DNN + MLEM synergy for imaging of neutrino interactions in LAr

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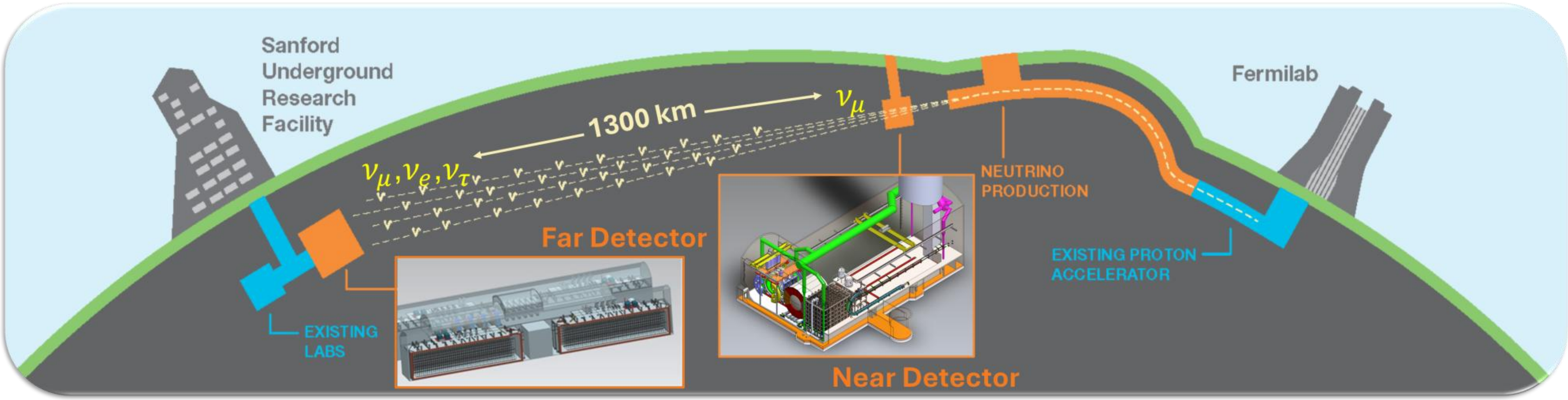
Neutrino Physics and Machine Learning conference
Tokyo, 29th October 2025

The Deep Underground Neutrino Experiment

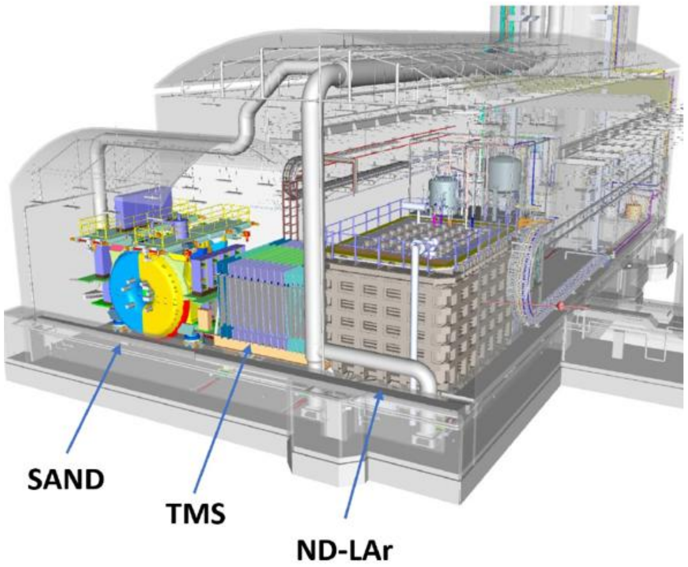
- **Characteristics**:
  - Under construction long baseline neutrino oscillation experiment
  - Up to 2.4 MW wideband neutrino beam peaked at 2.5 GeV
  - Near facility + 40 kt LAr Far Detector facility

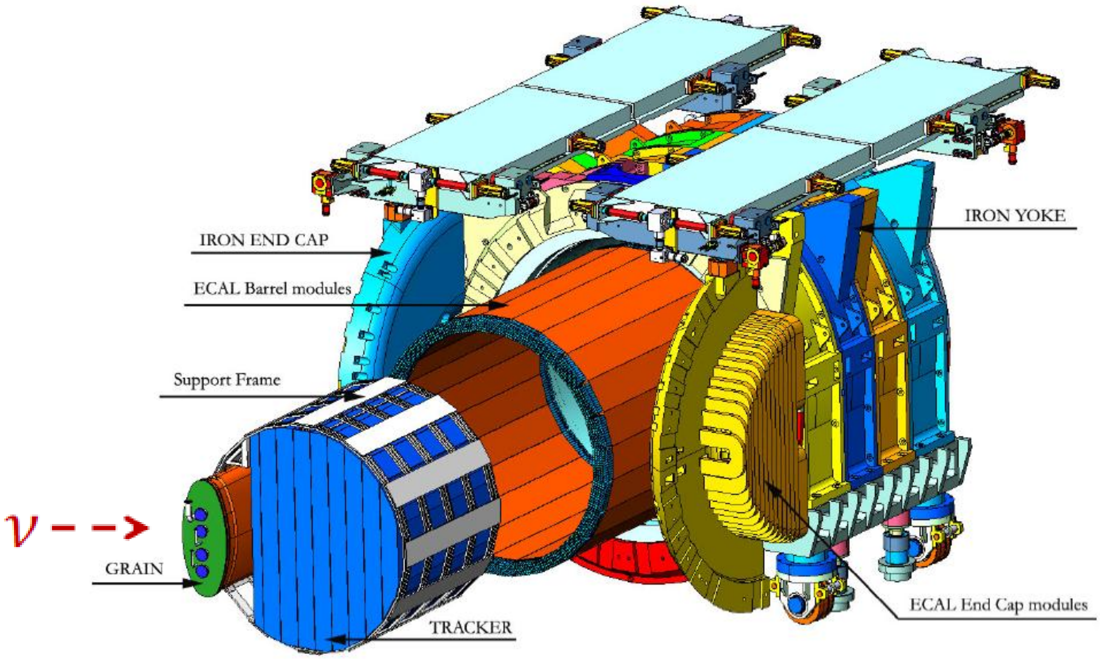
- **Physics goals**:
  - Neutrino mass ordering
  - CP violating phase in the leptonic sector
  - Neutrino mixing angles
  - Low energy neutrinos from astrophysical sources
  - Physics beyond the Standard Model



System for on-Axis Neutrino Detection

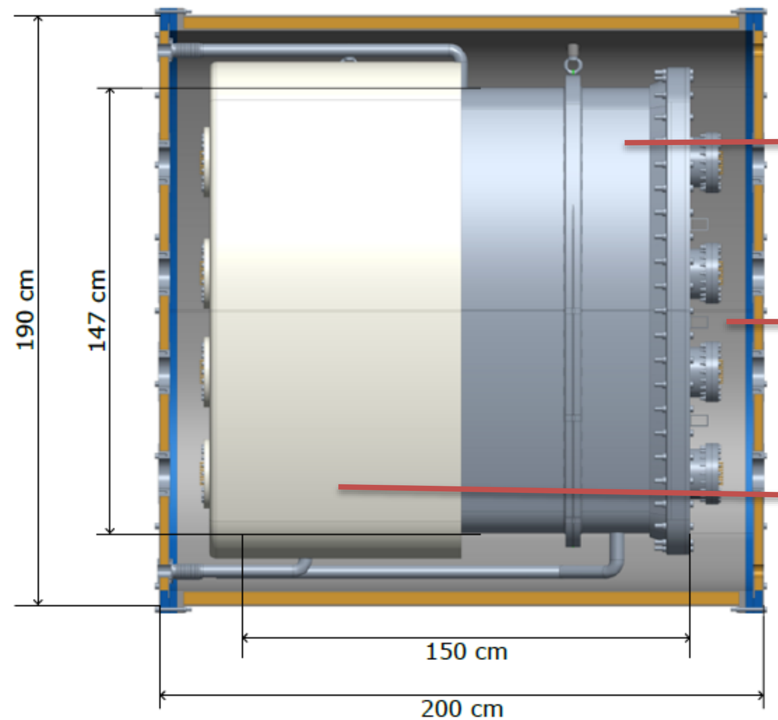
- SAND is one of the three detector components of the Near Detector complex.
- Multipurpose detector capable of detecting neutrino interactions on different target materials, performing **precision tracking** and **calorimetry** measurements.
- It will continuously monitor the beam on-axis, to **constrain systematic uncertainties for the oscillation analysis** and perform **precise cross-section measurements**.



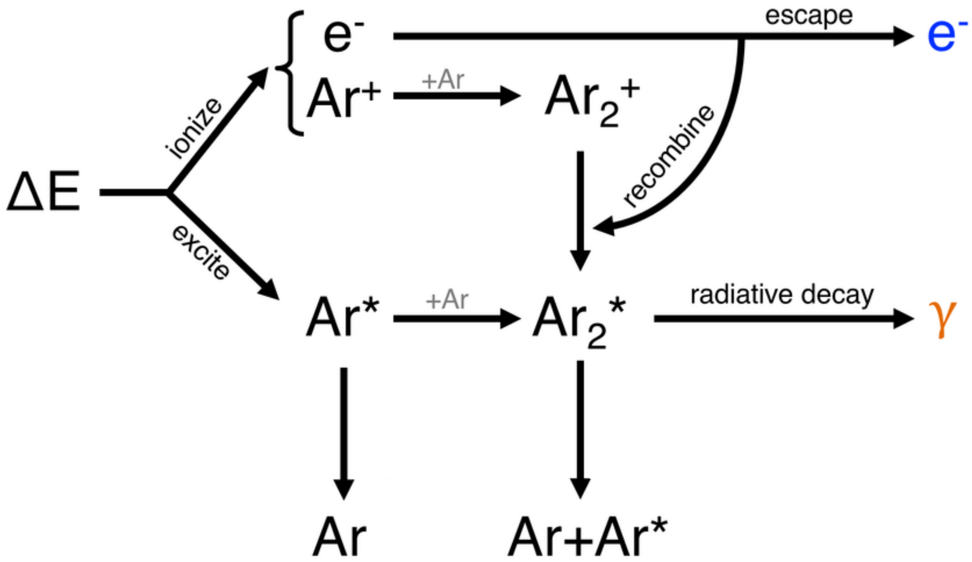


GRanular Argon for Interactions of Neutrinos

- GRAIN will be a **~1 ton liquid Argon active target** placed upstream in the magnetized volume of SAND.
- Synergy with Argon target in Far Detector to constrain nuclear effects.
- The expected event rate and pile-up (~10 tracks/spill, 10 μs spill time) is **challenging for a traditional TPC**.



Scintillation light in LAr

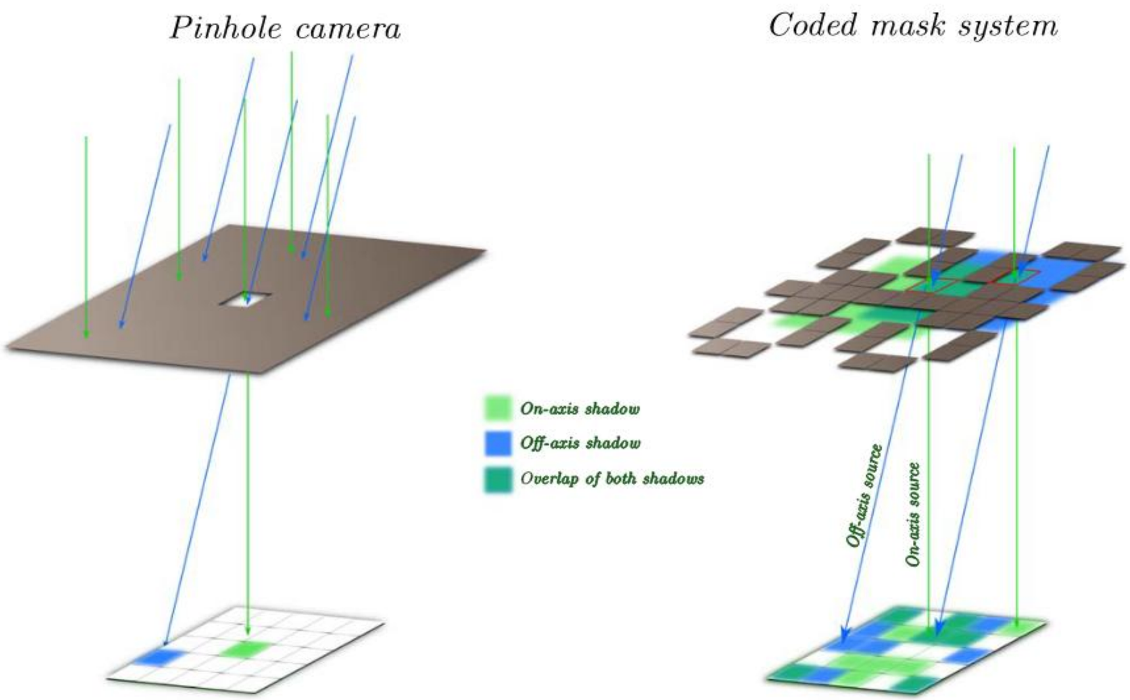


- When charged particles cross Liquid Argon, part of their deposited energy excites Ar atoms inducing photon emission, yielding 40,000 photons per MeV.
- **Imaging of scintillation light** with photographic cameras may offer a suitable alternative to charge collection.
- Moreover, such a detector would not require an electric field or its associated hardware.

Charge drift time (Ar, GRAIN dimensions):	$> 1\ \mu s$
Scintillation light emission time (Ar):	~ 7 ns

Coded Aperture Imaging

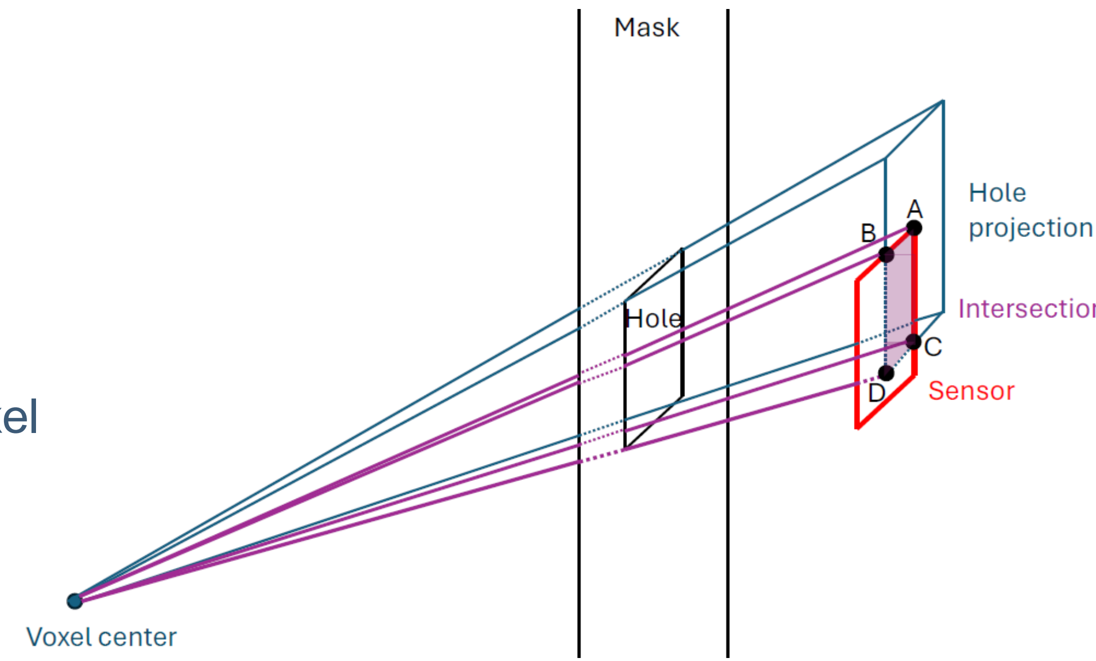
- One possible design of the cameras is based on **coded aperture masks**: arrays of opaque and transparent elements, positioned at a fixed distance from the SiPM sensor matrix.
- A classic pinhole camera can deliver excellent angular resolution, but it is inefficient owing to count loss caused by the opaque material.



- A coded aperture mask camera registers an **overlapping set of multiple images**, each set associated with one point source, **preserving angular resolution while improving efficiency**.

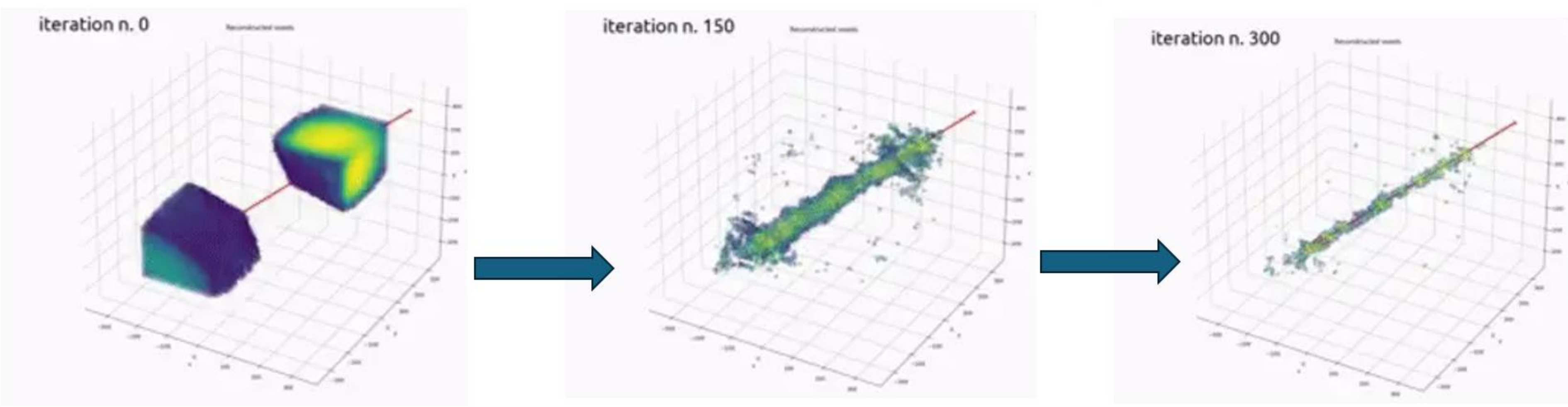
Reconstruction algorithm

- The goal is to **reconstruct the 3D distribution of the scintillation light source recorded by the sensors**, combining views from multiple cameras, using the **Maximum Likelihood Expectation Maximization** iterative algorithm.
- For this computation, the fiducial detector volume is divided into voxels.
- Measured photons from all cameras are propagated back into the LAr volume with an appropriate weight, which is added to the voxel value.
- This weight represents the Bayesian probability of the voxel to be a source of the detected photons.



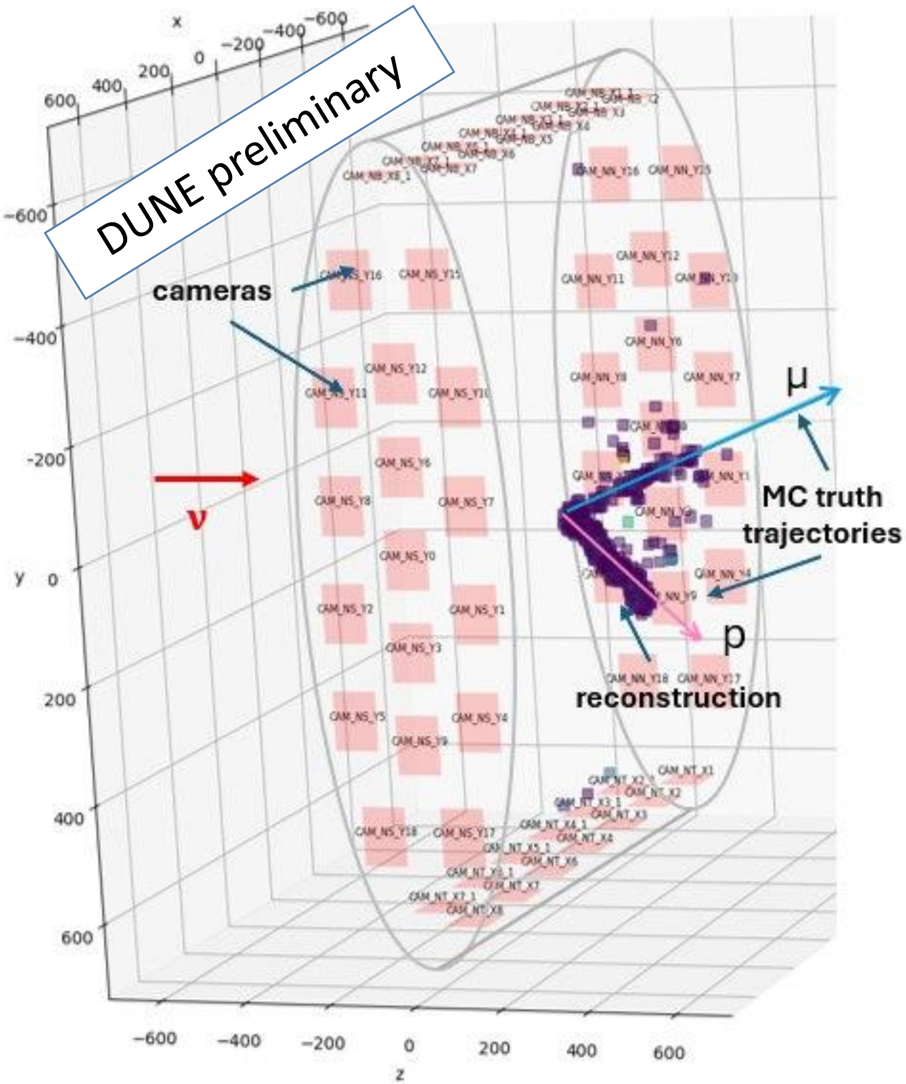
Maximum Likelihood Expectation Maximization

- The likelihood of the resulting photon source distribution is maximized through an **iterative process**.



- Currently, **each iteration takes about 1.5 s** on NVIDIA H100 80GB VRAM

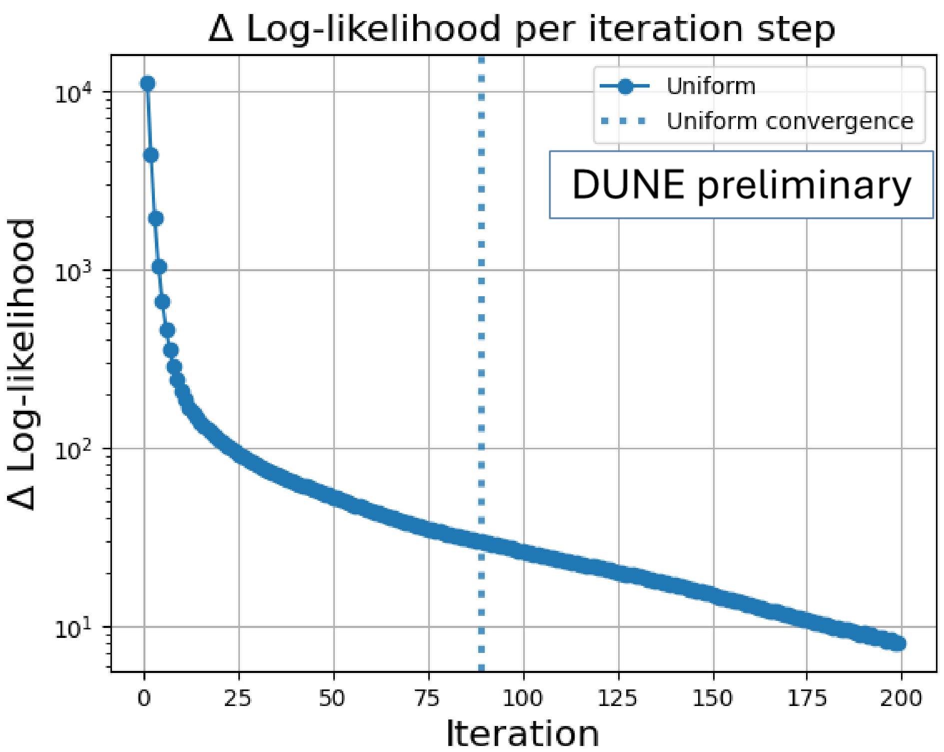
Reconstructed ν_μ interaction (MC)



- Display of a charged current quasi-elastic scattering ν_μ interaction
- 60 cameras are placed across the detector surface.
- The detector volume is voxelized into 18x18x18 mm^3 voxels.
- The reconstruction is implemented using OpenCL kernels running on GPU(s).

Deep Neural Network prior

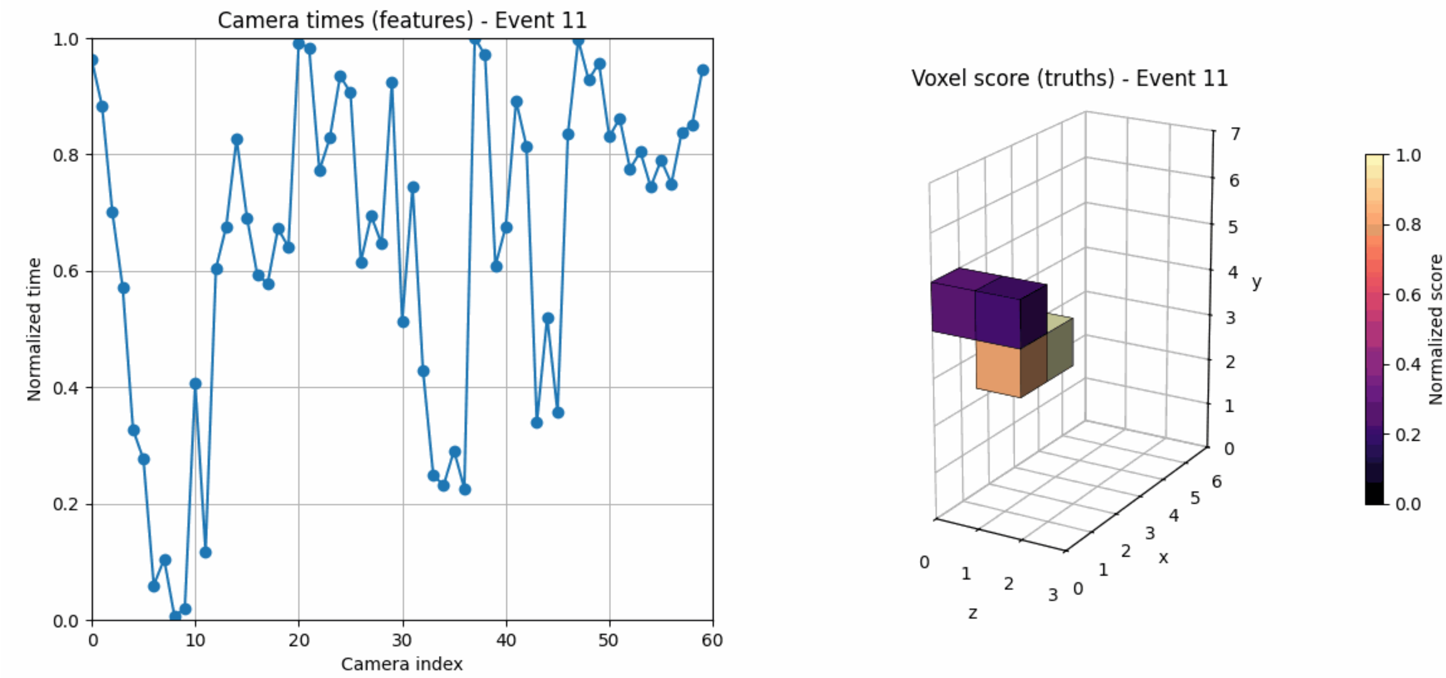
- The MLEM algorithm uses a uniform distribution as a prior.
- Using a reasonable estimation of the photon source distribution as **a prior could save some iterations to reach convergence,** defined as a log likelihood change < 50 between iterations.



- A **fully connected Deep Neural Network** (DNN) was trained to provide such prior on 3×10^5 simulated charged-current ν_μ interactions within the GRAIN LAr volume.

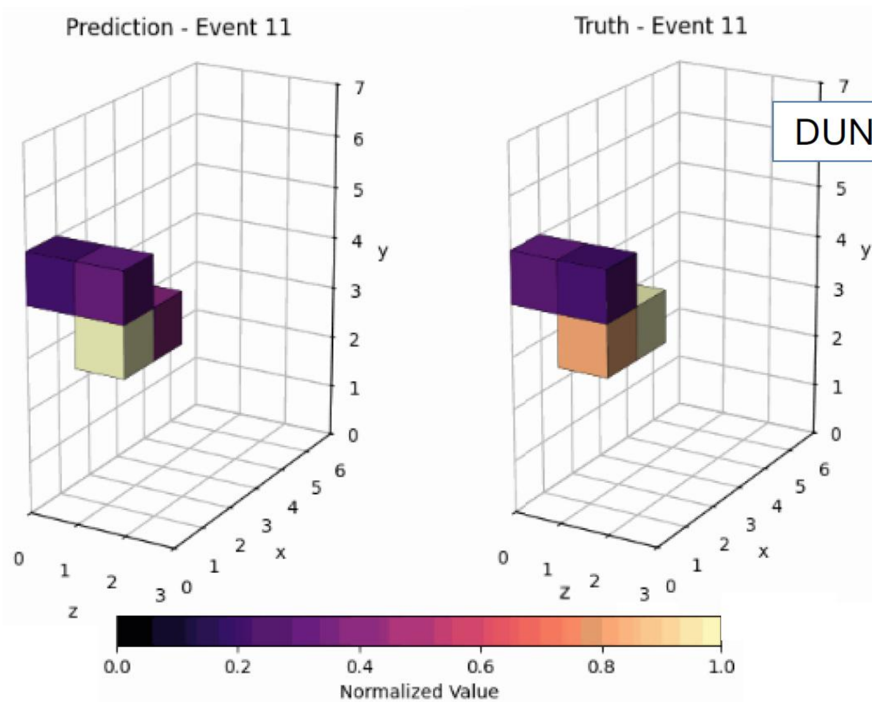
Data features and thruths

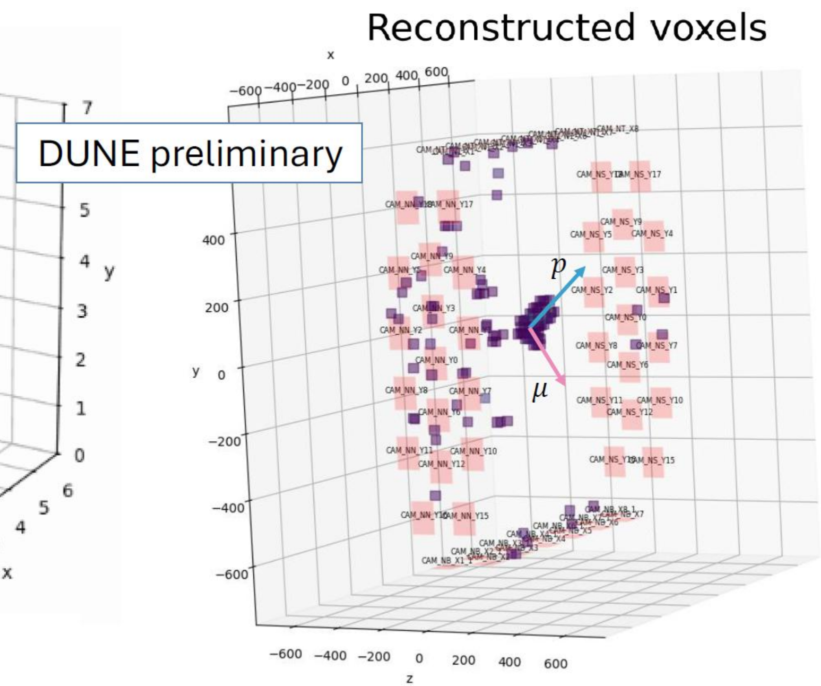
- The average hit times for each camera were used as **data features**.
- The Monte Carlo energy deposits, voxelized into 200 mm voxels, were employed as ground **truth**.
- Although these voxels are significantly larger than the 18 mm voxels used in the MLEM reconstruction, this coarse resolution provides a sufficiently accurate prior.



DNN training

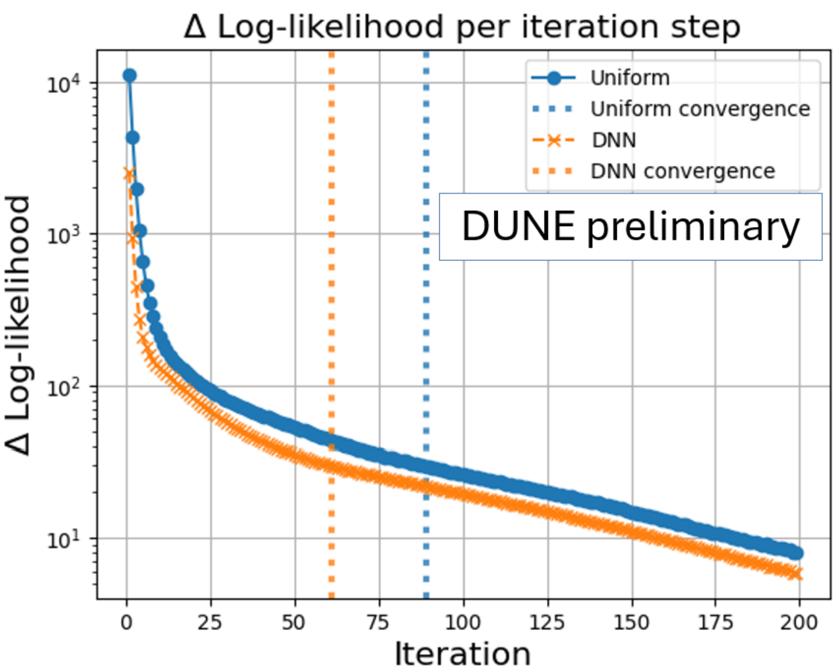
- The full dataset was split into 70% / 15% / 15% training / validation / test samples.
- The DNN hyperparameters were explored and optimized using **OPTUNA**, resulting in a **mean average error (on the normalized voxel score) of 0.01**.

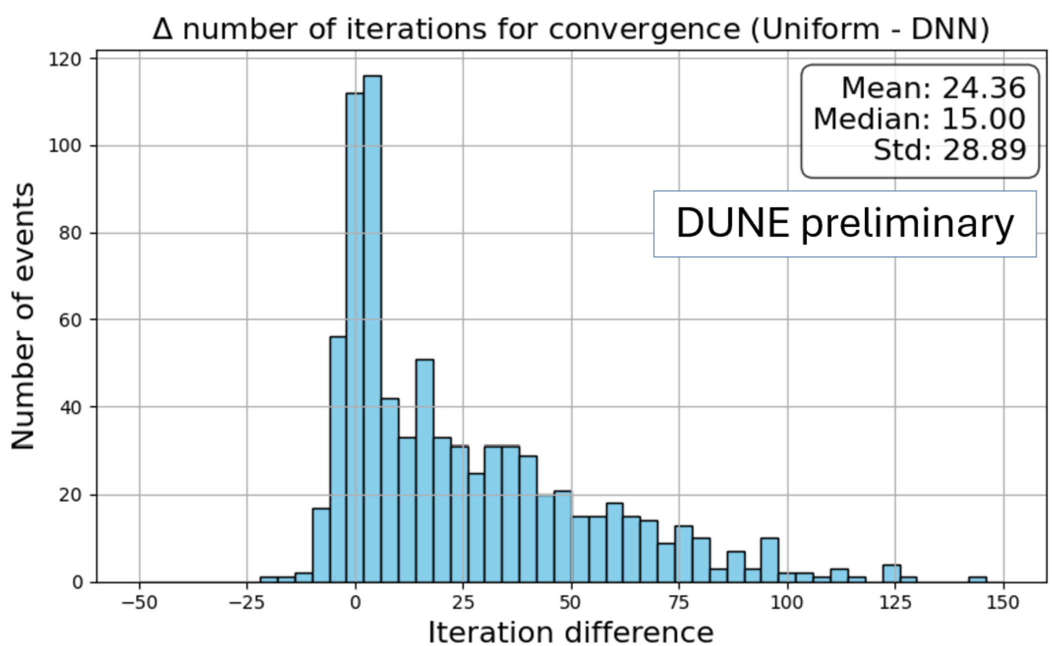




Performance evaluation

- The trained model was evaluated on 600 events as a prior for MLEM reconstruction.
- Preliminary results show that likelihood **convergence is reached approximately 20 iterations earlier** with the DNN prior compared to a uniform prior.





Conclusions

- Photographic cameras with **Coded Aperture Masks** exploit Argon scintillation light to detect tracks associated to charged particles.
- The iterative reconstruction algorithm, based on **Maximum Likelihood Expectation-Maximization**, combines the views of ~60 cameras providing a three-dimensional map of the energy deposited by charged particles.
- A fully connected **Deep Neural Network** was trained on simulated charged-current muon neutrino interactions, using timing information from the cameras, to provide a reasonable prior for the reconstruction.
- Preliminary results show reconstruction **convergence is reached approximately 10% iterations earlier**.

Backup: MLEM

Photon counting is described by a Poissonian pdf:

$$f(H_s|[\lambda_s]) = e^{-[\lambda_s]} \frac{[\lambda_s]^{H_s}}{H_s\,!}$$

$$[\lambda_s] = \sum_j \lambda_j\, w(j,s)$$

H_s number of detected photons by sensor *s*

λ_j unknown photon emission in voxel ***j***

$[\lambda_s]$ detected photons expectation value

w(j,s) is the weight → probability of a photon that originated in voxel ***j*** is detected by pixel ***s***

The likelihood for all sensors must be **maximized iteratively:**

$$\prod_s e^{-[\lambda_s]} \frac{[\lambda_s]^{H_s}}{H_s\,!} \Rightarrow \lambda_j^{k+1} = \frac{\lambda_j^k}{\sum_s w(j,s)} \cdot \sum_s \frac{H_s \cdot w(j,s)}{\sum_j w(j,s) \cdot \lambda_j^k}$$

k iteration number

Backup: DNN model