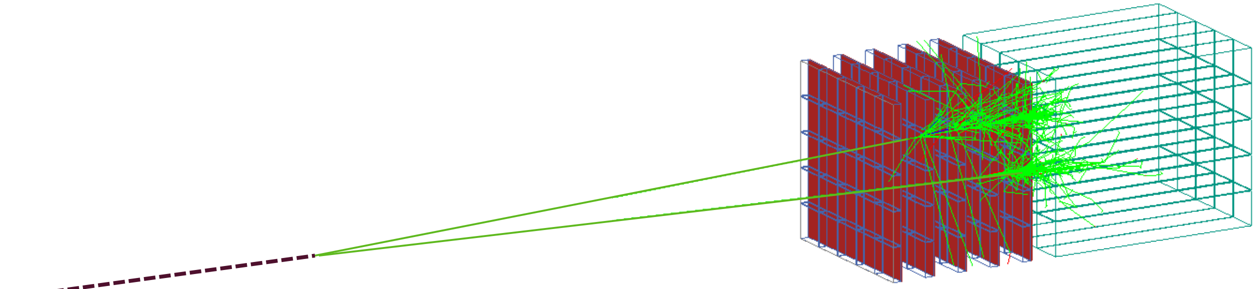
Photon Reconstruction of Axion-Like Particles with Graph Neural Networks at Beamdump Experiments

ETP Weekly Meeting

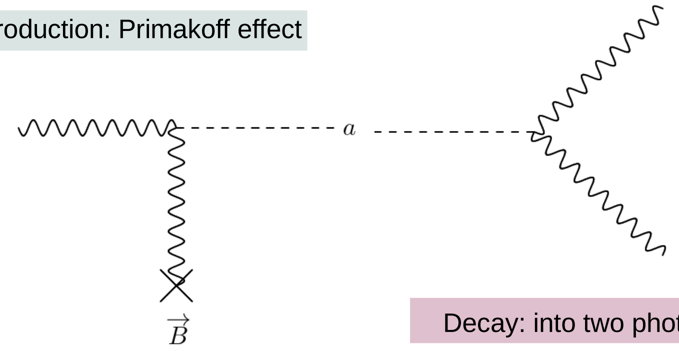
Kylian Schmidt



Axion-Like Particles (ALPs)

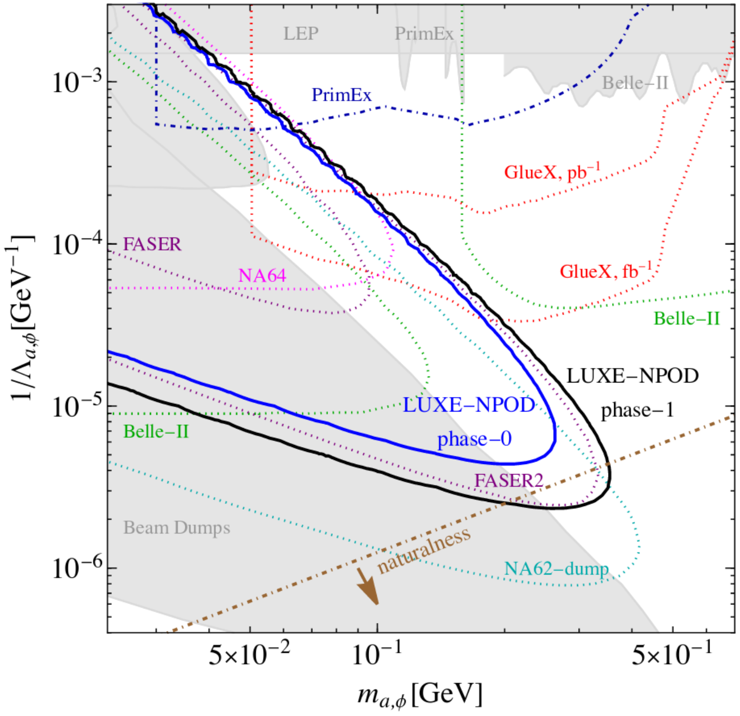
- Potentially ***long-lived pseudoscalars***
- Very light and feebly interacting with SM (New Physics)
- Here: ALP with dominant coupling to photons
- Characterized only by mass and coupling constant

Production: Primakoff effect



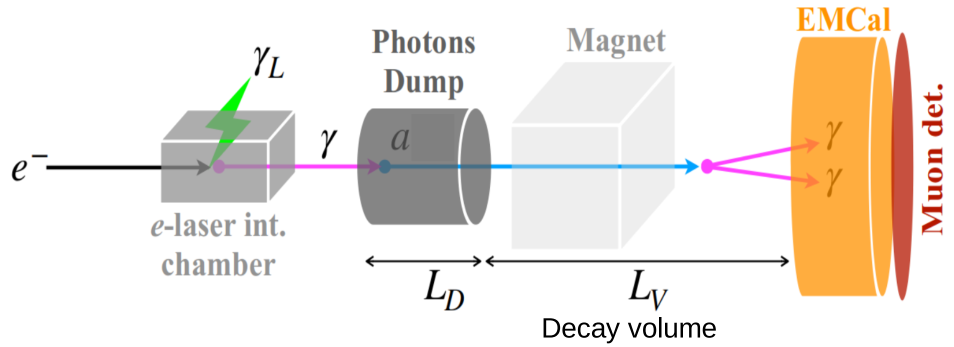
Decay: into two photons

ALP mass-coupling phase space
(from 10.1103/PhysRevD.106.115034)



LUXE-NPOD Beamdump Experiment

- Proposed Laser Und XFEL Experiment (LUXE) - New Physics at Optical Dump (NPOD) at DESY:
  - Electron beam & laser produce ***GeV photons***
  - Secondary production: ALPs arise from photons trough ***Primakoff production***
  - ALPs do not interact with the remaining dump material and freely decay
- Signal: two photons originating from ***same vertex*** inside the decay volume
- Background: reject SM neutrons, K_L and photons created outside the decay volume



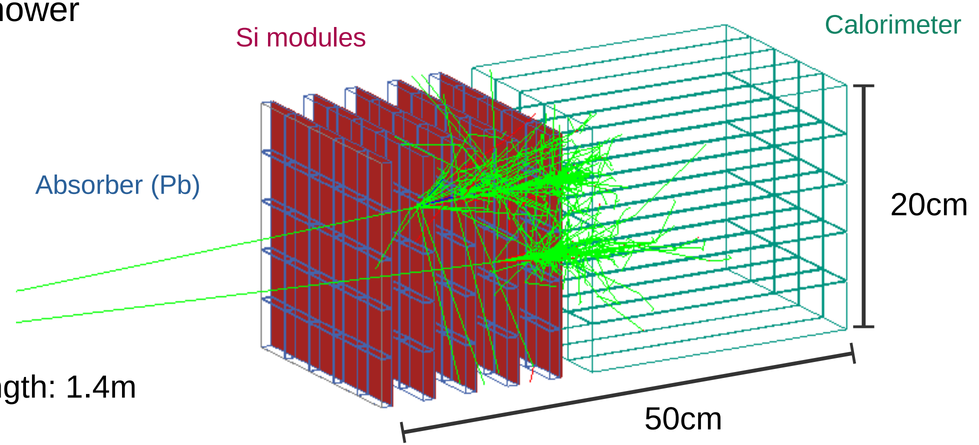
Sketch not to scale
(from 10.1103/PhysRevD.106.115034)

Can we reconstruct high-energy photons?

ETP Institute of Experimental Particle Physics

- Goal of this study: find direction of both photons and their common vertex
- Challenge: neutral particles do not leave tracks
- Approach: use the EM shower of the photons to find their direction
  - Place high Z material in front of detection layer
  - GeV photons shower into measurable low-energy EM particles
- Require new method to reconstruct photon from shower
- Simplified simulation of highly granular calorimeter

Geant4 simulation of potential LUXE-NPOD detector design

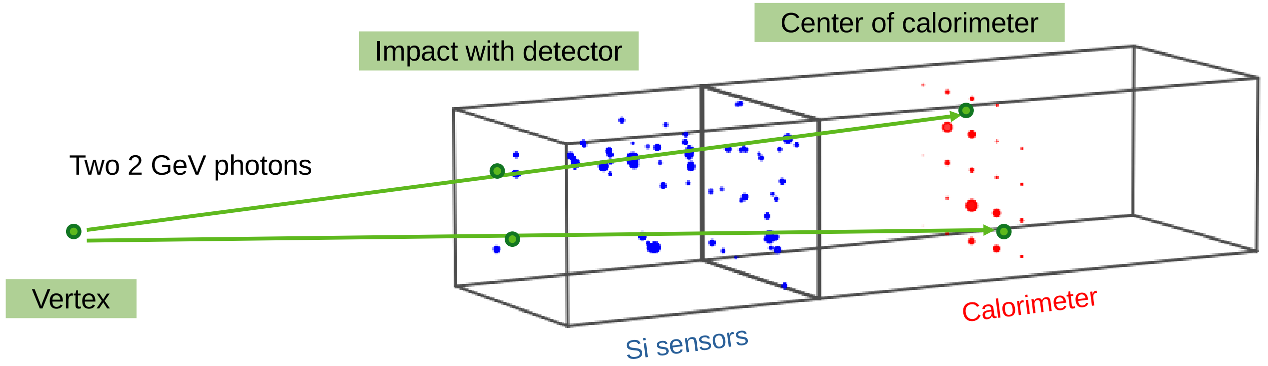


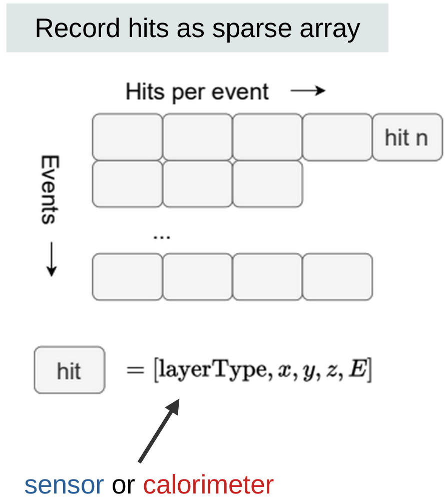
Decay volume length: 1.4m

Reconstruction goals

- Graph Neural Network approach:
  - Work directly on variable size 3D ***detector hits*** as cloud of points
  - Adapt to irregular detector geometries
  - Flexible changes in geometry

- Input: sparse array of all detector hits
- Training targets: ***vertex position*** and direction of each photon
- ***L2 loss*** between *true* and *predicted* direction

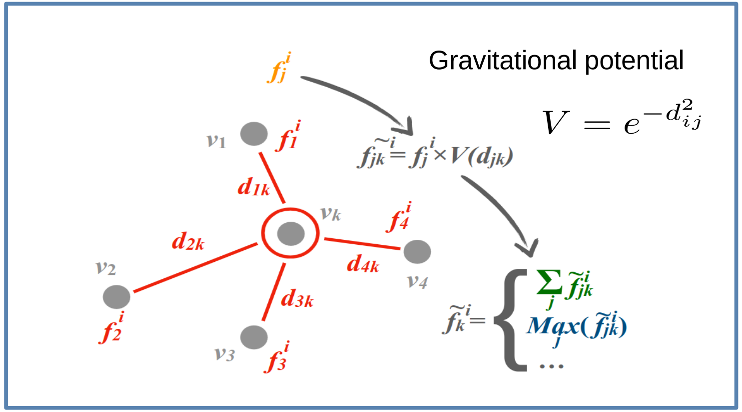




Graph Layers

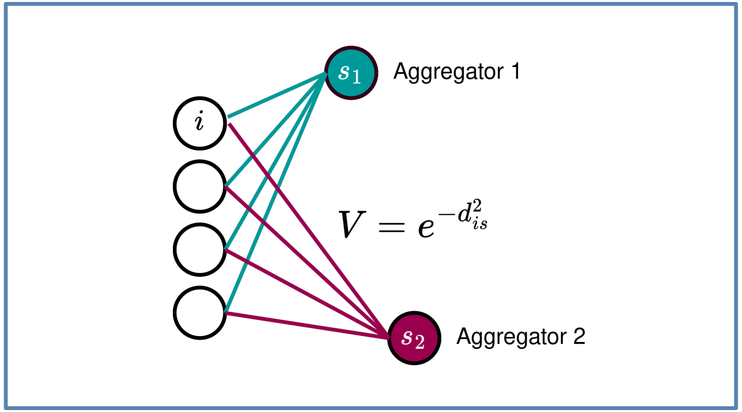
GravNet:

- Builds own representation graph for better clustering
- k-Nearest Neighbor algorithm ***weighted by edge distance***
- Excellent performance in grouping information
- No fixed number of output objects



GarNet:

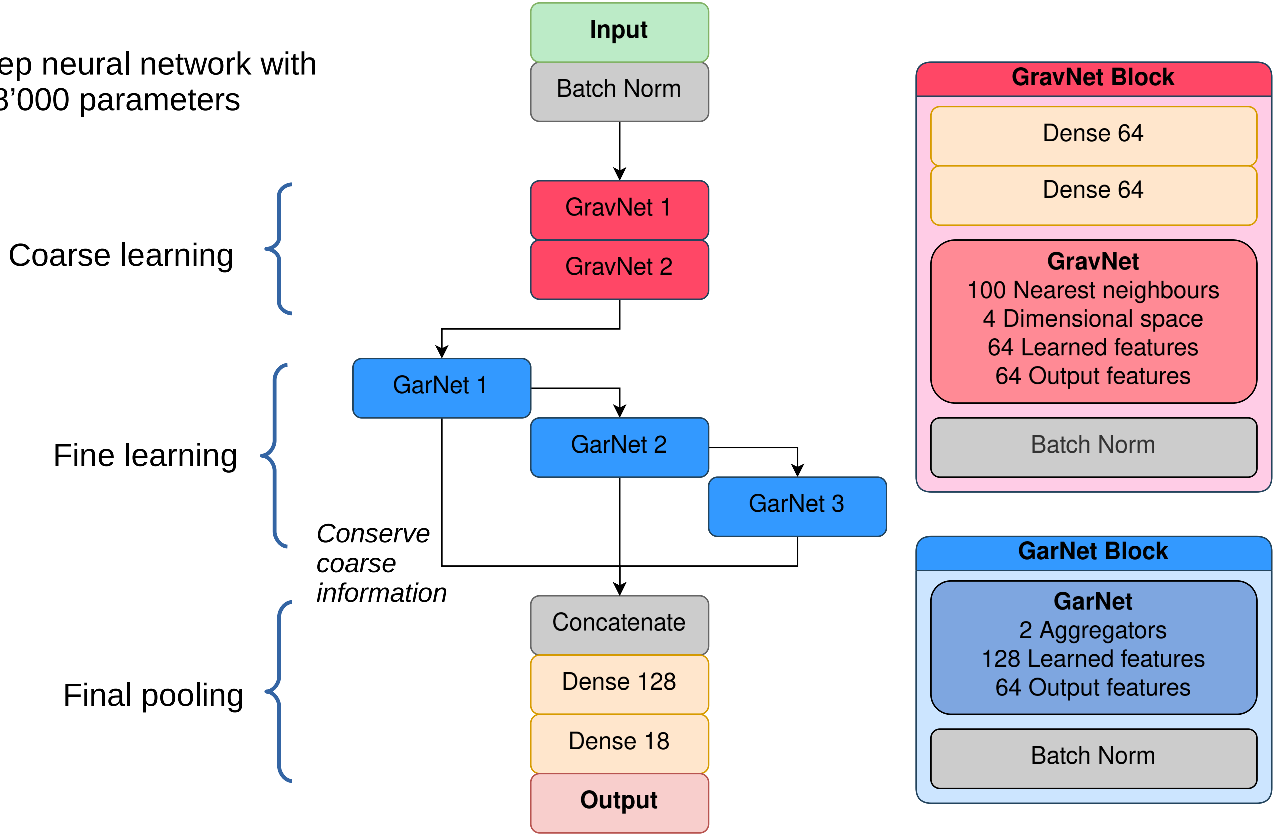
- Funnel the graph information into the desired shape
- Our case: two aggregators (one for each reconstructed particle)
- Each aggregator has new learned features
- Custom implementation for sparse data structures



Both layers are taken from arXiv:1902.07987

Architecture

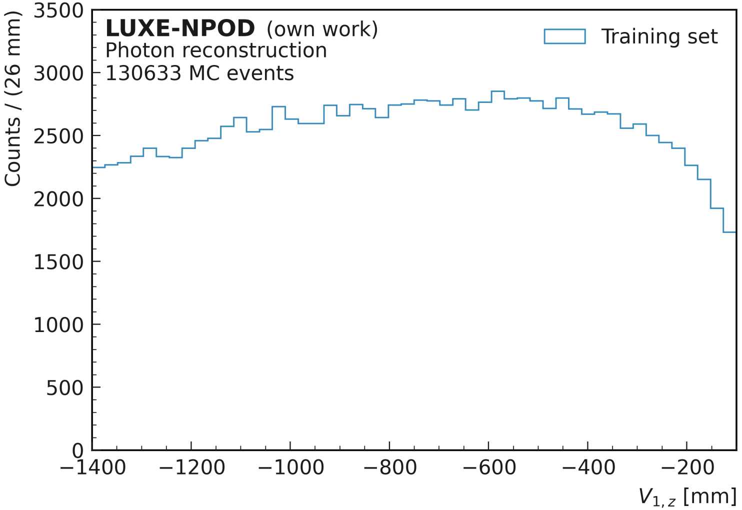
Deep neural network with 408'000 parameters



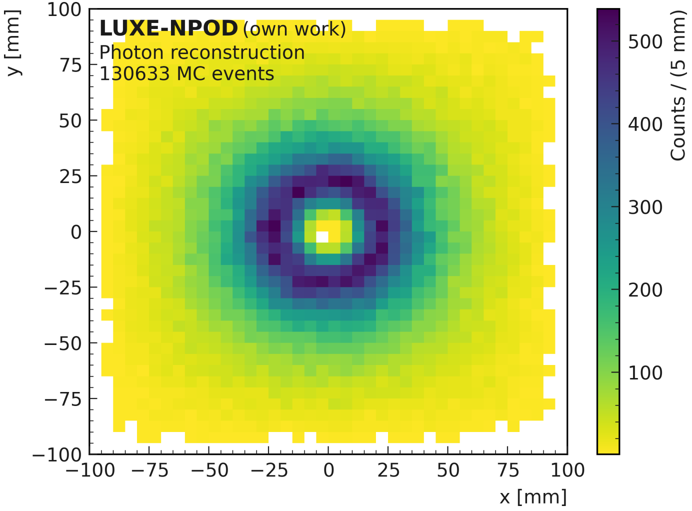
Demonstration Data-set

- Simplified data-set with two photons in detector
- Use ***well-resolved showers*** for proof-of-concept
- Both photons have 2 GeV (approx. LUXE-NPOD expectation) and same angle with the z axis
- Accept only events with minimal opening angle and that shower completely

Uniform vertex set along detector axis



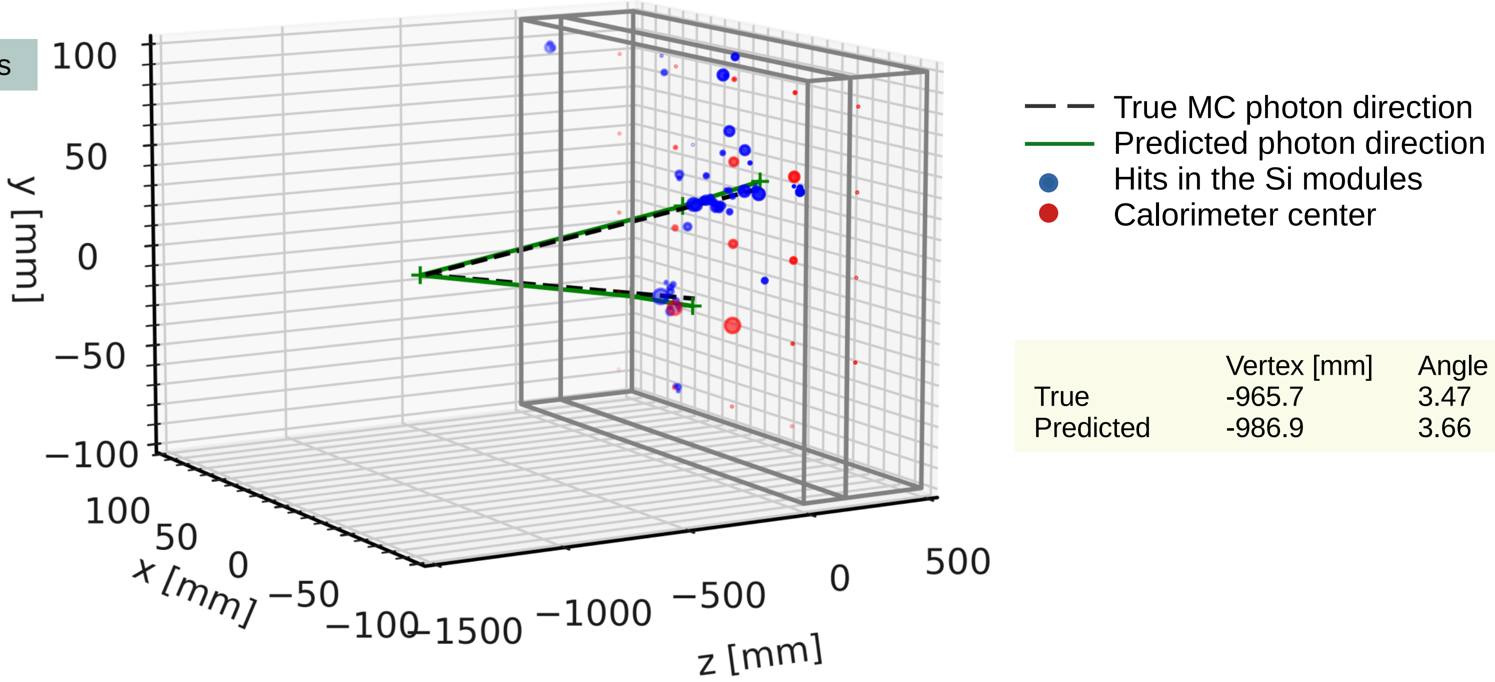
Photons impact at detector surface



Results – Event view

- Successfully reconstructed event
- Using 83 hits

Scaled *xy* axis

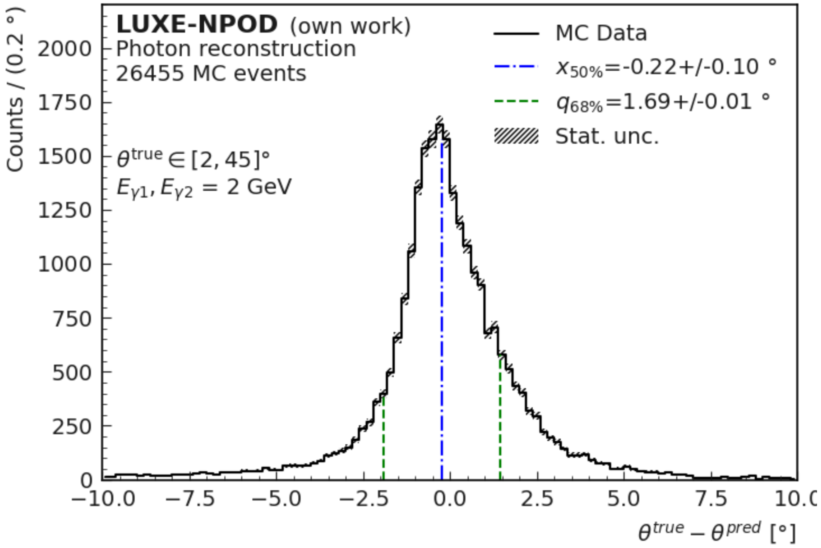


	Vertex [mm]	Angle [°]
True	-965.7	3.47
Predicted	-986.9	3.66

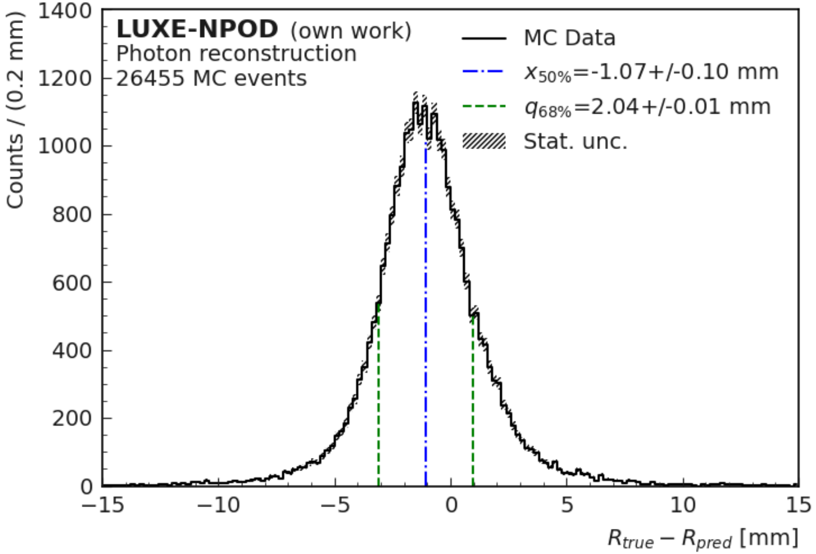
Results

- Resolution = 68%-percentile of distribution of the residuals
- Position on the detector surface accurate down to the size of a single sensor

Opening angle of both photons

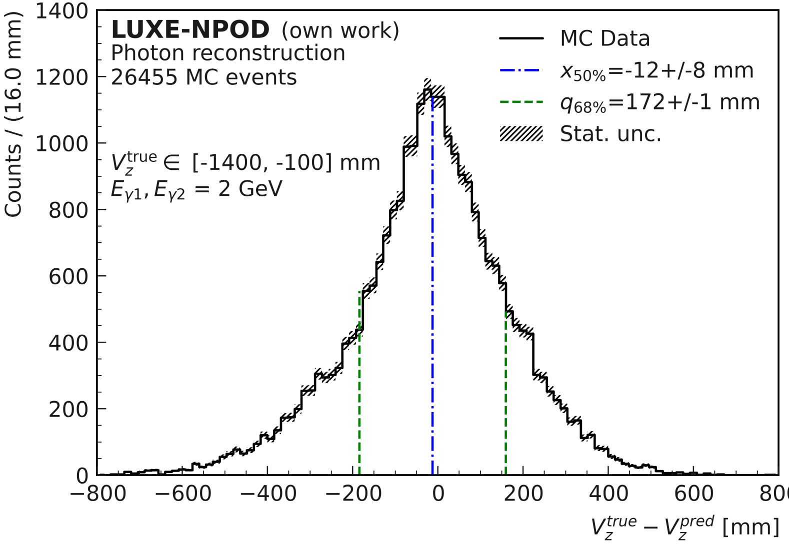


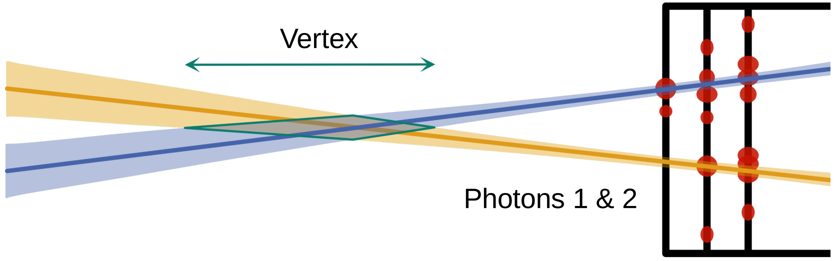
Distance to the z axis at the detector surface



Results – Vertex Position

- Reconstruct the common vertex of two photons
  - With the usage of Graph Neural Networks
  - Minimal detector information
  - Located ***far away*** from the decay position
- Vertex resolution is highly dependent on the distance between ***decay position*** and ***detector***
- Increasingly accurate near to the detector surface

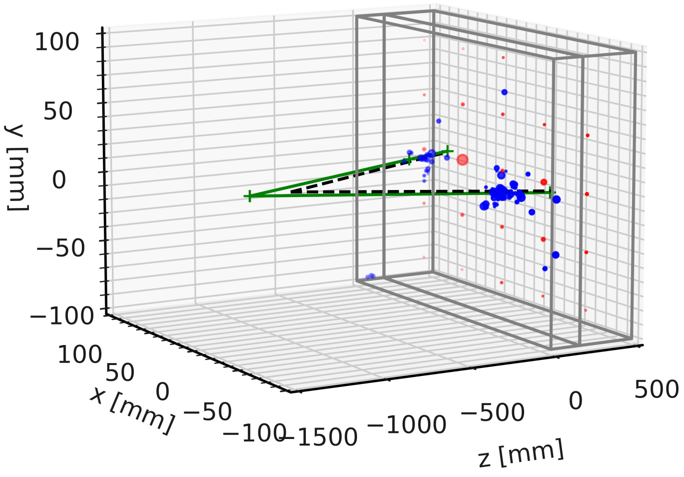




Hits in detector

Conclusion

- Able to reconstruct highly displaced neutral vertices from minimal sparse detector data
- Simplified model but very promising
- Retraining on a new geometry is much easier than with a classical algorithm

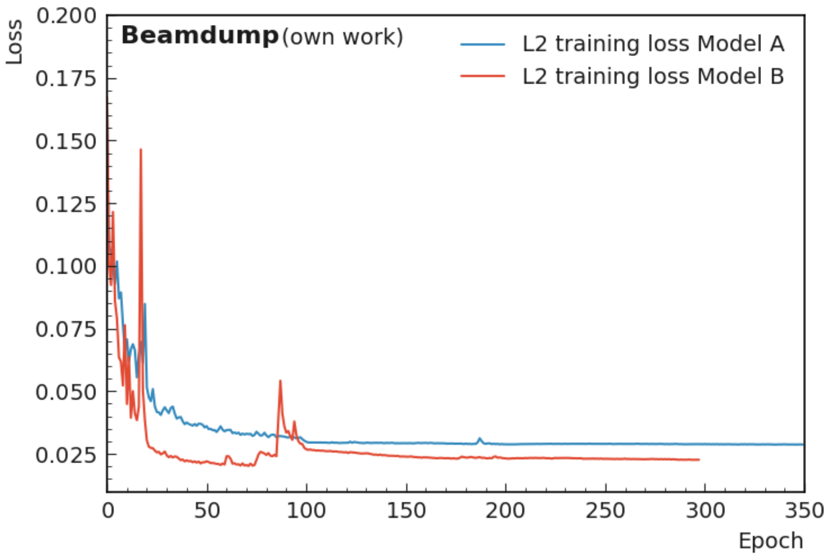


	Vertex [mm]	Angle [°]
True	-968.6	4.9
Predicted	-1209.4	4.0

Next steps

- Test on an actual Monte Carlo ALP simulation
- Unsupervised error estimation for partial or even missing showers
- Classifier with a softmax layer for neutron and photon identification
- Towards AI modeling by comparing possible detector geometries
  - Only change one parameter in the detector geometry
  - Keep training process the same
  - Compare based on metrics like position accuracy

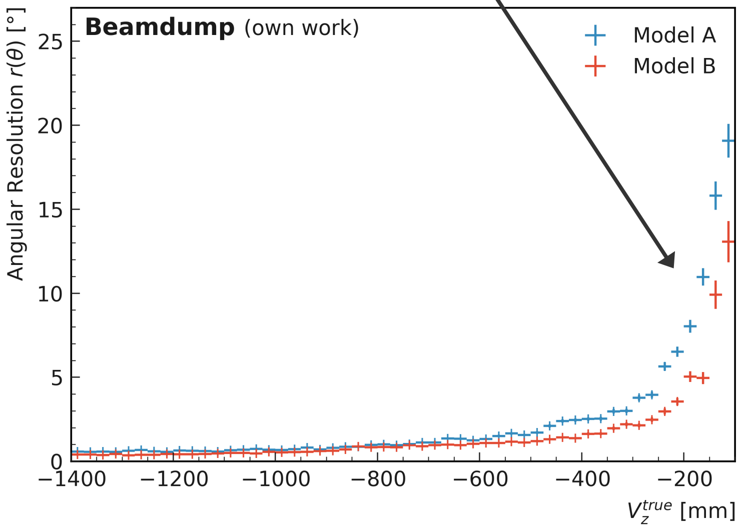
Backup – Training loss

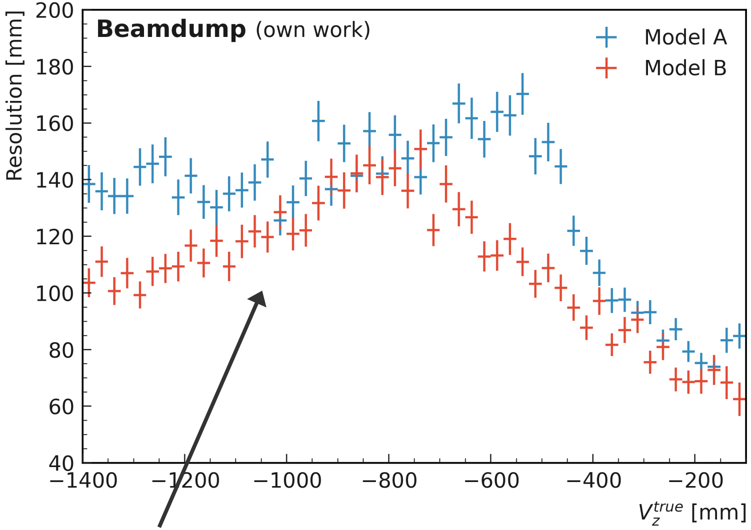


- Model A (used in the main slides):
  - Tracker-Absorber distance of 30 mm
  - Larger training batch sizes (110 hits / step)
  - Longer training 410 epochs
- Model B:
  - TA distance of 100 mm
  - Smaller batch sizes (60 hits / step)
  - Shorter training 360 epochs

Backup – Resolution over vertex position

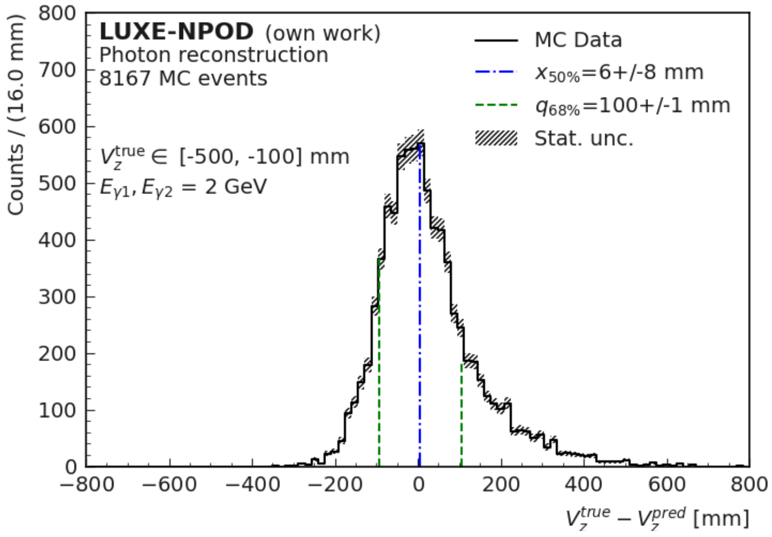
Explained by low amount of events in region with considerable shower leakage

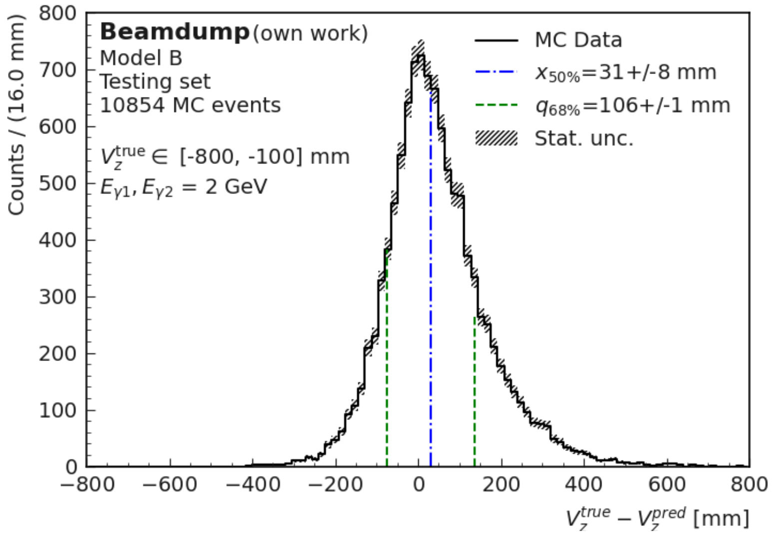




Angular constraints dominate in far region

Backup – Vertex resolution (near region)





Appendix: GravNet and GarNet in detail

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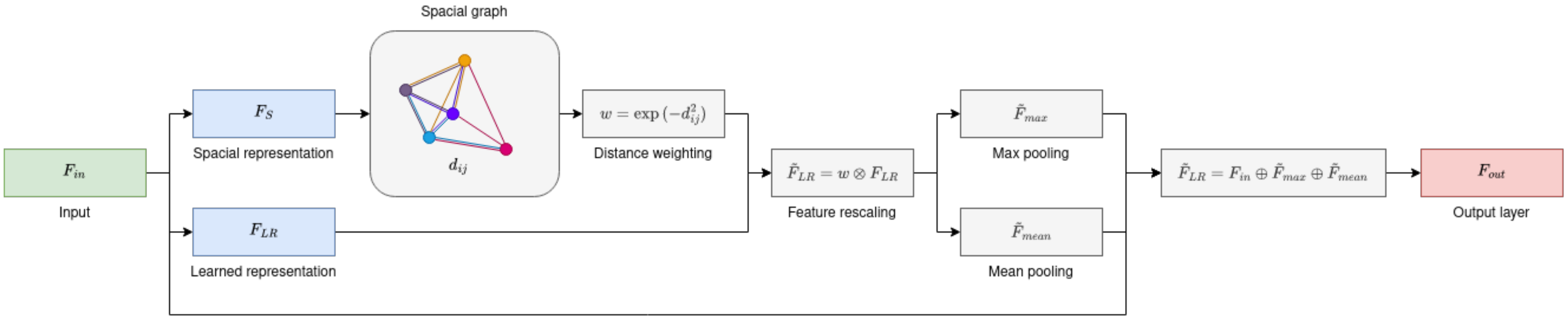
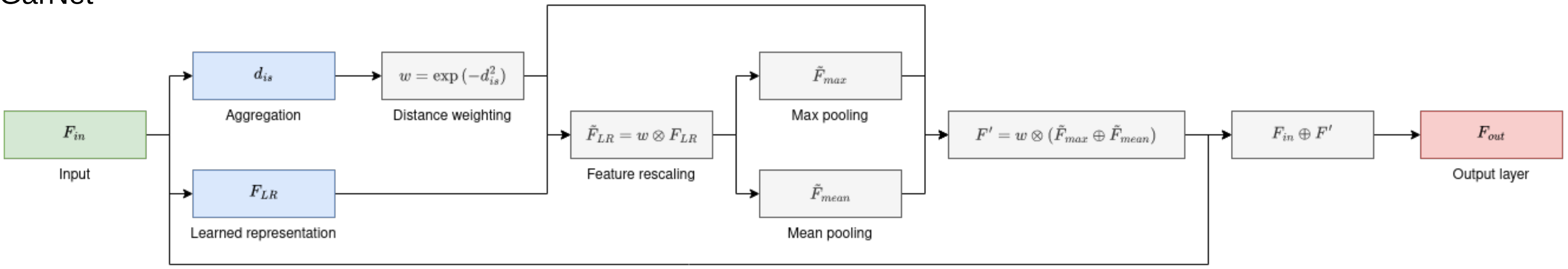
GravNet



GarNet



Complete LUXE+NPOD setup