

Open-Source Comparisons for Machine Learning Reconstructions in Neutrino Telescopes

Jeff Lazar *on behalf of many*

17 Jun., 2025

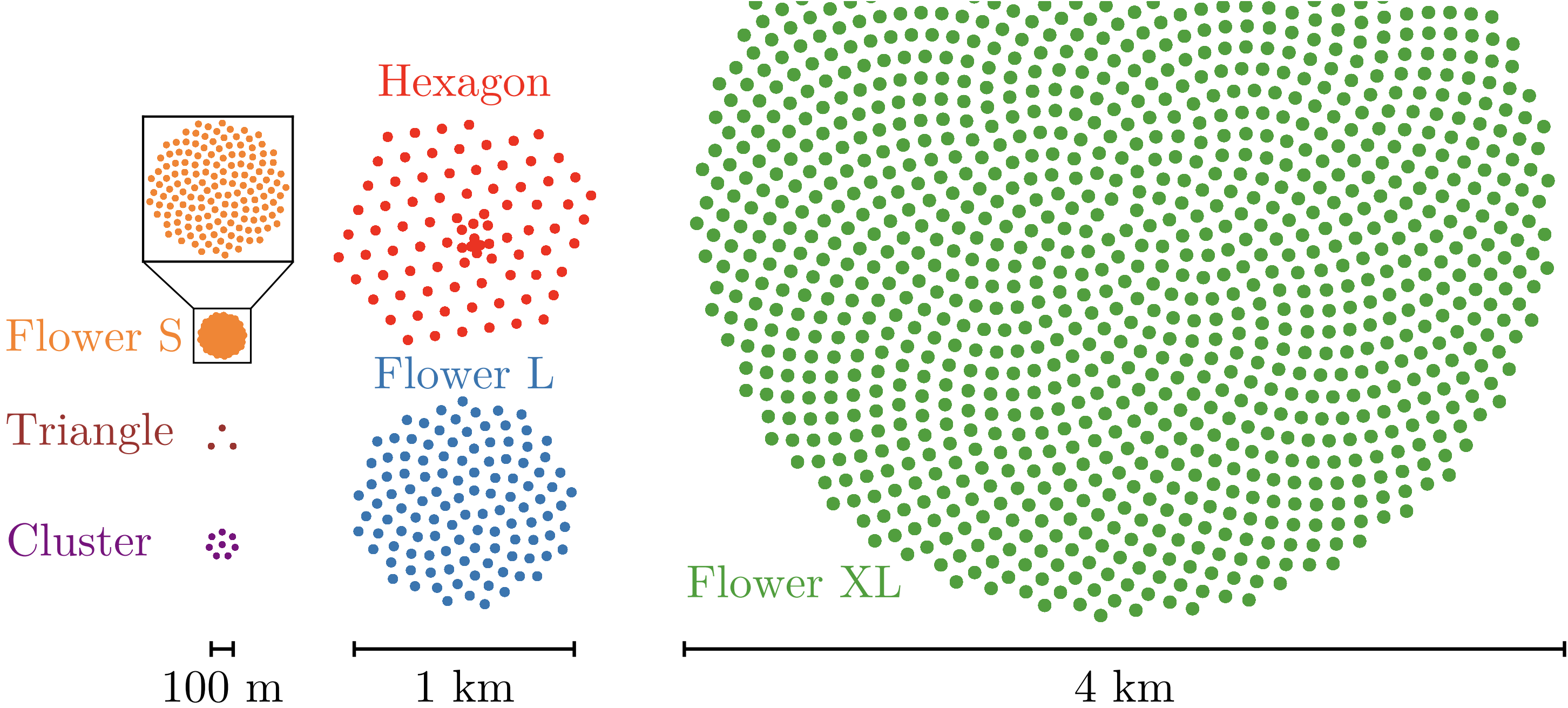
EuCAIFCon 2025

Cagliari, Sardinia, Italy



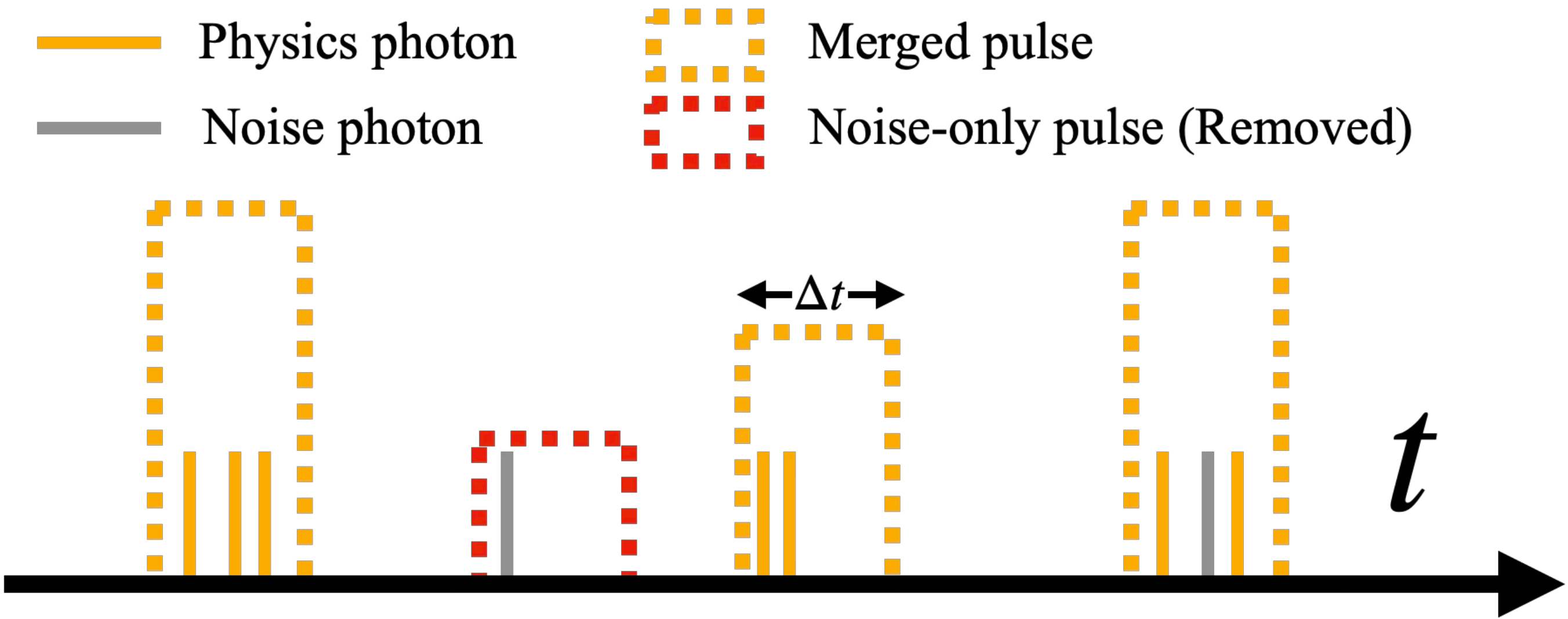
UCLouvain

Simulated Datasets

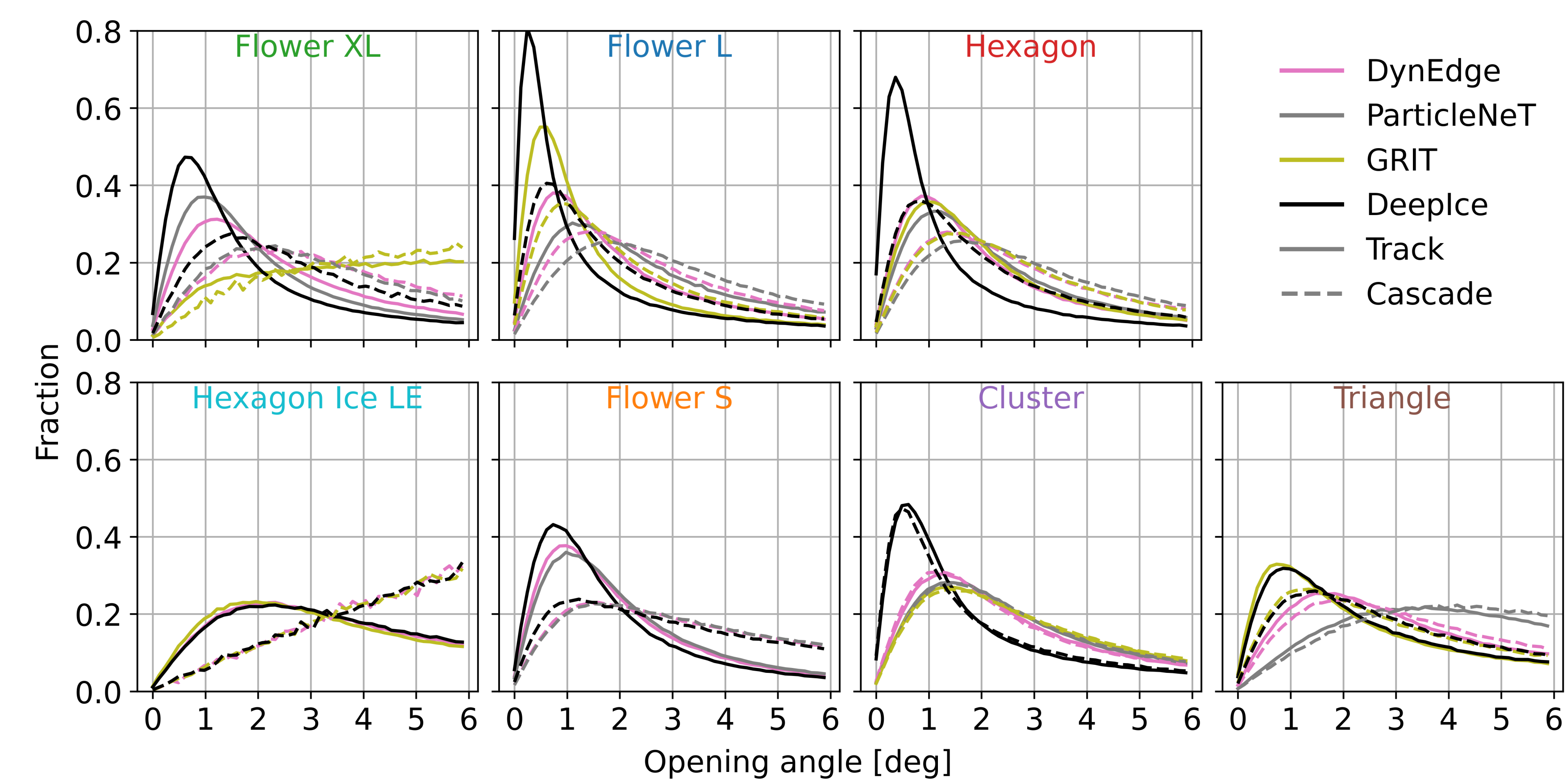


Simulate datasets within a variety of geometries inspired by real-world detectors with Prometheus framework

Add noise and merge photons to mimic detector effects



Reconstruction Comparisons



Compare reconstructions on direction, energy, morphology, interaction vertex, and inelasticity across a variety of models with GraphNeT ML framework

Come say hi :-)

Let’s talk about:

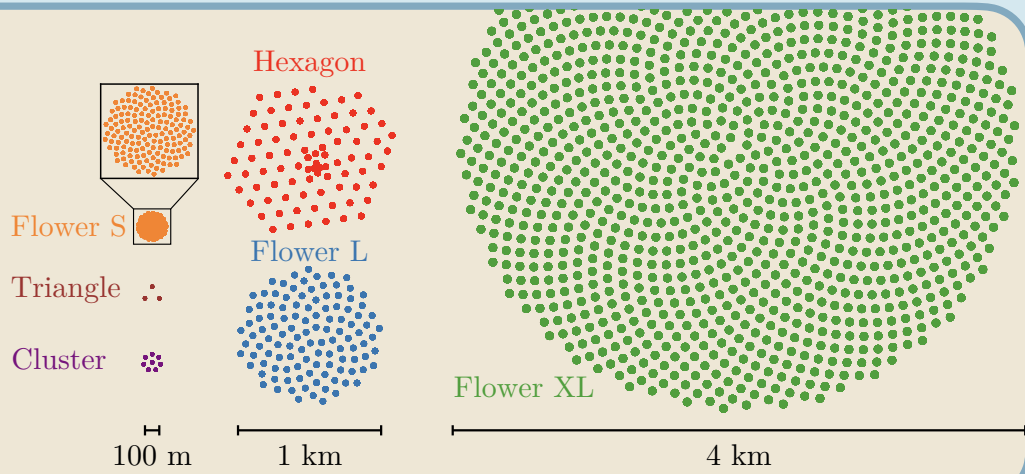
- my poster,
- open-source software,
- simulation,
- tau neutrinos,
- steep valleys, or
- Anything else !

Open-source, Cross-detector Comparisons for Machine Learning Reconstructions in Neutrino Telescopes

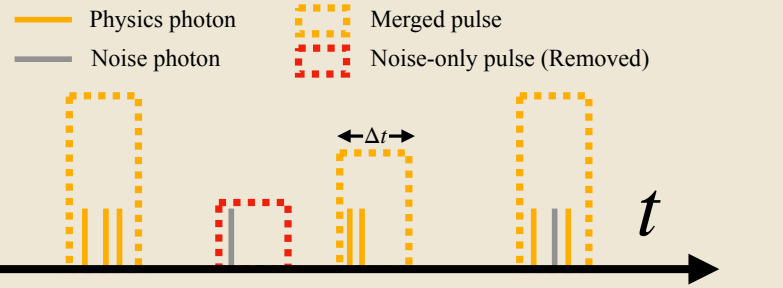
Jeff Lazar on behalf of Arturo Llorente Anaya, Stephan Meighen-Berger, Ivan Mozun-Mateo, Rasmus Ørsøe, Jorge Prado, Aske Røsted, and Philip Weigel

Detectors and Simulation Sets

We use the open-source `Prometheus`[1] package to simulate events in six detector geometries based on existing and proposed neutrino telescopes. Photon arrival times are recorded at the surface of the optical module, and any event that creates at least three pulses is considered to have triggered. In total, there were more than 124 million triggered events across the seven simulation sets.



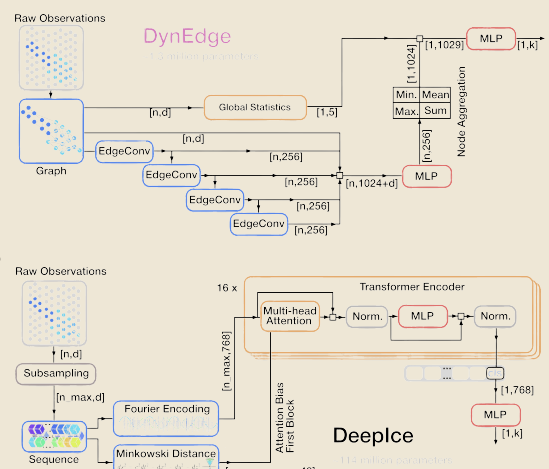
Pulse Merging and Event Building



After all photons from physical processes have been propagated, noise photons are added within the window. For each optical module, photons arriving at similar times are collected into *pulses*. The width of the time window is given by the detector-dependent transit-time spread, Δt . This encodes the timing uncertainty resulting from the photon's transit through the photomultiplier. Any pulses that are composed only of noise photons are thrown out, as they would likely be removed by low-level hit cleaning.

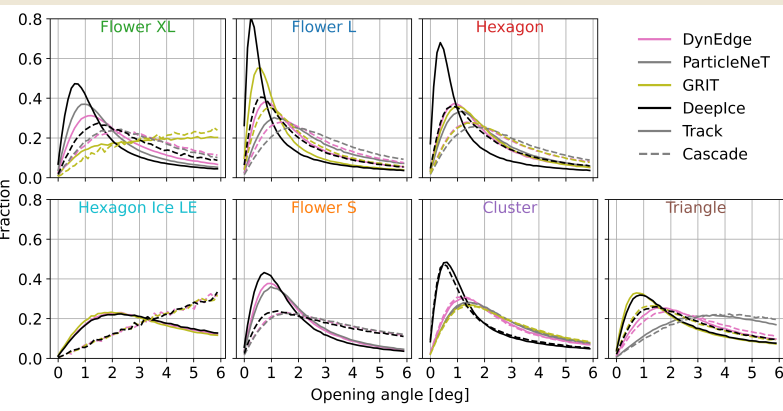
Machine-Learning Architectures

Test reconstructions on algorithms used across the field. Namely, DynEdge [2], ParticleNet [3], GRIT [4], and DeepIce [5]. The last architecture is from an open-science Kaggle challenge. We can also compare techniques, such as convolution and attention. These have all been implemented in the GraphNeT[6] machine-learning library.

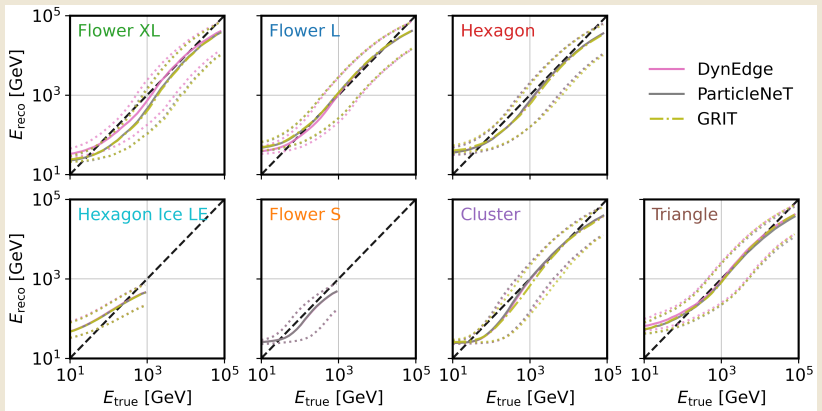


Reconstruction Comparison

We tested the architectures on reconstructing the neutrino direction, neutrino energy, event morphology, interaction vertex, and interaction inelasticity. Here, we present two studies on directional and energy reconstruction.



The transformer-based DeepIce architecture consistently outperformed other models for angular reconstruction; however, this model has ~100 times more parameters than convolutional models, requiring significantly larger training and runtime. Different architectures may have complementary roles across the processing chain.



In energy reconstruction, the performance of the three tested architectures was extremely comparable. This suggests that non-local effects, which attention-based models can detect, are less significant for energy reconstruction than for directional reconstruction.