Neutron reconstruction in the highly granular time-of-flight neutron detector at the BM@N experiment

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ML4NICA, St. Petersburg
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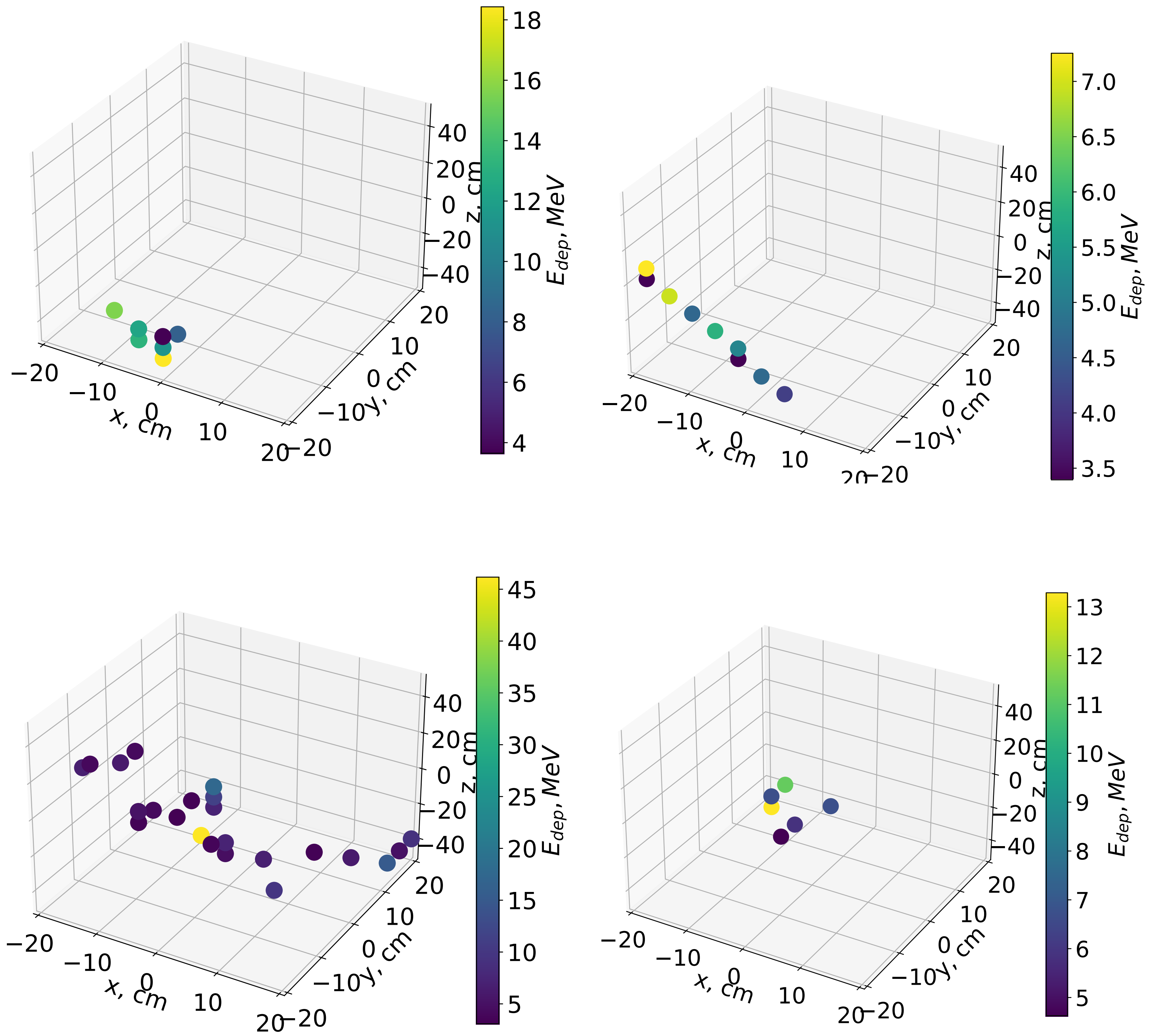


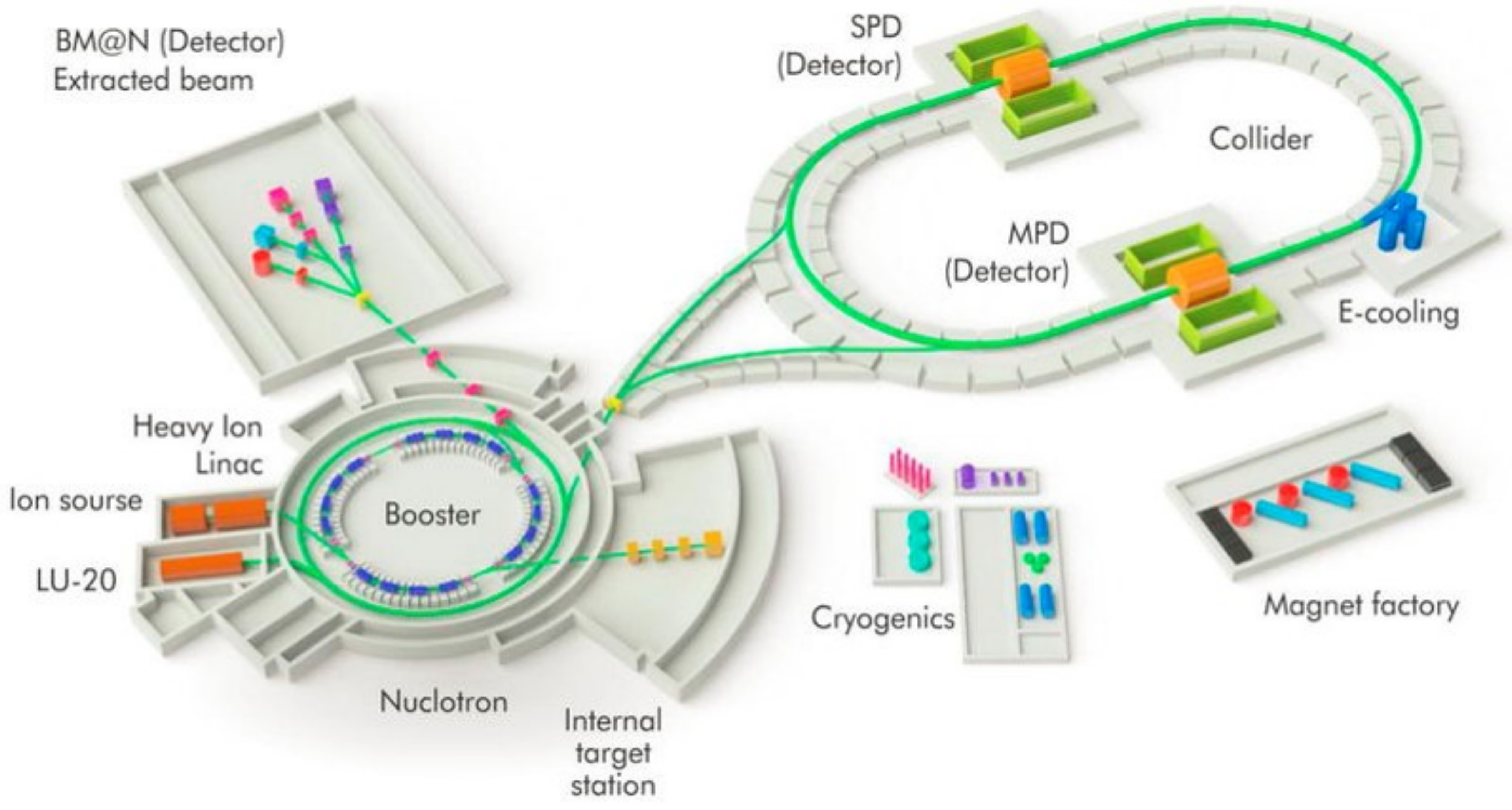
BM@N experiment

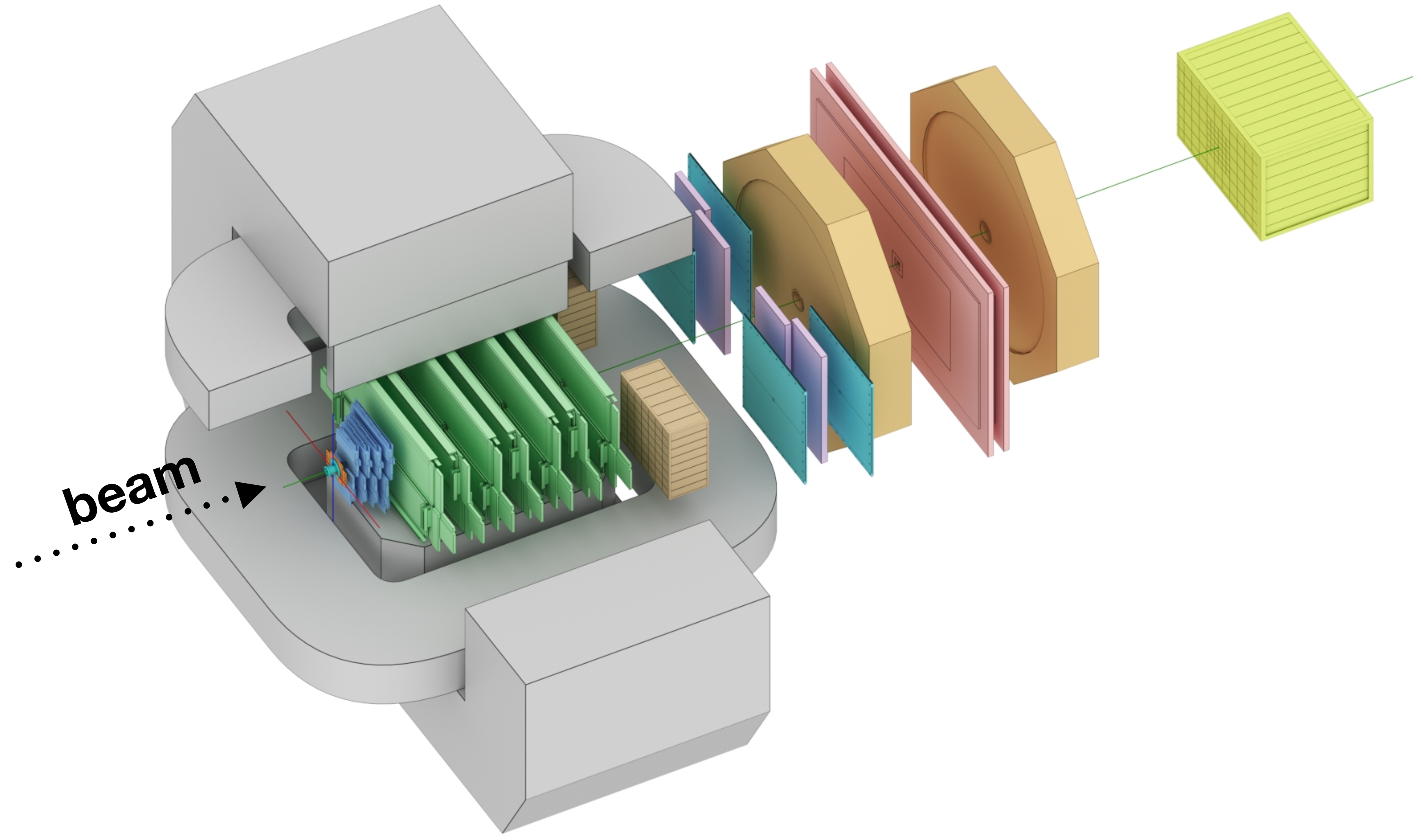
Studies of **B**aryonic **M**atter **at** the **N**uclotron (NICA, JINR Dubna)

- Heavy-Ion beam with energies up to 6A GeV interacts with fixed target

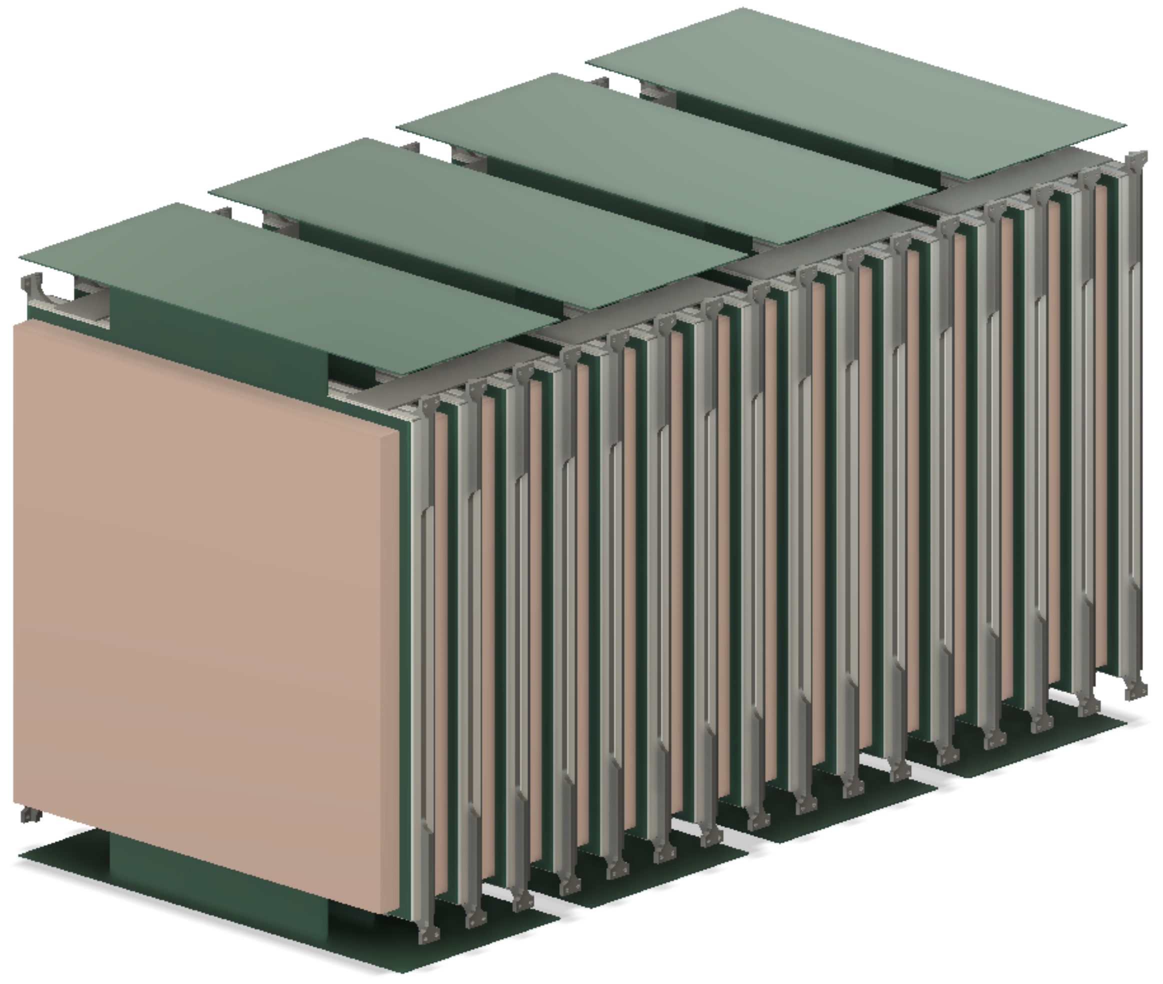
➡investigate the equation-of-state (EOS) of **dense nuclear matter** which plays a central role for the dynamics of core collapse supernovae and for the stability of neutron stars.

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

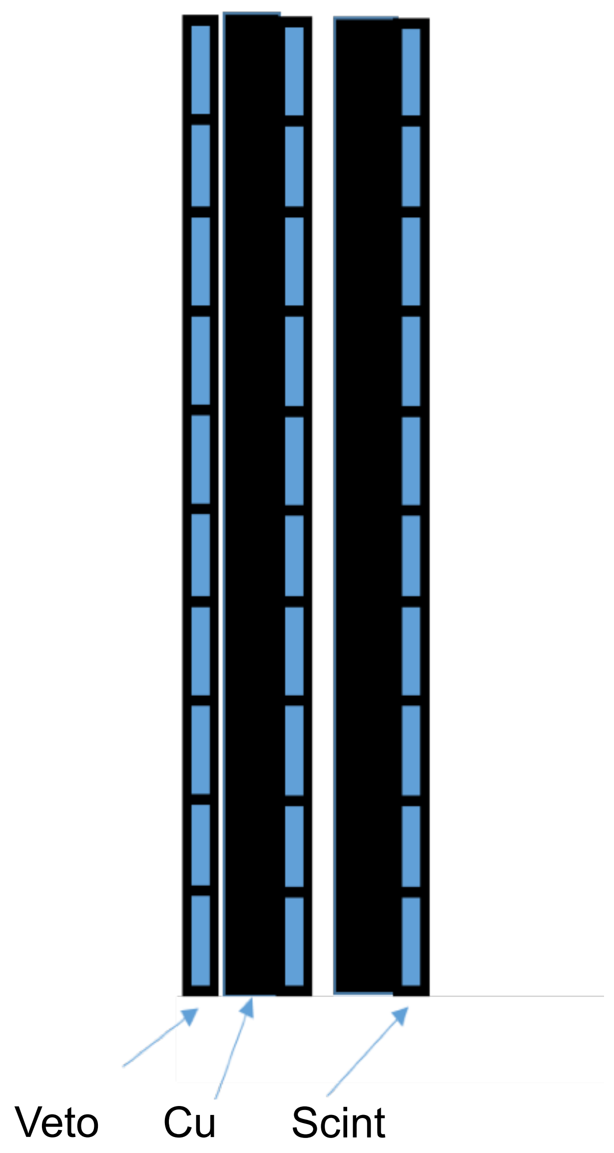




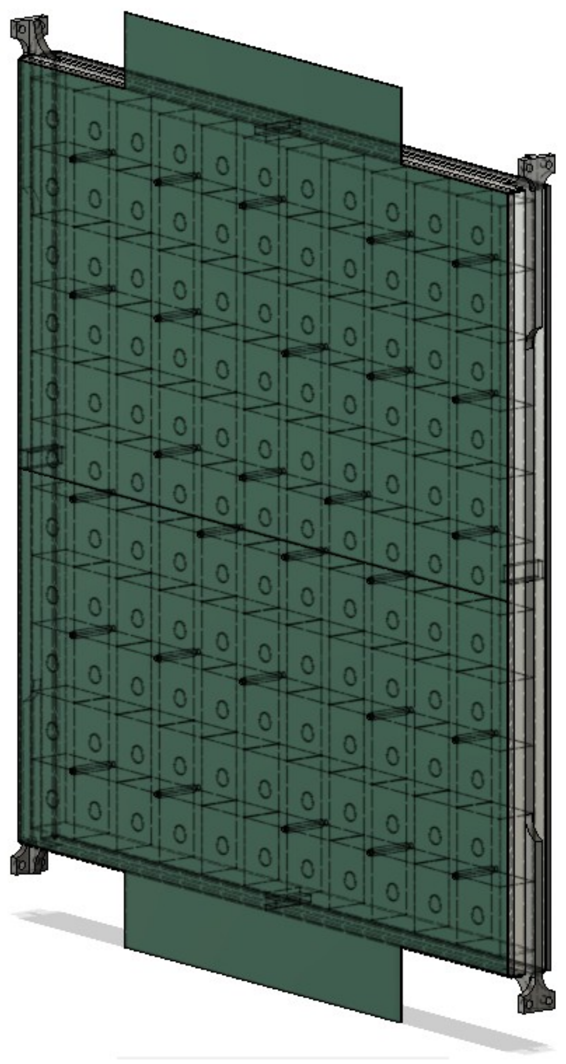
Highly granular time-of-flight neutron detector (HGN)

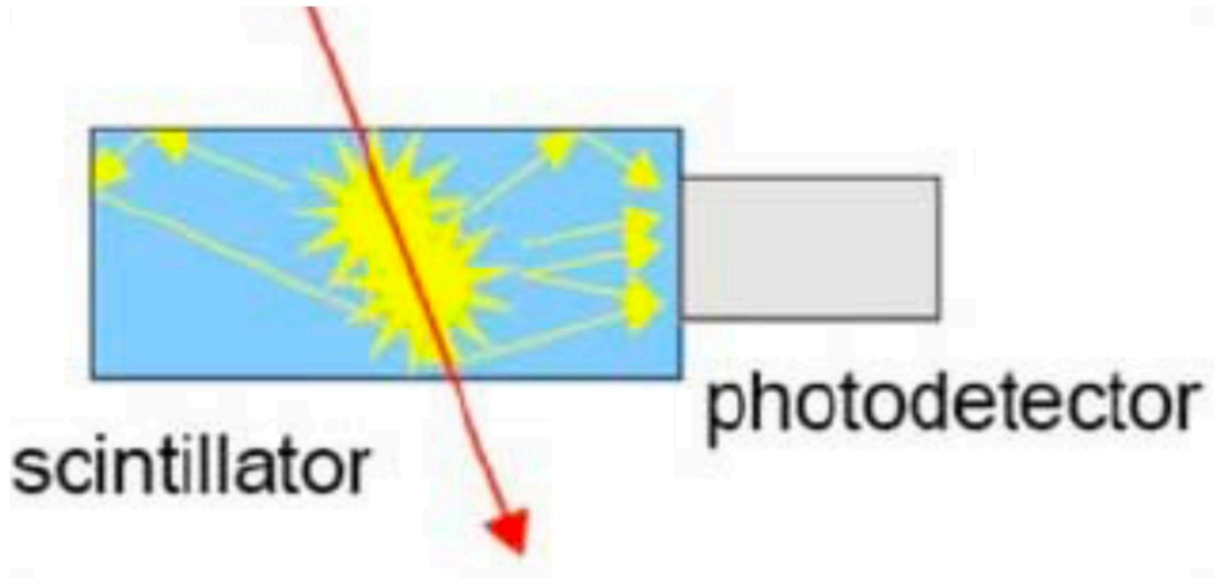


Longitudinal structure



Active layer

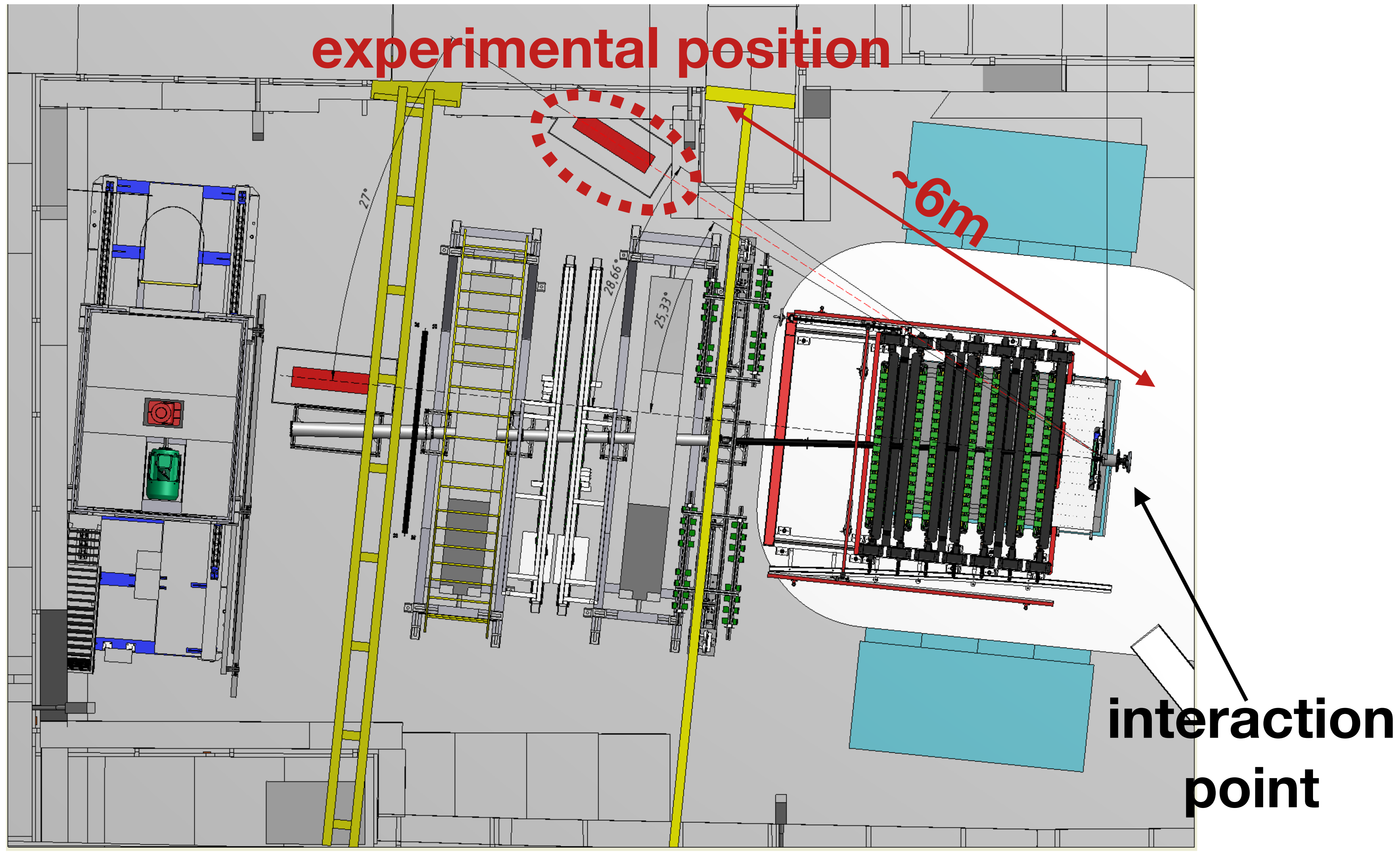




- 16 layers: *3cm Cu (absorber) + 2.5cm Scintillator + 0.5cm PCB; 1st layer — ‘veto’ before*
  ➡Total length: **~1m,** ~3 λ_{in}
  ➡ neutron absorption ~100%
  - Transverse size: **44x44 cm^2**
  - *11x11 scintillator cell grid*

- scintillator cells:
  - size: 4x4x2.5 cm^3,
  - **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 **27º to the beam axis at ~5m from the target**
- Monte-Carlo event simulations:
  - DCM-SMM model + Geant4 (QGSP_BERT)
  - ~500K events with fully simulated reactions **Bi+Bi @ 3 AGeV** (BM@N data rate ~10kHz)

Particles passing the HGN front wall

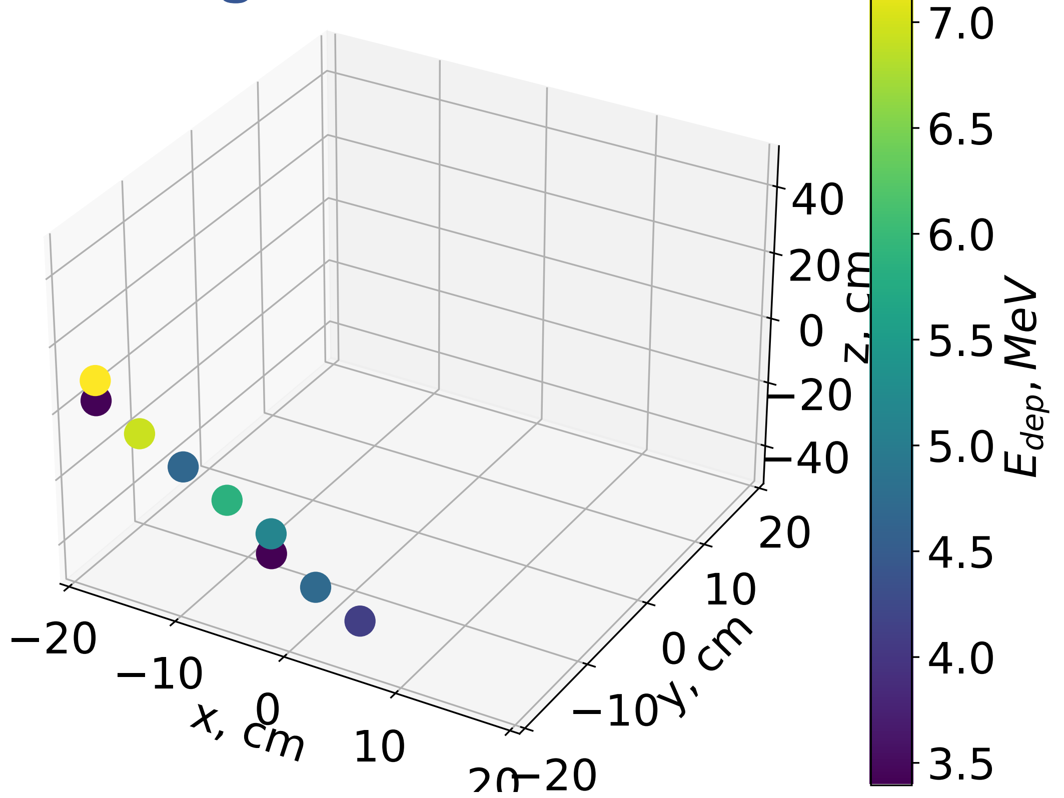
- Logical volume before the HGN front wall to capture particles in the detector acceptance
  - No access to hit-level labelling within event
- **~14% of events** with energy deposition in HGN **has no particle** (E_{kin} > 50MeV) passing the front wall
- Primary neutrons — produced in reaction, E_{kin} > 0.4 GeV to minimise presence of background neutrons
- Neutron multiplicity ≈1 => **event classification approach**

Imaging capabilities of the HGN

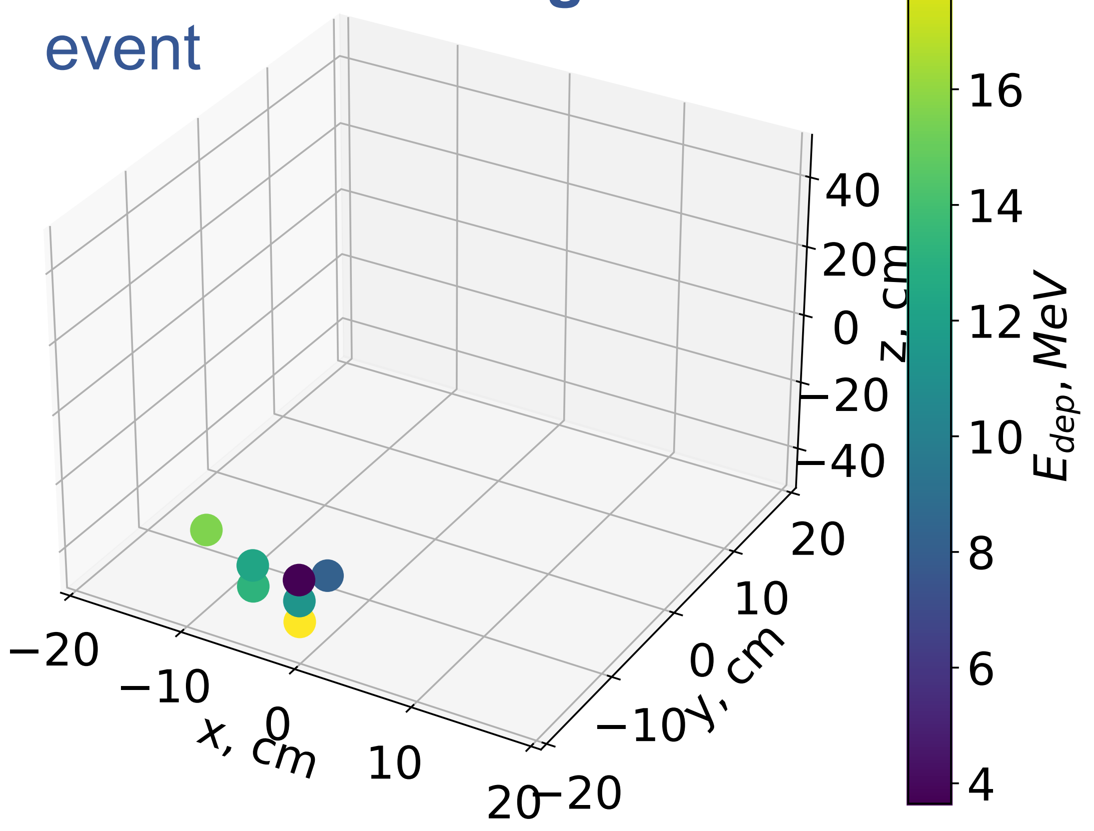
Event type signatures:

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

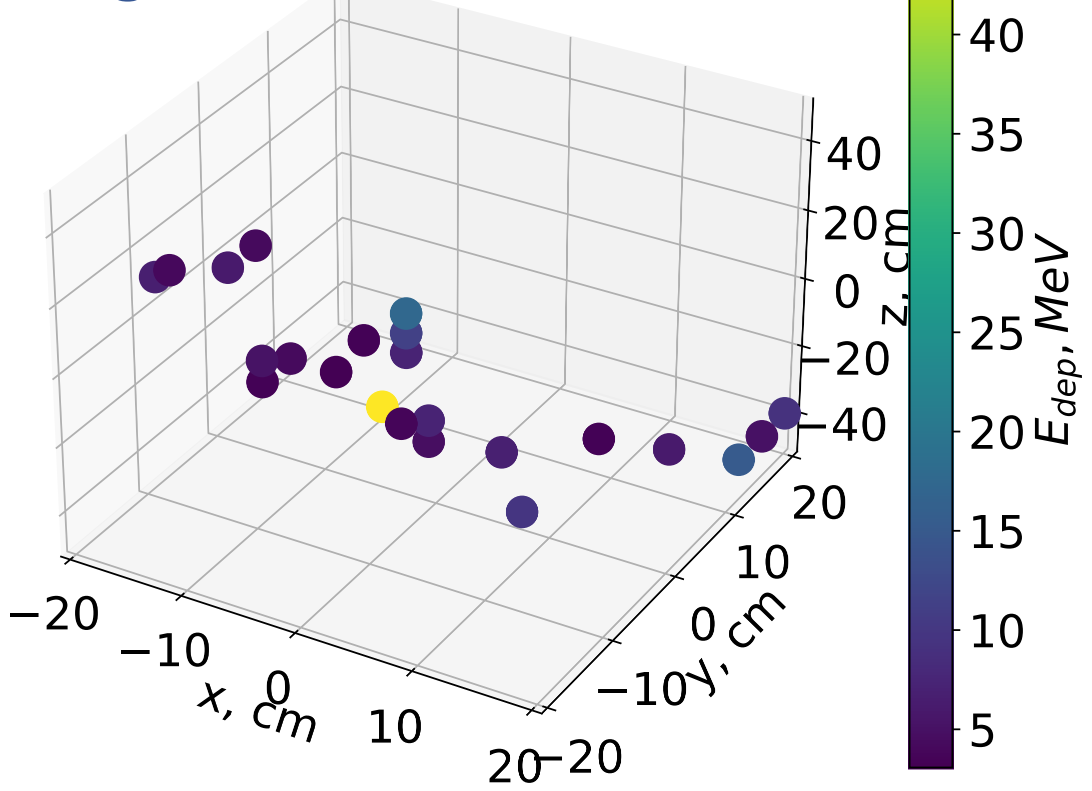
Charged particle track **background** event



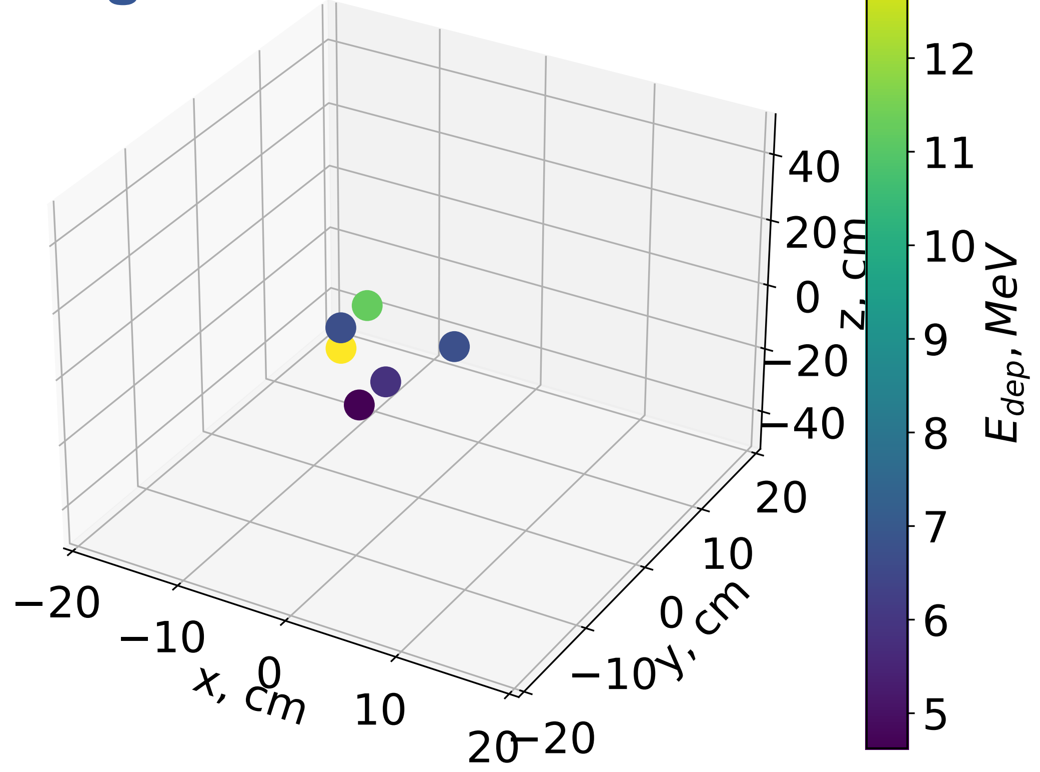
E/m shower **background** event



Signal neutron event



Signal neutron event



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

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

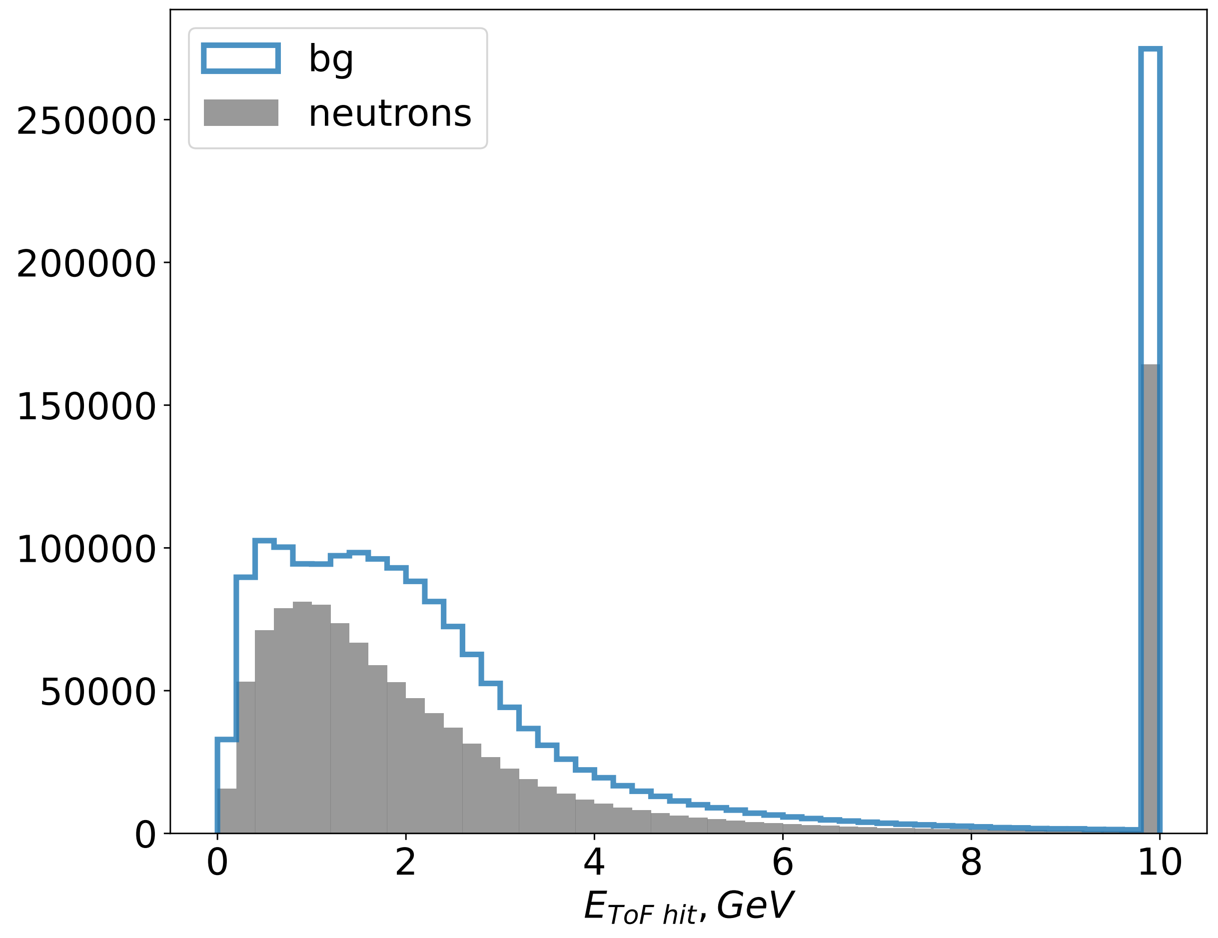
“Best” hit

- “Cheated” hit selection from simulation

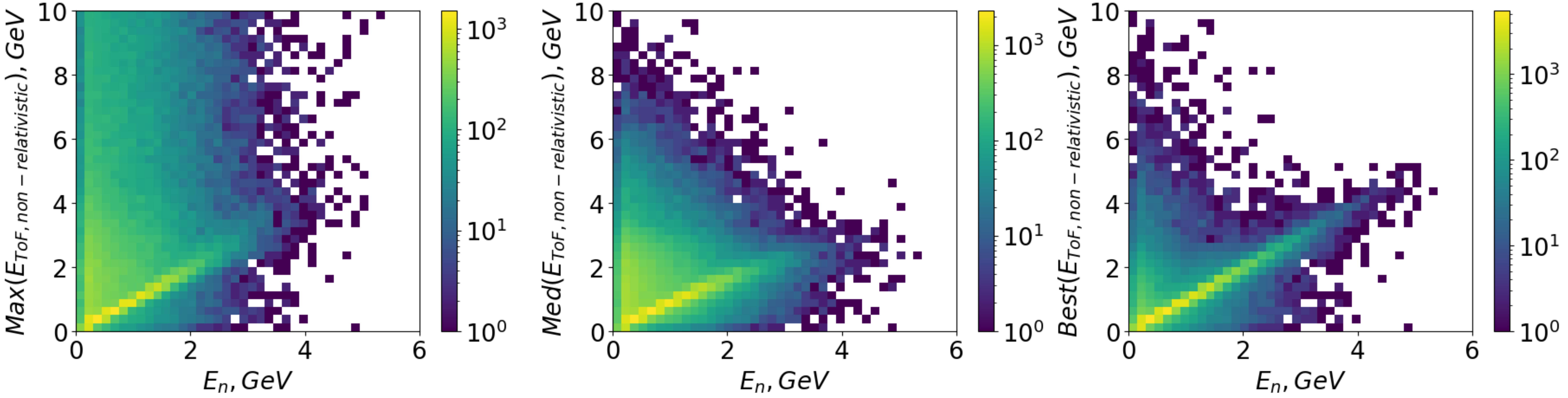
➡ suitable for event labelling

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

EToF distribution per hit



Events with a neutron (>50 MeV) passing front wall of the HGN at angle <10º



Dataset

Observables per hit:

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

***272844 events** with deposition >3 MeV* →

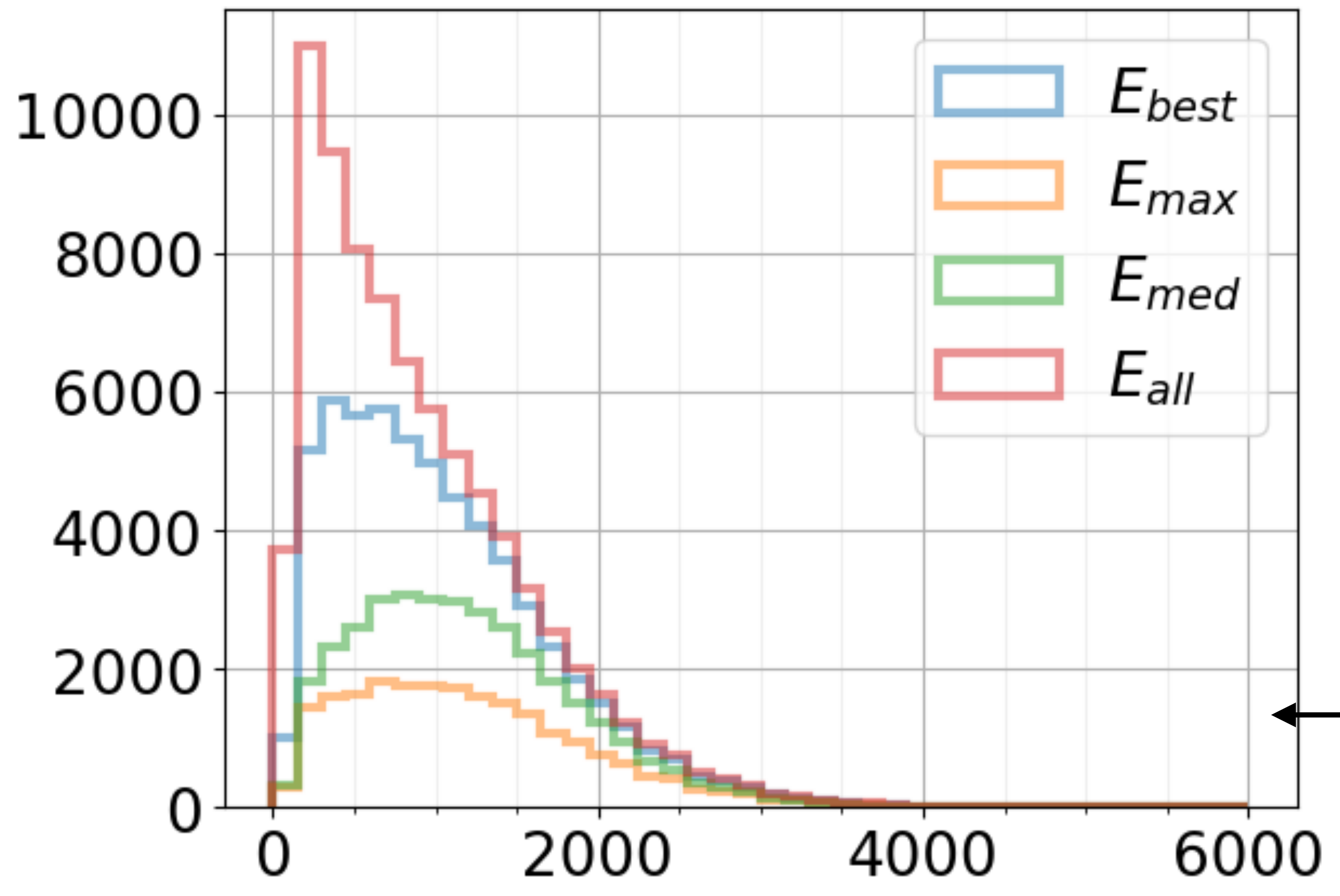
Signal event labeling:

- Single neutron,
- E_{kin} > 100 MeV,
- Angle to detector axis < 10º
- $\delta(E_{ToF}) < 40\%$
  - fastest - **21917 signals**
  - median - **34670 signals**
  - “best” - **58949 signals**

Chalenges:

- Small fraction of signal neutrons
- Event contamination by background energy deposition
- Neutron energy range is not typical for sampling calorimeters
  - 0-5 GeV vs. 10-250+ GeV
  - ➡ low number of hits corresponding to a neutron, high fluctuations in energy deposition

neutron energy

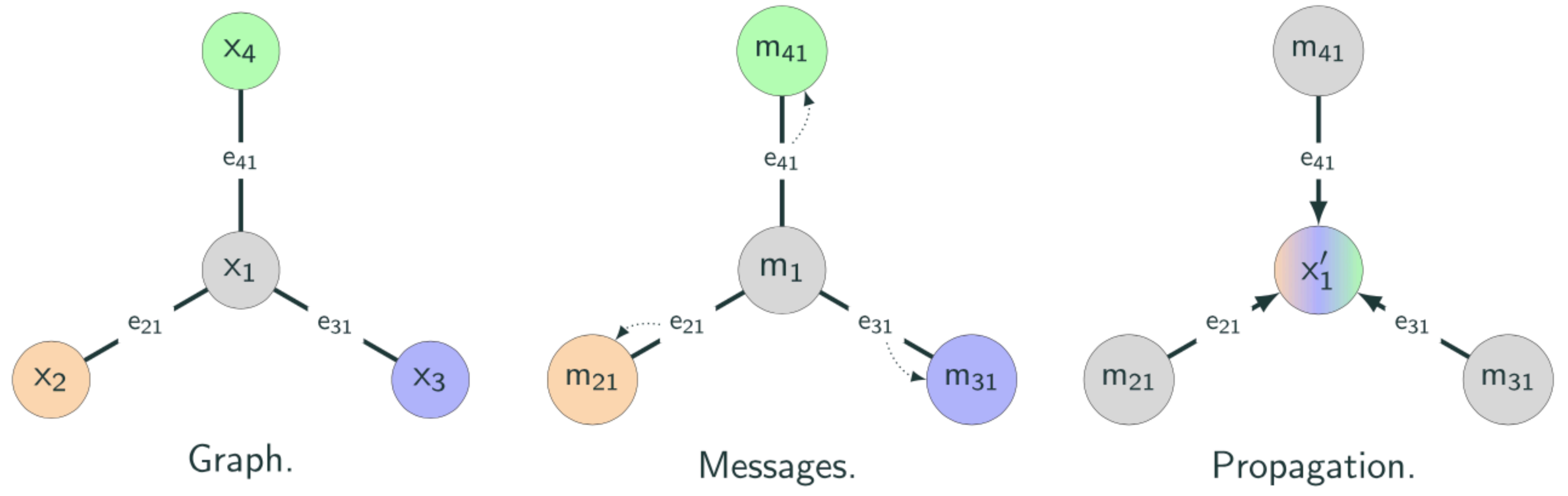


non-linear spectrum cut by different labelling

GNN in High Energy Physics

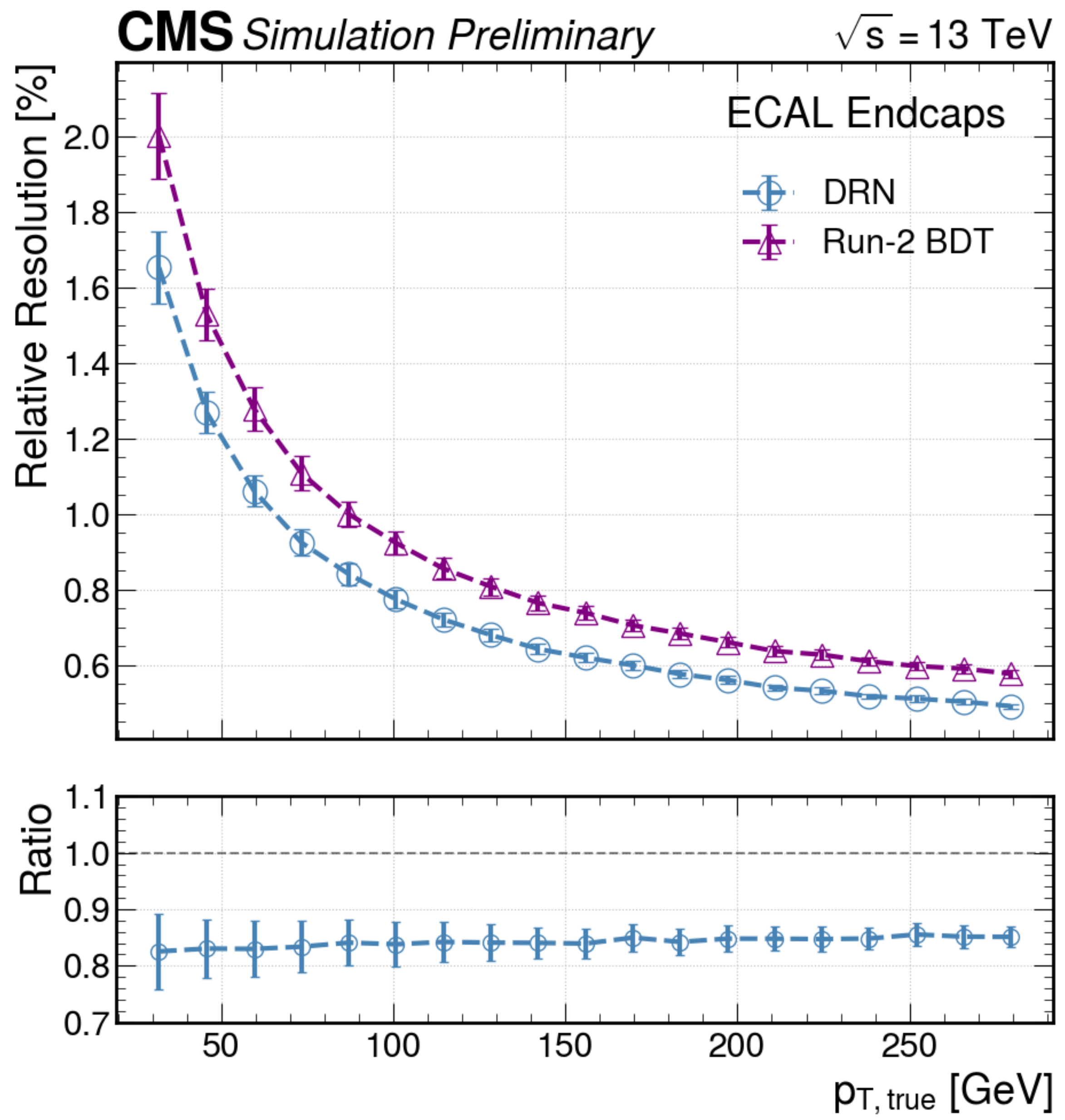
Why Graph Neural Networks:

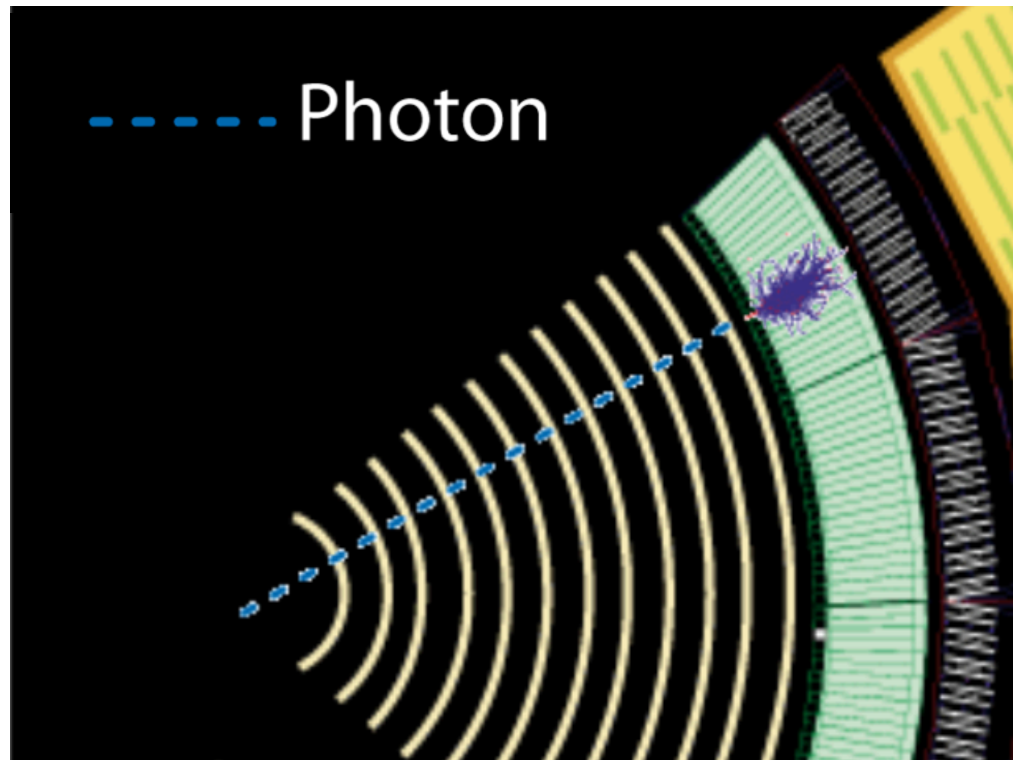
- Natural event representation
- Easily applied to sparse data with variable input size
  - typically we have signal only in small fraction of sensors
- Increasing number of successful implementations in HEP
- Performance improvement in comparison with commonly used Gradient Boosting (GB) models (or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

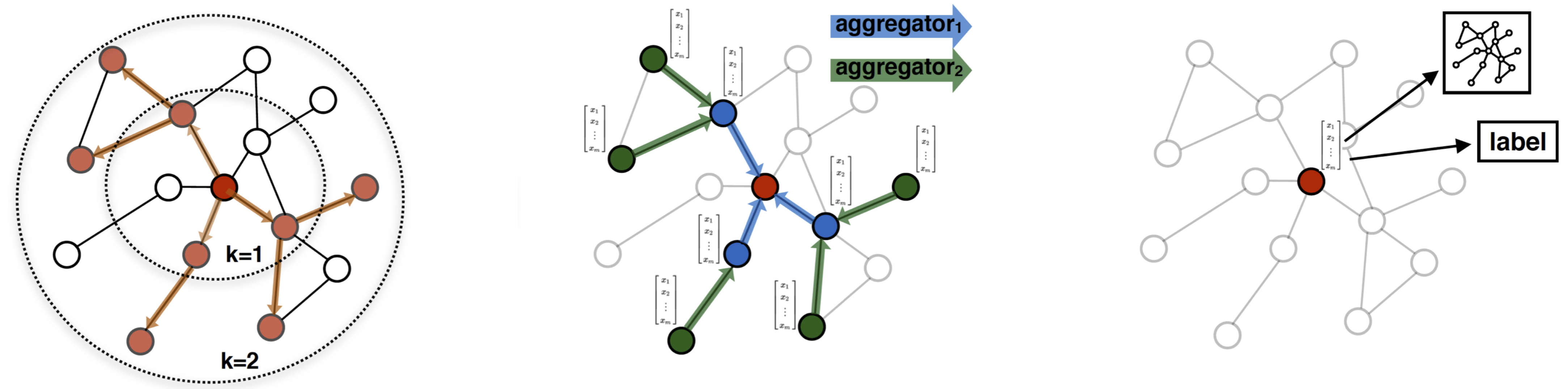
Classification models

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 **->** <u>Self-attention pooling</u> layer (1 node output) **->** MLP readout layer 32->16->1 + sigmoid
- BCE loss function

<u>GraphSAGE</u> (**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

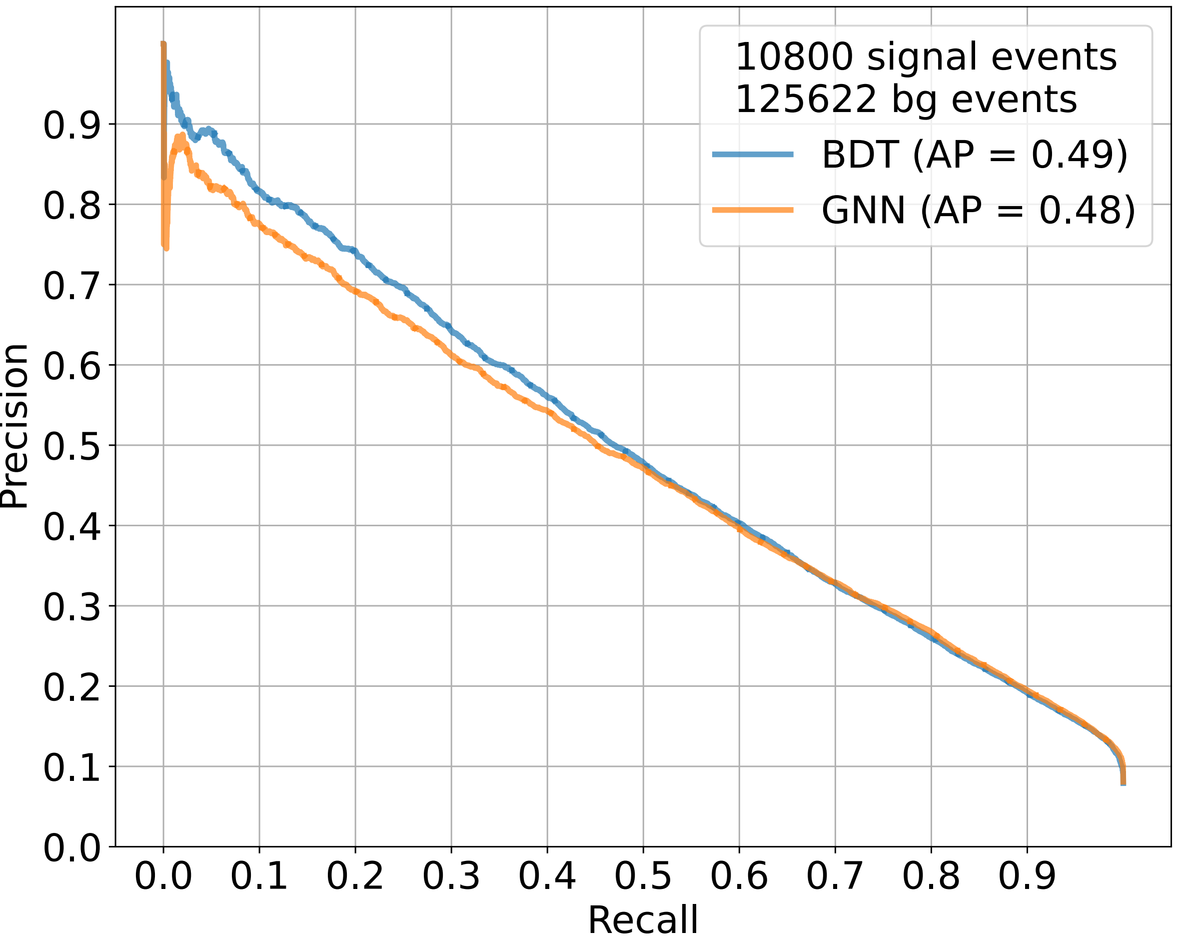
Gradient Boosting (GB) model with ***'first-principle'* feature set** based on global event properties and parameters of most informative hits.

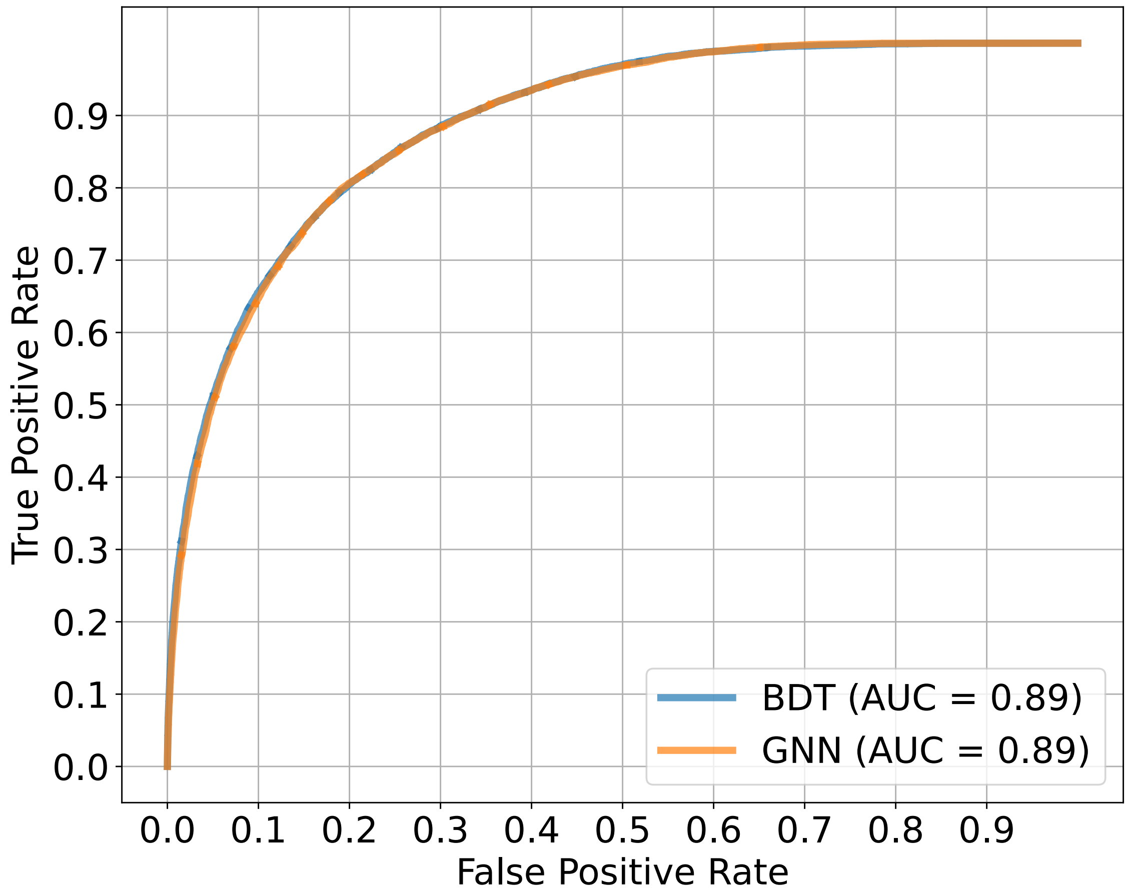
- 13 features in total
  - Fastest hit parameters (4)
  - Z_{min} hit parameters (4):
  - Global events parameters (6)
- Maxdepth = 6
- <200 boosting rounds

Train/test split 50% for both models

Classification performance

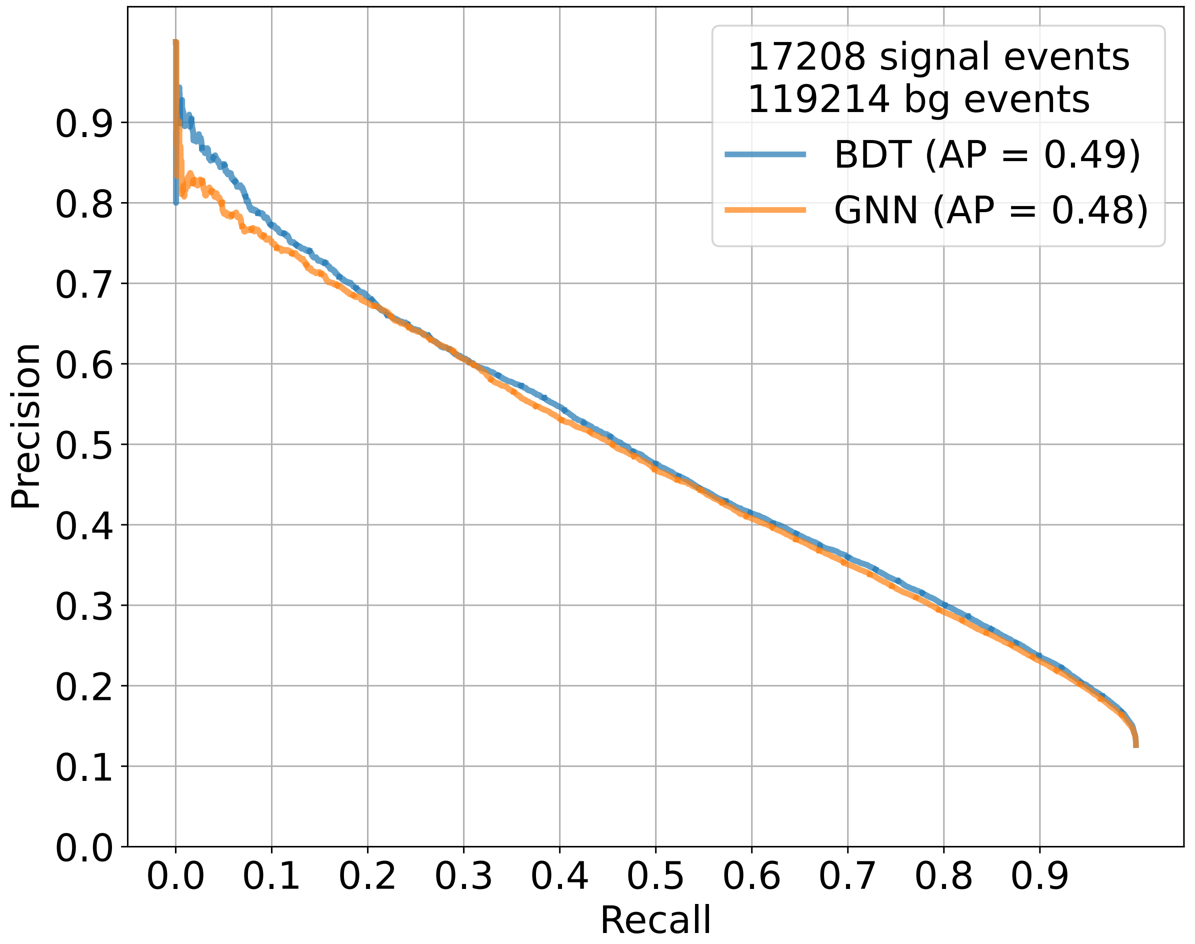
Fastest hit labelling

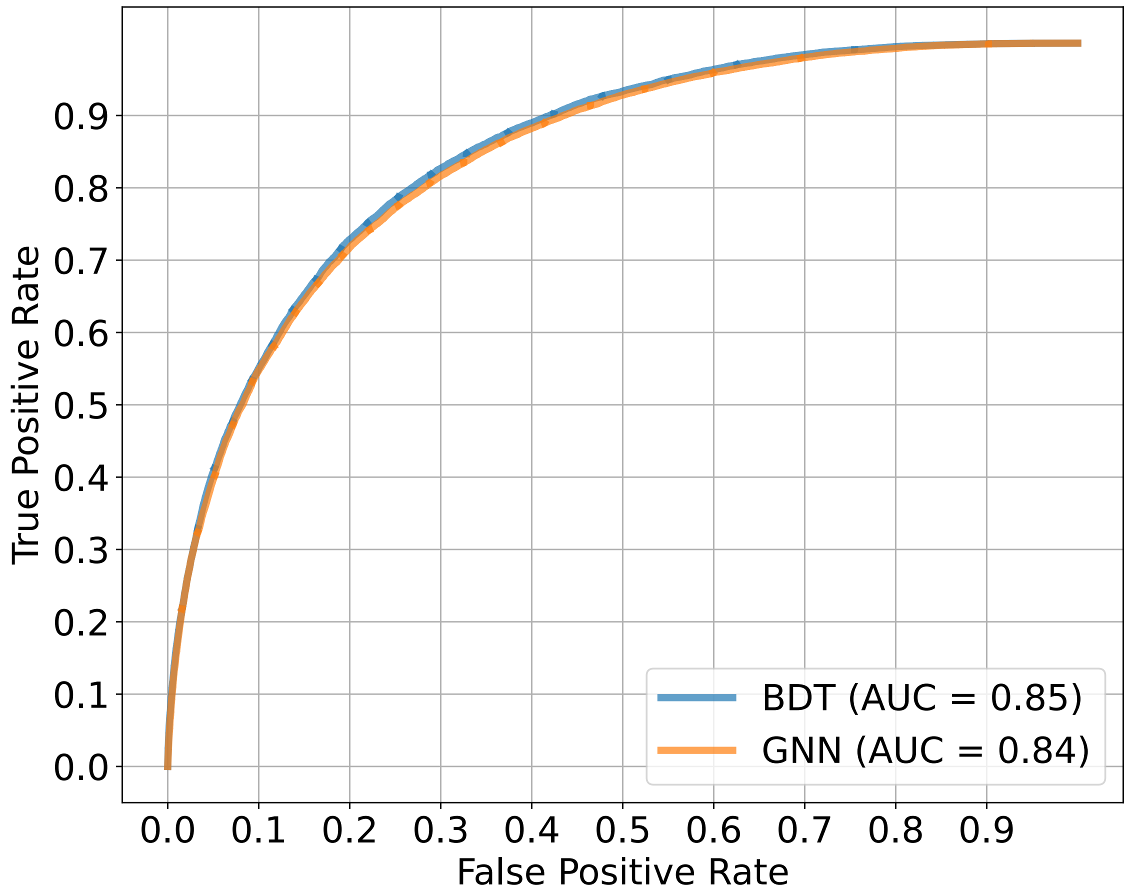




* some hints that models rely mostly on Max(E_{ToF}) distribution

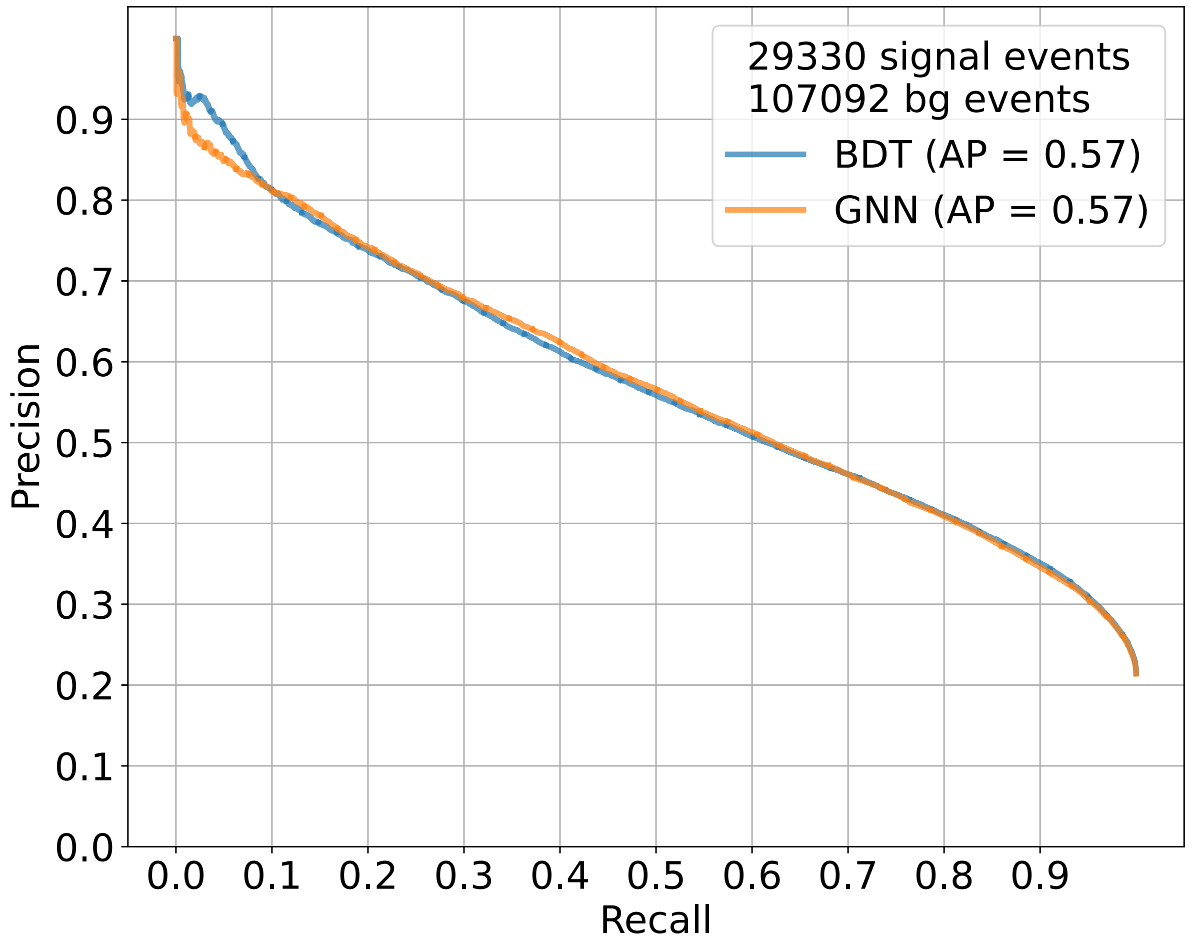
median labelling

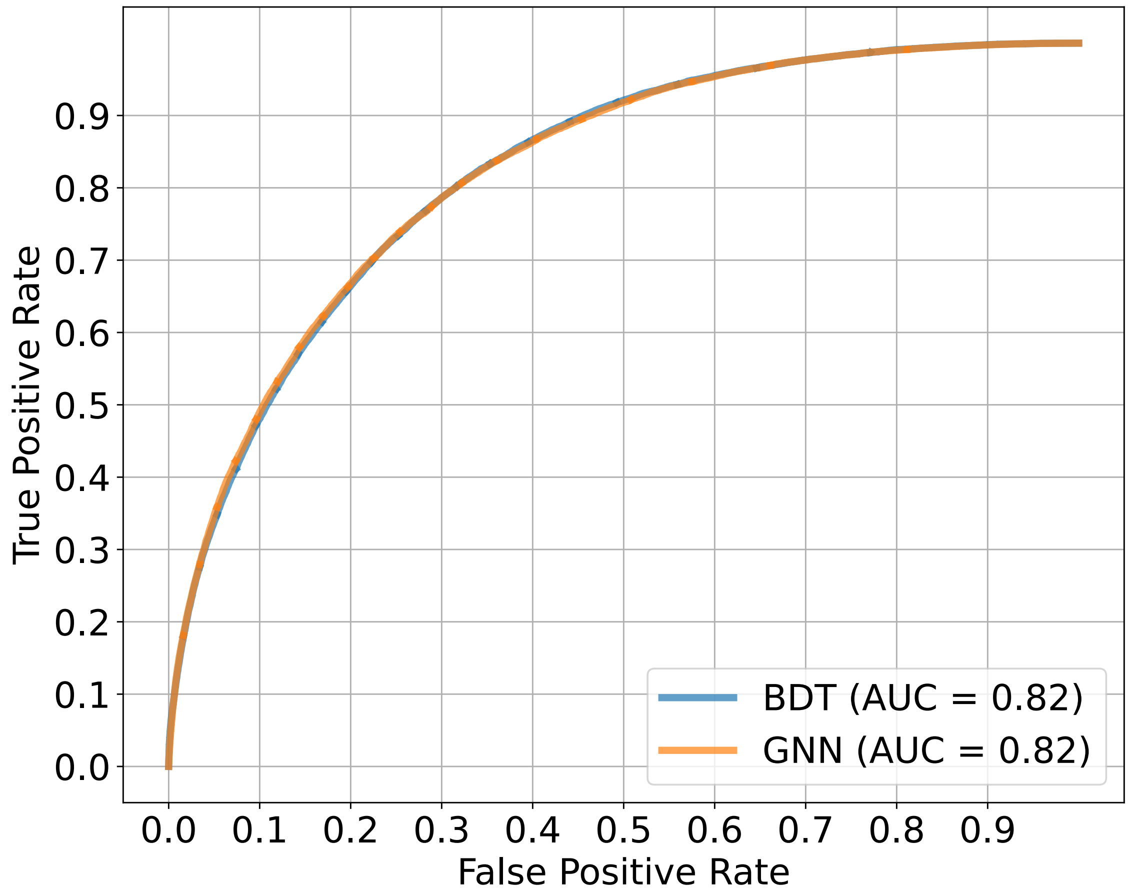




* some hints that models rely mostly on Med(E_{ToF}) distribution

“Best” hit labelling



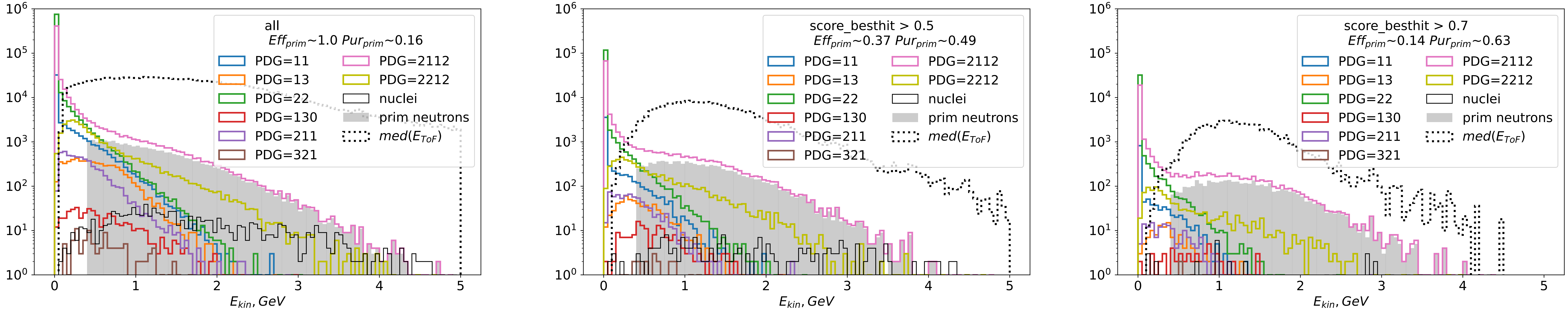


- Overall classification performance slowly decreases with loosening criteria of “good” neutron events (ROC_AUC)
- Larger signal/background ratio gives better PR
- Similar performance for BDT and GNN for all 3 labelling approaches

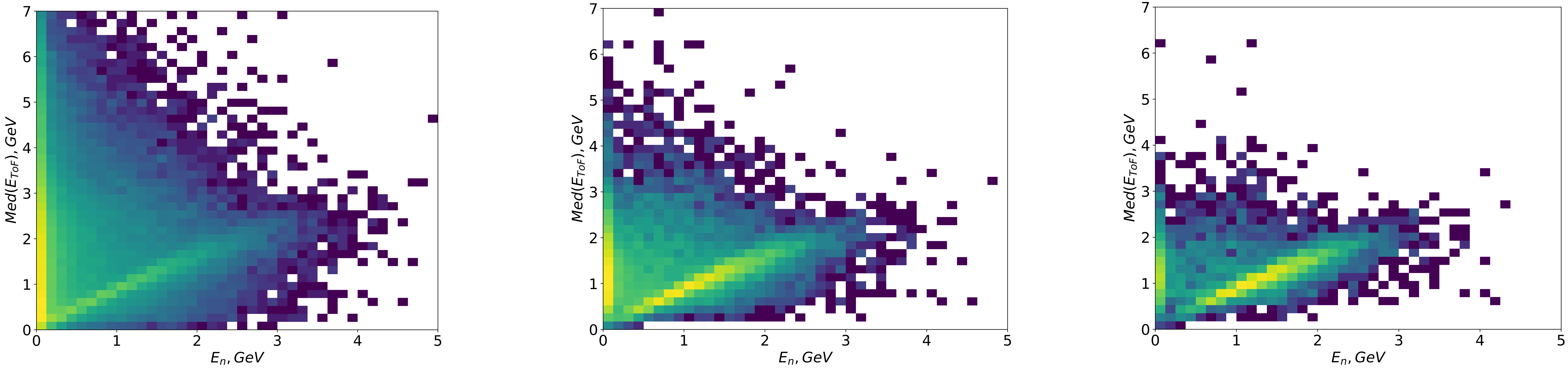
➡ ‘first-principle’ features look comprehensive in this setting

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

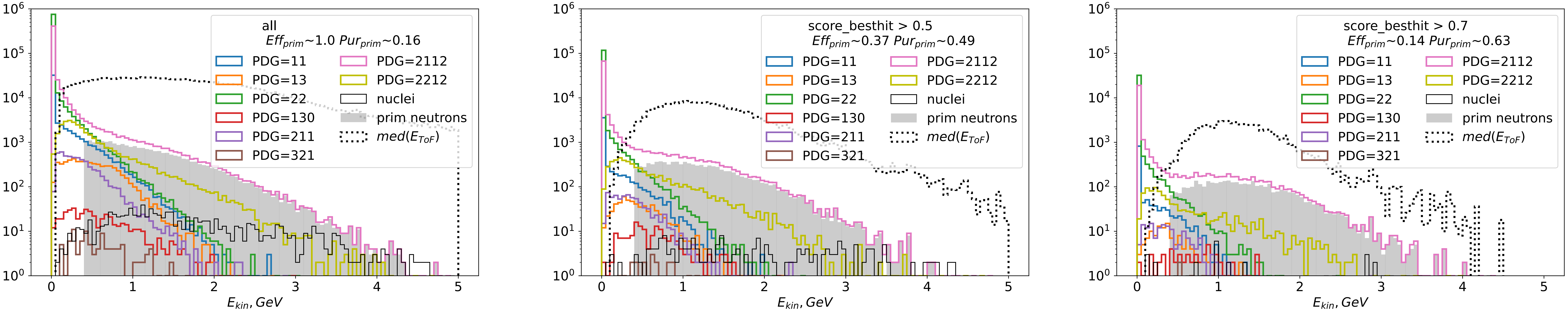
Example of resulting energy spectra



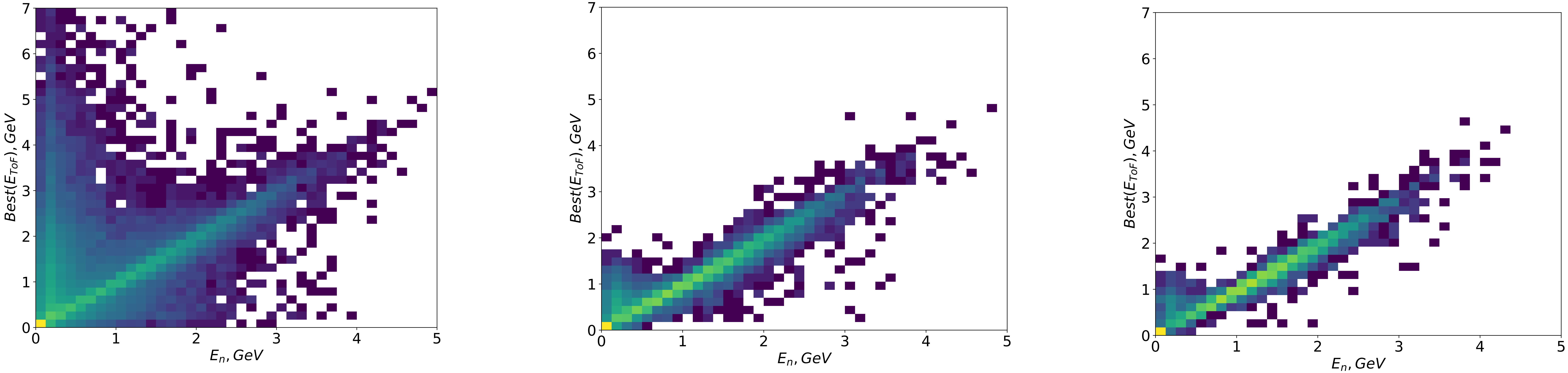
Median(E_{ToF}) neutron energy estimation (naive approach):



Example of resulting energy spectra



Best(E_{ToF}) neutron energy (to be estimated, e.g. by GNN):



Conclusion

- Event structure-based GNN and first principle GBDT classifiers were tested on a challenging problem of reconstructing neutrons at energies lower than 3GeV in presence of background energy depositions

➡ Similar performance of GNN and GBDT classifiers in various signal labelling settings gives a hint that GNN doesn’t learn more than first-principle event observables used in BDT

- Loose requirements on a ‘good’ neutron events gives better precision-recall characteristic of neutron selection
- Wide range of precision-recall-bias is available to trade for neutron energy spectrum reconstruction

Outlook:

- GNN-based neutron energy reconstruction in presence of background hits
- Evaluation of physics performance using estimated PR-characteristics is ongoing

Backup

Detector response

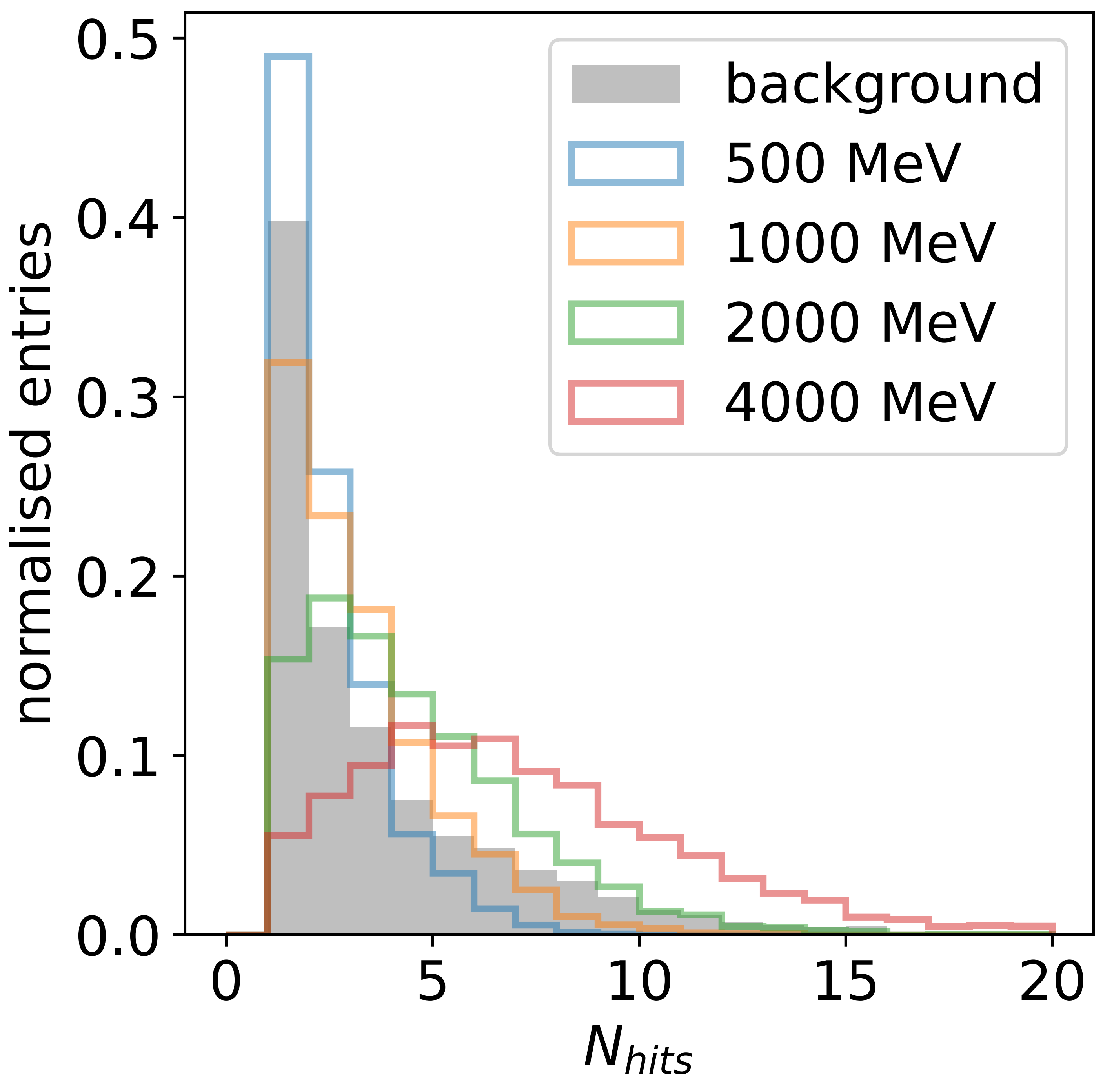
Position and deposited energy in scintillator cells

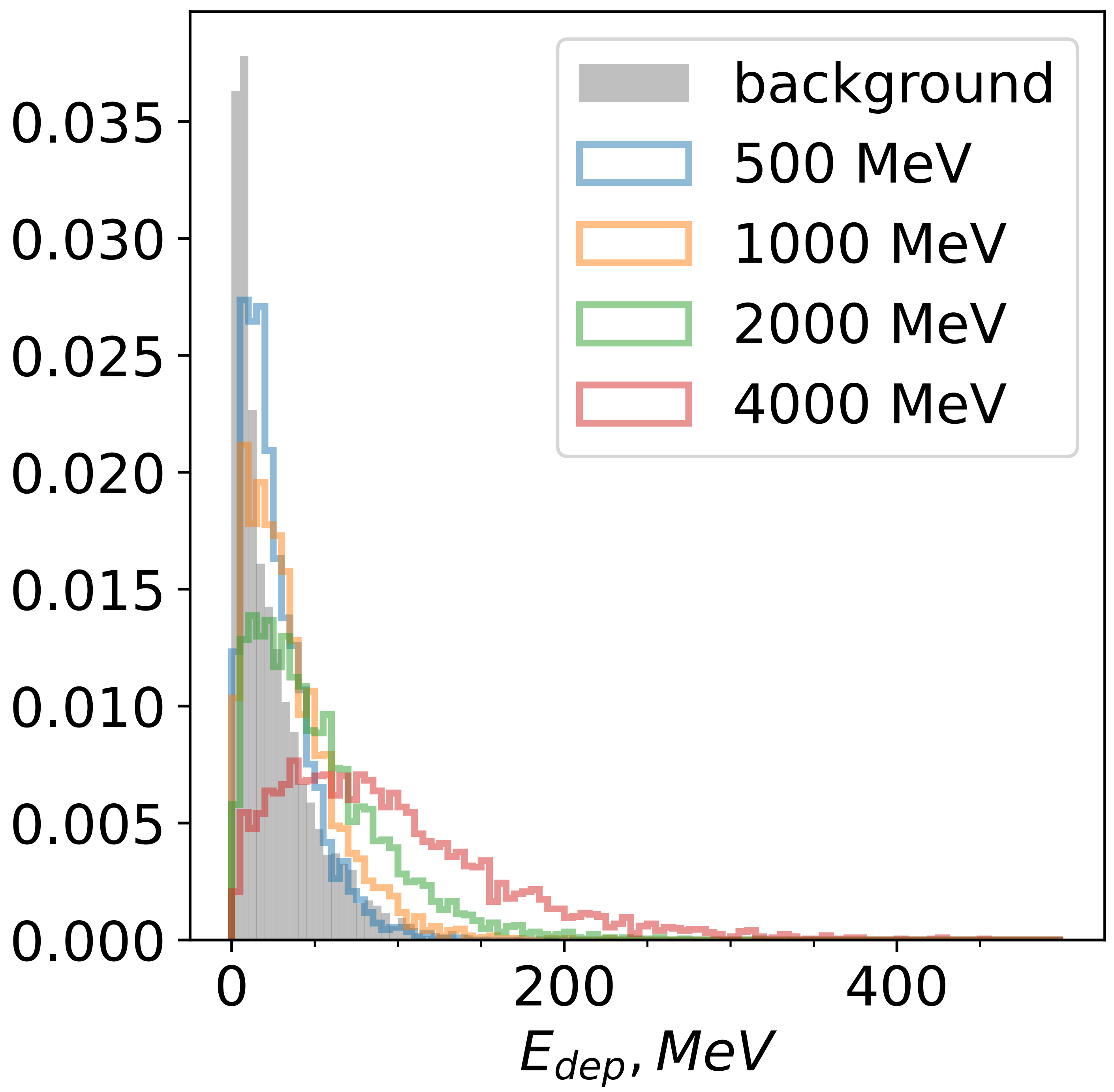
MC simulations:

signal - neutrons with discrete energies

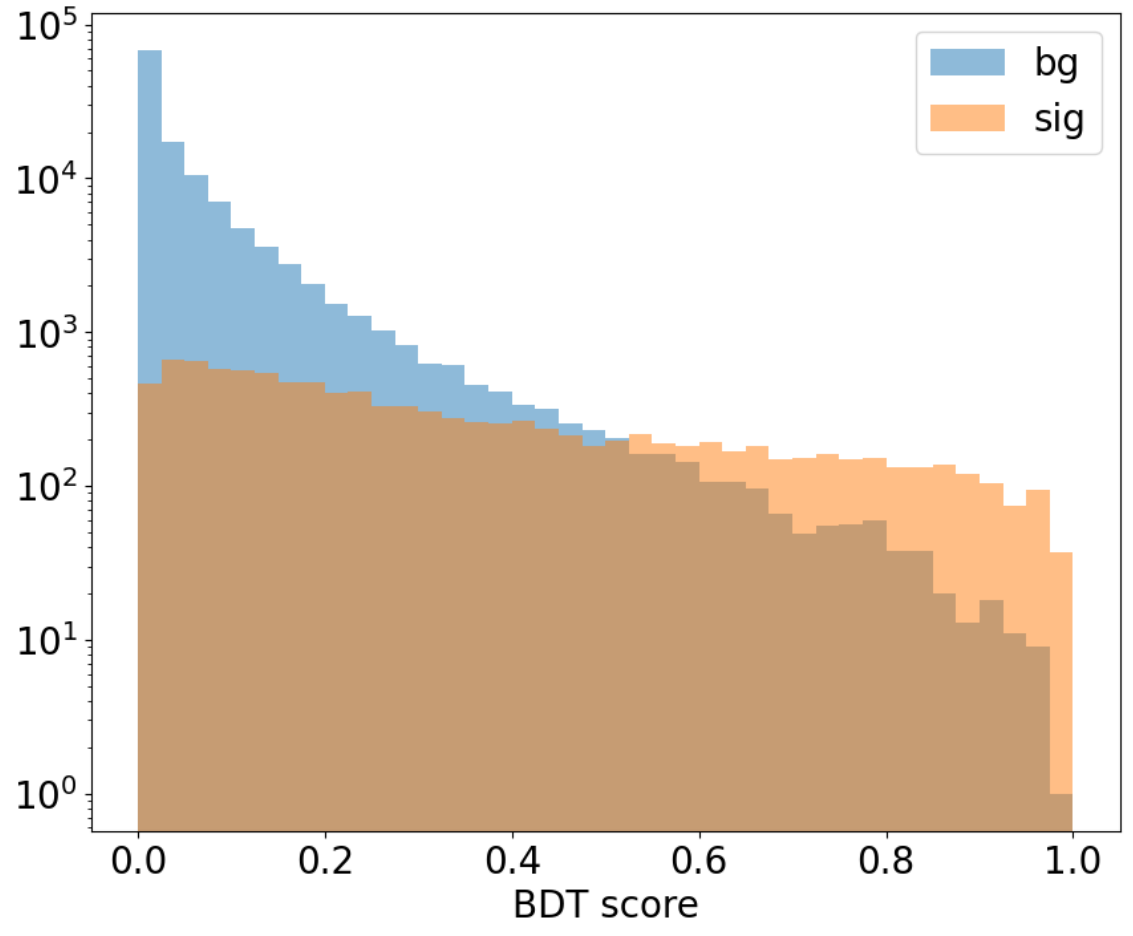
background - XeCsI @3.9AGeV (all but primary neutrons)

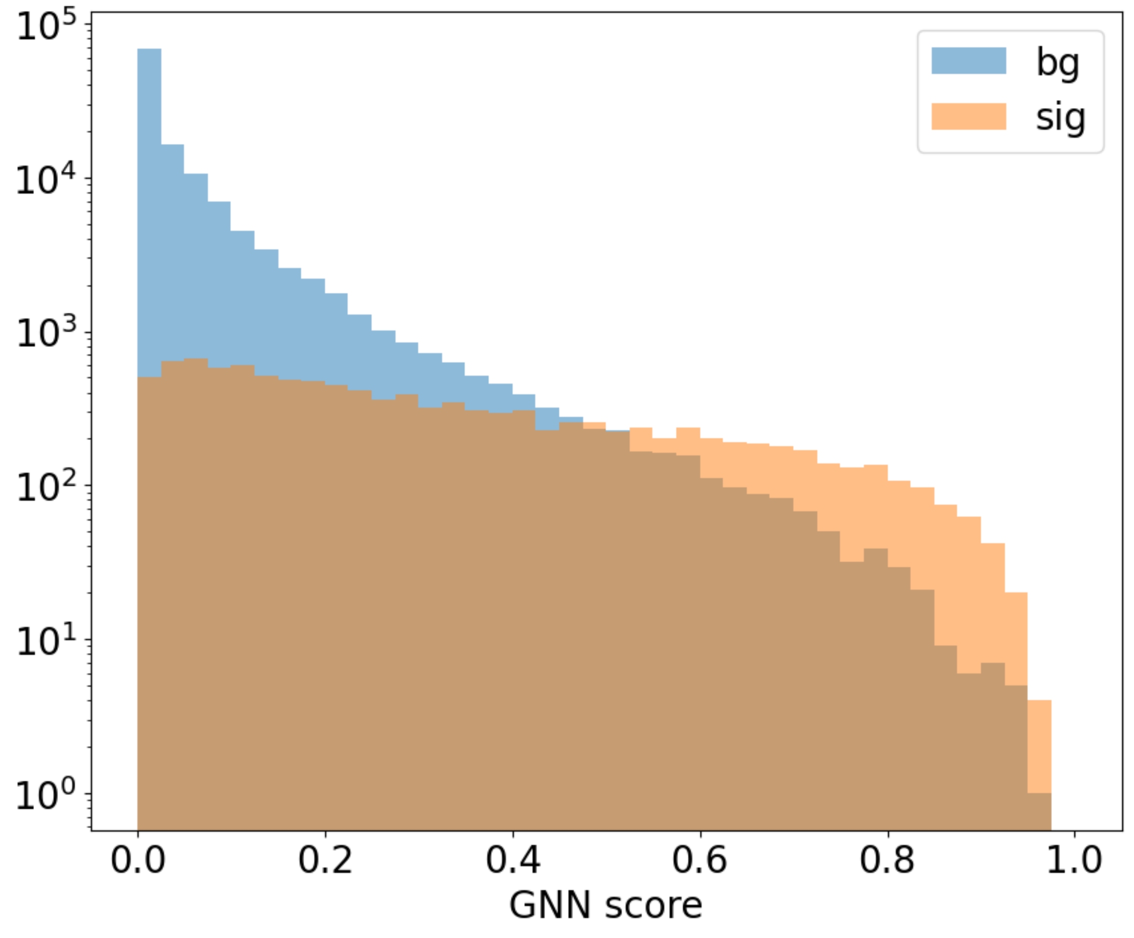
Event level:



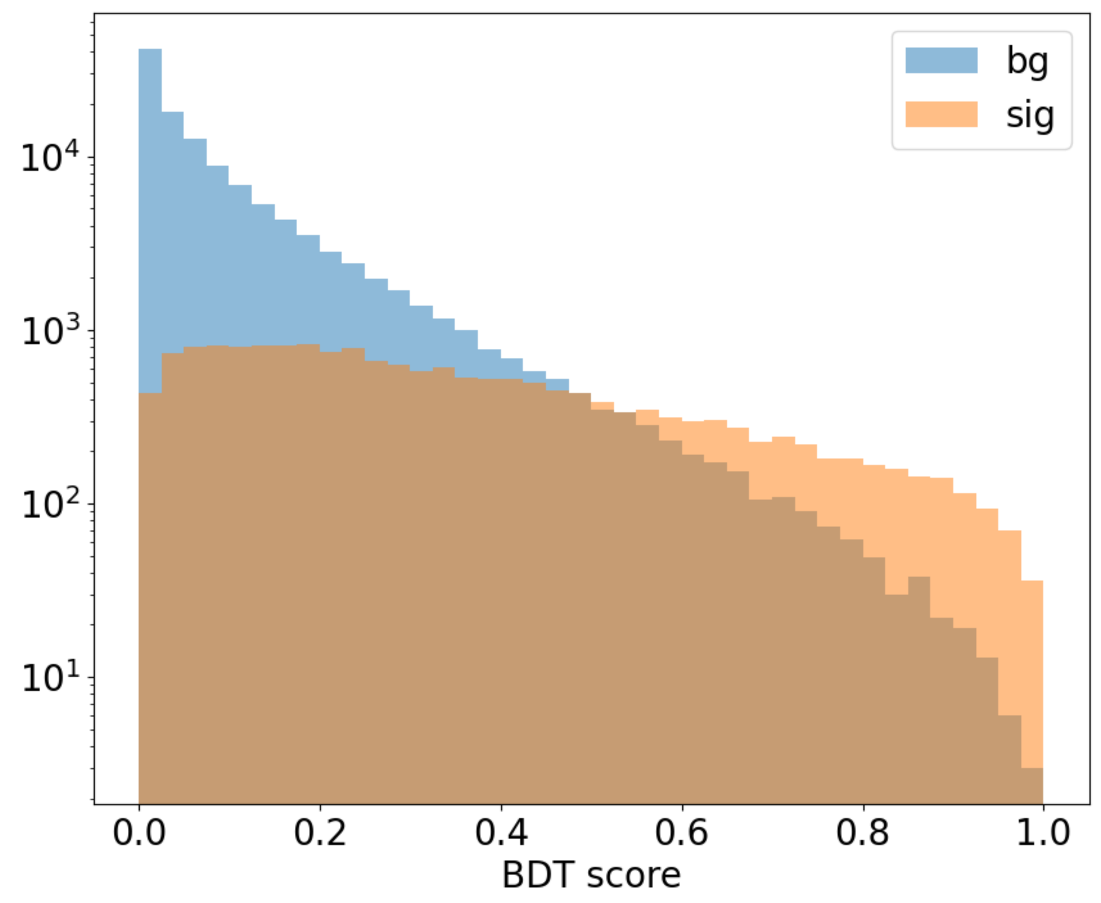


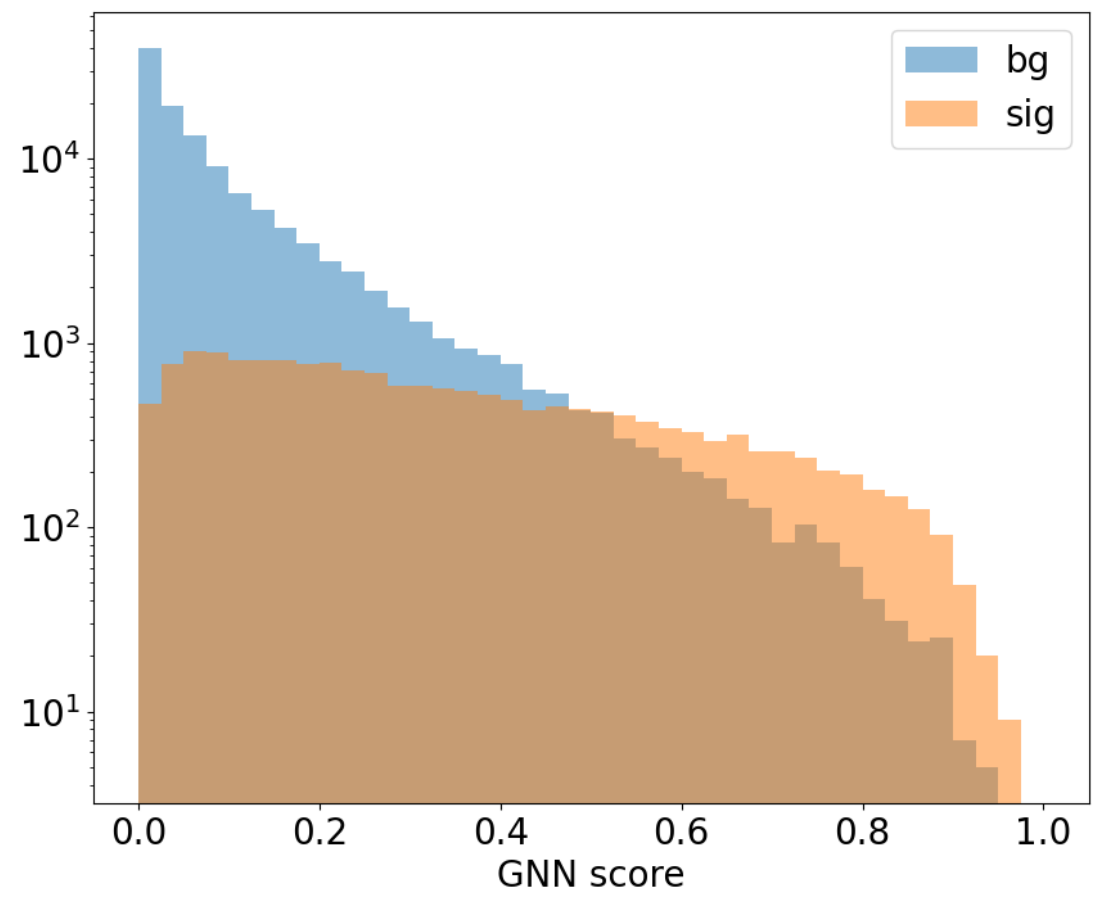
- Fastest hit
  - 10800 signal events
  - 125622 bg events
  - s/n = 0.086



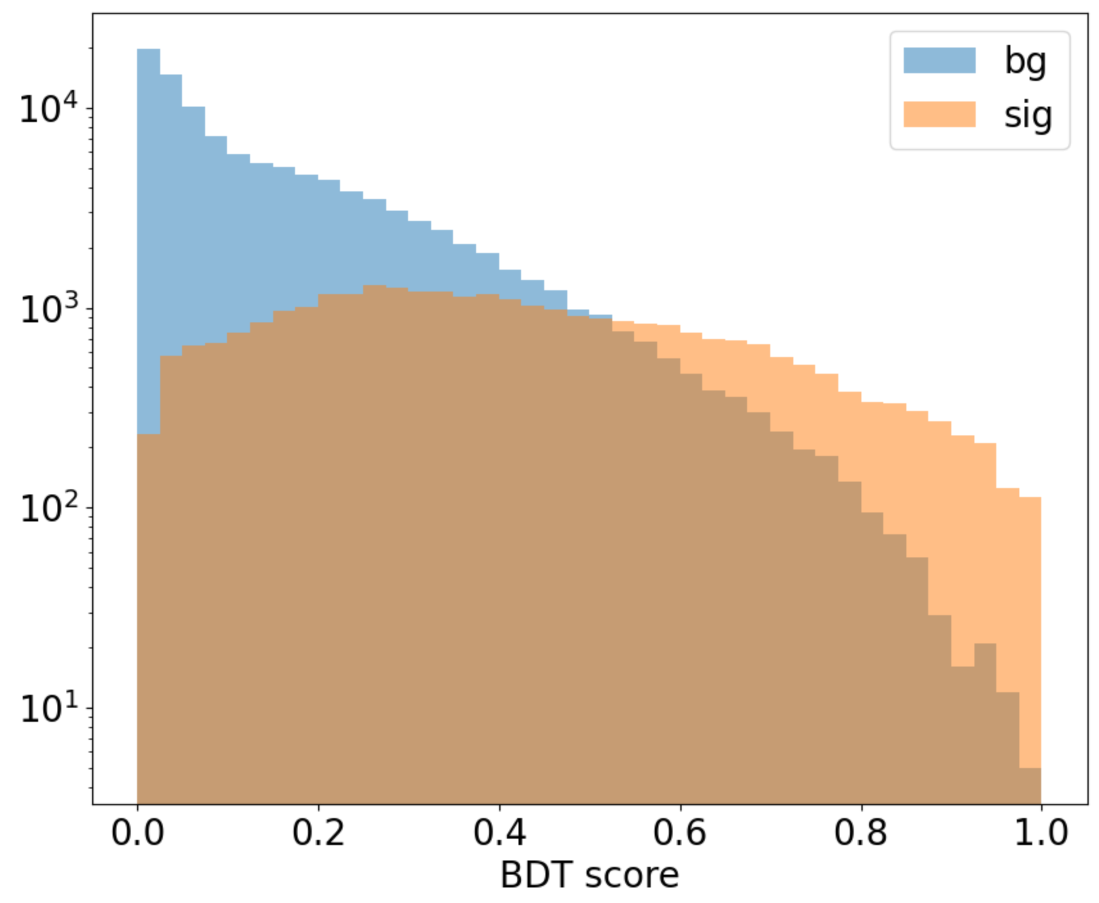


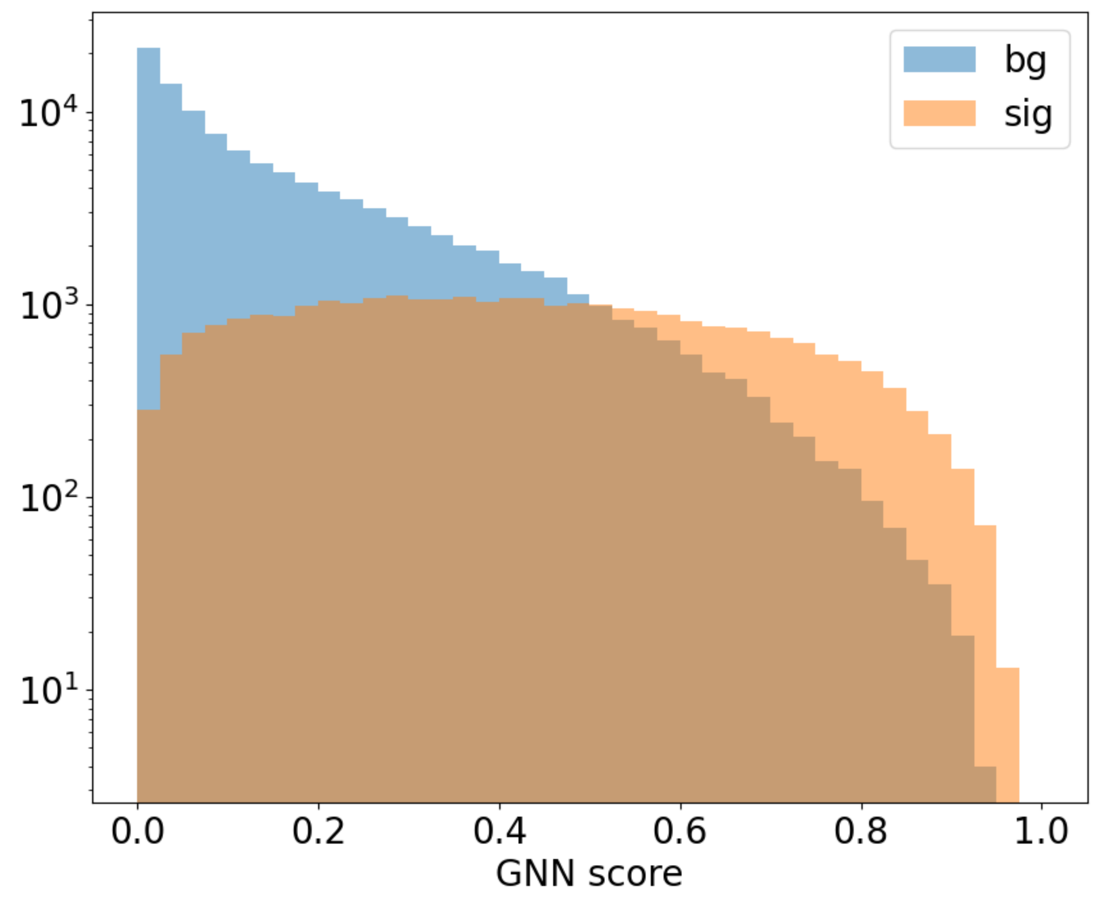
- Median of all hits
  - 17208 signal events
  - 119214 bg events
  - s/n = 0.144



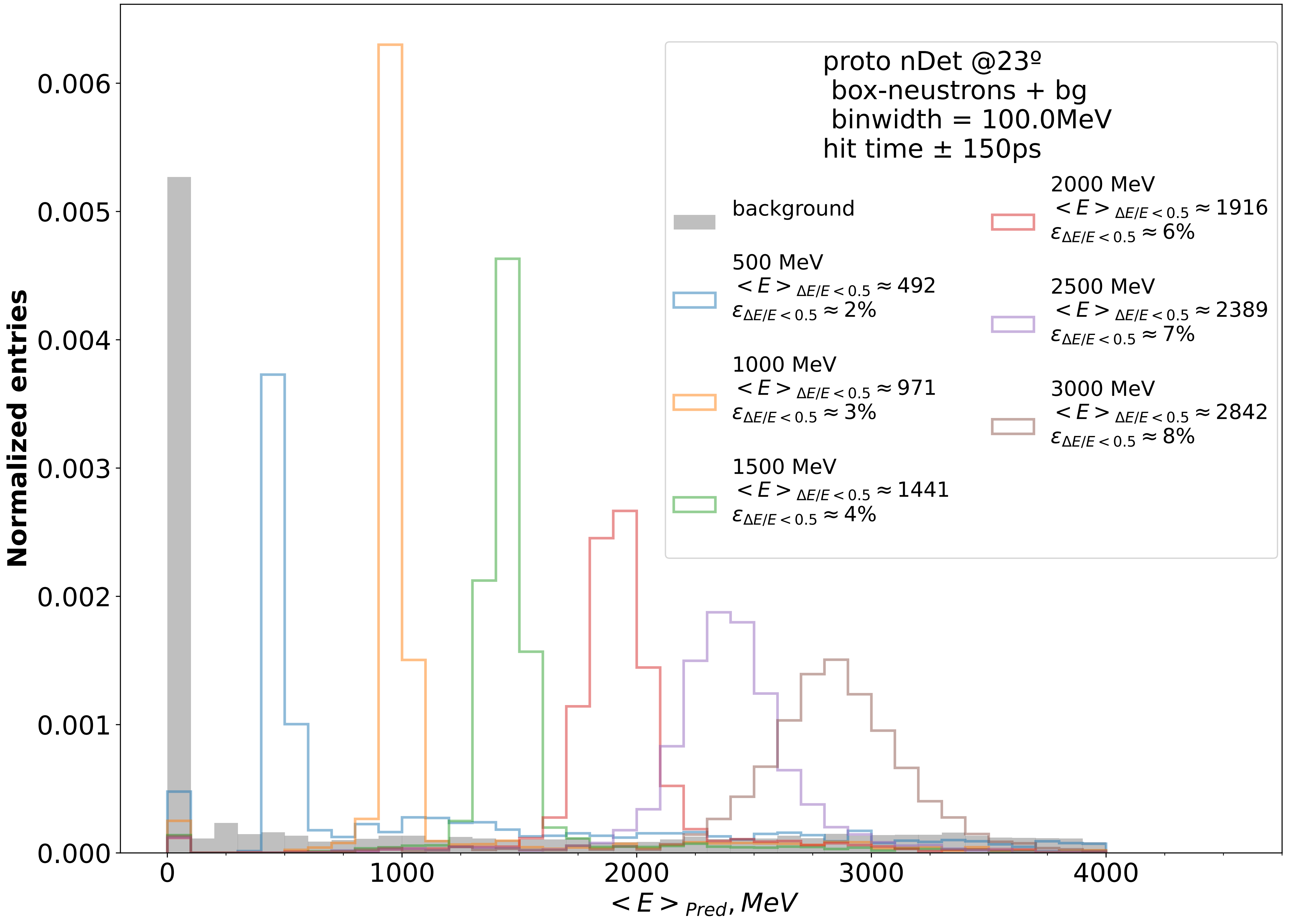


- “Best” hit
  - 29330 signal events
  - 107092 bg events
  - s/n = 0.274





Preliminary hit classification performance example for a simplified case of single neutron mixed with a random background event



Classification models XeCsI@3.9GeV

Event structure model PyG

Graph neural network (GNN)

- (x,y,z), E_{dep}, T_{hit} (after first hit) + E_{ToF} (optional)
- Fully connected hit graphs
  - 10 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

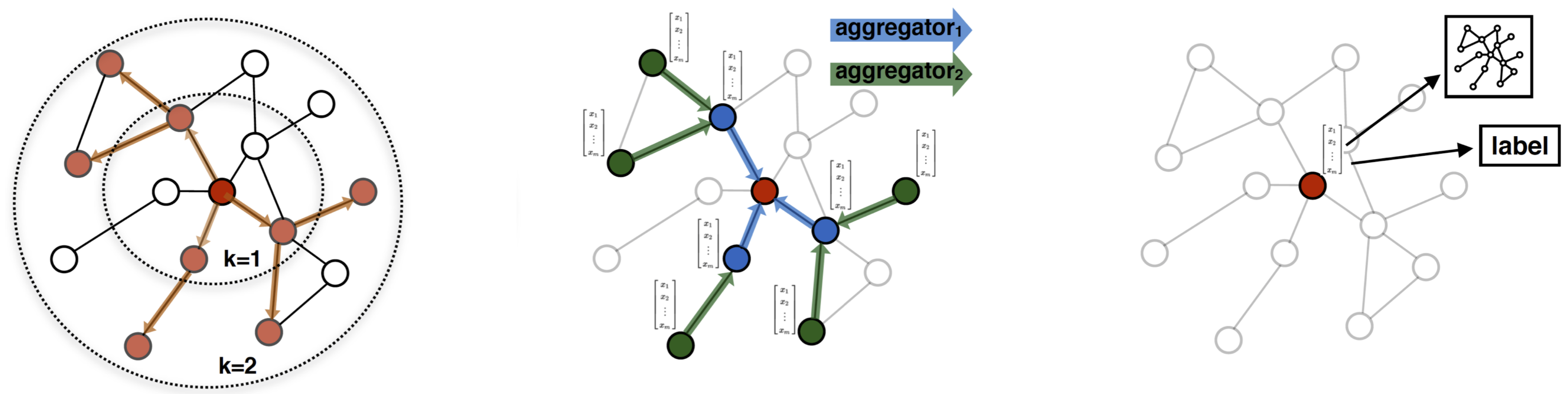
VS.

First principle model CatBoost

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

- 12(ToF)/13(no ToF) features in total
- Maxdepth = 6
- ~200 boosting rounds

GraphSAGE (**SA**mple and aggre**G**at**E**) architecture GNN:



Sample neighbourhood of graph nodes

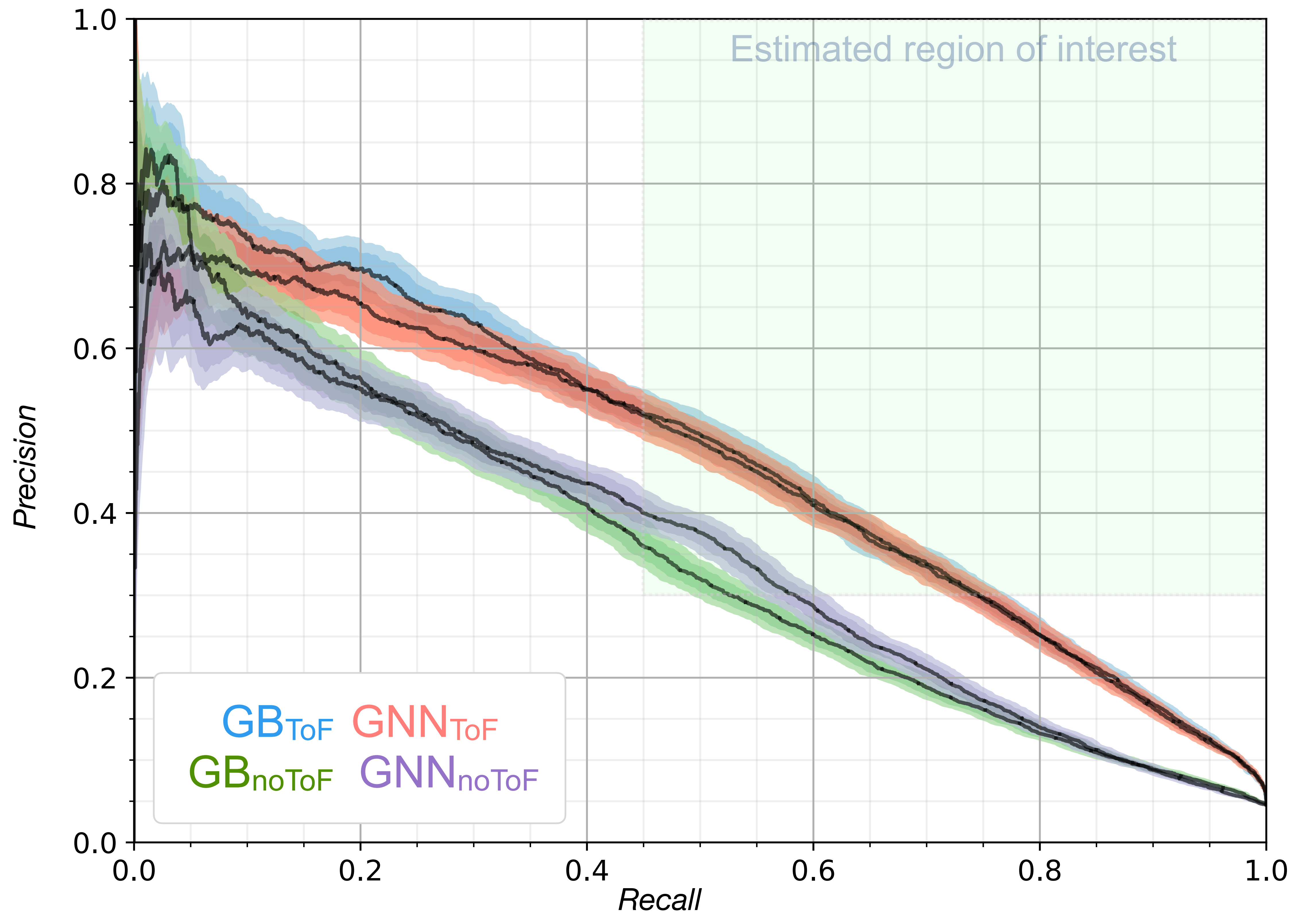
Aggregate feature information from neighbours

Get graph context embeddings for node using aggregated information

2 sets of GNN and GB **classifiers**:

1. Using $\mathbf{E_{ToF}}$ feature for classification
   - Biased to the parameters of simulations
2. **No time-of-arrival** information is **used**
   - Less dependent on simulation

Classification performance XeCsI@3.9GeV



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

- Fastest hit
  - 10800 signal events
  - 125622 bg events
  - s/n = 0.086

- Median of all hits
  - 17208 signal events
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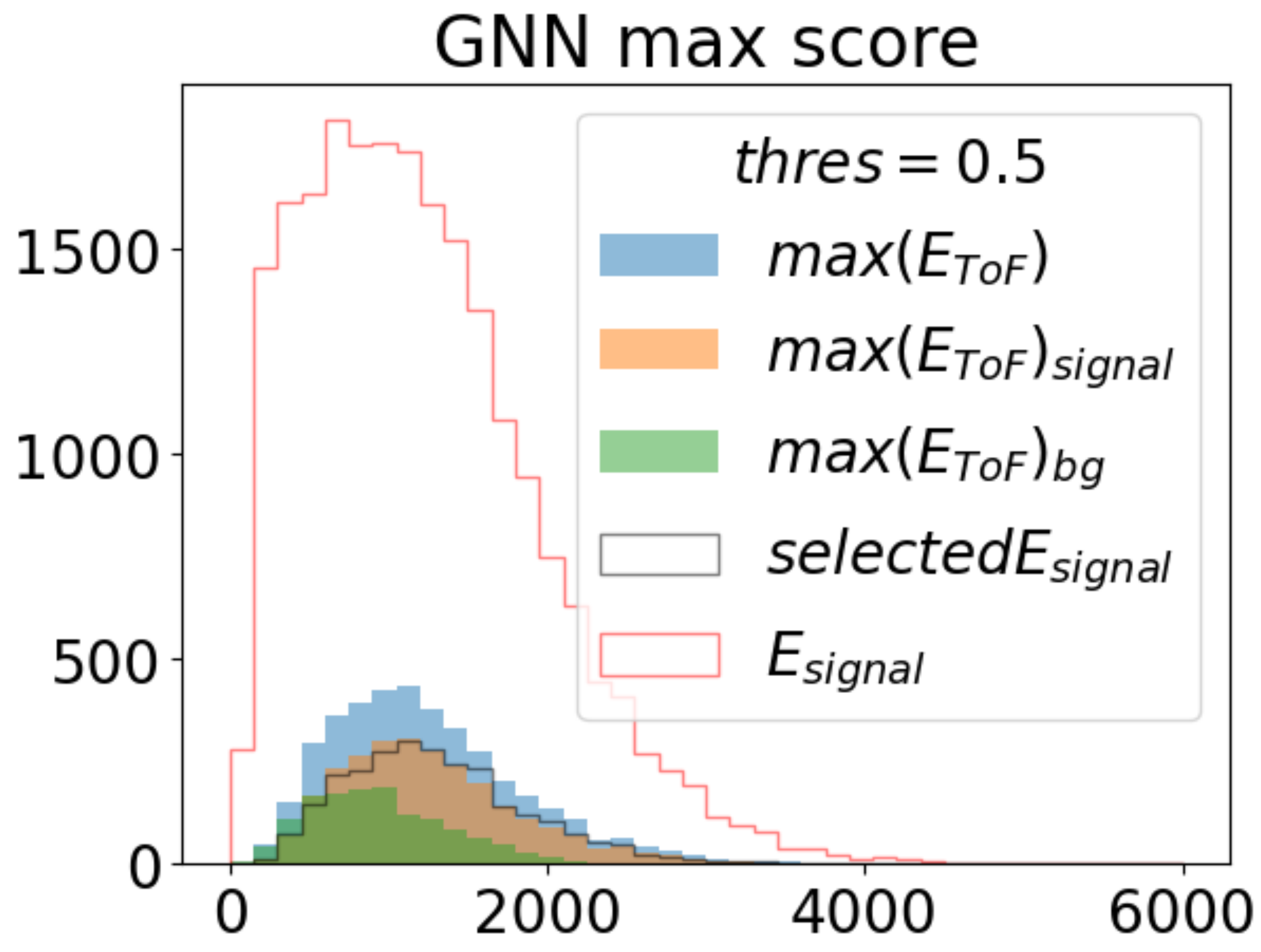
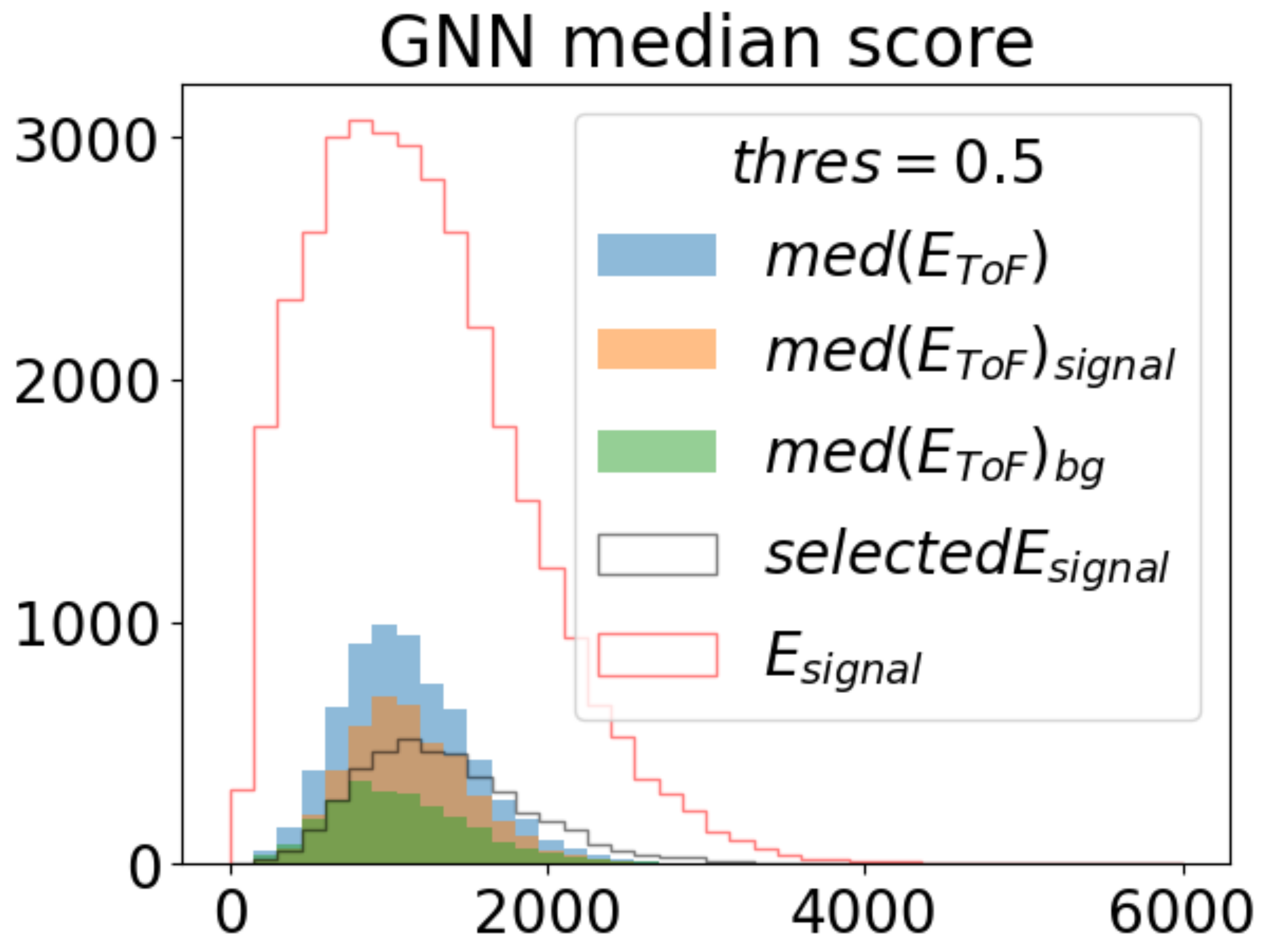
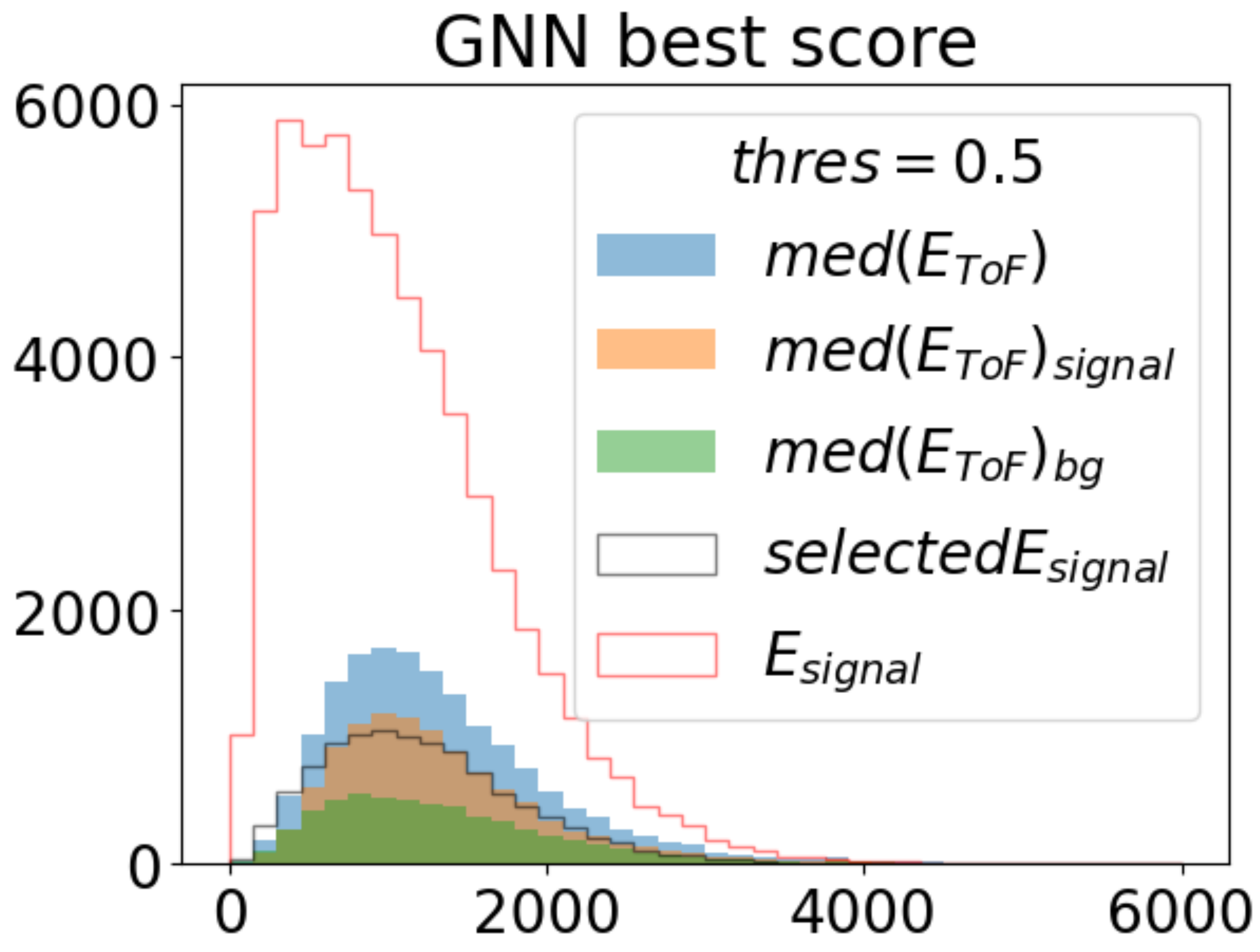
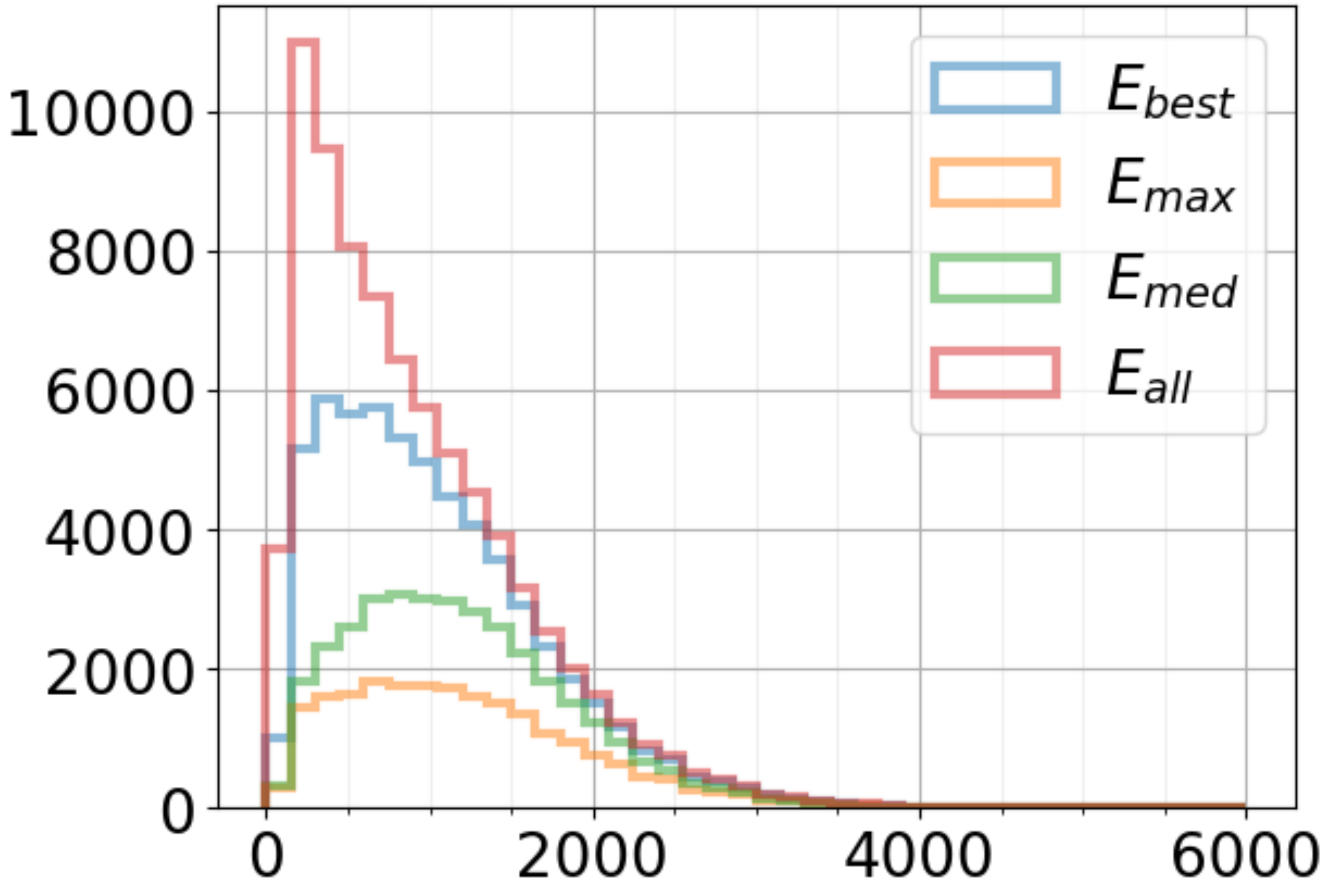


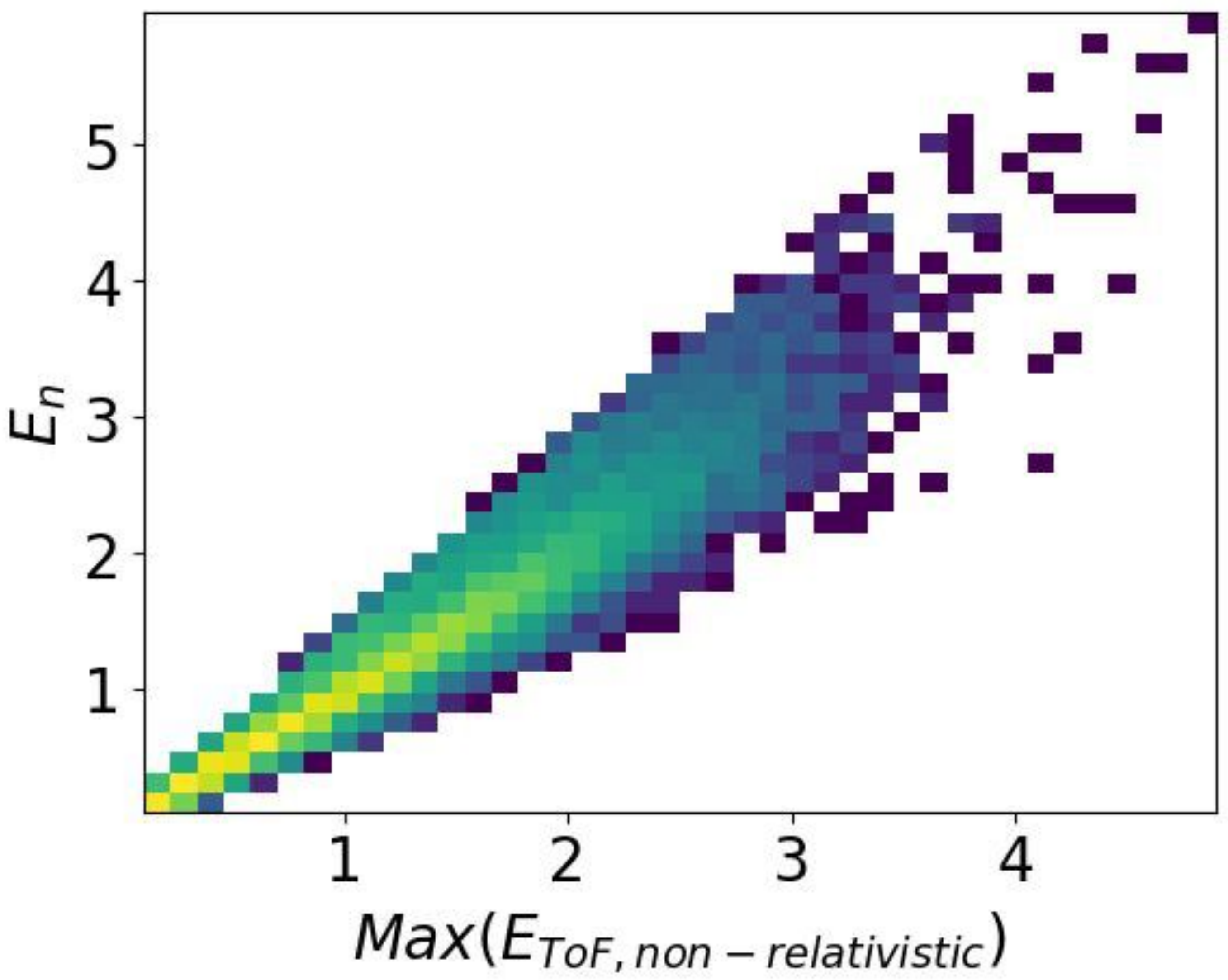




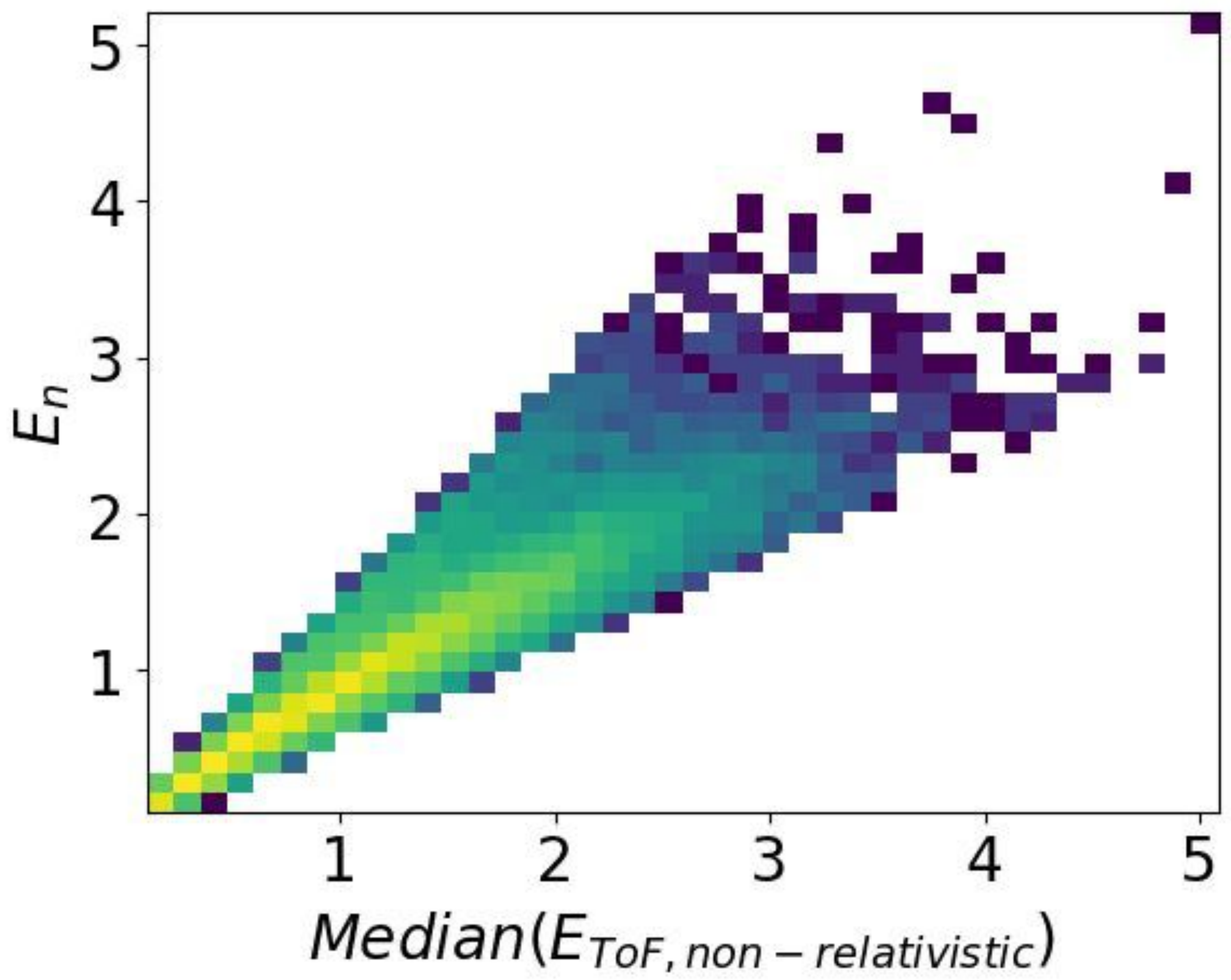
neutron energy

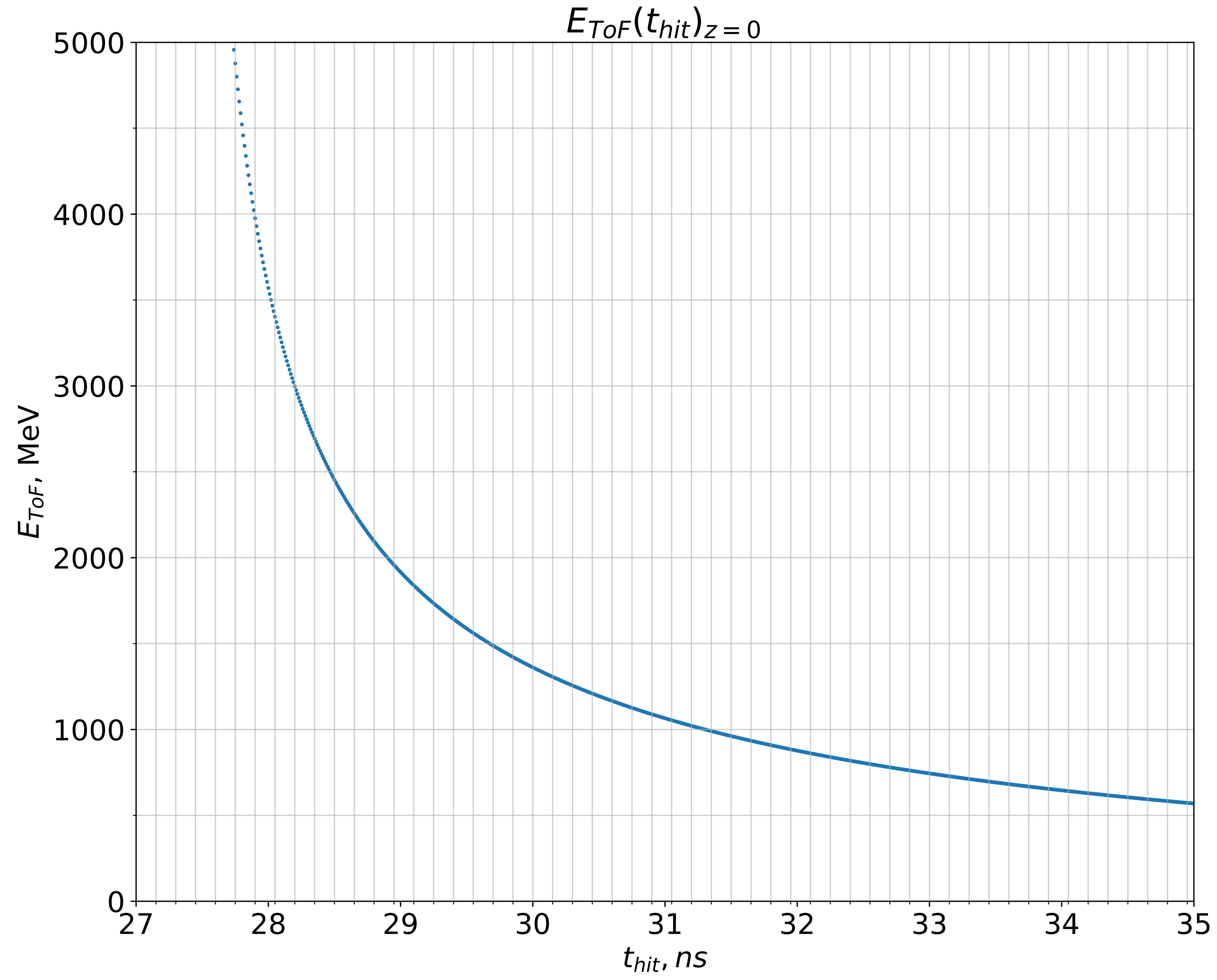


after max selection



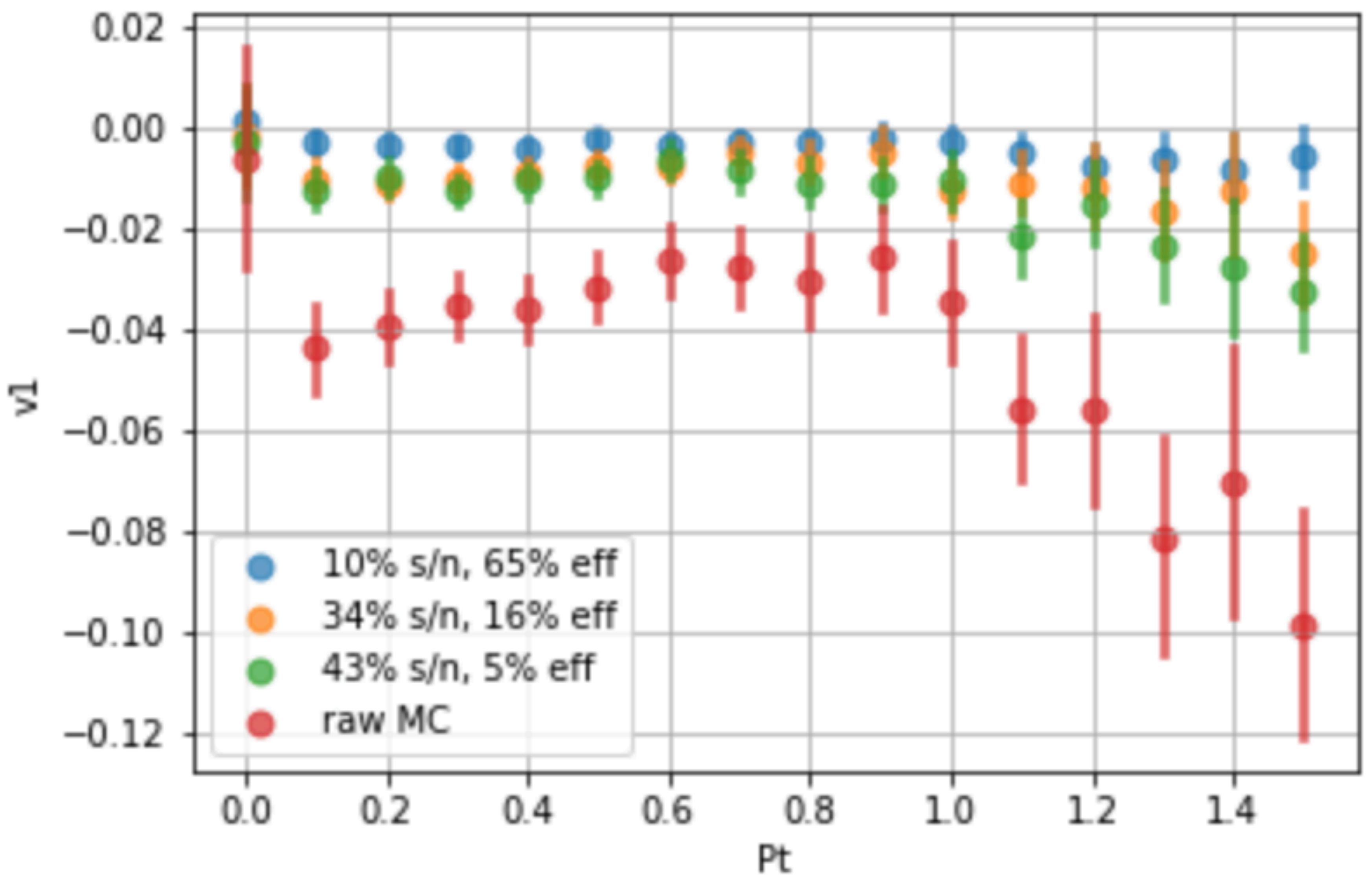
after med selection

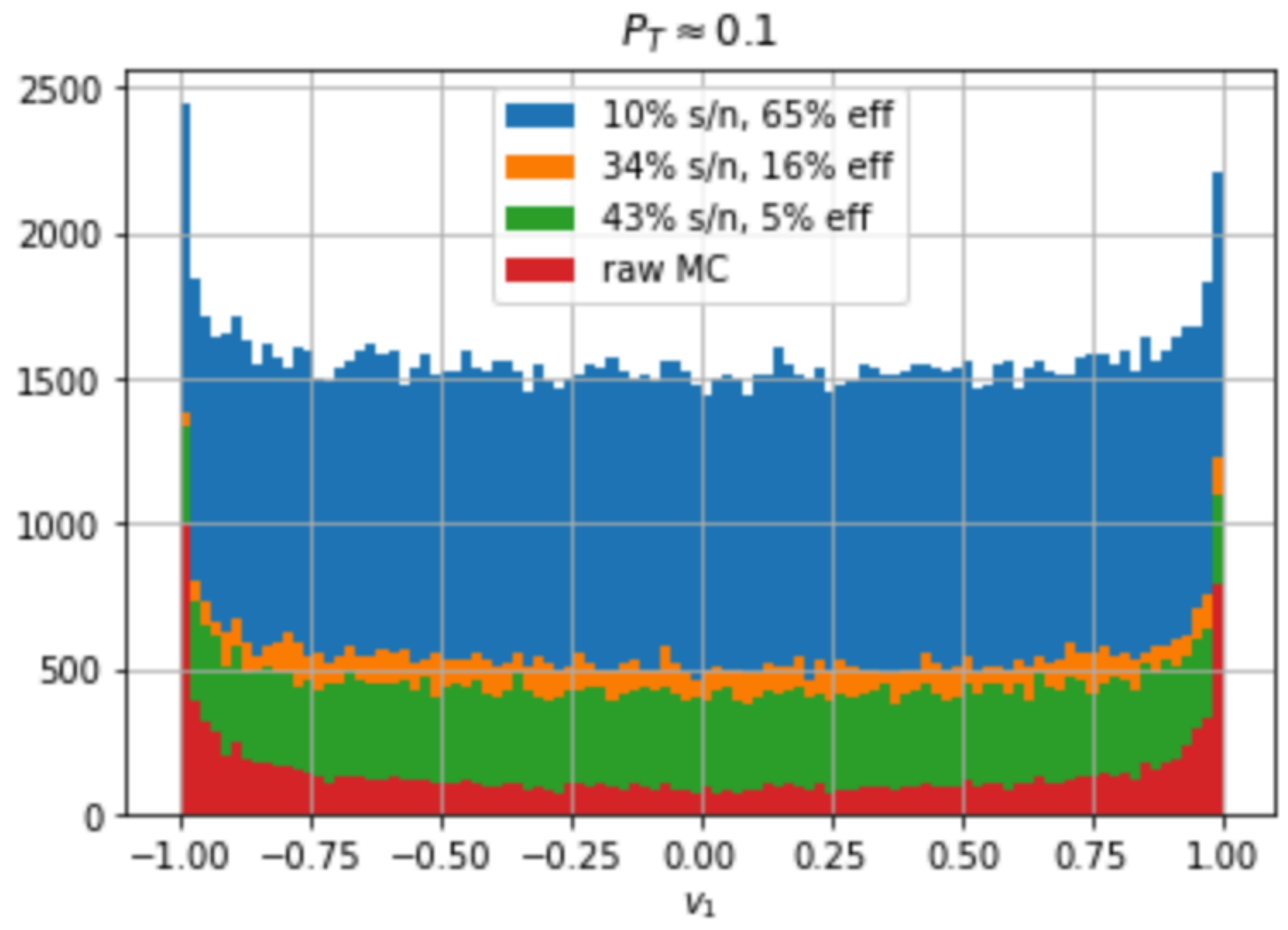


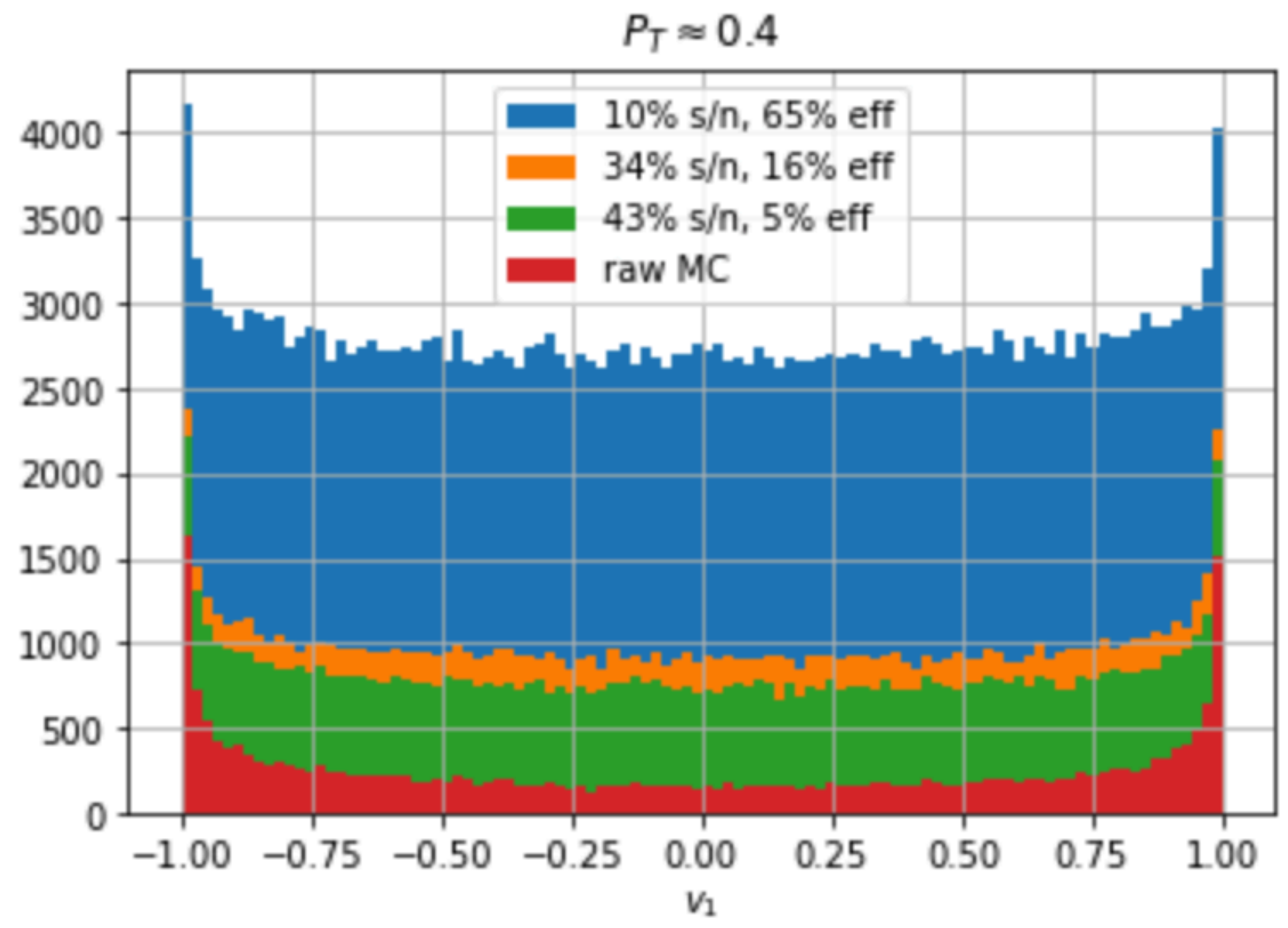


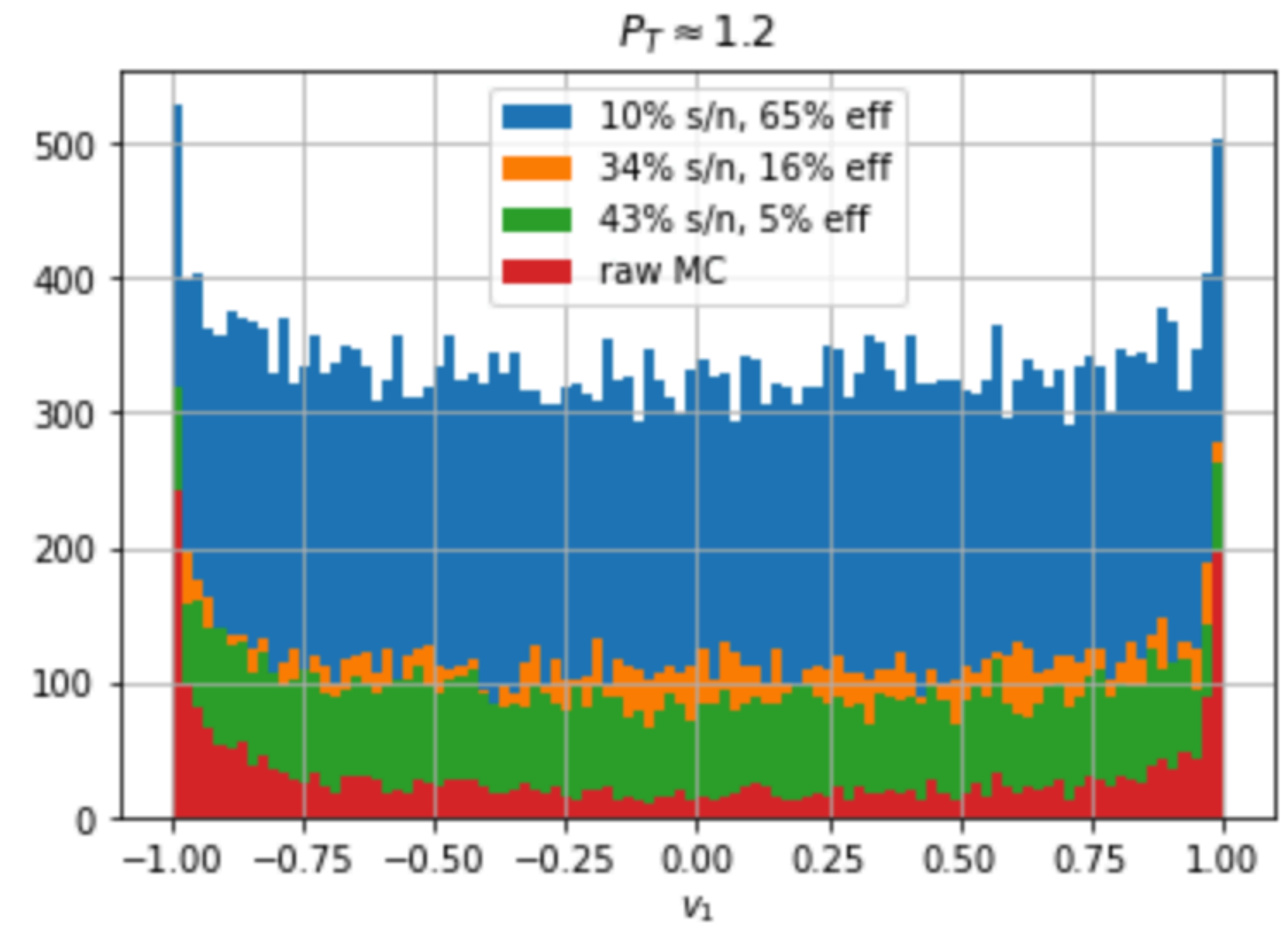
v1 vs Pt distortion

- signal - neutrons from sin reaction (4π)
- noise - Pt is sampled from signal, v1 - flat distribution
- s/n ratios from classifier test



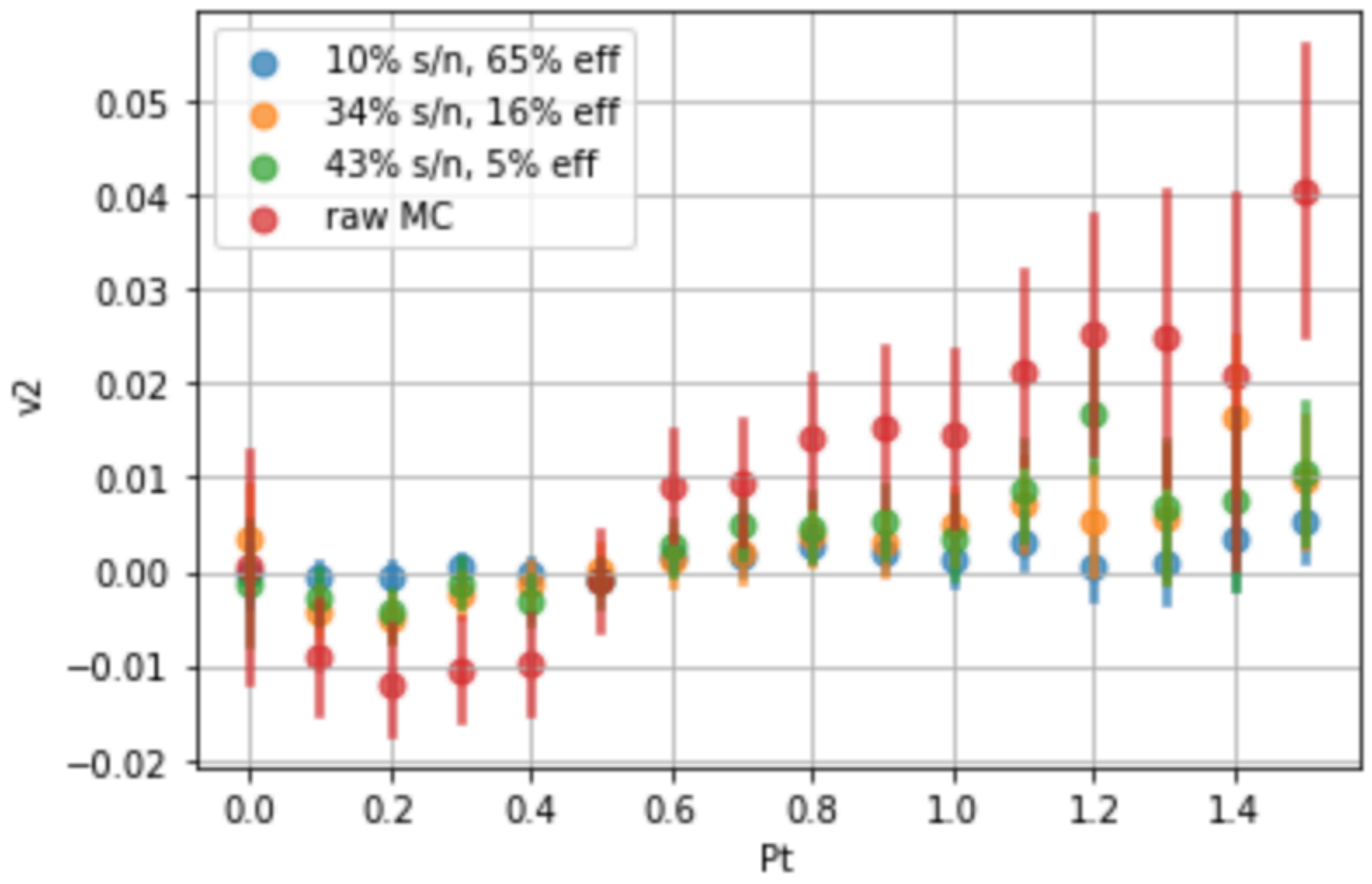


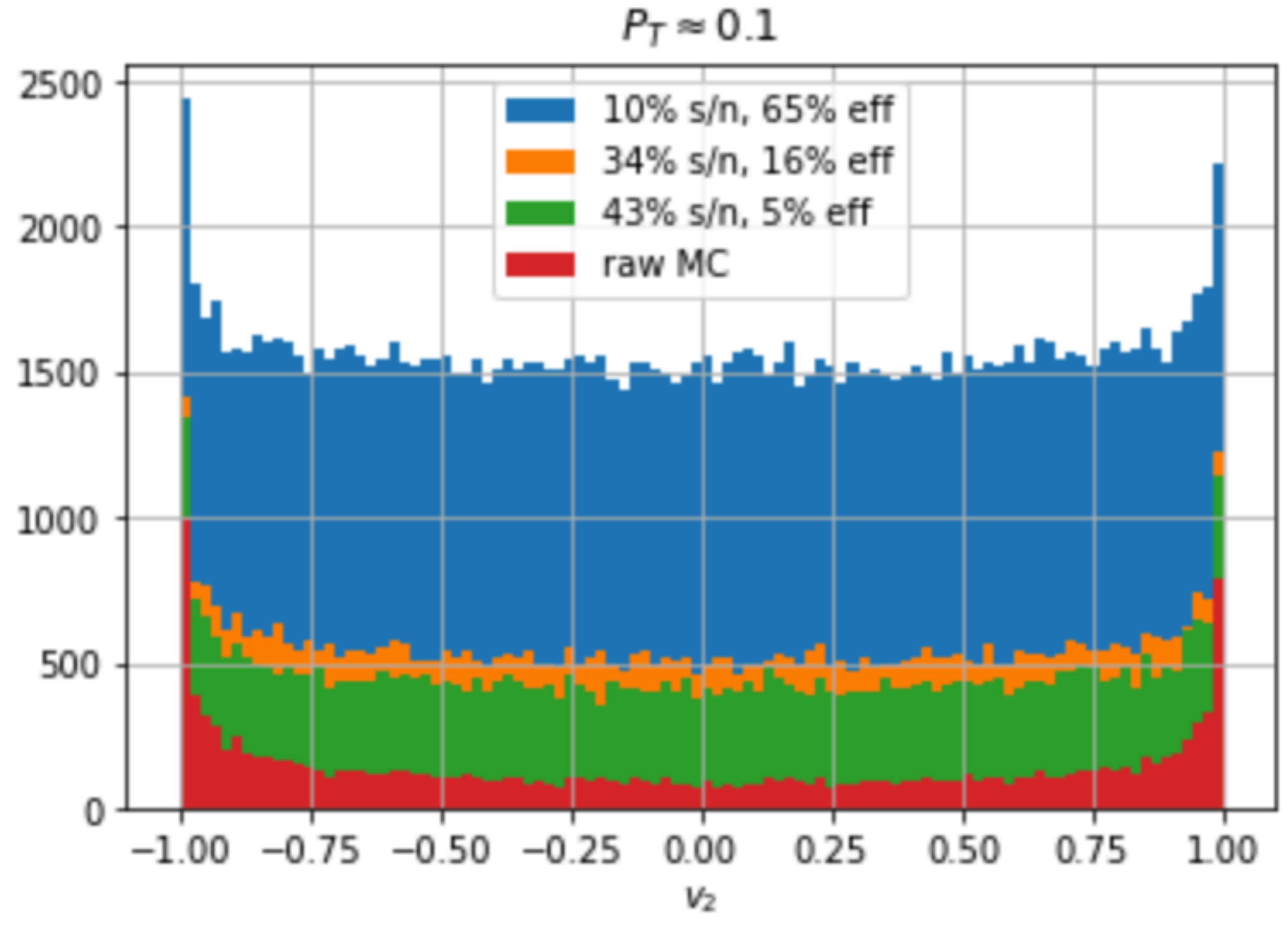


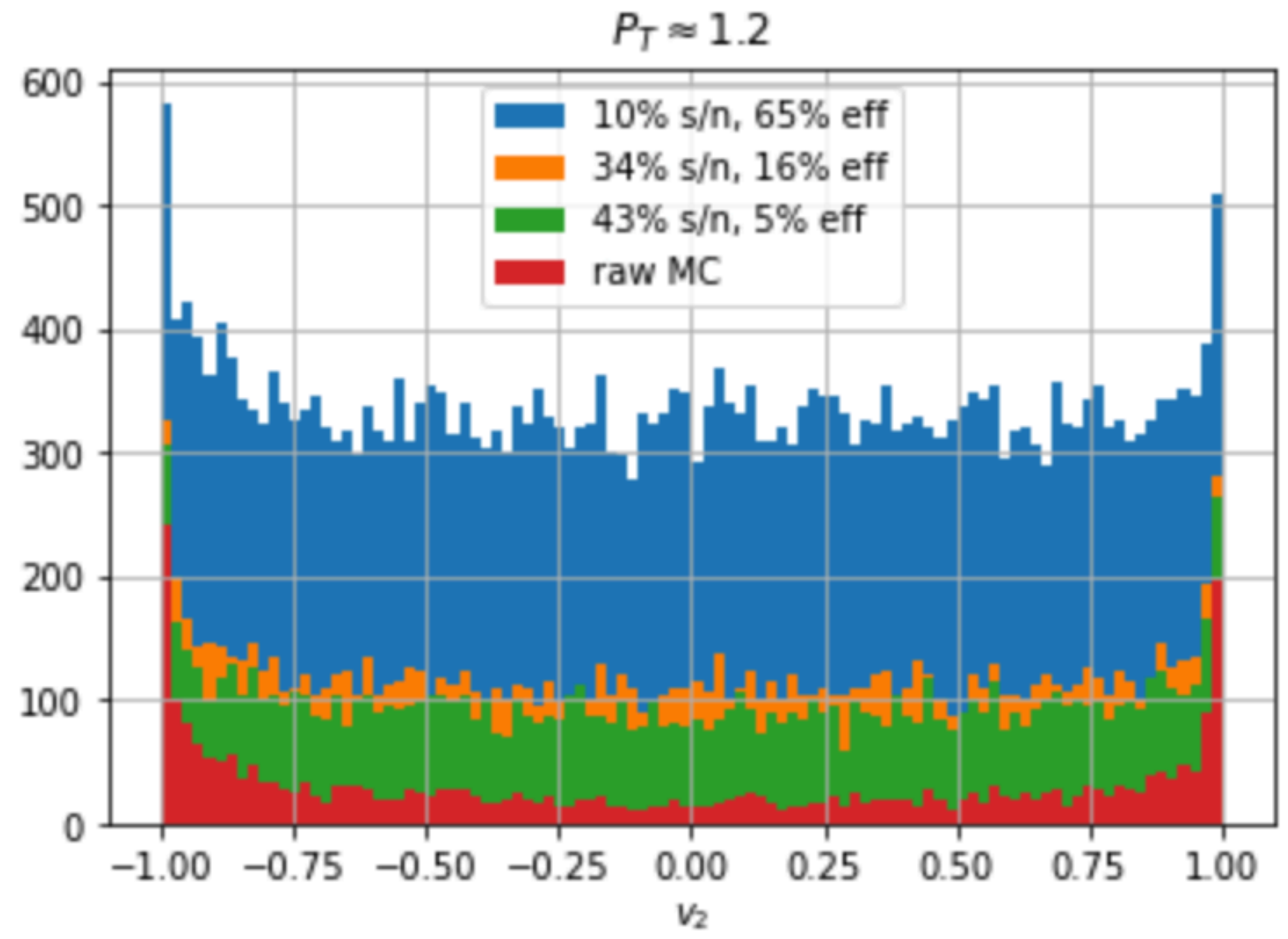


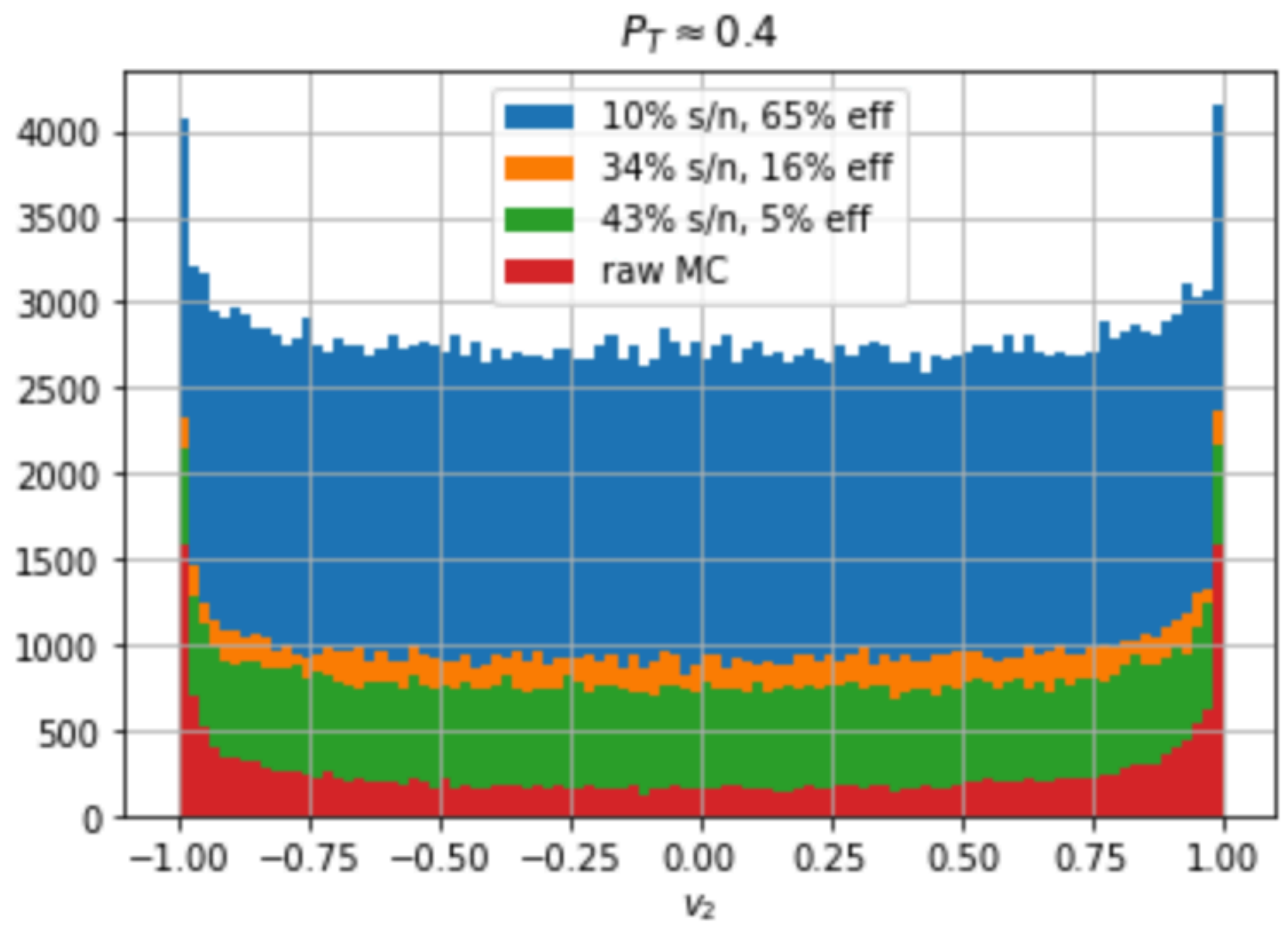
v2 vs Pt distortion

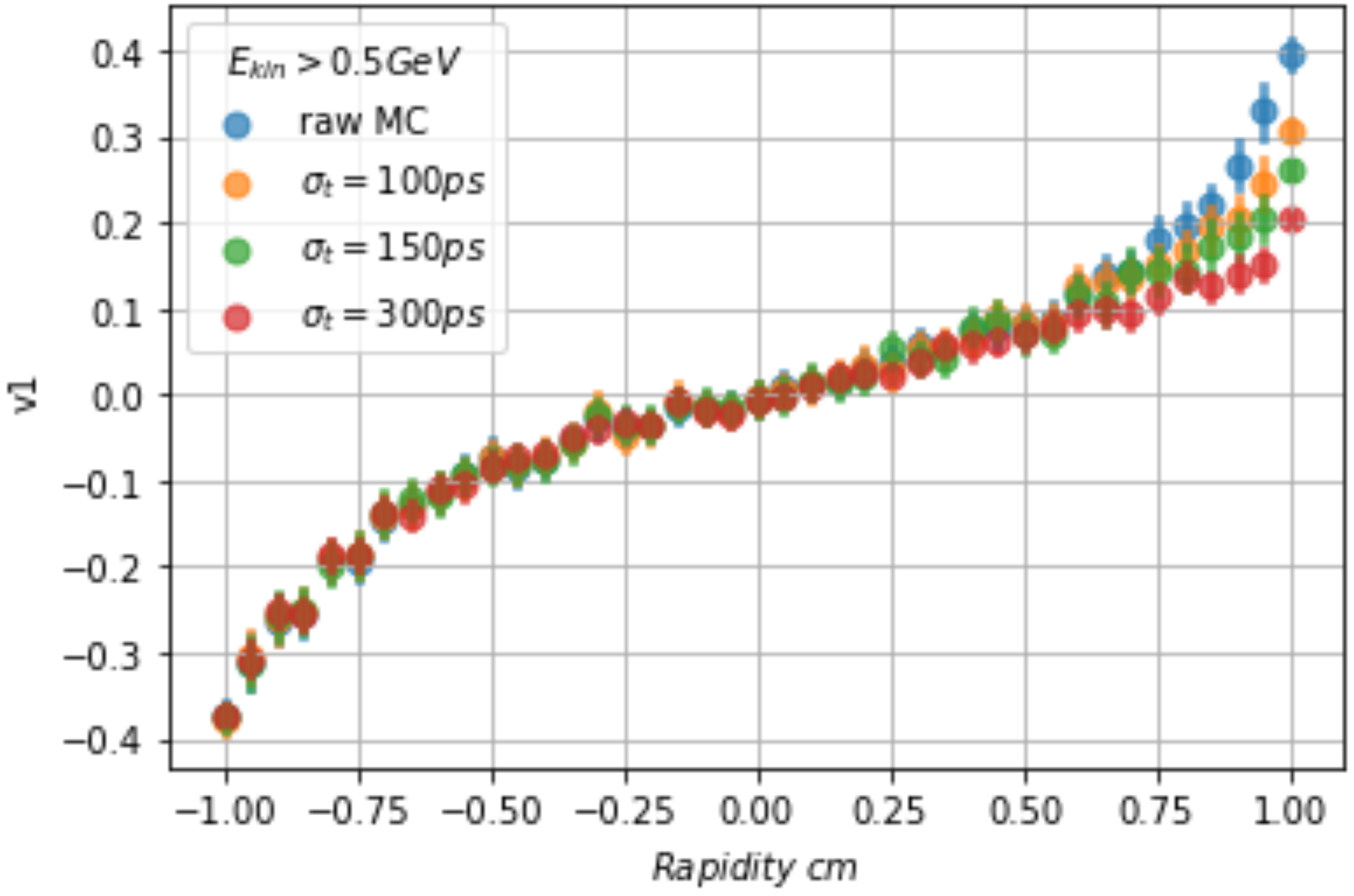
- signal - neutrons from sin reaction (4π)
- noise - Pt is sampled from signal, v2 - flat distribution
- s/n ratios from classifier test











$E_{kin} > 0.5 GeV$
raw MC
$\sigma_t = 100ps$
$\sigma_t = 150ps$
$\sigma_t = 300ps$
v1
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
Rapidity cm

Catboost feature set

CatBoost (BDT)

first-principle **feature set:**

Fastest hit:

‘eToF_first’

‘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 per event:

‘eToF_med’ - median ToF energy

'Esum',

‘cogZ', - E-weighted average z

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

'nHits',

'dt_stdev'