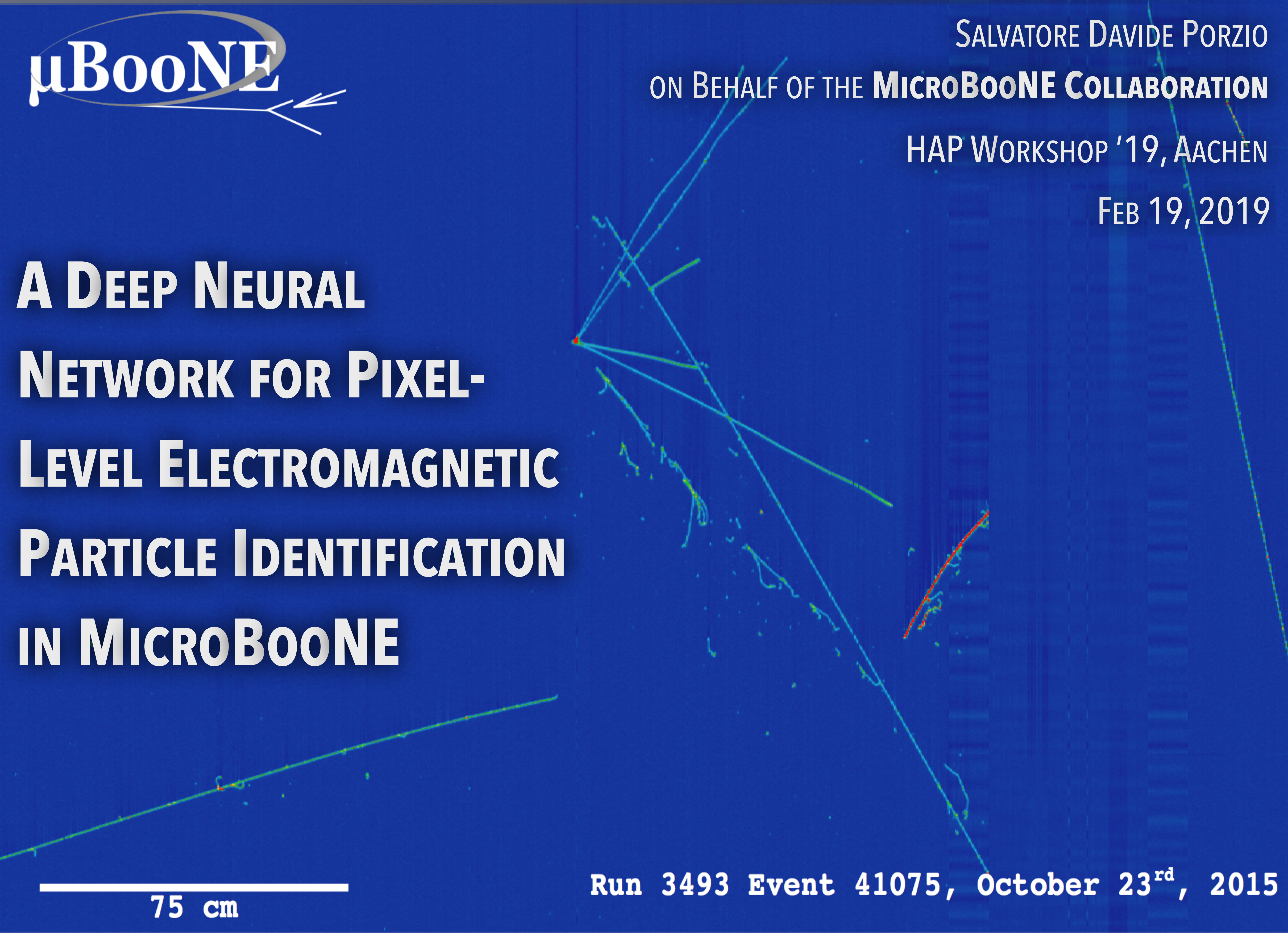
μBooNE

Salvatore Davide Porzio
on Behalf of the MicroBooNE Collaboration

HAP Workshop '19, Aachen
Feb 19, 2019

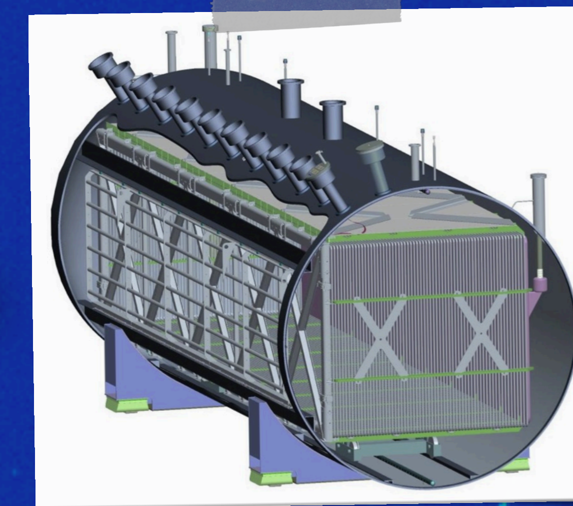
A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in MicroBooNE



µBooNE

MicroBooNE

Neutrino detector with excellent imaging capabilities

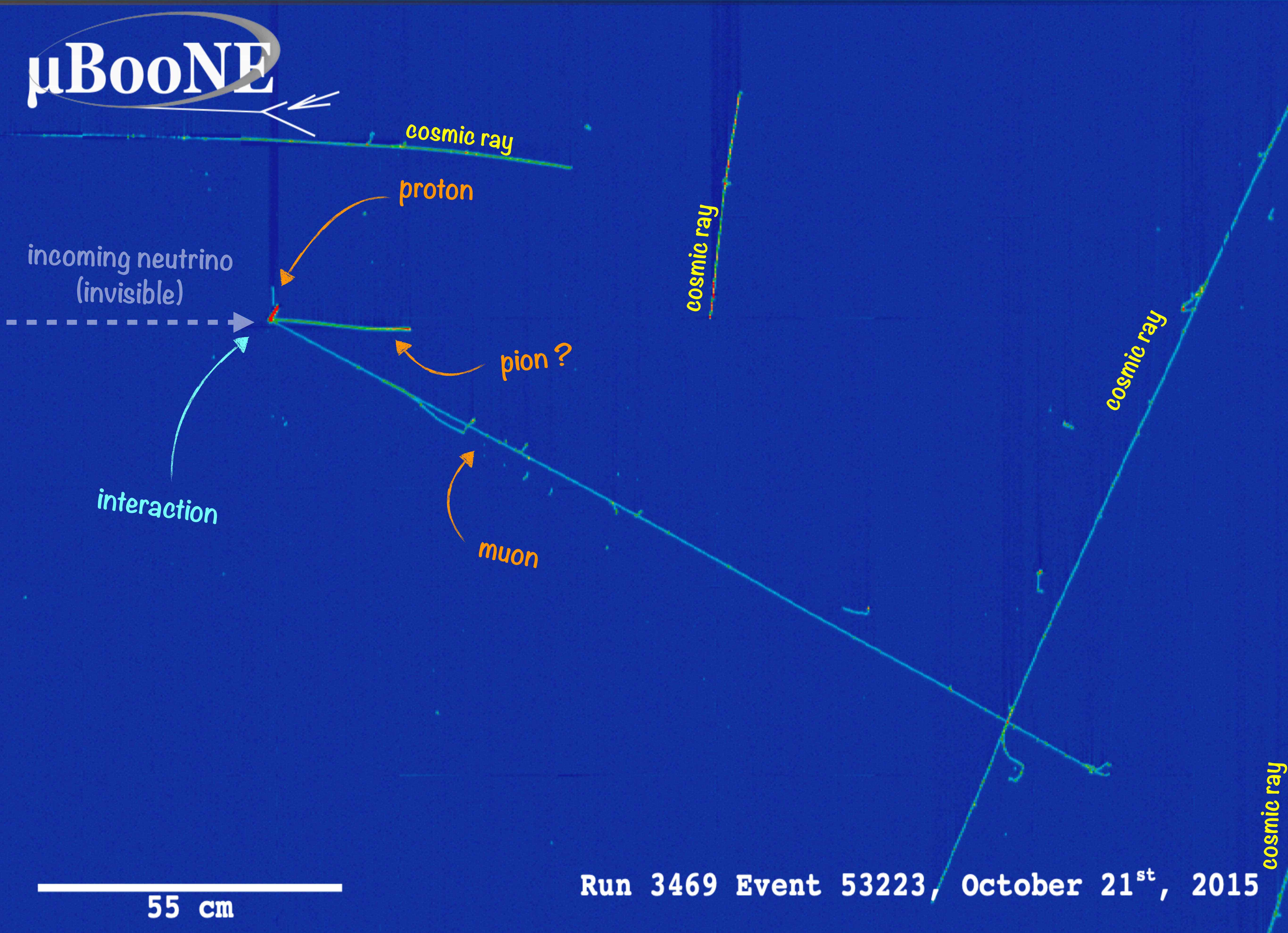


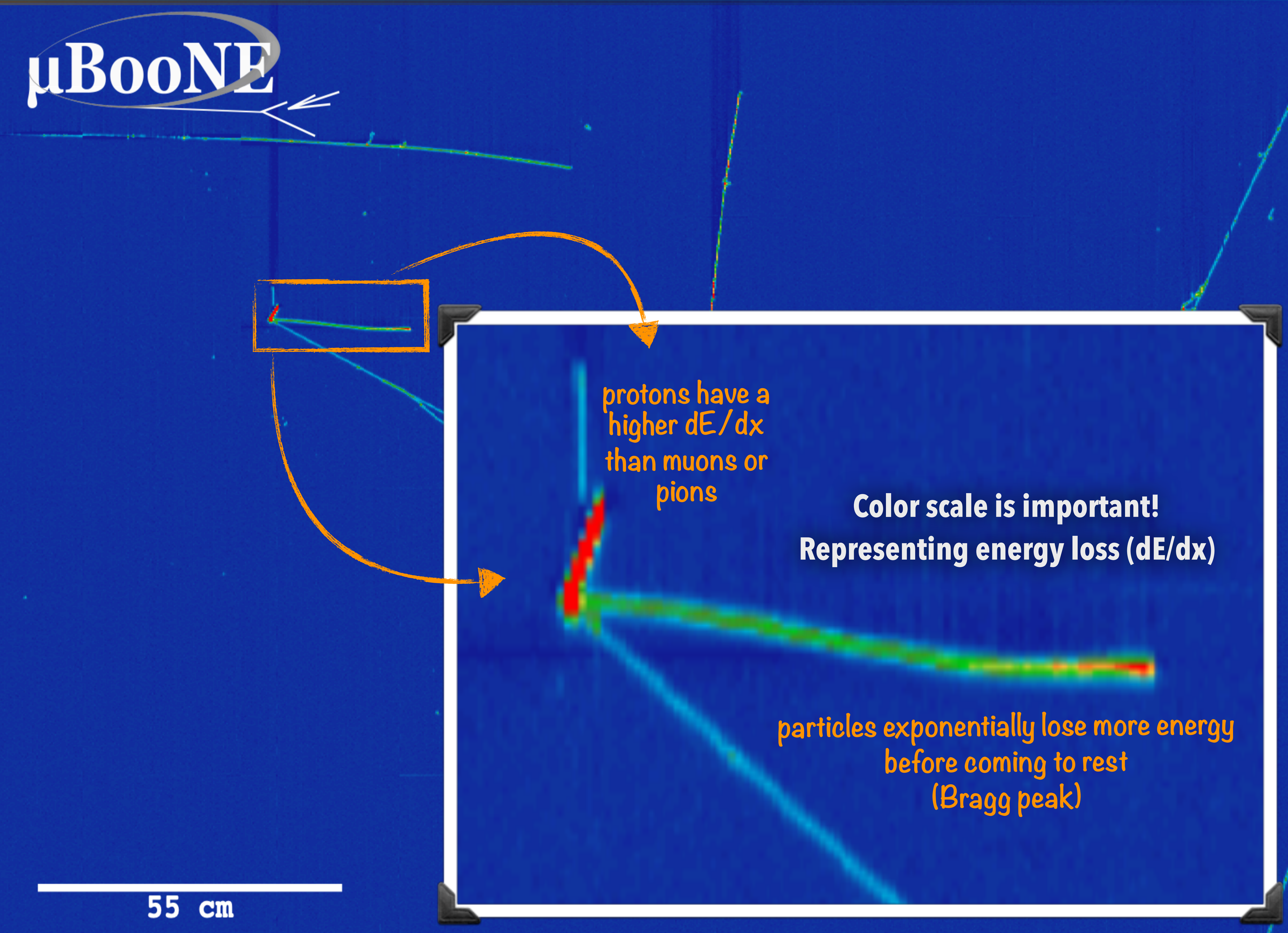
Lots of details on location and amount of charge created in the detector

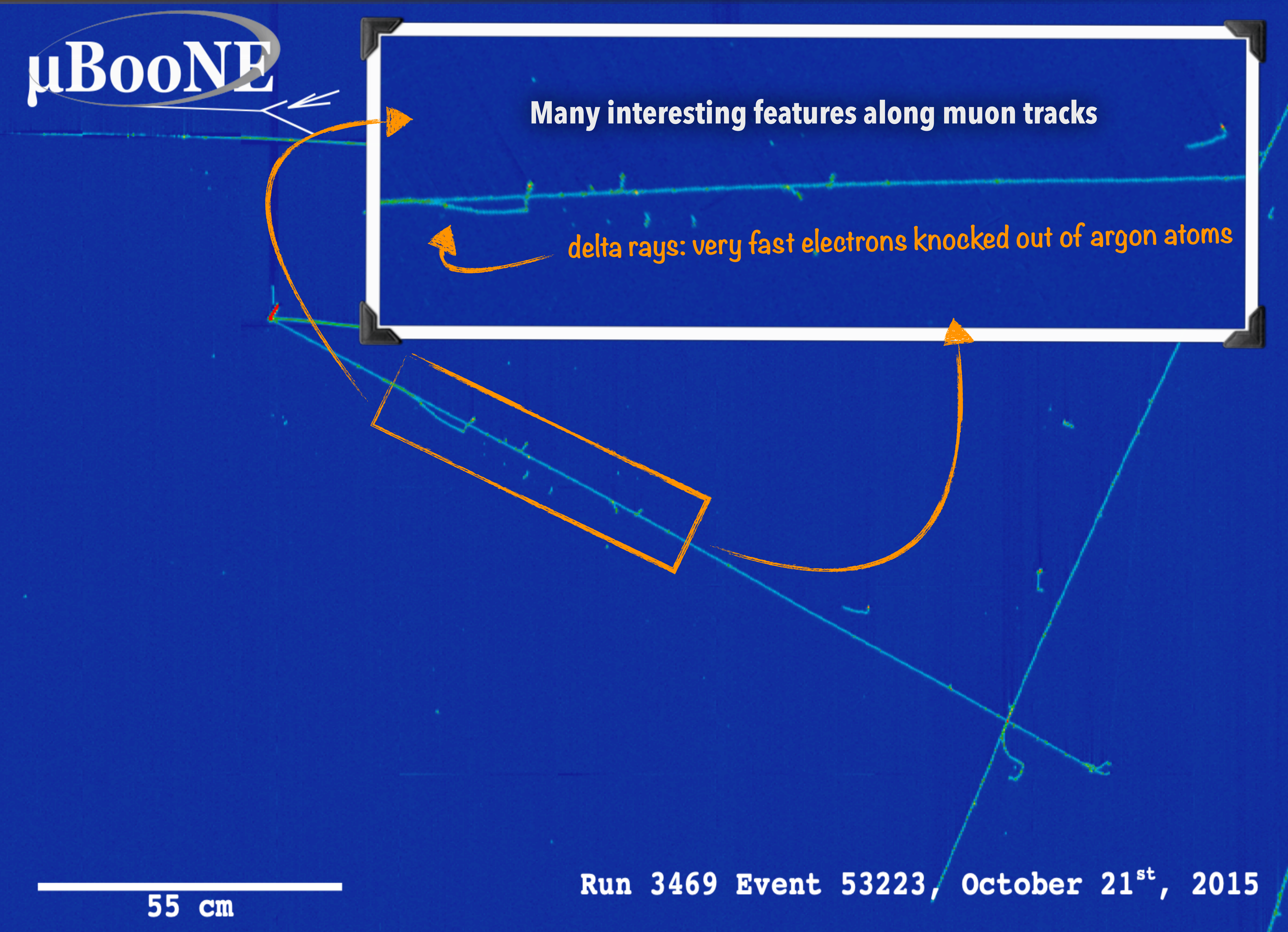
Many details but information density is sparse

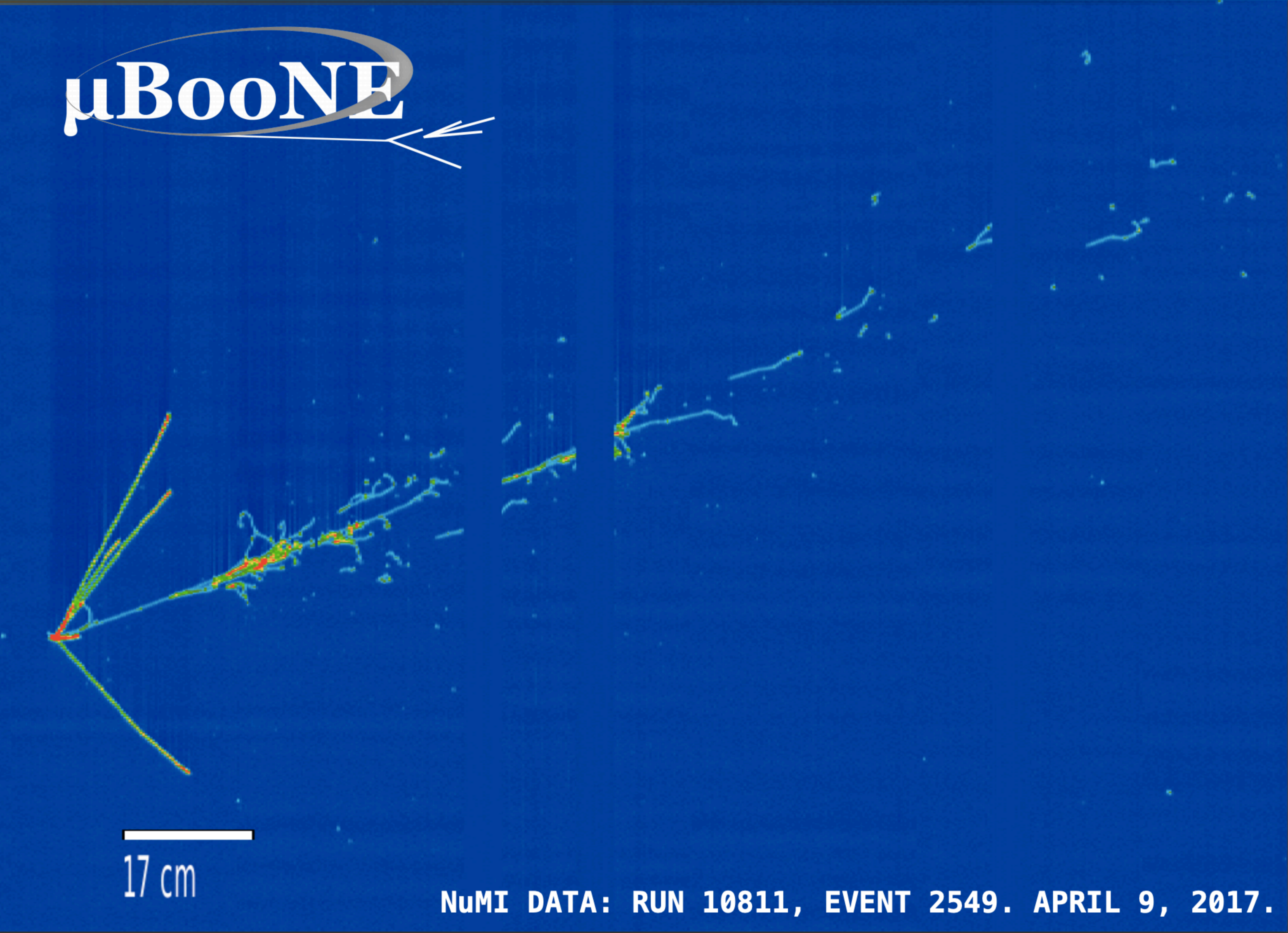
55 cm

Run 3469 Event 53223, October 21st, 2015

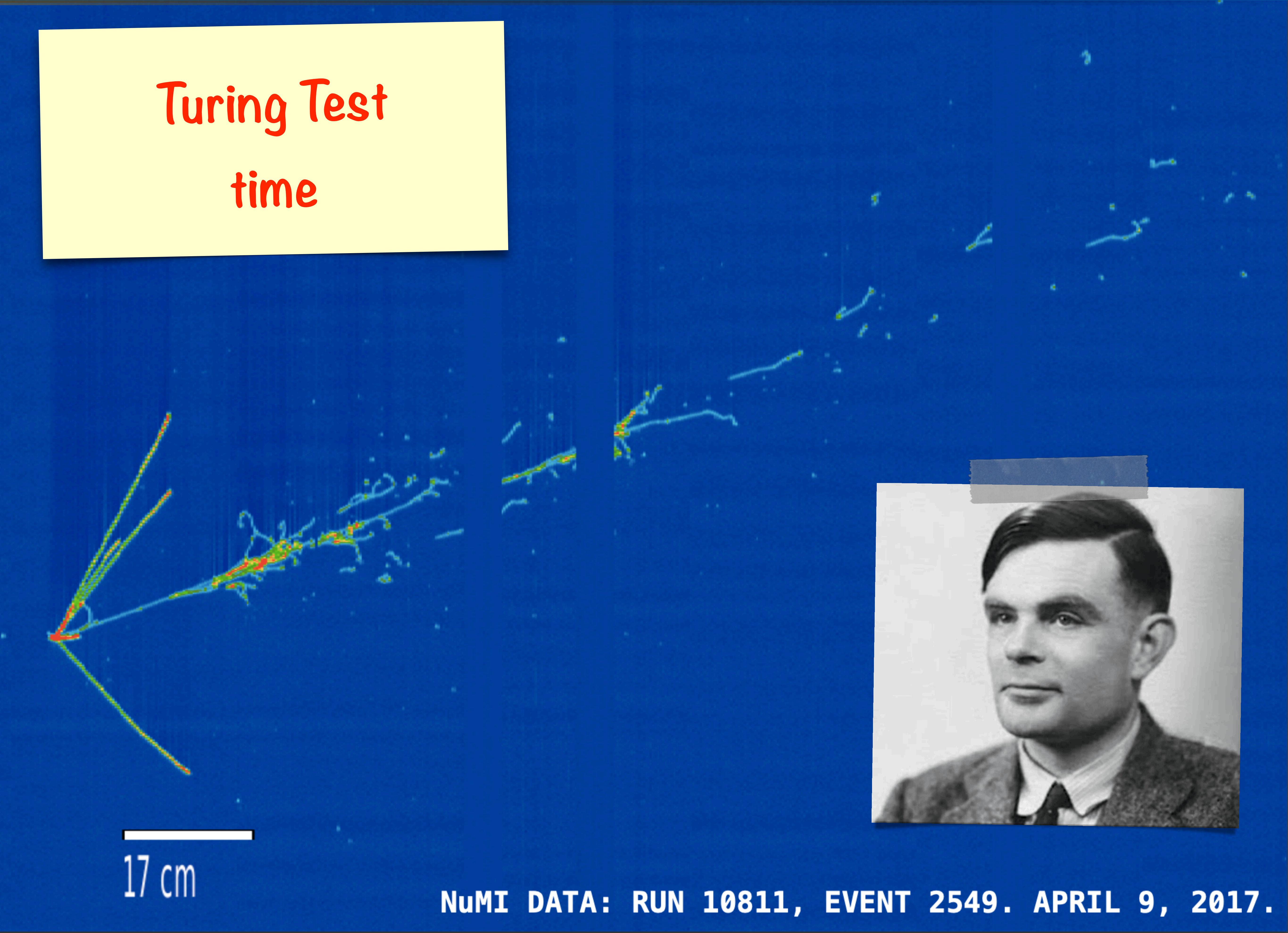

µBooNE
cosmic ray
proton
cosmic ray
incoming neutrino
(invisible)
pion ?
cosmic ray
interaction
muon
cosmic ray
55 cm
Run 3469 Event 53223, October 21st, 2015


µBooNE
protons have a higher dE/dx than muons or pions
Color scale is important!
Representing energy loss (dE/dx)
particles exponentially lose more energy before coming to rest
(Bragg peak)
55 cm

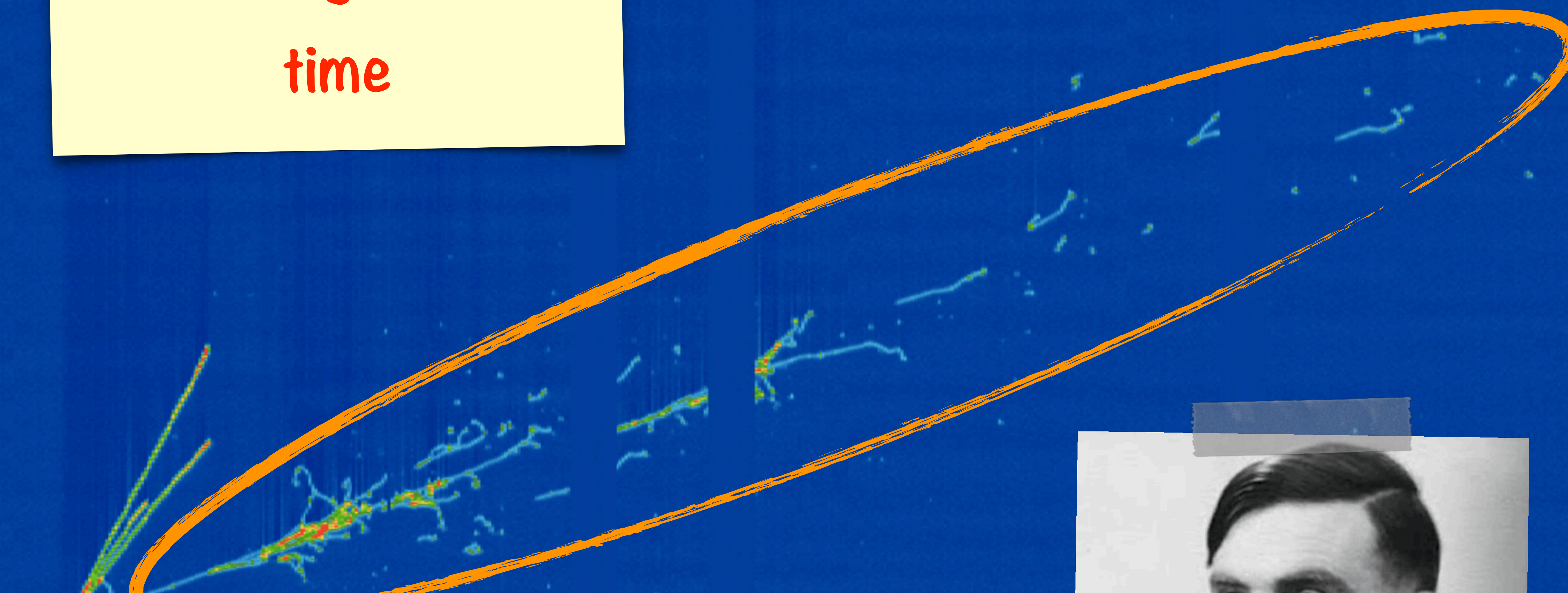

µBooNE
Many interesting features along muon tracks
delta rays: very fast electrons knocked out of argon atoms
55 cm
Run 3469 Event 53223, October 21st, 2015


µBooNE
17 cm
NuMI DATA: RUN 10811, EVENT 2549. APRIL 9, 2017.

Turing Test time



Turing Test time



NuMI DATA: RUN 10811, EVENT 2549. APRIL 9, 2017.

Unlike p, µ and π, creating tracks
EM particles (such as e or γ) will produce shower-like objects

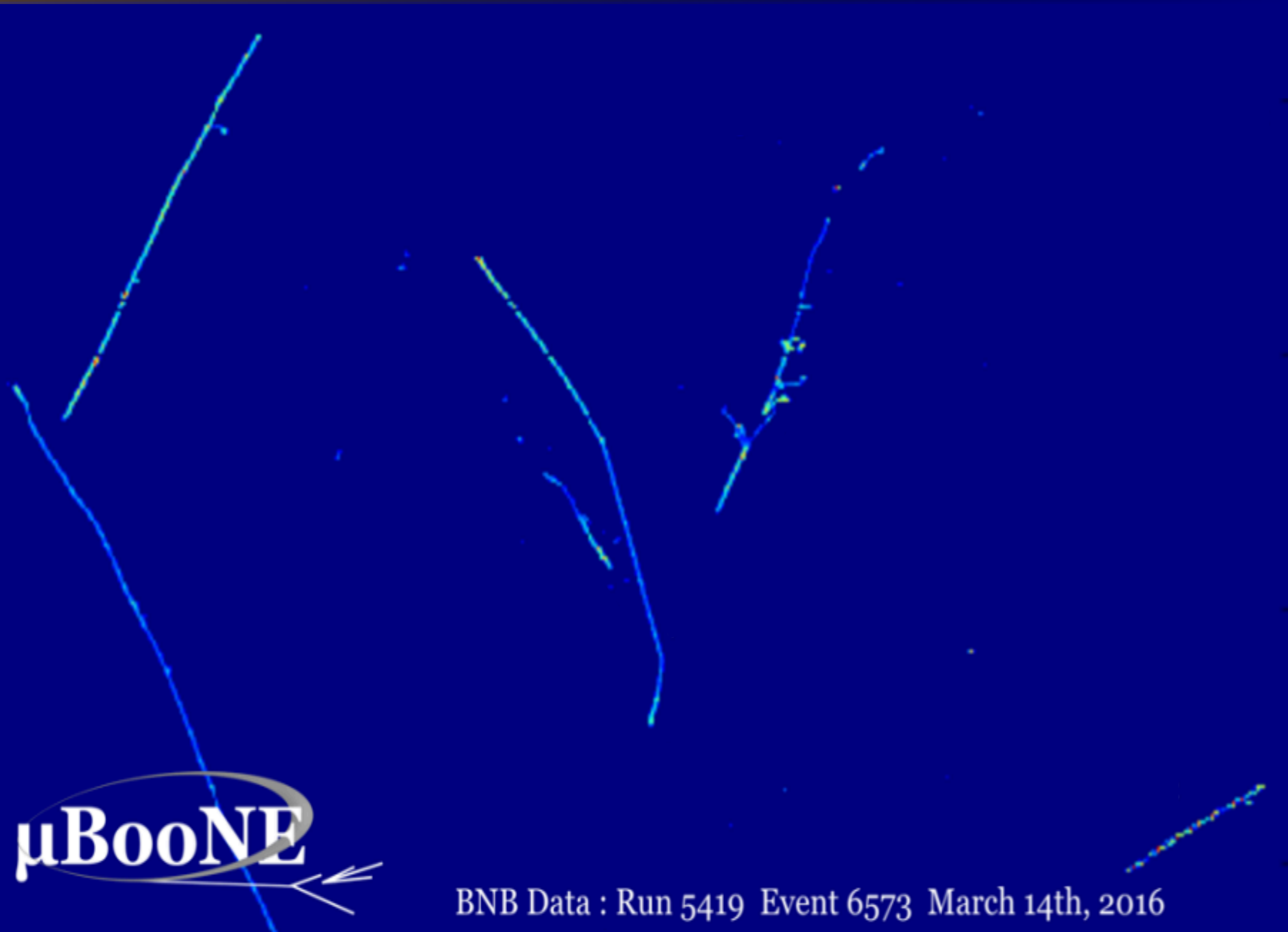
Distinguishing tracks from showers
is extremely important for MicroBooNE

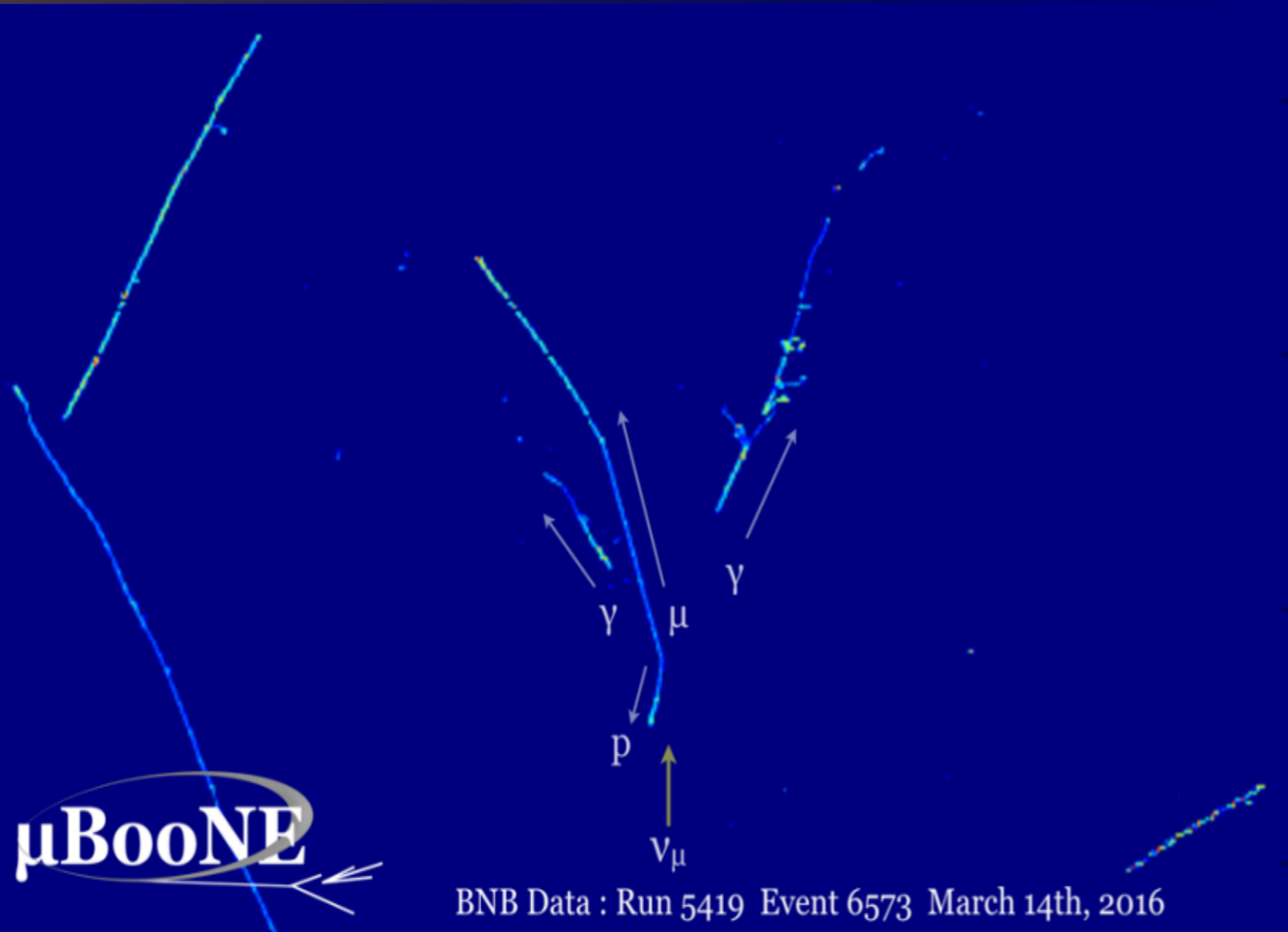
Allows for neutrino flavour ID

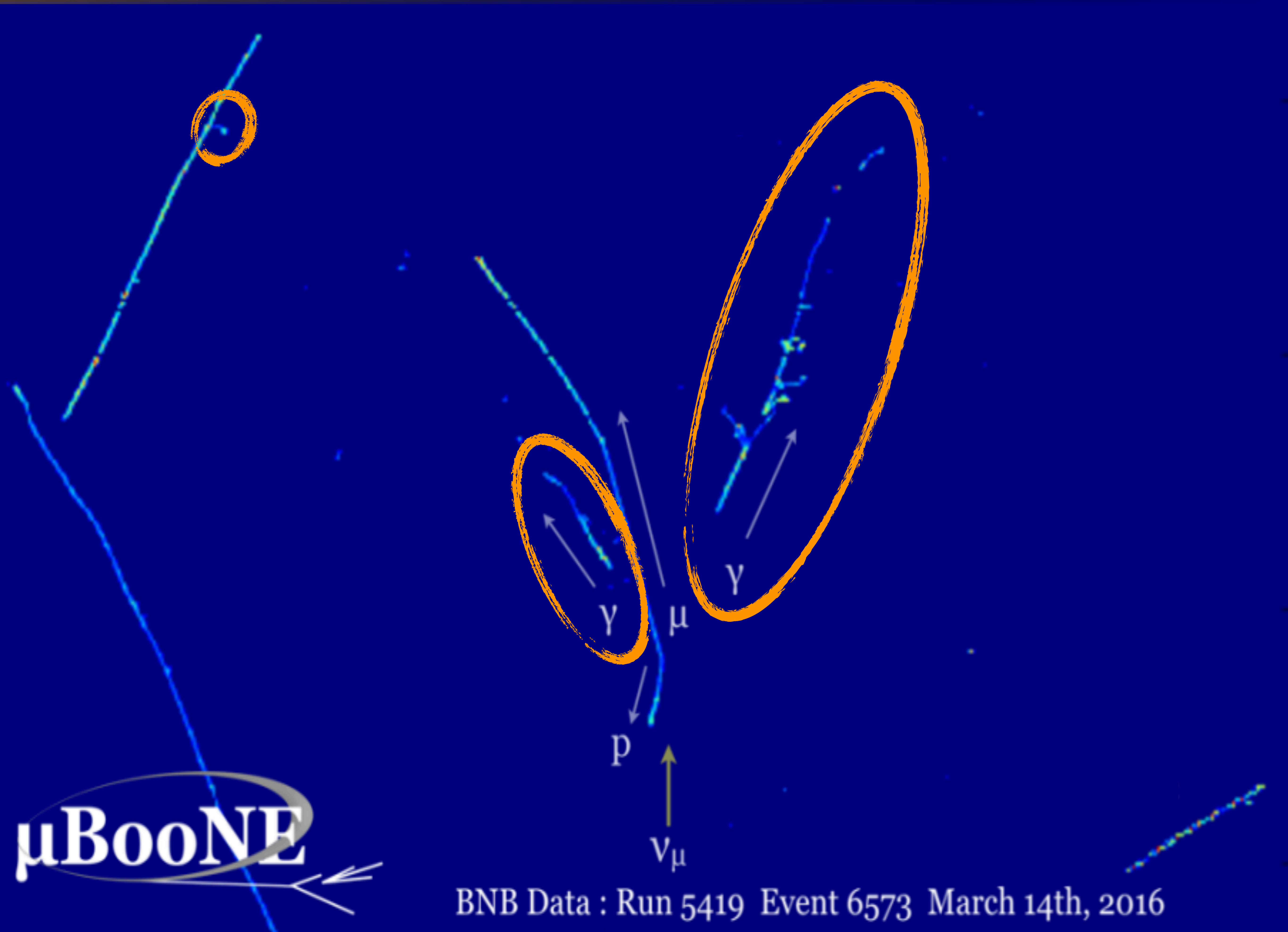
Unlike p, µ and π, creating tracks
EM particles (such as e or γ) will produce shower-like objects

CHALLENGE:

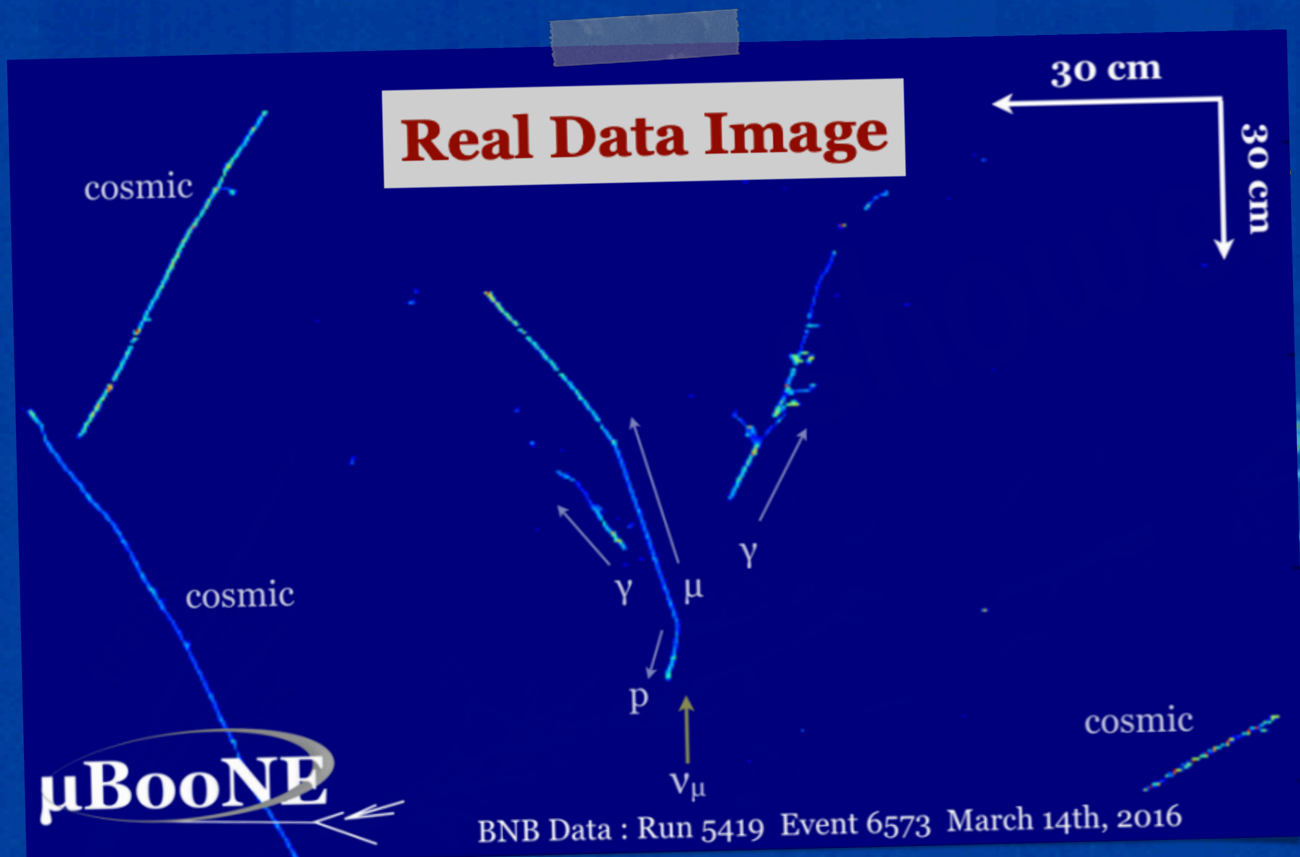
Can you tell tracks and showers apart?

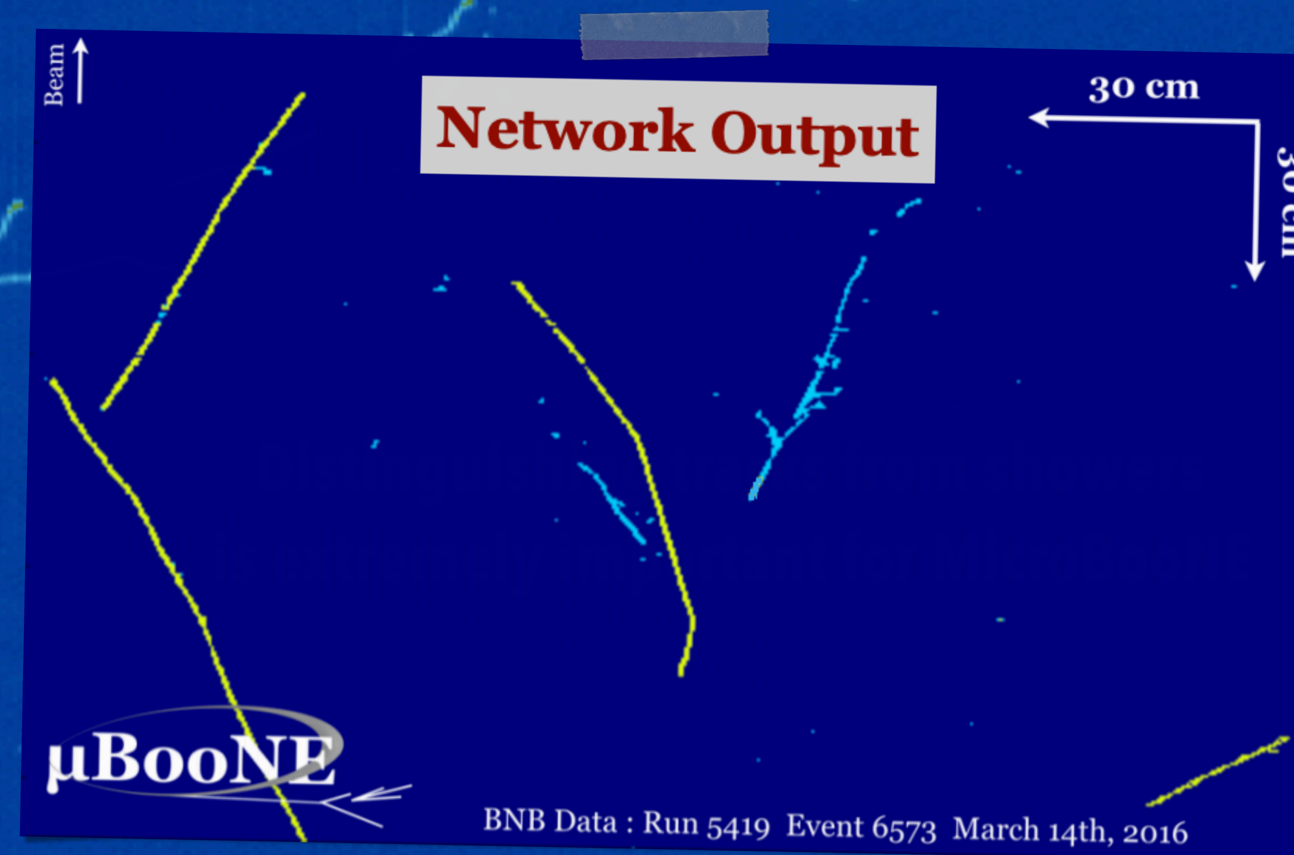

μBooNE
BNB Data : Run 5419 Event 6573 March 14th, 2016

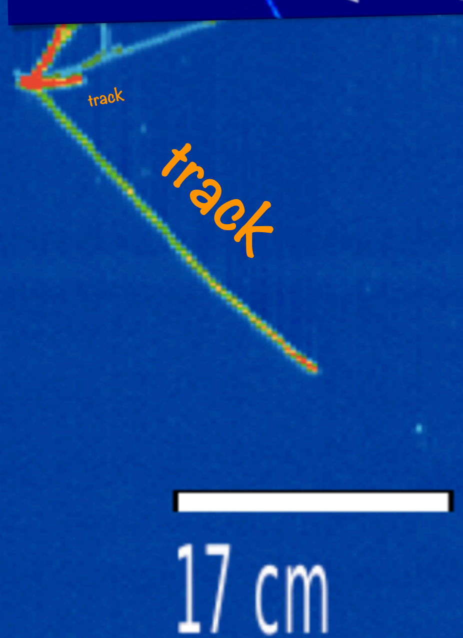

γ
μ
γ
p
ν_μ
μBooNE
BNB Data : Run 5419 Event 6573 March 14th, 2016


γ
γ
µ
p
ν_μ
µBooNE
BNB Data : Run 5419 Event 6573 March 14th, 2016

Unlike p, µ and π, creating tracks
EM particles (such as e or γ) will produce shower-like objects



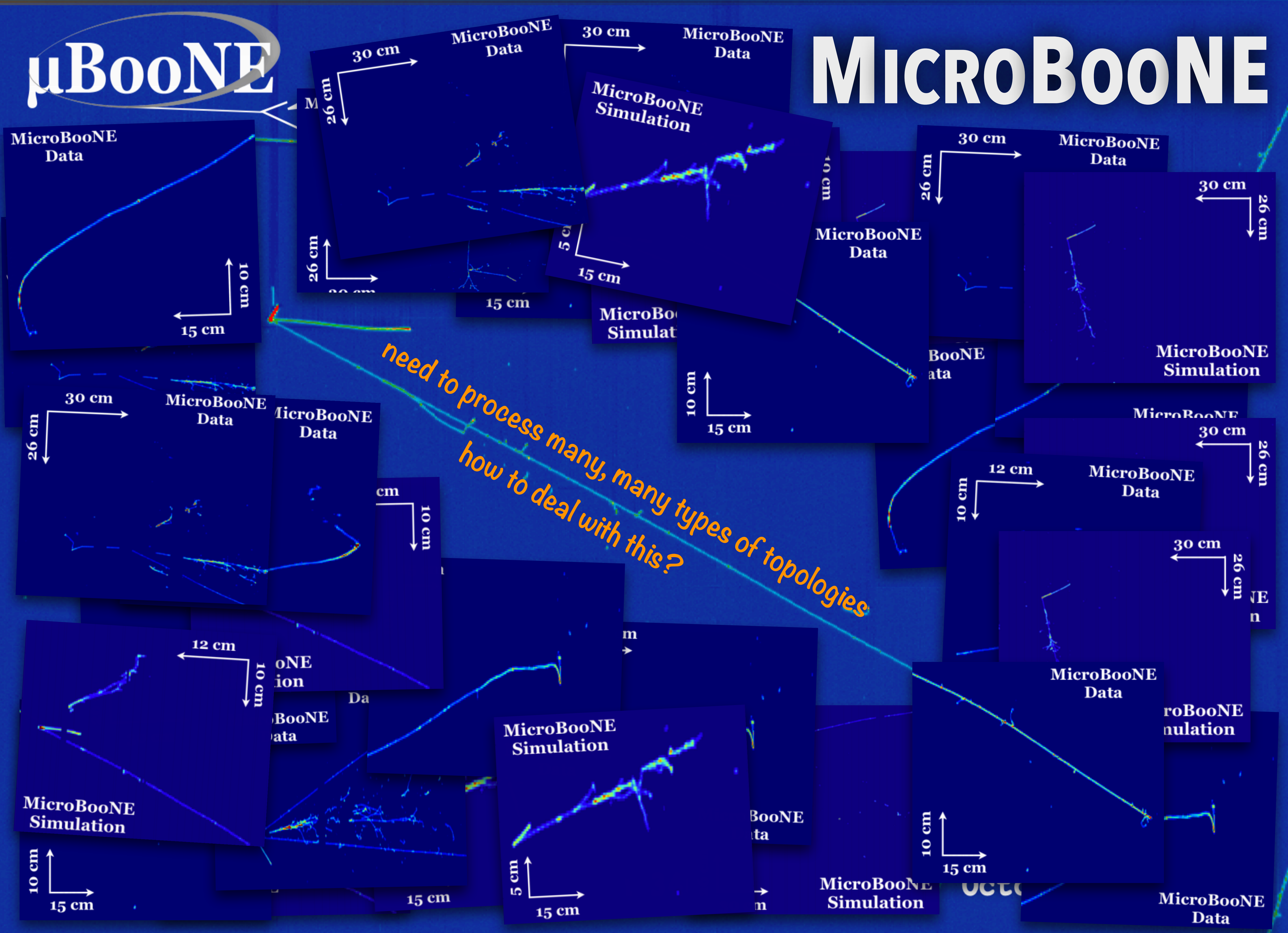




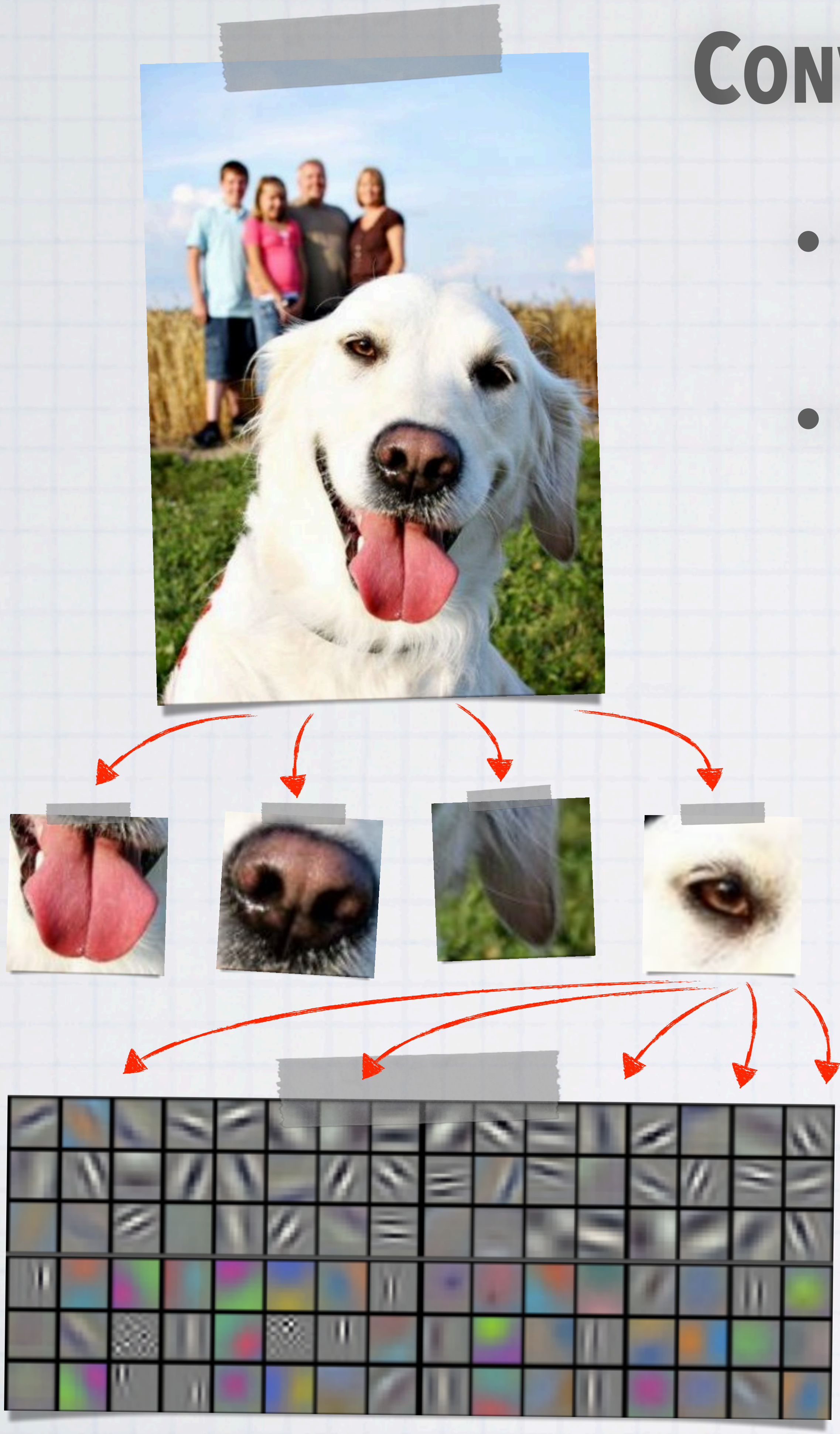
Machine Learning extremely adept at this type of tasks

NuMI DATA: RUN 10811, EVENT 2549. APRIL 9, 2017.

MicroBooNE

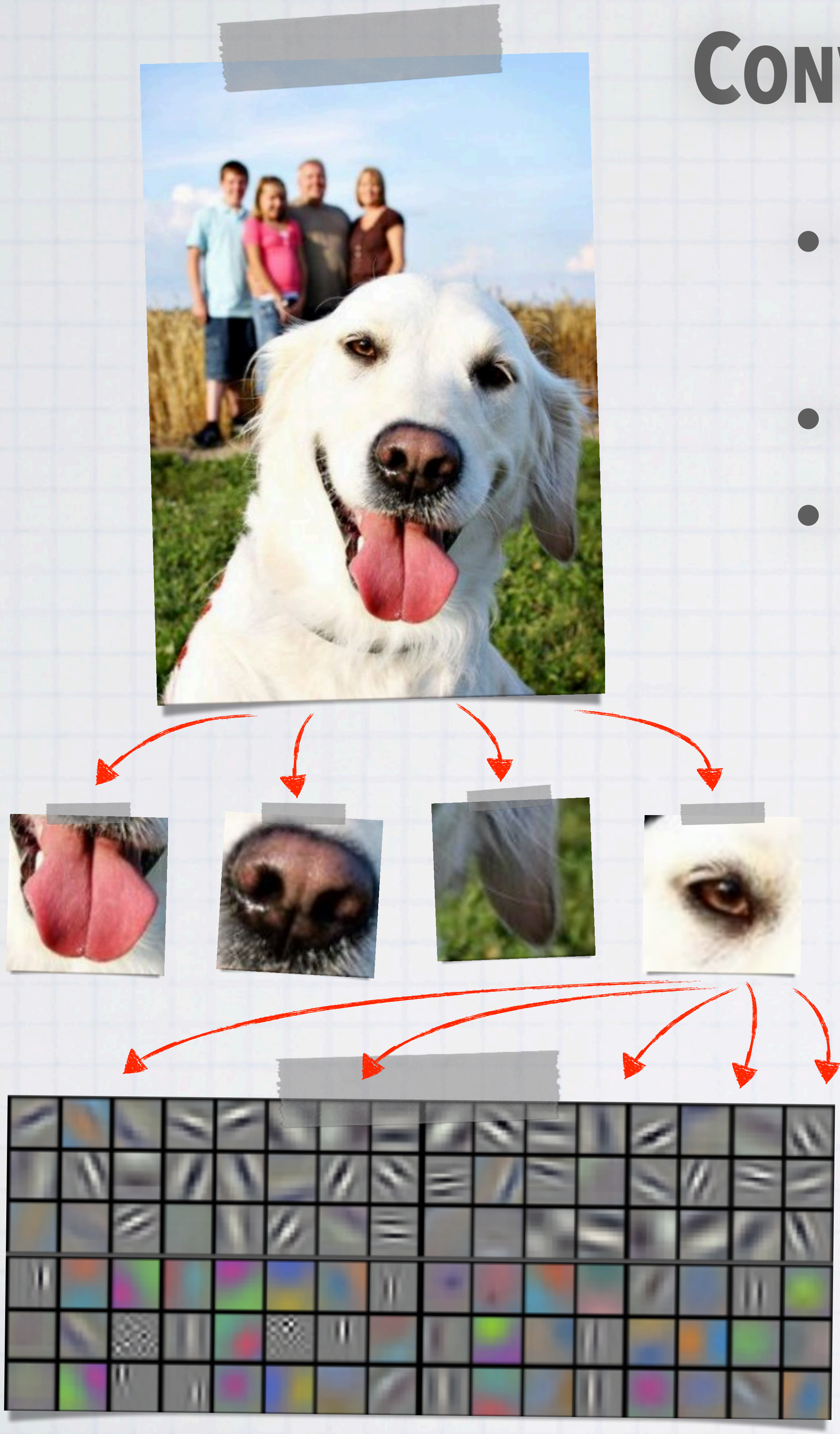

need to process many, many types of topologies
how to deal with this?

Convolutional Neural Networks

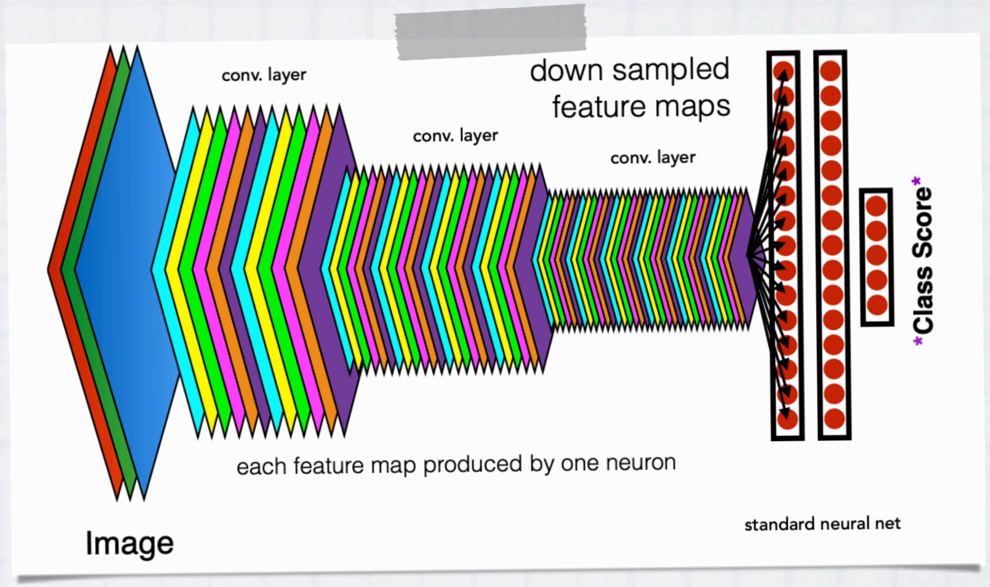


- **Convolutional Neural Network** (CNN) are very adept at image analysis.
- **Scalable** and **generalizable** technique.

Convolutional Neural Networks



- **Convolutional Neural Network** (CNN) are very adept at image analysis.
- **Scalable** and **generalizable** technique.
- CNNs can look for **local, translation-invariant patterns** among inputs and decompose an image into **collection of small features**.



ideal for image classification tasks

Convolutional Neural Networks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Published by IOP Publishing for Sissa Medialab
Received: December 20, 2016
Revised: February 11, 2017
Accepted: February 28, 2017
Published: March 14, 2017

Convolutional neural networks applied to neutrino events in a liquid argon time projection chamber

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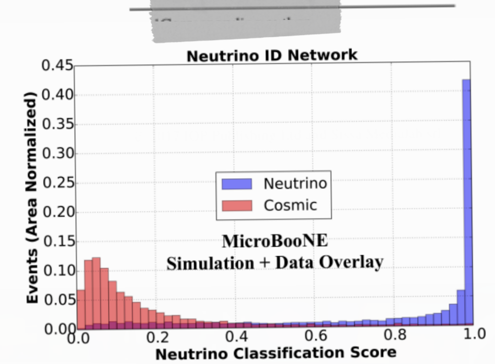
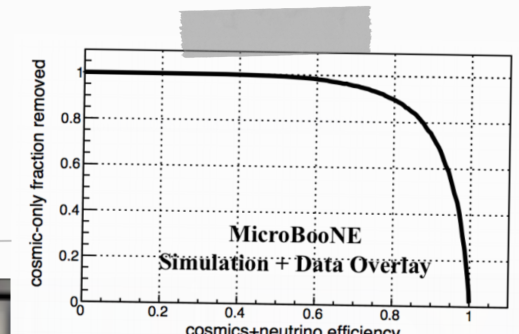
2017 JINST 12 P03011





Con
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Sca
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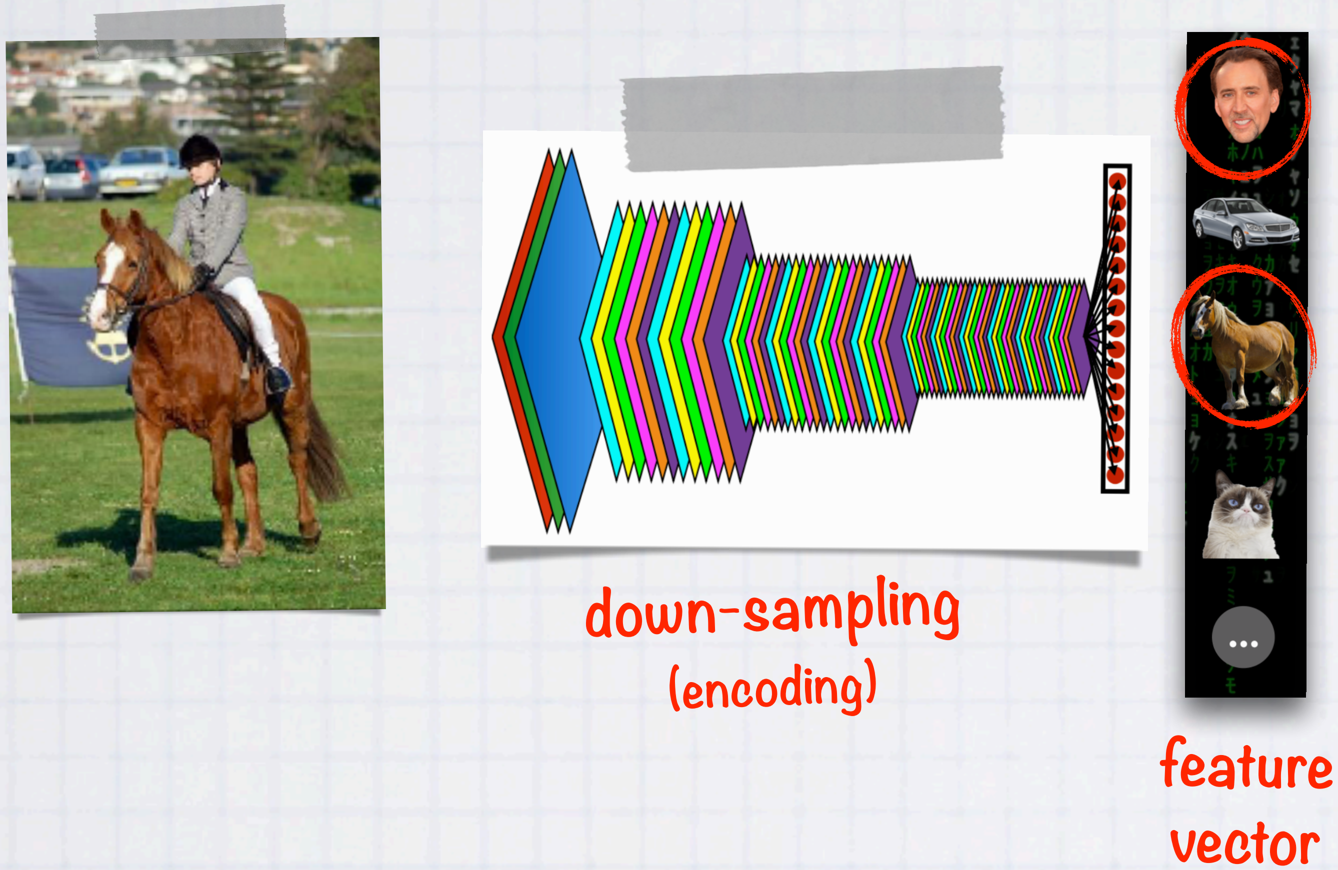
Obtained excellent results applying CNN to MicroBooNE data

Check out our CNN paper:
https://arxiv.org/abs/1611.05531

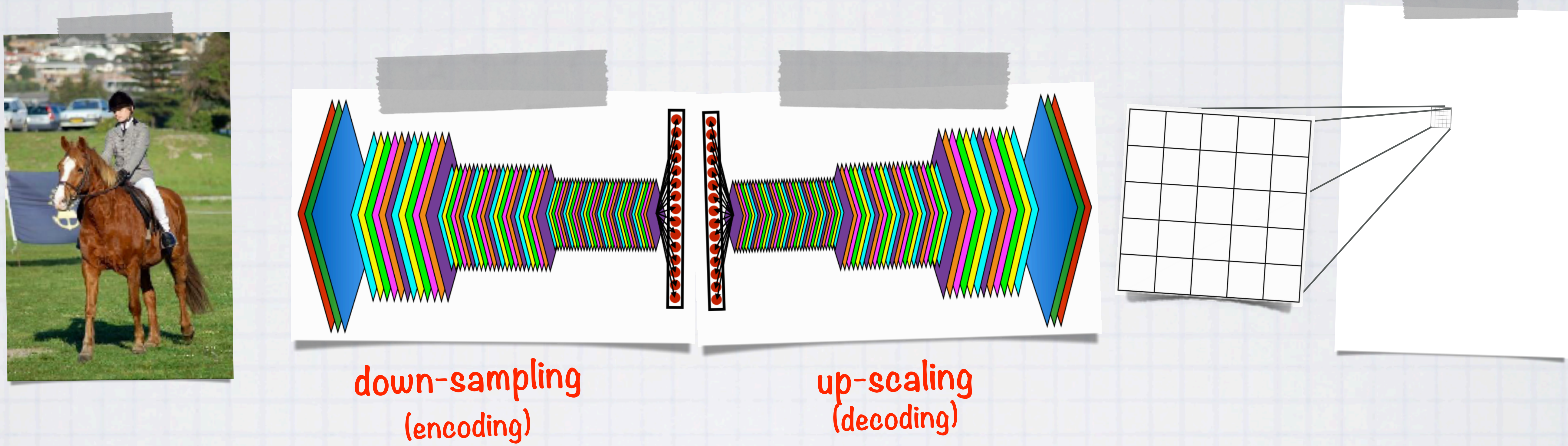
Semantic Seg-men-tation

- We want to do more than saying there are certain things in our images.



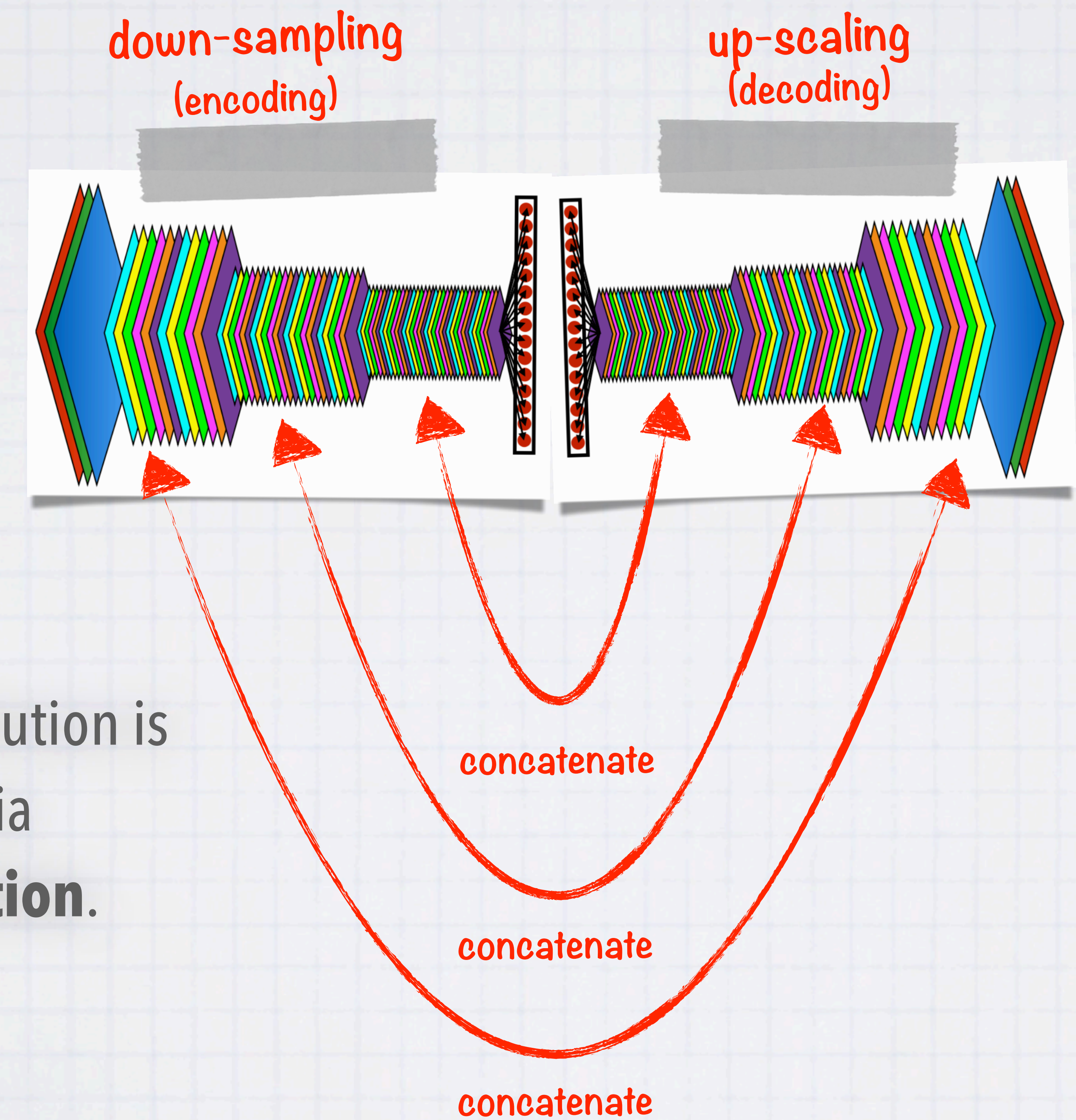
SEMANTIC SEG-MEN-TATION

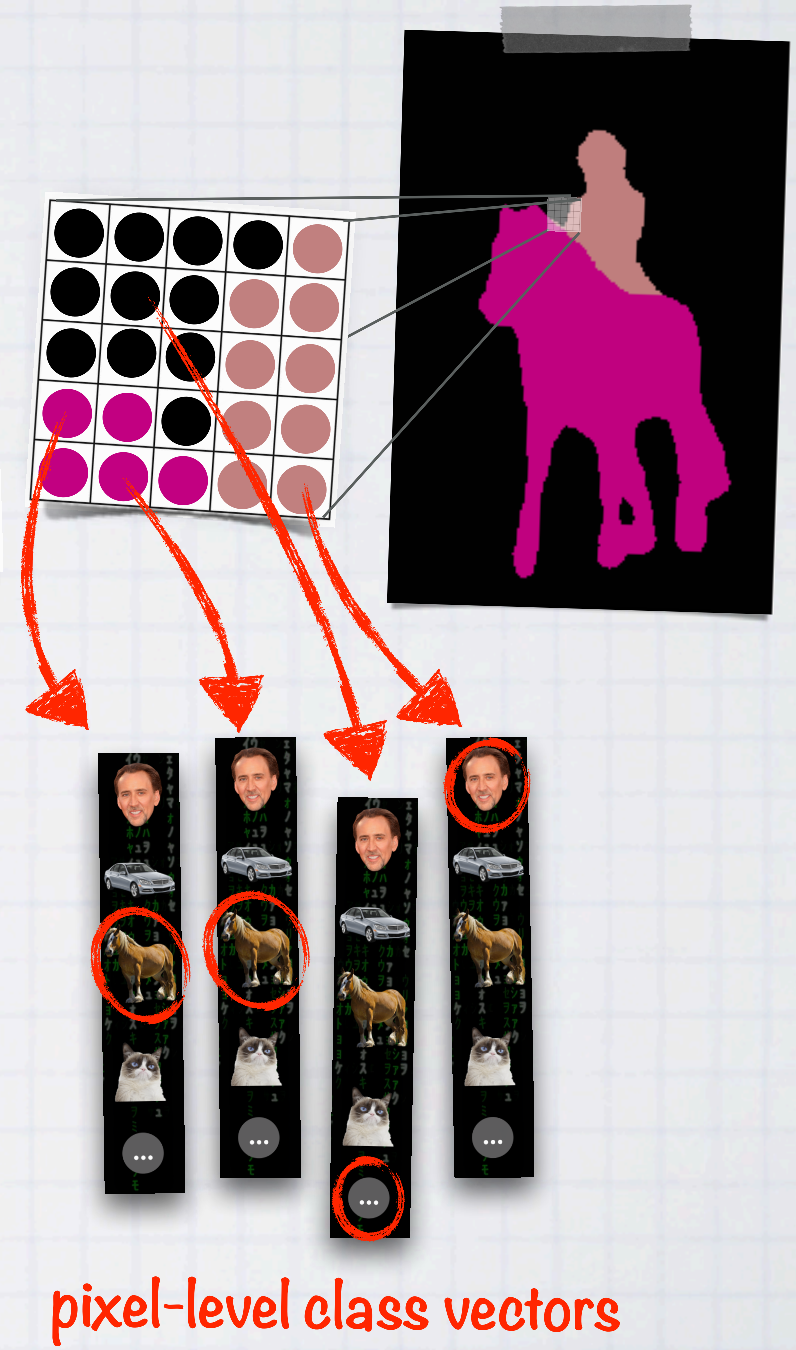
- A step forward is to have a **classification vector** at the **pixel level**, rather than for the overall image.
- We need to go from the **down-sampled feature maps** to **up-scaled images.**



Semantic Segmentation

- Key component of SS network is **encoding-decoding path information flow**.
- Allowing **information** about **spatial resolution** to **flow** from encoding path (best possible resolution) to decoding path.

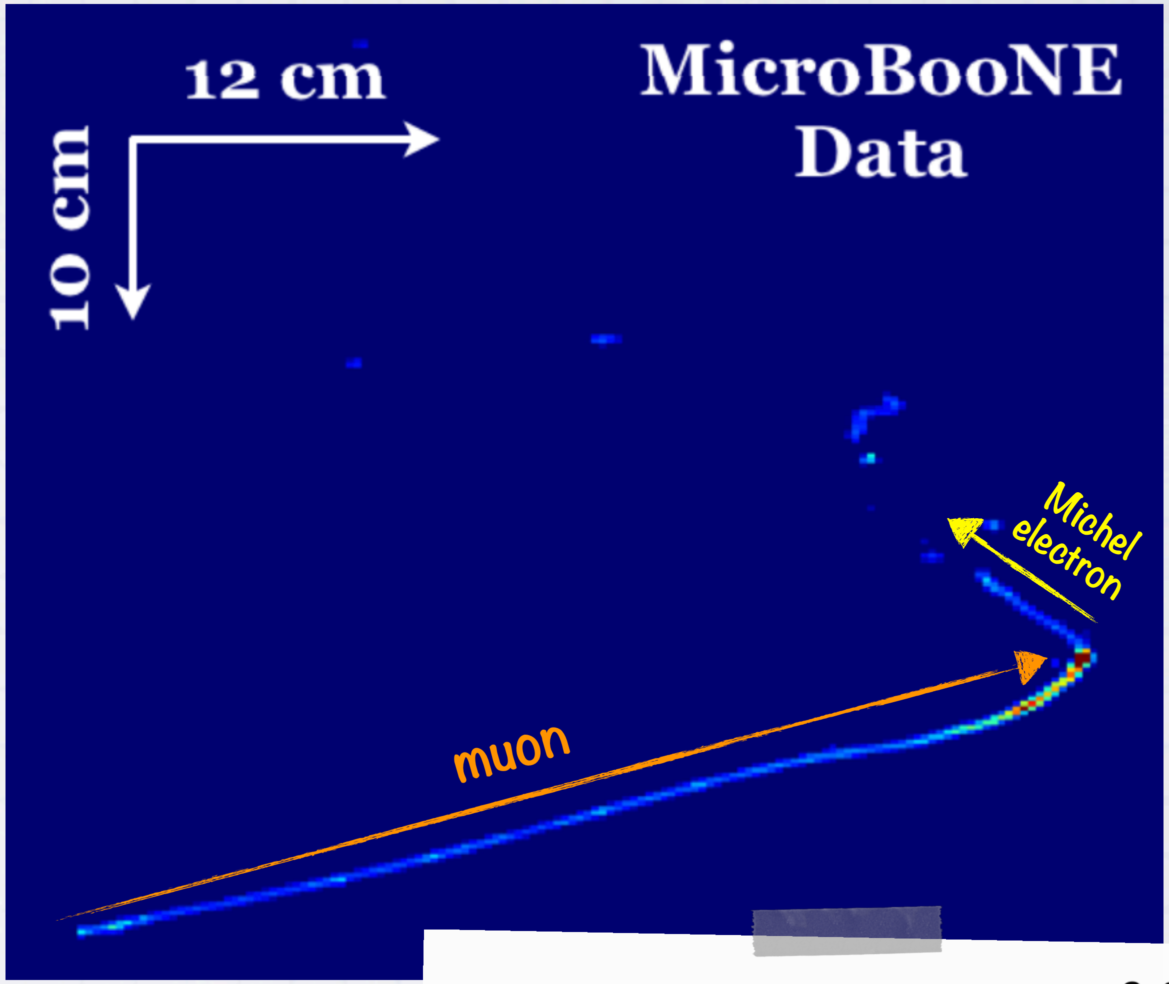


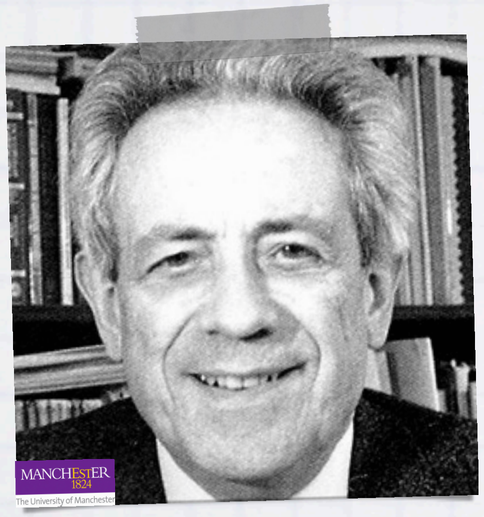


- Spatial resolution is recovered via **concatenation**.

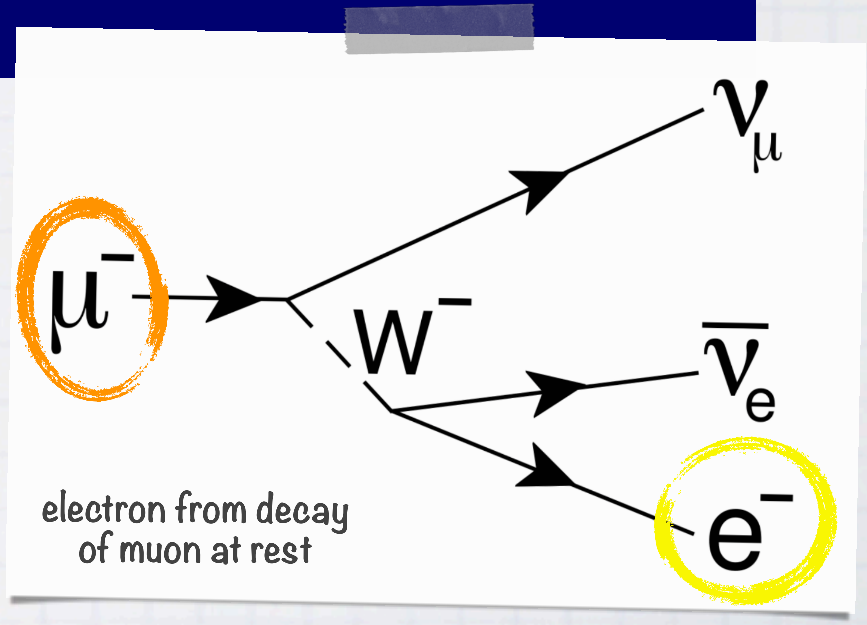
Performance in Data

- There is **no truth label** for real data.
- Performing tests comparing **(human) physicist prediction vs. network prediction** in both data and simulation.
- Using **Michel electrons**.



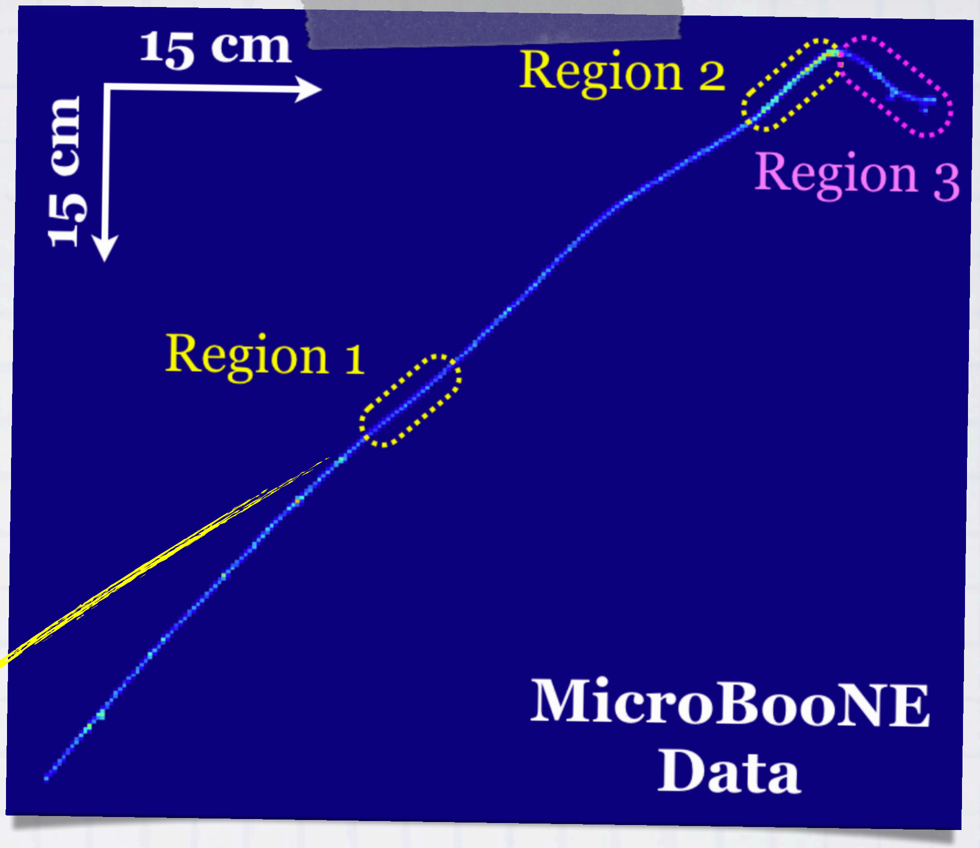


Louis Michel

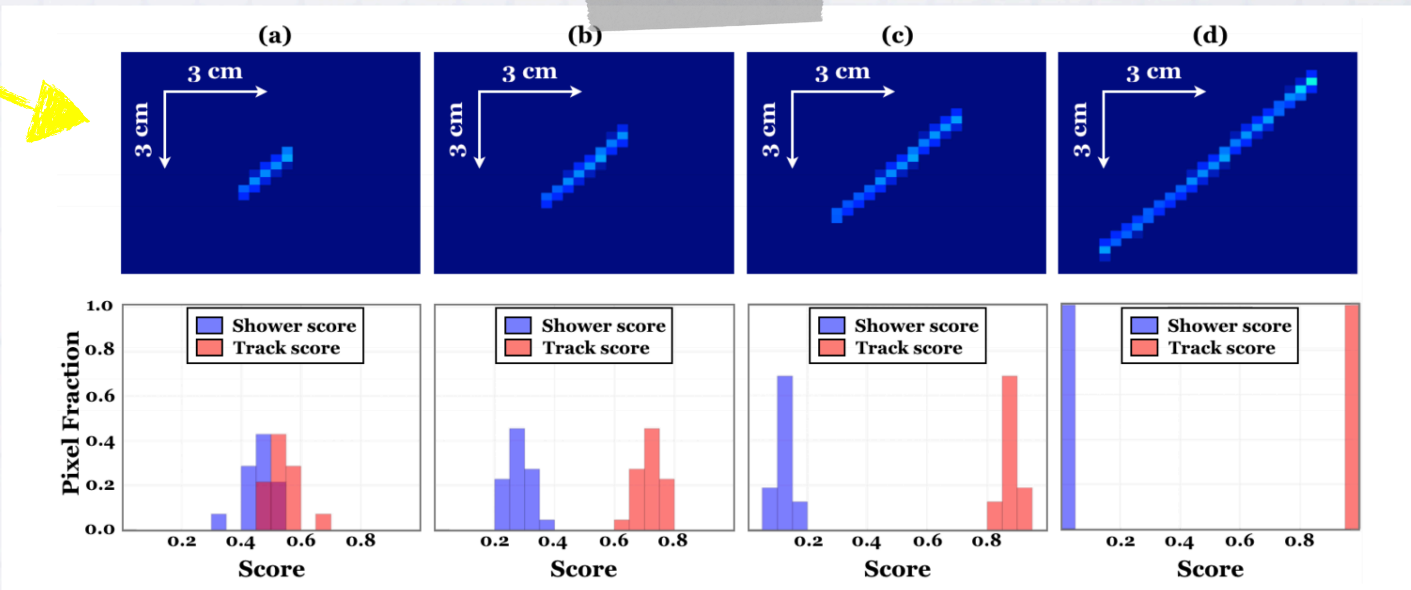


Inter-Pixel Correlation

- **Masking** all pixels outside of characteristics regions.
- **Qualitatively** verifying **particle topology** is effectively used as a metric by the network.



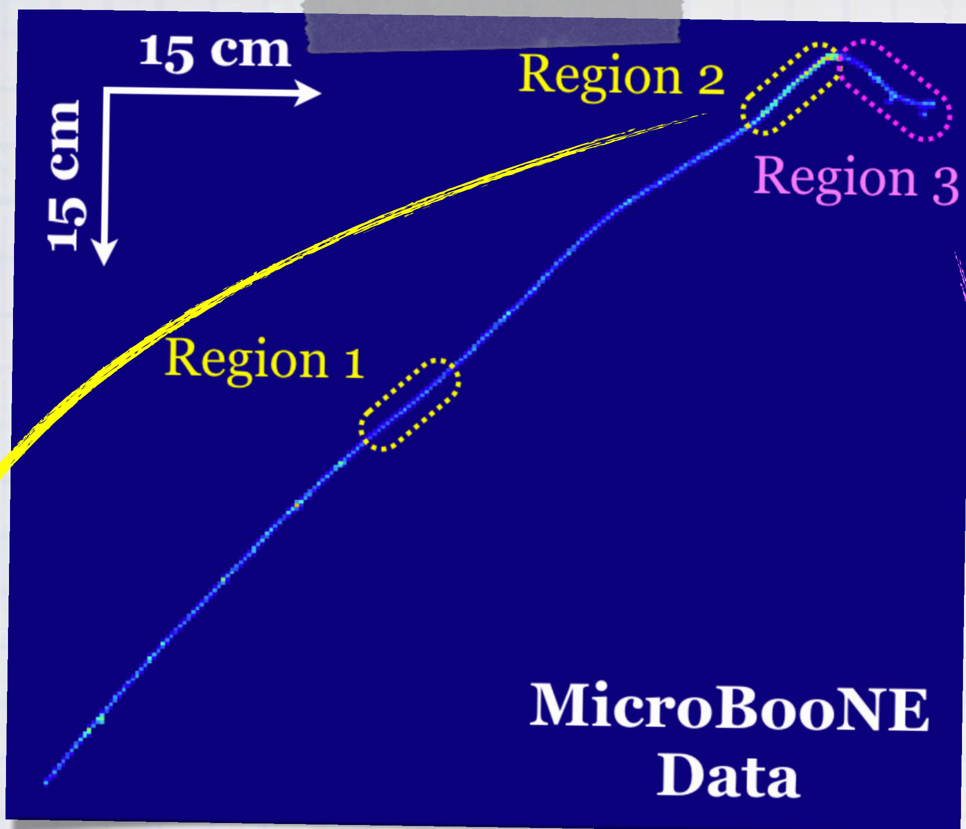
muon "track-ness"



separation increases with length

The network is indeed focusing on the length of a straight minimum ionizing particle trajectory!

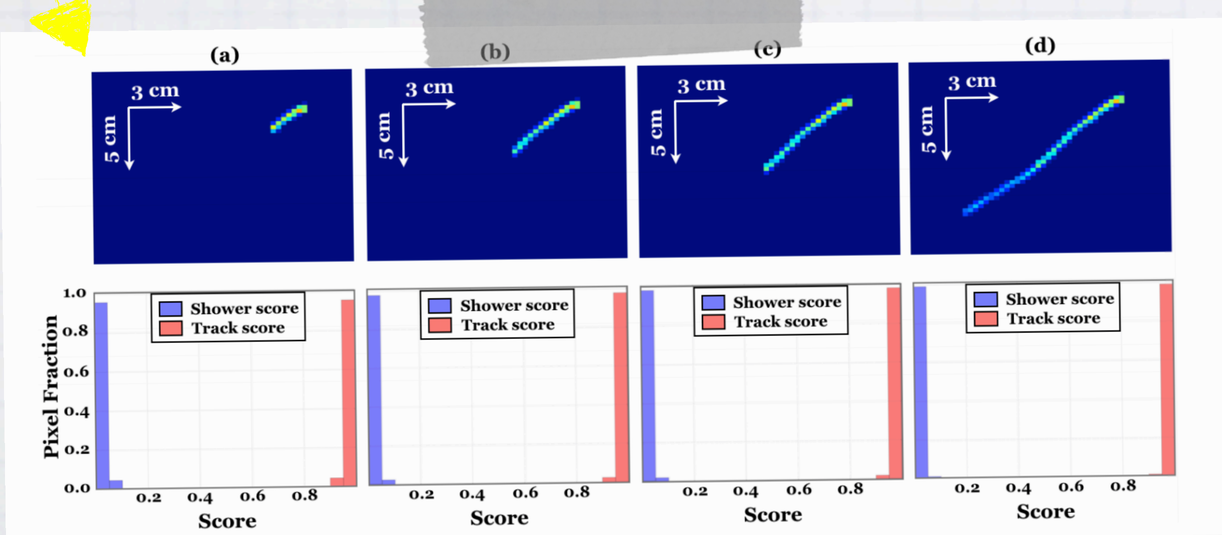
Inter-Pixel Correlation

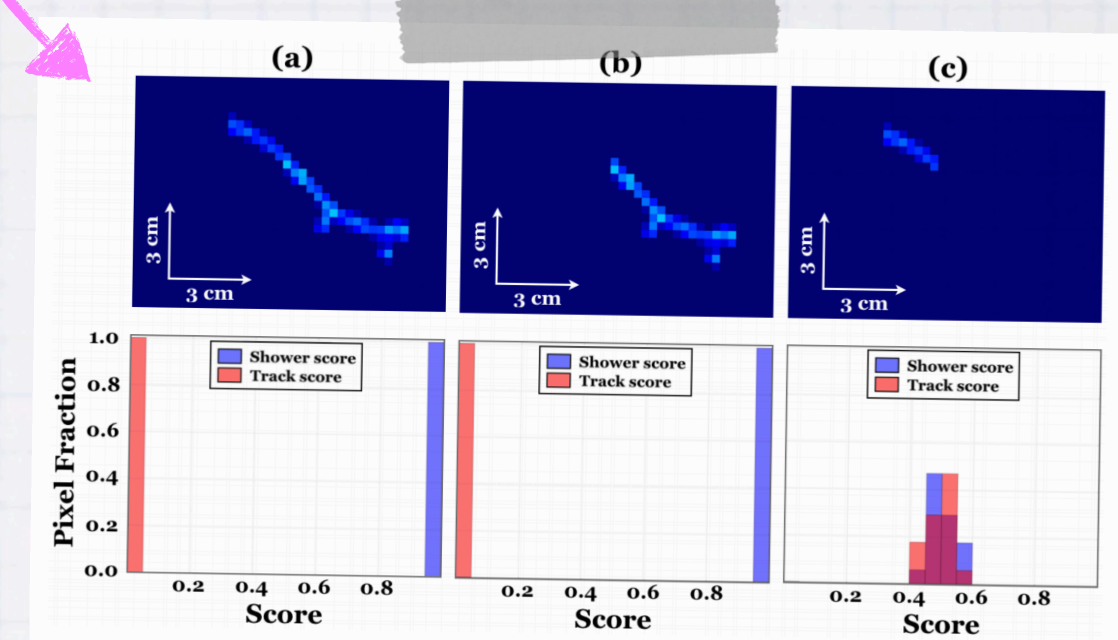


- **Masking** all pixels outside of regions.
- **Qualitatively** verifying particle topology is effectively used as a metric by the network.

electron "shower-ness"

Bragg peak (end of muon track)

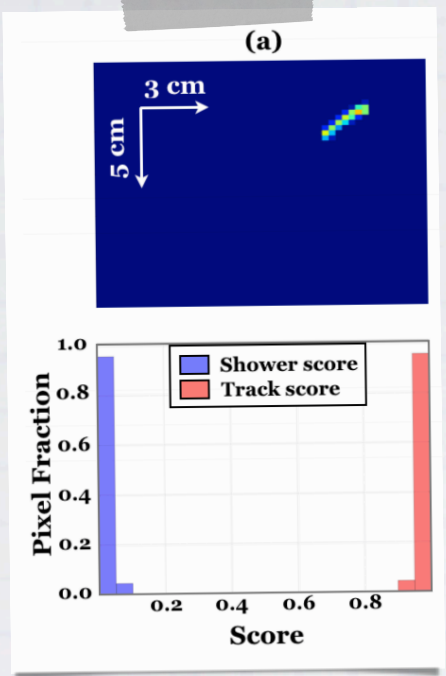




no increase with length, network focusing on dE/dx

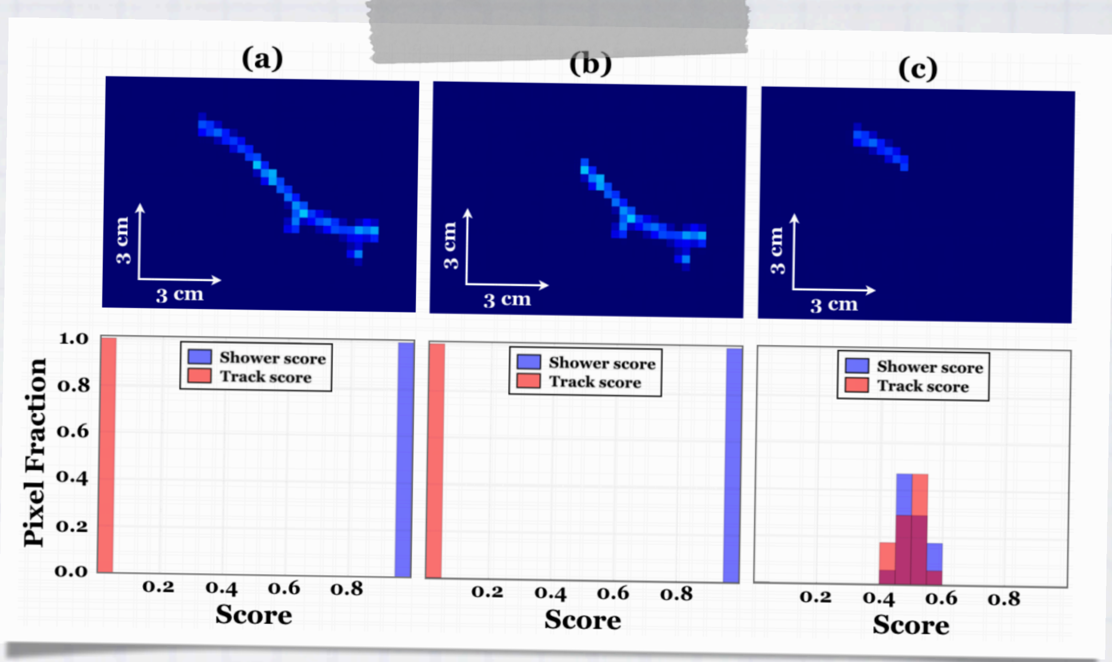
"branching" structure fundamental for shower id
without branching classification is ambiguous

Inter-Pixel Correlation



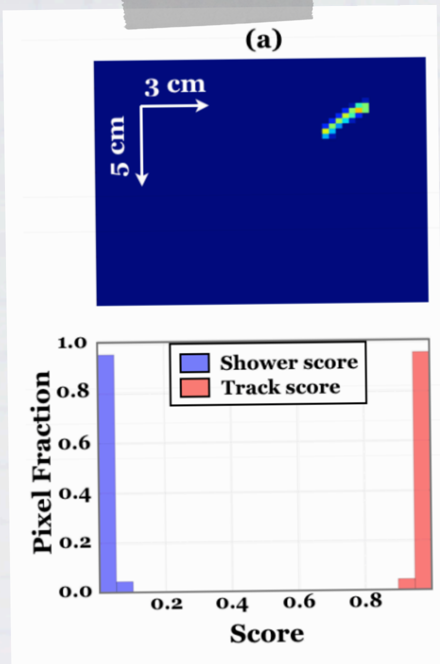
Bragg peak

+

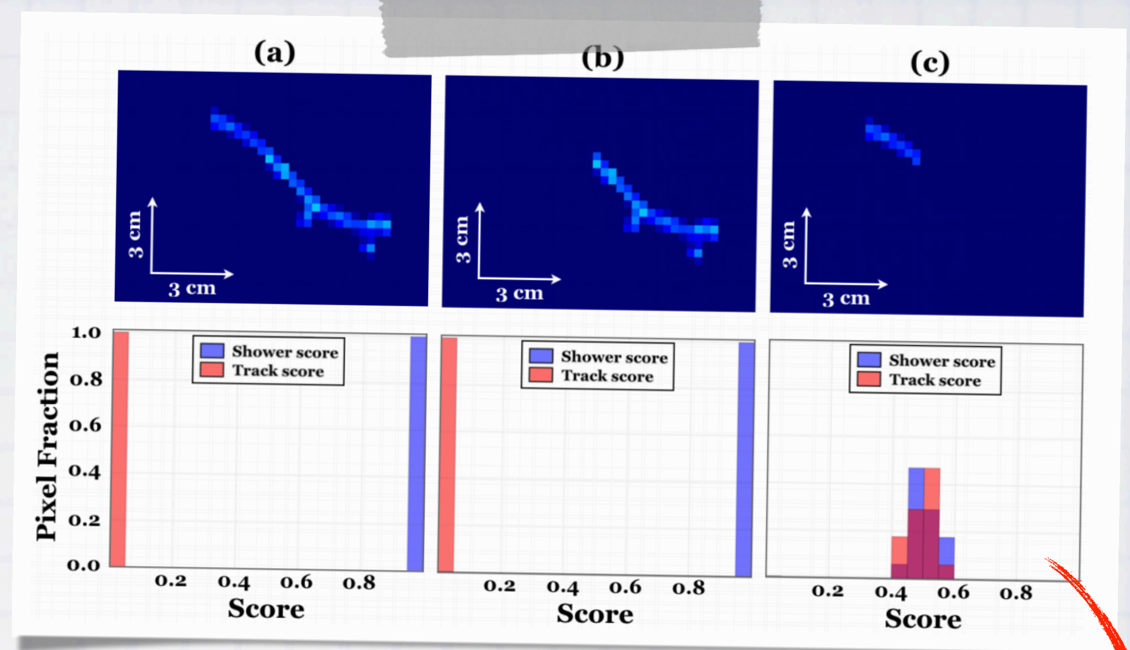


(truncated) electron shower

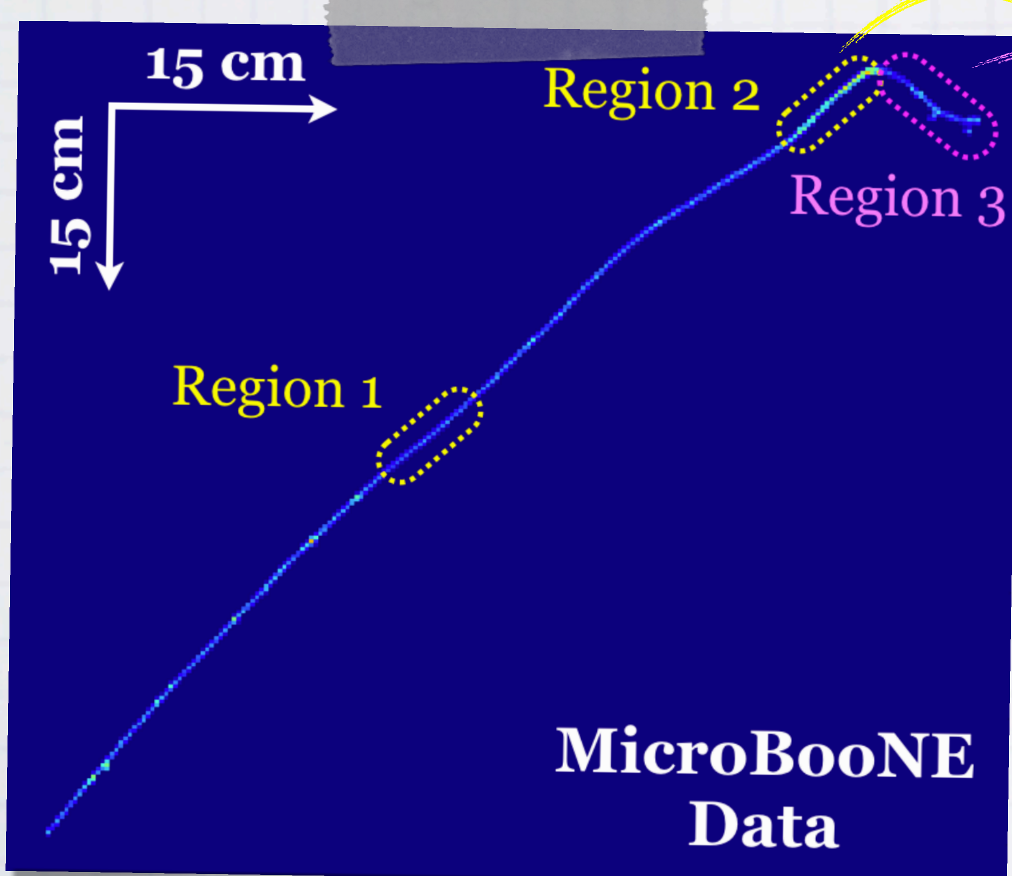
Inter-Pixel Correlation

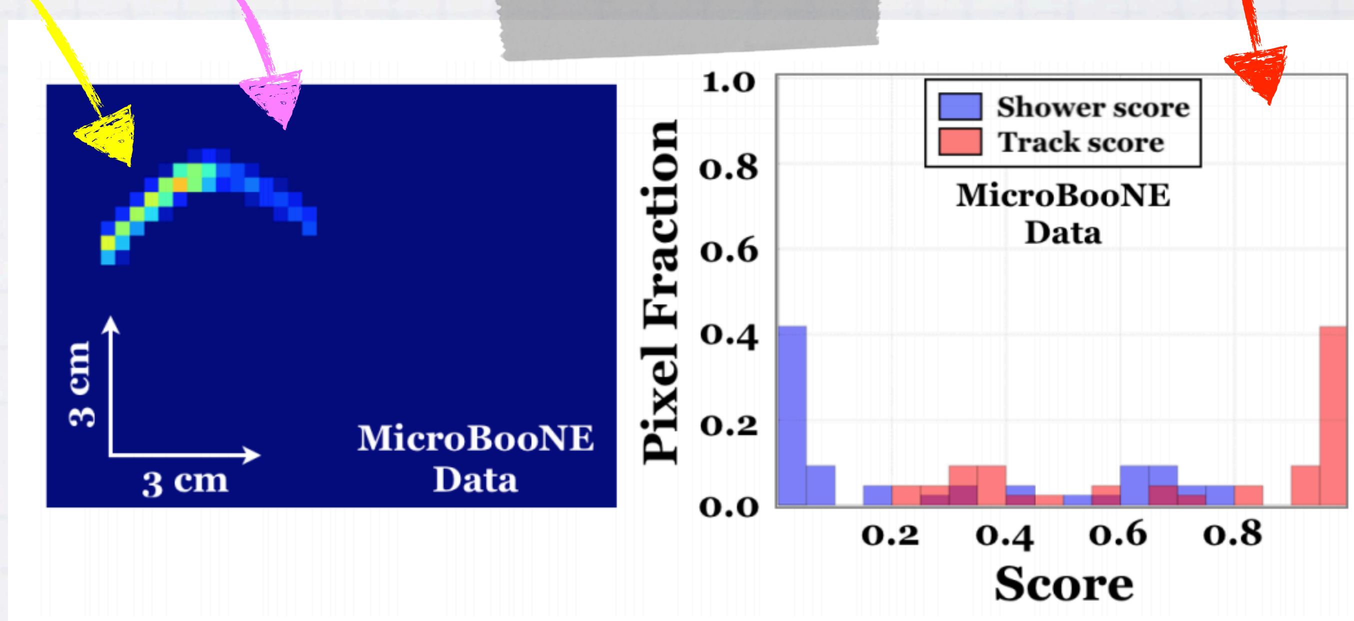


Bragg peak

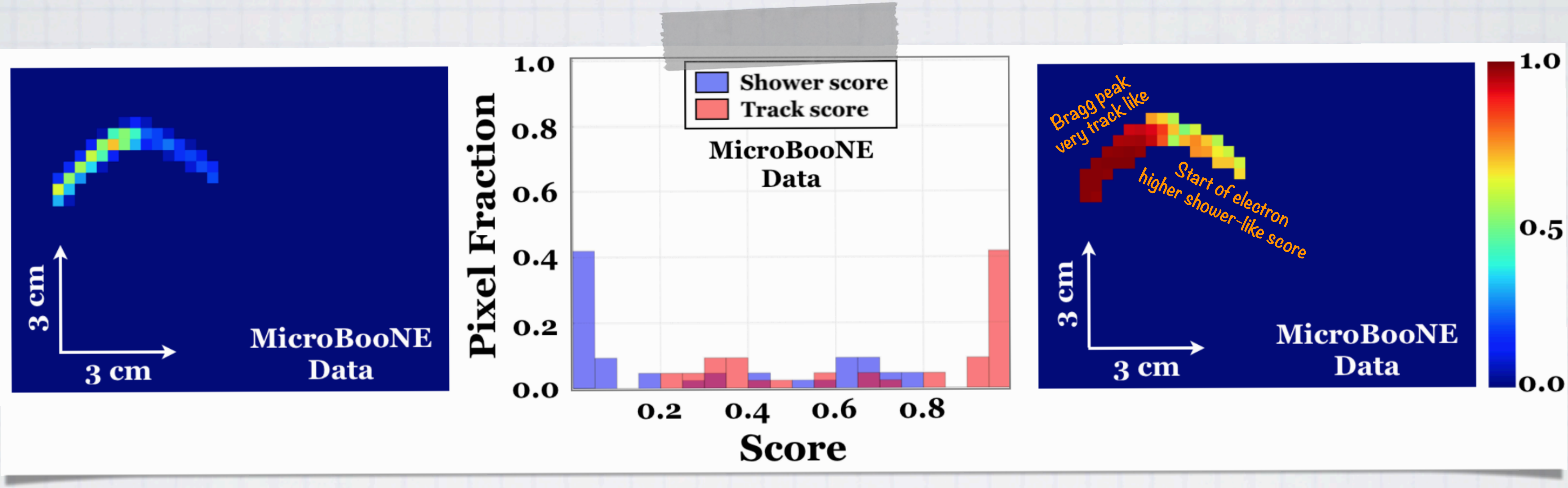


(truncated) electron shower





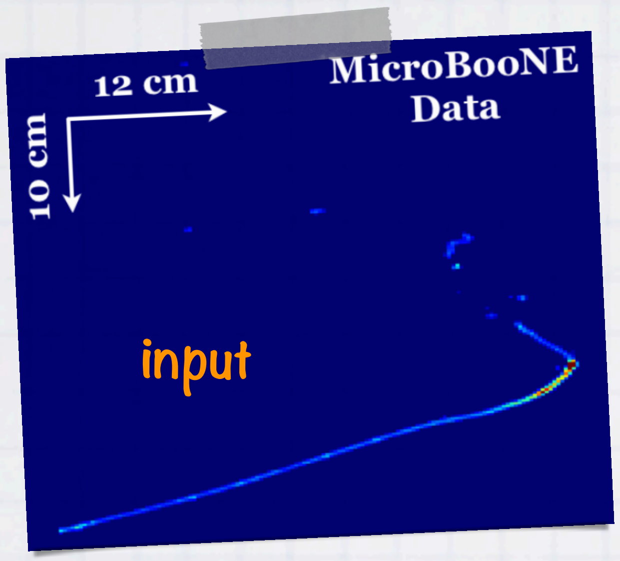
INTER-PIXEL CORRELATION

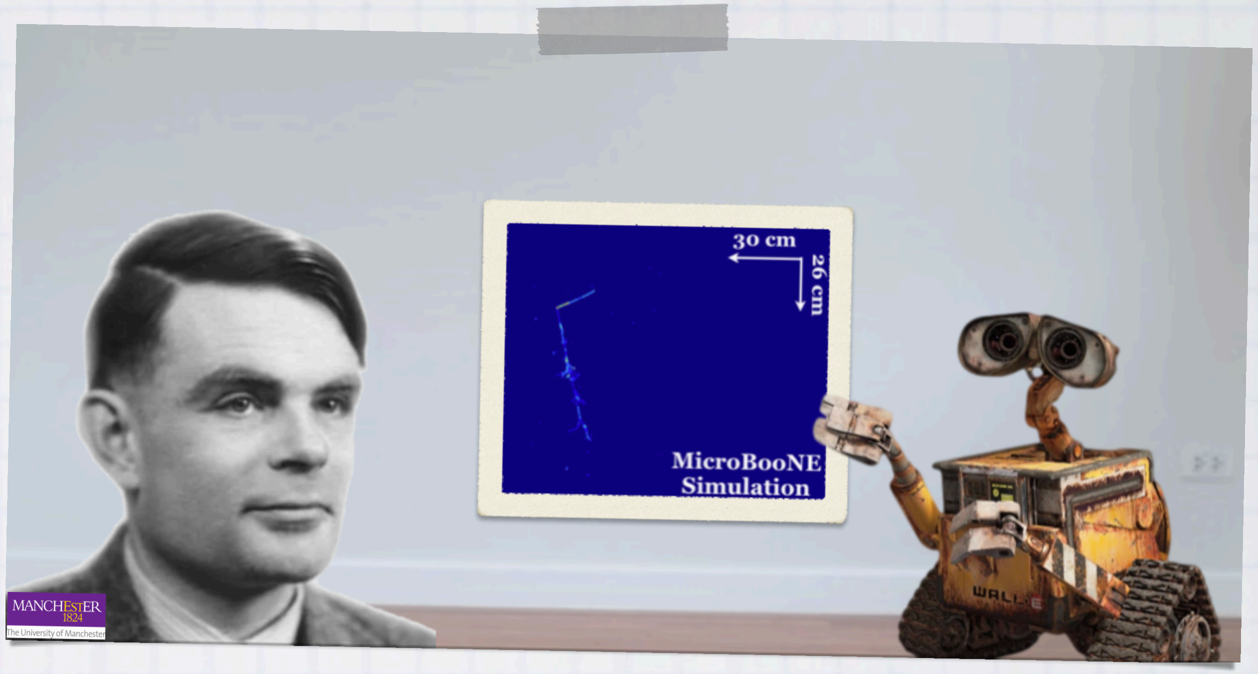


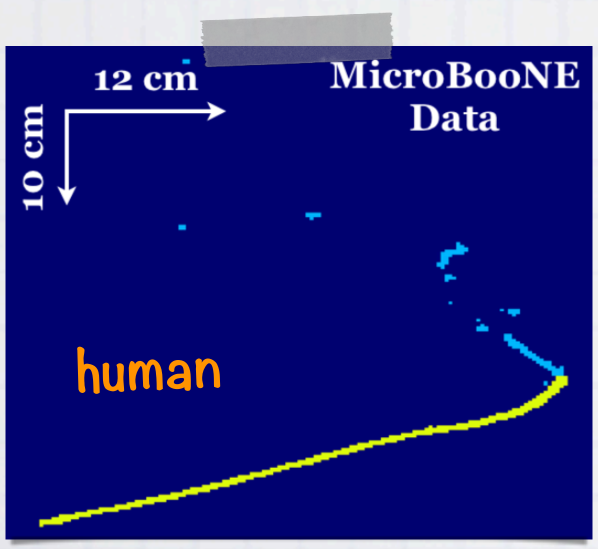
- Network's confidence on **Bragg peak** remains very high for **track-like classification**.
- Beginning portion of (truncated) **Michel electron** exhibits **higher likelihood** to be classified as **shower-like**.

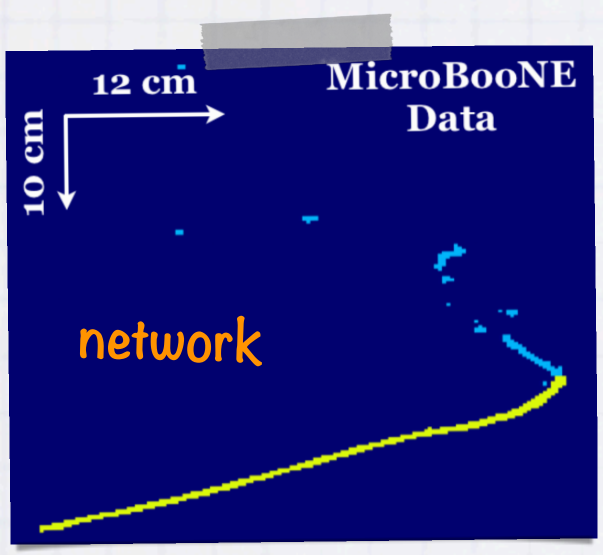
Performance in Data

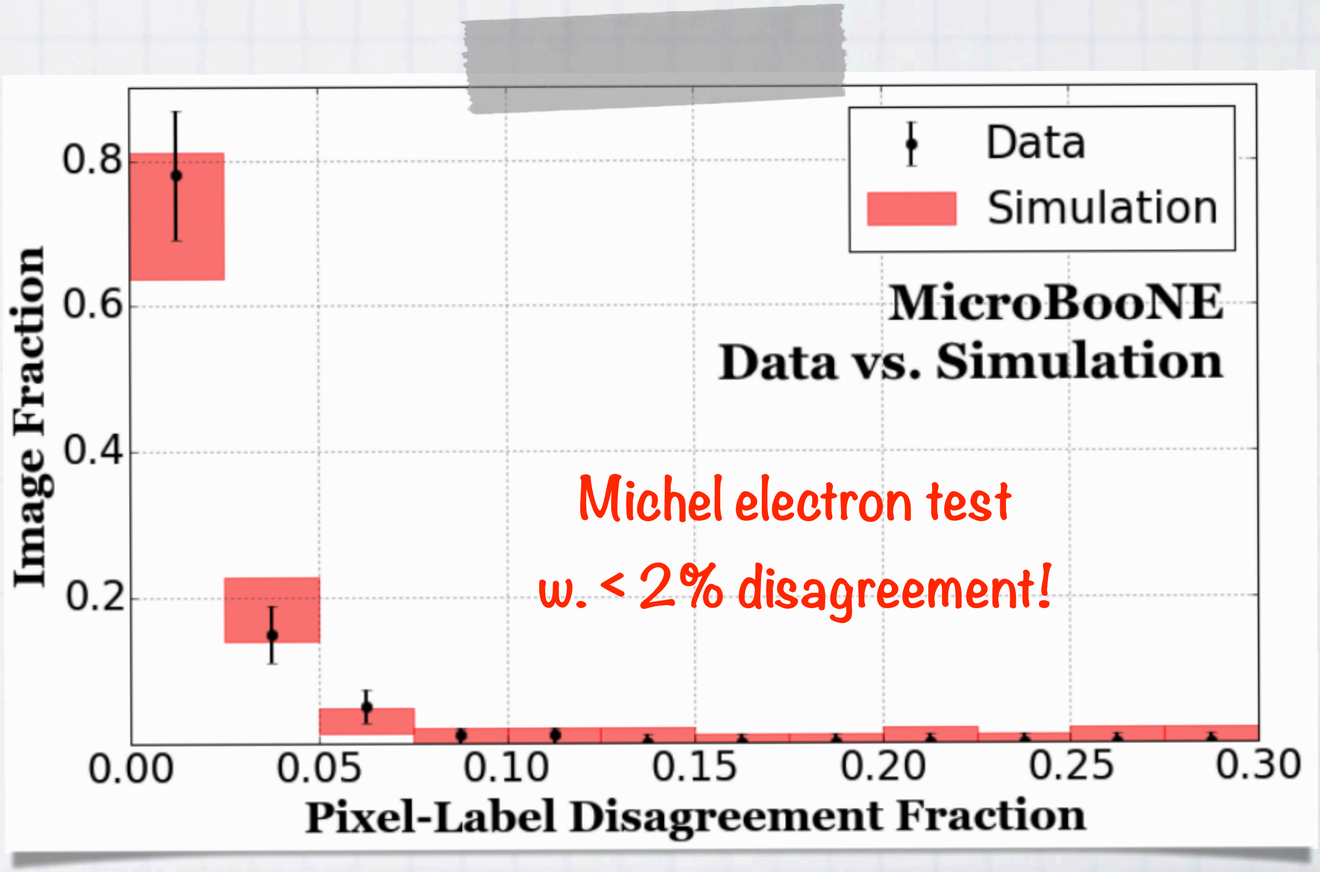
- Analogous to a **Turing test**.
- **Excellent agreement.**











CONCLUSIONS

- **MicroBooNE** is using **Deep Convolutional Neural Network** for physics analyses.
- First application of **Deep Semantic Segmentation Network** for **track/shower** separation in **LArTPC**.
- Validation on **real** LArTPC data (**first ever performed**) showing **excellent physicist-network agreement** (>96%).
- Qualitative tests confirming network able to focus on **intuitively physically-motivated quantities** in the image.


arXiv:1808.07269v1 [physics.ins-det] 22 Aug 2018

A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber

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(The MicroBooNE Collaboration)

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[29] *Tufts University, Medford, MA,*
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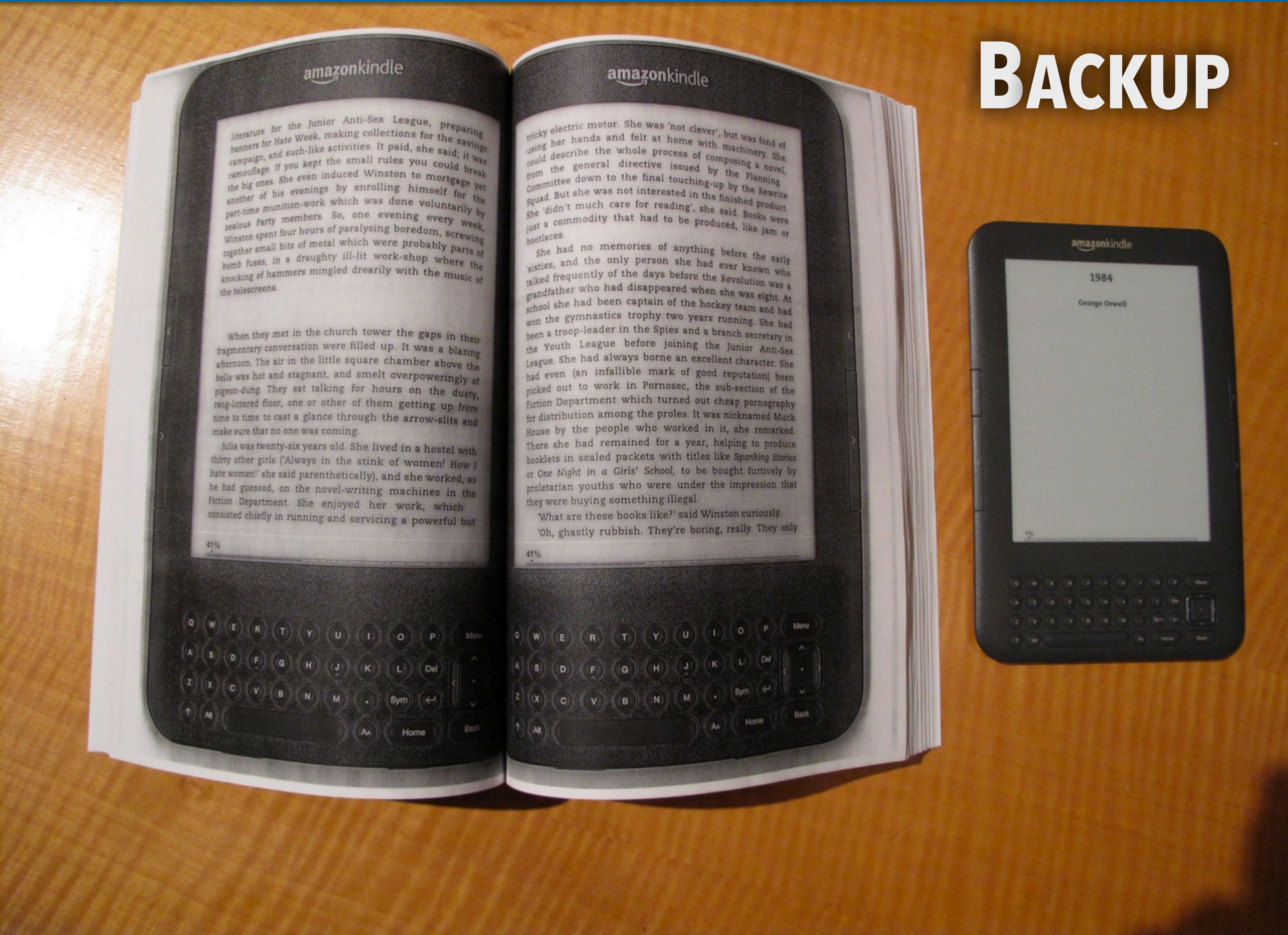
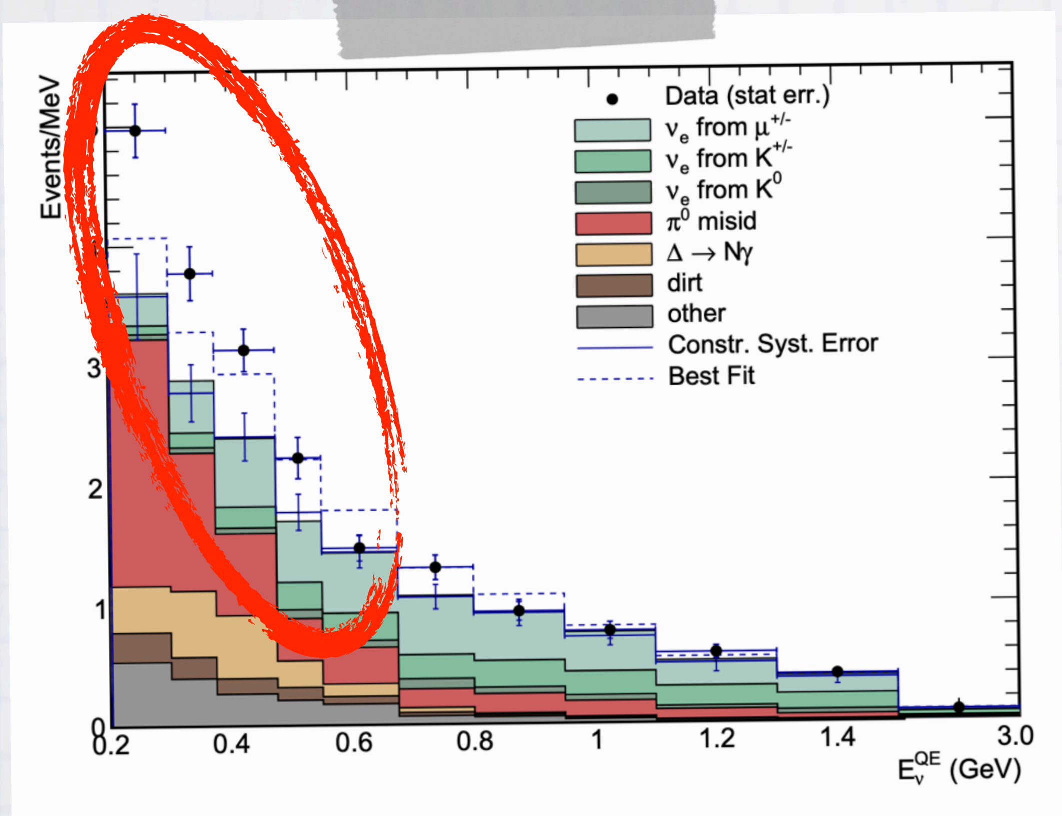
Check out our SSNet paper:

https://arxiv.org/abs/1808.07269

BACKUP

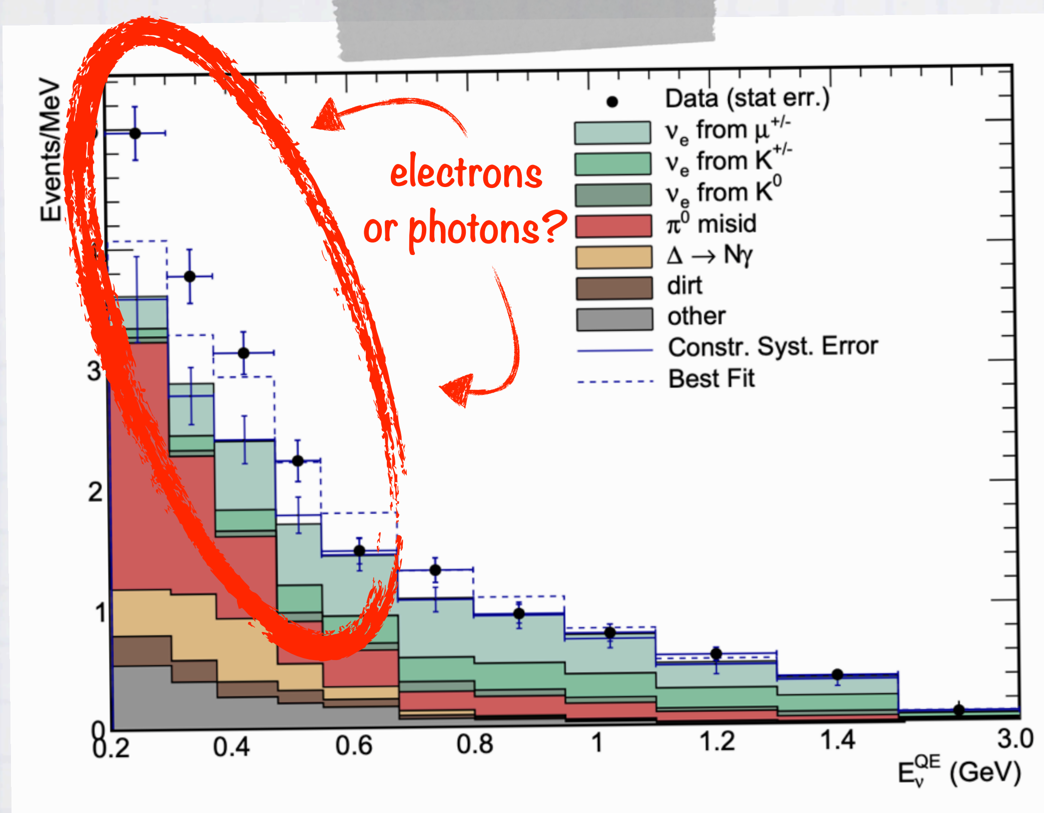

amazonkindle
literature for the Junior Anti-Sex League, preparing banners for Hate Week, making collections for the savings campaign, and such-like activities. It paid, she said; it was camouflage. If you kept the small rules you could break the big ones. She even induced Winston to mortgage yet another of his evenings by enrolling himself for the part-time munition-work which was done voluntarily by zealous Party members. So, one evening every week, Winston spent four hours of paralysing boredom, screwing together small bits of metal which were probably parts of bomb fuses, in a draughty ill-lit work-shop where the knocking of hammers mingled drearily with the music of the telescreens.
When they met in the church tower the gaps in their fragmentary conversation were filled up. It was a blazing afternoon. The air in the little square chamber above the bells was hot and stagnant, and smelt overpoweringly of pigeon-dung. They sat talking for hours on the dusty, twig-littered floor, one or other of them getting up from time to time to cast a glance through the arrow-slits and make sure that no one was coming.
Julia was twenty-six years old. She lived in a hostel with thirty other girls ('Always in the stink of women! How I hate women!' she said parenthetically), and she worked, as he had guessed, on the novel-writing machines in the Fiction Department. She enjoyed her work, which consisted chiefly in running and servicing a powerful but
41%
amazonkindle
tricky electric motor. She was 'not clever', but was fond of using her hands and felt at home with machinery. She could describe the whole process of composing a novel, from the general directive issued by the Planning Committee down to the final touching-up by the Rewrite Squad. But she was not interested in the finished product. She 'didn't much care for reading', she said. Books were just a commodity that had to be produced, like jam or bootlaces.
She had no memories of anything before the early 'sixties, and the only person she had ever known who talked frequently of the days before the Revolution was a grandfather who had disappeared when she was eight. At school she had been captain of the hockey team and had won the gymnastics trophy two years running. She had been a troop-leader in the Spies and a branch secretary in the Youth League before joining the Junior Anti-Sex League. She had always borne an excellent character. She had even (an infallible mark of good reputation) been picked out to work in Pornosec, the sub-section of the Fiction Department which turned out cheap pornography for distribution among the proles. It was nicknamed Muck House by the people who worked in it, she remarked. There she had remained for a year, helping to produce booklets in sealed packets with titles like Spanking Stories or One Night in a Girls' School, to be bought furtively by proletarian youths who were under the impression that they were buying something illegal.
'What are these books like?' said Winston curiously.
'Oh, ghastly rubbish. They're boring, really. They only
41%
amazonkindle
1984
George Orwell

2002



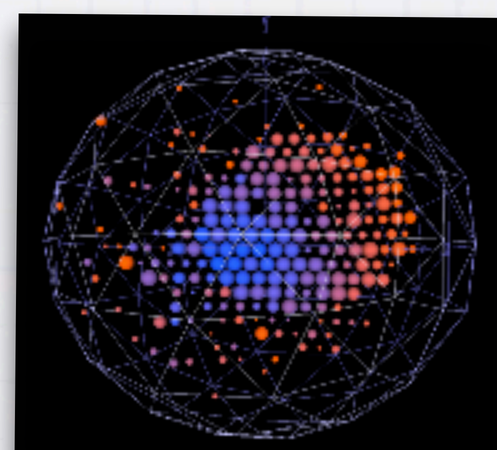
- MiniBooNE was a **neutrino oscillation** experiment.
- Observed a **4.5σ excess** of **electron-like** events at low-energy (**6σ** in combination with LSND).
- Result **inconsistent** with **Standard Model**!

2002

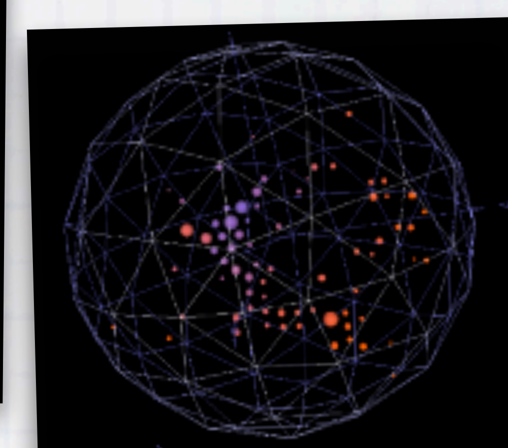


- MiniBooNE was a **neutrino oscillation** experiment.
- Observed a **4.5σ excess** of **electron-like** events at low-energy (**6σ** in combination with LSND).
- Result **inconsistent** with **Standard Model**!
- Is this really due to **ν-induced e⁻** or **misidentified γ**? MiniBooNE can't tell.

muon



electron or (possibly) di-photon

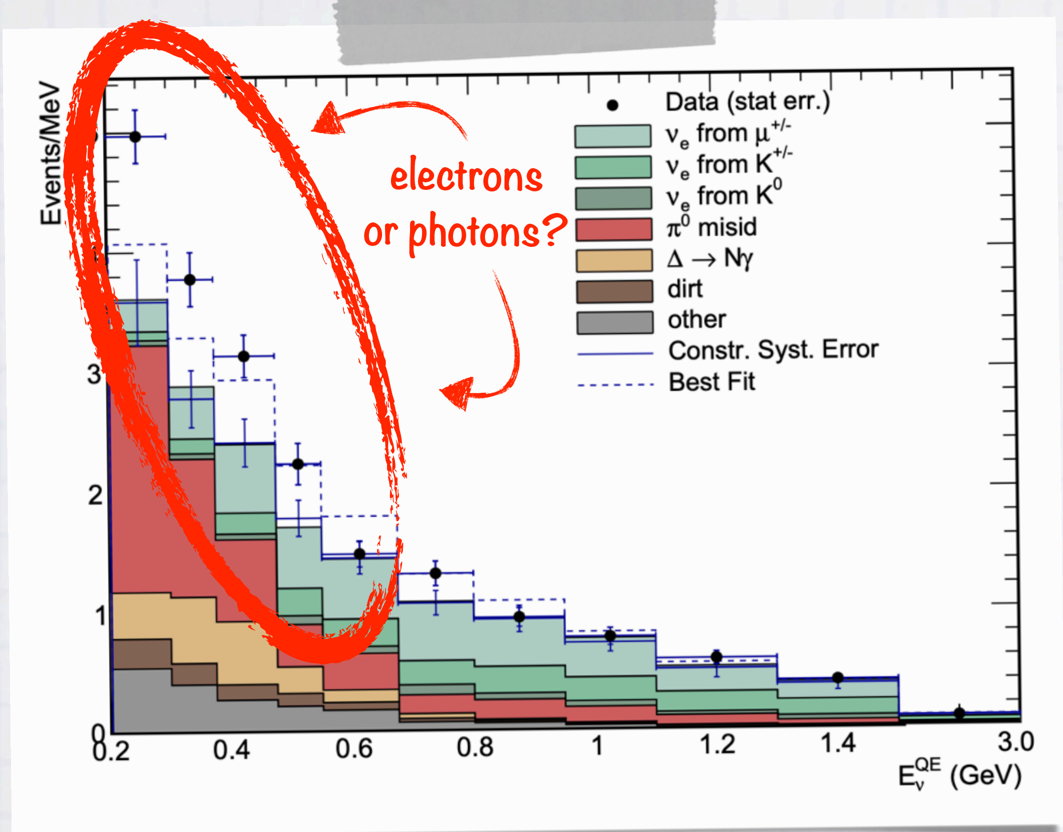


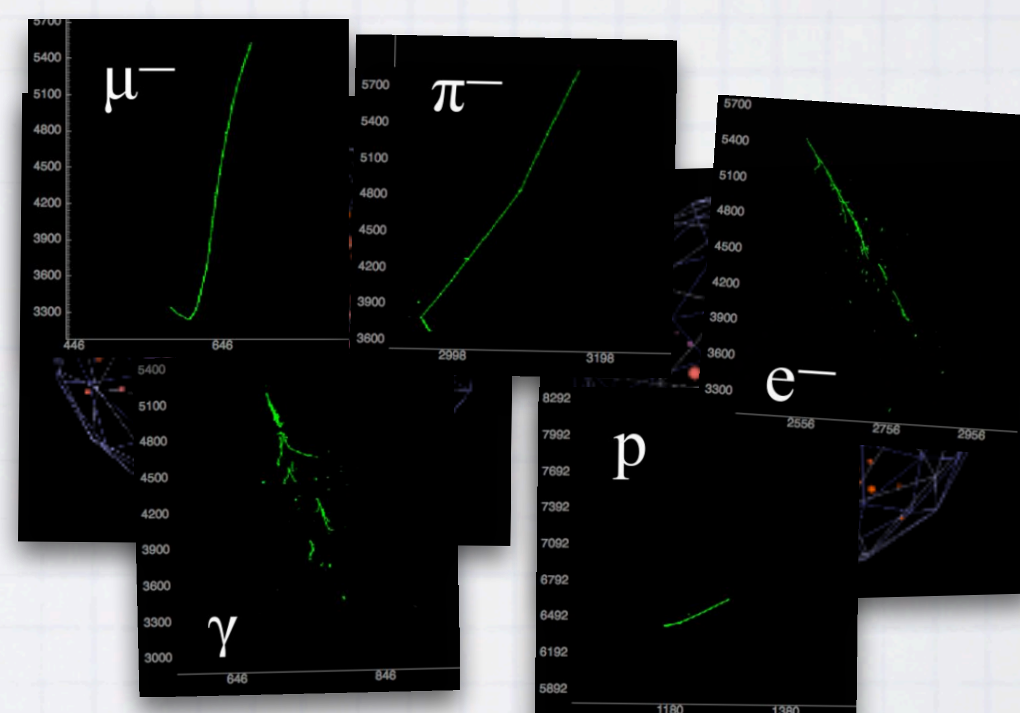
2002


MiniBooNE

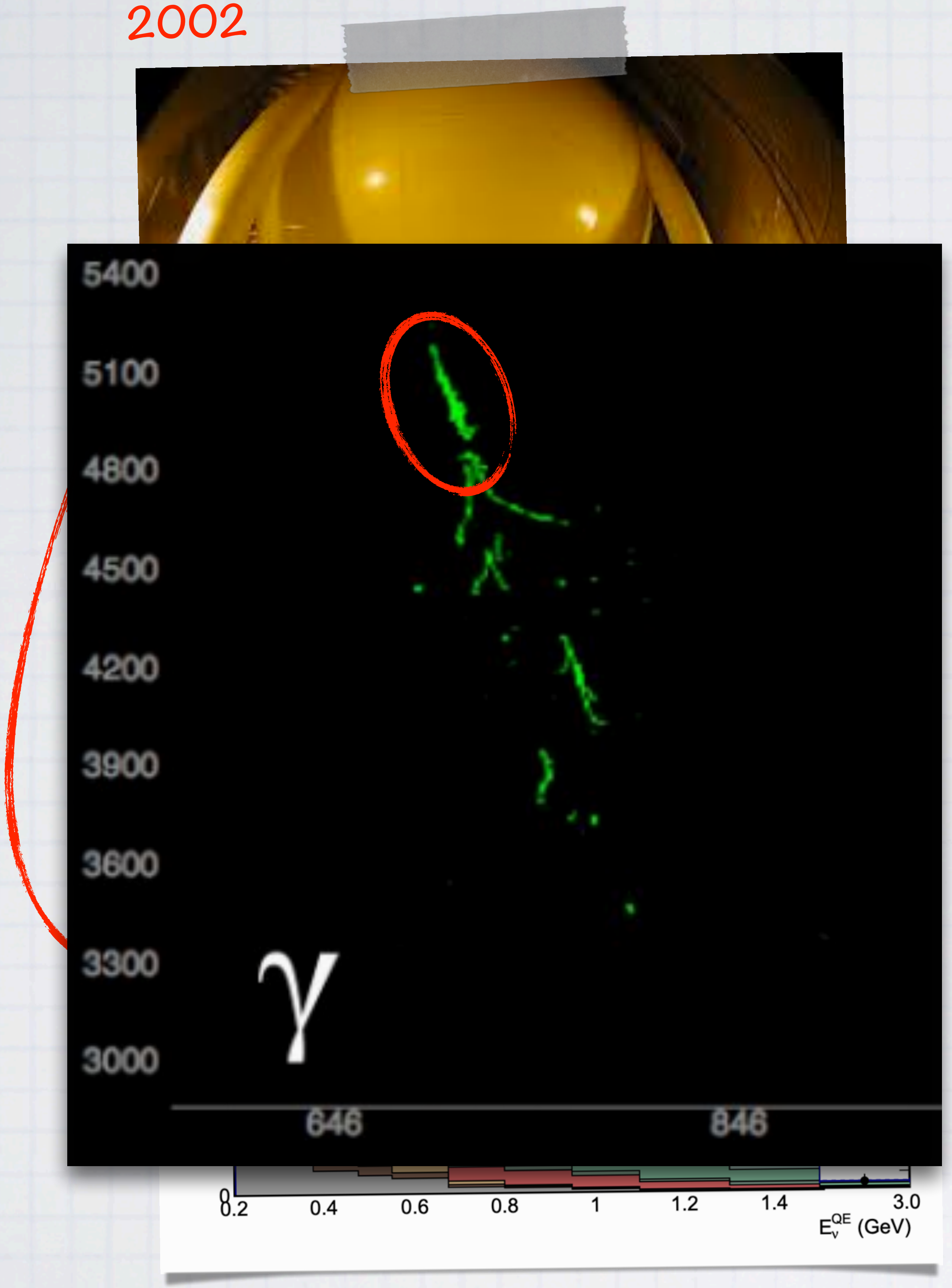
2015


MicroBooNE

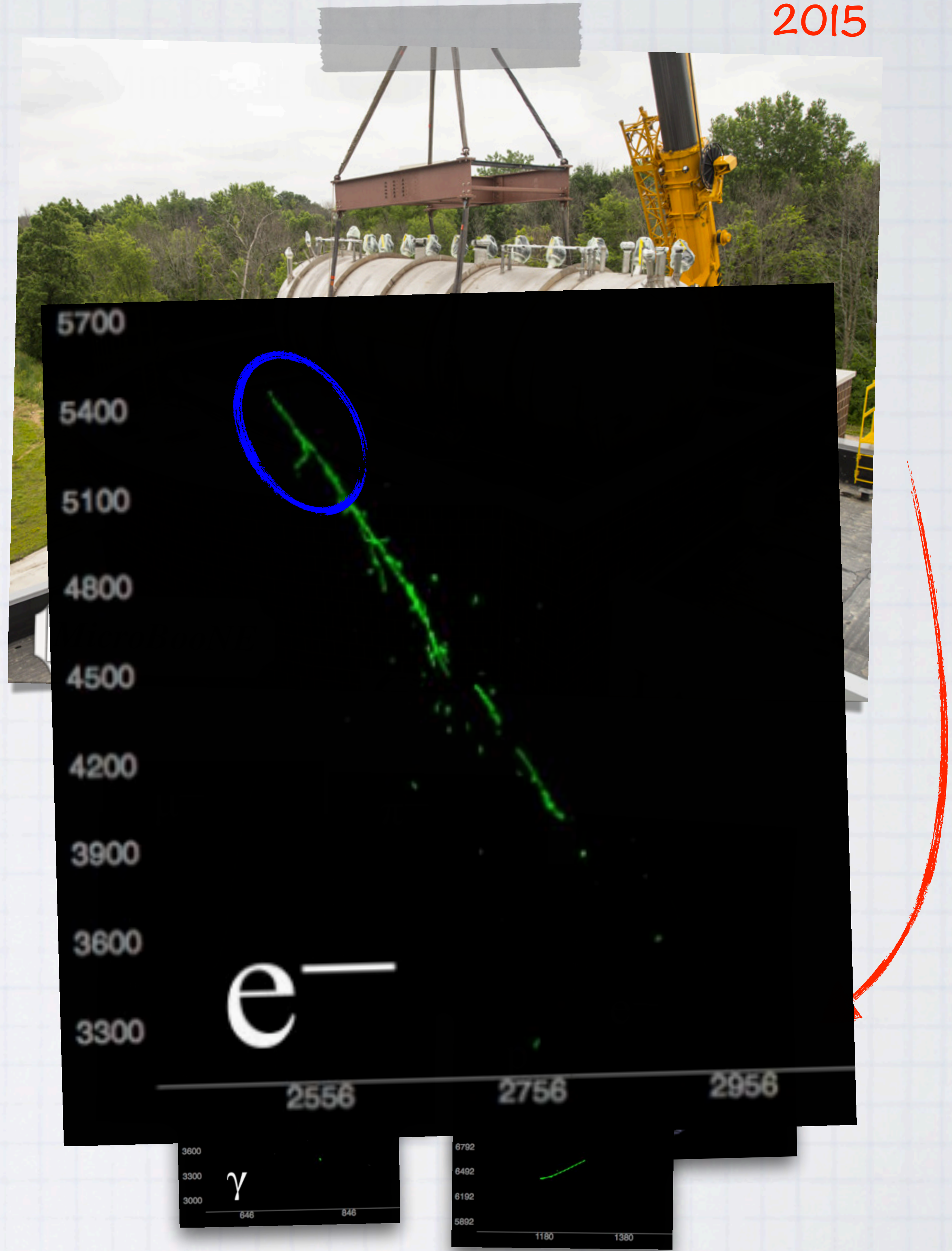

Events/MeV
Data (stat err.)
ν_e from $\mu^{+/-}$
ν_e from $K^{+/-}$
ν_e from K^0
π^0 misid
$\Delta \rightarrow N\gamma$
dirt
other
Constr. Syst. Error
Best Fit
0
1
2
3
0.2
0.4
0.6
0.8
1
1.2
1.4
3.0
E_ν^{QE} (GeV)
electrons
or photons?


μ^-
π^-
e^-
p
γ

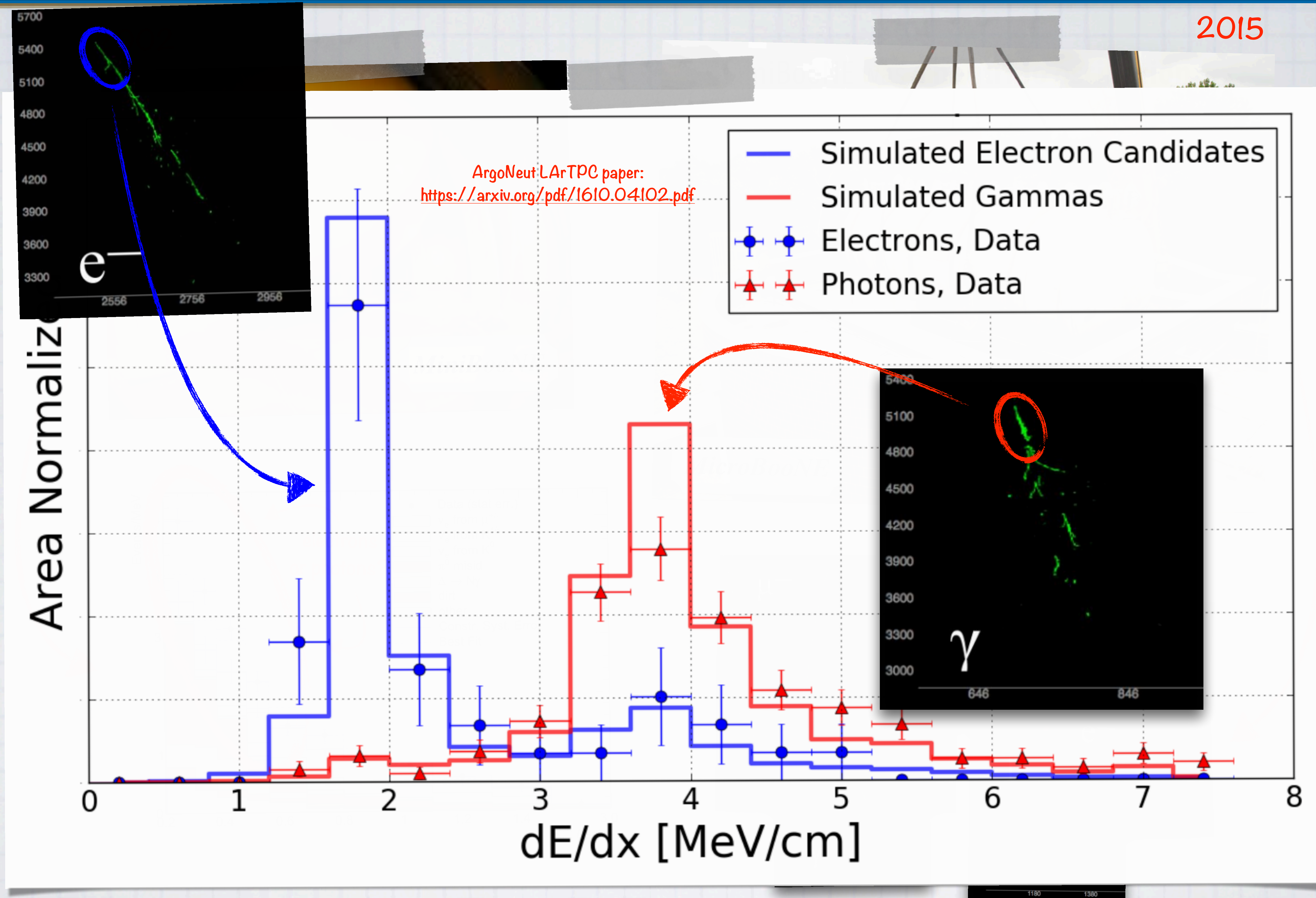
2002


5400
5100
4800
4500
4200
3900
3600
3300
3000
646
846
γ
0.2
0.4
0.6
0.8
1
1.2
1.4
3.0
E_ν^{QE} (GeV)

2015


5700
5400
5100
4800
4500
4200
3900
3600
3300
2556
2756
2956
e⁻
γ

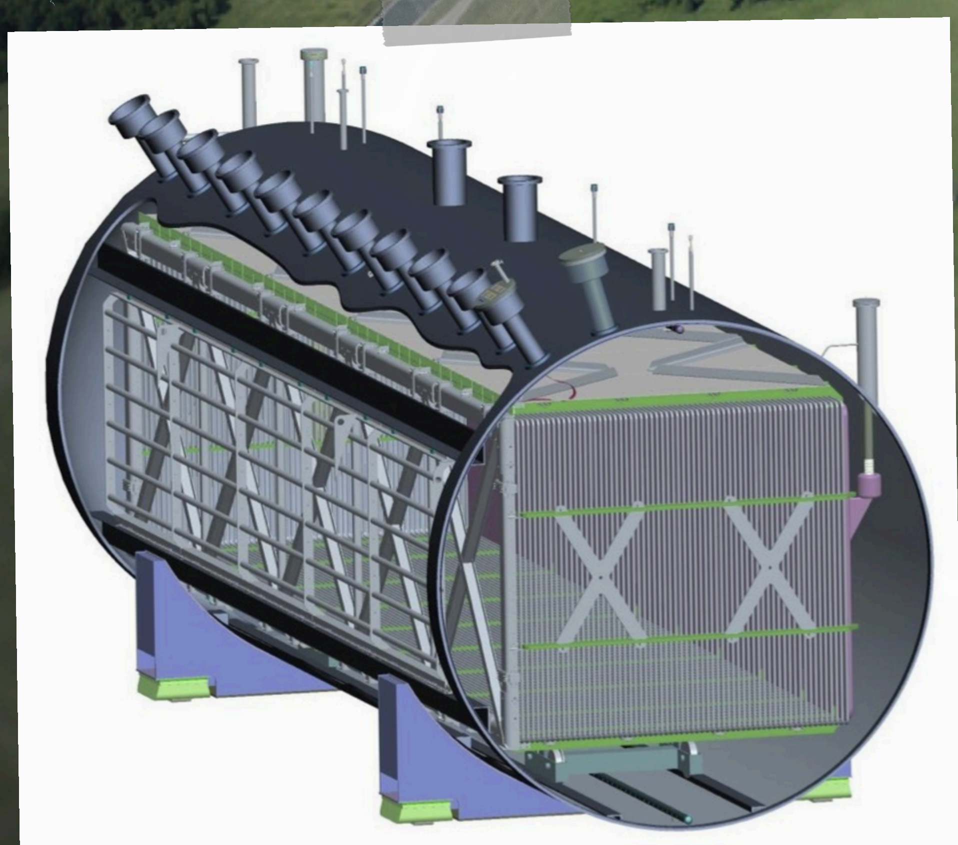
2015



- Thanks to excellent **e/γ separation**, **MicroBooNE** will be able to investigate the **nature of the low-energy excess**.

MicroBooNE

MicroBooNE



- Liquid Argon Time Projection Chamber (LArTPC)
- Short-Baseline Oscillation[1] Experiment (470 m baseline), along with SBND and ICARUS
- Receiving muon-neutrinos from BNB

1) Fermilab's short baseline program: arXiv:1503.01520 [hep-ex]

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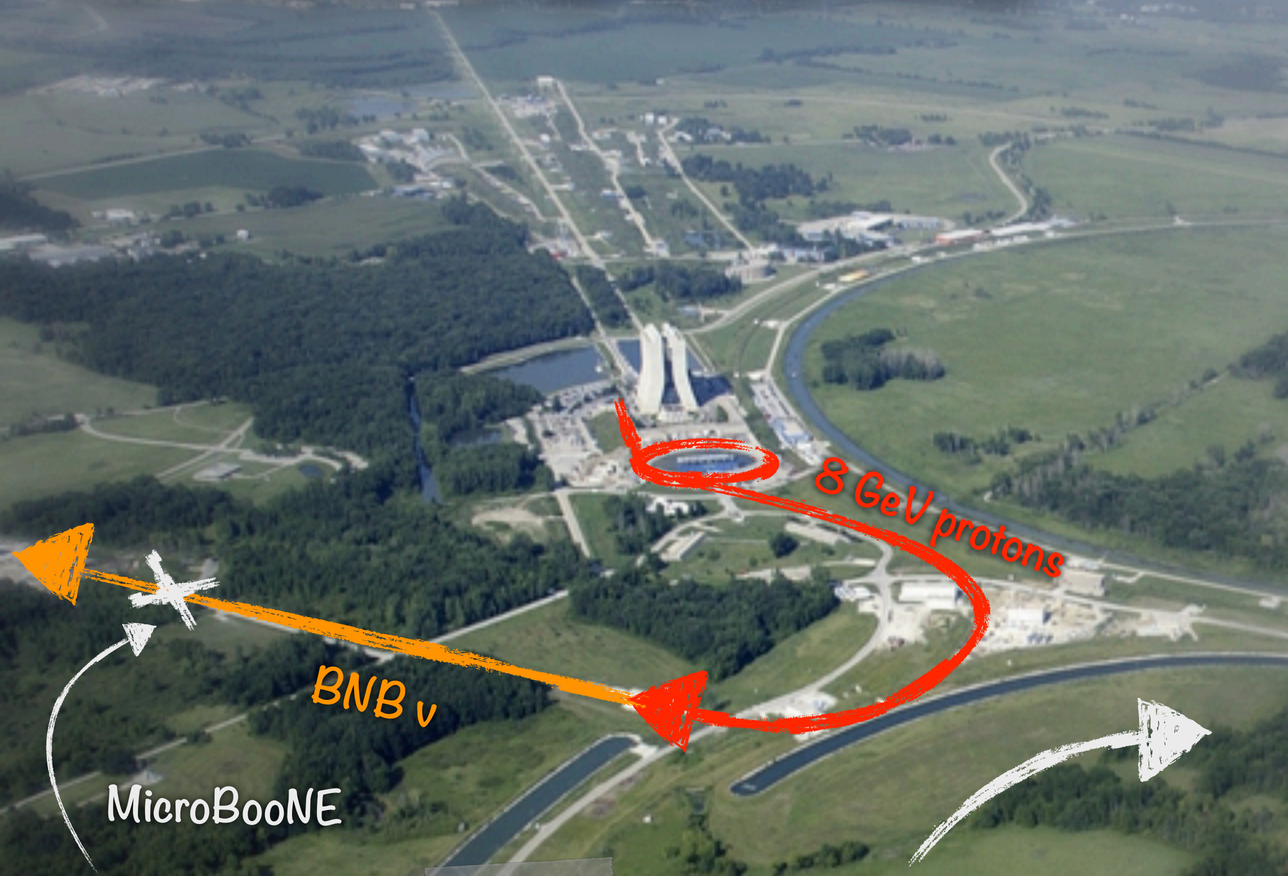
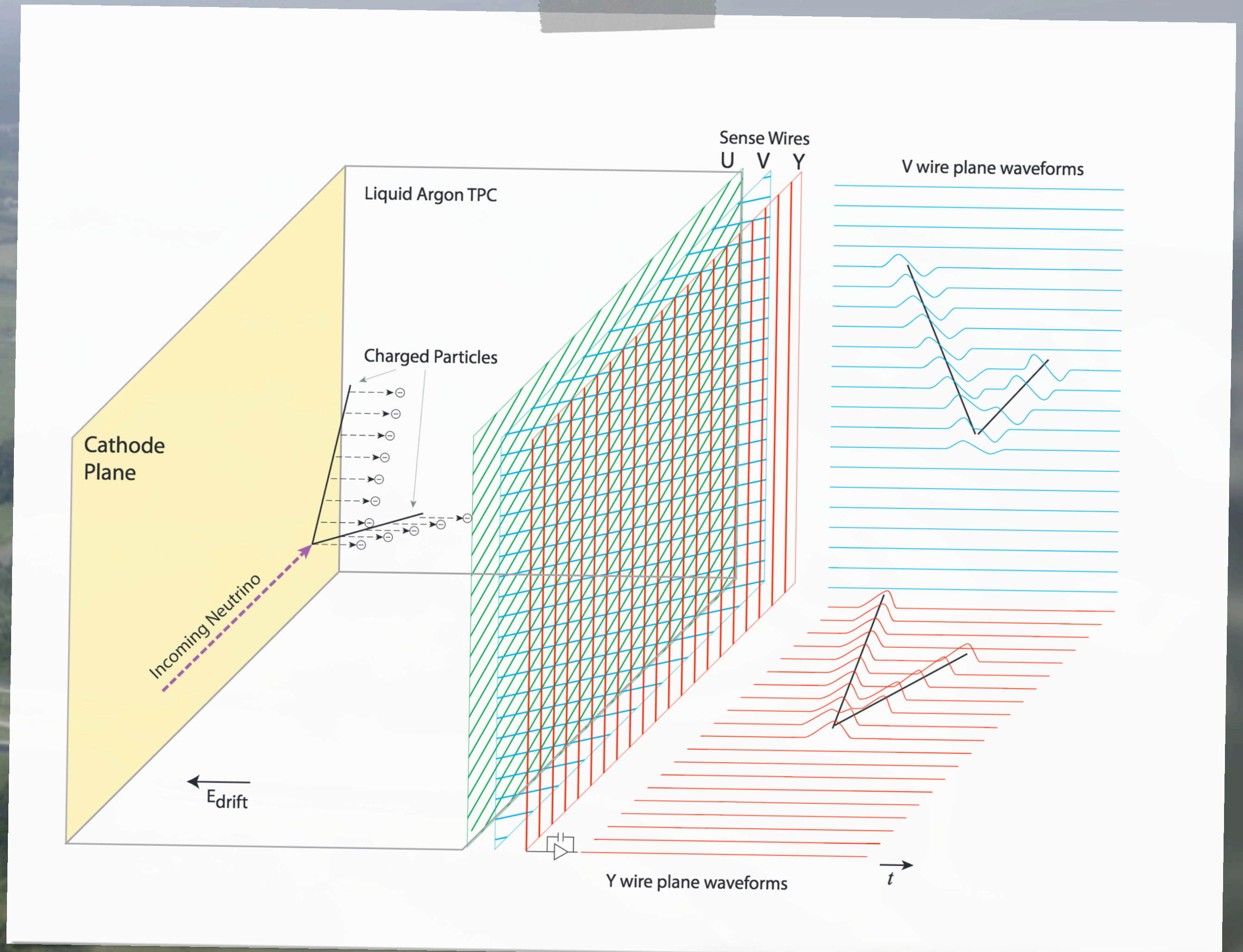
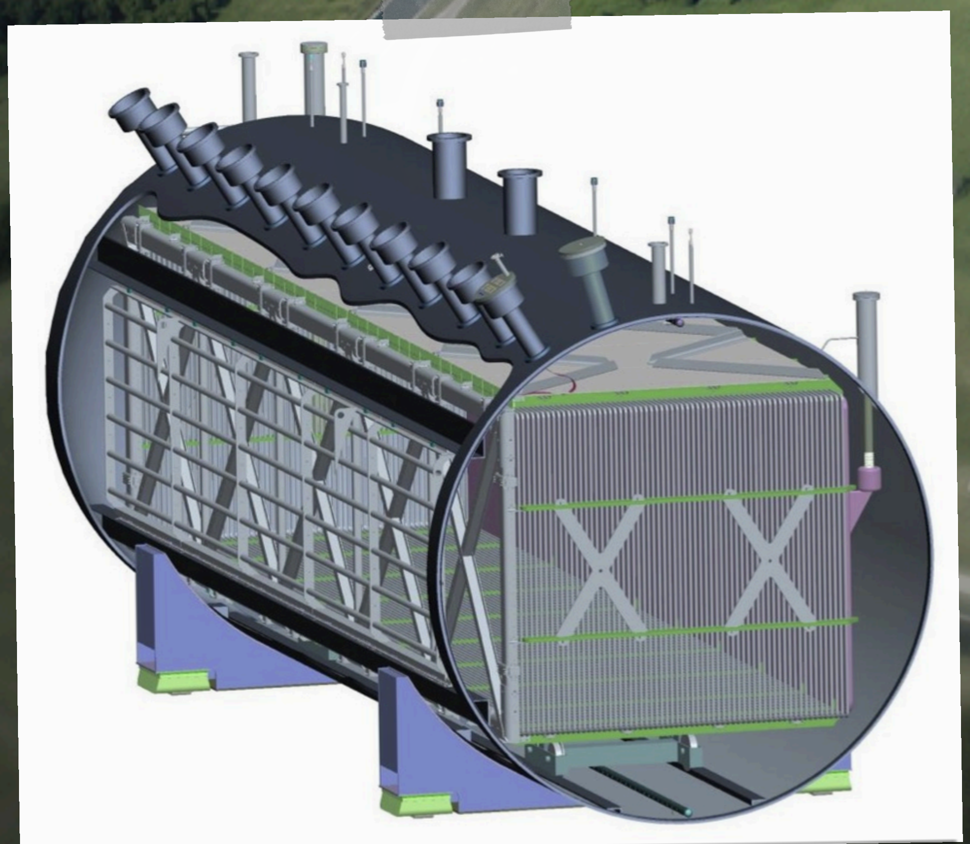
MicroBooNE

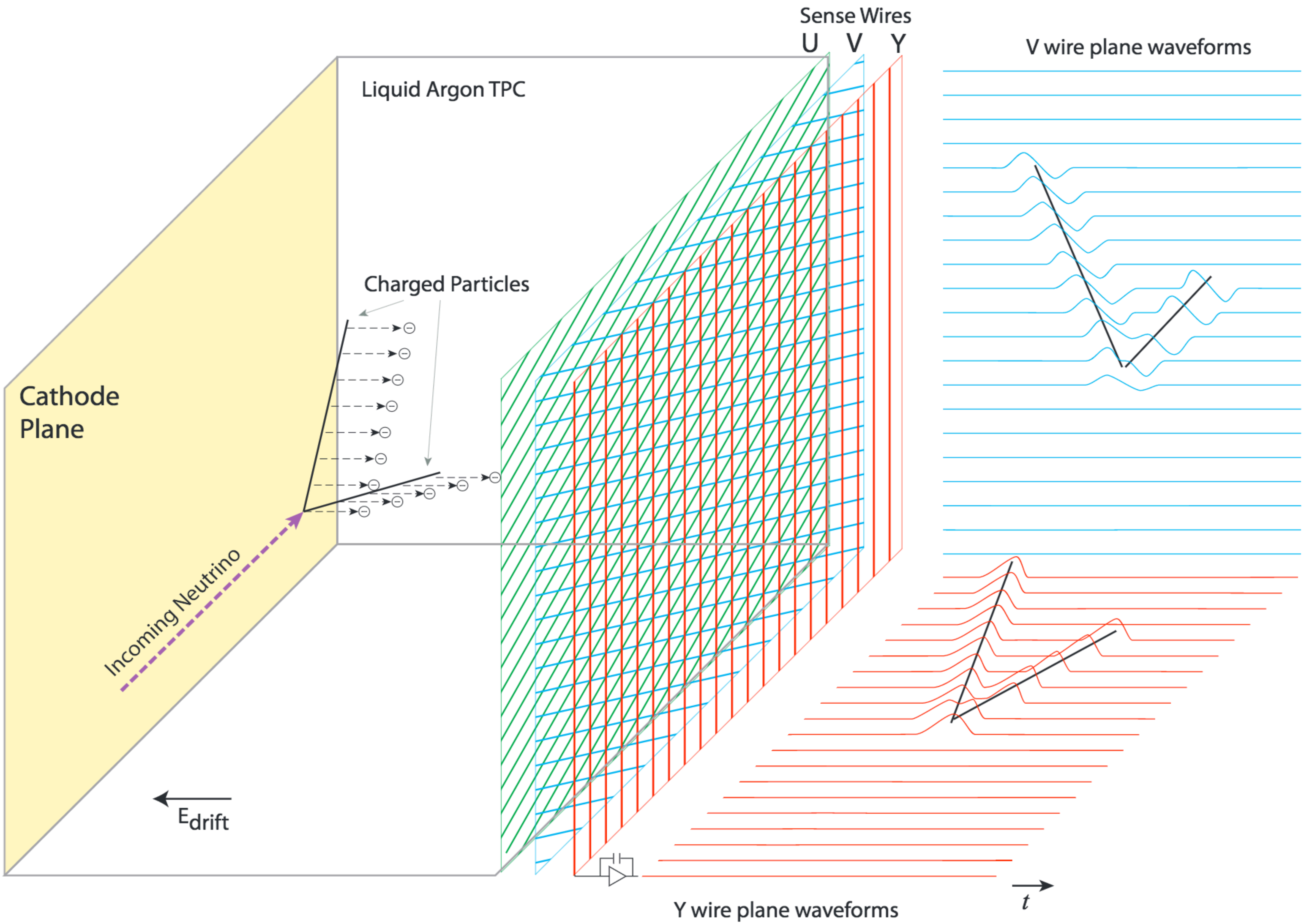




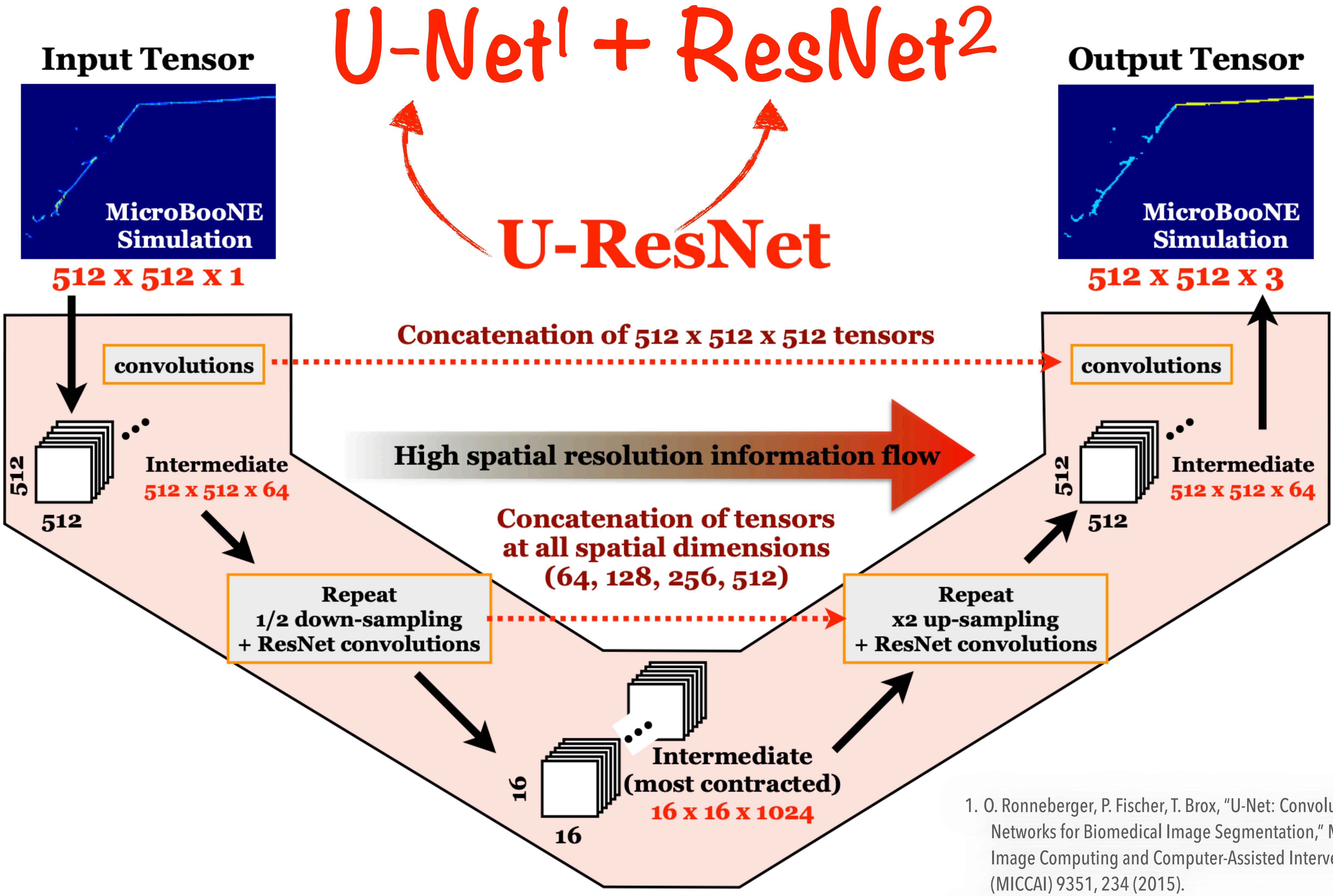


- Liquid Argon Time Projection Chamber (LArTPC)
- Short-Baseline Oscillation[1] Experiment (470 m baseline), along with SBND and ICARUS
- Receiving muon-neutrinos from BNB

- Filled with liquid argon at -168 °C
- Electric field at 273 V/cm
- Charged particle resulting from interaction ionize argon atoms
- Ionisation electrons drift towards wire plane.
- Collected charge makes possible stereoscopic view of event

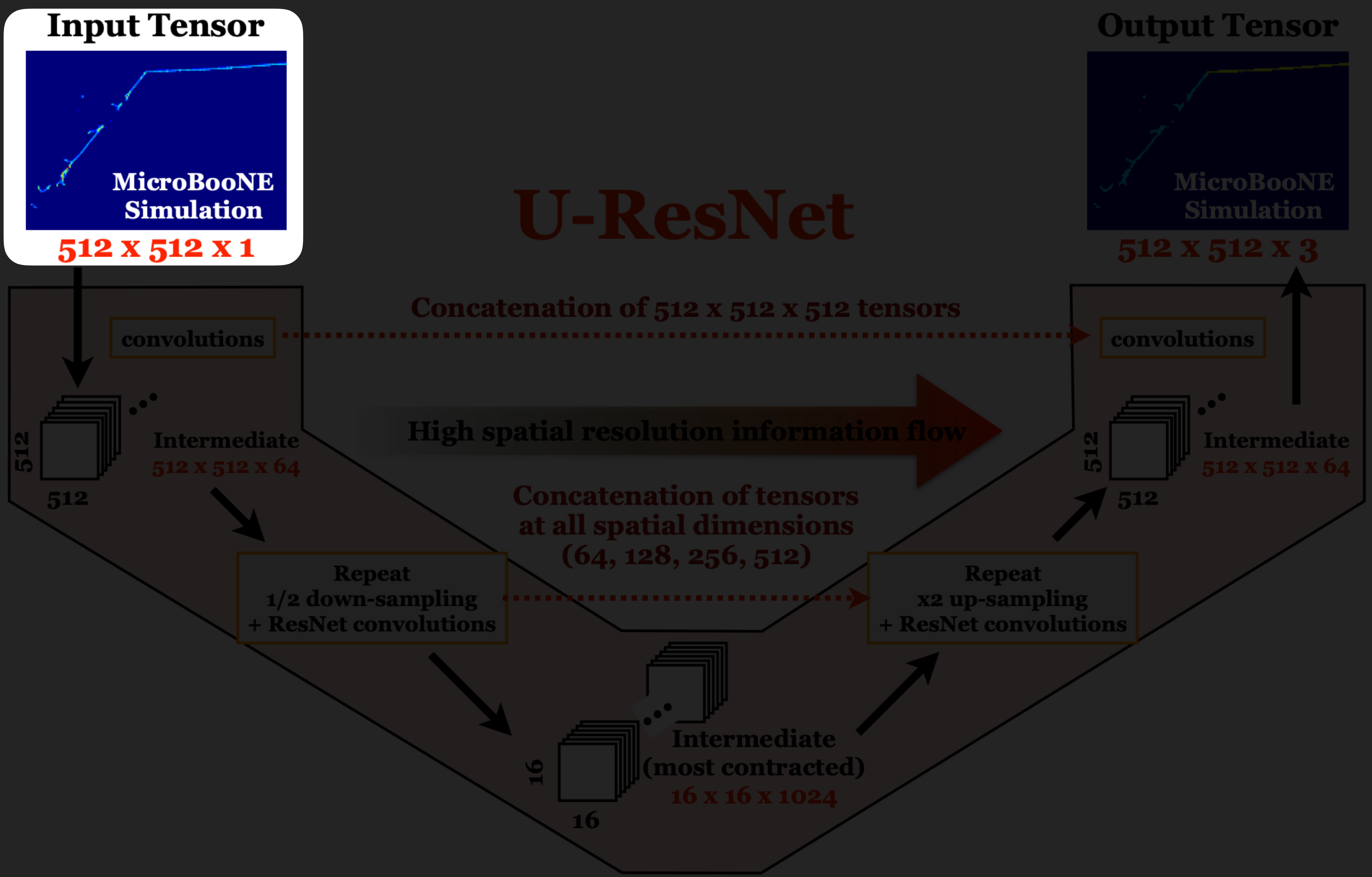


Sense Wires
U V Y
V wire plane waveforms
Liquid Argon TPC
Charged Particles
Cathode Plane
Incoming Neutrino
E_{drift}
Y wire plane waveforms
t

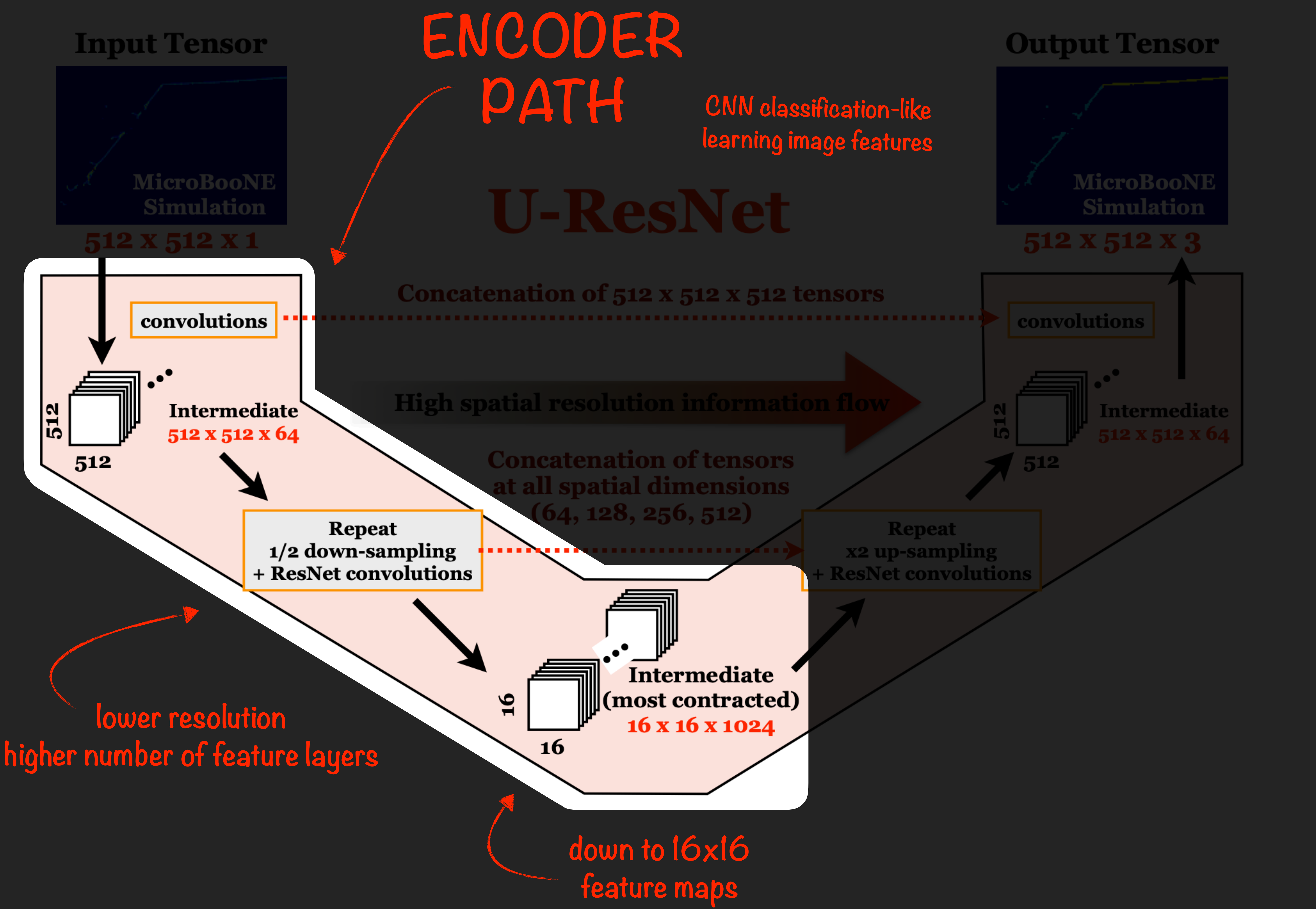


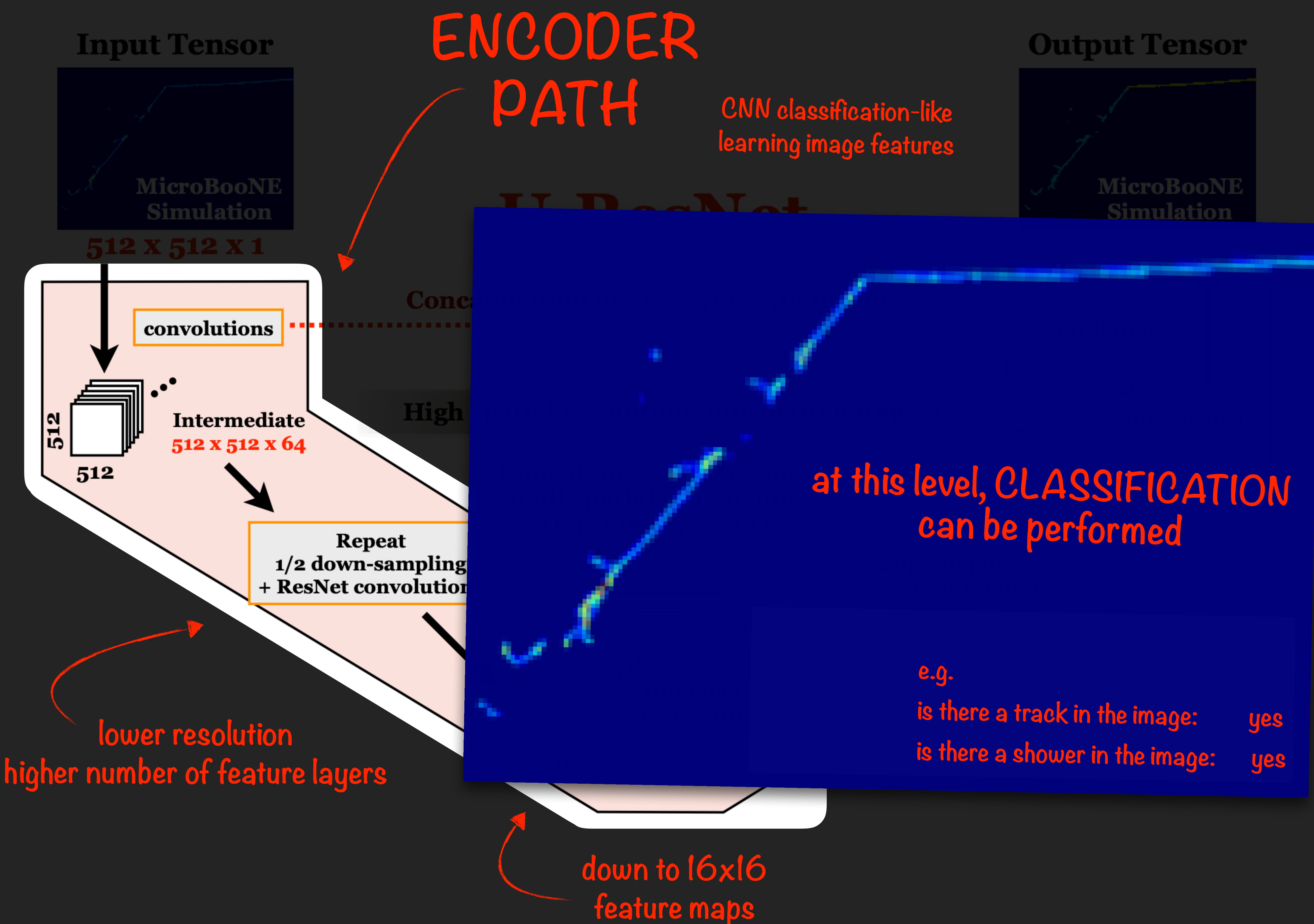
1. O. Ronneberger, P. Fischer, T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," Medical Image Computing and Computer-Assisted Intervention (MICCAI) 9351, 234 (2015).

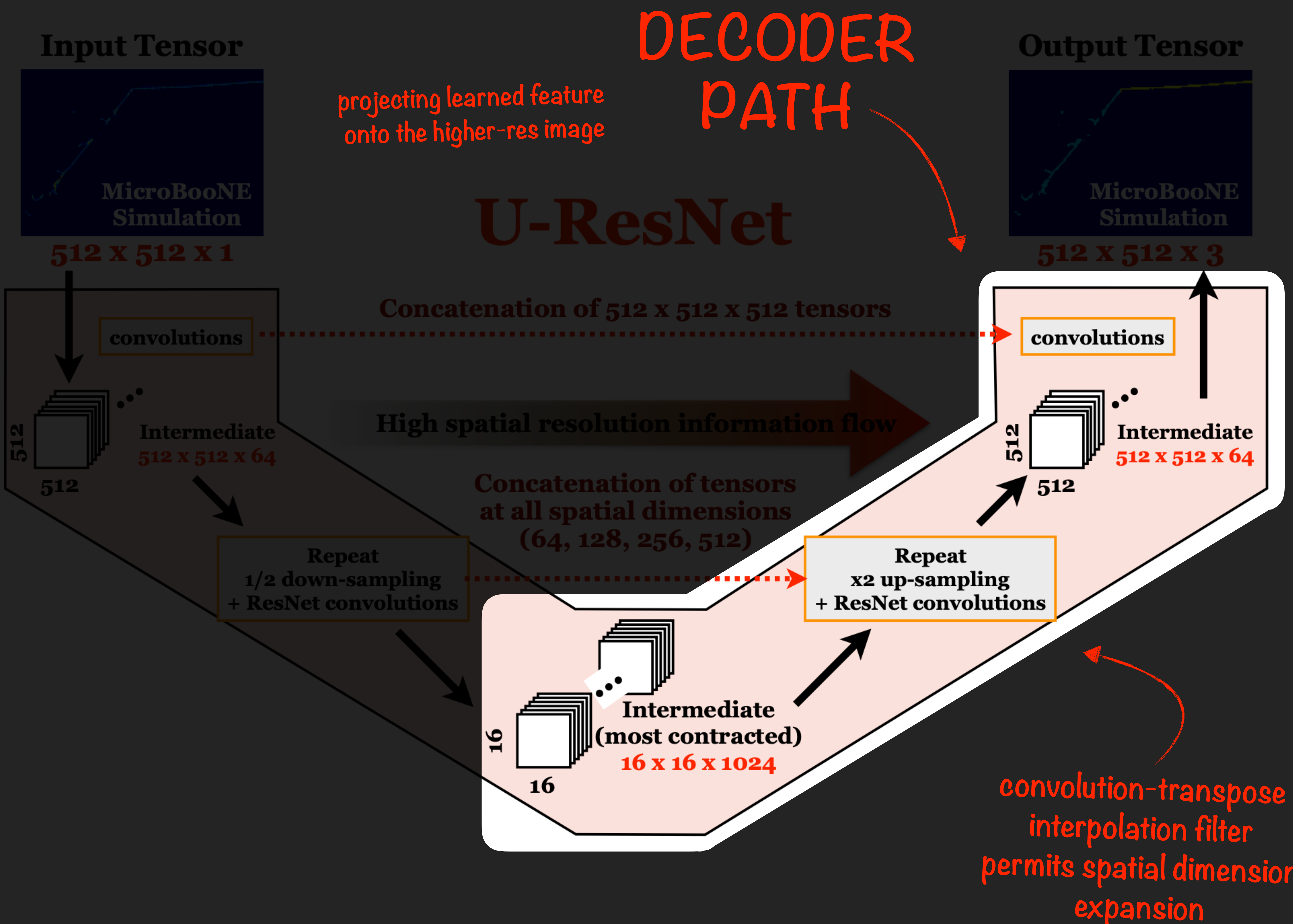
2. K. He, X. Zhang, S. Ren, J. Sun, "Deep Residual Learning for Image Recognition," Computer Vision and Pattern Recognition (CVPR), 2016 IEEE Conference on, 770 (2016).



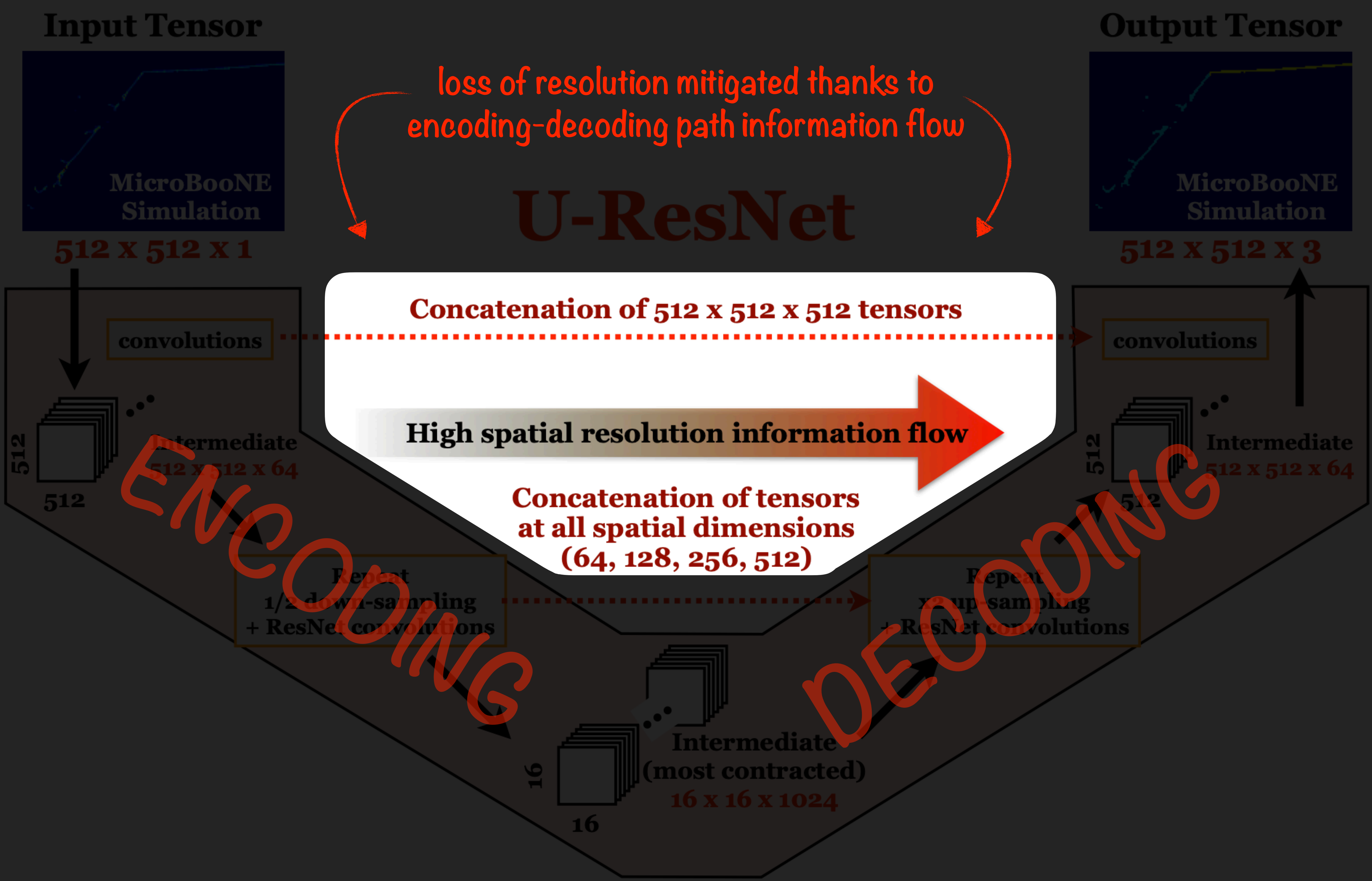
Input Tensor
MicroBooNE
Simulation
512 x 512 x 1
U-ResNet
Output Tensor
MicroBooNE
Simulation
512 x 512 x 3
Concatenation of 512 x 512 x 512 tensors
convolutions
convolutions
High spatial resolution information flow
Intermediate
512 x 512 x 64
512
512
Intermediate
512 x 512 x 64
512
512
Concatenation of tensors
at all spatial dimensions
(64, 128, 256, 512)
Repeat
1/2 down-sampling
+ ResNet convolutions
Repeat
x2 up-sampling
+ ResNet convolutions
Intermediate
(most contracted)
16 x 16 x 1024
16
16


ENCODER PATH
CNN classification-like
learning image features
Input Tensor
MicroBooNE Simulation
512 x 512 x 1
U-ResNet
Output Tensor
MicroBooNE Simulation
512 x 512 x 3
Concatenation of 512 x 512 x 512 tensors
convolutions
convolutions
High spatial resolution information flow
512
512
Intermediate
512 x 512 x 64
512
512
Intermediate
512 x 512 x 64
Concatenation of tensors
at all spatial dimensions
(64, 128, 256, 512)
Repeat
1/2 down-sampling
+ ResNet convolutions
Repeat
x2 up-sampling
+ ResNet convolutions
16
16
Intermediate
(most contracted)
16 x 16 x 1024
lower resolution
higher number of feature layers
down to 16x16
feature maps

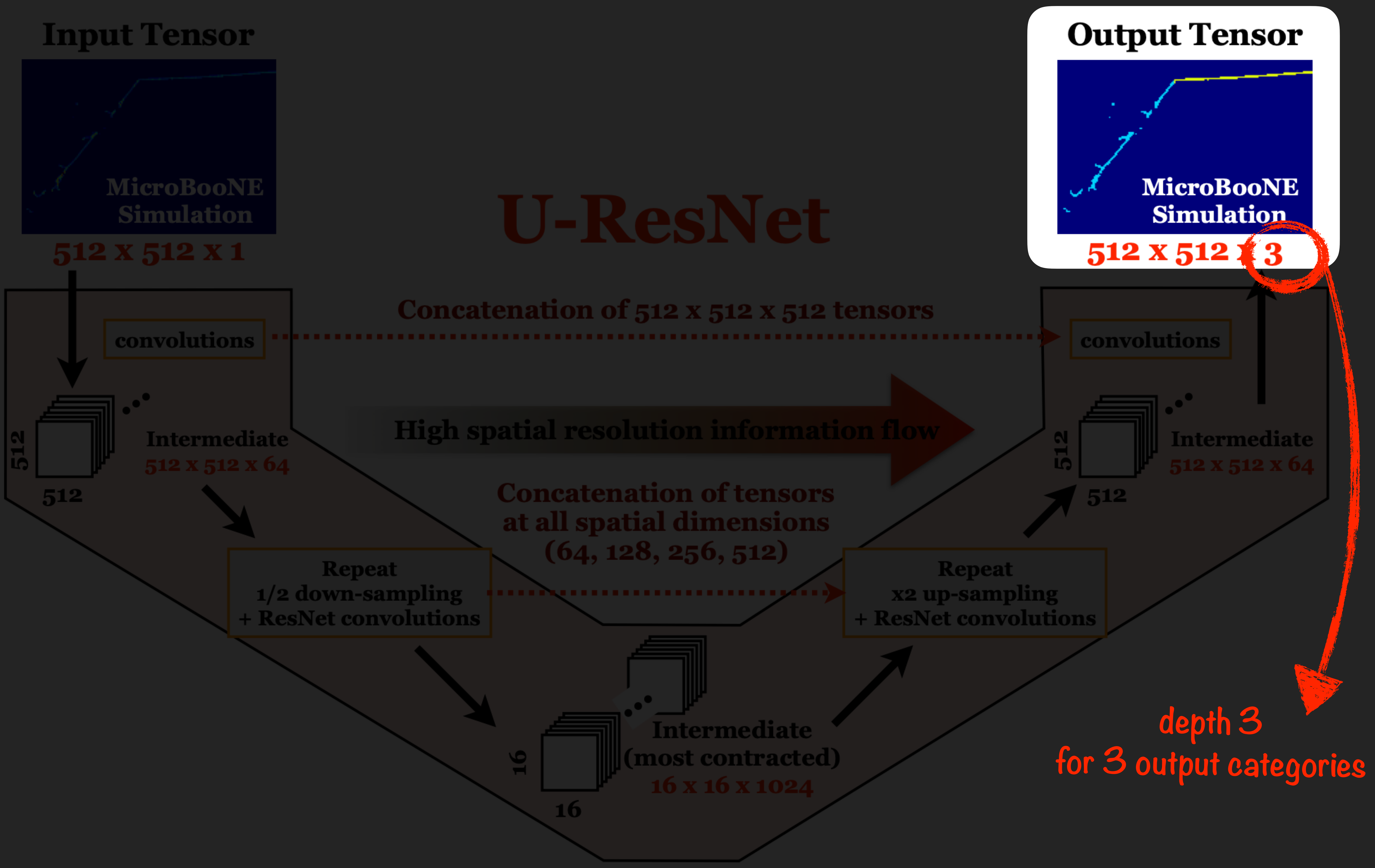

ENCODER PATH
CNN classification-like
learning image features
Input Tensor
MicroBooNE
Simulation
512 x 512 x 1
Output Tensor
MicroBooNE
Simulation
convolutions
512
512
Intermediate
512 x 512 x 64
Repeat
1/2 down-sampling
+ ResNet convolution
at this level, CLASSIFICATION
can be performed
e.g.
is there a track in the image: yes
is there a shower in the image: yes
lower resolution
higher number of feature layers
down to 16x16
feature maps

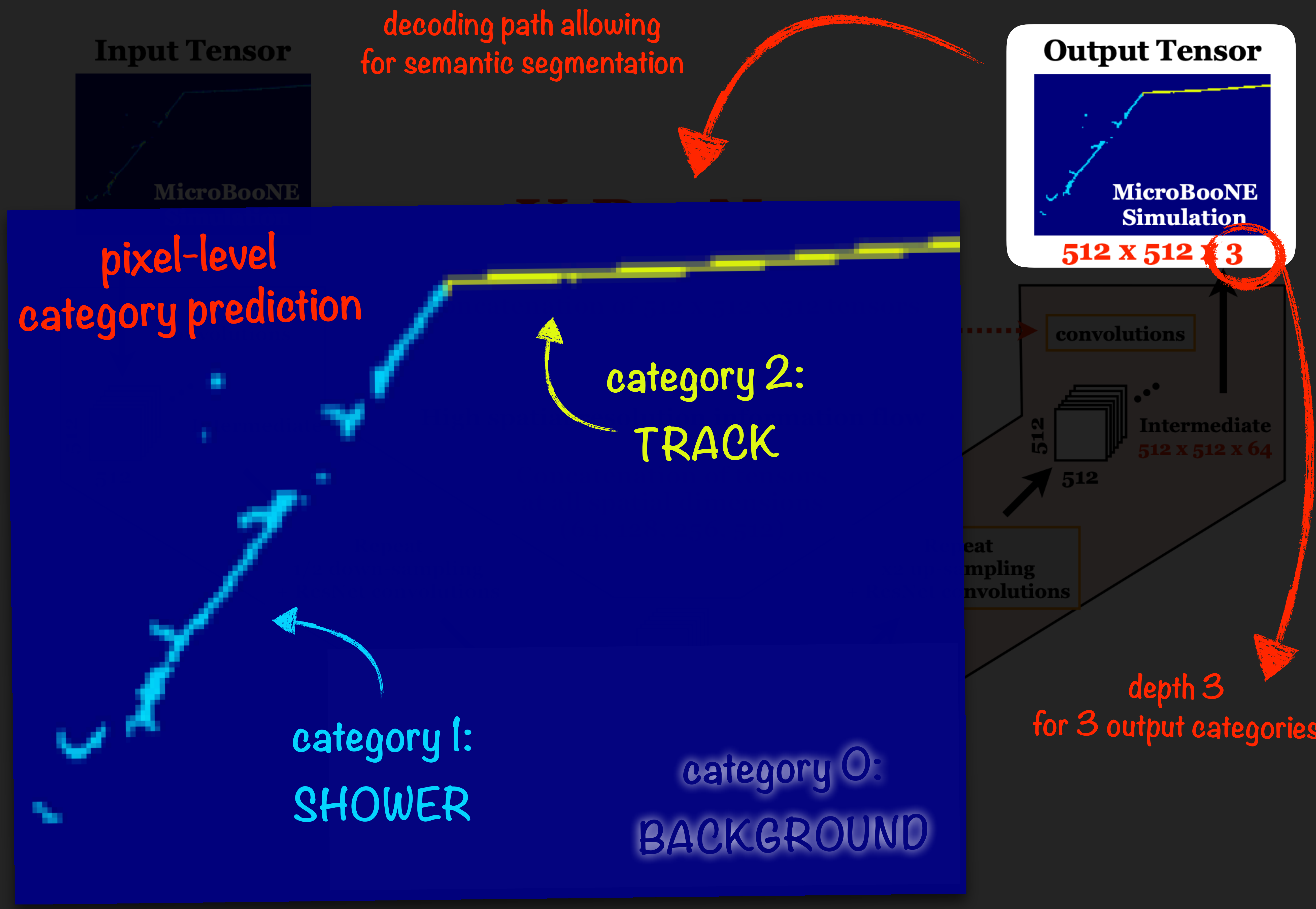

DECODER PATH
projecting learned feature onto the higher-res image
Input Tensor
MicroBooNE Simulation
512 x 512 x 1
U-ResNet
Output Tensor
MicroBooNE Simulation
512 x 512 x 3
Concatenation of 512 x 512 x 512 tensors
convolutions
convolutions
High spatial resolution information flow
512
512
Intermediate
512 x 512 x 64
512
512
Intermediate
512 x 512 x 64
Concatenation of tensors at all spatial dimensions (64, 128, 256, 512)
Repeat 1/2 down-sampling + ResNet convolutions
Repeat x2 up-sampling + ResNet convolutions
16
16
Intermediate (most contracted)
16 x 16 x 1024
convolution-transpose interpolation filter permits spatial dimension expansion

loss of resolution mitigated thanks to
encoding-decoding path information flow

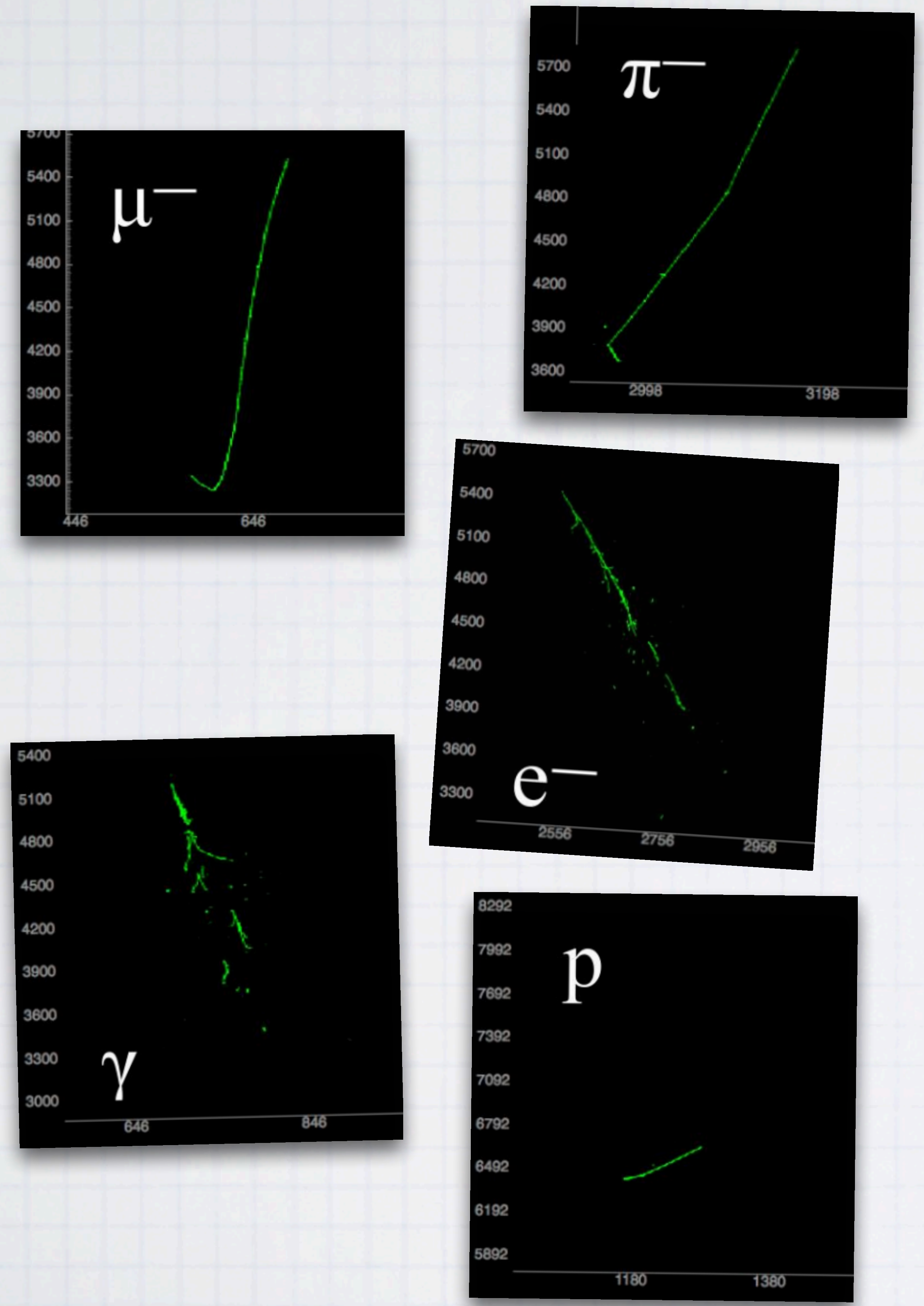


concatenation allows information about spatial resolution to flow
from encoding path (best possible resolution) to decoding path


Input Tensor
MicroBooNE Simulation
512 x 512 x 1
U-ResNet
Output Tensor
MicroBooNE Simulation
512 x 512 x 3
Concatenation of 512 x 512 x 512 tensors
convolutions
convolutions
High spatial resolution information flow
512
512
Intermediate
512 x 512 x 64
512
512
Intermediate
512 x 512 x 64
Concatenation of tensors
at all spatial dimensions
(64, 128, 256, 512)
Repeat
1/2 down-sampling
+ ResNet convolutions
Repeat
x2 up-sampling
+ ResNet convolutions
16
16
Intermediate
(most contracted)
16 x 16 x 1024
depth 3
for 3 output categories


decoding path allowing
for semantic segmentation
Input Tensor
MicroBooNE
Output Tensor
MicroBooNE
Simulation
512 x 512 x 3
pixel-level
category prediction
category 2:
TRACK
category 1:
SHOWER
category 0:
BACKGROUND
convolutions
Intermediate
512 x 512 x 64
512
512
depth 3
for 3 output categories

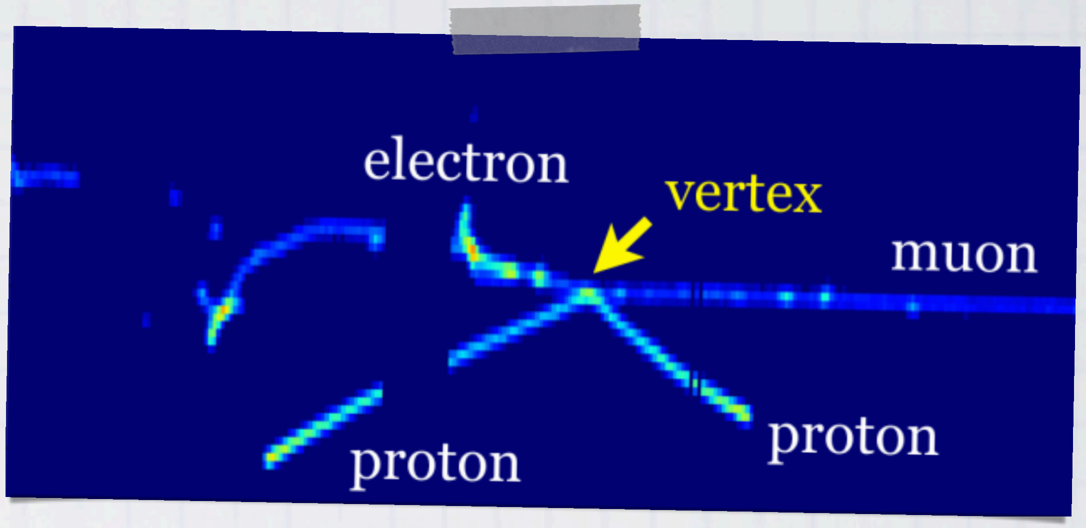
TRANSFER LEARNING

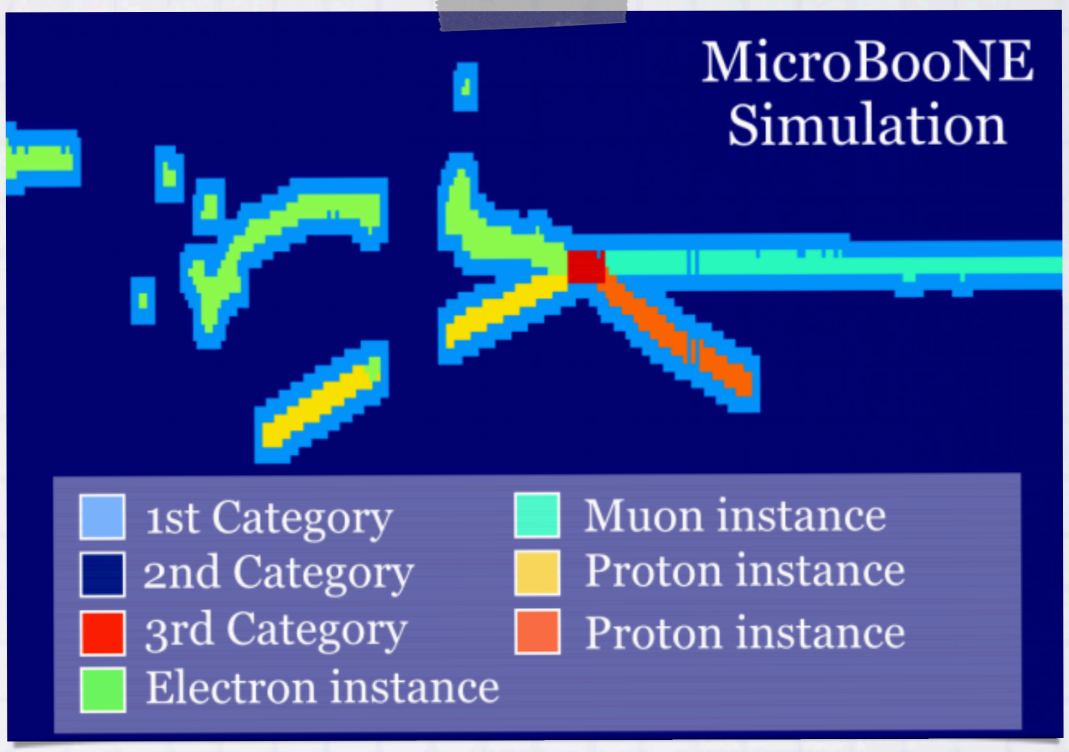


- CNN (see our previous paper) trained on **particle ID** (no semantic segmentation) using single particle images.
- **Transfer** pre-trained weights from **CNN to SSnet**.
- Provide **excellent initial state** for SSnet.
- SSnet training then performs fine-tuning.

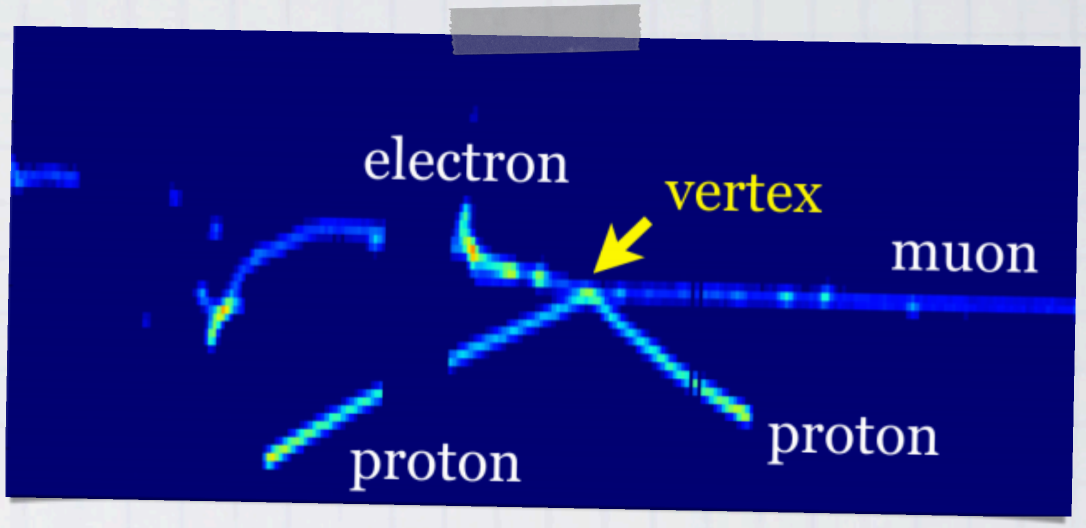
TRAINING

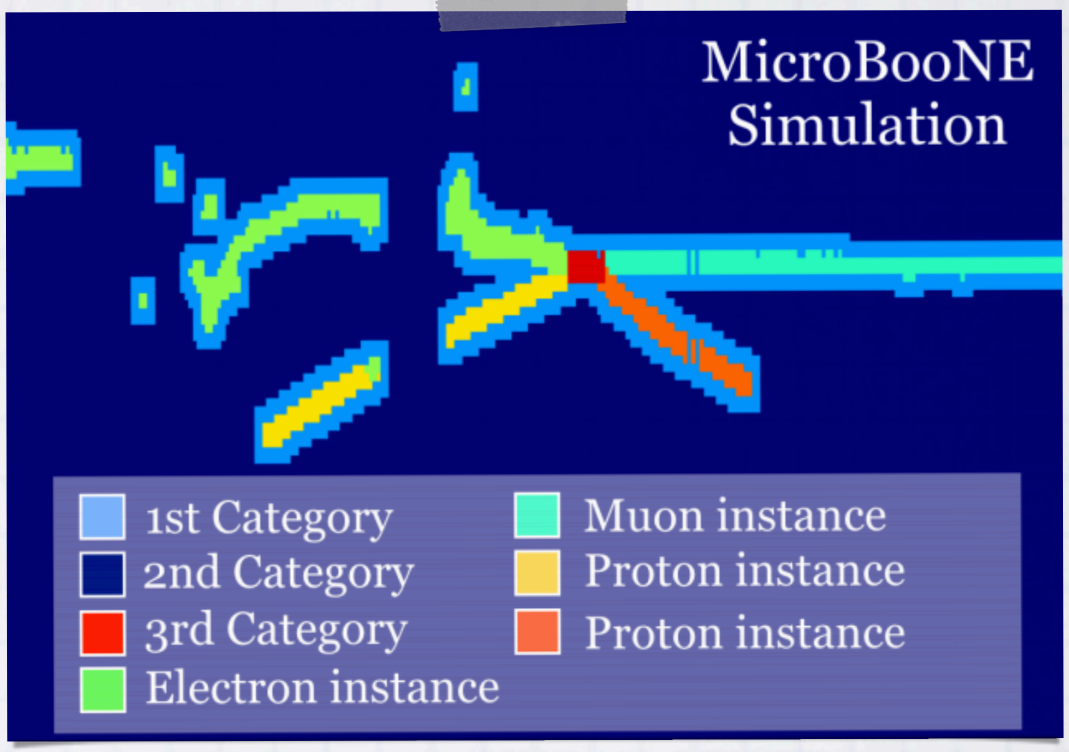
- Using "**transfer-learning**" technique.
- Initial network parameters from **initial classification task** (see our CNN paper)
    - Training is performed on "**particle bomb**" generated events.
    - Containing **multiple charged particles** sharing a vertex.





TRAINING





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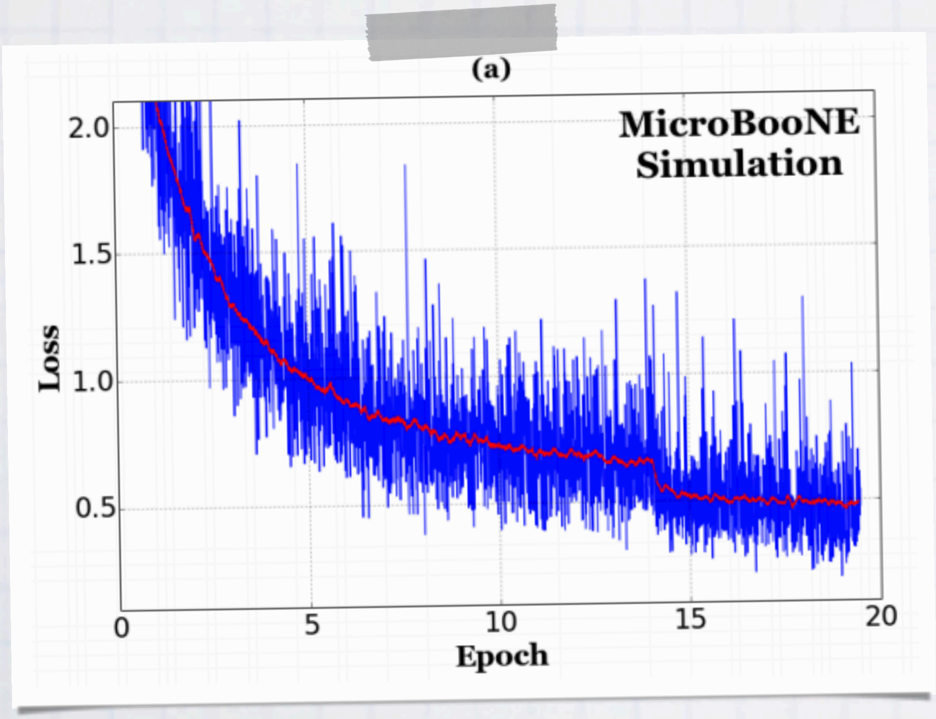
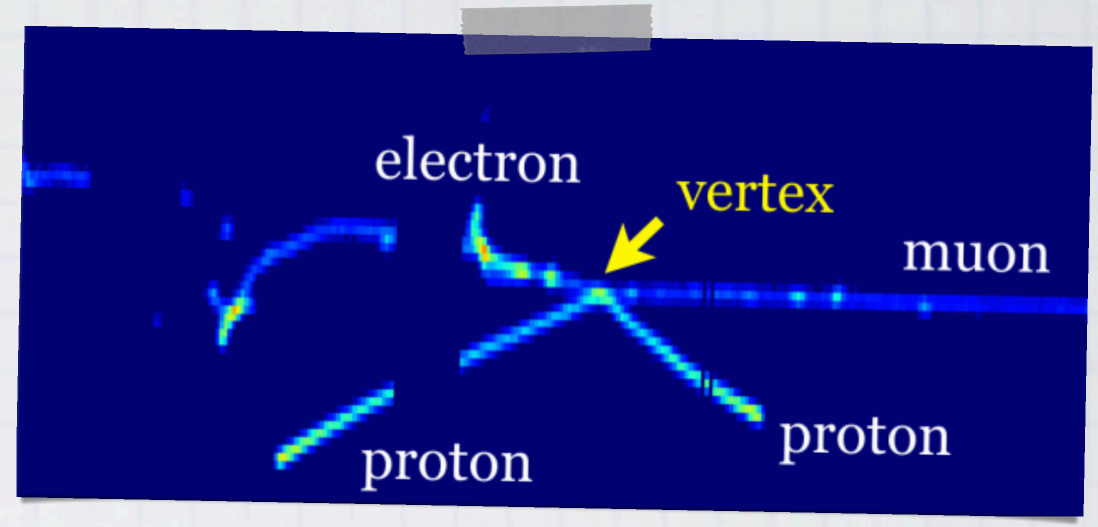
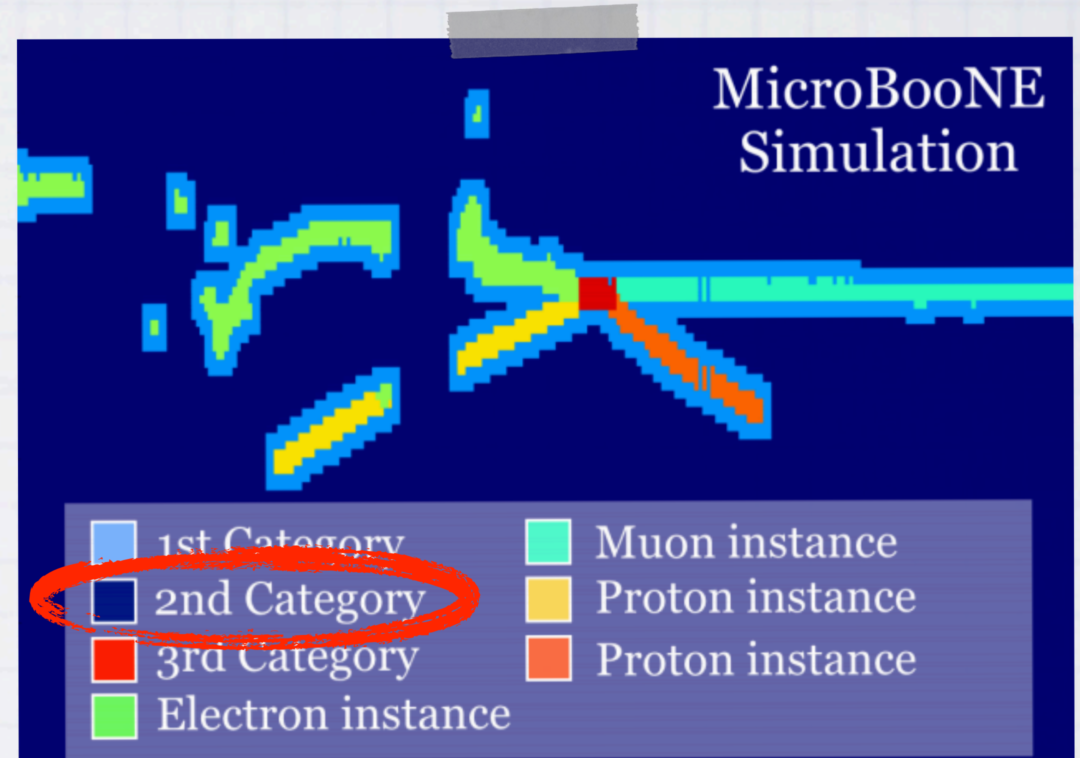


- Loss computed summing over **pixel-wise multinomial logistic loss**.

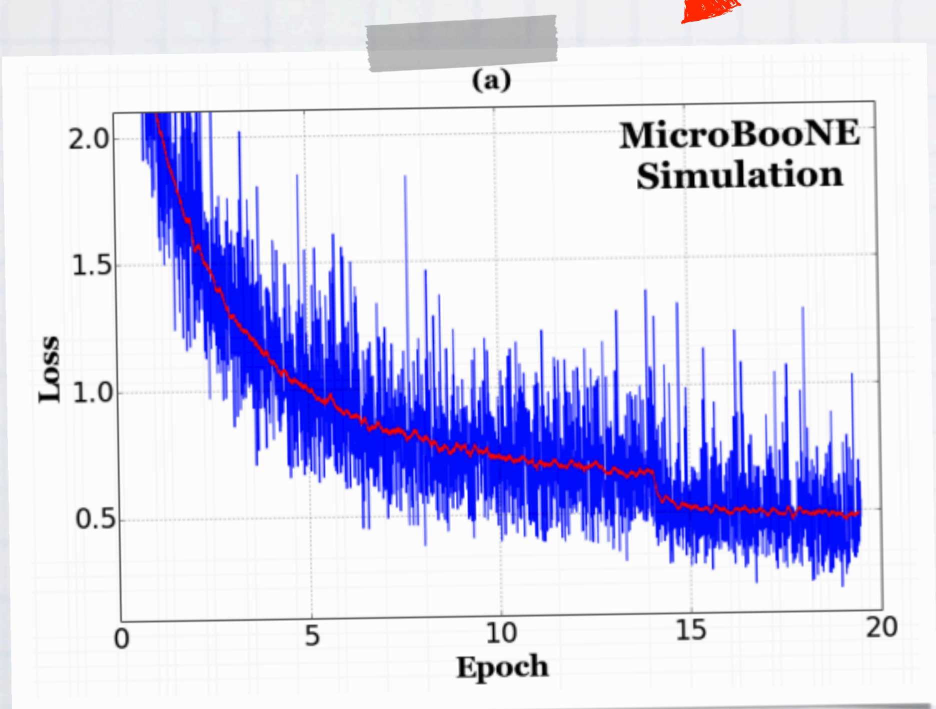
Training



- Using "**transfer-learning**" technique.
- Initial network parameters from **initial classification task** (see [our CNN paper])
  - Training is performed on "**particle bomb**" generated events.
  - Containing **multiple charged particles** sharing a vertex.



if unmitigated background dominates loss minimization!

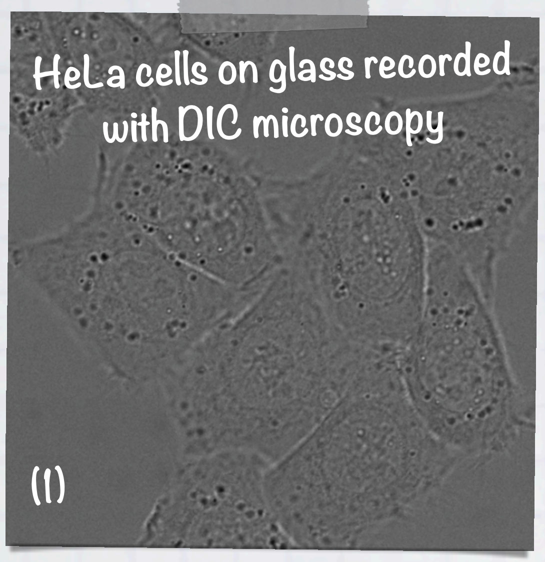


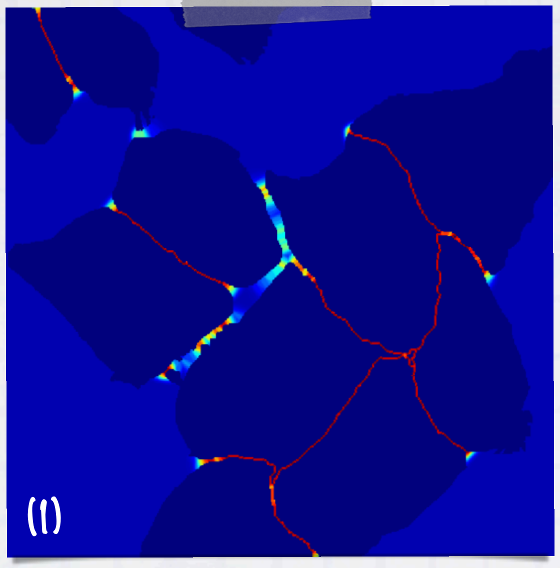
- Loss computed summing over **pixel-wise multinomial logistic loss**.
- But images are **mostly background**! We care more about **not-background** categories.

Pixel-Wise Loss

high vs. low information density

Pixel-Wise Loss



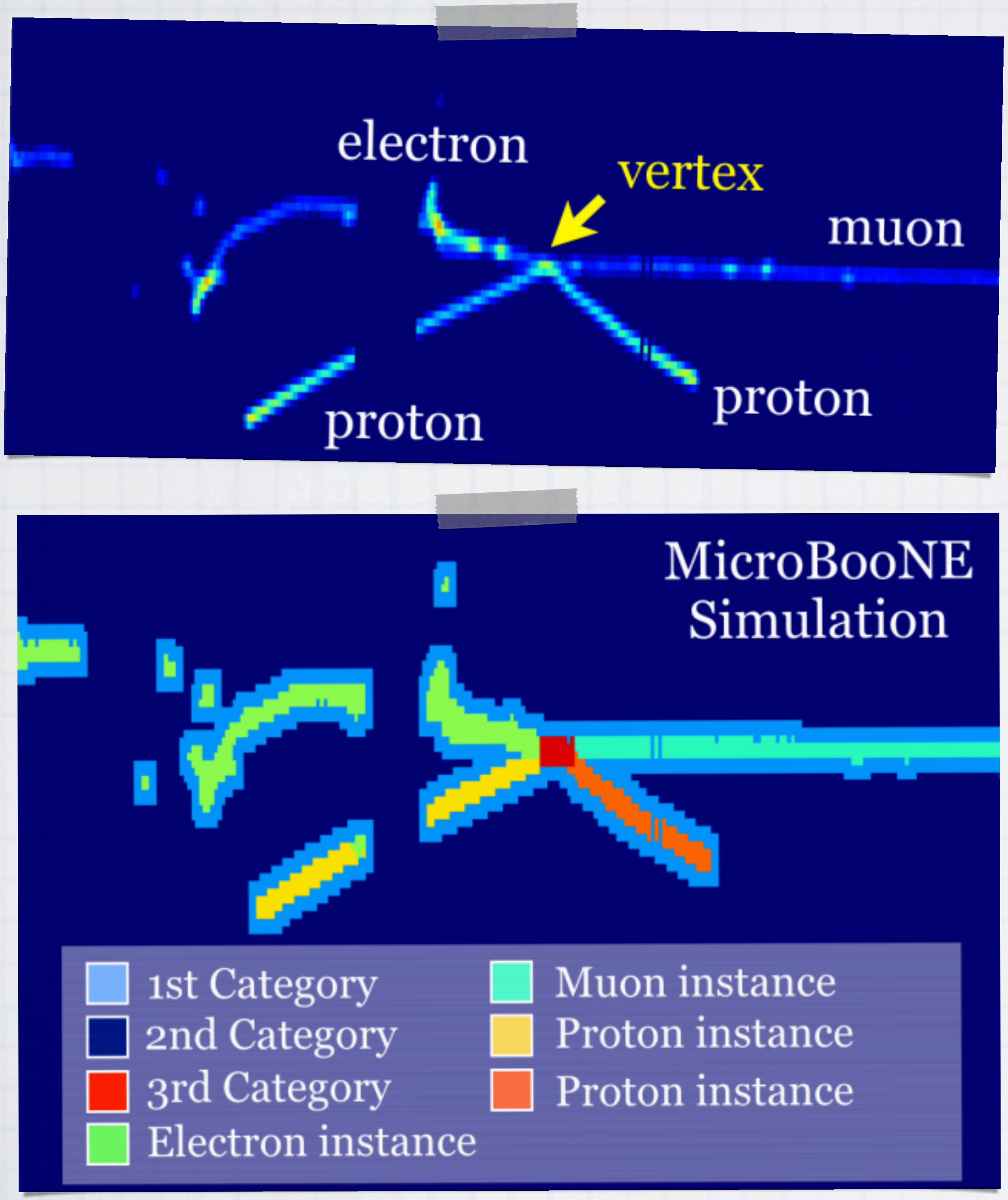


high vs. low information density

- A lesson to be learned from bio-medical imaging.
- **Low information density**.
- U-Net[1] introduces a **class-wise** (CL) **loss weighting factor** which is the reciprocal for the number of pixels in each class.

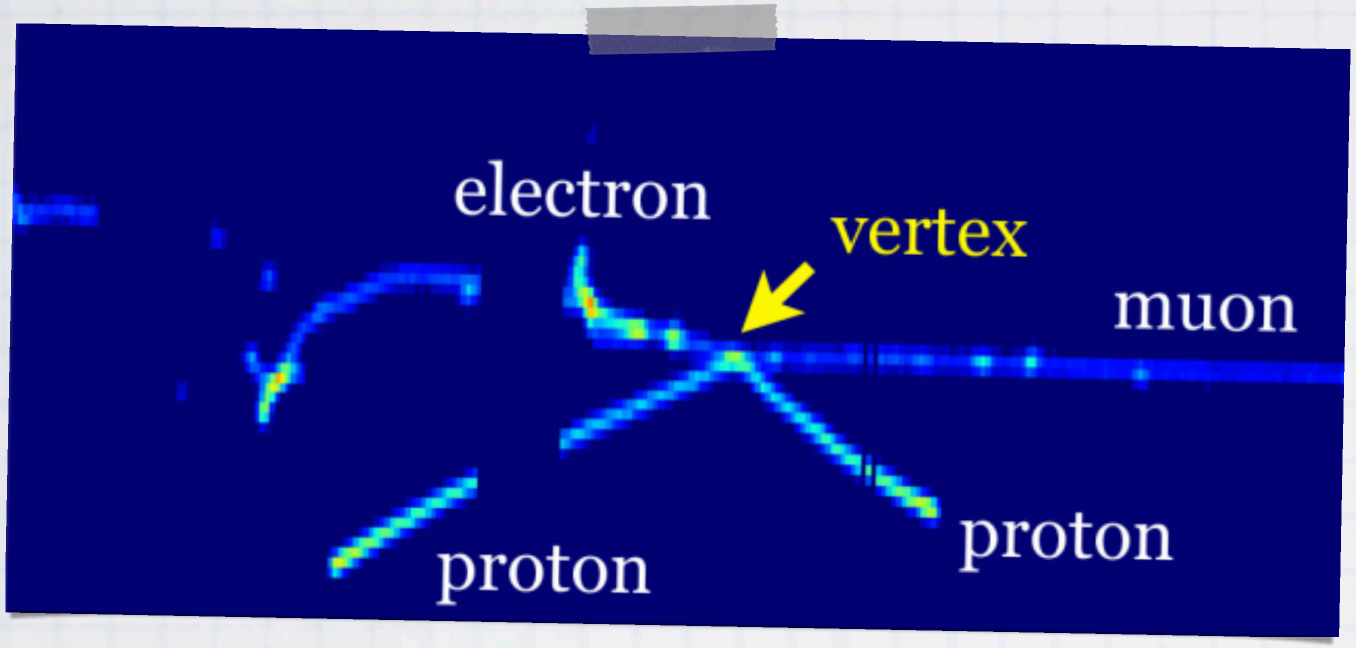
1. O. Ronneberger, P. Fischer, T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," Medical Image Computing and Computer-Assisted Intervention (MICCAI) 9351, 234 (2015).

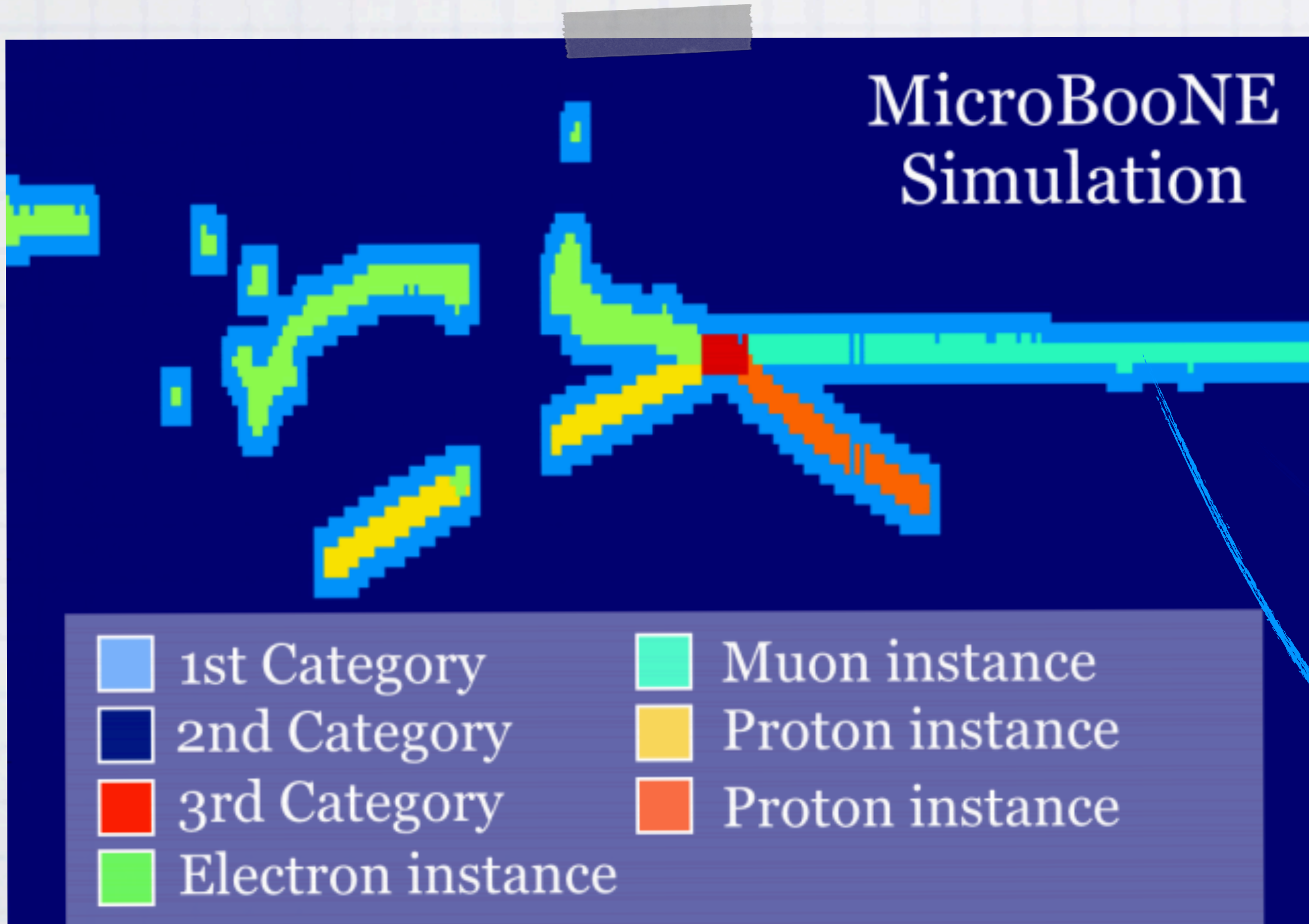
Pixel-Wise Loss



- **Pixel-wise** (PL) **loss weights** penalize mistakes.
- Weights **inversely proportional** to **pixel count** in each category.
- Allows network to **focus** on **challenging parts** of an image.
- Extremely effective for **low information density** images.

PIXEL-WISE LOSS





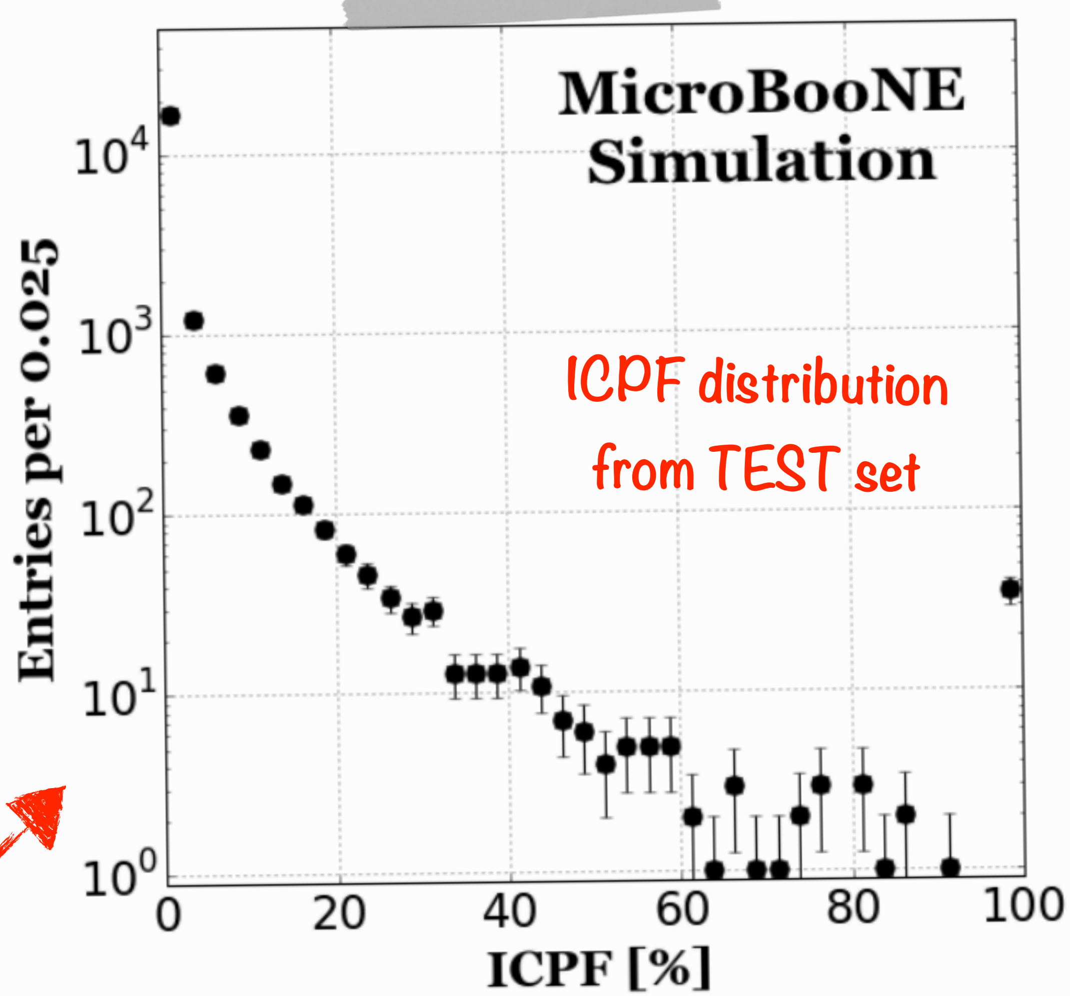
- **Pixel-wise** (PL) **loss weights** penalize mistakes.
- Weights **inversely proportional** to **pixel count** in each category.
- Allows network to **focus** on **challenging parts** of an image.
- Extremely effective for **low information density** images.

enhanced by separating background into 2 categories:

overall background

background separating features from overall background (2 pixels edge)

PERFORMANCE



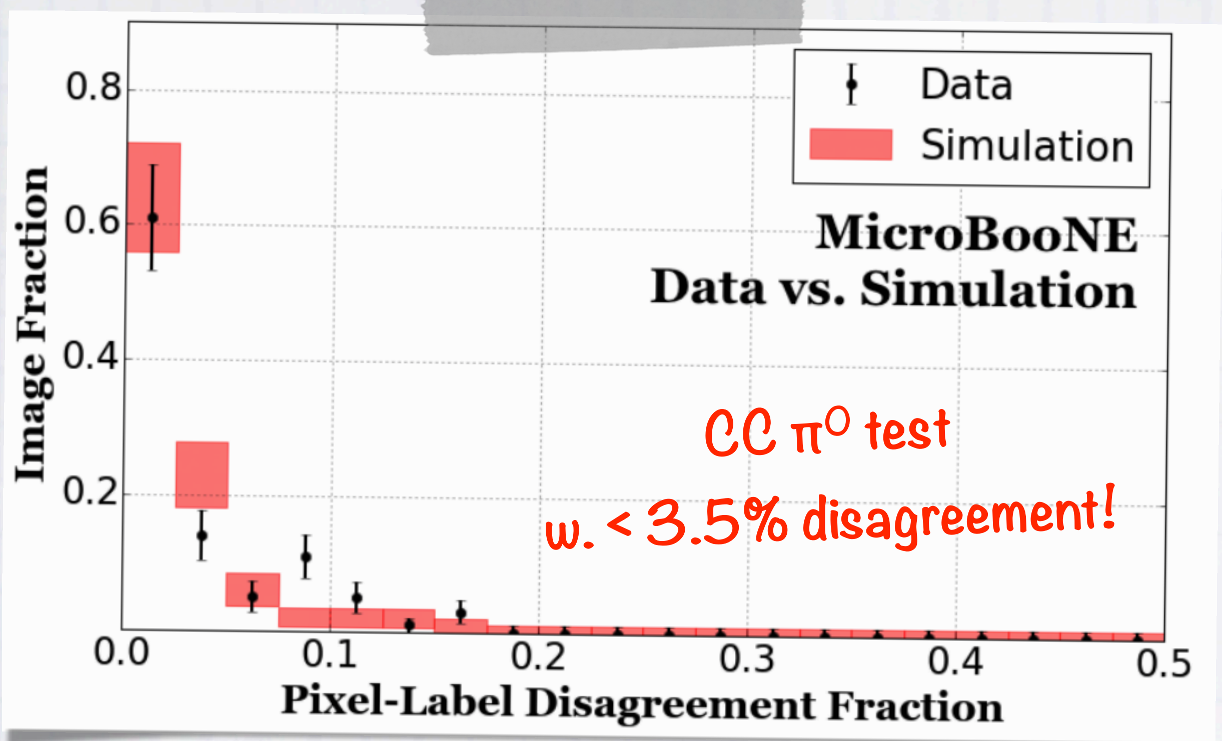
Sample	ICPF mean	ICPF 90%	Shower	Track
Test	1.9	4.6	4.1	2.6
ν_e	6.0	13.8	7.6	13.8
ν_μ	3.9	4.5	14.2	4.3
1e1p	2.2	5.7	2.8	4.0
1μ1p-LE	2.3	2.2	6.2	2.4
1e1p-LE	3.9	11.5	3.8	8.0

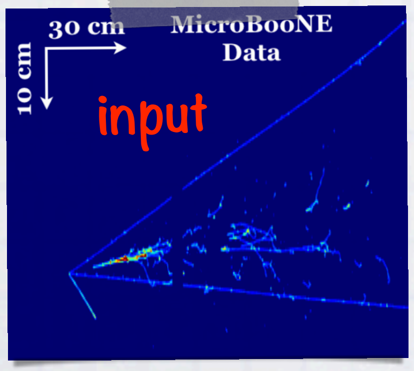
- **I**ncorrectly **C**lassified **P**ixel **F**raction (**ICPF**) as **performance metric**.
- Takes into account false positives, both for tracks and shower categories.

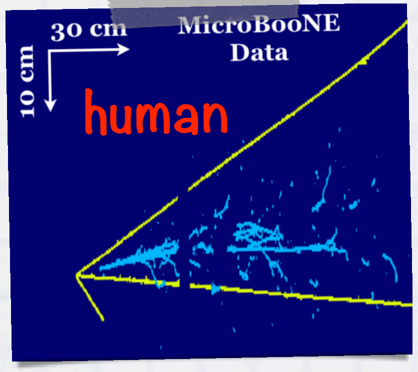
- Extremely **low ICPF**.
- Very well **below 10%** for test sample.
- **Performance varying** over **different signal domains**.

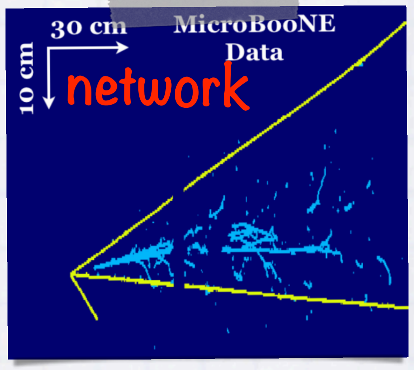
PERFORMANCE IN DATA

- There is **no truth label** for real data.
- Performing tests comparing **(human) physicist prediction vs. network prediction** in both data and simulation.









CONCLUSIONS

- **MicroBooNE** is using **Deep Convolutional Neural Network** for physics analyses.
- First application of **Deep Semantic Segmentation Network** for **track/shower** separation in **LArTPC**.
- Using **transfer-learning** and **pixel-wise error** to perform **pixel-level labelling** with average 6 - 4 % ICPF (for ν_e and ν_μ).
- Validation on **real** LArTPC data (**first ever performed**) showing **excellent physicist-network agreement** (>96%).

arXiv:1808.07269v1 [physics.ins-det] 22 Aug 2018

A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber

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Check out our SSNet paper:

https://arxiv.org/abs/1808.07269