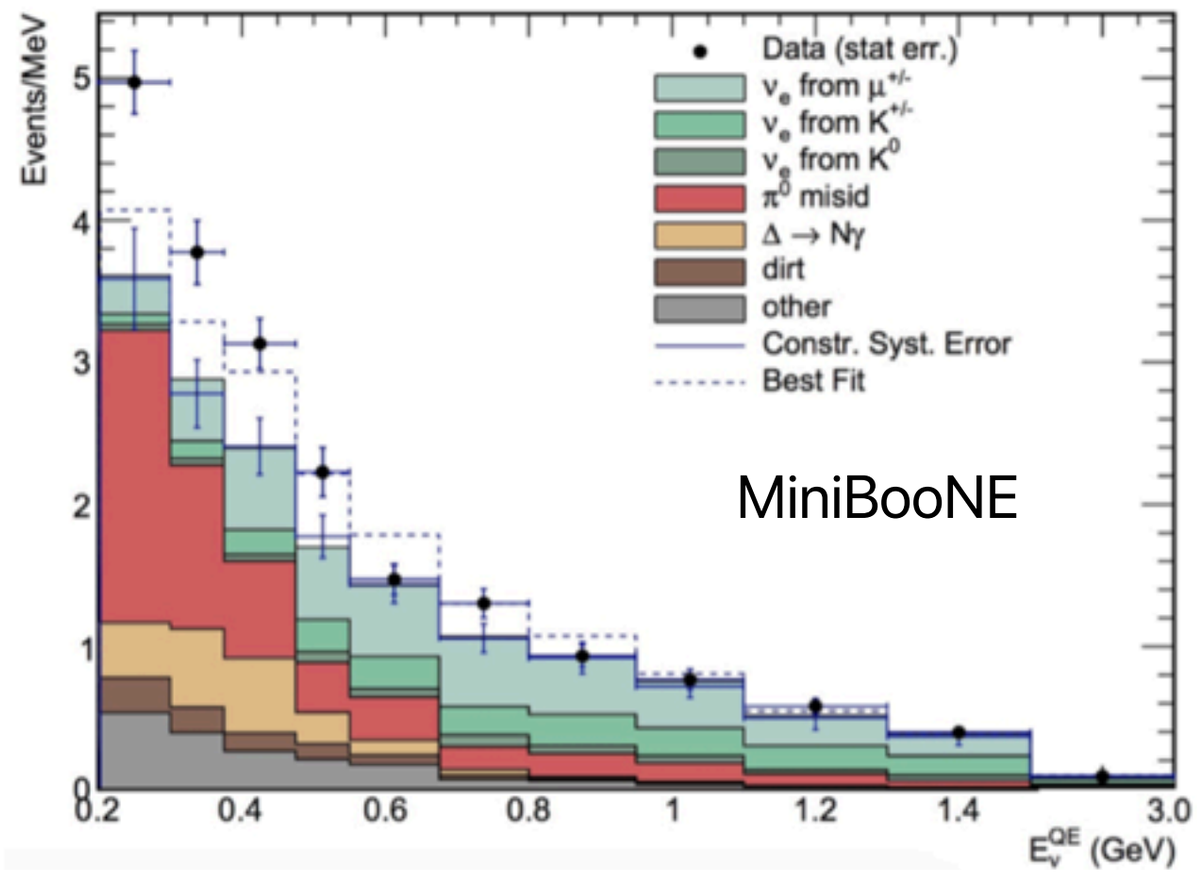
Status Of The MicroBooNE LEE Search And Application Of Deep Learning To LArTPC Data

R. SHARANKOVA TUFTS

The Neutrino LEE Search At Short Baselines



Phys. Rev. Lett. 121, 221801 (2018)

- MiniBooNE observed ν_e-like excess at low energy (LEE) hinting at physics beyond standard neutrino oscillation
- MicroBooNE is a LArTPC experiment aimed at probing the LEE observed by MiniBooNE with same neutrino beam
  - look for ν_e at 200-600 MeV

MicroBooNE Experiment

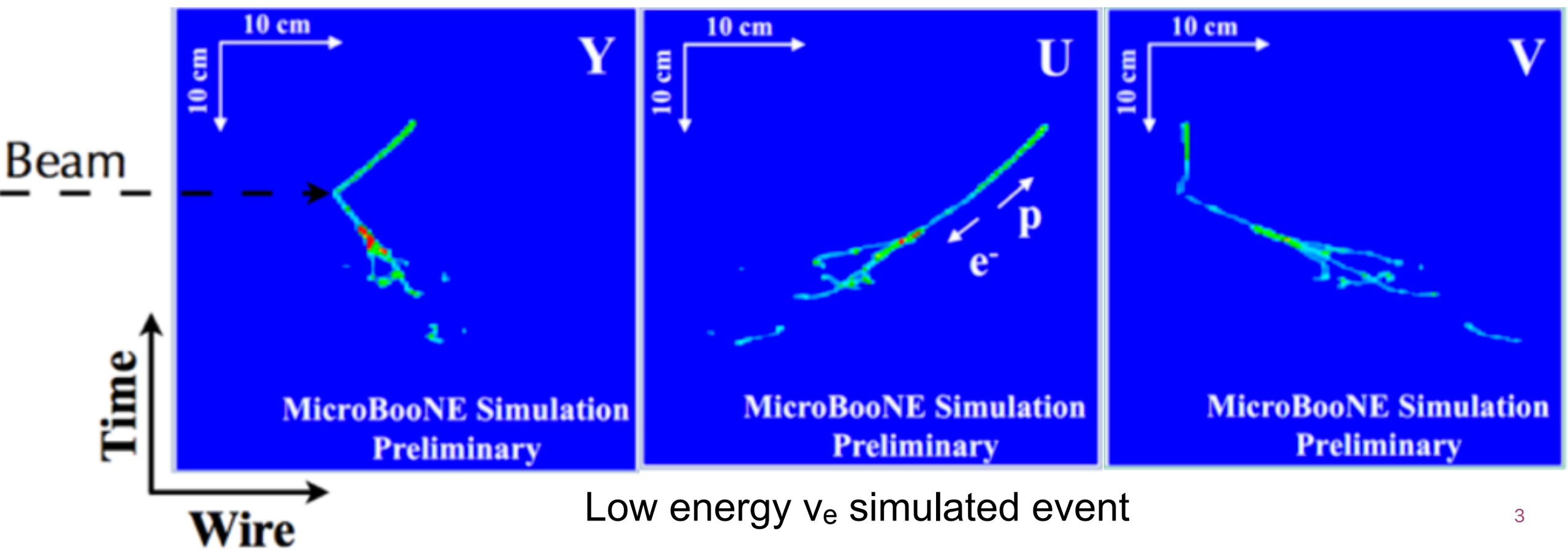
- 85t Liquid Argon time projection chamber (LArTPC)
  - observe ν from BNB at Fermilab (~470m)

See also R. Castillo, "Detector Physics with MicroBooNE", Wed 13:36

data is recorded as 2D images

1 image per readout plane

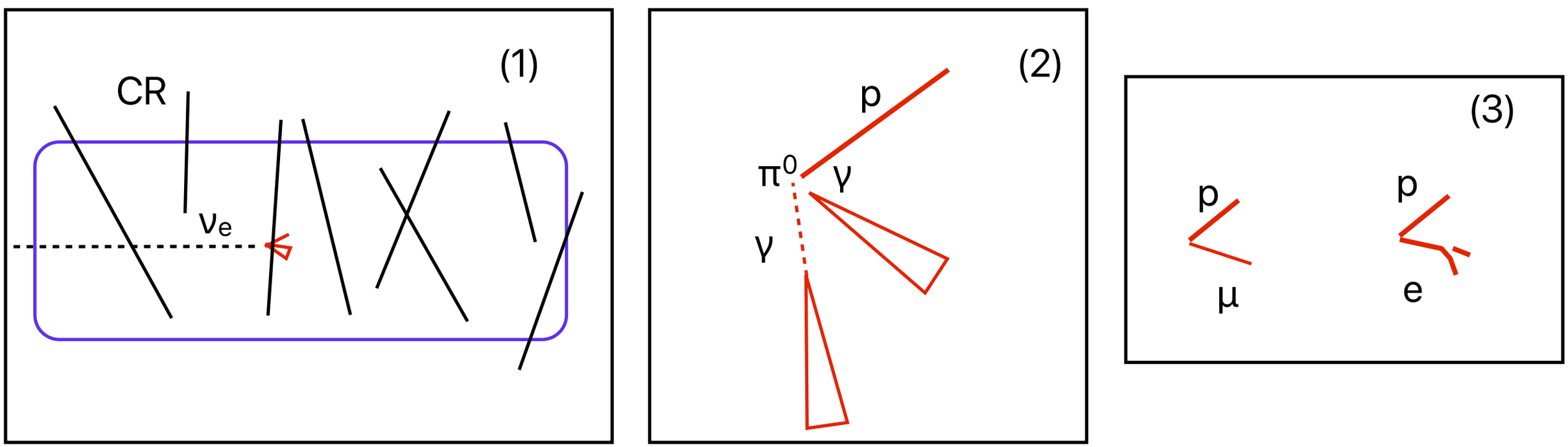
different particle signatures
e,γ: showers
μ, p: tracks



Low energy ν_e simulated event

Backgrounds In The MicroBooNE LEE Search

- MicroBooNE: surface detector => lots of cosmic rays (CR) (1)
- NC π^0: main BG in MiniBooNE (2)
  - LArTPC: highly granular, detached shower identification possible
  - dE/dx separation e/γ possible
- Low energy ν_μ (3): similar to low energy ν_e
- Dedicated BG rejection techniques developed

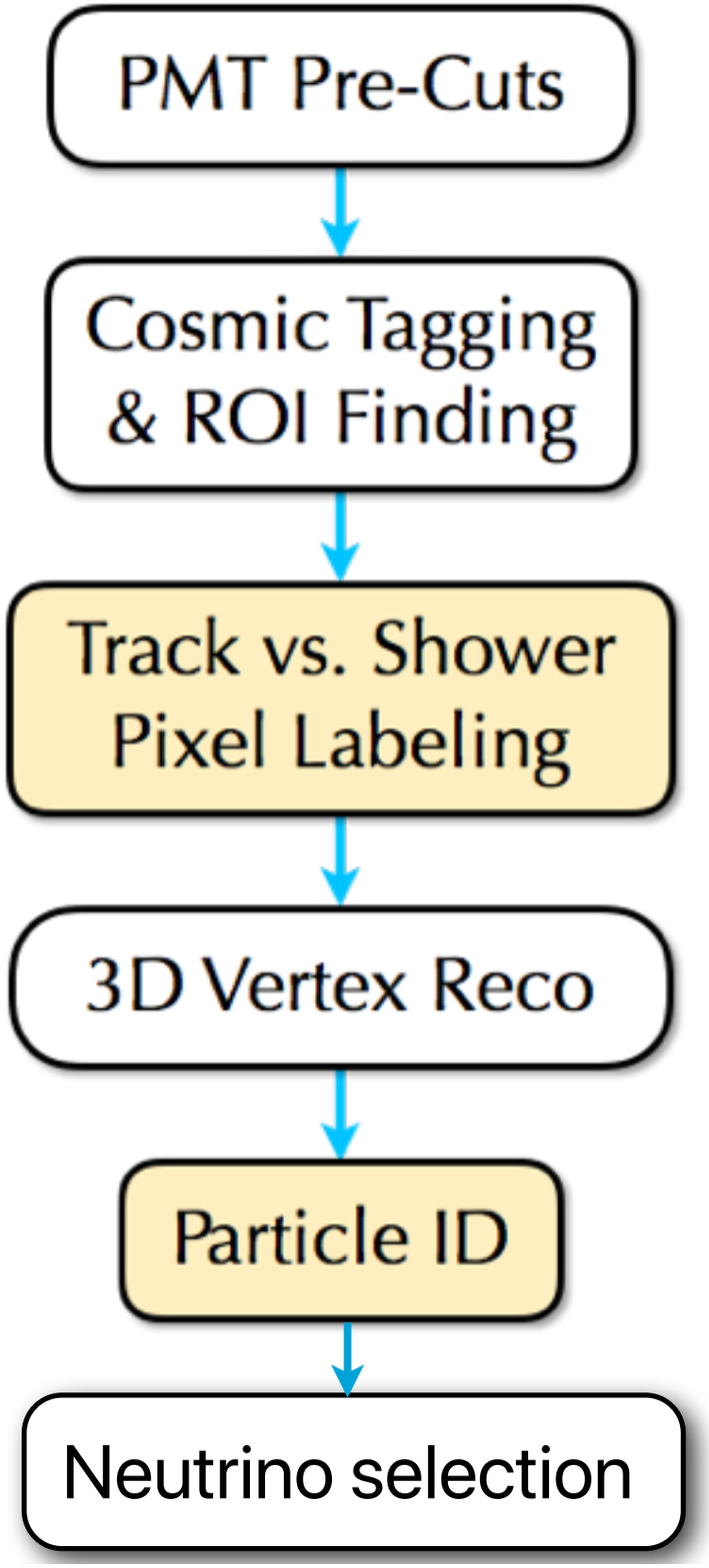


LEE Searches In MicroBooNE

- Multiple analysis groups
  - different event reconstruction approaches (Pandora, WireCell, TrajCluster, DL) and target signal channels (different final states)
  - multiple approaches enhance robustness of observation
- Deep Learning (DL) working group
  - signal definition: 200-600 MeV 1 shower 1 track (1e1p) events as product of ν_e CCQE interactions
  - select 2 track (1μ1p) events to constrain flux and x-sec systematics

See also W. Tang, "Recent Results from MicroBooNE", Tue 15:05

Deep Learning Group Analysis Chain

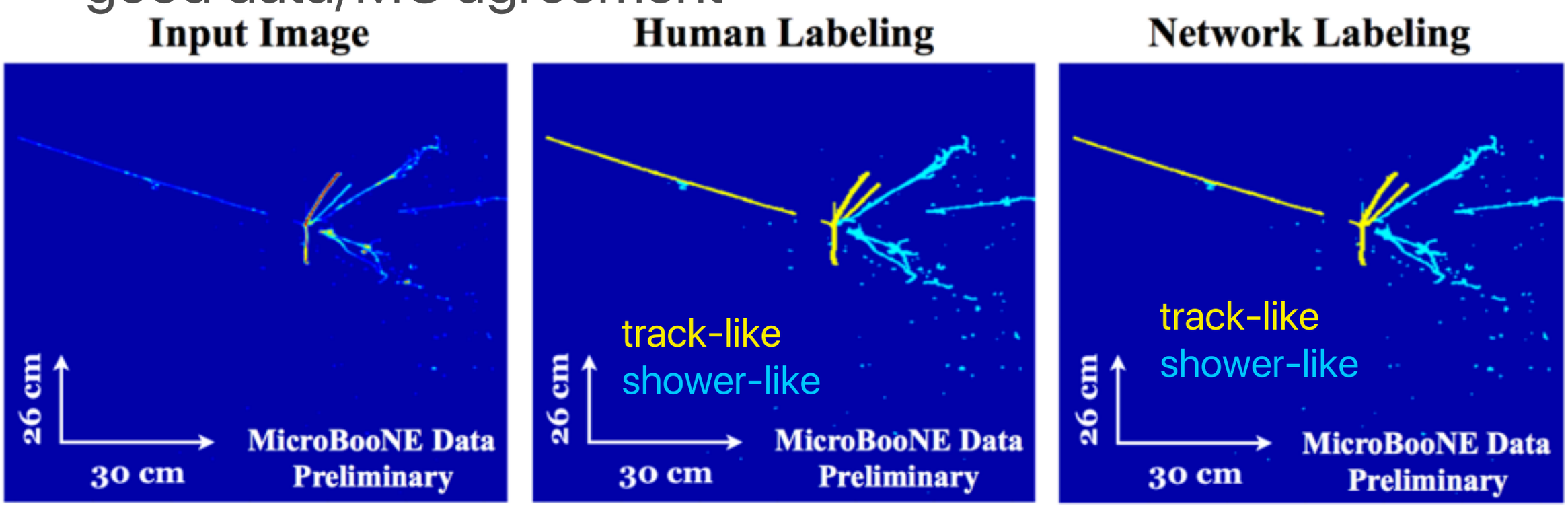


- Early studies of application of convolutional neural networks (CNNs) (JINST 12 (03), P03011) show promise
  - CNNs: tailored for image processing
- Our data is in 2D image format: easy to adopt CNNs
- Currently using CNNs in two places
  - track/shower pixel labeling
  - particle ID
- Meeting point of track/shower clusters used as vertex seed
- Rest of reconstruction: “traditional” algorithms

DL Techniques For MicroBooNE LEE Search

- Convolutional neural network for pixel-labeling (SSNet)
  - labels image pixels as track/shower-like
  - used for vertex finding
  - key input for 1e1p event selection
  - good performance on data
  - good data/MC agreement

Phys. Rev. D 99, 092001 (2019)

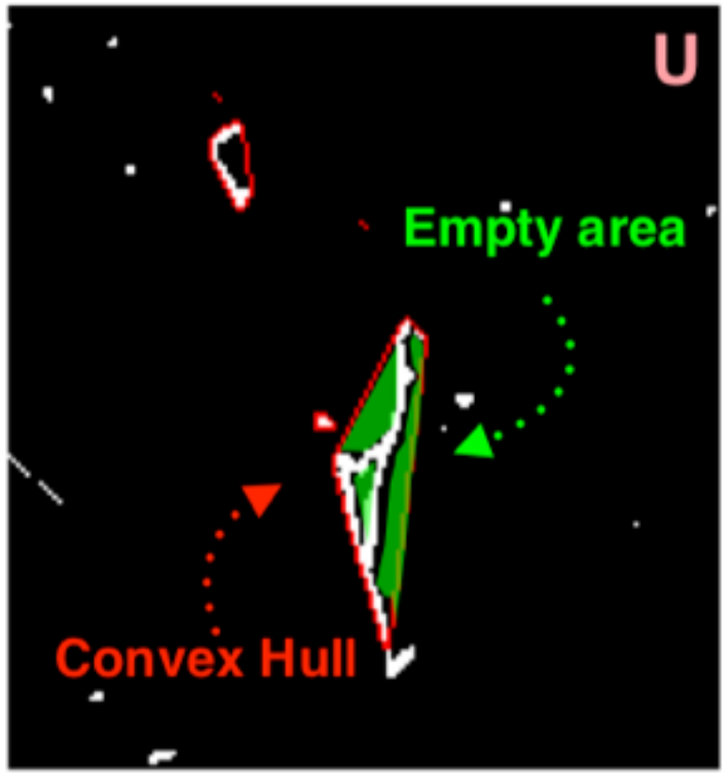


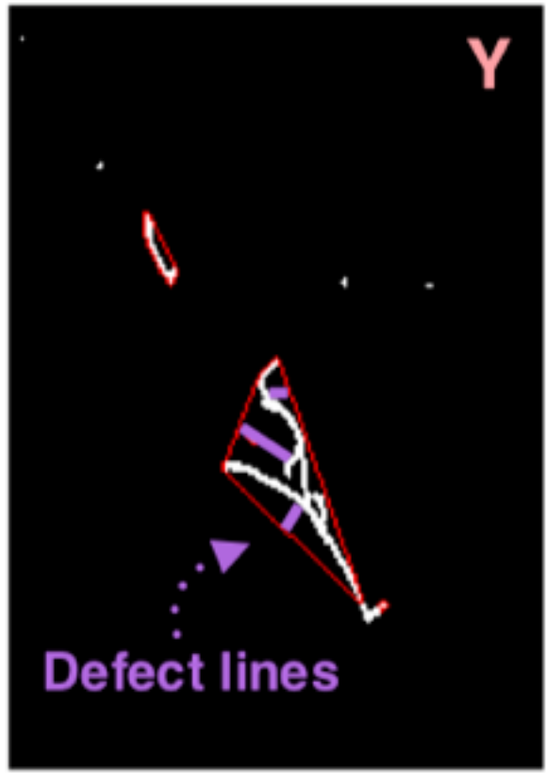
Background Rejection In The DL Analysis

- Use a mix of kinematic variables, neural network outputs & topological features
- Combine these using 3 boosted decision trees (BDTs)
- BDT variables
  - transverse momentum fraction p_T/p_{tot}
  - Bjorken x
  - normalized dQ/dx diff

$\eta = |(dQ/dx)_1 - (dQ/dx)_2| / ((dQ/dx)_1 + (dQ/dx)_2)$

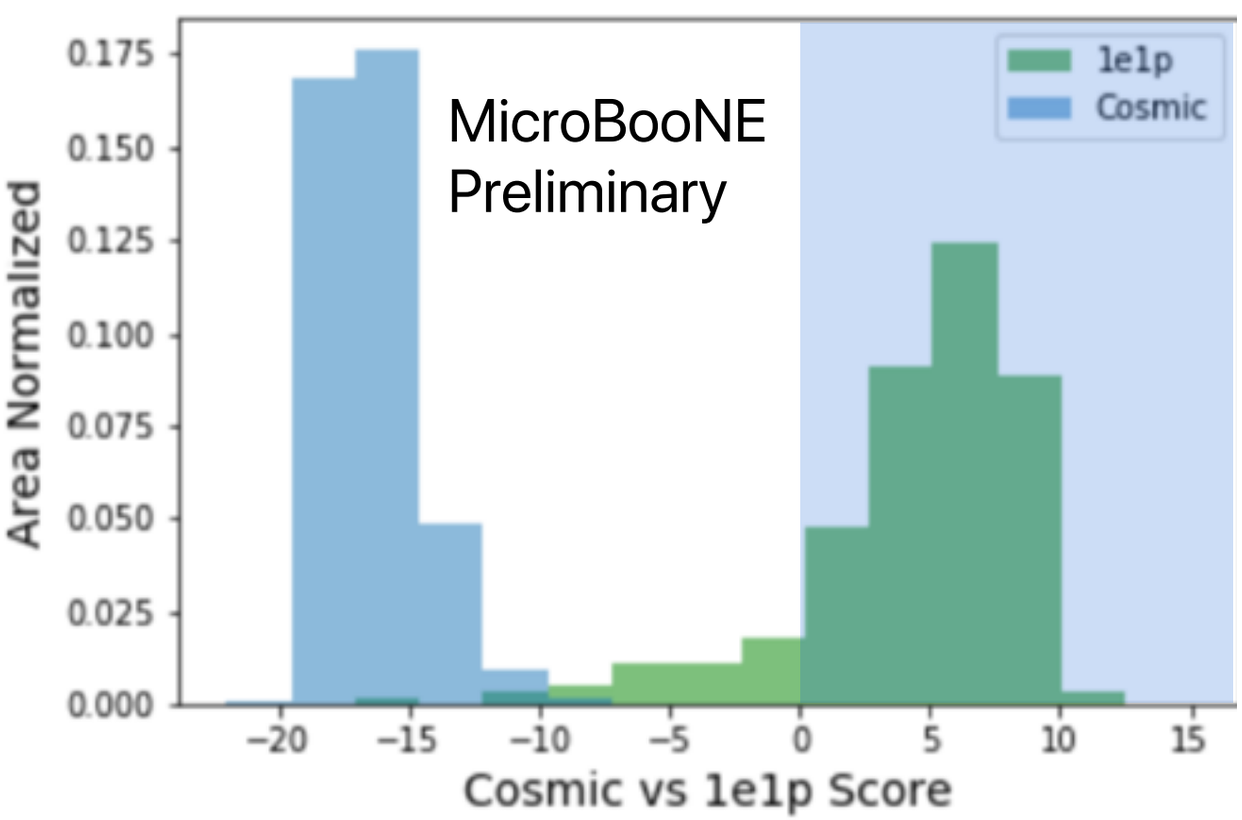
  - prong angles w.r.t. beam direction
  - prong angles in transverse plane
  - Multi-PID network scores
  - SSNet shower fraction
  - ***topological score*** looking for a branching along the particle path (low E ν_e vs ν_μ)

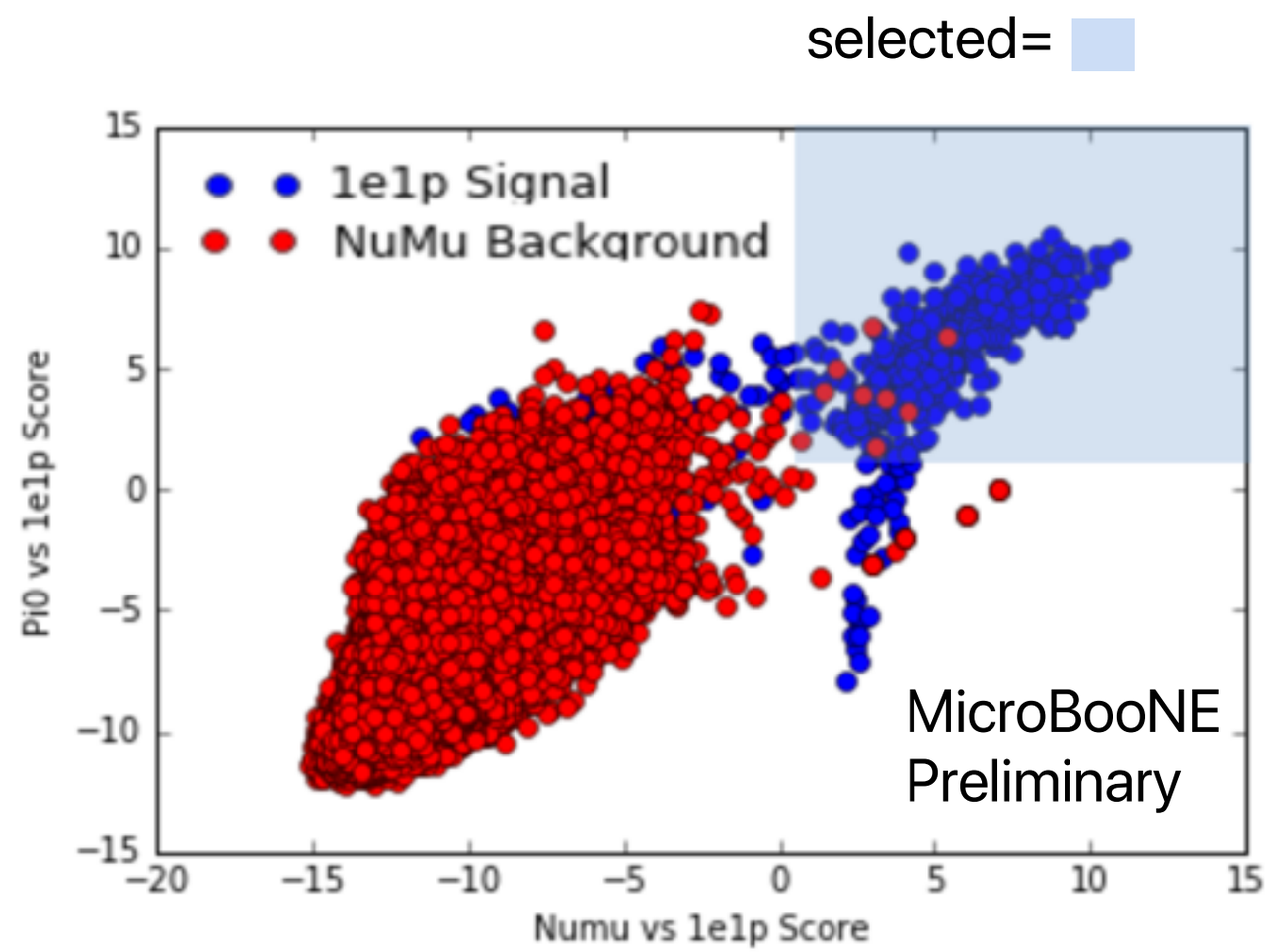




Background Rejection In The DL Analysis

- Train BDTs to reject 3 main BG classes
  - cosmic ray BG
  - π^0 from NC delta decay & ν interactions
  - mis-ID ν_μ
- High purity low energy ν_e selection



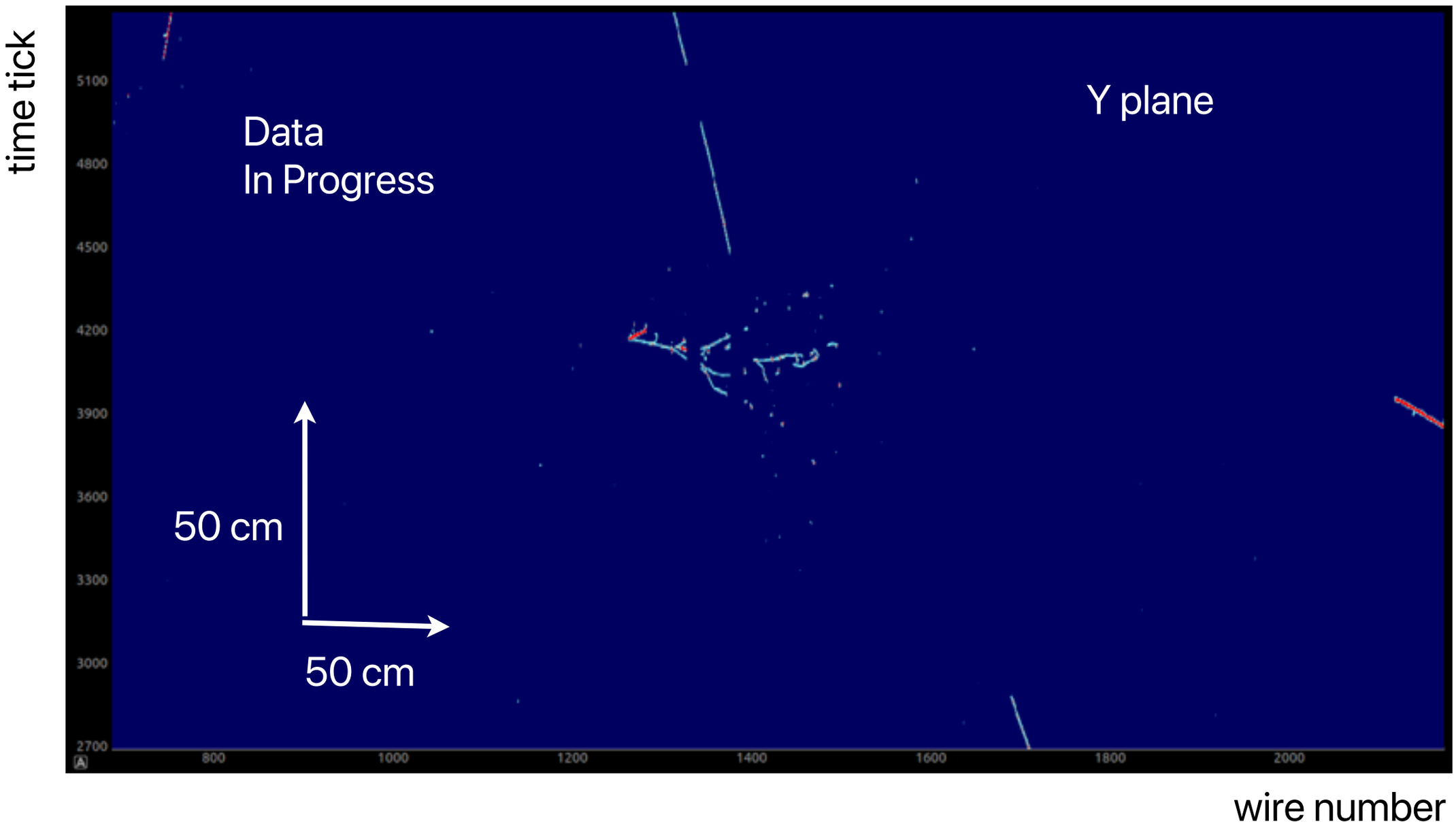


Selected Events

- After signal selection high-purity sample
- Selected events (simulated) breakdown
  - 87% of events CCQE + meson exchange current (MEC)
  - 8% CC π^+ and CC π^0 BG, 5% other modes
- Low cosmic BG
  - measurable BG

Examples Of Selected Events In Data

- Successfully 3D reconstructed & selected 1e1p events in MicroBooNE open dataset



Tagged cosmic BG has been removed from images

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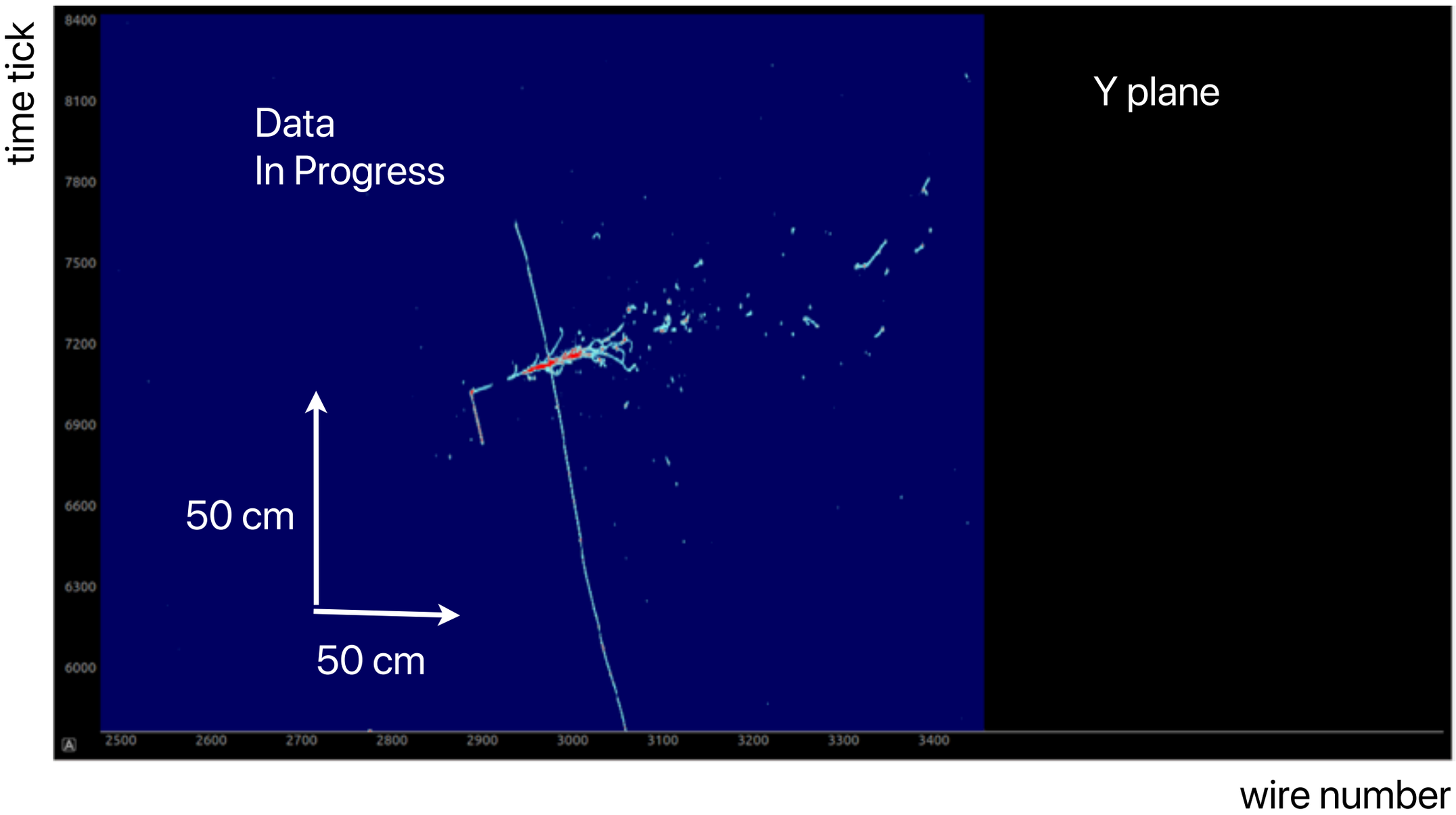

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Summary

- MicroBooNE is a short baseline neutrino experiment at FNAL searching for the LEE observed by MiniBooNE
- Deep Learning group LEE analysis
  - use CNNs as input to signal selection
  - achieved a highly pure ν_e signal selection
  - shown successful 3D reconstruction of neutrinos in data
  - developing more DL techniques to further improve a-priori signal efficiency & BG rejection before signal selection

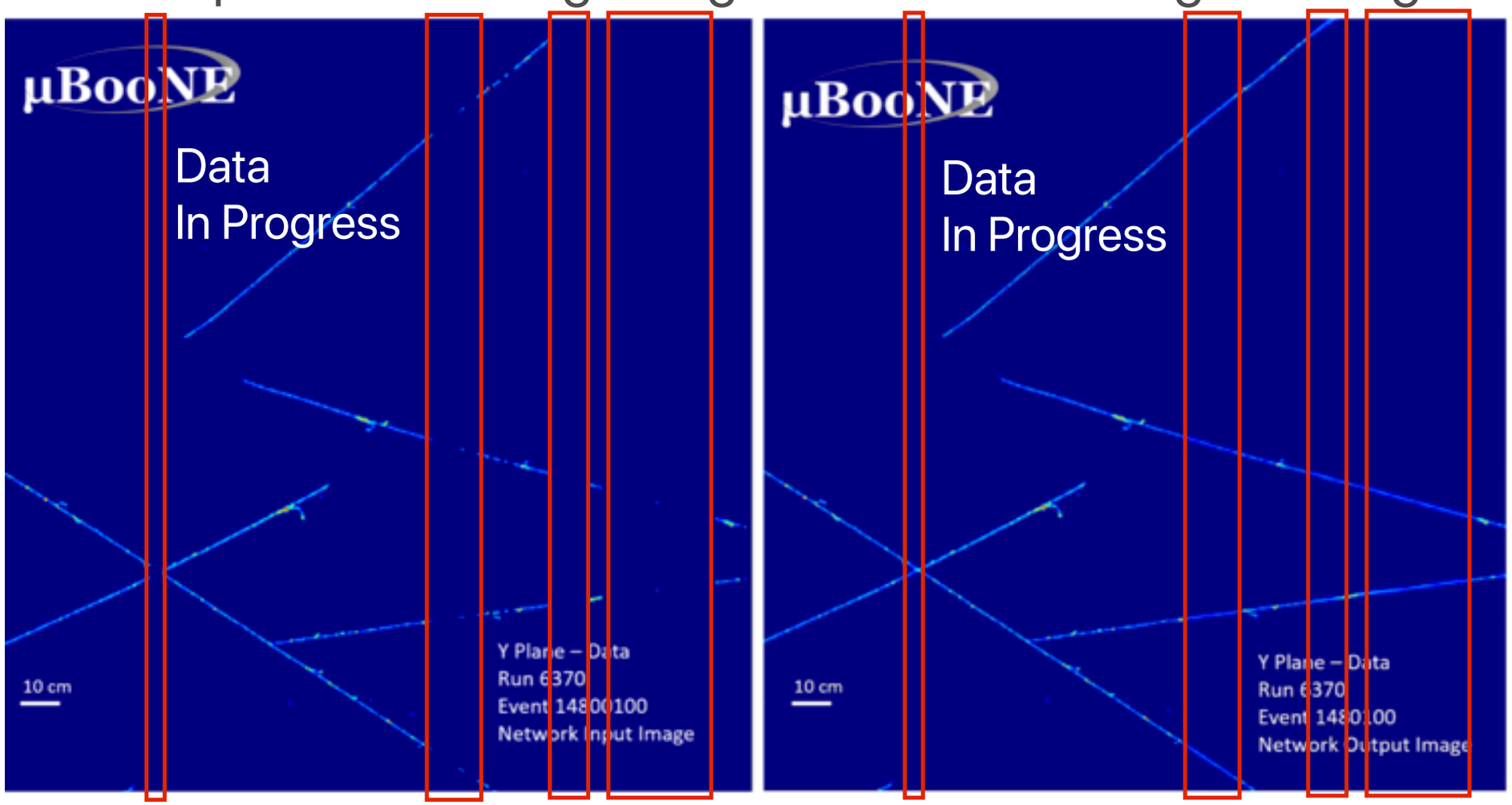
See K. Mason, "Using Convolutional Neural Networks to Reconstruct Dead Channels in MicroBooNE", Poster

See J. Mills, "Ancestor Particle Clustering in MicroBooNE Using Deep Learning Neural Networks", Poster

Backup Slides

Filling Charge In Dead Regions With InFill

- Multiple dead (unresponsive or noisy) readout wires: introduce "gaps" in 2D images
  - cannot follow track: broken muon tracks left after CR tagging
  - incomplete track/shower: affects energy reconstruction resolution
- InFill network: predicts missing charge for tracks crossing dead regions



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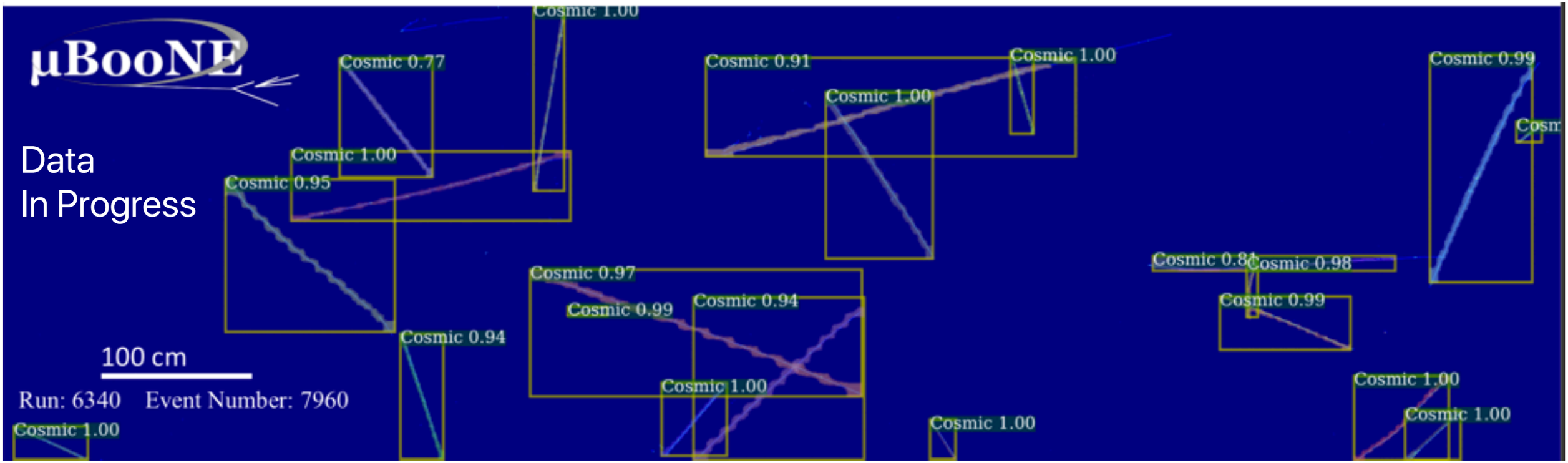
Ancestor Particle Clustering With Mask-R CNN

- Identify pixels in image corresponding to same interaction (ancestor)
  - cluster full neutrino interaction, not individual particles
  - cluster full cosmic rays (Michel decays included)
- Assign a category (cosmic muon, neutrino, proton etc) to each cluster
- Highly efficient for CR tagging



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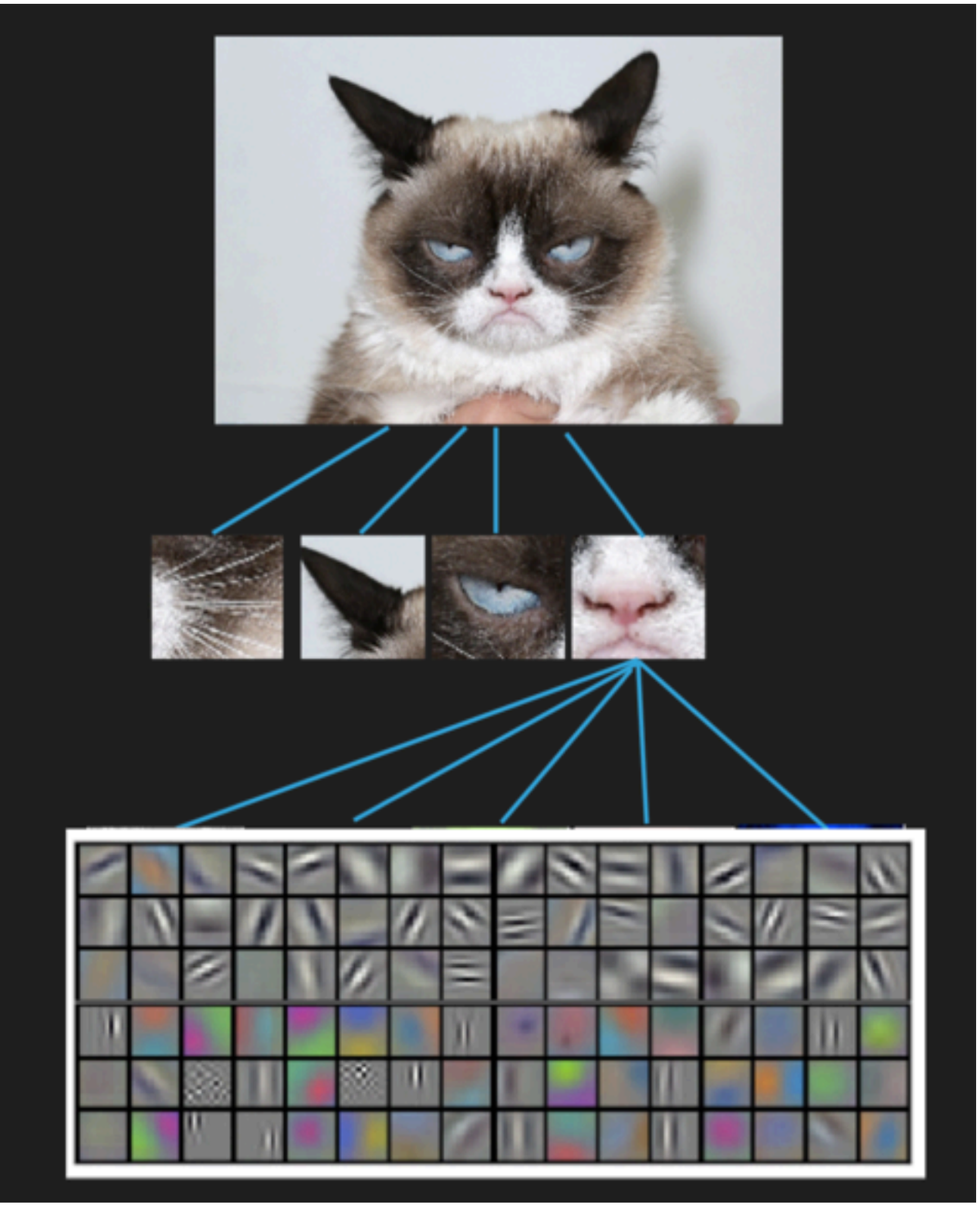
Brief Intro To Image Analysis

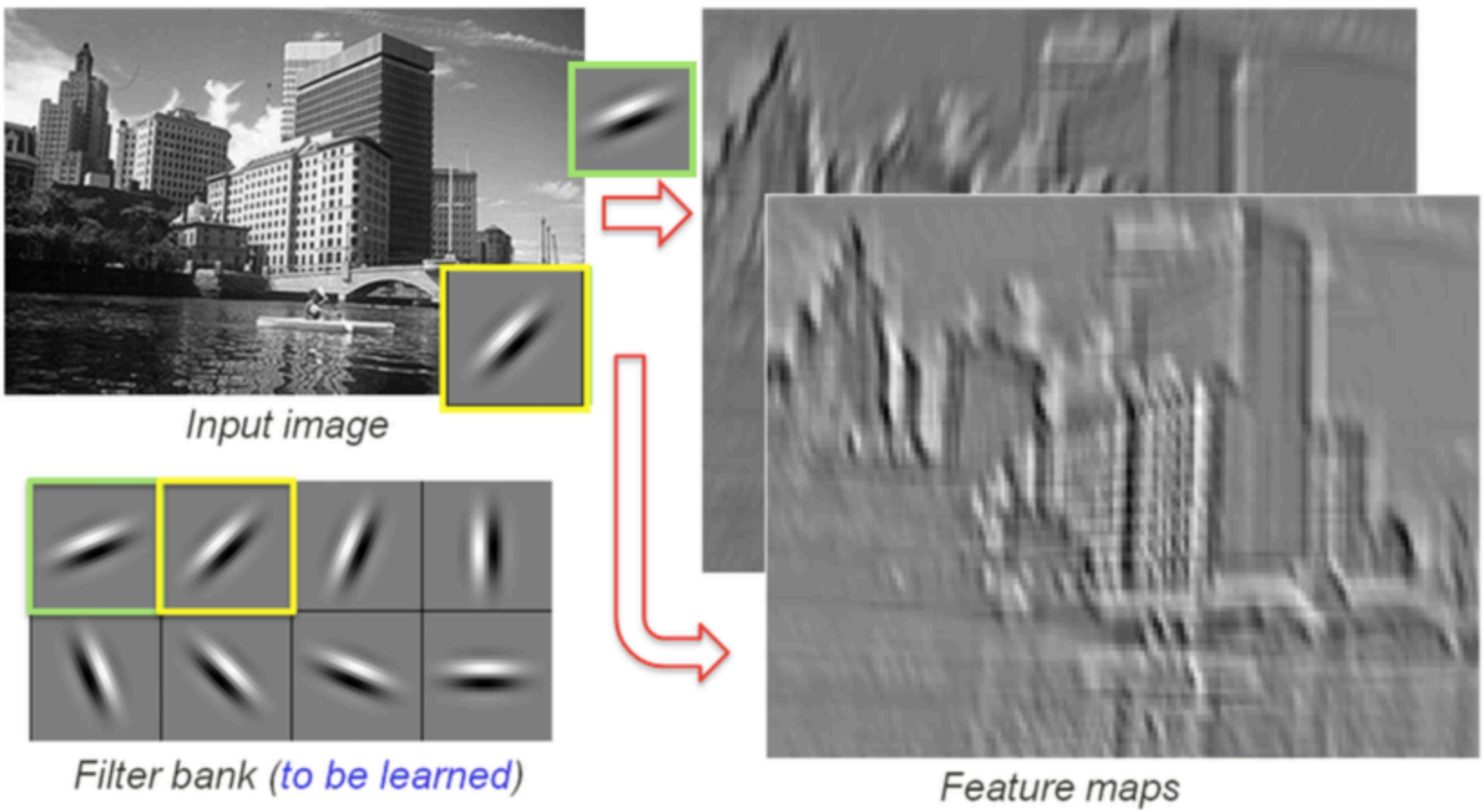


From T. Wongjirad

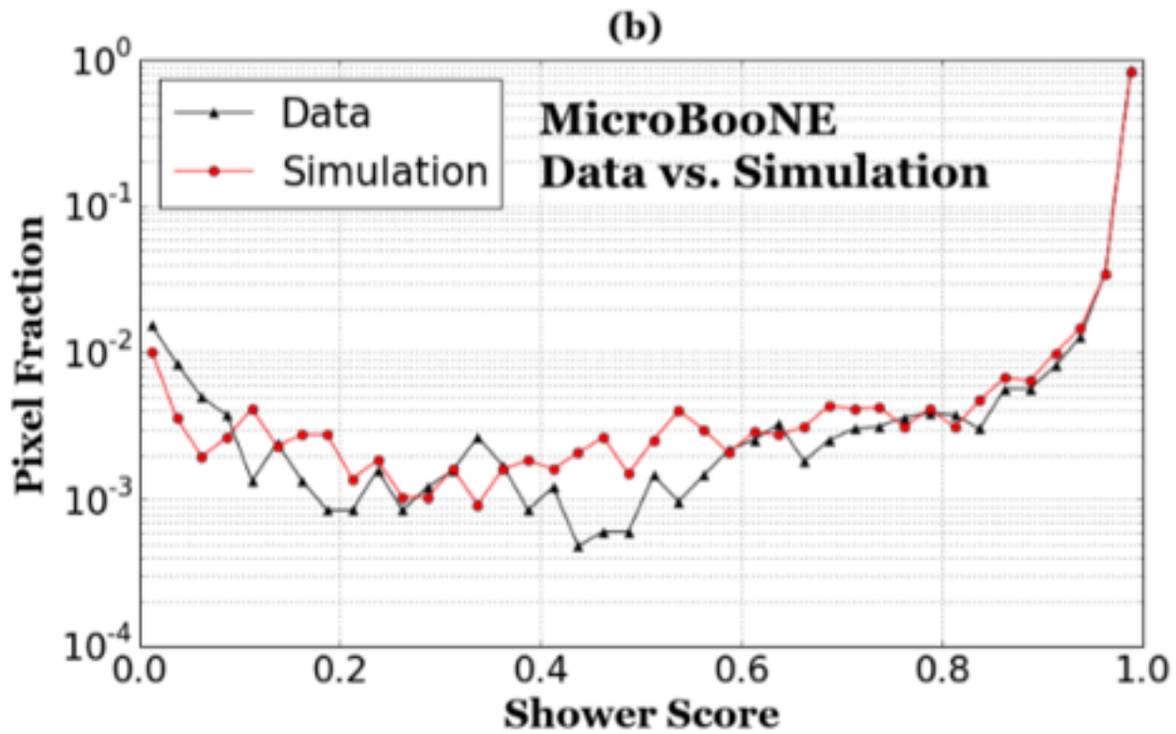
- To recognize an image, e.g. as a cat, decompose an object into a collection of small features
- Features composed of different patterns, lines and colors
- Convolutional neural networks (CNNs) extract features

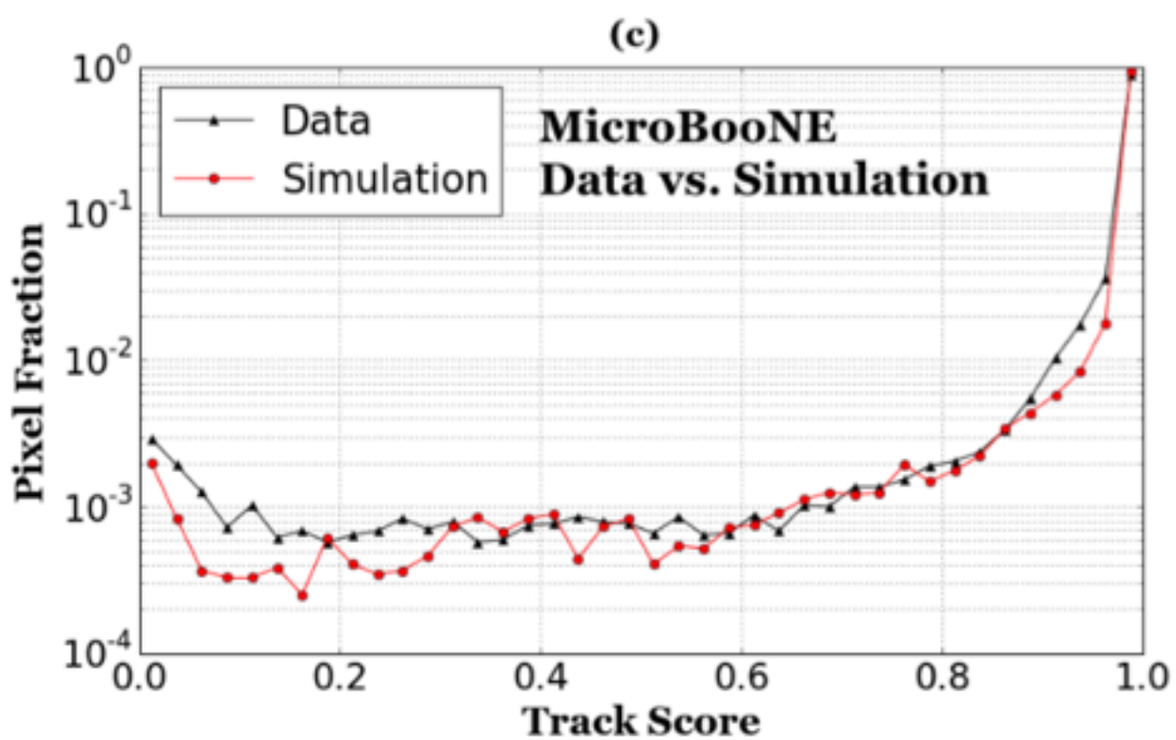
Convolutional Filter

- Core operation in a CNN is the convolutional filter: identifies the positions of patterns within an image
- In example below light and dark in output show where the pattern matches well



SSNet Output: Data Vs MC

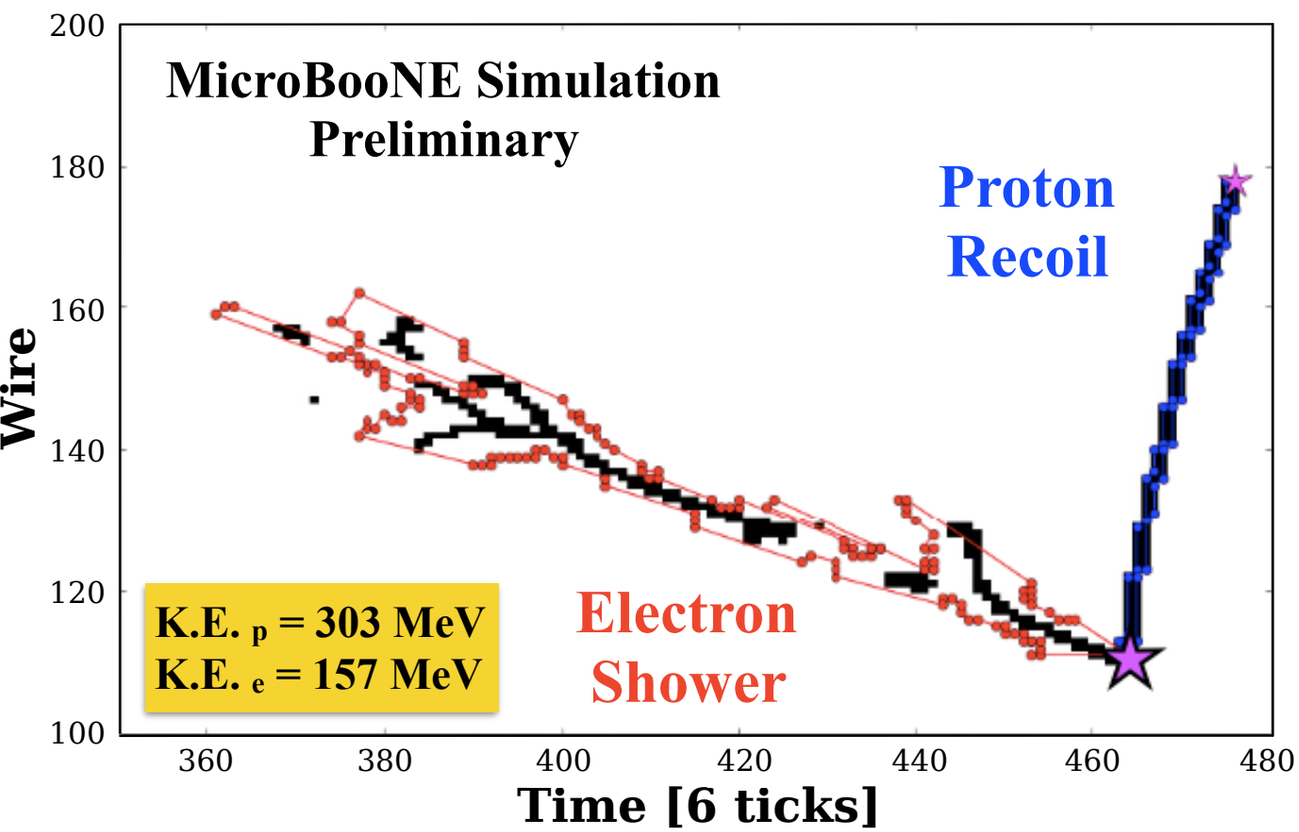


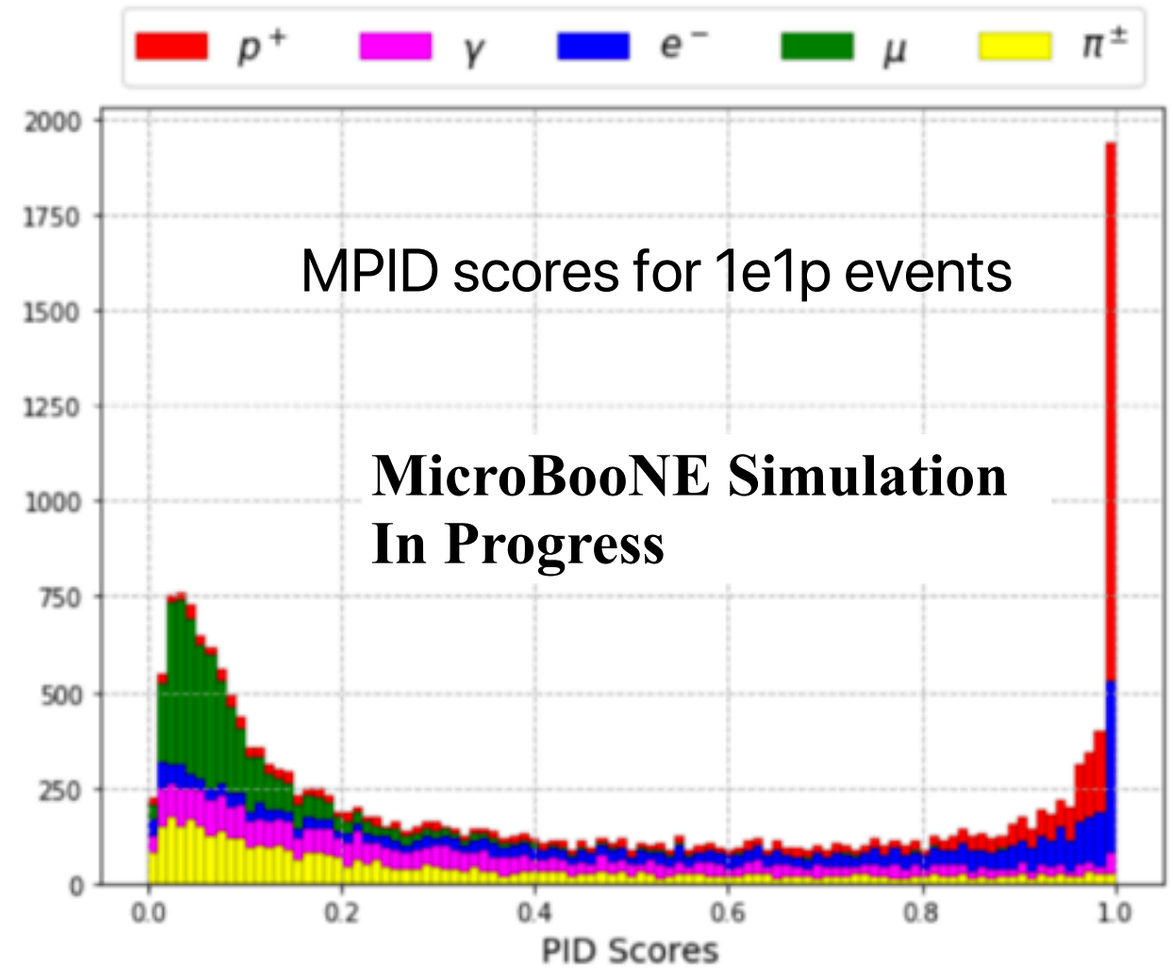


- Sample: stopping muons
  - independently selected using Pandora reconstruction
- Score distributions similar
- Robust to moderate difference in images as shown by peak pixel distributions
- Good data/MC agreement: can safely use in analysis

Particle ID Networks In MicroBooNE

JINST 12, P03011 (2017)



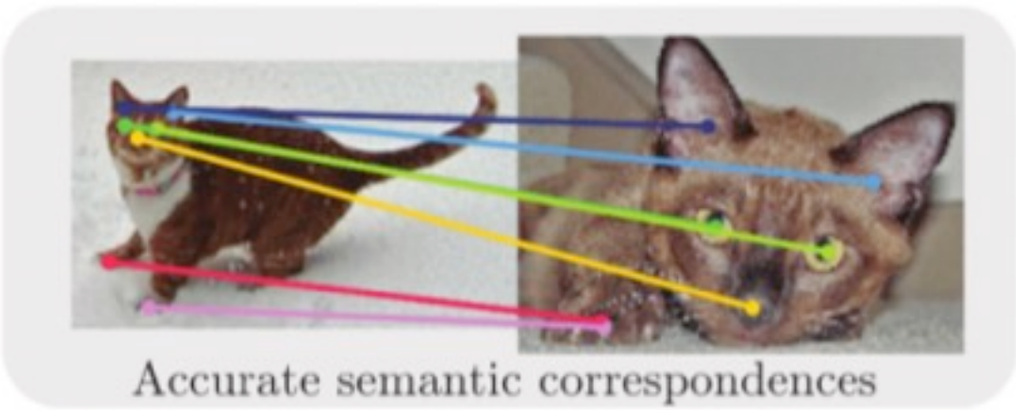


- After 3D vertex reconstruction, cluster pixels attributed to each single track or shower coming out of the vertex
- Feed individual particle clusters into a CNN trained to do single-particle identification (HighRes GoogleNet)

- Now: Multi-PID (MPID) network (extension of JINST 12, P03011 (2017))
  - assign labels to each reconstructed particle μ, $\pi^{+/-}$, p, e, γ

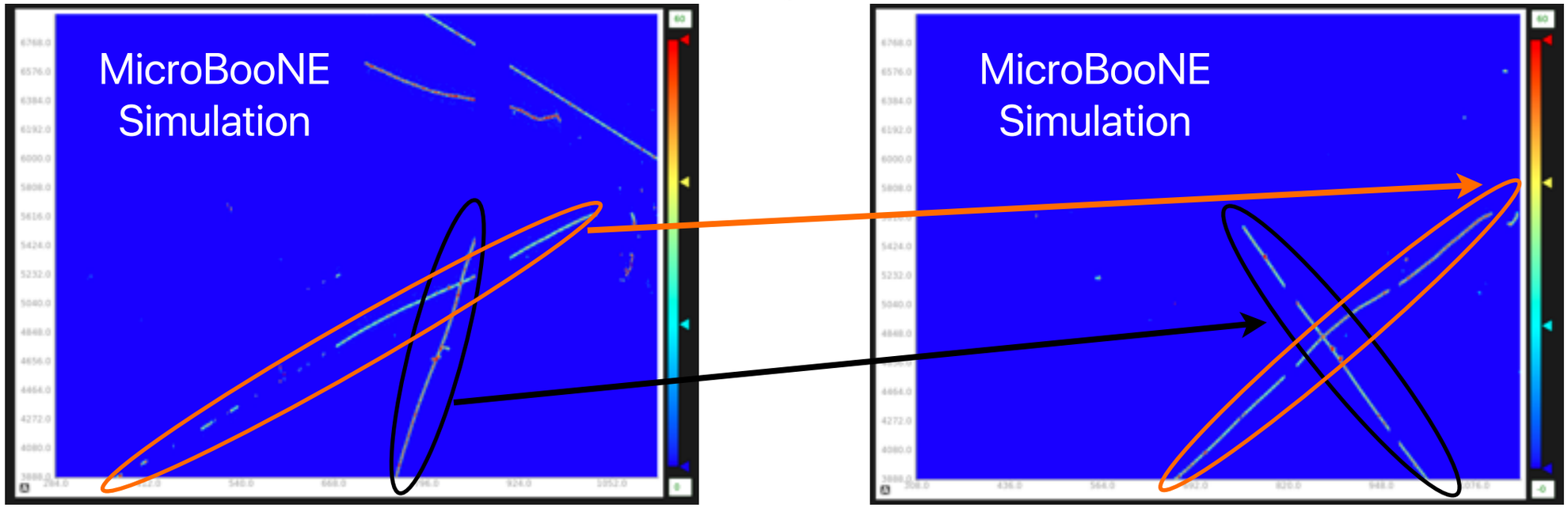
3D Point Reconstruction With LArFlow

- 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



- Application in MicroBooNE: LArFlow network
  - 3D points from matching 2D images => CR tagging in 3D!