The MicroBooNE Experiment and Applications of Machine Learning and Deep Learning

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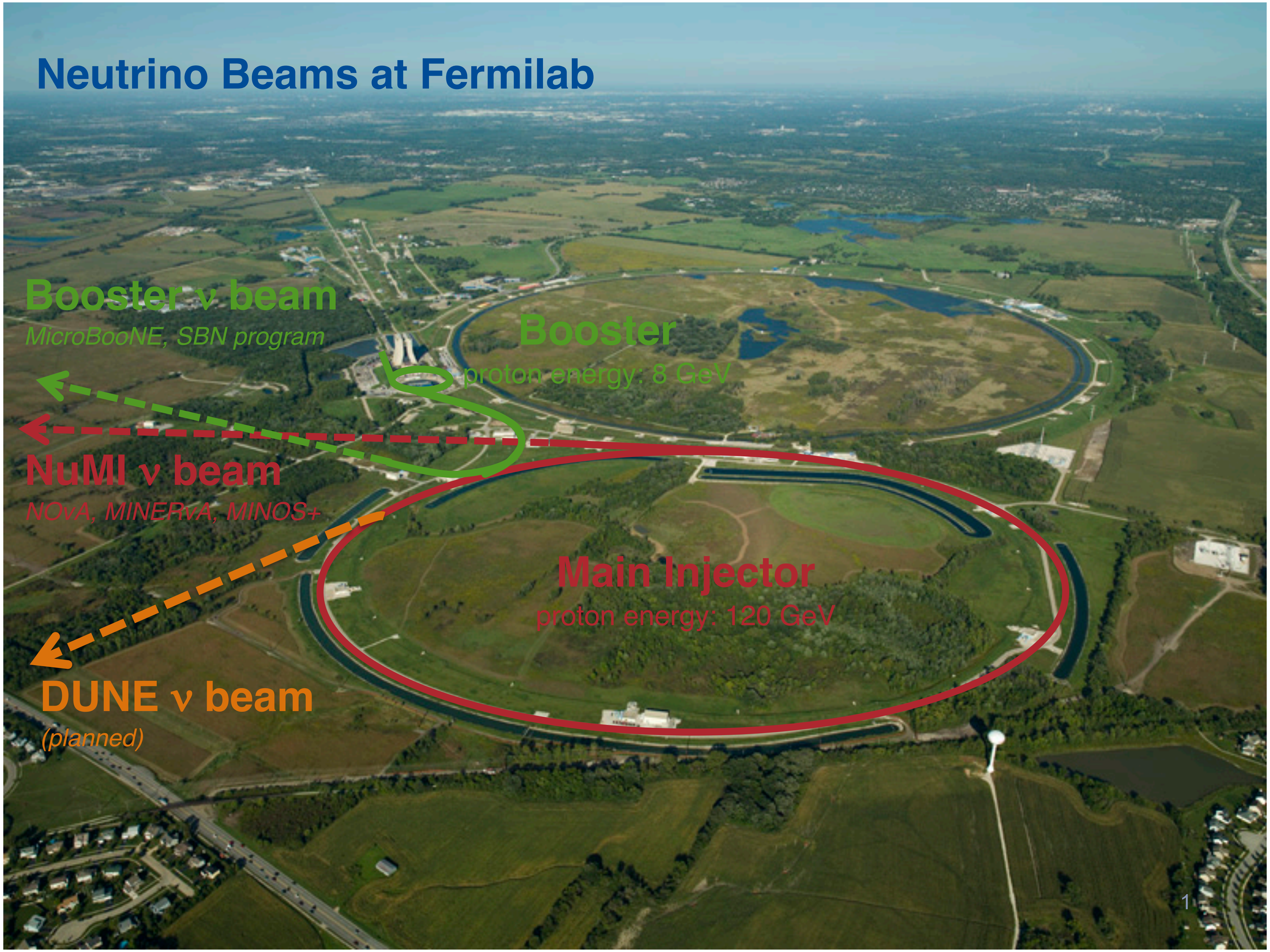
Neutrino physics at FNAL



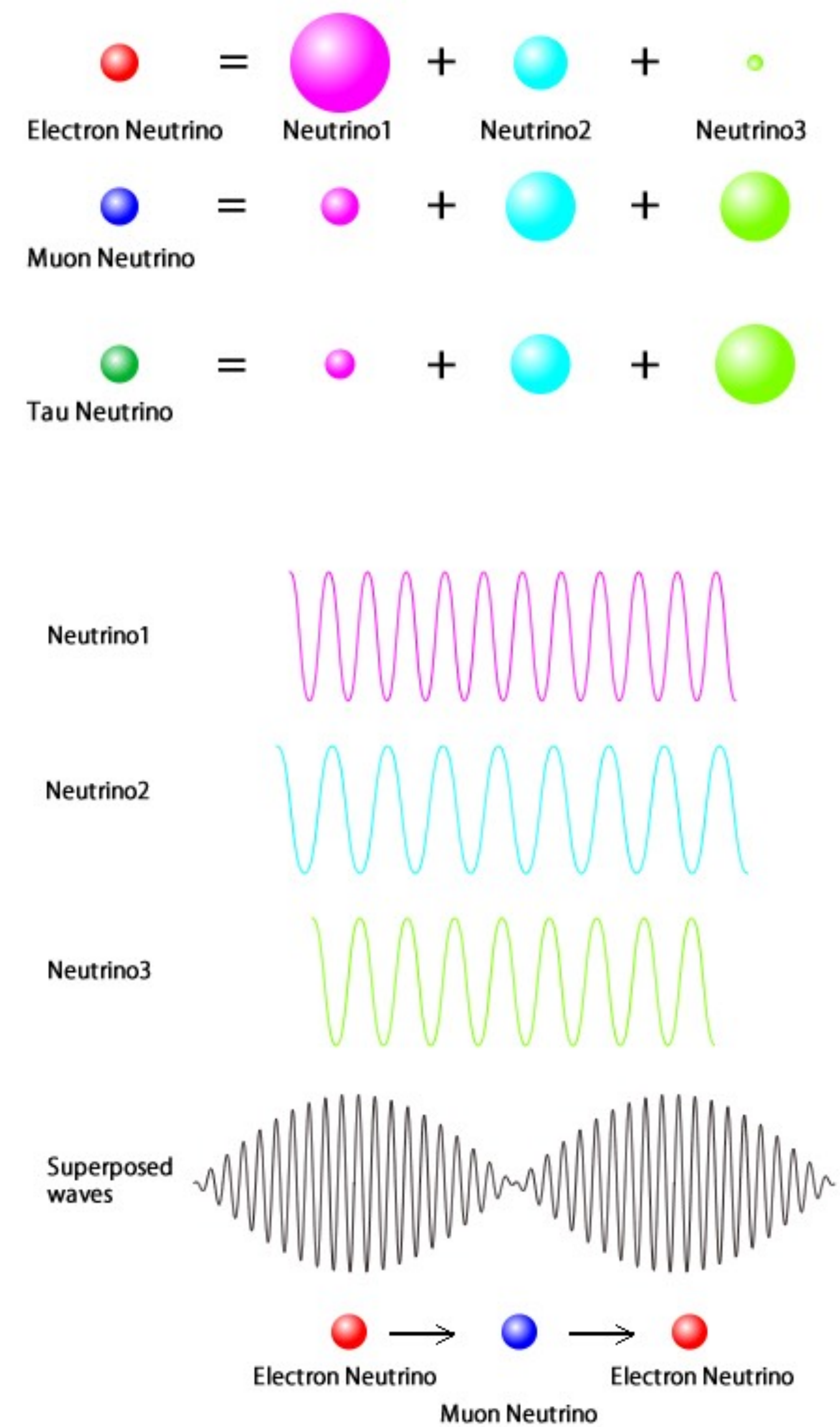
Slide from G. Zeller

Talk outline

- Neutrino physics and sterile neutrino searches
- The MicroBooNE experiment
  - LArTPC detector technology
  - Physics analyses
- Applications of Deep Learning (DL) in MicroBooNE
- Machine learning/DL applications in accelerator operations

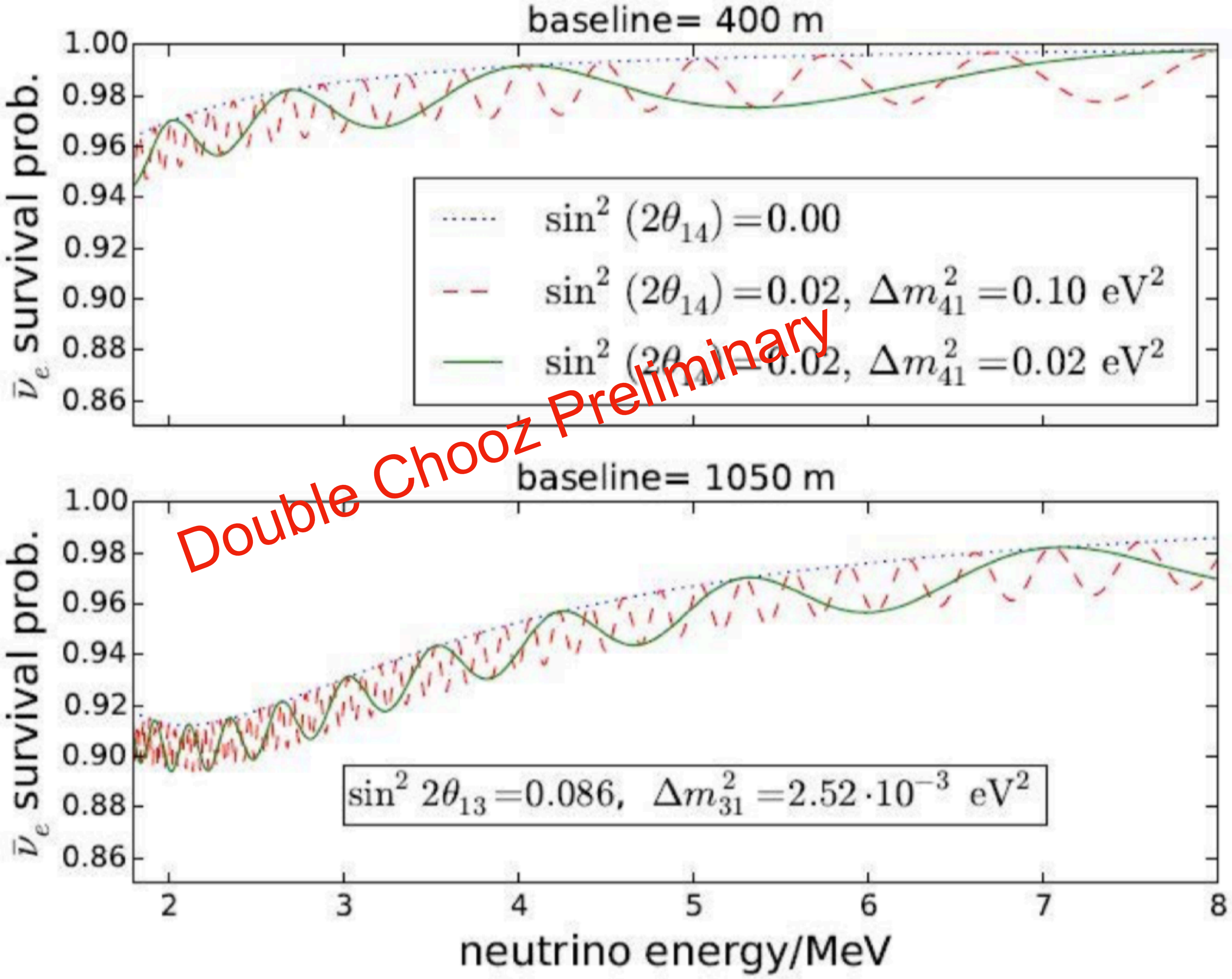
Neutrino flavors & oscillation

- Neutrinos are created and annihilated as eigenstates of the weak interaction (“flavors”): 3 flavors in Standard Model (e,μ,τ)
- Unlike charged leptons, flavor != mass eigenstate
  - Each flavor is a superposition of 3 mass eigenstates
- Neutrinos can change flavor when propagating: neutrino oscillation
- Neutrino oscillation is defined by 6 parameters
  - mixing angles θ_{21}, θ_{13}, θ_{32}
  - squared mass differences Δm_{21}^2, Δm_{32}^2
  - CP violating phase δ



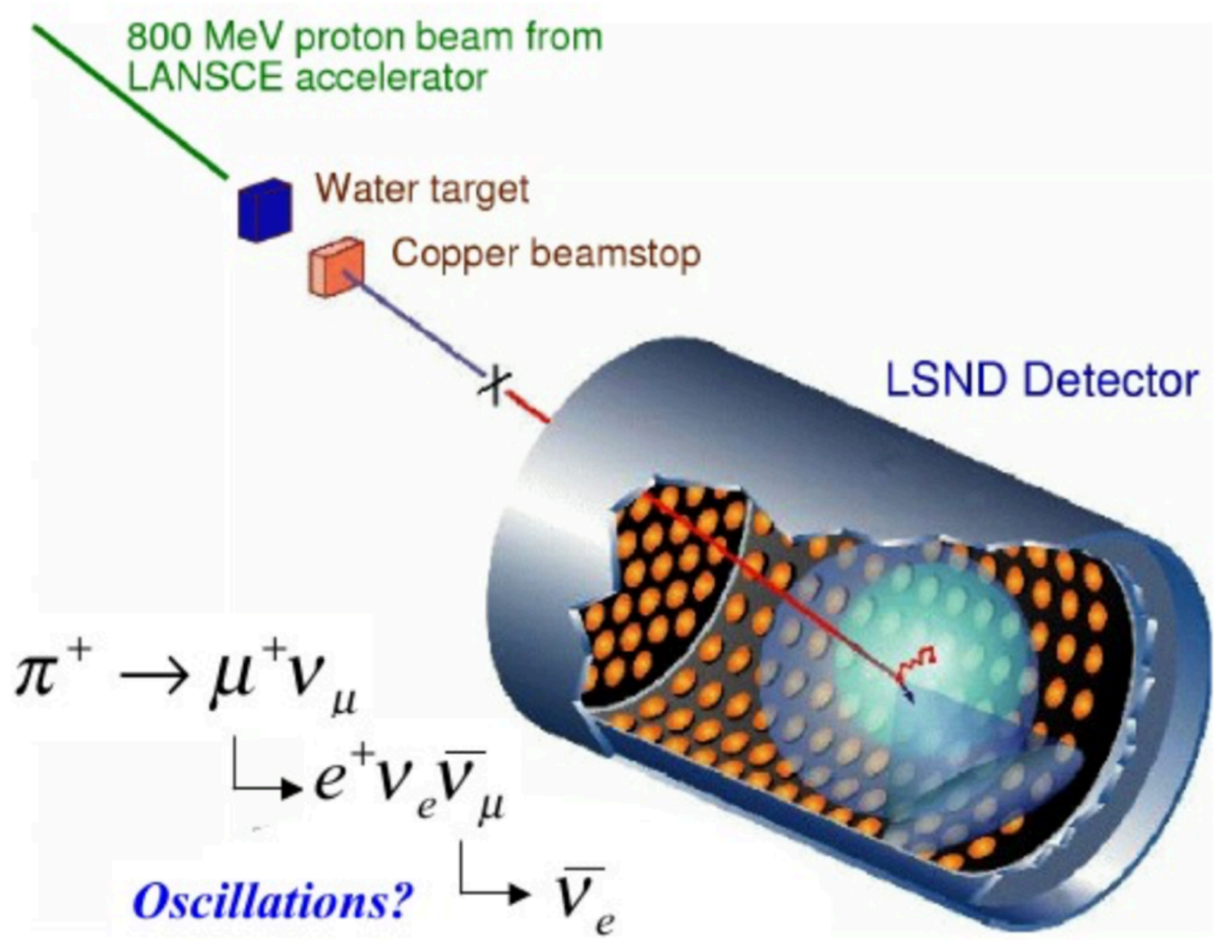
Neutrino flavors & oscillation

- Neutrino flavors & oscillation
  - 3-flavor neutrino oscillation paradigm well established by various neutrino oscillation experiments
  - 3 active neutrinos: supported by cosmology and collider experiments
- Short baseline experiments have observed neutrino spectra inconsistent with 3-flavor oscillation
  - one hypothesis: one for more “sterile” = inactive neutrino flavors enhance neutrino oscillation at short baselines

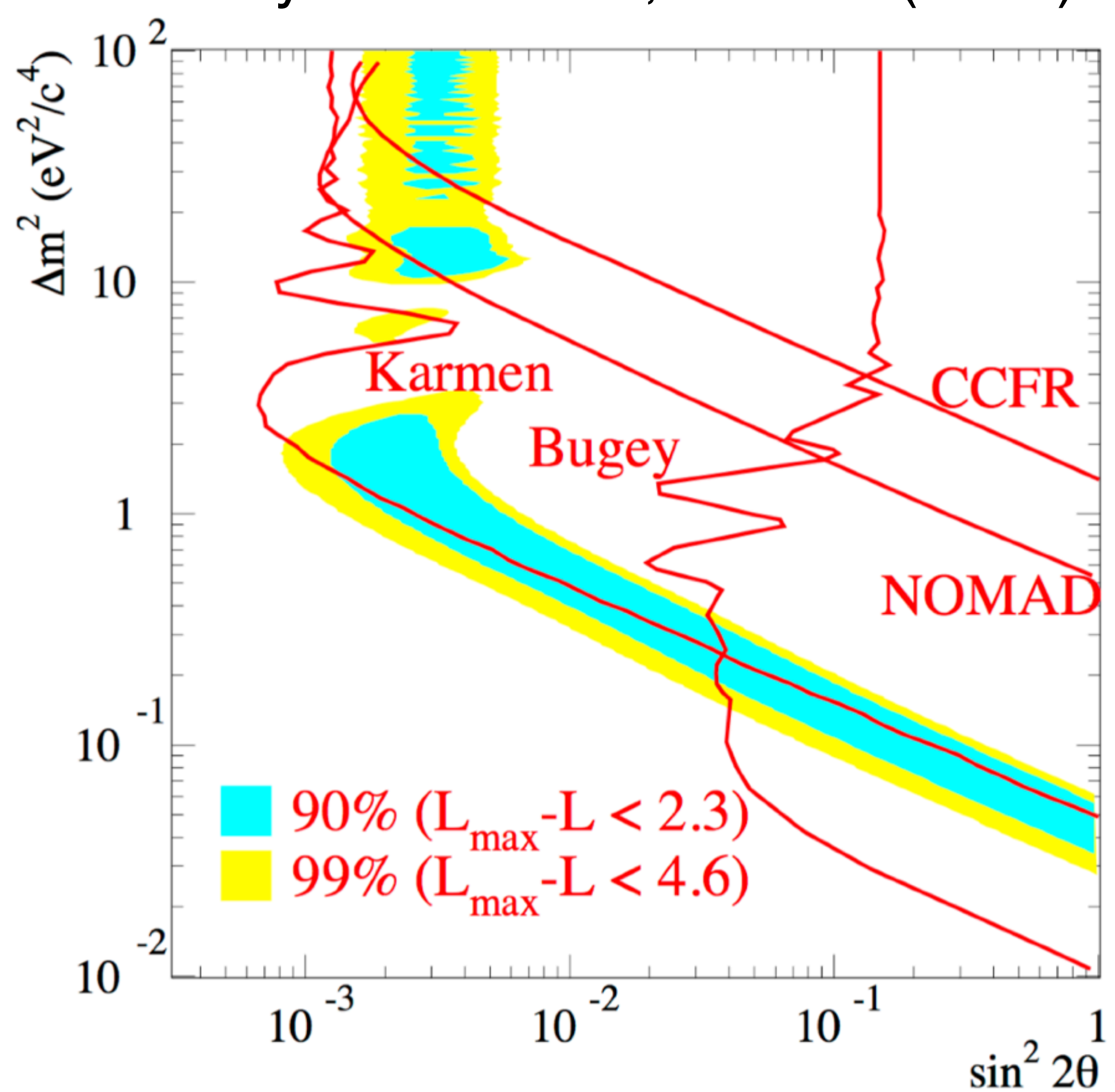


LSND anomaly

- LSND (Liquid Scintillator Neutrino Detector) at Los Alamos
- Using stopped pion source
  - low intrinsic $\bar{\nu}_e$ BG
- Neutrino energy: 10~55 MeV
- Baseline: 30 m

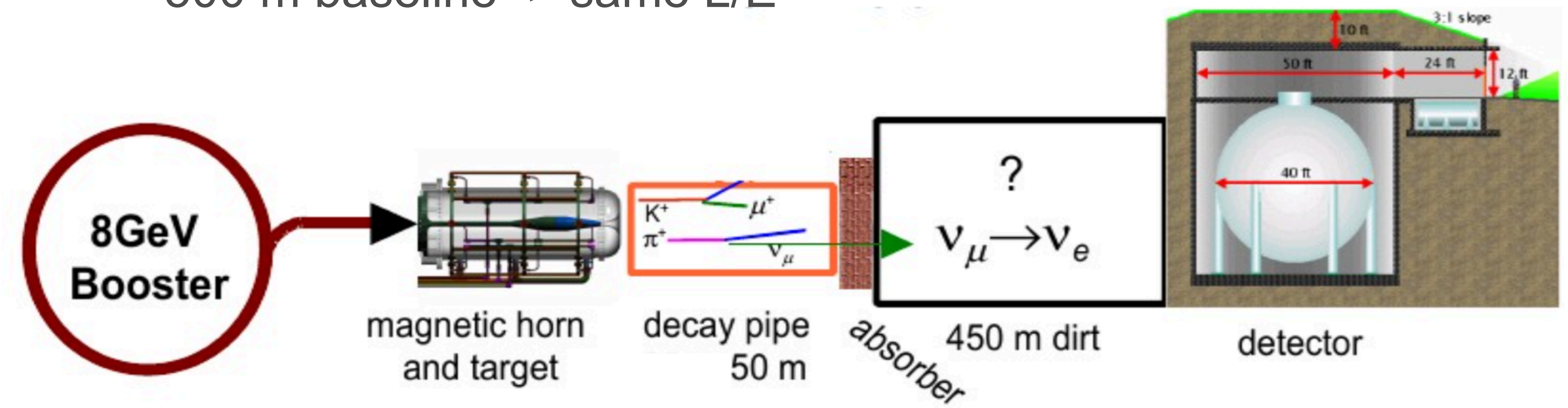


Phys. Rev. D 64, 112007 (2001)



The MiniBooNE “Low energy excess”

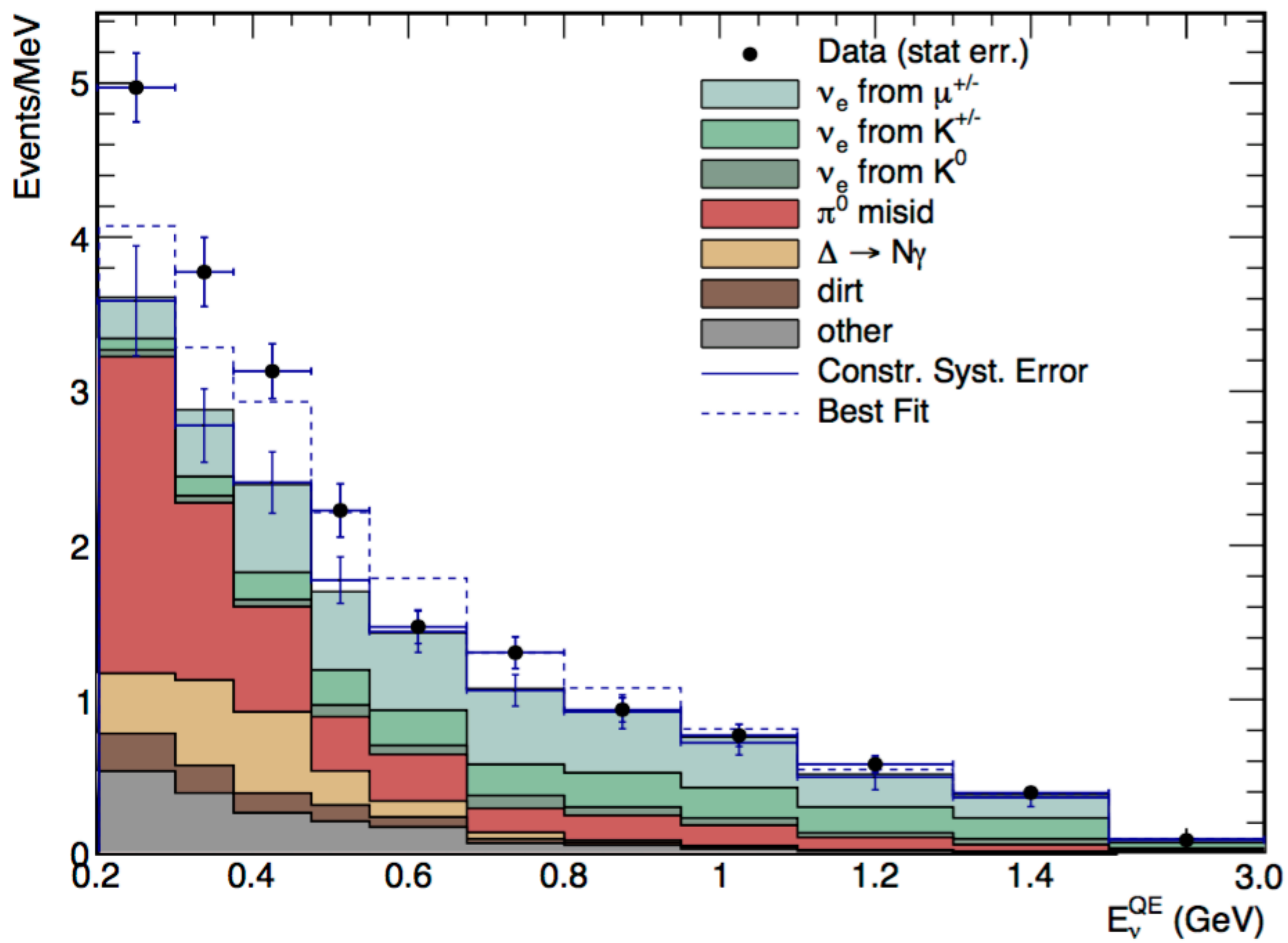
- MiniBooNE experiment at FNAL
  - mineral oil Cerenkov detector
  - goal: to investigate the LSND anomaly
  - neutrinos from Booster Neutrino Beam (BNB), ~700 MeV
  - ~500 m baseline -> same L/E

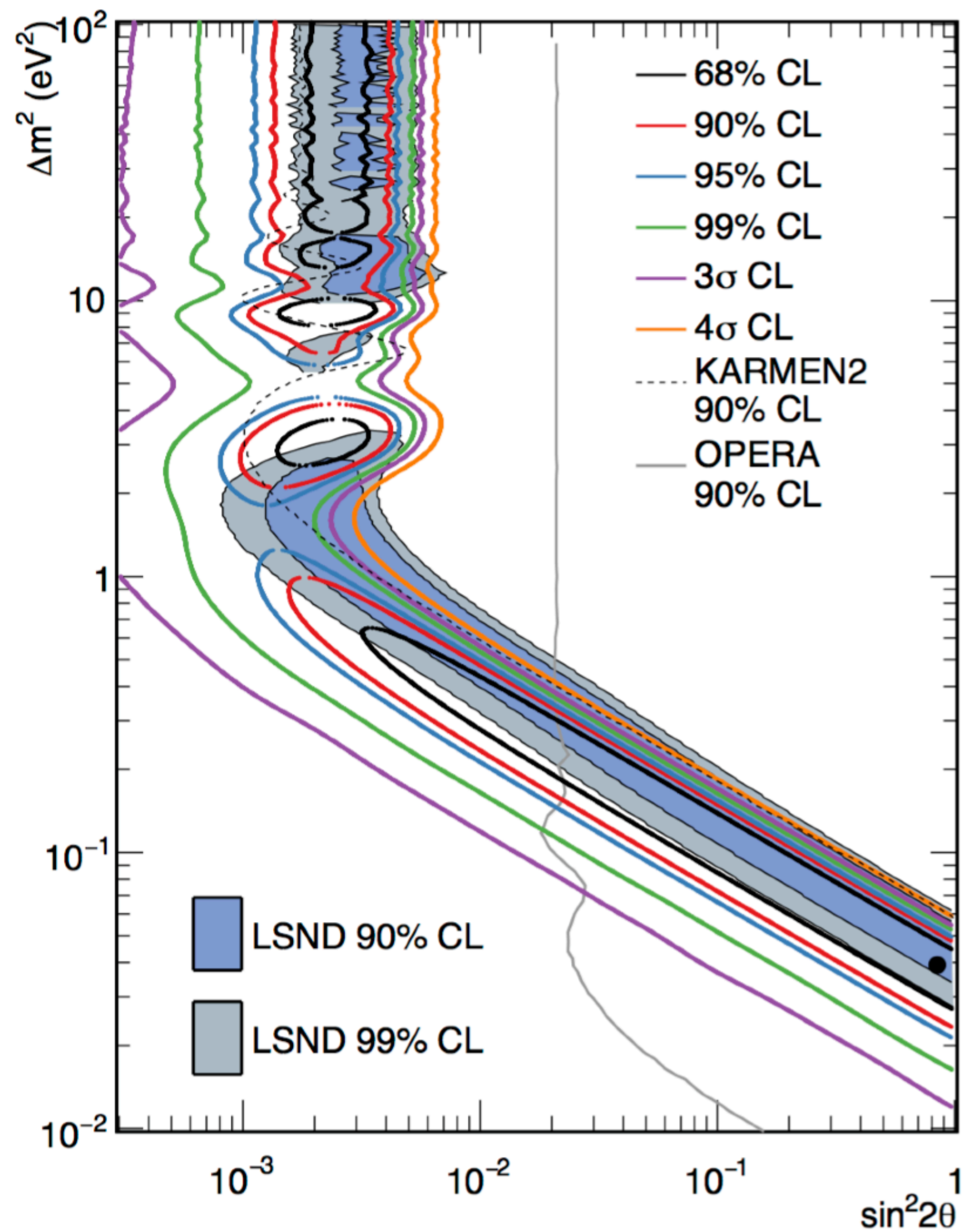


The MiniBooNE "Low energy excess"

- MiniBooNE result
  - 4.6σ excess of ve-like events in the 200-700 MeV region
  - combined with LSND >6σ
  - excess in both ν and anti-ν

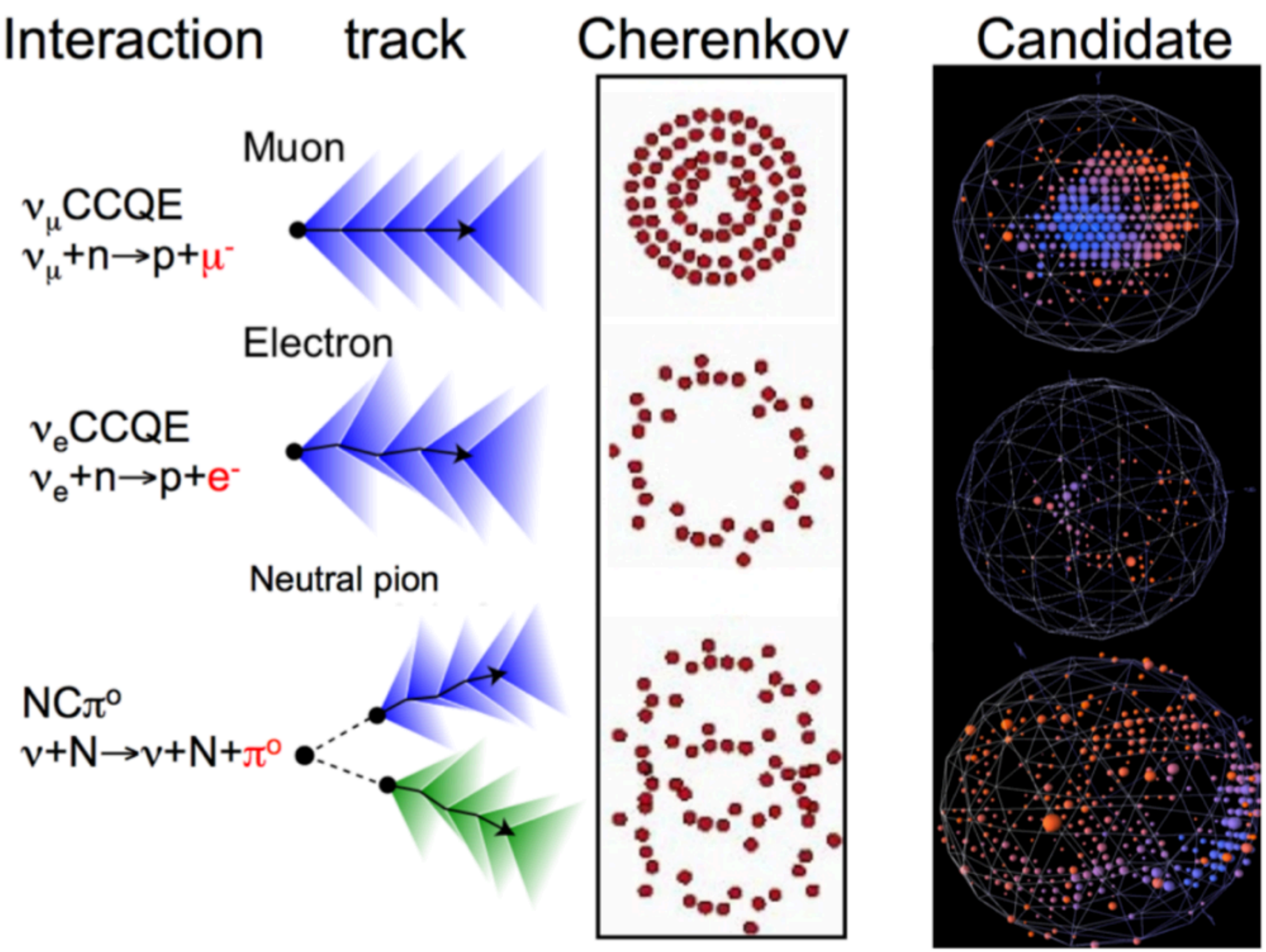
arXiv: 1805.12028

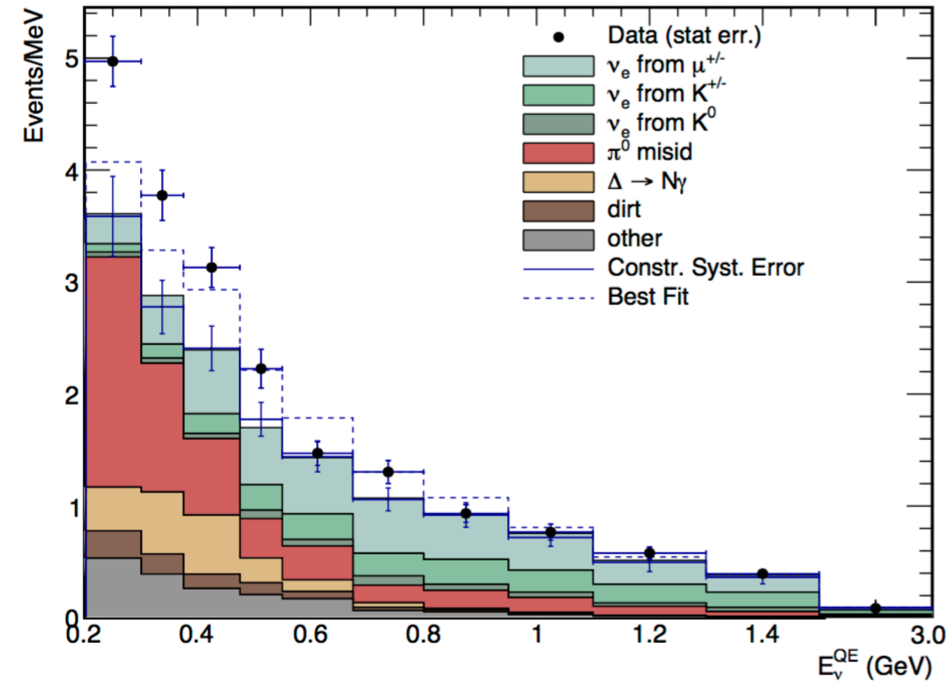




Limitations of Cerenkov detectors

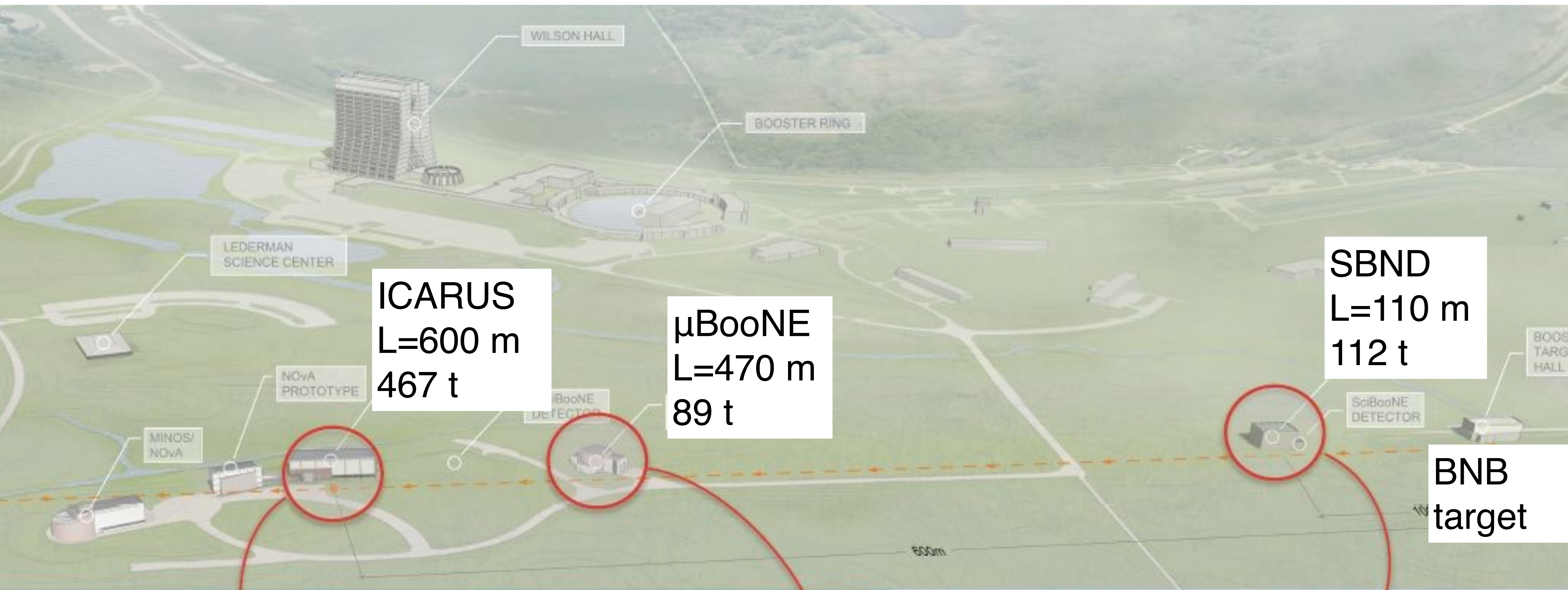
- MiniBooNE detector: mineral oil Cerenkov
  - differentiation of e/γ not possible
  - gamma BG dominant at low energy





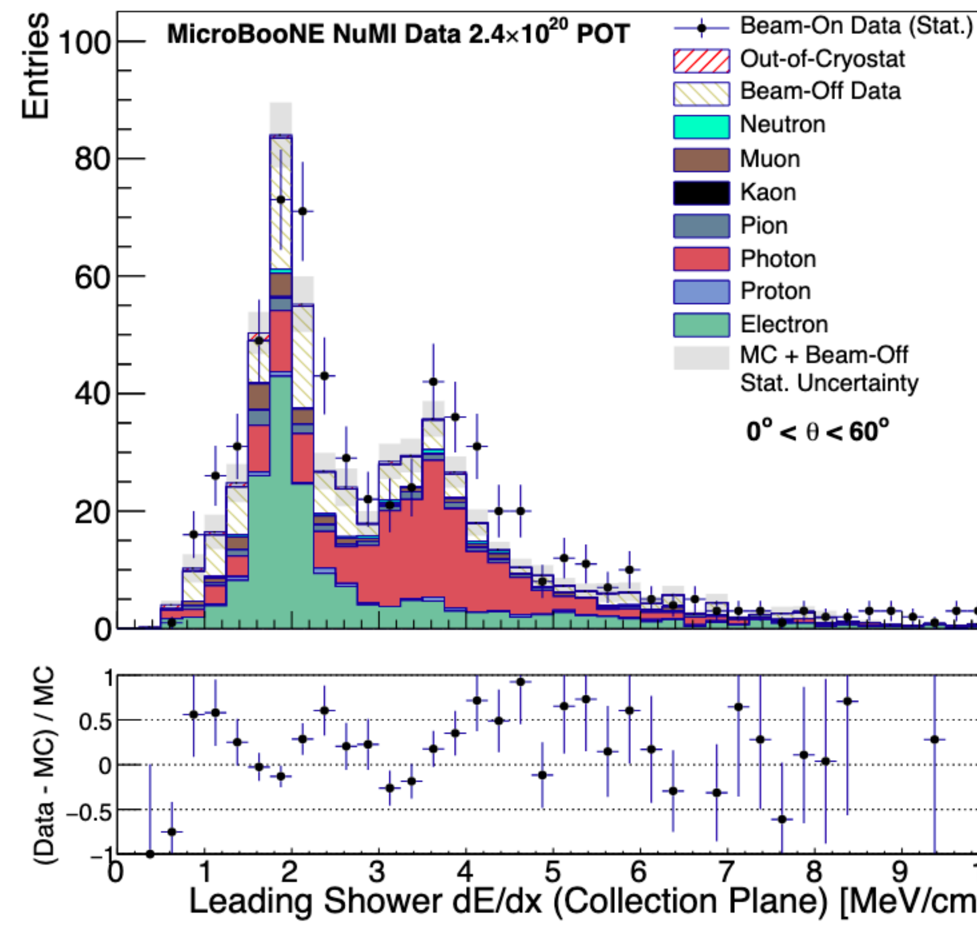
The SBN program at FNAL

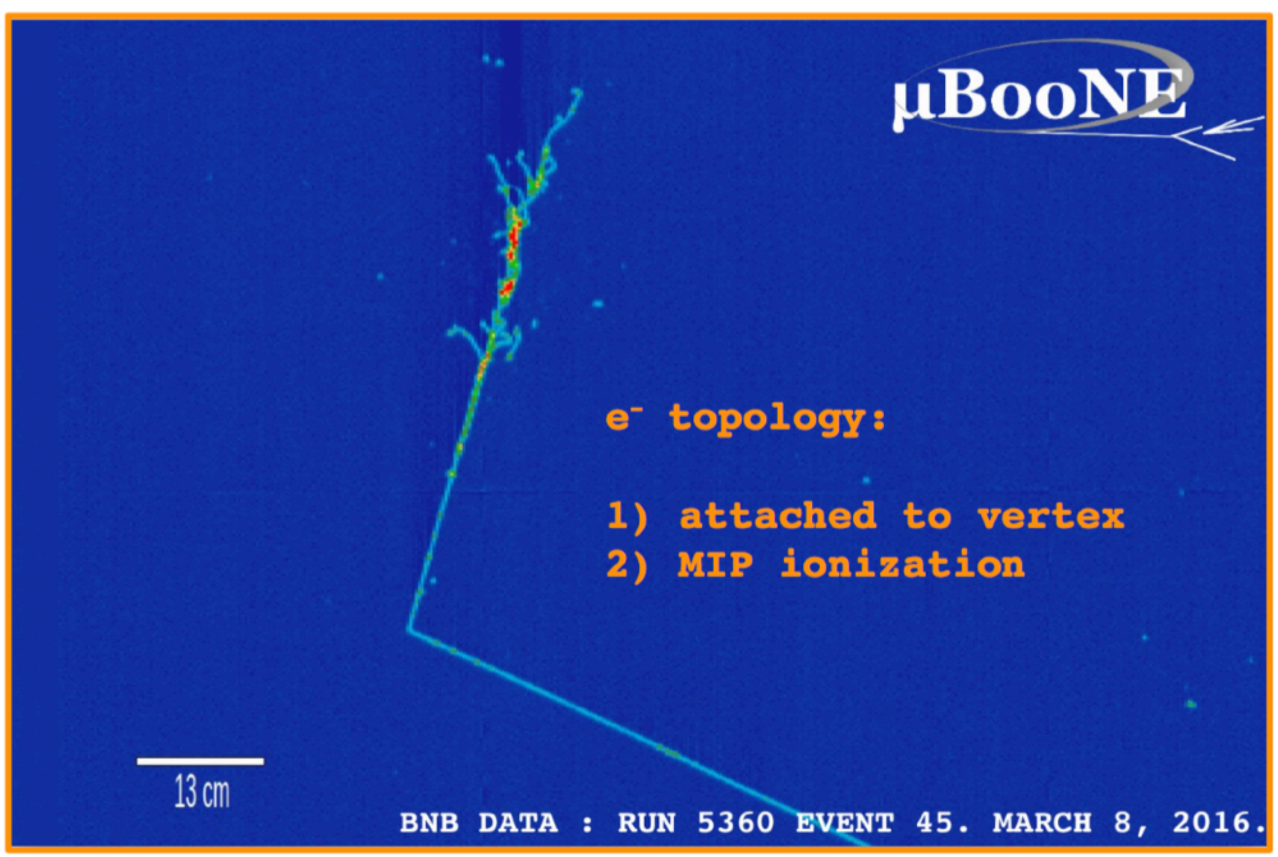
- Motivation
  - Hints of non-standard neutrino oscillations (reactor, LSND anomalies etc)
  - The MiniBooNE "low energy excess"
- Status
  - Phase 1: MicroBooNE (in operation)
  - Phase 2: SBND (under construction) and ICARUS (commissioning)

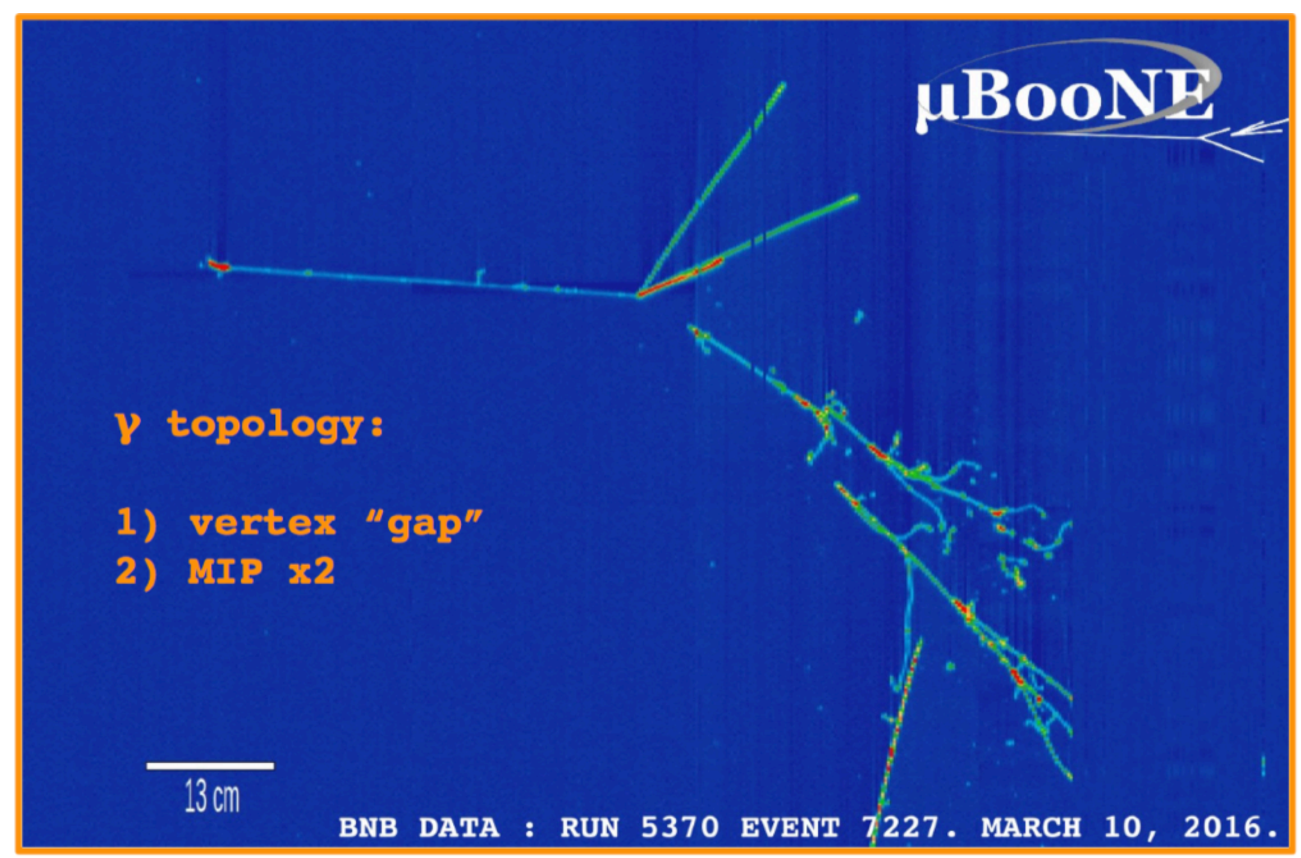


Why LArTPC?

- LArTPC: SBN detector technology
- Merits of noble gas TPCs:
  - highly-granular
  - very good spatial & energy resolution
  - e/γ differentiation using distance from vertex & dE/dx







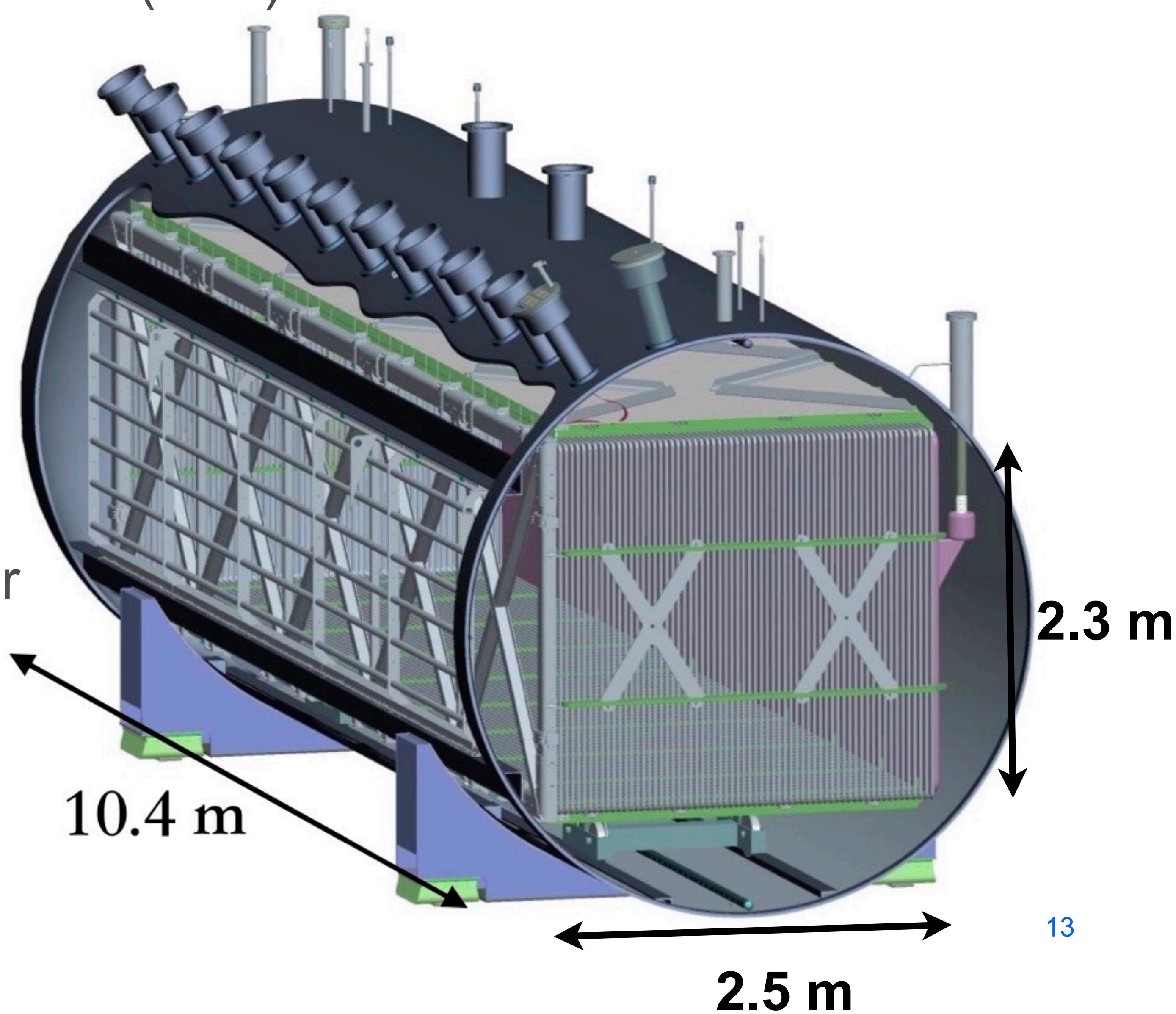
Why LArTPC?

- Why Argon?
  - Abundant (1% of atmosphere)
  - Easily ionizable (~55,000 e/cm)
  - pure Ar: high e mobility (long drift lengths) ✓
  - high scintillation yield (~40,000 photons/MeV) ✓
  - transparent to its scintillation
  - affordable ✓
- Scalable technology a must for next-generation, large-scale neutrino detectors (e.g. DUNE)

scalability

The MicroBooNE experiment

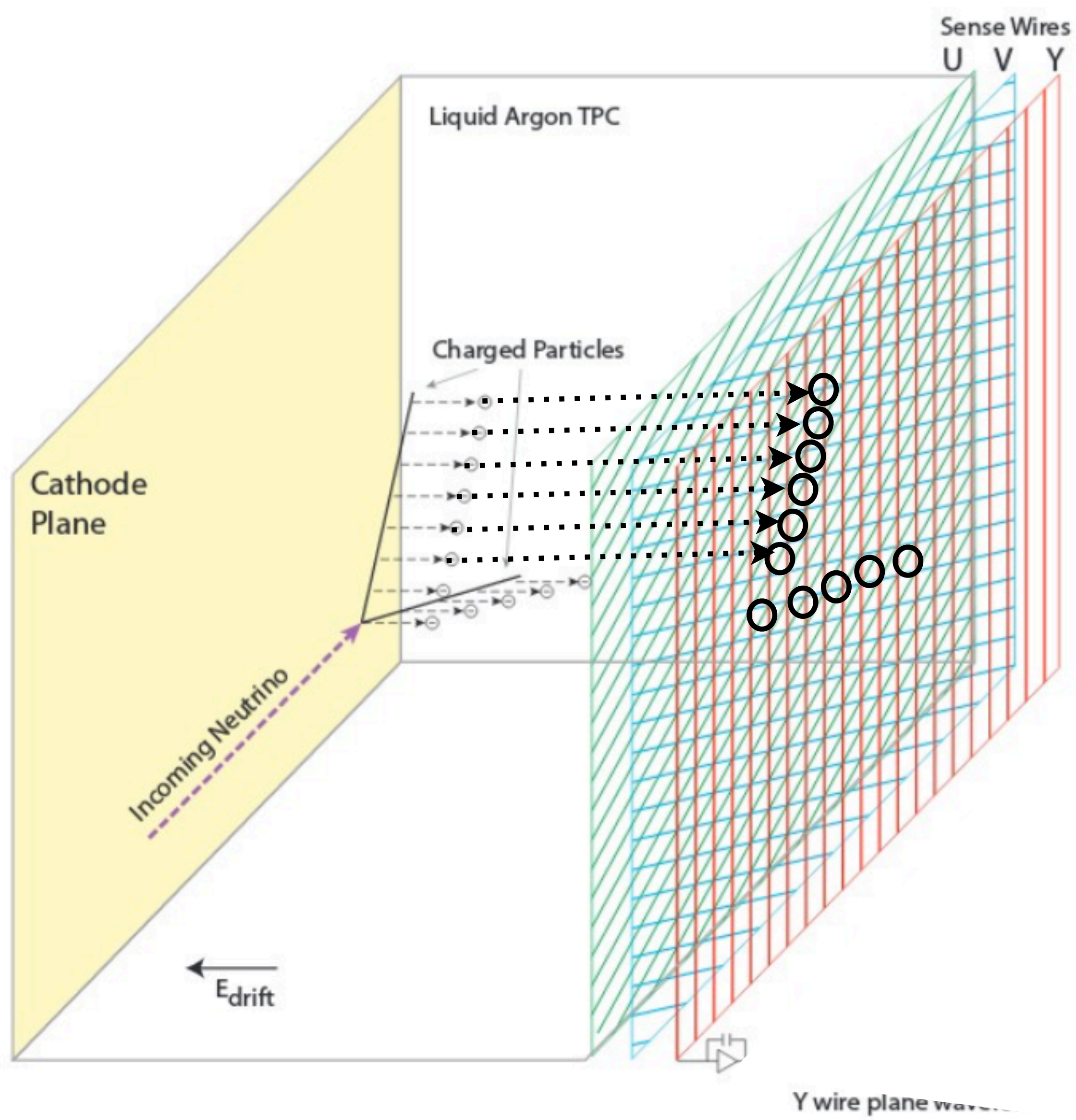
- Observing on-beam neutrinos from BNB (~470m baseline) and off-beam neutrinos from NuMI
- Main scientific goals:
  - Explore the MiniBooNE low energy excess (LEE)
  - Measure ν cross-sections on LAr
  - LArTPC R&D
- Detector
  - 85 t (active) LArTPC
  - 3 readout wire planes w/ 3mm pitch
  - 32 8' PMTs
- Since summer 2016: Cosmic Ray Tagger
  - plastic scintillator strips in 2 xy layers
  - cover top, bottom, and sides
  - 85% coverage of muons

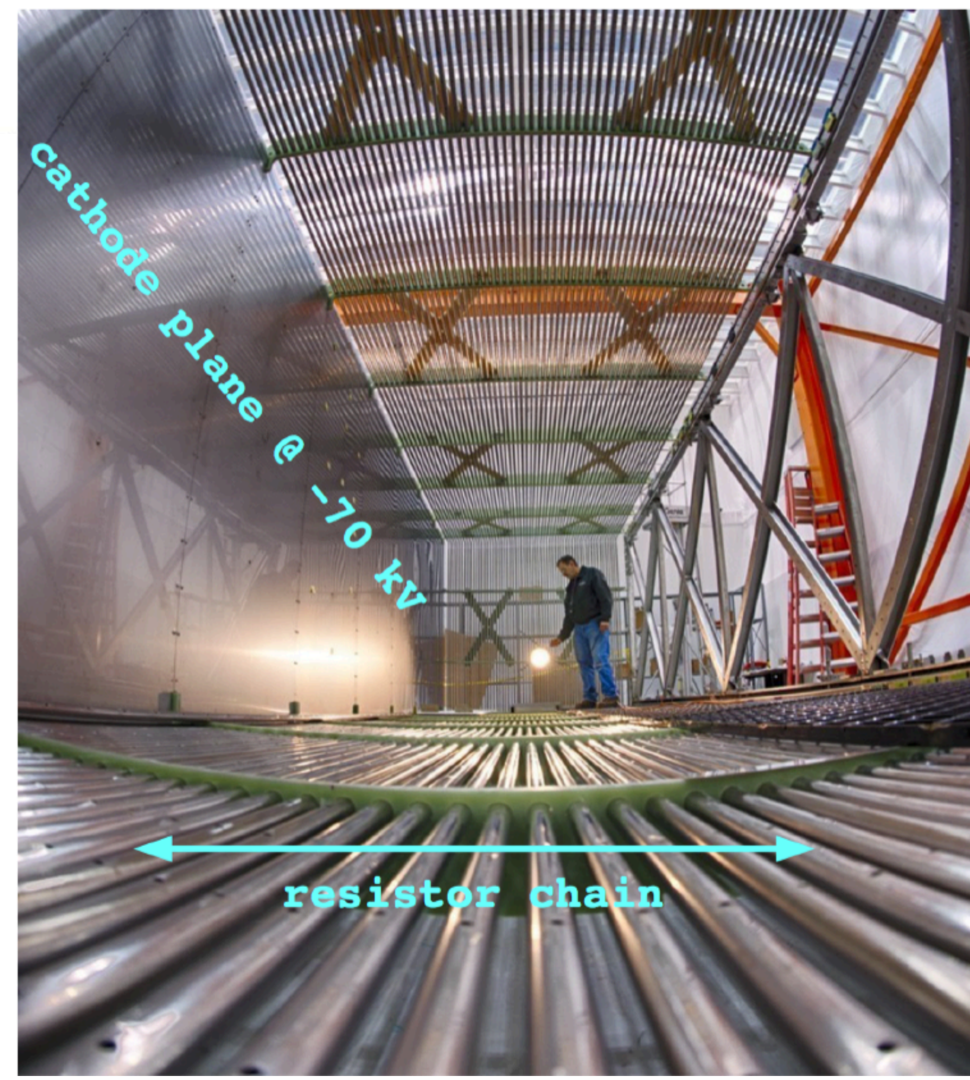


Working principle of LArTPCs

- Charged particles ionize Ar
  - Ionization e drift in electric field towards anode plane

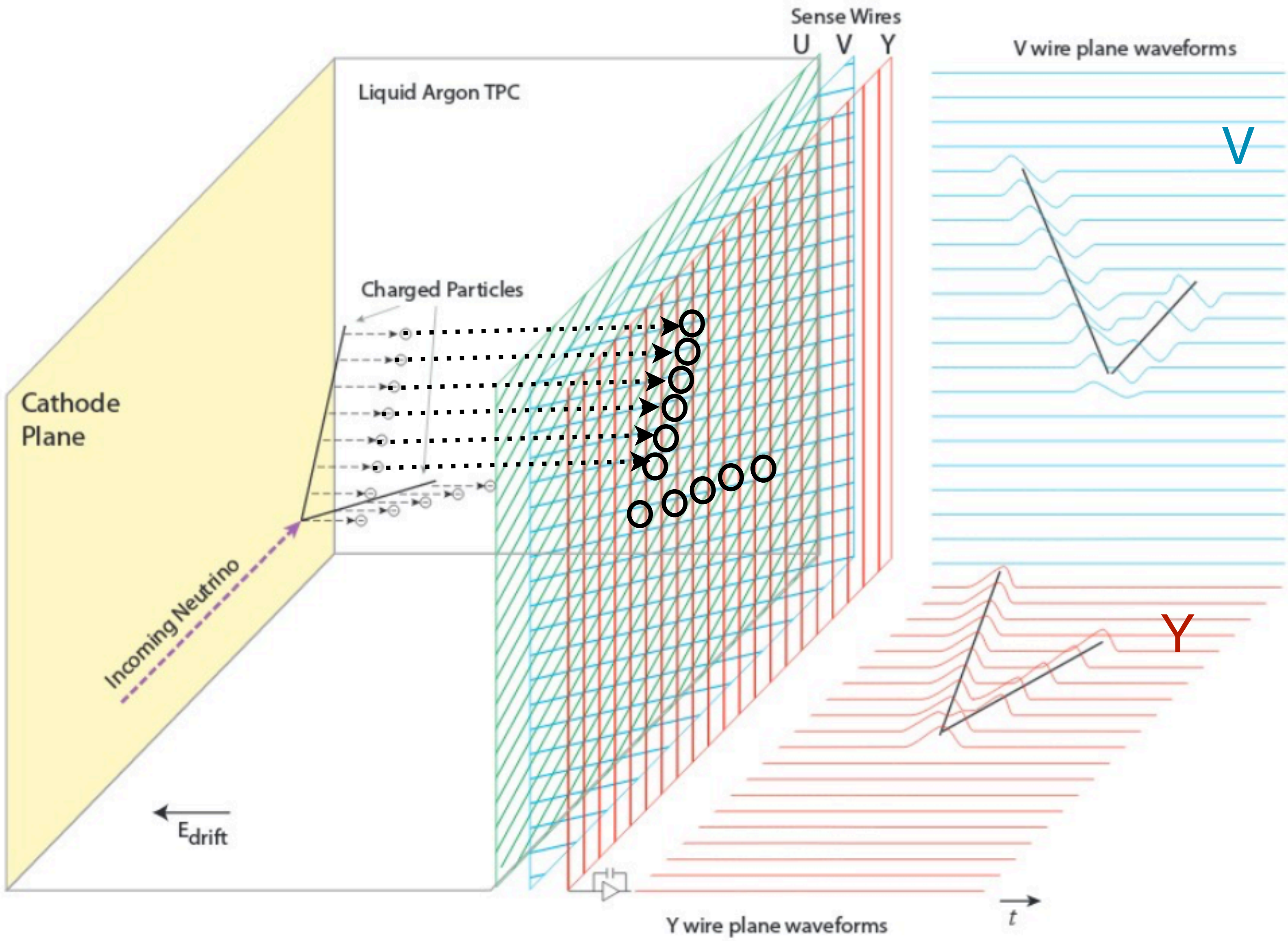
E field: 273 V/cm
e^- drift: ~0.1 cm/µs
2.3 ms for full drift distance



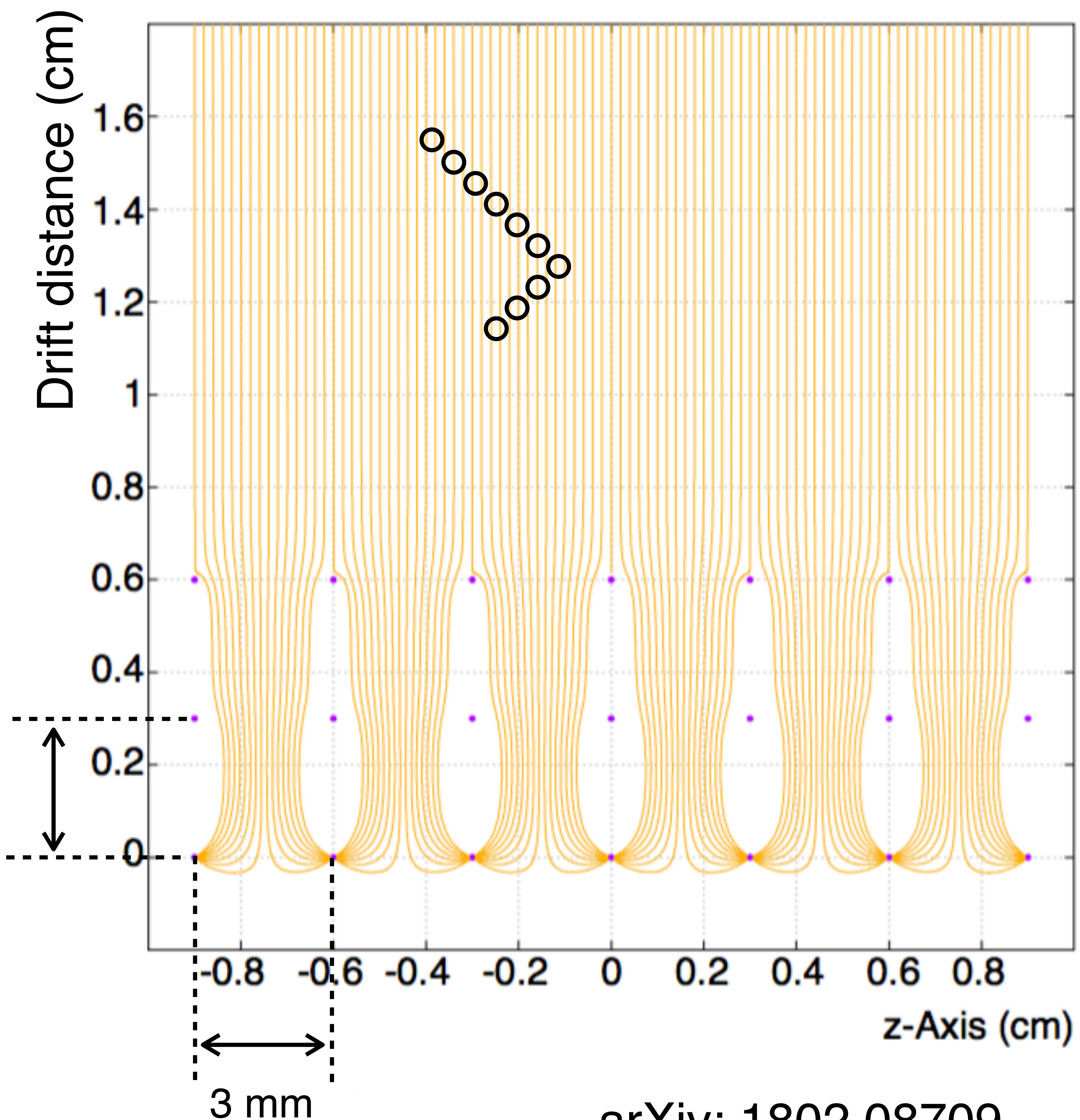


Working principle of LArTPCs

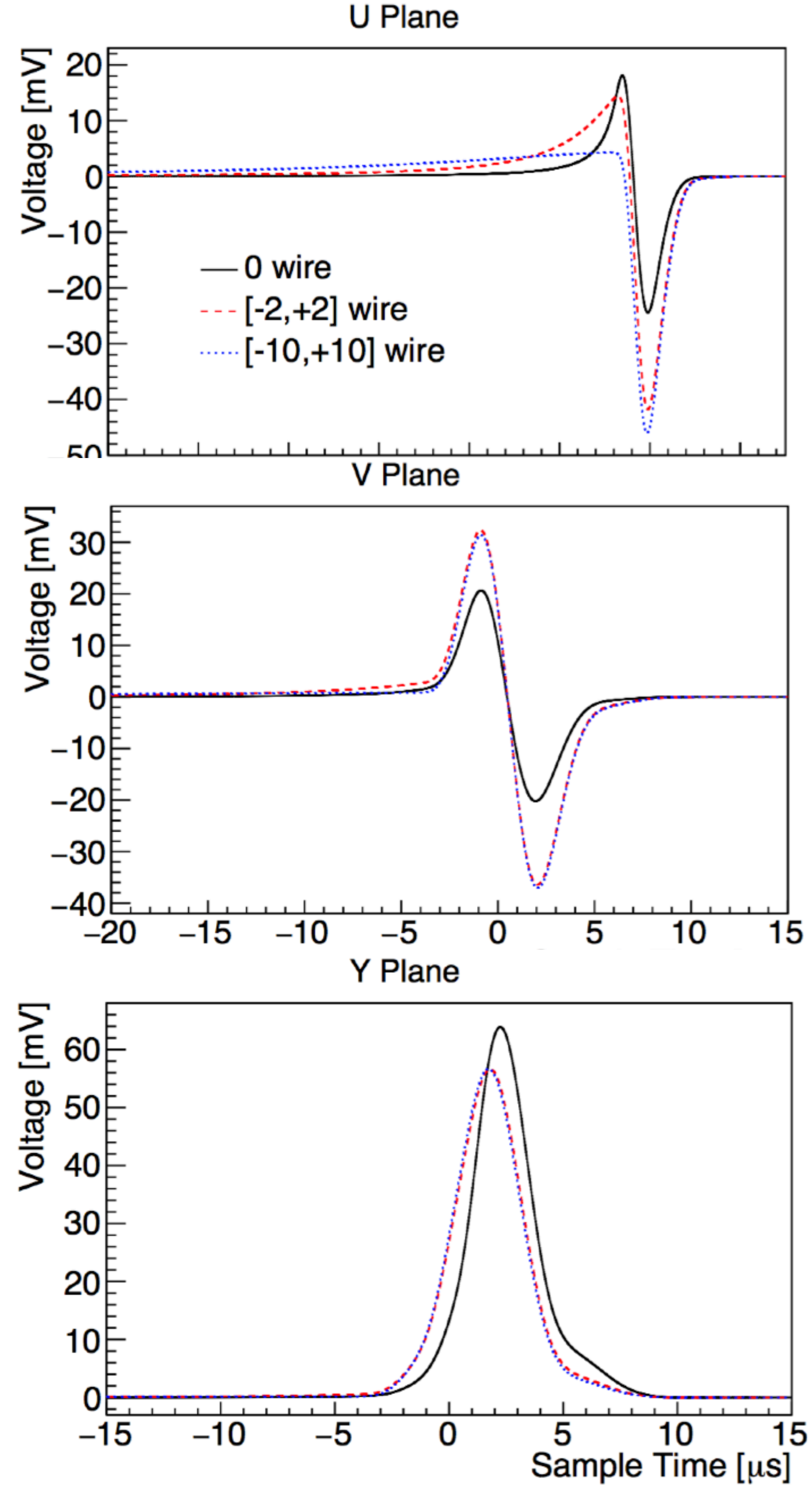
- Charged particles ionize Ar
  - Ionization e drift in electric field towards anode plane
  - Signal read out by 8256 wires on 3 wire planes



Charge signal formation



arXiv: 1802.08709

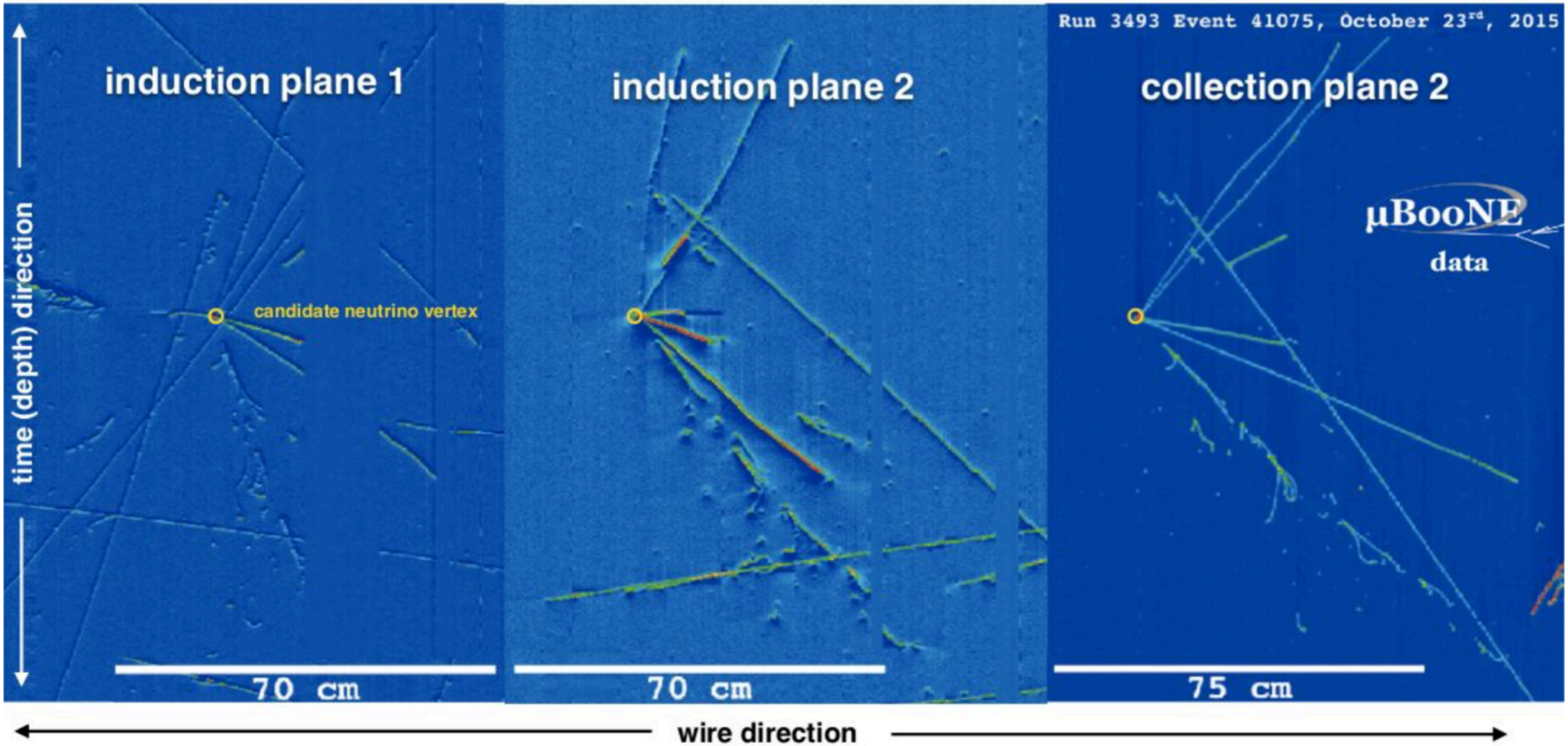


U: small, bipolar

V: small, bipolar

Y: large, unipolar

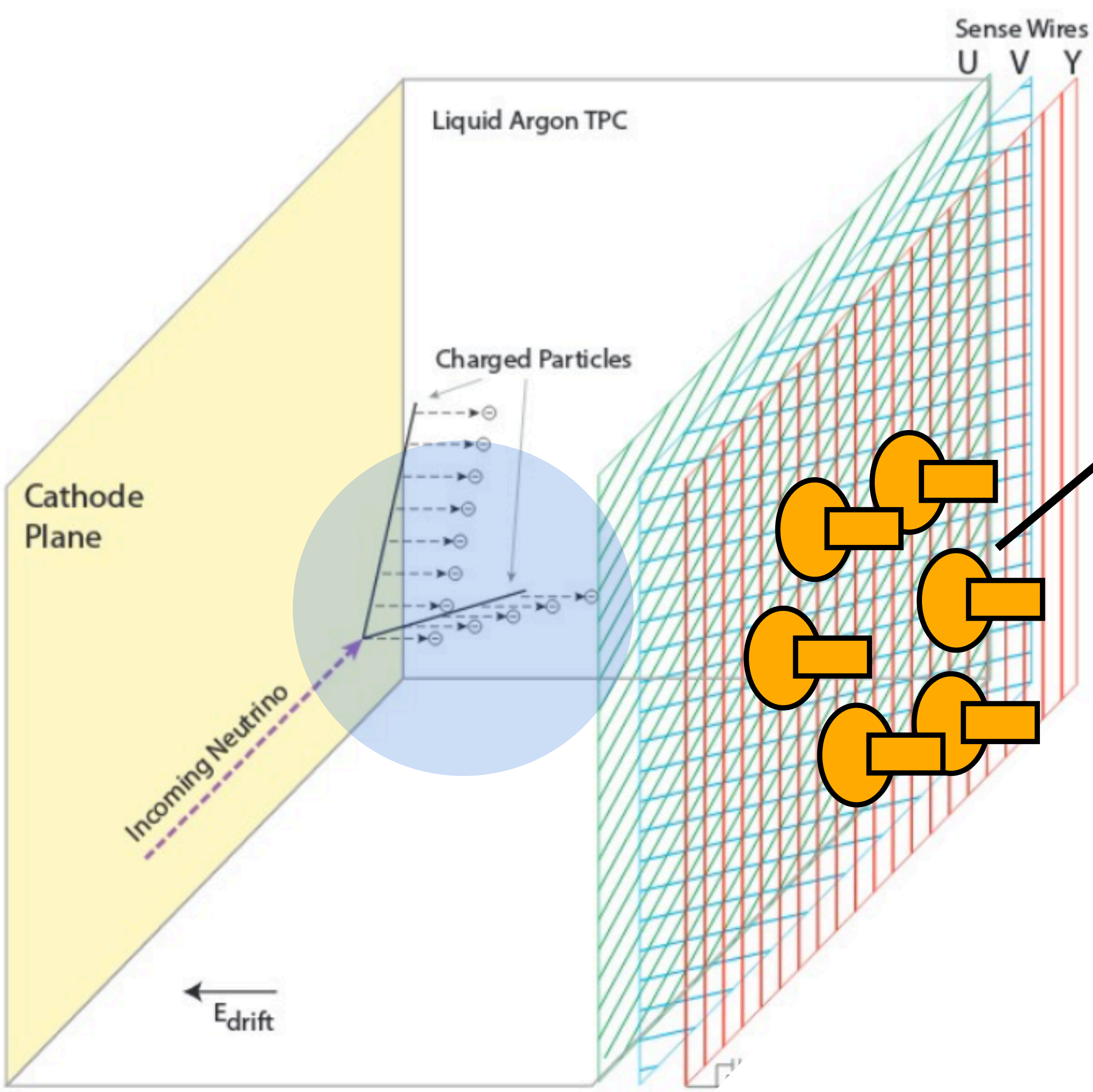
Charge signal formation



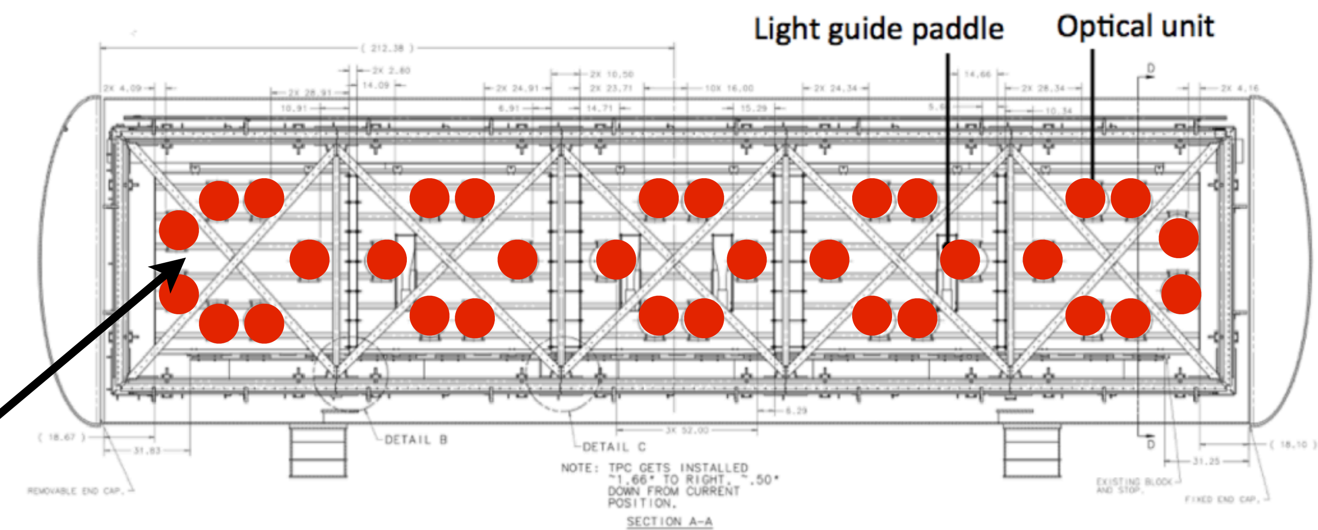
- Data is recorded as 2D “images” of charge on **wire** vs. **time**: projections of the 3D charged particle trajectories

Observing light in MicroBooNE

- Charged particles ionize Ar
  - Isotropic UV scintillation light
  - Observed by photon detection system

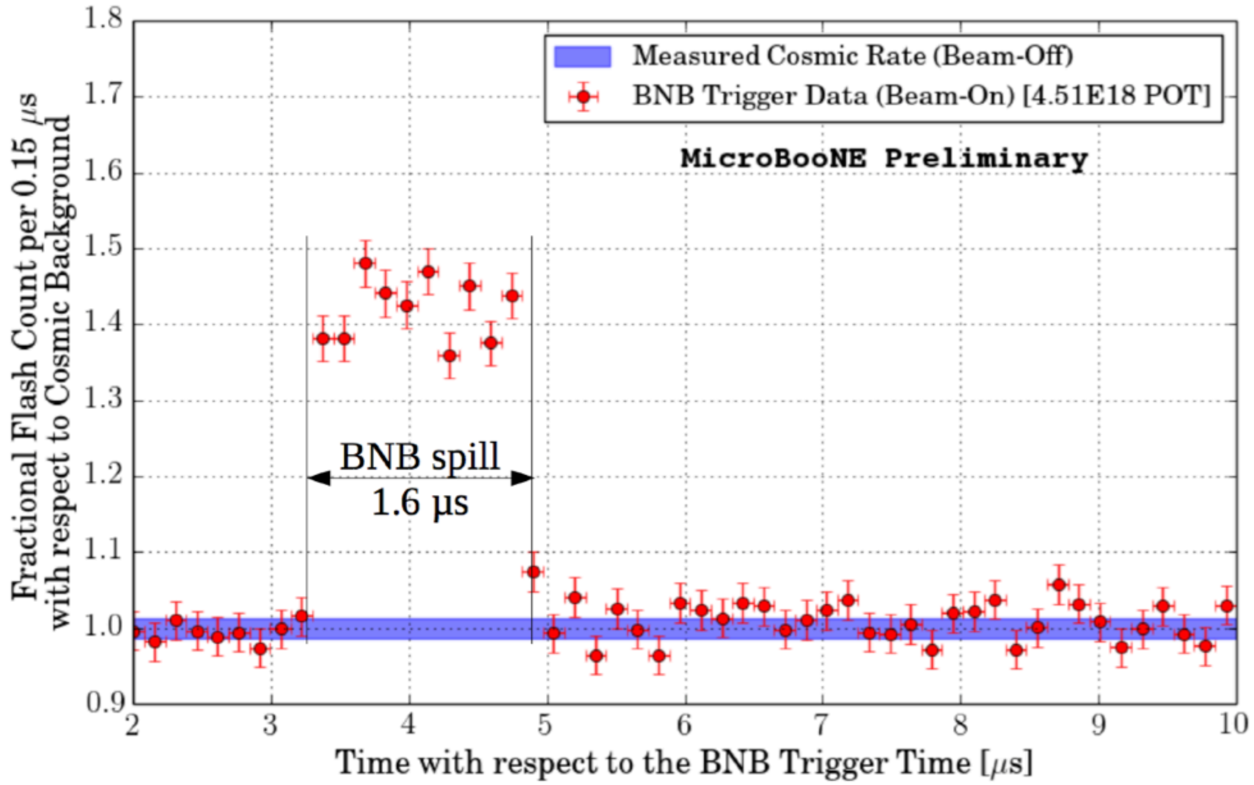


Light collection system records LAr scintillation



Importance of light in LArTPCs

- Most beam spills empty, contain only cosmic rays (CRs)
- Light data is an important handle for CR rejection
  - Trigger: require PMT activity in time with beam=> drop trigger rate by factor x50
  - Matching of TPC energy deposit to light data
    - Reject TPC activity not consistent with beam-window PMT data



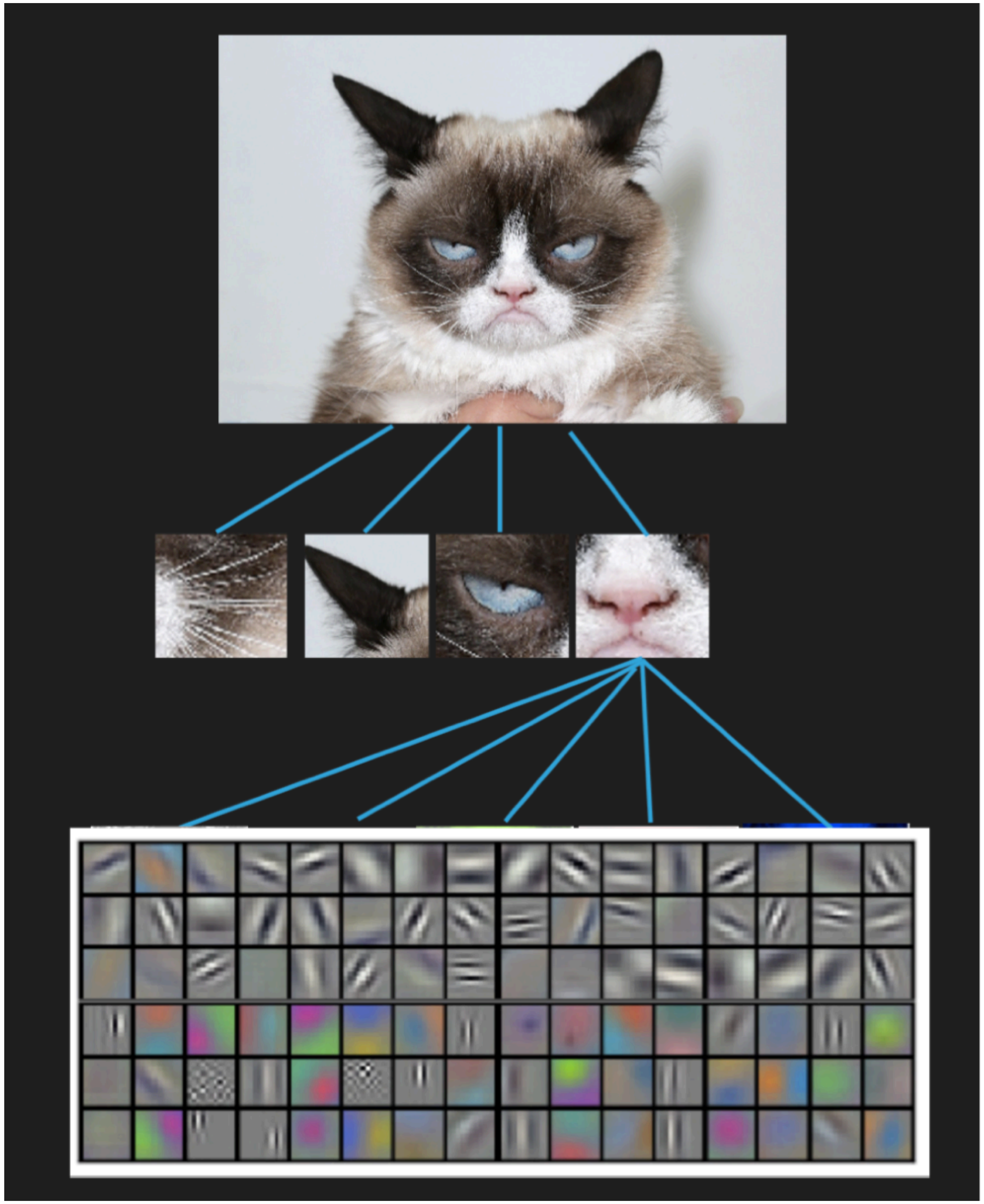
MicroBooNE Physics analyses

- MicroBooNE has multiple physics analysis groups using independent event reconstruction methods (Pandora, Wire-Cell, DL)
  - exploring new tools in this relatively new LArTPC technology
  - independent analyses = robust physics results
- All groups use some Machine learning/Deep learning tools
  - reconstructing neutrino daughter trajectories challenging in events dominated by large CR background (surface detector)
  - Improve processing time and precision in an automated (non-human supervised) reconstruction chain
    - Mis-reconstruction affects efficiency, purity, particle kinematics, final state particle content (the latter are difficult to model)

Deep Learning Analysis

- Deep Learning (DL) event reconstruction
  - 2D image data format: suited for computer vision applications
  - combines convolutional neural networks (CNNs) with standard algorithms
- First application of a CNN to MicroBooNE data showed promise (JINST 12 (03), P03011 (2017) and Phys. Rev. D 99, 092001 (2019))
  - since then have expanded use of DL tools & published several papers
  - final goal: full 3D reconstruction chain with CNNs
- CNN development in conjunction with physics analysis

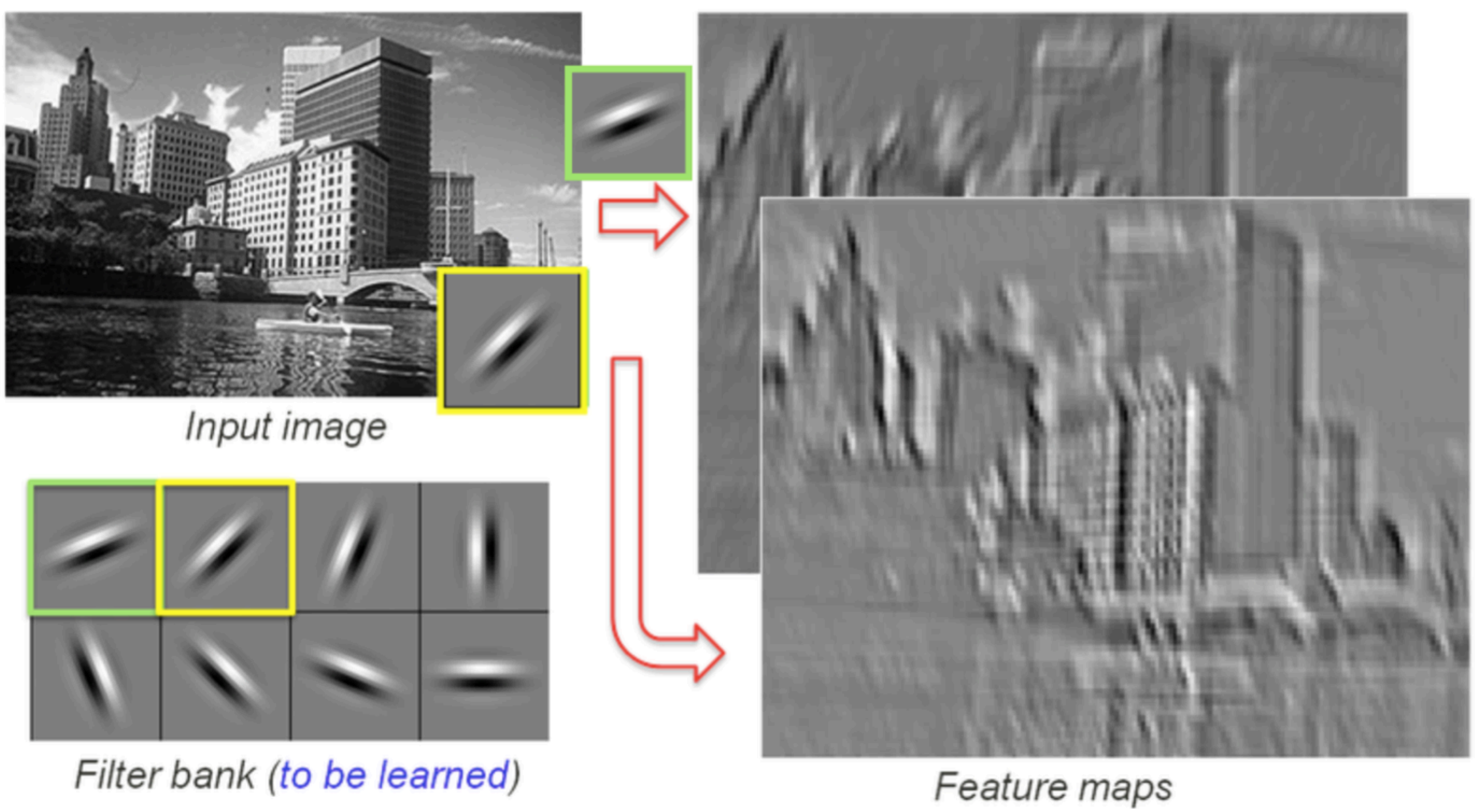
Image analysis with computer vision



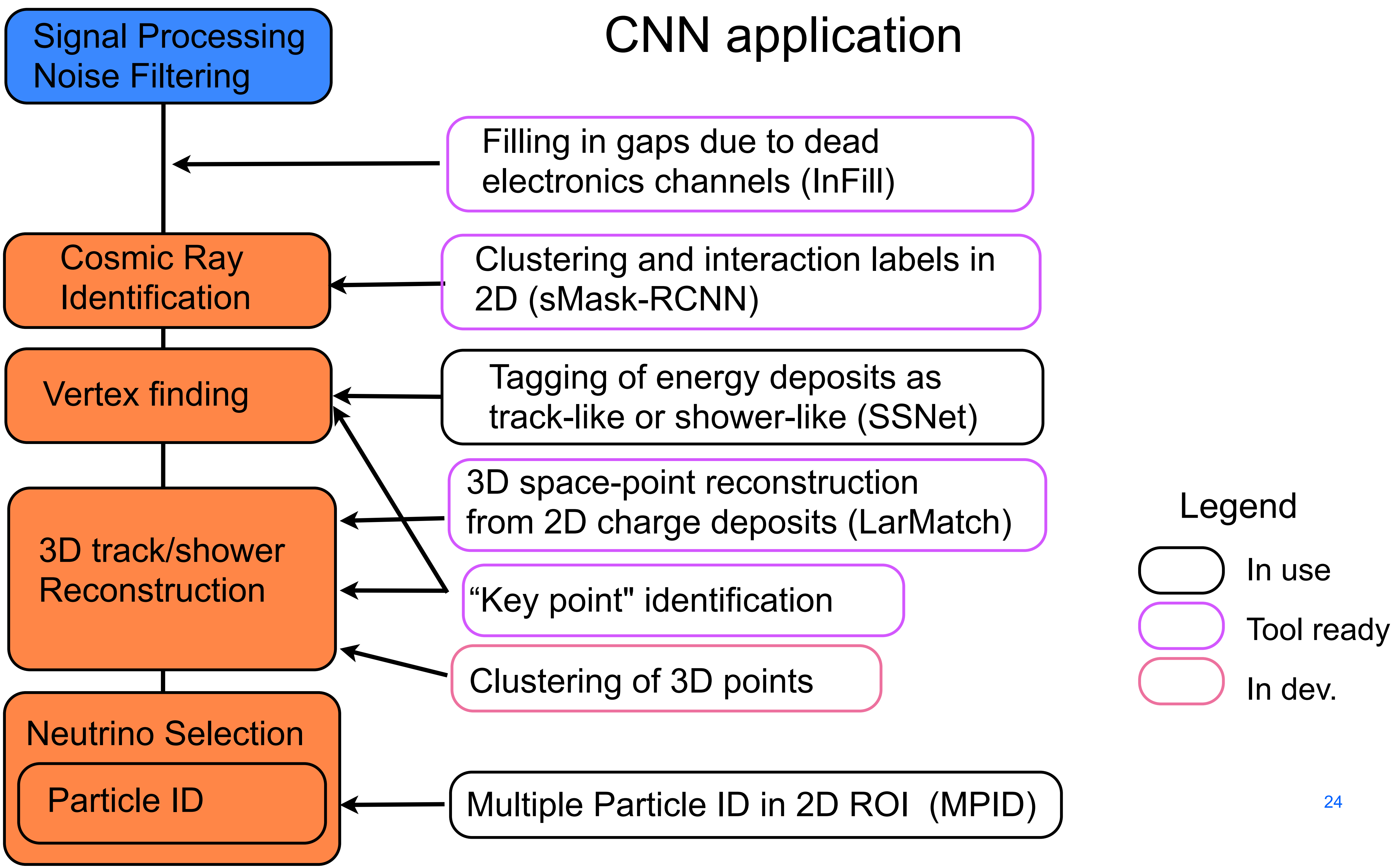
- To recognize an image, e.g. as a cat, decompose an object into a collection of small features
- Features composed of different patterns, lines and colors
- Convolutional neural networks (CNNs) often used
  - local connectivity
  - same weights for each layer
  - extract both local and global features & “context”

Convolutional Neural networks

- Type of a deep neural network well-suited for image-type data analysis
  - Versatile applications
- Core operation in a CNN is the convolutional filter: identifies the positions of patterns within an image
  - Dense: operates on all pixels
  - Sparse: operates on non-zero pixels only (saves on time and memory)
- In example below light and dark in output show where the pattern matches well



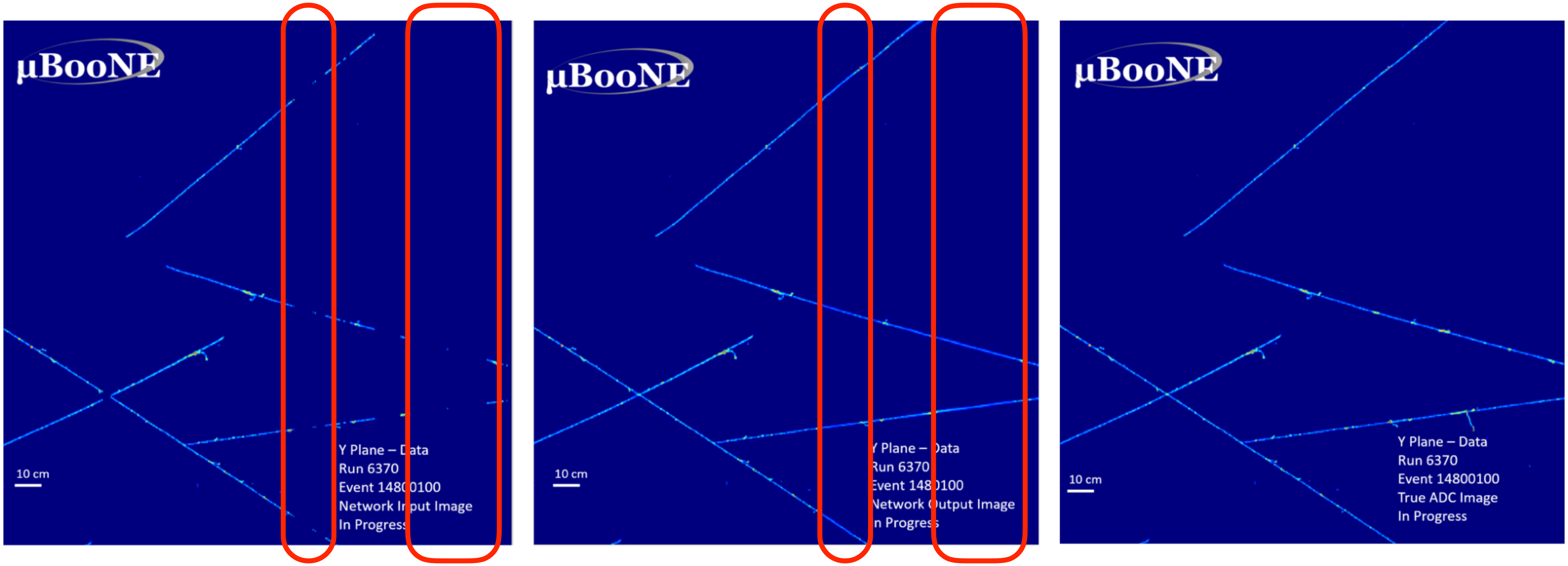
Neutrino candidate reconstruction flow in DL group



Reconstructing dead Channel Information with Infill

- MicroBooNE wire-plane images: multiple gaps due to unresponsive/noisy TPC channels
  - problem for CR tagging and 3D track reconstruction: partial tracks
- InFill: a generative CNN that reconstructs trajectories in dead regions
  - trained on data

K. Mason



Network input:artificial gaps

Network output

Original

Infill Network performance

- InFill performance on beam-off data
  - **99%** of pixels with charge predicted correctly ⇦ Important for trajectory reco
  - charge match 1/4 of pixels

Fraction of pixels (%)	Induction plane 1	Induction plane 2	Collection plane
Within 2 ADC*	27.2	20.2	25.2
Within 10 ADC	66.8	56.4	66.7
Within 20 ADC	84.5	75.1	84.9
Binary Accuracy	98.4	99.1	99.1

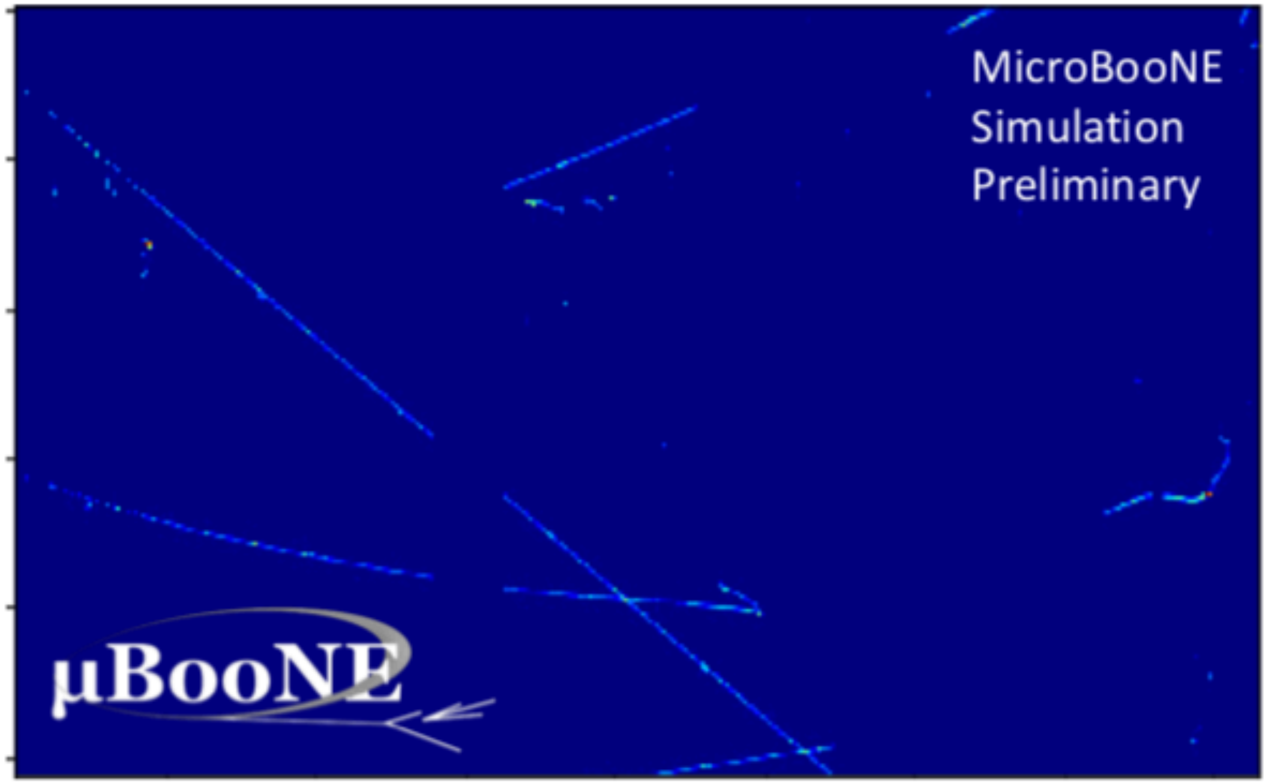
*ADC: arbitrary unit of integrated charge. Intensity in 2D wire plane images

Cosmic ray tagging with sMask-RCNN

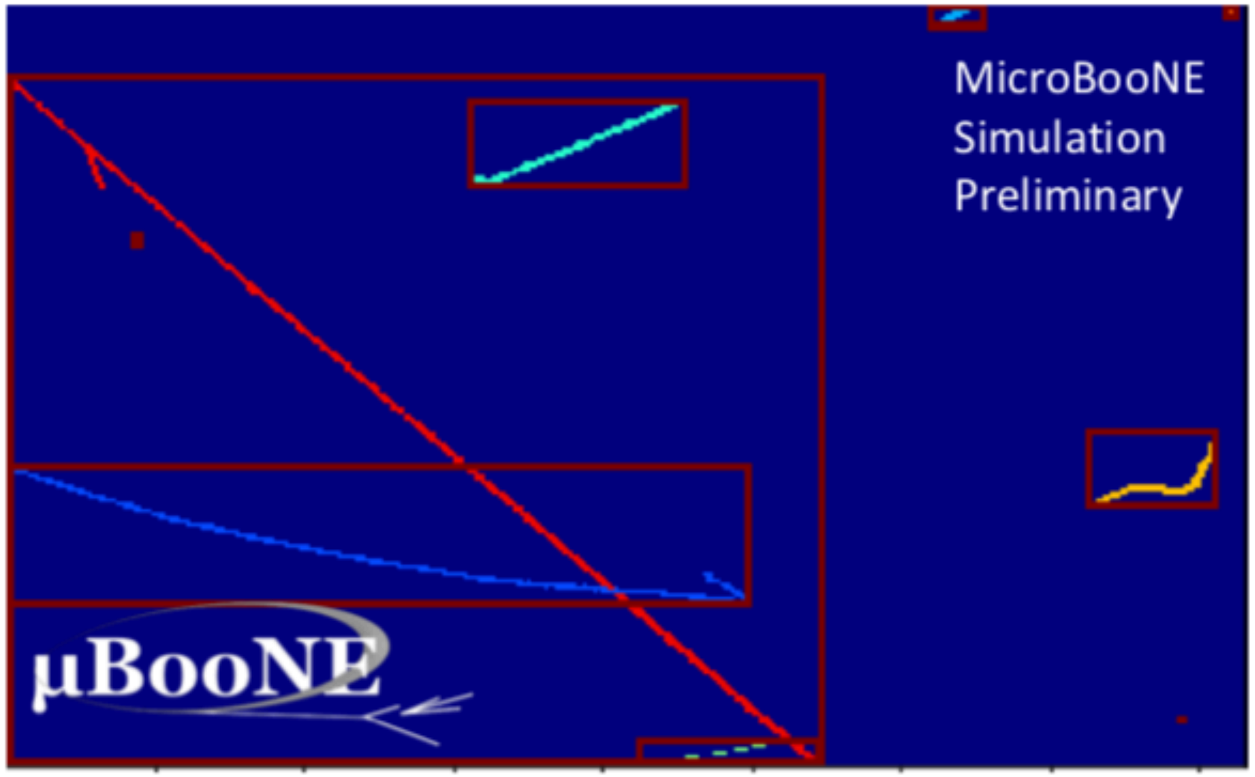
J. Mills

- Cosmic Ray background dominant in MicroBooNE data
- CR tagging: need to collect all pixels in 2D view
- sMask-RCNN: identifies 2D pixel clusters according to particle interaction

Raw image



Clustering by interaction



MICROBOONE-NOTE-1081-PUB

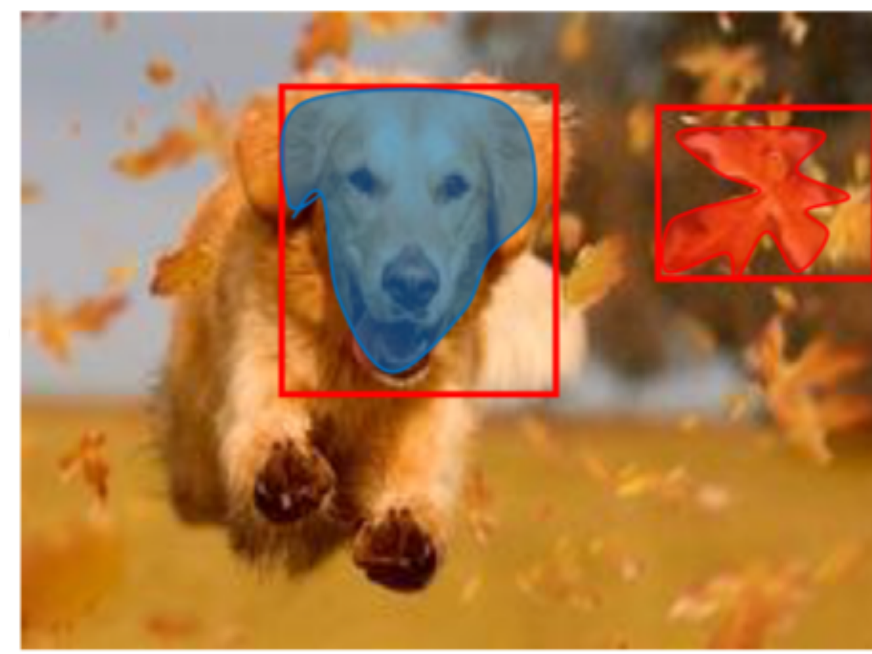
Cosmic ray tagging with sMask-RCNN

- sMask-RCNN: identifies 2D pixel clusters according to particle interaction

Boxes Proposed (RPN)

Boxes Classified (Classifier)

Masks (Clustering FCN)

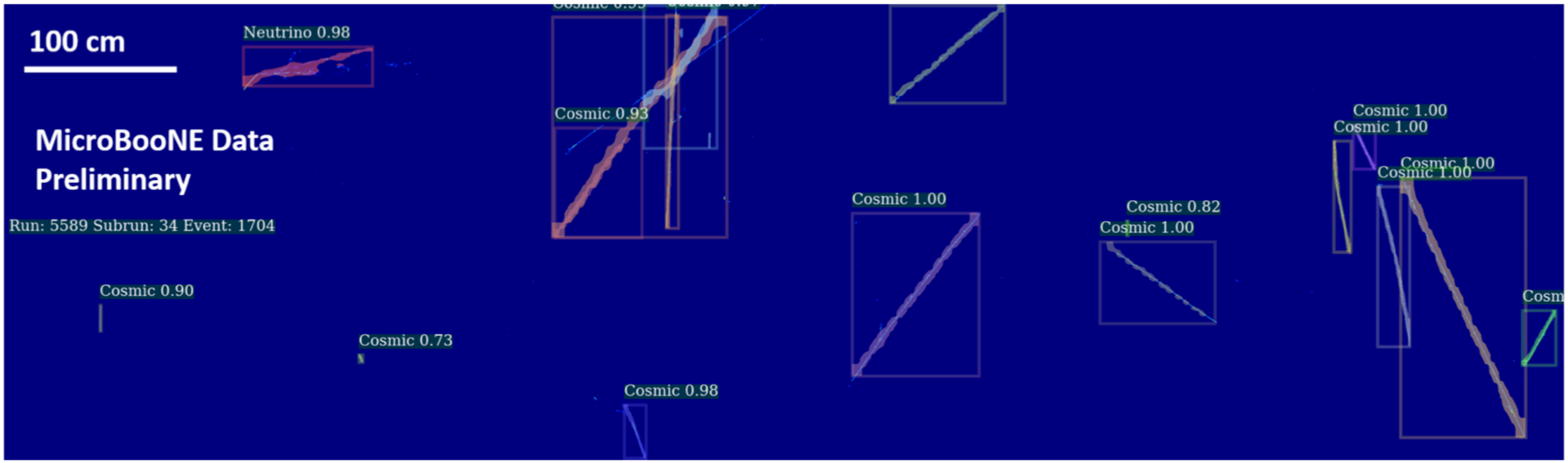


Step 1:
propose bounding box

Step 2:
classify

Step 3:
mask pixels

sMask-RCNN Example on data



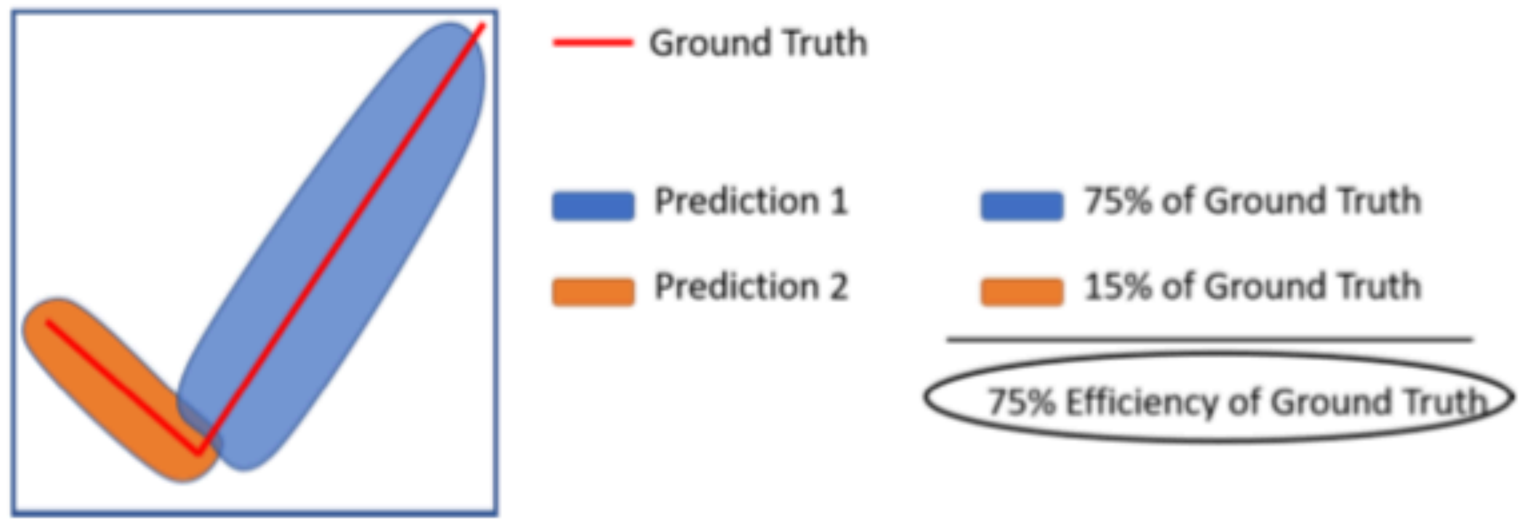
Beam-On data event. Selected as neutrino candidate by DL LEE analysis
Neutrino is correctly identified
Most CRs are correctly identified

Highly overlapping regions can be difficult (overlapping masks)

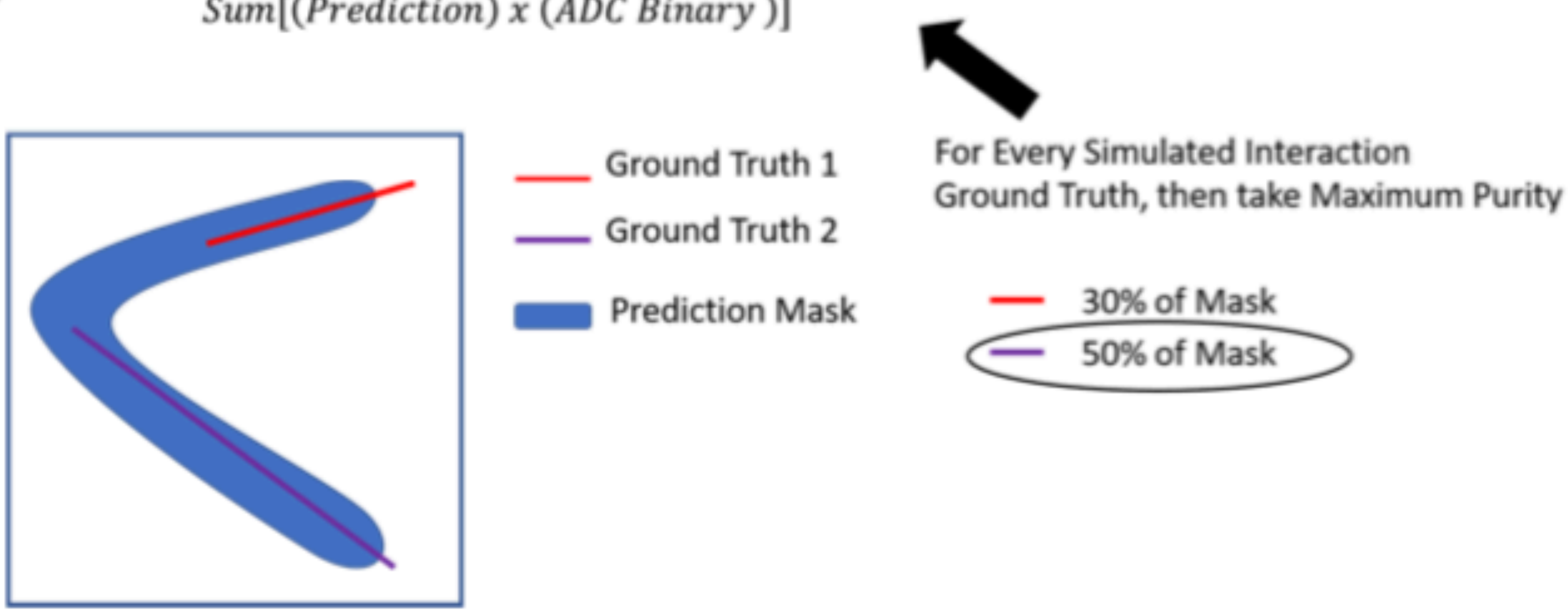
sMask-RCNN Network performance

Network performance estimated in terms of Efficiency vs. Purity

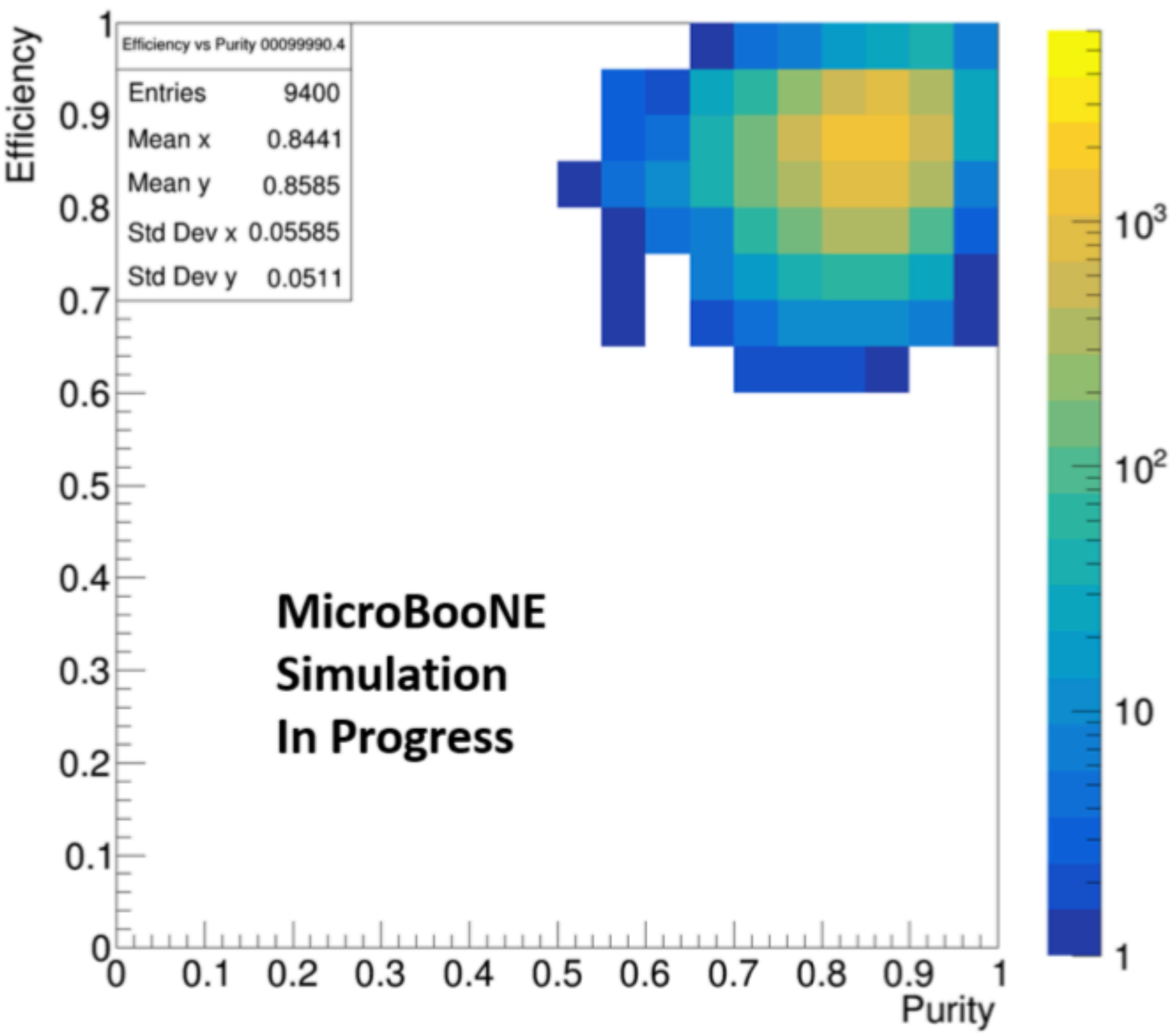
$$Efficiency = \frac{Sum[(Best\ Overlapping\ Prediction)\ x\ (Ground\ Truth)\ x\ (ADC\ Binary)]}{Sum[(Ground\ Truth)\ x\ (ADC\ Binary\ )]}$$

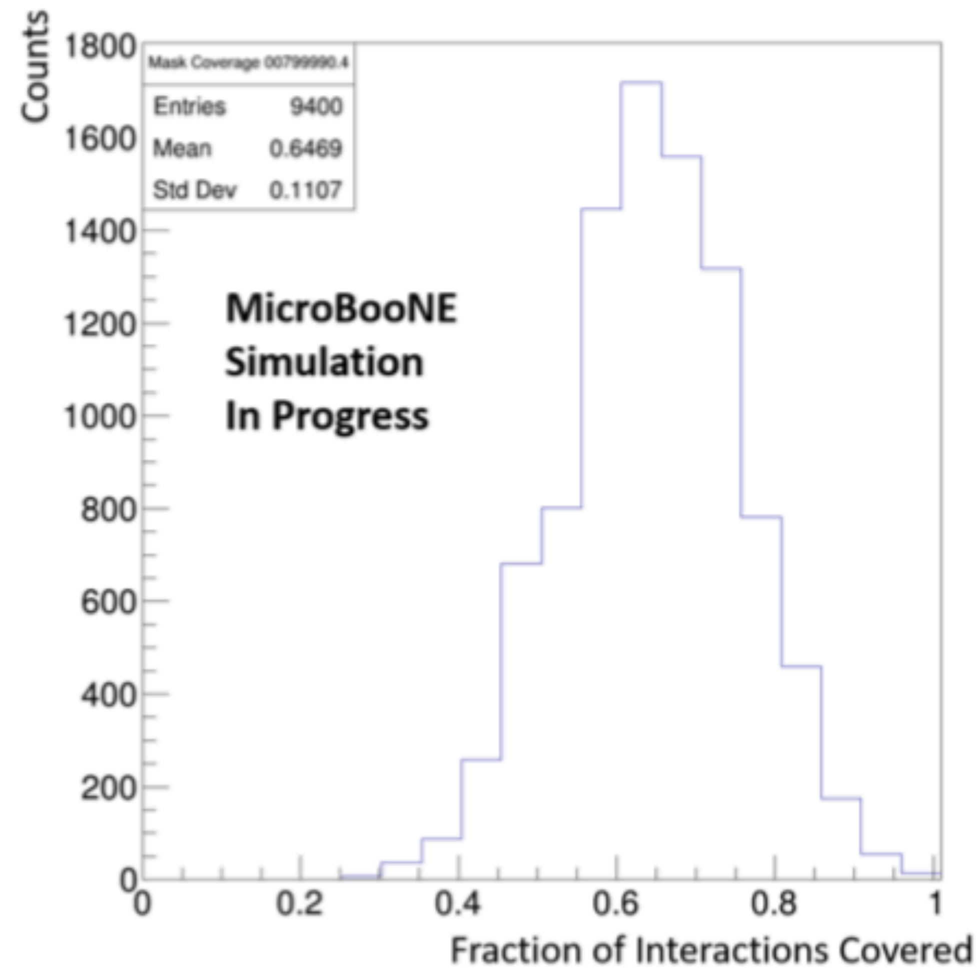


$$Purity = \frac{Sum[(Prediction)\ x(Ground\ Truth)\ x\ (ADC\ Binary)]}{Sum[(Prediction)\ x\ (ADC\ Binary\ )]}$$



sMask-RCNN Network performance

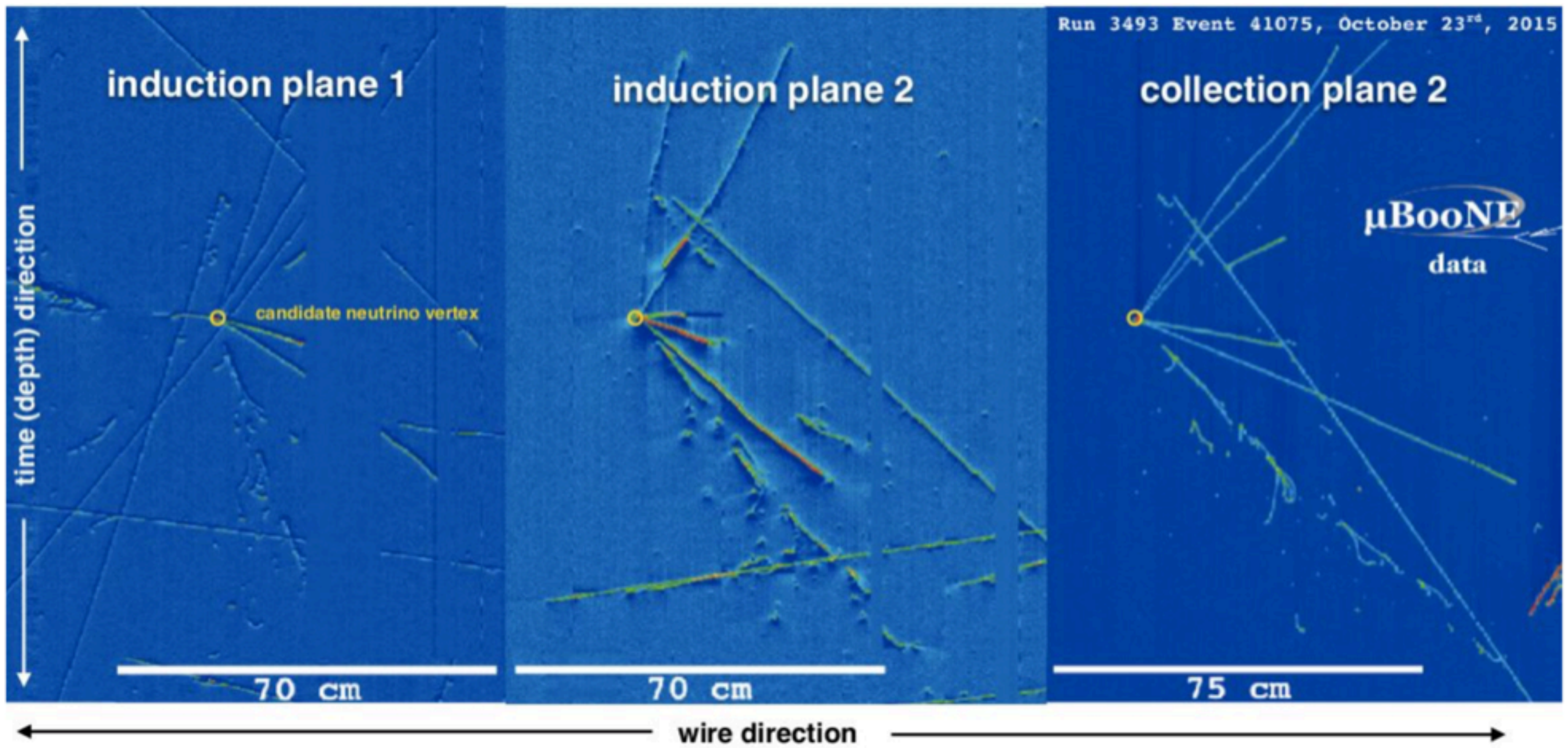




Mean efficiency at 84%
Mean purity at 85%

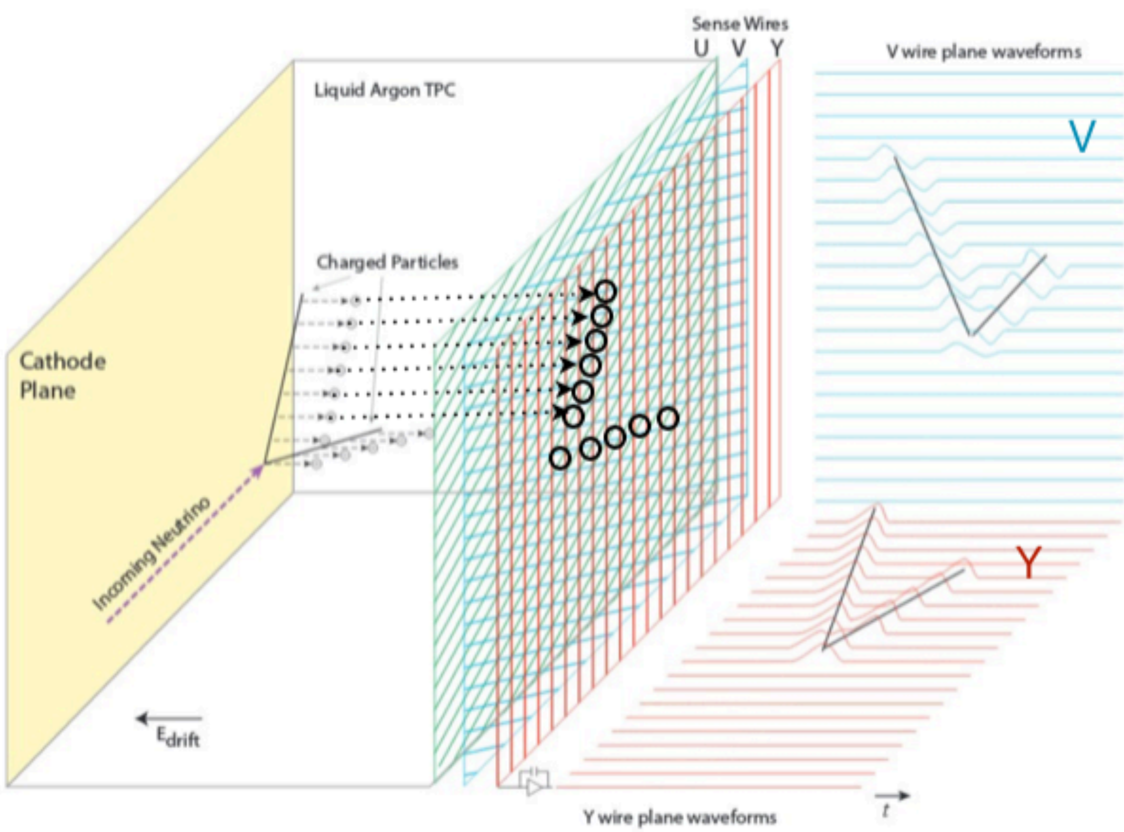
65% of interactions covered at >90%

Neutrino reconstruction: from 2D to 3D



Data recorded as 2D images of charge on **wires** vs **time:** projections of 3D trajectory

Three images for the three wire planes



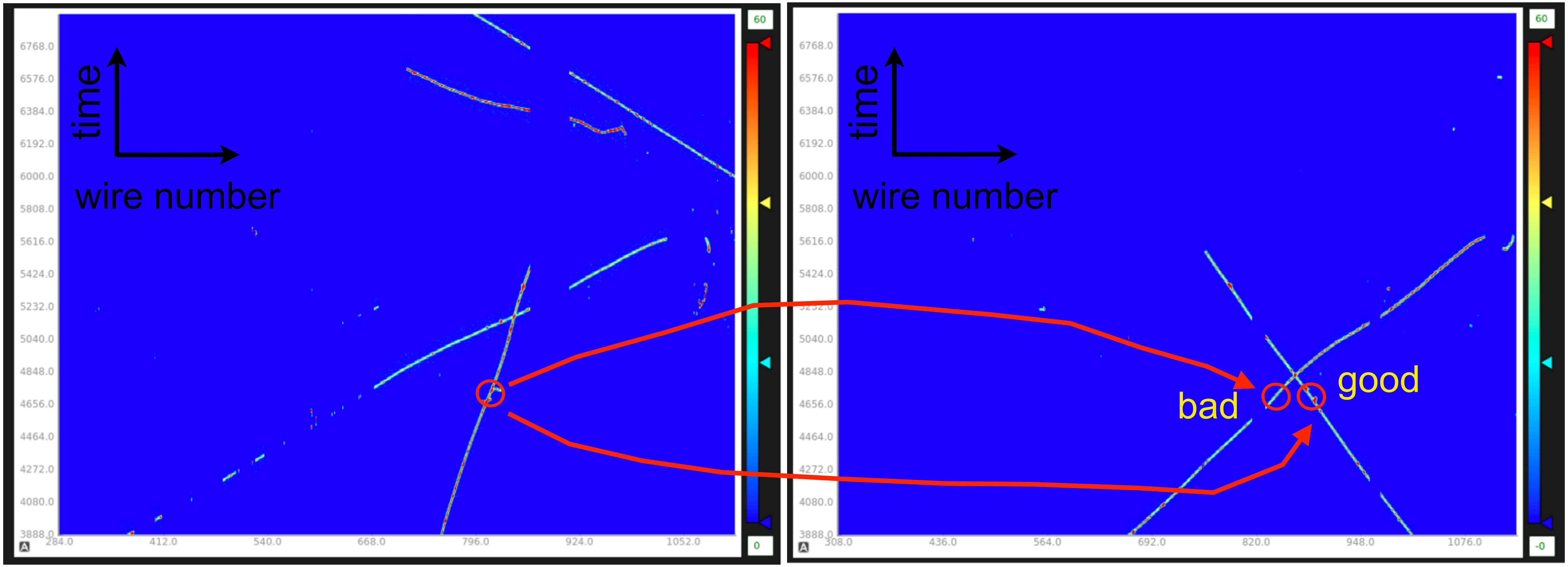
- To estimate neutrino energy, need to reconstruct the 3D trajectories of daughter charged particles
- Requires matching of same-time charge in the 2D projections
- Challenging when multiple trajectories in the same time slice (e.g. cosmic rays & neutrinos)
- Vertical tracks challenging: single time slice

3D space-point reconstruction with LArMatch

- Our solution: LArMatch algorithm. Image analysis approach
  - Generate possible wire-plane charge matches
  - CNN scores matches between 0 (bad) and 1 (good)
  - 3D space-point reconstructed from wire match

Charge depositions on Induction plane 1

Same time window charge depositions on Collection plane

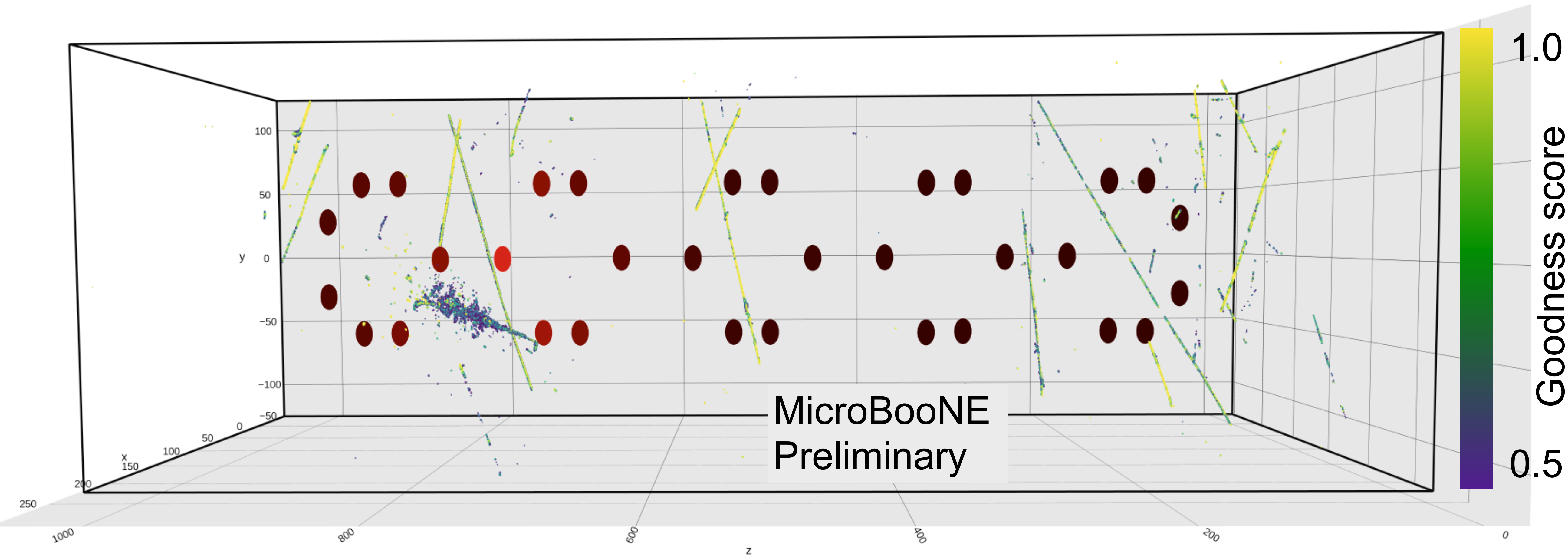


Development of LArMatch

- Novel technique
  - ***First*** CNN application to reconstruct 3D points directly from 2D LArTPC input
- LArMatch highlights
  - Takes advantage of sparsity of LArTPC data: sparse convolutions
  - Largely improved time and memory consumption w.r.t. dense networks
    - applicable to large data (DUNE)
  - Competitive performance with other reconstruction frameworks
  - Starting point for a fully DL based 3D reconstruction
  - MICROBOONE-NOTE-1082-PUB, publication being prepared

LArMatch Example on data

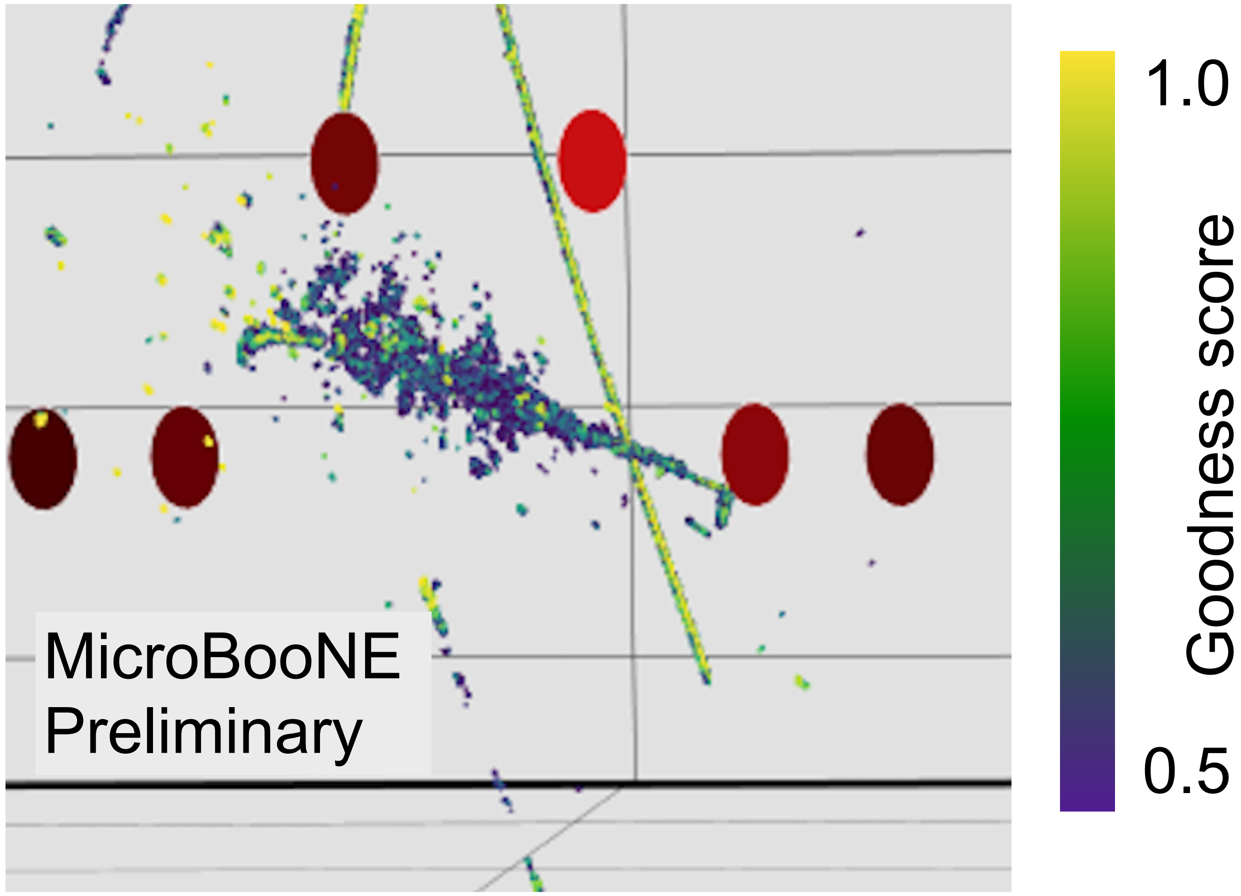
3D space points generated with LArMatch. BNB On-beam data. Neutrino candidate selected by MicroBooNE Deep Learning neutrino analysis (neutrino Boosted Decision Tree score in [0.5,0.7] range)



Color represents network score. Only showing points with score >0.5
Circles represent PMTs (brightness reflects amount of light observed)
Neutrino candidate (proton track + electron shower) successfully reconstructed

LArMatch Example on data

3D space points generated with LArMatch. BNB On-beam data. Neutrino candidate selected by MicroBooNE Deep Learning neutrino analysis (neutrino Boosted Decision Tree score in [0.5,0.7] range)

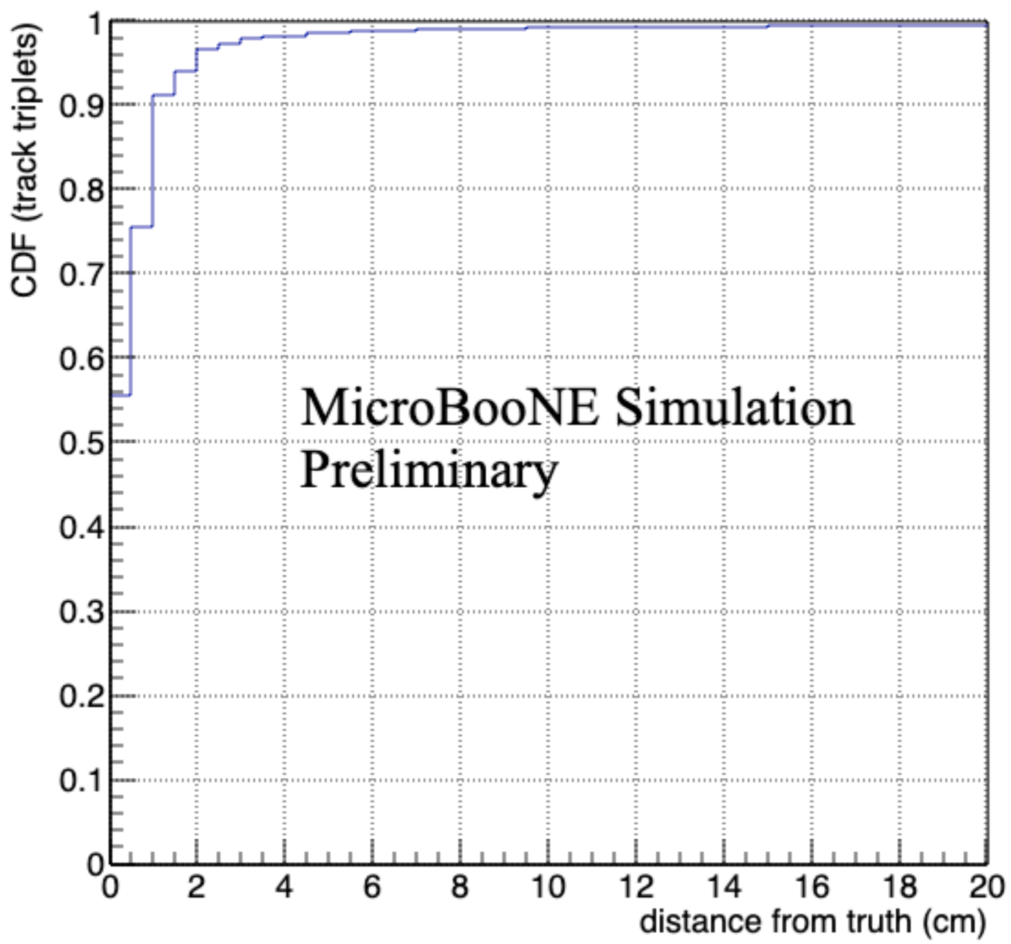


Color represents network score. Only showing points with score >0.5
Circles represent PMTs (brightness reflects amount of light observed)
Neutrino candidate (proton track + electron shower) successfully reconstructed

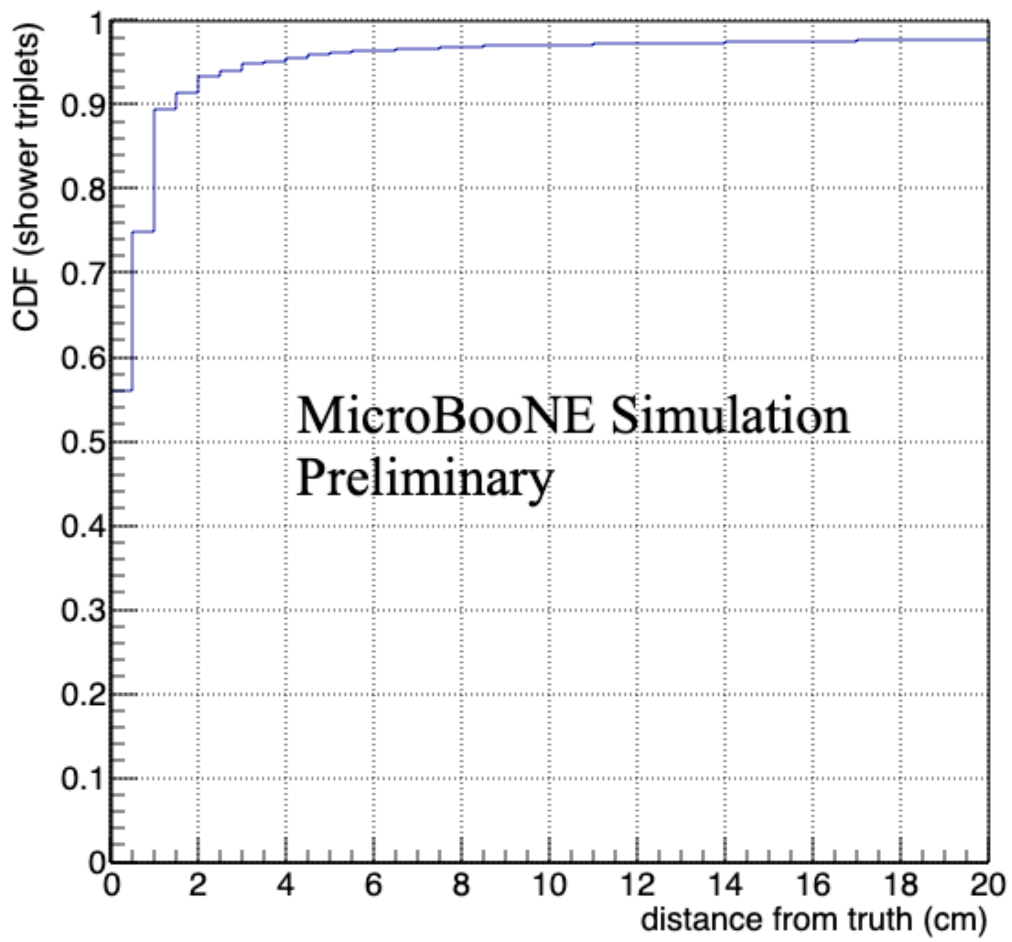
LArMatch Network performance

Estimating performance on cosmic ray + BNB neutrino simulation

Track



Shower

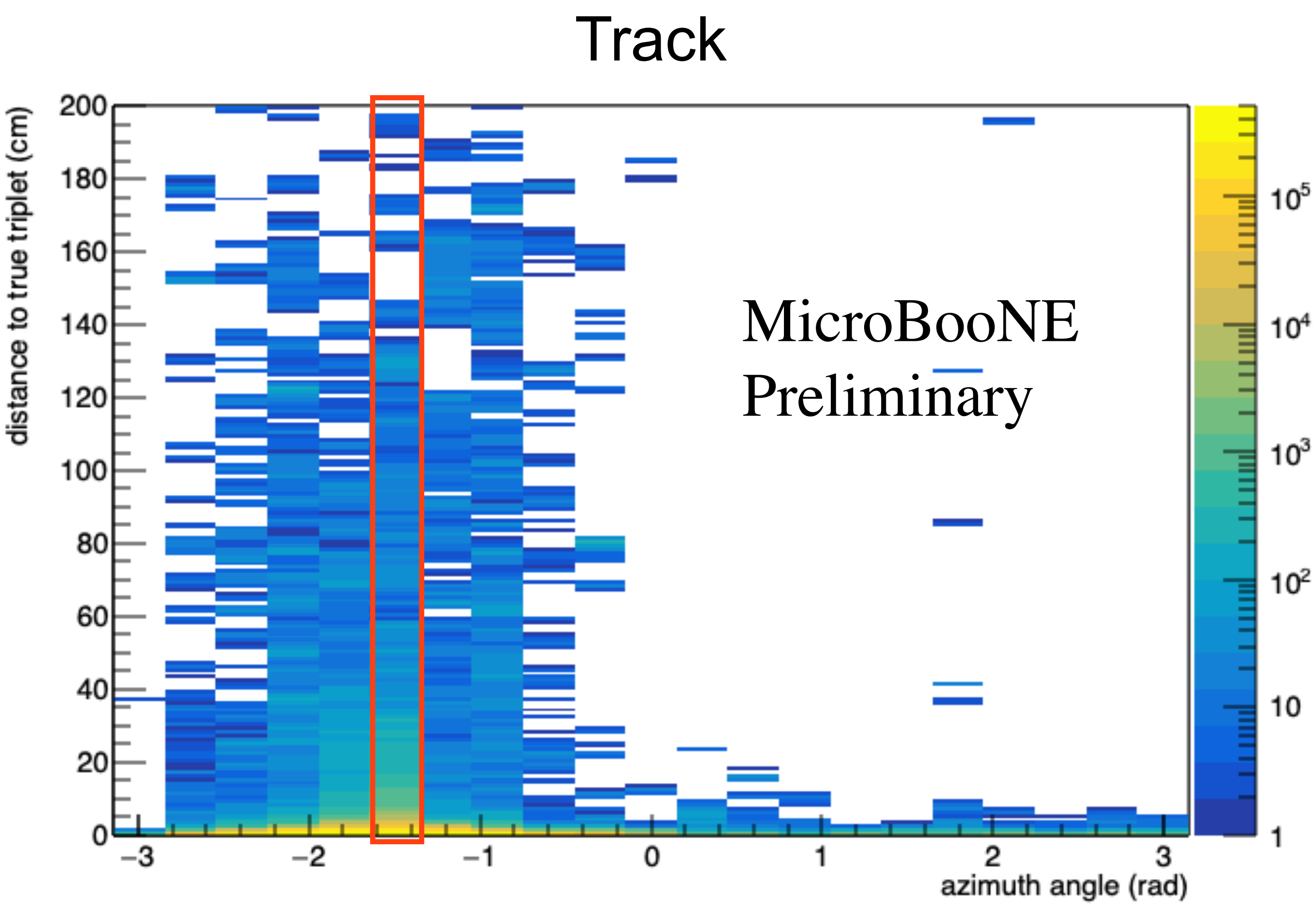


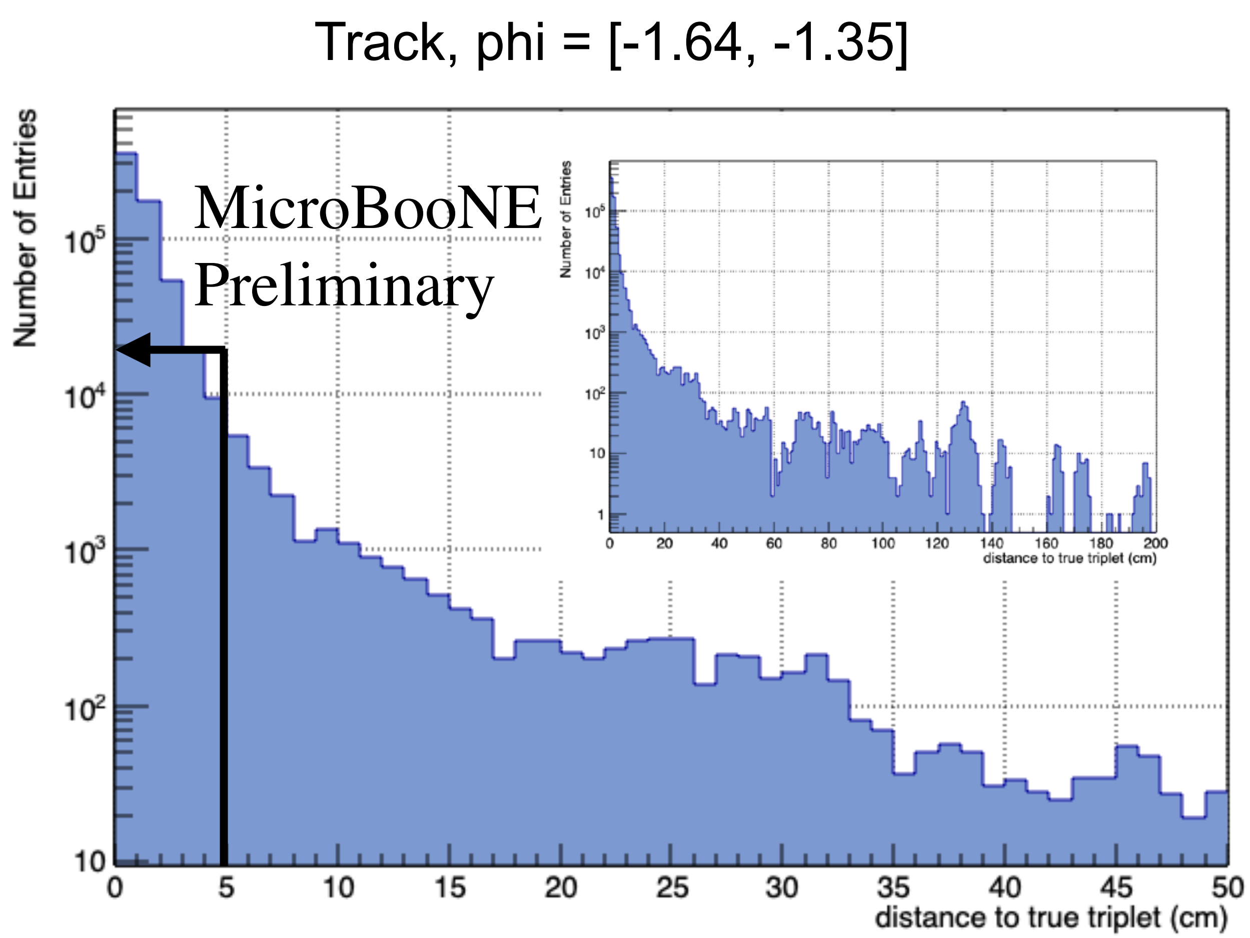
- Plotting distance from true 3D point for best-match* reconstructed points.
- **O(90%)** of reconstructed points are within 1 cm of truth, comparable to other algos
- This kind of precision possible thanks to LArTPC technology & CNN techniques

* Network outputs multiple predictions for each 3D point; keep only highest score

LArMatch Network performance: vertical tracks

- Vertical tracks challenging: all trajectory points fall within same time slice



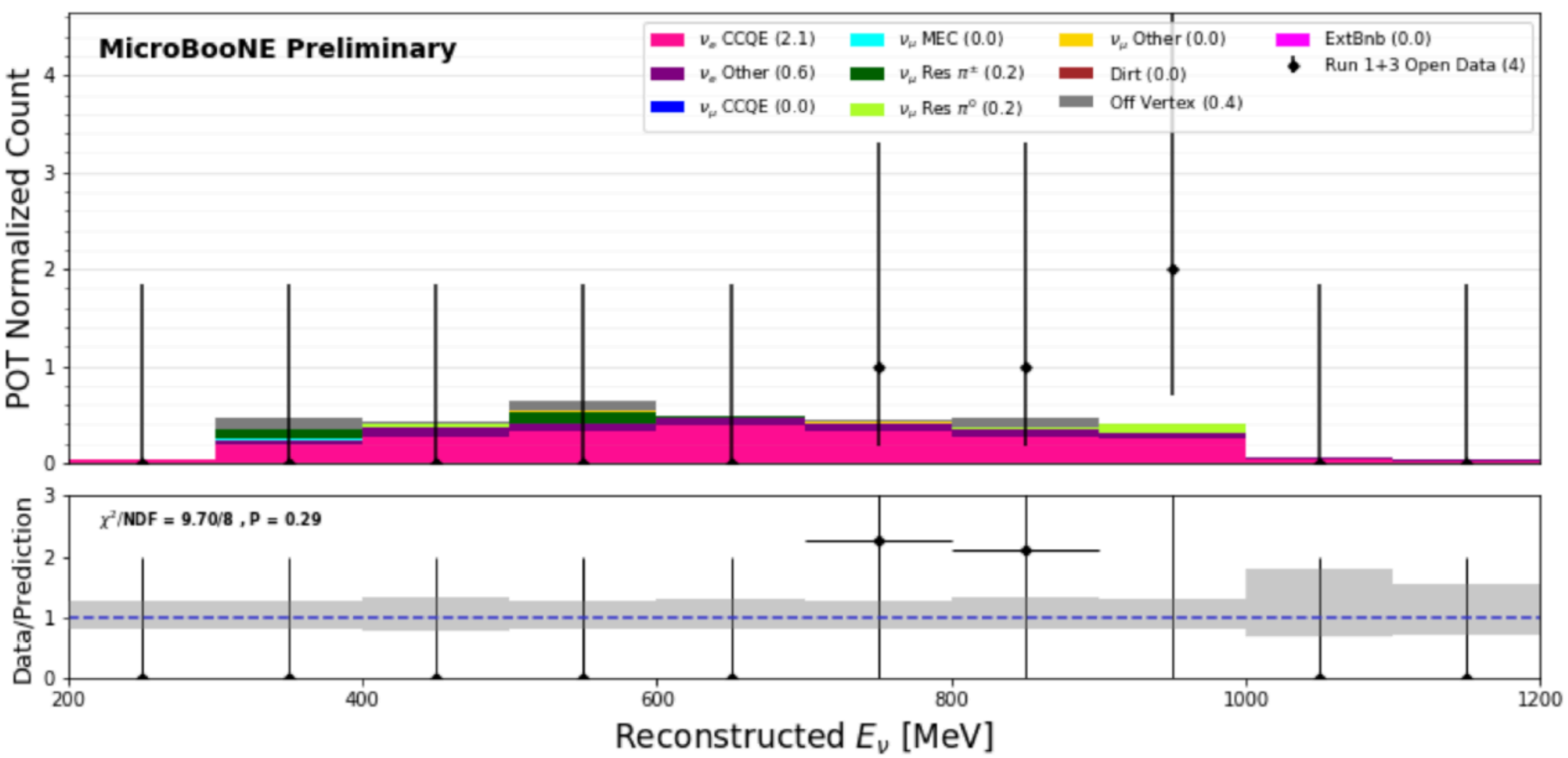


Left: distance from true 3D point for best-match reconstructed points vs. azimuth angle. Sample dominated by down-going CR tracks.

Right: Projection for vertical tracks. ***Majority or 3D points are within 5cm from truth***

Status of MicroBooNE LEE searches

- All analysis groups are working to finalize neutrino selections
- Demonstrated selections yielding high purity and efficiency in desired topology
  - open data sample results showcased at Neutrino 2020
- Vigorous work on sideband samples and fake-data events: demonstrate robustness of analyses
- Collaboration-wide discussions on statistical/model interpretations on-going
- Plan to release a series of LEE results very soon



MICROBOONE-NOTE-1086-PUB

ν_e CCQE events selected by DL LEE analysis (black) vs. stacked prediction (colored histograms)

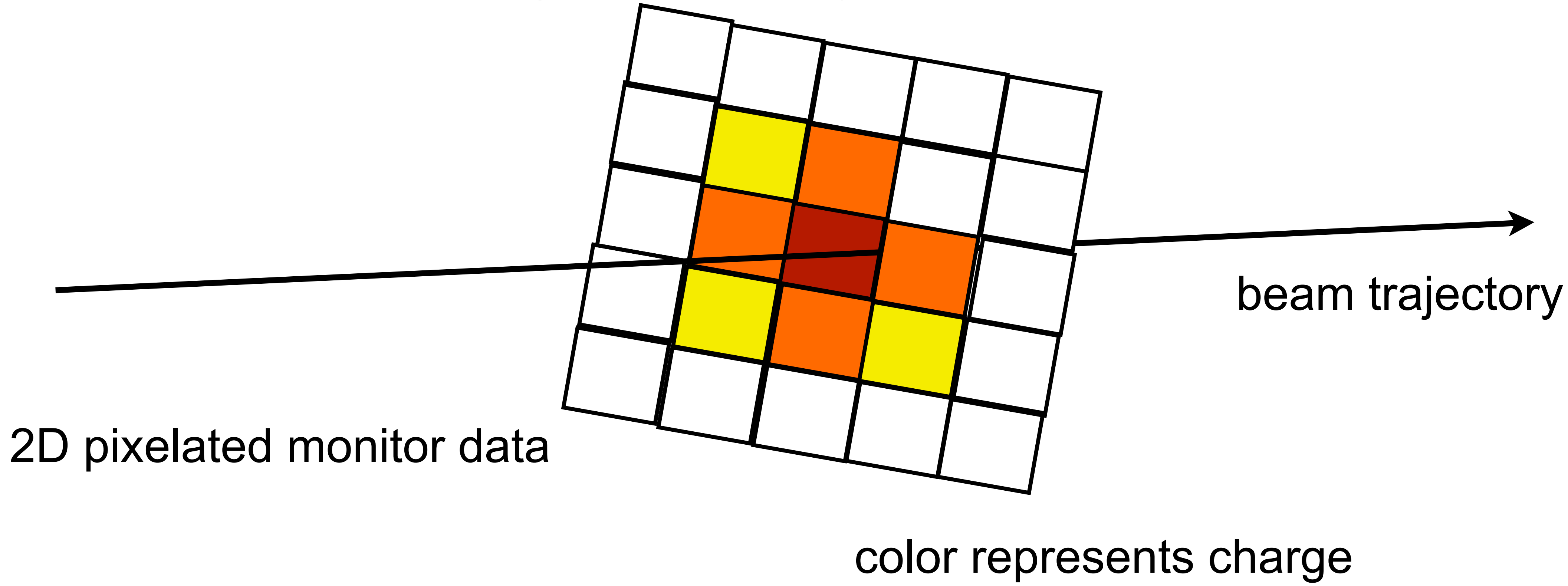
Run 1 open dataset
5.3×10^{19} POT

ML and DL applications in accelerator physics

- A lot of effort at FNAL and elsewhere to adopt ML/DL techniques in beam operations
  - DOE funding awarded to team led by Bill Pellico & Dr. Kiyomi Seiya
- Why use ML
  - Fast, automated reliable inference
  - Can be run on unconventional hardware (FPGA) for flexible use
- Just some examples of uses at FNAL (inexhaustive list!)
  - NuMI beam quality monitoring with a regression model (Athula Wickermasinghe)
  - Real-time monitoring of superconducting magnets with a DNN (Duc Hoang et al.)

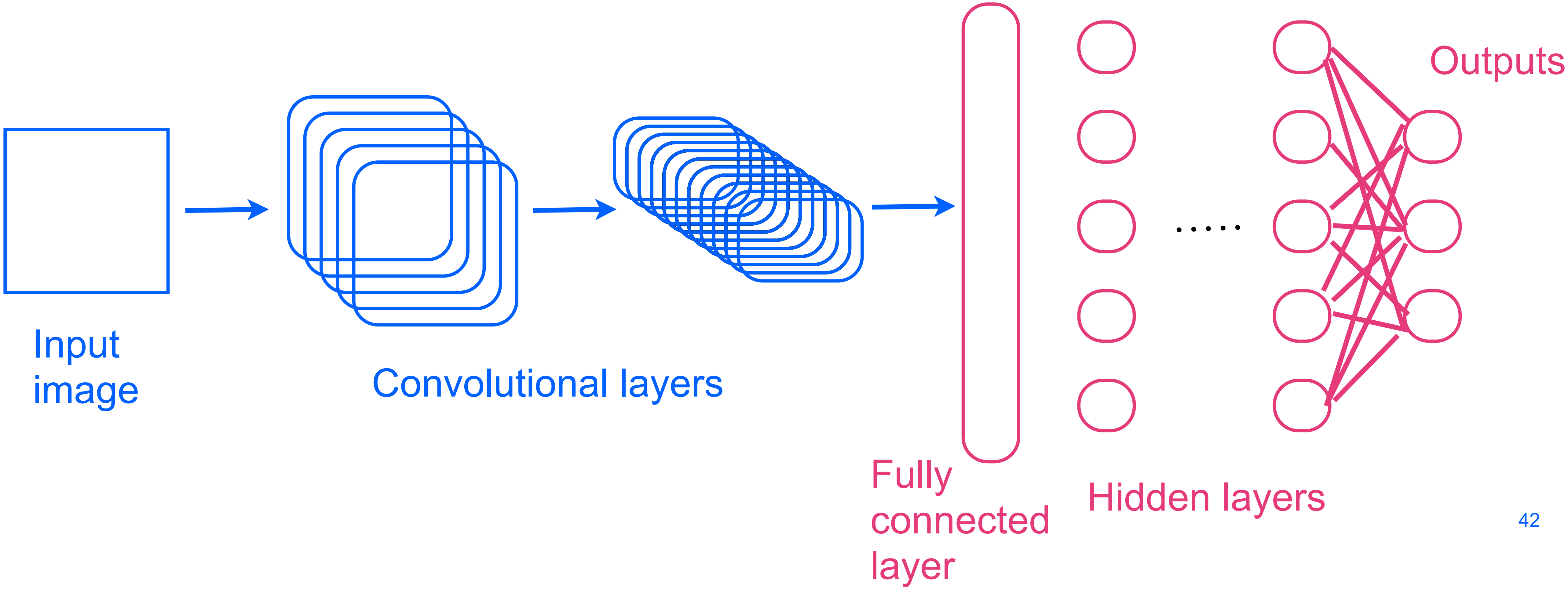
CNN application to beam operations

- Convolutional neural networks are very versatile
- Main strength: can correlate disparate sets of information
- Can imagine application of convolutional neural networks to 2D array-type monitor data to:
  - Correlate monitor data to beam condition/state; extract information from data on different beam parameters
    - e.g. correlate beam position/profile measurements to beam tuning parameters & be able to make predictions
  - Live-time monitoring and anomaly detection



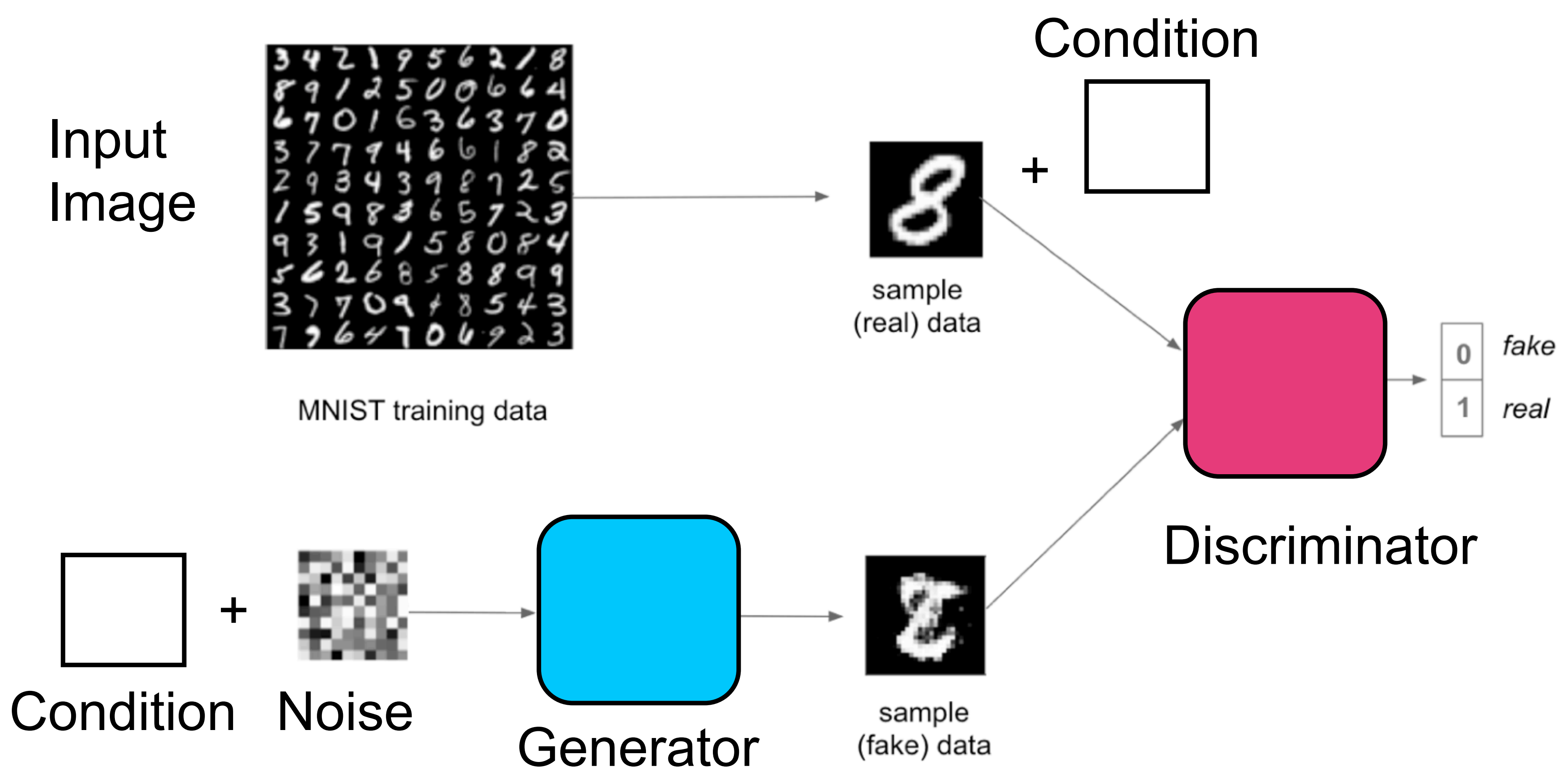
Understanding Beam status with CNNs

- Using 2D monitor array data, one can regress different parameters describing the beam state
  - Encoder extracts features
  - Regression network predicts beam parameters
- Regression in 2D (or 3D if using multiple arrays): more powerful than 1D



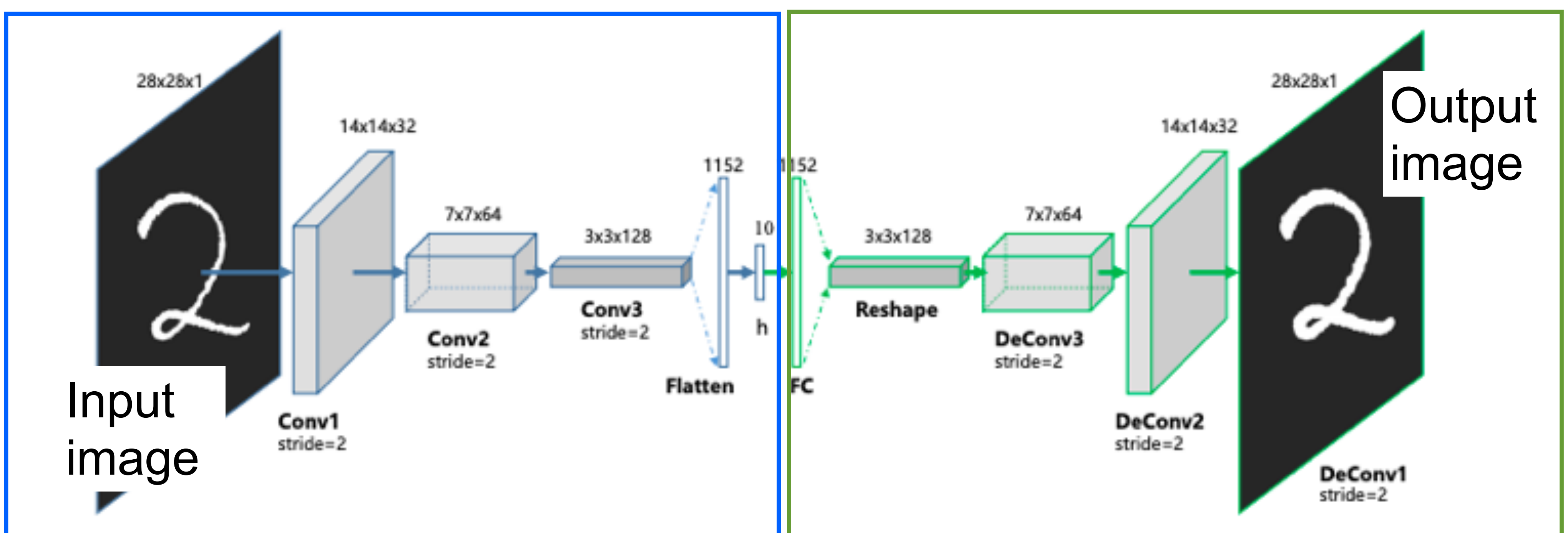
Understanding Beam status with CNNs (2)

- Recreating beam monitor data with a generative adversarial network (GAN)
  - can be tested agains beam simulations to better understanding
  - consists of two networks: a Generator, which creates fake data from noise (e.g. Gaussian noise), and a Discriminator, which classifies data examples as true or fake
  - G constantly trying to outsmart D, which is main driver for training
  - conditional GAN: both G and D output constrained by additional condition



Detecting anomalies with Autoencoders

- Autoencoder: type of neural network designed to learn features from data in unsupervised manner
  - Does not rely on truth for training: no need for precise simulations, only “regular” state monitor data
- Network comprises two parts:
  - Encoder: compresses data into a lower-dimension representation which captures correlations and interactions, disregards noise
  - Decoder: reconstructs the information to produce output (which mirrors the input)
- When fed anomalous input, the network loss will greatly degrade => indication of issues
- Implementation on FPGA makes it possible to run in real-time (O(microsec) inference)

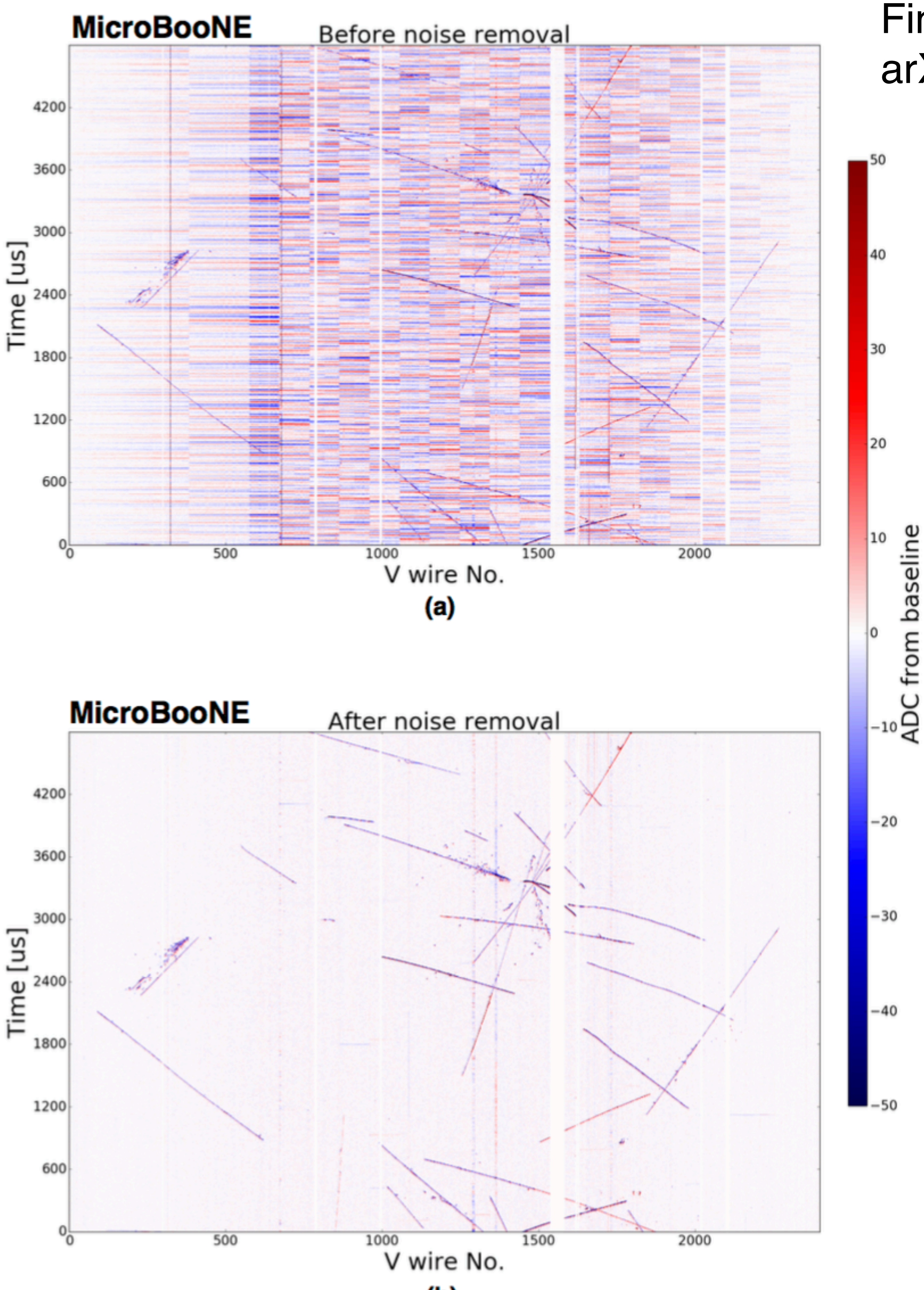


Summary

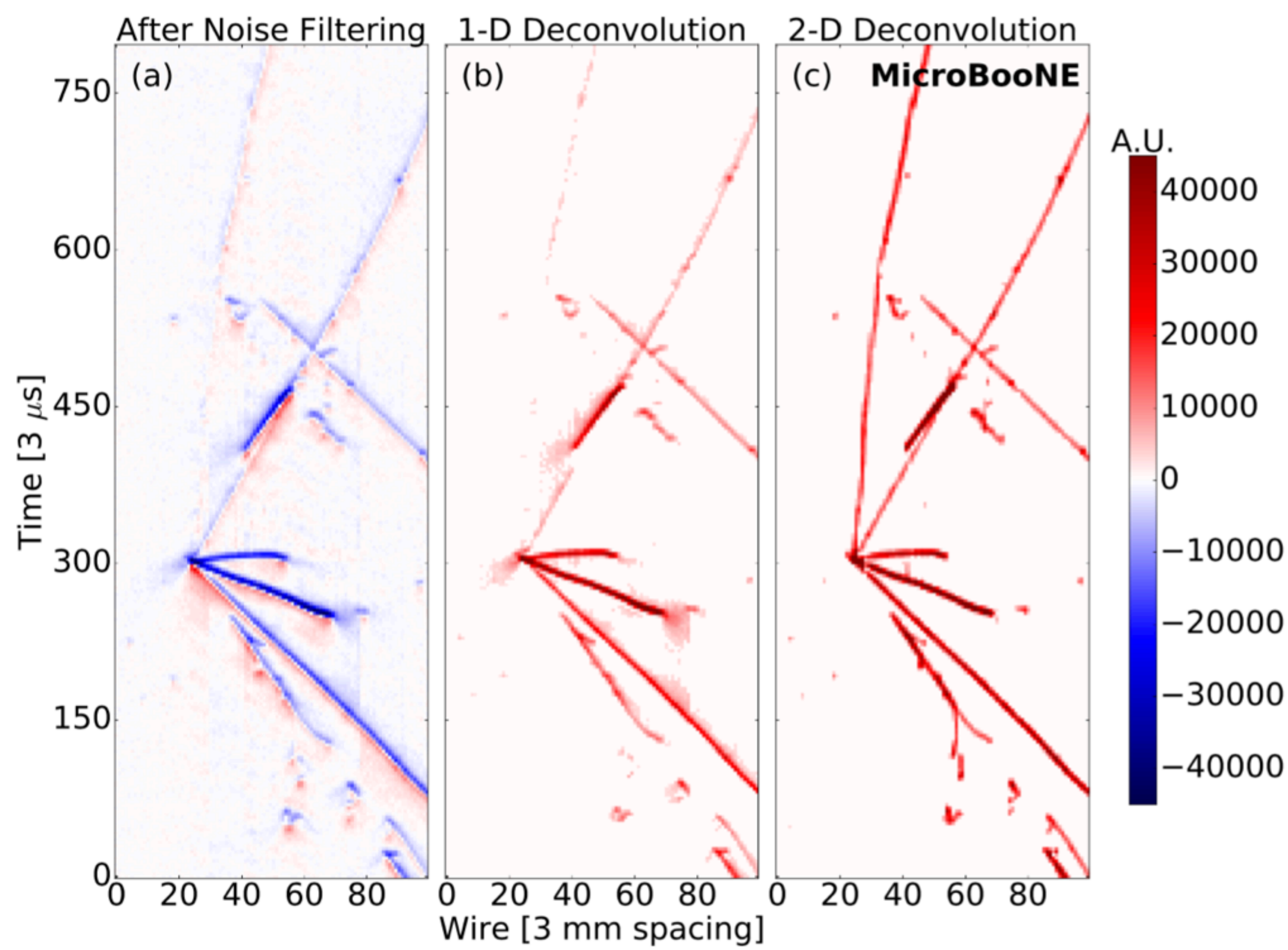
- SBN program aims to probe BSM physics with LArTPC detectors
  - MicroBooNE operational, SBN & ICARUS coming soon
- MicroBooNE employs ML/DL techniques in many stages of neutrino event reconstruction.
  - pioneering work: 1st application of CNN to LArTPC data
  - image augmentation, CR tagging, 3D reconstruction
  - performance tested on data & MC
  - tuned to improve physics analysis
- ML/DL application in accelerator operation
  - growing effort at FNAL and elsewhere
  - fast and reliable automated beam monitoring/tuning
  - CNNs could be an interesting new avenue

Backup

Noise reduction and signal deconvolution



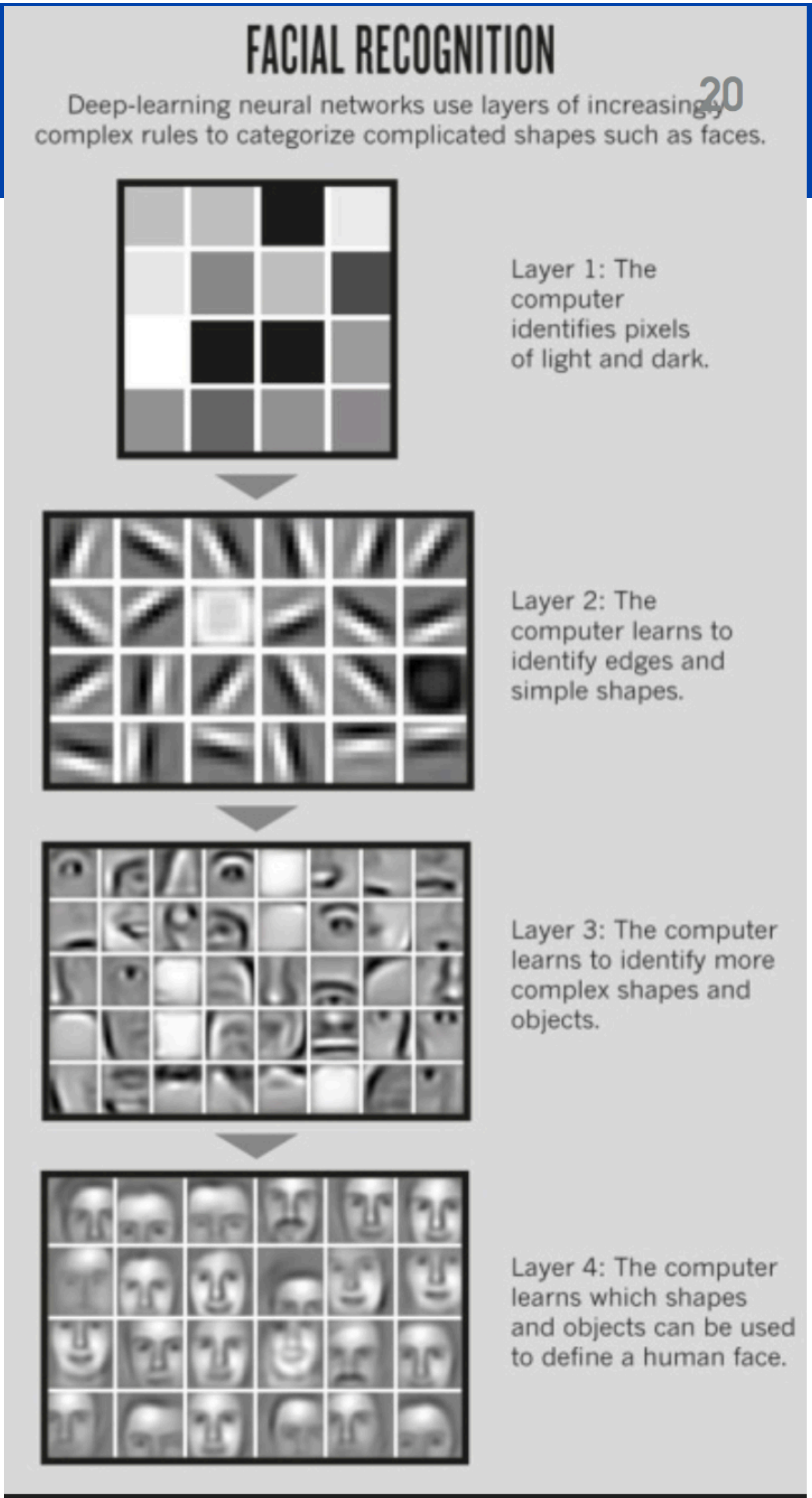
Final S/N after noise filtering is ~40 on collection plane!
arXiv:1705.07341



Deconvolve out electronics & field response
arXiv:1804.02583, 1802.08709

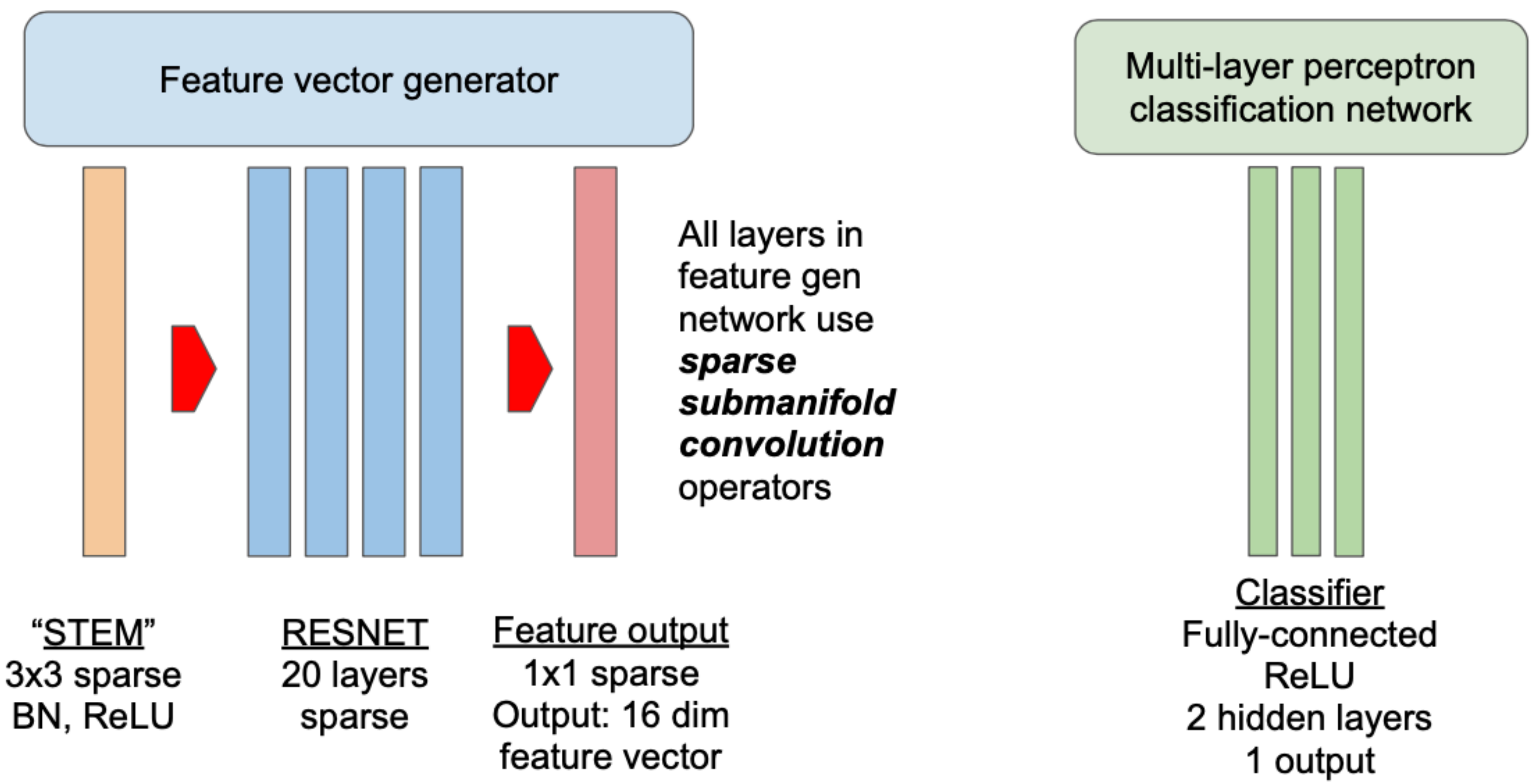
Convolutional networks

- Consider the task of facial recognition
- Begin with image pixels (layer 1)
- Start by applying convolutions on simple patterns (layer2)
- Find groups of patterns by applying convolutions on feature maps (layer 3)
- Do this multiple times
- Eventually the network learns to identify groups of patterns as faces



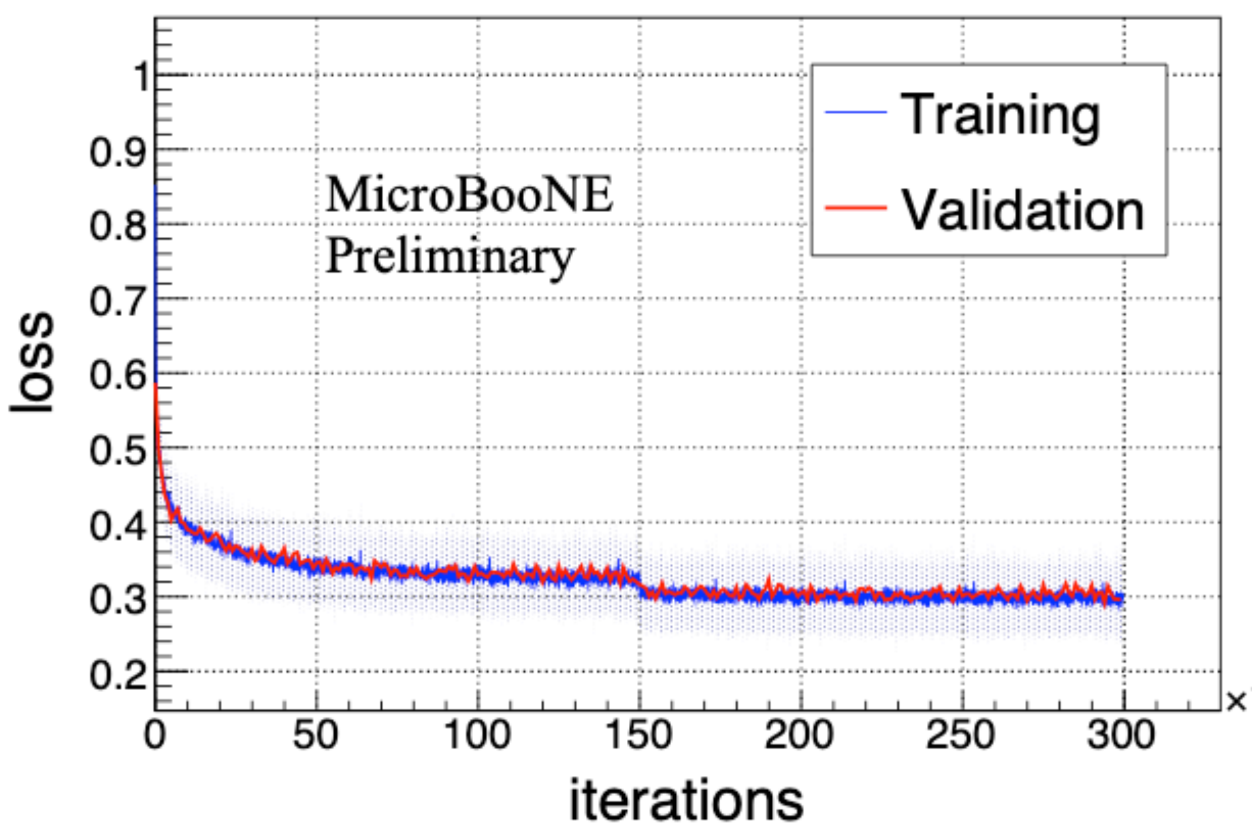
LArMatch Network

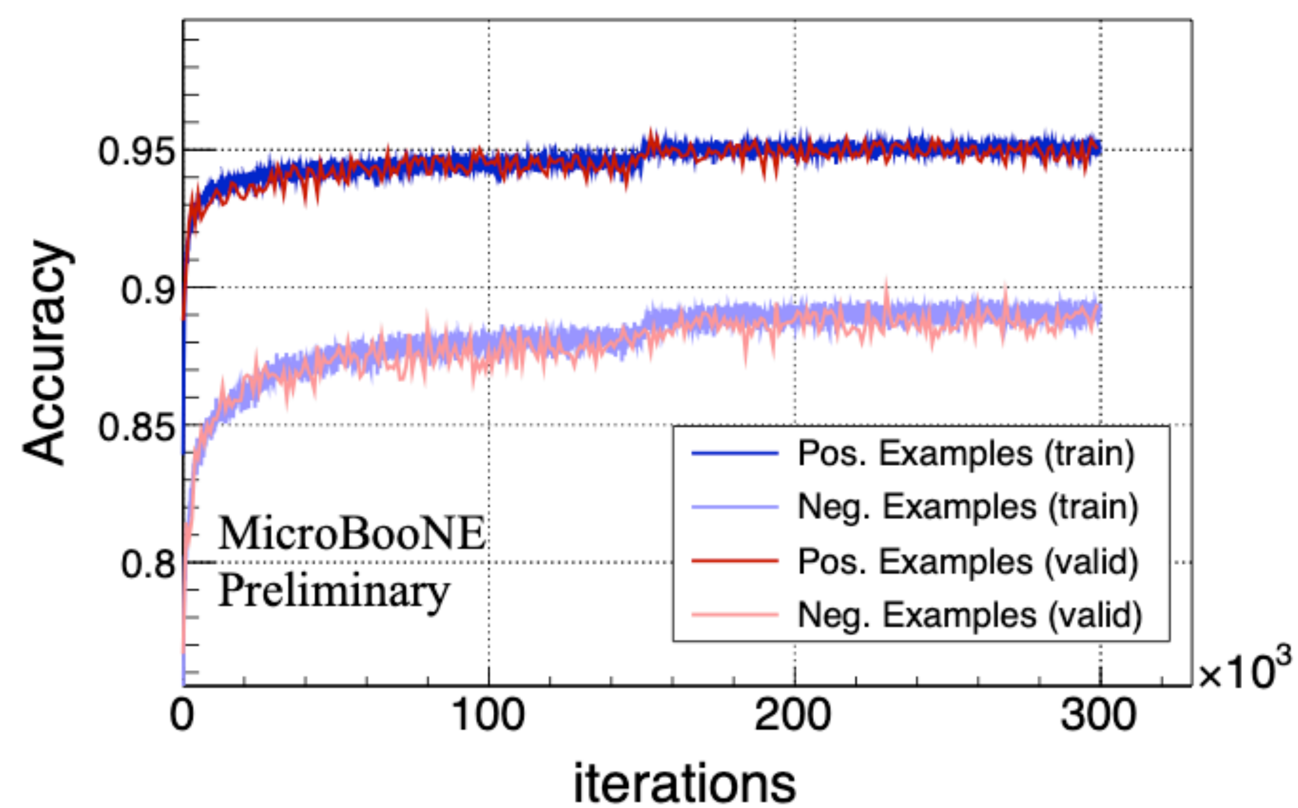
- Sparse CNN feature generator + MLP classifier
- Feed charge deposited on all 3 planes: helps reconstruct vertical tracks
- Generates a probability score for all geometrically possible combinations of charge on the 3 planes ("wire triplets")
- 3D space-points generated from wire triplets using detector geometry



Network training

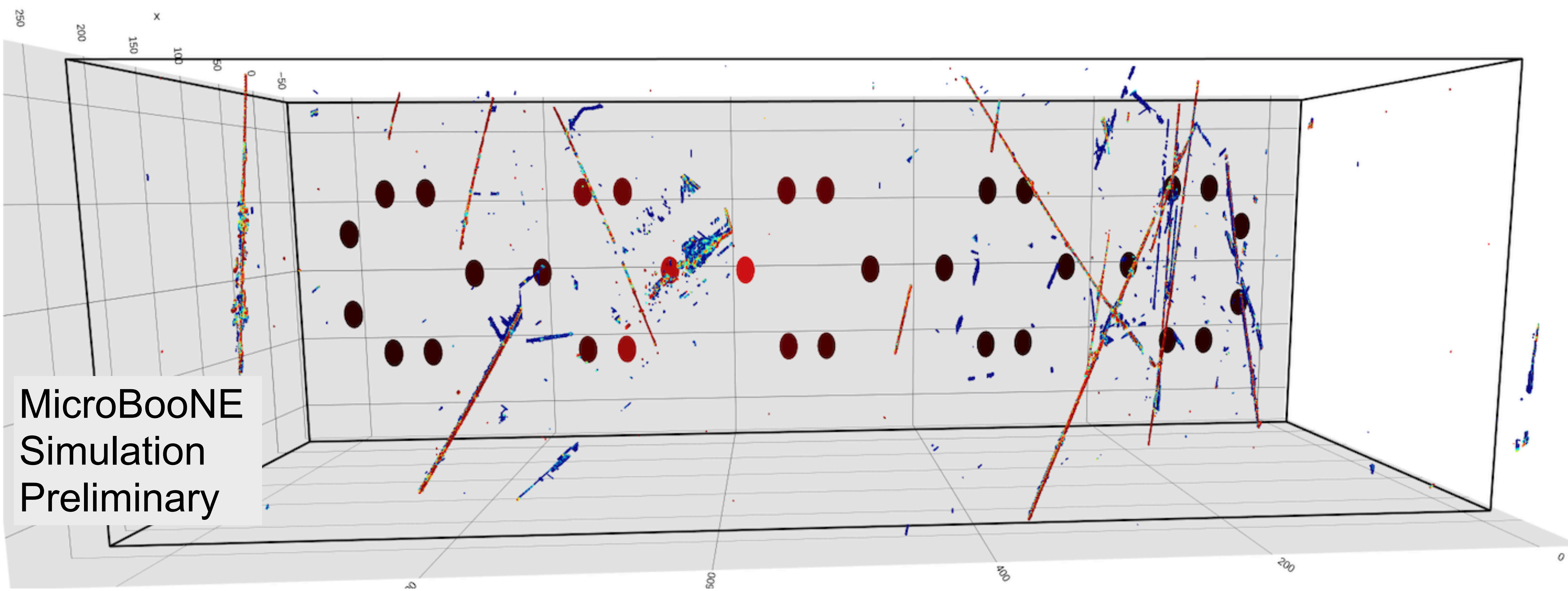
- Trained on 40,000 BNB + CR simulated events
- Learning rate updated at 150,000 iterations
  - 50,000 triplet examples per iteration
- Stopped training after 3.75 epochs
  - loss & accuracy plateaued
  - no overtraining observed





LArMatch Example on Simulation

3D space points generated with LArMatch. Cosmic ray + BNB neutrino simulation.

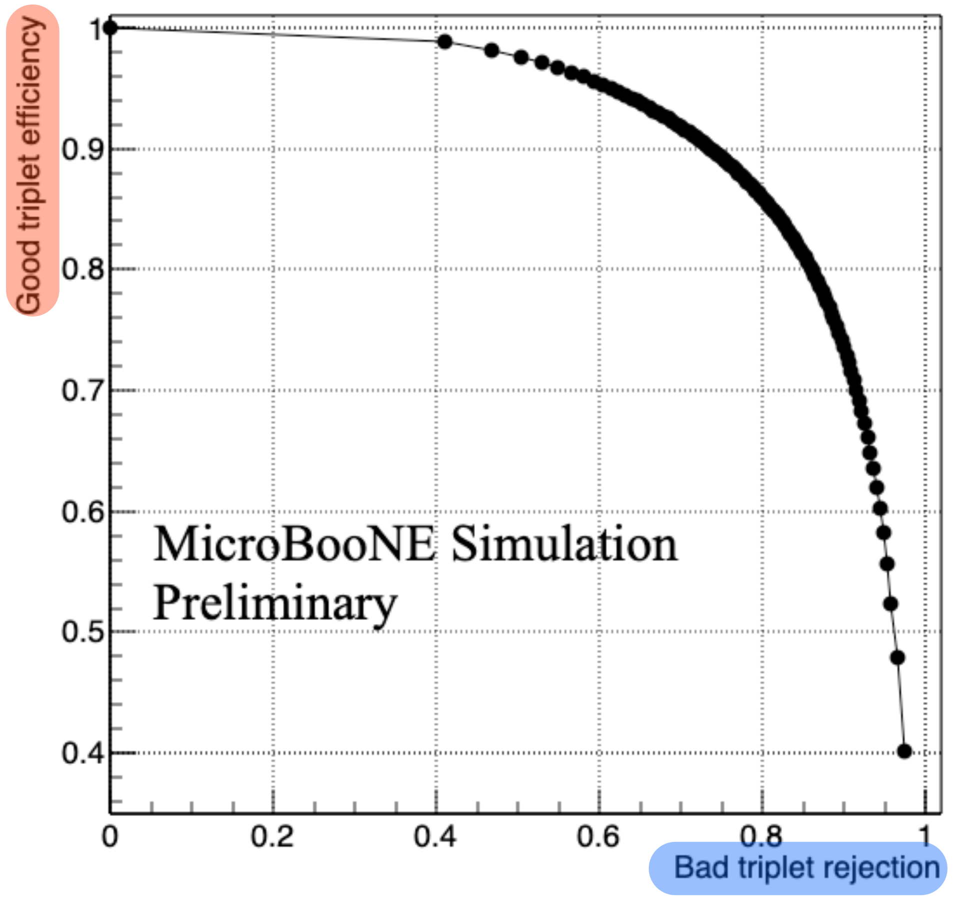


Color represents network score. Plotting all generated 3D points. Ghost (fake) points and unresponsive regions feature lower scores, trajectory ‘cores’ have high scores

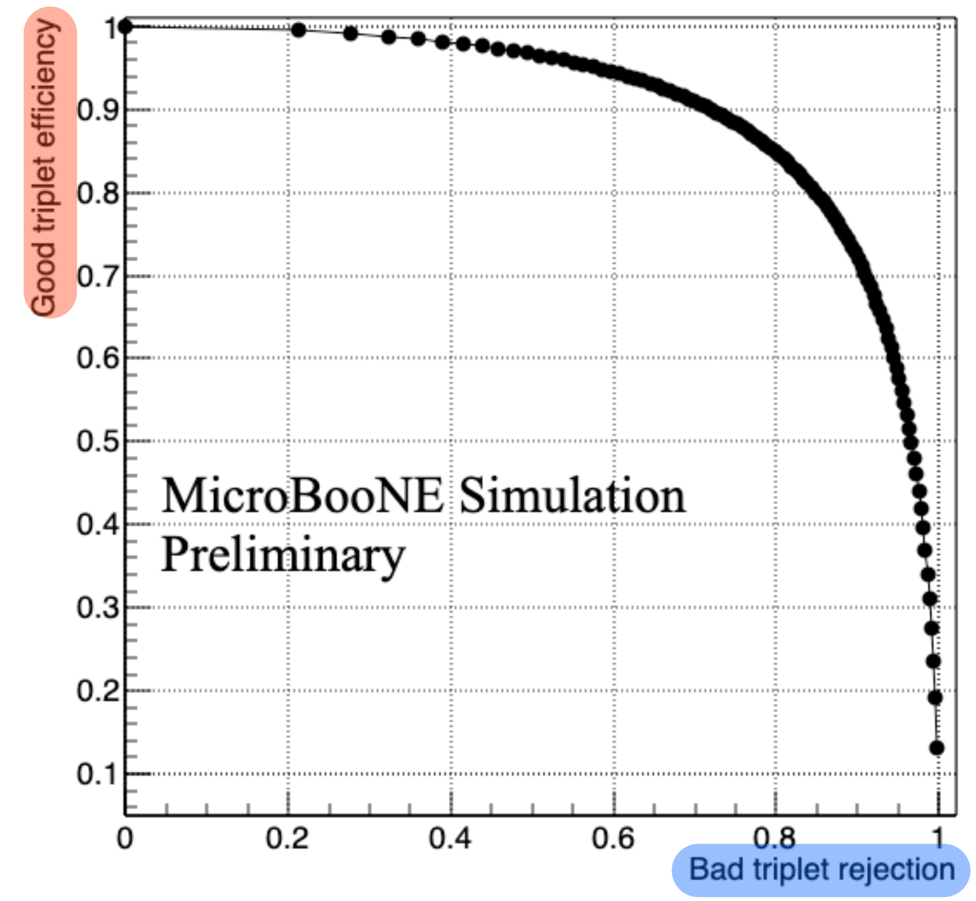
LArMatch Network performance

Estimating performance on cosmic ray + BNB neutrino simulation

Track



Shower



Plotting good point* efficiency vs bad point** rejection as a function of network score.

Network score reflects actual goodness of reconstructed points

*good point: within 1 cm from true 3D point
**bad point: >1 cm from true 3D point

Identifying particle content in ROI

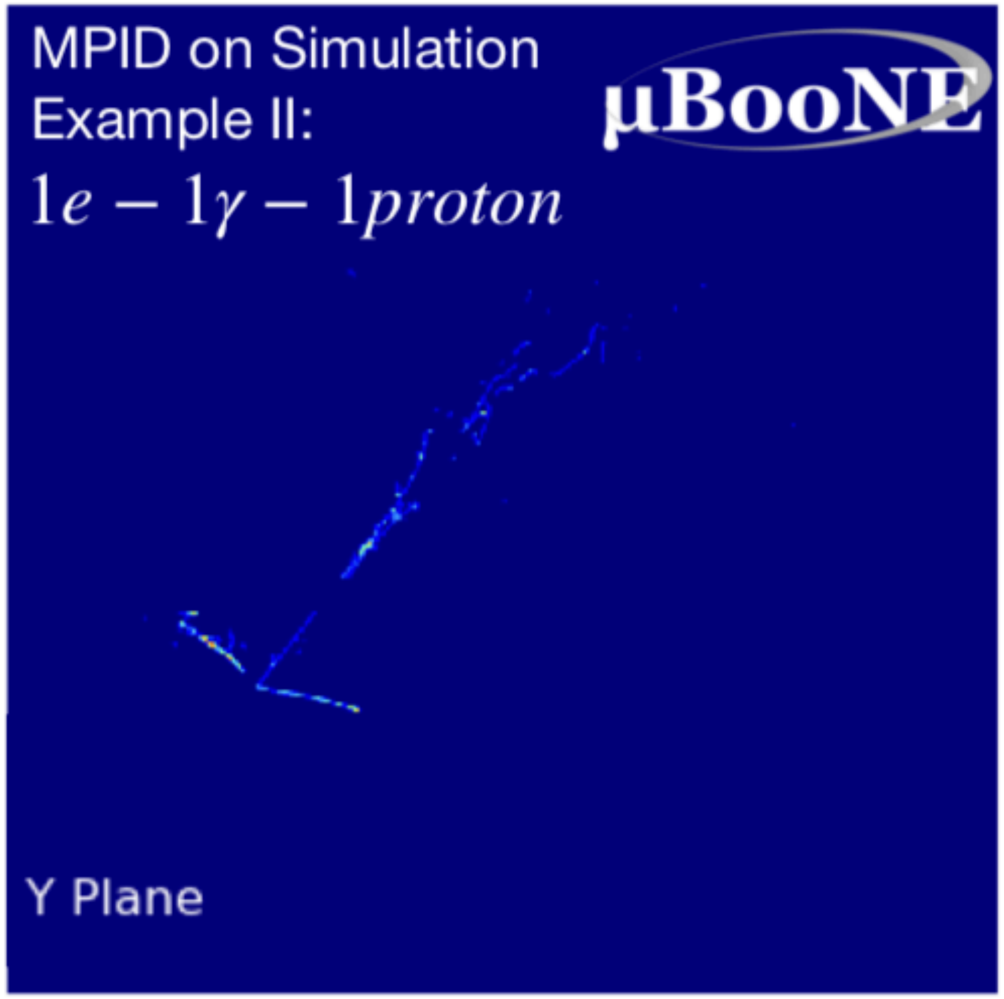
- DL LEE analysis looking for a specific event topology:
  1 lepton + 1 proton as products of a neutrino CCQE interaction

Target topology:
1e1p event

Identifying particle content in ROI

- DL LEE analysis looking for a specific event topology:
  1 lepton + 1 proton as products of a neutrino CCQE interaction

Irreducible background:
events with mis-reconstructed gammas
- gamma below energy threshold
- detached from vertex
- overlapping with e shower
- etc.

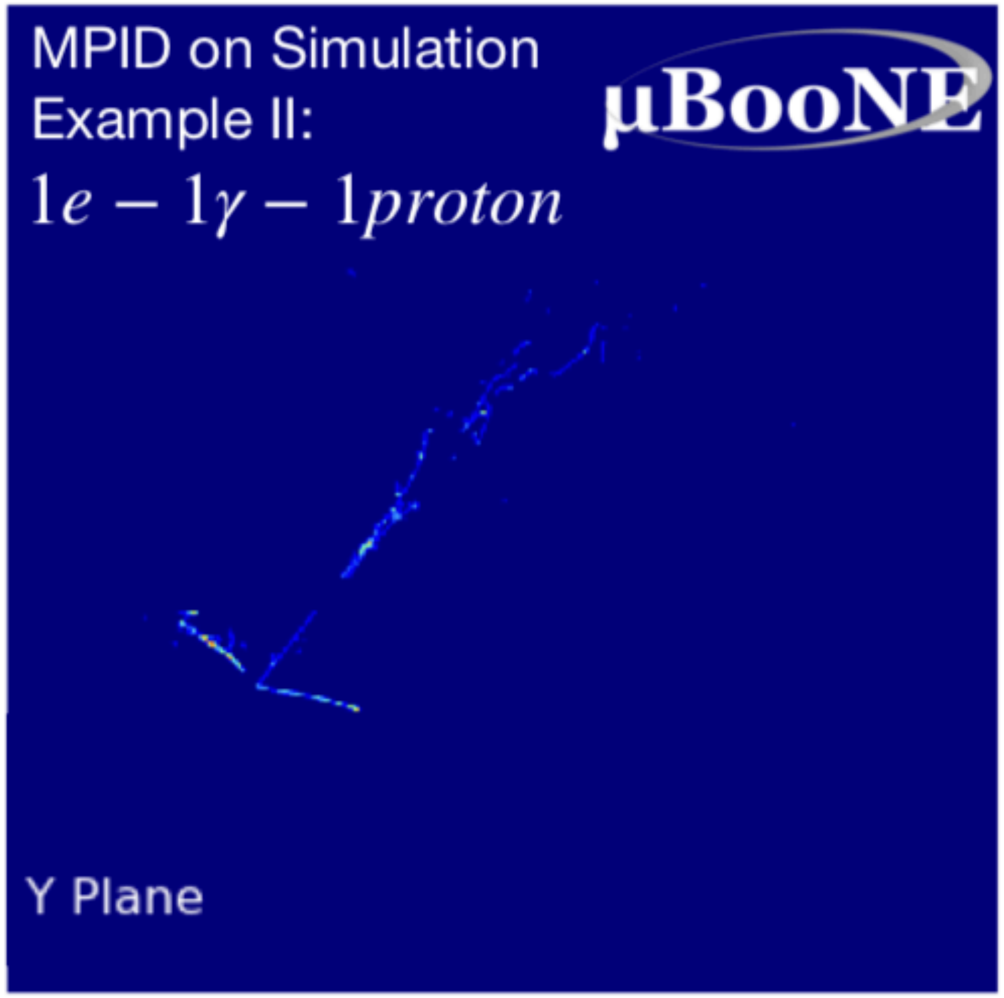


Identifying particle content in ROI

- MPID: CNN that labels particle content in ROI

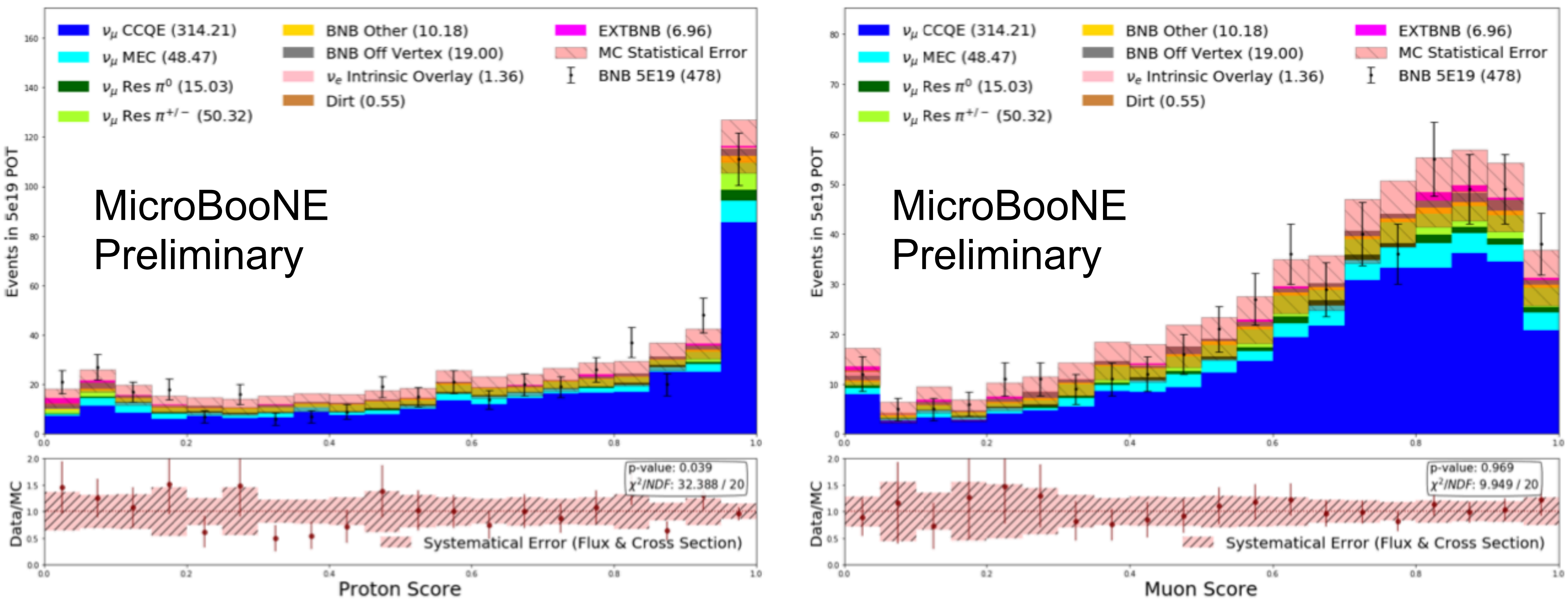
R. An

e^-	γ	μ^-	$\pi^\pm$	$proton$
0.98	0.1	0.02	0.03	0.97



e^-	γ	μ^-	$\pi^\pm$	$proton$
0.63	0.98	0.02	0.08	0.97

MPID Validation on data

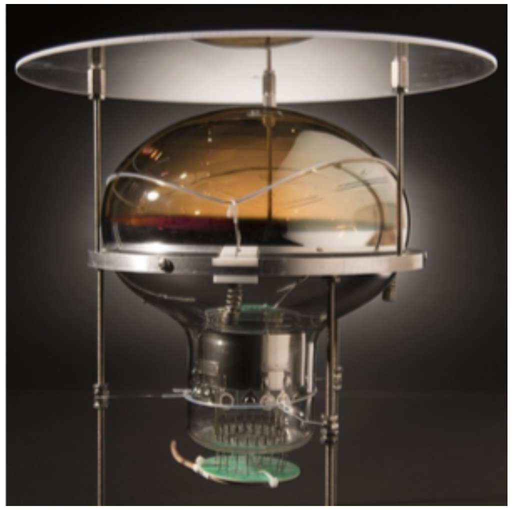


Plotting proton score and muon score for selected CCQE muon neutrino candidates in data (black points). Good agreement with stacked prediction (color)

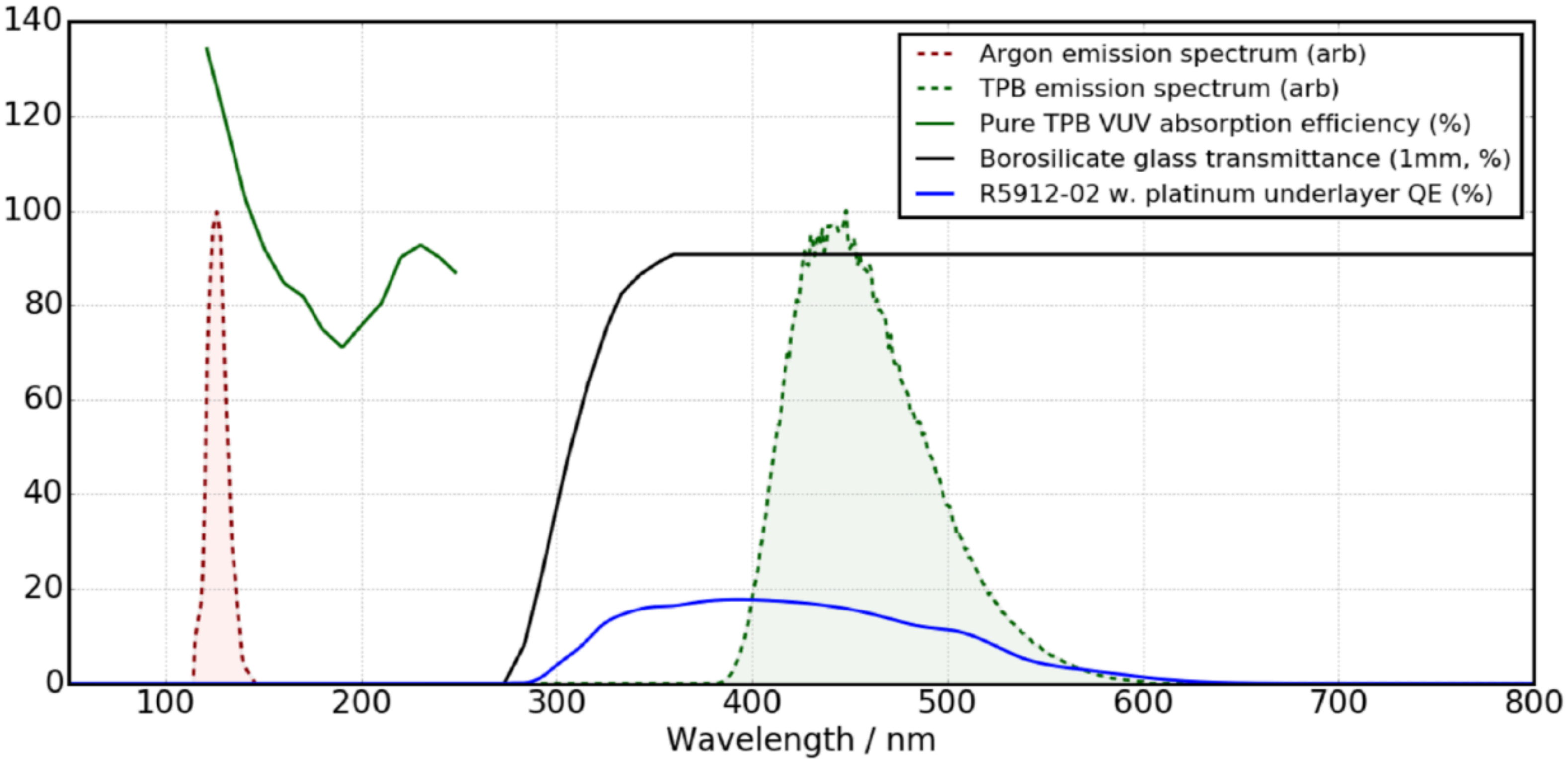
Neutrino candidate selection defined by DL LEE group.

Light collection system of MicroBooNE

TPB-coated plate

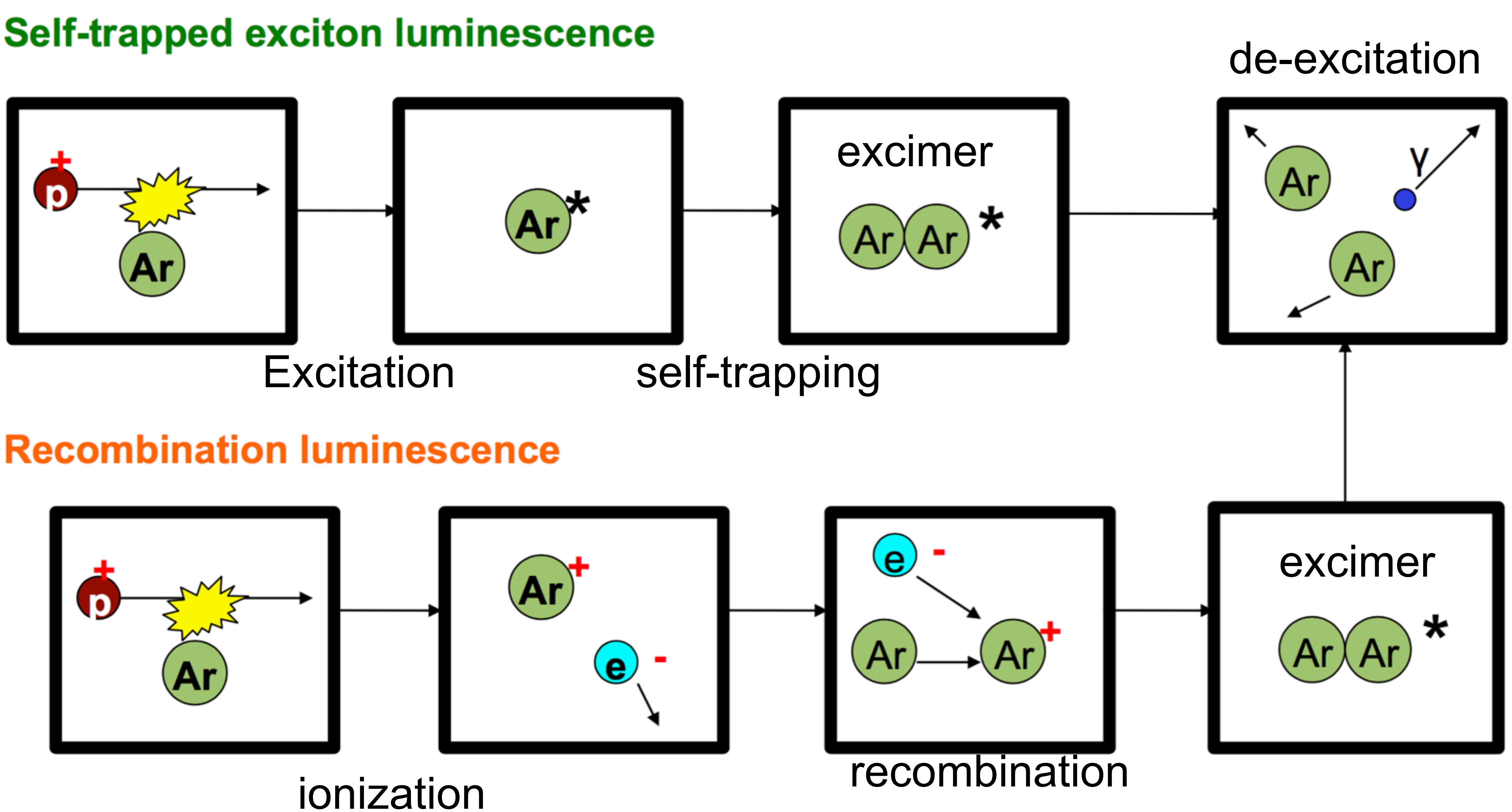


- 32 x 8 in PMTs (Hamamatsu) behind TPB-coated acrylic plates
- Role of TPB: shift LAr scintillation wavelength to 430 nm (in PMT sensitive region)
- PMT analog signals->splitters-> preamp & shaper (60ns)->digitized at 64MHz



LAr scintillation

- LAr: very bright scintillator (order of 10k photons/ MeV of deposited energy)
- Two main mechanisms of scintillation
- 128 nm UV photons released at de-excitation



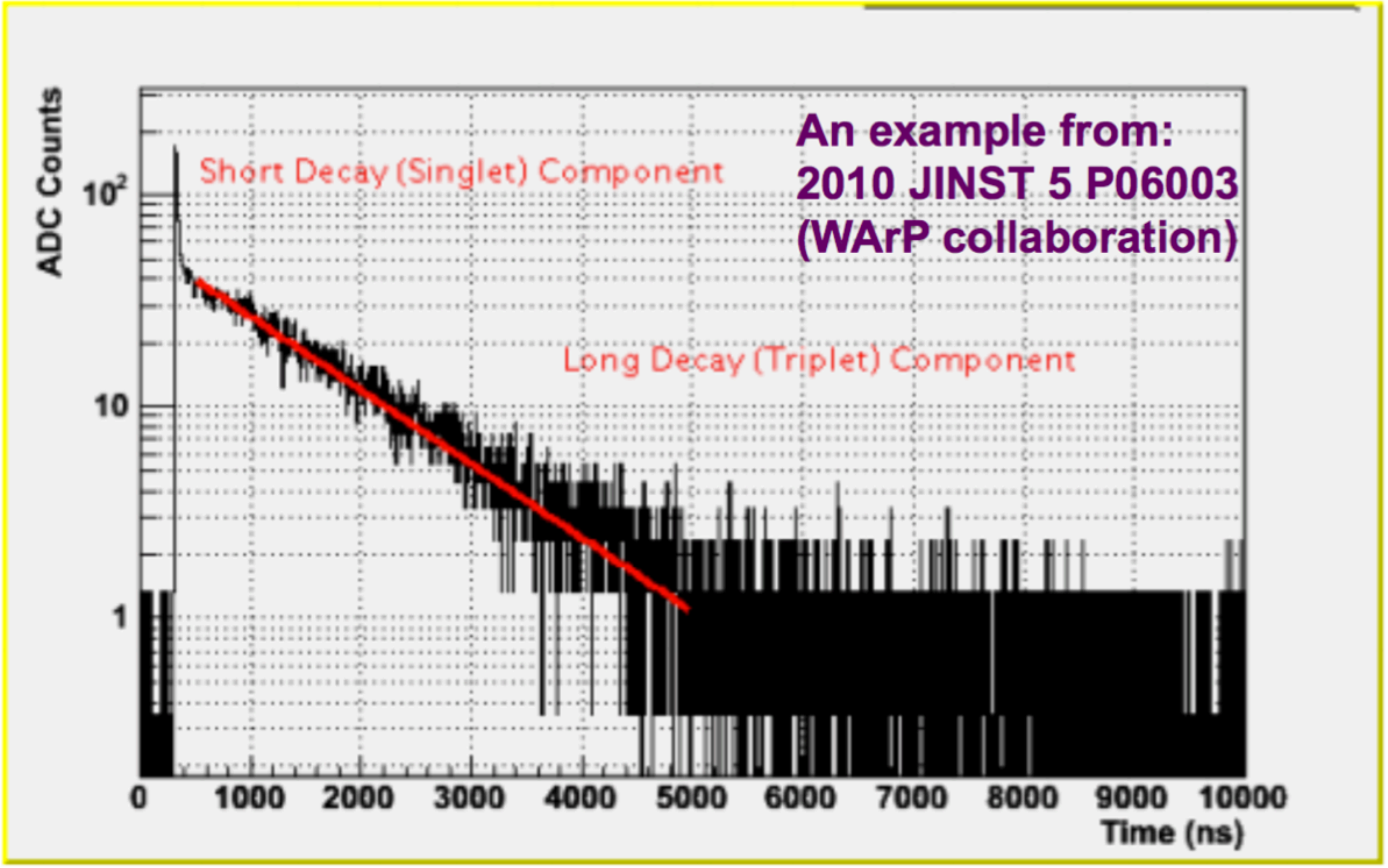
Illustrations by Ben Jones

LAr scintillation

- Excited states (excimers): Ar_2^+ core with bound electron
  - Singlet state Σ_u^1
  - Triplet state Σ_u^3

LAr is transparent to its scintillation!

- At de-excitation both states emit a 128 nm wavelength UV photon
  - Single state: decay time ~6 ns (prompt/fast light)
  - Triplet state: decay time ~1600 ns (late/slow light)



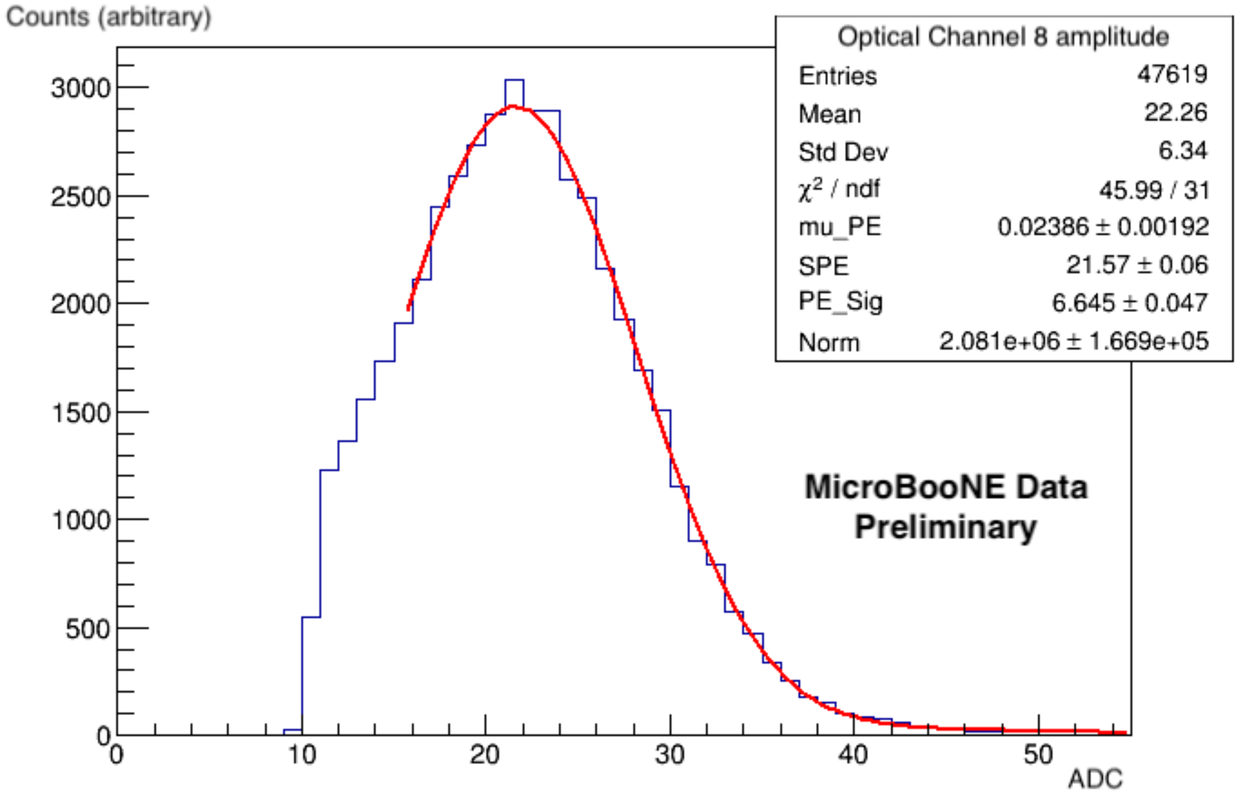
Prompt:late light ratio is dE/dx dependent

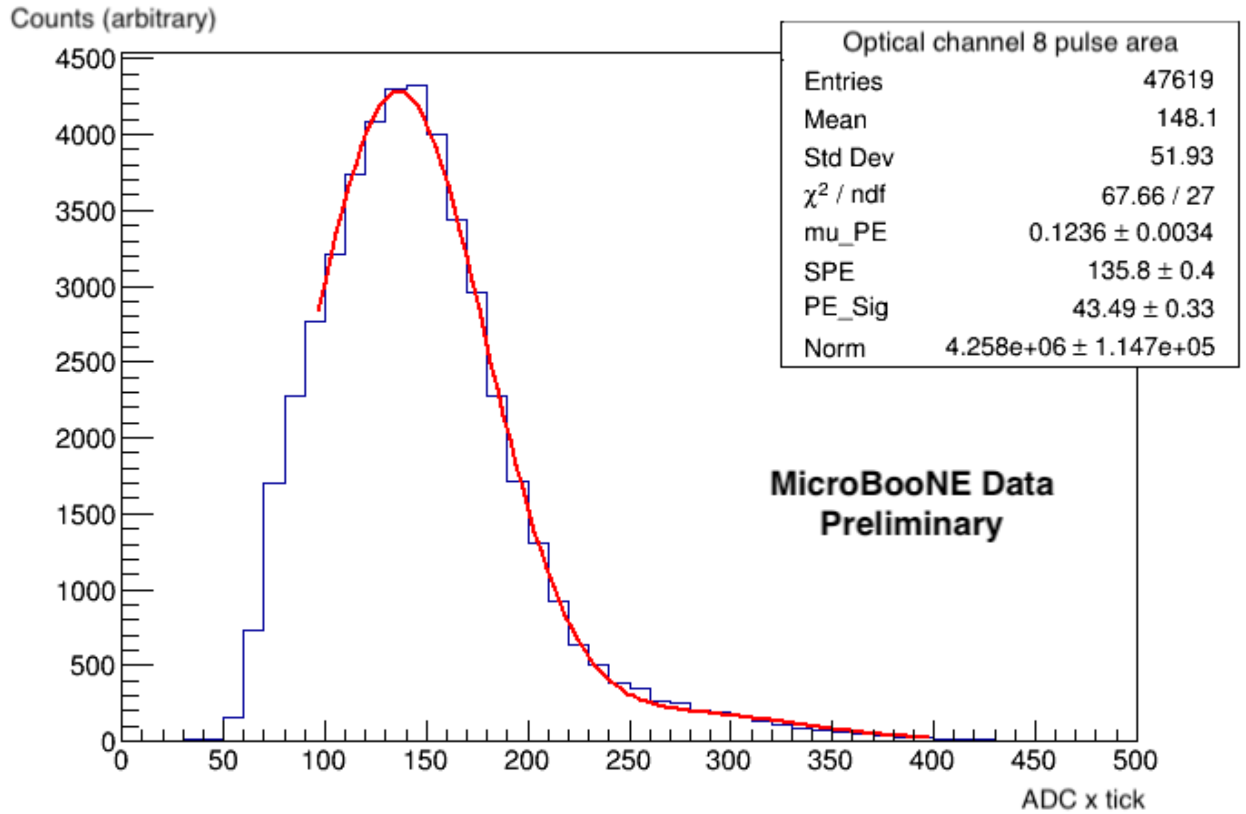
~25:75 for MIP

This can in theory be used for PID

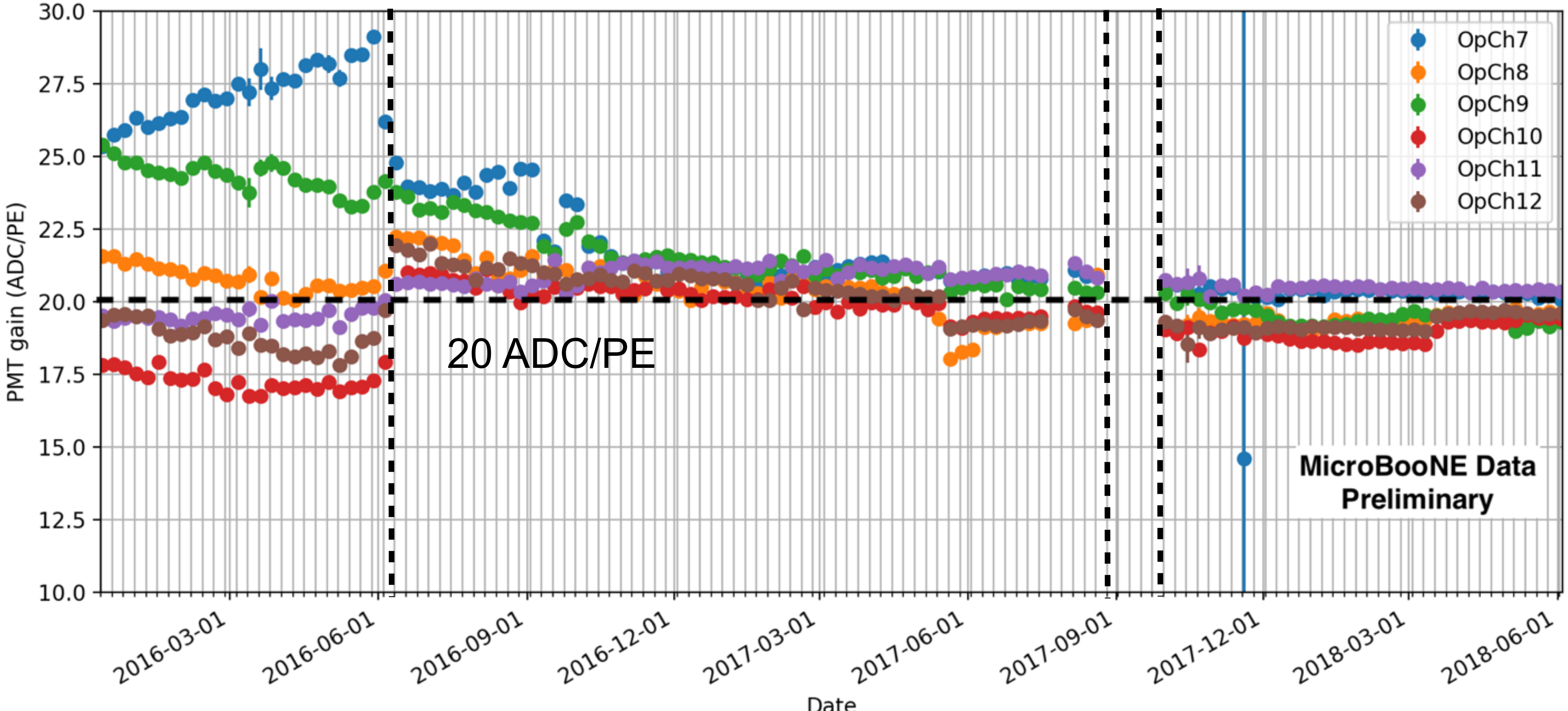
PMT Gain Calibration In Microboone

- Gain can vary with
  - HV instabilities
  - Light intensity
  - Temperature fluctuations
- I have been in charge of PMT gain calibration since 2018
  - Perform measurements
  - Maintain database
  - Implementation in optical reconstruction
- PMT gain measurements in MicroBooNE
  - ~200 kHz of SPE noise (origin unknown)
  - Collect O(1 PE) pulses
  - Multi-PE fit to pulse amplitude and area distributions: extract gain constants





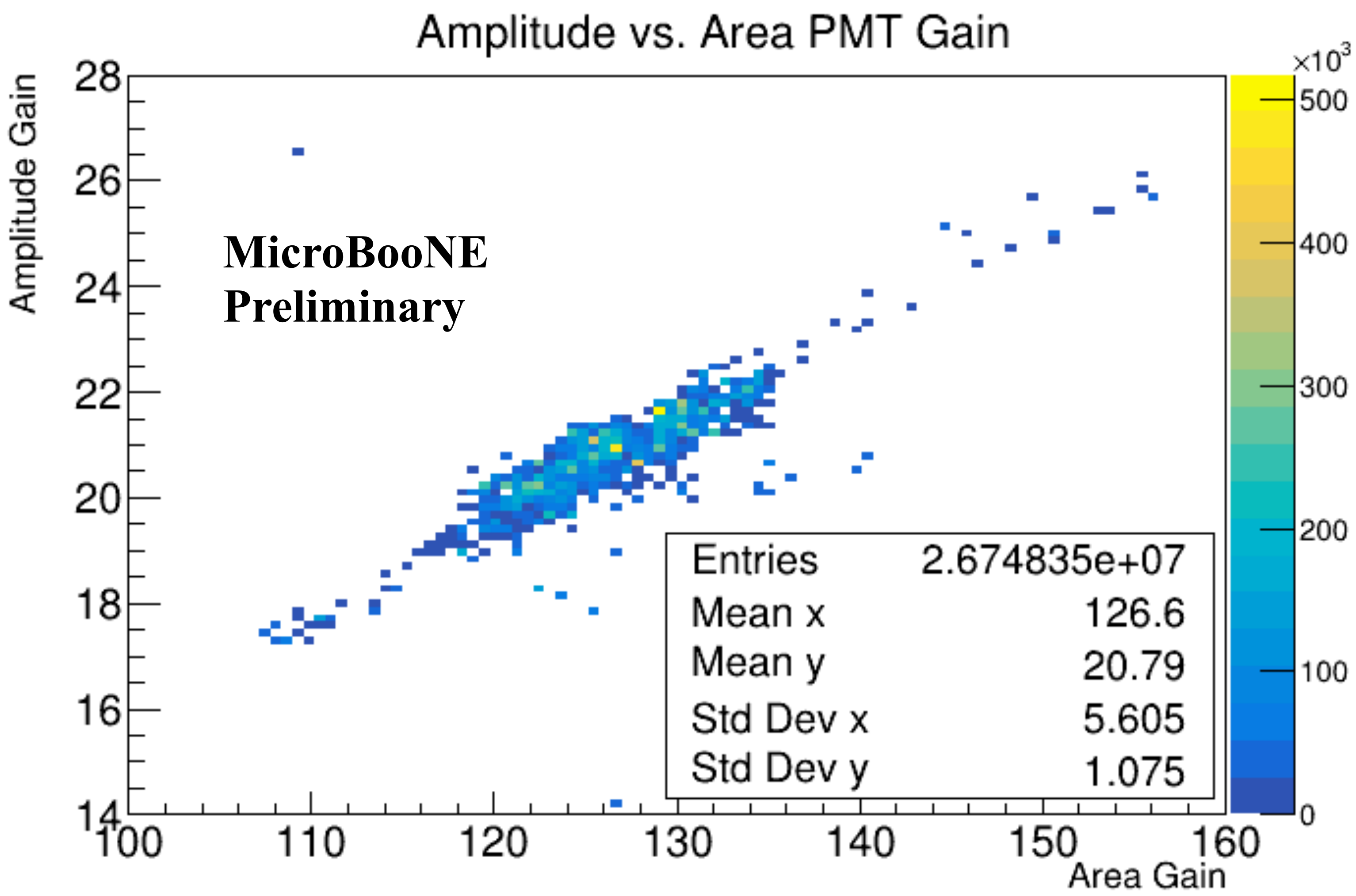
PMT gain Gain measurements



- Early on saw up to 30% deviation in gains for some PMTs
  - implemented procedural changes to minimize instabilities end of Run1
  - data/MC calibration important to ensure stability
- First time measuring PMT gain evolution in LArTPC over prolonged operation
  - MICROBOONE-NOTE-1064-TECH
  - valuable lessons for future LArTPC experiments
  - helps isolate & investigate other sources of light instability

PMT gain measurements with Single PE pulses

- Pure single-PE (SPE) case: pulse shape const (for each PMT) so area and amplitude correlated
- Area & amplitude multi-PE fits independent, but measured gains are correlated
  - Fitting procedure robust



PMT gain calibration performance

- Simulated PE: NsimPE = A/20 ADC (constant gain assumed)
- Calibrated PE: NrecoPE = A/gA
- Gain calibration minimizes PMT-to-PMT differences
  - Can measure remaining light yield instabilities independently

Residual of observed and simulated optical flash PE