μBooNE

Deep Neural Network Techniques R&D for LArTPC Data Reconstruction

Brookhaven National Lab EDG Seminar August 2018

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SLAC National Accelerator Laboratory

Outline

- Liquid Argon Time Projection Chambers
- Recent innovations in Computer Vision
- Deep Convolutional Neural Networks (CNN)
- Application for particle image analysis
- Wrap-up

Some people like buzzwords, some people don't.
My topic is about applying buzzword on buzzword.
Some of you might hate it, but hopefully some of you love it.

Liquid Argon Time Projection Chambers

Outline

- **Liquid Argon Time Projection Chambers**
- Recent innovations in Computer Vision
- Deep Convolutional Neural Networks (CNN)
- Deep CNNs for image data analysis
- Wrap-up

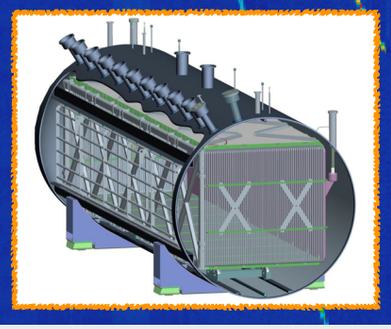
75 cm

Run 3493 Event 41075, October 23rd

LArTPC: Particle Imaging Detector

μBooNE

~mm/pixel spatial resolution
~MeV level sensitivity



MicroBooNE
~87 ton (school bus size)

ν_μ

Bubble Chamber

Liquid Argon Time Projection Chamber

- Chamber-like images: digitized electronics readout
- Calorimetric measurement + scalability to a large mass

2015

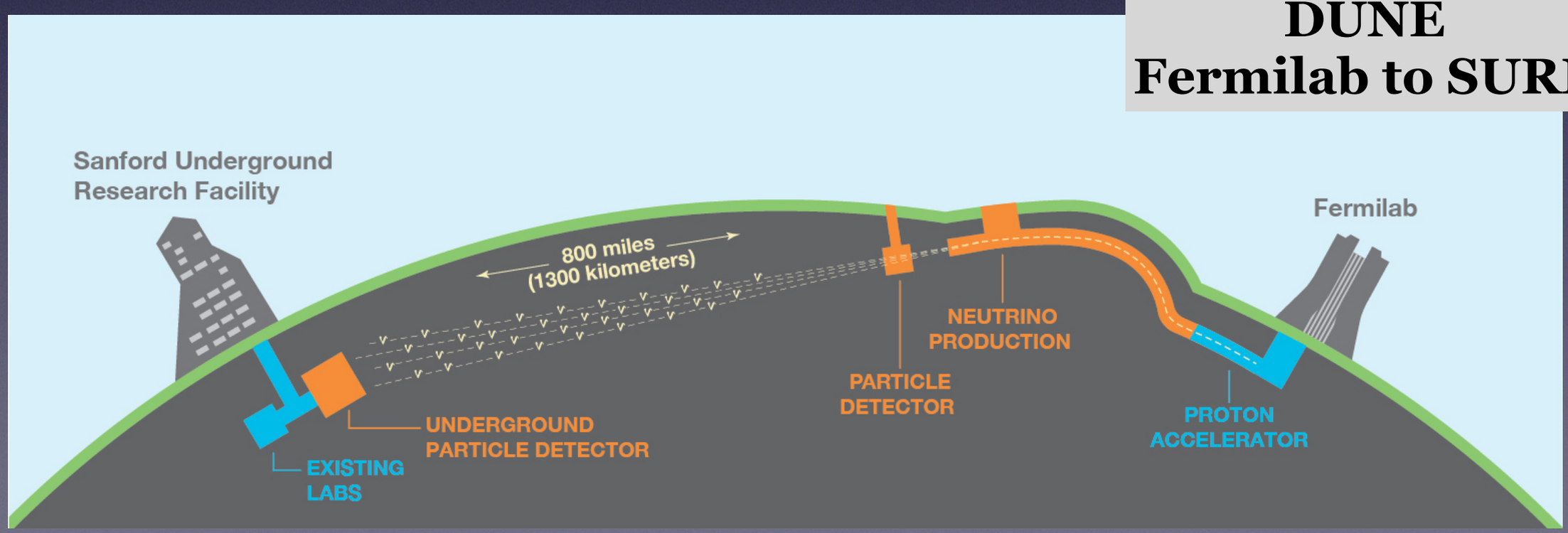
Neutrino Oscillation Experiments (II)

Accelerator-based oscillation experiments

DUNE: long baseline program (first beam expected @ 2026)

- Measure mass hierarchy and CP violation ($\nu_\mu \rightarrow \nu_e$ vs. $\overline{\nu}_\mu \rightarrow \overline{\nu}_e$)
- Rare physics processes (proton decay, n-$\overline{n}$, Supernova neutrinos)

DUNE
Fermilab to SURF



Neutrino Oscillation Experiments (II)

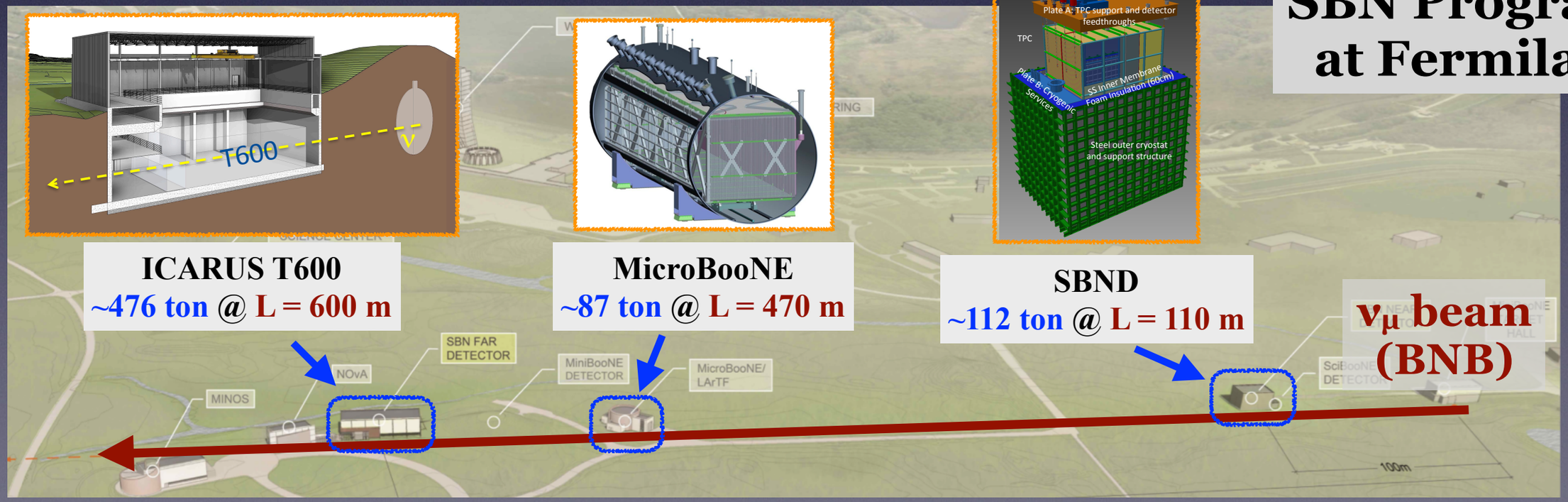
Accelerator-based oscillation experiments

DUNE: long baseline program (first beam expected @ 2026)

- Measure mass hierarchy and CP violation ($\nu_\mu \to \nu_e$ vs. $\bar{\nu}_\mu \to \bar{\nu}_e$)
- Rare physics processes (proton decay, n-$\bar{n}$, Supernova neutrinos)

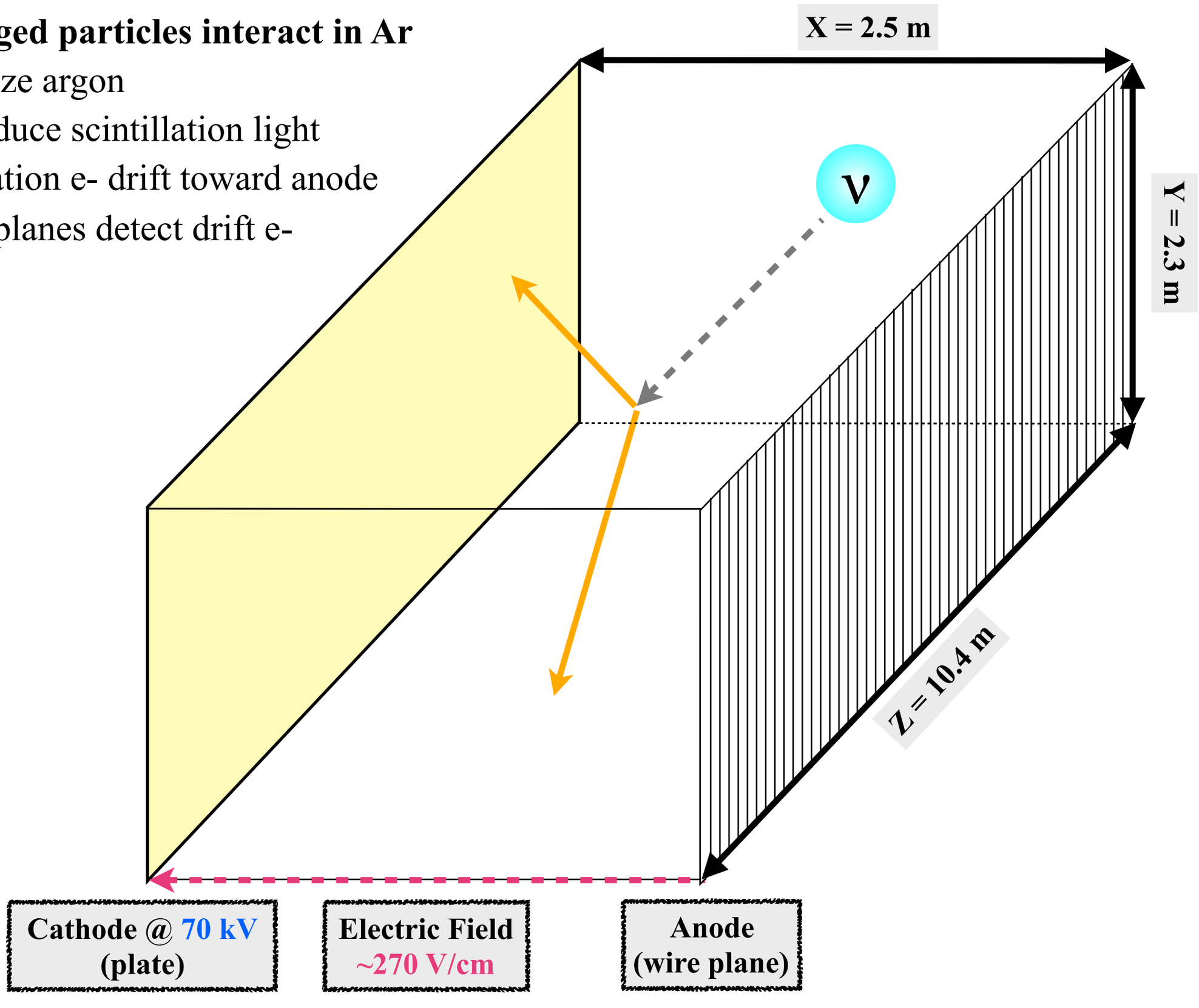
SBN: short baseline program (2015 ~)

- Measure $\nu_\mu \to \nu_e$ to investigate possible sterile neutrino oscillation
- Employs three LArTPC detectors at different baselines
- LArTPC R&D for DUNE



How MicroBooNE LArTPC Work (I)

1. **Charged particles interact in Ar**
   - Ionize argon
   - Produce scintillation light
2. Ionization e- drift toward anode
3. Wire planes detect drift e-



How MicroBooNE LArTPC Work (II)

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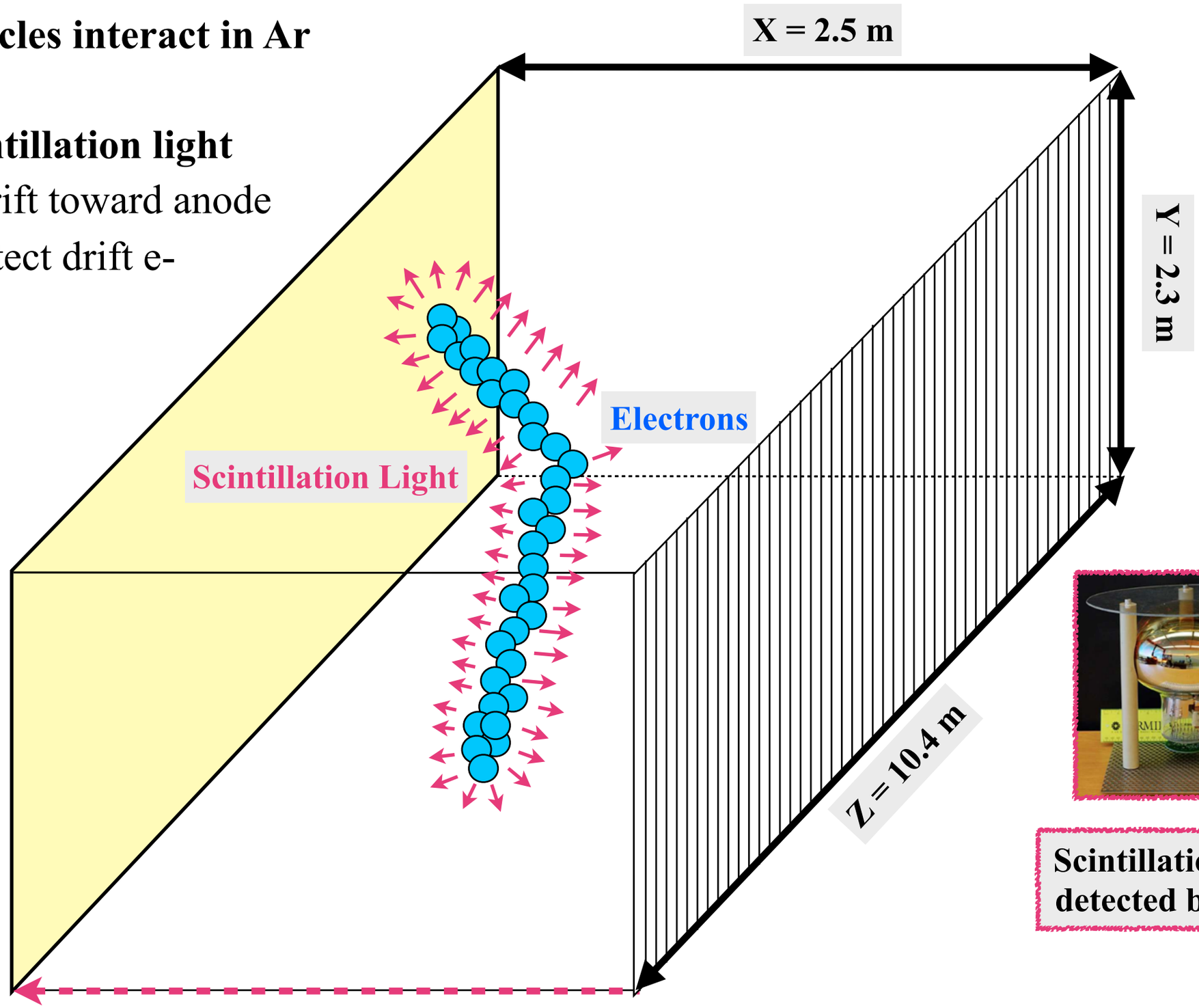
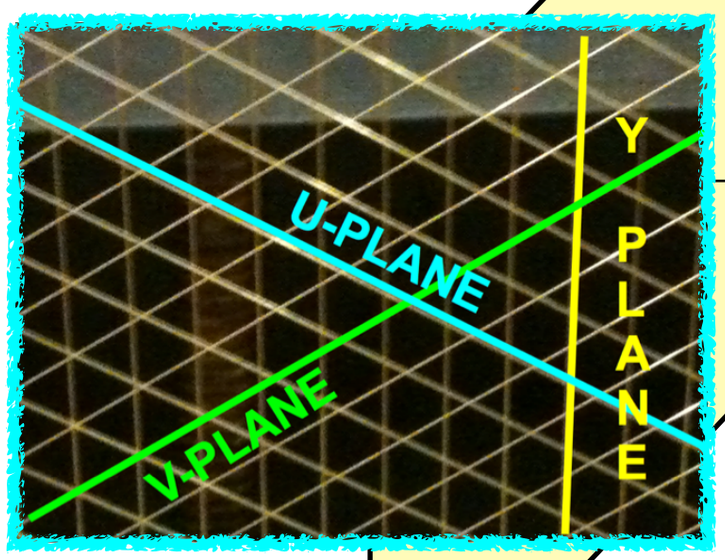


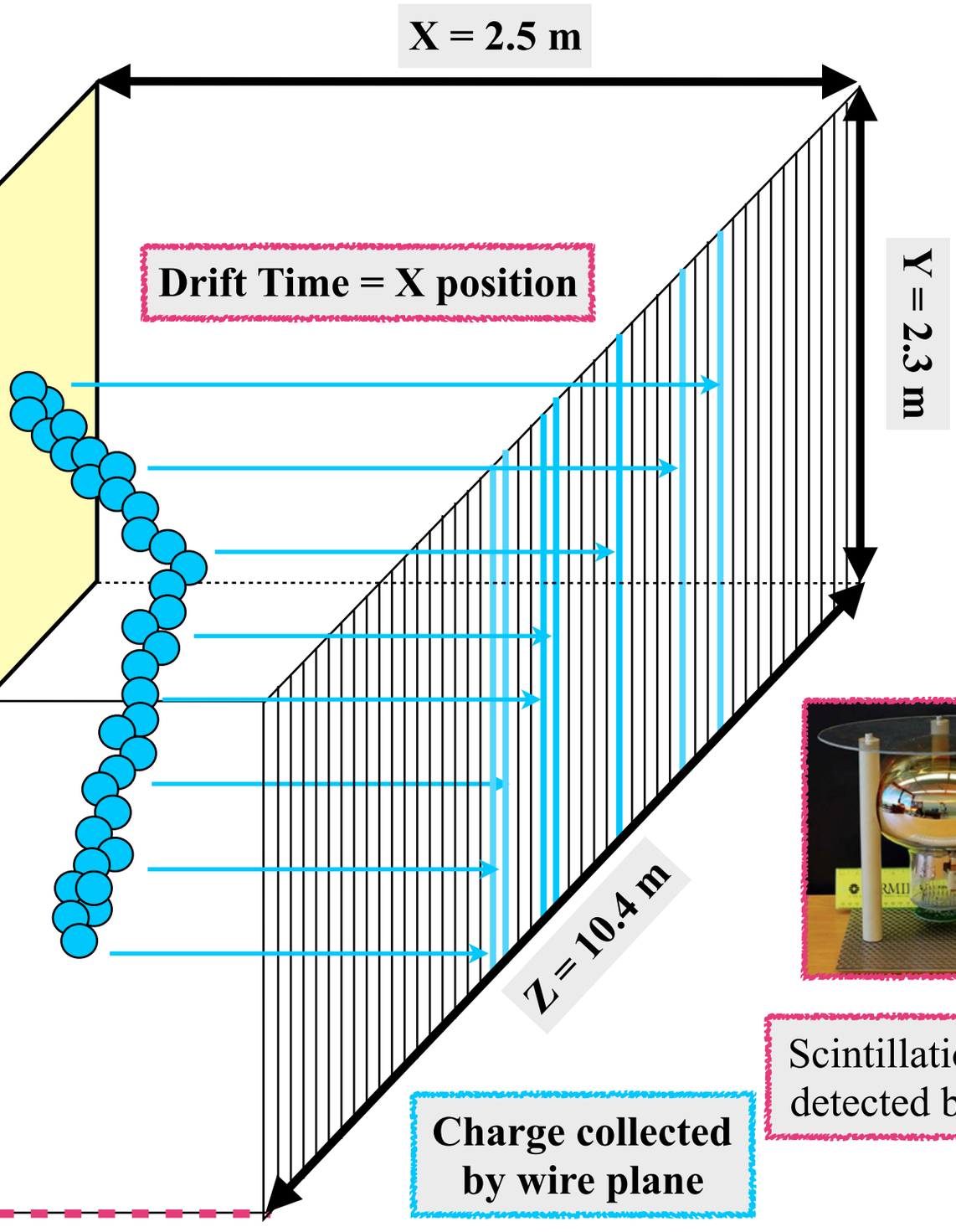
Scintillation Light detected by PMTs

How MicroBooNE LArTPC Work (III)

1. Charged particles interact in Ar
   - Ionize argon
   - Produce scintillation light
2. **Ionization e- drift toward anode**
3. **Wire planes detect drift e-**

Three Wire Planes





Scintillation Light detected by PMTs

Charge collected by wire plane

Cathode @ 70 kV (plate)

Electric Field ~270 V/cm

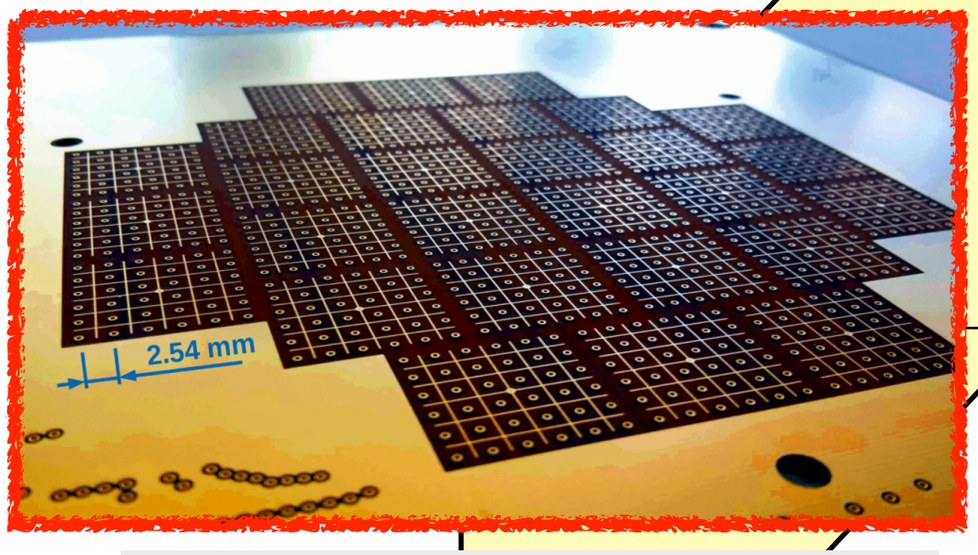
Anode (wire plane)

How ~~MicroBooNE~~ LArTPC Work (IV)

Pixel (DUNE ND)

1. Charged particles interact in Ar
   - Ionize argon
   - Produce scintillation light
2. **Ionization e- drift toward anode**
3. **~~Wire planes~~ detect drift e-**

pixel detector



[J. Assadi et al. arxiv 1801.08884]

X = 2.5 m

Y = 2.3 m

Z = 10.4 m

Drift Time = X position

Scintillation Light detected by PMTs

Charge collected by pixel-pad plane

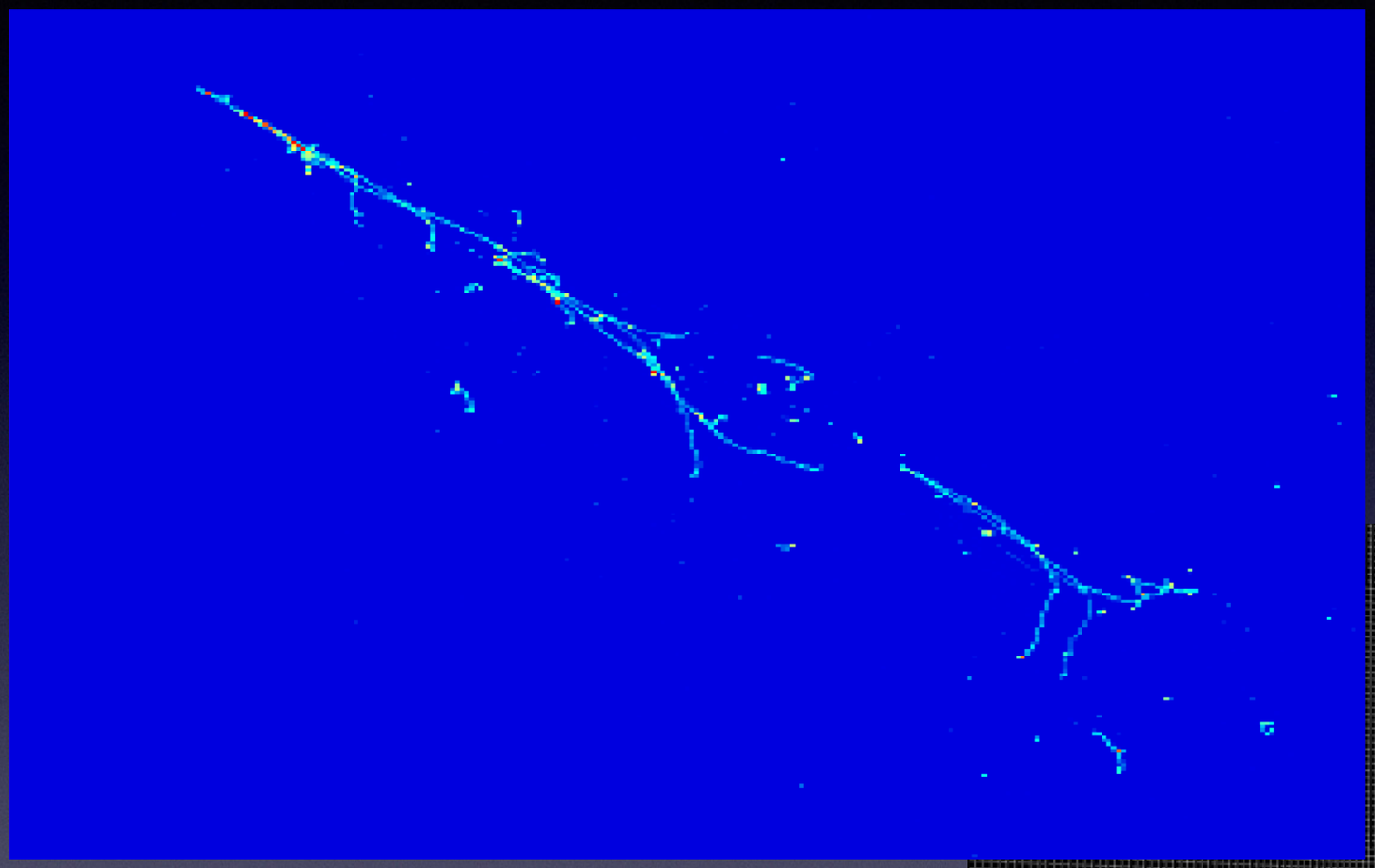
Cathode @ 70 kV (plate)

Electric Field ~270 V/cm

Anode (wire plane)

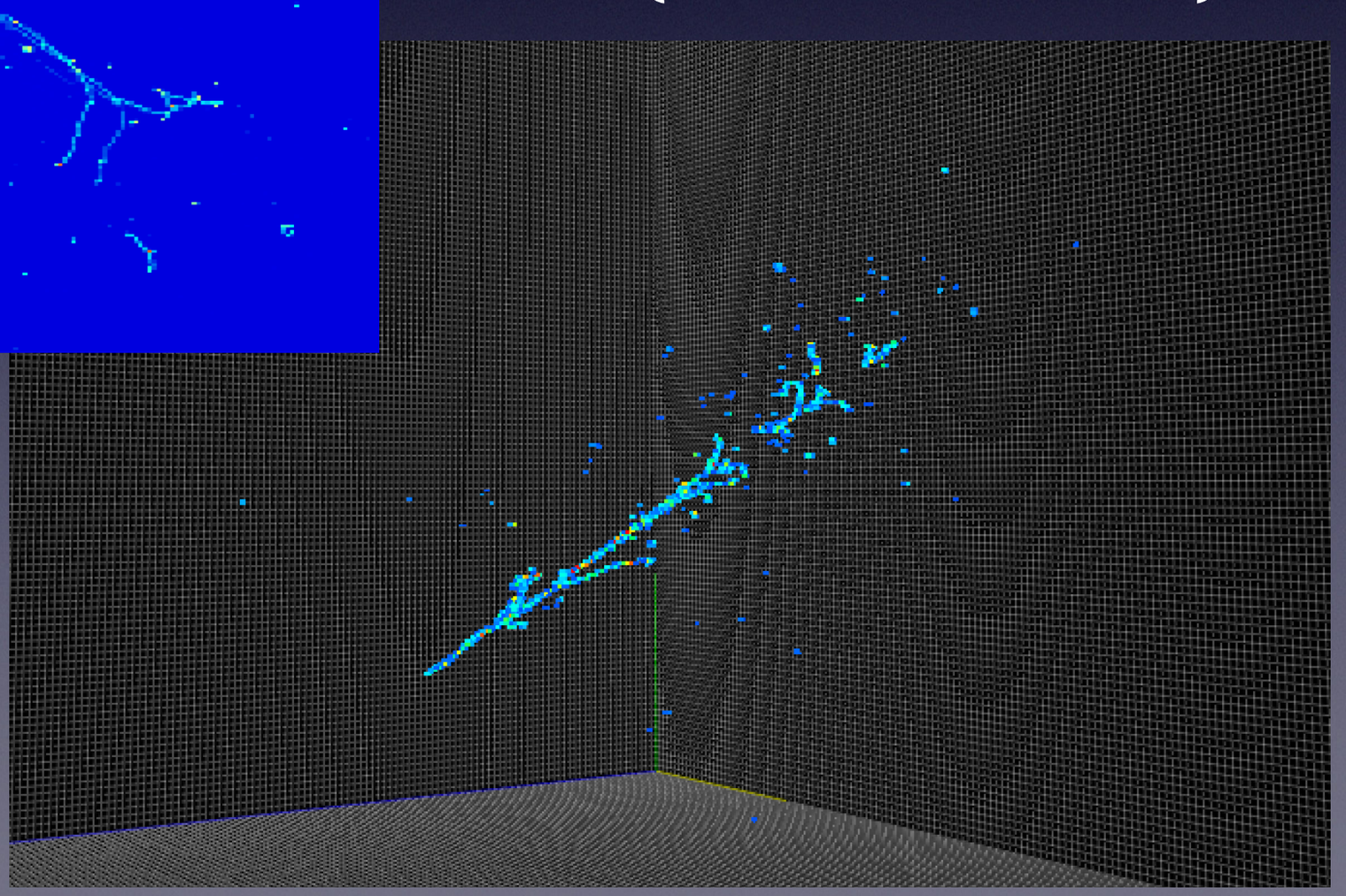
LArTPC: Particle Imaging Detector

... putting everything together ...



2D Projection
(Wire Detector)

3D Imaging
(Pixel Detector)



Challenges in LArTPC Data Analysis?

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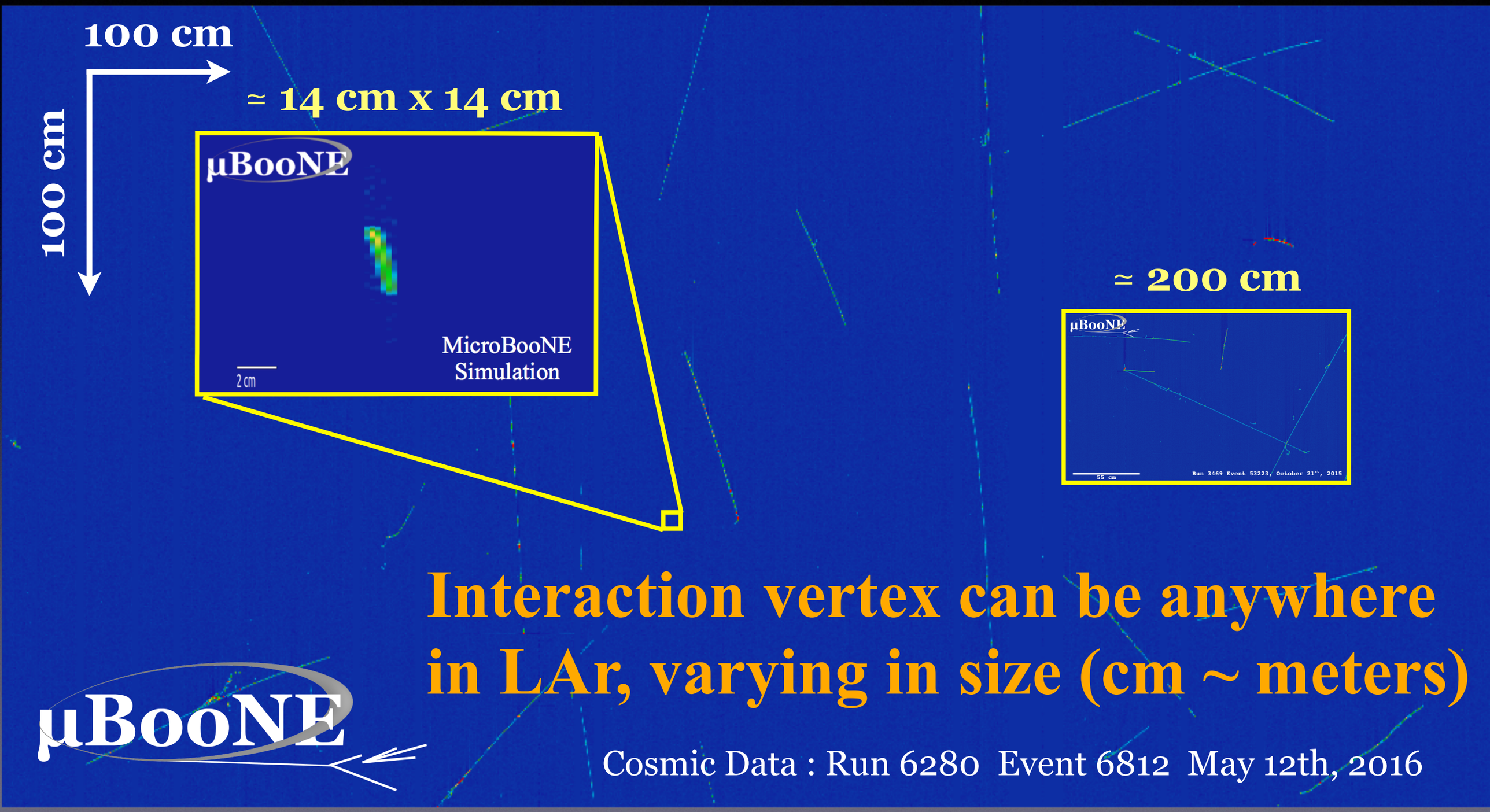

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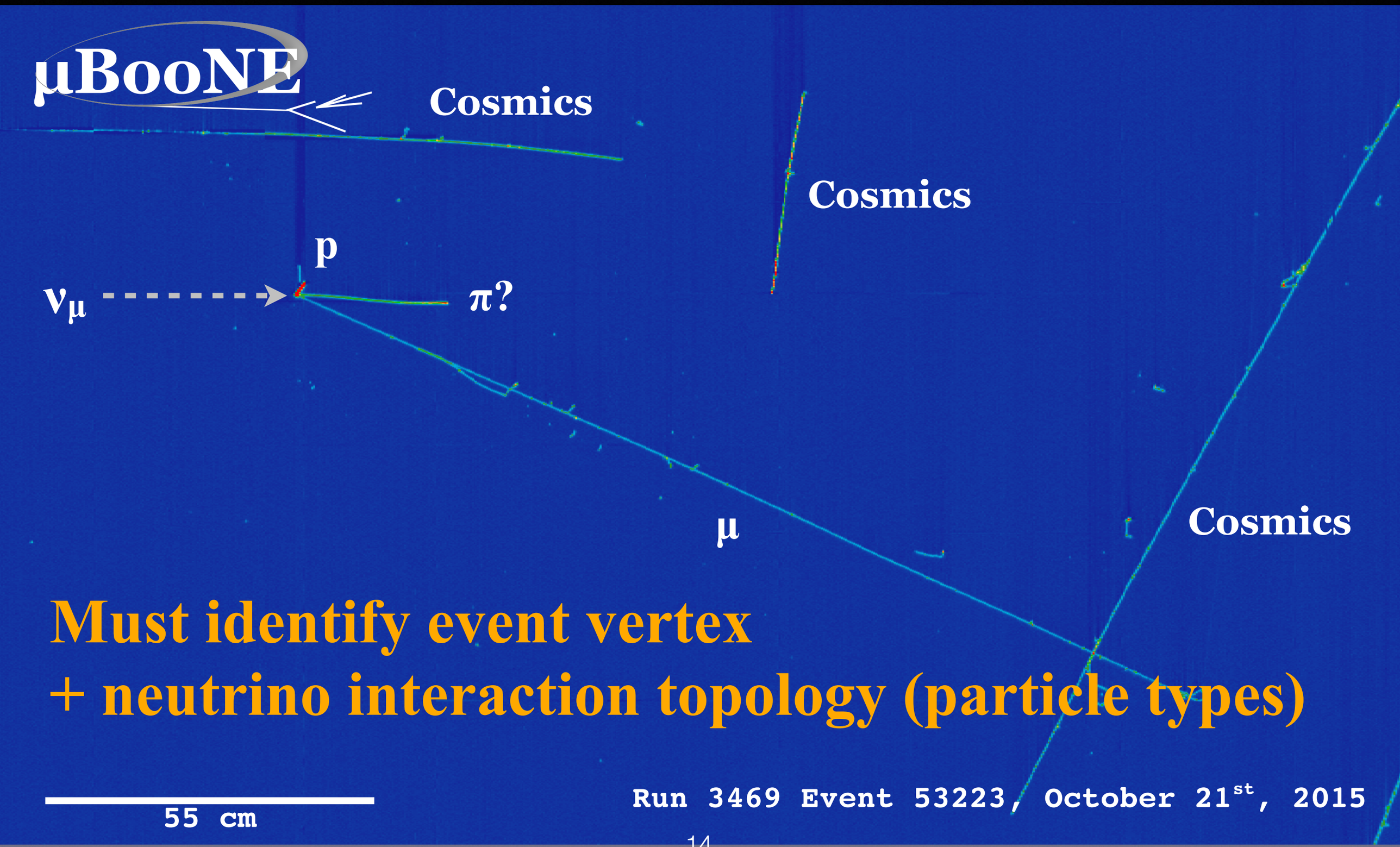

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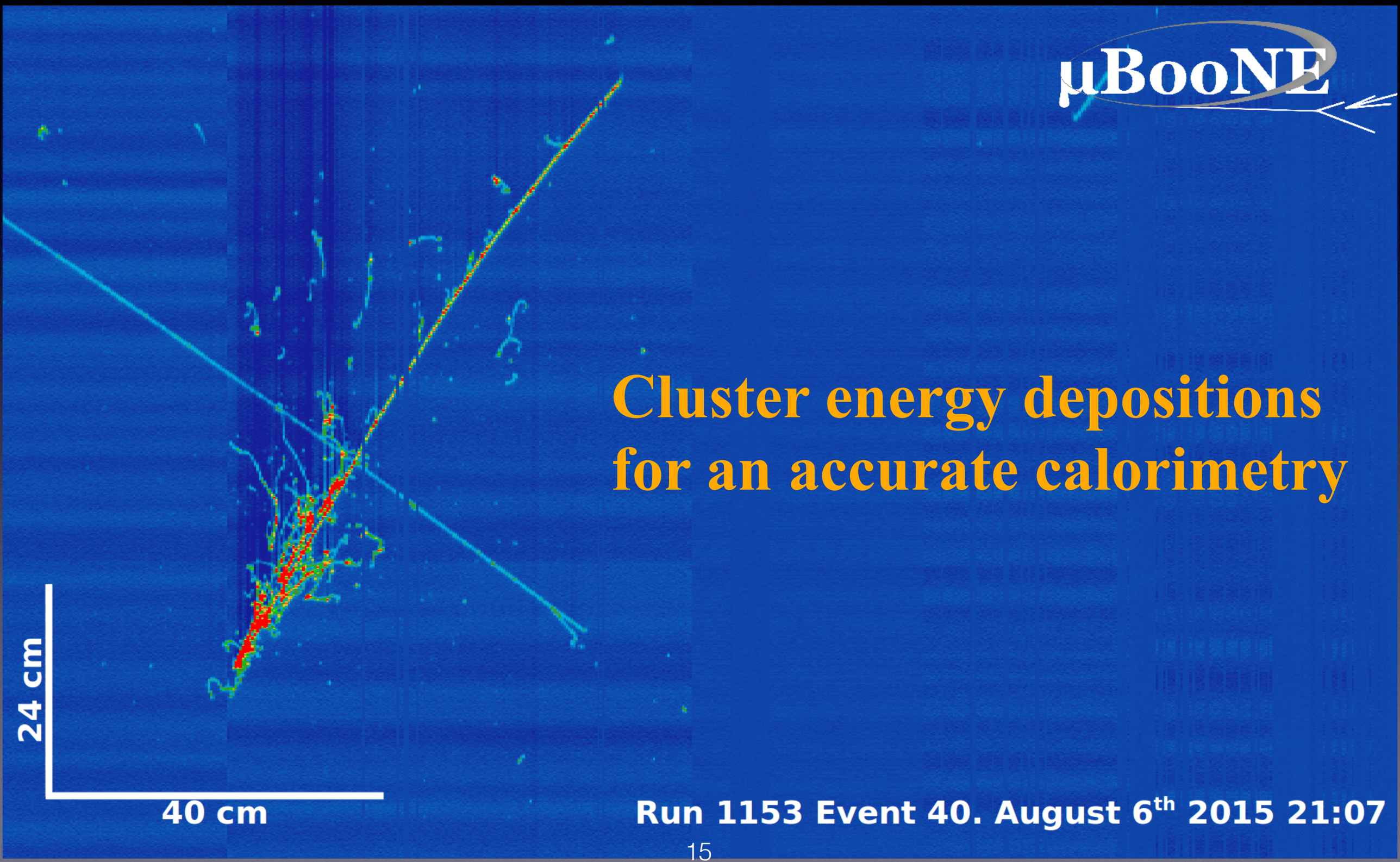
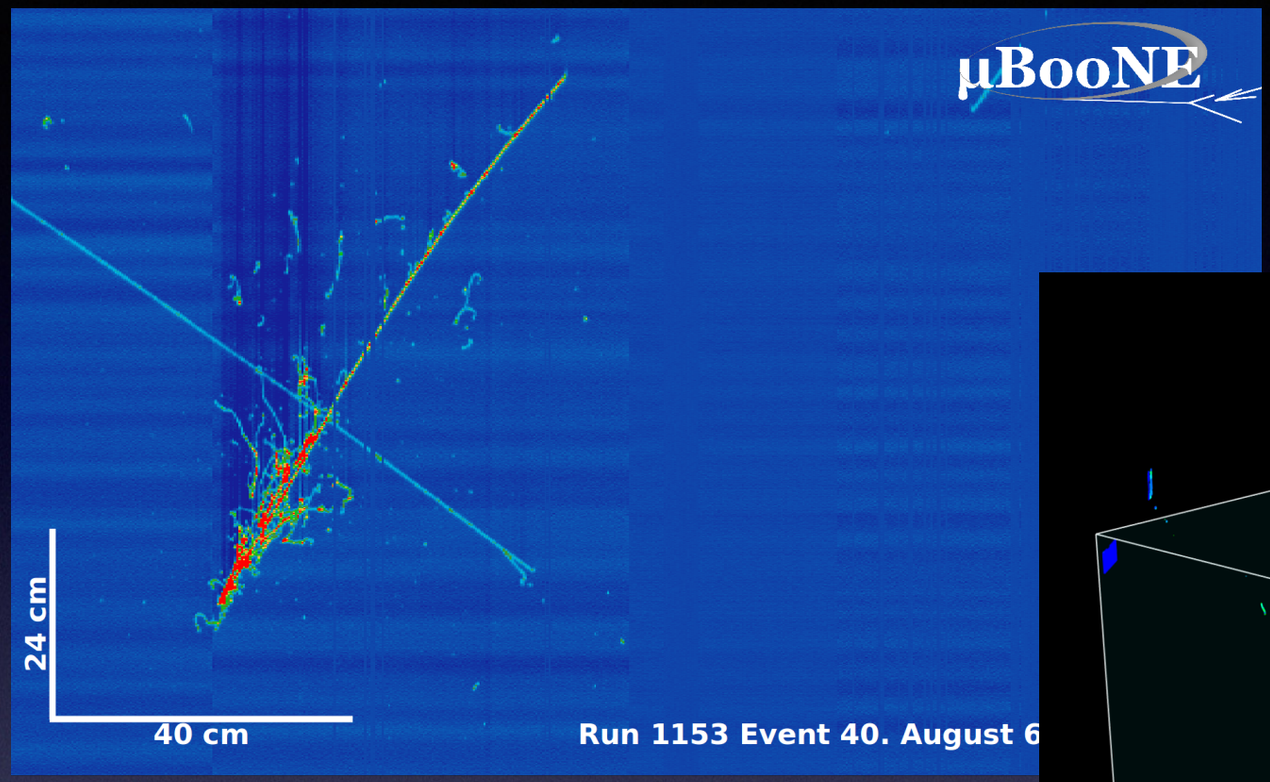
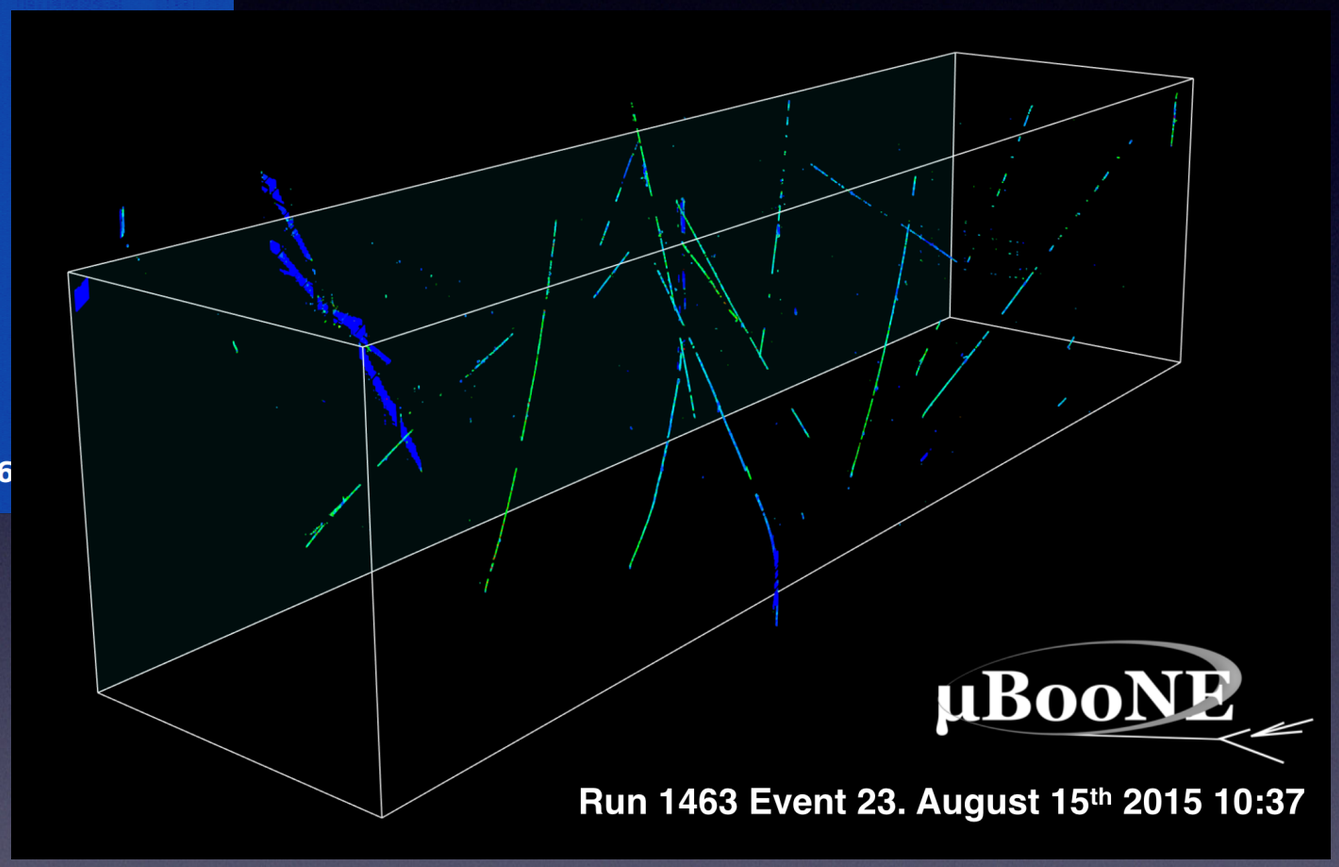


Challenges in LArTPC Data Analysis?



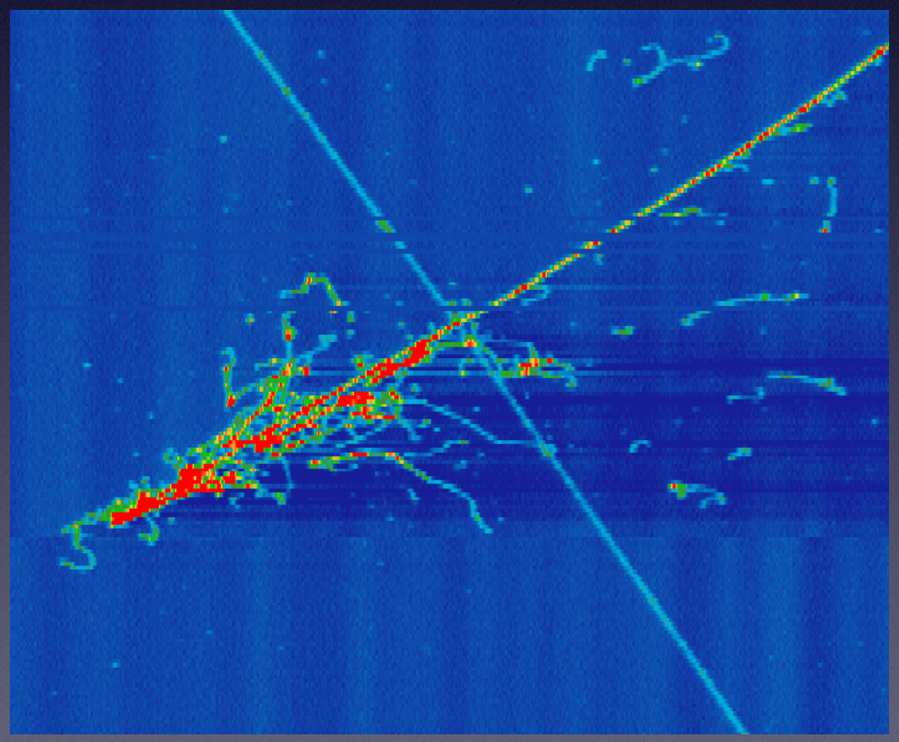


Deal with optical illusions in 2D projections + 3D pattern recognitions

Challenges in LArTPC Data Analysis?

Programming (!)

- pattern recognition algorithms = non-trivial
- need full-chain optimization
- scalability to a larger detector



Our data is an "image", a matrix of numbers

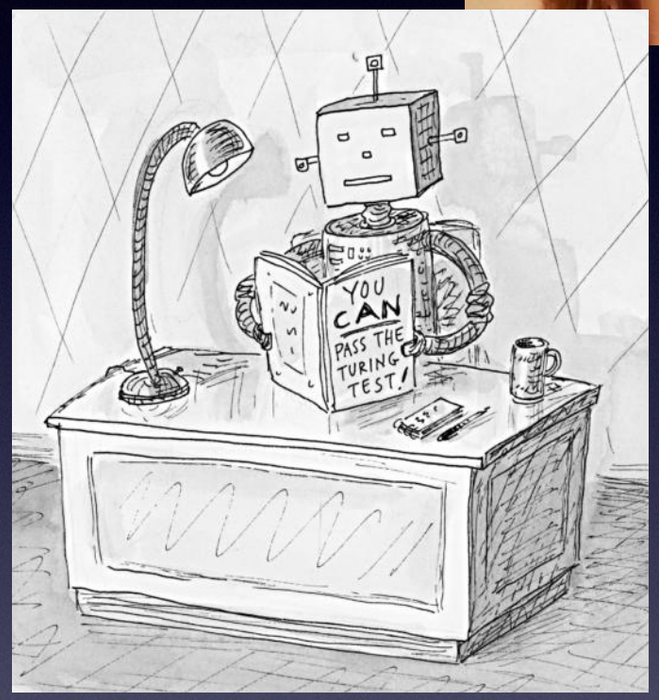
we wish

Not how it looks in our code

in reality

```
01101010100101011010101001011010
10111010101001010100010010101101
01010010110101010010101101010101
01011010101001010110101010101101
01010010101101010100101101010101
01011010101001010110101010010110
10101001010110101010101101010100
10101101010100110101101010100101
```

How it actually looks in our code



"Fake" celebrity images generated by DNN in 1024 x 1024 resolution

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- Deep Convolutional Neural Networks (CNN)
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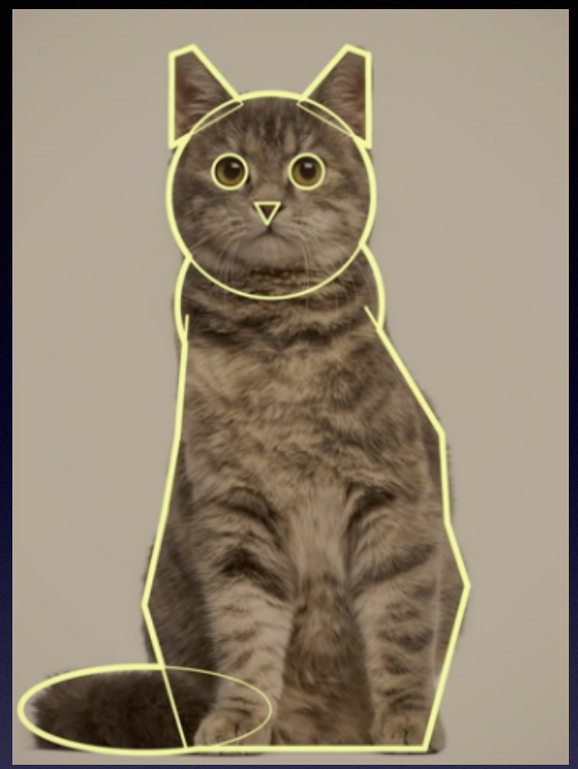
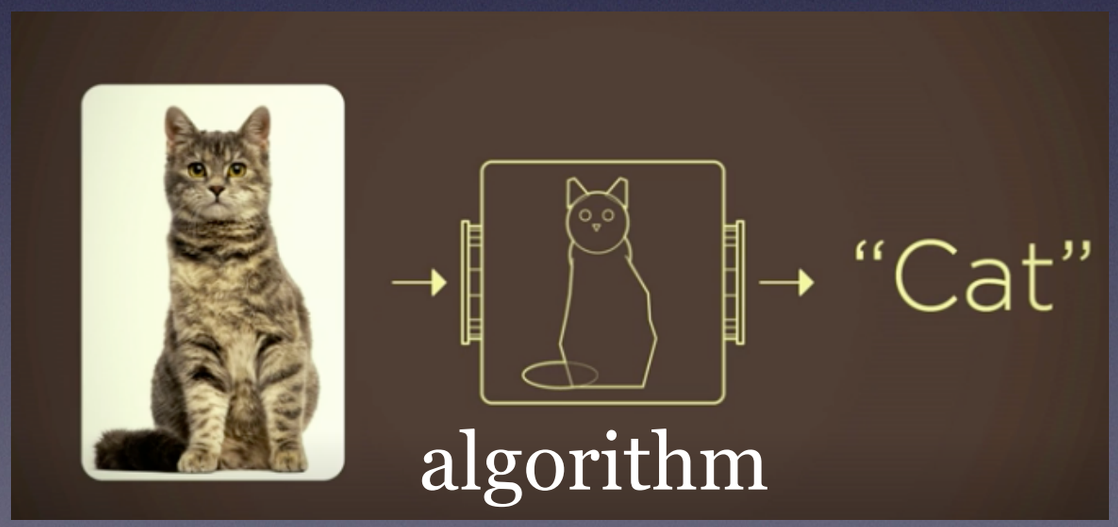
Classic Problem: Image Categorization





A cat
= collection of
certain shapes

Taken from slides by Fei-Fei's TED talk

Classic Problem: Image Categorization

… how about these?

Partial cat
(escaping fiducial volume)

Stretching cat
(DIS?)

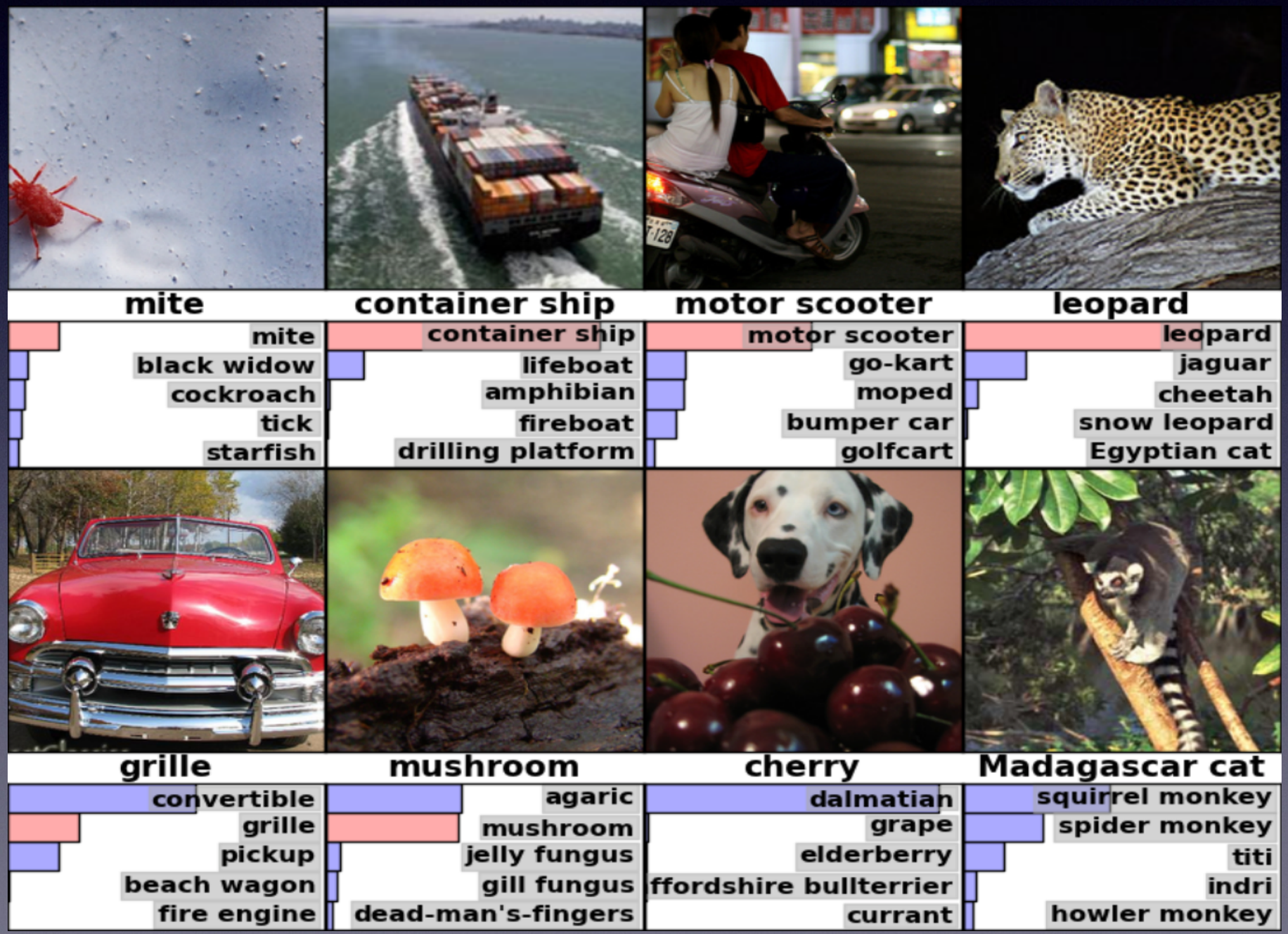
Outliers
(axions/dark matter)

Taken from slides by Fei-Fei's TED talk

Breakthrough in Computer Vision in 2012

***AlexNet*: 8-layers deep neural network**
Birth of "Deep Learning"

> 20,000 citations!

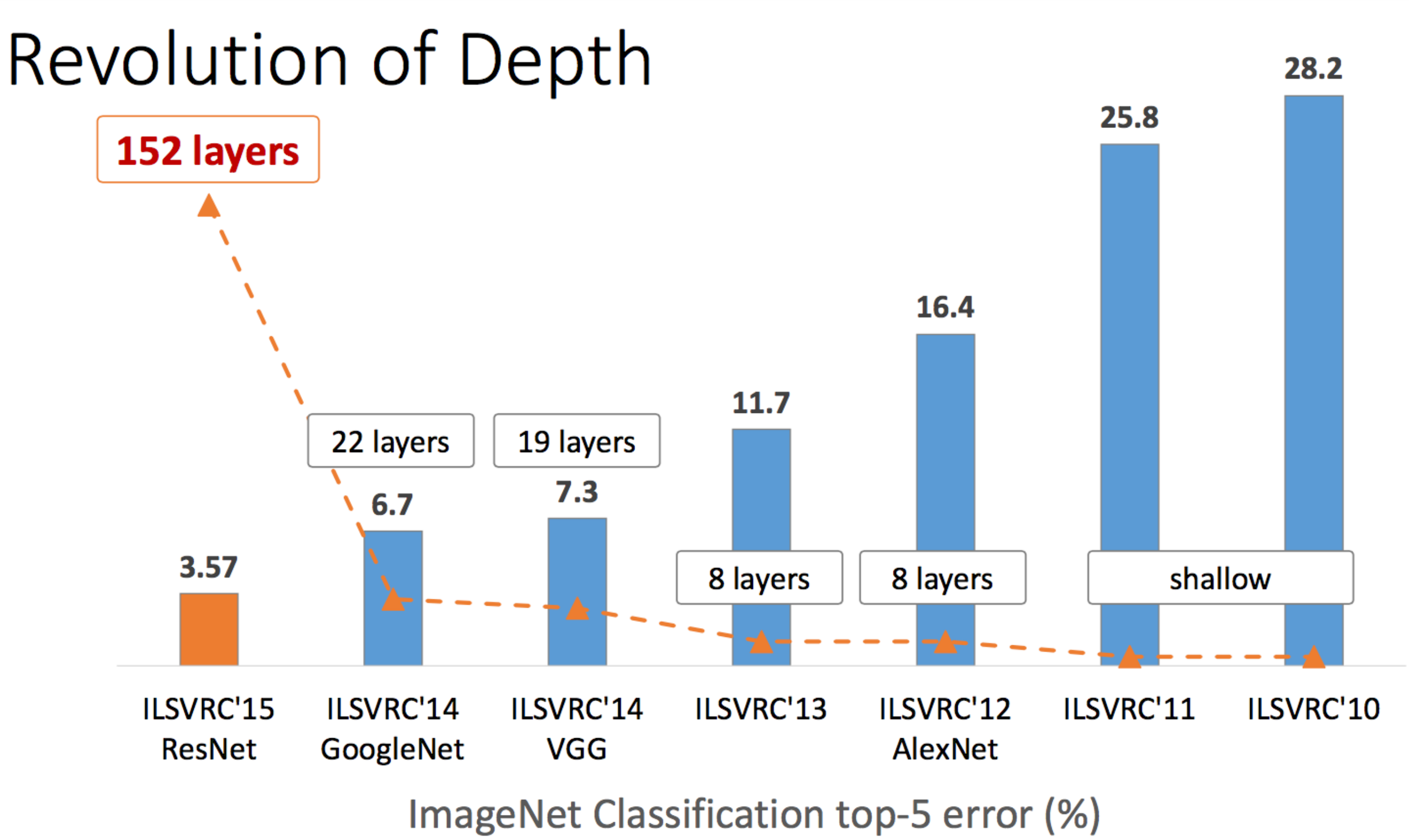


For my reference

Leopard

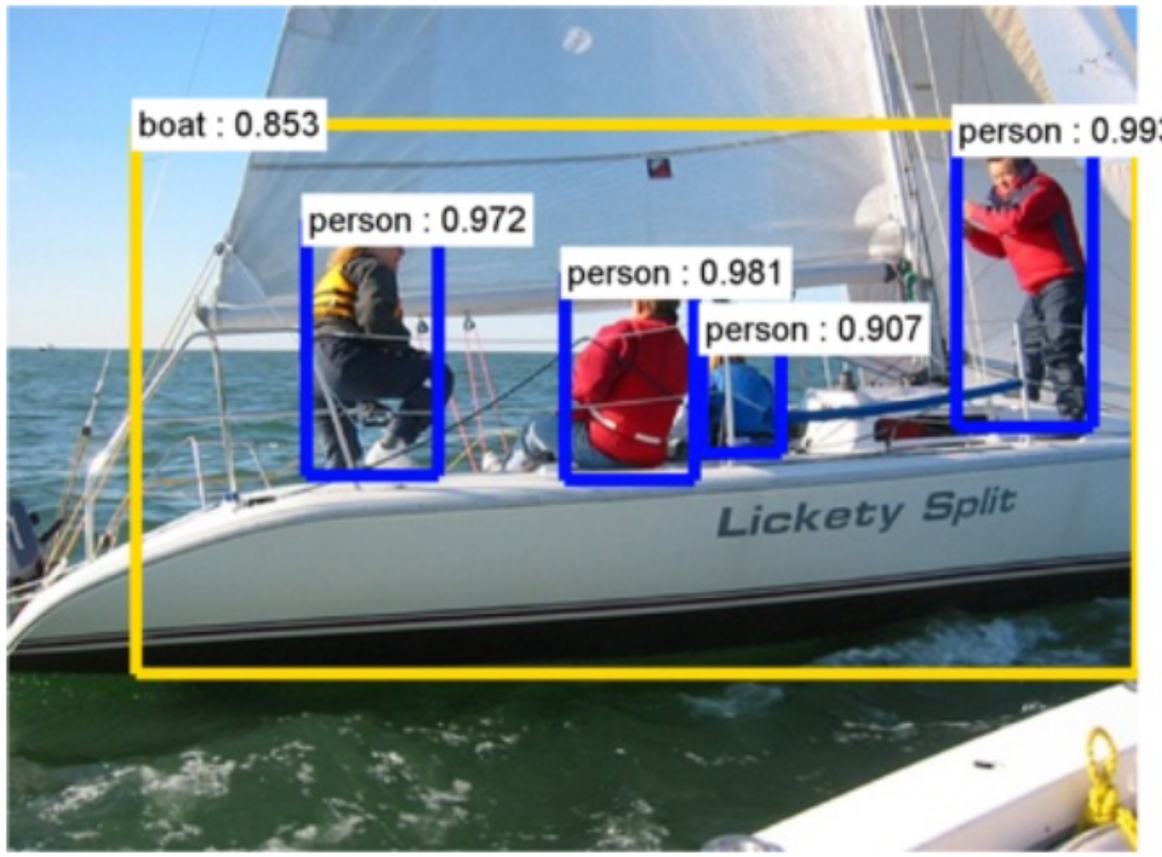
Jaguar

“Super-human” Performance in 4 years



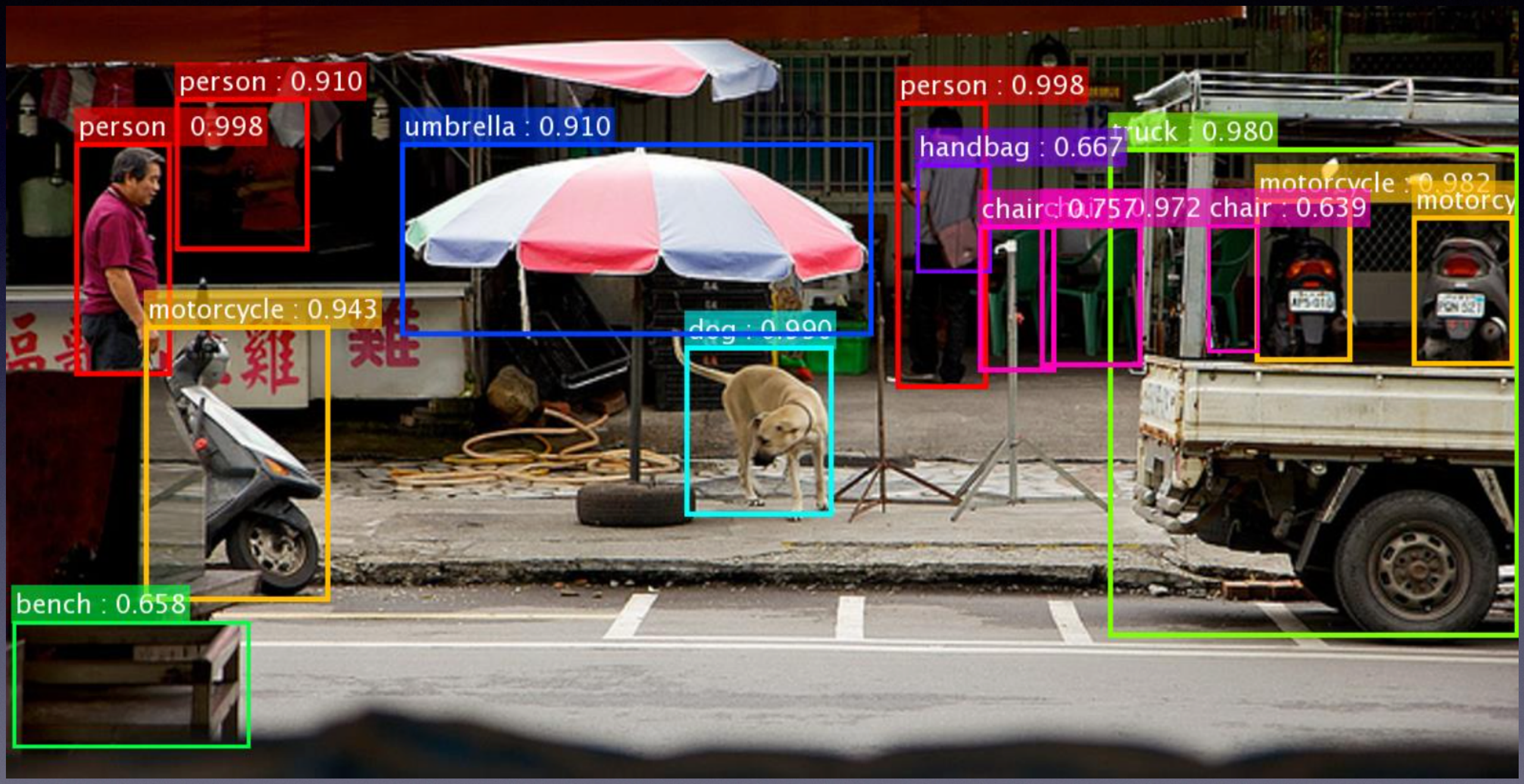
Beyond Image Classification
~ Object Detection ~

Image Classification
(what?)

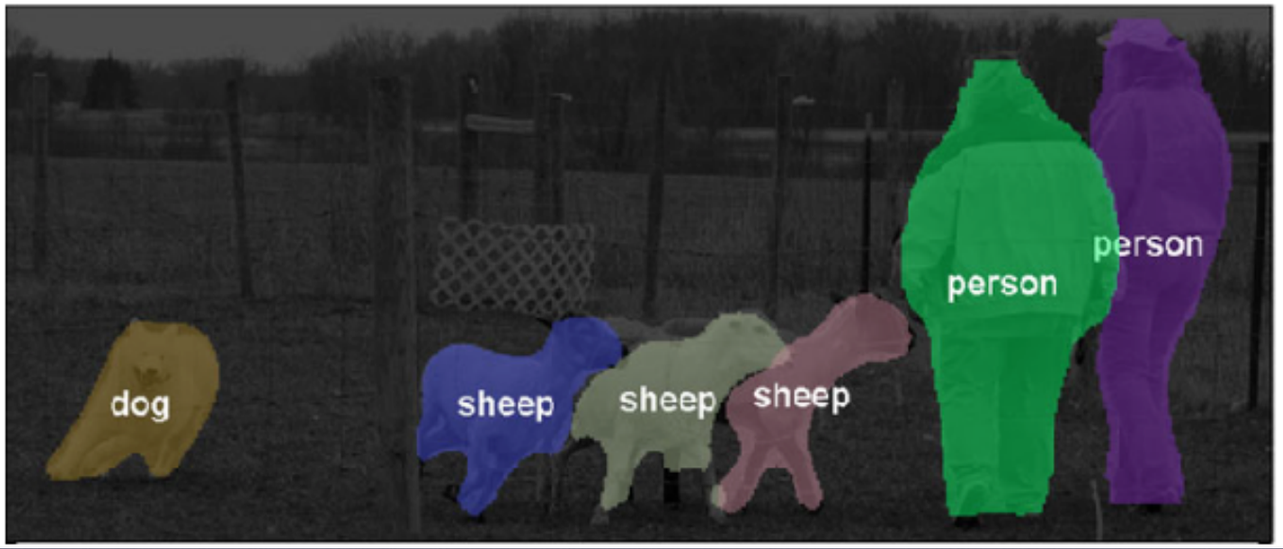


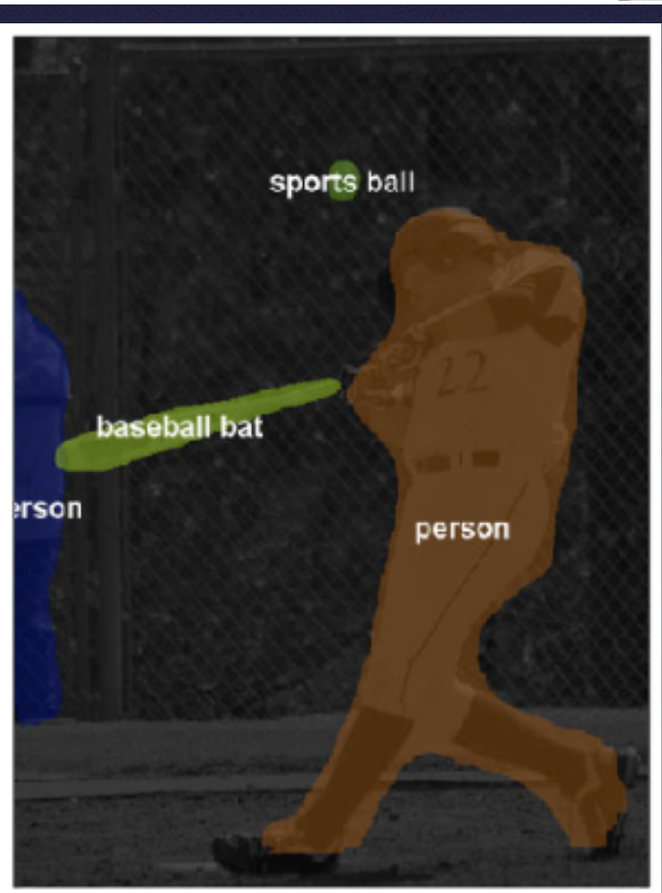
Object Detection
(what + where?)

Beyond Image Classification
~ Object Detection ~



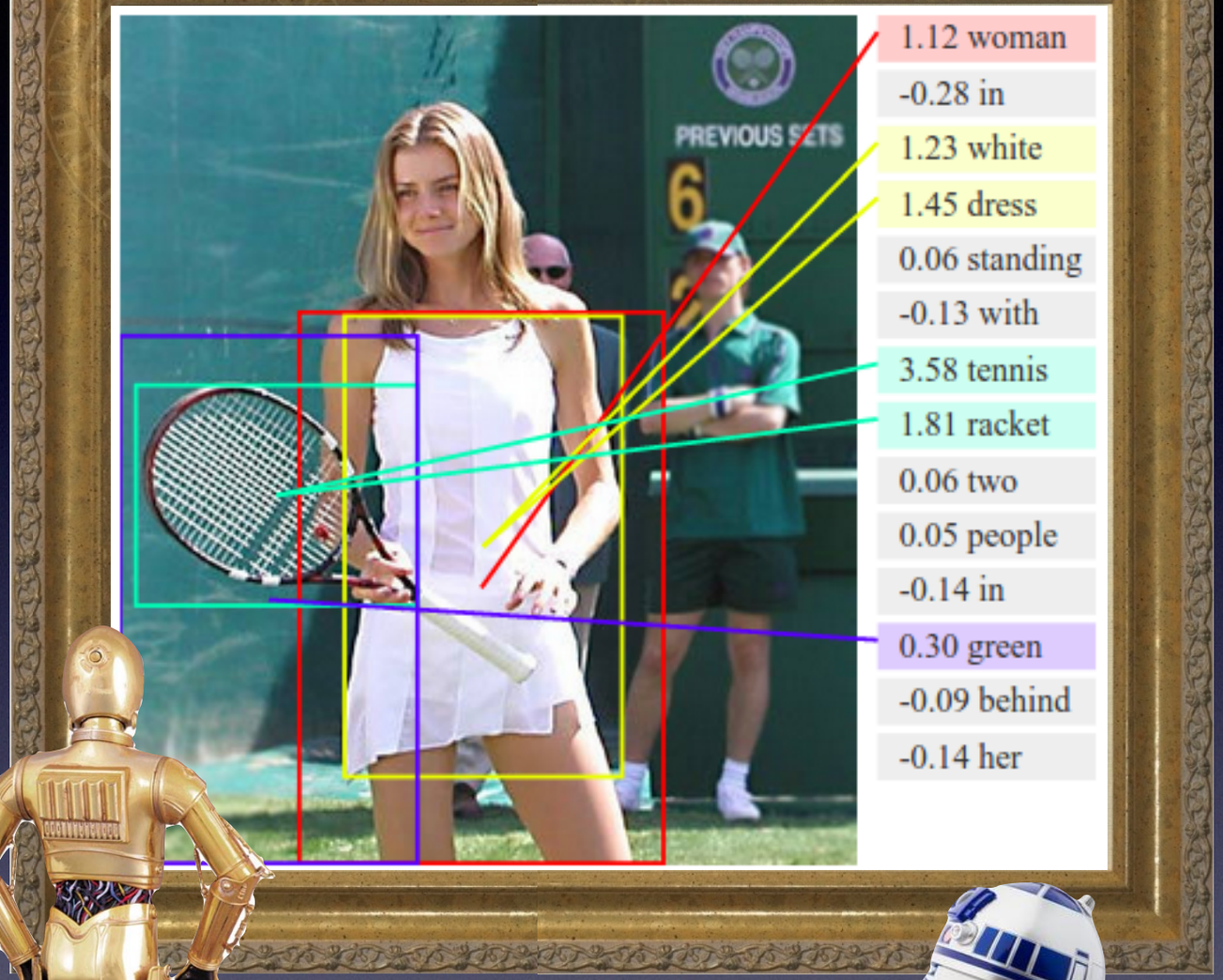
Beyond Image Classification
~ Pixel Segmentation ~





High precision donuts detection

Image context analysis



“Pose” detection

Convolutional Neural Network

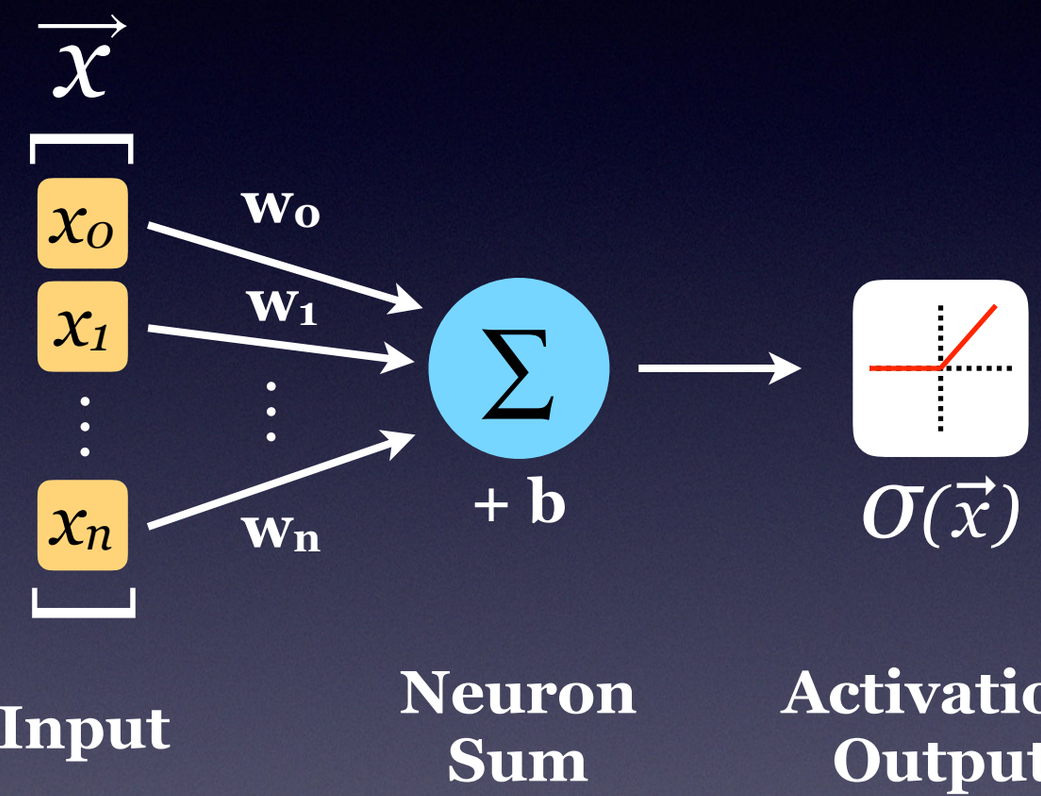
~ How does it work? ~

How a Simple Perceptron Works

Background: Neural Net

The basic unit of a neural net is the ***perceptron*** (loosely based on a real neuron)

Takes in a vector of inputs (x). Commonly inputs are summed with weights (w) and offset (b) then run through activation.

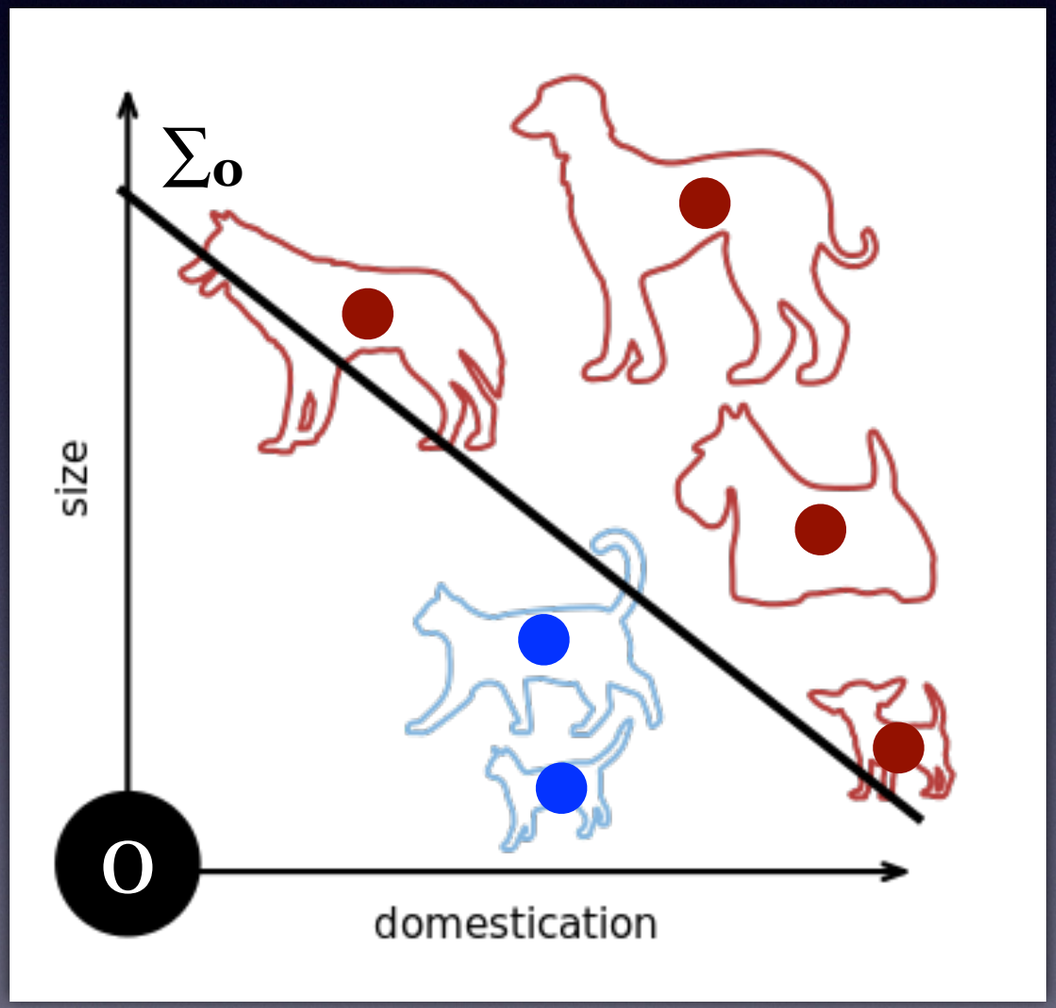


$$\sigma(\vec{x}) = \begin{cases} \vec{w}_i \cdot \vec{x} + b_i & \vec{w}_i \cdot \vec{x} + b_i \geq 0 \\ 0 & \vec{w}_i \cdot \vec{x} + b_i < 0. \end{cases}$$

How a Simple Perceptron Works

Perceptron 2D Classification

Imagine using two features to separate cats and dogs



from [wikipedia]

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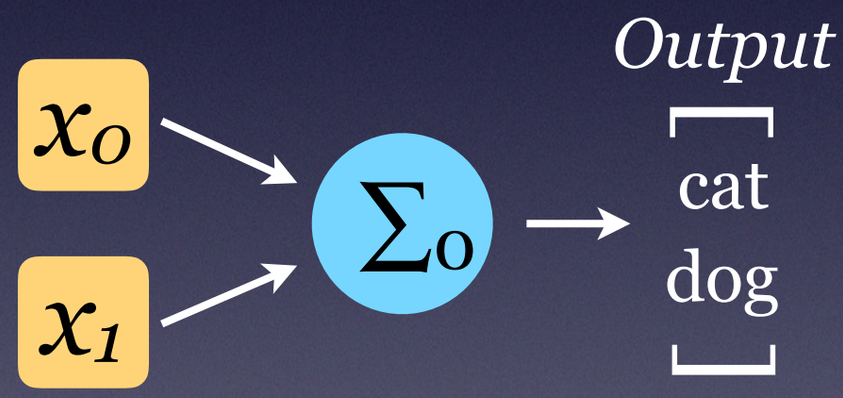
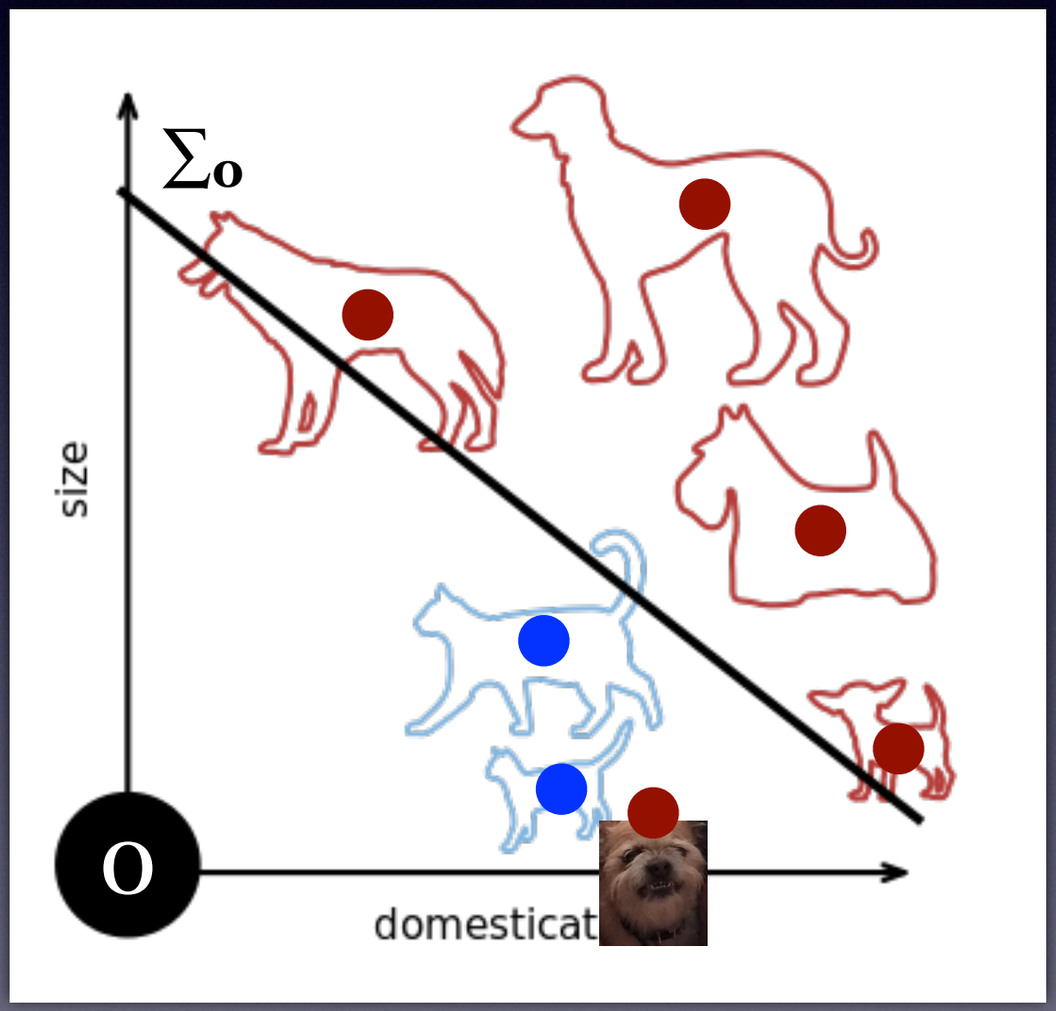


By picking a value for w and b, we define a boundary between the two sets of data

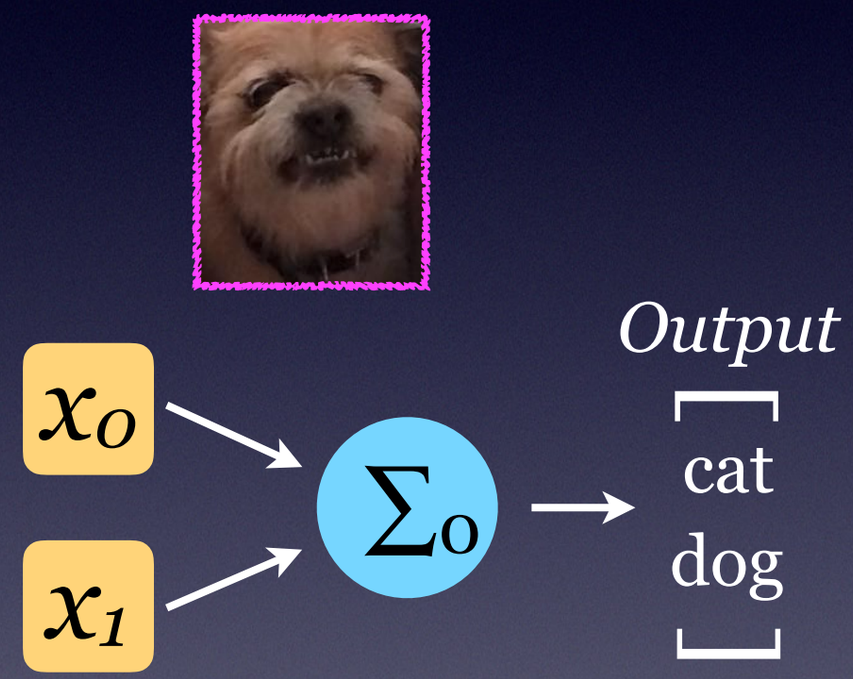
How a Simple Perceptron Works

Perceptron 2D Classification

Maybe we need to do better: assume a new data point (small but not as well behaved)



from [wikipedia]



How a Simple Perceptron Works

Perceptron 2D Classification

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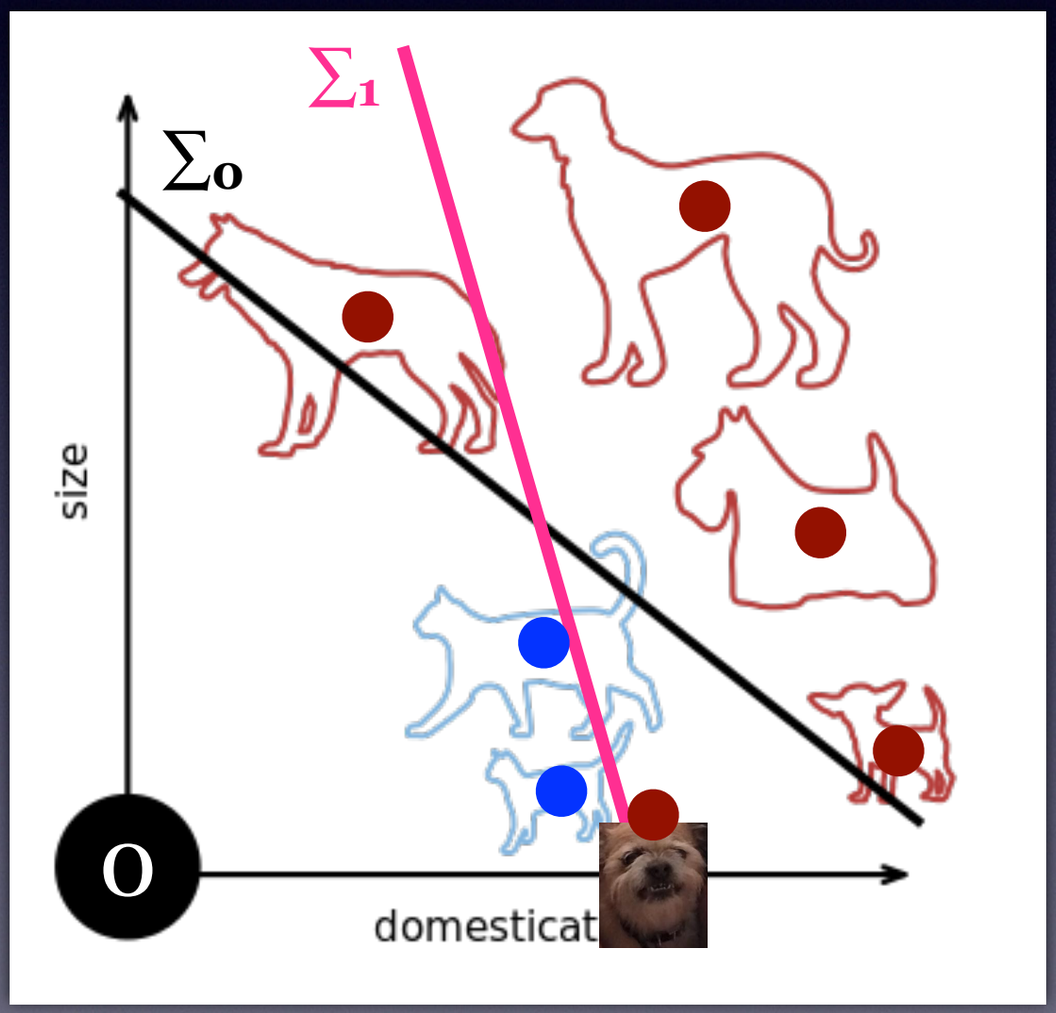

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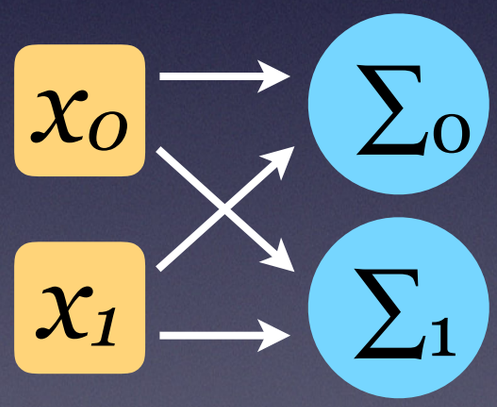
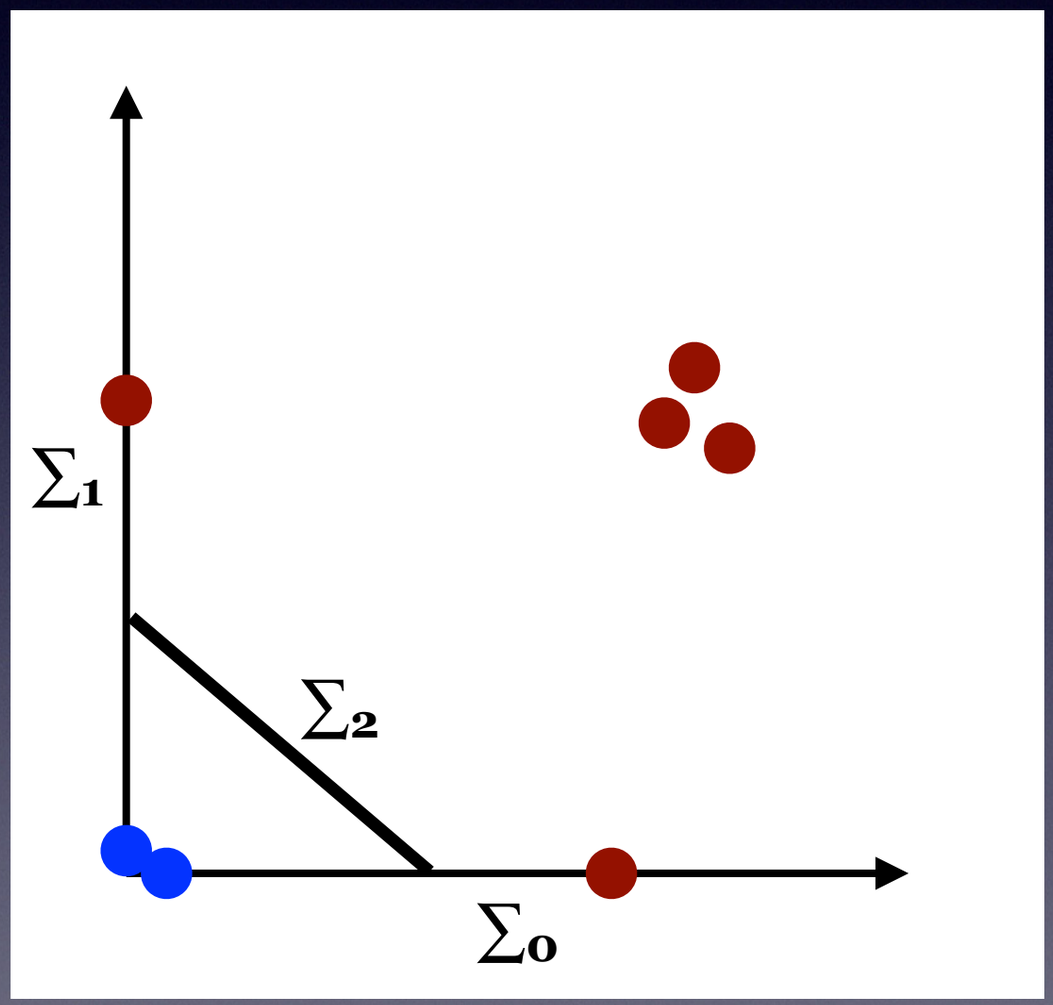


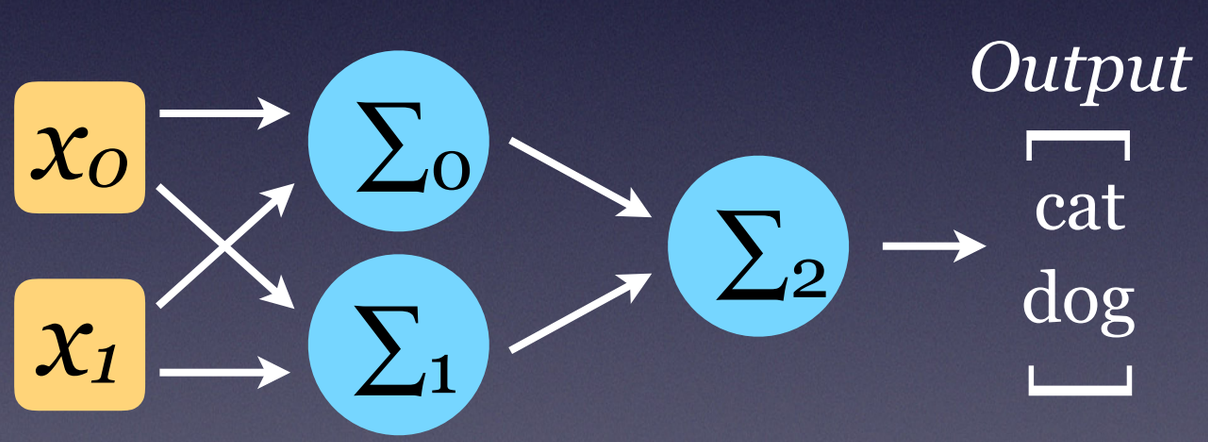
We can add another perceptron to help (but does not yet solve the problem)

How a Simple Perceptron Works

Perceptron 2D Classification

Maybe we need to do better: assume a new data point (small but not as well behaved)

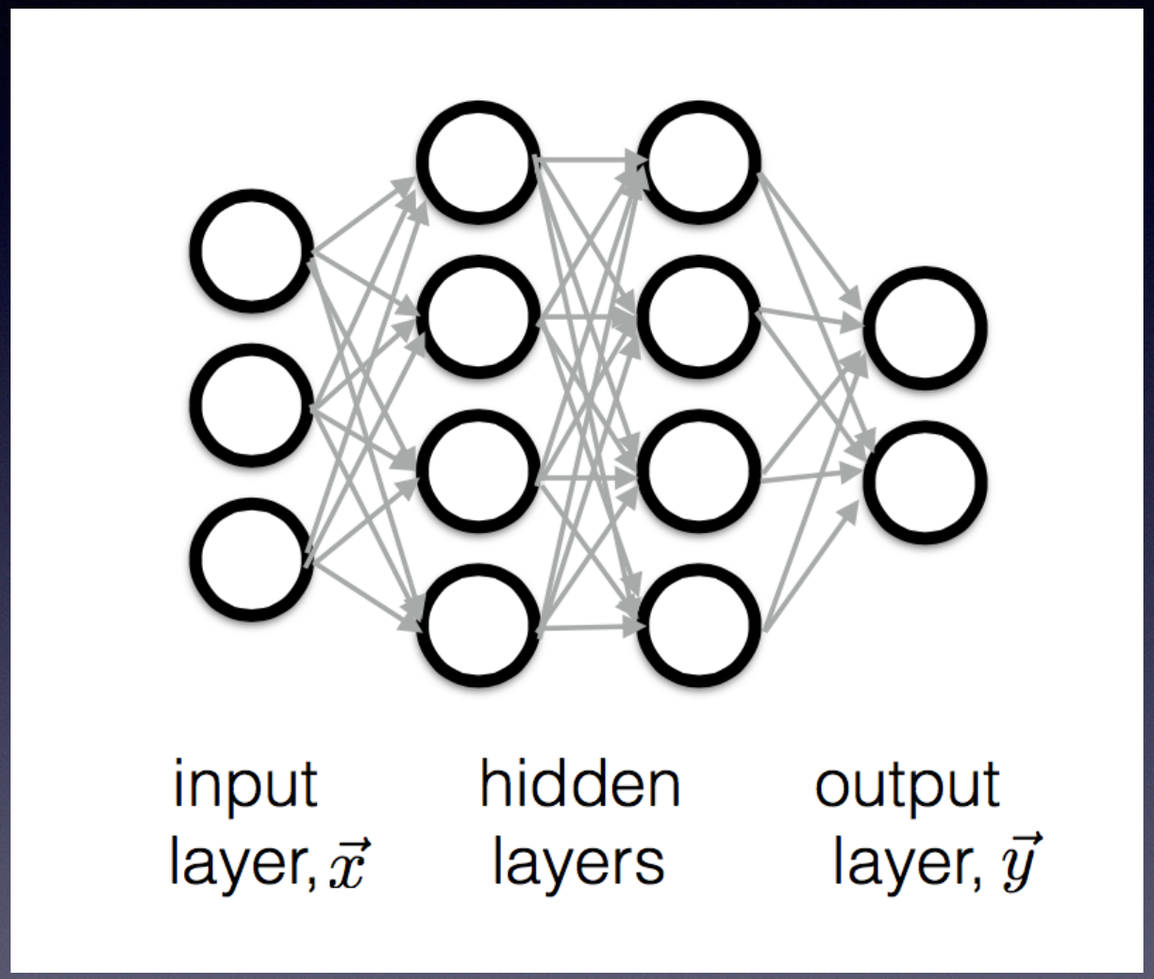




Another layer can classify based on preceding feature layer output

“Classical” Neural Net

Fully-Connected, Feed-forward, Multi-Layer Perceptrons



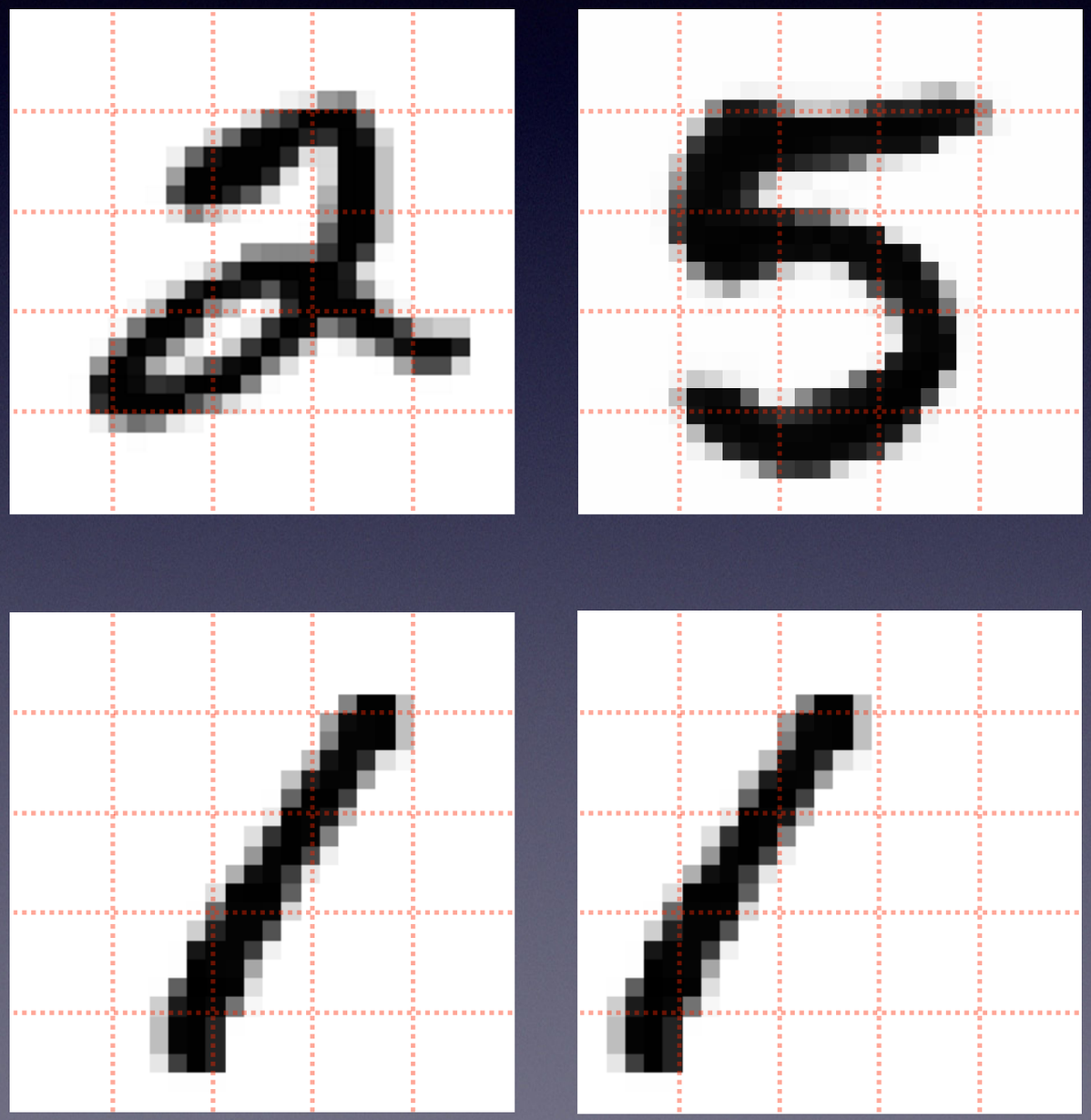
A traditional neural network consists of a stack of layers of such neurons where each neuron is ***fully connected*** to other neurons of the neighbor layers

"Classical" Neural Net

... is not ideal for image classification ...

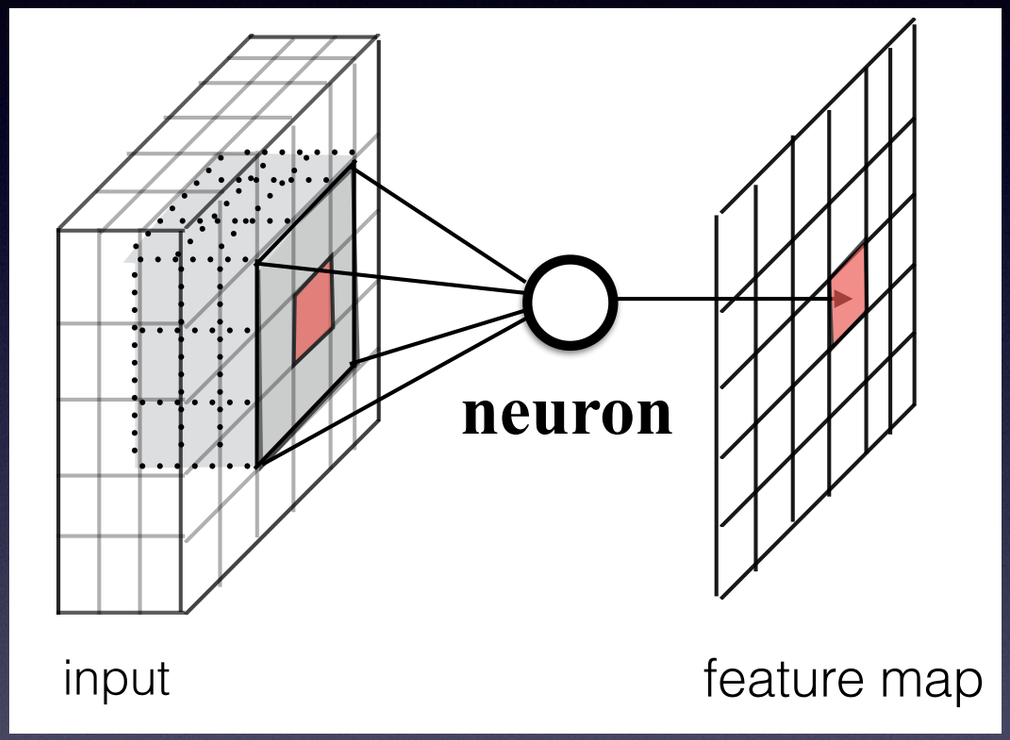
Image classification

- **What is input neurons?**
  - Every pixel value
- **How many weights?**
  - # of pixels in an image!
- **Fully connected?**
  - translation variant!



Convolutional Neural Networks

CNN introduce a ***limitation*** by forcing the network to look at only local, translation invariant features

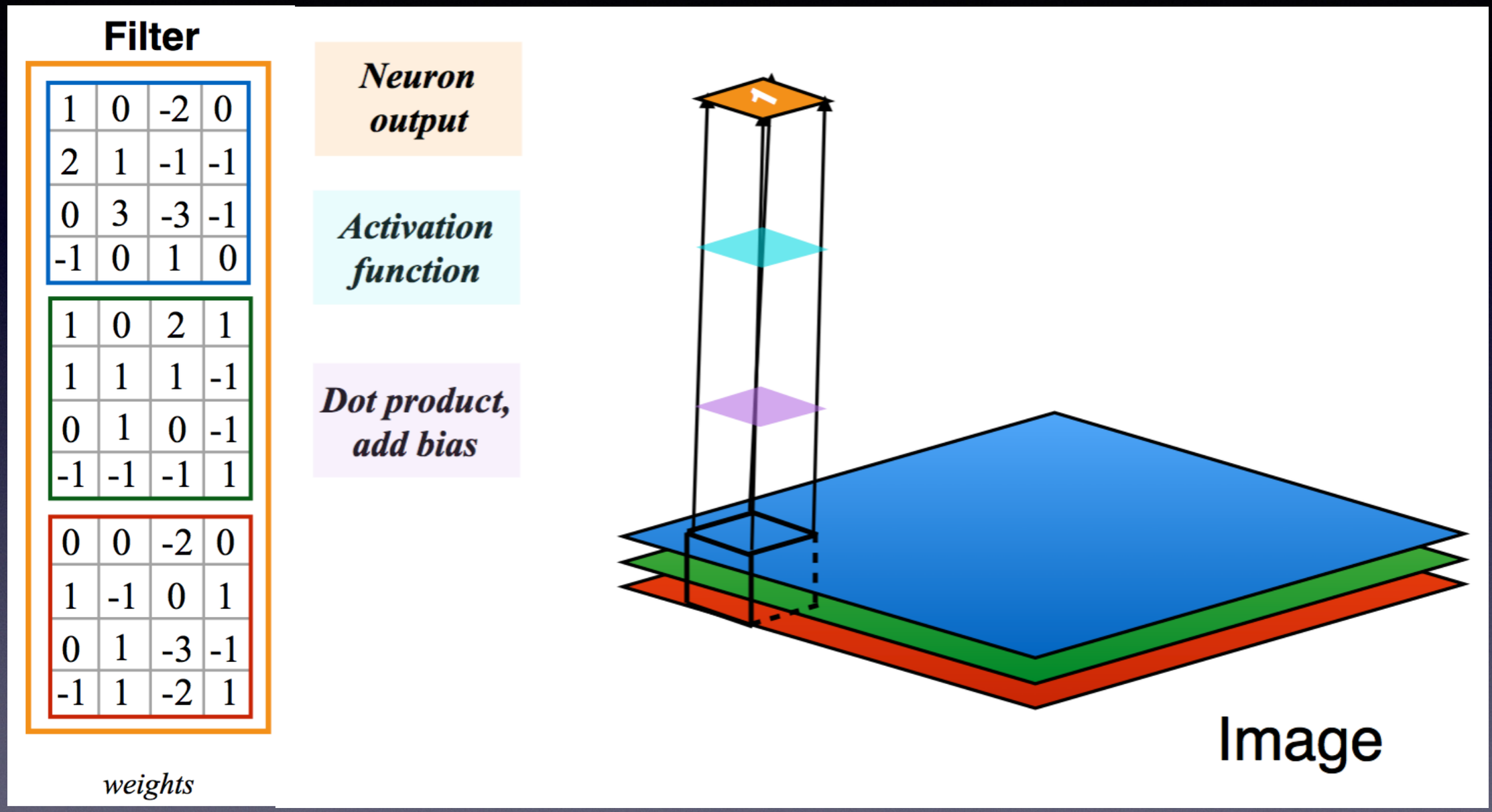


$$f_{i,j}(X) = \sigma\left(W_i \cdot X_j + b_i\right),$$

Activation of a neuron depends on the element-wise product of 3D weight tensor with 3D input data and a bias term

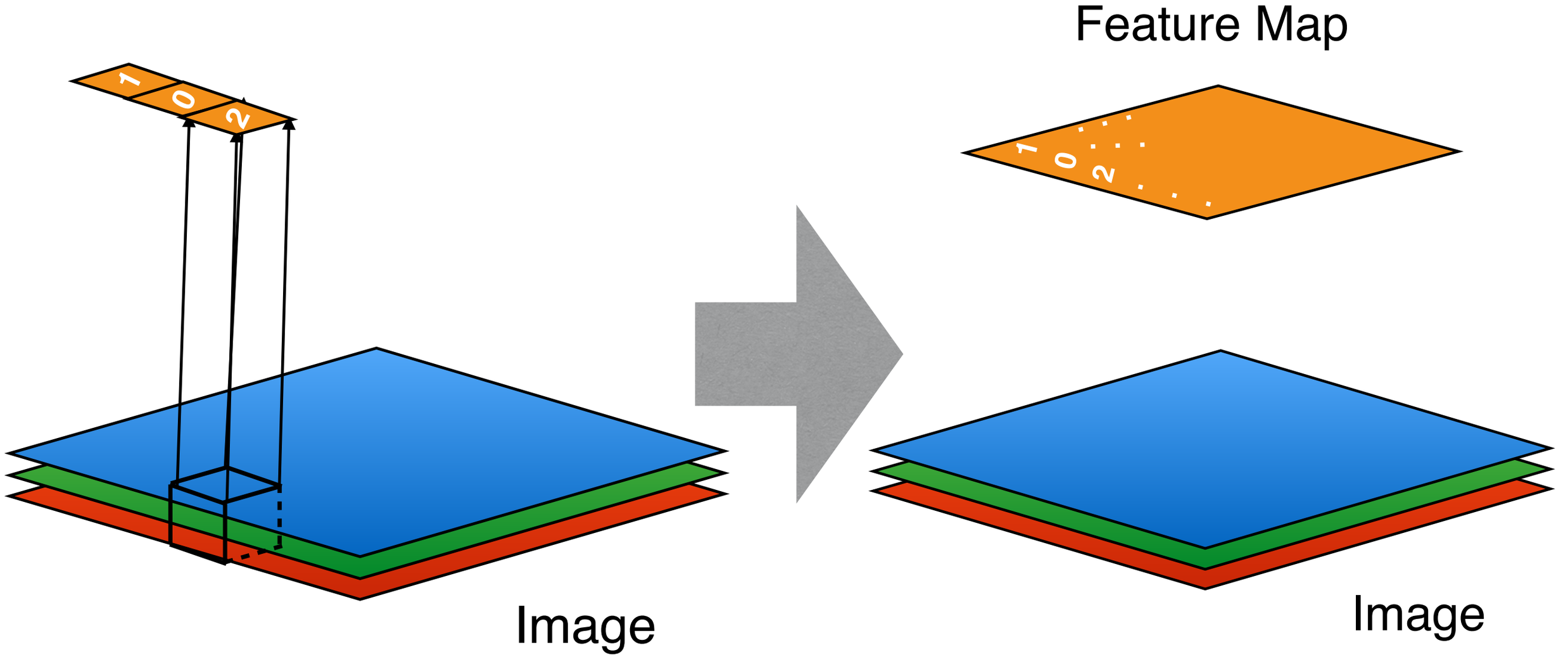
- Translate over 2D space to process the whole input
- Neuron **learns translation-invariant features**
  - Suited for a "***homogeneous***" detector like LArTPC
- **Output**: a "feature-enhanced" image (***feature map***)

Convolutional Neural Networks



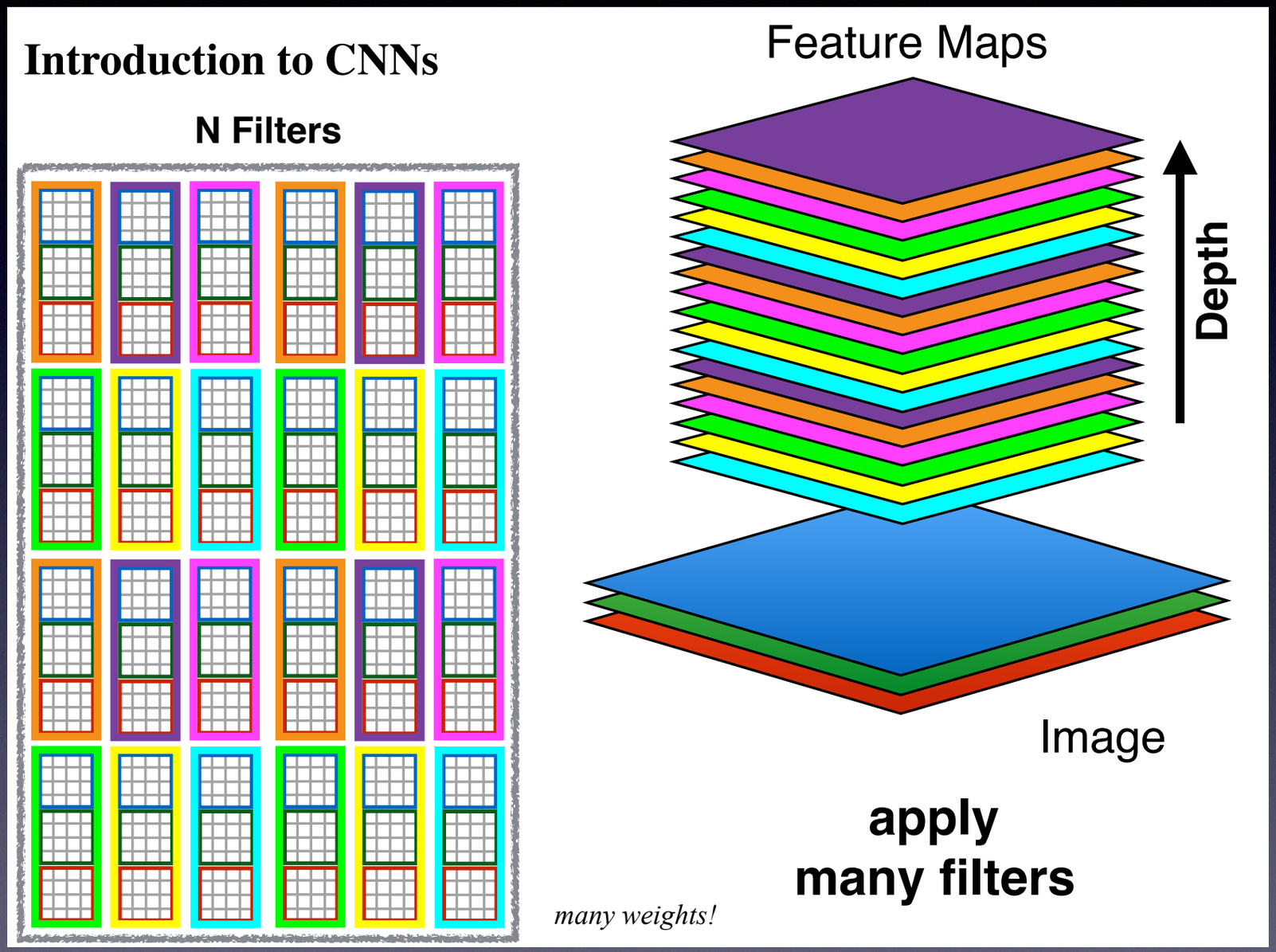
Toy visualization of the CNN operation

Convolutional Neural Networks



Toy visualization of the CNN operation

Convolutional Neural Networks

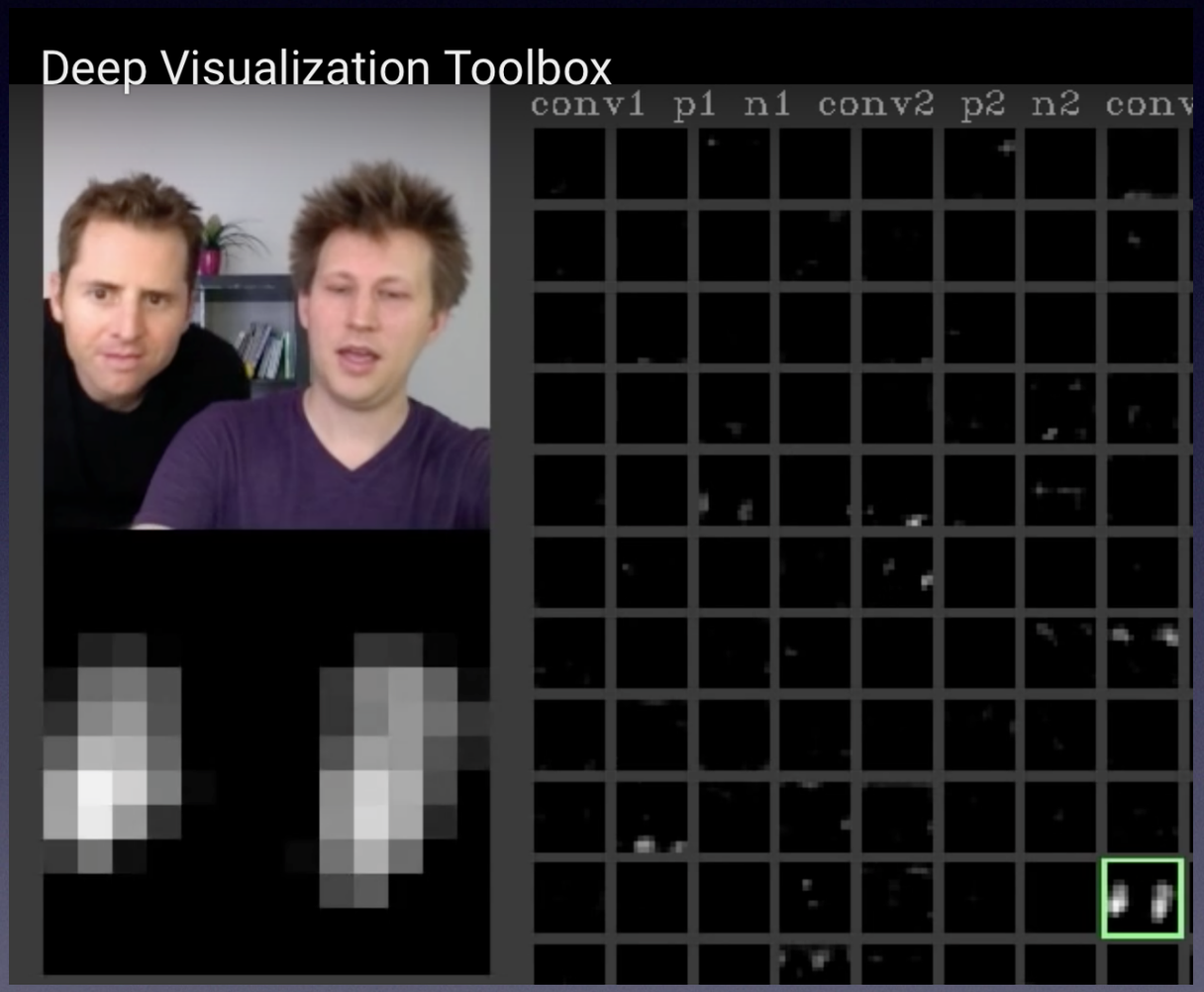


Toy visualization of the CNN operation

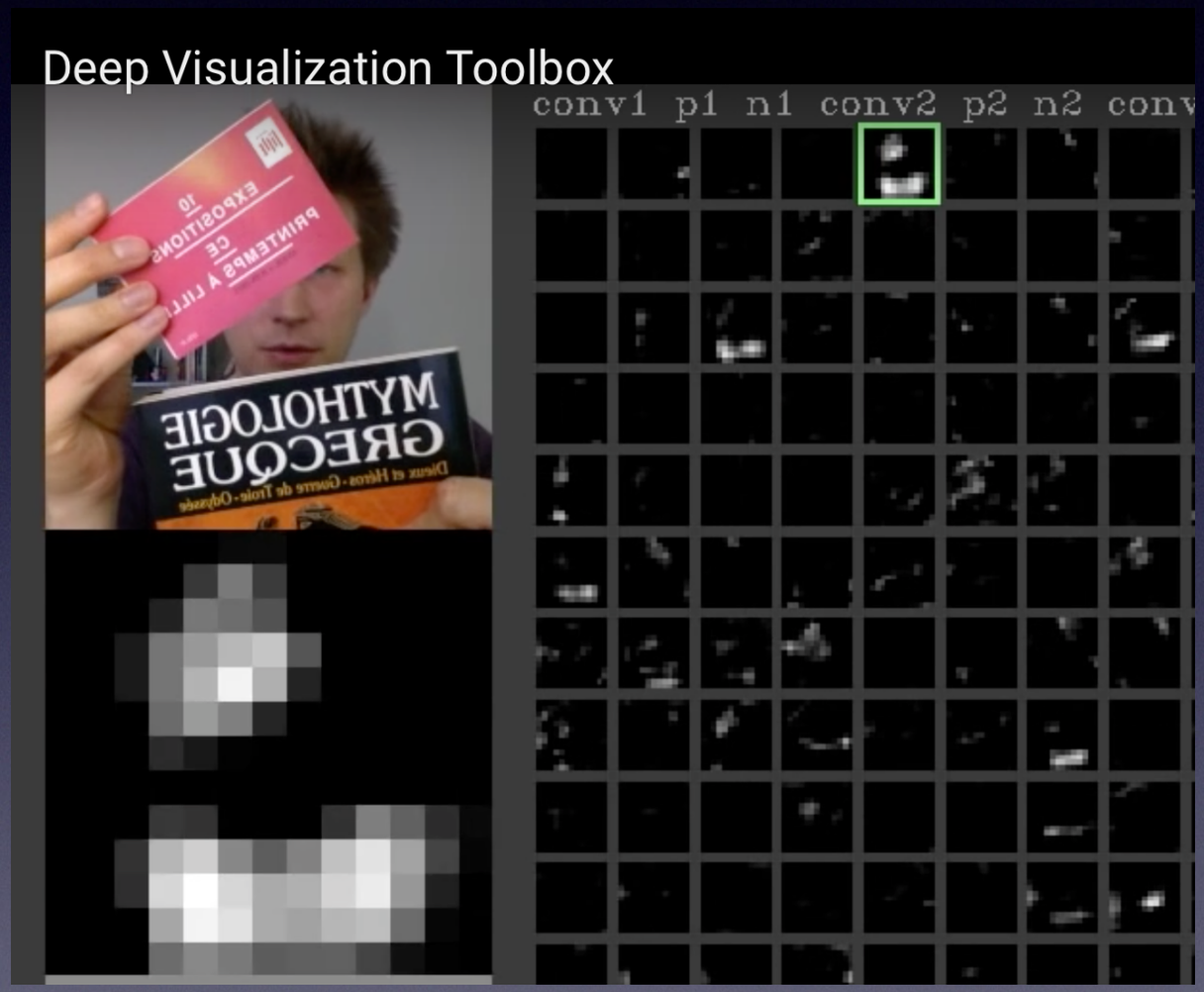
How Image Classification Networks Work

Feature map visualization example

- https://www.youtube.com/watch?v=AgkfIQ4IGaM



Neuron concerning face

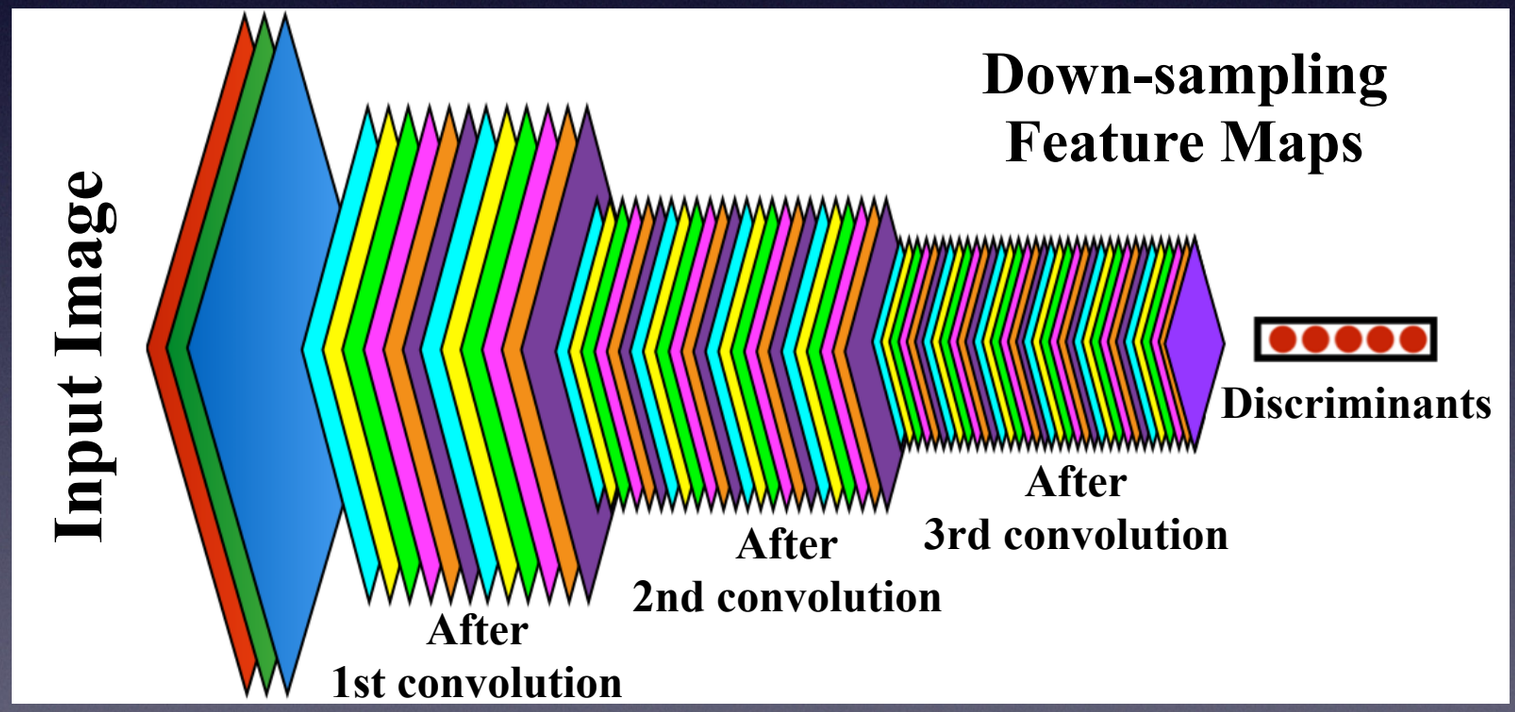


Neuron loving texts
(and don't care about your face)

How Image Classification Networks Work

Goal: extract features to give "single label" to an image

1. **Convolution operation**
2. **Down-sampling**

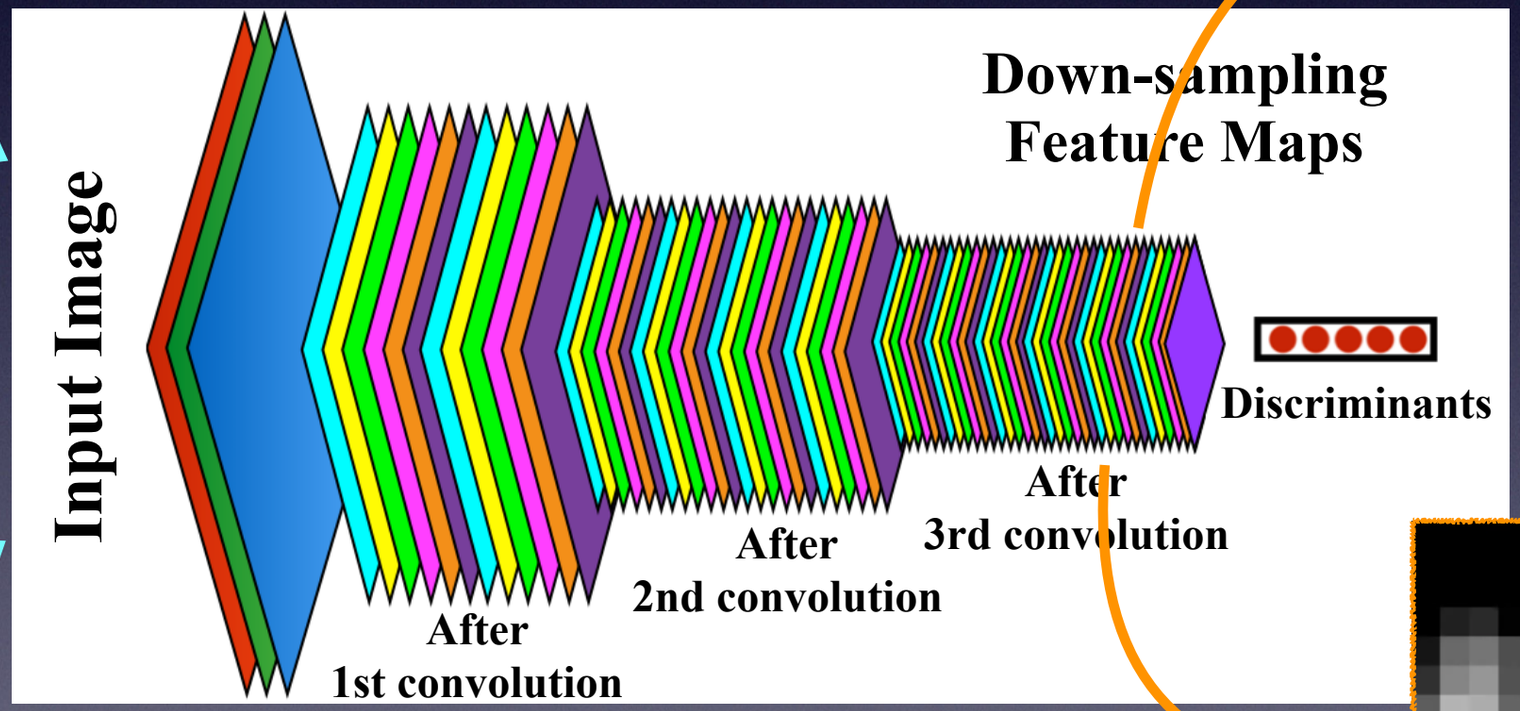


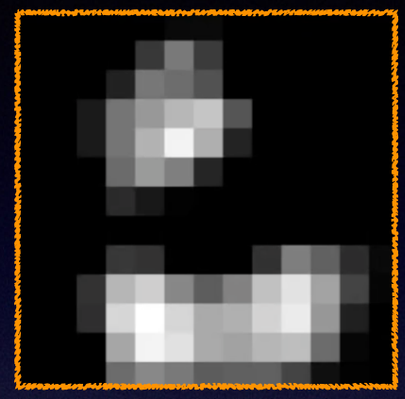
Series of convolutions
+ down-sampling

How Image Classification Networks Work

Goal: extract features to give "single label" to an image

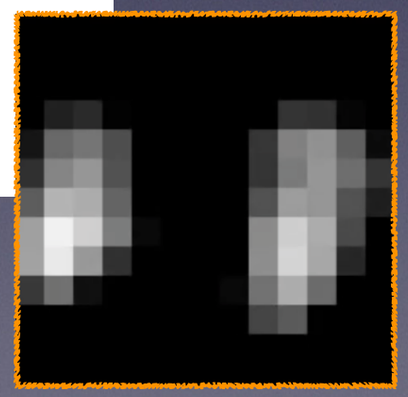
1. **Convolution operation**
2. **Down-sampling**





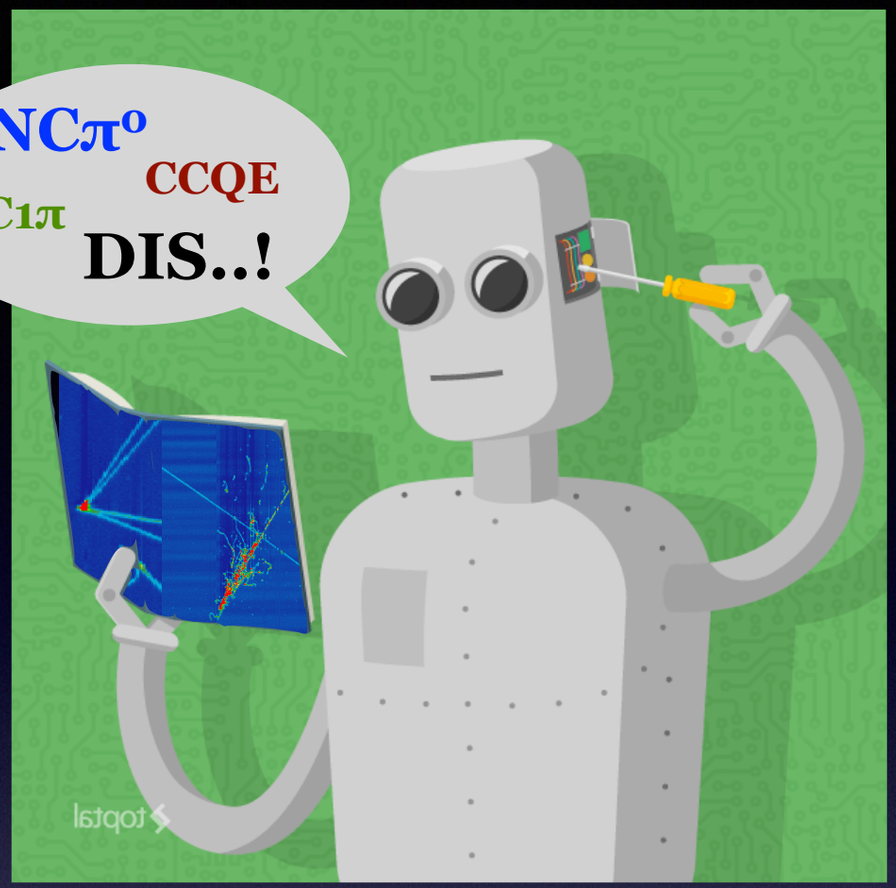
"Written Texts" feature map

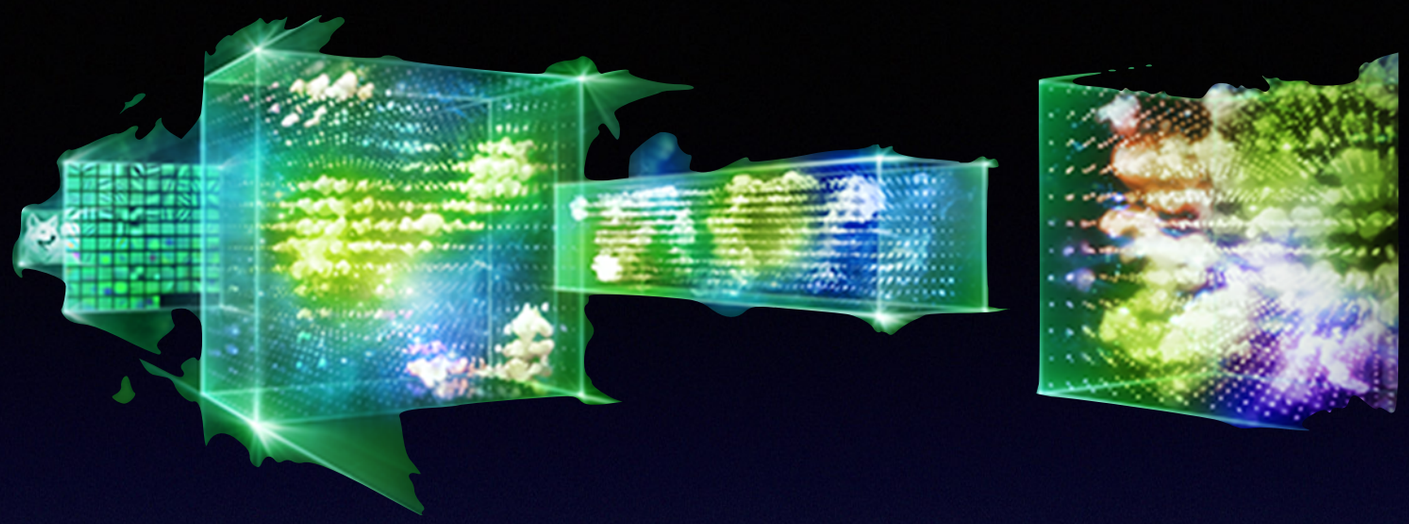
Series of convolutions + down-sampling



"Human Face" feature map

Image credit: DeepVis @ youtube





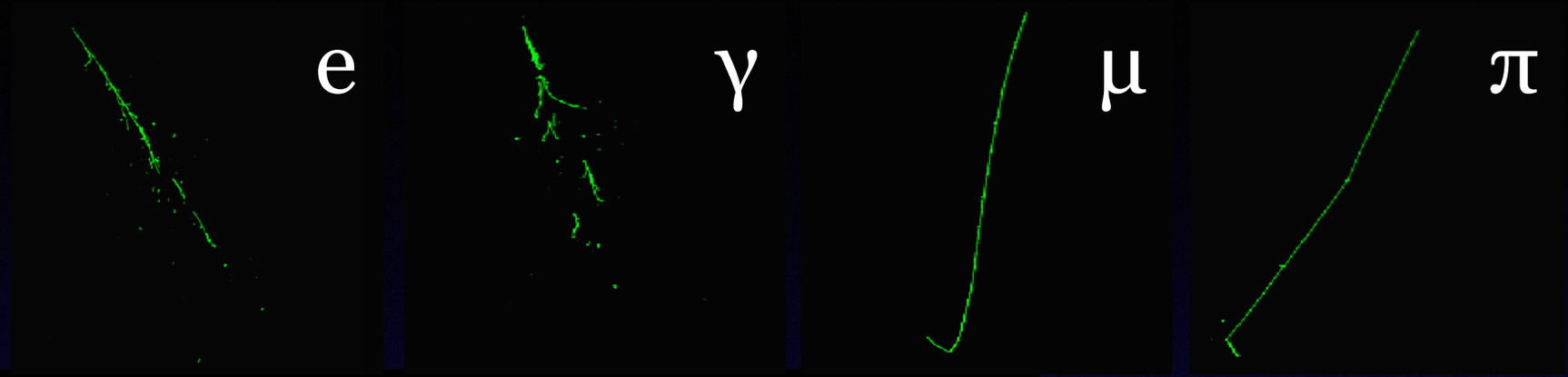
Deep Neural Network Applications

Outline

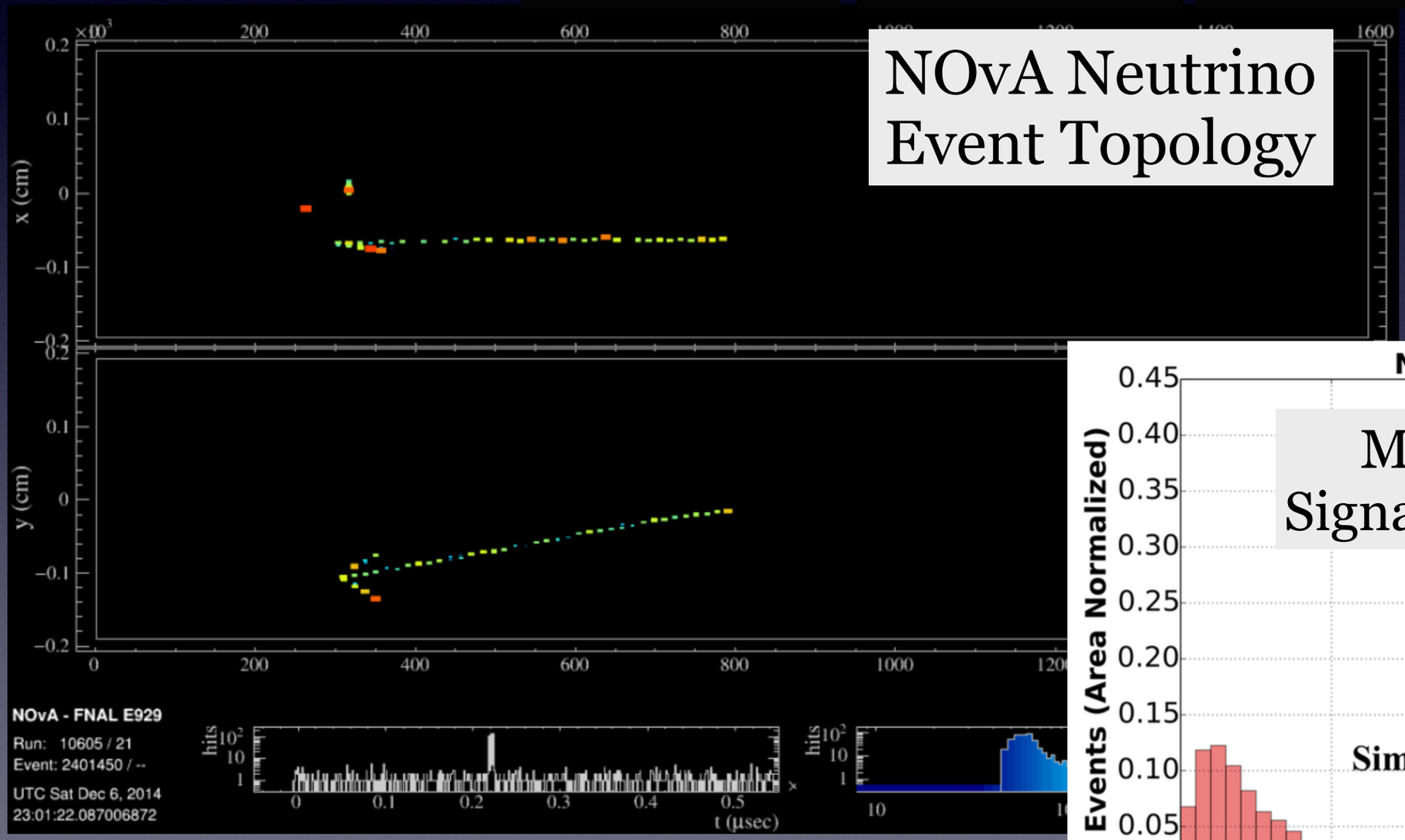
- Liquid Argon Time Projection Chambers
- Recent innovations in Computer Vision
- Deep Convolutional Neural Networks (CNN)
- **Deep CNNs for image data analysis**
- Wrap-up

Image Classification for Physics Analysis

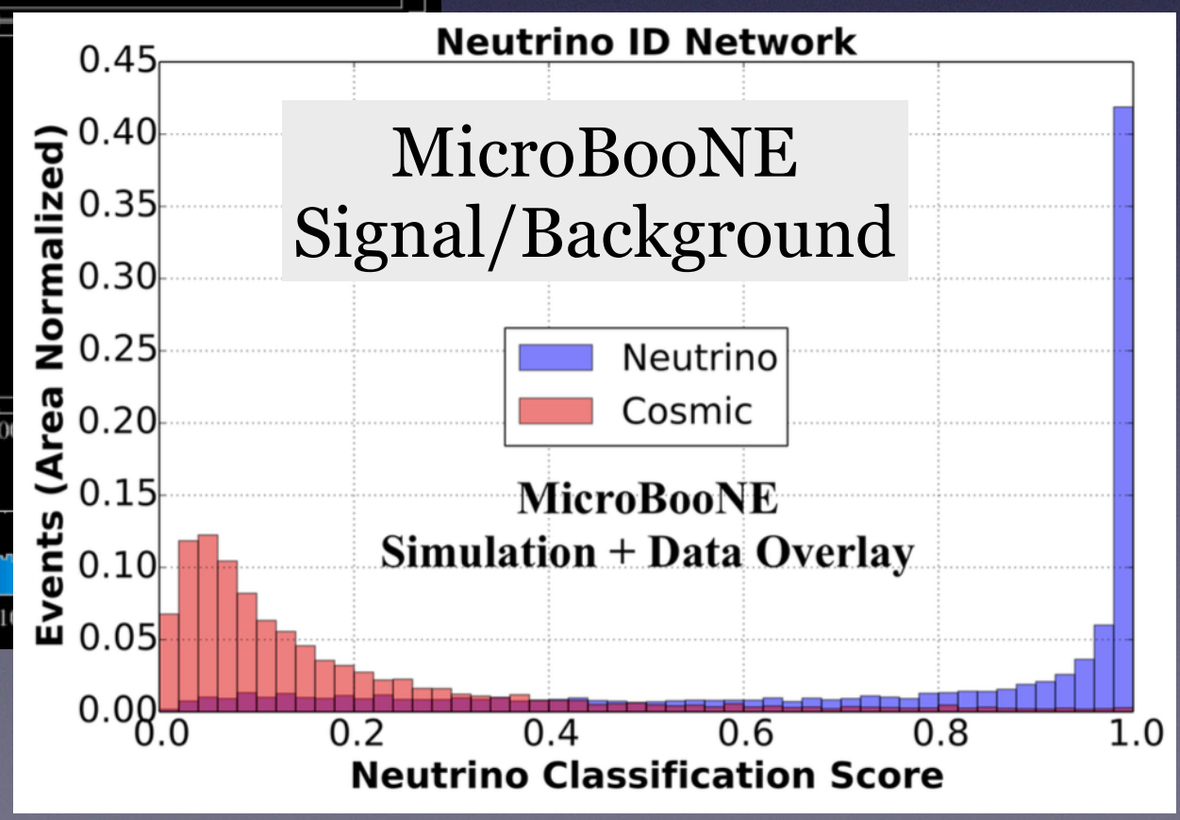
MicroBooNE Particle ID



NOvA Neutrino Event Topology



MicroBooNE Signal/Background



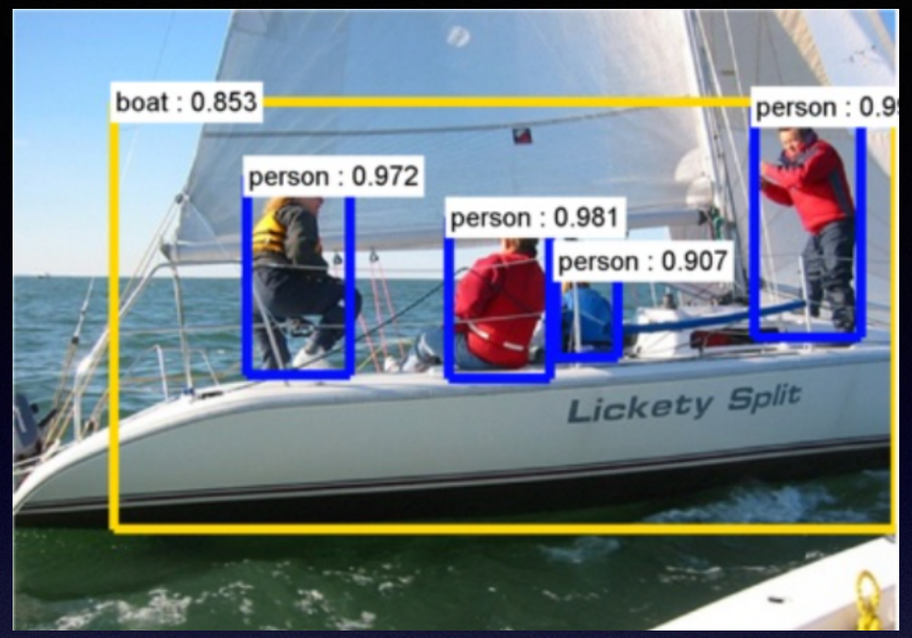
Beyond Image Classification

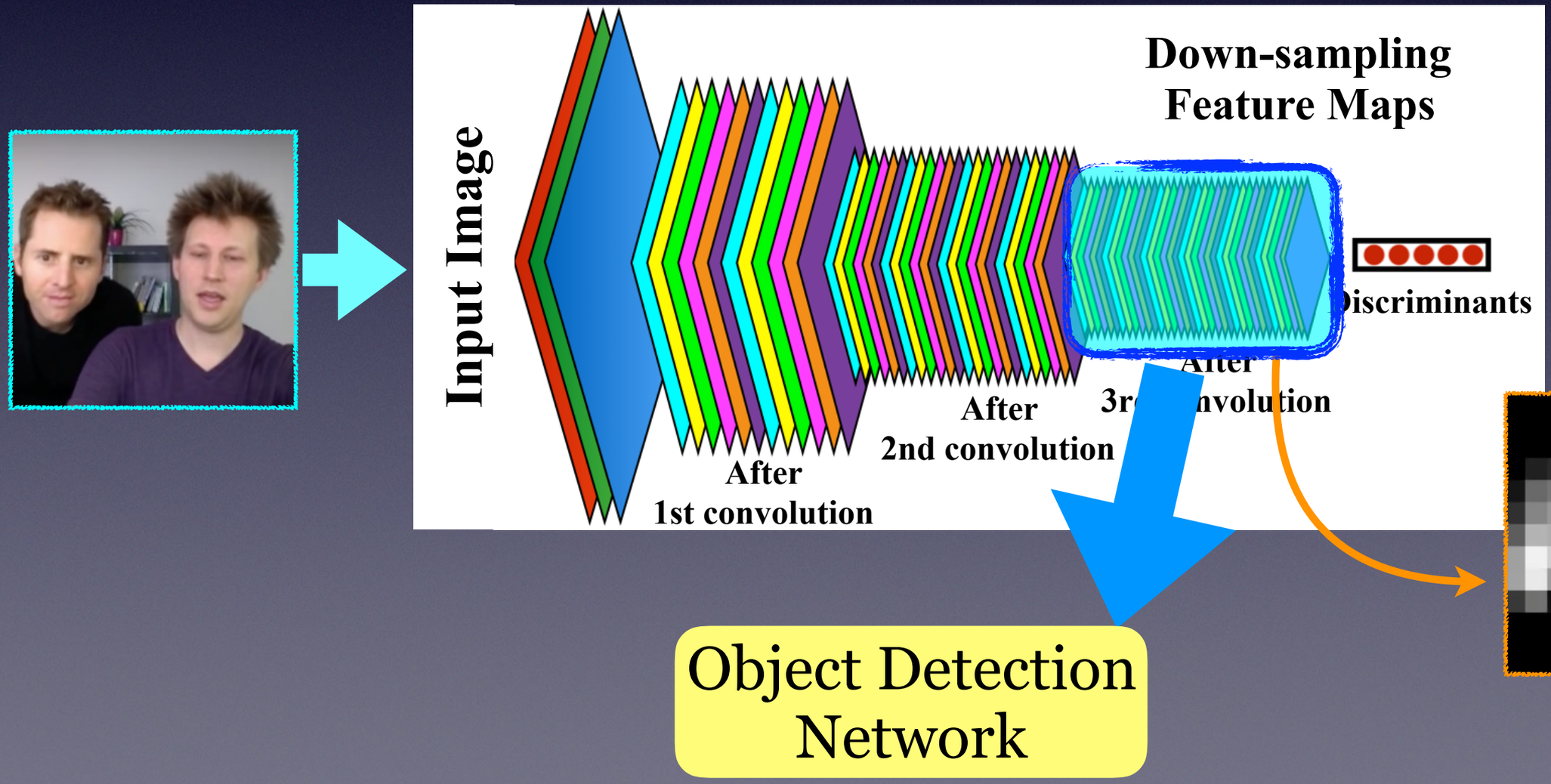
DNN for data reconstruction = “feature mining”?

Beyond Image Classification

Object Detection

- Key insight: "**localize**" a "**distinct feature**" in data
- Many applications for LArTPC data reconstruction!





Beyond Image Classification

Object Detection

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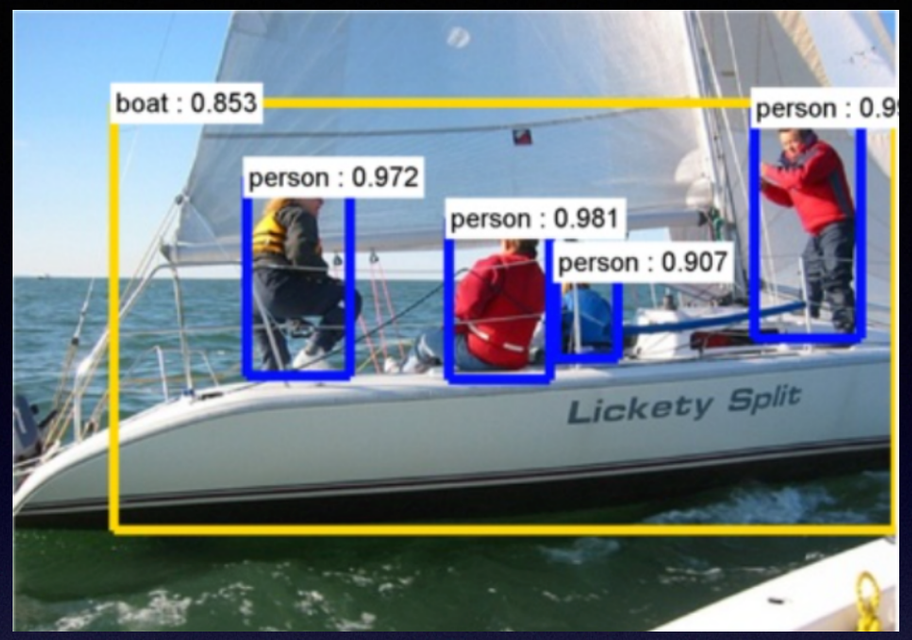
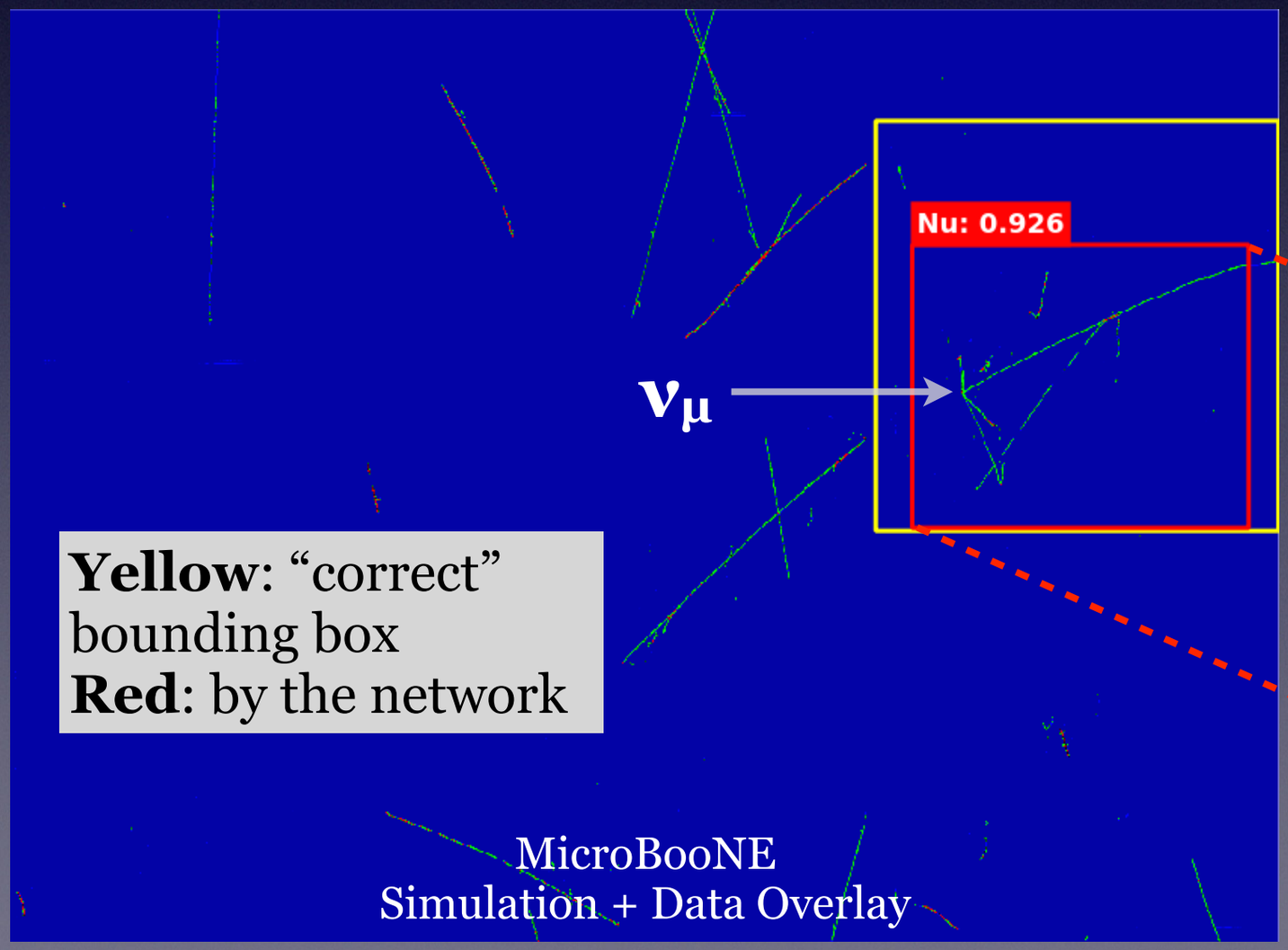




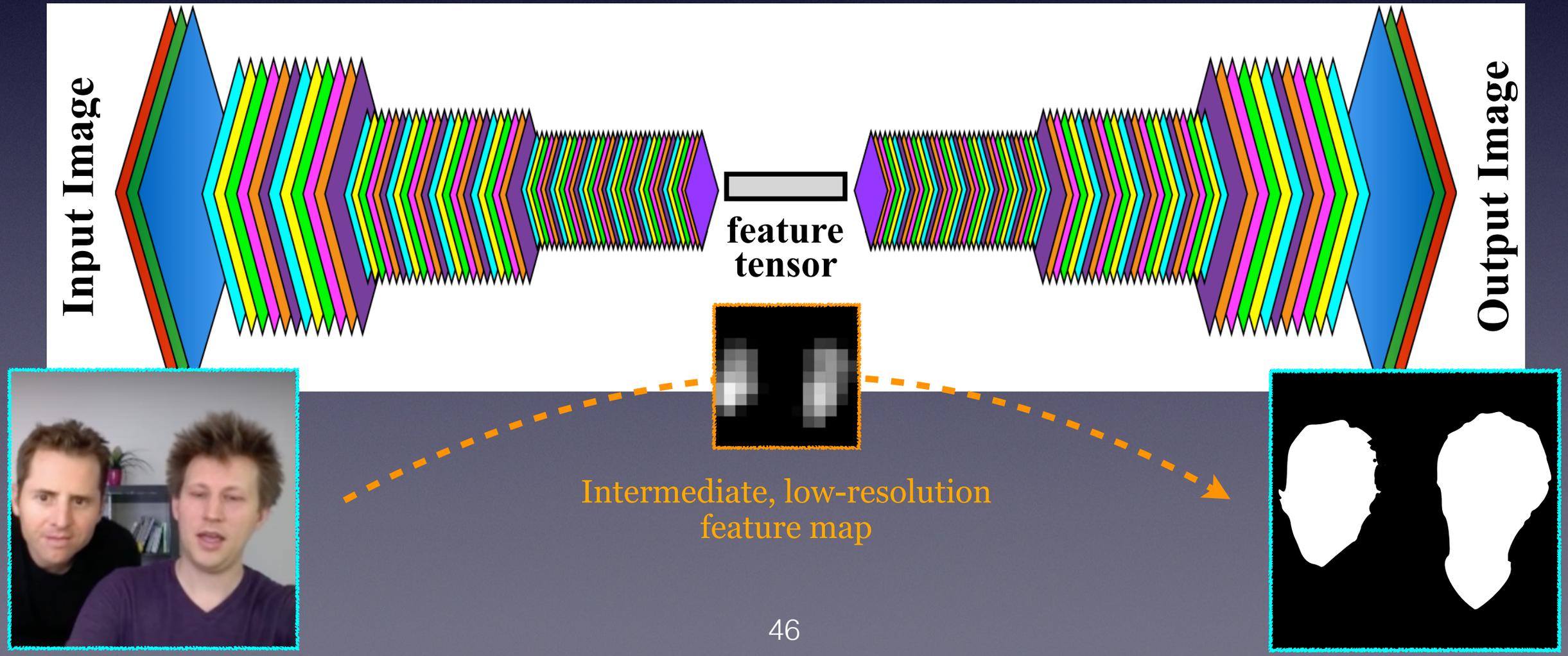
arxiv:1611.05531

Network Output
≃ 2.6m (width) x 1 m (height)

Beyond Image Classification

Pixel Segmentation

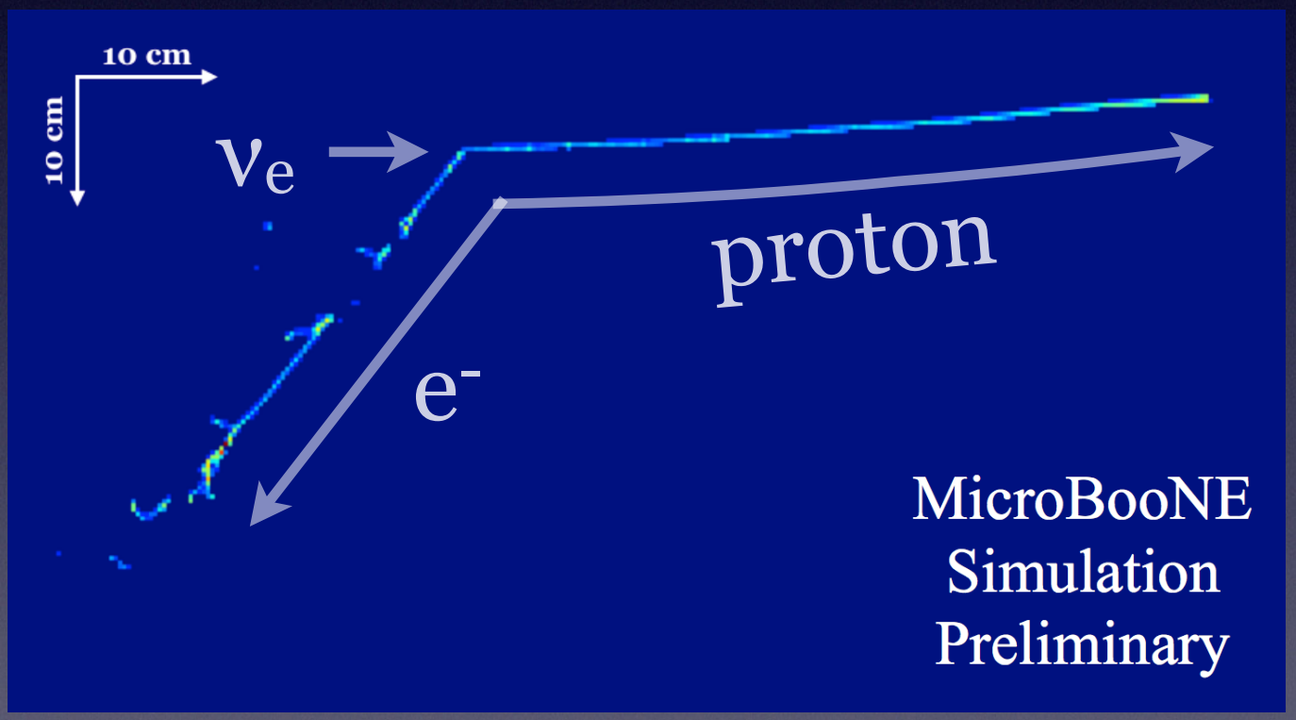
1. **Up-sampling**
   - Expand spatial dimensions of feature maps
2. **Convolution**
   - Smoothing (interpolation) of up-sampled feature maps

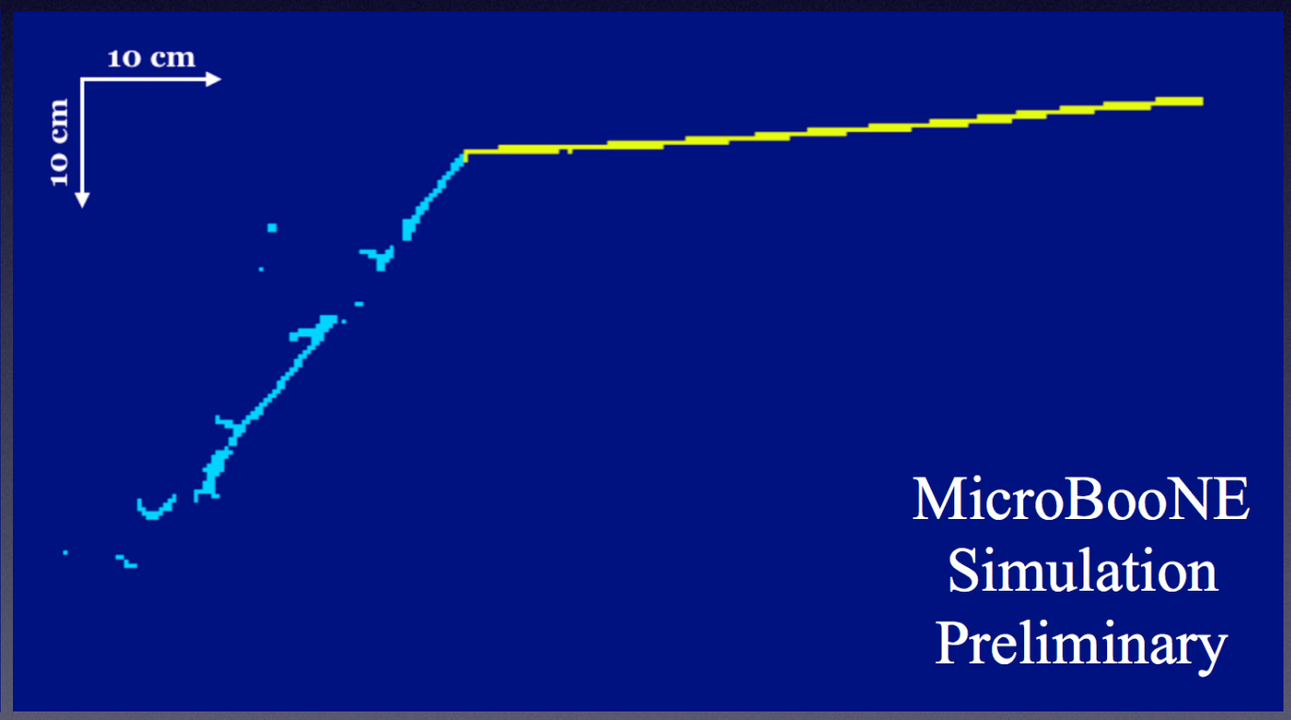


Beyond Image Classification

Pixel Segmentation

- **U-ResNet** can identify the pixel-level features
  - *Any* categorization at the pixel level (**reusable algorithm**)
  - Can easily visualize the local algorithm's response on an image





Example: **pixel-level categorization** by **U-ResNet**
(identify EM particles at full resolution)

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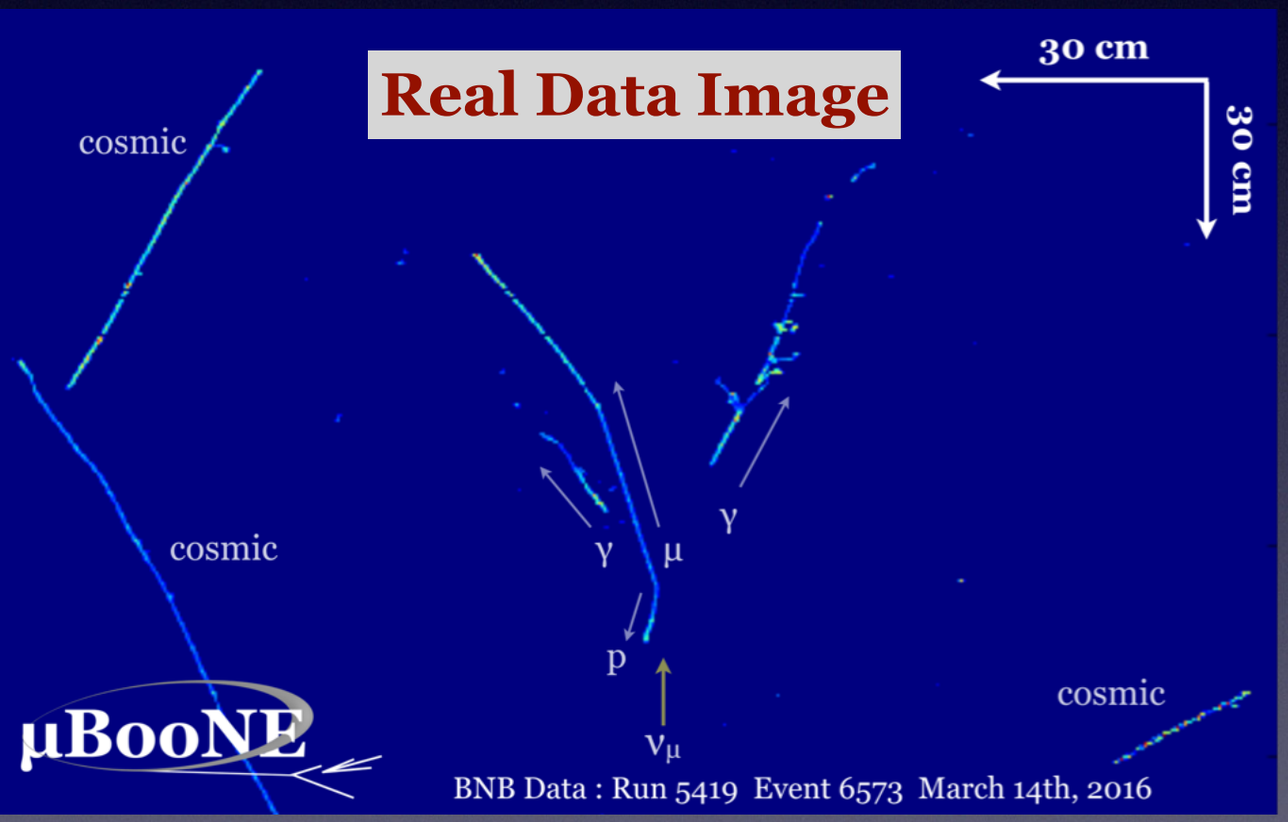

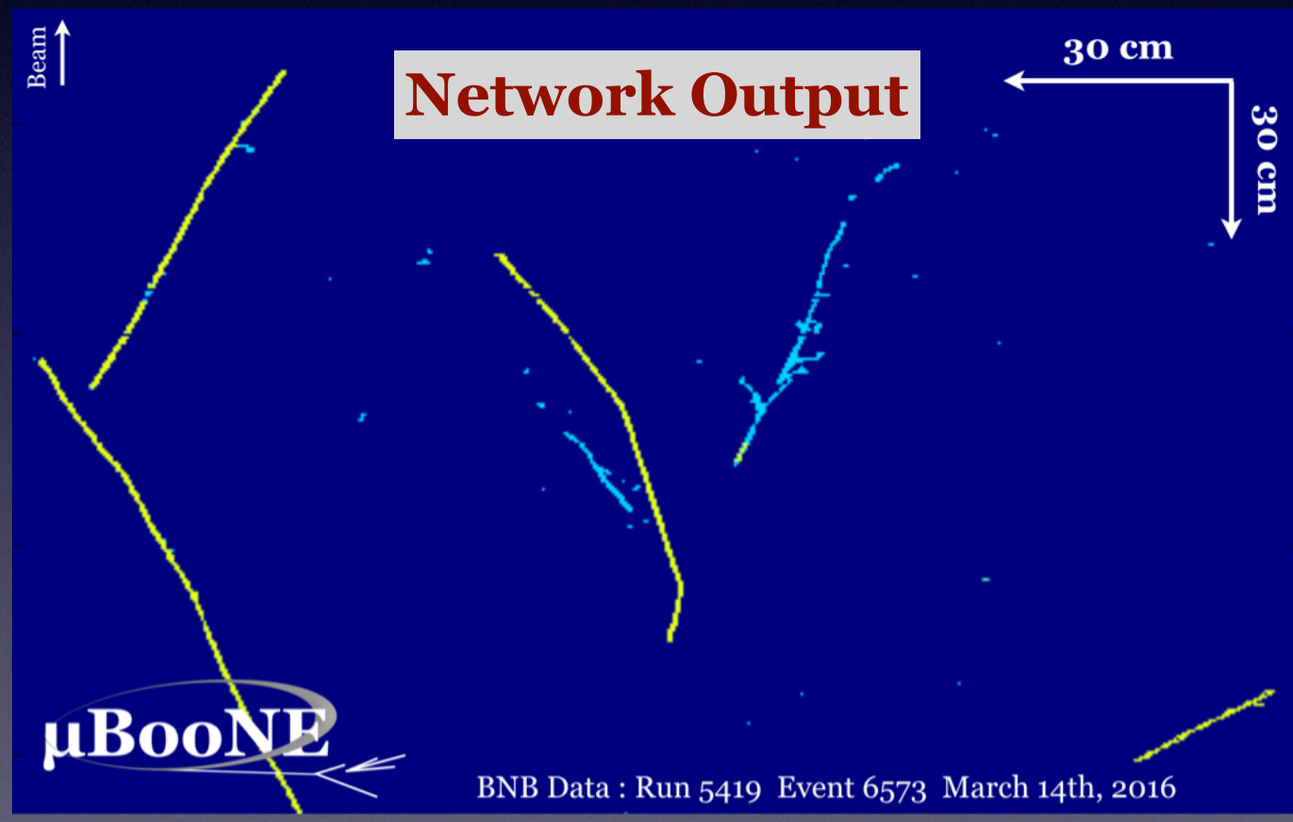

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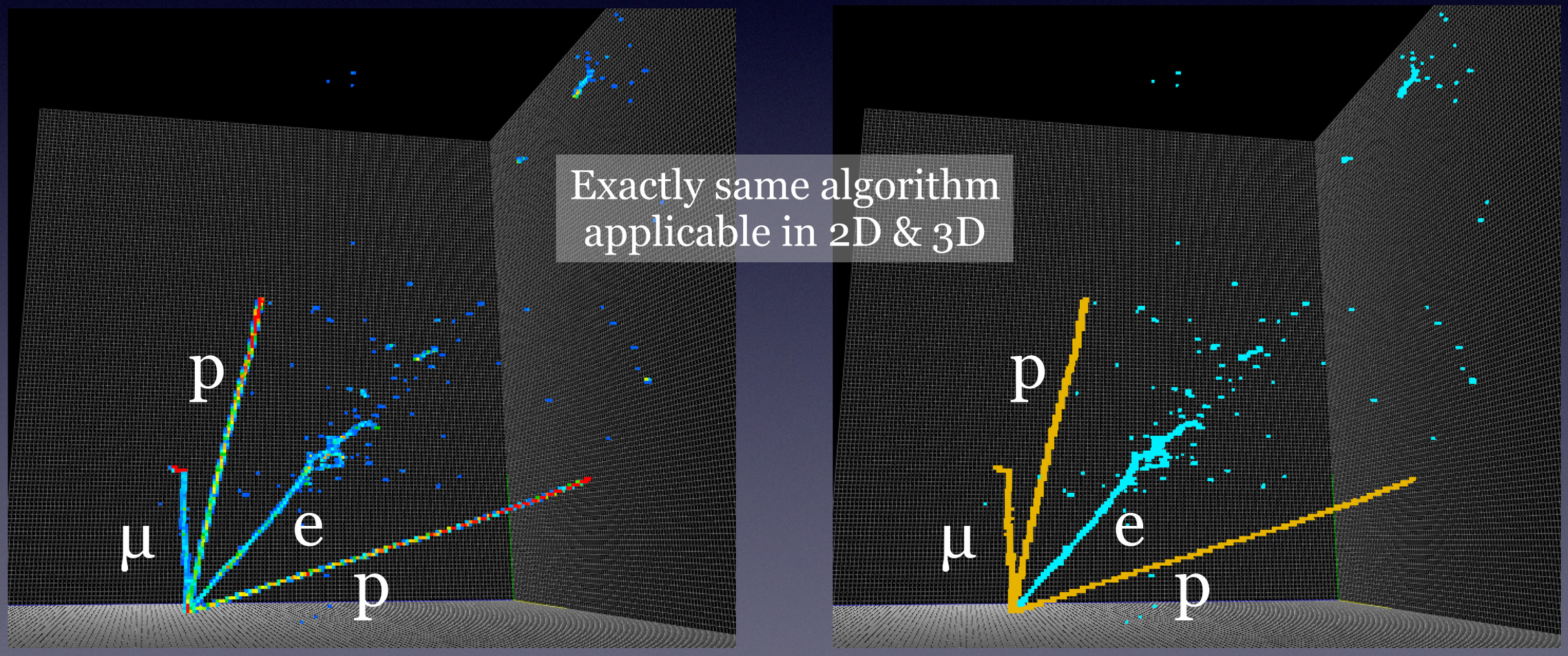
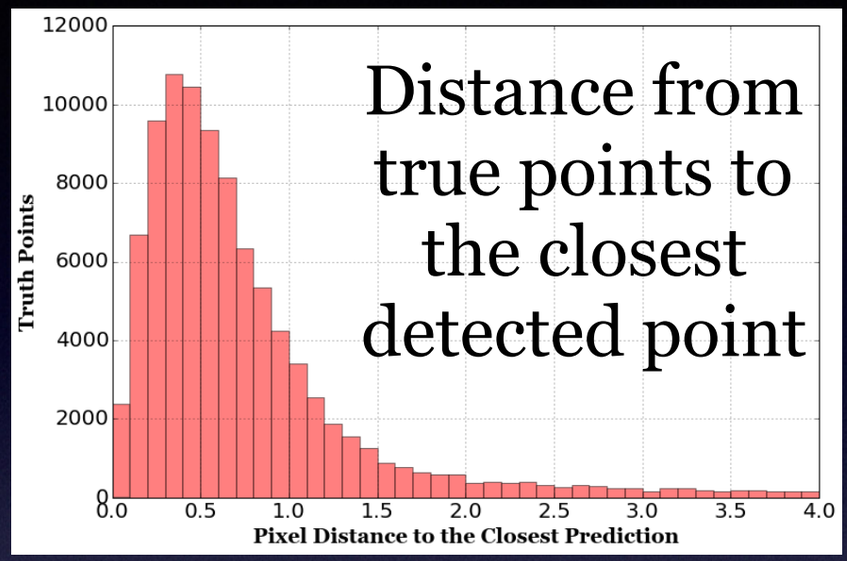


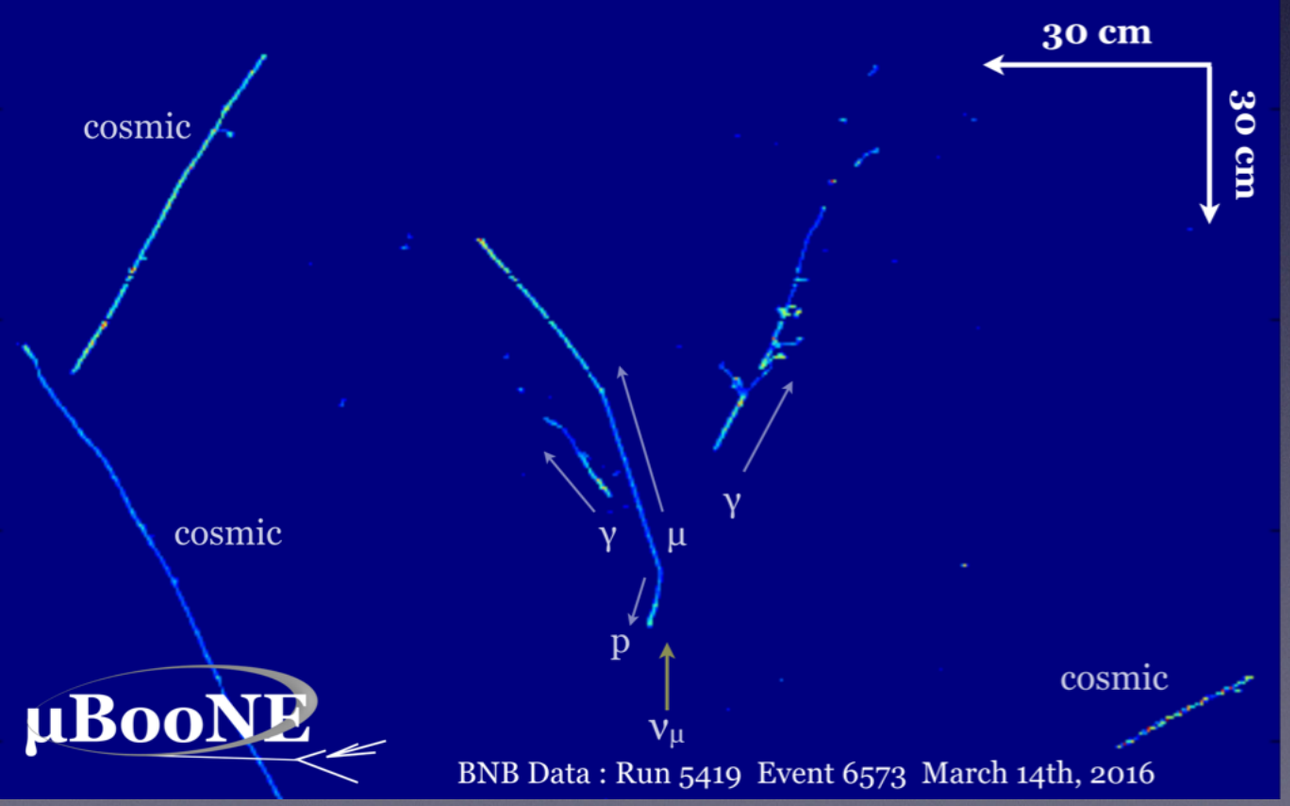
Example: **pixel-level categorization** by **U-ResNet**
(identify EM particles at full resolution)

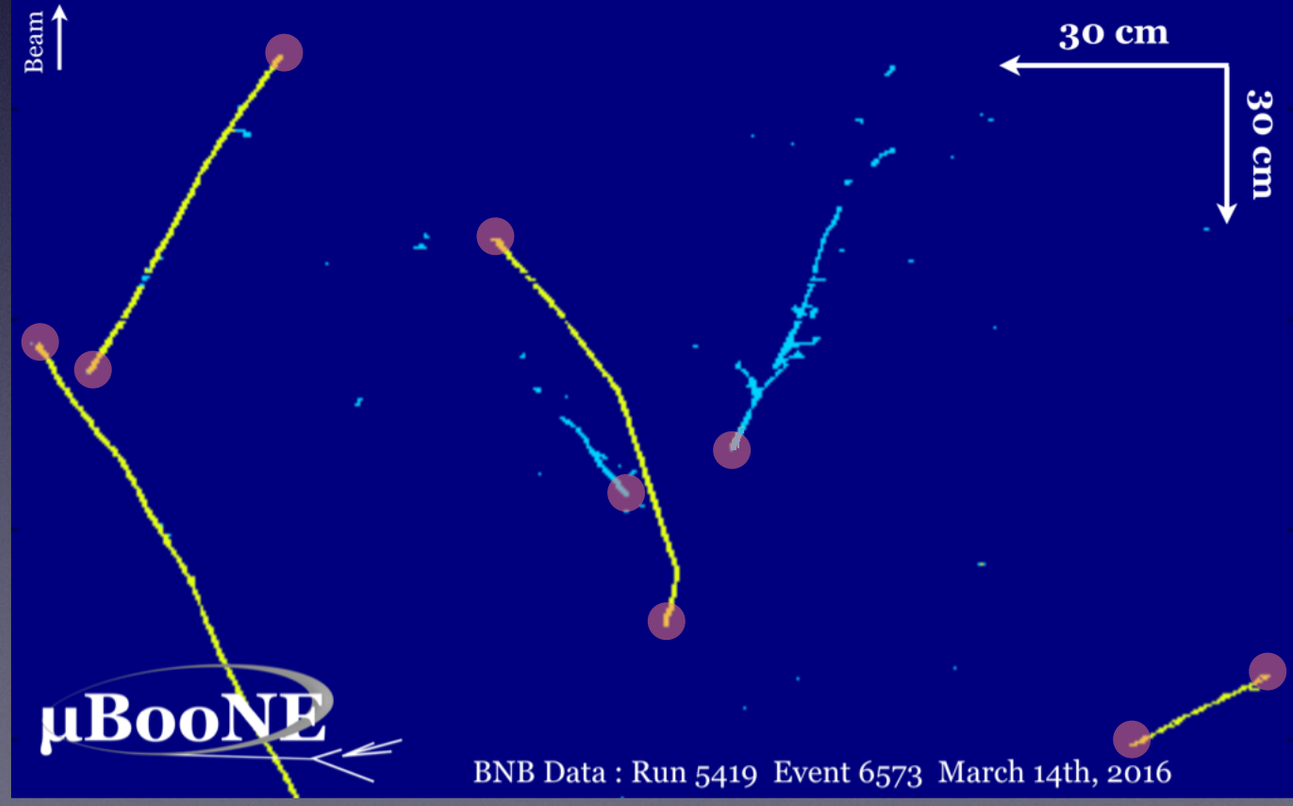
Multi-Task Network Cascade

Chain: Detection + Segmentation

- Identify track edges + shower start
- Simultaneously segment showers
  - Demonstration of “chain” optimization
  - Next step: clustering!



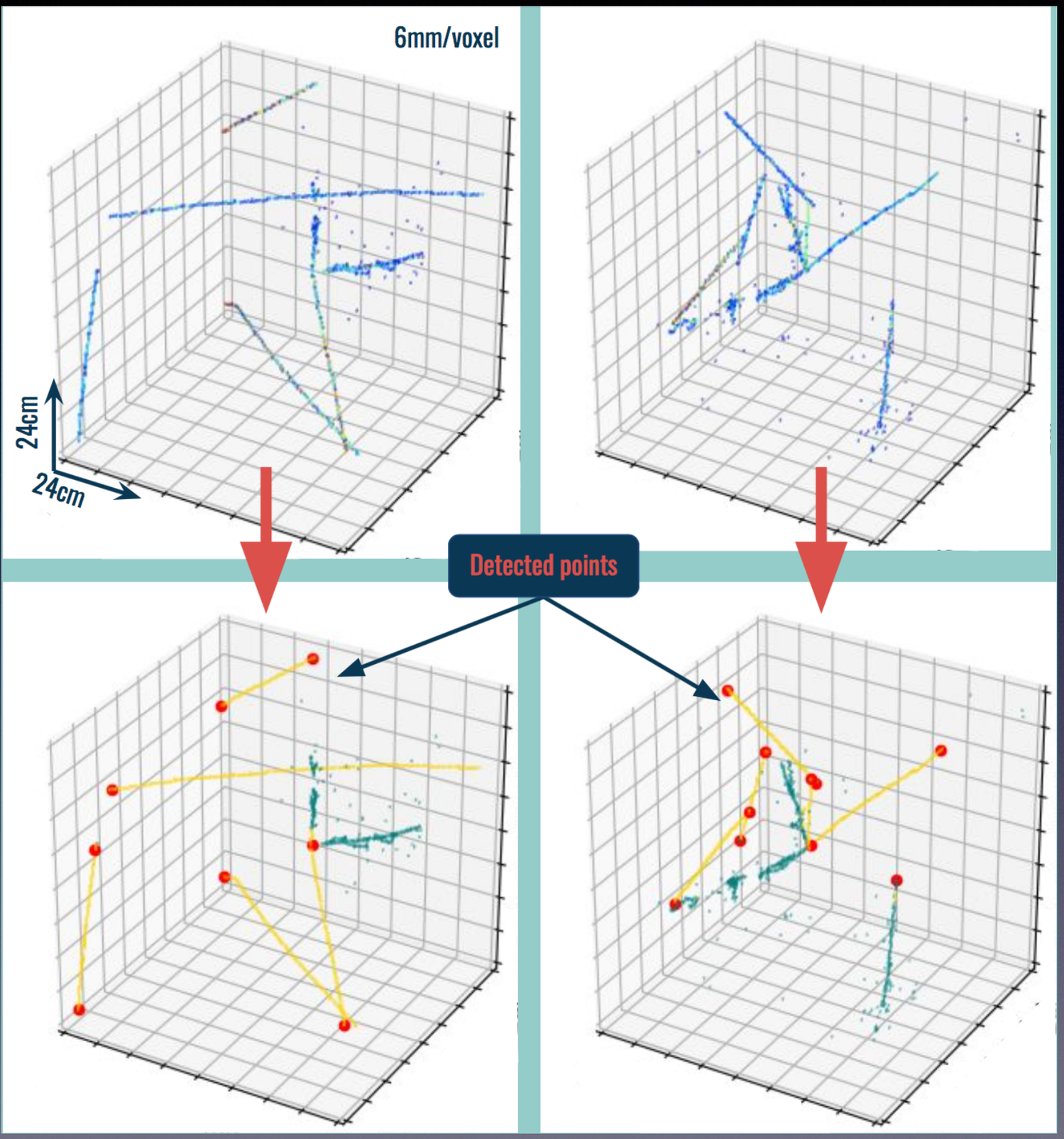




Network Input

Network Output

Multi-Task Network Cascade



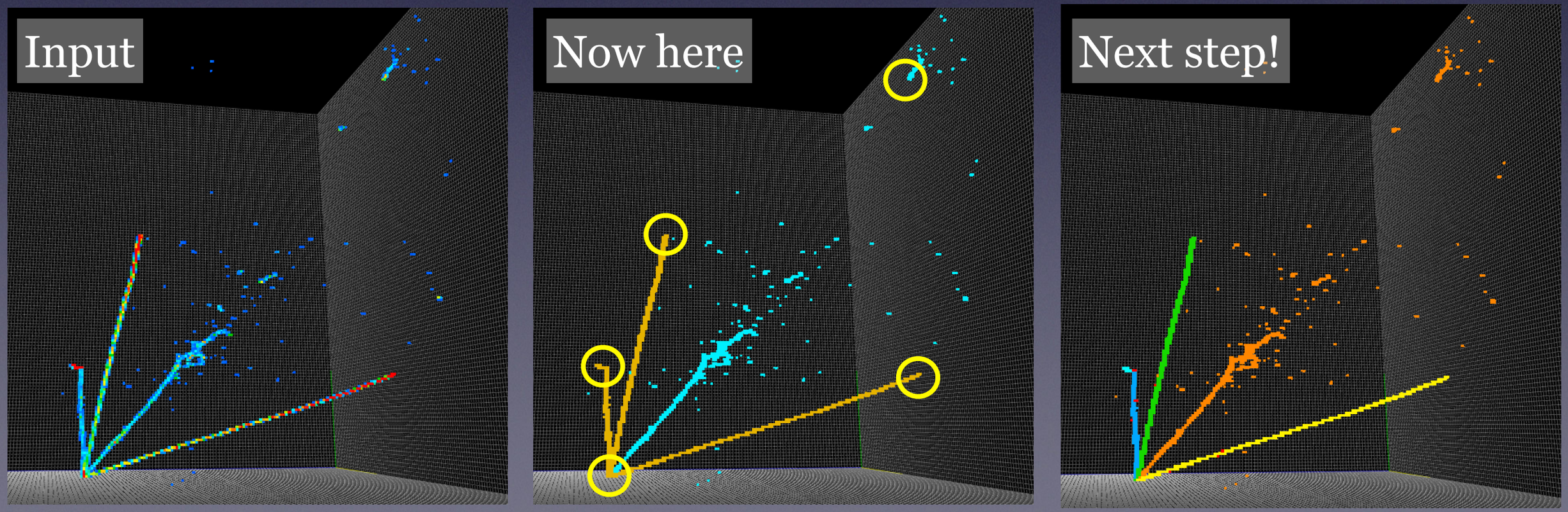
Still works for 2D & 3D

Laura Domine poster at Neutrino2018

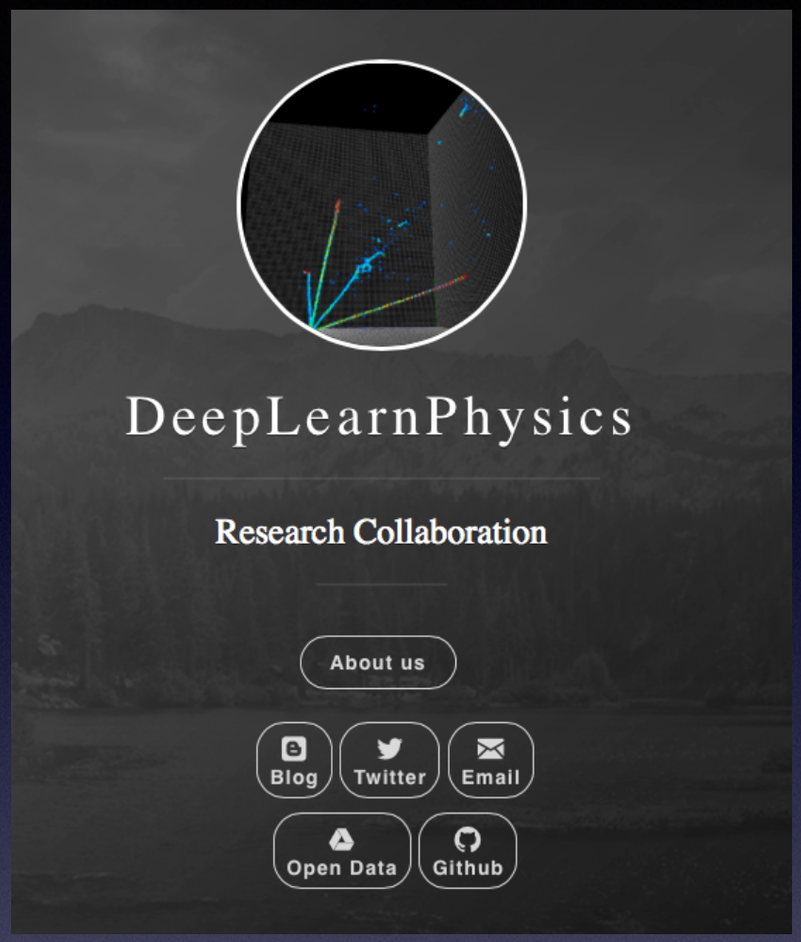
Deep Neural Network for Reconstruction

Where we are heading toward

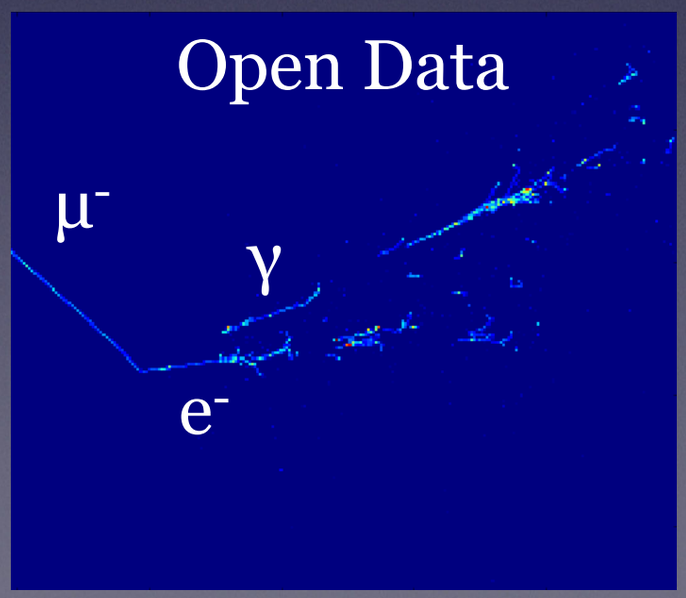
- **Full reconstruction chain**
  - Individual particle clustering & trajectory reconstruction
  - Interaction topology + particle hierarchy reconstruction
  - Energy reconstruction
- **Applications on HPC:** use distributed computing for a large scale network training, optimization, and data production

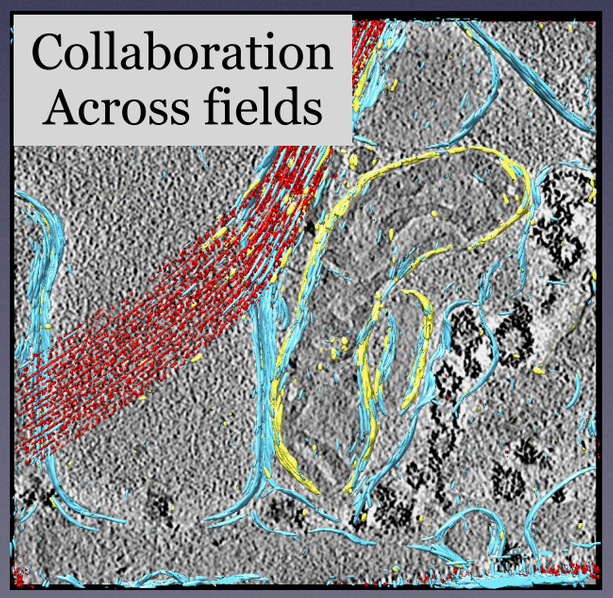


DeepLearnPhysics

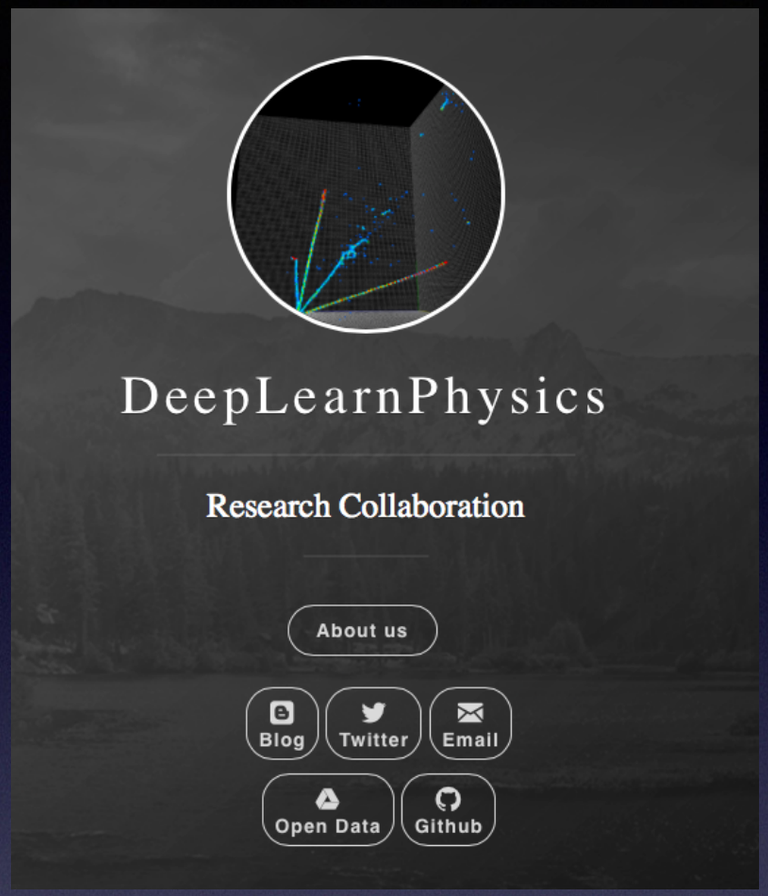


- Group of physicists mainly from neutrino TPC experiments
  - http://deeplearnphysics.org
  - MicroBooNE/SBND/ICARUS/DUNE/ NEXT/nEXO/non-HEP …
- Share software tools + open data
- Meetings/Blog posts to share experience, discuss problems, etc.





DeepLearnPhysics



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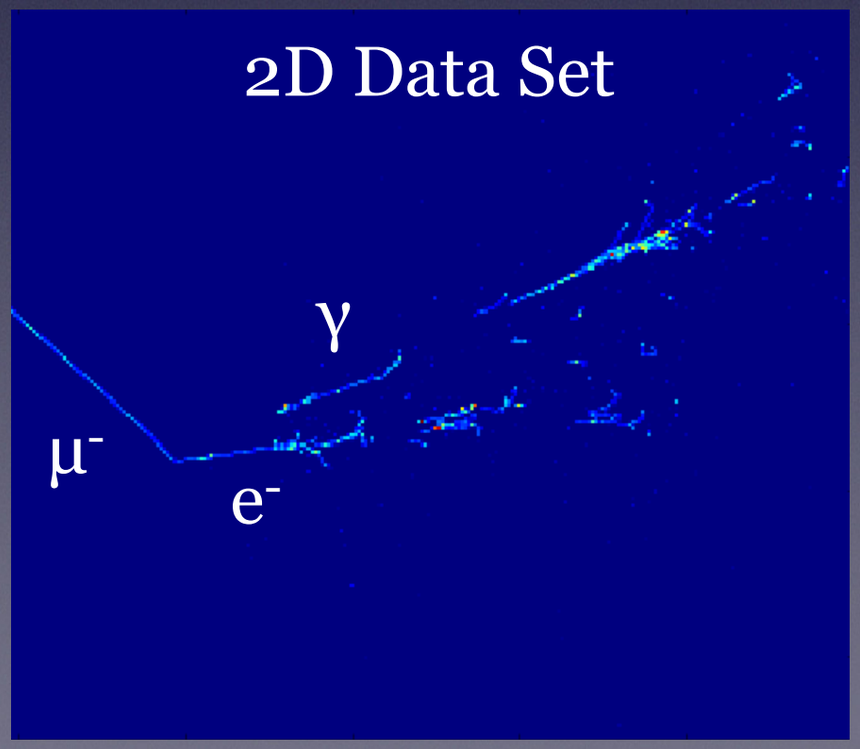
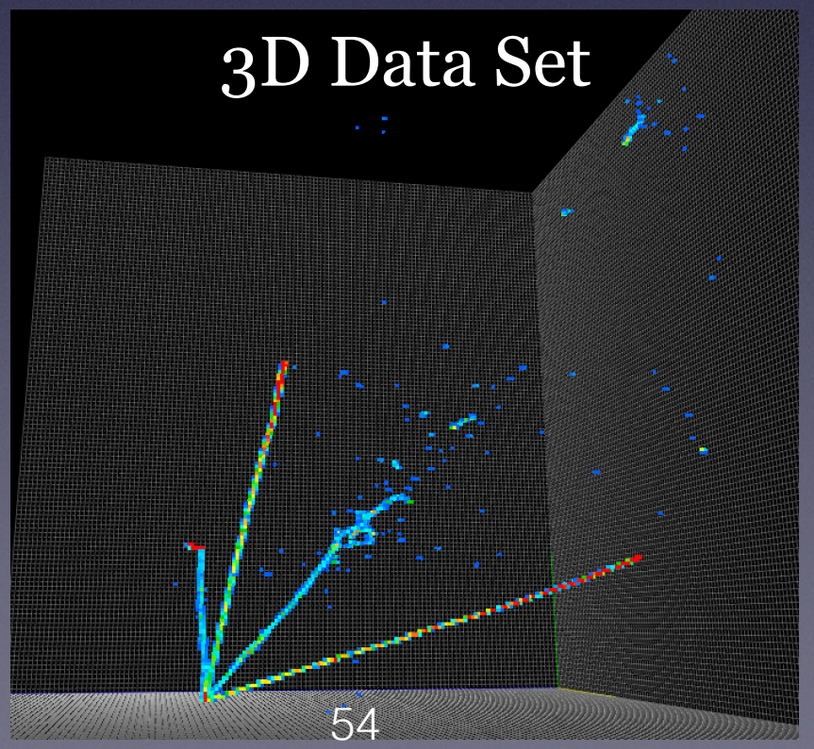
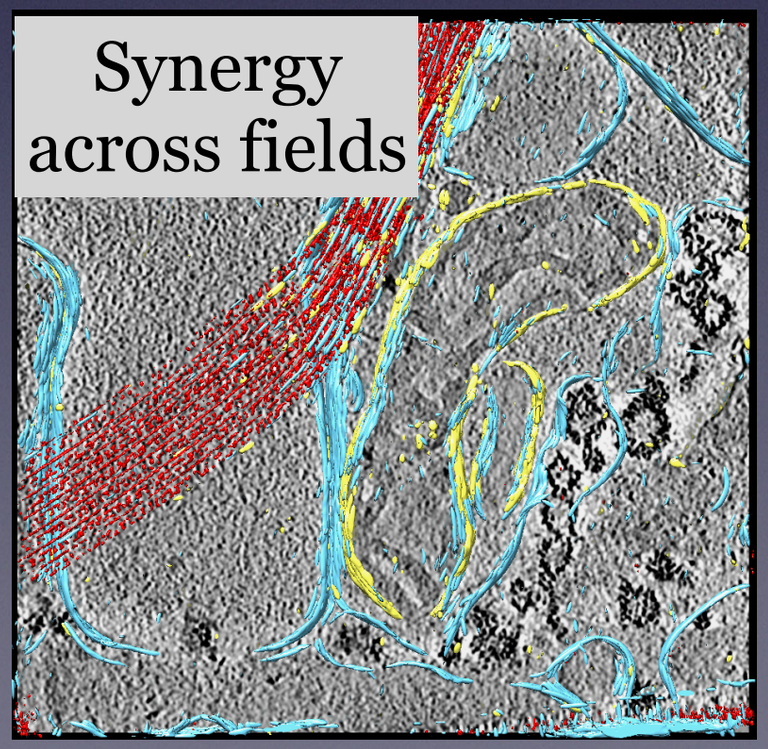




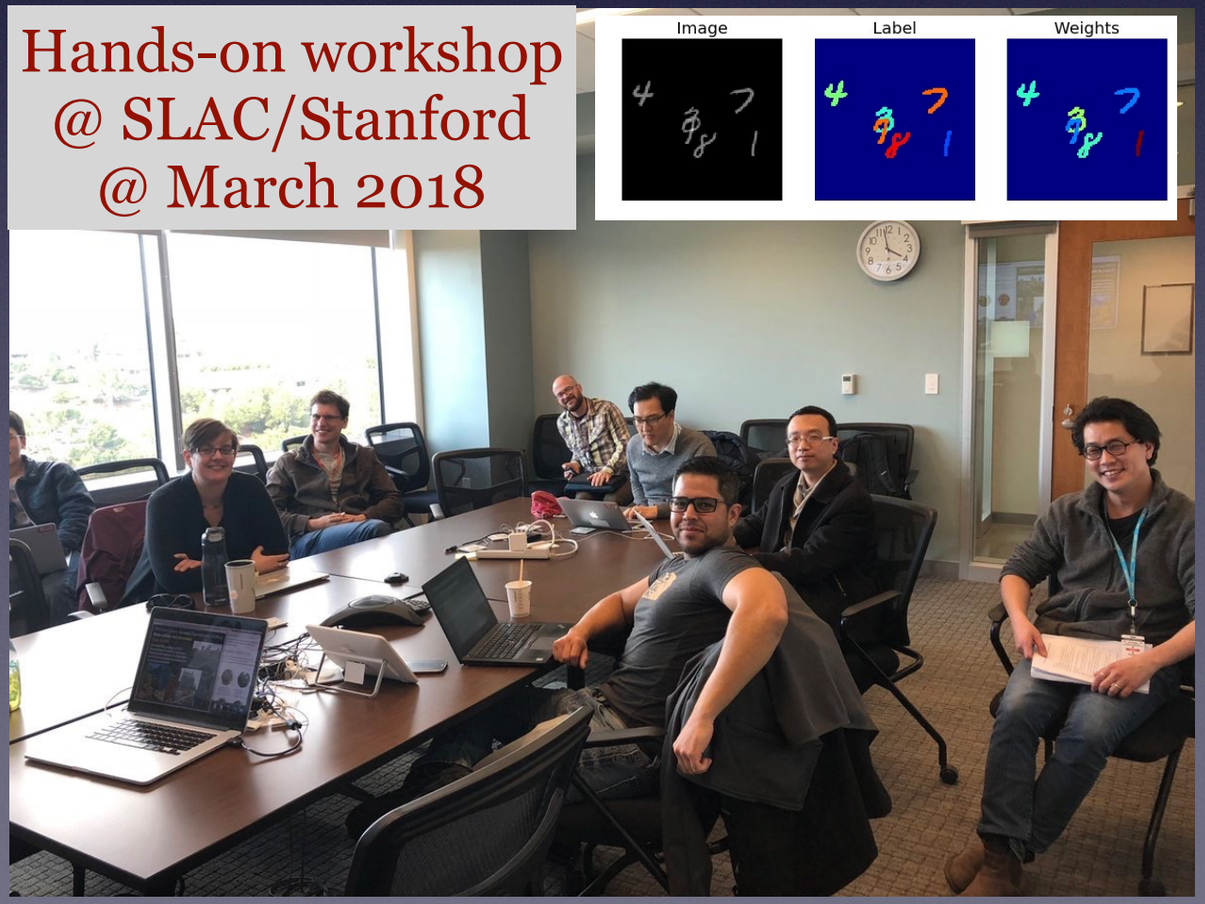


DeepLearnPhysics

Open-Source Software Development @ DLP

- Image/Volumetric data processing framework
  - Experiment agnostic design, Qt/OpenGL based visualization toolkit, C++/CUDA based software with extensive Python APIs
  - Interface to DL frameworks (MXNet, Pytorch, Tensorflow), Singularity container distribution for cloud deployment

Hands-on workshop
@ SLAC/Stanford
@ March 2018



Workshops to share & raise expertise

- "GPU for everyone": using free K80 GPU from Google cloud
- Where we synergy across fields
  - Collaboration with Stanford campus CS/ML, Cryo-EM, accelerator, photon-science,

… wrapping up …

Outline

- Liquid Argon Time Projection Chambers
- Recent innovations in Computer Vision
- Deep Convolutional Neural Networks (CNN)
- Deep CNNs for image data analysis
- **Wrap-up**

Wrap Up

- **LArTPC: particle imaging detector**
  - data reconstruction/analysis remains challenging
  - **wanted**: pattern recognition algorithms, optimization method for full chain, scalable computing method

- **DNN for data reconstruction**
  - Modern techniques in computer vision
  - Very active development in academia + industry for both algorithms and software utilizing “many-core”

- **Cross-disciplinary effort** including non-HEP
  - Energy frontier (LHC), cosmic frontier (LSST/EXO/NEXT), photon science (LCLS), Cryo-EM, QIS…
  - **DeepLearnPhysics** group for sharing tools/expertise

Back-Up Slides

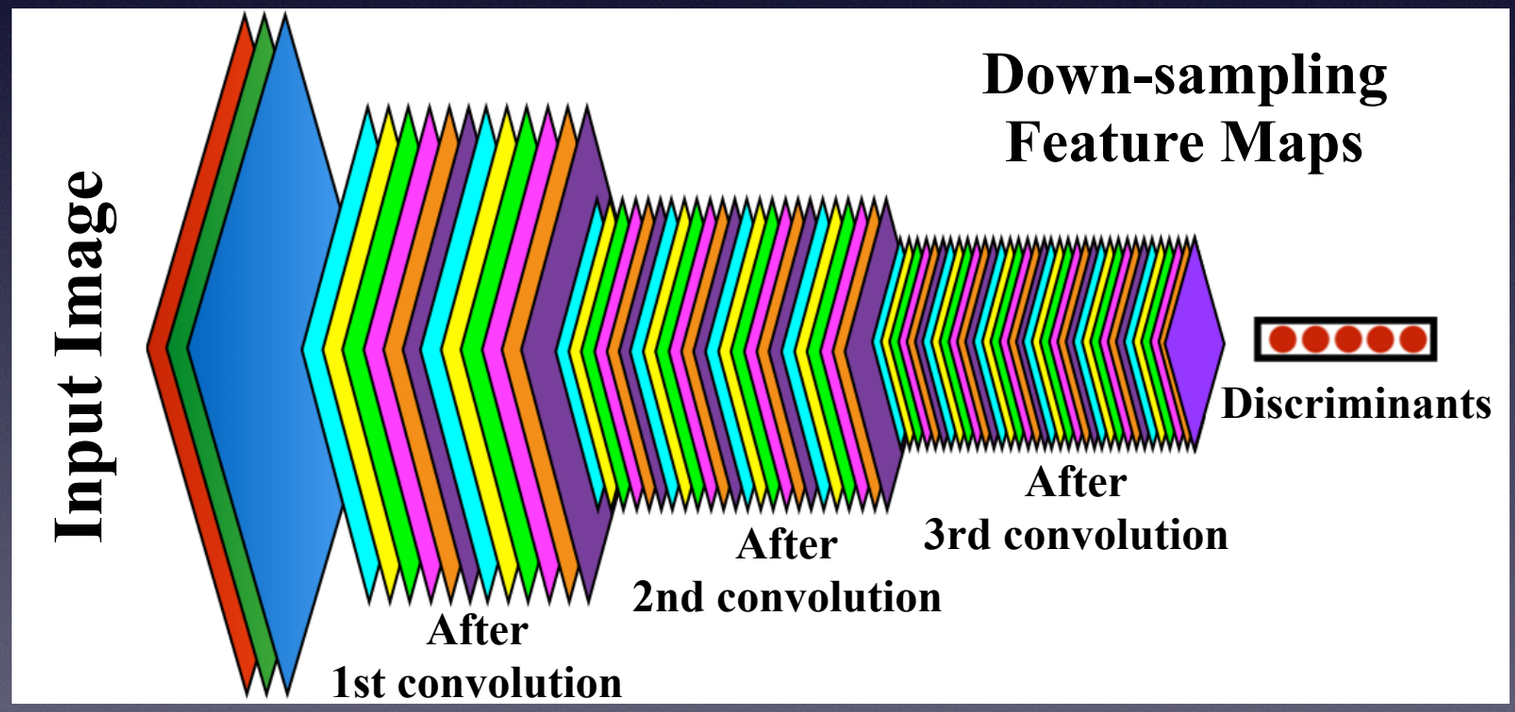
NN & CNN Basics

~ How Does It Work? ~

How Image Classification Networks Work

Goal: extract features to give "single label" to an image

1. **Convolution operation**
2. **Down-sampling**



Series of convolutions
+ down-sampling

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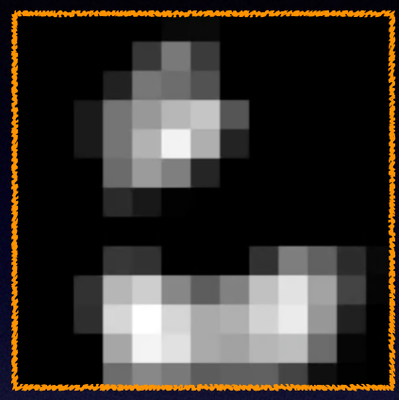
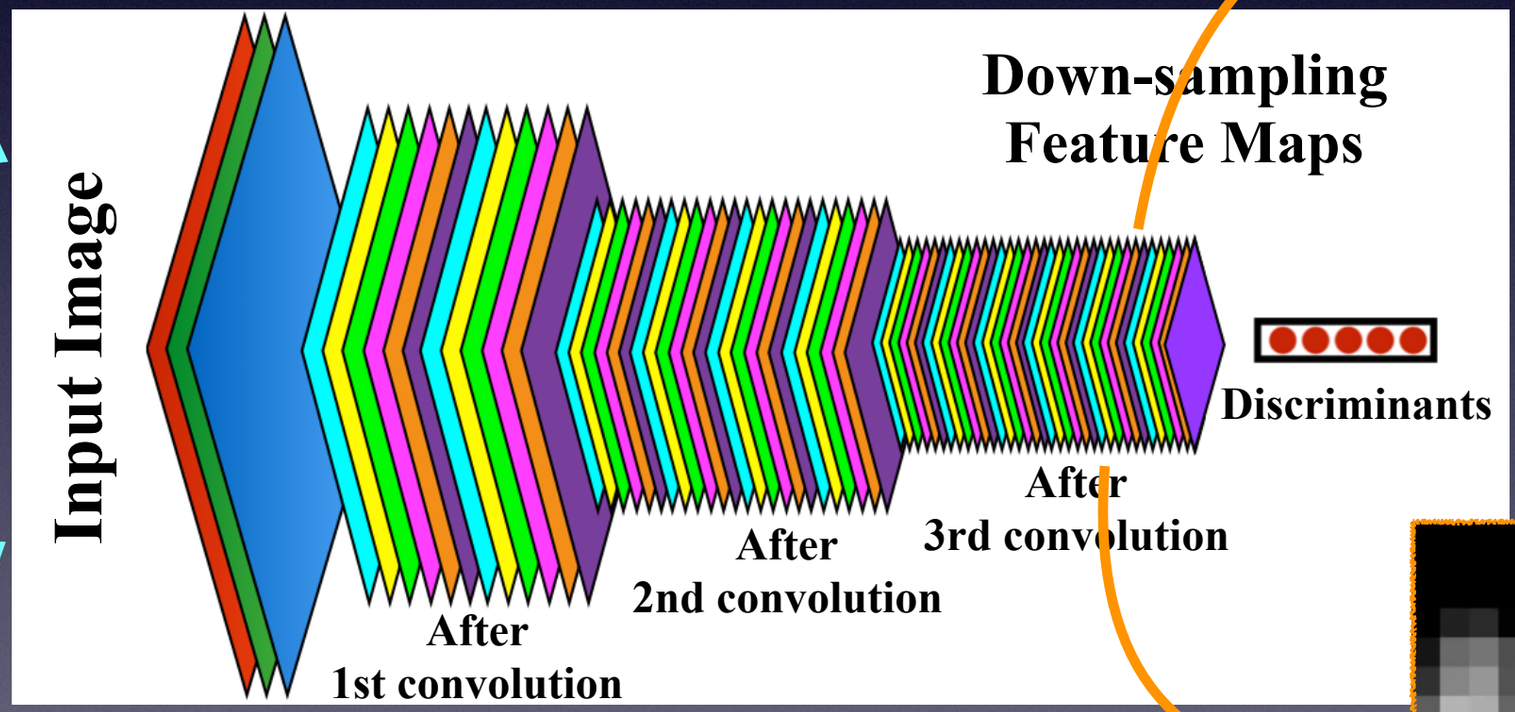
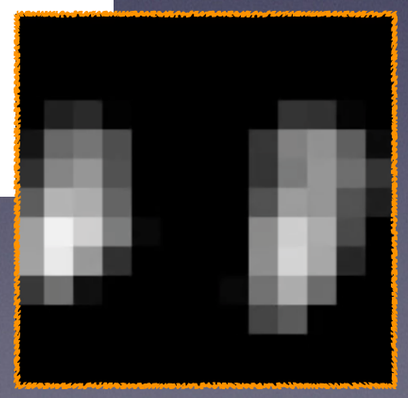


"Written Texts" feature map



Series of convolutions + down-sampling

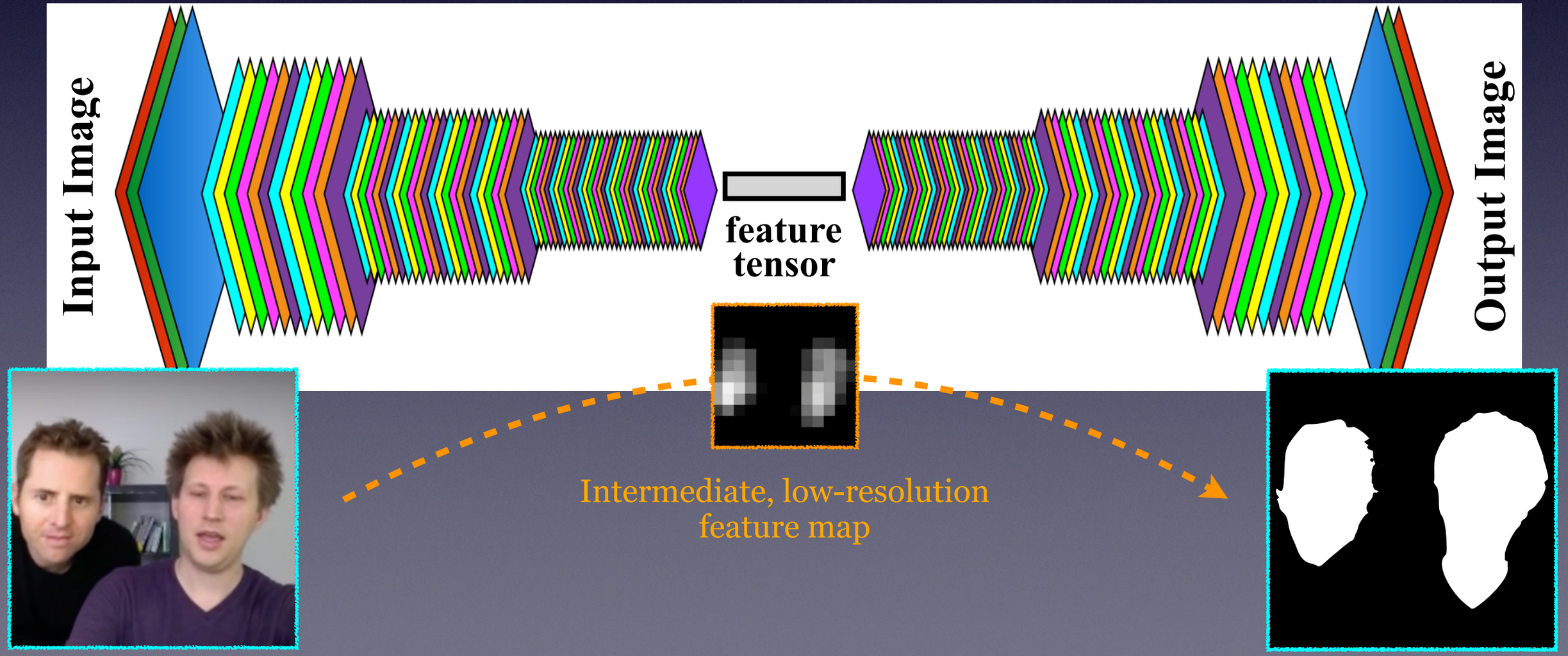


"Human Face" feature map

How SSNet Works

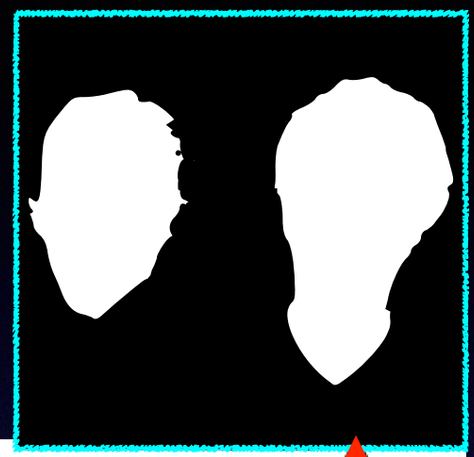
Goal: recover precise, pixel-level location of objects

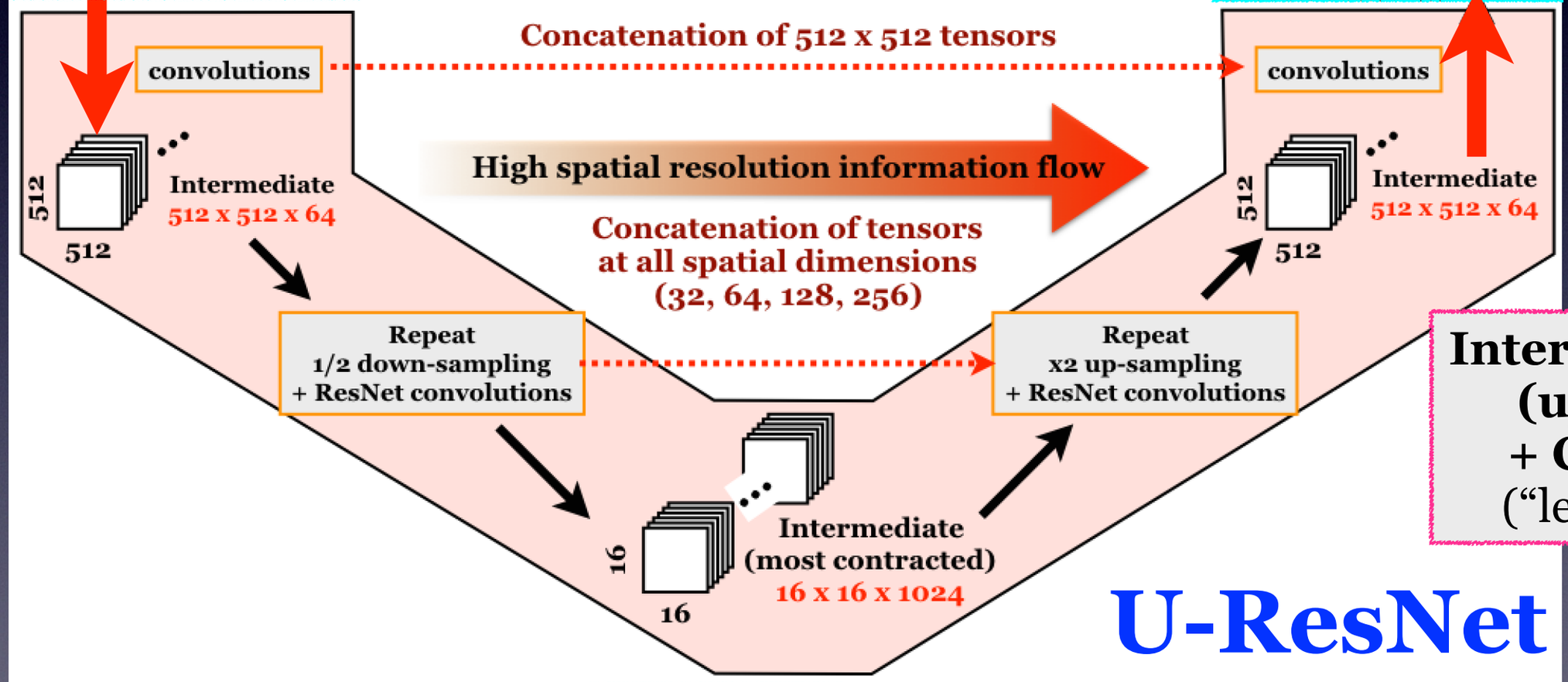
1. **Up-sampling**
   - Expand spatial dimensions of feature maps
2. **Convolution**
   - Smoothing (interpolation) of up-sampled feature maps



DNN for LArTPC Data Reconstruction

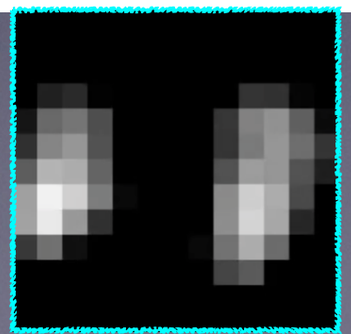
How does U-ResNet Work?





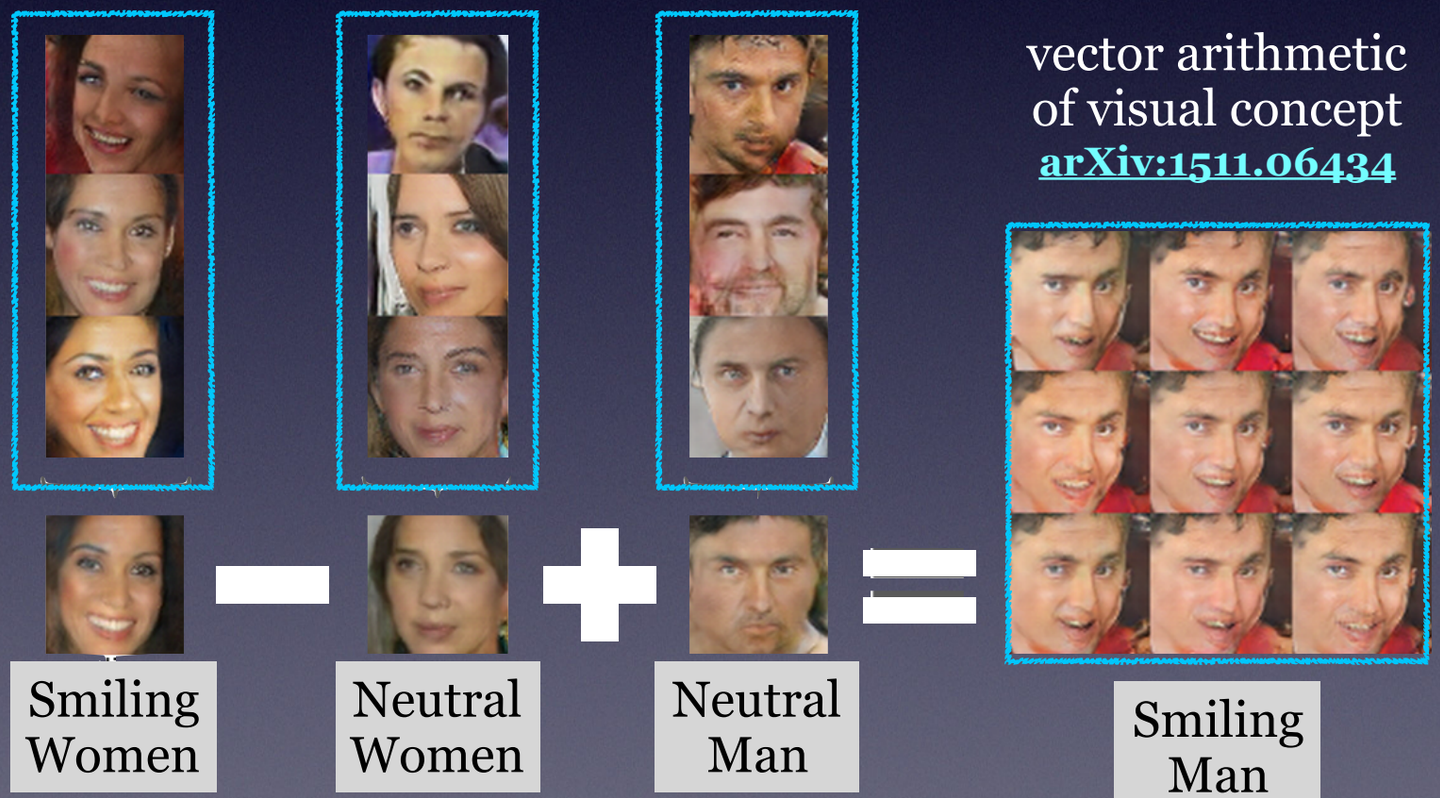
Interpolation filters (up-sampling) + Convolutions (“learnable” filter)

U-ResNet

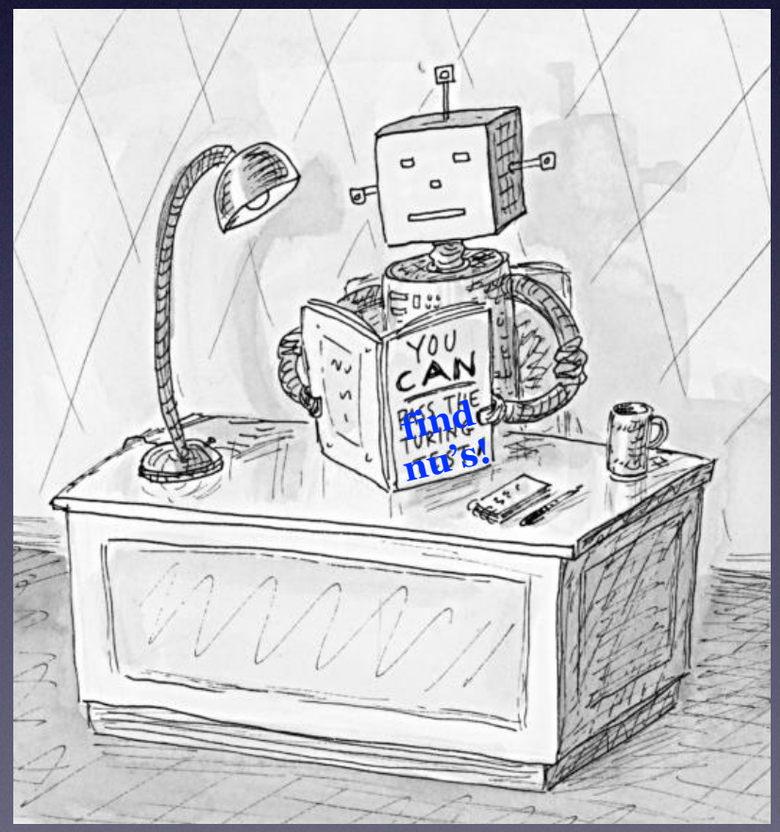


Down sampling + Convolutions to identify highly abstract features (e.g. “human face”)

… more exciting projects …



vector arithmetic of visual concept
arXiv:1511.06434



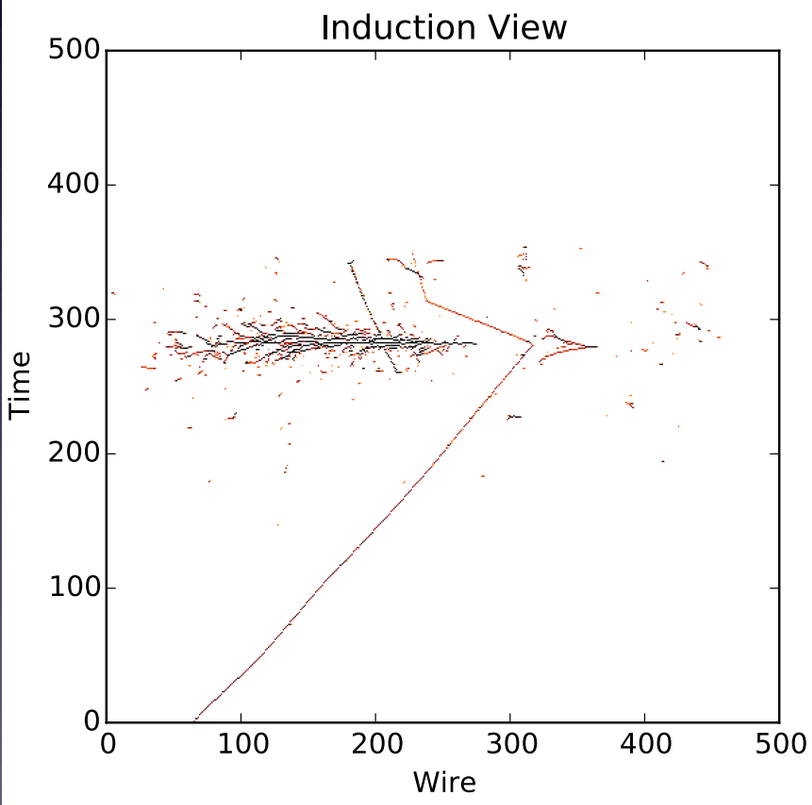
SBND Cosmic Rejection w/ U-ResNet

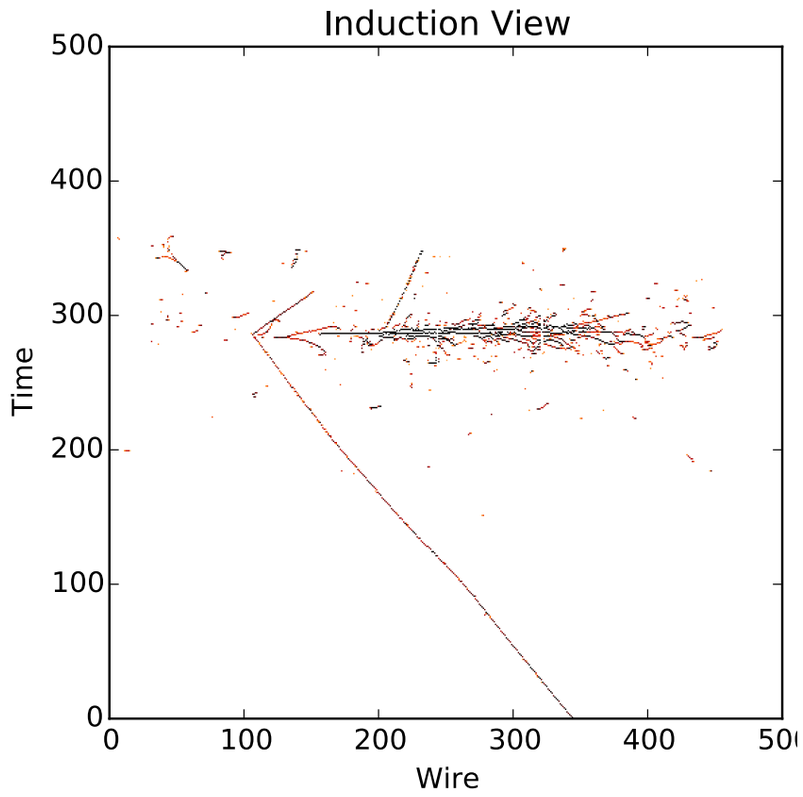
Collection plane view,
similar performance
on induction planes
(from C. Adams)

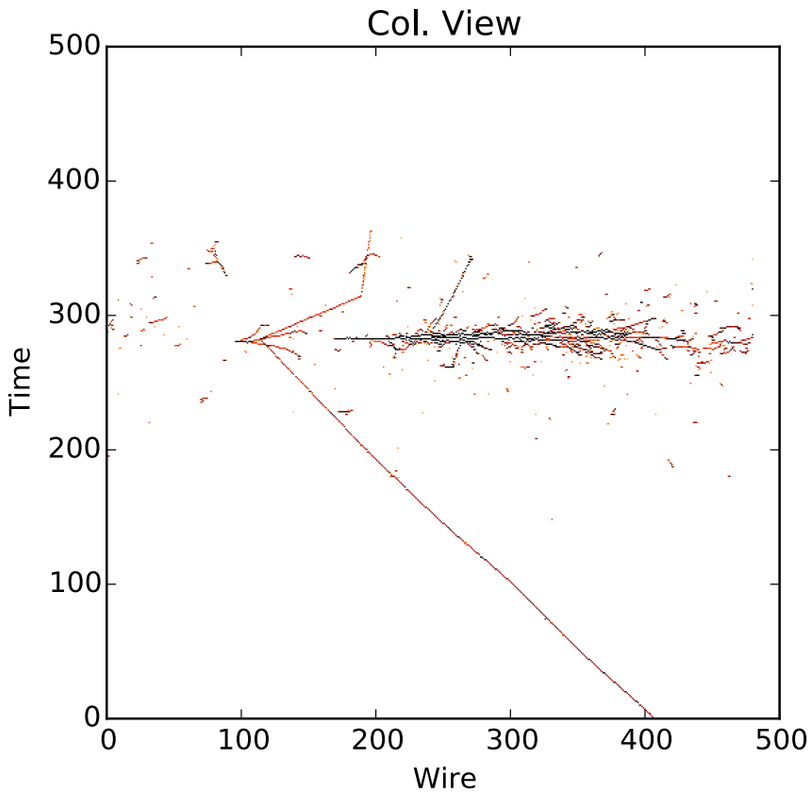
Our Input

DL @ DUNE FD Analysis

Each “pixel” is the integrated ADC response in that time/space slice. These maps are chosen to be 500 wires long and 1.2ms wide (split into 500 time chunks).





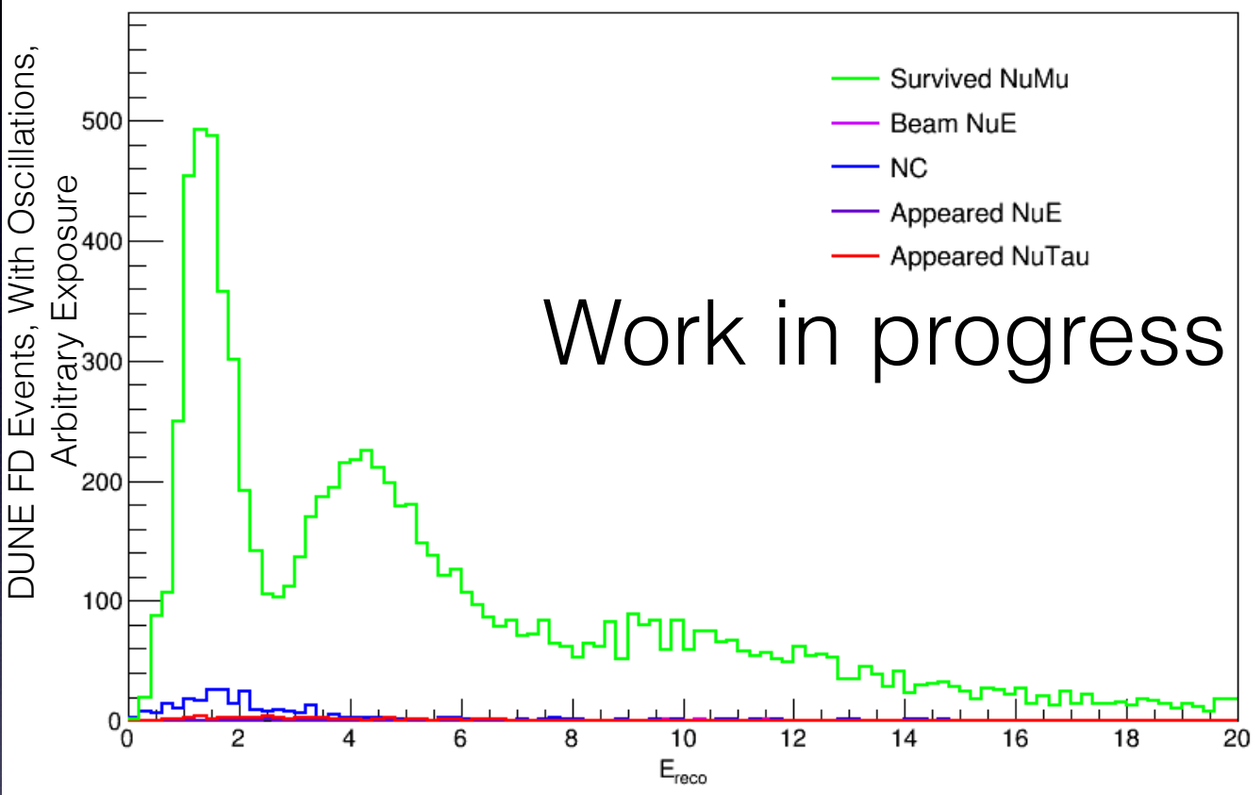


Slide 1/3 from A. Radovic

NuMu Selected Events Reconstructed Energy Spectr

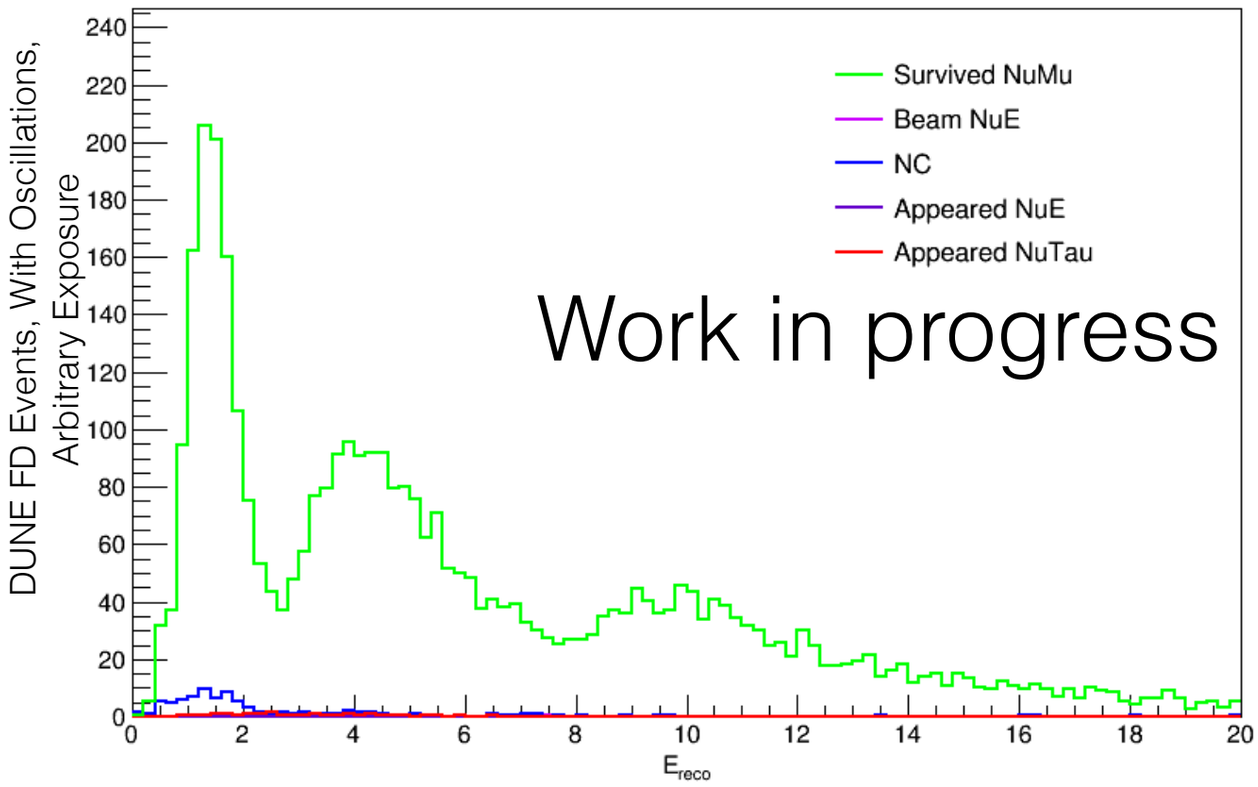
DL @ DUNE FD Analysis

Neutrino Beam



	NuMu	Appeared NuE	Beam NuE	NC	NuTau
Efficiency	**80.6**				
Rejection		99.0	98.7	**97.6**	81.5

Anti-Neutrino Beam



	NuMu	Appeared NuE	Beam NuE	NC	NuTau
Efficiency	**87.7**				
Rejection		99.6	99.3	**98.3**	81.4

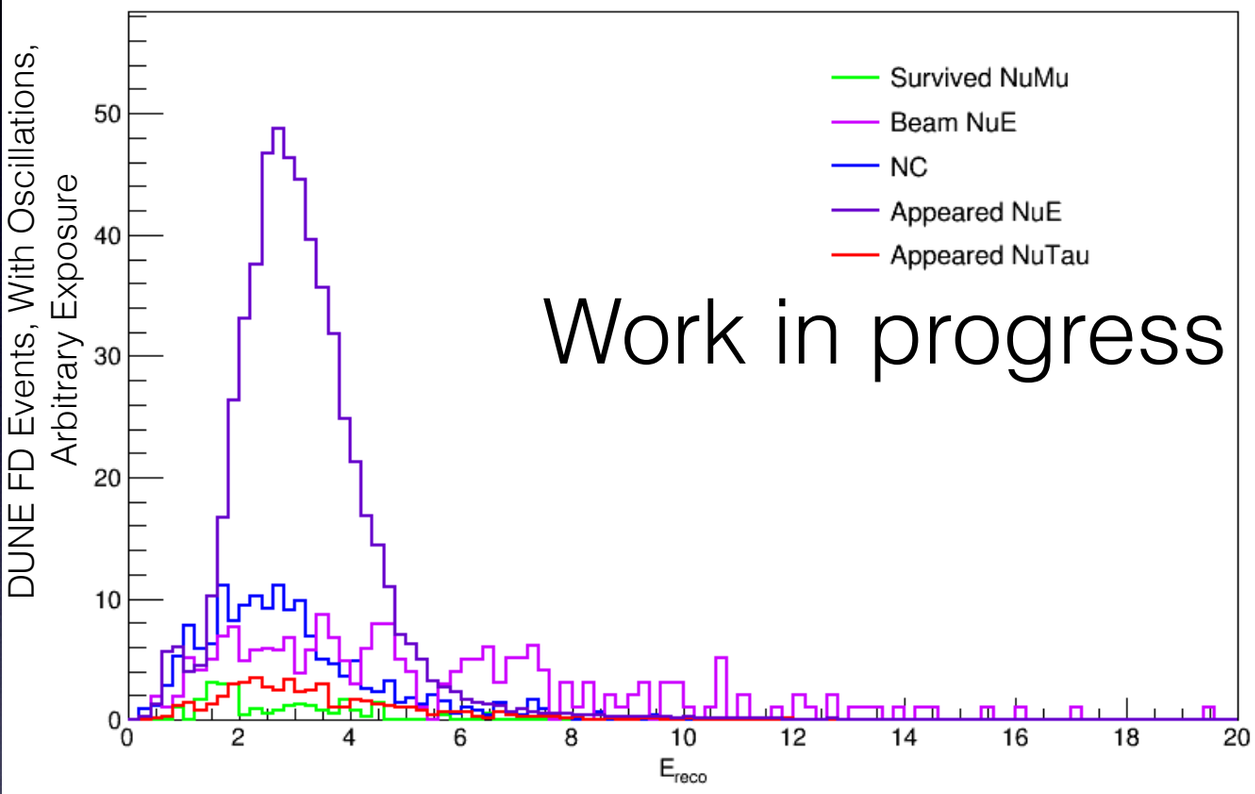
Alexander Radovic

Slide 2/3 from A. Radovic

NuE Selected Events, Reconstructed Energy Spectra

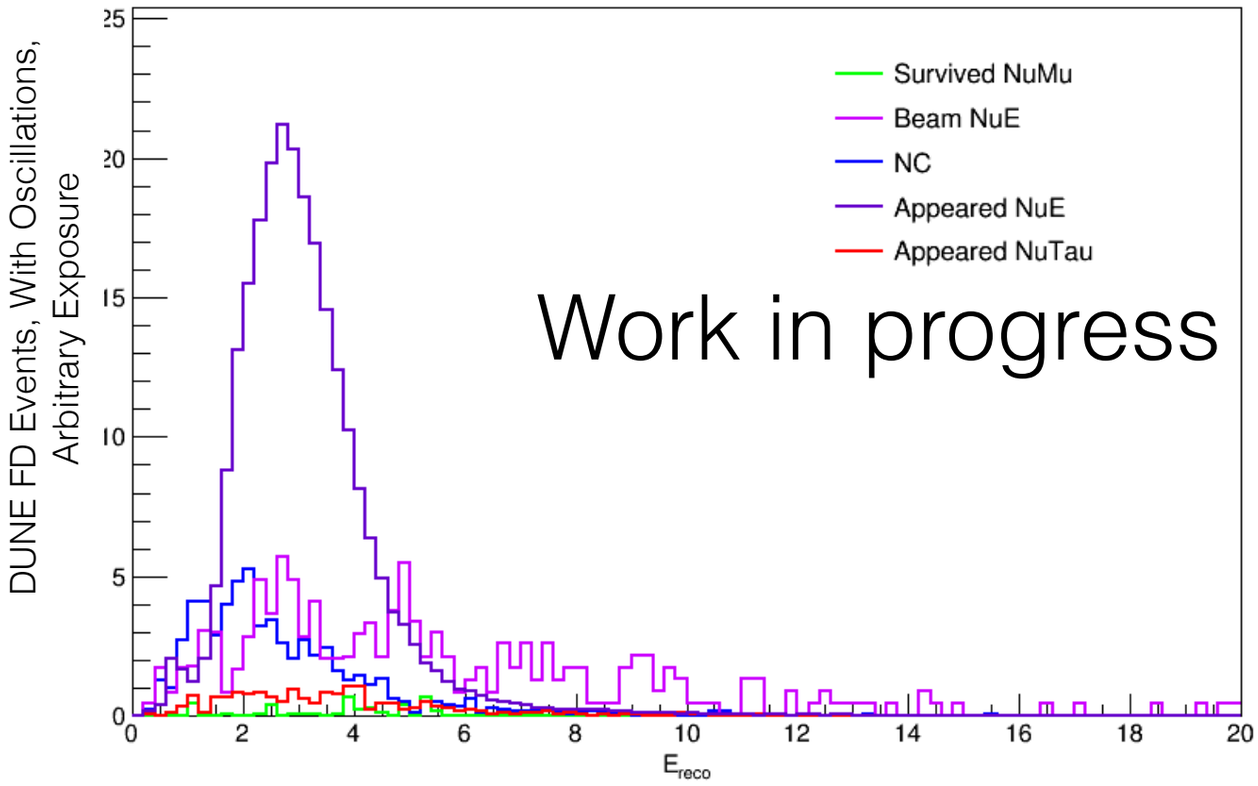
DL @ DUNE FD Analysis

Neutrino Beam



	Appeared NuE	NuMu	Beam NuE	NC	NuTau
Efficiency	**67.5**				
Rejection		99.8	52.1	**98.6**	85.8

Anti-Neutrino Beam



	Appeared NuE	NuMu	Beam NuE	NC	NuTau
Efficiency	**79.3**				
Rejection		99.9	48.2	**98.8**	87.6

Alexander Radovic

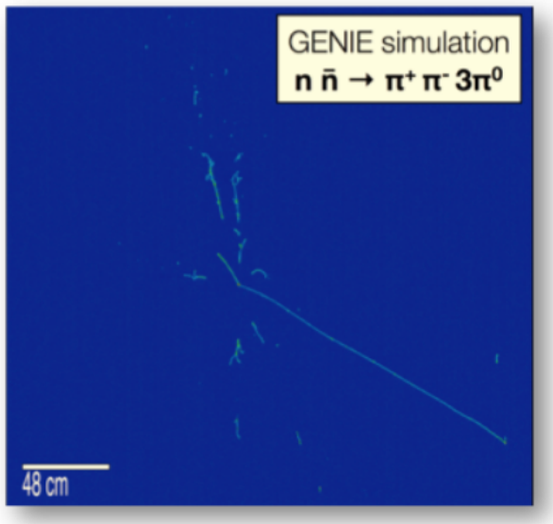
Slide 3/3 from A. Radovic

n-nbar Search in DUNE FD

Deep Learning application for rare event searches (and more) in DUNE

Group: Georgia Karargiorgi (Columbia U/U Manchester), Jeremy Hewes (formerly U Manchester), Yuyang Zhou (Columbia U)

CNN application in DUNE: originally developed as a DL-based analysis for a search for **rare neutron-antineutron oscillation events** (B-violating signature) in DUNE.



Simulated n-nbar event in DUNE; striking (“star event”) topology

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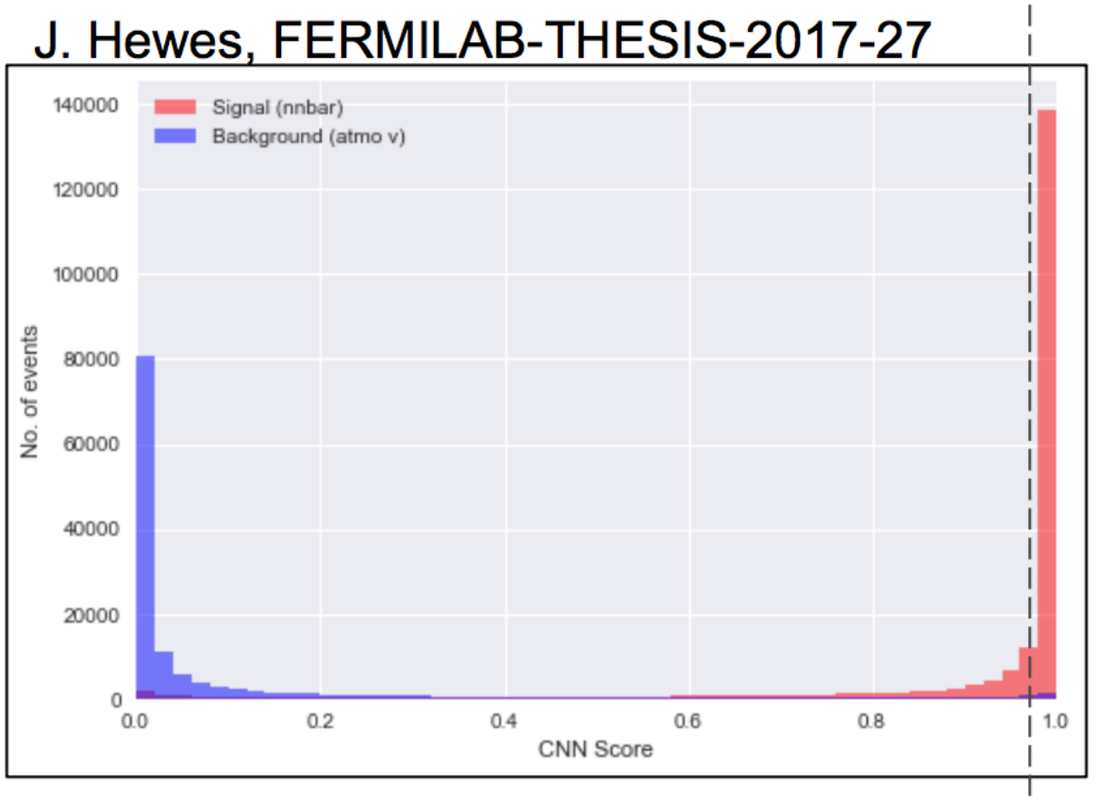
n-nbar Search in DUNE FD

CNN-based search for n-nbar in DUNE

vgg16 network

Trained to differentiate n-nbar events from atmospheric neutrino events* (training samples of 50k events), and tested (samples of 200k events).

*atmospheric neutrino events expected to be the dominant background in DUNE



An optimized cut on CNN score yields signal efficiency of 14% background mis-ID rate of 0.003%

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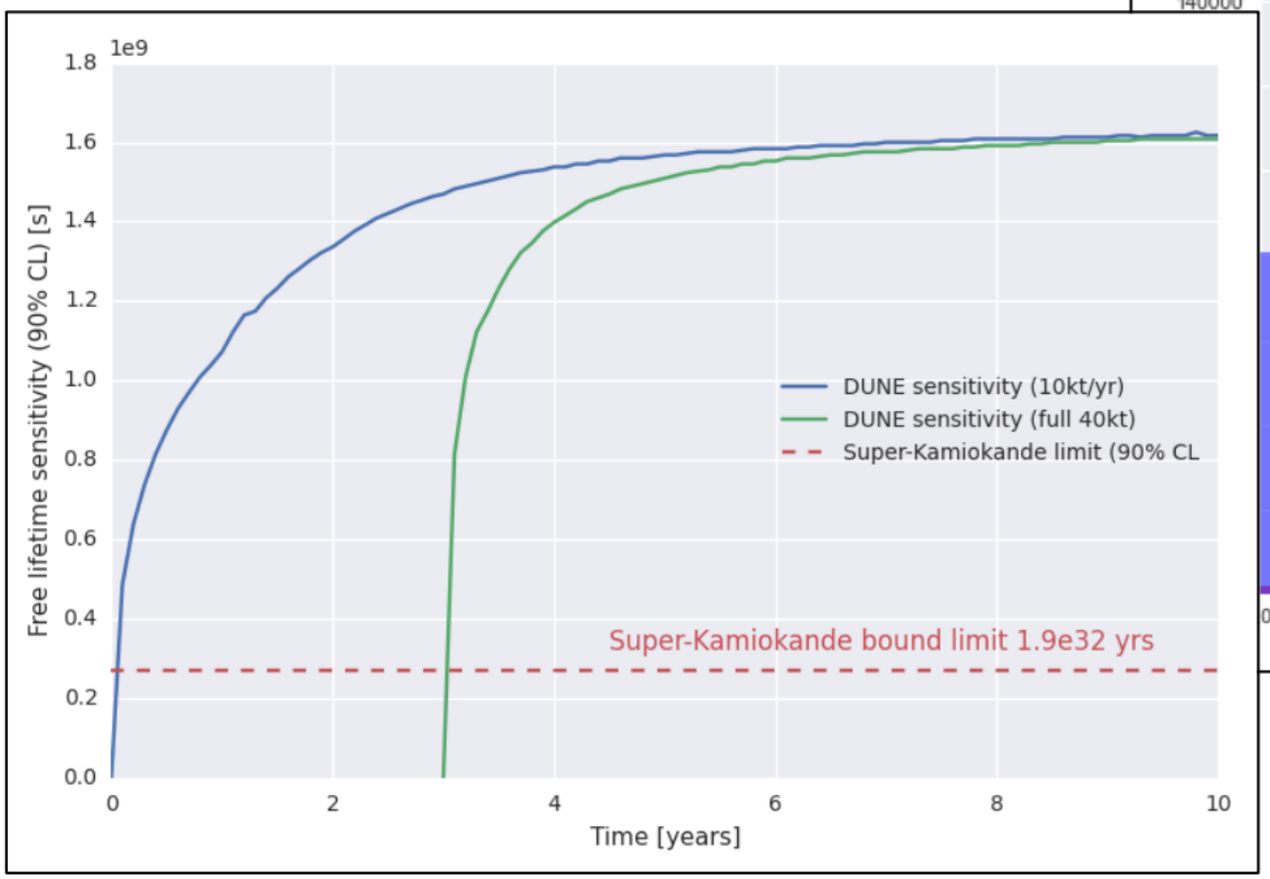
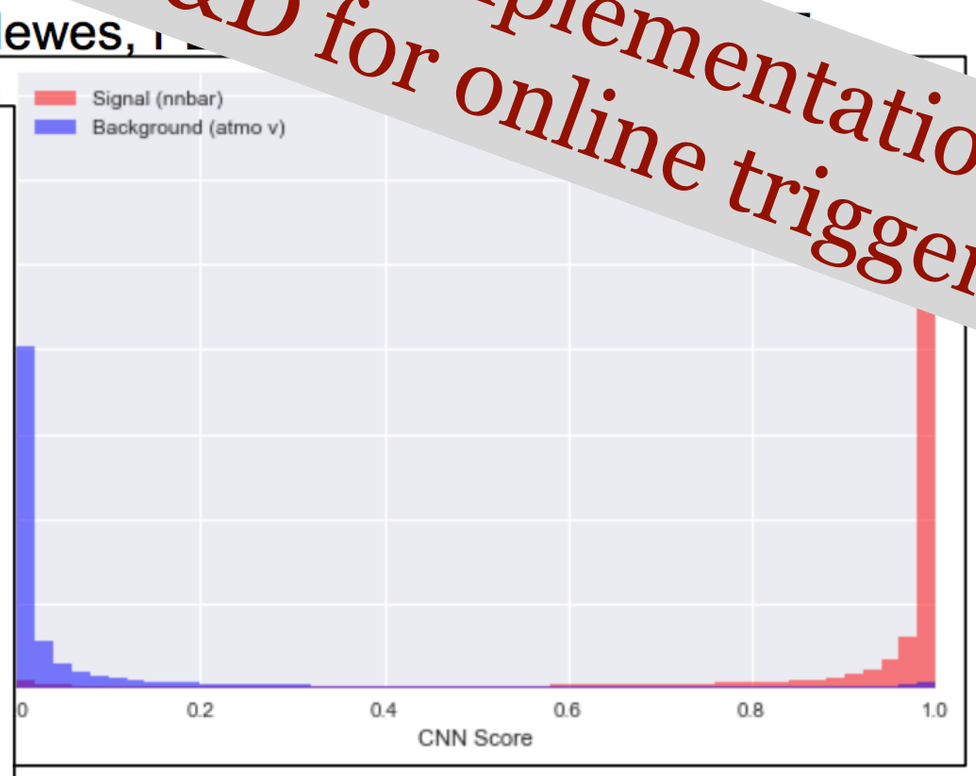
n-nbar Search in DUNE FD

CNN-based search for n-nbar in

J. Hewes,





FPGA Implementation
R&D for online trigger

Resulting projected sensitivity of DUNE for given efficiency and mis-ID rate, as a function of run time.
Sensitivity shows 5x improvement over current Super-K limit.

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Distributed CNN Training at PNNL

E. Church, J. Daily, C. Siegel, M. Schram, J. Strube, K. Wierman

MaTEx

Pacific Northwest NATIONAL LABORATORY

Proudly Operated by Battelle Since 1965

- Full event image: **3600 wires x 3600 time bins x 3 planes x 4 Bytes**
  - MicroBooNE simulated single particle events
  - **~150 MB / event**
- Even a moderately small network only leaves room for a mini-batch size of 1-2 events on a modern GPU, for full event fidelity
  - This is smaller than required given the latent space of the CNN → slow development. Distributed scaling of compute resources will help significantly.
  - Scaling allows increase in network depth too (if required)
- For deep learning, one wants large training samples.
  - Training may become quickly I/O bound and hence prohibitively slow
  - Even a dedicated ”large-mem” node cannot fit more than a few thousand samples into memory, at best.

→ We are studying PNNL’s MaTEx for distributed training

Easier to ”drop in” than say the uber solution, and locally supported!

→ And using in-memory loss-less image compression

Slide 1/2 from E. Church

DL Software @PNNL
Framework Development

Current status (preliminary)

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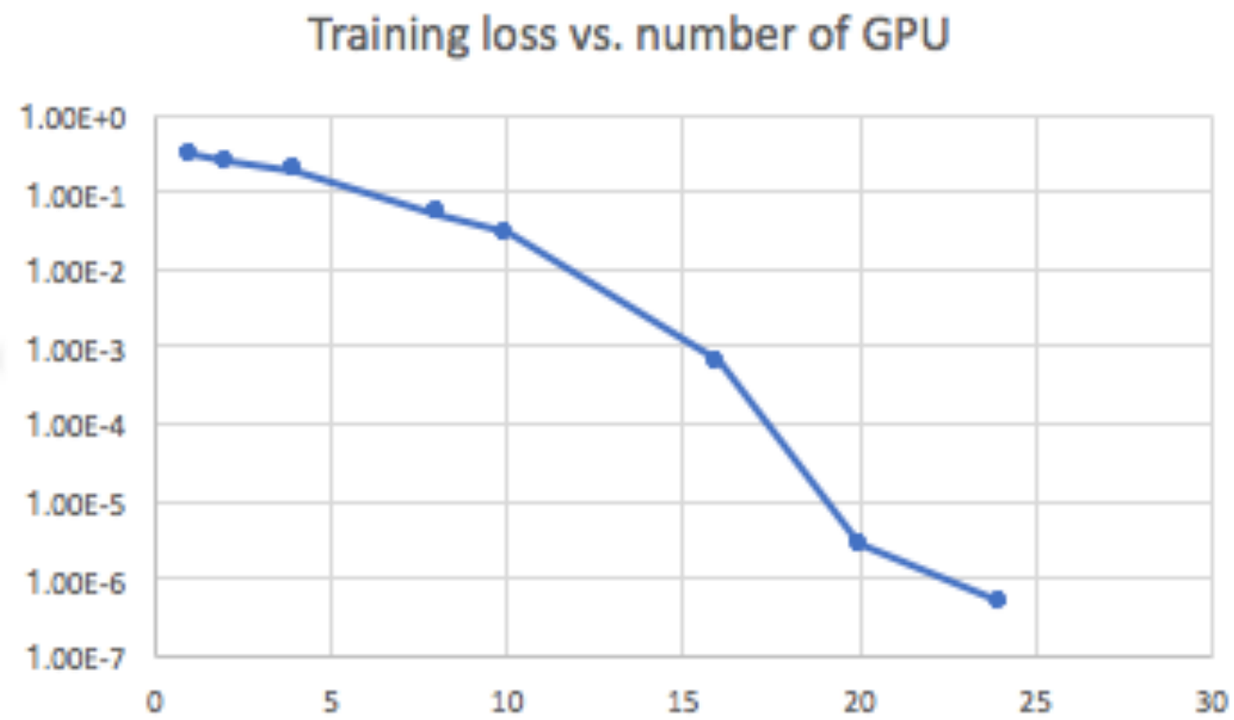
Training time: mini-batch size = 2, 10000 steps per GPU … 10 epochs

Identical networks, loss functions, optimizers and input data

→ MaTEx does not currently introduce noticeable overhead at this scale



For the same wall time, training improves with number of GPUs

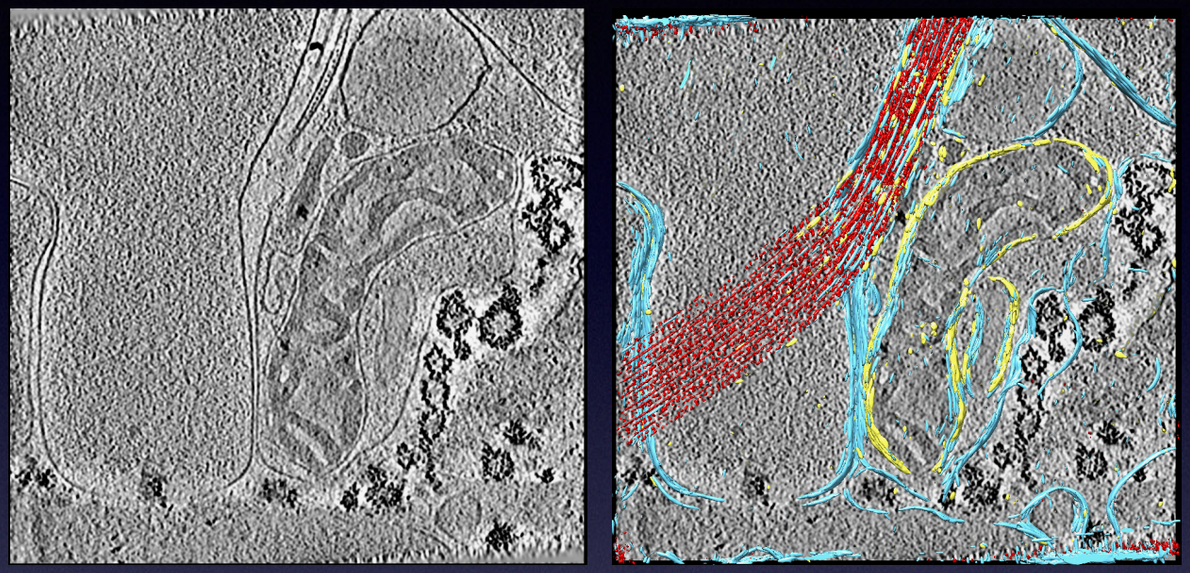
→ Studies ongoing, significant updates planned for CHEP2018

Slide 2/2 from E. Church

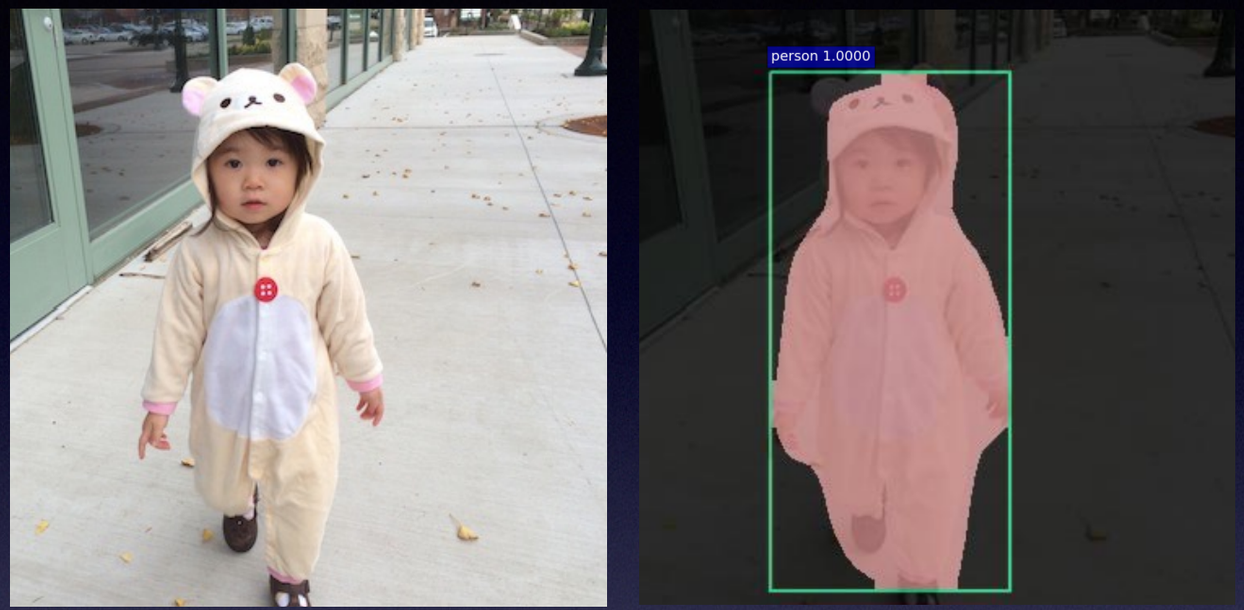
DL Software @PNNL
Framework Development

More Exciting Stuffs … come chat w/ me :)

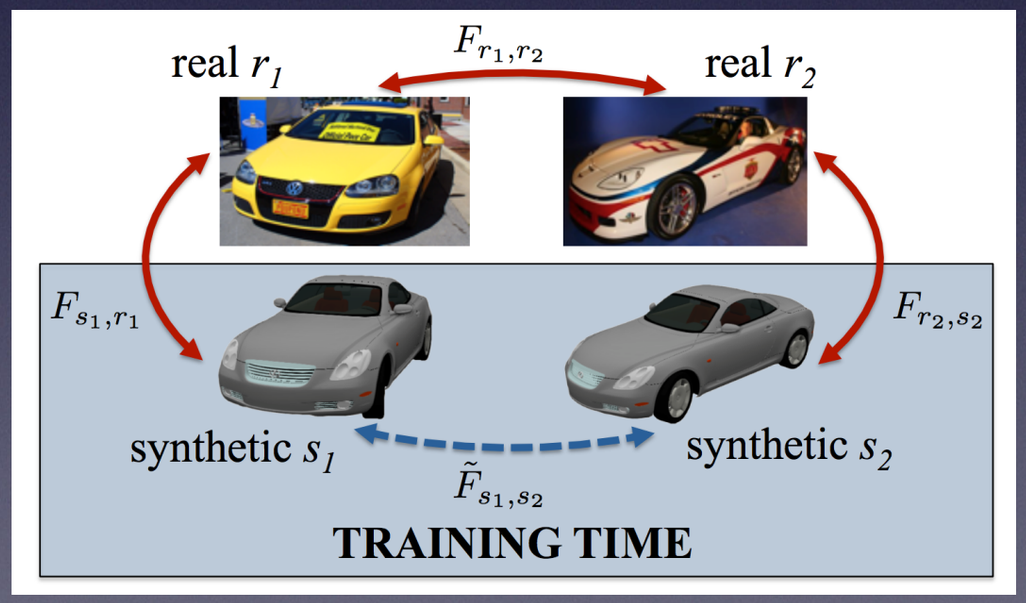
3D voxel labeling of Cryo-EM image (below: mitochondrion detection)



Multi-network Training Techniques R&D



Detection + Clustering (Mask R-CNN) of ATLAS jet images (w/ SLAC ATLAS group)



Pixel-Flow network for 3D track reco (via cross-plane pixel correlation)