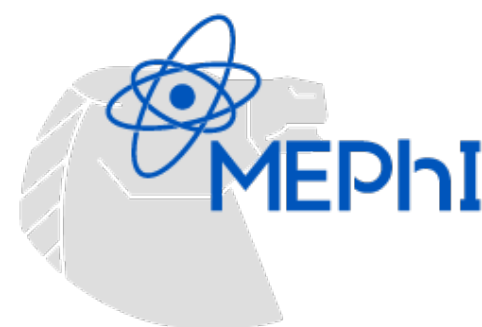
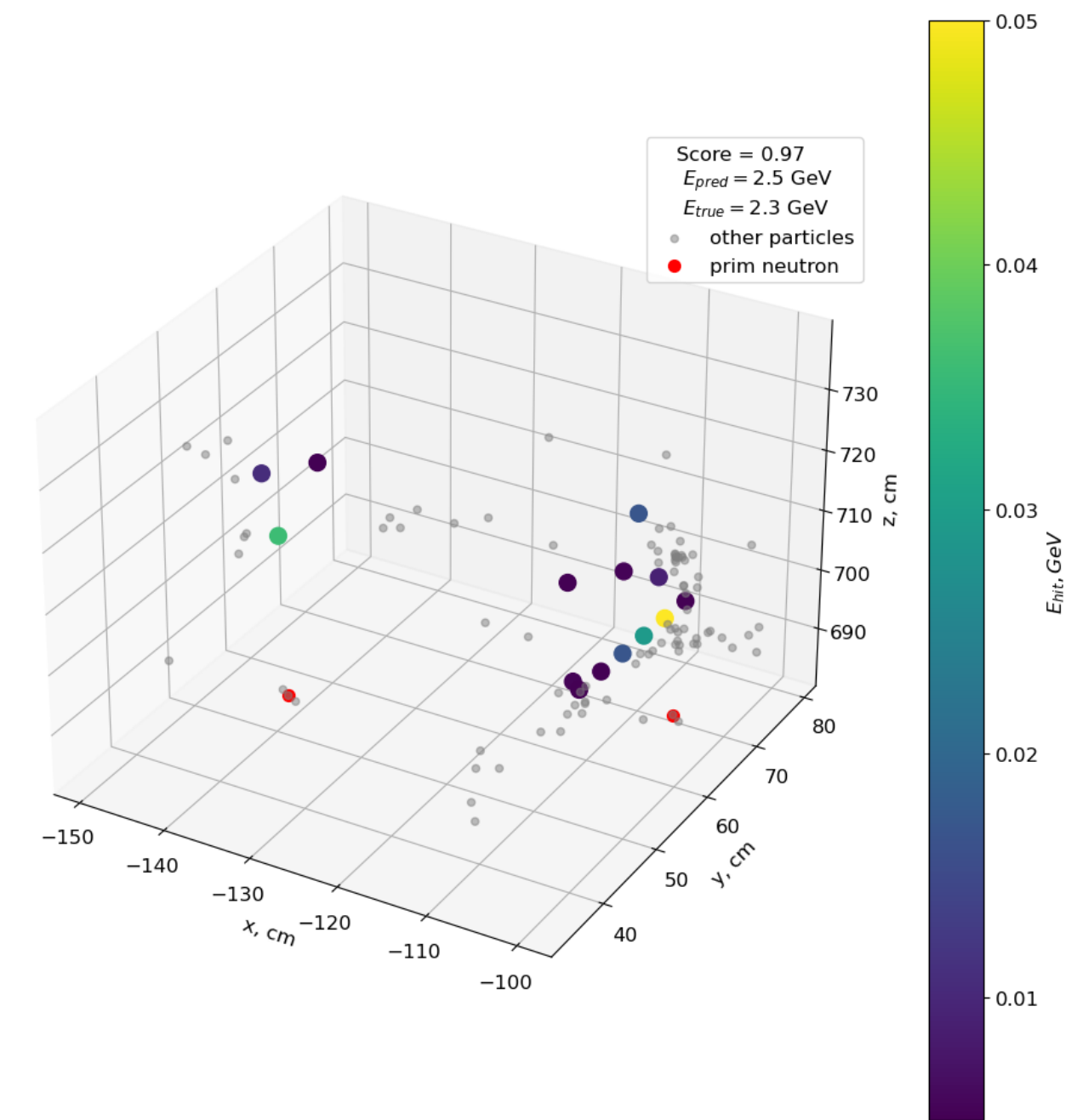


# ML-based neutron reconstruction in the HGND at the BM@N experiment

BM@N 12th Collaboration Meeting,

Vladimir Bocharnikov, HSE University  
on behalf of the HGND group

16.05.2024

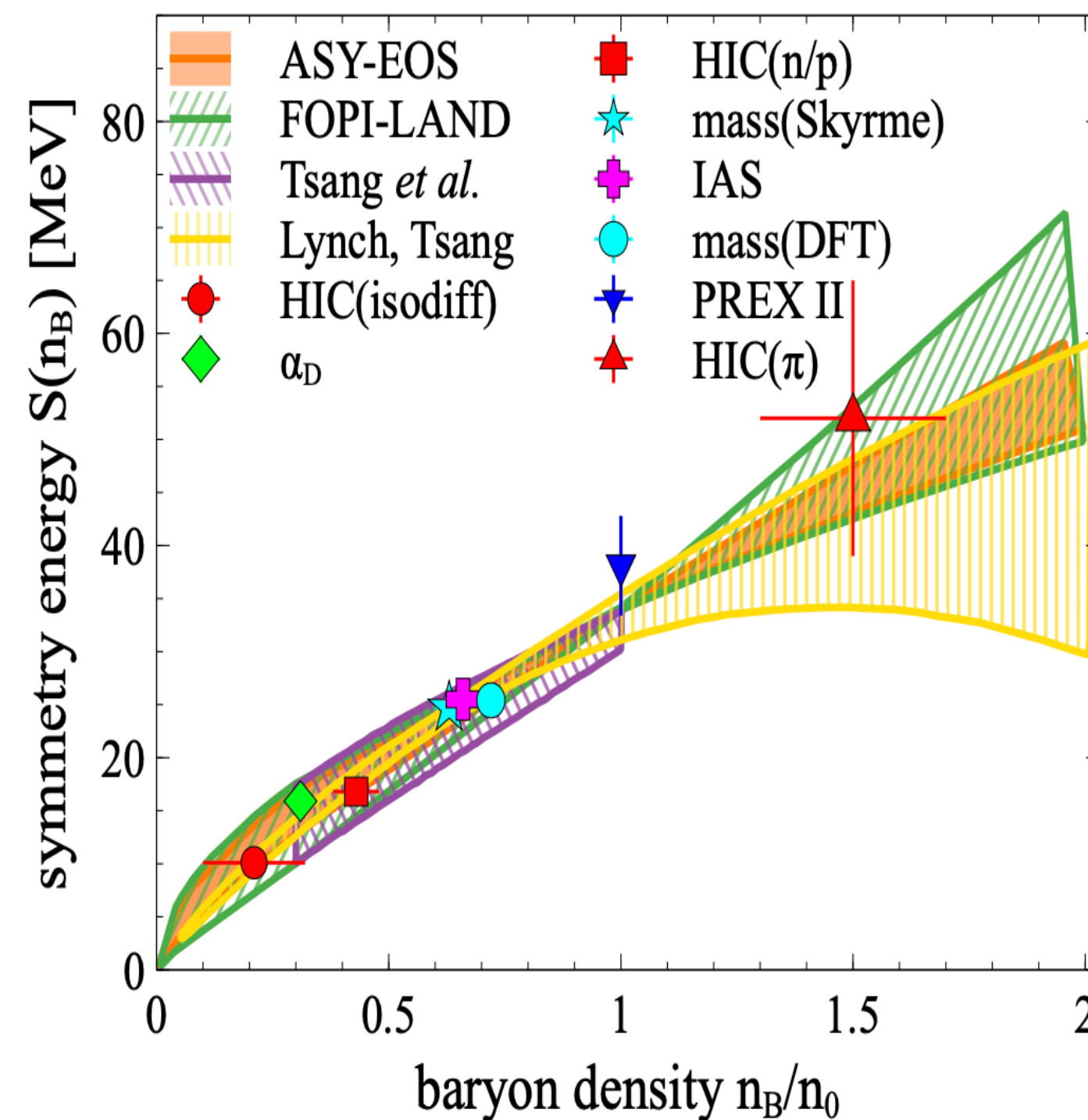
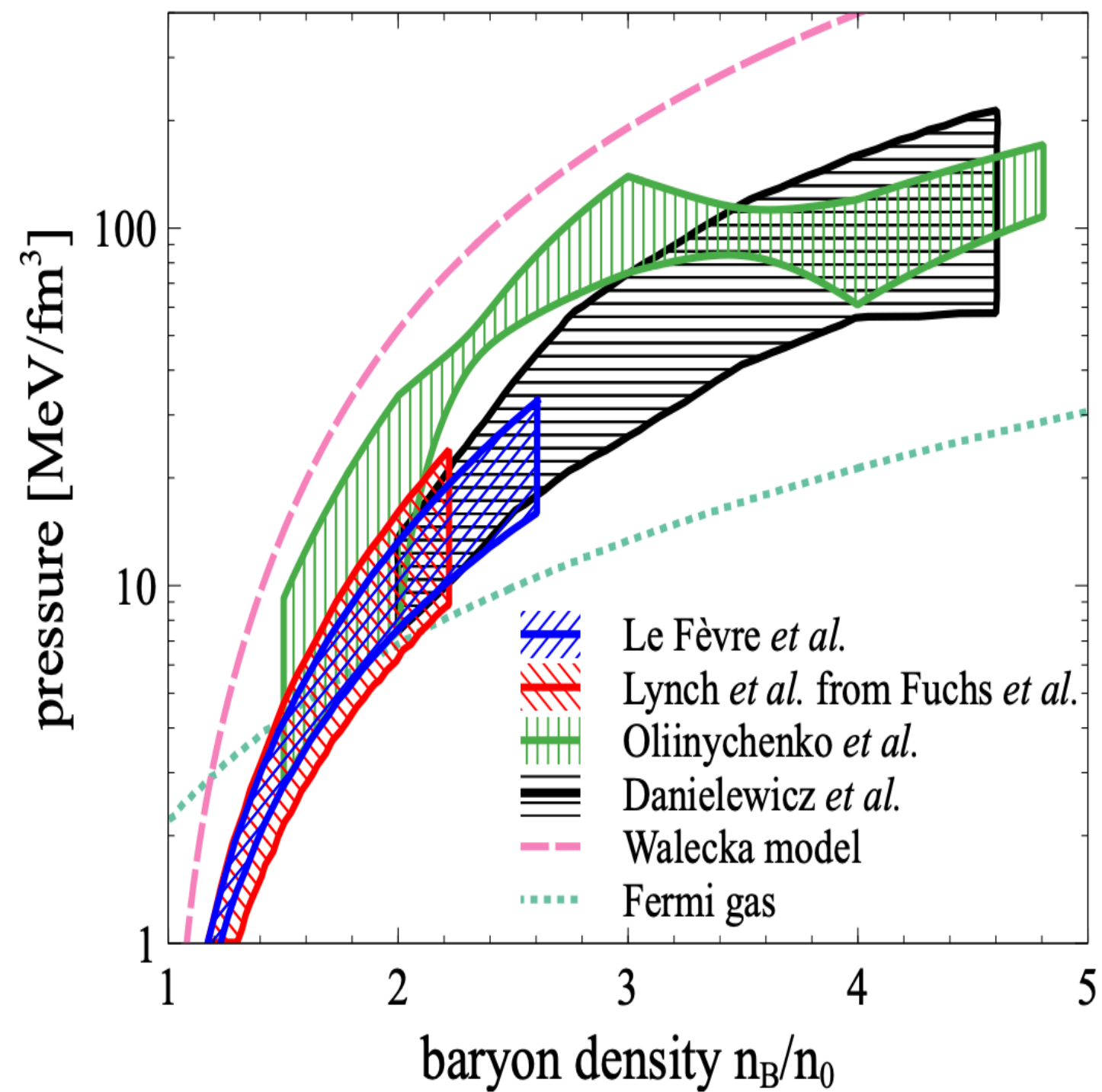


# EOS for high baryon density matter

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

# Motivation

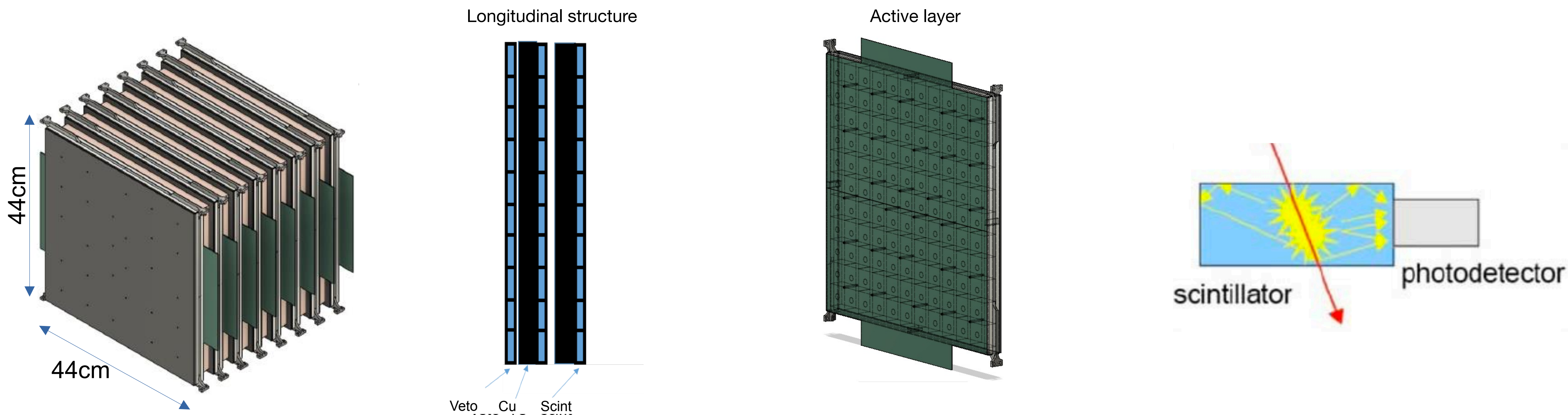
Measurements of neutron flow and yields require **reconstruction of neutrons**

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
  - Angular information can be extracted by “point-like” detector approximation or by use of high granularity
- Multi-parameter task  $\Rightarrow$  may benefit from **ML-based methods**



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

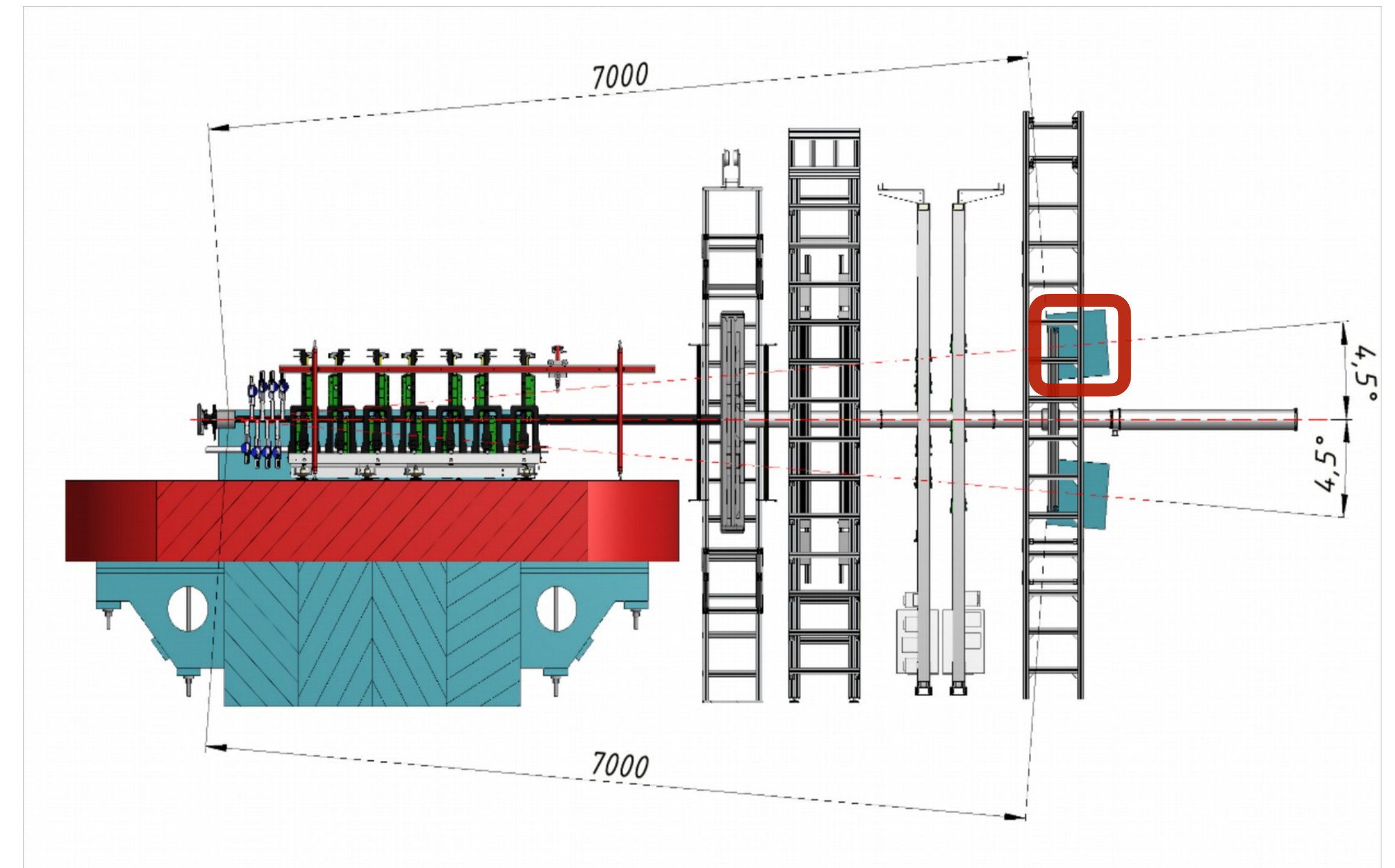
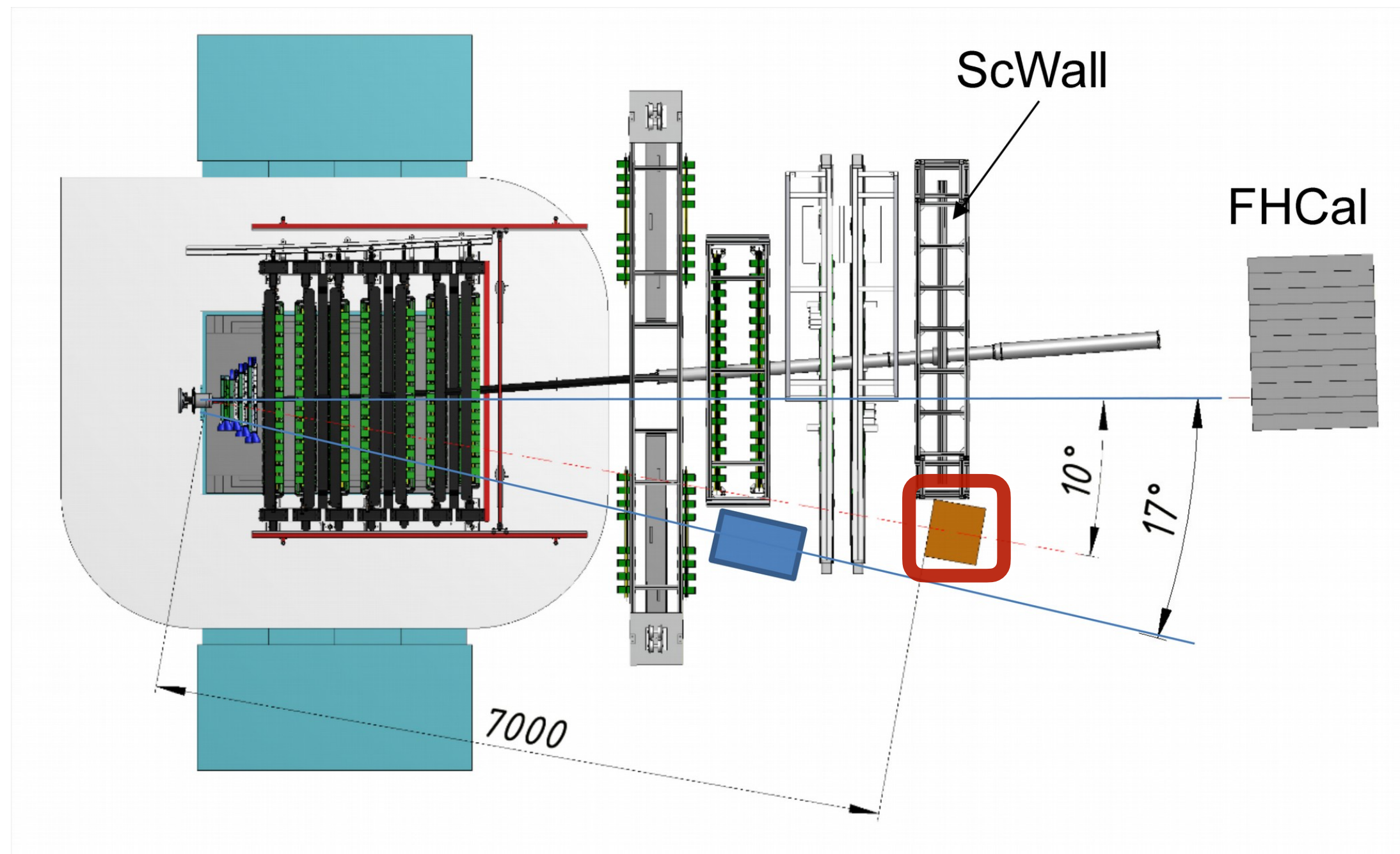


- (2x) 8 layers: 3cm Cu (absorber) + 2.5cm Scintillator + 0.5cm PCB; 1st layer — ‘veto’ before absorber
  - ➔ Total length: ~0.5m, ~1.5  $\lambda_{in}$
  - ➔ neutron detection efficiency ~60% @ 1 GeV
- Transverse size: **44x44 cm<sup>2</sup>**
- *11x11 scintillator cell grid*

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



# Configuration and Simulations

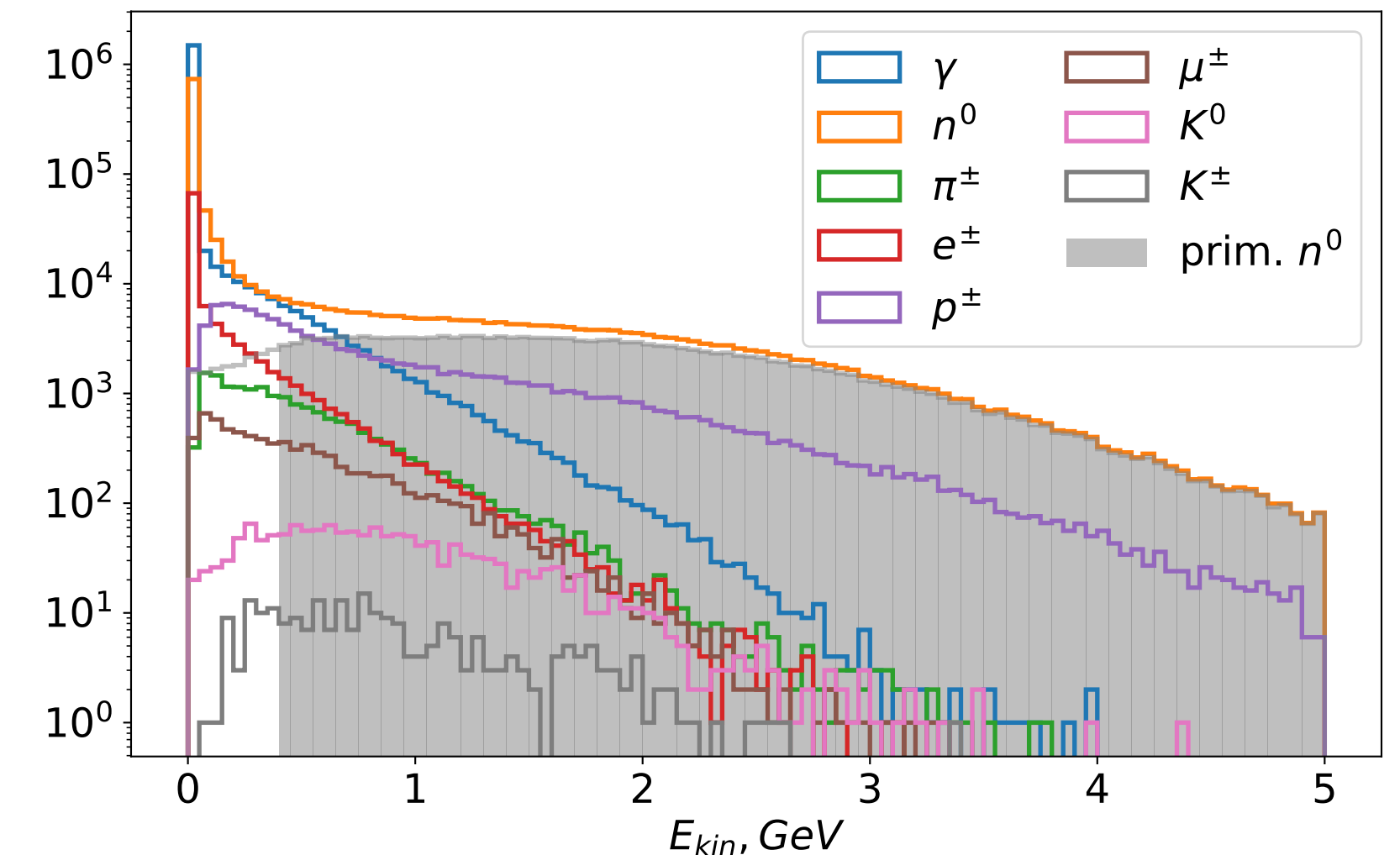


- HGND sub-detectors are located at  $10^\circ$  to the beam axis at  $\sim 7\text{m}$  from the target
- Monte-Carlo event simulations:
  - DCM-QGSM-SMM model + Geant4
  - **$\sim 600\text{K}$  events Bi+Bi @ 3 AGeV**
  - Only **top sub-detector** will be discussed further

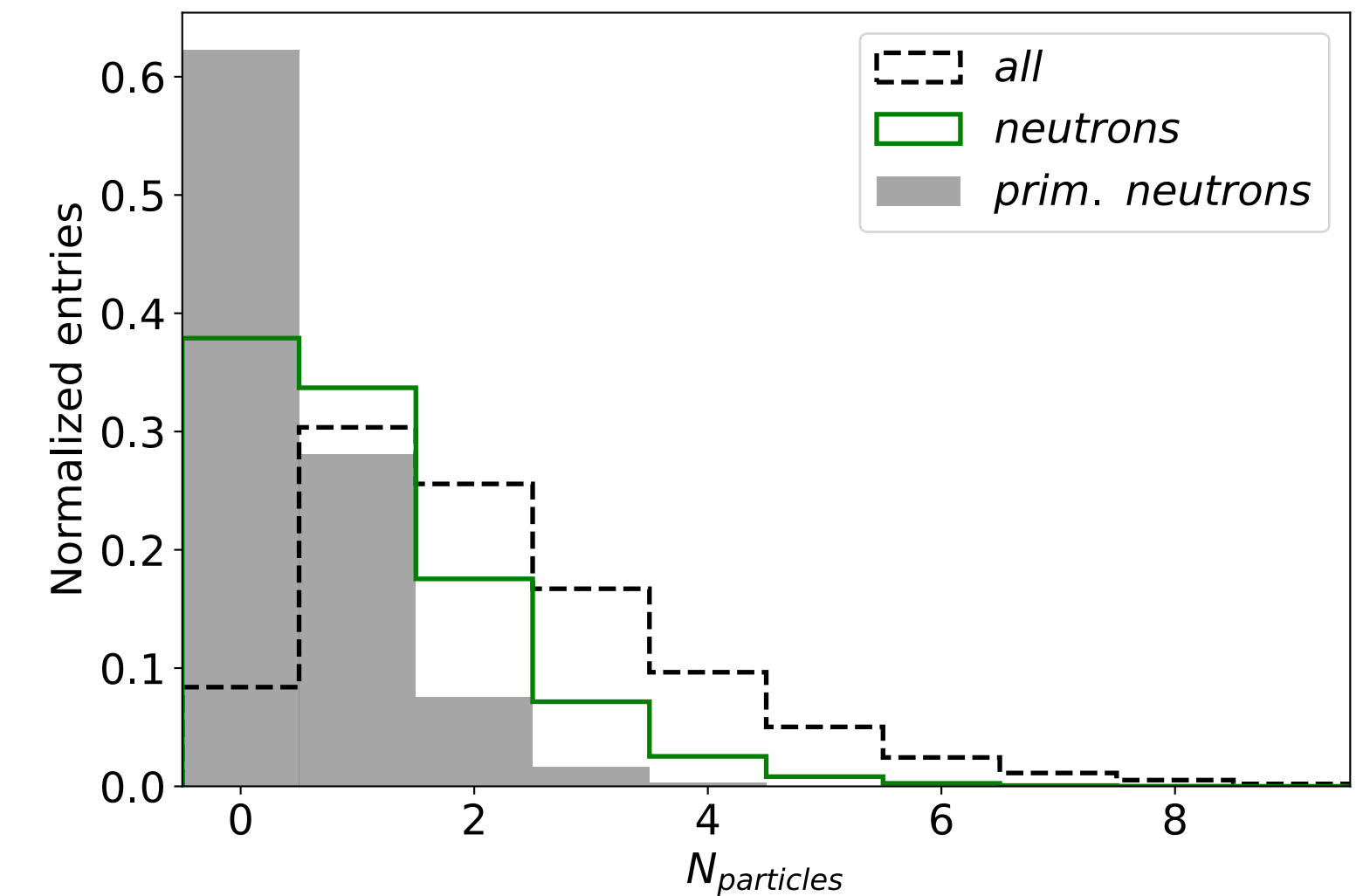
# Particles entering the HGND

- Logical volume on the HGND upstream surface is used to capture particles in the detector acceptance
- No access to hit-level labelling within event
  - ➔ particular hits caused by neutron species are not known
- **Primary neutrons:**
  - Produced in reaction
  - $E_{\text{kin}} > 0.4$  GeV to minimise admixture of background neutrons
    - Energy cut will be done after reconstruction to minimise bias
- **Binary identification problem** is approached. Events with neutron multiplicity  $>1$  are considered as “single neutron events”
- Energy reconstruction is aimed to reconstruct energy of fastest signal neutron in event

Energy spectrum per particle type



Particle multiplicity





# Neutron ToF energy

**ToF energy** for  $n^0$  hypothesis:

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

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

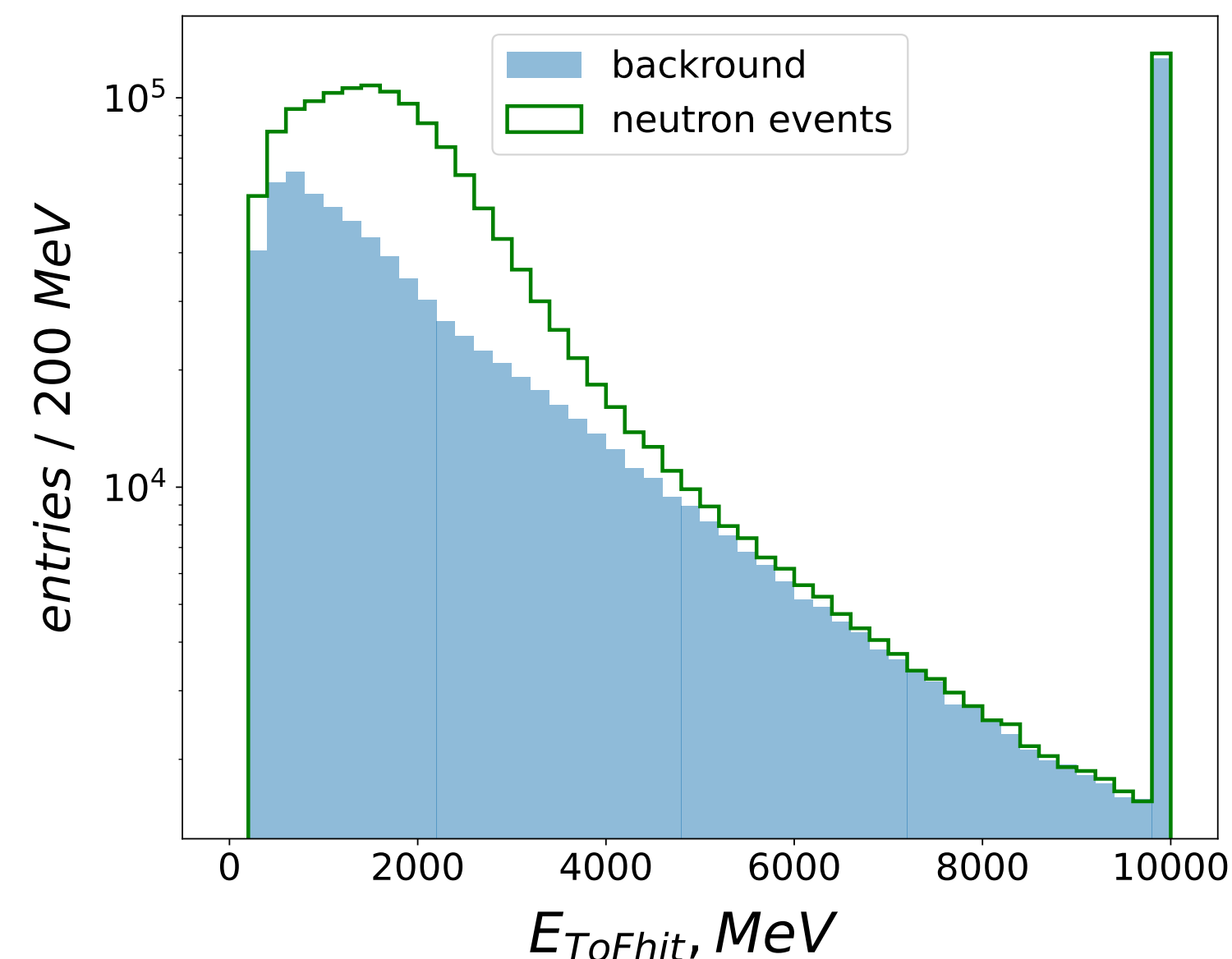
**Fastest hit**

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

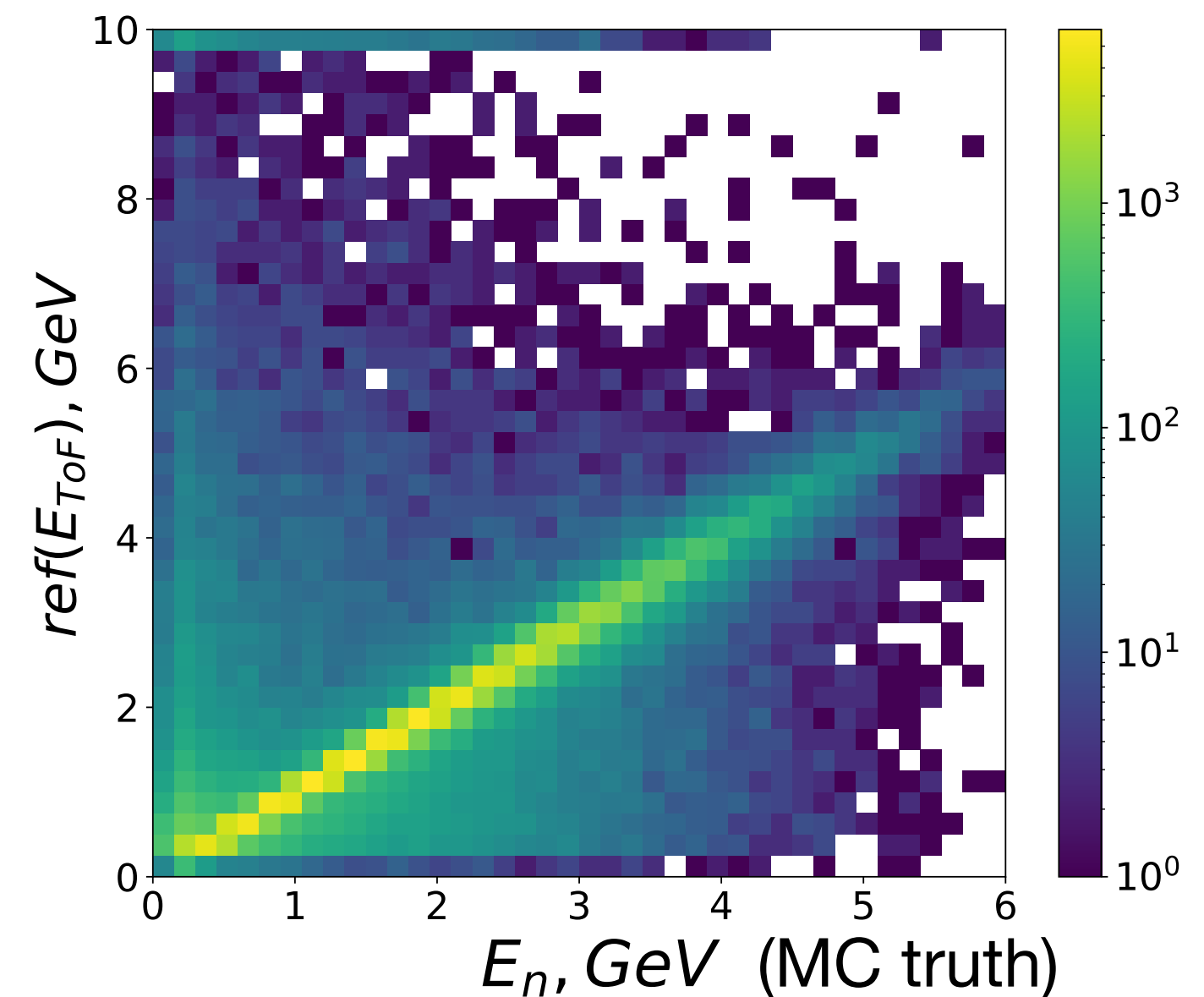
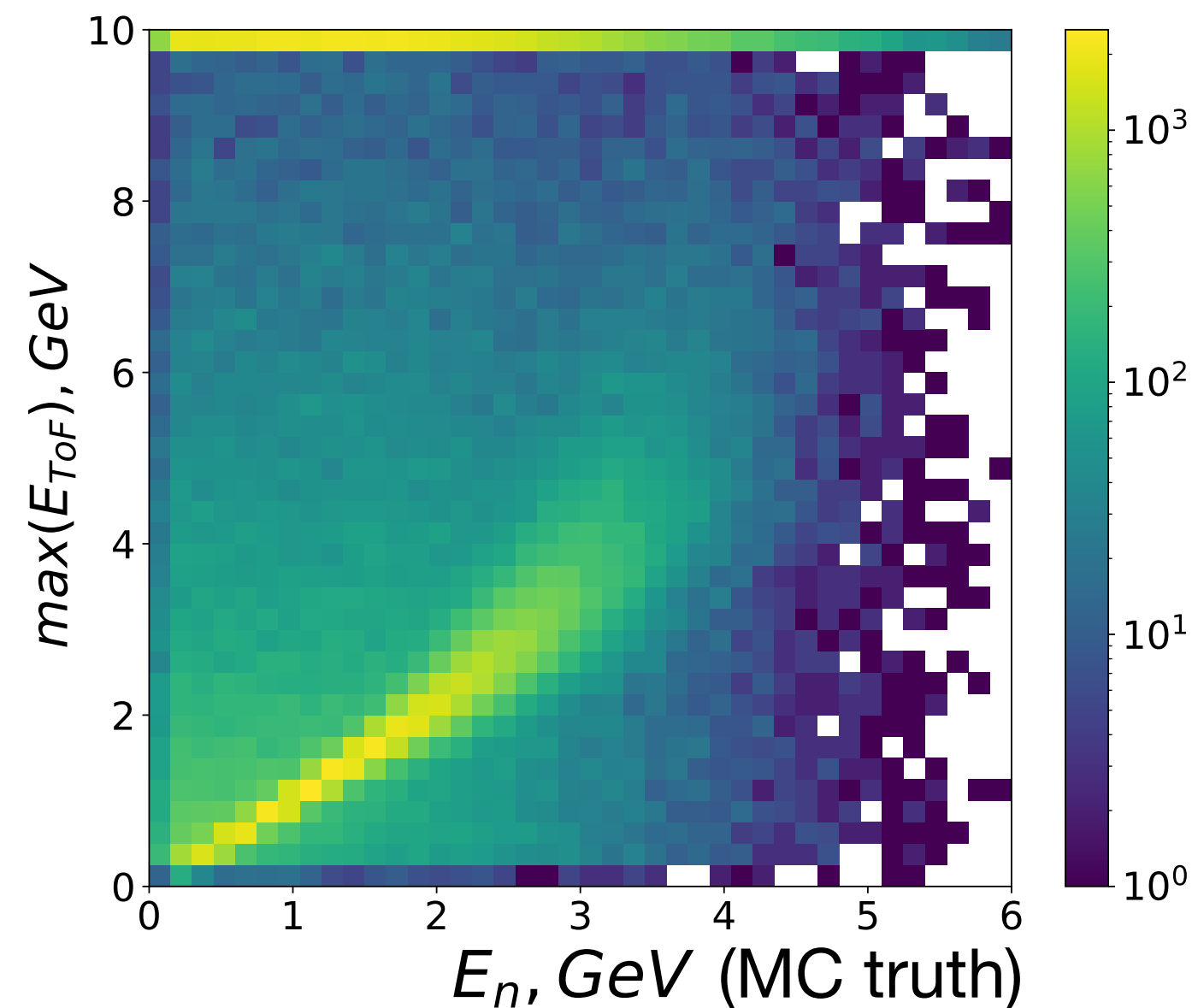
**Reference hit**

- MC truth hit with  $\min(|E_{ToF} - E_n|)$
- ➡ suitable for neutron event labelling
- ➡ additional estimation required
- ➡ we use ML approach

**Hit ToF distribution**



**Events with a neutron (>100 MeV) passing upstream wall of the HGND at  $10^\circ \pm 5^\circ$**





# Graph Neural Networks (GNN)

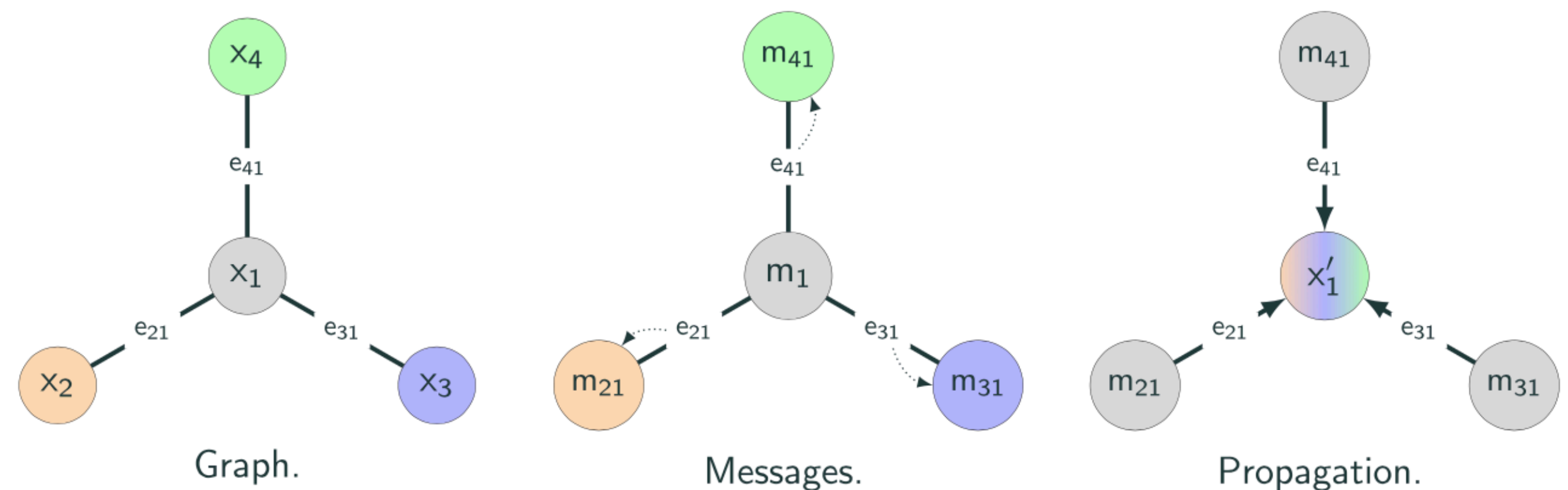
## Why Graph Neural Networks:

- 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 class “probability” — signal/background
  - Target value — neutron energy



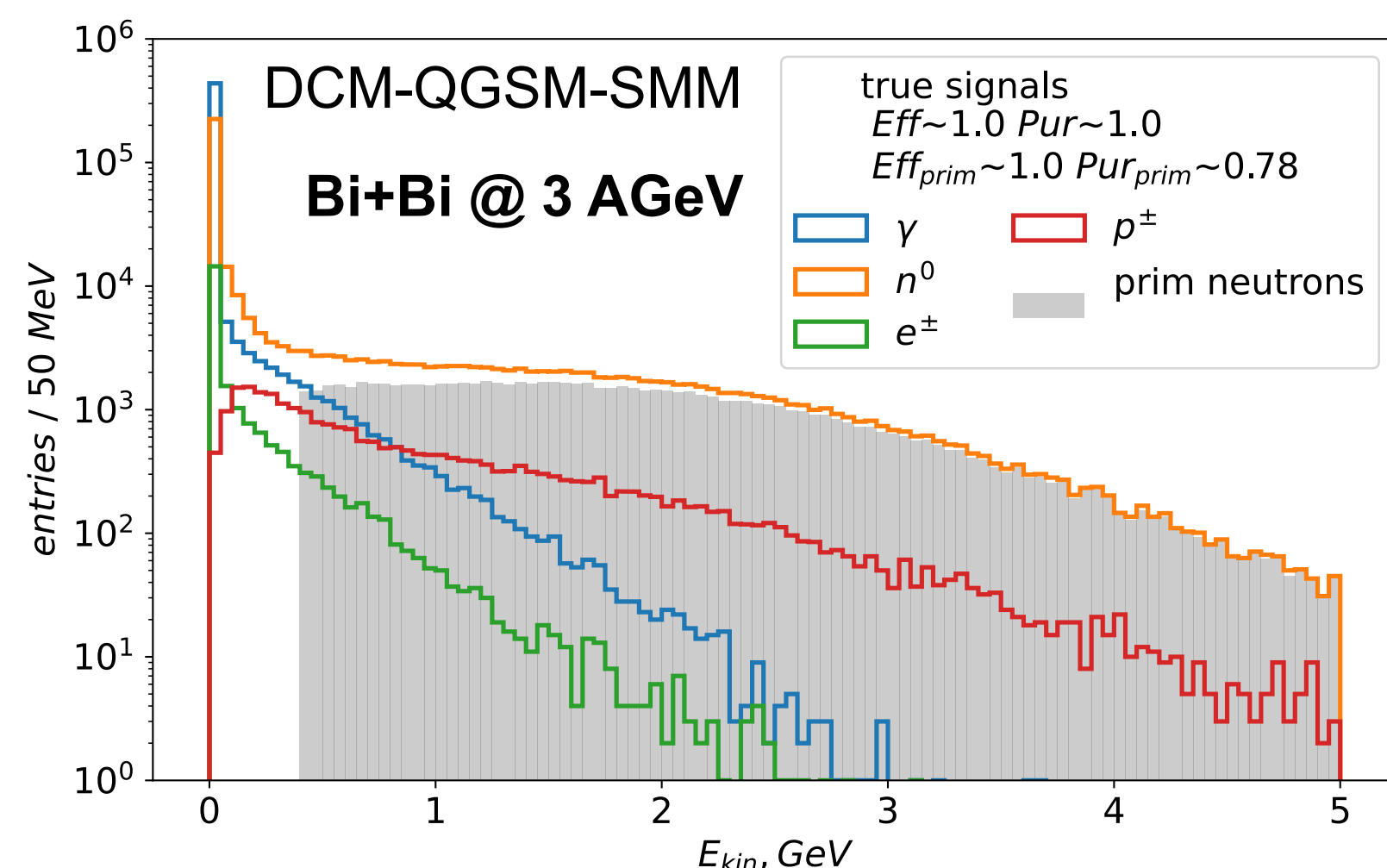
J. Gilmer *et al.*, “Neural message passing for quantum chemistry,” 2017.

# Reconstruction procedure

## Signal event labeling using upstream surface:

- at least 1 neutron:  $E_{kin} > 100$  MeV, Angle to z axis  $10^\circ \pm 5^\circ$ ,  $\delta(E_{ref}) < 40\%$ ,  $E_{target} = \max(E_n)$
- ~40% signal events
- significant background contribution
- more detailed MC particle tracking is under development to improve true neutron selection

## Selected signal events. Energy spectrum



## Graph construction:

- Nodes — hits. Observables per hit:
  - hit coordinates;  $E_{dep} > 3$  MeV  $\sim 0.5$  MIP; EToF
  - additional global event node with 4 parameters
- Constructed event graphs are split 50/50% to train and test procedure
- **2 independently trained models:**
  - **Classification GNN**
    - target variable — signal label (0/1)
  - **Energy regression GNN**
    - target variable —  $\max(E_n)$  per event
    - only signal events are used to train for energy regression model

# Reconstruction procedure

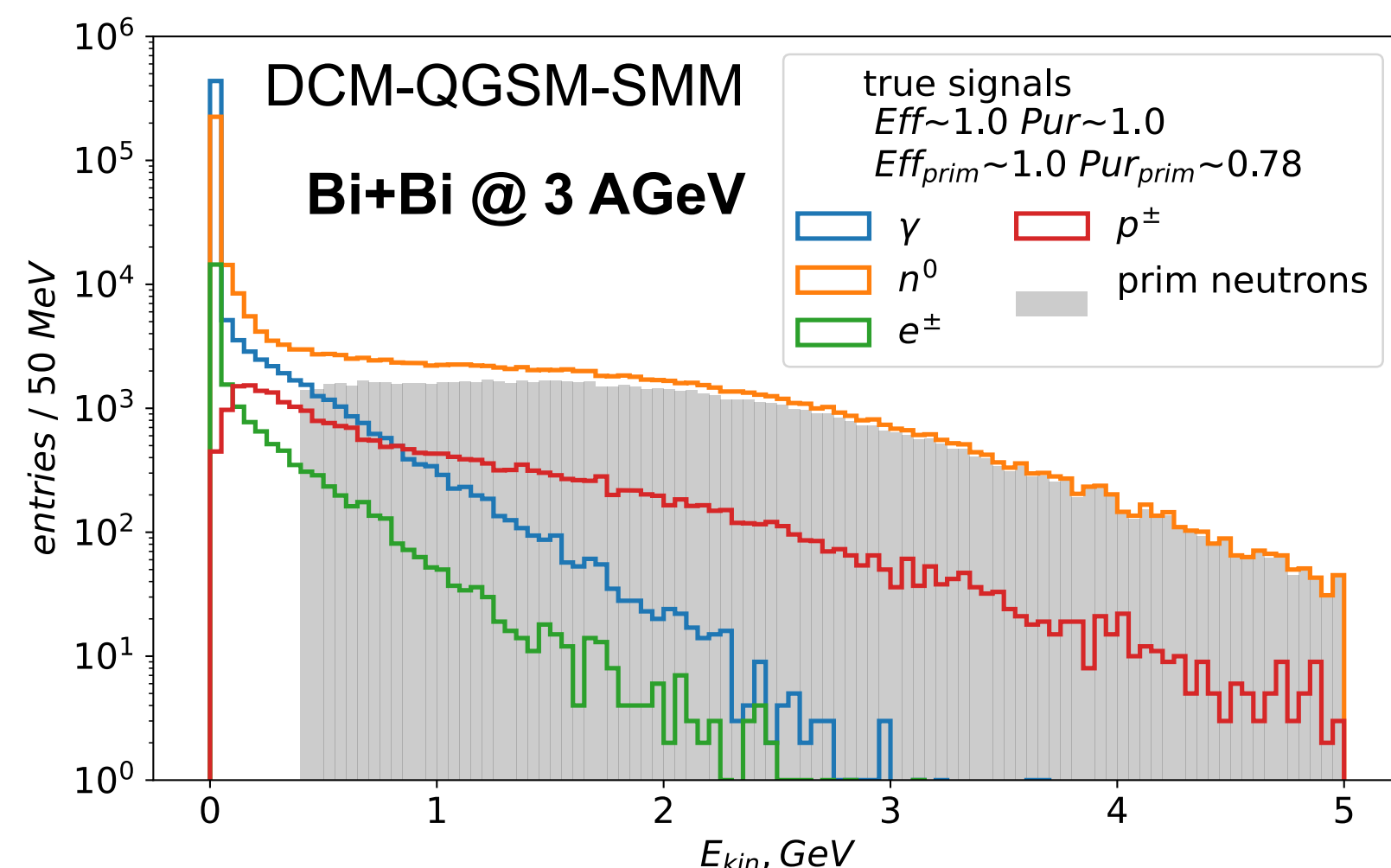
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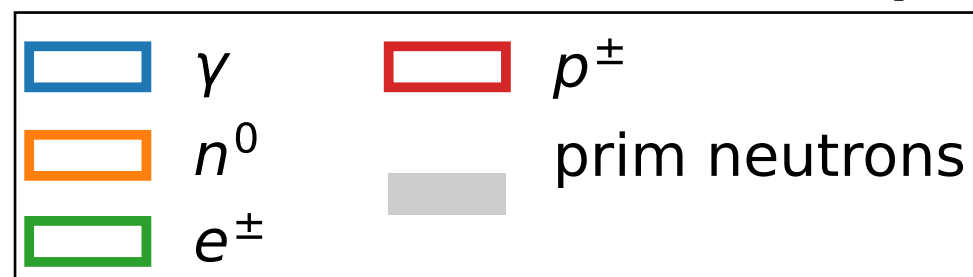




# Classification performance

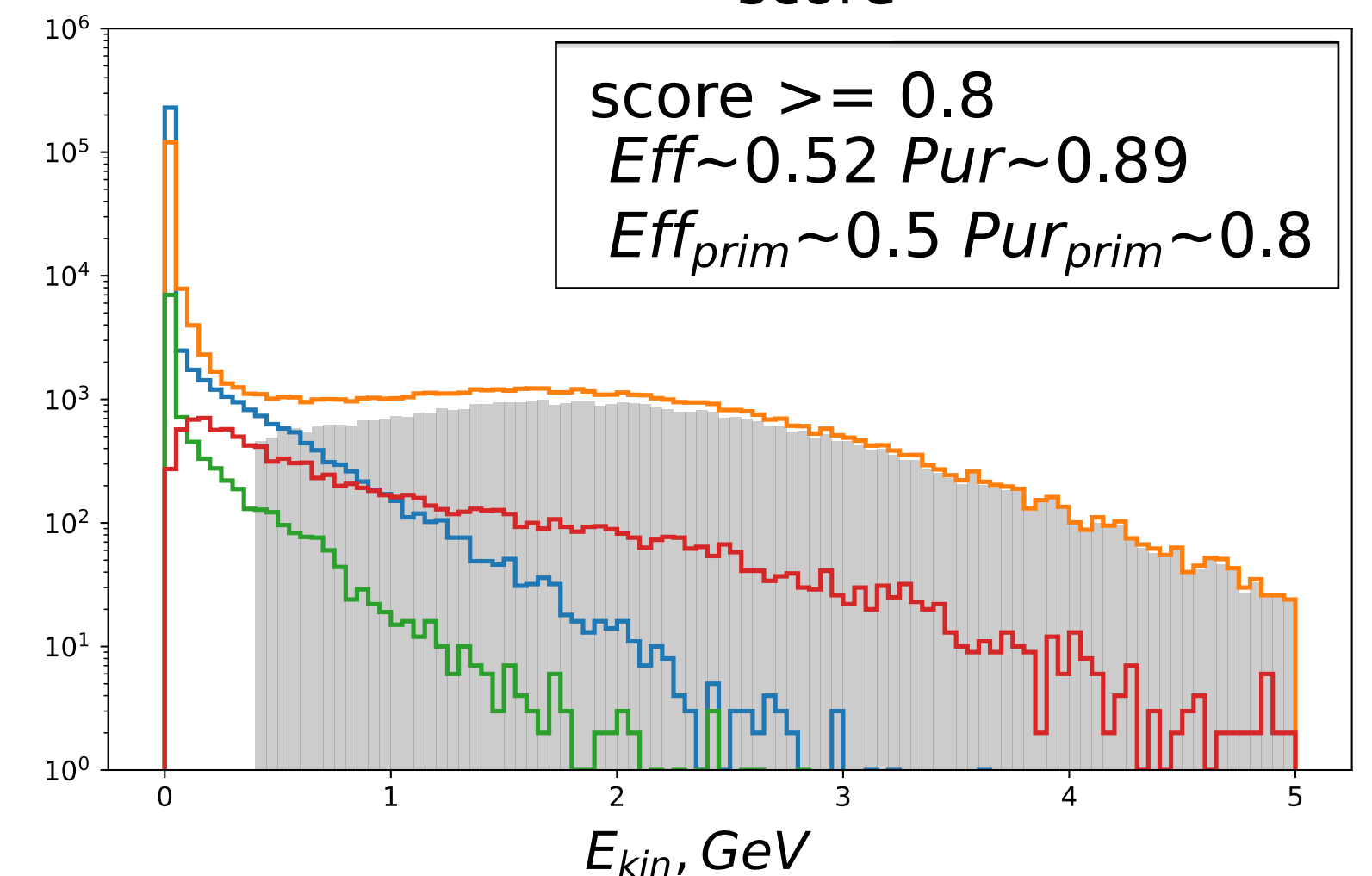
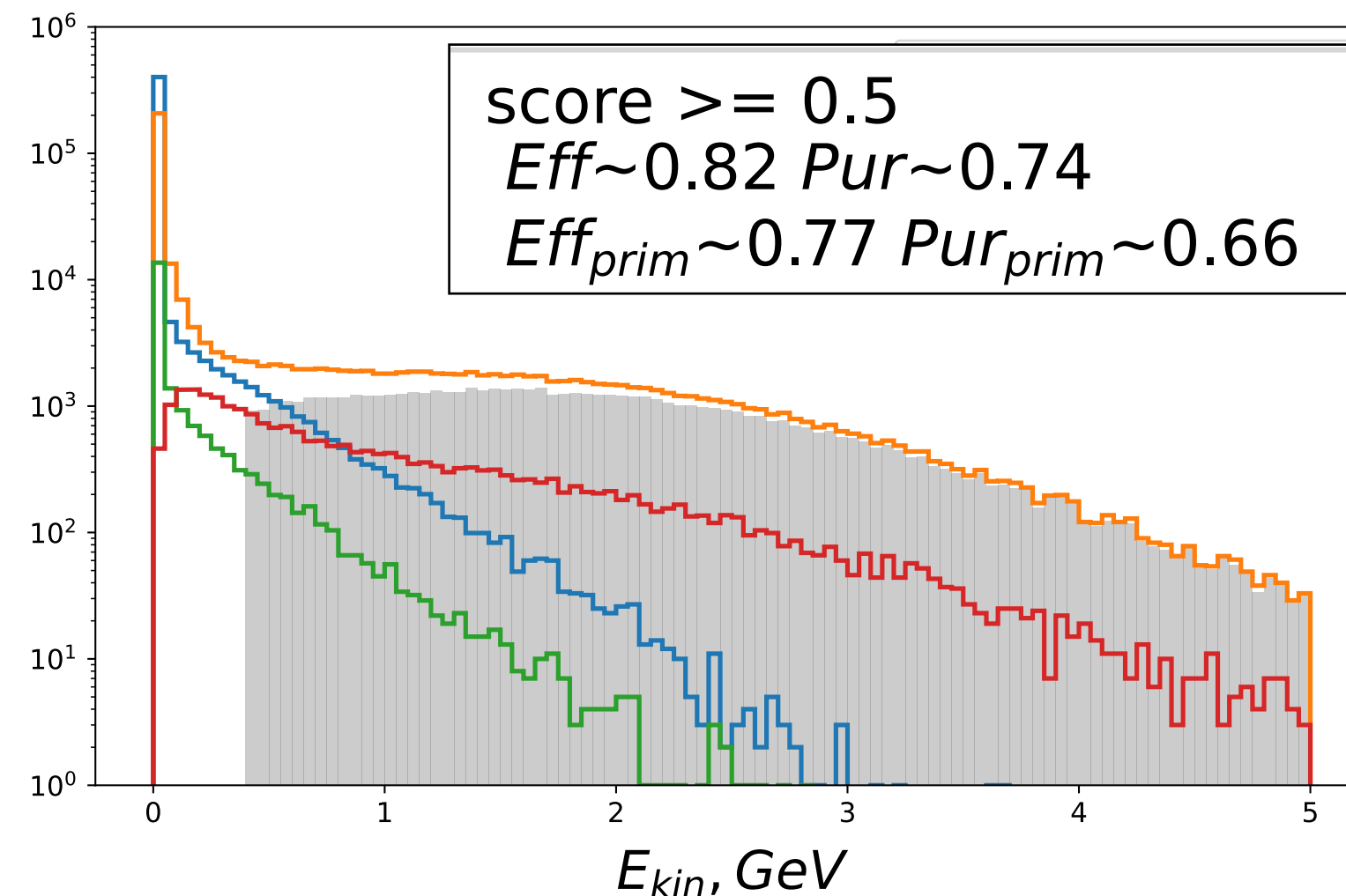
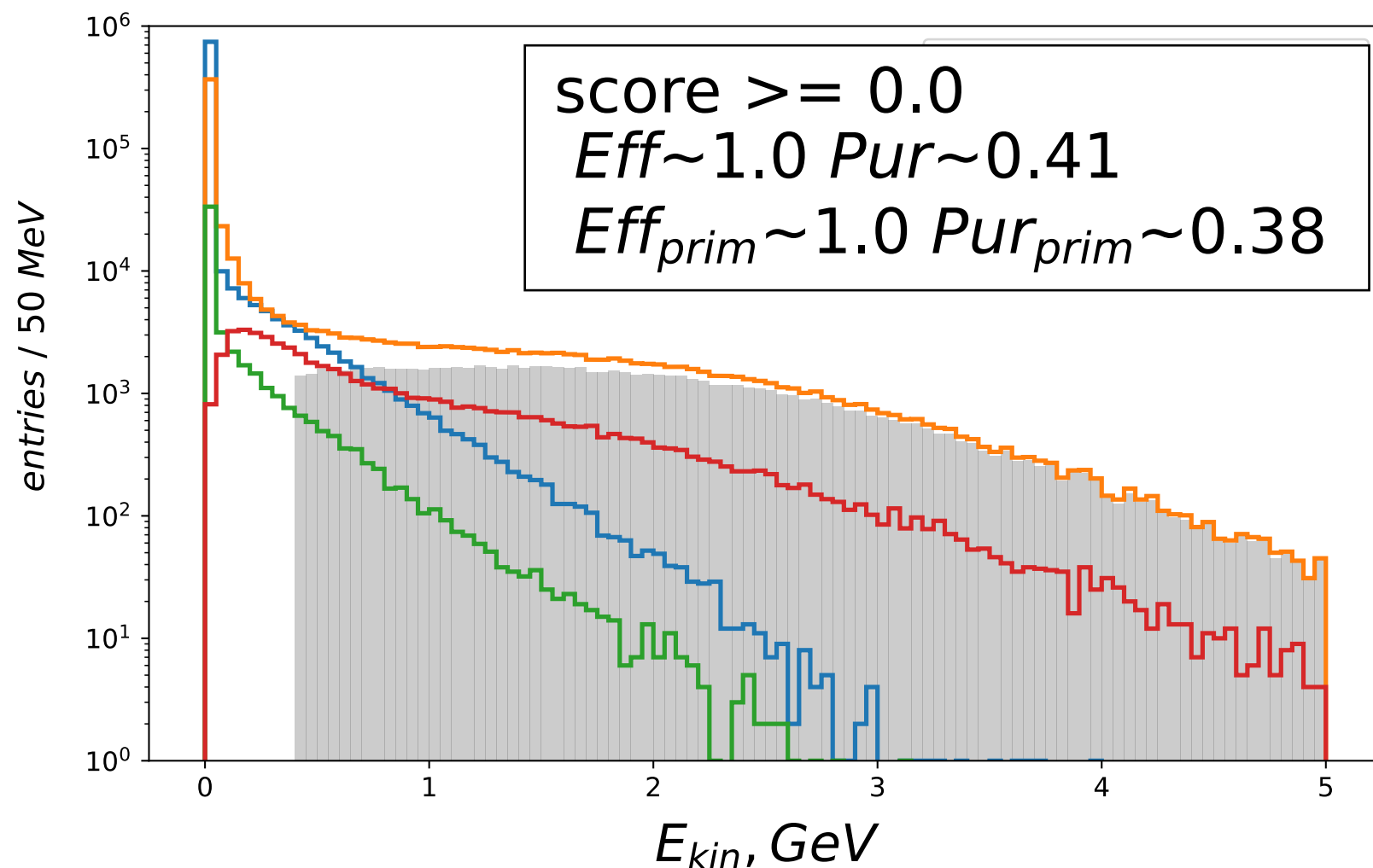
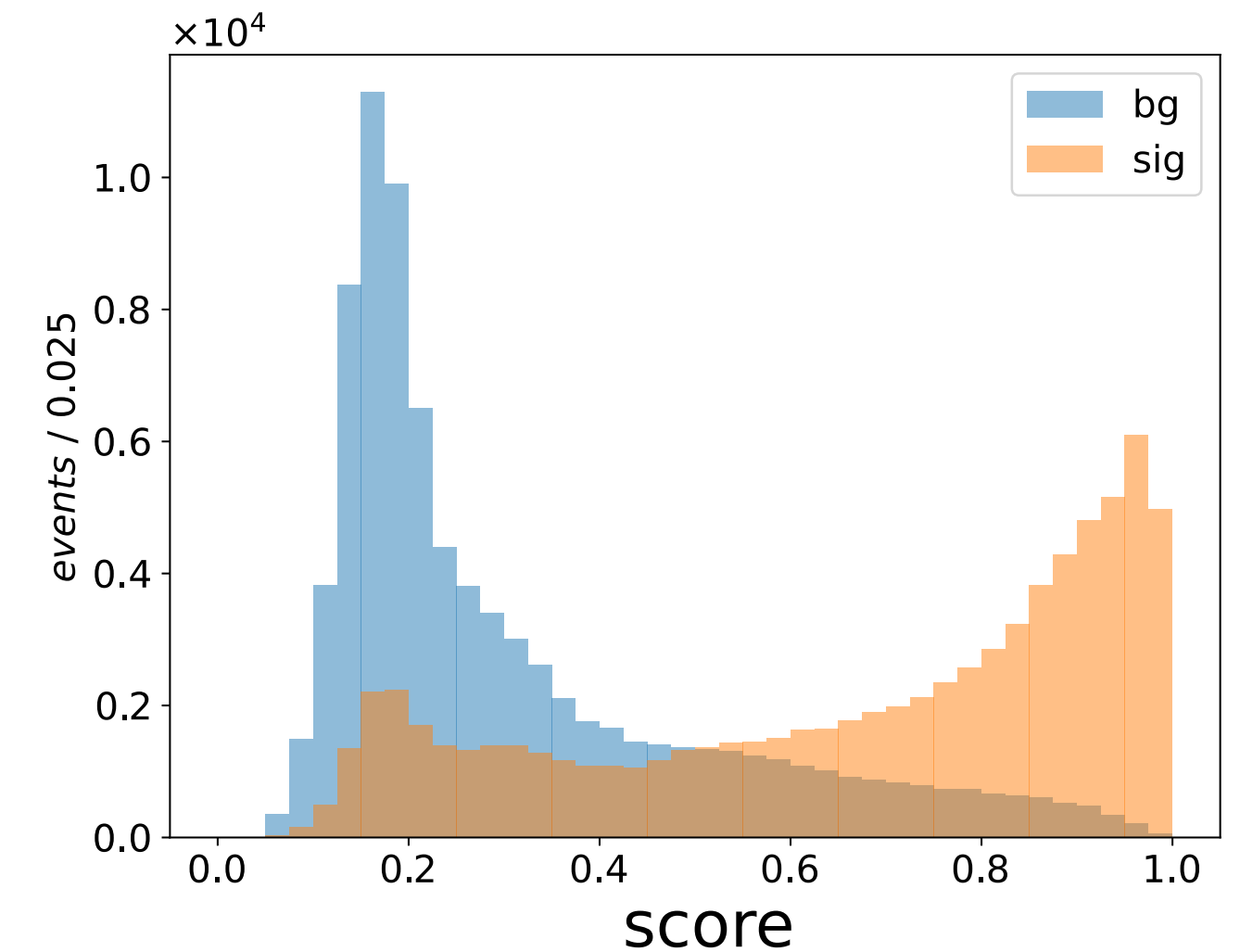
Test sample. 163327 events.

- Signal efficiency to purity ratio can be optimised by varying predicted class score threshold
- Model is capable to properly classify neutron events with background admixture
- Event-level examples are in the backup slides



DCM-QGSM-SMM  
Bi+Bi @ 3 AGeV

ML event class prediction

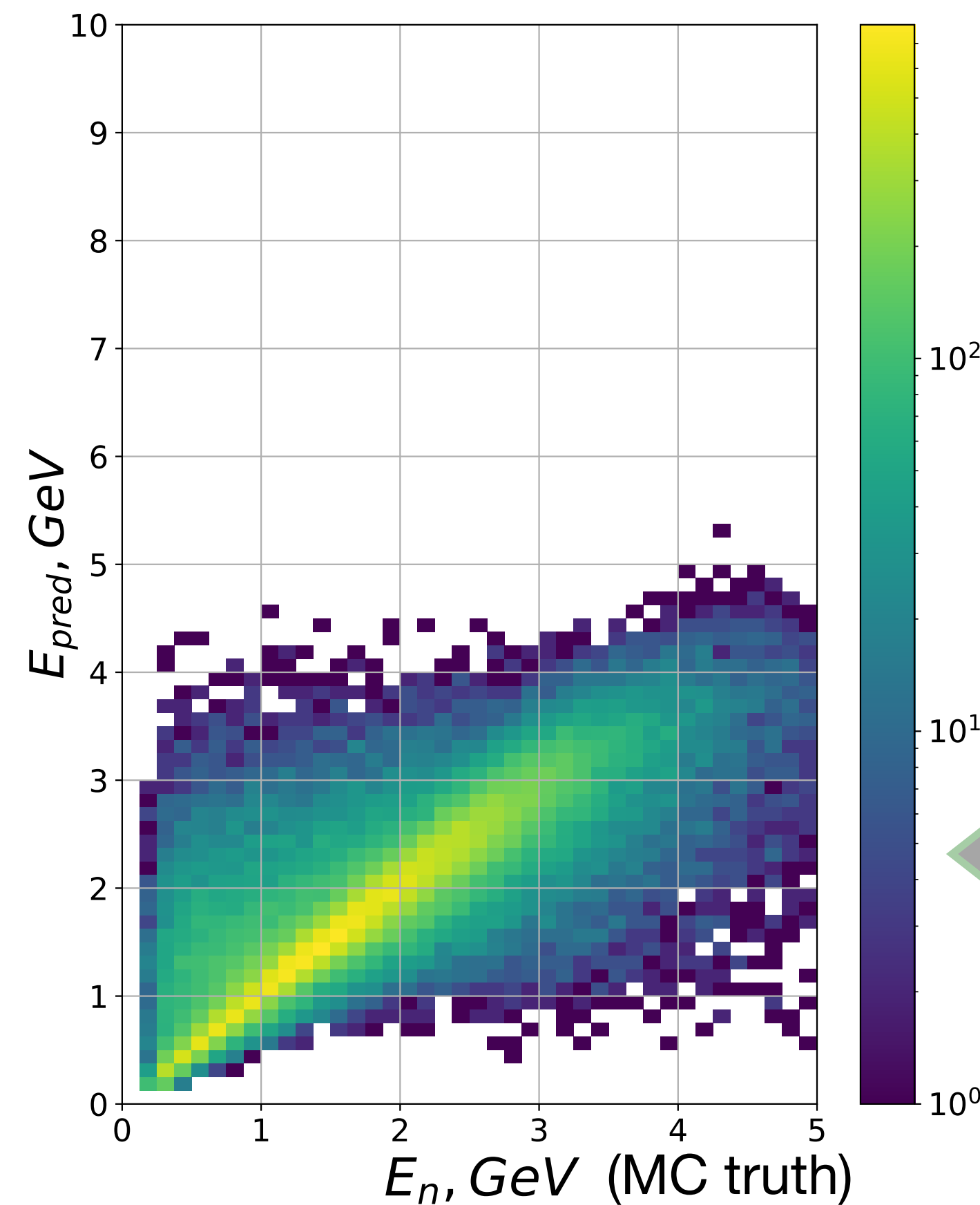


# Neutron energy reconstruction

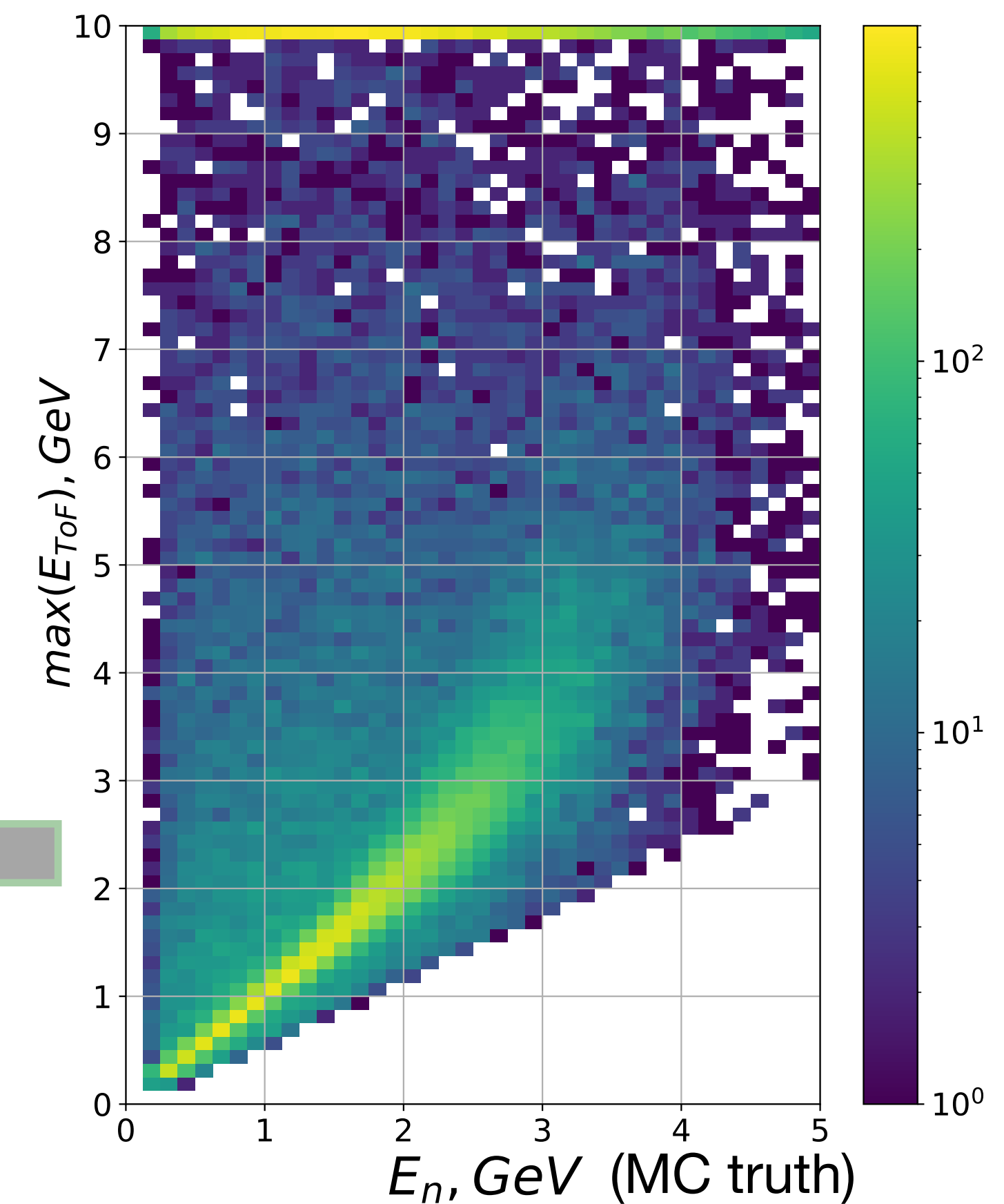
Test sample. 66159 signal events.

- well pronounced linear correlation up to 3-4 GeV
- For energies 2-4 GeV model compensates ToF overestimation
- Model tends to predict most probable values  $\Rightarrow$  asymmetric uncertainties

ML  $E_n$  prediction



Fastest hit  $E_{ToF}$  estimation



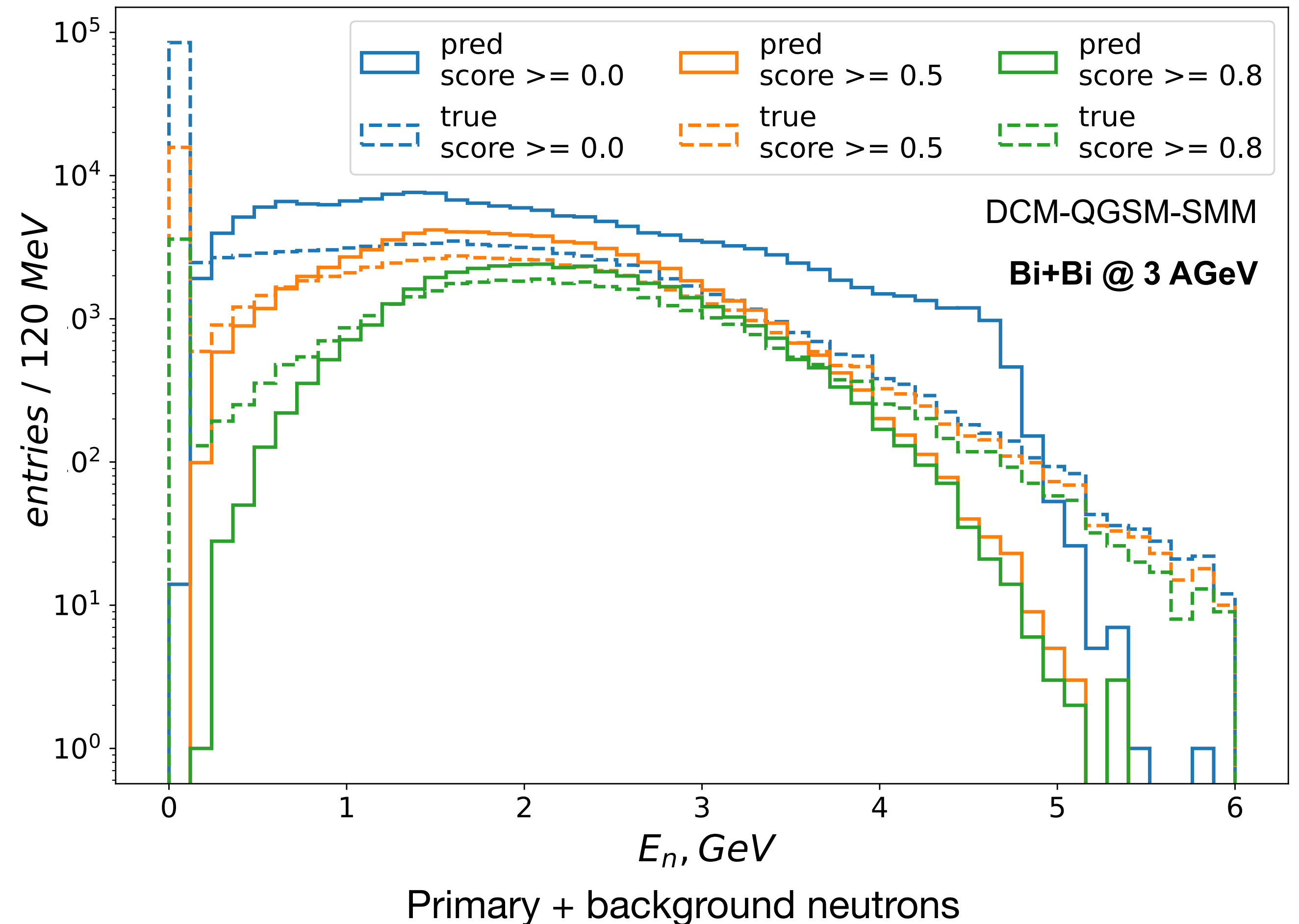
DCM-QGSM-SMM

Bi+Bi @ 3 AGeV

# Neutron energy spectrum

**Neutron energy spectrum** for test dataset (163327 events) after applying classification and energy regression models

- Spectra become closer by increasing classification score threshold
- Tails are less consistent between true and predictions
- Energy reconstruction GNN was not trained to predict 0 energies  $\Rightarrow$  background contribution spread over energy spectrum  
 $\Rightarrow$  possible solution: combined training



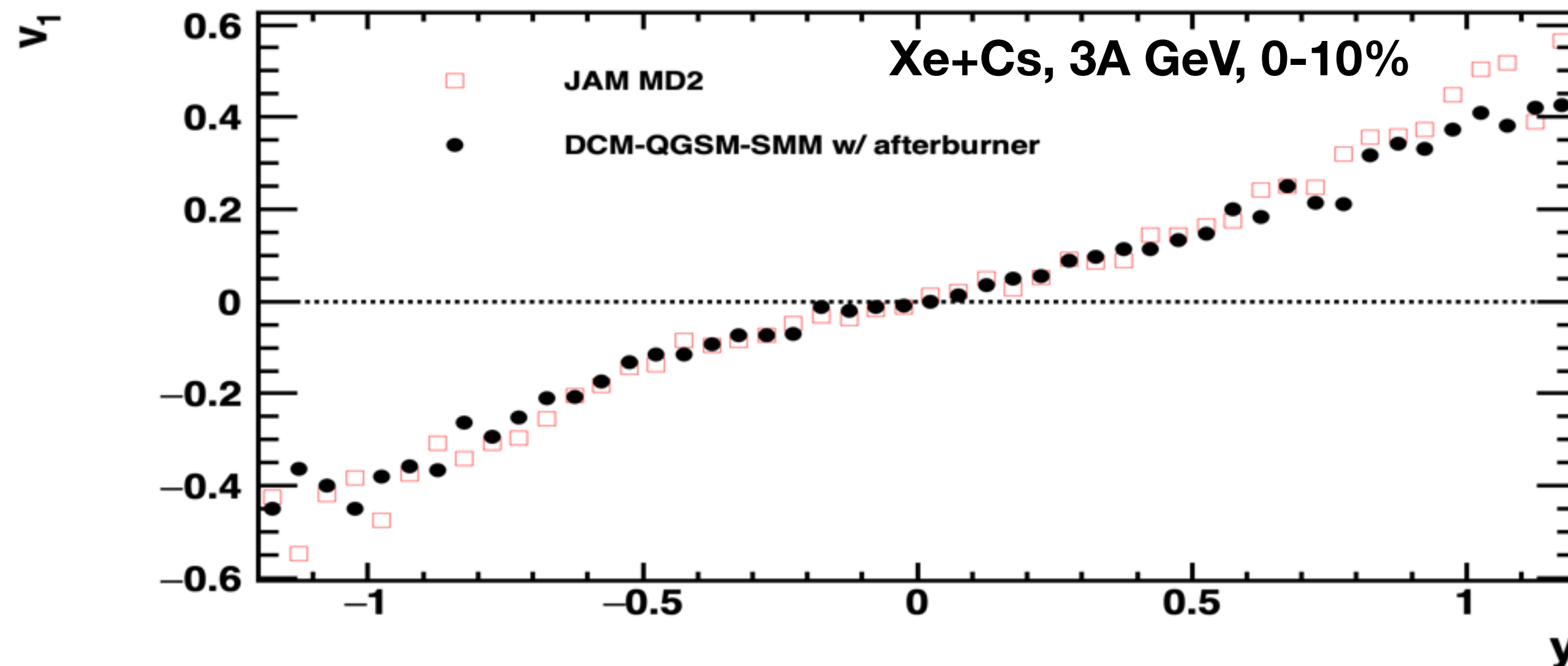
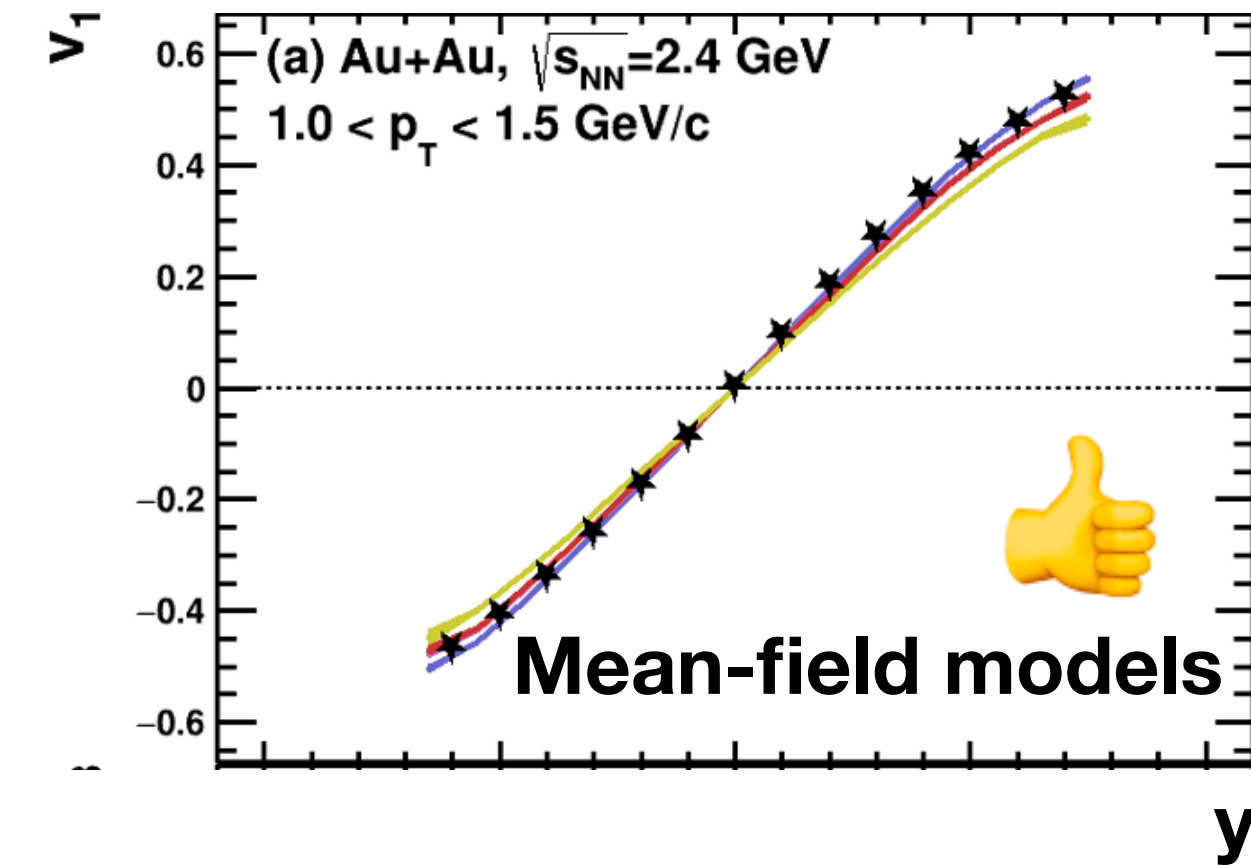
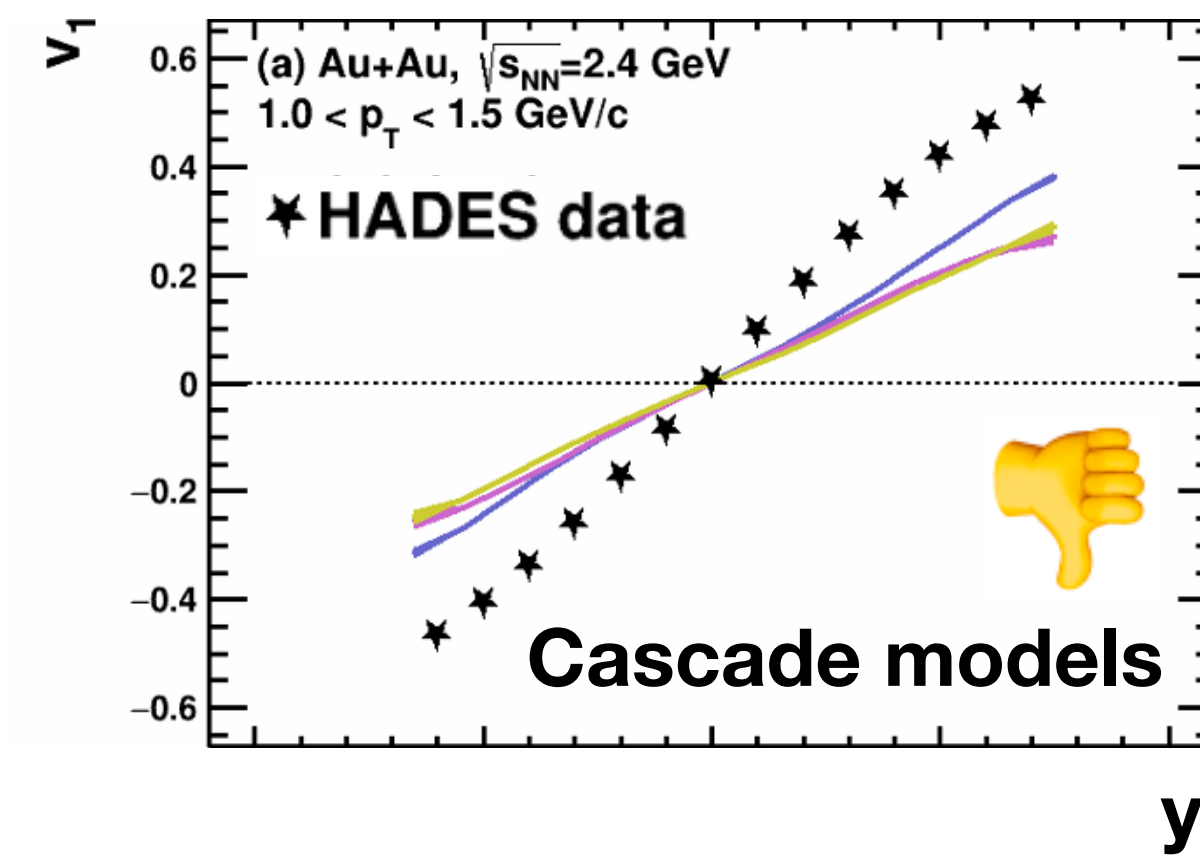


# Neutron flow status

For a performance study of neutron flow measurements one needs model with:

- Realistic spectator fragments
- Realistic flow signal

**Problem: there is no such model at the moment!**



**Solution: make an afterburner for DCM-QGSM-SMM model to have realistic flow signal**

- Simple afterburner has been prepared for the UniGen format

**Next steps:**

- Simulation and reconstruction within BmnRoot framework
- Flow measurements

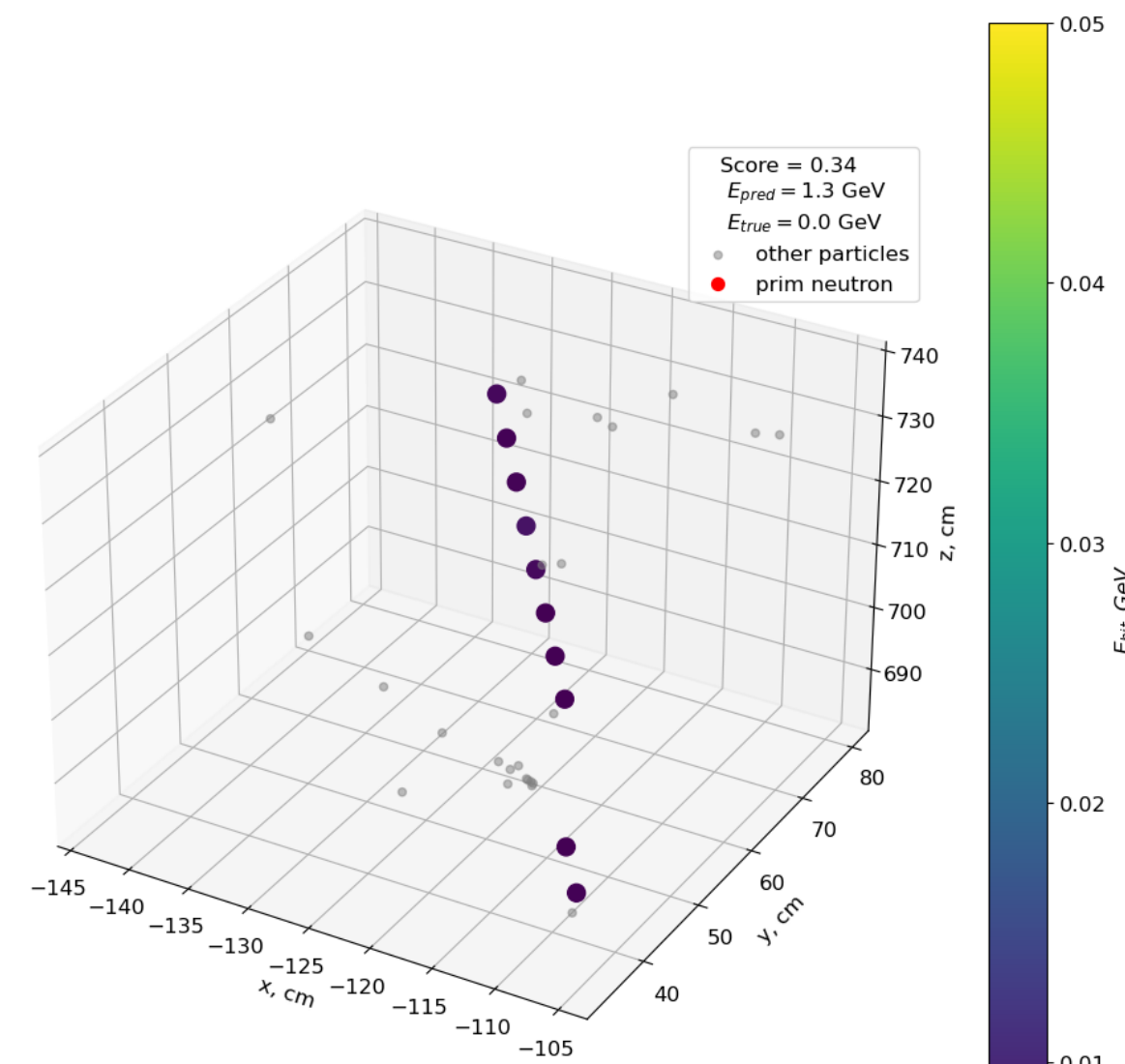
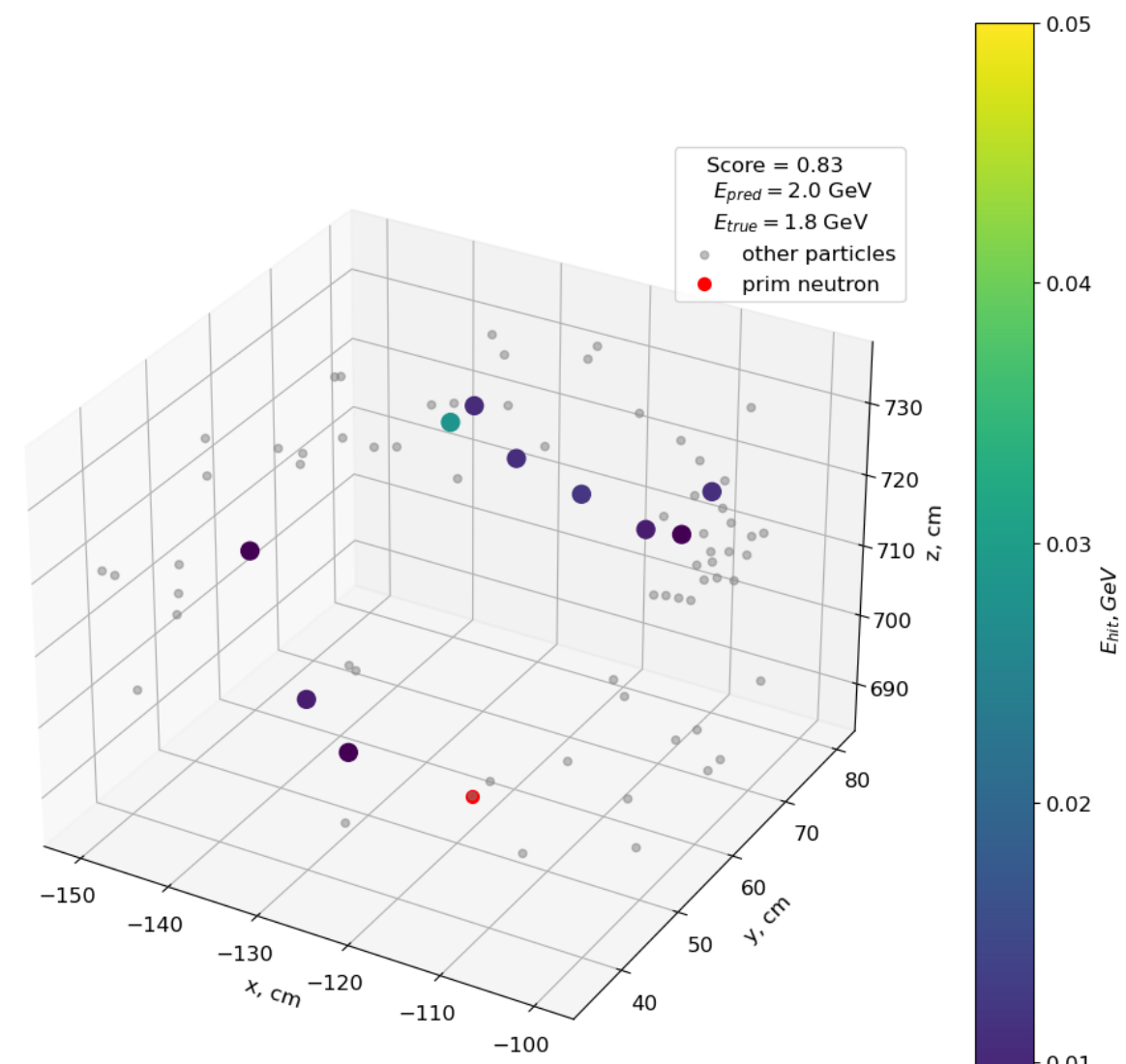
# Summary and Outlook

- Neutron reconstruction in the HGND is performed in 2 steps: classification, energy reconstruction. Machine learning approach and preliminary results are discussed.
  - High multiplicity scenario to be addressed
  - Hit-level labelling within event is under implementation in the BMNRoot
  - Utilise information of charged tracks projected to the HGND surface
  - Classical baseline neutron reconstruction is under development (see next talk)
- Performance study of neutron flow measurements is under preparation:
  - Afterburner for realistic flow signal in DCM-QGSM-SMM is prepared
  - Simulation and reconstruction is underway

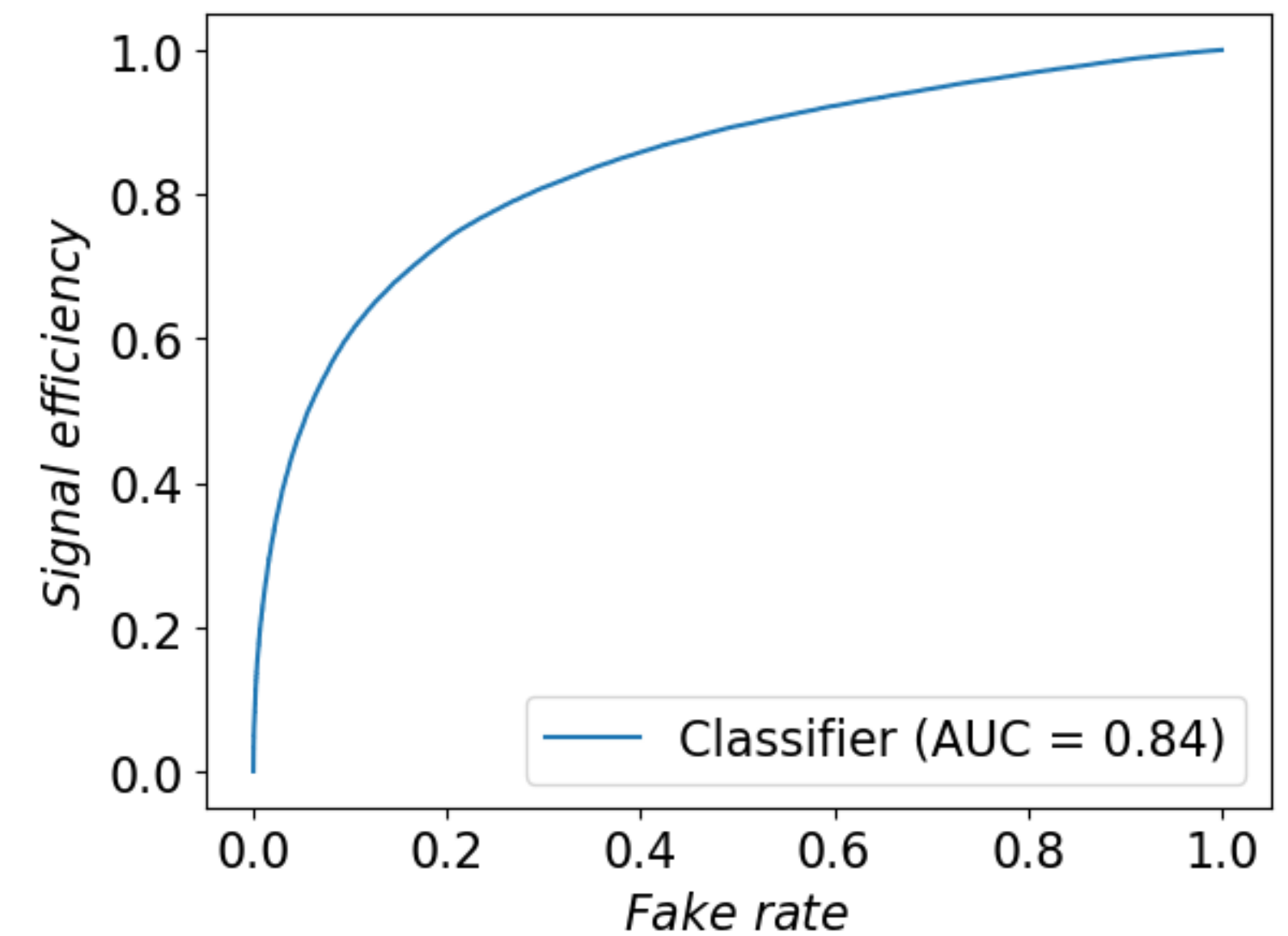
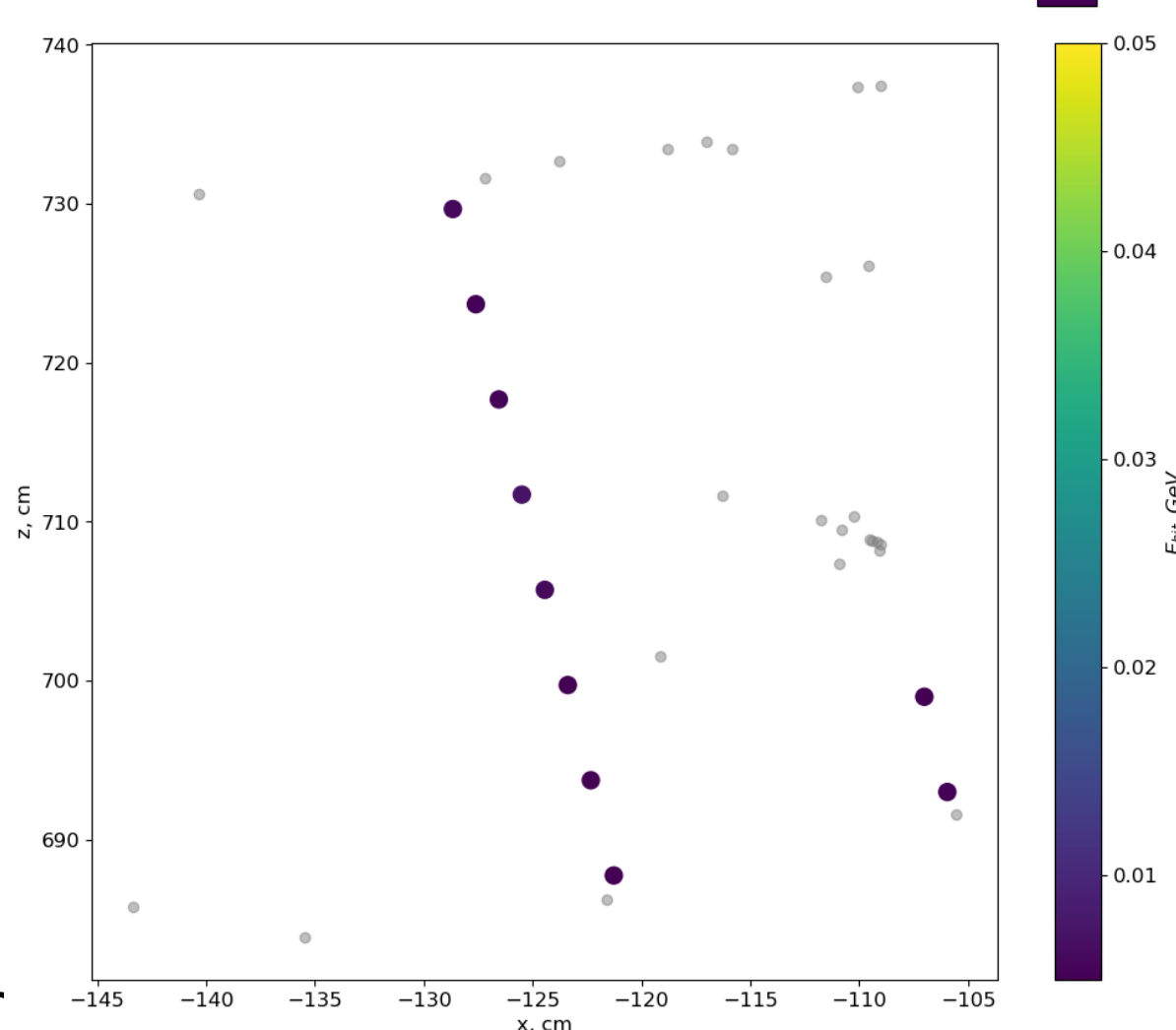
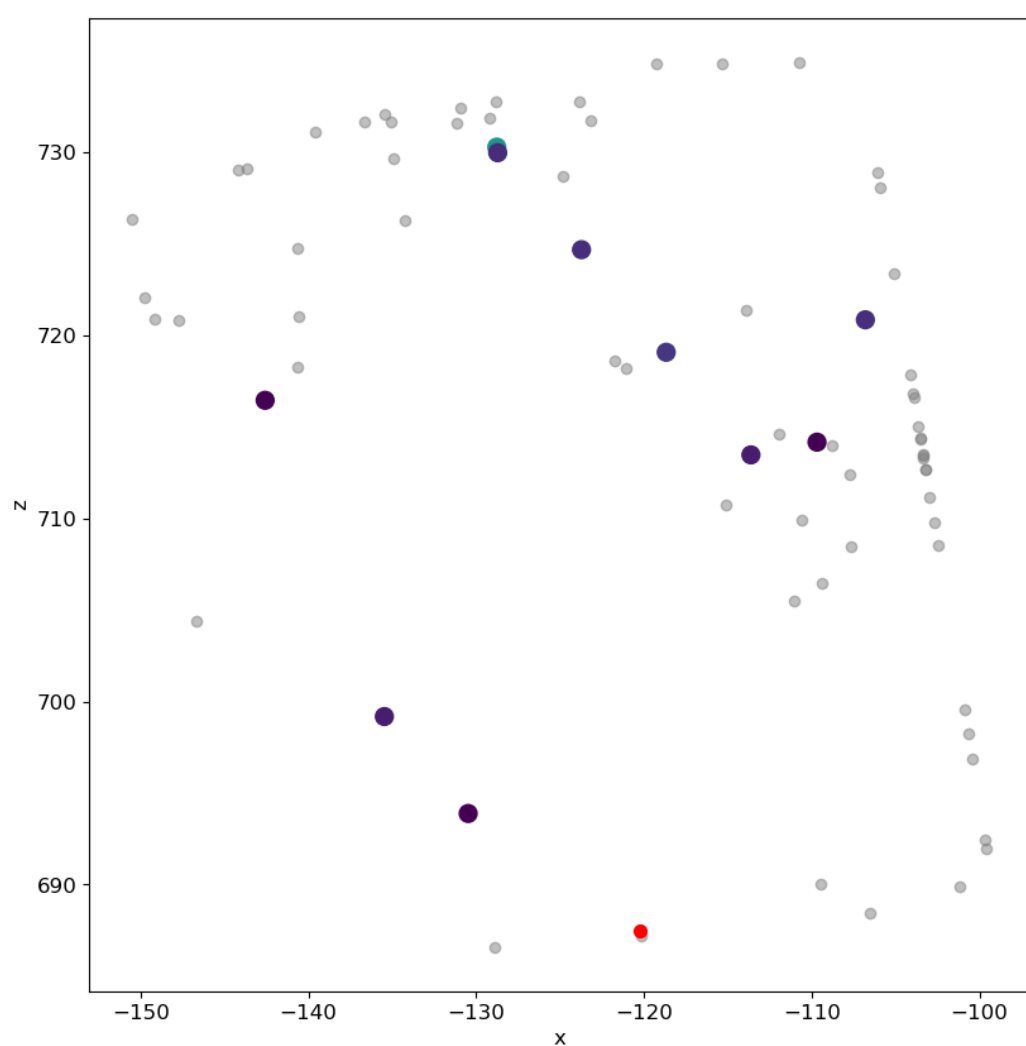
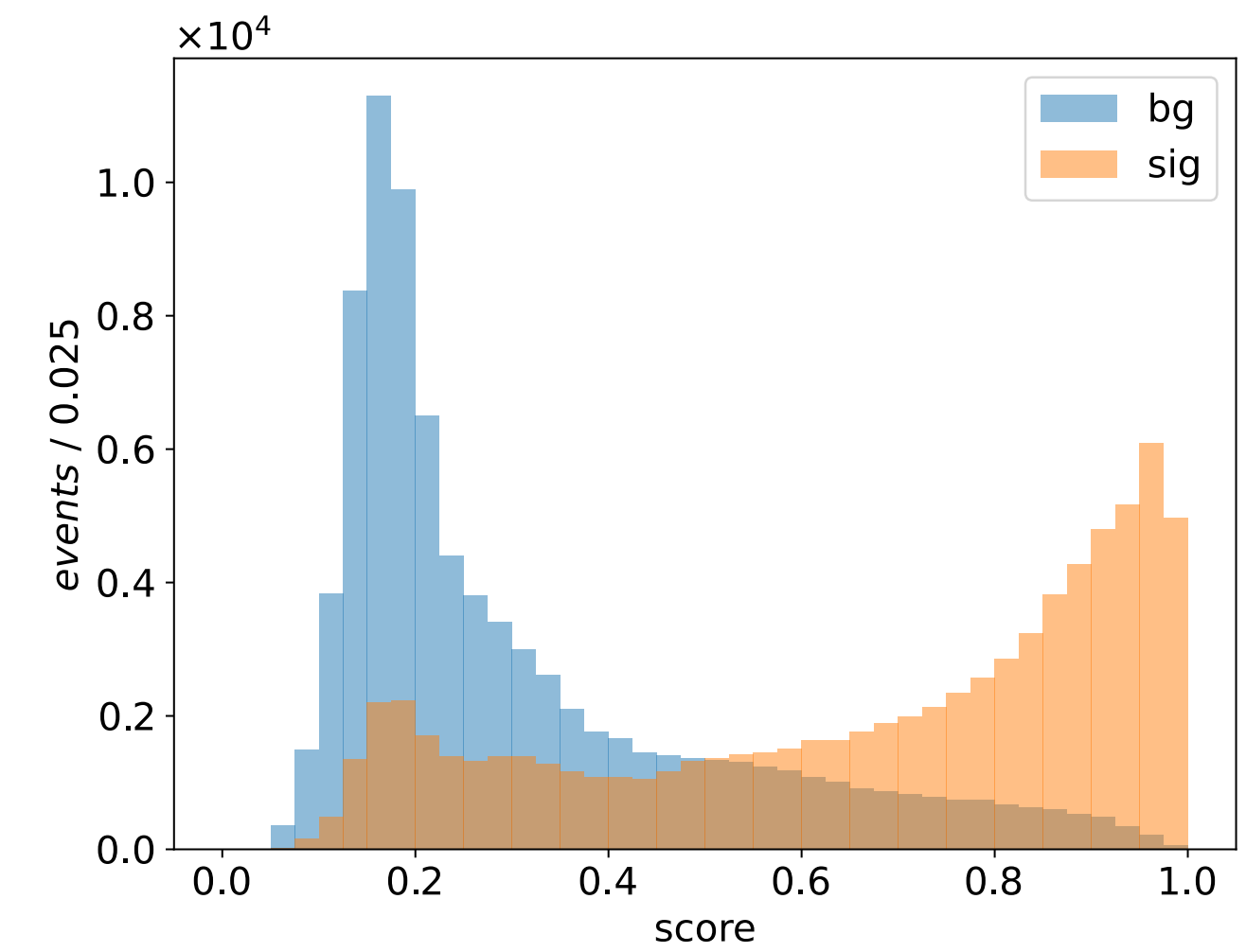
**Backup**



# Neutron event classification

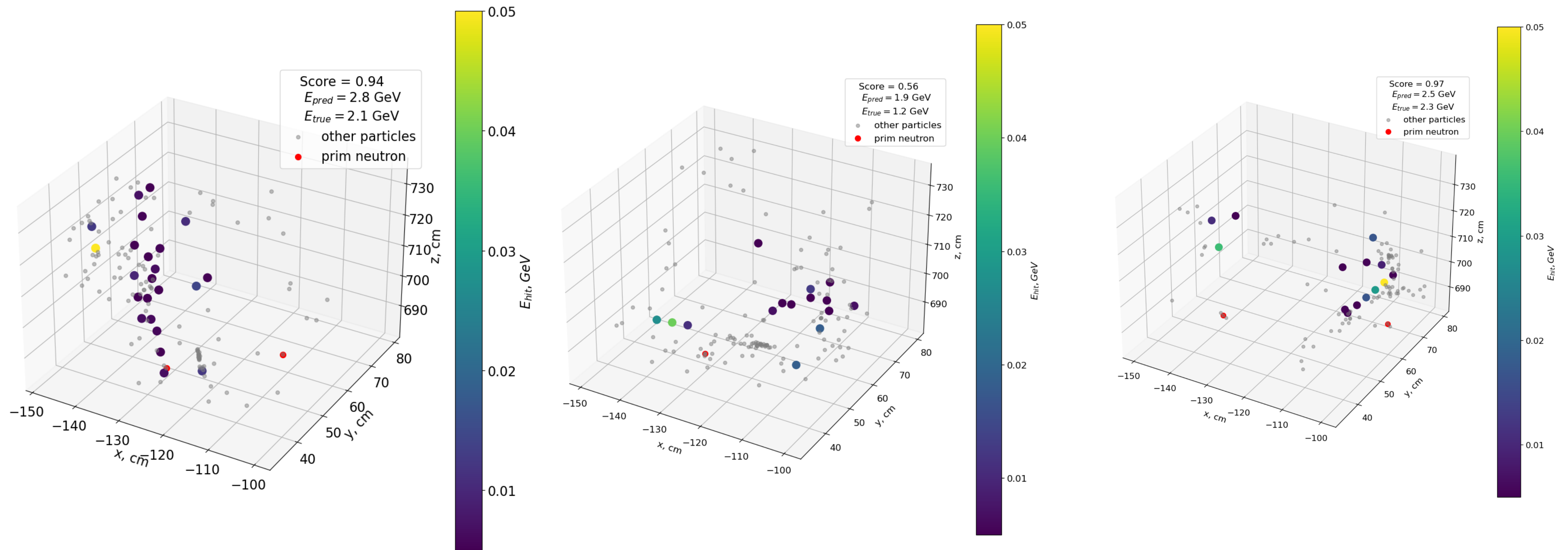


## ML event class prediction



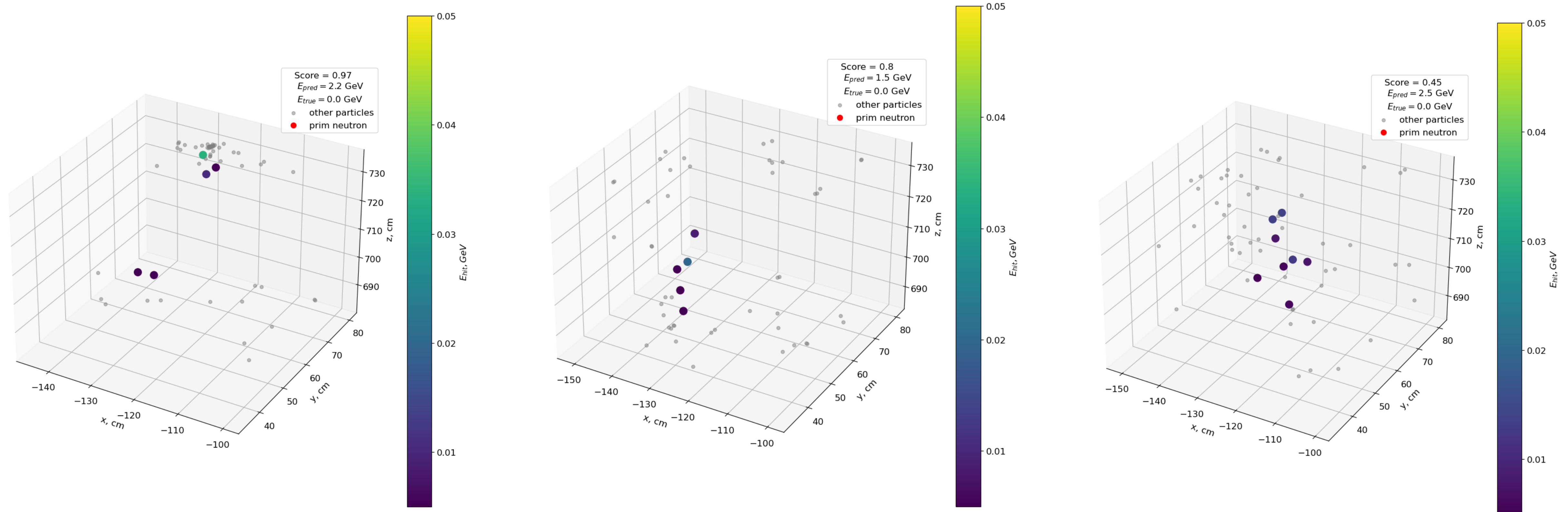
# Neutron event classification

## Event displays on test dataset



# Neutron event classification

## Event displays on test dataset

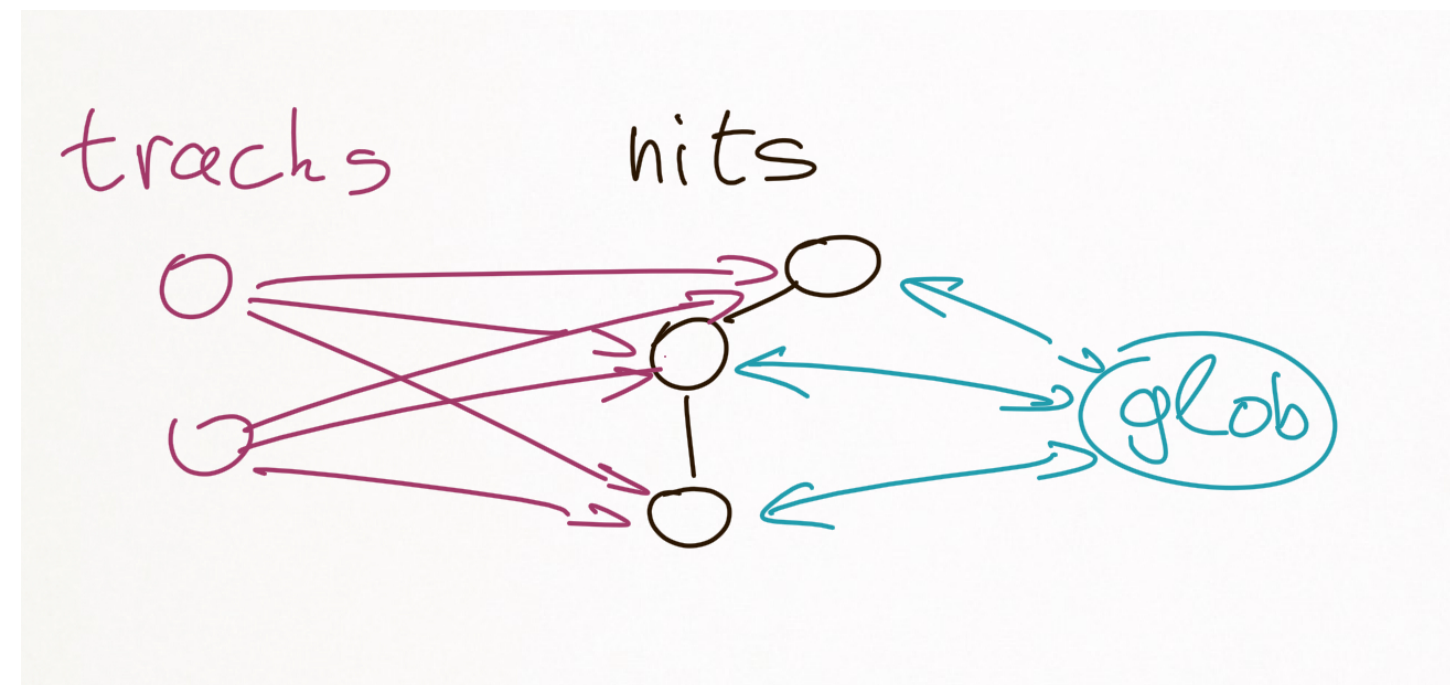




# Heterogeneous GNNs

## Heterogeneous GNN Model:

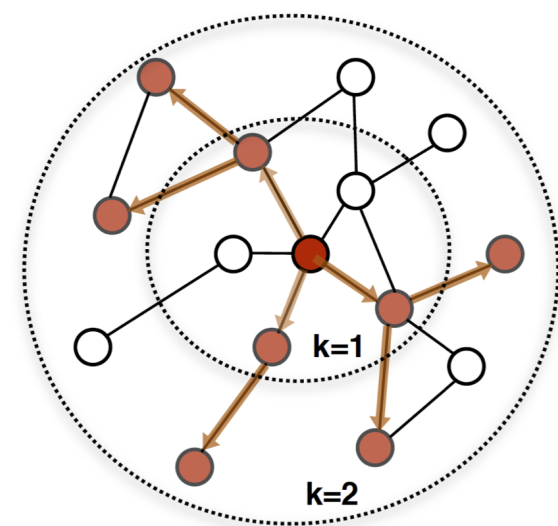
- graph construction:
  - Hit nodes
    - Edep, EToF, **pos**
  - Track nodes (e<sup>+-</sup>, p<sup>+-</sup>)
    - pos**, **p**
  - global node
    - nHits, eToF\_max, eToF\_med, Esum



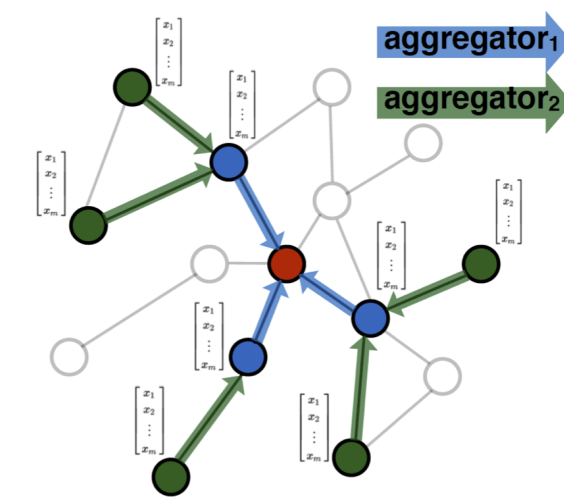
## GNN Model architecture:

- Radius graphs with  $r = 5\text{cm}$
- 8x GraphSAGE message passing layers with 512 hidden channels MLP readout layer
- Binary Cross Entropy loss function for event classification
  - Only signal events are used to train for energy regression model
- Mean Squared Error loss function for energy regression

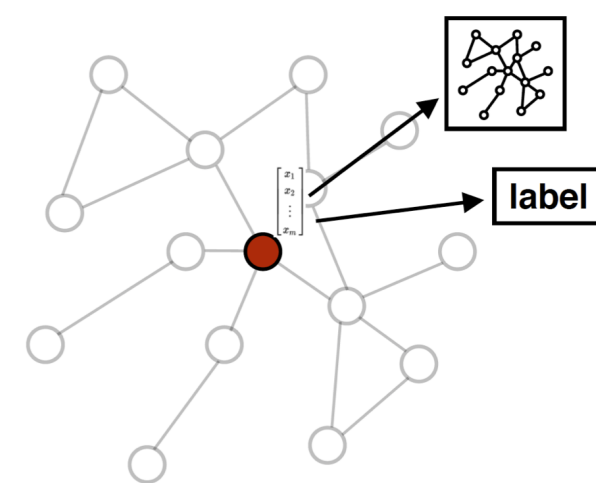
## GraphSAGE (SAmple and aggreGatE) architecture GNN:



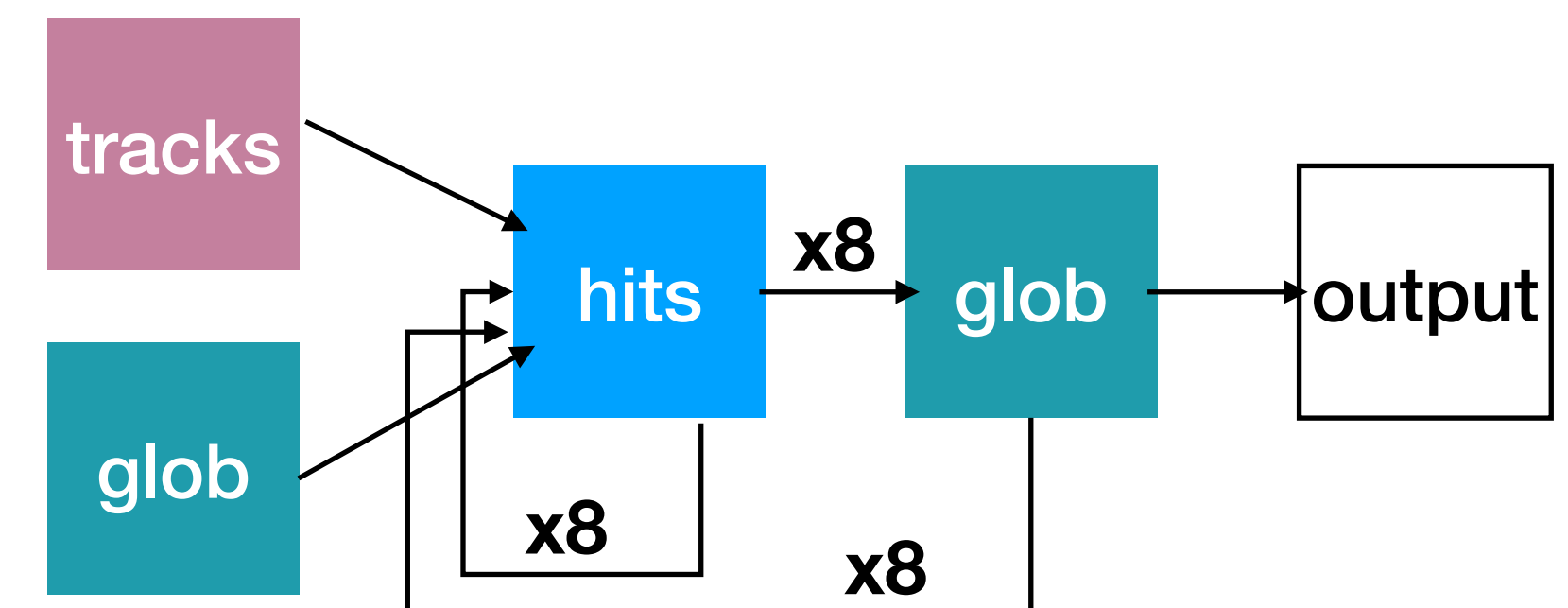
Sample neighbourhood of graph nodes



Aggregate feature information from neighbours

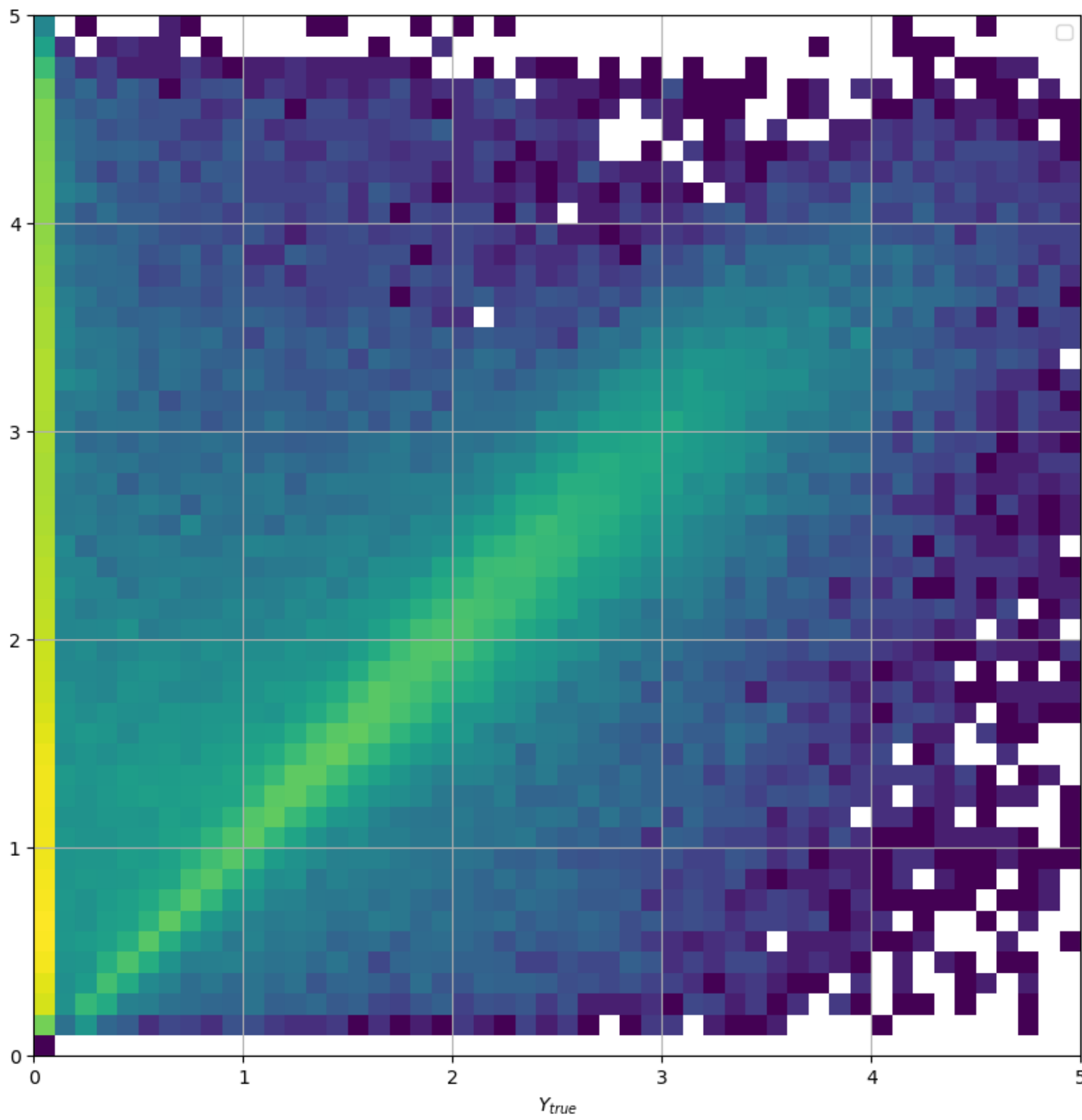


Get graph context embeddings for node using aggregated information

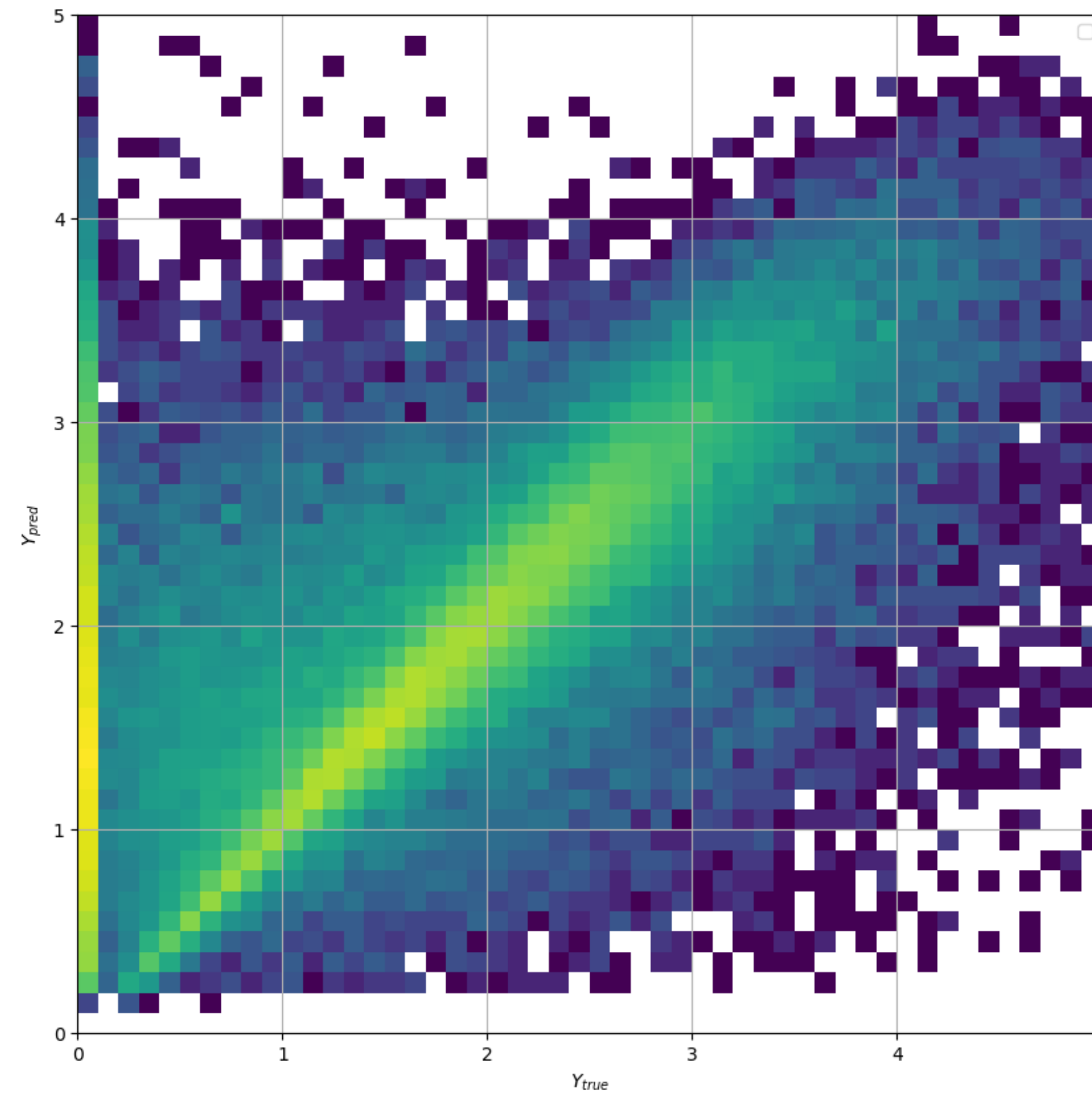


# Neutron reconstruction

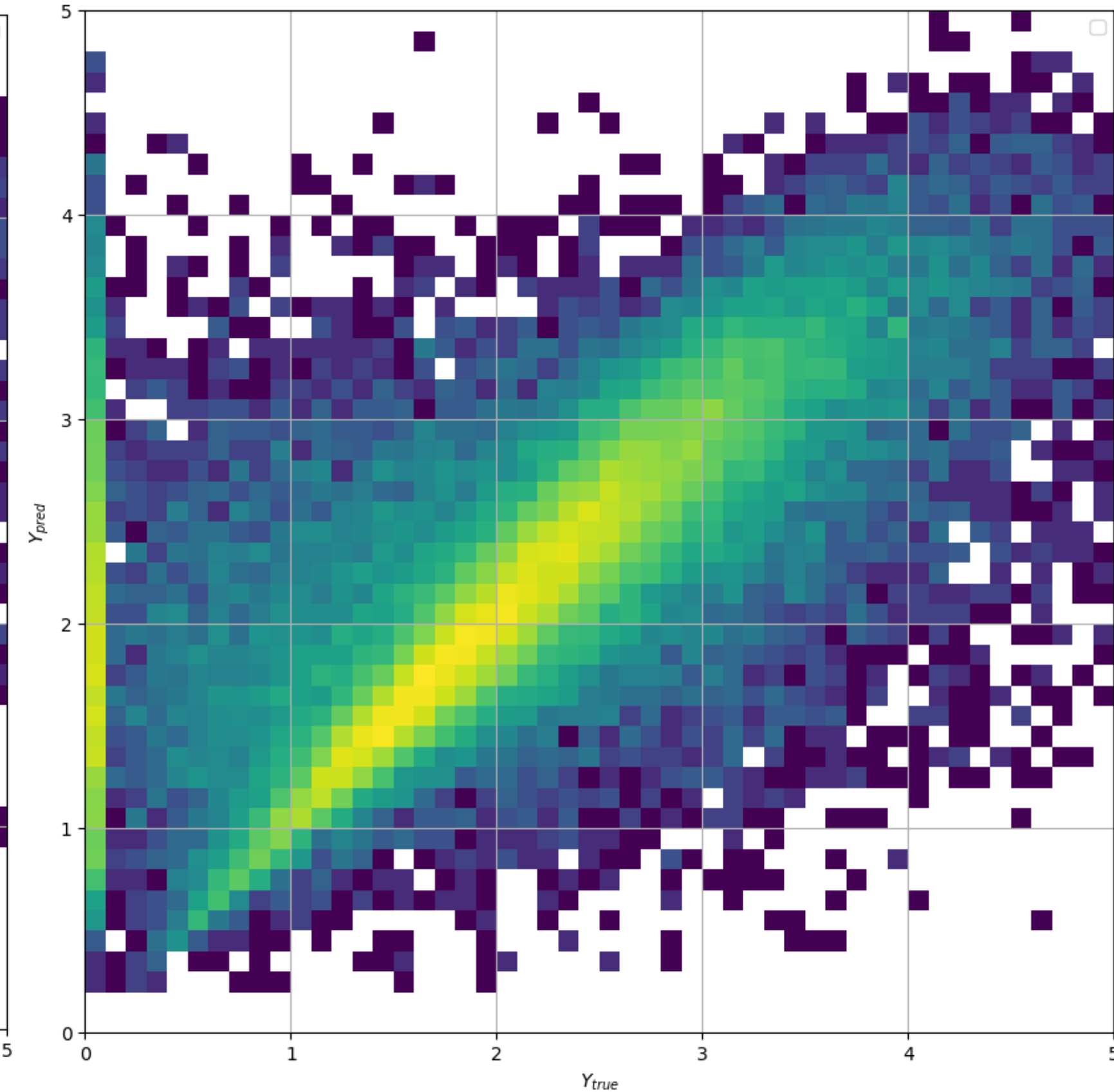
threshold = 0



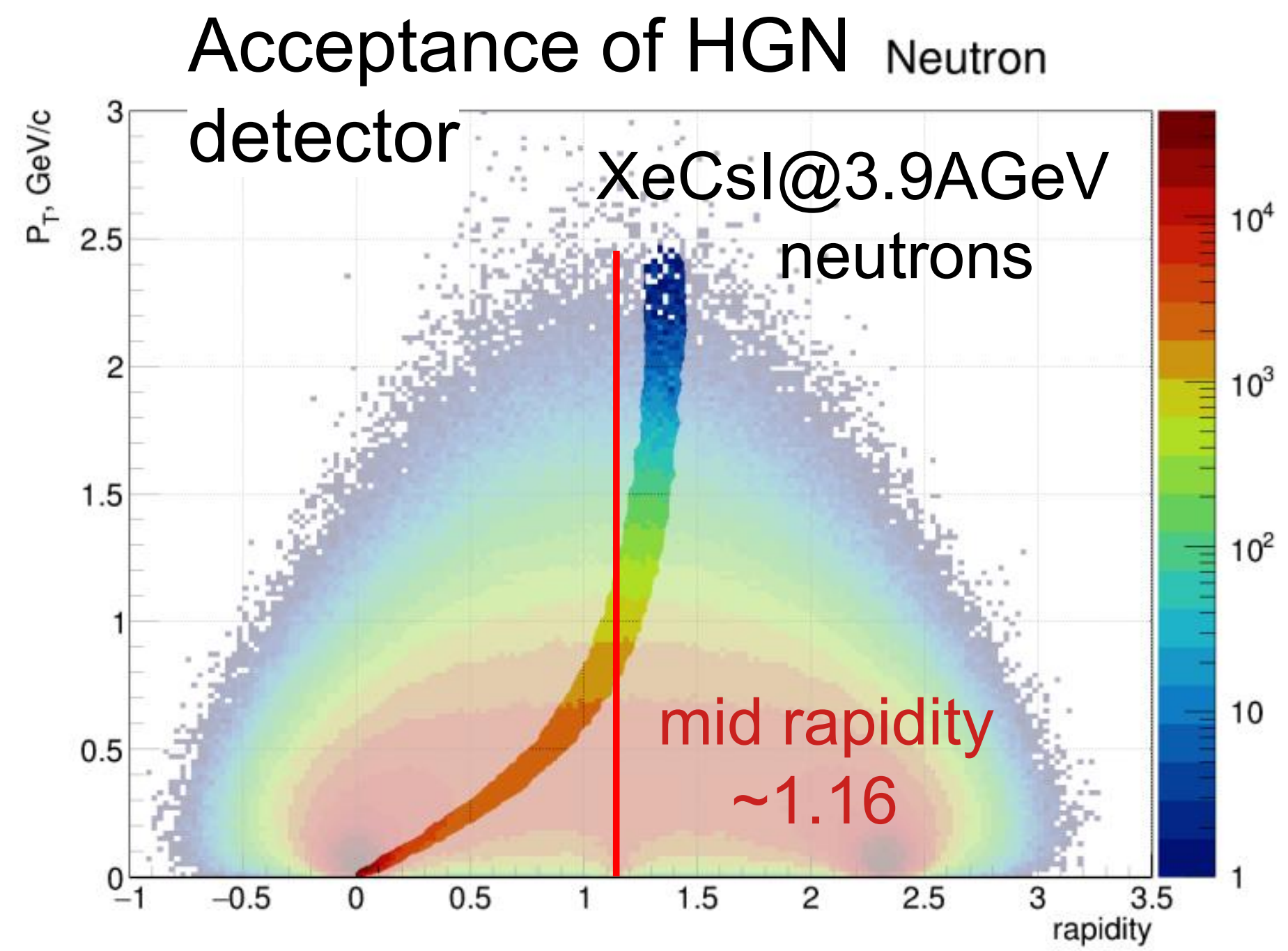
threshold = 0.5



threshold = 0.8



- Background contribution reconstructed energy is distributed similarly to signal neutrons

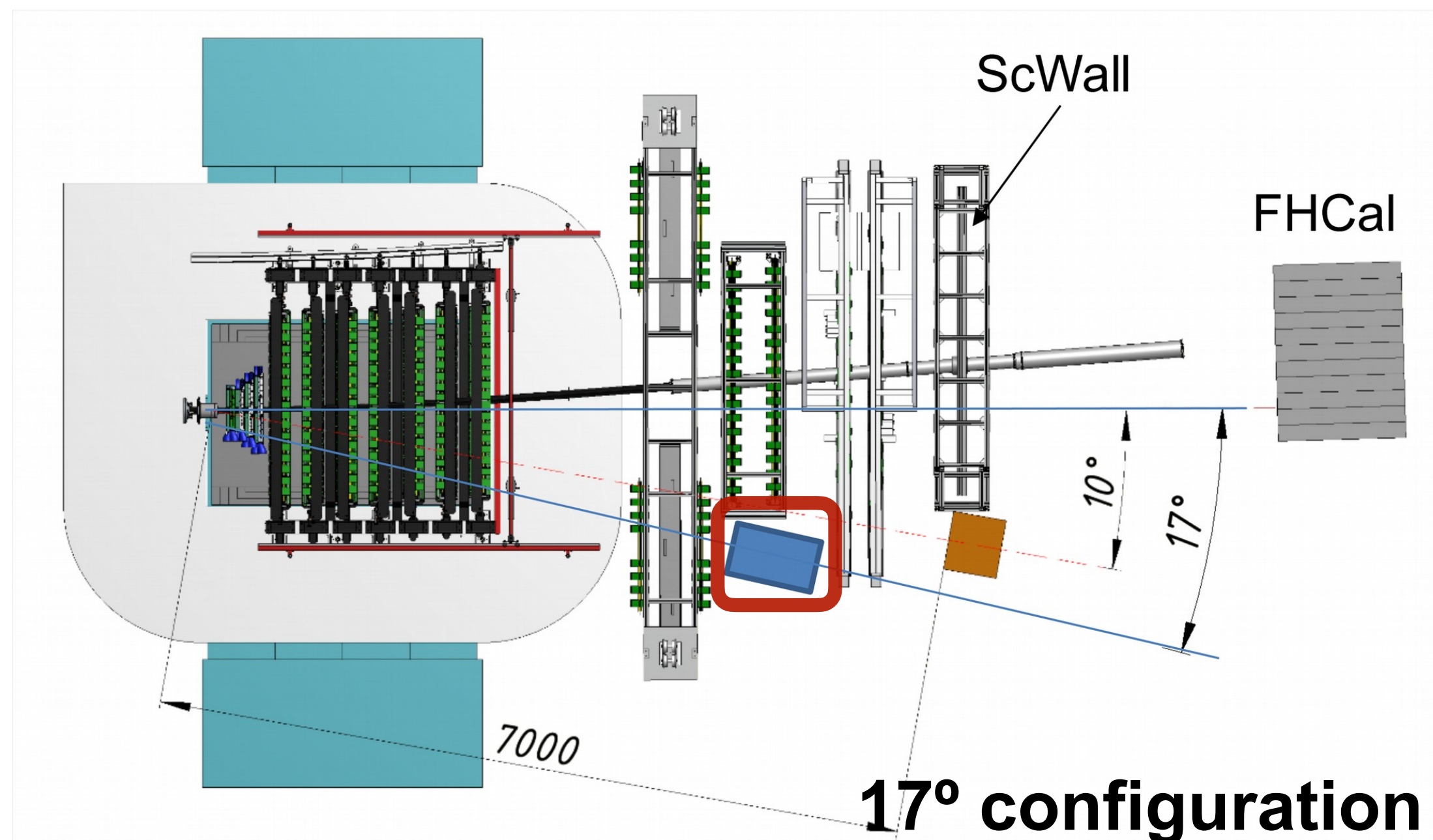




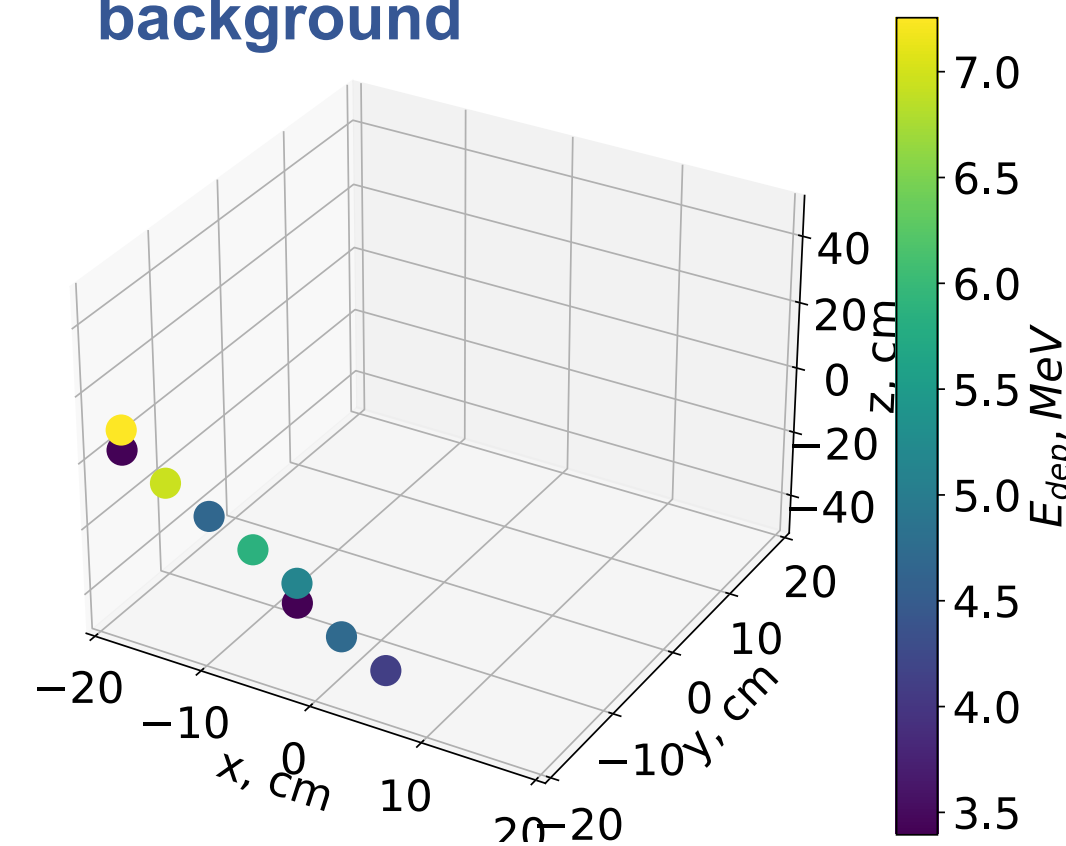
# Imaging capabilities of the HGND

## Detector image signatures:

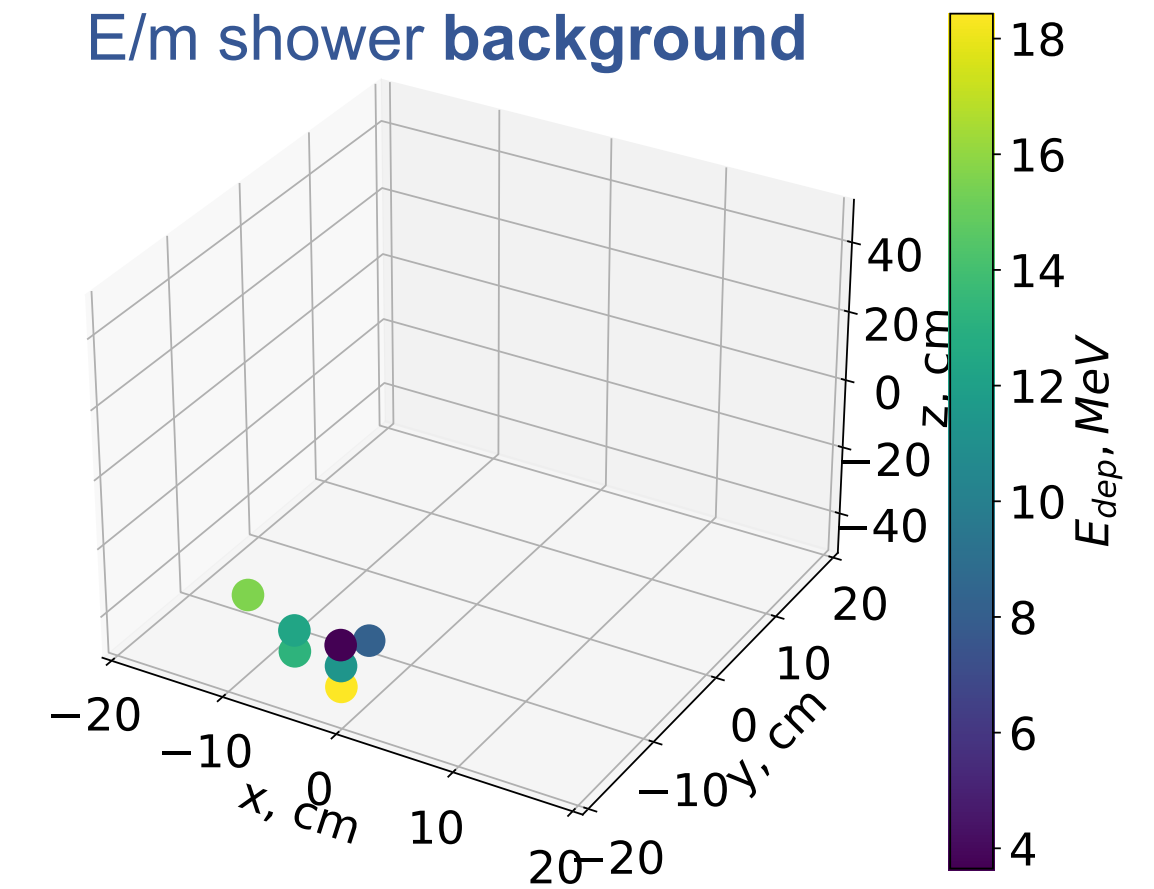
- **tracks** of charged particles
- compact **electromagnetic showers**
- sparse and irregular **hadronic showers**
  - no upstream track for neutral hadrons (including **neutrons**)



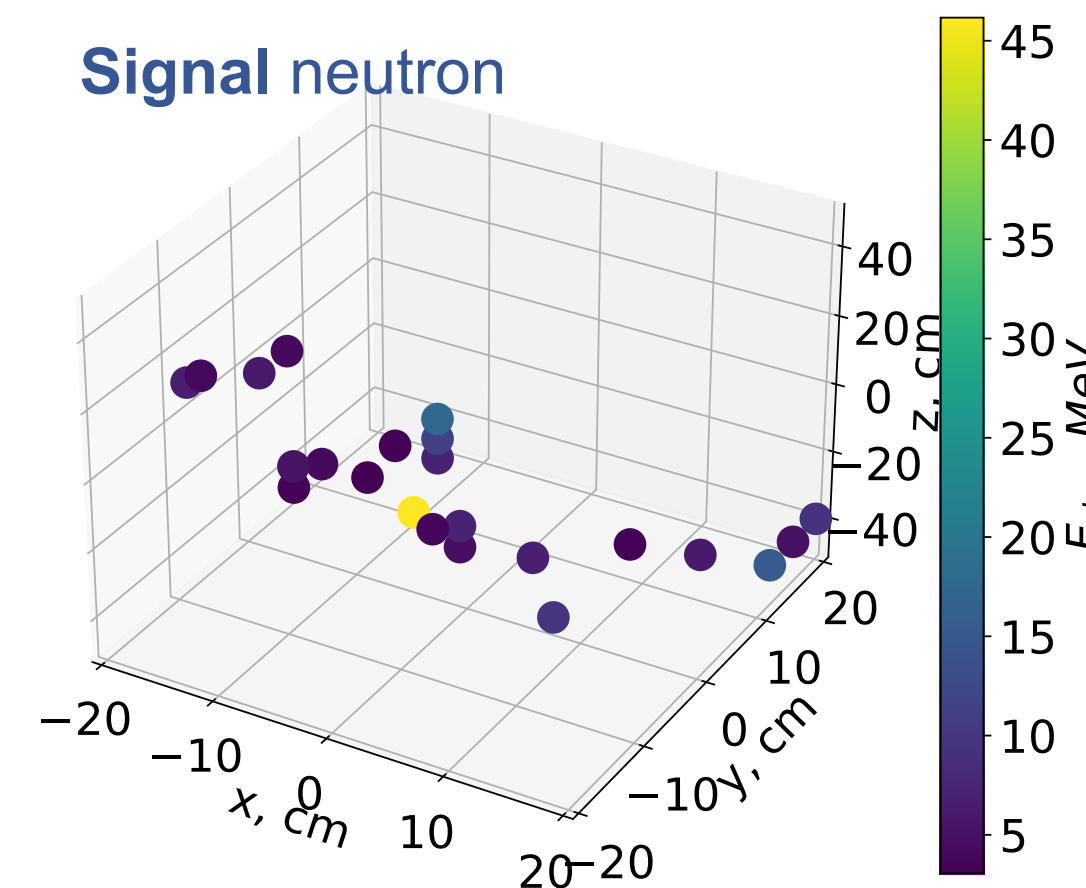
Charged particle track background



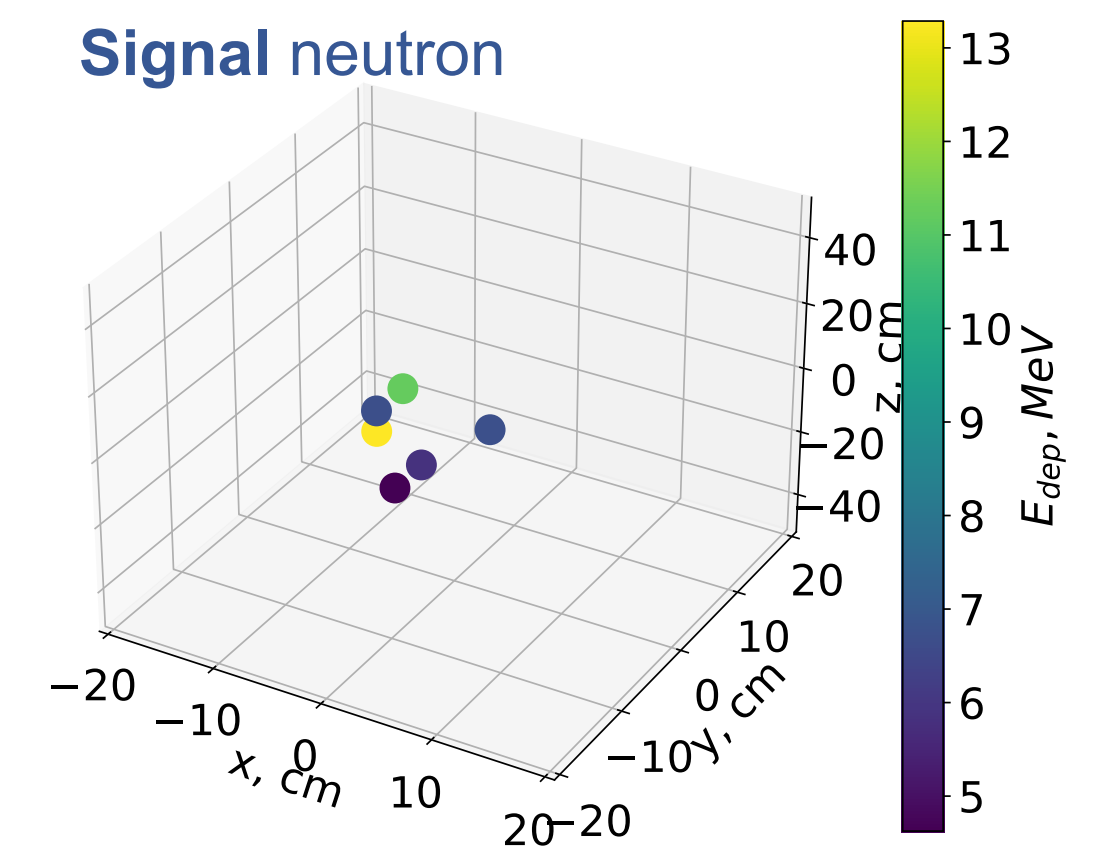
E/m shower background



Signal neutron



Signal neutron



# Data labeling

## Observables per hit:

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

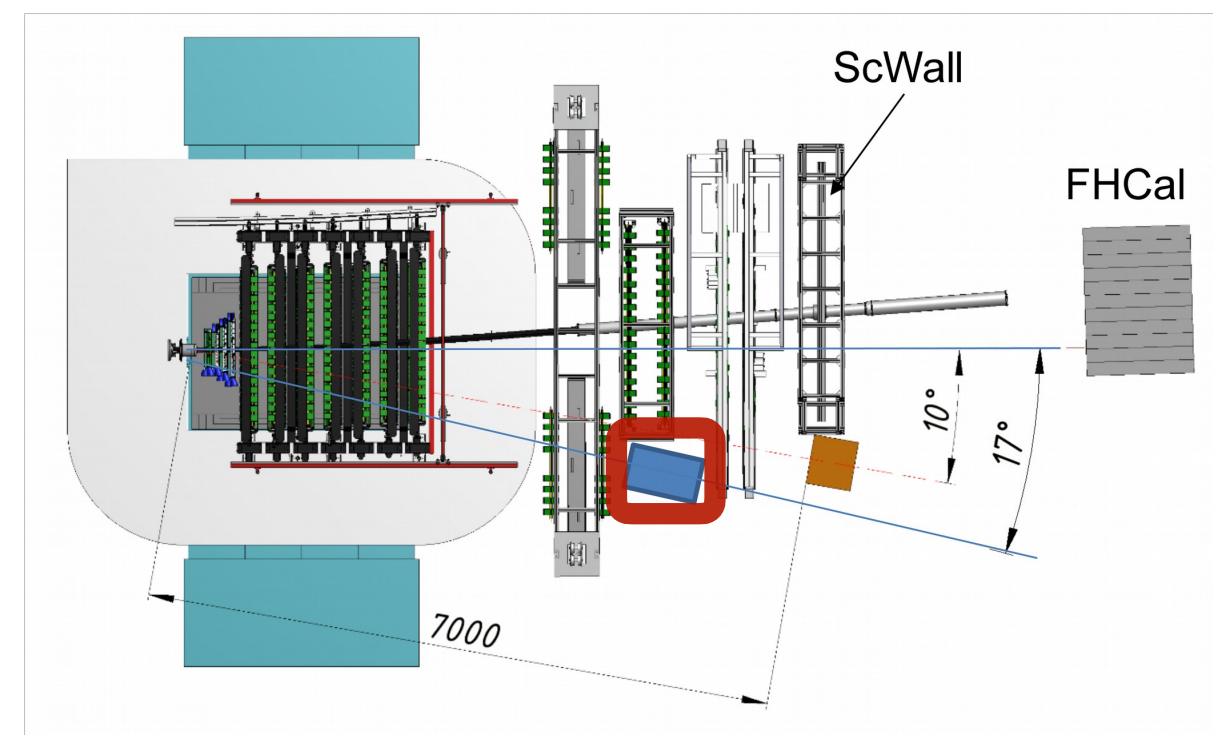
## Signal event labeling:

- 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:



**17° configuration**

