End-to-End Machine Learning Reconstruction for the Short Baseline Near Detector

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On Behalf of the SBND Collaboration

NPML 2025

October 29, 2025

Short Baseline Near Detector (SBND)

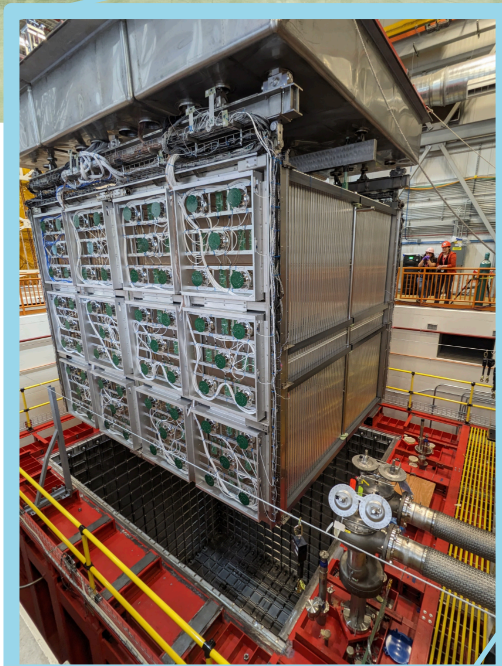
- Precision ν-Ar cross-sections
- Hunt for sterile neutrinos
- Beyond standard model searches

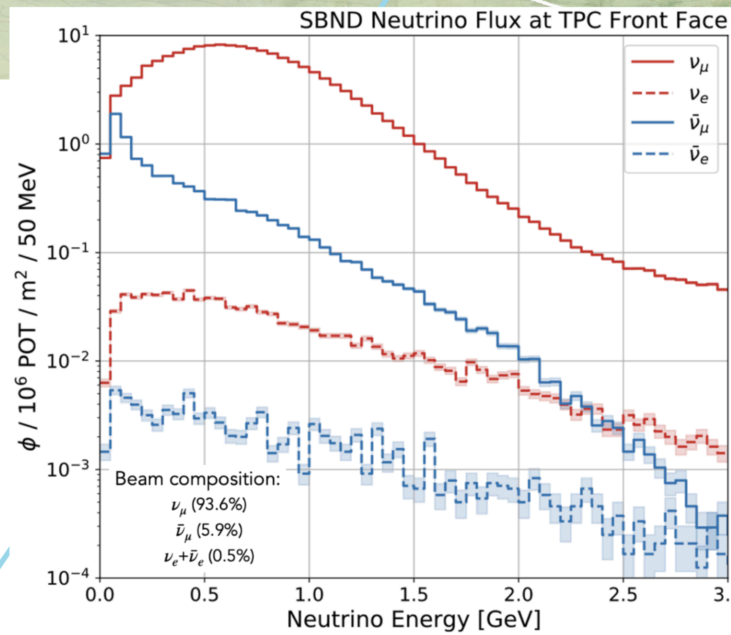
112 ton LArTPC

110 m from BNB target

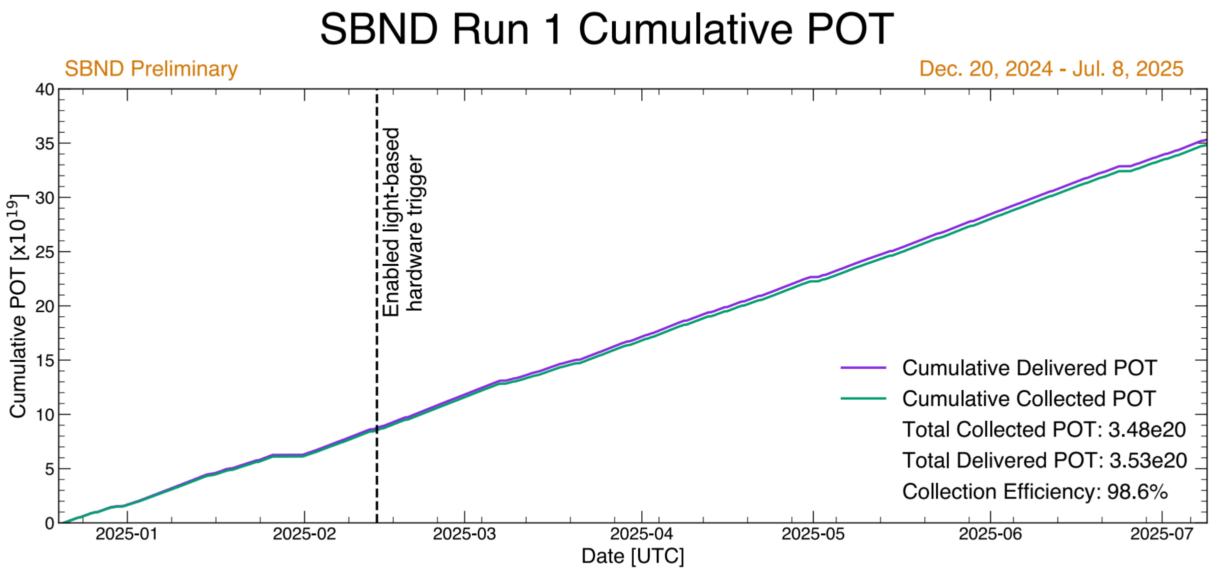
First ν **July 2024**

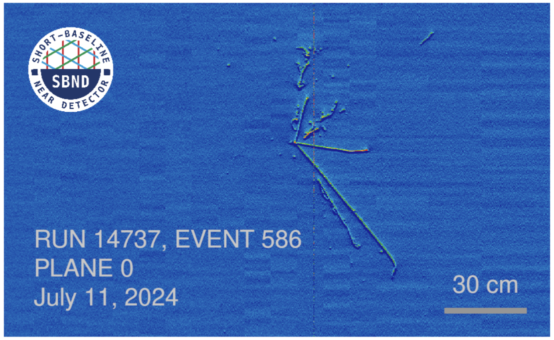
Largest ν-Ar dataset to date

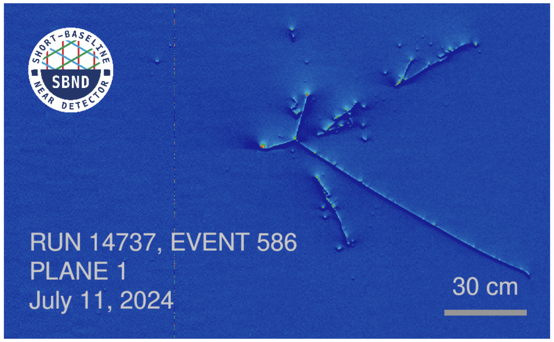


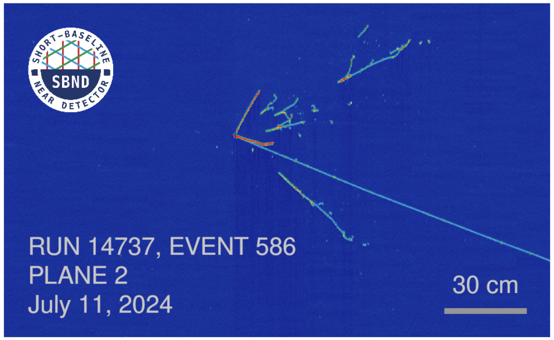


SBND Data Taking



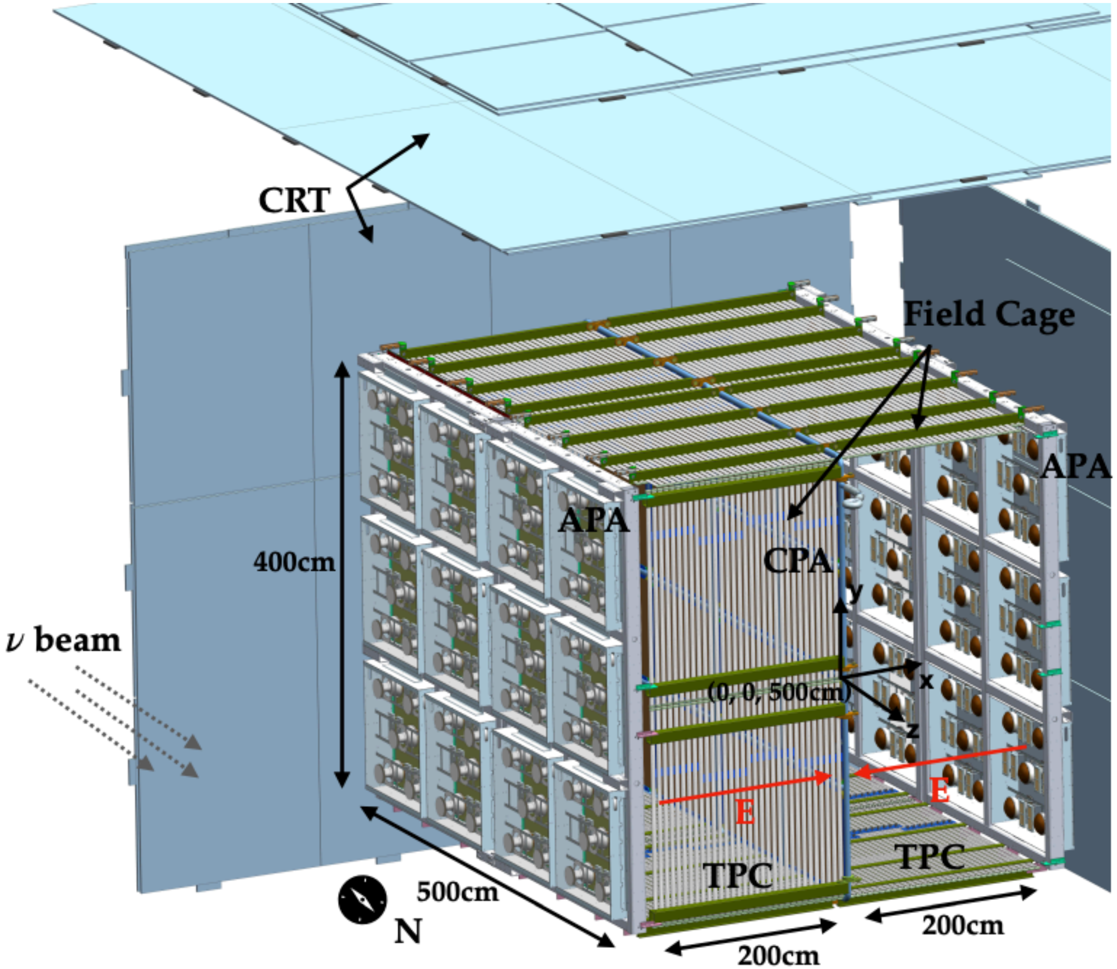






- Run 1 collected neutrinos from > 3.48e20 POT already equivalent to **3M NC & CC neutrino interactions**
- Expect **millions of neutrino interactions** for SBND's lifetime (10e20 POT)

SBND Specifications

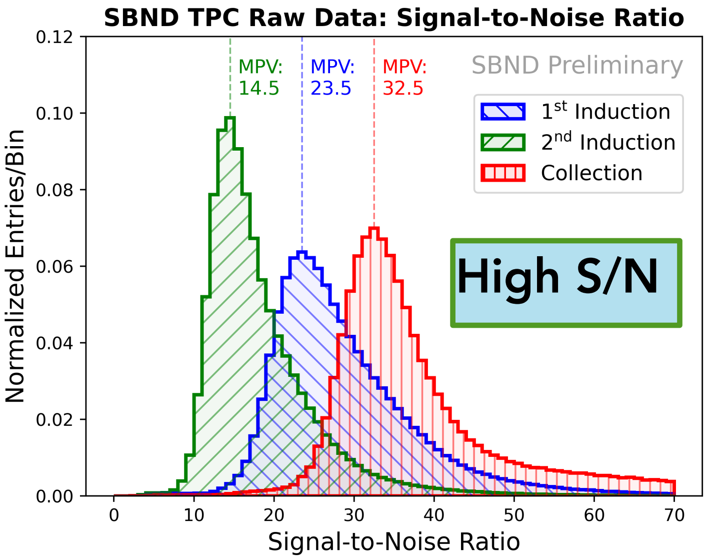


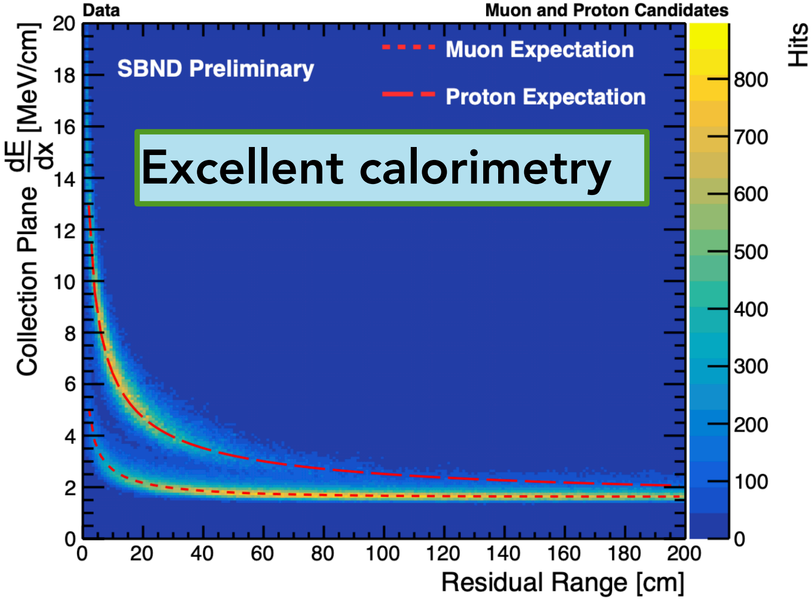
- SBND is a monolithic LArTPC with **2 TPCs** divided by a cathode plane assembly (CPA) [1]
- **3 mm** wire and inter-plane spacing
- Photon detection system has **17% coverage** of each APA wall [2]
- External cosmic ray tagger (CRT) with **4π coverage**

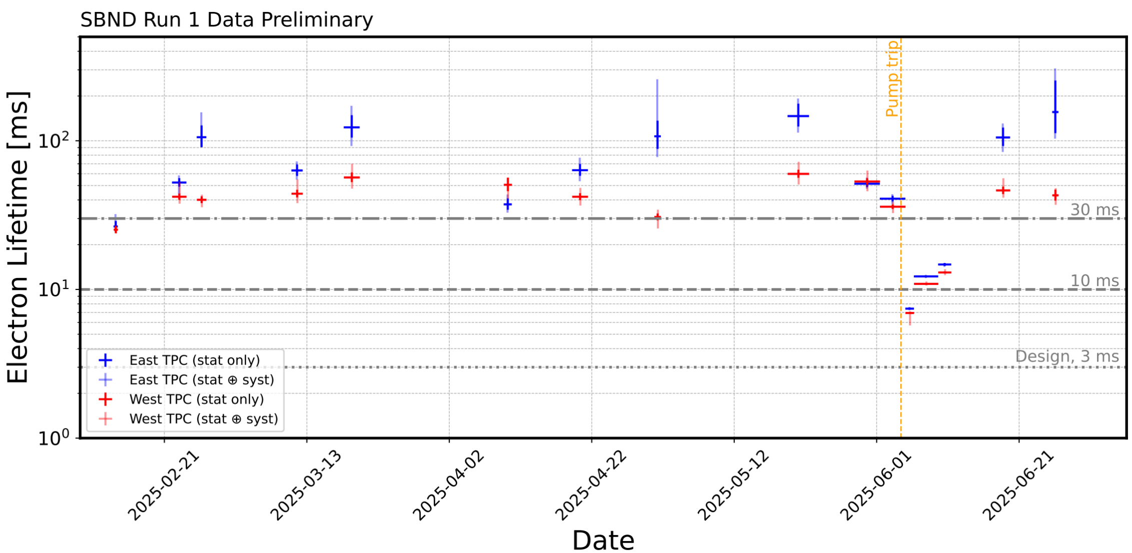
[1] Construction of precision wire readout planes for the Short-Baseline Near Detector (SBND) arXiv:2002.08424

[2] Scintillation Light in SBND: Simulation, Reconstruction, and Expected Performance of the Photon Detection System arXiv:2406.07514

Calibrations and Detector Performance







Stable operation conditions

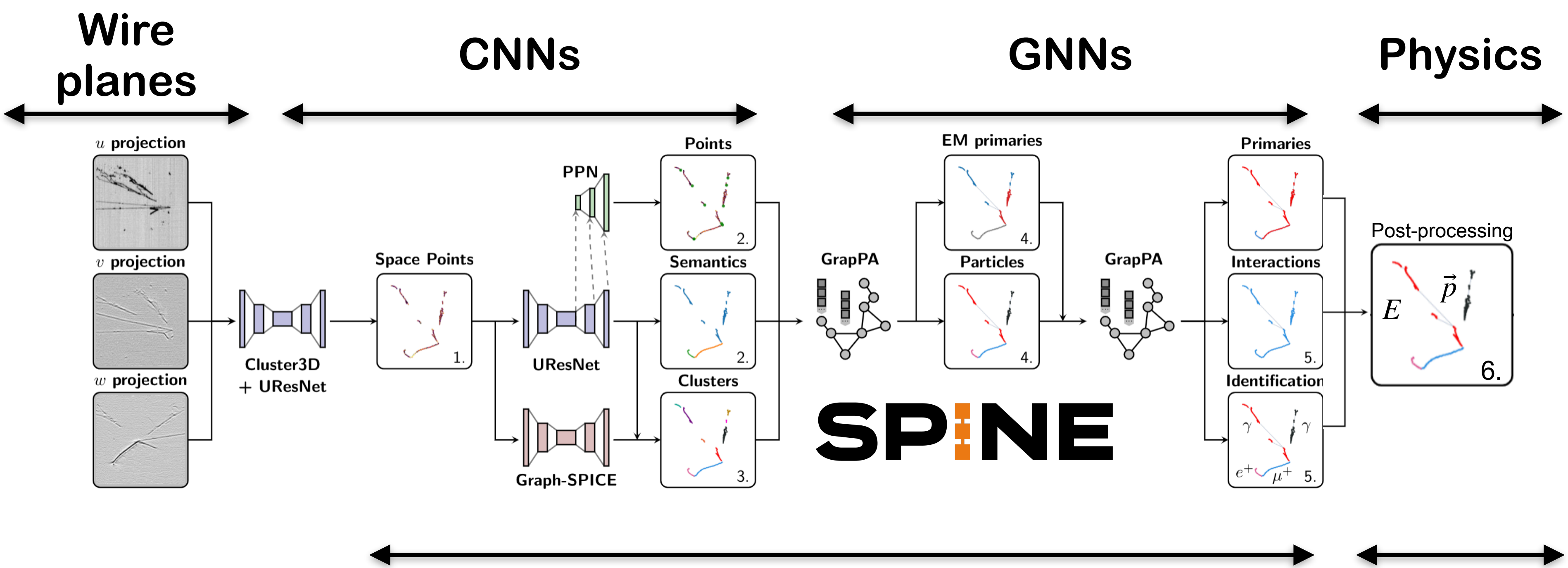
SPINE *for SBND* [3]

SPINE (**S**calable **P**article **I**maging with **N**eural **E**mbeddings) [4]

Fast - Process the entire SBND dataset (full 3 year data-taking) in 2 weeks

Automated - Only requires training, minimal manual optimization needed

Effective - High purity and efficiency neutrino identification and reconstruction



0.5 s / event **1 s / event**

[3] B. Carlson, Machine-Learning-Based Data Reconstruction Chain for the Short Baseline Near Detector, SLAC FPD Seminar

[4] F. Drielsma, K. Terao, L. Dominé, D.H. Koh https://arxiv.org/abs/2102.01033

SPINE *for SBND* [3]

SPINE (Scalable Particle Imaging with Neural Embeddings) [4]

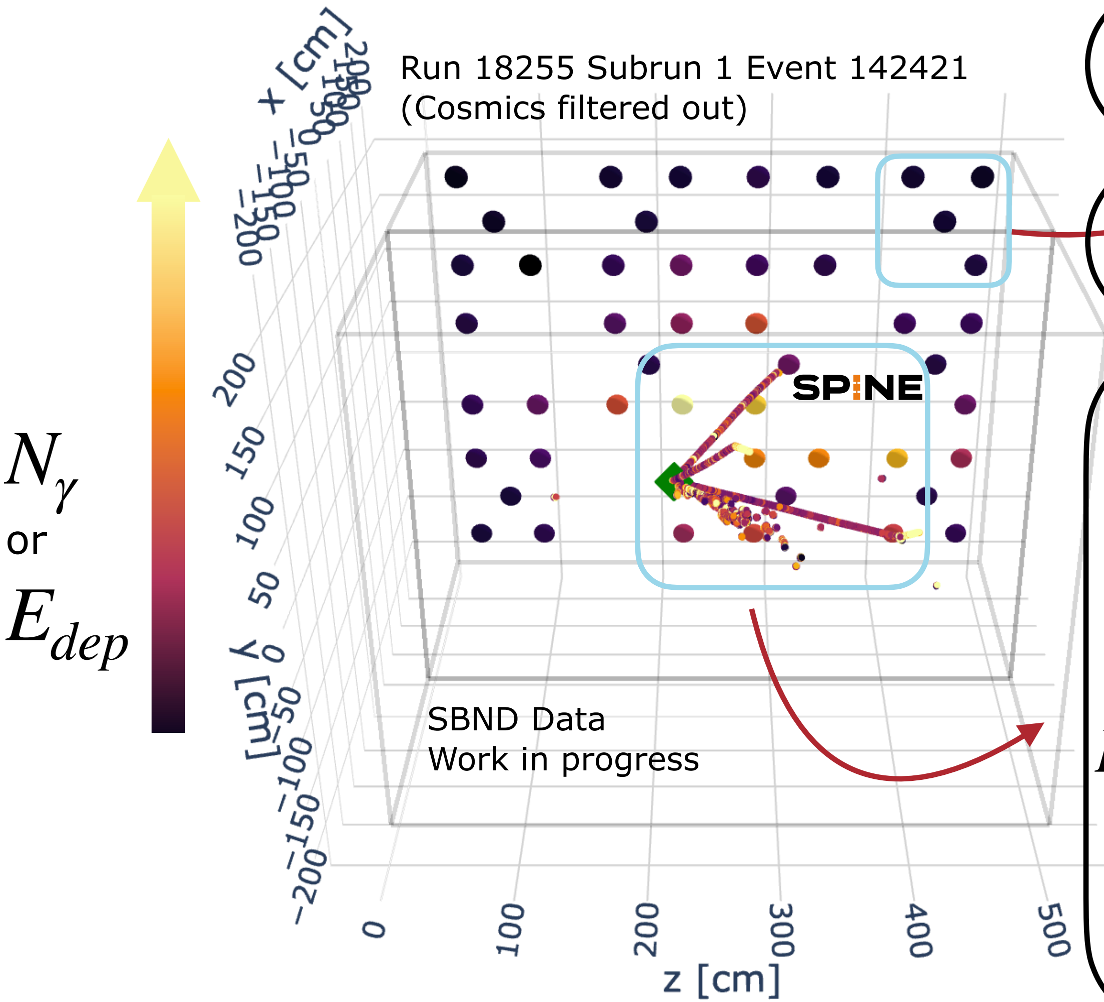
- **Fast** - Process the entire SBND dataset (full 3 year data-taking) in 2 weeks
- **Automated** - Only requires training, minimal manual optimization needed
- **Effective** - High purity and efficiency neutrino identification and reconstruction

See SLAC FPD Seminar for SBND full chain performance

[3] B. Carlson, Machine-Learning-Based Data Reconstruction Chain for the Short Baseline Near Detector, SLAC FPD Seminar

[4] F. Drielsma, K. Terao, L. Dominé, D.H. Koh https://arxiv.org/abs/2102.01033

Complimentary Subsystems



CRT
not used in SPINE yet

~ns timing resolution
~few cm resolution

PDS
N_γ

~ns timing resolution
~10s cm resolution

TPC
leverages detector calibrations

~ms timing resolution
3 mm resolution

Work function for Ar

Recombination

Deposited Charge

$$E_{dep} = W_i \cdot C_{calo} \cdot \frac{1}{R} \cdot e^{t/\tau} \cdot Q$$

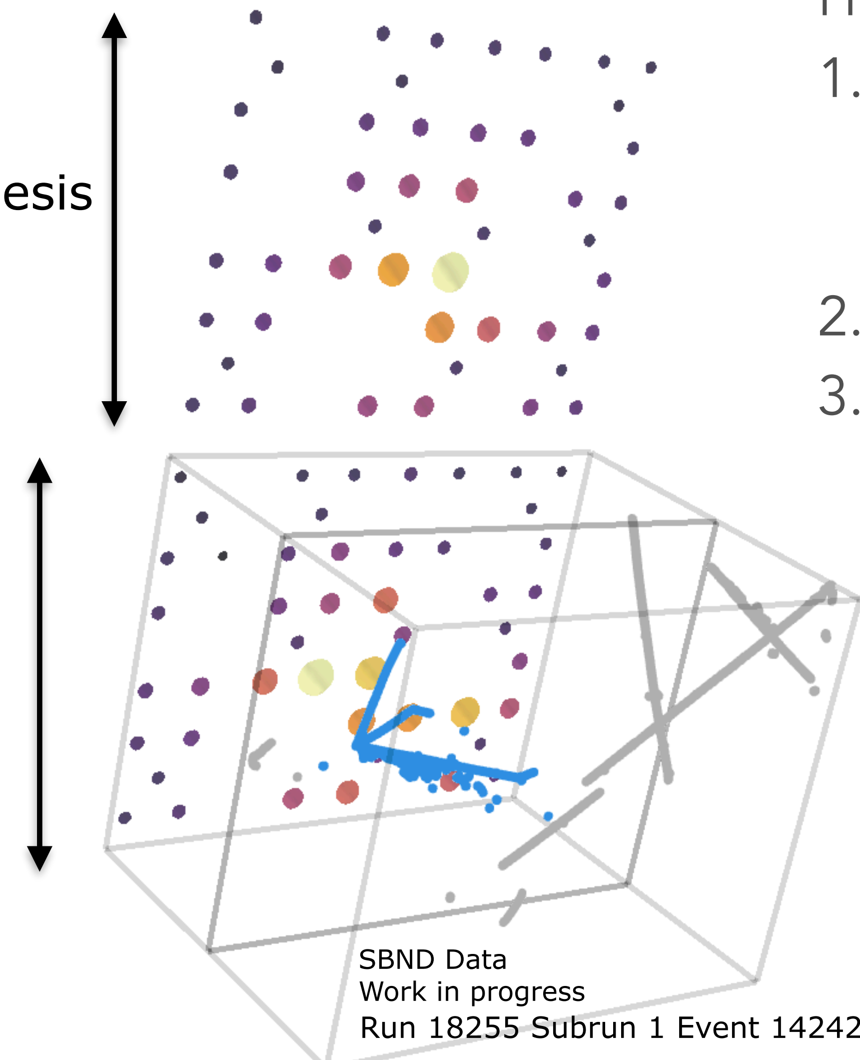
$[e^-/\mathrm{ADC}]$
Calorimetric constant (TPC gain)

Electron lifetime correction

Flash Matching

Hypothesis flash

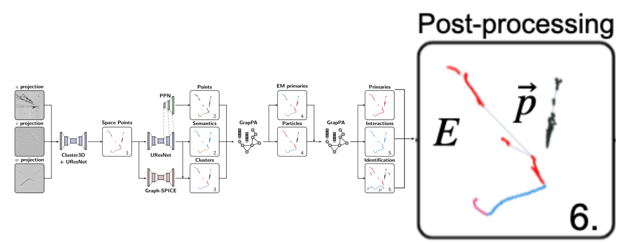
PMT flash



How do we use **light information?**

1. Compute hypothesis (H) from charge in interaction using semi-analytical model [5]
2. Flash score calculated using χ^2
3. Select interaction that matches flash (R) with lowest χ^2

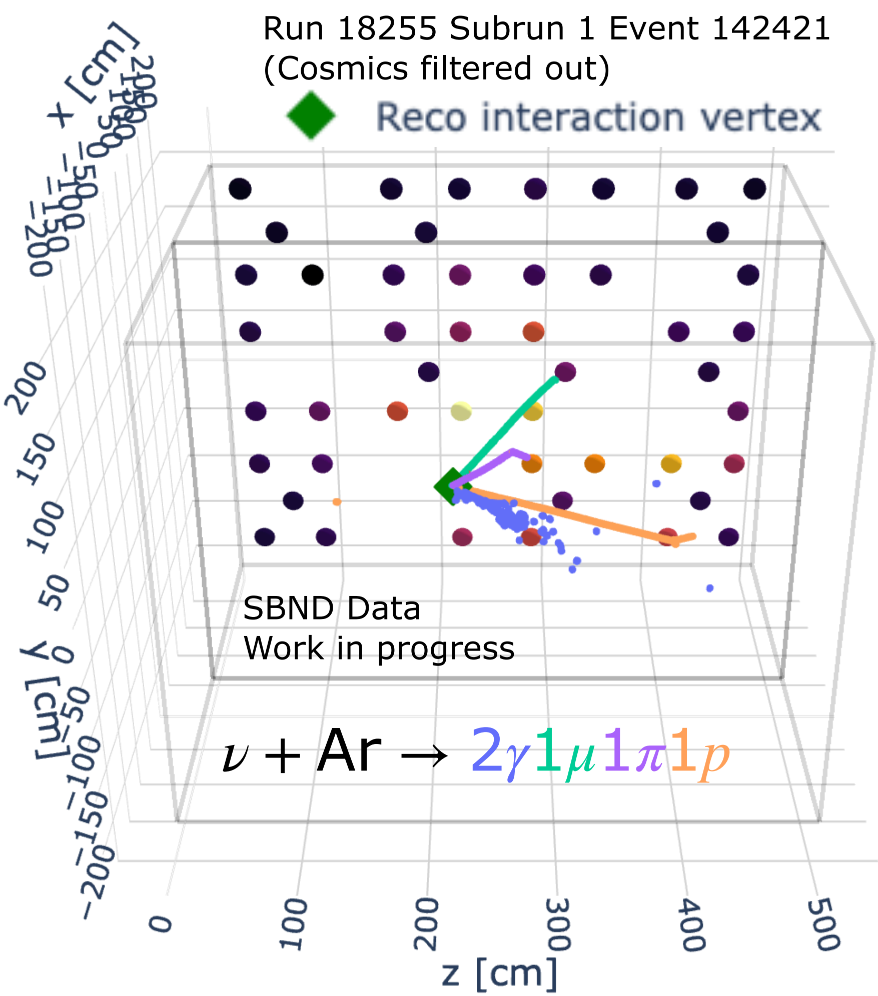
$$\chi^2 = \frac{1}{N_{PDS}} \sum_i \frac{(R_i - H_i)^2}{R_i}$$



[5] D. Garcia-Gamez, P. Green, A.M. Szelc
Eur. Phys. J. C 81, 349 (2021)

SBND SPINE Analyses

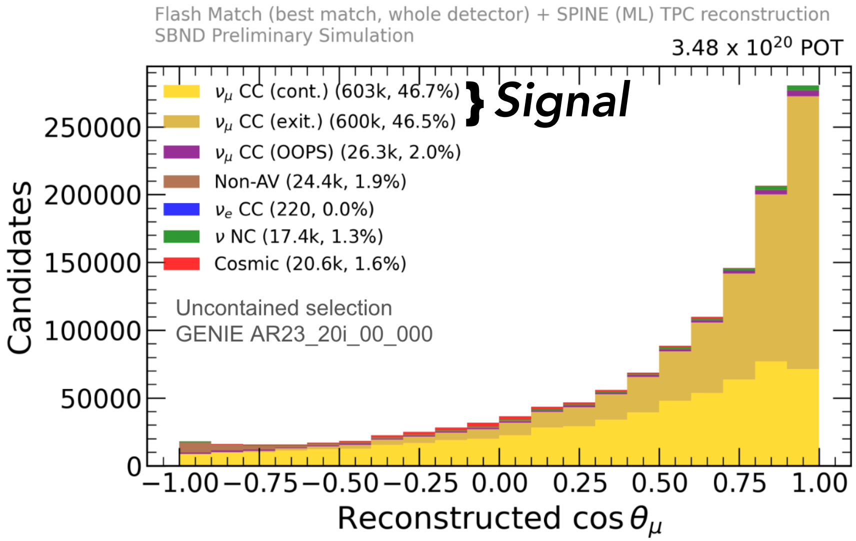
ν_μ CC Inclusive Selection

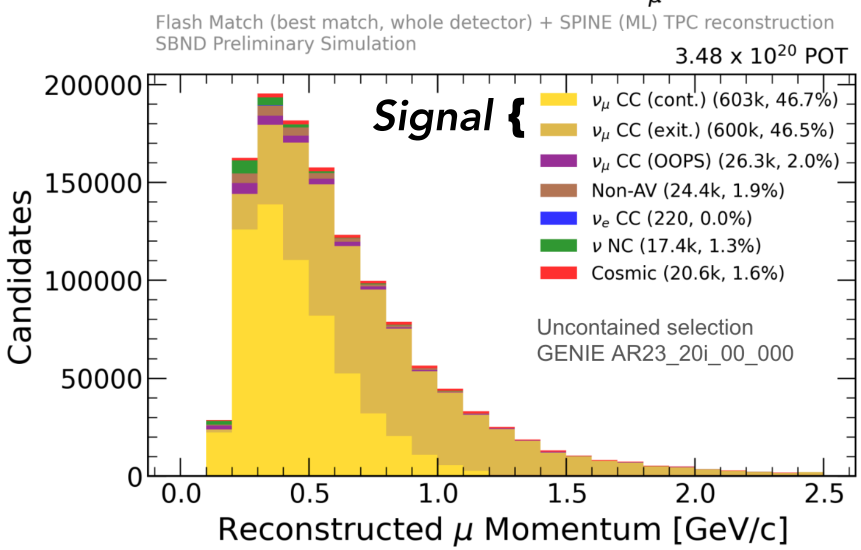


PID

- Utilize SPINE to select ν_μ CC candidate and muon
- Demonstrate ability to reject cosmics - largest background
  - >90% interactions pre-cuts
- Cross section and ν_μ disappearance searches
- Probe final state muon kinematics where there are minimal nuclear effects

ν_μ CC Inclusive Selection





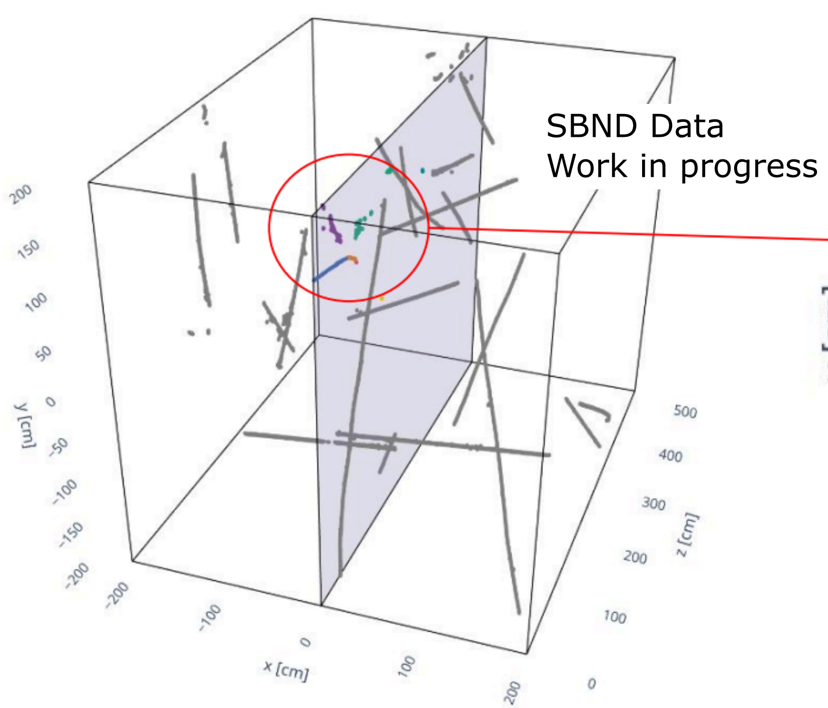
- Utilize SPINE to select ν_μ CC candidate and muon
- Demonstrate ability to reject cosmics - largest background
  - >90% interactions pre-cuts

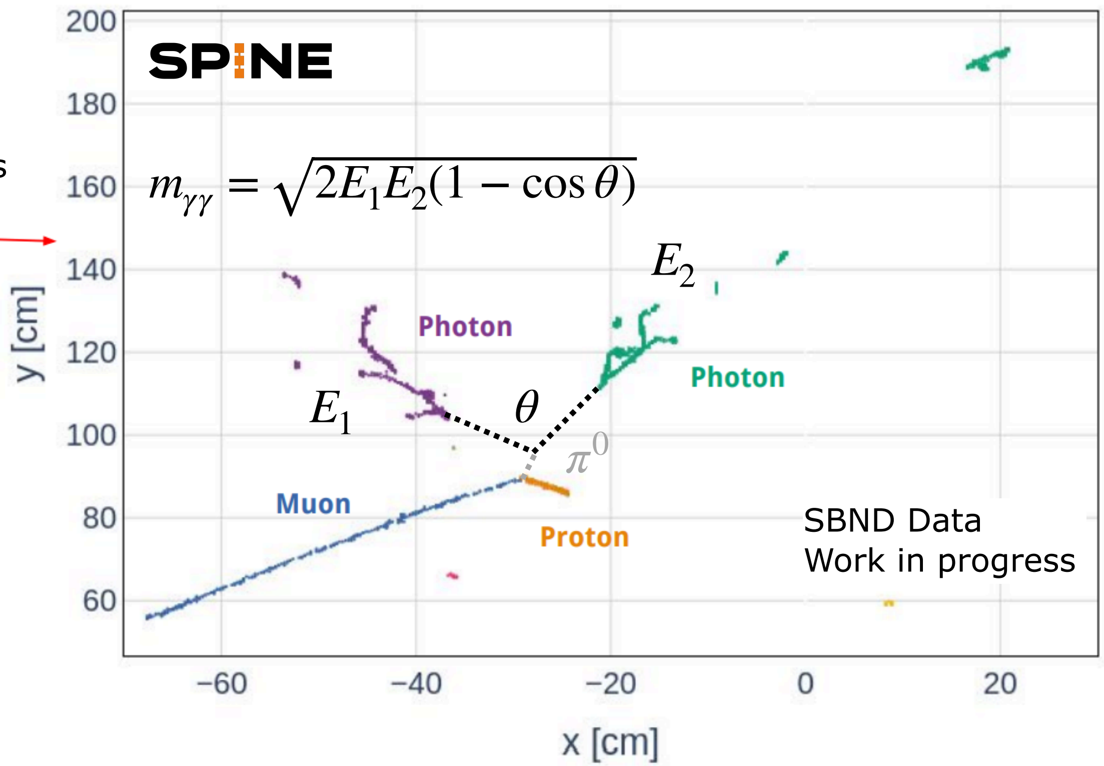
Contained	Contained or exiting
Purity = 93%	Purity = 93%
Efficiency = 91%	Efficiency = 79%

- Cross section and ν_μ disappearance searches
- Probe final state muon kinematics where there are minimal nuclear effects

π^0 Selections

- Background for electron searches
- Detector calibration, ensure $m_{\gamma\gamma}$ agrees with m_{π^0}
- Important for cross section measurements

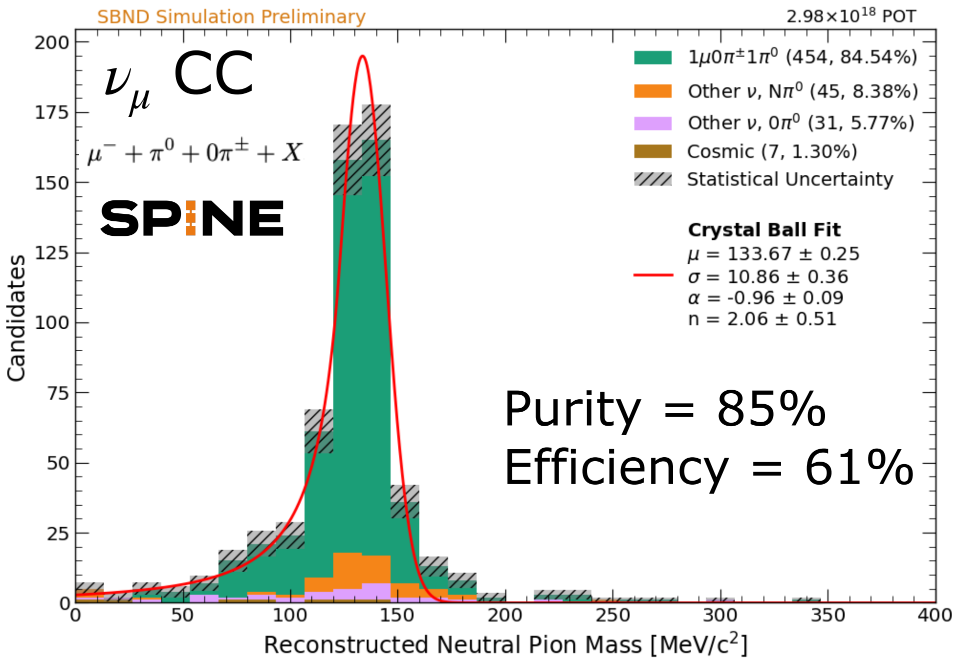


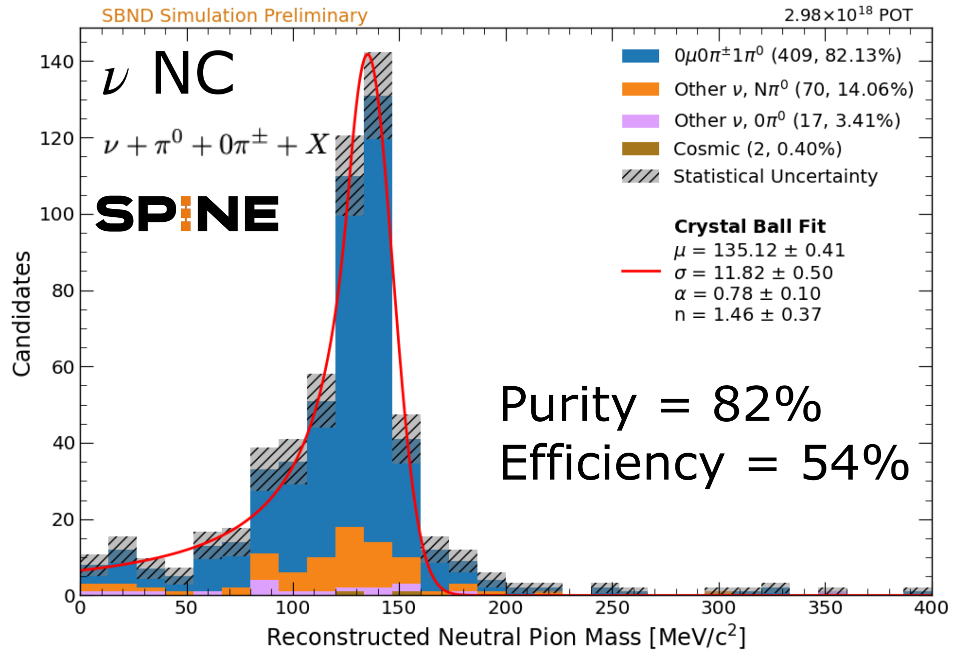


π^0 Selections

- Background for electron searches
- Detector calibration, ensure $m_{\gamma\gamma}$ agrees with m_{π^0}
  - Sharp peak for selected π^0 -> excellent shower reconstruction
- Important for cross section measurements

m_{π^0} = 134.98 MeV/c^2 [5]

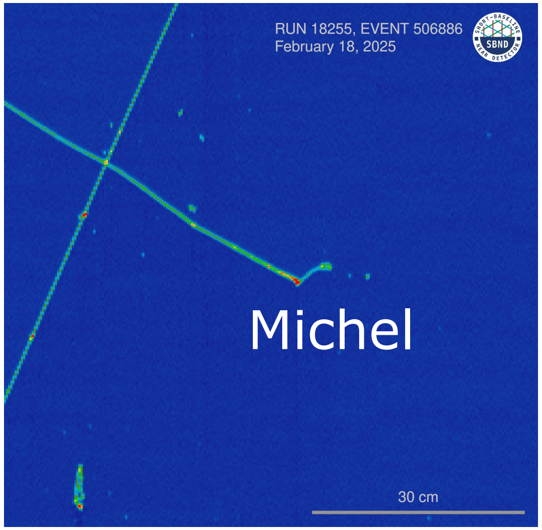


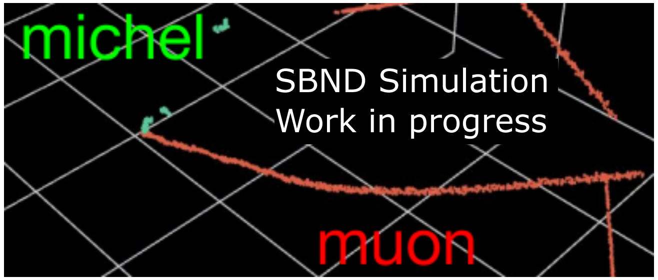


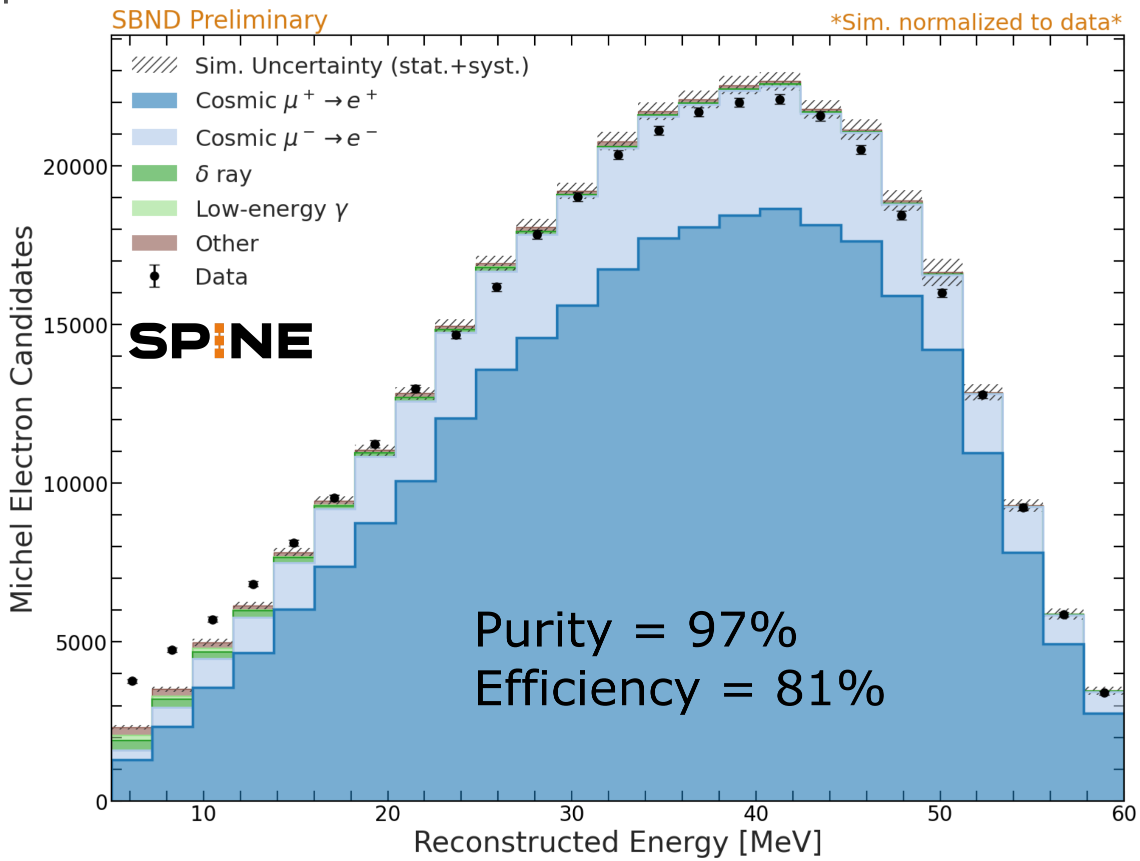
[5] https://pdglive.lbl.gov/Particle.action?node=S009

Michel e- Selection

- Michel electrons from decaying electrons from muons
- Useful for low energy calibrations, probe low E with unprecedented precision

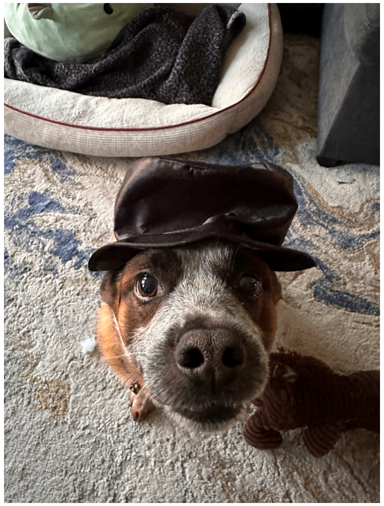






Conclusion

- SBND is calibrated and exhibits *excellent* performance
- Already collected 1yr or around **3M neutrino interactions** to-date
- SBND SPINE has many mature selections, ready to compare to data
  - Early simulation selections show promising performance
  - Michel selection can probe low energies with high purity sample




Thanks!

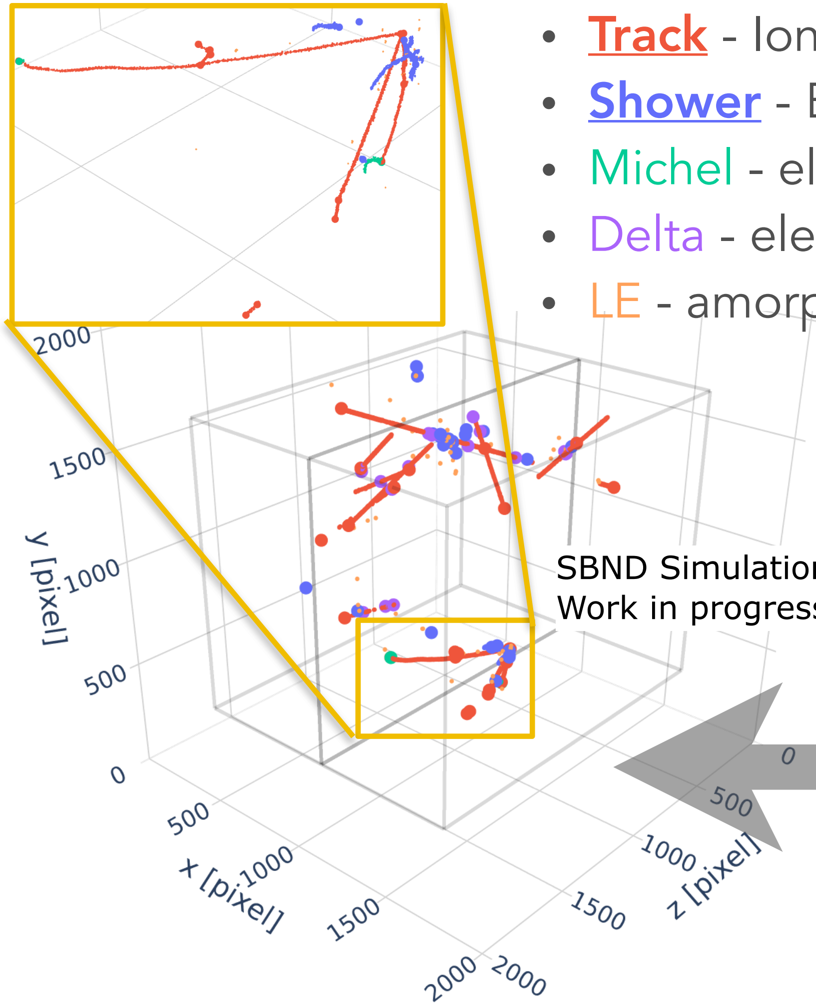
SBND Collaboration Meeting, Sheffield, June 2025

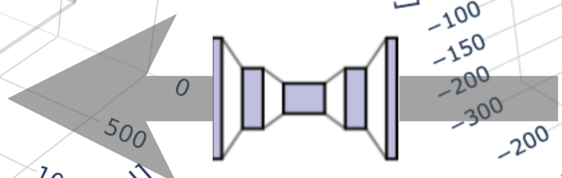
Semantic Segmentation

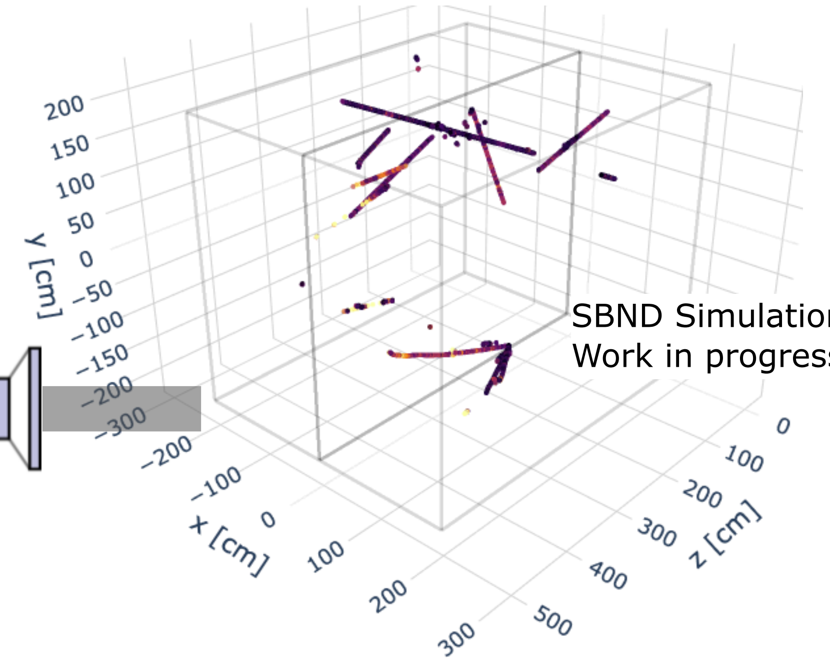
- Track - Ionizing, rectilinear, continuous
- Shower - EM shower
- Michel - electron from muon decay
- Delta - electron from track interaction
- LE - amorphous blips

Primaries

Secondaries





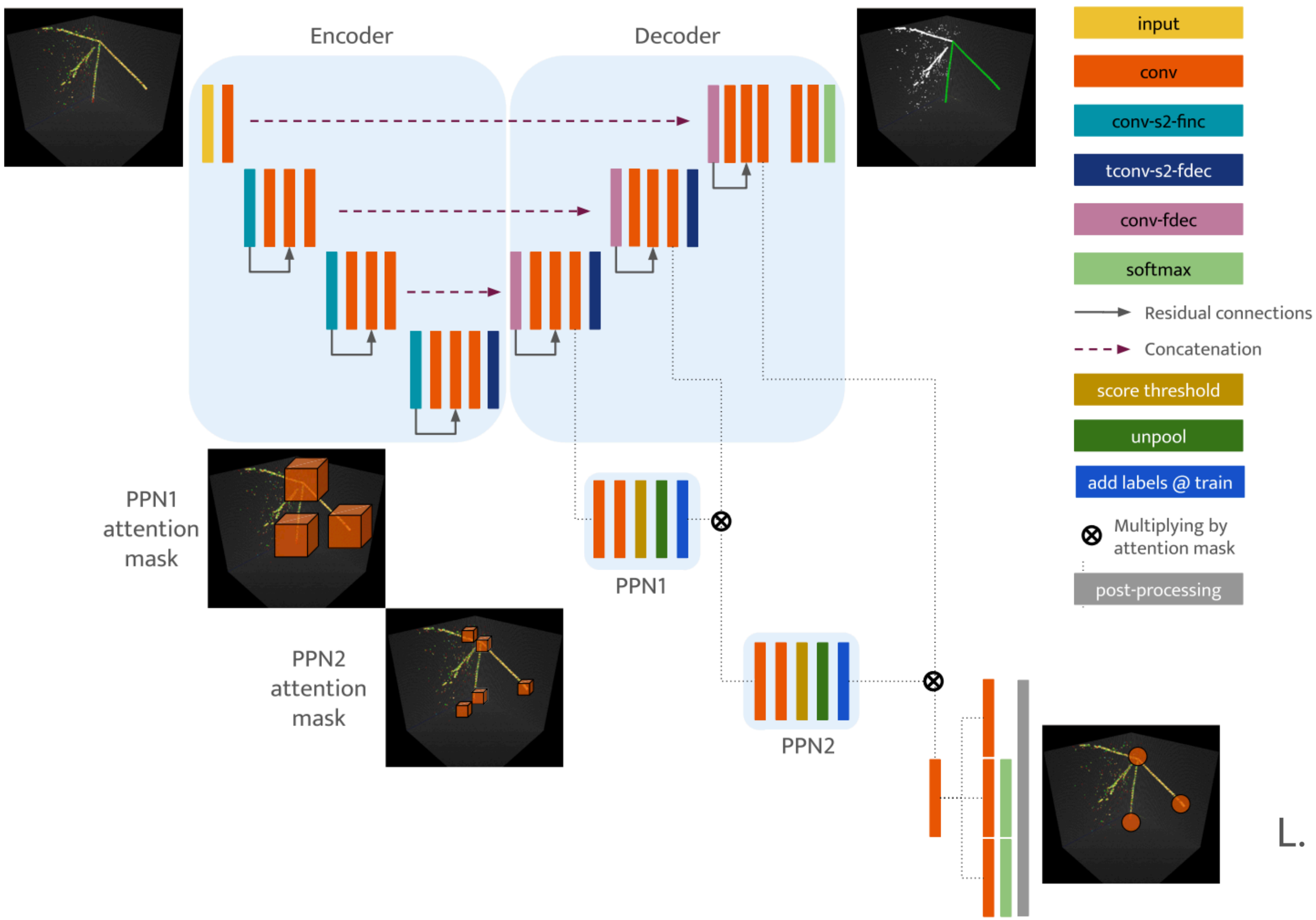


Neutrino + Cosmics

Deghosted Charge

PPN

- Point proposal network (PPN) learns attention mask for points of interest

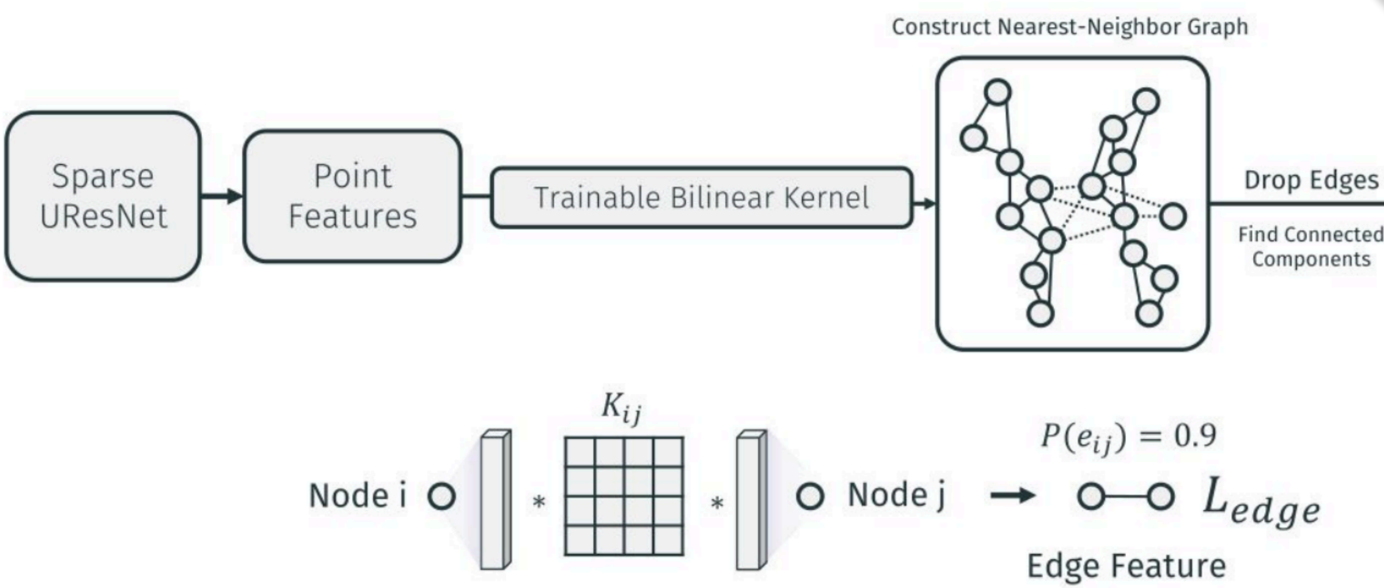


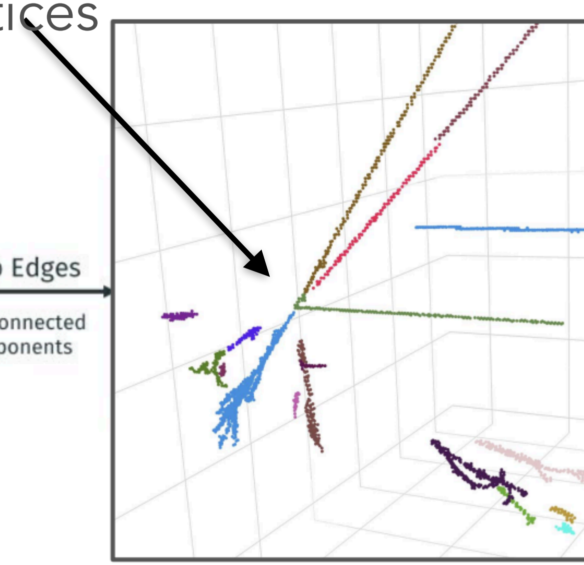
sub-voxel

L. Dominé et al.

Fragment Clustering

- Construct intermediate representation of particles called **fragments**
  - Reduces complexity of downstream GNNs
- GraphSPICE is "smart" version of DBSCAN
  - Avoids clustering particles together at vertices

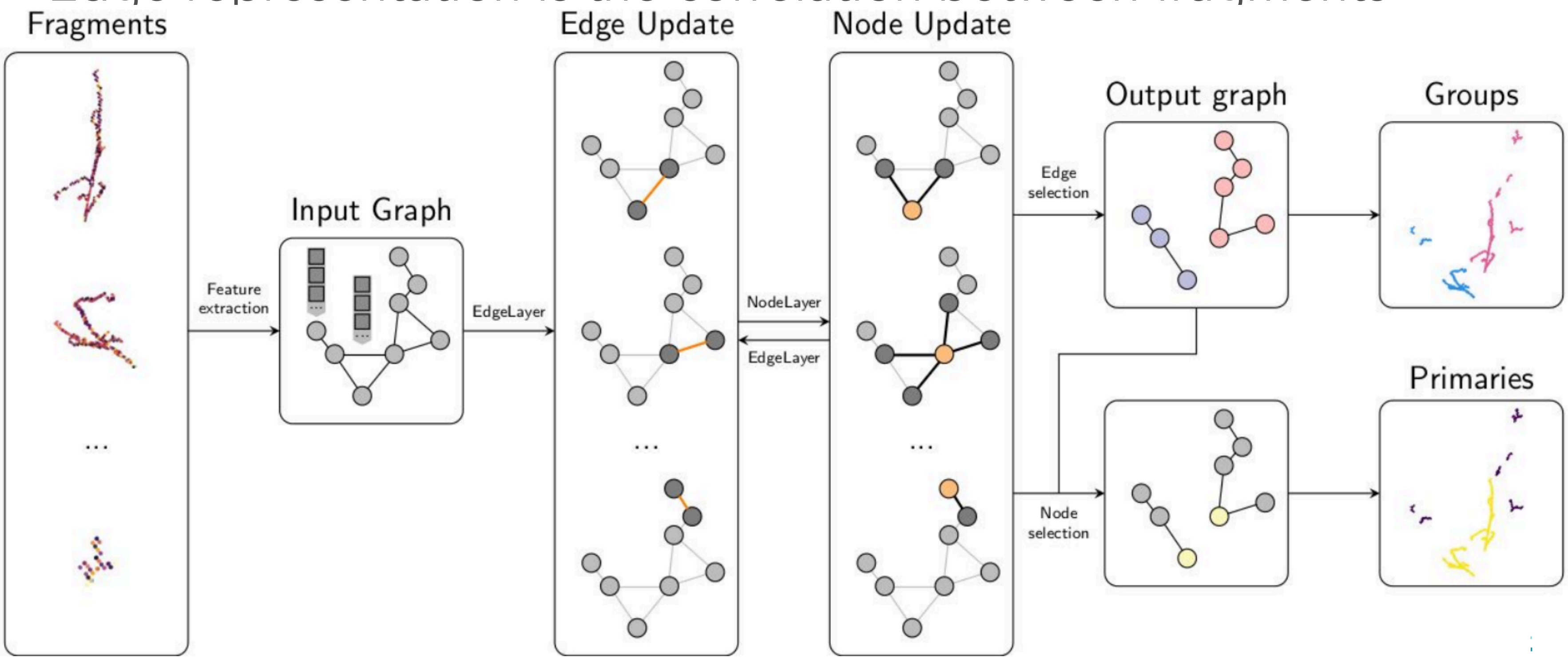




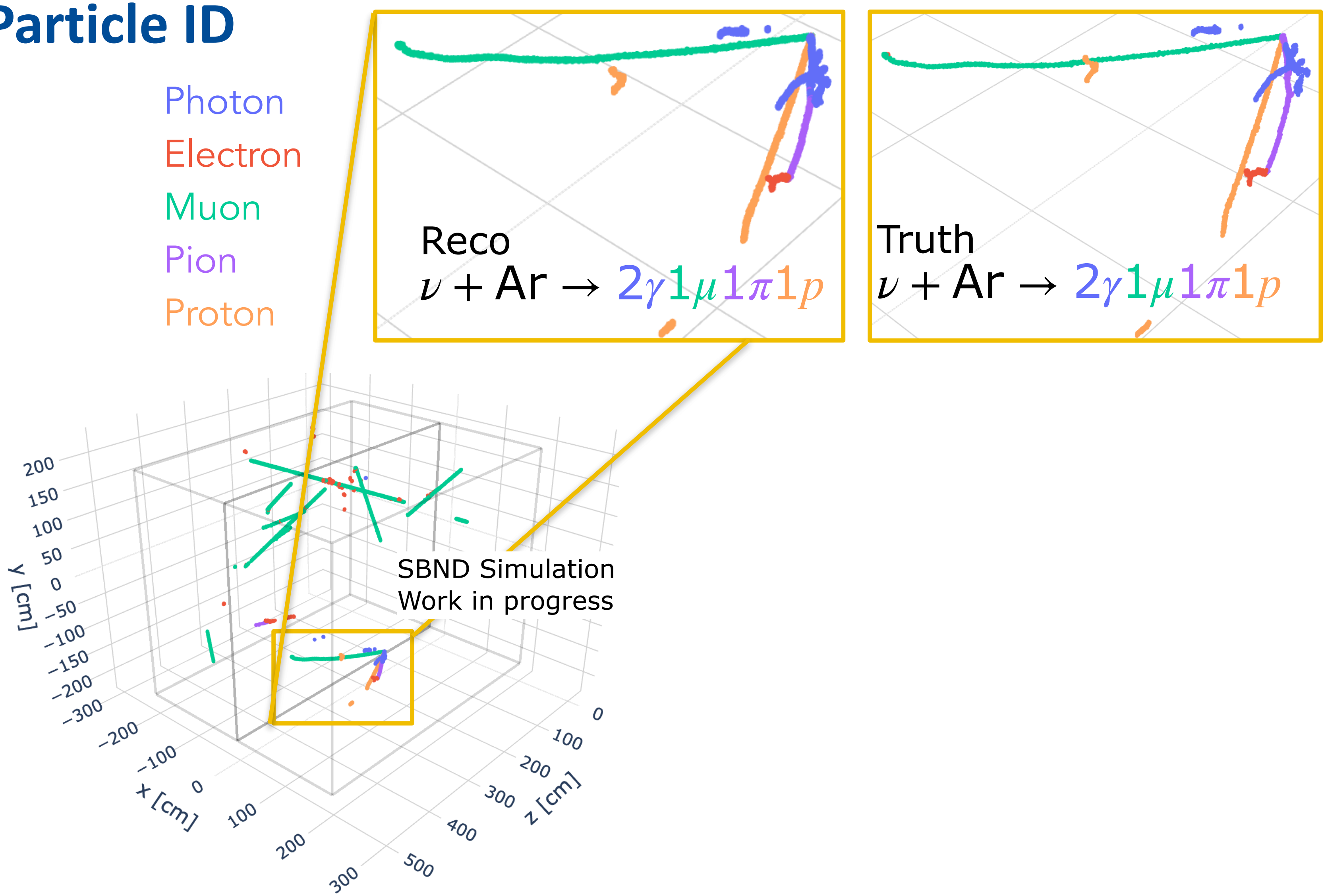
D. Koh et al.

Particle Clustering

- Aggregate fragments into **particles** using a Graph Neural Network (GNN)
- Edge representation is the correlation between fragments

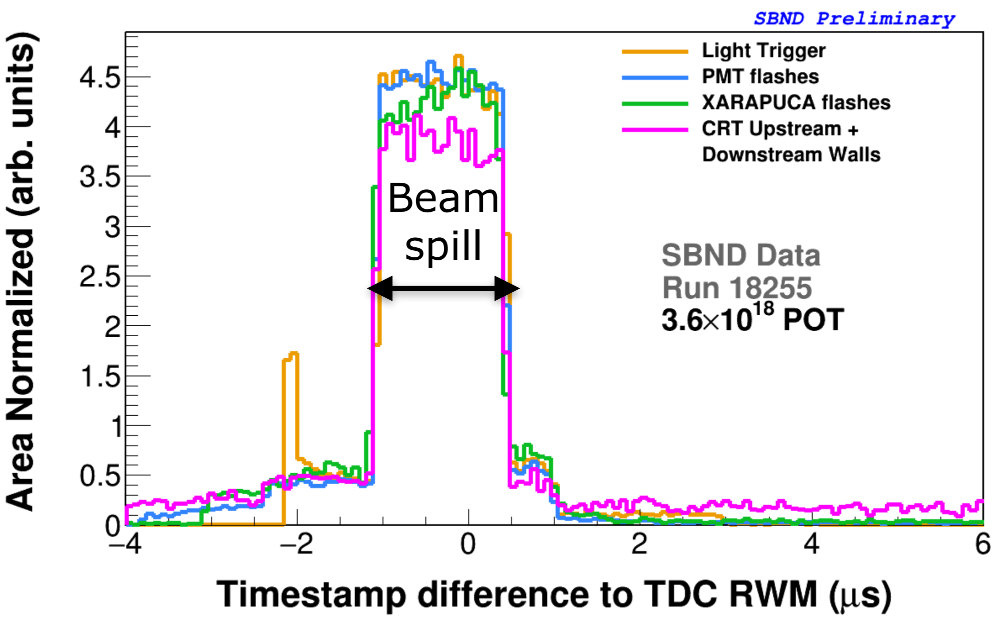


Particle ID



Neutrino + Cosmics

Calibrations and Detector Performance

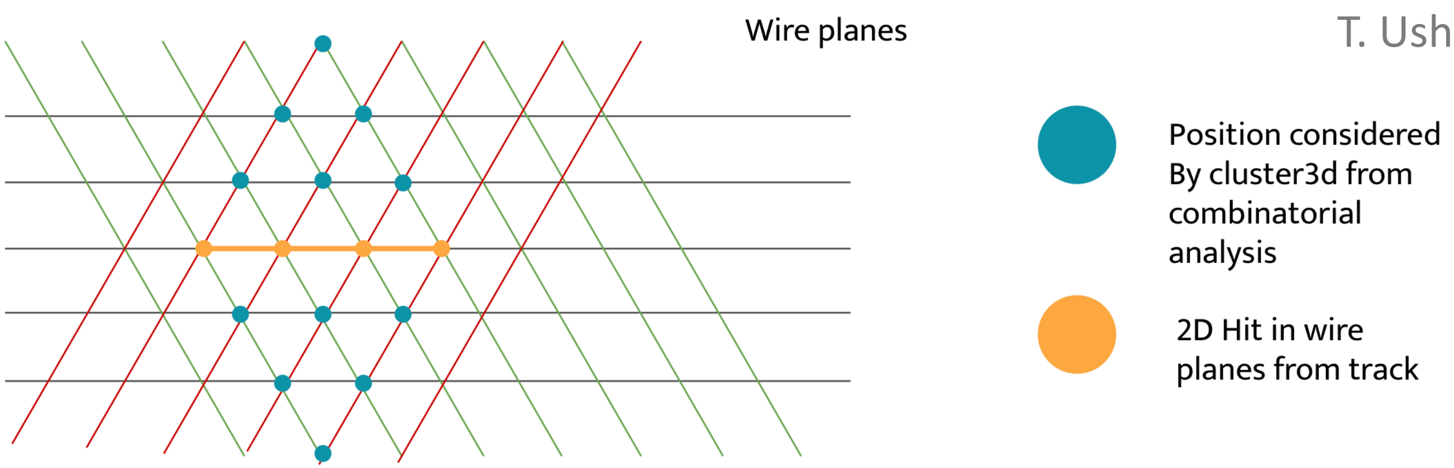


Subsystems synchronized and can identify beam-induced activity

2D -> 3D Projection

Consume 2D hits in each of 3 projections to make space points

- Finds pairs of hits compatible within a time threshold
- Forms a **space point** from 3 wires where 2 hits are compatible in time to form candidate space point

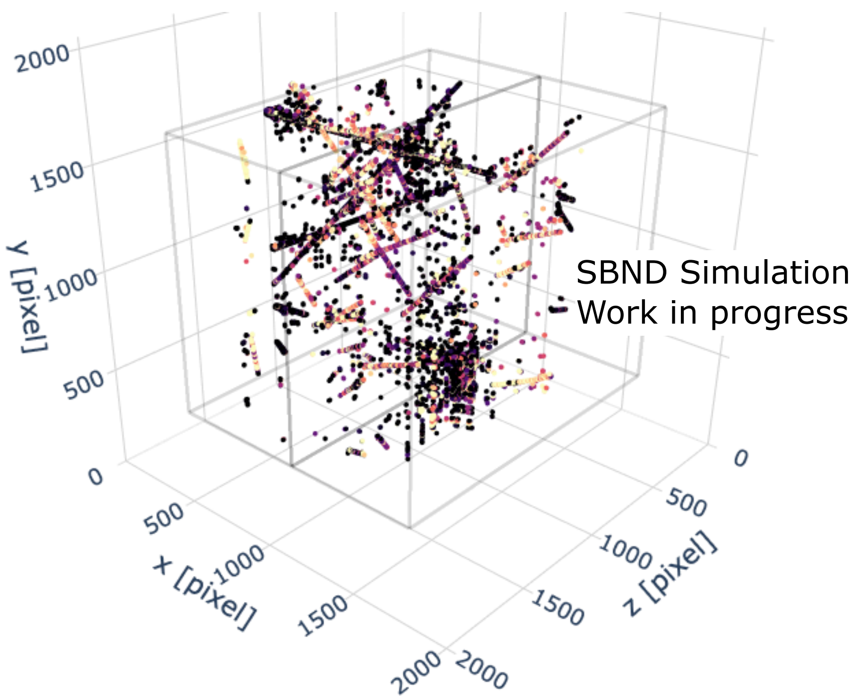


T. Usher

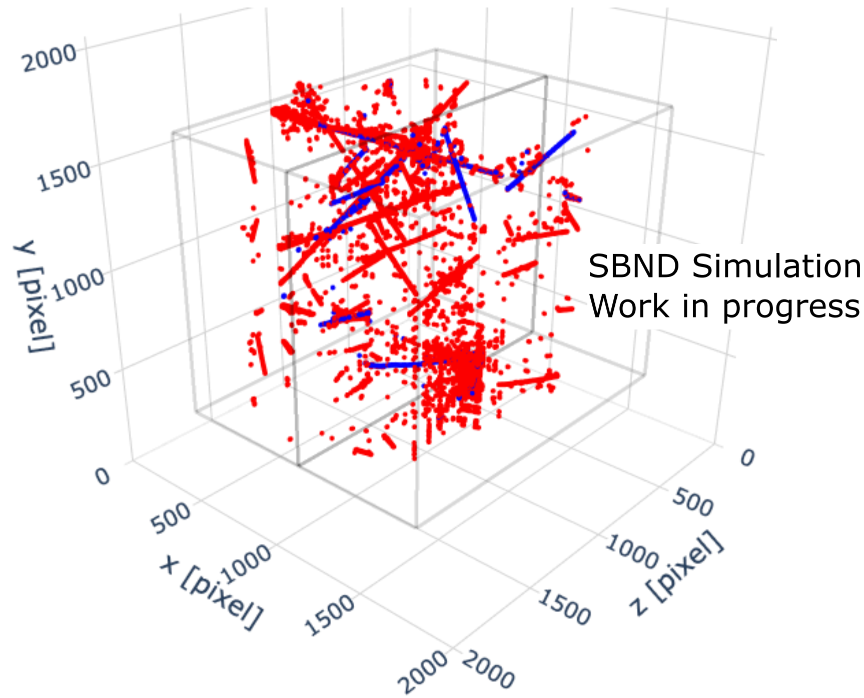
- False combinations create *ghost* points, which are de-ghosted using a UResNet CNN

Deghosting

- Label each point in simulation sample as ghost/non-ghost
- Learn ghost/non-ghost from reconstructed spacepoint information



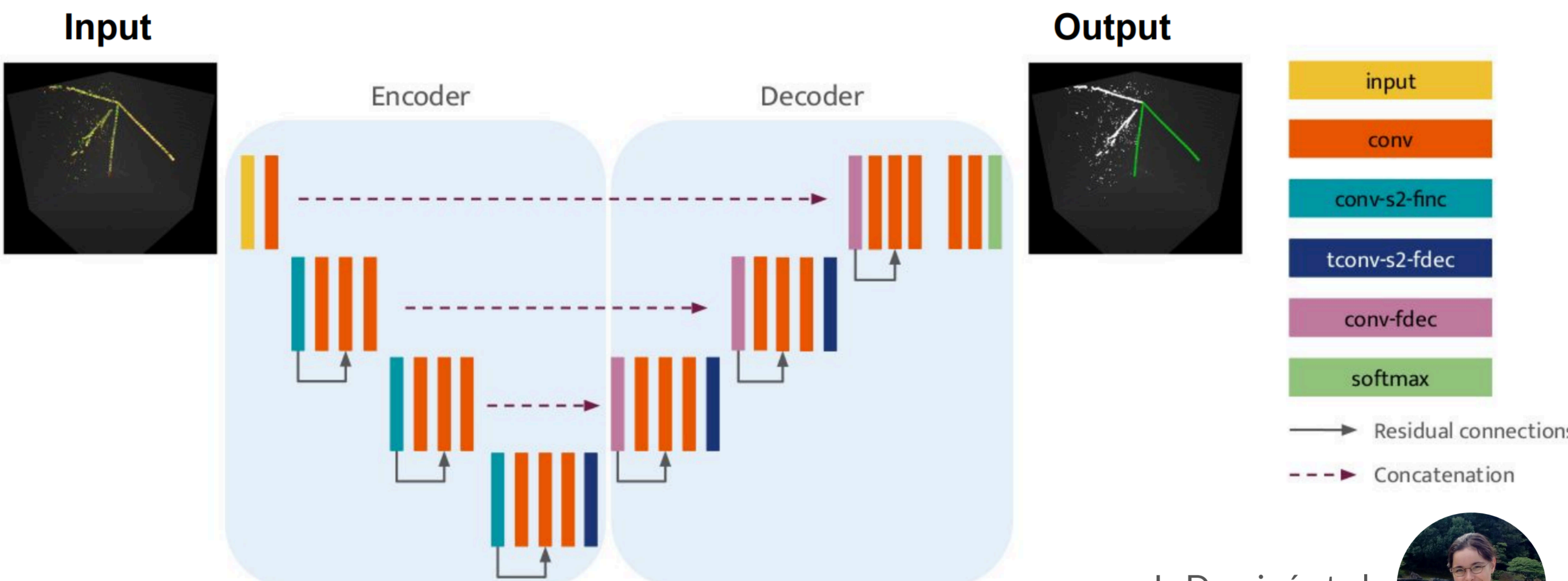
Raw Charge



Ghost vs Non-ghost label

UResNet Sparse CNN

- Point-wise feature extraction uses Sparse Convolutional Neural Network (CNN)
- UResNet architecture used as backbone feature extractor



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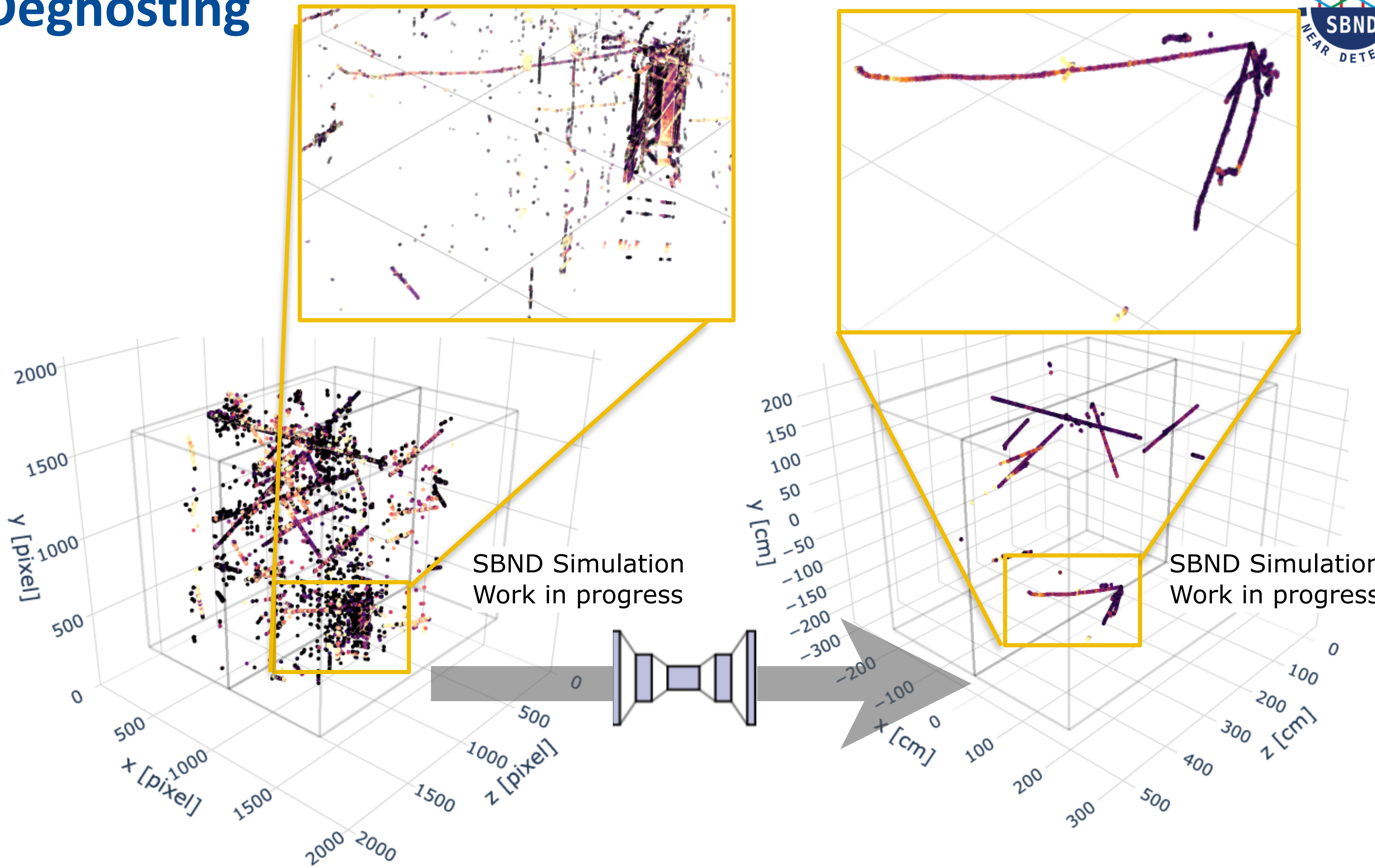
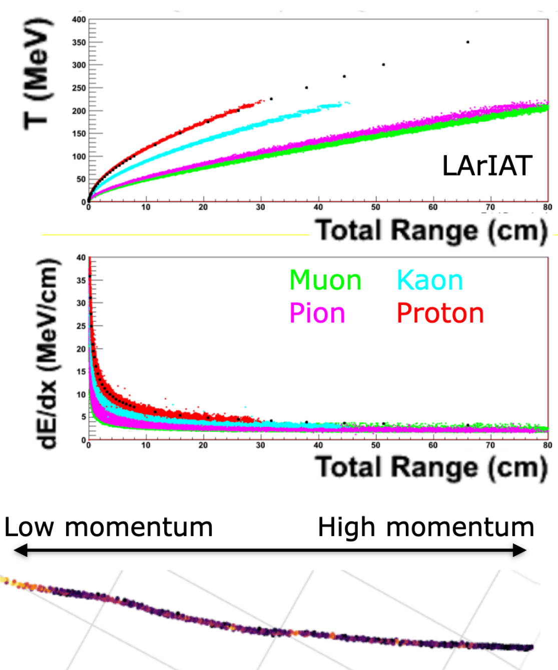
Deghosting



Raw Charge

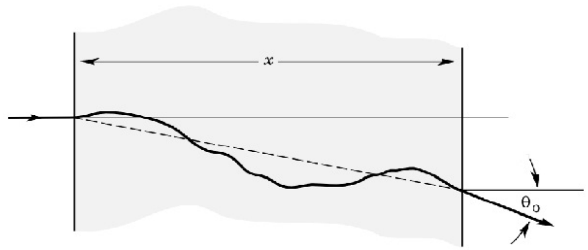
Deghosted Charge

Energy



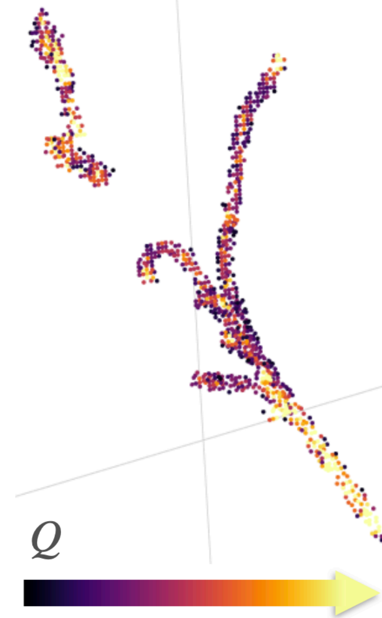
$$\Delta x = \int_0^{E_0} \frac{1}{dE/dx} dE$$

CSDA



$$\theta_0 = \frac{S_2}{p\beta c} z \sqrt{\frac{x}{X_0}} \left[1 + \epsilon \log\left(\frac{x}{X_0}\right) \right]$$

MCS



Work function for Ar | Shower adjustment factor | Electron lifetime correction

$$E_{\text{shower}} = W_i \cdot C_{\text{calo}} \cdot C_{\text{adj}} \cdot \frac{1}{R} \cdot \sum_Q e^{\frac{t_{\text{drift}}}{\tau}} Q$$

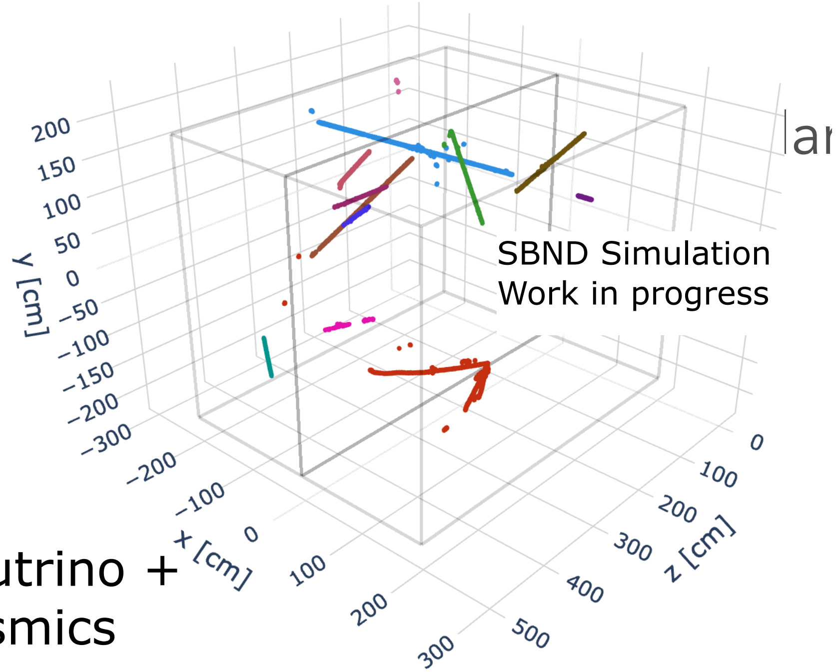
[MeV] | [MeV / e⁻] | [e⁻ / ADC] | [ADC]

Calorimetric constant (TPC gain) | Recombination factor | Deposited charge

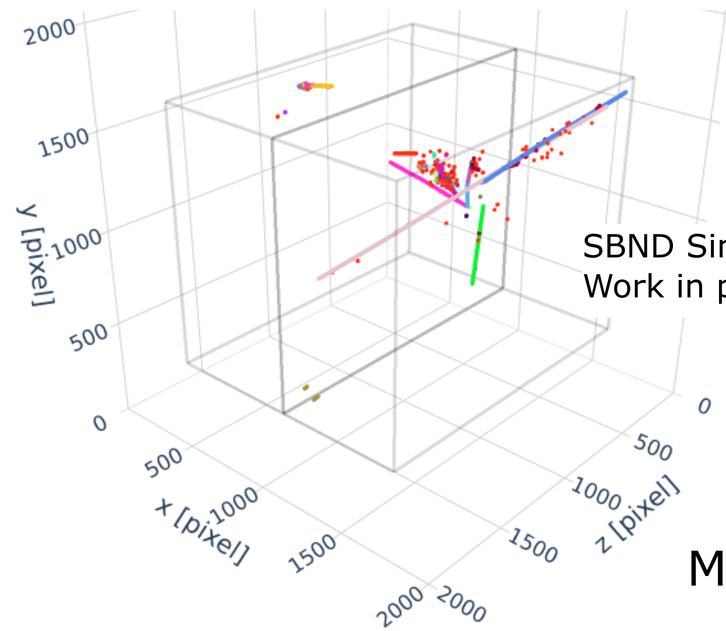
Calorimetric

Training Sample

- Multi-particle vertex multi-particle rain (MPVMPR) sample - 2 generators
  - Rain (MPR) <—> **cosmic activity**
  - Vertex (MPV) <—> **neutrino activity**
- Use this over neutrino + cosmics event generators to…
  - Sample particle abundances and energies from uniform



Neutrino + Cosmics



MPVMPR

UResNet Sparse CNN

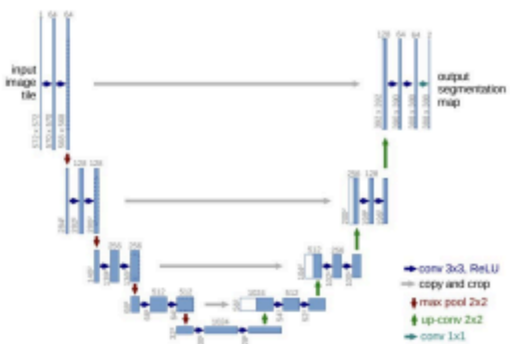
Semantic Segmentation

Backbone (L. Dominé)

UResNet (UNet + ResNet + Sparse Conv.) as the **backbone feature extractor**

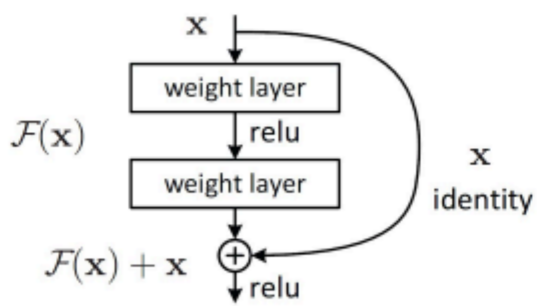
UNet

- Downsizing -> expand receptive field
- Skip connections -> preserve resolution



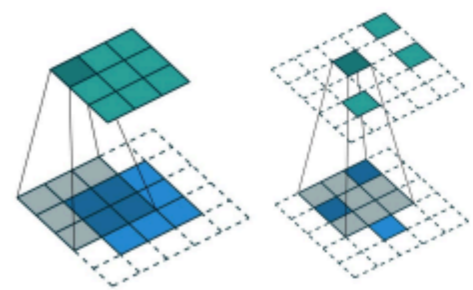
ResNet

- Identity bypass + convolution -> learns residual transform
- Speeds up learning, enables deeper networks



Sparse Convolutions

- Only applies convolutions on active pixels
- Saves memory, execution speed (dramatically)



ML-based Reconstruction for LArTPCs, F. Drielsma (SLAC)

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