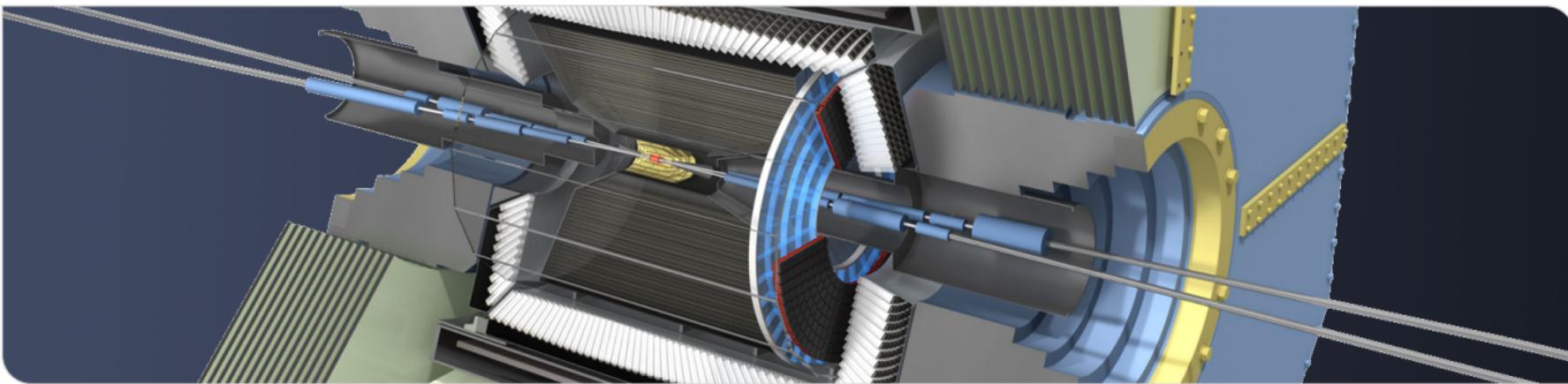


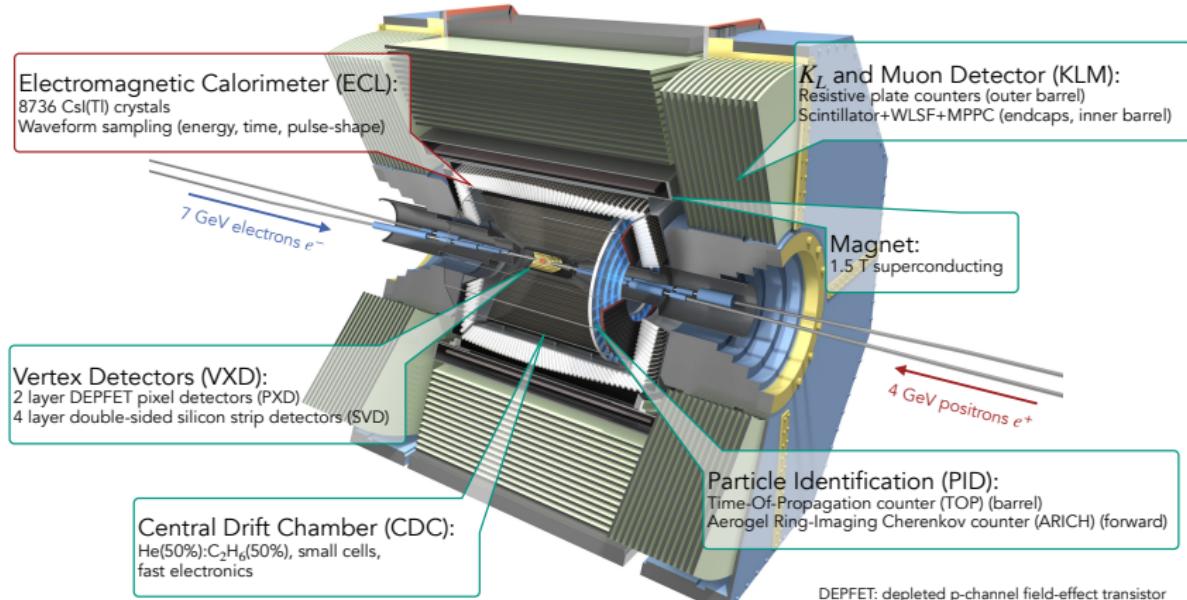
Improved Clustering in the Belle II Electromagnetic Calorimeter with Graph Neural Networks

CHEP 2023 - Track 9: Artificial Intelligence and Machine Learning

Isabel Haide, Florian Wemmer, Jonas Eppelt, Torben Ferber | 11. May 2023



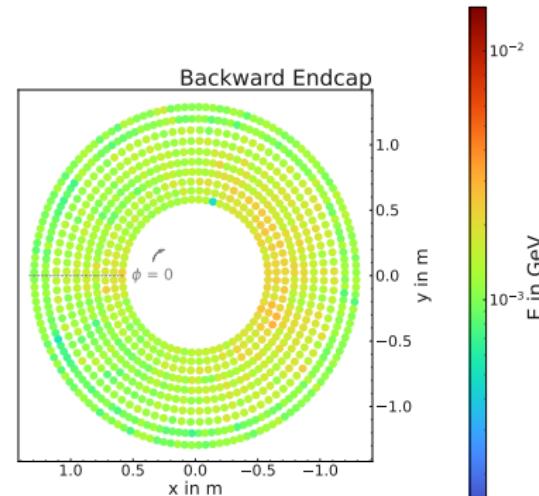
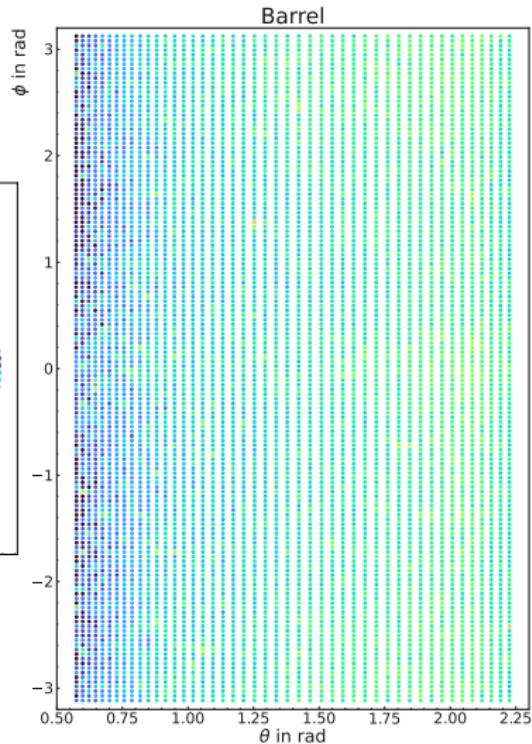
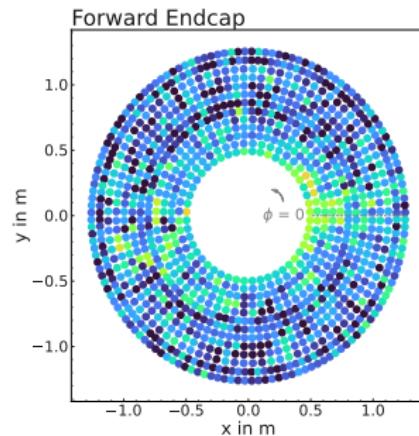
The Belle II Detector



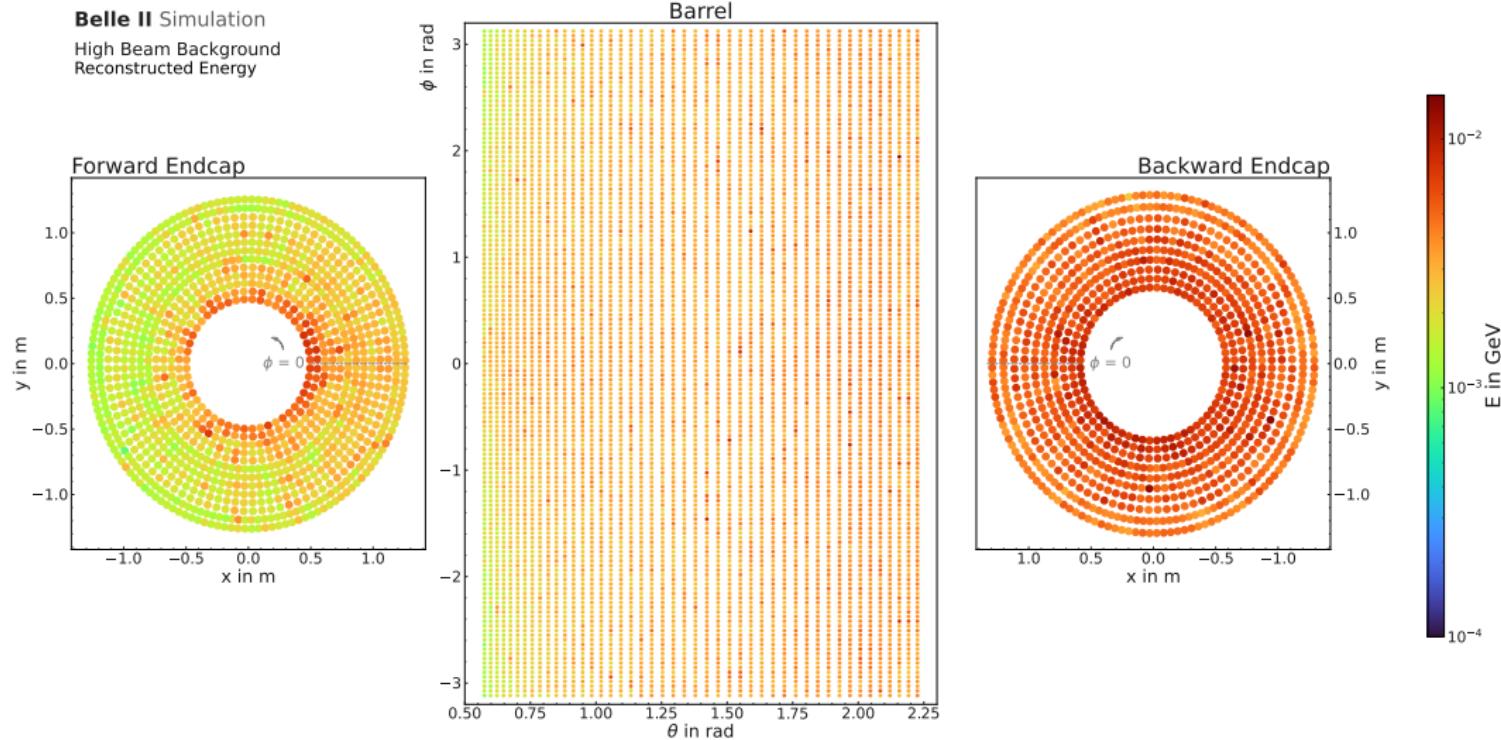
DEPFET: depleted p-channel field-effect transistor
WLSF: wavelength-shifting fibre
MPPC: multi-pixel photon counter

Beam Background in the ECL

Belle II Simulation
Low Beam Background
Reconstructed Energy

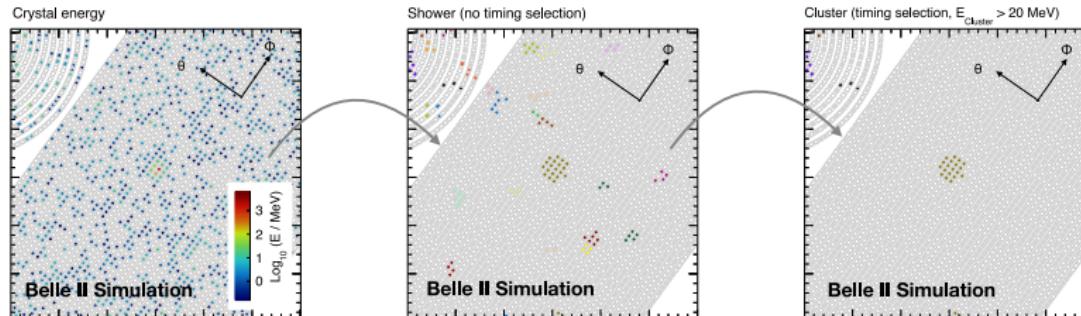


Beam Background in the ECL



Clustering Algorithms

- Clustering in the ECL is done at two separate times from data taking to physics analysis:
 1. During **online reconstruction** for Level 1 trigger decisions

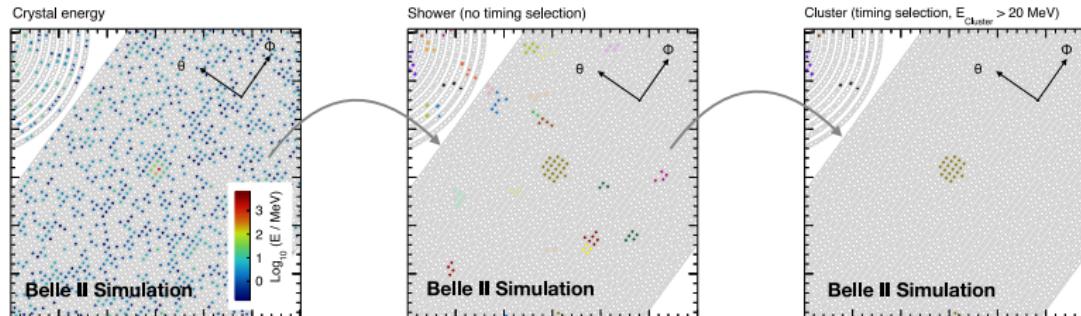


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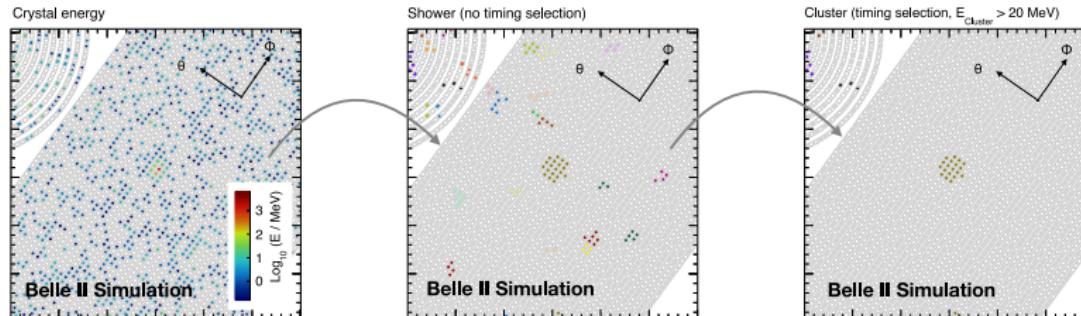
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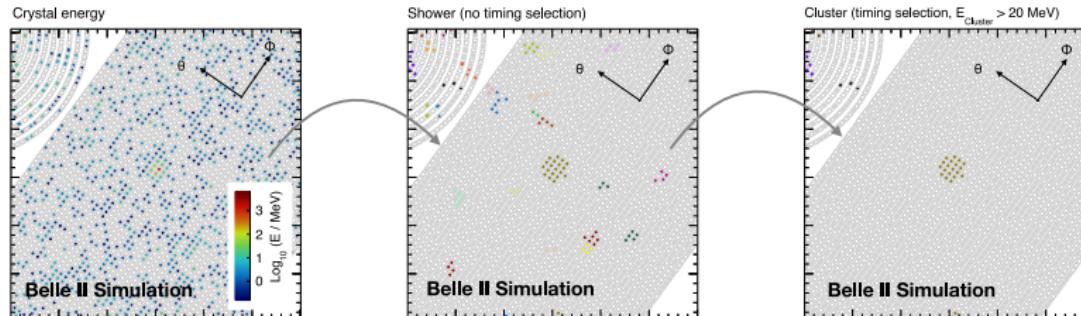
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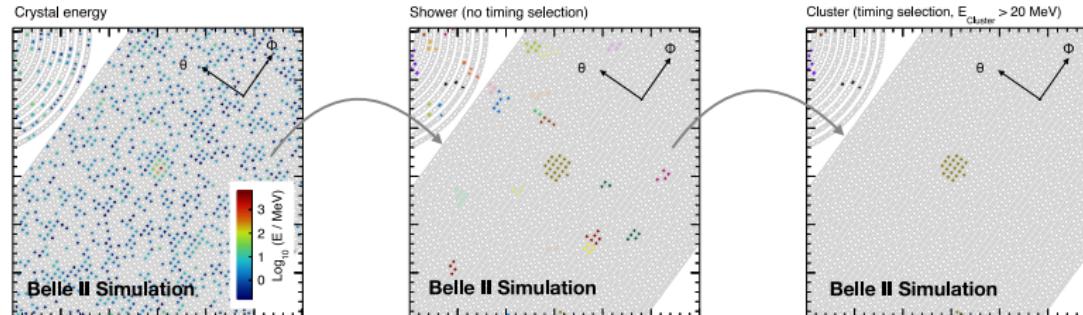
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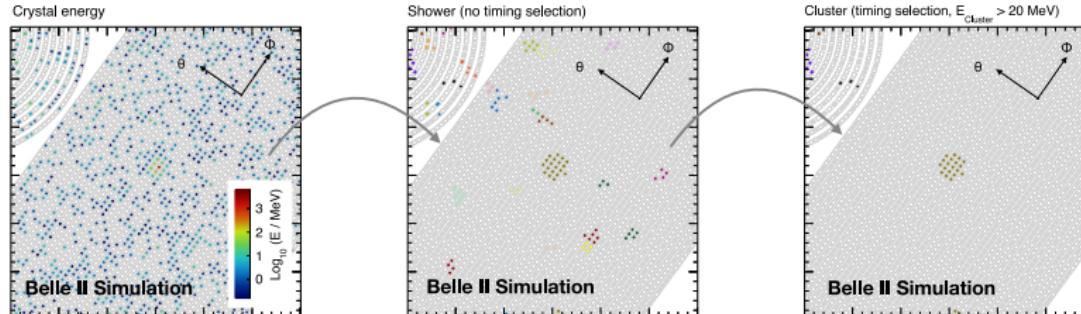
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- High background levels with increasing luminosity are additionally challenging



Clustering Algorithms

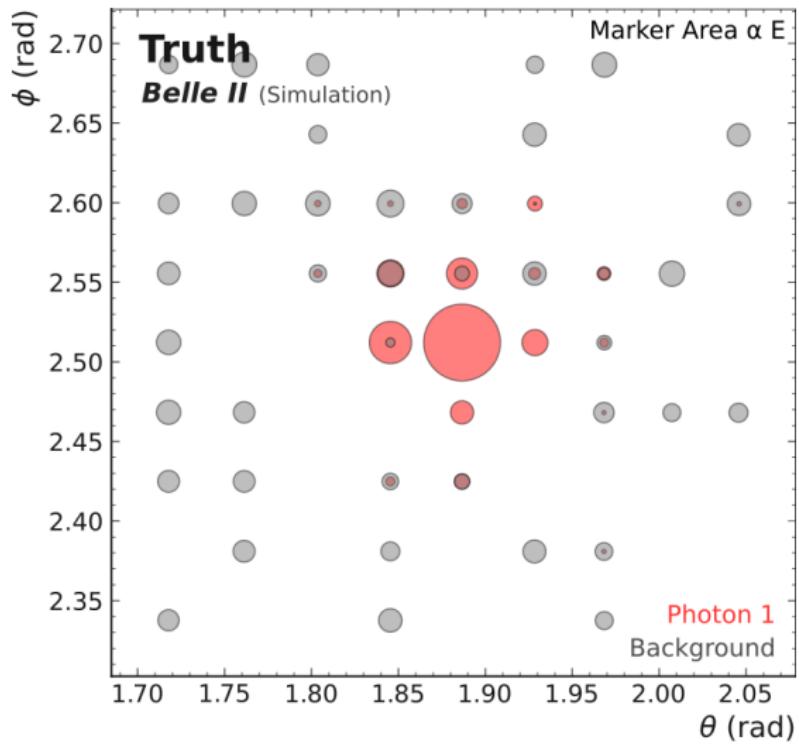
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 - Challenges: High energy resolution needed, separate overlapping particles
- High background levels with increasing luminosity are additionally challenging
- Irregular geometry in the endcaps and varying input sizes provide a good opportunity for **Graph Neural Networks**



Fuzzy Clustering Algorithm for Photon Reconstruction

Network Input:

- 9x9 grid of crystals centered on local maximum
- 1-2 photon cluster(s)
- Networks trained for both low and high beam background



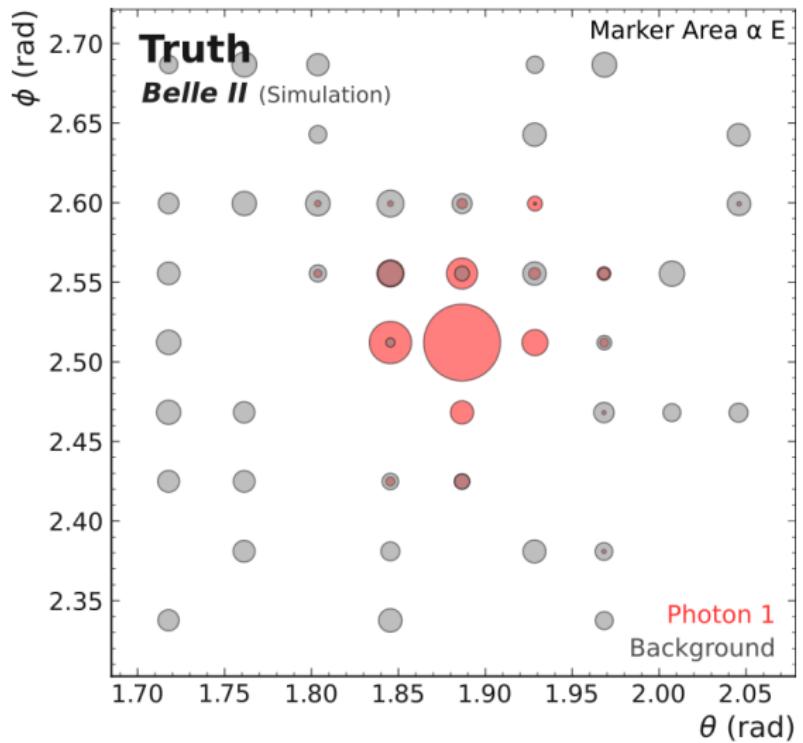
Fuzzy Clustering Algorithm for Photon Reconstruction

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Network Objective:

- Cluster energy depositions
- Fuzzy clustering:
 - ⇒ Assign weights $w_i \in [0, 1]$ with $i \in \{\text{bkg, photon 1, (photon 2)}\}$
 - ⇒ $\sum_i w_i = 1$ per crystal



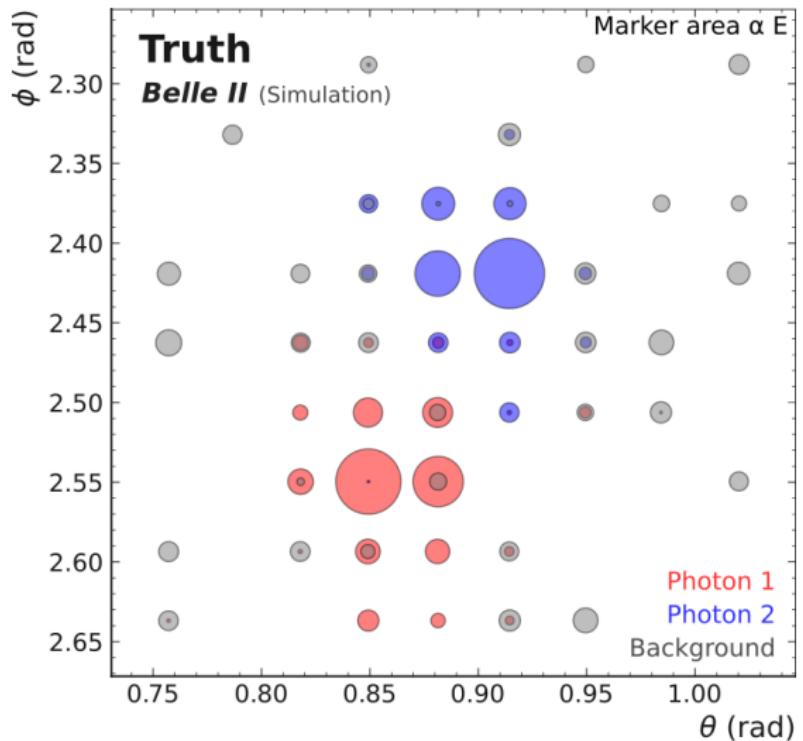
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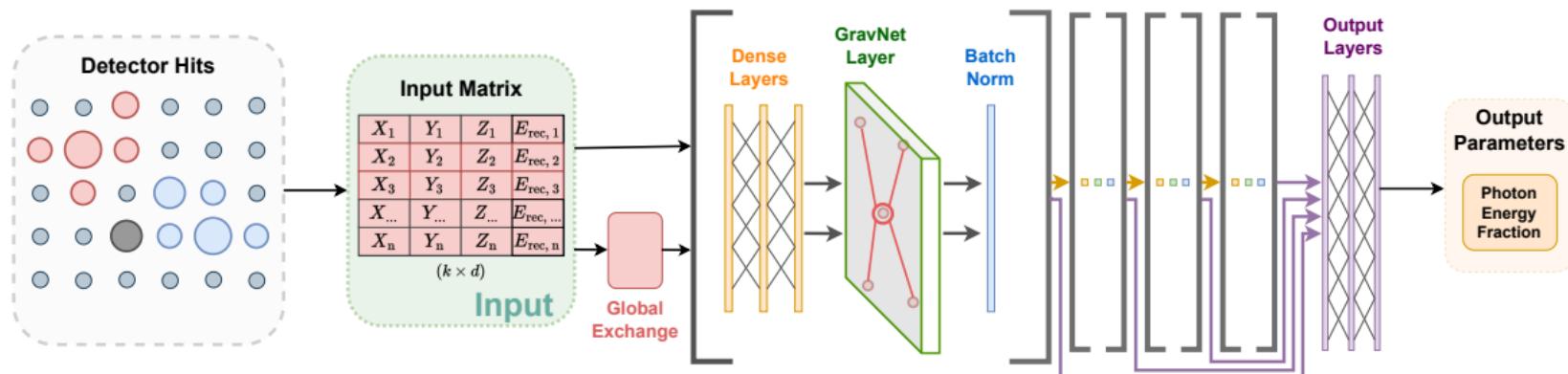
Fuzzy Clustering Algorithm for Photon Reconstruction

GravNet ([arXiv:1902.07987](https://arxiv.org/abs/1902.07987)) :

- End-to-end learning of representation spaces
- Adaptable to any detector geometry, easy addition of input features

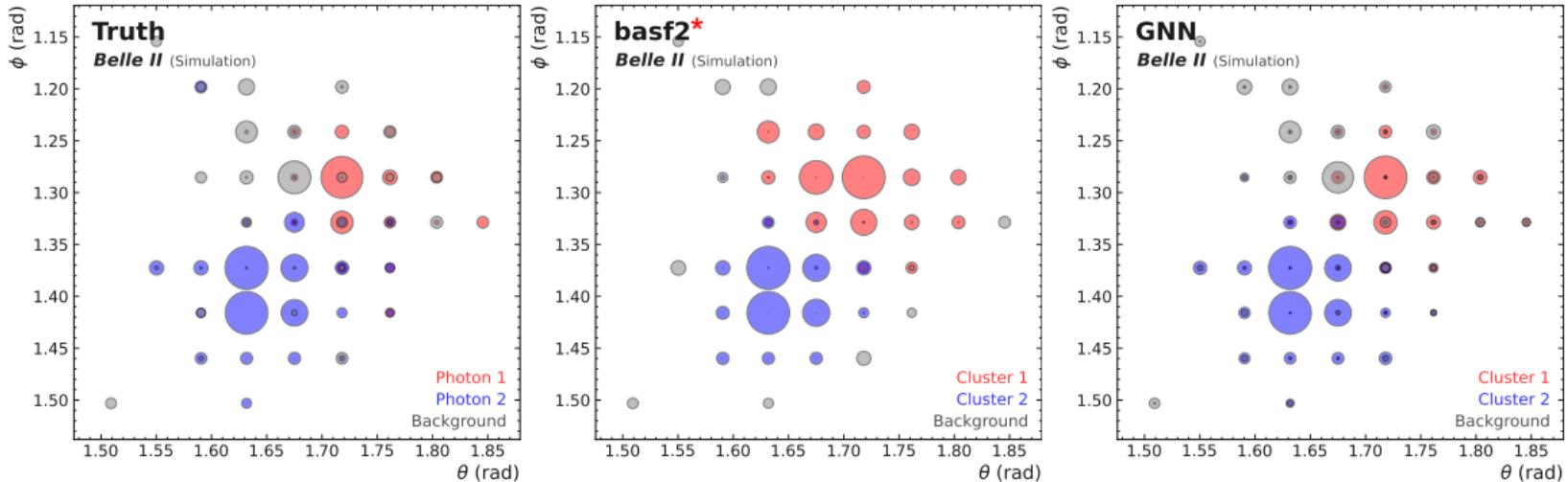
Features:

- Each crystal hit in 9x9 grid becomes node
- Node Features: Crystal Properties, Energy, Time, Pulse Shape Discrimination
[arXiv:2007.09642](https://arxiv.org/abs/2007.09642)



Adapted from L. Reuter

Results: Fuzzy Clustering



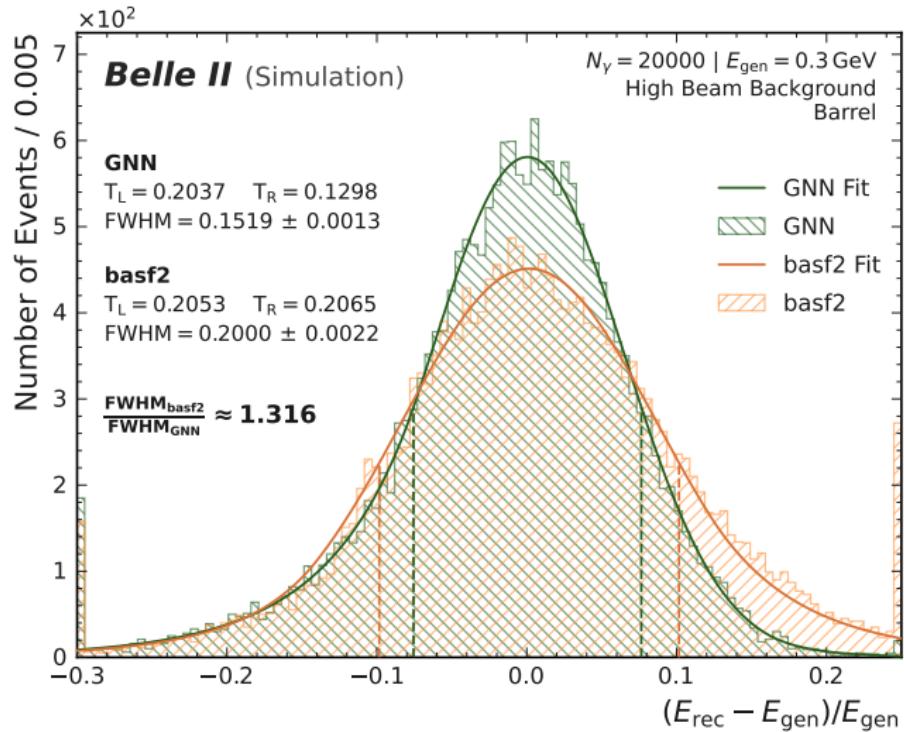
*basf2 (The Belle II Analysis Software Framework): [arXiv:1809.04299](https://arxiv.org/abs/1809.04299)

Calorimeter reconstruction in basf2: [arXiv:1808.10567](https://arxiv.org/abs/1808.10567)

Results: Fuzzy Clustering

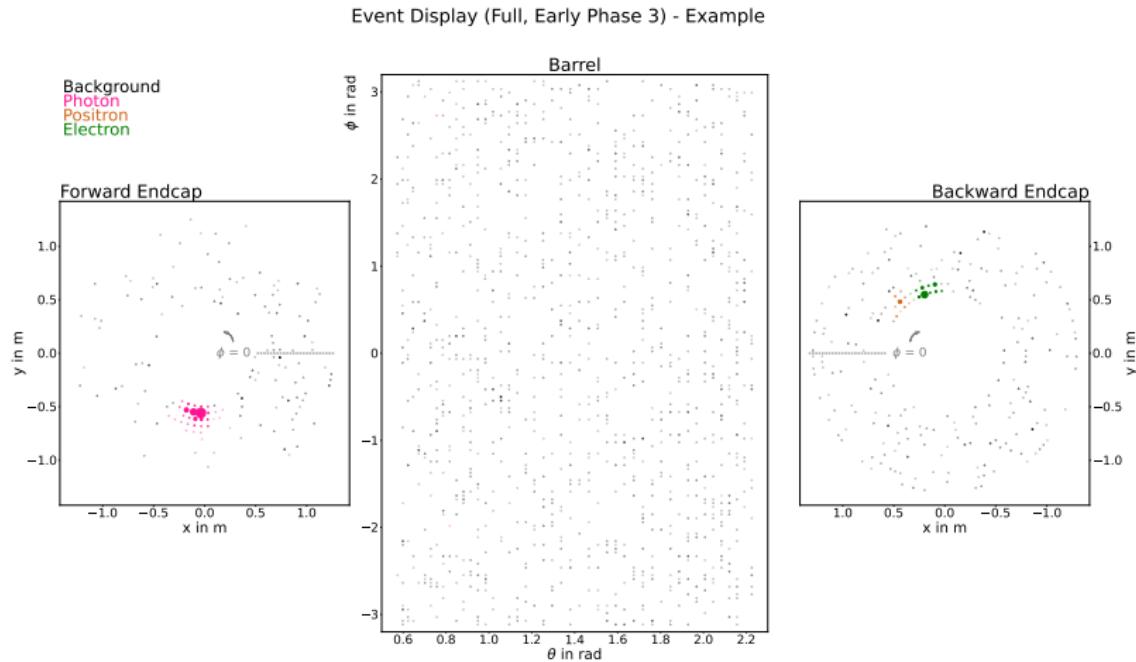
Summary:

- First application of GNN clustering algorithm at Belle II with:
 - Realistic detector geometry
 - Realistic beam background levels
- Improvements in energy resolution:
 - Single photons: Up to 30 % improvement with high beam background
 - Overlapping photons: Over 35 % improvement for the low energy photon in asymmetric photon pairs



Object Condensation (OC) for ECL Clustering

High improvements in photon energy resolution through fuzzy clustering, **but:**

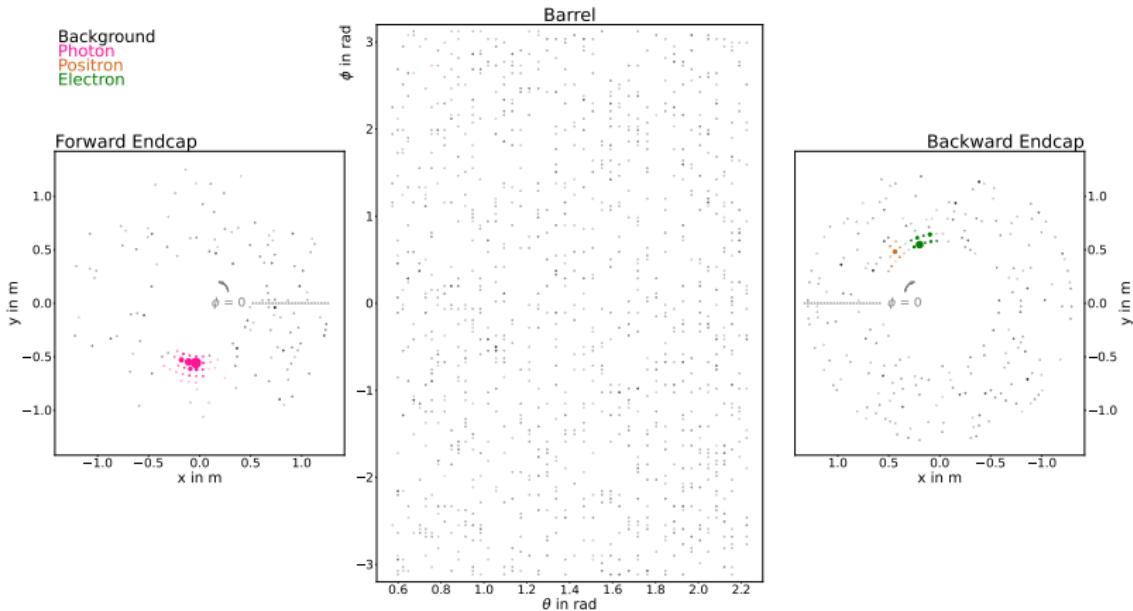


Object Condensation (OC) for ECL Clustering

High improvements in photon energy resolution through fuzzy clustering, **but**:

- In online reconstruction number of clusters is unknown

Event Display (Full, Early Phase 3) - Example

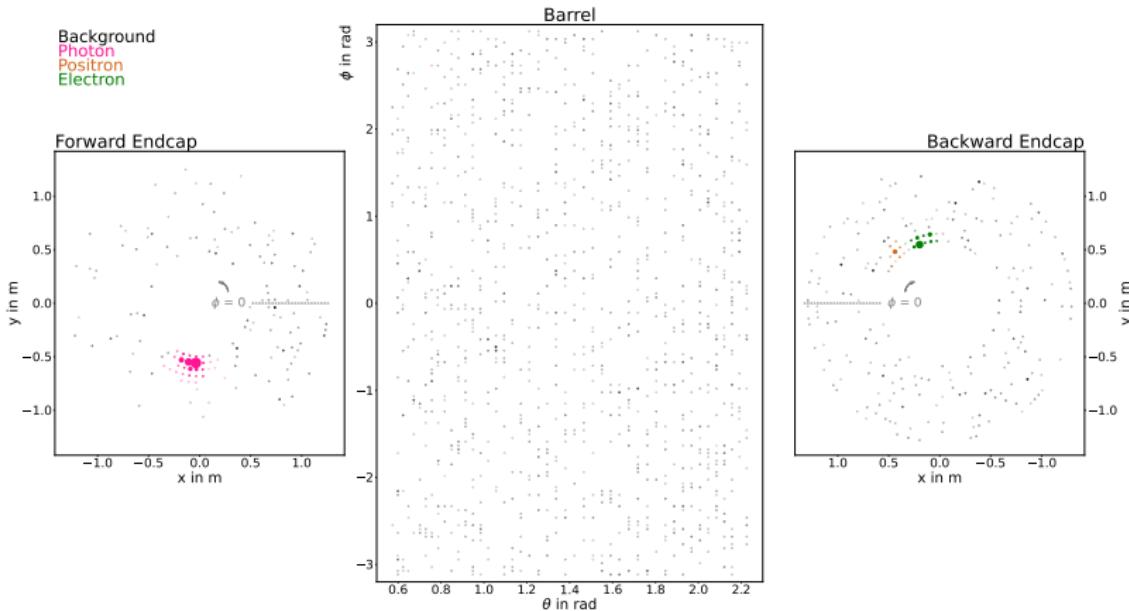


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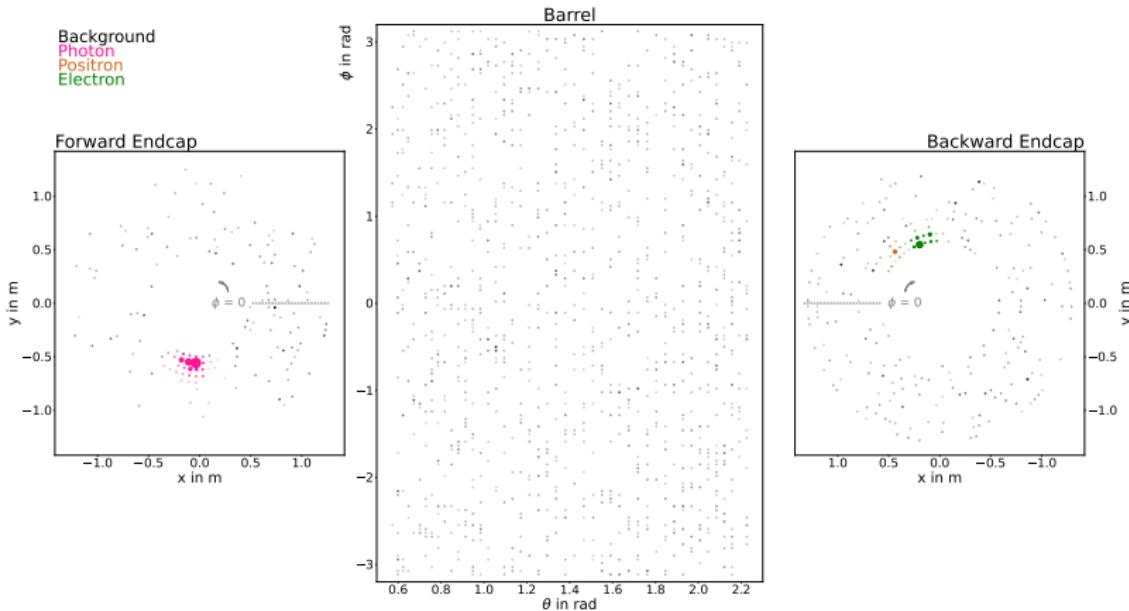
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Trigger efficiency needs to be improved for higher backgrounds and overlapping clusters

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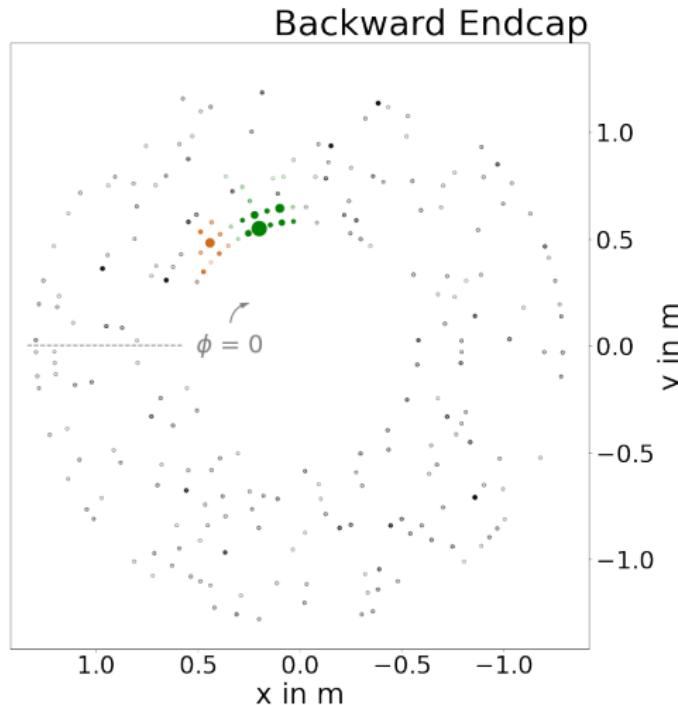


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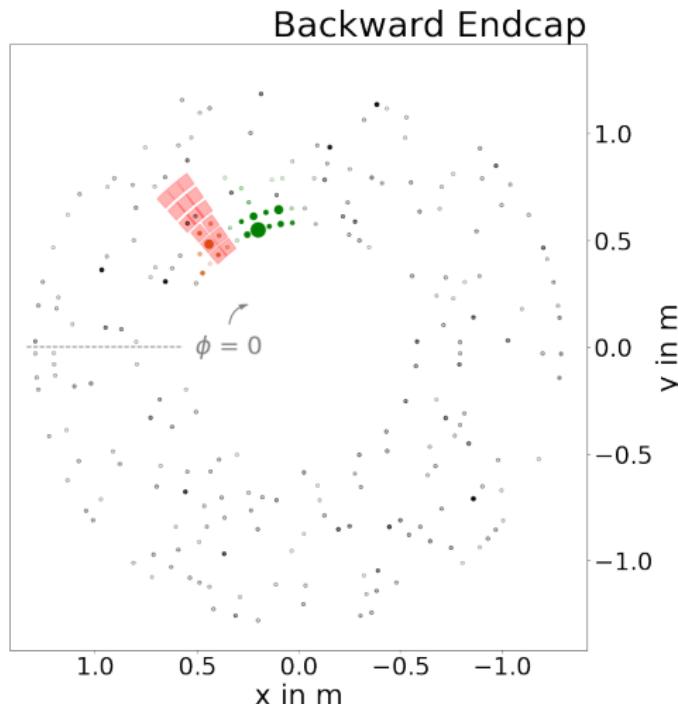


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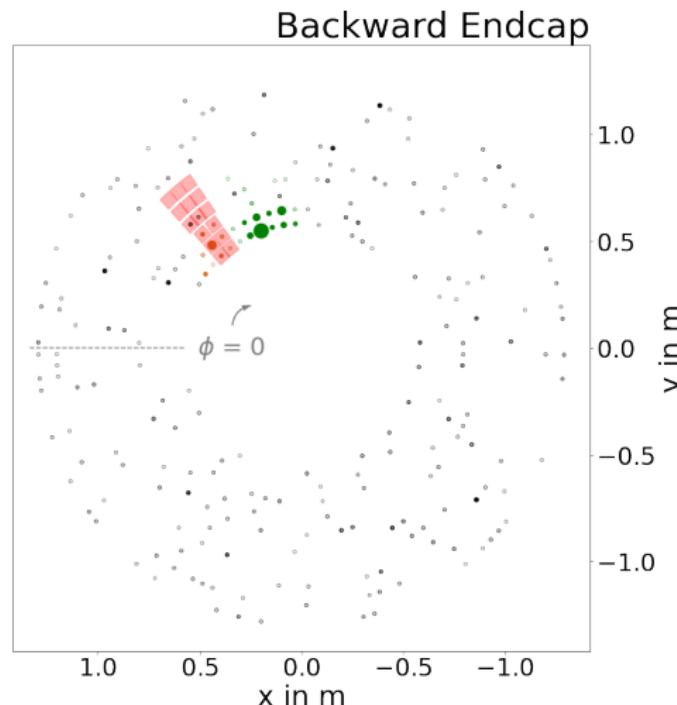
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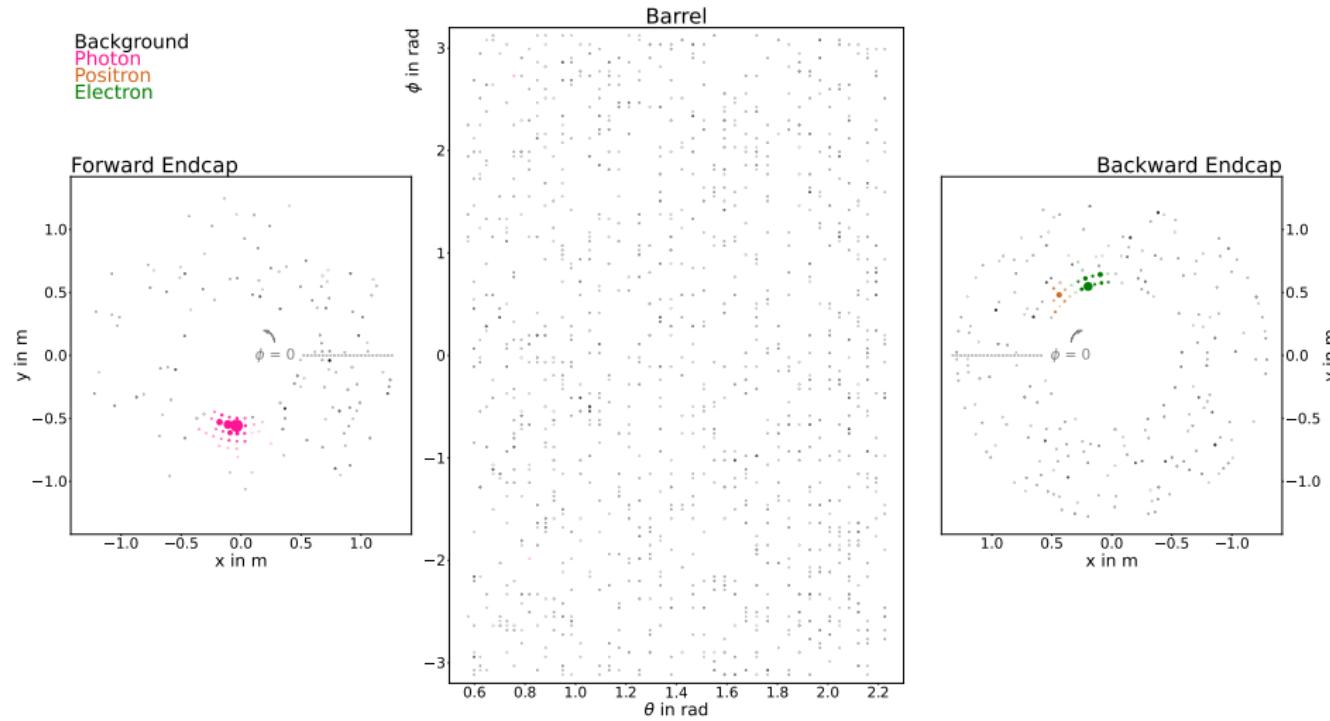
Trigger efficiency needs to be improved for higher backgrounds and overlapping clusters

- Better Bhabha detection, SM decays such as $e^+e^- \rightarrow \pi\pi\gamma$
- Low multiplicity searches, such as $e^+e^- \rightarrow a(\rightarrow \gamma\gamma)\gamma$

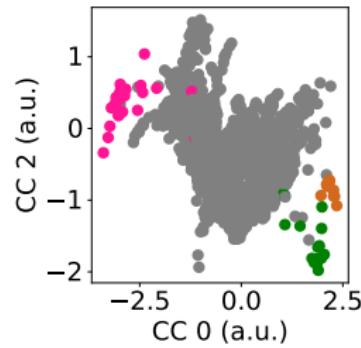
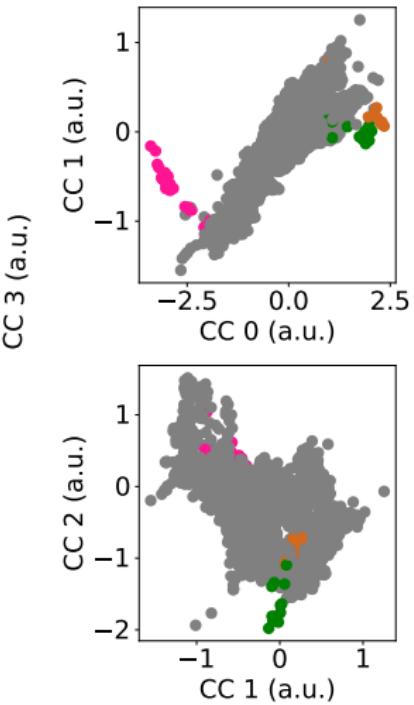
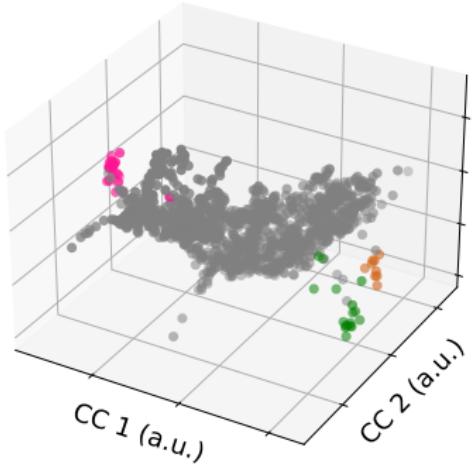


Inference for Object Condensation

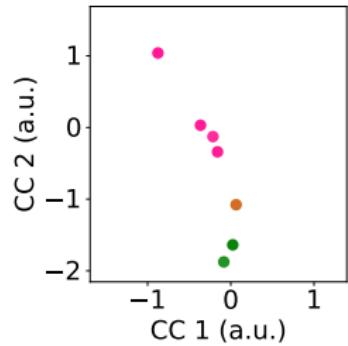
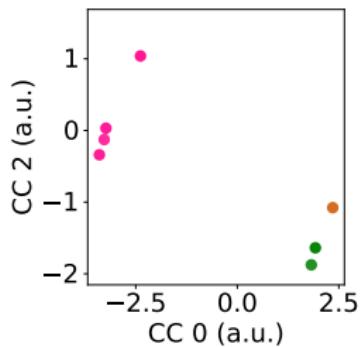
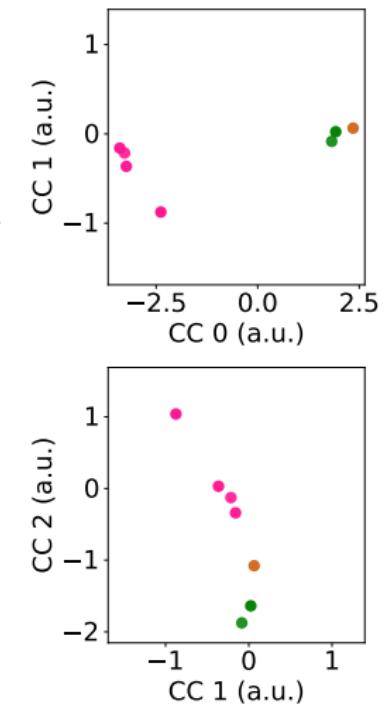
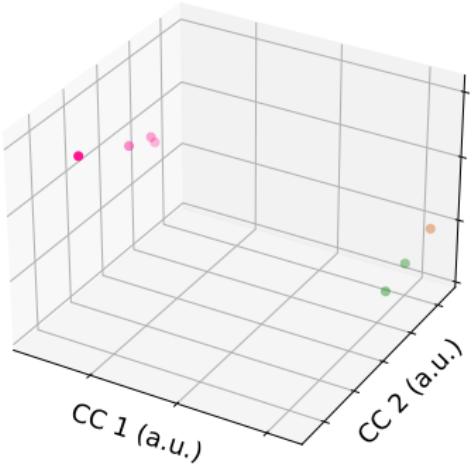
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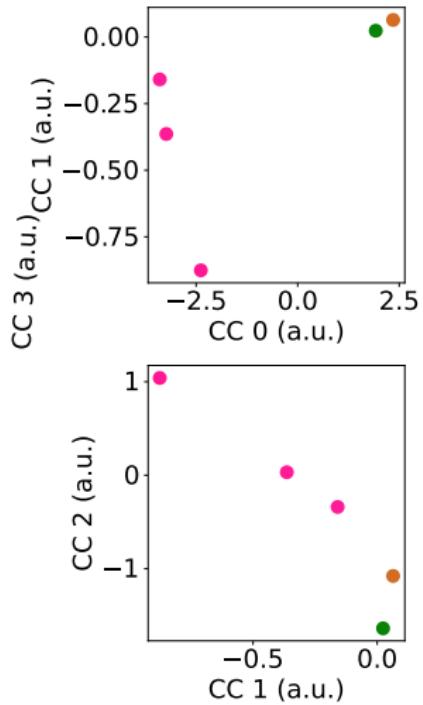
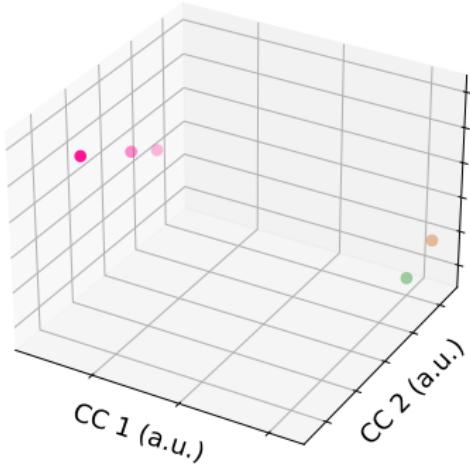
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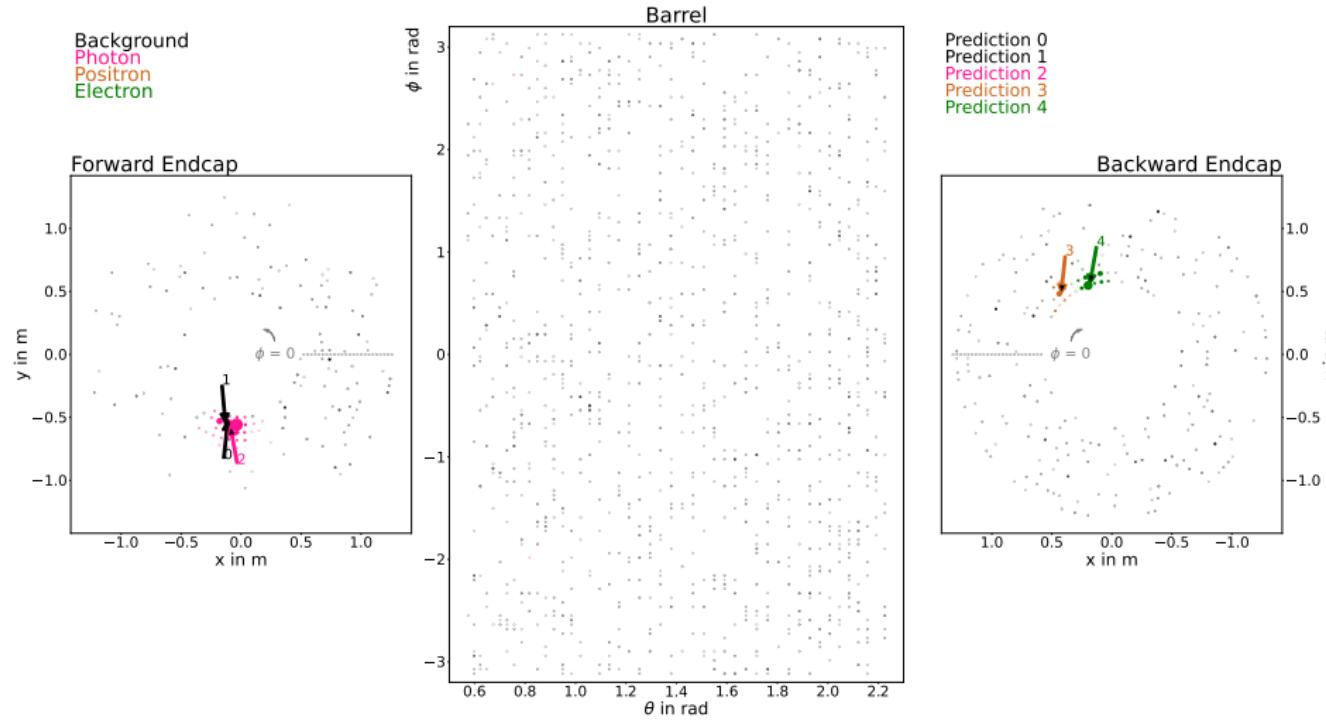


Inference for Object Condensation



Inference for Object Condensation

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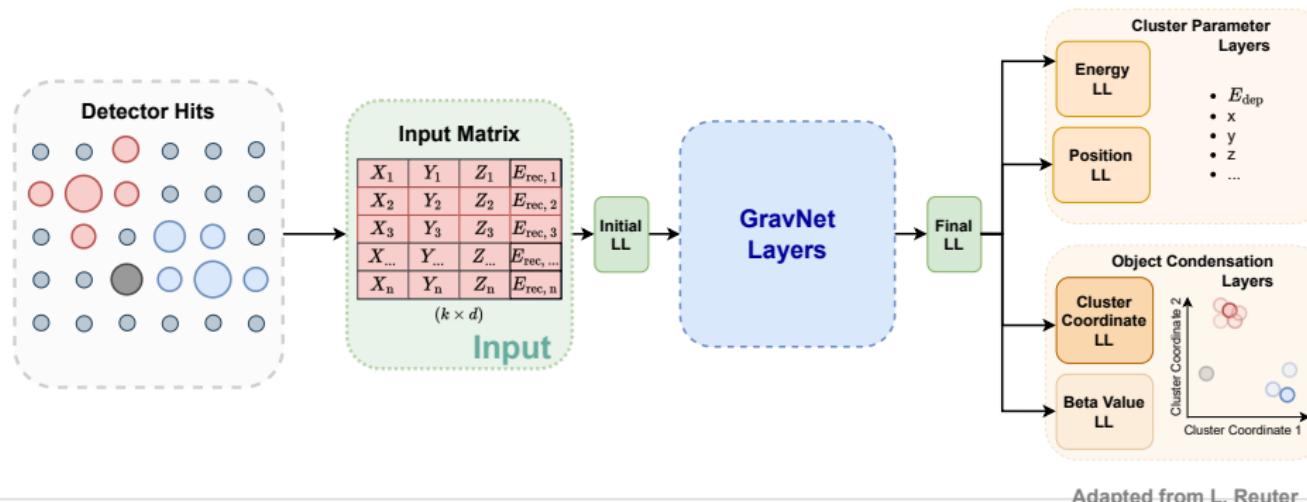
Algorithm Overview

Object Condensation:

- One-shot algorithm for both detection and reconstruction of clusters ([arXiv:2002.03605](https://arxiv.org/abs/2002.03605))
- Irregular geometry and varying input sizes in the ECL
→ GNN as base algorithm

Fast Inference:

- OC introduces potential to cluster vertices from same object together
- Each vertex gets a β -value assigned
→ Vertex with highest β -value invokes potential (= condensation point)
- Condensation points carry prediction for clusters

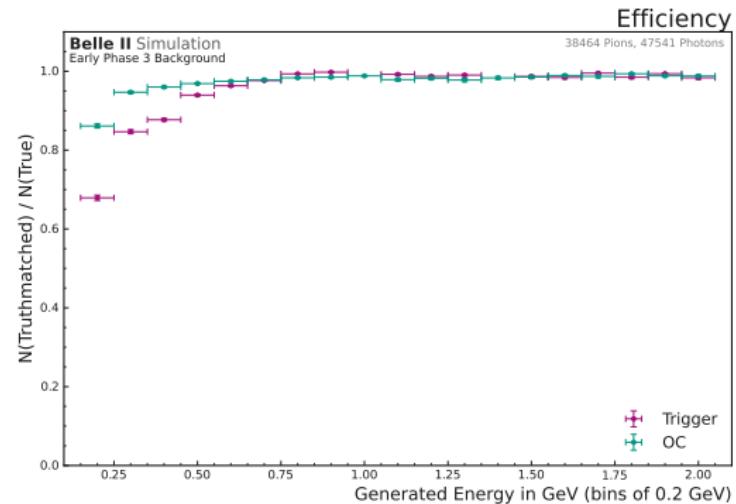
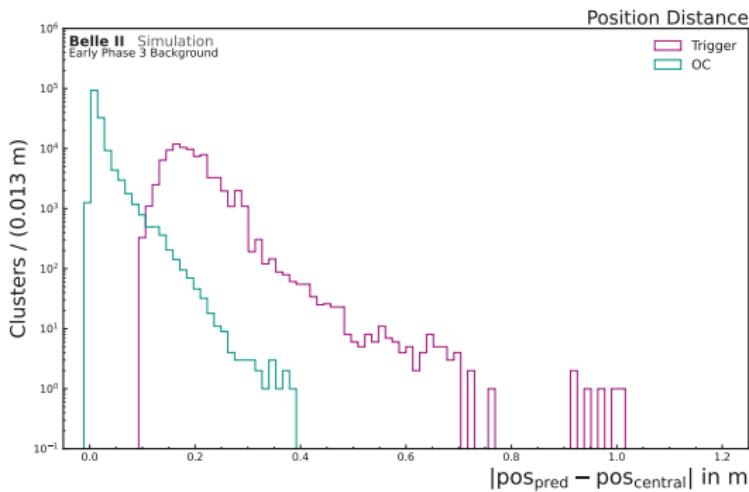


Adapted from L. Reuter

Current OC Improvements

- Network is trained on charged pions and photons between 0.05 and 2 GeV energy
- Training on 1-6 particles, inference on up to 10

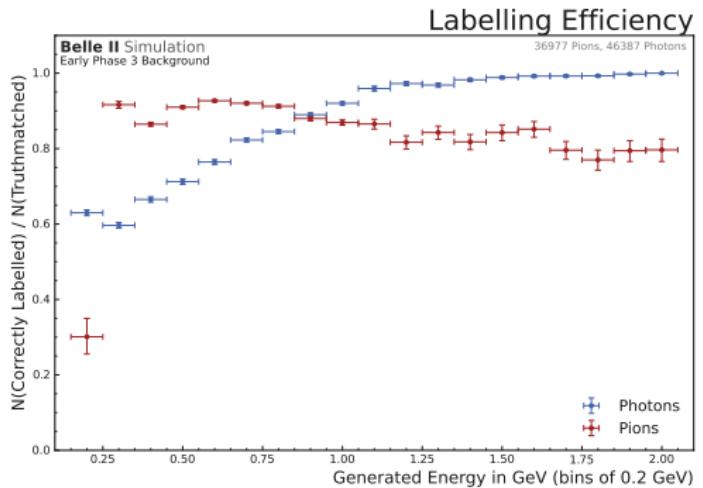
- Network predicts number of clusters and respective cluster parameters
- Current GNN has only 12414 parameters



Results: Object Condensation

Summary:

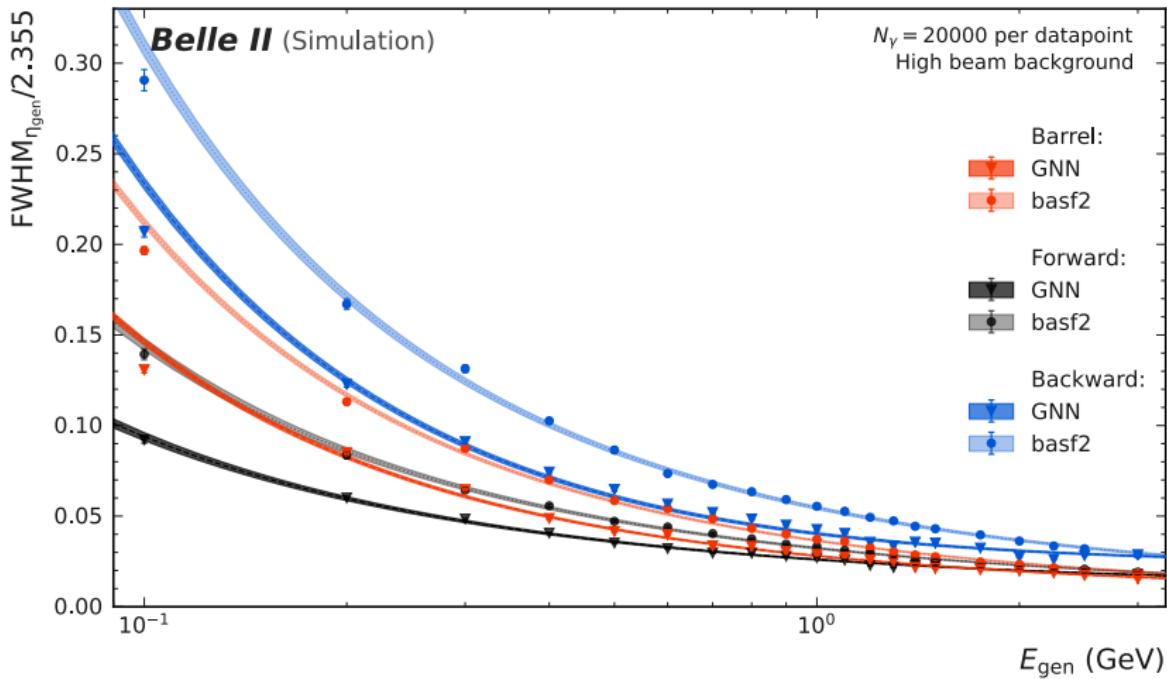
- First application of GNN object condensation at Belle II with:
 - Realistic detector geometry
 - Realistic beam background levels
- Improvements:
 - Increased efficiency over current trigger algorithm
 - Improved position resolution



Further Steps:

- Easy implementation of new prediction parameters
→ Addition of particle identification
- OC can improve trigger efficiency
→ implementation for testing on physics applications

Energy Resolution



Background Robustness

