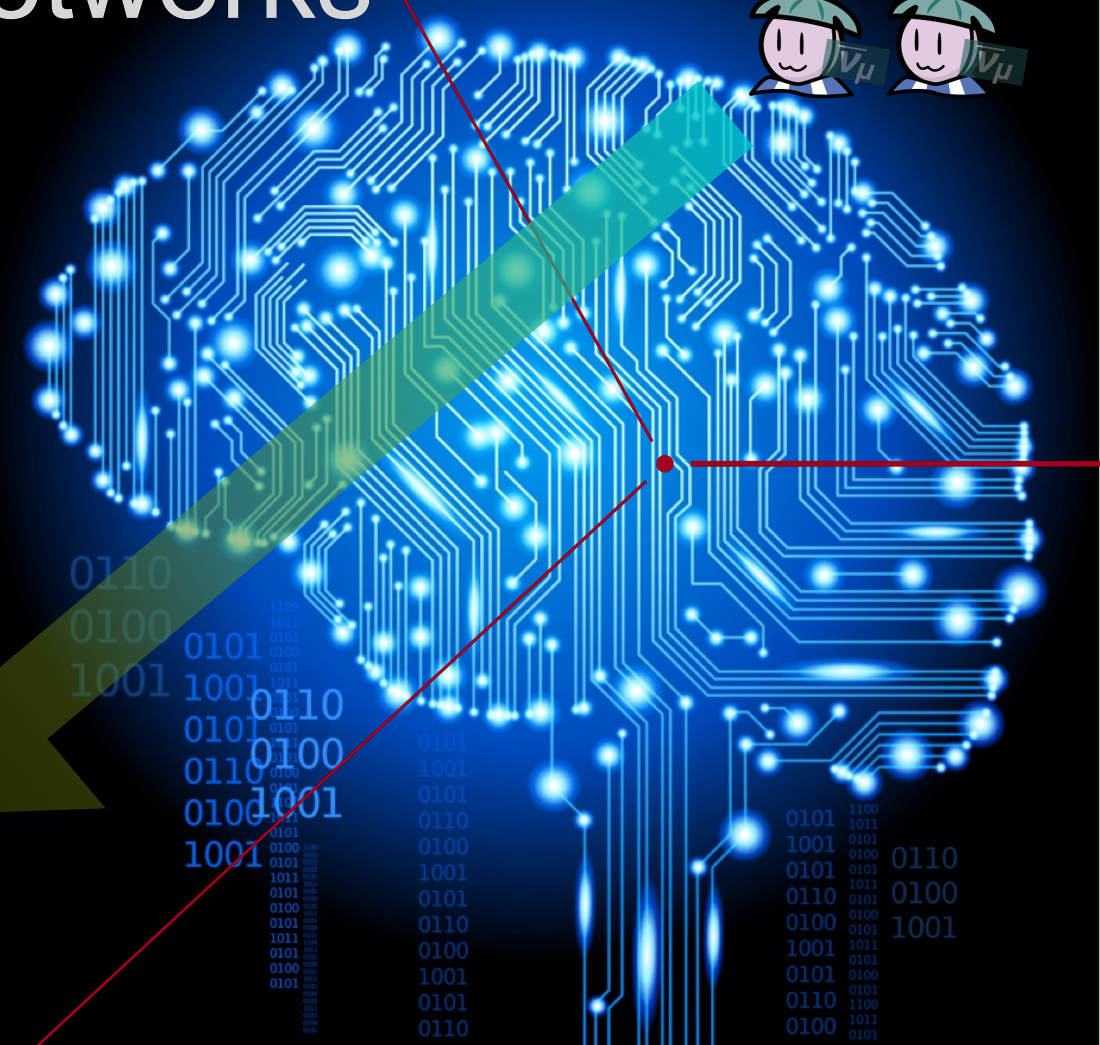
Deep Neural Networks for 3D Data Reconstruction

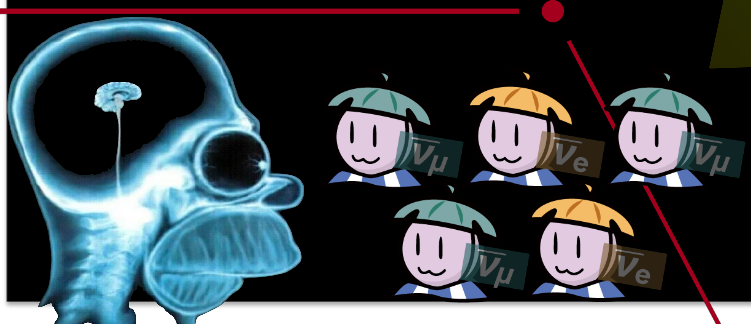
Kazuhiro Terao

SLAC National Accelerator Lab.

CPAD @ Brown University

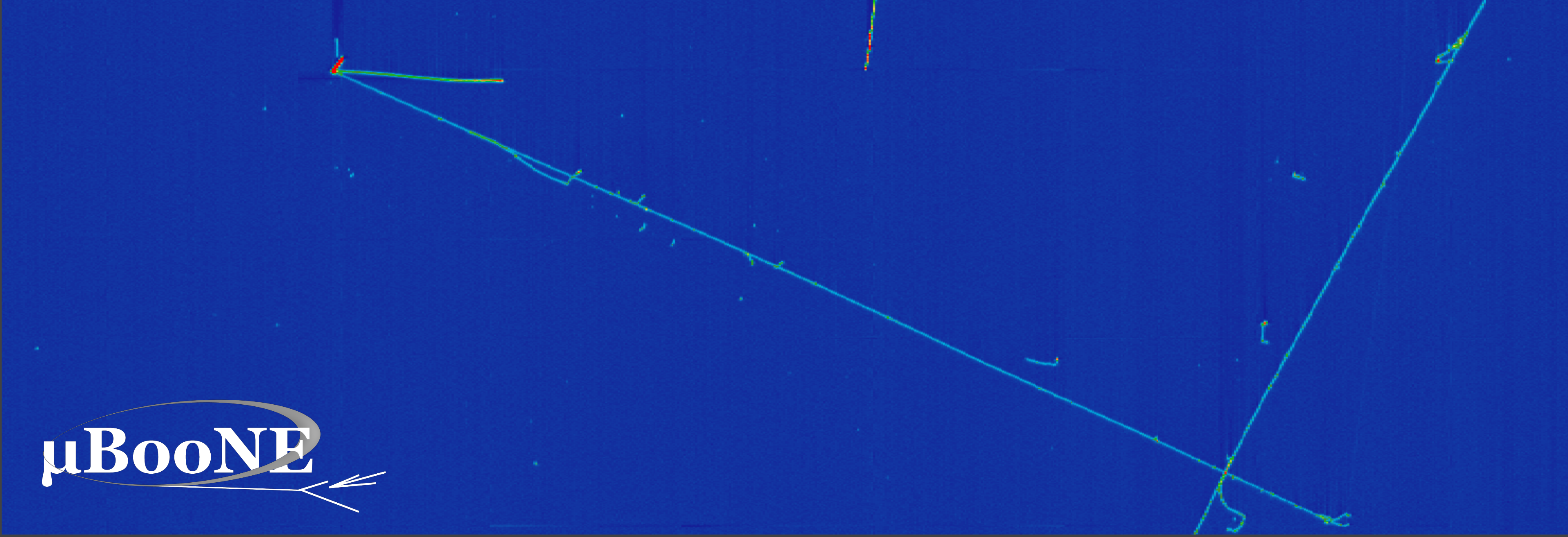
December 9th, 2018





U.S. DEPARTMENT OF ENERGY Office of Science

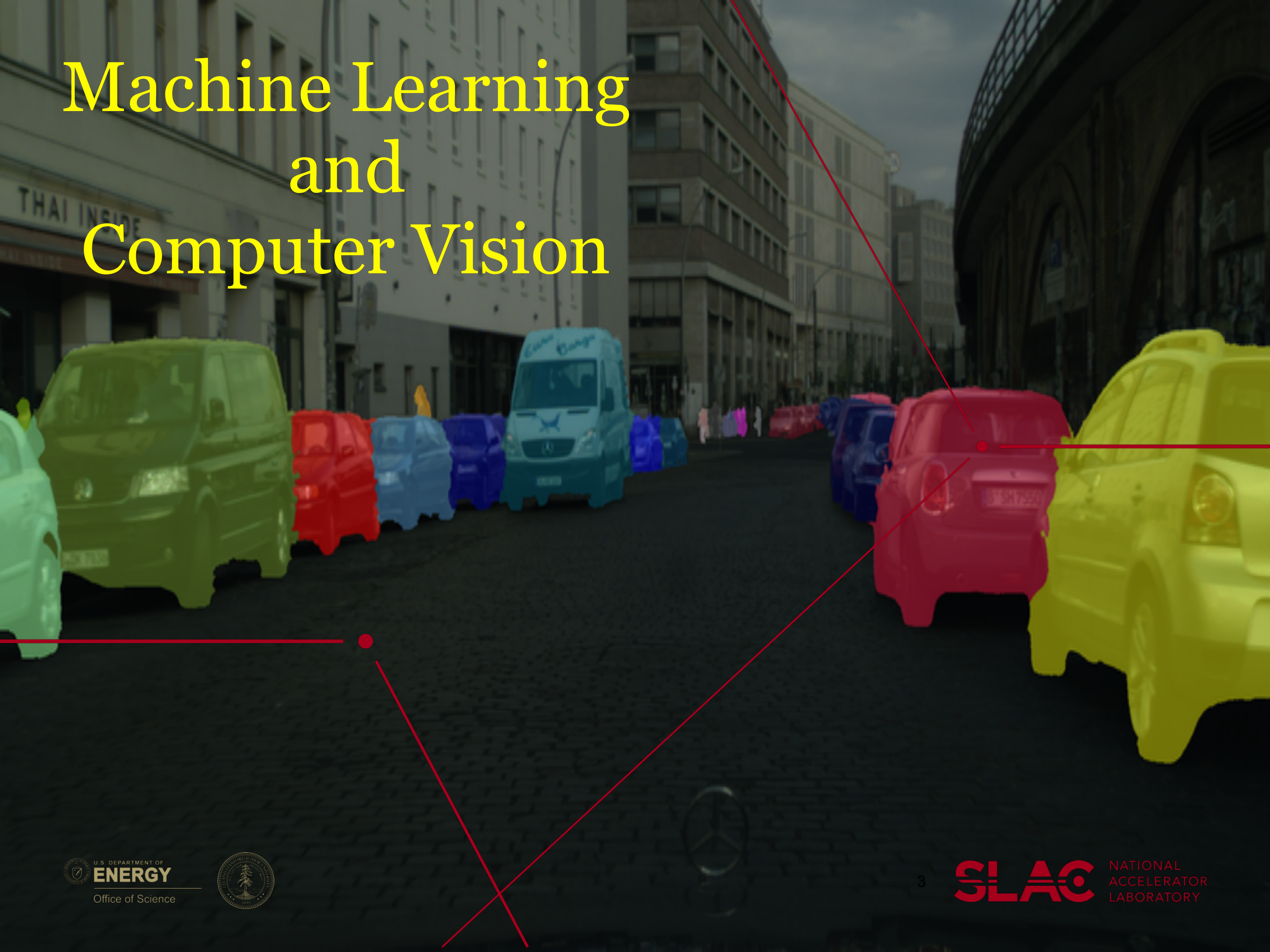
SLAC NATIONAL ACCELERATOR LABORATORY

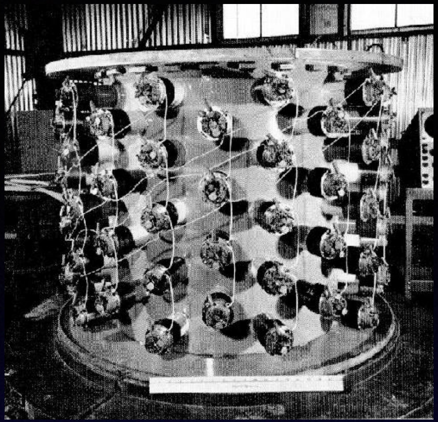
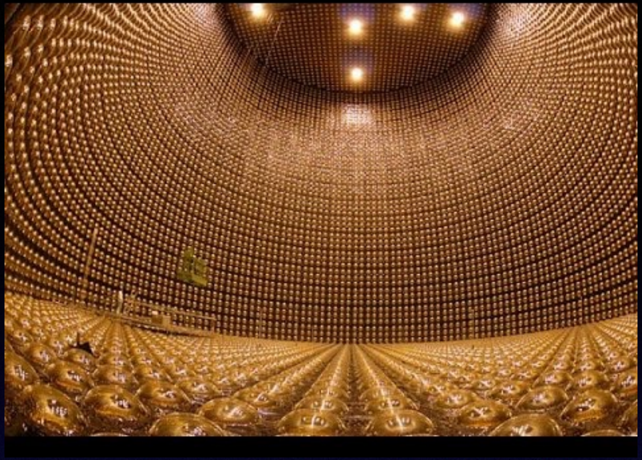
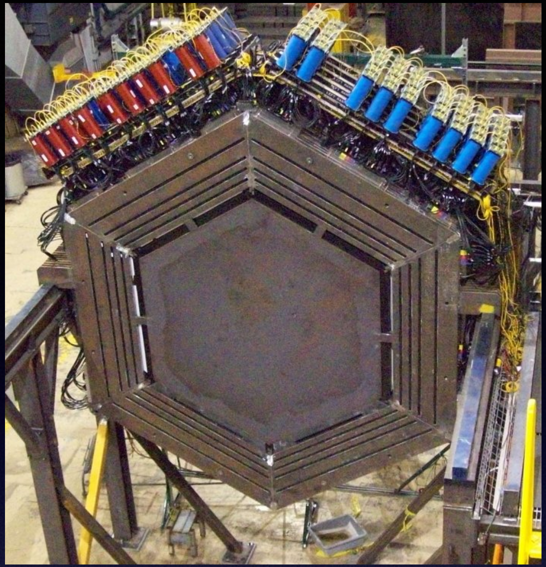
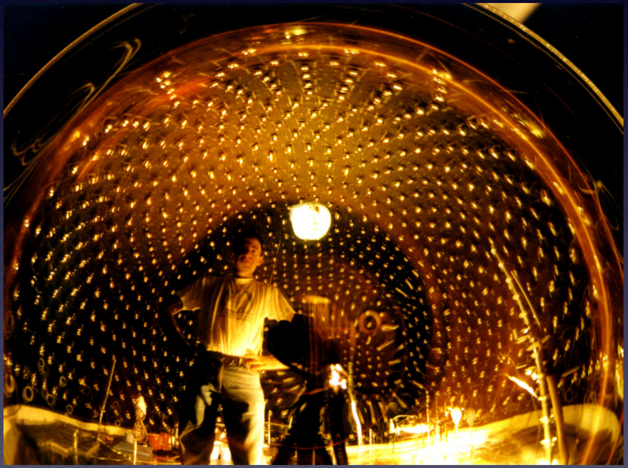
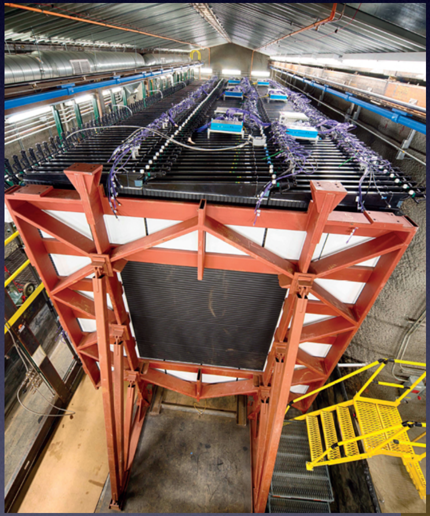
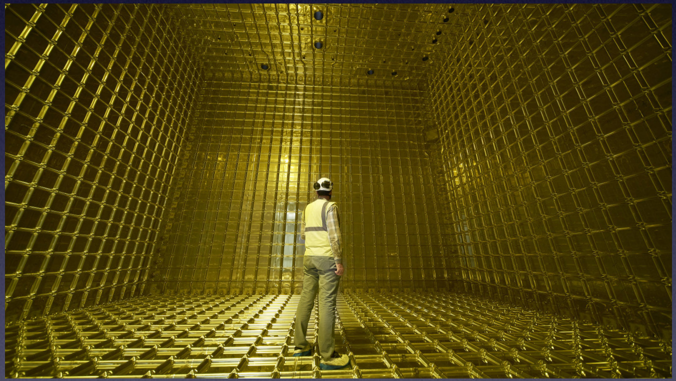
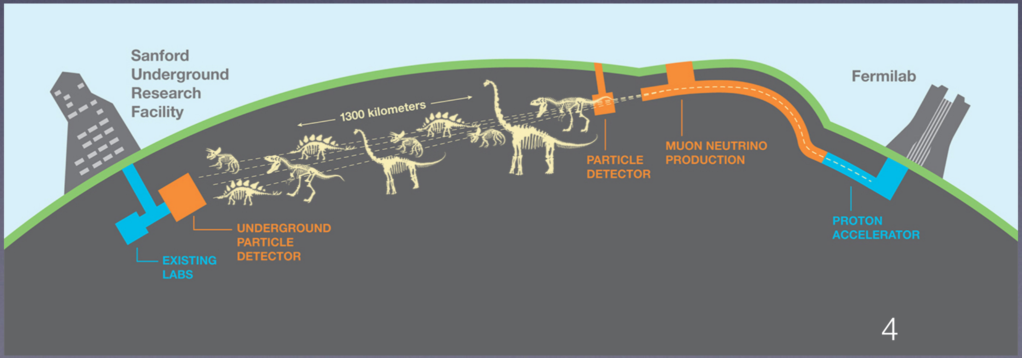
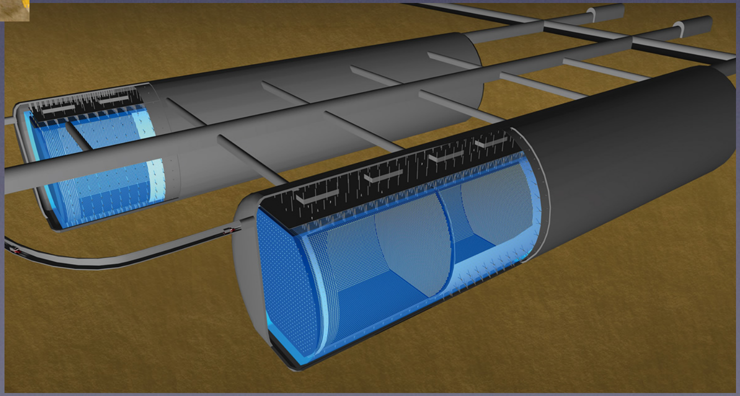


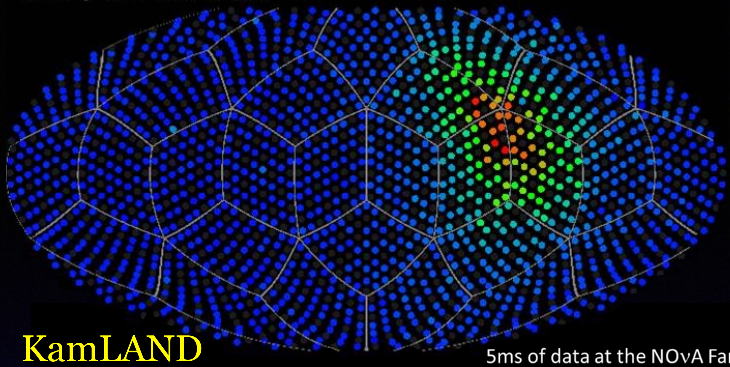
Outline

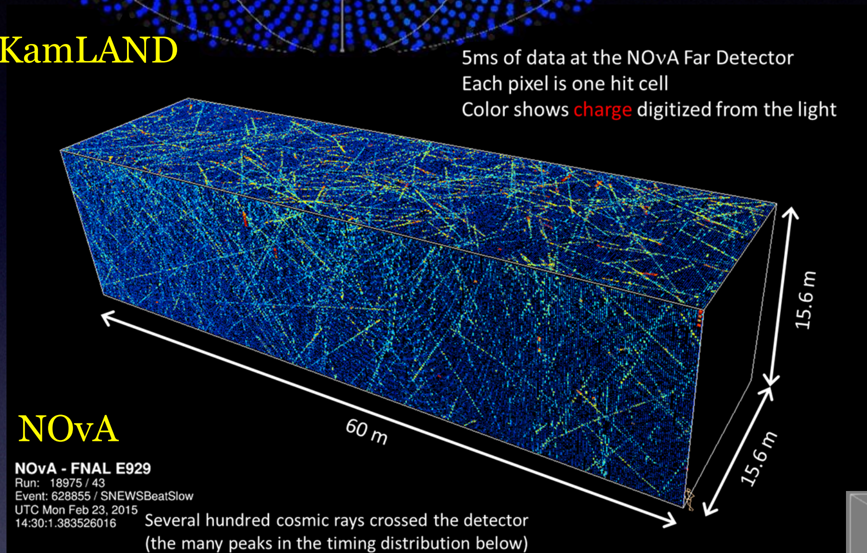
1. Machine Learning & Computer Vision
2. Applications in LArTPCs
3. Wrap-up

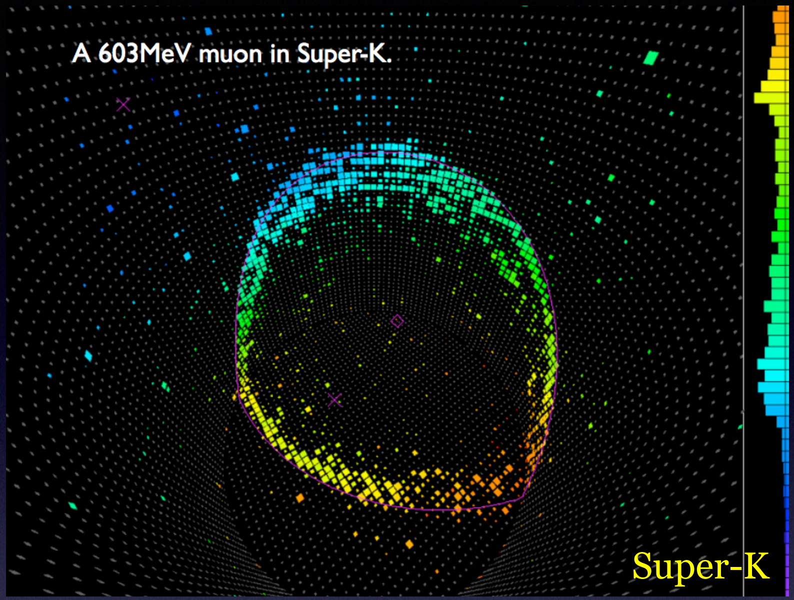
Machine Learning
and
Computer Vision

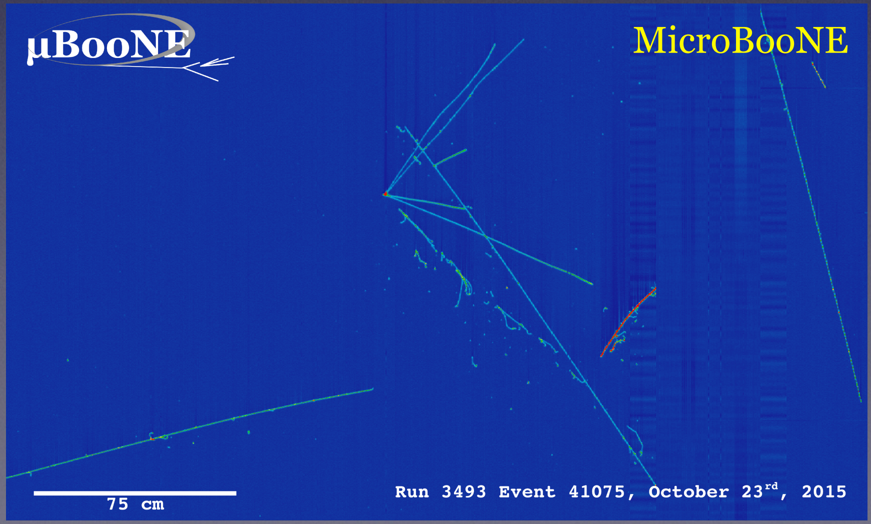


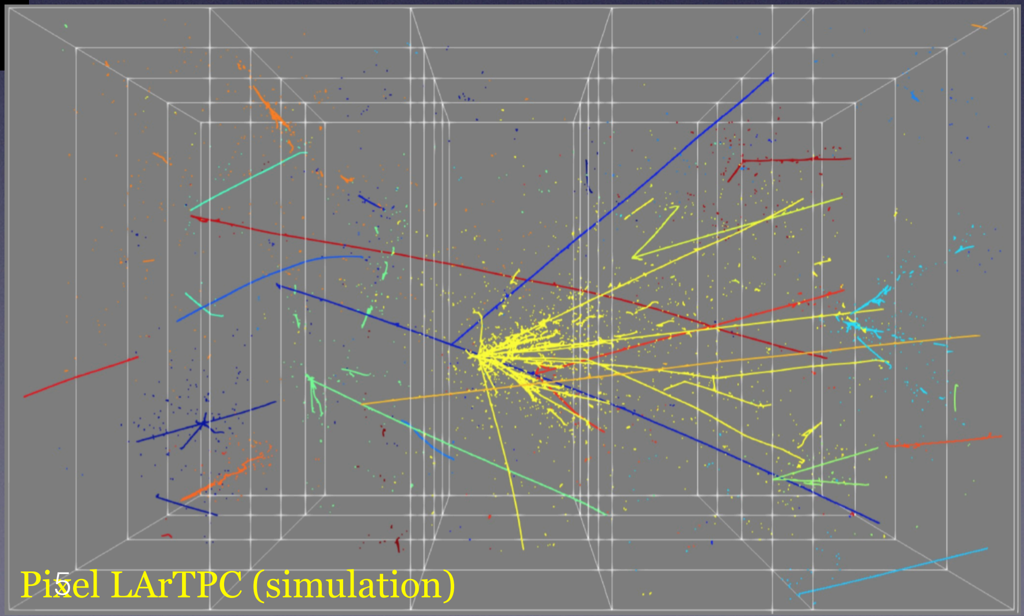







Sanford
Underground
Research
Facility
1300 kilometers
Fermilab
PARTICLE
DETECTOR
MUON NEUTRINO
PRODUCTION
UNDERGROUND
PARTICLE
DETECTOR
EXISTING
LABS
PROTON
ACCELERATOR


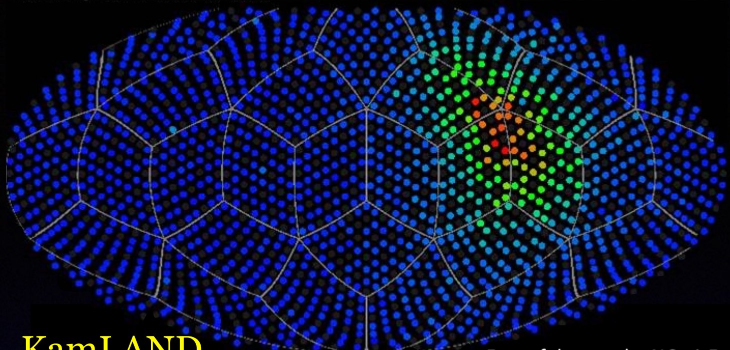

KamLAND

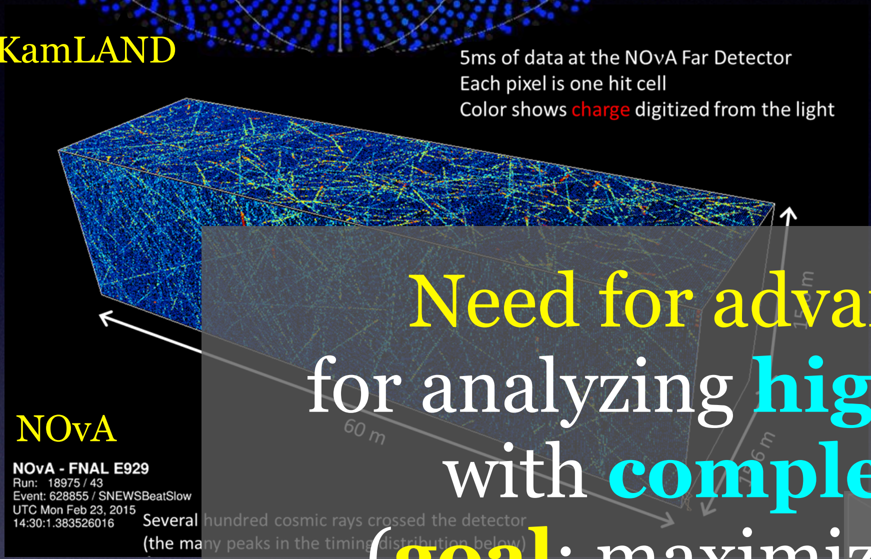

5ms of data at the NOvA Far Detector
Each pixel is one hit cell
Color shows charge digitized from the light
15.6 m
60 m
15.6 m
NOvA
NOvA - FNAL E929
Run: 18975 / 43
Event: 628855 / SNEWSBeatSlow
UTC Mon Feb 23, 2015
14:30:1.383526016
Several hundred cosmic rays crossed the detector
(the many peaks in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

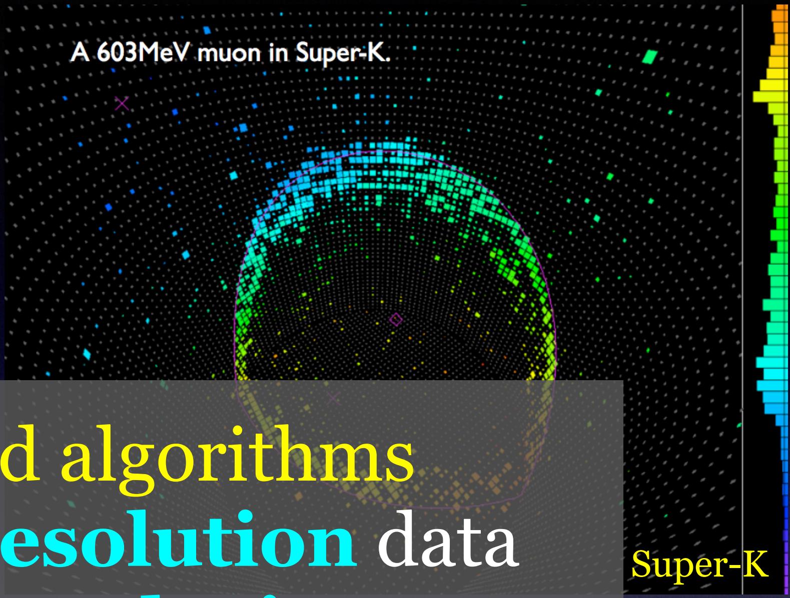

A 603MeV muon in Super-K.
Super-K

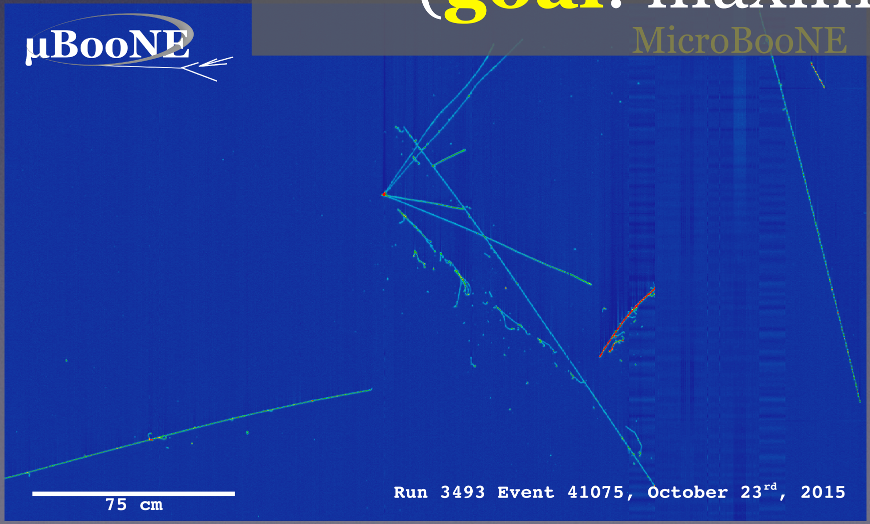

μBooNE
MicroBooNE
75 cm
Run 3493 Event 41075, October 23rd, 2015

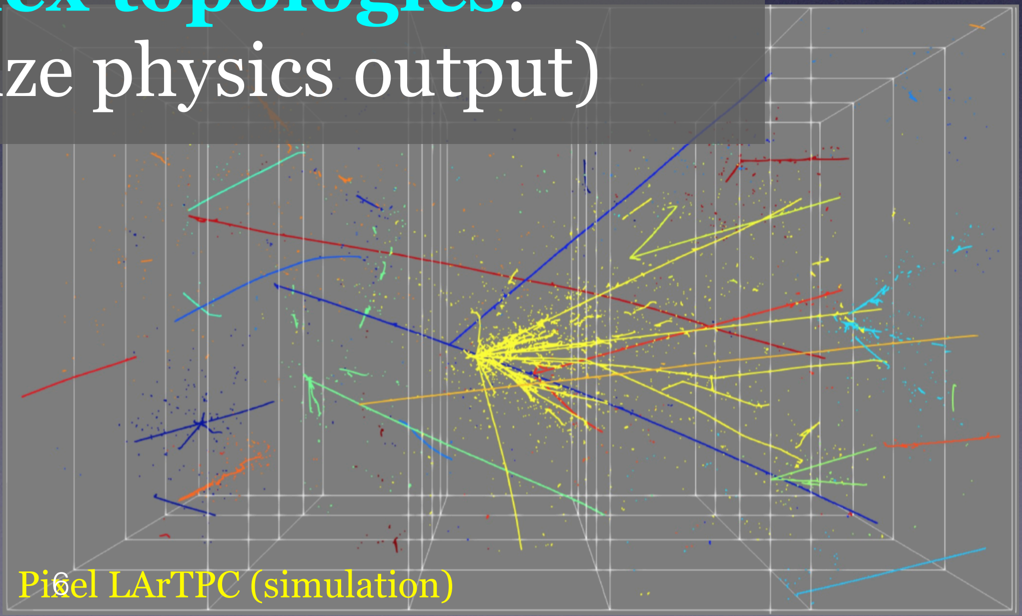

Pixel LArTPC (simulation)





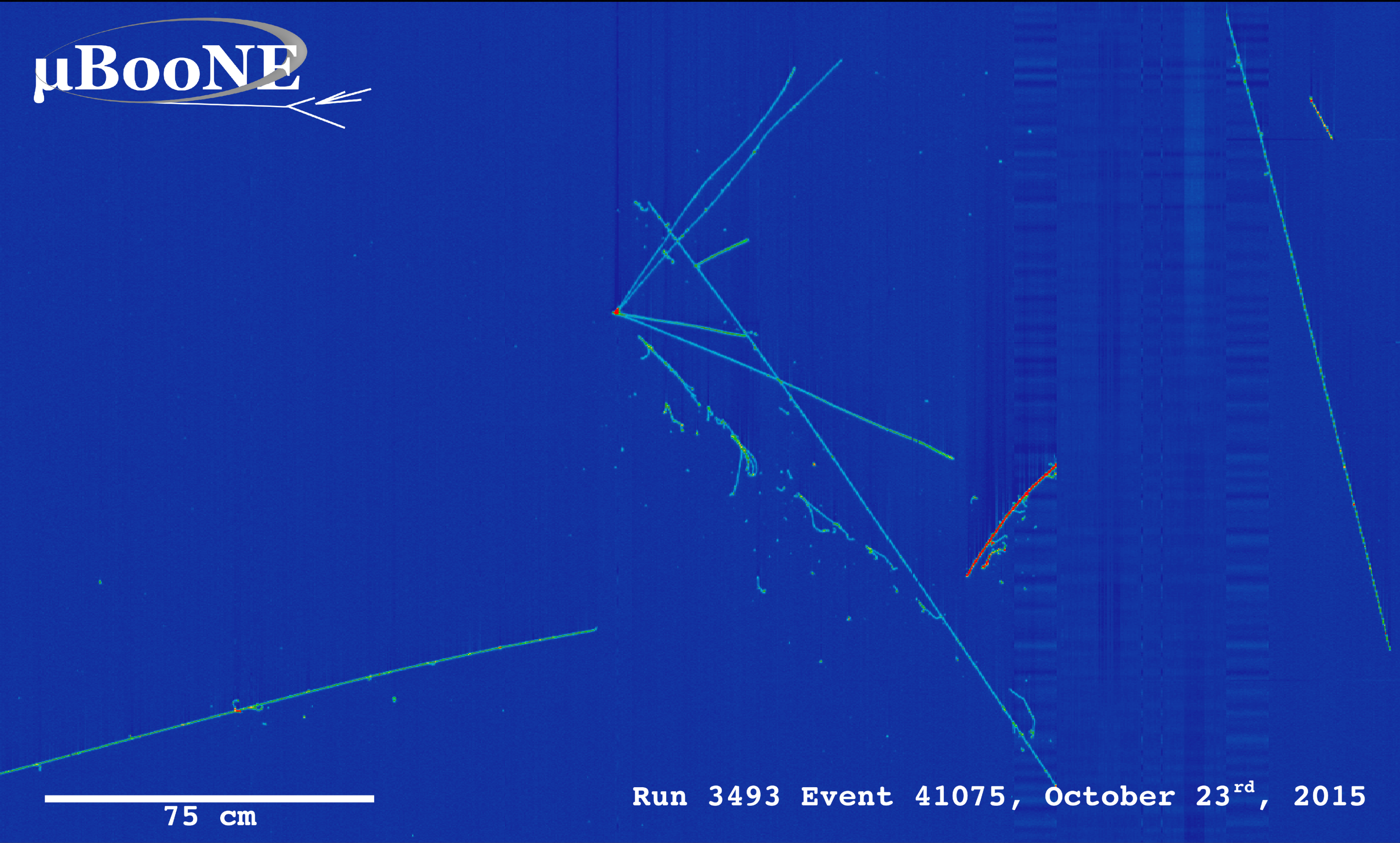




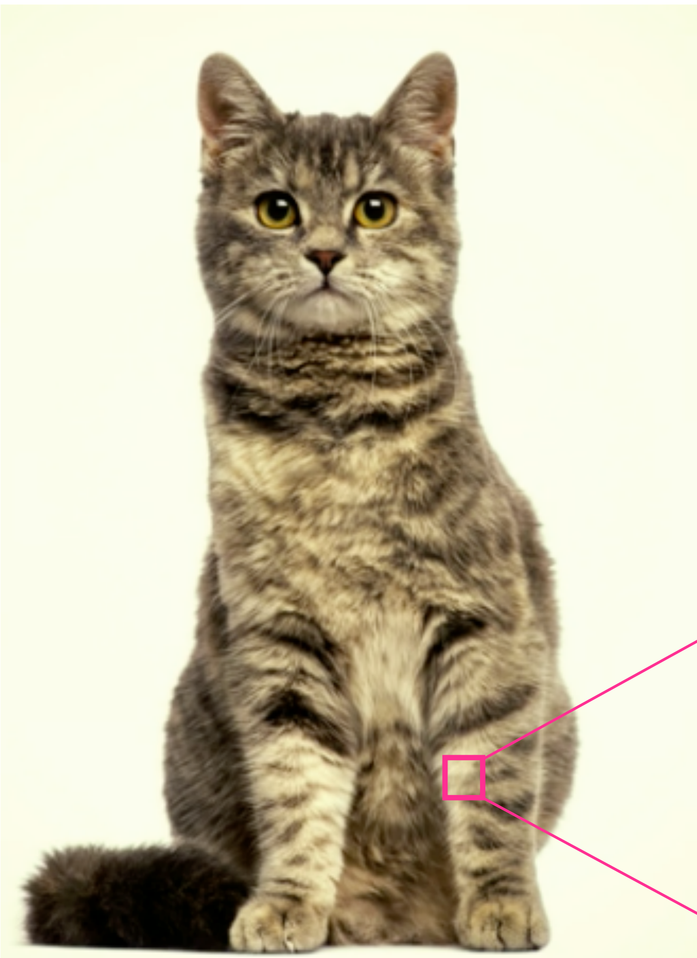


Need for advanced algorithms
for analyzing **high resolution** data
with **complex topologies**.
(**goal**: maximize physics output)

LArTPC Data Reconstruction



Machine Learning
Challenges in Computer Vision



How to write an algorithm to identify a cat?

... very hard task ...

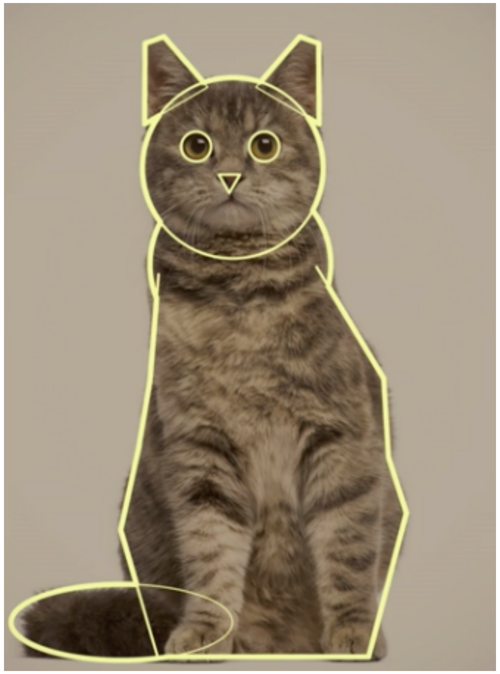
16	08	67	15	83	09	40	19	40	11	31	35	60	43	66	14	48	08	60	13
37	52	77	23	22	74	09	90	36	12	29	39	78	31	71	73	22	50	92	35
35	42	48	72	85	27	79	08	41	31	09	53	05	40	04	31	91	56	26	85
68	36	43	54	21	33	81	30	72	06	79	34	39	59	70	03	24	91	03	40
79	60	10	25	54	71	24	50	87	88	47	68	31	42	09	77	40	07	26	73
18	55	38	73	50	47	22	21	88	78	02	95	19	59	60	93	73	40	67	99
54	07	67	38	55	51	26	81	43	66	89	69	92	94	50	08	94	63	33	66
71	95	38	46	63	07	66	68	41	49	34	33	66	76	68	97	53	18	72	21
38	64	86	66	06	68	13	01	89	00	80	70	21	27	14	90	80	95	31	68
04	28	93	88	02	97	92	41	21	54	24	33	97	10	33	47	24	08	12	76
75	37	62	42	88	15	02	57	20	43	09	71	54	73	29	57	23	81	99	41
29	28	57	02	84	20	31	97	41	73	19	29	17	28	99	16	23	19	53	53
95	05	34	86	46	18	95	65	62	28	62	95	35	84	18	22	81	45	10	12
69	18	34	46	77	60	28	62	16	61	72	19	88	14	43	23	64	43	35	00
76	15	68	89	13	74	48	90	12	59	02	31	14	34	77	47	04	69	99	66
70	01	05	77	88	20	63	57	41	50	68	04	30	62	09	67	61	86	31	43
36	76	07	95	11	52	04	91	58	59	30	09	46	95	31	71	43	26	48	19
81	01	86	71	64	31	49	99	60	63	97	61	43	86	36	53	82	31	00	52
63	78	18	10	79	39	77	28	39	17	76	81	93	35	02	78	10	30	35	75
71	73	71	85	86	24	93	75	35	70	30	16	07	35	08	61	82	85	95	22

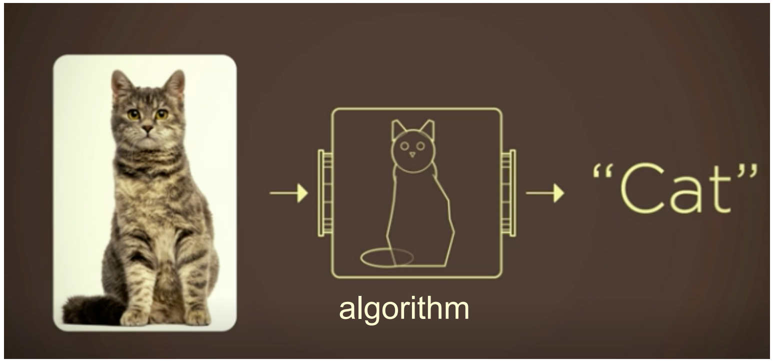
Image credits: TED talk by Fei-Fei Li

SLAC

Development Workflow for non-ML algorithms

1. Write an algorithm based on basic (physics) principles





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

Image credits: TED talk by Fei-Fei Li

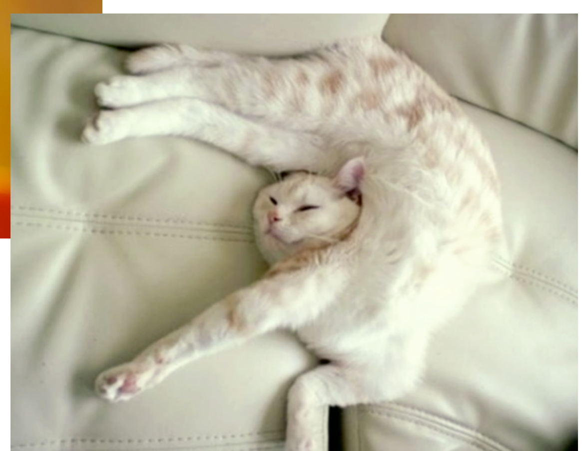
Machine Learning
Challenges in Computer Vision

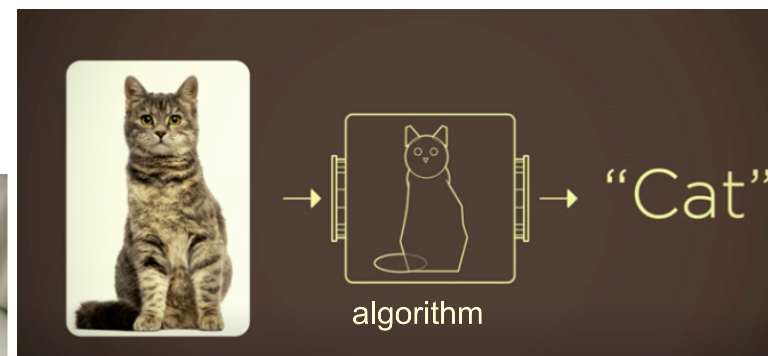
Development Workflow for non-ML algorithms

1. Write an algorithm based on basic (physics) principles
2. Run on simulation/data samples
3. Observe failures, 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 muon)

Stretching cat
(Nuclear FSI)





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

Image credits: TED talk by Fei-Fei Li

Development Workflow for non-ML algorithms

1. Write an algorithm based on basic (physics) principles
2. Run on simulation/data samples
3. Observe failures, 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.

Machine Learning

- **Learn patterns from data**
  - automation of steps 2, 3, and 4
- **Chain algorithms & optimize**
  - step 5 addressed by design
- **"Deep Learning"**
  - Revolutions in computer vision using deep **neural networks**

Natural
Neural
Network

Machine Learning
CNNs for Cat Image Analysis

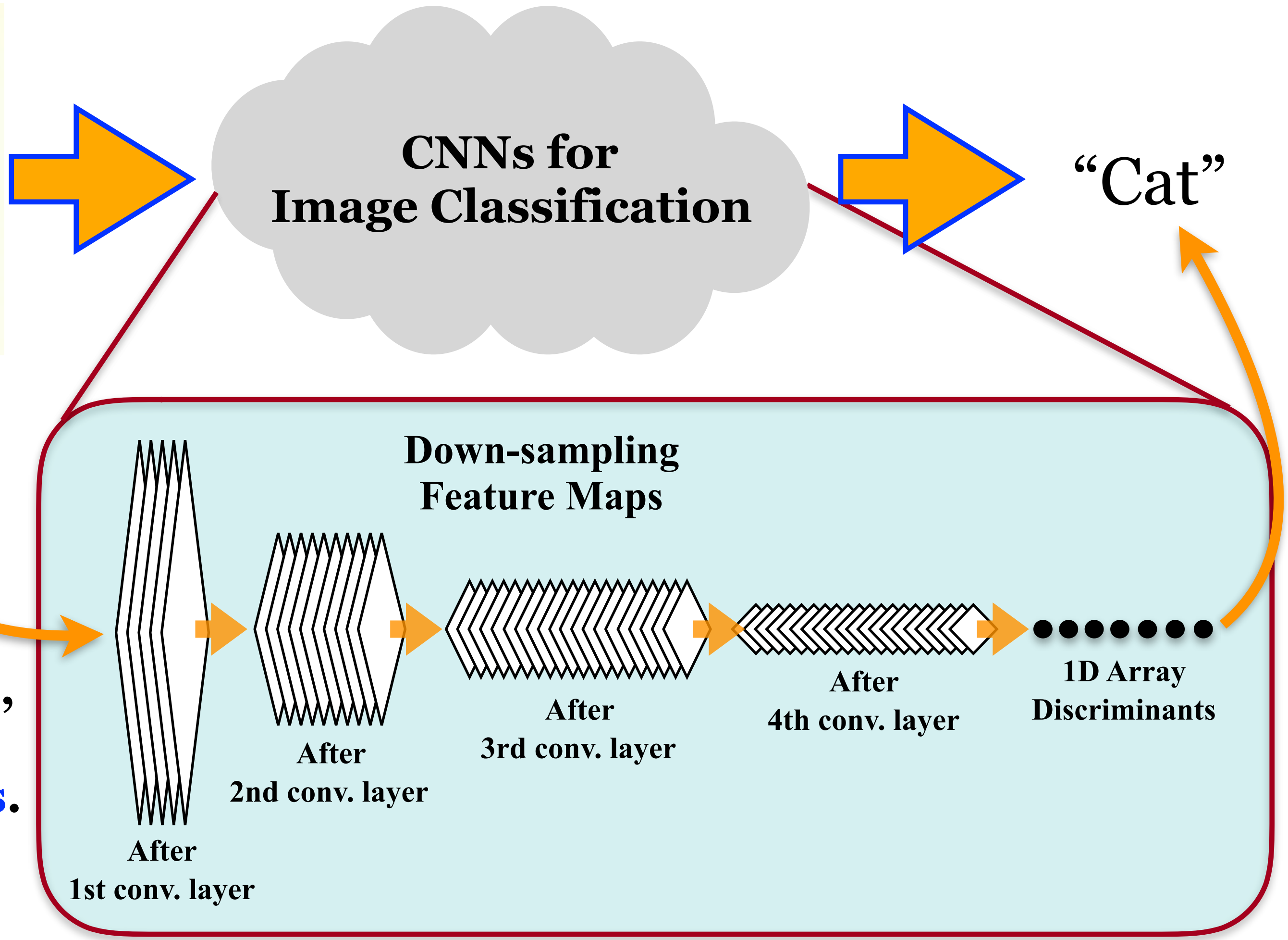
Convolutional Neural Networks (CNNs)

CNNs for Image Classification

“Cat”

CNNs for Cat Image Analysis

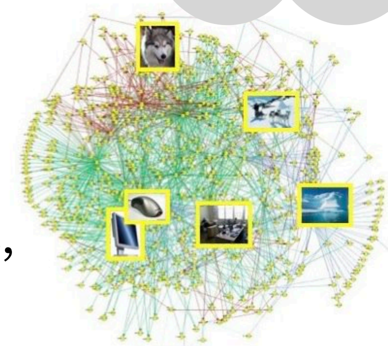
Convolutional Neural Networks (CNNs)



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

Convolutional Neural Networks (CNNs)

→ **CNNs for Image Classification** → "Cat"



2012 IMAGENET

Public image classification competition w/ 1.2M images, 1000 object categories.

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

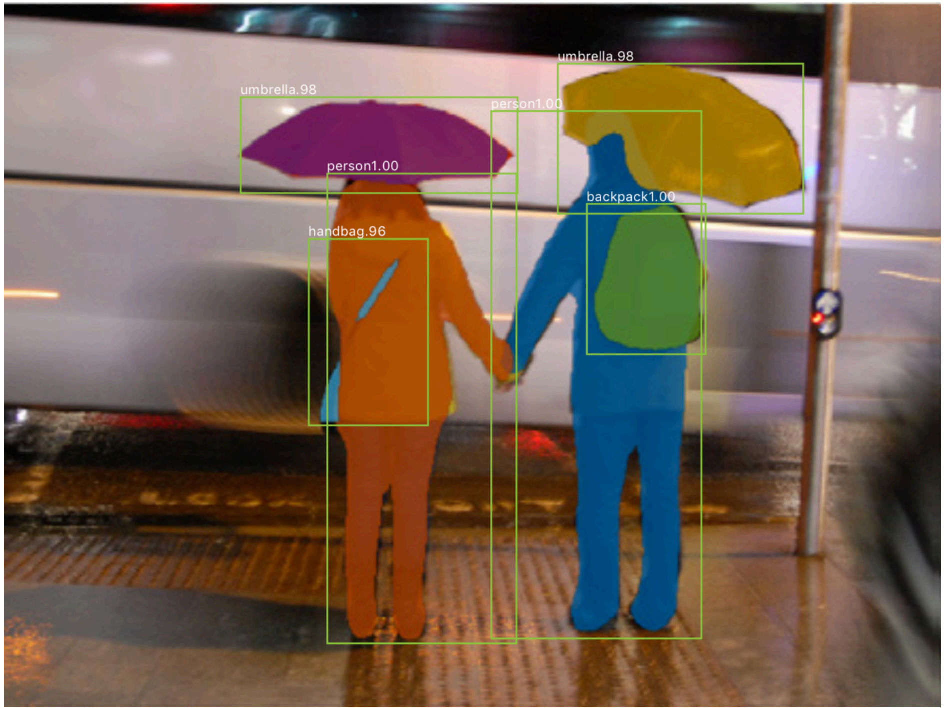
Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

> 30,000 citations

Abstract

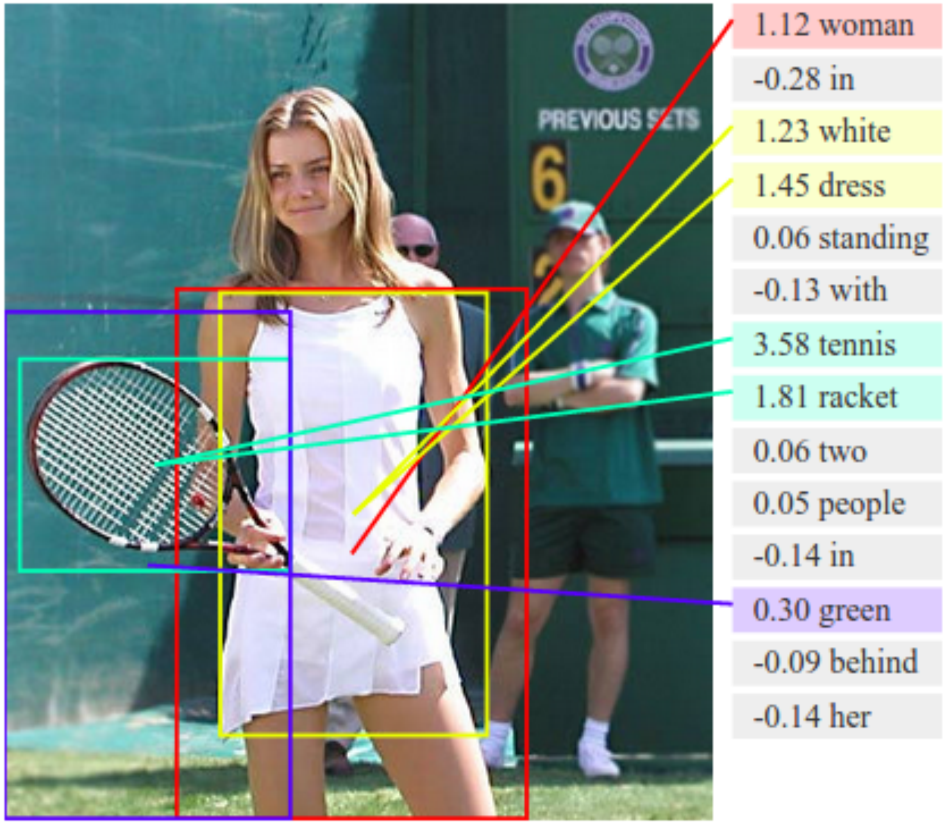
We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Detection of Image Contexts



Interpretation of Contexts' Correlation

"girl in pink dress is jumping in air."



Machine Learning for ~~Computer Vision~~ LArTPCs

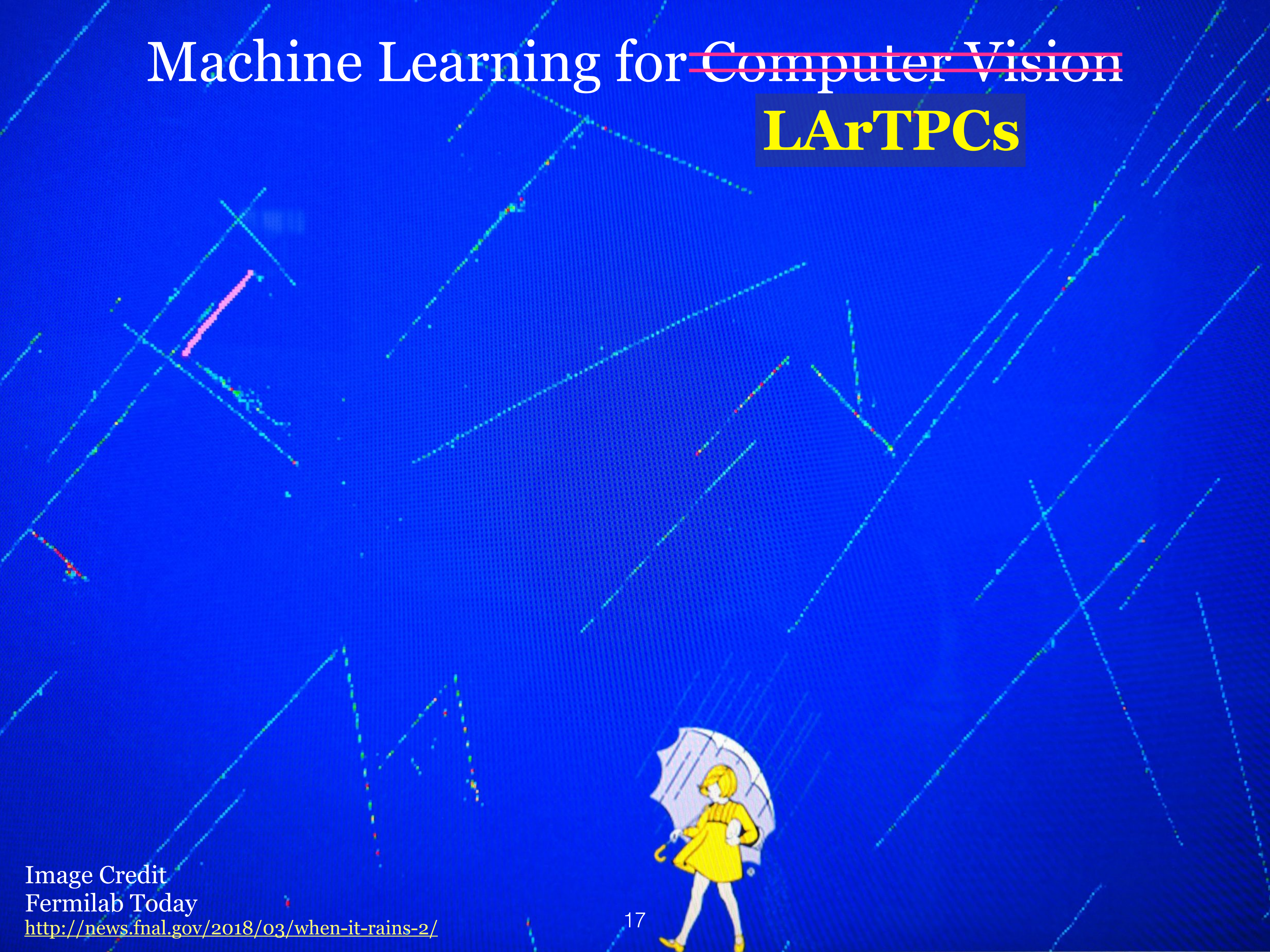
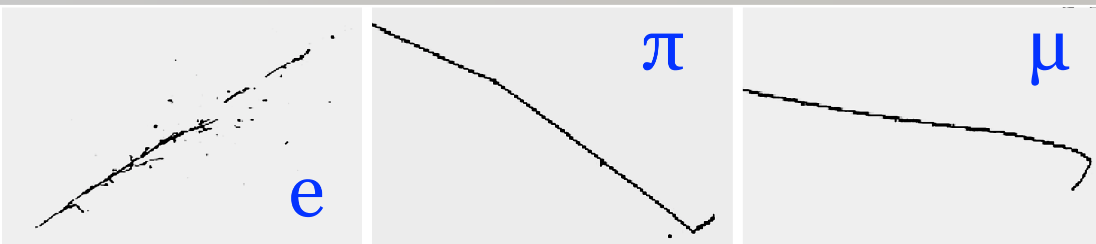


Image Credit
Fermilab Today
http://news.fnal.gov/2018/03/when-it-rains-2/

Early Demonstrations
Machine Learning for LArTPC Image Analysis



ML Technique @ MicroBooNE LArTPC Detector

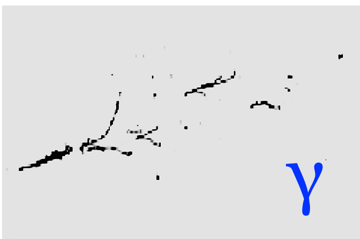
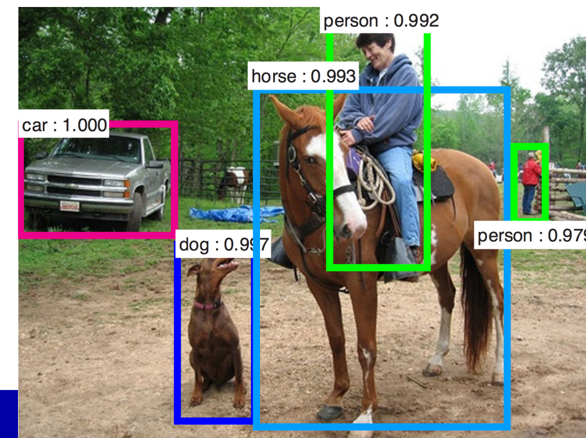
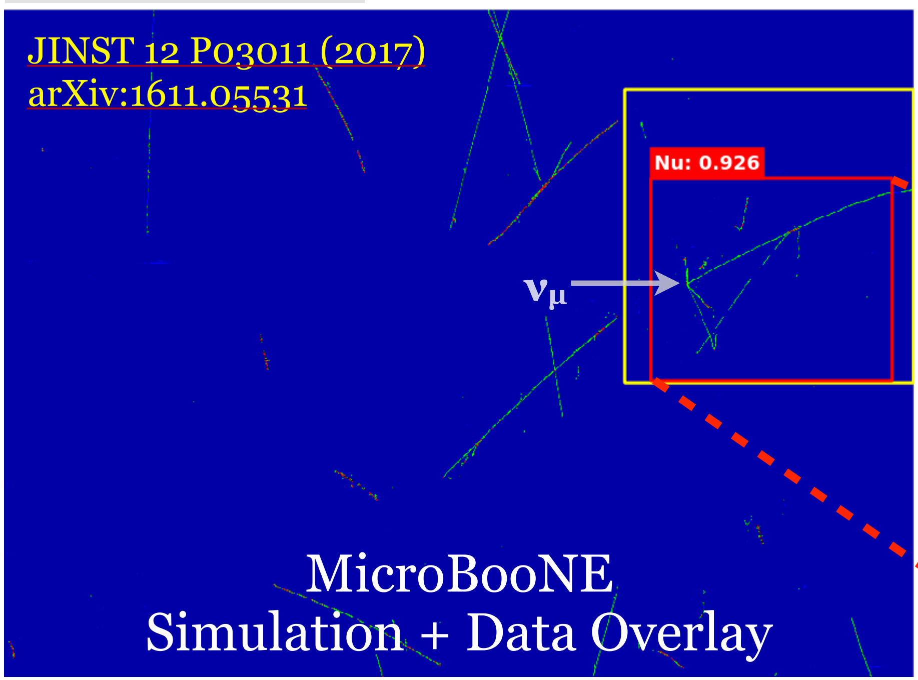


Image Classification

- Classify a whole image into object categories
- particle type identification from an image
- signal/background selection



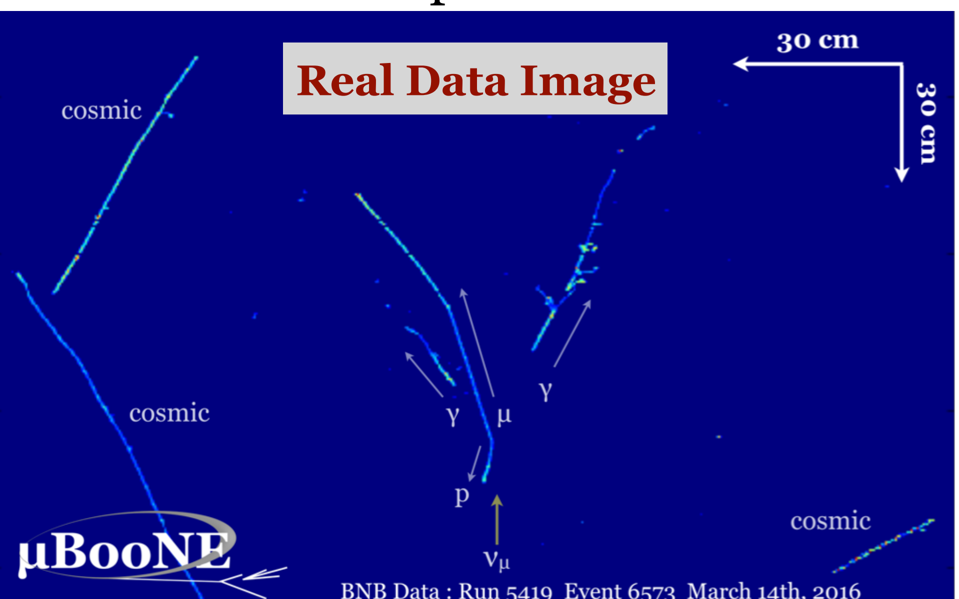


Early Demonstrations
Machine Learning for LArTPC Image Analysis

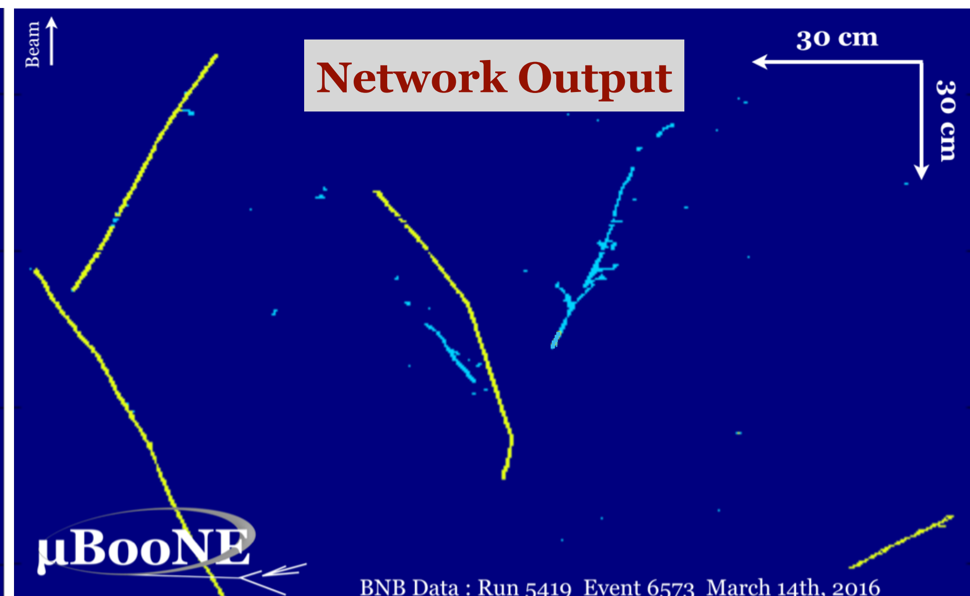
Semantic Segmentation

- 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

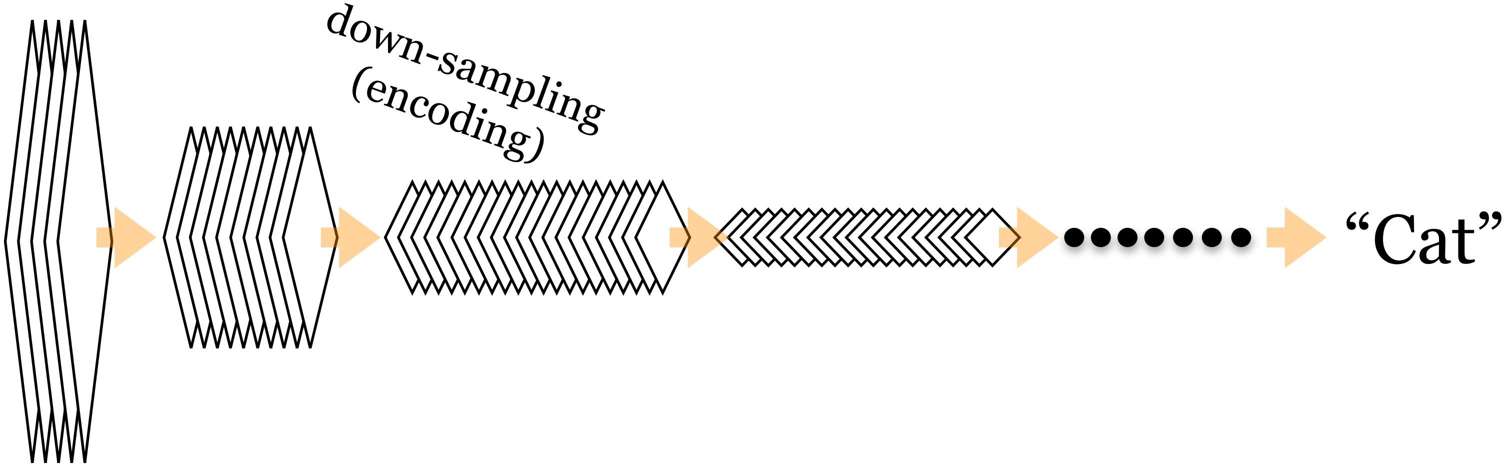


Network Input

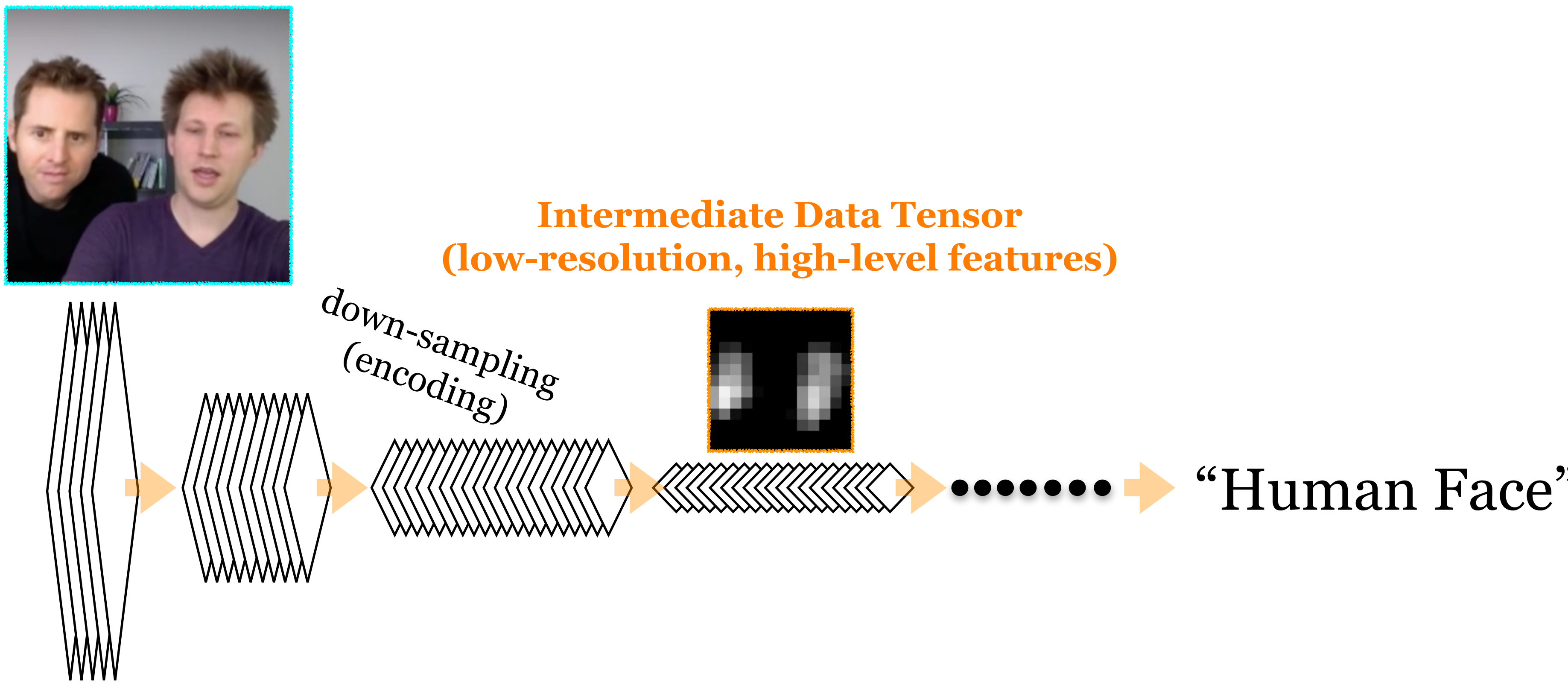


Network Output

How image classification works

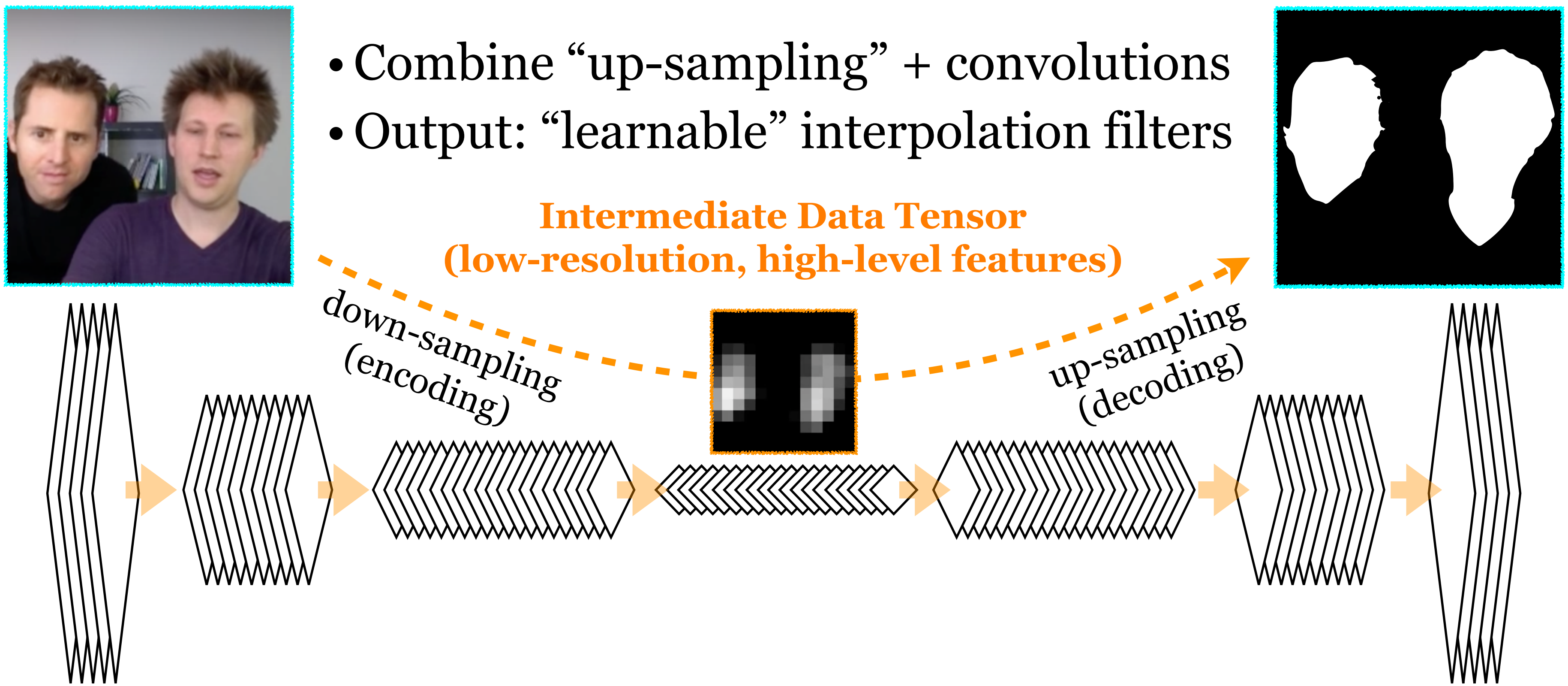


How image classification works



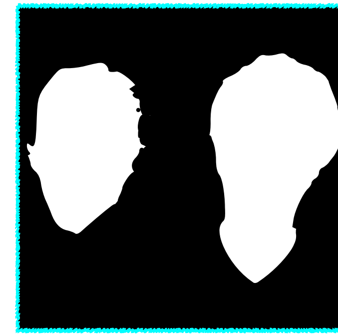
How pixel segmentation works

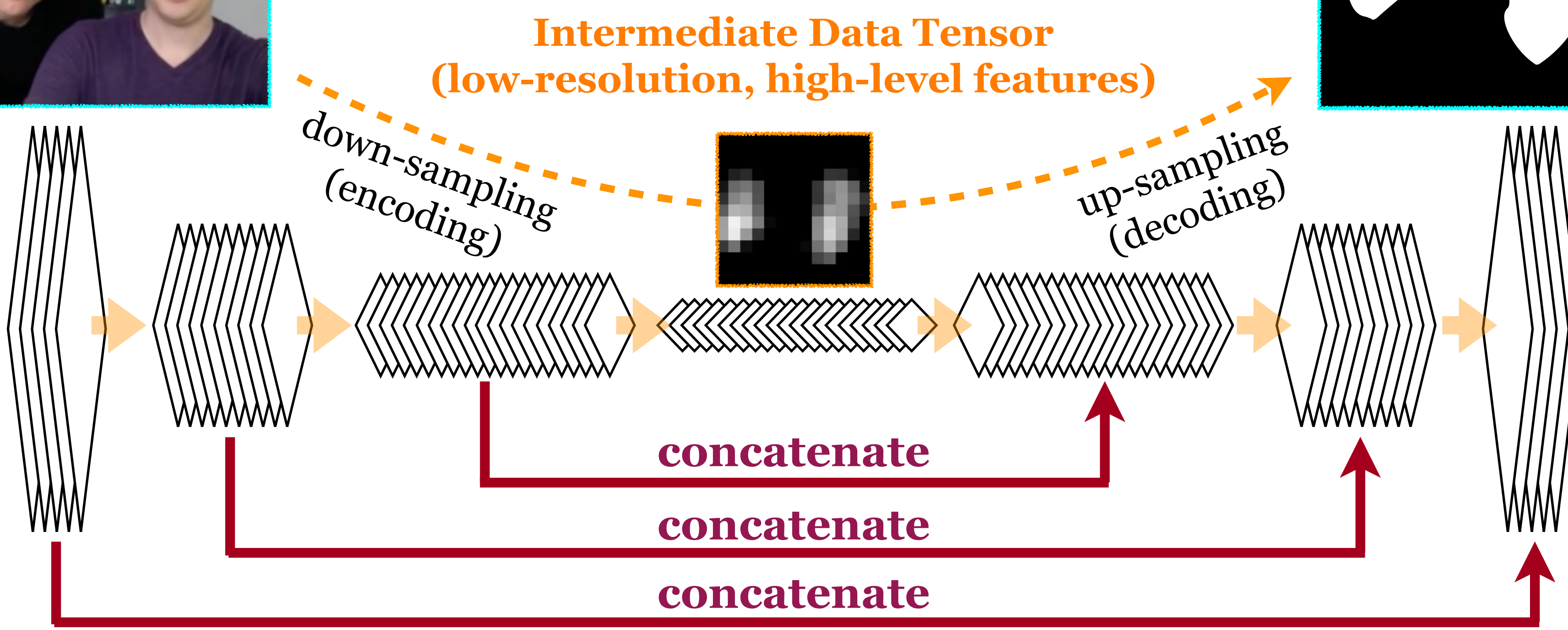
- Combine "up-sampling" + convolutions
- Output: "learnable" interpolation filters



How pixel segmentation works

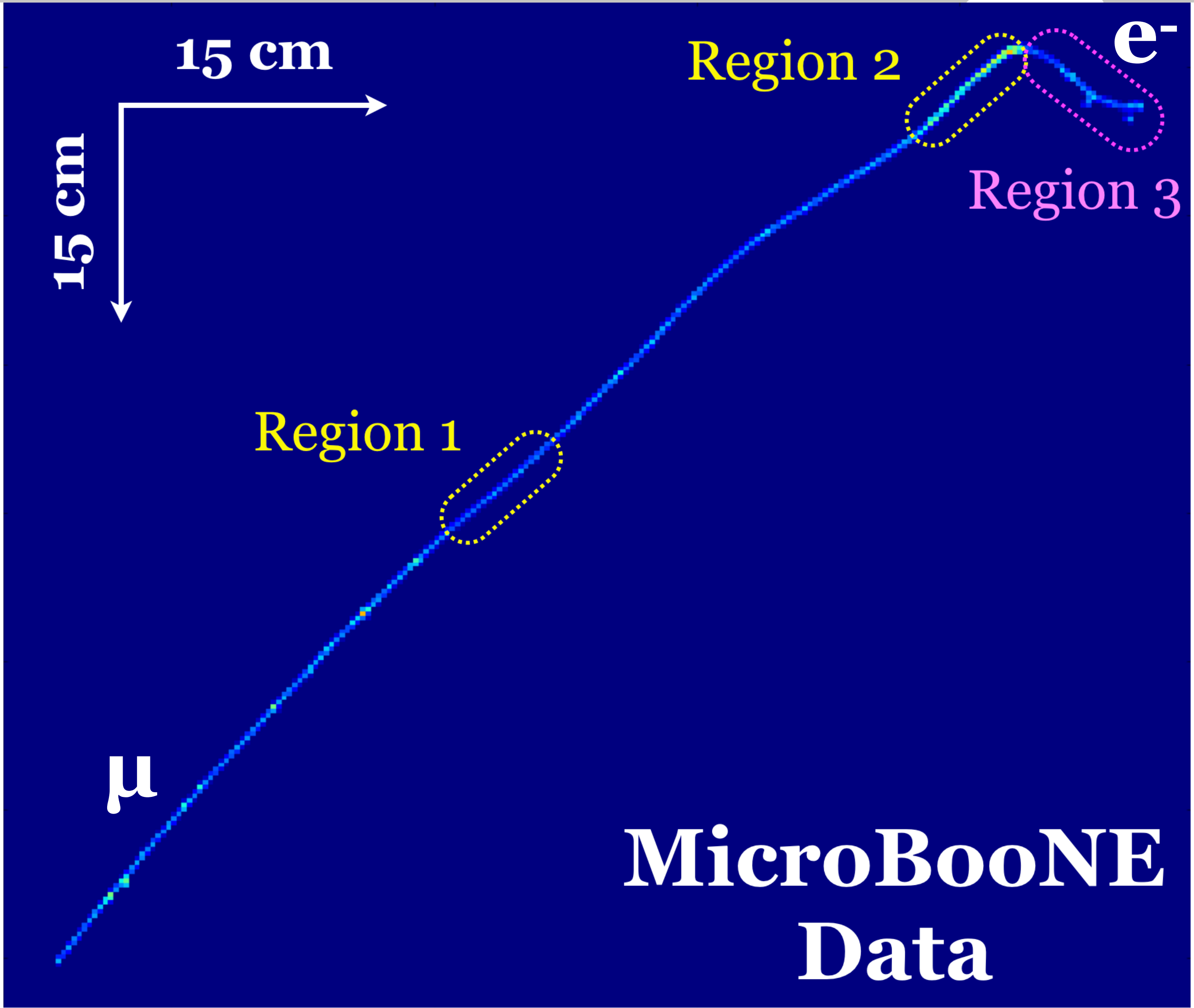
- Combine "up-sampling" + convolutions
- Output: "learnable" interpolation filters



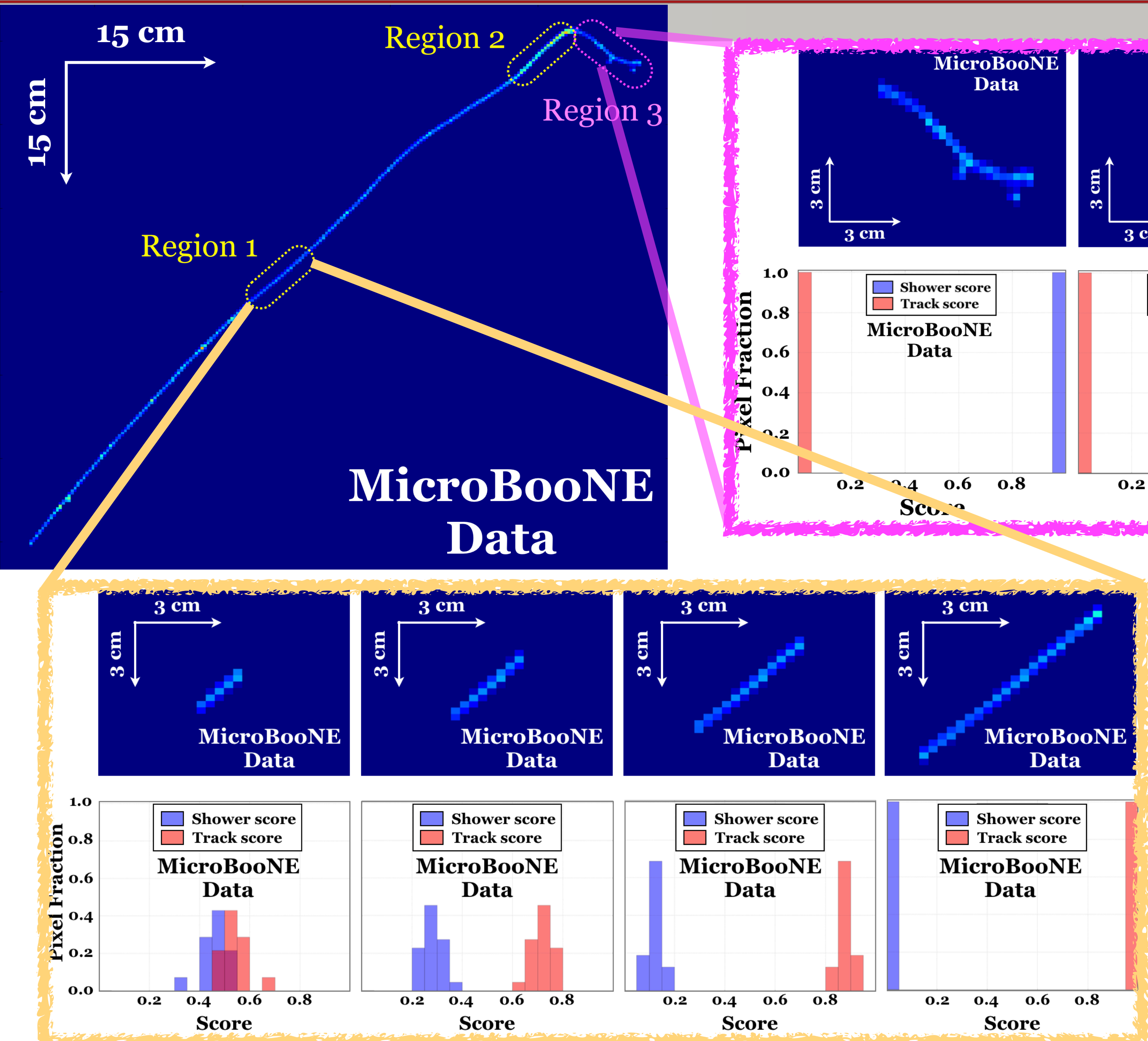


Concatenation recovers spatial resolution information

Early Demonstrations
Machine Learning for LArTPC Image Analysis



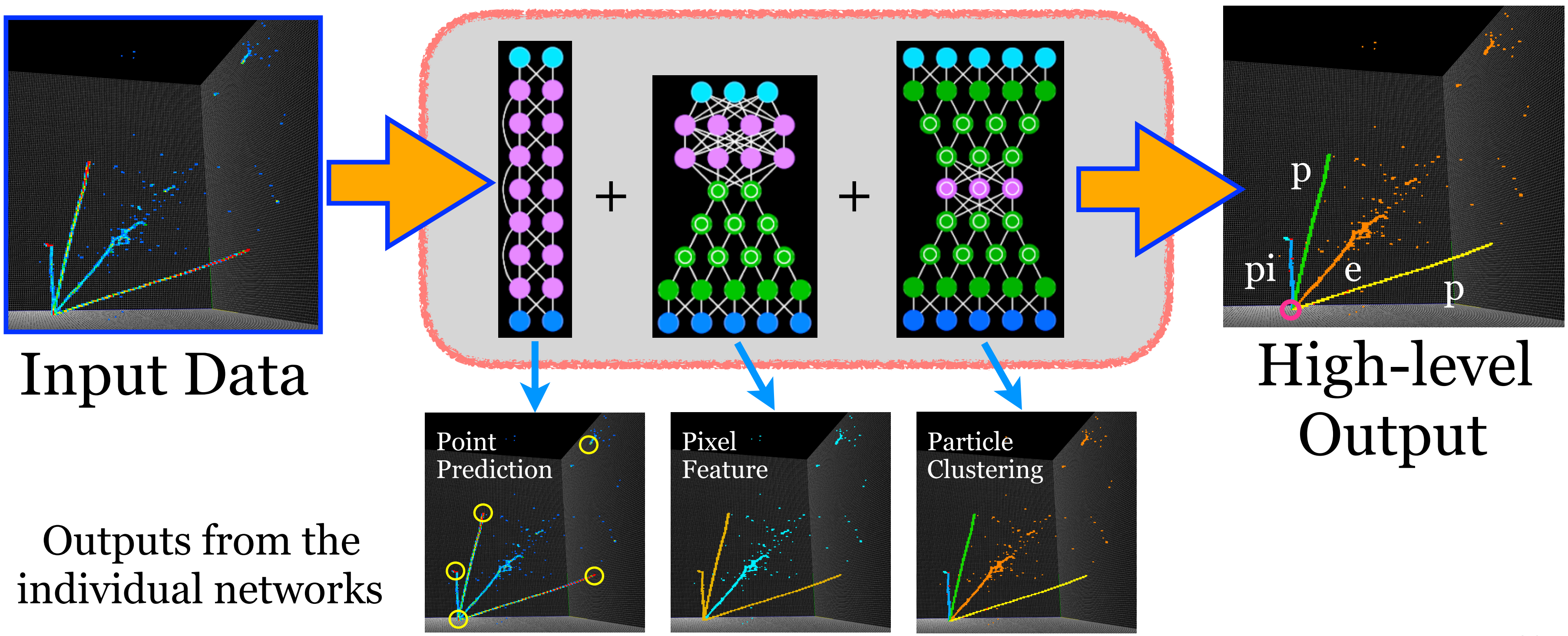
Early Demonstrations
Machine Learning for LArTPC Image Analysis



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

Multi-task Deep Neural Network

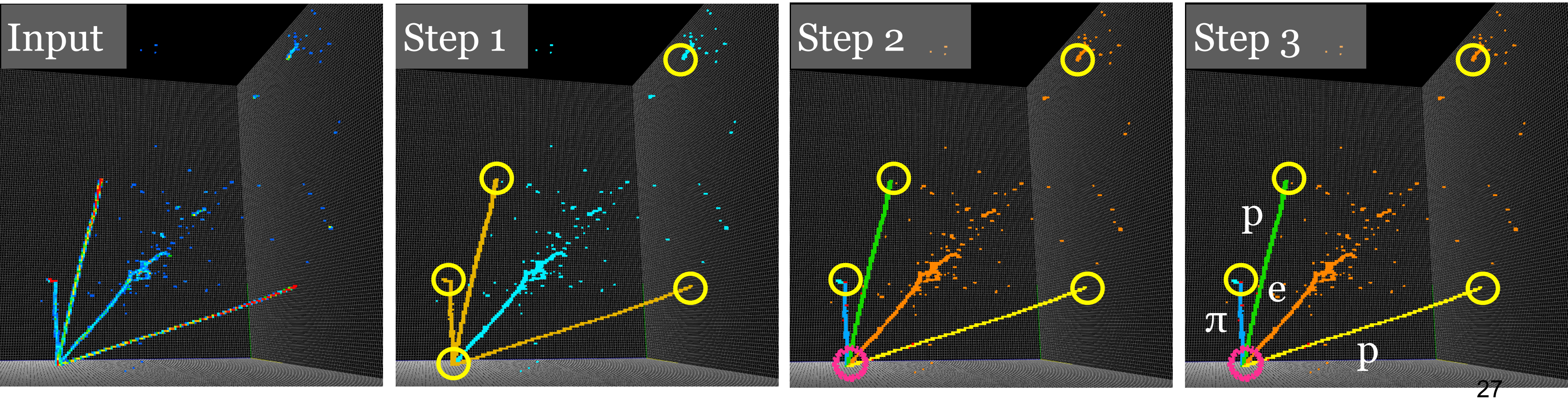
Introduce physical feature extraction tasks (reconstruction) to bias the data transformation. Implicitly introduce physics concepts + construct logic for the final output.



ML-based Full Data Reconstruction Chain

- A cluster of many task-specific networks in 2D & 3D
  - Vertex finding, clustering, particle ID, etc.

- [ ] 1. Key points (track edges) + pixel feature annotation
- [ ] 2. Vertex finding + particle clustering
- [ ] 3. Particle type + energy/momentum
- [ ] 4. Hierarchy building

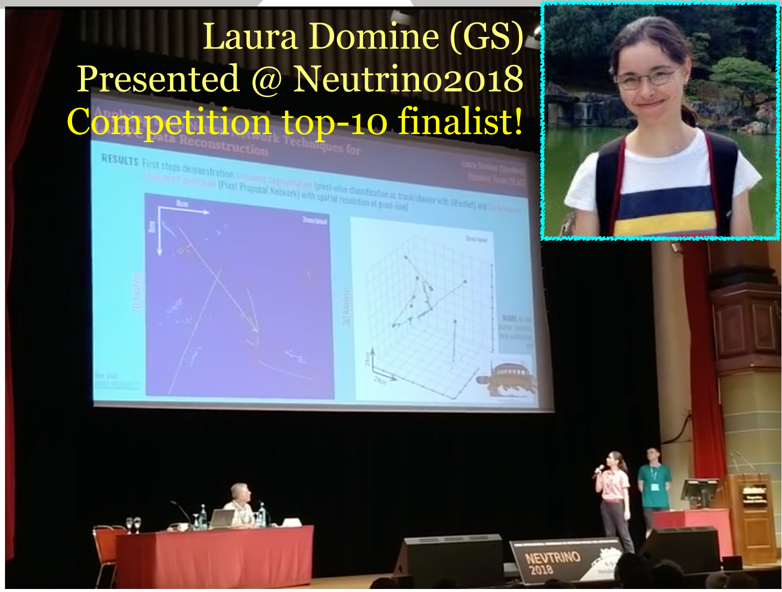


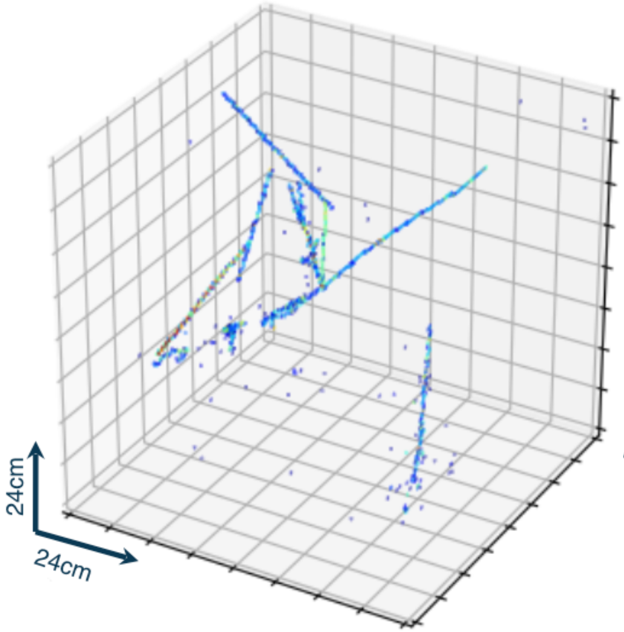
Toward Full 3D Reconstruction Chain
Machine Learning for Particle Image Analysis

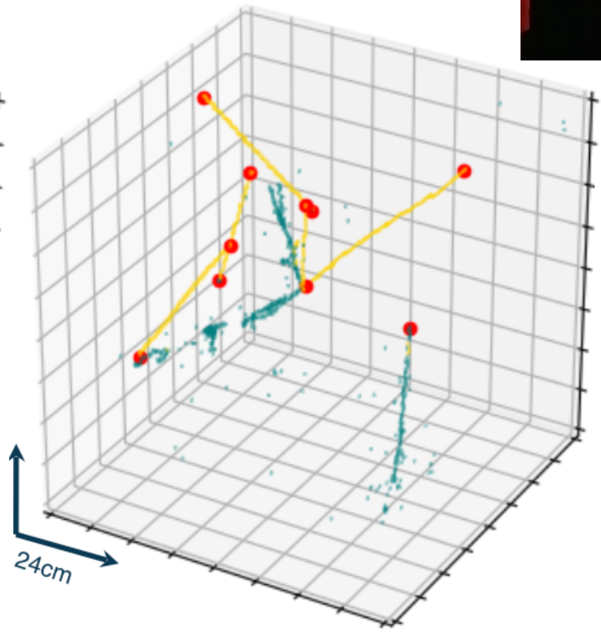
SLAC

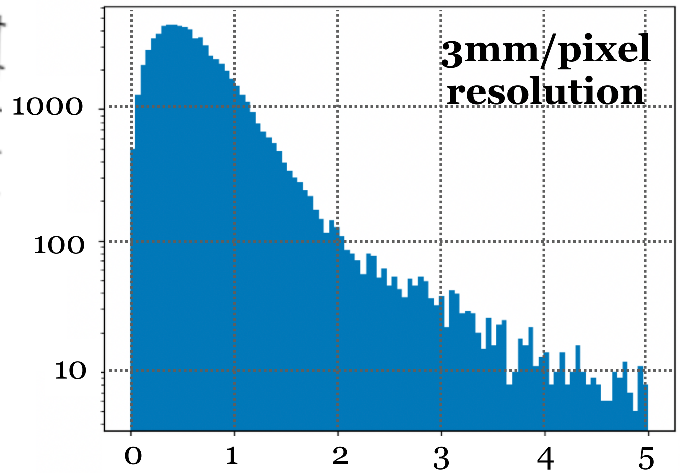
Multi-Task Network Cascade

- **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









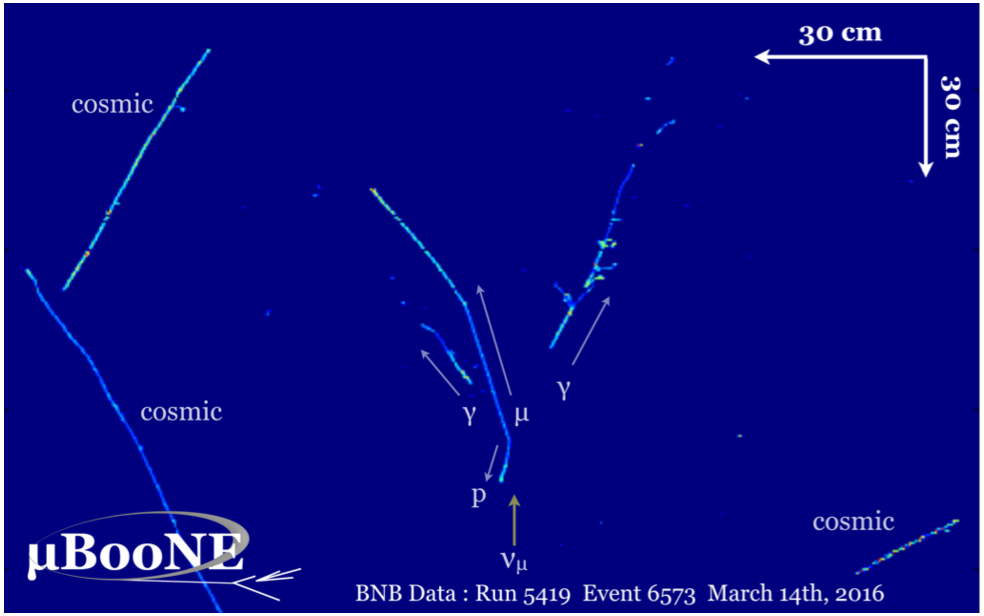
Pixel distance between the target truth point to the closest proposed point

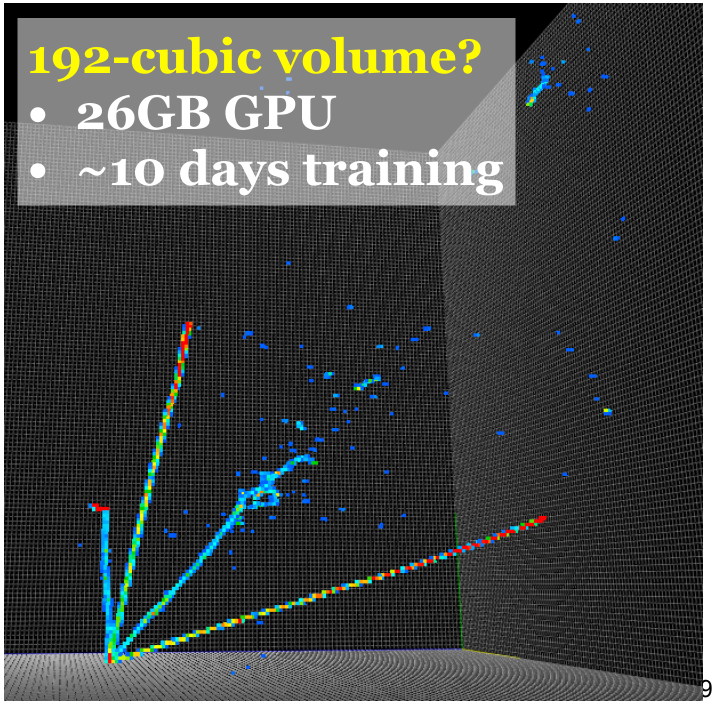
28

SLAC

"Applying for 3D" is simple, but is it scalable?

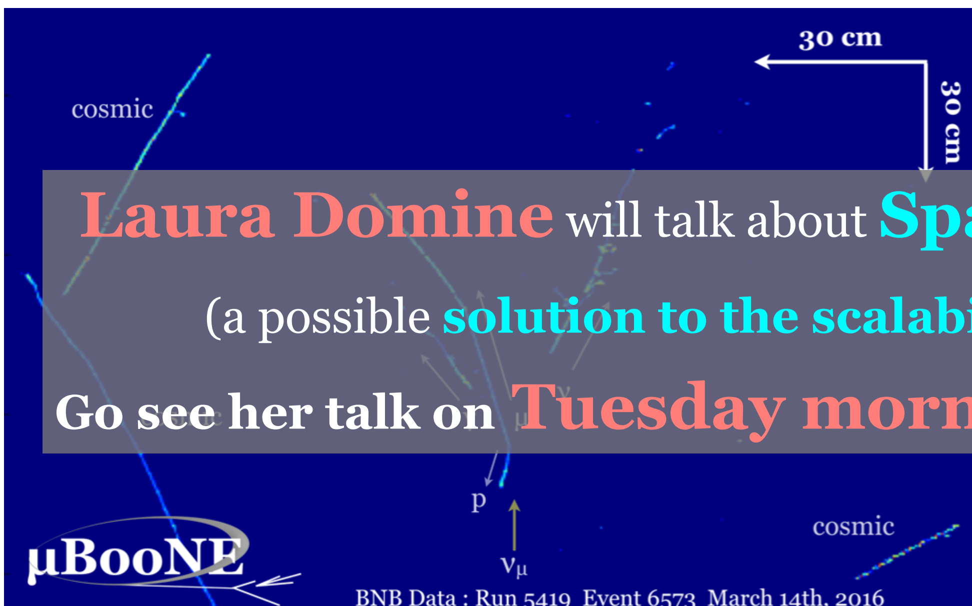
- LArTPC data is generally sparse but locally dense
  - Mostly zero-filled matrix. **CNN** = **dense matrix operation** = **bad!**
  - Matrix size (volume) scales by power low, but non-zero pixels scales almost linearly (most particle trajectories are locally 1D line)

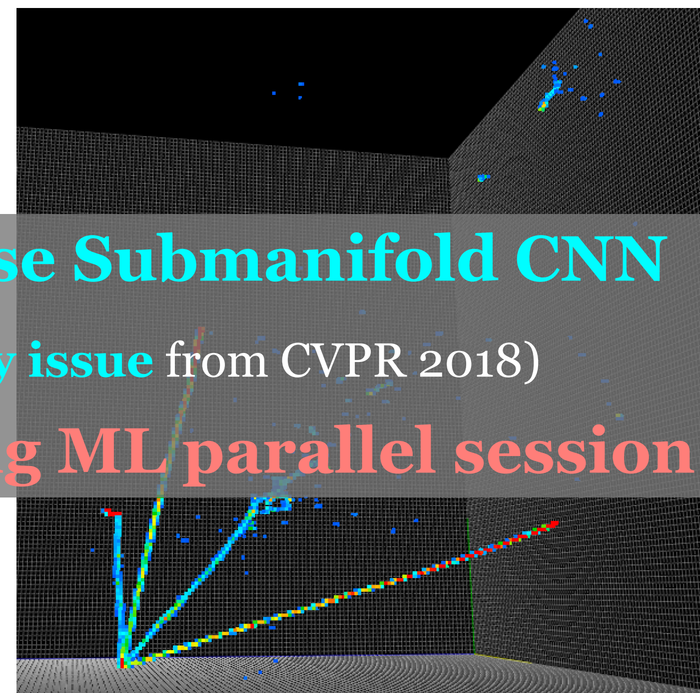




"Applying for 3D" is simple, but is it scalable?

- LArTPC data is generally sparse but locally dense
  - Mostly zero-filled matrix. **CNN** = **dense matrix operation** = **bad!**
  - Matrix size (volume) scales by power low, but non-zero pixels scales almost linearly (most particle trajectories are locally 1D line)





Laura Domine will talk about **Sparse Submanifold CNN**

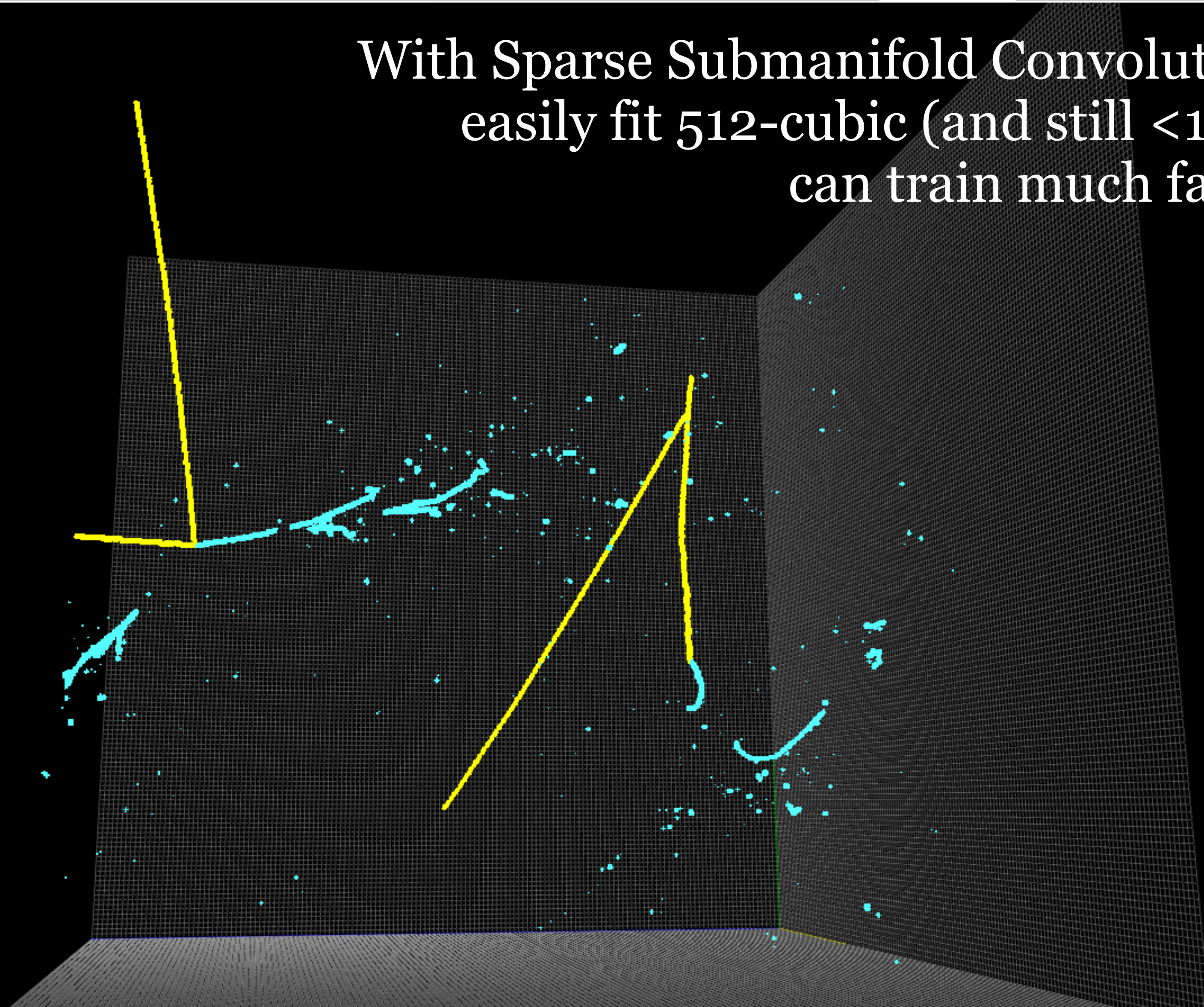
(a possible **solution to the scalability issue** from CVPR 2018)

Go see her talk on Tuesday morning ML parallel session

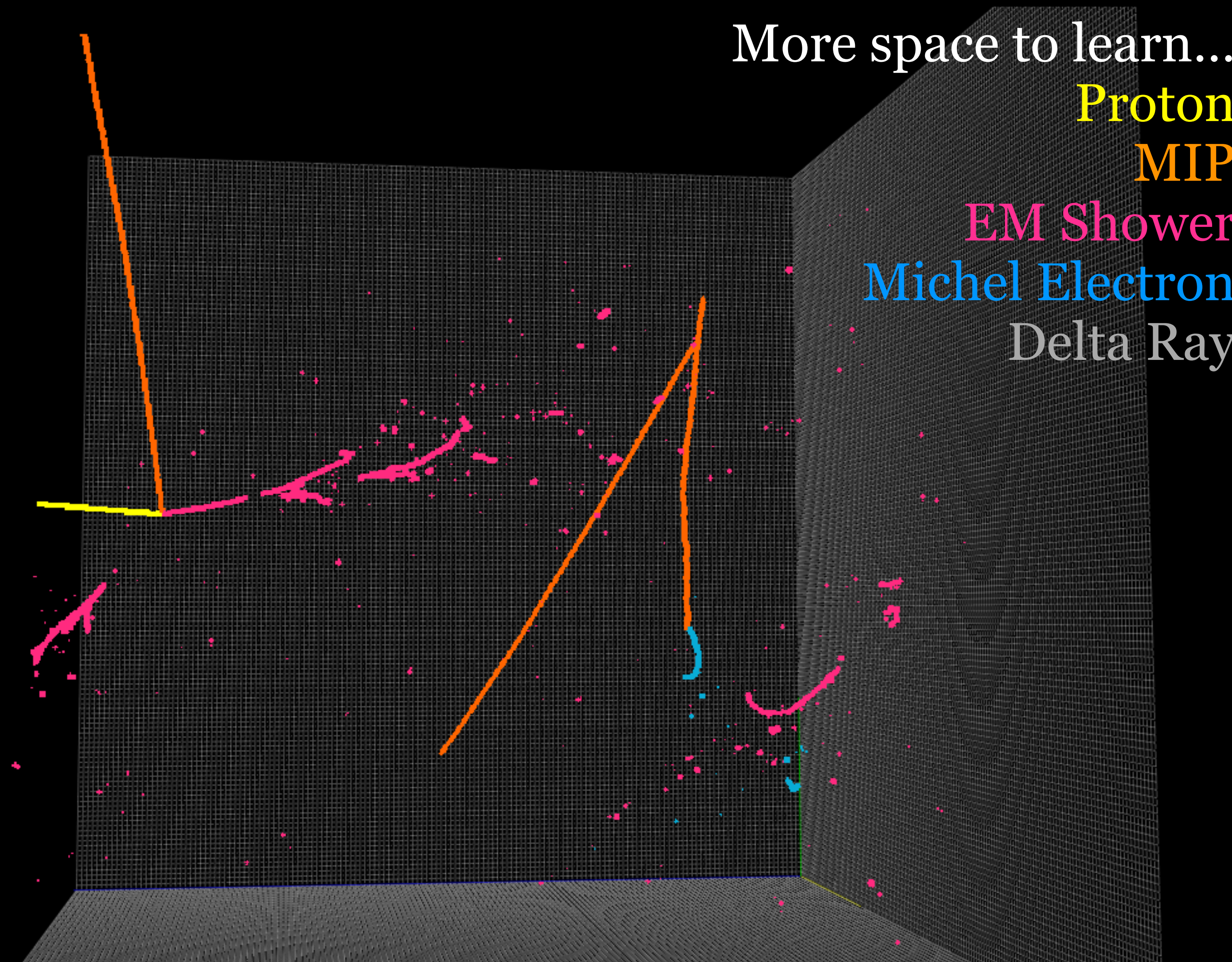
Toward Full 3D Reconstruction Chain
Machine Learning for Particle Image Analysis

SLAC

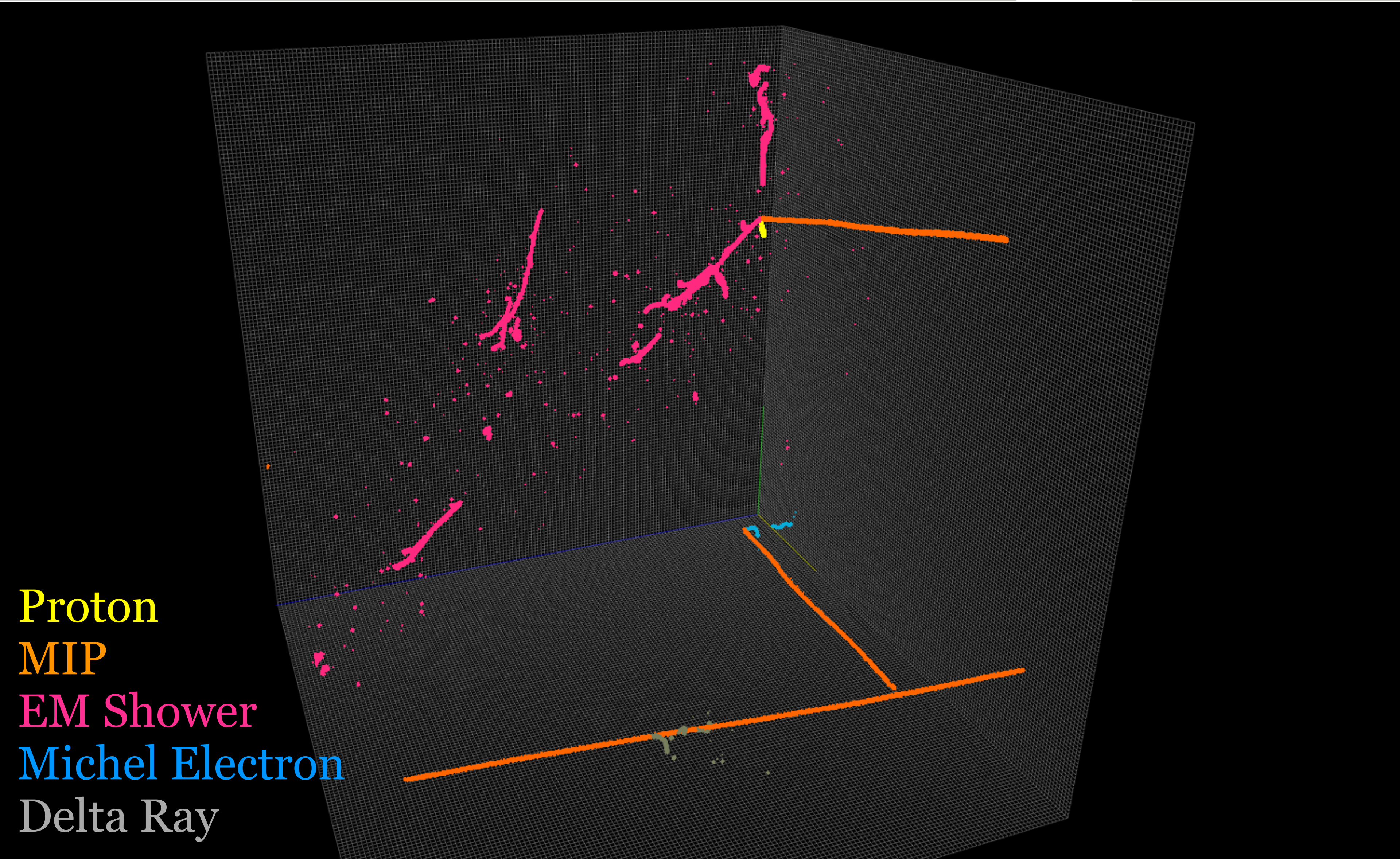
With Sparse Submanifold Convolution,
easily fit 512-cubic (and still <1GB)
can train much faster



Toward Full 3D Reconstruction Chain
Machine Learning for Particle Image Analysis



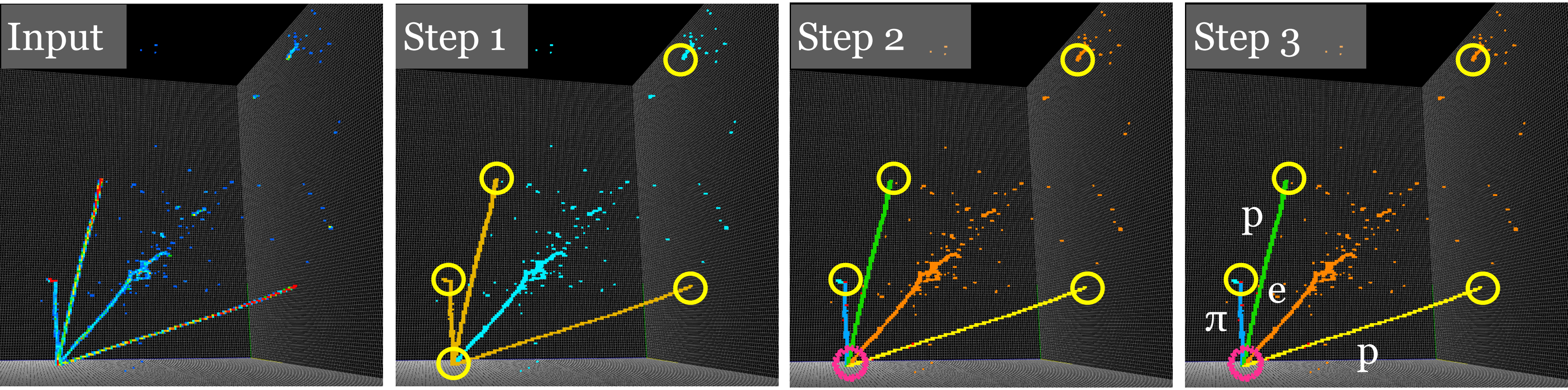
Toward Full 3D Reconstruction Chain
Machine Learning for Particle Image Analysis



… wrapping up …

Where we are…

- ☑ 1. Space point (track edges) + pixel feature annotation
- ☑ 2. Vertex finding + particle clustering
- ☑ 3. Particle type + energy/momentum
- ☐ 4. Hierarchy building

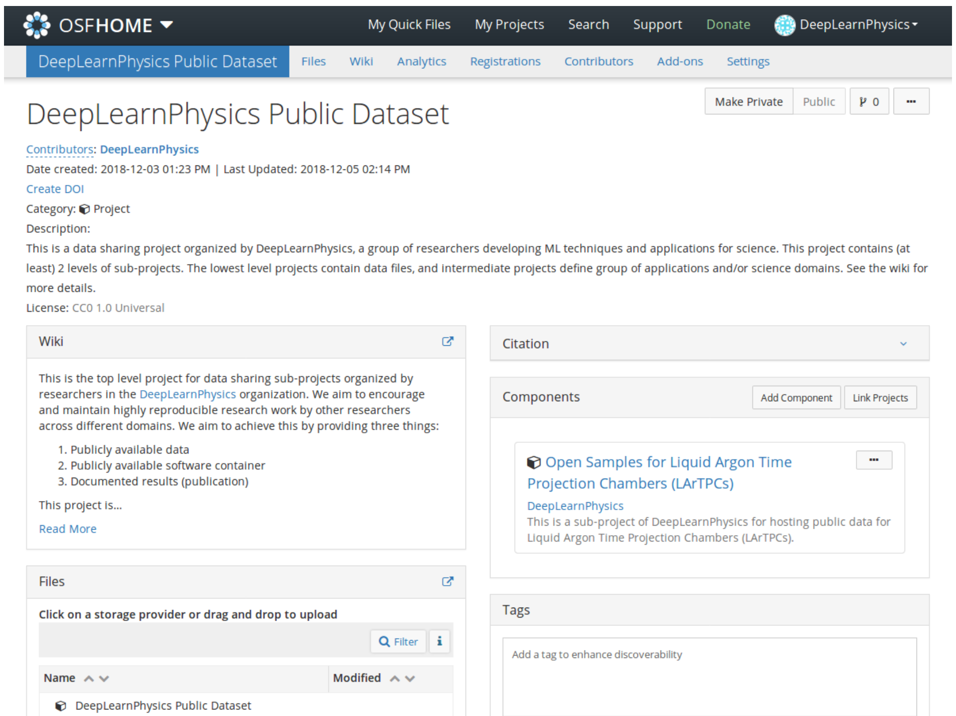


Aiming to complete the full chain v.1 in early 2019, move to physics analysis applications

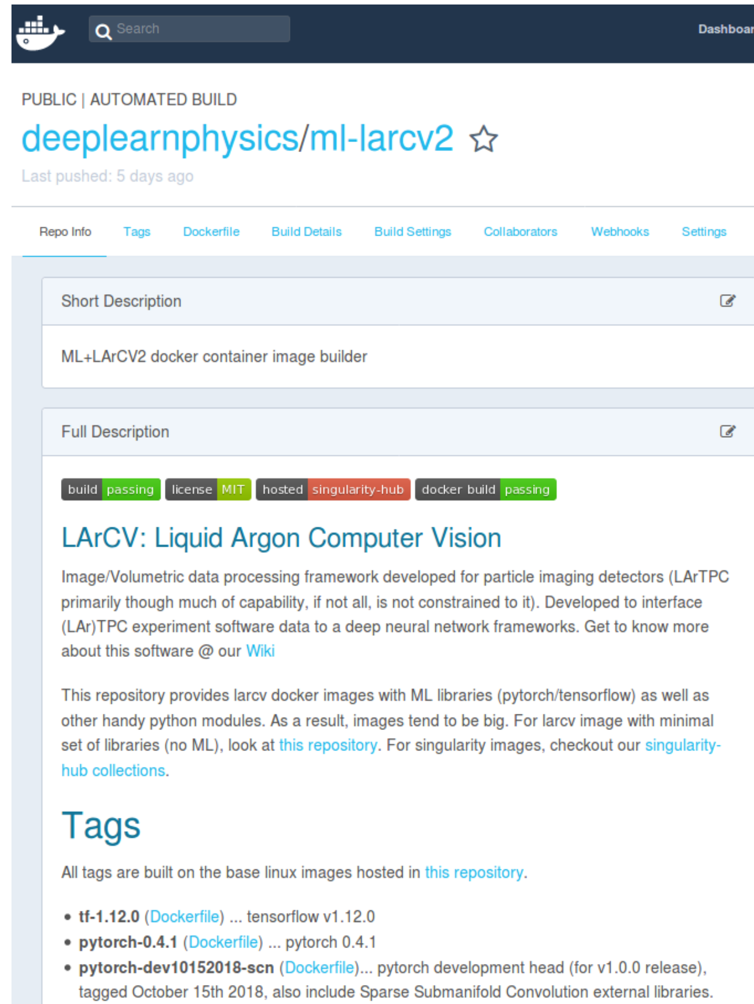
Sharing Our R&D
Machine Learning & Broader Impact

SLAC

Public Data Set: OSF



Software Containers

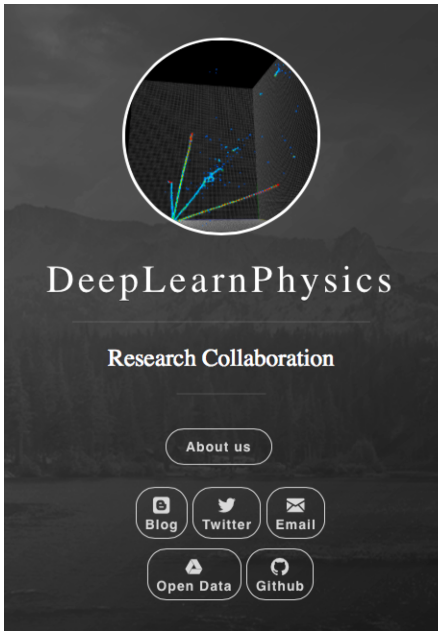


Travis CI

GitHub

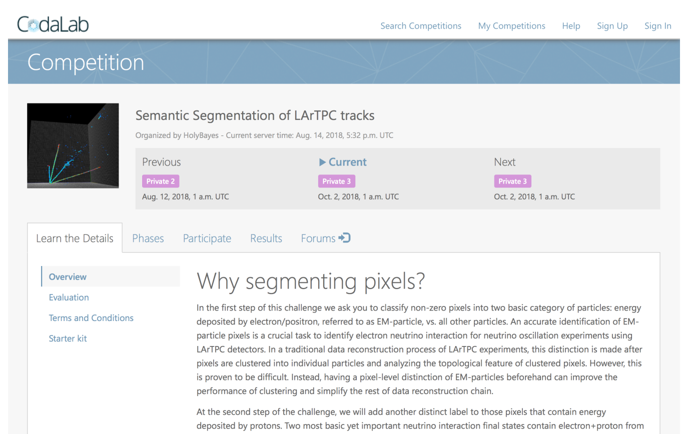
docker

Sharing Our R&D
Machine Learning & Broader Impact

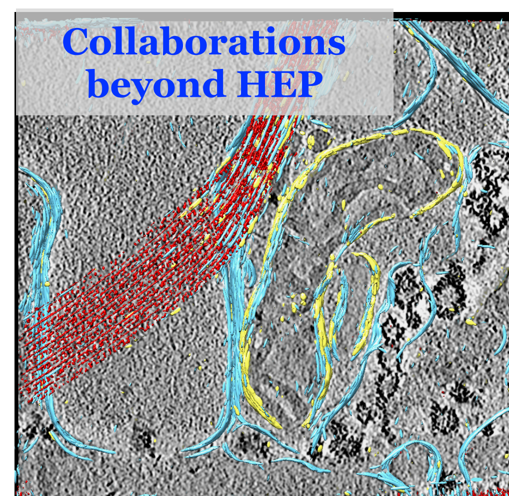


DeepLearnPhysics (deeplearnphysics.org)

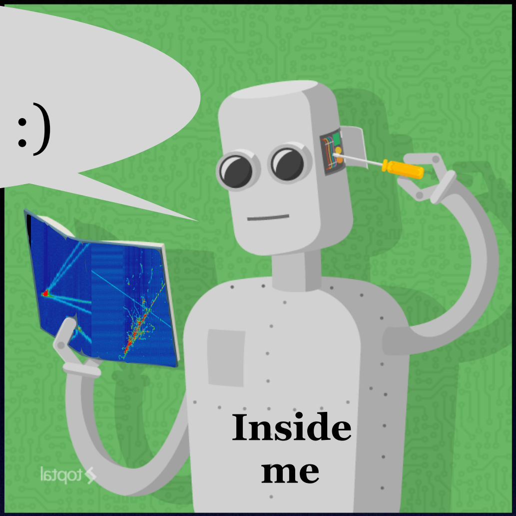
- **Collaboration** for ML technique R&D
  - ~70 members including HEP exp/theory, nuclear physics, BES (LCLS, SSRL), Cryo-EM, accelerator, AI/CS community
- **Open source** software/tools, containers, open data
  - our framework to collaborate & share reproducible results
- **Community building**
  - In-person tutorials (SLAC,LBNL,FNAL,BNL,VTech,MIT,Columbia…)
  - Sharing talk invitations, job/funding opportunities, etc.



Public challenge (collab. w/ LHC)



Thank you!
for your attention :)



Take Away Messages

1. **LArTPCs** are **high resolution particle imaging detectors**

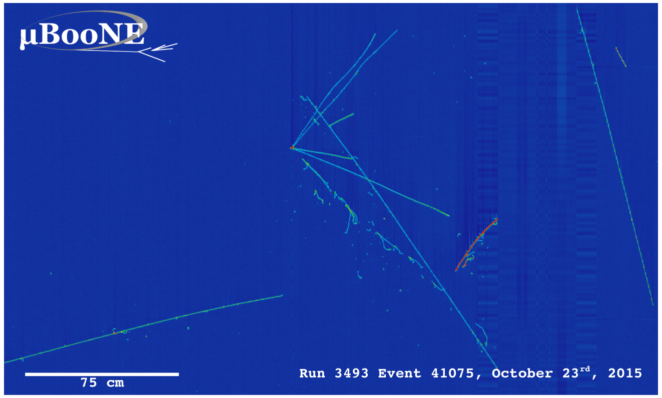
2. **Deep neural networks (DNNs)** are **efficient image feature extraction techniques** developed in computer vision

3. **DNNs** can be **used for ML-based full data reco chain**

4. **Scalability** can be **addressed using SSCN (see Laura's talk)**

5. **Reco chain** is **being developed toward physics results :)**

Collaboration / Synergies



Wire LArTPC for 3D

- WireCell team (BNL) on SBN/DUNE
- Cluster3D (SLAC) on SBN
- LArFlow (Tufts) on MicroBooNE

Pixel LArTPC

- Interest from LBNL/UTA/Bern/MSU
  - Looking forward to 2x2 ArgonCUBE modules
  - Plan/Start working with students specifically for DUNE ND

Computing

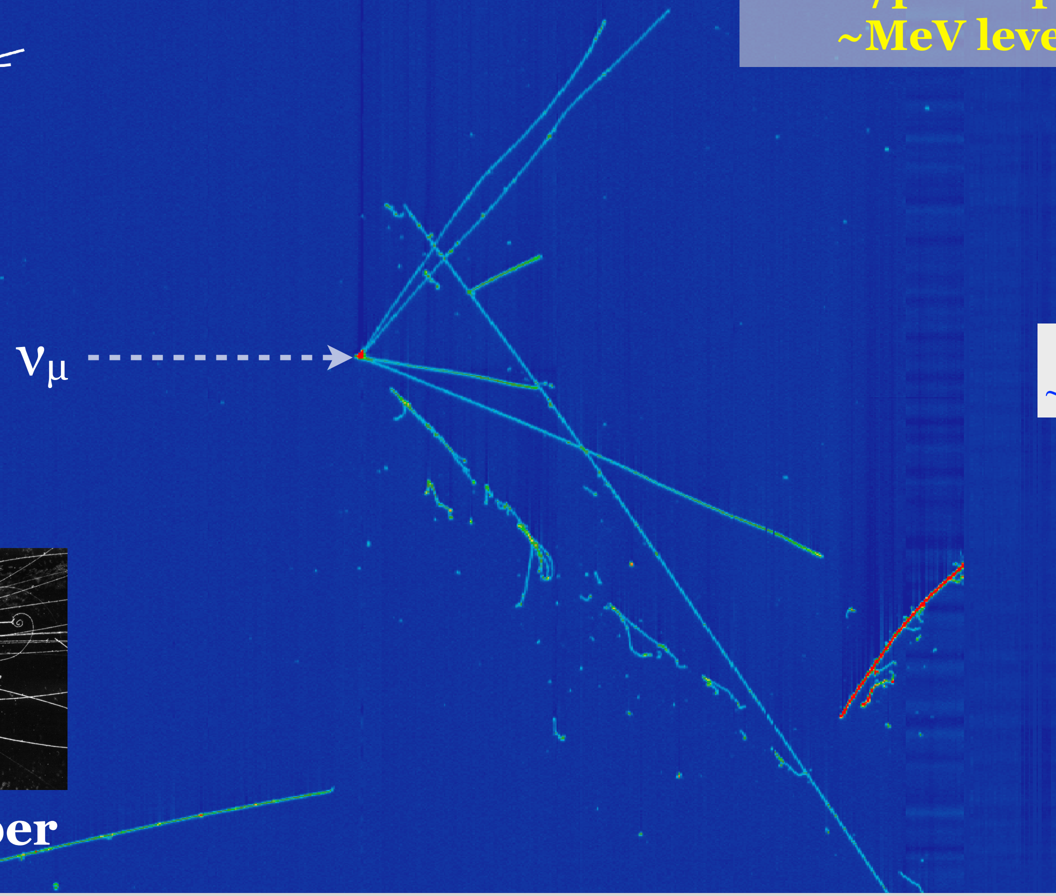
- ANL demonstrating our code on distributed environment
- ORNL+FNAL colleagues to submit ALCC for Summit HPC
- FPGA-based inference system R&D (HEP-wide + beyond)

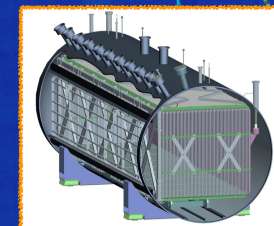
Back-up Slides

Next Neutrino Detectors?

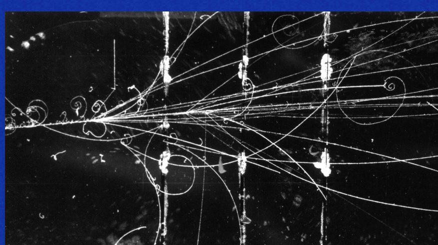
µBooNE

~mm/pixel spatial resolution
~MeV level sensitivity





MicroBooNE
~87 ton (school bus size)



Bubble Chamber

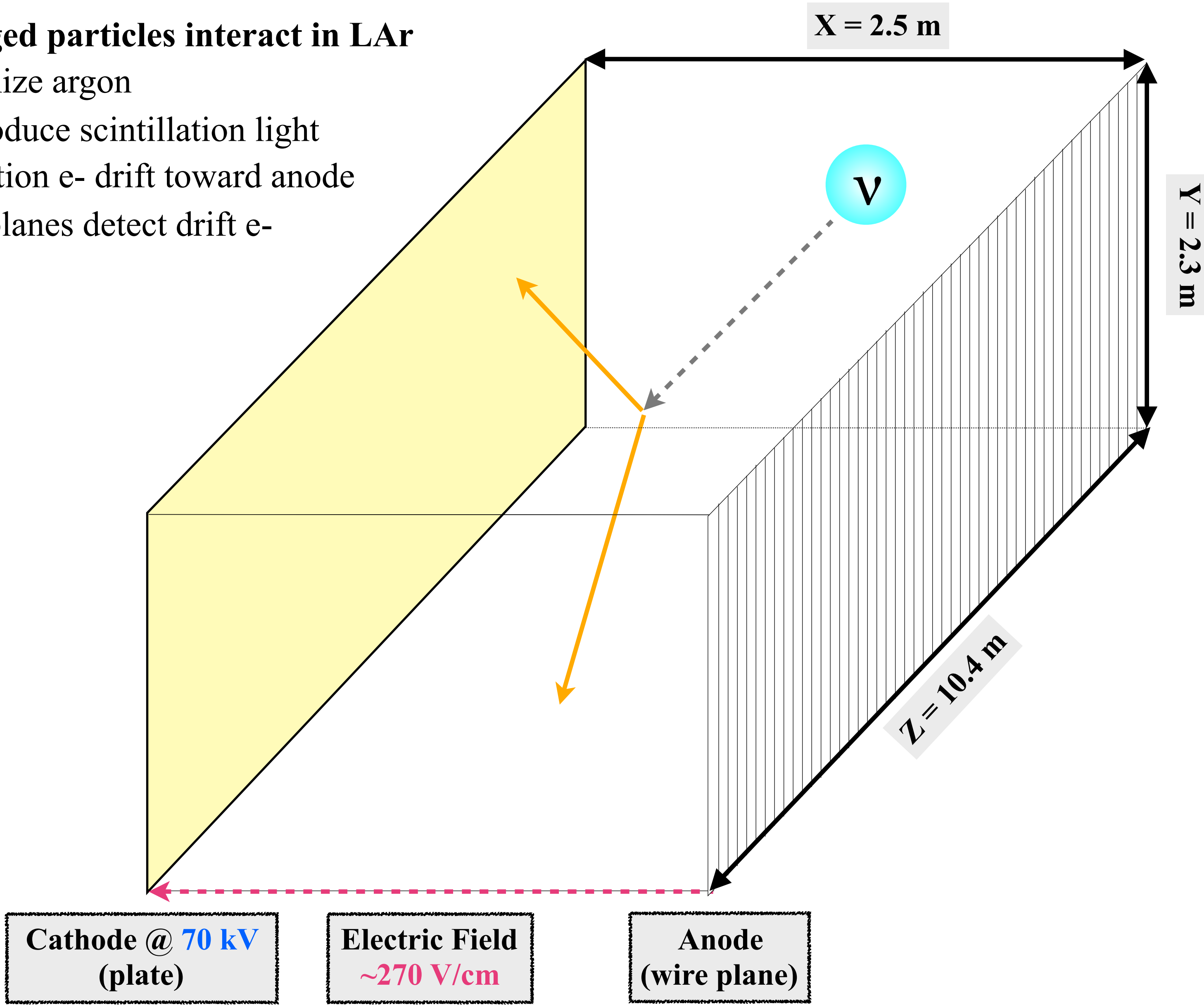
Liquid Argon Time Projection Chamber

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

2015

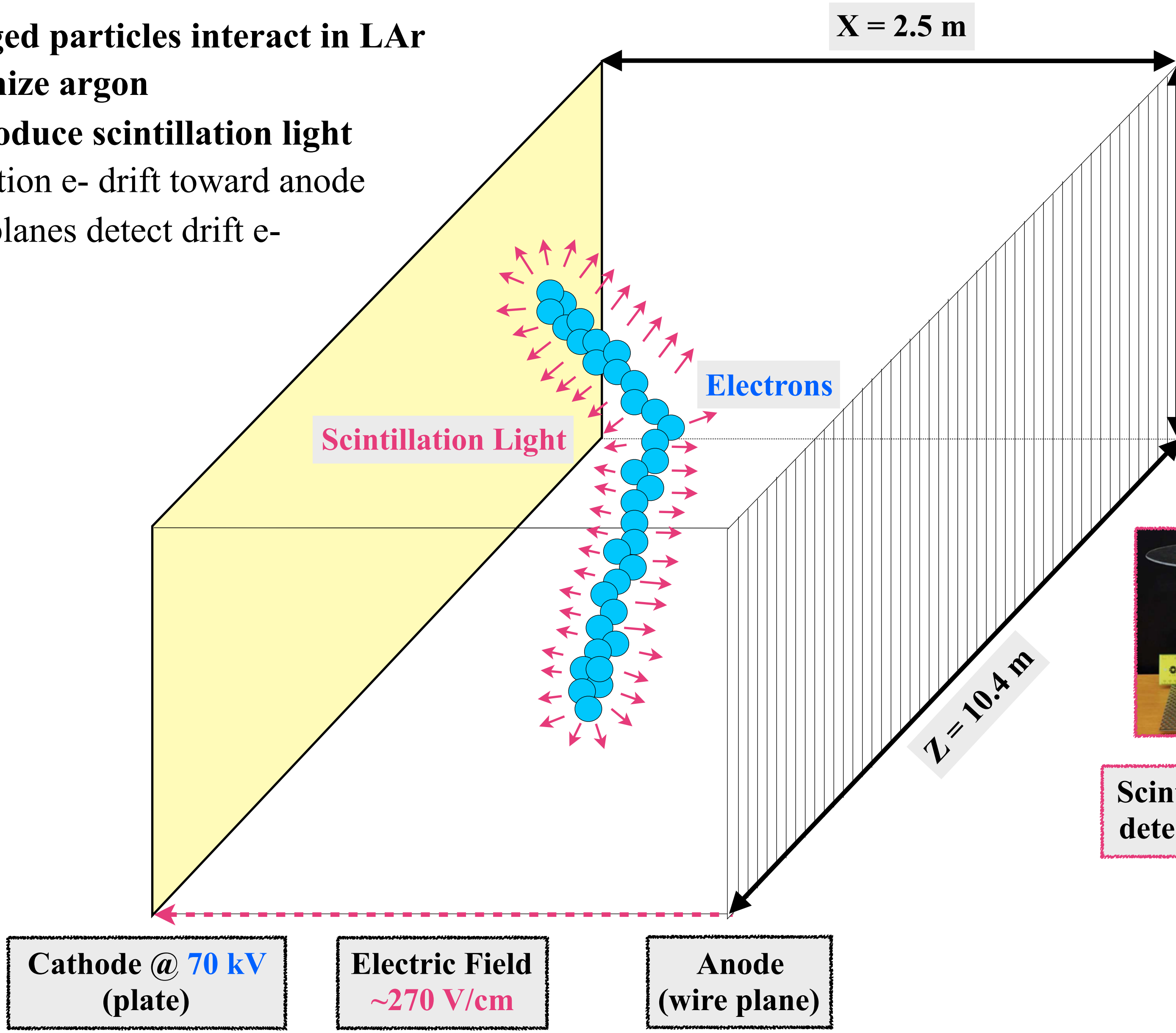
How Wire LArTPC (MicroBooNE) Work (I)

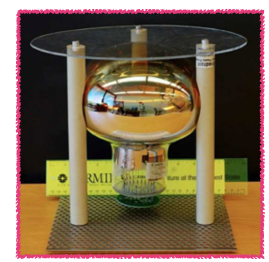
1. **Charged particles interact in LAr**
    - Ionize argon
    - Produce scintillation light
2. Ionization e- drift toward anode
3. Wire planes detect drift e-



How Wire LArTPC (MicroBooNE) Work (I)

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



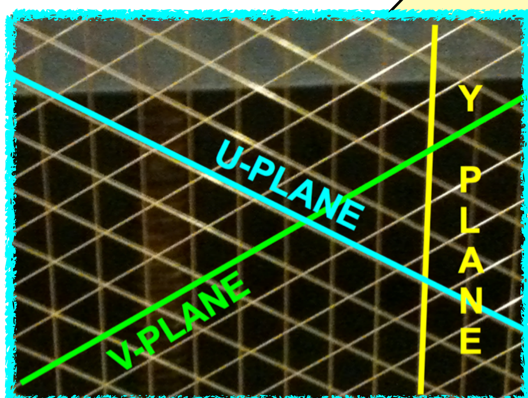


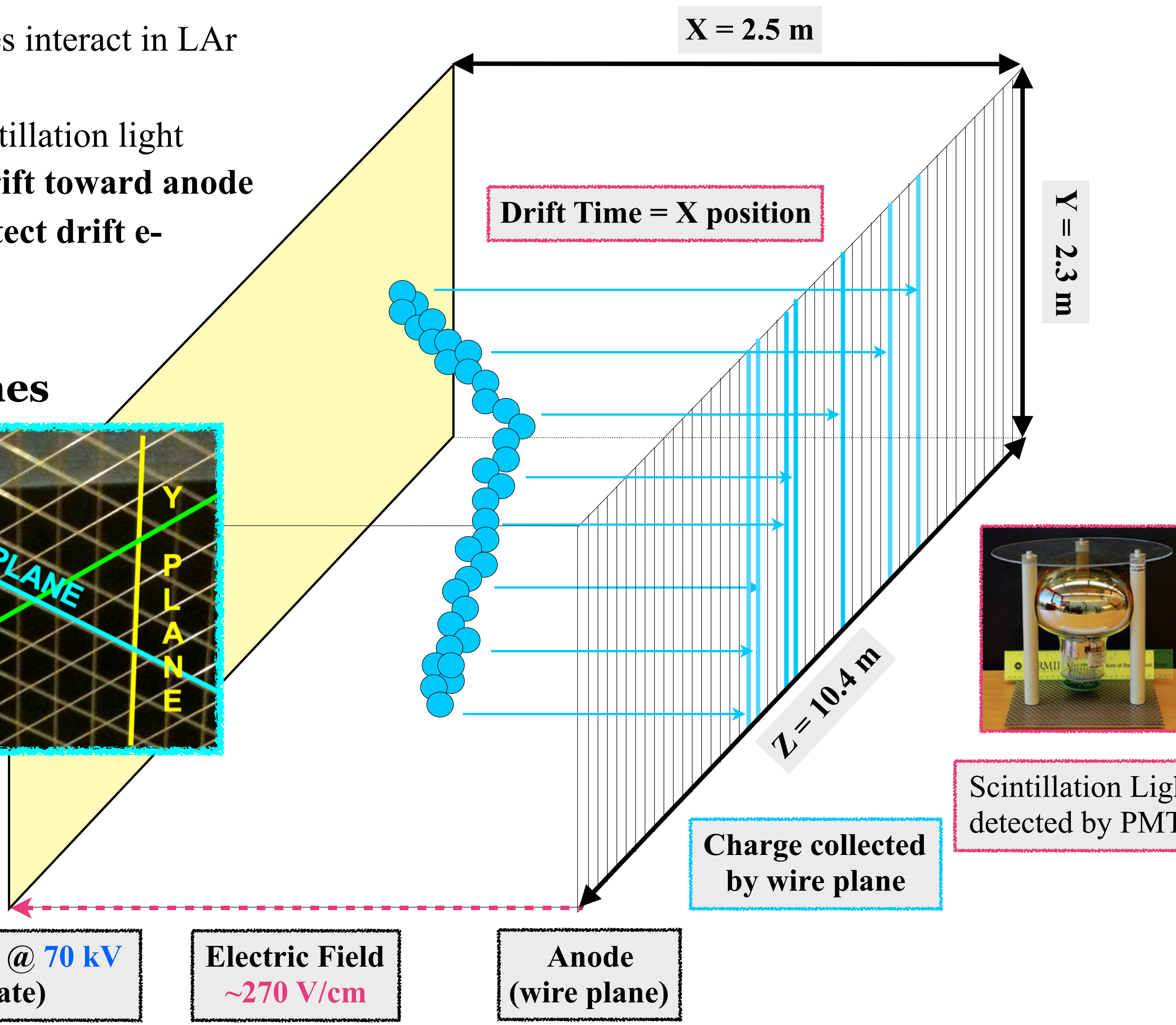
Scintillation Light detected by PMTs

How Wire LArTPC (MicroBooNE) Work (I)

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

Three Wire Planes



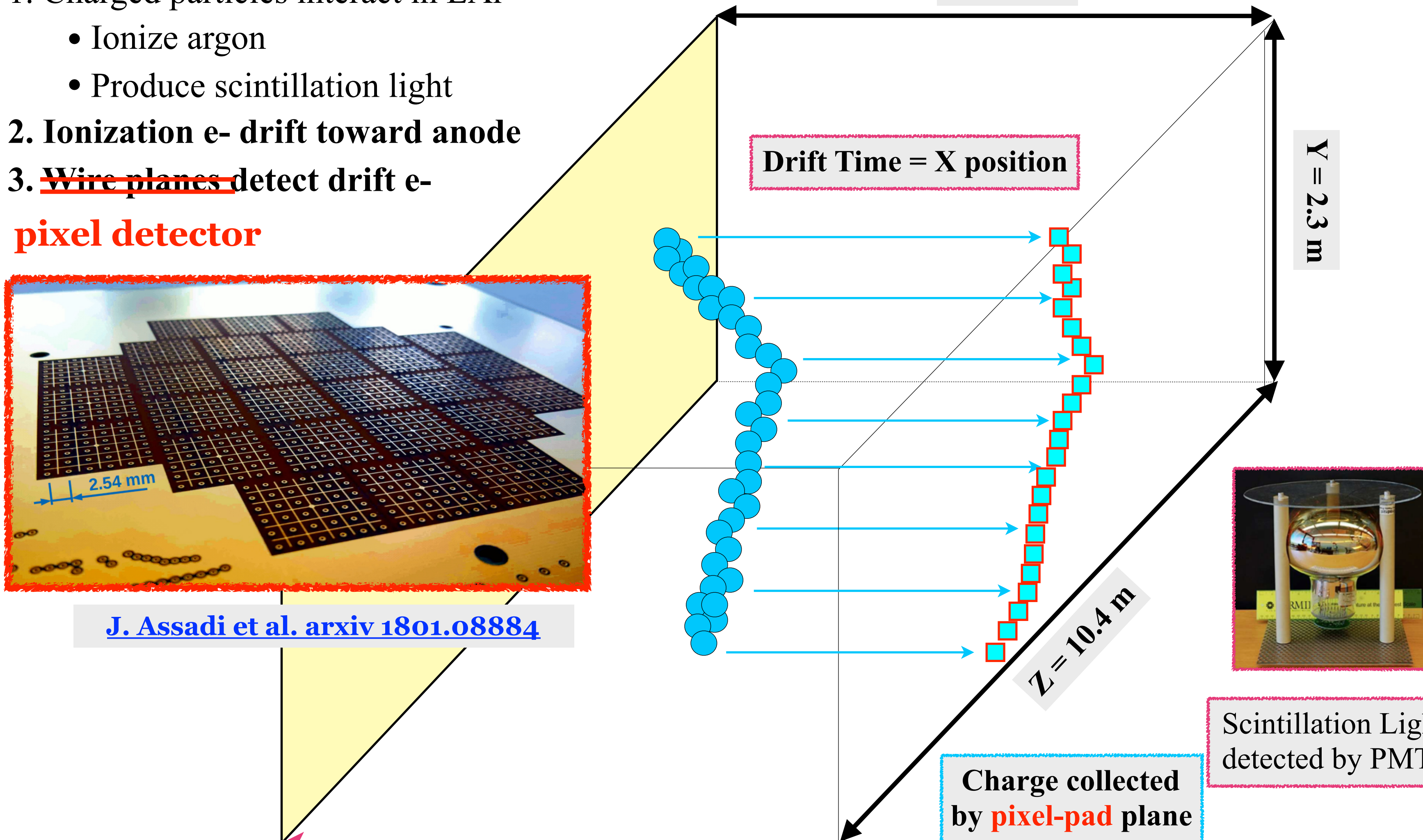


Scintillation Light detected by PMTs

How ~~Wire~~ LArTPC (~~MicroBooNE~~) Work (I)
Pixel **DUNE-ND**

1. Charged particles interact in LAr
   - 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

Scintillation Light detected by PMTs

Charge collected by pixel-pad plane

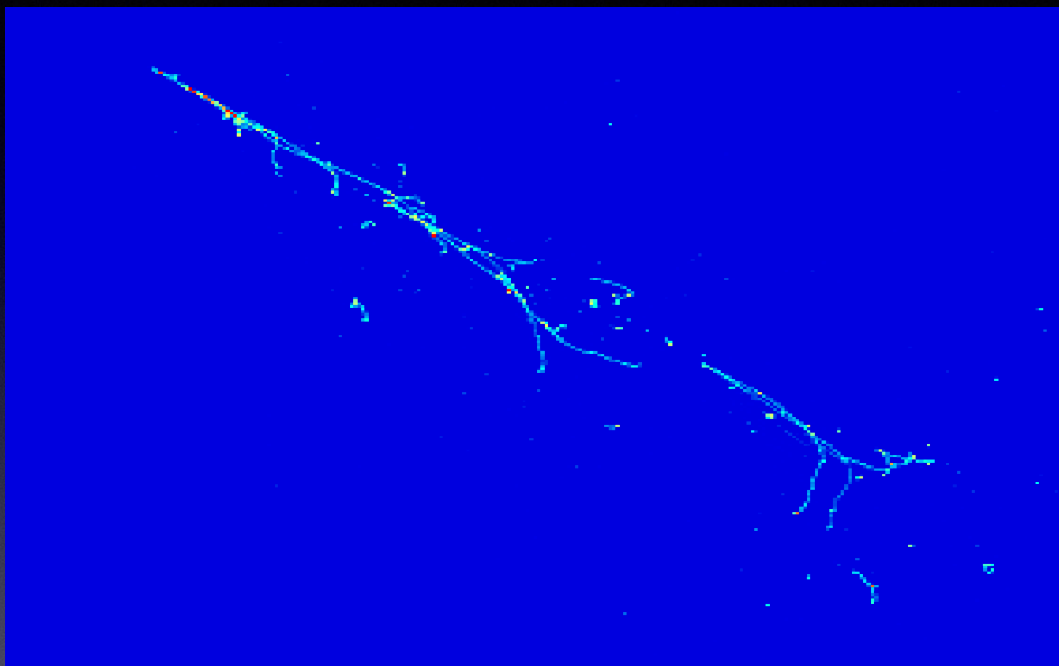
Cathode @ 70 kV (plate)

Electric Field ~270 V/cm

Anode (wire plane)

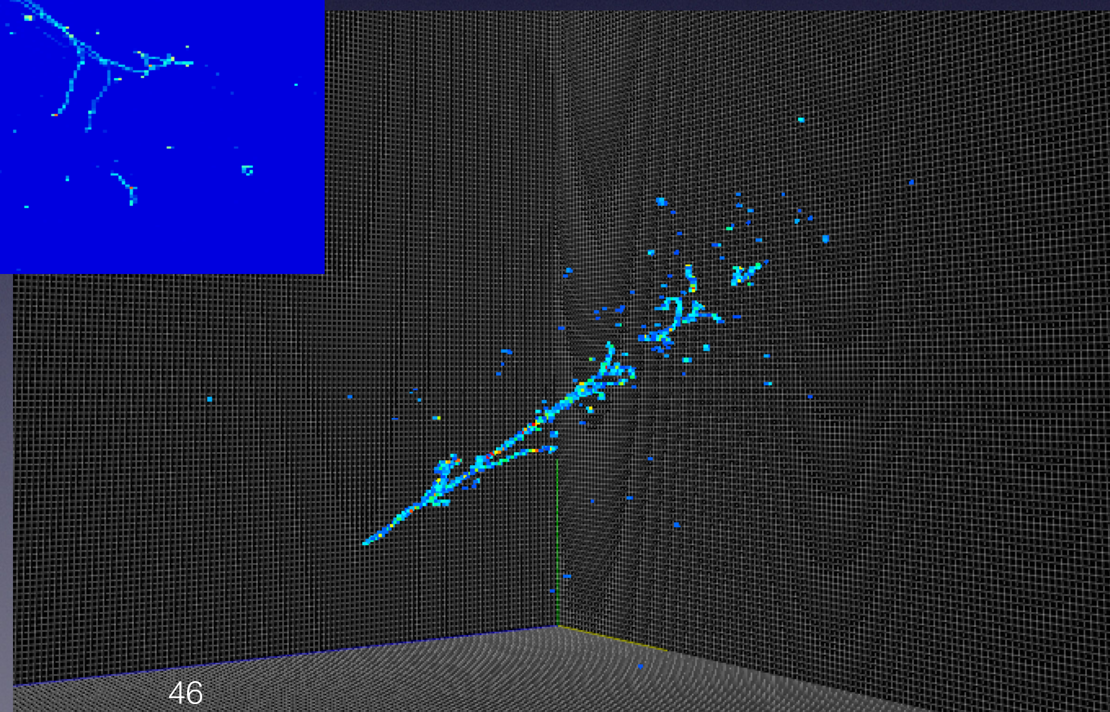
LArTPC: Particle Imaging Detector

... when things work ...



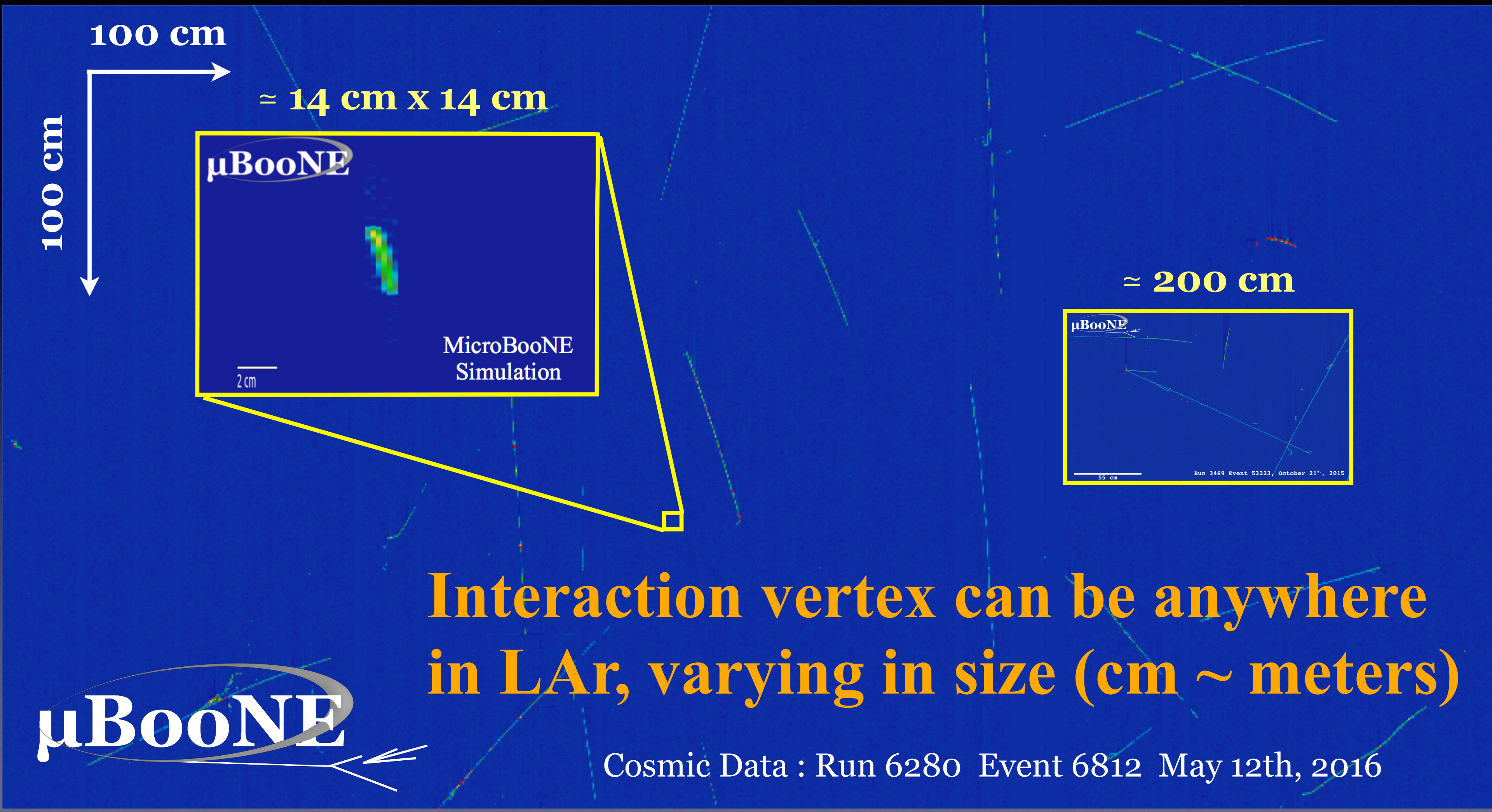
2D Projection
(Wire Detector)

3D Imaging
(Pixel Detector)

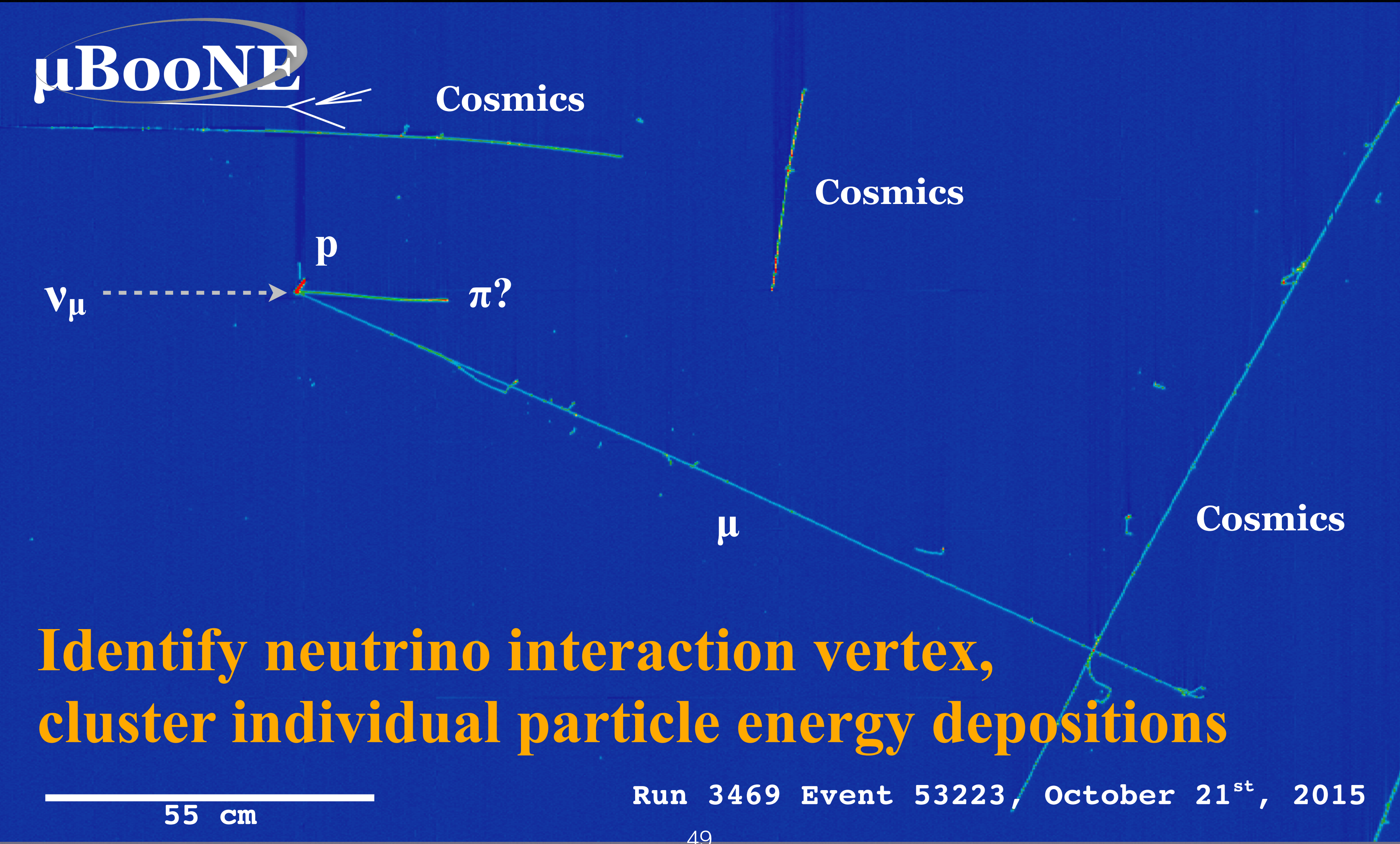


Challenges in Data Analysis?

Challenges in Data Analysis?



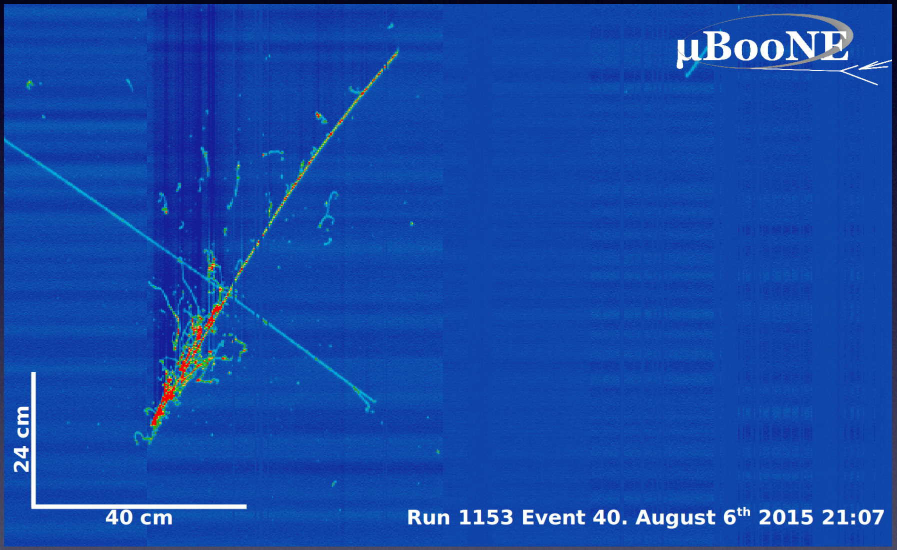
Challenges in Data Analysis?

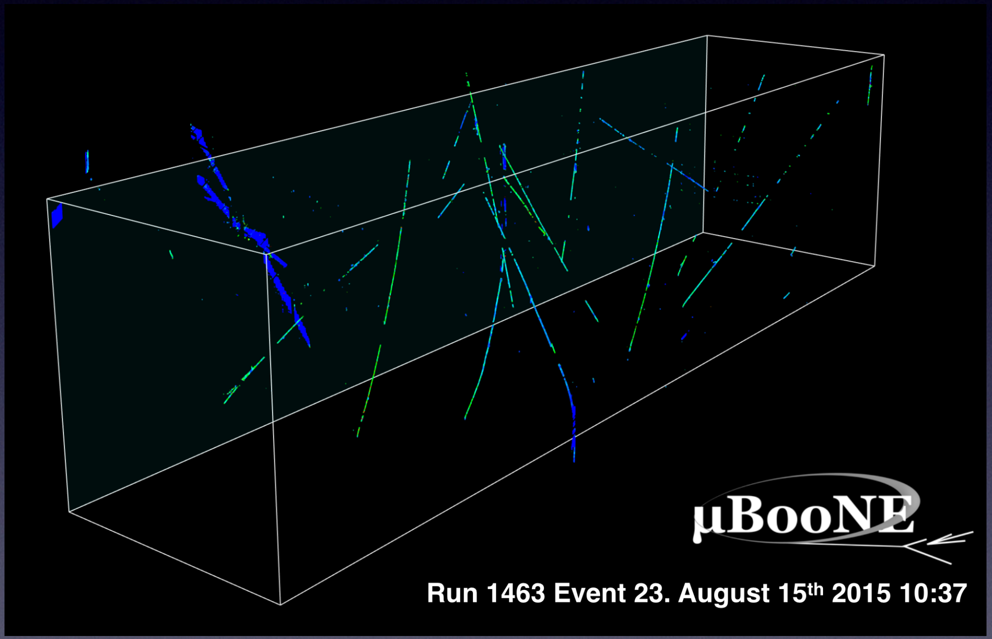


Identify neutrino interaction vertex, cluster individual particle energy depositions

Challenges in Data Analysis?

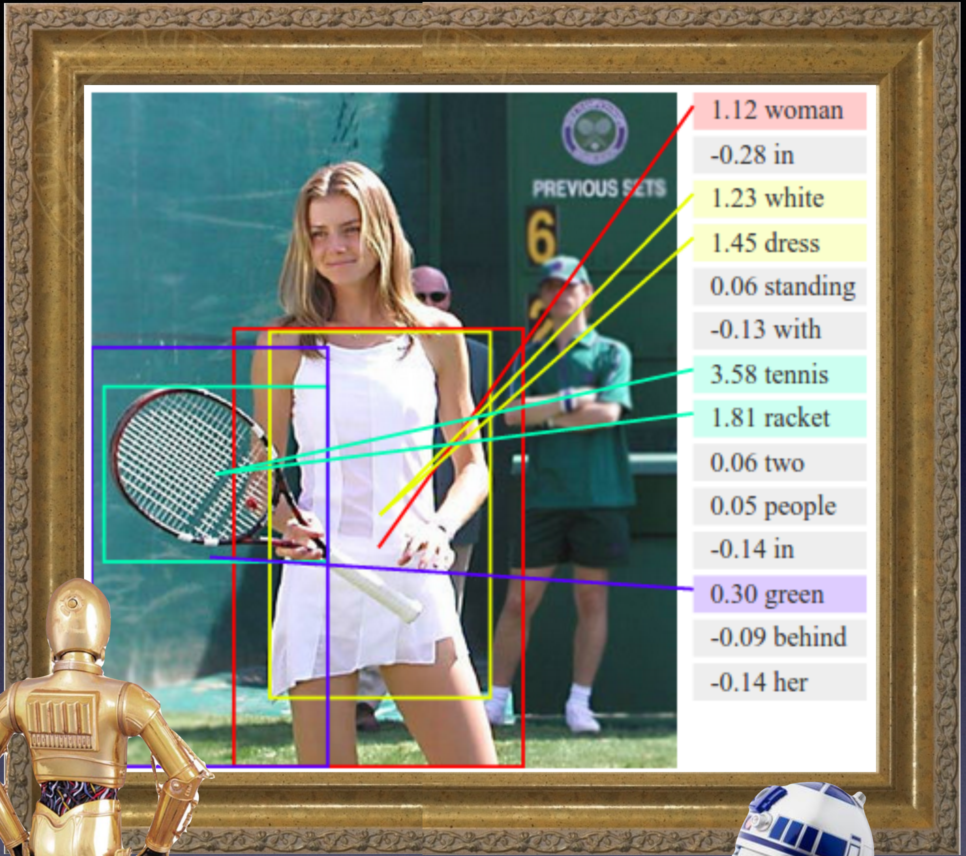
Deal with optical illusions in 2D projections
+ pattern recognitions in 3D





"Physics features" look obvious to human physicists (eyes) but hand-engineering algorithms to extract them turned out challenging…

Image context analysis



"Pose" detection

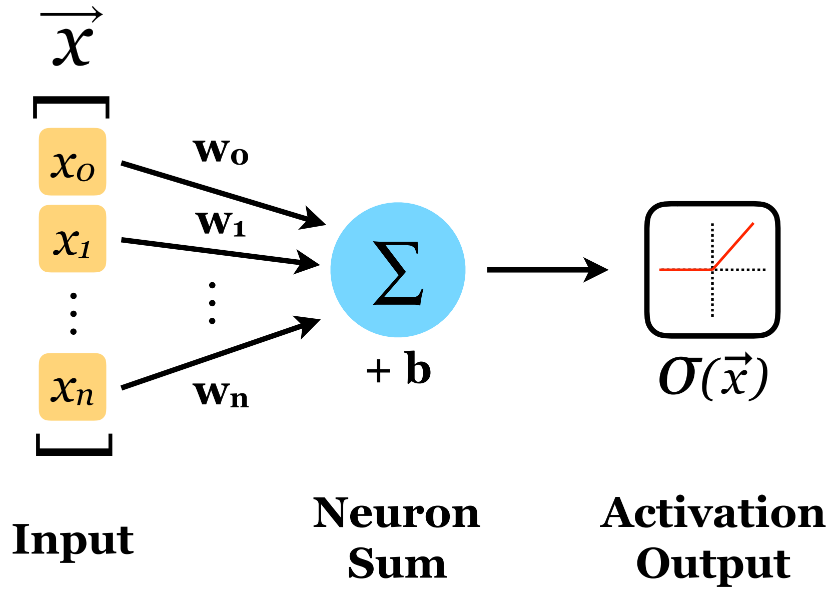
Convolutional Neural Network

~ How does it work? ~

Machine Learning Overview
Simple neural network (perceptron)

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.

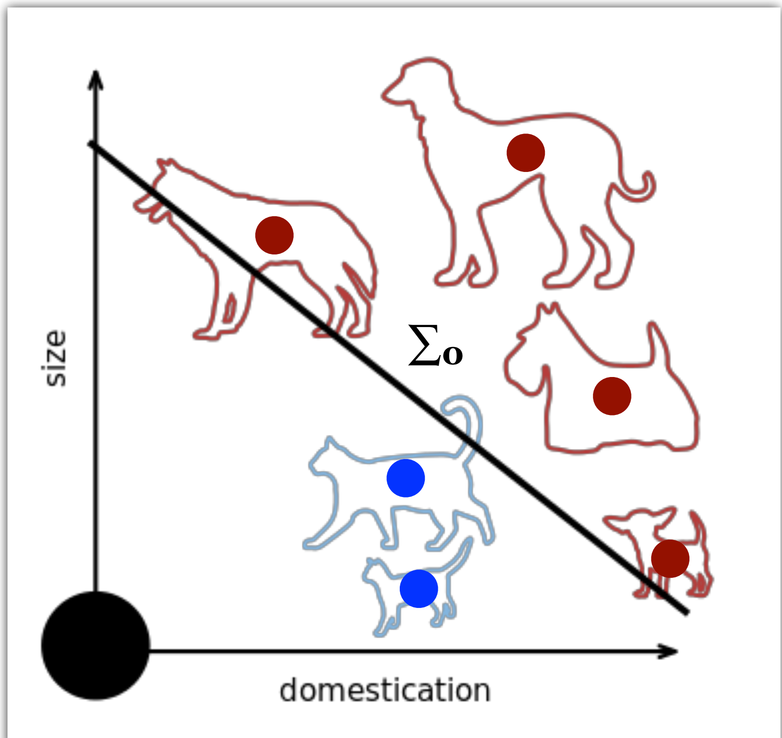


$$\sigma(\vec{x}) = \begin{cases} \vec{w}_i \cdot \vec{x} + b_i & \vec{w}_i \cdot \vec{x} + b_i \geq 0 \\ 0 & \vec{w}_i \cdot \vec{x} + b_i < 0. \end{cases}$$

Machine Learning Overview

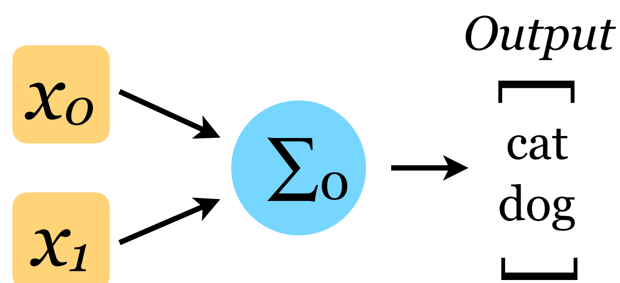
Simple neural network (perceptron)

Imagine using two features to separate cats and dogs



from [wikipedia]

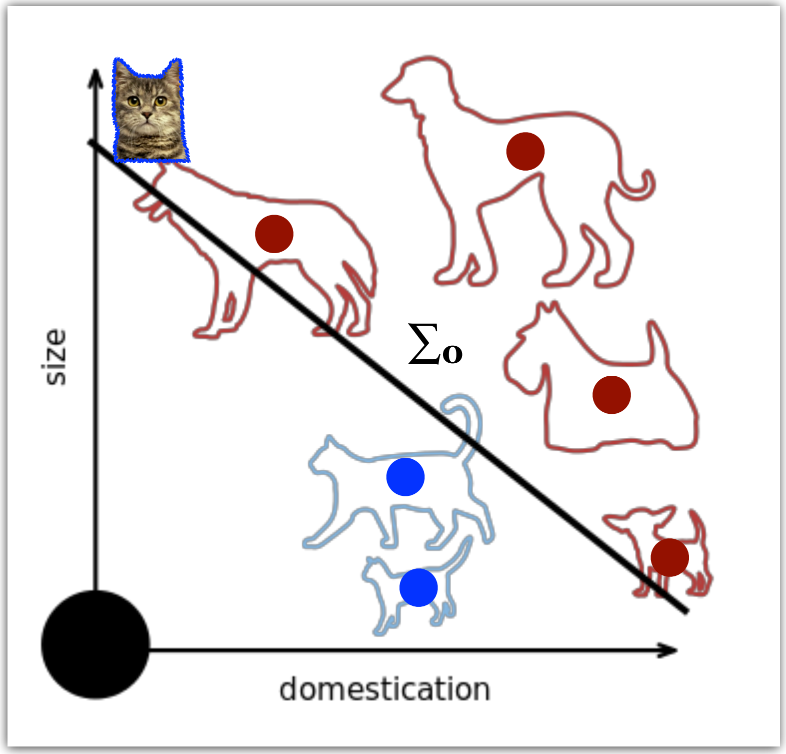
$$\sigma(\vec{x}) = \begin{cases} \vec{w}_i \cdot \vec{x} + b_i & \vec{w}_i \cdot \vec{x} + b_i \geq 0 \\ 0 & \vec{w}_i \cdot \vec{x} + b_i < 0. \end{cases}$$



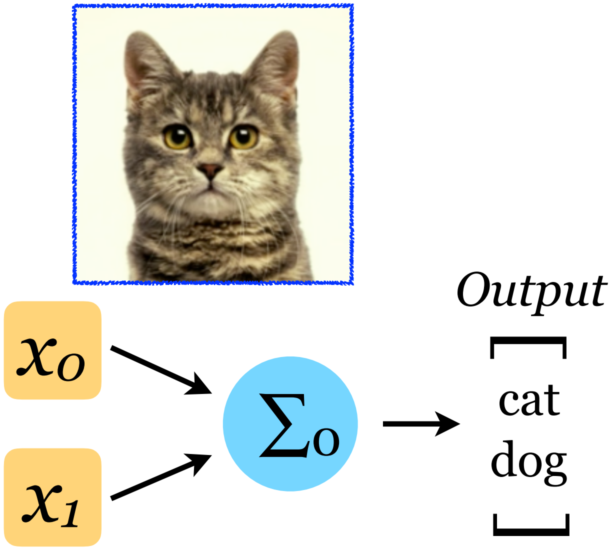
By picking a value for **w** and **b**, we define a boundary between the two sets of data

Simple neural network (perceptron)

What if we have a new data point?

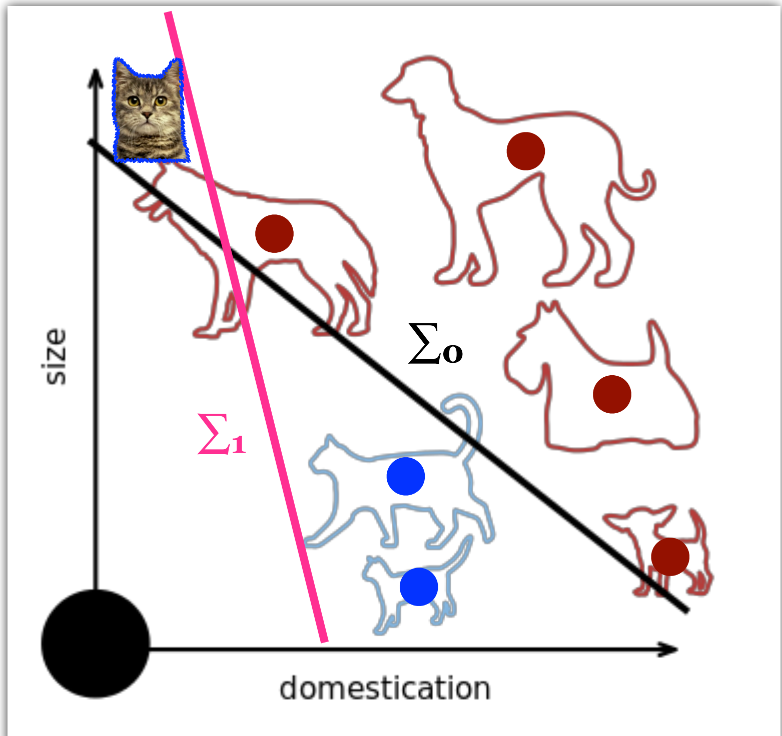


from wikipedia

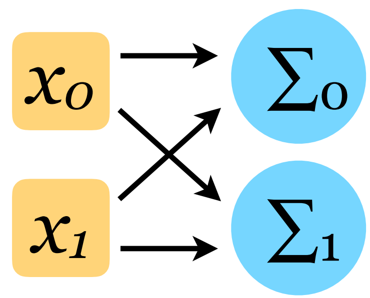


Simple neural network (perceptron)

What if we have a new data point?



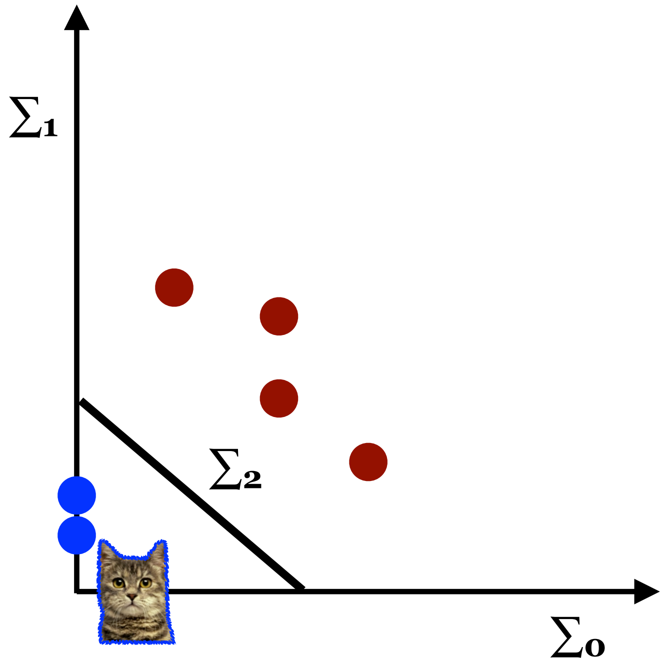
from [wikipedia]



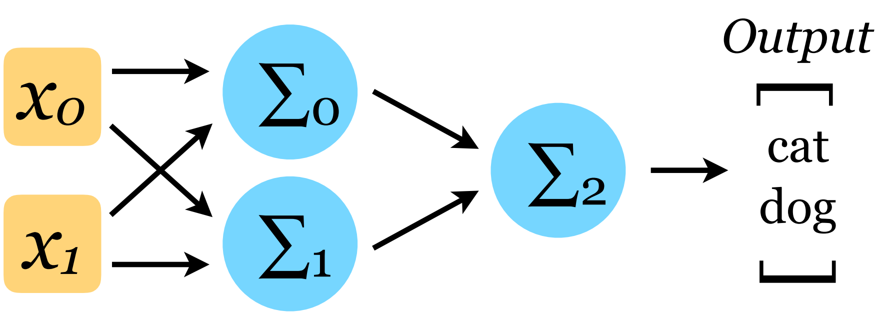
We can **add another perceptron** to help (but does not yet solve the problem)

Simple neural network (perceptron)

What if we have a new data point?



from wikipedia

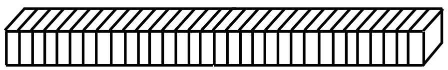


Another layer can classify based on preceding layer's output (of **non-linear activation**)

Machine Learning Overview

Back to analyzing a cat “image…”

Goal: Dog or Cat



1D array of discriminants

How?

This part can be done with a classic (fully-connected) neural network

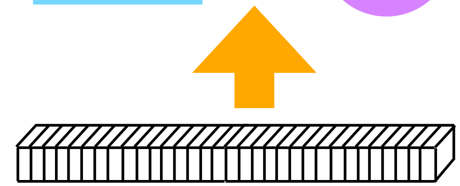
How can we extract “features” from “image”?

... the hard part ...

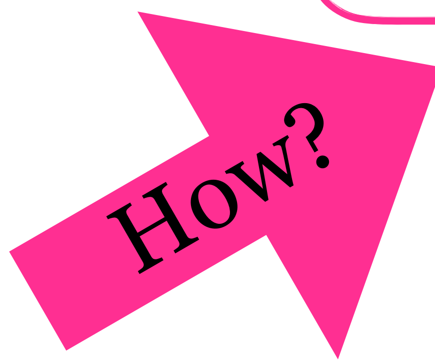
(where I have failed for long)

Machine Learning Overview
Back to analyzing a cat "image…"

Goal: Dog or Cat



1D array of discriminants



This part can be done with a classic (fully-connected) neural network

How can we extract "features" from "image"?

Convolutional Neural Network

Machine Learning Overview

Convolutional Neural Network (CNN)

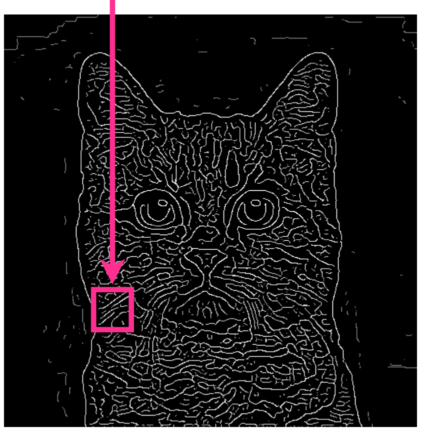
convolutional filter **(kernel)**

0	1	0
0	2	0
0	1	0

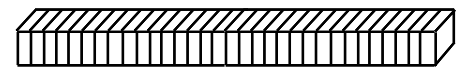
"weights"

$\otimes$ **"neuron sum"**

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



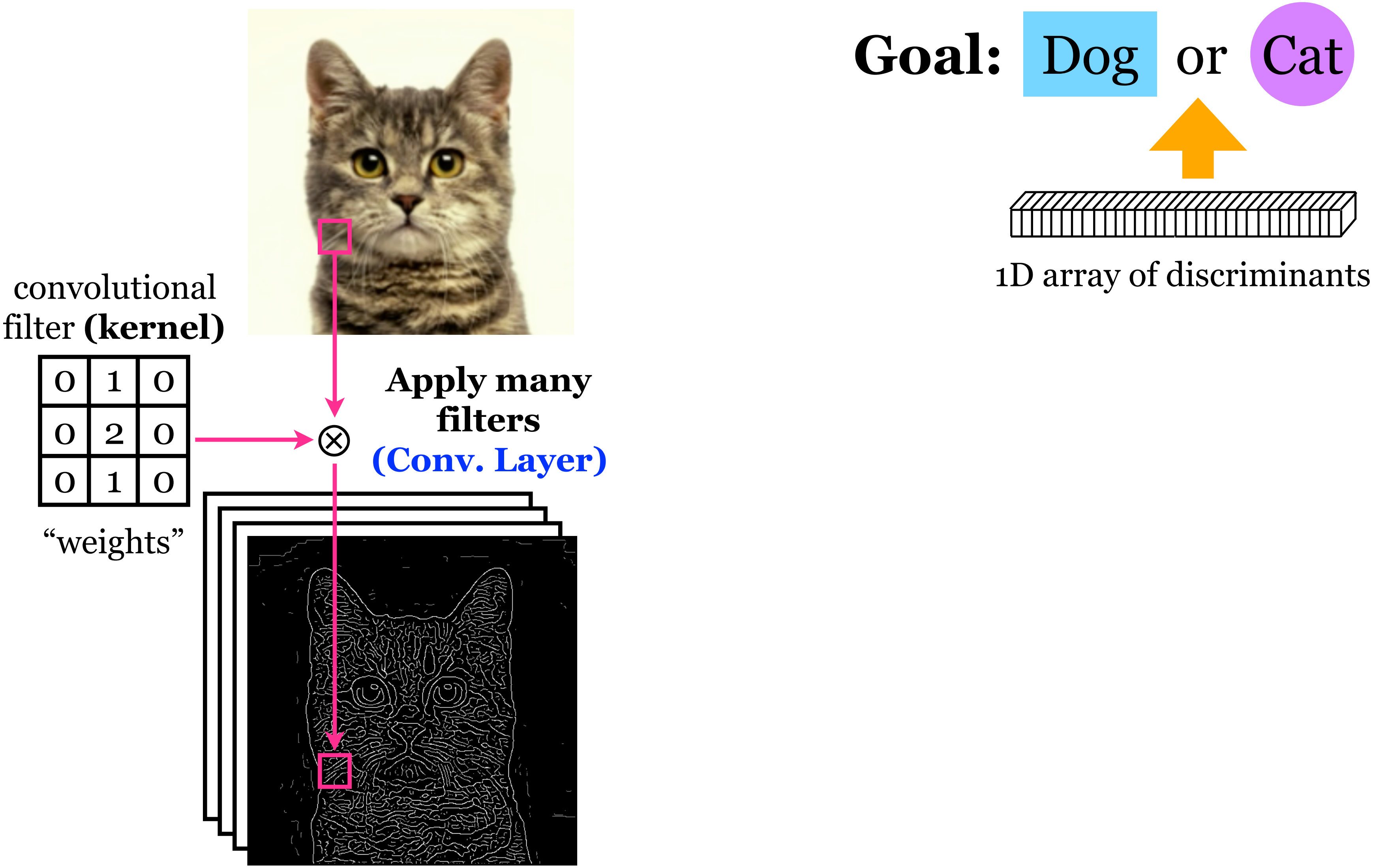
Goal: Dog or Cat



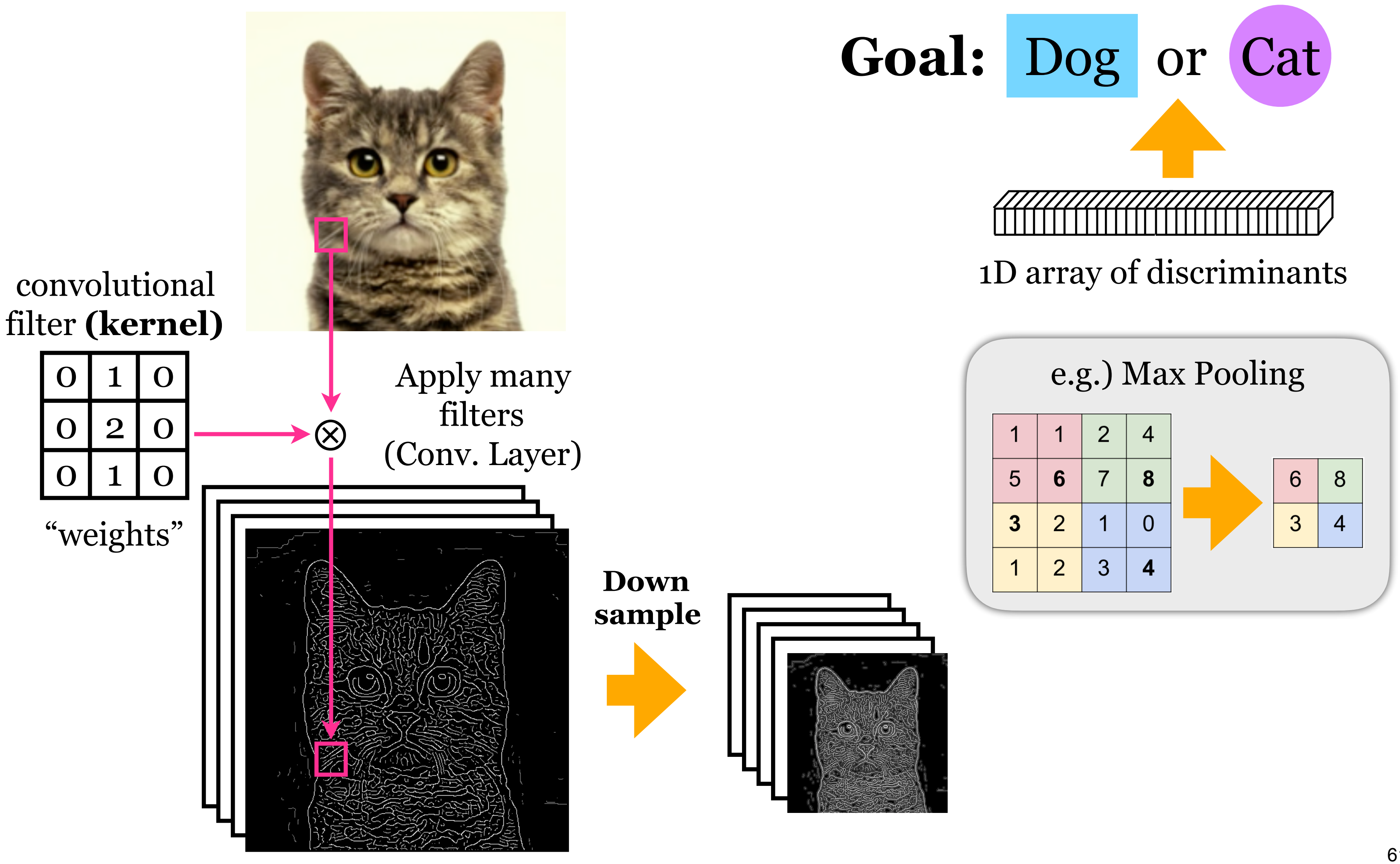
1D array of discriminants

Machine Learning Overview

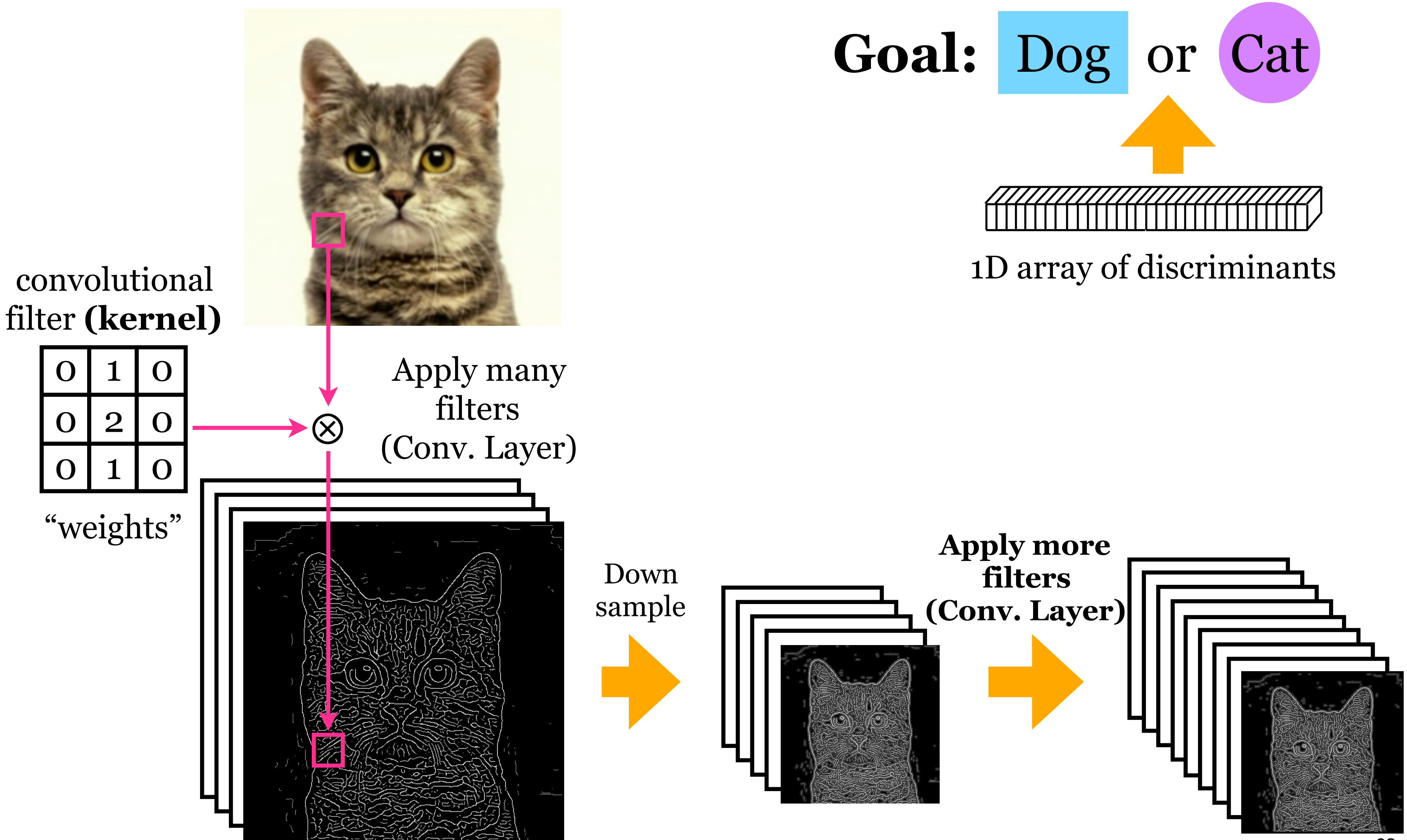
Convolutional Neural Network (CNN)



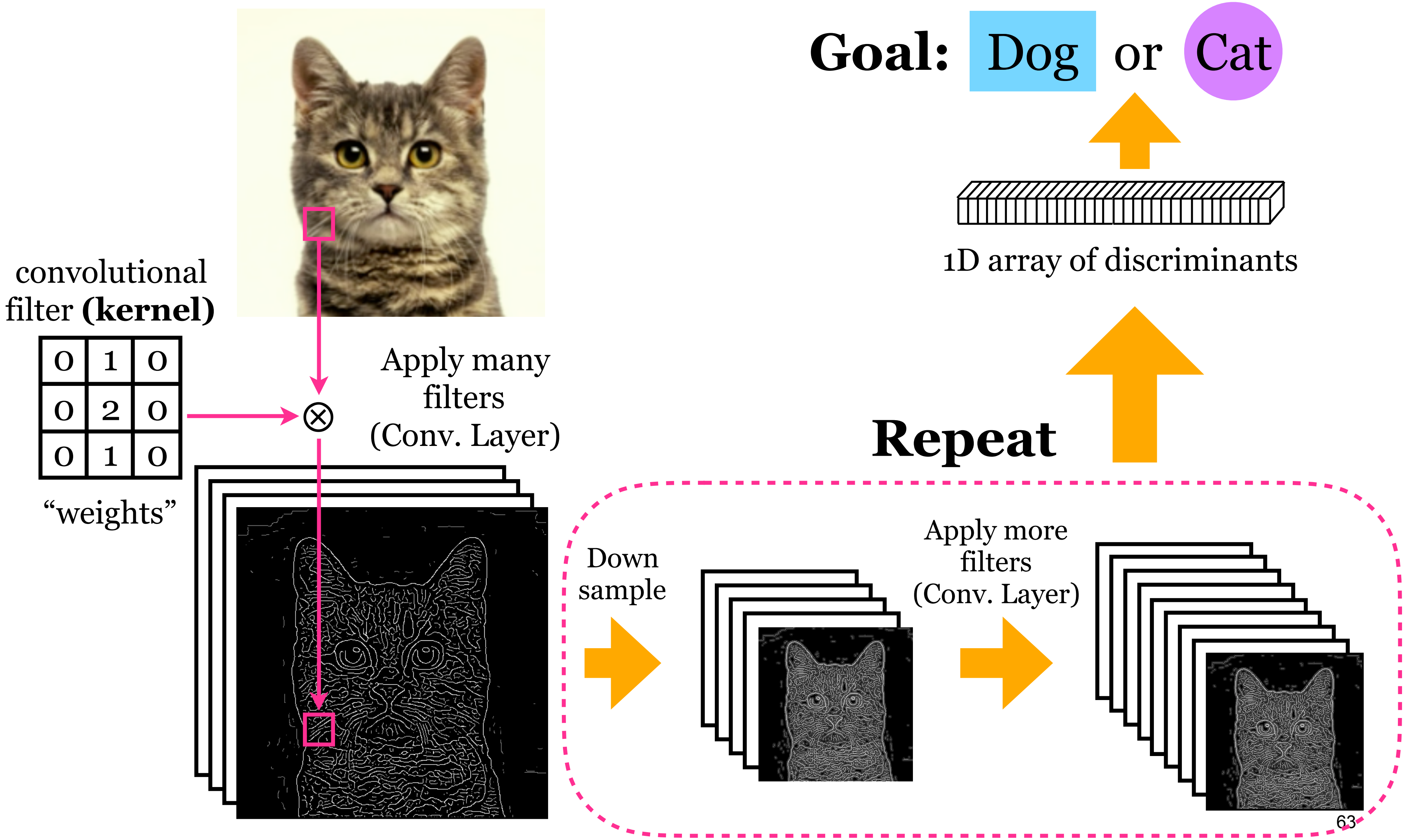
Machine Learning Overview
Convolutional Neural Network (CNN)



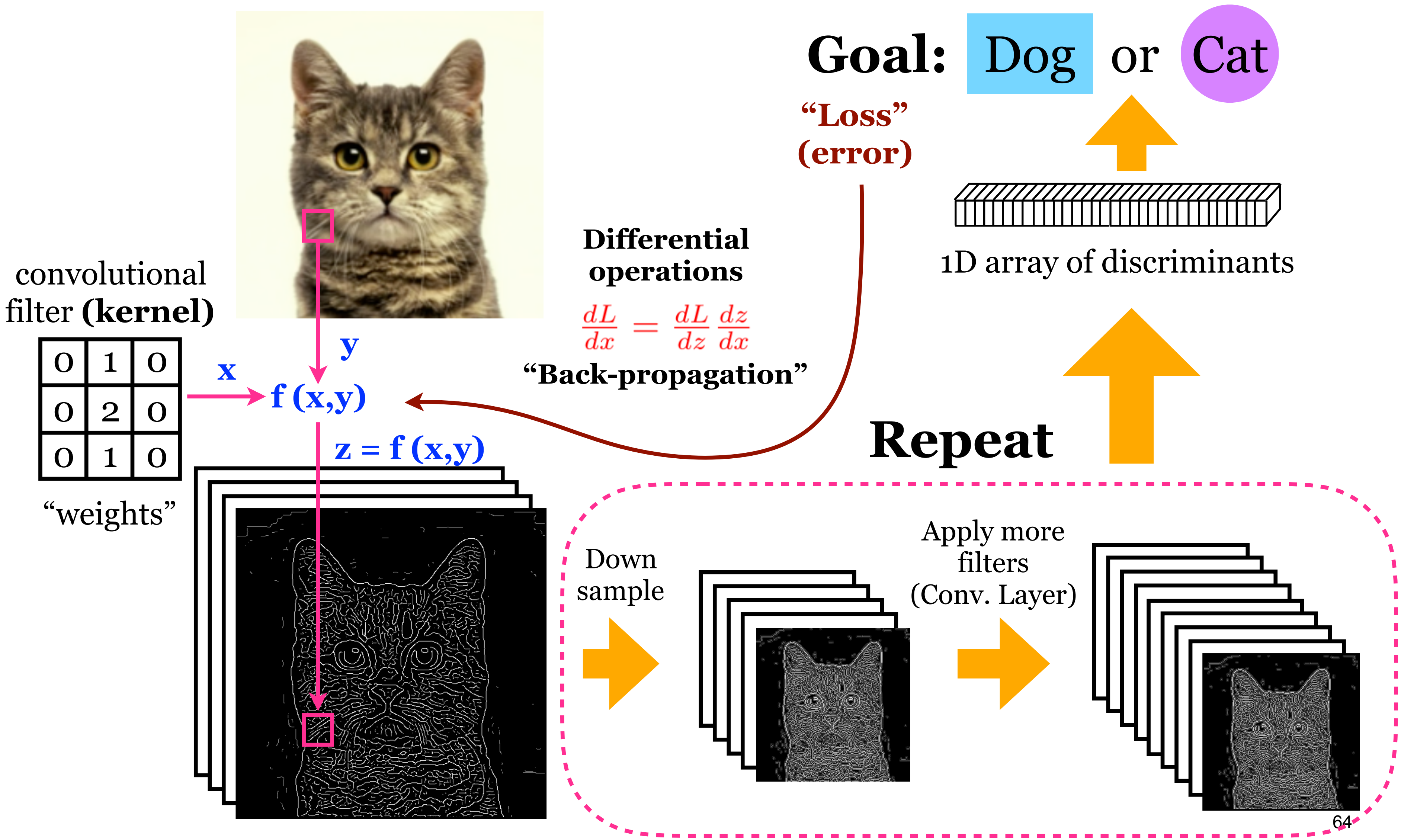
Machine Learning Overview
Convolutional Neural Network (CNN)



Machine Learning Overview
Convolutional Neural Network (CNN)

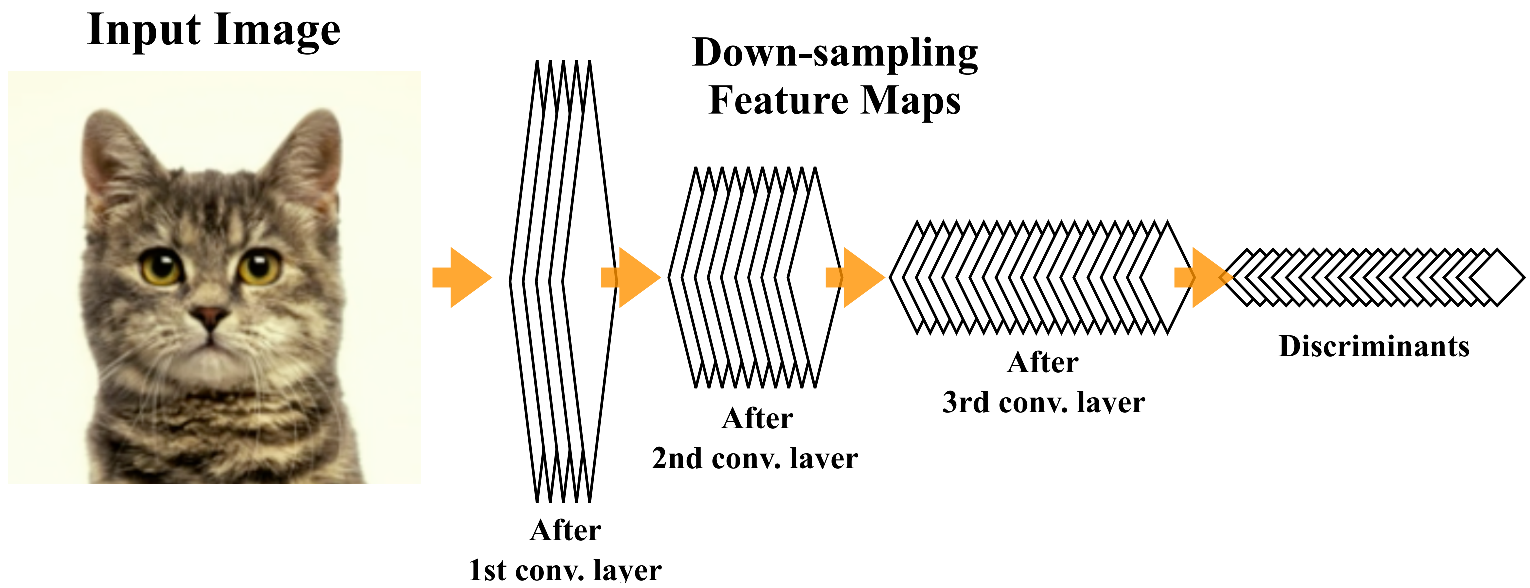


Supervised Training of CNN

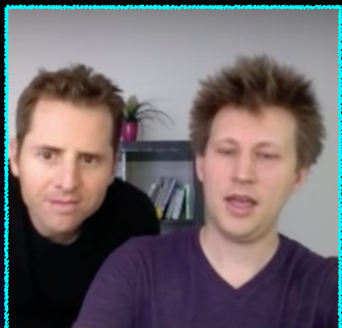


Summarizing CNNs

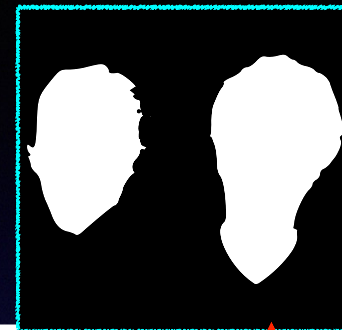
- **CNNs are "feature extraction machine"**
  - Consists of "convolution layers" with "kernels"
  - A chain of linear algebra operations = "massively parallel"
    - Suited for acceleration using many-core hardwares (e.g. GPUs)
- **CNN: data ⇔ distribution "Mapping"** (transformation)

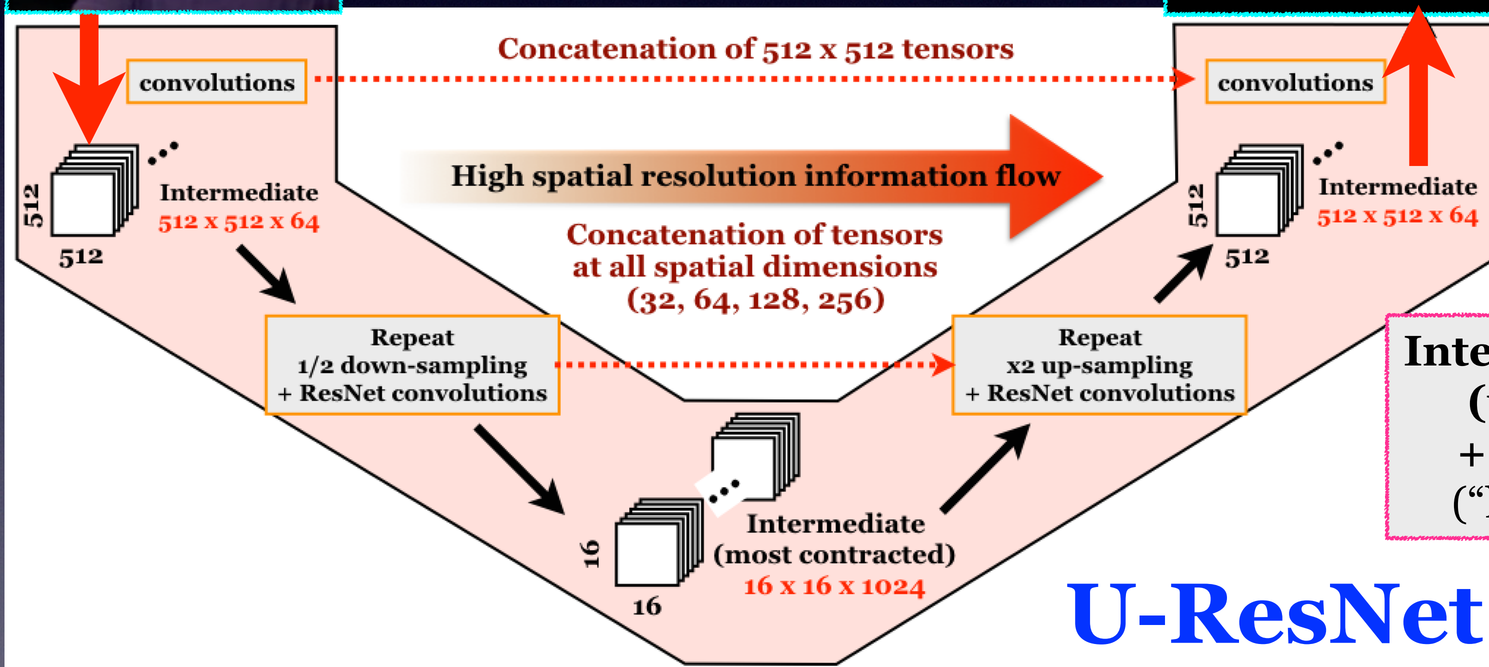


DNN for LArTPC Data Reconstruction

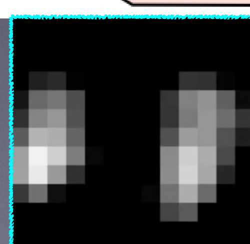


How does U-ResNet Work?





Interpolation filters (up-sampling) + Convolutions
("learnable" filter)



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

Validation with real data

Benchmarking SSNet w/ Real Data

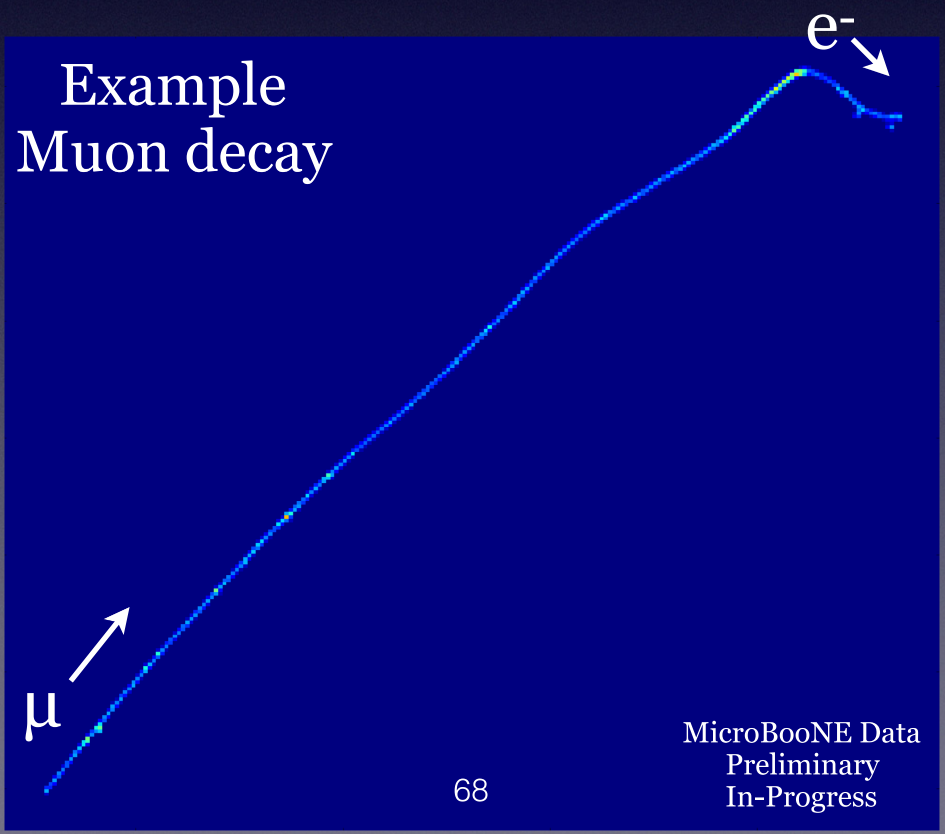
Samples (100 images per sample per sim/data)

A cosmic ray muon decay

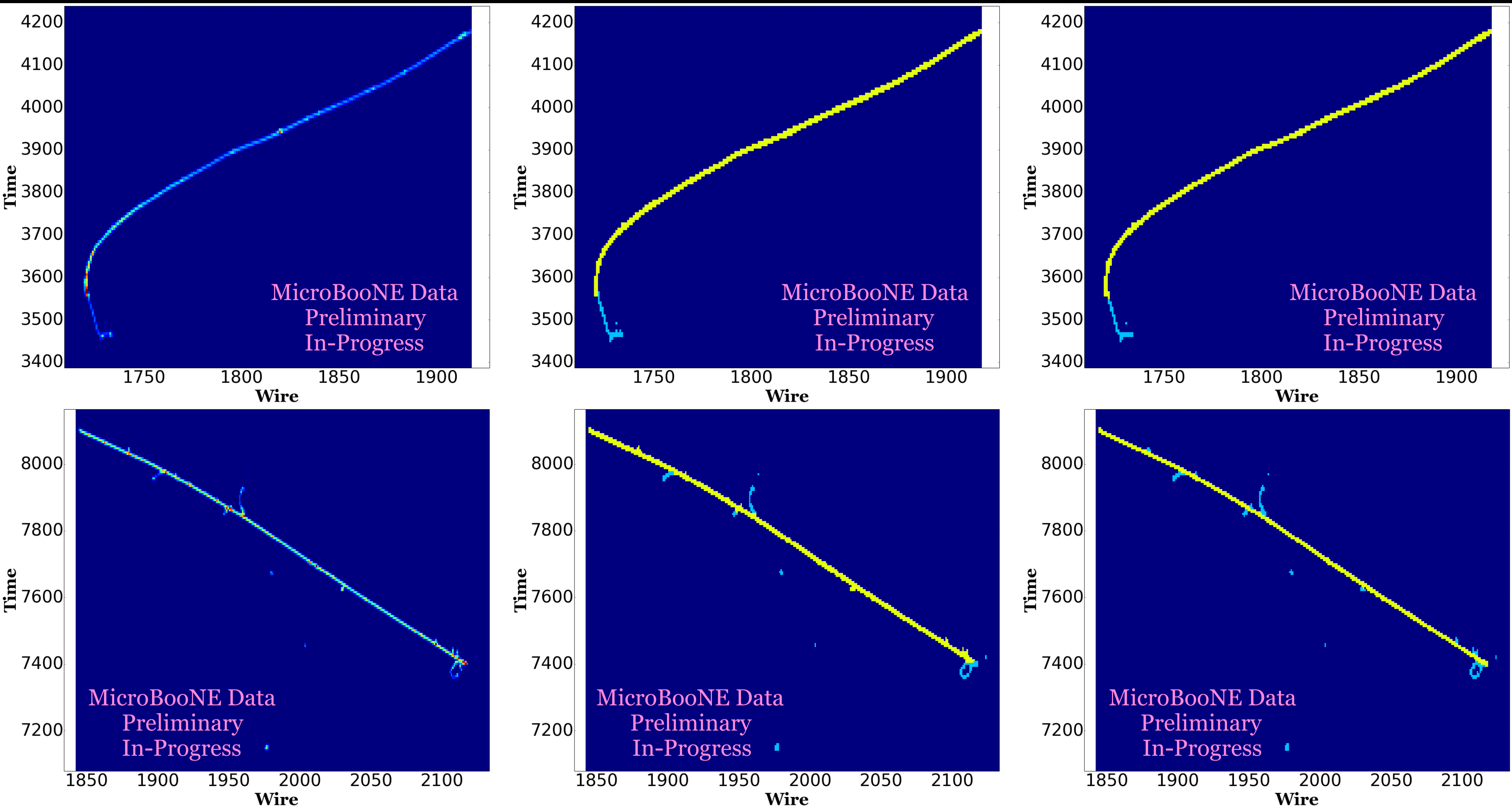
- Involves both "track" and "shower", simple and intuitive.

Neutrino interactions

- More complicated: varying particle types and multiplicity

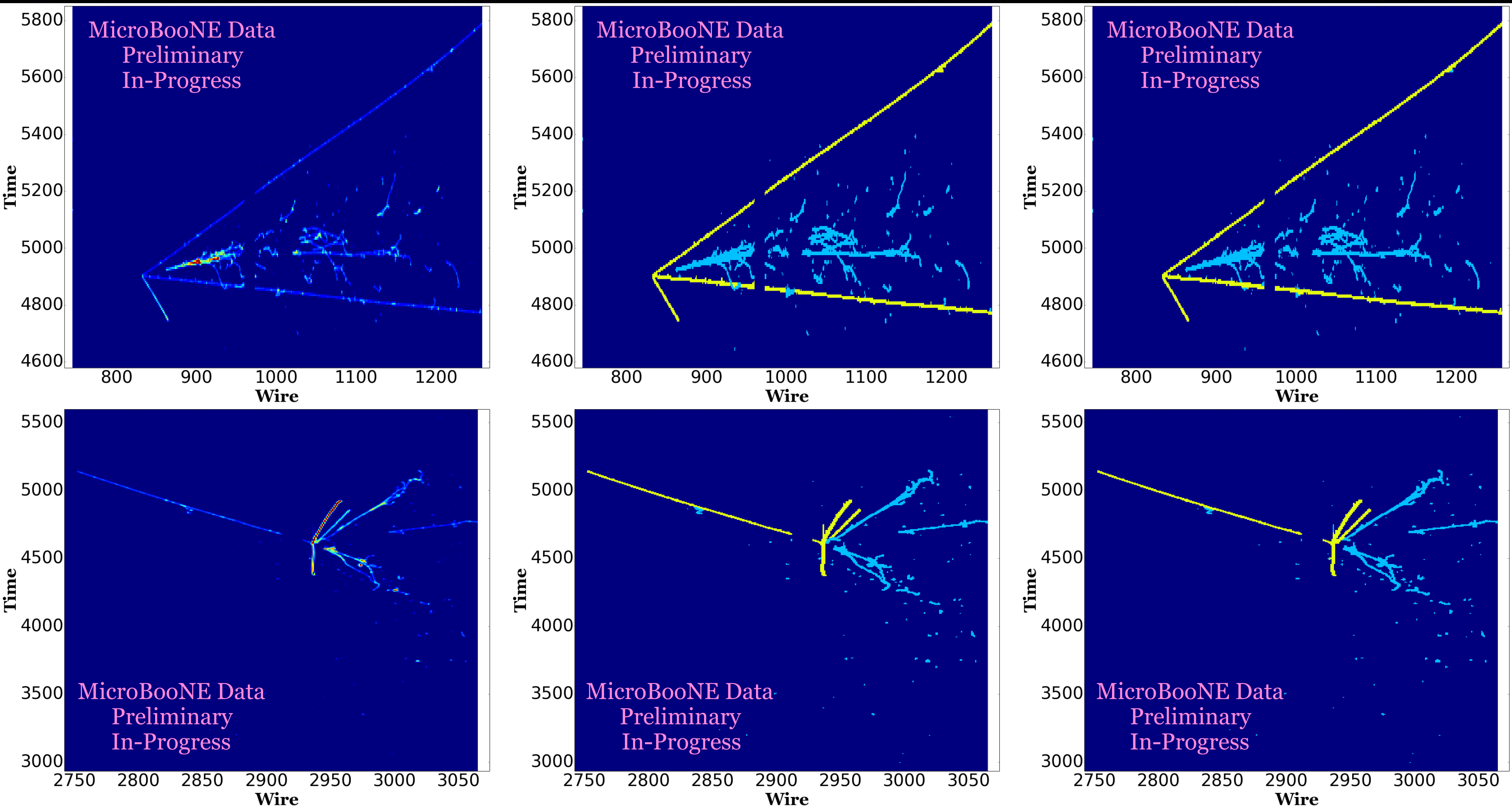


Decay Muons: Example Displays



Input Image　　Human Label　　SSNet Label

4 Visually Picked “Busy Neutrino Events”



Input Image Human Label SSNet Label

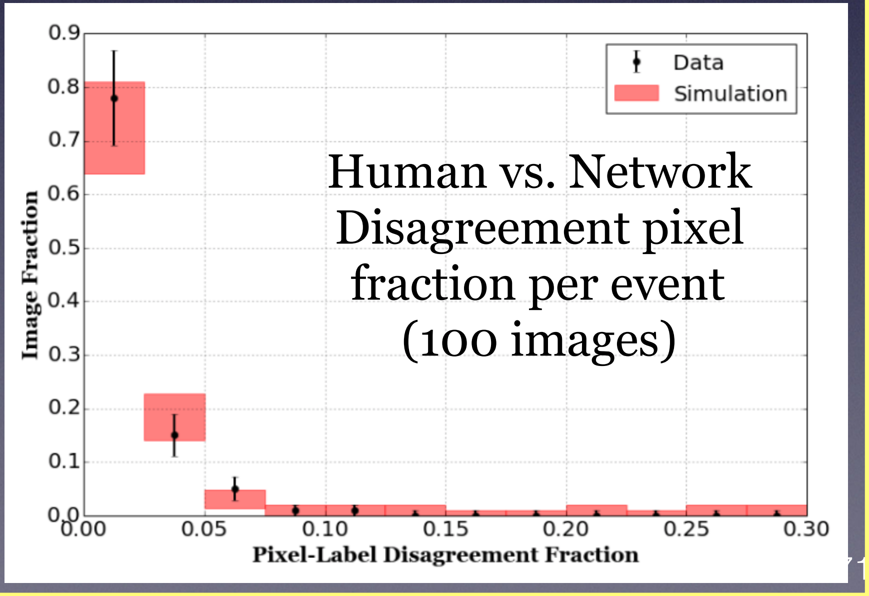
Overall Performance

- **Data/Simulation agreement within statistical error**
  - No systematic error included
- **Network does better than a human** analyzer (sim.)

Muon Decay

Disagreement rate mean/std in %

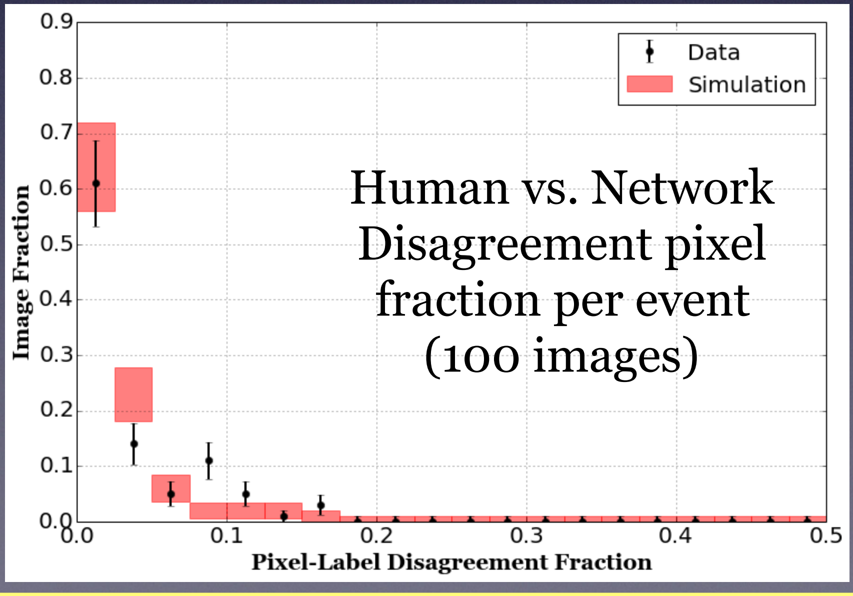
Sample	Data	Simulation	Simulation	Simulation
Label	Physicist	Physicist	Simulation	Simulation
Prediction	U-Resnet	U-ResNet	U-ResNet	Physicist
ICPF mean	1.8	2.6	2.5	2.3
ICPF 90%	3.3	4.4	4.5	3.1
Shower	6.2	5.7	4.0	3.9
Track	1.1	1.9	1.6	1.3



Neutrino w/ Gamma

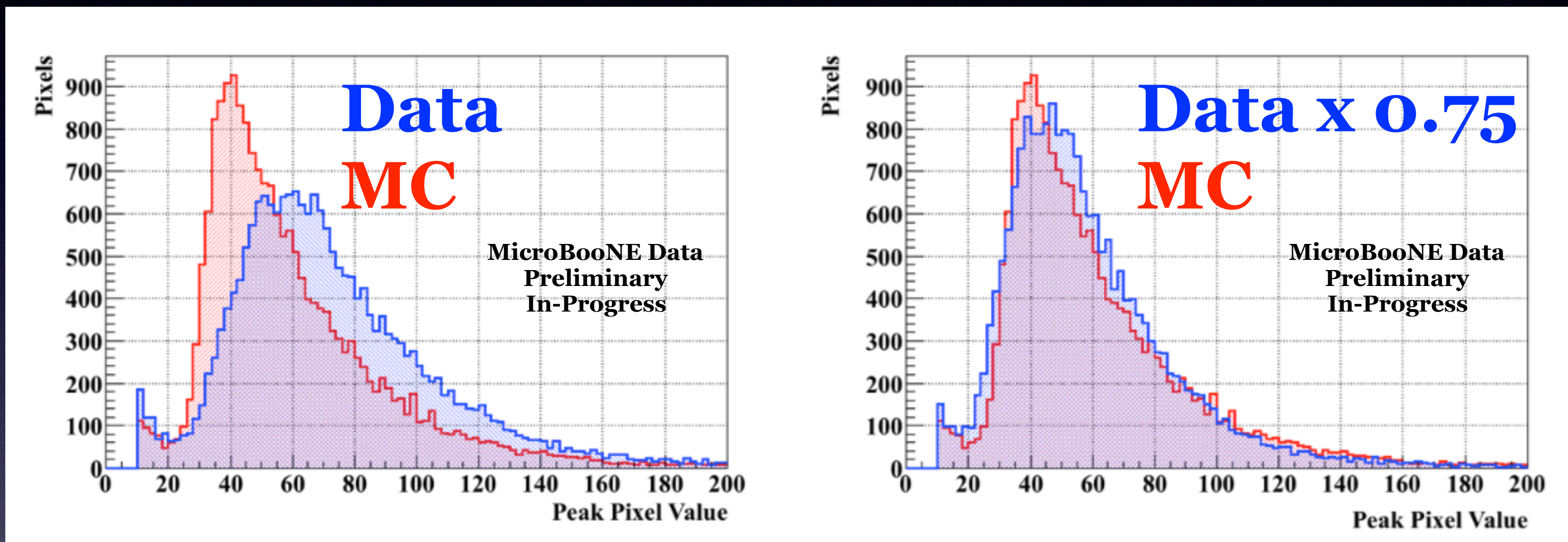
Disagreement rate mean/std in %

Sample	Data	Simulation	Simulation	Simulation
Label	Physicist	Physicist	Simulation	Simulation
Prediction	U-ResNet	U-ResNet	U-ResNet	Physicist
ICPF mean	3.4	2.5	1.8	2.0
ICPF 90%	9.0	5.7	4.6	4.8
Shower	4.8	3.4	3.0	2.6
Track	2.7	2.4	2.2	2.9



Decay Muons: Pixel Value Variation

Studied how network performance varies when pixel values are scaled by a constant factor



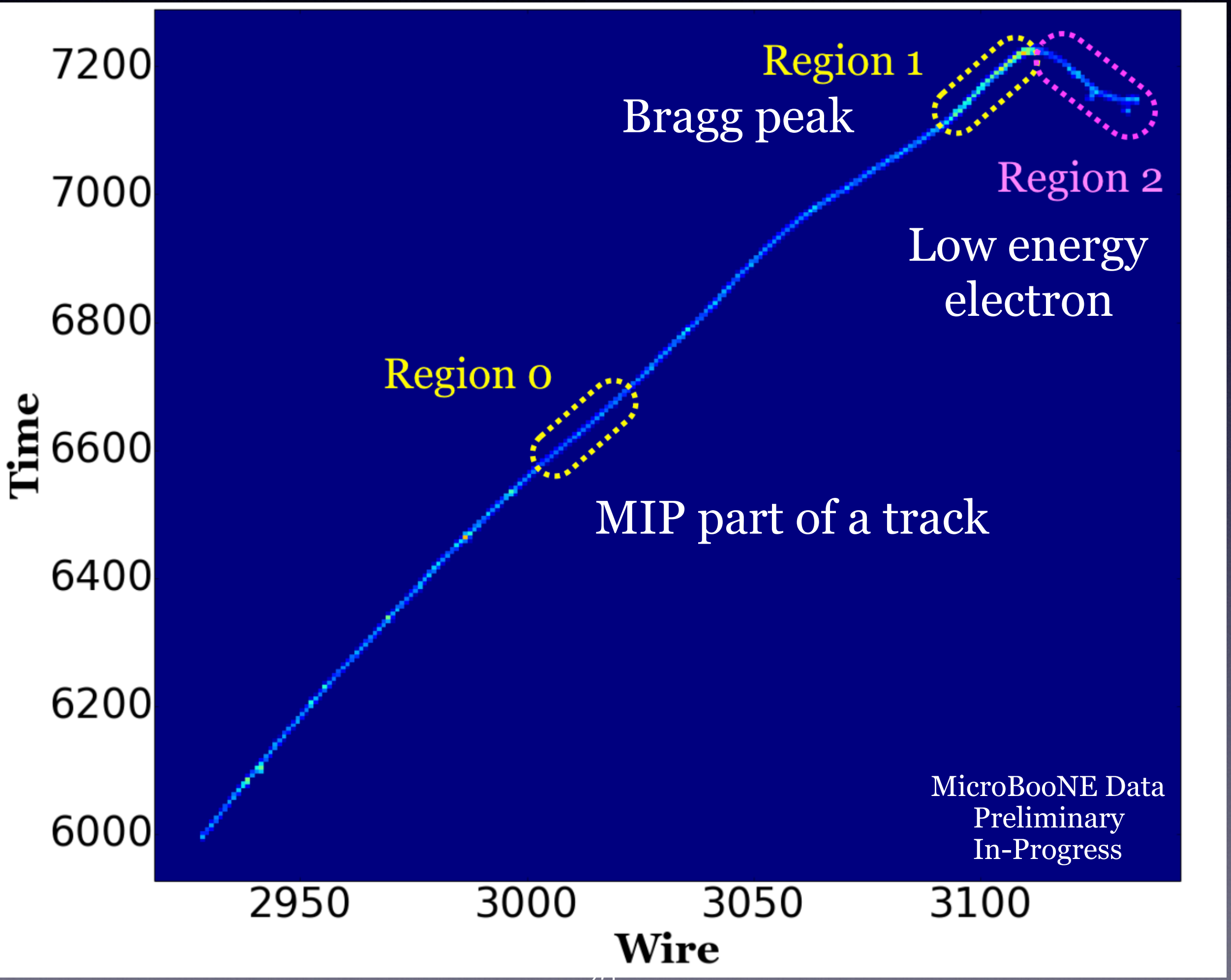
No scaling

Scaling Factor	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
Track	2.38	2.11	1.93	1.65	1.40	1.14	1.16	1.20	1.26	1.28	1.32
Shower	5.24	5.22	5.41	6.02	6.11	6.16	6.11	6.14	6.21	6.28	6.34
Combined	2.75	2.53	2.40	2.21	2.02	1.81	1.85	1.89	1.96	2.00	2.04

Change in the mean error rate is within 1% when pixel values are scaled within 20%, fairly robust

Decay Muons: Inter-Pixel Correlation

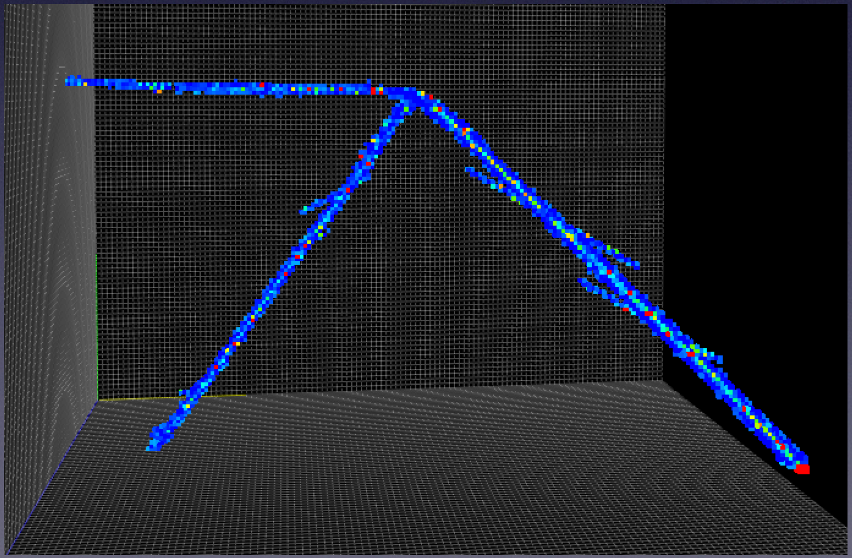
Study, qualitatively, how network reacts to interesting portions of an image

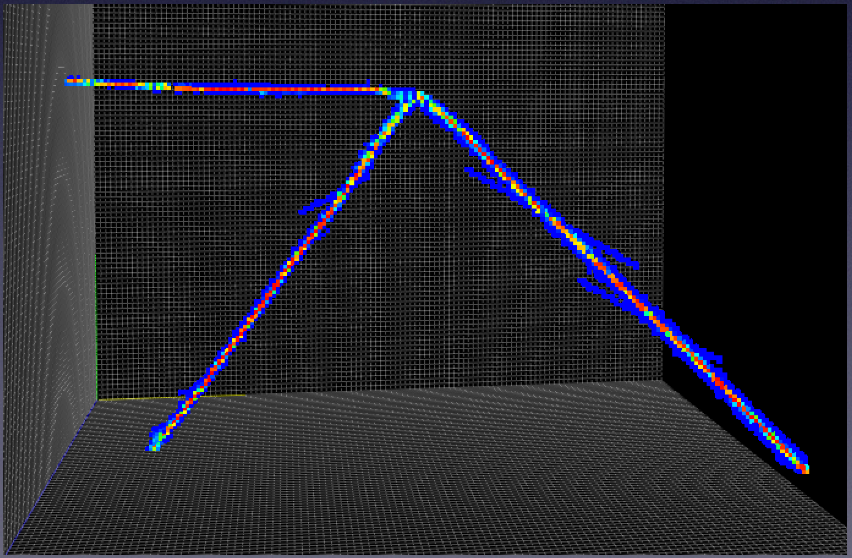


3D Data Reconstruction @ SLAC

Tracy Usher

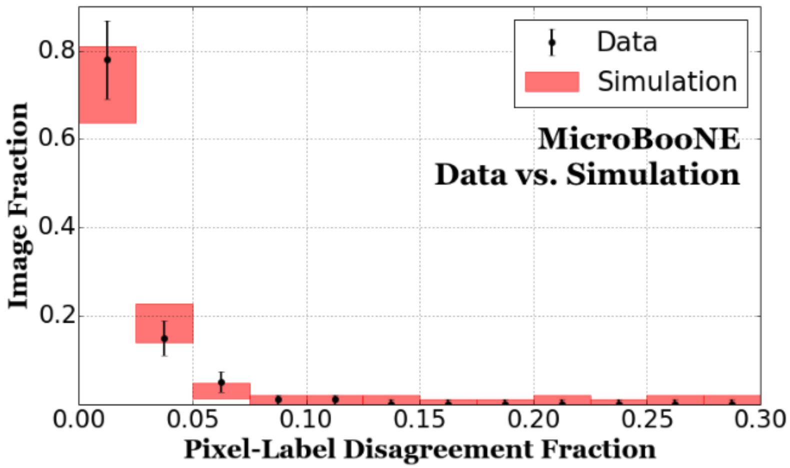
- Showing ML can be started above age of 60





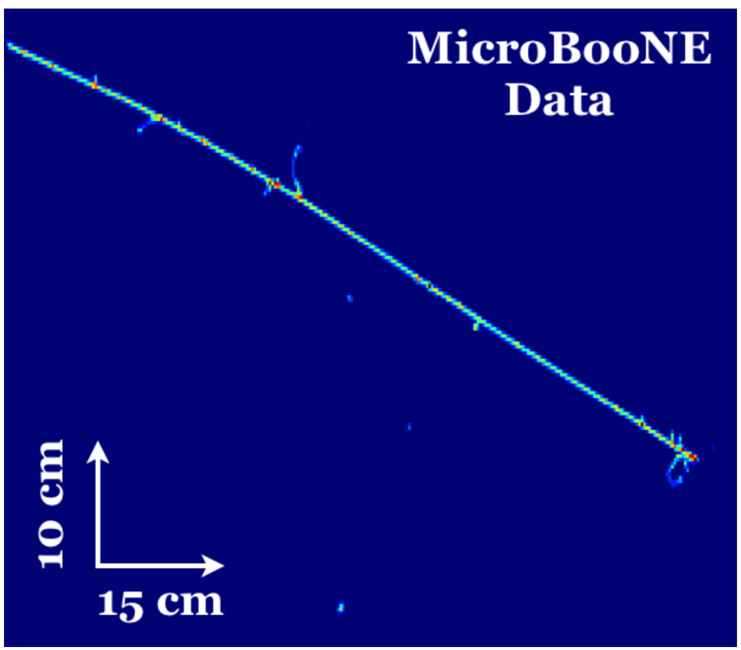
Tracy shows you can start ML above age of 60

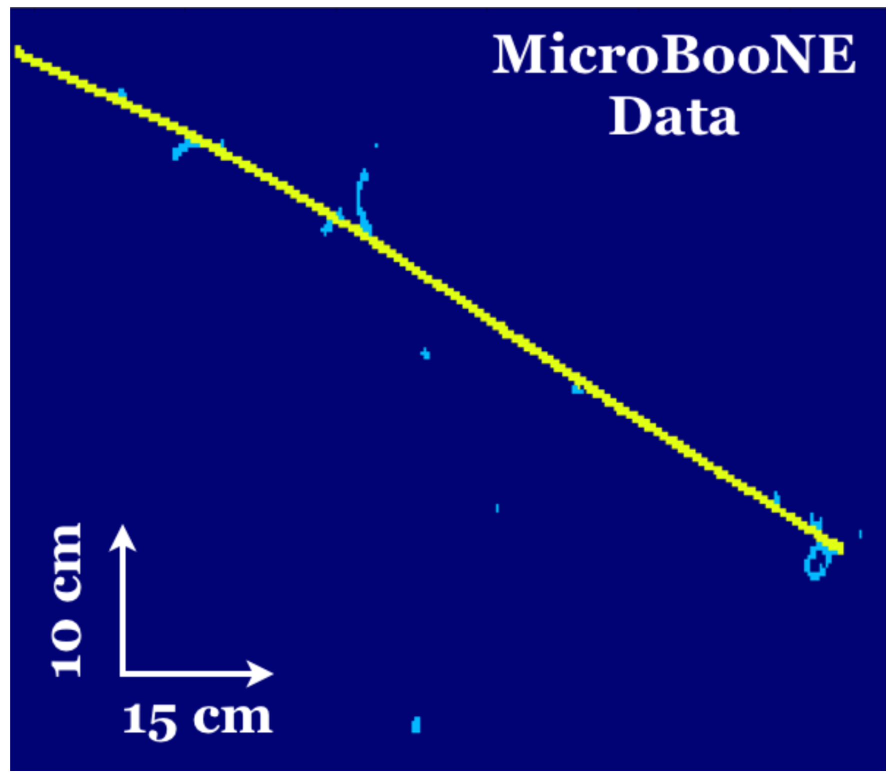
Progress Report
Machine Learning & Data Reconstruction



Technique Validation on Data

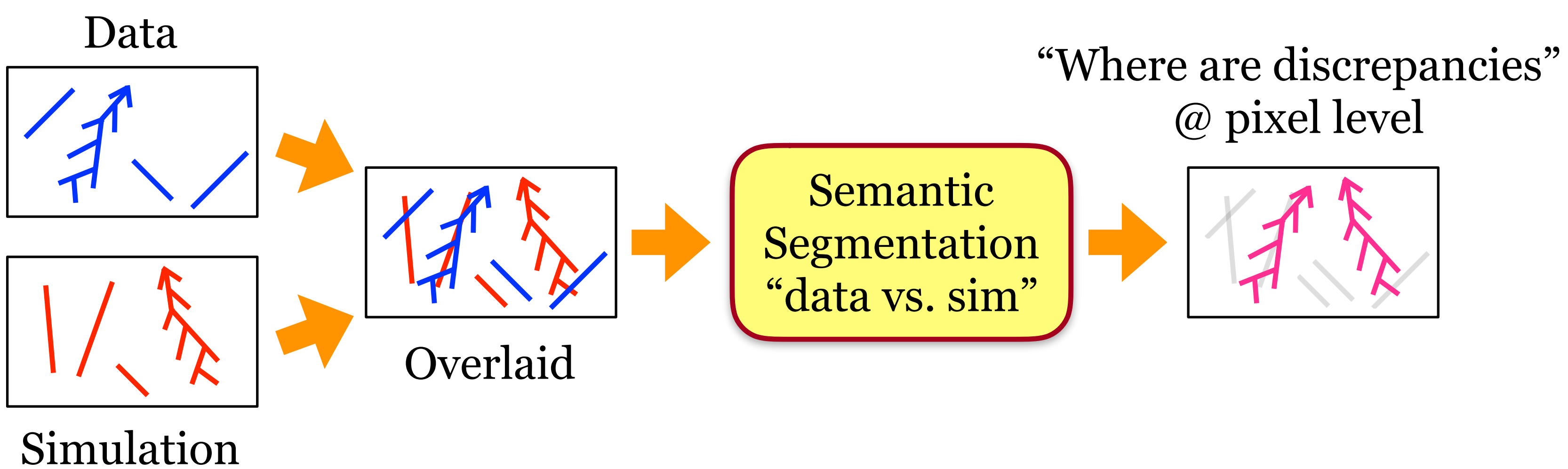
- Same paper … [arXiv:1808.07269](https://arxiv.org/abs/1808.07269)
  - Important for new techniques such as this
- Compared physicist vs. network predictions





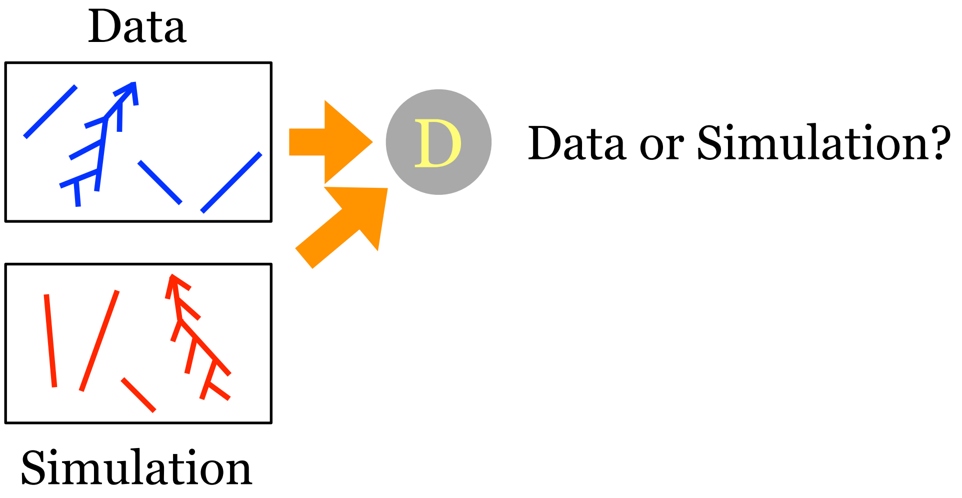
What can we do about imperfect simulation?

- **Problematic**: the “signal distribution” learnt by the algorithm may be different in two domains!
- **Mitigation techniques** in ML domain?
  - **Can** try CNN to “locate” where it is



What can we do about imperfect simulation?

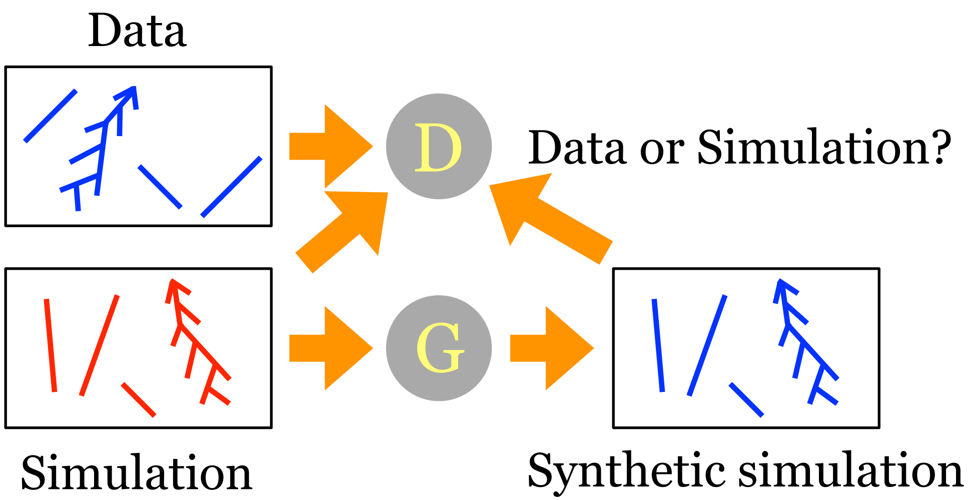
- **Problematic**: the "signal distribution" learnt by the algorithm may be different in two domains!
- **Mitigation techniques** in ML domain?
  - **Can** try CNN to "locate" where it is
  - **Can** try CNN to "fix" the discrepancy



Drawbacks of supervised learning & mitigations

What can we do about imperfect simulation?

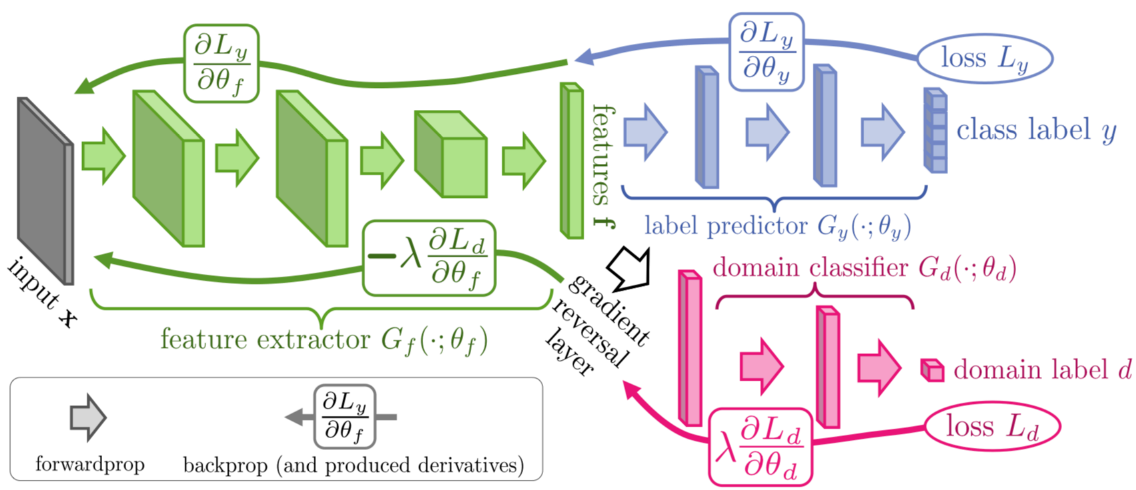
- **Problematic**: the "signal distribution" learnt by the algorithm may be different in two domains!
- **Mitigation techniques** in ML domain?
  - **Can** try CNN to "locate" where it is
  - **Can** try CNN to "fix" the discrepancy



Generative Adversarial Network
Can learn the "mapping" between the data and simulation "distributions". The generator network can be used as a synthetic image generator to train different neural networks

What can we do about imperfect simulation?

- **Problematic**: the "signal distribution" learnt by the algorithm may be different in two domains!
- **Mitigation techniques** in ML domain?
  - **Can** try CNN to "locate" where it is
  - **Can** try CNN to "fix" the discrepancy
  - **Can** try a training technique to minimize the effect



Maximize the loss for discriminate data vs. simulation, feature extractors are penalized to key on simulation specific information

Minerva Paper arXiv:1808.08332

Domain-Adversarial Training of Neural Networks
J. Mach. Learn. Res. 17 (2016)