Deep learning techniques for energy clustering in the CMS Electromagnetic Calorimeter

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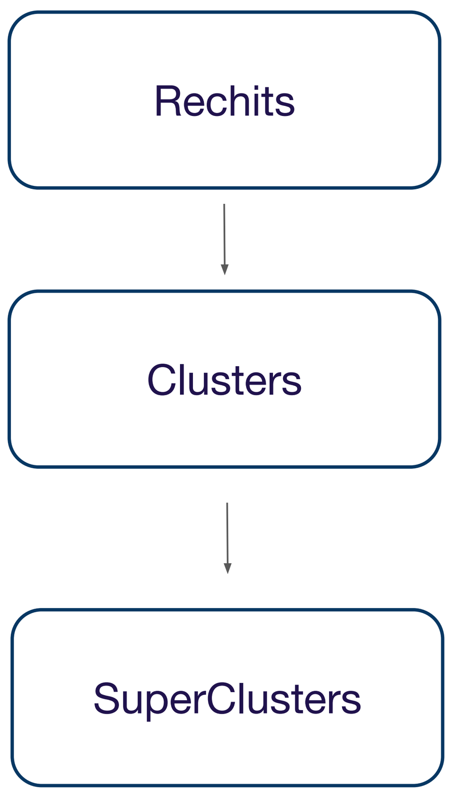
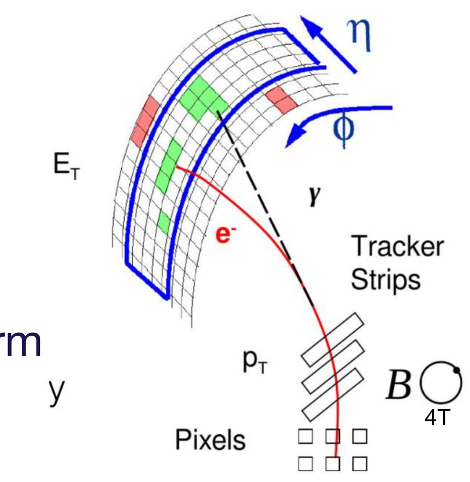
on behalf of the CMS Collaboration

SuperClustering in ECAL



Reconstructed energy deposits in the PbWO4 crystals of the calorimeter (rechits) left by particles.



Rechits are gathered together around the crystal with highest deposited energy to form **clusters**.

Each cluster represents a **single particle**.

➔ Or several overlapping particles.

Due to bremsstrahlung and photon conversion before the ECAL, the individual clusters have to be combined together to form a **SuperCluster**.

The energy of the initial particle can be reconstructed from the SuperCluster.

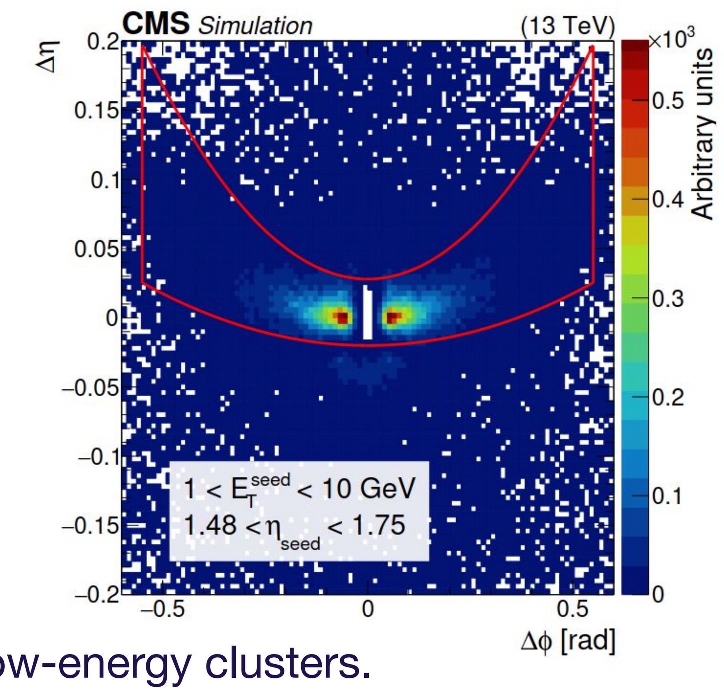
"Mustache" algorithm

The algorithm currently used in CMS for reconstruction of SuperClusters.

Purely **geometrical** approach:

➔ All the clusters falling into the specified "mustache" shape are considered as part of the SuperCluster. The size of the area depends on energy and position of the seed.

➔ "Mustache" shape due to the CMS magnetic field (spread along ϕ).



High efficiency: the algorithm is able to gather even low-energy clusters.

Downside: **suffers because of pileup (PU) and noise contamination.**

Energy regression is further applied that can **correct PU and noise on average**.

https://iopscience.iop.org/article/10.1088/1748-0221/16/05/P05014

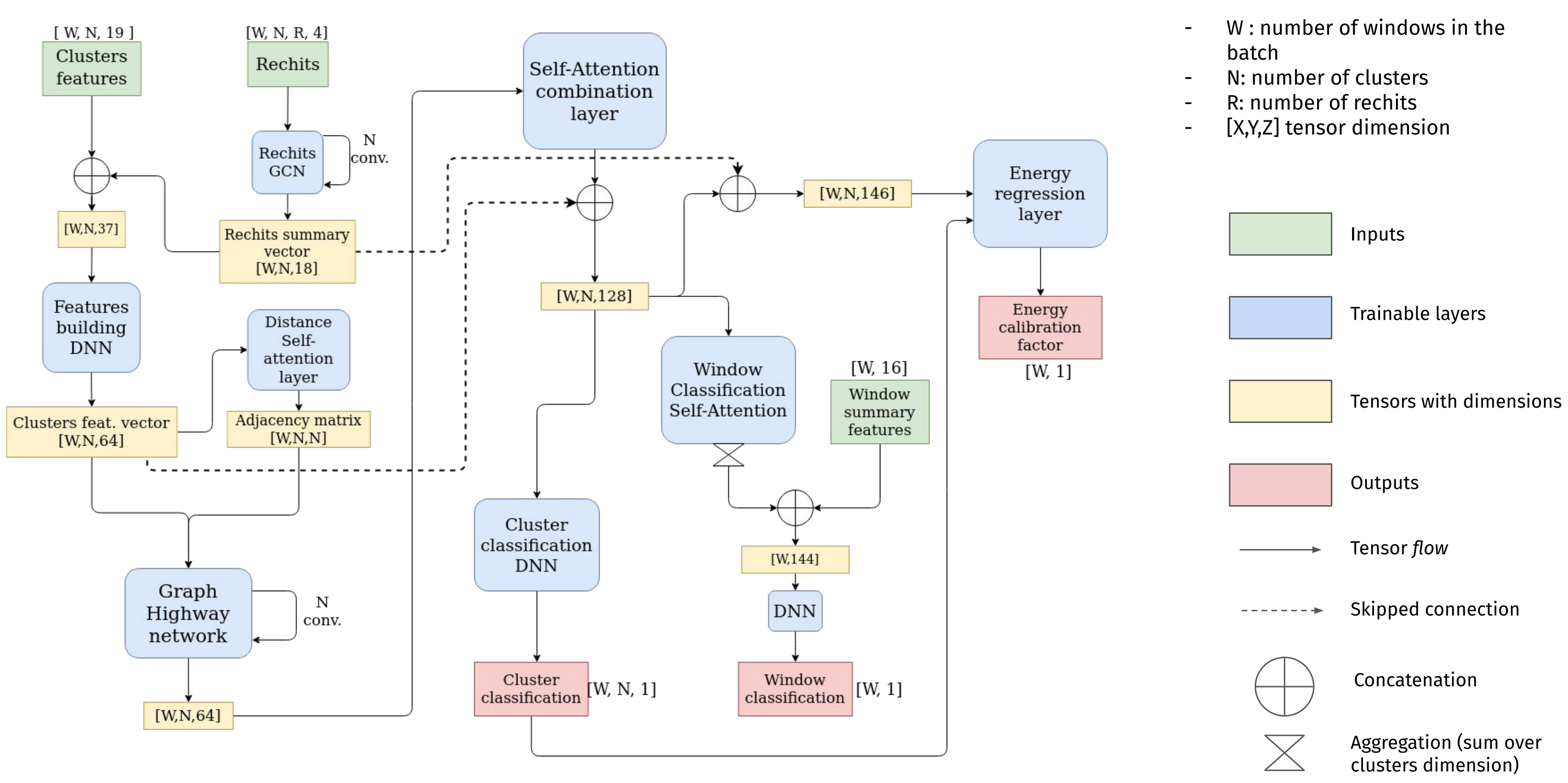
DeepSuperCluster model

Model architecture

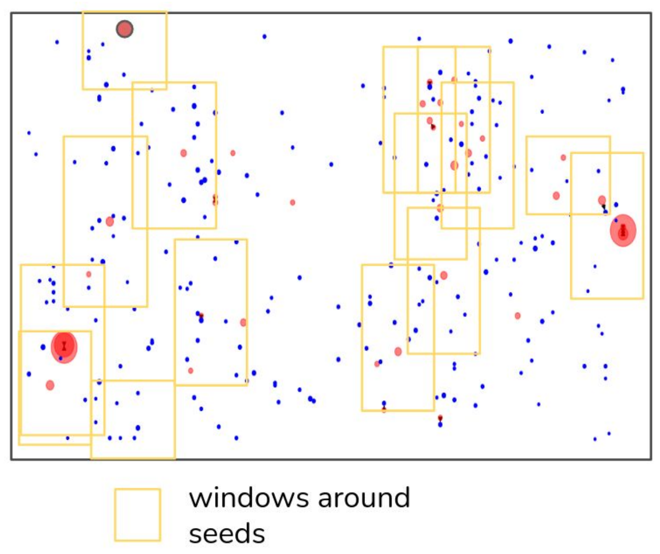
New **graph-based Machine Learning** algorithm for SuperClustering.

➔ **Maintains the efficiency while improving PU and noise rejection.**

➔ Graph NN are able to **aggregate the information between the neighbors.**



Dataset and Particle ID



Dataset for the training:

Electrons and photons generated uniformly in p_T = [1,100] GeV.

PU uniformly distributed between [55,75] interactions.

Windows opened around all the clusters with E_T > 1 GeV (**seeds**).

Model Input: **Cluster information** *(E, E_T, η, ϕ, z, number of crystals, …)*, **list of rechits**, **summary window features** *(max, min, mean of the crystal variables).*

Model Output: cluster classification (in/out of SC), particle classification, energy regression.

➔ Same network to identify the **flavor of the particle**.

➔ Extra dataset: sample containing **jets**.

➔ Goal: classify jets/electrons/photons.

➔ **Transfer Learning** was used to re-train only the ID part of the network to avoid the performance degradation for electrons/photons.

Results: Energy Resolution

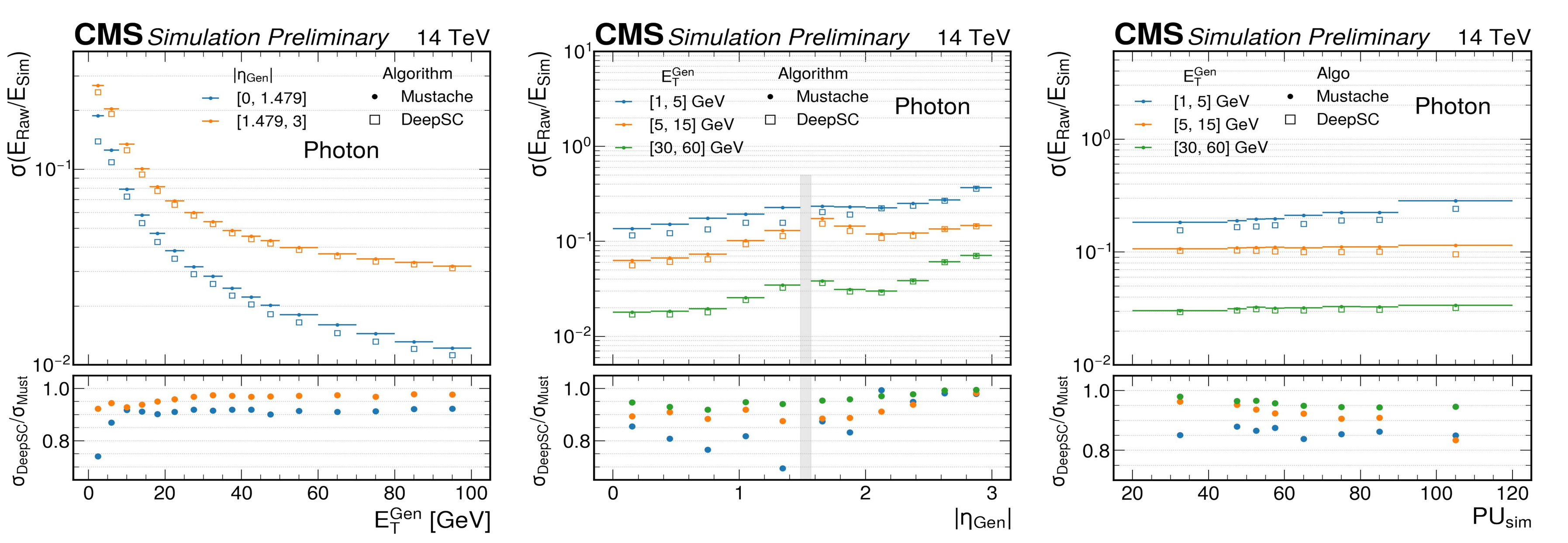
Resolution of the reconstructed uncorrected **SuperCluster energy** (E_{Raw}) divided by the **true energy deposits** in ECAL (E_{Sim}) versus:

- the transverse energy of the gen-level particle E_T^{Gen} (left)
- the gen-level particle position $|\eta_{Gen}|$ (center)
- the number of simulated PU interactions (right)

The resolution is computed as half of the difference between the 84% quantile and the 16% quantile (one σ) of the E_{Raw}/E_{Sim} distribution in each bin.

The lower panel shows the ratio of the resolution of the two algorithms:

$$\sigma_{DeepSC} / \sigma_{Mustache}$$



Significantly improved resolution, particularly for low E_T signals and at high PU.

Results: Particle Classification

➔ Particle classification performance (DeepSC model) for jet vs. photon (left) and photon vs. electron samples (right).

➔ Only ECAL variables are used.

➔ **High performance for jet vs. photon discrimination.**