(Some of the) ML-based Reconstruction in MicroBooNE

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- This talk is only on a subset of ML-based reconstruction efforts on MicroBooNE
- Describe a new workflow that combines several Convolutional Network Outputs with 3D point cloud reconstruction
- Preview of first application of these reco products for a inclusive CC Nue selection

Reco. Overview



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LArMatch: Wireplane Images to 3D Charge and Keypoints

Identifying true 3D locations of ionization by matching patterns across planes

Goal: augmenting between-plane charge consistency with local features and priors on particle trajectory paths



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LArMatch Network Architecture

Network can be divided into two parts:



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LArMatch Network Architecture

Network can be divided into two parts:

(1) CNN on (2D) images encodes relevant information for each pixel as 16-d vector.

Spacepoints are formed from simple spatially consistency and inherit pixel features.



LArMatch Network Architecture

Network can be divided into two parts:

(2) Each spacepoint is evaluated by multiple multilayer perceptrons which output various labels



LArMatch: Scores on Spaecepoint Proposals



LArMatch: Neutrino Keypoint Scores



LArMatch: Neutrino Keypoints

Keypoint labels are provided by learning a score between 0 and 1 that is proportional to distance to nearest keypoint. Final keypoint found by fitting spatial pattern.

Keypoint types:

- Track start/end
- Shower start
- Michel decay point
- Delta ray start

Types evaluated separately (non-exclusive)





<u>o</u> Keypoint Score (ghost points removed)
cale: Score inverse to distance to keypoint
Yellow: 1.0 (0 cm) → purple 0.0 (>10 cm)

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LArMatch: Neutrino Vertex Position Resolution

- In MC, 68% of reconstructed neutrino vertices are within 9.2mm of simulated interaction position
 - Wire spacing is 3mm, so this is within 3 wires, which is quite good



Vertex Resolution for MC Neutrino Interactions

Spacepoint Reconstruction

Spacepoint reconstruction into particle candidates greatly simplified by semantic labels from CNNs and other algorithms. Starts by separating passing points as

- Non-cosmic track-like
- Non-cosmic shower-like
- Cosmic track-like
- Cosmic shower-like



Cosmic designation from Wirecell in-time/out-of-time tagger.

Track/shower designation from SSNet (evaluated on 2D images with labels pushed to spacepoints)

Keypoints initially remove spacepoints in order to prevent overclustering (points from more than one particle)

Prong CNN

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Particle Clustering/Reco: Completeness and Purity

Photon Prong Purity vs Completeness



Muon Prong Purity vs Completeness



Purity: fraction of points within reco cluster from single particle

Completeness: fraction of true points from particle captured within cluster



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- A CNN to classify reconstructed 3D tracks and showers
 - Similar to work by NOvA: PhysRevD.100.073005
- Does particle identification (PID)
 - Outputs five score indicating how likely that the input is a muon, pion, proton, photon, or electron
- Outputs reconstruction quality metrics
 - Completeness prediction: fraction of true particle reconstructed in input track/shower
 - Purity prediction: fraction of reconstructed track/shower that was created from true particle

LArPID Inputs/Preprocessing

- In 2D images, select all pixels included in 3D prong hits
- Crop to 512 x 512 window. Center prong in image if it fits, otherwise crop around prong end point (if it's a track) or start point (if it's a shower)
- Normalize pixel values (subtract mean, divide by standard deviation)
- Provide full event images (with cosmics removed) along with prong images





plane 2 prong



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LArPID Network Architecture

- Use tried and tested ResNet architecture (arXiv:1512.03385)
- Limit CNN depth to 34 layers due to computational constraints



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LArPID: Used learned weighting for Multi-task loss

- Use learned weights to combine losses from three tasks (arXiv:1705.07115)
 - Loss = $exp(-s_{cr})L_{cr} + exp(-s_{pr})L_{pr} + 2exp(-s_{pc})L_{pc} + s_{cr} + s_{pr} + s_{pc}$
 - L_{cr} = mean square error completeness regression loss
 - L_{pr} = mean square error purity regression loss
 - L_{pc} = cross entropy particle classification loss
- Training sample: on the order of 100k prongs (tracks/showers) of each particle type (electrons, photons, muons, pions, and protons)
 - Weight L_{pc} contributions to account for class imbalance
- Validation sample:
 - 10k prongs, 2k per particle type
- Training
 - Data augmentation: randomly flip input images
 - Trained for 20 epochs with a variable learning rate scheduler:



LArPID: Classification Performance

- Results shown with true prong purity > 0.6 cut for accurate labels
- Overall validation accuracy: 91.1%



Validation Sample Accuracy Statistics

	True electrons	True photons	True muons	True pions	True protons
Fraction classified as electrons	83.5%	4.8%	0.1%	0.4%	0.1%
Fraction classified as photons	13.3%	94.7%	0.1%	0.2%	0.2%
Fraction classified as muons	0.4%	0%	93.6%	12.1%	0.2%
Fraction classified as pions	2.7%	0.4%	6.1%	85.9%	1.4%
Fraction classified as protons	0.2%	0.2%	0.2%	1.5%	98.2%

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LArPID: Completeness and Purity Regression



Prong image



Context Image



Original Scores Electron score=-3.6 Photon score=-0.03

Scores are log(∠(class|x))

Using secondary shower to classify as photon despite obscured information near vertex?

Prong image



Manipulated Context Image

[second shower pixels removed]



Original Scores Electron score=-1.53 Photon score=-0.25

Scores are log(∠(class|x))

Manipulation leads to less confidence in photon classification (but still favors photon-ness)

Prong image



Context Image



<u>Original Scores</u> Electron score= 0 Photon score= -7.02 Pion score= -6.02

Scores are $log(\mathcal{L}(class|x))$

Majority of pixels are of an electron: but it is an electron from the decay of a charged <u>pion</u>.

Manipulated Prong image



Manipulated Context Image



<u>Original Scores</u> Electron score= -0.01 Photon score= -5.02 Pion score= -8.63

Scores are $log(\mathcal{L}(class|x))$

Pion score drops significantly

Change the pion+electron stub into electron shower (from another event)

Image

Manipulated Context

Manipulated Prong image



<u>Original Scores</u> Electron score= -7.9 Photon score= 0.0 Pion score= -12.8

Scores are $log(\mathcal{L}(class|x))$

Gap moves classification to photon (despite shower trunk dE/dx being that from electron)

Move electron shower and detach from vertex

Manipulated Prong image



Manipulated Context Image



Move electron shower and detach from vertex

Original Scores Electron score= -7.9 Photon score= 0.0 Pion score= -12.8

Scores are $log(\mathcal{L}(class|x))$

Work on-going to more quantitatively interrogate the use of valuable context image: e.g. how about examples near/far outside the training sample kinematic domain?

The Proof of the Pudding is in the Eating

Ultimately, sufficient quality of these tools is in the ability to do physics. Testing with inclusive CC electron-neutrino and muon-neutrino

- · Selection simply utilizes:
 - Basic reconstruction quality cuts
 - Neutrino vertex found by LArMatch, doesn't overlap with tagged cosmic activity
 - Cuts on LArPID particle scores
 - No muon tracks
 - One forward-going electron shower identified with high confidence (high electron score, low photon and pion scores)

Inclusive CC Nue Selection Efficiency/Purity

- Backgrounds included: cosmic, CC numu, NC numu, and NC nue
- · Selection purity above 80%, efficiency rises above 60% around 1 GeV
- Caveat: MC samples used to calculate purity and efficiency numbers were also used in prong CNN training (additional MC simulation not available in time)
 - Large training sample, not much over-fitting
- · Selection is preliminary, performace will increase as selection criteria are refined



Inclusive CC nue Selection MC Predictions

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- We ran our new selection on a small MicroBooNE open data set
- New probable CC v_e events were found!
 - Event displays for four low-energy probable CC $\nu_{\rm e}$ events not identified in other reconstruction frameworks are shown on the following slides

Results still in the works, but have not yet seen signs of large problems due to domain shift

Example Data Event Selected

Reconstructed neutrino energy: 305.6 MeV







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Cosmic Removed 3D points and Clusters

Run 5339 Subrun 115 Event 5764



Example Data Event Selected



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- <u>New MicroBooNE reconstruction workflow completed</u>
 - Represents only a subset of all the ML work done on MicroBooNE
- Makes use of CNNs that greatly ease the task of 3D spacepoint reconstruction
- We have applied the outputs for a CC inclusive selection and early tests show promise
 - No large data/MC disagreement yet seen
 - Competitive with past analyses
- Public note on this selection coming soon (check out Matt Rosenberg's poster at Neutrino 2024)



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