High Quality Automated LArTPC Reconstruction for Neutrino Experiments

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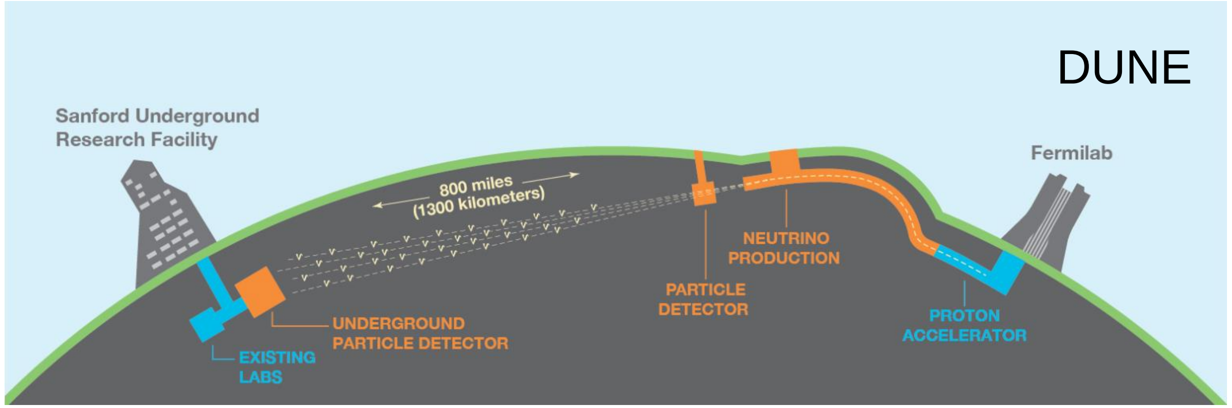
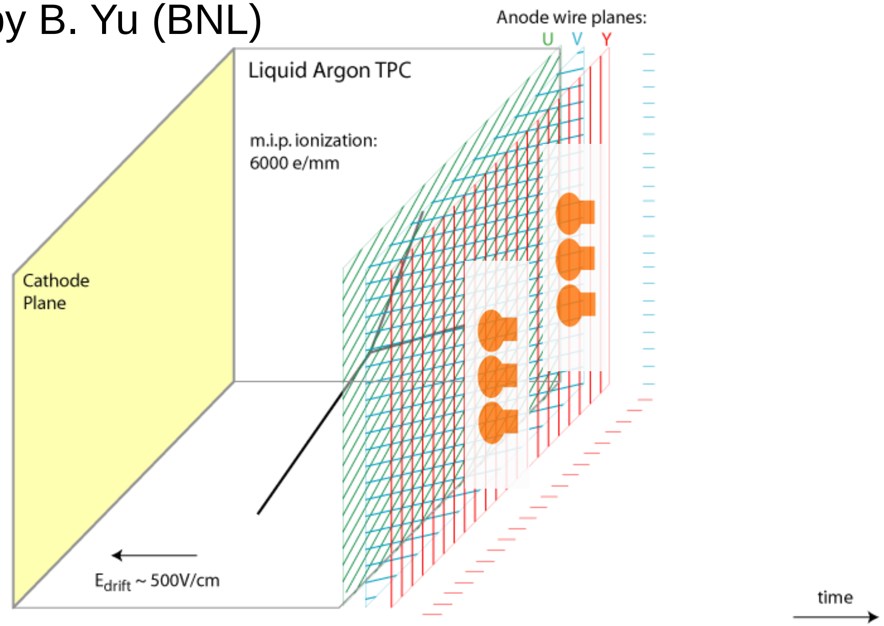
2022-03-30

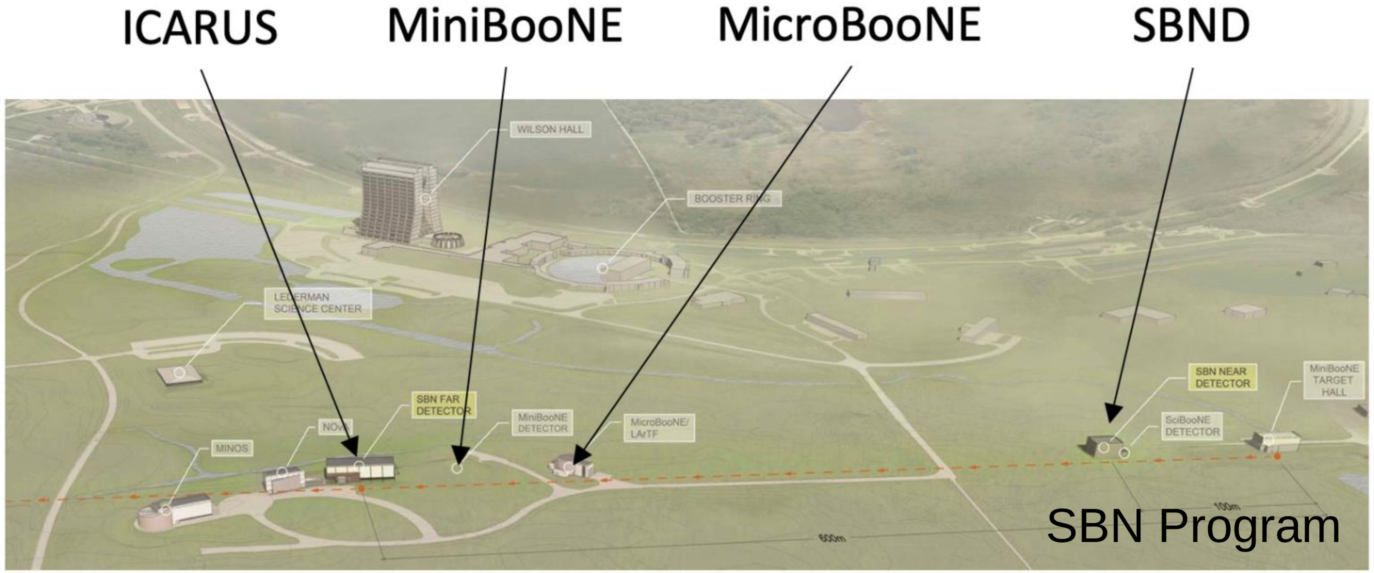
Liquid Argon TPC

- ~mm scale position resolution with multiple 1D wire readouts
- Particle identification (PID) with energy depositions and topologies



LArTPC Signal Formation Illustration
by B. Yu (BNL)





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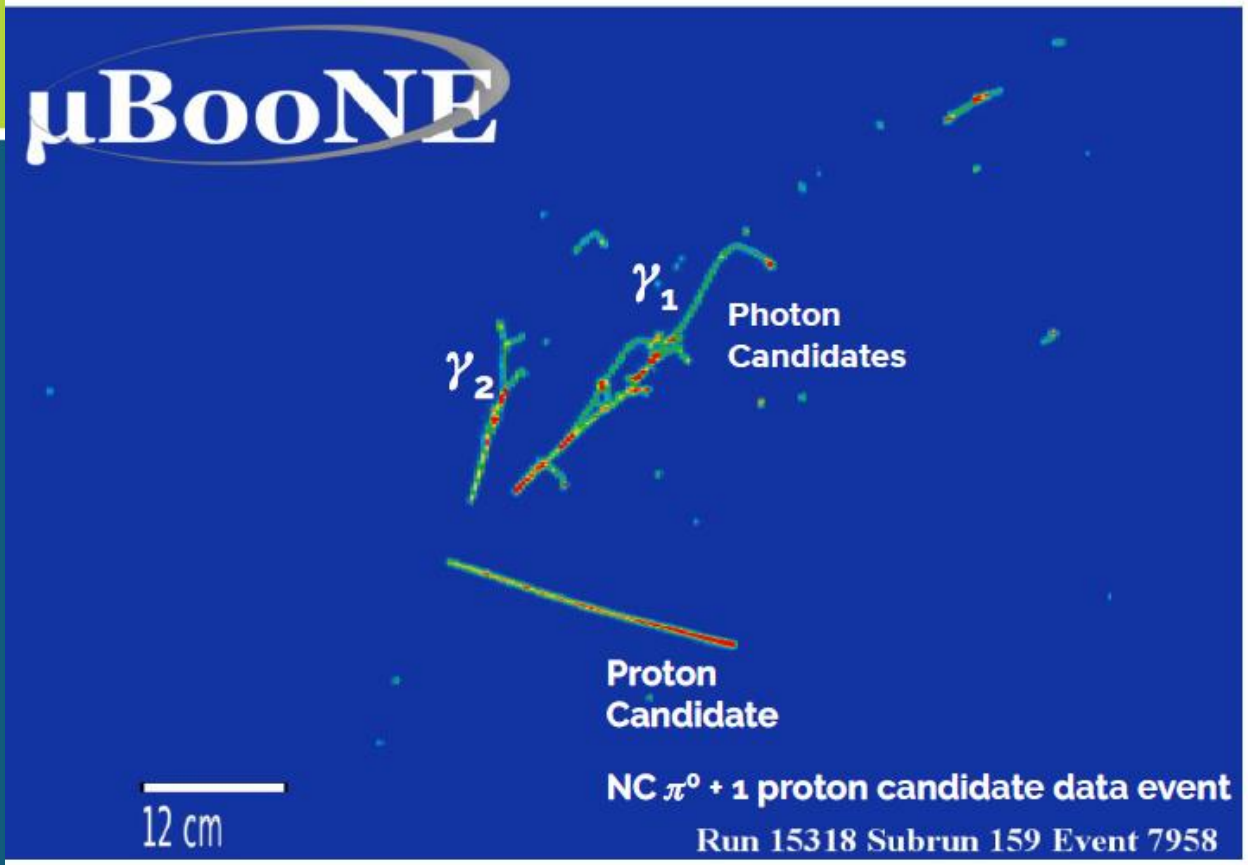
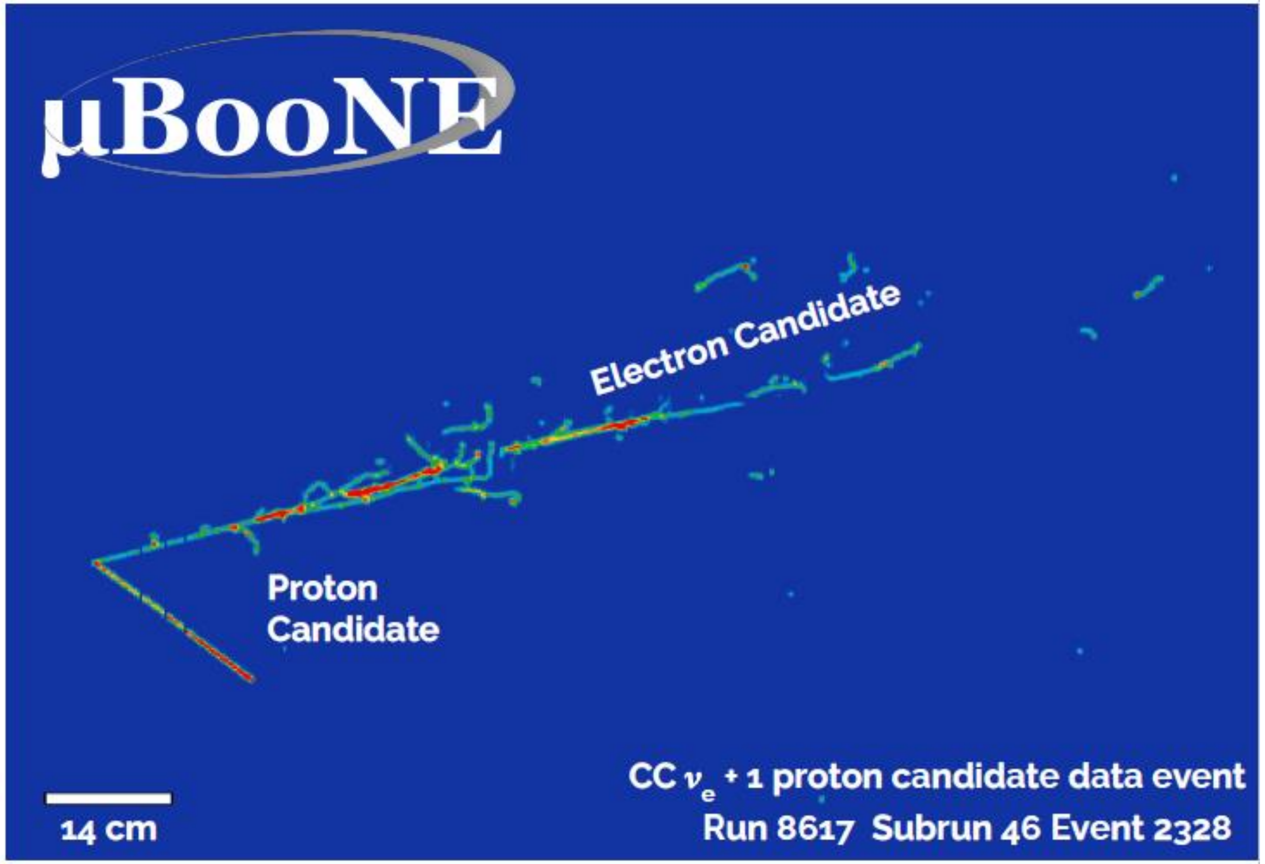
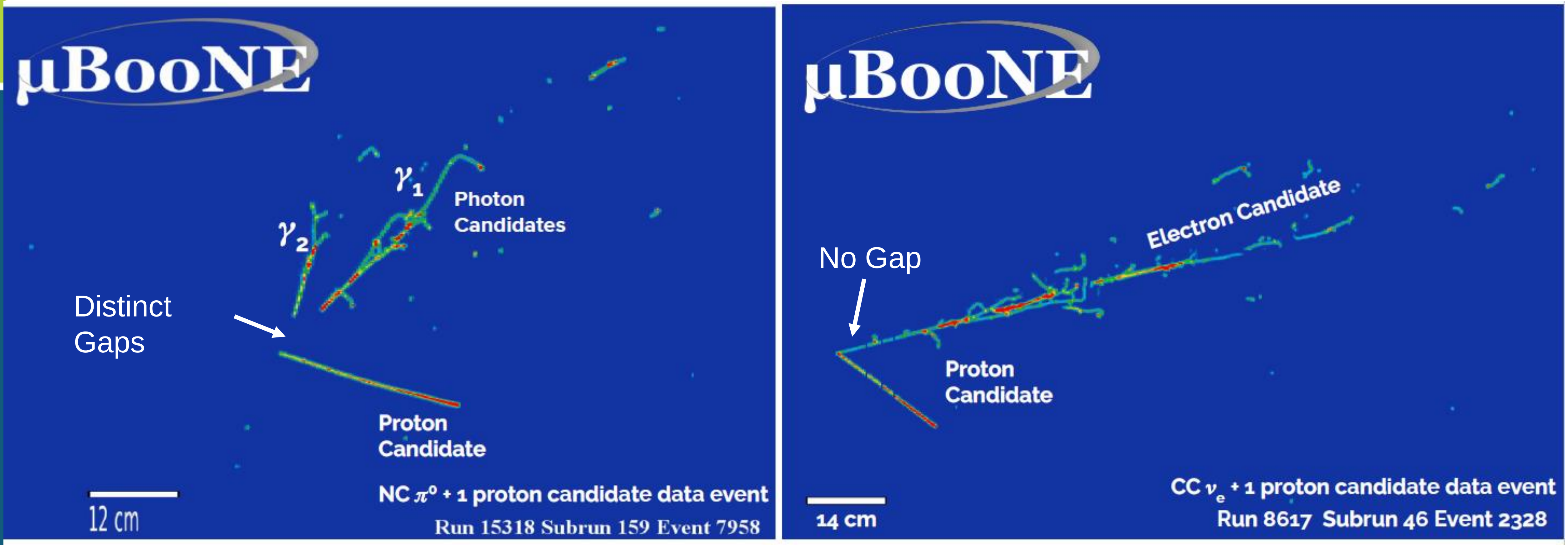
Separation of e and γ in LArTPC





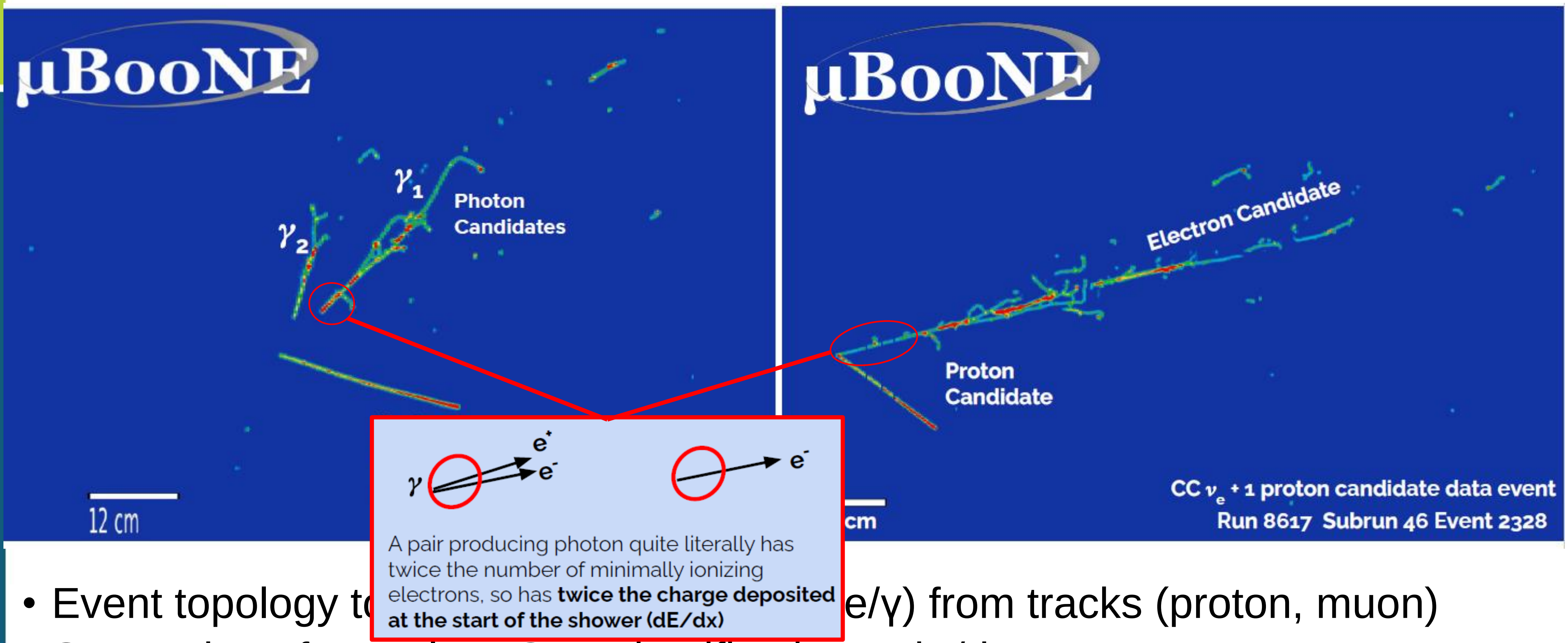
- Event topology to separate EM showers (e/γ) from tracks (proton, muon)

Separation of e and γ in LArTPC



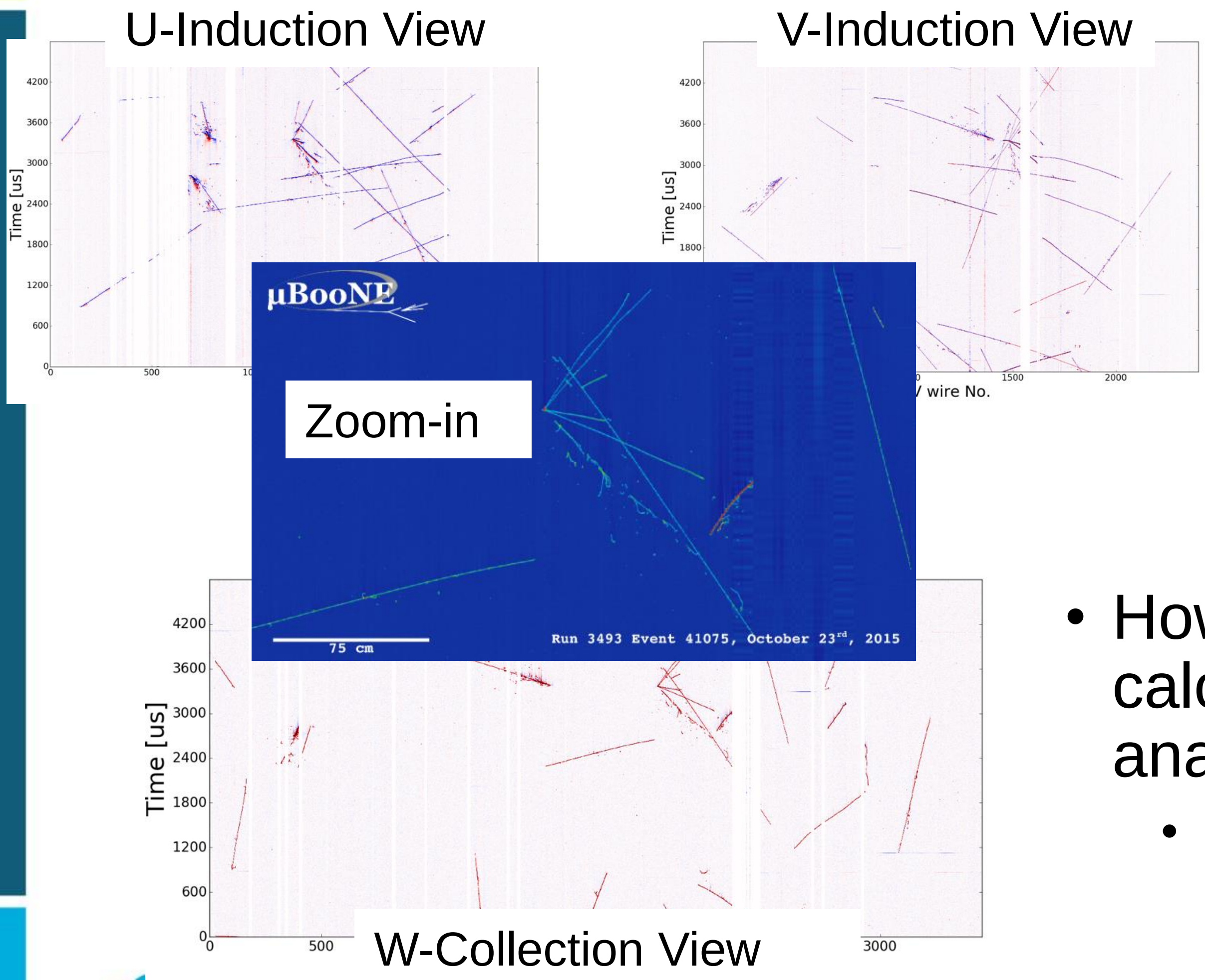
- Event topology to separate EM showers (e/γ) from tracks (proton, muon)
- Separation of e and γ : Gap Identification

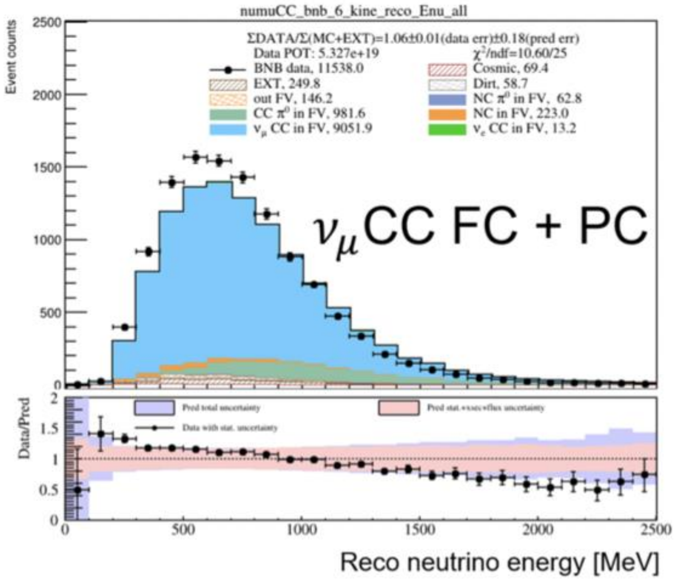
Separation of e and γ in LArTPC



- Event topology to … e/γ) from tracks (proton, muon)
- Separation of e and γ : Gap Identification + dE/dx
- Unique capability to identify ν_e charge-current (CC) interactions in LArTPC

Challenge in Automated Event Reconstruction





- How to convert the excellent resolution and calorimetry in these pictures to rigorous physics analyses?
  - Massive amount of information with tiny signal to background ratio → a big challenge for automated event reconstruction

Pandora Pattern Recognition

Track (p), daughter of primary p

- The most general pattern recognition algorithm with the longest history
  - Eur. Phys. J. C78, 82 (2018)

MicroBooNE Publications Using Pandora

JINST 12 P12030 (2017);
Eur. Phys. J. C79: 248 (2019
PRD 99, 091102 (2019);
Eur. Phys. J. C79 673 (2019)
JINST 15, P03022 (2020);
JINST 15 P02007 (2020);
PRD 101, 052001 (2020);
PRL 125, 201803 (2020);
JINST 15, P12037 (2020);
PRD 102, 112013 (2020);

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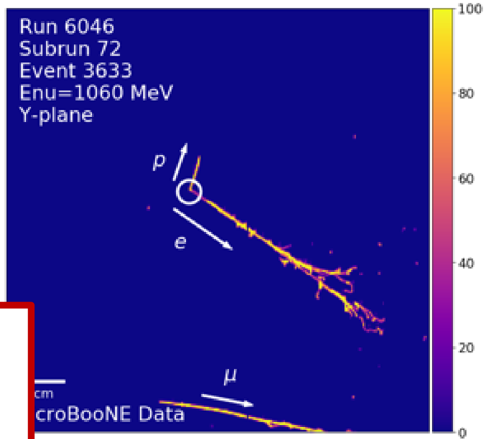
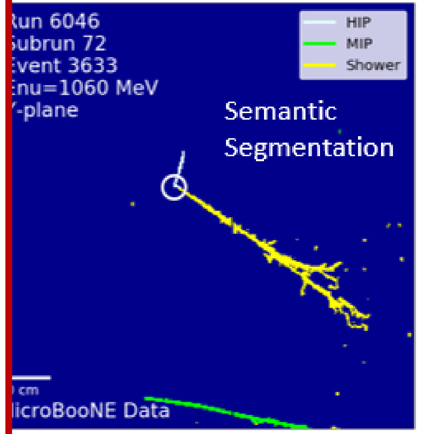
Deep-Learning (DL) Based Event Reconstruction

- Currently a hybrid approach of Deep-Learning and traditional

Semantic Segmentation
Using SparseSSNet (pixel-based



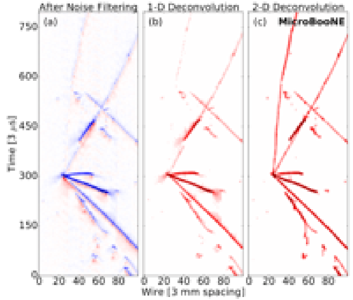


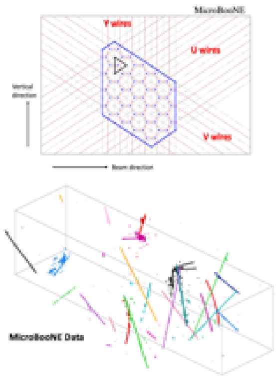
Wire-Cell Event Reconstruction

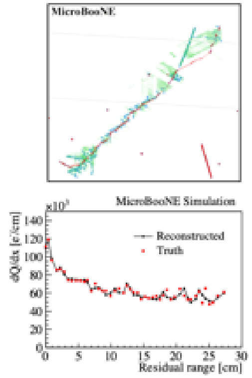
μBooNE

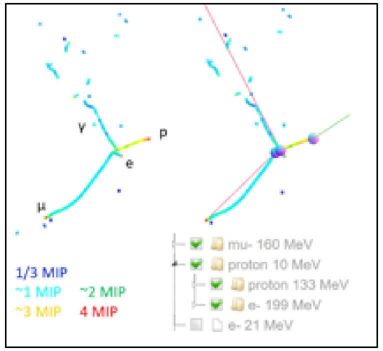
Wire-Cell

TPC simulation noise filtering signal processing	3D imaging clustering charge-light matching	3D trajectory & dQ/dx fitting cosmic muon tagger	multi-track fitting DL-3D vertexing particle identification









JINST 12 P08003 (2017)
JINST 13 P07006 (2018)
JINST 13 P07007 (2018)
JINST 16 P01036 (2020)

JINST 13 P05032 (2018)
JINST 16 P06043 (2021)

Phys. Rev. Applied 15 064071 (2021)
arXiv:2012.07928

arXiv:2110.13961

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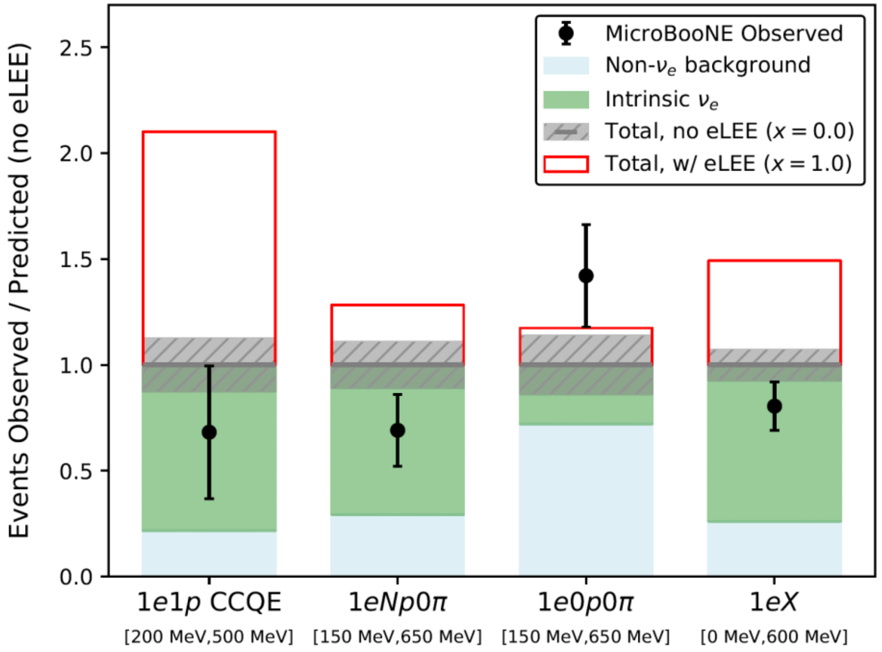
Search for Low-Energy Excess in ν_eCC

Comprehensive search for (examination of) the MiniBooNE low-energy excess in ν_eCC with multiple final-state topologies with different reconstruction paradigms

Channels	Reconstruction	Purity	Efficiency	Selected Events	References
CCQE 1e1p	Deep Learning	75%	6.6%	25	2110.14080
1e0p0π	Pandora	43%	9%	34	2110.14065
1eNp0π	Pandora	80%	15%	64	2110.14065
Inclusive 1eX	**Wire-Cell**	**82%**	**46%**	**606**	**2110.13978**

Wire-Cell based inclusive ν_eCC analysis (46% efficiency) currently leads sensitivity in searching for the LEE



arXiv:2110.14054

No excess of low-energy ν_e candidates!

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Wire-Cell Event Reconstruction

Wire-Cell

µBooNE

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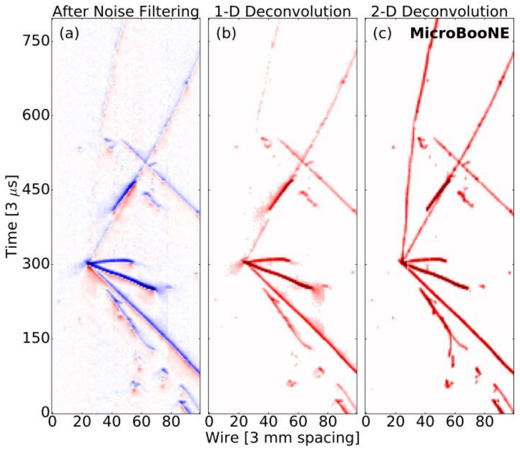
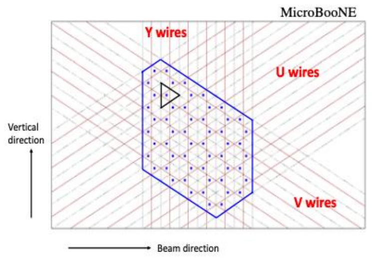
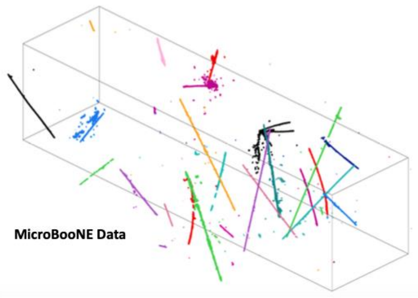
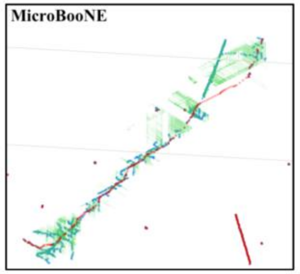


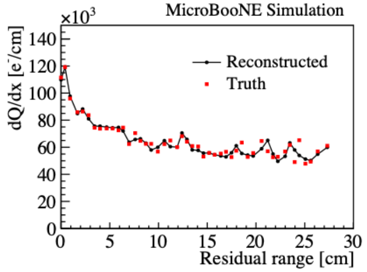
JINST 12 P08003 (2017)
JINST 13 P07006 (2018)
JINST 13 P07007 (2018)
JINST 16 P01036 (2020)



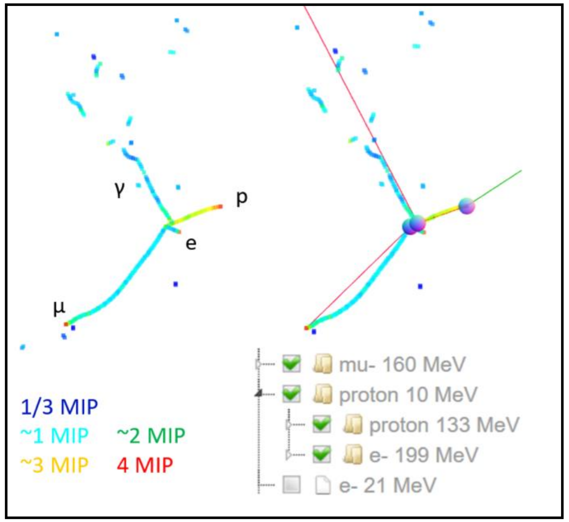


JINST 13 P05032 (2018)
JINST 16 P06043 (2021)





Phys. Rev. Applied 15, 064071 (2021)



JINST 17 P01037 (2022)

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Wire-Cell Tomographic Event Reconstruction

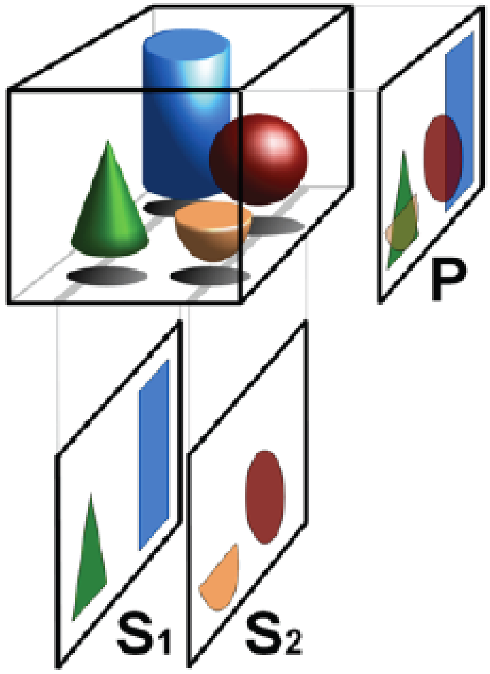
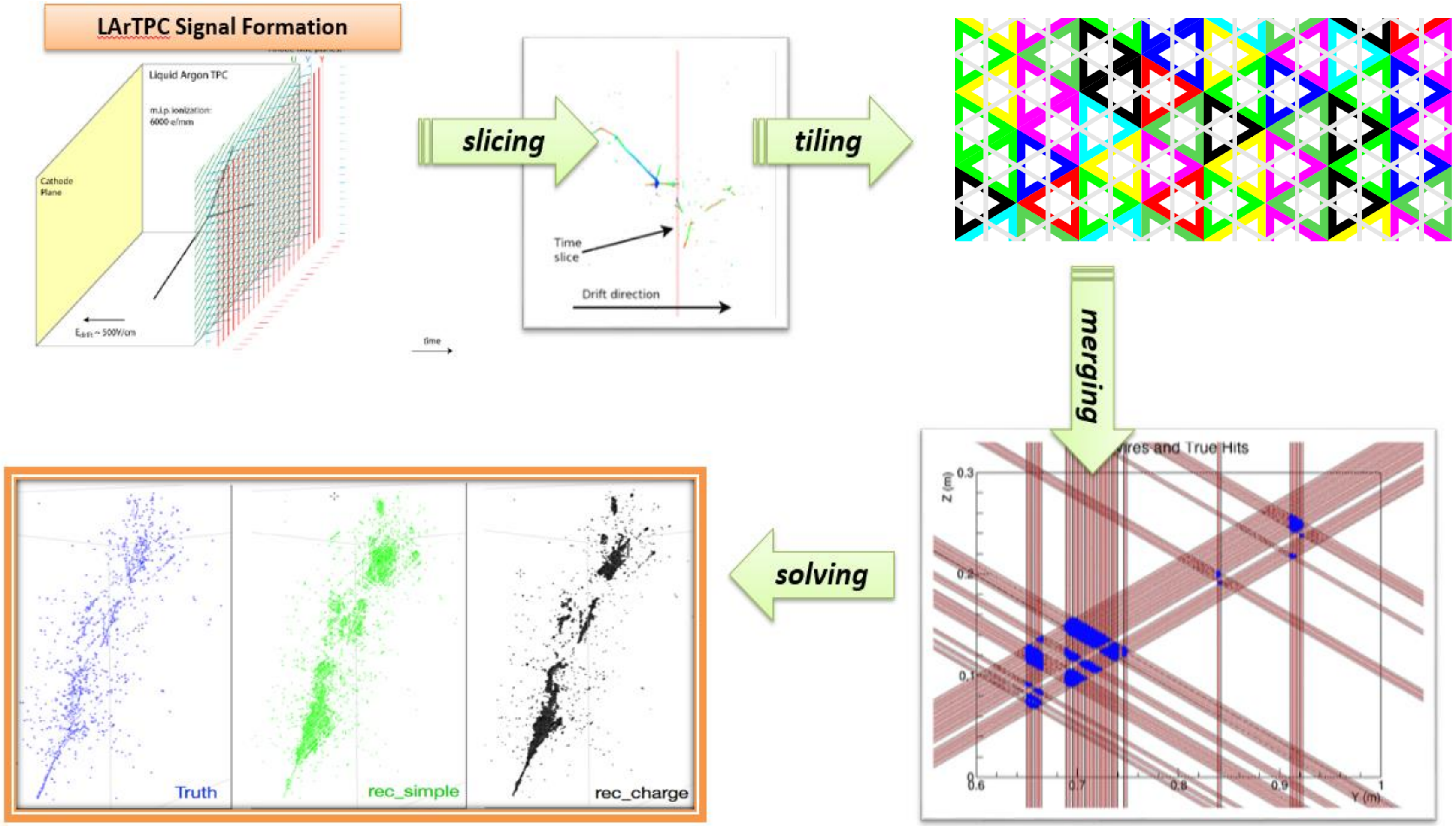


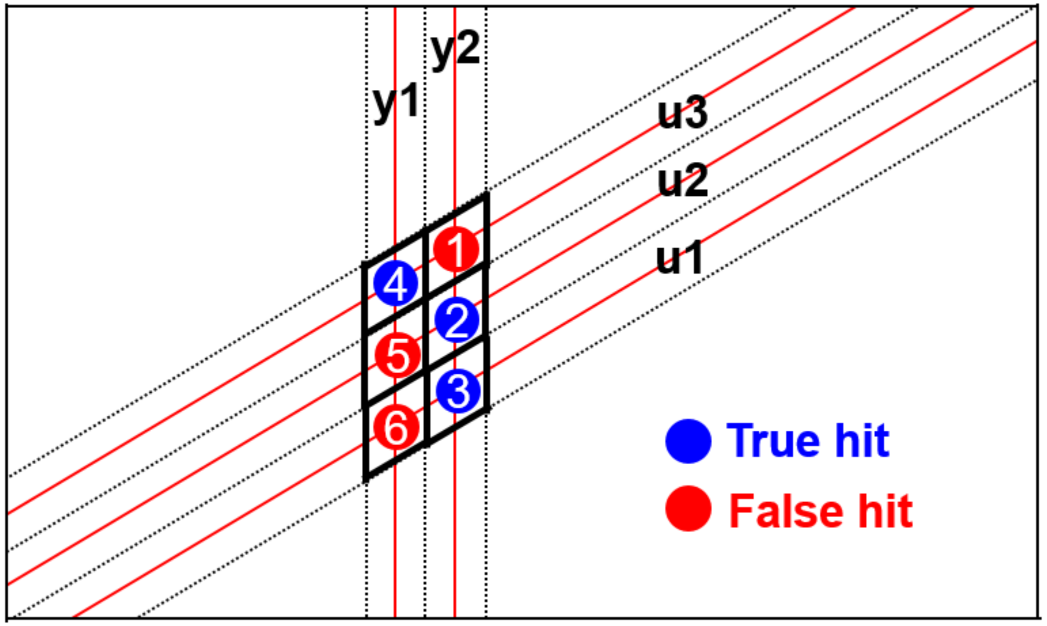
Fig.1:Basic principle of tomography: superposition free tomographic cross sections S1 and S2 compared with the projected image P

https://en.wikipedia.org/wiki/Tomography



"Three-dimensional Imaging for Large LArTPCs", JINST 13, P05032 (2018)

Solving: usage of Charge, Sparsity, Positivity, Proximity



measured charges on Wires $\boxed{y = A \cdot X}$ true charge to be resolved

$$\begin{pmatrix} y1 \\ y2 \\ u1 \\ u2 \\ u3 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & a & a & a \\ a & a & a & 0 & 0 & 0 \\ 0 & 0 & a & 0 & 0 & a \\ 0 & a & 0 & 0 & a & 0 \\ a & 0 & 0 & a & 0 & 0 \end{pmatrix} \begin{pmatrix} H1 \\ H2 \\ H3 \\ H4 \\ H5 \\ H6 \end{pmatrix}$$

matrix determined by geometry, a=1

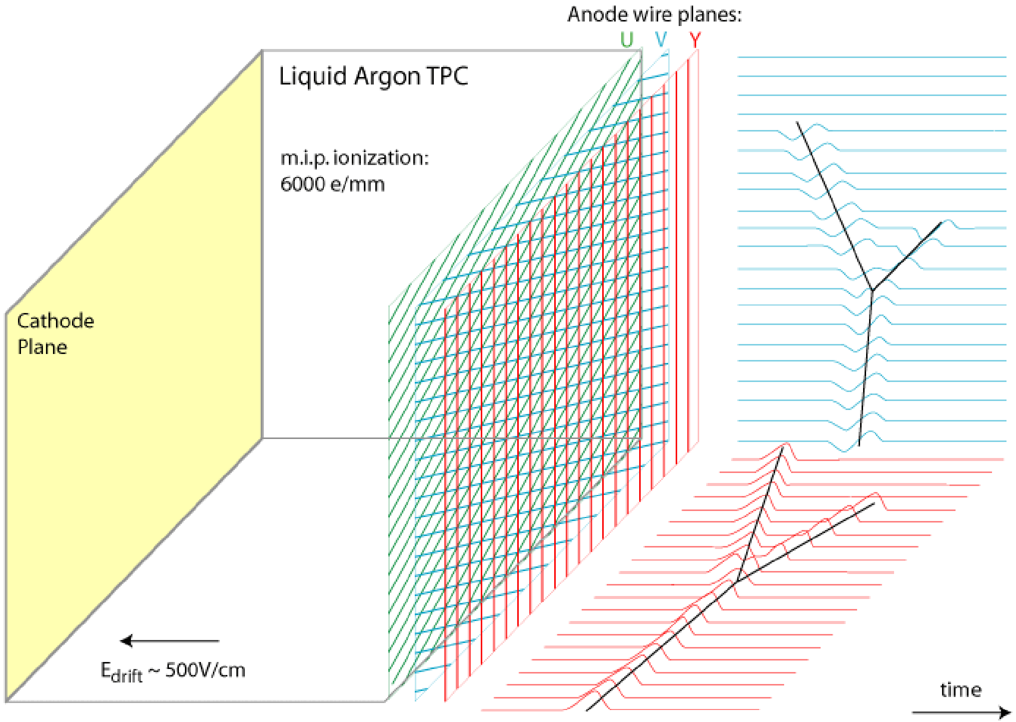
- The goal is to differentiate the true hits from fake ones by using the charge information
  - ~ large charge → true hits
  - ~ zero charge → fake hits
- Sparsity, positivity, and proximity information are added through compressed sensing (L1 regularization)

L1 reg. $O(N!) \rightarrow O(m \times N)$

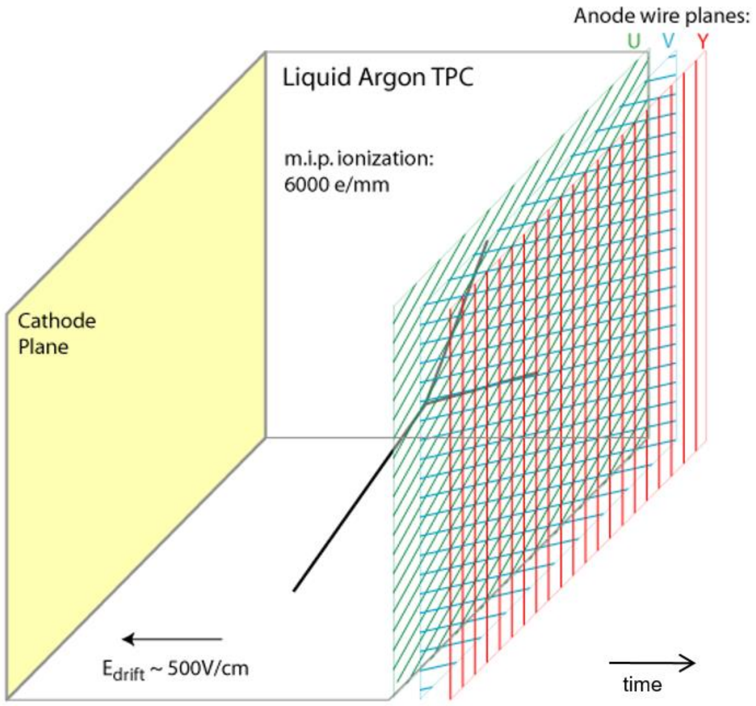
$$\chi^2 = (y - A \cdot x)^2 + \lambda \cdot \sum_i |x_i|$$

E. Candes, J. Romberg, T. Tao
arXiv-math/0503066

Traditional Reconstruction Approach: 2D matching → 3D



2D pattern recognition



Matching to 3D objects

Wire-Cell tomographic imaging is topology agnostic

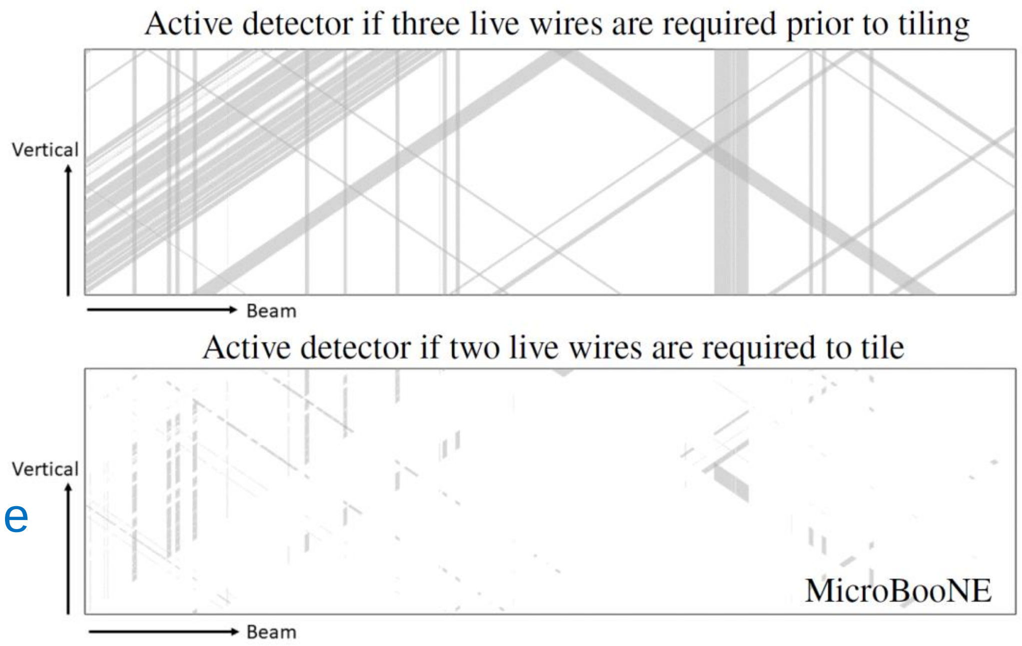

Bee
Run 10711 | Subrun 140 | Event 7036
View
System
cluster
Size
1
8
Opacity
0
1
Plain Color
General
Helper
Monte Carlo
Optical Flash
3-D Imaging
Box of Interest
Time Slice
sliced mode
opacity
0
width
6
position
84
Camera
Ortho Camera
Multi-view
2D View
Reset Camera
Fullscreen
Voice Control
Close Controls
µBooNE
slice #: 35 | slice x: 212.5

Overcome Challenges of 10% non-functional channels

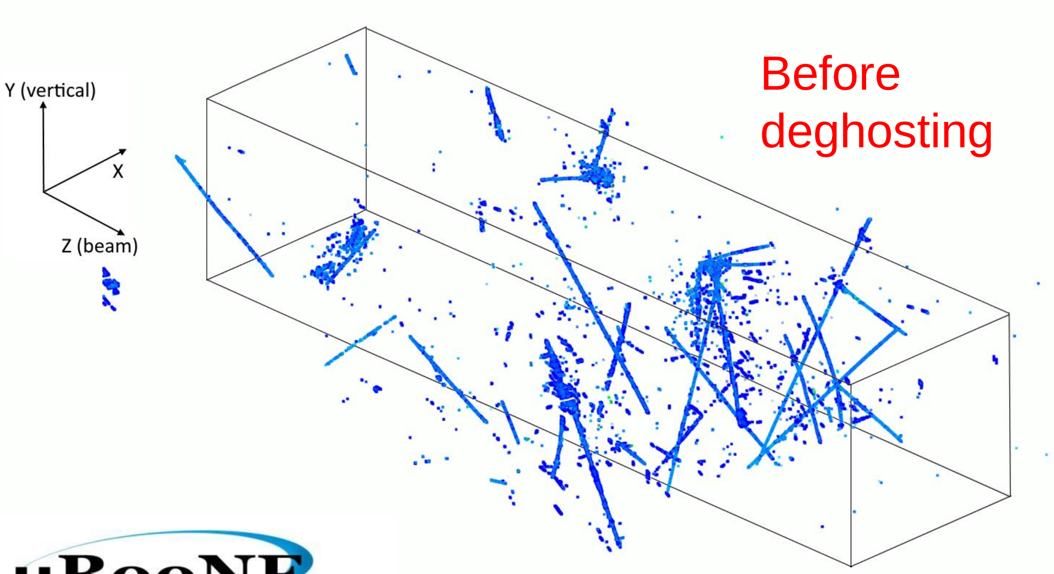
- Impact of 10% non-functional channels is reduced from **~30% → ~3% dead volume** by requiring only 2 out 3 wire planes in reconstruction when necessary
    - Utilizing coverage of 3 planes, but generating a lot of fake 3D activities (ghosts)
    - Dedicated algorithm in deghosting, clustering, charge solving etc. have to be developed

30% dead volume

3% dead volume

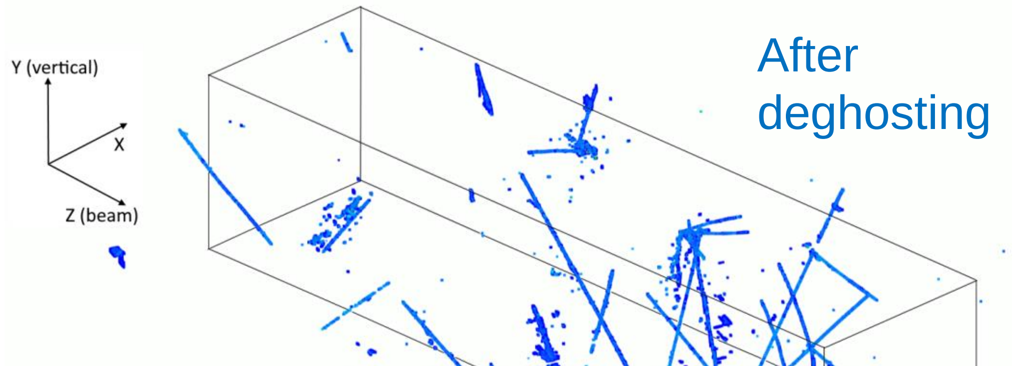


Before deghosting

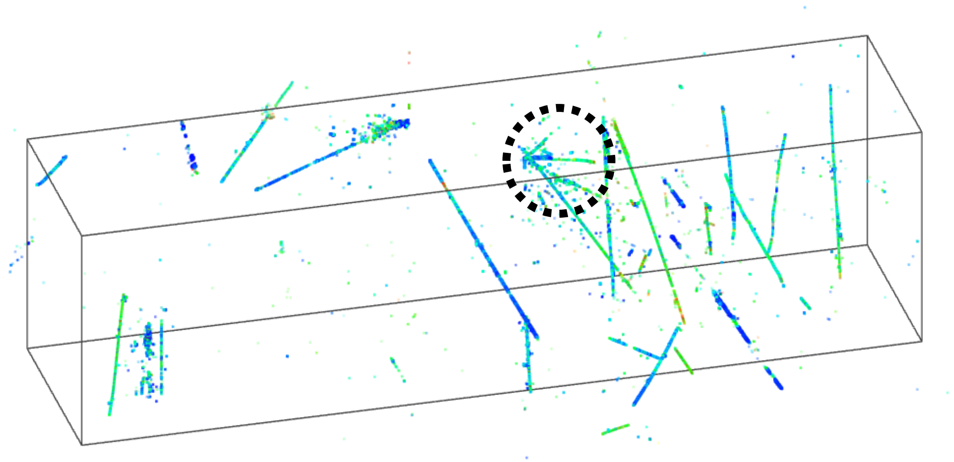


JINST 16, P06043

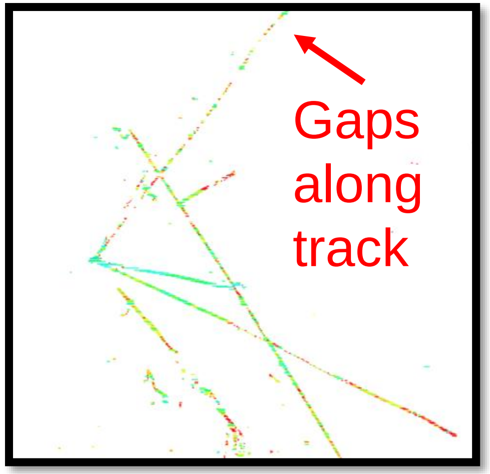
After deghosting



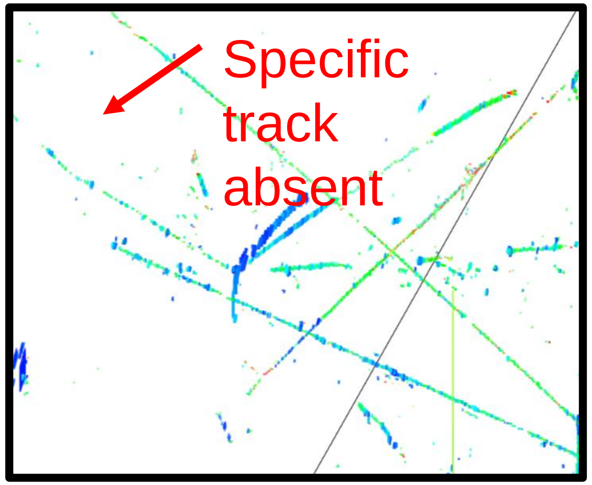
Old performance in 2015



Zoom in



Zoom in



Input of Wire-Cell imaging, quality of reconstructed charge was not sufficient to perform a good image reconstruction

TPC Signal Processing → Recover (or Unfold) Ionization Electrons

- Signal processing is based on deconvolution technique
    - $O(N^3)$ matrix inversion is achieved through a $O(N \log N)$ fast Fourier transformation
        - Top 10 algorithms in 20th century

- 1-D deconvolution described in B. Baller "Liquid Argon TPC Signal Formation, Signal Processing, and reconstruction techniques", [JINST 12, P07010 (2017)]()

Time domain

$$\mathrm{M}(t_0) = \int_t R(t - t_0) \cdot S(t) \cdot dt$$

Fourier transformation

$$M(\omega) = \mathrm{R}(\omega) \cdot \mathrm{S}(\omega)$$

Frequency domain

$$\mathrm{S}(\omega) = \frac{\mathrm{M}(\omega)}{\mathrm{R}(\omega)} \cdot F(\omega)$$

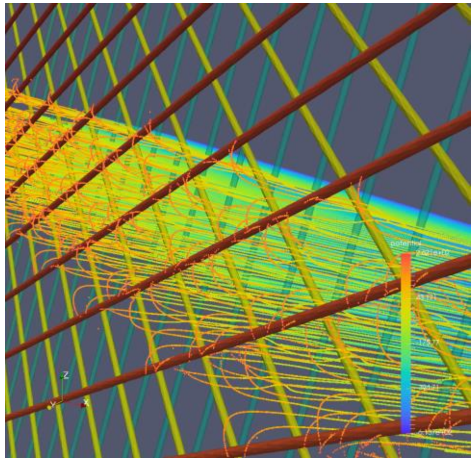
Back to time domain

Inverse-Fourier transformation

$$\mathrm{S(t)}$$

2-D Deconvolution

electron drift paths in 3D

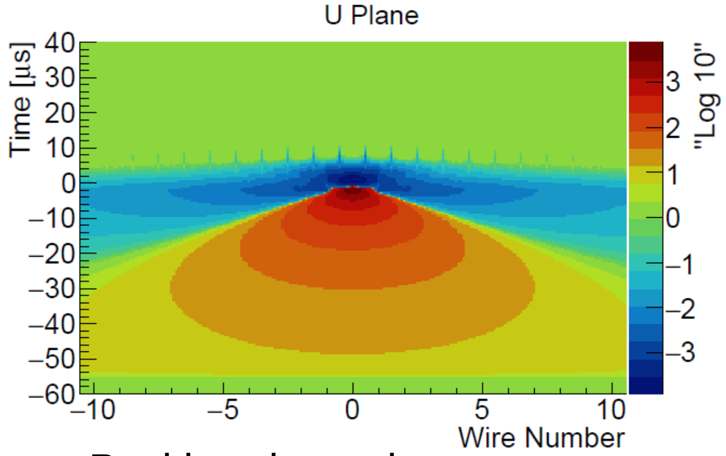


2D measurement formation

$$M(t',x') = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} R(t,t',x,x')\cdot S(t,x)dtdx + N(t',x')$$

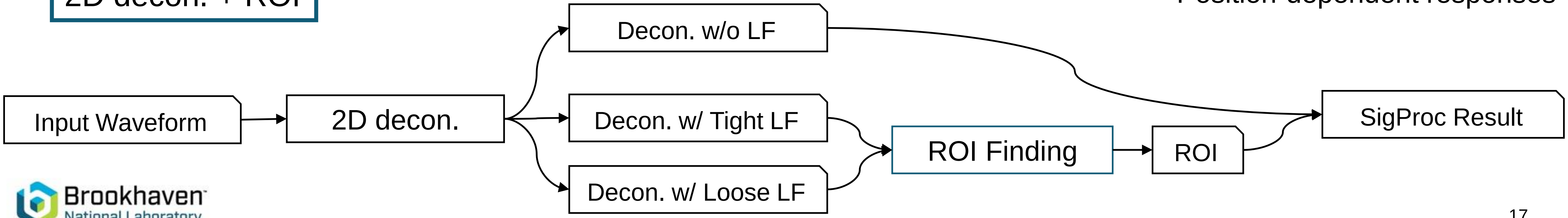
2D deconvolution

$$S(\omega_t,\omega_x) \sim \frac{F(\omega_t,\omega_x)\cdot M(\omega_t,\omega_x)}{R(\omega_t,\omega_x)} \quad \xrightarrow{IFT} \quad S(t,x)$$



Position-dependent responses

2D decon. + ROI



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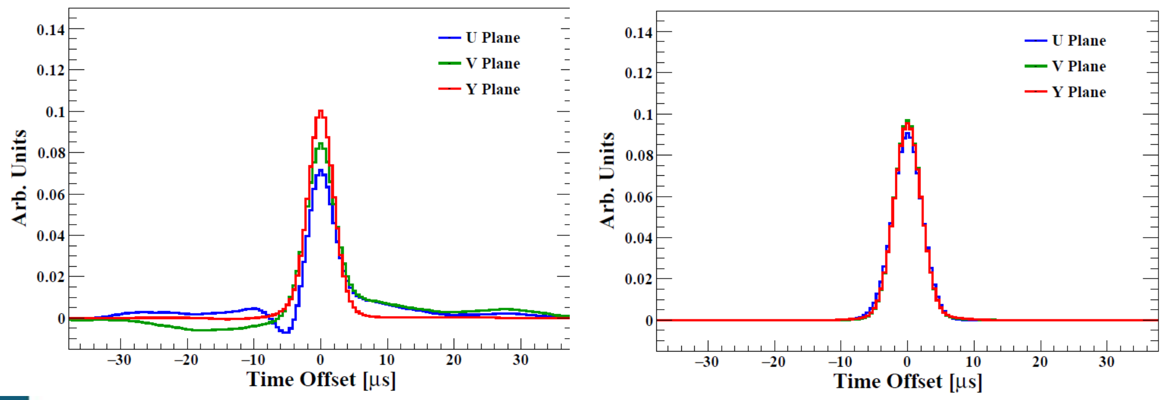
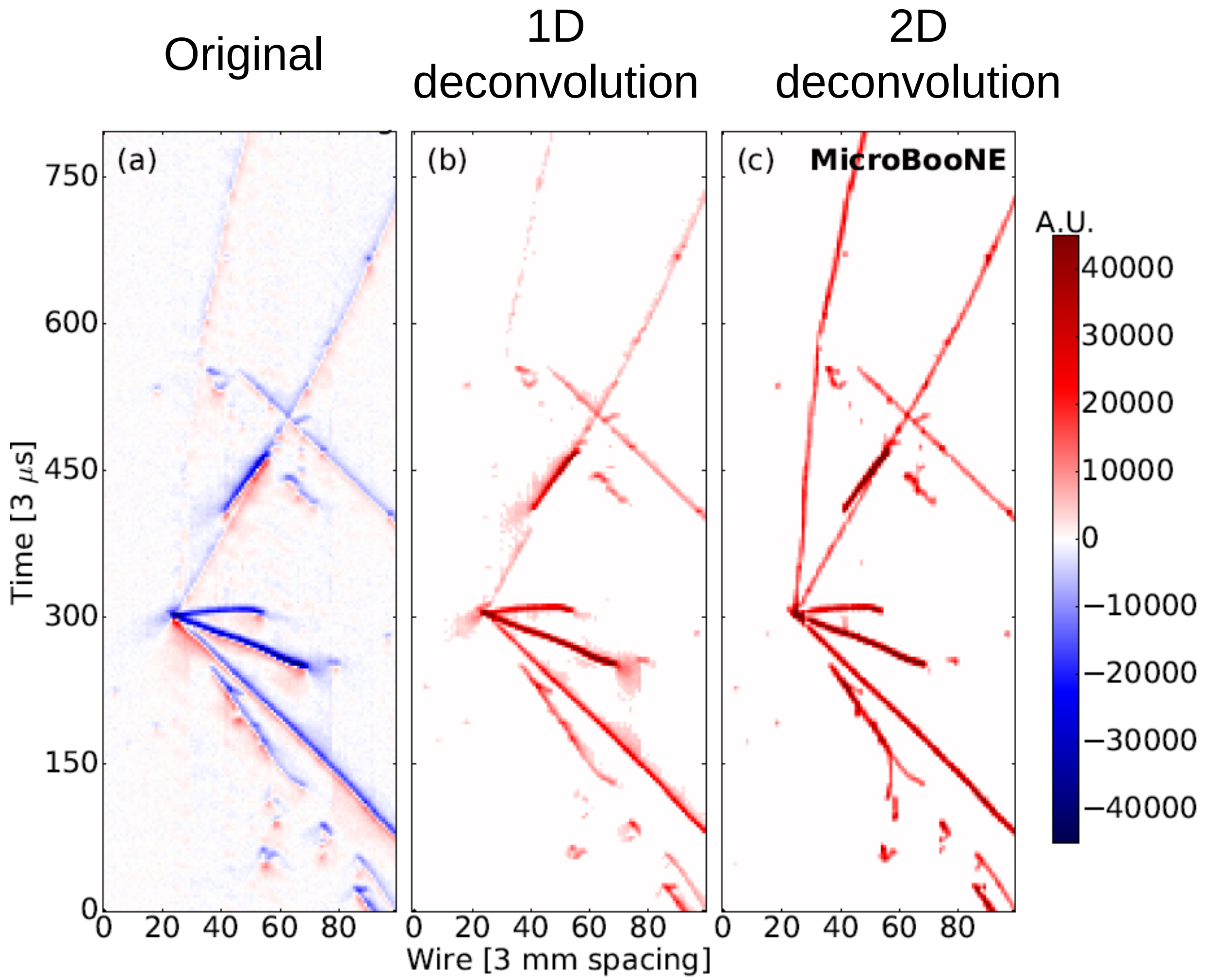
Improved TPC Signal Processing

1D deconvolution

2D deconvolution





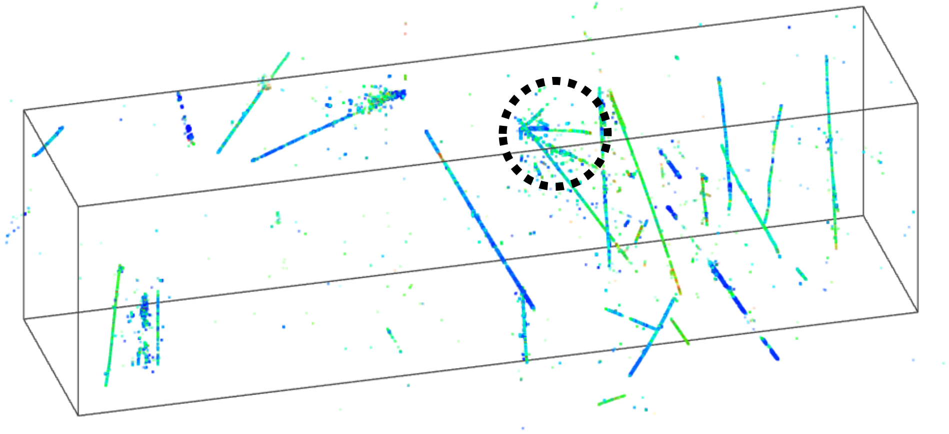
The 2D deconvolution algorithm in Wire-Cell allows to accurately recover the ionization electrons from recorded original signals

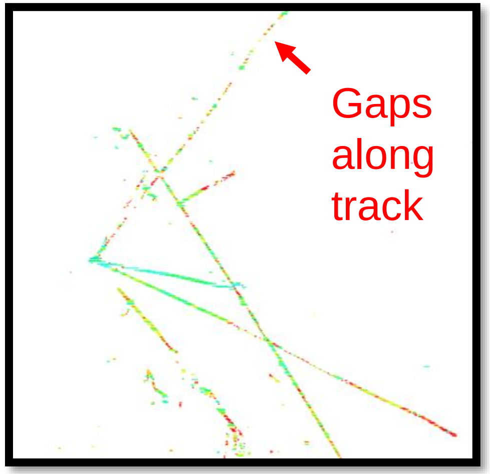
Same number of electrons are reconstructed from each projection wire plane

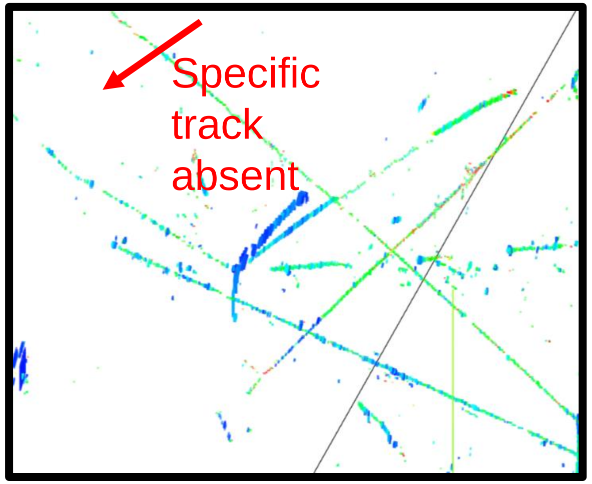
[JINST 13 P07006/7]

New Performance

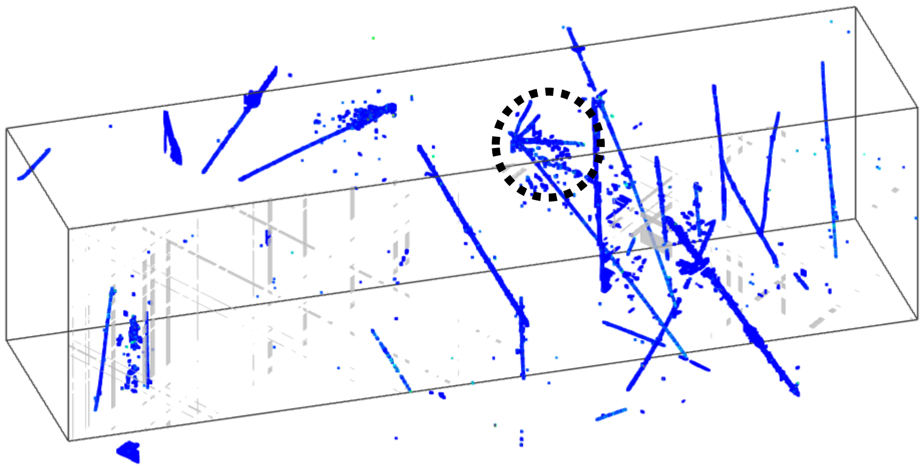
2015 1D deconvolution

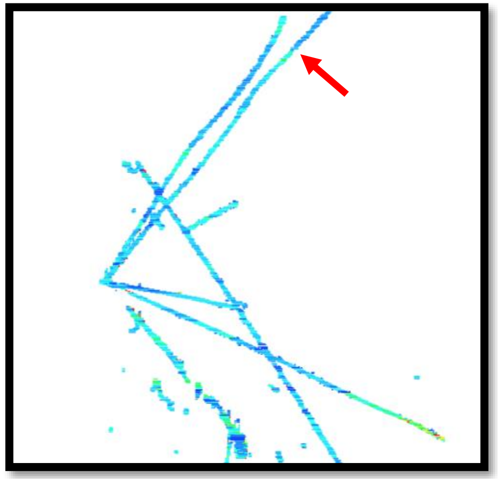


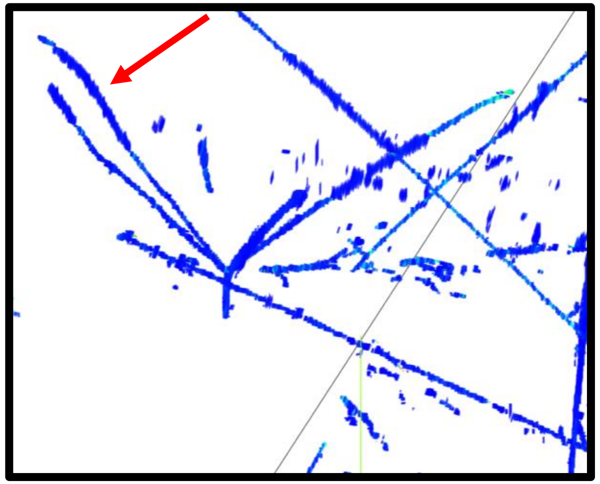




2018 2D deconvolution







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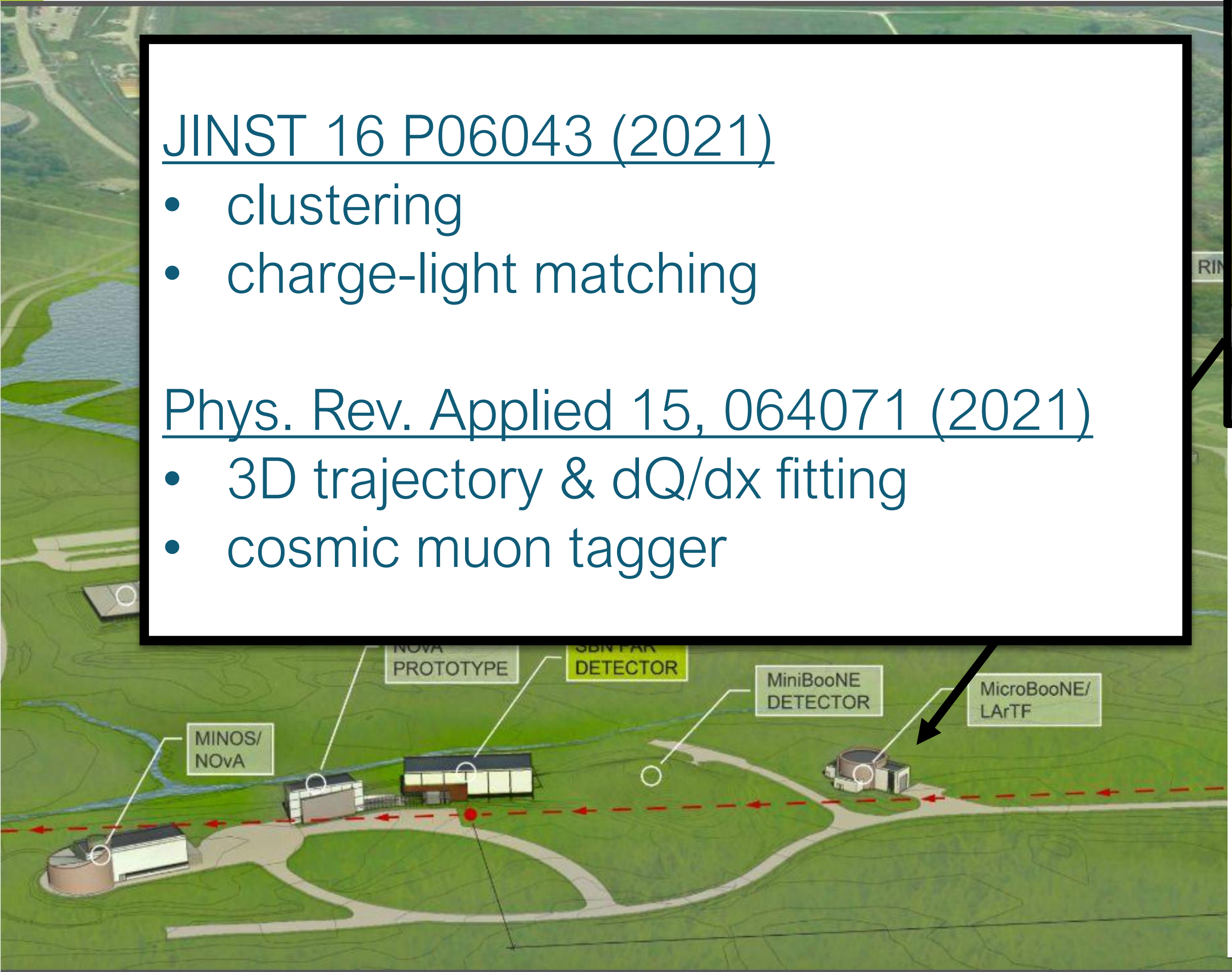
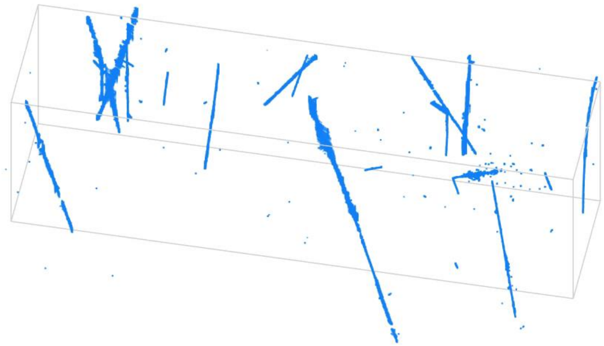
MicroBooNE detector operates near surface



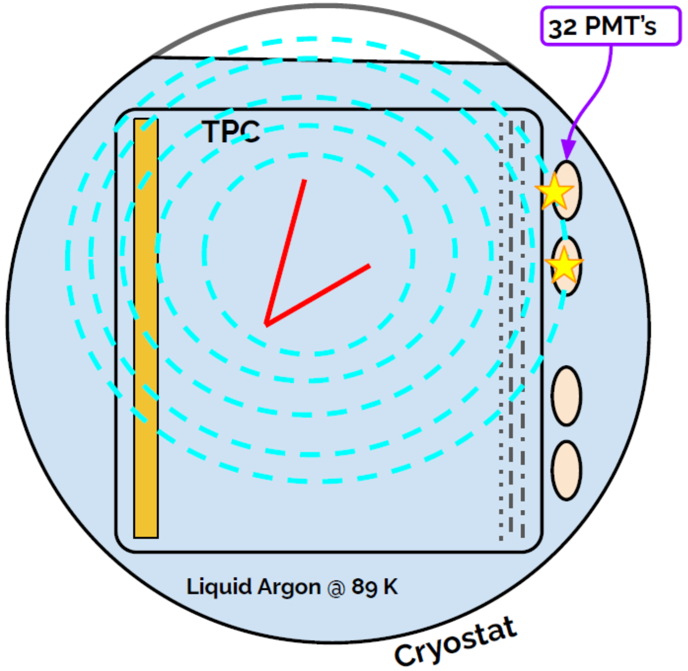
JINST 16 P06043 (2021)
- clustering
- charge-light matching

Phys. Rev. Applied 15, 064071 (2021)
- 3D trajectory & dQ/dx fitting
- cosmic muon tagger

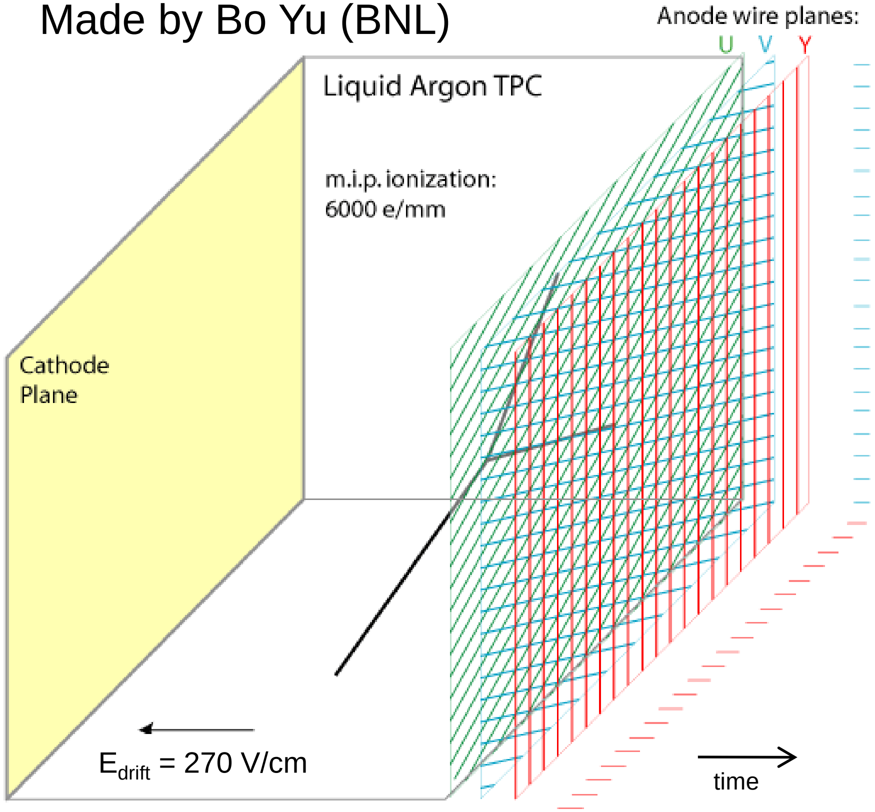


1 neutrino interaction in O(20) events
1 event includes 26 comic-ray muons

Cluster-flash (light) Matching



Made by Bo Yu (BNL)



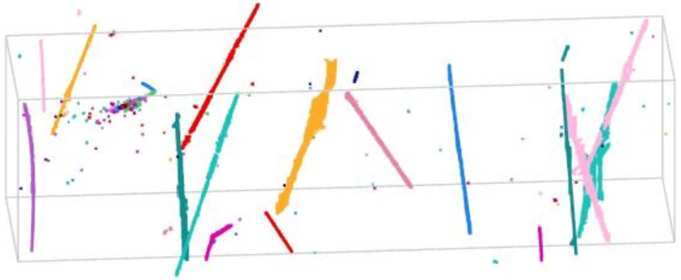
PMTs detect the scintillation light, time ~ns

Drift velocity 1.1 mm/μs → several ms drift time

- In LArTPC, the light (PMT) readout and charge (TPC) readout systems are decoupled
- The identification of neutrino interaction candidate requires matching the charge signal with the light signal in order to obtain the event time

Matching Principle

JINST 16 P06043 (2021)



Hypotheses Selection

Ma... Hyp...

Reconst...

- **Light signal proportional to (reconstructed 3D) charge**
- Known light acceptance given position
- Predicted vs. Measured light pattern with Compressed Sensing

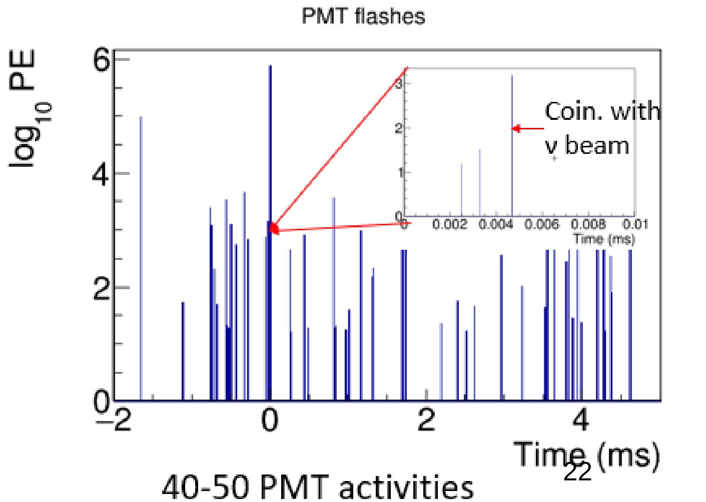
All possible hypotheses
- One cluster → at most one flash (inefficiency in the light system)
- One flash → many or zero TPC clusters within corresponding active volume (activities in inactive volume)

Core Charge-Light Matching Algorithm

$\chi^2 = \sum_i \sum_j \chi^2_{ij} + \chi^2_{p1} + \chi^2_{p2} + \chi^2_{p3}$	Overall test statistics to be minimized
$\chi^2_{ij} = \frac{(M_{ij} - \sum_k a_{ik} \cdot P_{ikj} - b_i \cdot M_{ij})^2}{\delta M^2_{ij}}$	Comparison of the measured and predicted light pattern
Rule 1st: $\chi^2_{p1} = \sum_i \frac{(\sum_k a_{ik} - 1)^2}{c_1^2}$	Each charge cluster can only be used once
Rule 2nd: $\chi^2_{p2} = \sum_i \frac{b_i^2}{c_2^2}$	Observed light flash may not correspond to any charge cluster
$\chi^2_{p3} = \lambda \cdot \sum_i \sum_k a_{ik}$	Compressed sensing to select the best pairs

M: Measured Light Pattern
P: Predicted Light Pattern
δ : Uncertainty
i : ith Light Flash
j : jth PMT
k : kth Charge Cluster

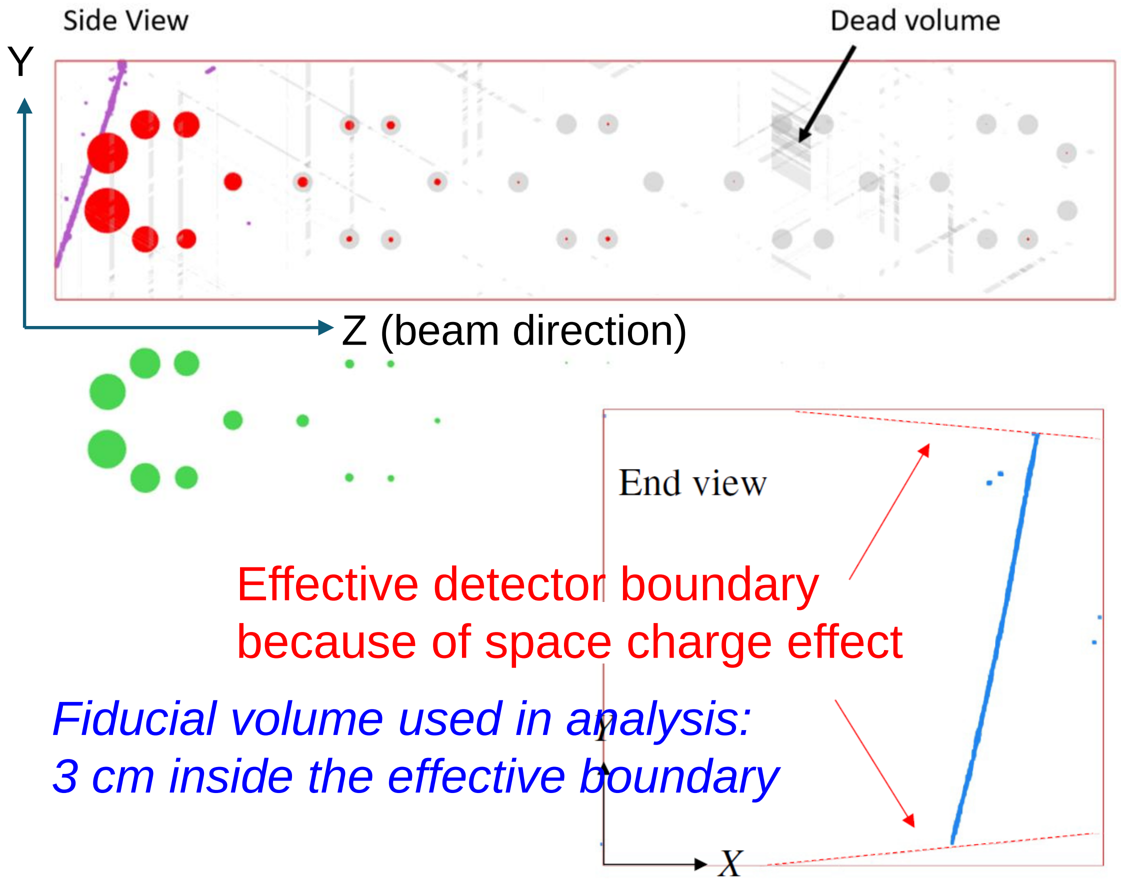
Aggressively pursue charge-light matching
Additional cuts to examine the "light mismatch" events



40-50 PMT activities

Rejecting Through-Going Muons (TGM)

- Only event with flash(light) time matching the neutrino beam spill window is a neutrino candidate

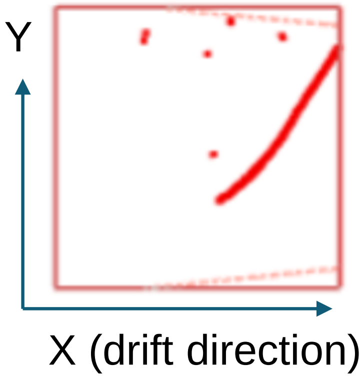


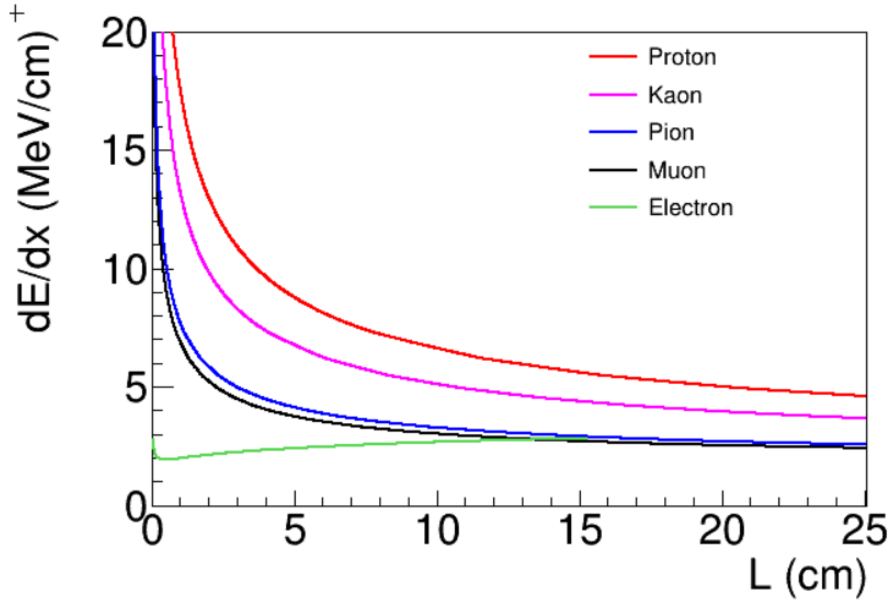
- TGM: cosmic-ray muons go all way through the active TPC volume

- Identification: the two endpoints of TPC cluster at/outside the effective detector boundary

	Neutrino:Cosmic-ray	
Charge-light matching	1 : 6.4	Improved by factor of 6
TGM rejection	1 : 0.9	

Rejecting Stopping Muons





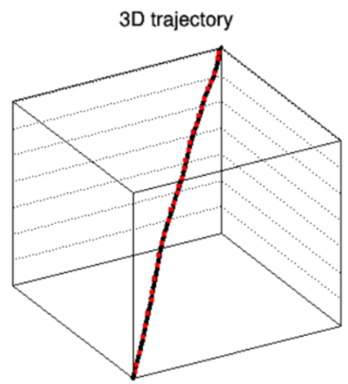
- STM: cosmic-ray muons enter and stop inside the active volume

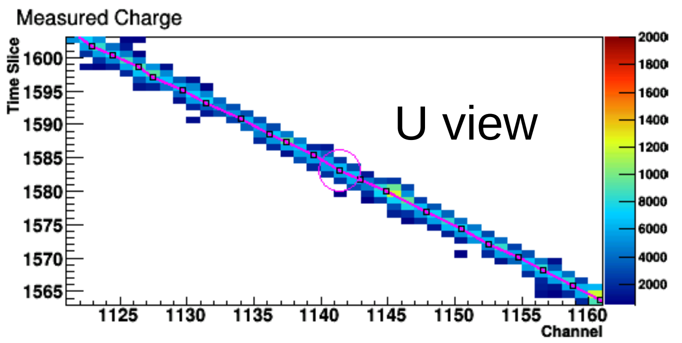
- Identified by directionality: from outside to inside
  - Tracks from neutrino activities will go out of detector from inside
  - Tracks from background will enter the detector from outside
- Trajectory and dQ/dx fitting → Bragg peak → directionality

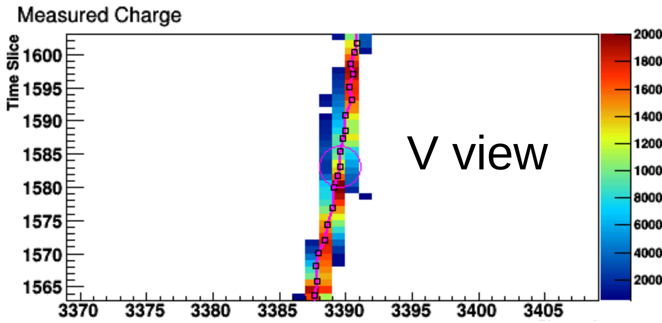
- dQ/dx vs. residual range is also important for the particle identification for tracks

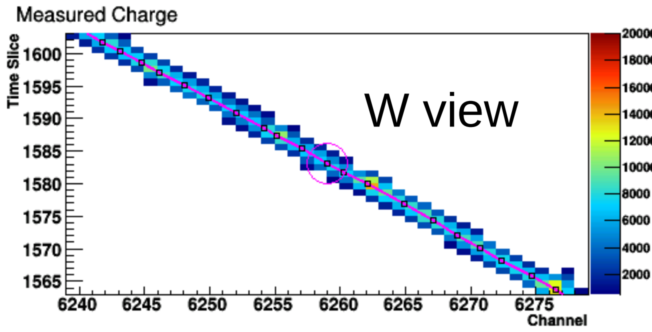
Principle of the Fit

- Come up with a 3D track hypothesis (3D trajectory points and dQ/dx)
- Predict the deconvolved signals on all projection views
- Minimize the difference between the observation and prediction

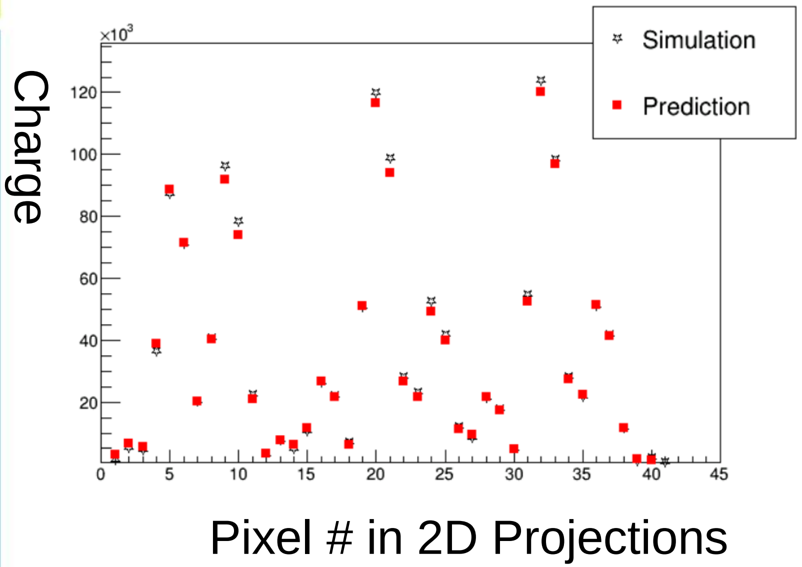


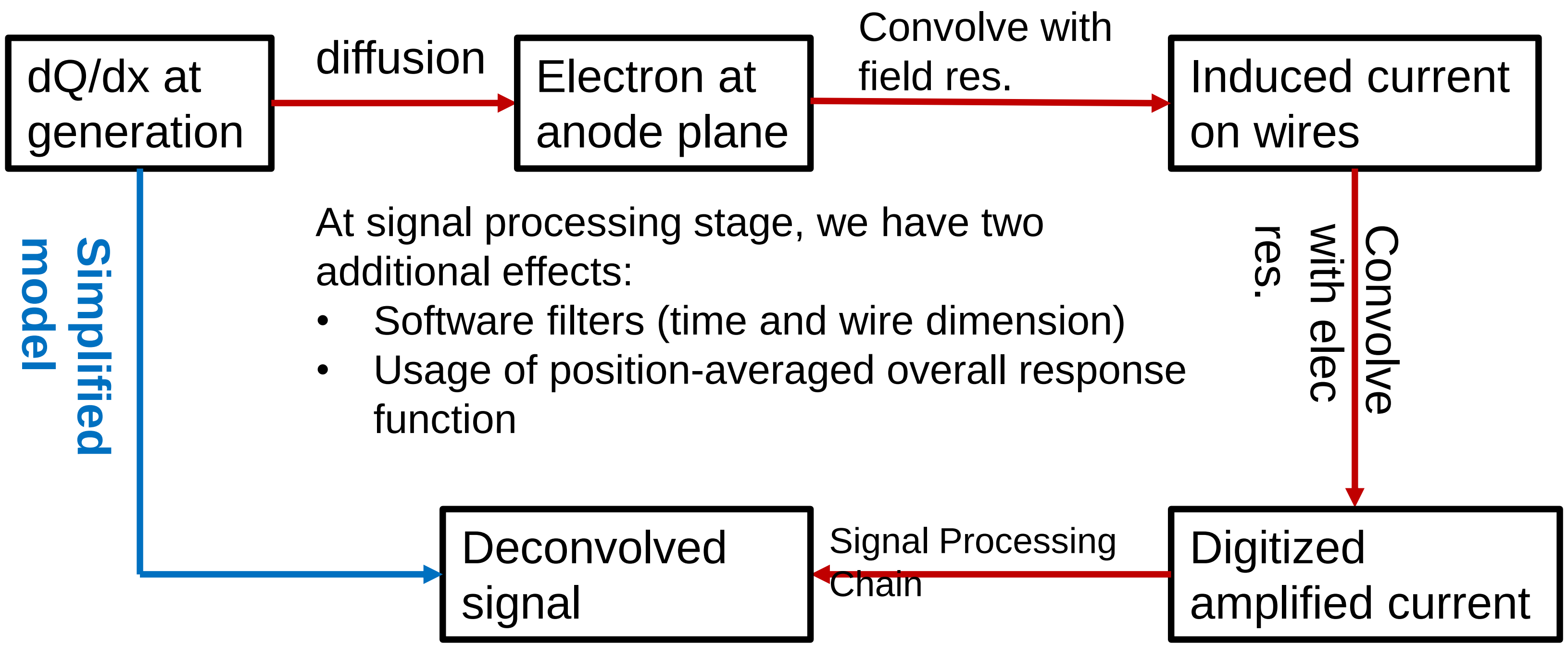






Simplified Prediction of the Deconvolved Signal





- Full process of signal formation and signal processing is complex → significant burden in computation
- A simplified model was developed

Trajectory and dQ/dx Fitting

Overall Test Statistics

$$T\left(x_j, y_j, z_j, Q_j\right) = T_U + T_V + T_W + T_{reg}$$

$$\mathrm{T}_{U/V/W} = \sum_j \sum_i \frac{q_i^2}{\delta q_i^2} \cdot dis\left(U/V/W\right)_{ij}^2$$

Unknowns

Measurements

i: pixel in 2D projection $\quad j$: 3D trajectory point

$$dis(U)_{ij}^2 = \Delta U^2 \cdot \left(U_i - U_j\left(x_j, y_j, z_j\right)\right)^2 + \Delta x^2 \cdot \left(t_i - t_j\left(x_j, y_j, z_j\right)\right)^2$$

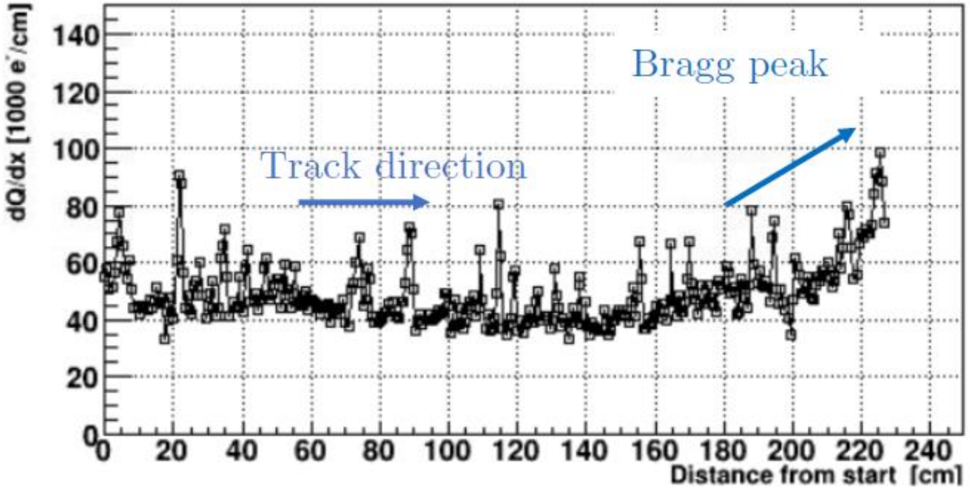
ΔU: bin size in U view, $\quad \Delta x$: bin siz in drift time t

Overall Test Statistics

$$T\left(x_j, y_j, z_j, Q_j\right) = T_U + T_V + T_W + T_{reg}$$

$$T_U = \sum_{i=U,T} \frac{\left(q_i - \sum_j R_{Uij} Q_j\right)^2}{\delta q_i^2},$$

R_{Uij}: smearing coefficients



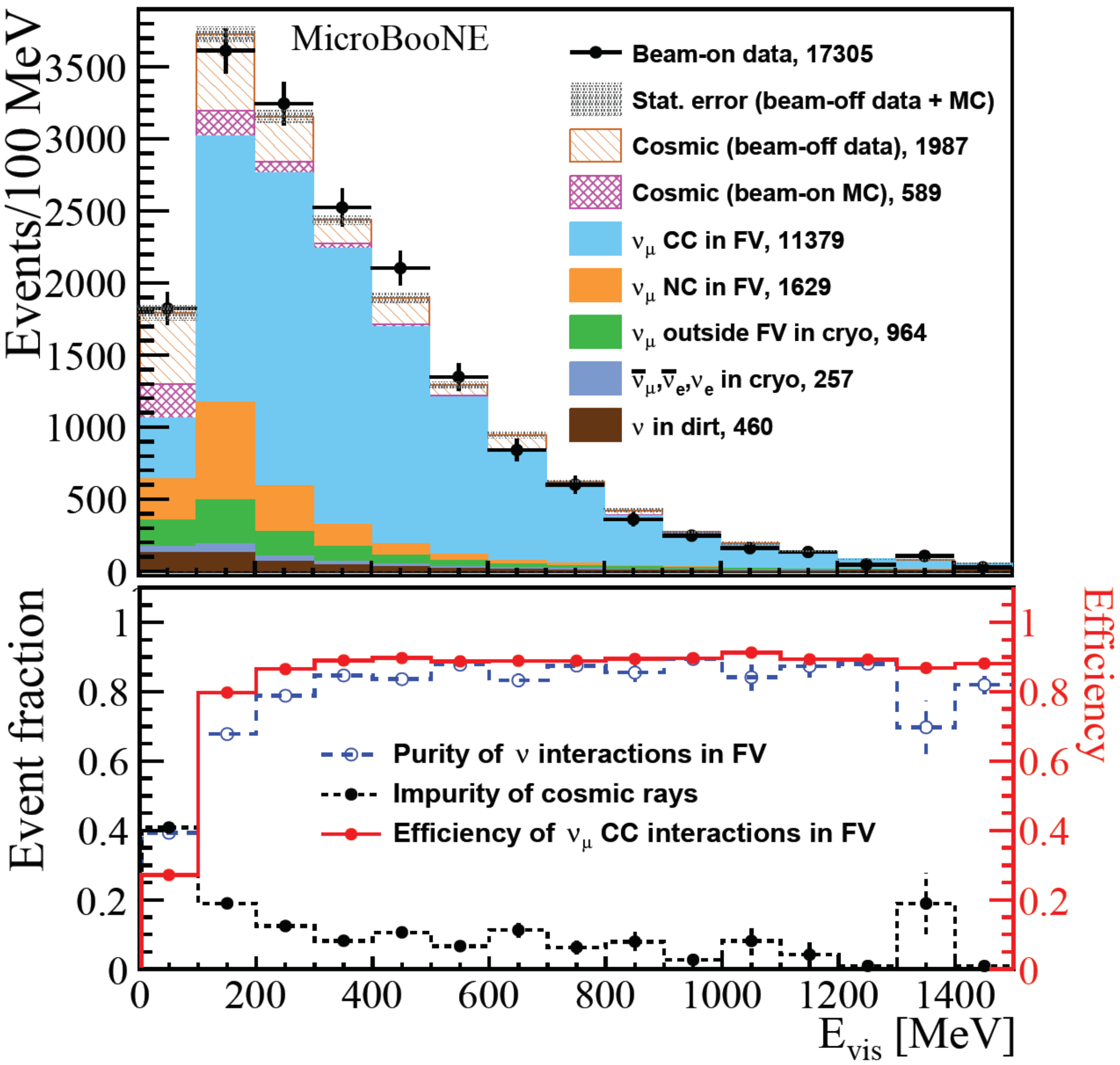
	Neutrino:Cosmic-ray	
Charge-light matching	1 : 6.4	Improved by factor of >6
TGM rejection	1 : 0.91	
STM rejection	1 : 0.36	Improved by factor of ~3
Additional Cuts	1 : 0.20	

Preselection

- Generic neutrino detection powered by many-to-many charge light matching and additional cosmic taggers to reject in-time coincidence cosmic-ray muons

  - 99.999% cosmic-ray muon background rejected
    - Start with 1:20,000 neutrinos to cosmics
    - End with 5.2:1 neutrinos to cosmics

  - 90% efficiency for ν_eCC and 80% efficiency for ν_μCC
  - ν_eCC purity ~0.4% at this stage



Phys. Rev. Applied 15, 064071

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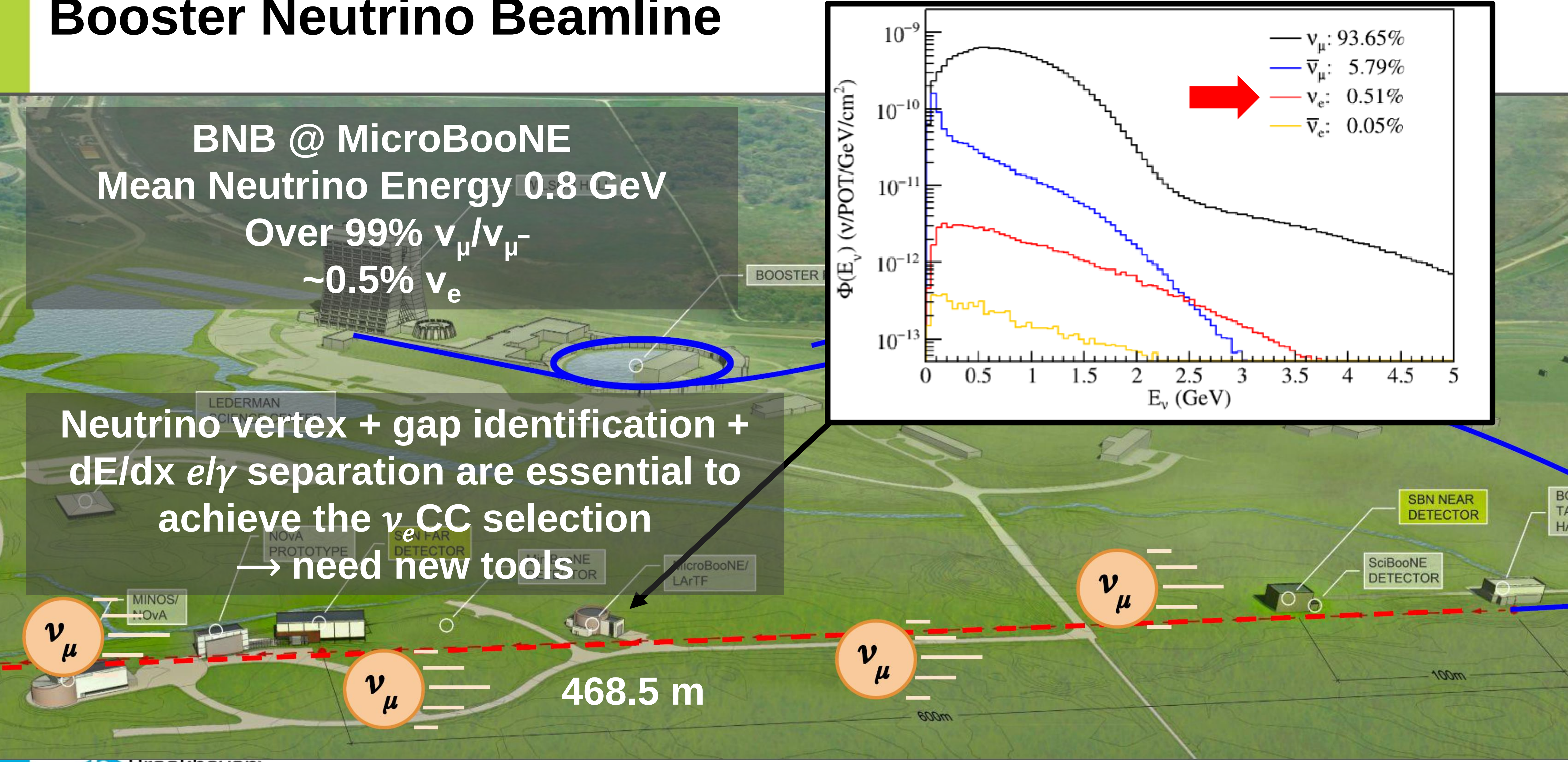
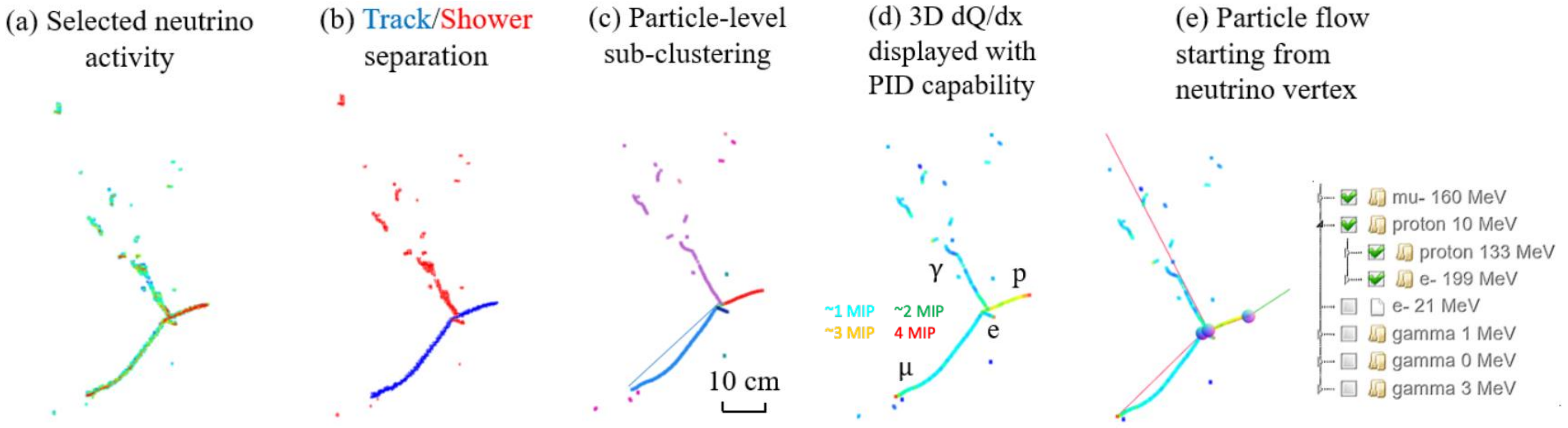
Booster Neutrino Beamline

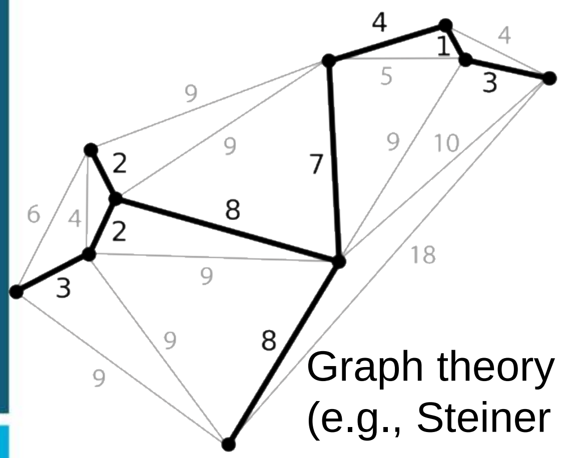
BNB @ MicroBooNE
Mean Neutrino Energy 0.8 GeV
Over 99% $\nu_\mu/\bar{\nu}_\mu$
~0.5% ν_e

Neutrino vertex + gap identification + dE/dx e/γ separation are essential to achieve the ν_eCC selection
⟶ need new tools

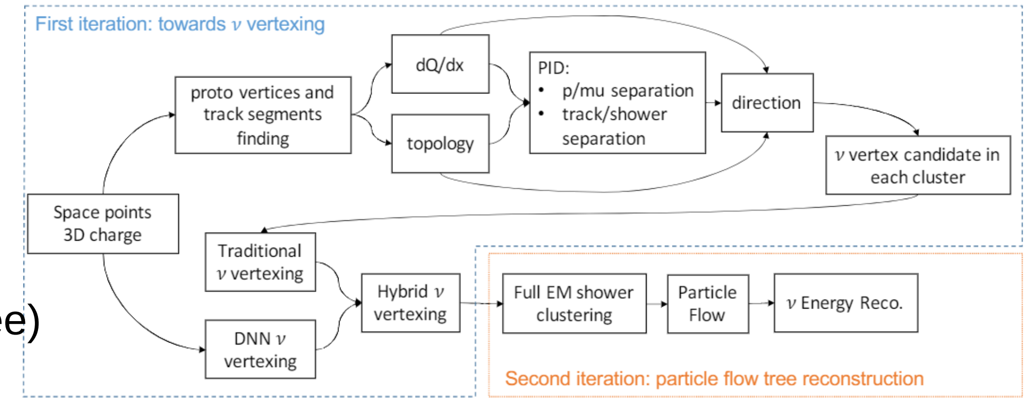


3D Pattern Recognition

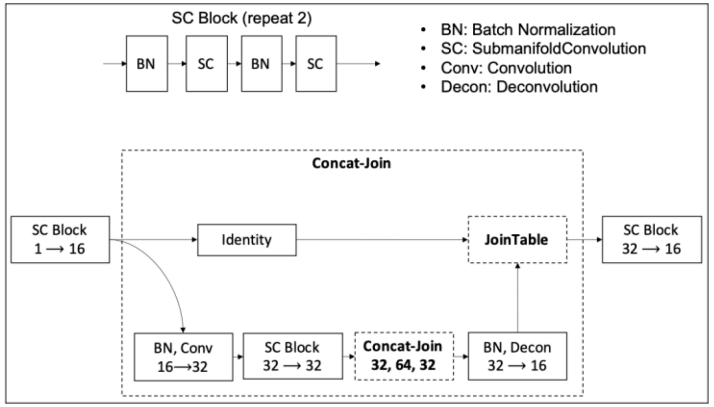




Graph theory
(e.g., Steiner tree)



Sparse Regression U-Net



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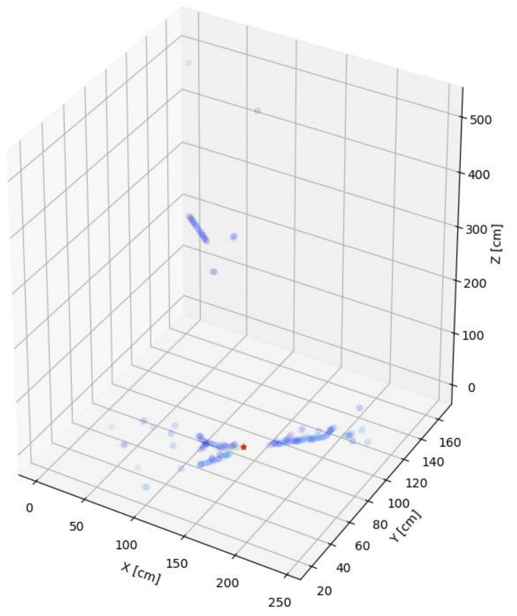
JINST 17 P01037 (2022)

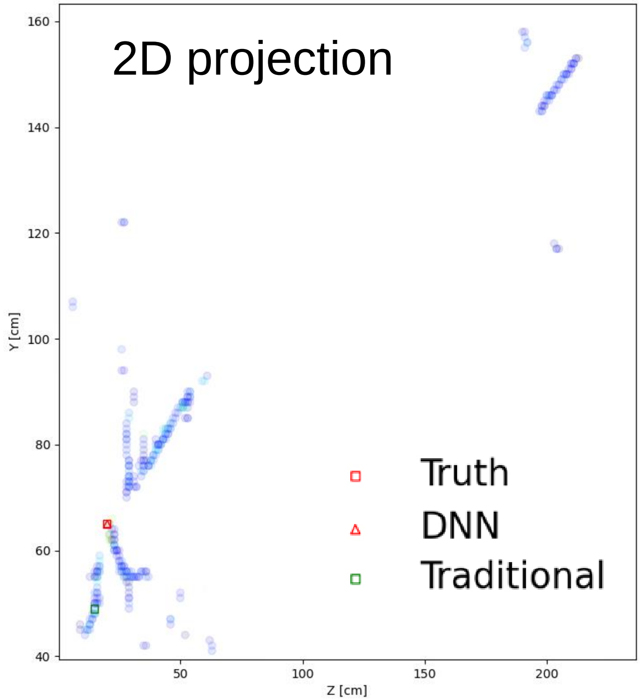
Deep Learning based Neutrino Interaction Vertex Finding

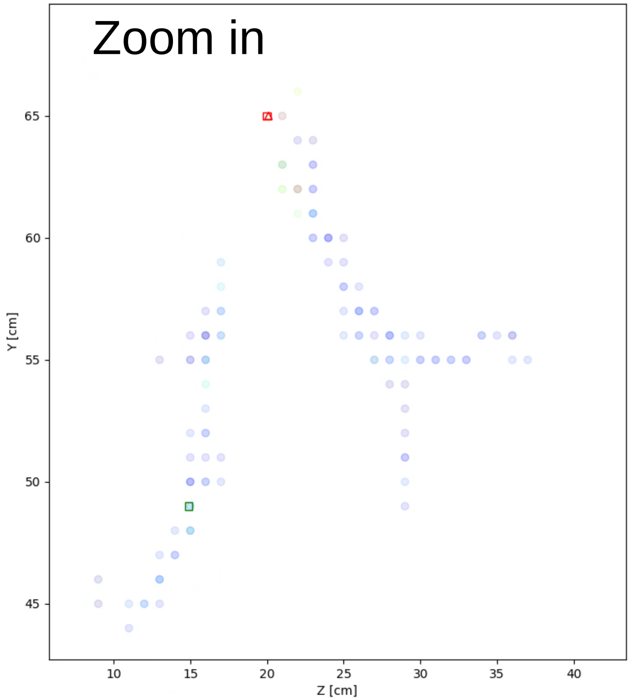
Regressional segmentation with a sparse U-Net

- U-Net: efficiently use geometry info which is critical
  - compared to graph networks
- Regressional loss on distance based “confidence map” to use a region of points instead of only one
  - otherwise, data is highly imbalanced (Z. Cao etc, arXiv:1812.08008)
- Sparse: boosted computing efficiency with our sparse 3D data
  - Submanifold Sparse Convolutional Networks (B. Graham etc, arXiv:1706.01307)

3D points from Wire-Cell







Regressional segmentation

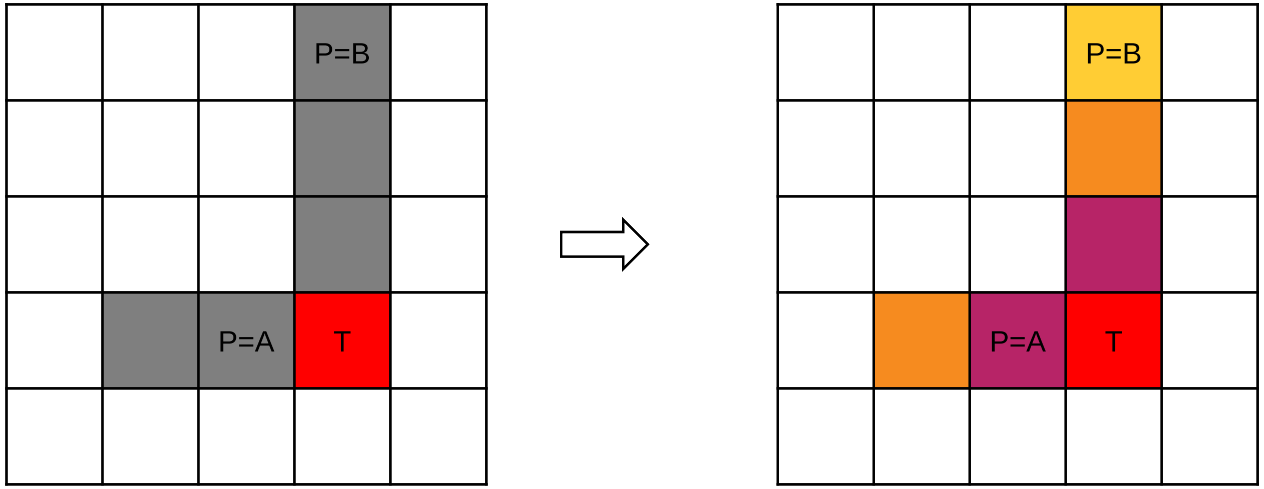
Initially we used Cross Entropy loss

- effectively only use the vertex information for one space point
- doesn't care about the distance between the prediction and the target.
    - while our main metric is this distance.

⟶ encode the distance information for a region of points

- predicting the full "confidence map" instead of only one point
- current mapping: $\mathrm{Conf}_{\mathrm{truth}} = \exp\left(-\frac{\|\vec{x} - \vec{v}_{\mathrm{truth}}\|^2}{2\sigma^2}\right)$

OpenPose:
https://arxiv.org/pdf/1812.08008.pdf

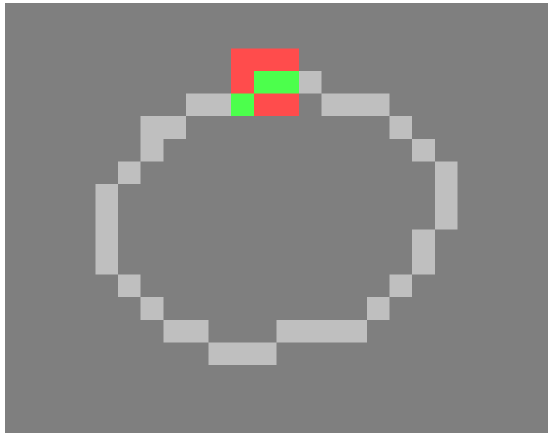


Network structure and data format

Used *SparseConvNet* to realized 3D sparse conv. DNN
https://github.com/facebookresearch/SparseConvNet

This work: https://github.com/HaiwangYu/uboone-dl-vtx

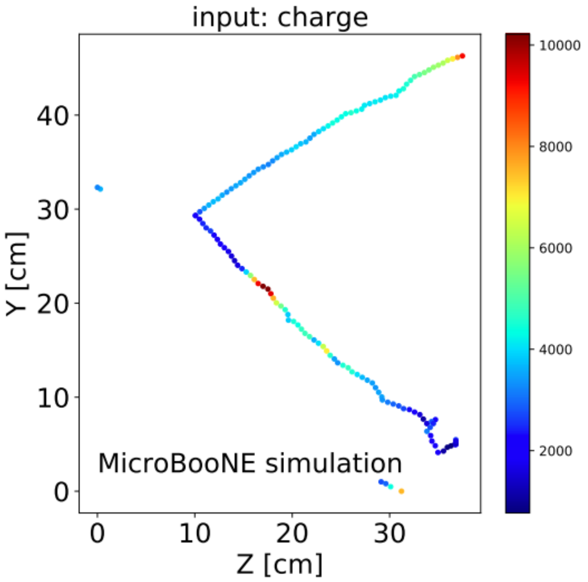
SparseConvNet



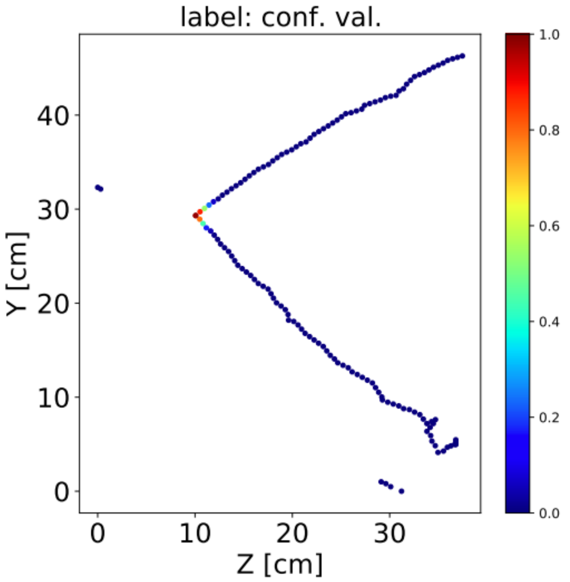
3D charge reco'ed from Wire-Cell → Sparse U-Net → Fully connected + sigmoid → confidence value for each voxel

coordinates			features		label
x	y	z	q	…	conf.
int	int	int	float	…	float
int	int	int	float	…	float
int	int	int	float	…	float
…	…	…	…	…	…

input: color is charge



label: color is truth confidence map



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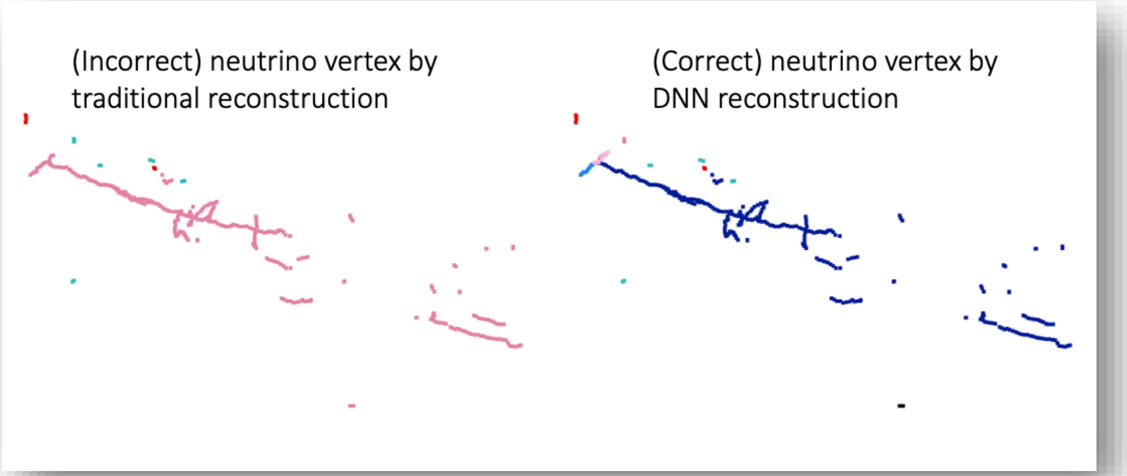
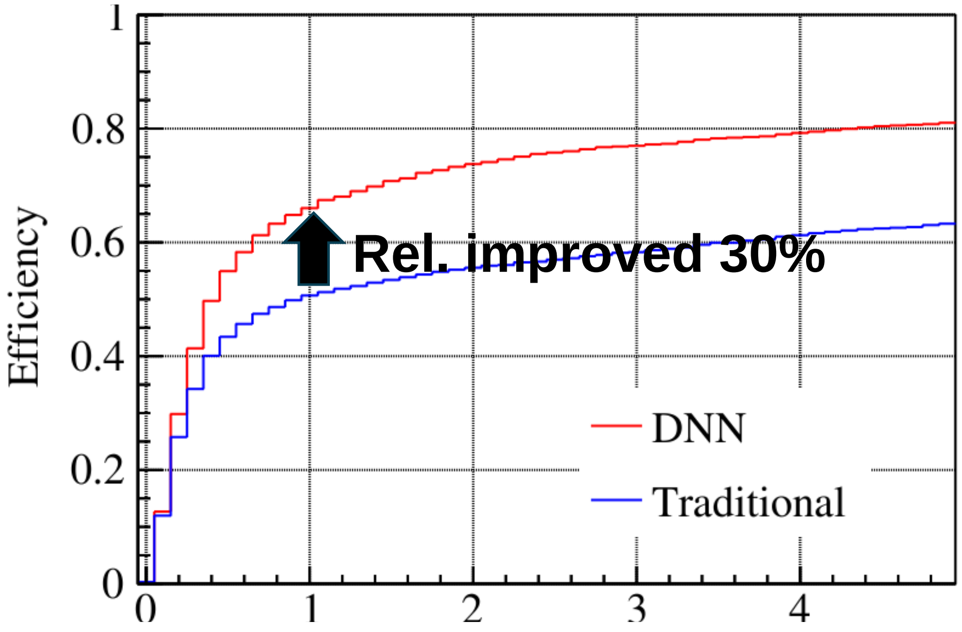
Deep Learning based Neutrino Interaction Vertex Finding

JINST 17 P01037 (2022)

Illustration of impact of vertex ID on the full event reconstruction



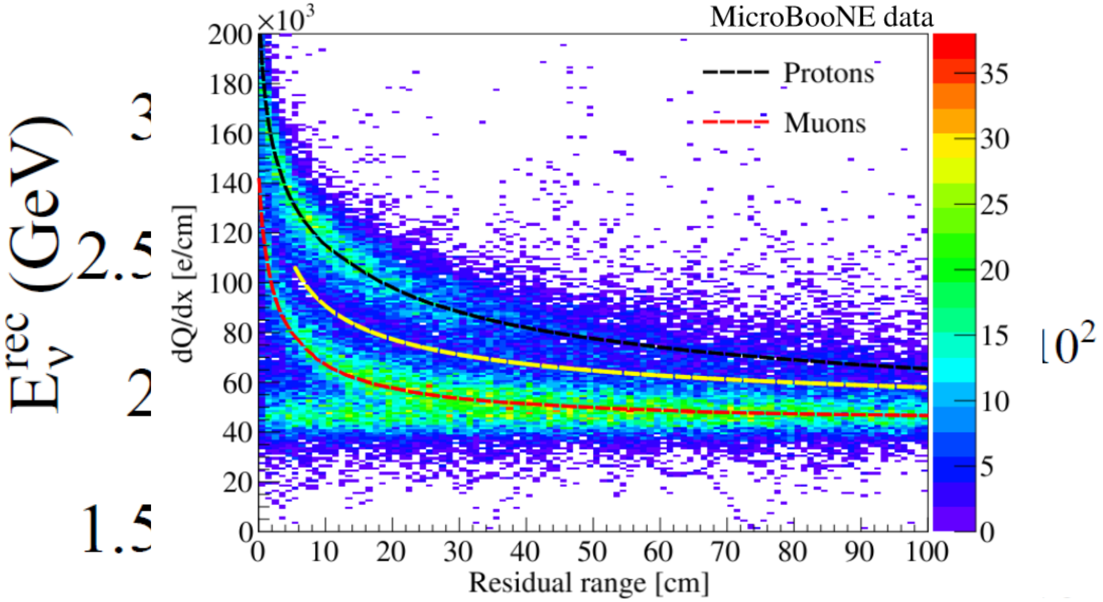
ν_eCC vertex identification efficiency



Distance between reco. and true vertex (cm)

Neutrino Energy Reconstruction

- Calorimetry energy reconstruction with particle mass and binding energy included if PID can be done
  - Track: Range, dQ/dx → dE/dx correction
    - Calibrated by stopped muons/protons
  - EM shower: scaling of charge
    - Calibrated by π^0 invariance mass

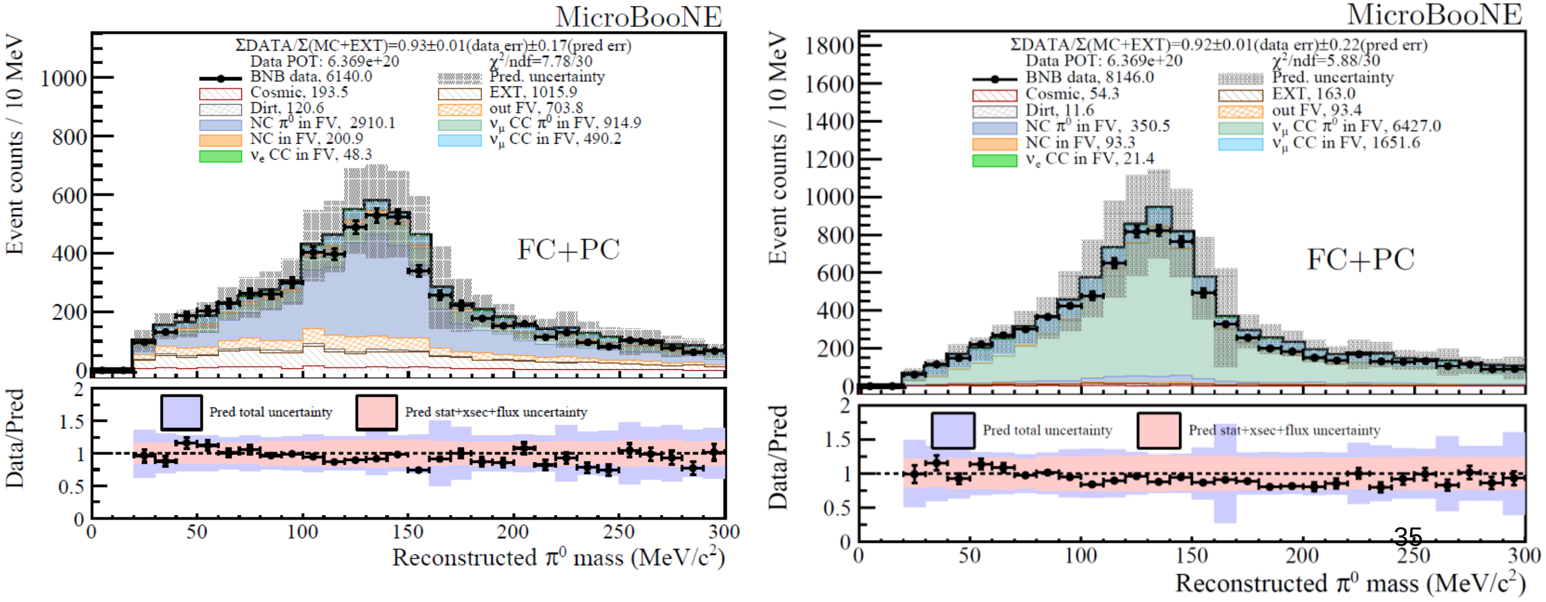


- Fully contained events

$\nu_e CC$ 10-15% resolution ~7% bias

$\nu_\mu CC$ 15-20% resolution ~10% bias

[JINST 17 P01037 (2022)](#)



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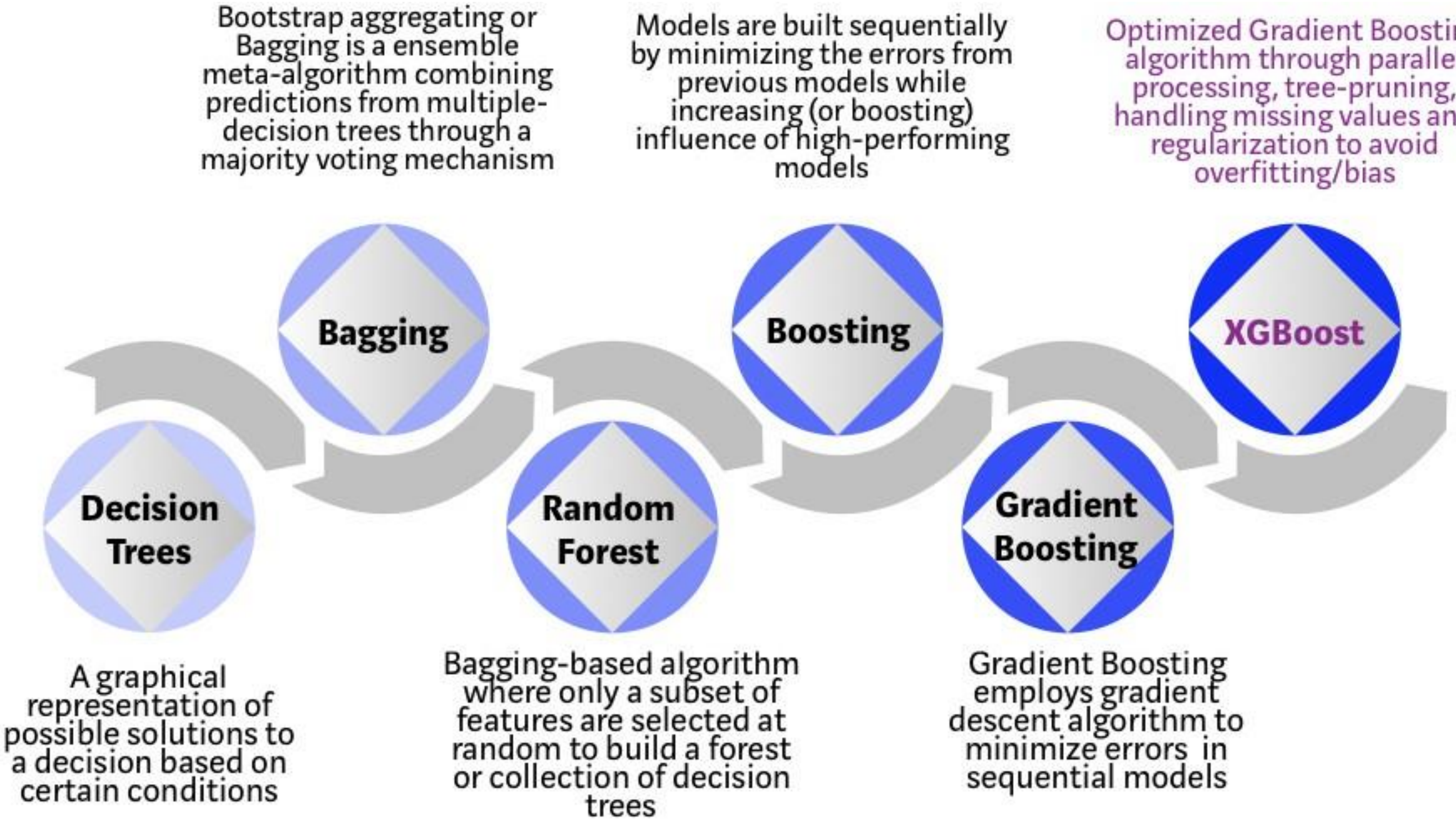
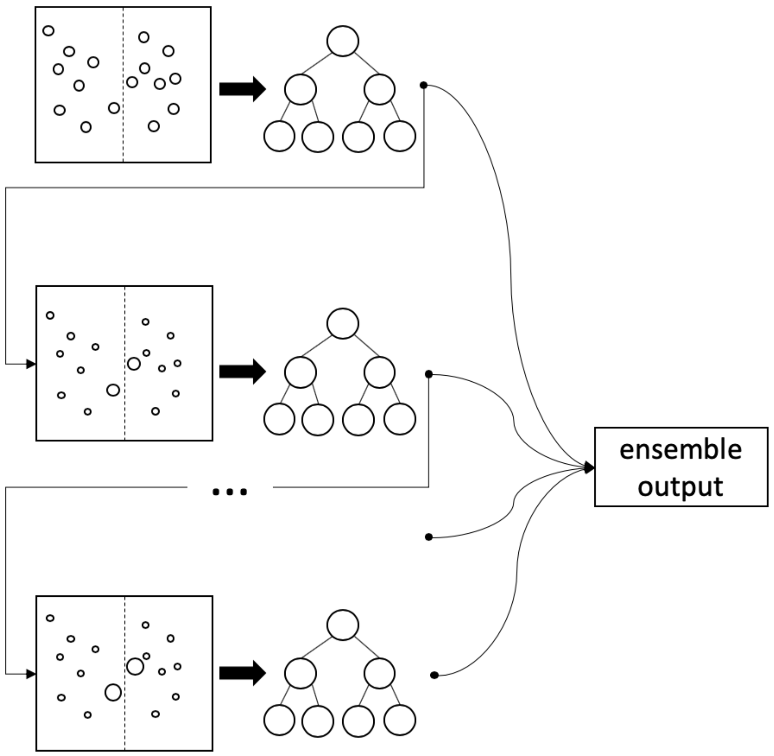
Boosted Decision Trees (BDT) for neutrino flavor tagging



Gradient Boosting



https://towardsdatascience.com/https-medium-com-vishalmorde-xgboost-algorithm-long-she-may-rein-edd9f99be63d

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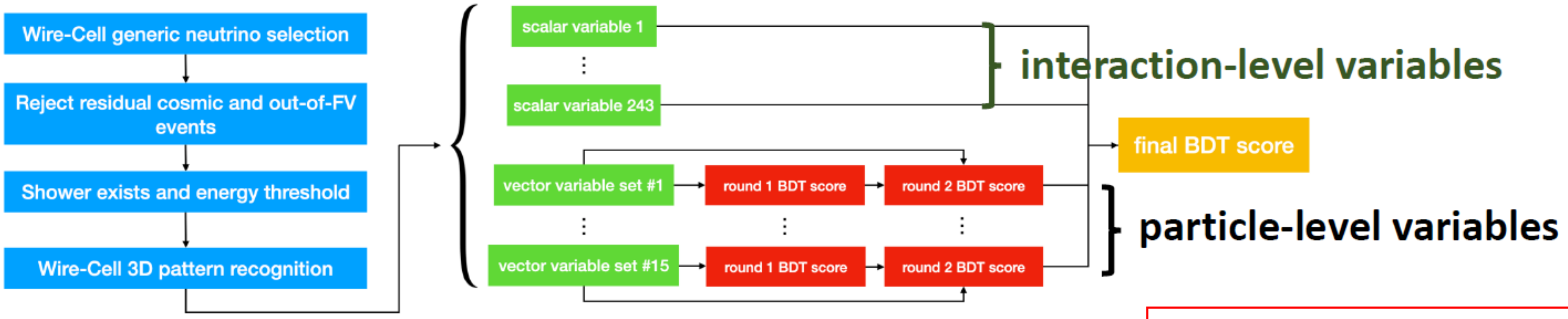
Neutrino Selection through Machine Learning

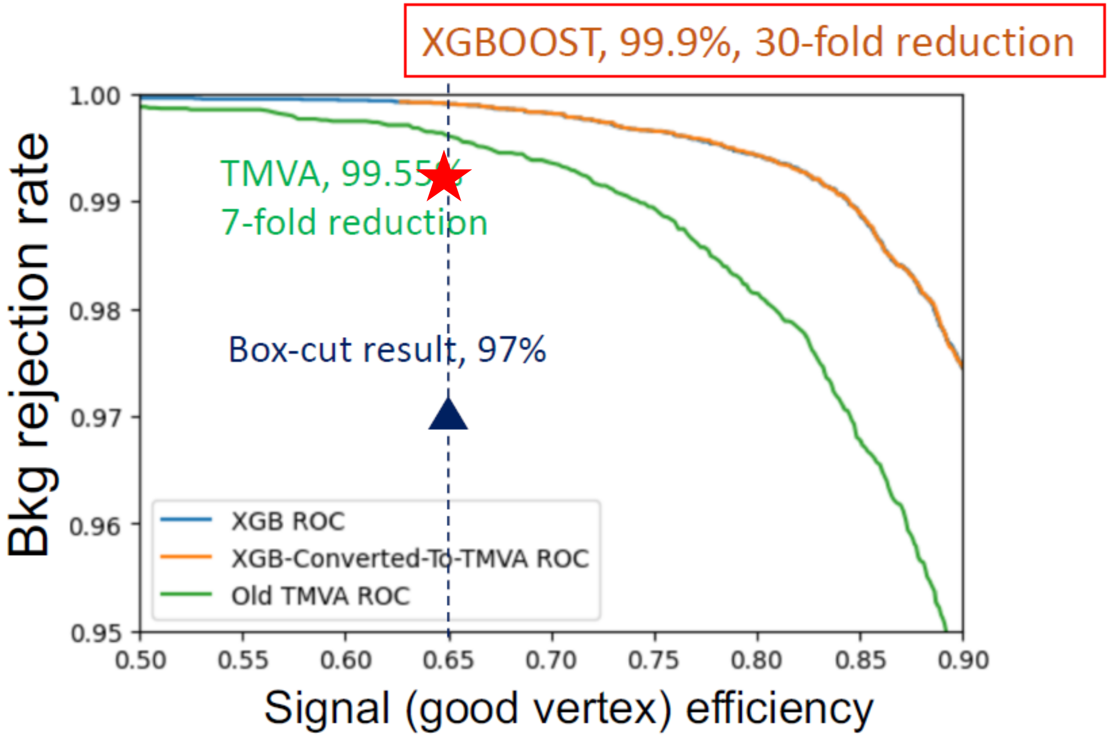


Human feature engineering

+

Maching learning algorithm:

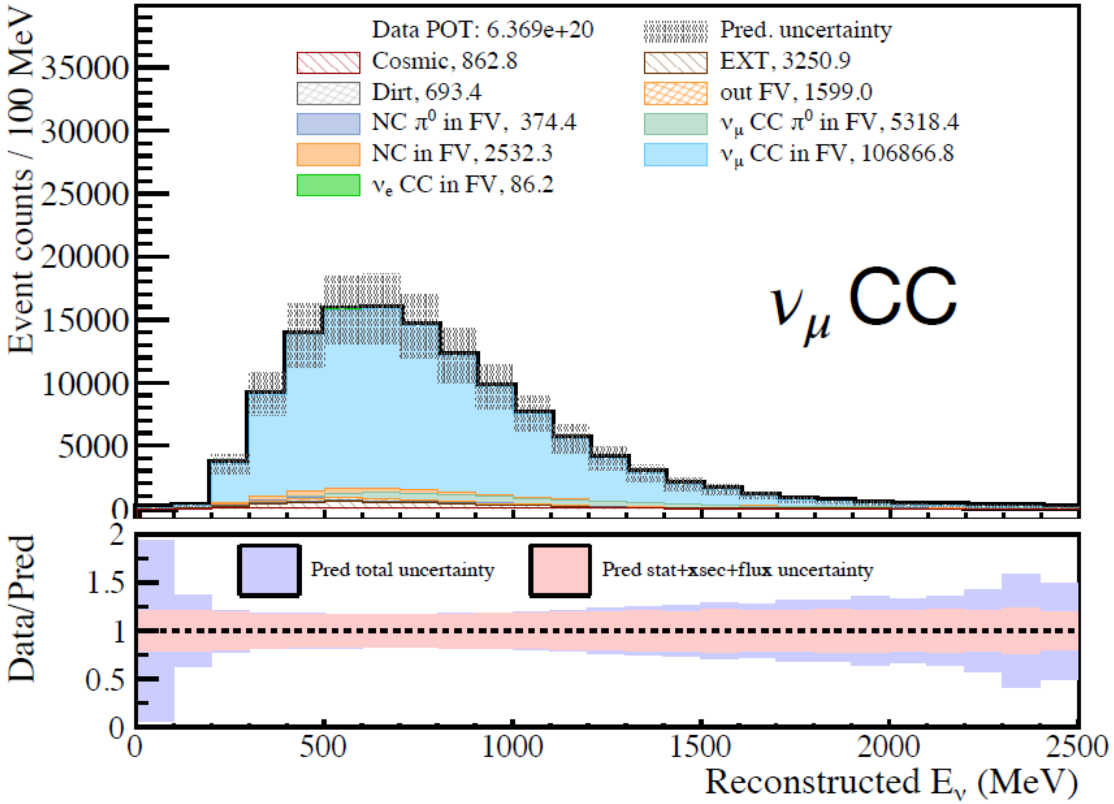
XGBOOST: extreme Gradient Boosting

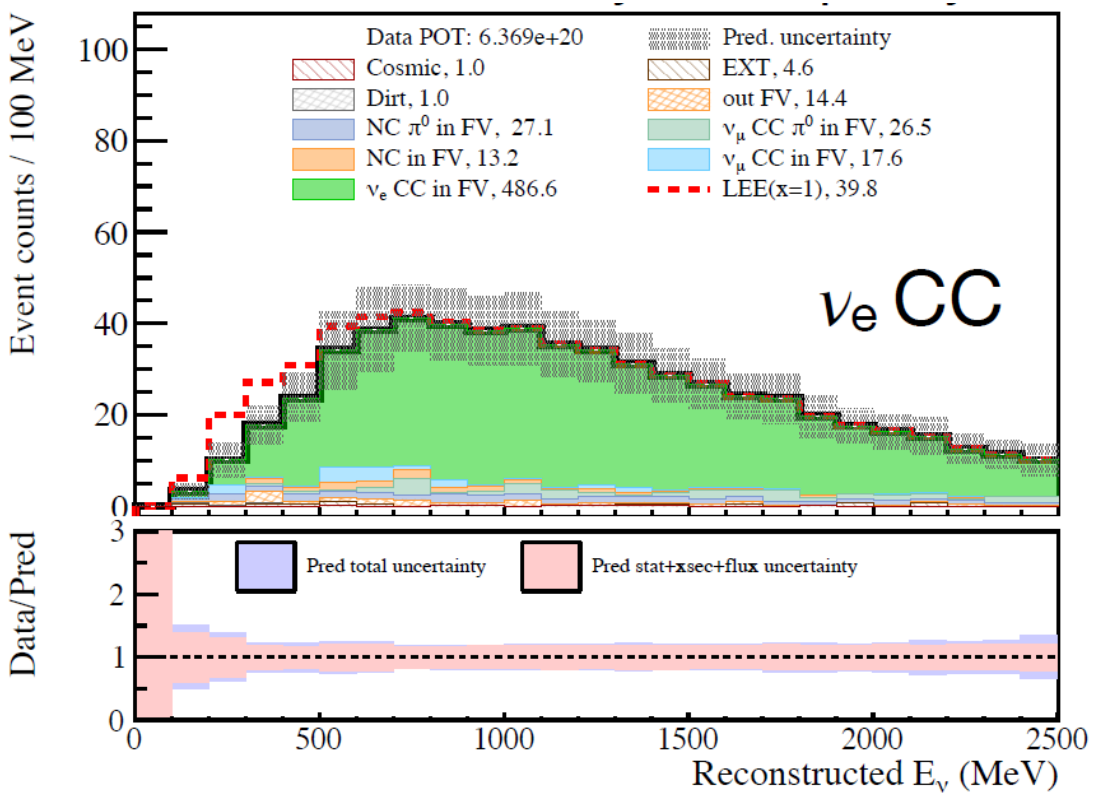


$$\frac{1-0.97}{1-0.999}$$

ν_μCC and ν_eCC Event Selection

arXiv:2110.13978





Efficiency: 68%
w.r.t to all ν_μCC w. vertex in fiducial volume
Purity: 92% (**>5** improvement in S/B)

Efficiency: 46%
w.r.t to all ν_eCC w. vertex in fiducial volume
Purity: 82% (**>800** improvement in S/B)

We are ready to do physics!

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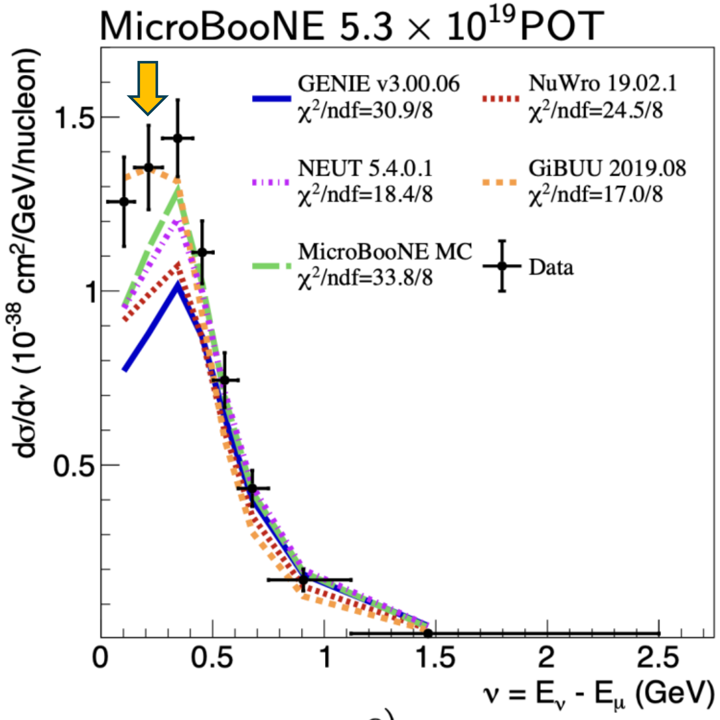
Application of Wire-Cell in Physics Analyses

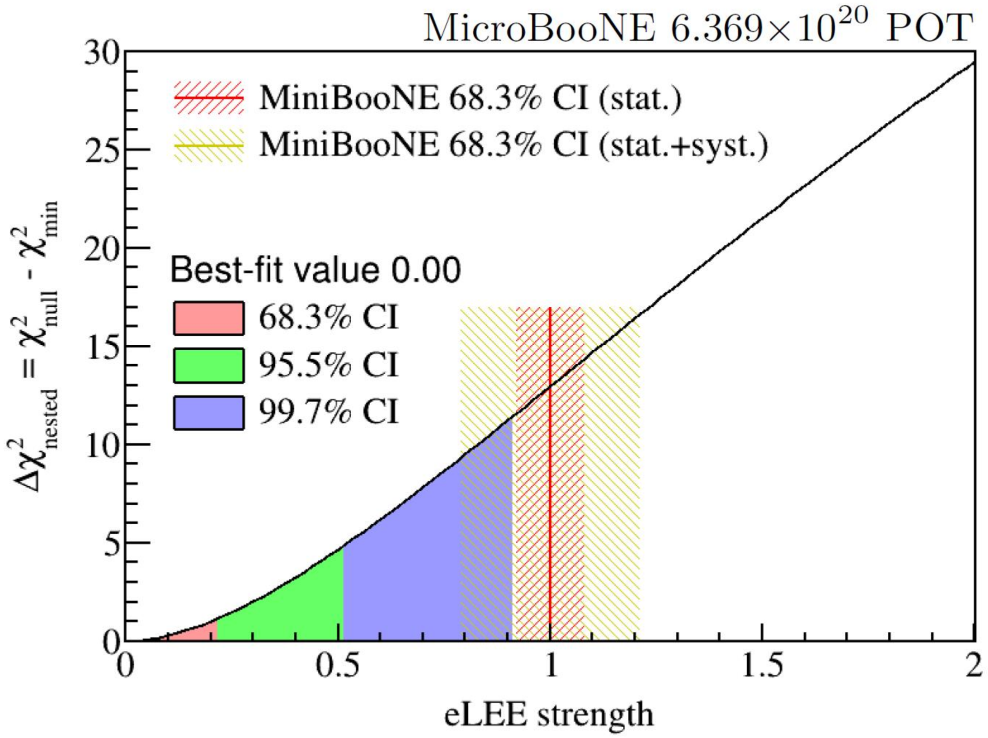
Energy-dependent Cross Section
arXiv:2110.14023, accepted by PRL



c)

- Good separation power of model predictions from different generators
- GiBUU's central prediction gives best agreement at low energy transfer for Ar ⇒ more contribution of 2p2h

Search for ν_e Low Energy Excess
arXiv:2110.13978



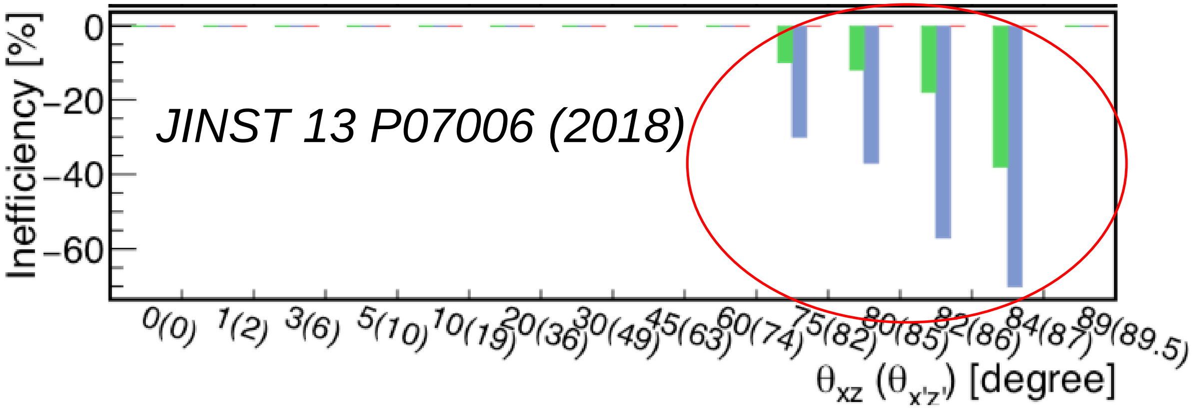
- 68% stat-only (full) uncer. MiniBooNE CI is disfavored at over 3σ (2.6σ)
- ν_e cannot be the sole explanation of MiniBooNE LEE!

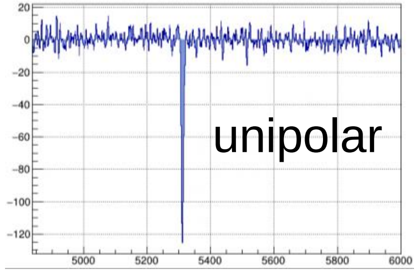
Future Developments

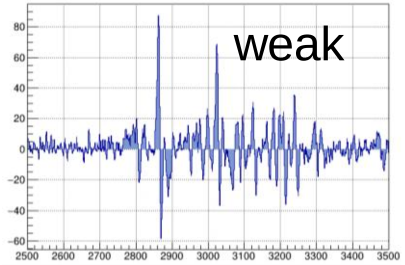
- DNN ROI finding
- RNN Energy Estimator
- Computing Parallelization/Acceleration

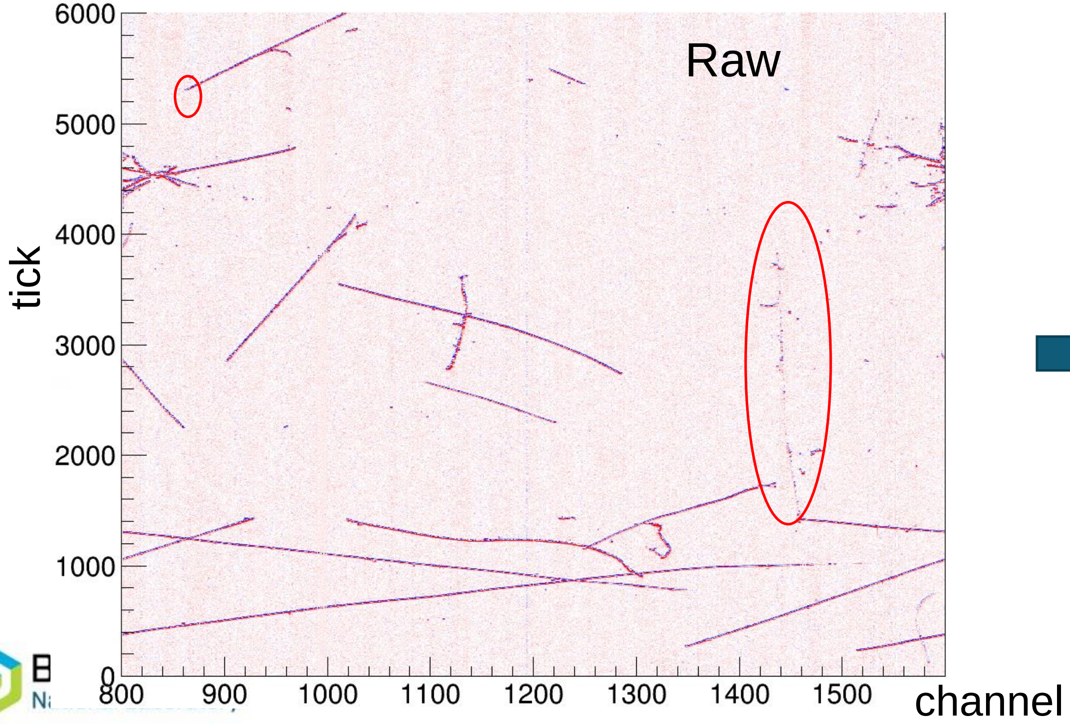
DNN ROI finding to improve LArTPC Signal Processing

- "Prolonged Track" – weak signal
- "Tear Drop" - distorted waveform
- Noisy dots - noise

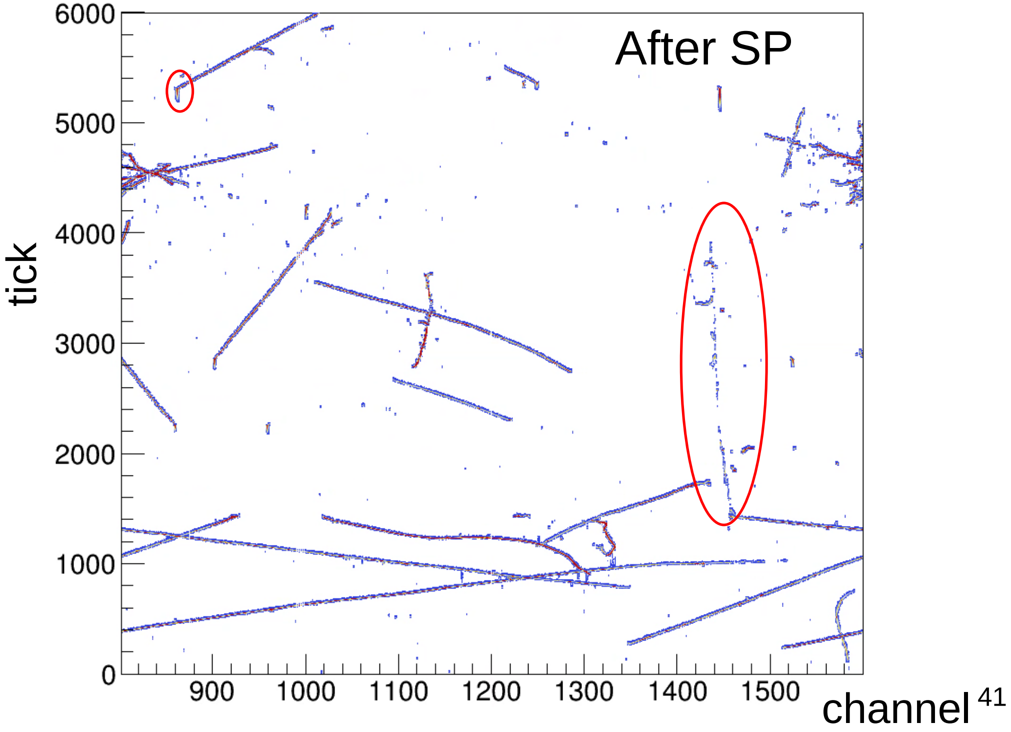








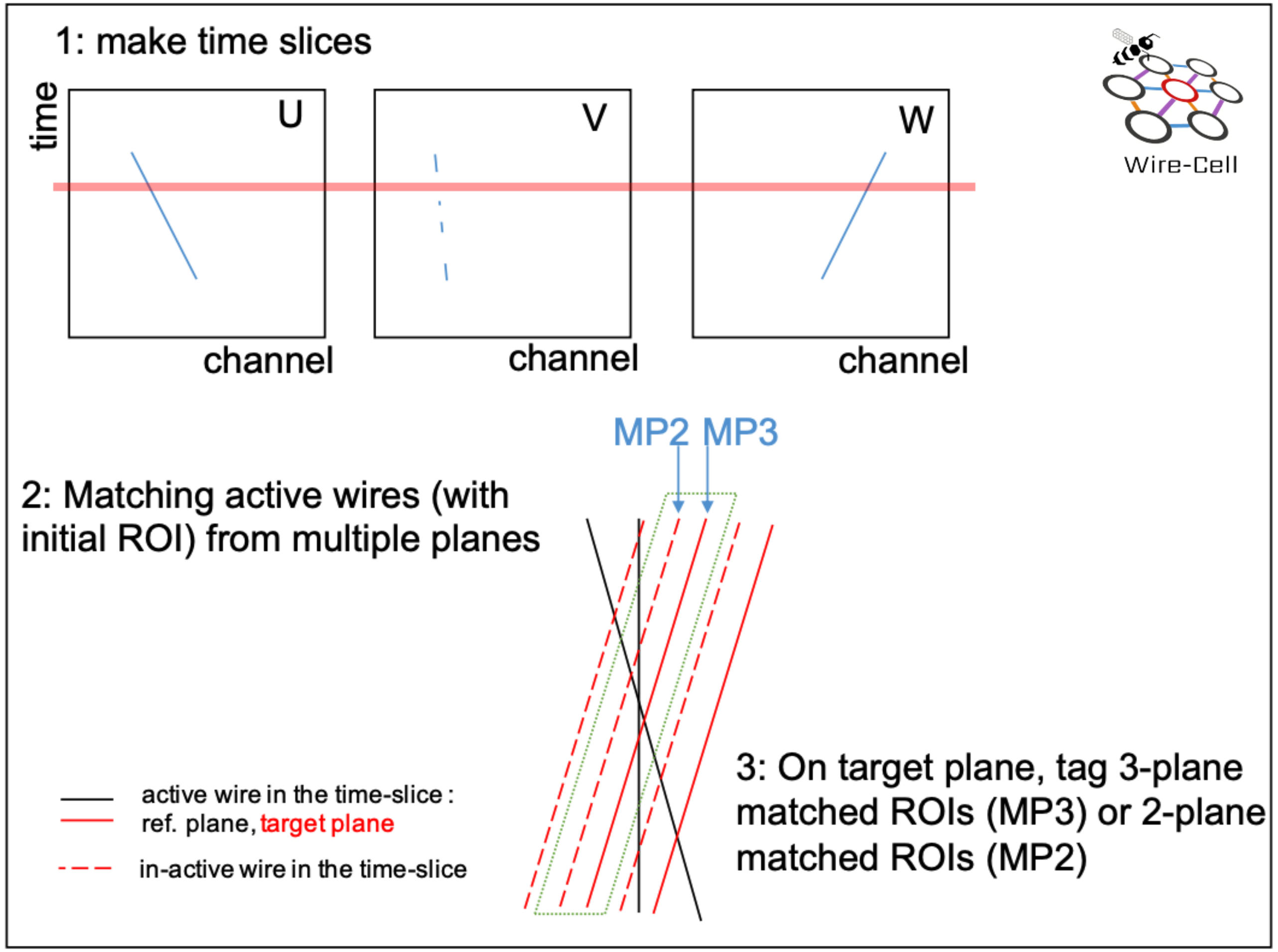
SP



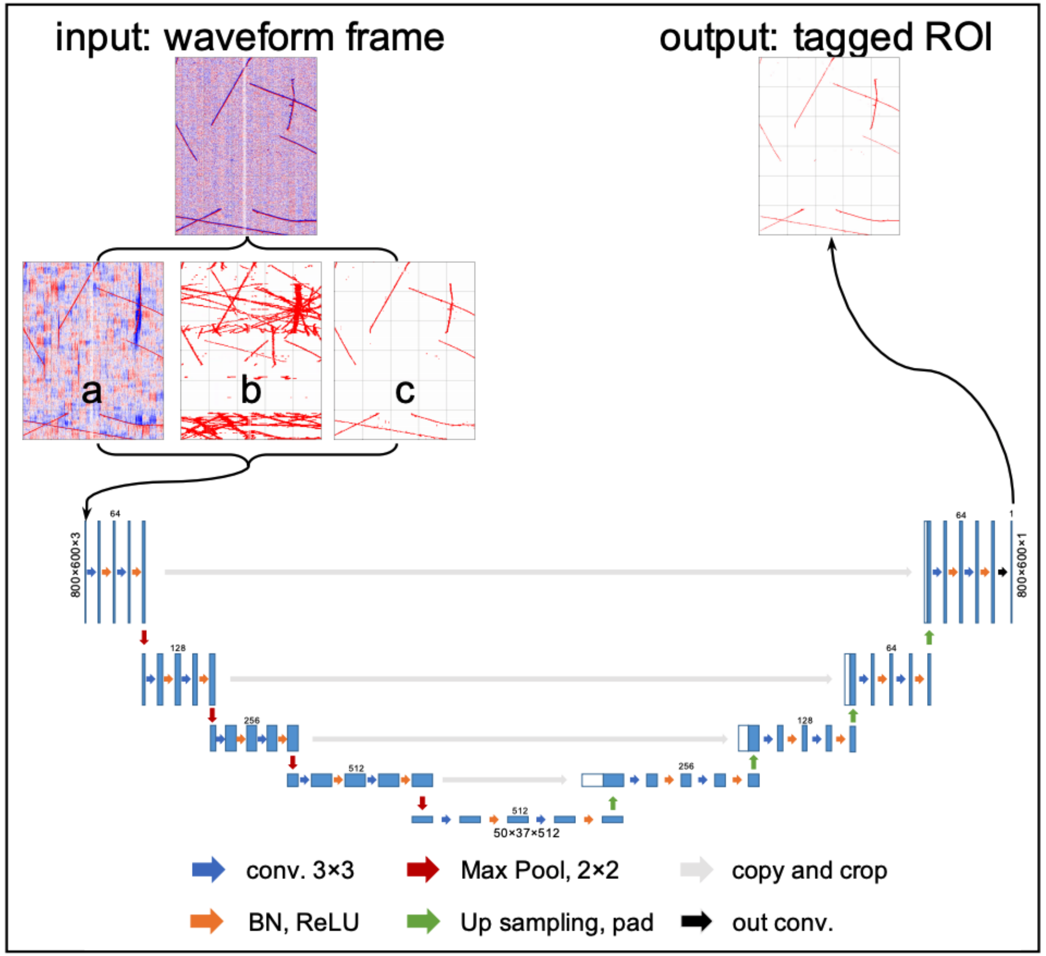
DNN ROI finding with multi-plane information

JINST 16 P01036 (2021)

Multi-plane information in Signal Processing

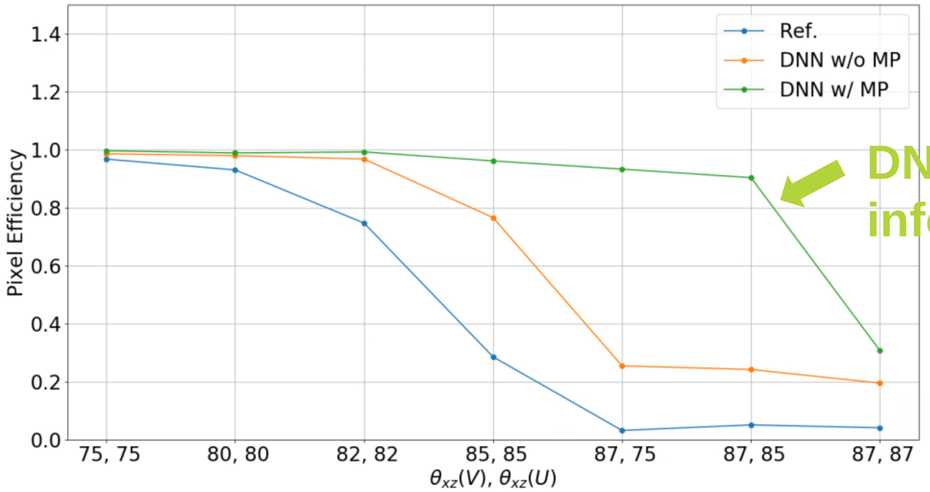


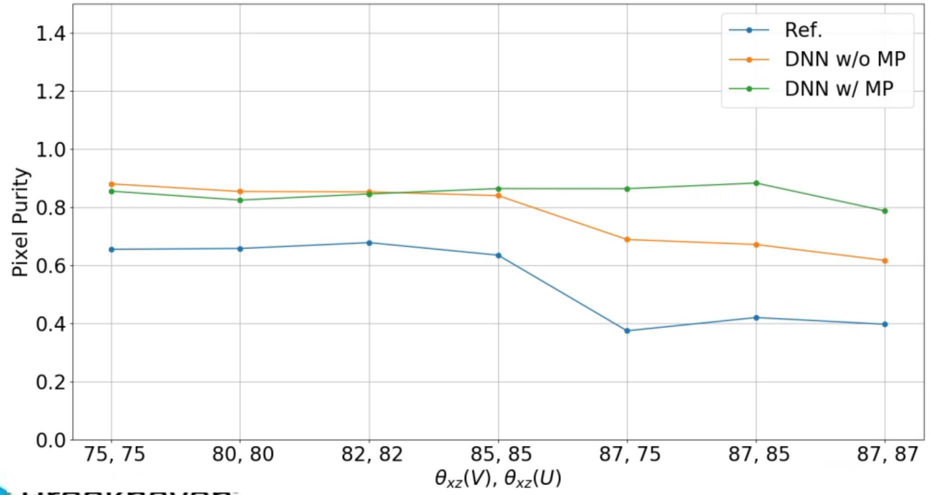
DNN ROI finding with multiple input channel



DNN ROI finding with multi-plane information

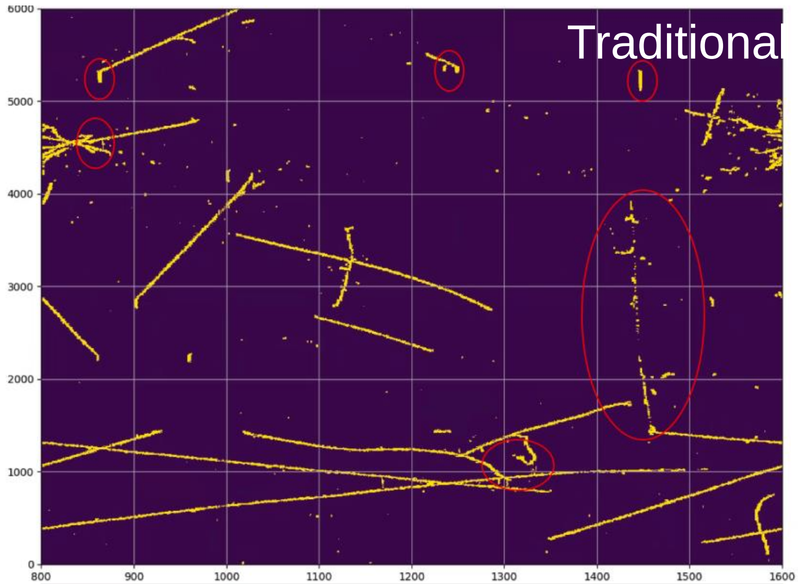
ProtoDUNE simulation
ROI finding on V plane (2nd induction)

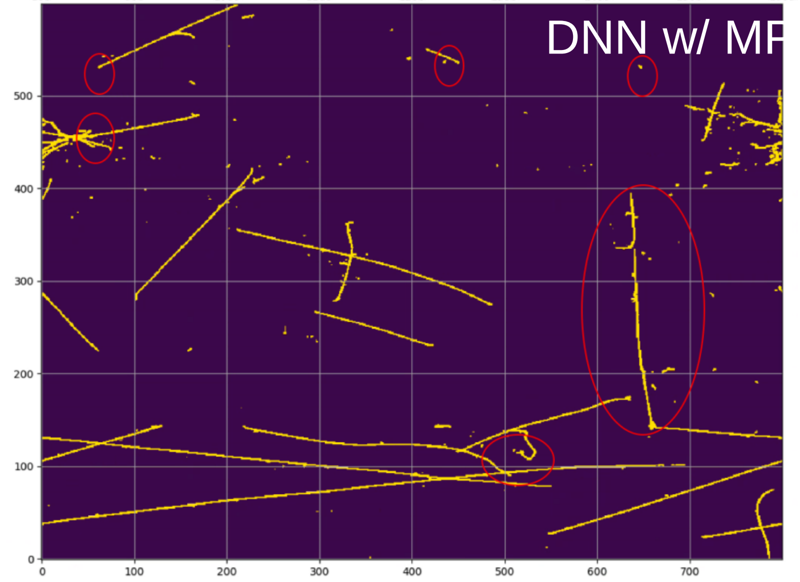




DNN With 3-plane information

tested on ProtoDUNE data





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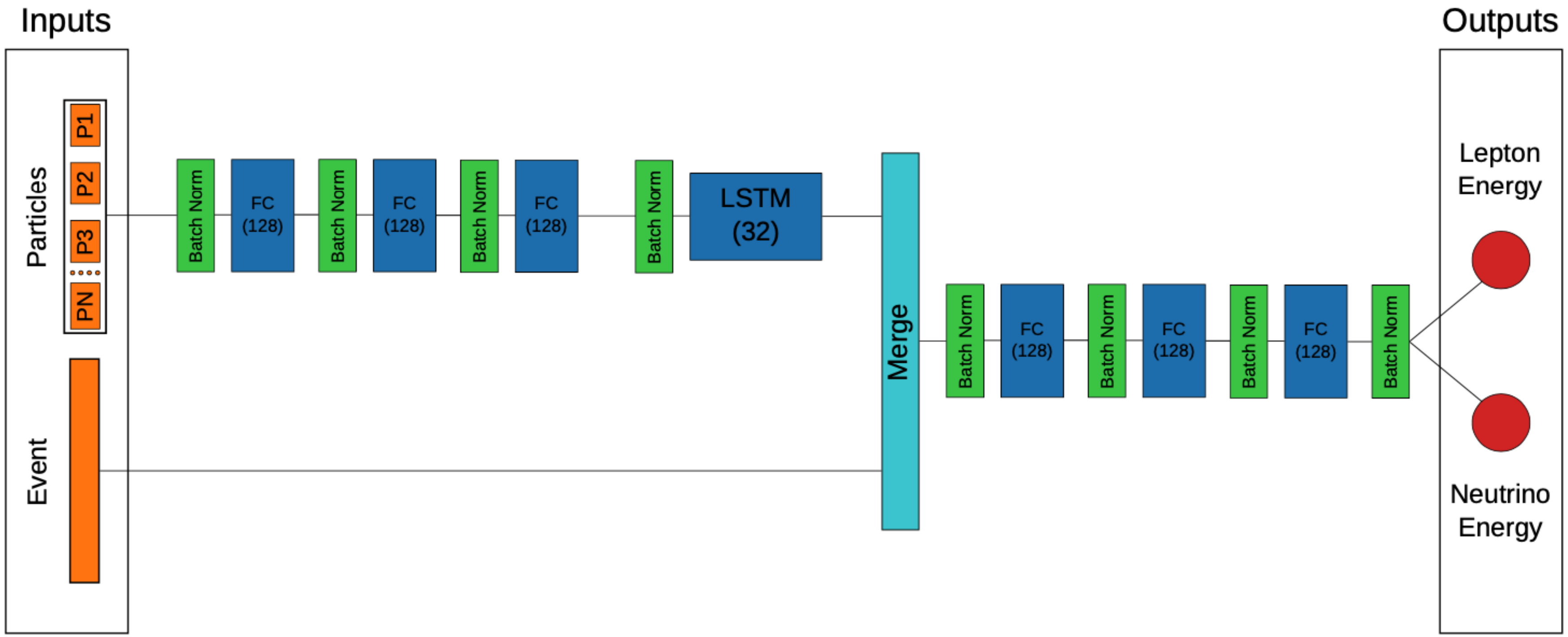
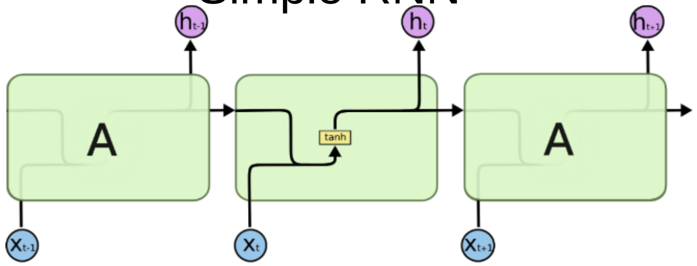
[JINST 16 P01036 (2021)](https://doi.org/10.1088/1748-0221/16/01/P01036)

RNN Energy Estimator: variable length list of particles ⟶ energy



Simple RNN



RNN EE

- Extracts information from each particle
- Aggregates it with a help of an LSTM neural network
- Then combines aggregated information with event level variables and predicts energy of neutrino and energy of the primary lepton.

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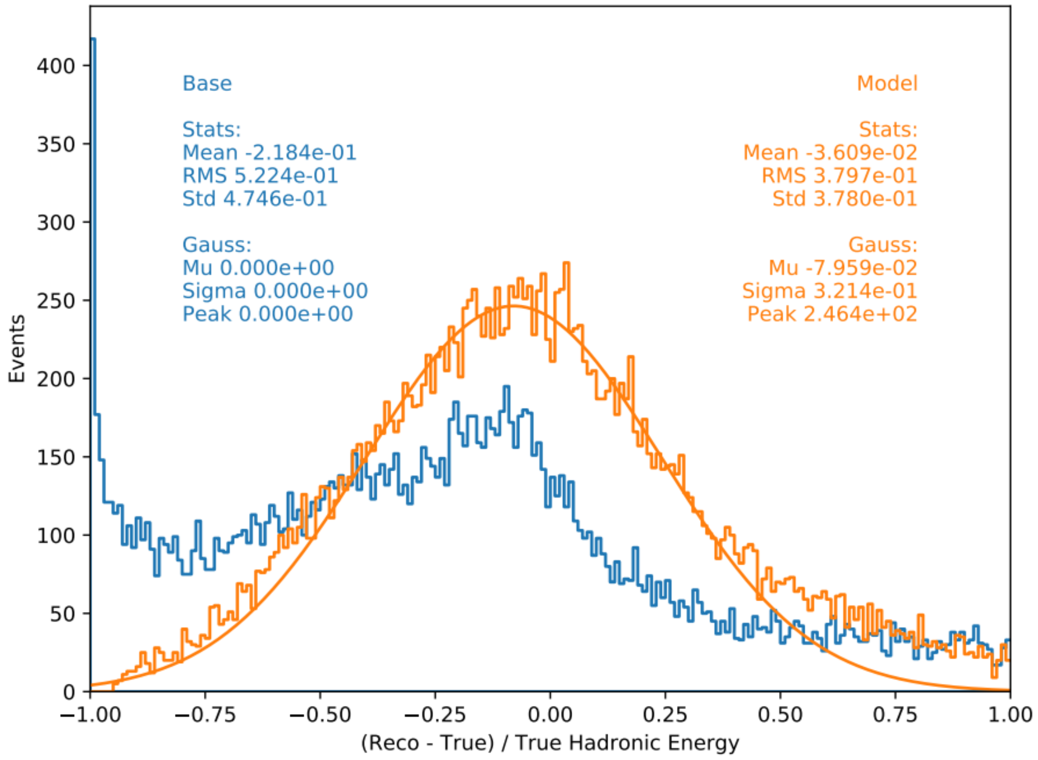
Initial results on MicroBooNE

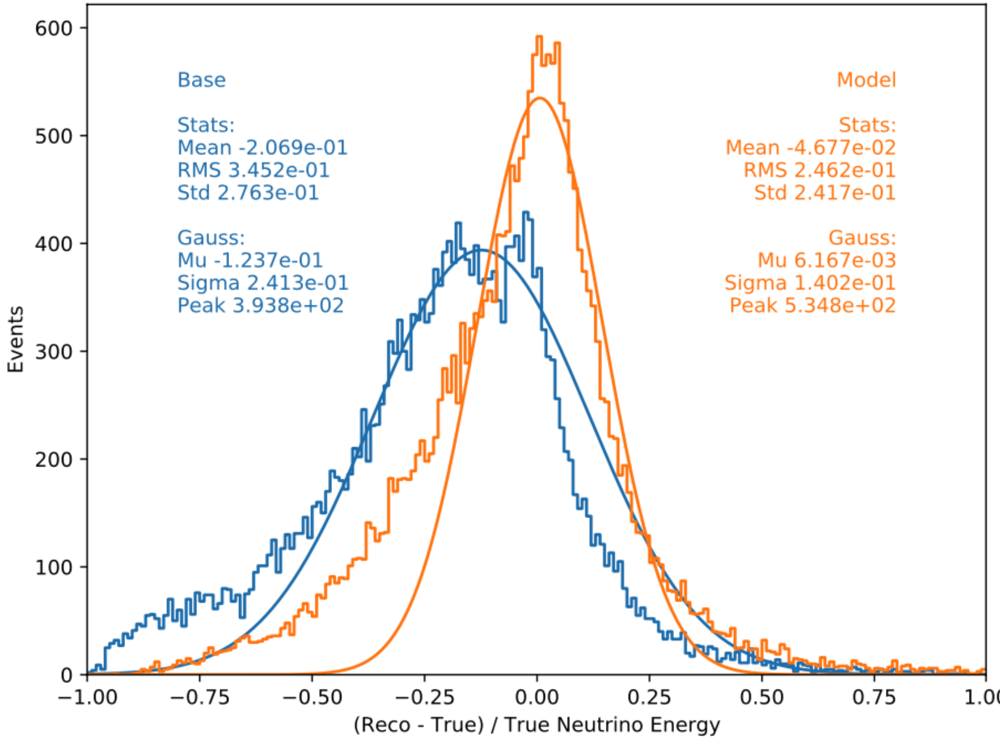
New RNN EE improved the neutrino energy reconstruction with first try:

- resolution: 24% ⟶ 14%
- bias: -12% ⟶ 0.6%

Hadronic energy reco: traditional vs. RNN-EE



Neutrino energy reco: traditional vs. RNN-EE



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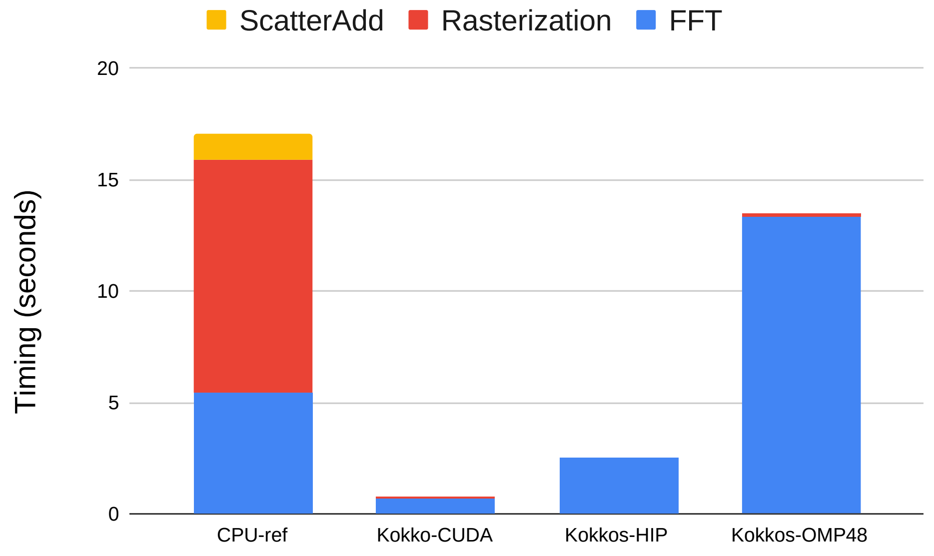
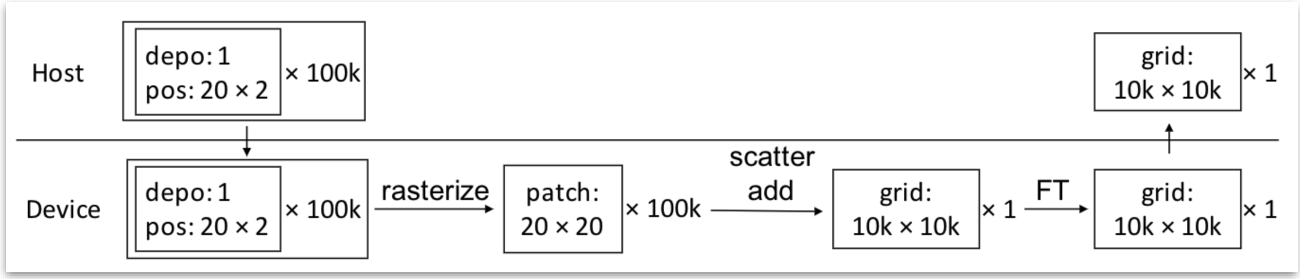
LArTPC simulation acceleration with portable solutions

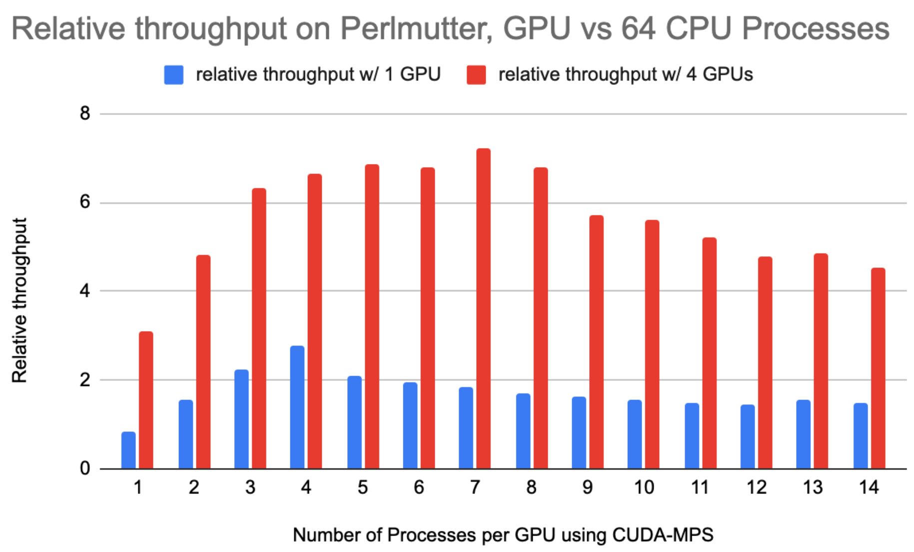
- LArTPC simulation is one of the most time-consuming components.
- A portable acceleration solution seems more attractive than dedicated ones, e.g., CUDA
- **Some serious refactoring performed to achieve efficient acceleration**
- Significant single process acceleration and node level throughput increasing observed
  - ~ 7 × per watt throughput using Kokkos-CUDA
- On-going work - FFT with CPU backend

arxiv:2203.02479



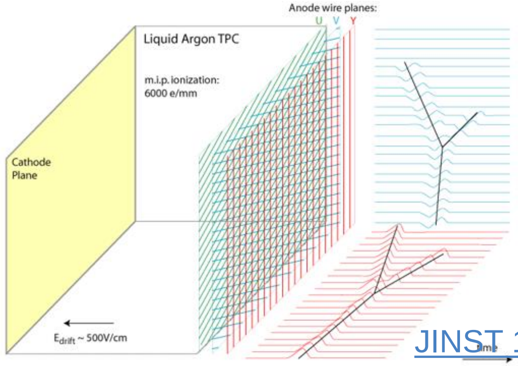
Wire-Cell LArTPC Sim. Kokkos Porting



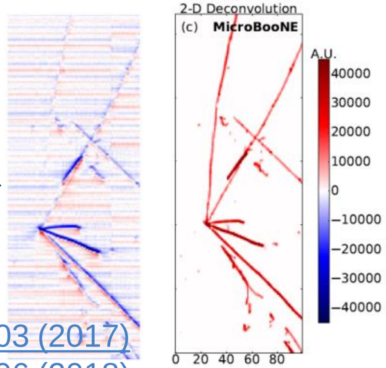


Summary

LArTPC Signal Formation



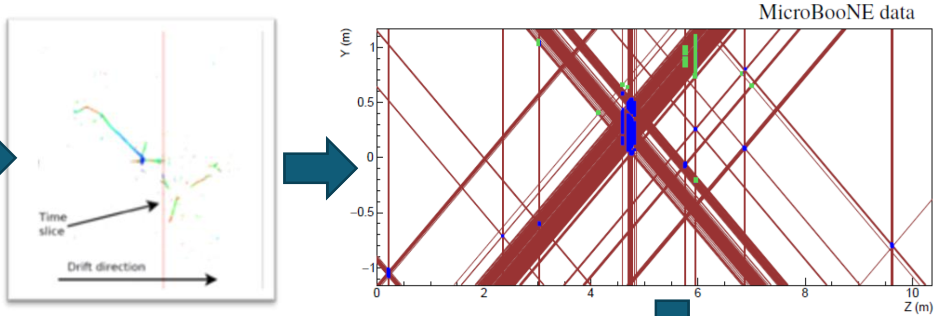
Noise Filtering and Signal Processing

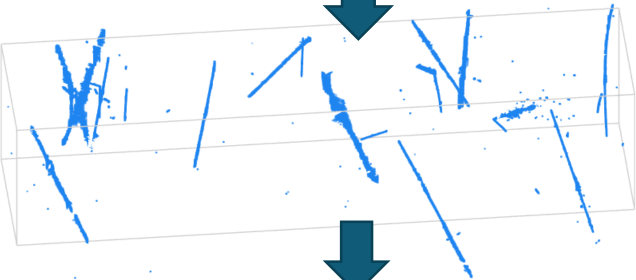


JINST 12, P08003 (2017)
JINST 13, P07006 (2018)
JINST 13, P07007 (2018)

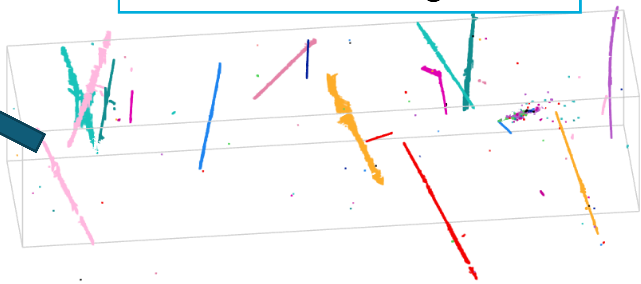
3D Imaging

JINST 13, P05032 (2018)

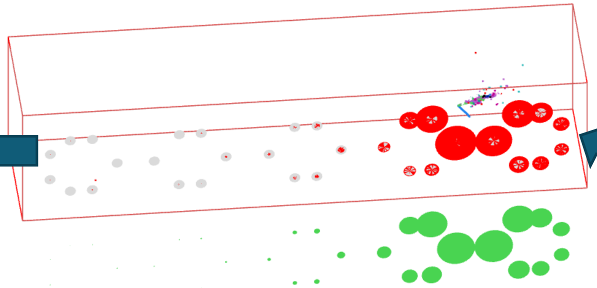




Clustering

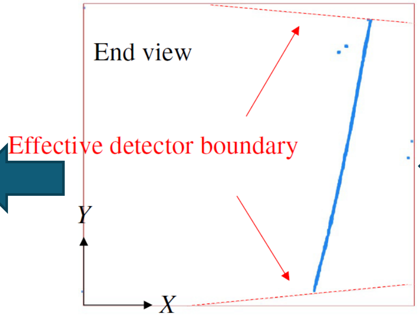


Charge-light matching



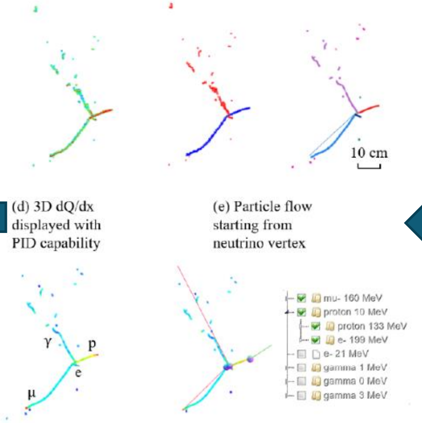
JINST 16, P06043 (2021)

Cosmic Ray Removal



Phys. Rev. Applied 15, 064071 (2021)
arXiv:2012.07928

3D Pattern Recognition



JINST 17 P01037 (2022)

Event tagger (nue, numu):

LEE,
cross section
…

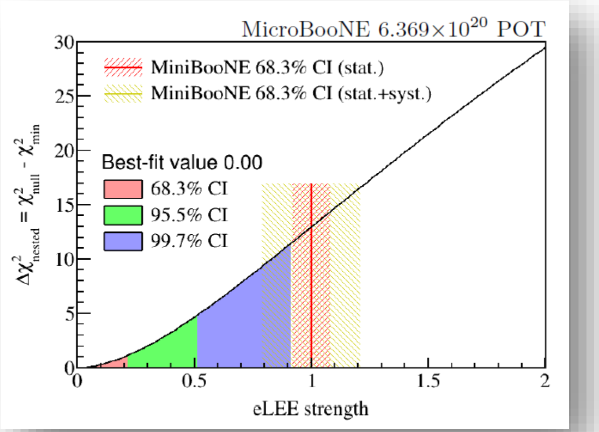
arXiv:2110.13978
arXiv:2110.14023

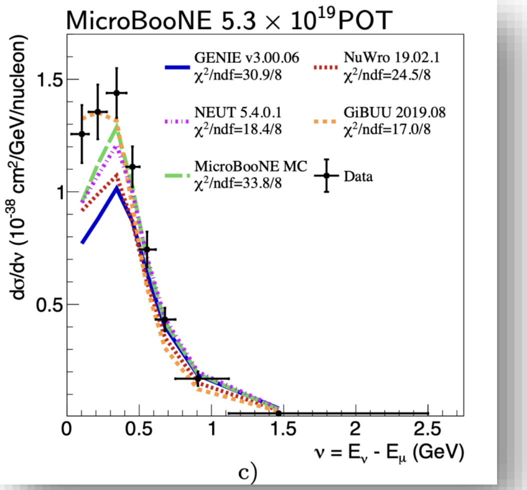
Summary (II)

- The development of Wire-Cell has paid off in the MicroBooNE experiment
- Knowledge cumulation from the developing
- Two main approaches: first principle & human learning

machine learning

- The LArTPC technology advancements made by MicroBooNE is building a solid foundation for next discoveries in neutrino physics (SBN & DUNE)





DUNE FD, SP

ProtoDUNE SP

SBND

MicroBooNE