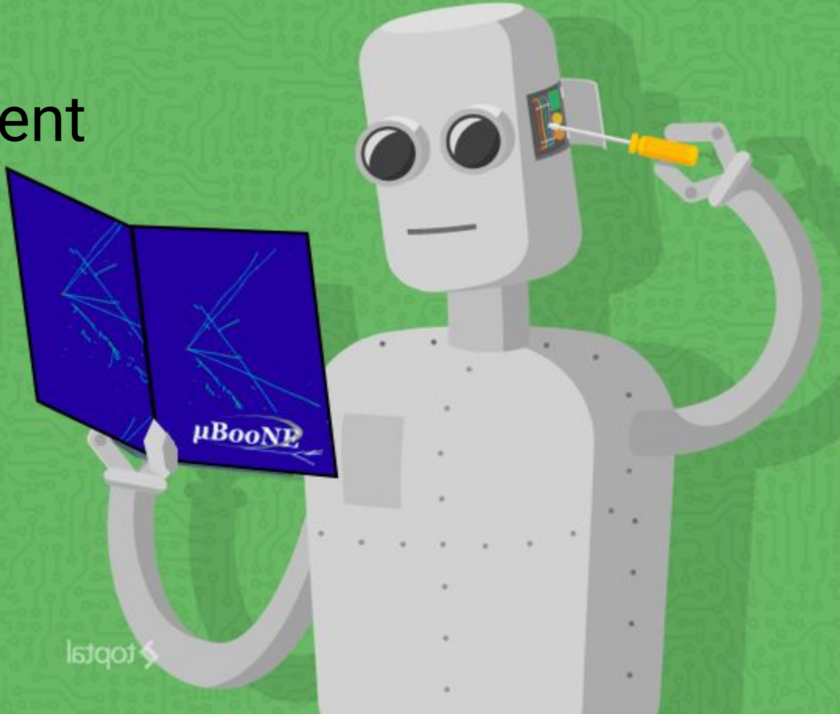
From Pixels to Neutrinos

Convolution Neural Networks Applied to the MicroBooNE experiment



Taritree Wongjirad (Tufts U.)

SLAC Seminar

June 6, 2019

Outline

Discuss efforts on the MicroBooNE experiment to use convolutional neural networks to improve physics analysis

- What are we trying to solve with CNNs? -- and why?
- From physics problem to ML problem
- Current Analysis Effort
- Developments

“Eyes” of the MicroBooNE detector -- a time-projection chamber,-- before installation

The MicroBooNE Experiment in a nutshell

"An accelerator neutrino oscillation experiment"

Neutrinos

"An accelerator *neutrino* oscillation experiment"

Neutrinos

Neutrinos are a type of the fundamental particle

Key stats:

- No electric charge
- Interacts only via weak force and gravity
- Very, very small mass: ~8 orders smaller than next heaviest particle!
- Come in three “flavors” -- based on what other particle they make during certain interactions

The Three “FLAVORS”

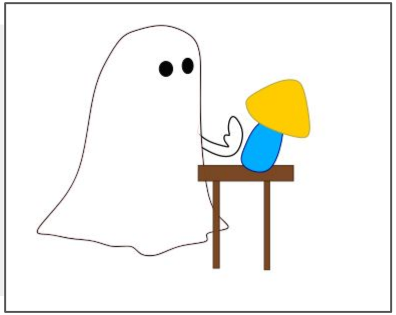
electron

muon

tau

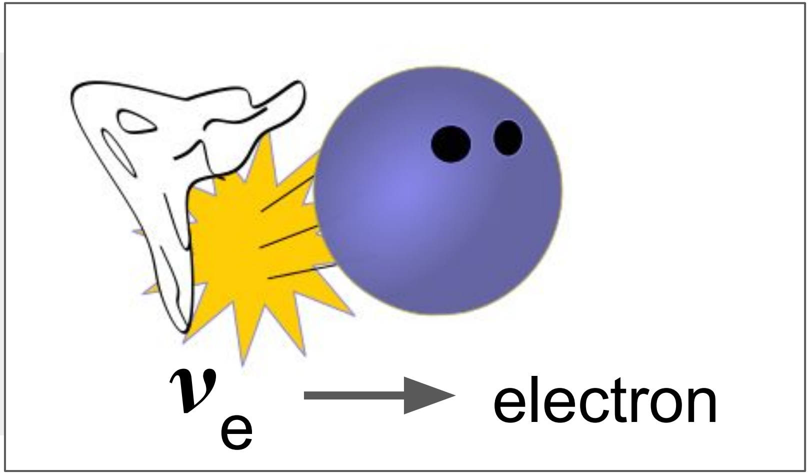
Life as Neutrino Physicist

No electric charge
=> ***observe indirectly***



Only Weak Force
=> ***rare process***

Flavor related to particle produced during certain interaction
=> ***key to identifying type***



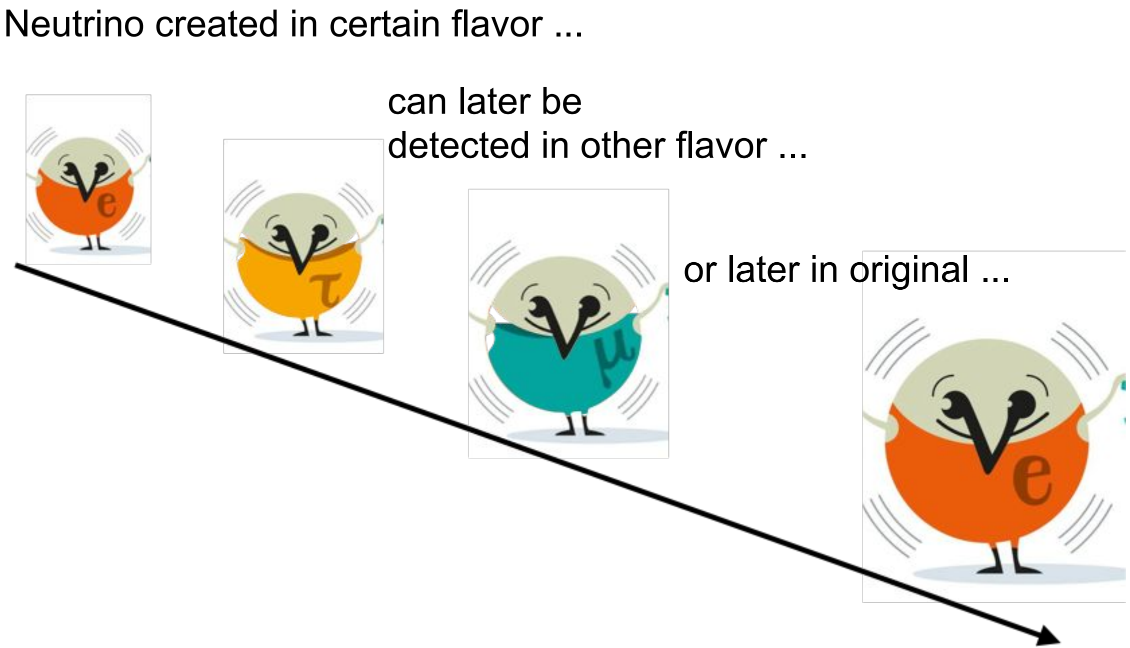
Neutrino Source

"An *accelerator* neutrino oscillation *experiment*"

MicroBooNE uses a high-intensity beam of neutrinos made at Fermi National Accelerator Lab

Neutrino Oscillations

“An accelerator neutrino *oscillation* experiment”



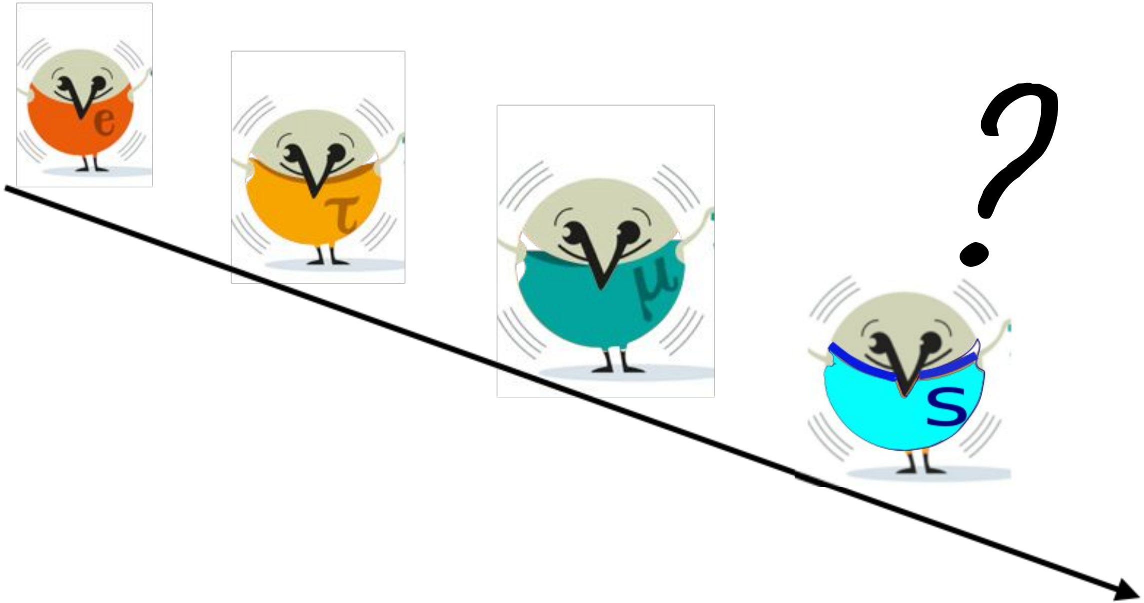
Goal is to look for evidence of Neutrino Oscillations

Flavor detected oscillations over distance traveled

Neutrino Oscillations

Anomalies in other past experiments can be interpreted as oscillations occurring because of new flavor or neutrino

Exciting if true!



MicroBooNE setup

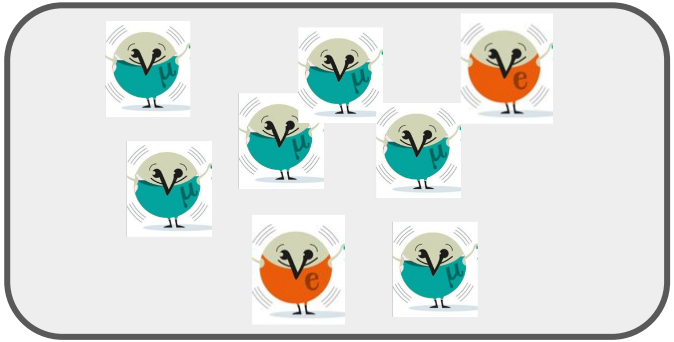
Beam created as almost entirely muon neutrinos

Given distance traveled and energy of neutrinos,
Should be the case @ detector

MicroBooNE setup

But if consistent with past Anomaly (measured in same beam line)

We will see ***excess*** of electron neutrinos (at low energies)



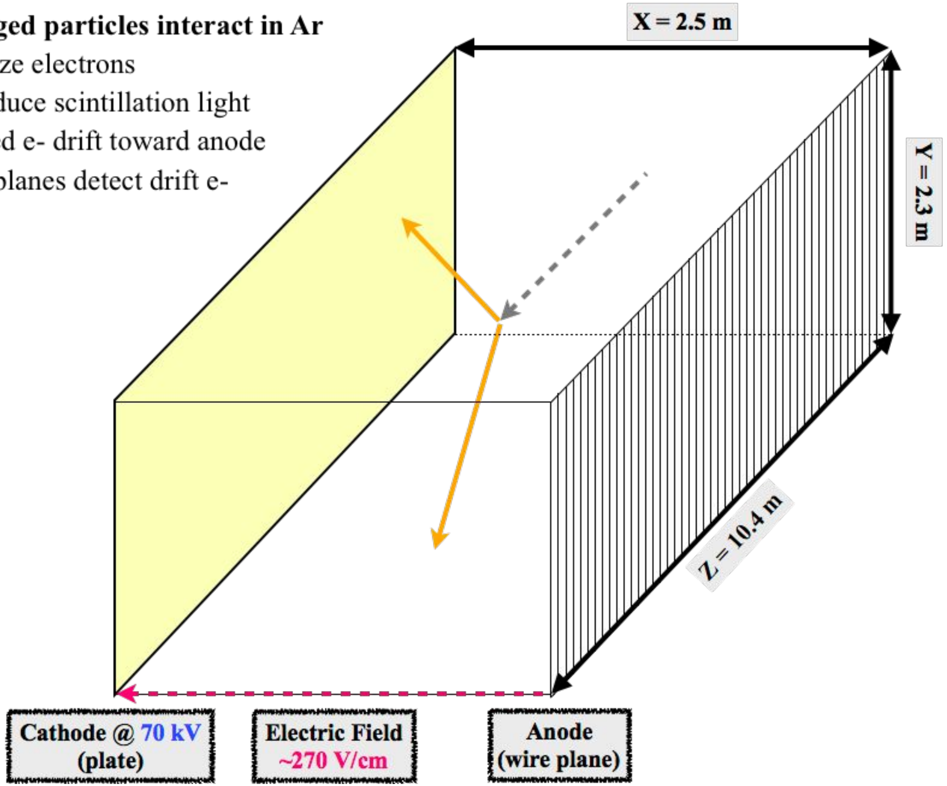
MicroBooNE setup

Our target measurement, then, is the energy of neutrinos and the counts of the different flavors

The detector, **a liquid argon time projection chamber**, provides high resolution images with which we can extract these measurements

Capturing Images of Neutrino Interactions

1. **Charged particles interact in Ar**
    - Ionize electrons
    - Produce scintillation light
2. Ionized e- drift toward anode
3. Wire planes detect drift e-



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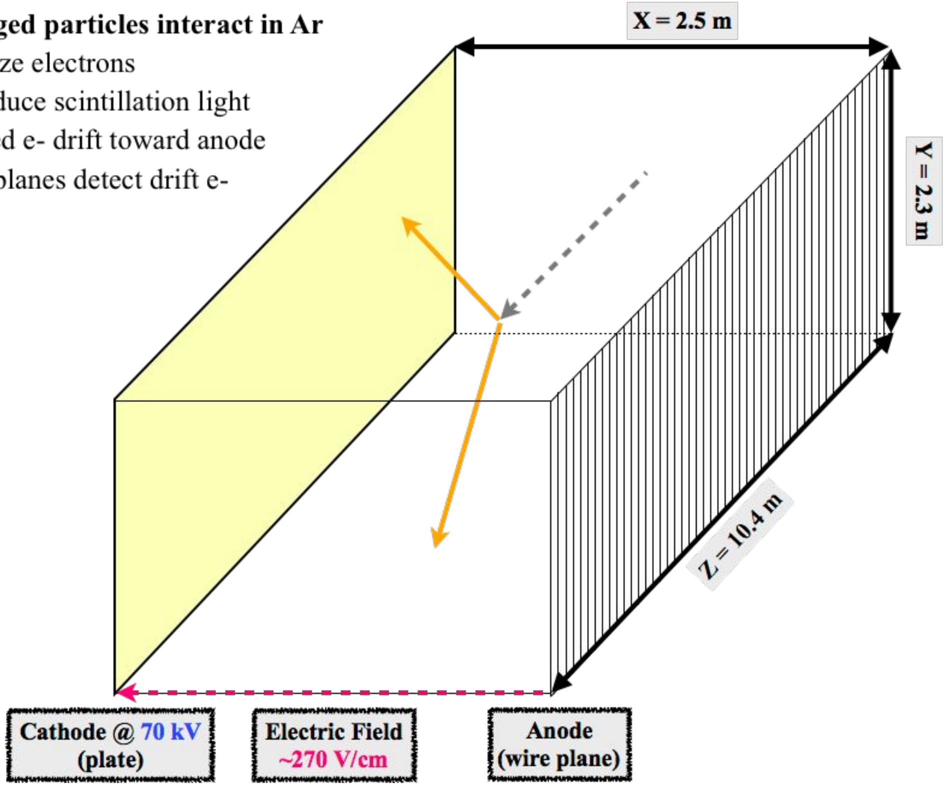
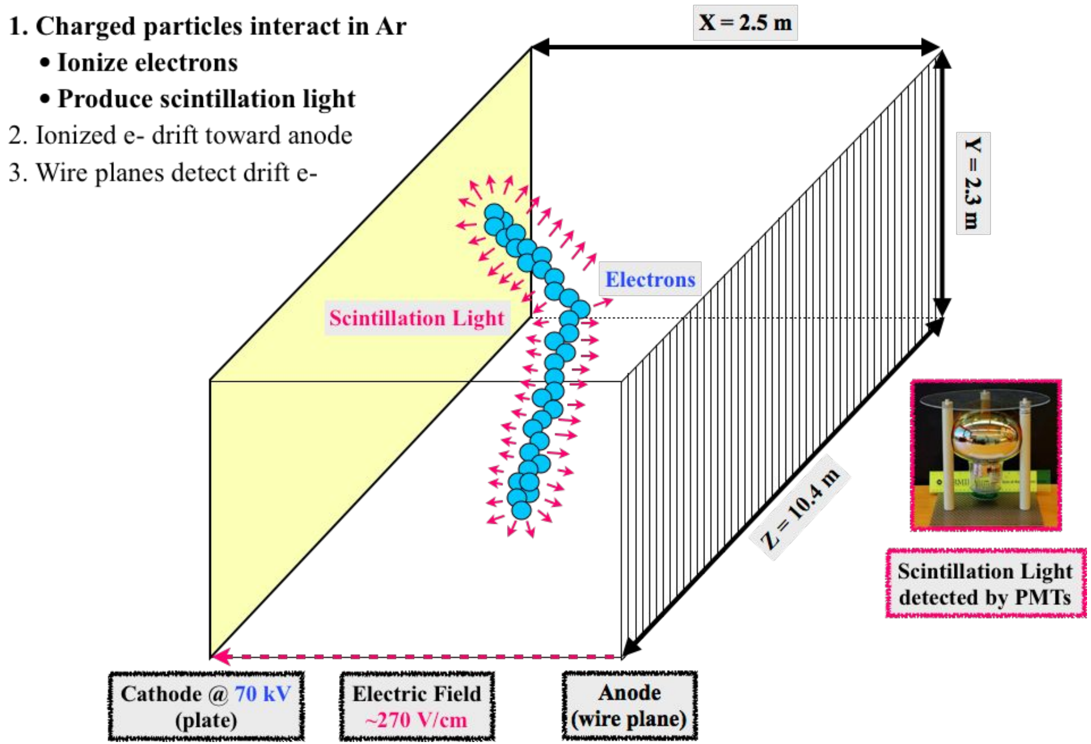


A neutrino (dashed grey) passes into the detector and interacts producing charged particles (solid yellow)

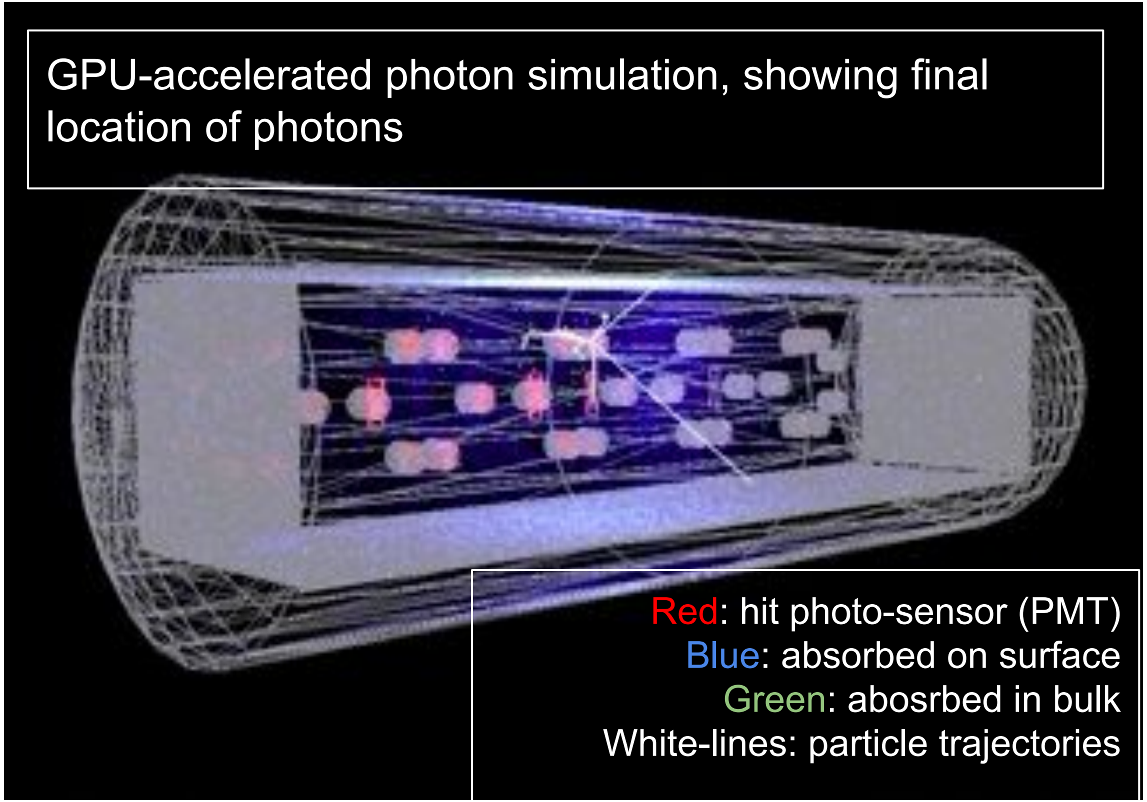
Capturing Images of Neutrino Interactions



Charged particles produce ionization electrons along path

(neutrino neutral and leaves no directy signature)

Capturing Images of Neutrino Interactions



Light also produced by charged particles.

Travels to sensors on short (ns) timescales

Light provides timing for event -- and course position info.

Capturing Images of Neutrino Interactions

1. Charged particles interact in Ar
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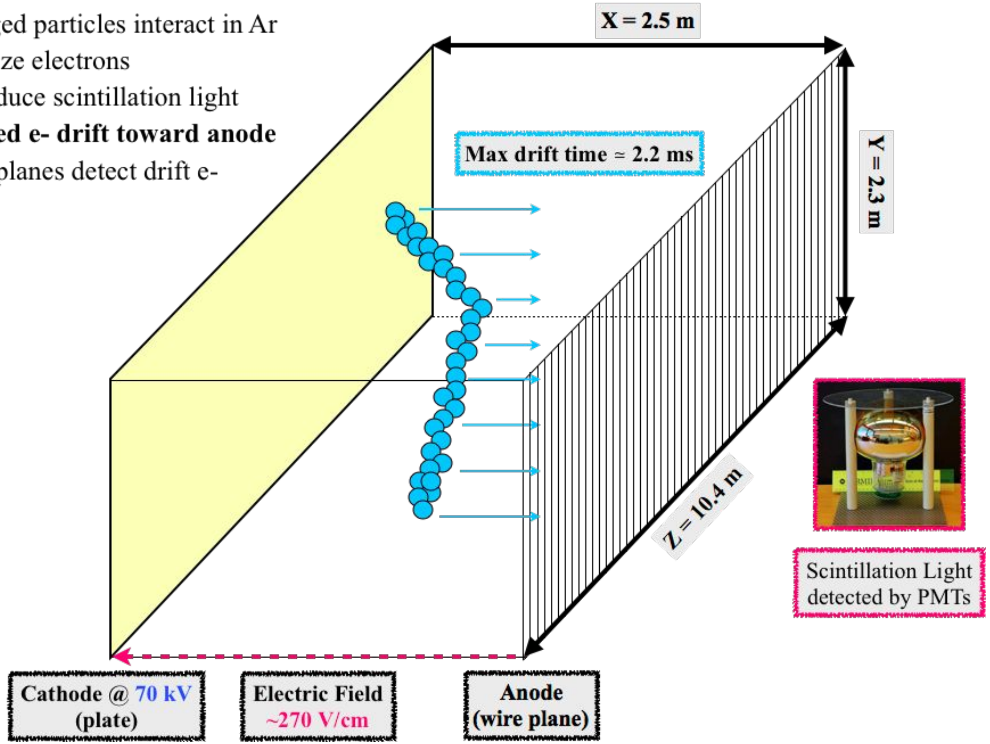
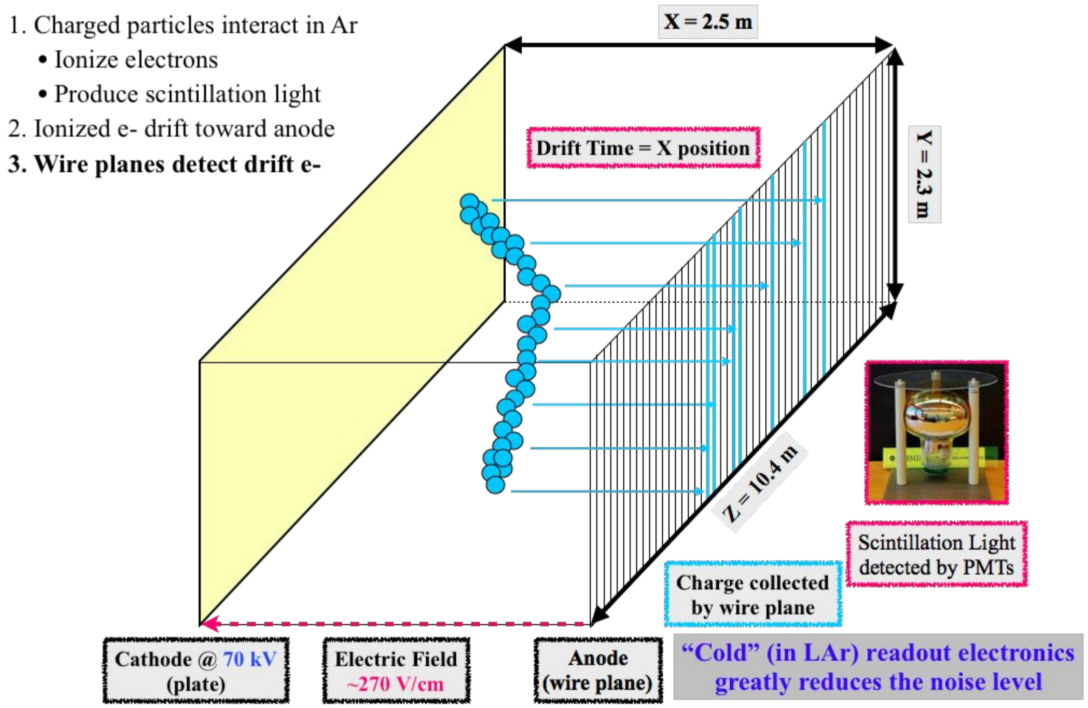


Ionization electrons drift towards wireplanes

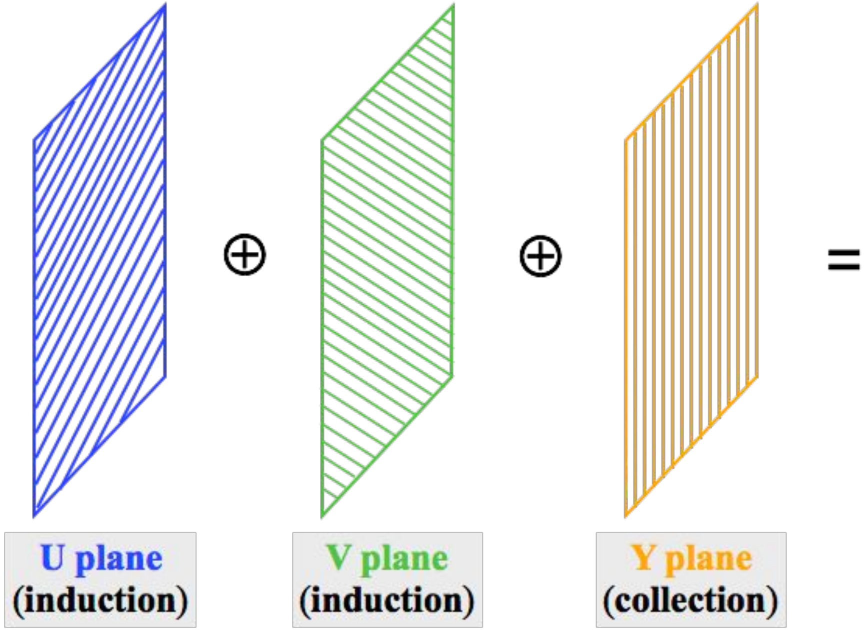
Capturing Images of Neutrino Interactions

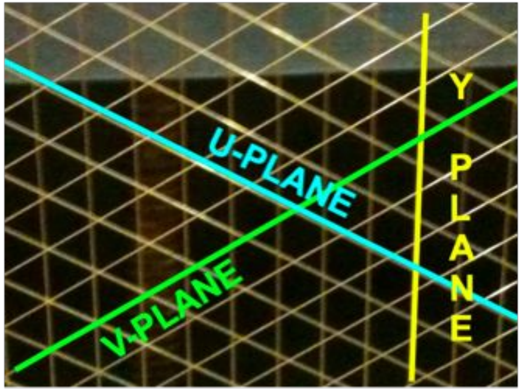


Ionization induce detectable signals on nearby wires

Capturing Images of Neutrino Interactions

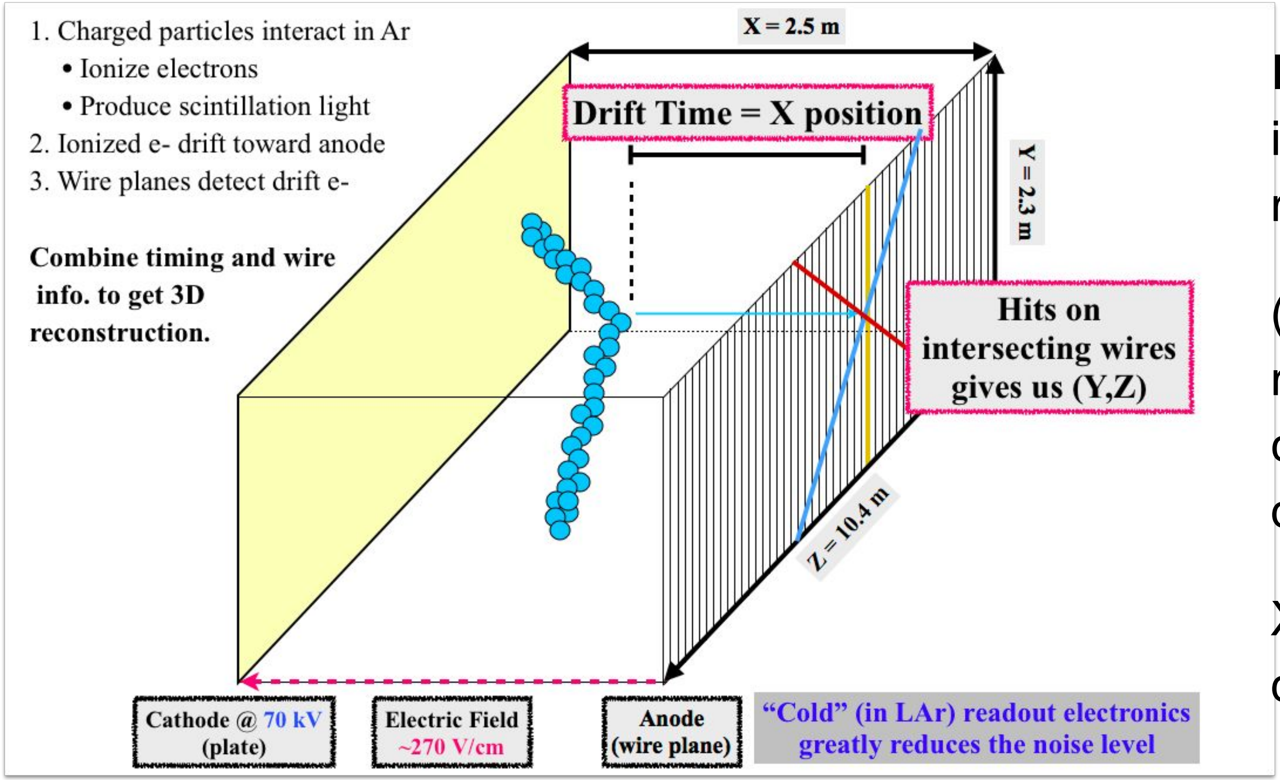
Three Wire Planes





8256 wires w/ pitch = 3mm
(Y, Z) = coincidence on wire

Capturing Images of Neutrino Interactions

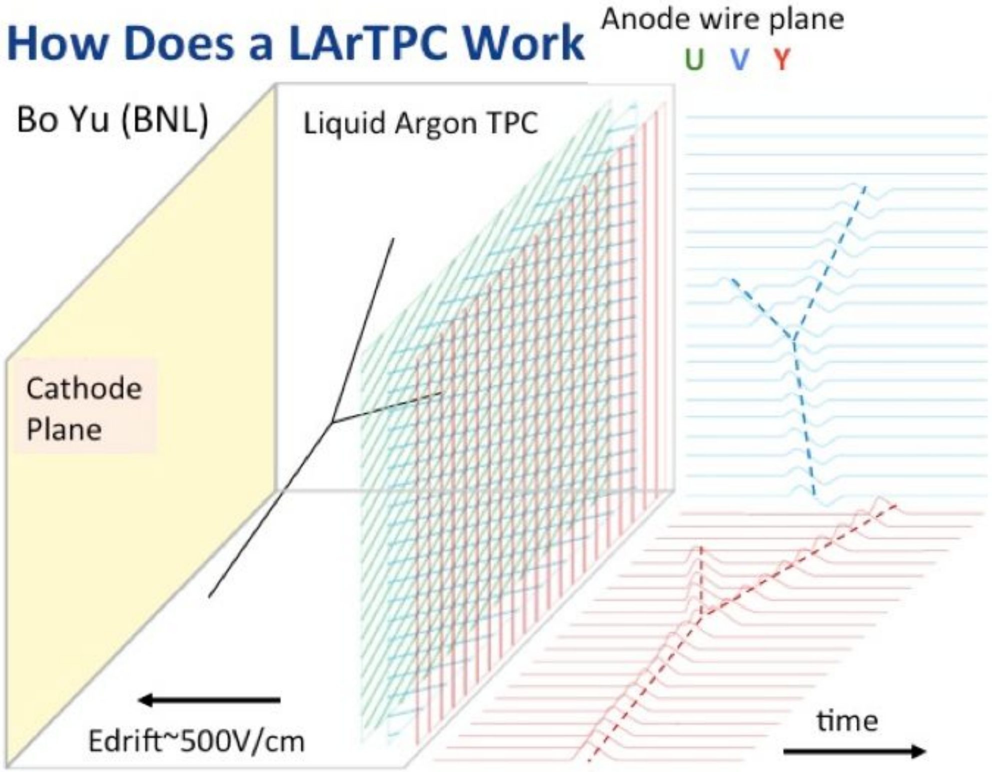


In principle: enough information for 3D reconstruction

(Y,Z) position of ionization recorded through coincident signals on different wire planes

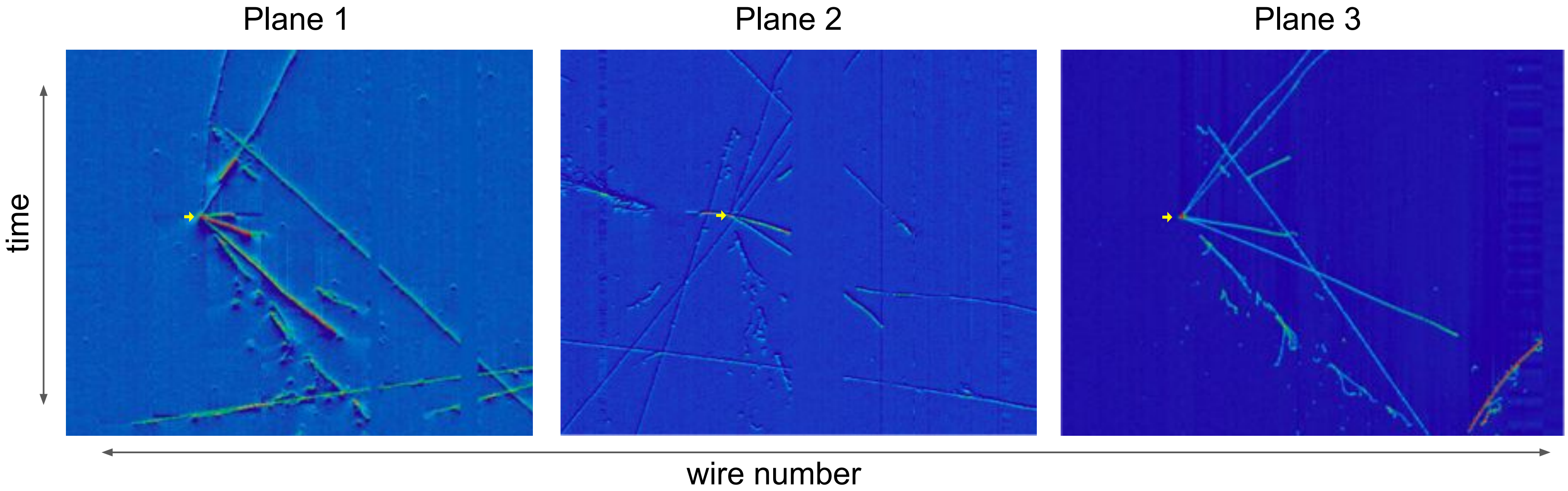
X position give by time delay from light signal

Capturing Images of Neutrino Interactions



Recording wire signals over time, detector produces image-like data

Capturing Images of Neutrino Interactions



Example of data event in MicroBooNE. View of same event for each projection.

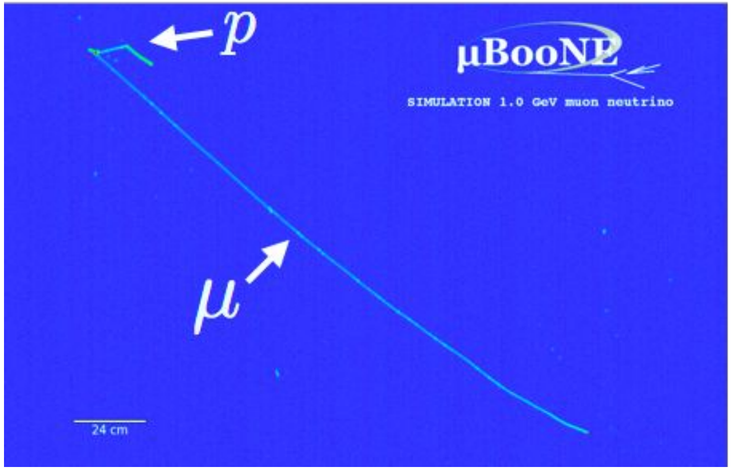
Color scale indicates amount of ionization electrons seen on wire at given time

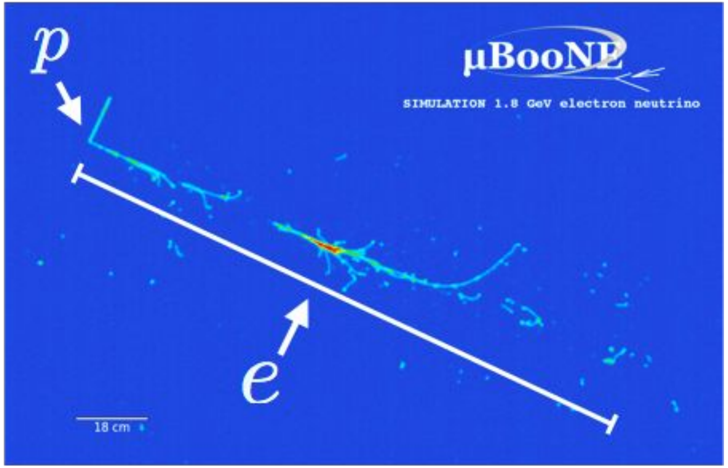
Measurables in the image

Flavor determined from finding partner lepton (muon,electron) produced in interaction

Neutrino energy inferred from momenta of resulting particles

$$\nu_\mu + n \rightarrow \mu + p \qquad \nu_e + n \rightarrow e + p$$



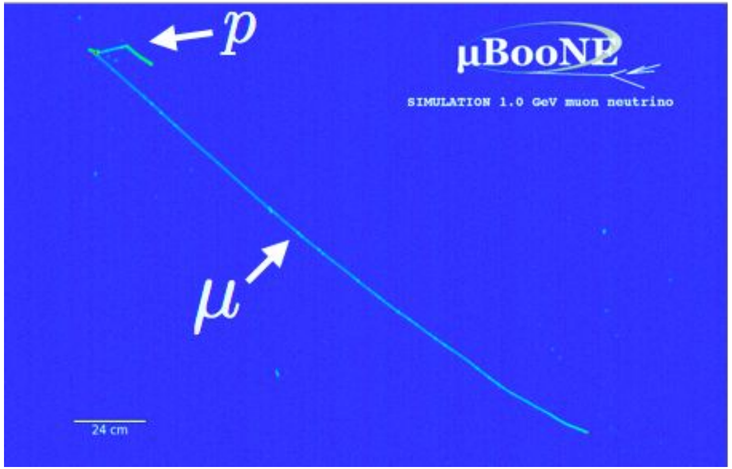


Measurables in the image

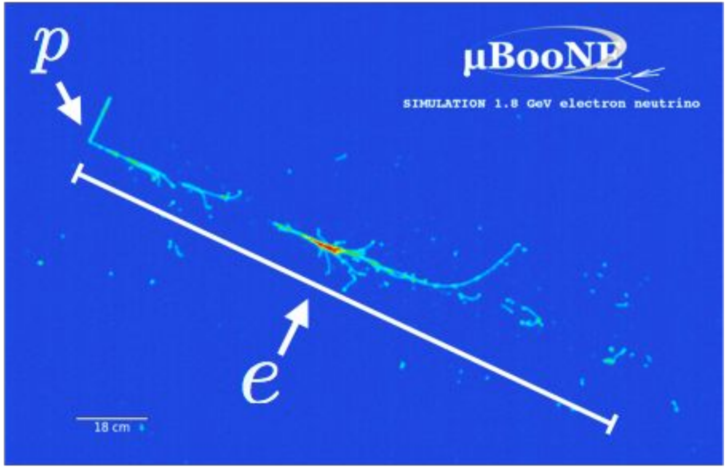
From ML perspective: **the problem is predicting class and energy from images**

We have simulations that can produce training examples with various labels

$$\nu_\mu + n \rightarrow \mu + p$$



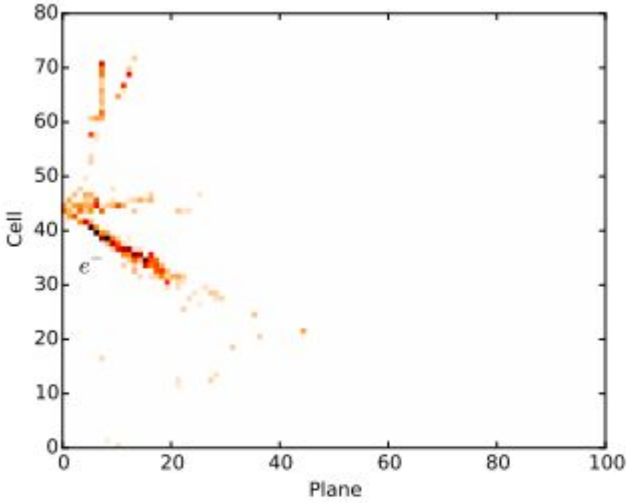
$$\nu_e + n \rightarrow e + p$$



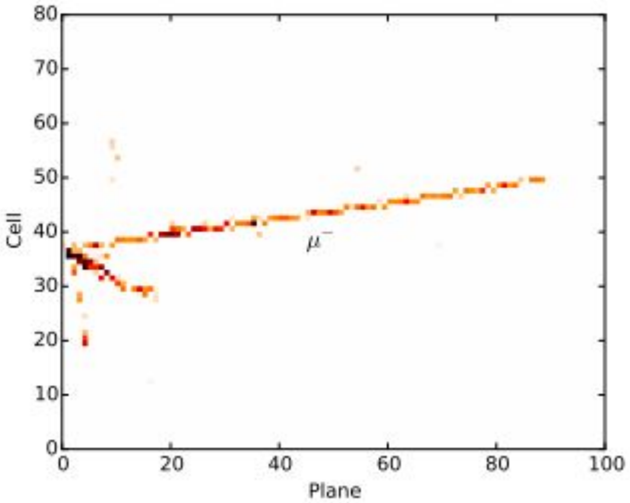
One approach: directly predict values

Example: CNNs have been used (another experiment) to predict the neutrino flavor

ν_e interaction



ν_μ interaction



Aurisano, A. *et al.* JINST 11 (2016) no.09

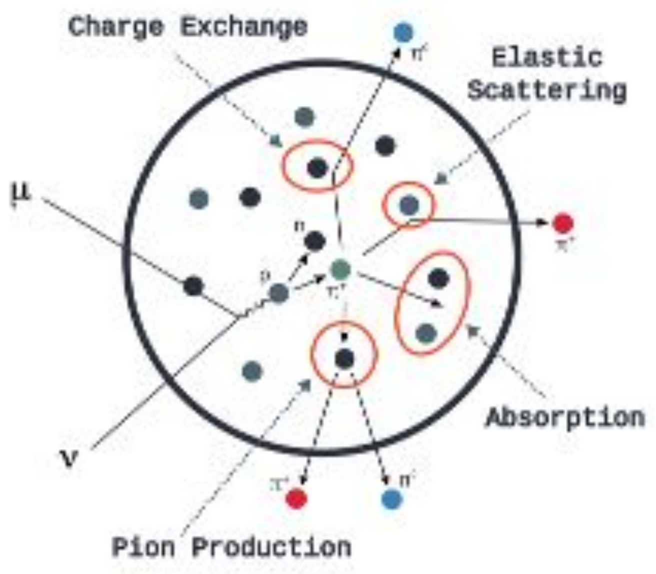
One approach: directly predict values

Issue with training network to target final observable: modeling uncertainties

Neutrinos hit constituents of the nucleus -- an extremely complicated system to model

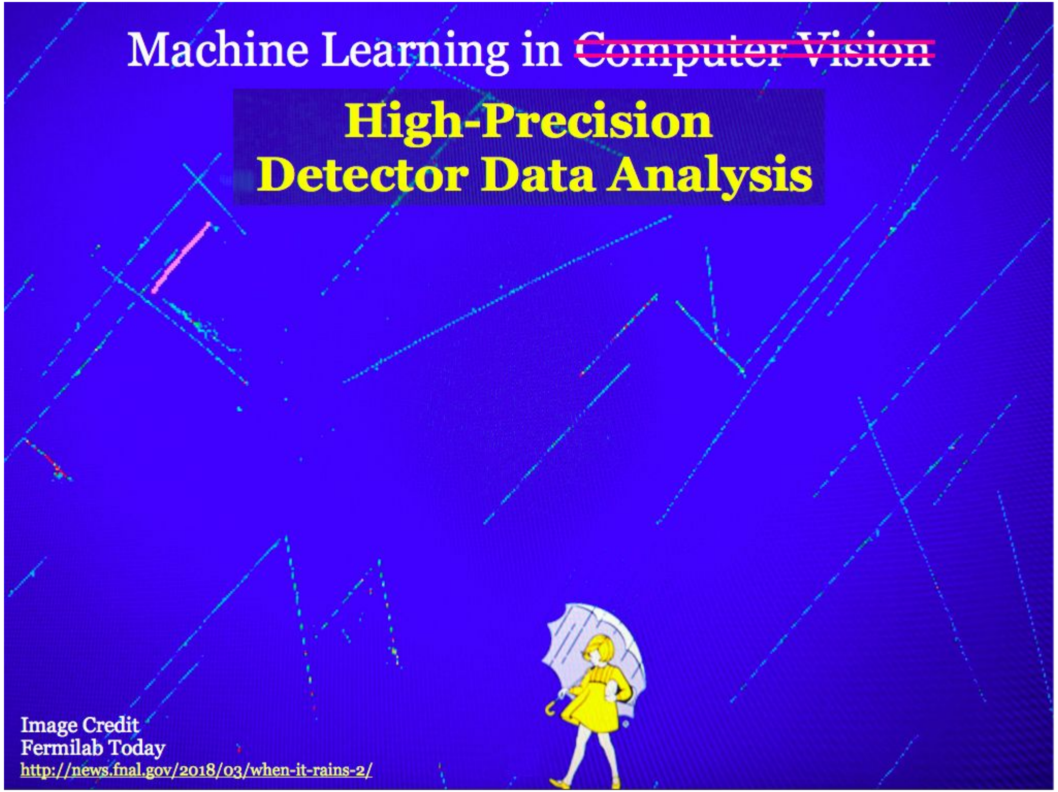
Neutrino energy inference influenced by knowing “type” of interaction

Can produce particles that cause patterns which fake the signal (primary e.g. photons from interaction can look like electrons)



Risk of model errors being trained into the networks

MicroBooNE specific issue: backgrounds



For MicroBooNE, lots of backgrounds from cosmic rays since detector is on the surface

Requires parsing of image to find neutrinos

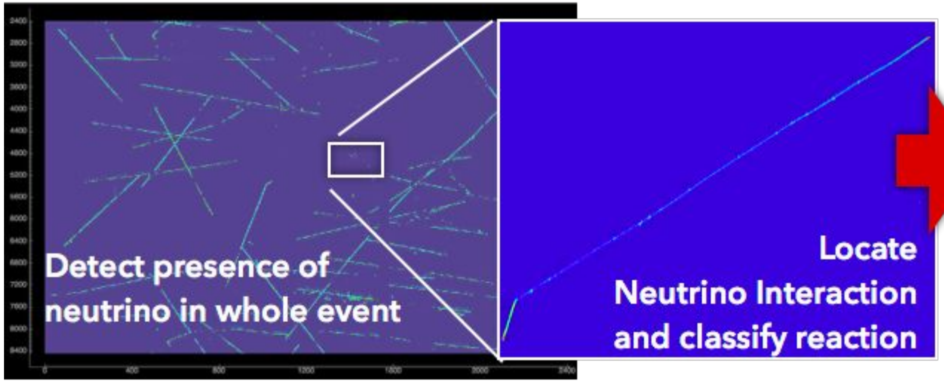
Images with target events only 1 in 1000-10,000

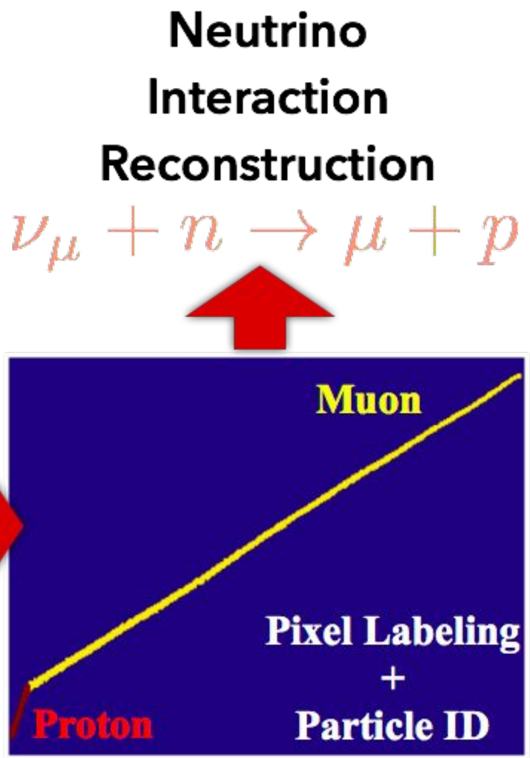
DL Reconstruction

Our goal is to produce constituent particles. Many techniques available

- Need object detection
- Classification

Evaluation with respect to analysis performance important



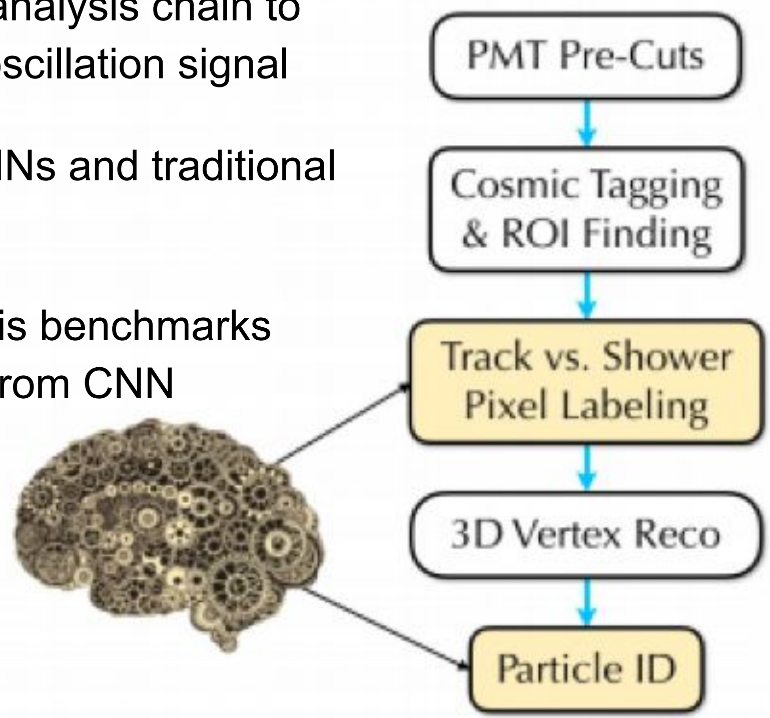


Current Analysis

Have built a full reconstruction/analysis chain to search for the oscillation signal

A mixture of CNNs and traditional algorithms

Working analysis benchmarks improvements from CNN techniques



Pre-selection using light

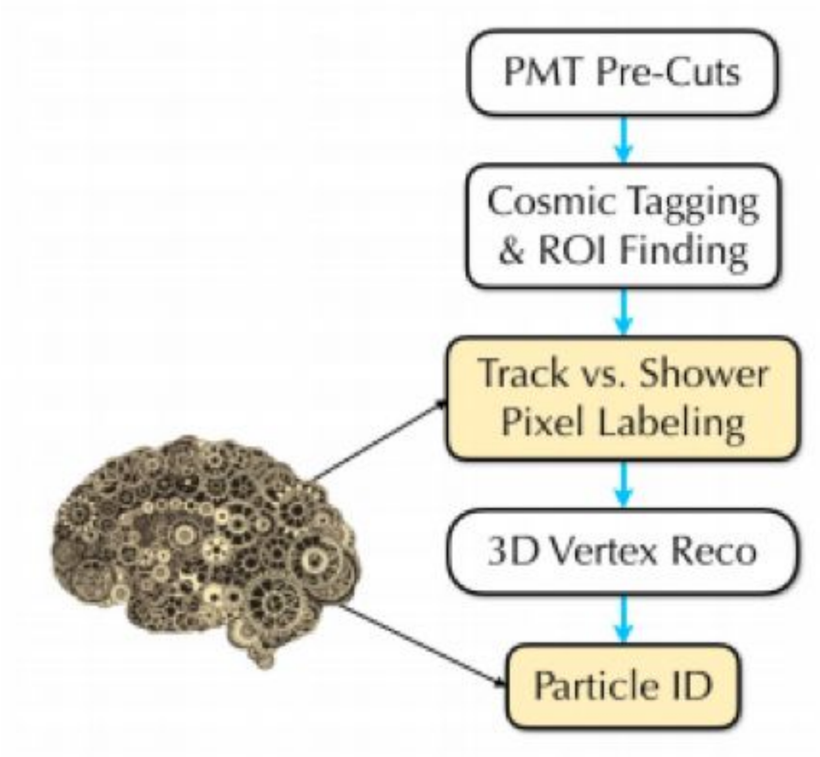
Choosing interesting regions and removing obvious backgrounds

CNN for shower (electron) versus track (muon) patterns

Reconstruct neutrino interaction

Particle classification

Current Analysis



First applications chosen as they are techniques where we could use non-signal data to evaluate network behavior on real data

Preparing the data

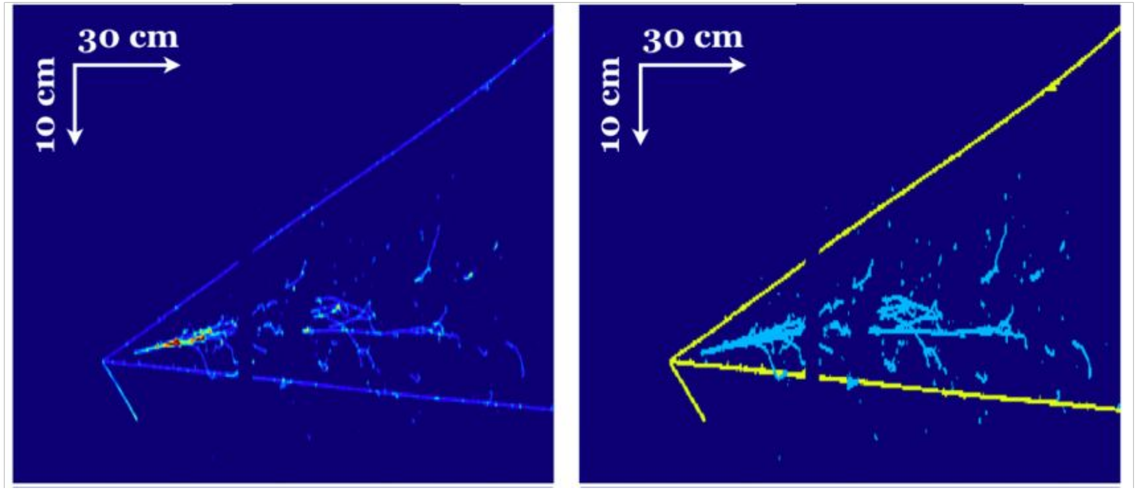
- Images preparation:
  - Noise filtering
  - pulse finding + zero suppression
  - Deconvolve wire response
    - Accounting for electronics response + expected induced signal
  - Downsample in time (summed) by factor of 6
- 3D consistent cropping
  - Full size: 3456 (wire) x 6448 (ticks)
  - Downsampled size: 3456 x 1008 -- both dimensions about 3 mm
  - Cropped into 832 wire x 512 ticks (24 images per plane)

Pixel labeling

In reconstructing events, useful to be able to separate two types of patterns: tracks and showers

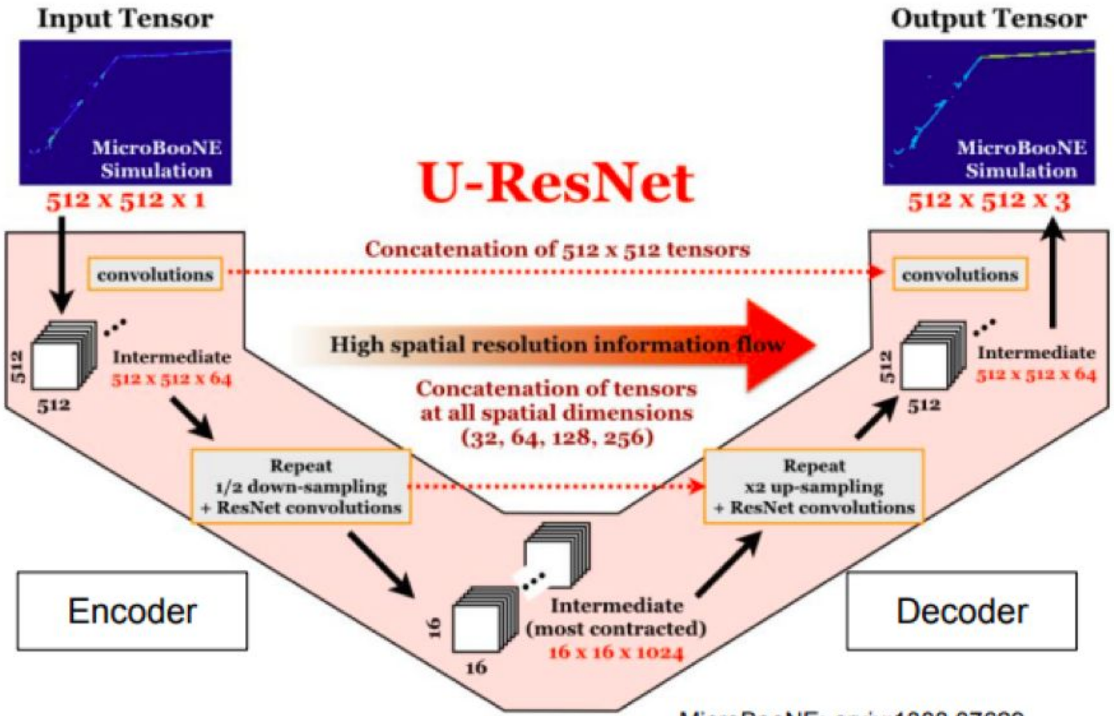
The Goal

yellow: track
cyan: shower



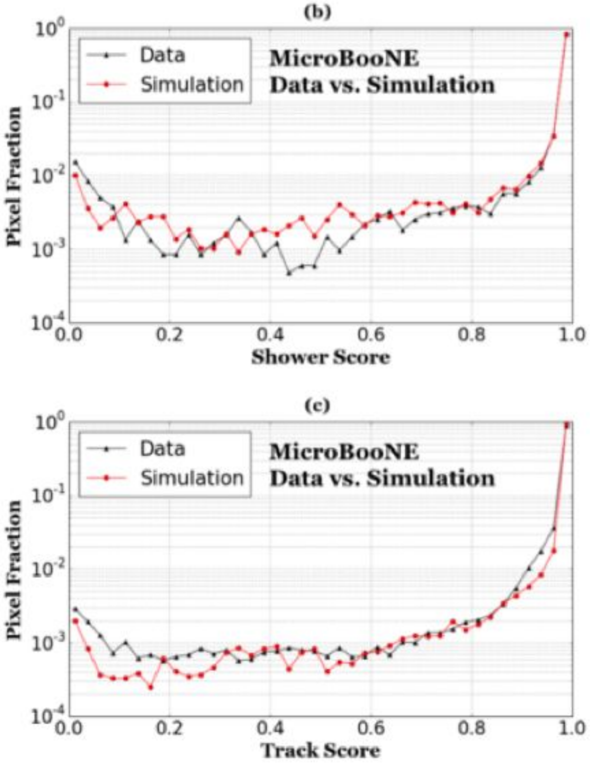
Pixel labeling

We use a U-Net for this problem

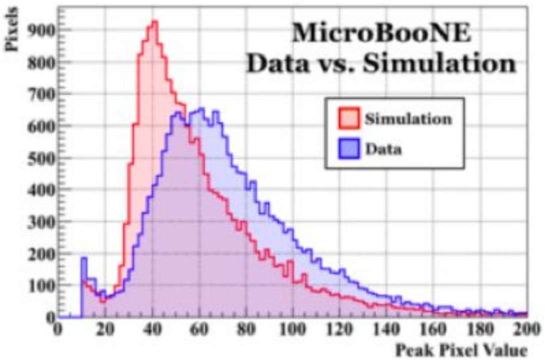


MicroBooNE: arxiv:1808.07629

Pixel labeling: behavior on real versus sim. images



- Sample: stopping muons
- Score distributions similar
- Robust to moderate difference in images as shown by peak pixel distributions

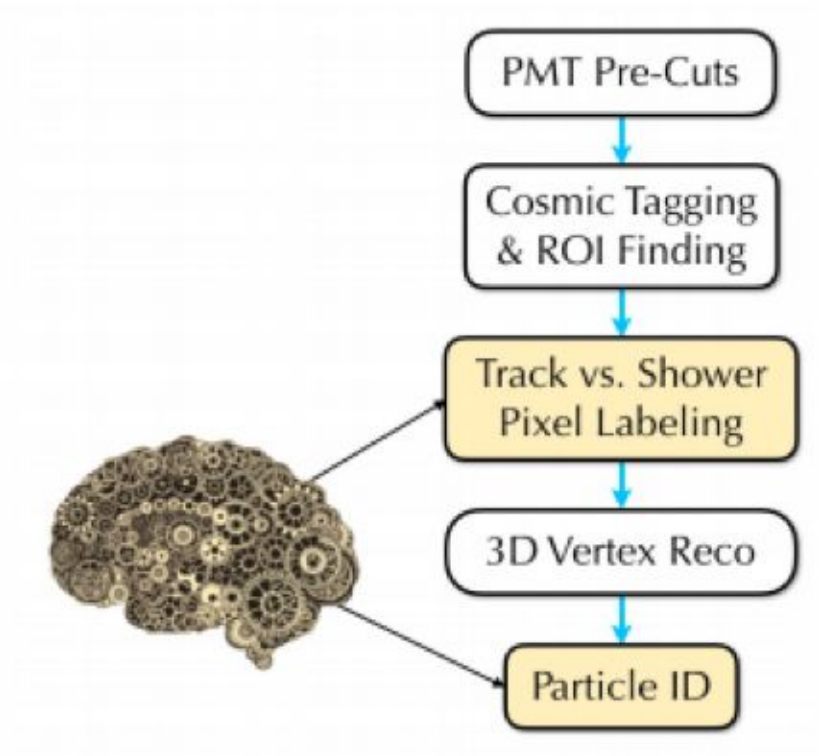


These are cosmic particles that come to rest in the detector

Mostly muons, many of which decay into electrons

Use to check track and shower labeling

Analysis Status



Analysis components complete

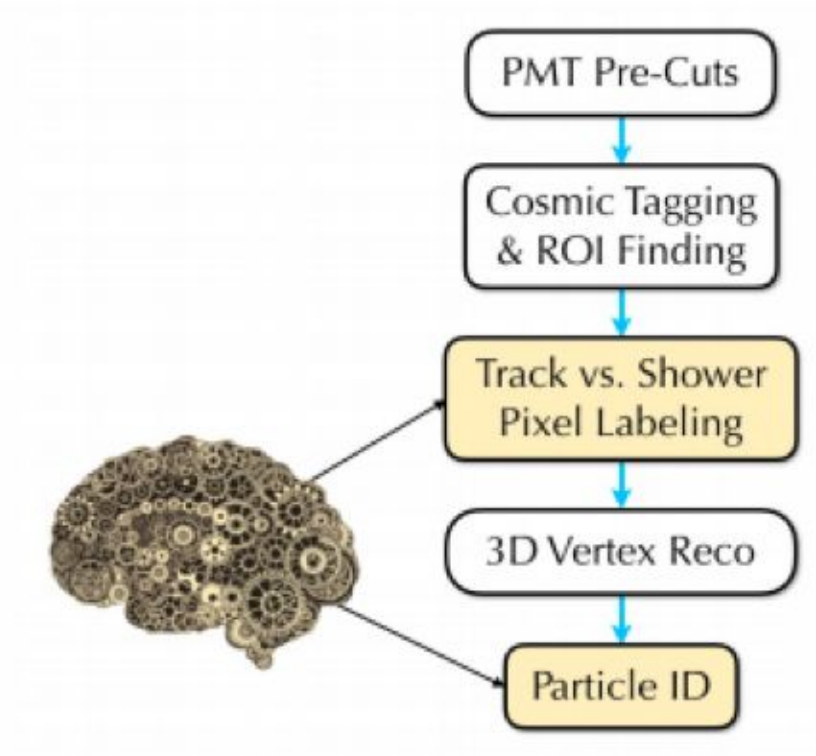
Evaluating:

- Data versus sim. differences through distributions of particle kinematics
- Sensitivity of analysis to see anomalous signal (or excluding it)

Not yet ready

- Hitting various performance milestone with simulation dataset
- Aim is to release result within year

Further CNN techniques in the works



Also tackling more parts of the reconstruction chain

Finding and removing non-neutrino tracks

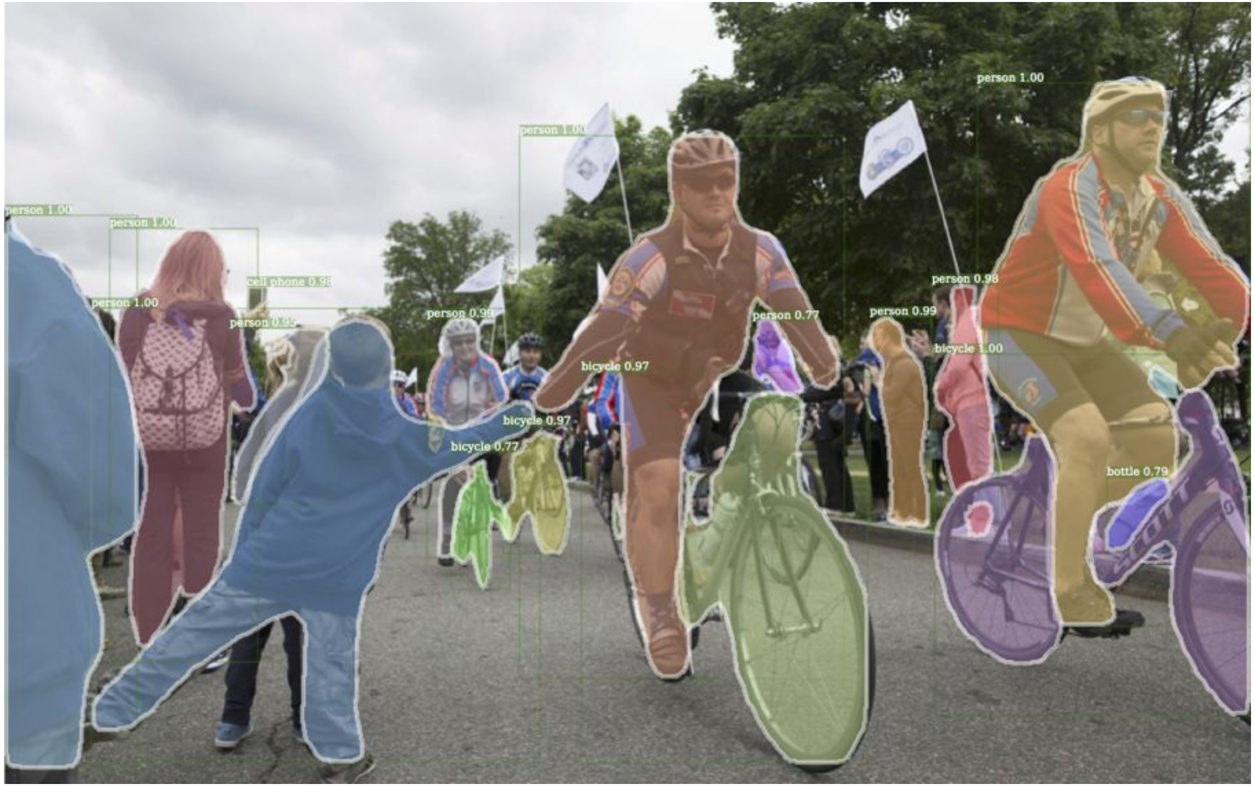
Providing 3D spacepoints to perform 3D reconstruction at earlier stage

“Reparing” images to assist track reconstruction

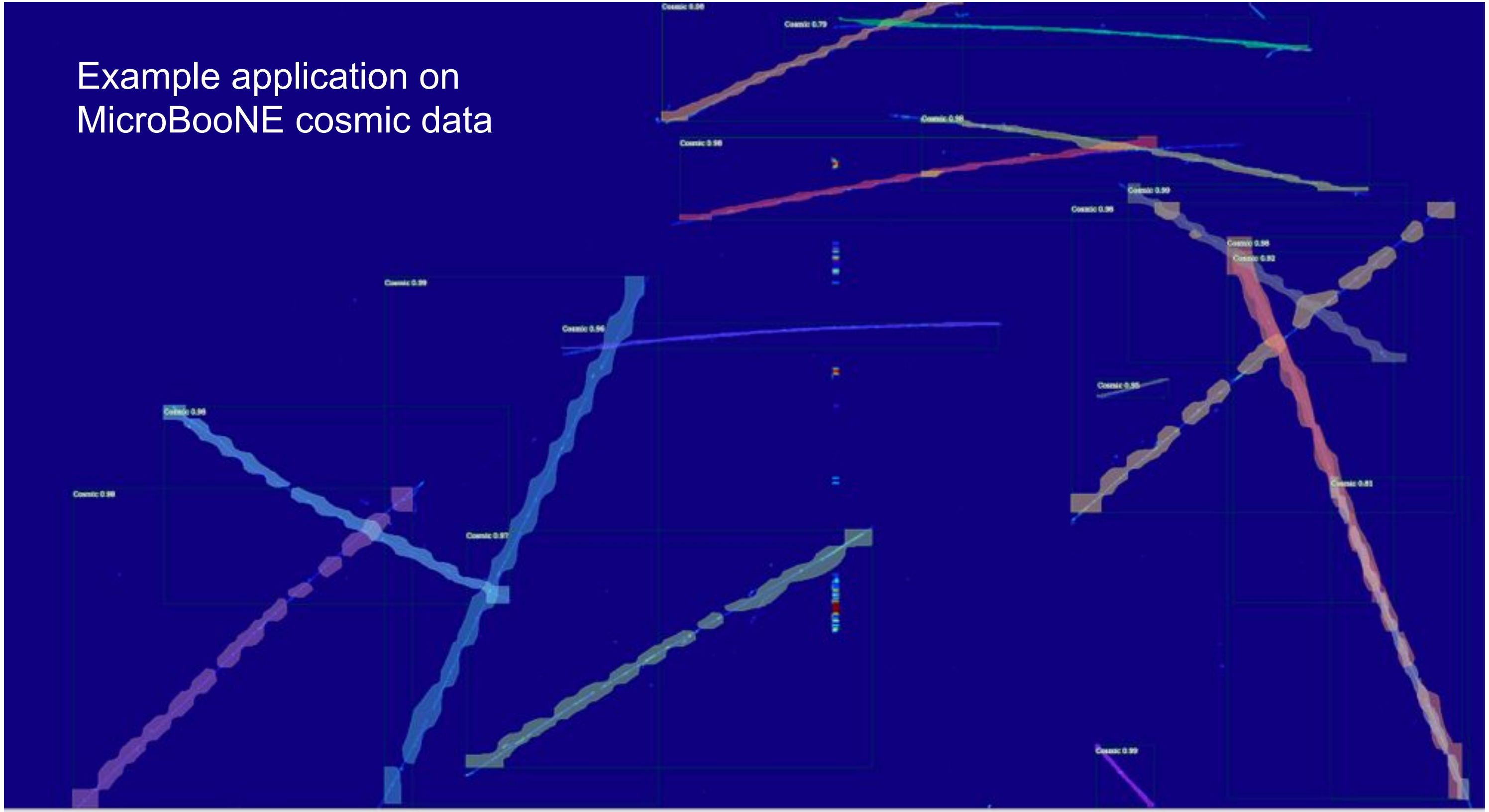
Applying Instance Aware Segmentation

Currently adapting Detectron

Mask-RCNN network

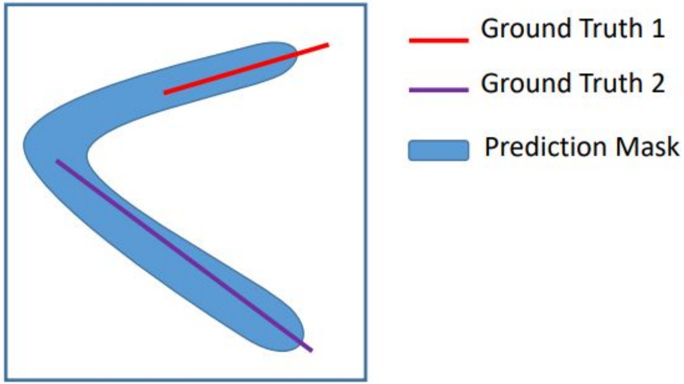


Mask R-CNN for cosmic detection and rejection

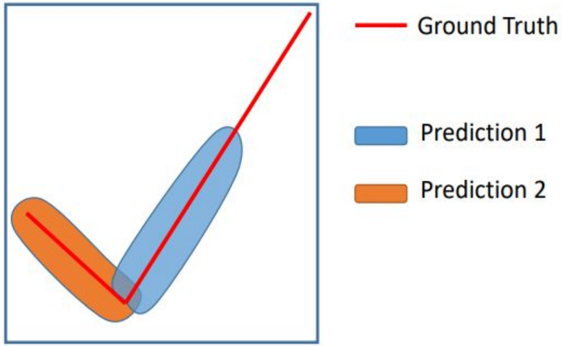


Mask R-CNN: evaluating performance

$$Purity = \frac{Sum[(Prediction)\ x (Ground\ Truth)\ x\ (ADC\ Binary)]}{Sum[(Prediction)\ x\ (ADC\ Binary\ )]}$$



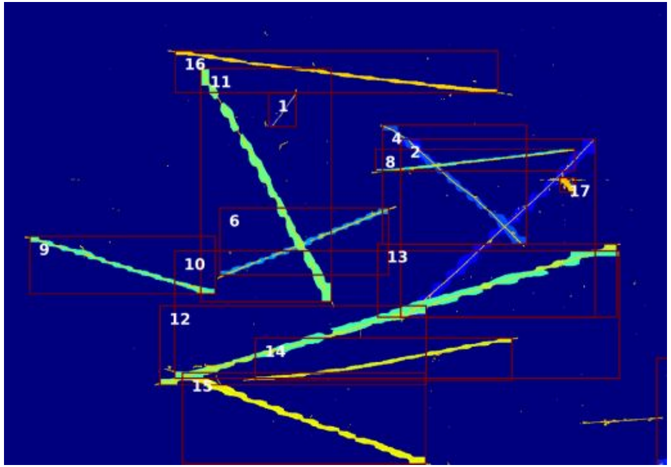
$$Efficiency = \frac{Sum[(Prediction\ \mathbf{Union})\ x\ (Ground\ Truth)\ x\ (ADC\ Binary)]}{Sum[(Ground\ Truth)\ x\ (ADC\ Binary\ )]}$$



Mask R-CNN: evaluating performance

- MCC 8 Simulation
- y – Plane
- Log Z Axis

- Specialized Epochs correspond to training on a dataset with more overlapping clusters



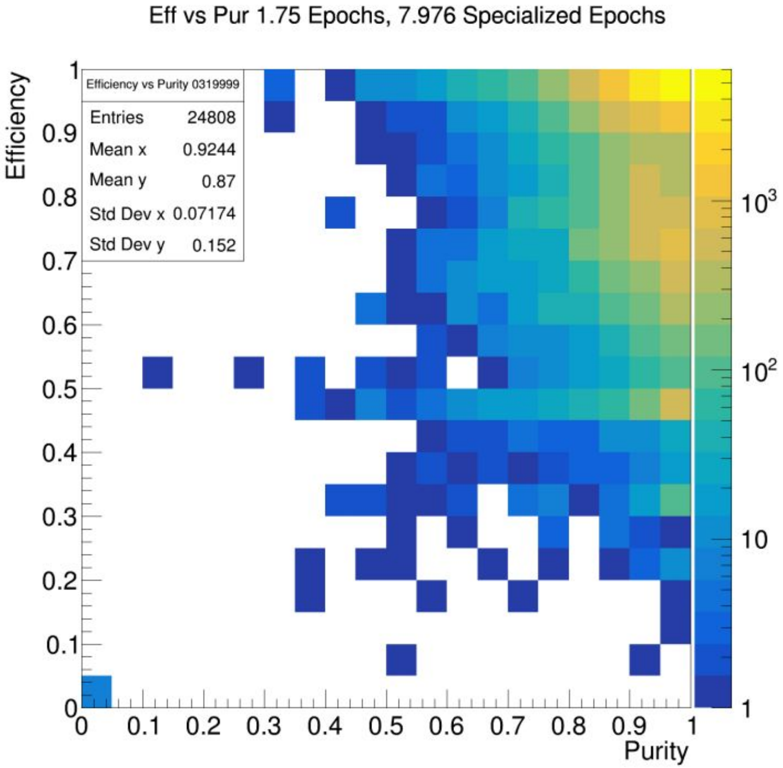


Image Repair and Tracking

- In industry: filling in blanked-out regions in images
- Using a similar idea to fill in missing parts of track in MicroBooNE
- Useful for 3D track reco (trajectory only, not calorimetry)

http://arxiv.org/pdf/1804.07723.pdf NVIDIA Corporation

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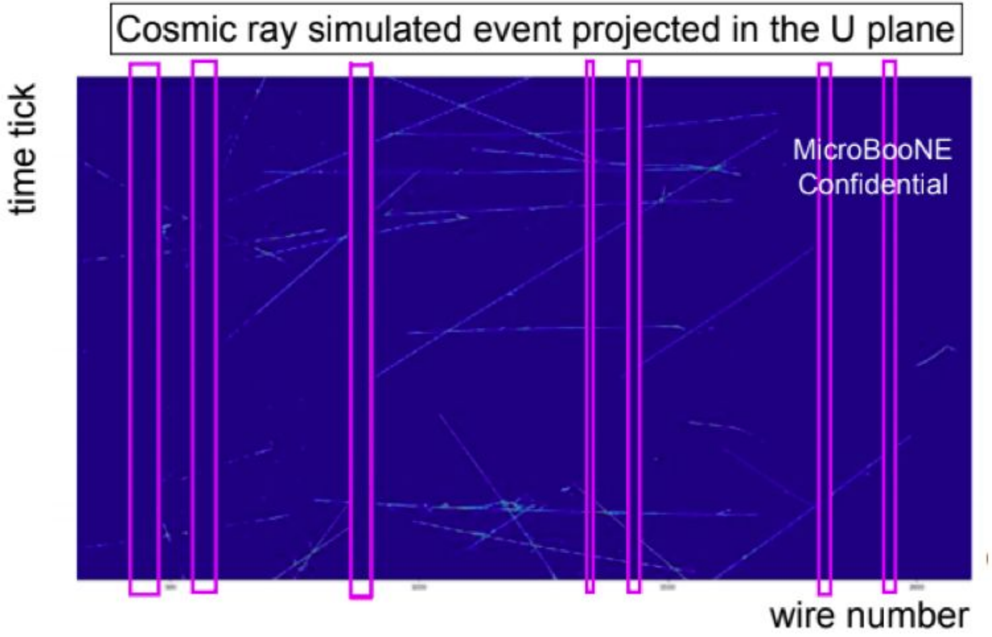
Image Repair and Tracking

- Tracking: clustering of continuos clusters of 3D points
  - difficult in regions w/ dead readout channels: track gaps

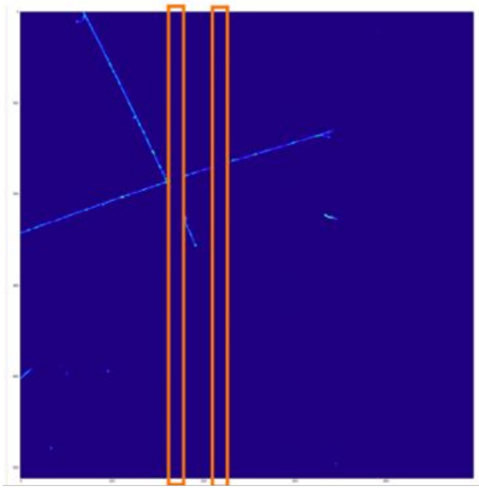


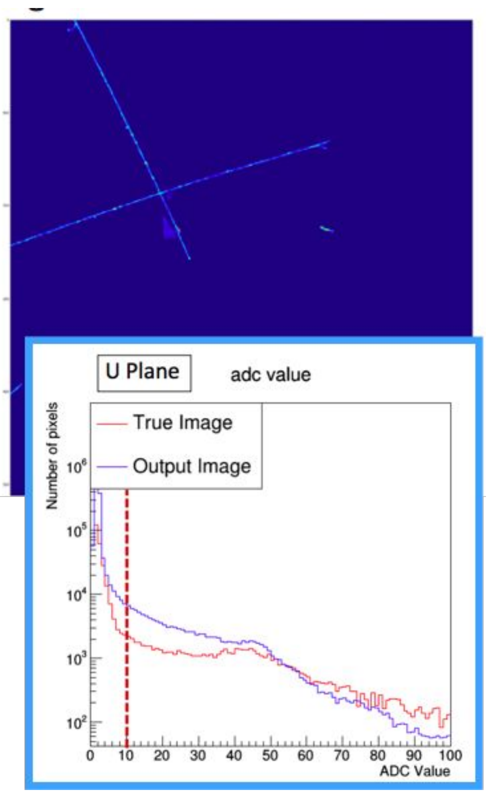
Gaps impair ability to track reconstruction to accurate get momentum

Currently try to detect when track ends in gap and remove events

Overcoming this can also help with efficiency

Image Repair and Tracking



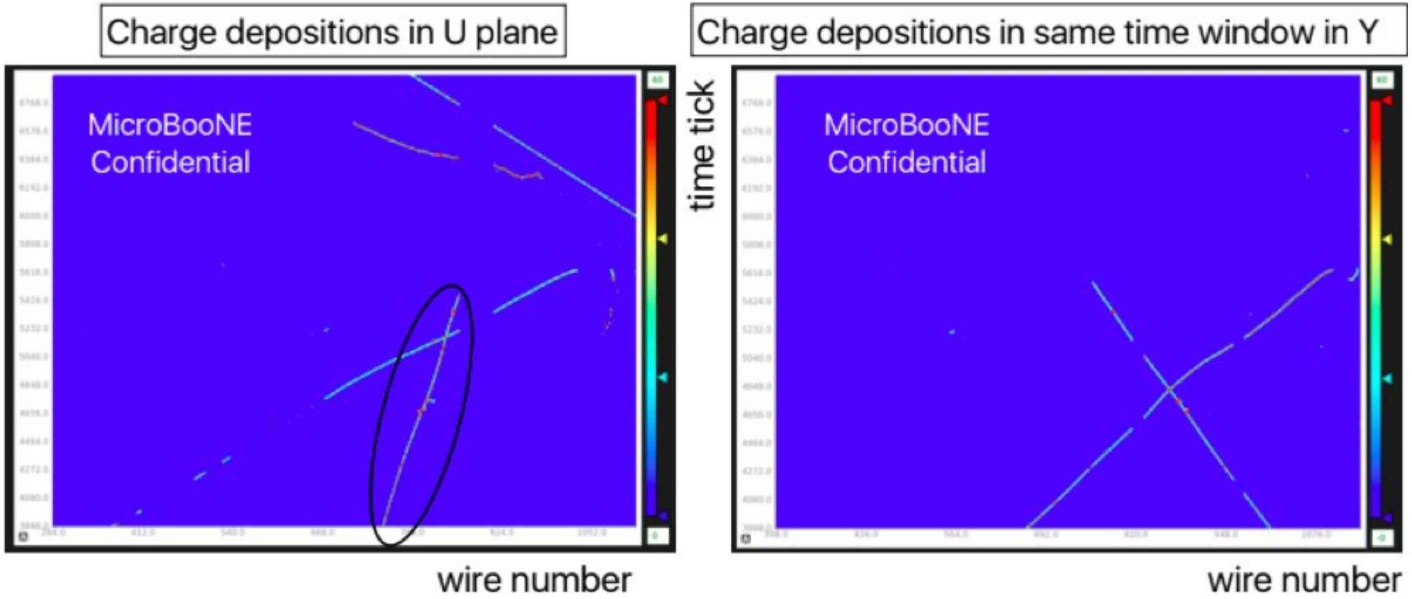


Fills in tracks -- but can produce regions that are “odd” looking

Research ways to penalize net for producing odd shapes -- similar to way GANs are trained

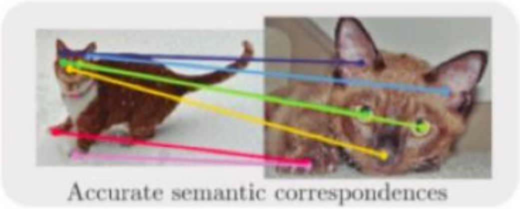
3D Space Points

- To reconstruct 3D position of a charge deposit: need to match charges in same time window on at least 2 wire planes
  - 3D position from wire intersection



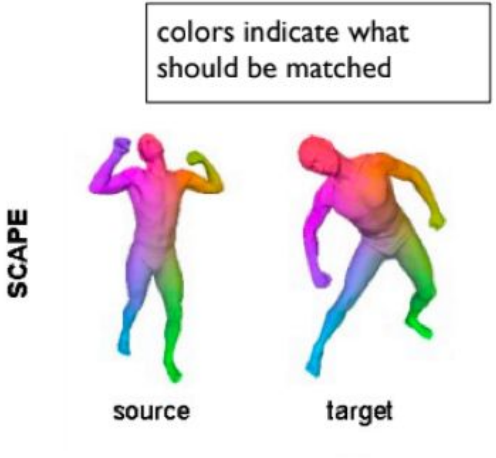
3D Space Points

- Goal of dense pixel correspondence: match regions of one image to another, connecting semantically similar items



Choy et al. "Universal Correspondence Network" NIPS 2016

Zhou, Krähenbühl et al. "Learning Dense Correspondence via 3D-guided Cycle Consistency" CPVR 2016



Wei et al. "Dense Human Body Correspondences Using Convolutional Networks" CPVR 2016

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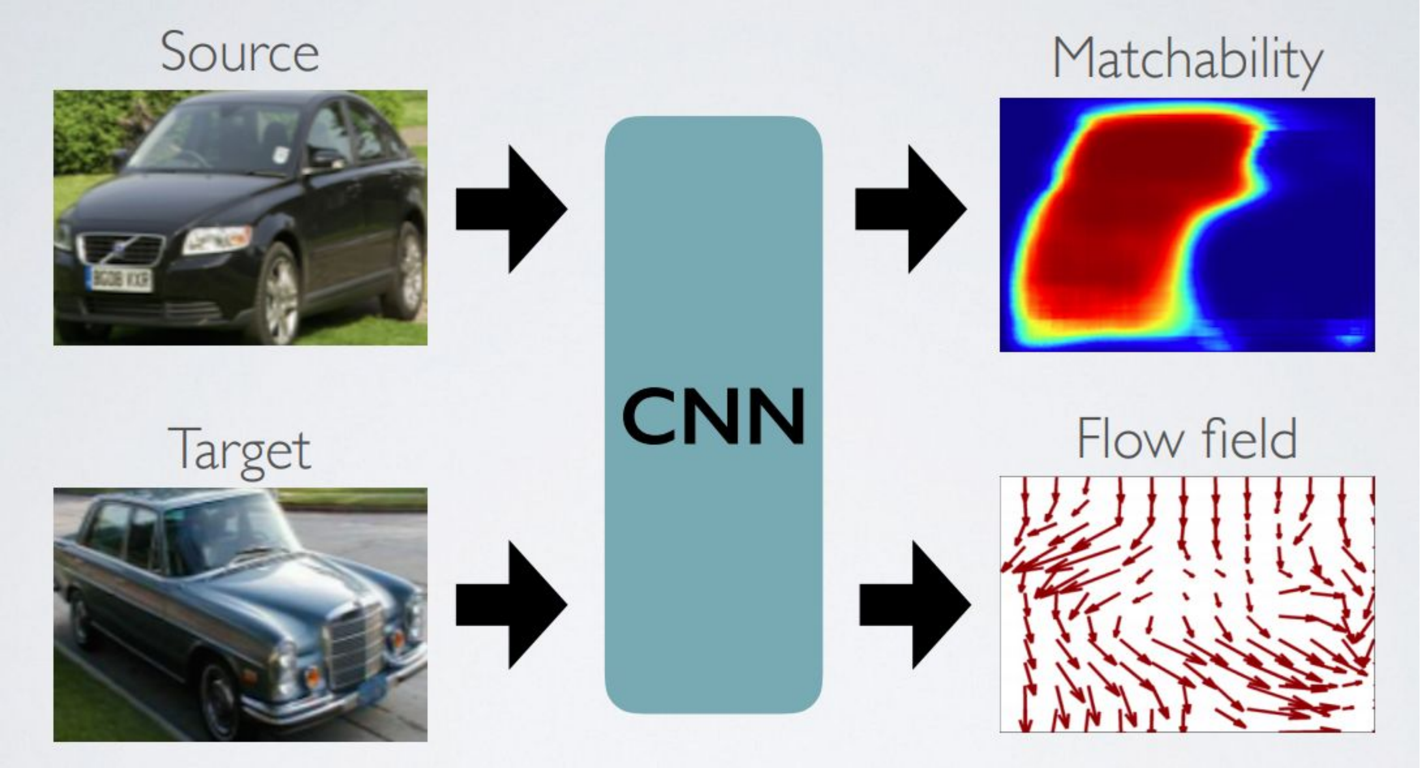
LArFlow



<u>in LArTPC context</u>

matchability = 0
when true target pixel in dead wires, below thresh, etc.

enforce same-time tick, so only wire-direction flow predicted

LArFlow

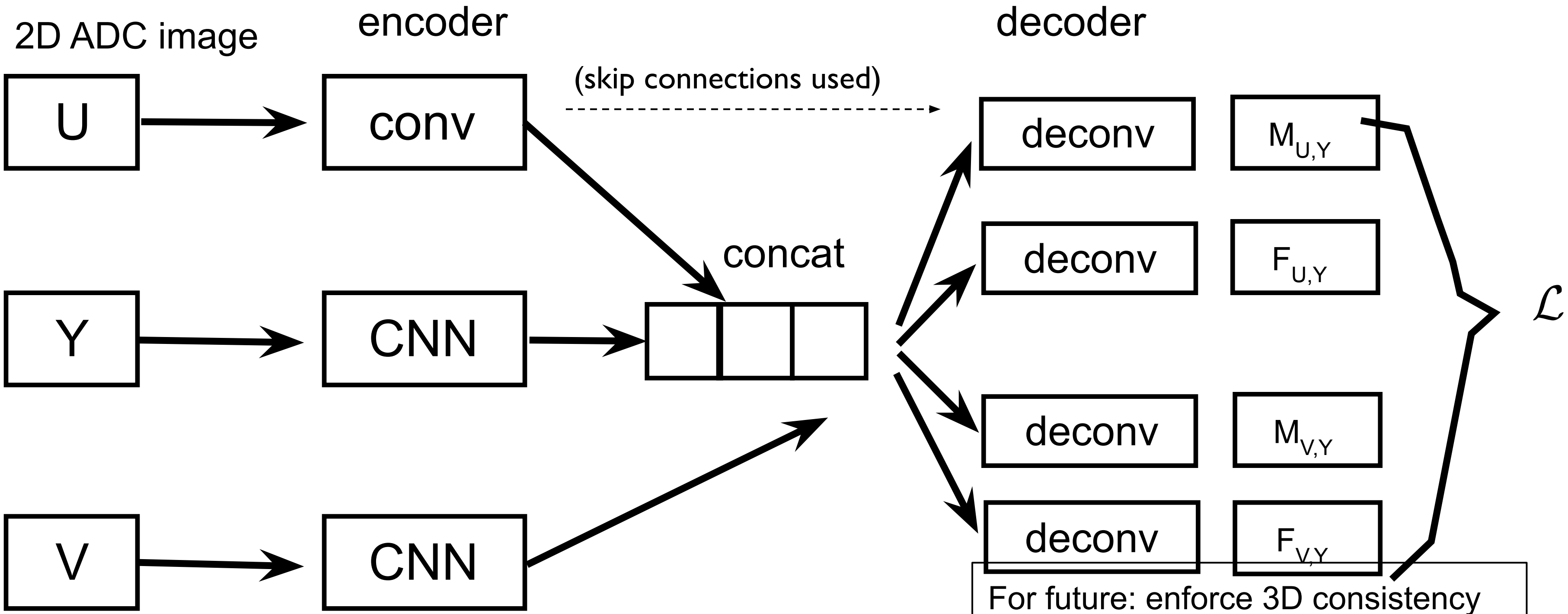
Network predicts correspondence between pixels (charges) in Y, U, V ADC images

For pixel i in Y plane: the CNN is asked to predict ***shift*** needed to move to pixel 1175

Which is where the corresponding pixel is in U plane

Correspondence prediction gives 3D space-point for that charge

LArFlow: Network



Loss function

$\mathcal{L} = \lambda M + F$

For future: enforce 3D consistency loss between Y->U and Y->V prediction

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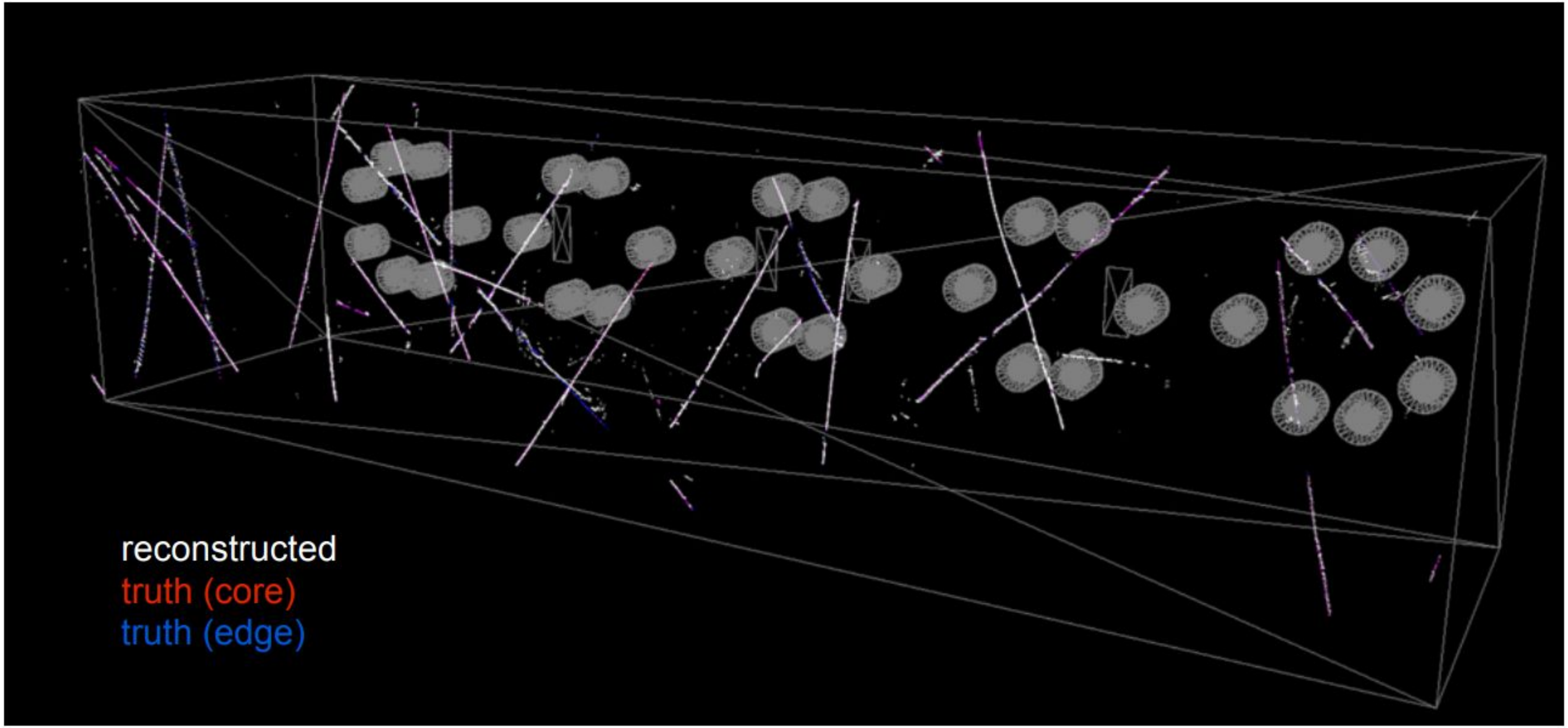
LArFlow: Loss



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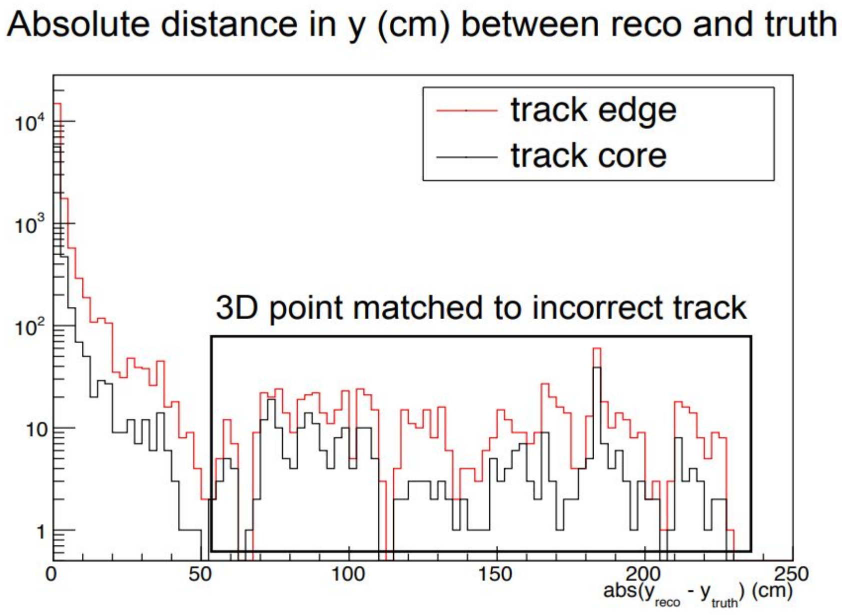
LArFlow: Initial Performance



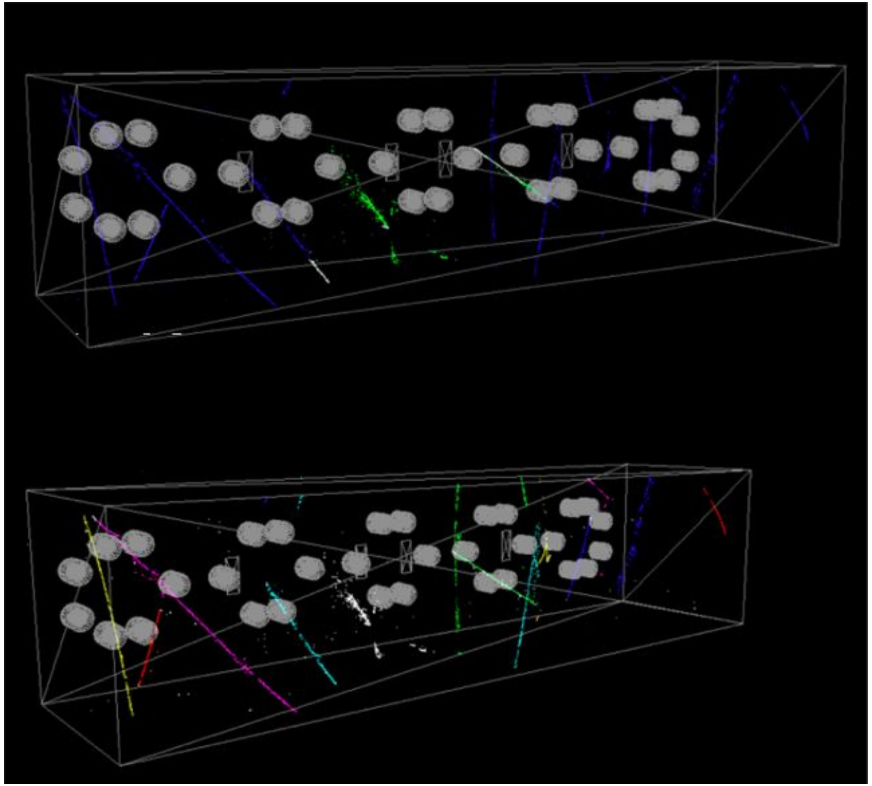
Within 10cm for 92% of hits
Within 50cm for 95% of hits
If flow prediction (U or V wire) is wrong, we shift to incorrect y

Have plans to use cosmic muon data to evaluate similar metrics

Good enough for cosmic rejection

Improvements in precision needed for neutrino reconstruction

LArFlow: Initial Performance

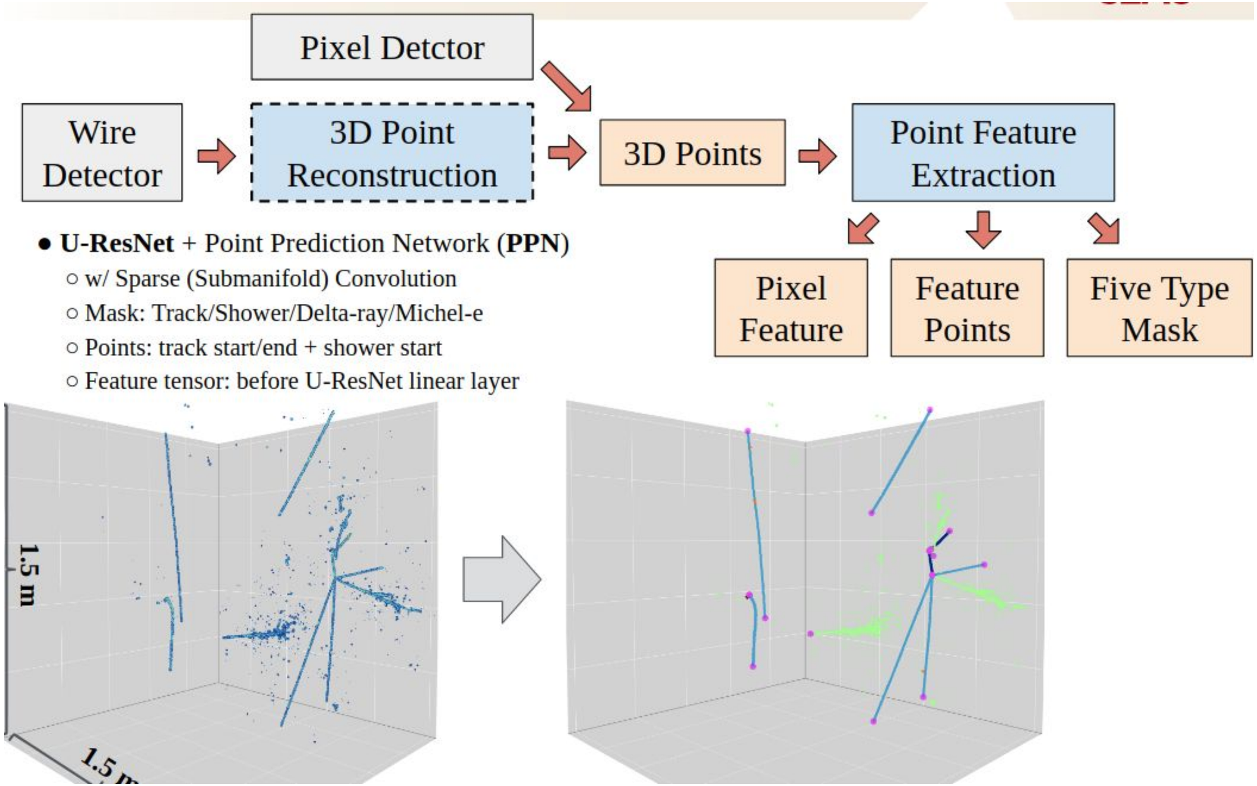


Top: combining 3D points with track/shower labeling

Bottom: using Mask-RCNN network to cluster cosmic muon candidates

Towards 3D space-point reconstruction

Our work is in collaboration with DL-based reco on space-points done here at SLAC



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Summary

CNNs well-suited to analysis of LArTPC images

Applications developed in conjuction with physics analyses -- important for knowing effect on ultimate goal

Moving towards an end-to-end reconstruction chain using networks

Stay tuned for analysis result!

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