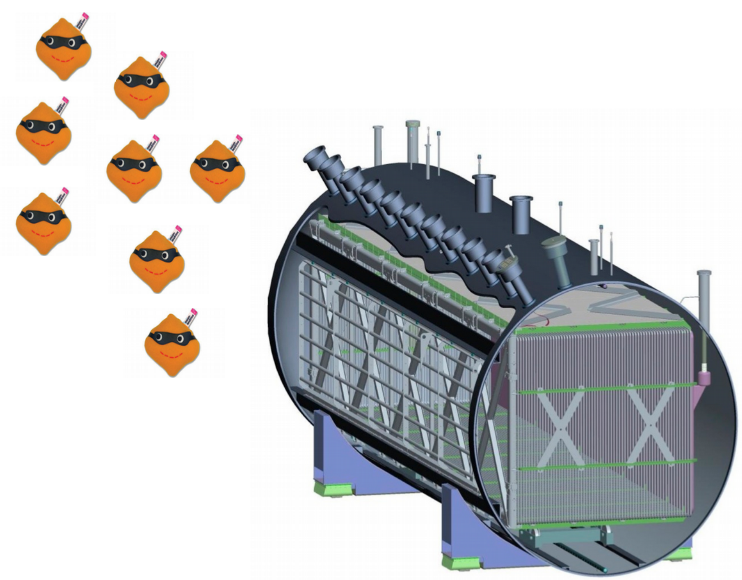
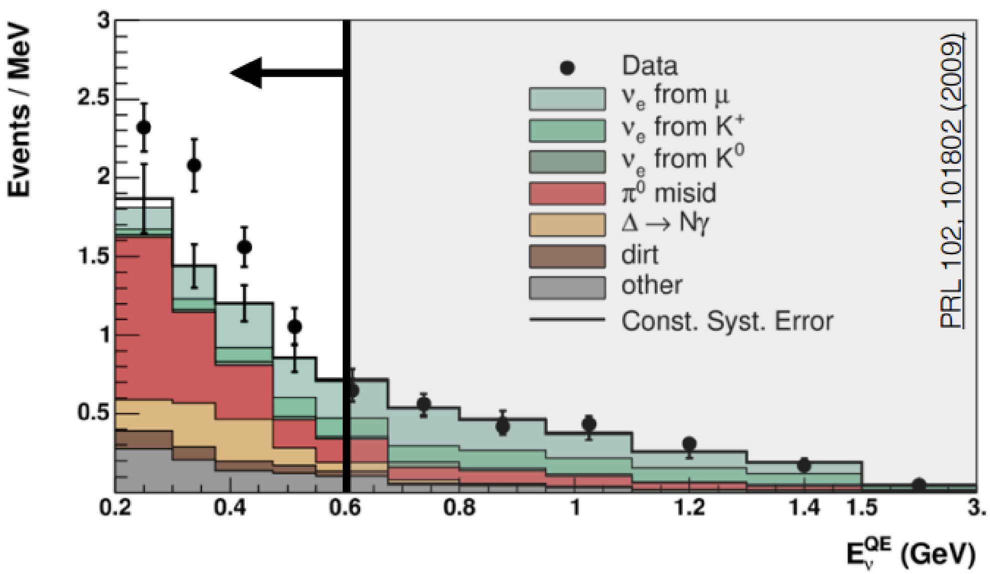
MicroBooNE Investigation of Low Energy Excess Using Deep Learning

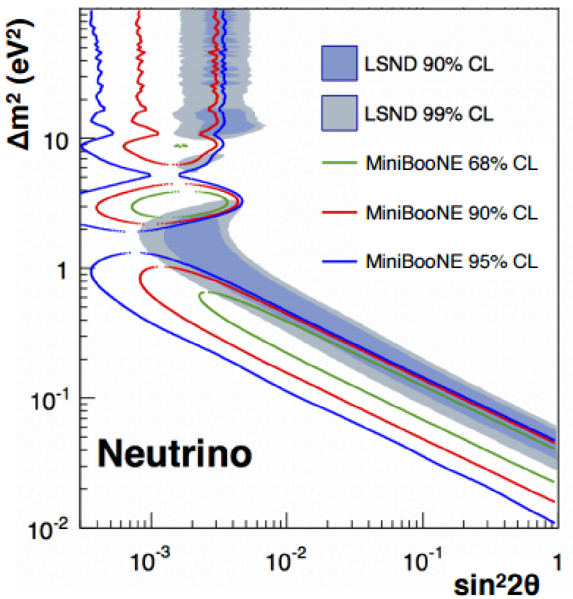
Jarrett Moon (MIT) on behalf of the MicroBooNE Collaboration

TeVPA 2017



The MiniBooNE Excess





- MiniBooNE was a short baseline oscillation experiment
- Saw a ~3σ ν_e- like excess between 200 & 600 MeV
- MiniBooNE's result is in tension with global 3+1 model fits
- Follow up with MicroBooNE! Why MicroBooNE?

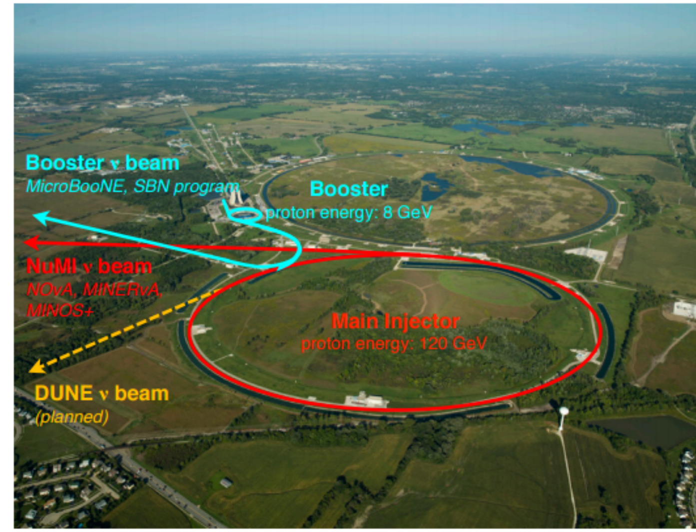
MiniBooNE
- Significant γ/e^- mis-id background
- $\sigma_{stat} \approx \sigma_{sys}$

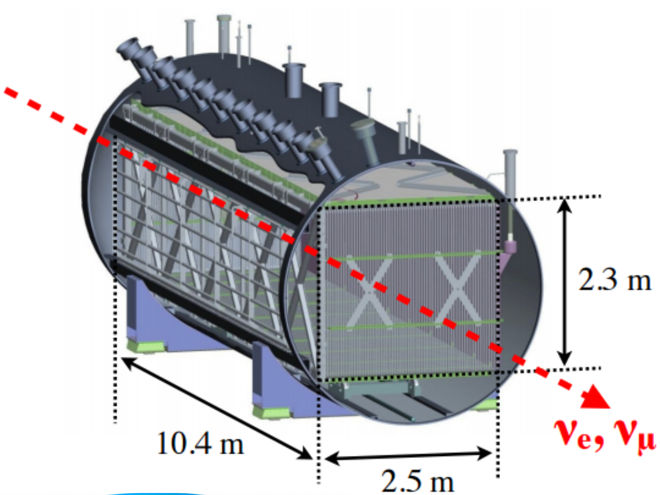
MicroBooNE
- Same beam, similar oscillation parameters, new detector tech
- γ/e^- mis-id is much improved

The MicroBooNE Experiment

μbooNE field cage being inserted into Cryostat (left)

Booster ν beam @ FNAL (right)

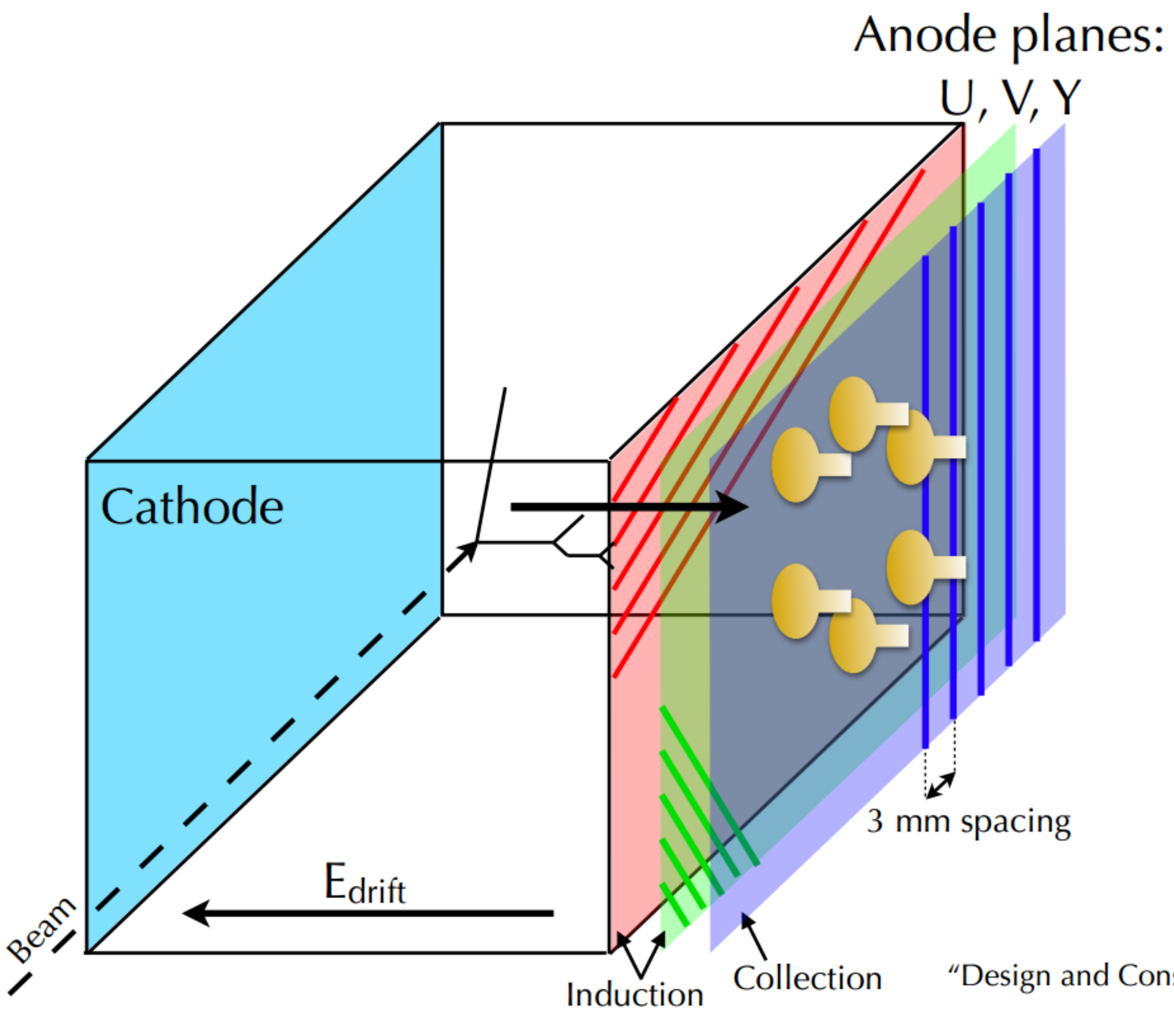


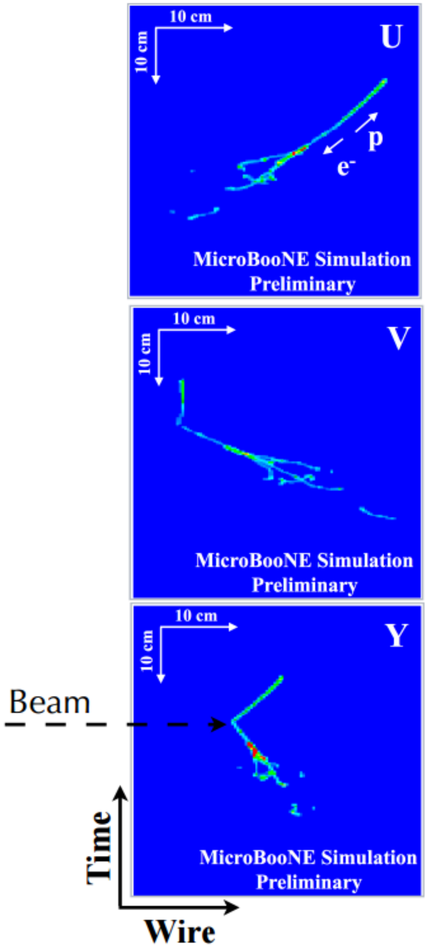


- **Micro** **B**ooster **N**eutrino **E**xperiment
- 85 ton active volume **L**iquid **Ar**gon **T**ime **P**rojection **C**hamber
- Located at FNAL on Booster Neutrino Beam
- $\nu_\mu \rightarrow \nu_e$ appearance experiment
- Running very smoothly so far!

μBooNE LArTPC

The MicroBooNE Detector





"Design and Construction of the MicroBooNE Detector"
JINST 12, P02017 (2017)

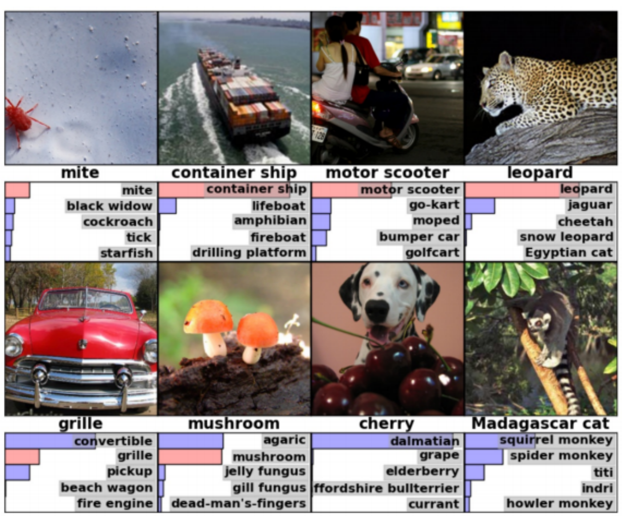
μBooNE

Deep Learning With CNNs

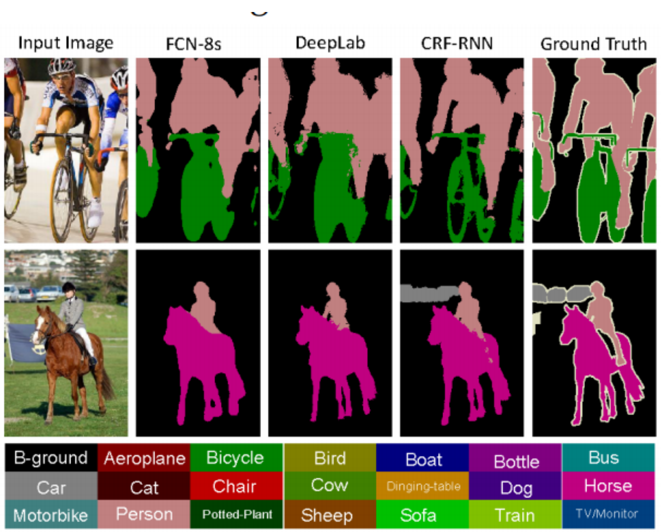
- For our purposes, Deep Learning means using convolutional neural networks (CNNs)
- CNNs were primarily developed for image recognition.
- MicroBooNE produces high resolution images with specific patterns we look for. Ideal for CNNs!
- Two types of interest, classification and semantic segmentation

A CNN trained to classify an image by what it contains (left)

A CNN trained to classify different pixels in an image by type (right)



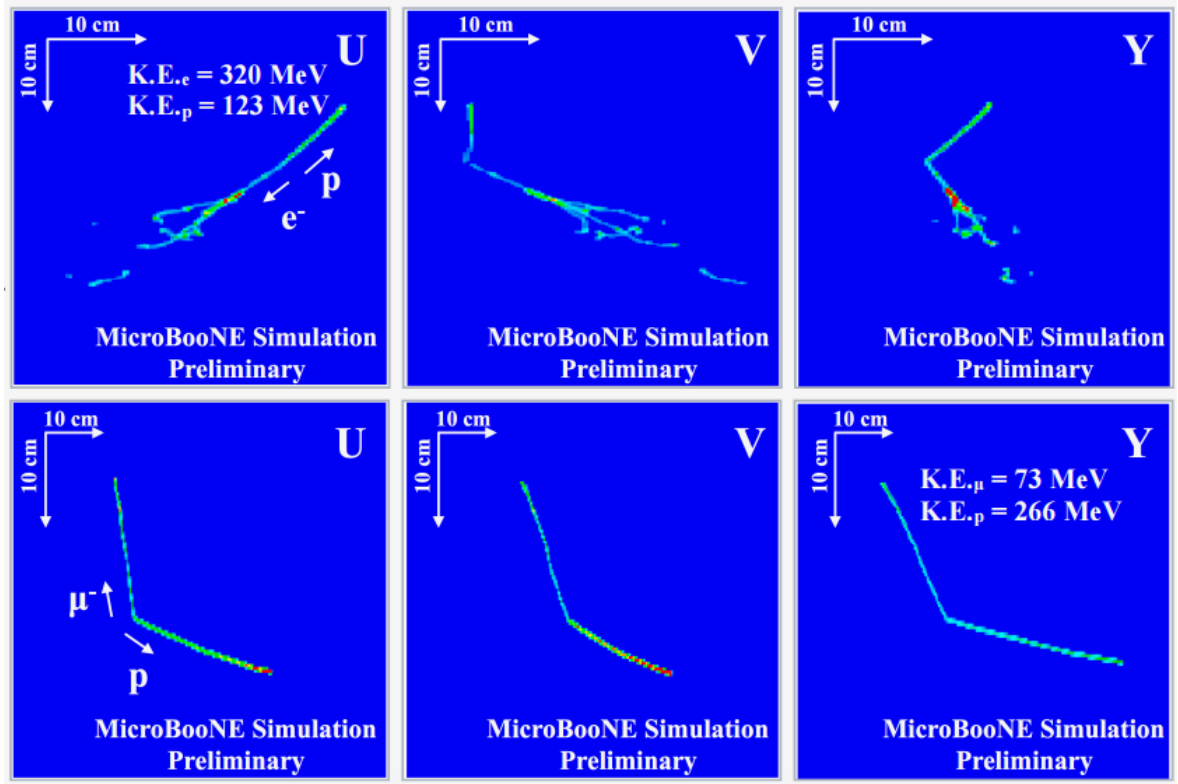
Example of CNN classification, from "ImageNet Classification with Deep CNNs", NIPS (2012)



Example of semantic segmentation, from "Conditional Random Fields as Recurrent NNs", ICCV (2015)

Signal Definition

- Looking for ν_e appearance signal and ν_μ to constrain background
- We choose subset of events producing one lepton and one proton
  - Lepton KE > 35 MeV, Proton KE > 60 MeV
- Chosen for low background (only intrinsic ν_e , constrain with ν_μ) and simple topology



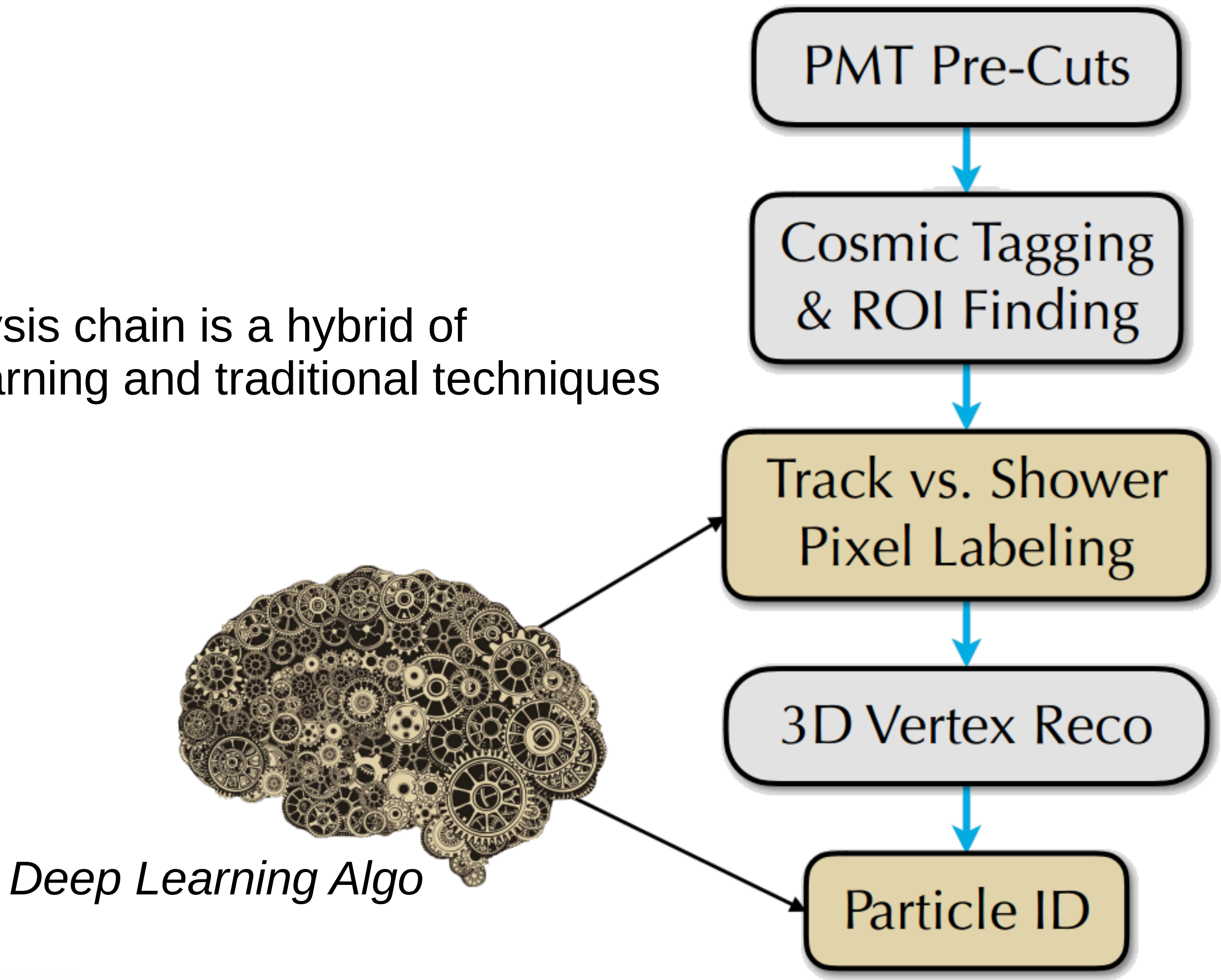
A 1e1p ν_e interaction (top)

A 1μ1p ν_μ interaction (bottom)

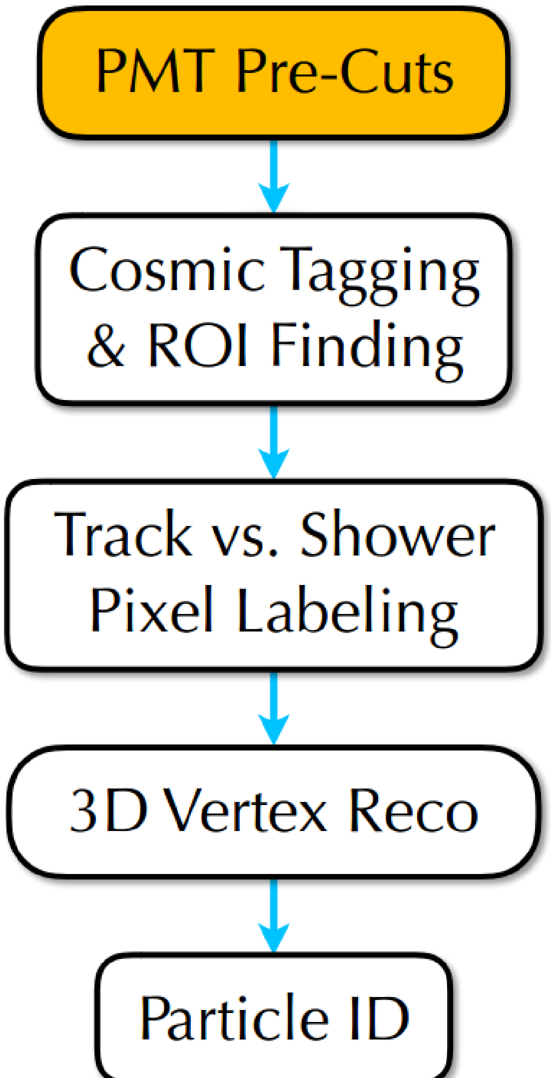
μBooNE

Reconstruction Chain

Full analysis chain is a hybrid of
Deep Learning and traditional techniques

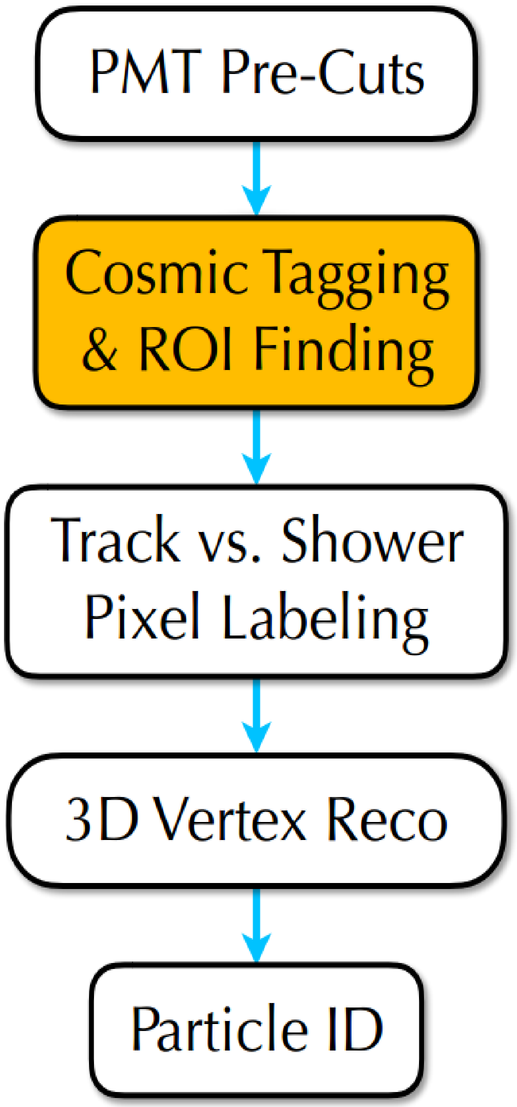


Reconstruction Chain



- Set of optical cuts to reject low energy background and noise
- Retains > 95% of neutrino events (From MC)
- Rejects > 75% of background (From off beam data)

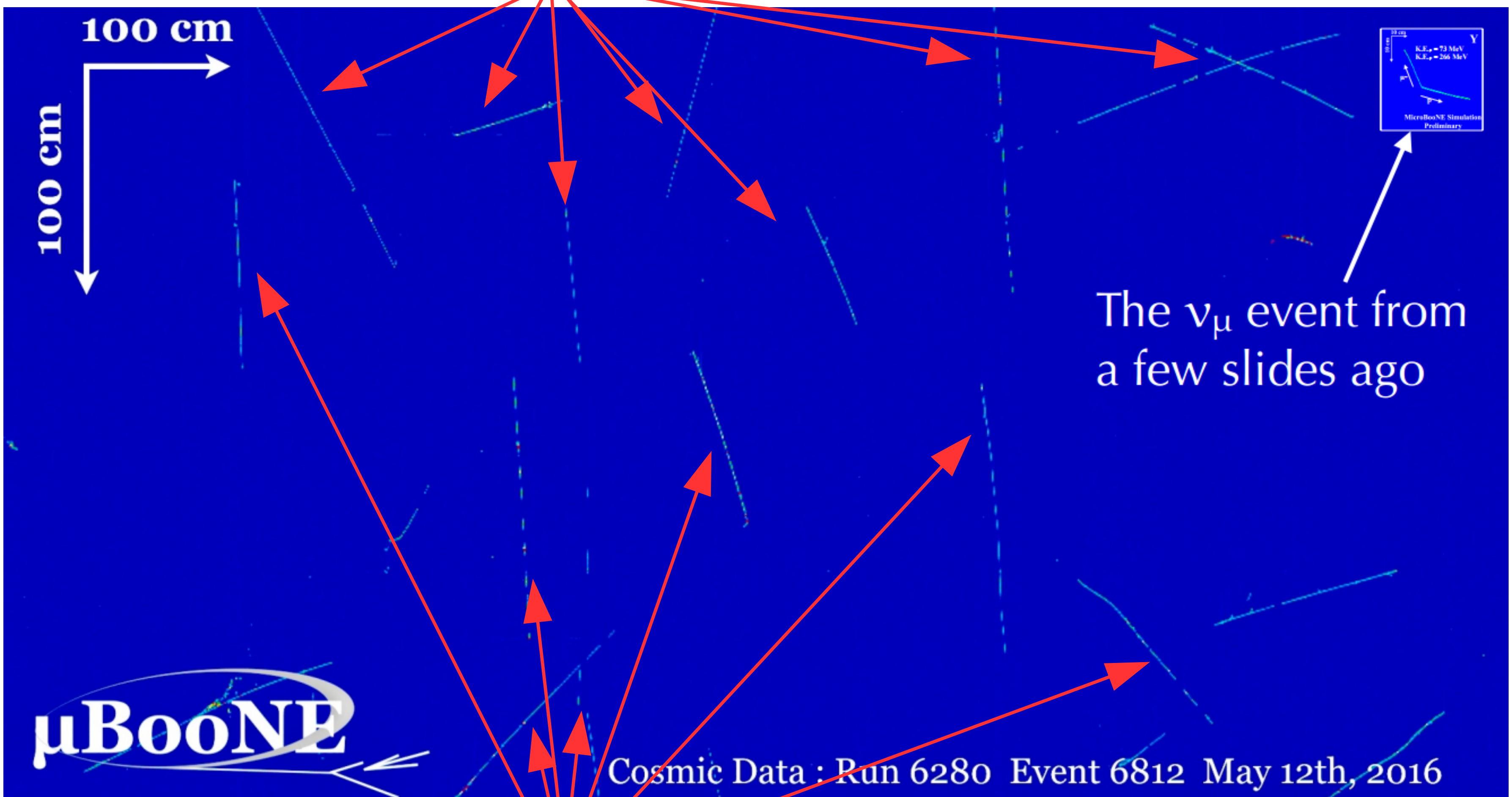
Reconstruction Chain



- Images still contain many cosmic tracks
- Neutrinos interactions are small compared to whole image
- Tag cosmic tracks and isolate regions associated with the neutrino

Cosmic Tagging

Cosmic tracks everywhere!

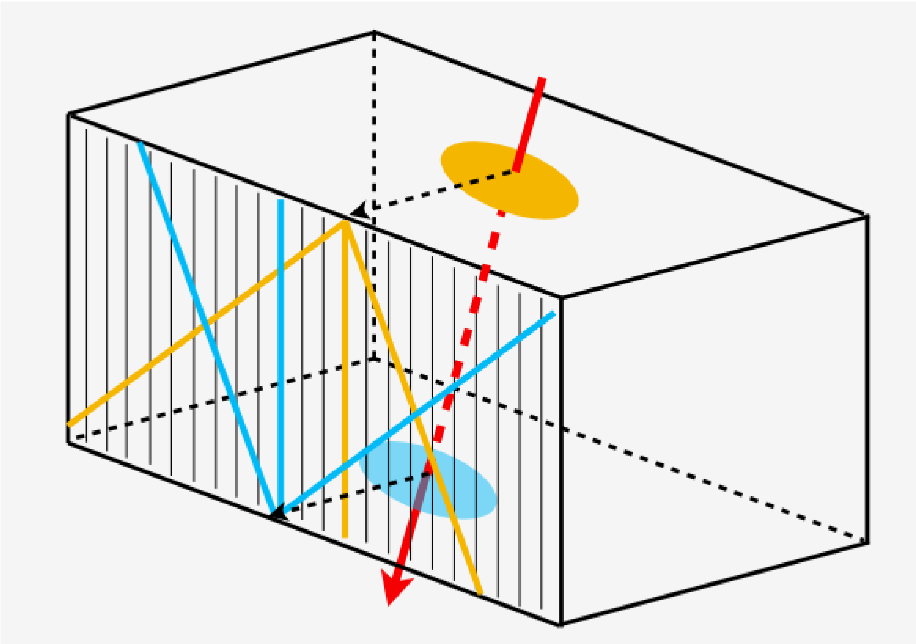


More down here!

Cosmic Tagging

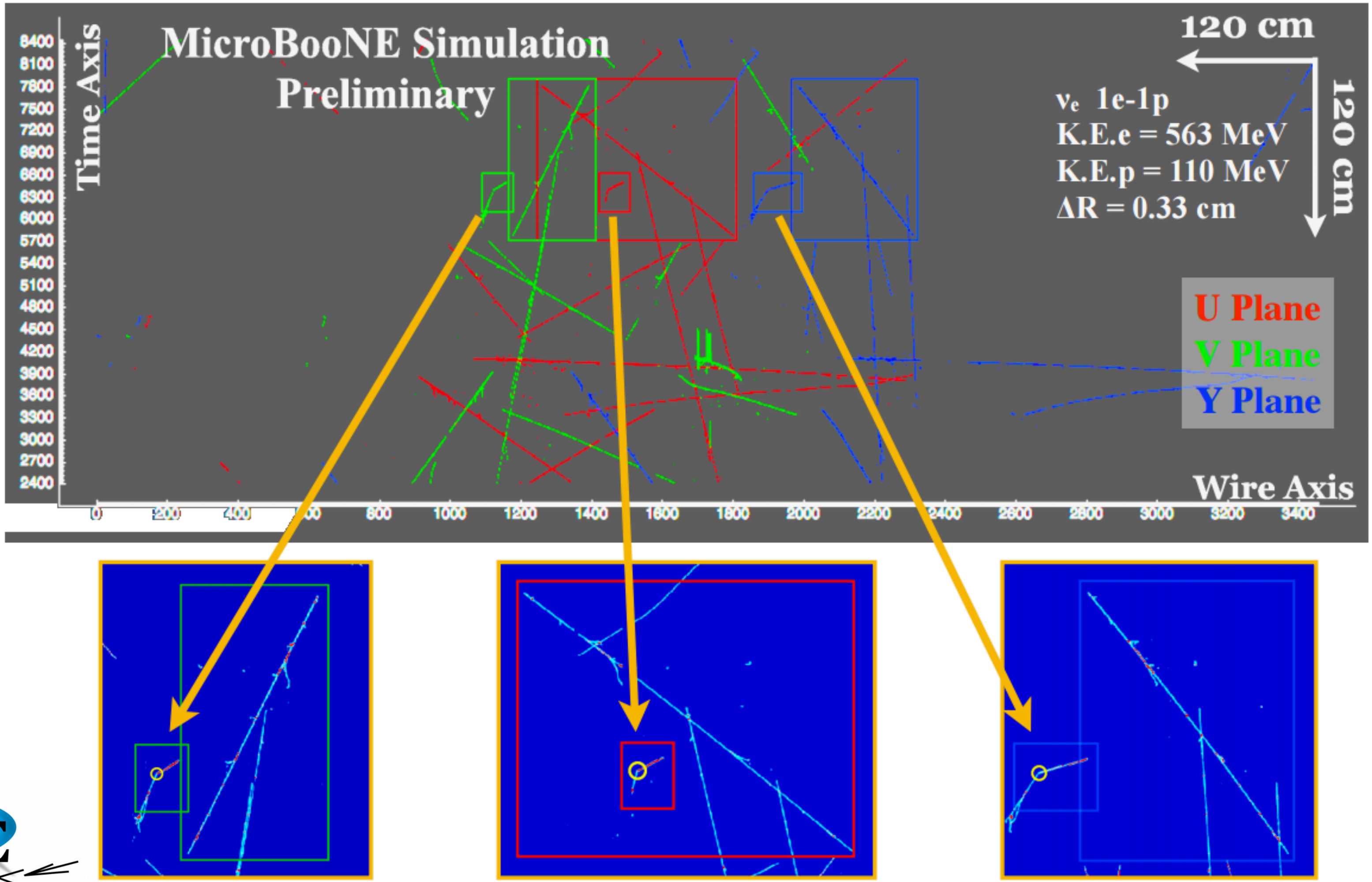
- We tag tracks that cross the TPC boundary
  - Top / Bottom: Track deposits charge on triplet of wires meeting at an edge
  - Upstream / Downstream : Track deposits charge on first / last wire in Y plane
  - Anode / Cathode : Crossing have a specific ΔT between PMT flash and wire signal

- Construct full track using 3D path finding matched to boundary pts



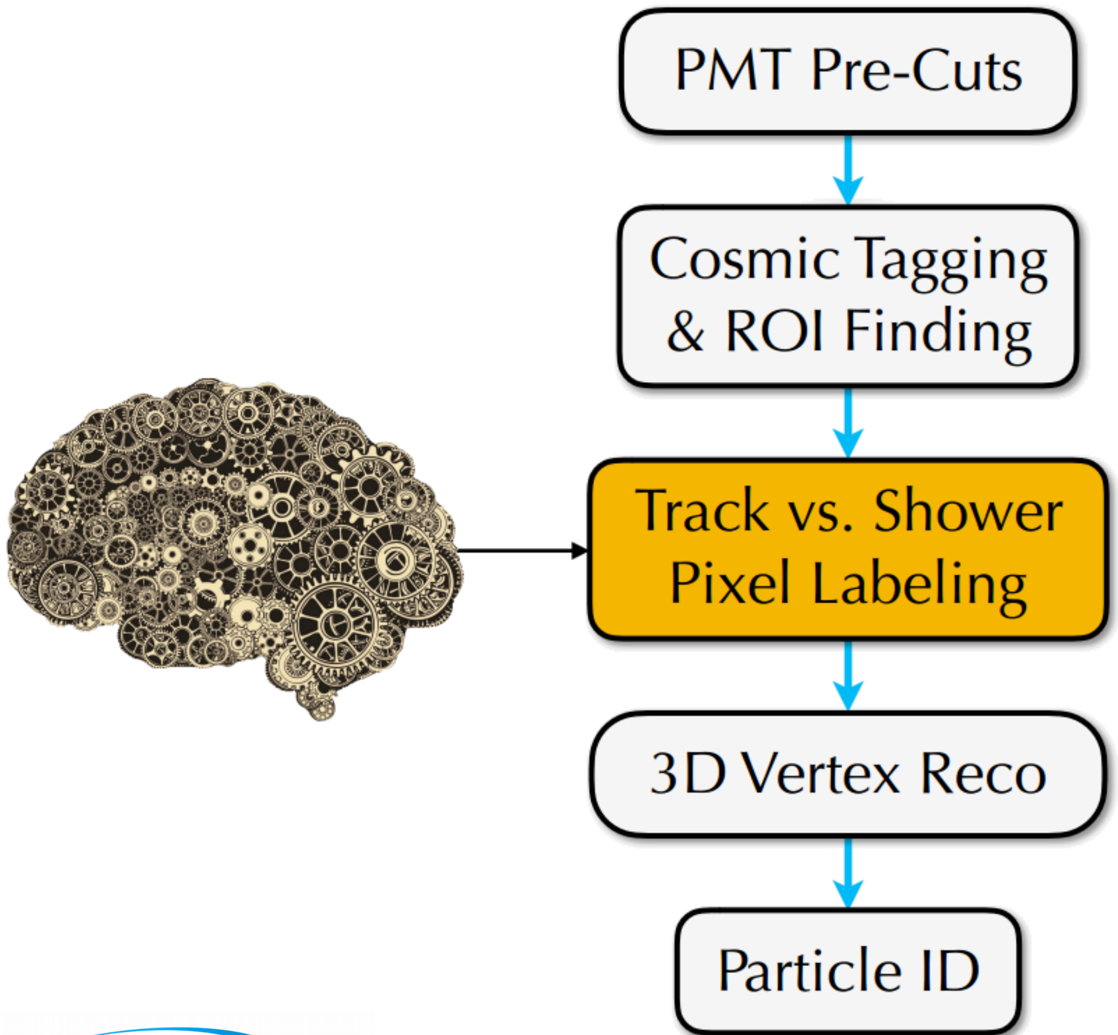
Regions of Interest

- Generate regions of interest (ROIs) by drawing 3D box around remaining pixel clusters



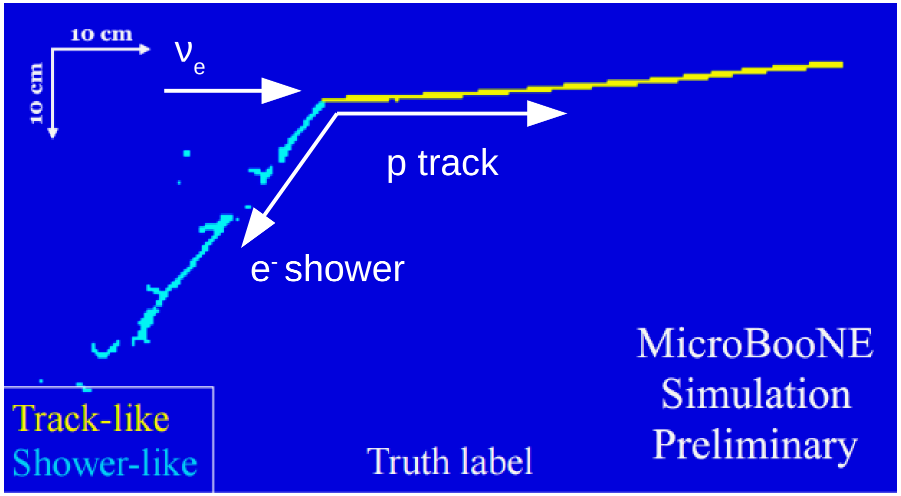
μBooNE

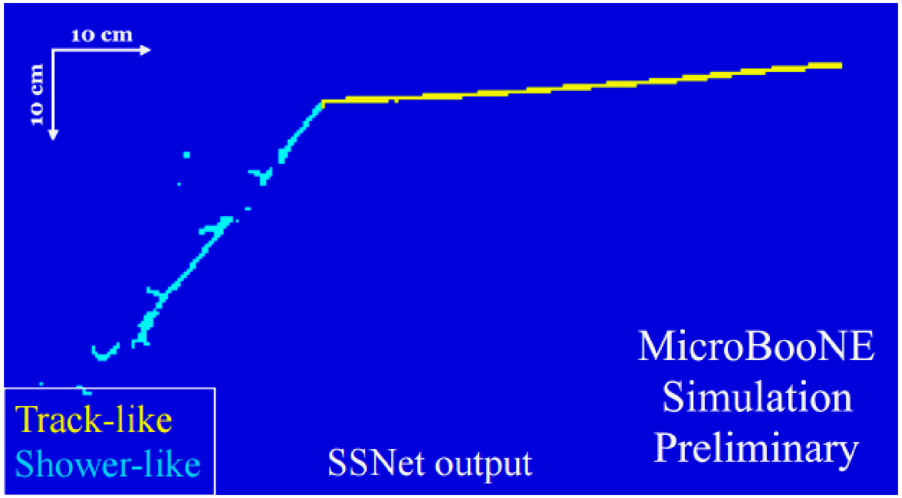
Reconstruction Chain



Pixel Labeling

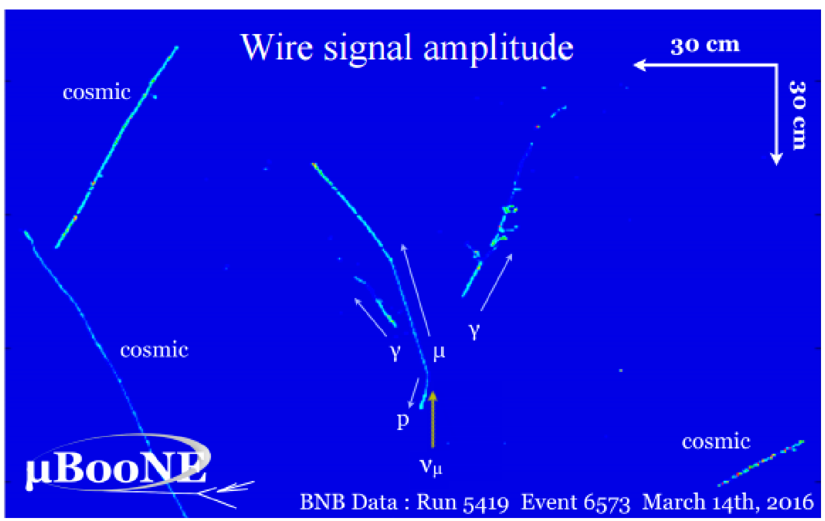
- We seek to separate track and shower clusters to aid in vertex reconstruction
- First use of Deep Learning, a semantic segmentation network labels each pixel as shower-like or track-like
- Overall labeling accuracy > 90%

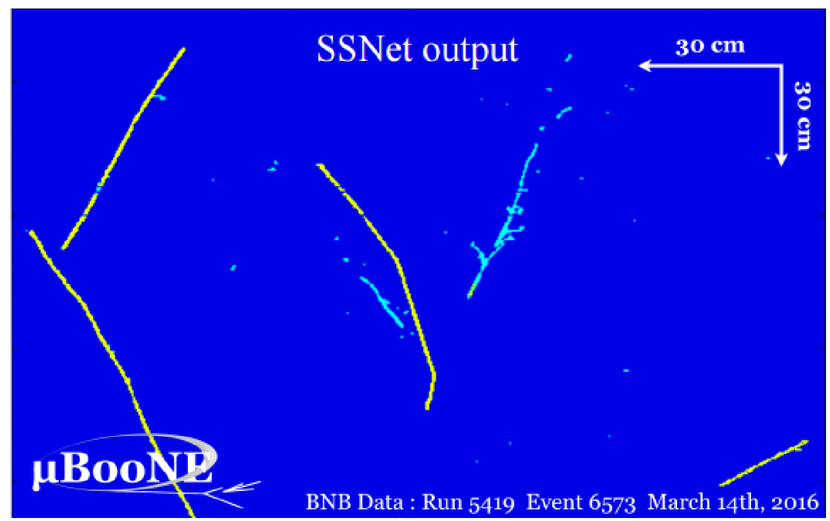




SSNet Accuracy on Data

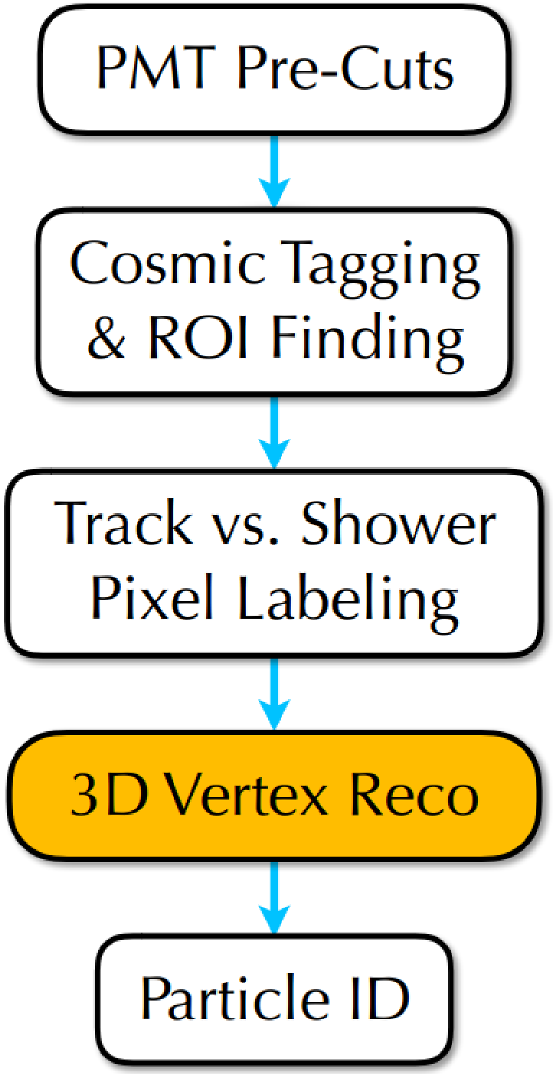
- Use a sample of CC π^0 events to test SSNet performance on protons, muons, and gammas in data
- In the example below, the proton and muon are correctly labeled as tracks. The two γ showers are mostly labeled as shower type, with the exception of the trunk





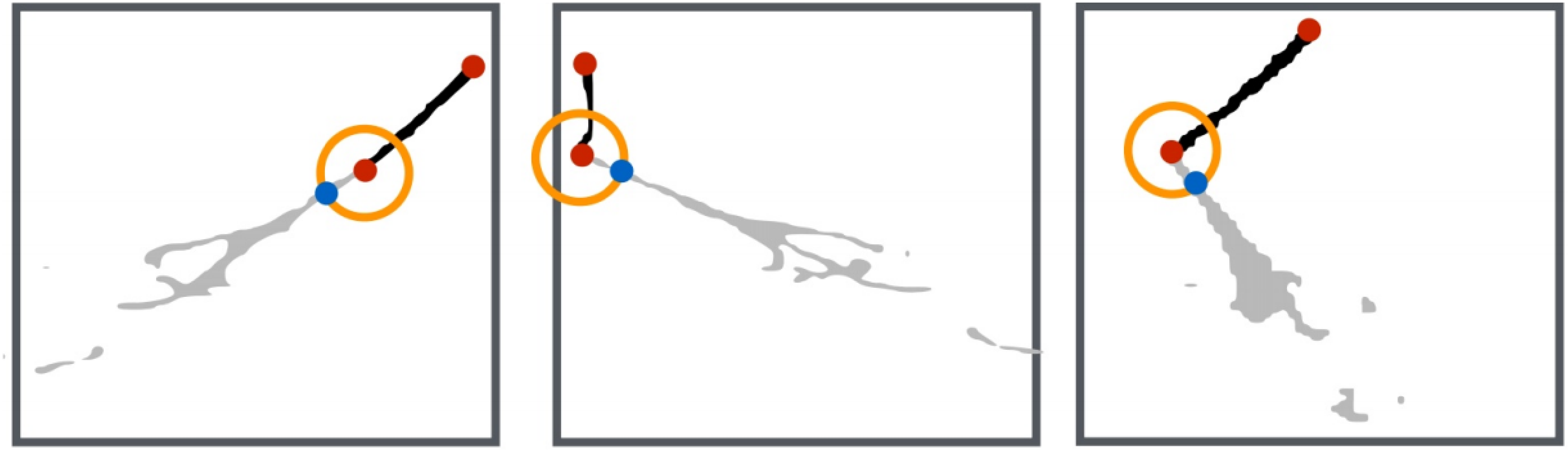
MicroBooNE Public Note, "Study Towards an Event Selection for Neutral Current Inclusive Single π^0 Production in MicroBooNE"

Reconstruction Chain



ν_e Vertex Reco

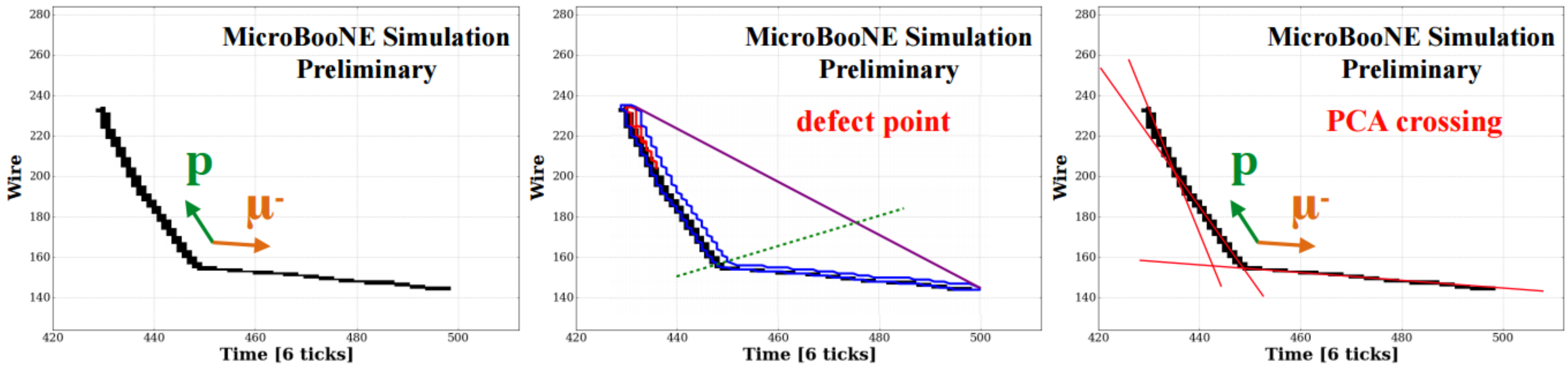
- Look for intersections of track-like and shower-like pixel clusters
- Correlate these intersections across planes
- Scan 3D region around points to find best match for where shower and track meet across all planes



µBooNE LArTPC

ν_μ Vertex Reco

- Per plane, create 2D vertex seeds at any kink points
  - Find defects in convex hull
  - Find intersections of component linear fits
- Scan space around each 2D seed using an angular metric to find best vertex point
- Combine information across planes, if vertices across planes are 3D consistent, claim a vertex at that point



Reconstruction Chain

PMT Pre-Cuts

↓

Cosmic Tagging & ROI Finding

↓

Track vs. Shower Pixel Labeling

↓

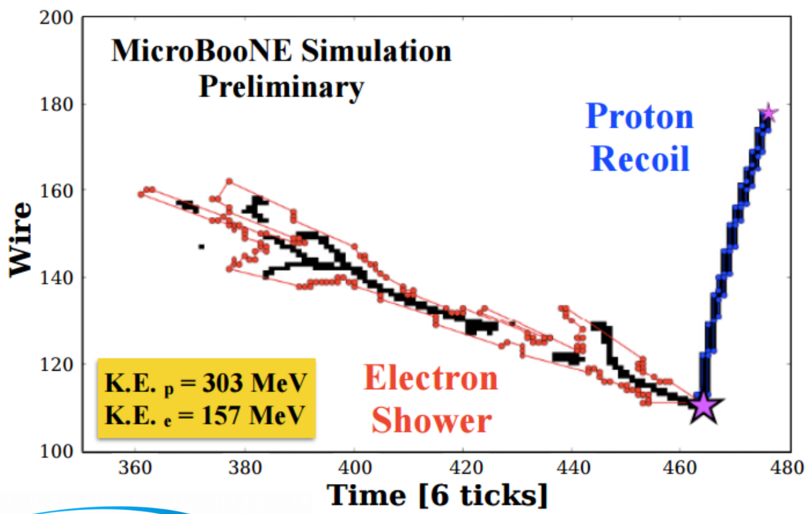
3D Vertex Reco

↓

Particle ID

Particle Identification

- Second stage of chain where Deep Learning is used
- After 3D vertex reconstruction, cluster pixels associated with a given track/shower emerging from a vertex
- Feed these individual clusters to a CNN trained to do particle type identification (HighRes GoogLeNet)
  - Note this differs from previous net which was trained only to broadly classify pixels by track or shower

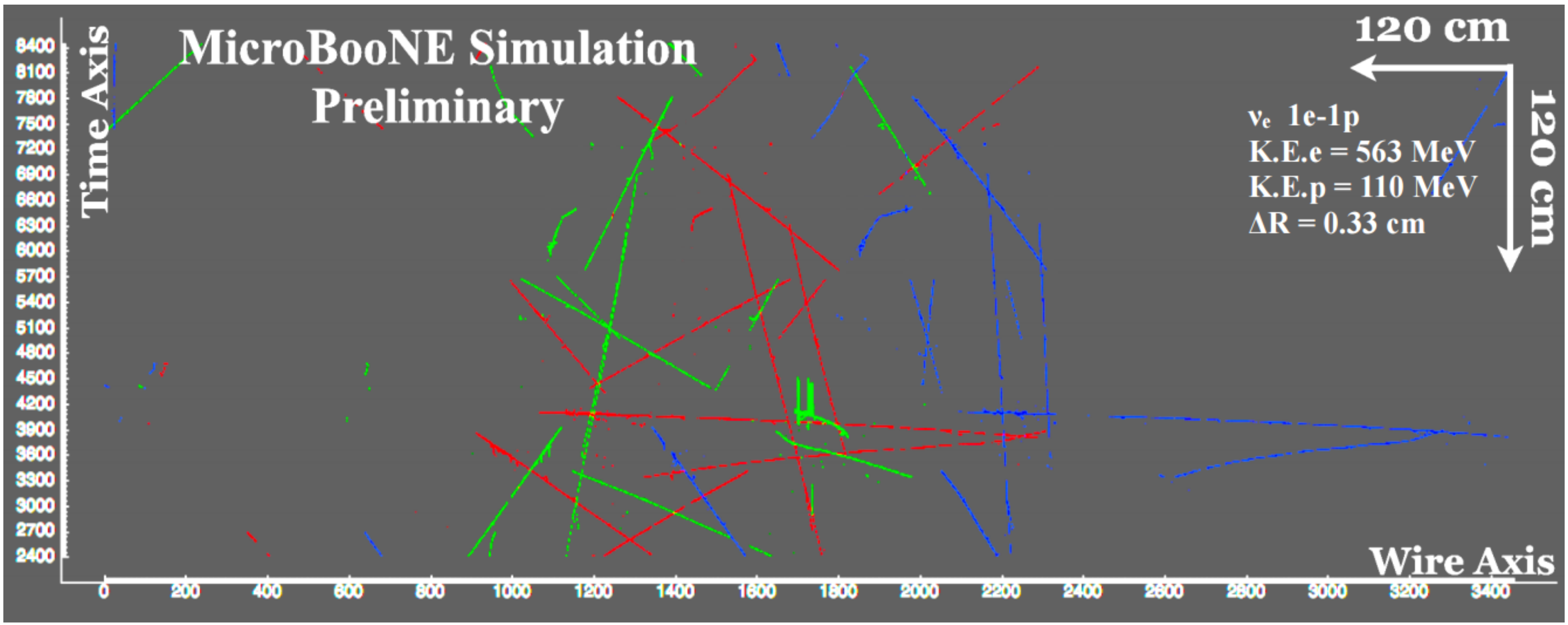


Particle	Correct ID
e^-	$77.8 \pm 0.7\%$
γ	$83.4 \pm 0.6\%$
μ^-	$89.7 \pm 0.5\%$
π^-	$71.0 \pm 0.7\%$
p	$91.2 \pm 0.5\%$

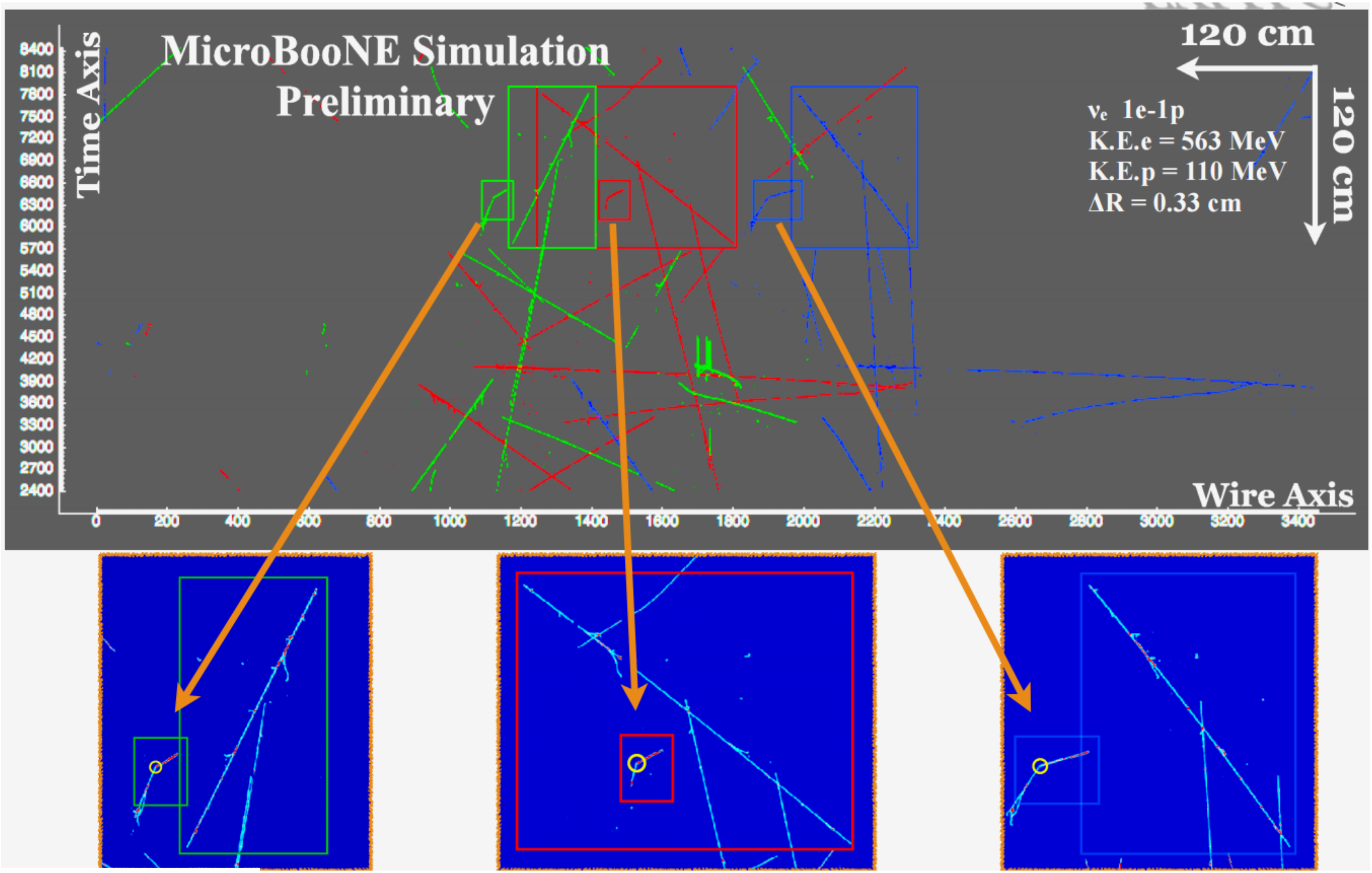
Substantial improvement over MiniBooNE which offered no similar detailed PID

JINST 12, P03011 (2017)

Processed Event Example



Processed Event Example



Summary

- Fully automated reconstruction chain for performing low energy analysis. Includes a mix of traditional and Deep Learning algos
- Efficiency and systematics studies in progress
- Progress will inform on low energy excess and provide tool development for future LArTPC programs

Thank You!

Questions?

Backups

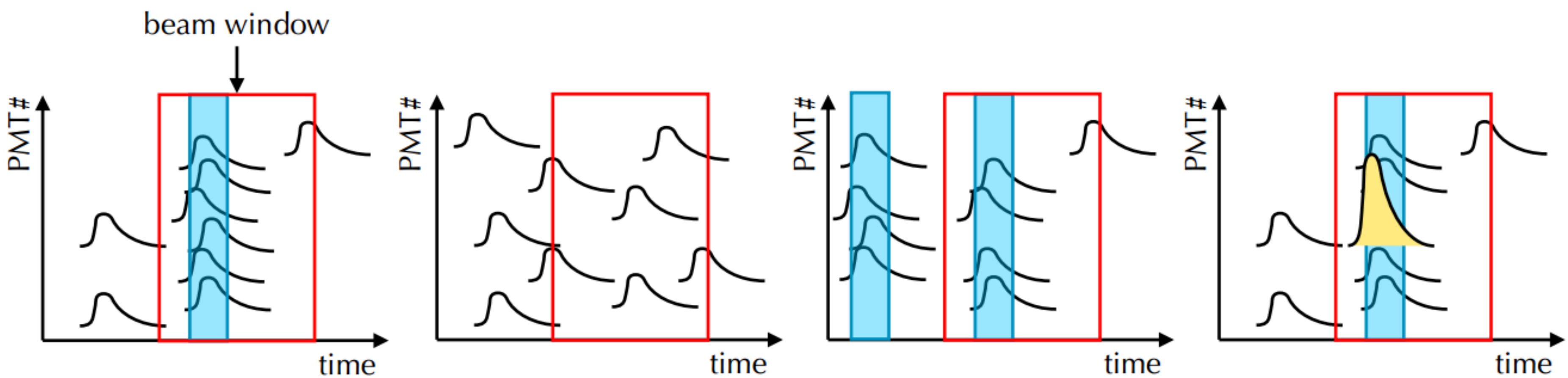
More Detail on Deep Learning

https://www.youtube.com/watch?v=AgkfIQ4IGaM

- Convolutional neutral networks have several important properties
  - “Neurons” scan over the image looking at a limited set of pixels at each point
  - They “learn” local, translationally invariant features
  - Each layer of neurons builds on the features found by the previous ones to reach increasing levels of complexity/abstraction
- In the above, the black-and-white boxes show the “activation” of neurons in response to the images; the neuron highlighted on the right responds to faces, while the one on the left responds to text

μBooNE LArTPC

Optical PreCuts



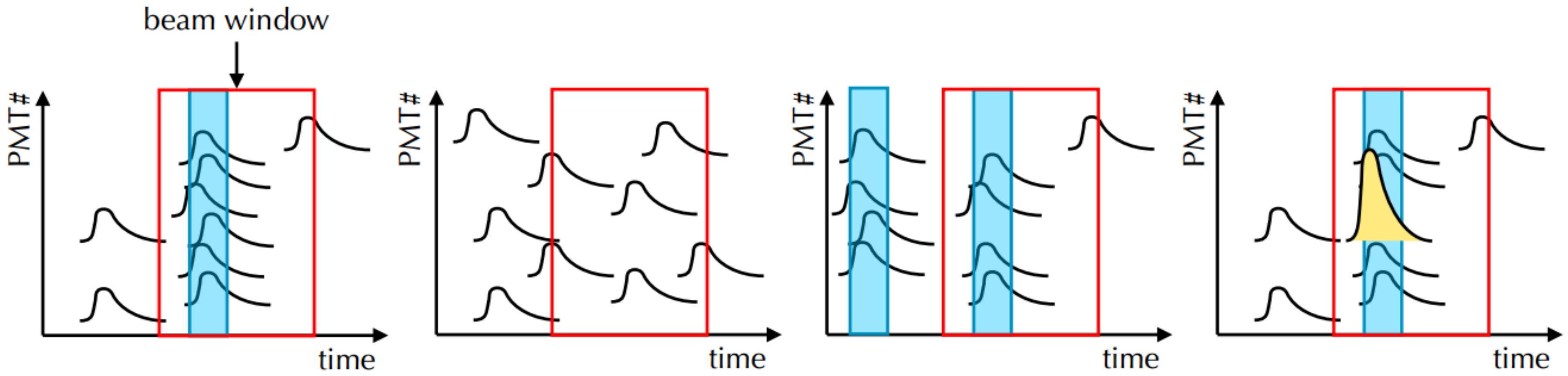
Keep: All possible neutrino events

Reject: Random, single-photoelectron noise

Reject: In-time flash caused by Michel electron, from the decay of pre-beam cosmic muon

Reject: PMT-based noise

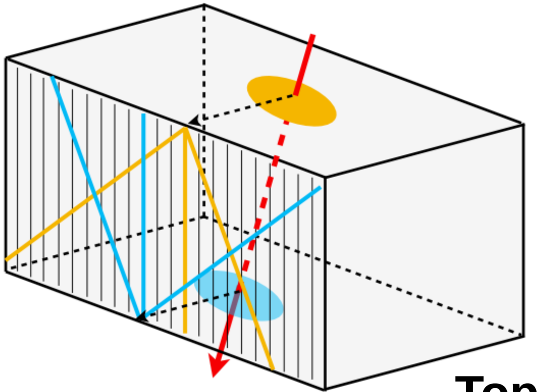
Optical PreCuts



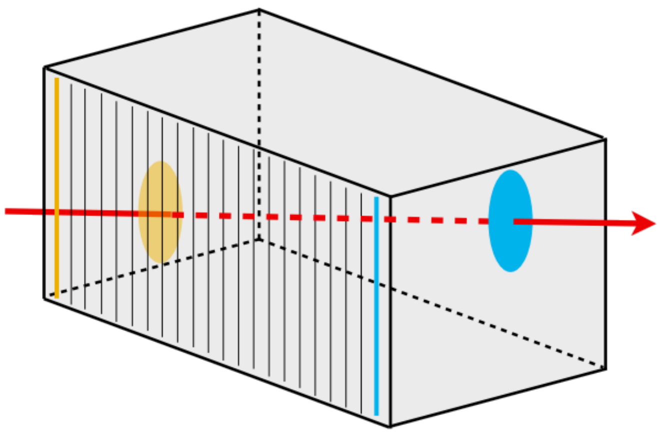
- Reject: Random, single-photoelectron noise (~200 kHz)
  - No time correlation between these single-photoelectron pulses
  - Require 20 photoelectrons in 93.75 ns — this becomes the definition of a "signal"
- Reject: In-time flash caused by Michel electron, from decay of a cosmic muon
  - Require no signal for 2 μs before the beam window
- Reject: PMT-based noise
  - Limit the total amount of the light collected by a single PMT to <60% of the total light
- Keep >96% of neutrinos (based on simulations)
- Reject >75% of background (based on rejection of off-beam data)

μBooNE

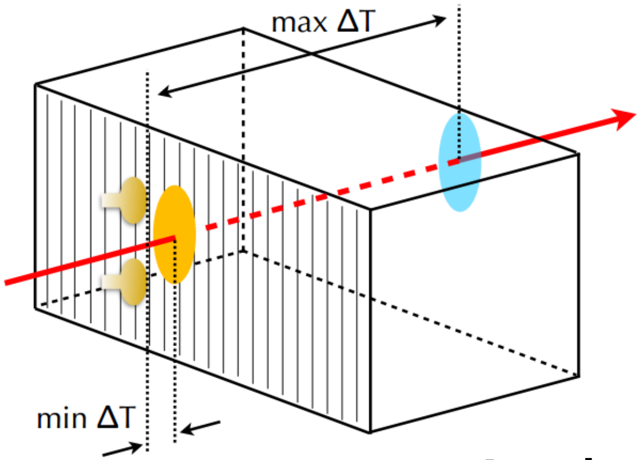
Cosmic Tagging



Top / Bottom



Upstream / Downstream



Anode / Cathode

CNN PID Performance

Sample	Electron	Photon	Muon	Pion	Proton
Detection Accuracy (%)	77.8 +/- 0.7	83.4 +/- 0.6	89.7 +/- 0.5	71.0 +/- 0.7	91.2 +/- 0.5
Most frequuent MisID (%)	γ (19.9)	e^- (15.0)	π^- (5.4)	μ^- (22.6)	μ^- (4.6)