Track Reconstruction in Liquid Scintillators with Graph Neural Networks

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Short reminder on neutrino physics

Neutrino oscillation and masses

- Neutrinos only interact weakly
- Neutrinos have masses
- Neutrinos can change flavor
- Different mass and flavor eigenstates

Open Questions:

- Mass hierarchy
- CP violation
- Majorana particle

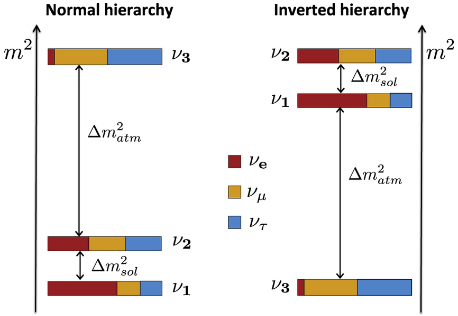


Figure: mass hierarchy
arXiv:1310.4340

Neutrino observation with scintillation detectors

Neutrino detection:
Inverse β Decay: $\overline{\nu_e} + p \rightarrow \overline{e} + n$
$\rightarrow$ Positron immediately gives signal
$\rightarrow$ Neutron releases γ after $\overline{t} \approx 200\mu s$

Background:

- Cosmic muons triggering cosmogenics

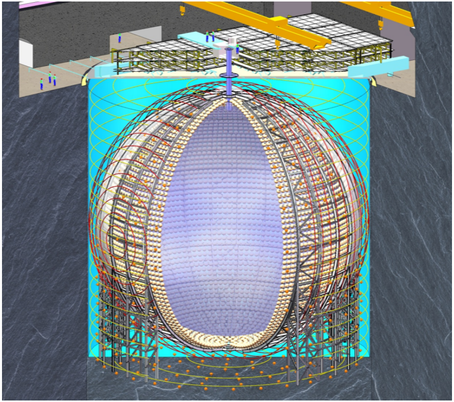


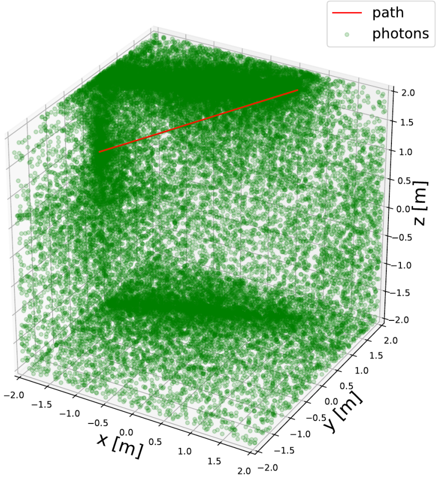
Figure: Jiangmen Underground Neutrino Observatory (JUNO), `https://www.etap.physik.uni-mainz.de/research-groups/ex-juno/` 30.07.2020

Motivation

Muon path reconstruction in liquid scintillators with artificial neural networks
$\rightarrow$ Reconstruct photon emission distribution from PMT response

- Reconstruction is crucial in neutrino detection
- Spacial muon tracking can reduce veto volume
- Shower identification could work as spatial veto

TOY - Monte Carlo



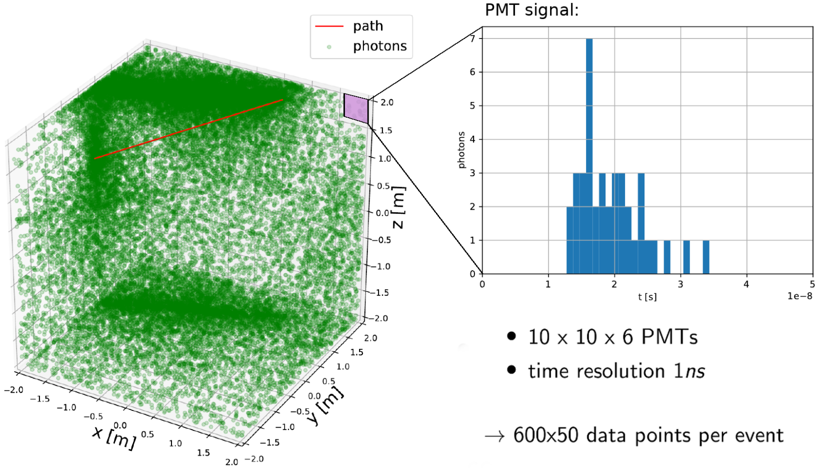
Simulation:

- 4 x 4 x 4 m
- Random, straight path
- 10 photons/ 0.001 m
- Peak with 5000 photons
- Absorption with $mfw = 80$m
- Scattering with $mfw = 25$m

Not included:

- Cherenkov light
- Attenuation
- Other path types

Data set

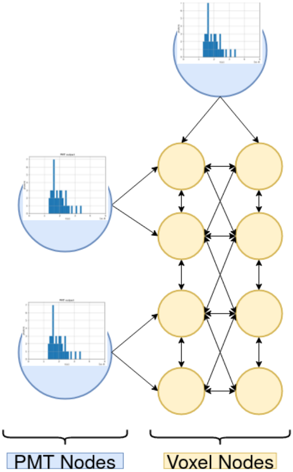


- 10 x 10 x 6 PMTs
- time resolution 1*ns*

→ 600x50 data points per event

Architecture Idea

- Photon distribution representation by [20,20,20] voxels
- Network should propagates photons back to their origin

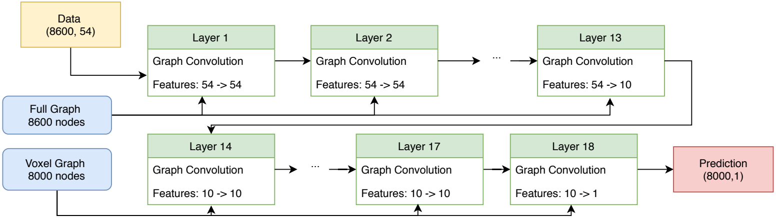


Full Graph

- 8600 nodes (8000 voxels + 600 PMTs)
- Each PMT node has edges to the closest voxel nodes
- Each voxel node has 26 edges to neighbors

→ Graph resembles geometrical structure of the setup

Architecture



$\rightarrow$ Implemented in python with pytorch and dgl

Graph Convolution Layers:

$$\nu_i^{(l+1)} = f(b^{(l)} + \sum_{j \in \mathcal{N}(i)} \frac{1}{c_{ij}} \nu_j^{(l)} \cdot W^{(l)}) \tag{1}$$

ν_i - node, $\mathcal{N}(i)$ - neighboring nodes, b bias, W - weights, l - layer

Wasserstein Loss

Wasserstein distance: metric defined between probability distributions on a metric space

Sinkhorn distance:

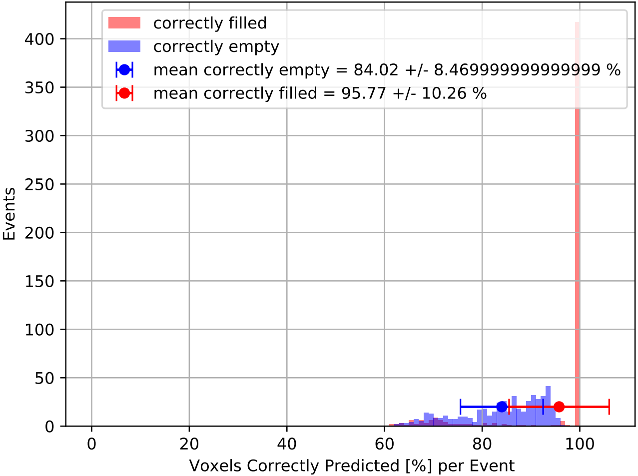
$$d_{M,\alpha}(r,c) = \min_{P \in U_\alpha(r,c)} \langle P, M \rangle \tag{2}$$

with M - cost matrix, P - transport matrix, r and c distributions, $U(r,c)$ joint probability matrices

- Reshape form [20,20,20] into 3D point cloud with photons as weights
- 3D point cloud uses coordinates of the filled voxels
- Supports autograd

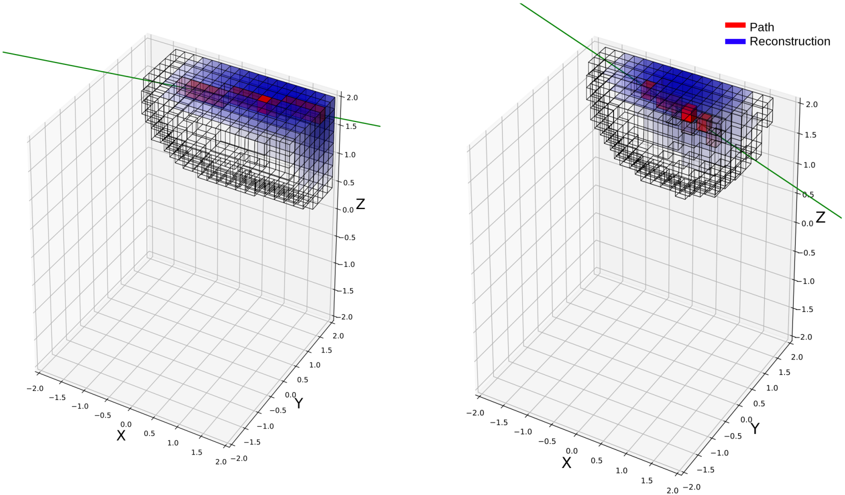
$\rightarrow$ Including spacial gradients

Results - work in progress



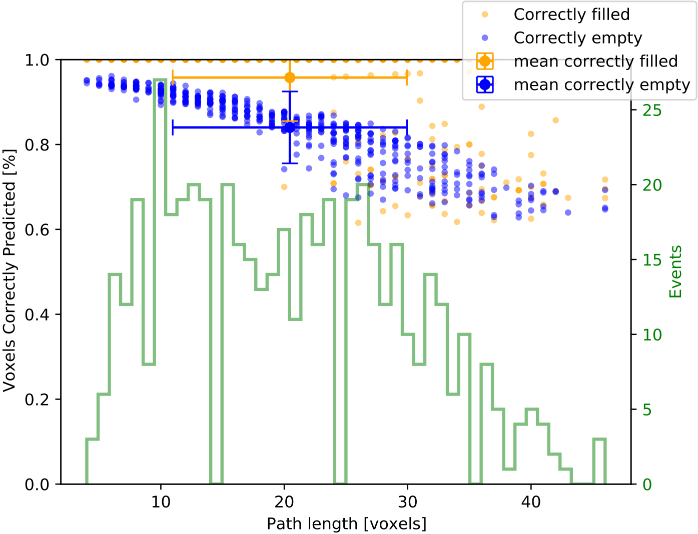
→ Only ≈ 16% of the detector volume would need to be vetoed

Results - work in progress



→ Reconstruction surrounds path, but to many voxels are filled

Results - work in progress



→ Especially short paths are reconstructed nicely

Conclusion

$\rightarrow$ **Graph Neural Networks can reconstruct muon tracks, but there is room for improvement**

Next Steps:

- Further improvement of the predictions
- Improve photon sum
- Include more complex paths
- More complex simulation

Outlook:

- Could be used to improve the muon veto by a spacial information
- Architecture could be adjusted for different detector setups

Thank you!