



Weekly report

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Working status



- **For defense:**
 - Preparing the slides. 70% finished.
 - Both anonymous review are received, no critical comments.
- **ATLAS HH combination:**
 - Discussed with Hideki and Mingshui, connected with ATLAS HHComb contact.
 - Touching the HHComb and HHMLComb framework.
- **Calorimeter reconstruction with DGCNN:**
 - Got some preliminary results.

Introduction

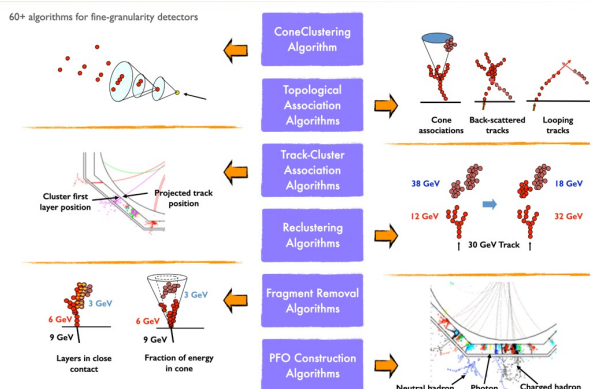
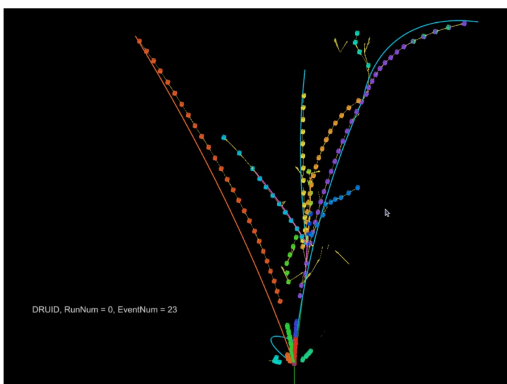
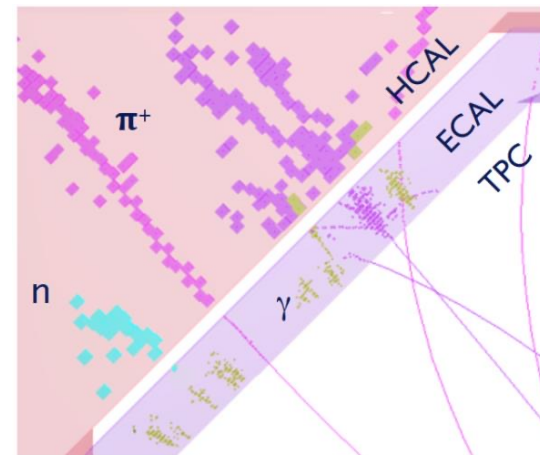
- **Particle Flow approach for the future collider:**

- Combine the info of tracker + calorimeter.
- High granularity calorimeter:
 - Precise 3D points measurement.
 - Reconstruction: pattern recognition for clusters.

- $$\sigma_{Jet} = \sqrt{\sigma_{track}^2 + \sigma_{EM}^2 + \sigma_{Had}^2 + \sigma_{confusion}^2}$$

- Particle Flow Algorithm:

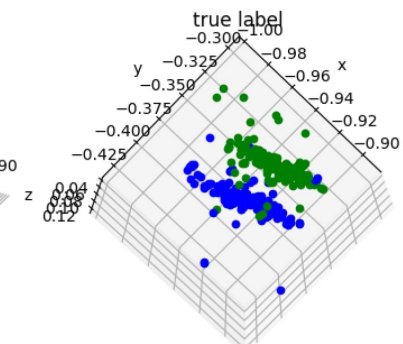
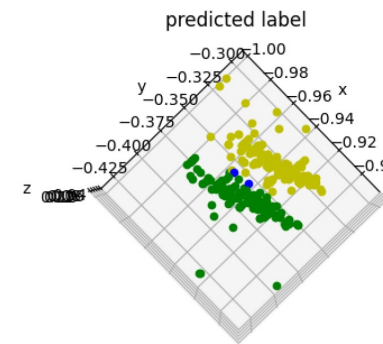
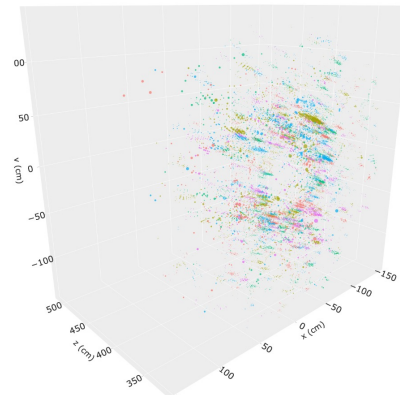
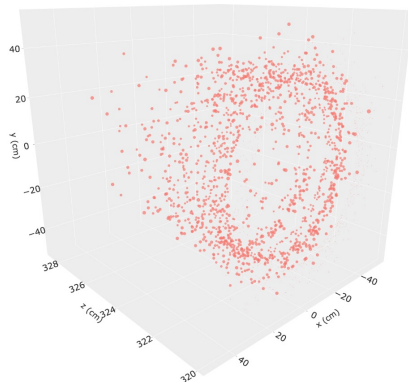
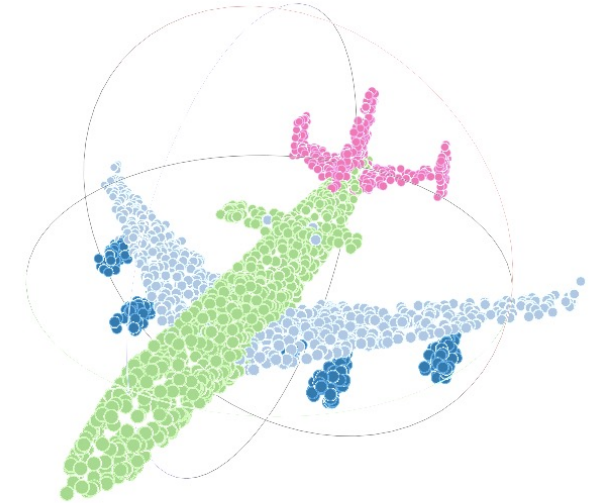
- PandoraPFA: hand-tuned algorithms for clustering. **Artificial recognition.**
- ArborPFA: arbor-structure of shower structure. **Much Smarter and simpler.**



Introduction



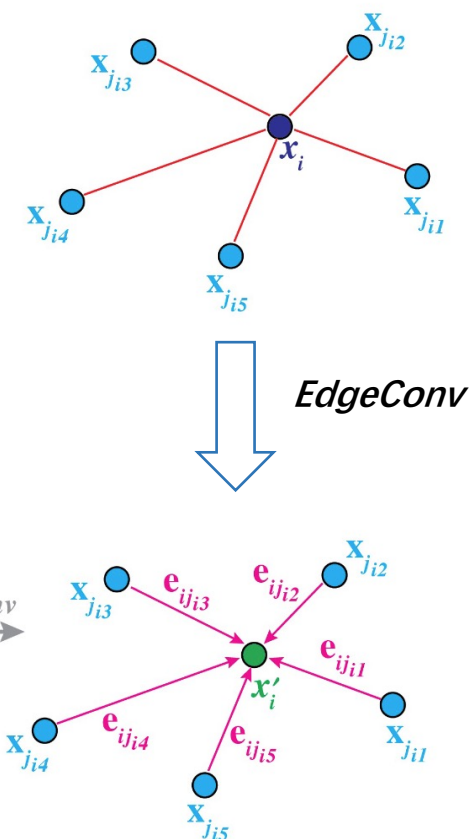
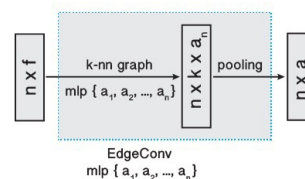
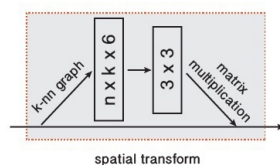
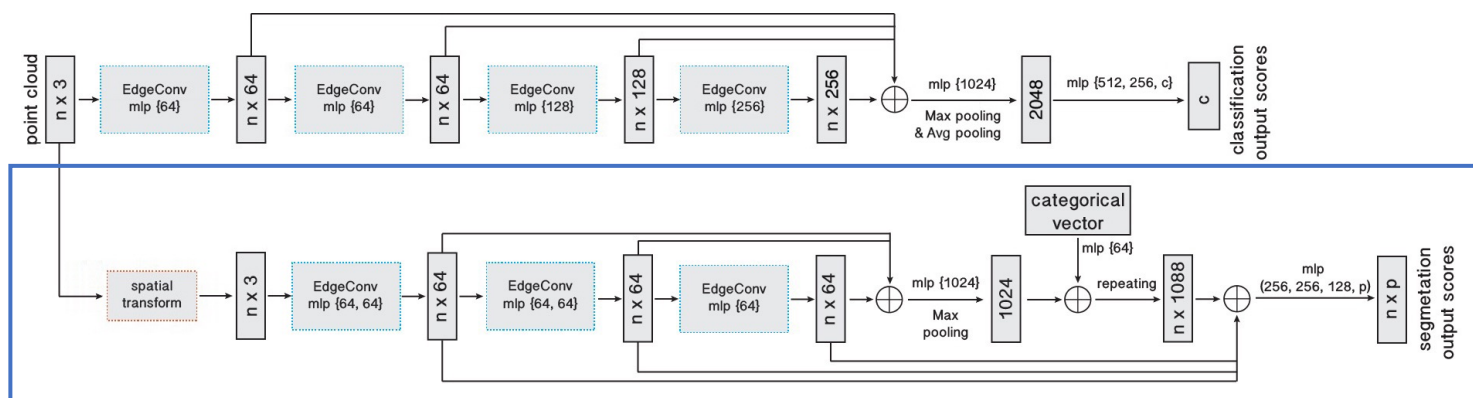
- **Particle Flow approach for the future collider:**
 - In 2020s AI era: **point cloud**.
 - HG calorimeter hits are naturally point clouds.
 - **Why not try AI models for the pattern recognition?**
 - Better performance, more flexible model for detector optimization, etc.
 - Reconstructing the clusters in HG calorimeter:
 - [CMS for HGCAL](#)
 - [Calice for ILD \(Si-W ECAL\)](#)



Deep learning clustering

• Model: Dynamic graphic CNN (DGCNN)

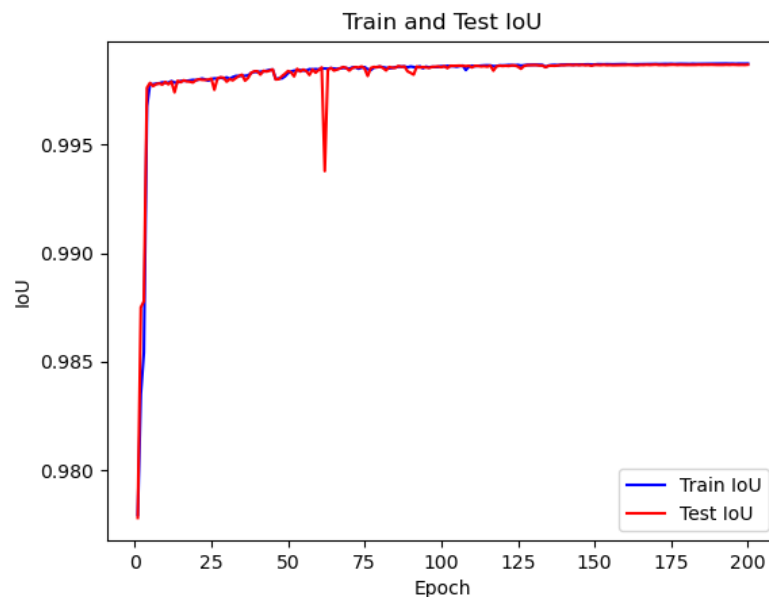
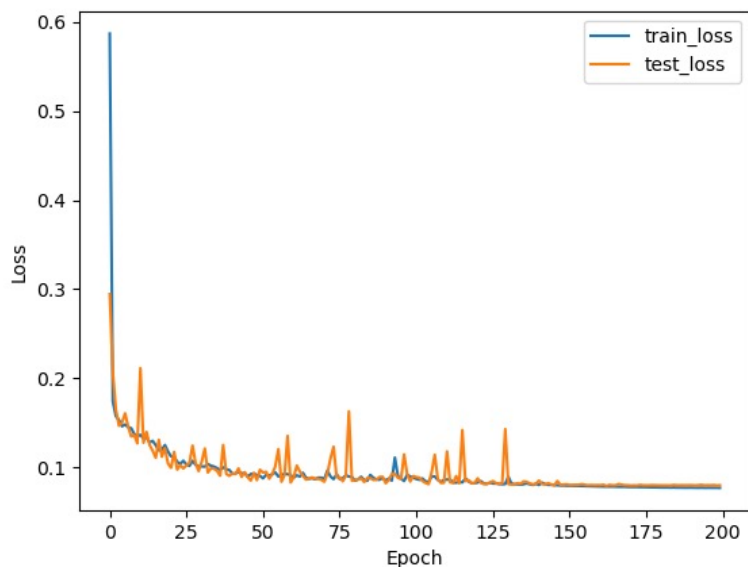
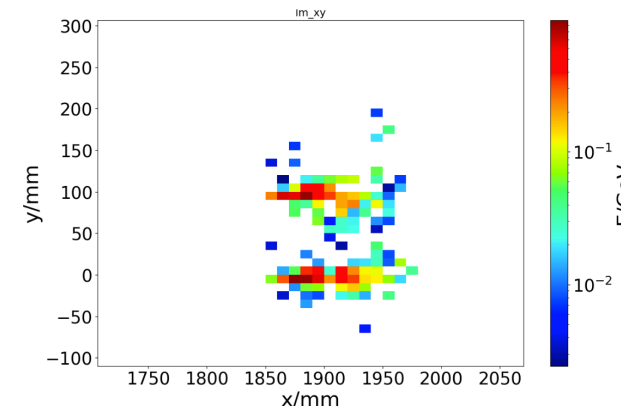
- CNN-based model for graphic dataset.
- Proposed the **EdgeConv** to handle the graph structure.
- Is able to handle classification and **segmentation** tasks.
- Application: [ParticleNet for c-tagging in CMS](#).



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, $\theta_\gamma \in [88^\circ, 90^\circ]$, $\phi \in [0^\circ, 3^\circ]$
 - γ_2 : $E_\gamma \in [3, 7]$ GeV, $\theta_\gamma \in [90^\circ, 92^\circ]$, $\phi \in [0^\circ, 3^\circ]$
- 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

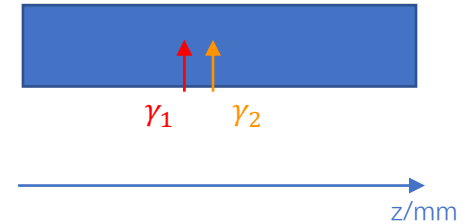
Now using the model
as a black box, but we
are able to tune it if
necessary.

Deep learning clustering



- **Application: di-photon separation.**

- 2 photons, $E=5$ GeV, $\theta = 90^\circ$, $\phi = 0^\circ$, generate @ ECAL surface, scan the distance.
- Photon reconstruction with DL + energy splitting:



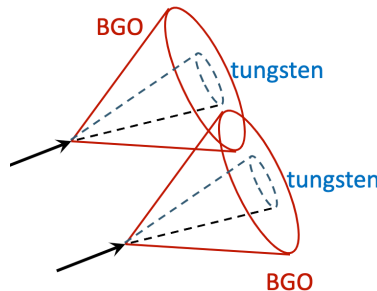
- For hit [a]:

P[1]	P[2]	...
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Traditional: hit[a] belongs to particle [i] with $\max(P[i])$.



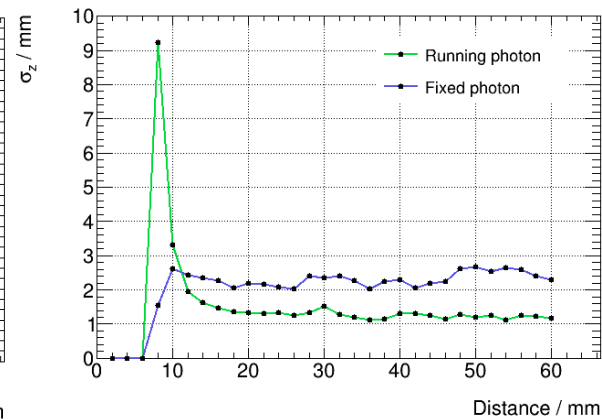
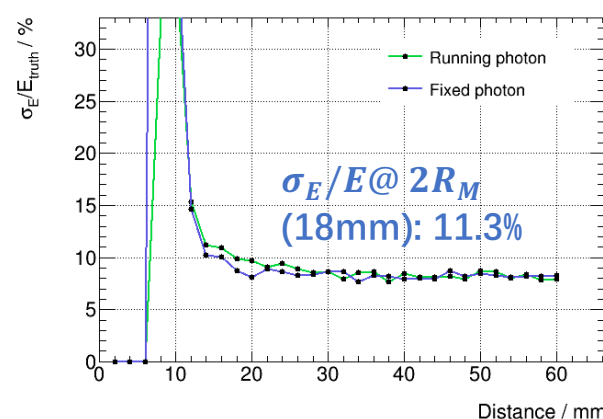
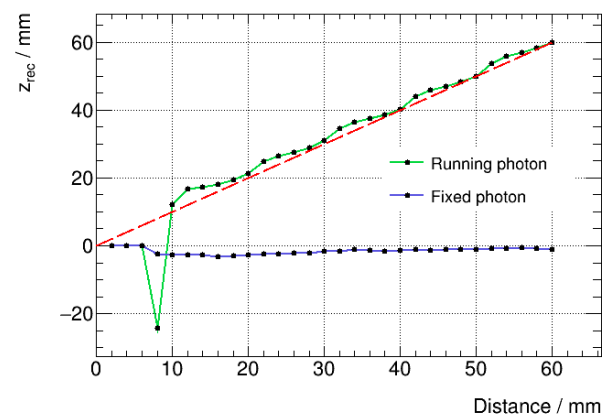
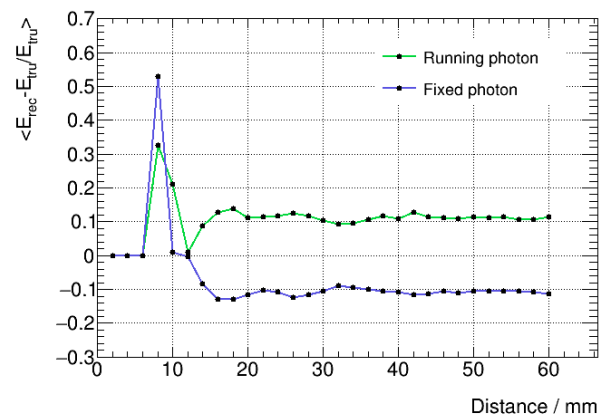
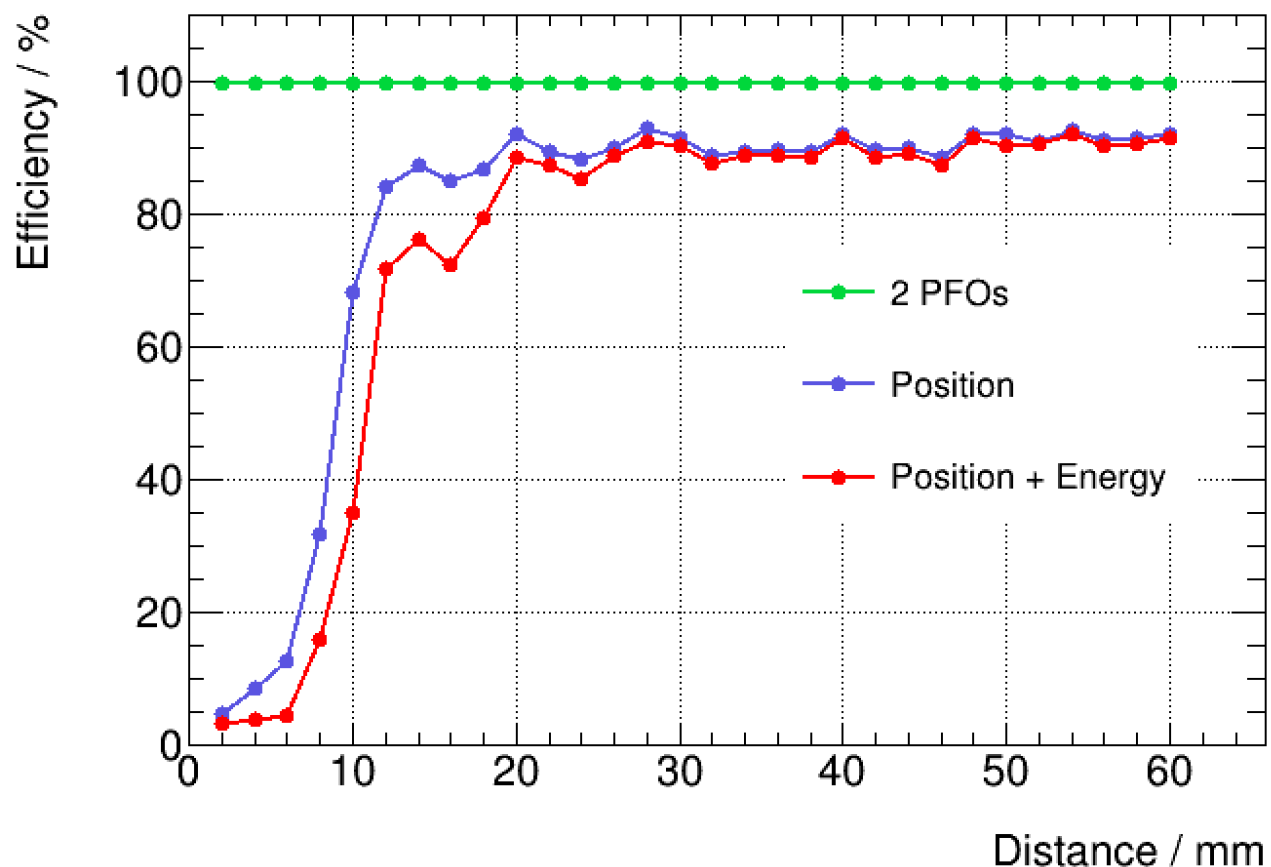
$P[i]$: probability that hit [a] belongs to shower (particle) [i].
→ Particle [i] contributes $P[i]$ to hit [a].
→ **Split hit[a] to several parts.**



Would be useful for dealing with large overlap showers.

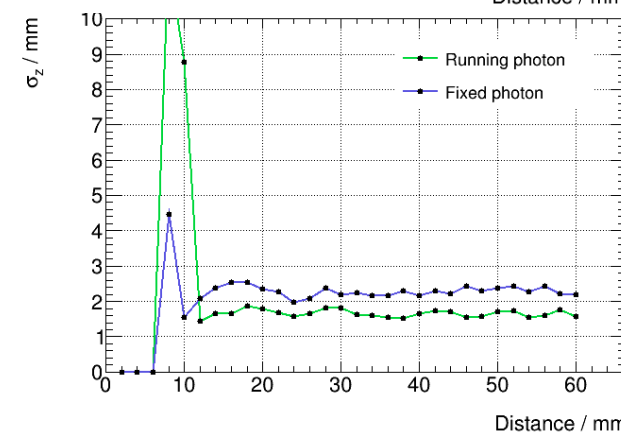
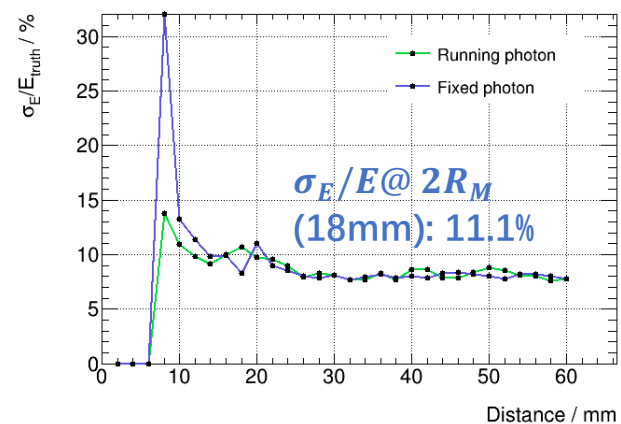
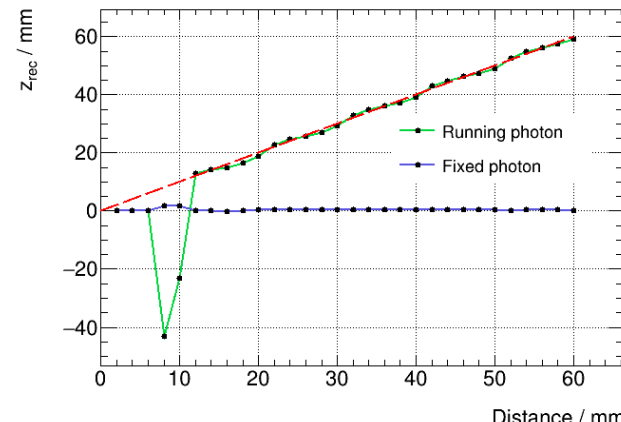
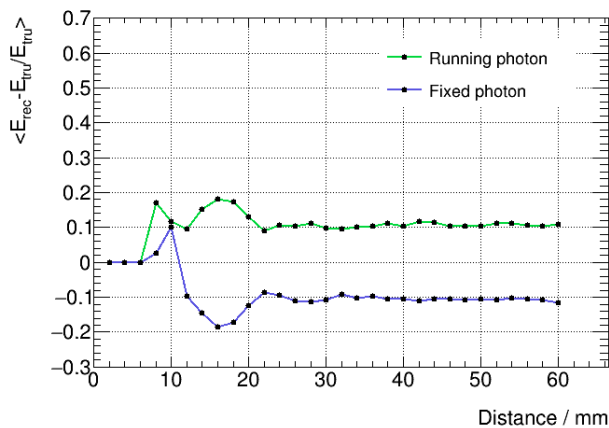
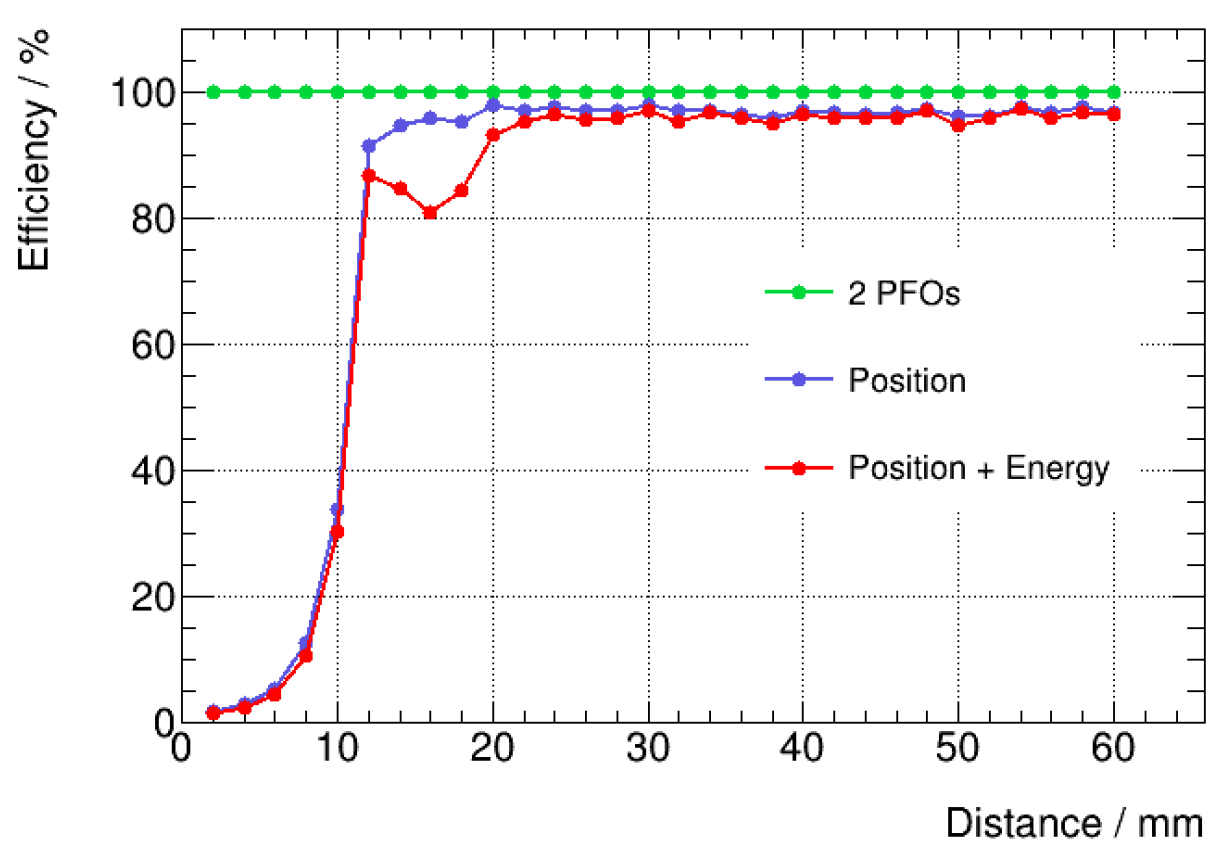
Performance

- Application: di-photon separation (no splitting)



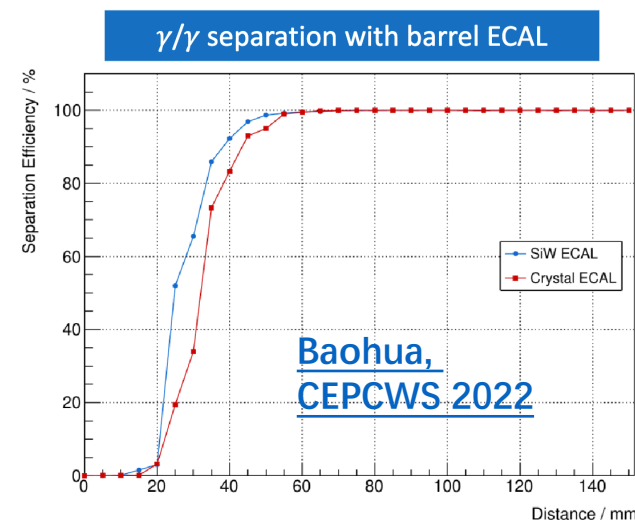
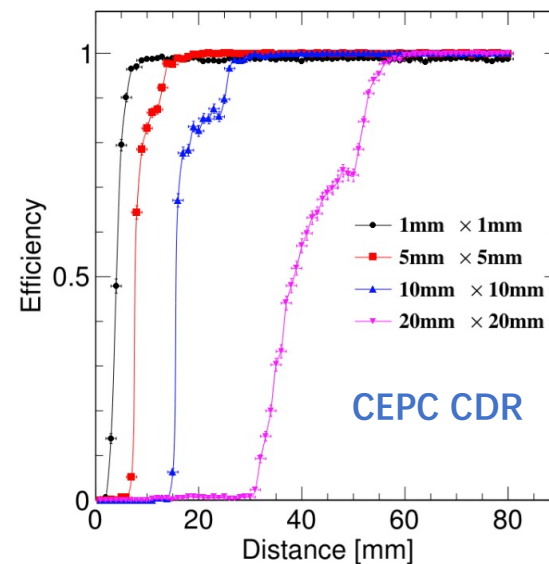
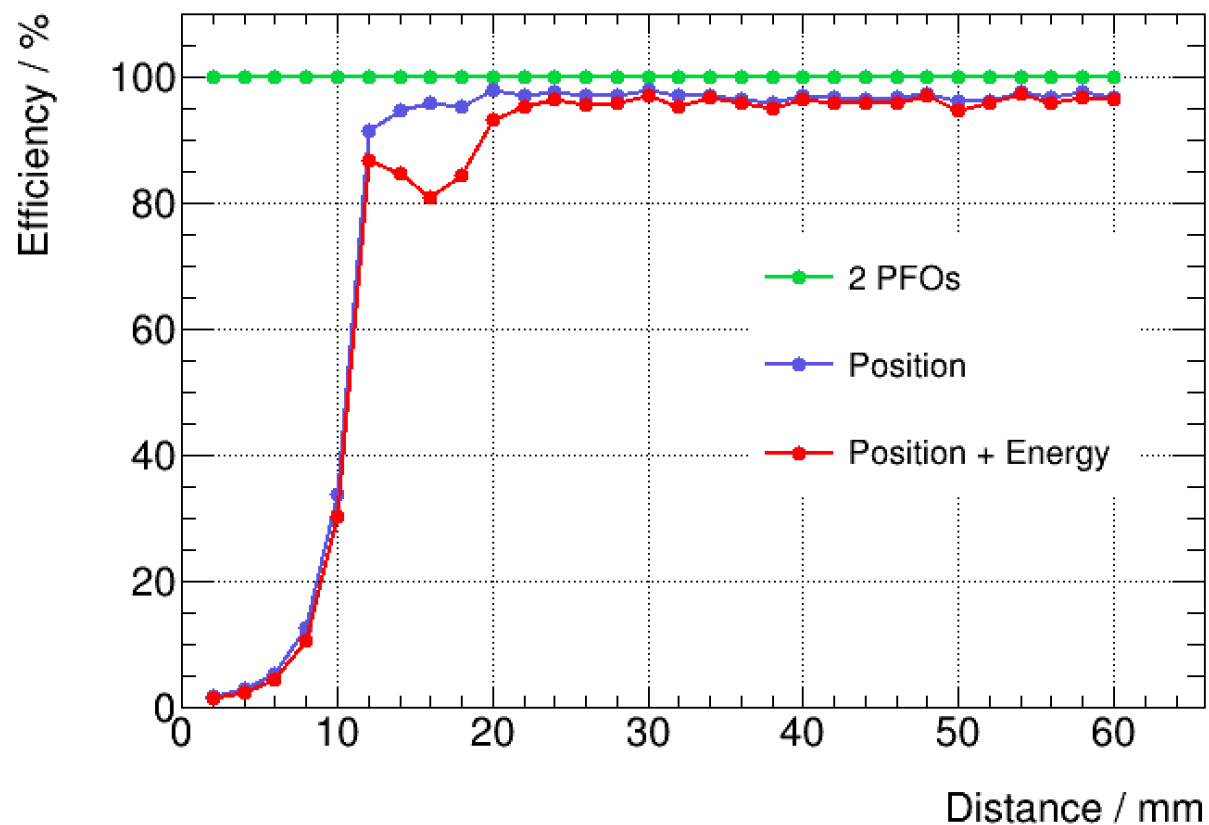
Performance

- Application: di-photon separation (splitting)



Performance

- Application: di-photon separation (splitting)



Summary and outlook



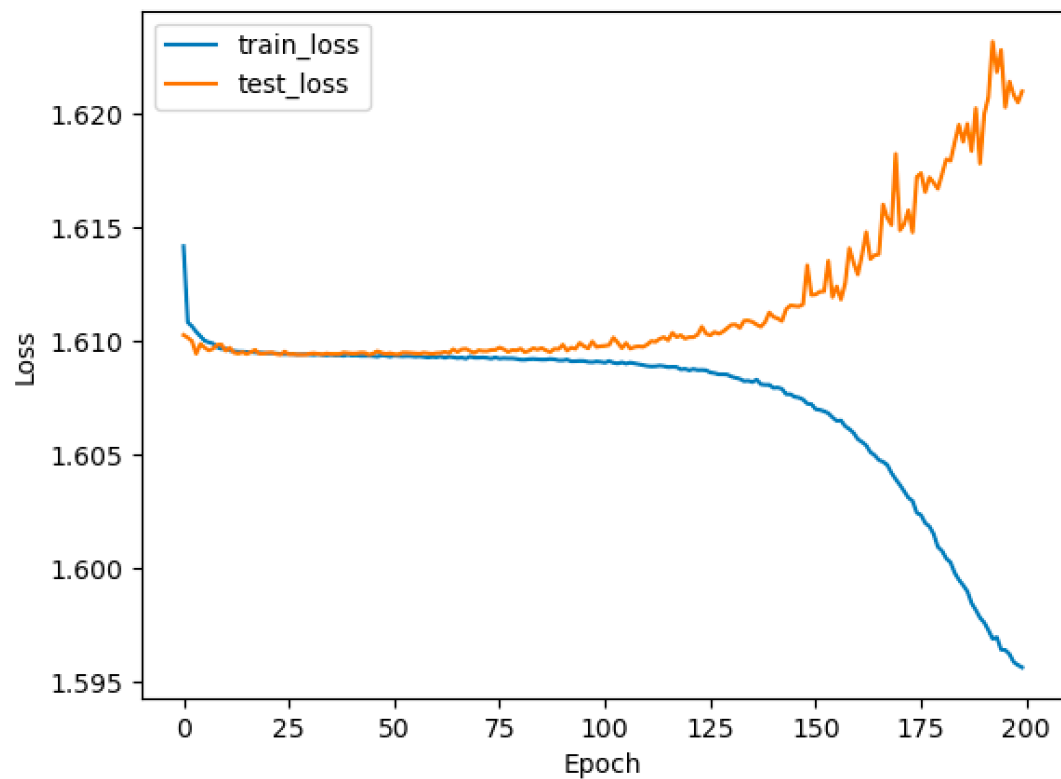
- **Calorimeter clustering with deep learning:**
 - Showed the feasibility of separating 2 photons, obtained better performance than CDR.
 - Overtraining problem
 - Tried to train with float number of photons, but the model did not converge.
- **Next step:**
 - Tune the model to overcome the overtraining 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



- Loss function

With 5 Gam in event



With floated photon number (1~5)

