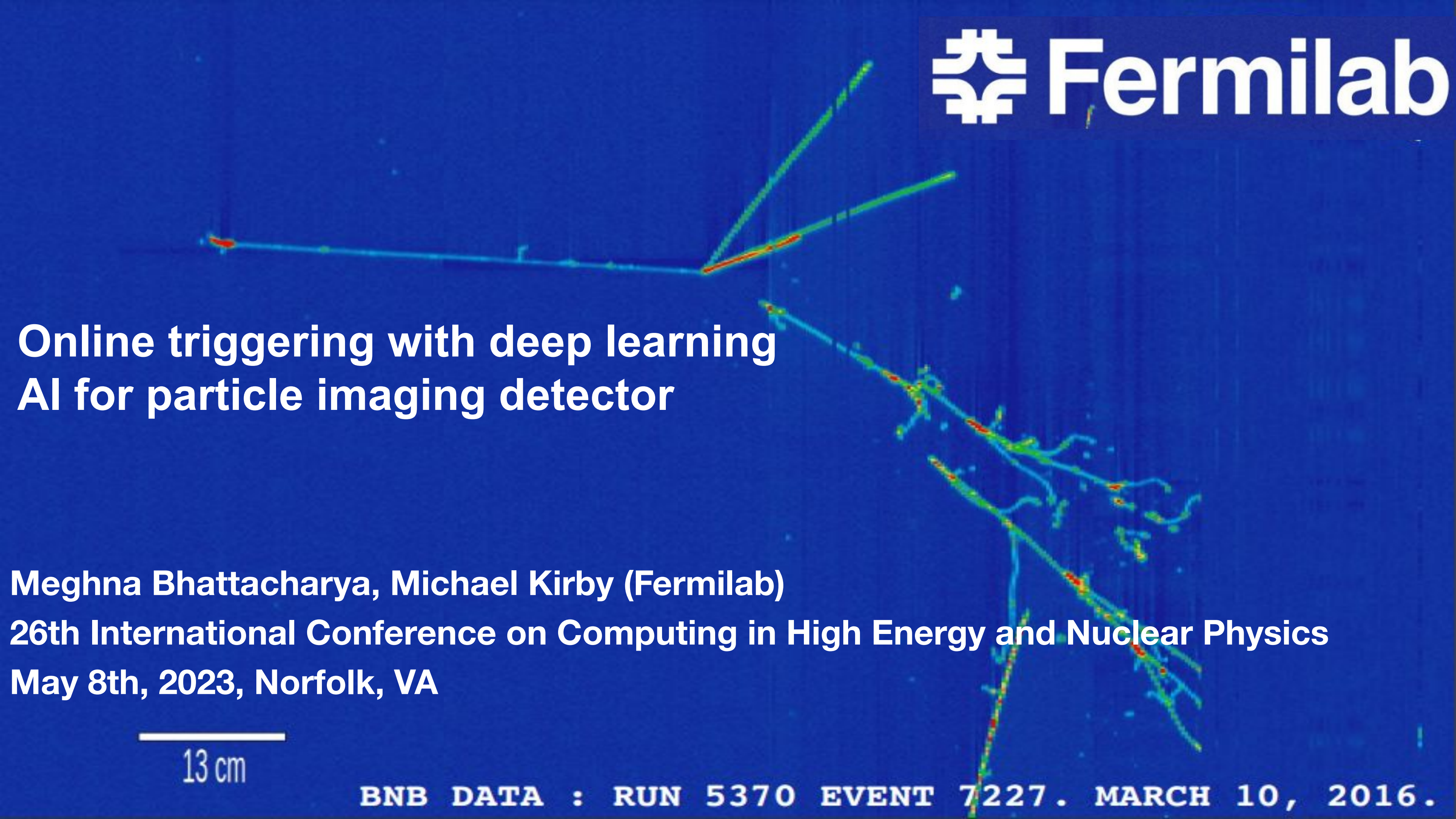
Online triggering with deep learning AI for particle imaging detector

Meghna Bhattacharya, Michael Kirby (Fermilab)

26th International Conference on Computing in High Energy and Nuclear Physics

May 8th, 2023, Norfolk, VA

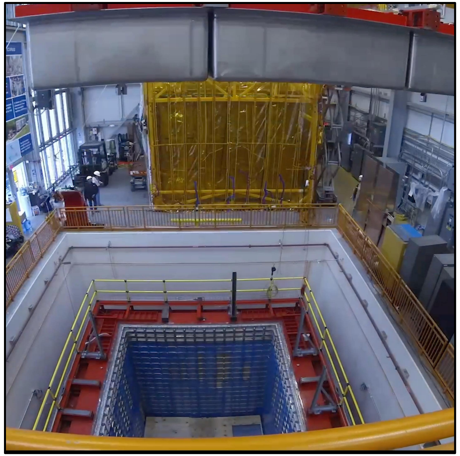


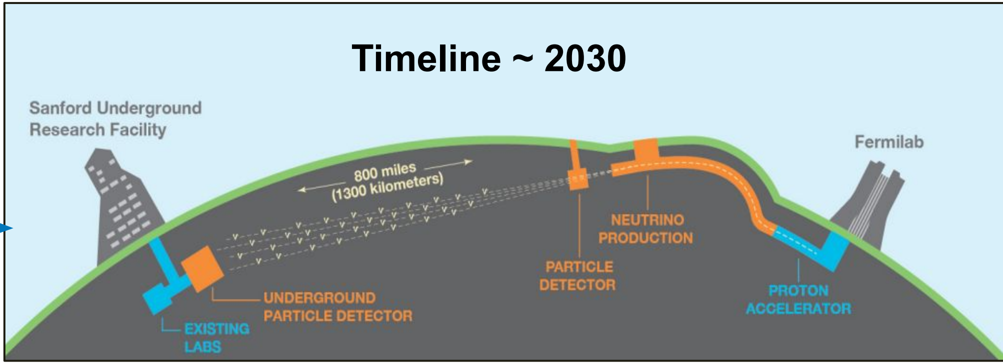
Particle Imaging Detectors : LArTPCs

Data taking 2015-2021

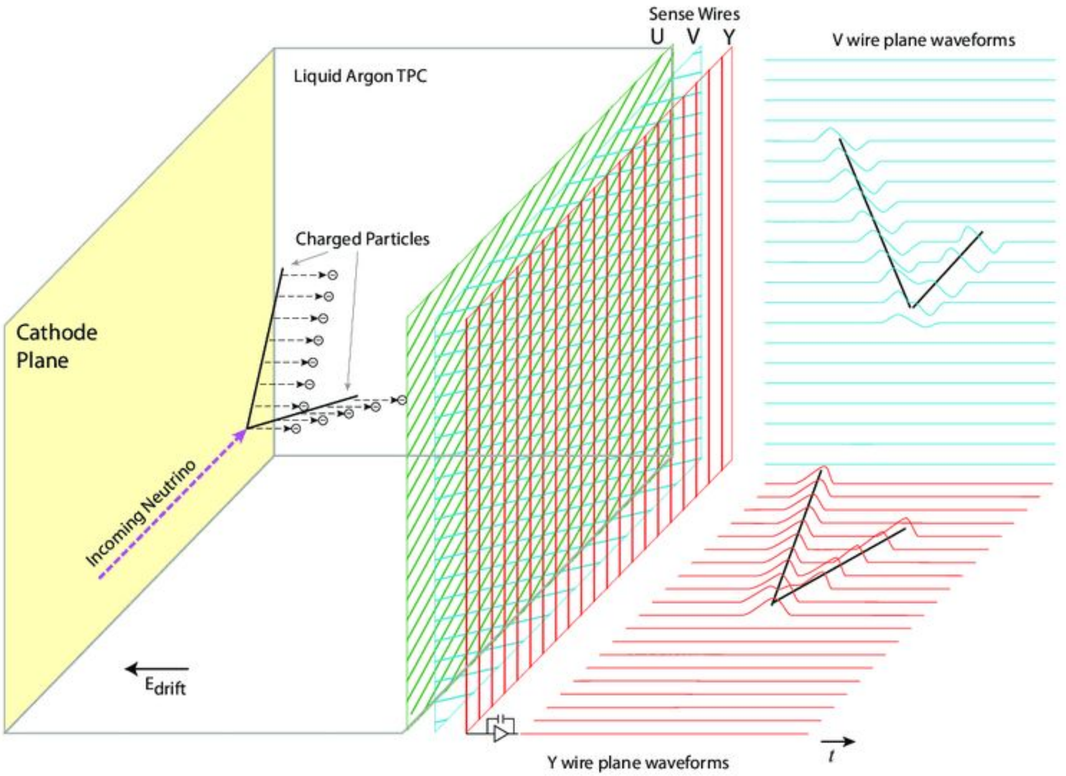
Data taking 2022-2027

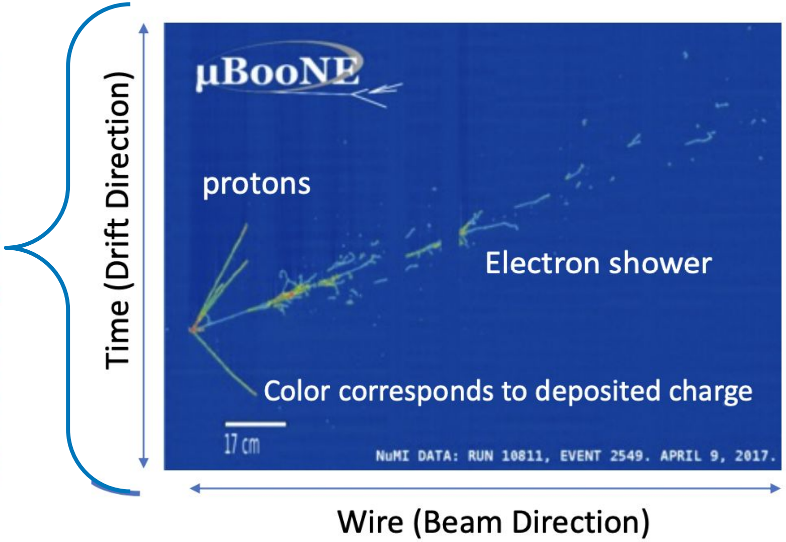
Data taking starts 2023





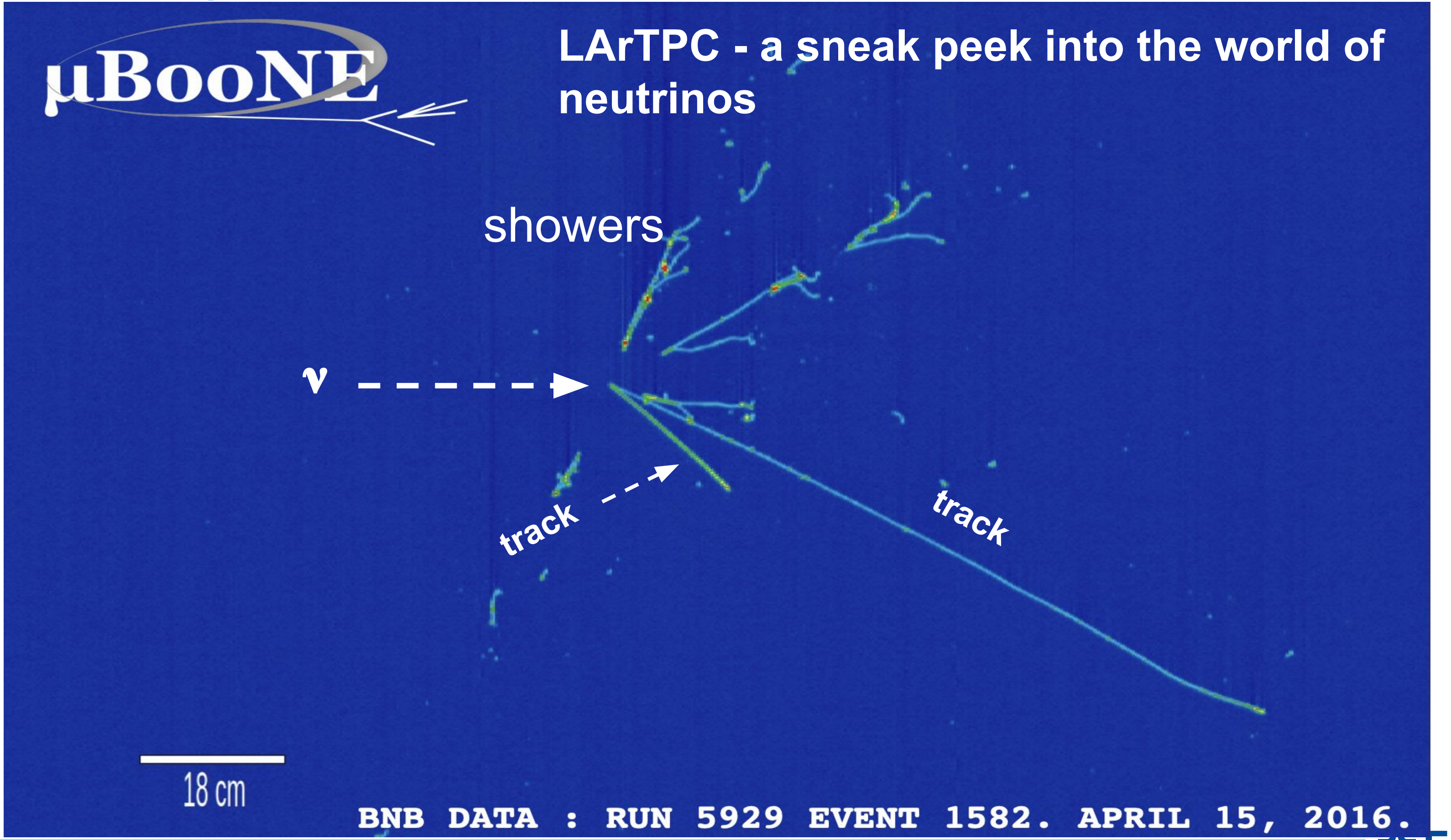
The Crux of LArTPCs : Next Gen Particle Imaging Detectors



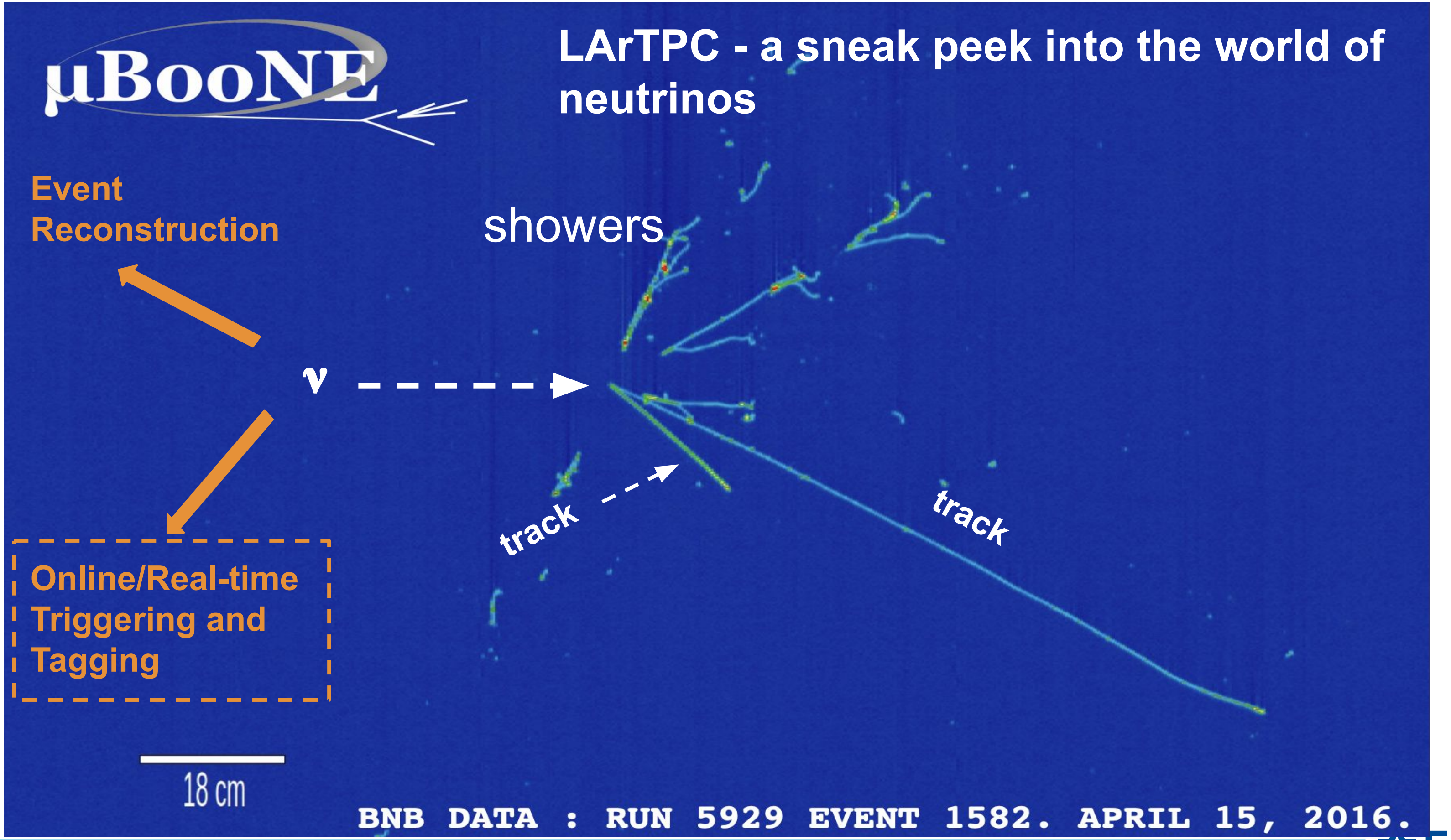


- **Excellent particle imaging detector**
- **mm scale spatial resolution**
- **Light signal by PMTs Current generation LArTPCs**

LArTPC Images :



LArTPC Images :

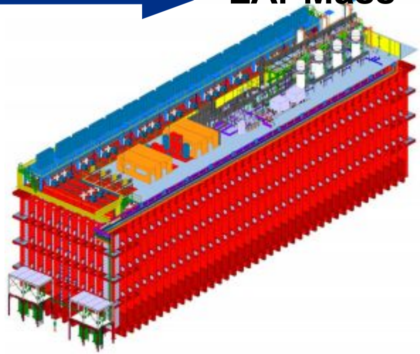


Next Gen LArTPCs

Bigger Detectors → more neutrino interactions expected

Challenge - efficient, fast turnaround data processing to meet physics goals

LAr Mass: 1X → ~ 5X → ~ 500X



µBooNE

SBN Program

DUNE

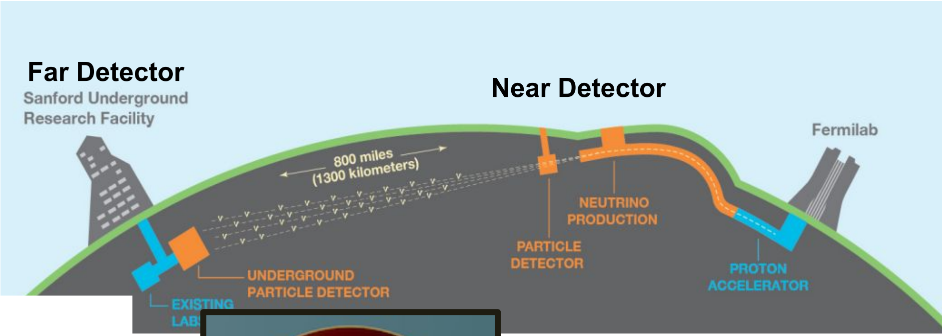
#channels: 1X → 5X → ~100X

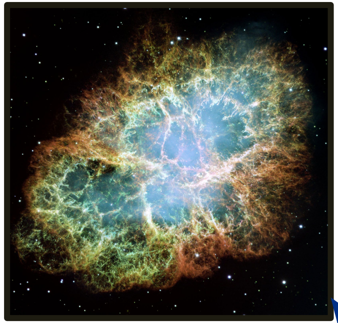
Data rates: 33 GB/s → 45 GB/s → 5 TB/s

DUNE - Future Flagship Experiment @ Fermilab

- World's largest multi kiloton LArTPC detector

- One of the major physics goals
  - study rare (off-beam) events at Far Detector





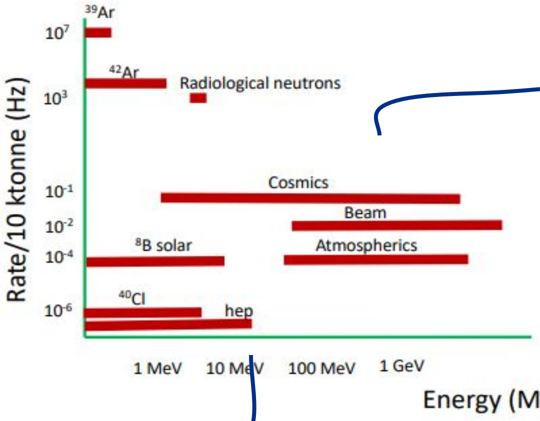
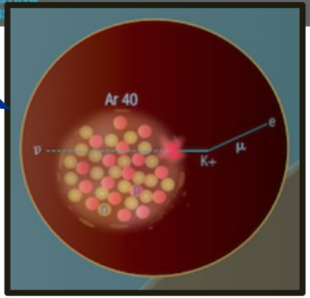


Figure 7.2: Expected physics-related activity rates in a single 10 kt module.



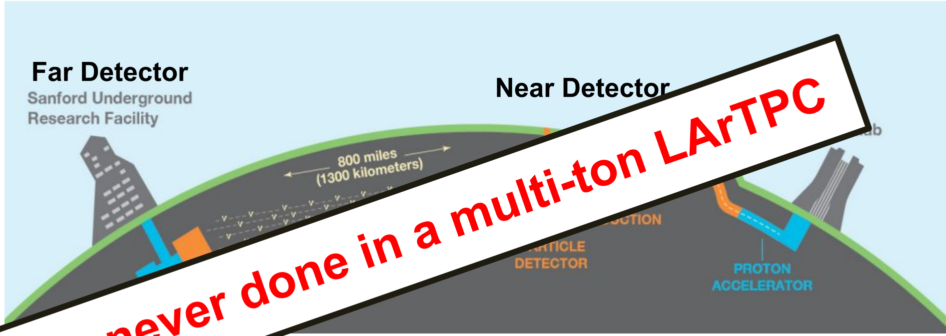
Expected data rate ~1.15 TB/s/ 10kT

Requirement : efficient and continuous data processing

Fermilab

DUNE - Future Flagship Experiment @ Fermilab

- **World’s largest multi kiloton LArTPC detector**
- **One of the major physics goals**
  - **study rare (off-beam) events at Far Detector**
- **Requirement : efficient and continuous data processing**



Implement a TPC data-driven trigger system - never done in a multi-ton LArTPC

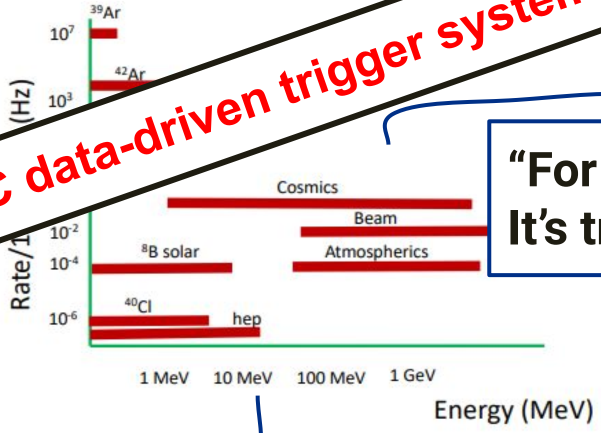
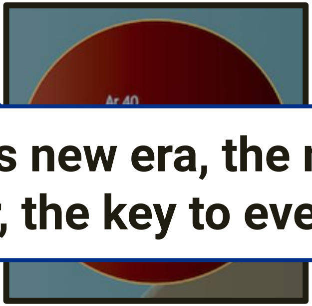
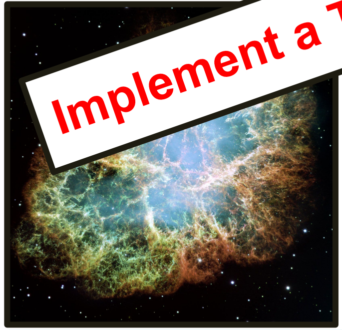


Figure 7.2: Expected physics-related activity rates in a single 10 kt module.

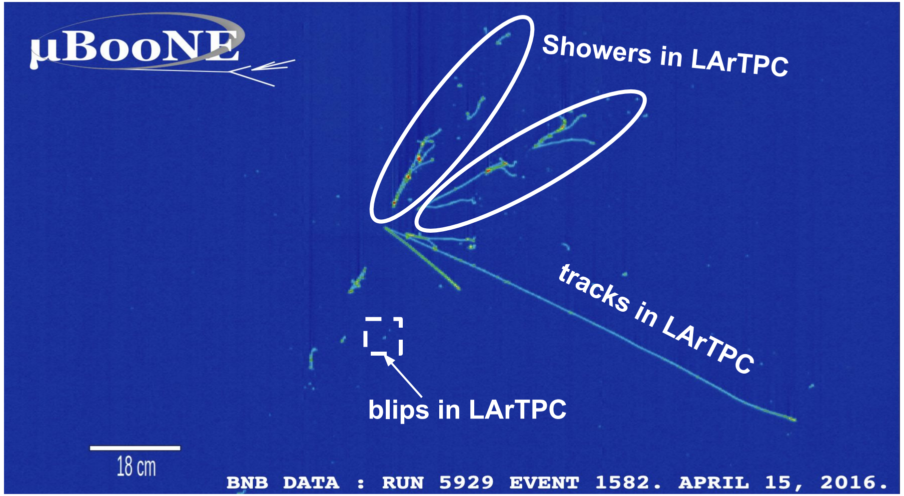


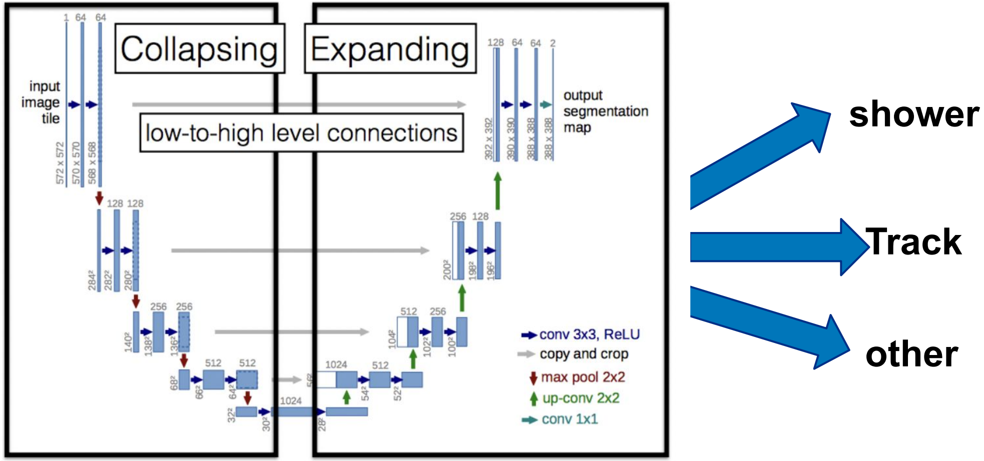
“For in this new era, the neutrinos bring It’s trigger, the key to everything” - Chatgpt



ML based Trigger Algorithm

- Parallel trig. algorithm: Identify ν & ν-like interactions





Shower - electron, photon, michel, delta

Track - Muons, Pions (MIP) or Protons (HIP)

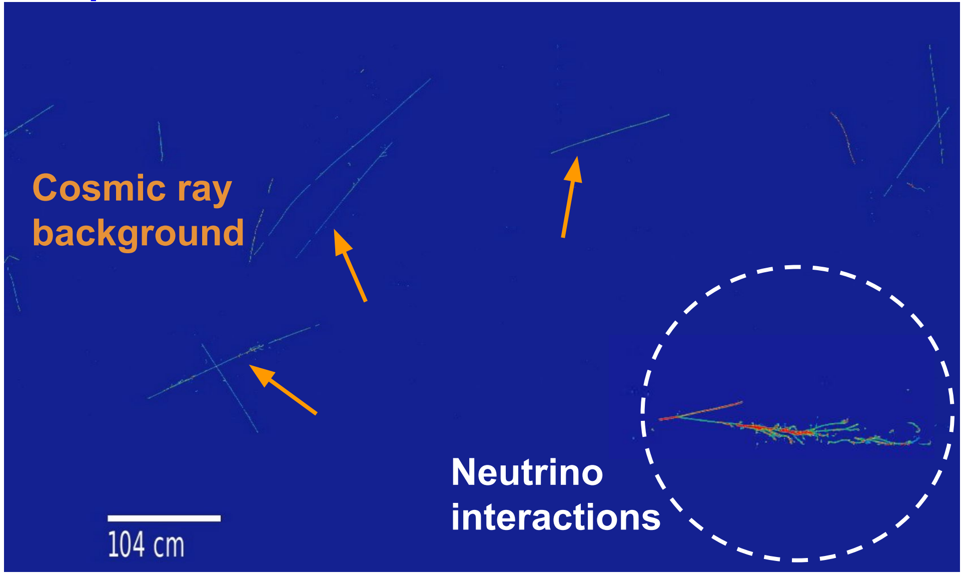
Other - Low energy blips

Dataset Info :

- MicroBooNE open data set in hdf5 format : https://microboone.fnal.gov/documents-publications/public-datasets/

- Simulated neutrino interactions, overlaid on top of cosmic ray data
- Goal : develop a TPC-data based ML algorithm
  - Use wire waveform information from opendata

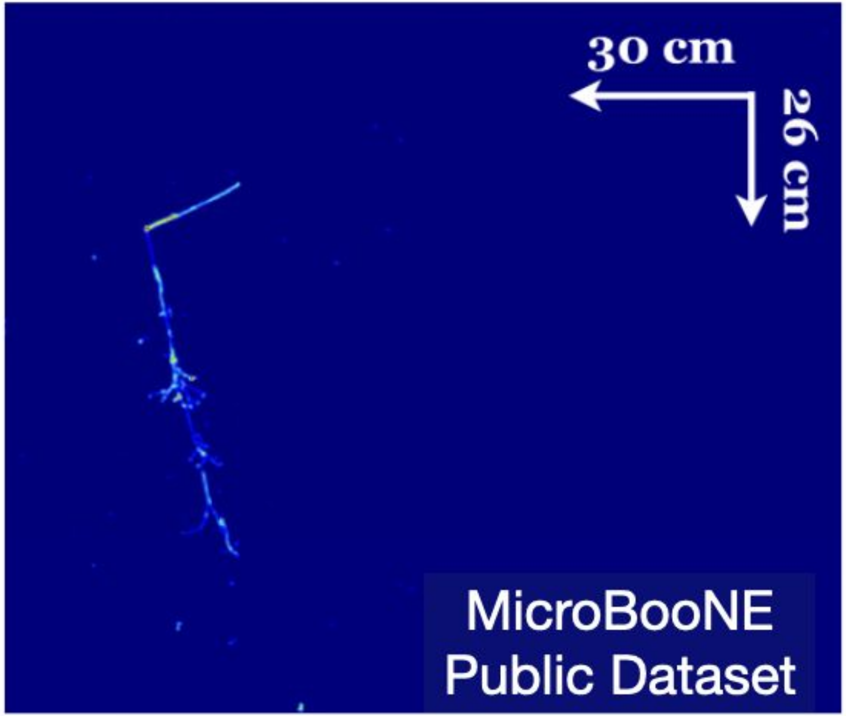
- Training logistics -
  - Crop image around highest pixel value
  - 512 X 512 pixel maps as input
  - Samples
    - Trained on ~34,000 events
    - Validation ~ 4,000 events
    - Test sample ~ 4,000 events



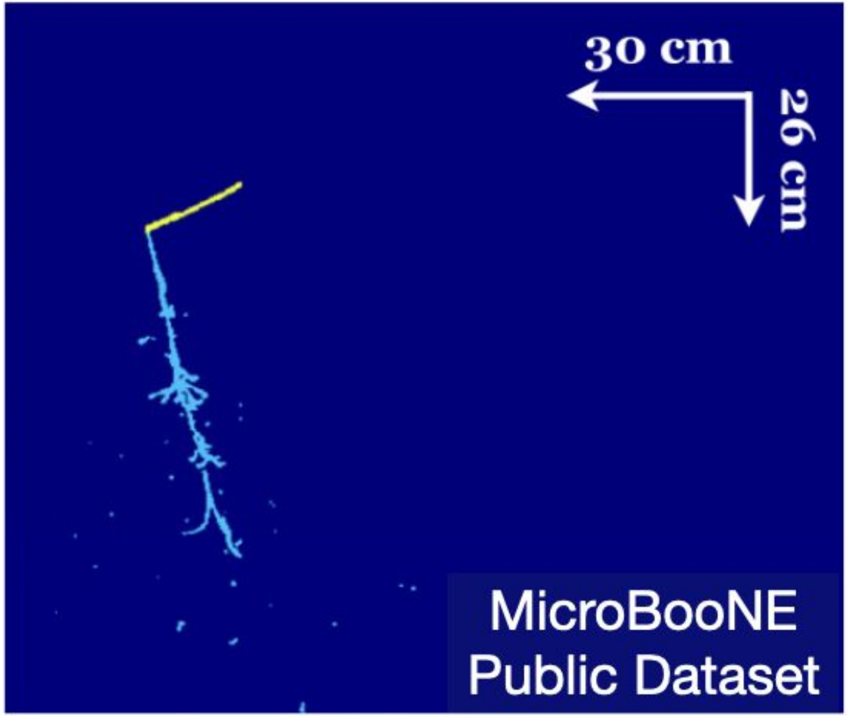
MicroBooNE Public Data Sets: a Collaborative Tool for LArTPC Software Development
Giuseppe Cerati, Track 8

Semantic Segmentation Ingredients :

Cropping around highest pixel value



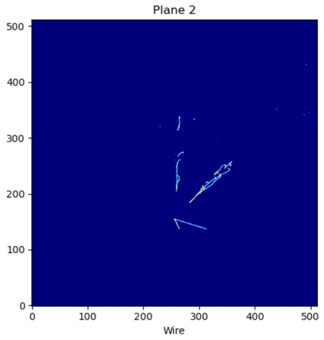
Corresponding pixel truth map

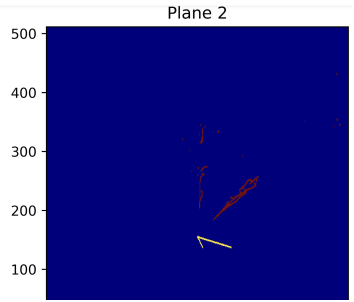


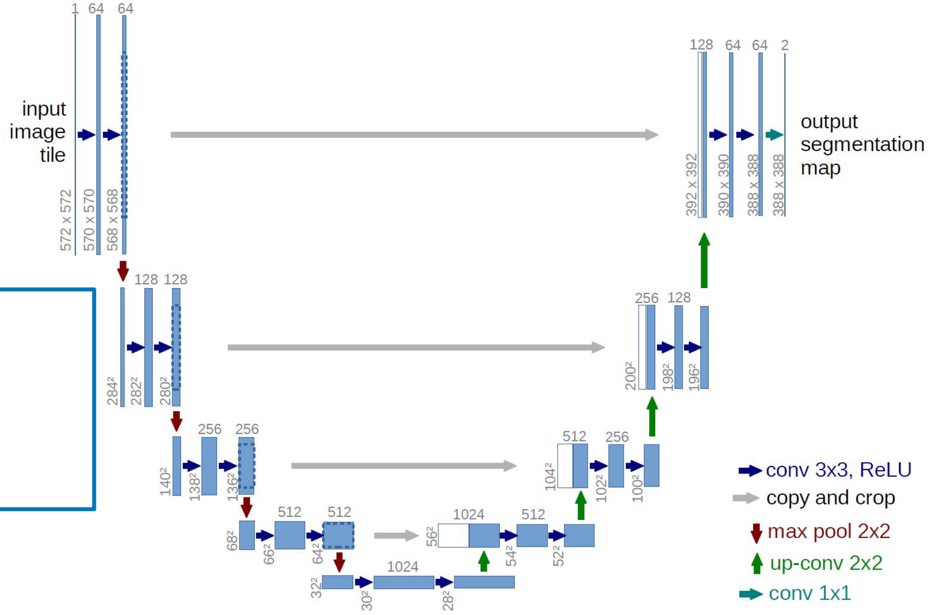
Pixel-level object recognition - Classify every pixel into pre-defined semantics (labels)

Network Architecture :

- Sparse images ⟶ < 1 %
- NVIDIA - Minkowski Engine
- Training on Nvidia A100, Elastic Analysis Facility at Fermilab
- Test on CPU



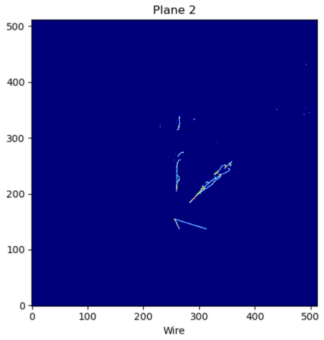


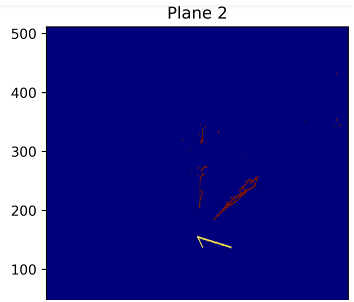


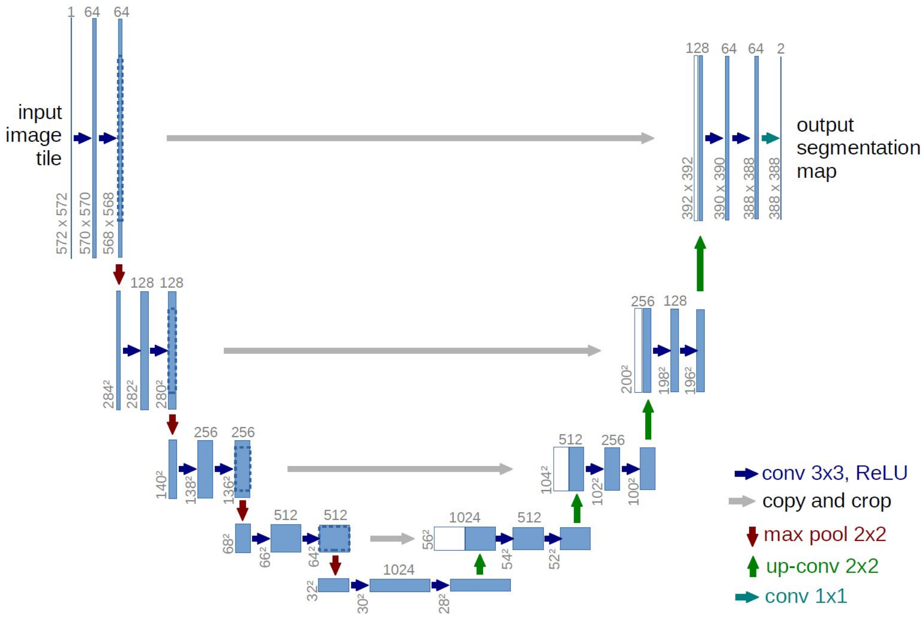
Sparse approach ⟶ less matrix multiplication ⟶ better timing and memory usage ⟶ well suited for trigger algorithm

Network Architecture :

- Depth = 5 (downsample steps)
- Filters = 64
- Kernel Size = 3X3
- Cross Entropy Loss Function
- Class imbalance
    - Class wise loss weighting
- ADAM optimizer
- Learning Rate = 1e-4
- Output 512 X 512 with 3 channels per pixel encoding a probability (SoftMax classifier)

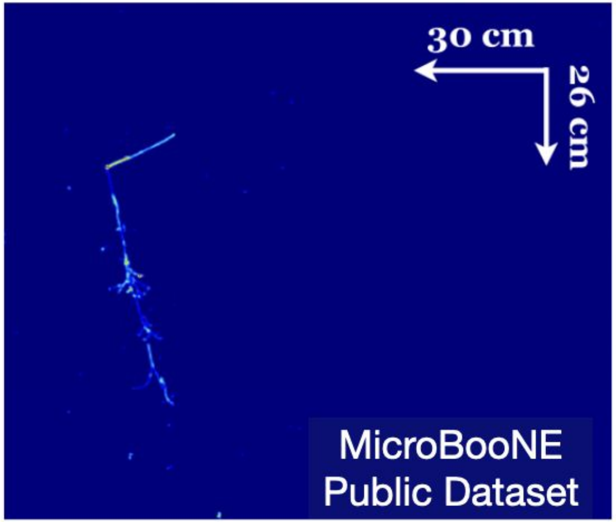




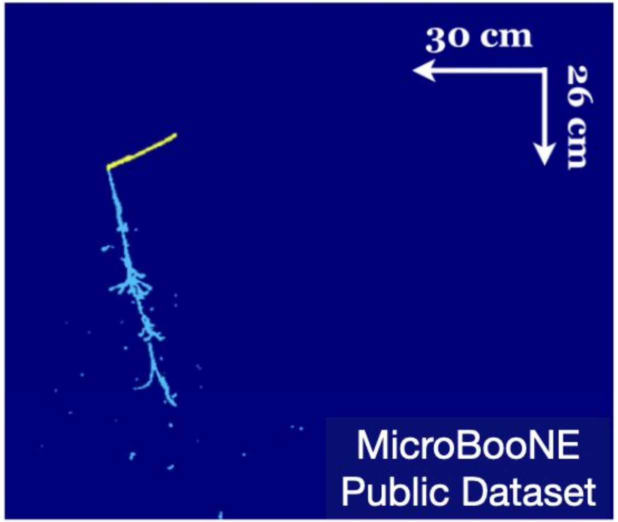


Network Prediction :

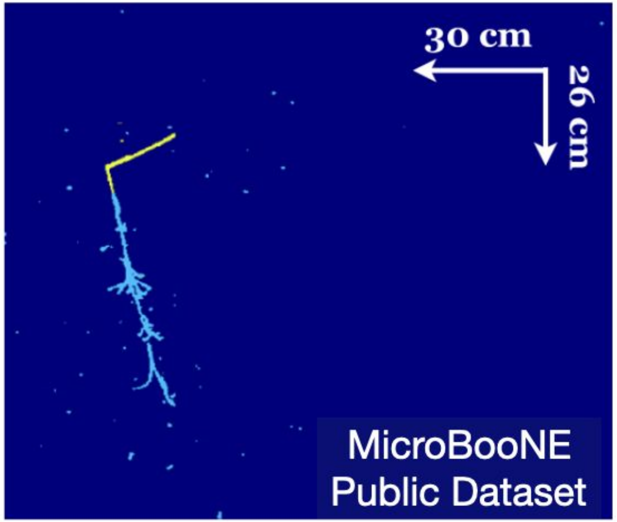
ADC Values



Ground truth

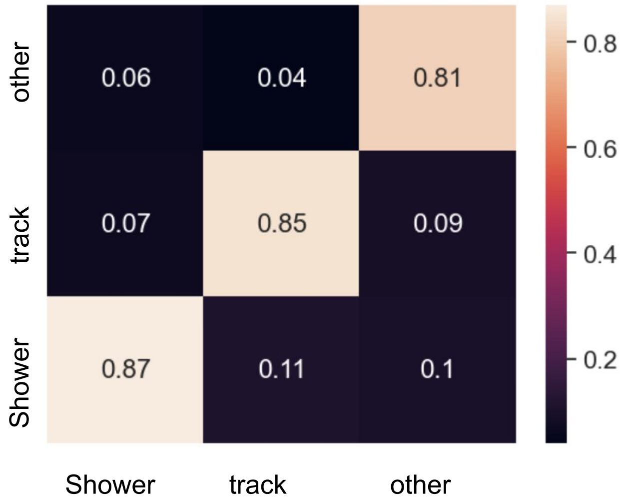


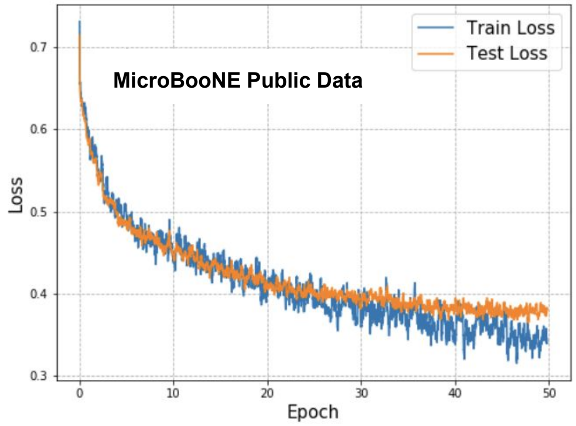
Predicted image

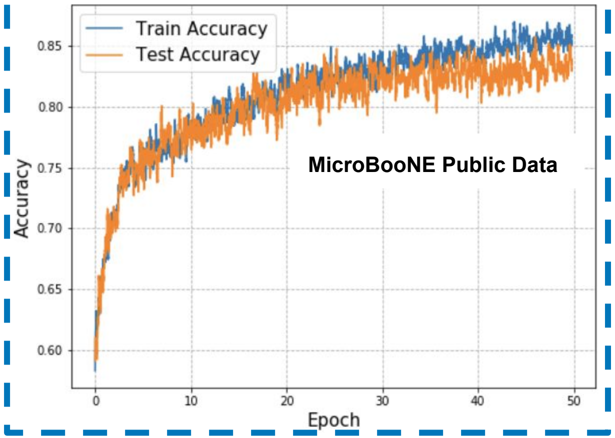


Overall accuracy of the network 85%

Preliminary Network Performance :







The performance tests were done on an Intel core i7-8750H CPU 2.2 GHz

Network Used	Memory Usage	Inference time
Sparse approach	0.3GB	~0.23 s
Dense approach	2 GB	~3 s

Summary :

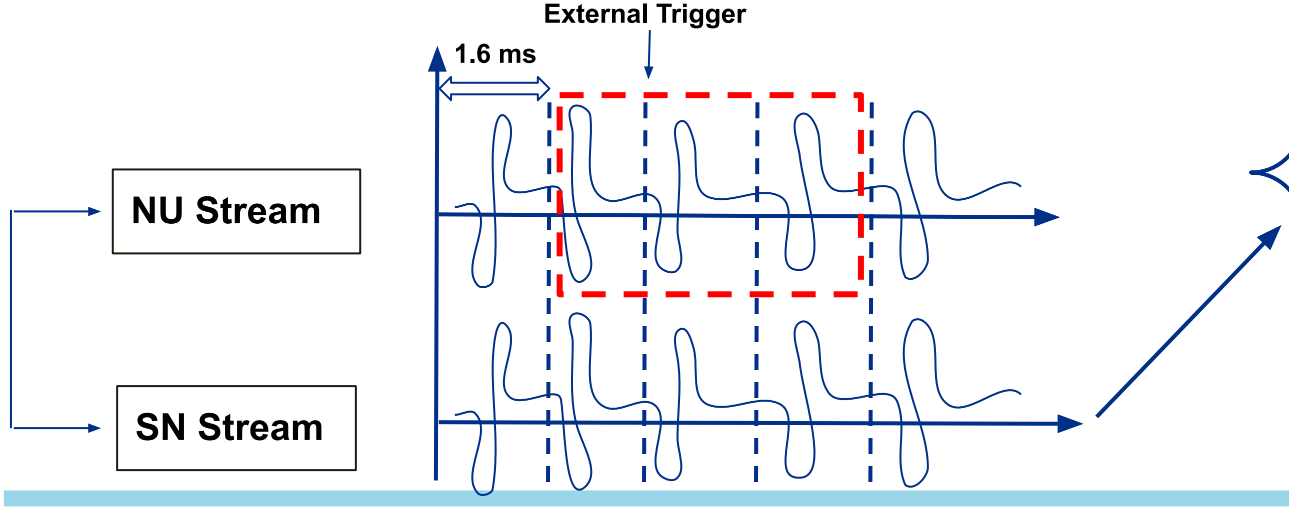
- Promising results in terms of timing and memory usage for a trigger algorithm
- Further classification among shower
    - Target : Identify EM showers in low energy region
    - Potential for calibration purposes
        - Using Michel electrons
- Future possibility includes triggering on some of the on-beam activities
- Possibility to use ML tools on specialized hardware such as FPGA (power efficient)

TPC Based Trigger System R&D

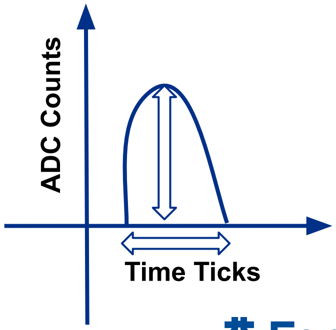
- **Excellent opportunity at MicroBooNE for R&D**
- **Modify the readout system at MicroBooNE to test DUNE trigger design**

NU : externally triggered data stream, not sensitive to Supernova events

SN : Continuous readout, Regions of Interest (ROI) - waveform over certain threshold



Trigger Primitives :
SN ROI Summary
- **Amplitude**
- **Integral**
- **Time over threshold**



Thank you!

This research is based upon work supported by the US Department of Energy, Office of Science, Office of High Energy Physics

U.S. DEPARTMENT OF ENERGY | Office of Science

In collaboration with University of Chicago, Data Science Institute

THE UNIVERSITY OF CHICAGO DATA SCIENCE INSTITUTE