

Augmented Signal Processing in Liquid Argon Time Projection Chambers with a Deep Neural Network

- Software Effort to Improve LArTPC Reconstruction
- *JINST* 16 (2021) 01, P01036

Haiwang Yu (BNL)

CPAD Instrumentation Frontier Workshop 2021

18-22 March 2021



Signal Processing (SP) of Liquid Argon TPC (LArTPC)

LArTPC is the central detector in many next-gen neutrino experiments, e.g. DUNE, SBN etc.

- Calorimetry and rich topology information

LArTPC wire-readout measures induced charge $\otimes$ response

Signal Processing (SP) of LArTPC resolves charge from the original measurement:

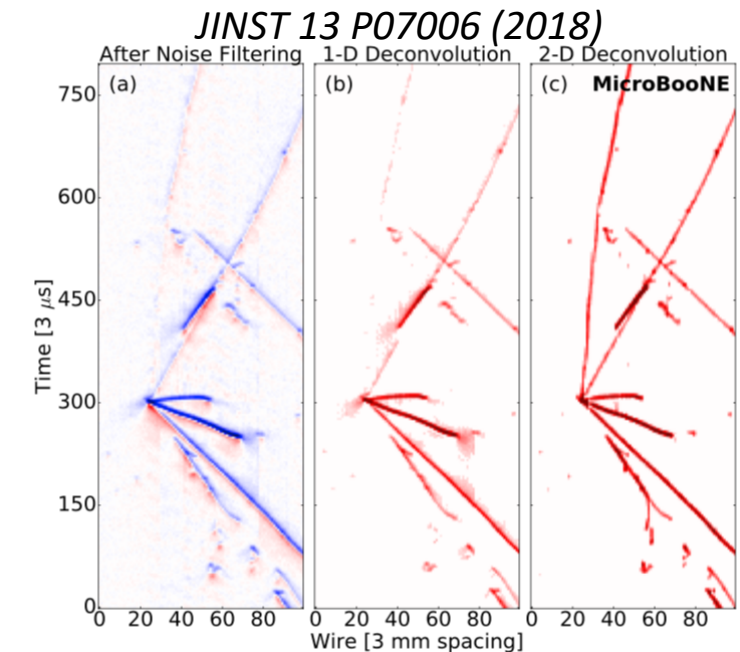
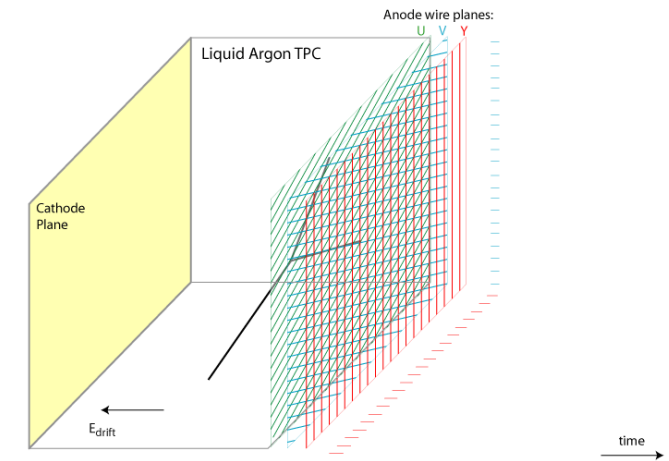
$$M(t', x') = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} R(t, t', x, x') \cdot S(t, x) dt dx + N(t', x')$$

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

Current state of the art SP algorithm based on 2D deconvolution:

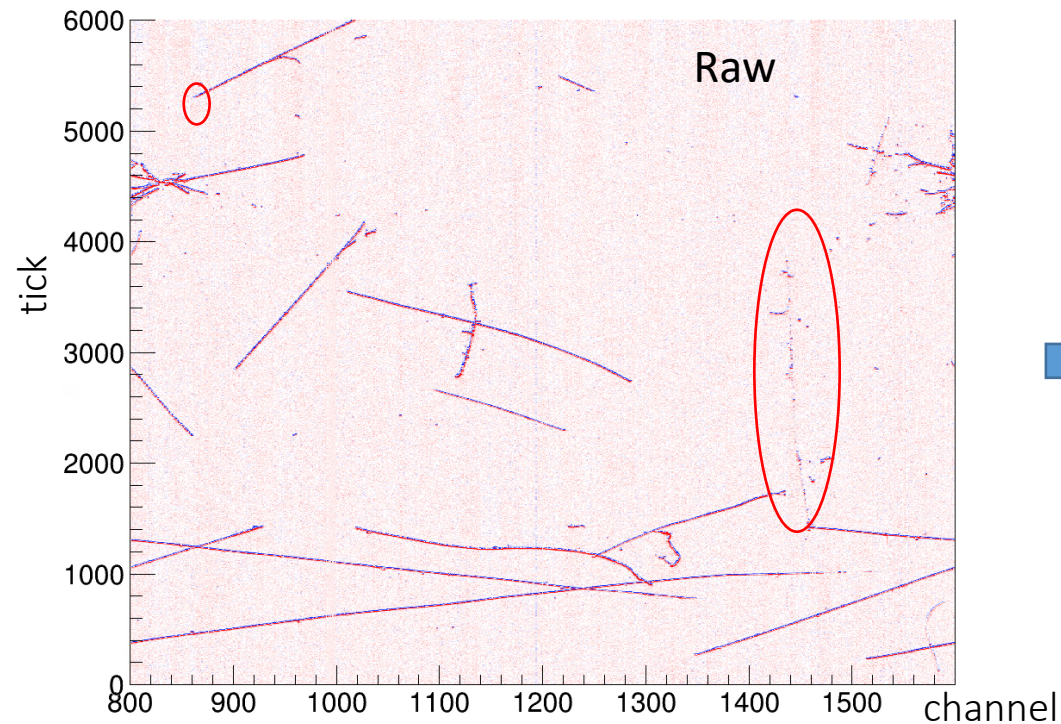
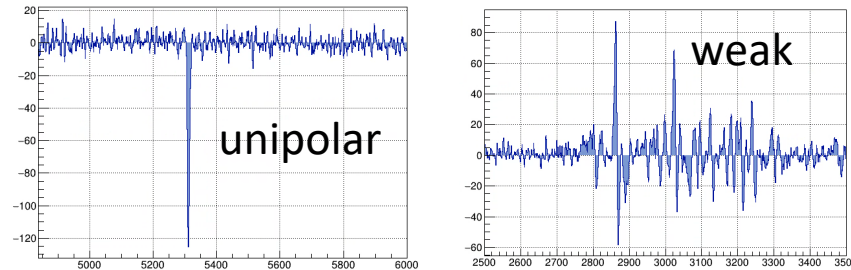
JINST 13 P07006 (2018)

Signal formation in a 3 plane LArTPC “Single-Phase” wire-readout, from Bo Yu (BNL), <https://lar.bnl.gov/wire-cell/>

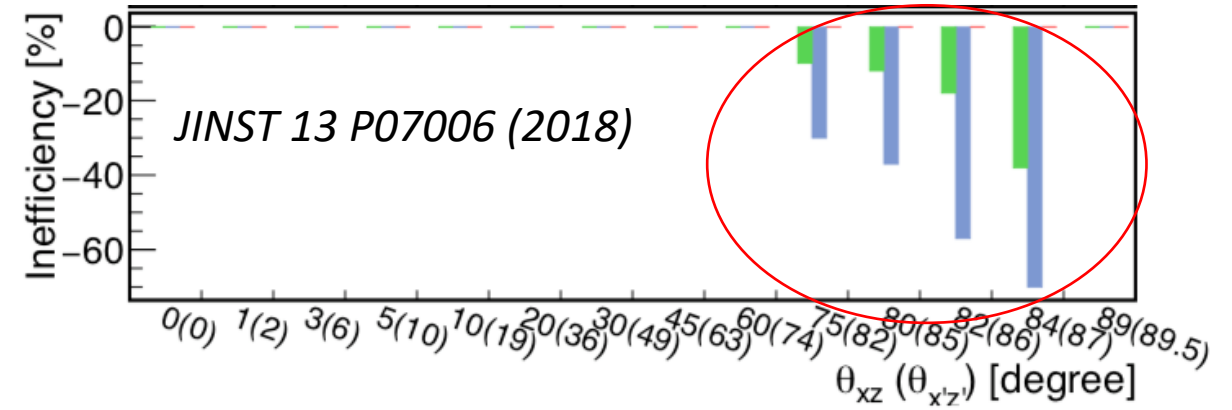
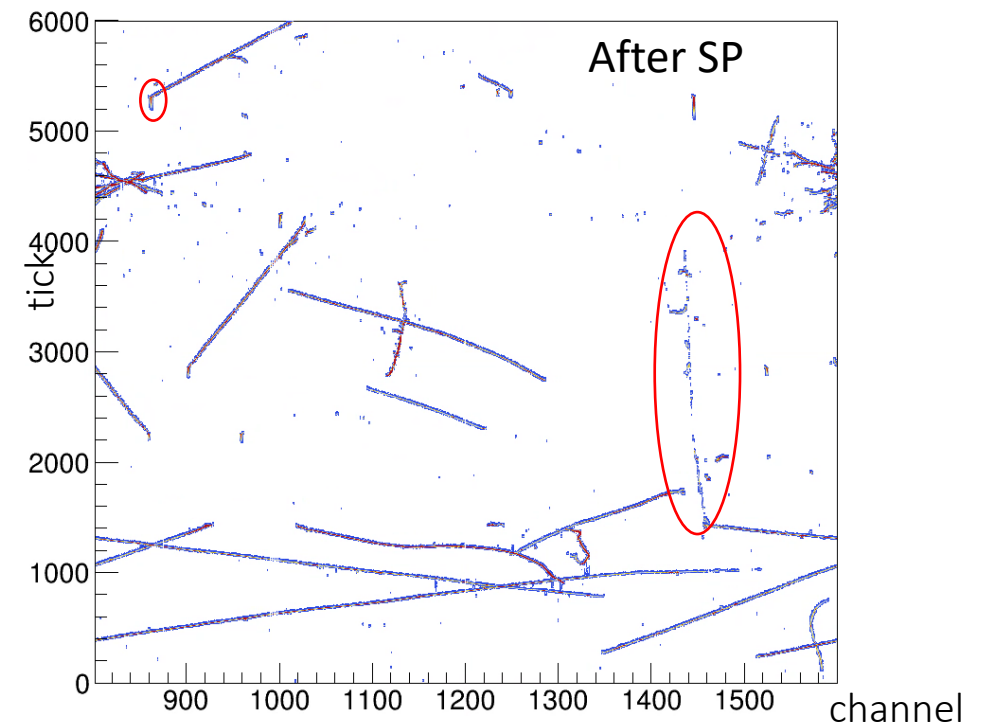


Remaining Challenges in Current Signal Processing (SP)

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

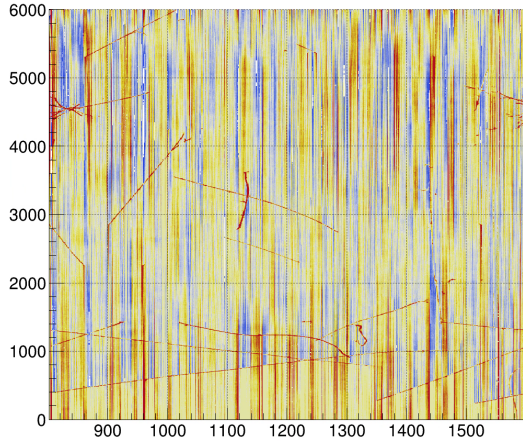


SP



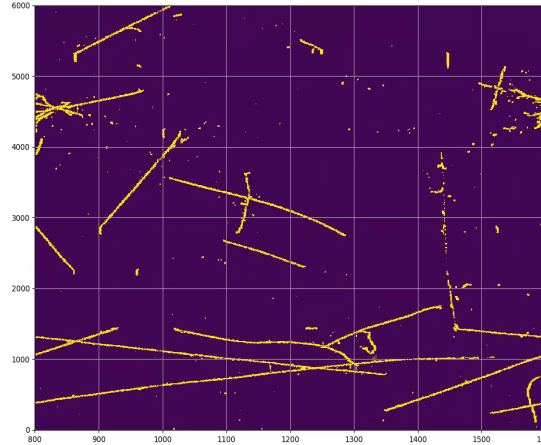
Need to improve “ROI” (Region of Interest) finding

Decon for charge
Waveform $\rightarrow$ charge, dense

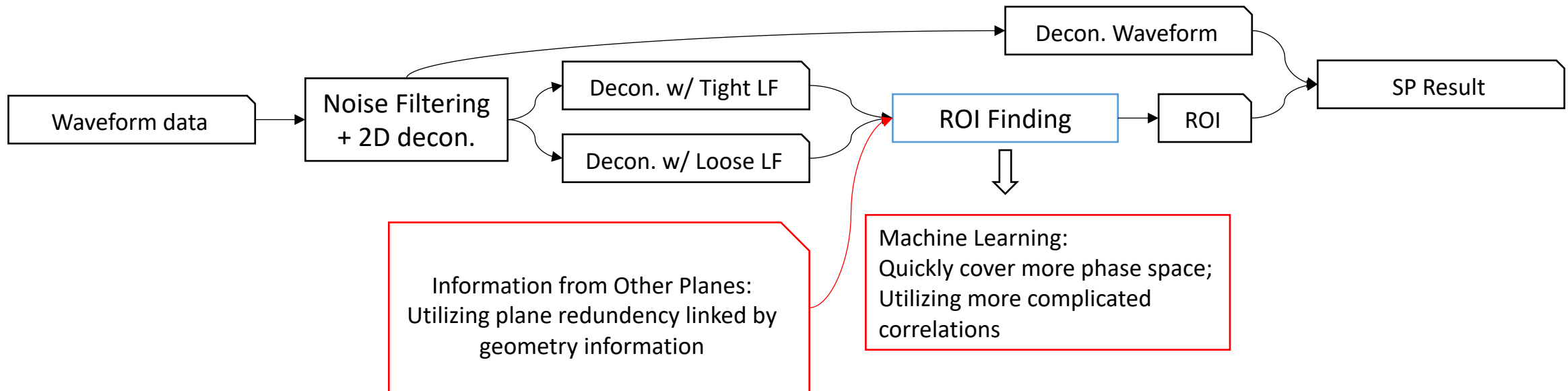
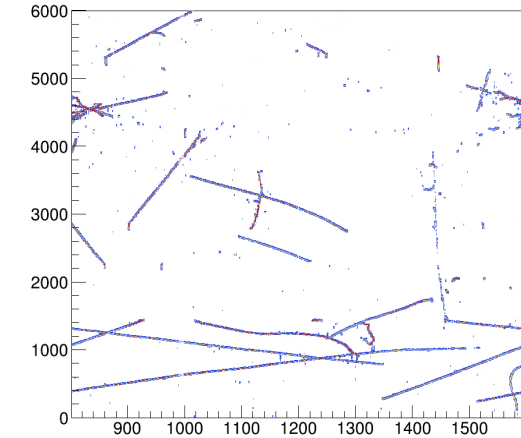


+

ROI:
Hit finding, sparsify



SP result:
Sparse, charge



ROI finding as semantic segmentation

2D semantic segmentation – UNet

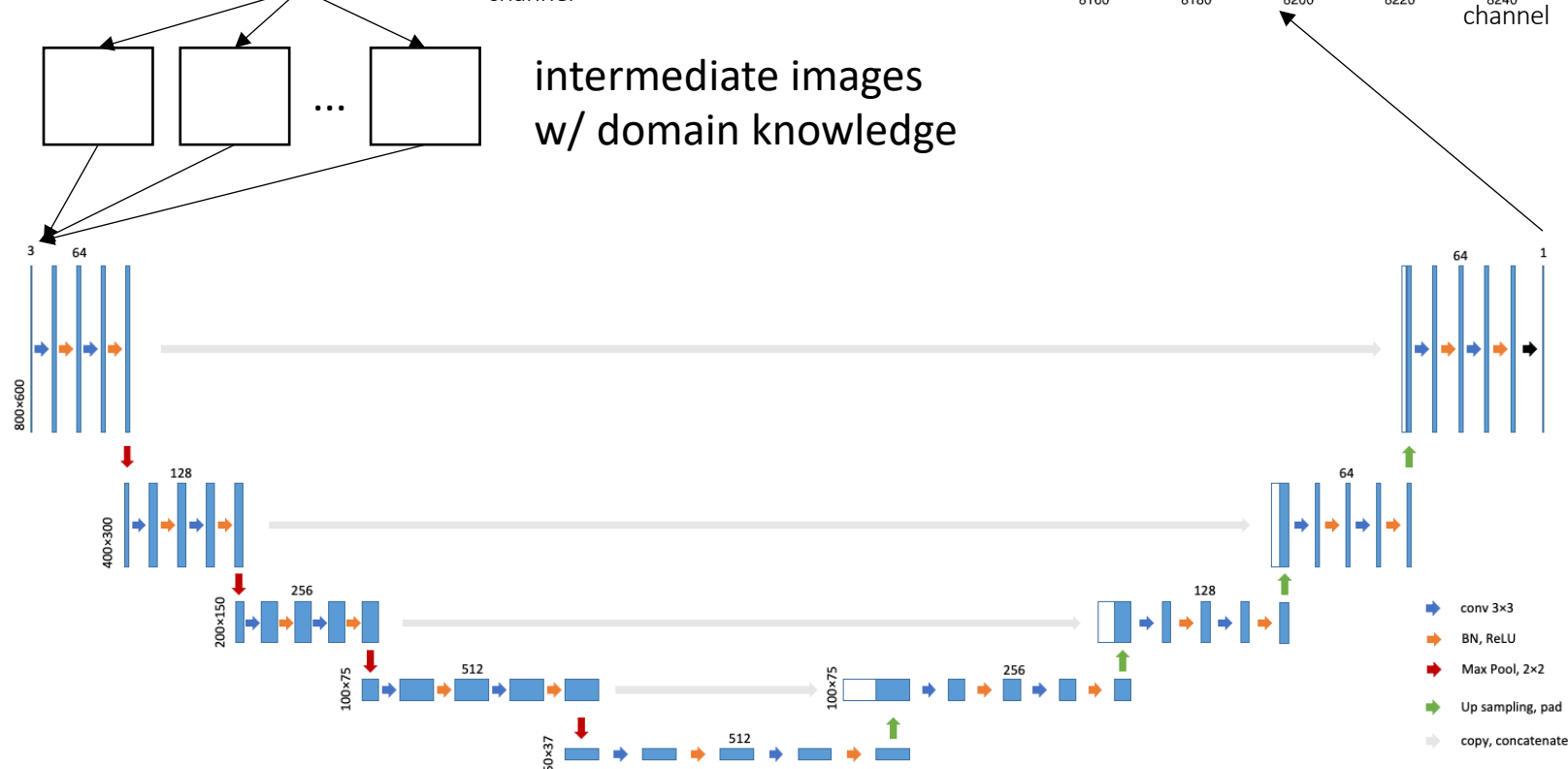
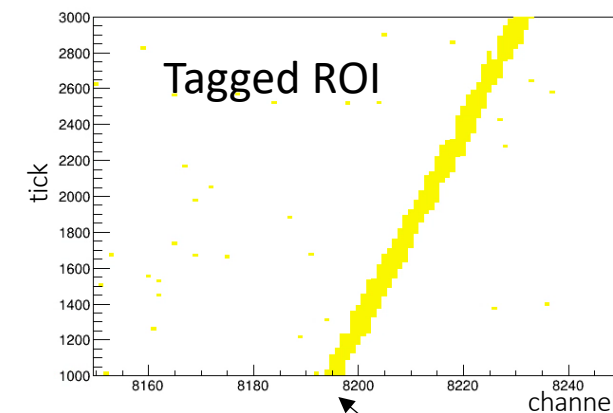
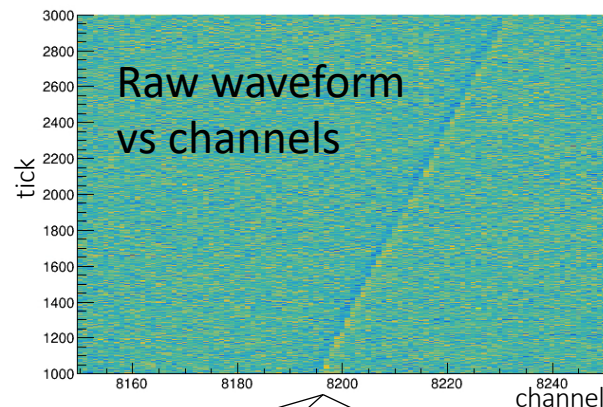
- arXiv:1505.04597

UNet: auto encoder-decoder + skip connections

- Output is sparsely connected components
- Input and output are similar at leading order

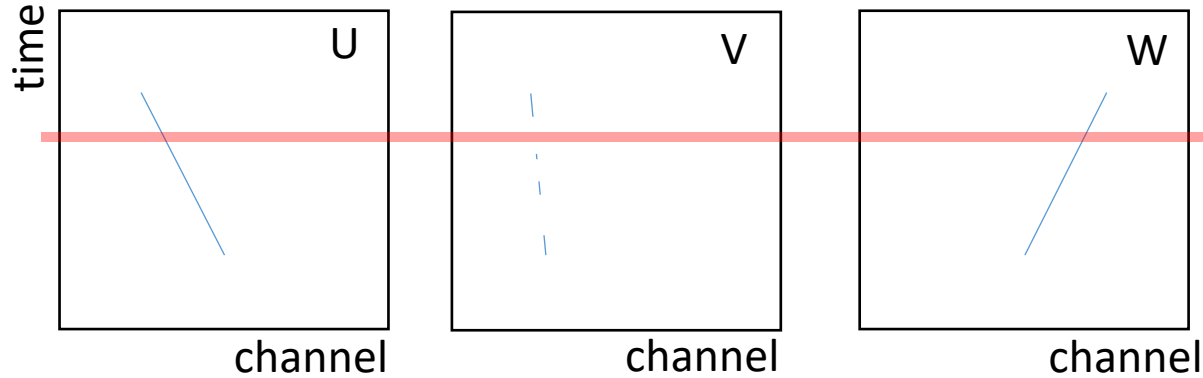
Forked a Pytorch implementation:

<https://github.com/HaiwangYu/Pytorch-UNet>

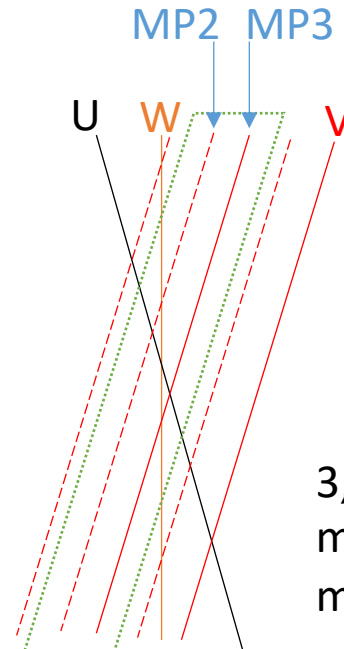


Muti-Plane Information – Geometry

1, make time slices



2, Matching active wires (with initial ROI) from multiple planes



3, On target plane, tag 3-Plane matched ROIs (MP3) or 2-Plane matched ROIs (MP2)

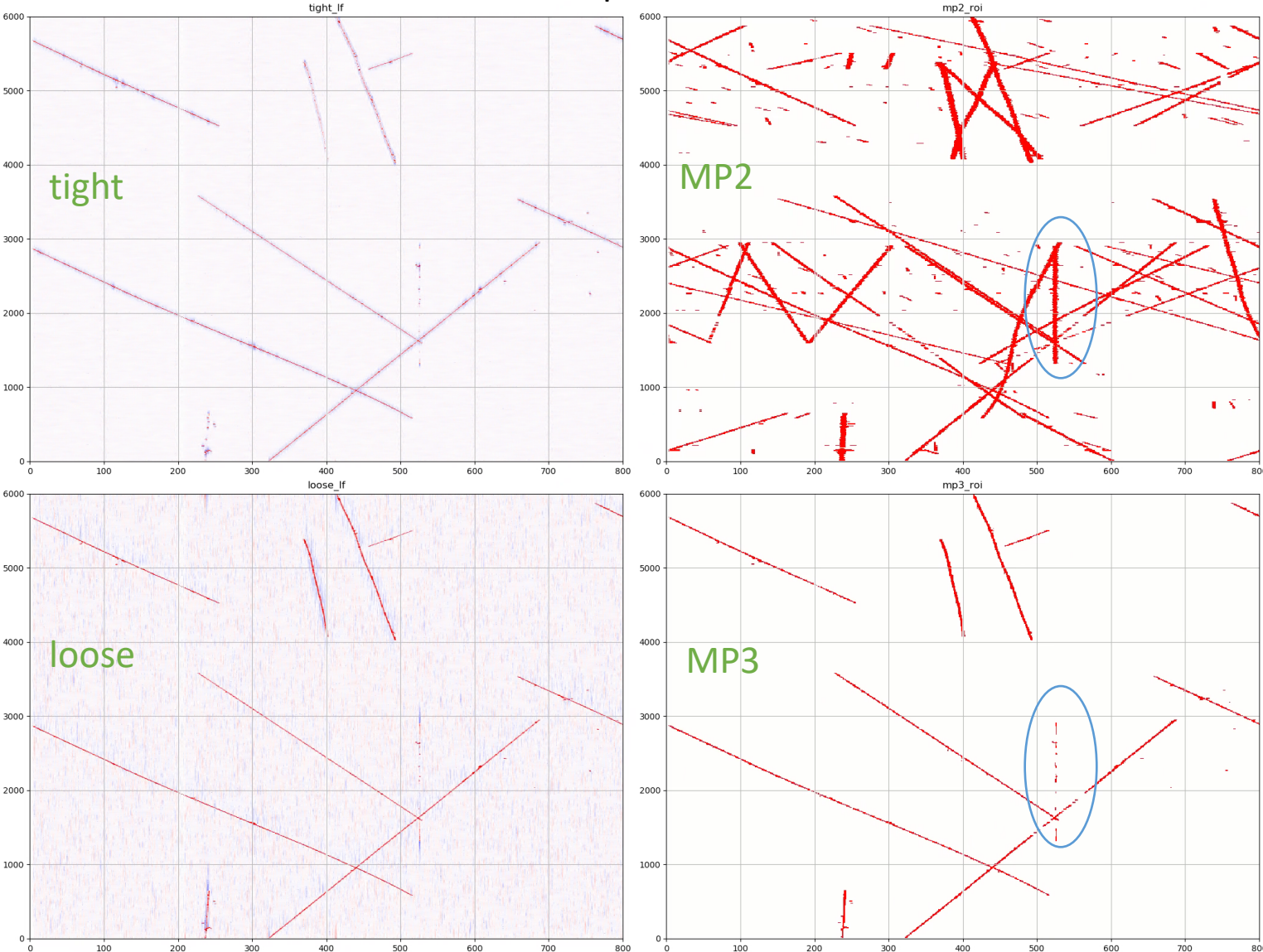
Using other plane information projected to the target plane: utilizing plane redundancy

- Inspired by Wire-Cell '3D Imaging'.
 - *arxiv:1803.04850*
- Key algorithm "Fast projection" realized using "RayGrid" tools:
<https://github.com/WireCell/wire-cell-docs/blob/master/presentations/updates/20190321/latexmk-out/img.pdf>

- active wire in the time-slice :
- ref. plane, **target plane**
- - - in-active wire in the time-slice

Input and label for DNN - ProtoDUNE Single-Phase simulation

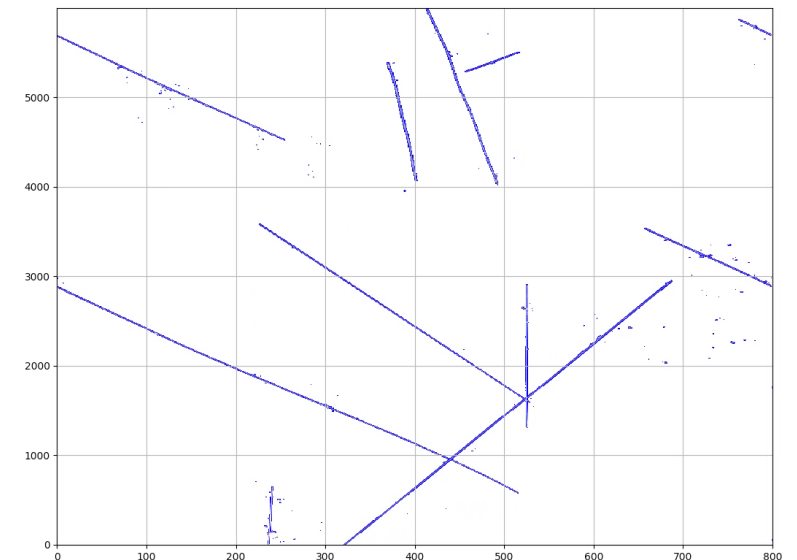
Input candidates



tight/loose: deconvolution with tight/loose
low frequency filter

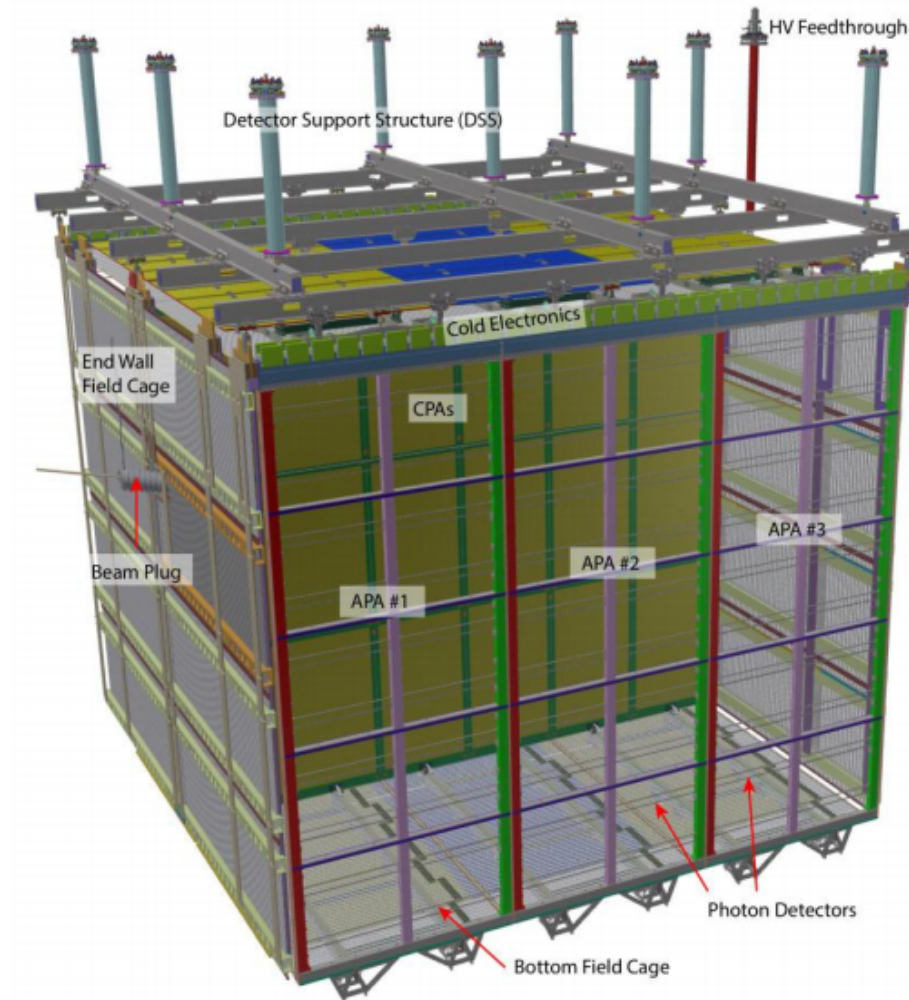
label was made by rasterization of charge
depos – 2D gaussian response

Label



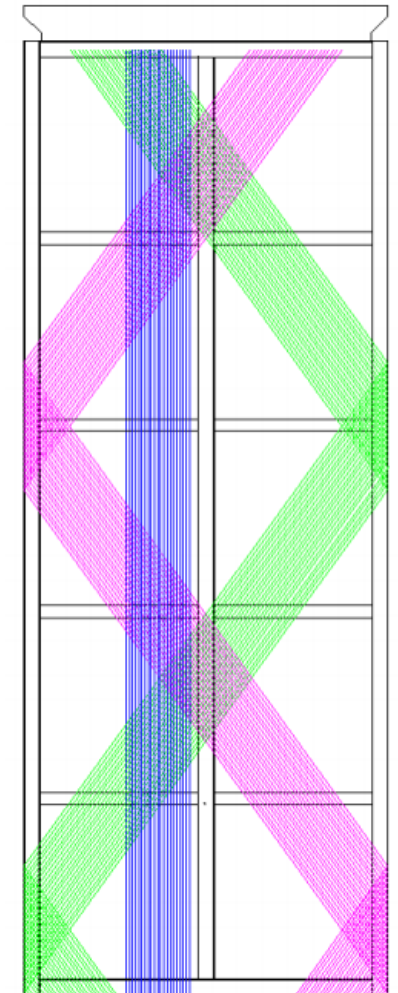
ProtoDUNE Single-Phase

ProtoDUNE Single-Phase (the NP04 experiment at CERN) is designed as a test bed and full-scale prototype for the elements of the first far detector module of DUNE (next-generation, long-baseline neutrino oscillation experiment).



major components of the ProtoDUNE-SP TPC
from arxiv:1706.07081

Sketch of a ProtoDUNE-SP APA
from arxiv:1706.07081

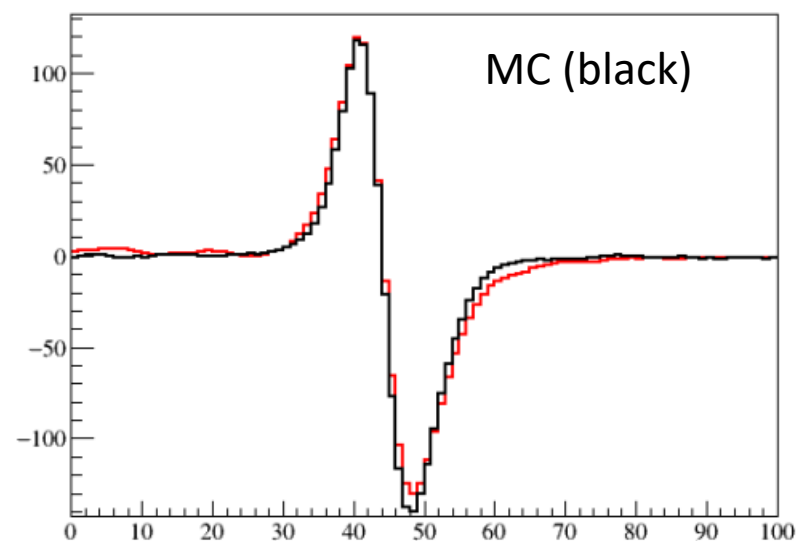


Signal Simulation Validation

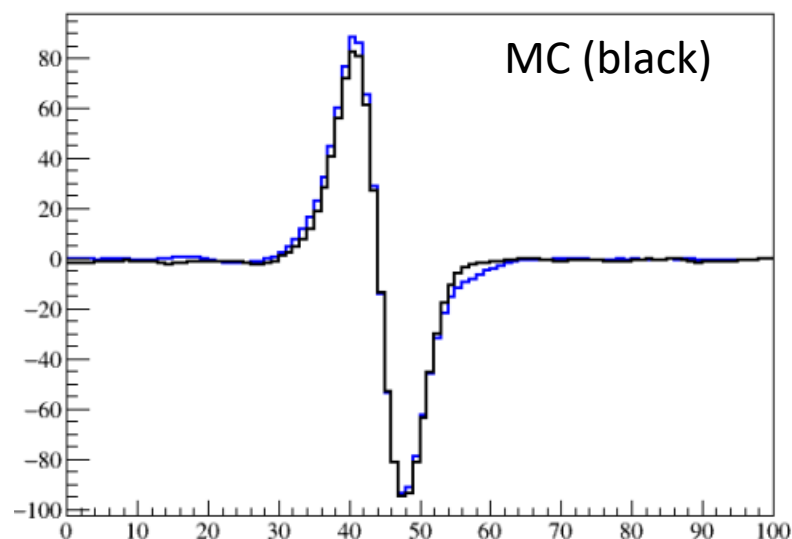
2D convolution based simulation for LArTPC

- *JINST 13 P07006 (2018)*
- Software stack:
 - LArSoft for the generator and Geant4 simulation
 - Wire-Cell Toolkit for the detector response

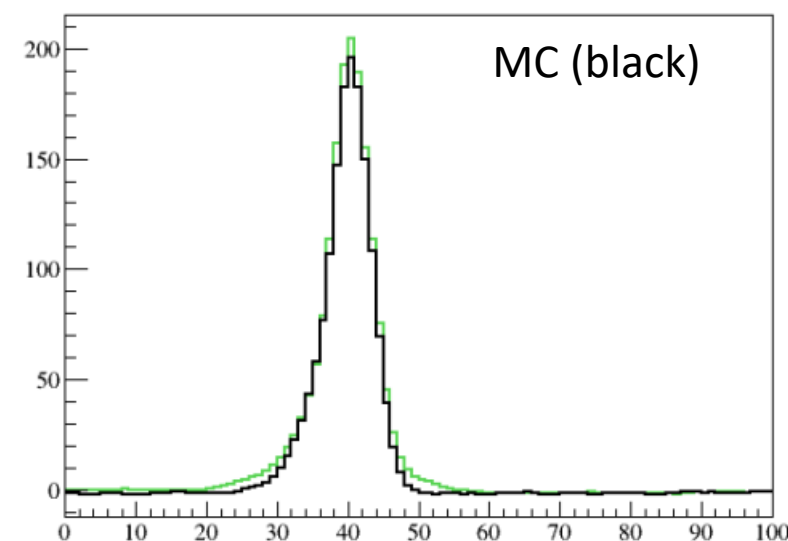
Average waveform: data vs. MC



U plane
MC scaling: 1.6
Tick: [570, 970]
Ch: [8050, 8200]



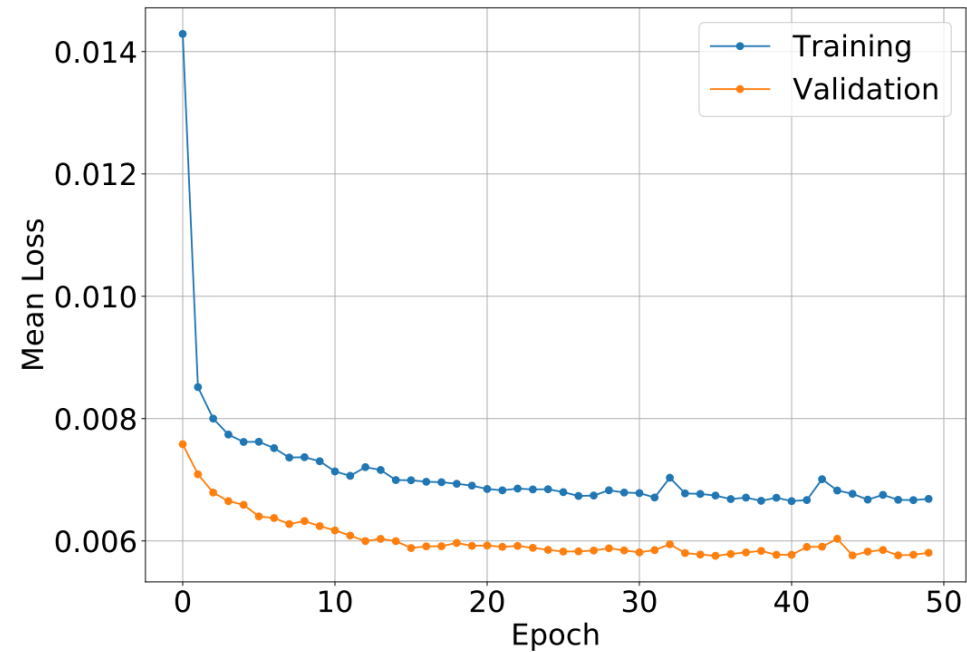
V plane
MC scaling: 1.6
Tick: [570, 970]
Ch: [8950, 9200]



W plane
MC scaling: 1.6
Tick: [570, 970]
Ch: [9500, 9750]

Efficient network – 500 samples already provide good performance – 6 min/epoch

- Platform: I9-9900K, 32 GB memory, Nvidia GTX 2080 Ti 11GB, Samsung 970 500GB NVMe SSD
- Sample: 500 APA Planes using cosmic generator (450 training, 50 validation)
- Loss: cross entropy
- Optimizer: Stochastic Gradient Descent with momentum



Evaluation with simulation

- DNN ROI finding has higher efficiency and purity than the reference ROI finding especially at large angles.
- More effective on tracks have asymmetric angles induction planes
- DNN w/o MP information performs slightly better than Ref. but much worse than DNN w/ MP information

pixel based evaluation:

$$\text{eff} = (0 + 3 + 0)/(0+3+4) = 3/7$$

$$\text{purity} = (0 + 3 + 0)/(0+4+1) = 3/5$$

a



b



c

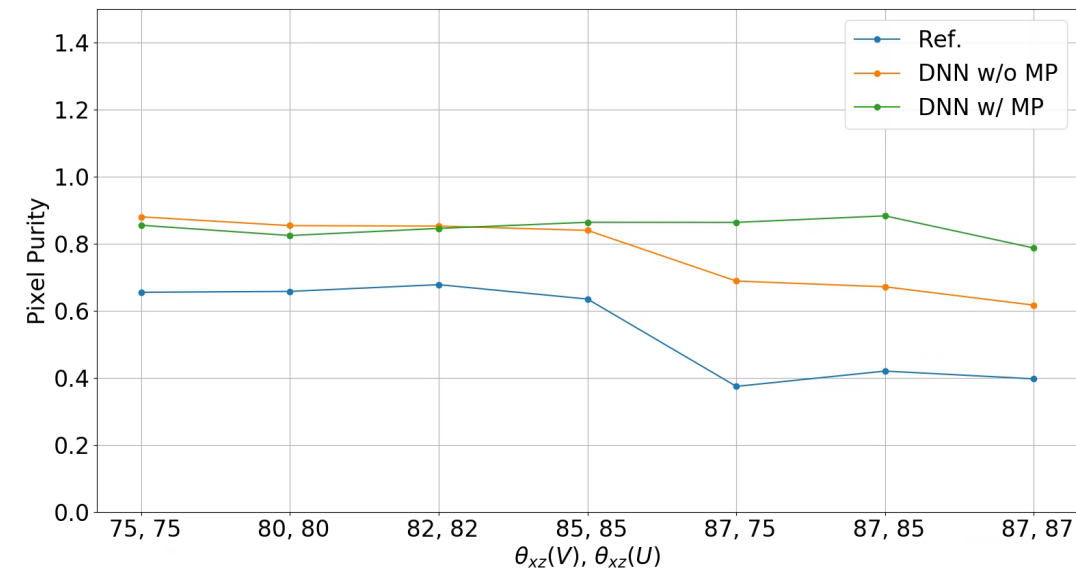
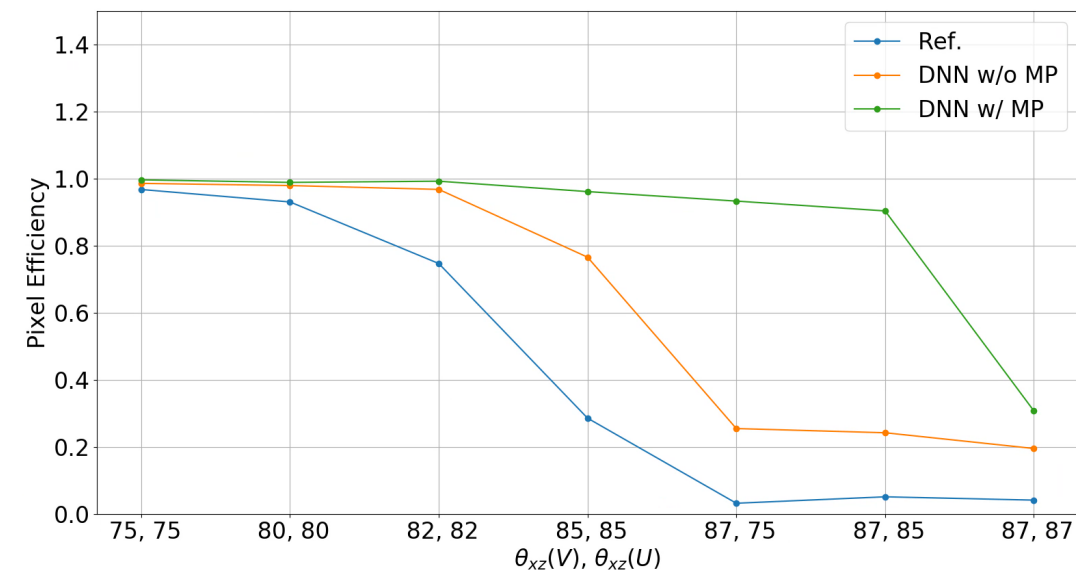


pixel labeled as ROI from truth

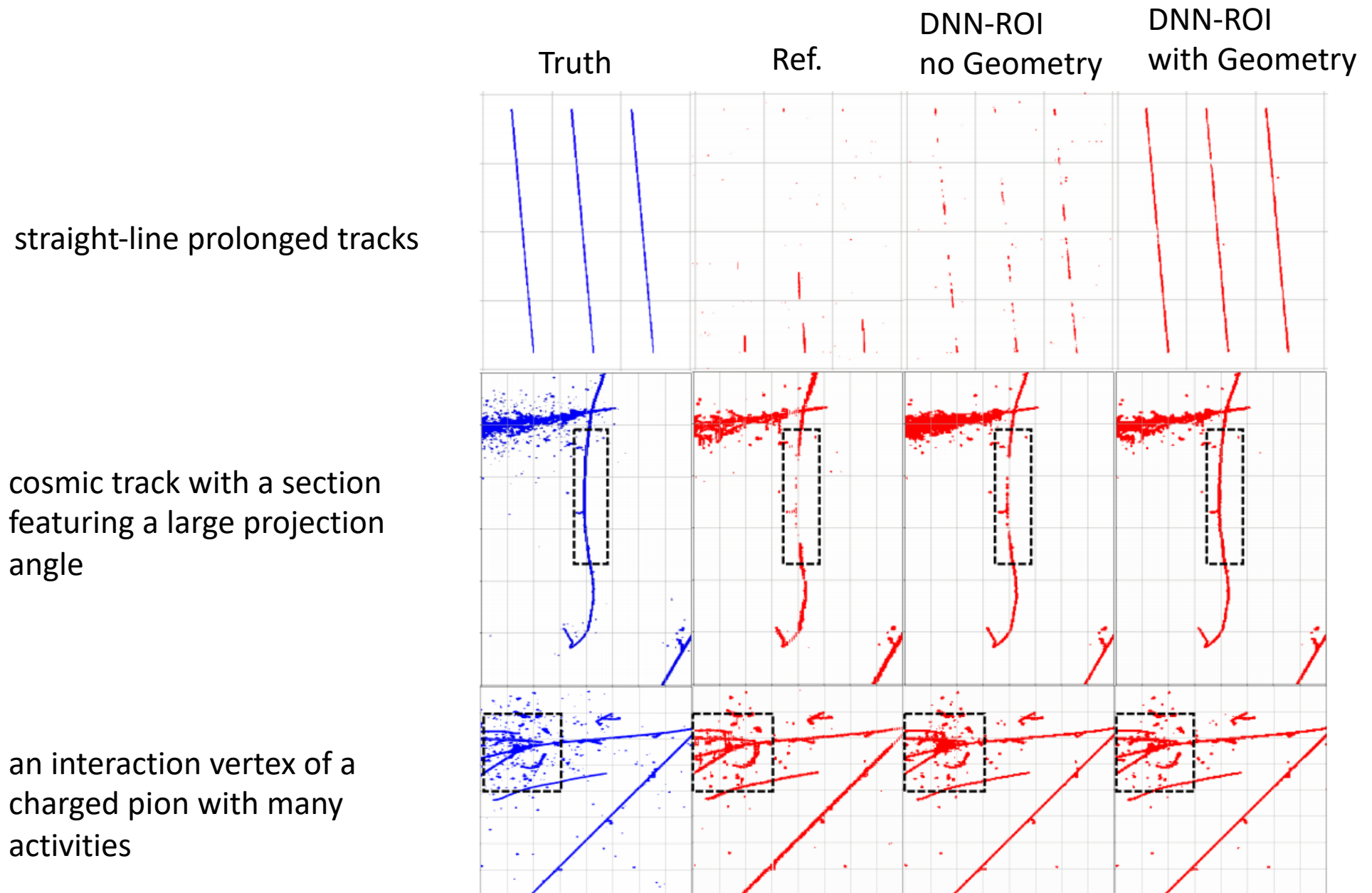


pixel labeled as ROI from reco.

ROI finding on V plane



Example ROI finding event displays on simulated data



Reference SP

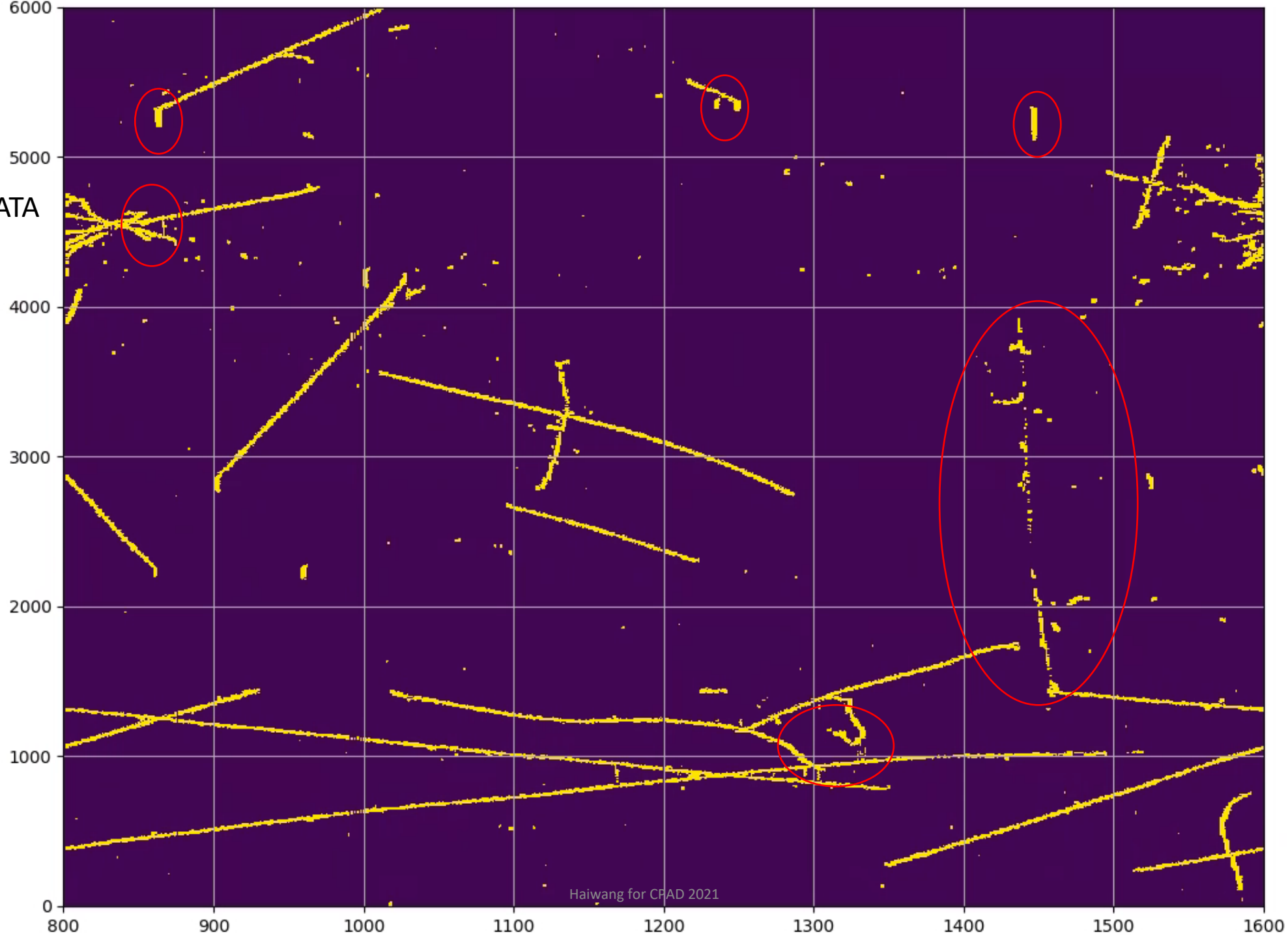
ProtoDUNE DATA

run: 5145

subRun: 1

event: 26918

V plane



DNN-SP

ProtoDUNE DATA

run: 5145

subRun: 1

event: 26918

V plane

500

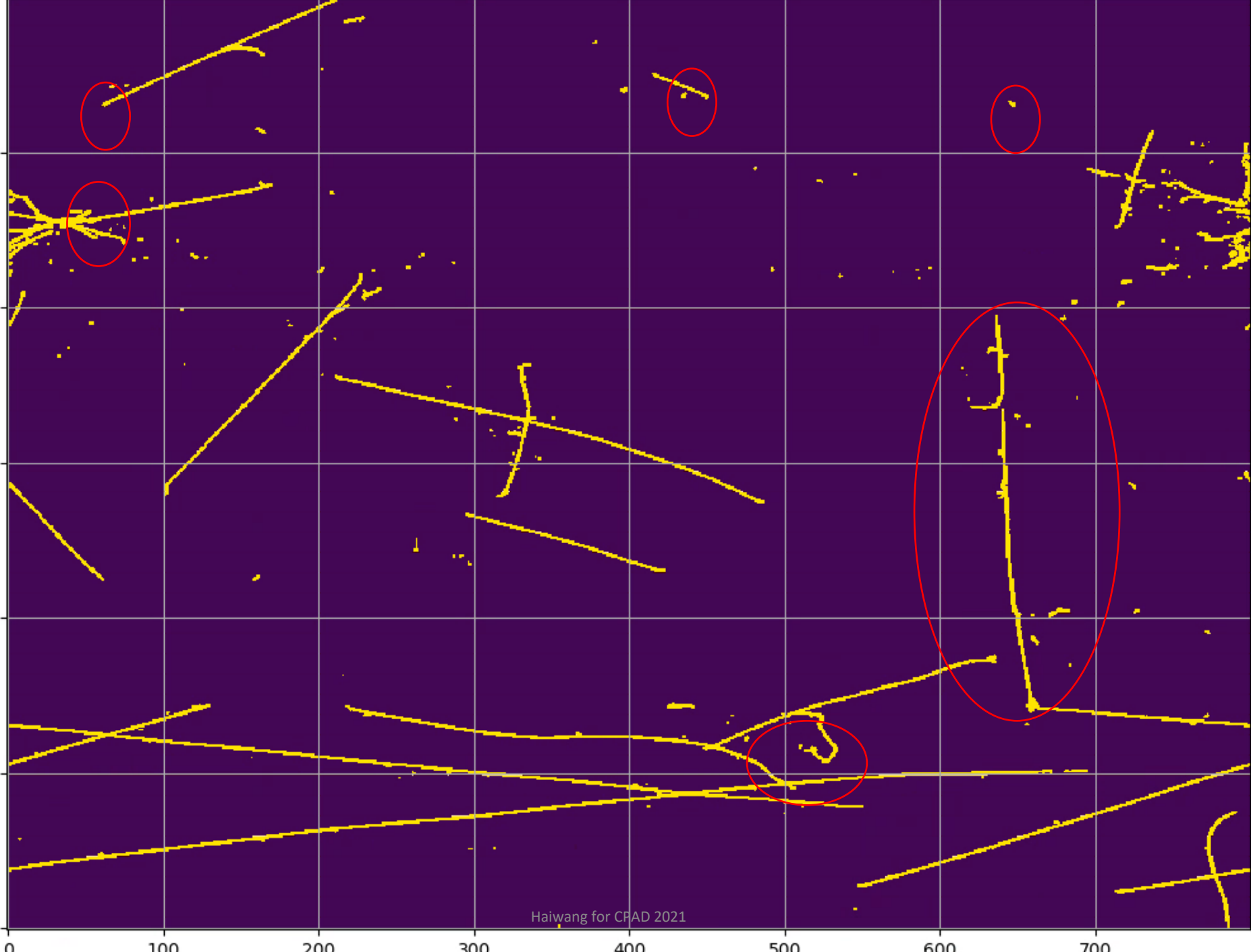
400

300

200

100

0



Reference SP

ProtoDUNE-SP Data

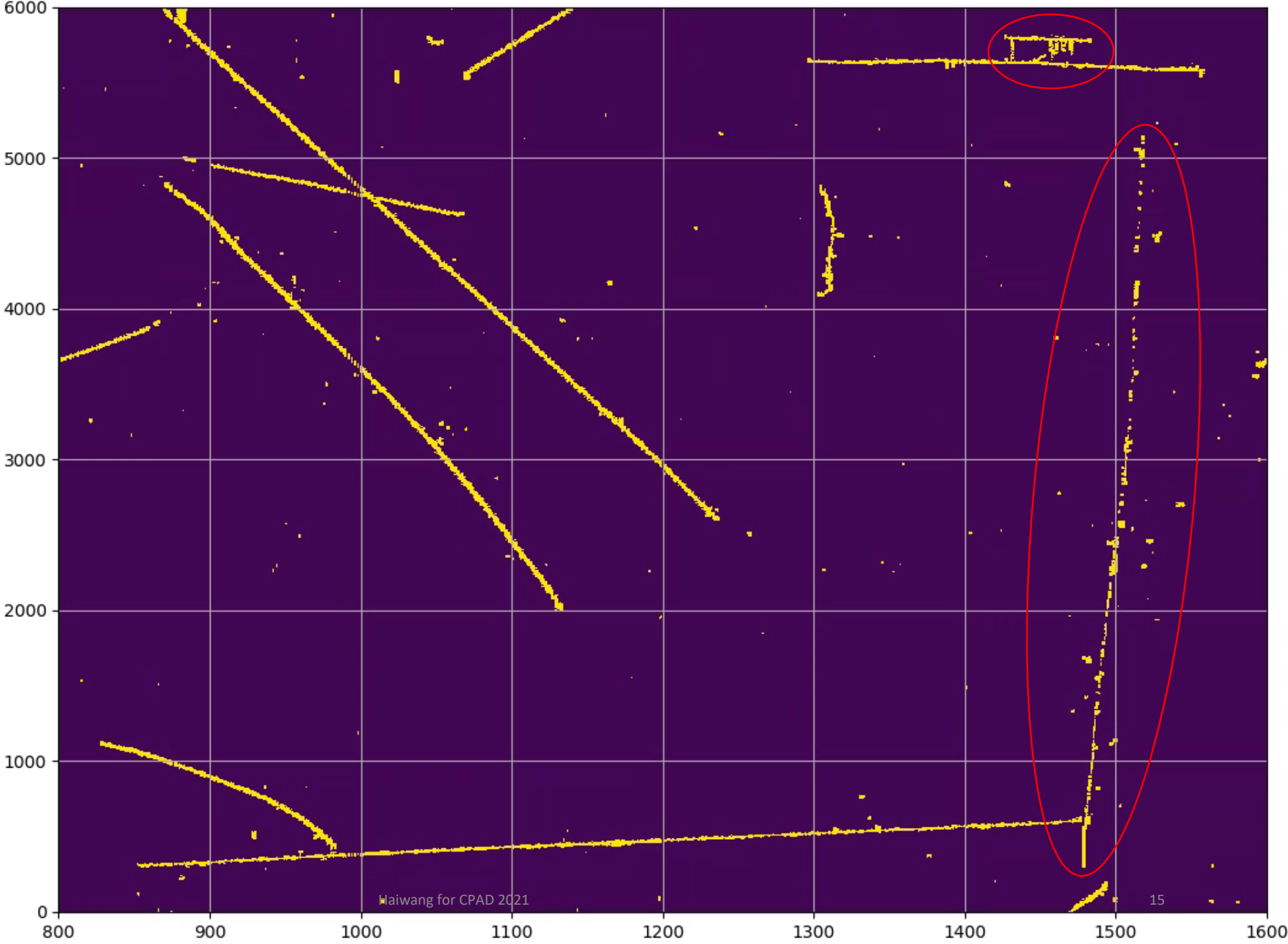
run: 5145

subRun: 1

event: 26945

V plane

ProtoDUNE: how and why
L. Manenti: X02.00001
and other ProtoDUNE Talks



DNN-SP

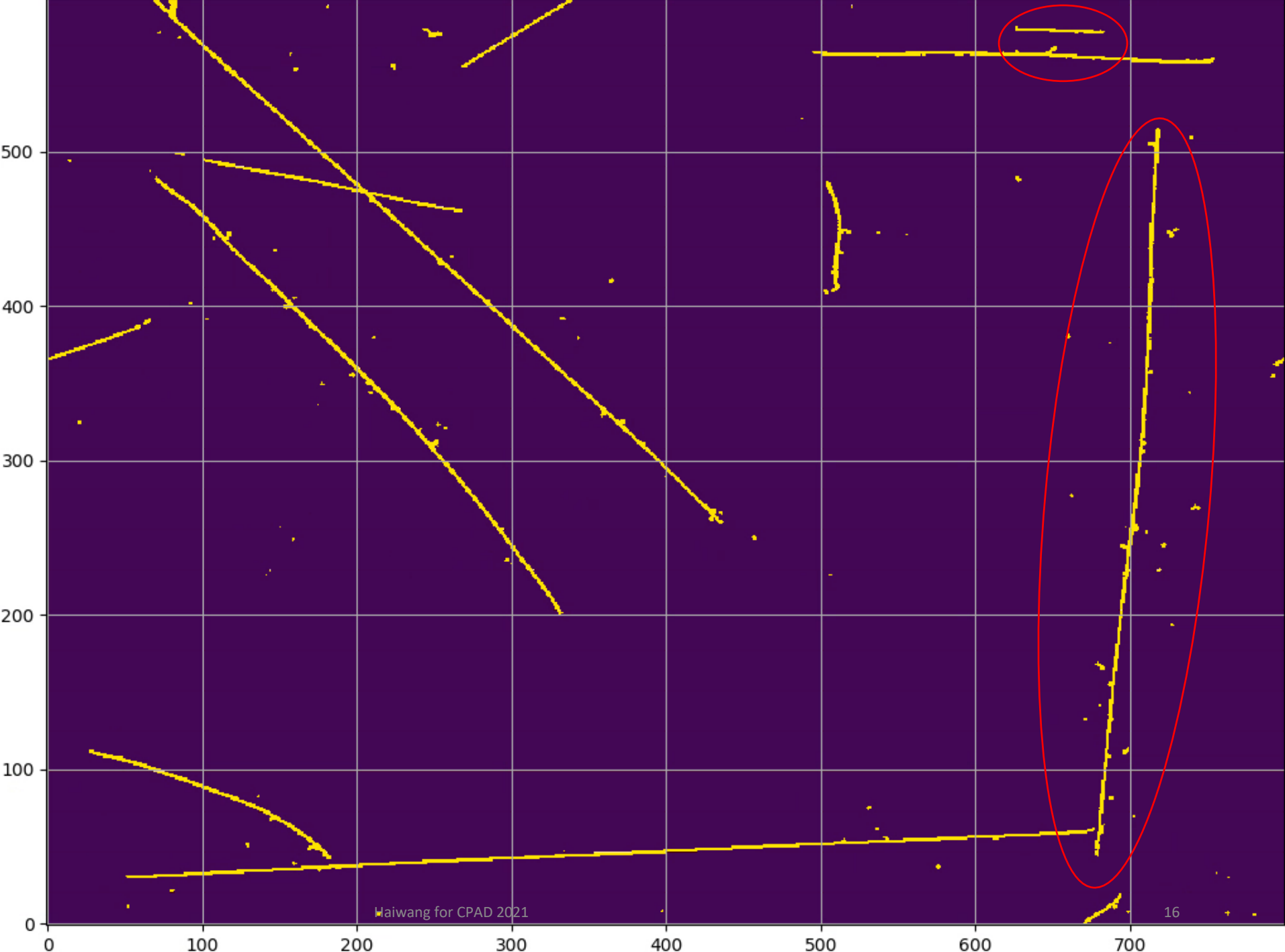
ProtoDUNE-SP Data

run: 5145

subRun: 1

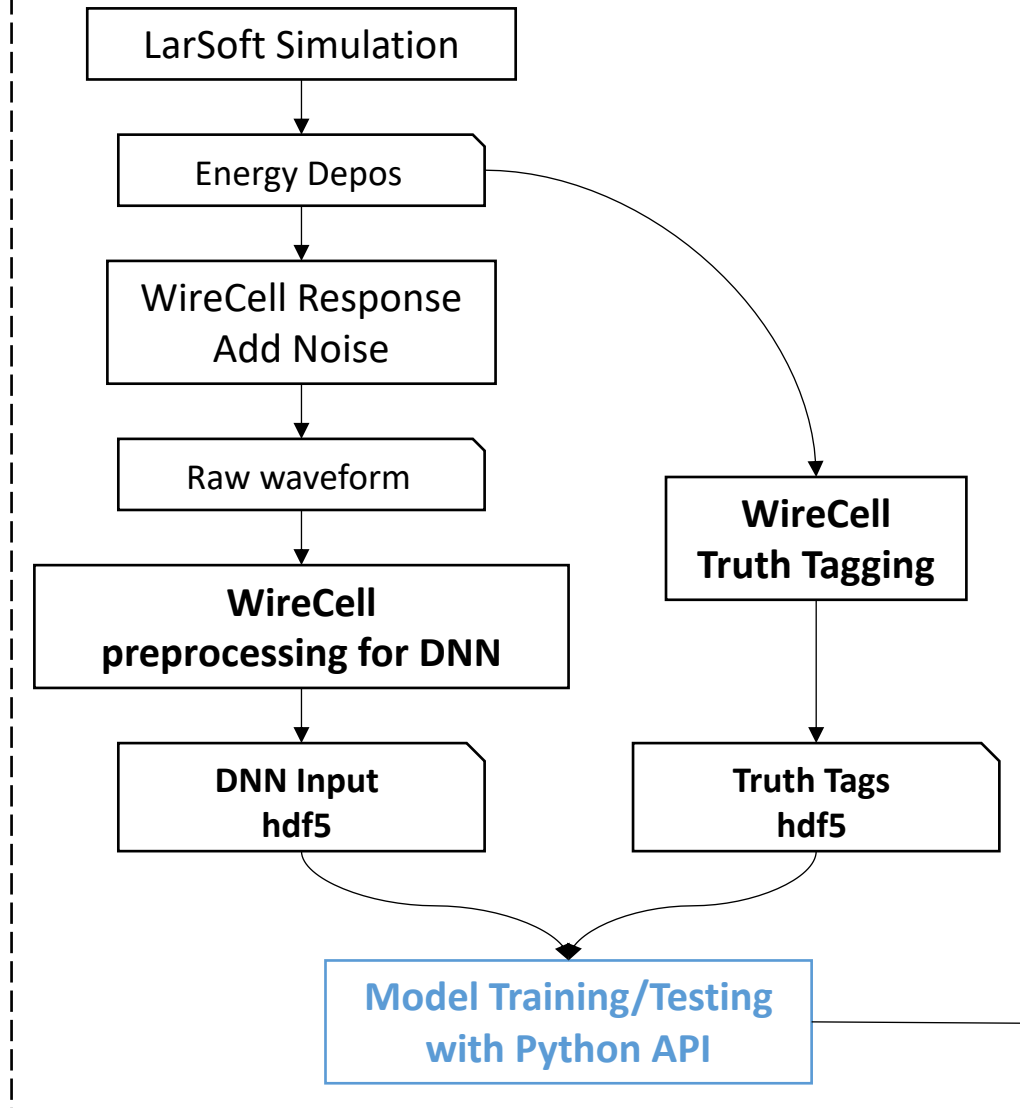
event: 26945

V plane



Deep-Learning in Wire-Cell Toolkit

Training workflow

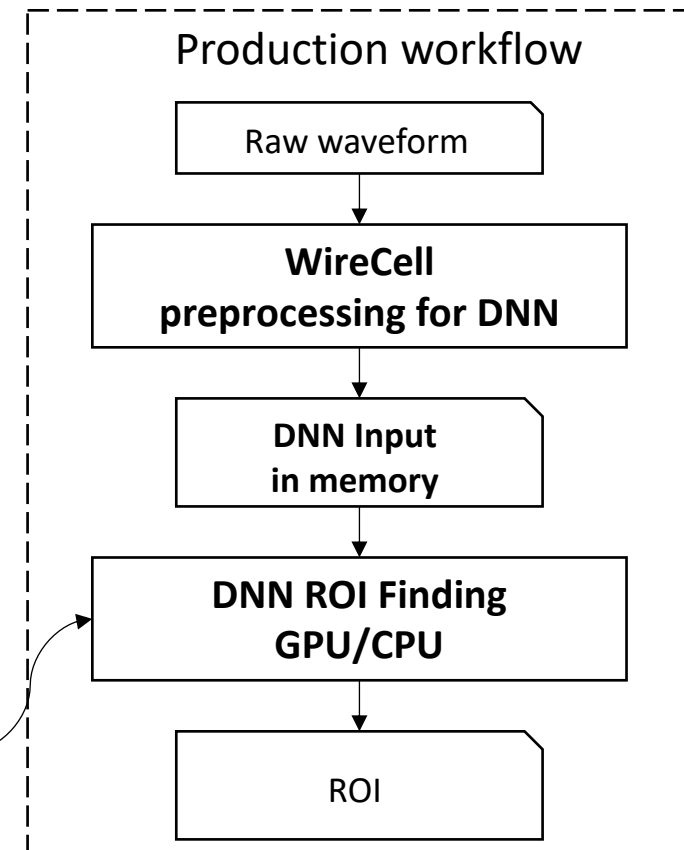


Established initial machinery for Deep-Learning in Wire-Cell Toolkit

<https://github.com/WireCell/wire-cell-toolkit>

- Data preparing in LarSoft/Wire-Cell
- Training with python
- Production with C++

Production workflow



DNN ROI finding algorithm provides a software improvement on LArTPC reconstruction

- based on the the hardware feature - redundant wire plane
- combines domain knowledge with machine learning
- significant improvement on both simulation and ProtoDUNE-SP data

Ref. *JINST 16 (2021) 01, P01036* for more.

Wire-Cell: <https://lar.bnl.gov/wire-cell/>

Backup

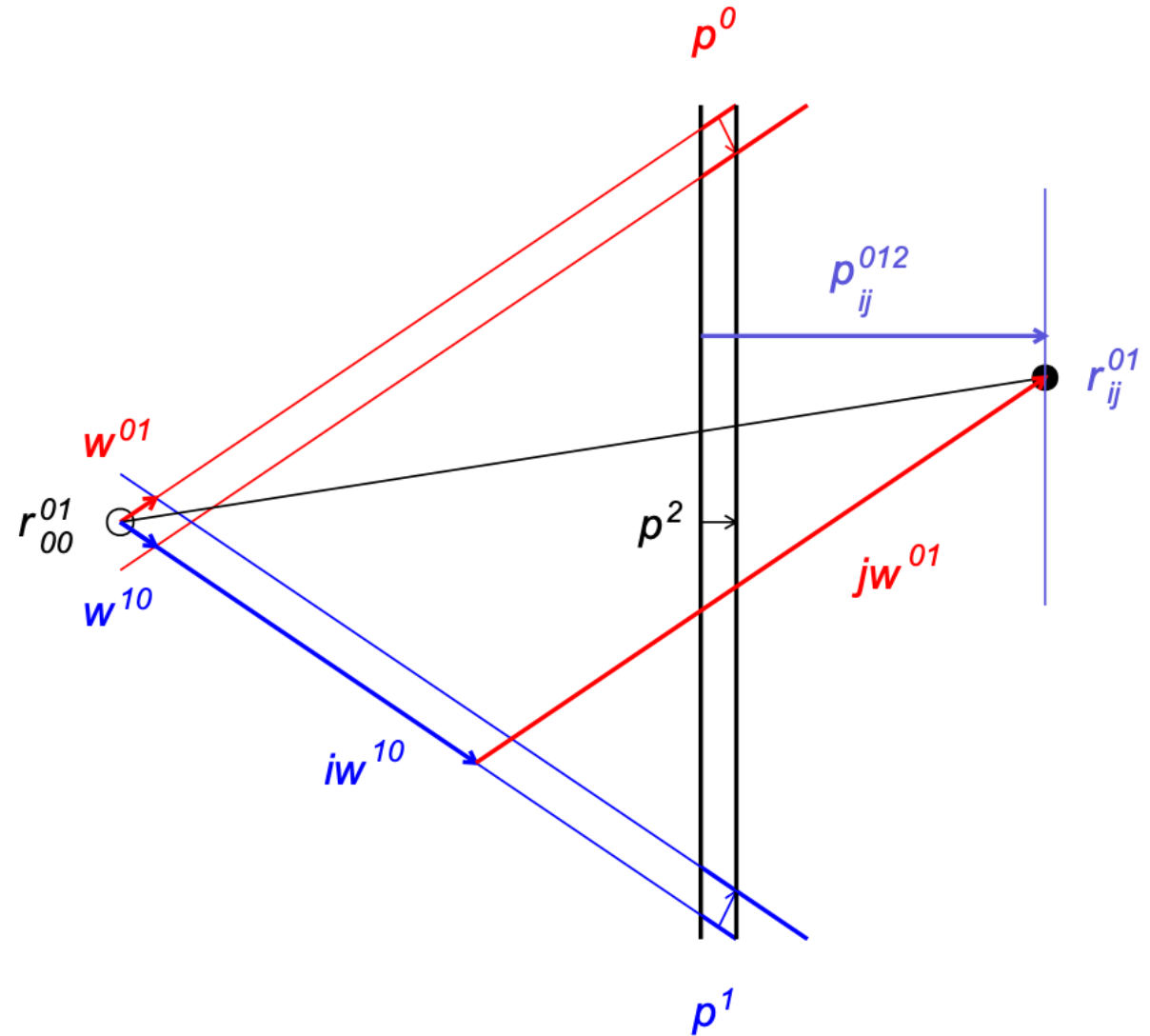
RayGrid fast projection

Non-orthogonal coordinate system

$$r_{ij}^{lm} = r_{00}^{lm} + jw^{lm} + iw^{ml}$$

Projection on the “n” plane

$$p_{ij}^{lmn} = (r_{ij}^{lm} - c^n) \cdot \hat{p}^n$$

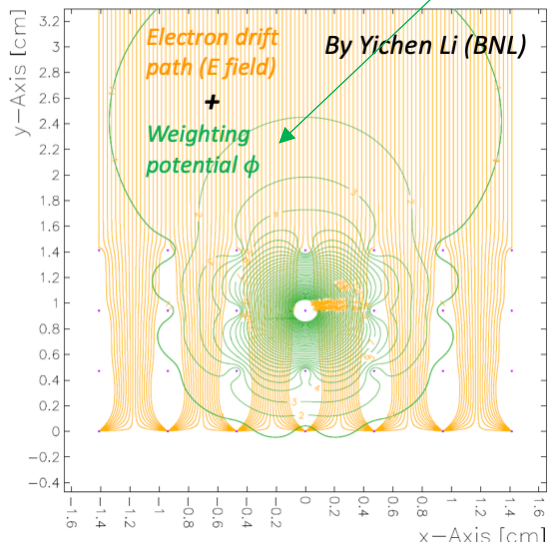


WireCell Detector Response Simulation

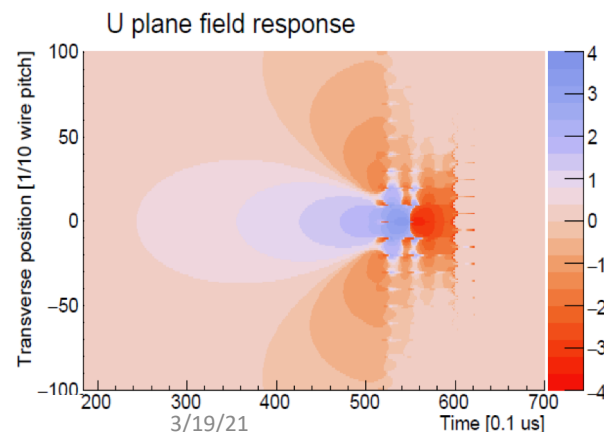


Ramo's theorem

$$i = e\vec{v} \cdot \vec{E}_v = e\vec{v} \cdot (-\nabla\phi)$$



Garfield, a drift-chamber simulation program User's Guide, Veenhof, R. (1993)



Hanyu Wei' talk, DUNE collab. meeting May 2019

Response matrix:

- Field response from Garfield simulation
- Electronic response

2D convolution – realized by FFT and IFFT

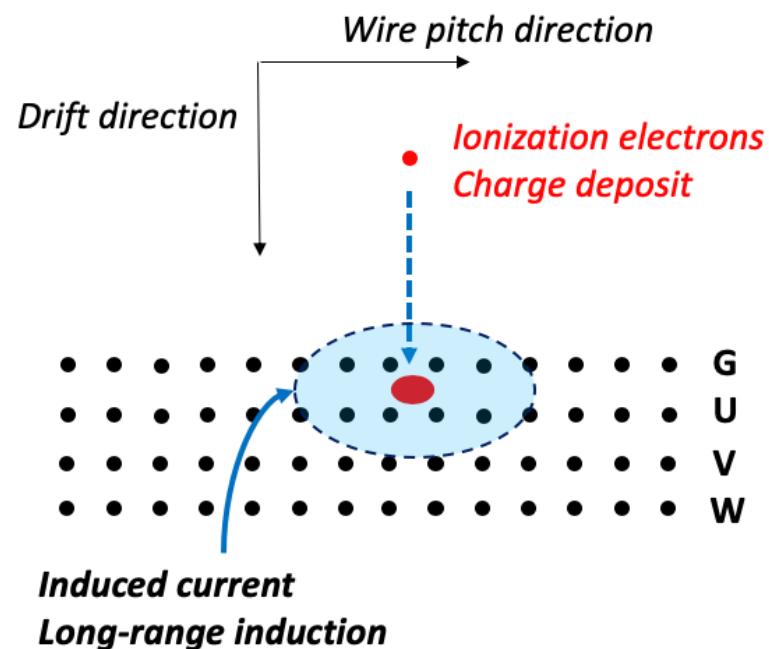
Add inherent electronics noise

- M. Diwan. *Basic mathematics of random noise part 1/2*

Refer: JINST 13 P07006 (2018)

2D Conv.

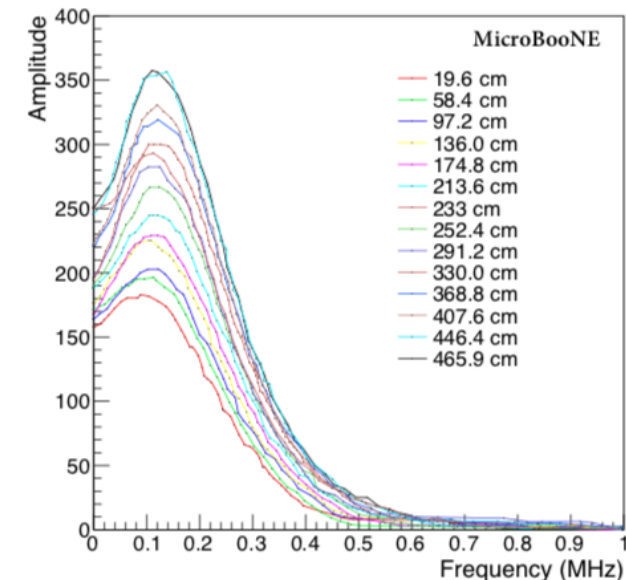
$$M(t', x') = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} R(t, t', x, x') \cdot S(t, x) dt dx + N(t', x')$$



Haiwang for CPAD 2021

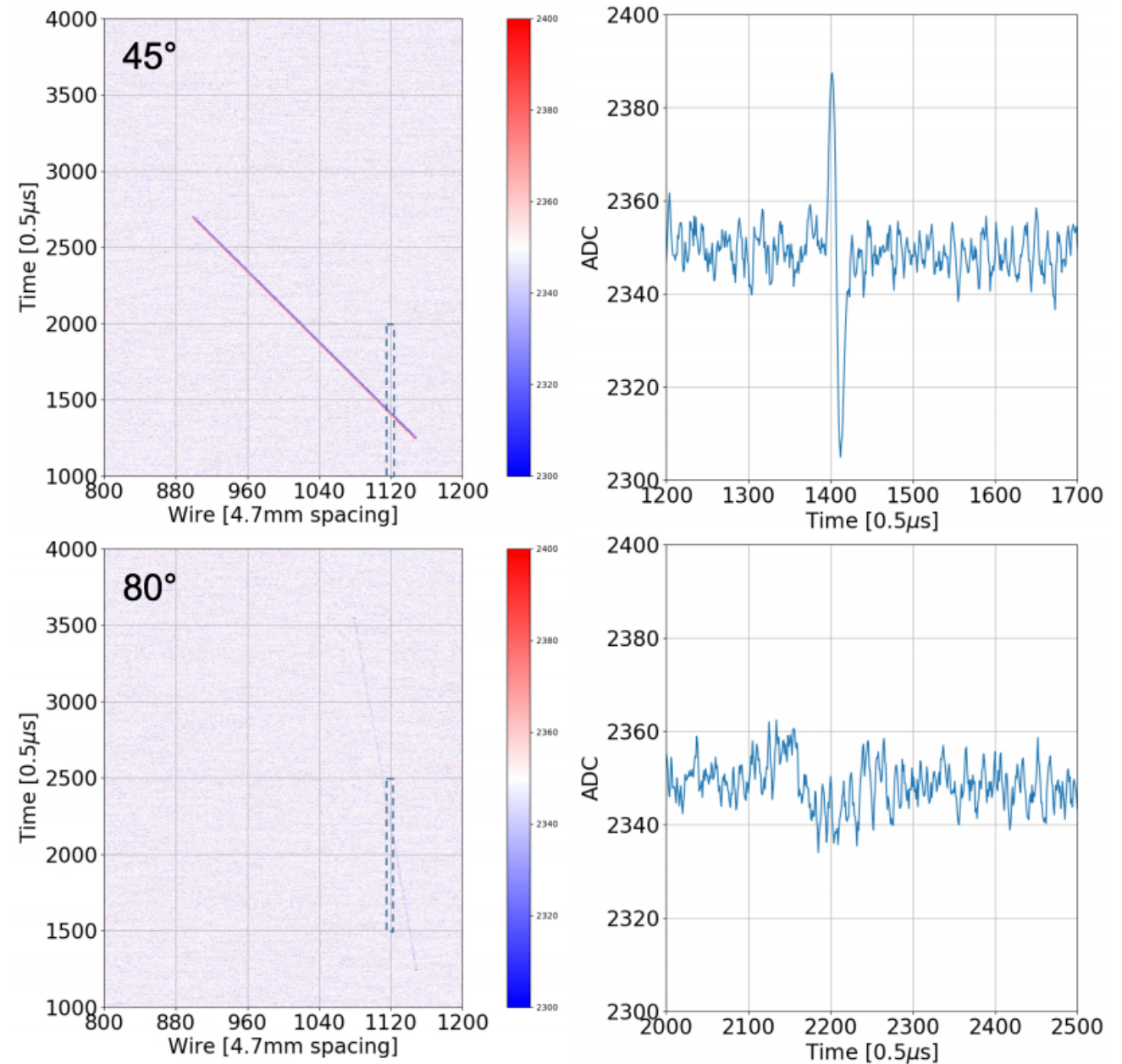
Hanyu Wei' talk, DUNE collab. meeting May 2019

Inherent electronic noise spectrum for different lengths of wires, JINST 13 P07006 (2018)

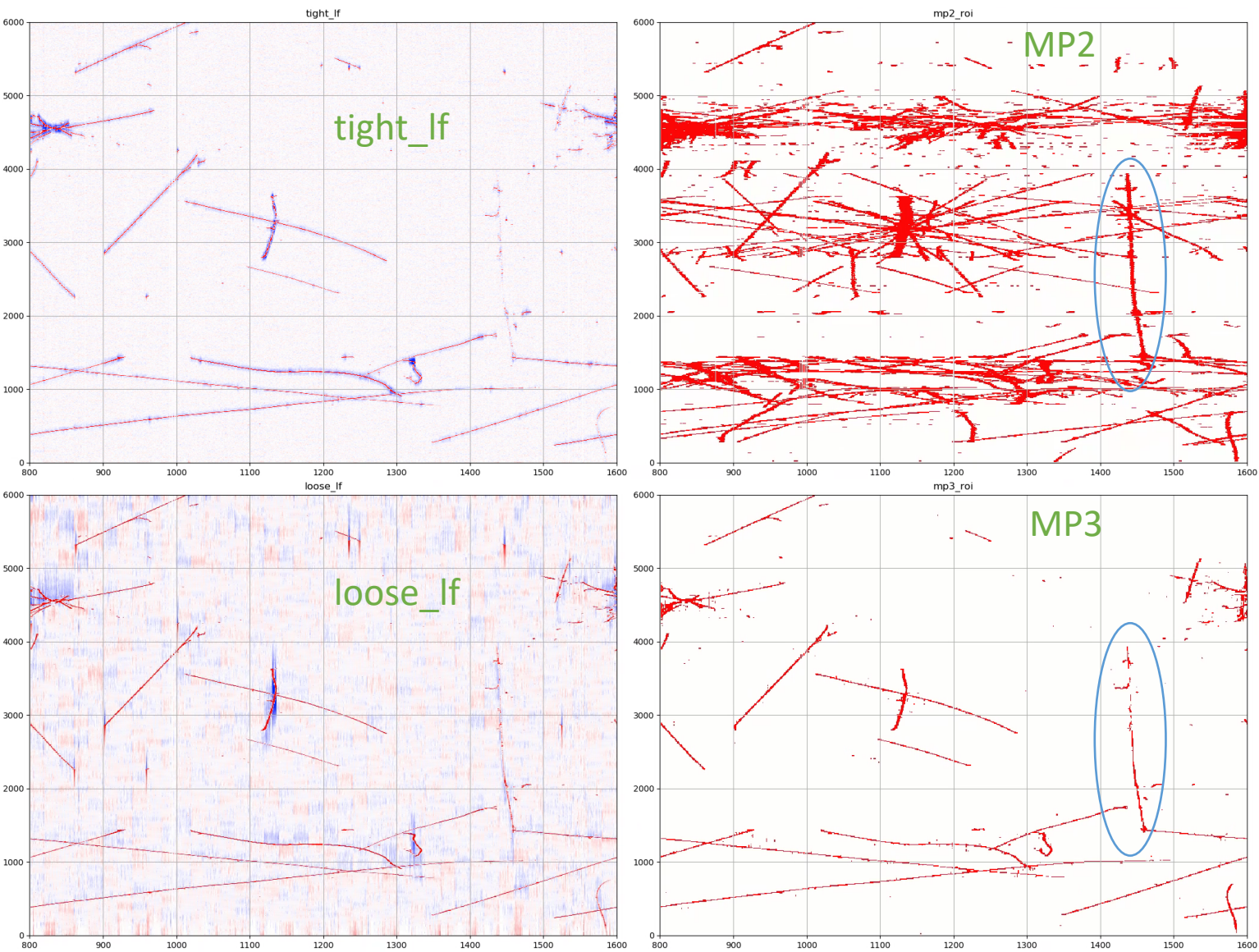


Signal vs. track angle

projection of a minimum ionizing particle (MIP) track on one induction plane



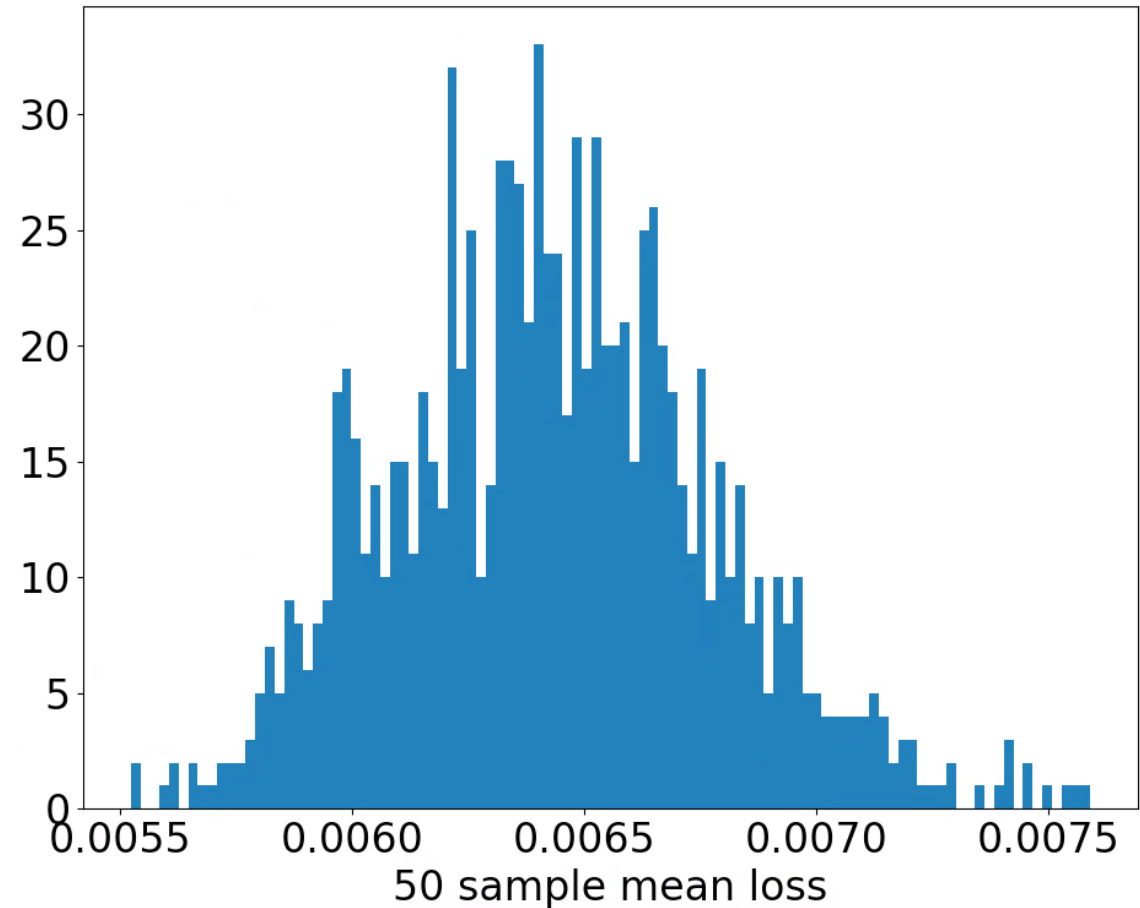
Input Candidates for DNN - ProtoDUNE data



	Unit Time	Total Time
Generator	2 sec/event	0.3 hour/500events
G4	23 sec/event	3.2 hour/500events
detector response, truth tagging and waveform preprocessing	68 sec/APA	9.4 hour/500 APA
Network training	6 min/epoch (1 epoch: 1 iteration of 500 APA sample)	5 hour/50epoch
Sum		17.9 hour

Mean loss of image samples are also expected to vary

We validated this hypothesis using a bootstrapping method. 1000 test samples (each sample contains 50 images) were random chosen from a test data set. Mean loss value was calculated for each sample and the distribution is shown below. We can see that the sample mean loss has a Gaussian like distribution that varies from 0.0055 to 0.0075.



Reference SP

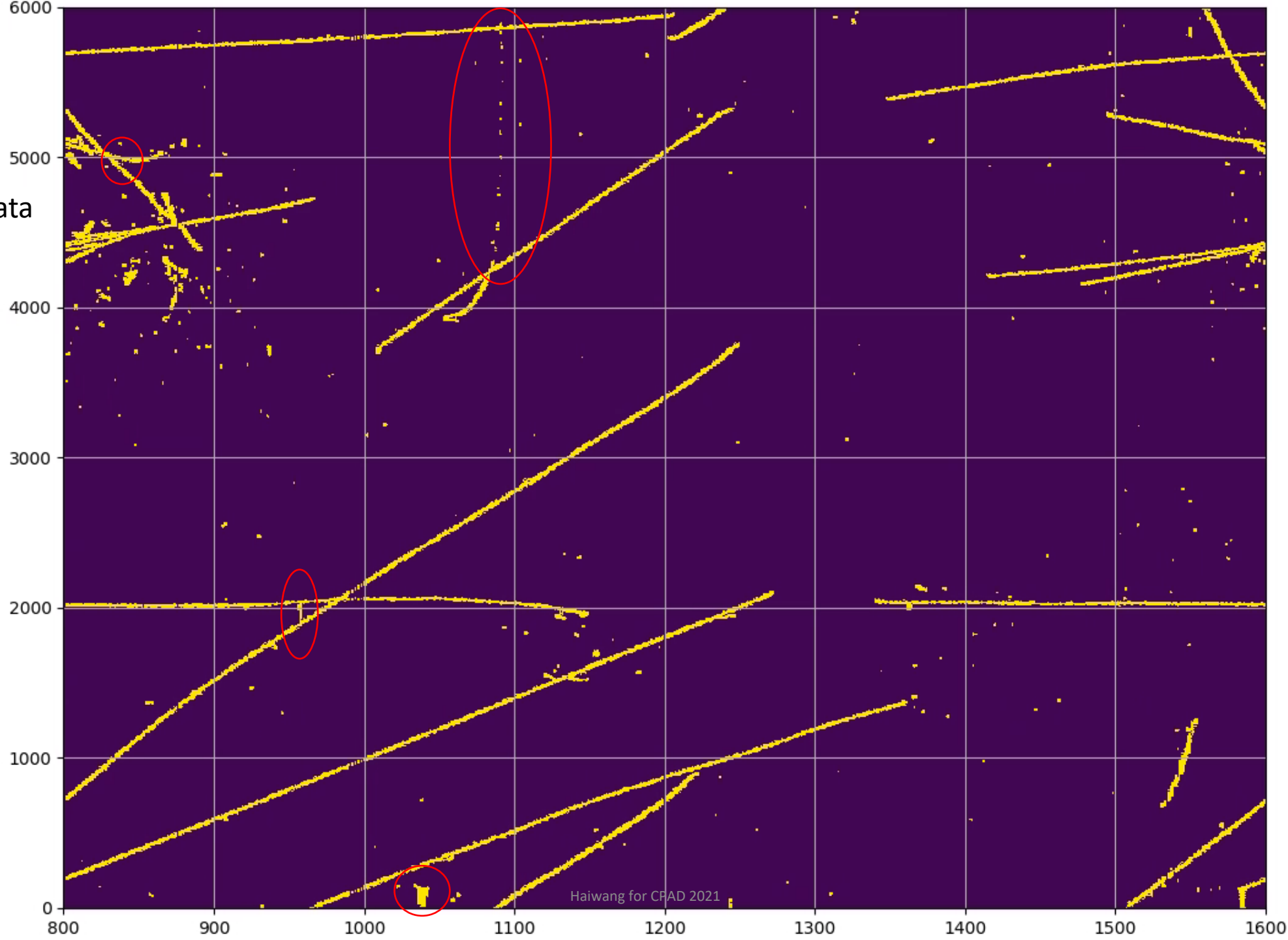
ProtoDUNE Data

run: 5145

subRun: 1

event: 26925

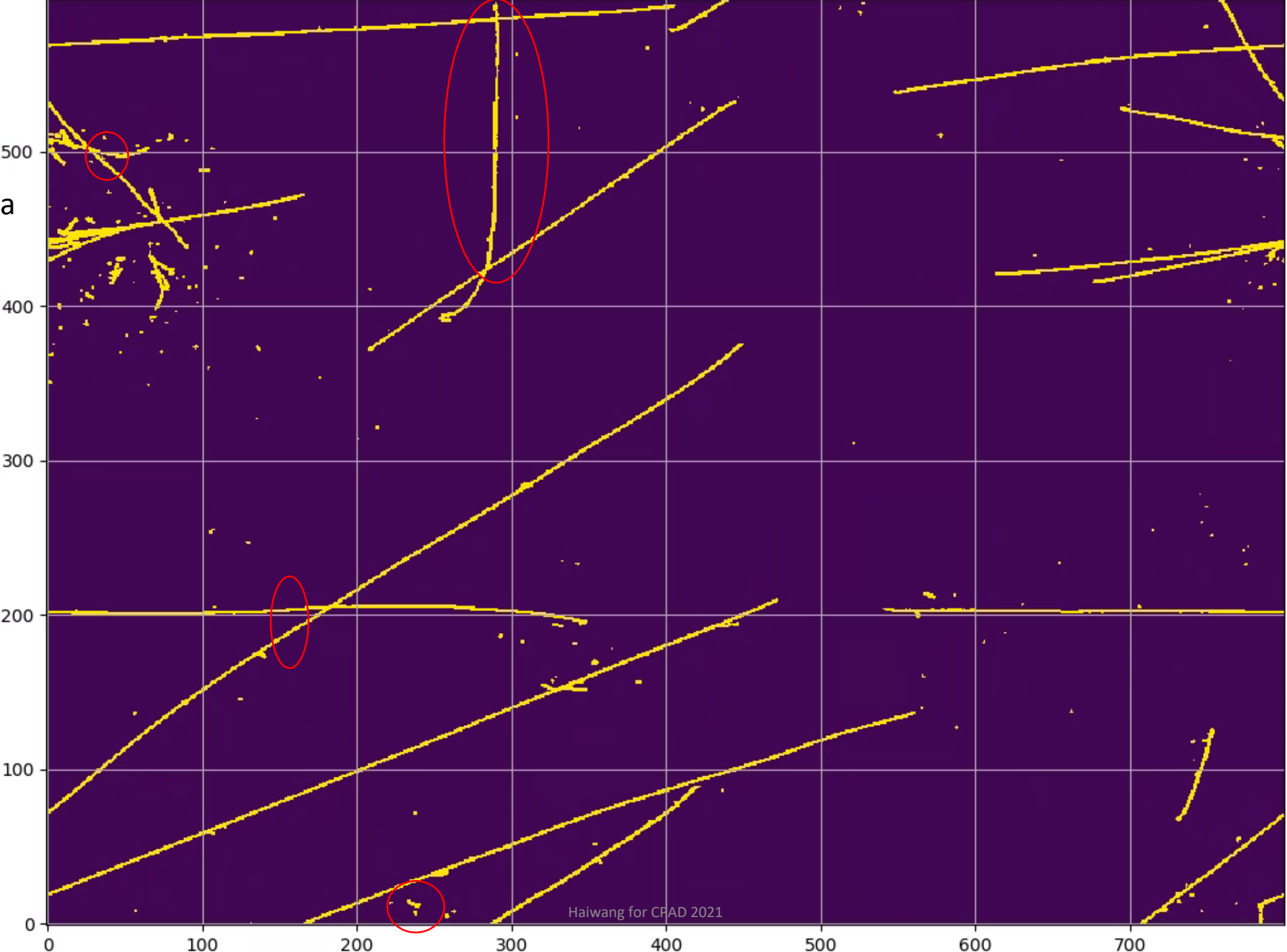
V plane



DNN-SP

ProtoDUNE Data
run: 5145
subRun: 1
event: 26925
V plane

3/19/21



Haiwang for CPAD 2021