Translating Near to Far Detector with Deep Learning for DUNE-PRISM

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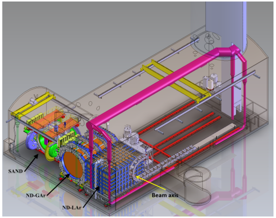
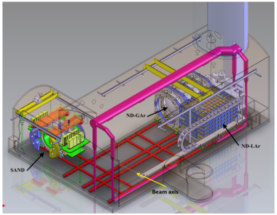
DEEP UNDERGROUND
NEUTRINO EXPERIMENT

DUNE Detectors

- Far Detector (FD)
  - → Multiple 17kt LArTPCs with wire readout
- Near Detector (ND) complex:
  - → ND-LAr
    - → Primary LAr target at ND
    - → Designed for high intensity neutrino beam — modular optically isolated drift volumes and pixel readout
  - → Muon spectrometer (Phase 1) + Gaseous Ar target (Phase 2)
  - → System for on-Axis Neutrino Detection (SAND) — beam monitor
  - → Precision Reaction Independent Spectrum Measurement (PRISM)
    - → ND-LAr + muon spectrometer able to move up to 33m off-axis from beam
    - → Sample different fluxes from neutrino beam



↓ PRISM!



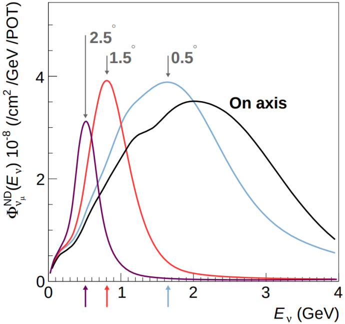
PRISM

- ND supports long-baseline oscillation measurements by constraining elements in convolution:

$$N_\nu^{near}(E_{rec}) = \int dE_\nu \, \phi_\nu^{near}(E_\nu) \times \sigma_\nu^{Ar}(E_\nu) \times D_\nu^{near}(E_\nu, E_{rec})$$

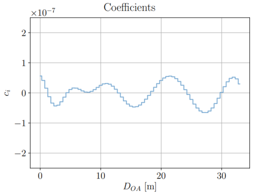
$$N_\nu^{far}(E_{rec}) = \int dE_\nu \, P_{osc}(E_\nu | \boldsymbol{\theta}) \times \phi_\nu^{far}(E_\nu) \times \sigma_\nu^{Ar}(E_\nu) \times D_\nu^{far}(E_\nu, E_{rec})$$

- PRISM allows for ND measurements at different fluxes
  - → Helps break degeneracies in fitting simulation to data from a single observation



PRISM Linear Combination

- Off-axis positions can be linearly combined to make approximate a target FD oscillated flux from ND measurements



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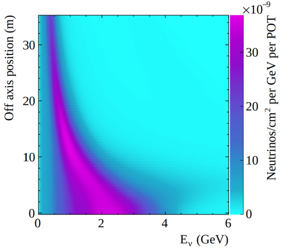

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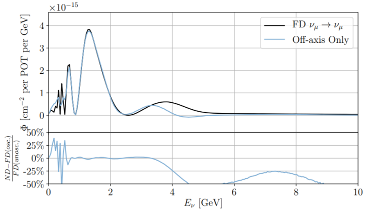
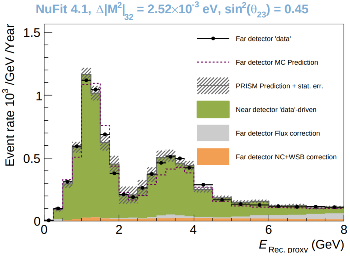


- "PRISM style" oscillation analysis:
  - $\rightarrow$ Calculate weights $\boldsymbol{c}$ for an oscillation hypothesis

$$\phi_\nu^{near}(E_\nu, x_{OA}) \times \boldsymbol{c} = \phi_\nu^{far}(E_\nu)\, P_{osc}(E_\nu | \boldsymbol{\theta})$$

  - $\rightarrow$ Multiply ND data by weights to get ND measurement in FD oscillated flux
  - $\rightarrow$ Extrapolate to FD to get data-driven FD prediction
  - $\rightarrow$ Compare with FD data to get likelihood of oscillation hypothesis

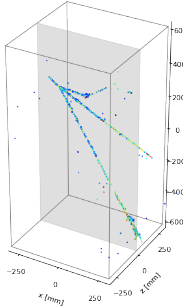


Translating from Near to Far

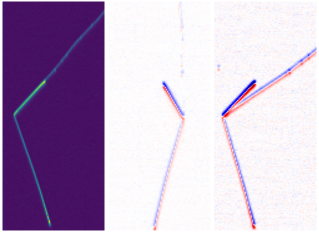
- Producing FD prediction from ND measurements in oscillated flux requires correcting for backgrounds, selection, and resolution
  - → Data-driven methods for backgrounds and for selection due to containment under development
  - → Still need to understand differences in energy resolution and particle identification

- Apply machine learning by treating ND and FD detector response as images from two domains of detector technology
- Initial focus on translating events contained in ND-LAr
- Complete translation requires:
  - → Infilling non-active regions between ND drift modules (later slides)
  - → Incorporate muon spectrometer reconstruction

Near Detector



Far Detector



Generating Paired Data

- Generate paired data by simulating the same charge depositions at both detectors
- Put pairs into same coordinate system by projecting each 3D ND pixel response onto a wire and time for each wire plane

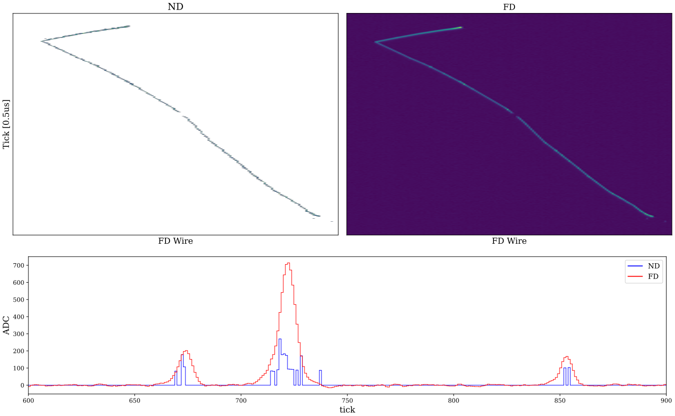
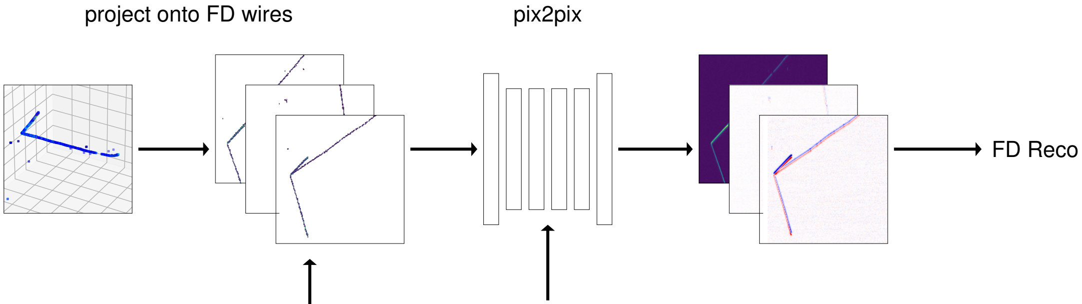


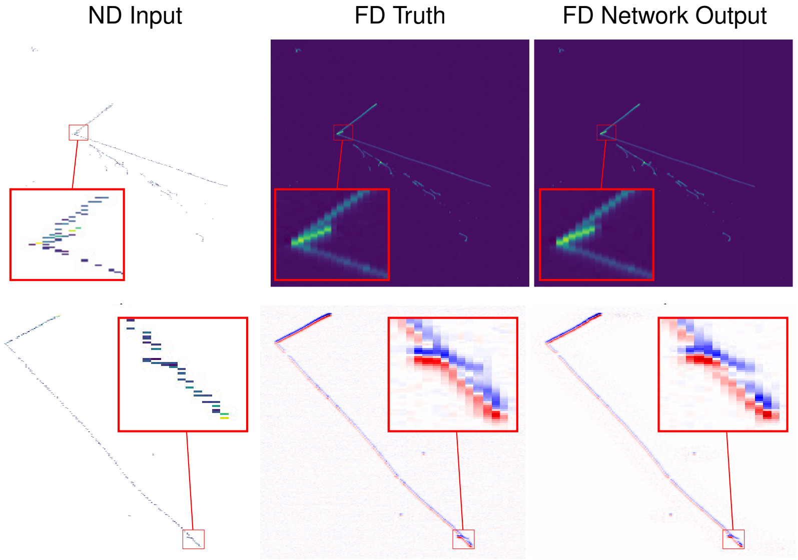
Image-to-Image Translation w/ pix2pix



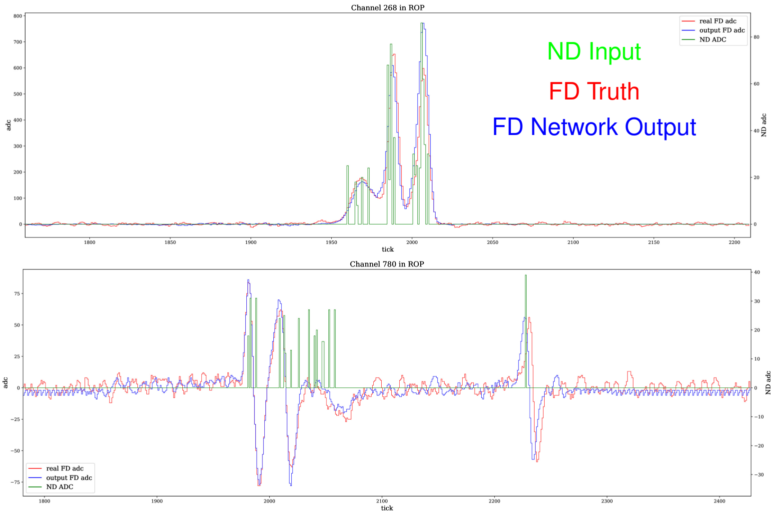
- Full FD resolution projection
- Input channels include ADC, wire projection info, ND + FD drift distances

- Conditional GAN architecture
- 9-block ResNet generator with up/downsampling layers
- PatchGAN discriminator
- L1 loss applied in signal region only

Results - Image Translation

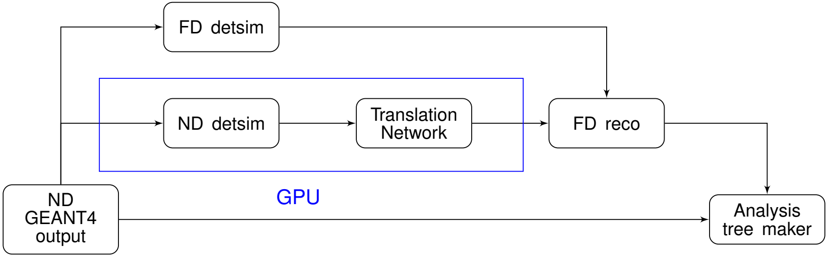


Results - Wire Trace

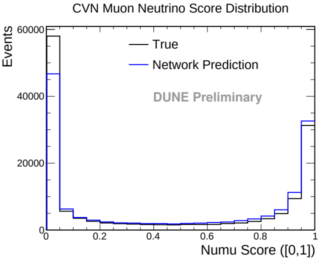


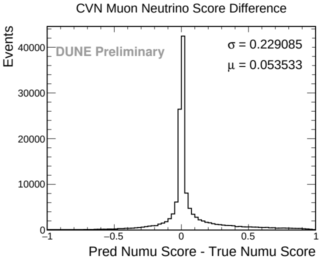
Evaluating with Reconstruction

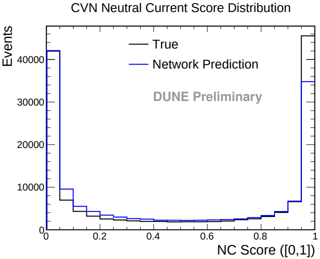
- Use torchscript + libtorch to import trained model into C++ to use in FD simulation chain
- Generate analysis files for ND events with predicted FD reconstruction from network
  → And ”true” FD reco from resimulating charge depositions at FD
- Key reco variables:
  → CVN scores: CNN acting on hits to classify neutrino flavour
  → Reconstructed neutrino energy: calorimetric energy reconstruction

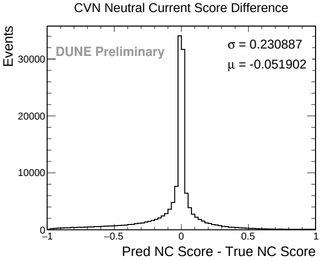


CVN scores

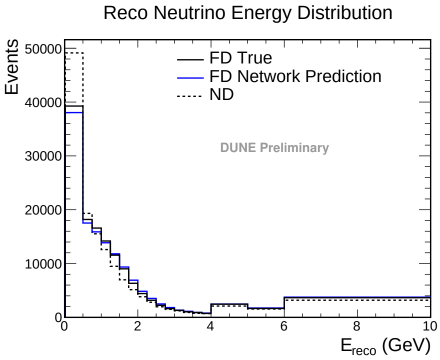

CVN Muon Neutrino Score Distribution
Events
60000
40000
20000
0
0
0.2
0.4
0.6
0.8
1
Numu Score ([0,1])
True
Network Prediction
DUNE Preliminary

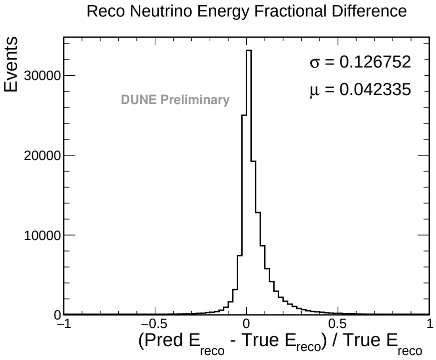

CVN Muon Neutrino Score Difference
Events
40000
30000
20000
10000
0
−1
−0.5
0
0.5
1
Pred Numu Score - True Numu Score
DUNE Preliminary
σ = 0.229085
μ = 0.053533


CVN Neutral Current Score Distribution
Events
40000
30000
20000
10000
0
0
0.2
0.4
0.6
0.8
1
NC Score ([0,1])
True
Network Prediction
DUNE Preliminary


CVN Neutral Current Score Difference
Events
30000
20000
10000
0
−1
−0.5
0
0.5
1
Pred NC Score - True NC Score
DUNE Preliminary
σ = 0.230887
μ = -0.051902

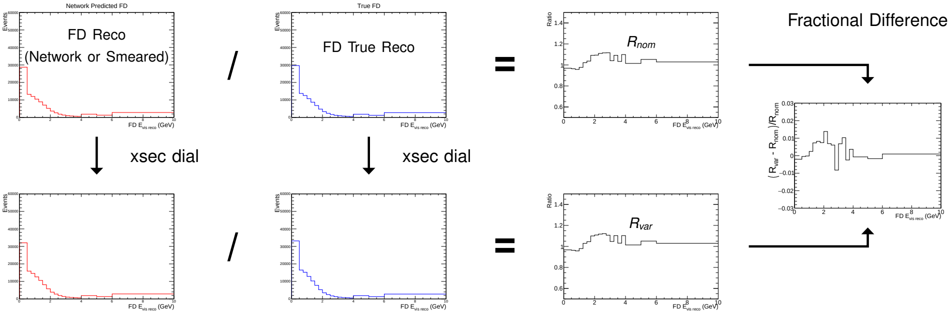
Reconstructed Energy





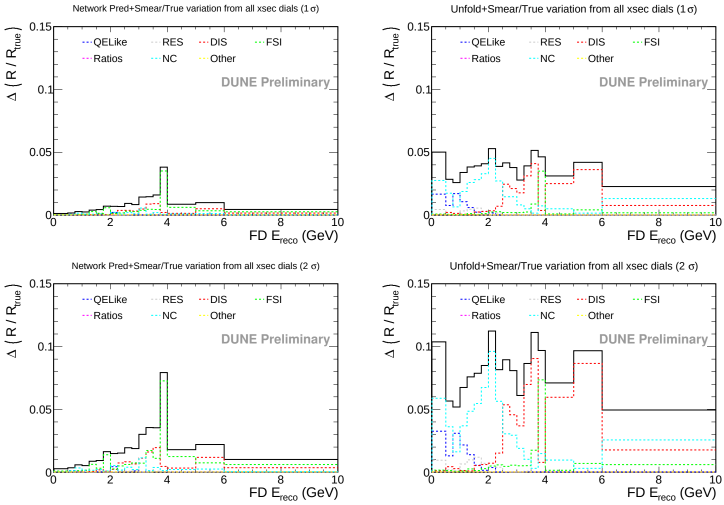
Cross Section Systematics

- Consider how the network predicted FD reconstructed energy varies under cross-section systematic reweighting
  - $\rightarrow$ Compare with smearing matrix approach — using MC to unfold $E_{rec}^{ND} \rightarrow E_{\nu}$ and smear $E_{\nu} \rightarrow E_{rec}^{FD}$
- Want cross section systematics to cancel between prediction and data
  - $\rightarrow$ Look ratios of FD predicted spectra with ”true” FD spectrum under systematic reweights



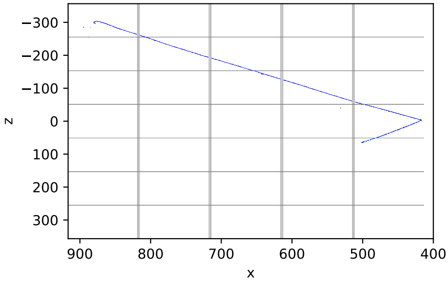
Results - Cross Section Reweighting

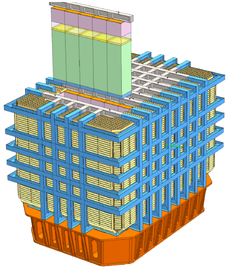
- All cross section reweights added in quadrature at 1 and 2 σ



Filling in Dead Regions in ND-LAr

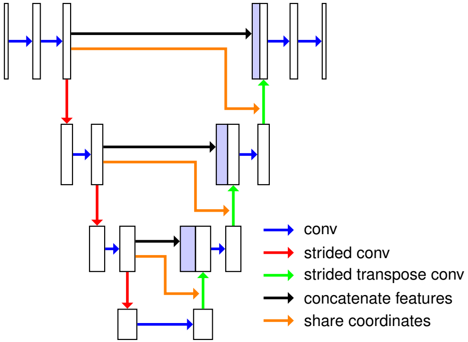
- Time to face a caveat — need to predict FD detector response in the non-active ND regions between drift modules to correctly translate
- Difficult to do this after wire projections since positions of gaps are not well defined in this projection
- Attempt to infill gaps between drift modules at the 3D pixel response level





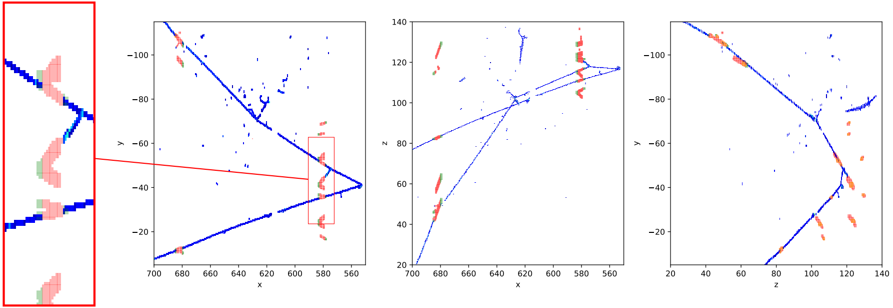
ML with Sparse Tensors

- Consider generating detector response in the non-active region as an inpainting problem in 3D
- Voxelised ND-LAr has size $\mathcal{O}\left(10^9\right)$ — need to use sparse tensors
  - $\rightarrow$ A sparse tensor is an N dimensional extension of a sparse matrix
  - $\rightarrow$ MinkowskiEngine is a library that implements all standard neural network layers for sparse tensors
- Implement a U-Net architecture using sparse tensor layers

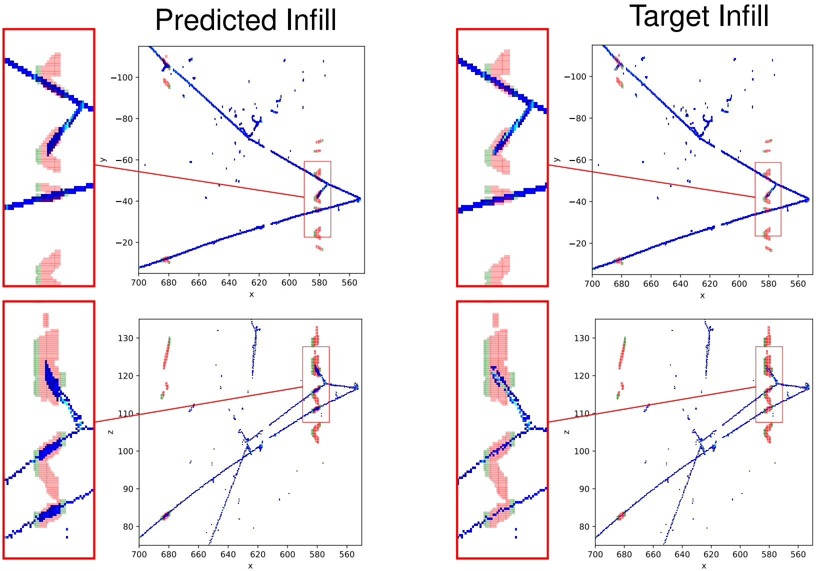


Training to Infill

- Create training data by removing voxels using a randomly shifted mask of ND-LAr's drift module gaps
- Architecture requires all relevant coordinates to be defined in input
  - → Use active pixels neighbouring the gaps to make reflections into gaps
  - → Smear the reflected pixels to produce a mask of expected infill coordinates



Infill Results — Early!



Summary

- PRISM allows oscillation physics to be studied with very little model-dependence if detector extrapolation is handled well

- Developed image-to-image translation approach to extrapolation
  - → Generated paired ND-FD dataset
  - → Model predictions show good agreement with truth for FD reconstruction
  - → Demonstrated network removes a significant fraction of cross-section uncertainty compared to MC smearing

- Developed infill network to fill gaps in ND before translation
  - → Using U-Net for sparse tensors
  - → Initial results promising — more model tuning and exploration to do

Thank you!