Electron Neutrino Reconstruction for the ICARUS Experiment

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Neutrino Physics and Machine Learning 2024

Overview

- Short Baseline Program (SBN) and ICARUS at Fermilab
- Deep learning for LArTPC Event Reconstruction A bird's eye view
- Preliminary Results on BNB and NuMI ν_e Reconstruction
- Conclusion & Future Work

Neutrino Oscillations

- **Neutrino Oscillations** is one major example modification to the Standard Model (SM) from experiment
 - Neutrino flavor state from a W⁺ decay is a superposition of mass eigenstates, where mixing is governed by the Pontecorvo-Maki-Nakagawa-Sakata (PMNS) Matrix:

Flavor Eigenstates

$$|\nu_e \rangle, |\nu_{\mu} \rangle, |\nu_{\tau} \rangle$$
 $|\nu_{\alpha} \rangle = \sum_{i} U_{\alpha i}^* |\nu_i \rangle$ Mass Eigenstates
 $|\nu_1 \rangle, |\nu_2 \rangle, |\nu_3 \rangle$
Two-flavor approximation:
 $P(\overline{\nu_{\alpha}}^{-} \rightarrow \overline{\nu_{\beta}}) = \sin^2 2\theta \sin^2(\Delta m^2 \frac{L}{4E})$
Experiments control the L/E parameter, where L is usually
referred to as the baseline.

Neutrino Oscillation pattern observed by KamLAND

Image Credit: DOI: <u>10.1016/j.revip.2016.04.003</u>

Short Baseline Anomalies: An Example from MiniBooNE

- MiniBooNE: Excess of ν_e events in ν_μ → ν_e mode observed over backgrounds, 4.5σ deviation from expectation.
- This excess cannot be explained by the Standard Model (sterile neutrinos?)





II. The Short Baseline Neutrino Experiment and ICARUS

The Short Baseline Neutrino (SBN) Program at Fermilab



Booster Neutrino Beam (BNB)

- The Booster Neutrino Beam (BNB) produces neutrinos using 8.89 GeV momentum Booster synchrotron protons incident on a Beryllium target.
- $p + Be \to \pi^+, K^+, K_L^0 \to \nu_\mu + \mu^+ + \dots$
- In neutrino mode, the flux is dominated by
 - ν_{μ} (93.6%) and $\bar{\nu}_{\mu}$ (5.9%)
 - Intrinsic v_e/\overline{v}_e contamination of ~0.5%
- Majority of ν_{μ} flux from pion decay in flight ($\pi^+ \rightarrow \mu^+ + \nu_{\mu}$) until ~2GeV, where K^+/K_L^0 decay dominates.





Image Credit: A Proposal for a Three Detector Short-Baseline Neutrino Oscillation Program in the Fermilab Booster Neutrino Beam, ICARUS-WA104, LAr1-ND, MicroBooNE Collaboration, C. Rubbia (CERN, GSSI, Aquila, INFN LNGS, Assergi) for the collaboration.

Neutrinos at the Main Injector (NuMI) Beam

- The Neutrinos at the Main Injector (NuMI) Beam produces neutrinos using 120 GeV protons incident on graphite target.
- Higher primary proton beam energy → more K production → relatively high v_e content (~4-5%).
- ICARUS is 6° off-axis from the NuMI beam line.
- Rich physics programs using NuMI beam at ICARUS:
 ν Ar cross section measurements, BSM searches, etc.



Image Credit: Marta Babicz, ICARUS T600 Trigger Study at the Short-Baseline Neutrino Experiment (EP-NU meeting) https://indico.cern.ch/event/864614/contributions/3859763/attachments/2038762/3413897/EPNU_talk.pdf.

- Time projection chamber with 760-ton liquid argon medium, 500
 V/cm nominal electric field applied between cathode and anode plane.
- Neutrino-argon interaction creates charged particles, which in turn releases ionization electrons that drift towards the anode plane.
- Maximum electron drift time is ~1ms with 500 V/cm
- Photon signals detected within ~ns at PMTs.





ICARUS Detector: Example Neutrino Candidate Event



ICARUS Detector: Example Neutrino Event



ICARUS Detector: Example Neutrino Event



SPINE: Scalable Particle Imaging with Neural Embeddings

- Goal: Automated feature extraction for from LArTPC images
 - Interpretable: chain of neural networks specializing in various sub-tasks
 - Allows detailed and informative error analysis, if certain parts of the chain fails
 - Automatic optimization: entire chain is trainable simultaneously using gradient-based optimization



SP NE



Step 0: Remove 2D->3D Reconstruction Artifacts (Deghosting) Later ML stages use the cleaned image on the right



Step 1: Identify Pixel-Level Features Sparse-CNN for shape classification and interest point detection



Step 2: Identify Individual Particles CNN for pixel-to-fragment clustering, GNN for fragment-to-particle aggregation



Step 3: Group particles to parent interactions GNN, predict which particles have common ancestral interactions (edge prediction)



Step 4: Identify Cross-Particle Correlations (GNN for particle type prediction, inference with contextual information) IV. Preliminary Results

Preliminary Results: Cuts (BNB)



- Signal Definition: 1eNp0π[±]0γ Topology with a tagged PMT information consistent with the [0, 1.6us] beam window ("1eNp+FM").
- <u>Visible</u> 1eNp: 1eNp topologies in which all participating particles deposit ≥ 25 MeV (30 MeV for protons)
- Fiducial Cut:
 - True and reconstructed vertex must be inside fiducial volume.
- Conversion Distance Cut:
 - Photons can travel some distance before pairproducing to EM shower cascade; *e* showers deposit energy from the beginning.
 - Require ≤ 0.8 cm for electrons

Preliminary Results (BNB)



Selected 1eNp Signals (True ν_e 's) from BNB ν_μ + intrinsic ν_e + Out-of-time Cosmics

(Reconstruction with predicted particle types)

Preliminary Results (1. BNB v_e Intrinsic + Cosmic)

- To estimate efficiency, we use a BNB intrinsic v_e only MC dataset. (~3.5k v_e interactions with nonzero deposited E).
- Reconstruction efficiency is ~51%, with dominant error mode due to $1eNp \rightarrow 1\gamma Np$.
- Energy Reconstruction:
 - *E_e* (Electron Energy):
 - Calorimetric reconstruction from wire
 plane charge information
 - $E_p^{(i)}$ (Proton Energy):
 - Bethe-Bloch range-based energy estimation



True v_e 1eNp Interactions (931)

Preliminary Results (1. BNB v_e Intrinsic + Cosmic)



Preliminary Results (2: BNB v_{μ} + v_{e} + out-of-time cosmic)

- For purity and background rejection estimates, we use the BNB ν Flux (~13k neutrinos, 99.5% ν_μ, 0.5% ν_e) simulation.
- Estimated Purity: 66.67%
- MicroBooNE ν_e 1eNp0π Efficiency/Purity:
 15%/80% with 40 MeV proton energy threshold DOI:https://doi.org/10.1103/PhysRevD.105.112004
- Selection rejects all (100%) simulated in-time cosmic (~291k cosmic ray dataset) backgrounds.



Preliminary Results (4: NuMI + out-of-time cosmic)

- NuMI v_e candidates (D. Carber):
 - Containment required for visible particles (5cm margin from detector boundaries)
 - Optical flash timing within NuMI Beam window (9.6µs wide)
 - \geq 1 reconstructed *e* with $E_e \geq$ 10 MeV.
 - \geq 1 reconstructed *p* with $E_p \geq$ 40 MeV.
- 1e1p: Efficiency: 73.3%, Purity: 72.7%



Selected 1e1p Candidates

Conclusion

- Demonstrated application of SPINE ML-based reconstruction chain to ICARUS BNB and NuMI electron neutrino reconstruction
- Selection Purity and Efficiency:
 - BNB 1eNp: 51% / 67%
 - NuMI 1e1p: 73% / 73%
- BNB Visible Reconstructed Neutrino Energy resolution: FWHM is ~20% for the fractional error

Future Work

- Validate analysis on large-statistics sample
- Integrate flux, interaction, and detector systematic uncertainties
- Data vs. Simulation Studies

A. Reserve Slides

Vertex Reconstruction Resolution



True Interactions (v_e)

Defining the Signal (BNB)

- Event topology for v_e selection:
 - Aim for simple and abundant electron neutrino topology
 - 1eNp, with $N \ge 1$.
 - Single electron (1*e*) topology prone to background contamination from NC $\pi^0 \rightarrow \gamma\gamma$ decays
 - Require no primary photons for u_{μ} NC π^{0} rejection
- Conclusion:
 - $1eNp0\pi^{\pm}0\gamma$ Topology for ν_e candidate
- Left: simulated 2.7K charge-current electron neutrino interactions (ν_e CC) in ICARUS



2698 BNB v_e CC Intrinsic (3.5K v_e Total)

- Goal: Automated feature extraction for from LArTPC images
 - Interpretable: chain of neural networks specializing in various sub-tasks
 - Allows detailed and informative error analysis, if certain parts of the chain fails
 - **Easy-optimization**: entire chain is trainable simultaneously using gradient-based optimization





Top View of West ICARUS T300 module (West and East T300 combine to form the T600 Detector)

Image Credit: https://thesis.unipd.it/handle/20.500.12608/52881

- Each U, V, and Y wire planes provide a 2D projection view of the charged particle ionization path
- A 3D representation of a charge particle ionization path may be reconstructed from the 2D views, provided the initial timing information.



Rubbia, C & Antonello, Matteo & Aprili, P. & Baibussinov, B. & Baldo-Ceolin, M. & Barze, Luca & Benetti, P & Calligarich, E & Carci, Nicola & Carbonara, F. & Cavanna, Flavio & Centro, Sandro & Cesana, A & Cieslik, Krzysztof & Cline, D. & Cocco, Alfredo & Dabrowska, Anna & Dequal, Daniele & Dermenev, A & Zmuda, J.. (2011). Underground operation of the ICARUS T600 LAr-TPC: first results. Journal of Instrumentation - J INSTRUM. 6. 10.1088/1748-0221/6/07/P07011.

- The ICARUS T600 detector is composed of three major subsystems:
 - Time Projection Chambers (TPCs): allow high resolution imaging of particle trajectories.
 - Photomultiplier Tubes (PMTs): scintillation light from charged particles used for interaction timing information
 - Cosmic Ray Tagger (CRTs): tagging system for crossing and exiting particles



The ICARUS T600 Detector: Trigger System

- ICARUS Trigger system exploits 360 PMTs installed behind TPC wire planes to recognize beam-related neutrino events within the 1.6μs spills of the Booster Neutrino Beam (BNB).
- Detector receives "early warning" signals 35ms before the protons hit the BNB target, hence the beam spill windows
 are known.



Preliminary Results: Cuts (BNB)



• The reconstruction chain may be separated into two submodules: **convolutional** and **graphical** neural network branches.



Graph NN

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Pixel-level Tasks are handled by a sparse-convolutional neural

• The reconstruction chain may be separated into two submodules: **convolutional** and **graphical** neural network branches.



- Pixel-level Tasks are handled by a sparse-convolutional neural network architecture called Sparse-UResNet.
 - **1. Tomographic Artifact Removal**: remove false positive 3D spacepoints from 2D -> 3D tomographic reconstruction.
 - 2. Semantic Segmentation: classify each pixel to activity type
 - **3. Point of Interest** (track start/end, EM shower start) detection.
 - 4. Particle Clustering: cluster pixel into different ancestral particles.



• After particle clustering, each group of pixels realized from the same particle is **abstracted into a node feature vector of a graph.**



- By aggregating all outputs from the ML chain, we can reconstruct the full geometric information of a given LArTPC image.
- For each particle, we predict its
 - Type (γ, e, μ, π, p)
 - Primary Score (indicates whether a particle is a primary deposition of an interaction)
 - Parent Interaction Group
- Example:
 - for every interaction (group of particles) in an image, search for interactions with one primary electron and more than one primary proton.





Tomographic Reconstruction: Building 3D Spacepoints

- ML Based reco. Chain is developed for 3D images
- Tomographic Reconstruction (three 2D projections -> 3D) essential for ML-reco. Chain on Wire LArTPCs
- In each U, V, and Y projections (indexed by p = 0,1,2), let $h_p^{(i)} = (t_p^{(i)}, w_p^{(i)})$ be a single *i*-th 2D hit:
 - $t_p^{(i)}$: time measured along drift-axis (\hat{e}_x basis, by convention)



Wire 2D hits in given projection

- $w_p^{(i)}$: wire number measured along the wire-direction basis $\hat{e}_p = \lambda_p \hat{e}_y + \kappa_p \hat{e}_z$, since wire planes are slanted at $\pm 60^\circ$ (basis transform).
- **Cluster3D** is a traditional algorithm which combines 2D hits that are compatible in time and wire to propose 3D positions.
 - Find pairs of hits $\left(h_p^{(i)}, h_q^{(j)}\right)$ which are compatible in time: $\left|t_p^{(i)} t_q^{(j)}\right| < \delta_t$
 - Form a 3D "doublet" candidate spacepoint: $x_{ij} \coloneqq \frac{1}{2} \left(t_p^{(i)} + t_q^{(j)} \right) \hat{e}_x + \begin{bmatrix} e_p \\ e_q \\ e_p \times e_q \end{bmatrix}^{-1} \begin{bmatrix} w_{p,i} \\ w_{q,j} \\ 0 \end{bmatrix}$ Best estimate of time Change of Basis



- If a third plane hit $h_r^{(k)}$ is compatible with x_{ij} , register it as a "triplet" x_{ijk} .
- In short, find pairs of wires that meet each other (have crossing point) and find wire hits that are compatible in time.

Liquid Argon Time Projection Chamber (LArTPC)

- Several detector properties affect event reconstruction:
- TPC-related:
 - Recombination:
 - Ionization electrons may recombine with nearby argon ions, underestimating yield.
 - Diffusion:
 - Smearing of electron cloud as function of drift time.
 - Electron Lifetime:
 - Average capture time of a free ionization electron by an electronegative impurity in Lar.
 - Space-charge Effect:
 - Accumulation of positive argon ions induce local distortions of electric field
 - Transparency



Image Credit:

https://indico.cern.ch/event/286883/contributions/654014/attachments/533407/735520/Prezent acjaNCBJ_6-12-2013.pdf

Conversion Distance Cut

- Electron and Photon Electromagnetic Showers can be distinguished in LArTPCs using the displacement of the EM shower's start position from the neutrino interaction vertex.
- **Conversion Distance**: compute the minimum distance between all primary track startpoints and EM shower.
- If the conversion distance exceeds 0.8cm, override shower particle type to photon.





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Event Displays



Event Displays



Event Displays



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