Particle Flow, with Machine Learning, in ATLAS

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On behalf of ATLAS collaboration

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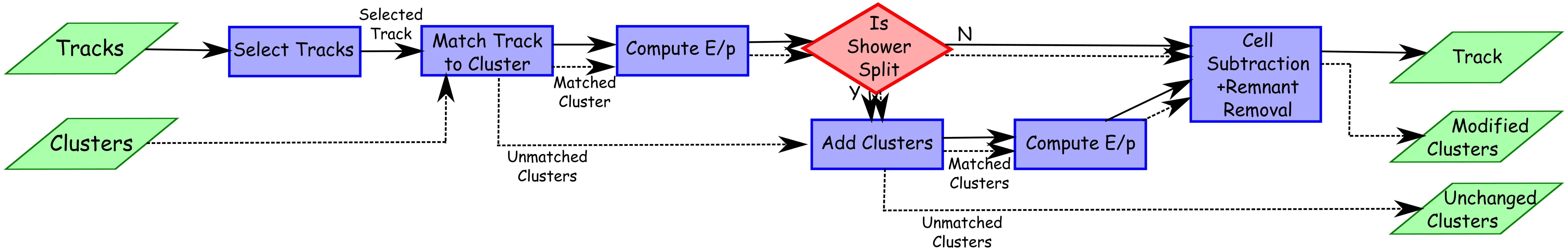
Particle Flow



Particle Flow
(Eur. Phys. J. C 77 (2017) 466)

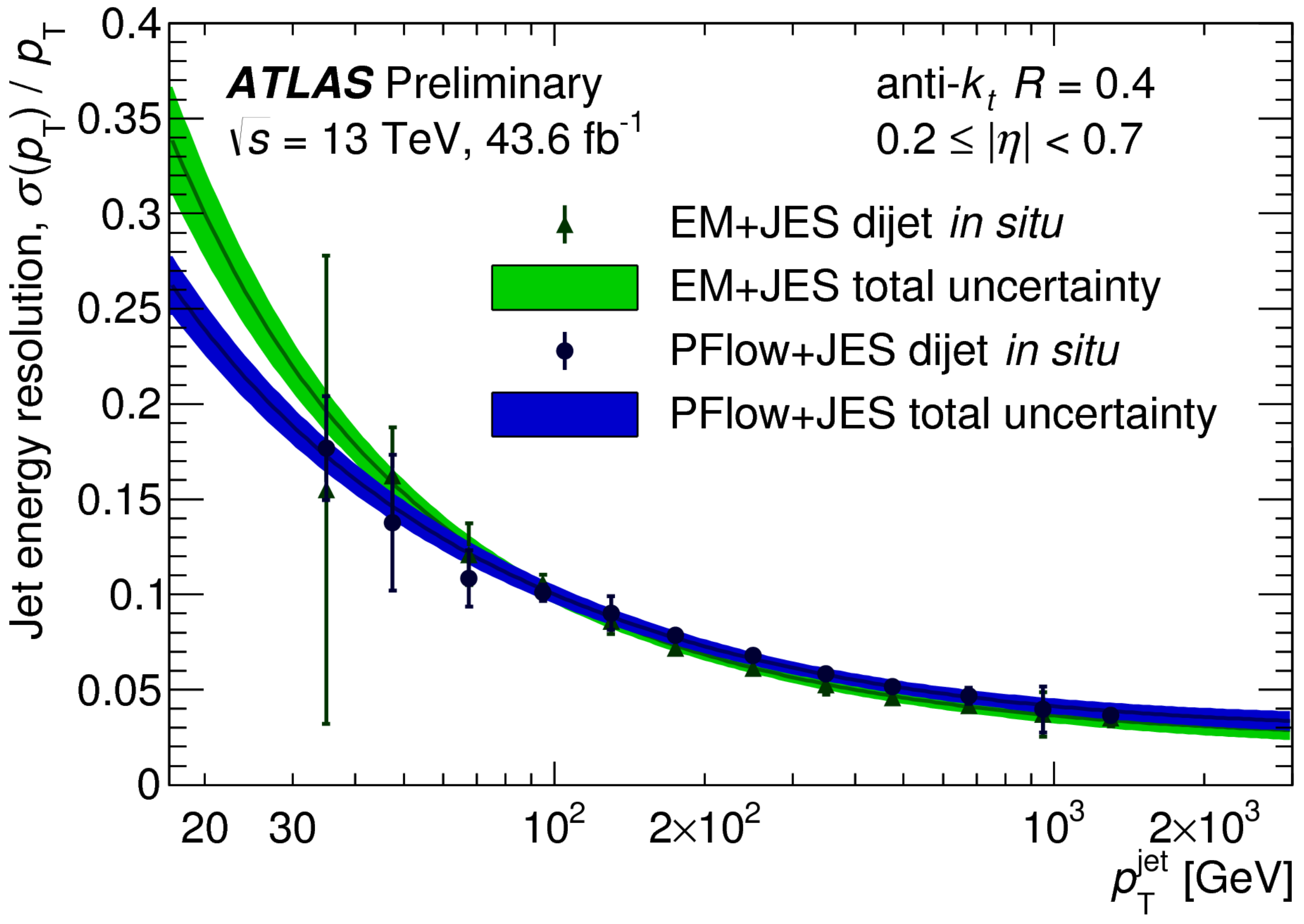
- Starts with Inner Detector tracks and calorimeter topological clusters as input.
- Matching algorithms associate them to each other, and when appropriate subtract out the charged calorimeter shower (based on reference measurements of e/p distributions and their shower shapes).
  - Charged shower is removed calorimeter cell by cell following an ordering principle which strives to first remove the high density core of the shower.
- Used for jet reconstruction
  - Tau reconstruction uses a different particle flow algorithm optimised for taus.
- Output objects have links to other objects (electrons/muons/photons/taus).
  - Links based on underlying ID tracks and calorimeter topoclusters.
  - Allows to redo decisions at Analysis Object Data (AOD) level, after Tier0 reconstruction.

Shower Subtraction

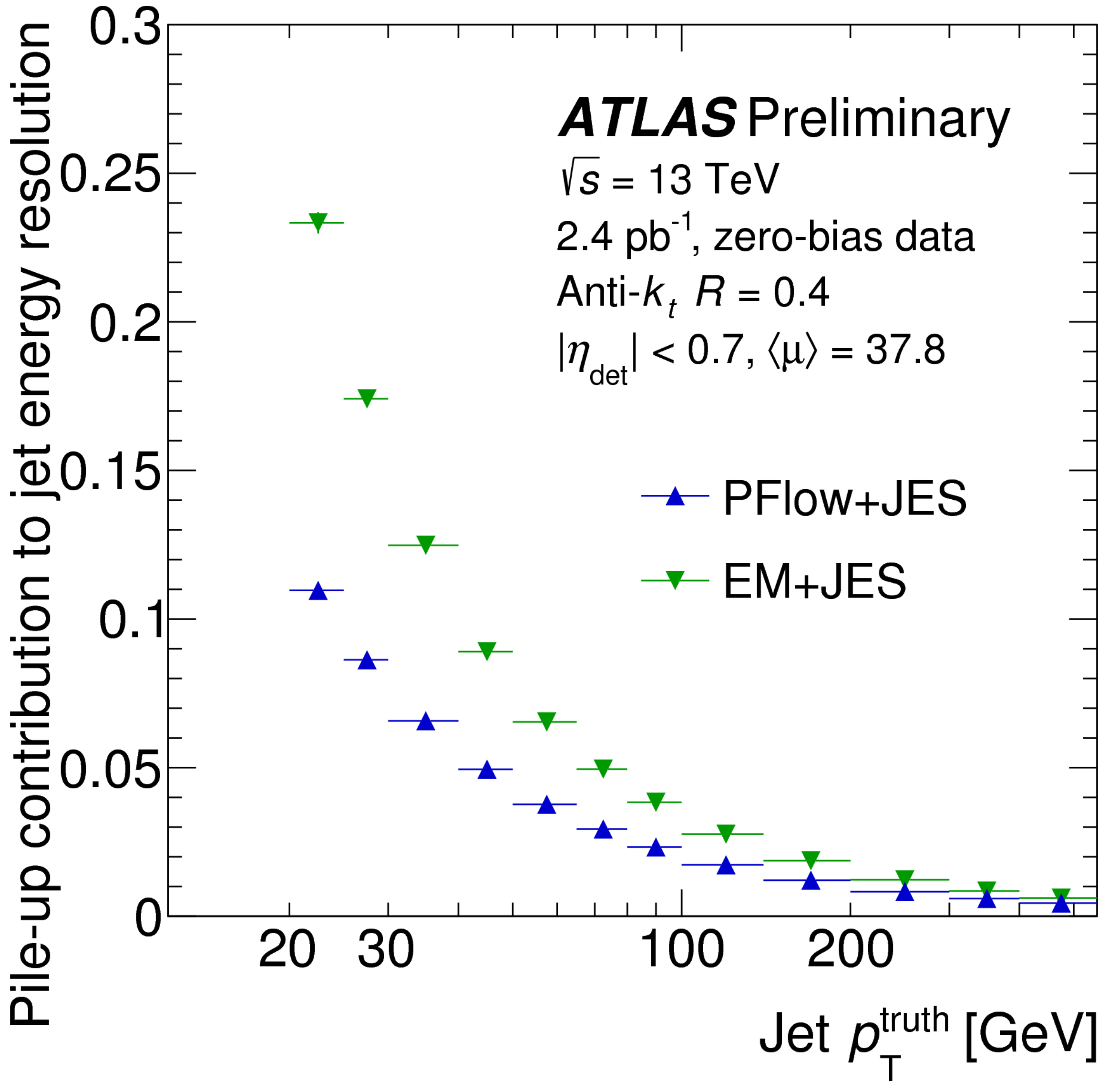
- Calorimeter cells are removed one ring at a time using physics knowledge.
  - Looks rather like a photo with pixels (calorimeter cells) - motivated looking at image based ML techniques

Small Radius Jet Performance

ATLAS-JETM-2018-005



ATLAS-JETM-2019-01



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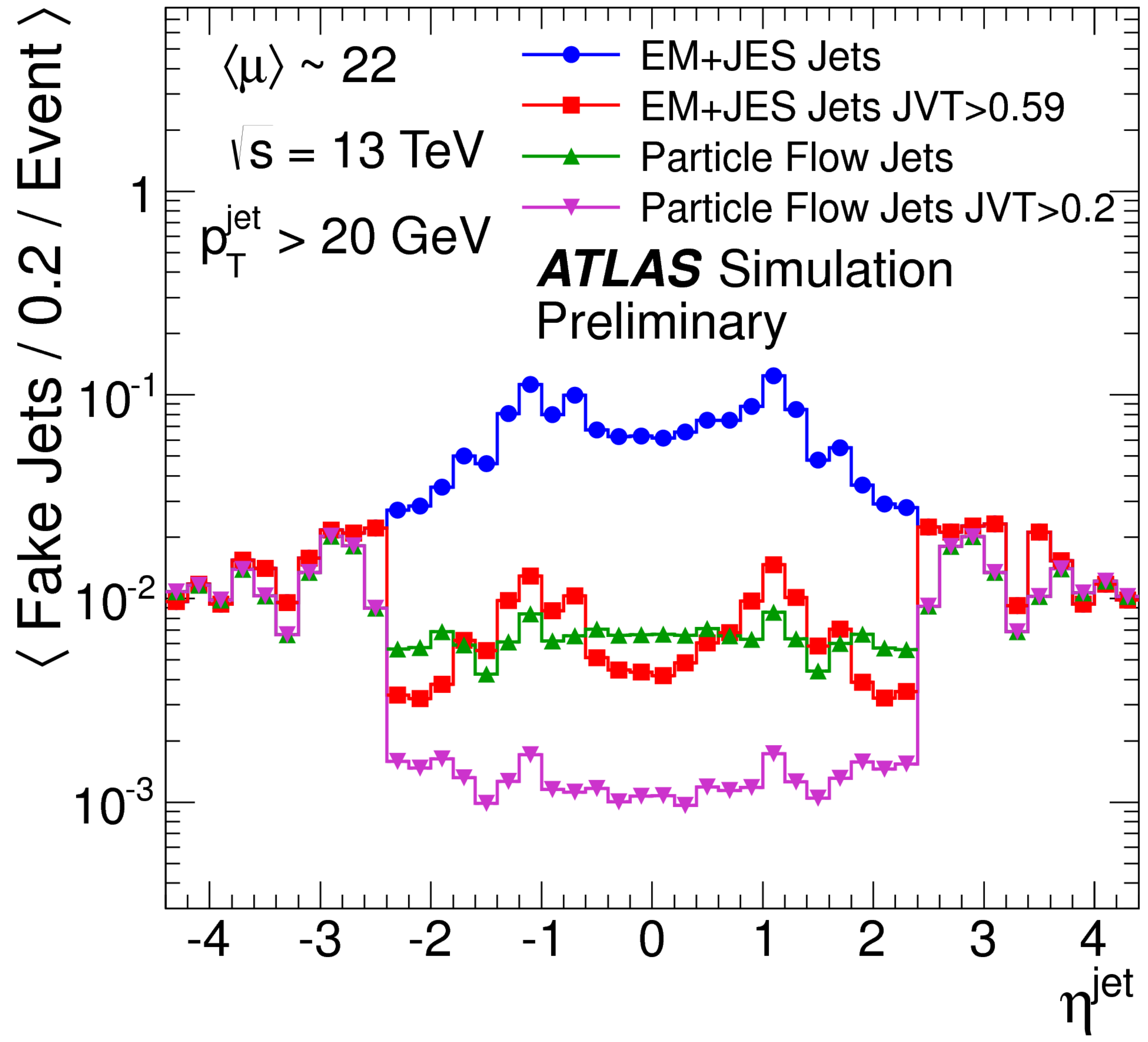
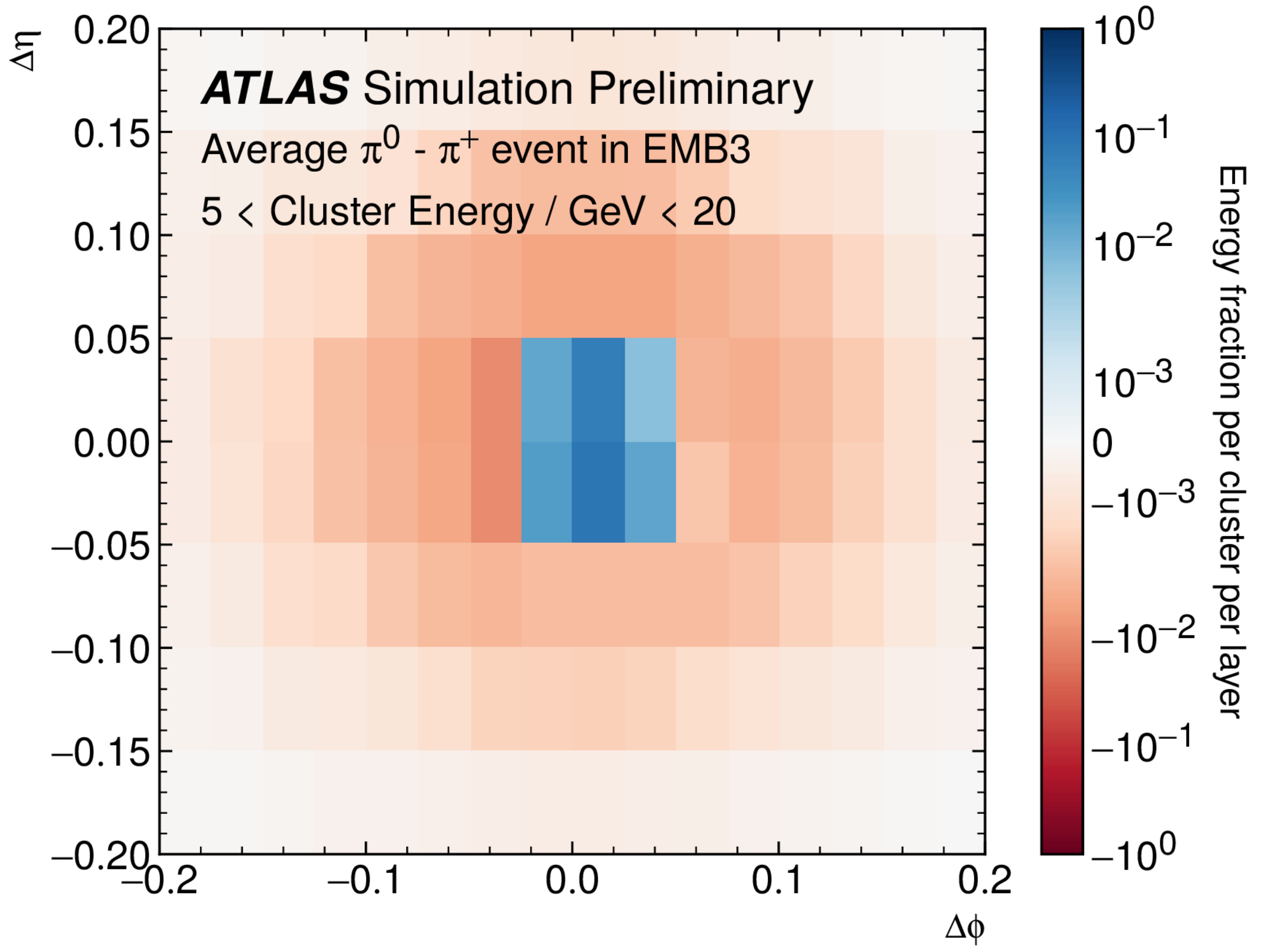
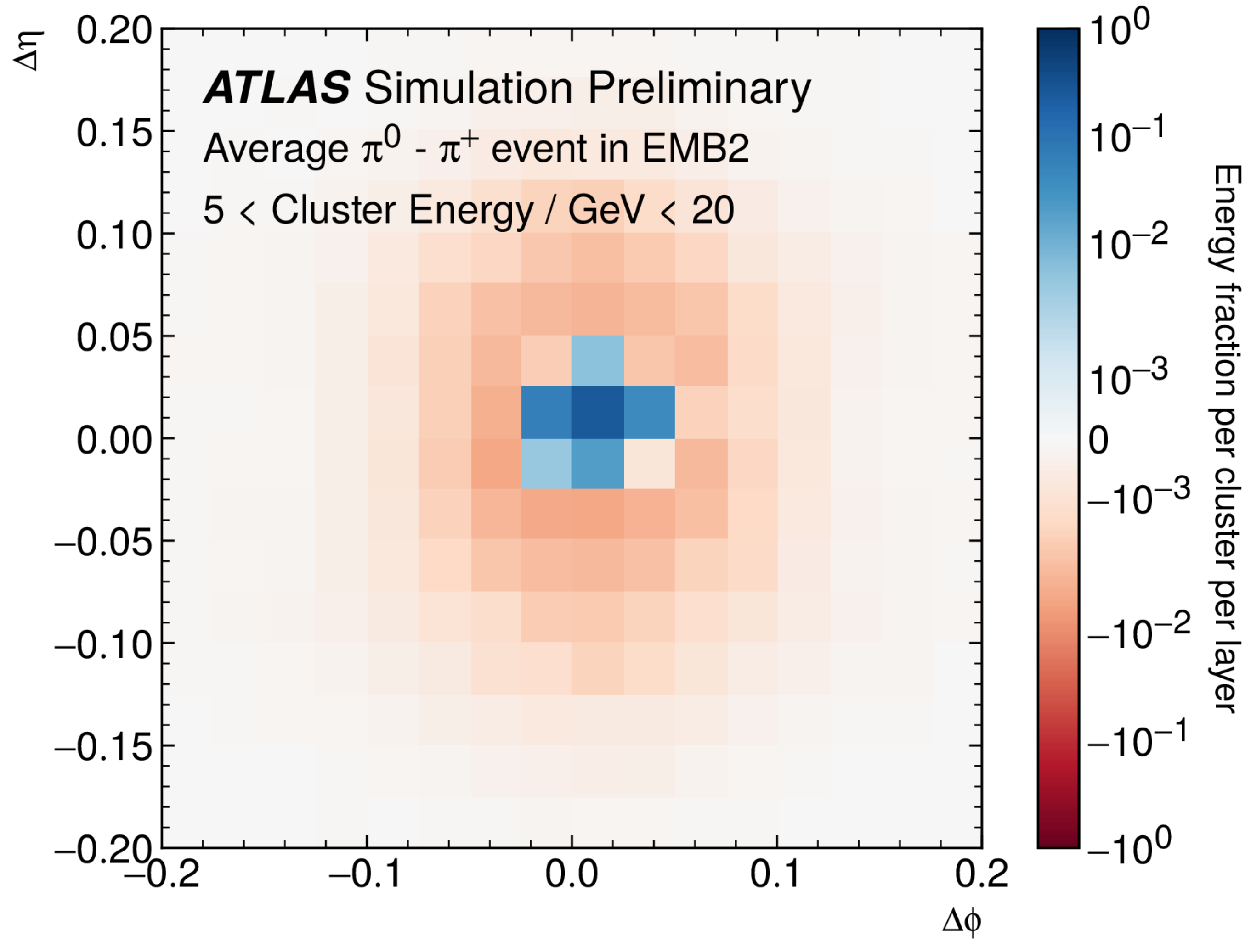


- Improved Particle Flow jet resolution at low P_T (left)
  - Due to smaller contribution to resolution from pileup (middle)
- Fewer Particle Flow pileup jets are reconstructed for the same Hard Scatter efficiency (right)
- Particle Flow is a not big fraction of CPU usage in ATLAS reconstruction
  - Main motivation to look at Machine Learning is to gain physics performance.

Machine Learning

ATL-PHYS-PUB-2020-018





- "LC Topo" (LCW) scheme calibrates individual topoclusters via the Local Hadron Calibration , which is applied to topocluster inputs prior to input to jet finding - has been used for large radius jet finding in ATLAS.
  - Can replace topocluster inputs calibrated to LCW scale with ML calibrated topoclusters.
- Alternative calibration scheme has been studied using Machine Learning (LC)
  - Used samples of isolated charged and neutral pions, without pileup. Calorimeter cluster settings are as used in 2018 data taking conditions.
  - Have considered particles with |eta| < 0.7 (uniform detector layout)

Machine Learning

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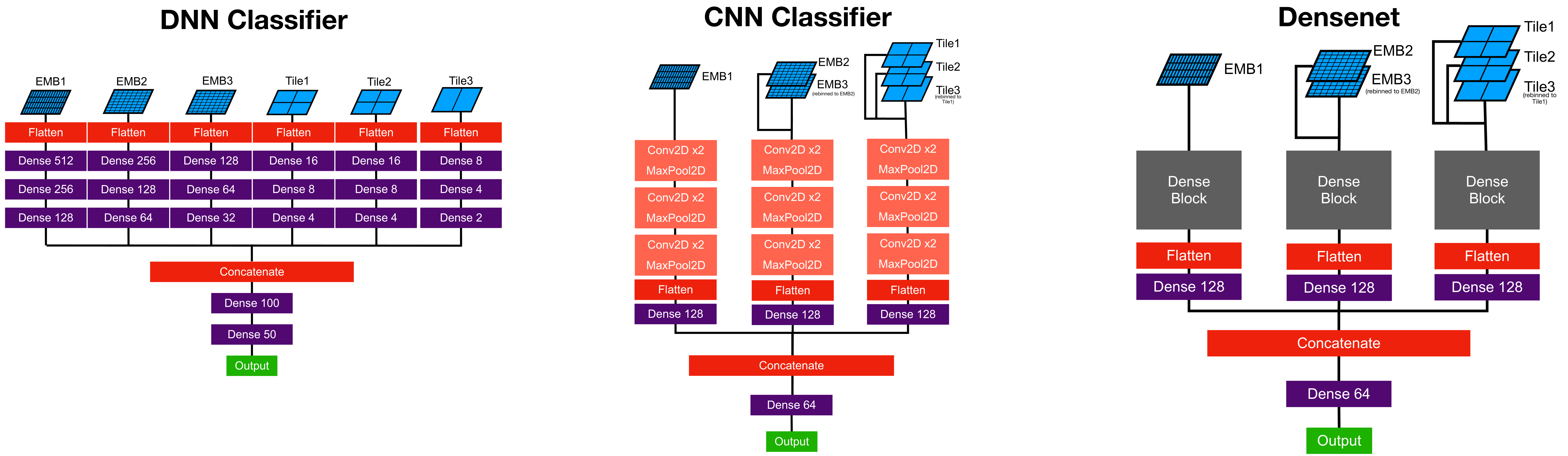
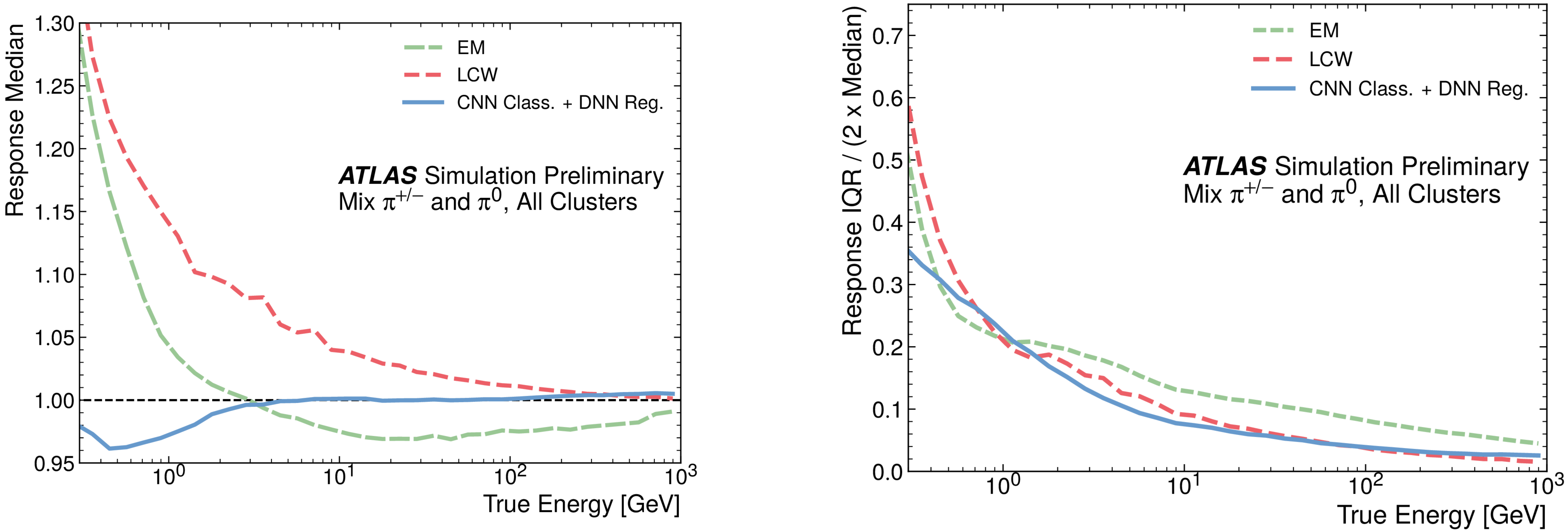


- Deep Neutral Network (DNN), Convolutional Neural Network (CNN) and Densely Connected Convolution Network (DenseNet) have been studied.
- Currently ATLAS LCW scheme uses a Likelihood:
  - Classification step using Likelihood ratio, making use of the cluster energy, eta position, longitudinal depth and average cell energy density.
  - Calibration step deploys calorimeter cell signal weighting which depend on cluster energy and location.
  - The Machine Learning schemes also do both classification and regression.

Machine Learning

ATL-PHYS-PUB-2020-018



- Combined classification and regression test:
  - Compare LCW to combination of CNN Classifier (best) and DNN regression (best)
  - High performance of CNN classifier ensures that the correct energy regression is applied in this mixed particle sample.

Machine Learning in Particle Flow

- Ultimate goal would be to replace classical shower subtraction algorithm with ML approach
  - We know from older studies that used MC truth information to do the subtraction that there are large potential gains to be had
  - Motivation is improved physics performance (fraction of compute resource usage is very small in ATLAS particle flow).
- As a first step we retrained the topocluster calibration algorithms to instead predict the reconstructed topocluster energy based on the combined track and topocluster properties.

Energy Prediction

- Key step in particle flow is to lookup how much energy a charged particle deposited in the calorimeter
    - Then one can remove it from the calorimeter measurements and replace with the track measurement.
- Currently we use single particle Monte Carlo to measure the ratio of matched calorimeter energy to track energy (e/p), binned in a way (track energy, track eta and calorimeter layer of shower core) to capture variations.
    - Measurement is done with Gaussian fit to e/p distribution.
    - Mean and width saved in lookup table
    - Then you look up the mean of the e/p and the expected calorimeter energy is e/p multiple by the track energy. The width is used to quantify whether remaining energy is noise etc.
    - ML replaces the lookup of the mean only currently - a large part of the project funded by STFC IRIS was to put in place the complex code to do this. Then should be straightforward to re-use for other use cases in particle flow.

Machine Learning in Particle Flow

- Created new software tool that takes the NN inputs as an argument, setup from reco quantities for each track-cluster system, in the event
  - Uses ONNX runtime to run inference and provide a predicted energy deposit for the calorimeter - model in keras was converted to ONNX. Training code is based on code used for topocluster calibration provided by R. Bates (Triumf).
  - Currently validating C++ athena implementation against original keras NN in standalone python (used ROOT tuples for training and inference) - with help of experts are seeing fewer and fewer differences.
  - Standalone setup gives reasonable results (plots are not public).
  - Final steps will then be:
    - to toggle the energy prediction from the current setup to the new NN setup and compare
    - prepare the athena code for a MR into master nightlies (NN off by default, we won't use this for initial processing in Run 3).

ATLAS EXPERIMENT

"At CERN in the ATLAS experiment, we have integrated the C++ API of ONNX Runtime into our software framework: Athena. We are currently performing inferences using ONNX models especially in the reconstruction of electrons and muons. We are benefiting from its C++ compatibility, platform*-to-ONNX converters (* Keras, TensorFlow, PyTorch, etc) and its thread safety."

–ATLAS Experiment team, CERN (European Organization for Nuclear Research)

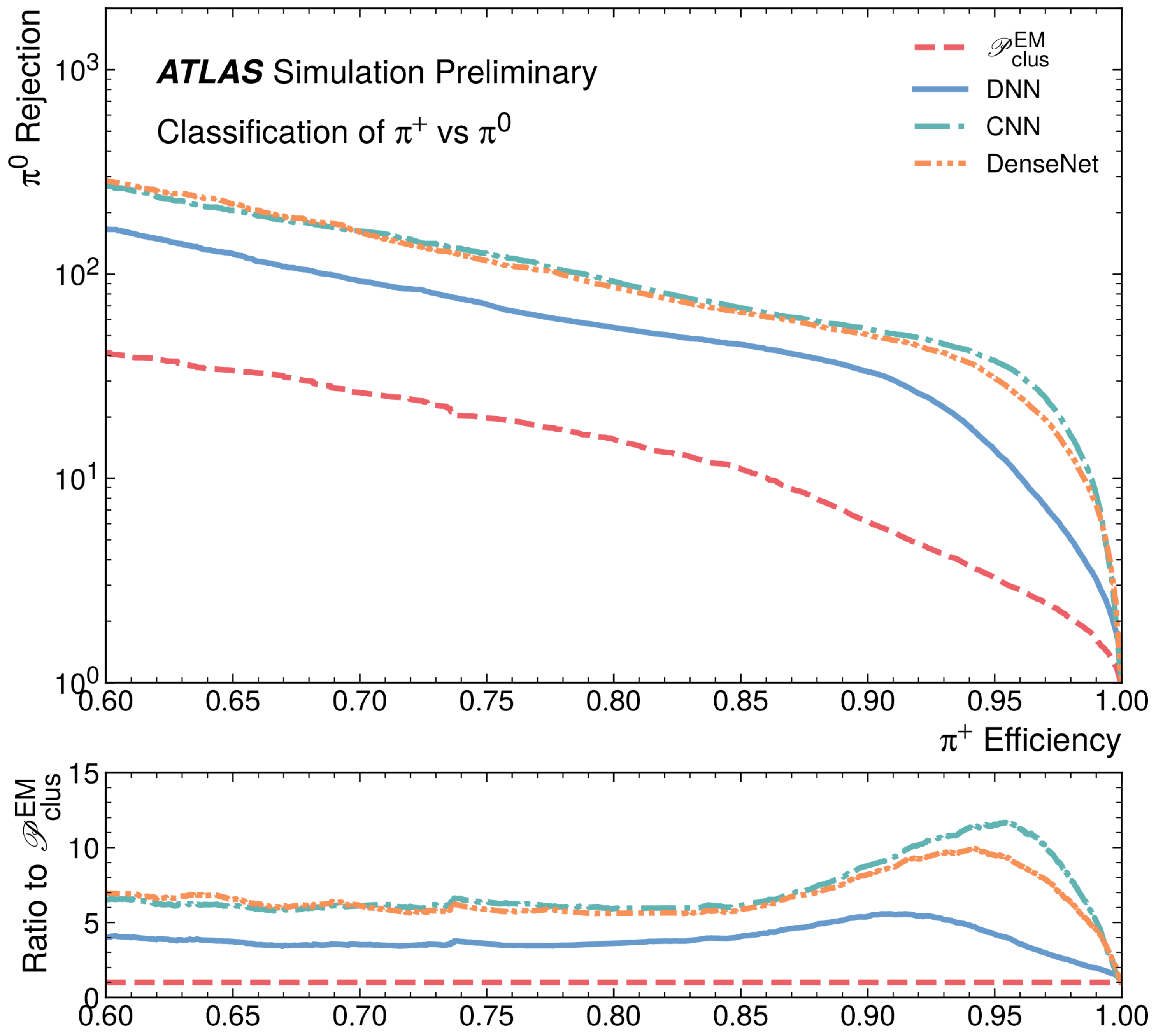
Conclusions

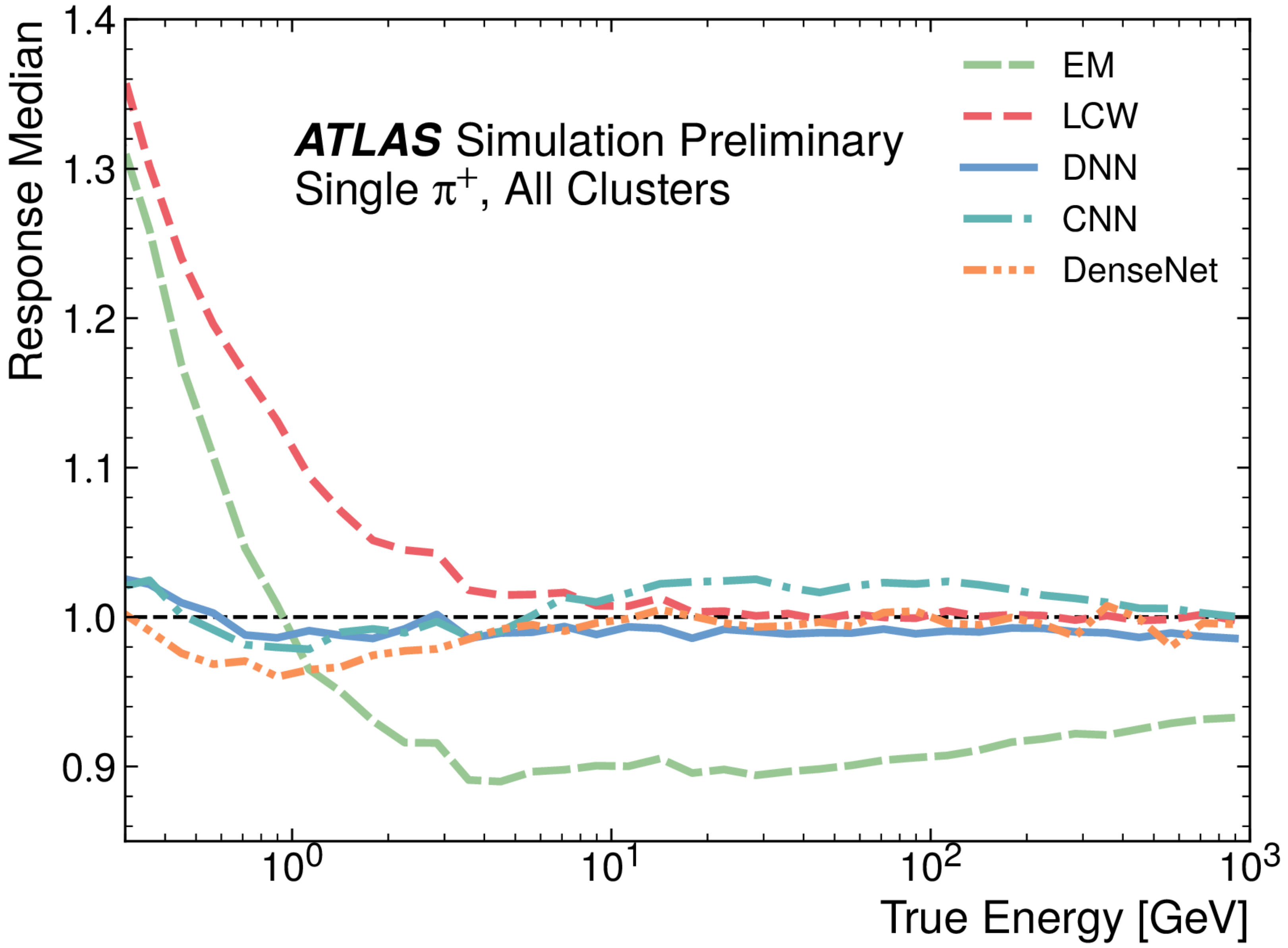
- Overview of particle flow algorithm and current Run 2 performance shown.
- Different ML models that have been studies were discussed
  - Should be new PUB note out soon with even more architectures for calibrations.
  - The setup of ML usage in ATLAS particle flow code done in this project puts us in a good position to then try out other models for the same task and to use such models for other tasks in particle flow.
  - Ultimate longer term aim will be to decide how much of ATLAS particle flow can be replaced with ML for Run 4 HL-LHC - generally ATLAS has a plan to evaluate how much more ML to use and whether to run "classic" algorithms on GPU for HL-LHC.

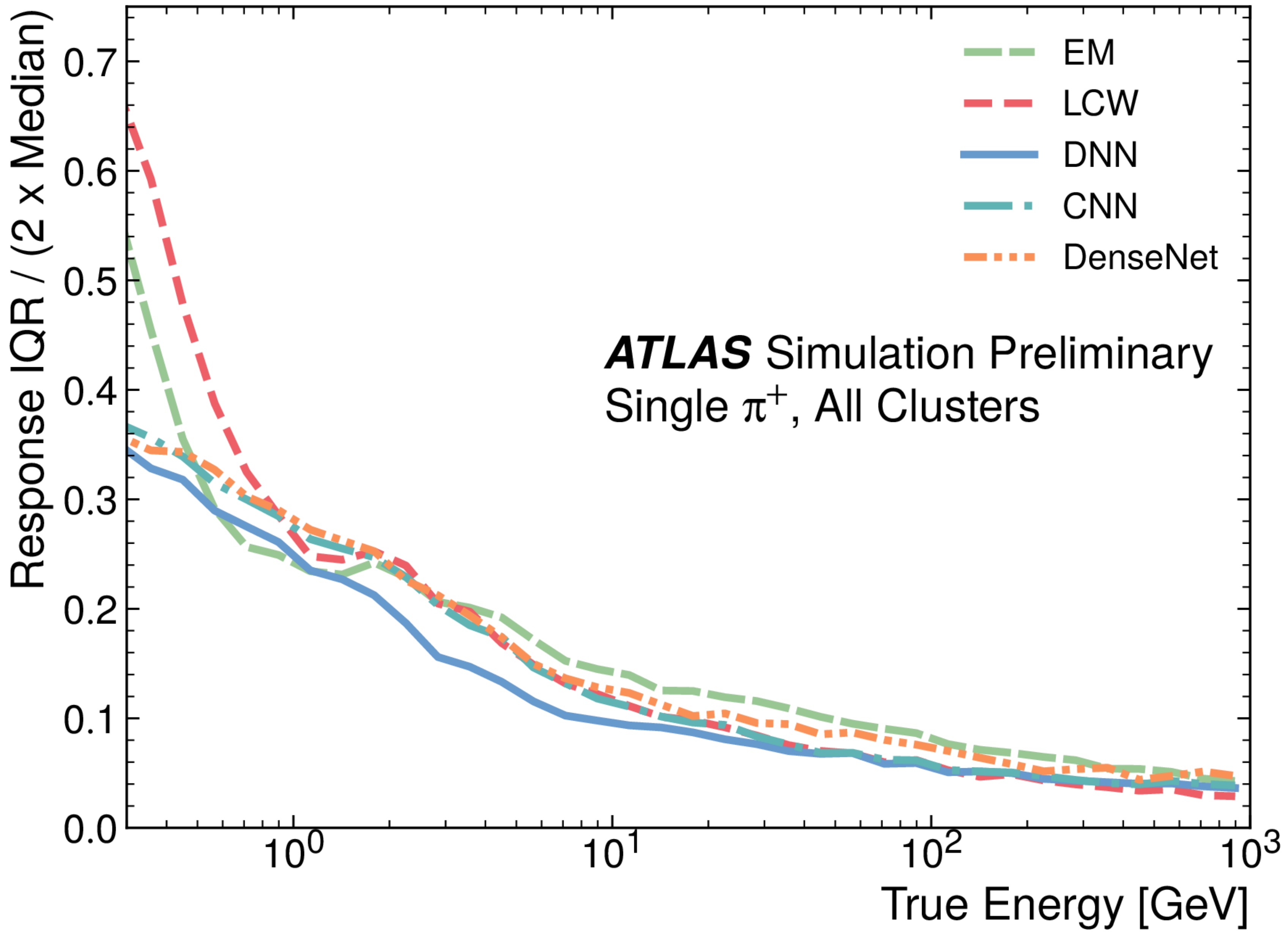
Extras

Machine Learning

ATL-PHYS-PUB-2020-018







- For the classification problem, shown on the left, all three schemes perform better than the LCW scheme (ρ_{EM}^{clus})
  - DNN not as good as CNN, Densenet.
- For the regression problem, shown in the right two plots, all three schemes perform better than the LCW scheme.
  - DNN gives best resolution and has good linearity.