Machine Learning on Hadronic Calorimeter

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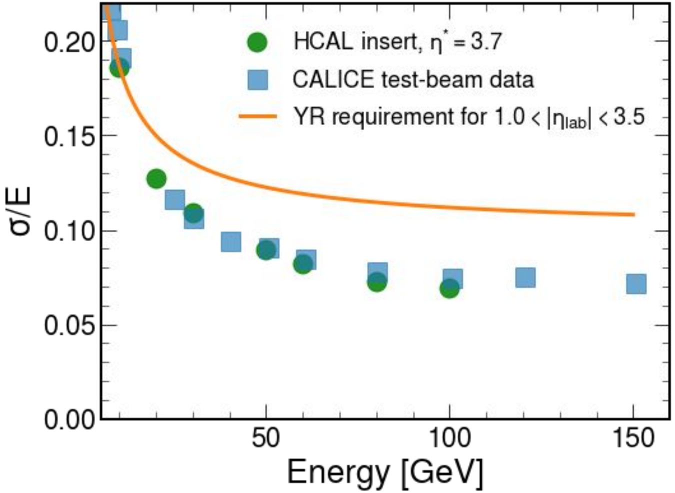
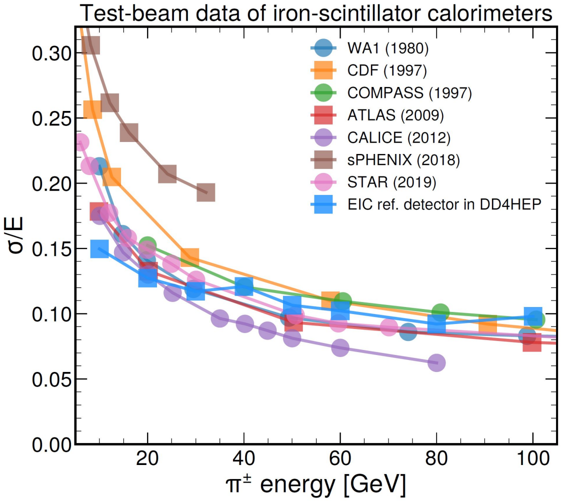
Hadronic Calorimeter performance
Simplest reconstruction (“Strawman”)

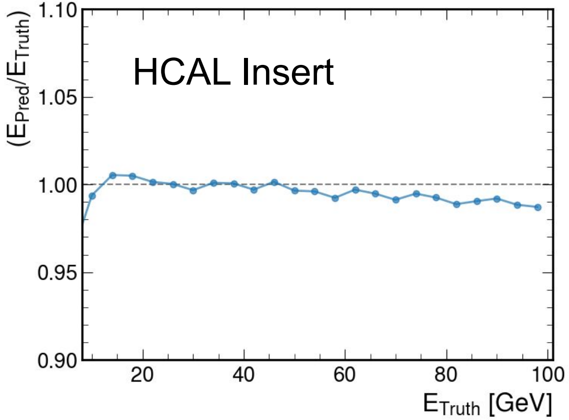
Resolution (HCAL Insert)



Resolution (HCAL)



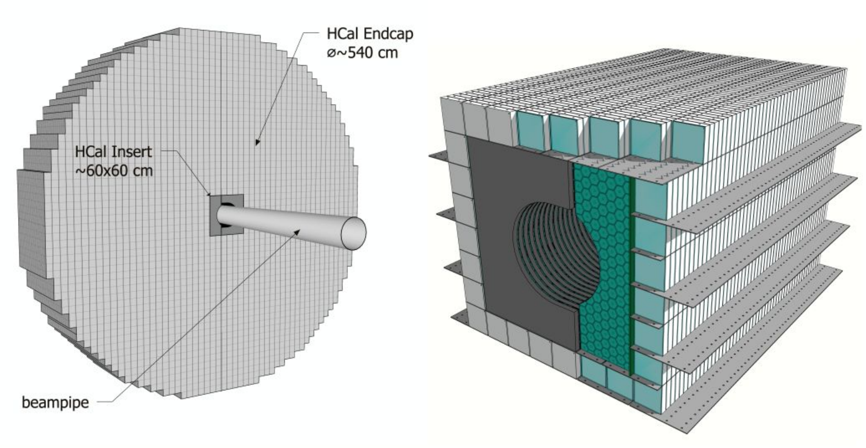
Energy response (HCAL Insert)

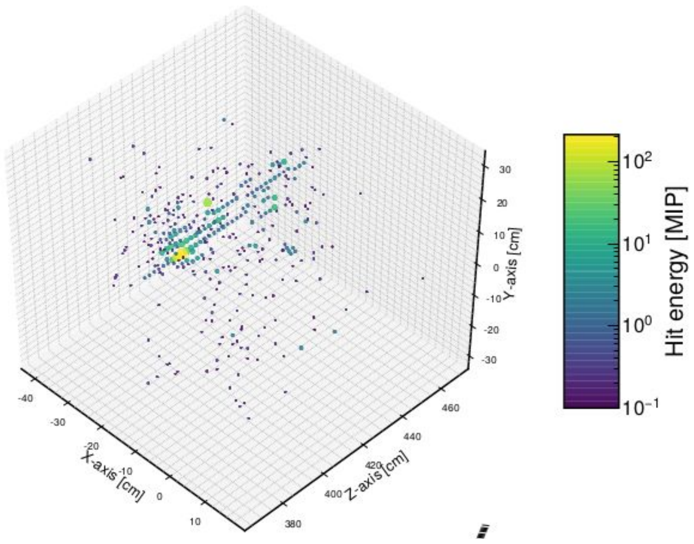


$$Strawman = \frac{\sum \text{Cell Energy}}{\text{sampling fraction}}$$

- Adopted Calorimeter (both HCAL and HCAL insert) configuration from previous experiments in DD4Hep simulation
- With simplest reconstruction, reproduced the resolution from previous experiments

Exploiting calorimeter info





- Yields 5D showers (E, X, Y, Z, t)
- These information can be exploited for sophisticated reconstruction algorithms (AI)

Towards AI Driven Detector Design

Goals:

- Use Deep Neural Network to transform GEANT4 simulation into differentiable models for high-dimensional optimization

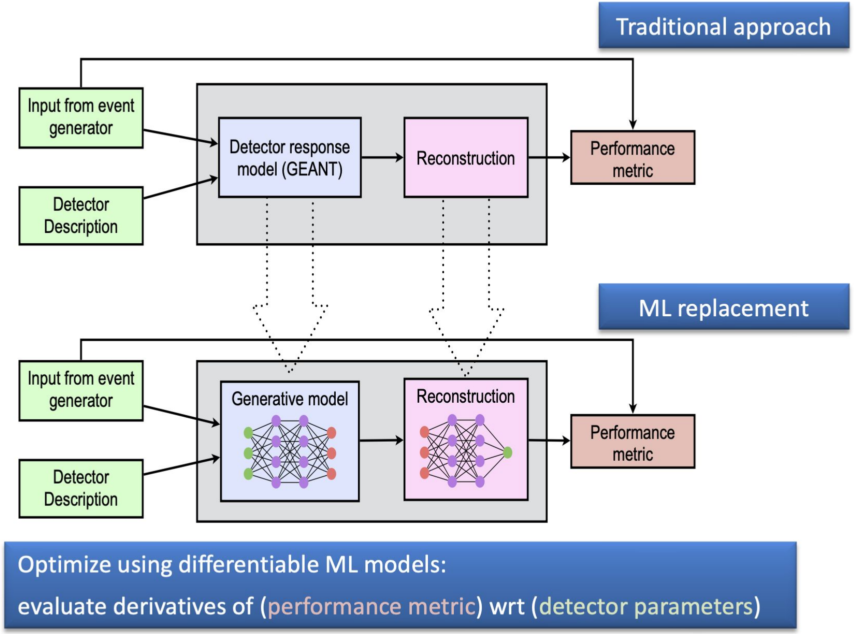
- Develop a framework for future application for various detector design

Approach:

- Use EIC detector simulation to train and surrogate model (differential)

- Use surrogate model to optimize the detector parameters

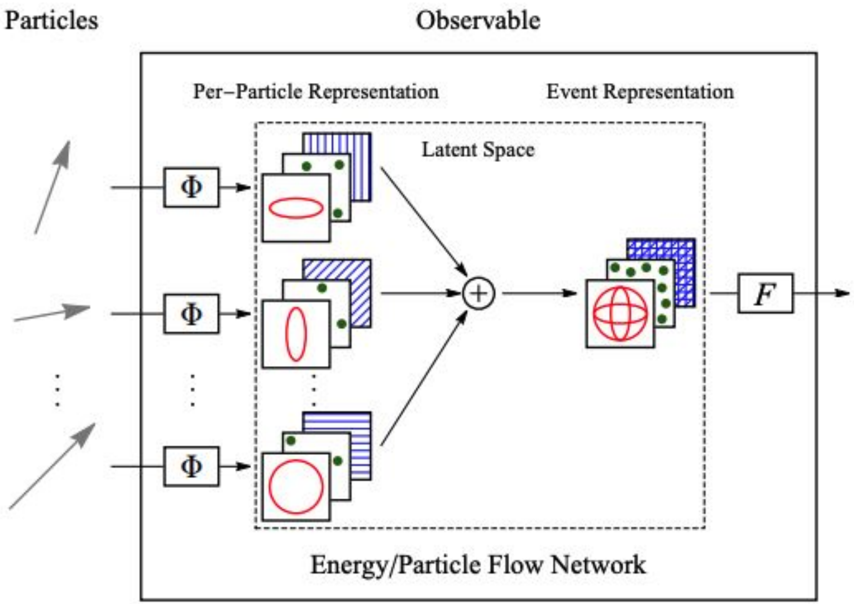
- Using hadron calorimeter simulation



Energy regression with Particle Flow Network

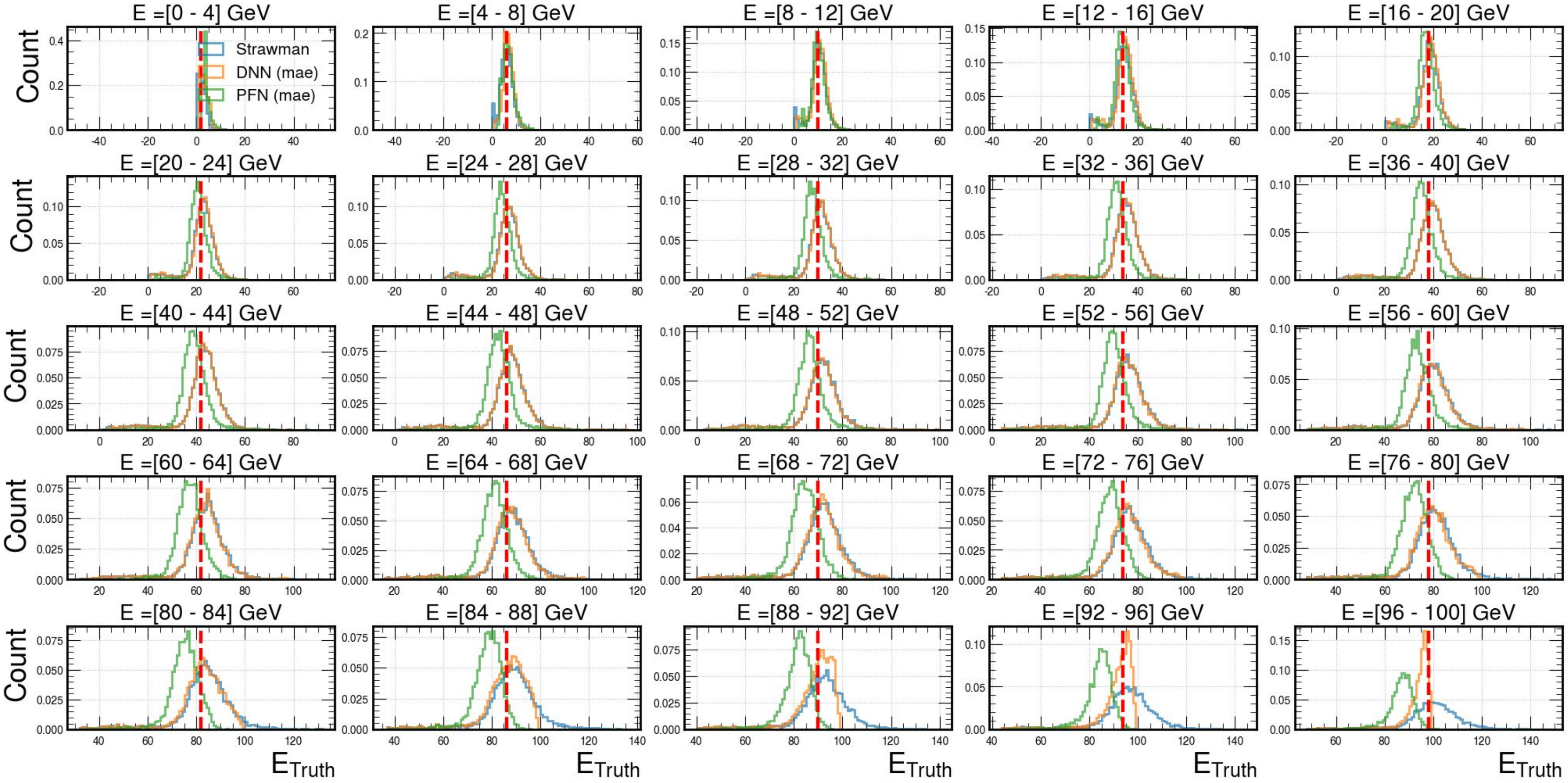
- Pion reconstruction in ATLAS detector showed improved performance over image based description [ATLAS-JETM-2022]

- 4 input E, X, Y, Z (cell information) one output
- Train to predict generated energy



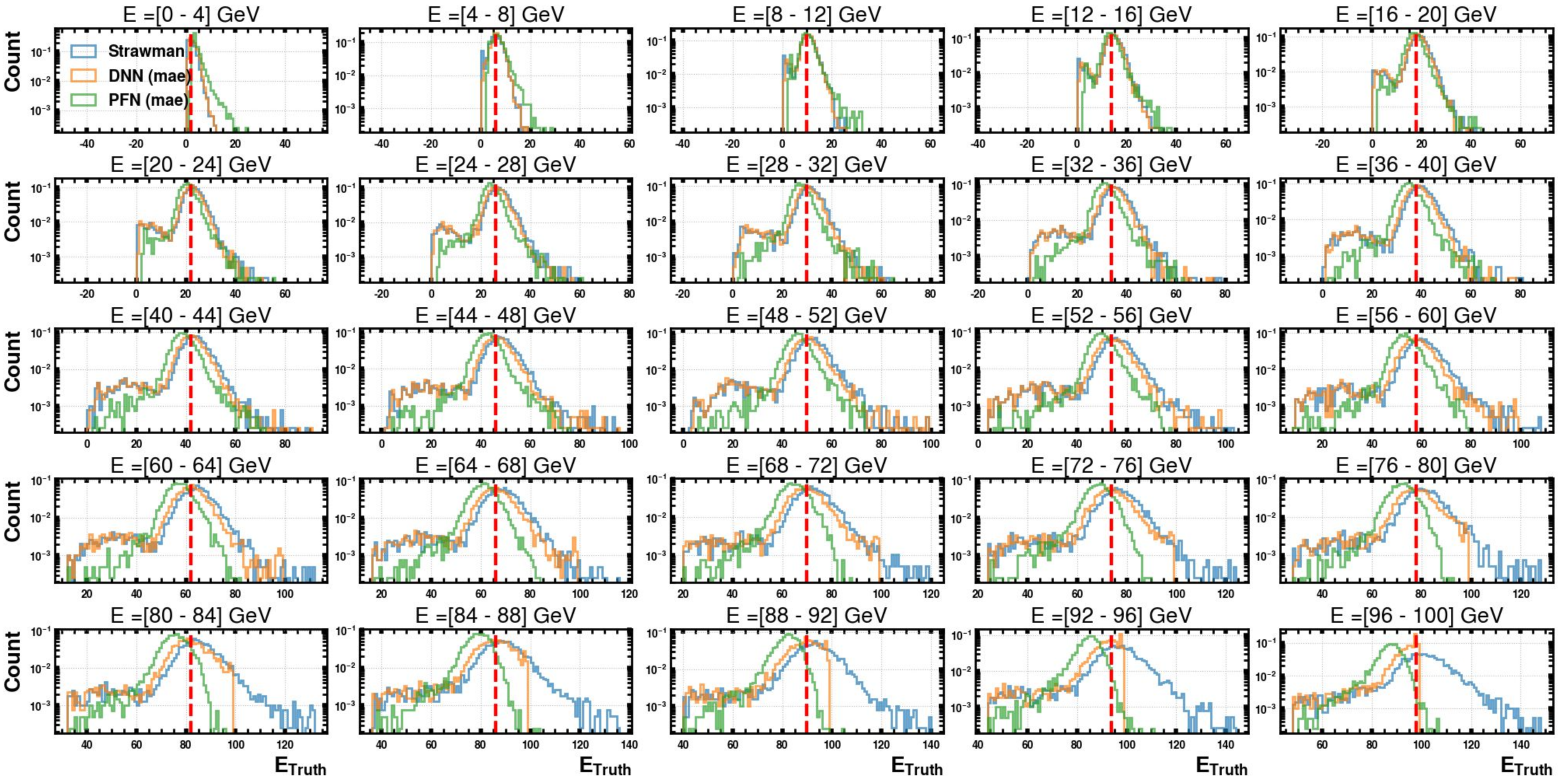
arxiv.1810.05165 [hep-ph]

Energy response for HCAL Insert



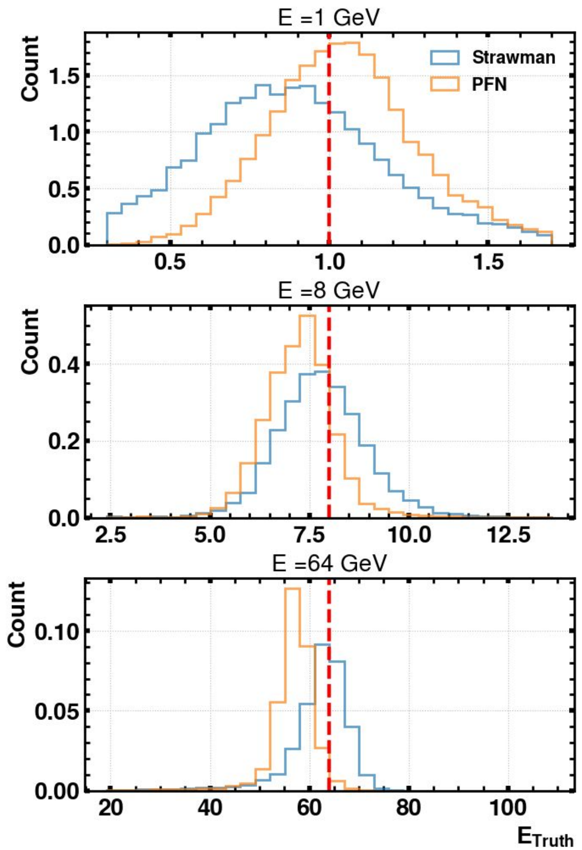
Vertical red line is mean position of generated energy

PFN efficient to reconstruct lower energy tail



PFN is efficient learns to reconstruct the lower energy tail

Energy response for HCAL



$$Strawman = \frac{\sum \text{Cell Energy}}{\text{sampling fraction}}$$

Energy generated in Uniform log space (1, 2, 4, ..64) GeV

Next Steps:

- Train on simple segmentation
  - ❖ 3 cluster sum, based on fixed segmentation
  - ❖ Probably will have highest change in performance

- **Add Transverse information of Cell**
  - ❖ Cell X, and Cell Y
  - ❖ Vary fineness and find optimal cell granularity or layering

- **Full Cell information**
  - ❖ Probably where working with GNN or DeepSets would be most benefit
  - ❖ Given decent time resolution, adding time information would help

We believe AI can be useful in clustering in 5D

Conclusion

- Using strawman, calorimeter performance is comparable with existing experiments results
- Optimization with PFN in progress
- Energy generated in uniform log space helps in regression at lower energy scale
- AI can potentially improve the performance with 5D clustering

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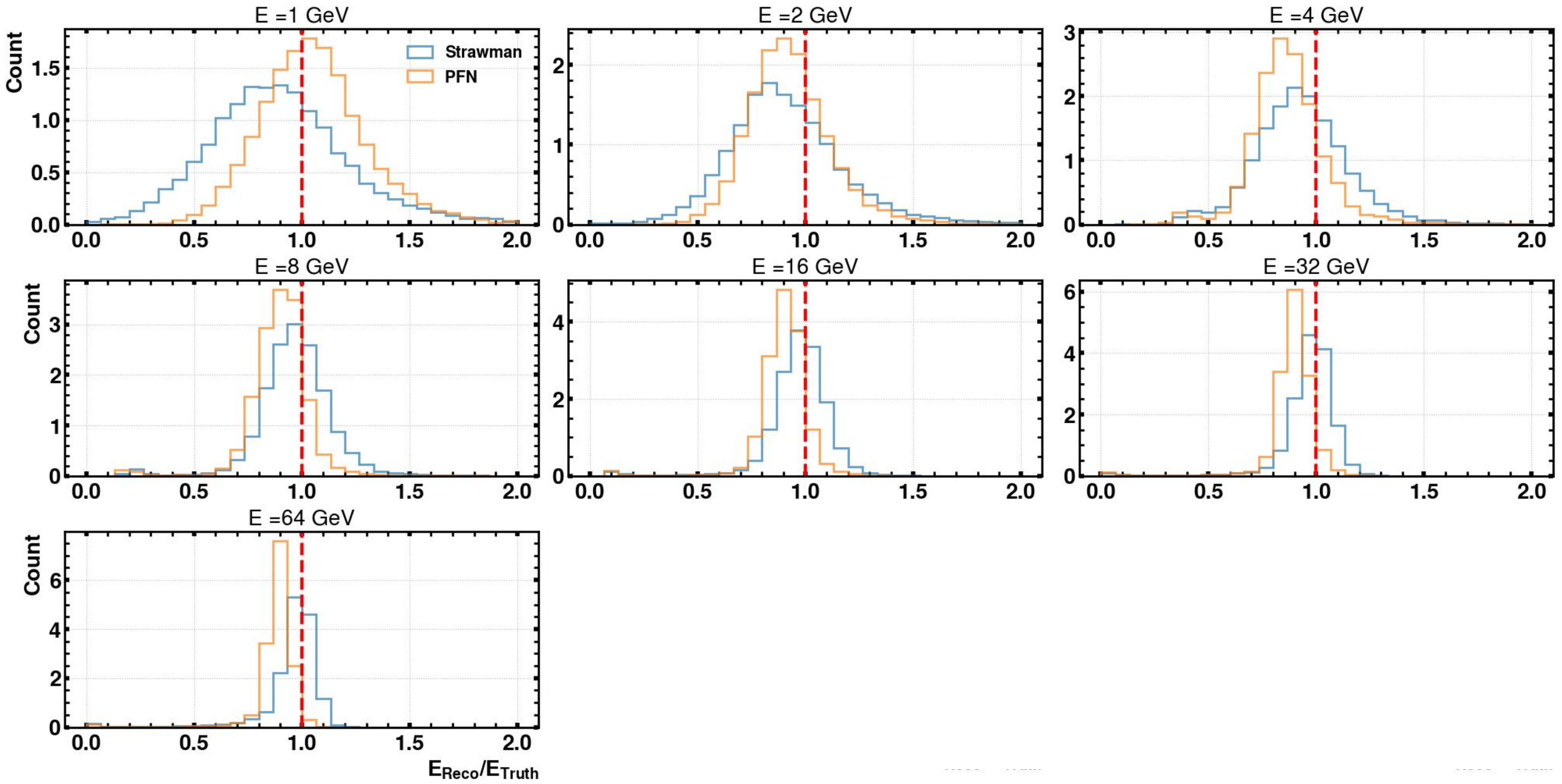
Thanks to M. Arratia, K. Barish, F. T. Acosta, UC, Berkeley, and LLNL group

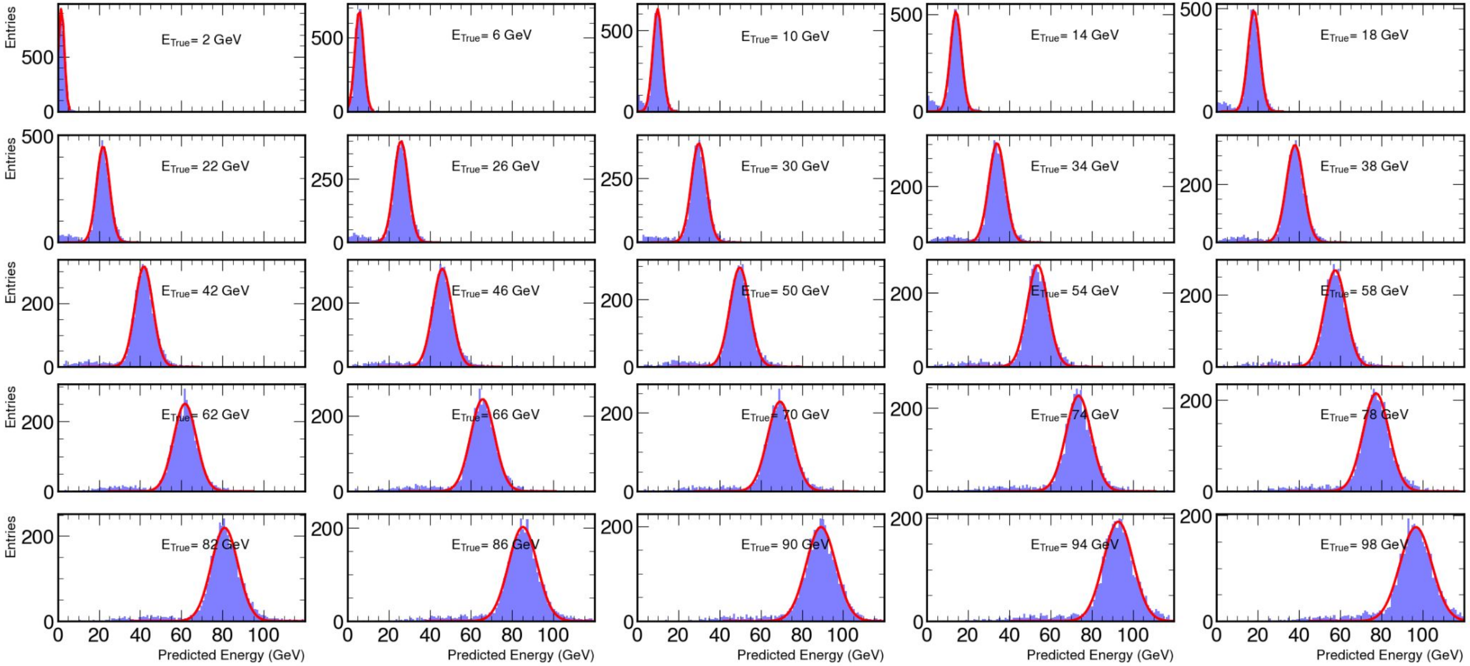
Back up

E_{Pred}/E_{Truth} HCAL



HCAL Insert Strawman

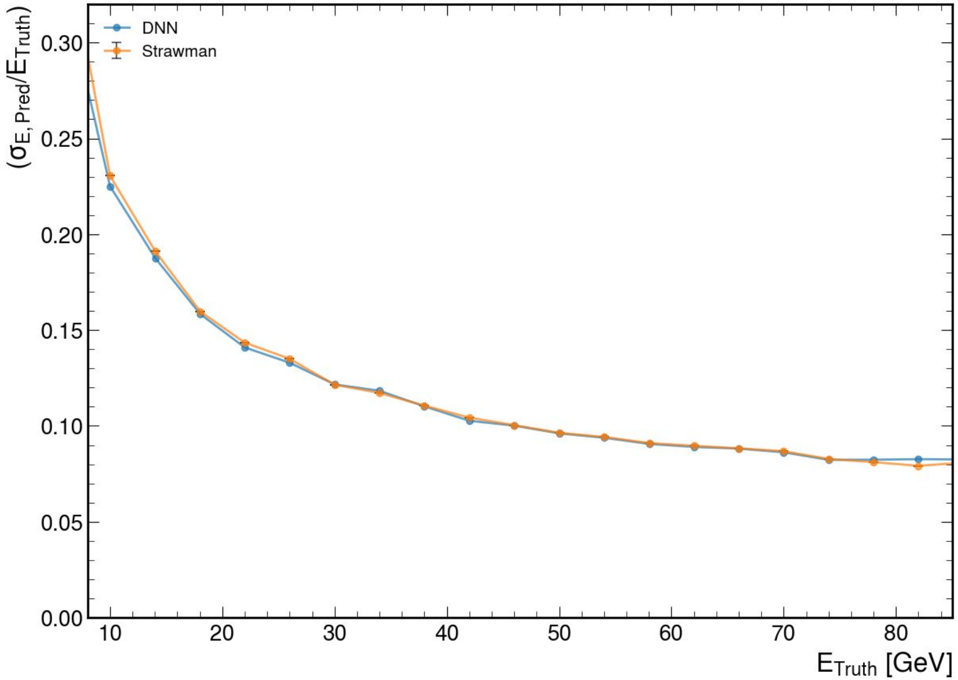
- Particle : π^+
- Energy = Uniform [0 -100] GeV
- Constant η^* =3.7



Overall nice Gaussian energy response

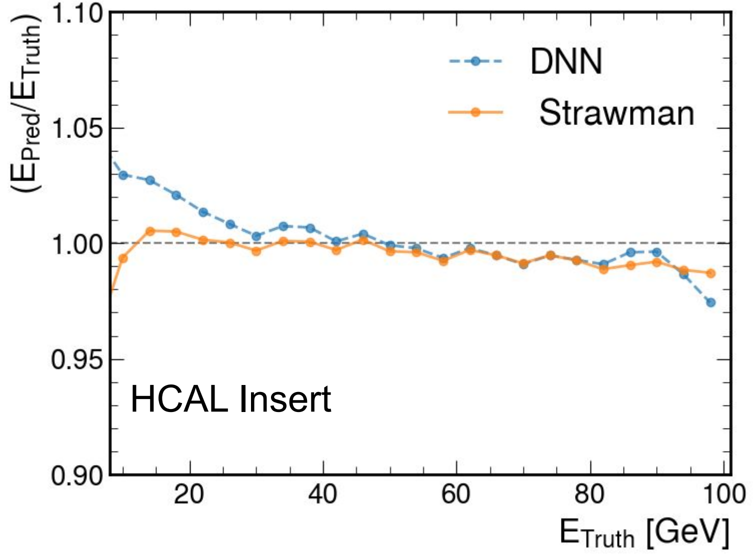
Resolution DNN vs strawman
HCAL Insert Strawman

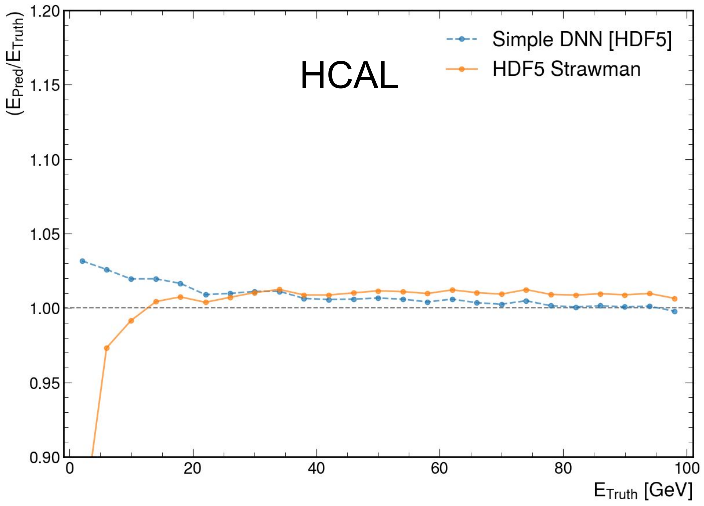
- Particle : π^+
- Energy = Uniform [0 -100] GeV
- Constant η^* =3.7



Energy scale DNN vs strawman

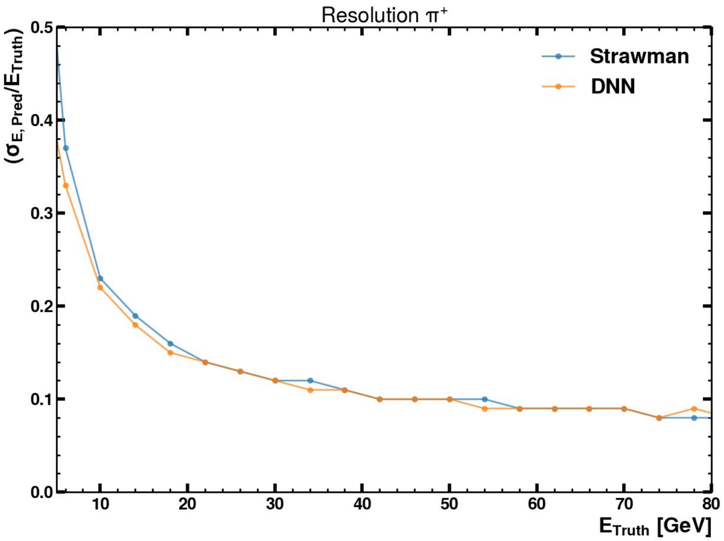
- Particle : π^+
- Energy = Uniform [0 -100] GeV

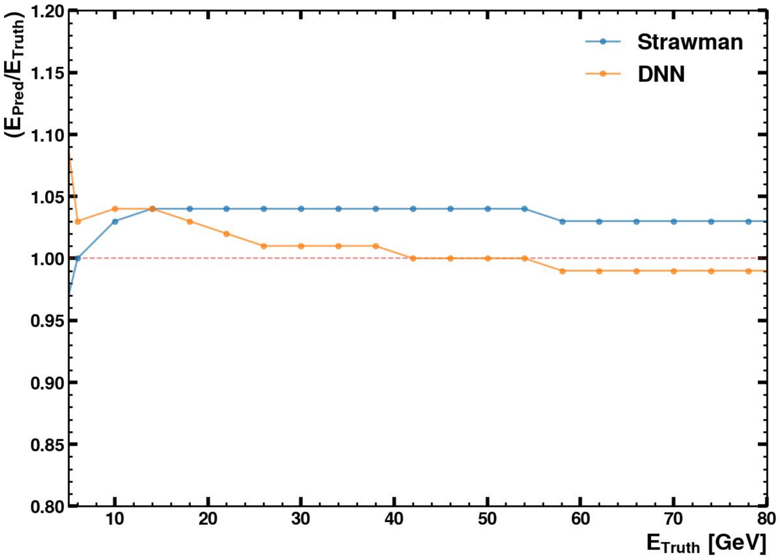




In linear scale, at lower energy value DNN is off by few percentage

Performance of Simple Deep Neural Network (DNN)
HCAL Insert



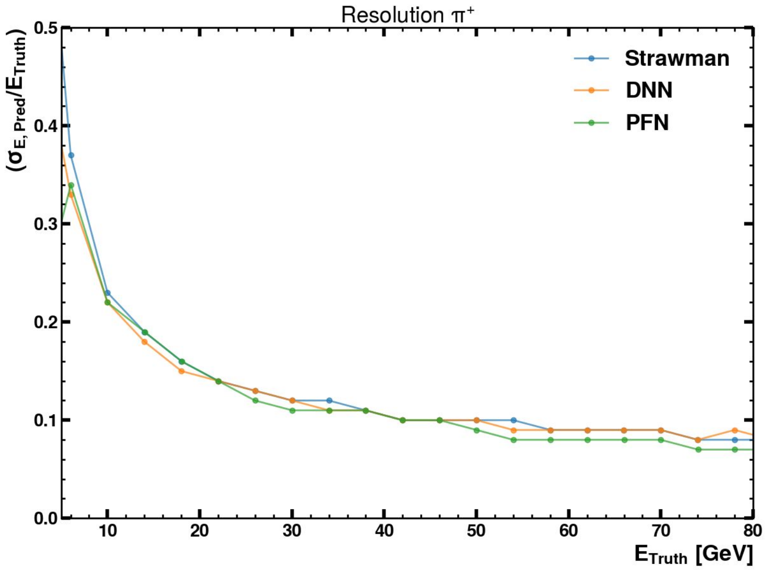


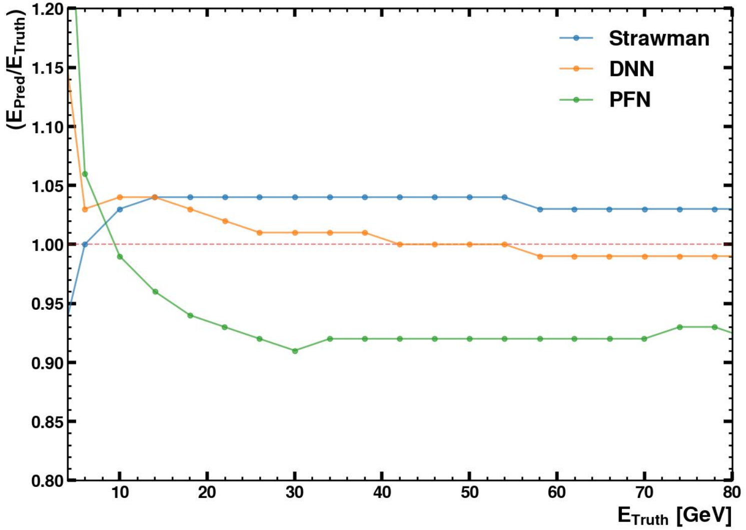
DNN architecture:

- 1 input (cluster sum/sampling fraction) and 1 output
- 4 hidden layer
- 64 nodes per layer
- Mean absolute error for loss

$$Resolution = \frac{sigma}{mean}$$

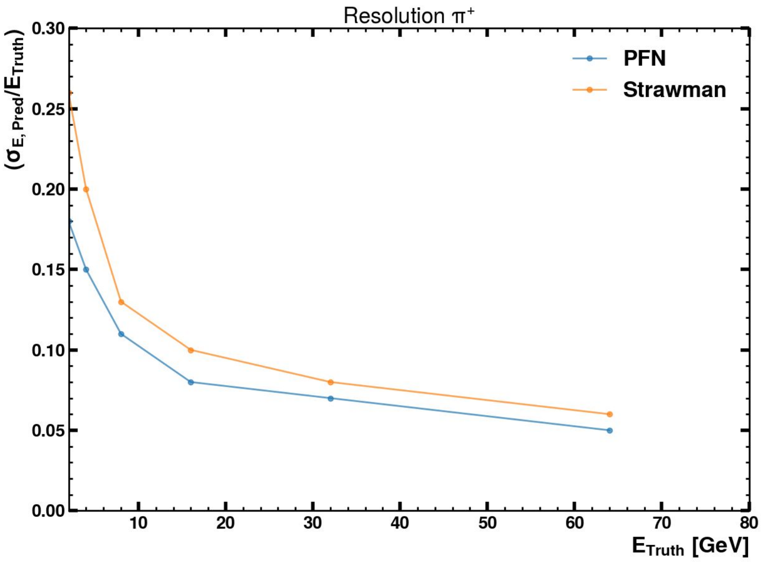
Particle Flow Network

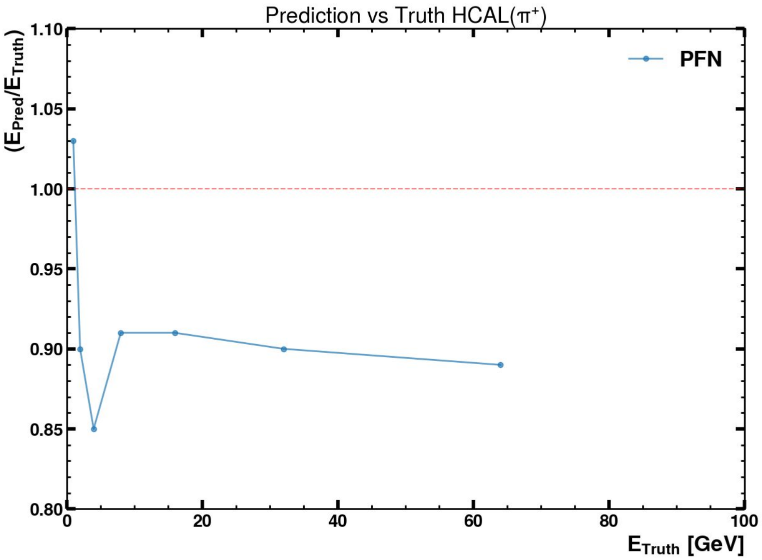




Scale is energy dependent at lower energy value

HCal resolution





Energy scale is flat with 10 % off