Deep Learning Applications for Liquid Argon Time Projection Chamber-based Neutrino Detectors

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ν_e ν_μ ν_τ

Neutrinos are...

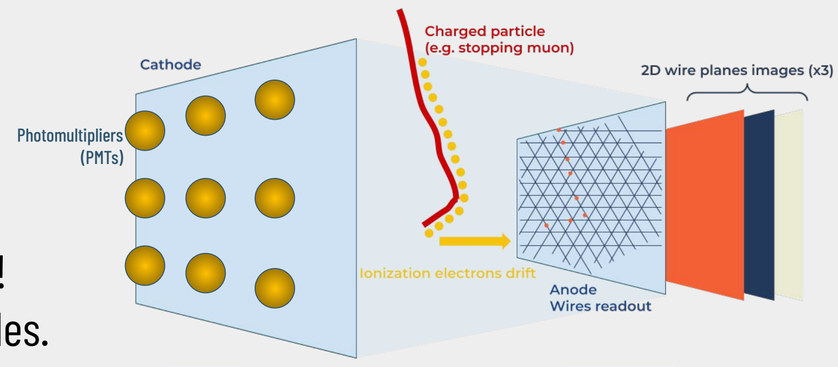
Abundant Produced by the Big Bang, the sun, stars, supernovas, nuclear reactors, ... most abundant!

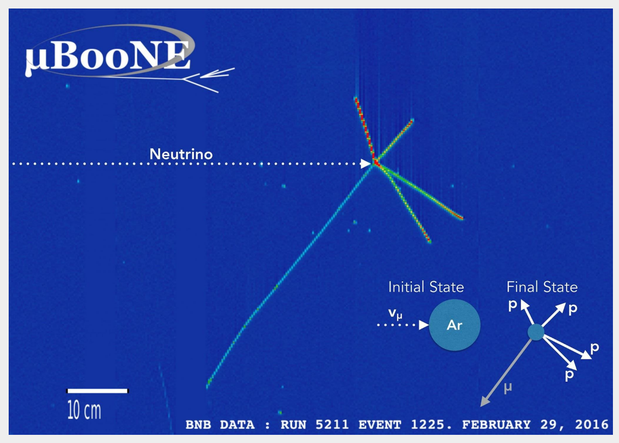
Light Exact mass is unknown, but lightest of all particles.

Oscillating between (at least) three flavors

Ghosts that interact weakly and very rarely = hard to study

Key to many physics puzzles such as matter-antimatter asymmetry, grand unification theories, etc

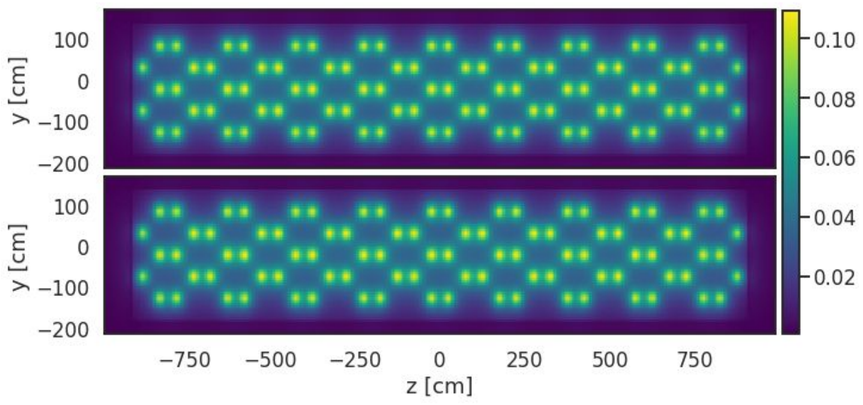




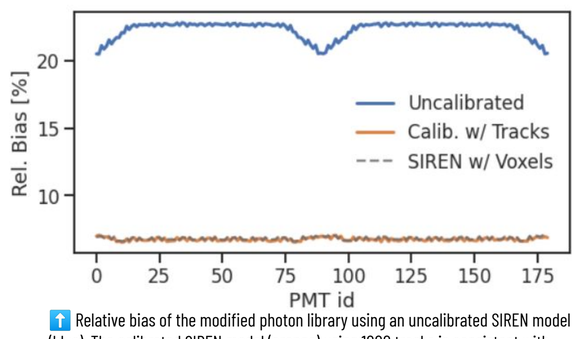
LArTPCs are precision neutrino detectors

SIMULATE

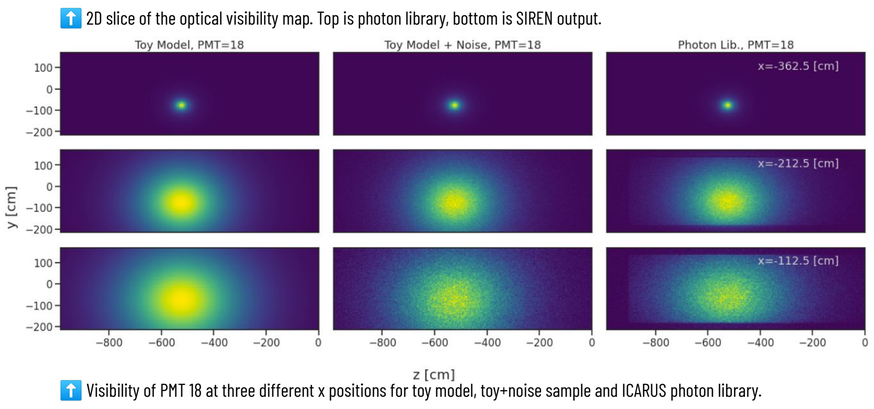
LIGHT Propagation with Implicit Neural Representation (SIREN) for Scalability



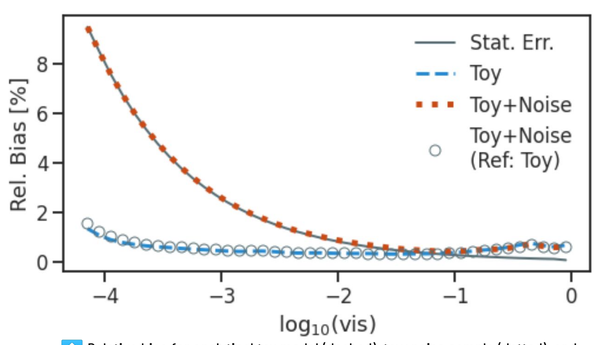
⬆️ 2D slice of the optical visibility map. Top is photon library, bottom is SIREN output.



⬆️ Relative bias of the modified photon library using an uncalibrated SIREN model (blue). The calibrated SIREN model (orange) using 1000 tracks is consistent with re-training the SIREN model with all the voxels from the modified photon library.

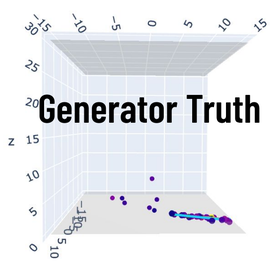


⬆️ Visibility of PMT 18 at three different x positions for toy model, toy+noise sample and ICARUS photon library.



⬆️ Relative bias for analytical toy model (dashed), toy+noise sample (dotted), and expected statistical error (solide).

CHARGE Differentiable Simulation to extract model parameters from data



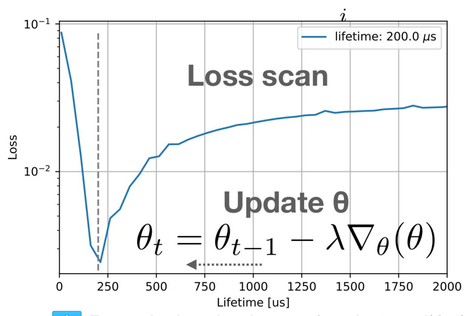
FORWARD

BACKWARD

Differentiable Simulation (θ)

Pixel-wise L2 loss for direct comparison

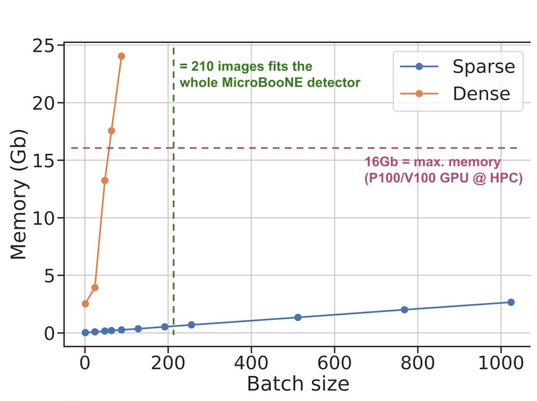
Data



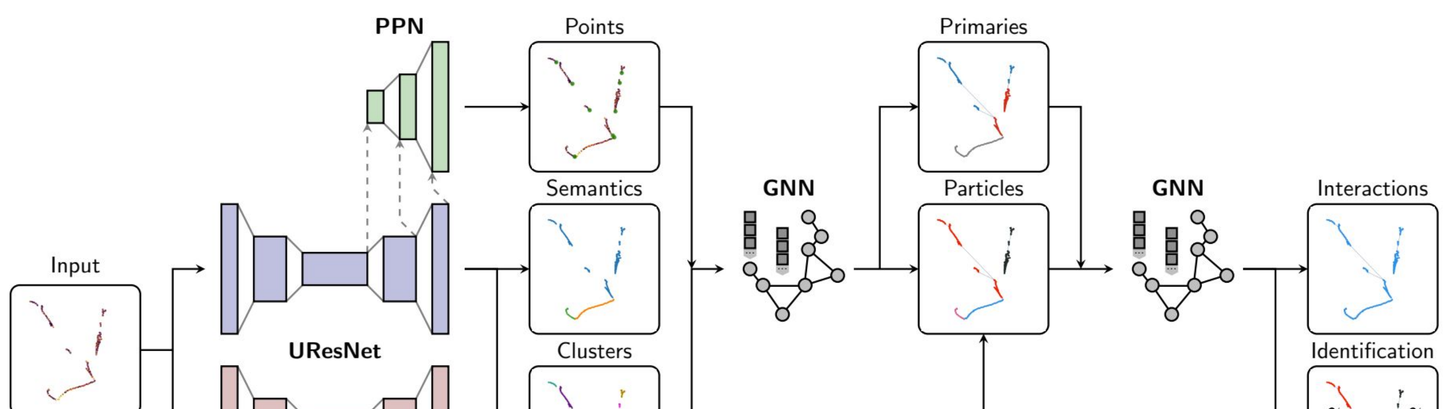
⬆️ Example: loss landscape for electron lifetime

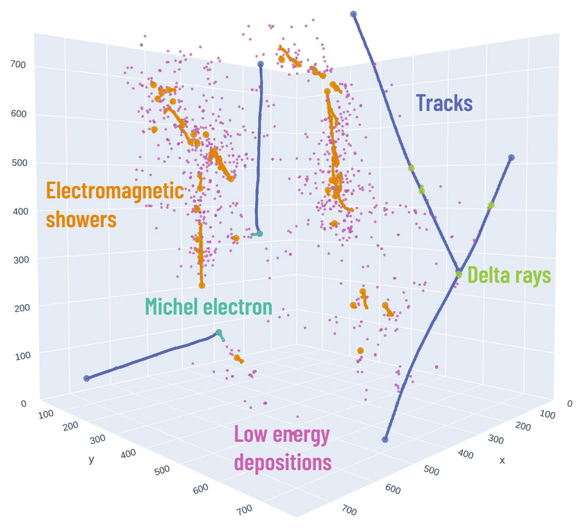
RECONSTRUCT

Convolutional and Graph Neural Networks for a hierarchical end-to-end reconstruction chain using sparse convolutions

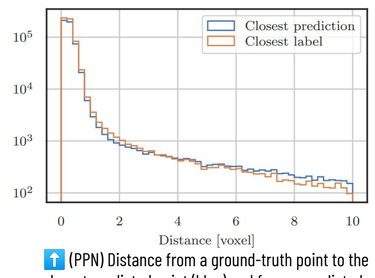


⬆️ Sparse convolutions enable us to fit large detectors data on a single GPU.





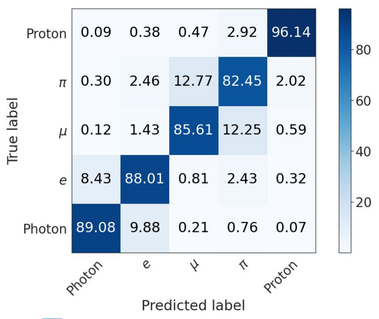
⬅️ True voxels semantic type and true particle endpoints.



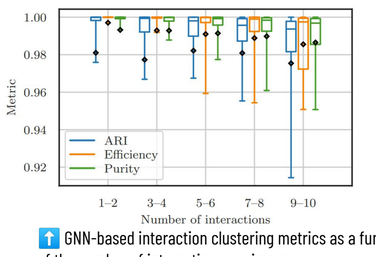
⬆️ (PPN) Distance from a ground-truth point to the closest predicted point (blue) and from a predicted point to the closest ground truth point (orange).

⬇️ UResNet-based semantic segmentation performance.

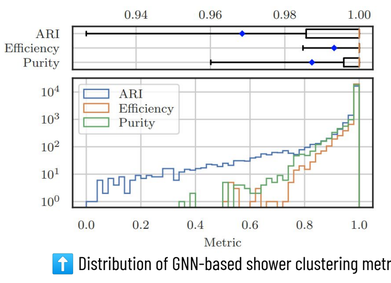
Semantic Type	% Voxels	% Correct
Shower	26.3%	97.7%
Track	58.5%	99.5%
Michel	1%	95.4%
Delta	1.4%	87.2%
LowE	12.8%	98.1%



⬆️ Particle type identification (PID) confusion matrix.



⬆️ GNN-based interaction clustering metrics as a function of the number of interactions per image.

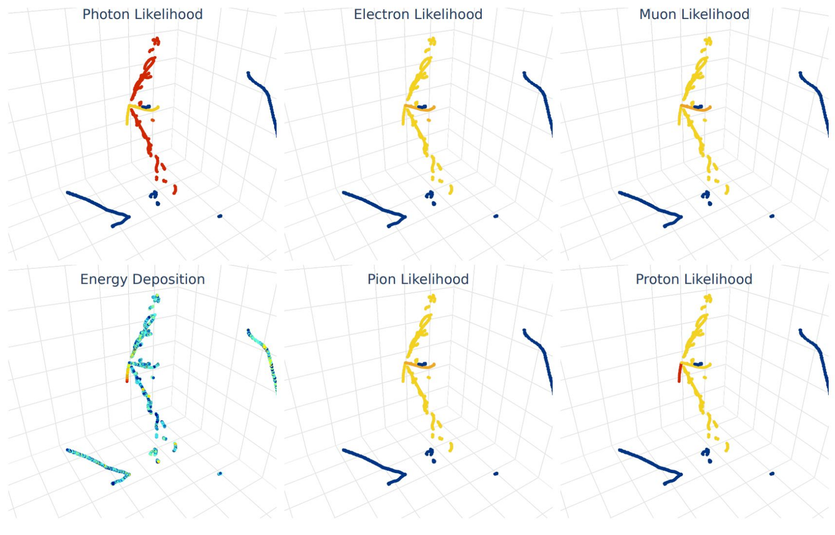


⬆️ Distribution of GNN-based shower clustering metrics.

ANALYZE

Uncertainty Quantification for Semantic Classification

⬇️ Example of high-entropy misclassification from a multi-particle evidential GNN (Bayes Risk). Red is higher likelihood than yellow. Particles that do not originate from a vertex are colored in dark navy.



Ensembling methods

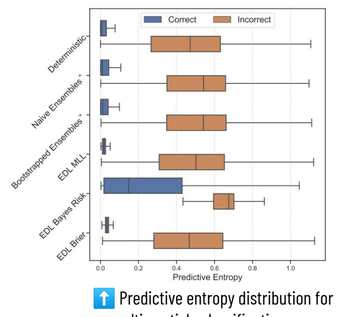
Training multiple instances of the same architecture with different random initialization seeds

Monte Carlo Dropout

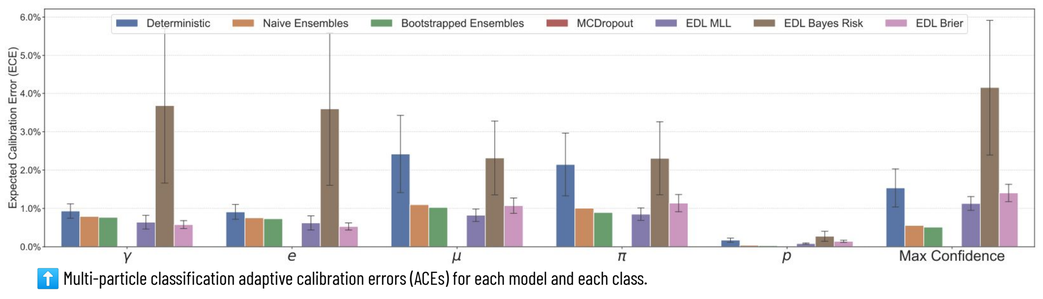
Bayesian technique approximating the network's posterior distribution of class predictions through multiple forward passes of dropout regularized networks

Evidential Deep Learning

Model the posterior distribution analytically



⬆️ Predictive entropy distribution for multi-particle classification.



⬆️ Multi-particle classification adaptive calibration errors (ACEs) for each model and each class.

REFERENCES

[1] Drielsma, Francois, et al. "Scalable, end-to-end, deep-learning-based data reconstruction chain for particle imaging detectors." *arXiv preprint arXiv:2102.01033* (2021).

[2] Sitzmann, Vincent, et al. "Implicit neural representations with periodic activation functions." *Advances in Neural Information Processing Systems* 33 (2020): 7462-7473.

LArTPC Open Dataset: https://dx.doi.org/10.17605/OSF.IO/VRUZP