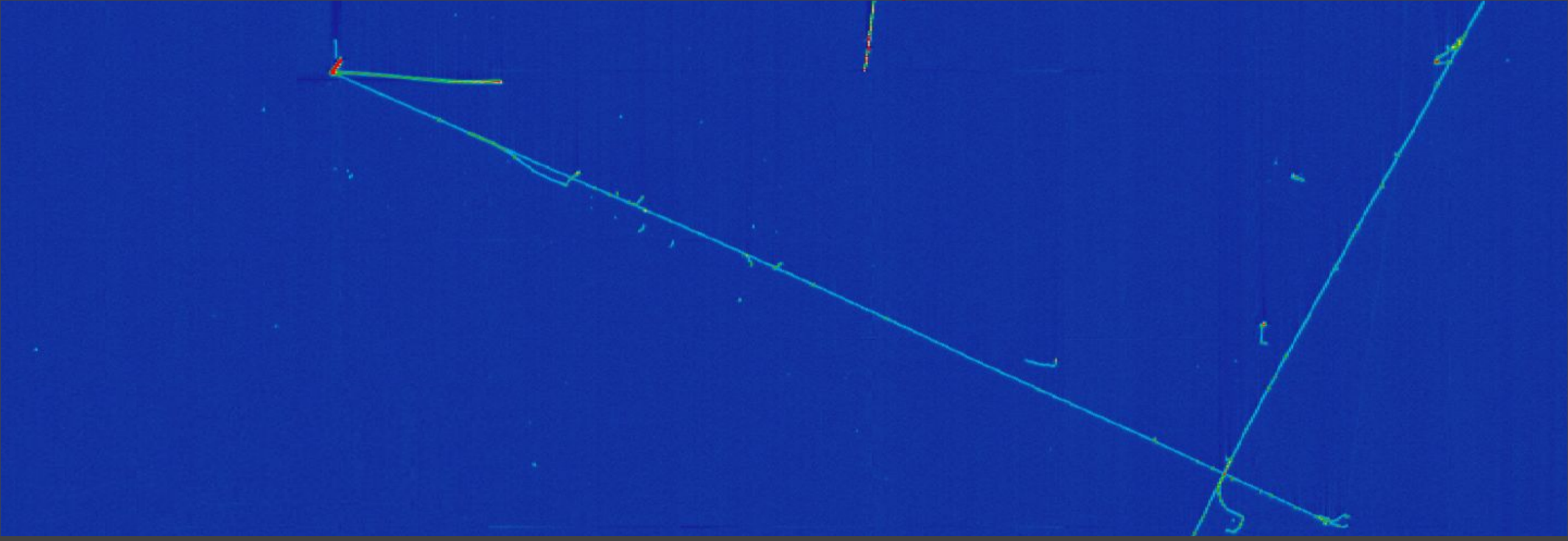


Machine Learning for Particle Image Neutrino Detectors

at the HEP Intensity Frontier

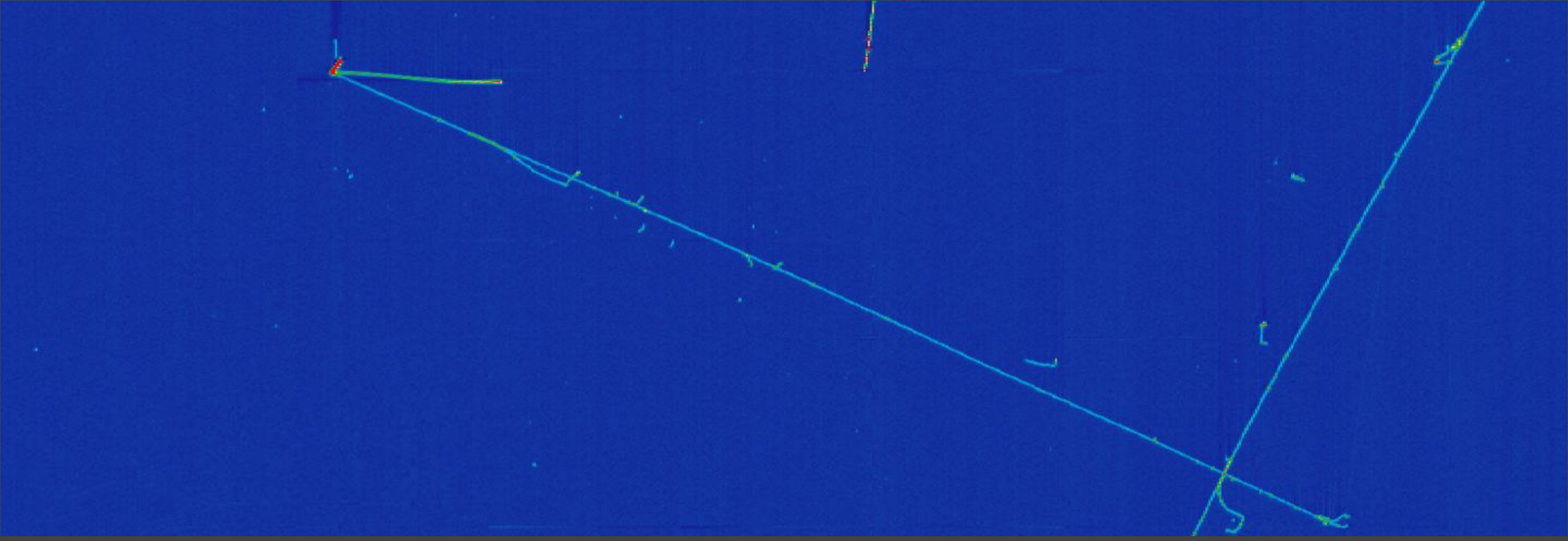
Kazuhiro Terao & Laura Domine

SLAC National Accelerator Lab.

ACAT @ Saas-Fee (11-15 Mar. 2019)

U.S. DEPARTMENT OF ENERGY
Office of Science

SLAC NATIONAL ACCELERATOR LABORATORY



Outline:

- Neutrino detectors
- Machine learning applications
- Toward 3D ML-based data reconstruction

Me: Neutrino Physicist

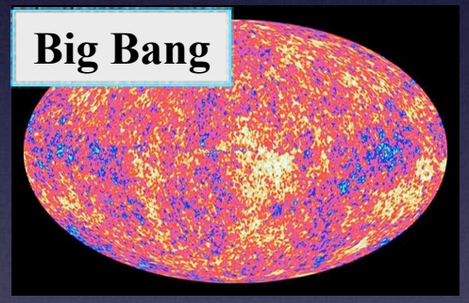
- **Neutrinos?**
  - One of least understood elementary particles

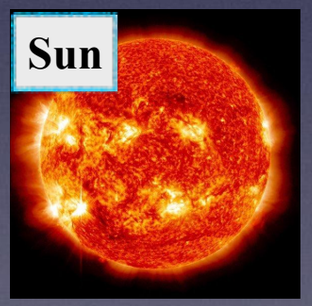
Me: Neutrino Physicist

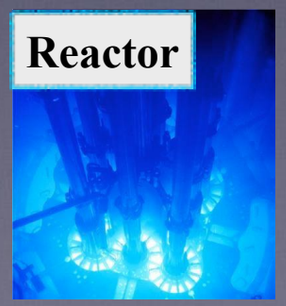
- **Neutrinos?**
  - One of least understood elementary particles
  - **They are everywhere**
    - 400 trillion neutrinos pass your body every second
    - Your body generates ~340 million neutrinos a day
  - **They come from everywhere**

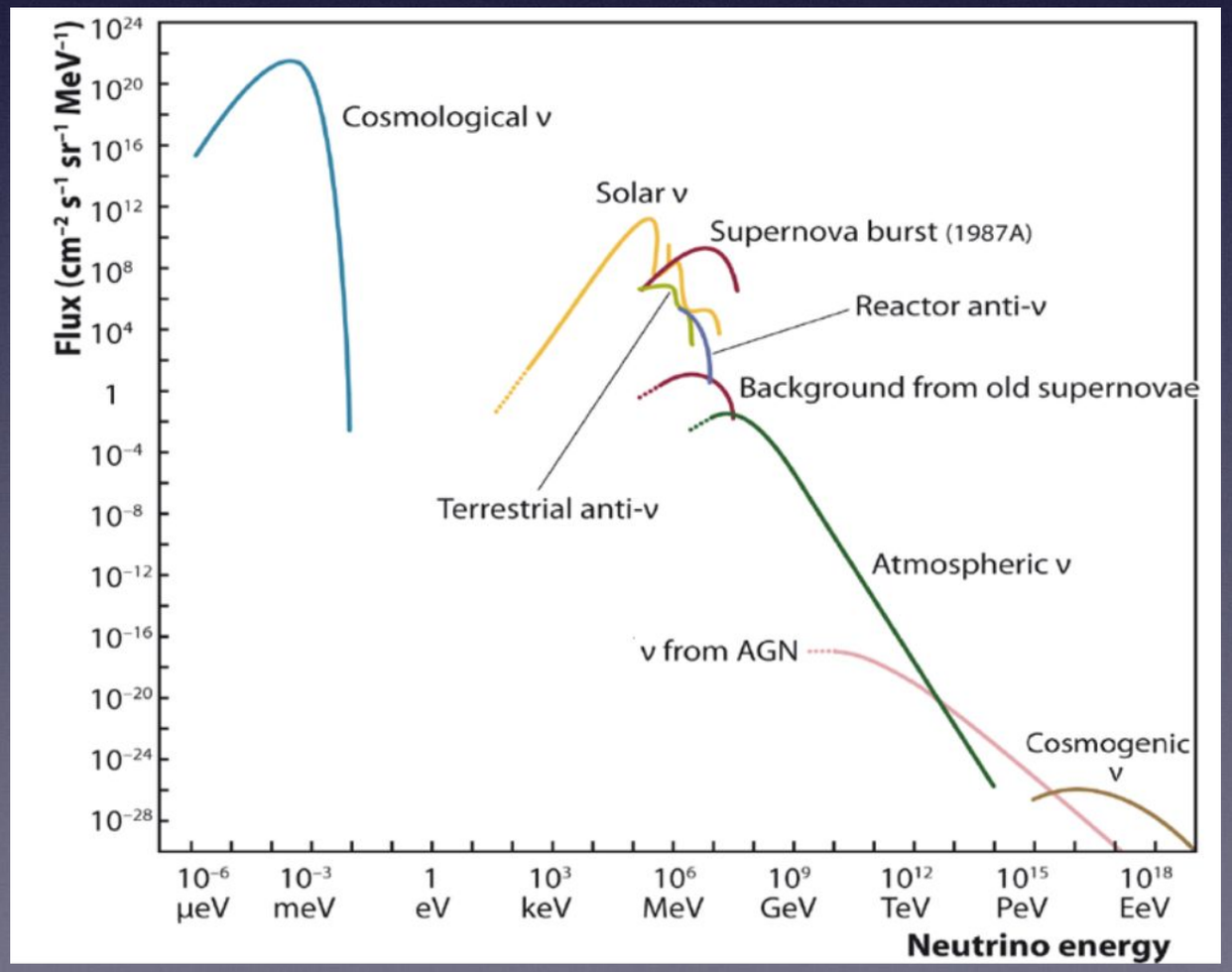
10^{38} neutrinos/second from our Sun

EPJ H37 (2012) 3:515-565

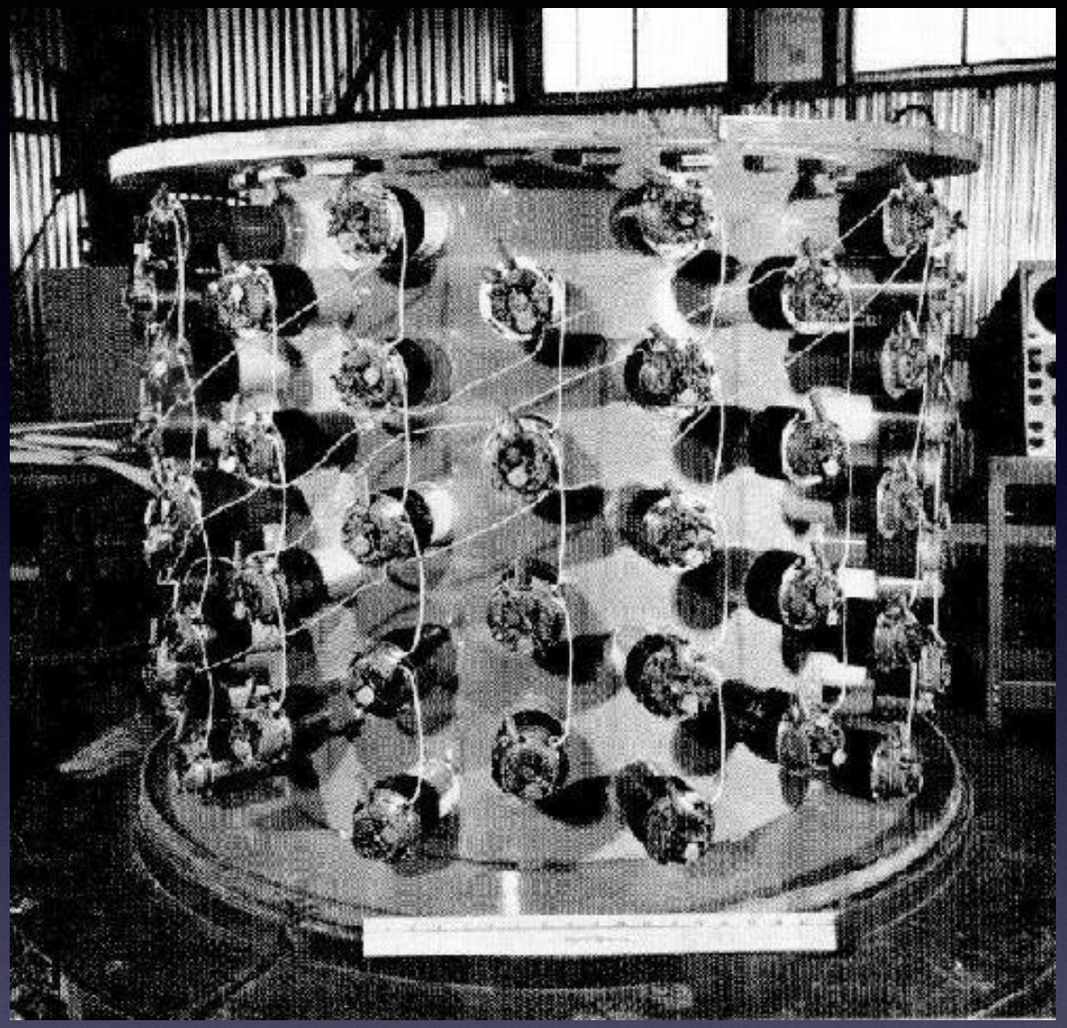




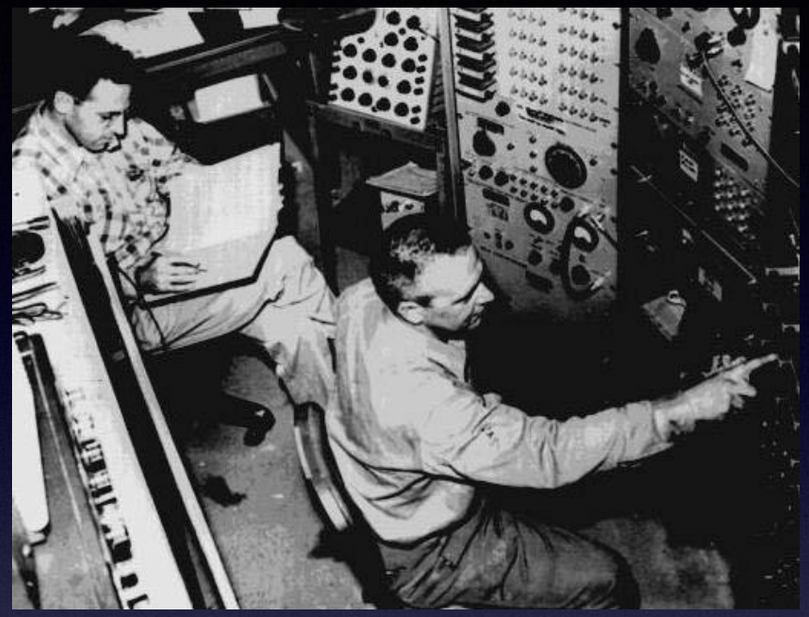




Early days neutrino detection



Cd-doped water
0.4 ton, 100 PMTs
(1956)



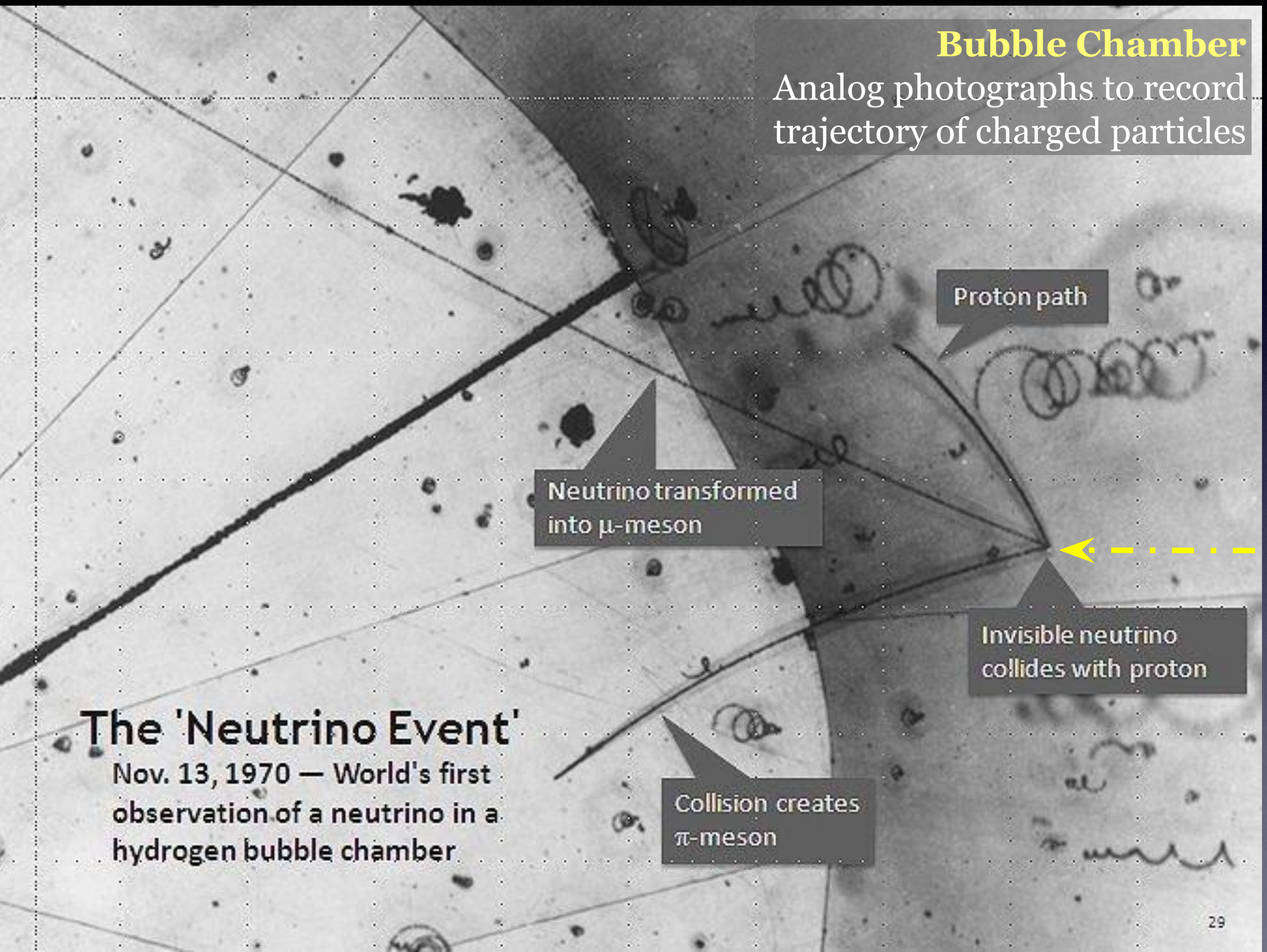
Inverse Beta Decay (IBD)

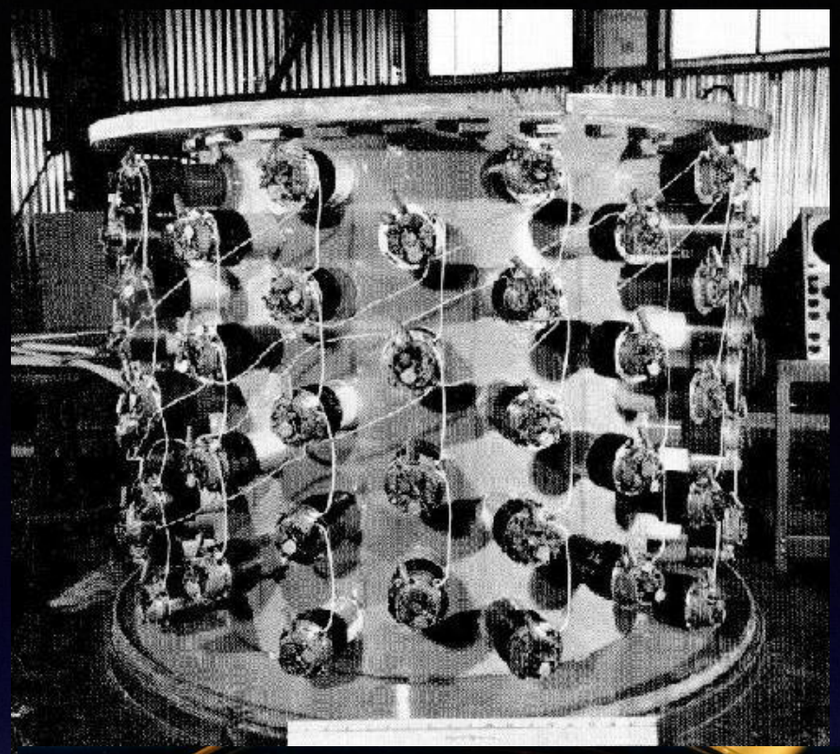
$$\bar{\nu}_e + p \rightarrow e^+ + n$$

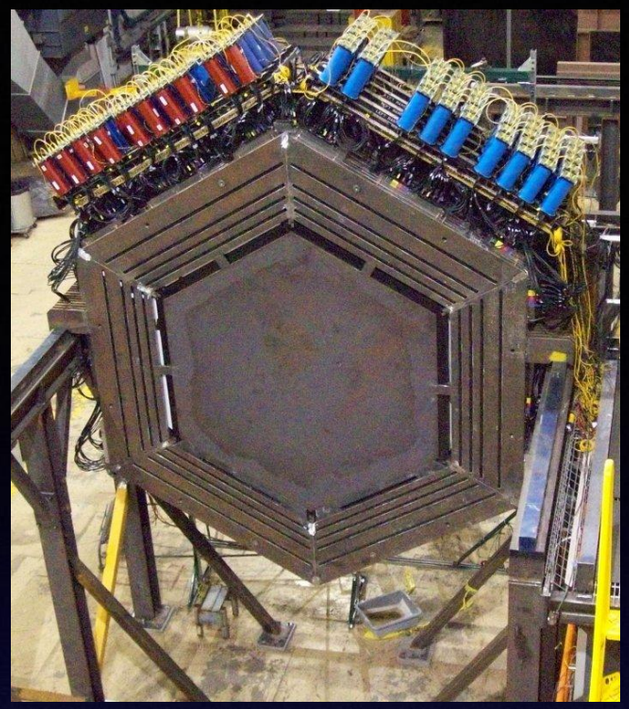
by Reines & Cowan (Nobel Prize 1995)

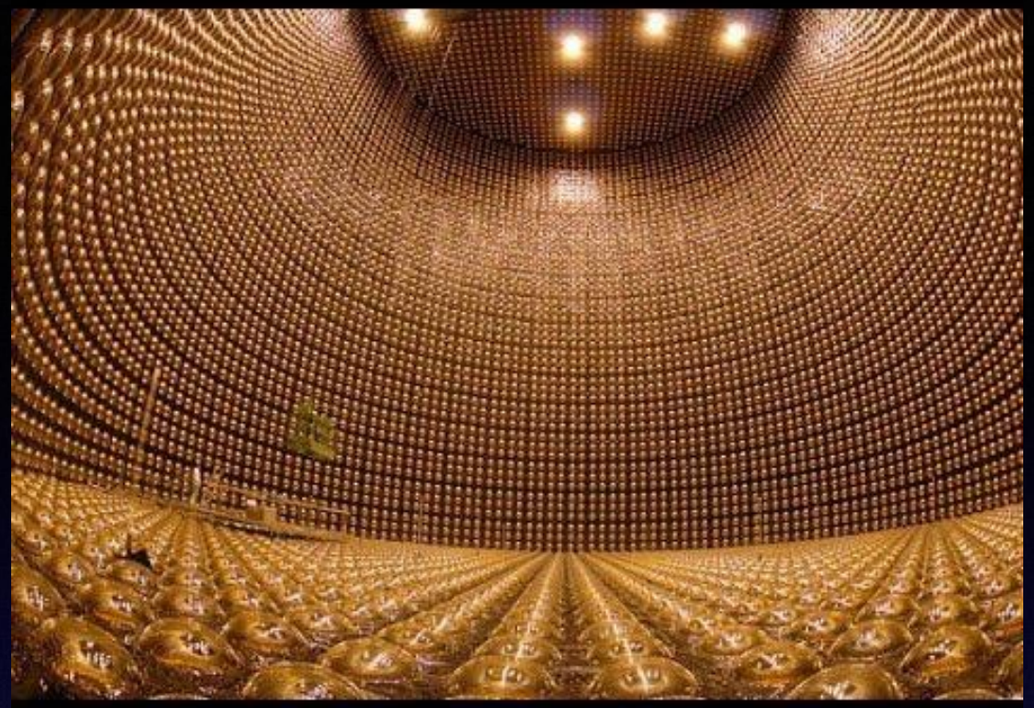
First neutrino detection

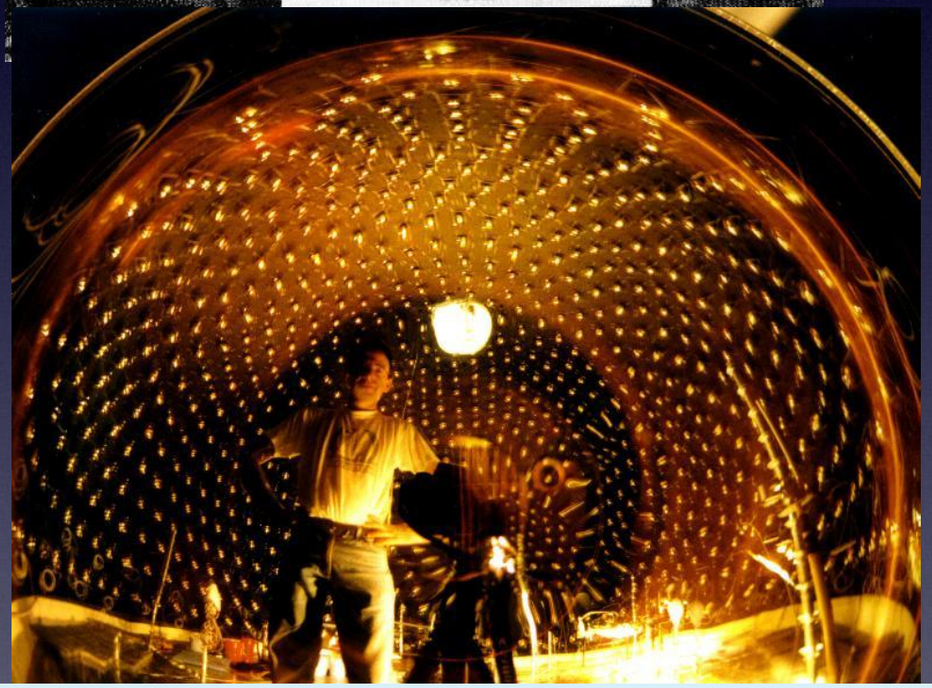
Early days particle imaging

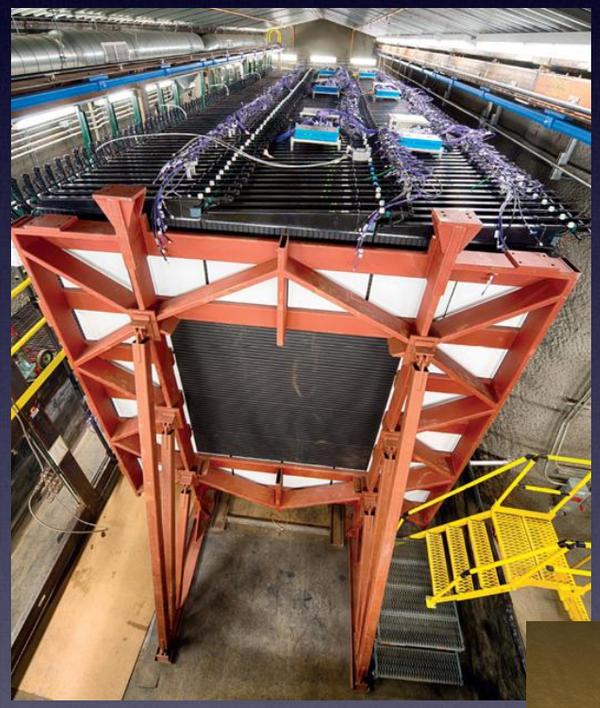


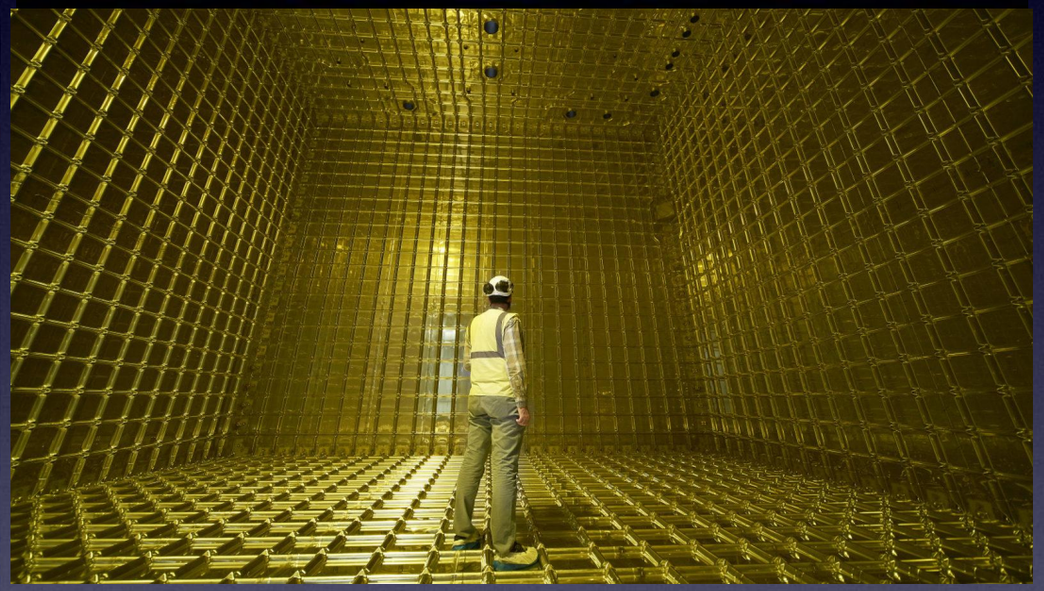


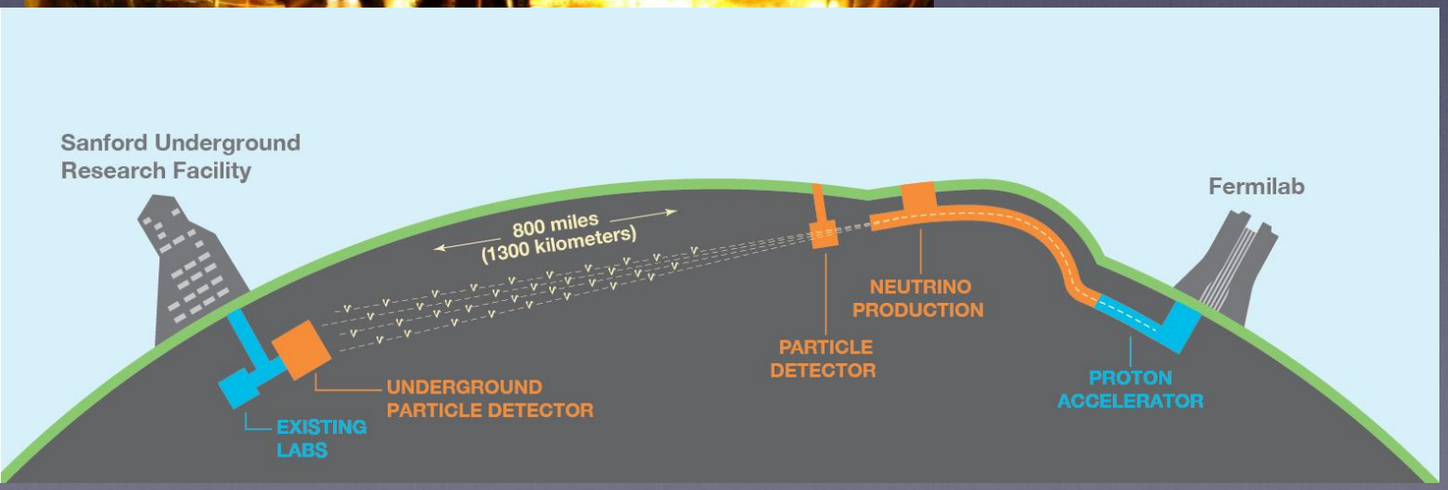


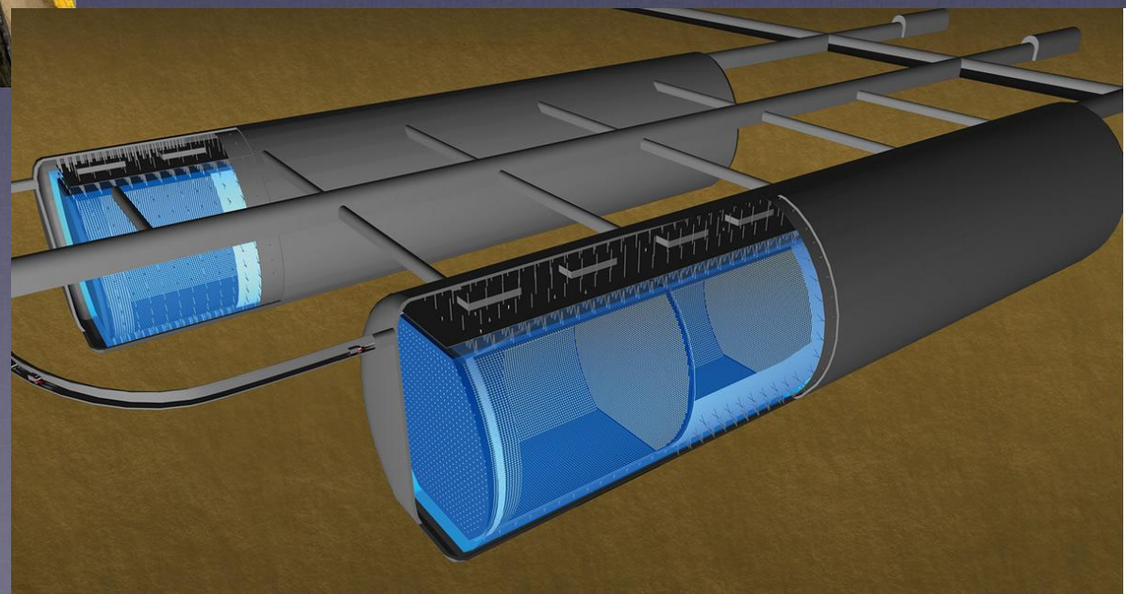


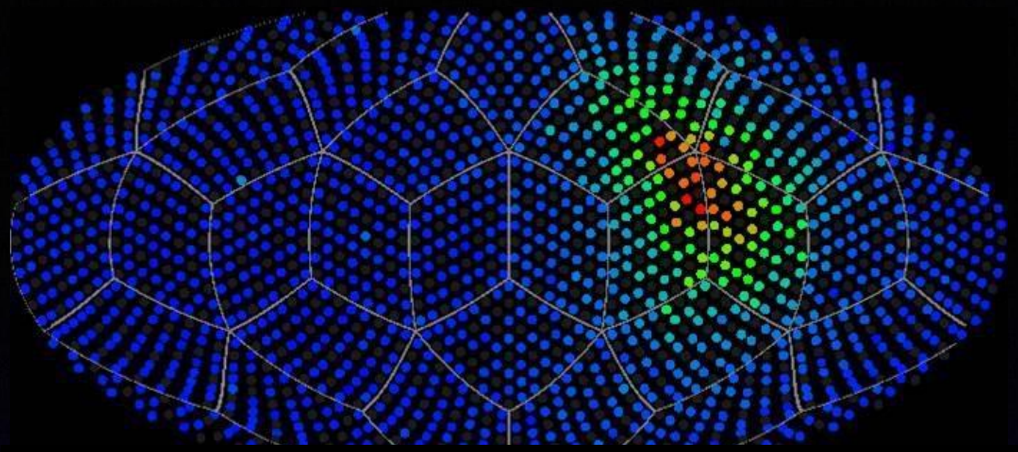


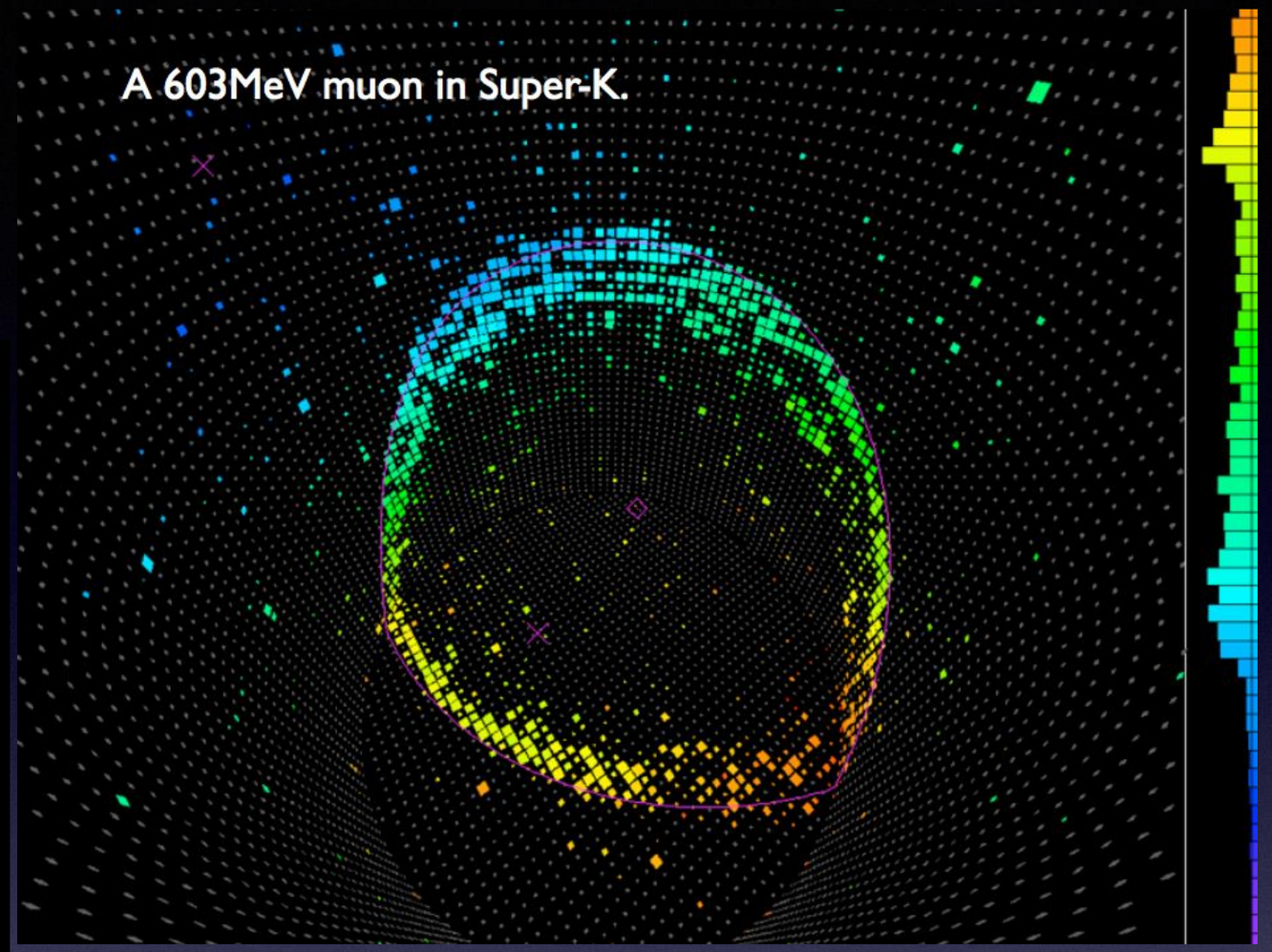


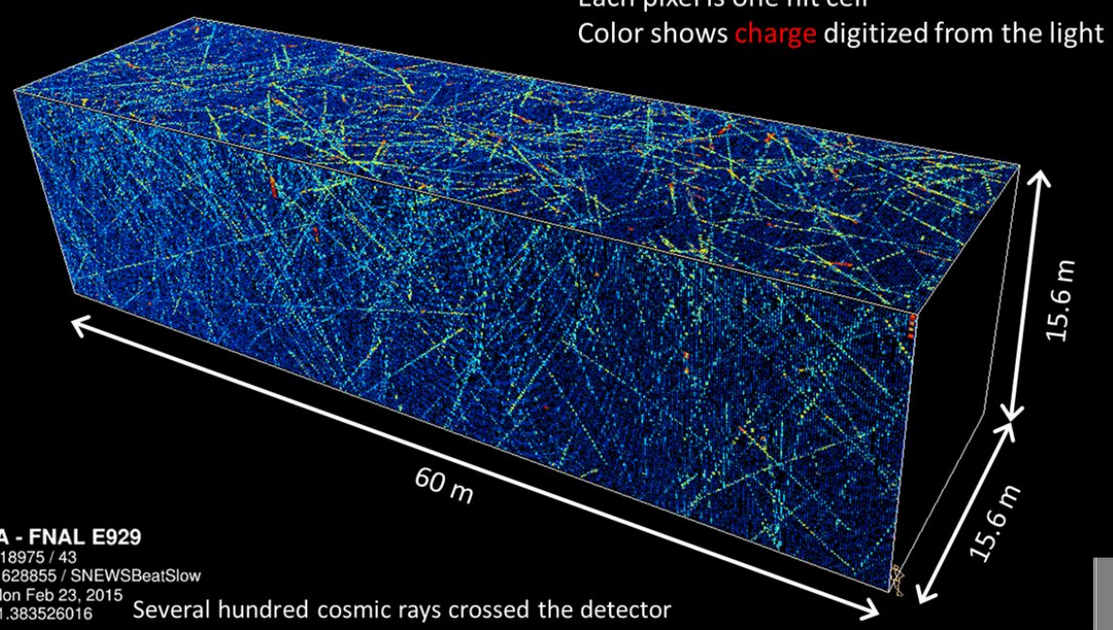


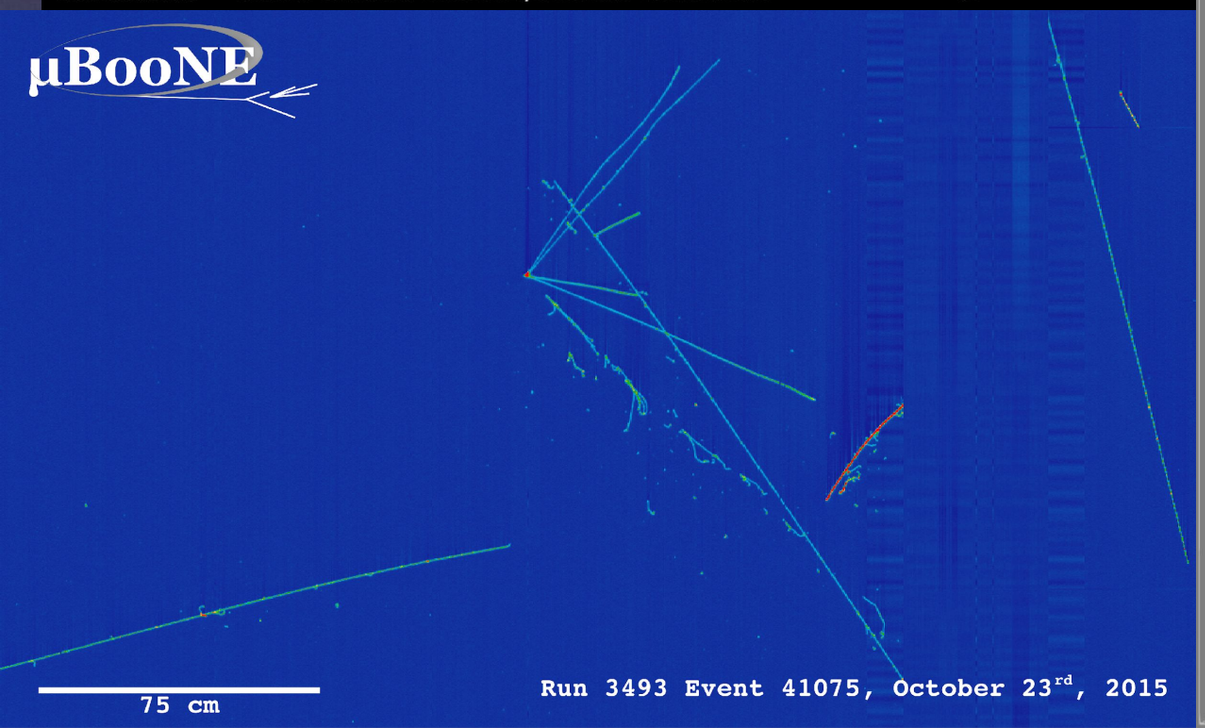

Sanford Underground
Research Facility
Fermilab
800 miles
(1300 kilometers)
NEUTRINO
PRODUCTION
PARTICLE
DETECTOR
UNDERGROUND
PARTICLE DETECTOR
EXISTING
LABS
PROTON
ACCELERATOR

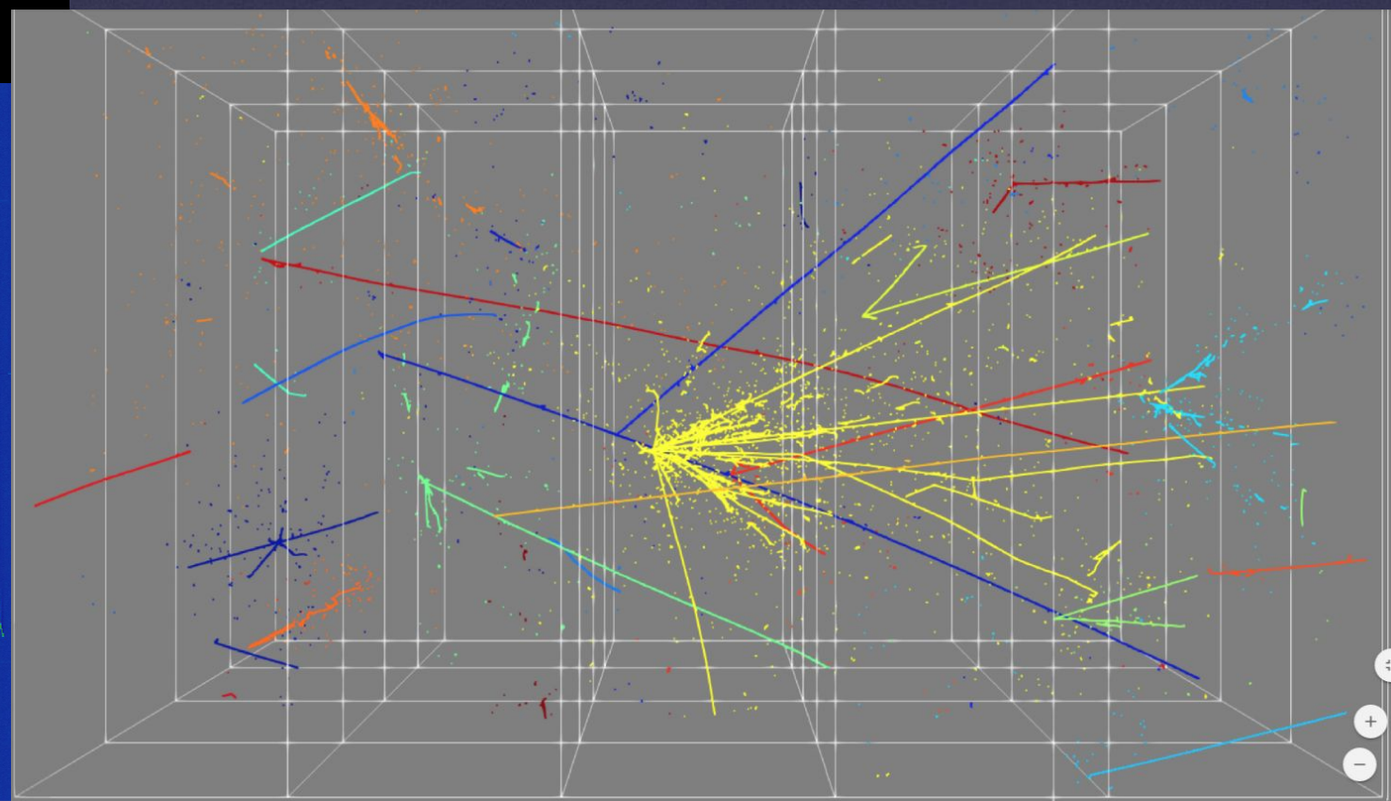


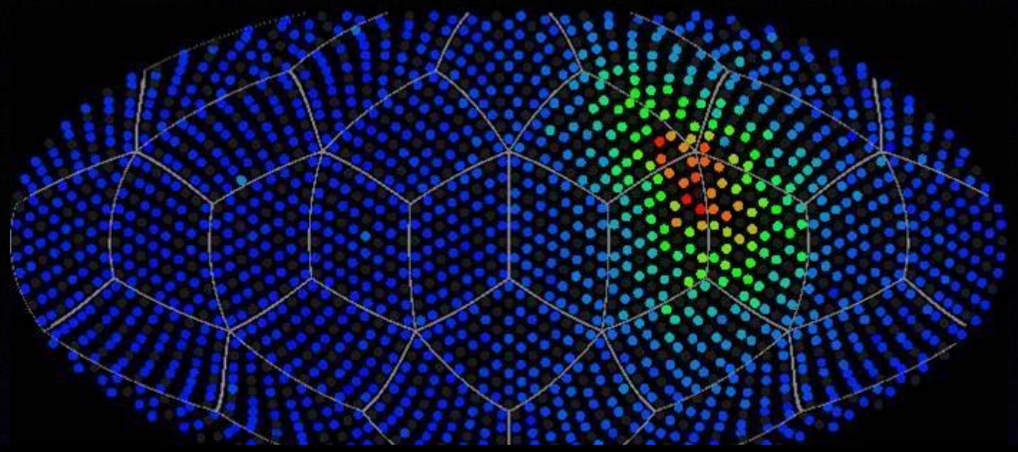


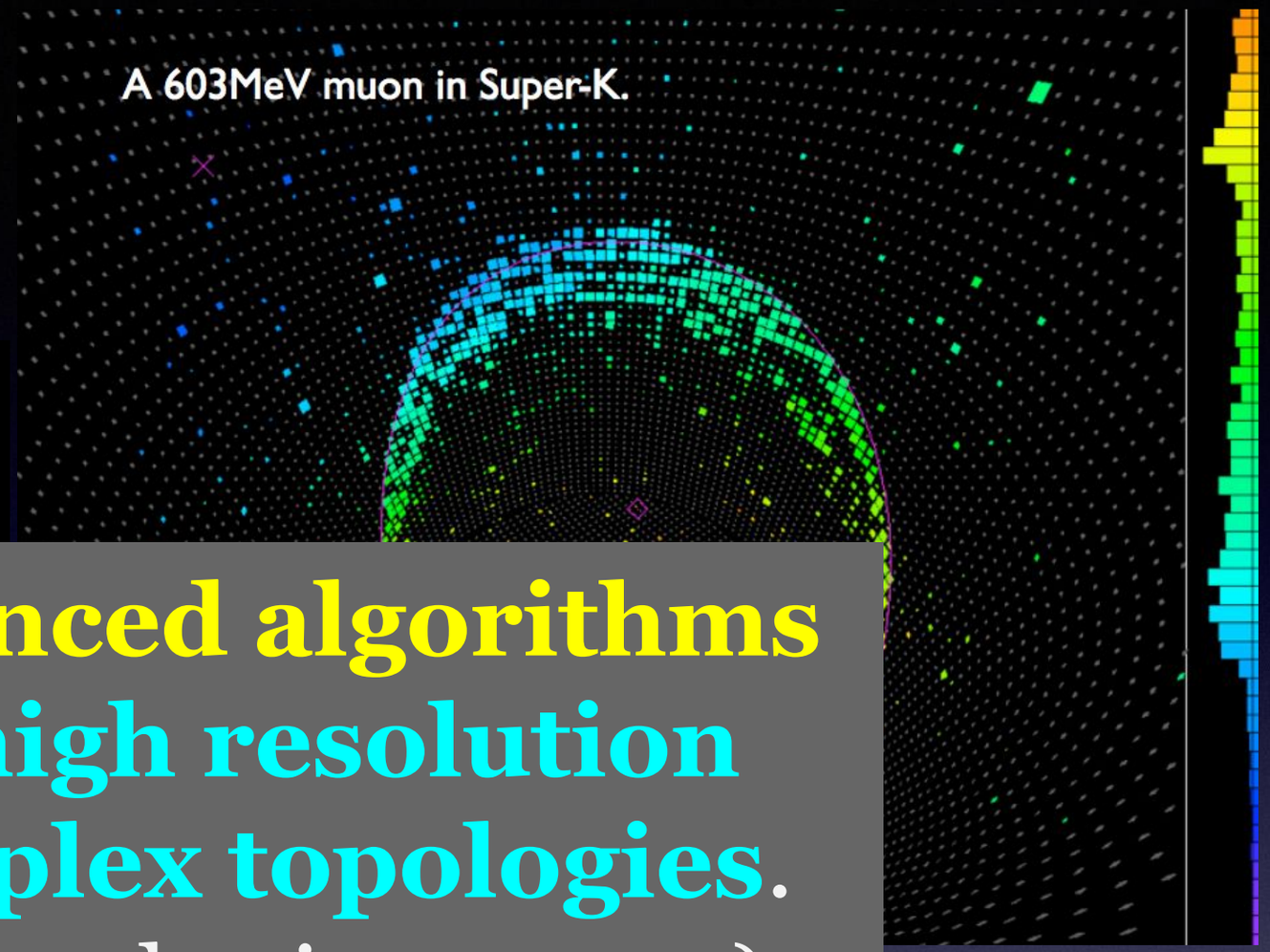

A 603MeV muon in Super-K.


5ms of data at the NOνA Far Detector
Each pixel is one hit cell
Color shows charge digitized from the light
60 m
15.6 m
15.6 m
NOvA - FNAL E929
Run: 18975 / 43
Event: 628855 / SNEWSBeatSlow
UTC Mon Feb 23, 2015
14:30:1.383526016
Several hundred cosmic rays crossed the detector

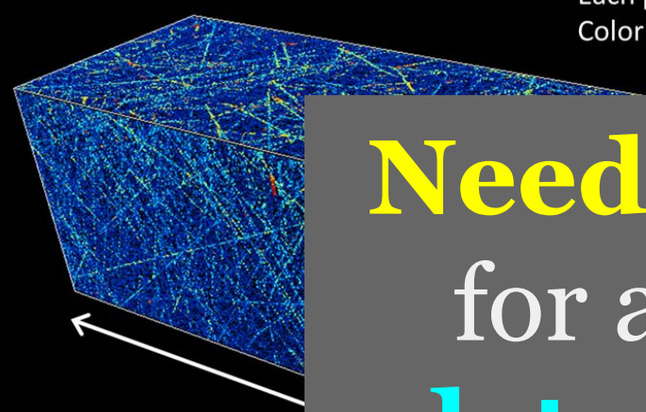

μBooNE
75 cm
Run 3493 Event 41075, October 23rd, 2015





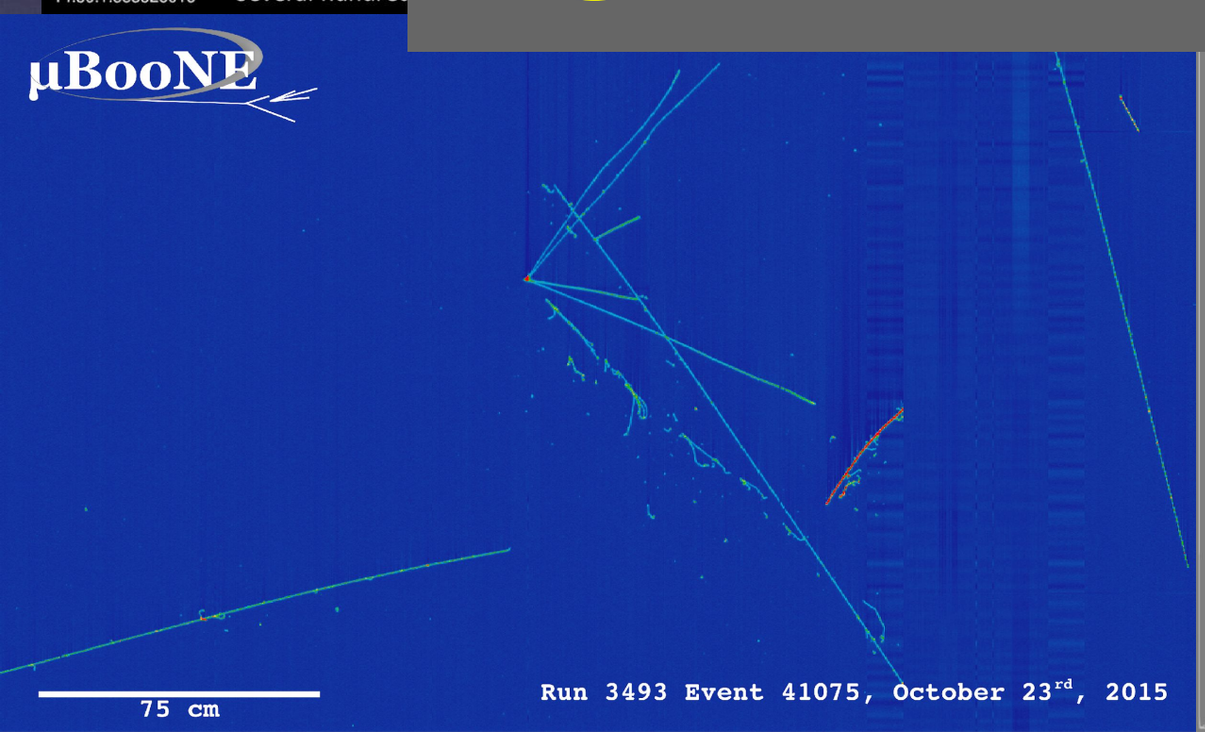


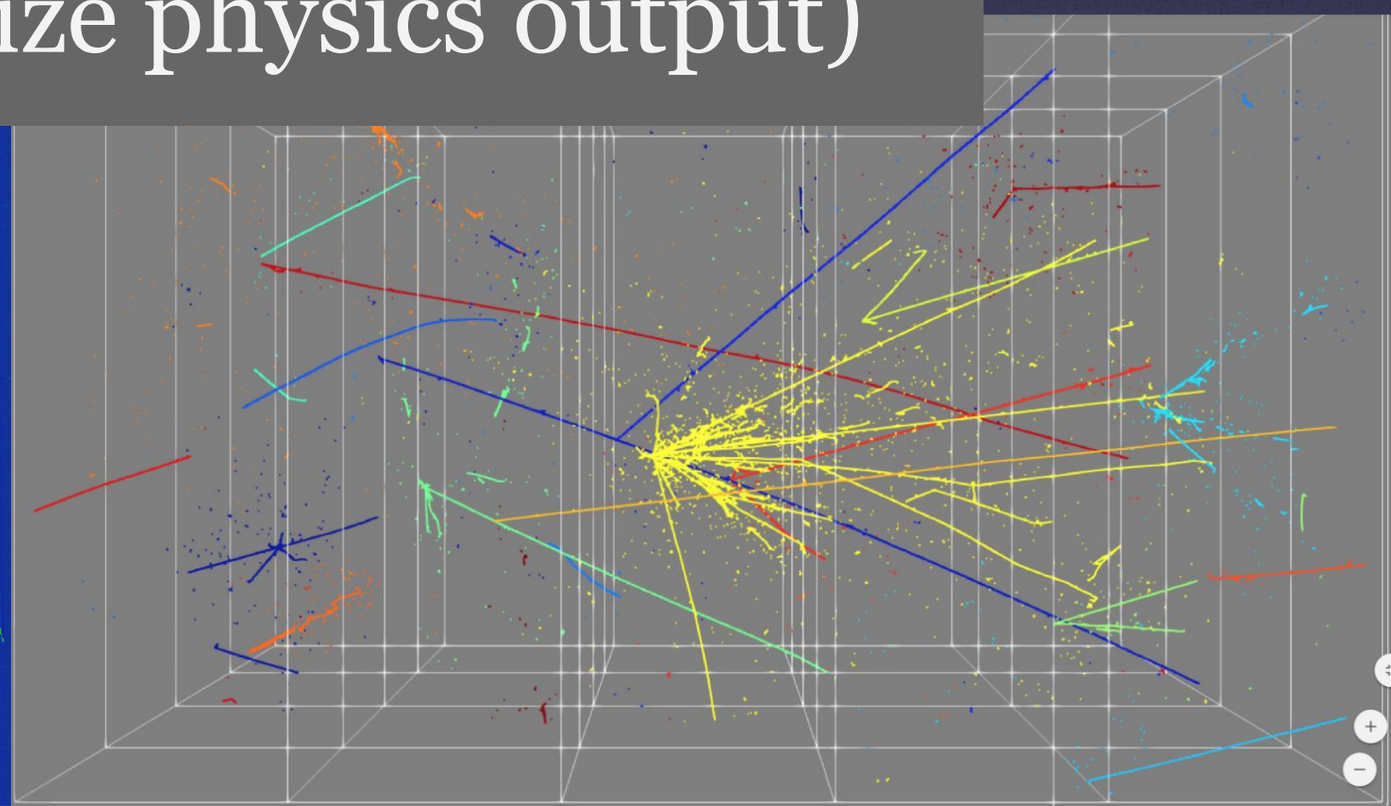
5ms of data at the NOνA Far Detector
Each pixel is one hit cell
Color shows charge digitized from the light



NOvA - FNAL E929
Run: 18975 / 43
Event: 628855 / SNEWSBeatSlow
UTC Mon Feb 23, 2015
14:30:1.383526016
Several hundred

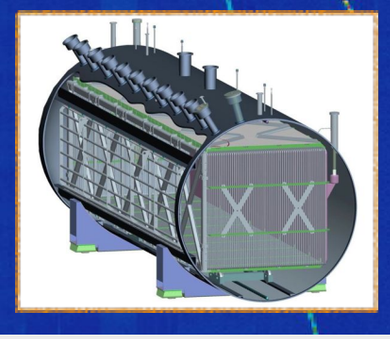
Need for advanced algorithms for analyzing high resolution data with complex topologies. (goal: maximize physics output)





Hi-Res Particle Imaging

~mm/pixel spatial resolution
~MeV level sensitivity



MicroBooNE
~87 ton (school bus size)

ν_μ

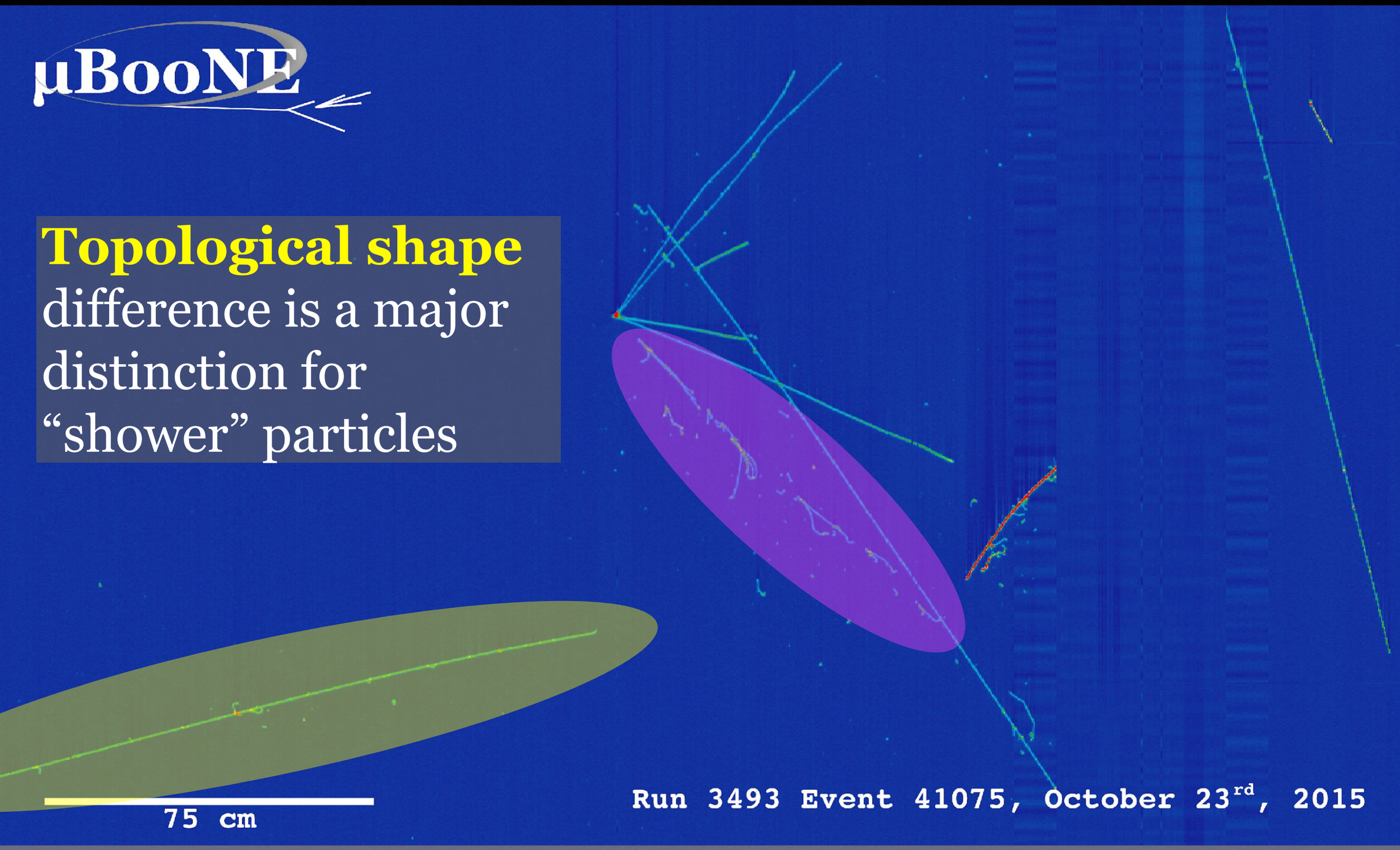
Bubble Chamber

Liquid Argon Time Projection Chamber

- High resolution photograph of charged particle trajectories
- Calorimetric measurement + scalability to a large mass

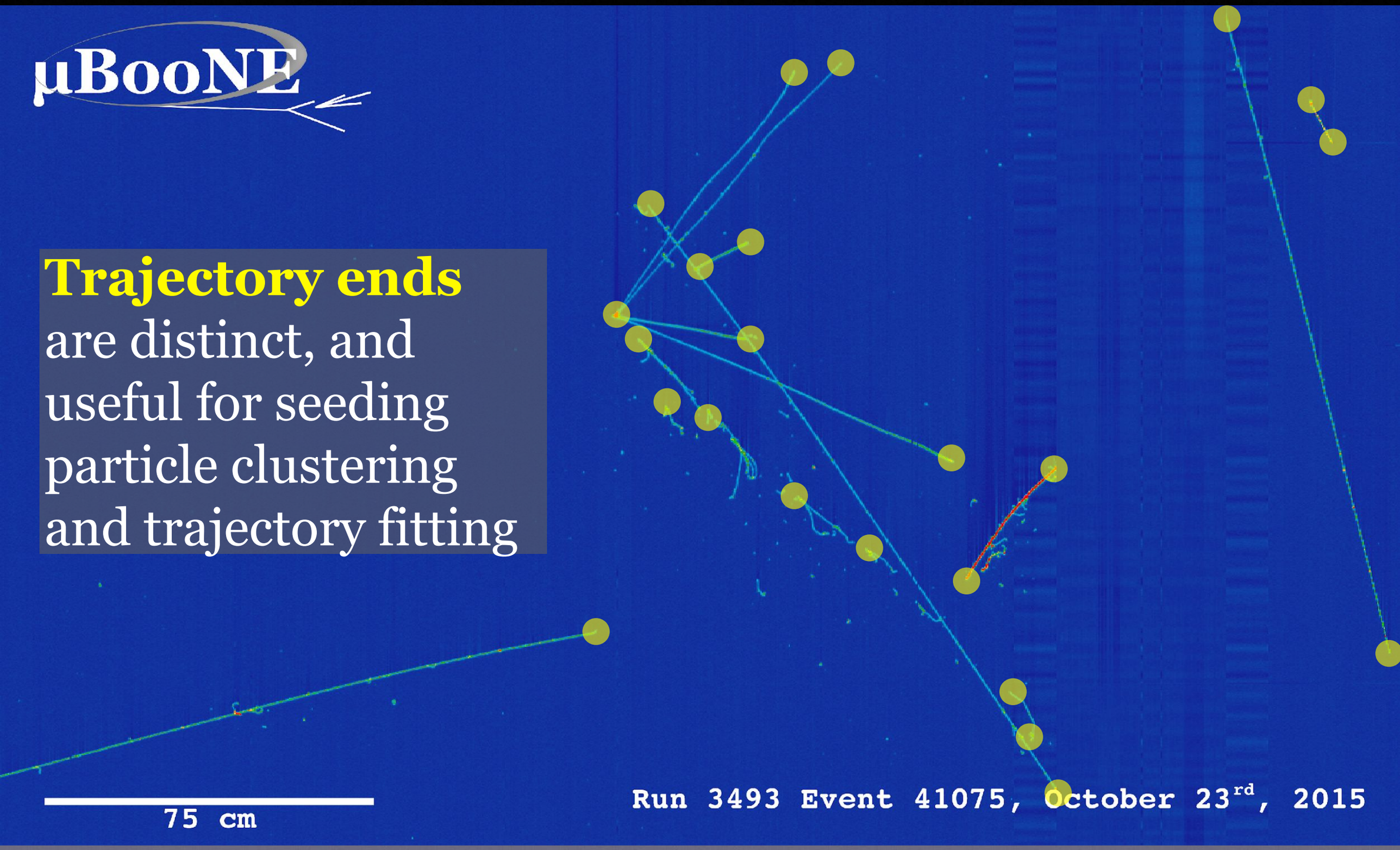
2015

Hi-Res Particle Imaging



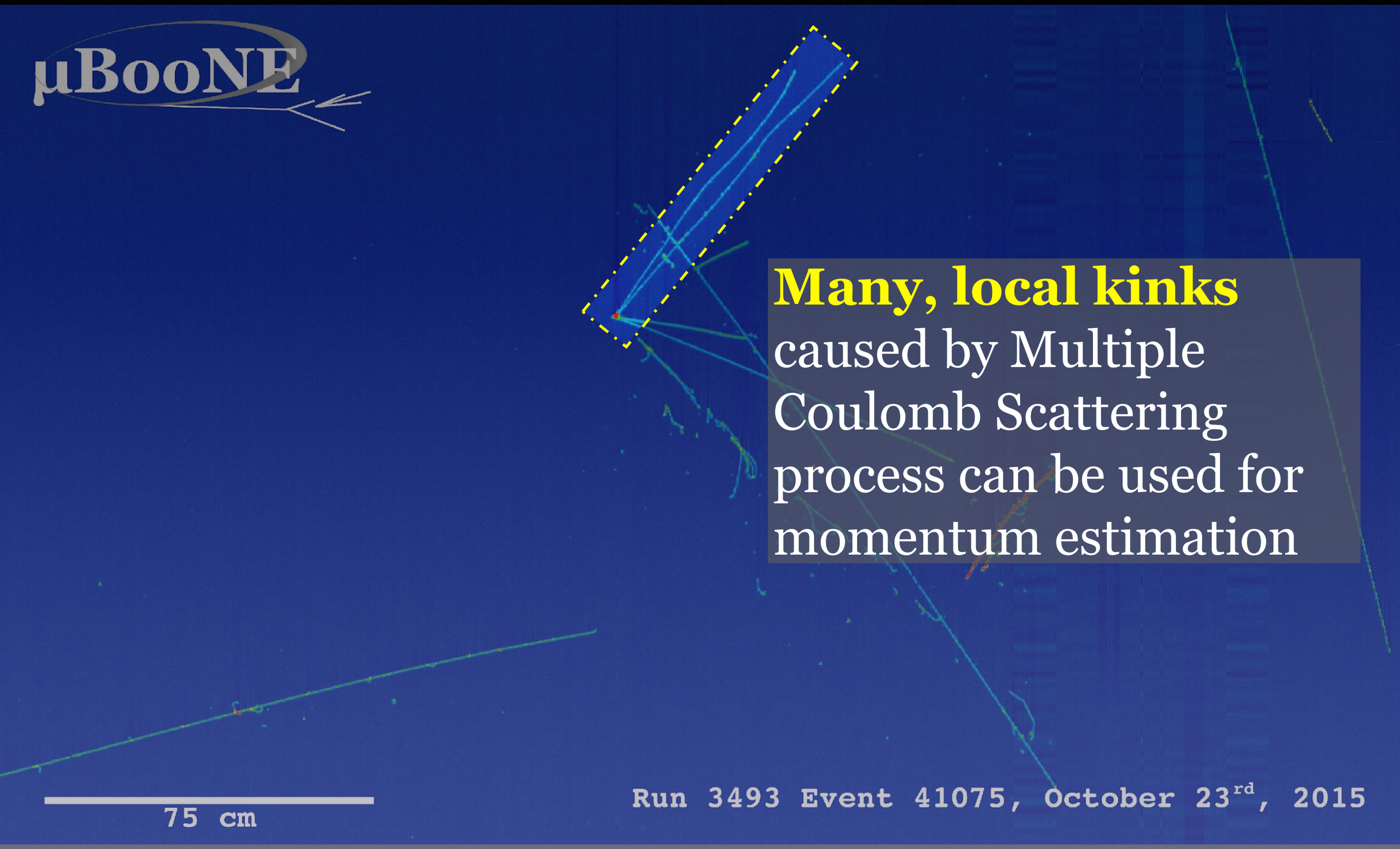
Topological shape difference is a major distinction for "shower" particles

Hi-Res Particle Imaging



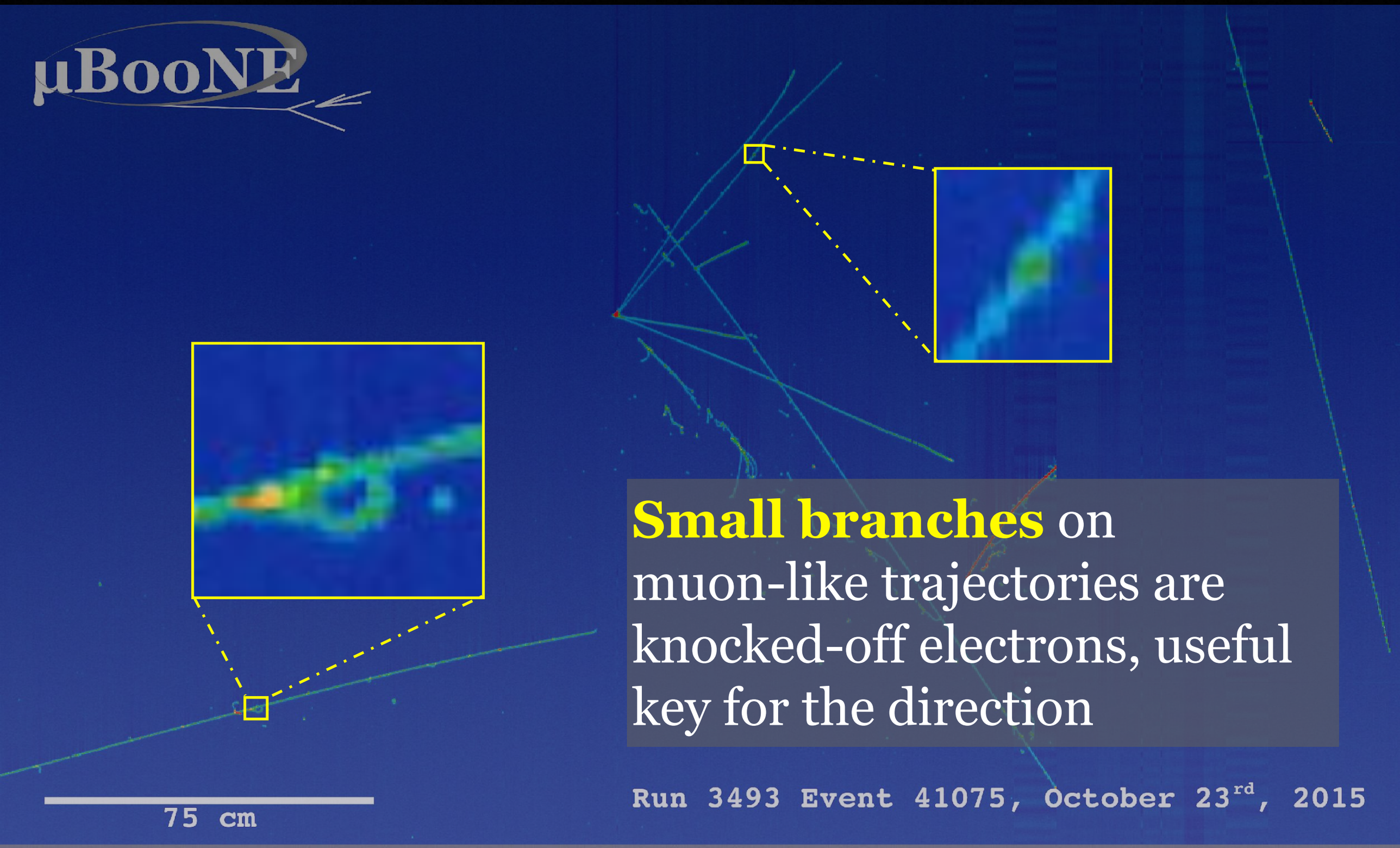
Trajectory ends are distinct, and useful for seeding particle clustering and trajectory fitting

Hi-Res Particle Imaging



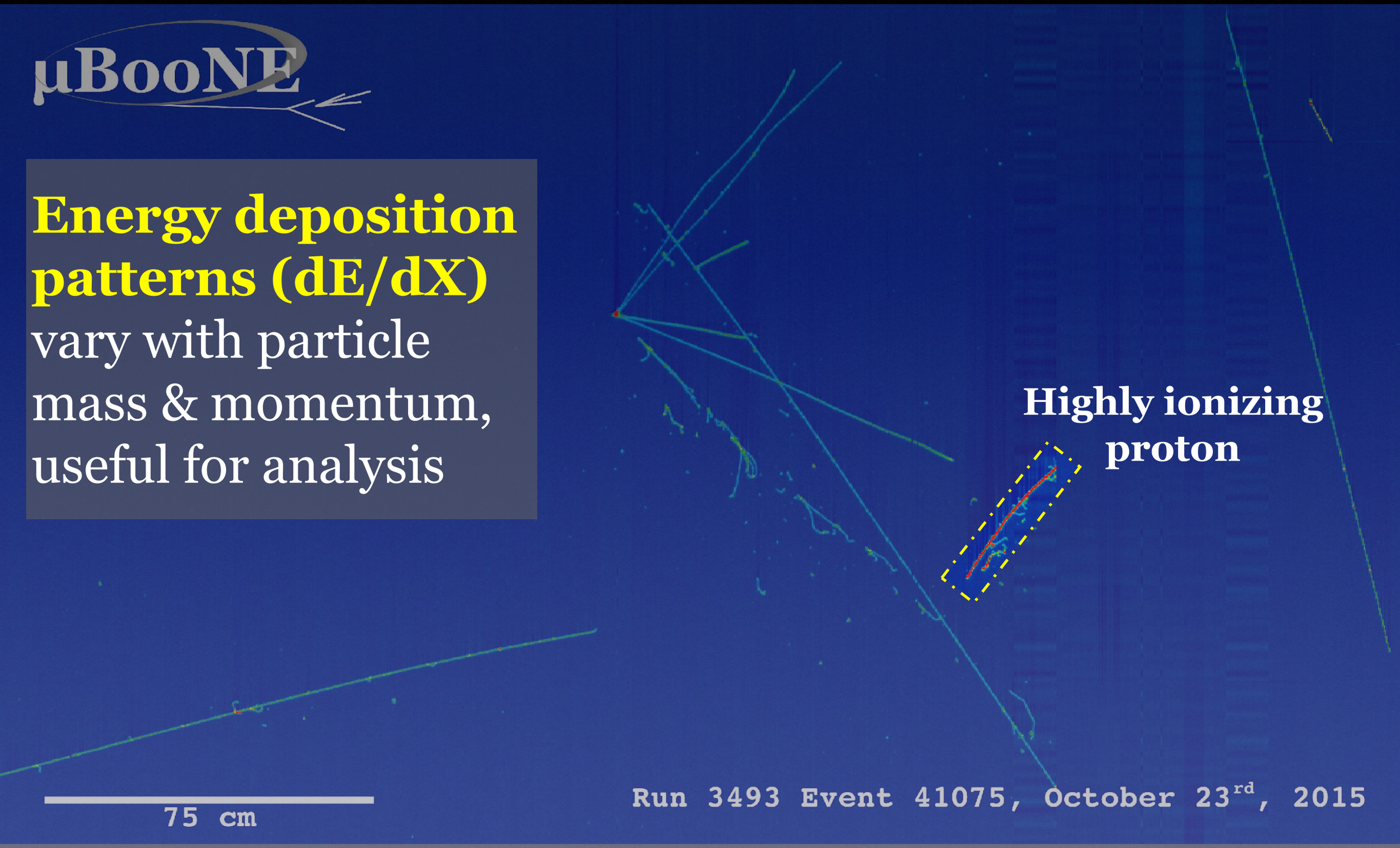
Many, local kinks caused by Multiple Coulomb Scattering process can be used for momentum estimation

Hi-Res Particle Imaging



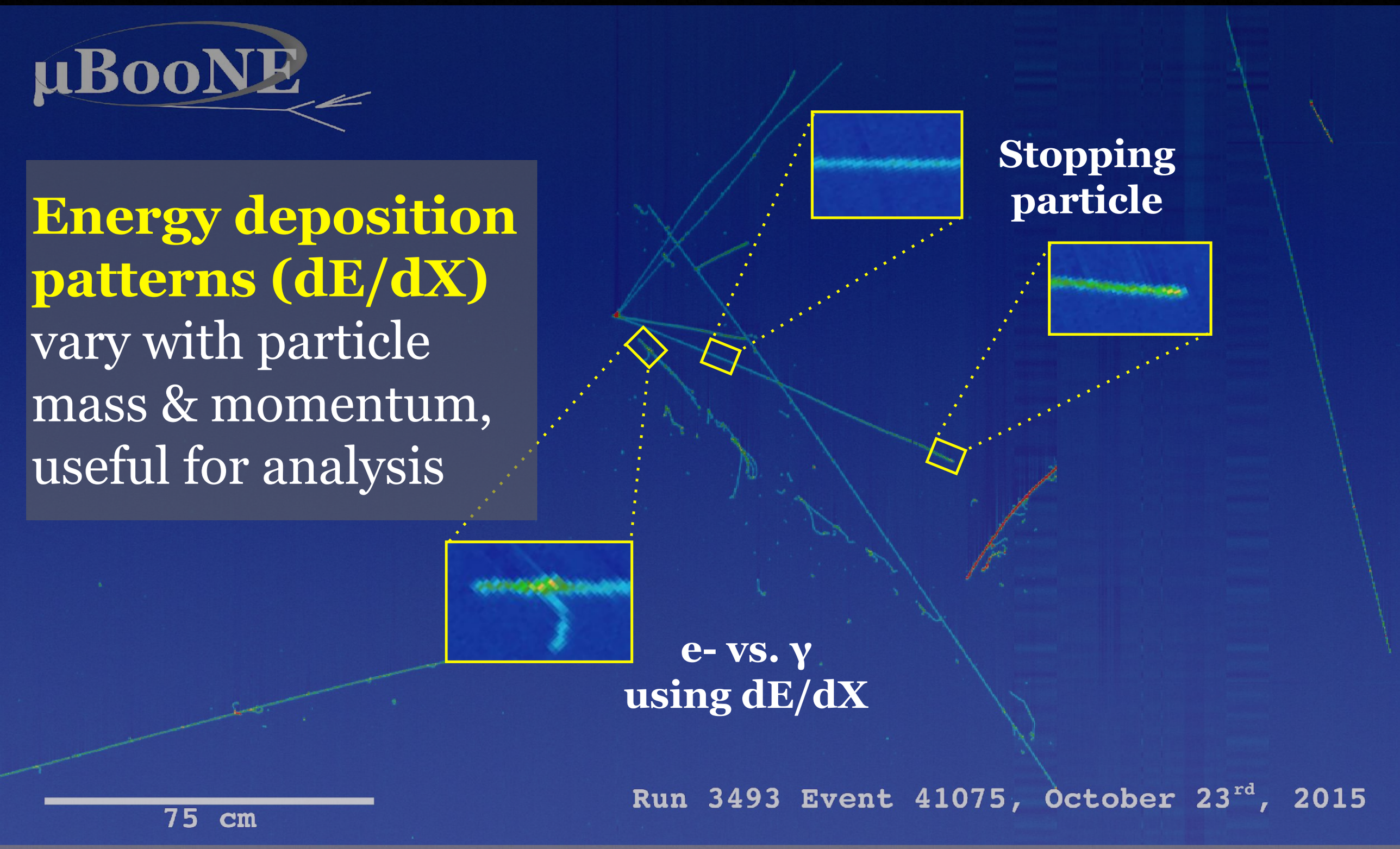
Small branches on muon-like trajectories are knocked-off electrons, useful key for the direction

Hi-Res Particle Imaging



Energy deposition patterns (dE/dX) vary with particle mass & momentum, useful for analysis

Hi-Res Particle Imaging



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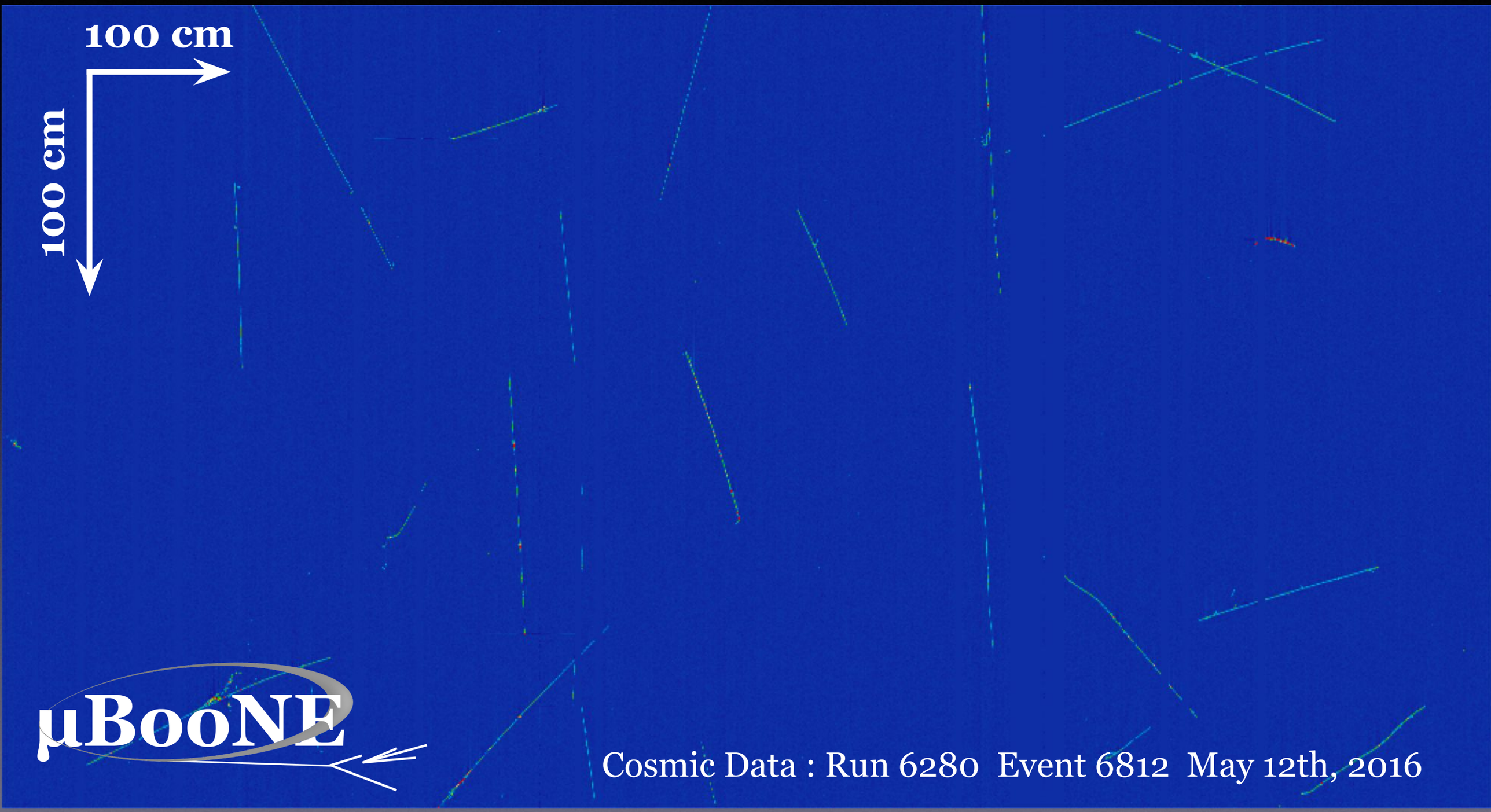
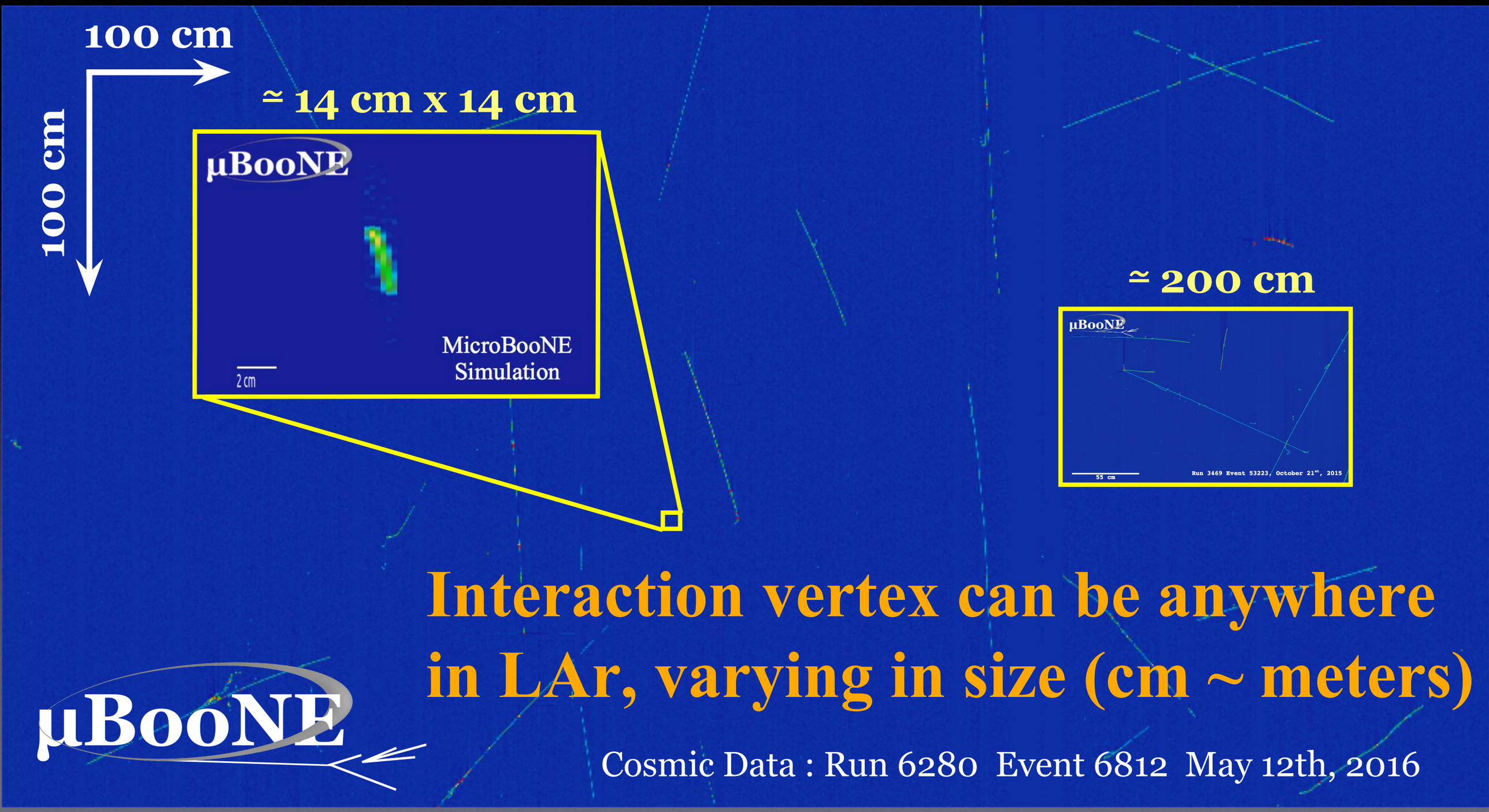


Hi-Res Particle Imaging

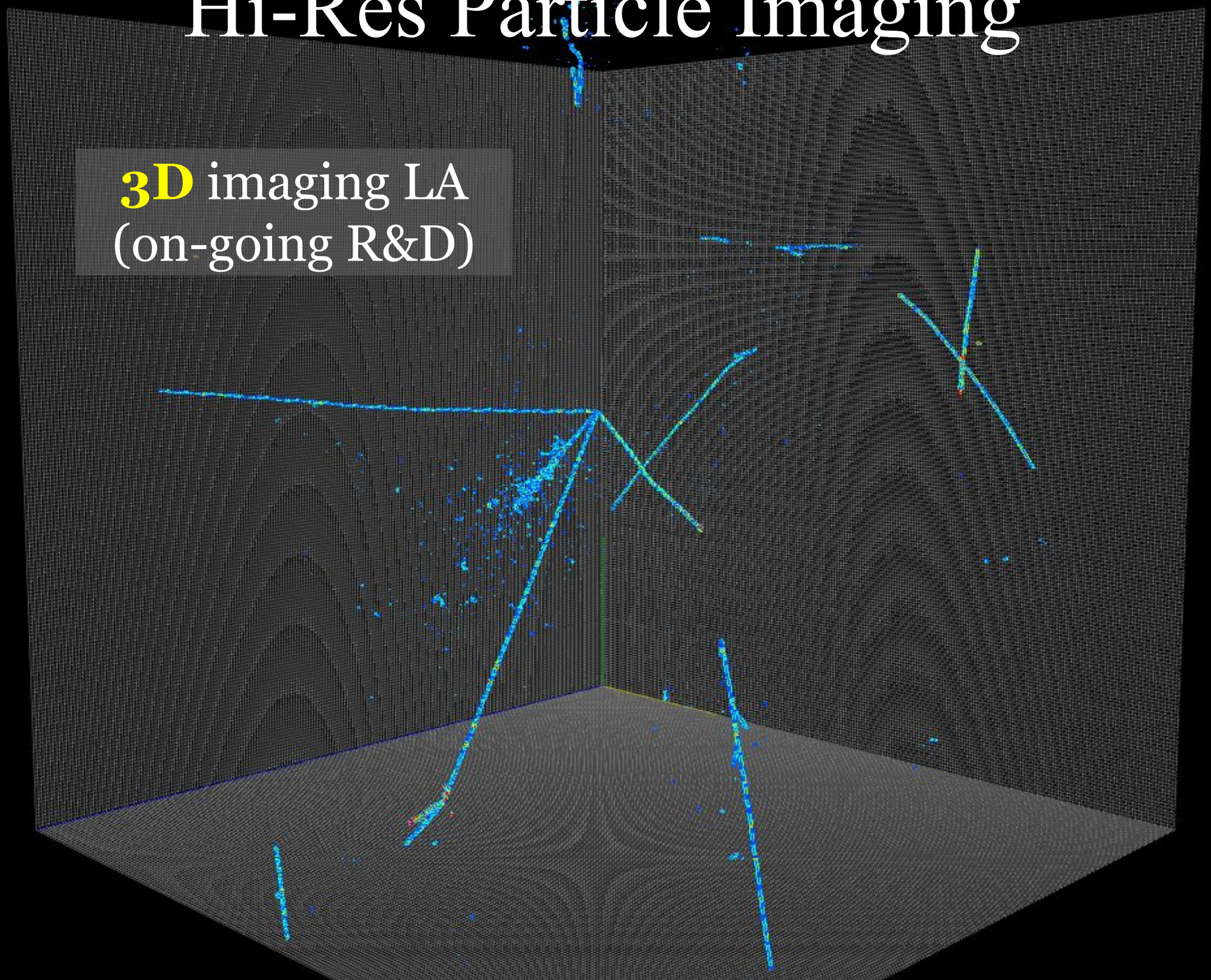


Interaction vertex can be anywhere in LAr, varying in size (cm ~ meters)

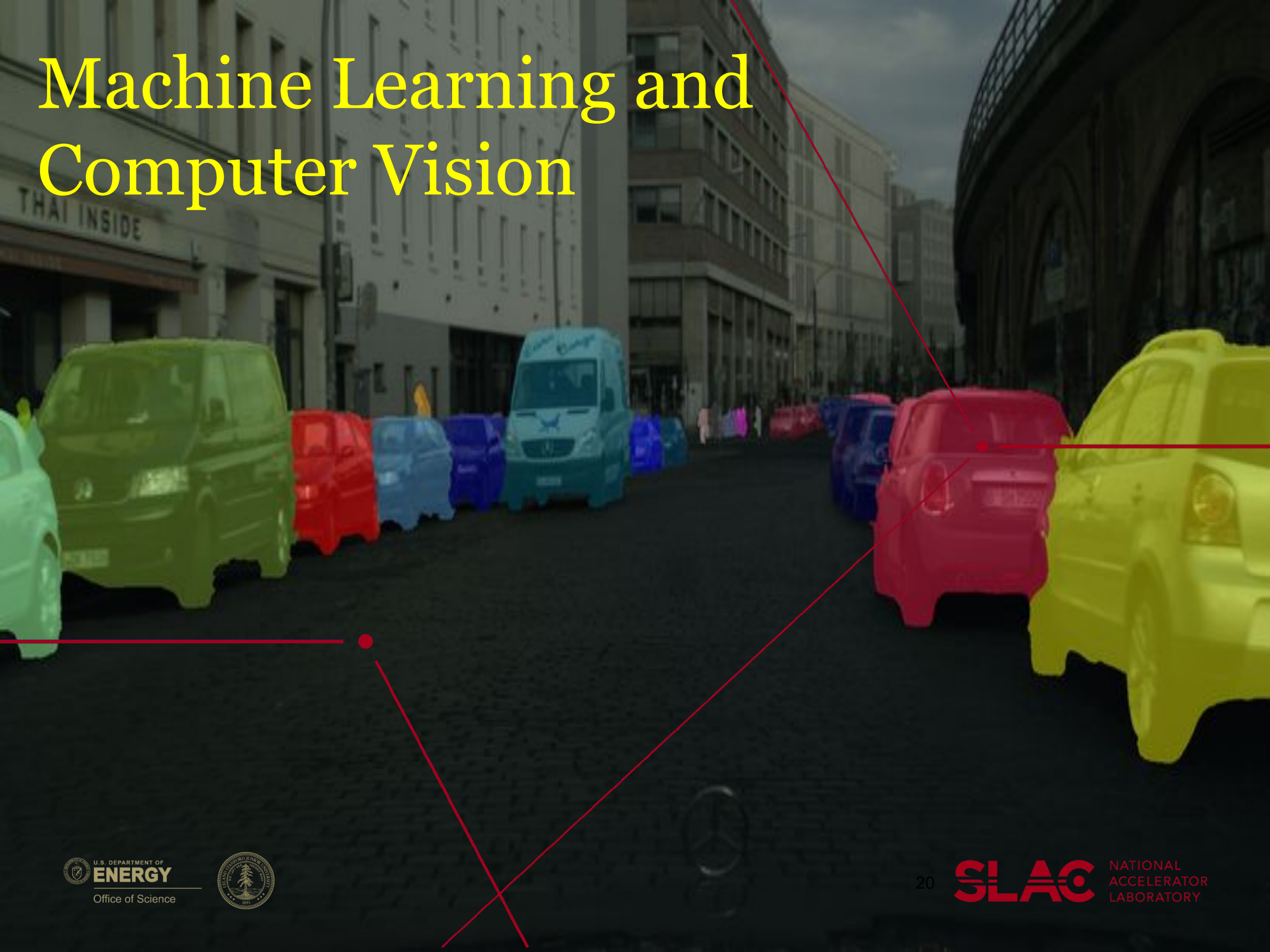
μBooNE

Cosmic Data : Run 6280 Event 6812 May 12th, 2016

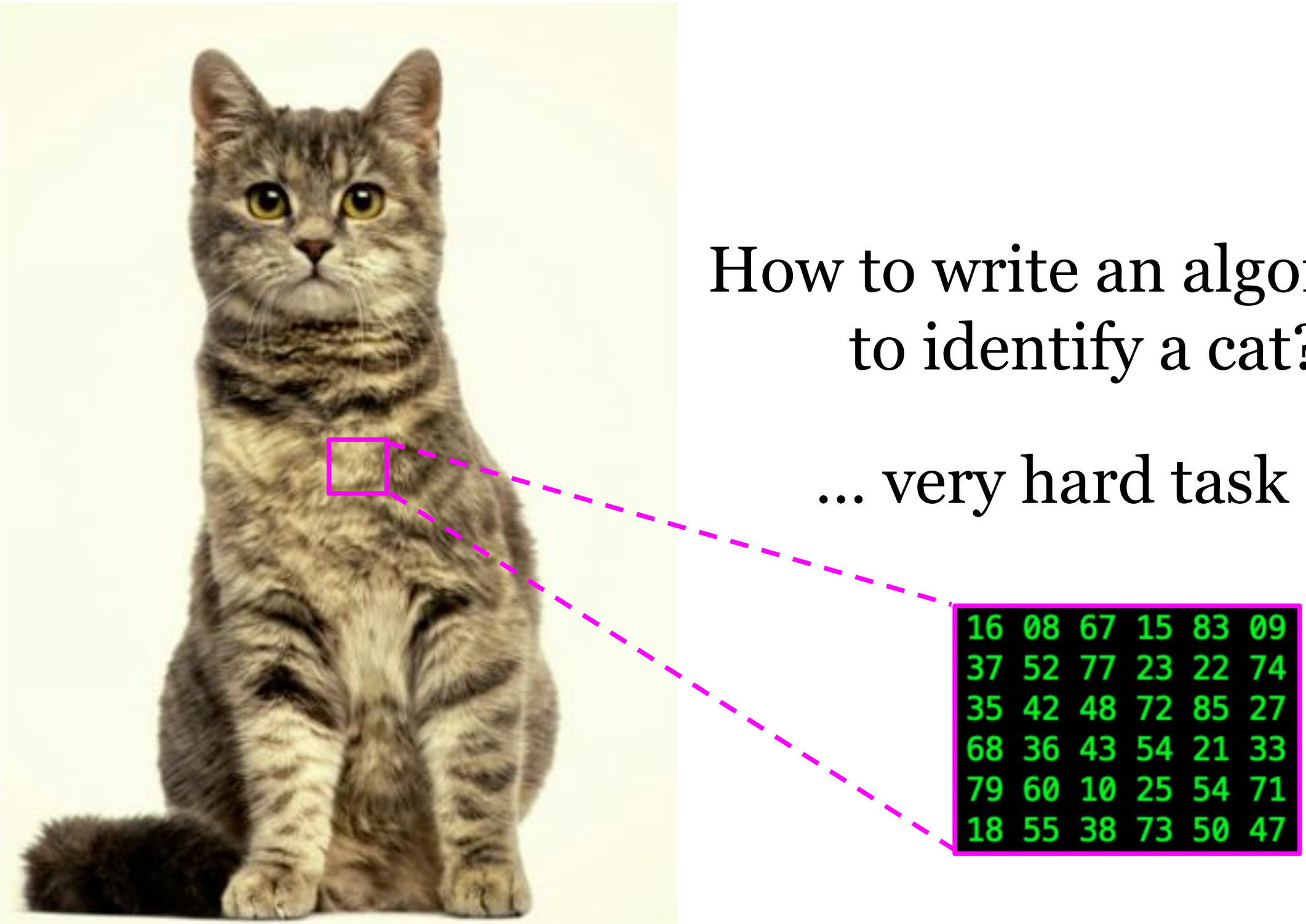
Hi-Res Particle Imaging



Machine Learning and Computer Vision



Find A Cat
Machine Learning in Neutrino Physics

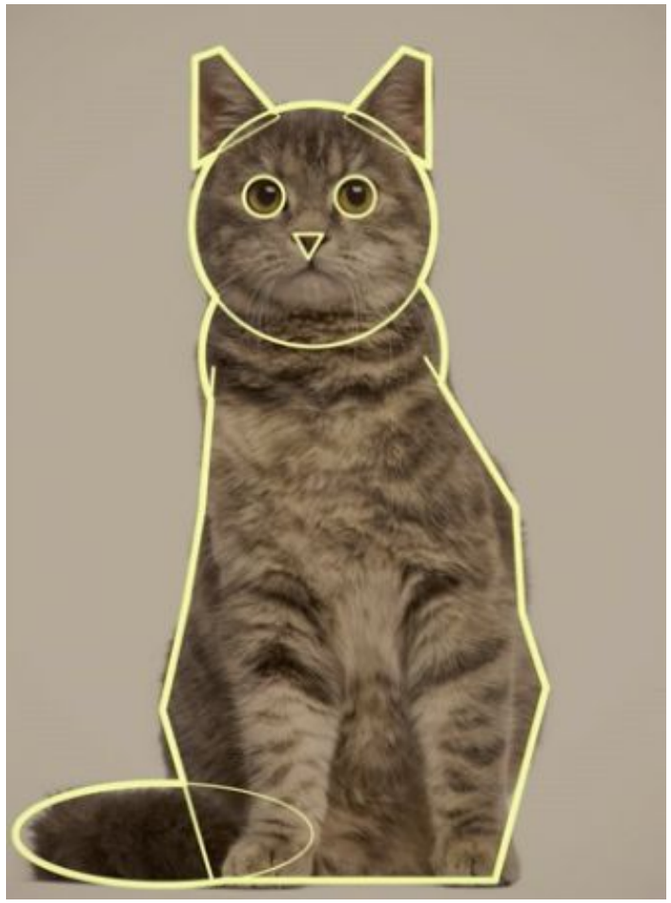


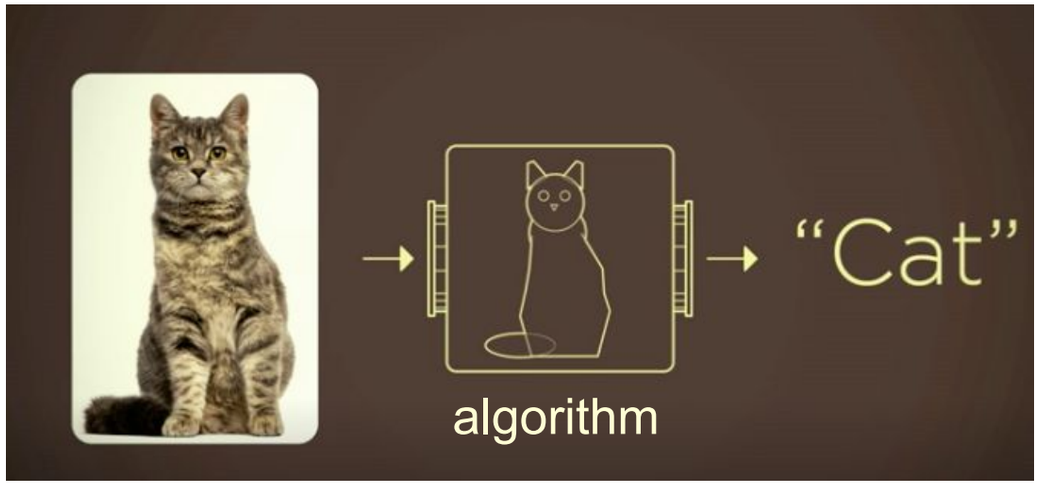
How to write an algorithm to identify a cat?

... very hard task ...

Development Workflow for non-ML reconstruction

1. Write an algorithm based on physics principles





A cat = collection of certain shapes
(or, a neutrino)

Find A Cat
Machine Learning in Neutrino Physics

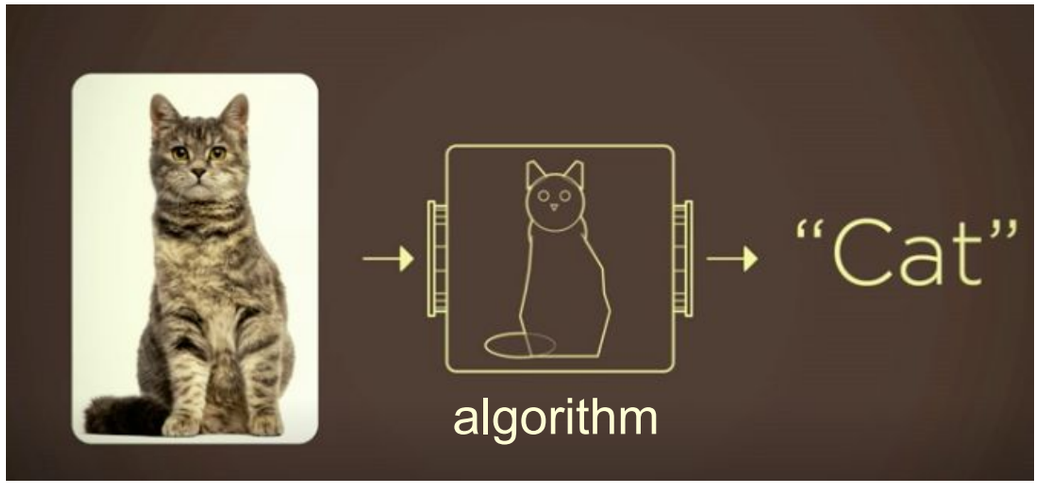
SLAC

Development Workflow for non-ML reconstruction

1. Write an algorithm based on physics principles
2. Run on simulation and data samples
3. Observe failure cases, implement fixes/heuristics
4. Iterate over 2 & 3 till a satisfactory level is achieved
5. Chain multiple algorithms as one algorithm, repeat 2, 3, and 4.

Partial cat
(escaping the detector)

Stretching cat
(Nuclear FSI)



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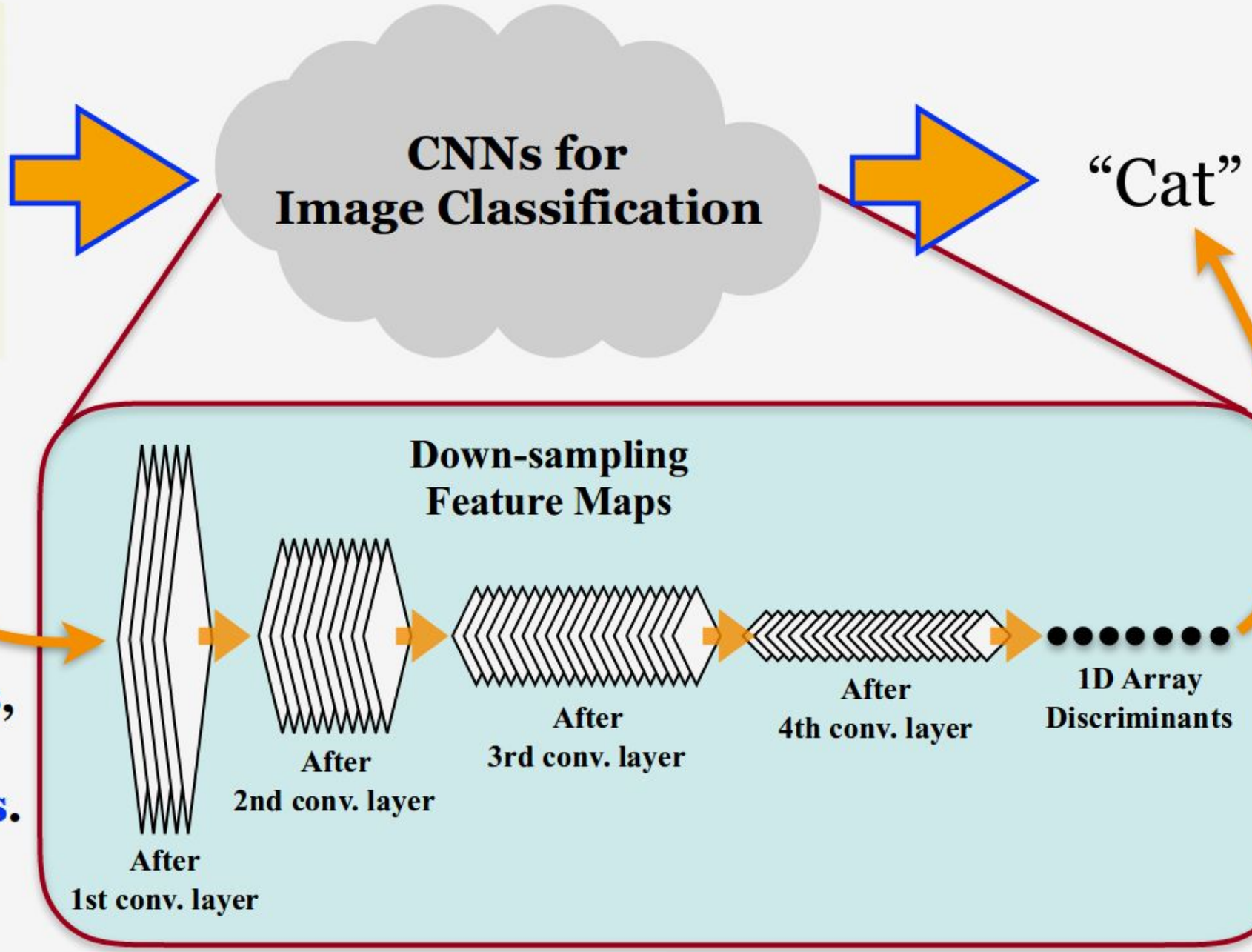
Machine Learning

- "**Learn patterns from data**"
  - automation of steps 2, 3, and 4
- "**Chain algorithms & optimize**"
  - step 5 addressed by design

CNN for "Image Classification"
Machine Learning in Neutrino Physics

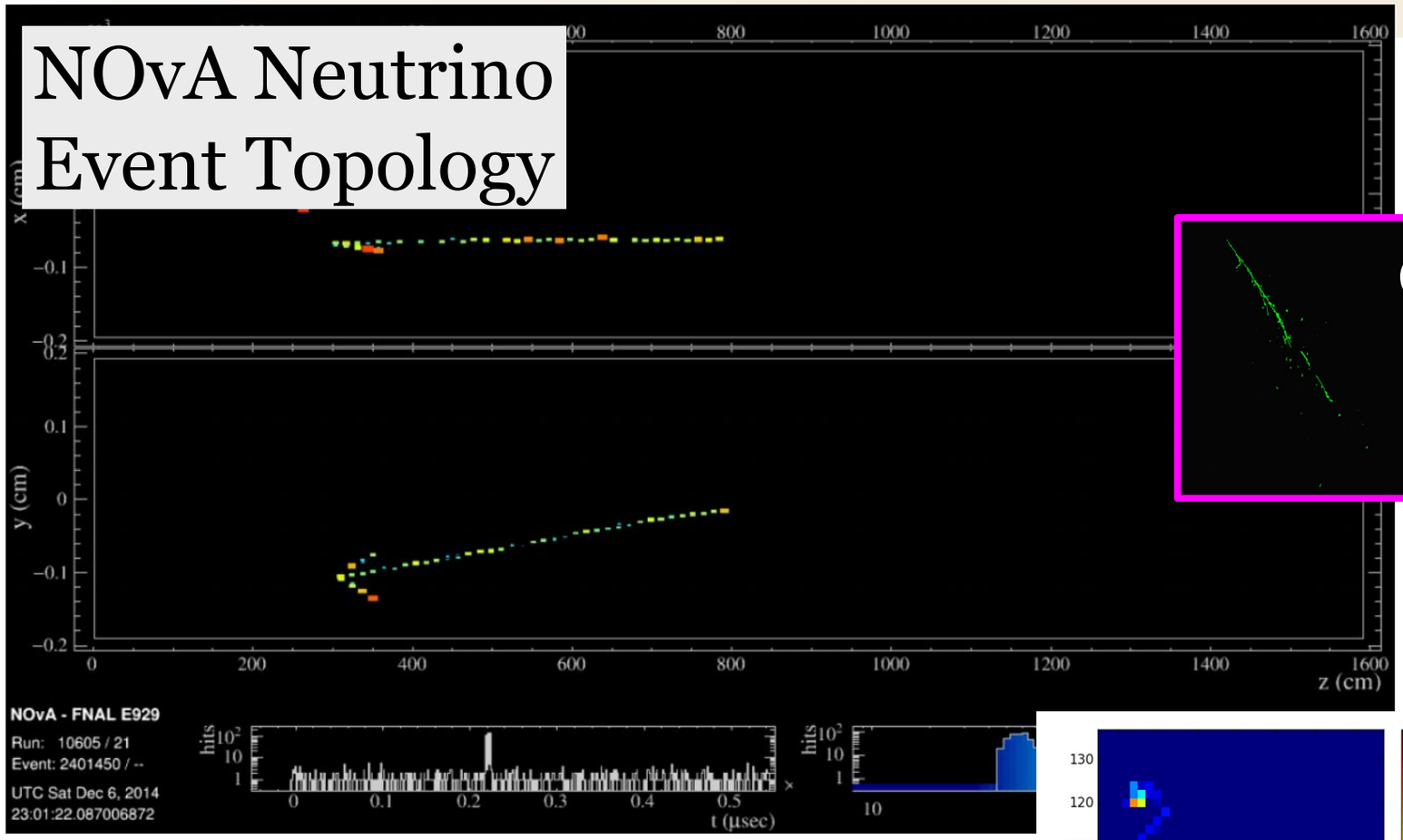
SLAC

Convolutional Neural Networks (CNNs)

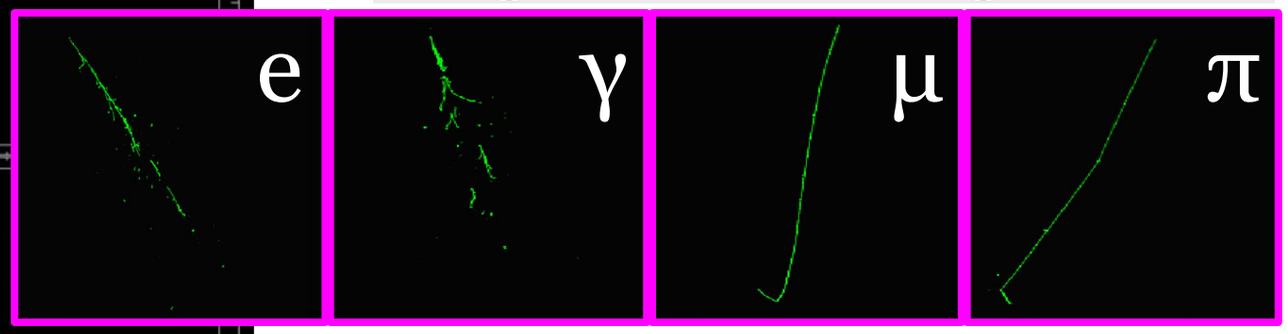


CNNs are effective image **feature extractors**, and also **data transformers**.

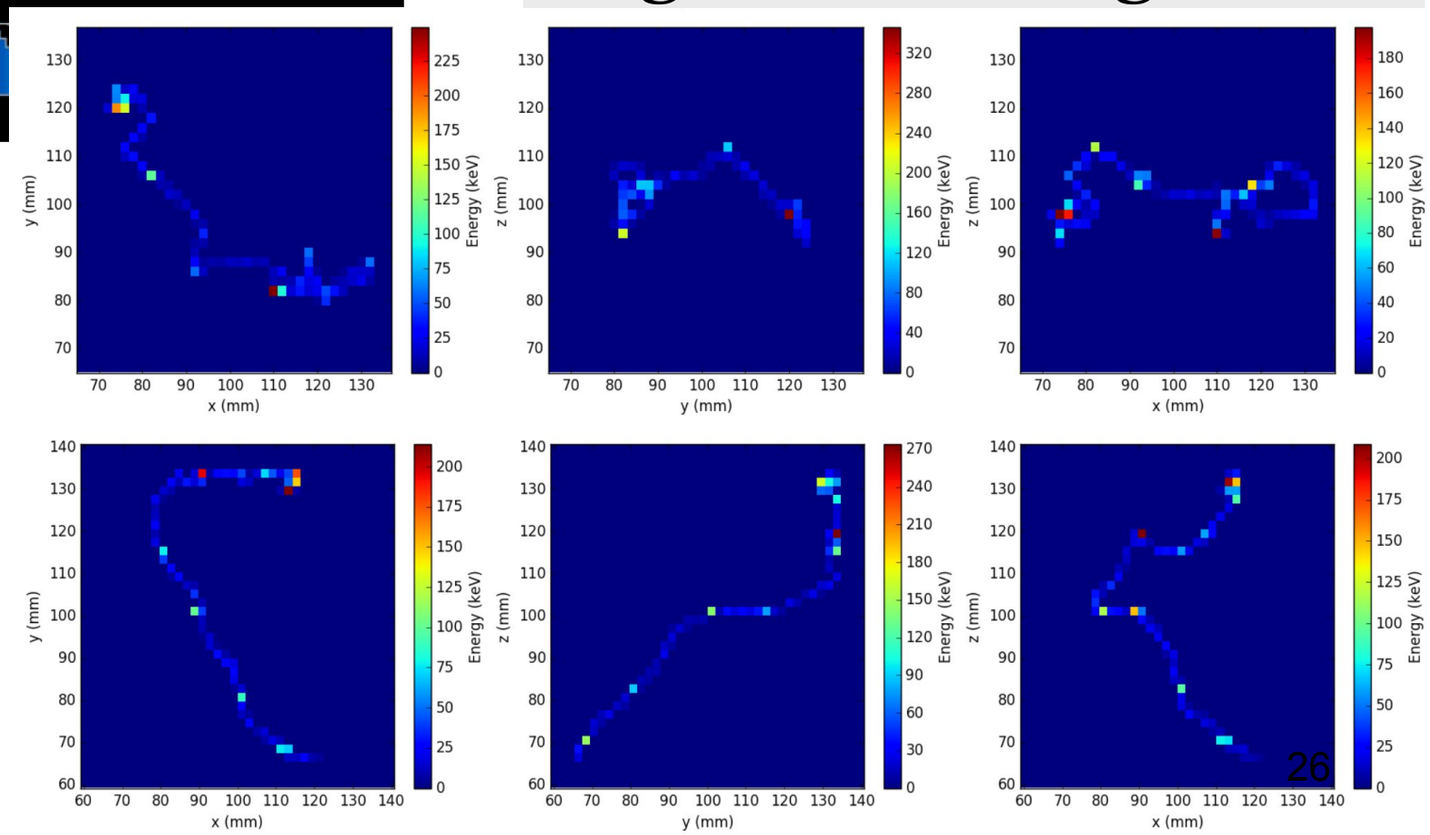
CNN for "Image Classification"
Machine Learning in Neutrino Physics



LArLIAT
Signal vs. Background



NEXT
Signal vs. Background



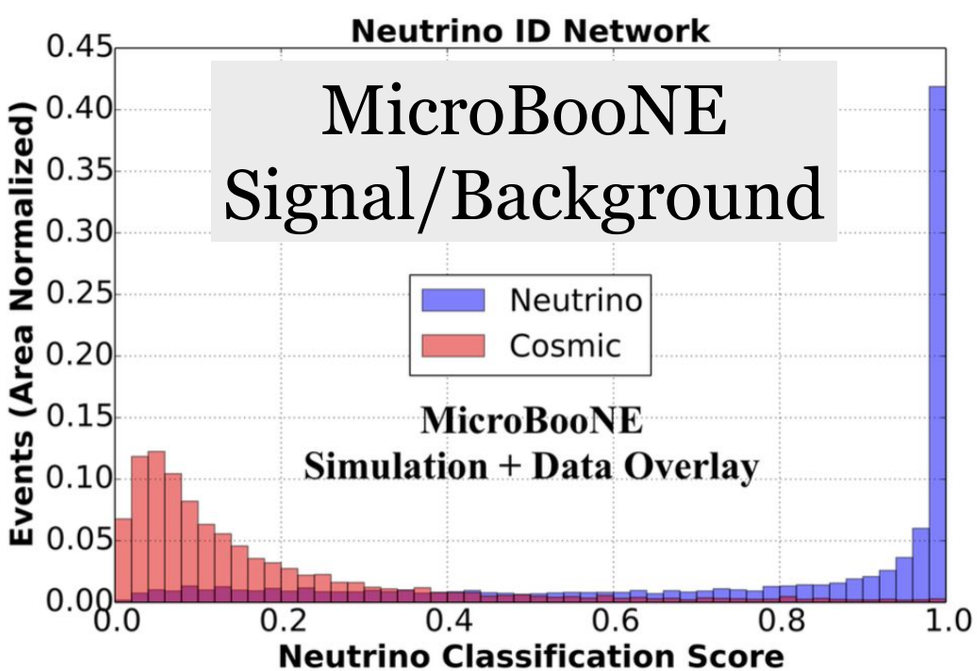
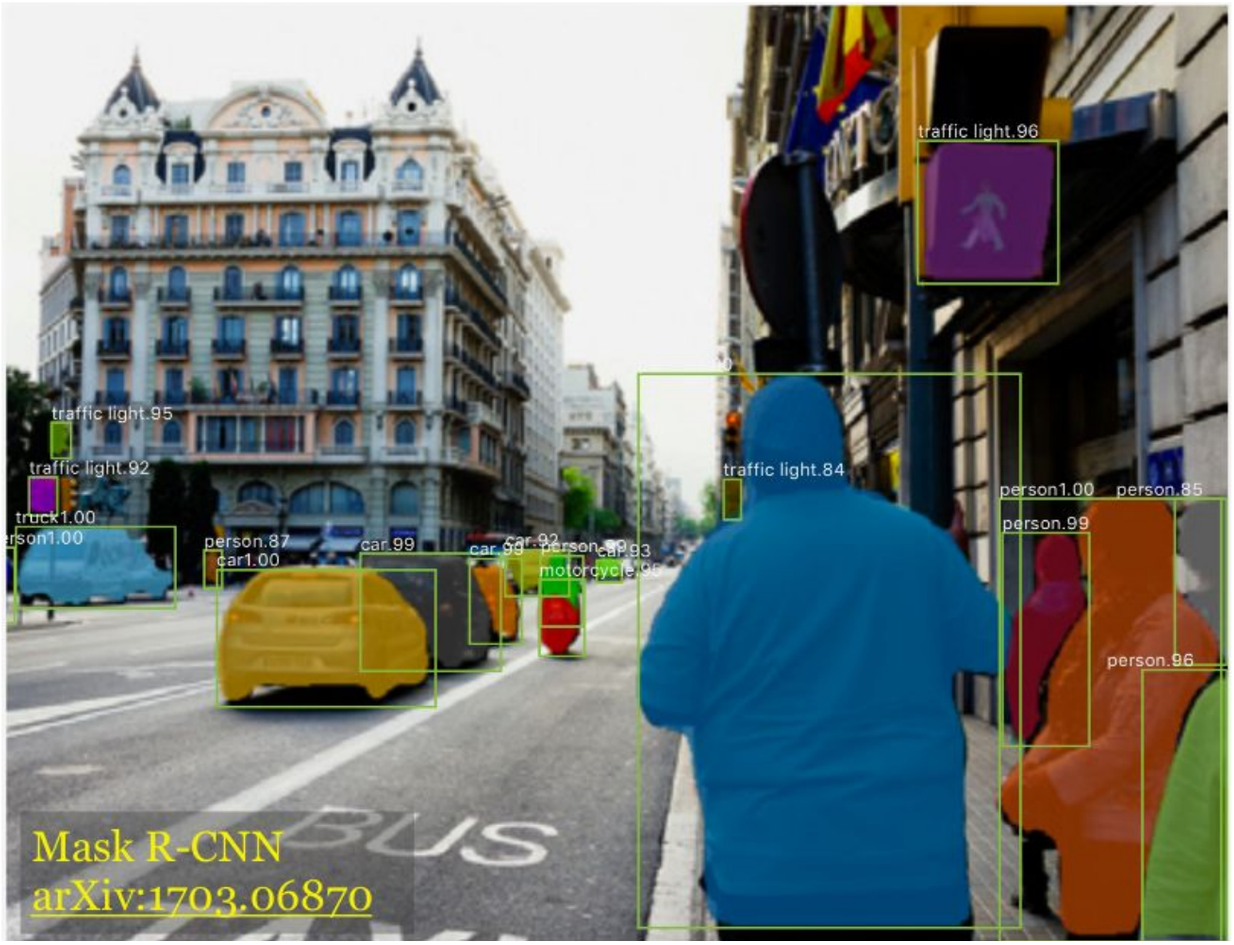
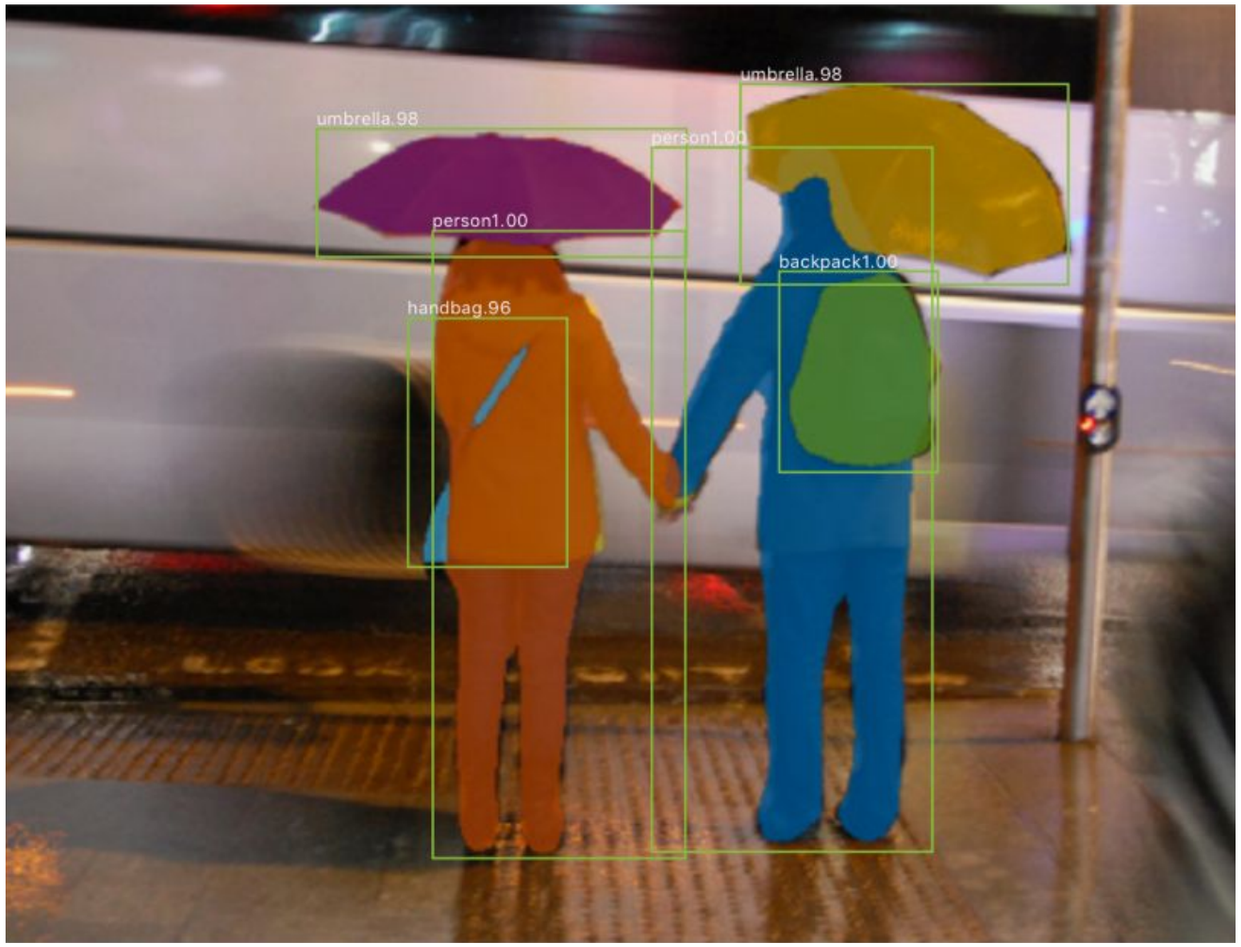


Image Context Detection



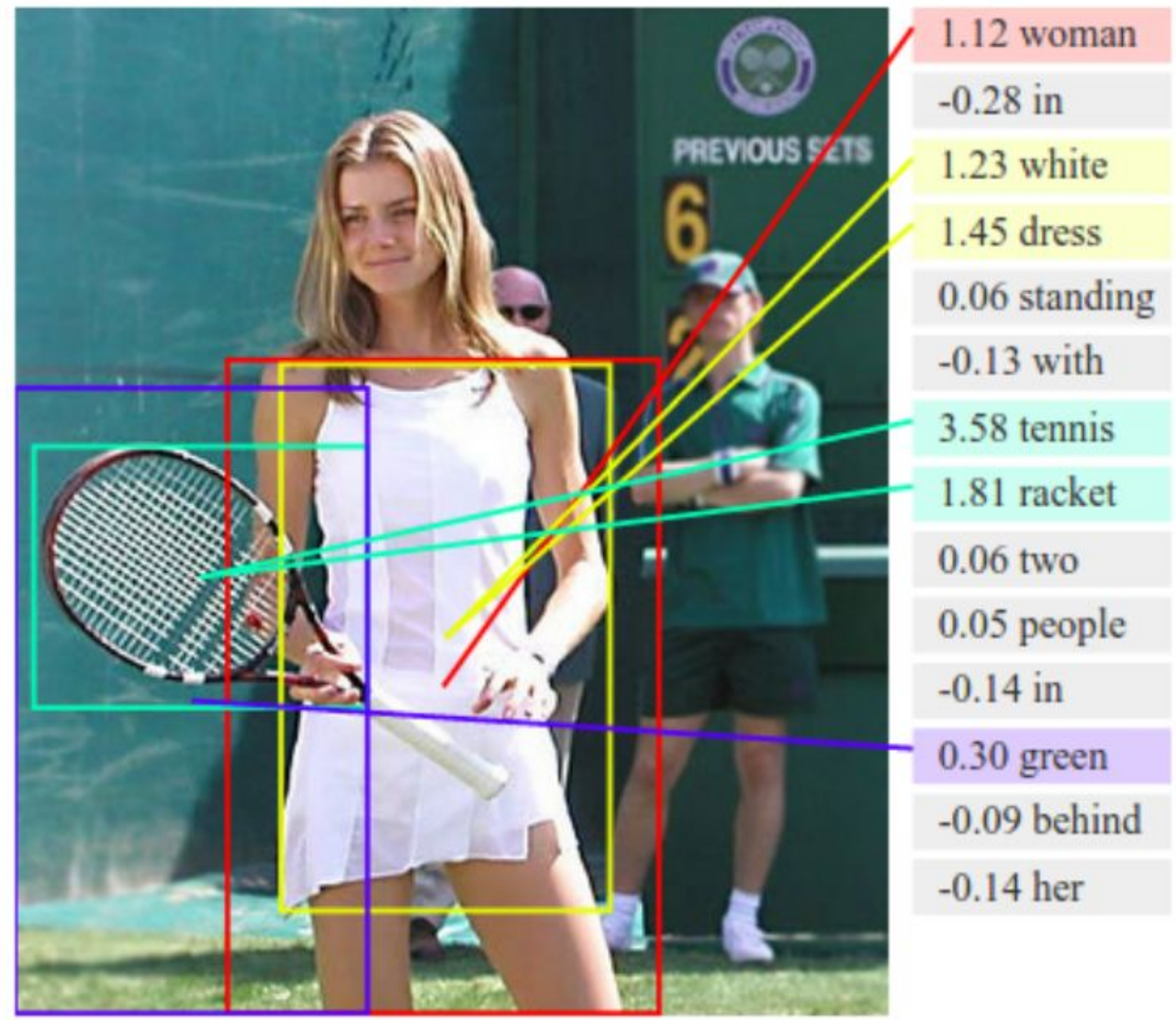


WHAT is WHERE and HOW in an image?
Machine Learning in Neutrino Physics

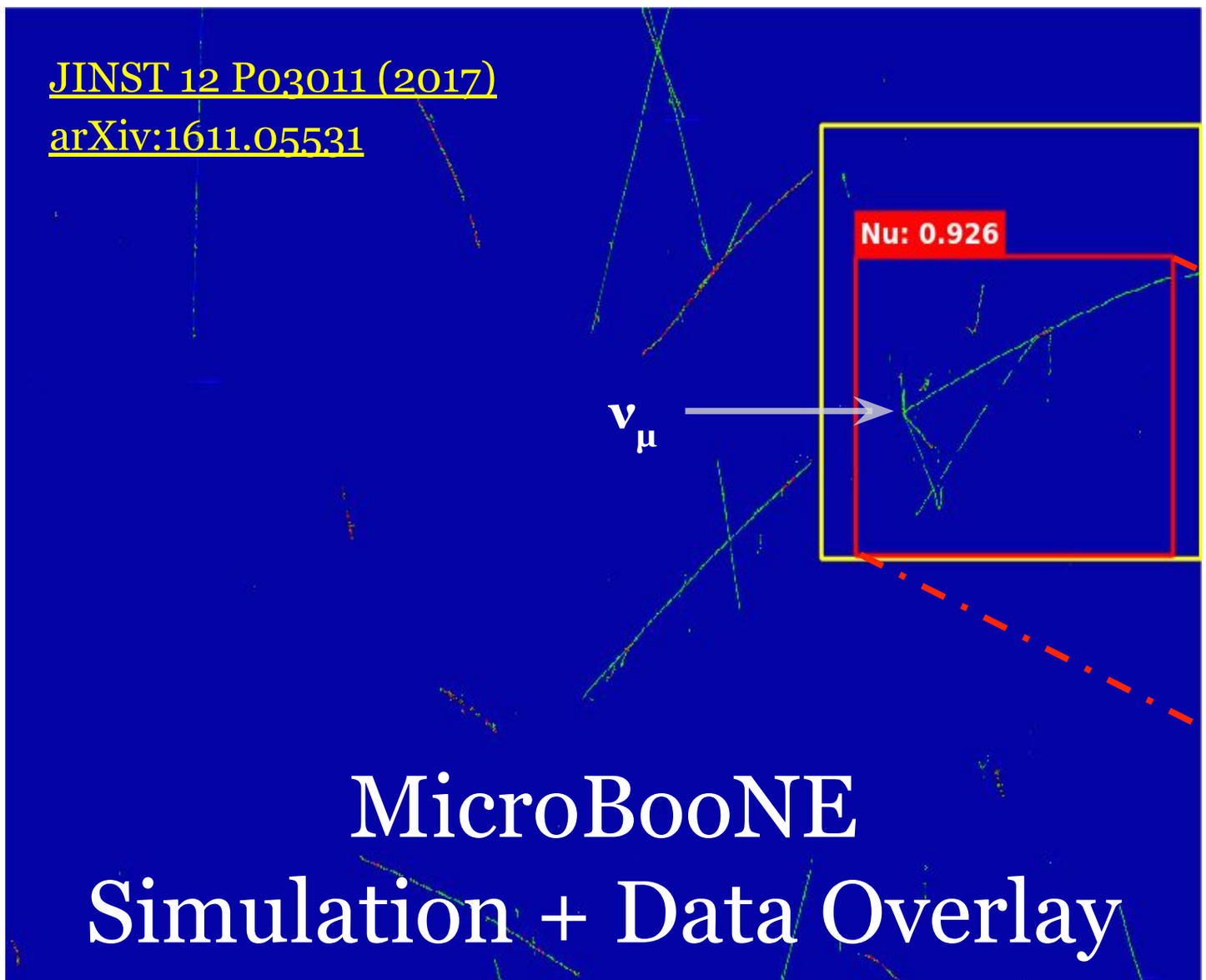
SLAC

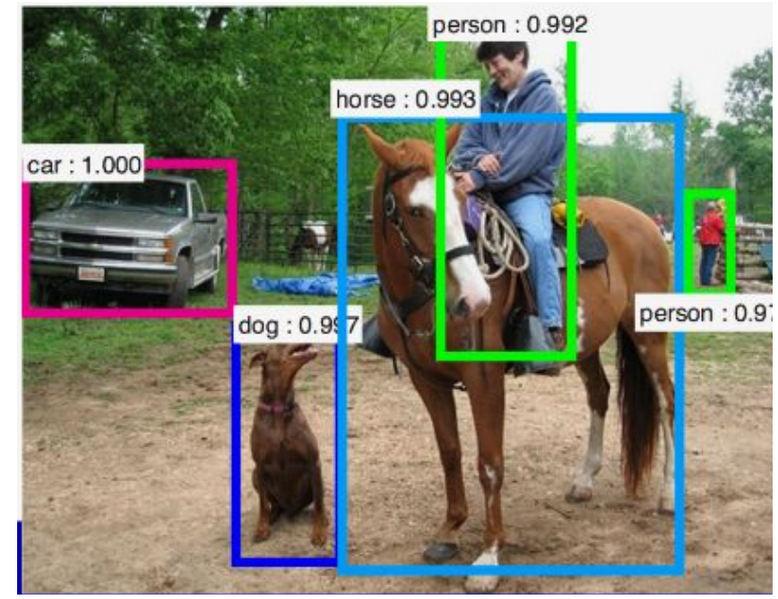
Interpretation of Contexts' Correlation

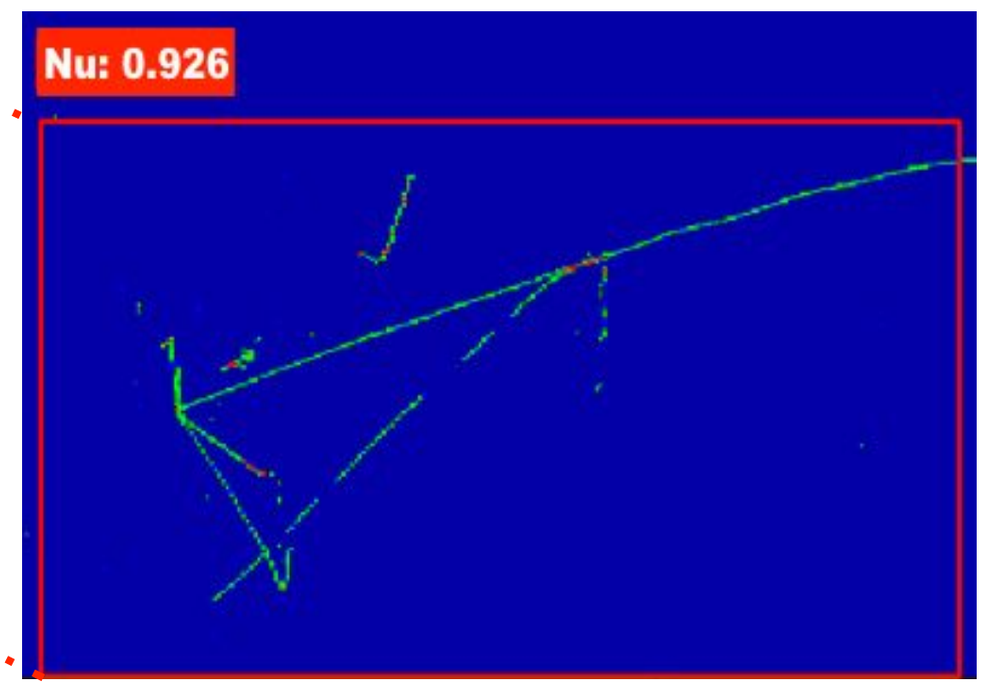
"girl in pink dress is jumping in air."



Object Detection for Neutrino Finding (MicroBooNE LArTPC)







Task: propose a rectangular box (location & size) that contains neutrino interaction

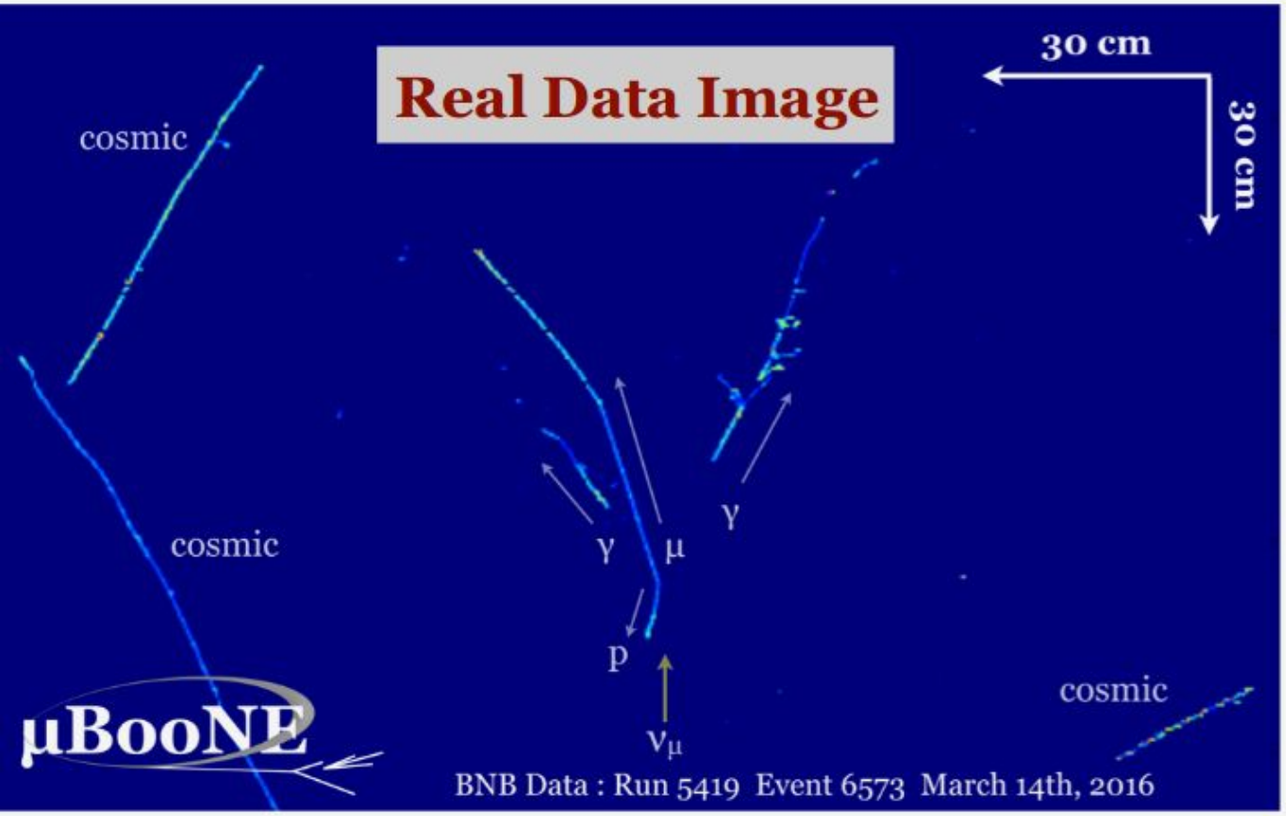
Beyond Image Classification
Machine Learning in Neutrino Physics

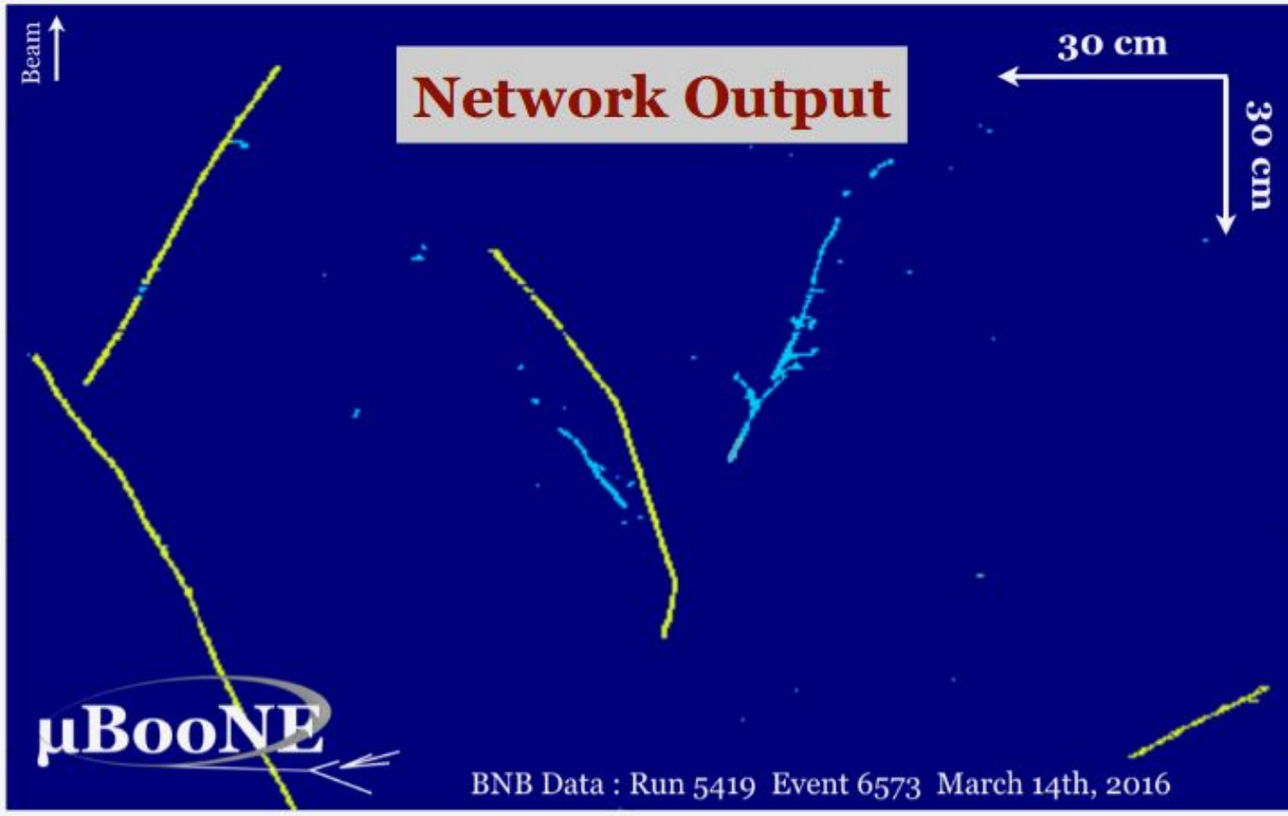
SLAC

Semantic Segmentation

- Recently published … arXiv:1808.07269
- Pixel-level object classification
  - Separation of EM-particle from other types
  - Key input information for particle clustering
- First time deep neural network validated on LArTPC data

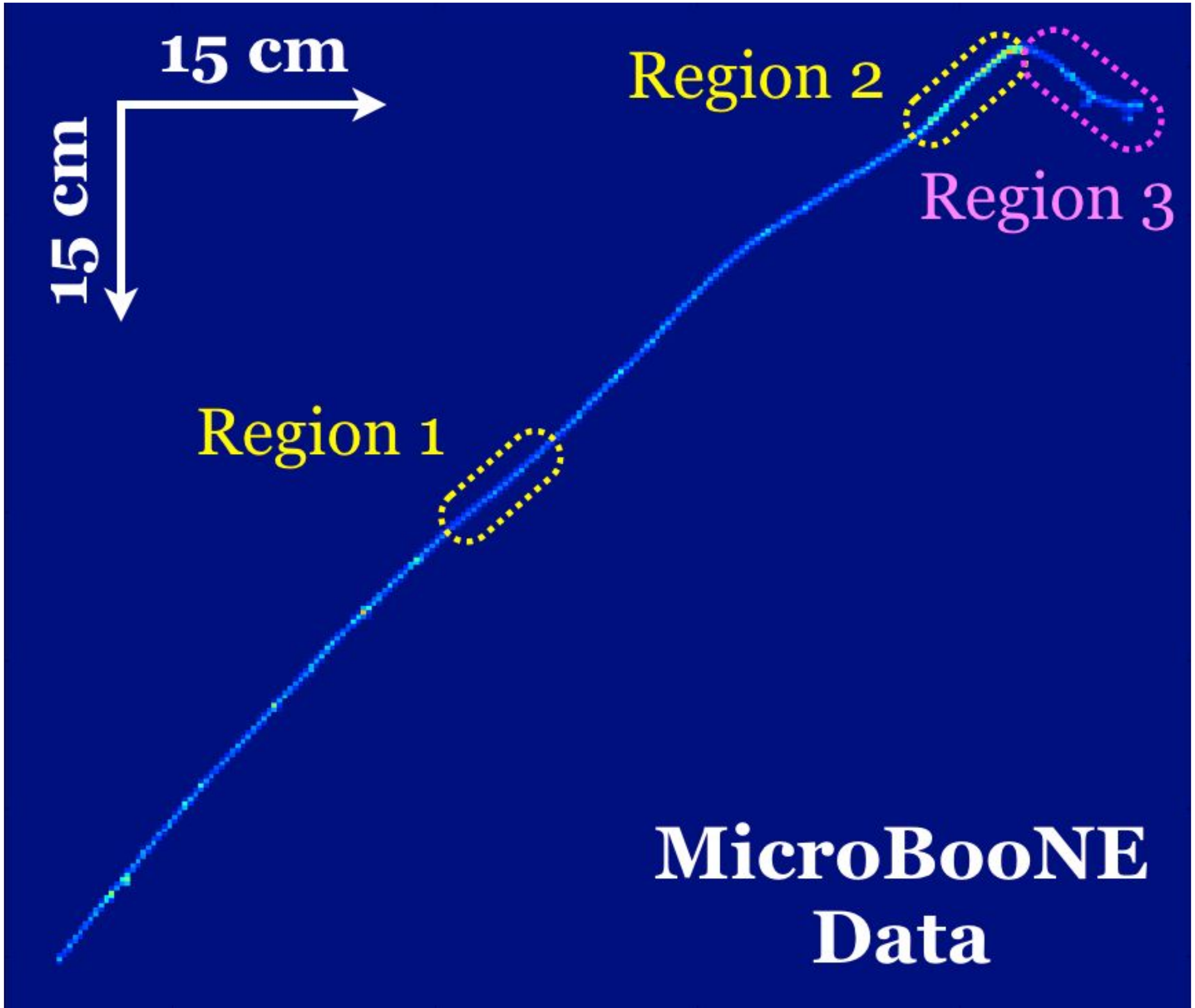
ML Technique @ MicroBooNE LArTPC Detector



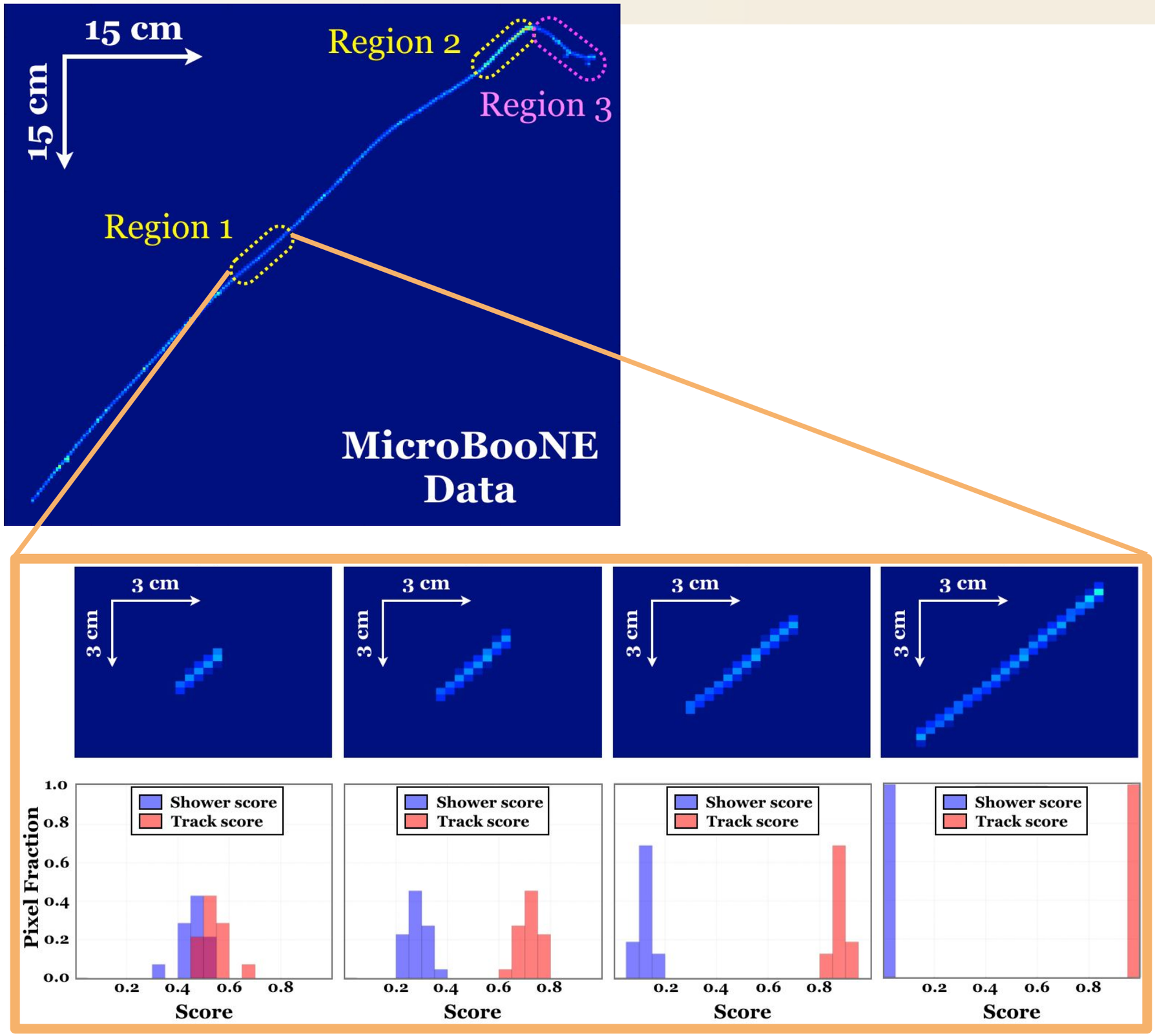


Network Input **Network Output**

Pixel-level Feature Information
Machine Learning in Neutrino Physics

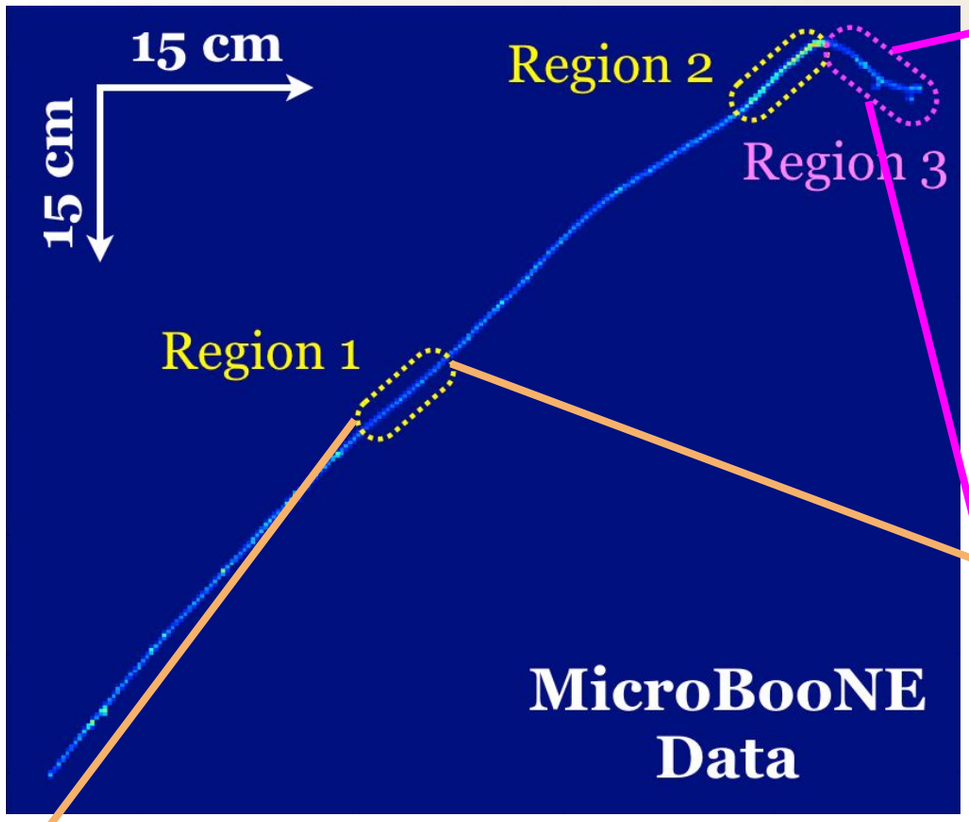


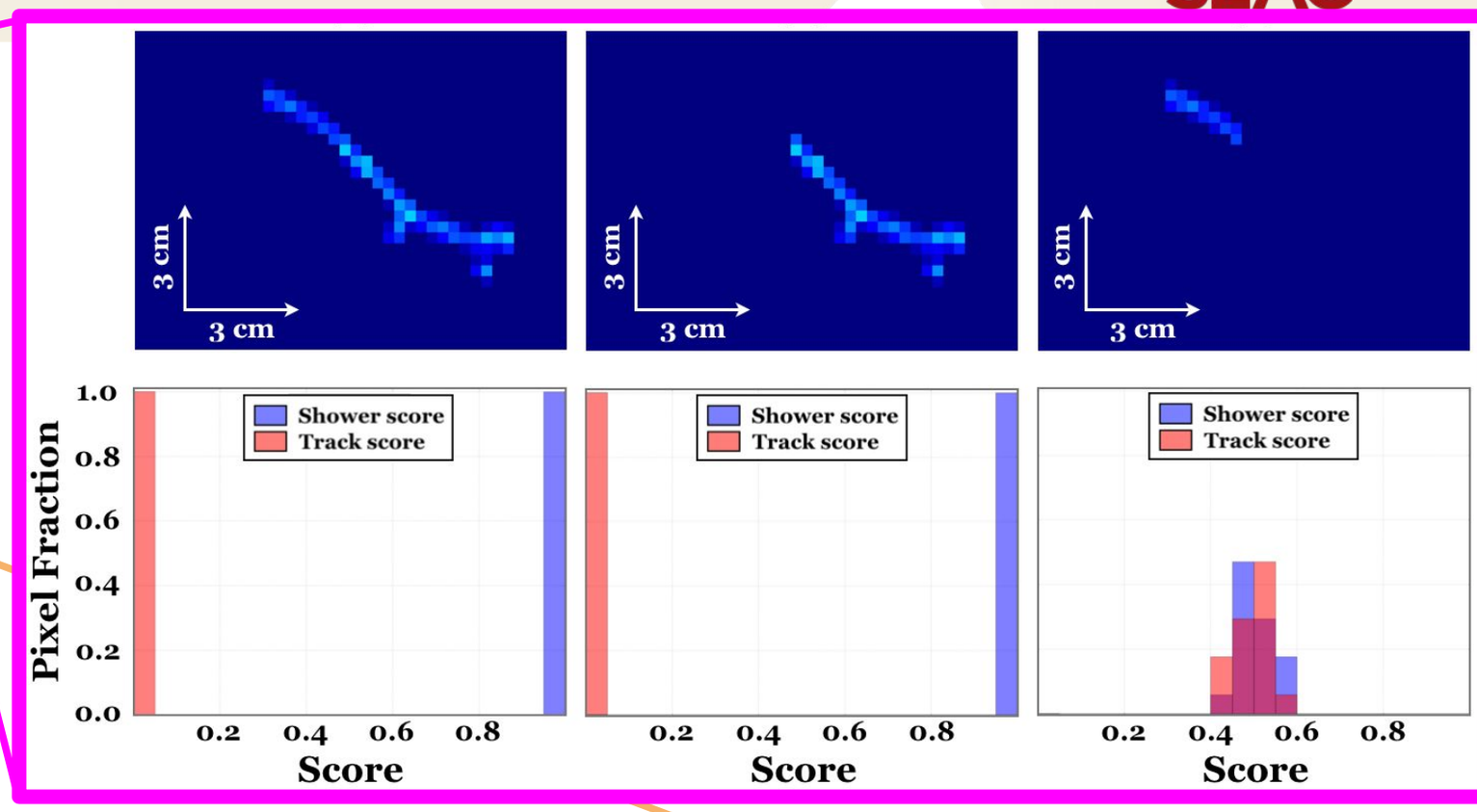
Pixel-level Feature Information
Machine Learning in Neutrino Physics

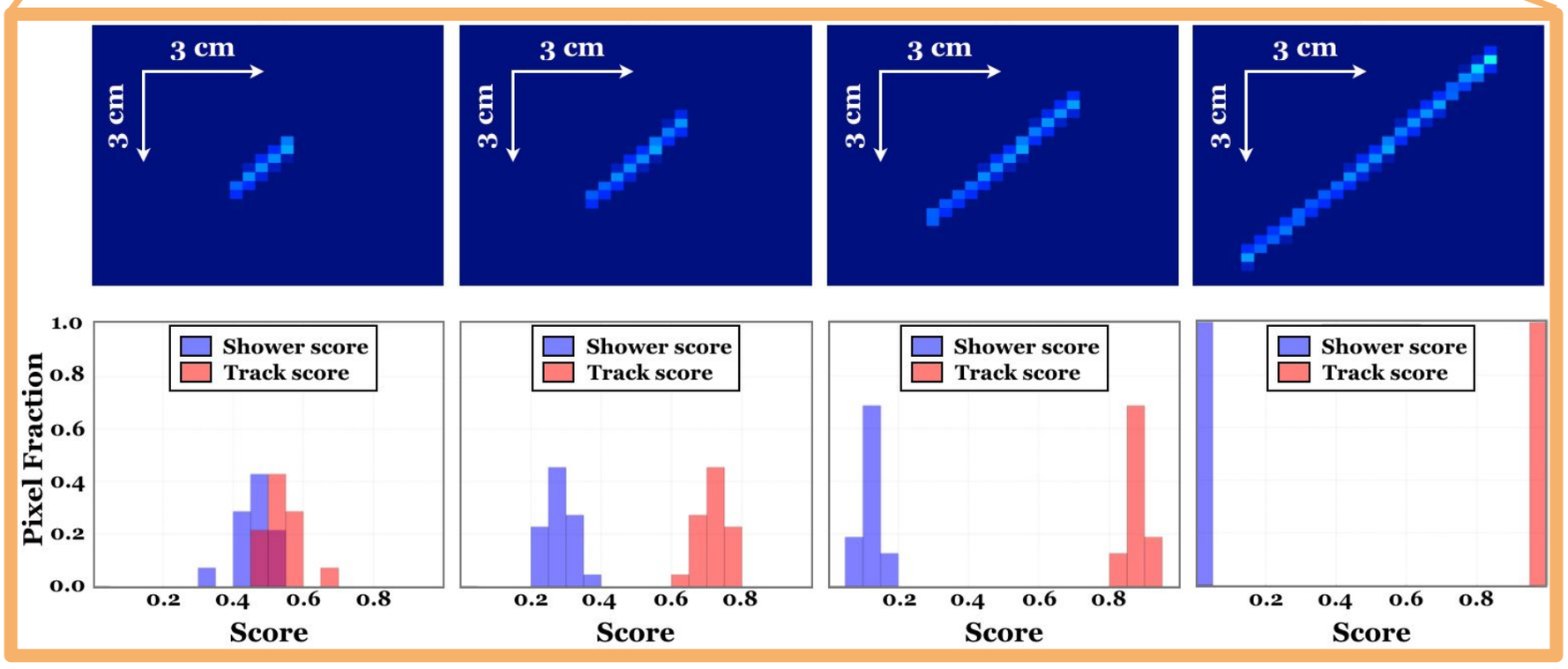


Localized features at the pixel-level are useful to inspect **correlation of data features & algorithm responses**

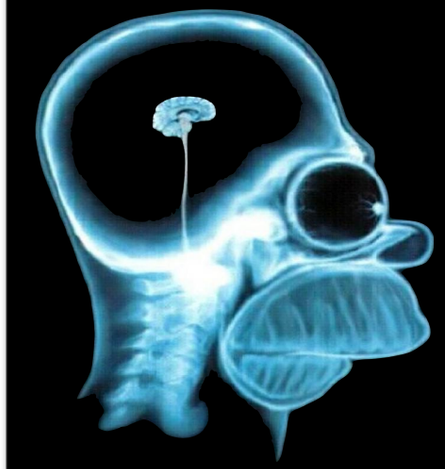
Pixel-level Feature Information
Machine Learning in Neutrino Physics



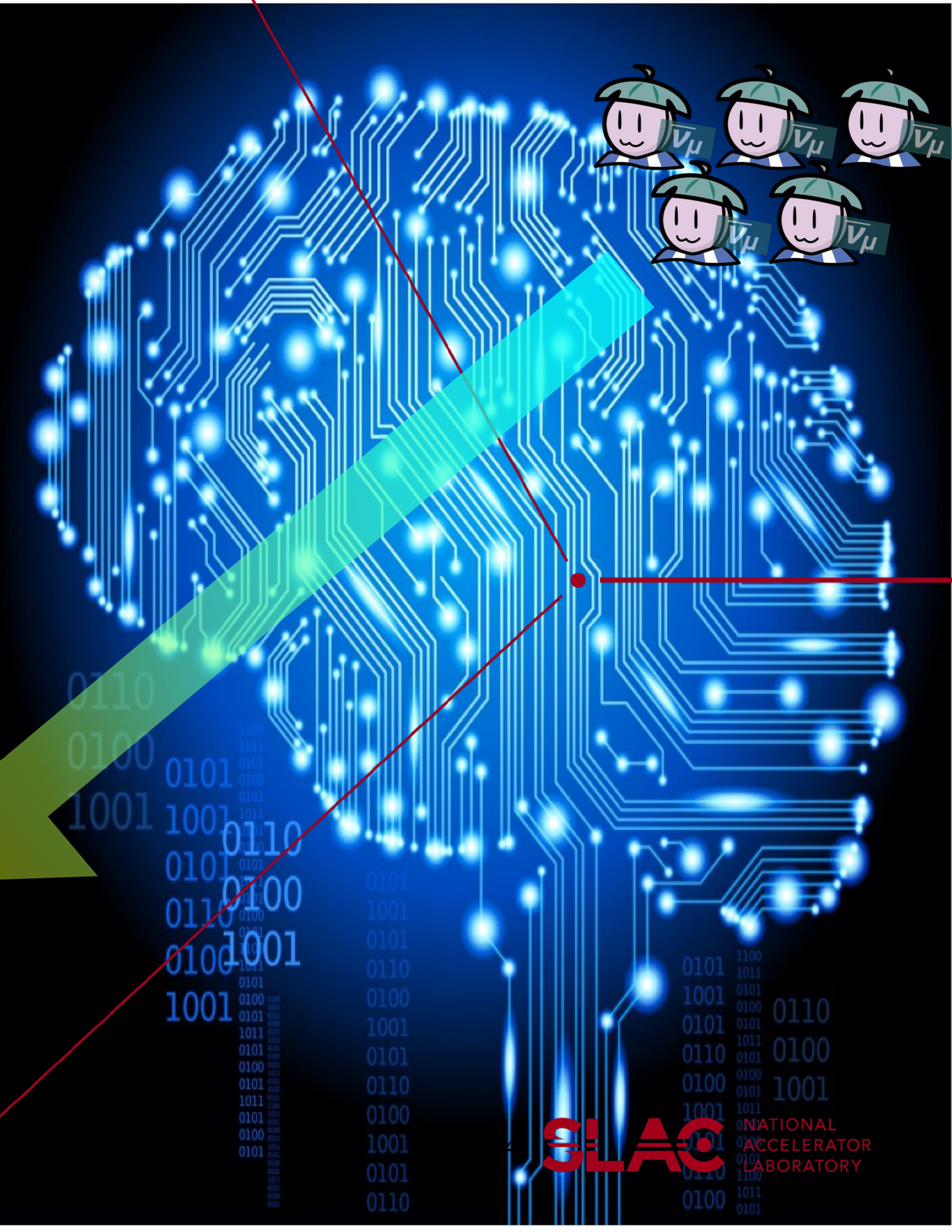


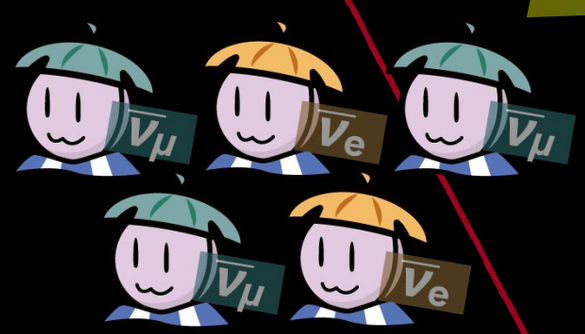


Localized features at the pixel-level are useful to inspect **correlation of data features & algorithm responses**



ML-based 3D Data Reconstruction





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Office of Science

SLAC NATIONAL ACCELERATOR LABORATORY

Toward "Reconstruction Chain"
Machine Learning in Neutrino Physics

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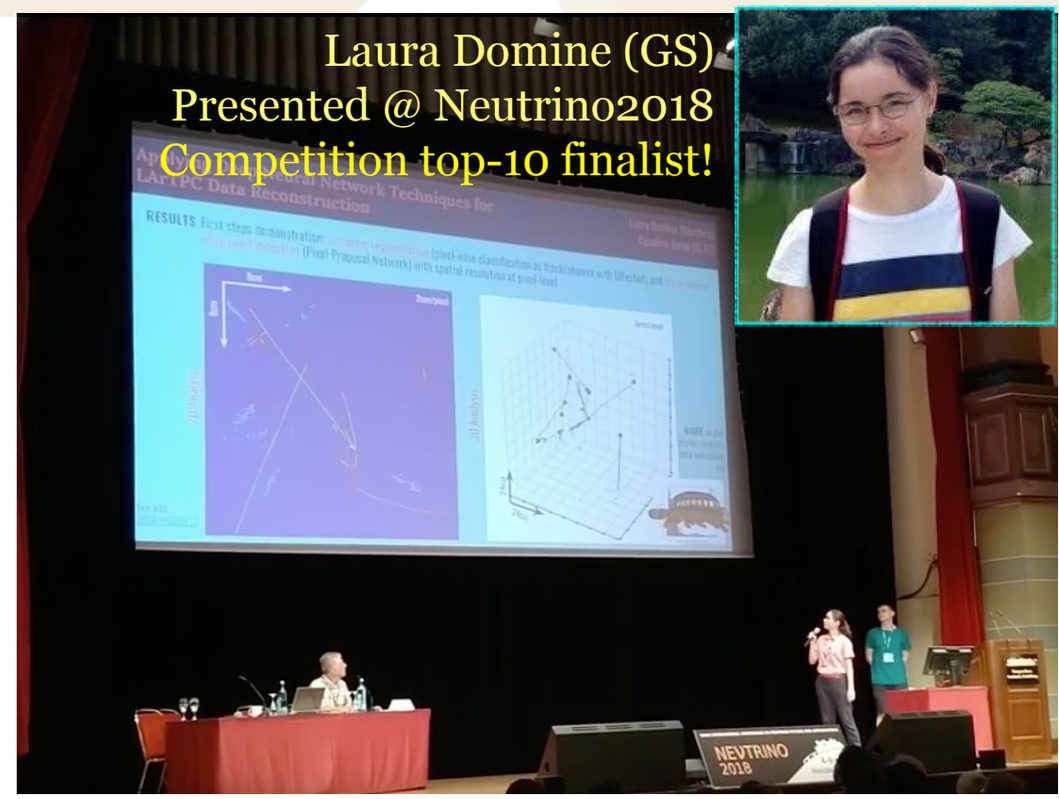
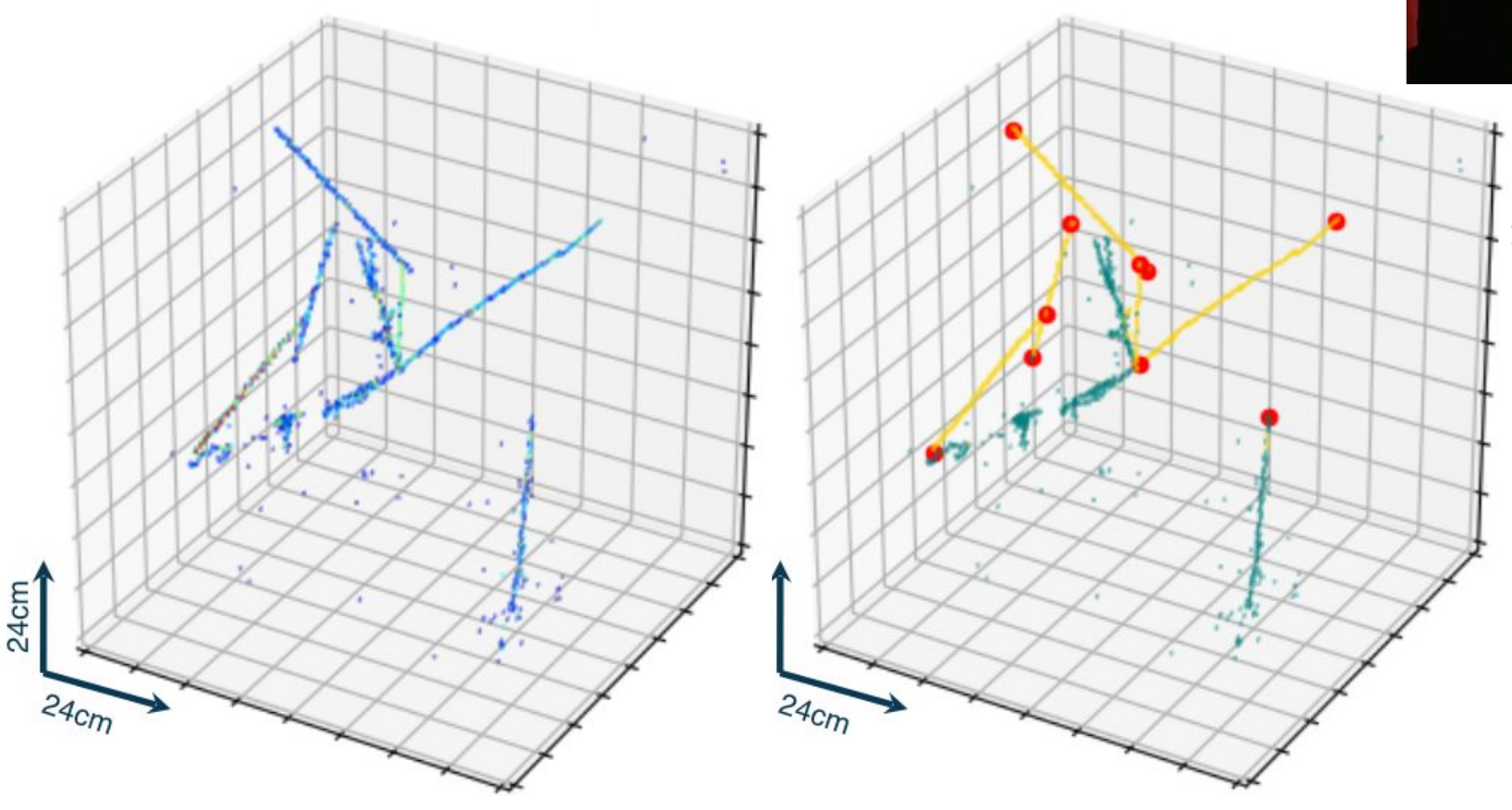
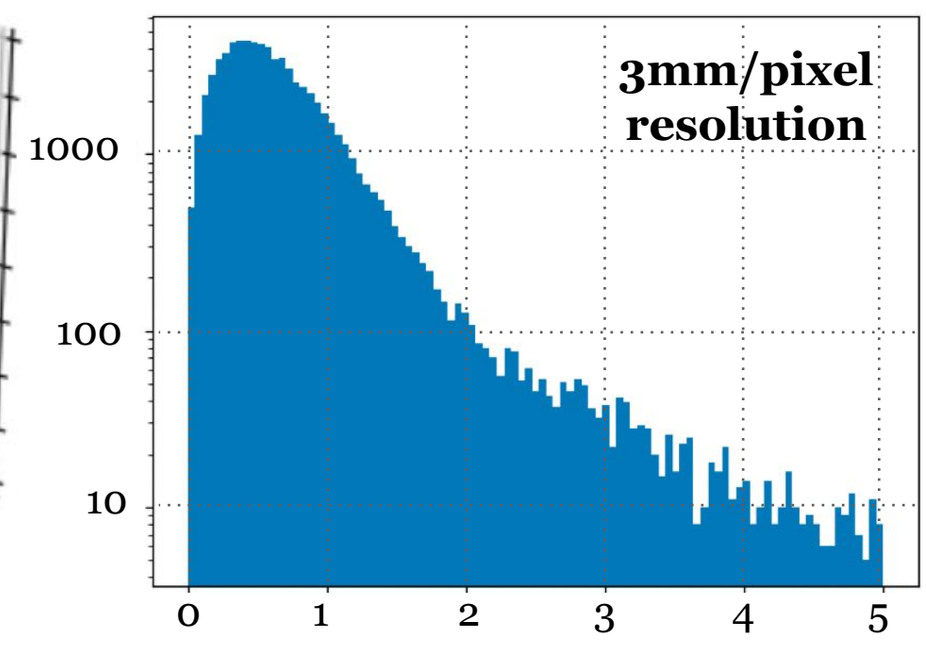
Multi-Task Network Cascade

- **Chain of Segmentation + Detection**
  - Feature points: "shower start" and "track edges"
  - Classify each pixel into "shower" vs. " track"
- **Extension to 3D data**
  - Change in tensor dimensions, identical algorithms







Pixel distance between the target truth point to the closest proposed point

35

Toward "Reconstruction Chain"
Machine Learning in Neutrino Physics

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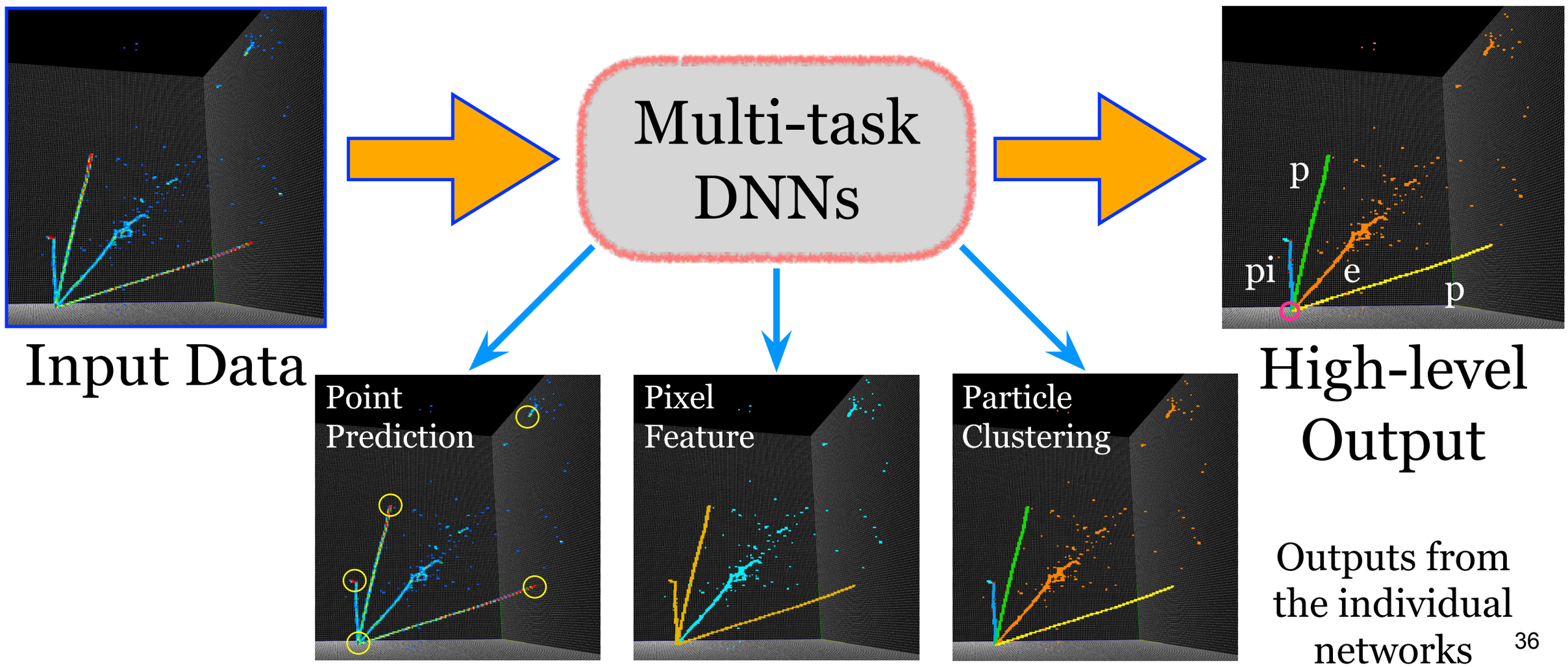
Multi-task DNN for Physics Reconstruction

Introduce physical feature extraction tasks (auxiliary targets) to bias the data transformation path to support producing a logical conclusion. Optimize the whole reconstruction chain.



Outputs from the individual networks

Deep CNN for LARGE Detectors? (scalability)
Machine Learning for Particle Image Analysis

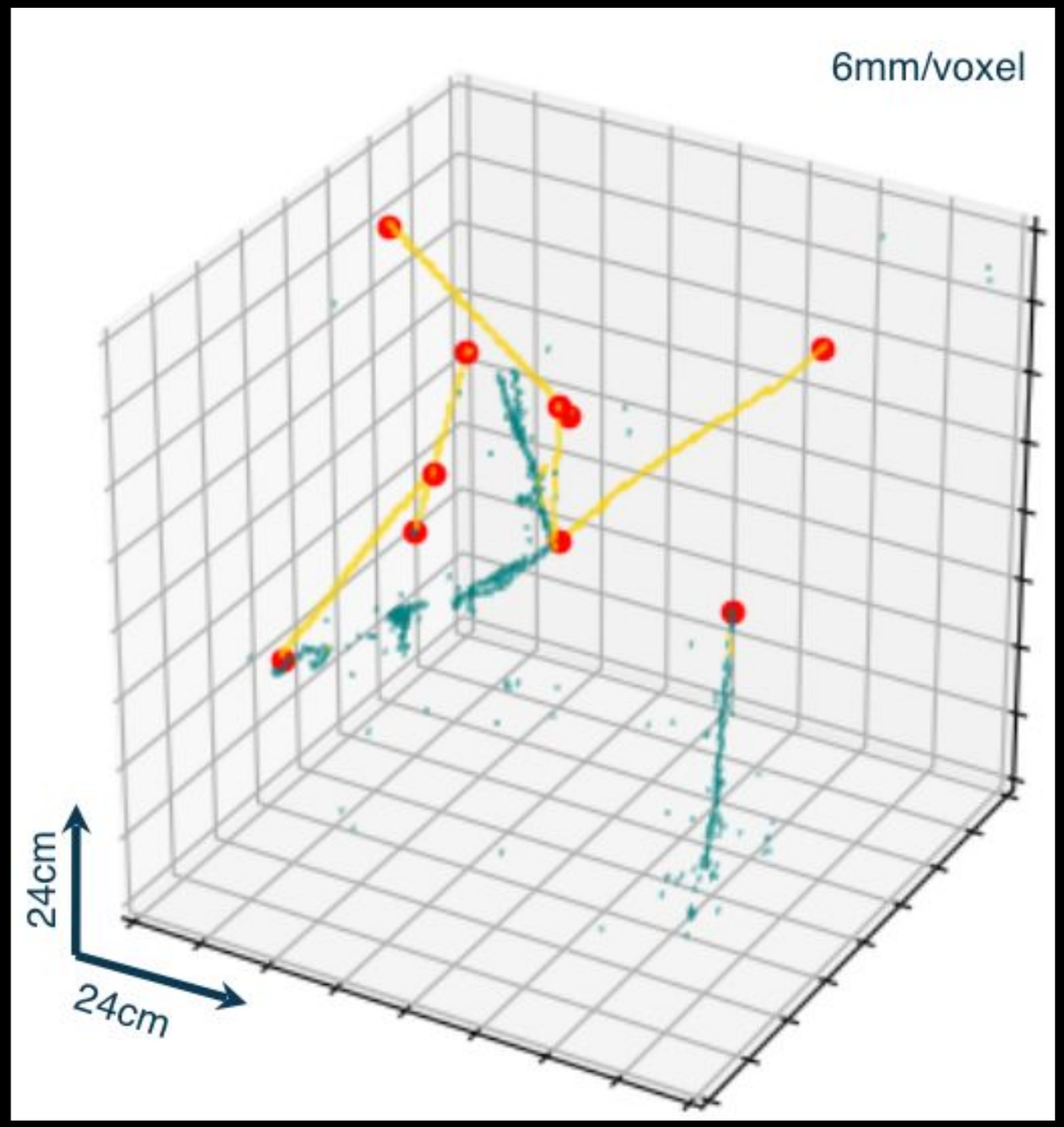
SLAC

Data feature: generally sparse, locally dense image, and very large volume (1 E10-20 pixels)

Issues using standard CNNs

- **Inefficient** calculations ("zero" matrix elements)
- **Prohibitive resource** usage (memory, time)
- **Degraded performance**

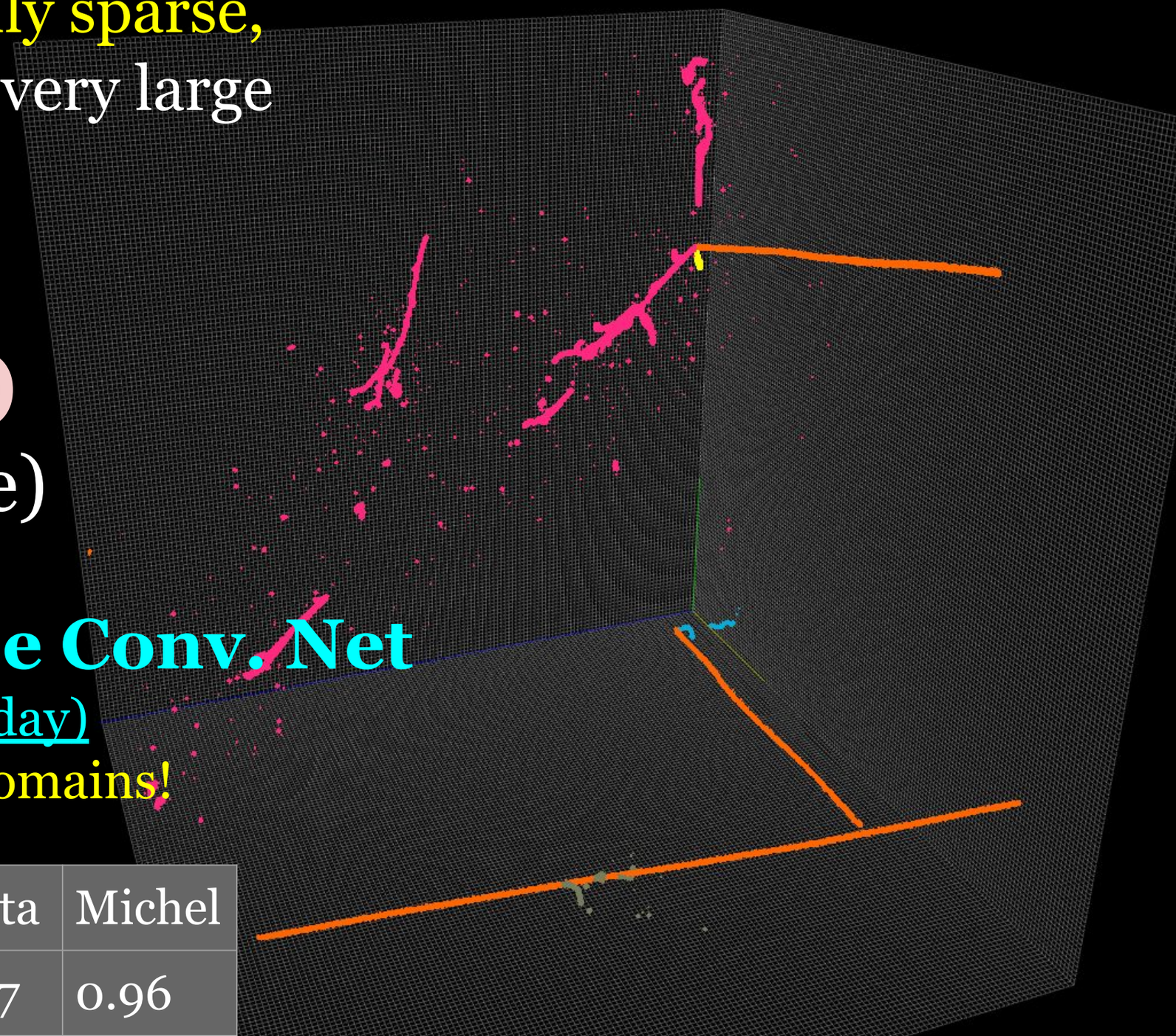
... terrible scaling = garbage!



Deep CNN for LARGE Detectors? (scalability)

Machine Learning for Particle Image Analysis

Data feature: generally sparse, locally dense image, and very large volume (1 E10-20 pixels)



Got a solution :)
(right: 768^3 volume)

Submanifold Sparse Conv. Net
Talk by Laura Domine (Thursday)
Great for LArTPC and other domains!

Type	HIP	MIP	Shower	Delta	Michel
Acc.	0.99	0.98	0.99	0.97	0.96

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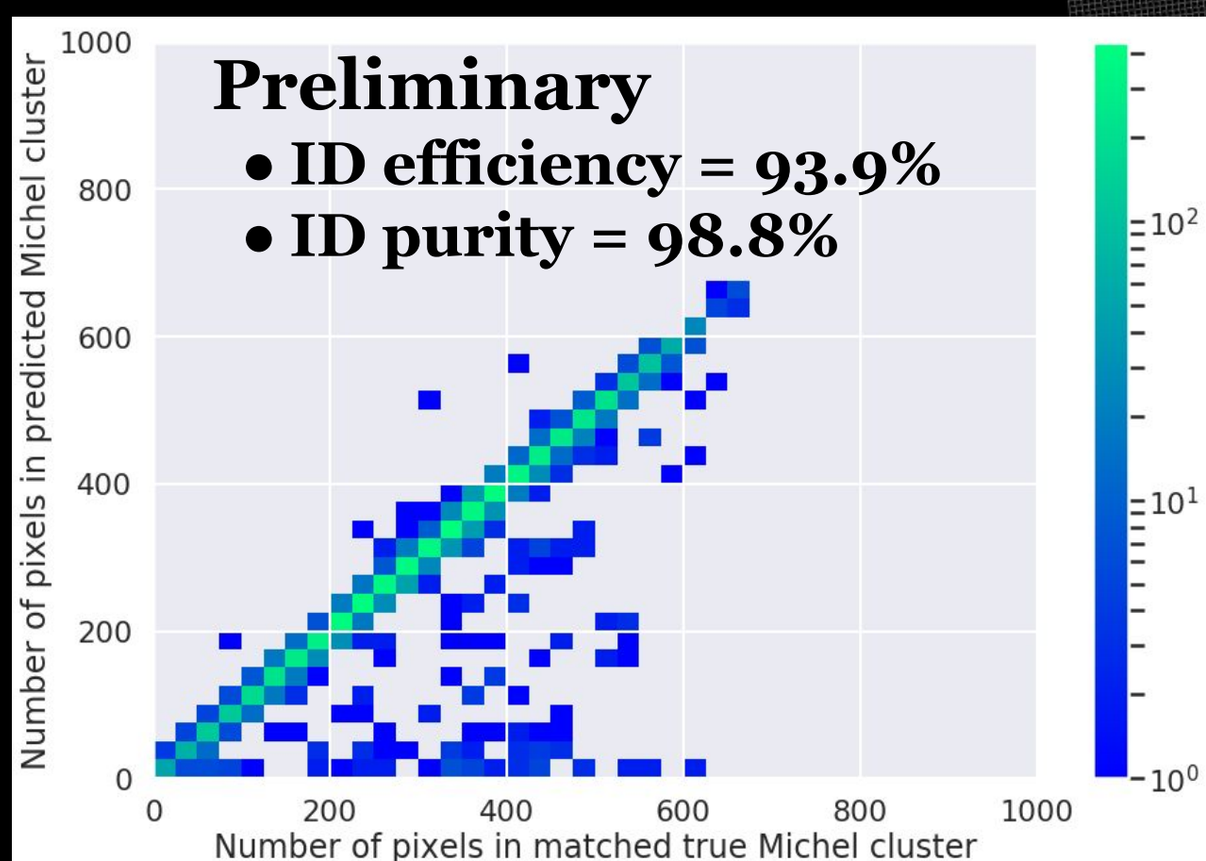
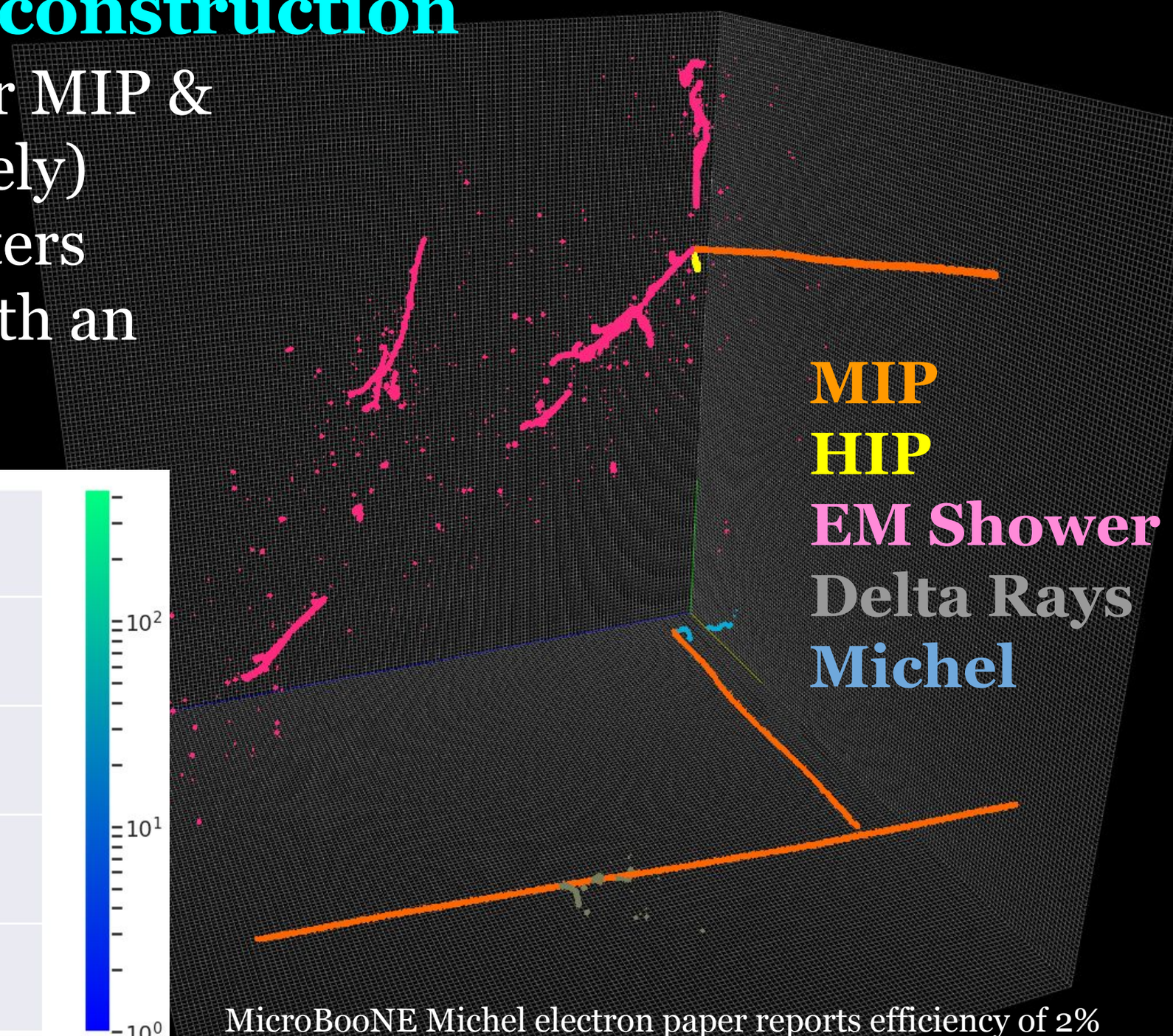
Michel Electron Reconstruction

- Run spatial DBscan for MIP & Michel pixels (separately)
- Keep only Michel clusters which edge touches with an edge of a MIP cluster





MicroBooNE Michel electron paper reports efficiency of 2% with purity of 80-90%, tuned for high purity (calibration)

Reproducible technique sharing is important...

- Submanifold Sparse Conv. Net for scalability
  - See Laura's talk, and our benchmark ... arXiv: 1903.05663
  - Open data sample: DOI 10.17605/OSF.IO/VRUZP
  - Software stuck: Singularity or Docker container
  - Implementation: github repo

Toward HPC: contact them if you want help!

- SSCN + Horovod + custom MPI for production
- Corey Adams (ANL)
  - KNL/GPU nodes @ ALCF
- Eric Church, Jan F Strube, Alexander R. Hagen (PNNL)
  - SummitDev Intel Power8, now moving onto Power9

Experimental neutrino physics:

- **Detector trend: particle imaging**
  - LArTPC is the current frontier for imaging
- **Many applications from computer vision**
  - ML-based full data reconstruction being developed
  - Active but not mentioned: data/sim domain adaptation
- **Next few years**
  - Integration of ML-based reconstruction
  - Data/Simulation domain adaptations
  - Software stack development toward HPC

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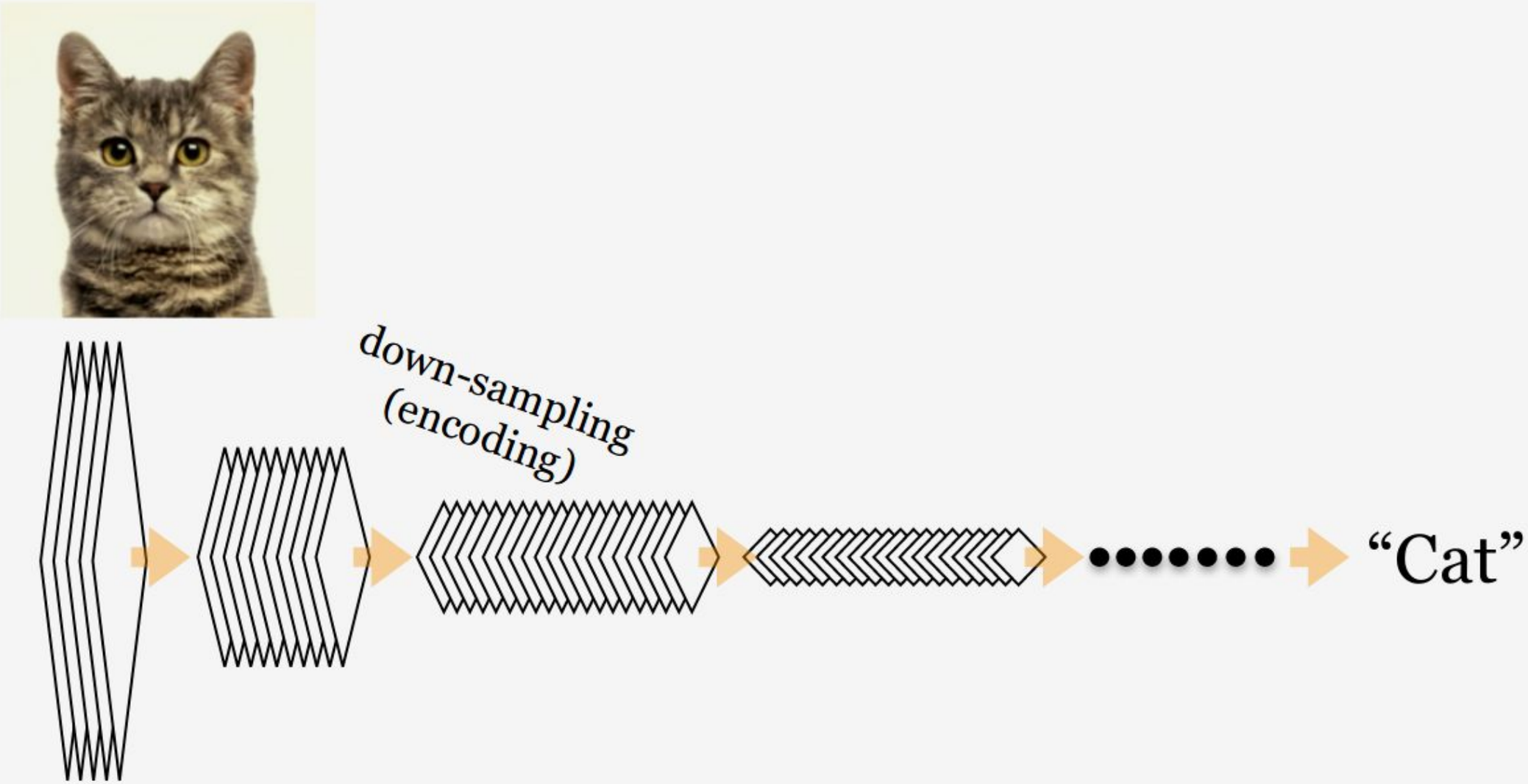
Thank you for listening

and

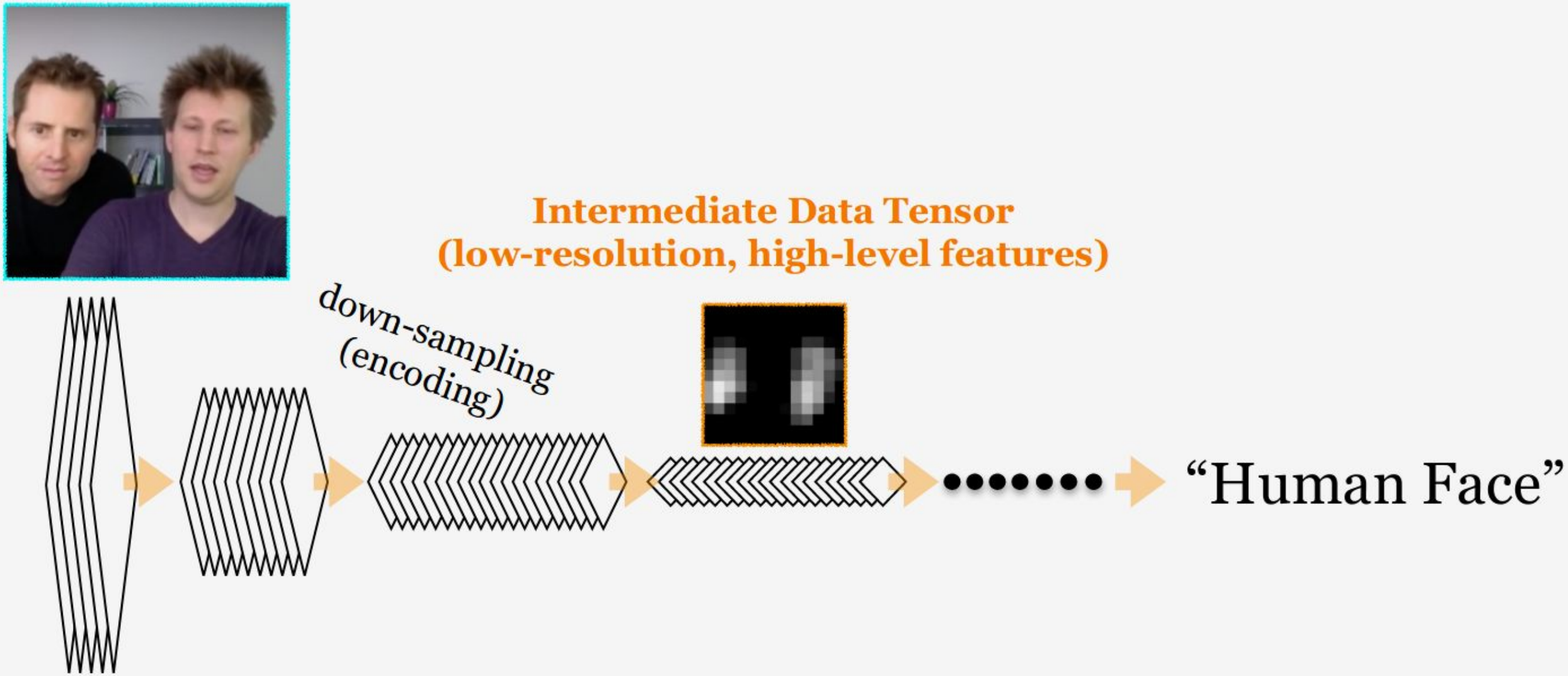
Thank YOU for organizing ACAT2019!

Back Up Slides

How image classification works

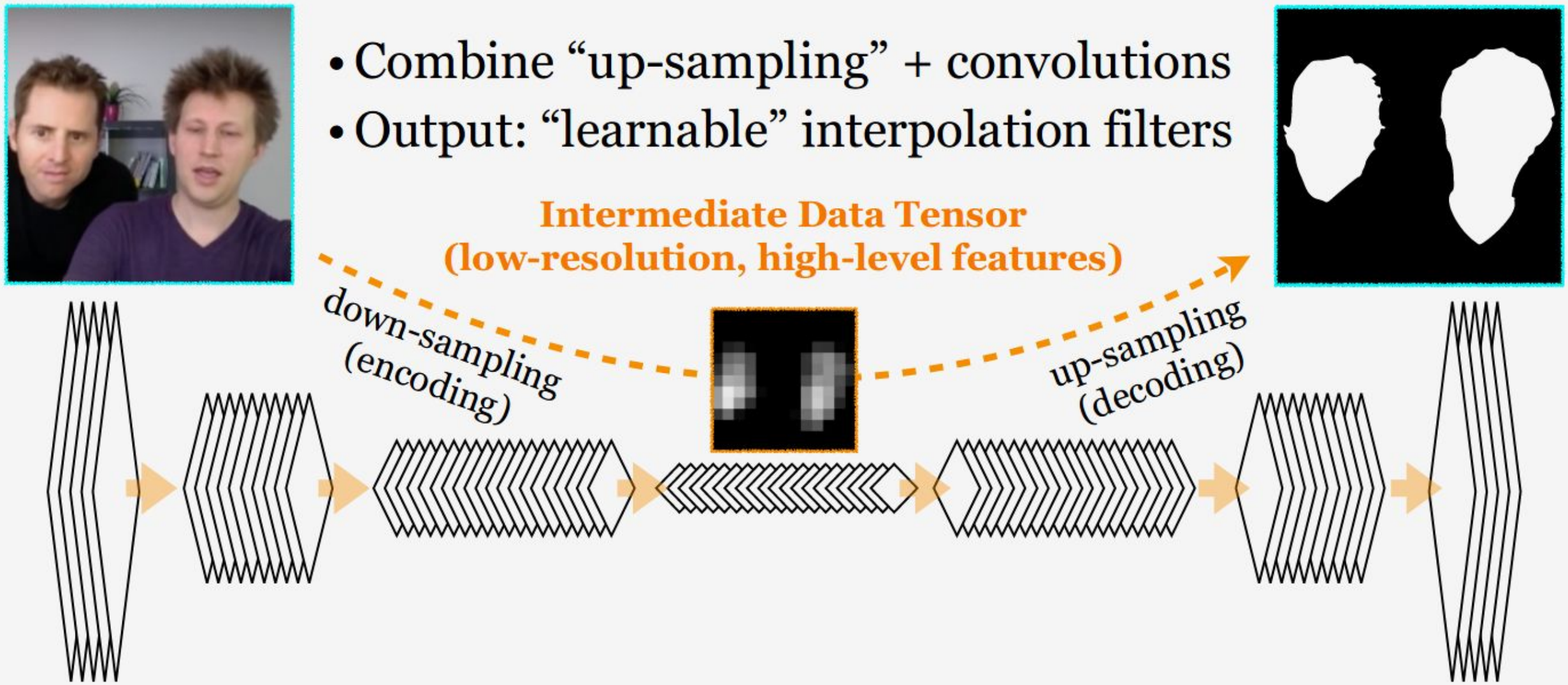


How image classification works



How pixel segmentation works

- Combine "up-sampling" + convolutions
- Output: "learnable" interpolation filters



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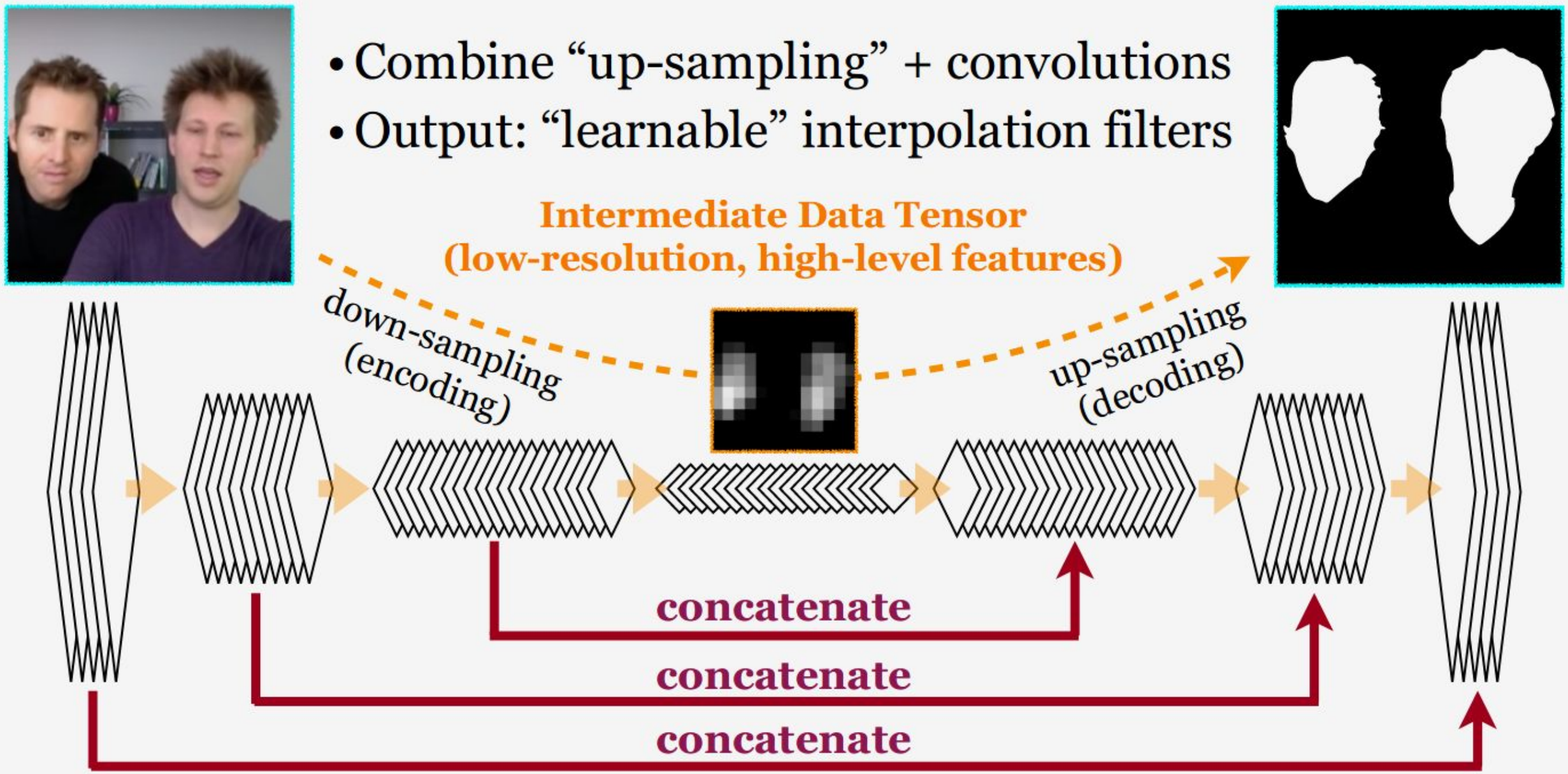
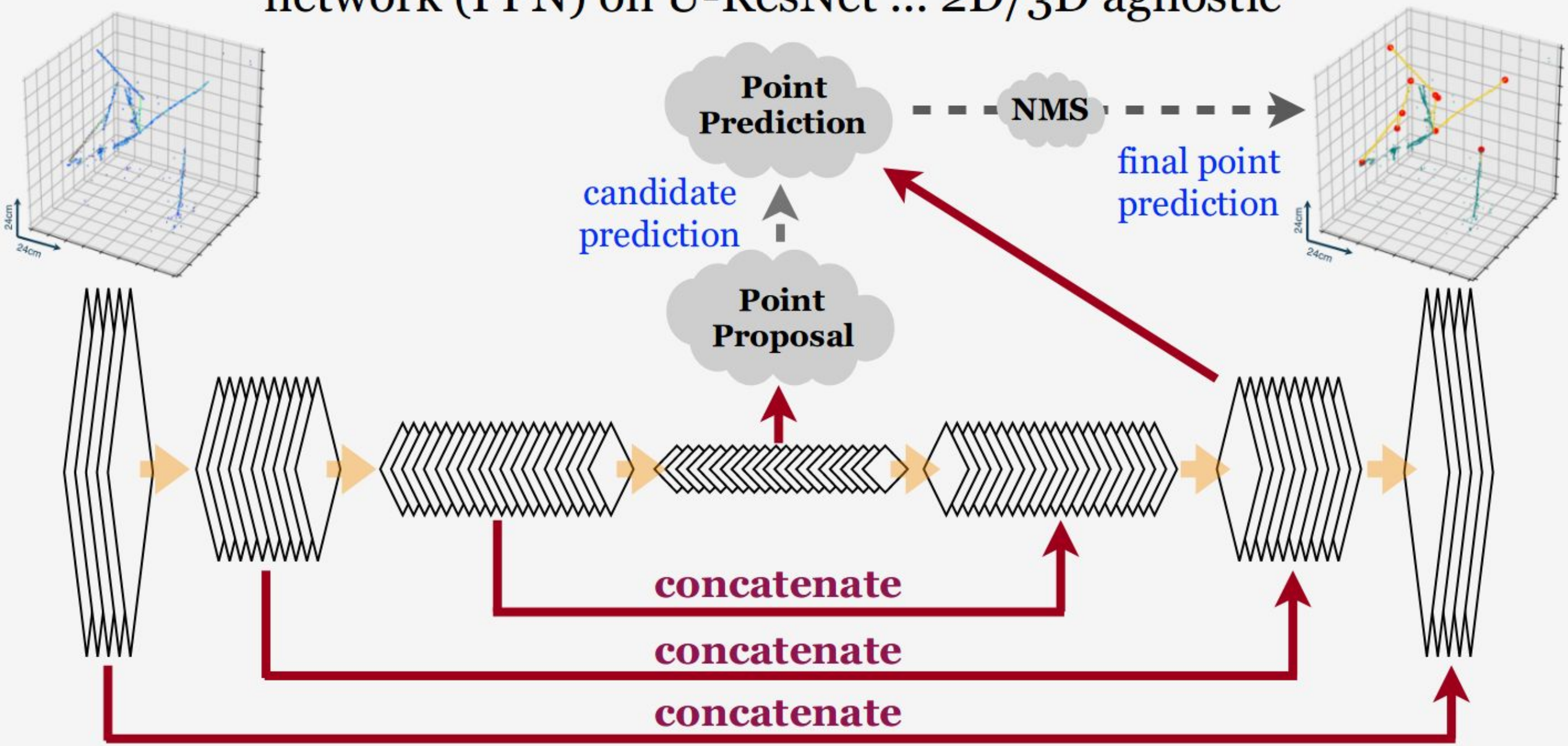


Concatenation recovers spatial resolution information

HO HO HO
Machine Learning for Particle Image Analysis

Parasitic multi-task scheme for point prediction network (PPN) on U-ResNet ... 2D/3D agnostic



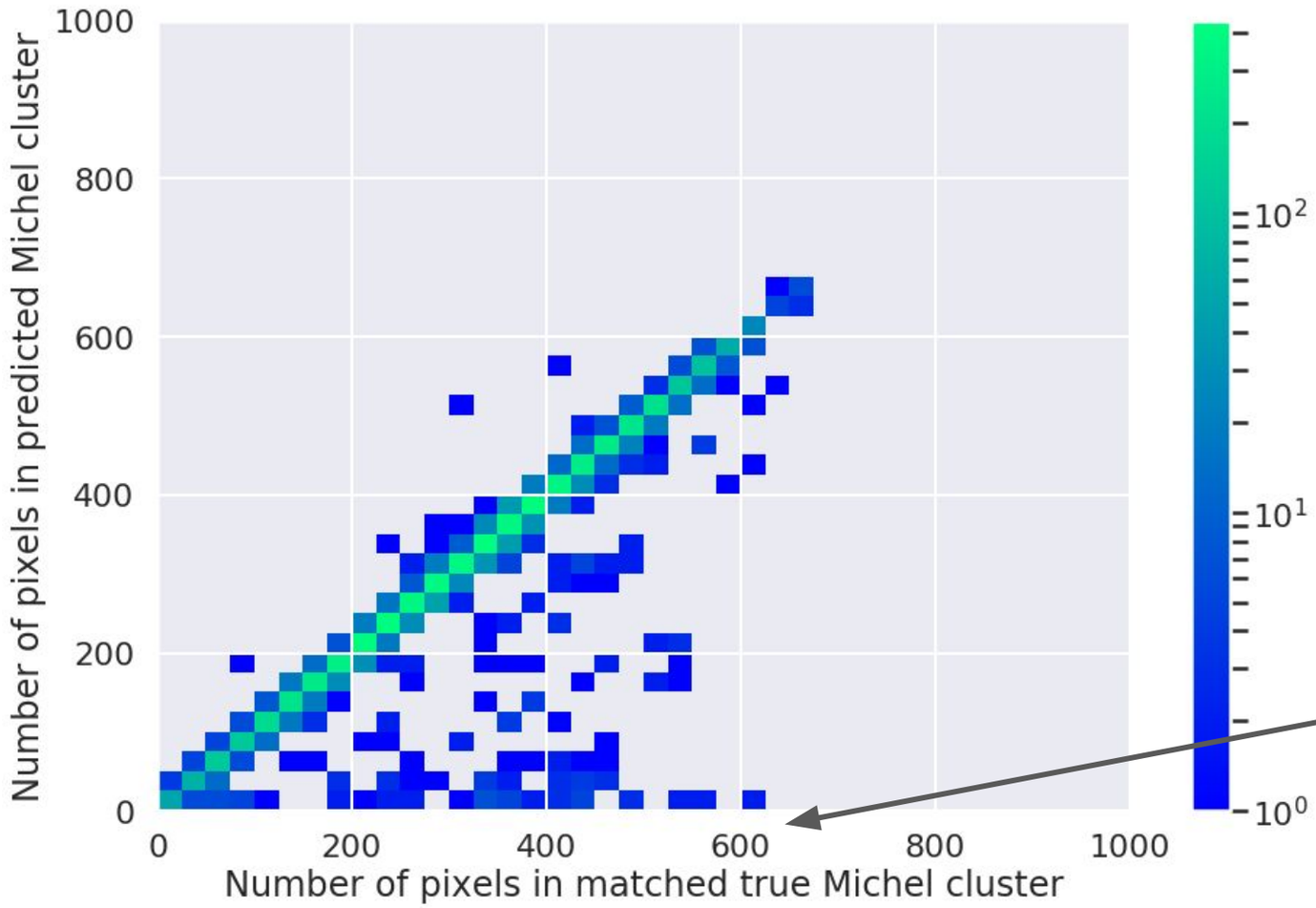
Concatenation recovers spatial resolution information

Relabeling study

Relabeled dataset = lonly primary ionization is labelled as Michel electrons

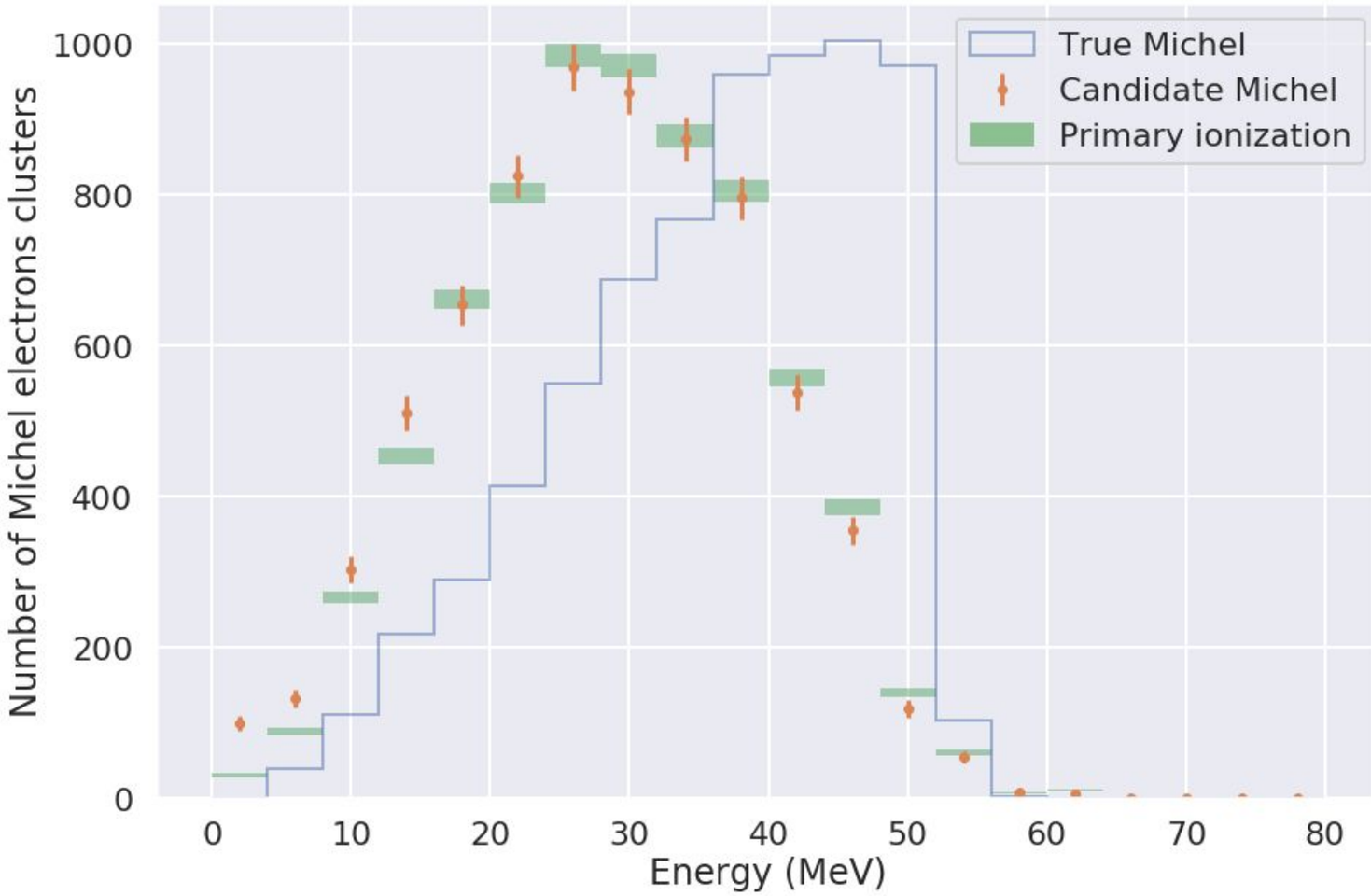
Train data	**Regular**		**Relabeled**	**Relabeled + Weighting**
Test data	**Regular**	**Relabeled**		
HIP	98.0%	98.1%	98.1%	99.3%
MIP	99.4%	99.2%	99.4%	98.1%
EM shower	99.4%	97.9%	99.2%	99.2%
Delta rays	85.7%	94.8%	96.0%	97.2%
Michel electrons	**56.6%**	**94.4%**	**94.7%**	**95.7%**

Number of pixels in candidate vs matched Michel cluster



Underclustering

Michel electrons energy spectrum reconstruction



Sample size	7105
Identification purity	98.8%
Identification efficiency	93.9%
Cluster efficiency	96.1%
Cluster purity	97.8%

First ML-based approach
Simulation only, next step is data!

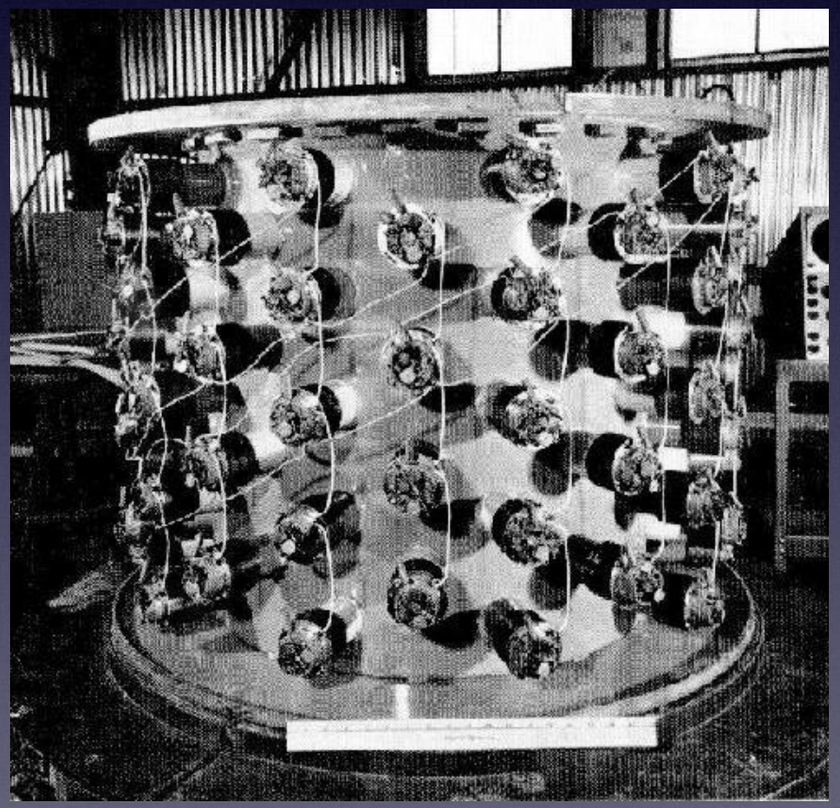
Detectors

Detecting Neutrinos: BMB

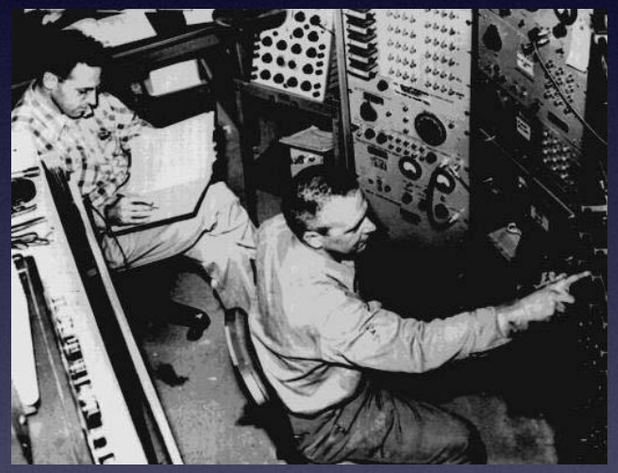
We cannot observe neutrinos, but we can detect particles that come out of a neutrino interaction.

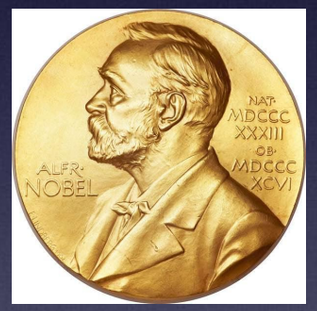
Neutrino Oscillation Experiments (I)

Evolution of Detectors



Cd-doped water
0.4 ton, 100 PMTs





Inverse Beta Decay (IBD)

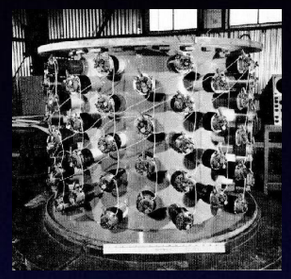
$$\bar{\nu}_e + p \rightarrow e^+ + n$$

by Reines & Cowan (Nobel Prize 1995)

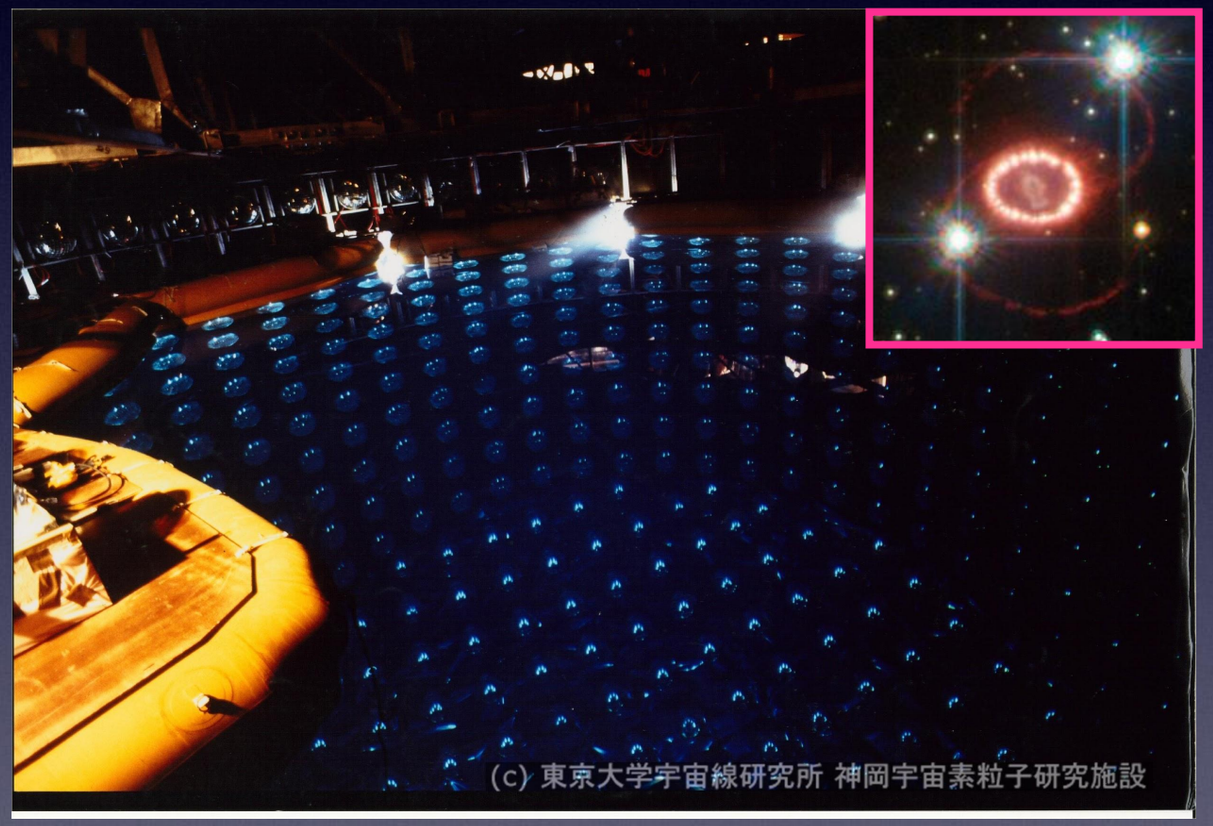
First neutrino detection

Neutrino Oscillation Experiments (I)

Evolution of Detectors



Cd-doped water
0.4 ton, 100 PMTs
(1956)

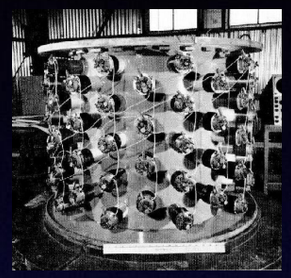


KamiokaNDE Detector
3 kton ultra-pure water, 1000 20” PMTs
(shared Nobel Prize 2002)

Birth of neutrino astrophysics!

Neutrino Oscillation Experiments (I)

Evolution of Detectors



Cd-doped water
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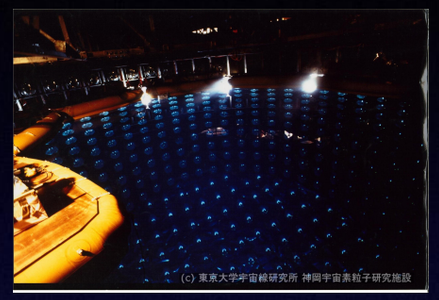
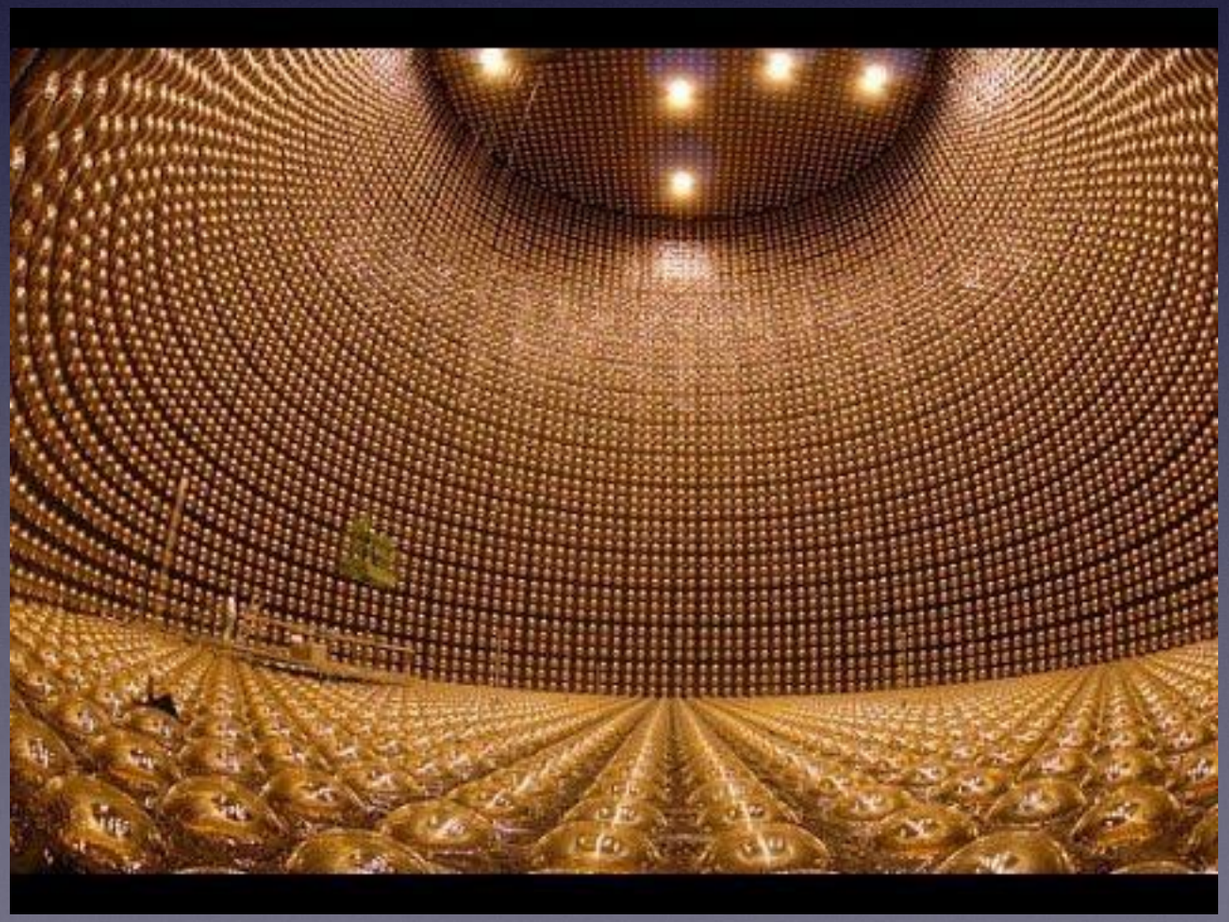
(1956)



Ultra-pure water
3 kton, 1000 PMTs
(1983)

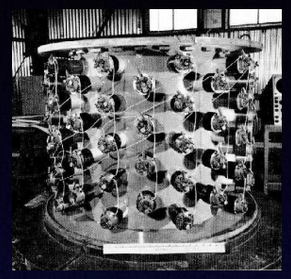
Discovery of ν_{atmo} oscillation!

Super-KamiokaNDE
50 kton ultra-pure water,
11000 PMTs
(shared Nobel Prize 2015)

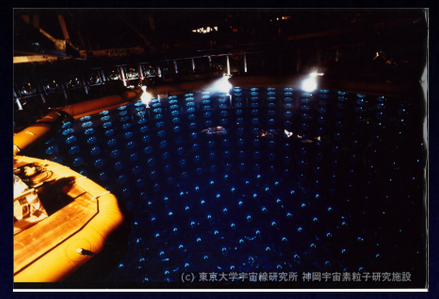


Neutrino Oscillation Experiments (I)

Evolution of Detectors



Cd-doped water
0.4 ton, 100 PMTs
(1956)



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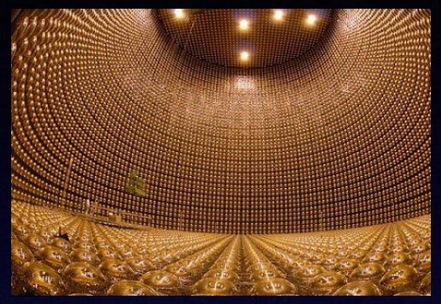
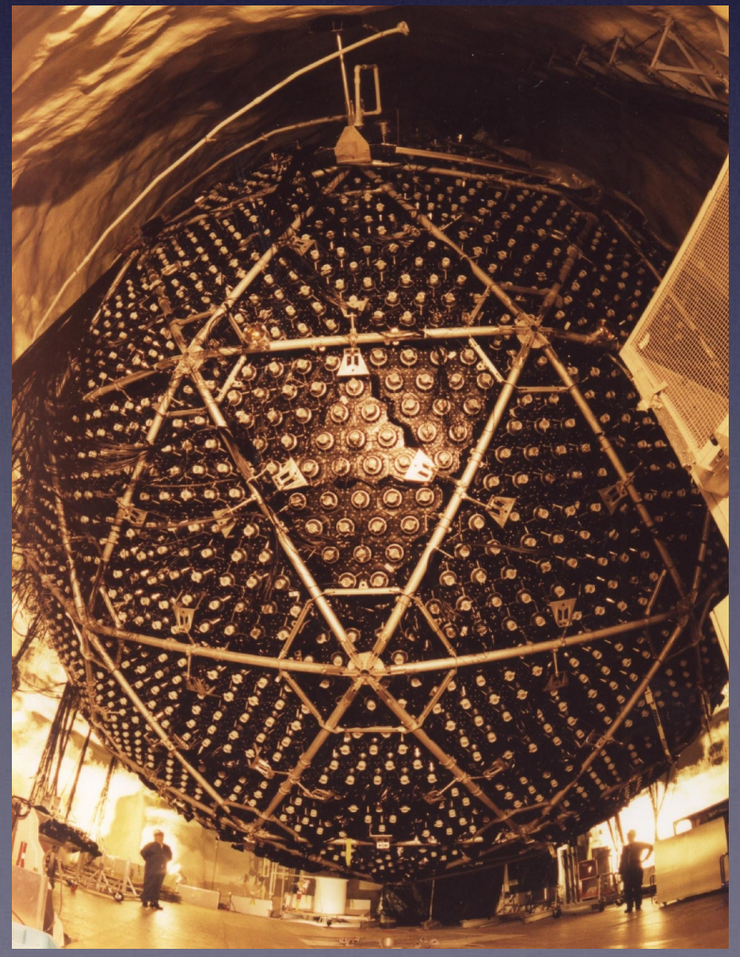


Ultra-pure water
50 kton, 11000 PMTs
(1996)

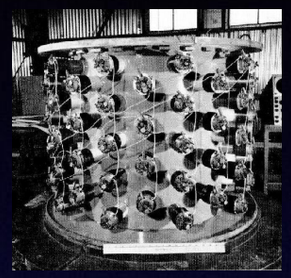
Discovery of ν_{solar} oscillation!

SNO
1 kton heavy-water Cherenkov,
9600 PMTs
(shared Nobel Prize 2015)



Neutrino Oscillation Experiments (I)

Evolution of Detectors



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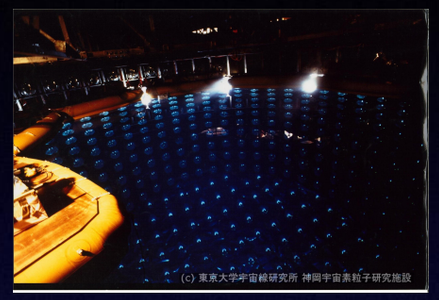

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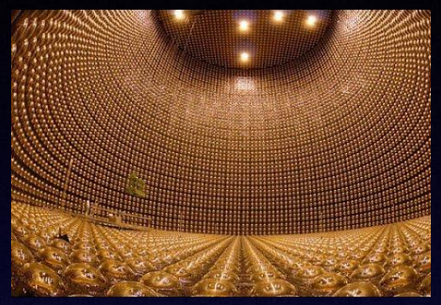

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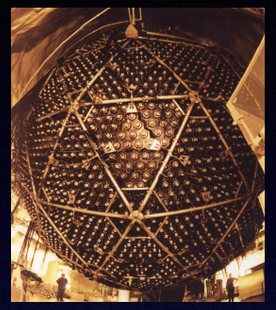
(1996)



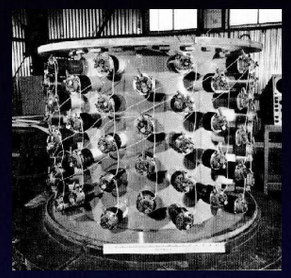
Heavy water
1 kton, 9600 PMTs
(1999)

Reactor neutrino oscillation!
(the solar model is right!)

KamLAND
1 kton liquid scintillator, 1900 PMTs
My first neutrino experiment
(undergraduate RA @ UC Berkeley)

Neutrino Oscillation Experiments (I)

Evolution of Detectors



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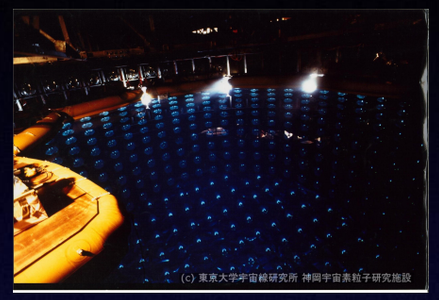

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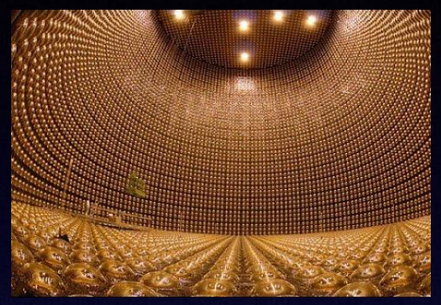

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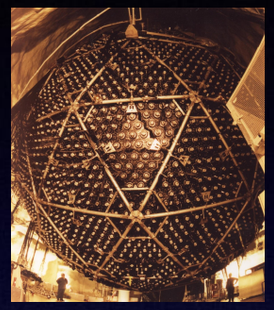
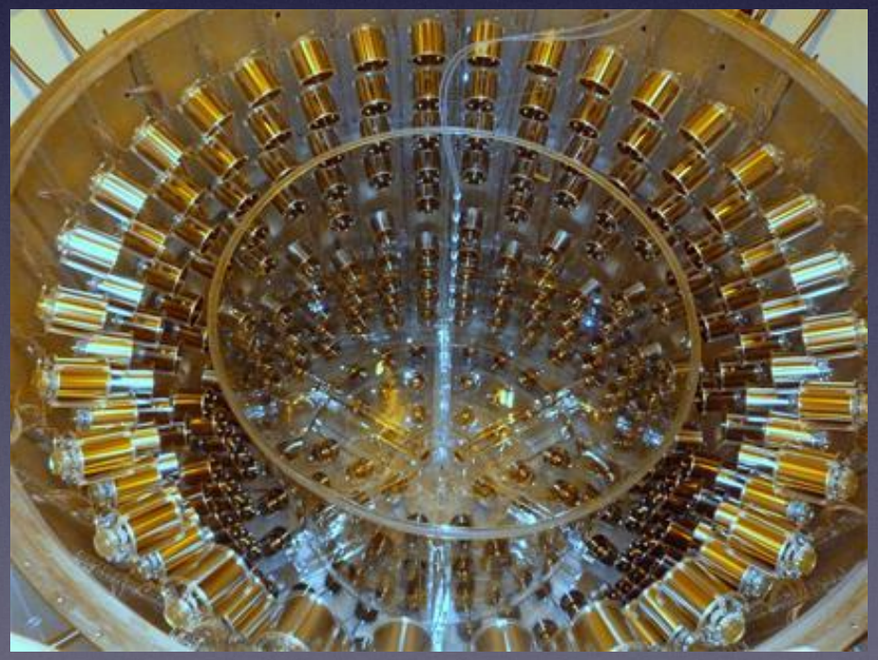
50 kton, 11000 PMTs
(1996)



Heavy water
1 kton, 9600 PMTs
(1999)

Liquid Scintillator
1 kton, 1900 PMTs
(2002)



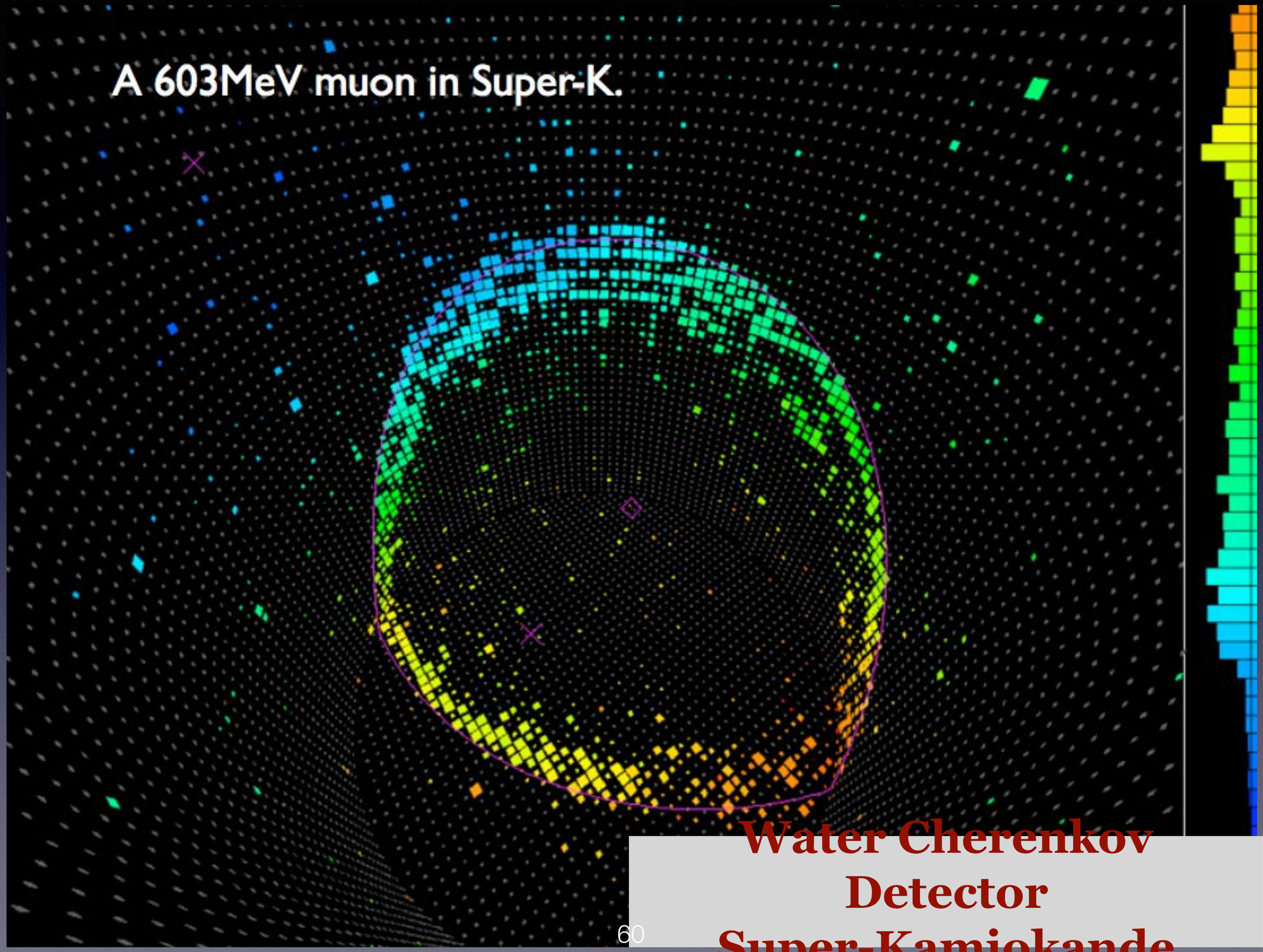
Gd-doped liquid scintillator
RENO, Daya Bay, Double Chooz

"Near" & "Far" design
2 x 16 ton detectors with 400 PMTs each (Double Chooz)

My Ph.D thesis! (MIT)

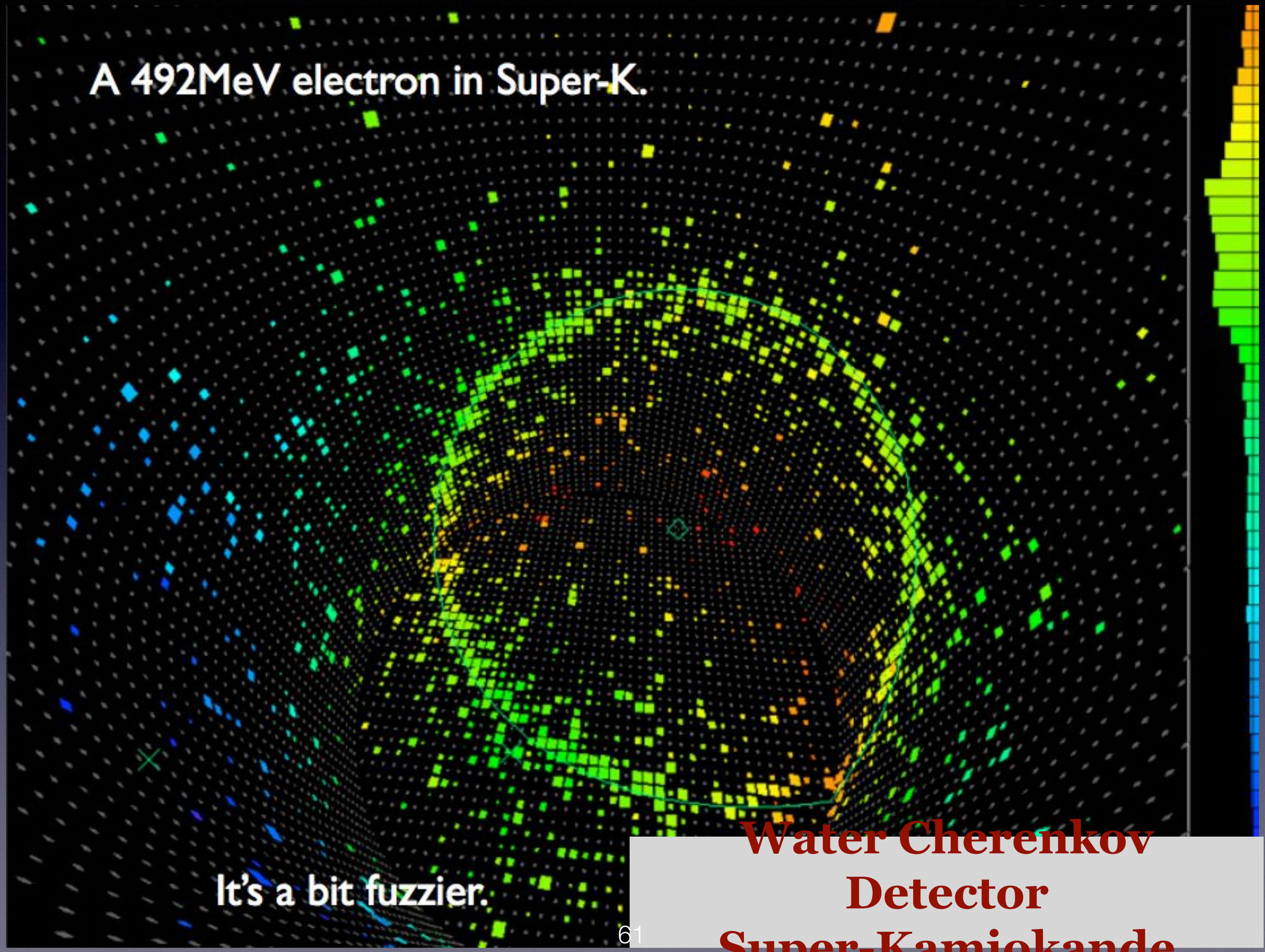
"Last mixing angle" θ_{13} Experiments!

Neutrino Oscillation Experiments (I)



Water Cherenkov Detector Super-Kamiokande

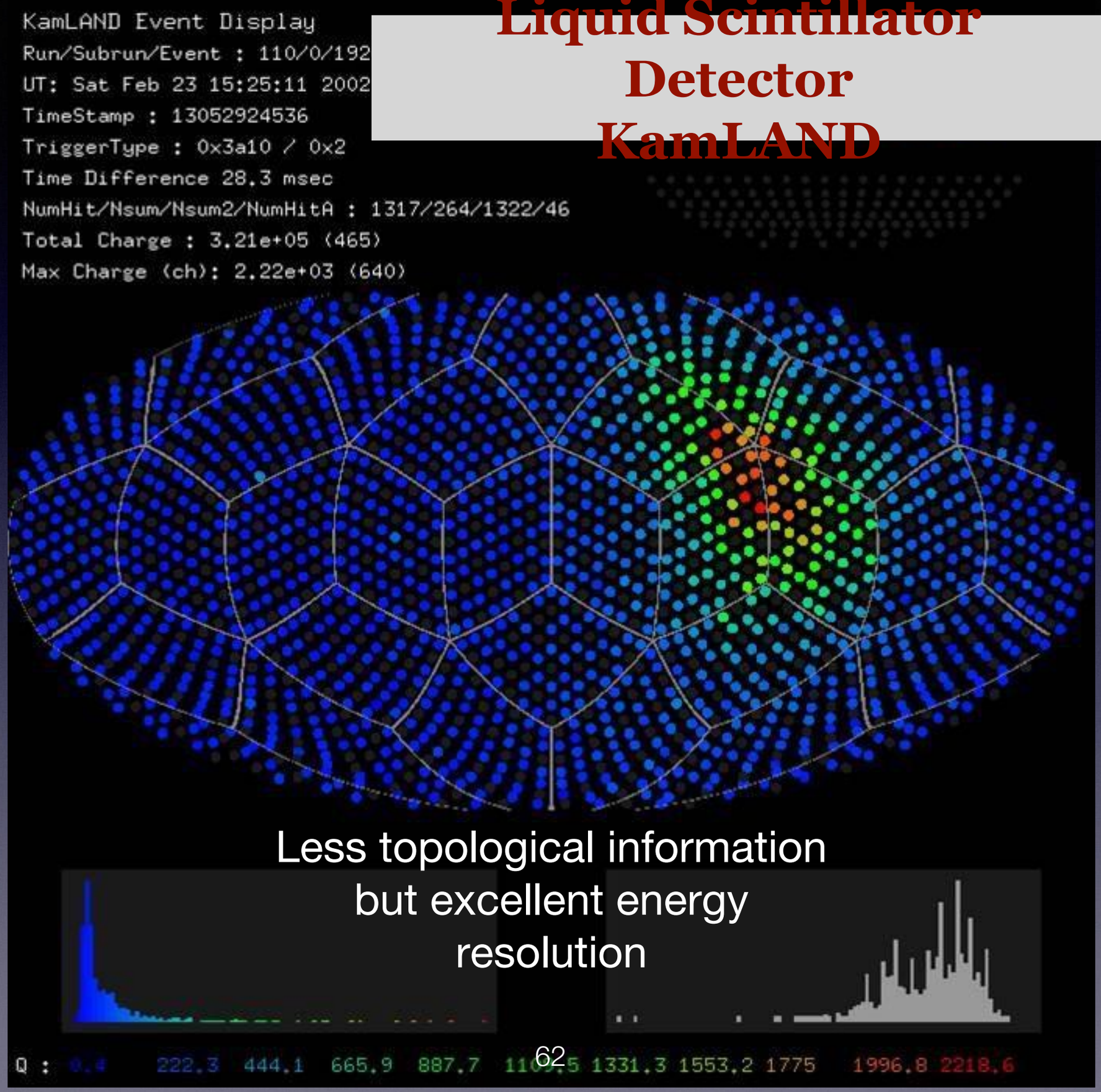
Neutrino Oscillation Experiments (I)



Water Cherenkov Detector Super-Kamiokande

Neutrino Oscillation Experiments (I)

Liquid Scintillator Detector KamLAND



Less topological information but excellent energy resolution

Neutrino Oscillation Experiments (II)

How can we do better?

Three important detector features for oscillation measurement

$$P(\nu_\mu \to \nu_e) = \sin^2 2\theta \sin^2\left(\frac{1.27\ \Delta m^2\ L}{E_\nu}\right)$$

Good Energy Resolution

Precise E_ν reduce oscillation uncertainty

Large Mass (scalable)

"More" statistics to measure rare physics process

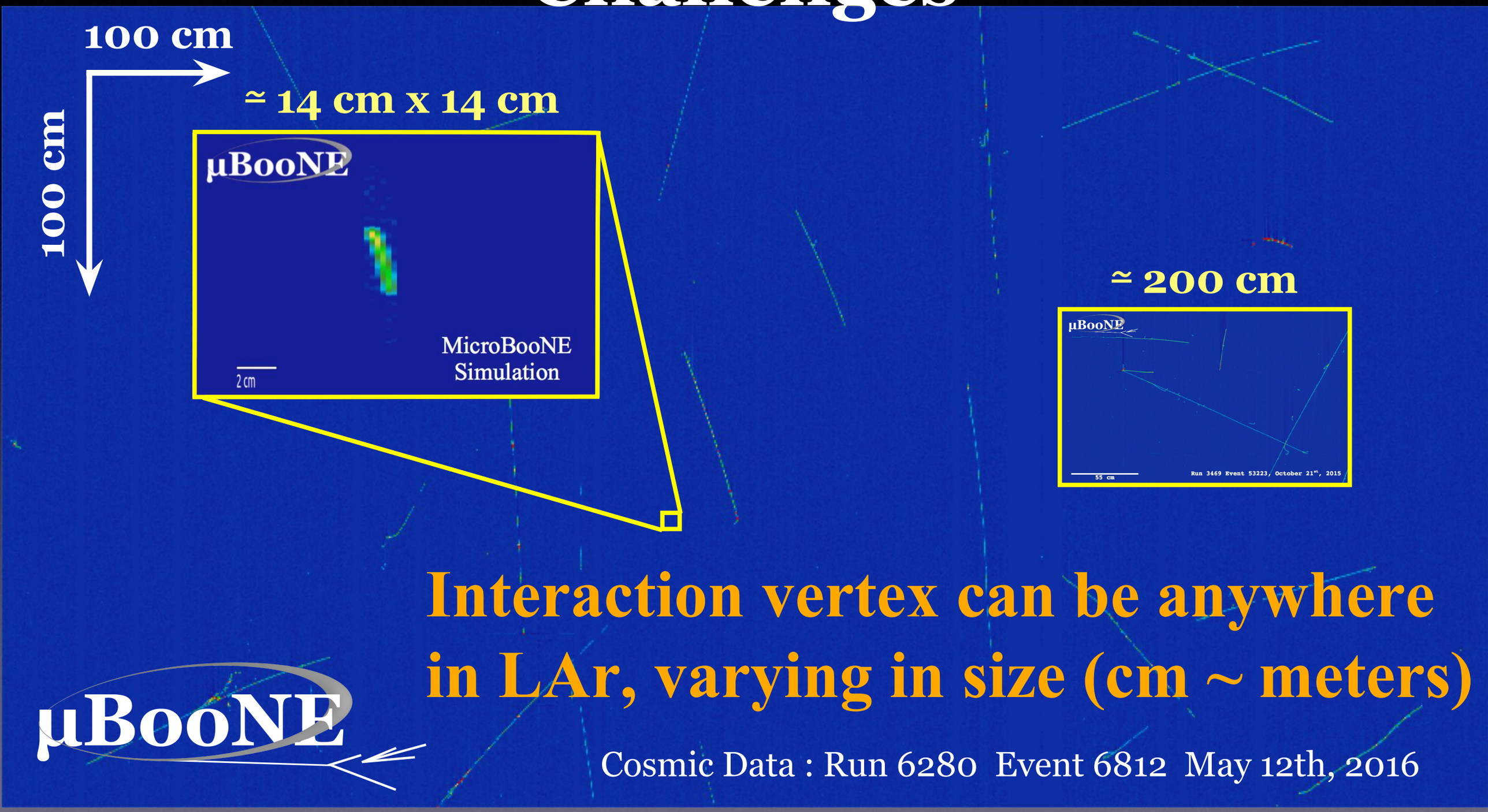
Particle ID Capability

Better ν identification background rejection

Challenges

Analysis Challenges

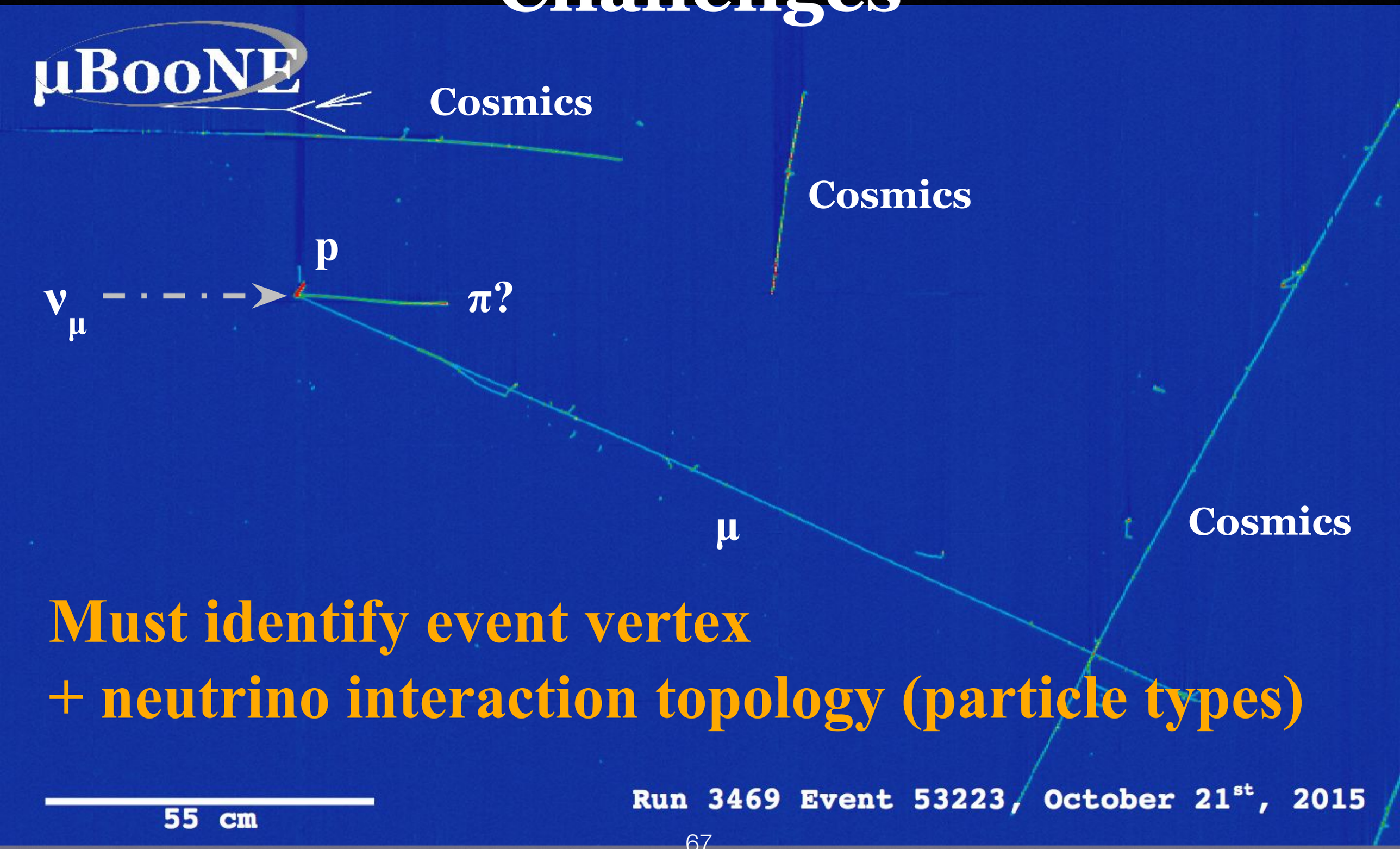
Analysis Challenges



Interaction vertex can be anywhere in LAr, varying in size (cm ~ meters)

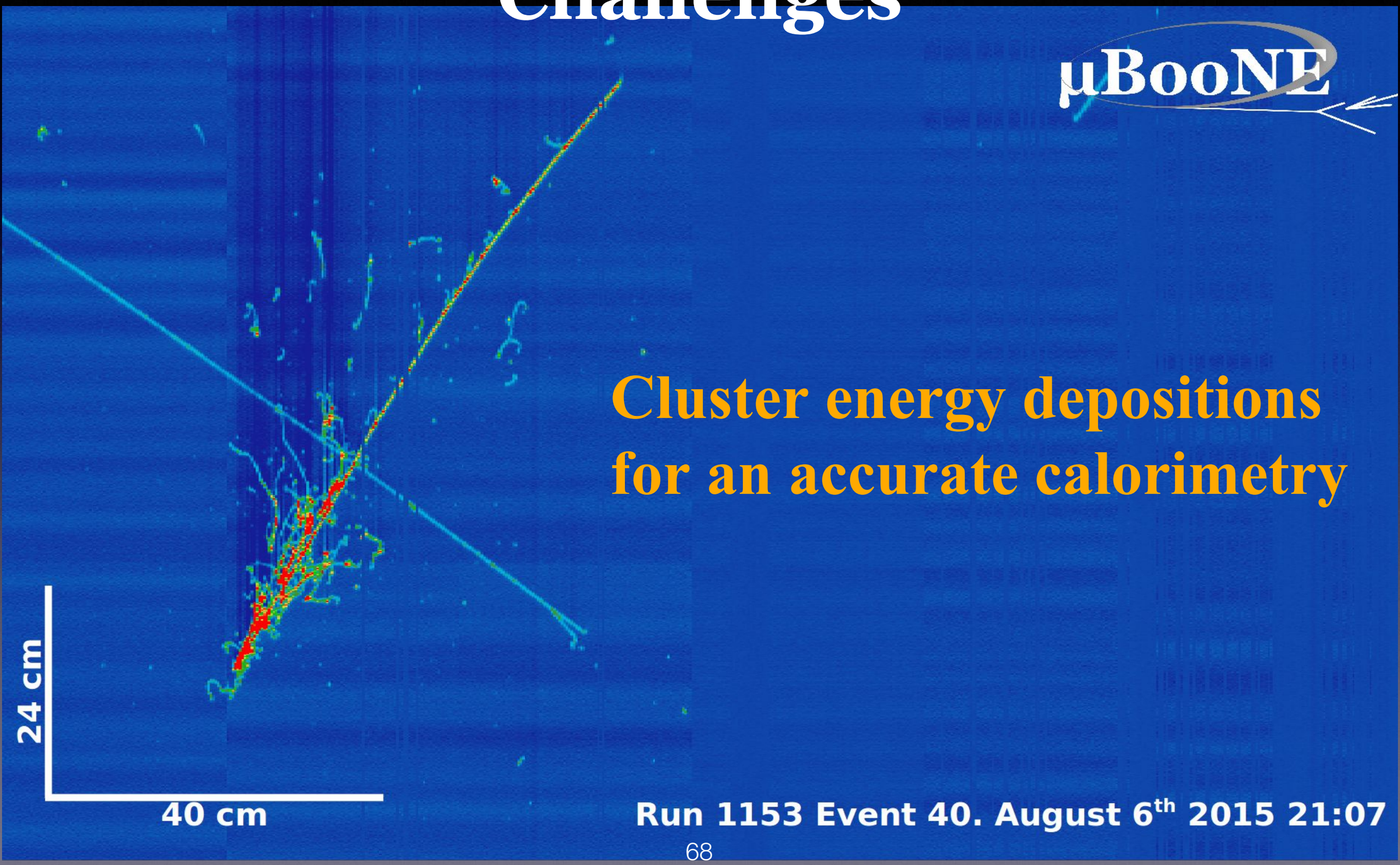
Cosmic Data : Run 6280 Event 6812 May 12th, 2016

Analysis Challenges



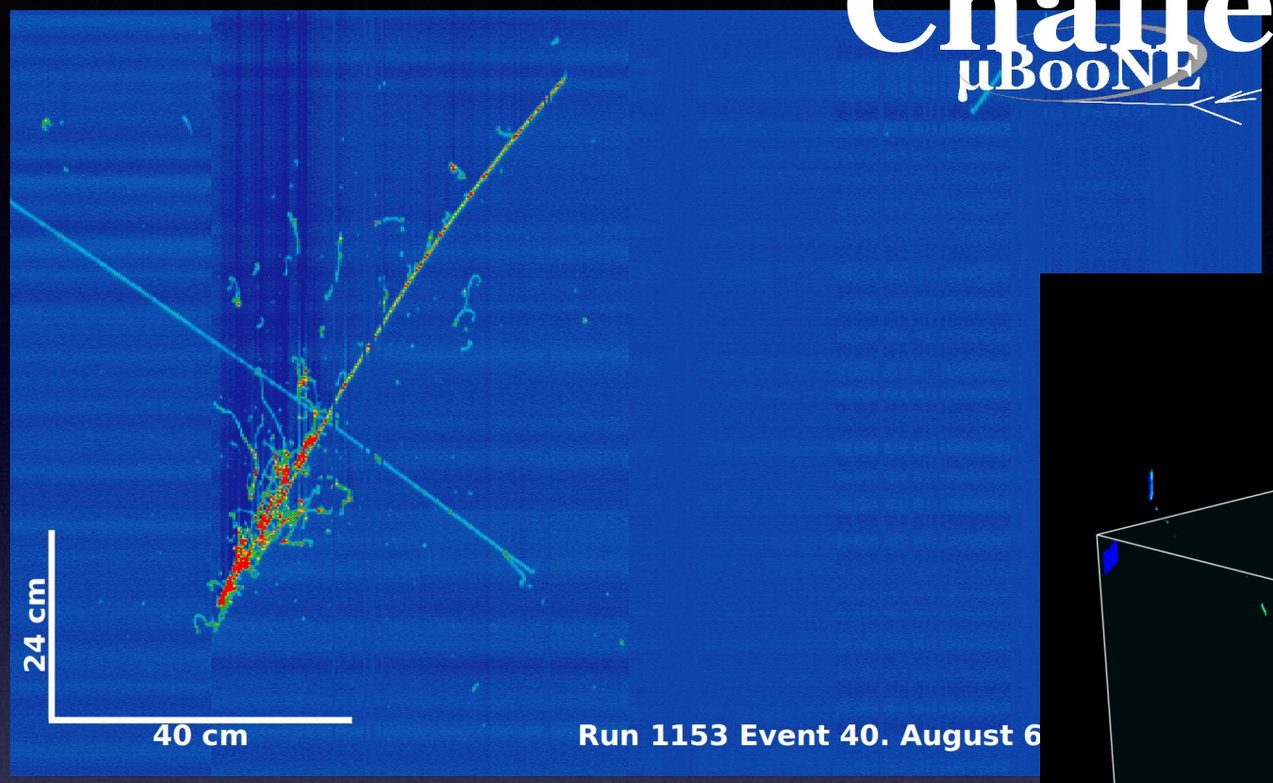
Must identify event vertex
+ neutrino interaction topology (particle types)

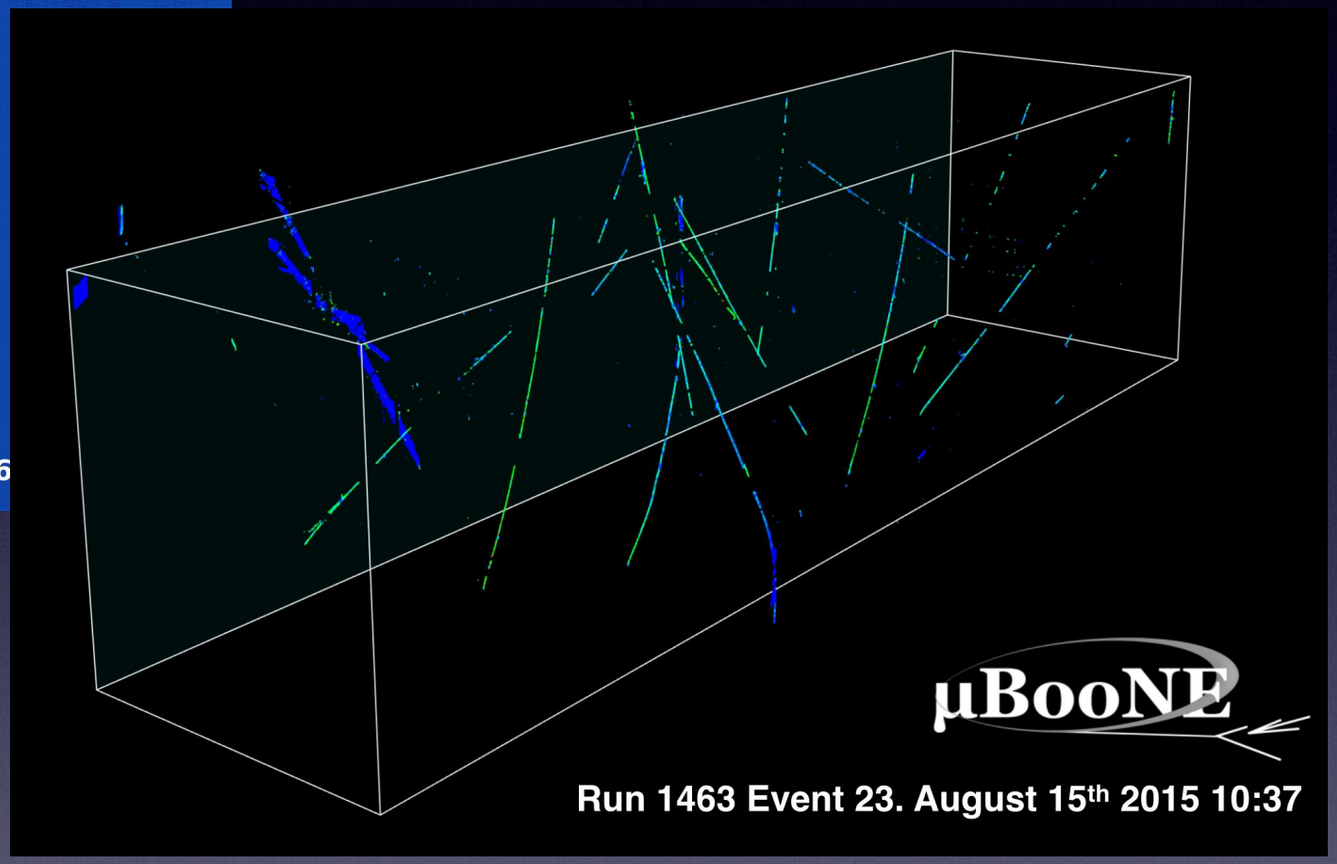
Analysis Challenges



Cluster energy depositions for an accurate calorimetry

Analysis Challenges





Deal with optical illusions in 2D projections + 3D pattern recognitions