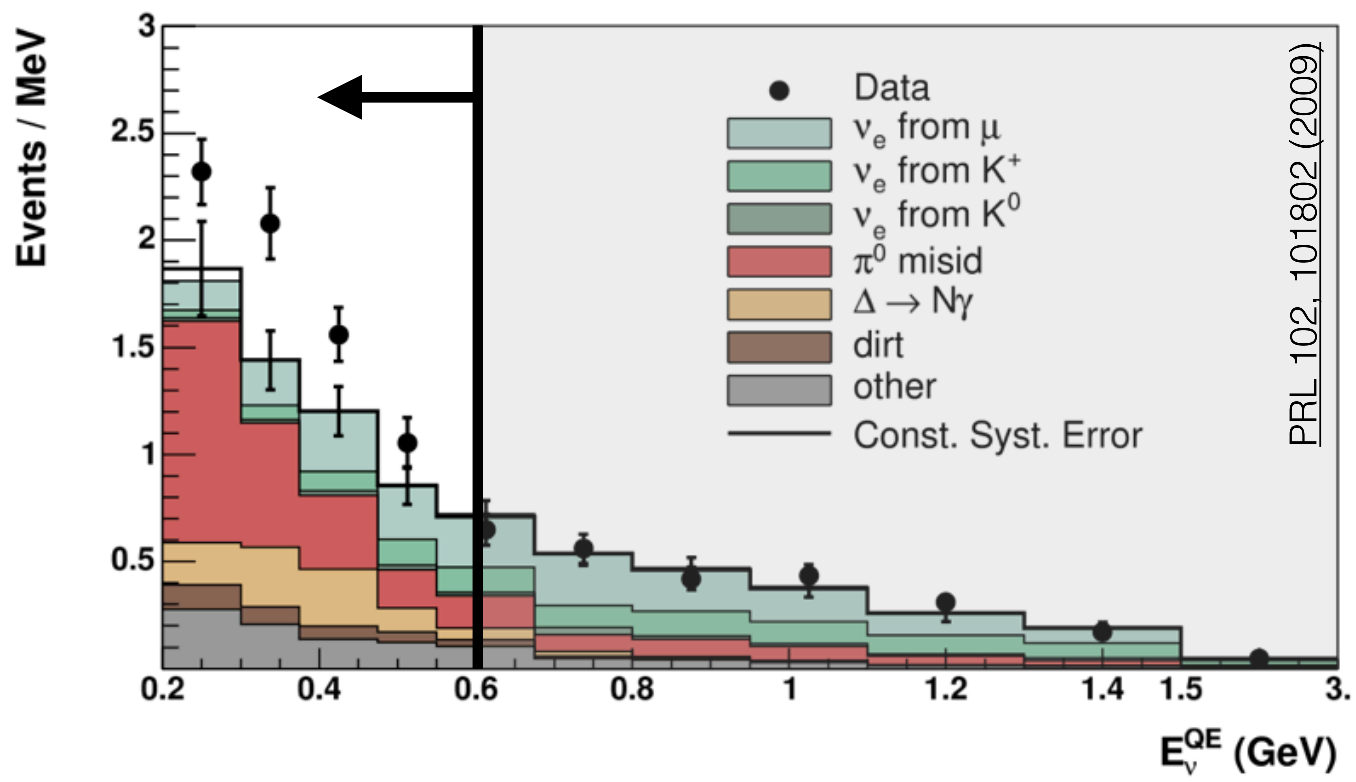
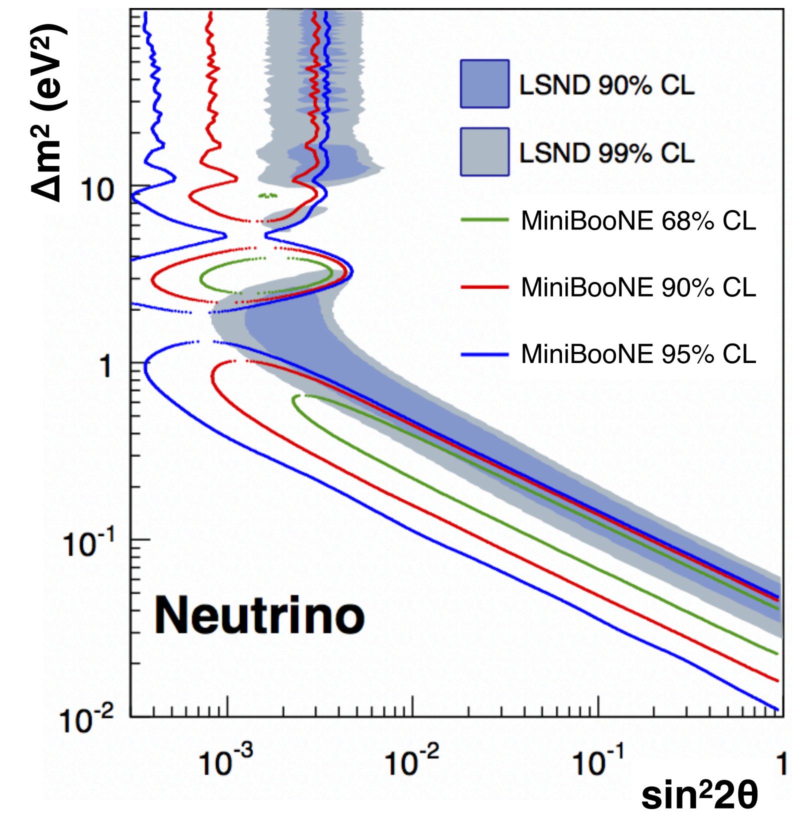
MicroBooNE Investigation of Low-Energy Excess Using Deep Learning Algorithms

Lauren Yates
Massachusetts Institute of Technology
On Behalf of the MicroBooNE Collaboration

DPF 2017

MiniBooNE Low-Energy Excess



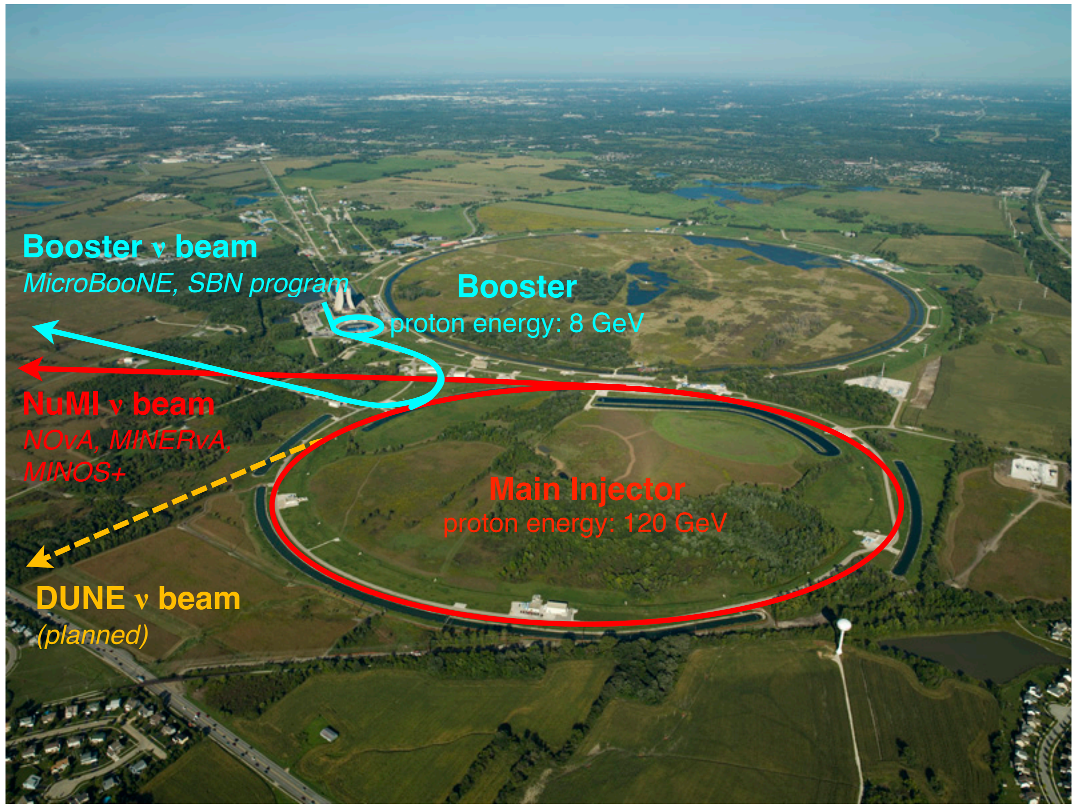


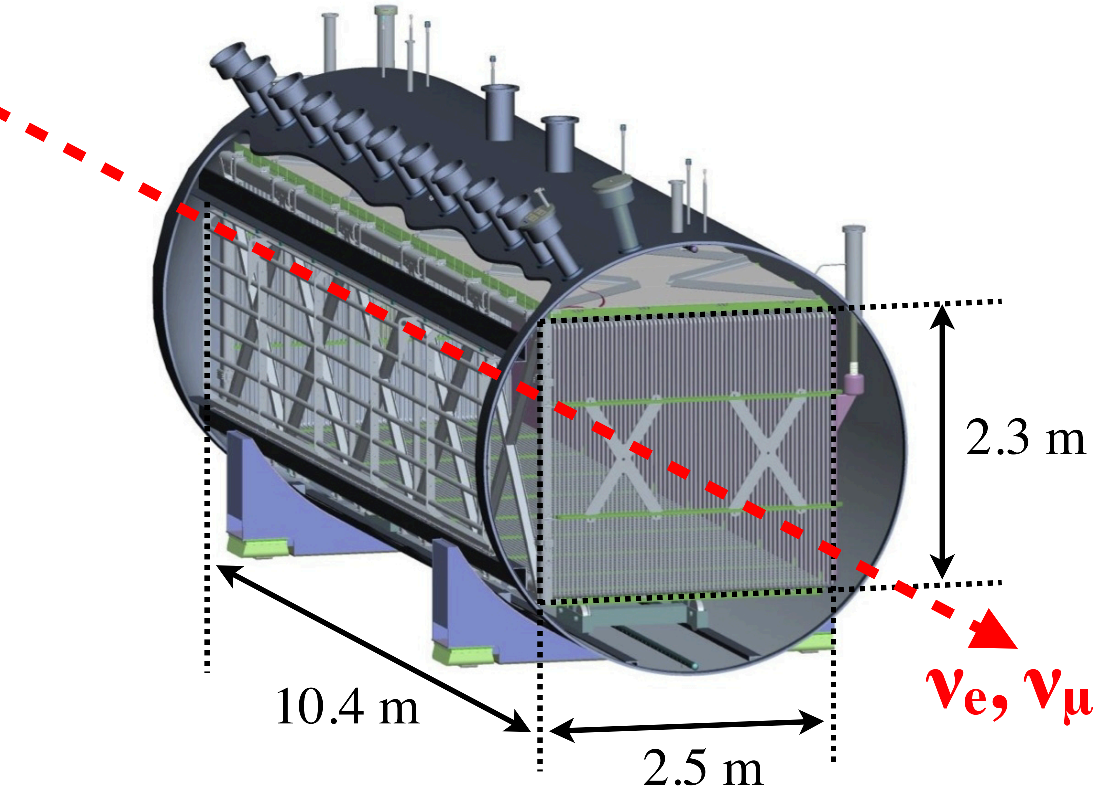
- MiniBooNE saw a ~3σ ν_e-like excess between 200 and 600 MeV
- MiniBooNE's neutrino result is in tension with global 3+1 model fit

- MiniBooNE
  - Significant fraction of background from γ/e^- mis-ID
  - Systematic error ≈ statistical error

- MicroBooNE
  - Same beam and similar baseline
  - LArTPC gives better γ/e^- separation, better background rejection

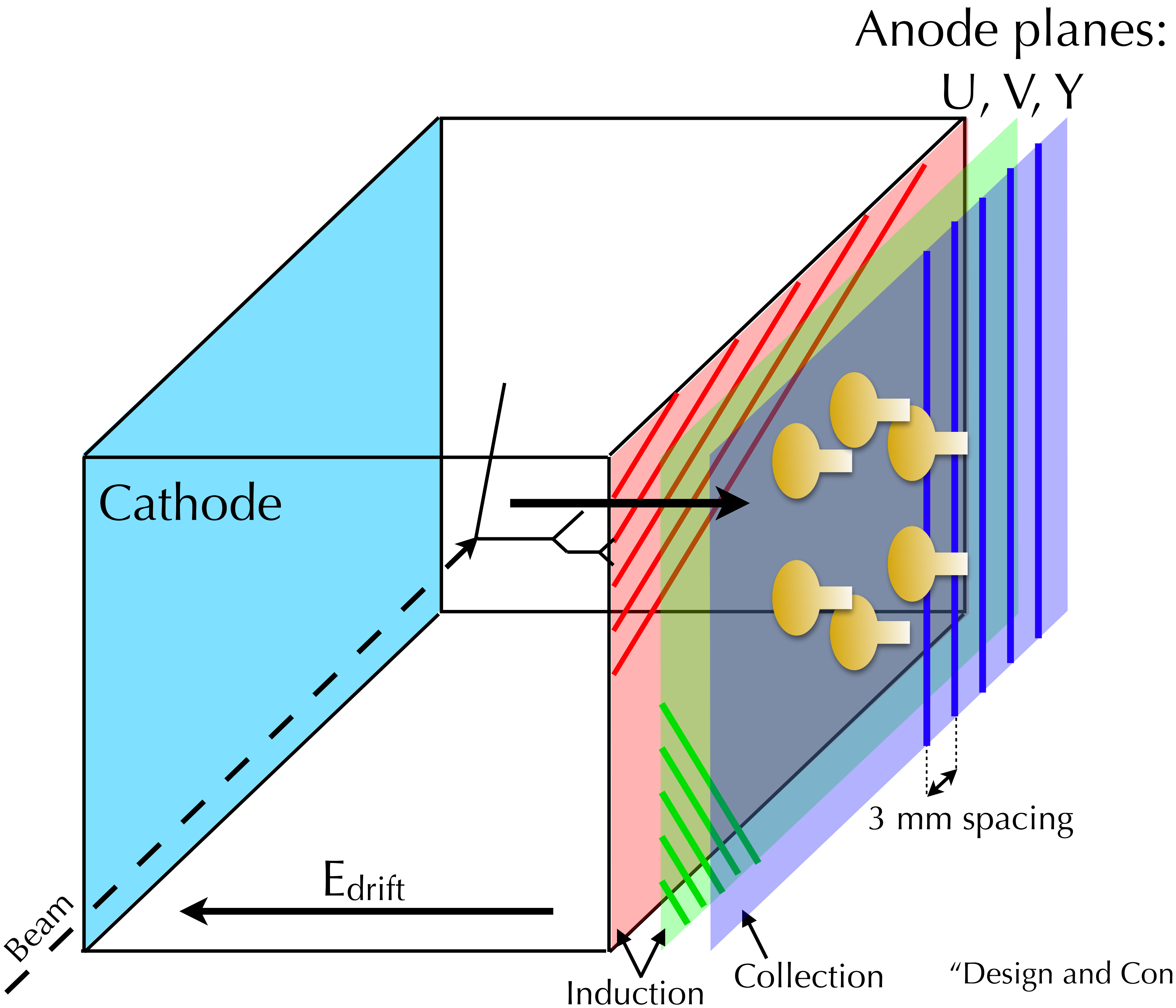
The MicroBooNE Experiment

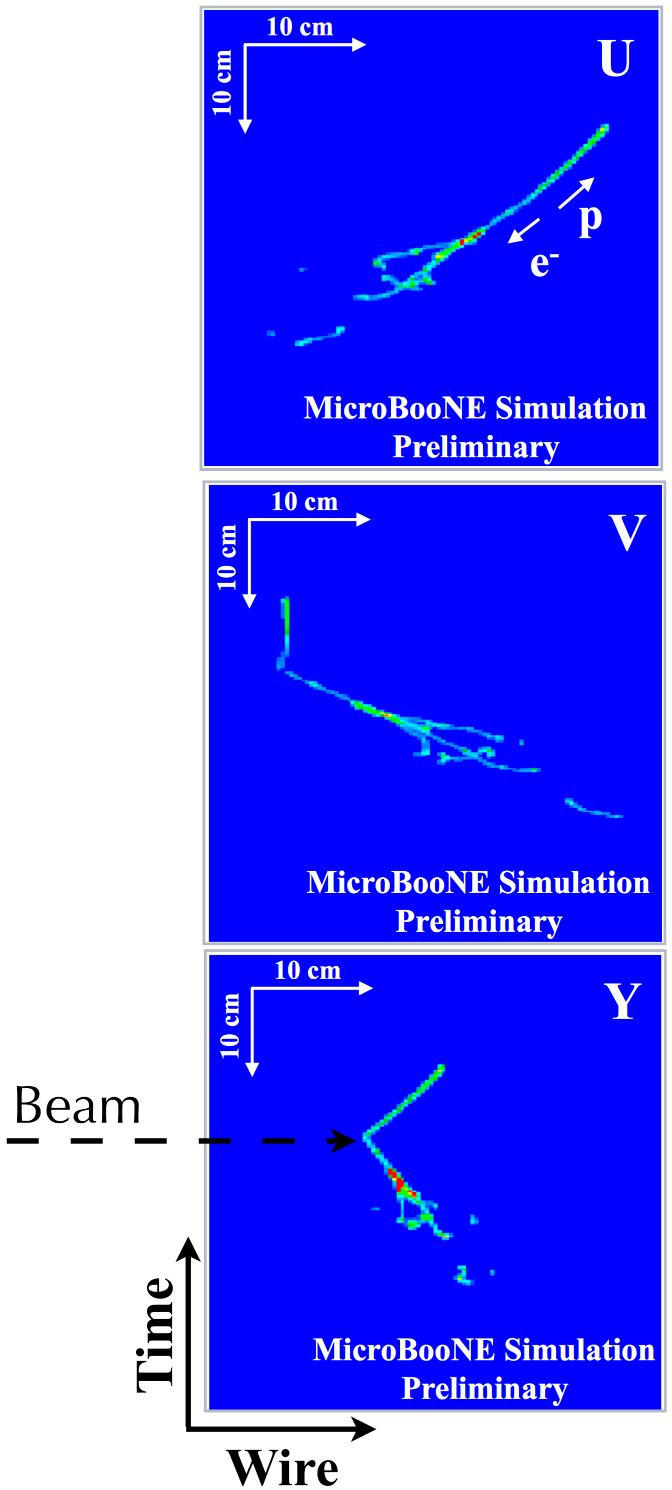




- **Micro Boo**ster **N**eutrino **E**xperiment
- 85 ton (active) **L**iquid **Ar**gon **T**ime **P**rojection **C**hamber
- Located in the Fermilab Booster Neutrino Beam
- $\nu_\mu \rightarrow \nu_e$ appearance experiment
- >95% detector uptime
- 6.1×10^{20} POT on tape in the first 18 months of running, of proposed 6.6×10^{20} POT in three years

The MicroBooNE Detector

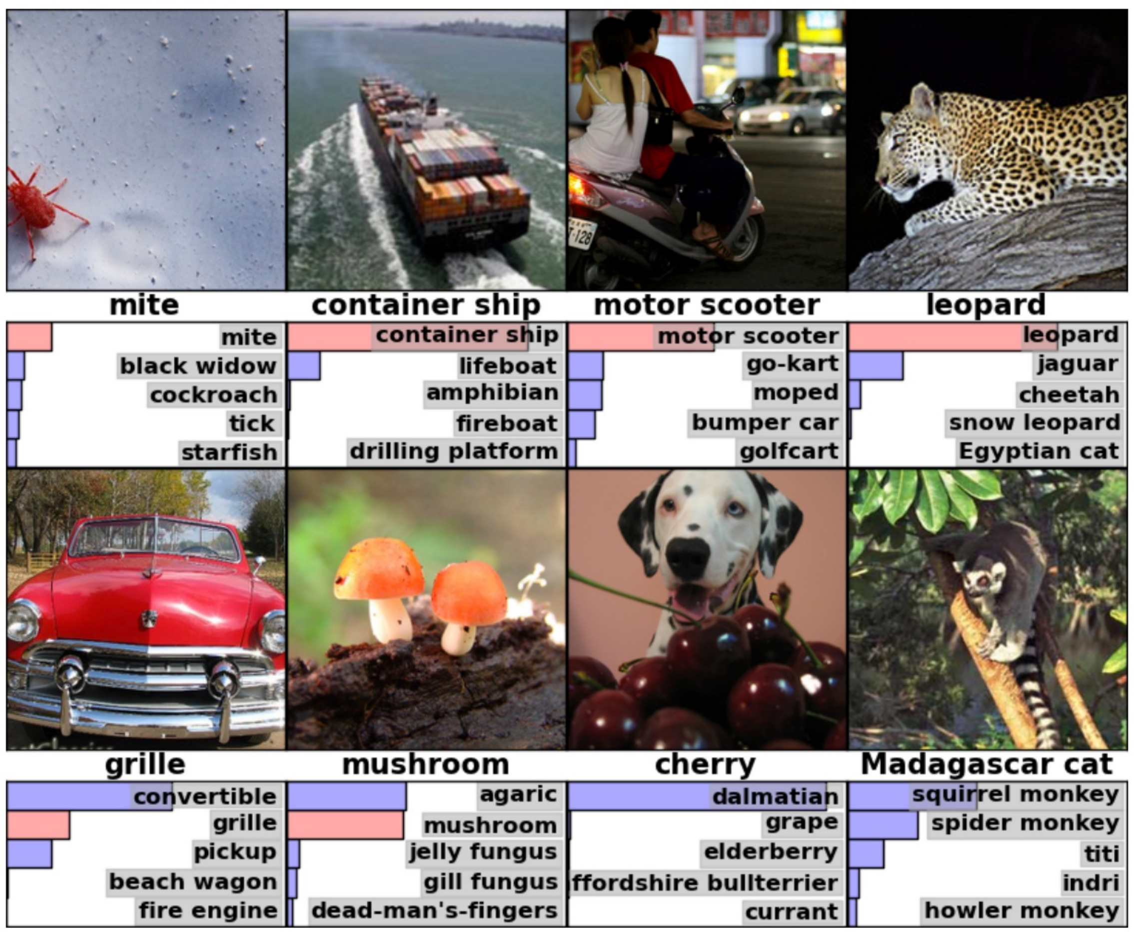




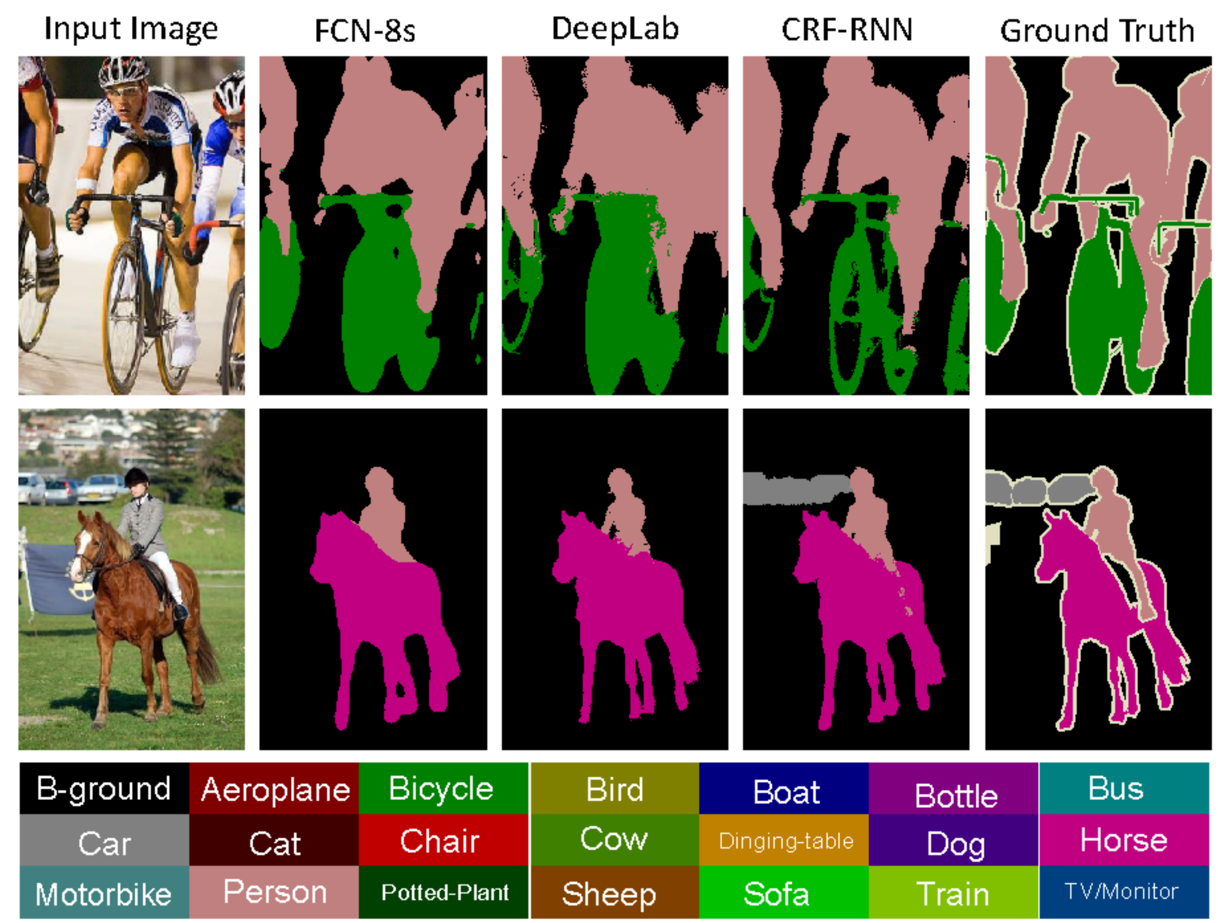
"Design and Construction of the MicroBooNE Detector"
JINST 12, P02017 (2017)

A Few Words About Deep Learning

- For us, deep learning ≈ convolutional neural networks (CNNs)
- CNNs have been developed primarily for image analysis; we apply them to MicroBooNE event displays
  - For more, see T. Wongjirad's talk from Tuesday (here)
- I will discuss two uses: classification and semantic segmentation



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



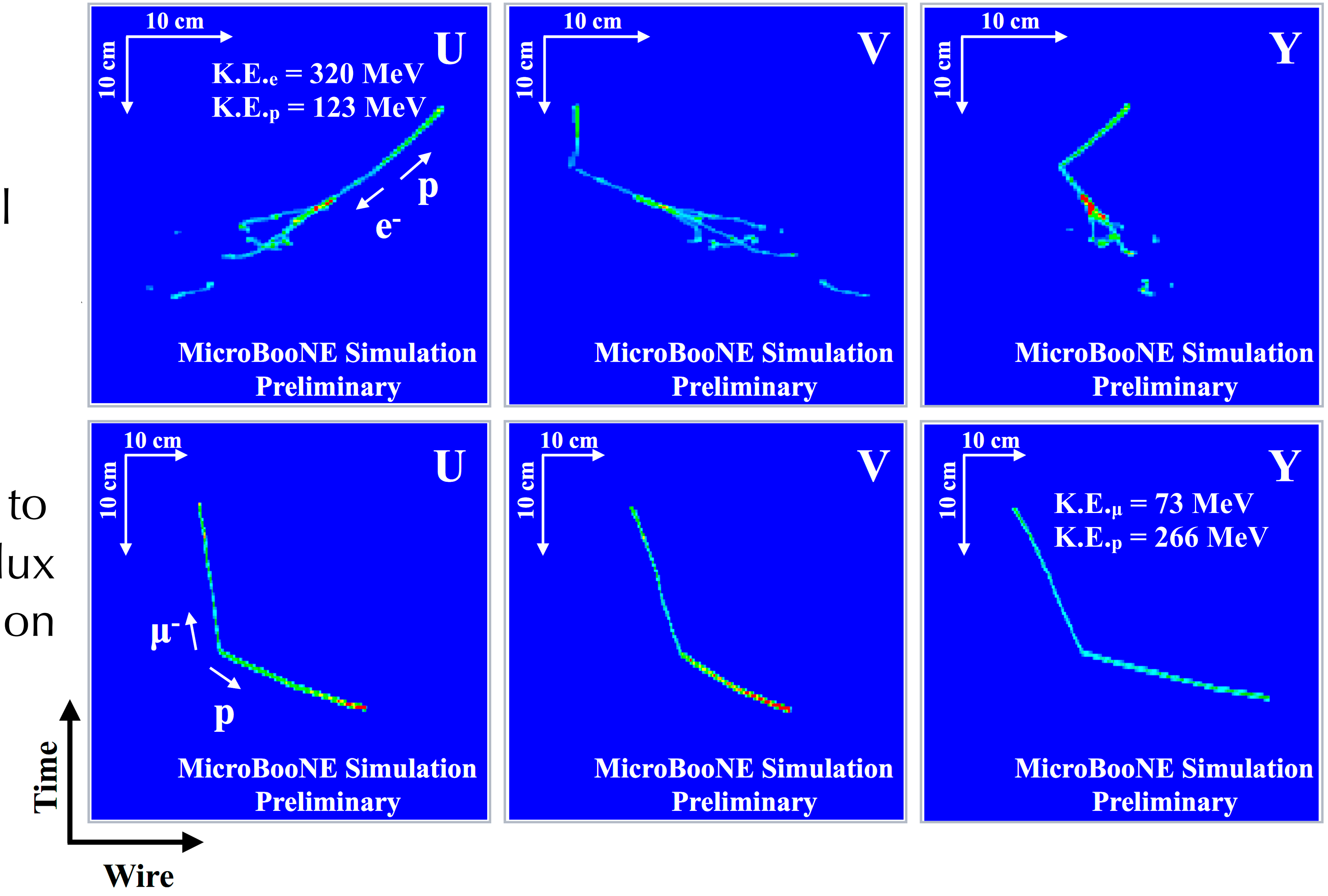
Example of semantic segmentation, from "Conditional Random Fields as Recurrent NNs", ICCV (2015)

Definition of the Signal

- Define signal to be events with one lepton and one proton (1l-1p) topology
  - Lepton (electron or muon) with kinetic energy >35 MeV
  - One proton with kinetic energy >60 MeV (possibly others below that energy threshold)
- These are "golden events" — low background (~only intrinsic ν_e, constrained by ν_μ)

ν_e event: signal

ν_μ event: used to constrain the flux and cross-section systematics



Overview of Reconstruction Chain

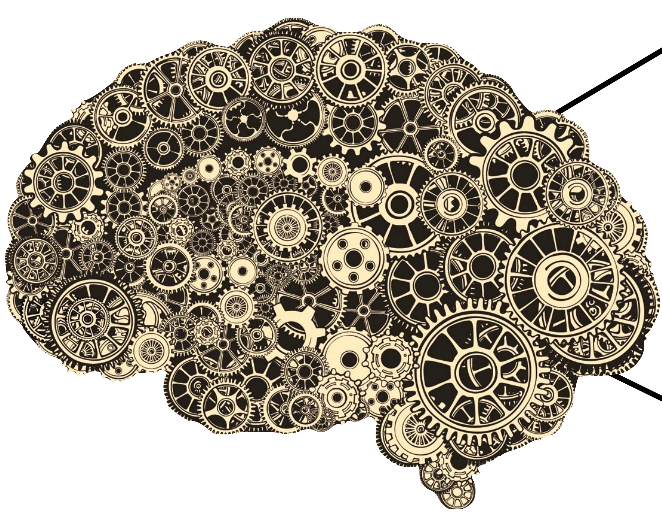
PMT Pre-Cuts

Cosmic Tagging & ROI Finding

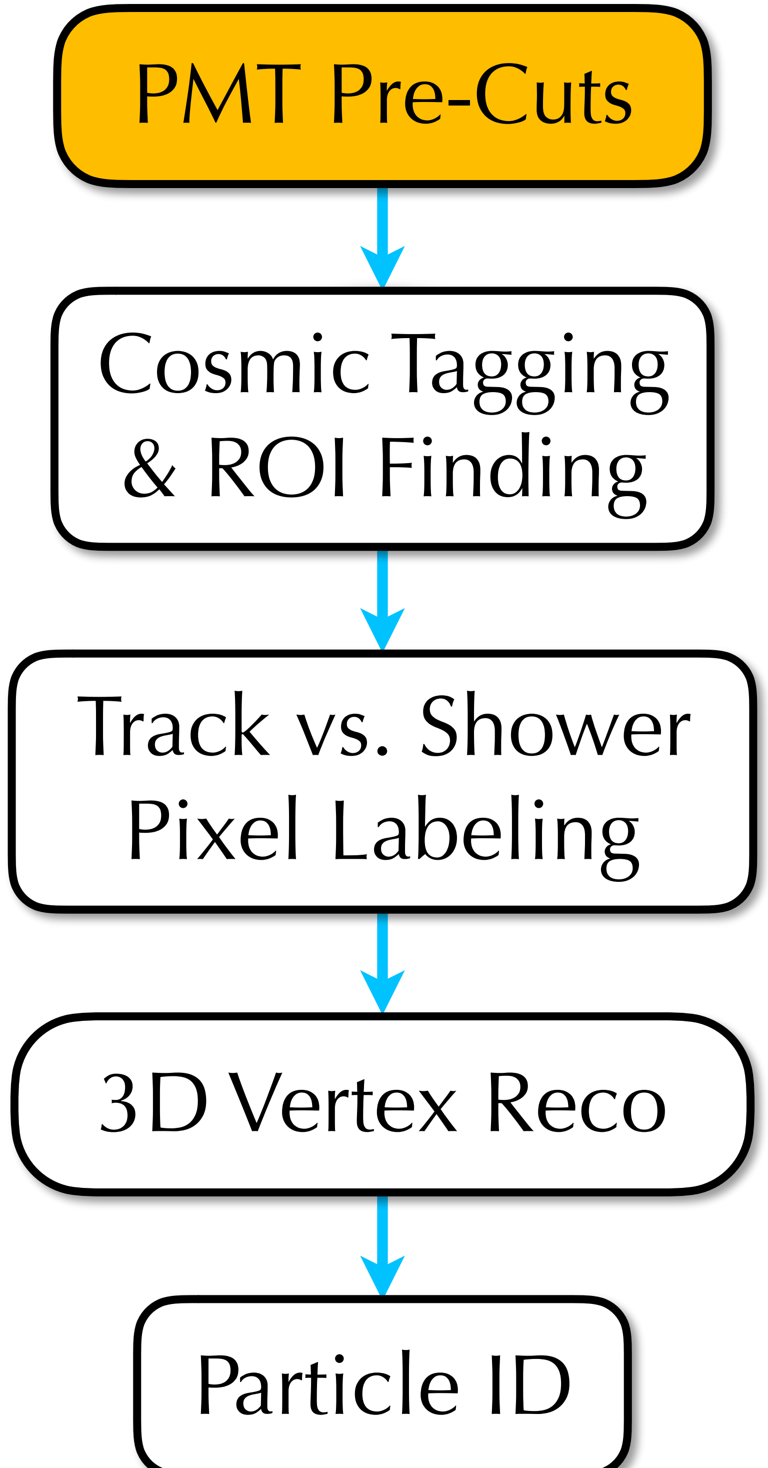
Track vs. Shower Pixel Labeling

3D Vertex Reco

Particle ID



Reconstruction Chain



- PMT pre-cuts reject low-energy noise and other backgrounds
- Keep >96% of neutrinos (based on simulations)
- Reject >75% of background (based off-beam data)

Reconstruction Chain

µBooNE

PMT Pre-Cuts

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Cosmic Tagging & ROI Finding

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Track vs. Shower Pixel Labeling

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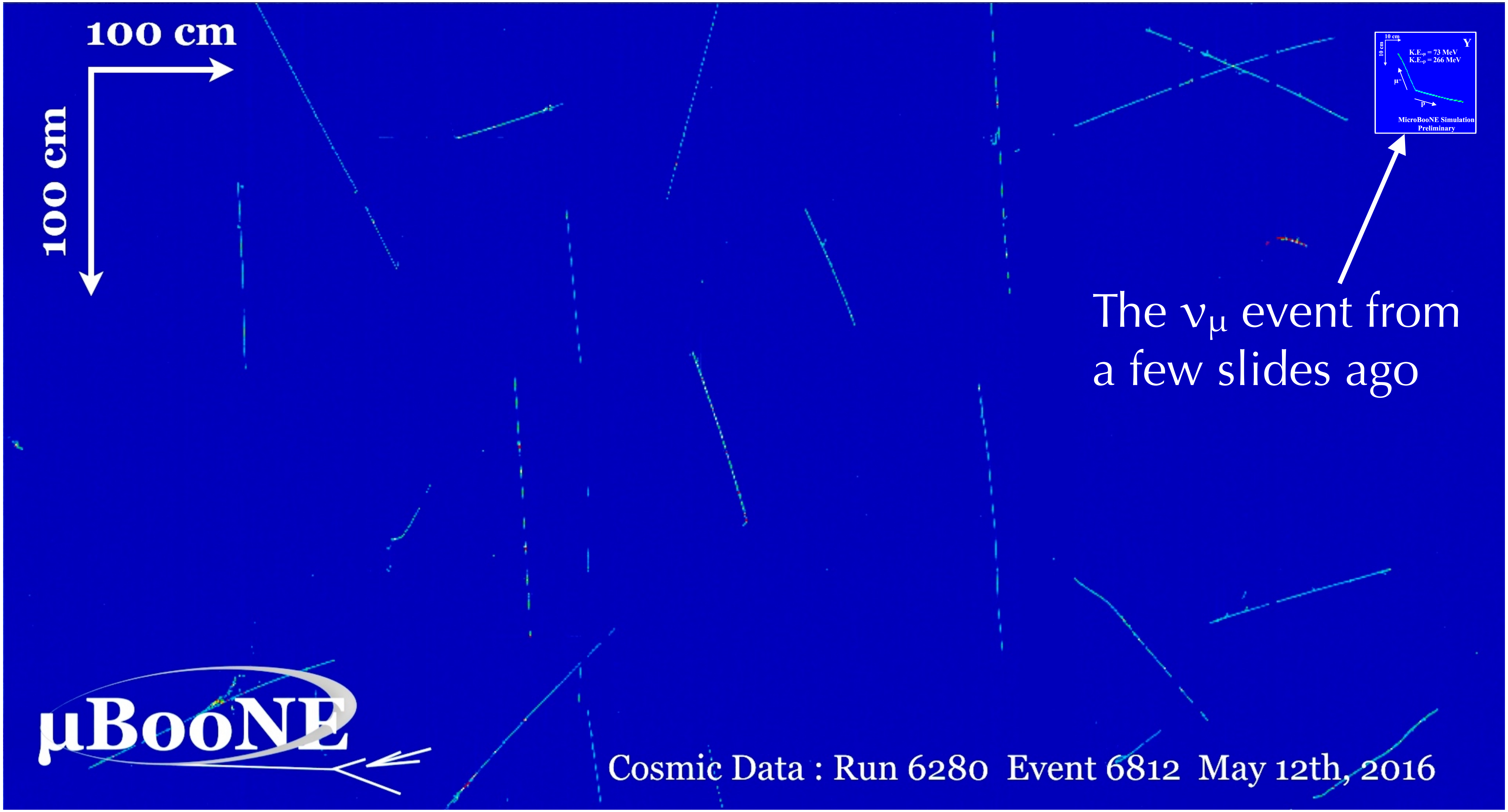
3D Vertex Reco

↓

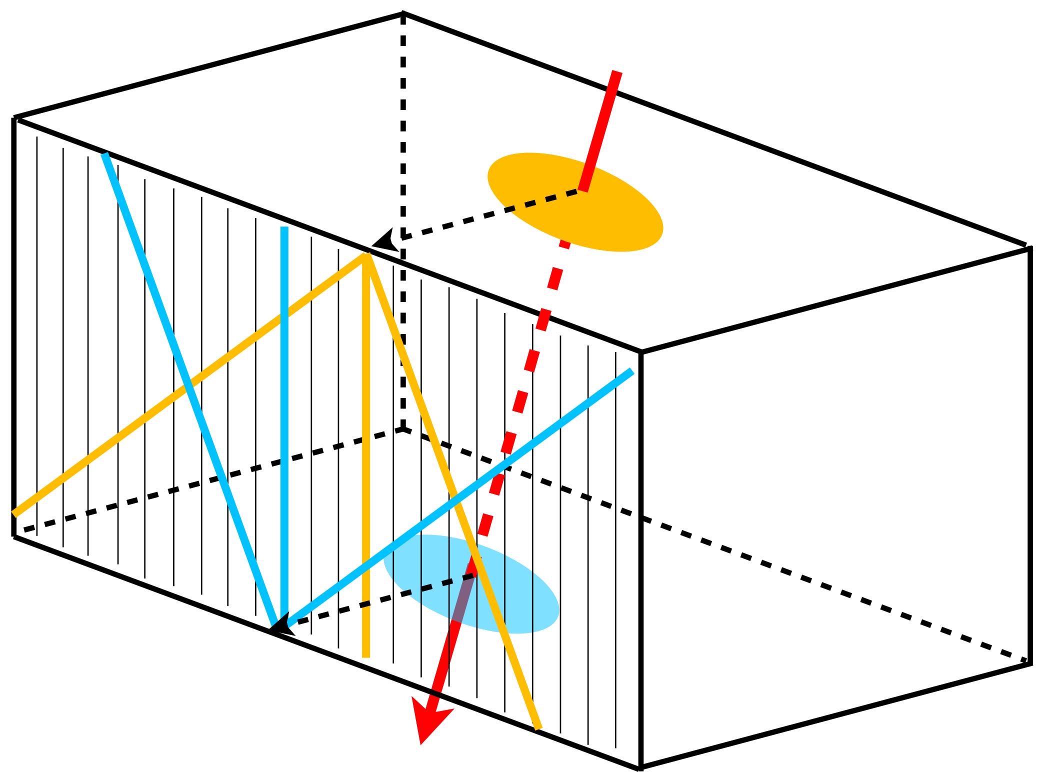
Particle ID

An Event Display



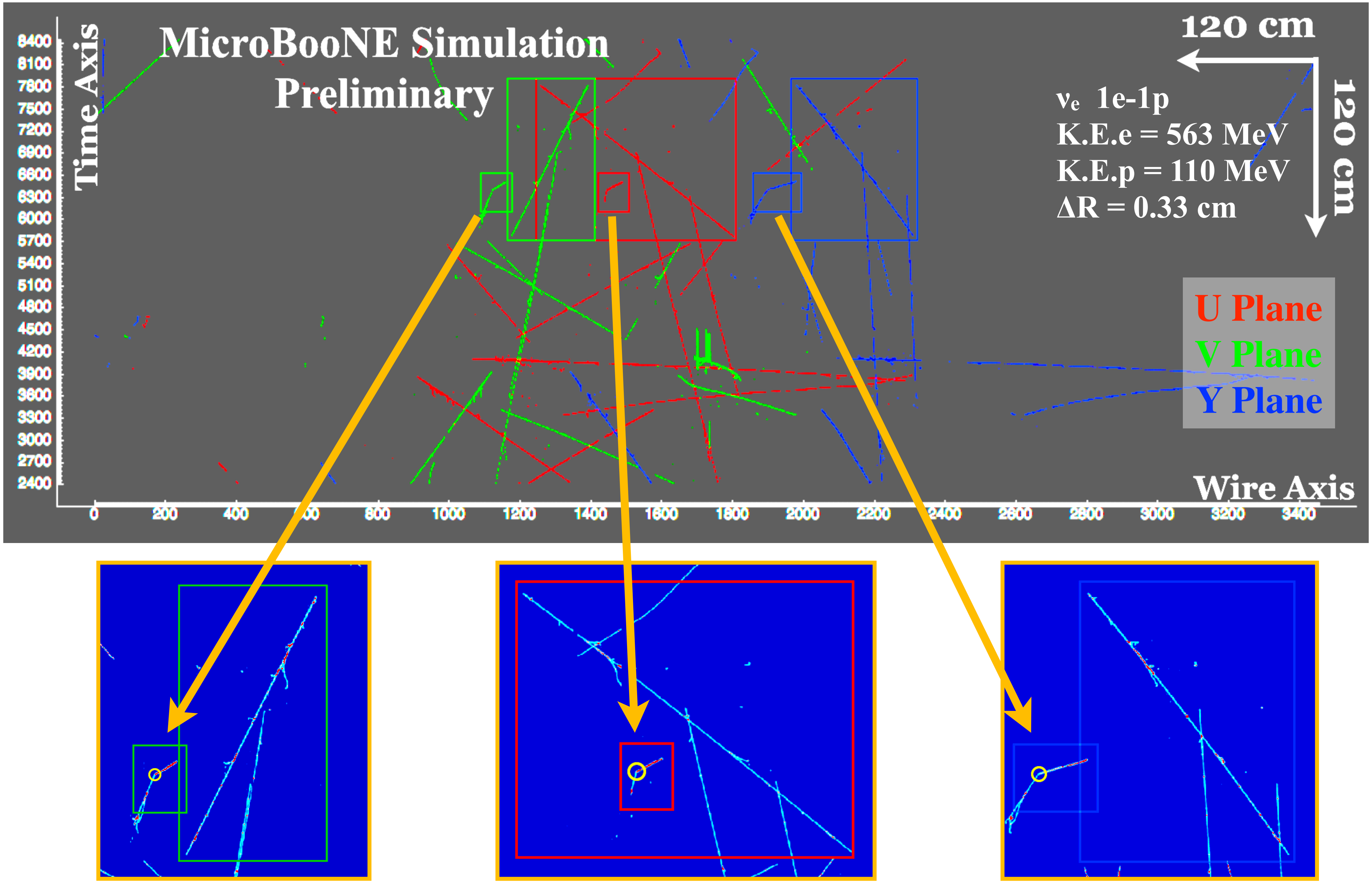
These low-energy neutrino events are small, and we have lots of cosmics

Cosmic Pixel Tagging



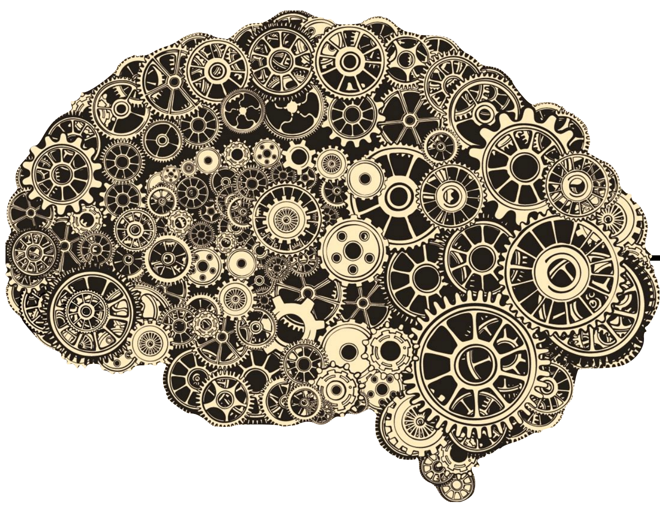
- Cosmic and other background tracks cross the TPC boundary
- Identify and tag these boundary crossing points
  - Top/bottom: crossings deposit charge on triplets of wires that meet at the boundary
  - Upsteam/downsteam: crossings deposit charge on the first/last wires on the Y plane
  - Anode/cathode: crossings have specific ΔT between PMT flash and wire signal
- Build up from end points by following charge using 3D path finding

Region-of-Interest Finding



After tagging cosmic tracks, draw 3D region-of-interest (ROI) box around untagged pixels

Reconstruction Chain



PMT Pre-Cuts

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Cosmic Tagging & ROI Finding

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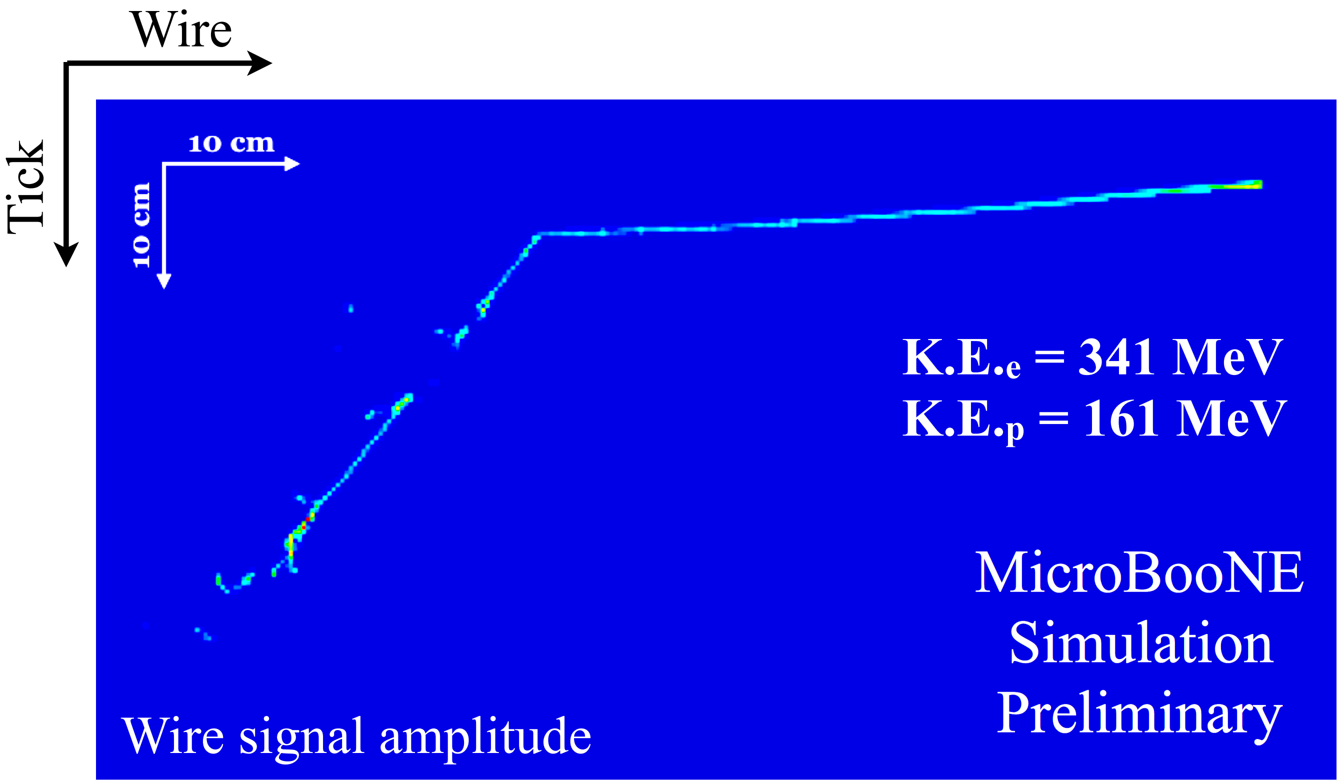
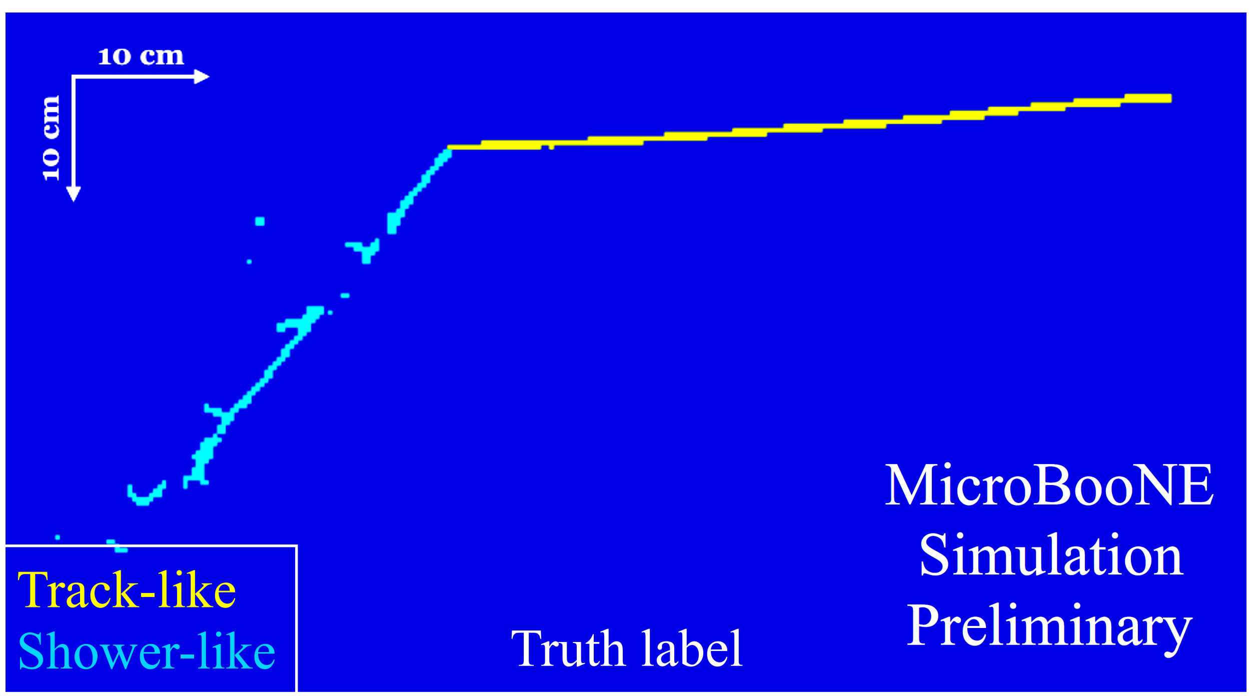
Particle ID

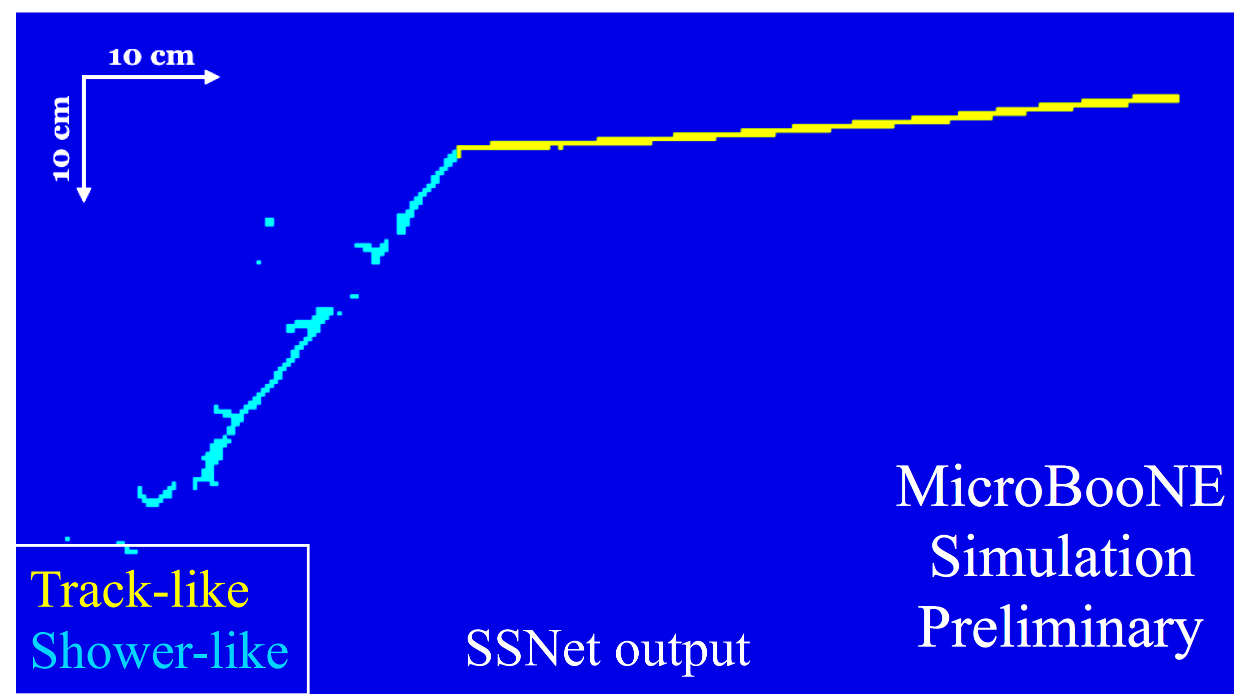
Track vs. Shower Pixel Labeling

µBooNE



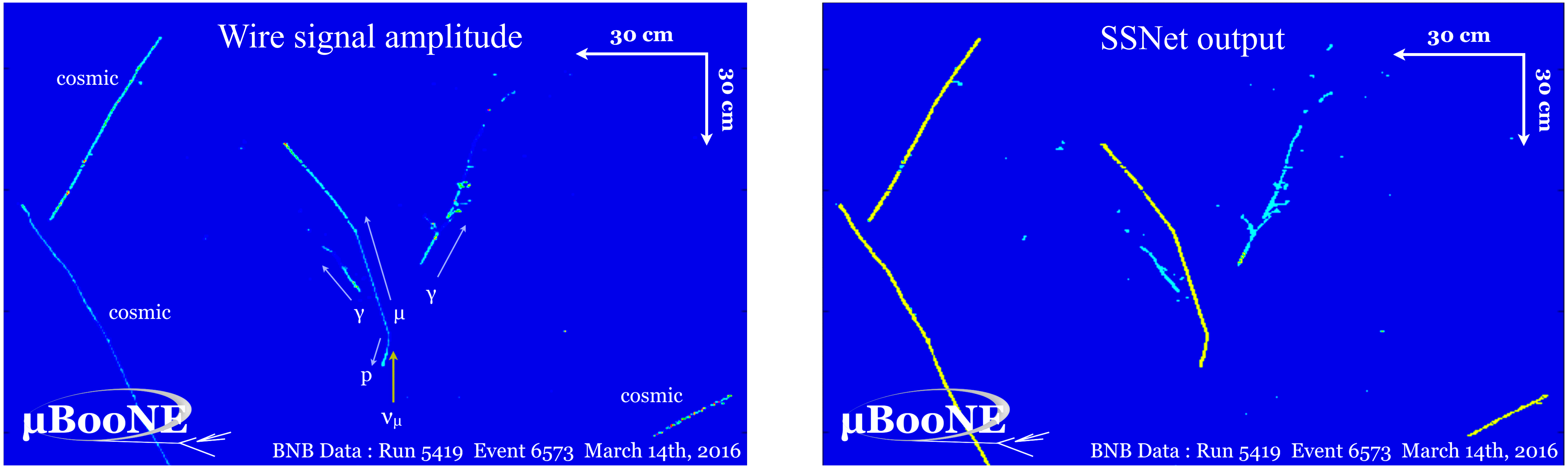
- Goal: separate tracks and showers to make the 3D vertex reconstruction and track/shower clustering more efficient
- Semantic segmentation network (SSNet) takes in the wire information and labels each pixel in the image as "track-like" (yellow), "shower-like" (cyan), or "background" (blue)





SSNet Performance on Data

- To study the performance of SSNet on data, we ran over a sample of selected CC π^0 events
  - "Study Towards an Event Selection for Neutral Current Inclusive Single π^0 Production in MicroBooNE", MicroBooNE Public Note MICROBOONE-NOTE-1006-PUB
- Here, the proton and muon are correctly labeled as track-like
- The two γ showers are correctly labeled as shower-like, except the beginning "stub" of one is labeled as track-like
- Overall, SSNet pixel labeling accuracy >90%



Reconstruction Chain

PMT Pre-Cuts

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3D Vertex Reco

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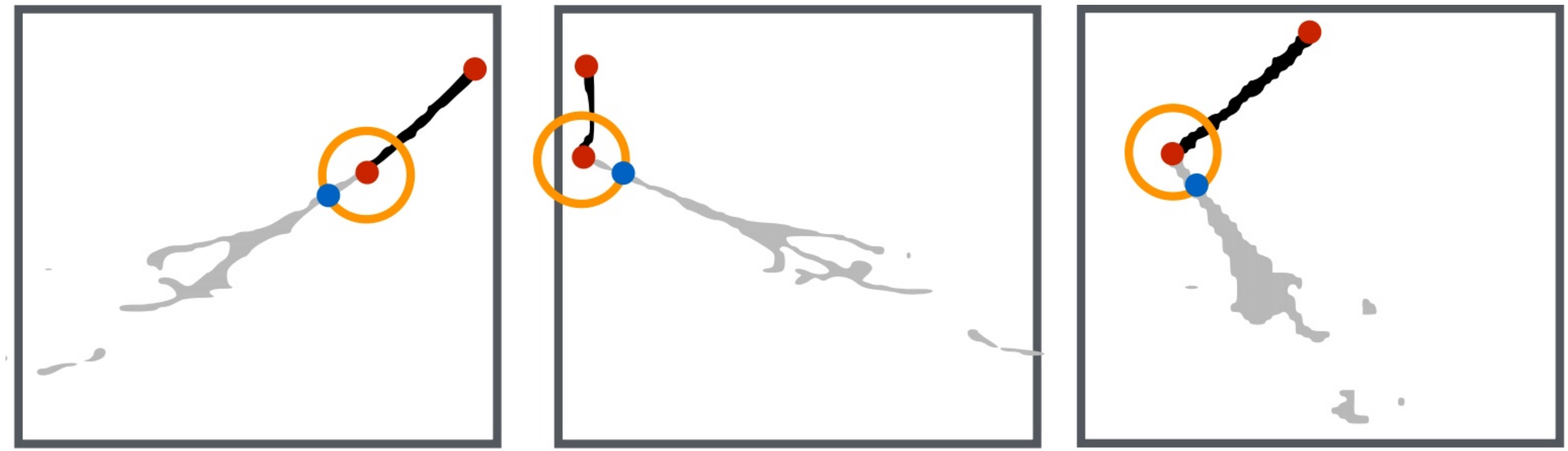
Particle ID

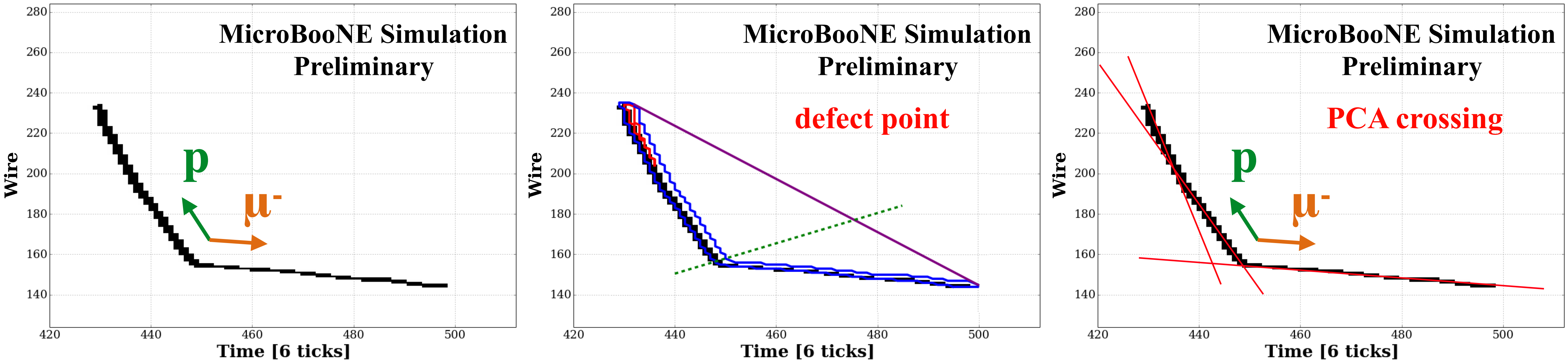
3D Vertex Reconstruction



If both track-like and shower-like pixels are found (e.g., a ν_e event):

- For each plane: find endpoint of track where shower is attached
- Correlate these endpoints across planes to identify 3D region
- Scan 3D space around the candidate vertex
- Add a vertex at the 3D point that best matches where the track and shower meet across all three planes

3D Vertex Reconstruction



If there are only track-like pixels (e.g., ν_μ normalization sample):

- For each plane: create 2D vertex seeds at any kink points
- Scan space around each seed to find the best vertex point
- Combine information from all three planes
- If the best vertices from each plane are 3D-consistent, add a vertex at that 3D point

Reconstruction Chain

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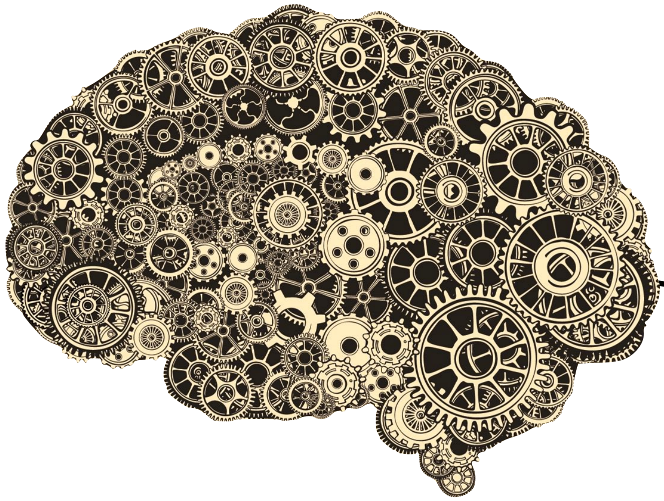
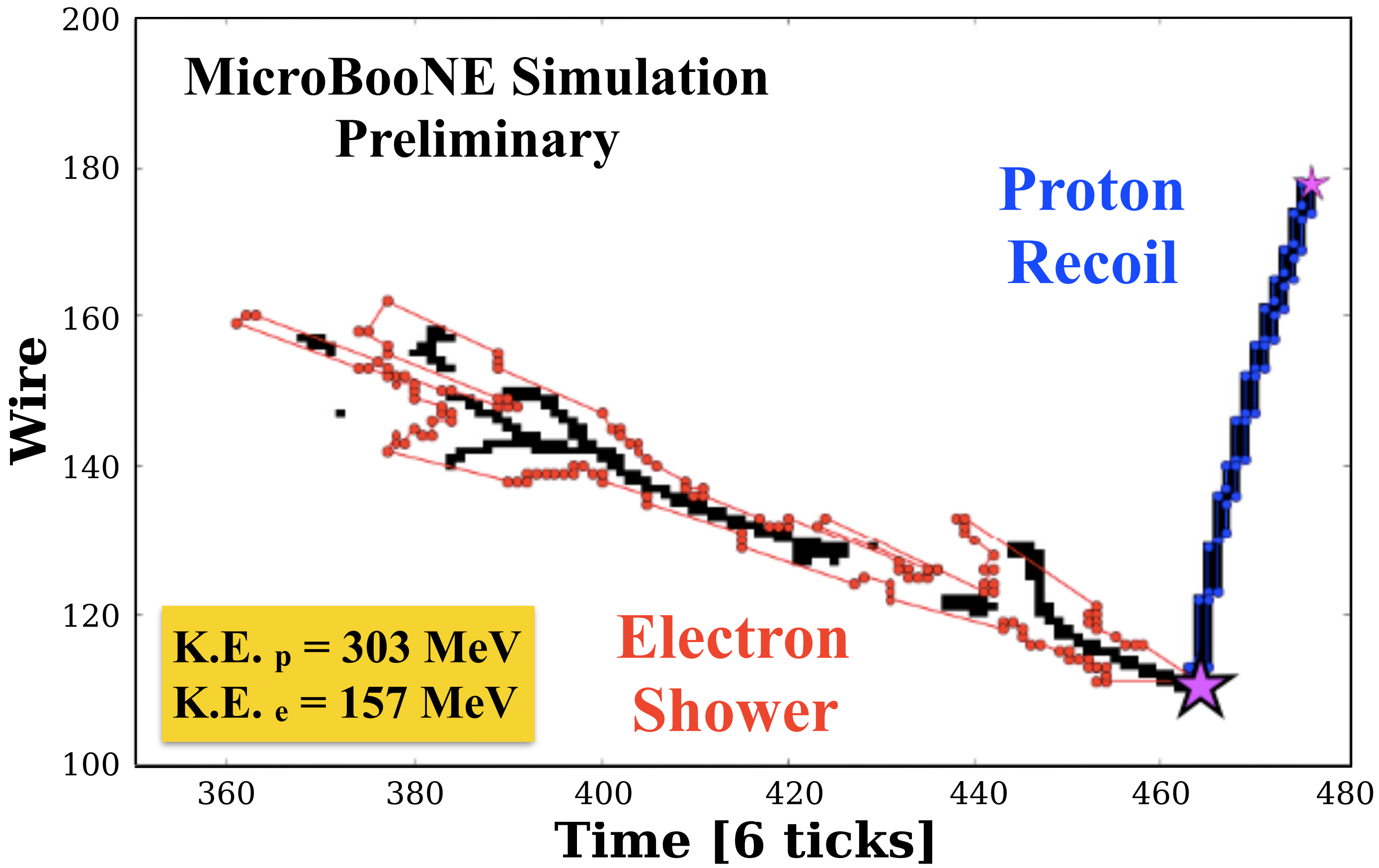


Particle Identification

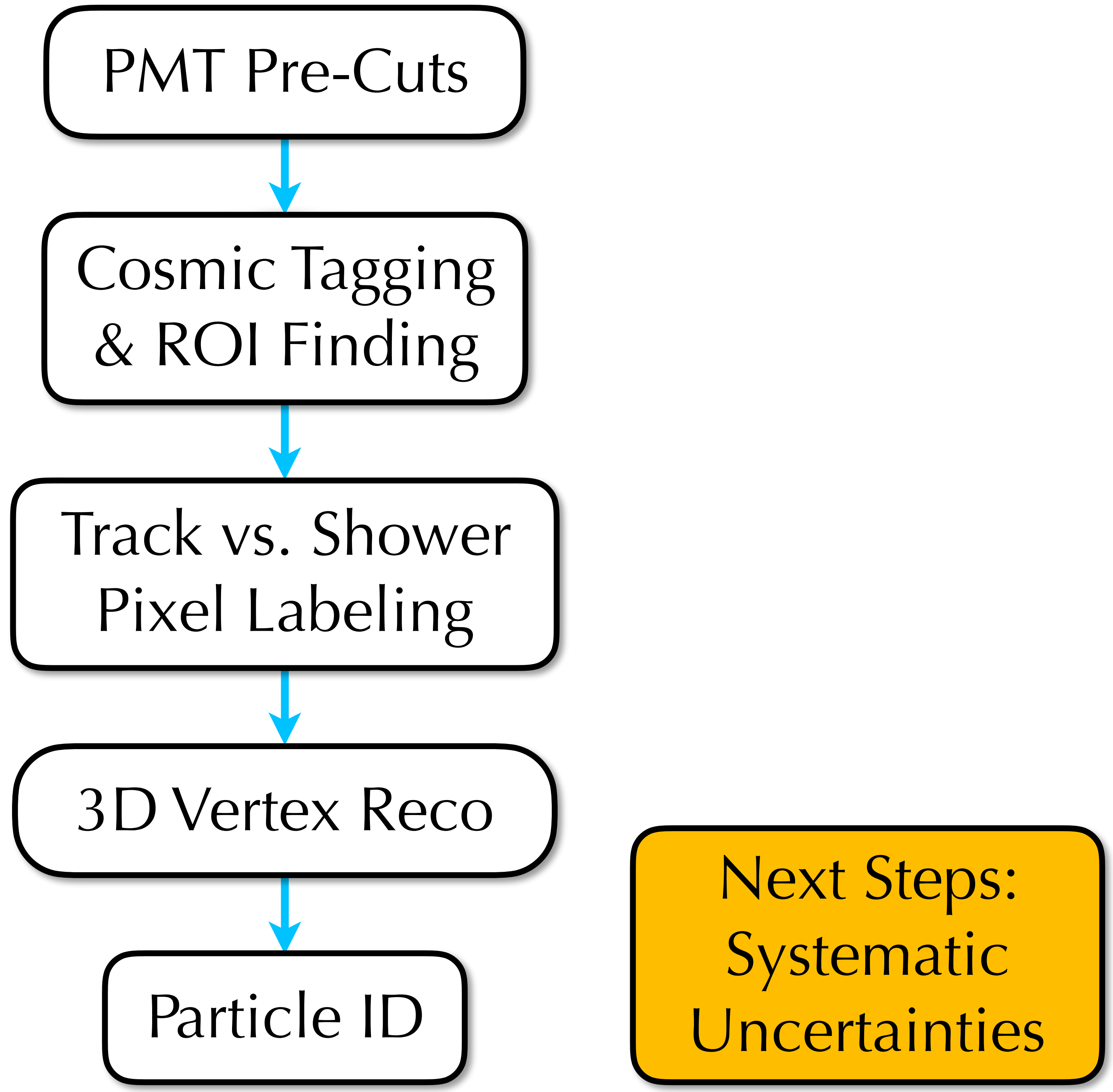
μBooNE



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

- After 3D vertex reconstruction, cluster pixels attributed to each single track or shower coming out of the vertex
- Feed individual particle clusters into a CNN trained to do single-particle identification (HighRes GoogLeNet)
- Led to MicroBooNE's first collaboration publication!
  - "Convolutional Neural Networks Applied to Neutrino Events in a LArTPC", JINST 12, P03011 (2017)

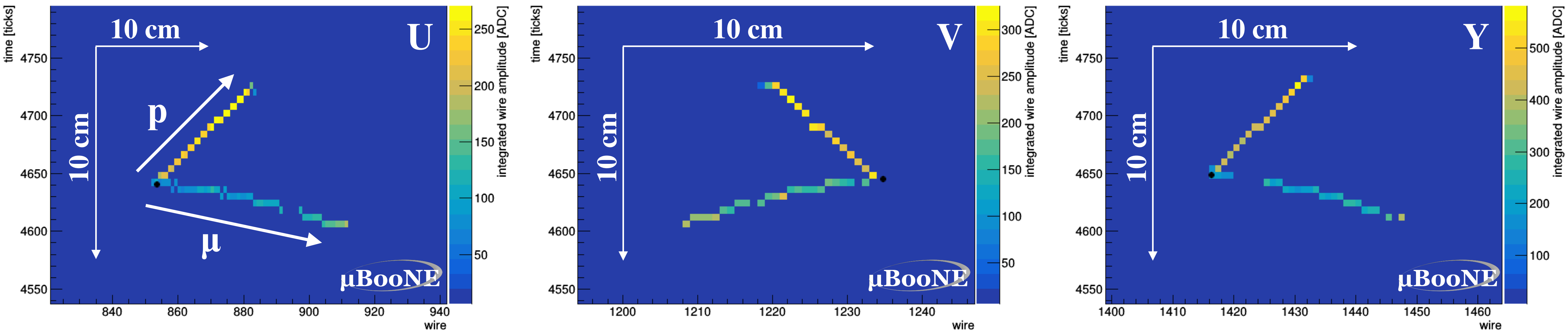
Reconstruction Chain



Topological Sidebands

- In general, a "sideband" study uses events that are outside the "analysis box" but have important similarities to events inside it
- Typically, use events that are similar in their kinematics — instead, we consider events that are similar in topology
- In particular, we want to draw sidebands from data to help us understand CNN performance on simulations vs. detector data
- We plan to use these samples to:
  - Test simulation vs. data agreement
  - Study efficiencies
- Examples of topological sidebands
  - CC π^0 — has a 1μ-1p vertex like ν_μ events; already used to test SSNet
  - NC π^0, where one photon converts near the vertex — has 1e-1p topology like ν_e
  - Stopping muons — track + EM shower topology, like ν_e
  - "Chimera" events

Chimera Events

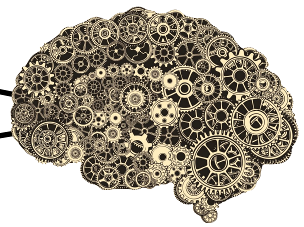


- Chimera events are made by "copy-pasting" single-particle components from cosmic ray data that are selected and combined to create neutrino-like events (in terms of topology)
  - Use proton and stopping muon for ν_μ, proton and electron (or EM shower) for ν_e
  - Allow for but want to minimize spatial translation; do not allow rotation
  - Truncate the entering portion of muon tracks, so they appear contained within the fiducial volume of the detector
- They can provide a sample of data-based events that cover the entire physics parameter space of interest for our signal
- Above: One of the first ν_μ-like chimeras

Summary

μBooNE

- Fully automated reconstruction chain for low-energy neutrino events, which includes traditional and deep learning algorithms
  - Reject cosmic backgrounds
  - Find the neutrino interaction within the event
  - Separate tracks and showers, cluster
  - Reconstruct 3D vertex
  - Identify individual particles

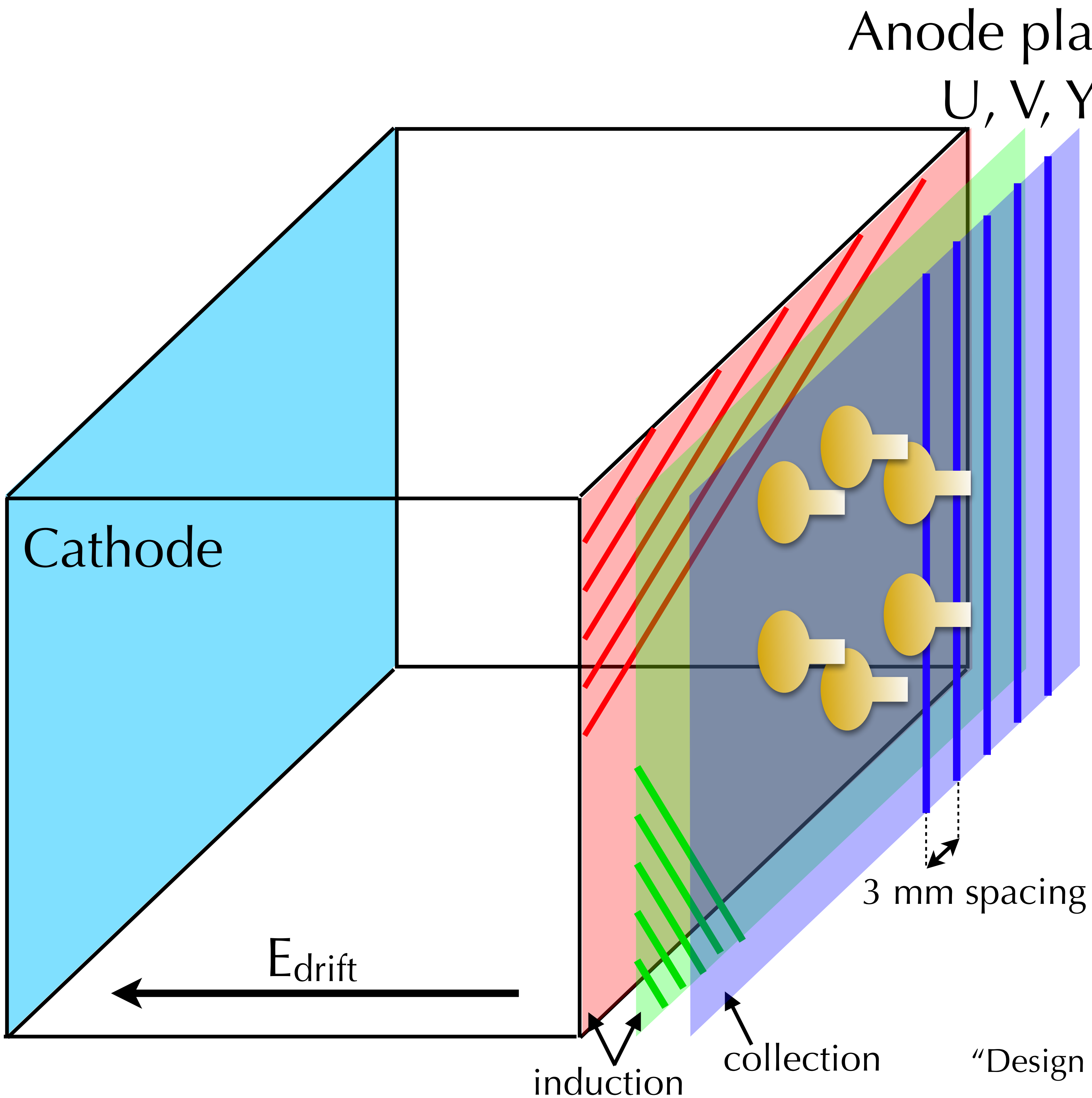


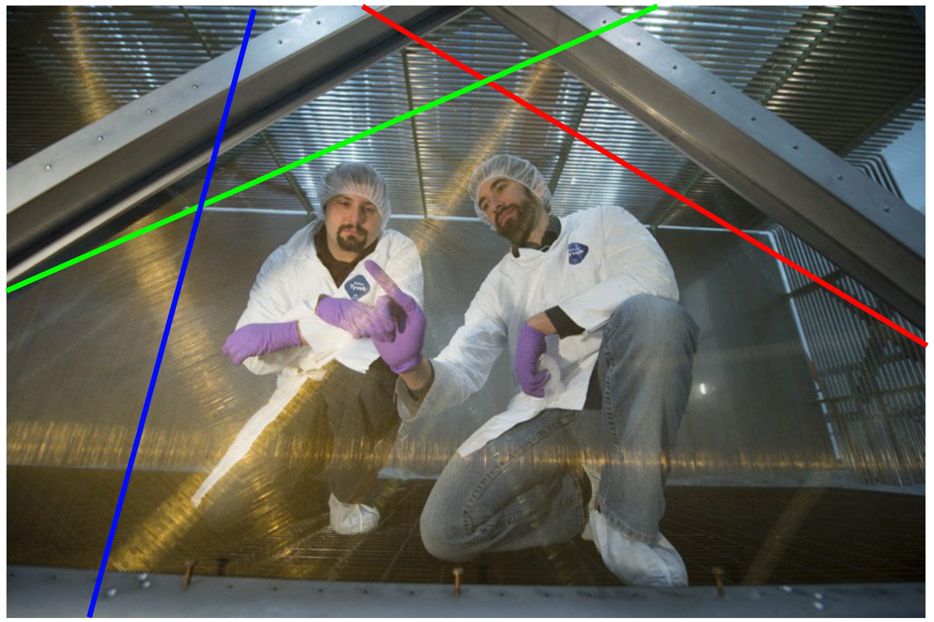
- Full 3D reconstruction in progress
  - dE/dx, event selection
  - Physics!
- Efficiency and systematics studies in progress
- Important development for upcoming LArTPC programs

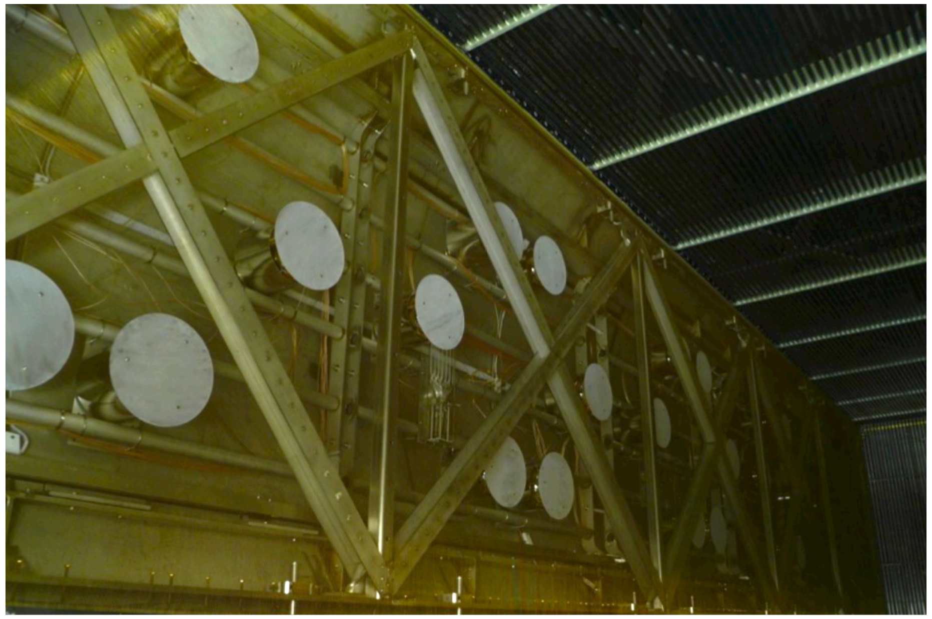
Thank you!

Backup Slides

The MicroBooNE Detector







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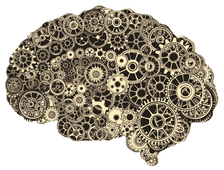
A Few Words About Deep Learning

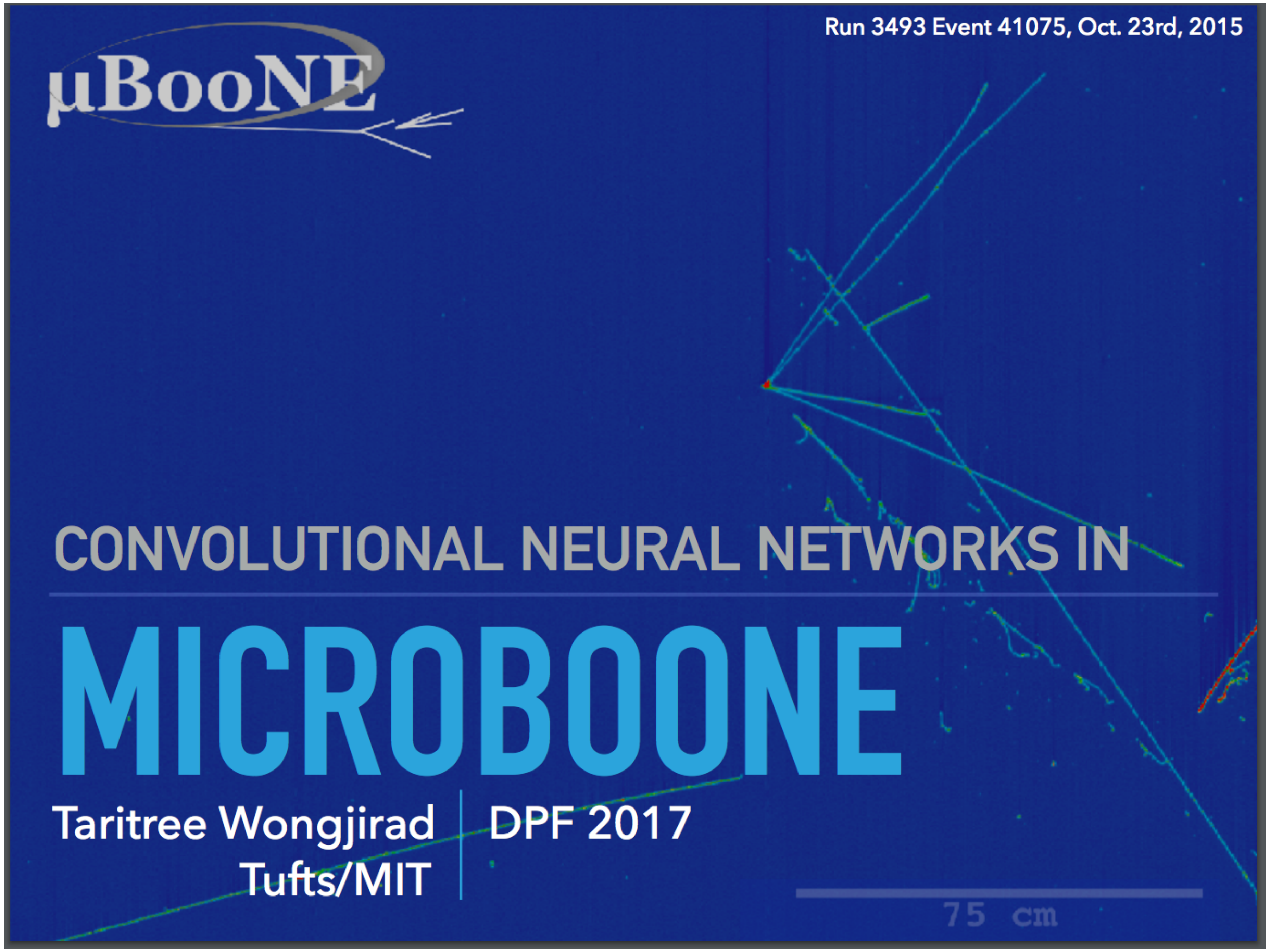


https://www.youtube.com/watch?v=AgkfIQ4IGaM

- 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

More on Deep Learning

- See T. Wongjirad's talk from Tuesday (here)



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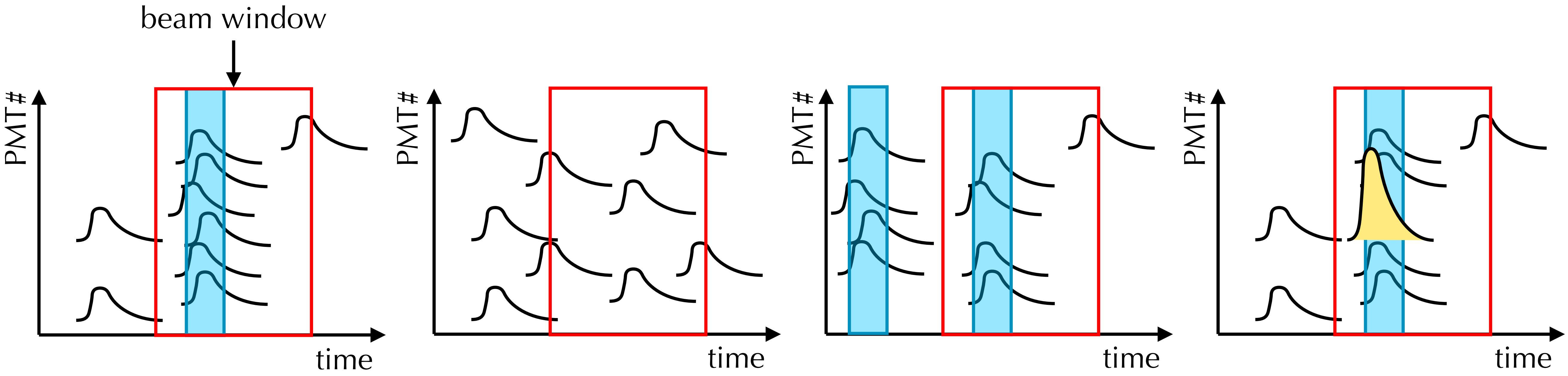


Keep: All possible neutrino events

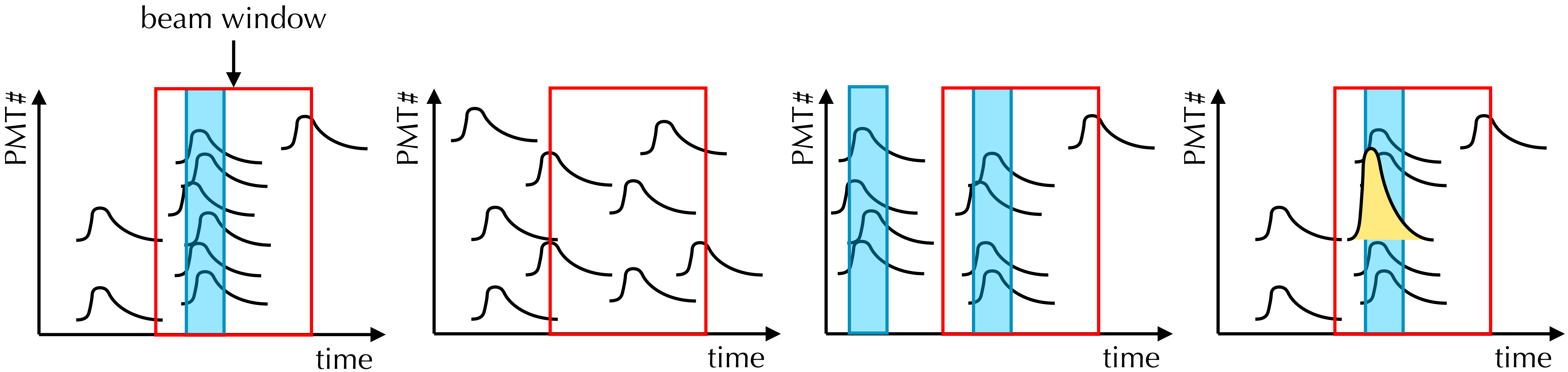
Reject: Random, single-photoelectron noise

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

Reject: PMT-based noise

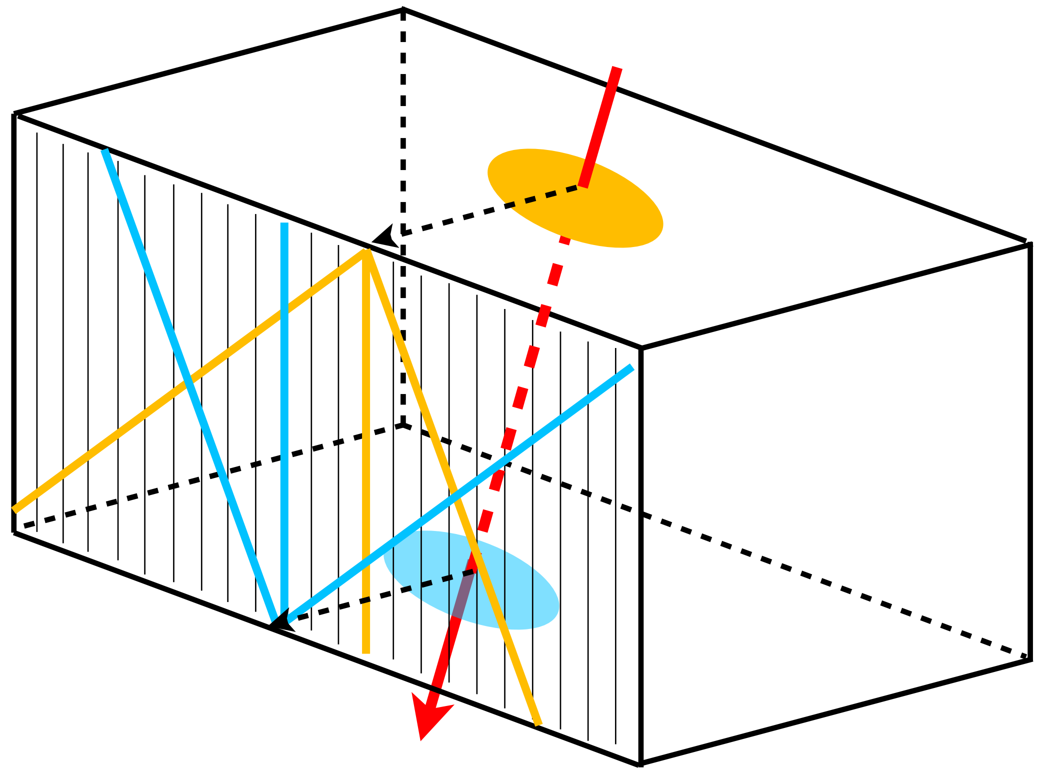
- Keep >96% of neutrinos (based on simulations)
- Reject >75% of background (based on rejection of off-beam data)

PMT Pre-Cuts



- 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)

Cosmic Pixel Tagging



- Cosmic and other background tracks cross the TPC boundary
- Identify and tag these boundary crossing points
  - **Top/bottom**: crossings deposit charge on triplets of wires that meet at the boundary
  - Upsteam/downsteam: crossings deposit charge on the first/last wires on the Y plane
  - Anode/cathode: crossings have specific ΔT between PMT flash and wire signal
- Connect end points by following the charge using 3D path finding

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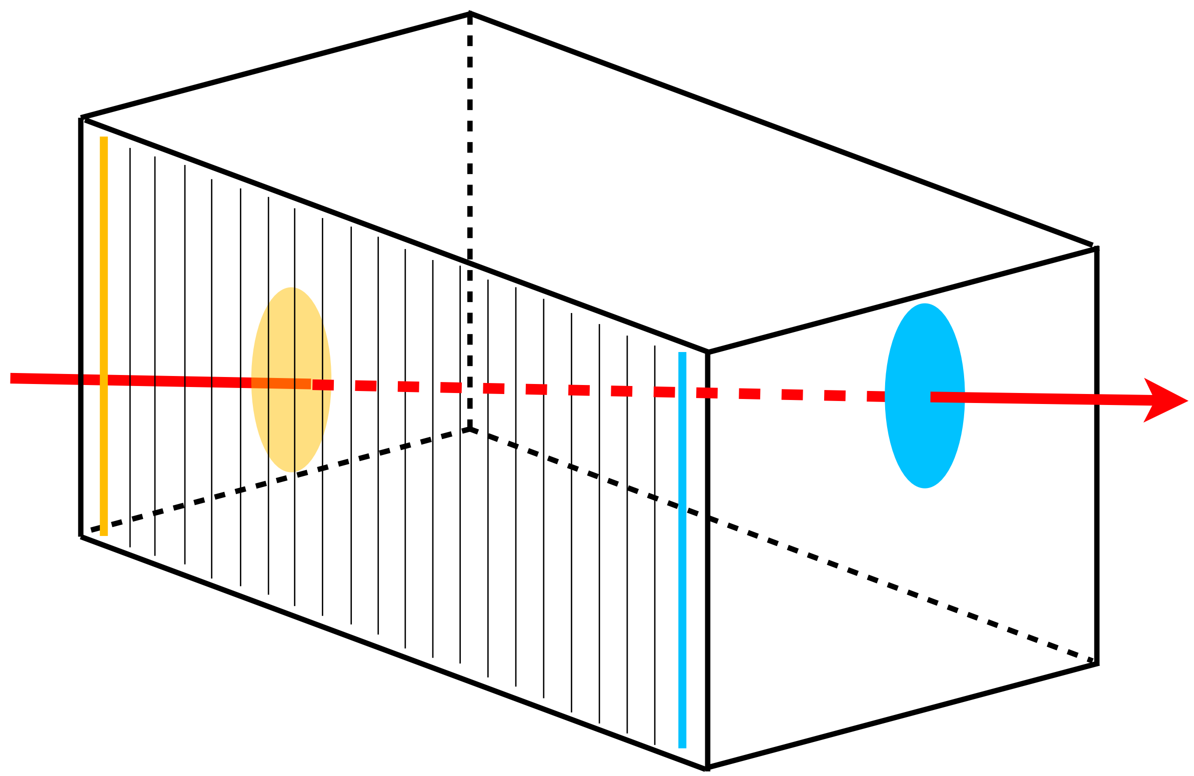

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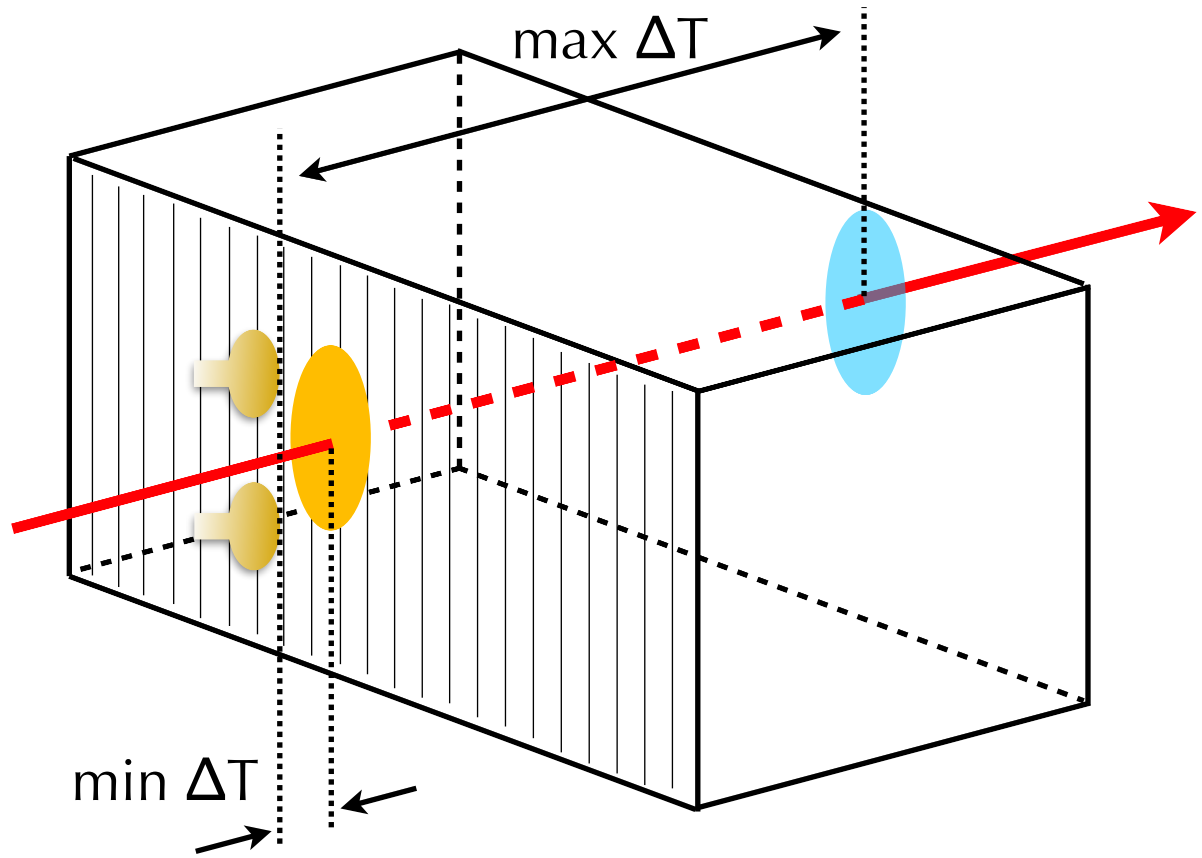

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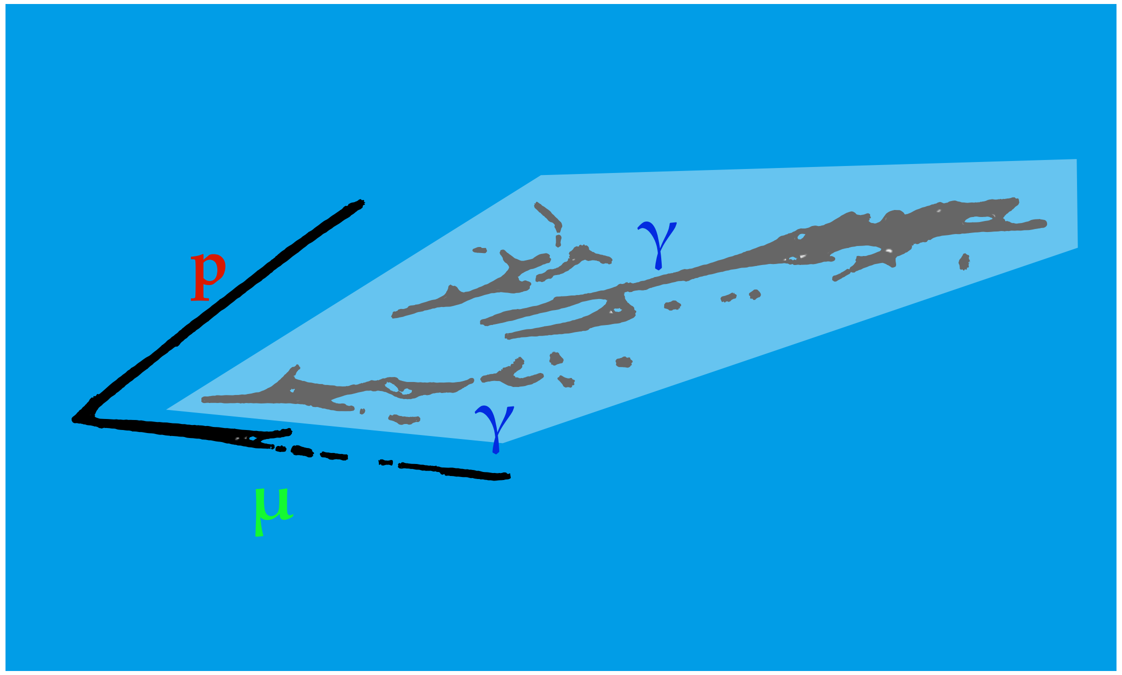
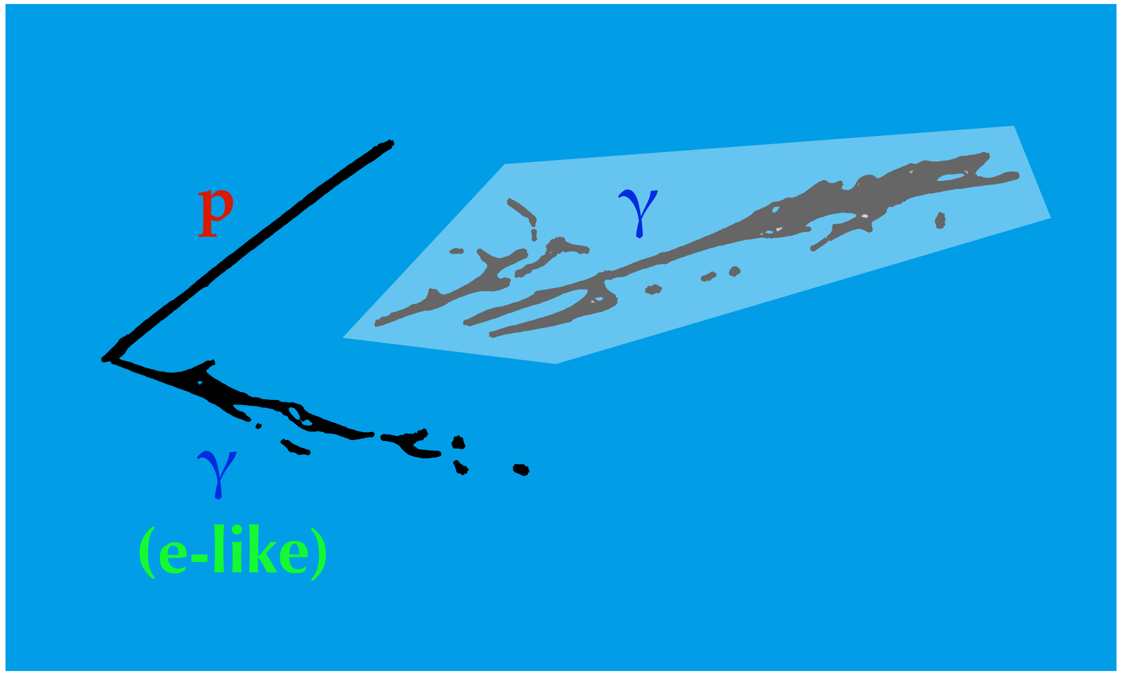
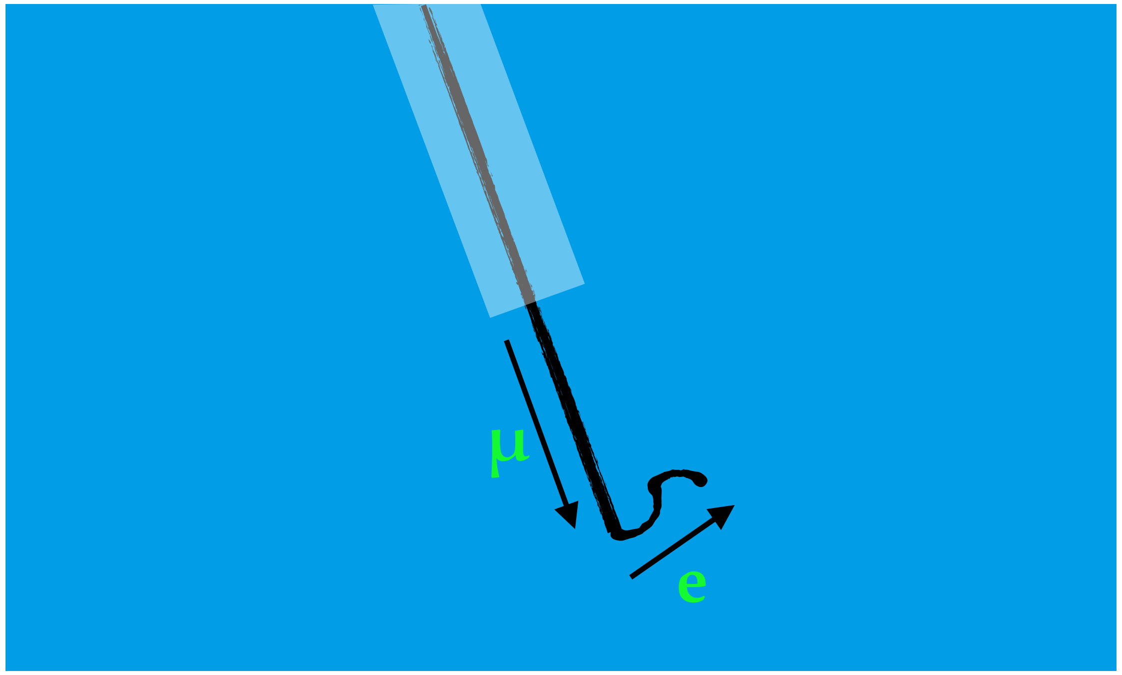
Examples of Topological Sidebands



CC π^0



NC π^0, one γ converts near vertex



Truncated stopping muon