Deep learning techniques for energy clustering in the CMS electromagnetic calorimeter

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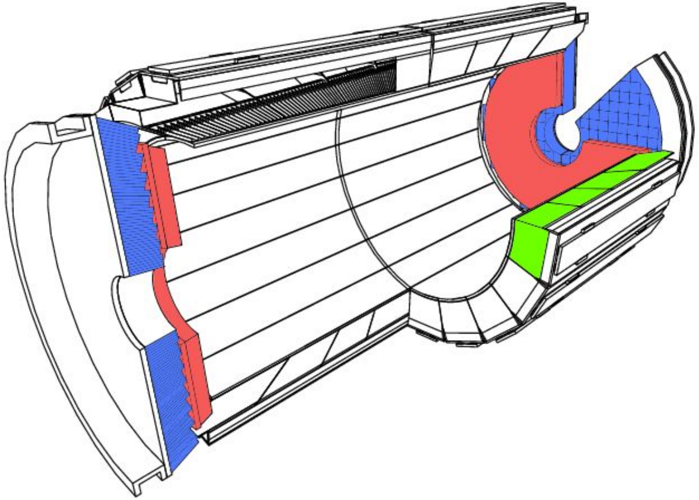
ICHEP2022 Bologna - July 6th-13th
08/07/2022

Outline

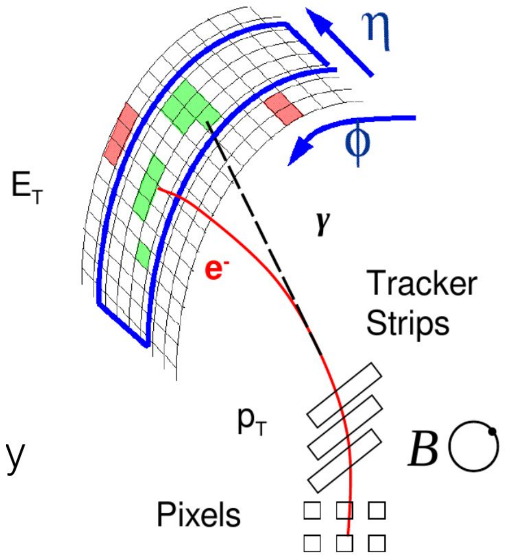
CMS ECAL: Compact, homogeneous, hermetic and fine grain calorimeter

- 75848 lead-tungstate ($PbWO_4$) scintillating crystals
- Ecal Barrel (EB): 0 < η < 1.48
- Ecal Endcap (EE): 1.48 < η < 3
- Preshower (ES): two Lead/Si planes per side, 1.65 < η < 2.6



- SuperClustering reconstruction
- "Mustache"
  - Algorithm
  - Performance
- "DeepSC": GraphNN SuperClustering
  - Concept
  - Architecture
  - Input variables and training
- Preliminary performance:
  - Jet discrimination
  - Energy resolution and scale

SuperClustering in ECAL



Magnetic field and material in front of ECAL

↓

Electrons and photons fragment in multiple energy deposits in ECAL

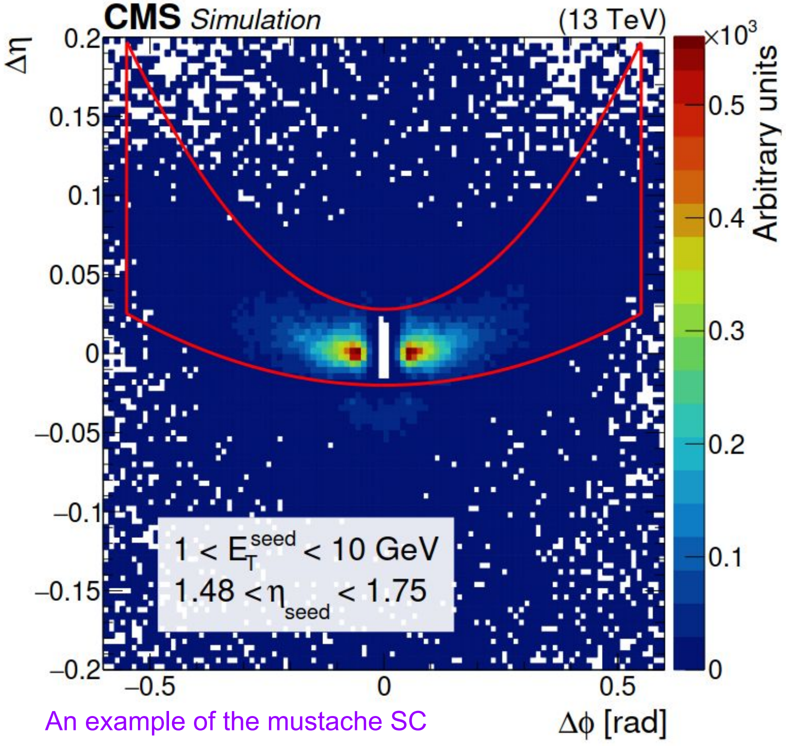
Rechits → Clusters → SuperClusters

Rechits
- Reconstructed **energy deposits in crystals**

Clusters
- **Rechits are gathered** together around the crystal with highest energy to form clusters
- Each cluster represents a **single particle**

SuperClusters
- Bremsstrahlung and photon conversion before the ECAL, **clusters have to be combined together to form a SuperCluster**
- Particle **energy reconstructed using SuperClusters**

The algorithm currently used in CMS for reconstruction of SuperClusters



An example of the mustache SC distribution for electron JINST 16 (2021) P05014

Purely geometrical approach:

- All the clusters falling into the specified “mustache” shape are collected to form the SuperCluster
- The size of the “mustache” window depends on energy and position of the seed (most energetic cluster)
- “Mustache” shape due to the CMS magnetic field (spread along φ)

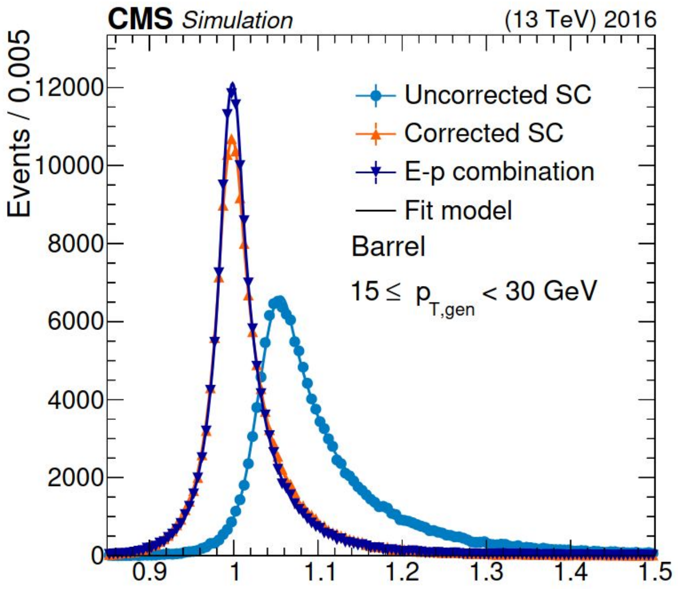
High efficiency: able to gather even low-energy clusters

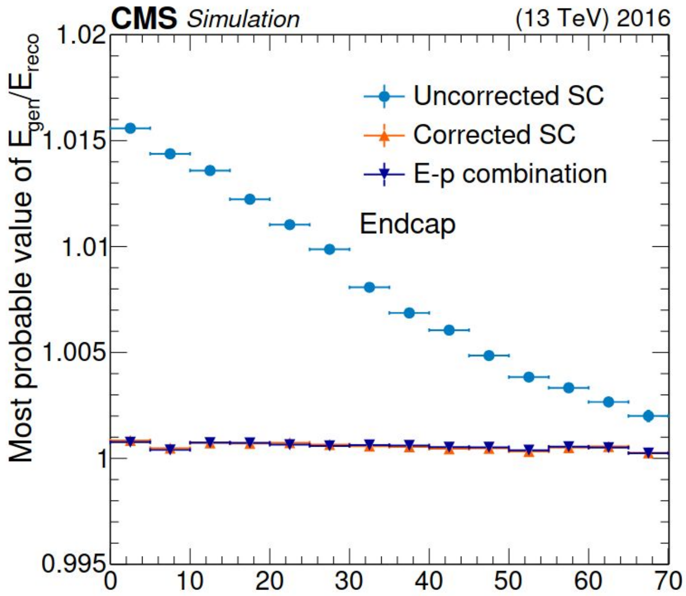
Suffers from pileup (PU) and noise contamination

Energy regression is further applied to correct PU and noise contamination on average

SuperClusters into Particle-Flow

clusters, SCs, tracks associated to electrons and tracks associated to converted photons are given as an input to Particle Flow → **Linking between the input objects** is done for Electrons and Photons → Refined SCs are built → Selections applied to define **electrons and photons, built from refined SC using track information** → **SuperClusters, electron and photon energy calibrated with regressions** using ECAL and tracker information





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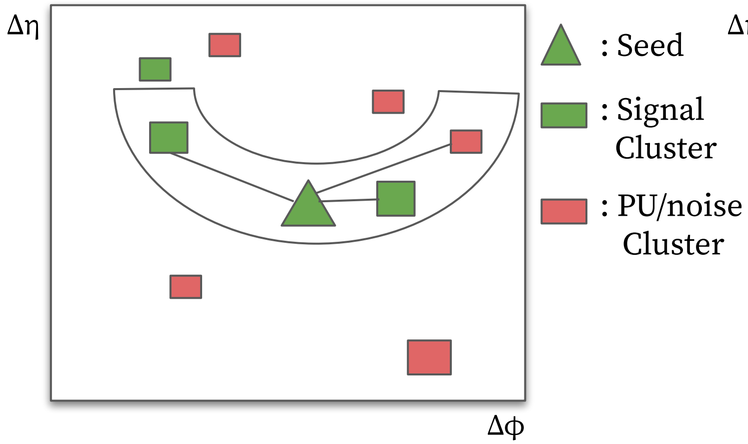
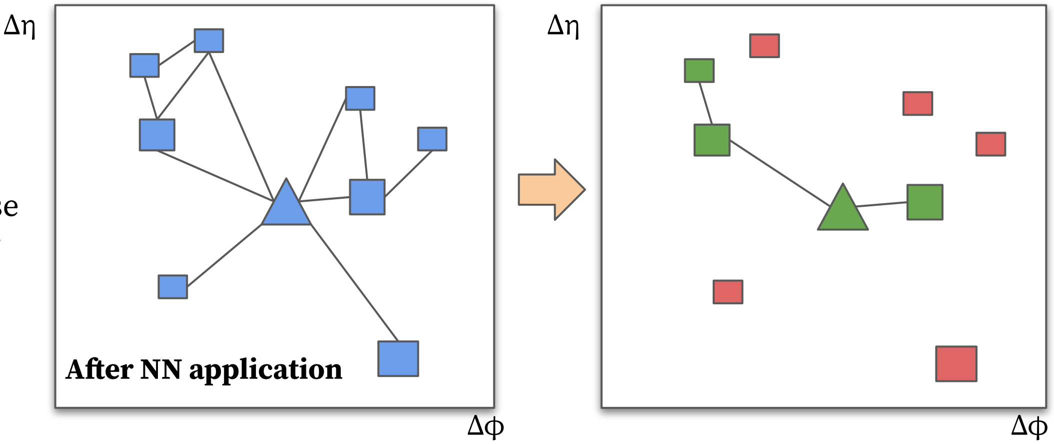
Improving SuperClustering algorithm

Mustache SuperClustering (RAW energy)



GraphNN SuperClustering (RAW energy)



Purely geometrical algorithm

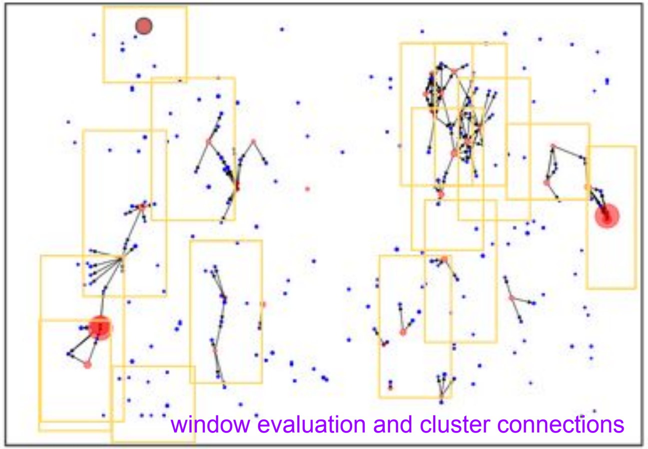
Evaluated on one cluster at a time

Large efficiency for signal, but also large PU and noise contamination
→ regression needed to fully recover the energy

Based on Graph Convolutional Networks (GCN)

Evaluated on all the clusters together in a region around the seed

Filters noise/PU on a cluster by cluster basis:
- Better cluster purity than Mustache, while keeping the same signal efficiency
- Cleaner input to the Particle Flow algorithm



New algorithm for the SuperClusters with ML technique

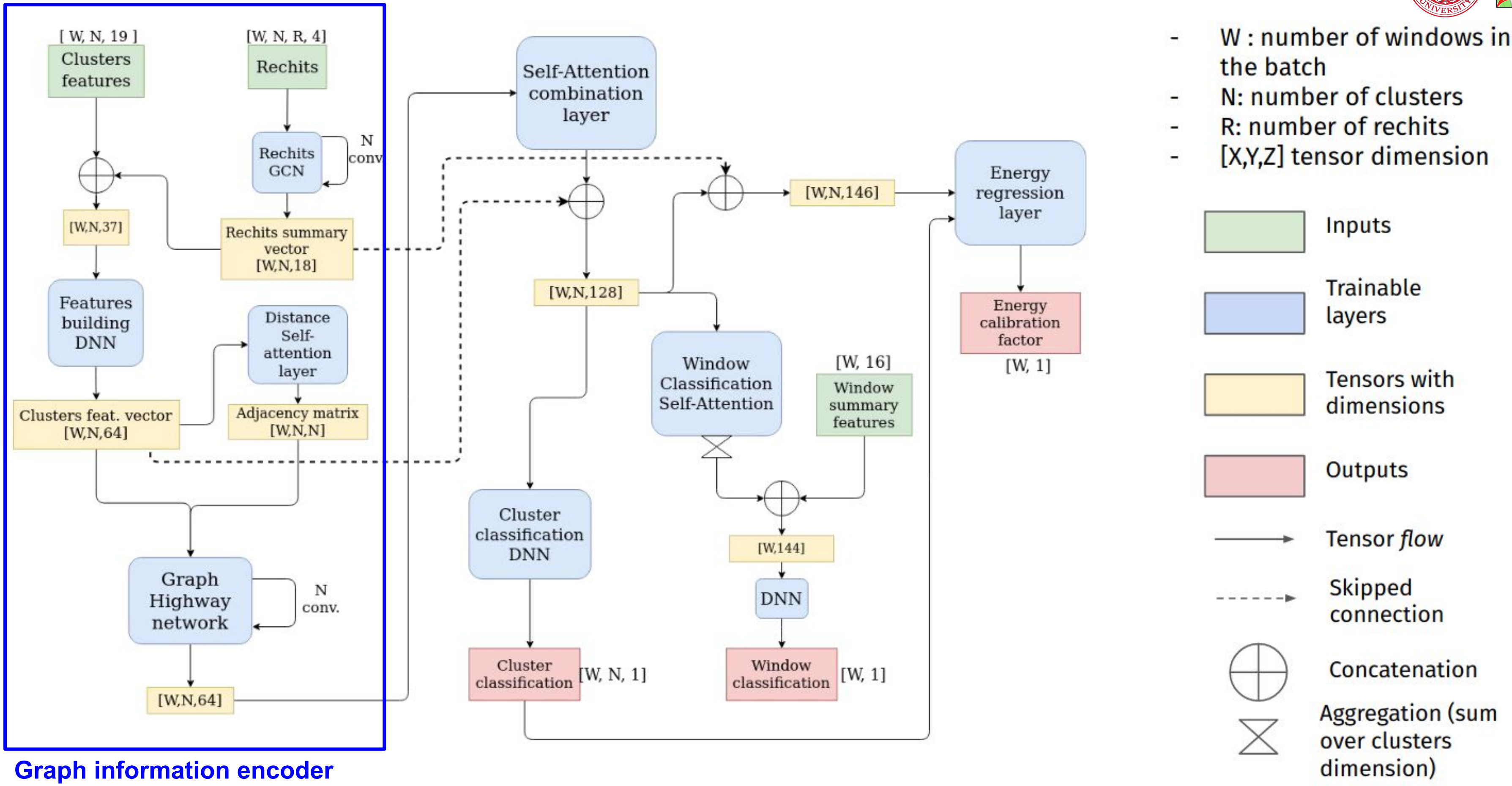
Windows are opened around all the clusters with E_T>1 GeV (seeds)
(Window dimensions are η-dependent)

The outputs: cluster classification (in/out of SC), window classification (electron/photon/jet), energy regression.

Inputs:
- Cluster information: E, E_T , η, φ, z, number of crystals, relative to seed: is_seed_flag, Δη, Δφ, ΔE, ΔE_T
- List of Rechits for each cluster: energy, η, φ, z
- Summary window features: max, min, mean of the crystal variables: E_T , E, Δη, Δφ, ΔE, ΔE_T

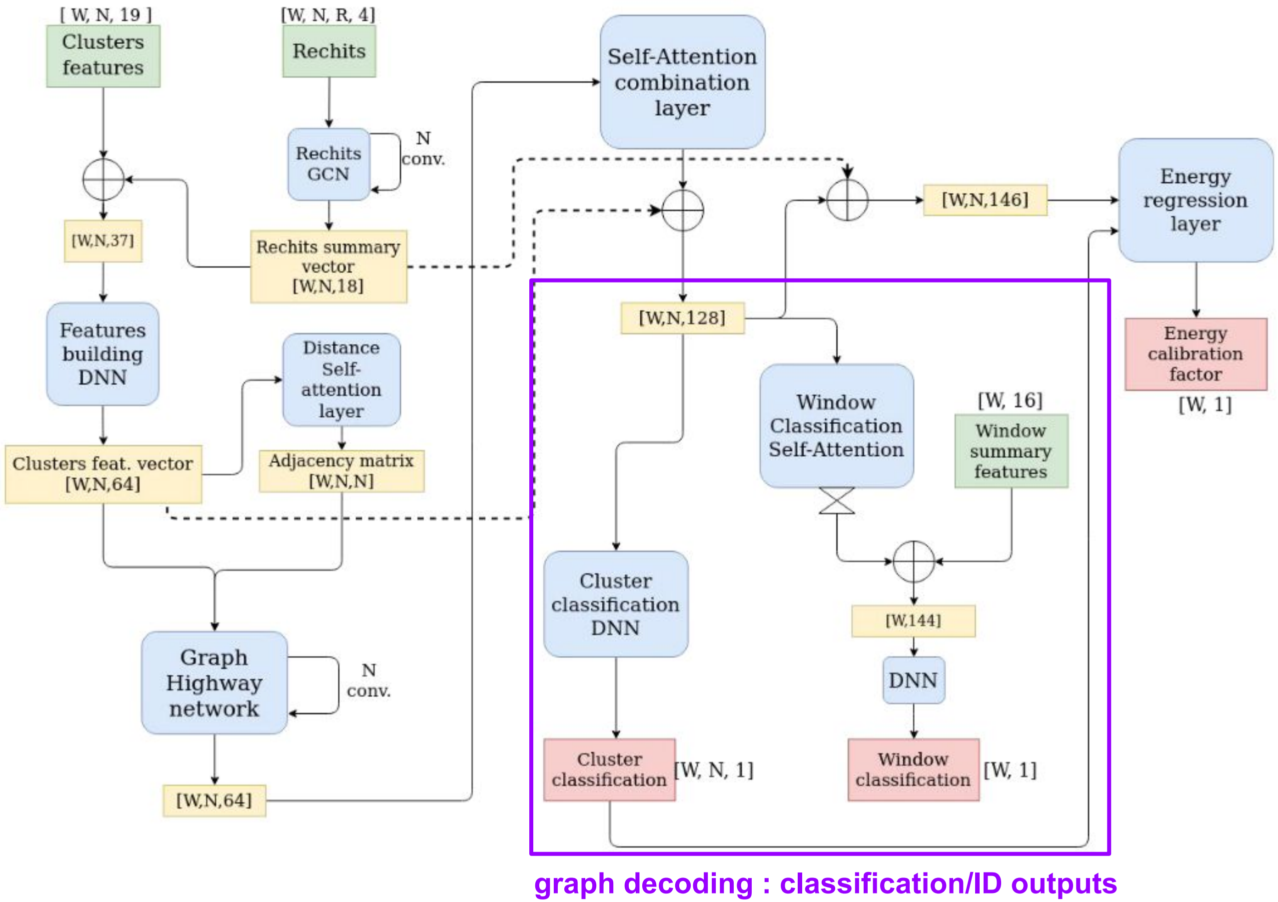
Training and testing the dataset:
- Full simulation of electrons and photons generated uniformly in p_T=[1,100] GeV
- PU uniformly distributed between [55,75] interactions

GraphNN SuperClustering: Architecture



- W : number of windows in the batch
- N: number of clusters
- R: number of rechits
- [X,Y,Z] tensor dimension

GraphNN SuperClustering: Architecture



- W : number of windows in the batch
- N: number of clusters
- R: number of rechits
- [X,Y,Z] tensor dimension

Inputs

Trainable layers

Tensors with dimensions

Outputs

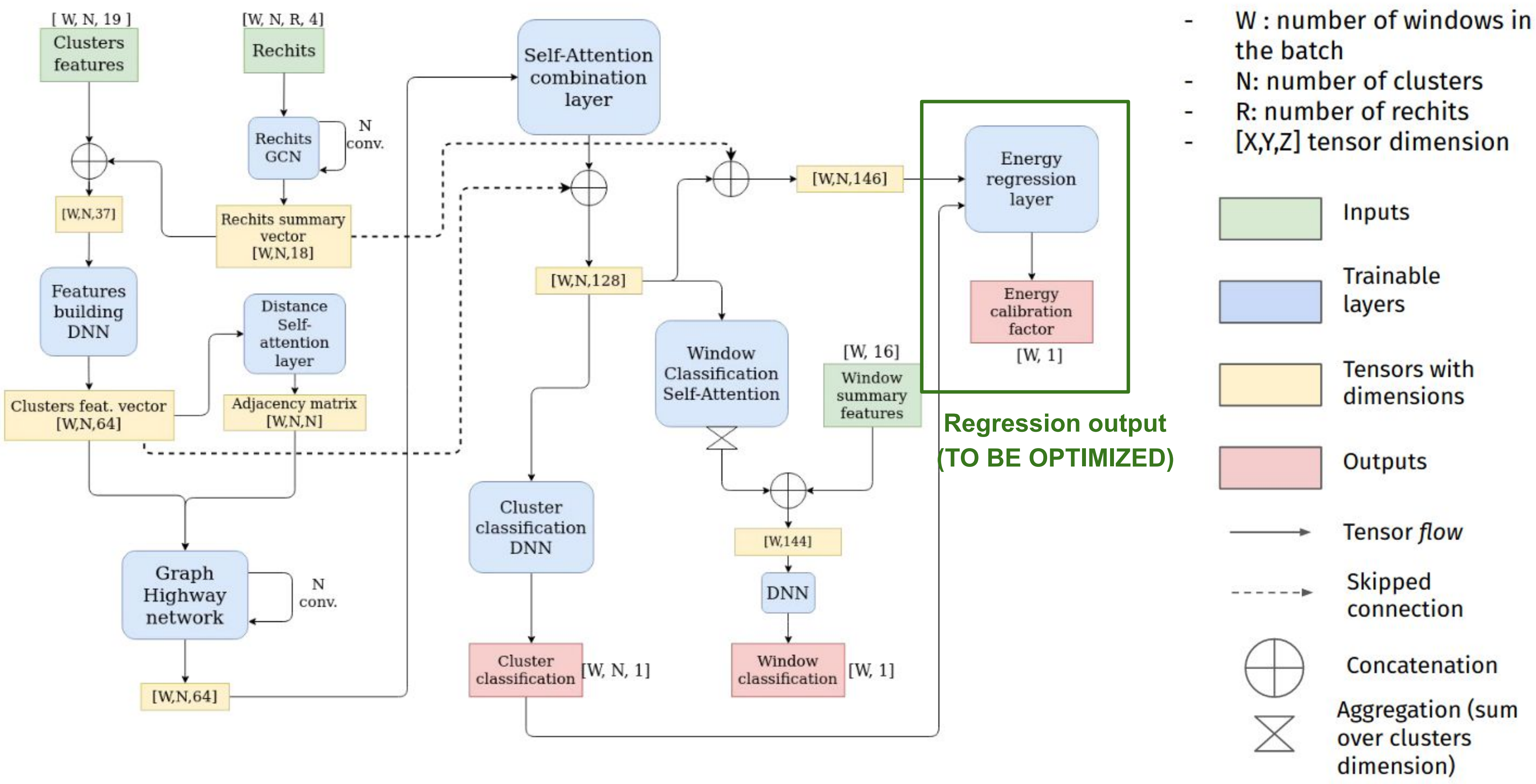
Tensor *flow*

Skipped connection

Concatenation

Aggregation (sum over clusters dimension)

GraphNN SuperClustering: Architecture

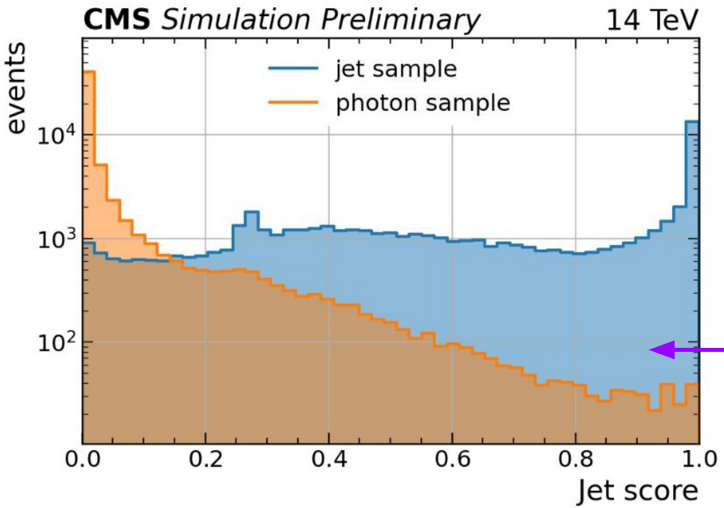


Window classification

Same network can be used to identify the flavor of the particle:

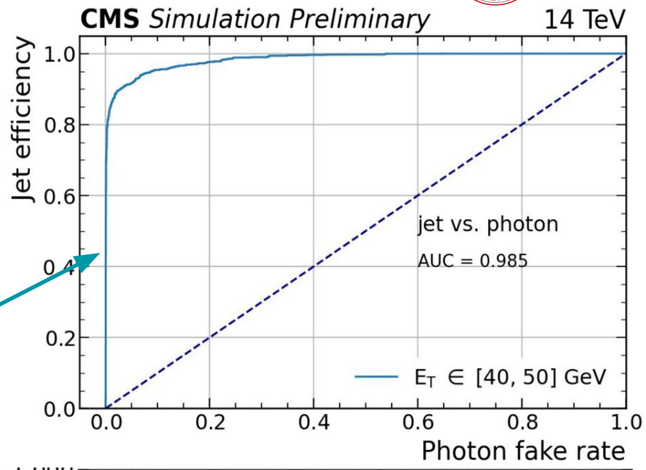
- Identify the clusters belonging to jets
- Use only ECAL information
- Train using a jet dataset (uniform in p_T=[1,100] GeV and [55,75] PU)
- Avoid performance degradation for electrons/photons, Transfer Learning is used to re-train only the ID part of the network

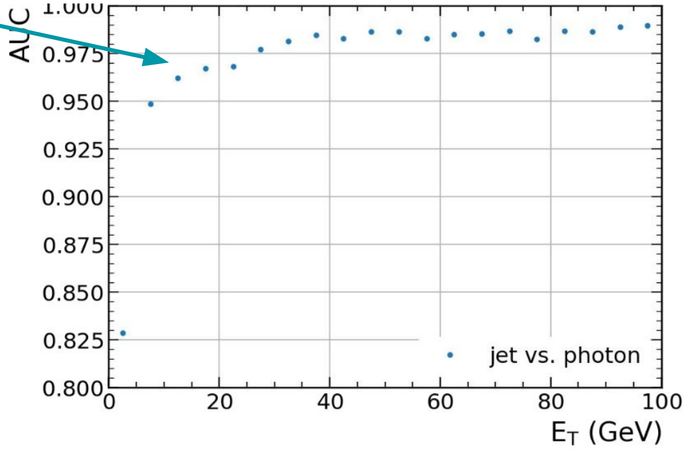
Similar performance for electrons



Efficiency and fake rate built from jet and photon samples

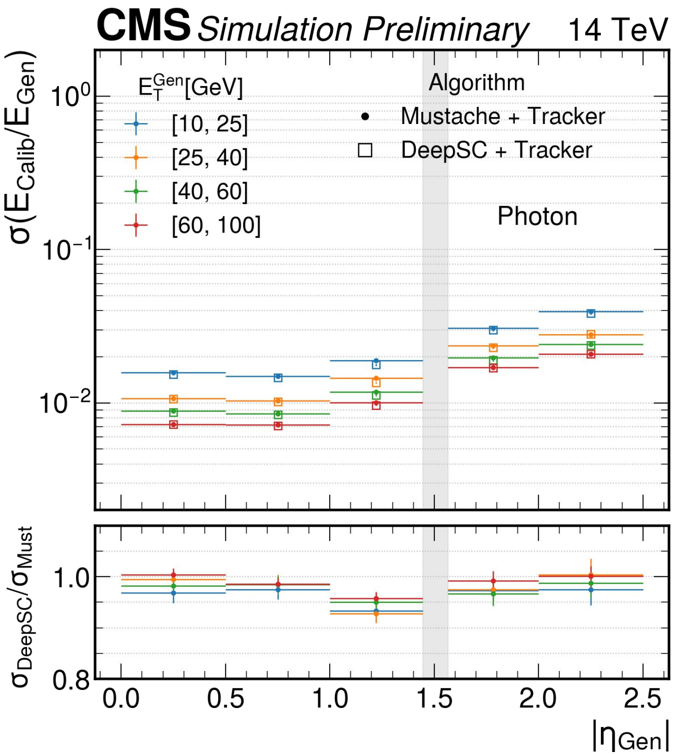
Likelihood to be predicted as jet (score) for the jet and photon sample

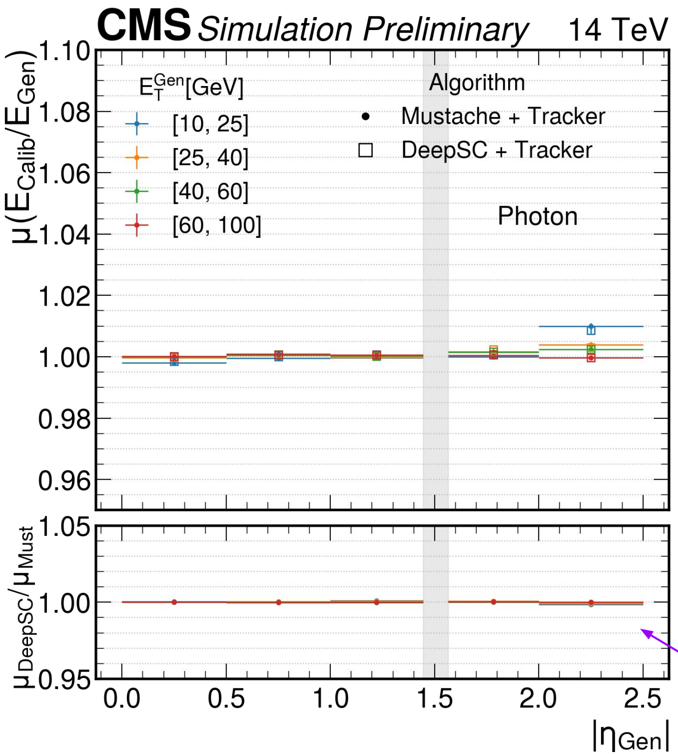




Resolution and scale:

- Reconstructed calibrated (regression) photon energy (E_{calib}) divided by the true energy of the simulated particle (E_{gen})
- Estimated fitting with a Cruijff function



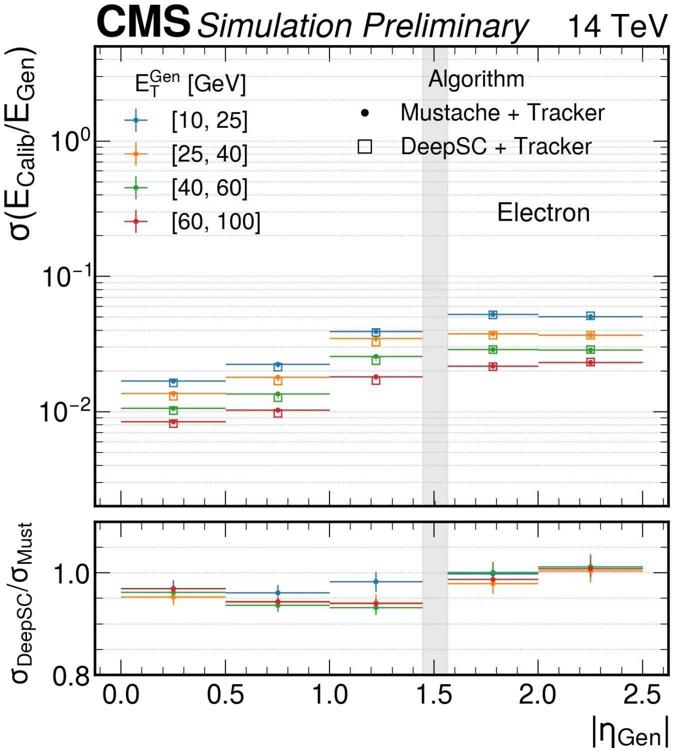


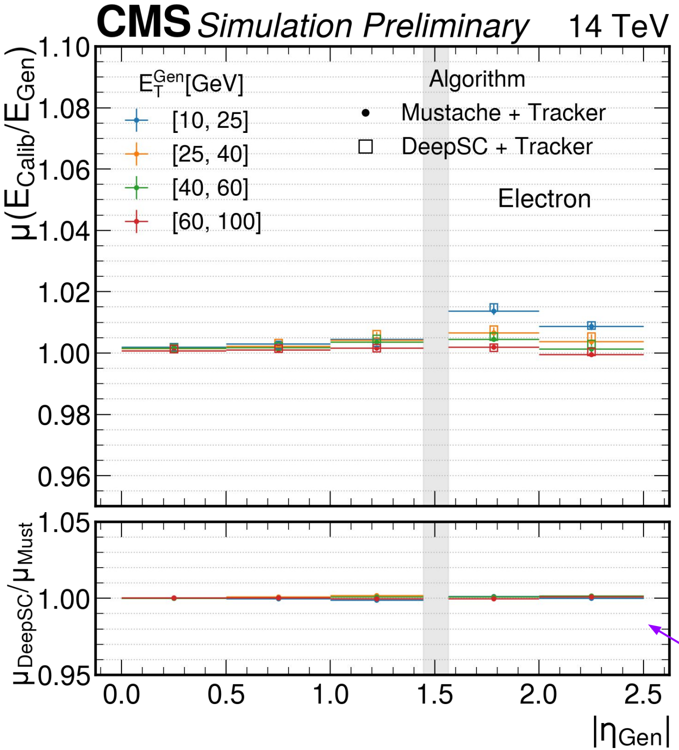
stable scale

Energy scale and resolution performance: Electrons

Resolution and scale:

- Reconstructed calibrated (regression) electron energy (E_{calib}) divided by the true energy of the simulated particle (E_{gen})
- Estimated fitting with a Cruijff function





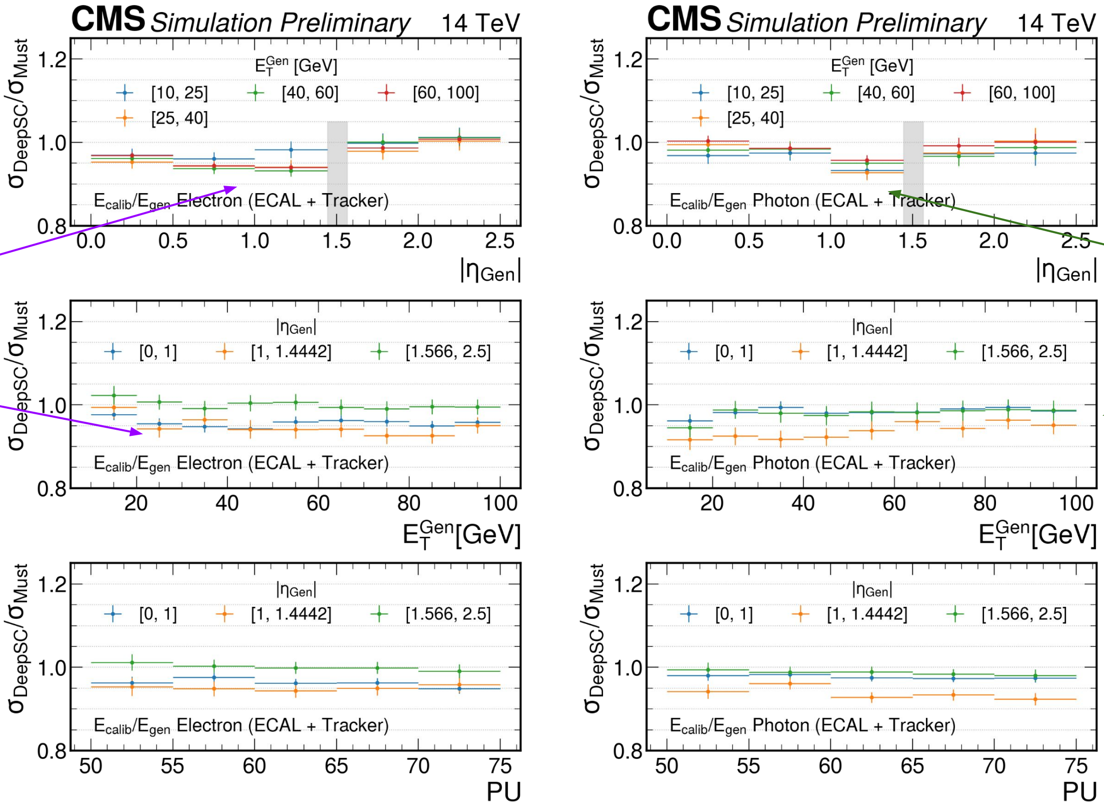
stable scale

Energy scale and resolution performance: SC summary

Resolution and scale:

- Reconstructed calibrated (regression) SuperCluster energy (E_{calib}) divided by the true energy of the simulated particle (E_{gen})
- Estimated fitting with a Cruijff function

clear improvement for electrons in EB 4th module (more material)



clear improvement for photons in EB 4th module (more material)

electrons fragment more than photons:

By construction "Mustache" behaves better for electrons

Improvement as a function of PU

Summary

- **SuperClustering reconstruction**
  - Because of conversion and brehmsstrahlung, multiple ECAL energy deposits (clusters) need to be collected to reconstruct photons and electrons

- **"Mustache"**
  - Current reconstruction algorithm
  - Large efficiency for signal, but also large PU and noise contamination (regression needed to fully recover the energy)

- **"DeepSC": GraphNN SuperClustering**
  - Evaluate all the clusters together in a region around the seed
  - Filters noise/PU on a cluster by cluster basis (cleaner input to the Particle Flow algorithm)

- **Preliminary performance:**
  - Jet discrimination: AUC jets vs photons > 0.95
  - Very stable energy scale
  - Up to 10% resolution improvement for photons and electrons

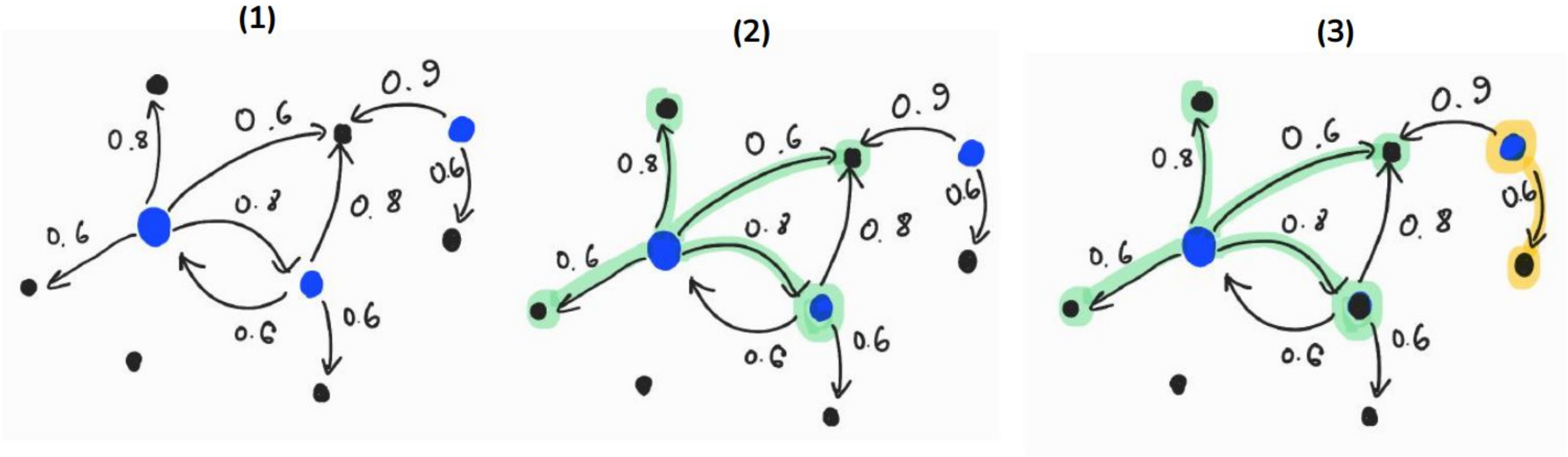
- **To do list:**
  - Full validation on data and on a broader simulation sample

Backup

Collecting algorithm

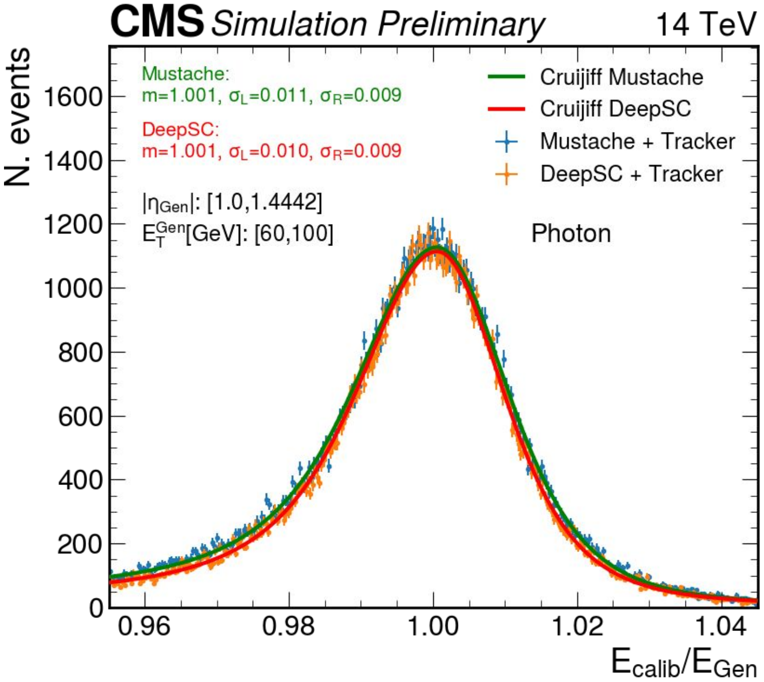
1. Start from the highest energy seed
2. Collect all the connected clusters passing the selection threshold (1).
3. Iterate. If another seed is taken it cannot form another SuperCluster.

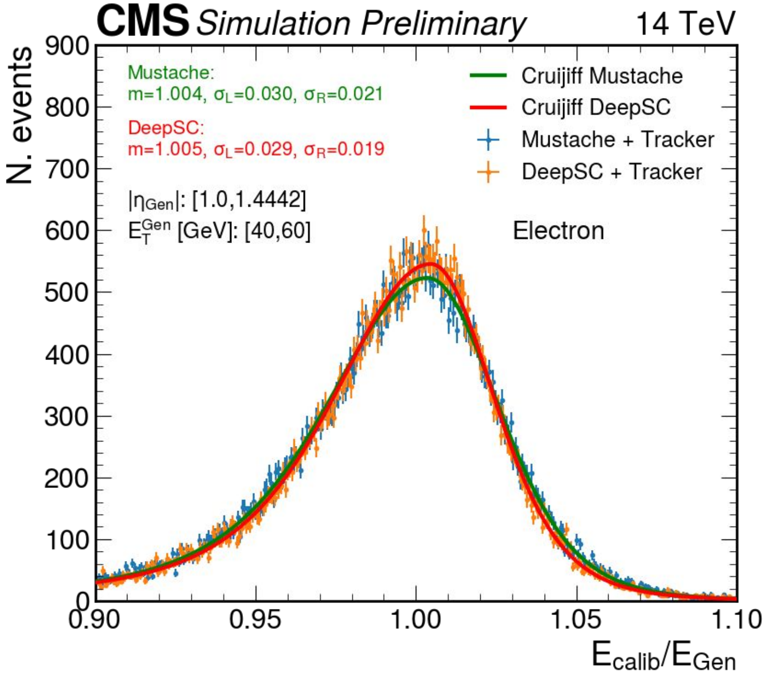
→ solid, simple algo. Similar procedure as Mustache



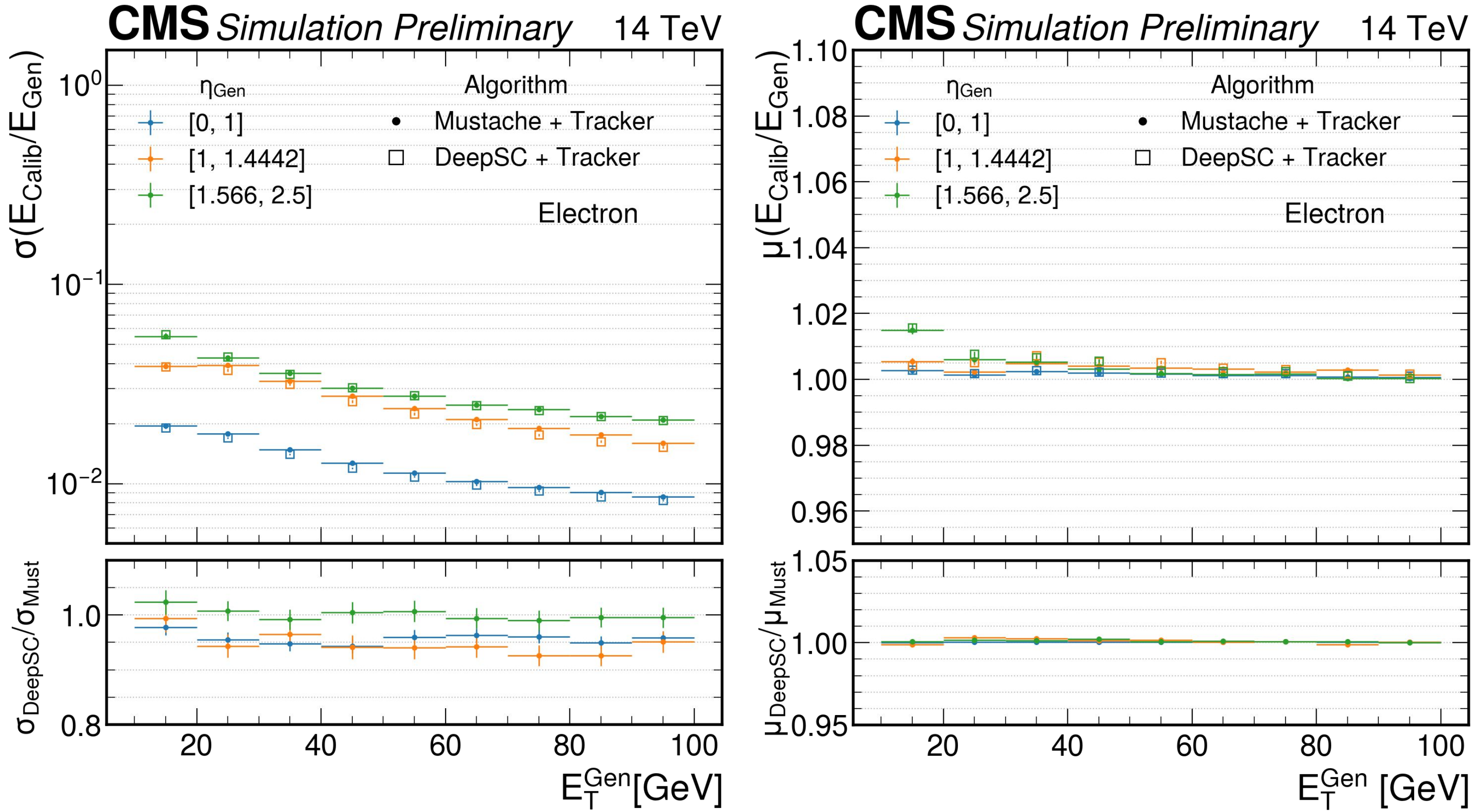
Cruijff fit

$$Cruijff(x,\mu,\sigma_L,\sigma_R,\alpha_L,\alpha_R) = \begin{cases} e^{-\frac{(x-\mu)^2}{2\sigma_L^2+\alpha_L(x-\mu)^2}} & \text{if x-}\mu<0 \\ e^{-\frac{(x-\mu)^2}{2\sigma_R^2+\alpha_R(x-\mu)^2}} & \text{if x-}\mu>0 \end{cases}$$





Electron - Regression



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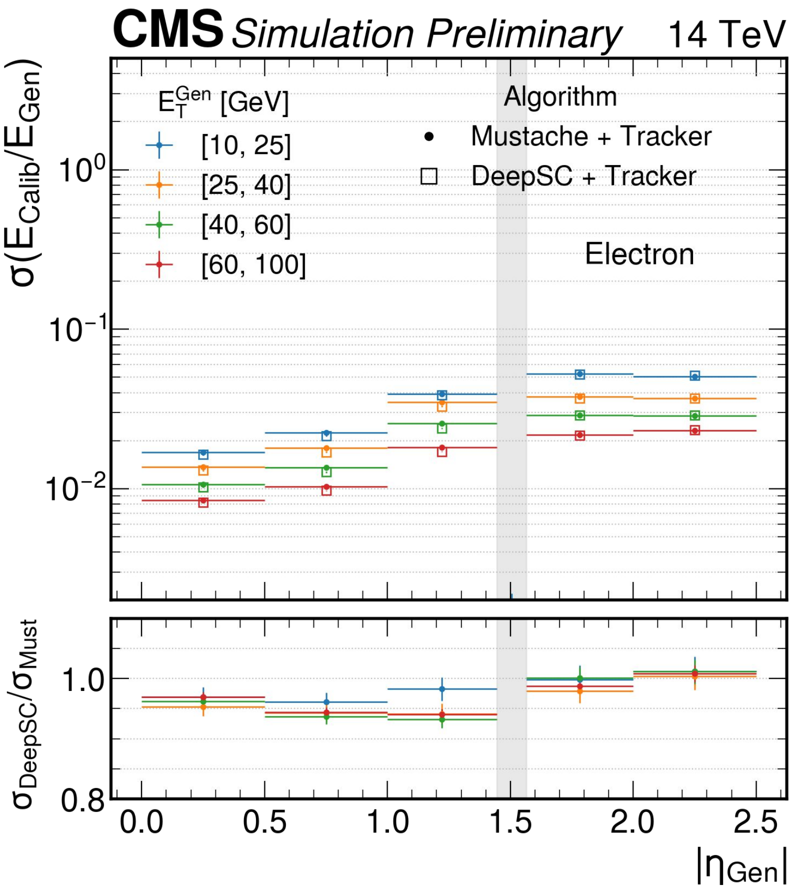
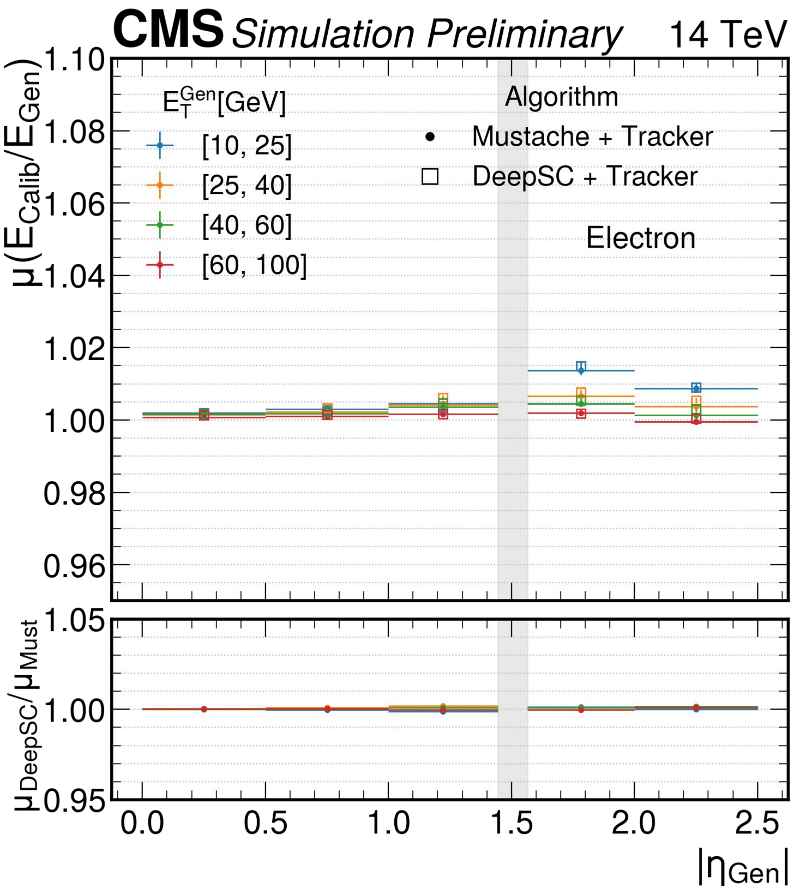
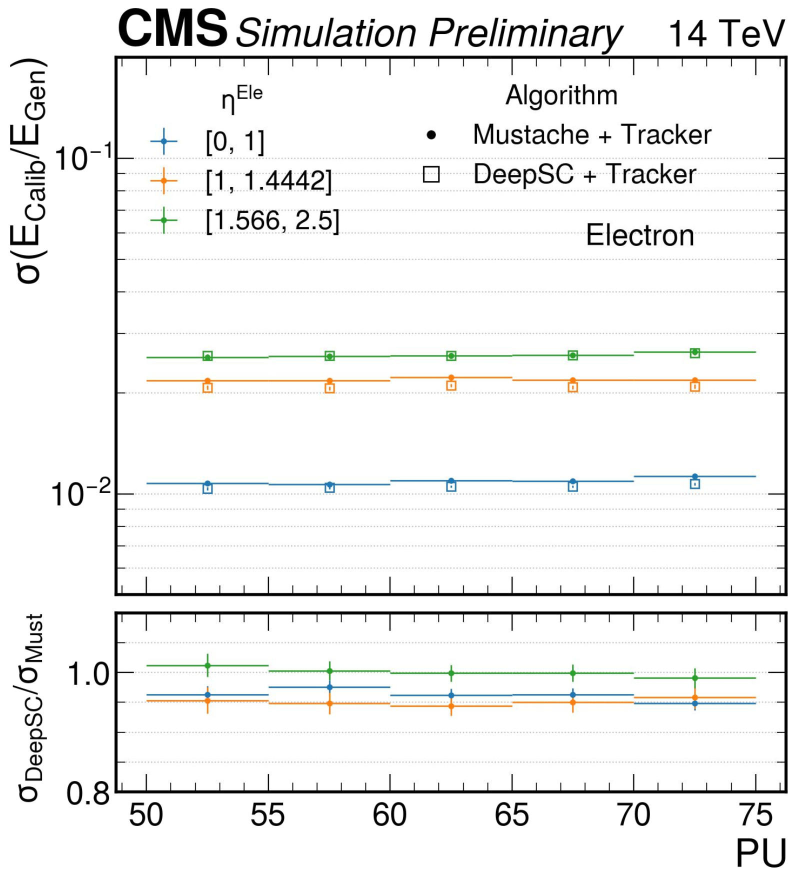
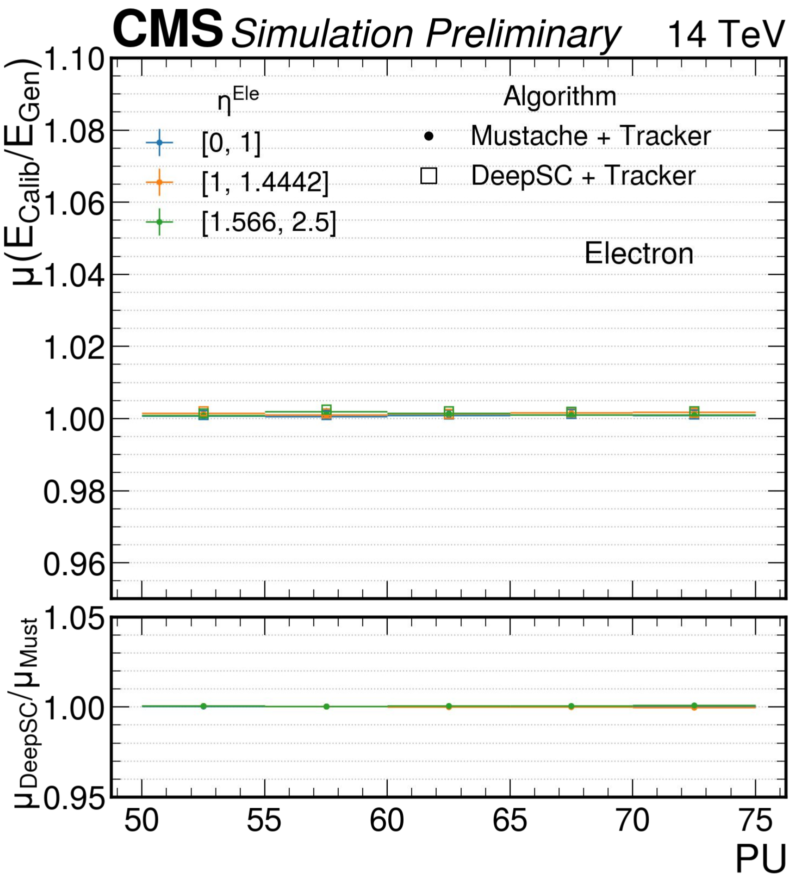
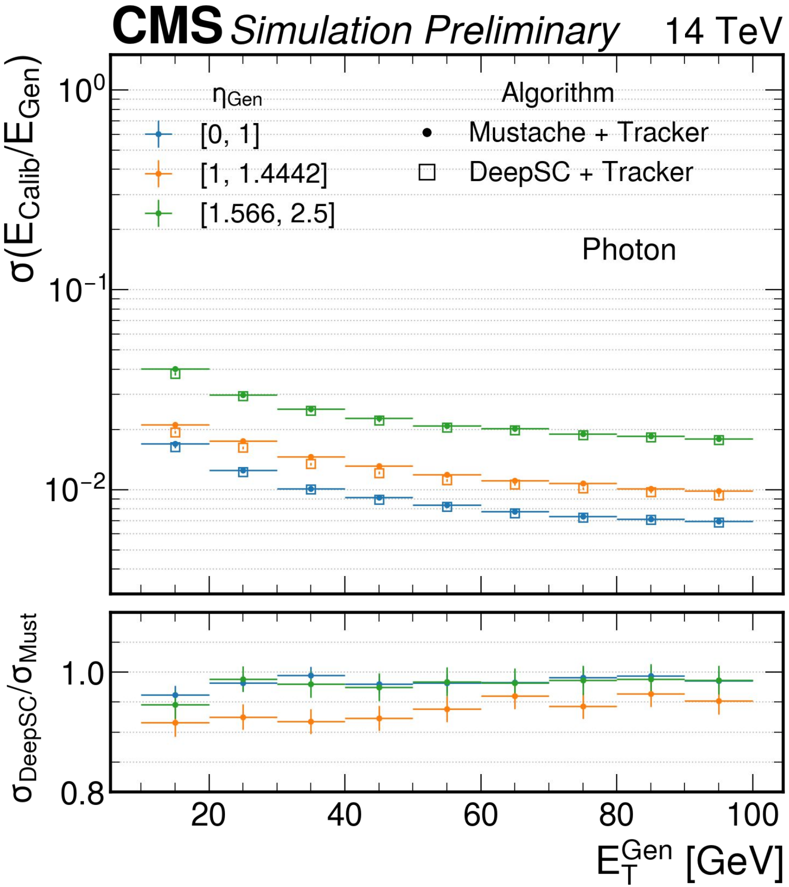


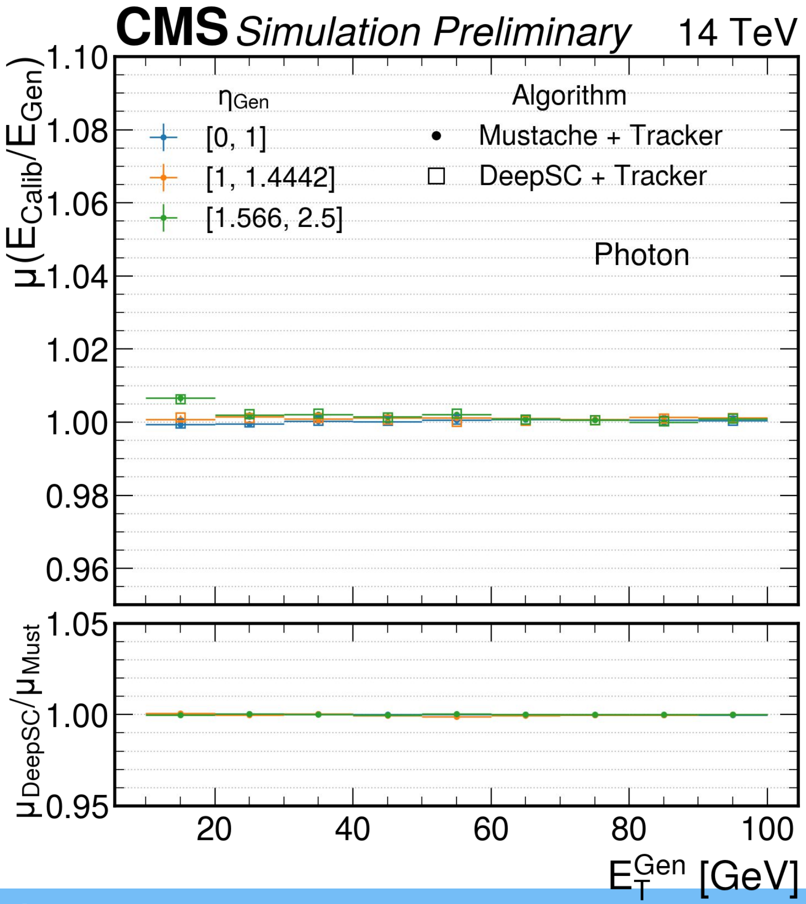


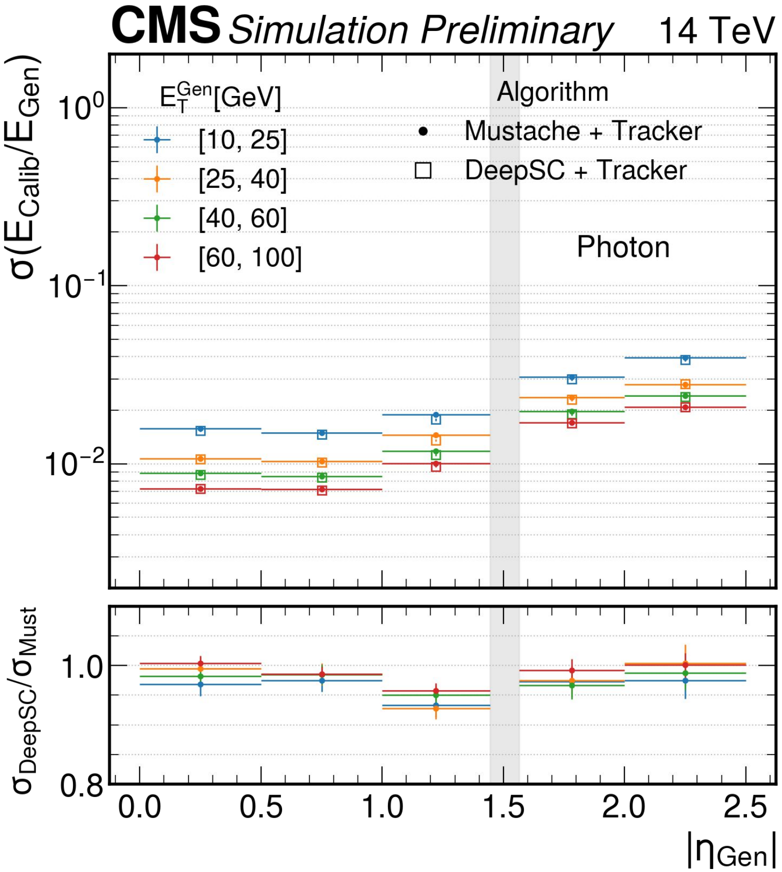

CMS Simulation Preliminary 14 TeV
$\sigma(E_{Calib}/E_{Gen})$
η^{Ele}
[0, 1]
[1, 1.4442]
[1.566, 2.5]
Algorithm
Mustache + Tracker
DeepSC + Tracker
Electron
10^{-1}
10^{-2}
$\sigma_{DeepSC}/\sigma_{Must}$
1.0
0.8
50
55
60
65
70
75
PU

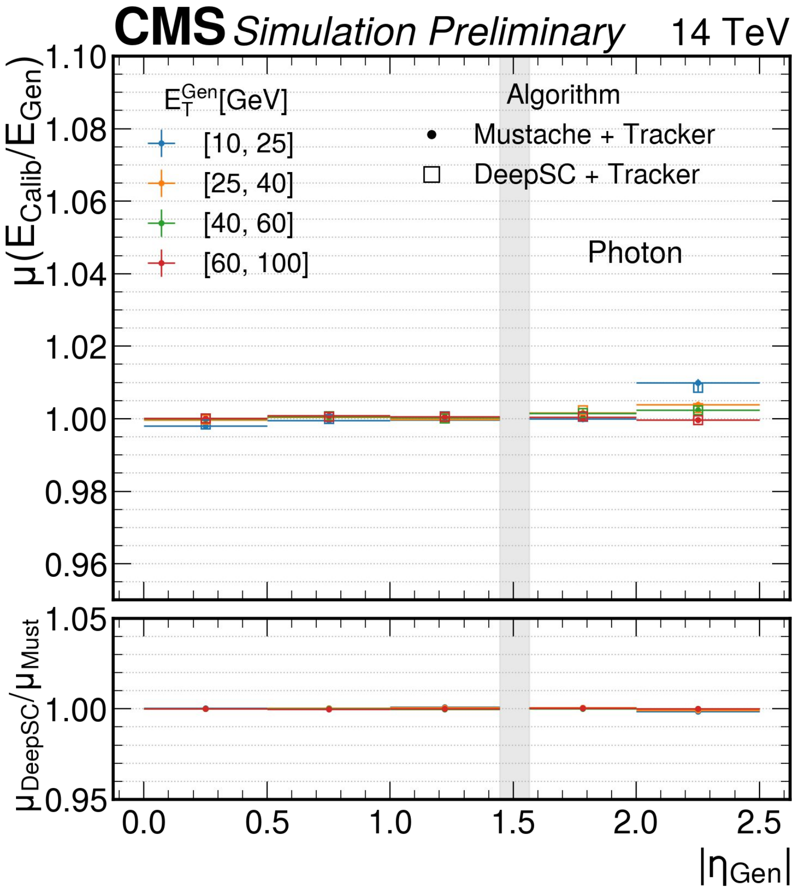

CMS Simulation Preliminary 14 TeV
$\mu(E_{Calib}/E_{Gen})$
η^{Ele}
[0, 1]
[1, 1.4442]
[1.566, 2.5]
Algorithm
Mustache + Tracker
DeepSC + Tracker
Electron
1.10
1.08
1.06
1.04
1.02
1.00
0.98
0.96
μ_{DeepSC}/μ_{Must}
1.05
1.00
0.95
50
55
60
65
70
75
PU

Photon - Regression






CMS Simulation Preliminary 14 TeV
$\sigma(E_{Calib}/E_{Gen})$
E_T^{Gen}[GeV]
[10, 25]
[25, 40]
[40, 60]
[60, 100]
Algorithm
Mustache + Tracker
DeepSC + Tracker
Photon
$\sigma_{DeepSC}/\sigma_{Must}$
$|\eta_{Gen}|$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$\mu(E_{Calib}/E_{Gen})$
E_T^{Gen}[GeV]
[10, 25]
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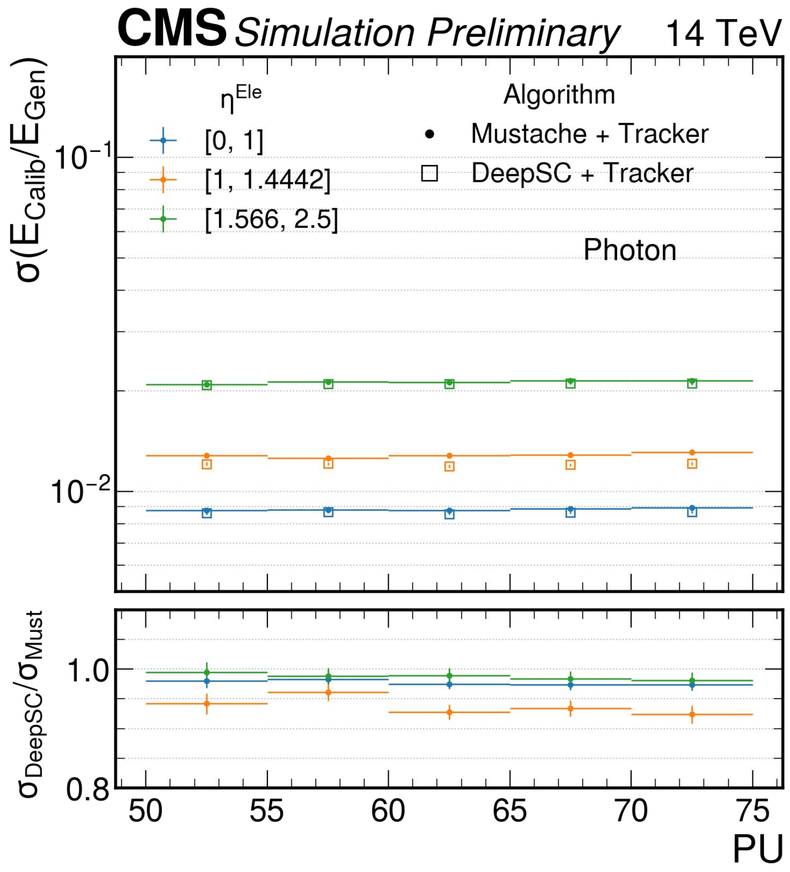
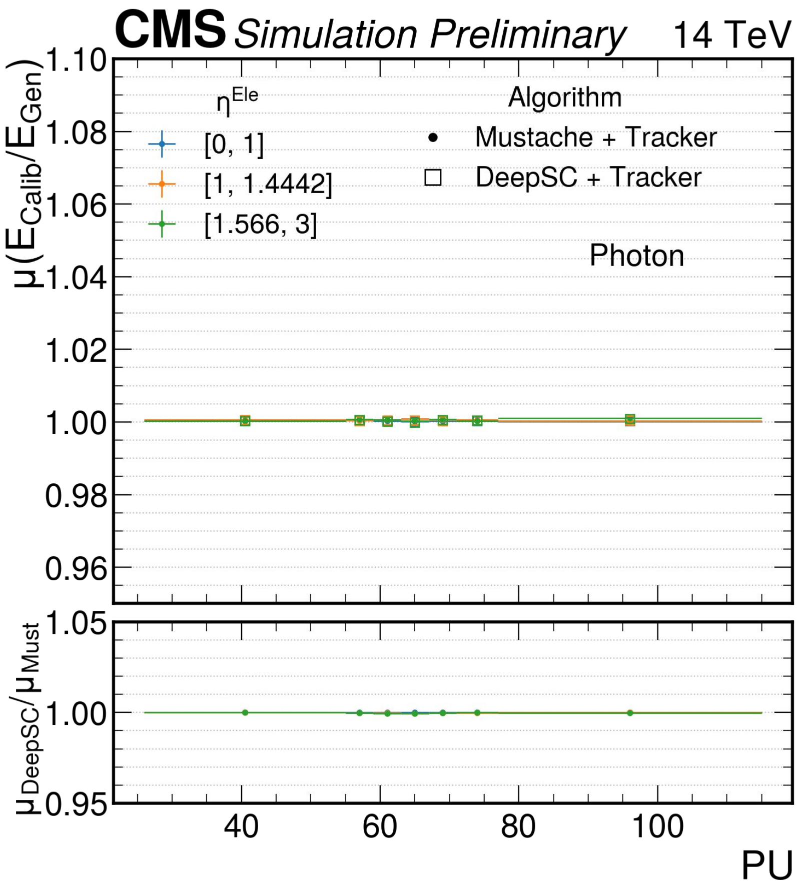
[40, 60]
[60, 100]
Algorithm
Mustache + Tracker
DeepSC + Tracker
Photon
μ_{DeepSC}/μ_{Must}
$|\eta_{Gen}|$

Photon - Regression





Summary plots - SC scale