Calorimeter clustering with DGCNN

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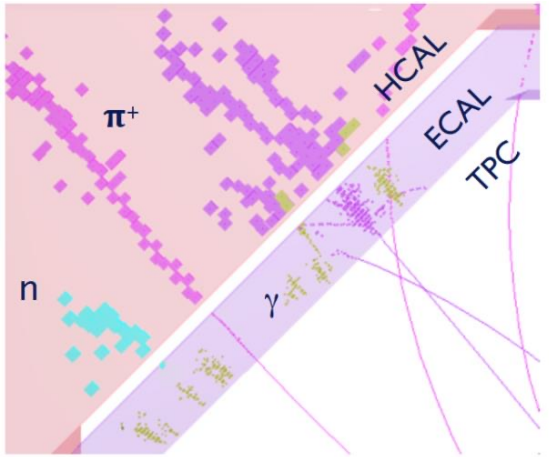
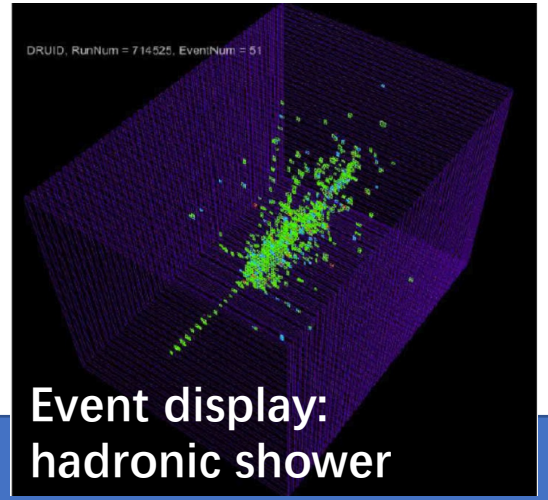
Introduction

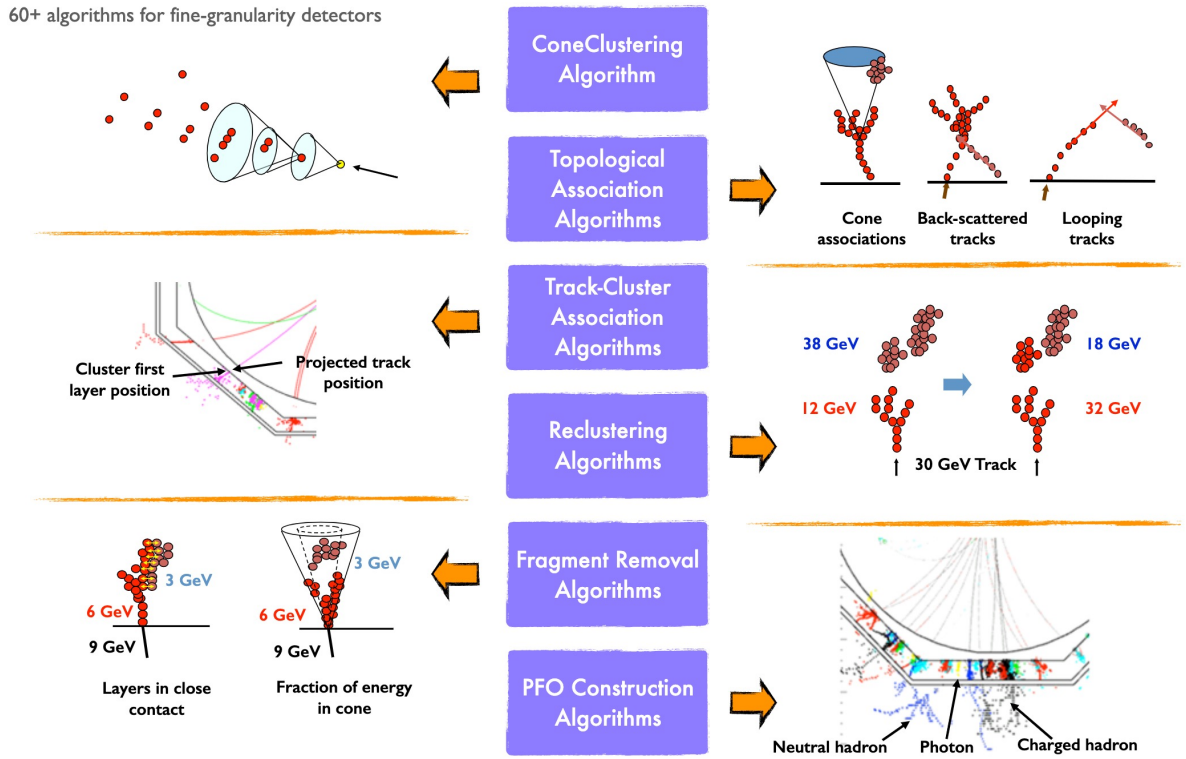
- **Particle Flow approach for the future collider:**
  - Combine the info of tracker + calorimeter.
  - High granularity calorimeter:
    - Precise 3D points measurement.
    - Reconstruction: pattern recognition for clusters.
    - $\sigma_{Jet} = \sqrt{\sigma_{track}^2 + \sigma_{EM}^2 + \sigma_{Had}^2 + \sigma_{confusion}^2}$
  - CEPC calorimeter for the Particle Flow:
    - ECAL: Si-W, cell size $1\times1\ \mathrm{cm}^2$, 30 layers
    - HCAL: GRPC-based simi-digital calorimeter, cell size $1\times1\ \mathrm{cm}^2$, 40 layers.

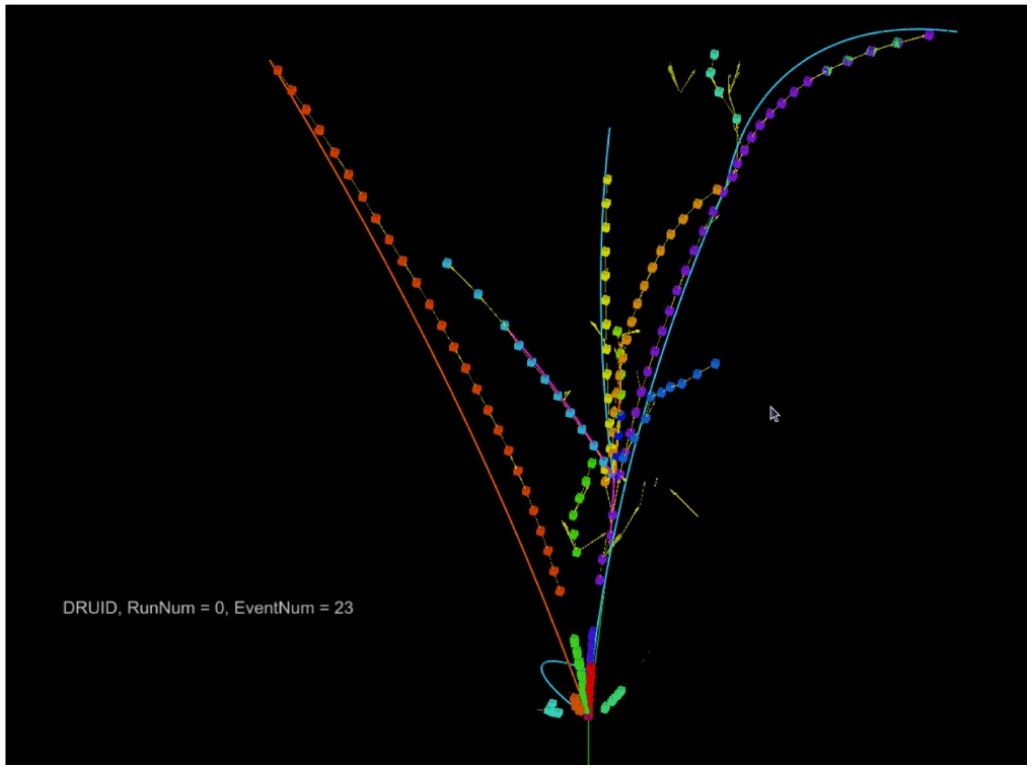




Introduction

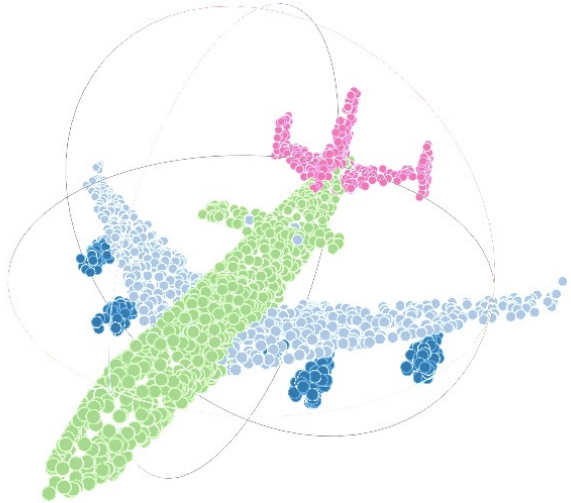
- **Traditional Particle Flow Algorithm**
  - PandoraPFA: hand-tuned algorithms for clustering. **Artificial recognition.**
  - ArborPFA: arbor-structure of shower development.

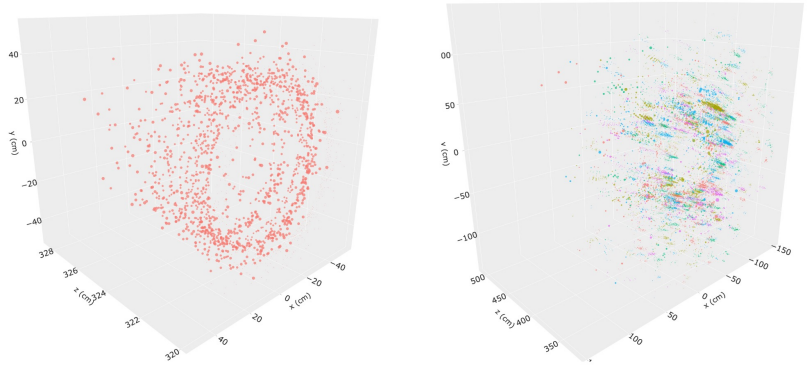


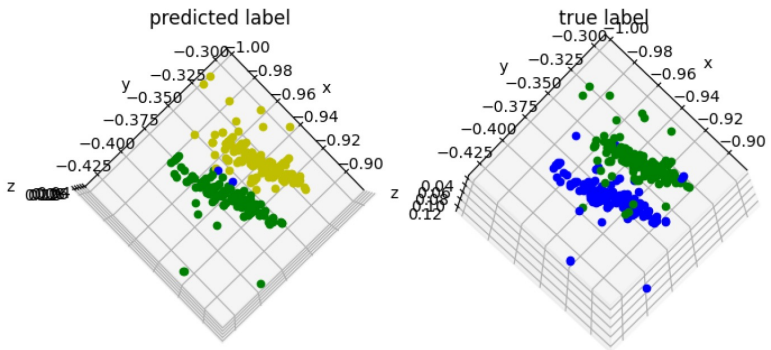


Introduction

- **Particle Flow approach for the future collider:**
  - In 2020s AI era: **point cloud**.
    - HG calorimeter hits are naturally **point clouds.**
    - **Why not try AI models for the pattern recognition?**
      - Better performance, more flexible model for detector optimization, etc.
    - Input data: spatial coordinates and features of hits: (x, y, z, E, T)
  - Reconstructing the clusters in HG calorimeter:
    - CMS for HGCAL
    - Calice for ILD (Si-W ECAL)

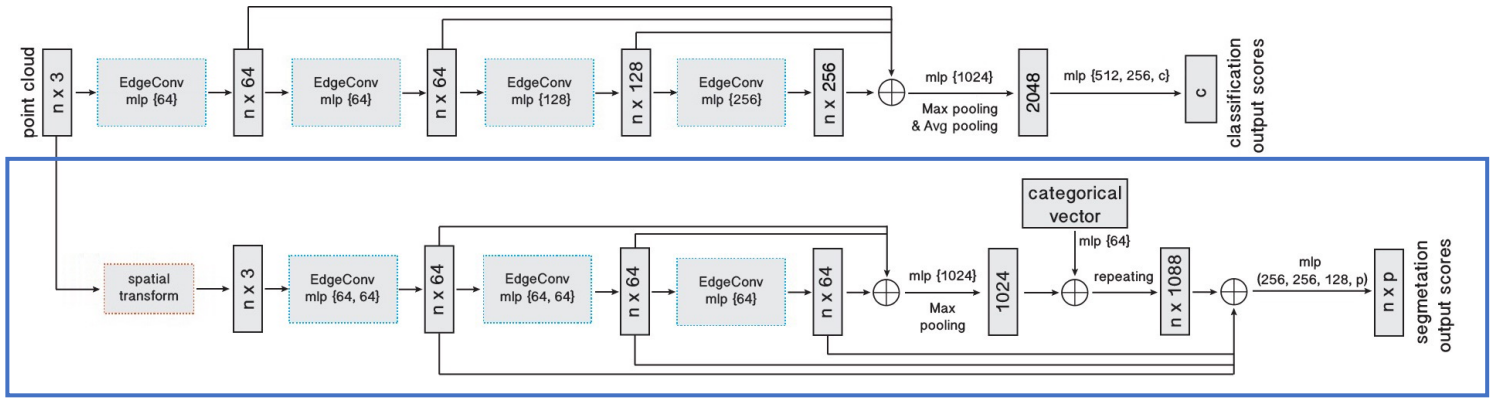


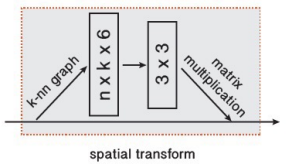


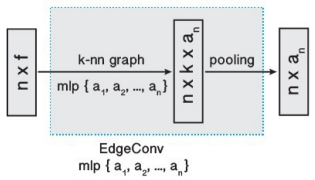


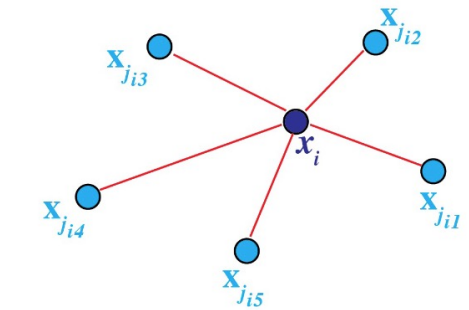
Deep learning clustering

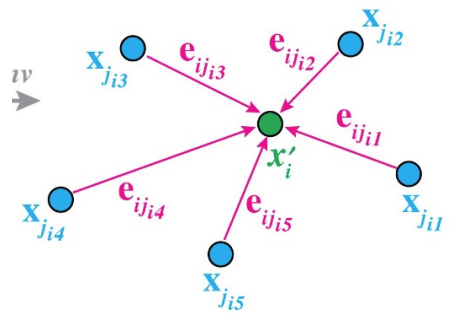
- **Model: Dynamic graphic CNN (DGCNN)**
  - CNN-based model for graphic dataset.
  - Proposed the ***EdgeConv*** to handle the graph structure.
  - Is able to handle classification and **segmentation** tasks.
  - Application: ParticleNet for c-tagging in CMS.





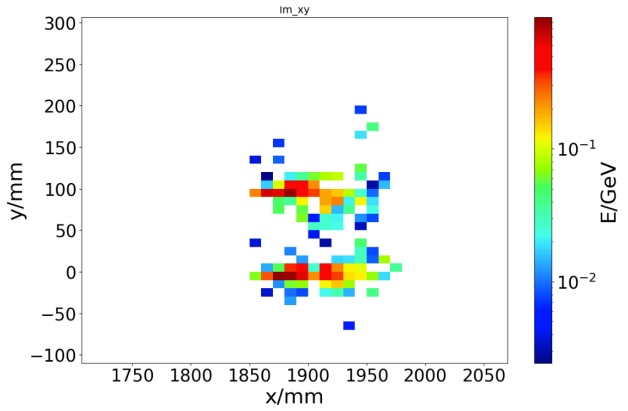


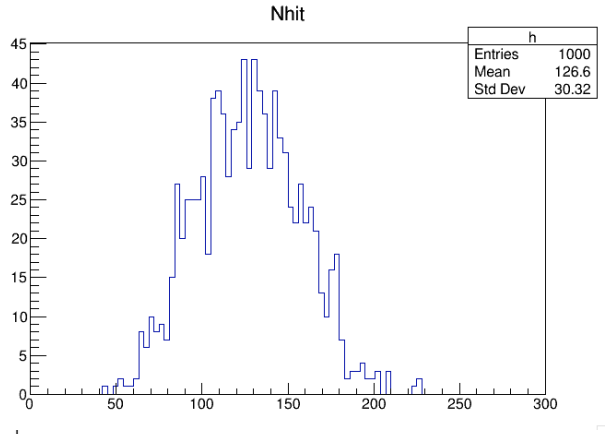


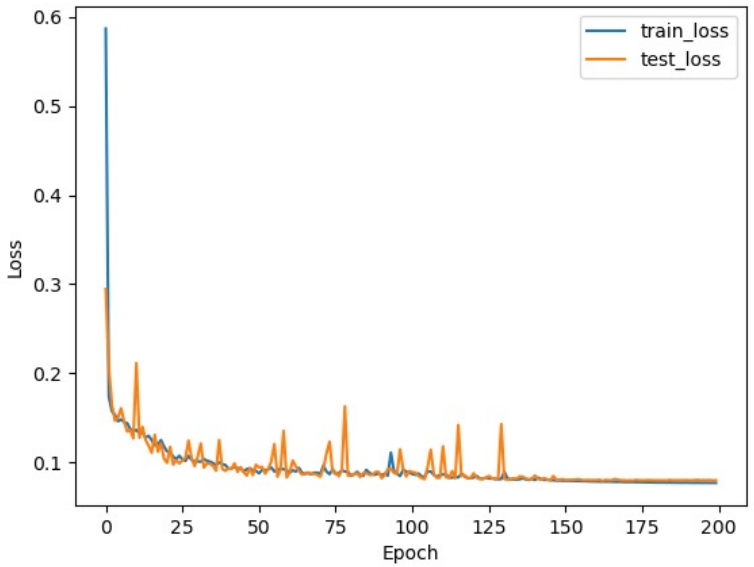


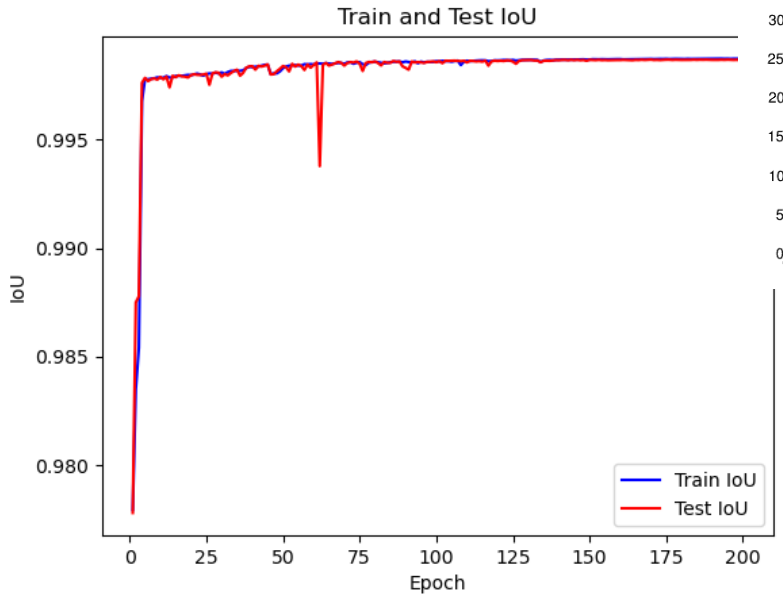
Deep learning clustering

- **Model training for di-photon separation:**
  - Simulated samples: CEPC-v4, 2 nearby photons, 10k events.
    - γ_1: $E_\gamma \in [3,\ 7]$ GeV, $\theta_\gamma \in [88°, 90°]$, $\phi \in [0°, 3°]$
    - γ_2: $E_\gamma \in [3,\ 7]$ GeV, $\theta_\gamma \in [90°, 92°]$, $\phi \in [0°, 3°]$
    - Nhit: ~200 / event.
  - 8k for training, 2k for test, 200 epoch. Run with 4 CPU (8G mem/CPU)+4 GPU (V100). Time consuming: <2h.







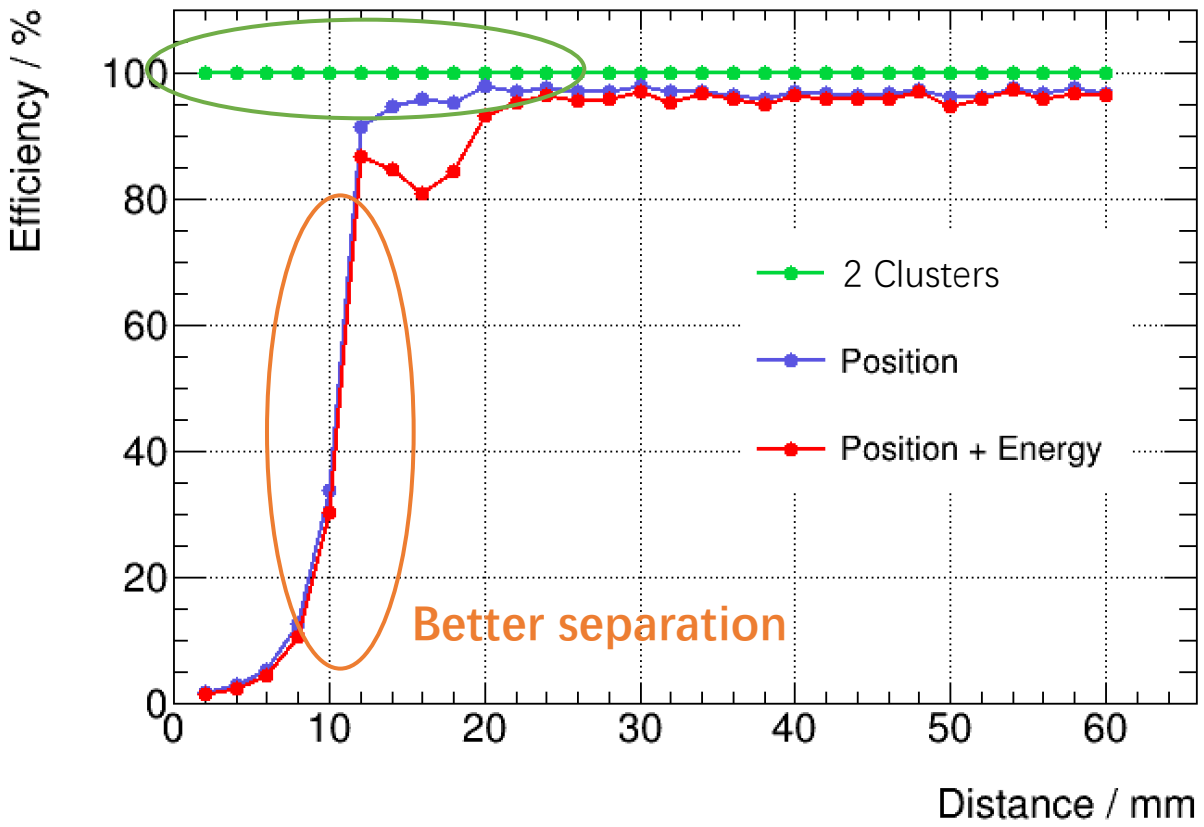


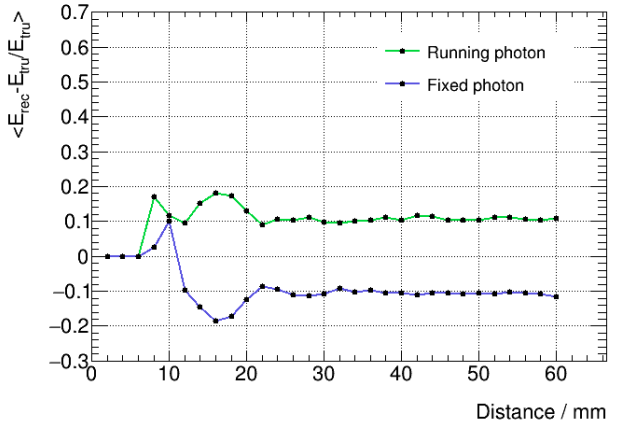
Input: (x, y, z), hit tag.
Loss: cross entropy

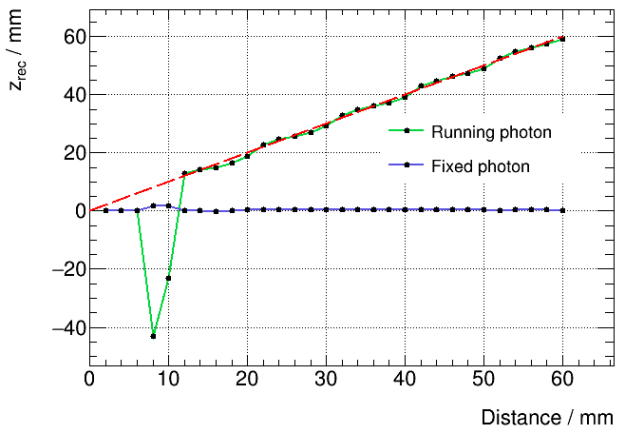
Performance

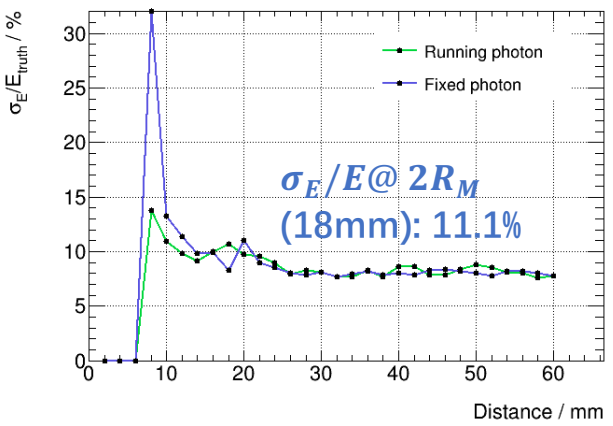
- **Application: di-photon separation**

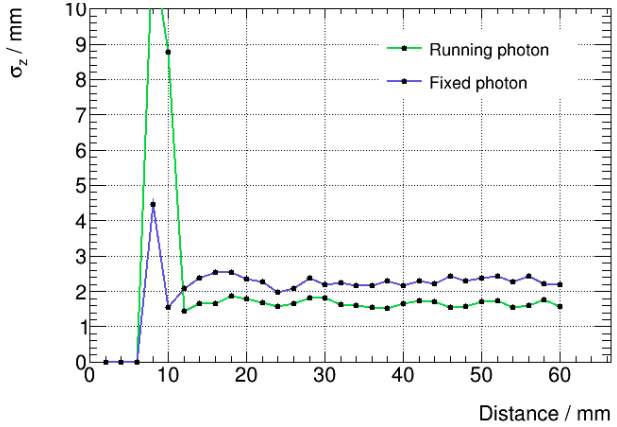
Overtraining: always split to 2 clusters.





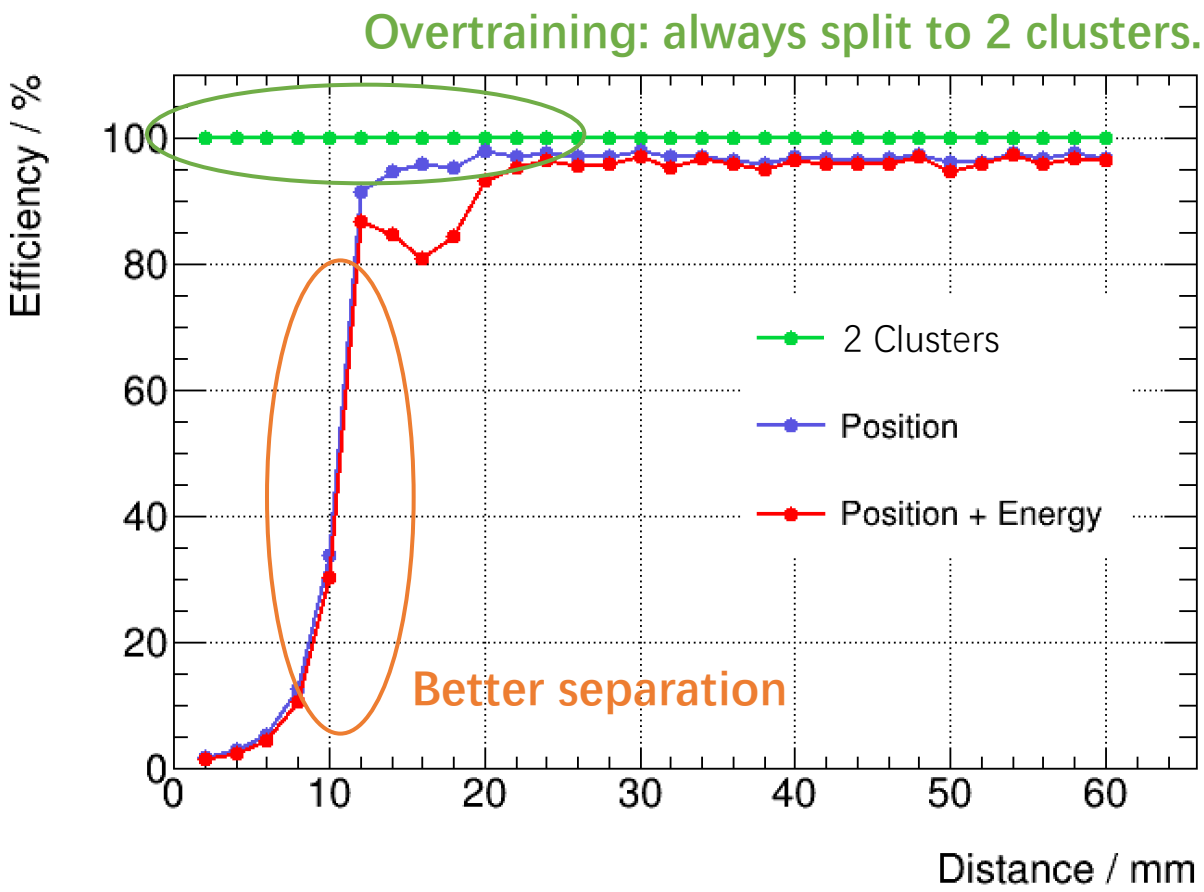


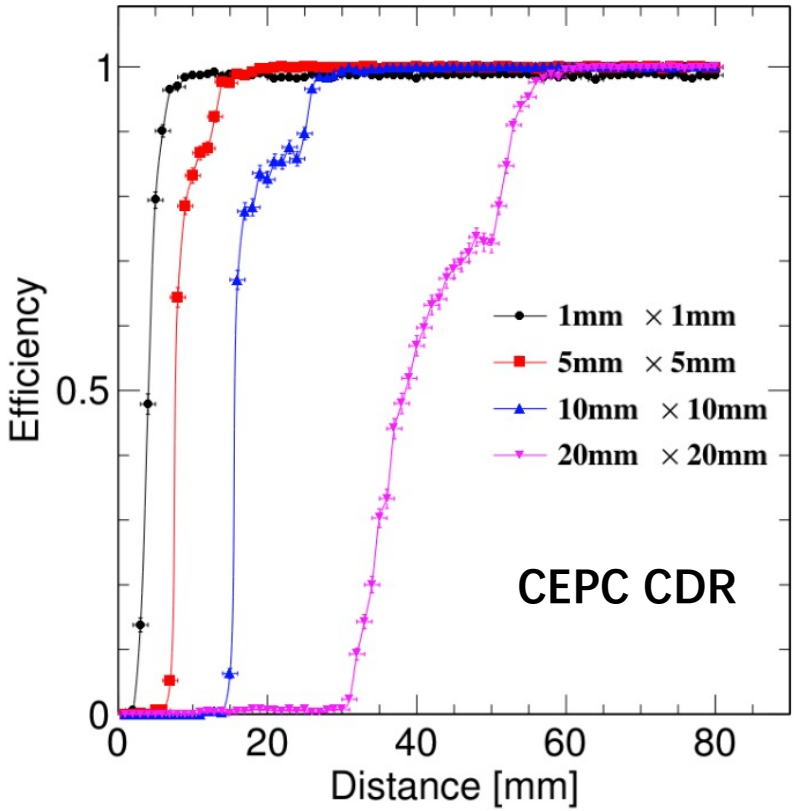




Performance

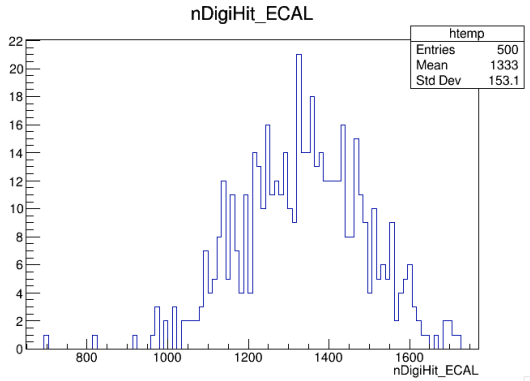
- **Application: di-photon separation**



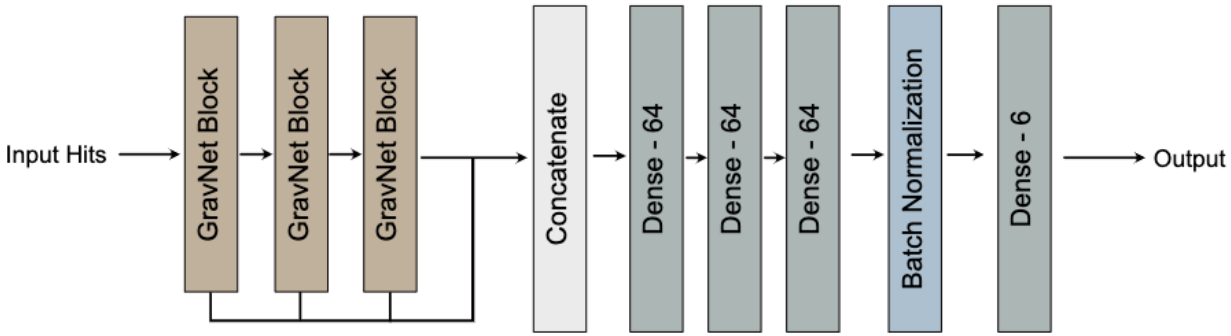


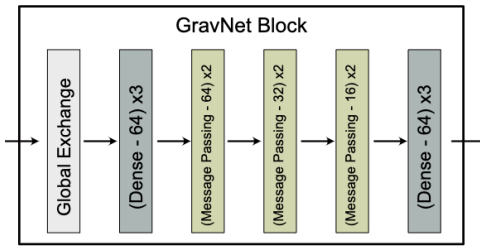
Discussion

- **The model is not stable in training:**
  - Tried the following cases but none of them worked:
    - Add hit energy as feature in training;
    - Tune the loss function from one-hot cross entropy to weighted;
    - Train with mixed Nphoton samples: 1~5 photons;
    - Train with crystal ECAL sample: wider shower, more hits, more difficult to separate.



- **Other models: e.g. GravNet in CMS [arxiv:1902.07987]**
  - Net architecture: included attention machinism.
  - Loss: potential loss L_V, condensation score loss L_β, payload loss L_P .





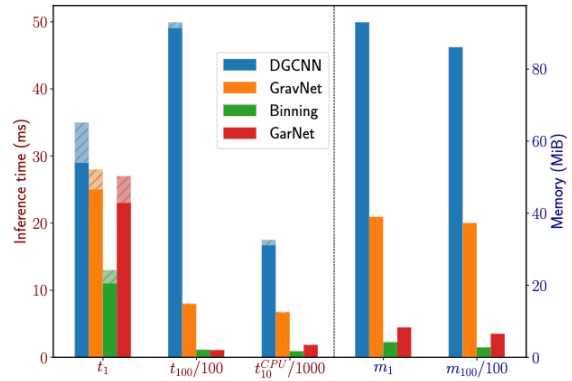


Fig. 5: Comparison of inference time for the network architectures described in the text, evaluated on CPUs and GPUs with different choices of batch size. The shaded area represents the $+1\sigma$ statistical uncertainty band.

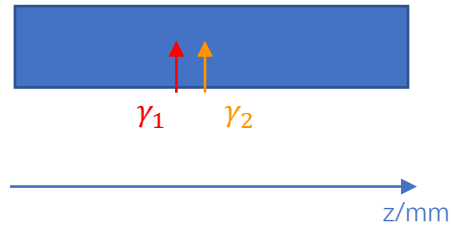
Summary and outlook

- **Calorimeter clustering with deep learning:**
  - Showed the feasibility of separating 2 photons, obtained better performance than CDR.
  - Overtraining problem
    - Tried to train with float number of photons, but the model did not converge.
- **Next step:**
  - Tune the model to overcome the overtraining and un-converge.
    - Model structure, loss, etc.
  - Add energy and time info as point feature.
    - Simply tried but did not converge either.
  - Try other models, e.g. GravNet that CMS and Calice used.
- **Future:**
  - Add track info as bias.
  - Final target: a deep learning based PFA.

Backup

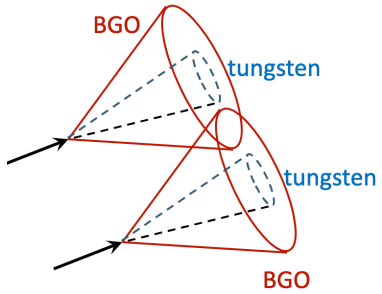
Deep learning clustering

- **Application: di-photon separation.**
  - 2 photons, E=5 GeV, $\theta = 90°$, $\phi = 0°$, generate @ ECAL surface, scan the distance.
  - Photon reconstruction with DL + energy splitting:



  - For hit [a]: | P[1] | P[2] | ··· | **Traditional: hit[a] belongs to particle [i] with max(P[i]).**

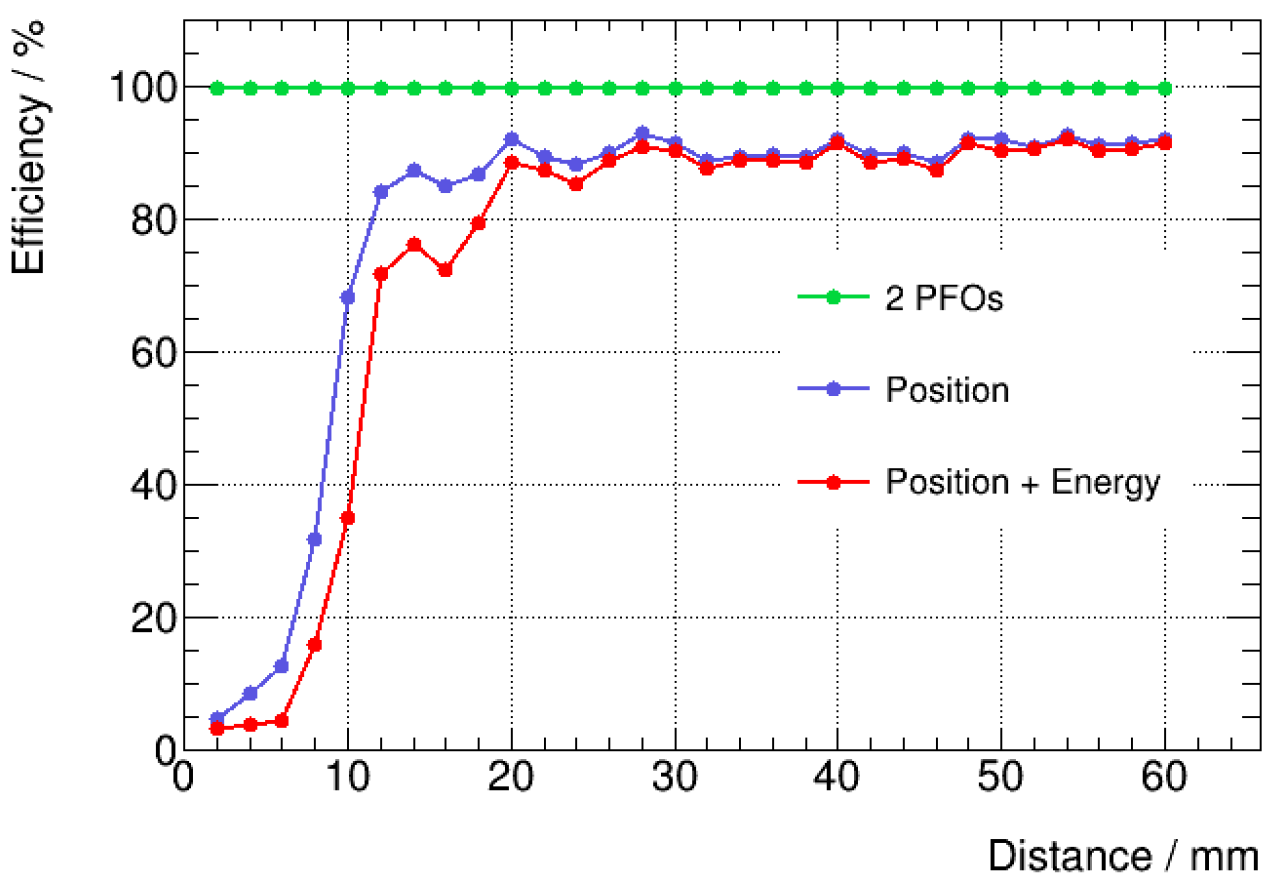
P[i]: probability that hit [a] belongs to shower (particle) [i].
→ Particle [i] contributes P[i] to hit [a].
→ **Split hit[a] to several parts.**

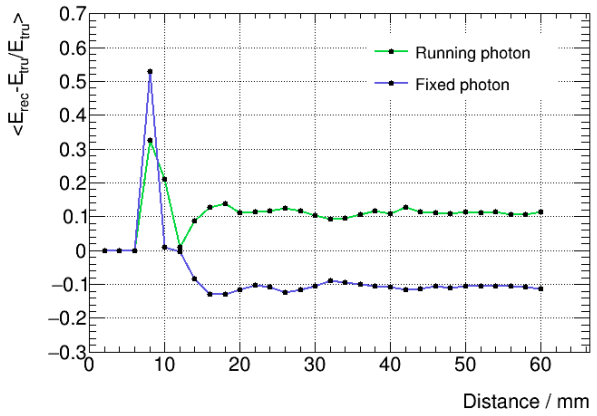


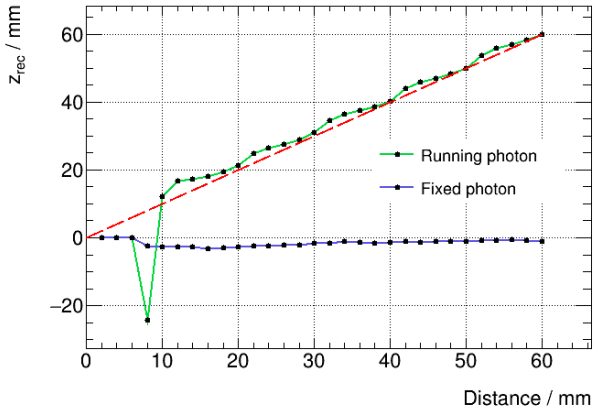
Would be useful for dealing with large overlap showers.

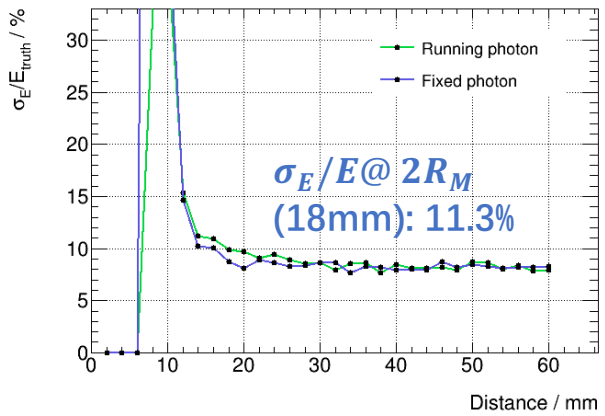
Performance

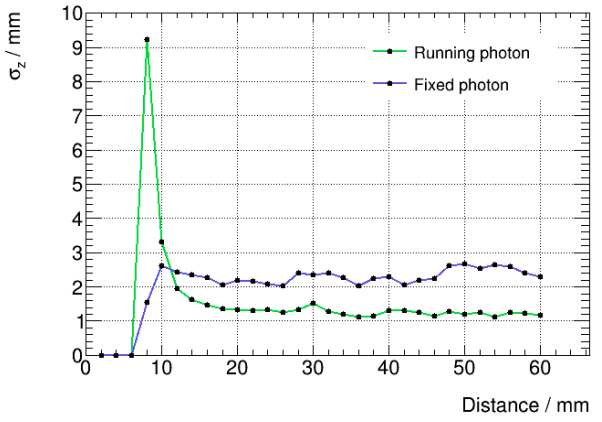
- **Application: di-photon separation**







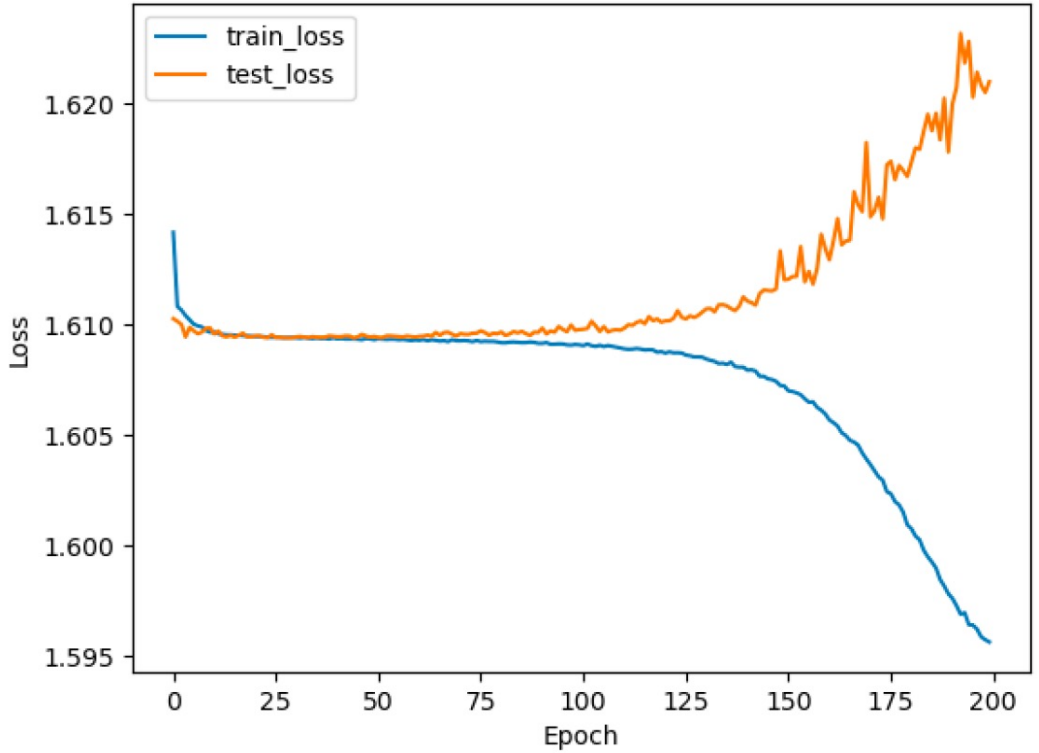




Issue

- **Loss functions for failed training**

With 5 Gam in event



With floated photon number (1~5)