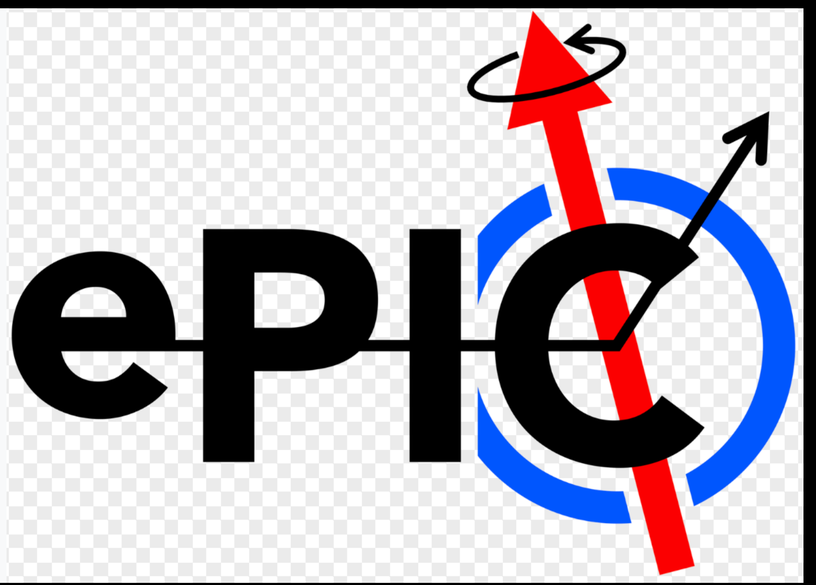
BHCal Energy Calibration using ML

Churamani Paudel

With Prof. David Ruth

New Mexico State University

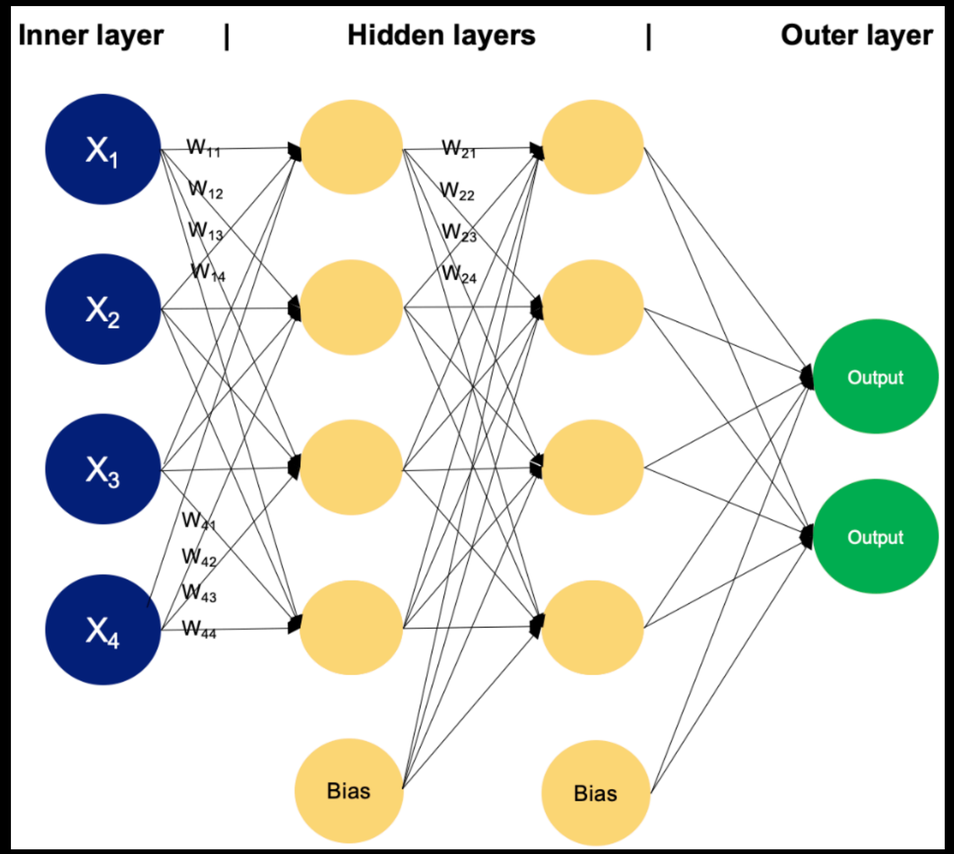


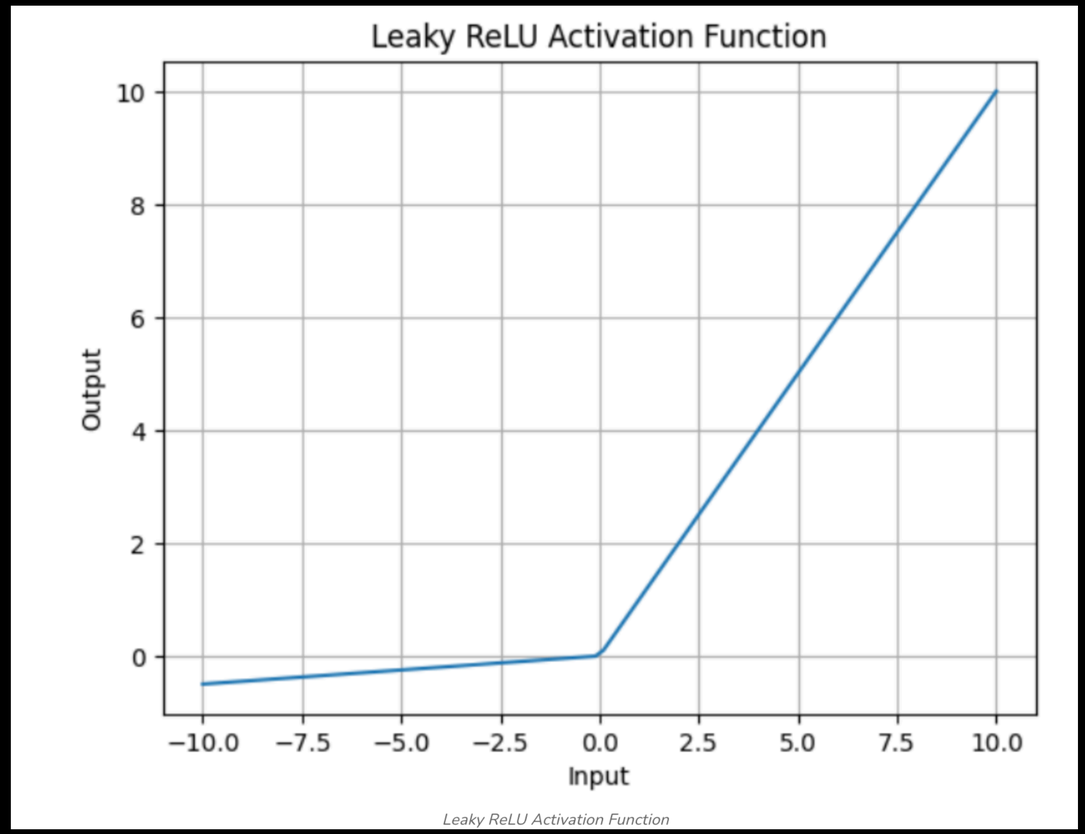
Introduction

- **Last talk:** initial BHCal ML calibration was tested with DIS Sample
- Some of the corrections applied on tuple script to deal with discretness in the spectra
- Feature correlation for calibrating true neutron energy looked, found weak correlation in NC DIS sample 26.02.0, NN can not learn true energy neutron calibration, rather it learns Geometry and Kinematics
- **This talk**: similar workflow was applied to ePIC 26.04.1 CC DIS Sample
- Comes with strong feature correlation, found to be better sample to train the NN
- Goal: is to calibrate neutron energy at BHCal using ML tools

Neural Network: MultiLayer Perceptron (MLP)

Input Feature Vectors

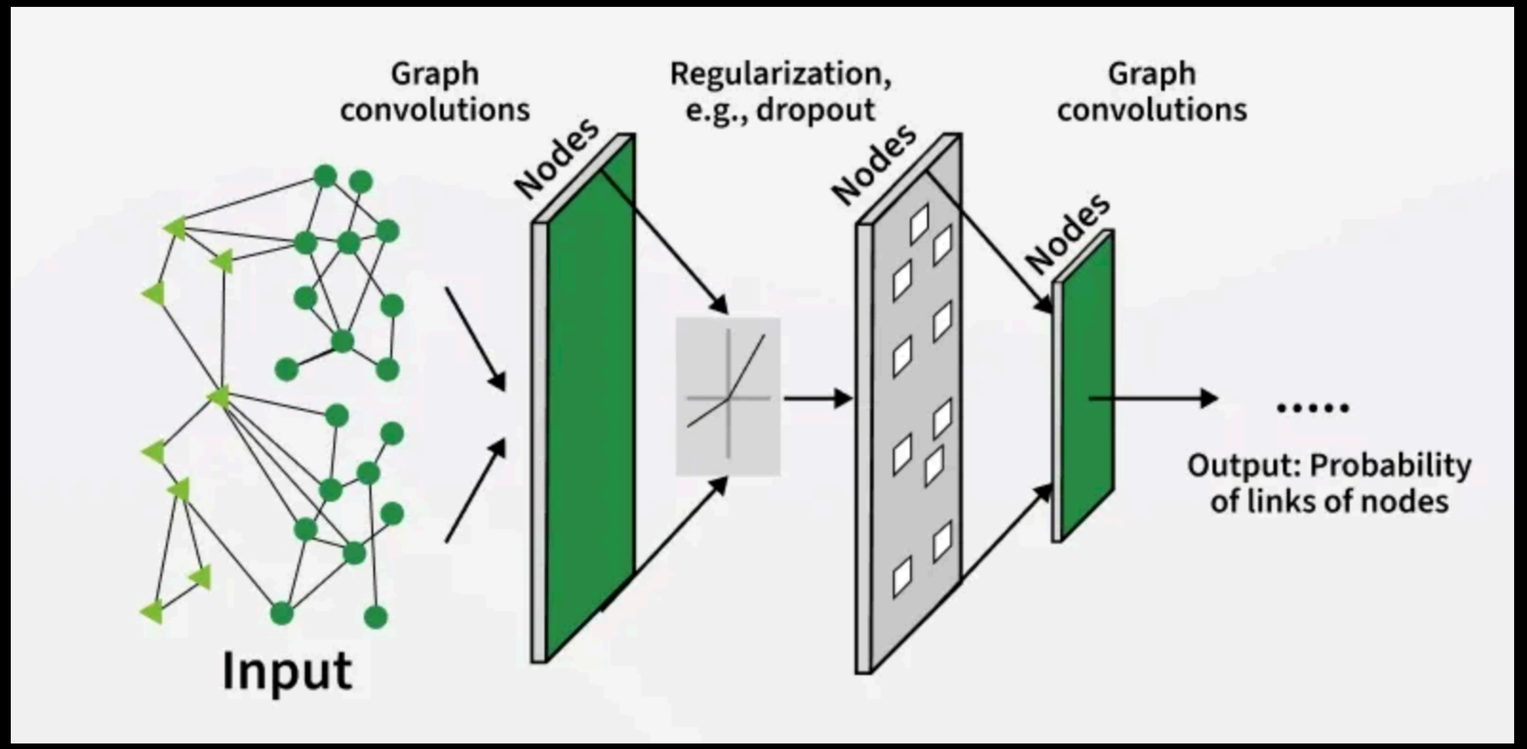


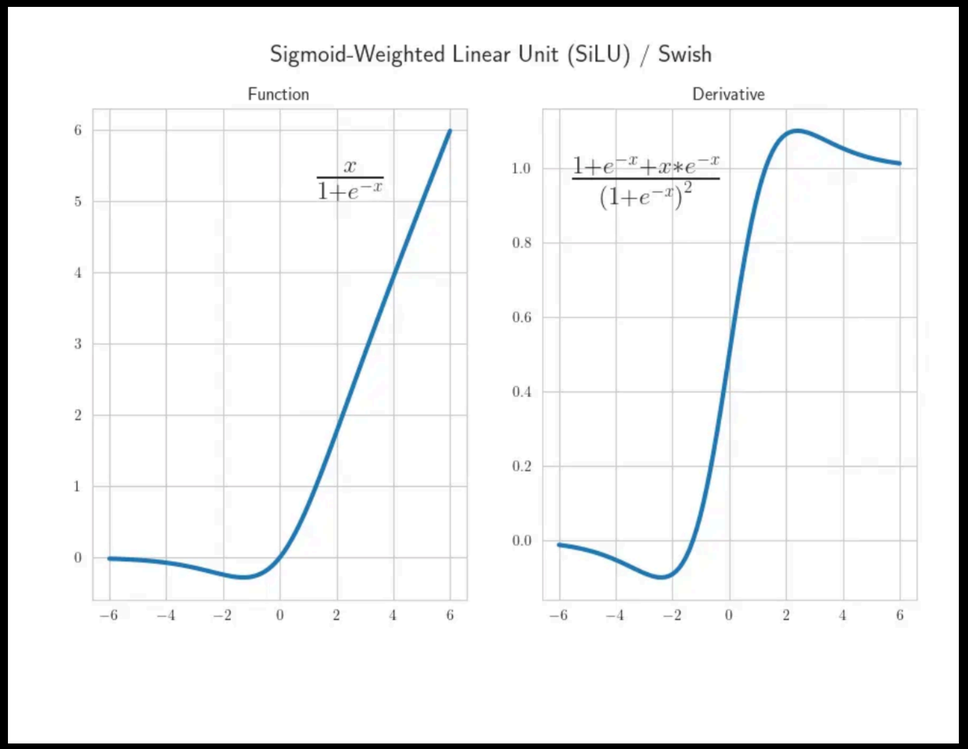


Leaky ReLU Activation Function

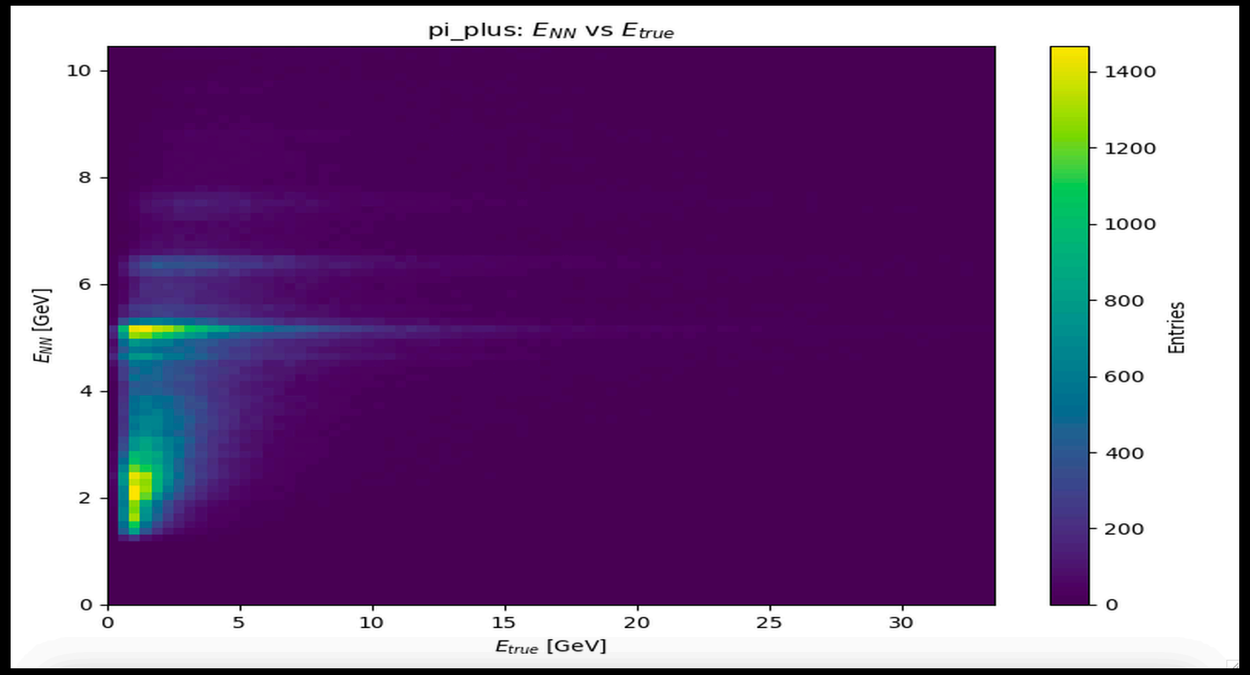
HuberLoss

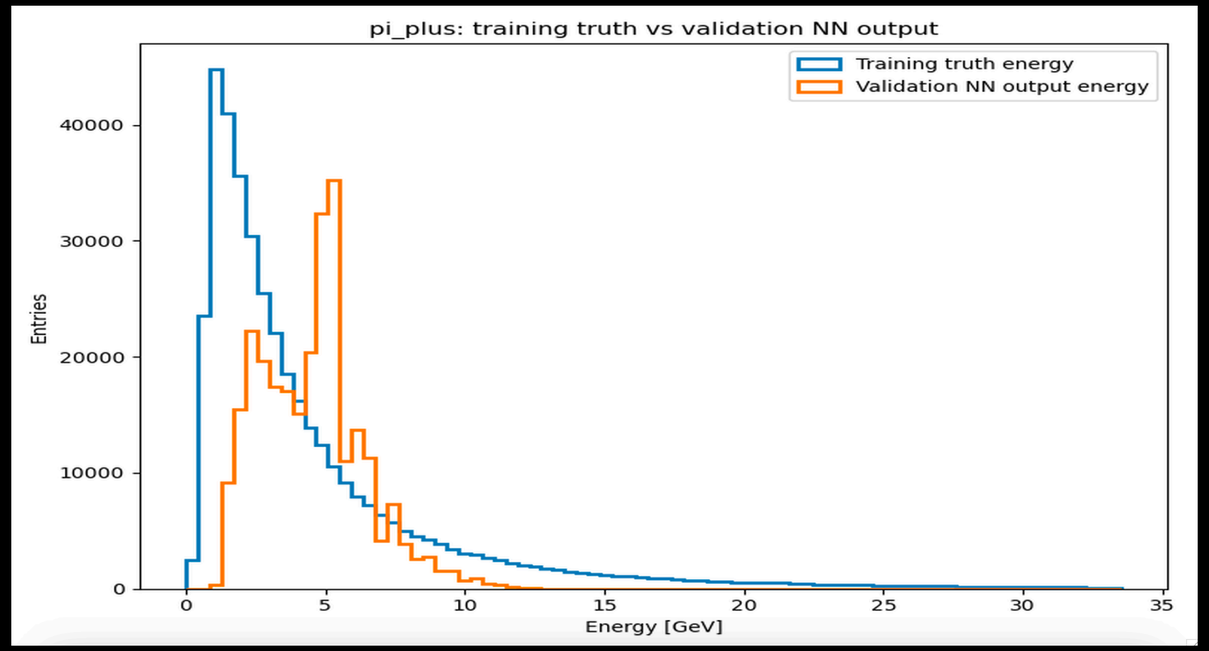
Graph Neural Network (GNN)





Previous Issue(s) (recap)





corr(eBHCalCluster, ePar) ≈ -0.07

corr(ePar, etaPar) ≈ +0.68

But single particle

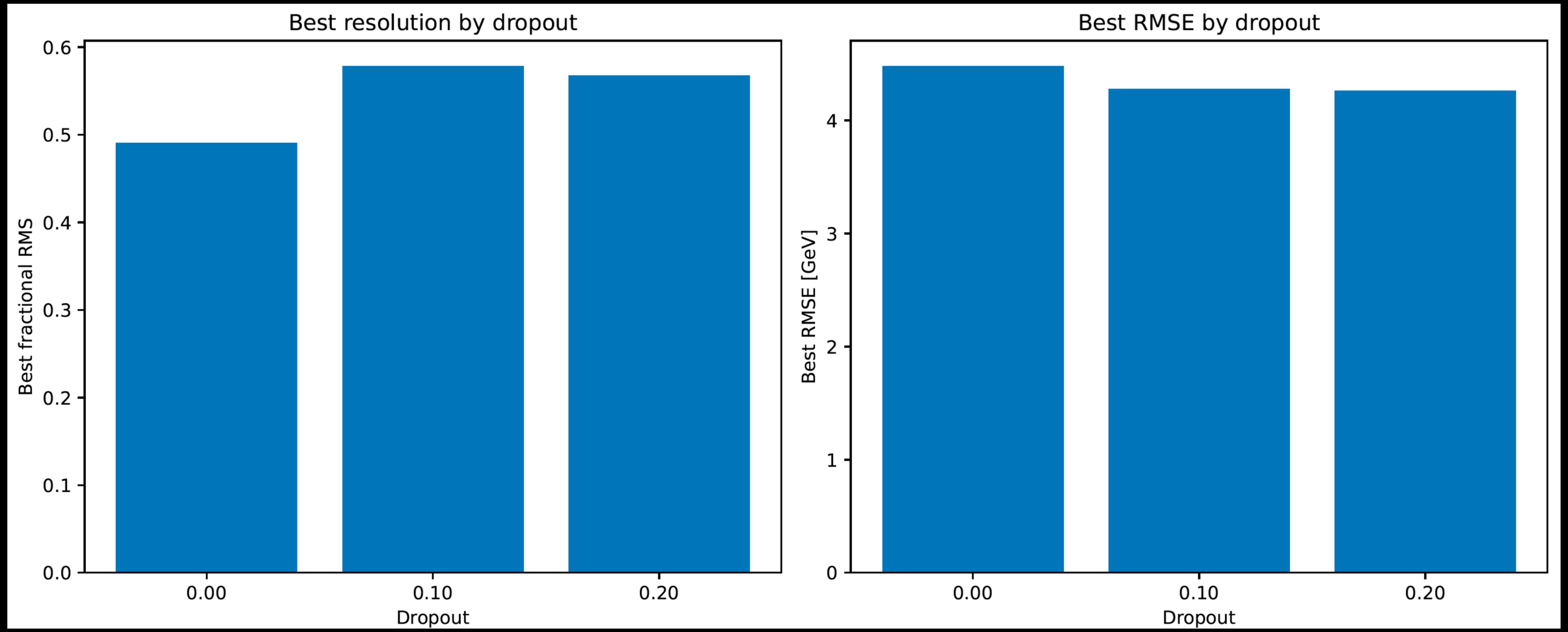
corr(eBHCalCluster, eKinPar) = +0.635

corr(eBHCalEventSum, eKinPar) = +0.635

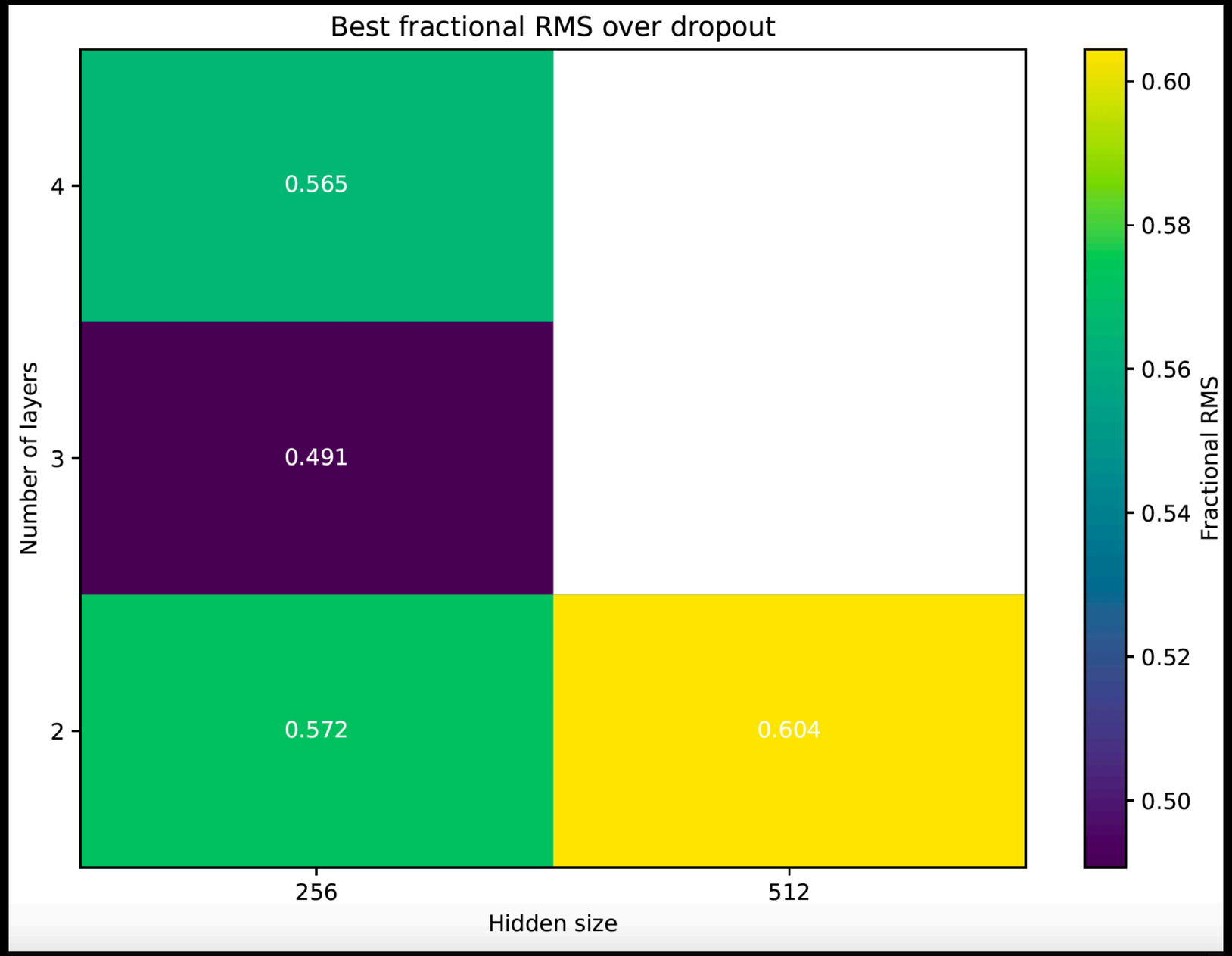
corr(eBHCalLead, eKinPar) = +0.558

corr(eBHCalCone03, eKinPar) = +0.588

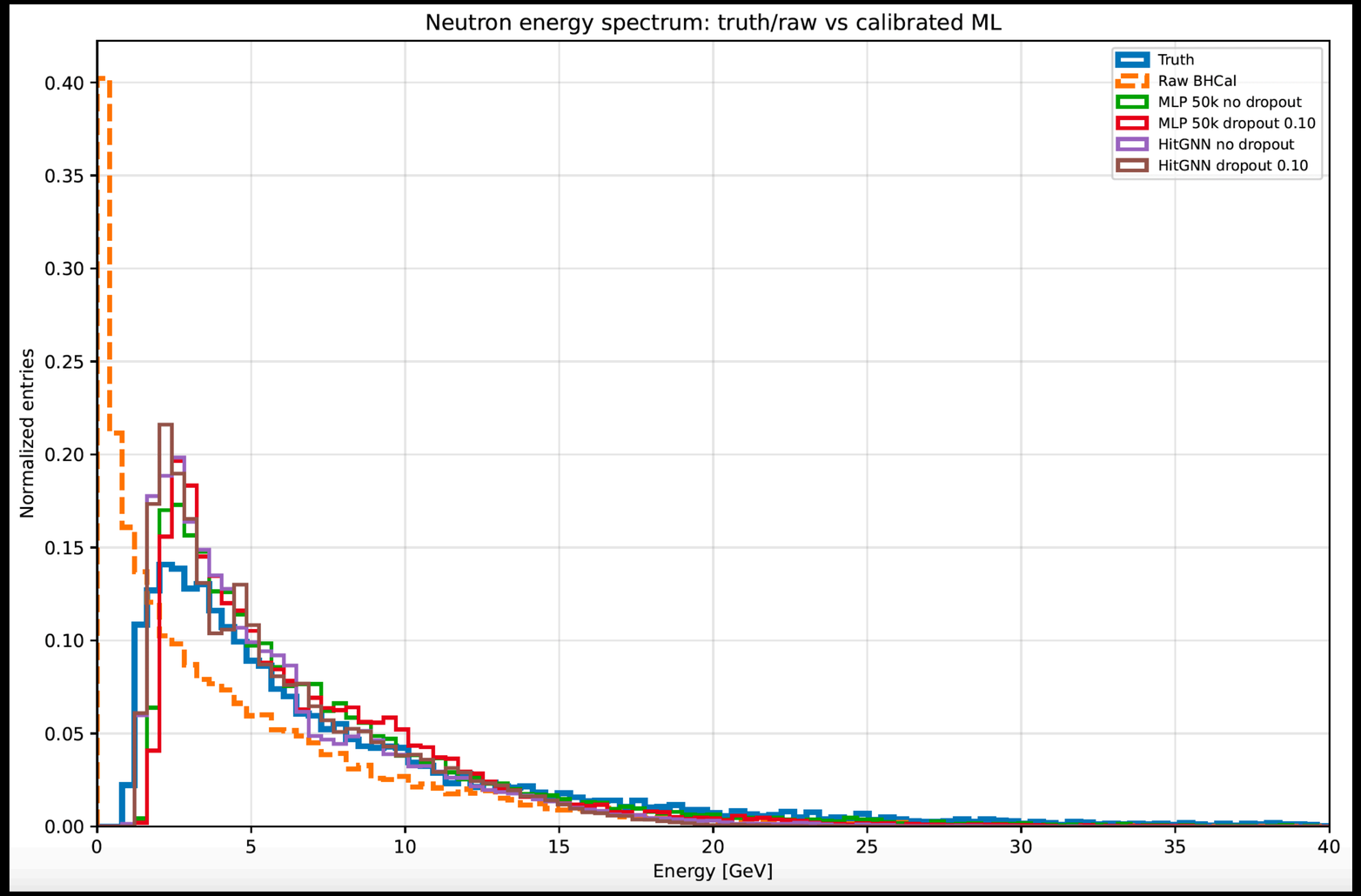
Resolutions based on dropout



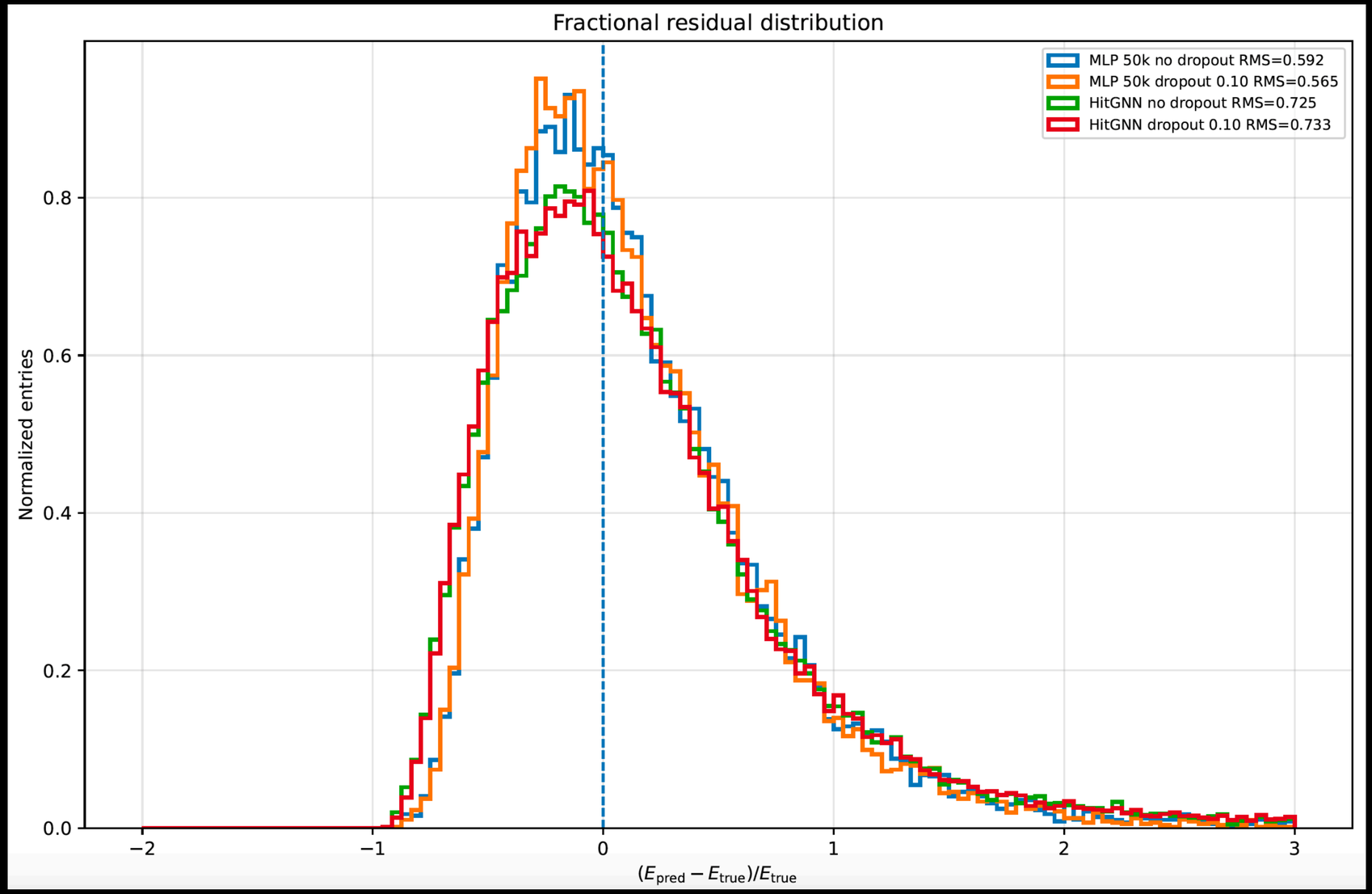
Best fractional RMS over dropout



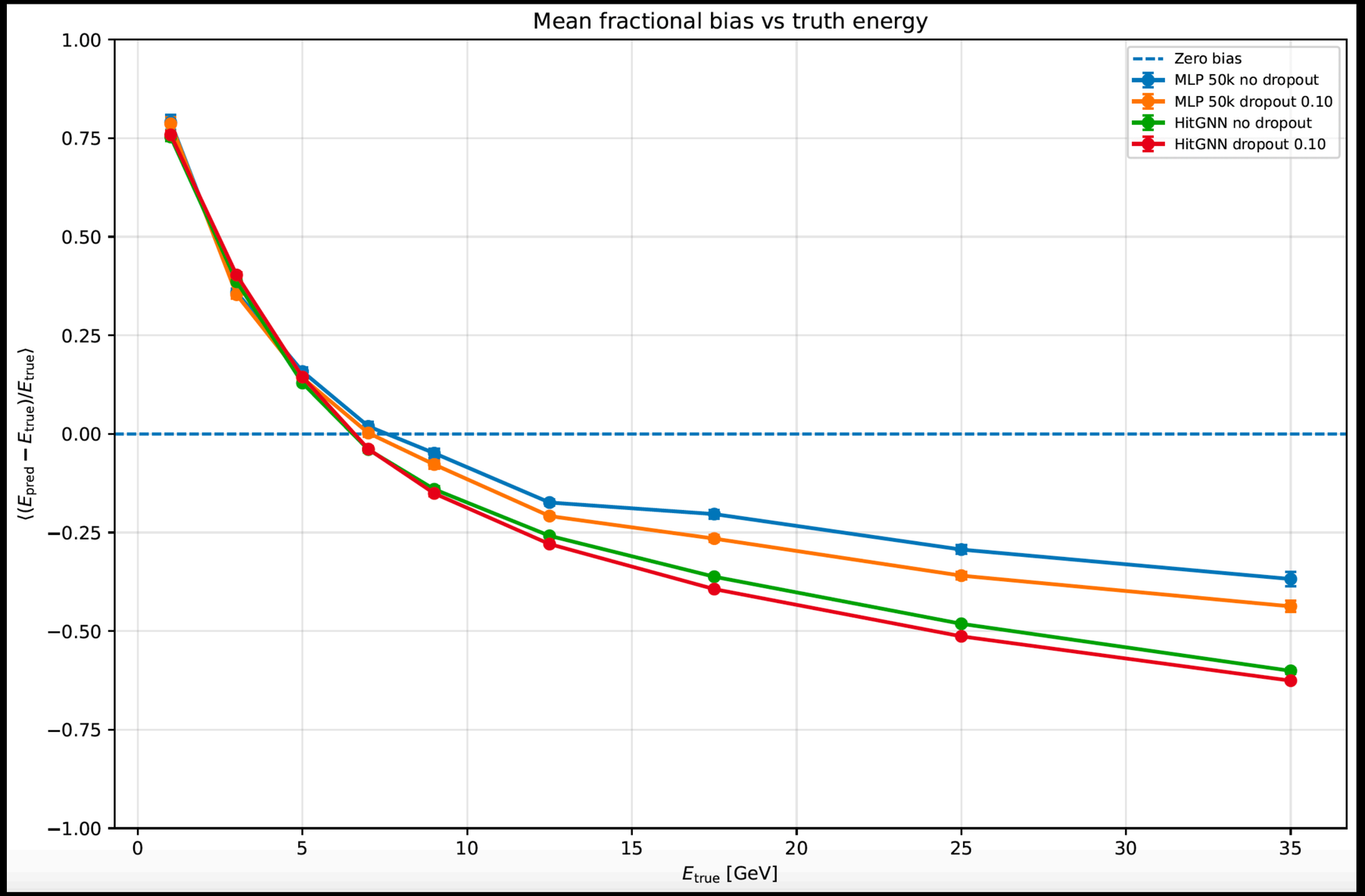
Neutron energy spectrum (50k) neutrons



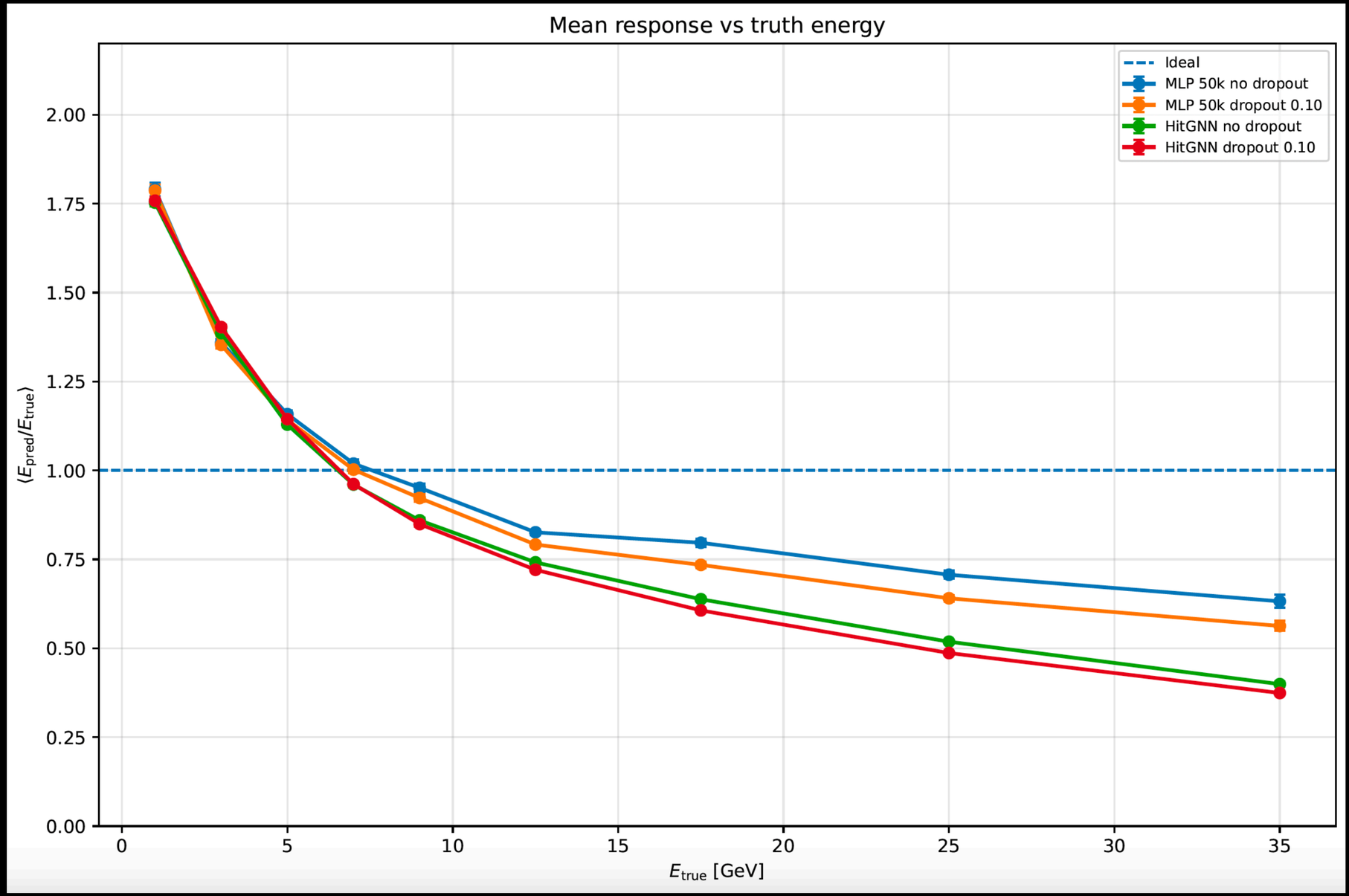
Fractional residual distribution



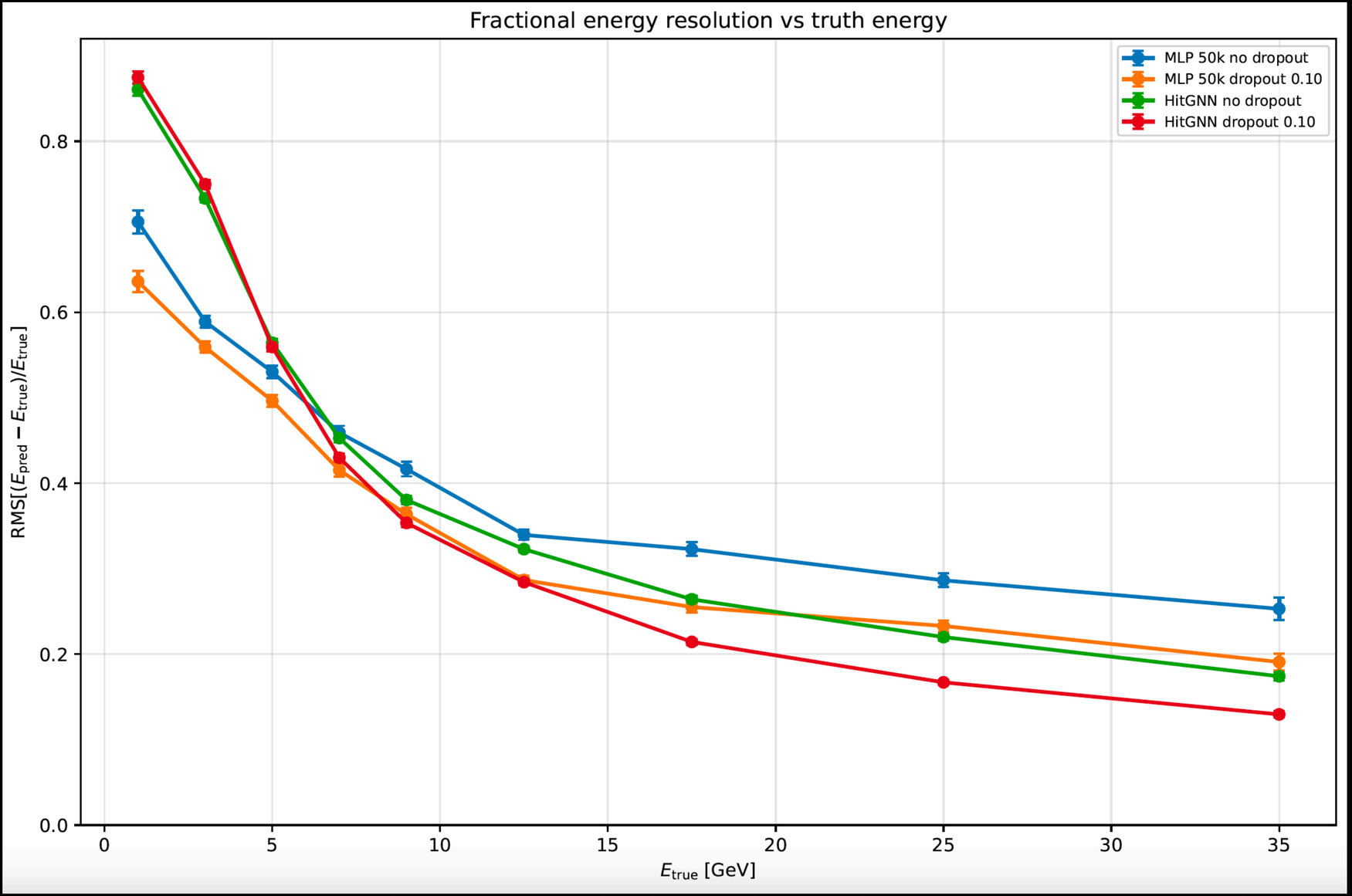
Mean fractional bias vs truth energy



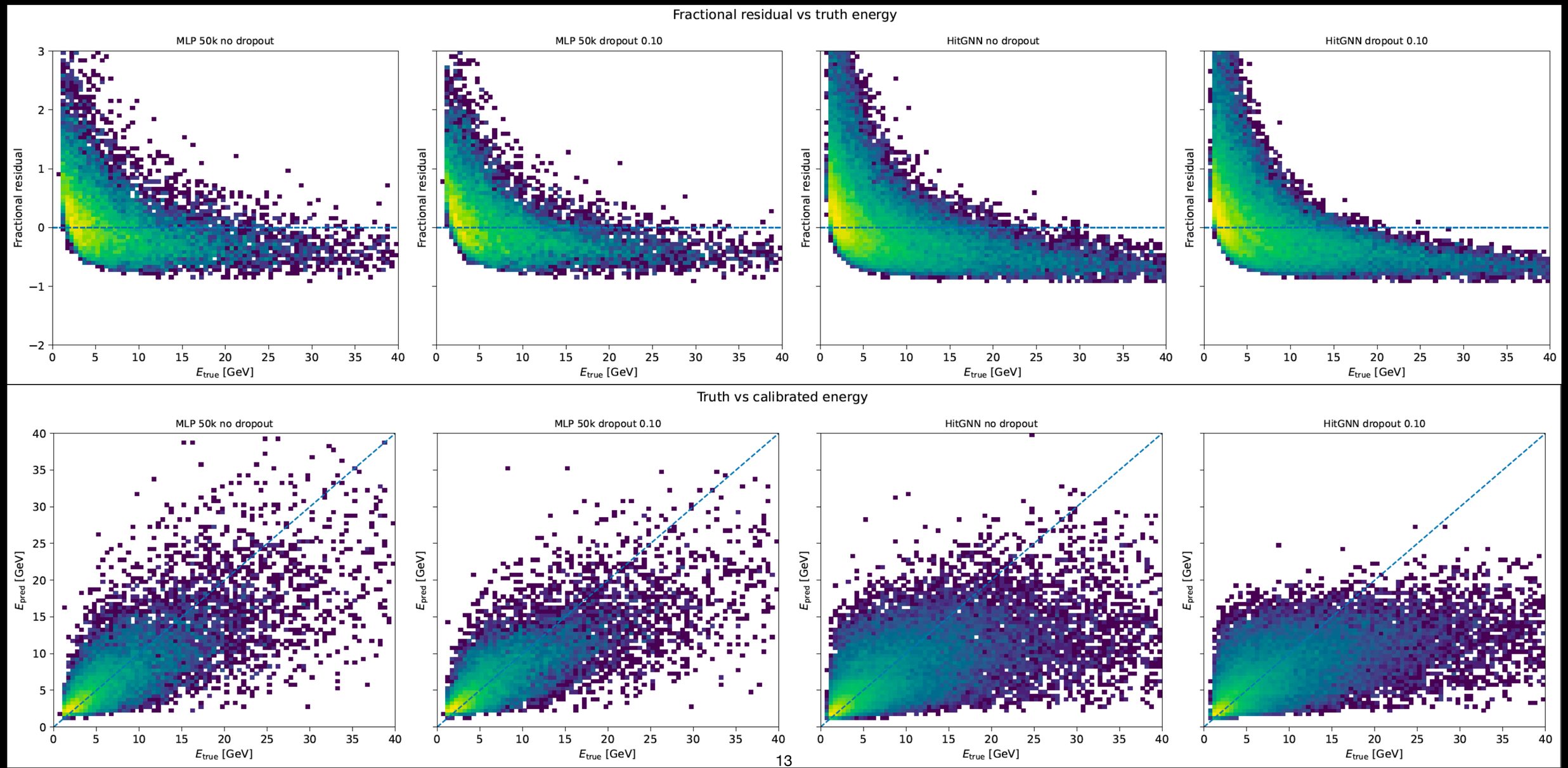
Mean response vs truth energy



Fractional energy resolution vs truth energy



MLPP vs GNN performance



Summary and next steps

- Issue of discrete bands on energy is resolved, but the NN response is still energy dependent, with slight overprediction at low energy and underprediction at high energy,
- GNN is further being explored for potential use.
  Feature Graph level, MLP outperforms GNN, but at BHCal/Hit level, GNN perormance improved and competing with MLP
- Train MLP/GNN on larger sample, network artchitecture and longer training, continue hyperparameter tuning etc
- Further study on Energy Dependence