Reconstruction of neutrino events with scintillation light in the SAND detector

G. Santoni
University of Bologna and INFN Bologna

Dark Matter and Neutrino Topical School
Institute H. Poincaré, Paris, 7th May 2025

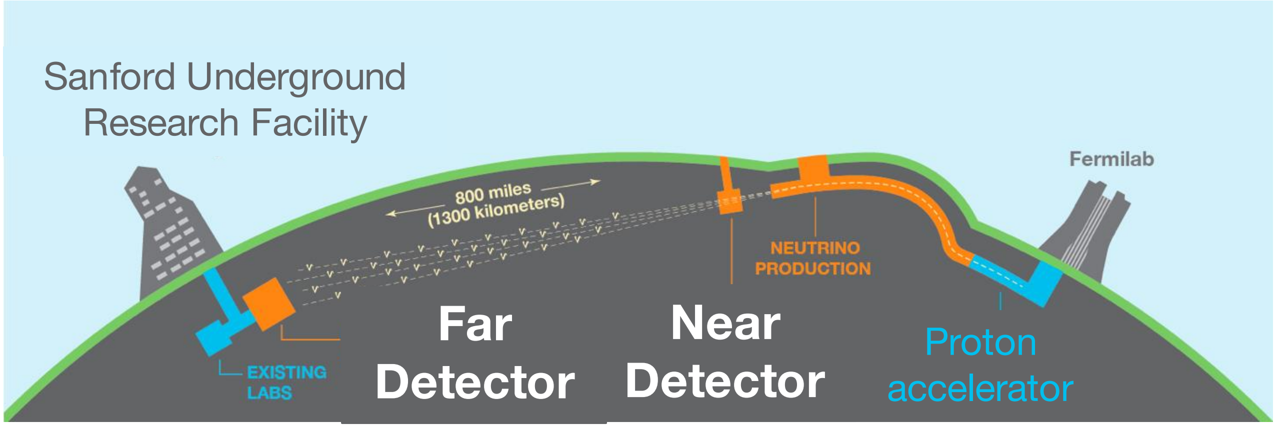
Outline

GOAL: study the performance of a track-finding algorithm to reconstruct charged-current quasi-elastic (CCQE) muon-neutrino events inside a LAr active target with scintillation light.

This presentation is organized as follows:

- **DUNE experiment**
- **SAND detector and GRAIN active target**
- **Track-finding algorithm**
- **Results and conclusions**

The DUNE experiment



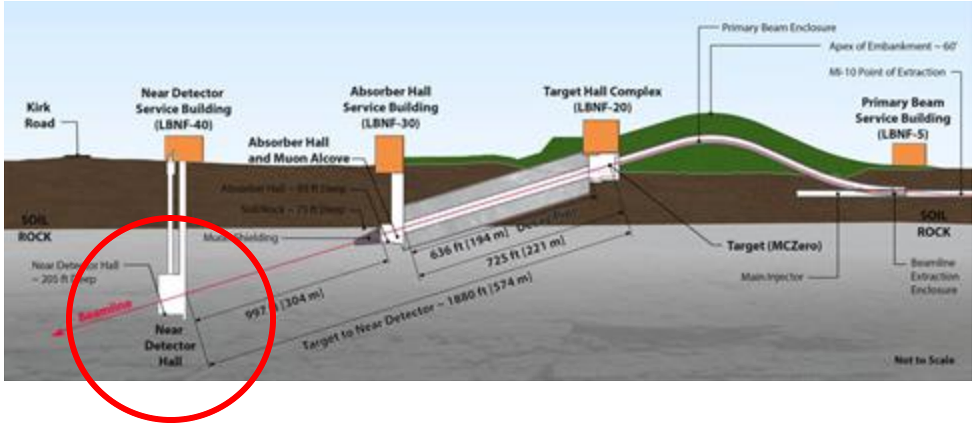
Physics goals

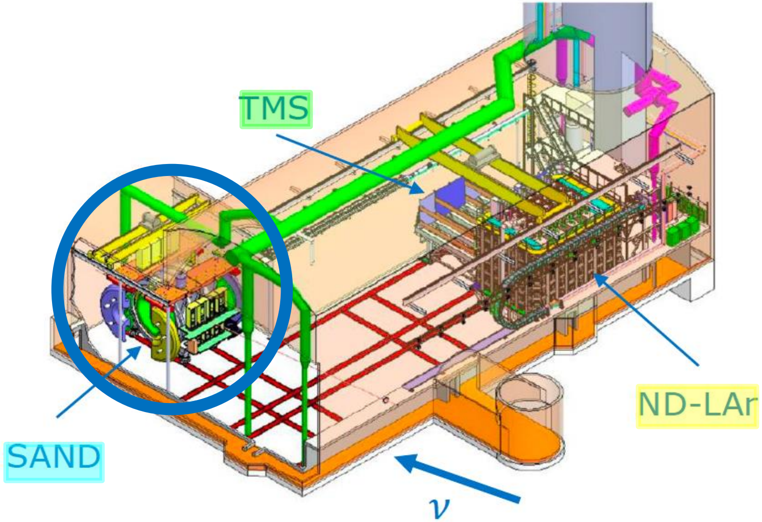
- Mass ordering
- CP-violating phase
- Mixing angles
- Supernovae neutrinos
- Physics beyond the Standard Model

Characteristics

- Most intense wide-band $\nu_\mu/\bar{\nu}_\mu$ beam
  - energy peaked at 2.5 GeV
  - 1.2 MW beam power
- Capable Near Detector
- 40 kton Far Detector ~1300 km away

The Near Detector complex



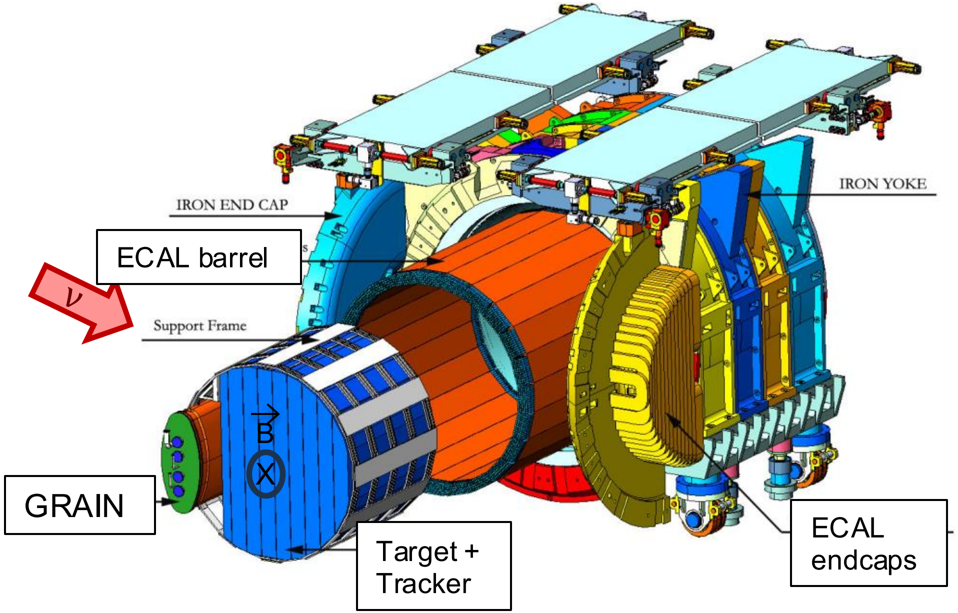


Goals of the Near Detector

- Monitoring the stability of the beam
- Reducing systematic uncertainties (1-3%)
- Fine-tuning of neutrino interaction models

- 100 t LAr TPC – ND-Lar
- Magnetic muon spectrometer – TMS
- Multipurpose magnetized detector - SAND

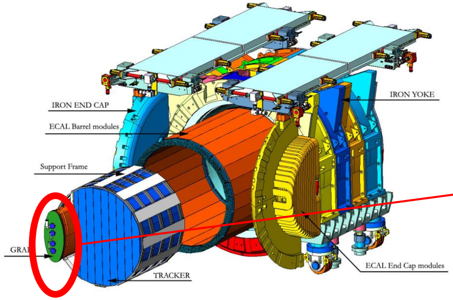
SAND at Near Detector

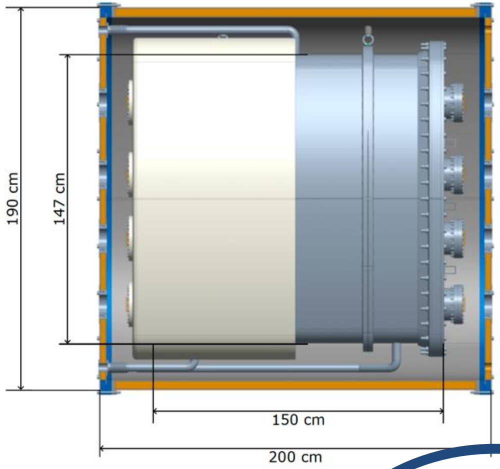


Physics goals

- on-axis beam monitoring to detect time-dependent energy spectrum changes on a weekly basis
- reduction of systematic uncertainties and nuclear smearing effects on the reconstructed energy
- precise absolute and relative flux measurements of $\nu_e, \bar{\nu}_e, \nu_\mu, \bar{\nu}_\mu$
- short-baseline physics studies

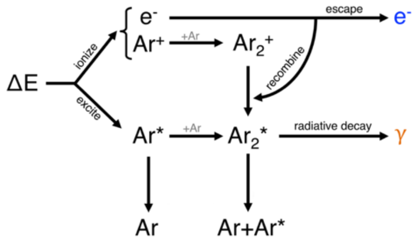
GRAIN - Granular Argon for Interaction of Neutrinos



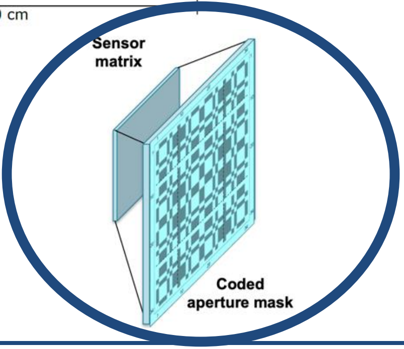


- $\sim$1 t LAr active target
- Tracking and calorimetric measurements
- $\nu - \mathrm{Ar}$ interactions
- 10 tracks/spill (10 μs)

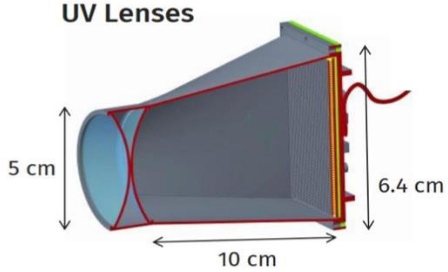
GRAIN will exploit the **Ar scintillation light** produced by the passage of a charged particle



2 possible optical systems:



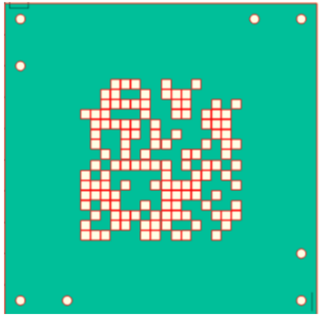
Coded-aperture cameras



Lenses

Coded aperture cameras

3 mm hole side

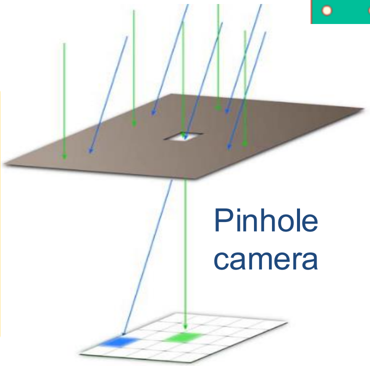


mask

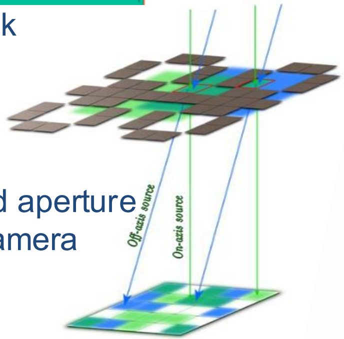
Novel technique

imaging of Ar scintillation light produced by the passage of a charged particle.

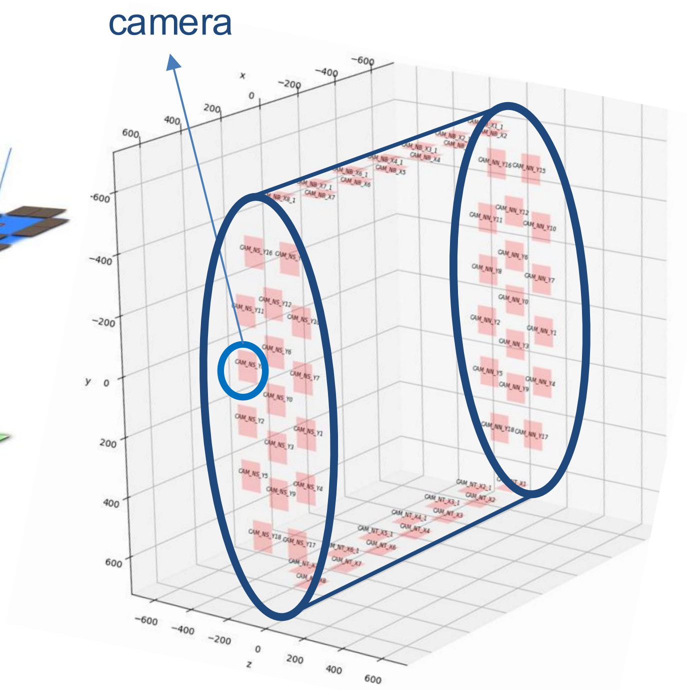
The **light encoded** by the mask is used to reconstruct the photon source distribution



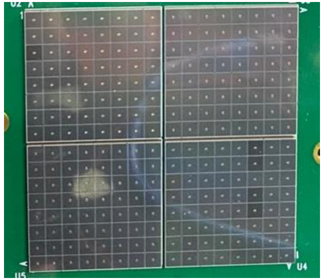
Pinhole camera



Coded aperture camera

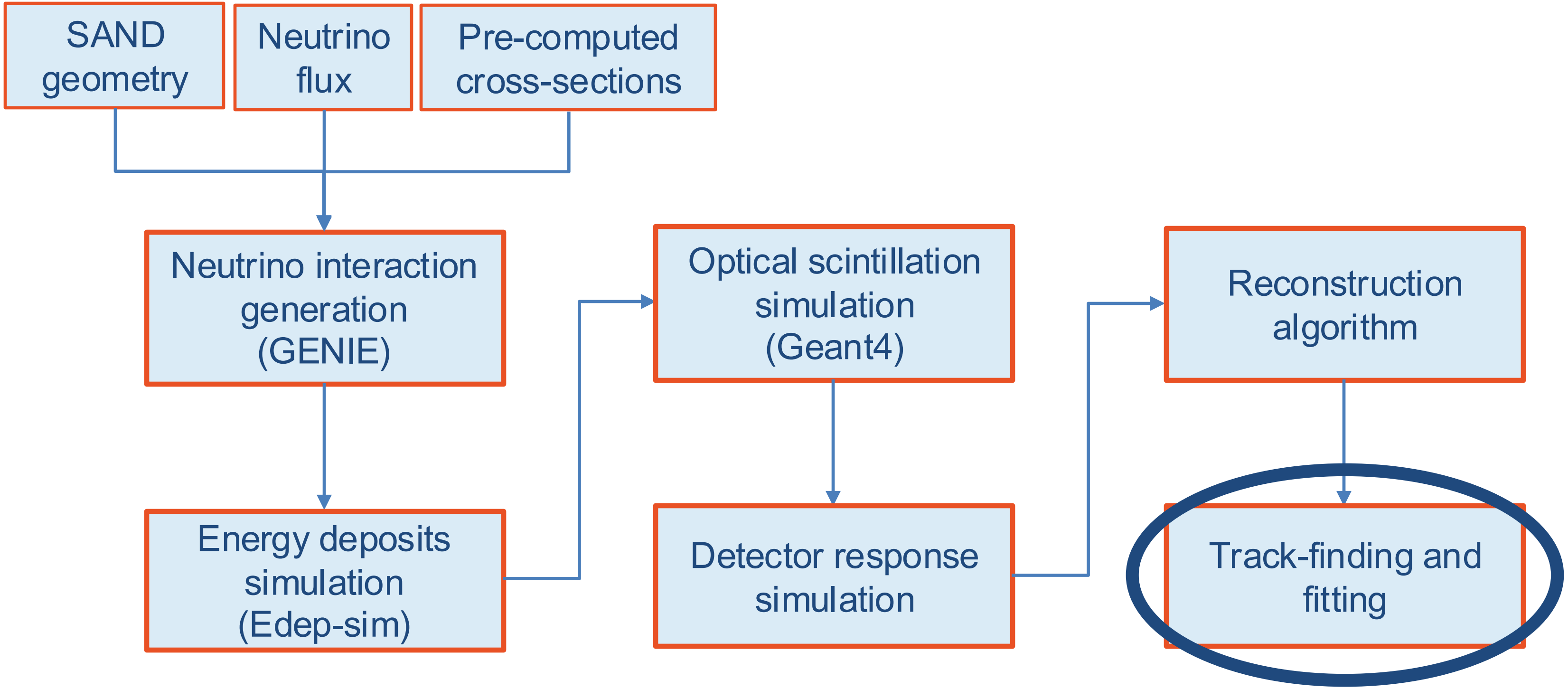


3.2 mm pixel side



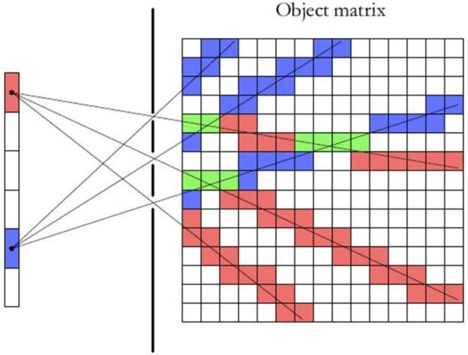
sensor

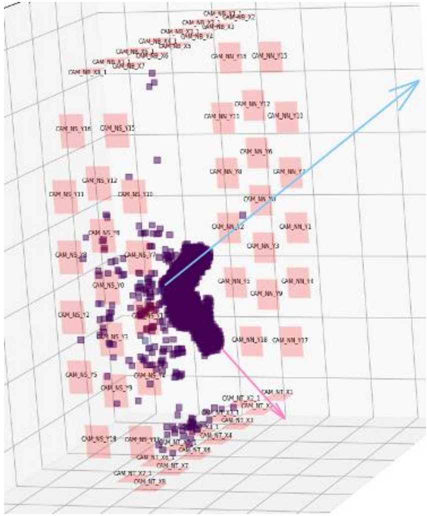
Simulation/Reconstruction Chain



Reconstruction algorithm

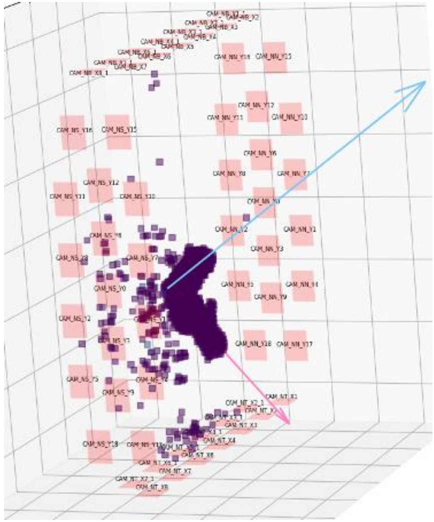
- 3D iterative algorithm based on maximum likelihood expectation maximization
- Backpropagation of the detected photons in the LAr volume through all mask holes, weighted appropriately
- Weights represent the Bayesian probability of the voxel to be a source of the detected photons, computed analytically
- Algorithm implemented using 4 GPUs and 120GB RAM to store weights
- As output, we obtain a **3D voxelized distribution of emitted photons**



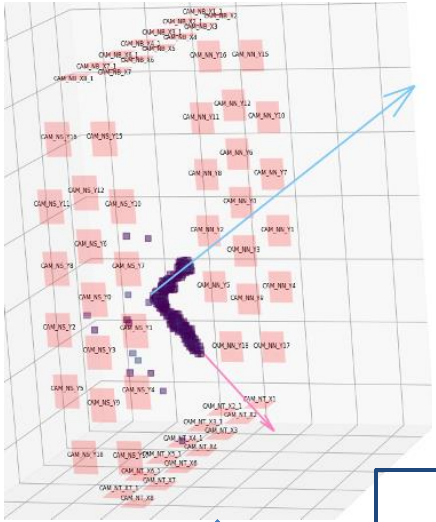


Photon source distribution

Track finding algorithm



Photon source distribution

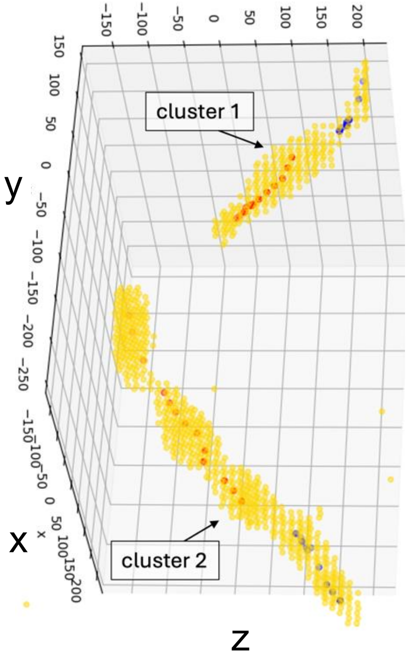


Voxel-selection
(score > 0.5% max)

Clustering algorithm

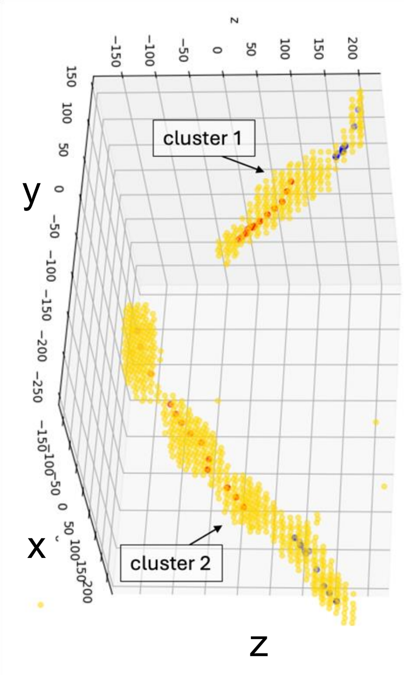
+

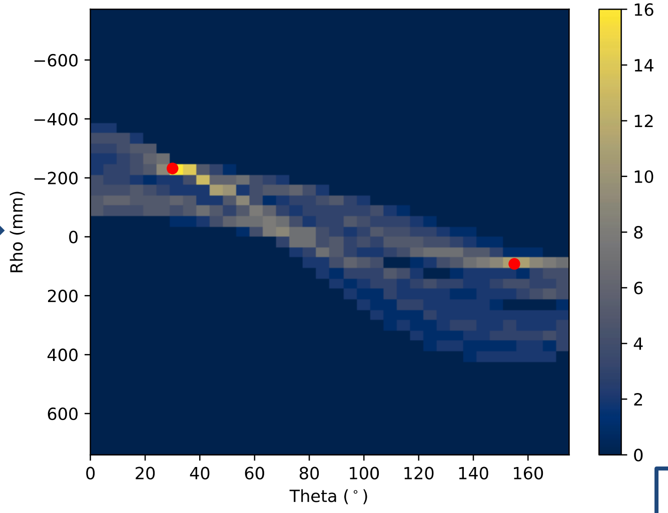
Feature extraction
(local principal curve)



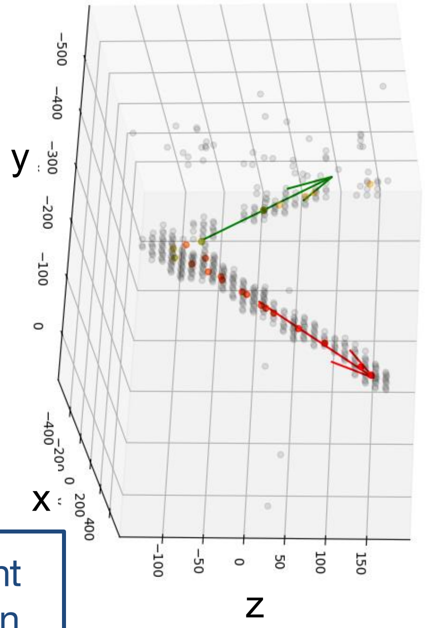
Track points

Track finding





2D Hough transform

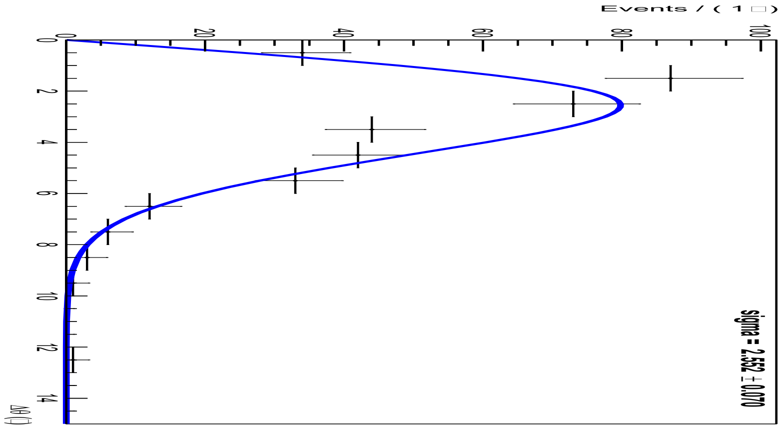


Track-point association

Linear fit

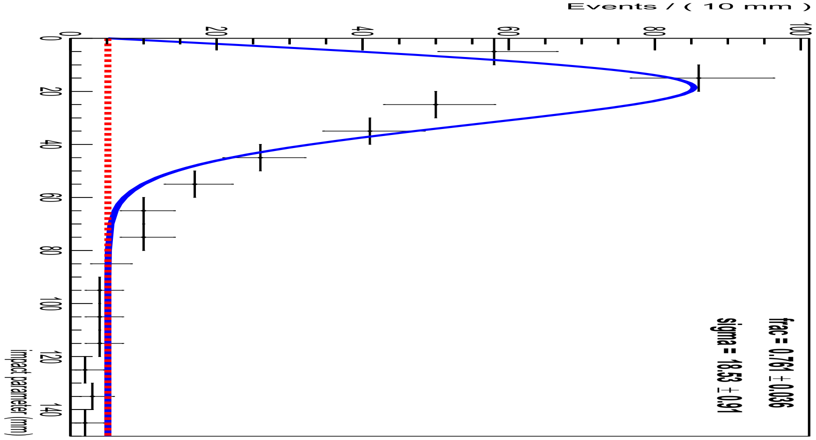
Results

Angle between the reconstructed and the Monte Carlo-truth directions



Angular resolution: $\sigma_\theta = (2.5 \pm 0.1)^\circ$

Closest distance between the Monte Carlo-truth vertex and the reconstructed track (impact parameter)



Position resolution: $\sigma_x = (19 \pm 1)\ \mathrm{mm}$

Conclusions and future perspectives

- I **studied** and **optimized** the **track finding** algorithm applied to the reconstruction for CCQE ν_μ events

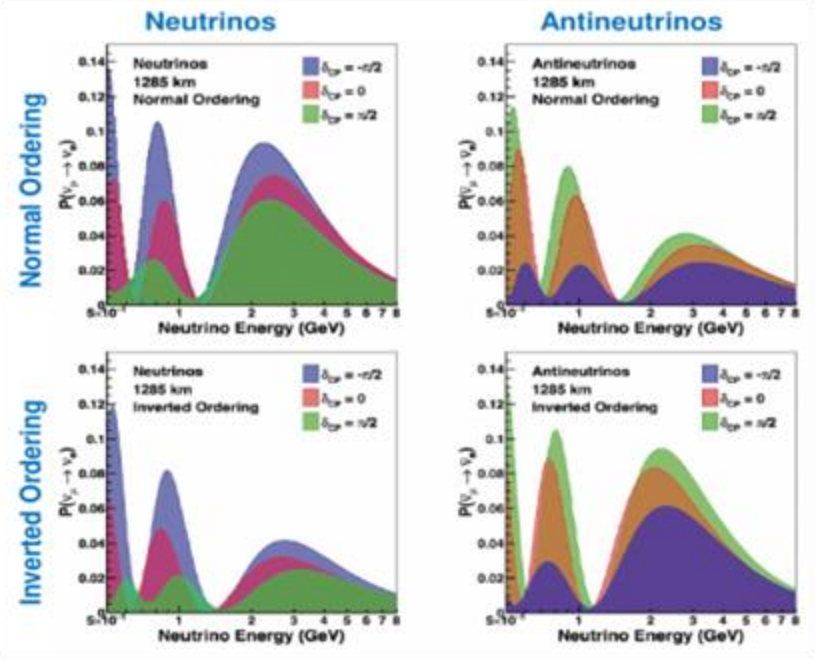
- the resolution I obtained ($\sigma_\theta \sim 2.5°$, $\sigma_x \sim 19\ \mathrm{mm}$) is sufficient to achieve **track matching** with other SAND sub-detectors

- future **improvements** should focus on the **track finding efficiency**:
  - better quality of the reconstructed voxel-distribution
  - systematic studies on the local principal curve parameters
  - alternative algorithms for track finding

Thanks for your attention!

Backup

DUNE physics



The value of the **CP phase** and the **mass ordering**, influence the oscillation probability → is possible to **disentangle** the two effects

Different behaviours for neutrino/antineutrino modes

Near and Far Detector

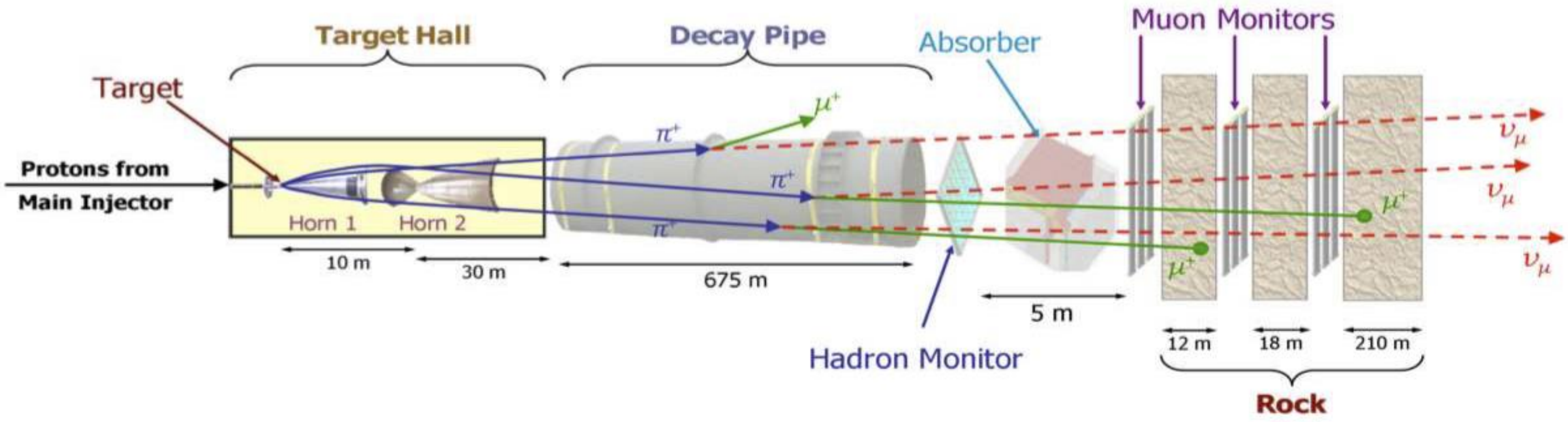
Near Detector will contribute to reduce systematic uncertainties due to neutrino-Ar interactions:

$$\frac{dN^{FD}_{\nu_e}}{dN^{ND}_{\nu_\mu}} = \frac{\int \Phi^{ND}_{\nu_\mu}(E_\nu) P_{\nu_\mu \to \nu_x}(E_\nu) F(E_\nu) \boxed{\sigma^{Ar}_{\nu_e}(E_\nu)} R^{Ar}_{\nu_e}(E_\nu, E_{rec}) \epsilon^{FD}_{\nu_e}(E_\nu, E_{rec}) dE_\nu}{\int \Phi^{ND}_{\nu_\mu}(E_\nu) \boxed{\sigma^{Ar}_{\nu_\mu}(E_\nu)} R^{Ar}_{\nu_\mu}(E_\nu, E_{rec}) \epsilon^{ND}_{\nu_m u}(E_\nu, E_{rec}) dE_\nu},$$

Far Detector will contribute to enlarge the event statistic:

- 17 600 ton of Ar for each TPC (~ 10 kton of fiducial volume)
- Long time of data taking (~ 20 years)
- 1.2 MW power

Neutrino beam



Dark Matter searches

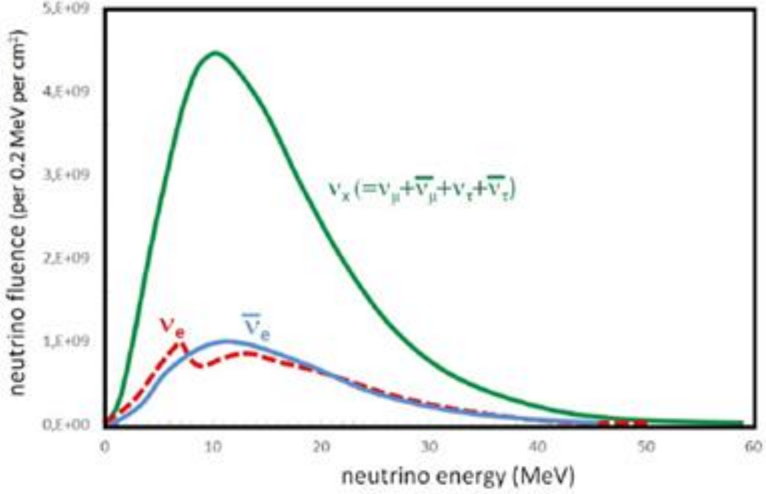
- low mass DM candidates can be produced by proton interaction in the target
- ND: signal search for the relativistic scattering of low-DM, having high flux
- FD: enough sensitivity to detect Boosted DM signals from the universe (Galatic Halo, the sun…)

Supernovae neutrinos

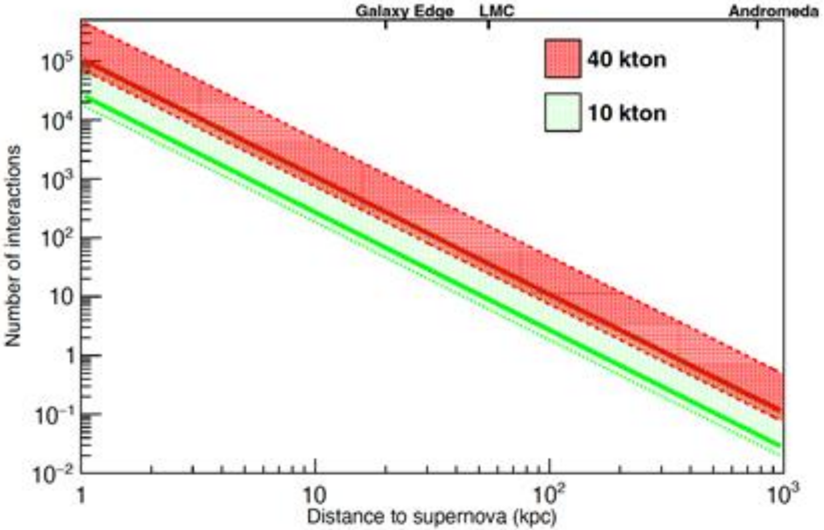
DUNE FD mostly sensitive to ν_e

Detection channels:

- $\nu_e + {}^{40}\mathrm{Ar} \rightarrow e^- + {}^{40}\mathrm{K}^*$ (dominant)
- elastic scattering



SN neutrinos energy spectrum



estimated number of neutrino interactions in DUNE as a function of the distance to the SN

3D iterative reconstruction

Maximum Likelihood Expectation Maximization Algorithm

- Describe the pdf of the detected data -> samples of a set of random variables
- Calculate the probability that any initial distribution density in the object under study can produce the observed data.
- The distribution density with the highest probability is the maximum likelihood estimate of the original object

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

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

Log-likelihood maximization

$$\lambda_j^{k+1} = \frac{\lambda_j^k}{\sum_s p(j,s)} \cdot \sum_s \frac{H_s \cdot p(j,s)}{\sum_j p(j,s) \cdot \lambda_j^k}$$

- H_s number of detected photons by pixel *s*
- λ_j unknown photon emission in voxel to be estimated from measured data
- $p(j,s)$ probability of a photon that originated in voxel *j* is detected by pixel *s*

- k = iteration number
- $\lambda_j^0 > 0$ initial distribution

Clustering algorithm

Sometimes the reconstructed tracks present clusters. The causes can be the presence of multiple tracks, neutral particle decays and the cut on the voxel's amplitude.

To perform LPC algorithm on the whole track, we want to take into account all the clusters.

→ DBSCAN algorithm

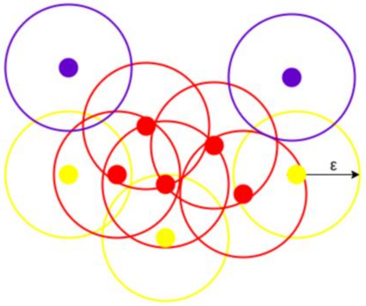
DBSCAN is a density-based clustering algorithm that works on the assumption that clusters are dense regions in space separated by regions of lower density.

ϵ = 36 mm
minPoints = 6

Parameters:
– **Epsilon** ϵ, radius of the circle to be created around each data point to check the density.

– ***minPoints***, the minimum number of data points required inside that circle for that data point to be classified as a **Core** point.

Point classification:
Core point, Border point and Noise point, depending on the points' density inside the ϵ-circle around them.



Local Principal Curves algorithm

Given a **set of points** $\boldsymbol{X_i(x,y,z)}$ and choosing a initial **location** $\boldsymbol{u}$, the algorithm finds the LPC points following this iterative procedure:

1. Computes the **local centre of mass**: $\boldsymbol{m(u_l)} \equiv u_l + s(u_l)$,

where $s(u) = \frac{\sum_{i=1}^{N} w_i(u)(X_i - u)}{\sum_{i=1}^{N} w_i(u))}$ and $w_i(u)$ are the weights, that decrease monotonically with increasing distance from u to X_i, following a Gaussian density function.

2. Finds the **next local neighbourhood location**: $\boldsymbol{u_{l+1}} = m(u_l) + t \times \gamma_l$,

where $\gamma_l = \gamma(u_l)$ is the normalised eigenvector corresponding to the largest eigenvalue of the local symmetric 3x3 covariance matrix $\sum(u) = \frac{\sum_{i=1}^{N} w_i(u)(X_i - u)(X_i - u)^T}{\sum_{i=1}^{N} w_i(u)}$ and t is the step size.

$\boldsymbol{m(u_l), m(u_{l+1})\ldots}$ **are the LPC points**

It **stops** when:
– it reaches N_{max} of LPC points

– LPC points converge

Reference paper: *Implementation of a local principal curves algorithm for neutrino interaction reconstruction in a liquid argon volume,* J.J. Back et al.

Parameters

- N_{max}, maximum number of LPC points
- R_{thr}, convergence threshold
- h, a constant bandwidth parameter that steers the size of the local neighbourhood
- t, the step size
- t_{min}, minimum step, to avoid too close ℓpc points

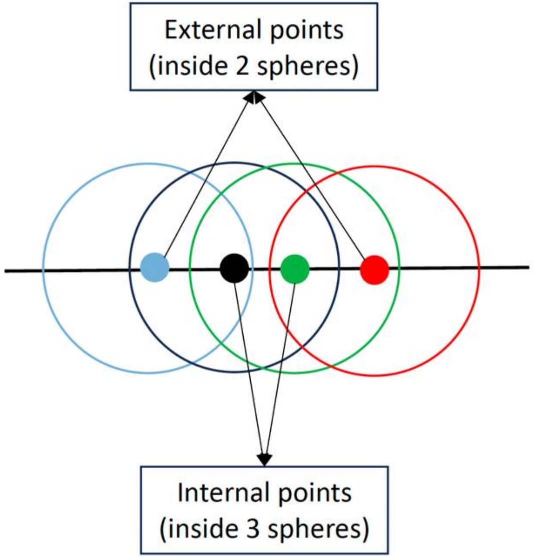
ℓpc **parameters**	
N_p	200
R_{thr}	10^{-3}
h	30 mm
t	55 mm
t_{min}	12 mm

Local principal curve refinement

The ℓpc often stops before the end of the track. To solve this problem, the idea is re-applying the ℓpc algorithm on the remaining track points, not yet processed by ℓpc.

1. Selection of the voxels already processed by ℓpc
imagine a sphere around each ℓpc point (taken as the center of the sphere): if the track point is inside **at most two spheres**, it is considered as external, otherwise not.

2. Re-application of ℓpc
selecting the remaining points, the ℓpc algorithm is re-applied on them.

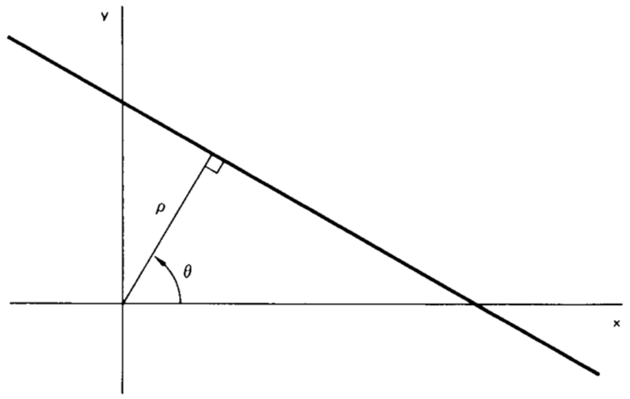


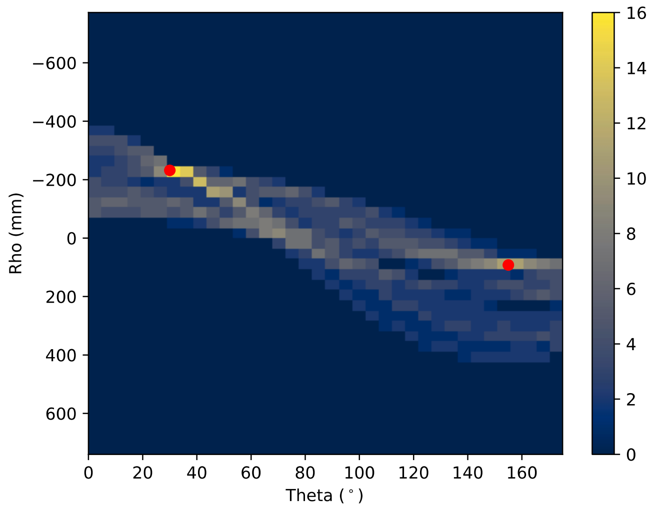
Hough transform

Given a set of points $\{(x_1, y_1), \dots, (x_n, y_n)\}$, each set of lines passing through a point (x_i, y_i) corresponds to a sinusoid in the $\rho - \theta$ plane, defined by:

$$\rho = x_i \cos\theta + y_i \sin\theta$$

Points on the same line share the same value of ρ and θ: these parameters define the line passing through the collinear points.





Analysis

Track finding algorithm applied to 326 events

Sometimes, the reconstruction of the voxel distribution is **not** sufficient for an **optimal application of the ℓpc algorithm**.

Hough Transform occasionally **struggles** to find track candidates, with a subsequent **lack of collinear points** associated.

→ we did not detect two tracks for every event

↓

Linear fit applied only to the collinear clusters with **more than 4 ℓpc points**