ML methods of neutron identification and energy reconstruction using HGND

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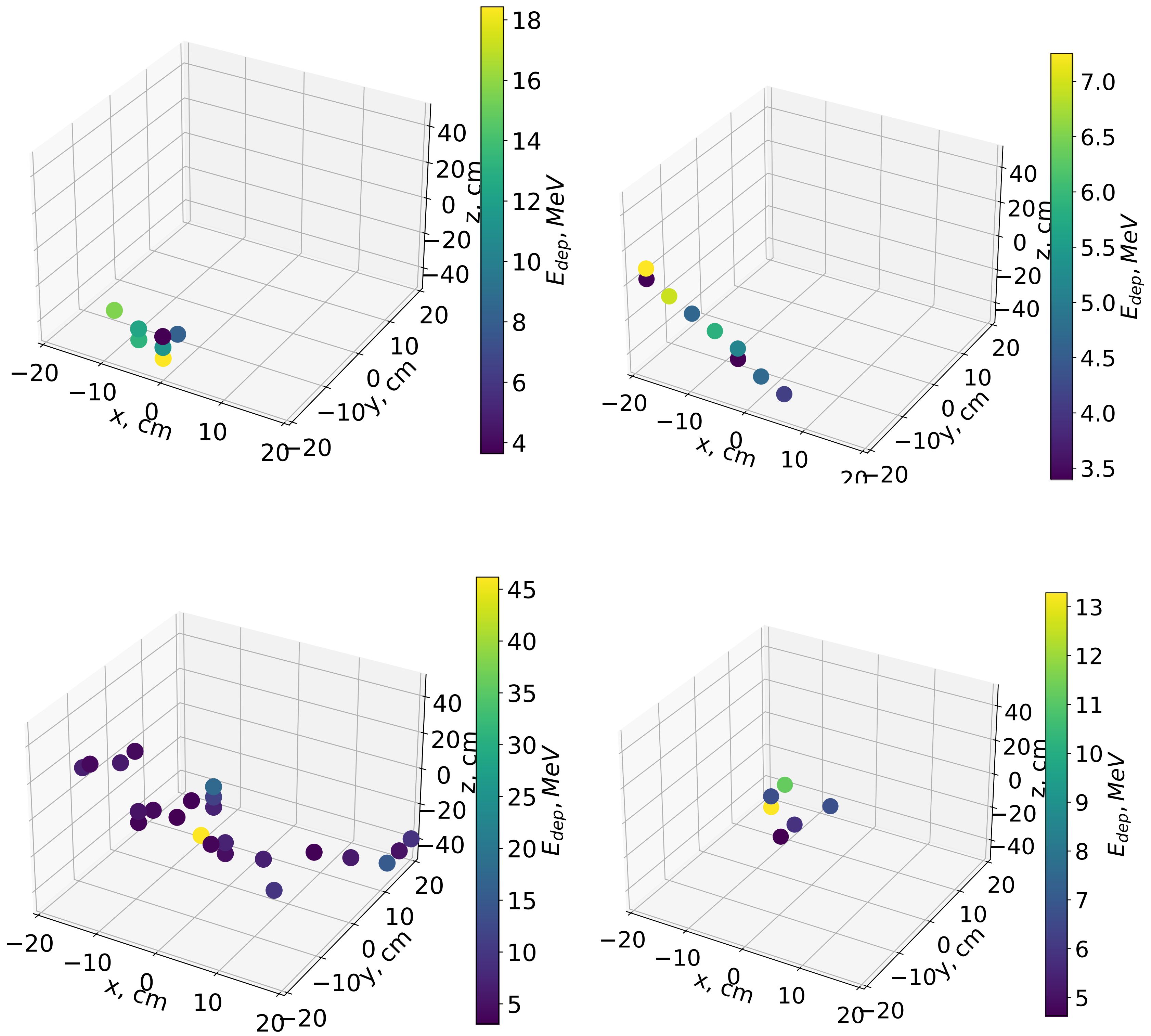
BM@N Collaboration meeting, Dubna
28-30.11.2023



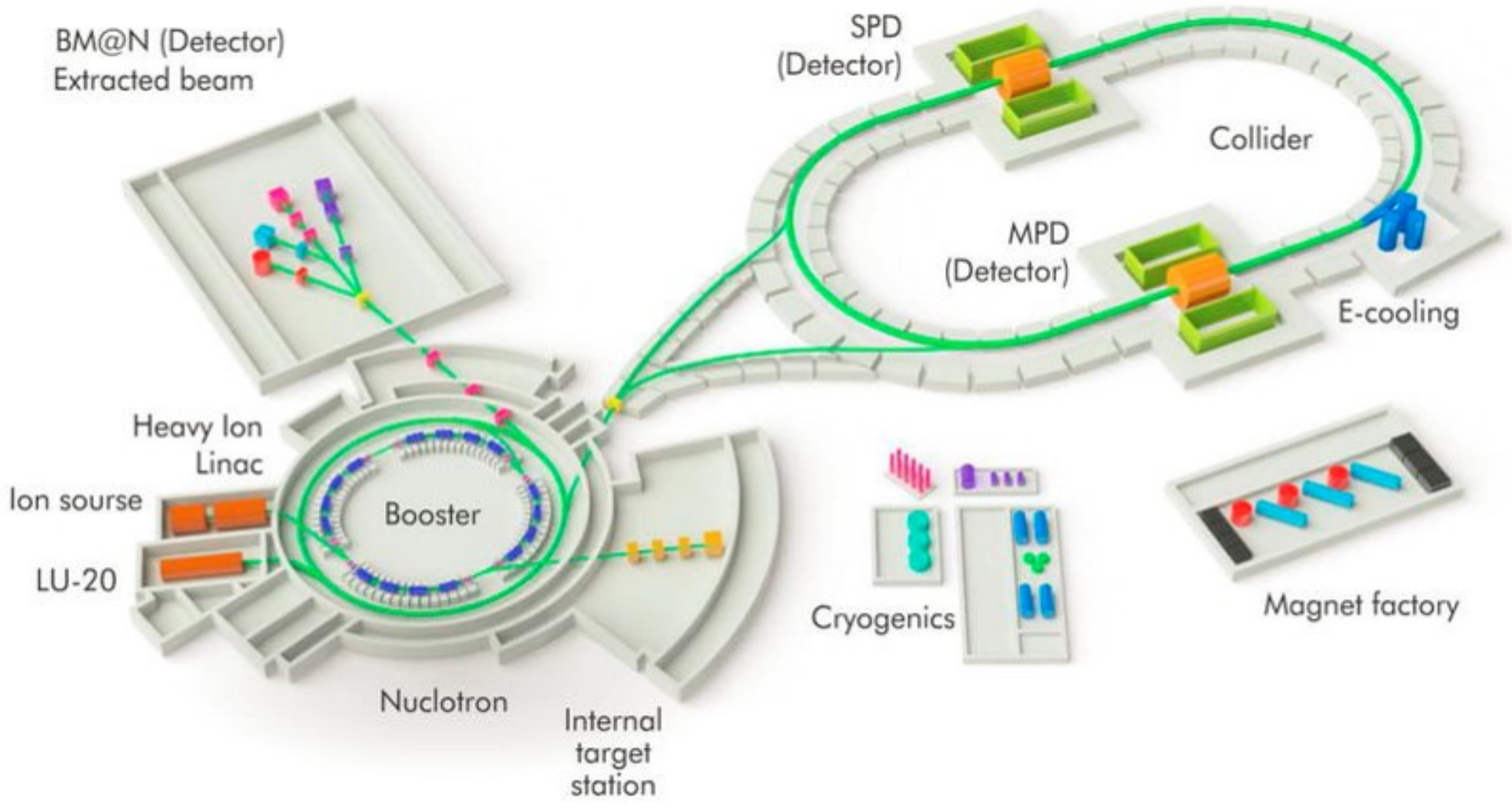
LAMBDA · HSE

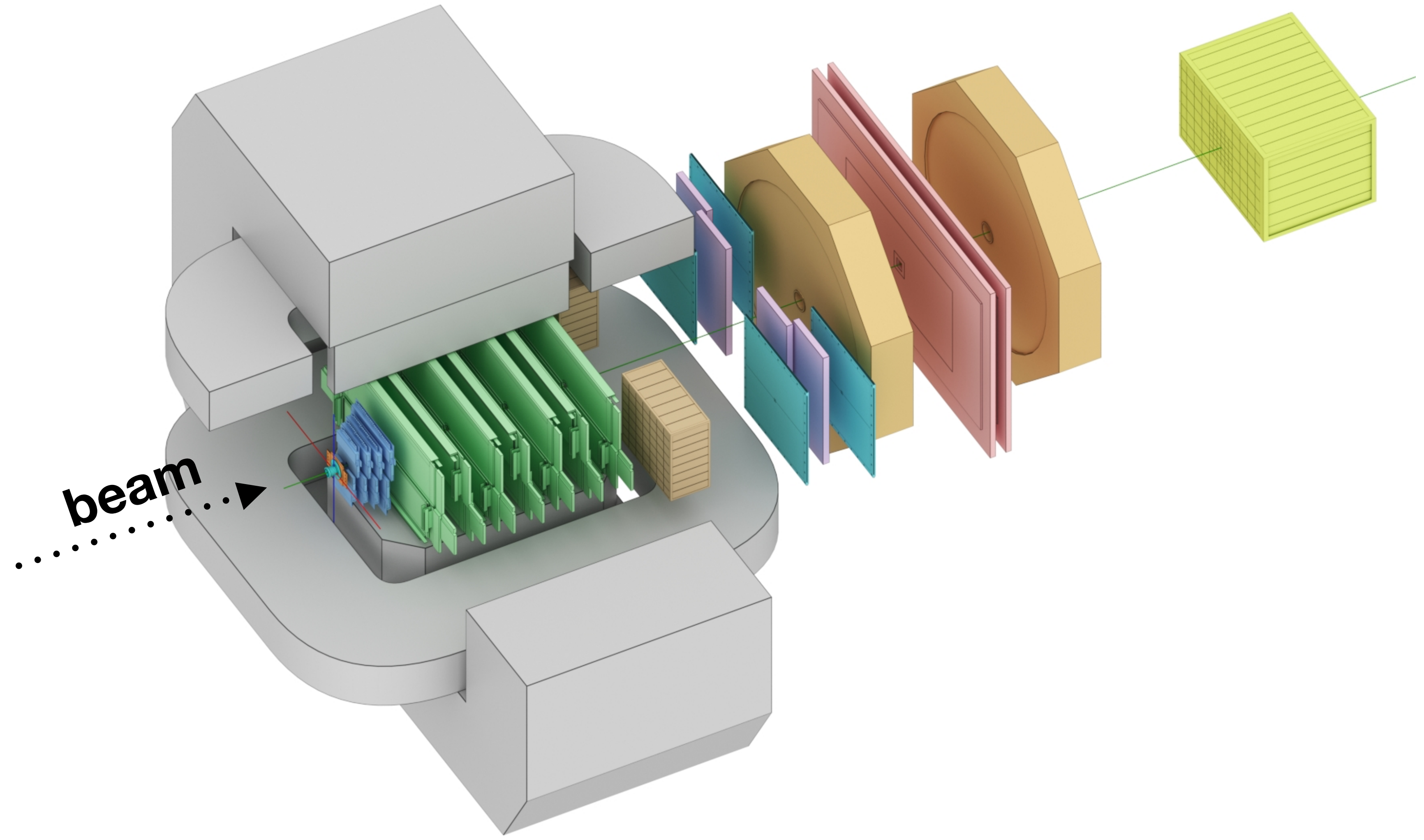
BM@N experiment

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.

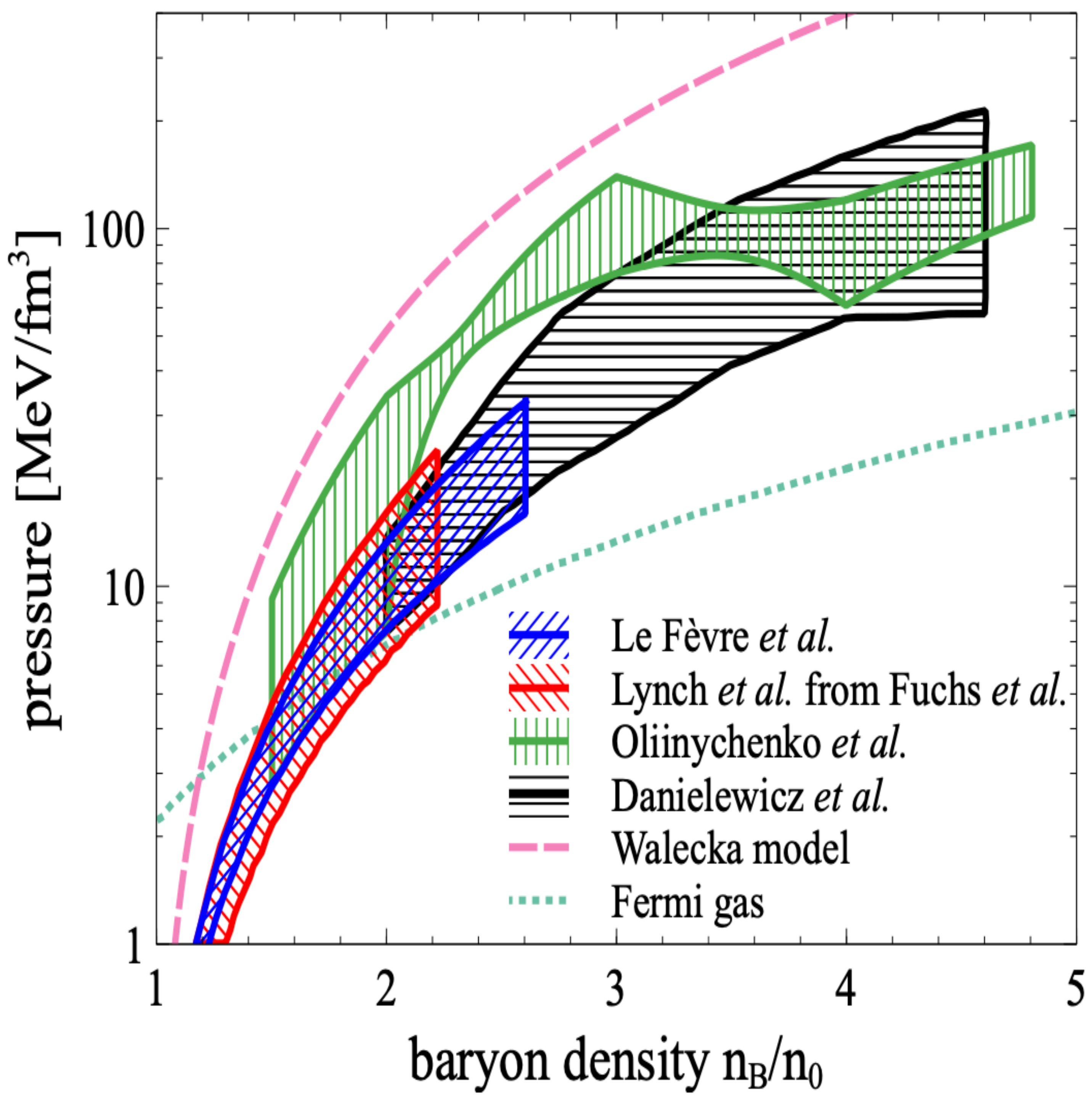




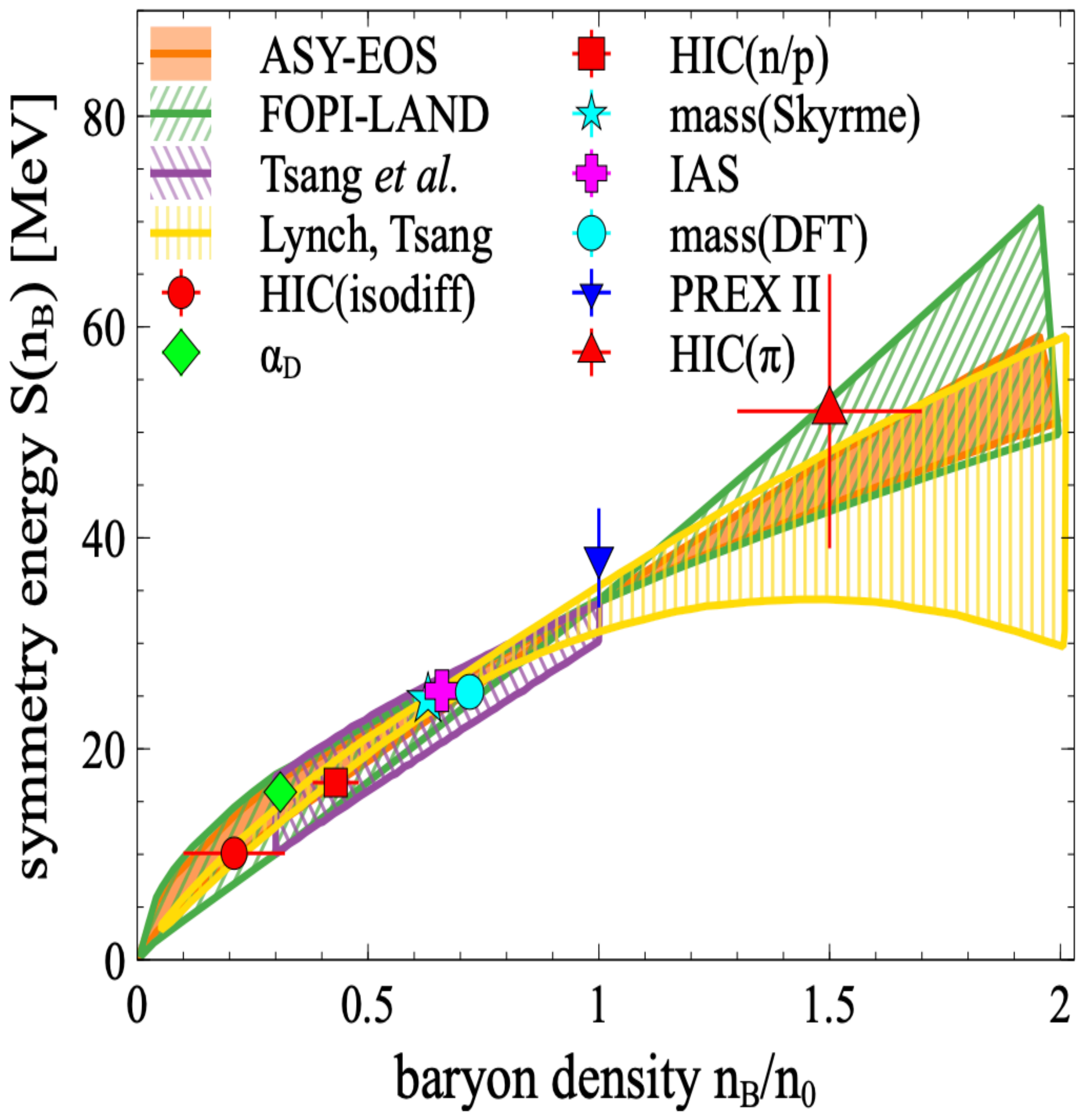
EOS for high baryon density matter

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**

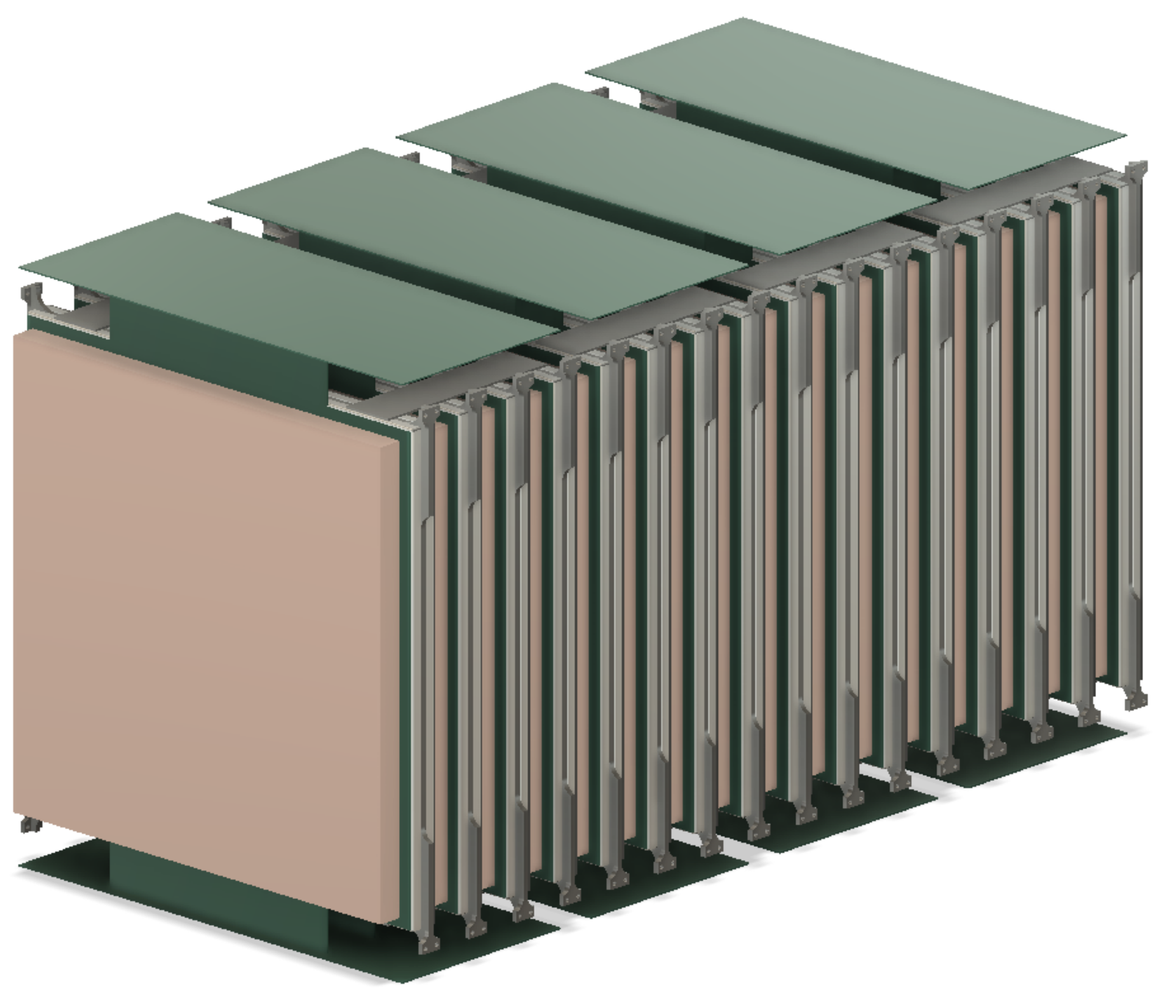
- **Neutron flow** measurements are essential to further constrain symmetry energy
- Sensitive observables:

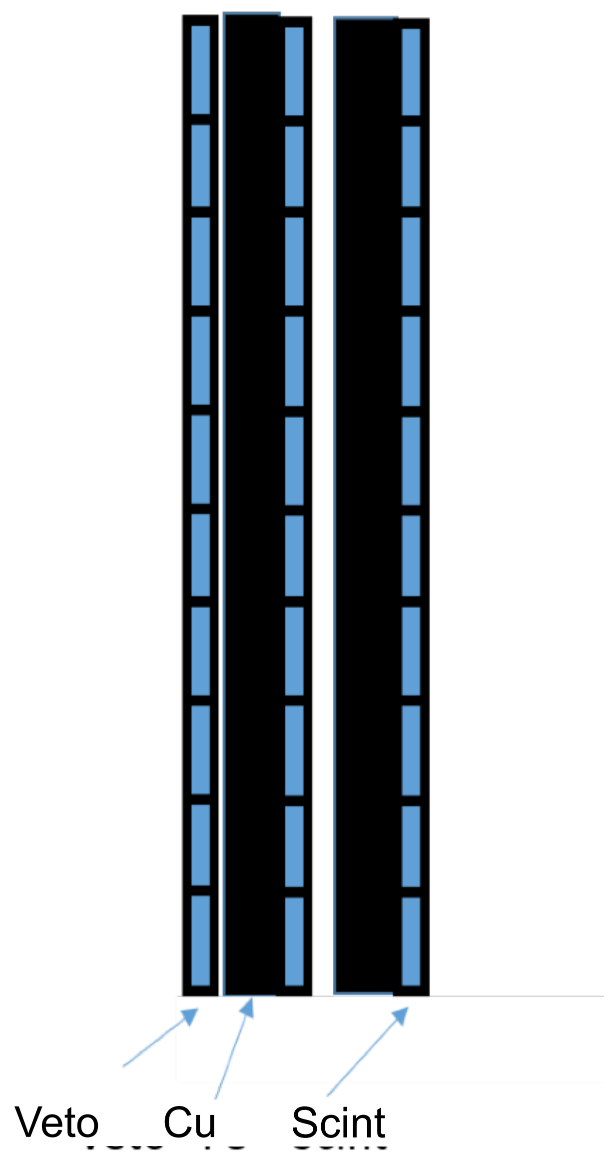
Anisotropy flow coefficients:

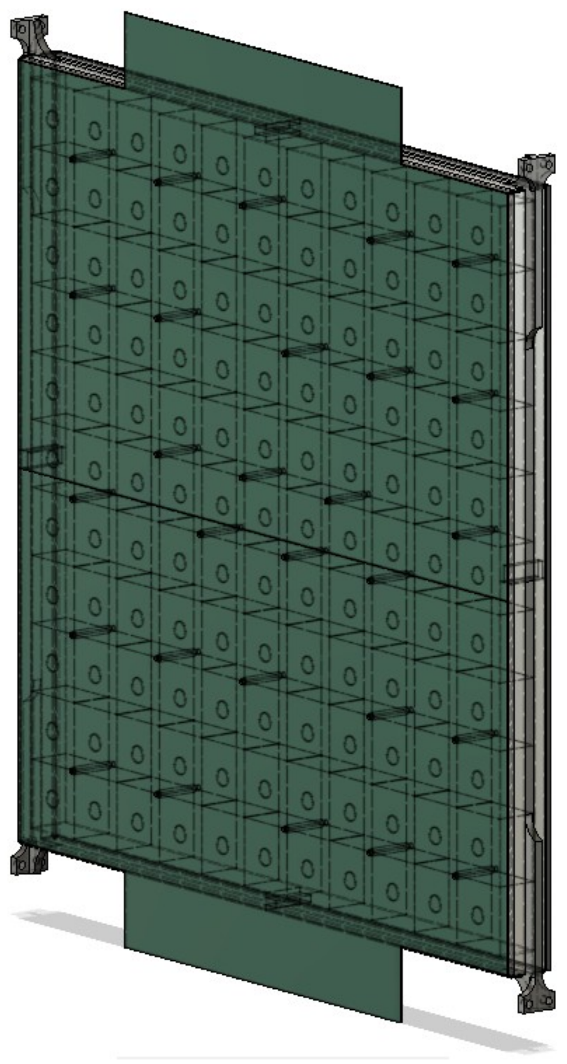
$$\frac{dN}{d\phi} \propto 1 + 2\sum_{n=1} v_n \cos[n(\phi - \Psi_{RP})], \quad v_n = \langle \cos[n(\phi - \Psi_{RP})] \rangle$$

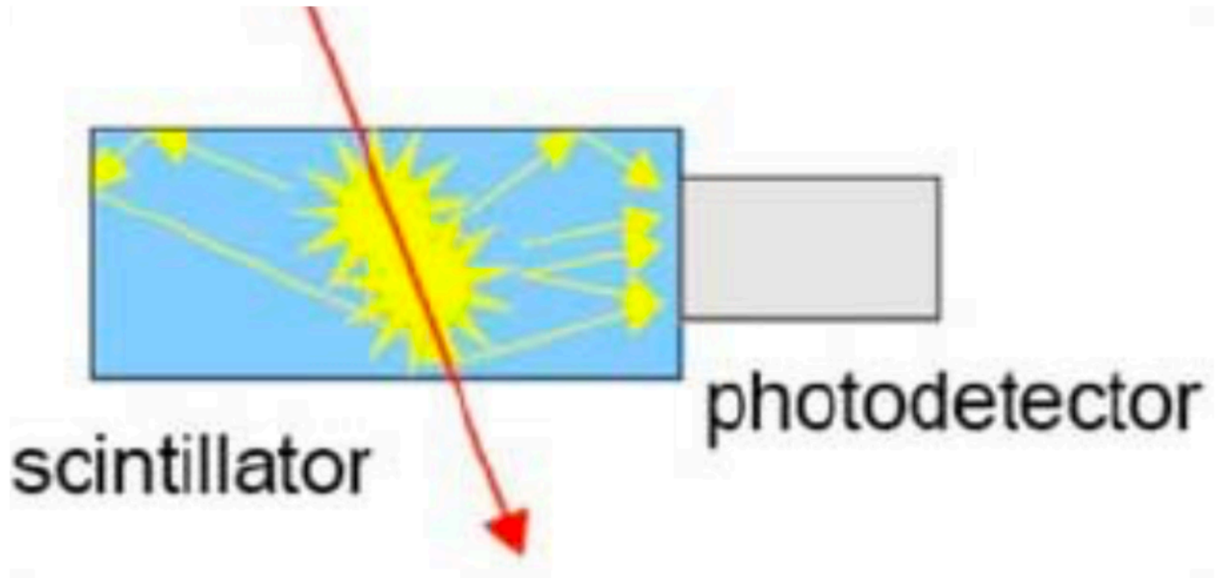
A. Sorensen et. al., arXiv:2301.13253 [nucl-th] (2023)

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





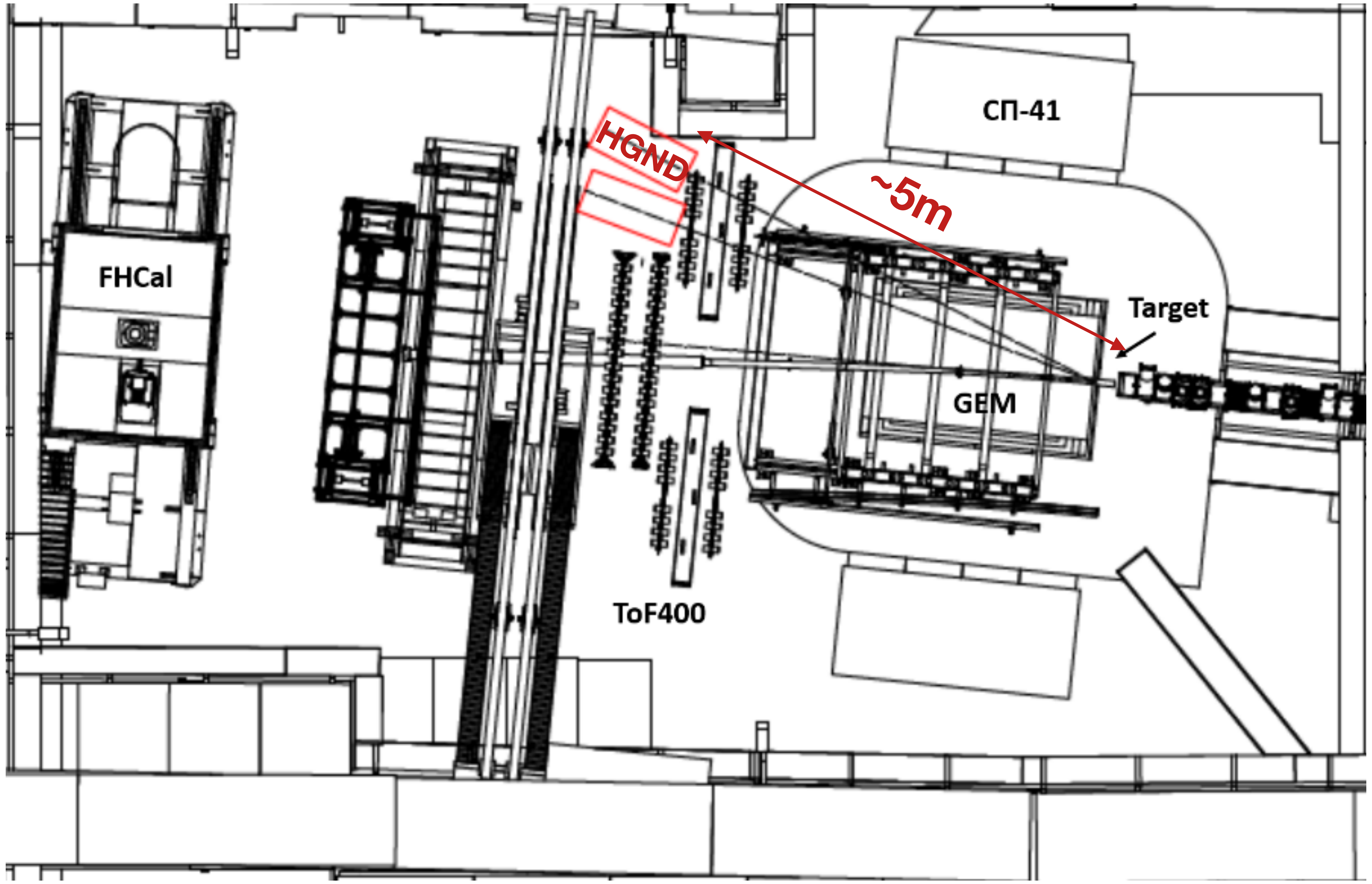




- 16 layers: *3cm Cu (absorber) + 2.5cm Scintillator + 0.5cm PCB; 1st layer — 'veto' before*
  ➡Total length: **~1m,** ~3 λ_{in}
  ➡ neutron absorption ~100%
  - Transverse size: **44x44 cm²**
  - *11x11 scintillator cell grid*

- 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



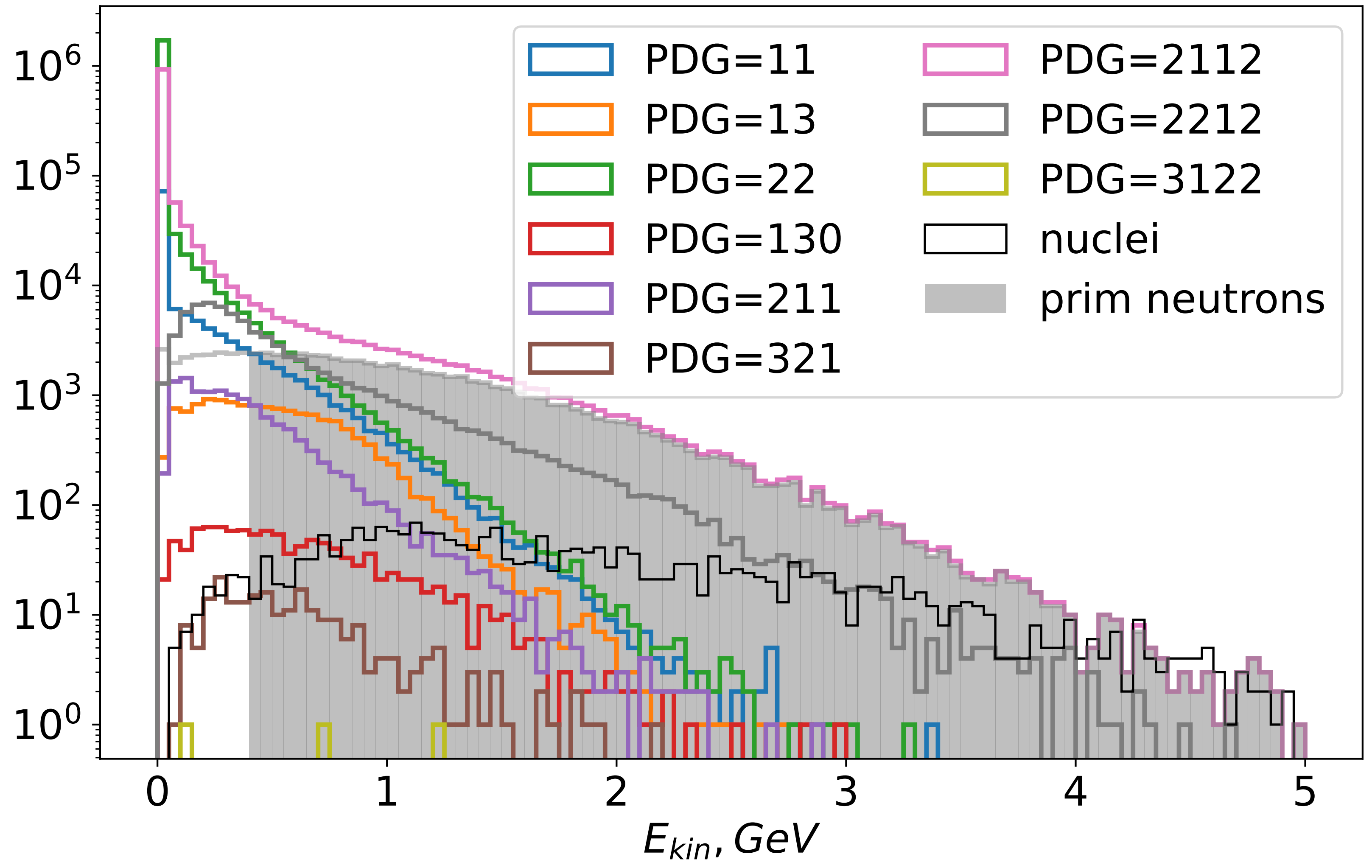
Preliminary test configuration:

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

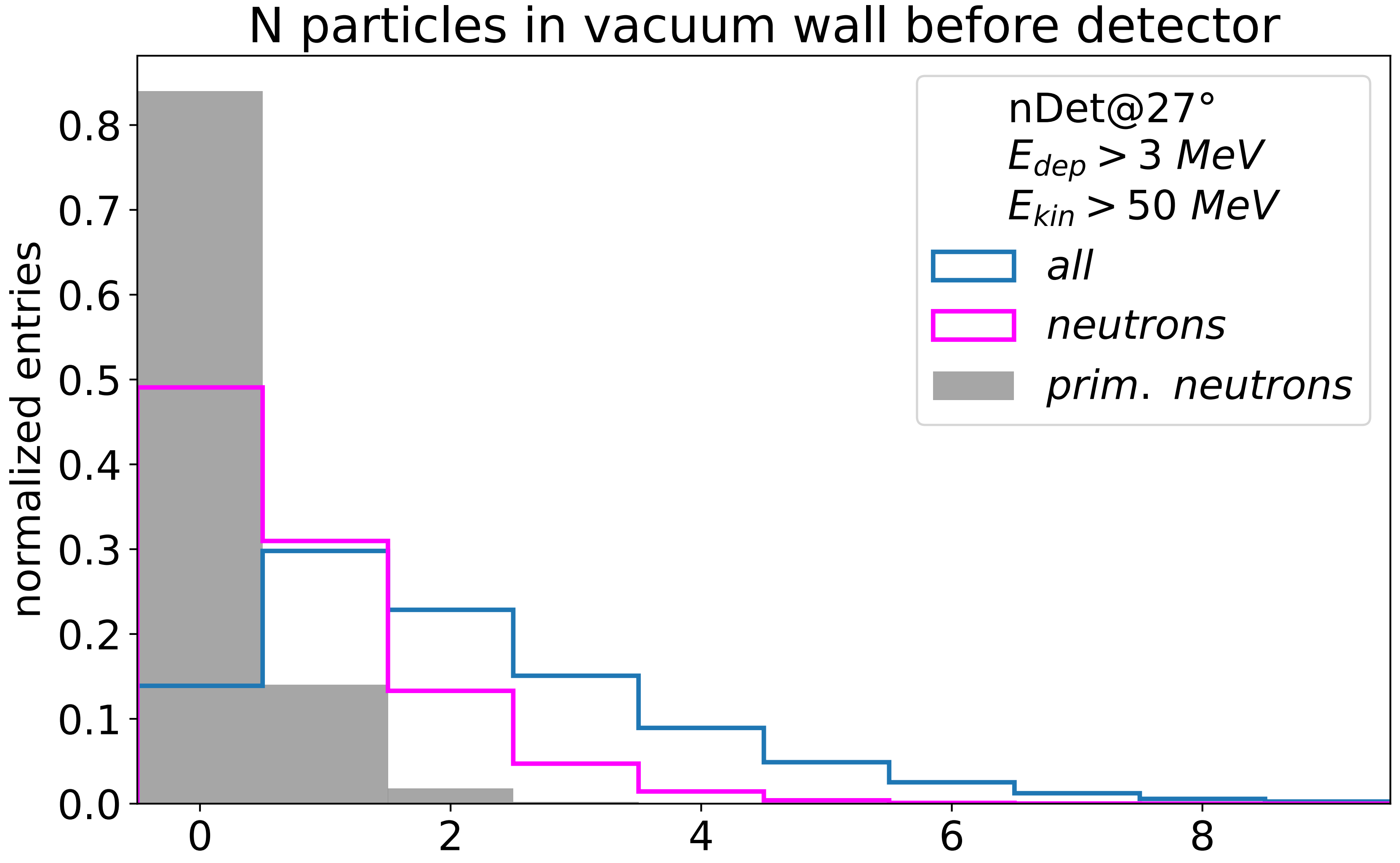
Particles entering the HGND

- 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



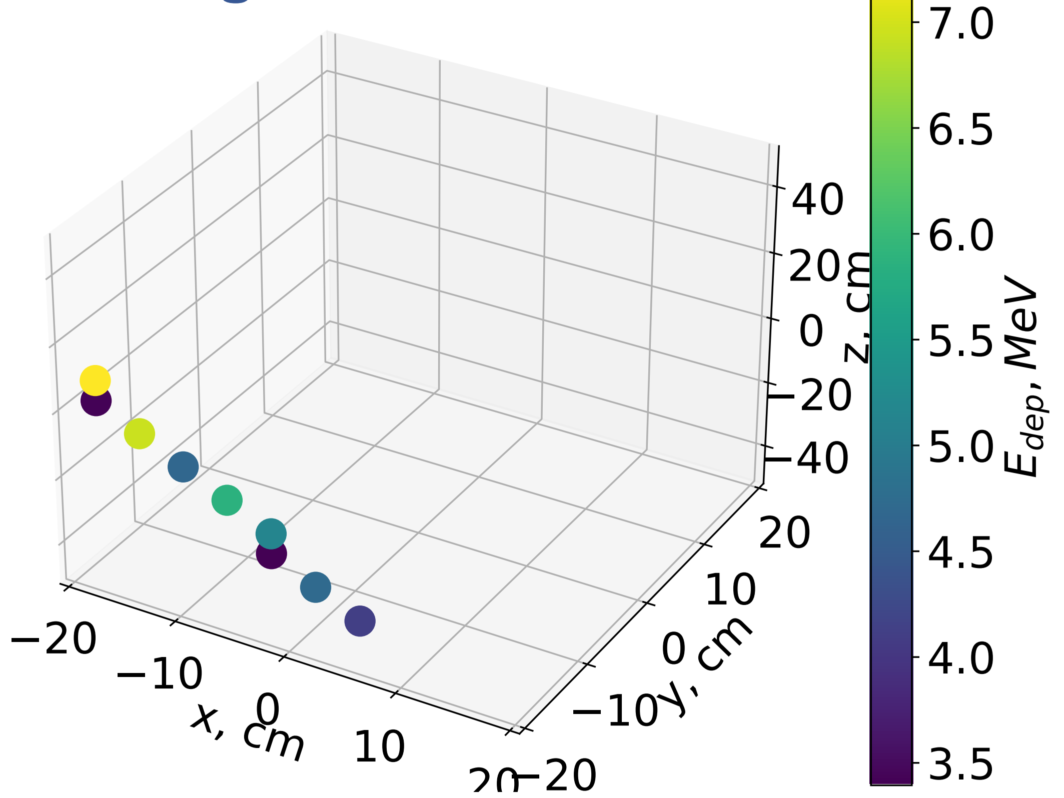
Imaging capabilities of the HGND

Event type signatures:

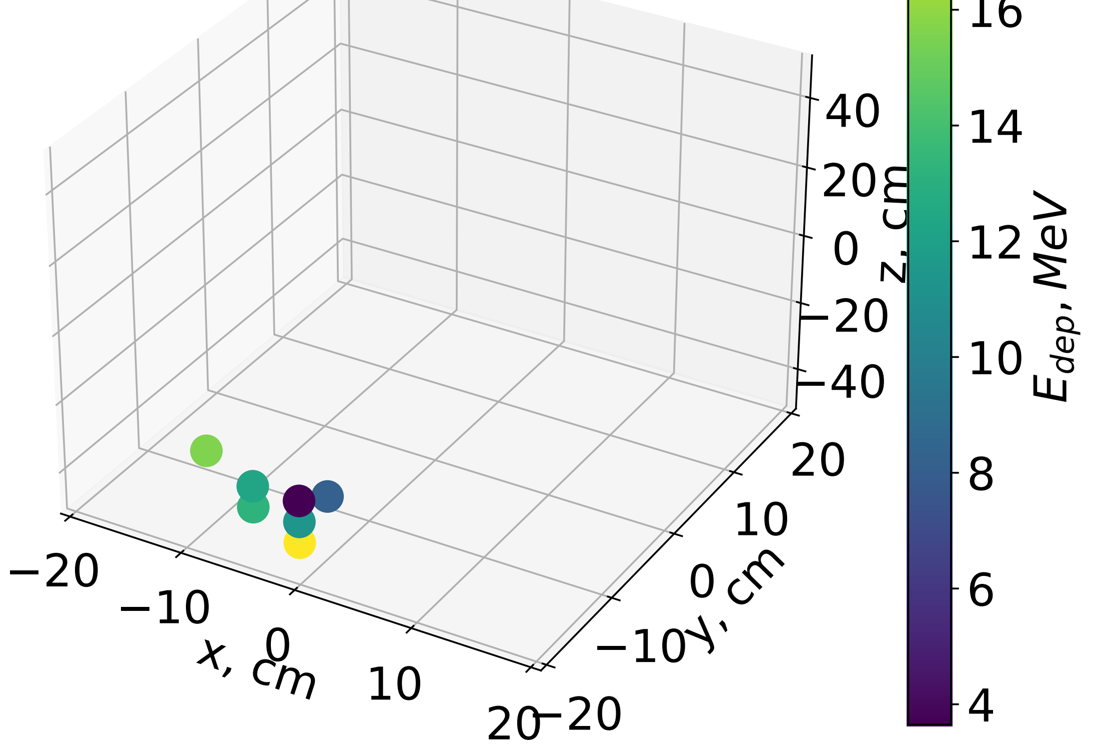
- **tracks** of charged particles
- compact **electromagnetic showers**
- sparse and irregular **hadronic showers**
  - no upstream track for neutral hadrons (including **neutrons**)

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

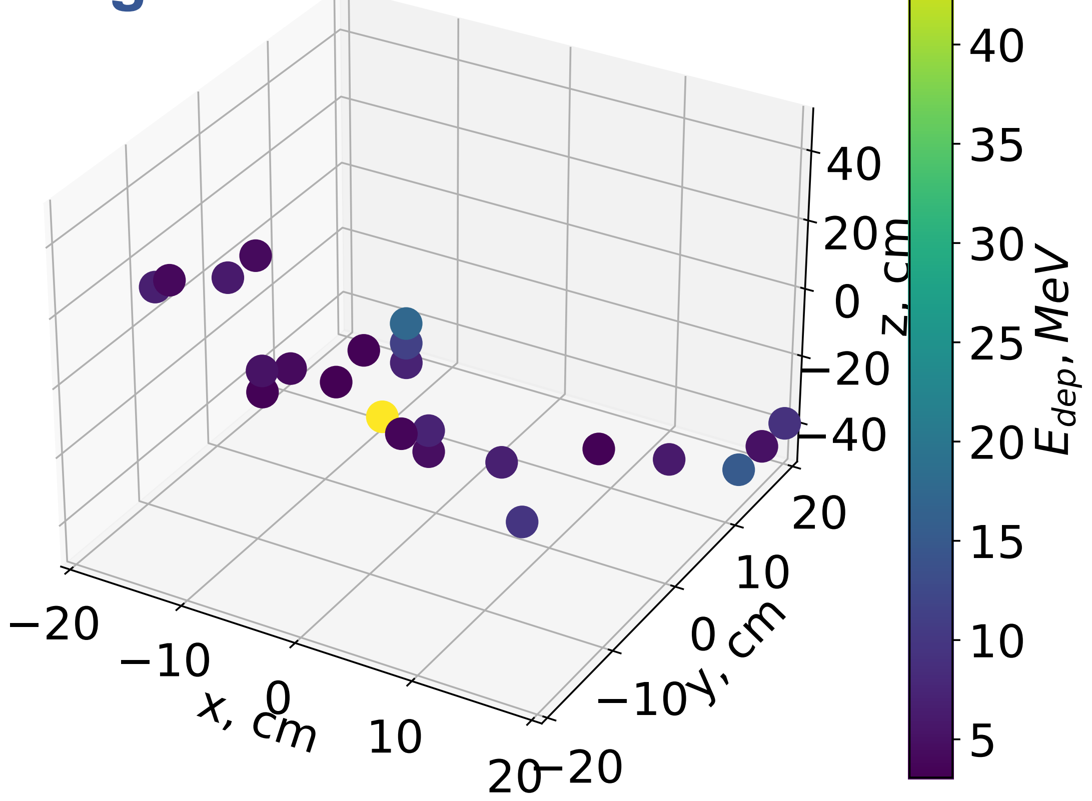
Charged particle track **background** event



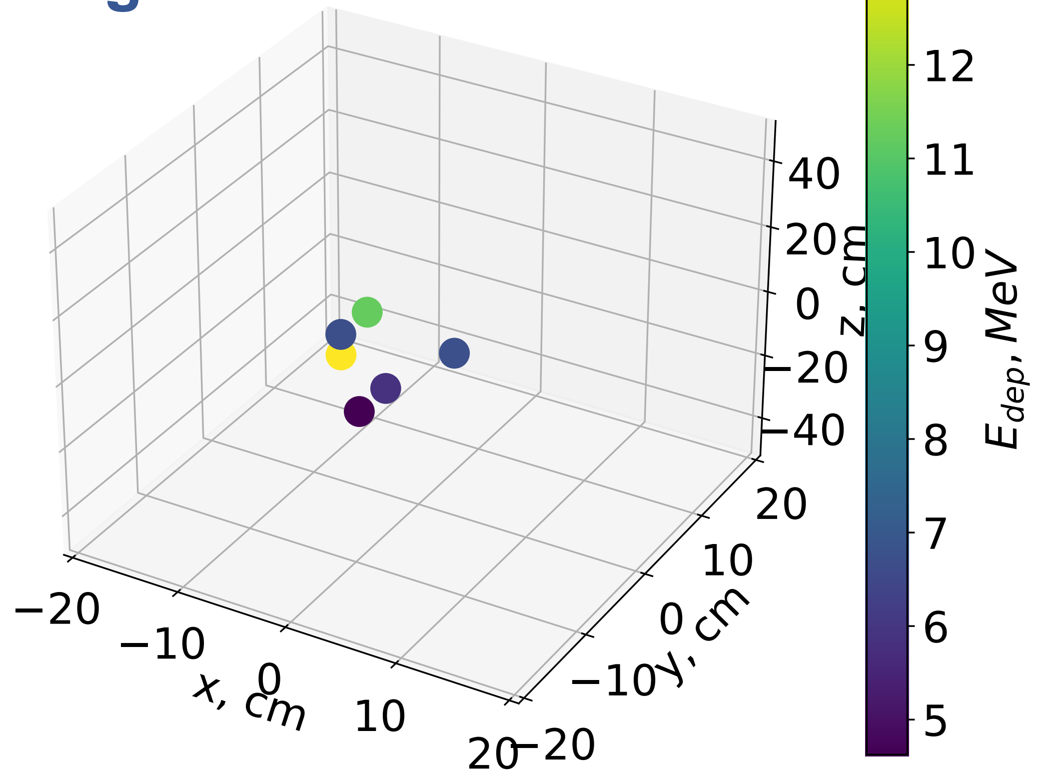
E/m shower **background** event



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}>10GeV are rejected

Fastest hit

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

Median of all hits

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

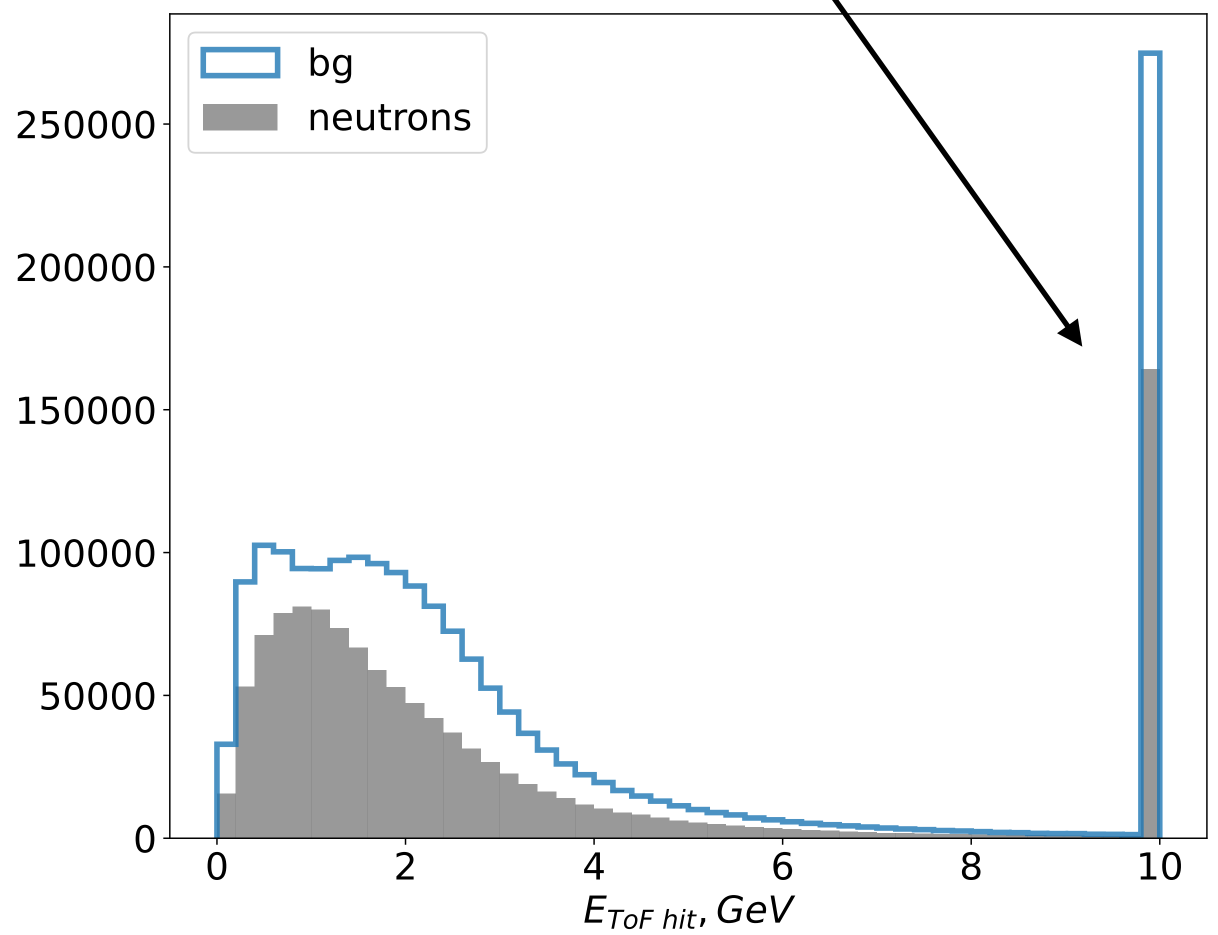
Reference hit

- MC truth hit with min(|E_{ToF} - E_n|)

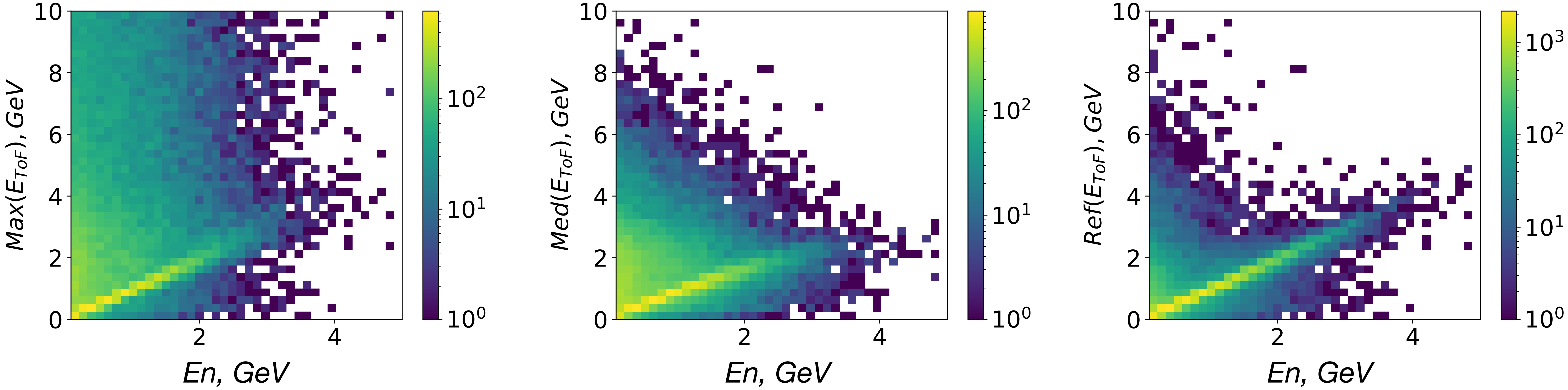
➡ suitable for event labelling

➡ additional estimation model required: fast, median, ML, etc

EToF distribution per hit



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



Visible correlation with target energy even by naive approach.

Data labeling

Observables per hit:

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

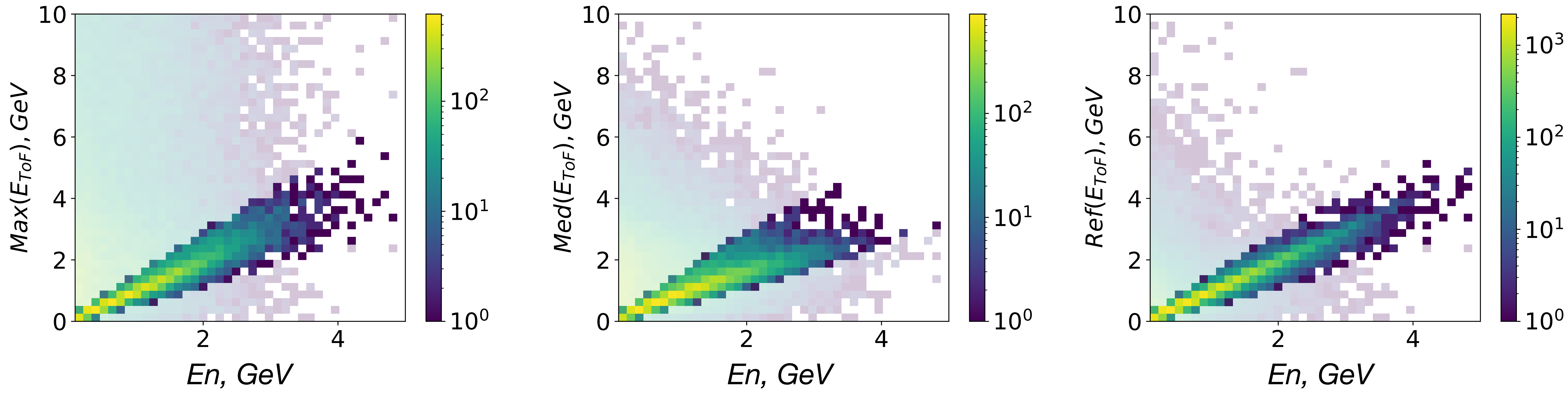
Signal event labeling:

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

272844 events in total
with deposition >3 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) PyG

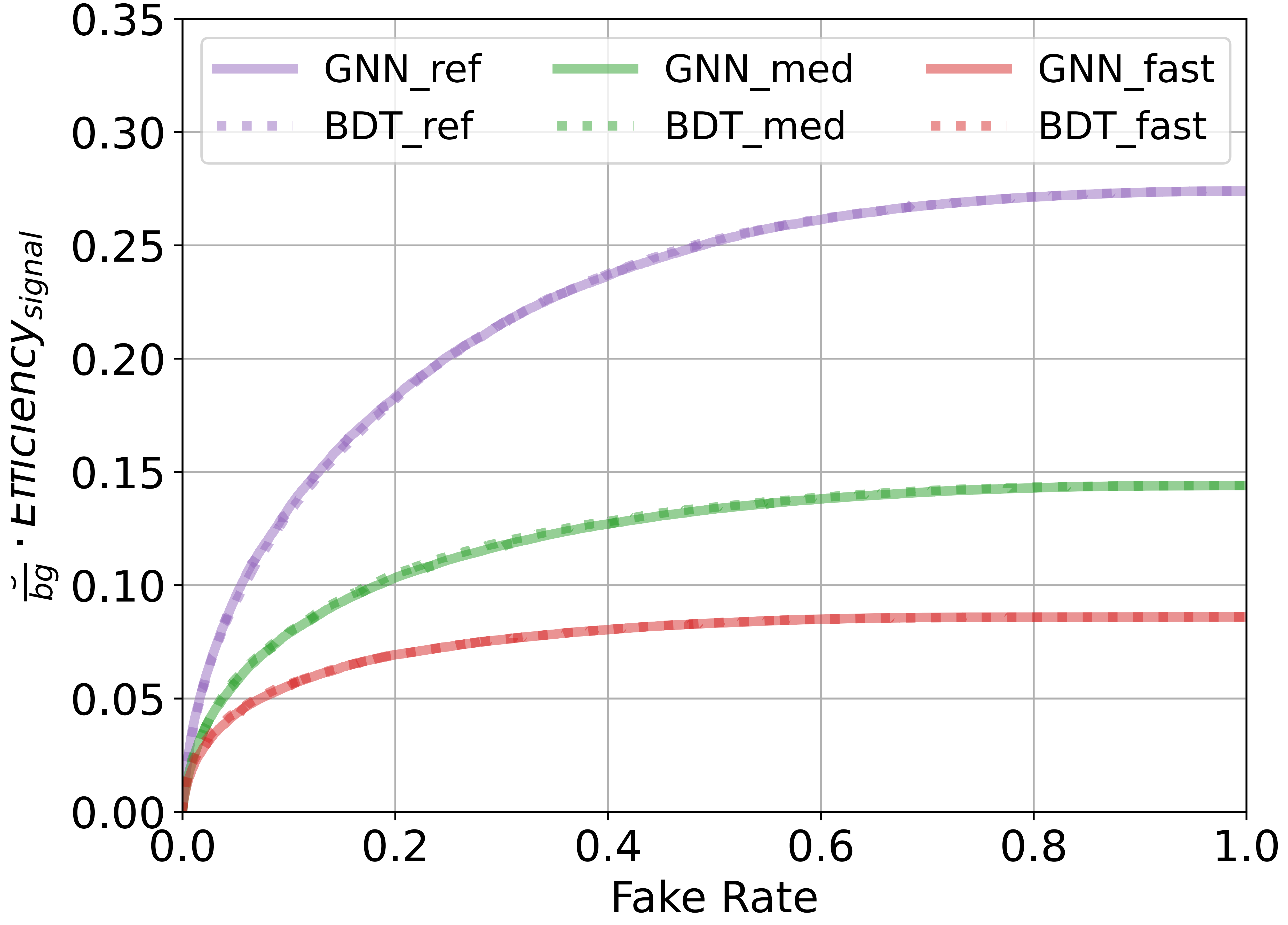
- Graph event representation
  - Observables per graph node (hit): (x,y,z), E_{dep}, E_{ToF}
  - Captures event topologies
- Increasing number of successful implementations in HEP

Boosted Decision Tree (BDT) CatBoost

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

- 13 hand-crafted features

Classification performance

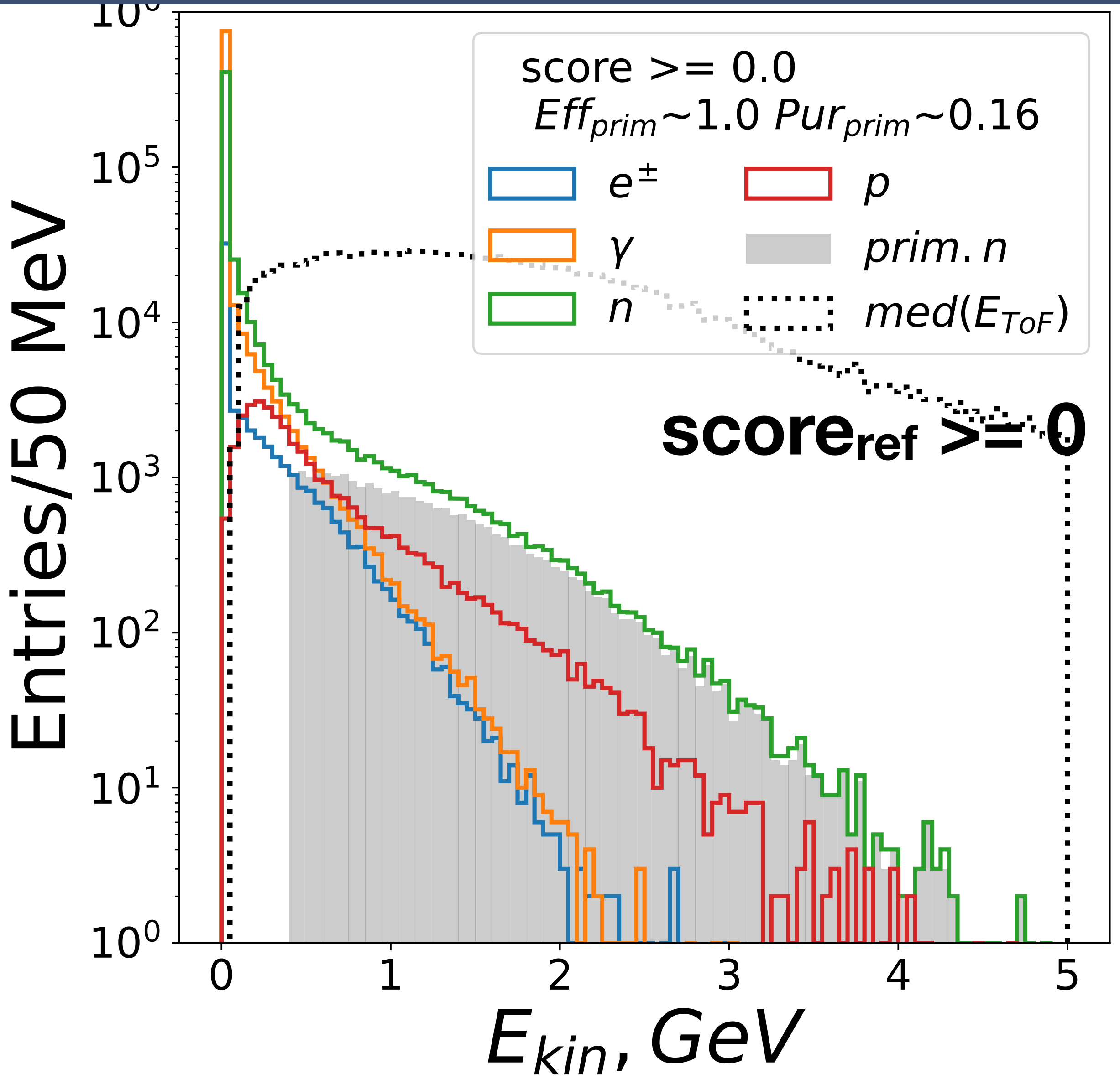


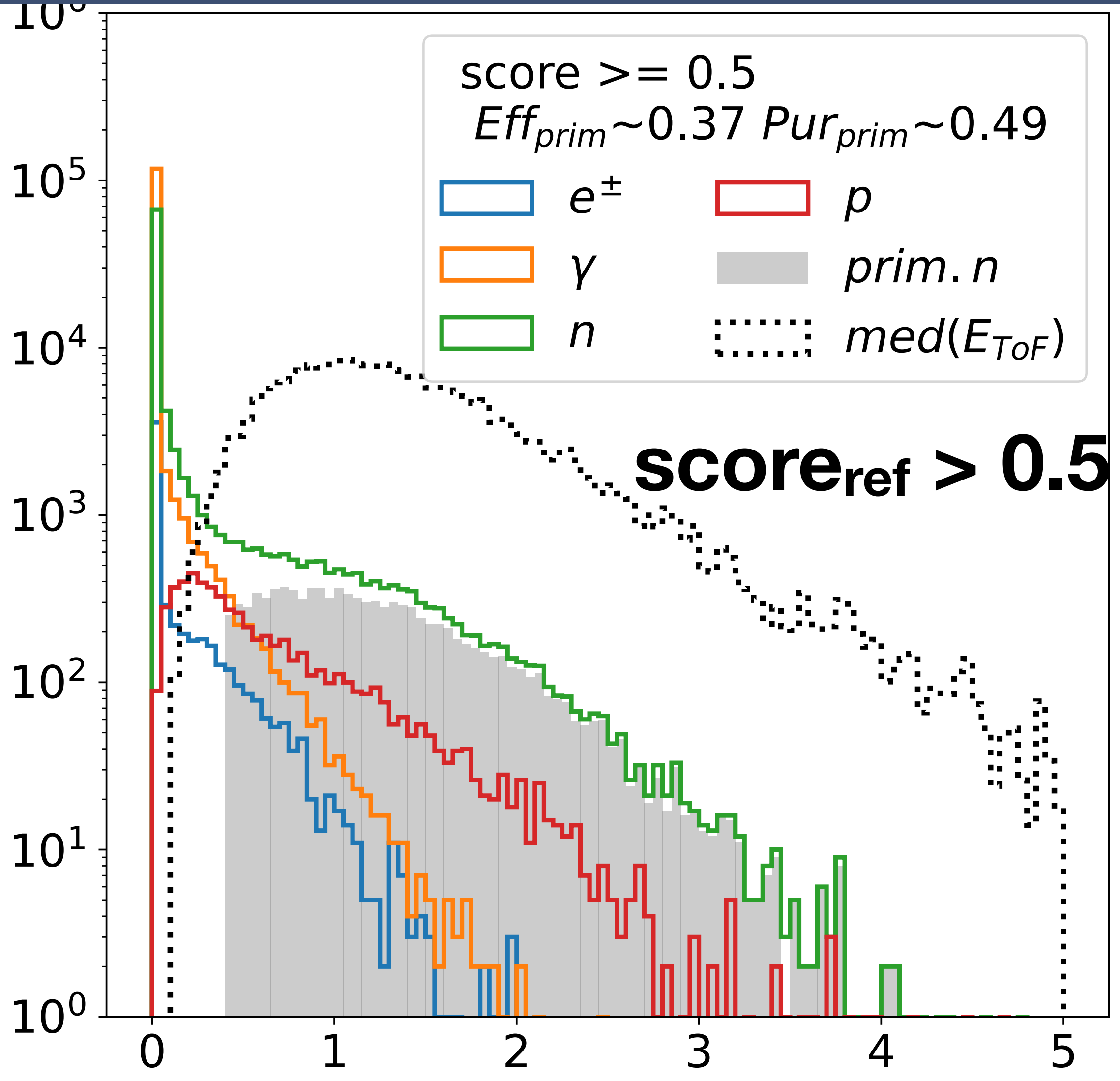
- Same performance between GNN and BDT pairs for all 3 labelling approaches

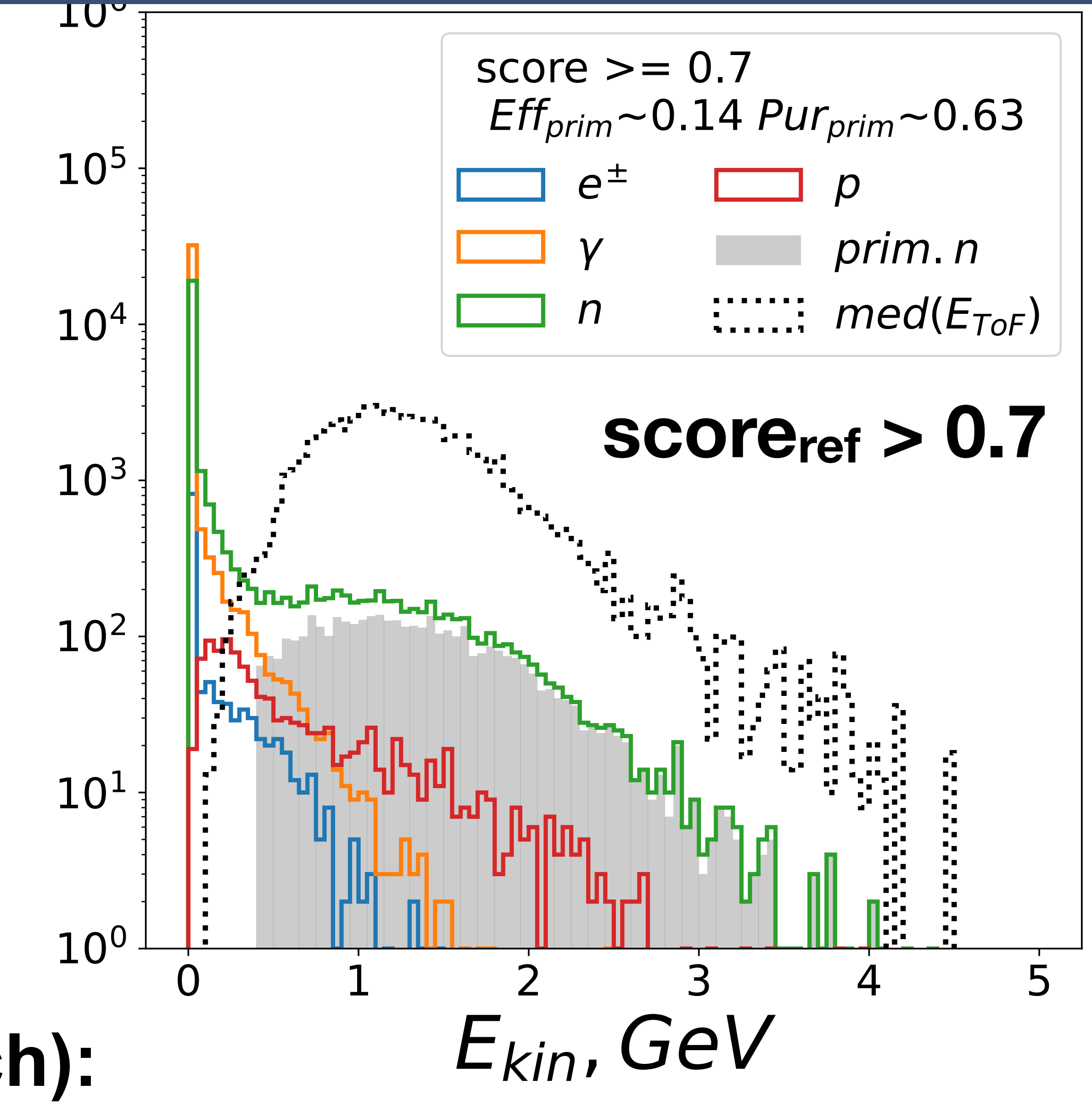
➡ all information is extracted from data in a given setting

- Increasing signal fraction by loosening criteria of “good” neutron events gives dominating effect in classification performance

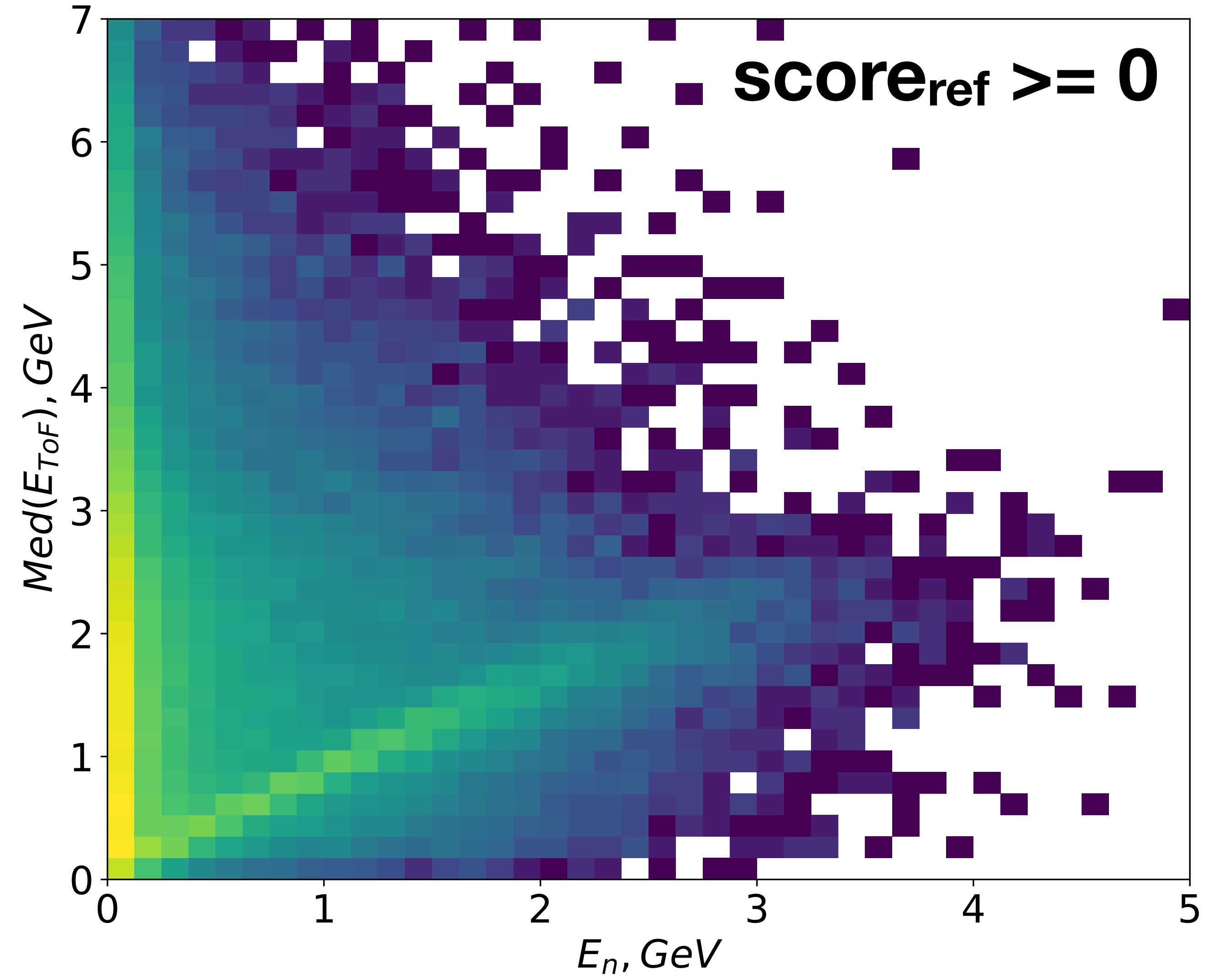
Example of resulting energy spectra

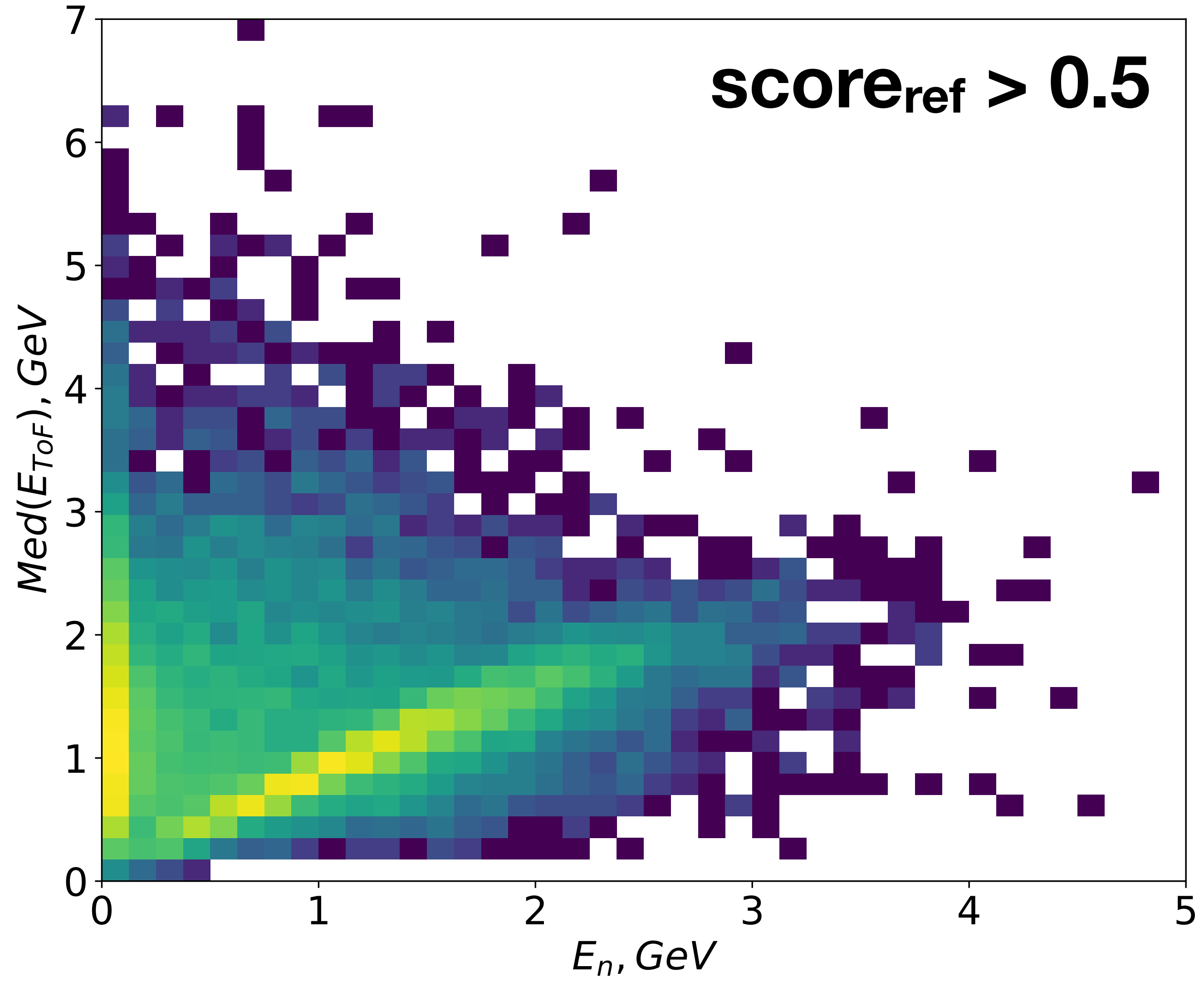


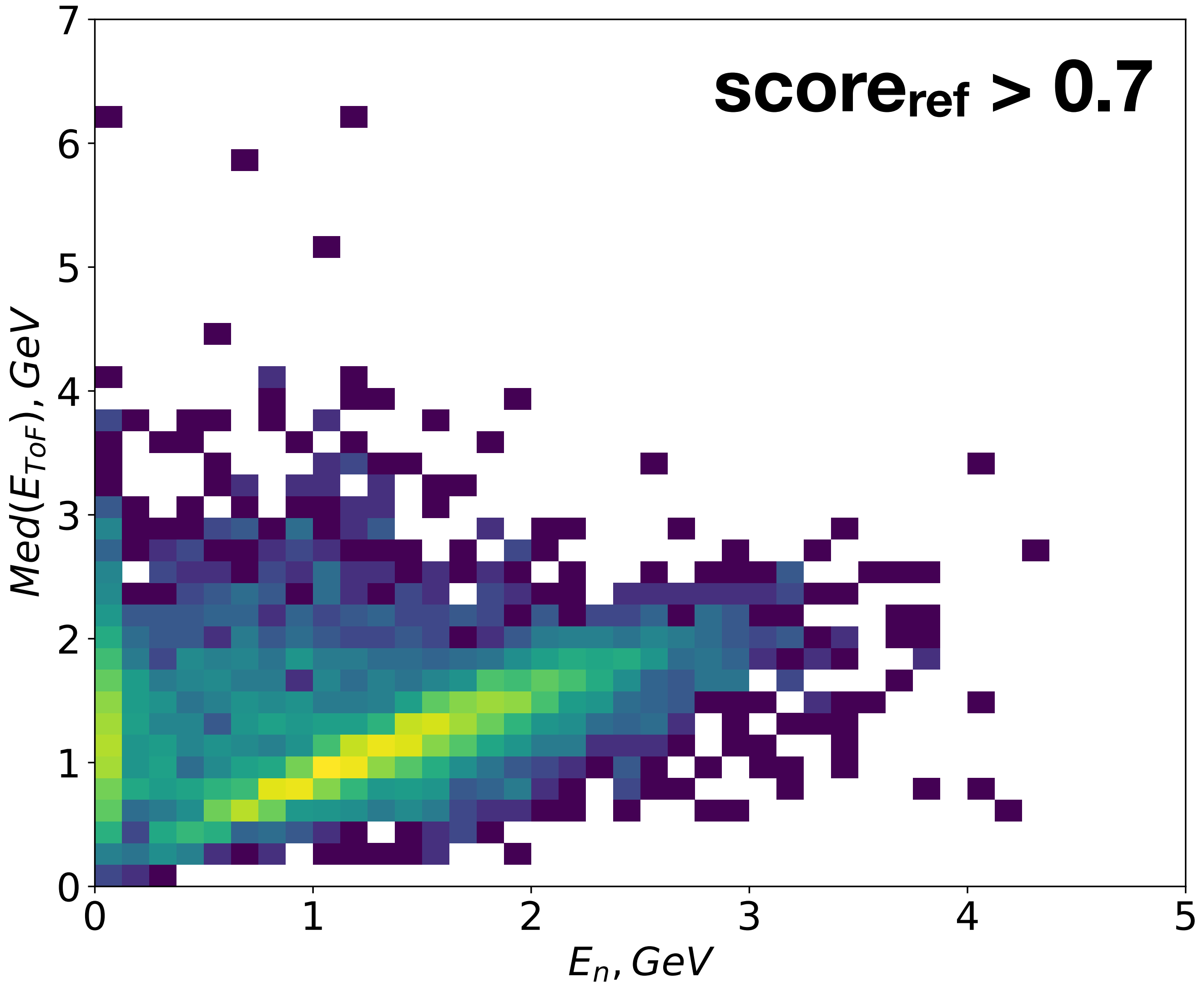




Median(E_{ToF}) neutron energy estimation (naive approach):

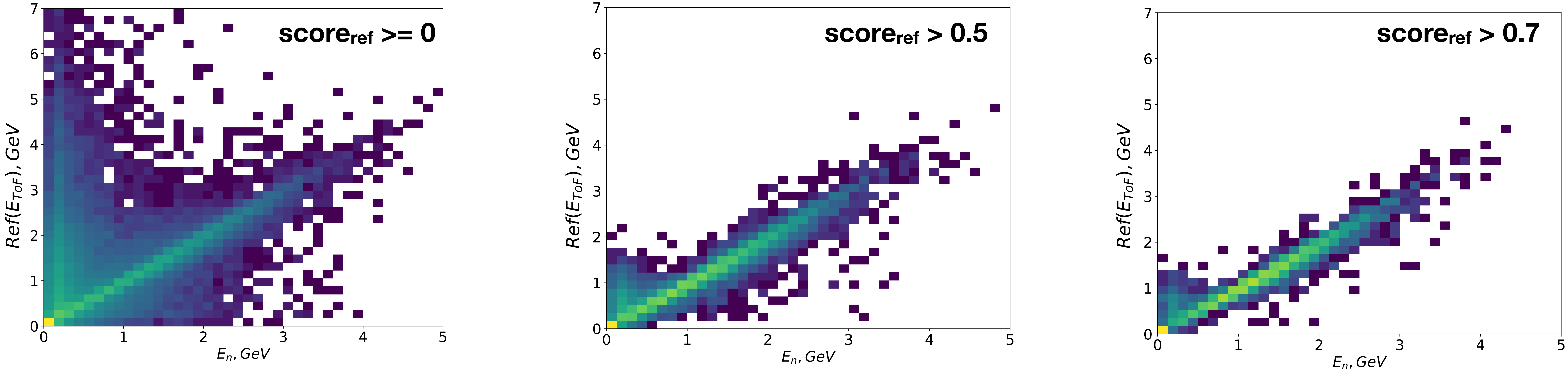






Neutron reconstruction outlook

Refference ToF energy



- 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

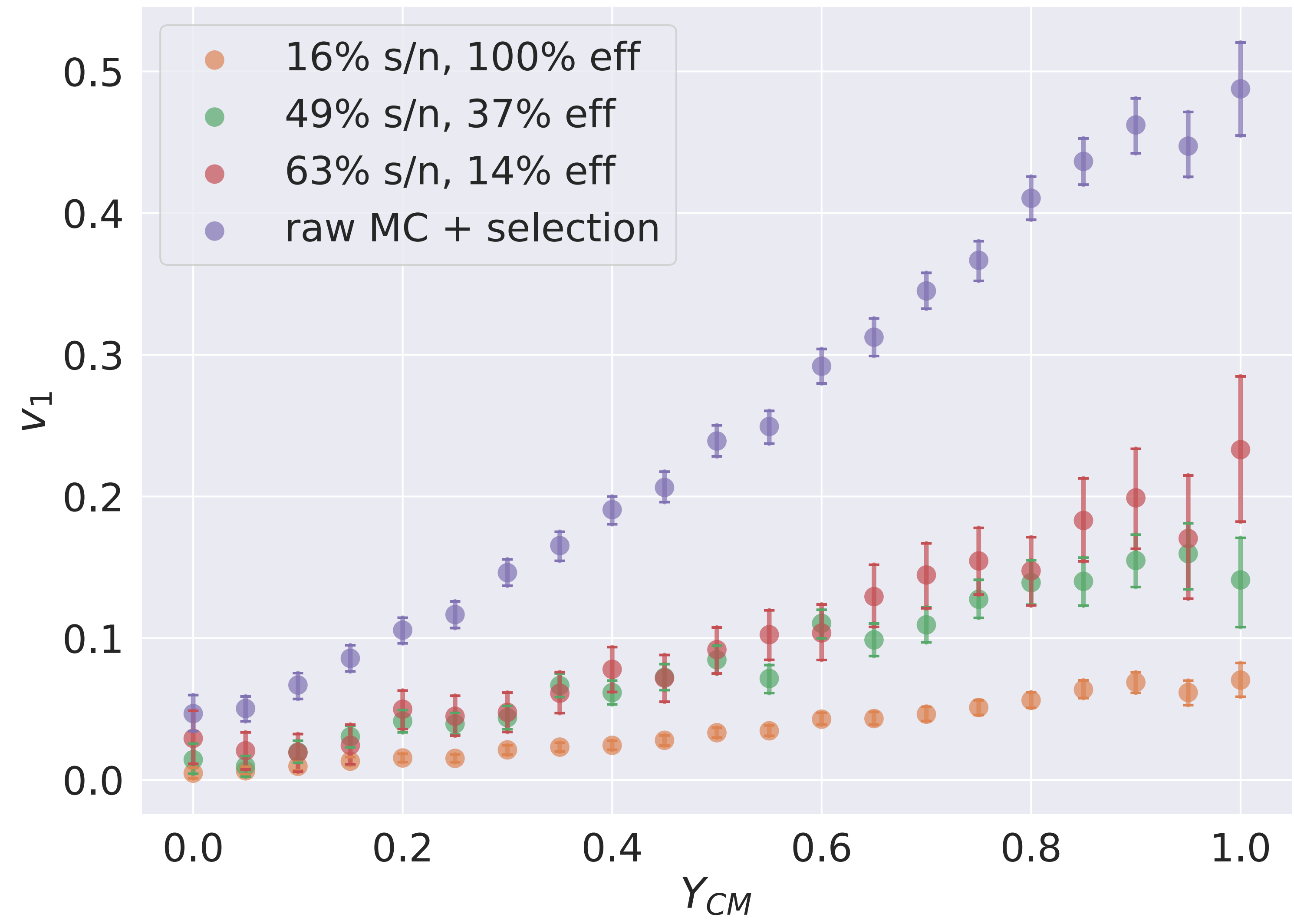
- Data source: all primary neutrons from initial DCM-QGSM-SMM Bi+Bi @ 3 AGeV reaction
  - MC truth information
  - primary neutrons randomly sampled according to classifier efficiency
  - mixed with uniformly distributed $v_{1/2}$ as background (P_T and Y_{cm} are sampled from selected neutrons) according 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 Pt selection criteria:
  - $E_{kin} > 0.4$ GeV
  - Impact parameter $\in (6, 9)$ fm
  - Rapidity in c.m. $\in (-0.2, 0.2)$

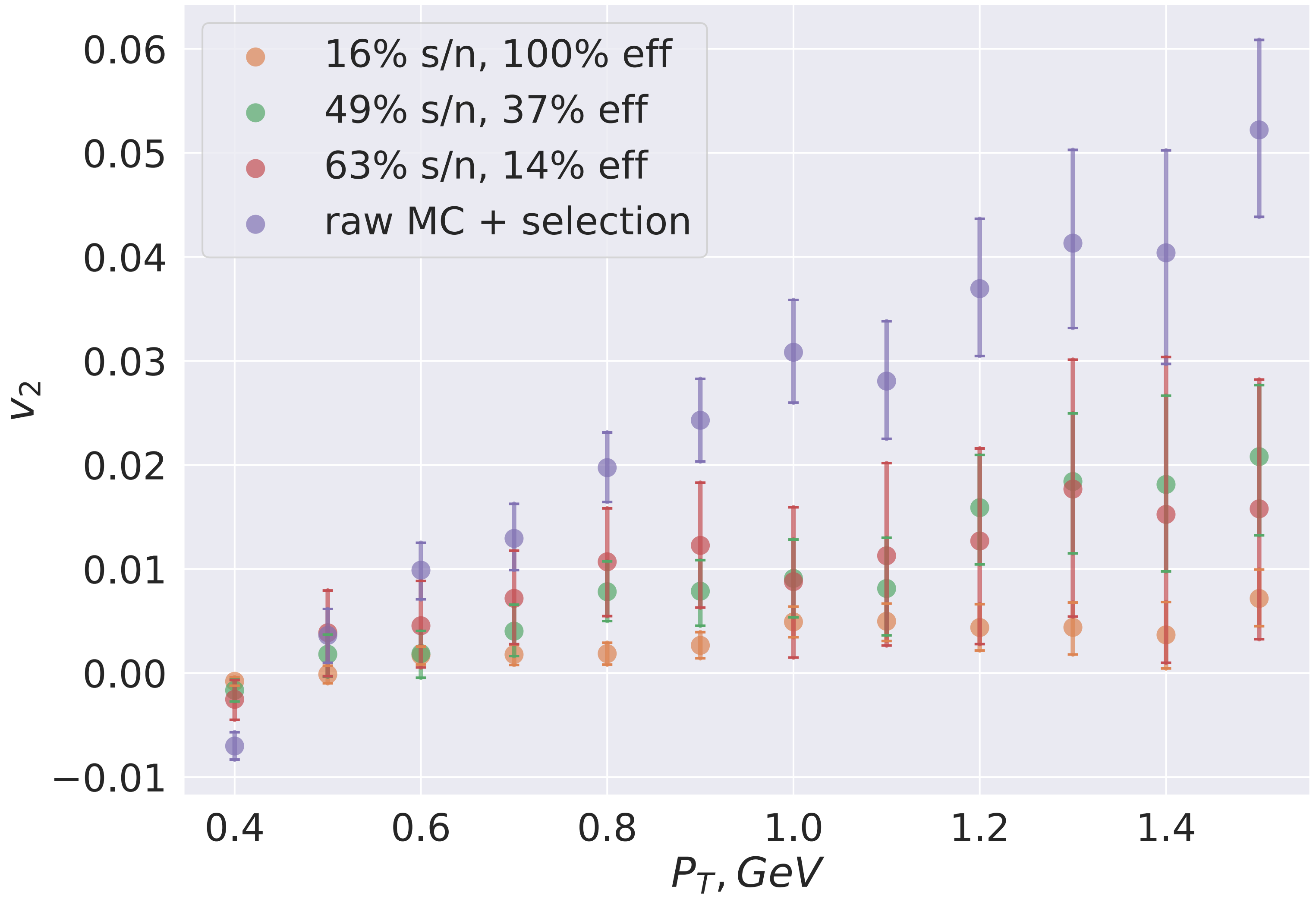
  ➡ 1382287 neutrons initially

$v_{1/2}$ amplitude increases with purity, stat. uncertainty is affected by neutron reconstruction efficiency

v_1 vs rapidity distortion



v_2 vs P_T distortion



Anisotropic Flow Coefficients

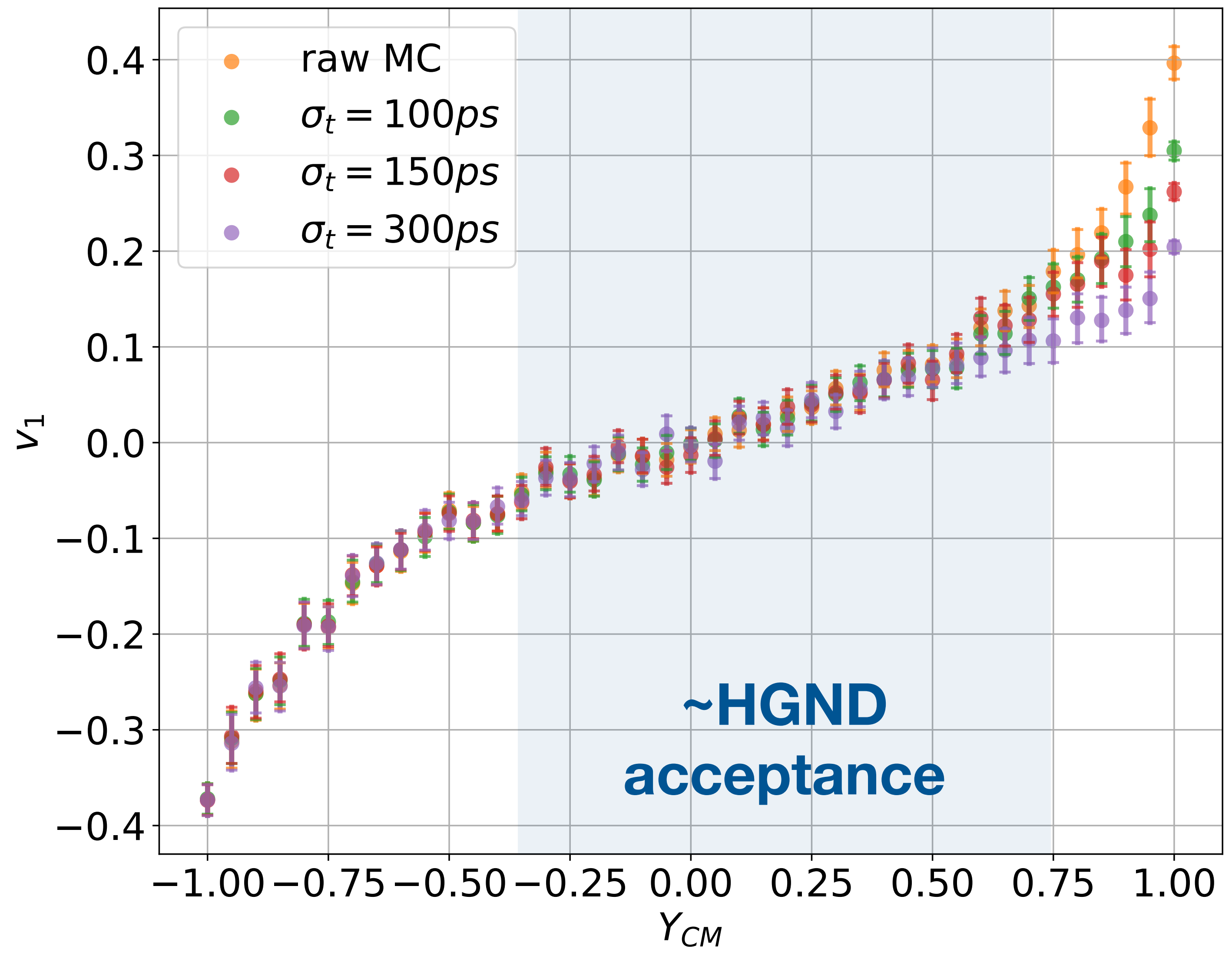
Influence of HGND time resolution on flow coefficients

- Data source: all primary neutrons from initial DCM-QGSM-SMM Bi+Bi @ 3 AGeV reaction
  - MC truth information
  - Y_{CM} and P_T are converted to time at distance of 5.72m along **p** and recalculated after time smearing
- v_1 vs Y_{CM} selection criteria:
  - E_{kin} > 0.5 GeV
  - Impact parameter ∈ (6, 9) fm
  - p_T ∈ (1., 1.5) GeV
- v_2 vs Pt selection criteria:
  - E_{kin} > 0.5 GeV
  - Impact parameter ∈ (6, 9) fm
  - Rapidity in c.m. ∈ (-0.2, 0.2)

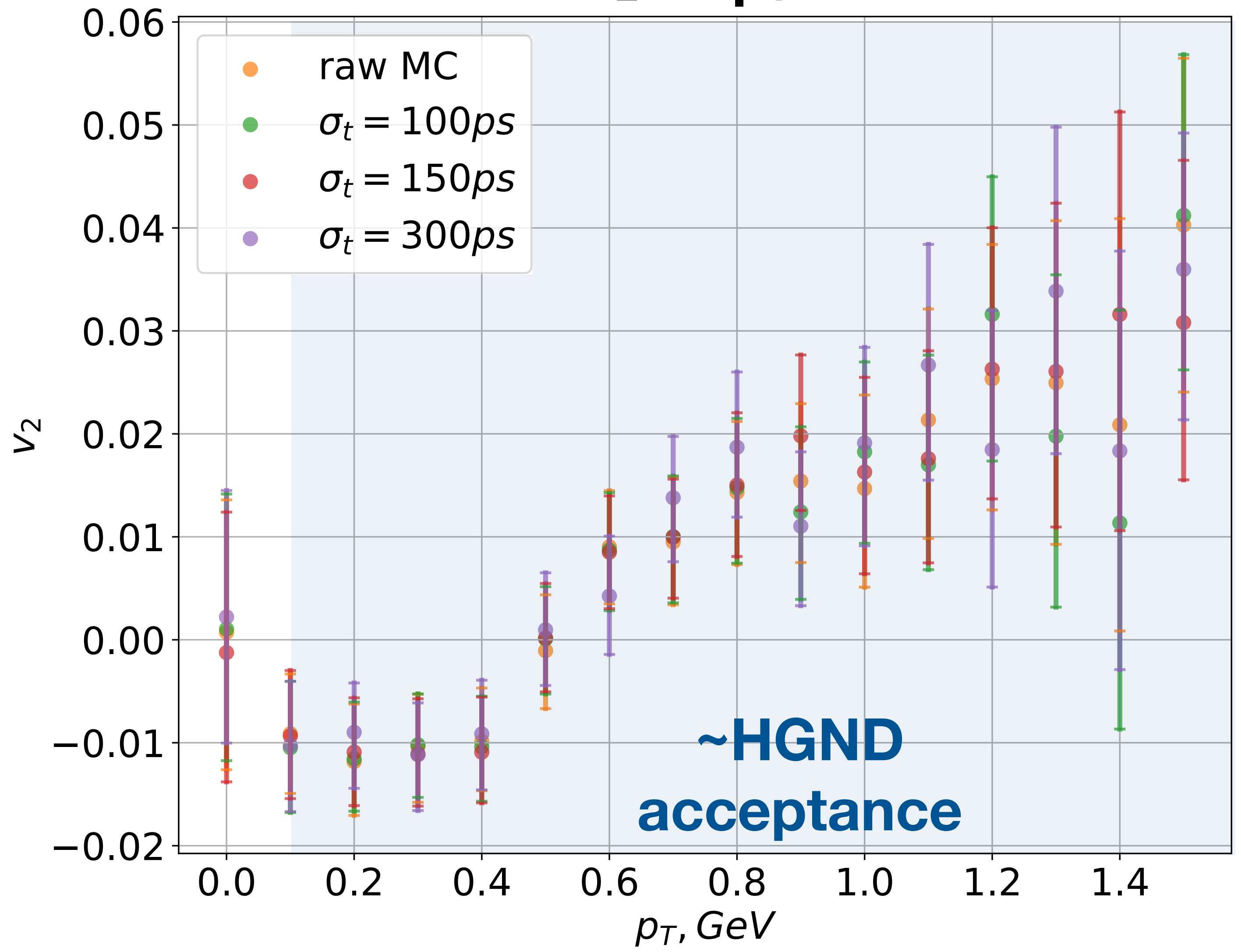
p_T and rapidity cuts are on distorted values)

Time resolution effect gets noticeable only at forward rapidities

v_1 vs rapidity



v_2 vs p_T



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

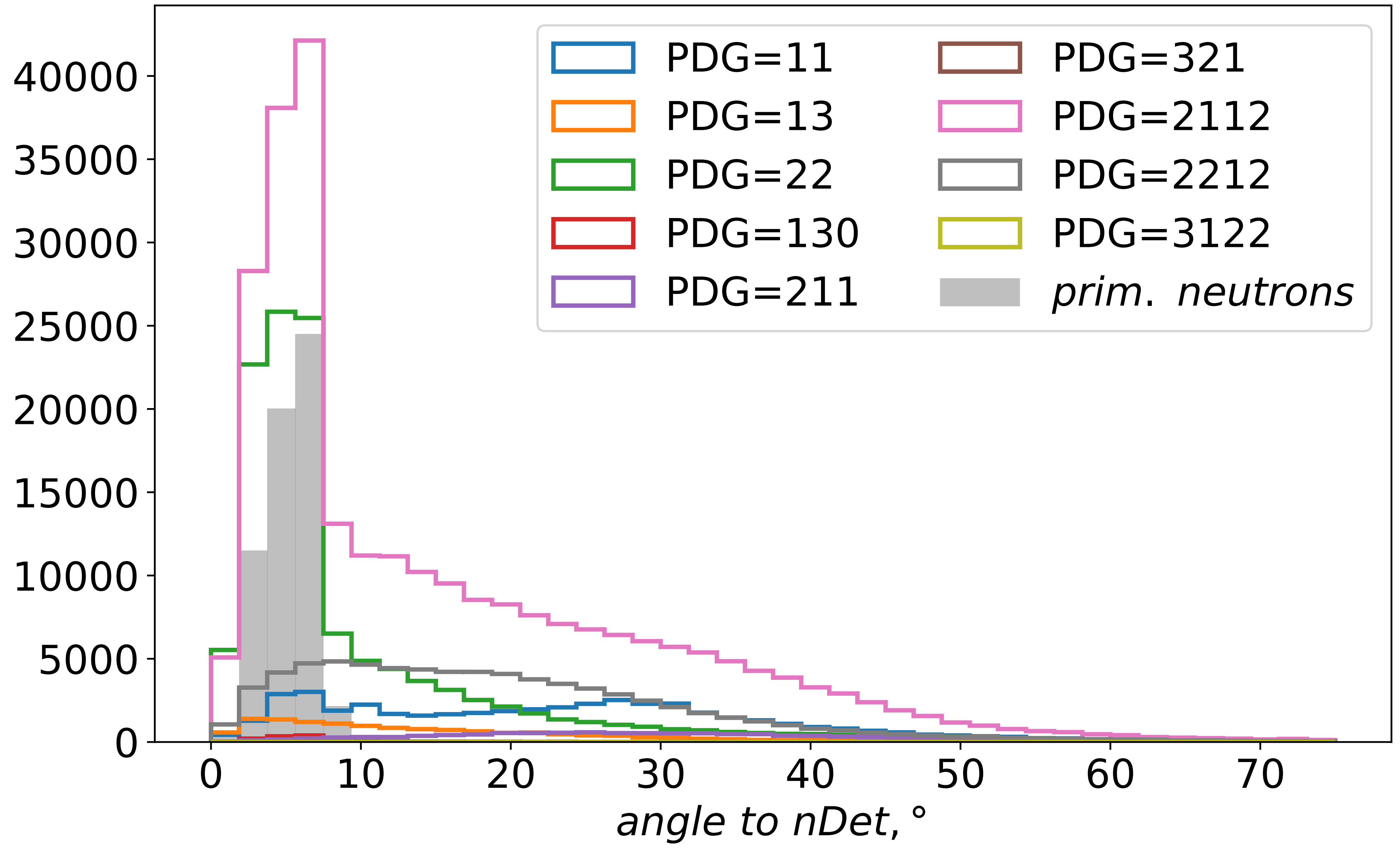
➡ Fast-sim methods are foreseen to be beneficial

Summary

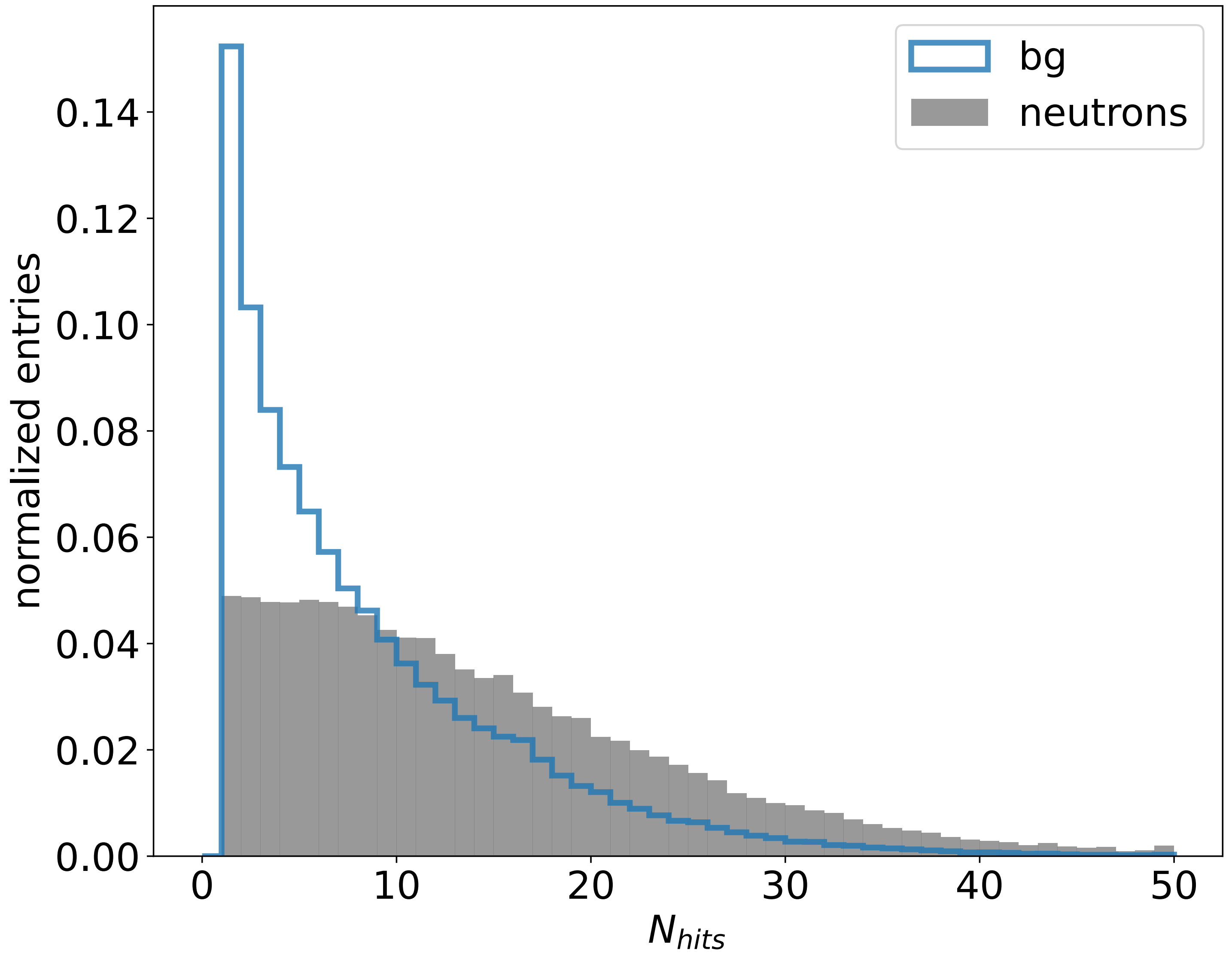
- HGND at the BM@N provides additional information source to access the EOS of dense nuclear matter
- Challenging task of neutron reconstruction using hybrid time-of-flight and imaging calorimetry technique is discussed
- First estimation of neutron flow measurement performance is done
- A number of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

Backup

Angular spectrum per particle type



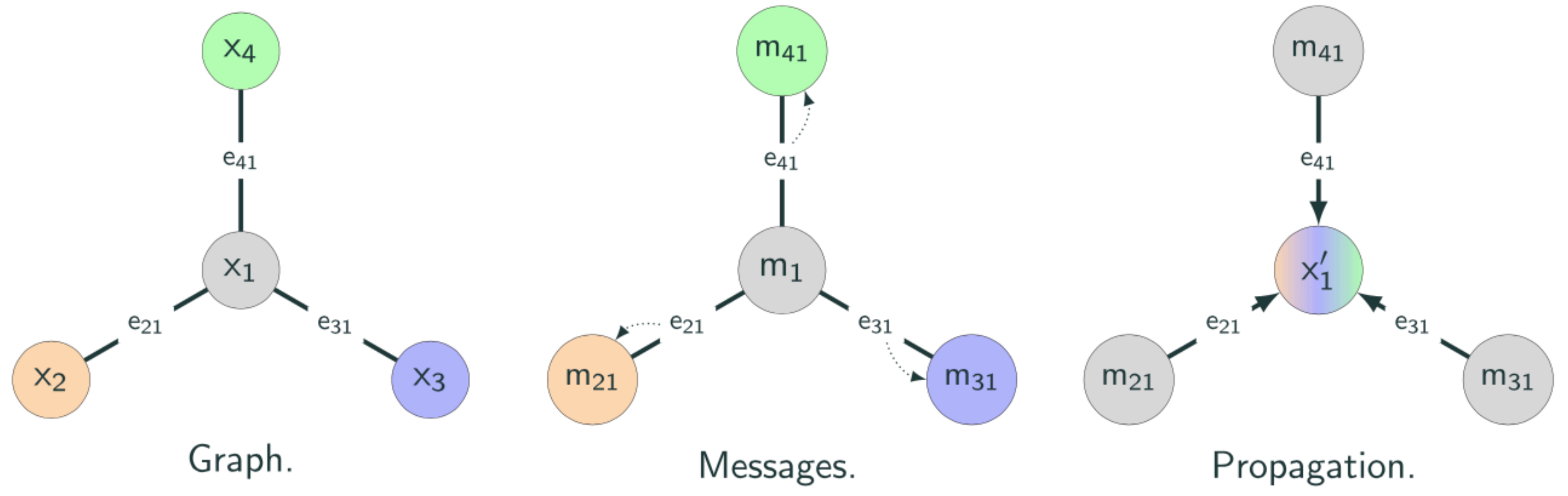
Number of hits



GNN in High Energy Physics

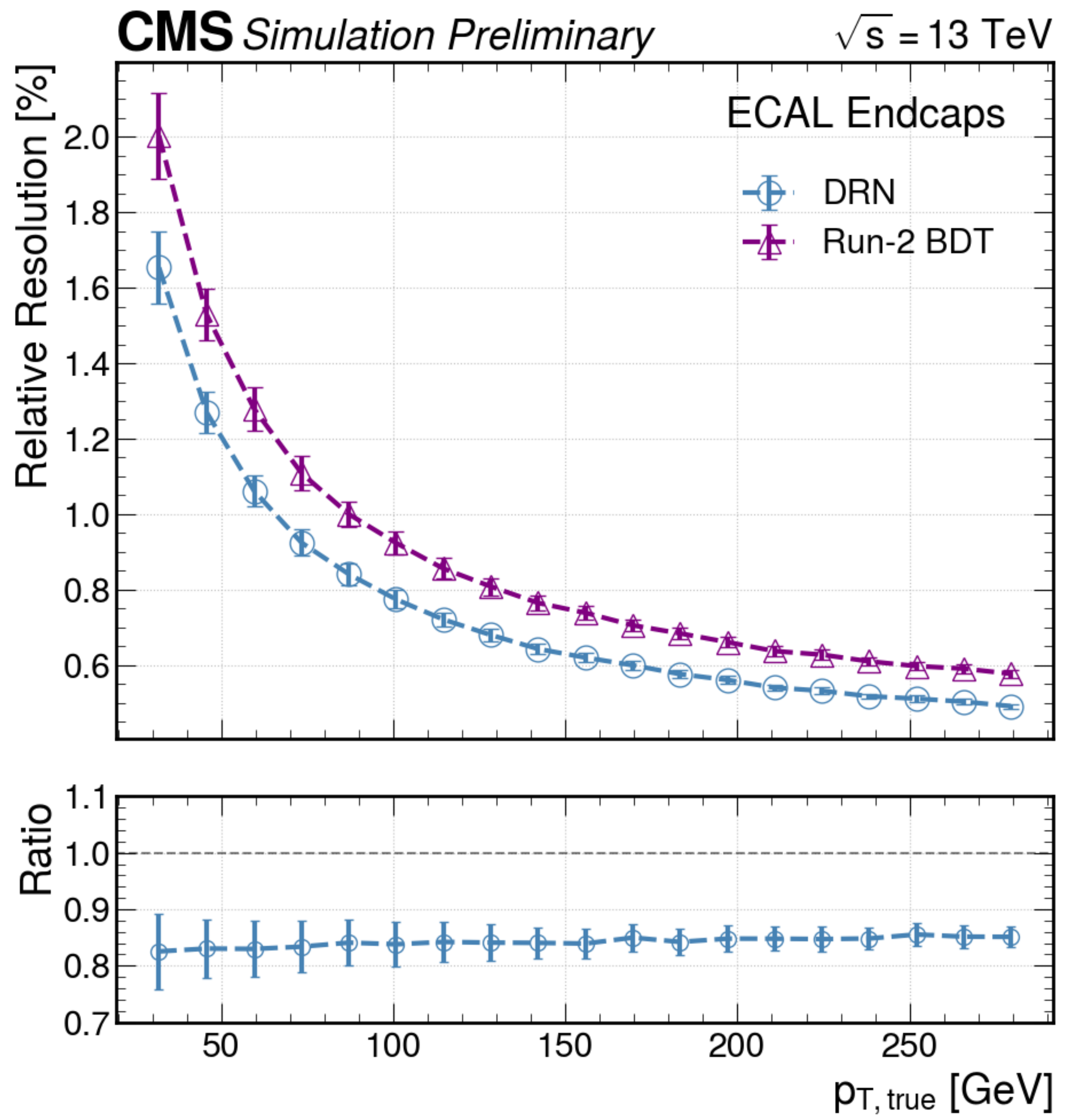
Why Graph Neural Networks:

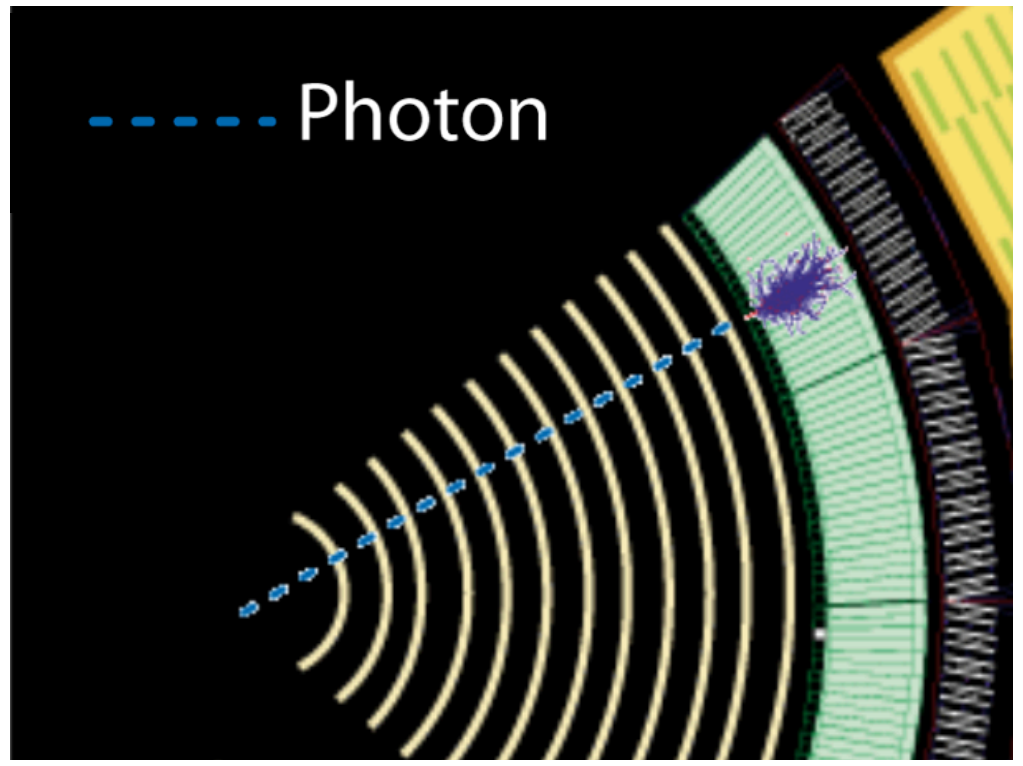
- Natural event representation
- Easily applied to sparse data with variable input size
  - typically we have signal only in small fraction of sensors
- Increasing number of successful implementations in HEP
- Performance improvement in comparison with commonly used Gradient Boosting (GB) models (or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

P. Simkina, Machine learning techniques for calorimetry

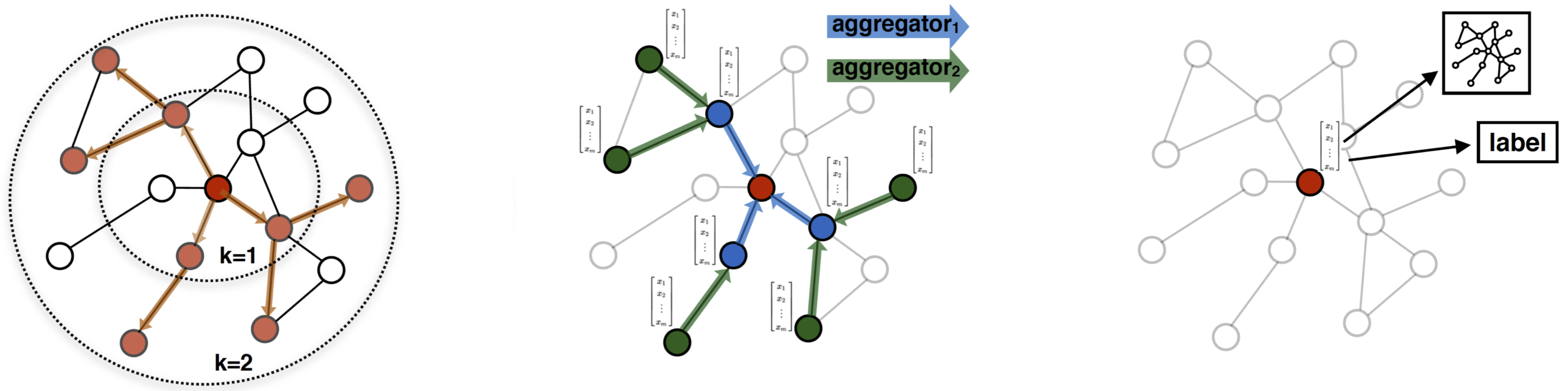
Classification models

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 (**SA**mple and aggre**G**at**E**) 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:

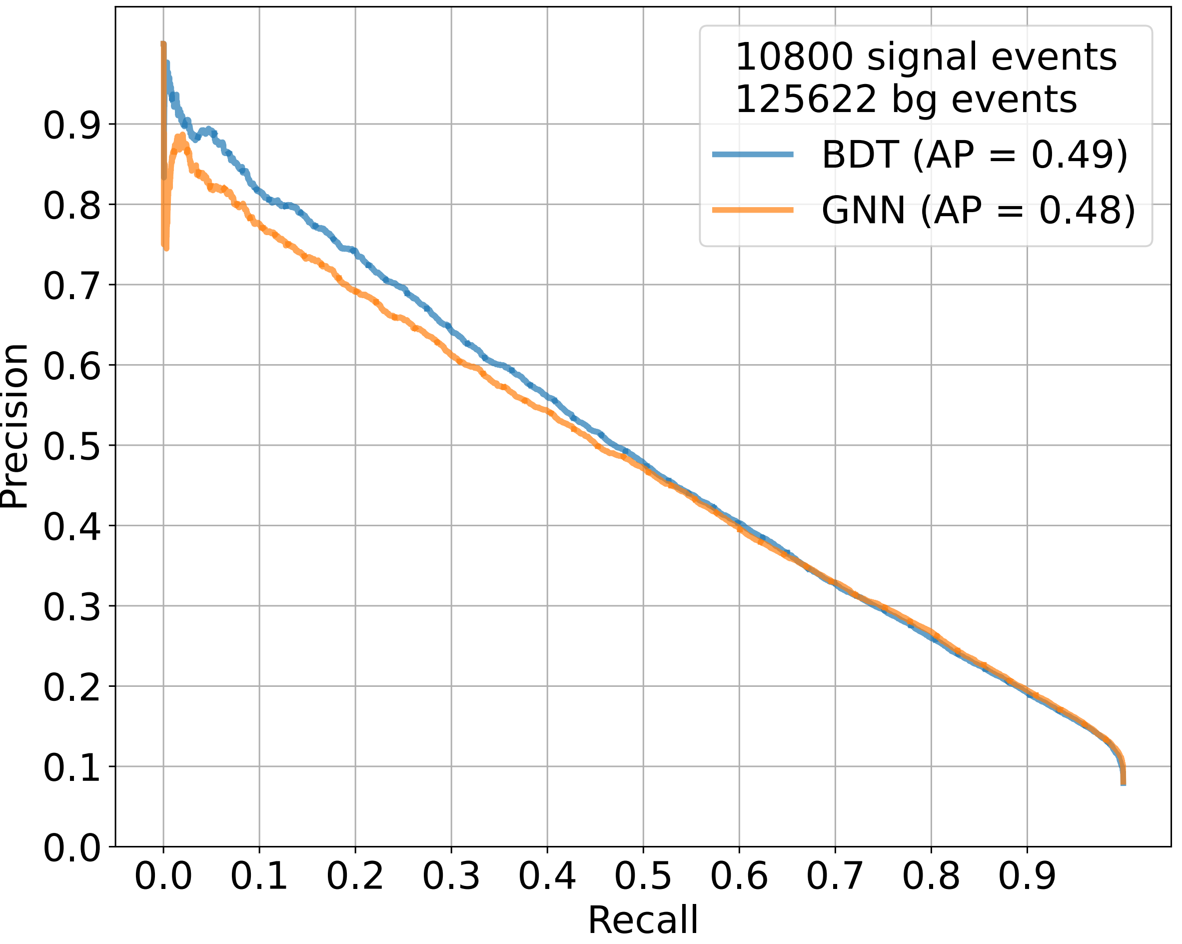
- ’dt_zmin’,
- ‘R_zmin', - distance to (0,z)
- ‘Z_zmin',
- ‘E_zmin’,

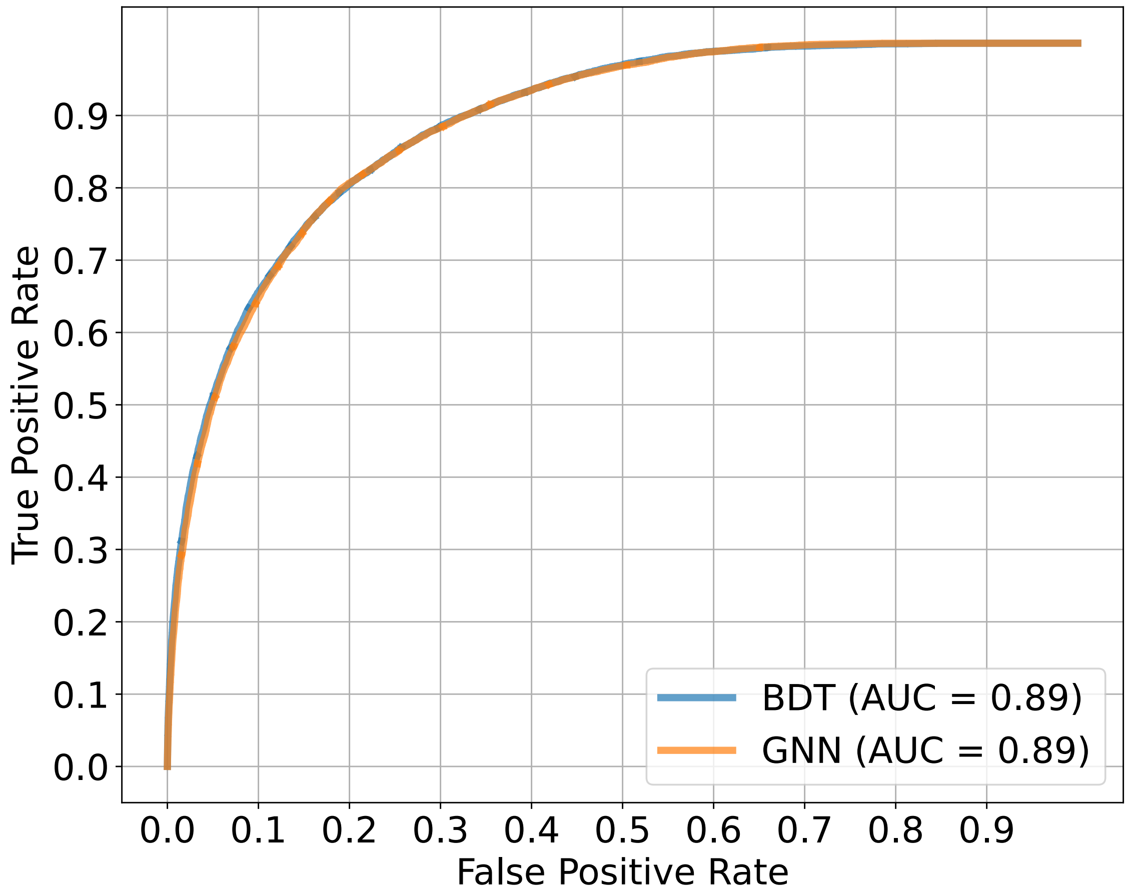
Global:

- 'Esum',
- ‘cogZ', - E-weighted average z
- 'cogR', - E-weighted average distance to (0,z)
- 'nHits',
- 'dt_stdev'

Classification performance

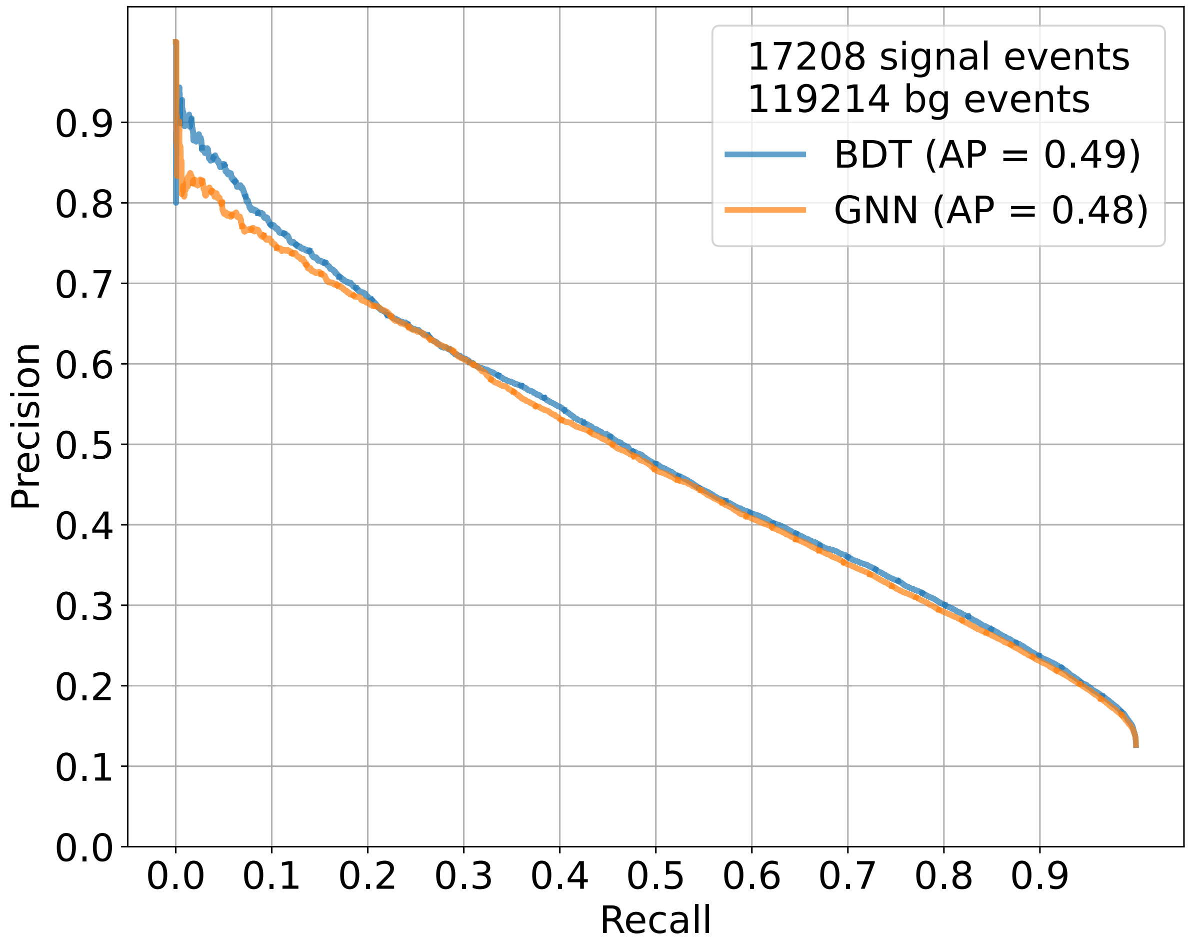
Fastest hit labelling

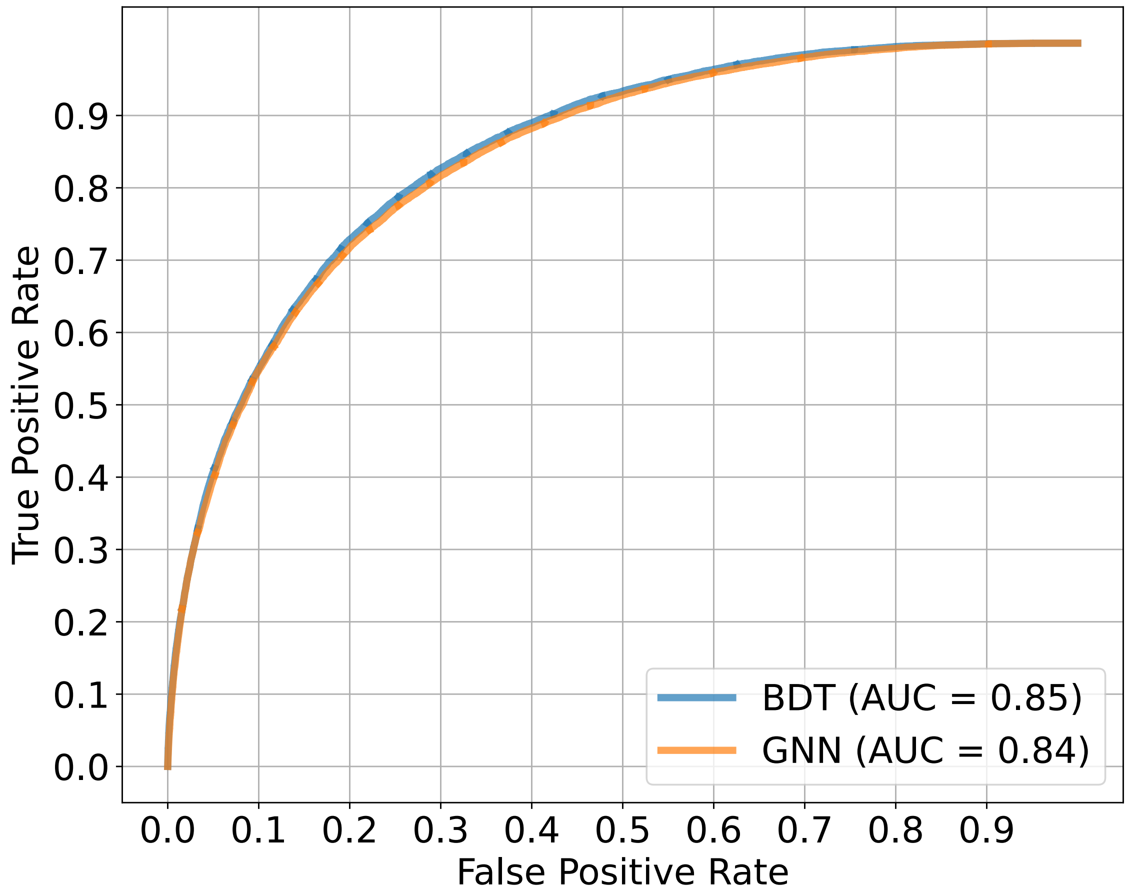




* some hints that models rely mostly on Max(E_{ToF}) distribution

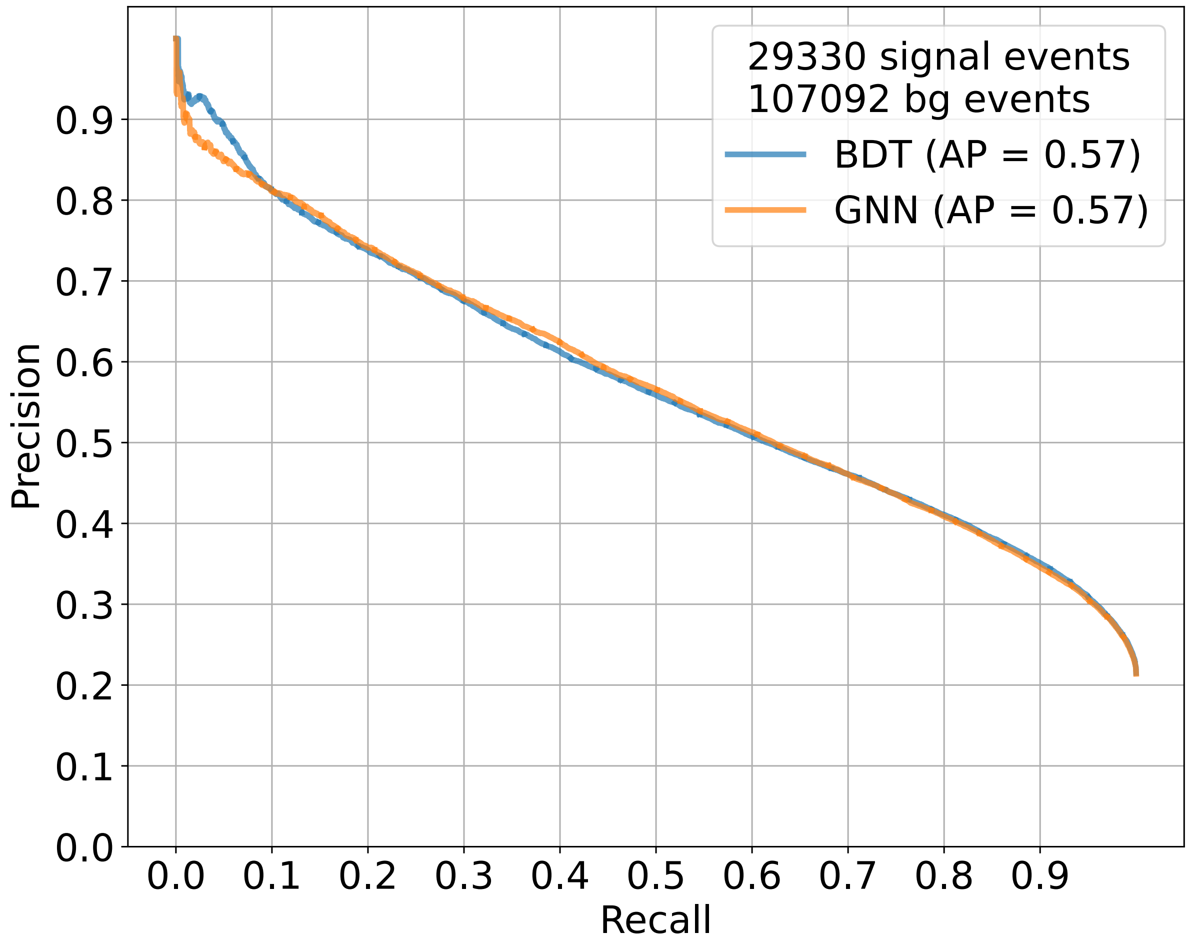
median labelling

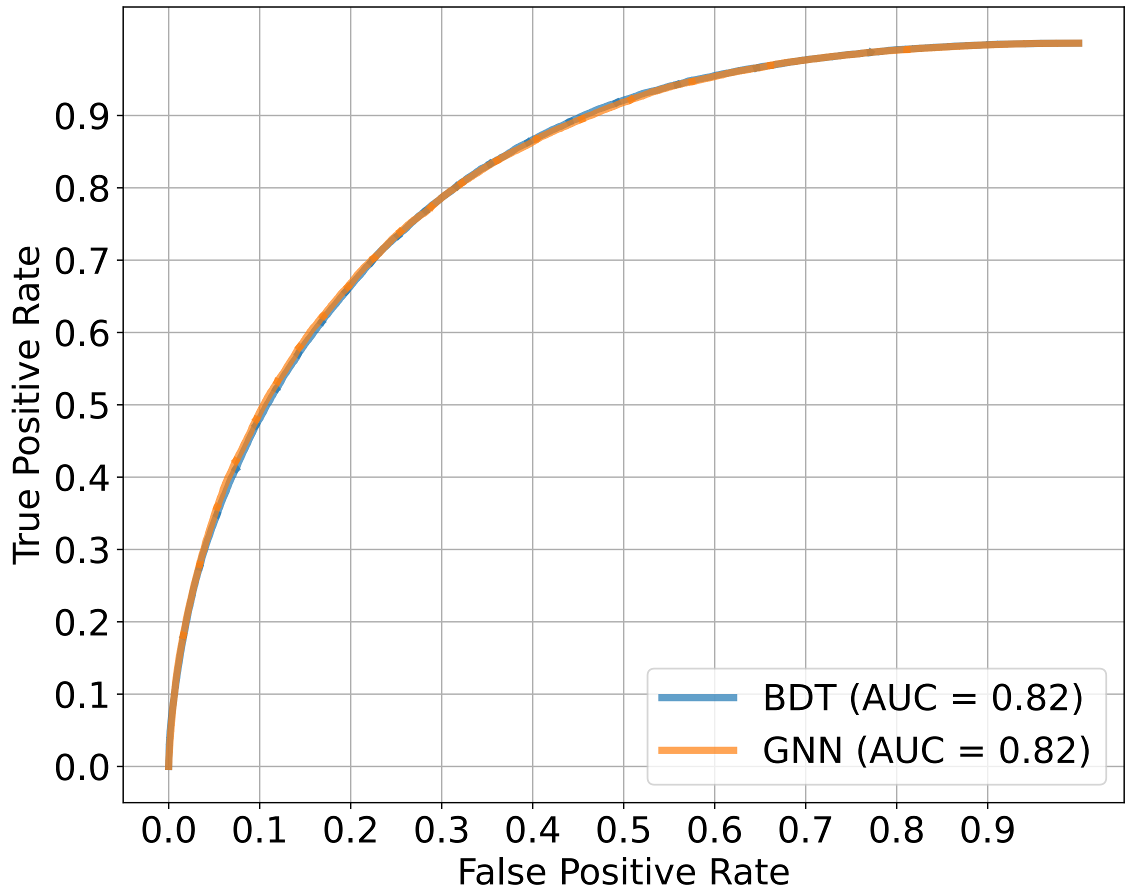




* some hints that models rely mostly on Med(E_{ToF}) distribution

“Best” hit labelling

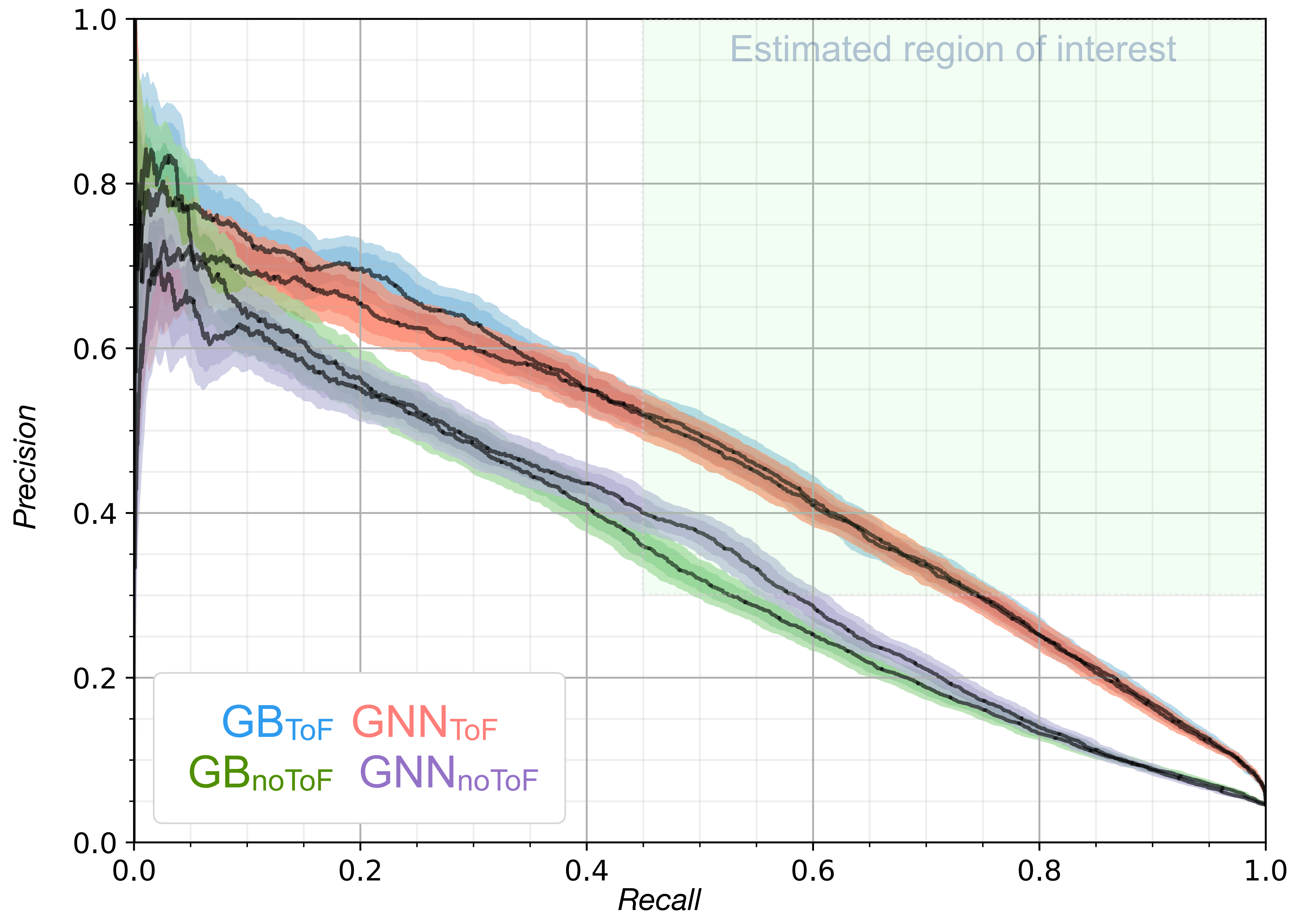




- Overall classification performance slowly decreases with loosening criteria of “good” neutron events (ROC_AUC)
- Larger signal/background ratio gives better PR
- Similar performance for BDT and GNN for all 3 labelling approaches

➡ ‘first-principle’ features look comprehensive in this setting

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



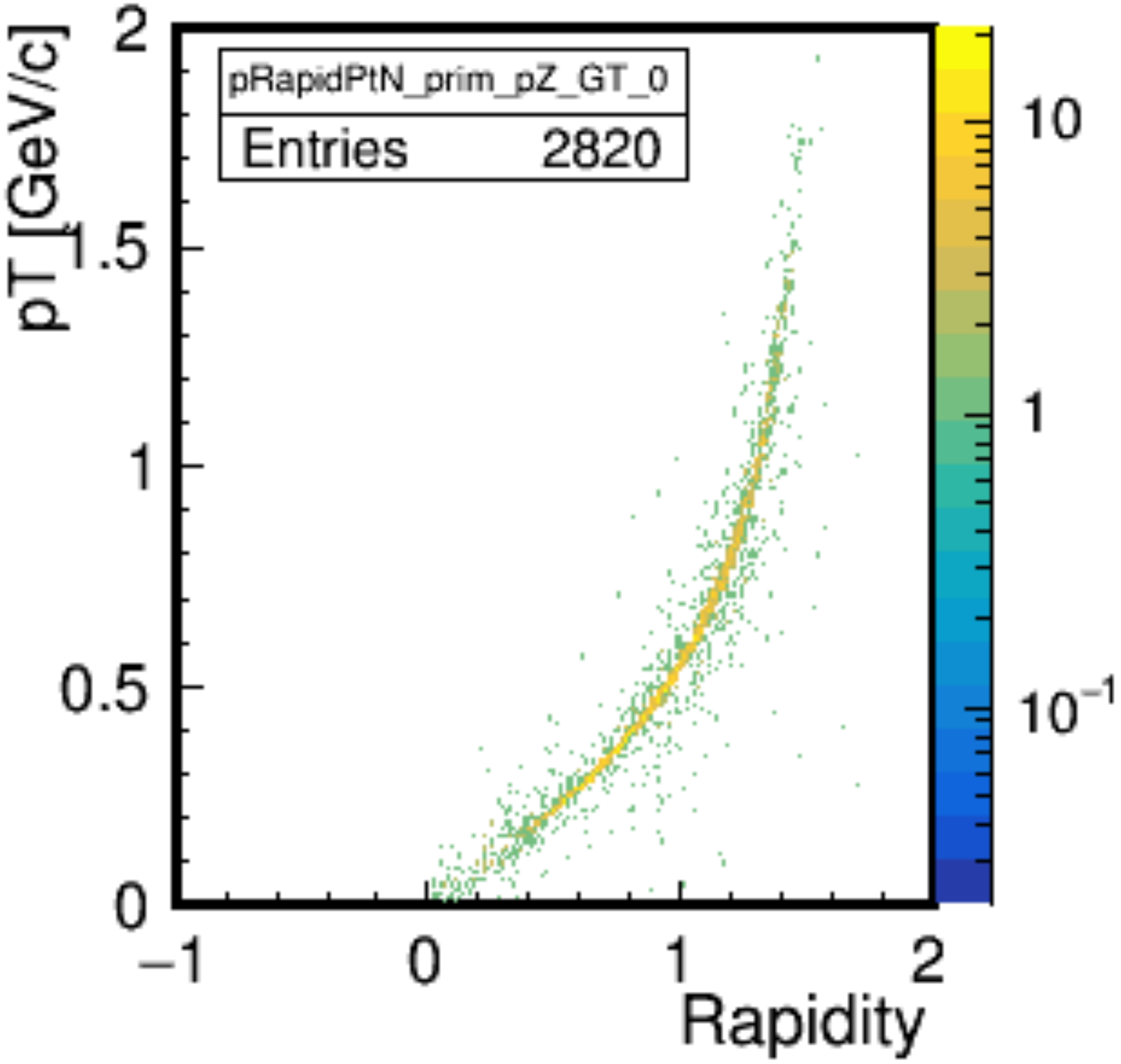
Region of interest:

~ Precision threshold - exclude flat neutron flow hypothesis

~ Recall threshold - covers most of neutron E_{kin} spectrum

- **Similar performance using** target feature $\mathbf{E_{ToF}}$
- **Excluding $\mathbf{E_{ToF}}$** variable increases significance of event topologies for events with N_{hits}>1 => **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

MMU package for PR-uncertainties


pRapidPtN_prim_pZ_GT_0
Entries 2820
pT [GeV/c]
Rapidity
10
1
10^{-1}