Introduction to LArTPC Event Reconstruction

Haiwang Yu

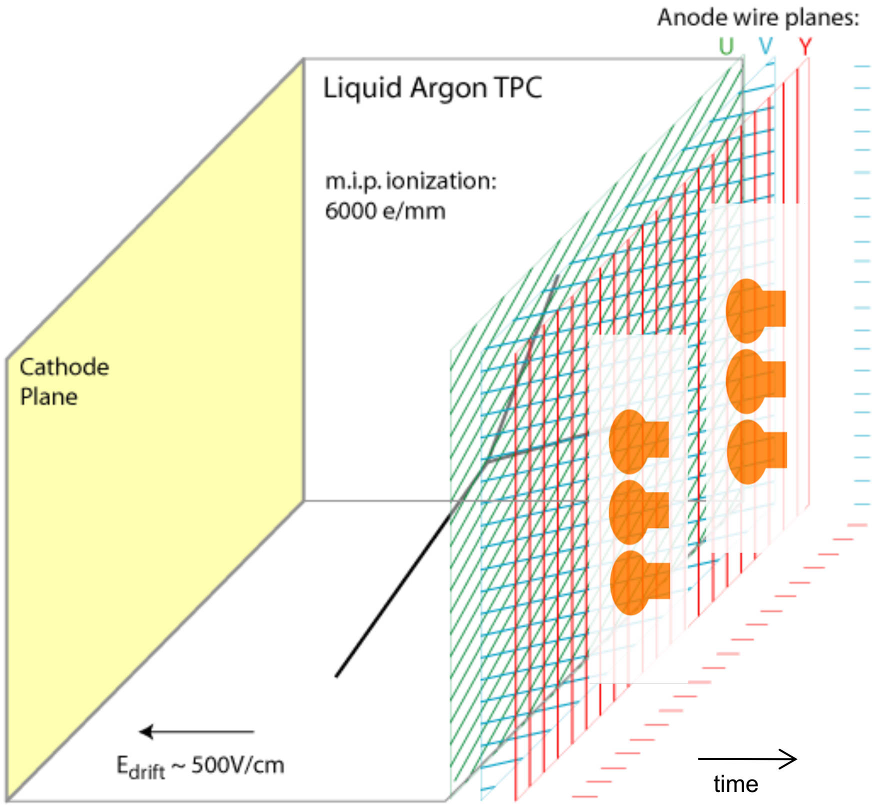
Electronic Detector Group, Physics Department

07/13/23

@BrookhavenLab

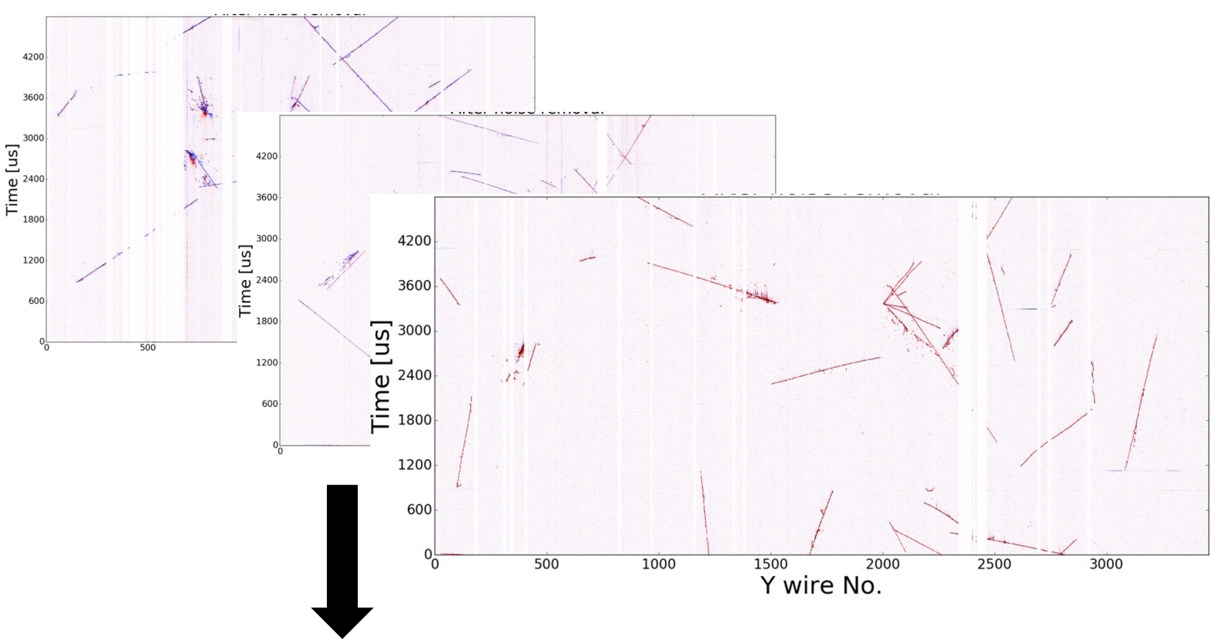
Liquid Argon Time Projection Chamber (LArTPC) and its Event Reconstruction

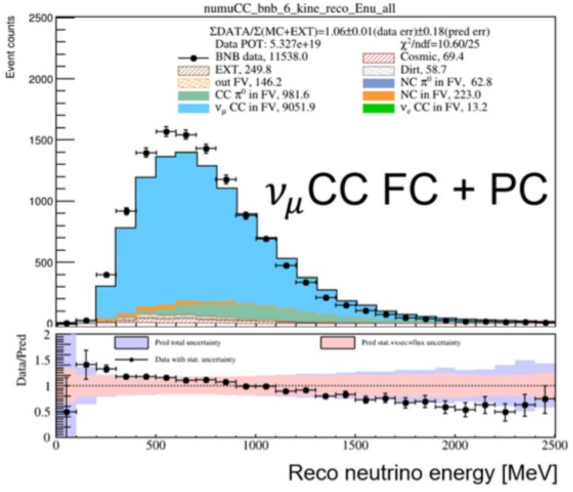
Massive LArTPC with wire readout
~mm scale position resolution in 3D



drift speed 1.6 m / milisec
wire pitch 3 mm

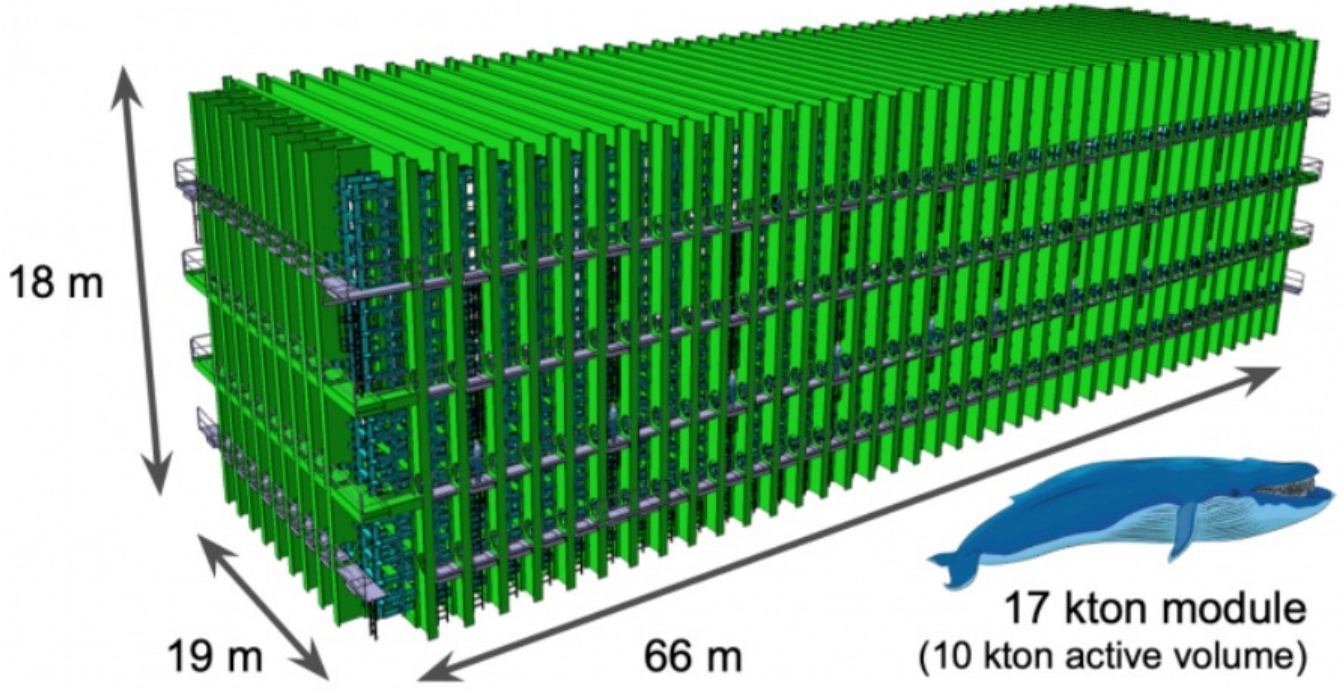
From Bo Yu (BNL)





Why massive?

- ☐ Event Rate = Target Mass × Neutrino Flux ⊗ Cross Section ⊗ Oscillation Probability
- ☐ For DUNE, to achieve Required precision, We need 10s of kiloTons of target mass
  - DUNE CDR: arxiv:1512.06148
  - Key to understand many design choices and challenges



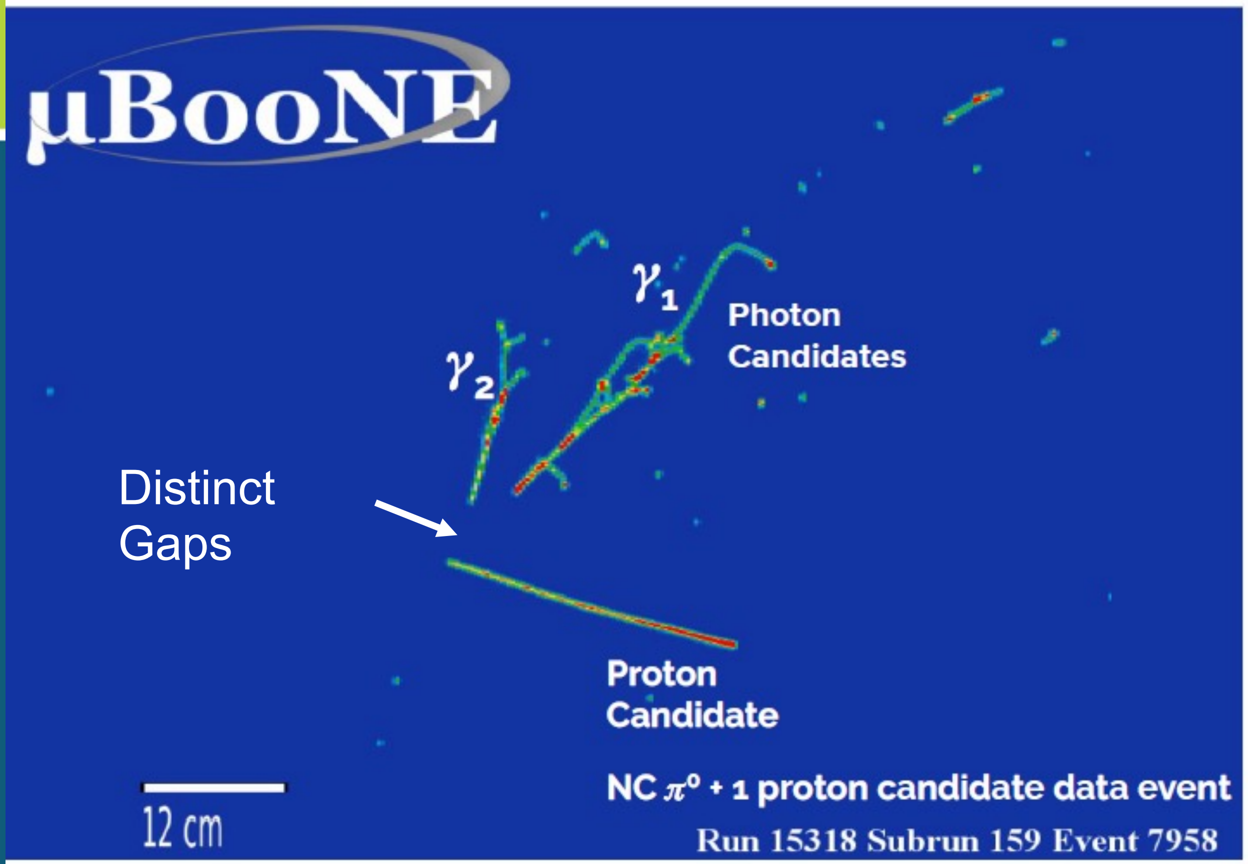
https://sites.slac.stanford.edu/neutrino/experiments/dune

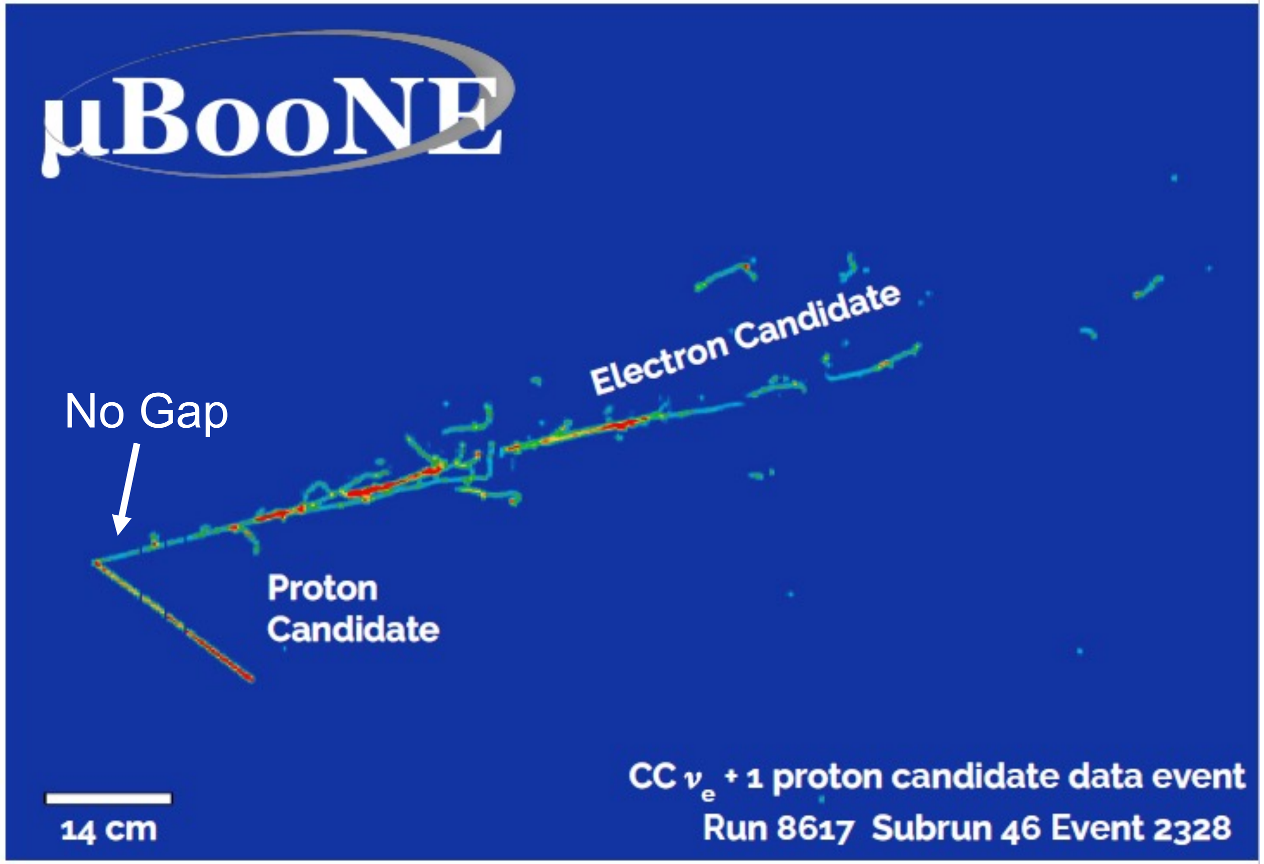
Why LAr?

	He	Ne	Ar	Kr	Xe
Atomic Number	2	10	18	36	54
Boiling Point [K] @ 1atm	4.2	27.1	87.3	120	165
Density [g/cm^3]	0.125	1.2	1.4	2.4	3
Radiation Length [cm]	755.2	24	14	4.9	2.8
dE/dx [MeV/cm]	0.24	1.4	2.1	3	3.8
Scintillation [γ/MeV]	19,000	30,000	40,000	25,000	42,000
Scintillation λ [nm]	80	78	128	150	175
Cost ($/kg)	52	330	5	330	1200

LAr combines abundant signal (ionization/scintillation), good dielectric, low diffusions, and low cost http://lar.bnl.gov/properties/

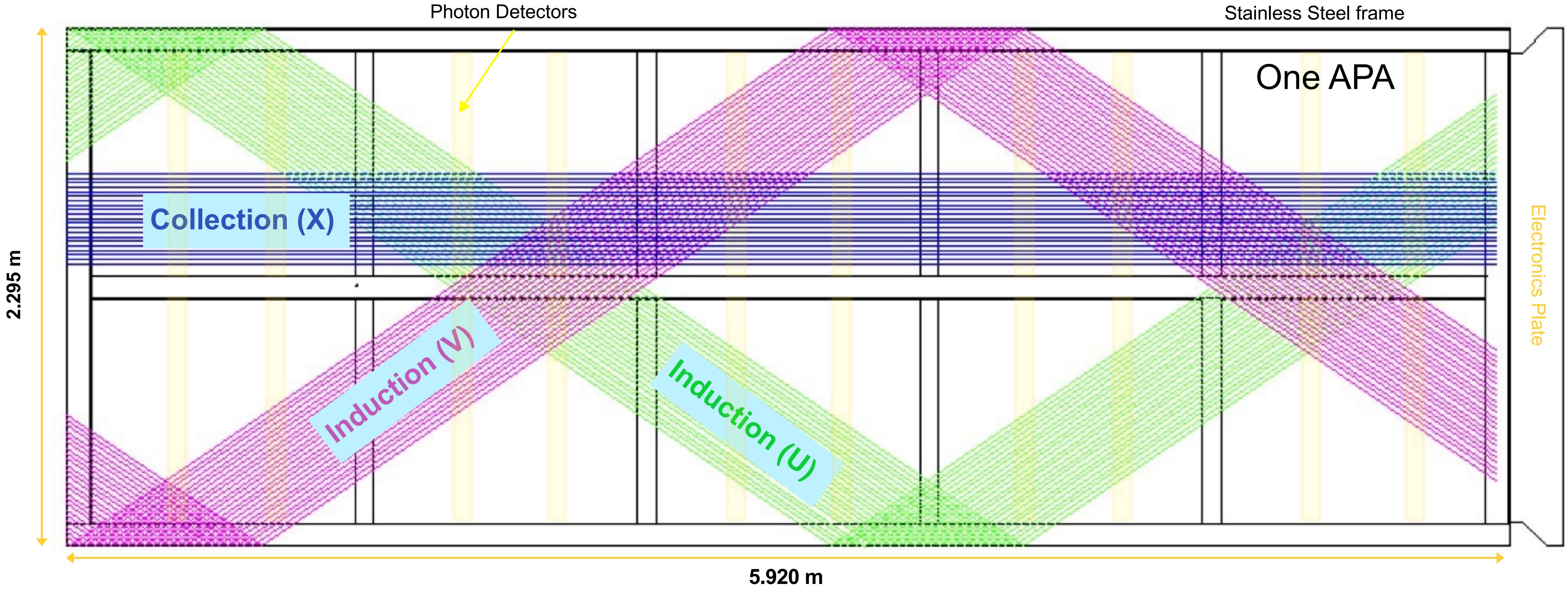
Why high res?





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

Why Wire?



- ❑Modular design for transportation and underground installation
- ❑Three (1D) wire planes with ~ **2560** readout channels. In comparison, would require half million channels for a 2D pixel readout with similar resolution (~ 5 mm pitch)
  - Considerations of cost and power consumption of electronics inside LAr

Wire-Cell Event Reconstruction

TPC simulation

noise filtering

signal processing

3D imaging

clustering

charge-light matching

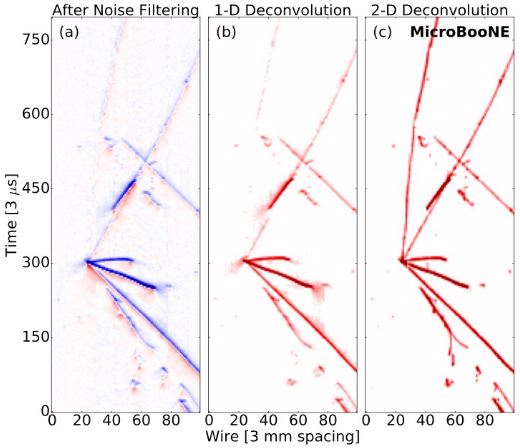
3D trajectory & dQ/dx fitting

cosmic muon tagger

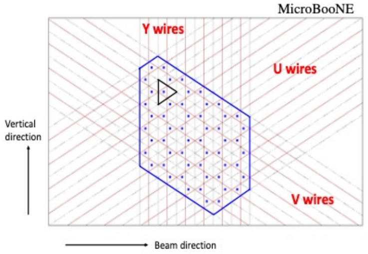
multi-track fitting

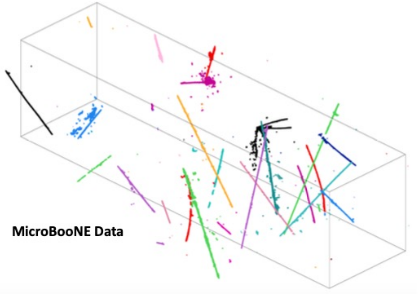
DL-3D vertexing

particle identification

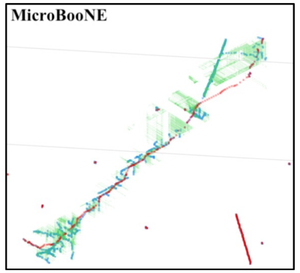


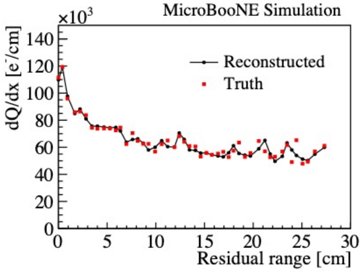
JINST 12 P08003 (2017)
JINST 13 P07006 (2018)
JINST 13 P07007 (2018)
JINST 16 P01036 (2020)



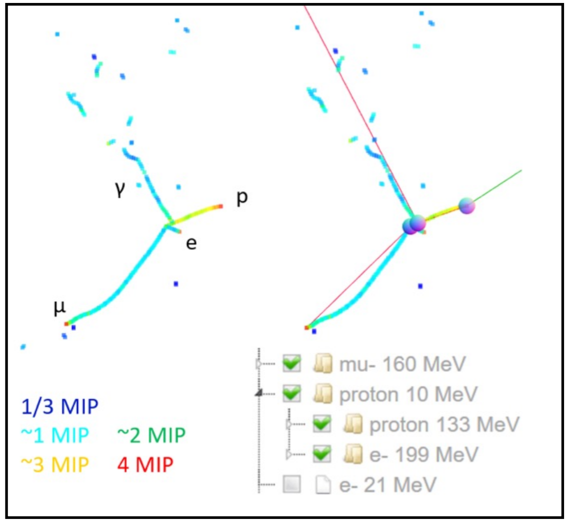


JINST 13 P05032 (2018)
JINST 16 P06043 (2021)





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



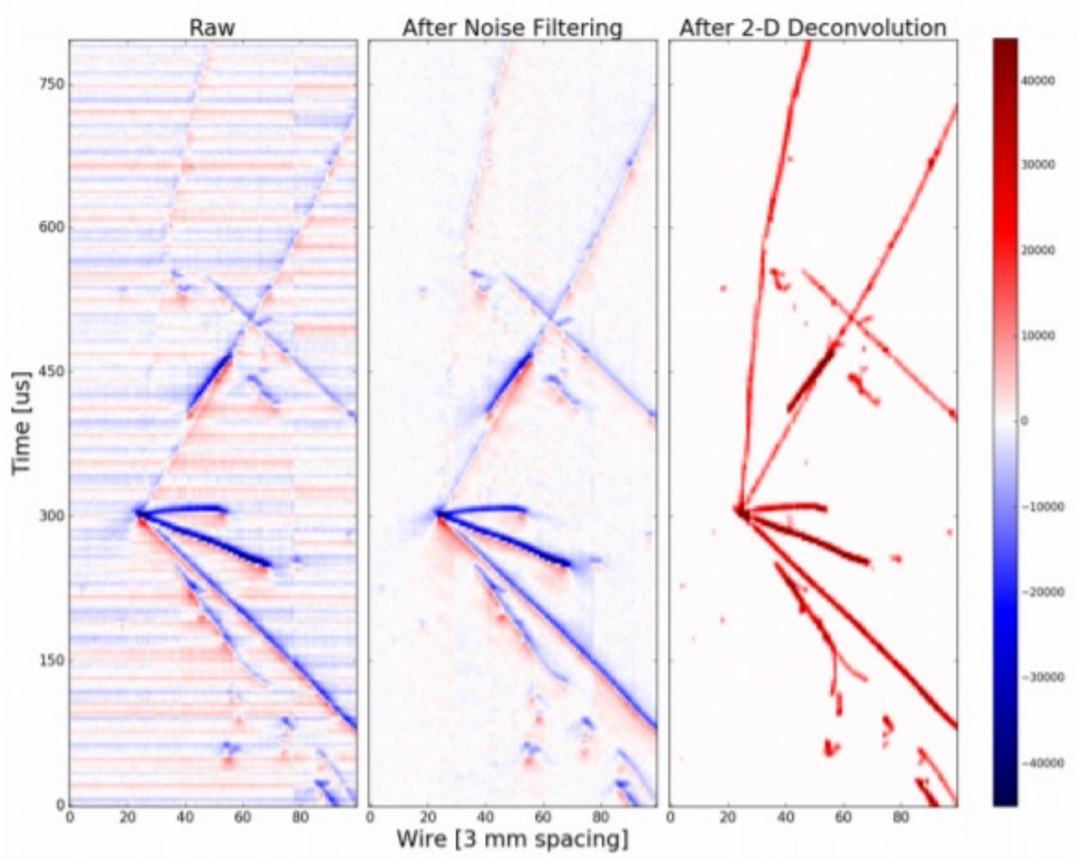
JINST 17 P01037 (2022)

Wire-Cell Low Level Signal Processing

- ☐ Noise filtering
  - Coherent noise – channel-by-channel correlated
- ☐ Signal processing
  - Remove “field response” and “electronic response”

$$M(x',t') = \int_{-\infty}^{\infty}\int_{-x_0}^{x_0} R(x-x',t-t')S(x,t)dxdt$$

Online display: http://lar.bnl.gov/magnify/



Digital Signal Processing

☐ Fundamental theory of linear time-invariant (LTI) system:

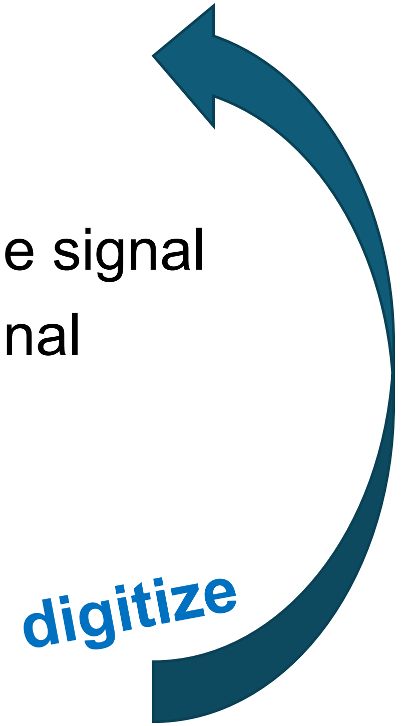
- Any LTI system can be characterized entirely <u>by a single function</u> called the system's **impulse response**

$$y = Ax$$

- y: measured discrete-time signal
- x: the (unknown) true signal
- A:Response matrix

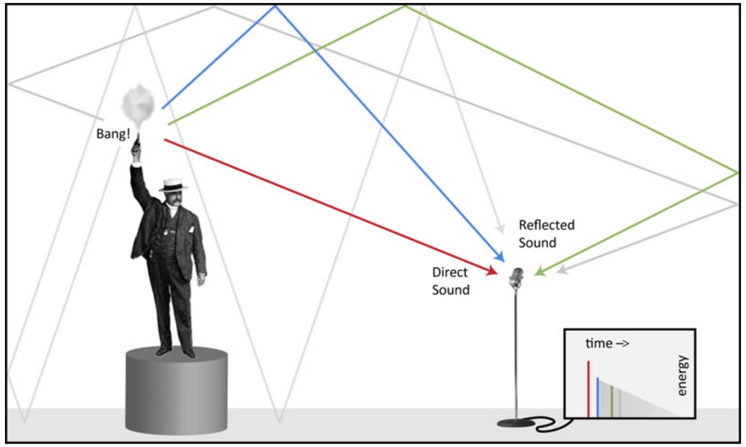
$$\mathrm{x}(t) \longrightarrow \boxed{h(t)} \longrightarrow \mathrm{y}(t) = h(t) * x(t)$$

$$= \int_{-\infty}^{\infty} h(t-\tau)x(\tau)d\tau$$



Impulse response

Room
acoustic
response



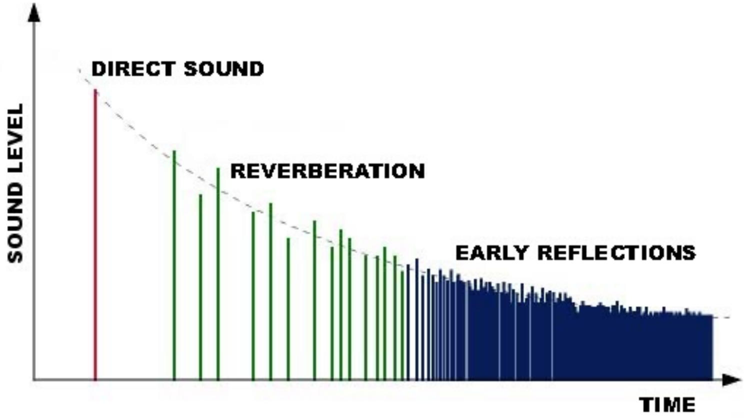
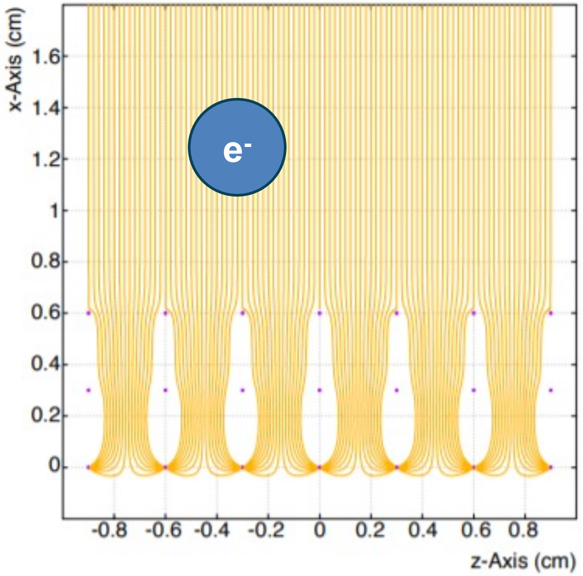
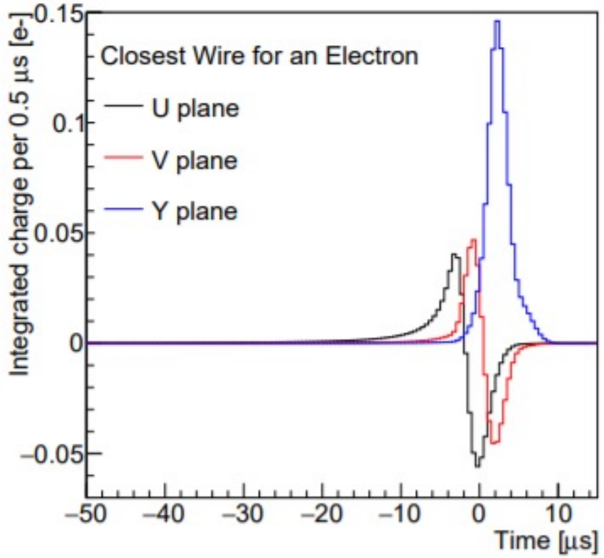


Image credit: www.prosoundweb.com

$h(t)$

LArTPC
field + electronic
response

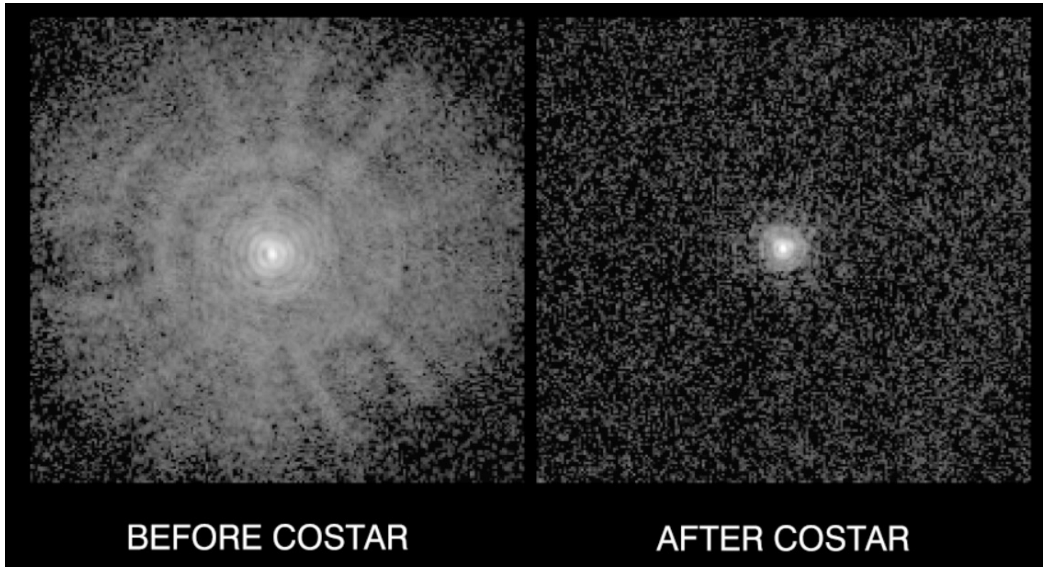




JINST 13 P07006 (2018)

2D Impulse response

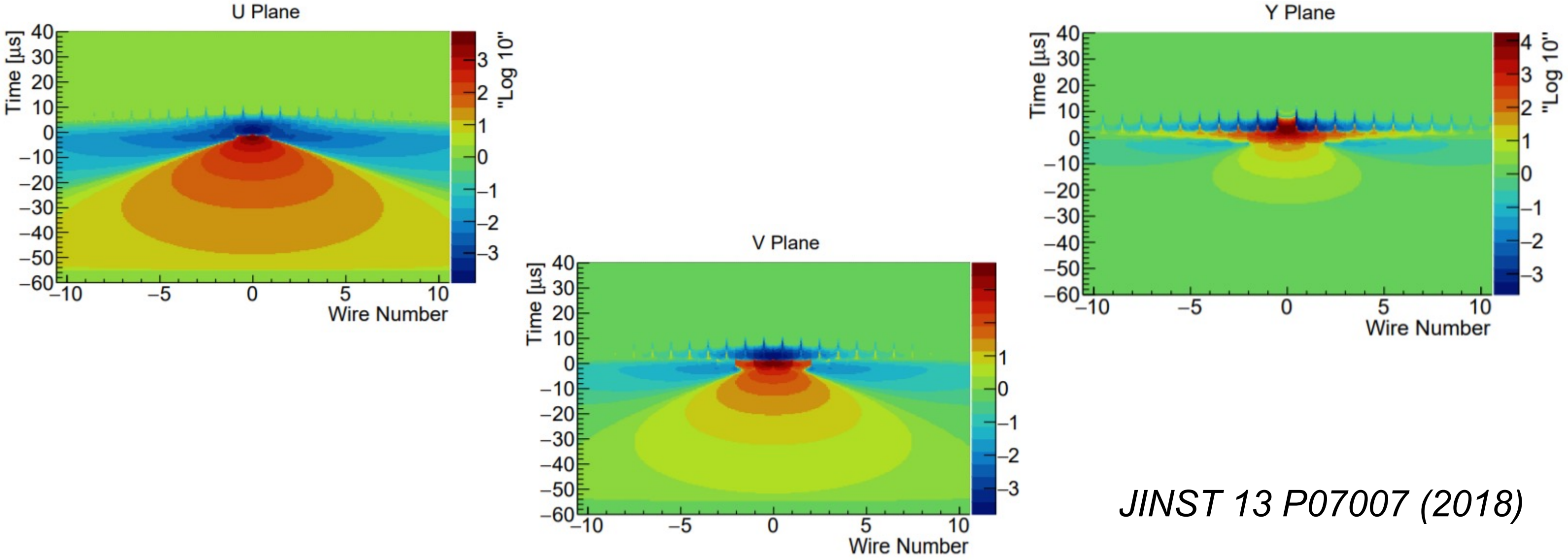
Camera
optical
response



Hubble telescope impulse response (Image credit: http://web.mit.edu)

$$\boxed{h(x, y)}$$

LArTPC 2D response:
y: t * drift velocity
x: wire number * pitch



JINST 13 P07007 (2018)

Change of Basis

$$\begin{pmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{pmatrix}$$

$$\begin{tikzcd}
\text{Time Domain} & \mathrm{x}(t,w) \arrow[r] & \boxed{h(t,w)} \arrow[r] \arrow[d, "\text{DFT}"] & \mathrm{y}(t,w) = h(t,w) * x(t,w) \arrow[d, "\text{DFT}"] \\
\text{Frequency Domain} & X(f,s) \arrow[r] \arrow[u, "\text{IDFT.}"] & \boxed{H(f,s)} \arrow[r] & \mathrm{Y}(f,s) = H(f,s) \cdot X(f,s)
\end{tikzcd}$$

$$\begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

- ❑ Discrete Fourier Transform;
  - Convolution -> multiplication: matrix diagonalization
  - FFT algorithm: $O(N^2) \rightarrow O(N \log N)$: fast computation
  - Frequency-domain filters: reduce noise, regularize fluctuations

2-D Deconvolution

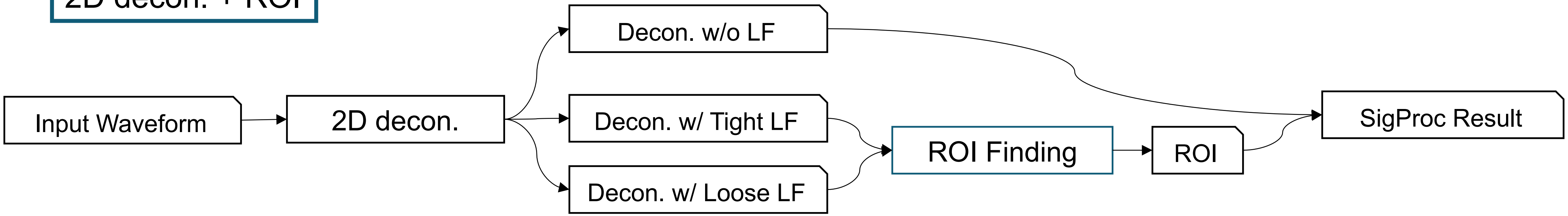
2D measurement formation

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

2D deconvolution

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

2D decon. + ROI



Input Waveform

2D decon.

Decon. w/o LF

Decon. w/ Tight LF

Decon. w/ Loose LF

ROI Finding

ROI

SigProc Result

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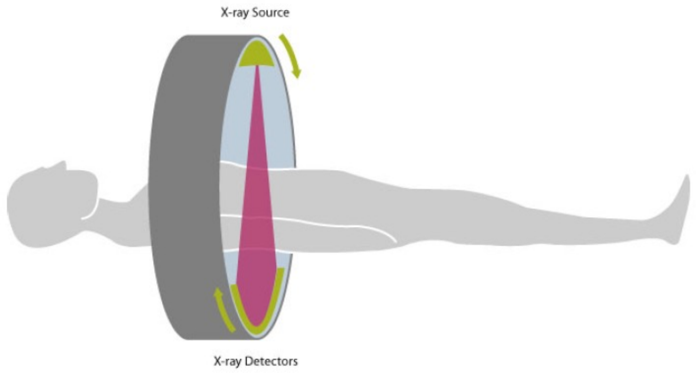
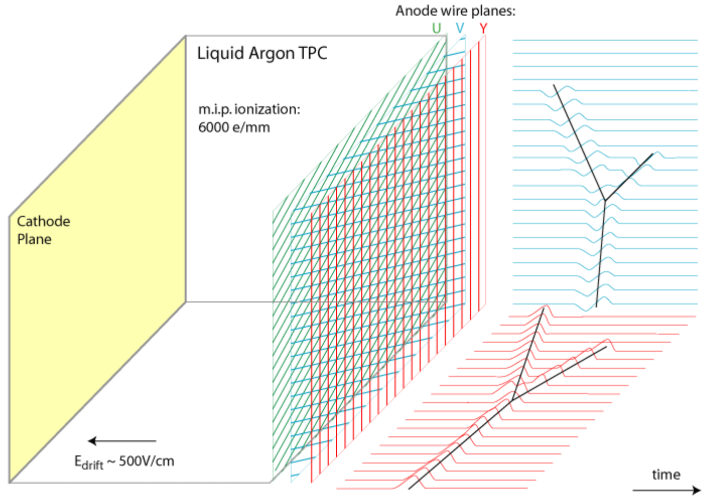
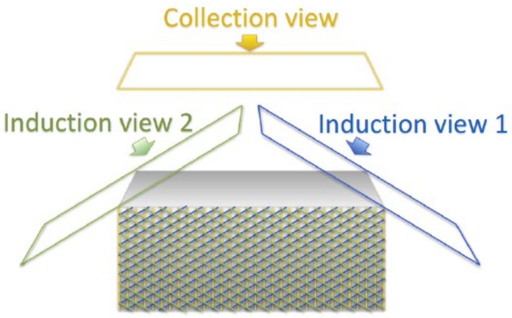
Wire-cell Tomographic Reconstruction







- ☐ CAT Scan
  - Detector (x-ray generator/receiver) moves across the object (body)
  - Axial projections (~180) by detector rotation
  - Cross section can be reconstructed at each position along detector movement

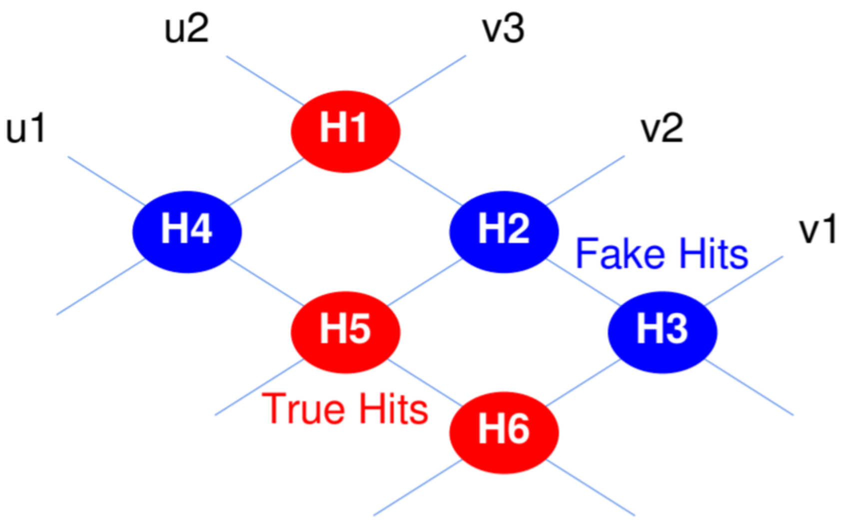
- ☐ LArTPC
  - Objects (ionizing electrons) move across detectors (wire planes)
  - Axial projections (~3) by wire orientation
  - Cross section can be reconstructed at each time slice along electron drift

Construct Linear Equations

$$y = Ax$$

$$\begin{pmatrix} u1 \\ u2 \\ v1 \\ v2 \\ v3 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} H1 \\ H2 \\ H3 \\ H4 \\ H5 \\ H6 \end{pmatrix}$$

Use two planes as an illustration



At one time slice

y: measured charge signal on each wire
x: the (unknown) true charge deposition in each possible cell
A: bi-adjacency matrix connecting wires and cells (determined solely by wire geometry)

Desired Solution $x = \begin{pmatrix} H1 \\ 0 \\ 0 \\ 0 \\ H5 \\ H6 \end{pmatrix}$

Solve underdetermined linear problem: regularization

$$\chi^2 = (y - Ax)^T \cdot V^{-1} \cdot (y - Ax)$$
$$\equiv \|y' - A'x\|_2^2,$$

- Previous example has 6 unknowns, 5 equations: under-determined system

$$x = \boxed{(A^T V^{-1} A)}^{-1} A^T V^{-1} \cdot y$$

↓

non-invertible, 2 zero-eigenvalues out of 6.

- Adding constraints: find the sparsest solution (applies to most physics events): L0-regularization

minimize $\|x\|_0$, subject to: $y = Ax$

(L0-norm: number non-zero elements)

NP-hard!

https://web.stanford.edu/~yyye/lpmin_v14.pdf

Procedure

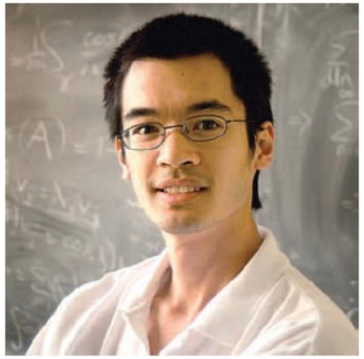
- Remove unknowns until equations can be solved, then find the best solution with the minimum χ^2
- a combinatorial problem
  - 2 out of 6: 15 combinations
  - 10 out of 40: 0.8 billion combinations

Compressed Sensing (L1-regularization)

- Breakthrough: mathematical proof that L0 problem can be well approximated by the L1 problem (Compressed Sensing, *Candes, Romberg, and Tao, 2005*.)

Emmanuel Candes. *(Photo courtesy of Emmanuel Candes.)*

Justin Romberg. *(Photo courtesy of Justin Romberg.)*



Terence Tao. *(Photo courtesy of Reed Hutchinson/UCLA.)*

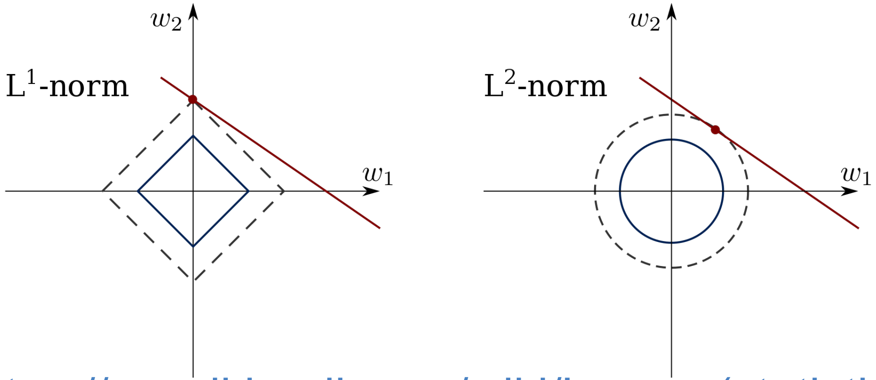
https://arxiv.org/abs/math/0503066

minimize $\|x\|_1$, subject to: $y = Ax$

(L1-norm: sum of absolute values of the elements)

Or, equivalently, minimize

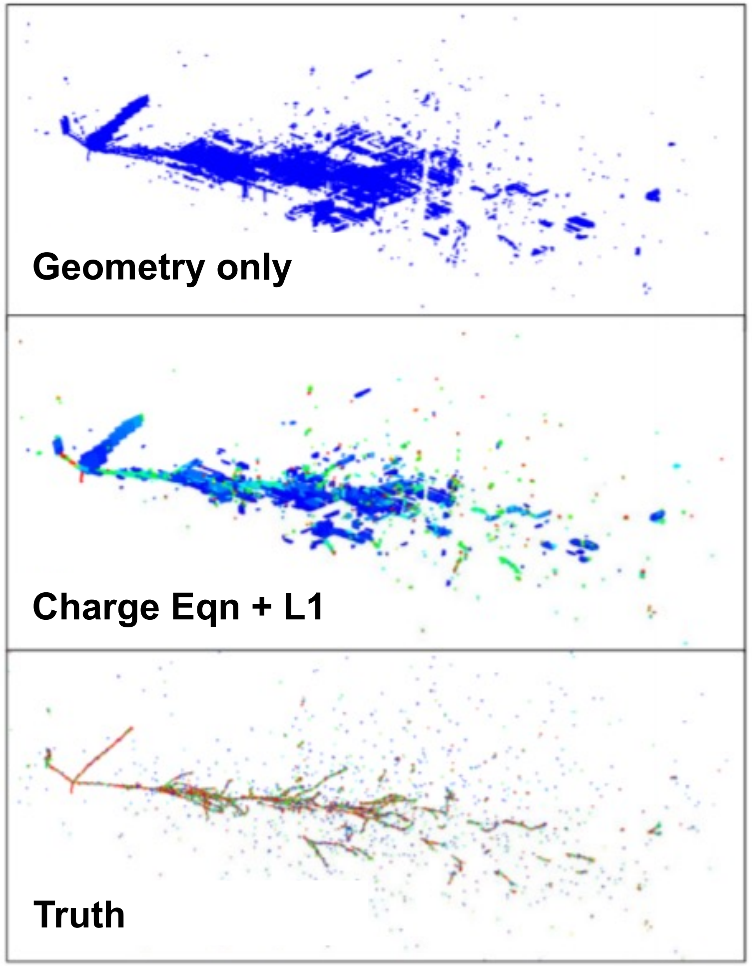
$$\chi^2 = (y - Ax)^T \cdot V^{-1} \cdot (y - Ax) + \lambda \left|\left|x\right|\right|_1$$



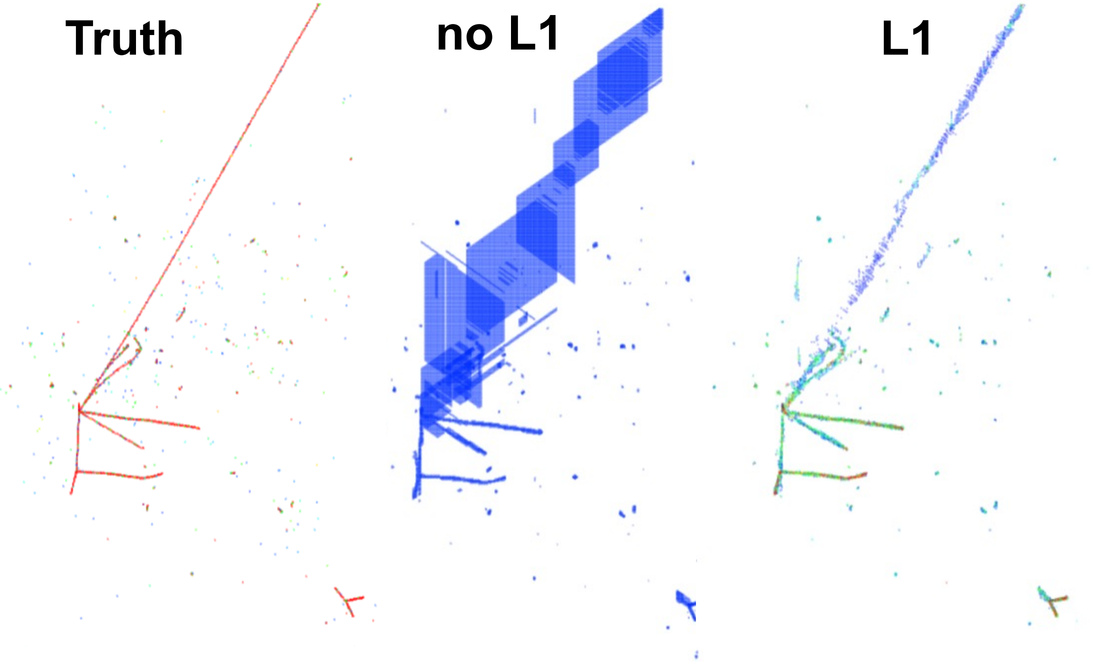
https://en.wikipedia.org/wiki/Lasso_(statistics)

Performance in Wire-Cell

Wire-Cell



JINST 13, P05032 (2018)



- Typically, ~tens of seconds to reconstruct the whole 3D image (originally a few hours)

Run 10711 | Subrun 140 | Event 7036

cluster

Size 1 8

Opacity 0 1

Plain Color

Time Slice

sliced mode ☐

opacity 0

width 6

position 84

Camera

Ortho Camera ☑

Multi-view ☐

2D View

♫ Voice Control ☐

slice #: 35 | slice x: 212.5

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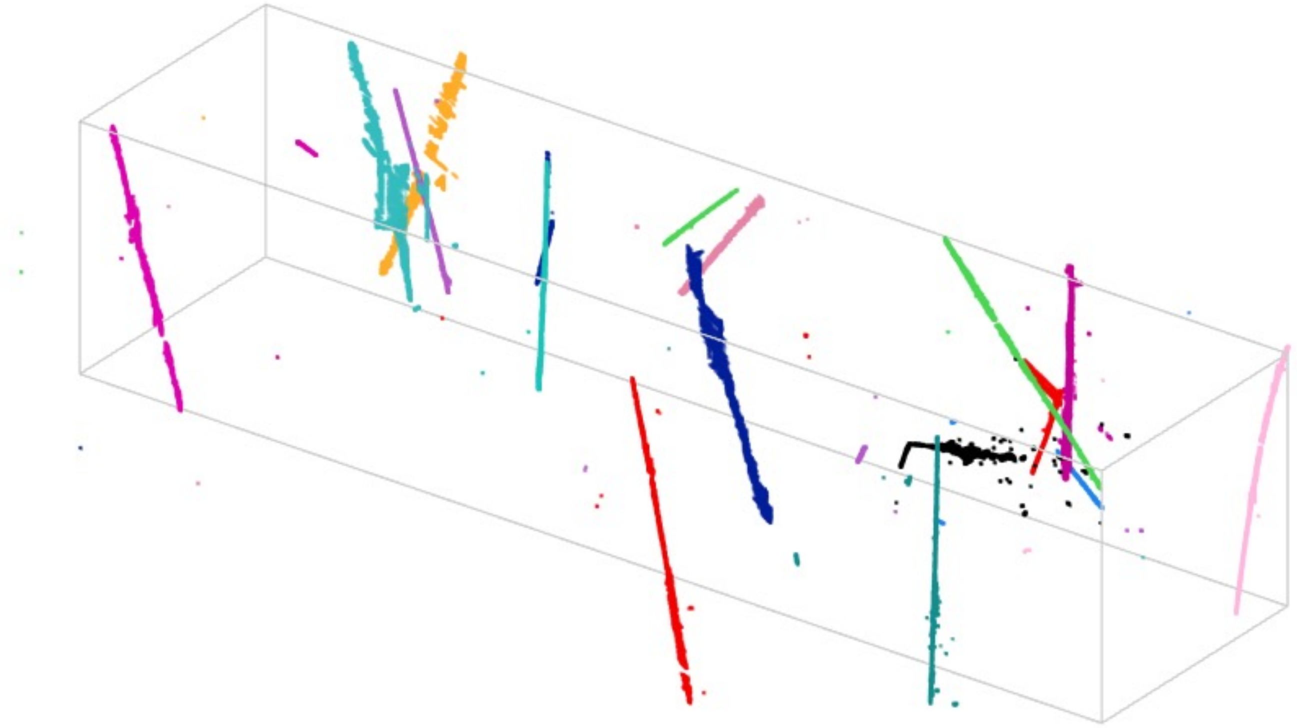
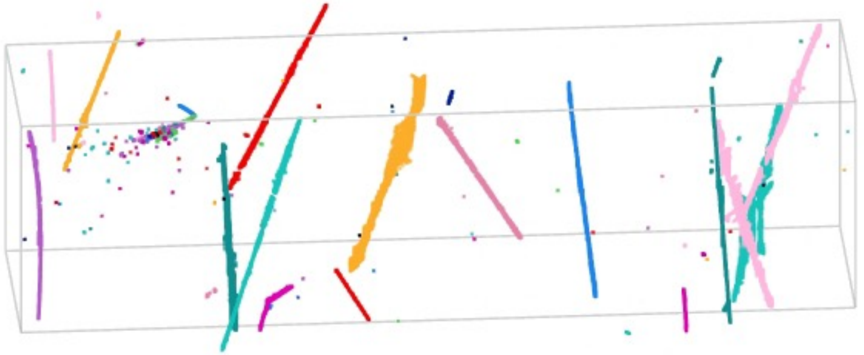


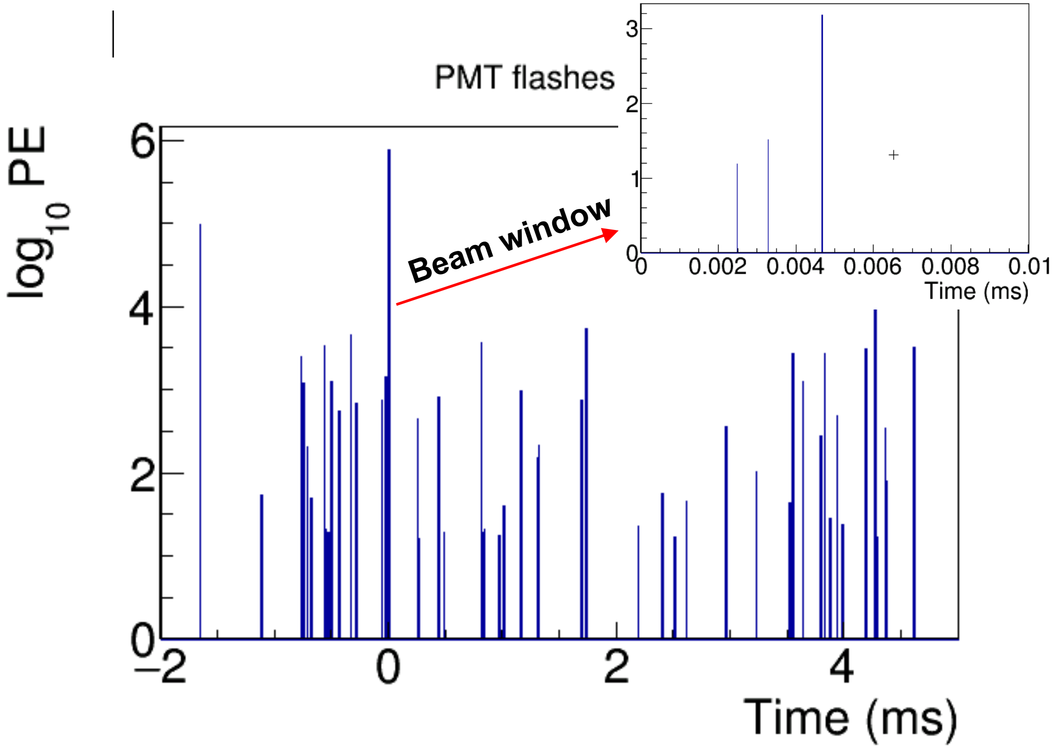
[An example MicroBooNE event after 3D reconstruction](#)

Finding Neutrino Interaction

4.8 ms drift window



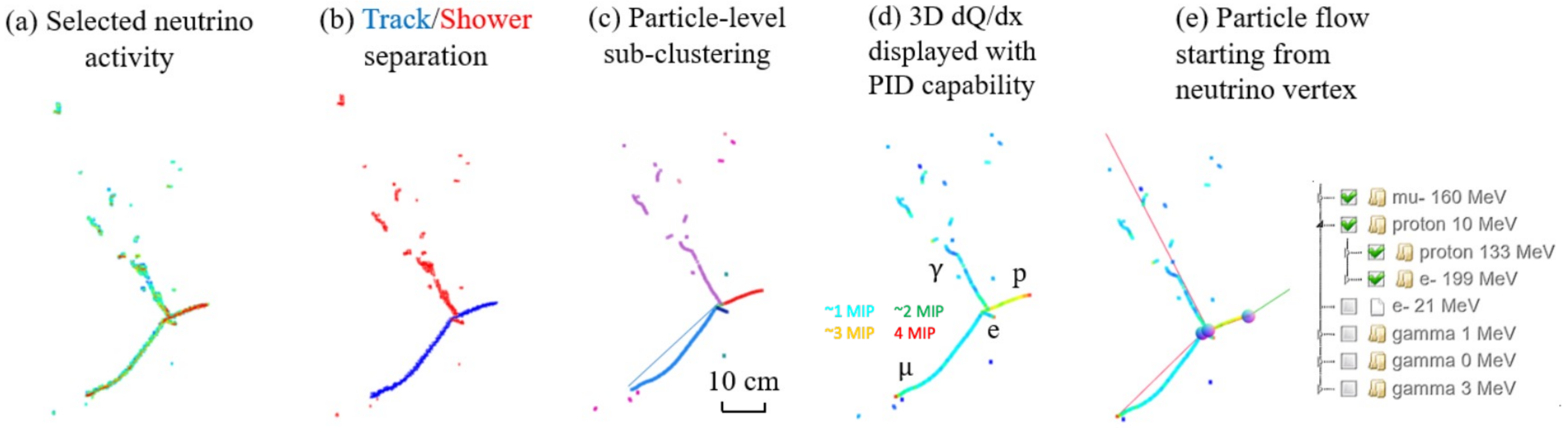
20-30 TPC activities



40-50 PMT activities

- ❑ 3D Cluster based on proximity (kd-tree)
- ❑ associate the light flash to the corresponding TPC cluster based on light pattern

3D Pattern Recognition

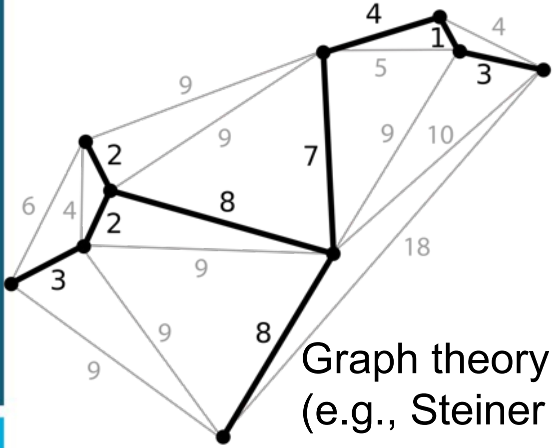

(a) Selected neutrino activity

(b) Track/Shower separation

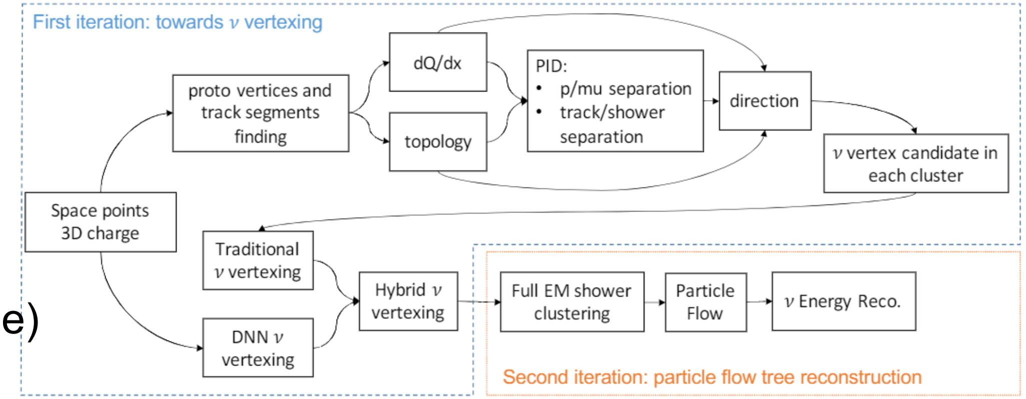
(c) Particle-level sub-clustering

(d) 3D dQ/dx displayed with PID capability

(e) Particle flow starting from neutrino vertex



Graph theory (e.g., Steiner tree)


First iteration: towards ν vertexing

Space points 3D charge

proto vertices and track segments finding

dQ/dx

topology

PID:
- p/mu separation
- track/shower separation

direction

ν vertex candidate in each cluster

Traditional ν vertexing

DNN ν vertexing

Hybrid ν vertexing

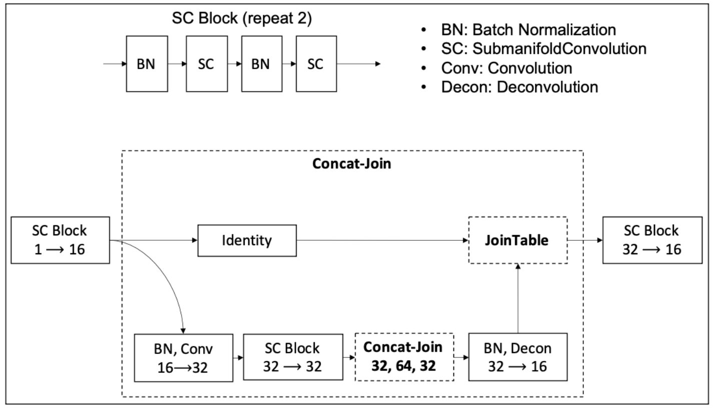
Full EM shower clustering

Particle Flow

ν Energy Reco.

Second iteration: particle flow tree reconstruction

Sparse Regression U-Net


SC Block (repeat 2)

BN → SC → BN → SC

- BN: Batch Normalization
- SC: SubmanifoldConvolution
- Conv: Convolution
- Decon: Deconvolution

Concat-Join

SC Block 1 ⟶ 16

Identity

JoinTable

SC Block 32 ⟶ 16

BN, Conv 16⟶32

SC Block 32 ⟶ 32

Concat-Join 32, 64, 32

BN, Decon 32 ⟶ 16

JINST 17 P01037 (2022)

Software and Hardware

- ☐ Implementation and execution of algorithms
- ☐ Software stack:
  - Operating system: Linux ...
    - Container: docker, singularity
  - Programing language: C++, Python...
    - libraries: boost, ROOT, Numpy, PyTorch ...
  - Version control: git ...
  - Editing: vim, VS Code ...
  - job management: HTCondor, slurm ...
- ☐ Hardware: HTC/HPC, workstation, cloud? ...

Demo

- Prerequisites: Linux OS (bare metal or VM)
- https://github.com/HaiwangYu/nusteam23
- Tools used in the demo:
  - git, Linux commands, singularity container, bash script, editor
  - wire-cell-toolkit (C++, jsonnet)
    - gen/src/DepoTransform.cxx
    - sigproc/src/OmnibusSigProc.cxx
  - ROOT

More

- ☐ Read paper: JINST 13 P05032 (2018)
- ☐ Try the demo by yourself