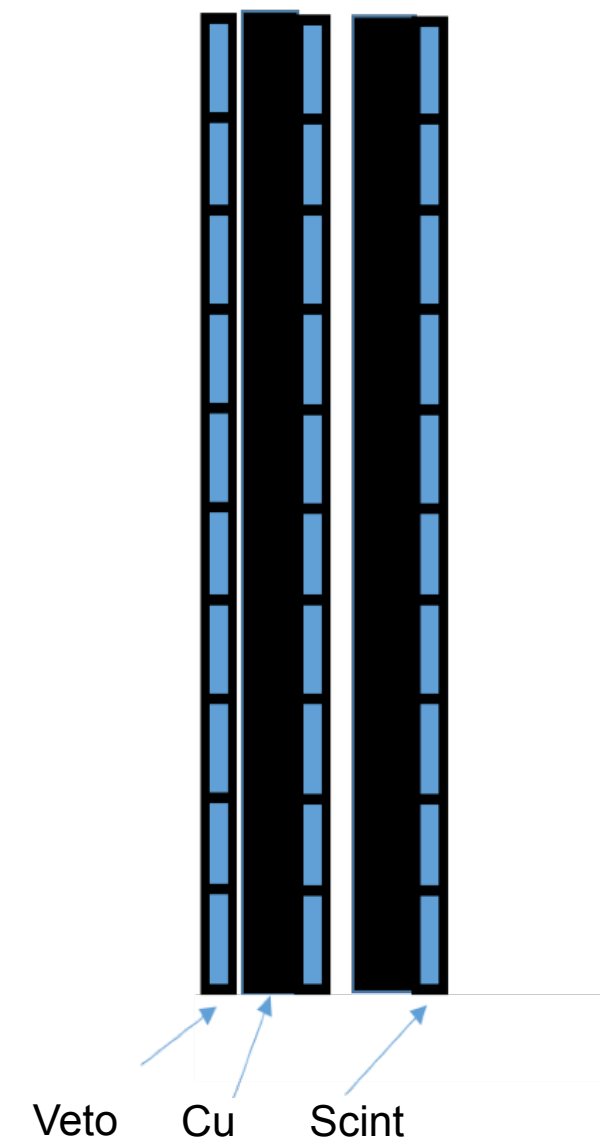
$$\frac{dN}{d\phi} \propto 1 + 2 \sum_{n=1} v_n \cos[n(\phi - \Psi_{RP})], \quad v_n = \langle \cos[n(\phi - \Psi_{RP})] \rangle$$

A. Sorensen *et al.*, arXiv:2301.13253 [nucl-th] (2023)

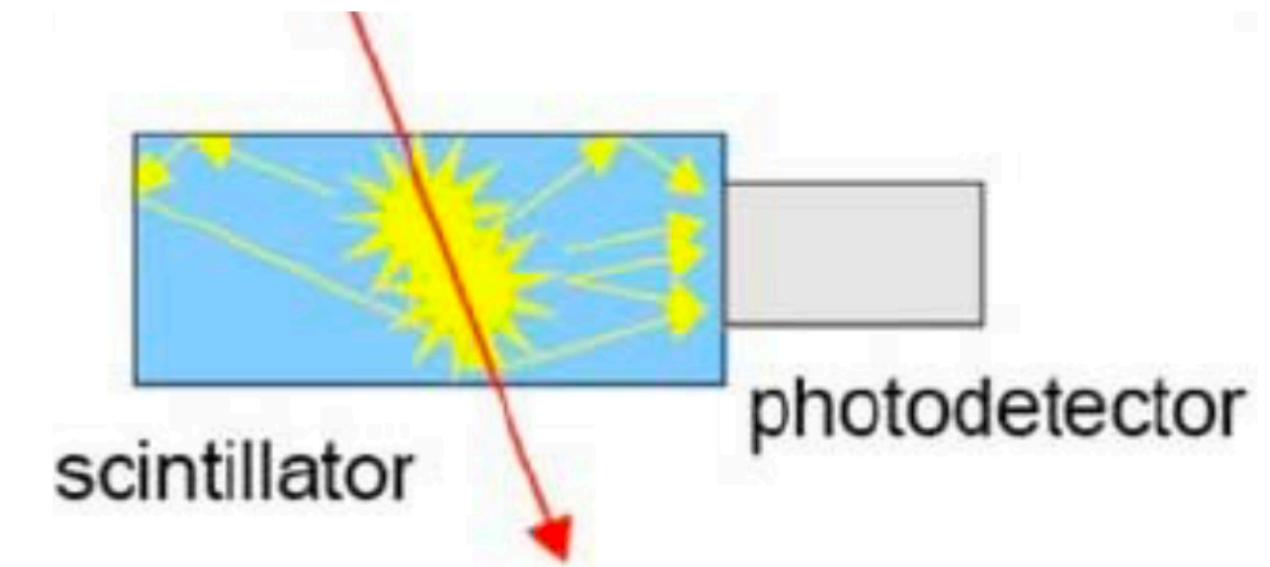
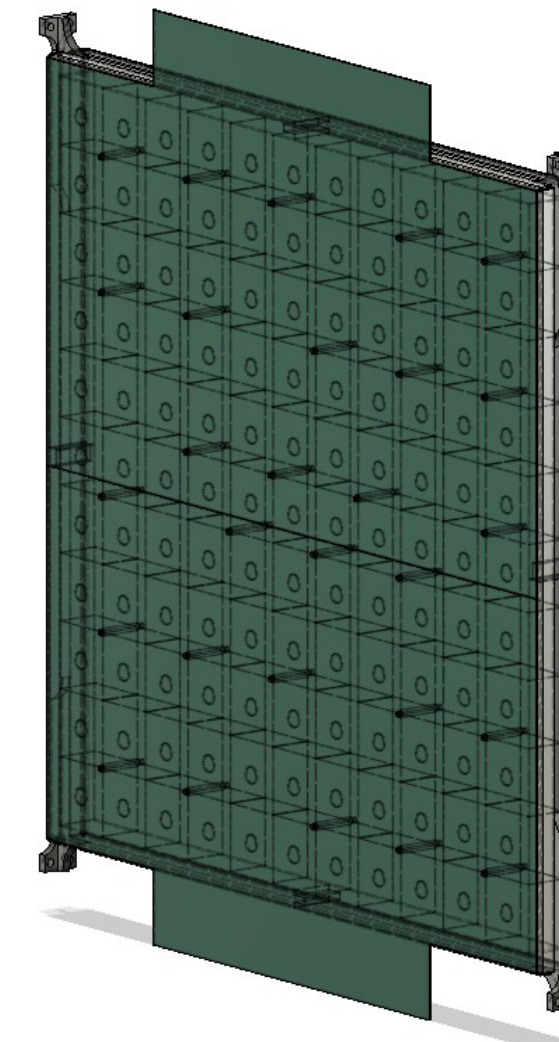
Highly granular time-of-flight neutron detector (HGND)



Longitudinal structure



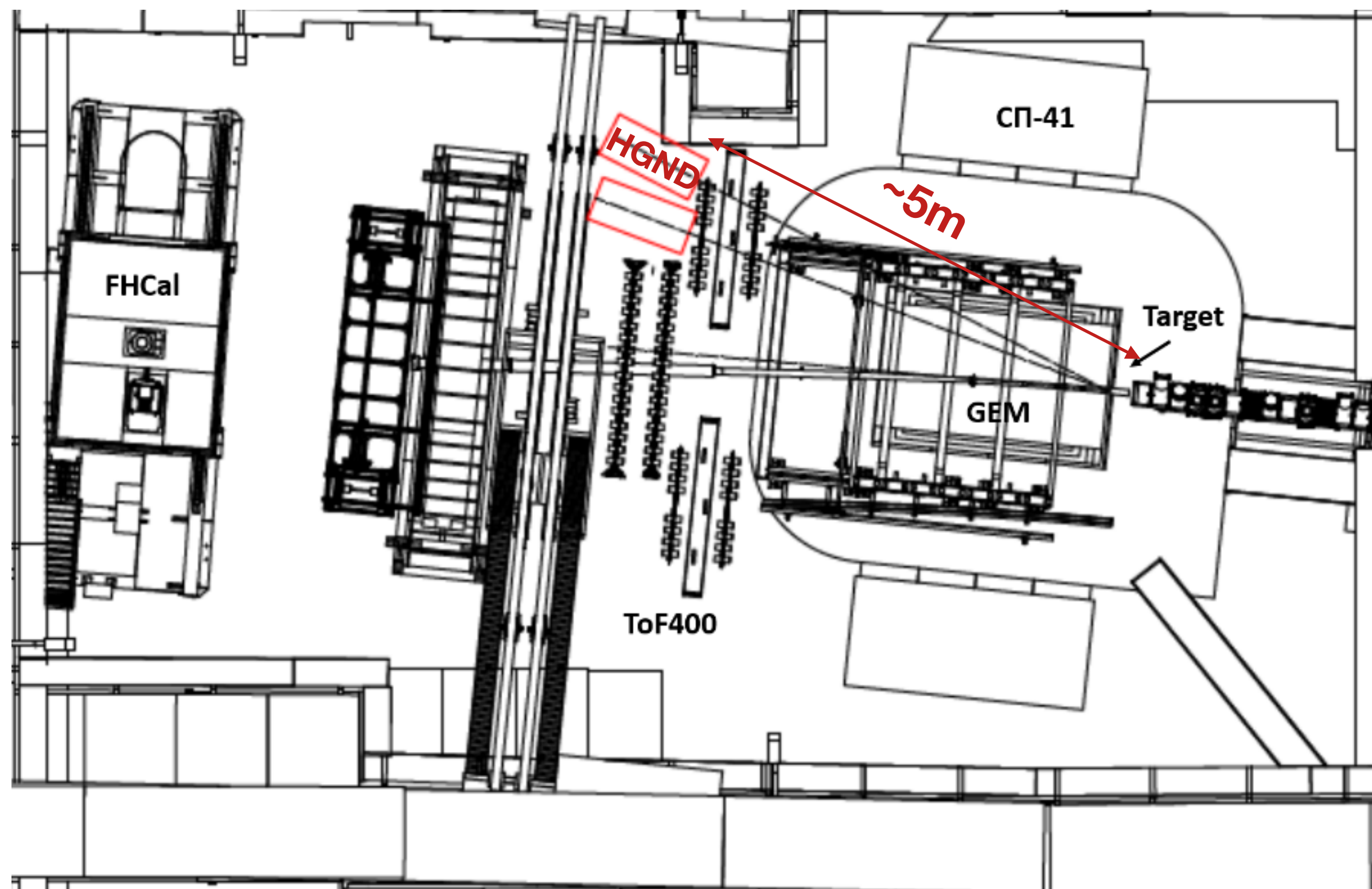
Active layer



- 16 layers: 3cm Cu (absorber) + 2.5cm Scintillator + 0.5cm PCB; 1st layer — ‘veto’ before
- ➔ Total length: ~1m, $\sim 3 \lambda_{in}$
- ➔ neutron absorption $\sim 100\%$
- Transverse size: **44x44 cm²**
- **11x11 scintillator cell grid**

- scintillator cells:
 - size: 4x4x2.5 cm³,
 - **total number of cells: 1936**
 - light readout by silicon photomultiplier
 - expected time resolution per cell: ~ 150 ps

Experimental setup and simulations

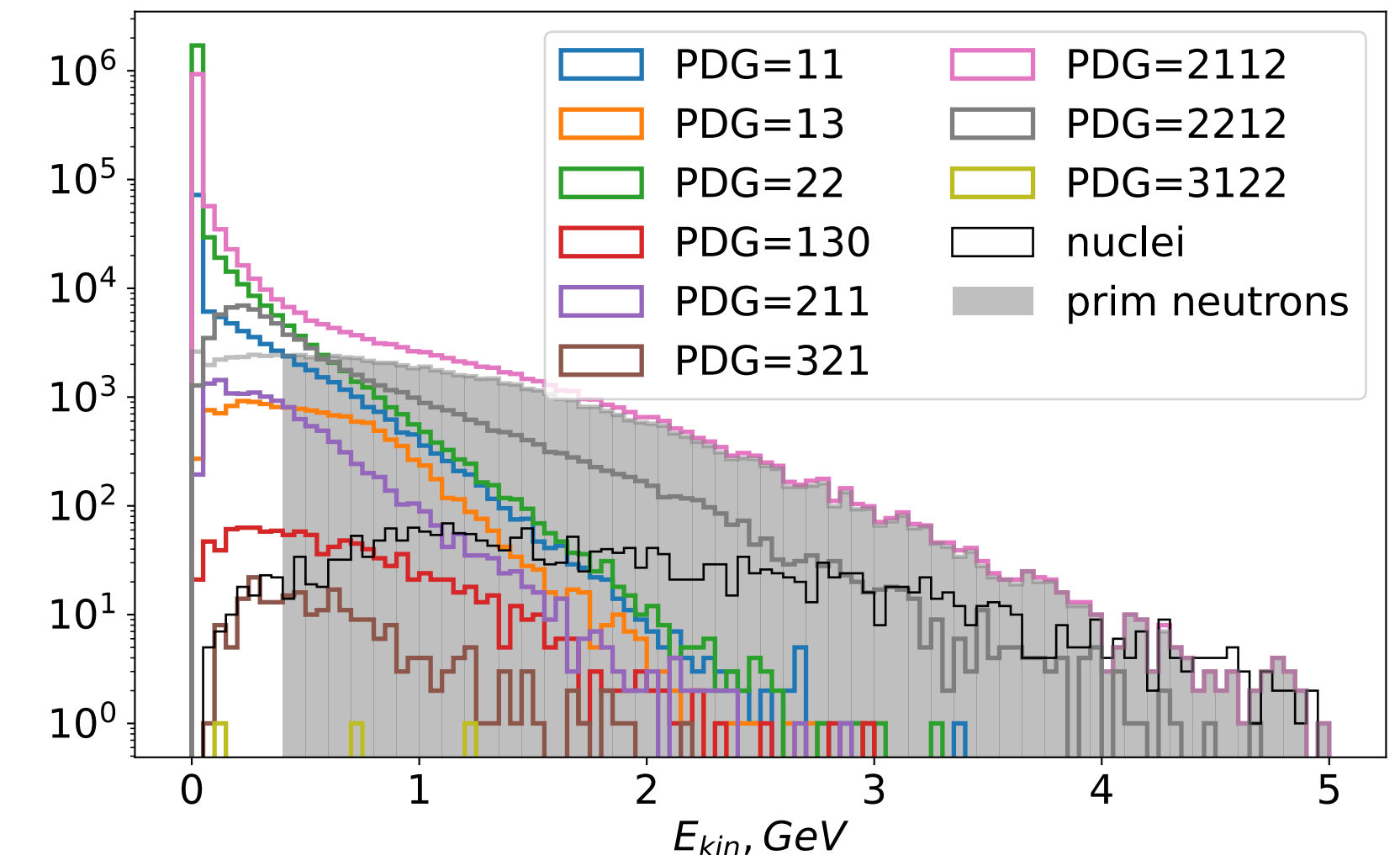


- Neutron detector is located at 23° to the beam axis at $\sim 5\text{m}$ from the target
- Monte-Carlo event simulations:
 - DCM-QGSM-SMM model + Geant4
 - $\sim 500\text{K}$ events with fully simulated reactions **Bi+Bi @ 3 AGeV** (BM@N data rate up to $\sim 10\text{kHz}$)

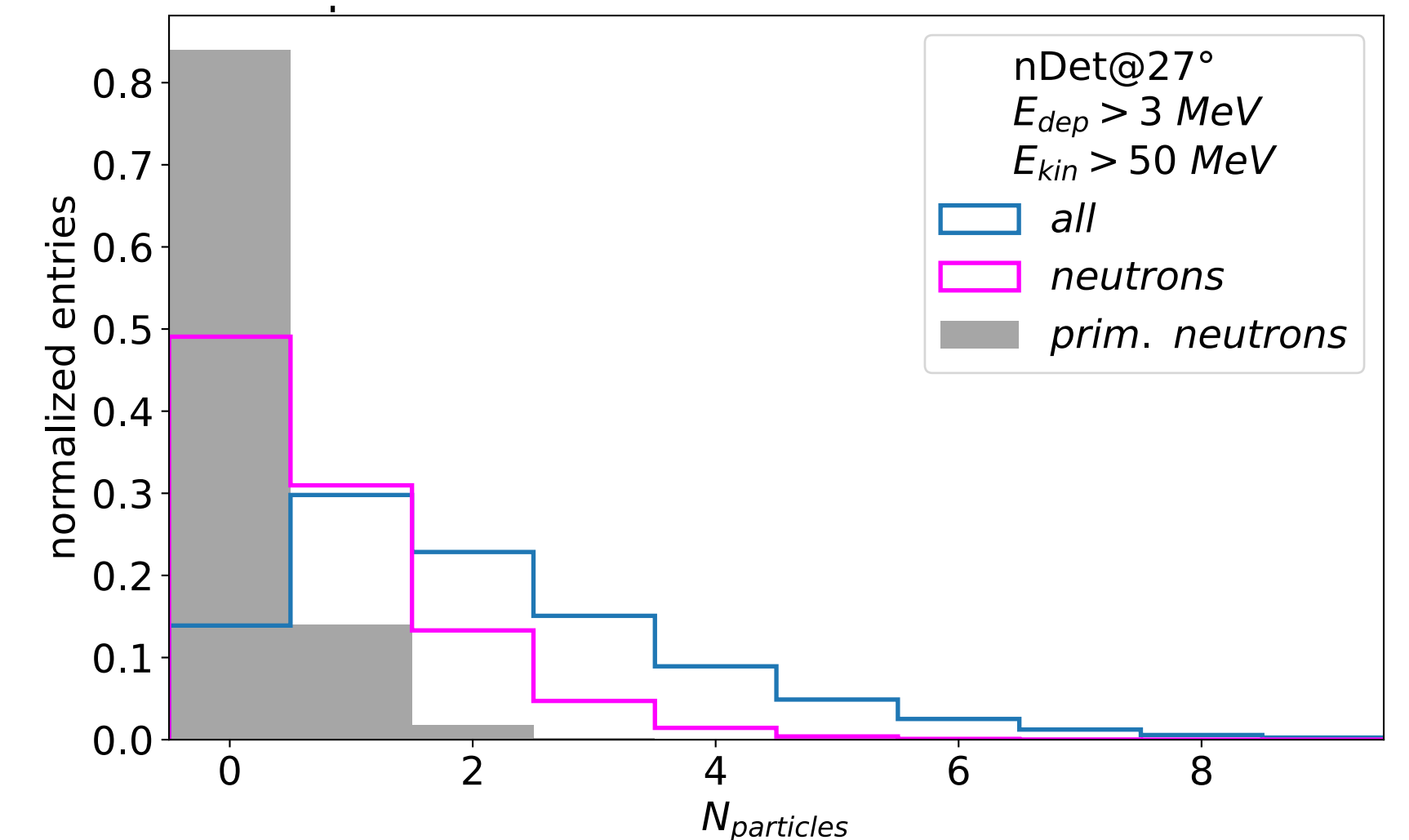
Particles entering the HGND

- Logical volume on the HGND upstream surface is used to capture particles in the detector acceptance
- No access to hit-level labelling within event
- **Primary neutrons:**
 - Produced in reaction
 - $E_{kin} > 0.4$ GeV to minimise admixture of background neutrons
 - Energy cut will be done after reconstruction to minimise bias
- ~14% of events with energy deposition in HGN have no particles entering through upstream surface
- Neutron multiplicity is ~0/1 => **event classification approach**

Energy spectrum per particle type



Particle multiplicity



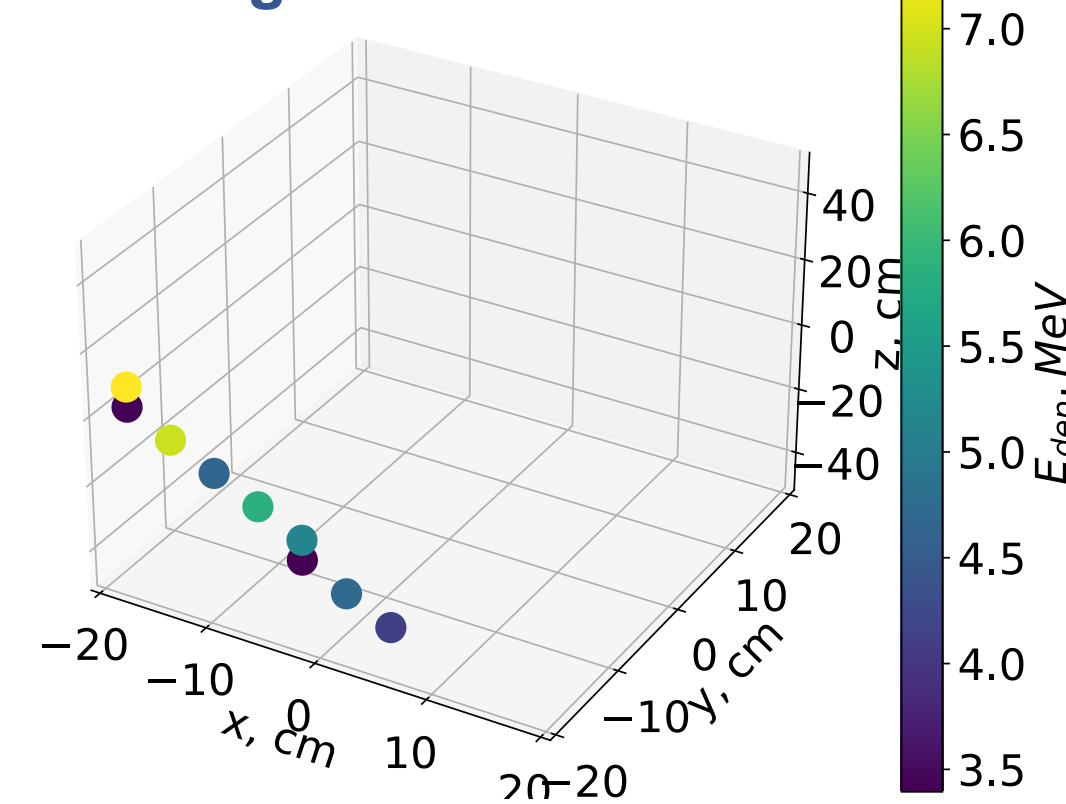
Imaging capabilities of the HGND

Event type signatures:

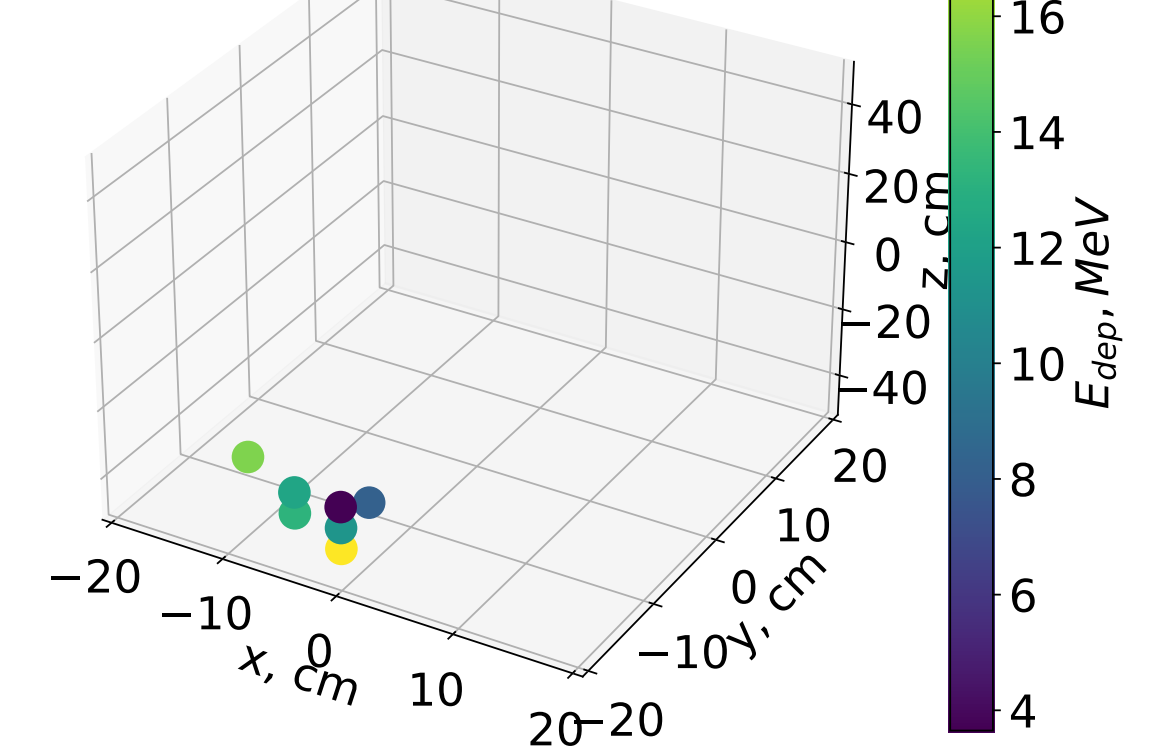
- **tracks** of charged particles
- compact **electromagnetic showers**
- sparse and irregular **hadronic showers**
 - no upstream track for neutral hadrons (including **neutrons**)

we use HGND event image to identify neutron and ToF to reconstruct it's energy

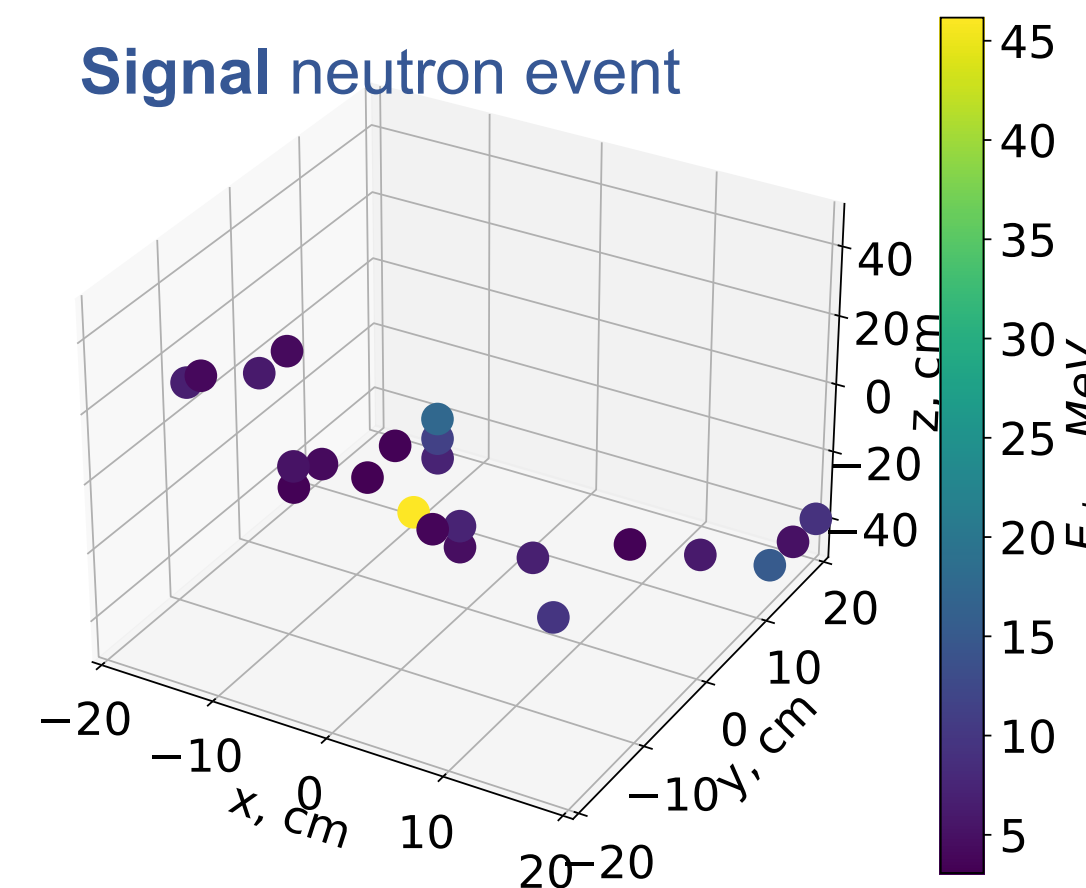
Charged particle track background event



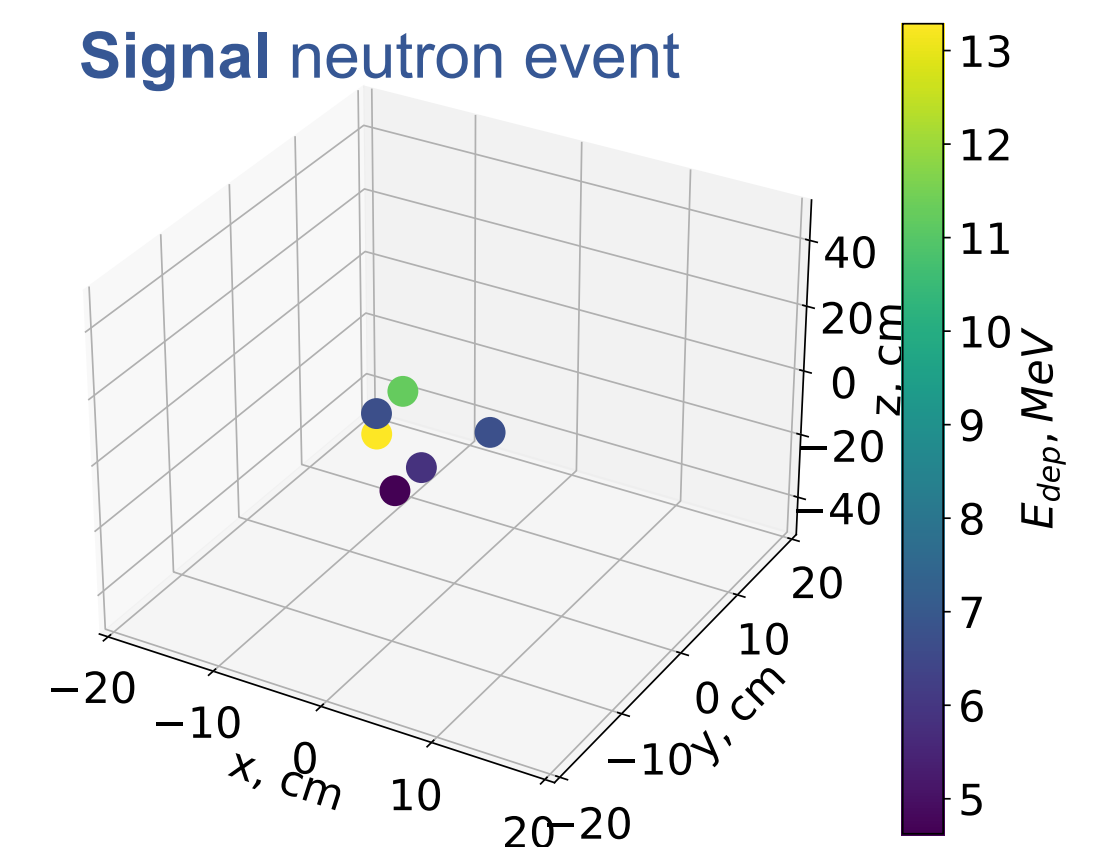
E/m shower background event



Signal neutron event



Signal neutron event



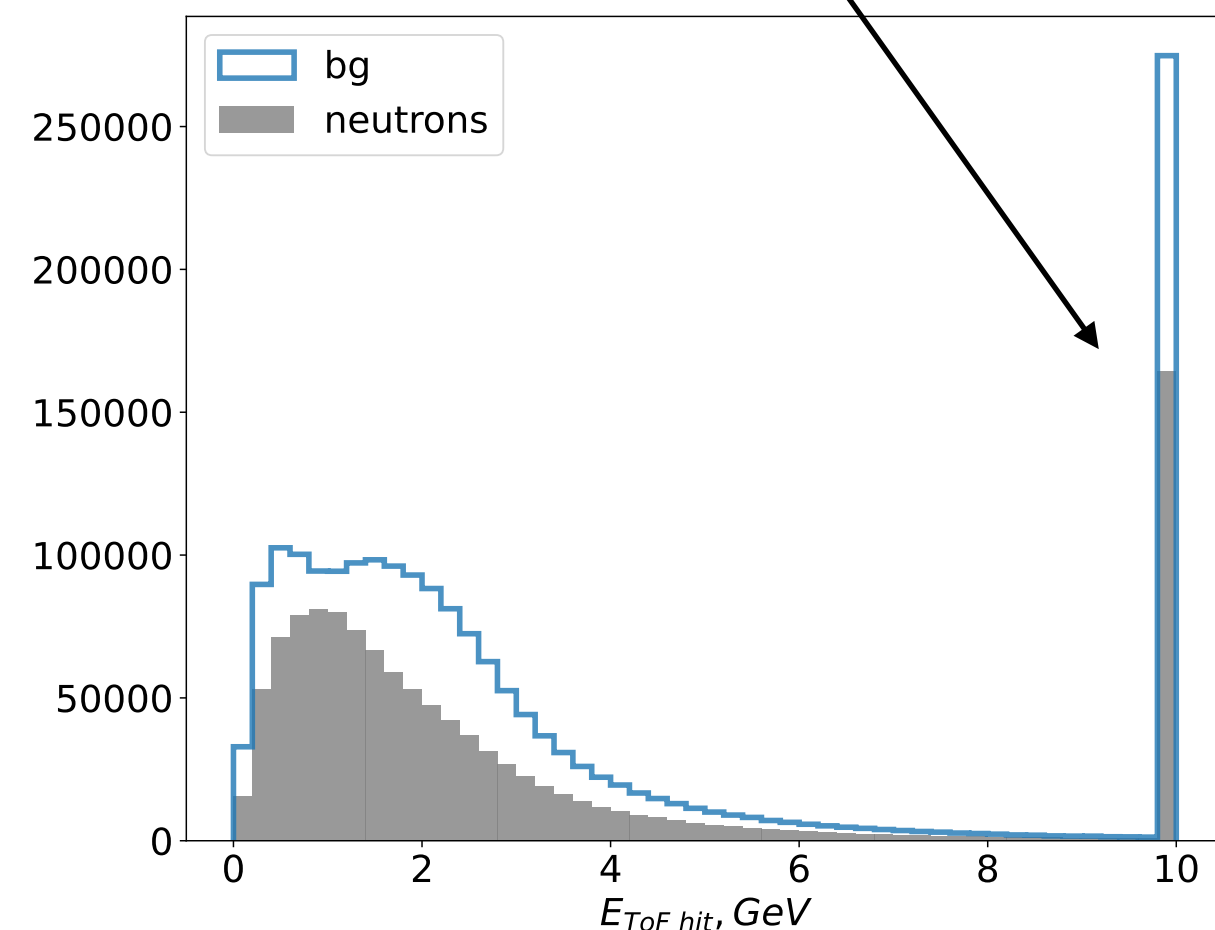
Neutron ToF energy

Time-of-flight (ToF) energy for n hypothesis:

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

- hits with $E_{ToF} > 10\text{GeV}$ are rejected

EToF distribution per hit



Fastest hit

- naive reconstruction
- bias from fast hits (bg + time uncertainty)

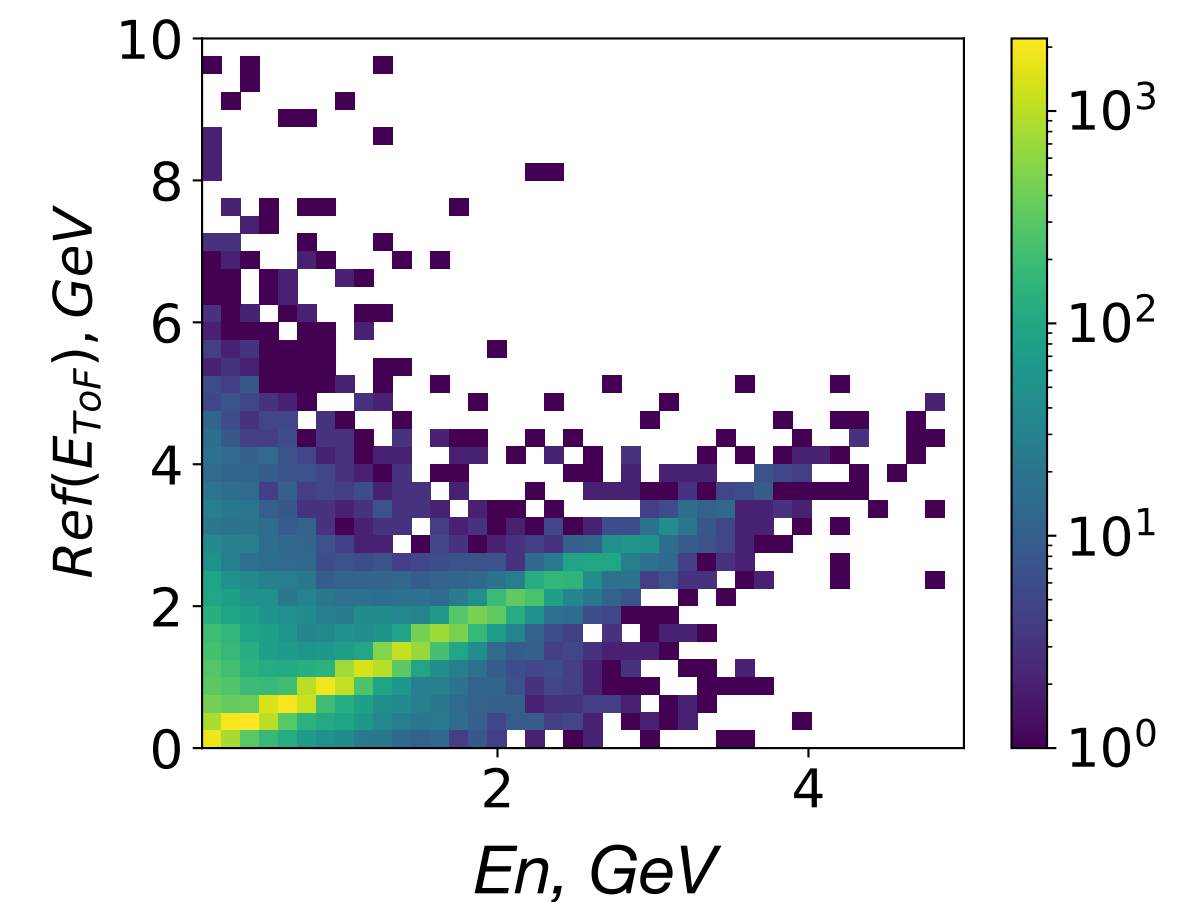
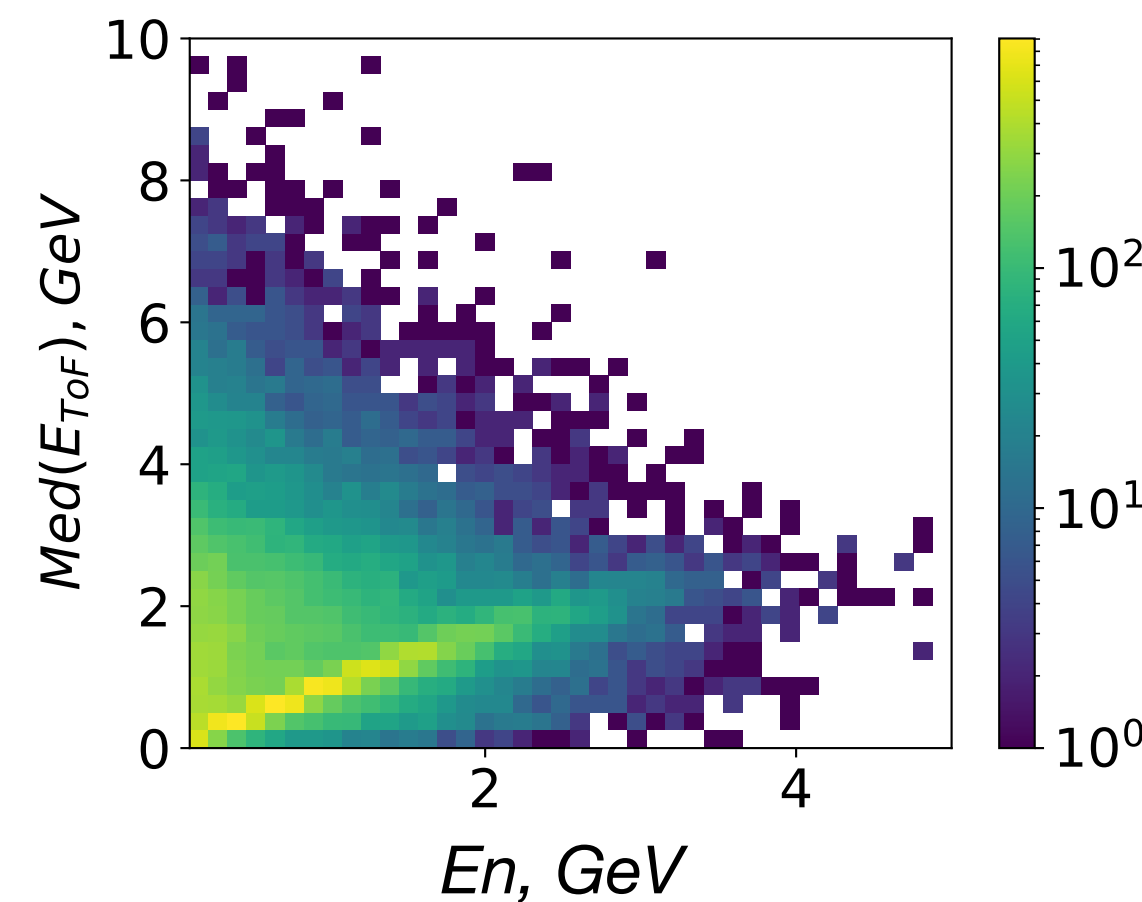
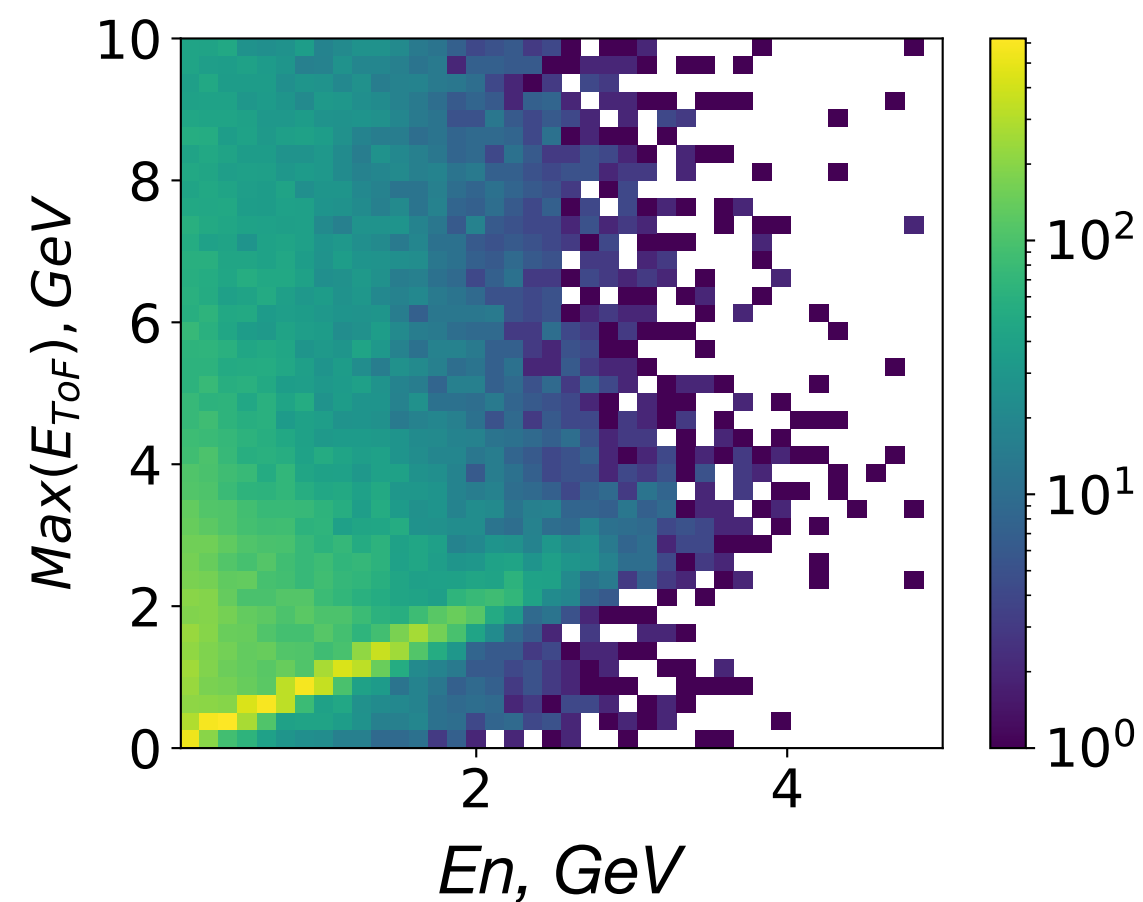
Median of all hits

- naive reconstruction
- more balanced uncertainty
 - fast hits
 - shower tails

Reference hit

- MC truth hit with $\min(|E_{ToF} - E_n|)$
 - ➔ suitable for event labelling
 - ➔ additional estimation model required: fast, median, ML, etc

Events with a neutron (>100 MeV) passing front wall of the HGN at angle <10°



Visible correlation with target energy even by naive approach.

Data labeling

Observables per hit:

- $(x, y, z)_{\text{hit}}$
- $E_{\text{dep}} (>3 \text{ MeV})$
- $T_{\text{hit}} + \mathcal{N}(0, \sigma = 150 \text{ ps}) < 40 \text{ ns}$

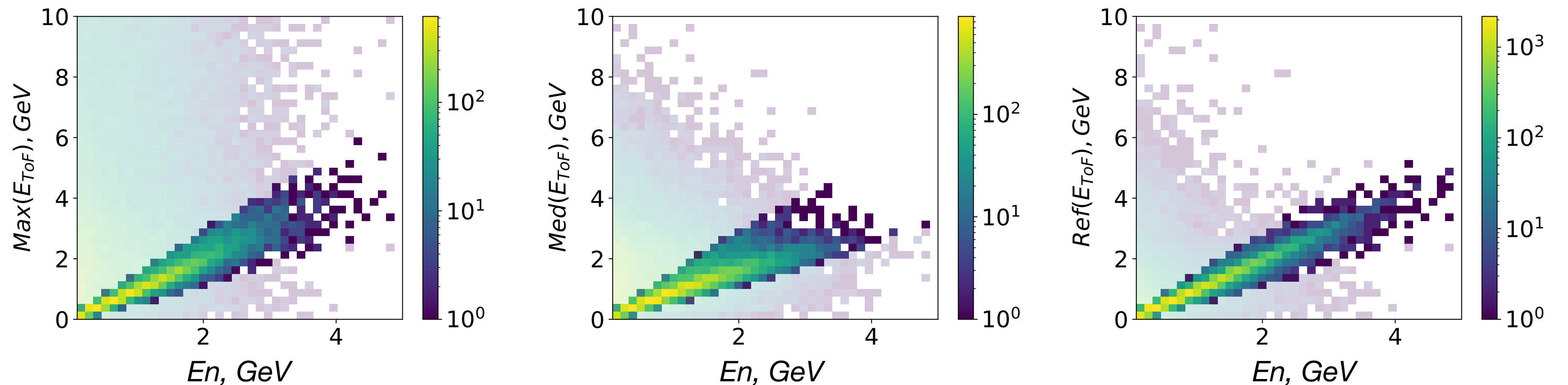
Signal event labeling:

- neutron,
- $E_{\text{kin}} > 100 \text{ MeV}$,
- Angle to detector axis $< 10^\circ$
- $\delta(E_{\text{ToF}}) < 40\%$

272844 events in total
with deposition $>3 \text{ MeV}$

- fastest - **21917 signals**
- median - **34670 signals**
- reference - **58949 signals**

Energy correlation for selected signal events:



Reconstruction challenges

- Small fraction of signal neutrons
- Event contamination by background energy deposition
- Neutron energy range is not typical for sampling calorimeters
 - 0-5 GeV vs. 5-250+ GeV
 - ➔ low number of hits corresponding to a neutron, high fluctuations in energy deposition
- ➔ **Machine Learning - based reconstruction** looks promising to deal with this challenges

Classification models

2 classification models are trained independently for crosscheck

Graph neural network (GNN)



- Graph event representation
- Observables per graph node (hit): (x,y,z) , E_{dep} , E_{ToF}
- Captures event topologies
- Increasing number of successful implementations in HEP

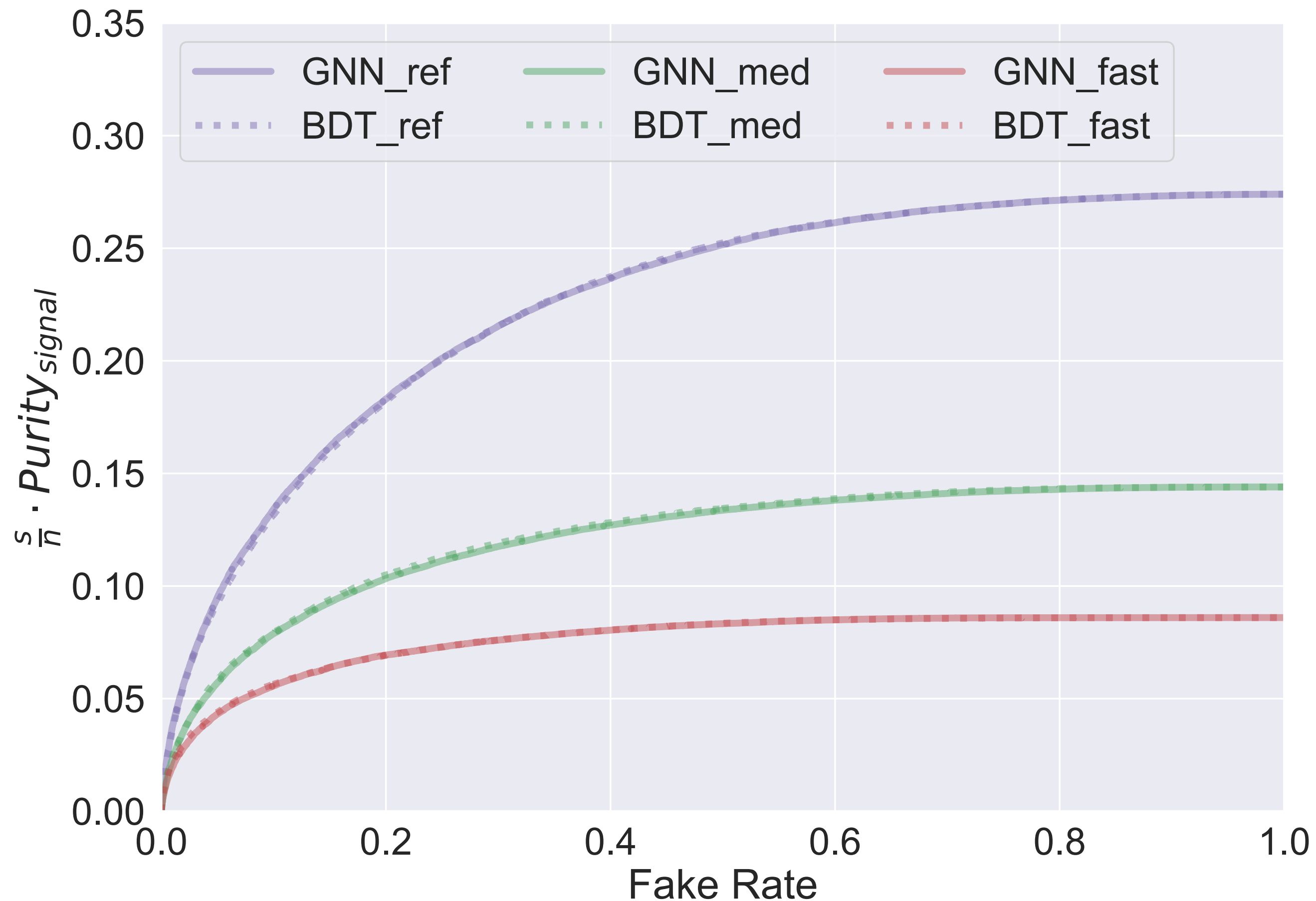
Boosted Decision Tree (BDT)



'first-principle' feature set based on global event properties and parameters of most informative hits.

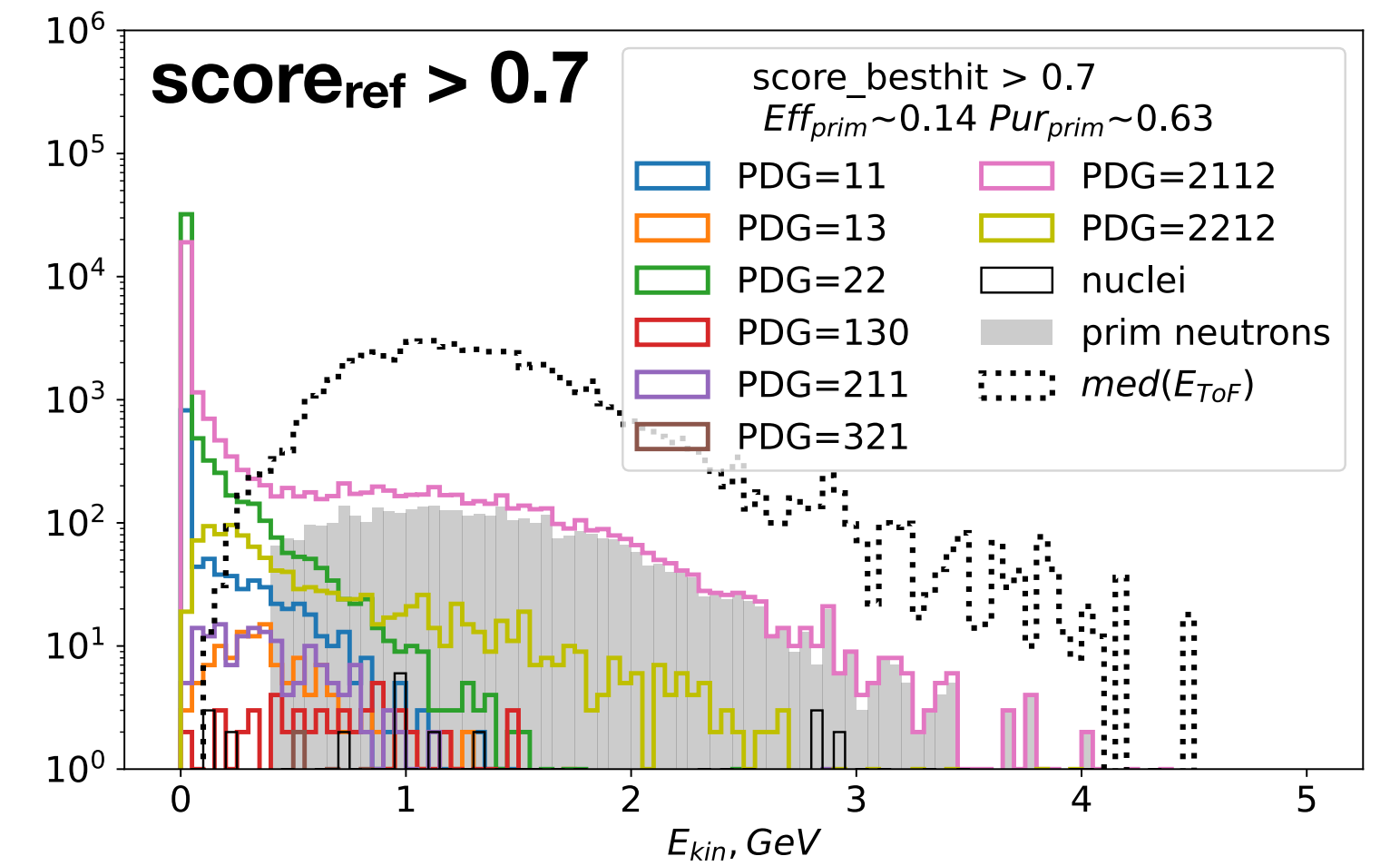
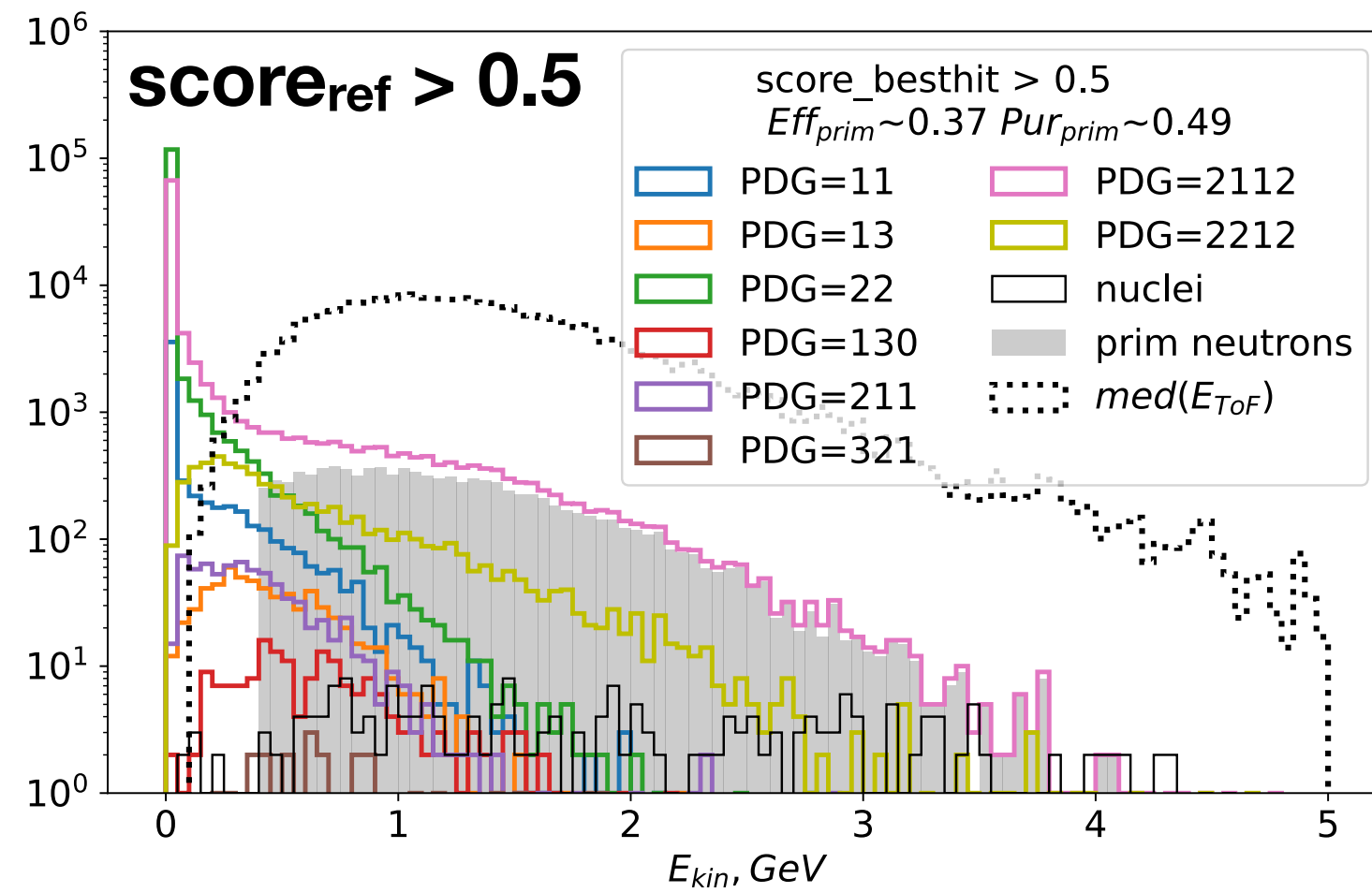
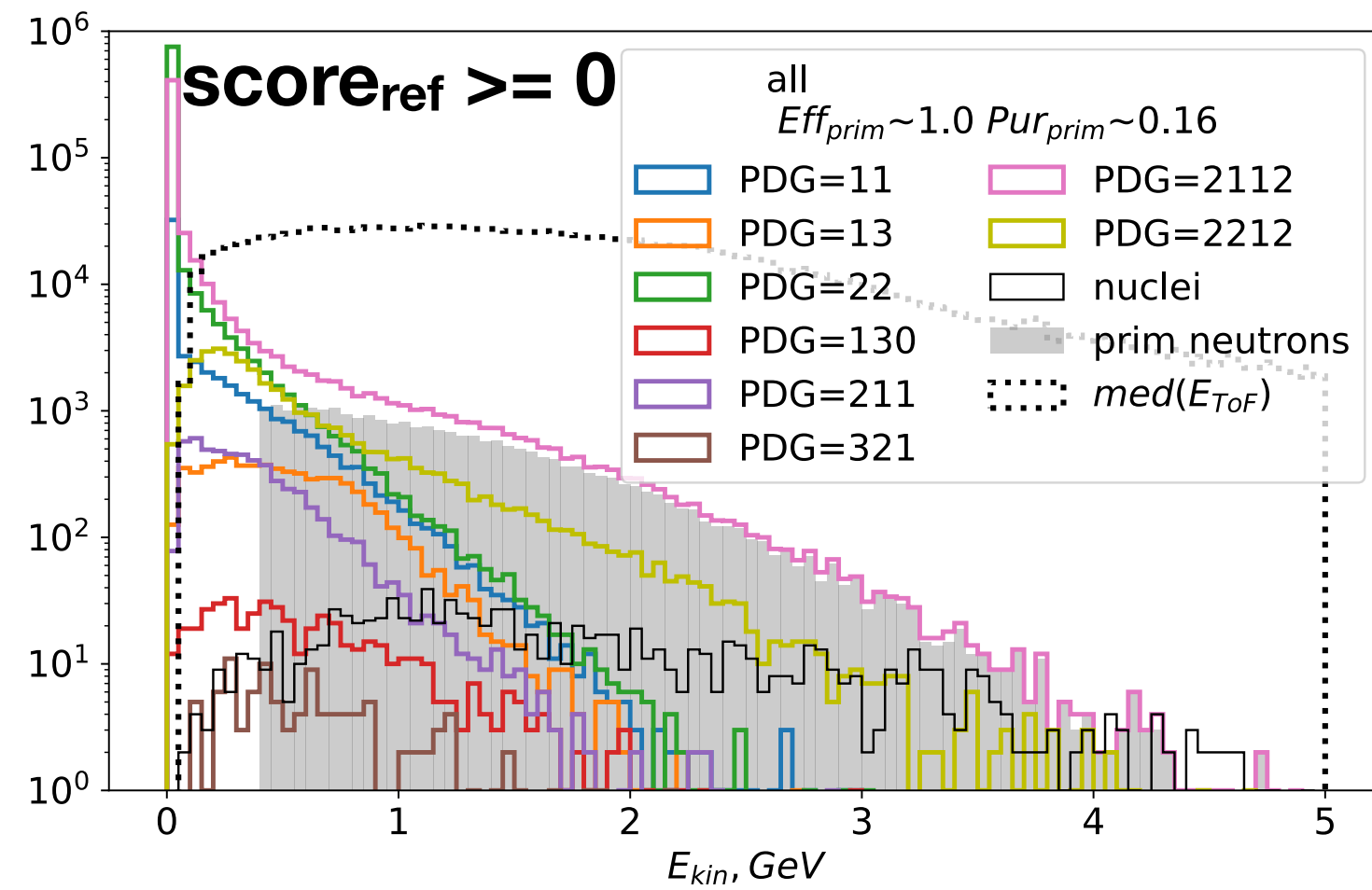
- 13 hand-crafted features

Classification performance

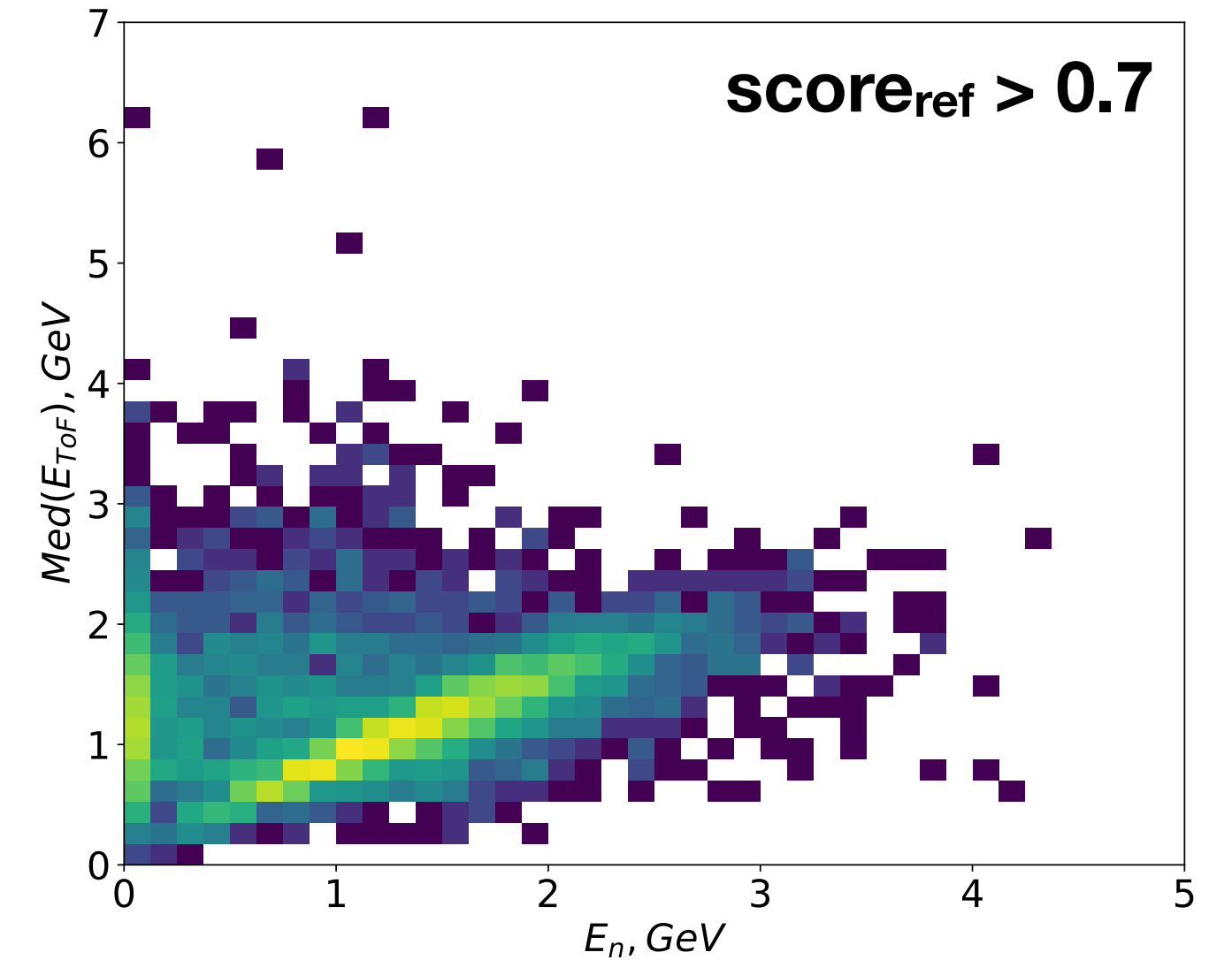
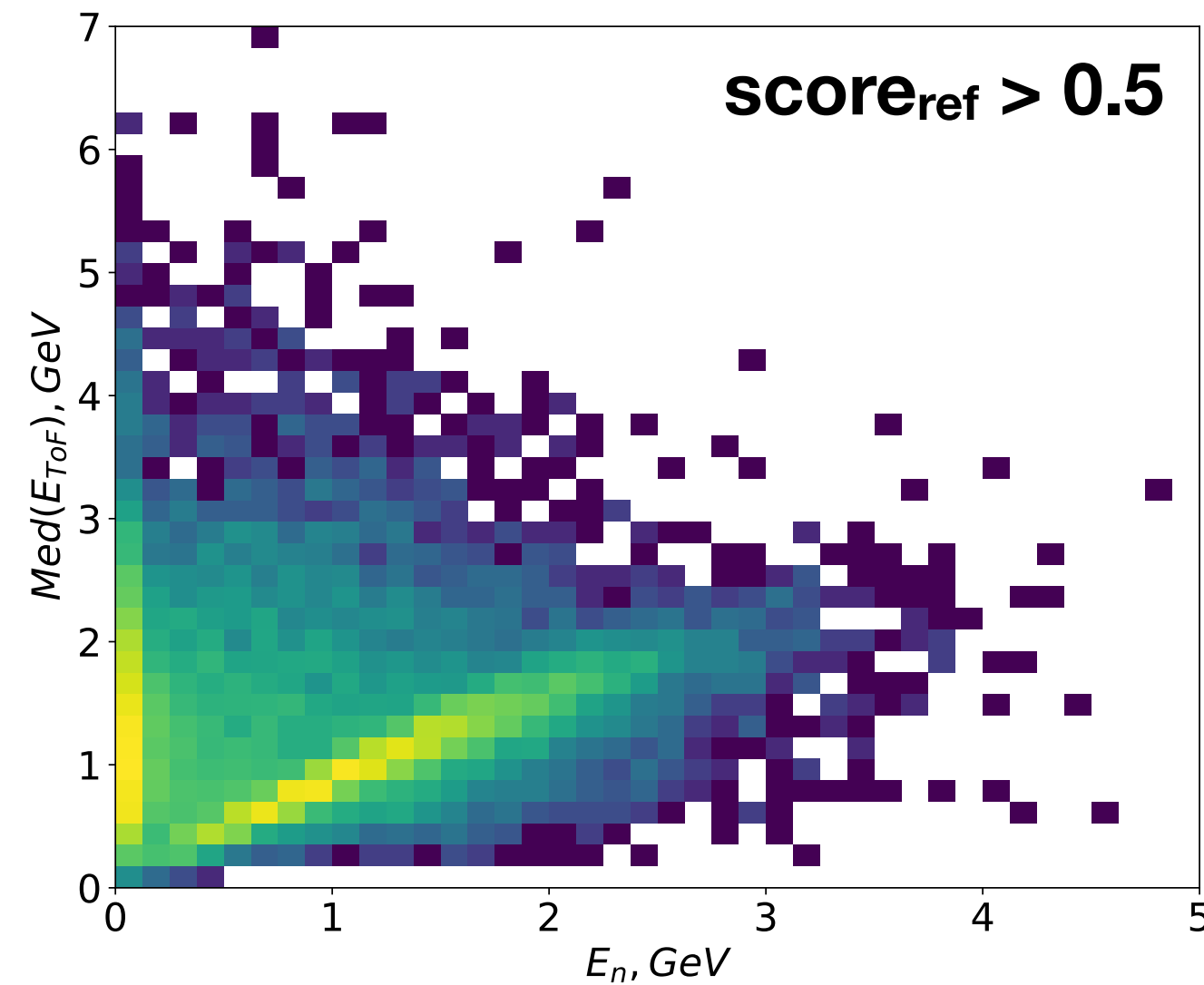
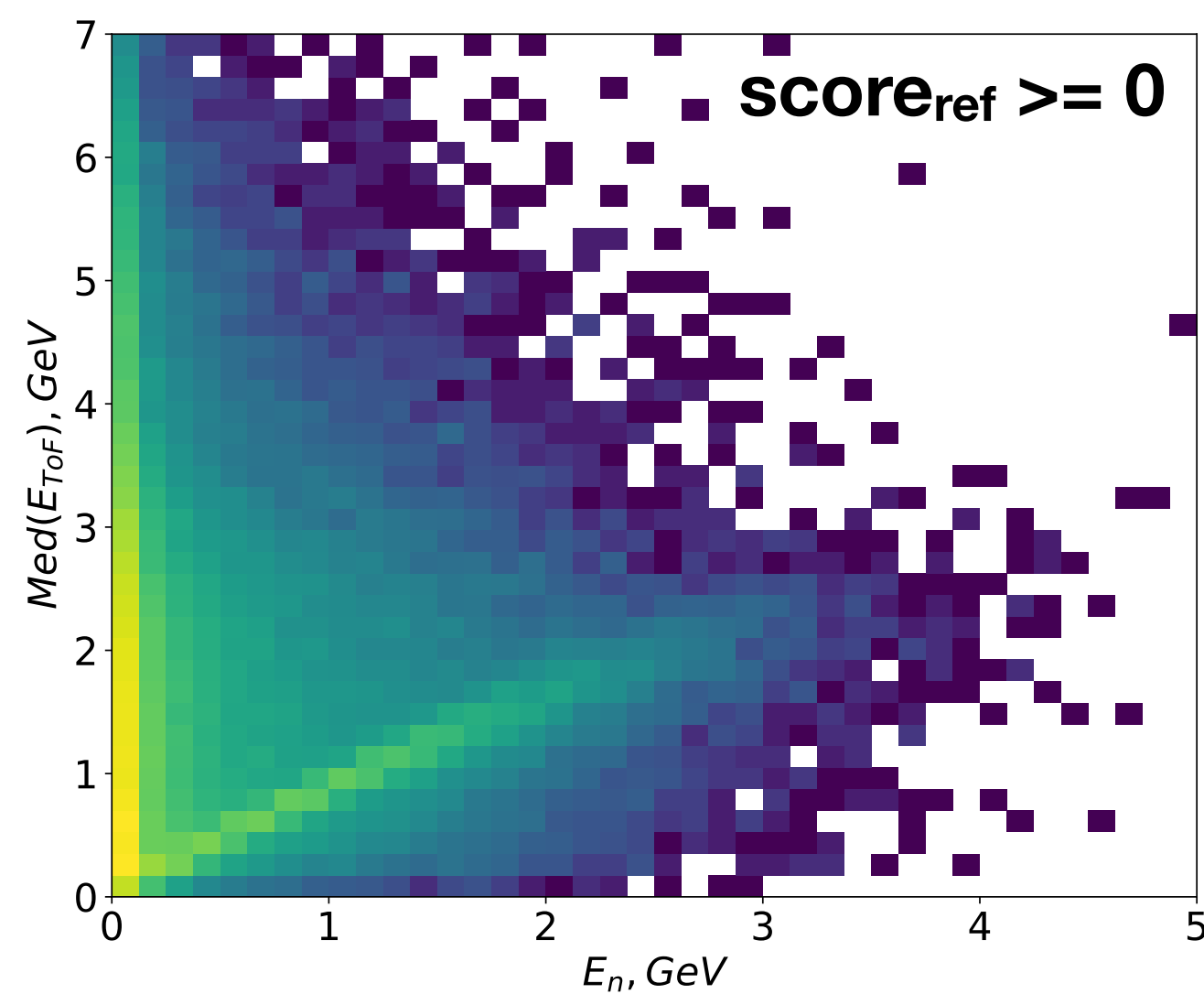


- Same performance between GNN and BDT pairs for all 3 labelling approaches
- ➔ all information is extracted from data in a given setting
- Increasing signal fraction by loosening criteria of “good” neutron events gives dominating effect in classification performance

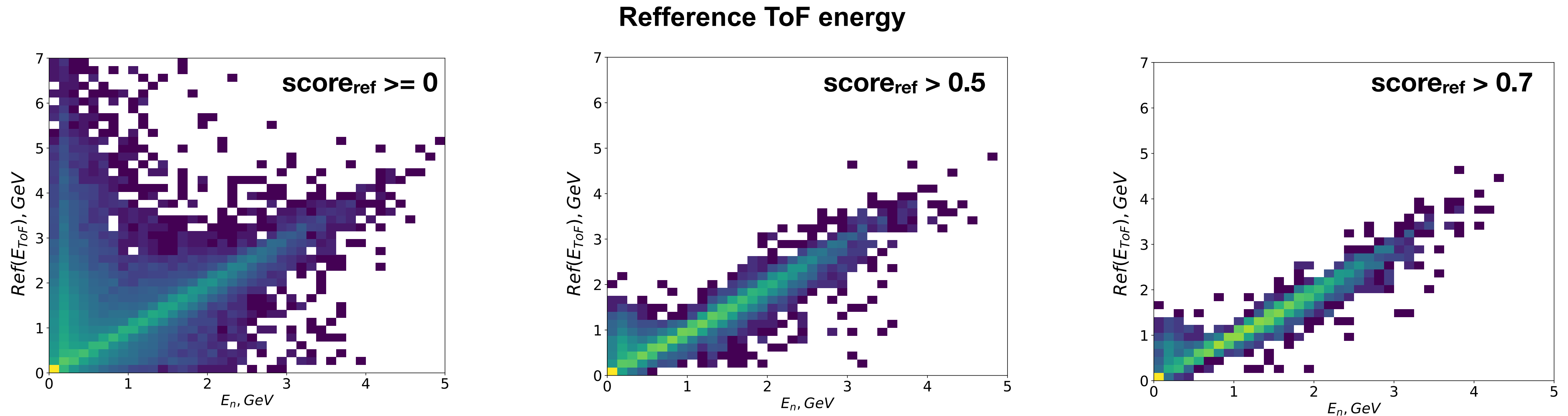
Example of resulting energy spectra



Median(E_{ToF}) neutron energy estimation (naive approach):



Neutron reconstruction outlook



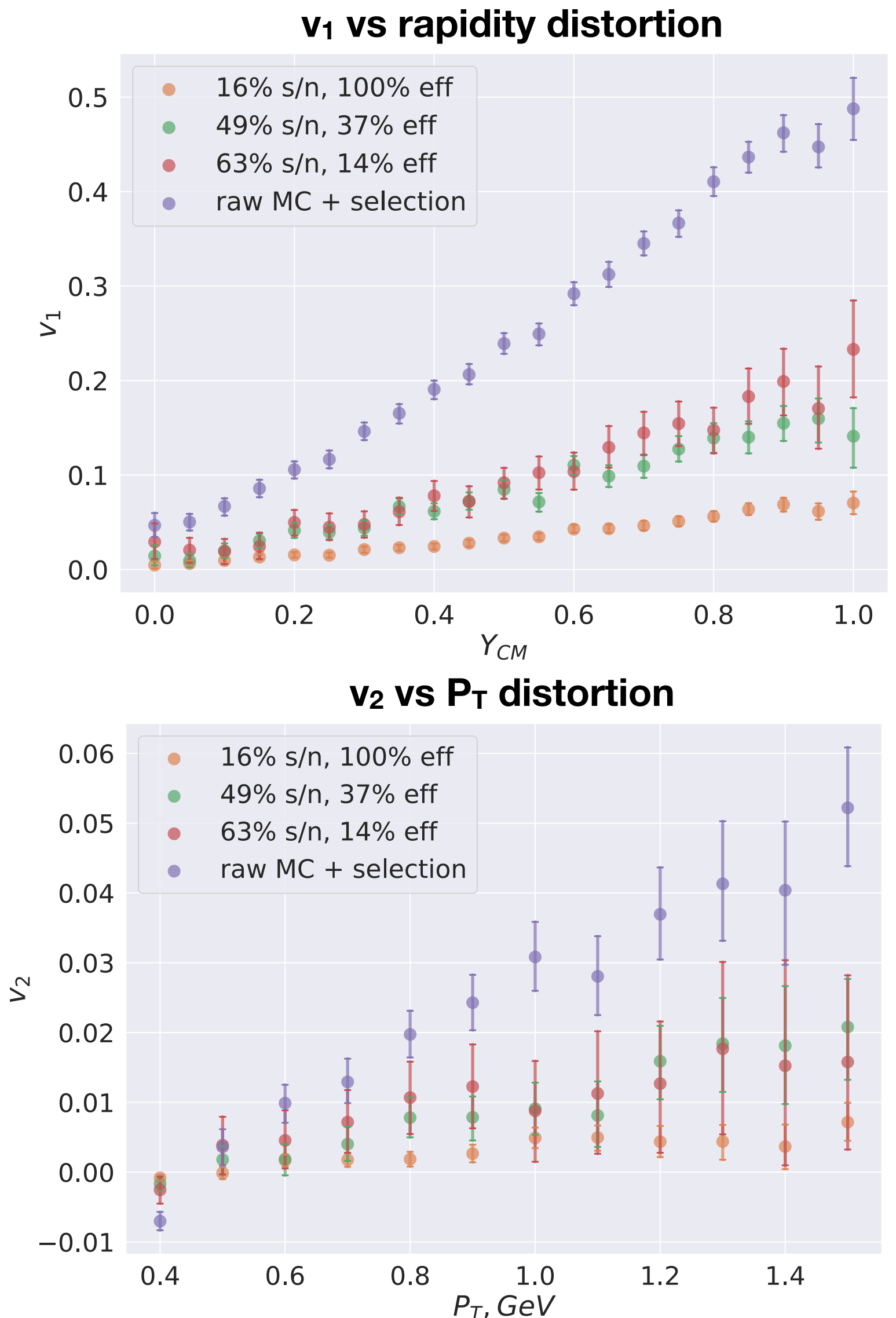
- Reference hit reconstruction will provide better energy resolution
 - ➔ GNN-based reconstruction method is under development
- Classification models rely on E_{ToF} distributions which may vary in different simulation settings
 - ➔ to be crosschecked
- Detailed MC truth information on event level can provide more hints to the classification models

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_2 vs P_T selection criteria:
 - $E_{kin} > 0.4$ GeV
 - Impact parameter $\in (6, 9)$ fm
 - Rapidity in c.m. $\in (-0.2, 0.2)$
 - ➔ 1382287 neutrons initially

$v_{1/2}$ amplitude increases with purity, stat. uncertainty is affected by event yield



Anisotropic Flow Outlook

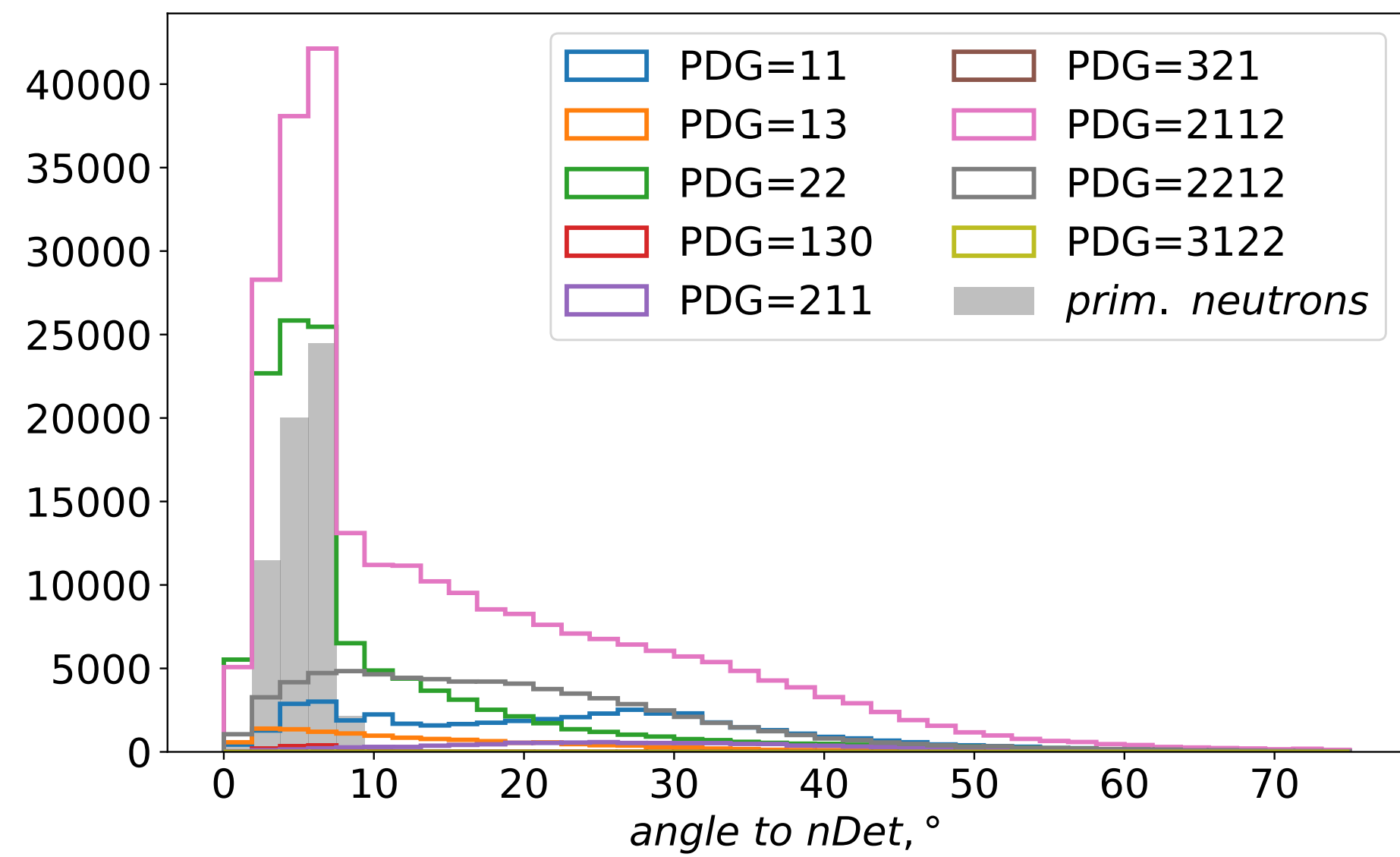
- Higher simulation statistics with different flow parameters in the model is needed to estimate neutron flow coefficient measurement performance in the HGND acceptance
 - ➔ ability to include all reconstruction effects in the estimation
 - ➔ better understanding of background contributions
- CPU heavy task
 - ➔ Fast-sim methods are foreseen to be beneficial

Summary

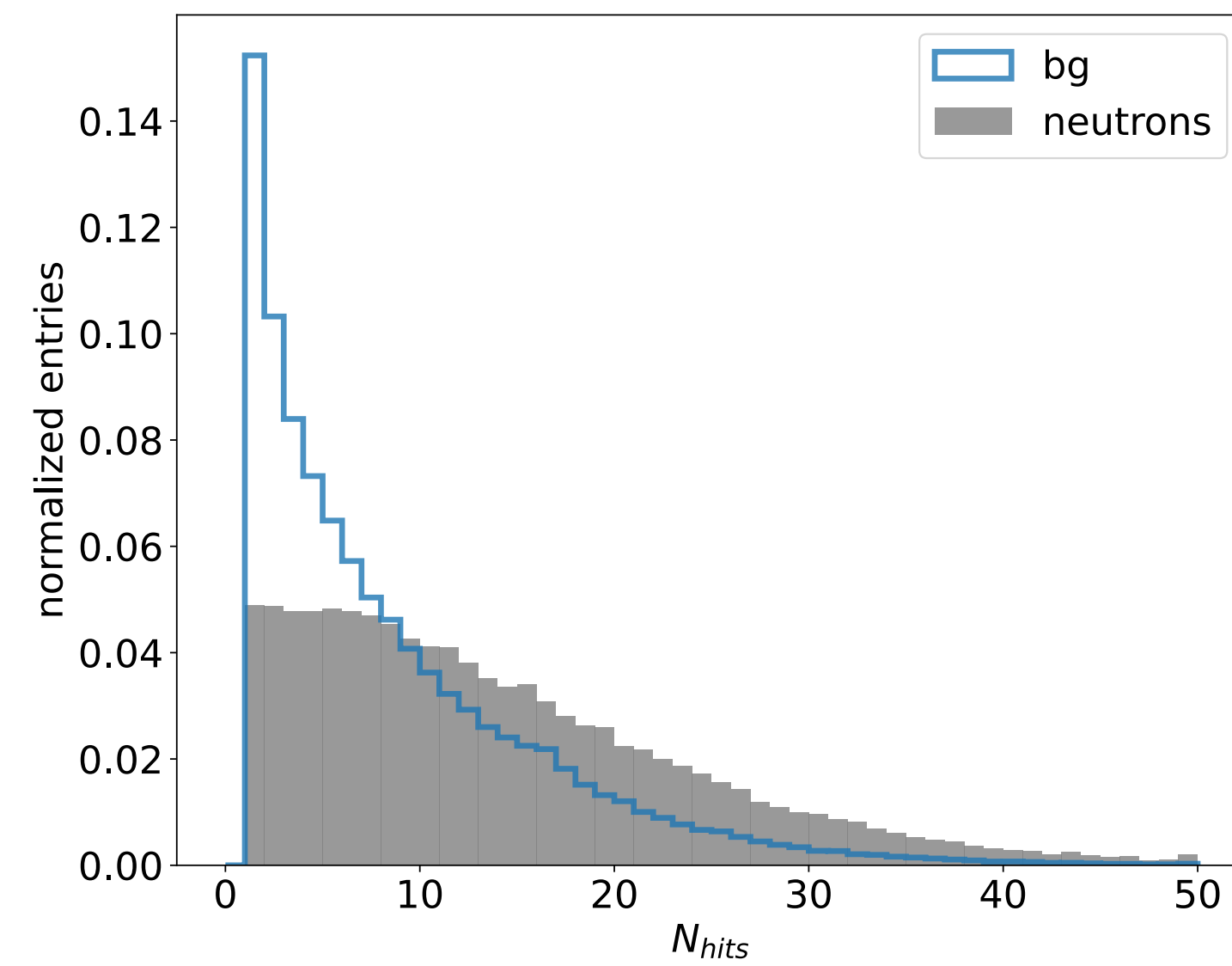
- HGND at the BM@N provides additional information source to access the EOS of dense nuclear matter
- Challenging task of neutron reconstruction using hybrid time-of-flight and imaging calorimetry technique is discussed
- First estimation of neutron flow measurement performance is done
- A number of tasks were addressed for future studies

Backup

Angular spectrum per particle type



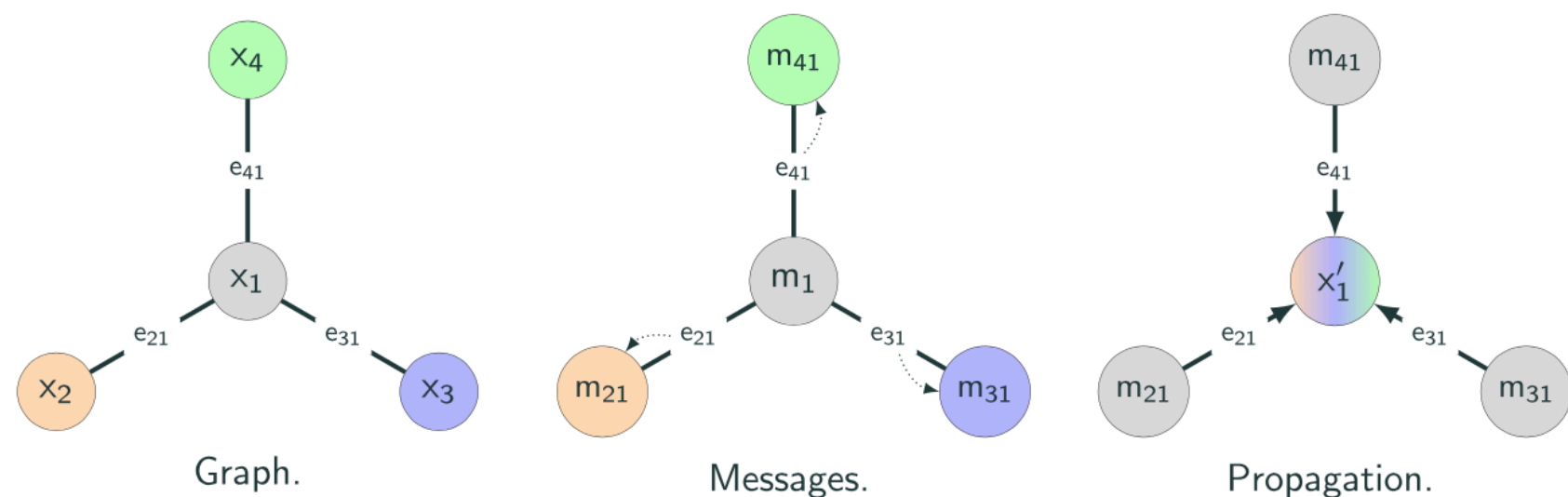
Number of hits



GNN in High Energy Physics

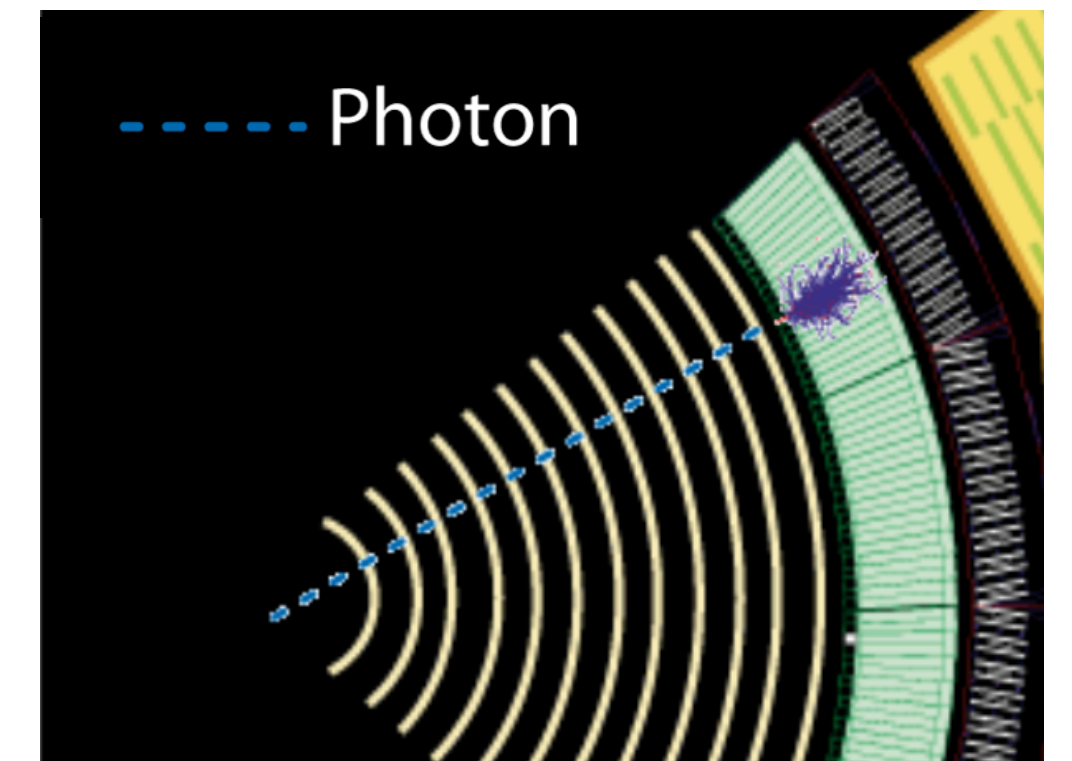
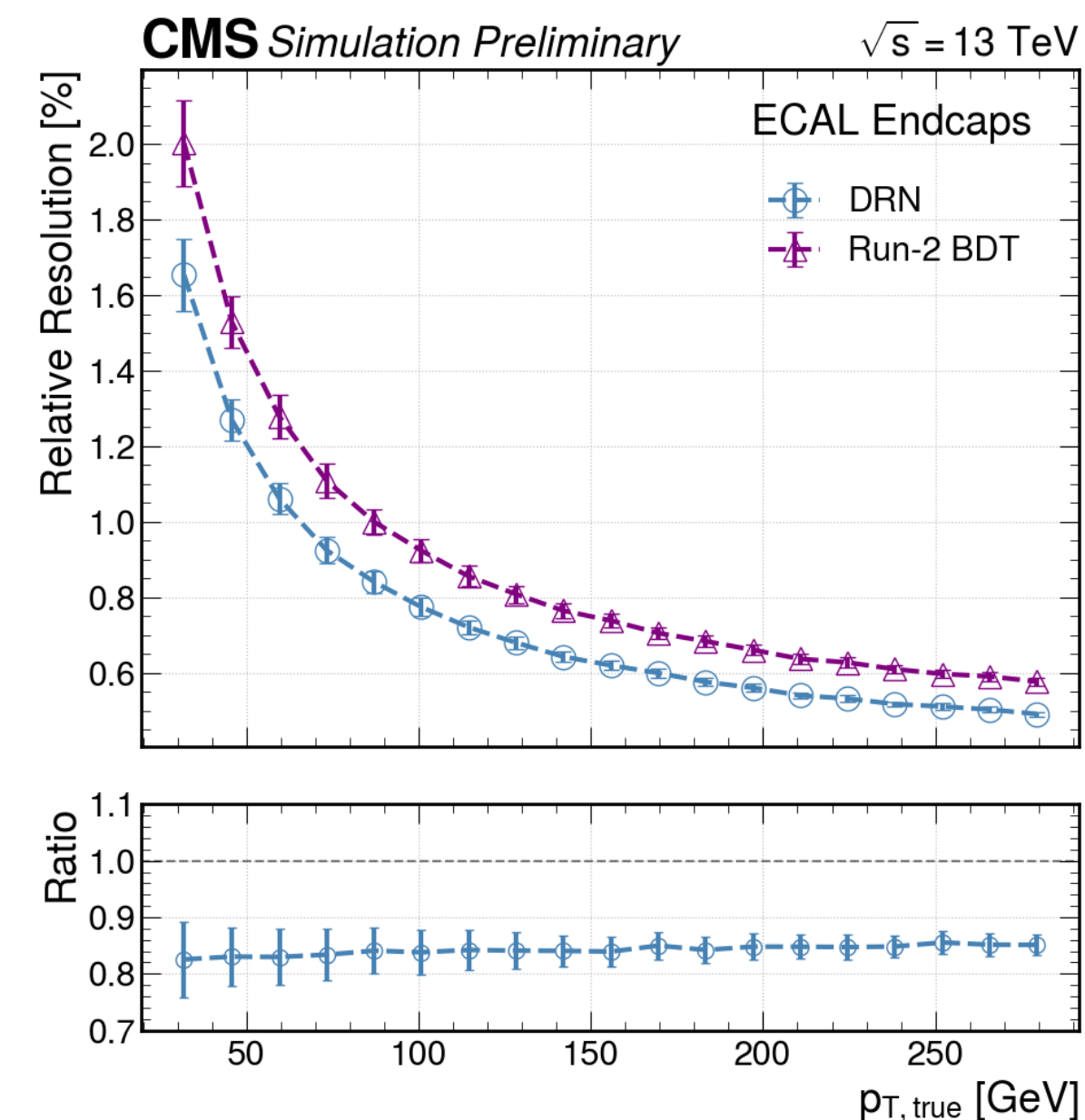
Why Graph Neural Networks:

- Natural event representation
- Easily applied to sparse data with variable input size
 - typically we have signal only in small fraction of sensors
- Increasing number of successful implementations in HEP
- Performance improvement in comparison with commonly used Gradient Boosting (GB) models (or Boosted Decision Tree (BDT) in HEP language)



J. Gilmer et al., "Neural message passing for quantum chemistry," 2017.

Example on calorimeter energy resolution



- > 10% photon energy resolution improvement of GNN-based model compared to GB

Classification models

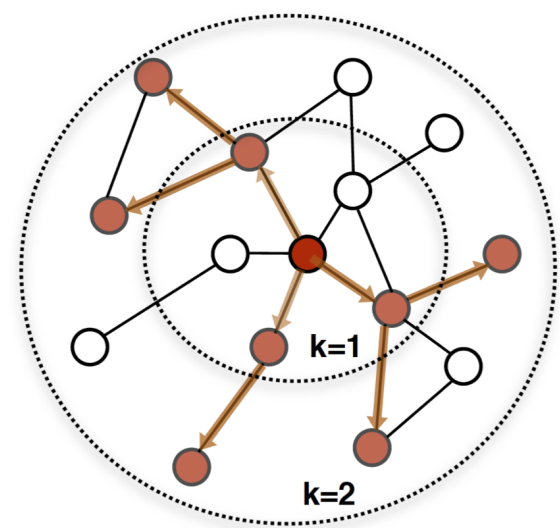
Event structure model



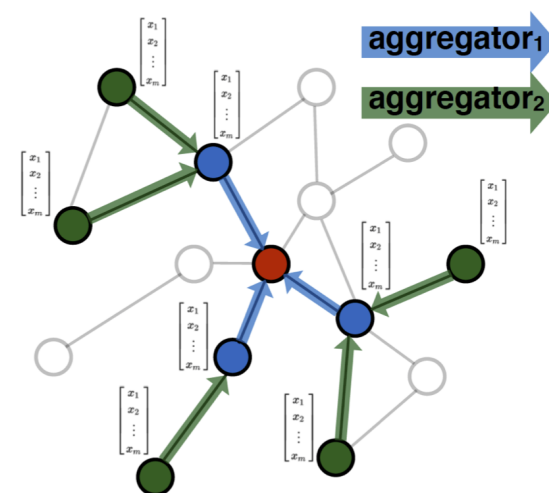
Graph neural network (GNN)

- (x, y, z) , E_{dep} , T_{hit} (after first hit), E_{ToF} (optional)
- Fully connected hit graphs
 - 100 in batch
- 2x GraphSage layers with 32 hidden channels + batchnorm + dropout -> Self-attention pooling layer (1 node output) -> MLP readout layer 32->16->1 + sigmoid
- BCE loss function

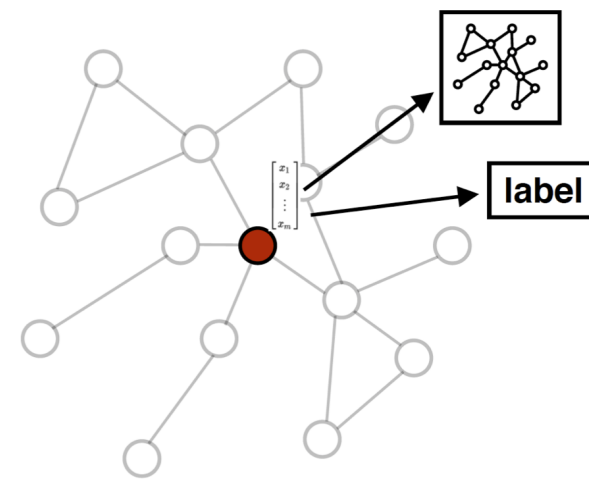
GraphSAGE (SAmples and aggreGatE) architecture GNN:



Sample neighbourhood of graph nodes



Aggregate feature information from neighbours



Get graph context embeddings for node using aggregated information

First principle model



Gradient Boosting (GB) model with '**first-principle**' feature set based on global event properties and parameters of most informative hits.

- 13 features in total
 - Fastest hit parameters (4)
 - Z_{min} hit parameters (4):
 - Global events parameters (6)
- Maxdepth = 6
- <200 boosting rounds

Train/test split 50% for both models

Classification models

CatBoost (BDT)

first-principle feature set:

1st hit:

'R_first', - distance to (0,z)

'Z_first',

'E_first',

Zmin hit:

'dt_zmin',

'R_zmin', - distance to (0,z)

'Z_zmin',

'E_zmin',

Global:

'Esum',

'cogZ', - E-weighted average z

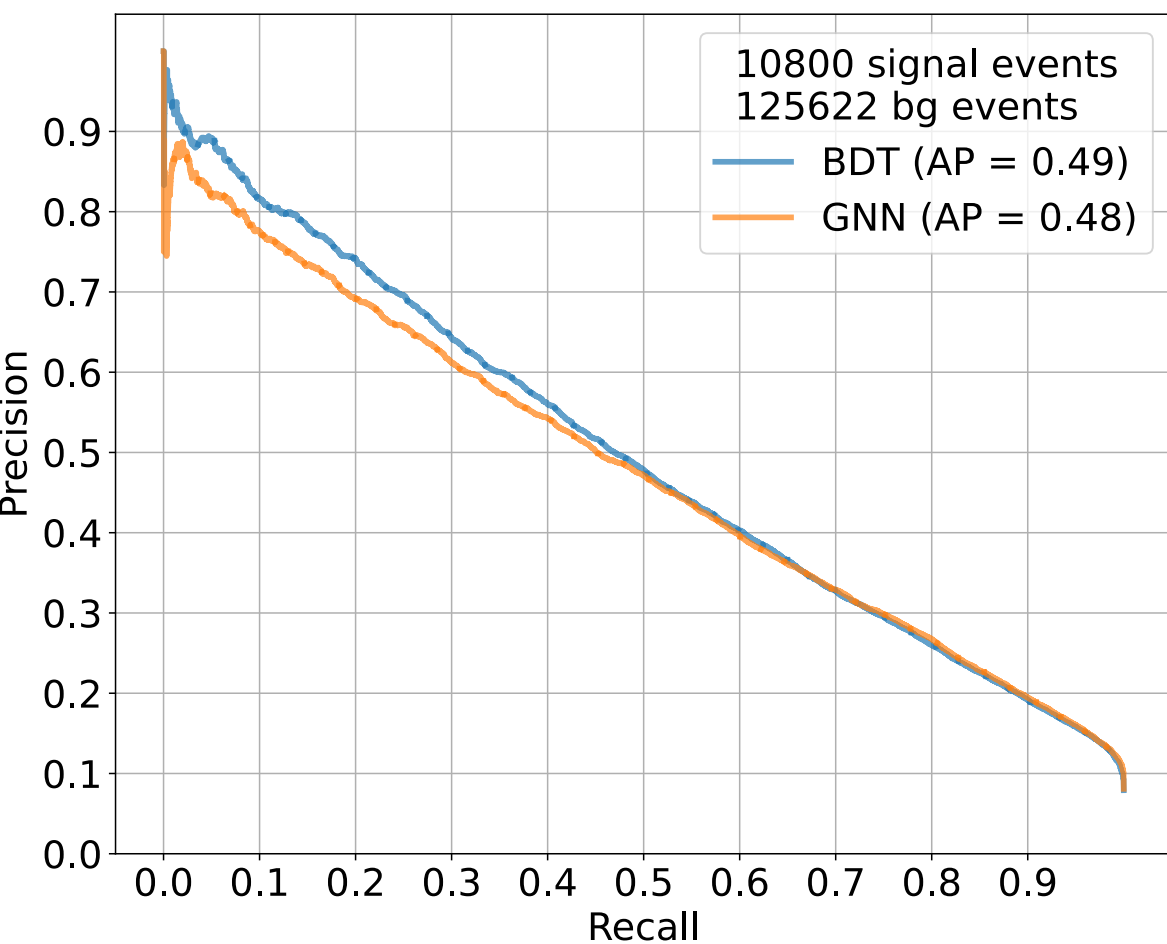
'cogR', - E-weighted average distance to (0,z)

'nHits',

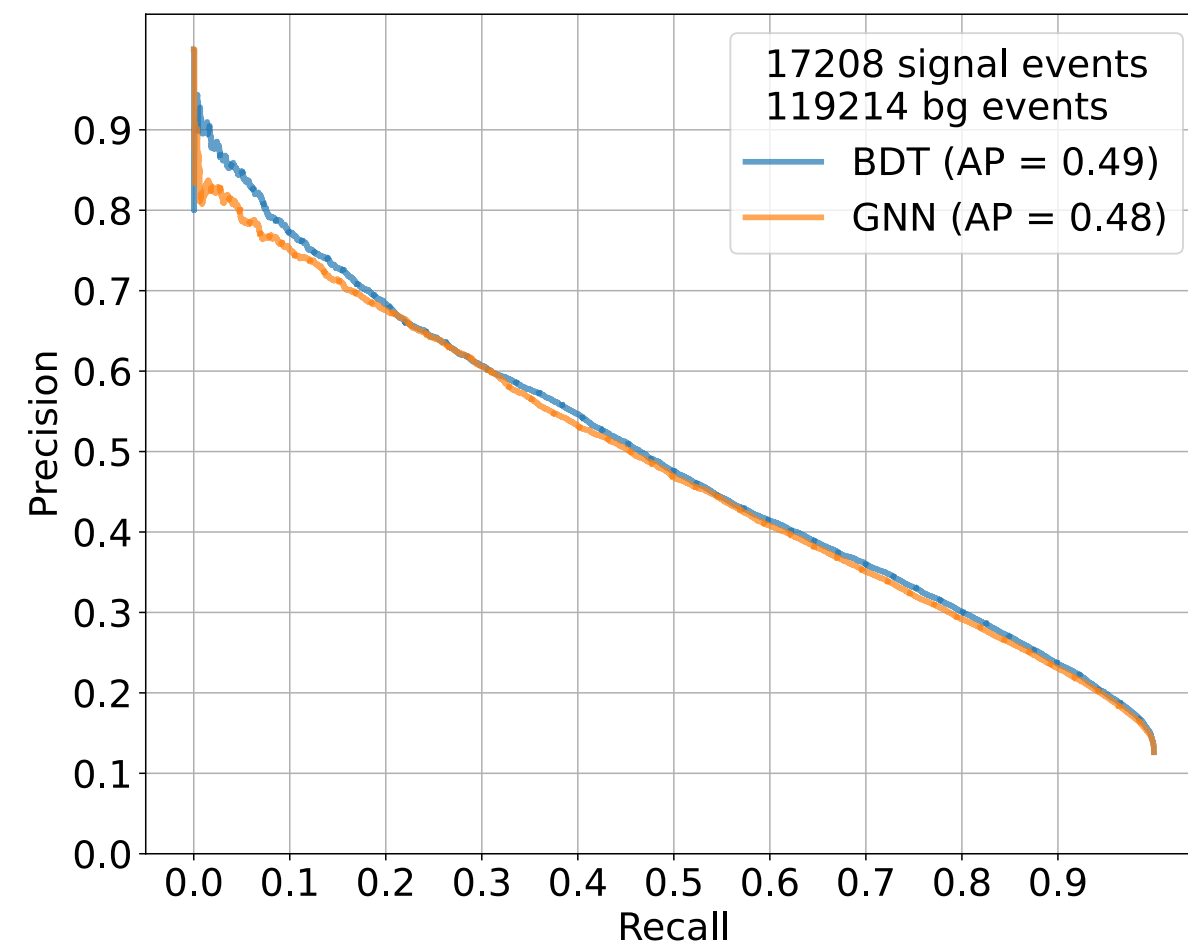
'dt_stdev'

Classification performance

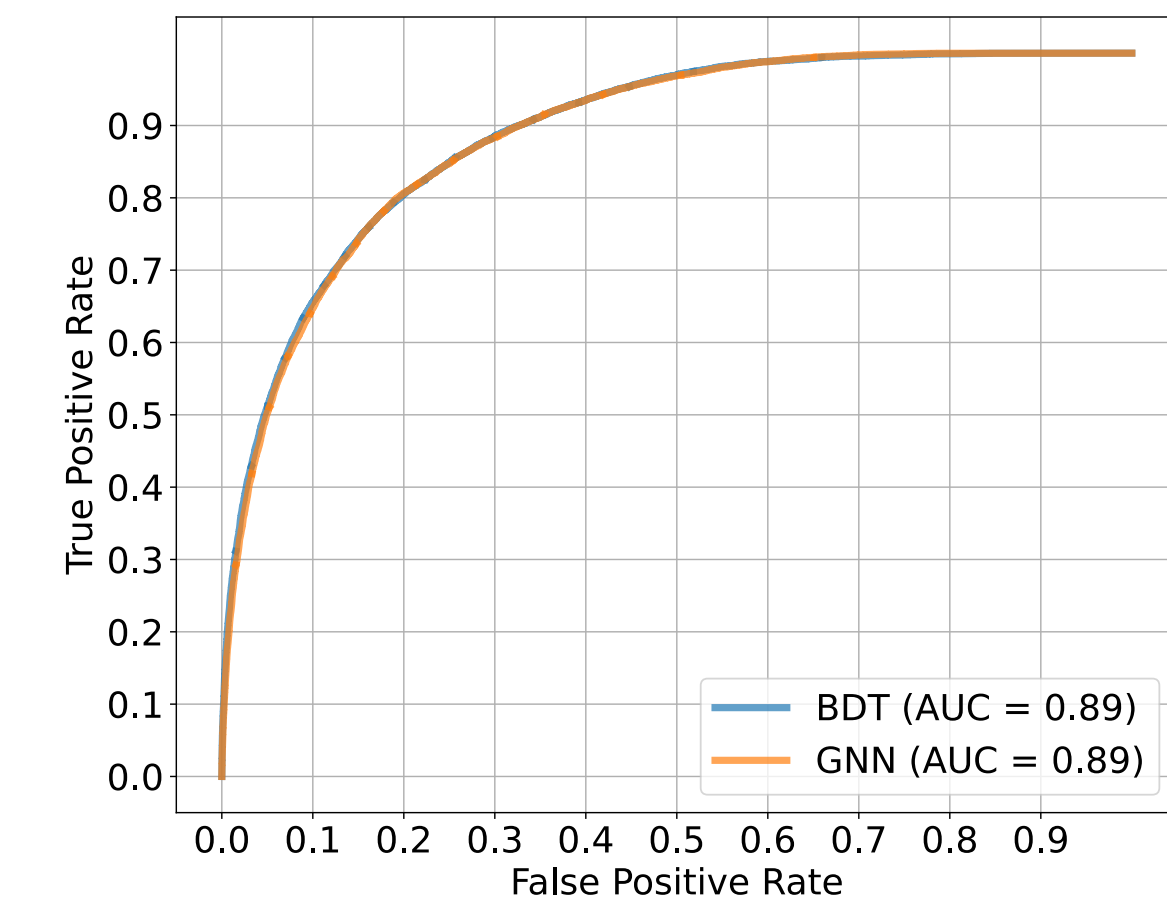
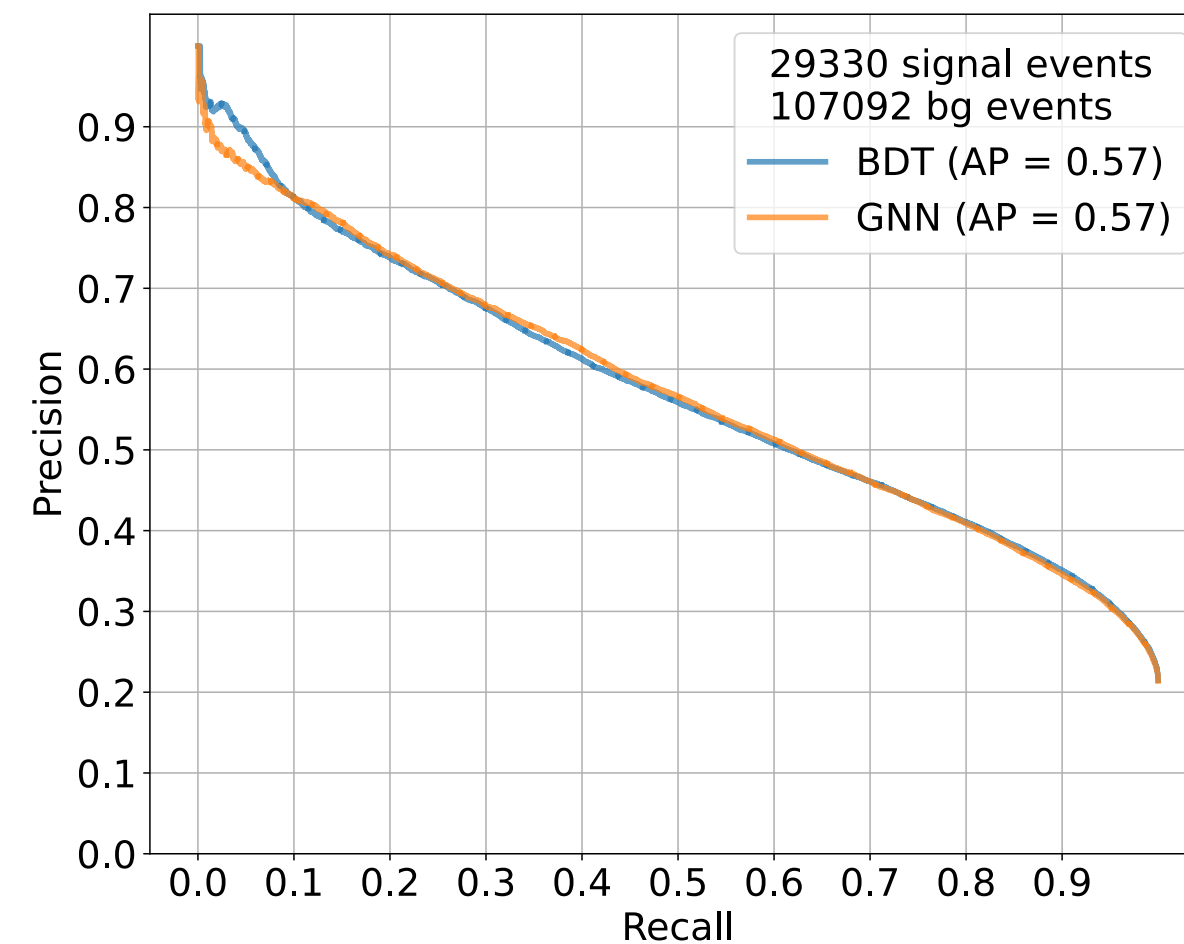
Fastest hit labelling



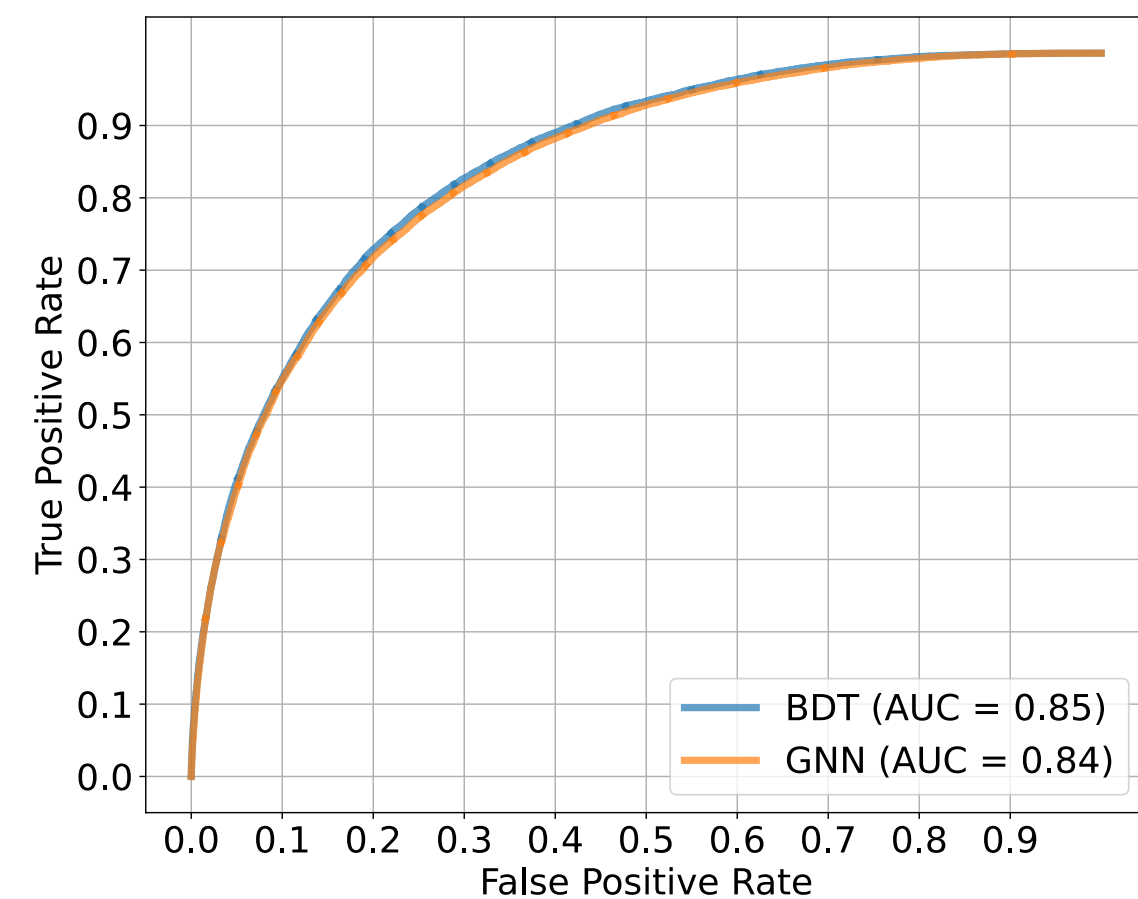
median labelling



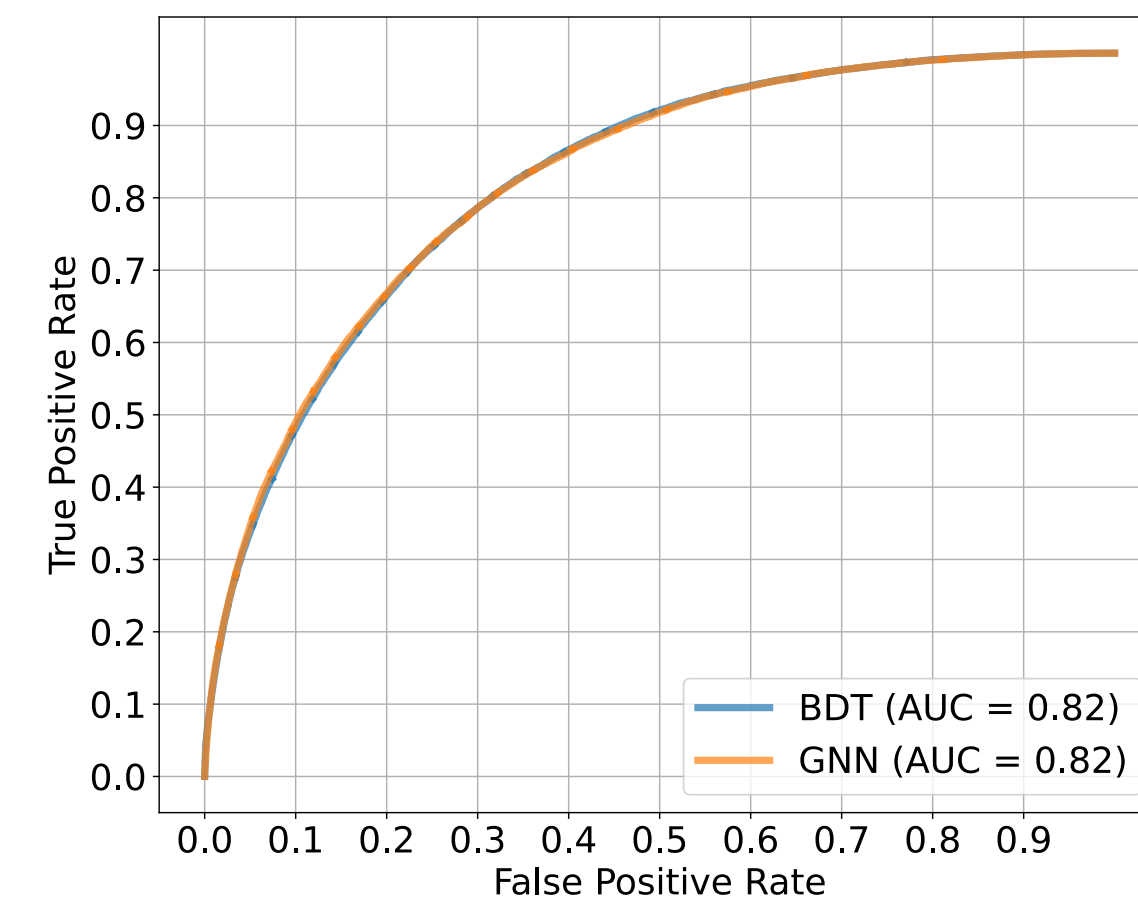
“Best” hit labelling



* some hints that models rely mostly on Max(E_{ToF}) distribution

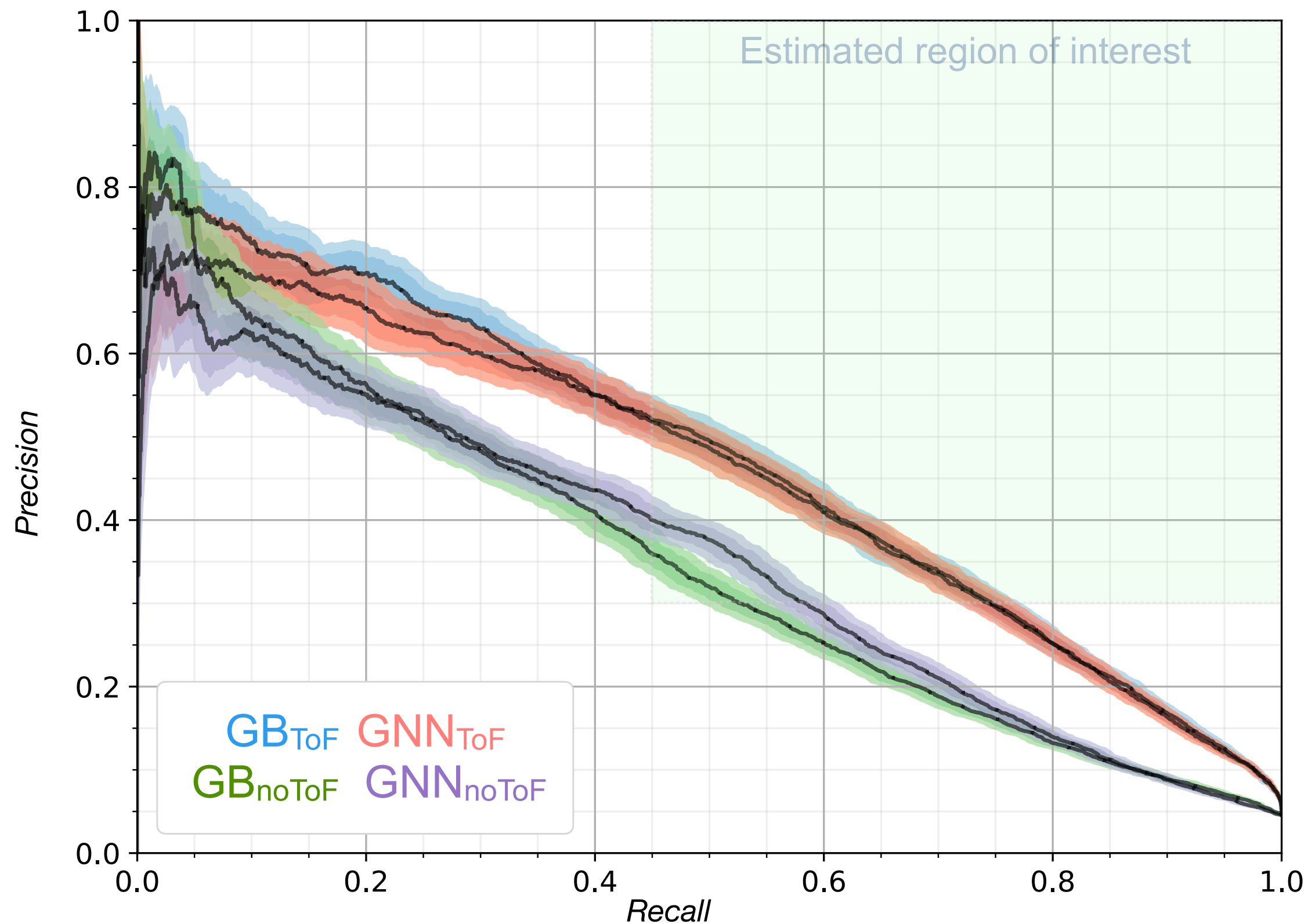


* some hints that models rely mostly on Med(E_{ToF}) distribution



- Overall classification performance slowly decreases with loosening criteria of “good” neutron events (ROC_AUC)
- Larger signal/background ratio gives better PR
- Similar performance for BDT and GNN for all 3 labelling approaches
- ➔ ‘first-principle’ features look comprehensive in this setting

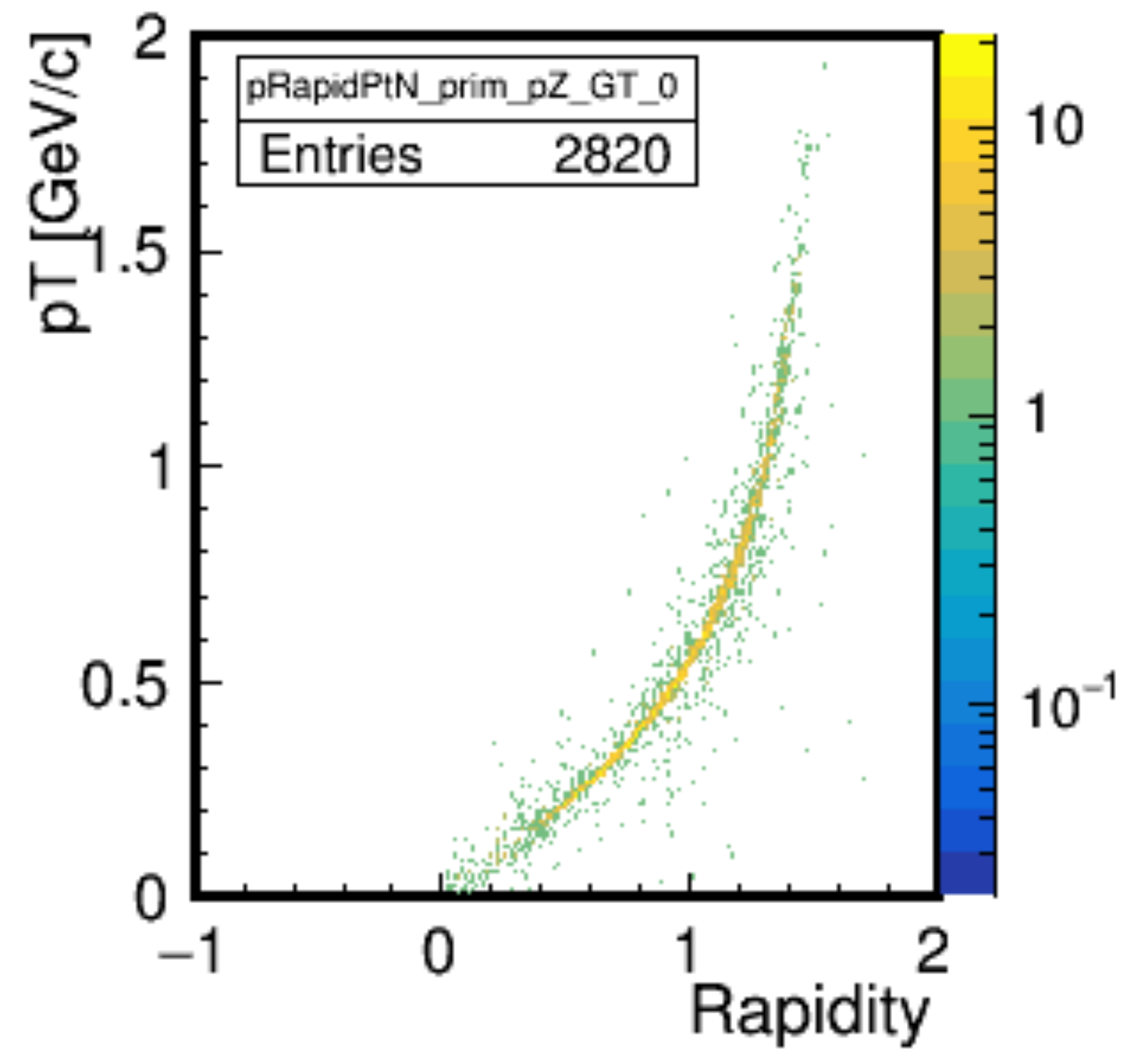
$$P = \frac{TP}{TP + FP} \quad R = \frac{TP}{TP + FN} \quad TPR = \frac{TP}{P} \quad FPR = \frac{FP}{N}$$



Region of interest:

- ~ Precision threshold - exclude flat neutron flow hypothesis
- ~ Recall threshold - covers most of neutron E_{kin} spectrum

- **Similar performance using target feature E_{ToF}**
- **Excluding E_{ToF} variable increases significance of event topologies for events with $N_{\text{hits}} > 1 \Rightarrow$ slight increase of GNN performance compared to GB**
- Possible limits of GNN performance:
 - Large fraction of single hit events and irregular event signatures for given dataset
 - ➔ GNN can be more beneficial at higher energies and higher detector granularities



- v_1 smearing by time resolution

