中国科学院近代物理研究所
Institute of Modern Physics, Chinese Academy of Sciences

AI/ML在中微子实验中的应用

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IMP, CAS

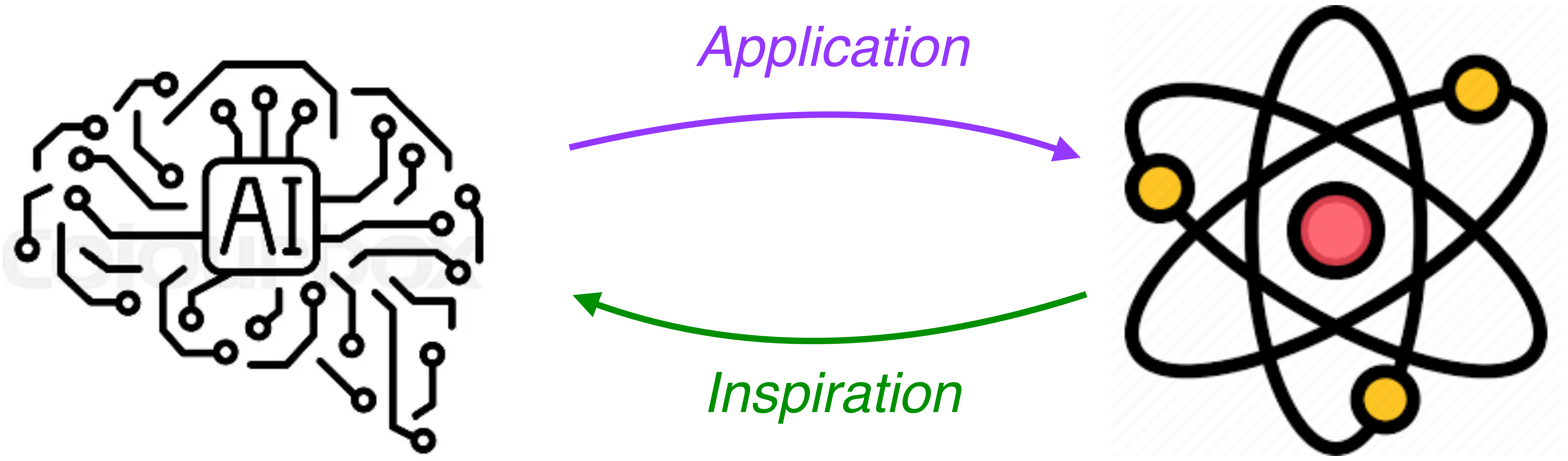
第一届中微子、原子核物理和新物理研讨会 · 兰州

2025/7/24

Machine Learning in PP/NP

- The ongoing revolution in the field of AI/ML has significantly influenced the particle physics and nuclear physics community

- The applications include but not limited to
  - Operation of accelerators and detector systems: beam monitoring, trigger, anomaly detection, automatic shift, etc
  - Improving sensitivity by extracting more information from data: simulation and reconstruction
  - Improving Monte Carlo calculations for lattice QCD
  - ……



- Non-uniform detector geometries
- Sparse data with high dynamic range
…

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Machine Learning in NOvA and DUNE

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A convolutional neural network neutrino event classifier

PHYSICAL REVIEW D **99,** 012011 (2019)

Improved energy reconstruction in NOvA with regression convolutional neural networks

PHYSICAL REVIEW D **100,** 073005 (2019)

Context-enriched identification of particles with a convolutional network for neutrino events

Interpretable Joint Event-Particle Reconstruction for Neutrino Physics at NOvA with Sparse CNNs and Transformers

Alexander Shmakov [*1] **Alejandro Yankelevich** [*2] **Jianming Bian** [2] **Pierre Baldi** [1] **for the NOvA Collaboration**

PHYSICAL REVIEW D **102,** 092003 (2020)

Neutrino interaction classification with a convolutional neural network in the DUNE far detector

Deep-Learning-Based Kinematic Reconstruction for DUNE

Eur. Phys. J. C (2022) 82:903
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THE EUROPEAN PHYSICAL JOURNAL C
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Regular Article - Experimental Physics

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THE EUROPEAN PHYSICAL JOURNAL C
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Regular Article - Computing, Software and Data Science

Neutrino interaction vertex reconstruction in DUNE with Pandora deep learning

DUNE Collaboration

A lot yet to be published

Machine Learning in NOvA and DUNE

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PRL **118,** 231801 (2017) — PHYSICAL REVIEW LETTERS — week ending 9 JUNE 2017

Constraints on Oscillation Parameters from ν_e Appearance and ν_μ Disappearance in NOvA

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Improve

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F. Psihas,[1,3] E. Niner,[2] M. Groh,[3] R. Murphy,[3] A. Aurisano,[4] A. Himmel,[2] K. Lang,[1]

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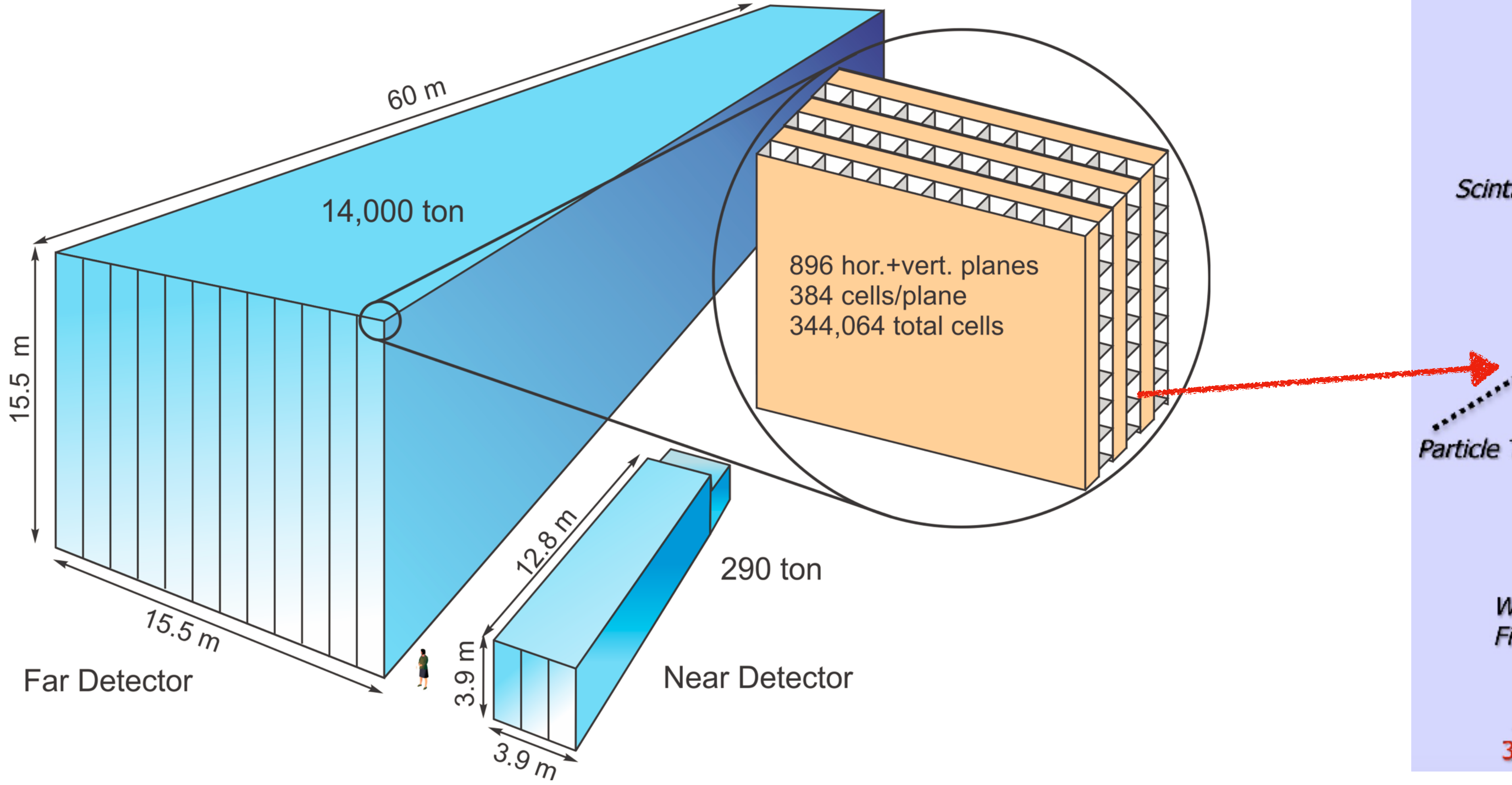
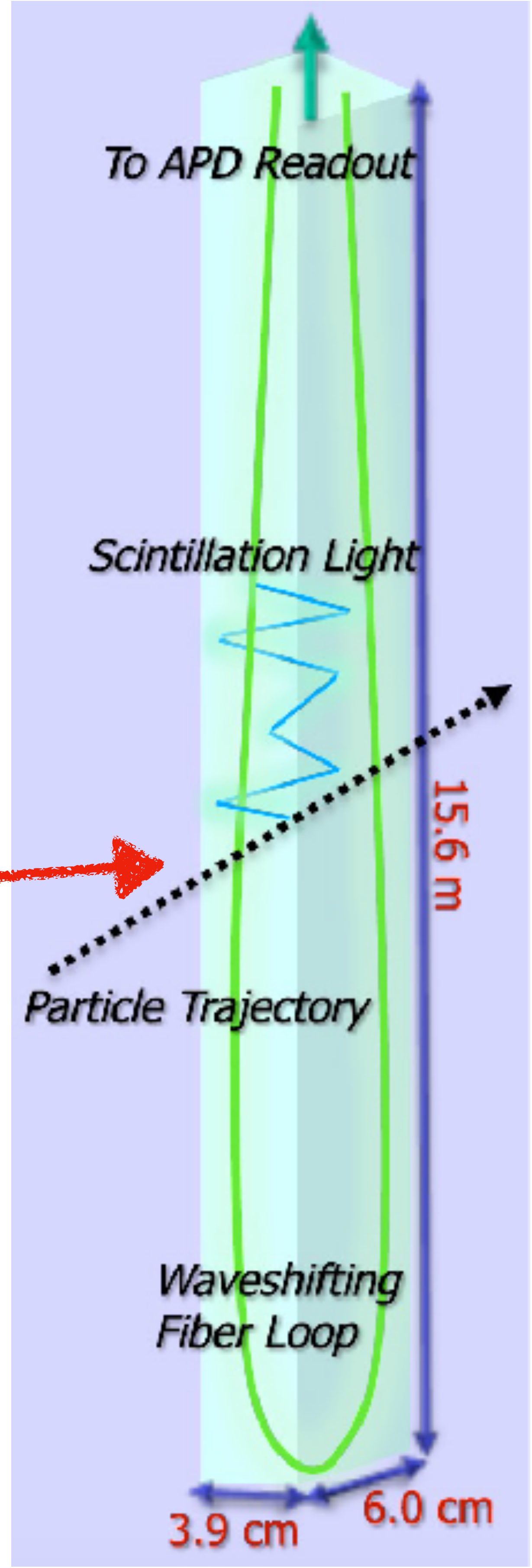
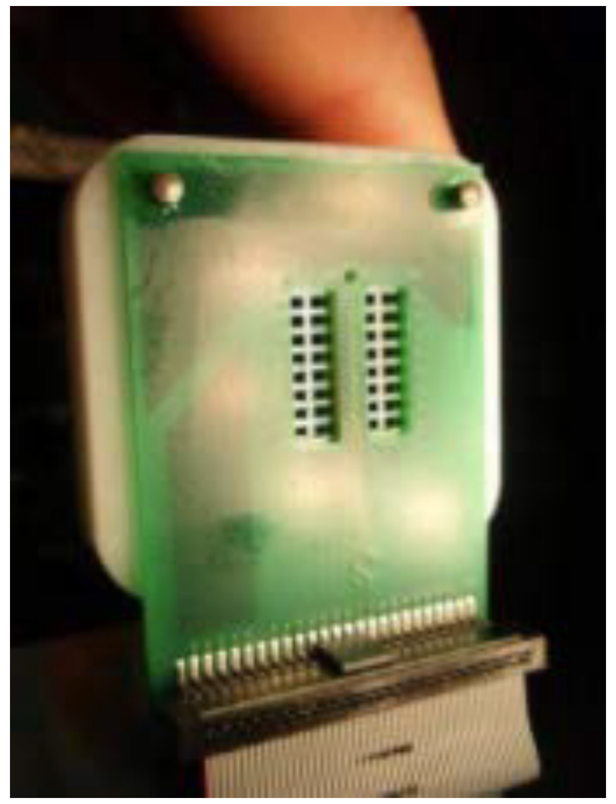
NOvA Detector



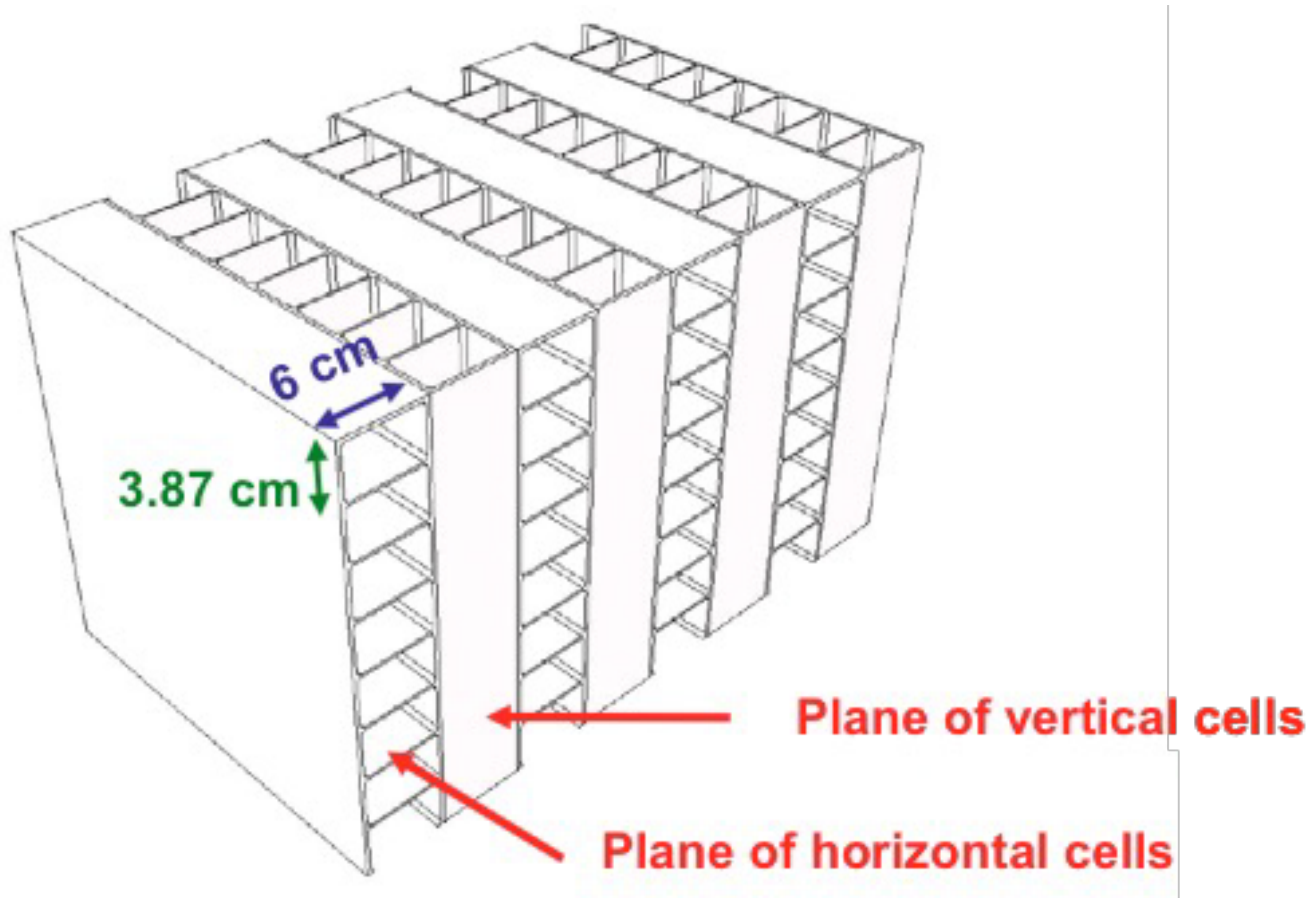


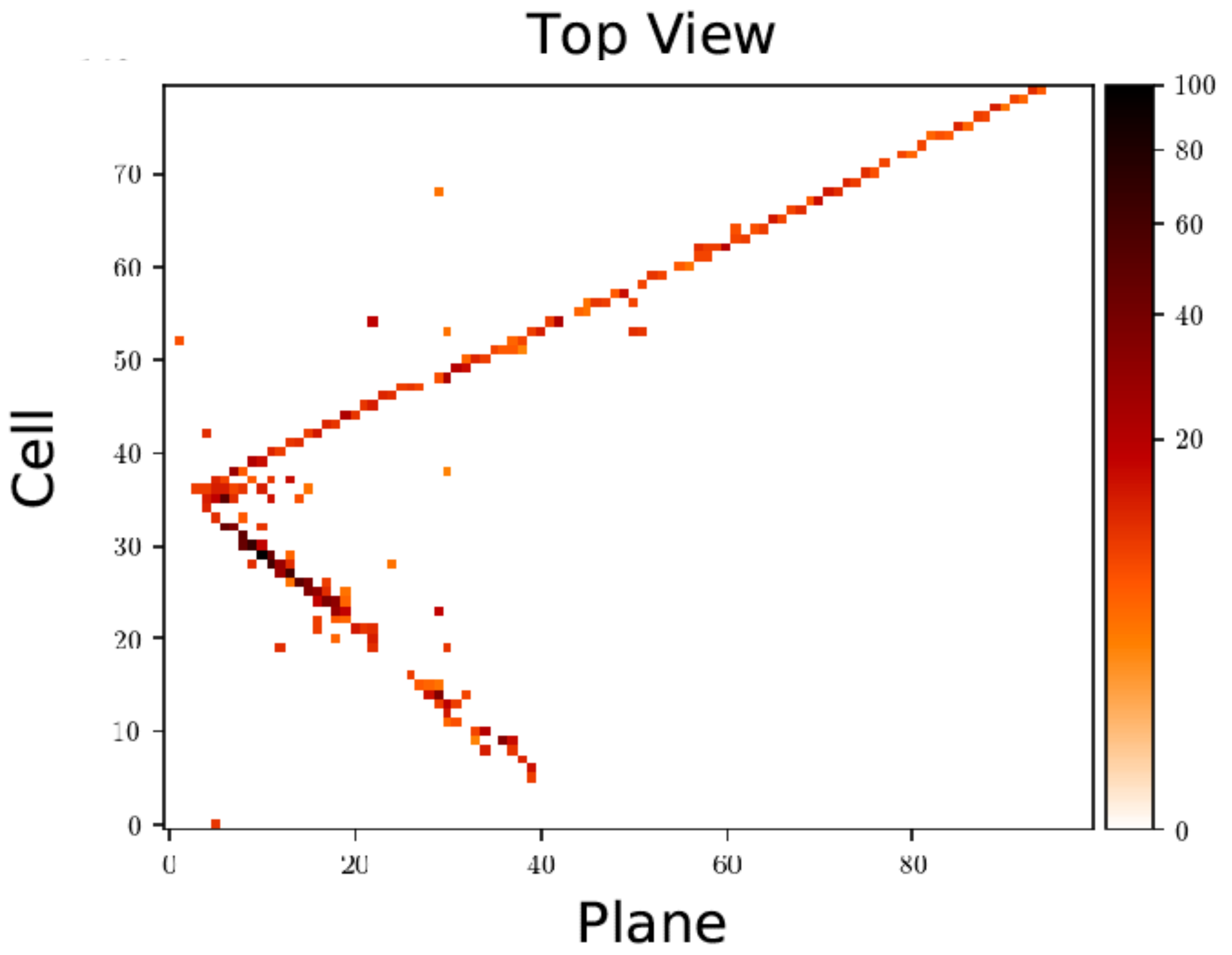


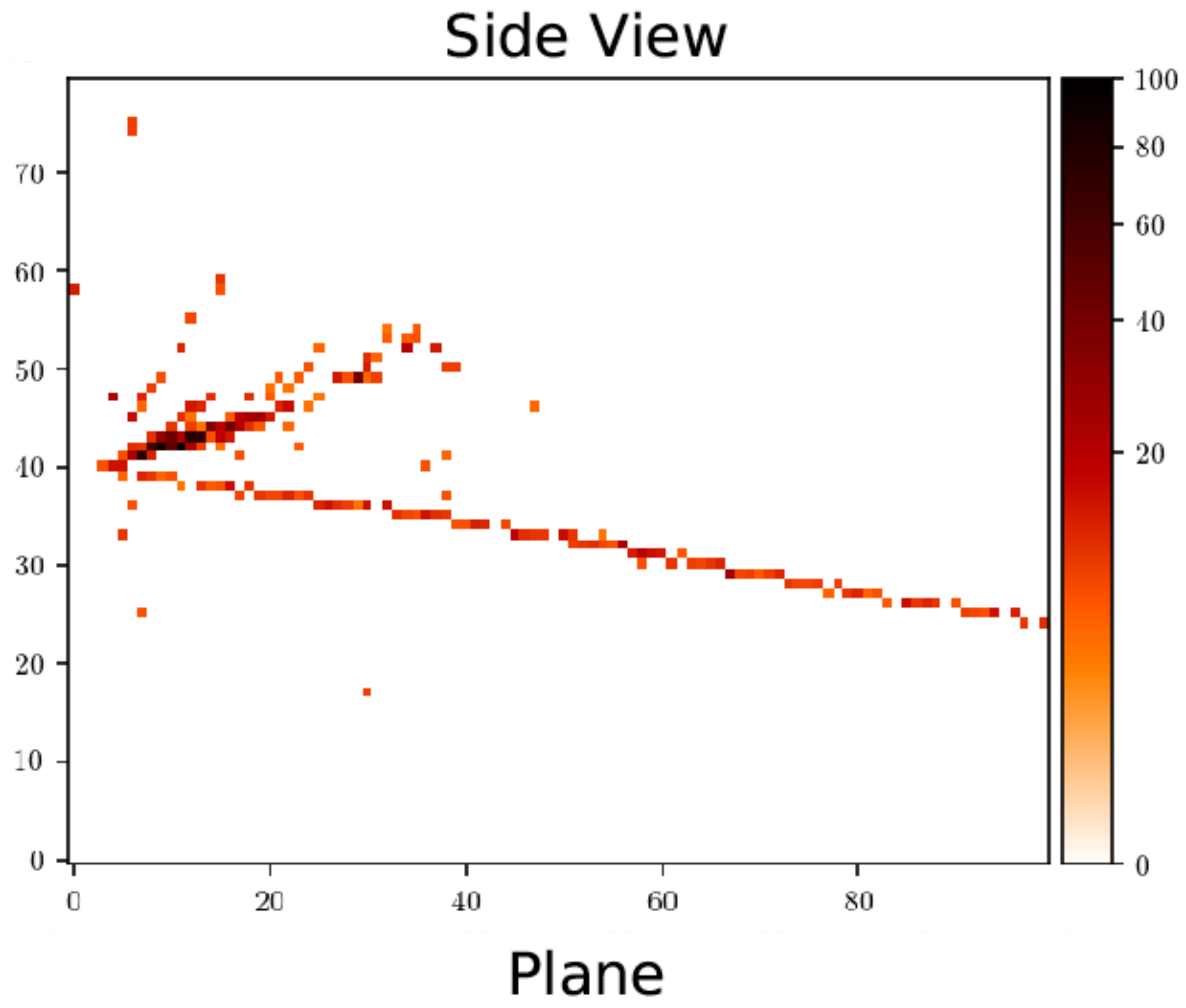
- FD and ND are functionally identical to minimize systematics
- Composed of highly reflective extruded PVC cells filled with liquid scintillator. Scintillation light captured and routed to Avalanche Photodiode (APD) via wavelength shifting fiber (WLS)
- Cells arranged in planes, assembled in alternating horizontal and vertical directions → provide 3D views of the events

Detector Views

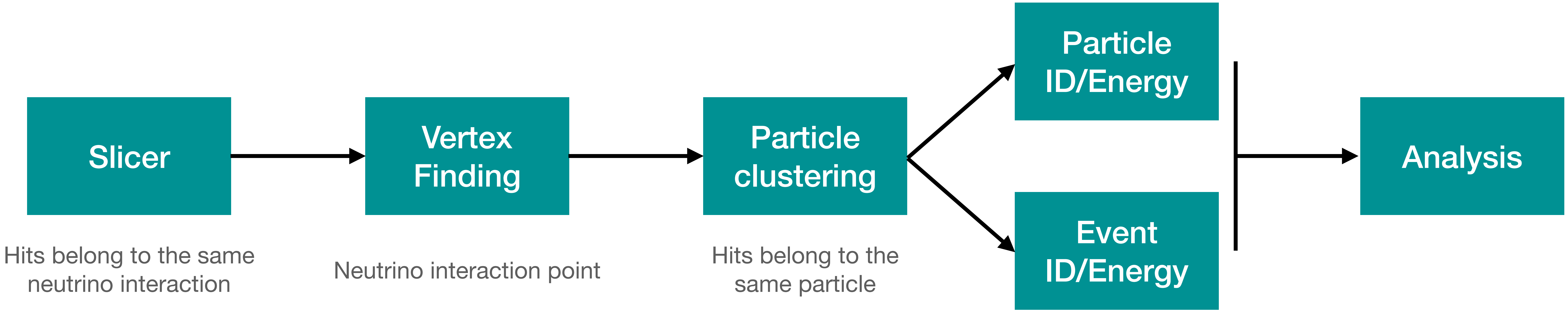
- NOvA detectors are naturally segmented
- Producing a pair of pixel maps (Cell number v.s. Plane number) for the Top and Side view of each interaction







Event Reconstruction in NOvA

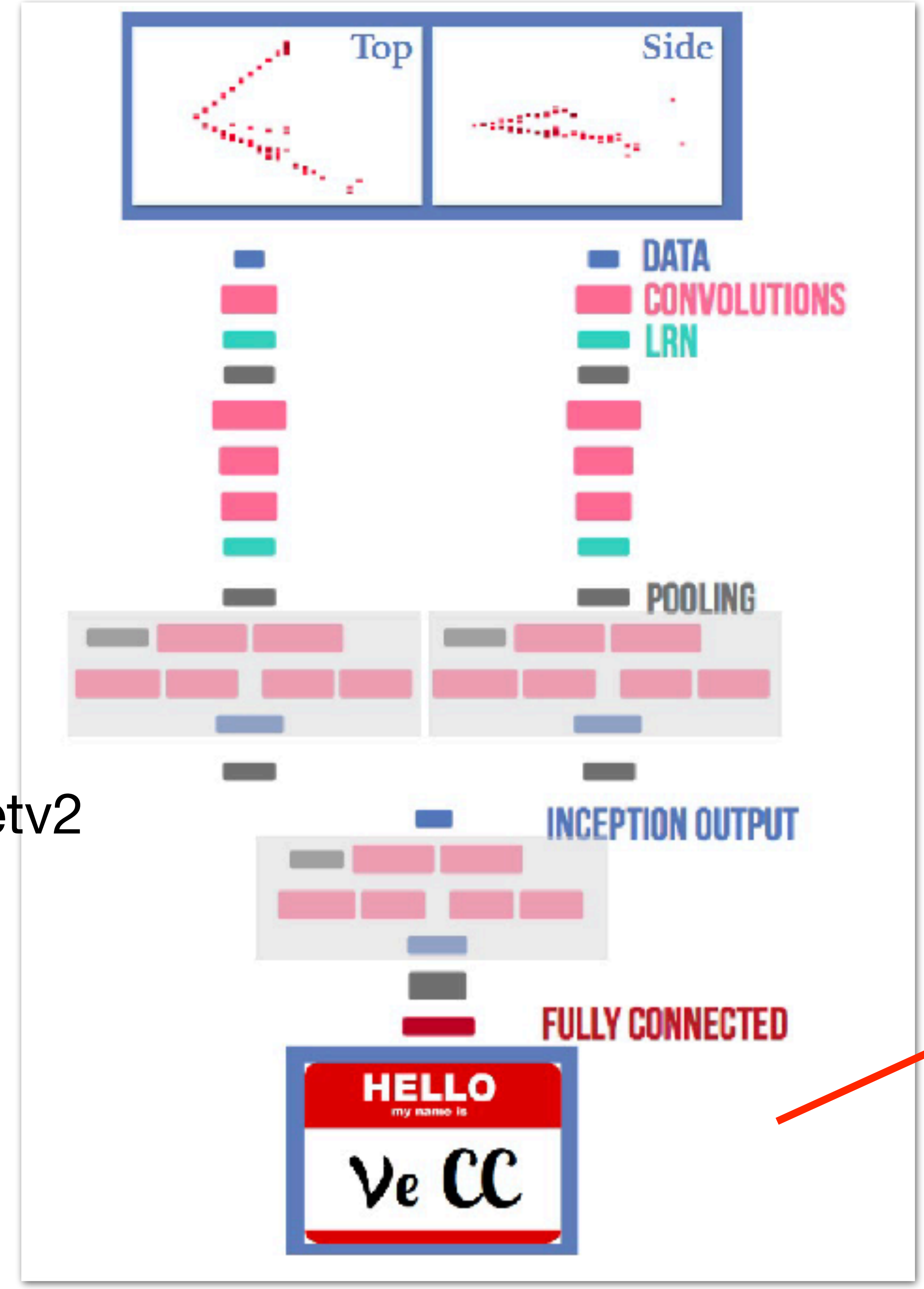


- NOvA uses a variety of algorithms to reconstruct physics information for which slicing is a core input
- Machine learning is making significant contribution in the reconstruction chain and can replace “traditional” kinematic based algorithms in most cases
- Neutrino flavor and particle classification: CNN, Transformer; Energy reconstruction: CNN

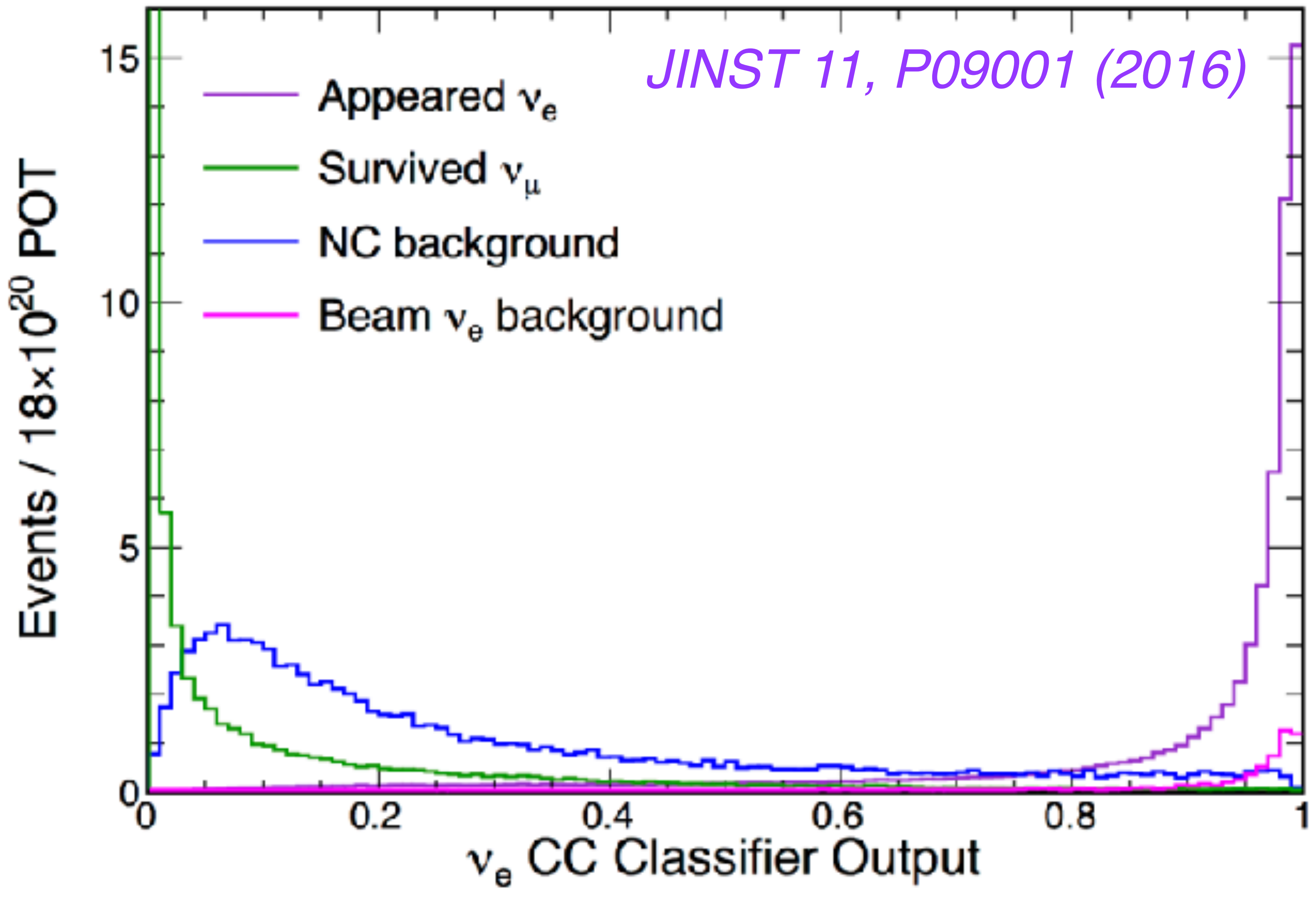
CNN-based Event Classifier (EventCVN)

- CVN: a convolutional neural network, based on modern image recognition technology, identifies neutrino interactions directly from pixel maps

CNN architecture
2016: GoogleNet
Now: Modified MobileNetv2



CVN output in the far detector MC



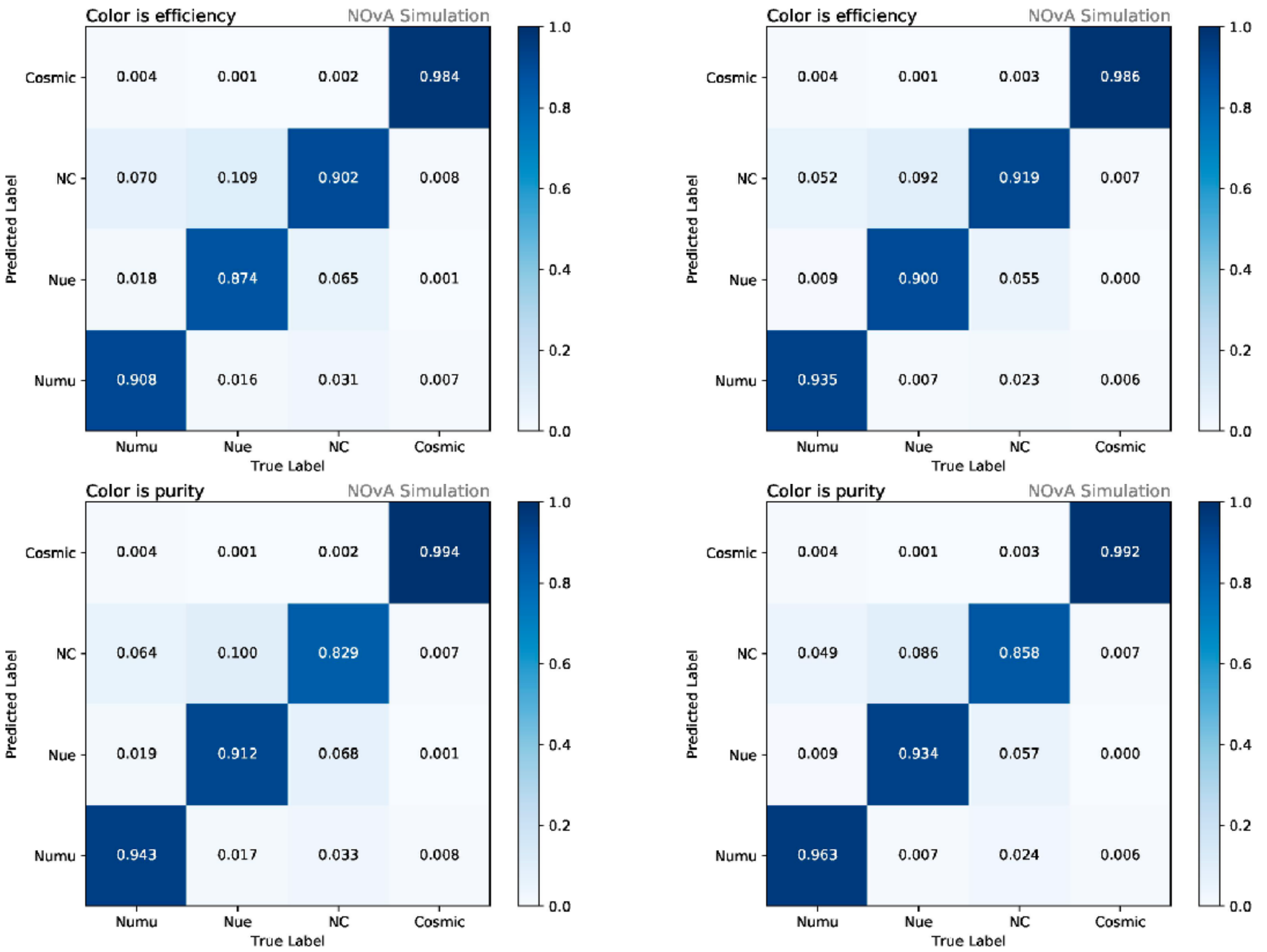
Select ν_μ ($\bar{\nu}_\mu$) CC and ν_e ($\bar{\nu}_e$) CC candidates from neutrino (anti-neutrino) beam with CVN

CNN-based Event Classifier (EventCVN)

- Similar performance for neutrino and anti-neutrino modes
- Anti-neutrino mode shows slight increase in efficiency
- Purity over 90% for all interaction flavors

neutrino mode

anti-neutrino mode



TransformerCVN for Event and Particle Classification

- Transformer: attention based network, ideal for training on variable-length collection of objects such as prongs

  "TransformerCVN" = Transformer+CNN

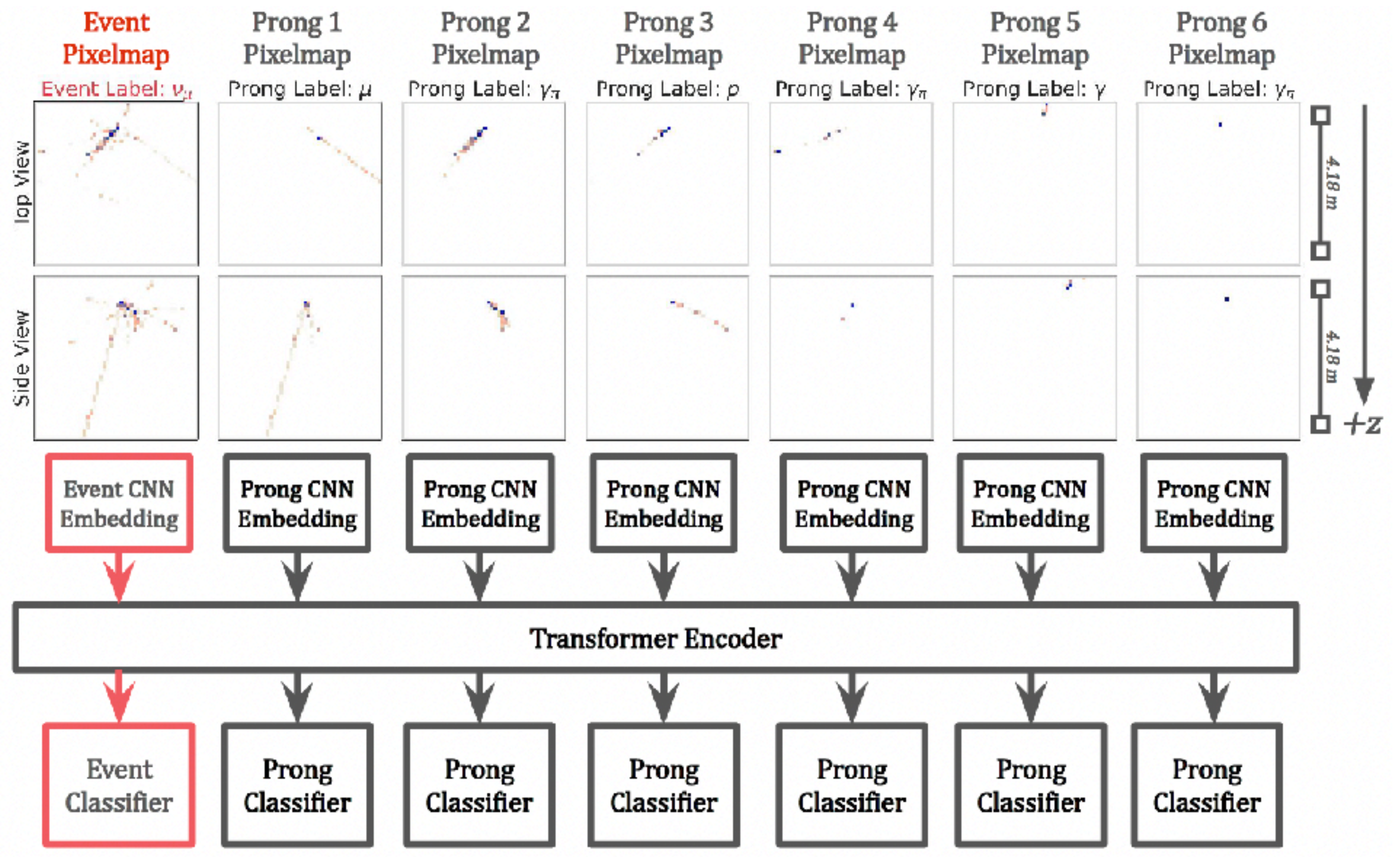
- Combines the spatial learning enabled by convolutions with the contextual learning enabled by attention

- Classifies each event and reconstructs every individual particle's identity

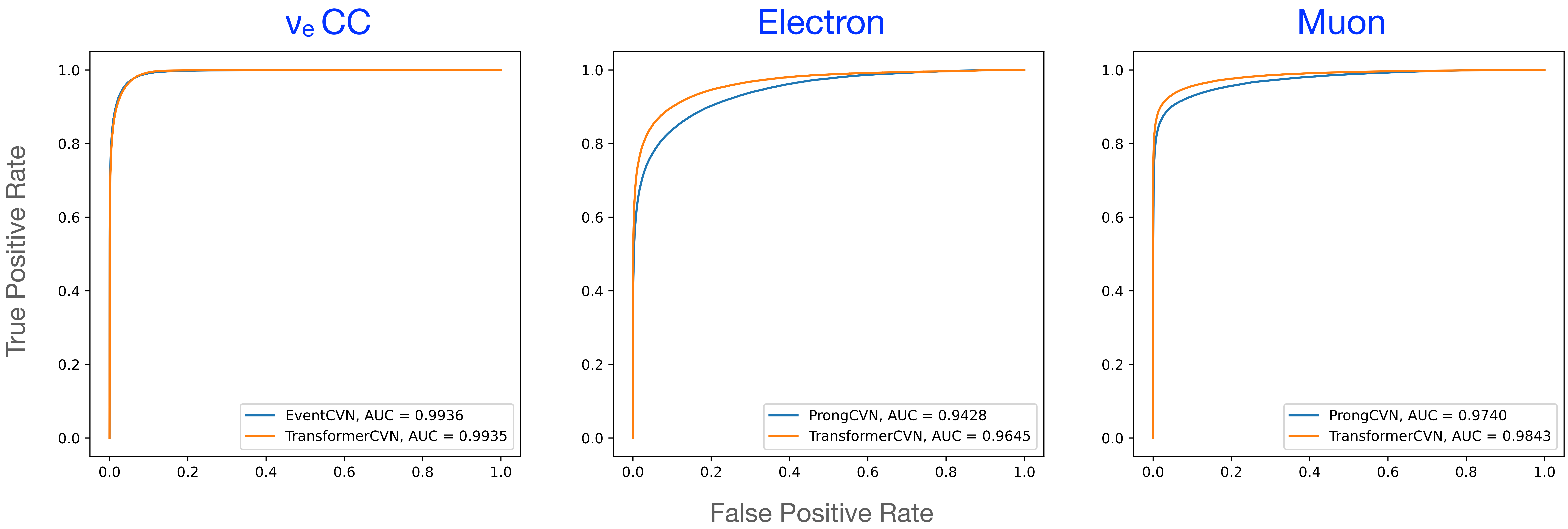
- Attention mechanisms

  - focus on regions with high importance, reduce the computing burden and enhance performance

  - enable performing interpretability studies



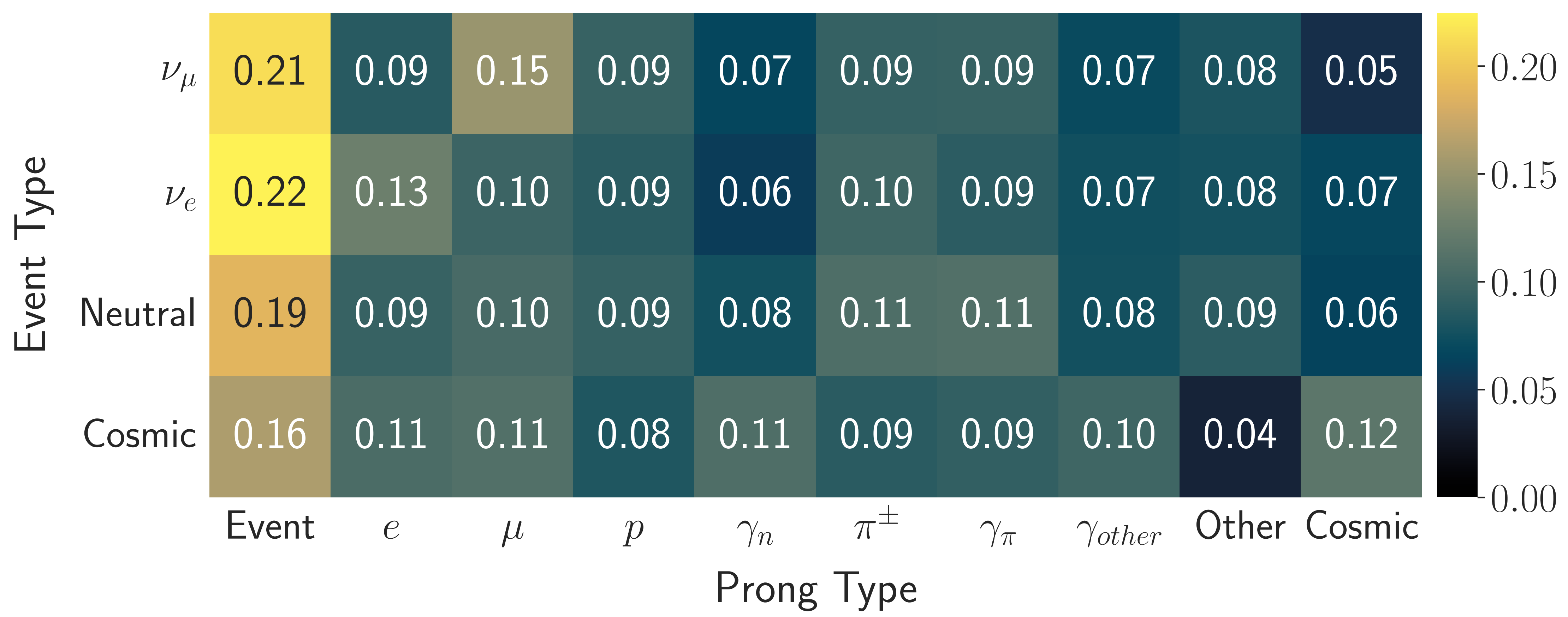
TransformerCVN for Event and Particle Classification



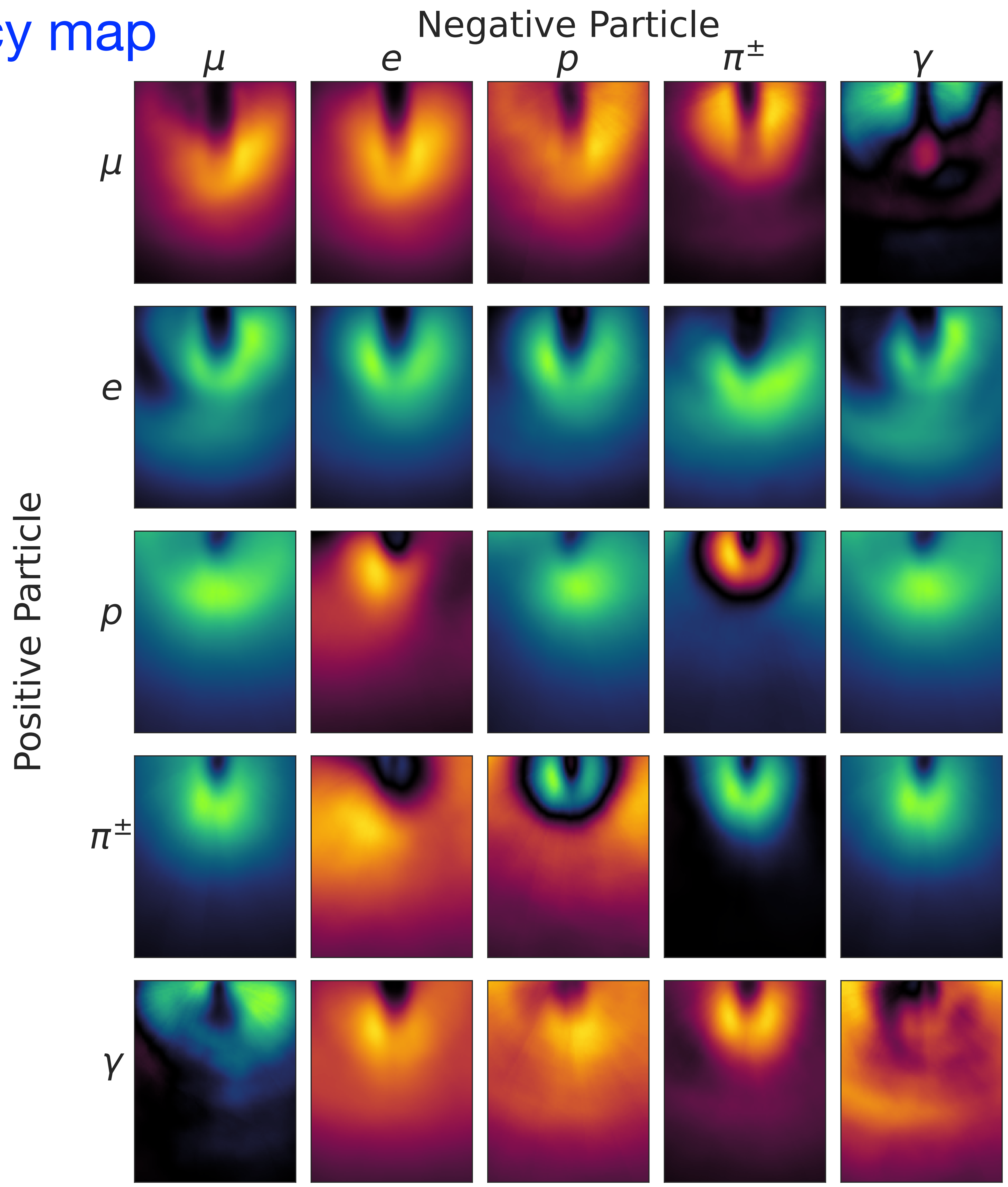
- Comparable performance of identifying neutrino flavors compared to our benchmark network (EventCVN)
- Great improvement in particle identification, benefits from the additional context provided by all prongs and the transformer's attention mechanism, compared to our benchmark network (ProngCVN)

TransformerCVN for Event and Particle Classification

Attention map

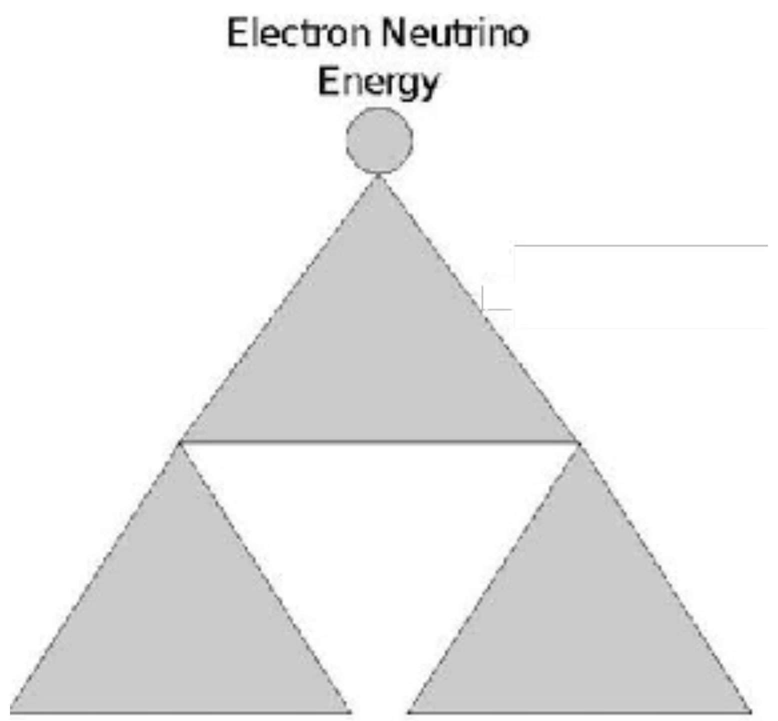


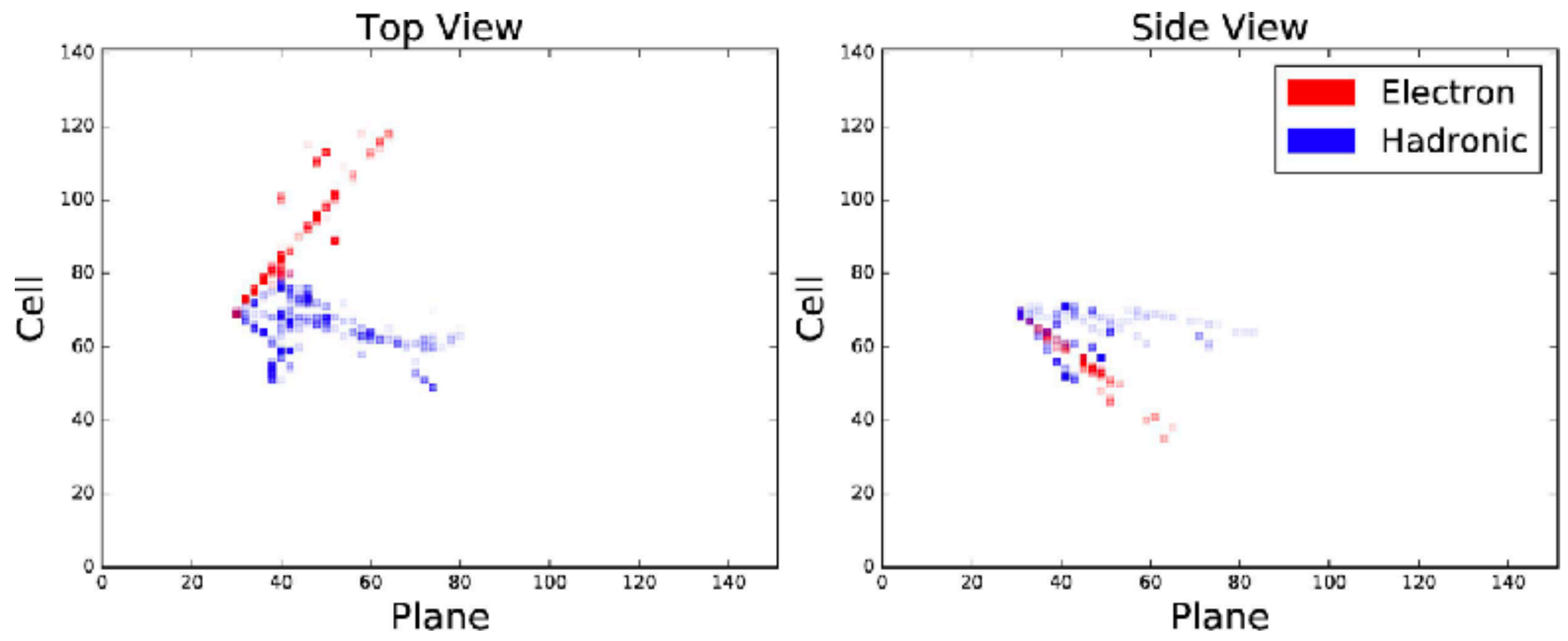
Saliency map



- Interpretability of the network
  - Attention map: importance of each input to each output
    - Diagnose neural network and explain decision
  - Saliency map: derivative of a network output w.r.t the input pixel
    - Study salience to understand which regions the Transformer focuses on to identify a particle

Regression CNNs for Energy Estimation

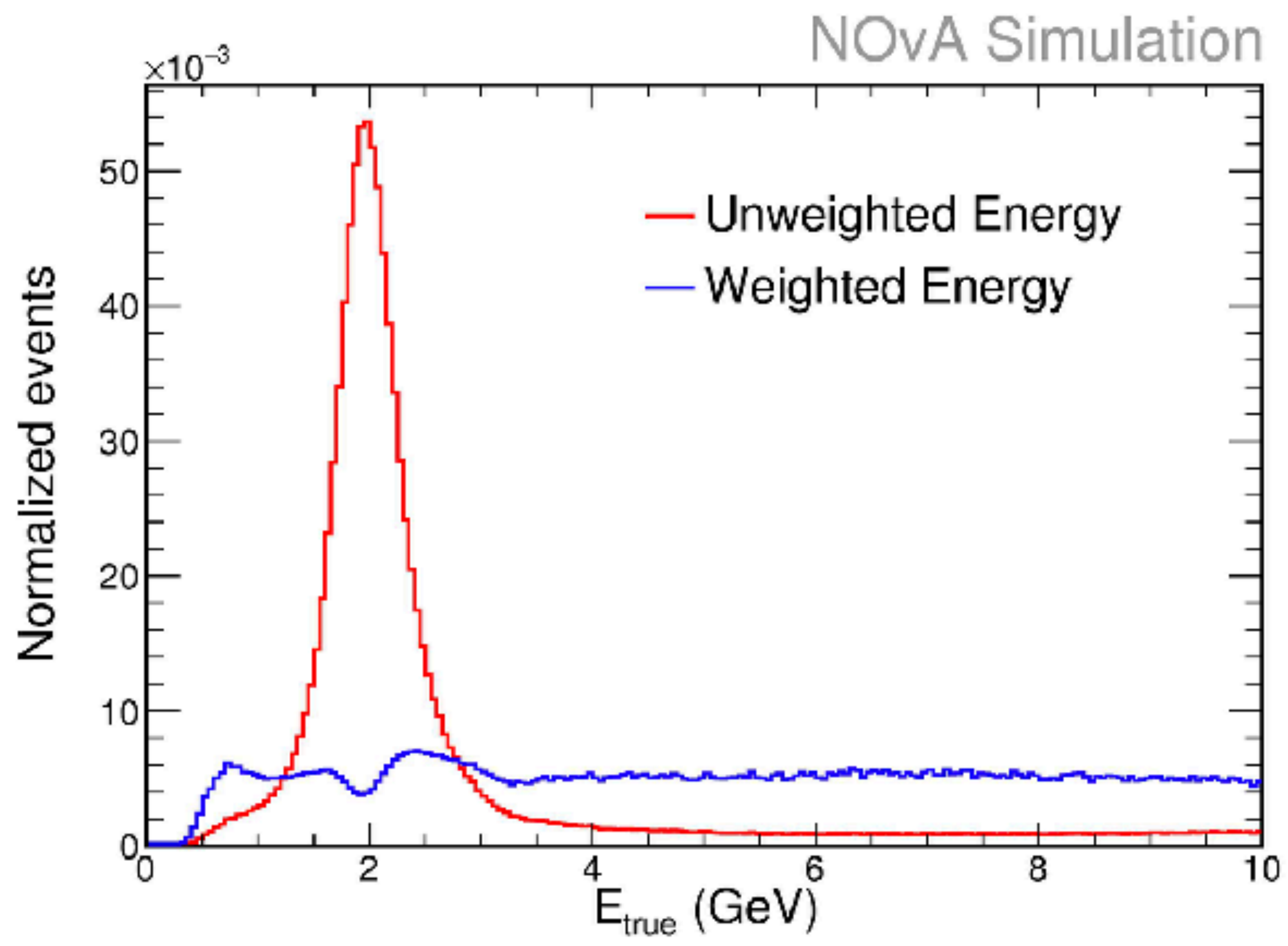




PhysRevD.99.012011

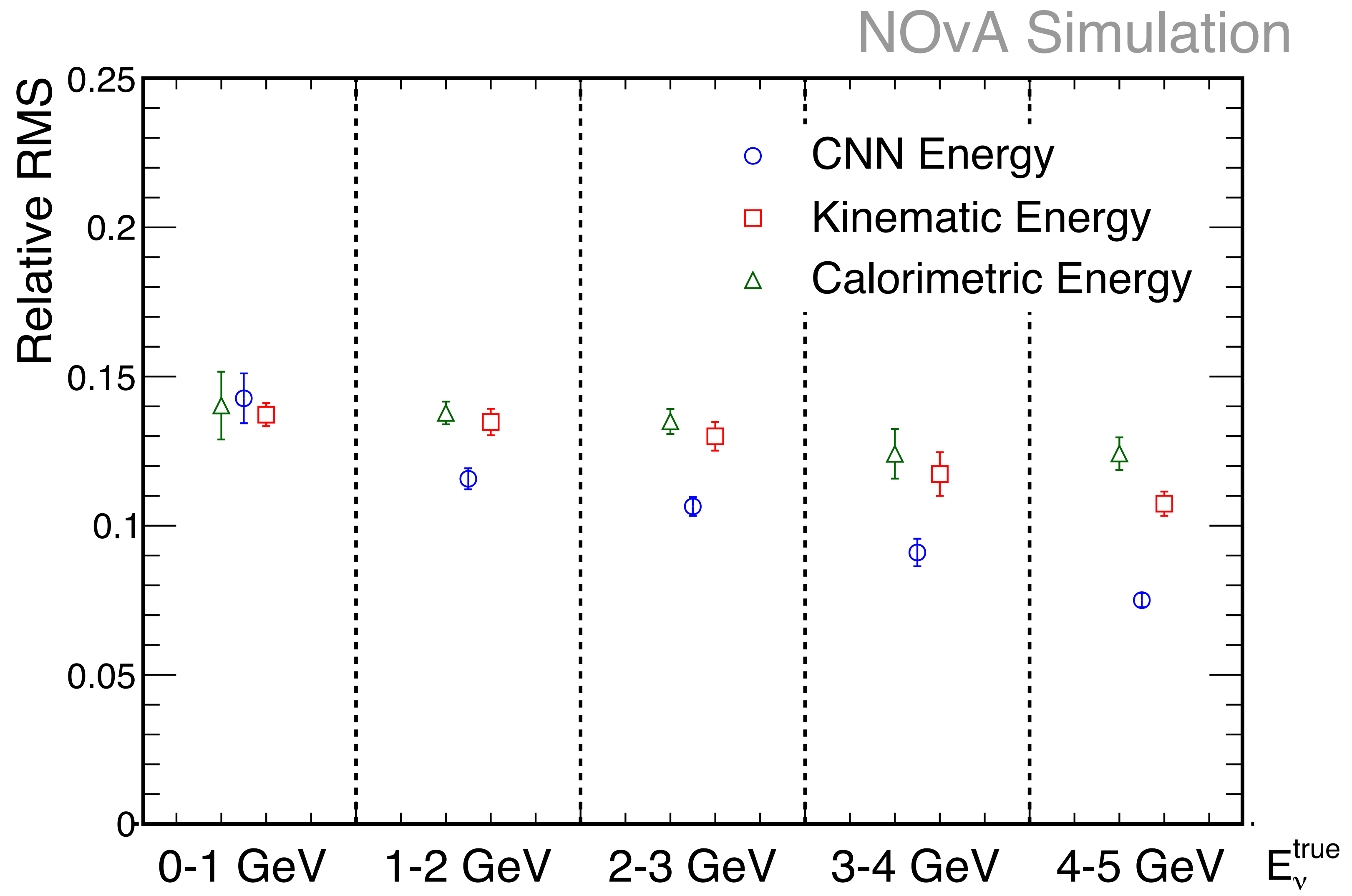
- The CNN architecture used is an adapted ResNet
- Weighting scheme so the loss function sees a flat energy distribution, to control energy dependence
- Use mean absolute percentage error instead of square of errors to decrease the effects of outliers

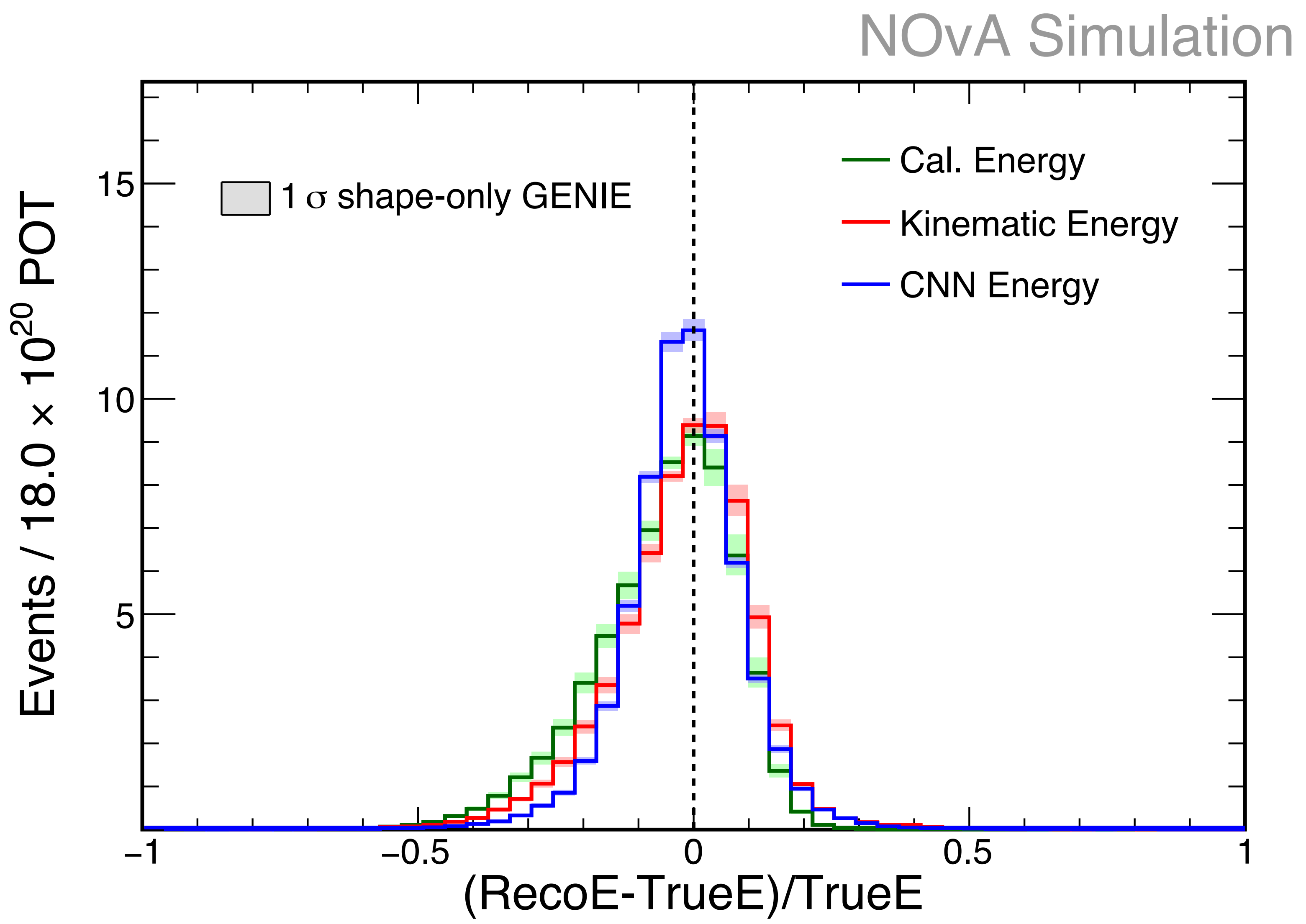
$$L(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^{n}) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_{\mathbf{W}}(\mathbf{x}_i) - y_i}{y_i}\right|$$

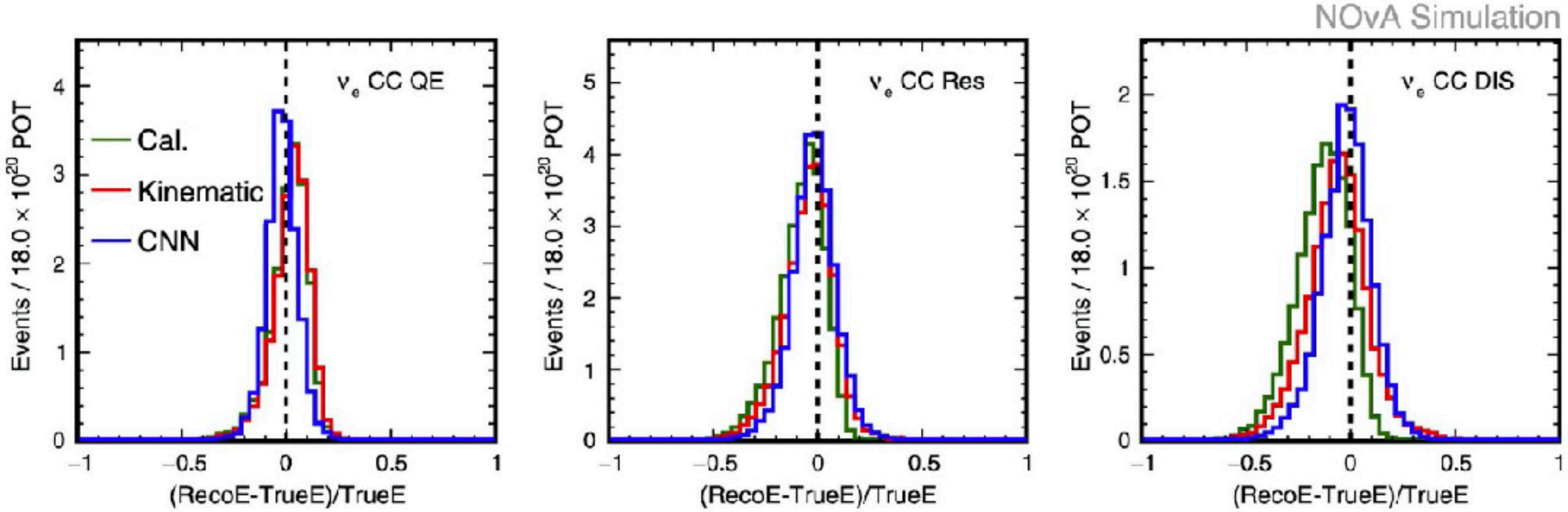


Regression CNNs for Energy Estimation

- Regression CNN shows a better resolution compared with kinematics-based energy reconstruction
- Shows smaller systematic uncertainties due to neutrino interaction simulation
- Good stability over interaction types

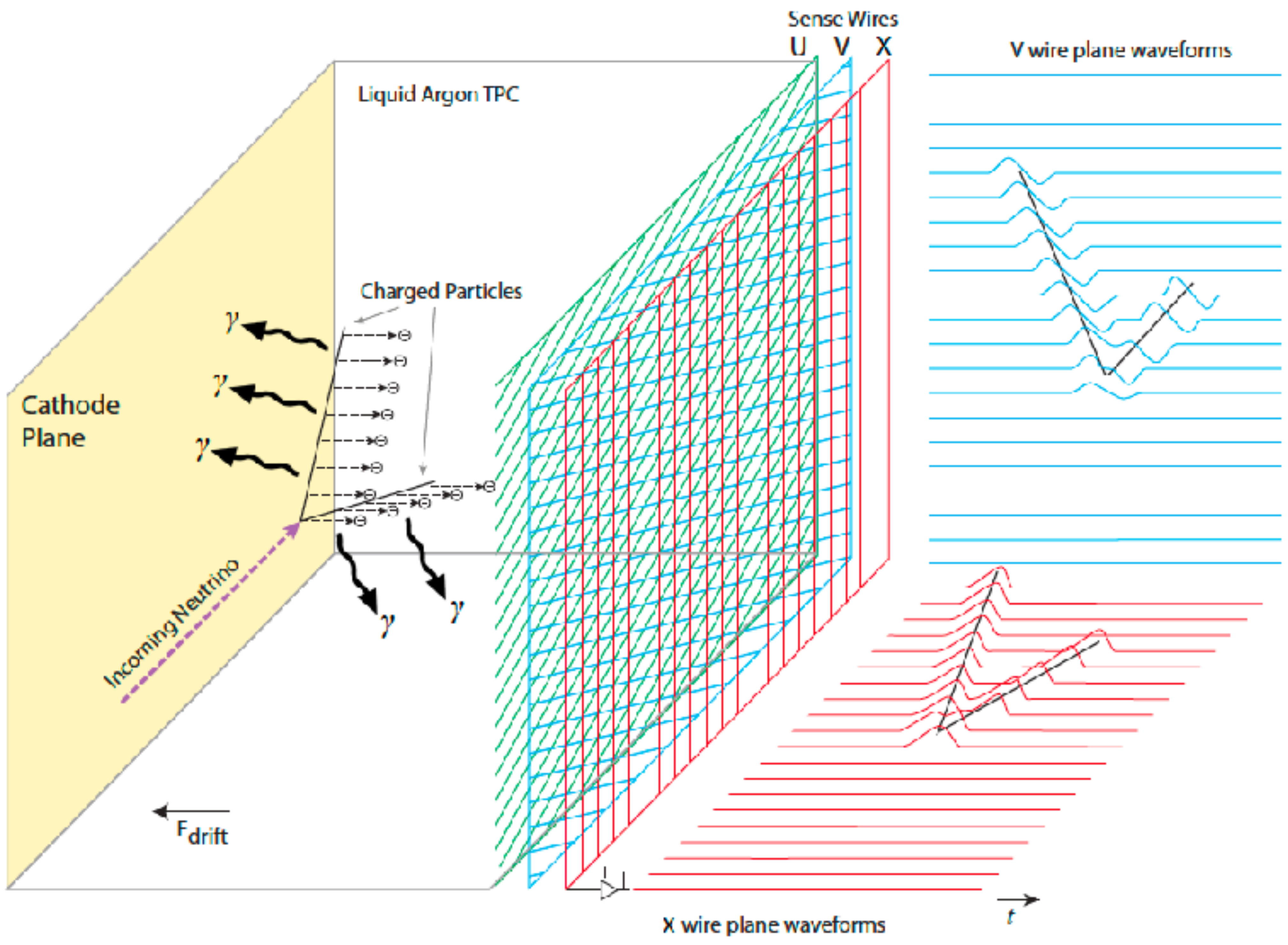






Also trained for electron energy, hadronic energy, ν_μ energy, etc

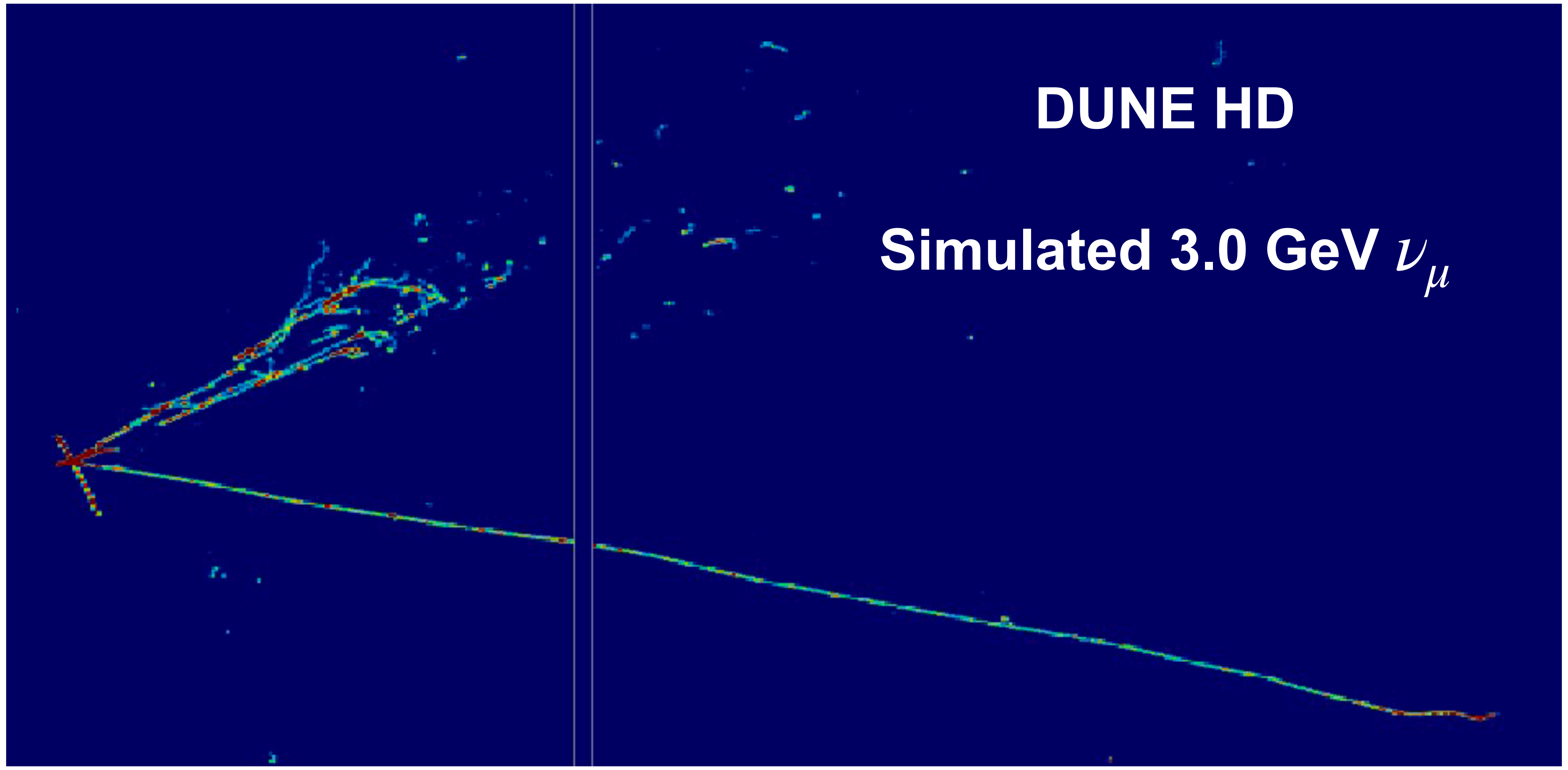
DUNE detector: LArTPC

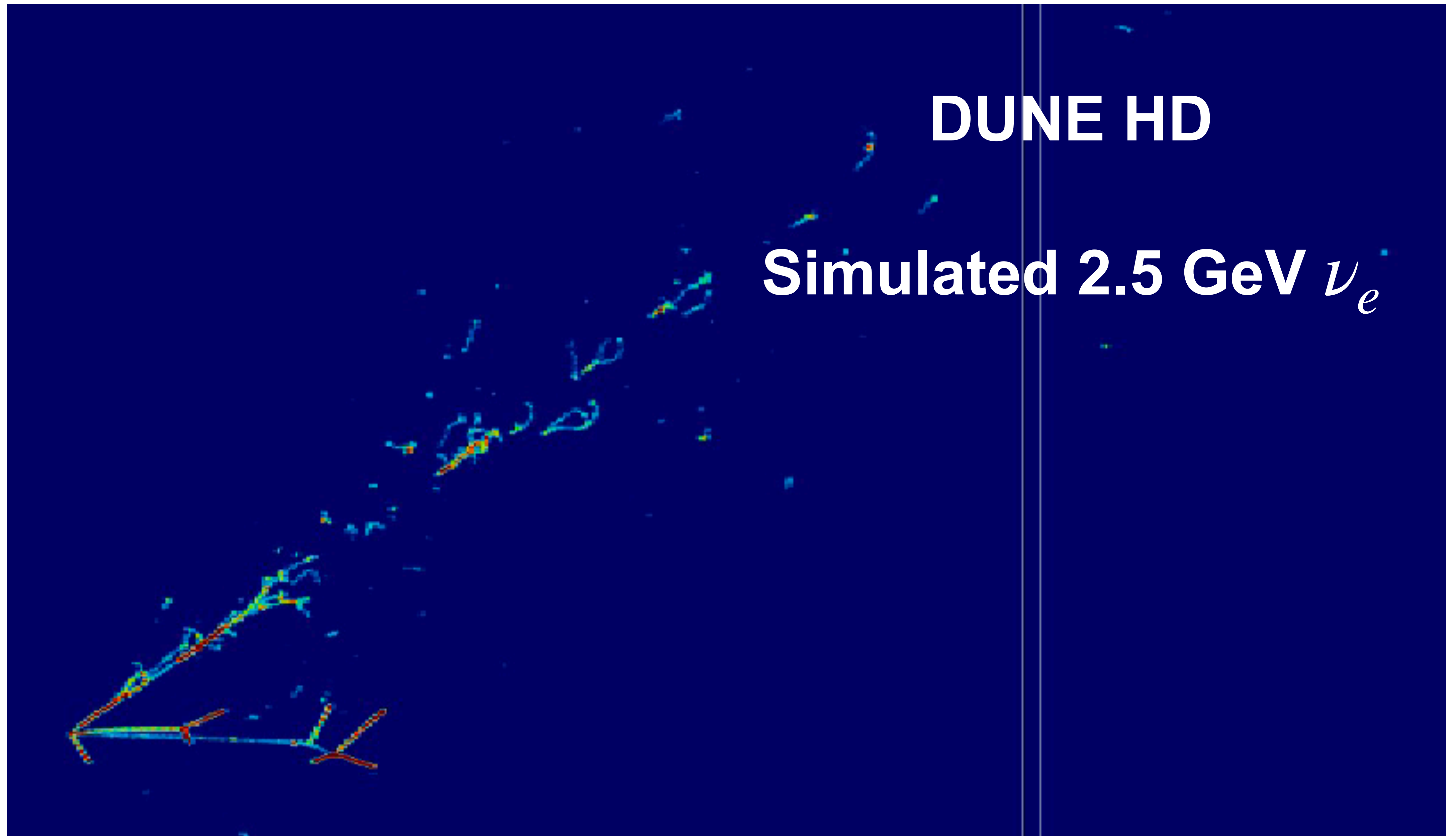


- Charged particles ionize argon atoms
- Ionized electrons drift opposite to the E field in the LAr and are collected on the anode wire/PCB planes (~ ms) → 2D spatial location
- Argon scintillation light (~ ns) detected by photon detectors, providing event start time t_0
- Electron drift time projection → enable 3D spatial location
  - Clean separation of ν_μ and ν_e CC events
- Low threshold for charged particles → good neutrino energy reconstruction

Tracker & Calorimeter

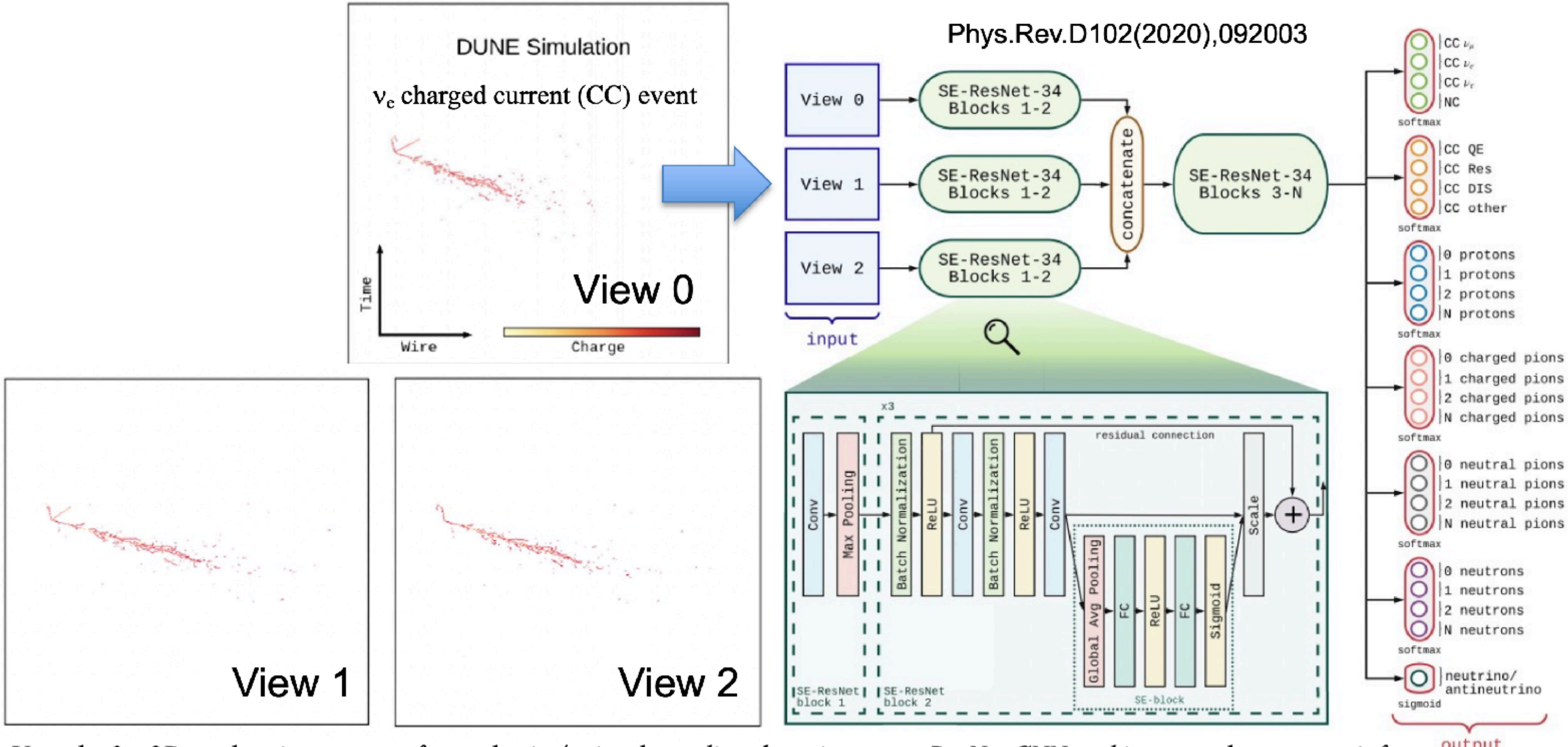
Liquid Argon TPC





- The high-resolution pixel map readout is ideal for image processing neural networks to reconstruct neutrino events
- Developing AI-based reconstruction chain:
  - Energy, direction, vertex (regression, CNN)
  - Particle ID, neutrino flavor ID (classification, CNN, Transformer)
  - Shower/track clustering (image segmentation, CNN, GNN)

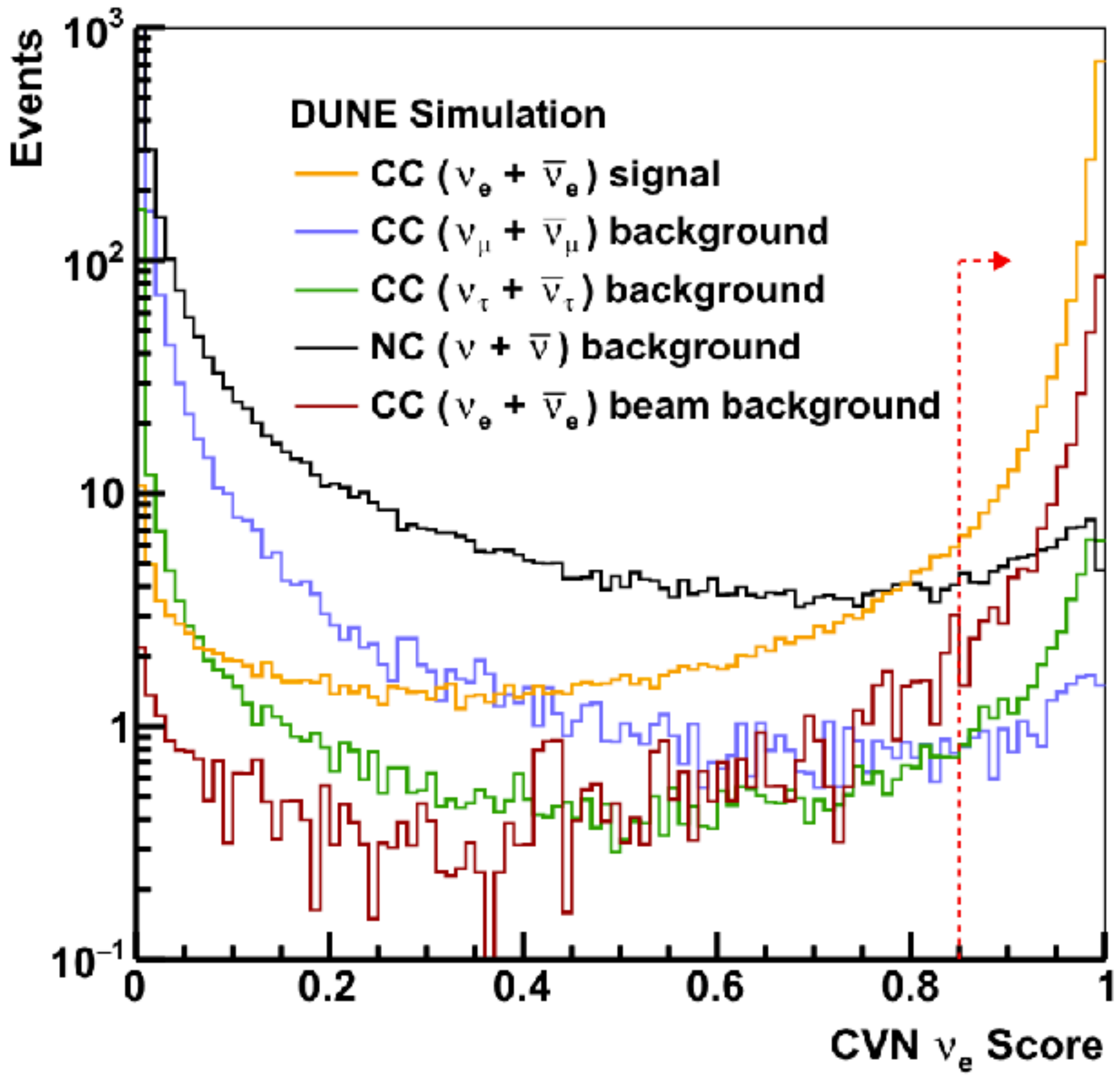
CNN for classification and regression

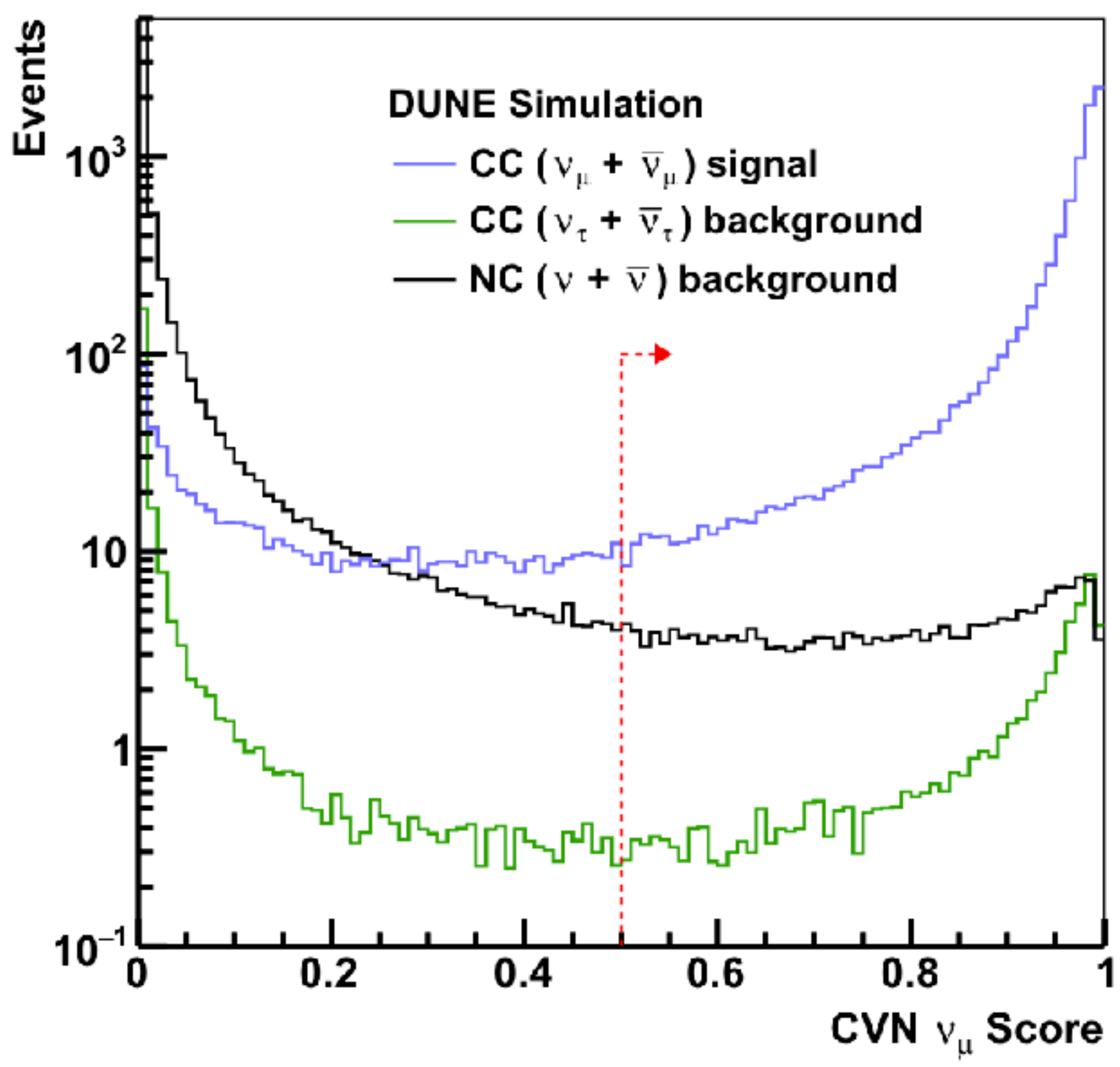


Uses the 3 x 2D readout images, one for each wire/strip-plane, directly as input to a ResNet CNN architecture, then merges information across the 3 planes and uses a fully connected layer at the end for neutrino flavor classification or energy regression

CNN for classification and regression

- The primary goal of the CVN is to efficiently and accurately produce event selection of ν_e CC and ν_μ CC in FHC, $\bar{\nu}_e$ CC and $\bar{\nu}_\mu$ CC in RHC
- The ν_e and ν_μ efficiencies in both FHC and RHC beam modes all exceed 90% in the neutrino flux peak

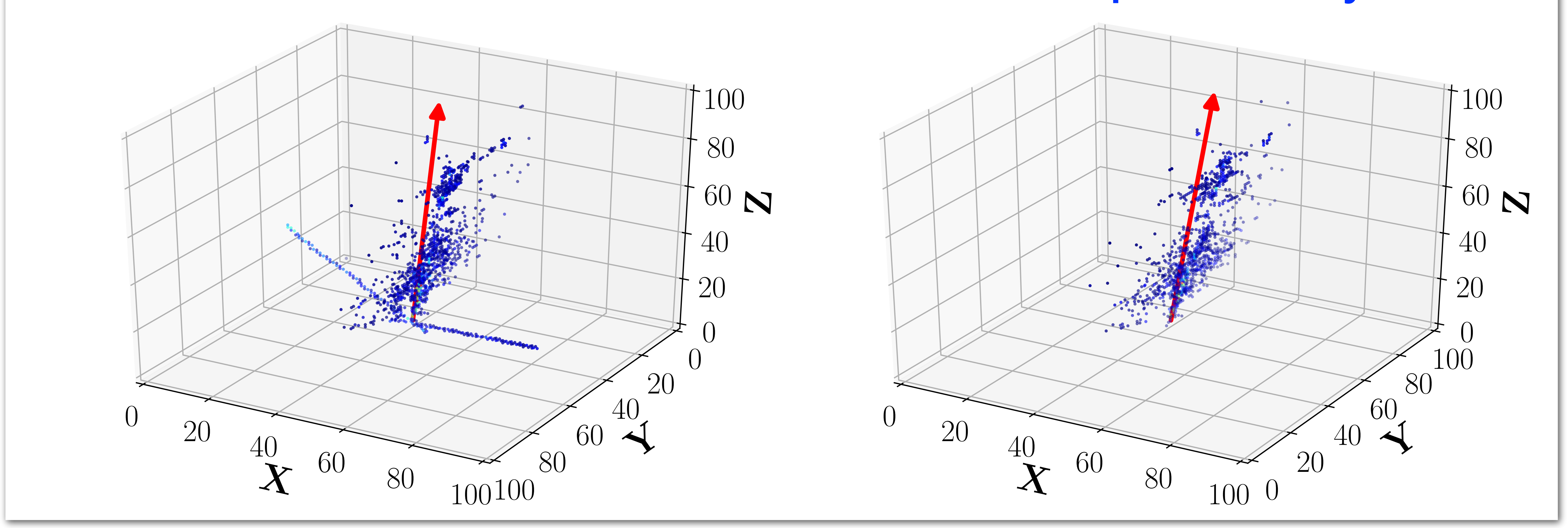




3D Particle Direction Reconstruction

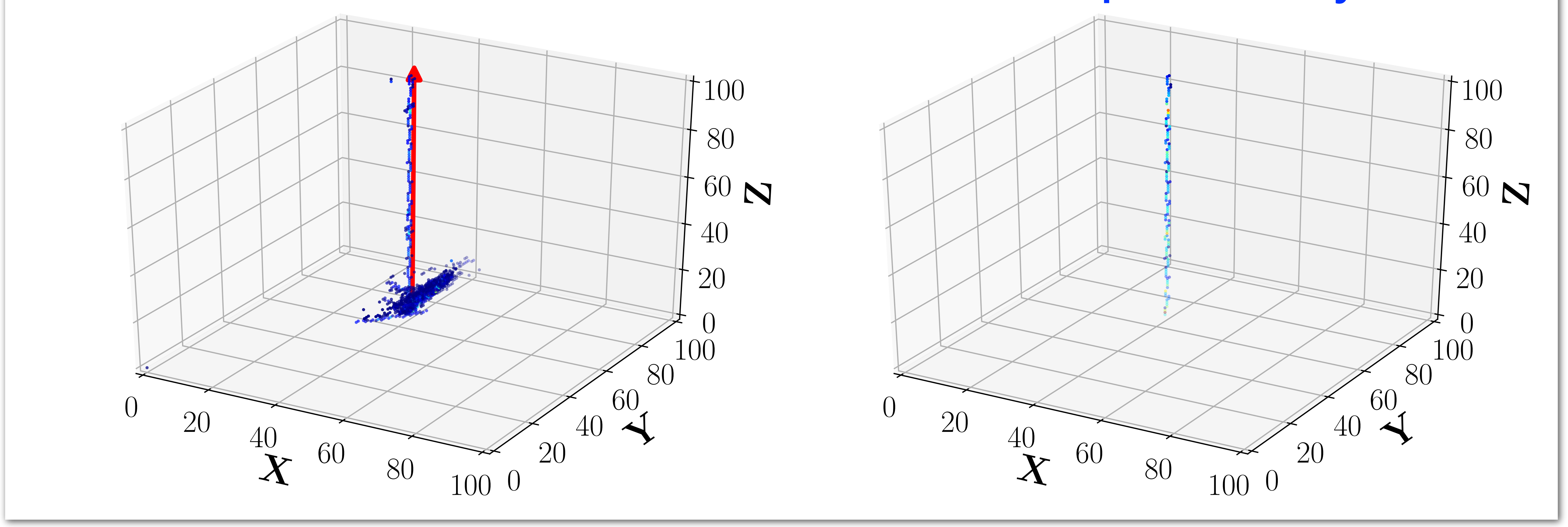
- The 2-D planar views provide incomplete information about the interaction geometry, resulting in less precise 3-D information reconstruction
- **For direction reconstruction**, the 3-D pixel maps are created by combing spatial and charge information from all 3 planes
  - These 3-D pixel maps are 100x100x100 pixels which are 125x125x250 cm for ν_e CC event, and 500x500x1000 cm for ν_μ CC event

Full Event | Lepton Only



ν_e CC

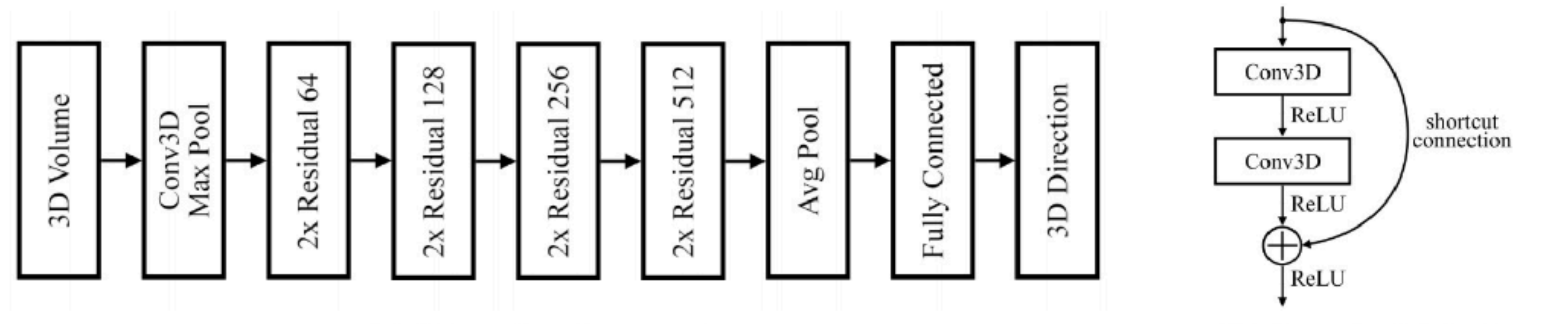
Full Event | Lepton Only



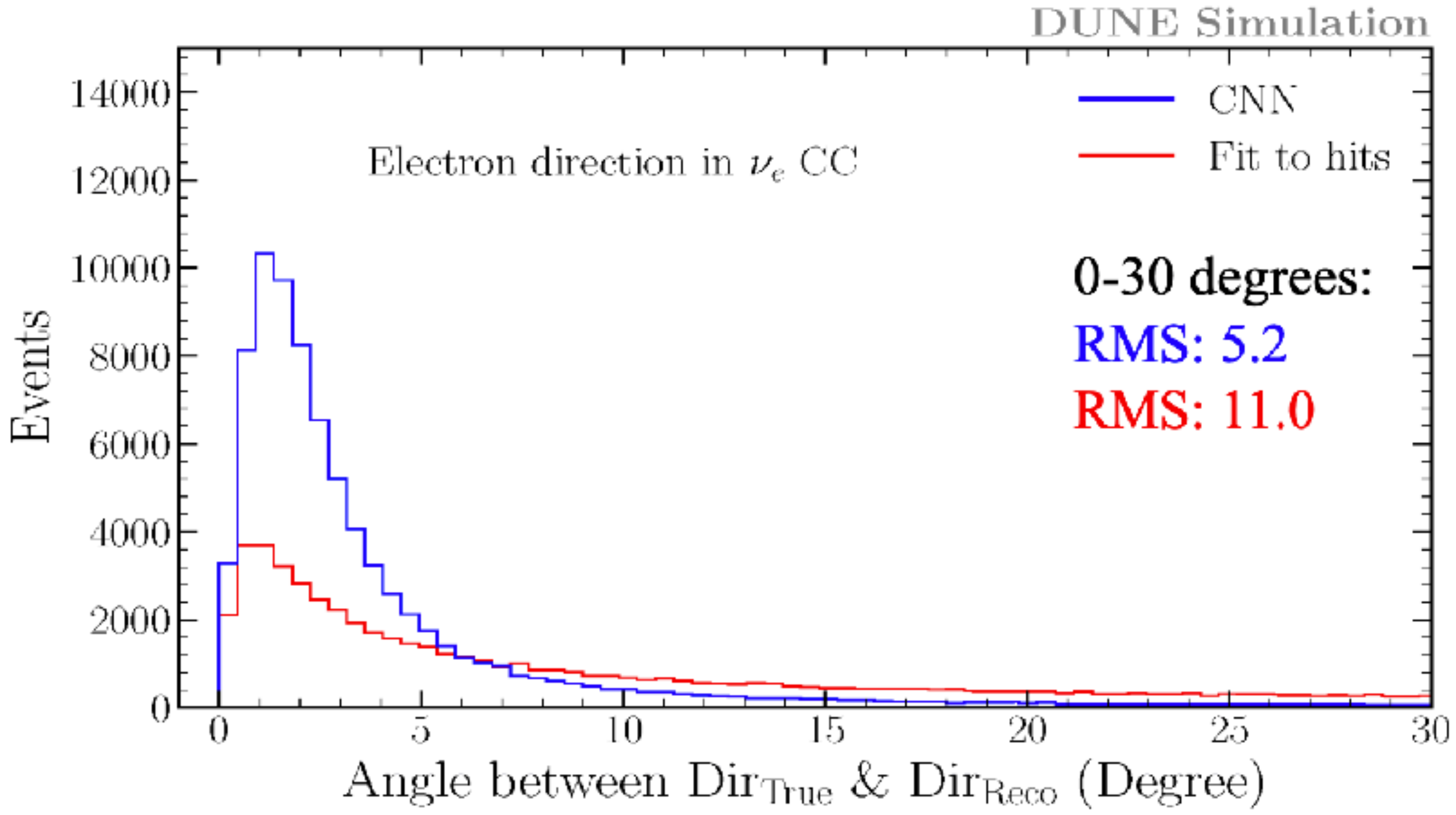
ν_μ CC

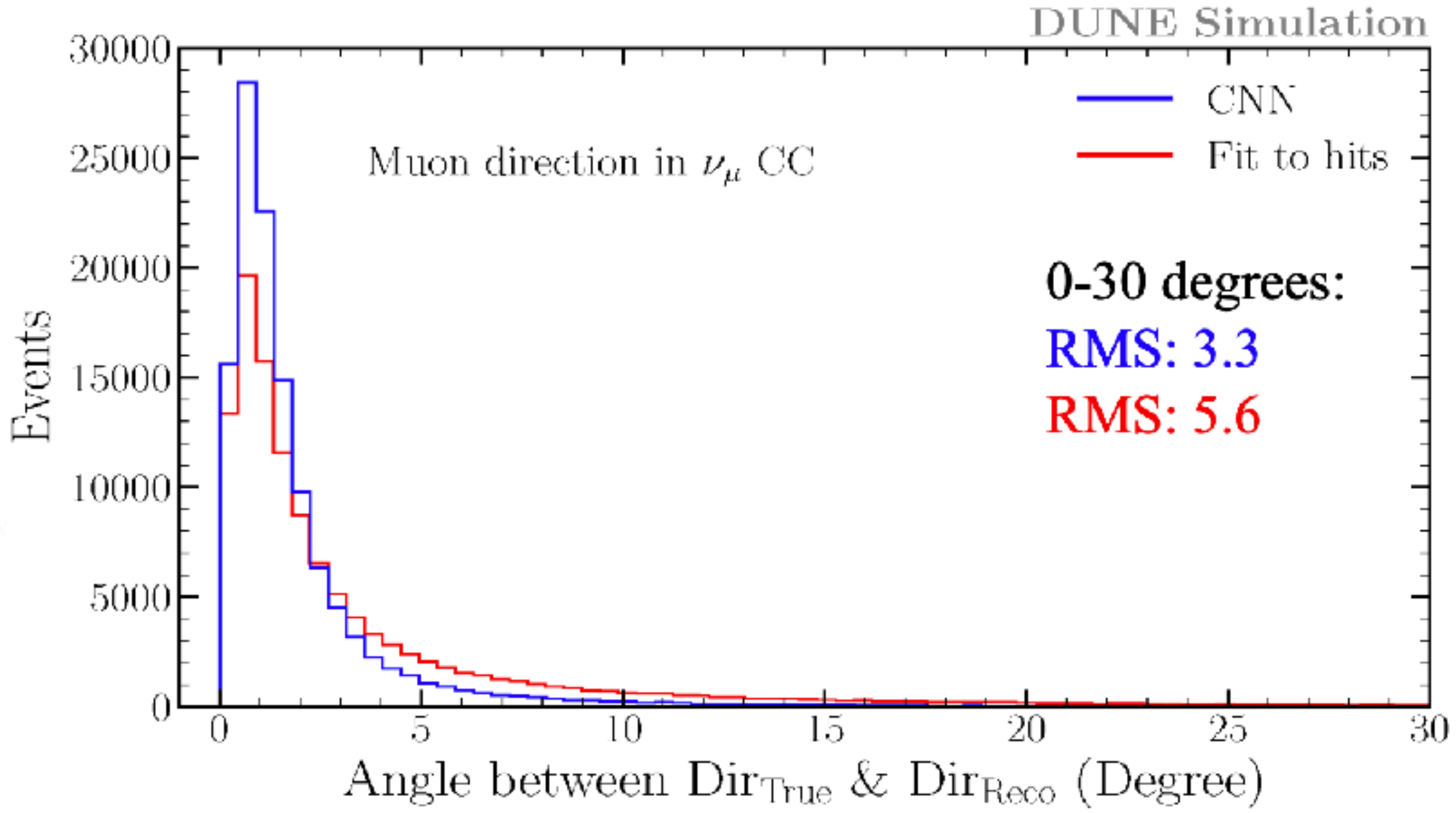
3D Particle Direction Reconstruction

- The 3-D CNN model is built on a series of “residual blocks” and a linear layer to output 3-D direction vectors
- achieves resolution improvements of 65% for electron directions and 50% for muon directions



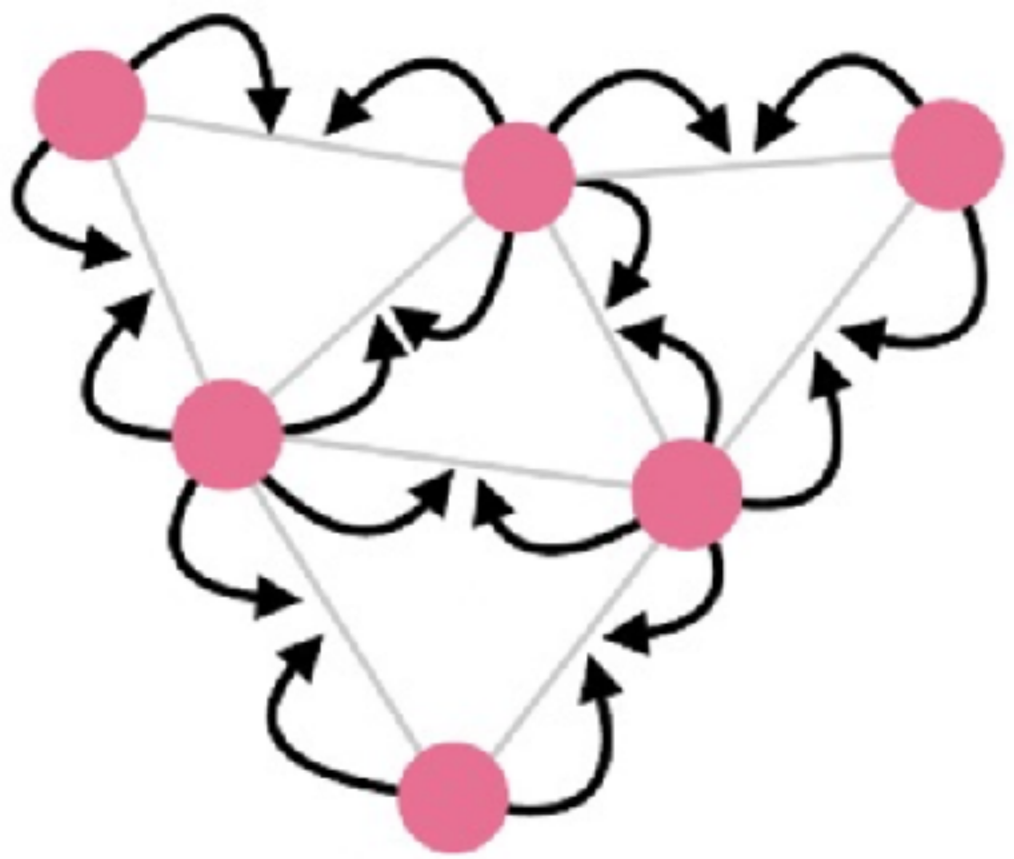
(a) Direction Regression (b) Residual block

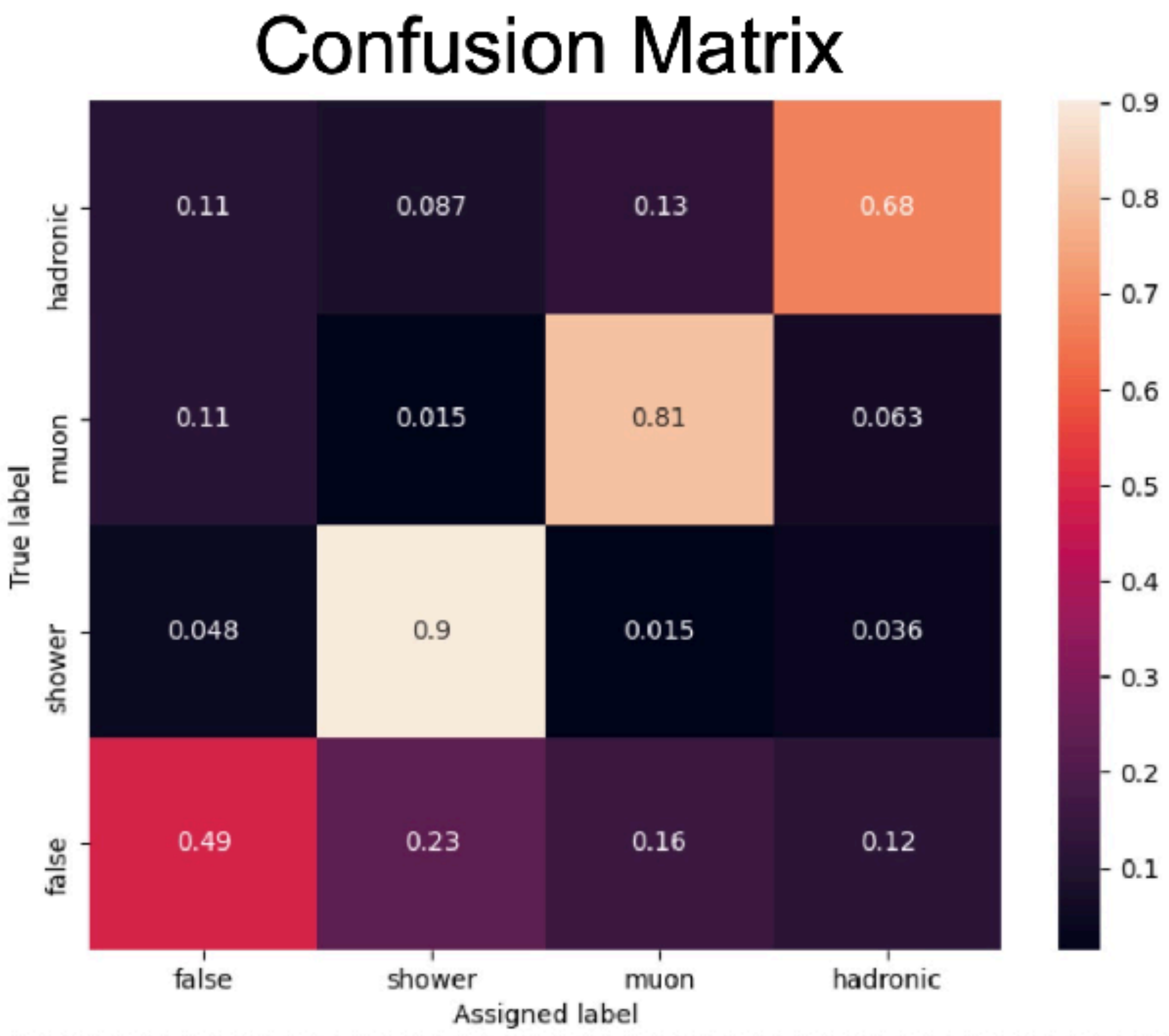




Graph Neural Network for Object Reconstruction

- Graph Neural Networks (GNN): define input data as a graph represented by nodes and edges, convolutions on nodes and edges rather than the entire pixel to speed up training
- Successfully cluster LArTPC showers/tracks with GNN in ExtExa.TrkX project (a collaboration developing GNN reconstruction for HEP)
  - Implementing under DUNE context





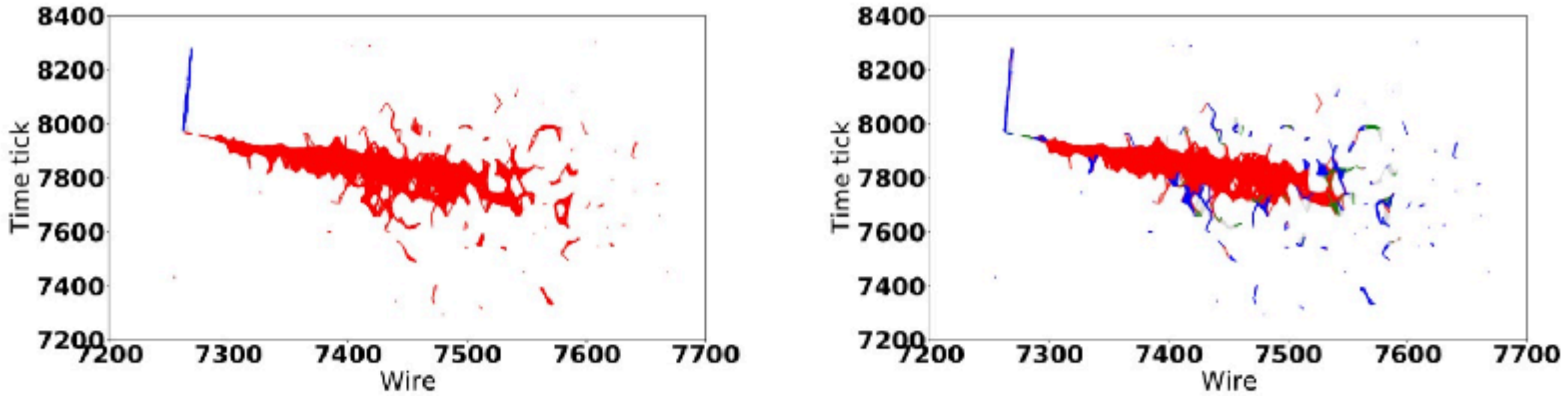
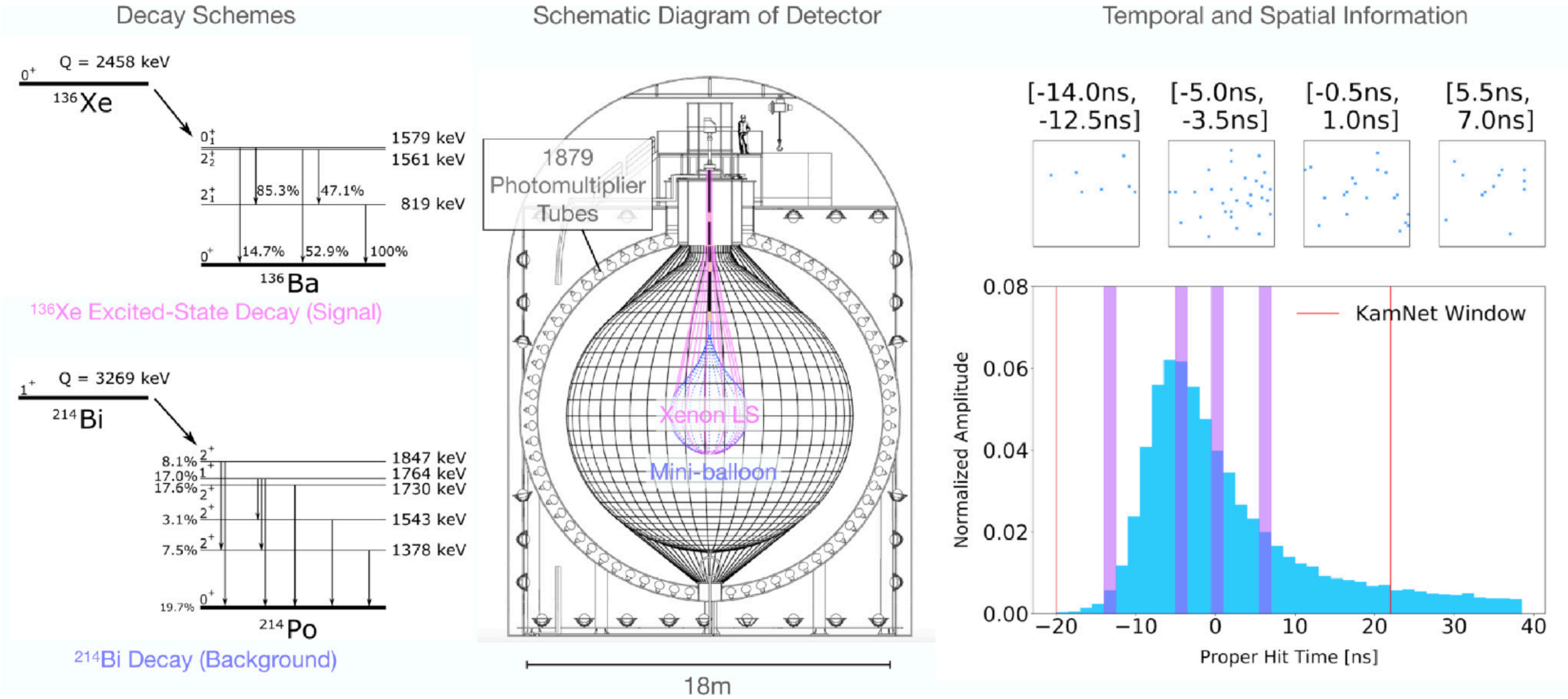


Figure 2. Example graph of a ν_e interaction (left: ground truth, right: model output). Shower-like edges are drawn in red, hadronic edges are drawn in blue, muonic edges are drawn in green and false edges are drawn in grey.

V Hewes, A. Aurisano etc,, EPJ Web of Conferences 251, 03054 (2021), arXiv:2403.11872

KamLAND-Zen

PHYSICAL REVIEW C ***107****, 014323 (2023)*



KamLAND-Zen

PHYSICAL REVIEW C **107**, 014323 (2023)

CNN + LSTM

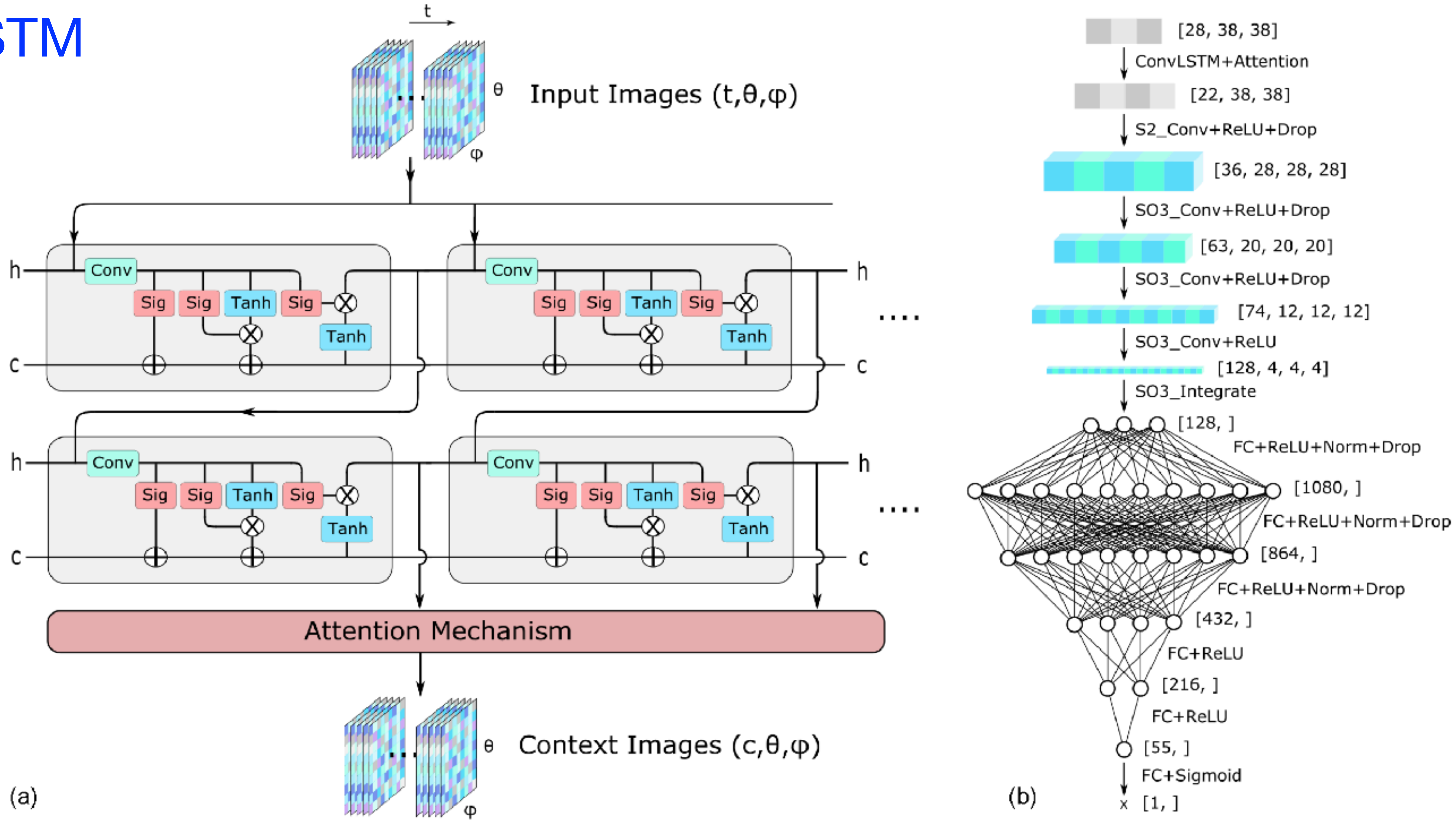
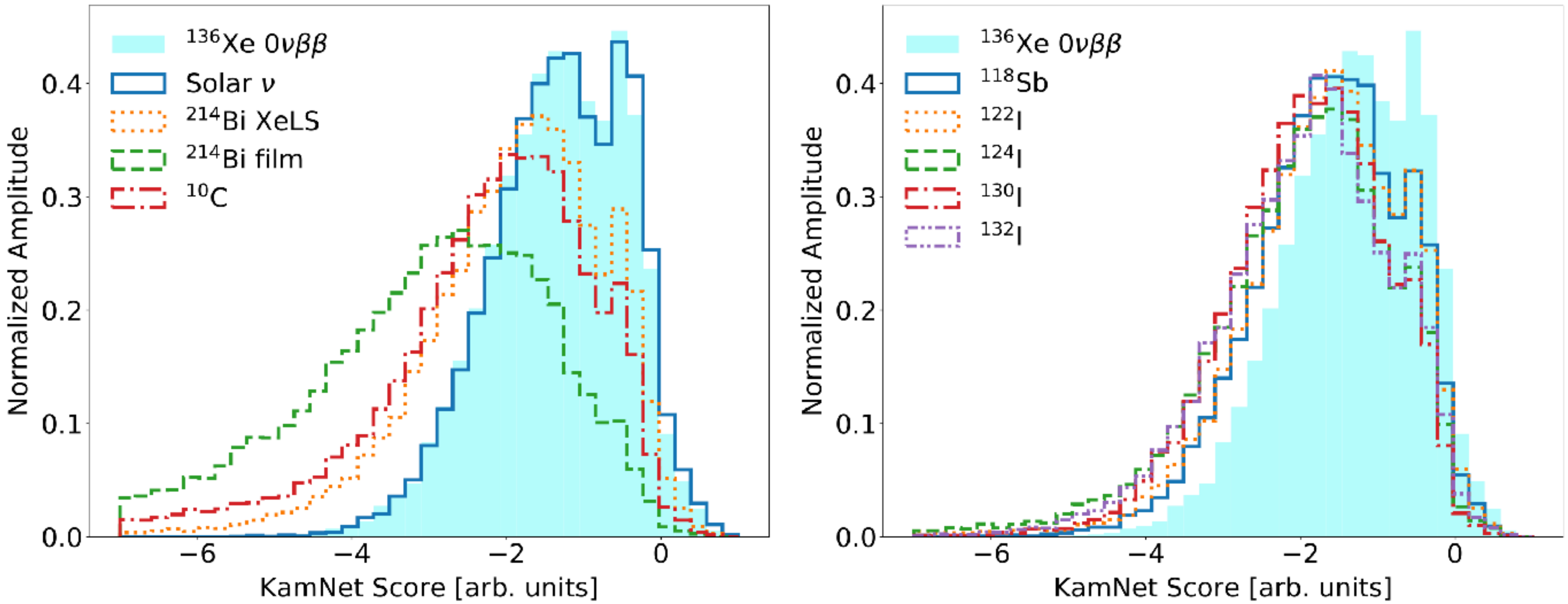


FIG. 2. (a) Schematic diagram of the AttentionConvLSTM layer, including two ConvLSTM layers and attention mechanism. (b) Diagram of KamNet.

KamLAND-Zen

PHYSICAL REVIEW C **107**, *014323 (2023)*

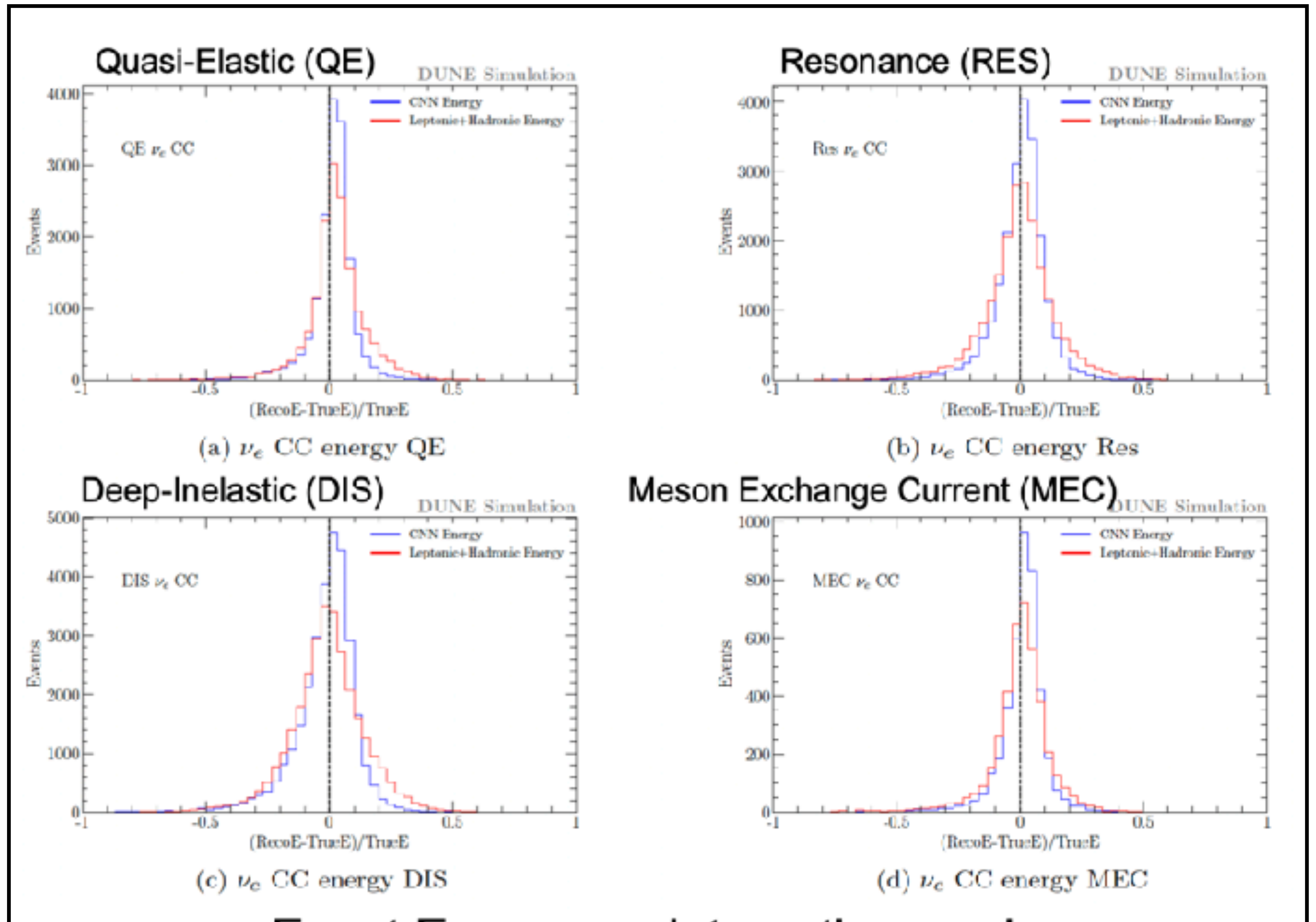


(a) (b)

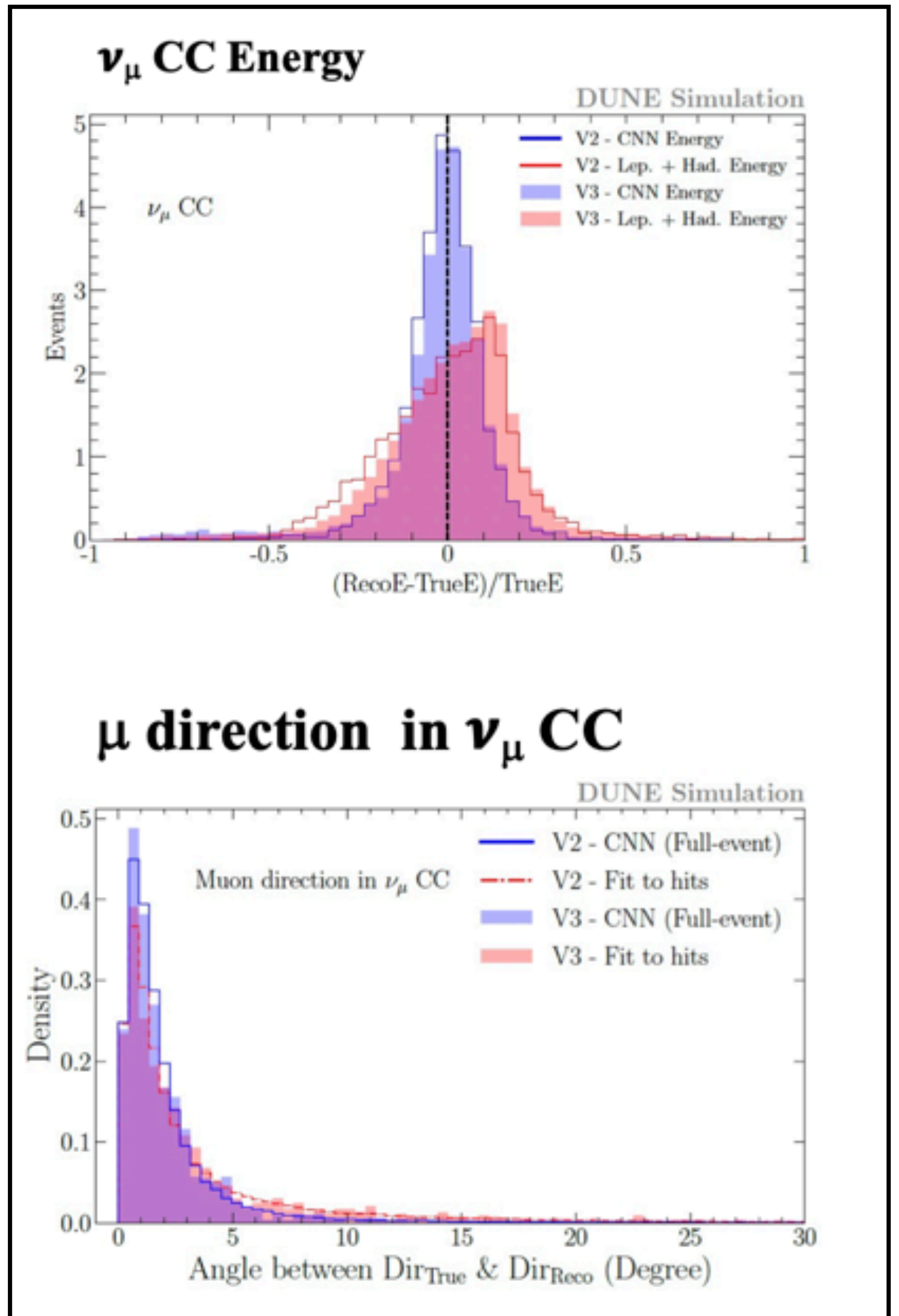
FIG. 5. (a) KamNet score spectrum for common backgrounds in KamLAND-Zen 800, including solar neutrino, ^{214}Bi, and ^{10}C backgrounds. (b) KamNet score spectrum for dominant long-lived spallation backgrounds in energy ROI. All histograms have been normalized to unity. Except for Solar ν, all backgrounds has lower KamNet score compared to ^{136}Xe, and thus they can be efficiently rejected by making cut on KamNet score.

Challenges

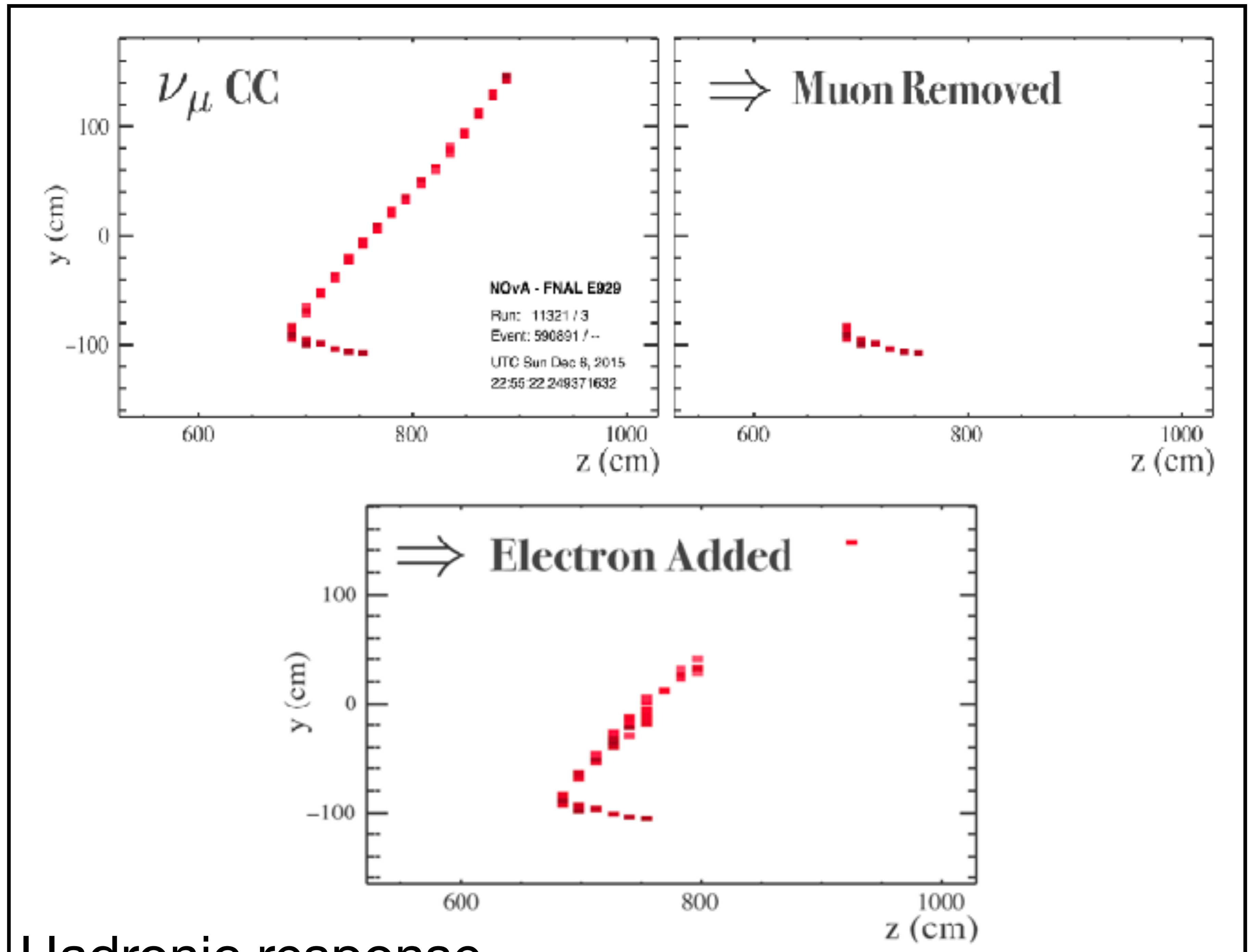
- Finding optimized models: detector geometry, electronic readout, physical events
- Robustness of ML models: training sample and reality
- Interpretability of ML techniques



ν_e Event Energy vs. interaction modes

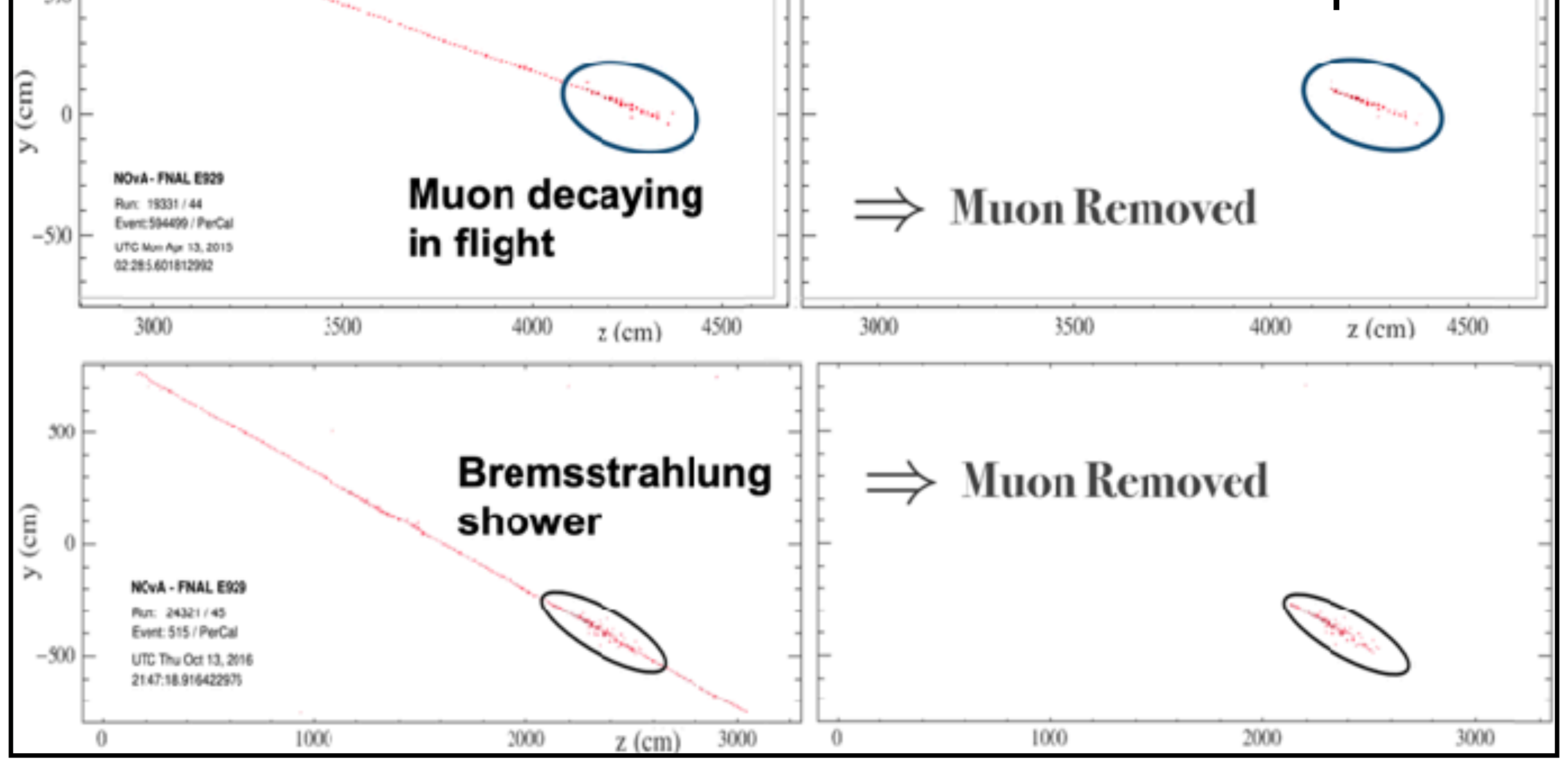


GENIE version 2.12.10 vs 3.0.4



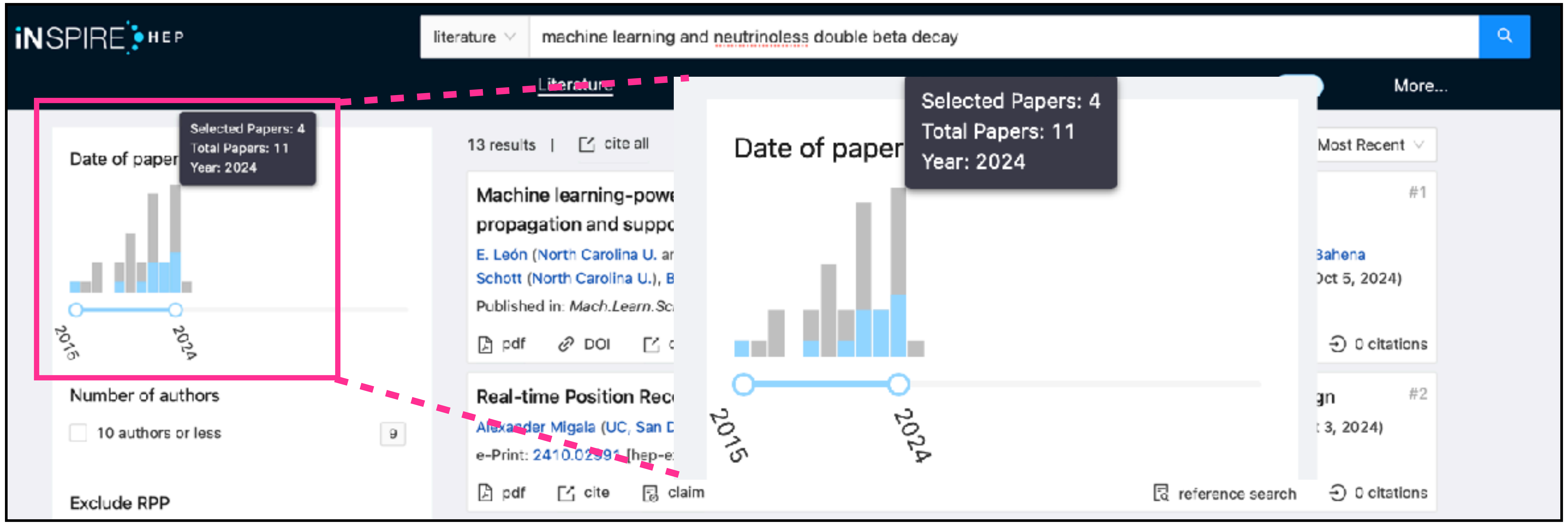
Hadronic response

EM response



Summary

- There is huge potential to boost the detection efficiency/sensitivity with the help of AI/ML techniques
    - Replacement or augmentation of traditional analyses with ML models that can exploit complex detector signatures, assist detector operation and anomaly detection
- Challenges along the way: performance and validity
    - New models: Graph Neural Networks, Unsupervised training, …
    - Expansive data comparison, impact analysis, uncertainty studies and cross-checks to improve robustness and interpretability

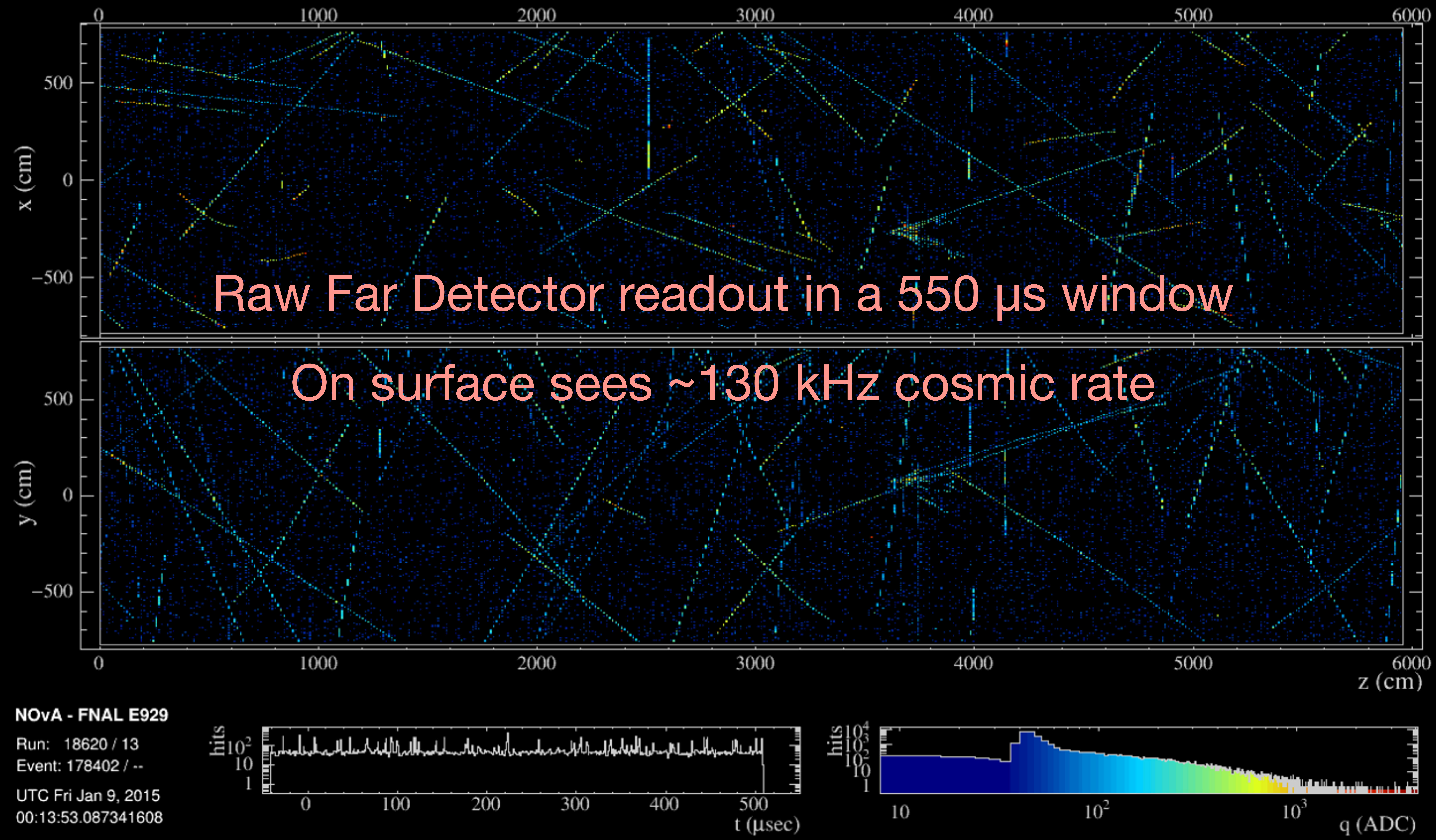


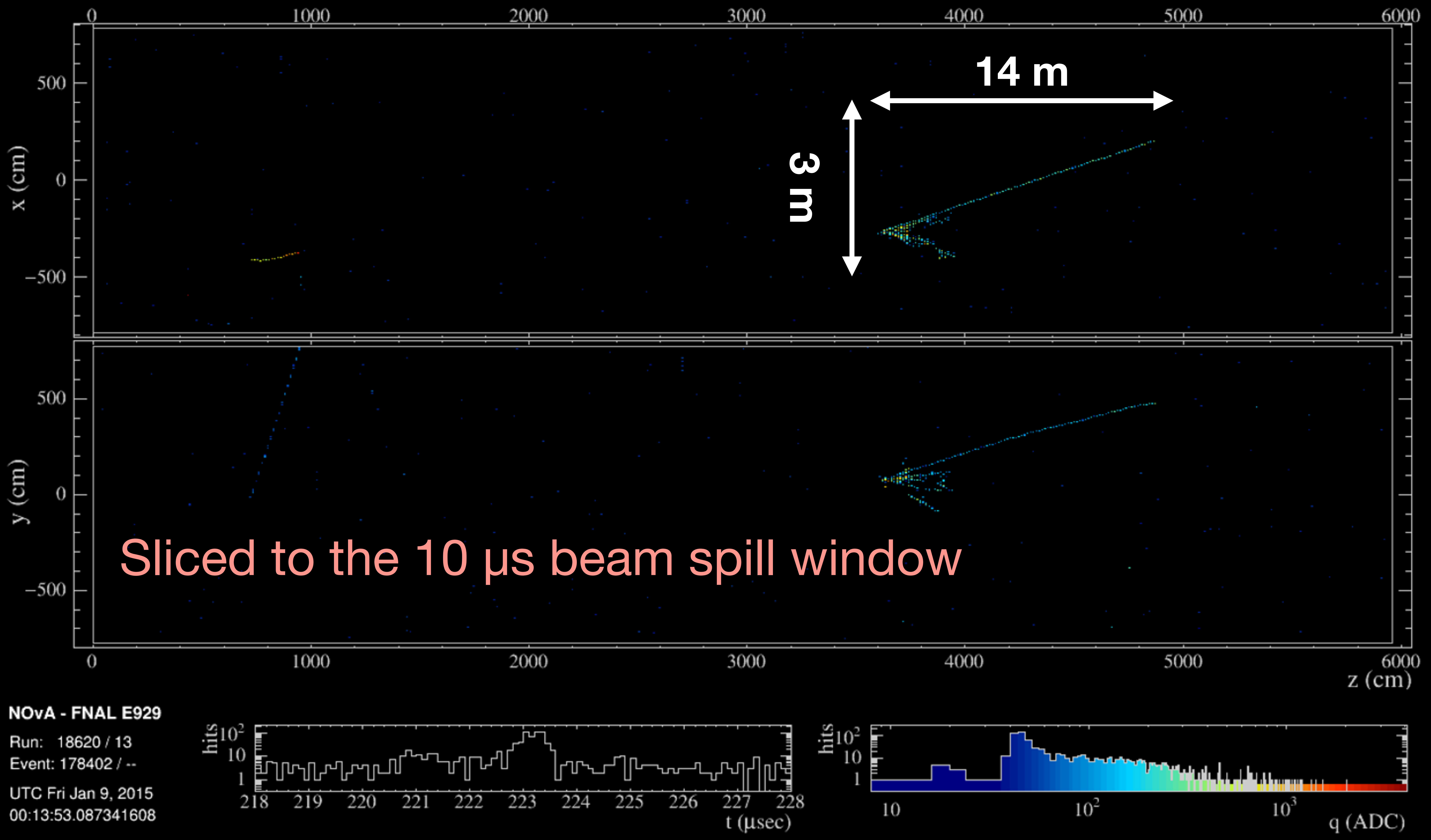
Thanks!

Backup

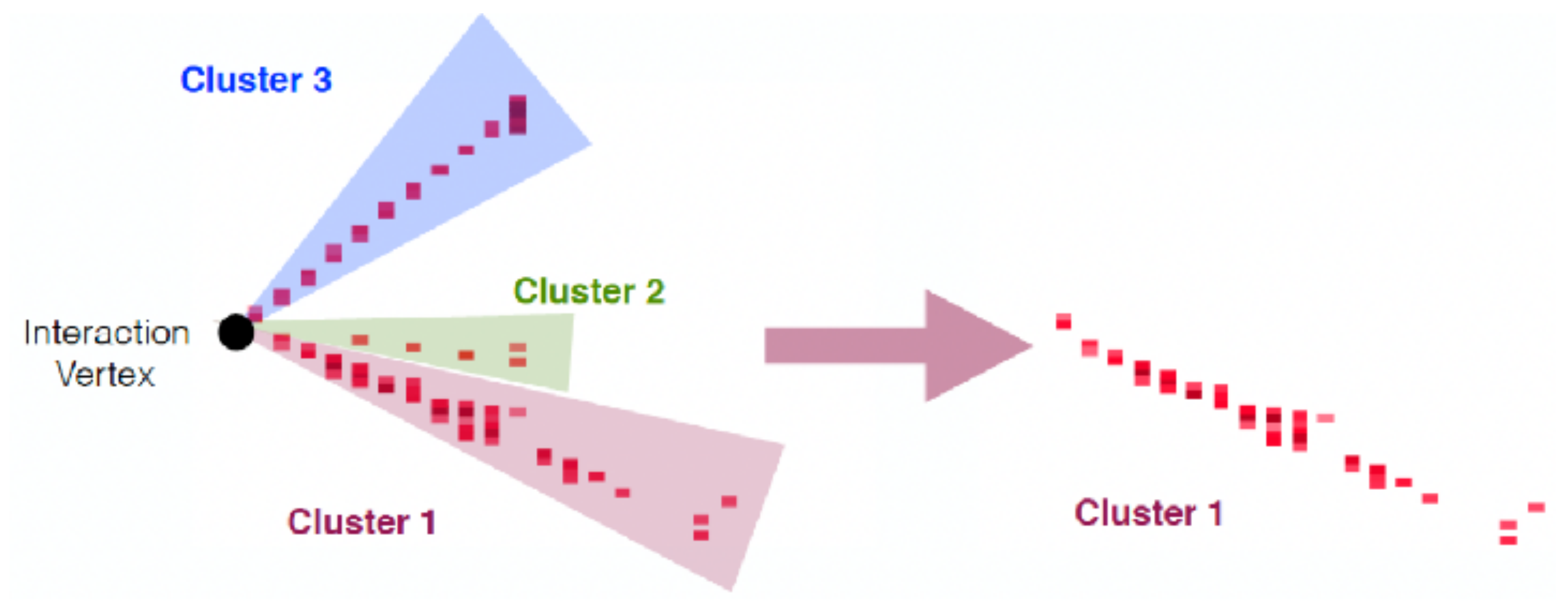
Raw Far Detector readout in a 550 μs window

On surface sees ~130 kHz cosmic rate




14 m
3 m
x (cm)
y (cm)
z (cm)
Sliced to the 10 μs beam spill window
NOvA - FNAL E929
Run: 18620 / 13
Event: 178402 / --
UTC Fri Jan 9, 2015
00:13:53.087341608
hits
t (μsec)
q (ADC)

CNN-based Particle Classifier (ProngCVN)



- Single particles are separated using geometric reconstruction methods
- Classify particles using both views of the **particle** and both views of the entire **event**
- This shows the network contextual information about single particles

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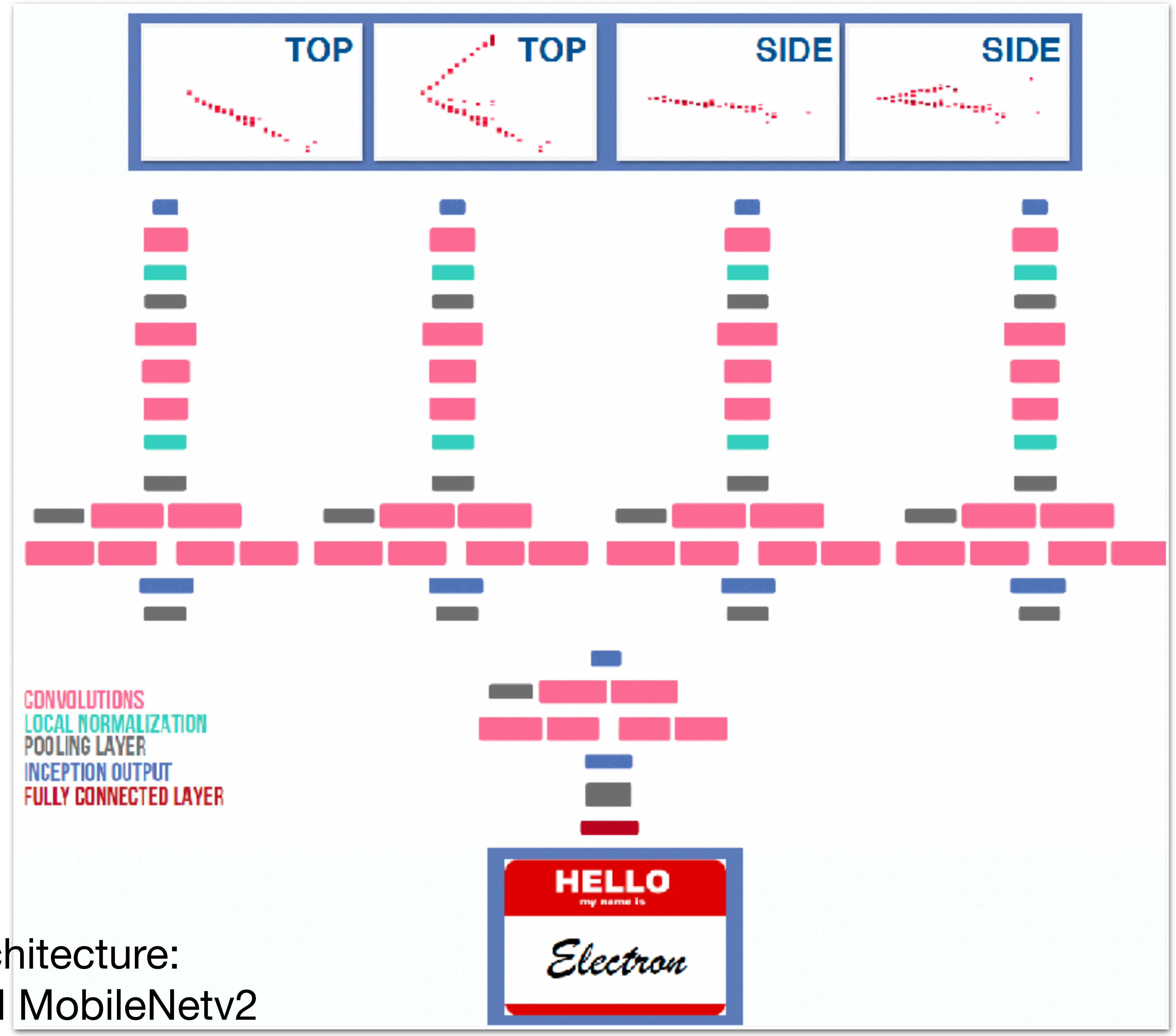
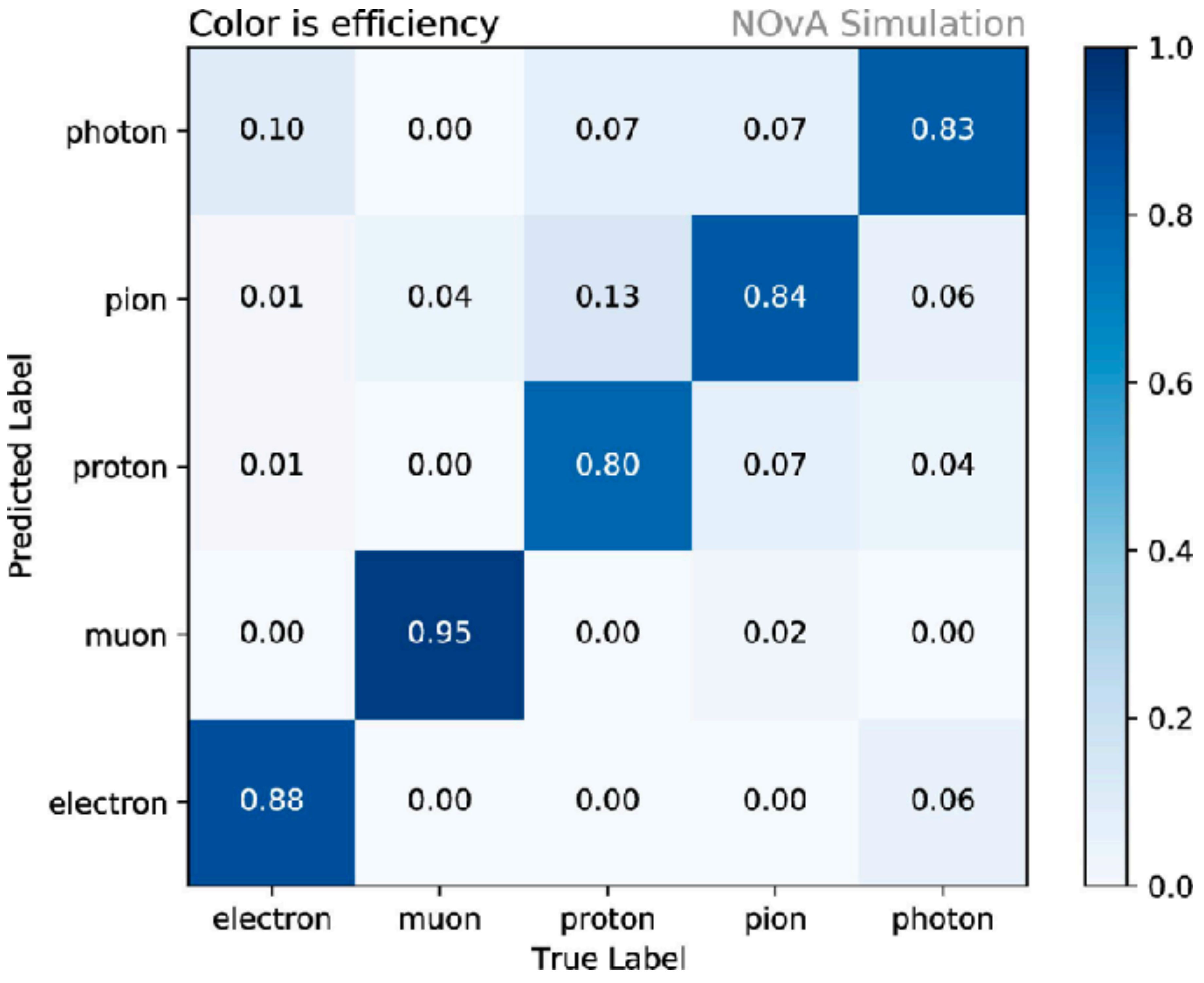
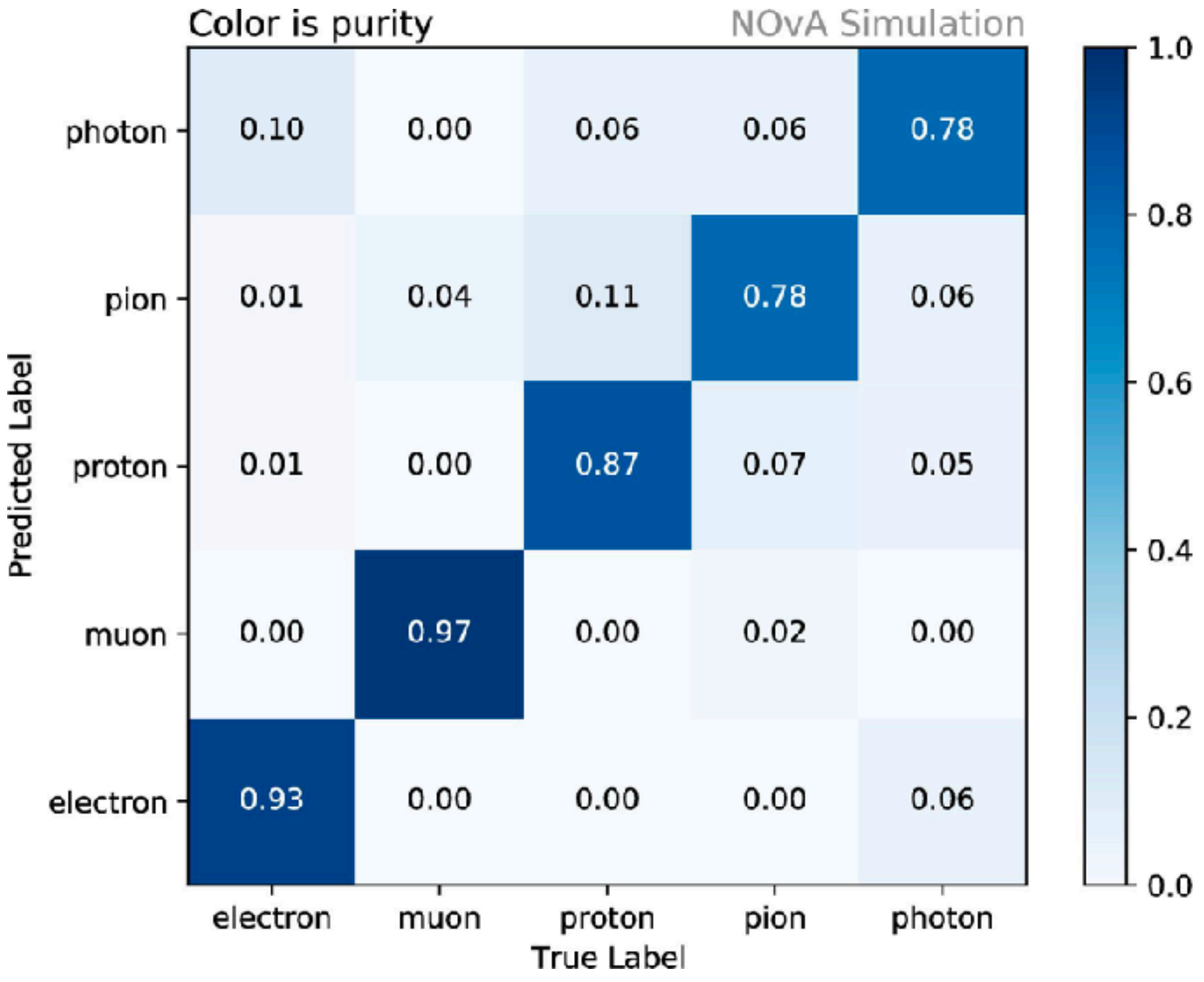


CNN architecture:
Modified MobileNetv2
Four-tower Siamese structure

CNN-based Particle Classifier (ProngCVN)

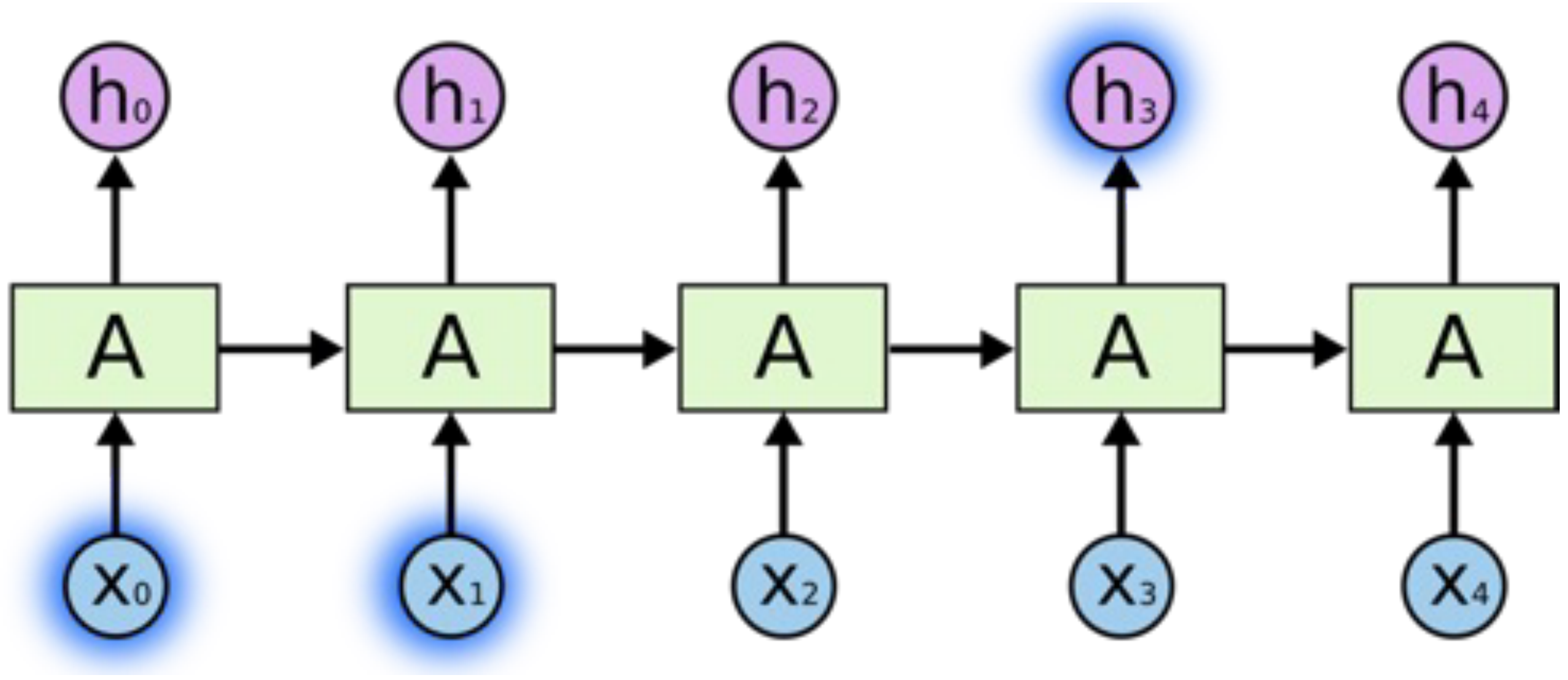


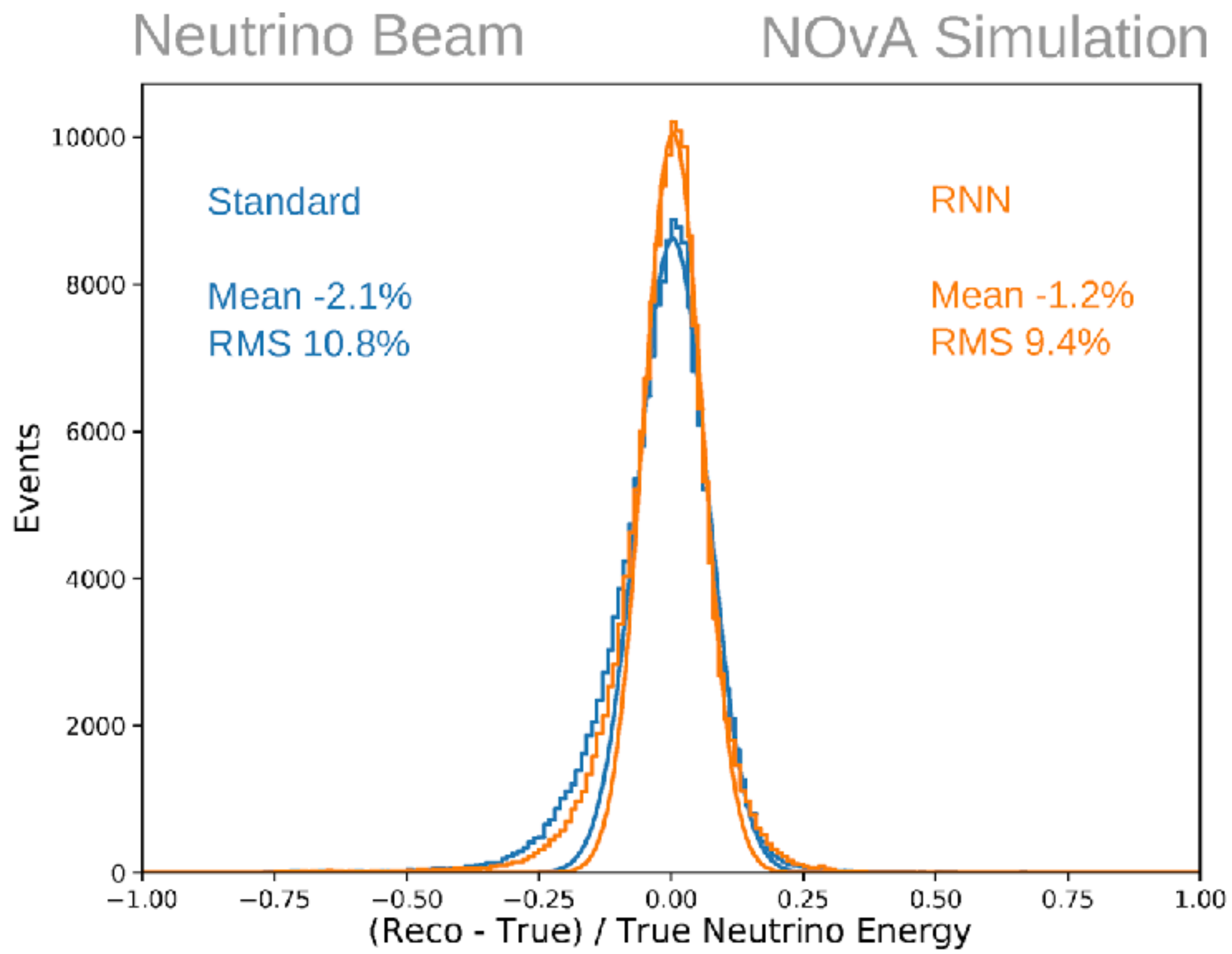


- Improvements were found in both efficiency and purity for all particle types, compared to the particle-only network
- In particular ~10% increase in the efficiency of selecting photons and pions

LSTM for Energy Estimation

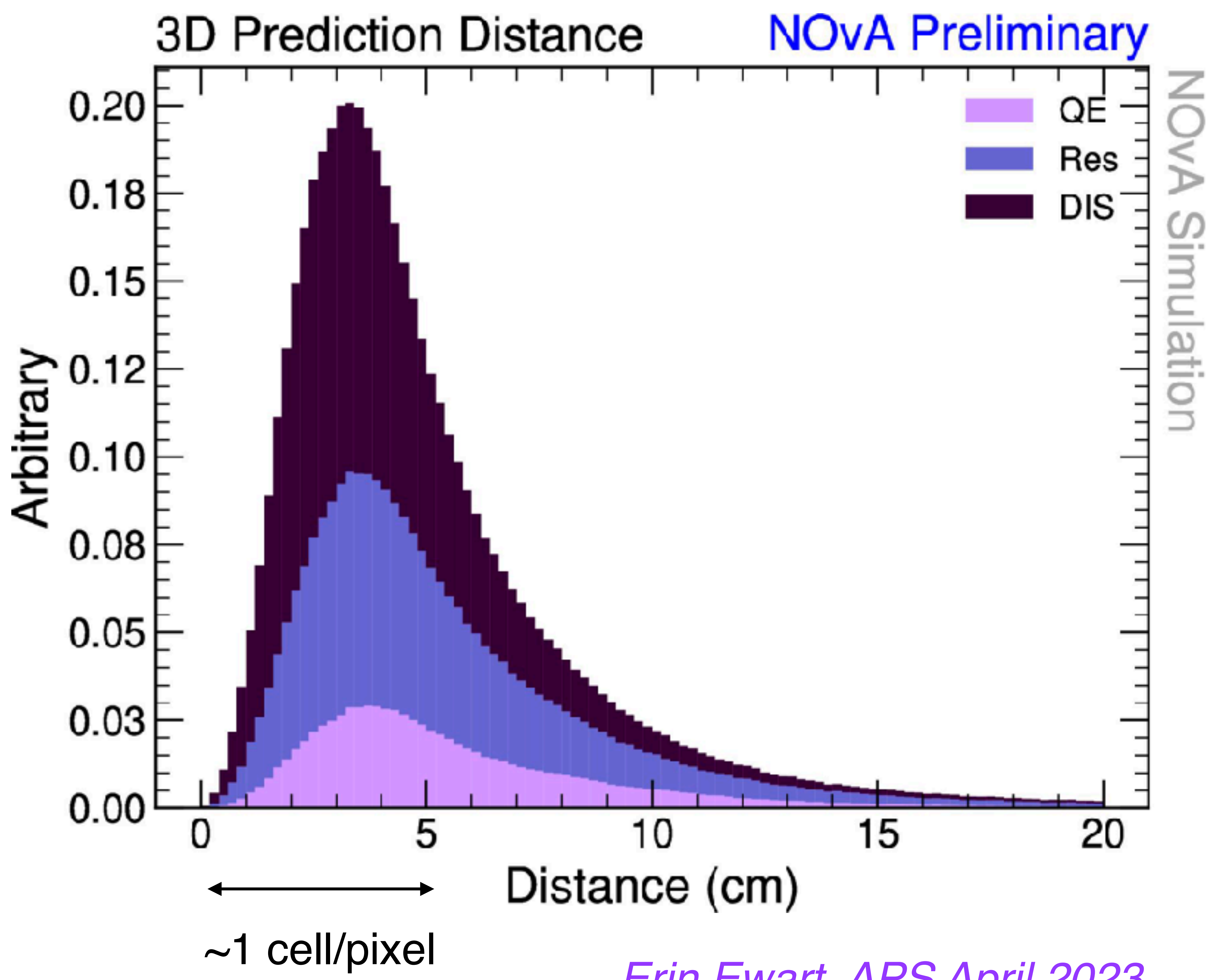
- Long Short-Term Memory (LSTM) is a type of recurrent neural network
- Takes a number of traditional reconstruction quantities as inputs
- Trained with artificially engineered sample to increase network resilience
- Resolution comparable with regression CNN





ML Vertexer (VertexCVN)

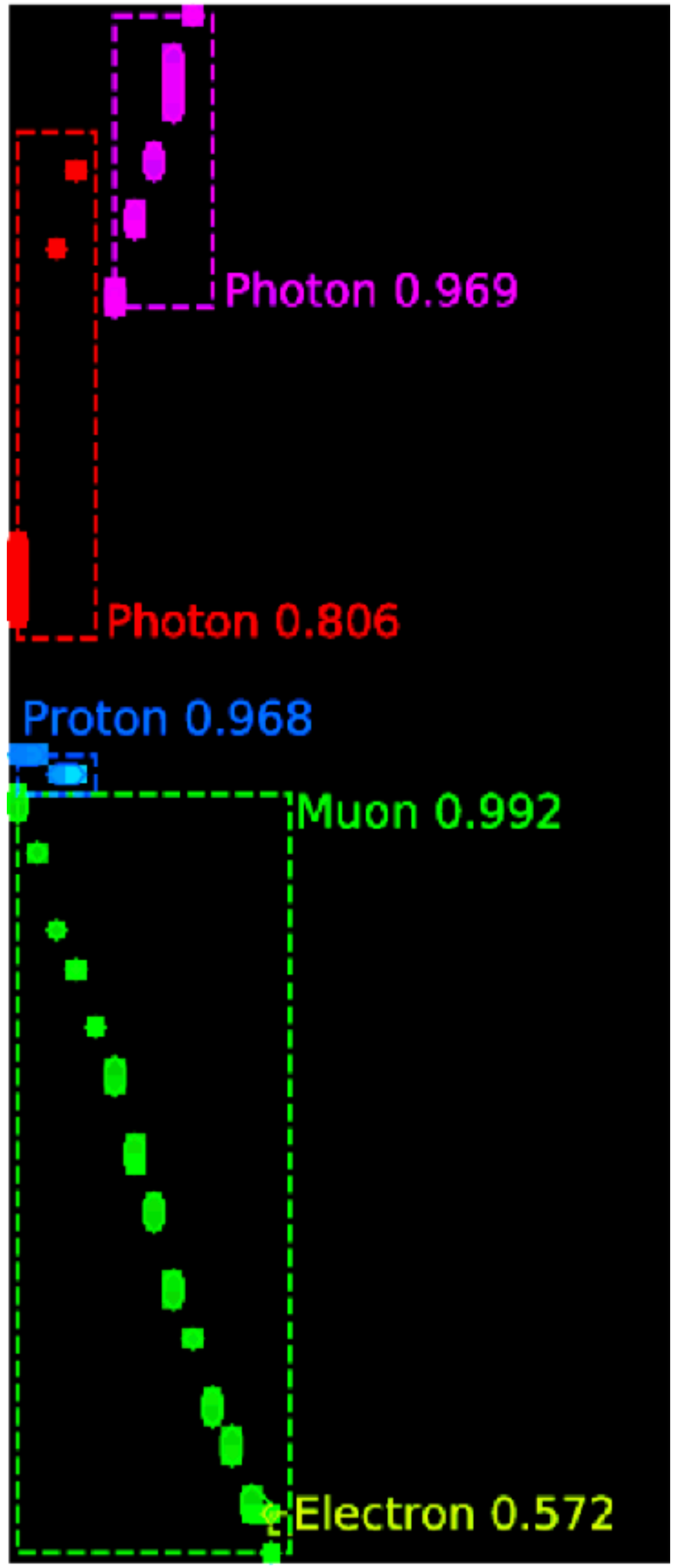
- More accurate vertex finding, means more accurate on
  - Clustering hits to form individual particle tracks/showers
  - Identifying particle types
  - Energy estimation
- Same network architecture as EventCVN (modified MobileNetv2) was explored to predict one 3D vertex
- Shows good performance across interaction types



Erin Ewart, APS April 2023

Full Event Reconstruction with Image Segmentation

- Full event reconstruction on a hit-by-hit basis using instance segmentation:
  - Bounds: Create a bounding box around each particle with a Region-based CNN (RCNN)
  - ID Score: Use a softmax function to classify the particle contained within each box
  - Clusters: Group together hits, identify hits, then individual hits are combined to form clusters
- Very powerful in PID and clustering efficiency
- No dependence on other reconstruction (vertex, etc)
- However, it's quite slow to run on CPUs, and more work needs to be done to run at scale



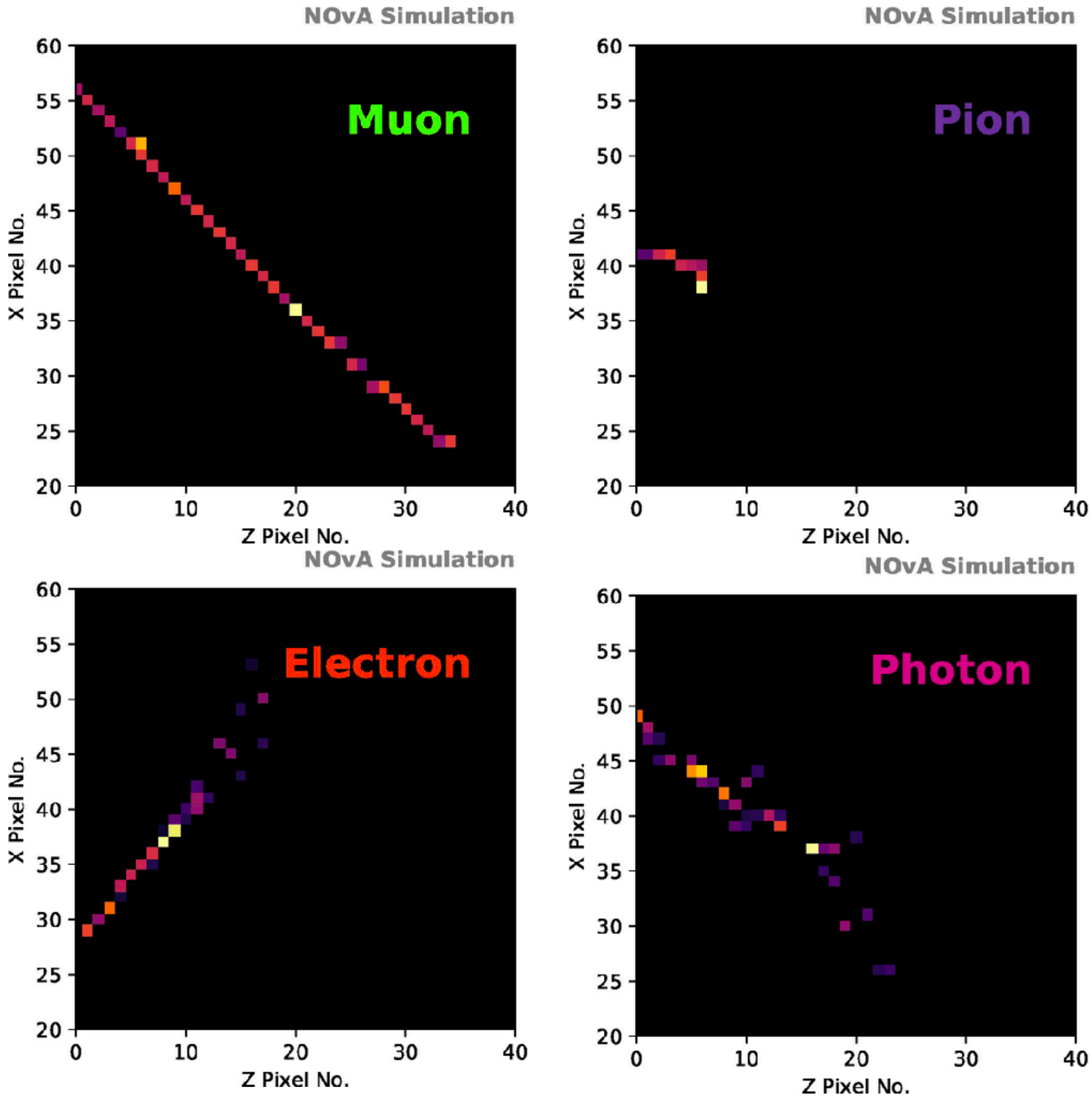
Cosmic filtering with a NN

- Network based on ResNet18 backbone with a siamese structure
  - Takes in two event images (top-view and side-view) as input
- Softmax output with five labels: ν_μ, ν_e, ν_τ, NC, and cosmic score
- Training sample contained 1M+ ν_μ, ν_e, and NC events in both beam modes and 5M+ cosmic events
  - Not trained separately for neutrino/antineutrino mode
- Performs better than traditional cosmic rejection in all samples

Data Sample	Traditional Cosmic Rejection	Cosmic Rejection Neural Network
ν_e	93.21	99.71
$\bar{\nu}_e$	92.81	99.82
ν_μ	93.22	99.20
$\overline{\nu_\mu}$	92.82	99.20
ν NC	93.24	97.08
$\bar{\nu}$ NC	92.79	96.82
Cosmic ν	7.80	5.00

Single particle ID

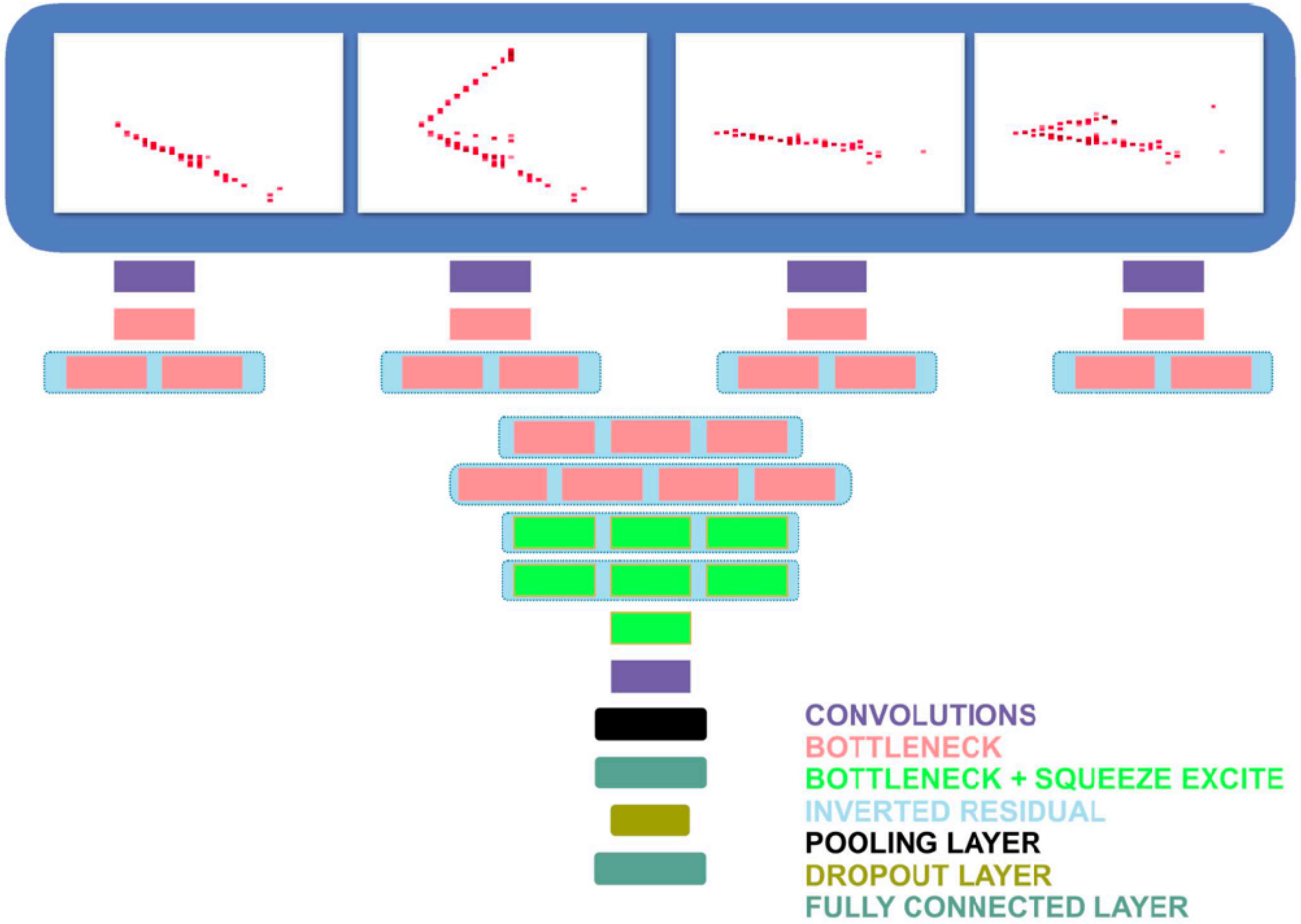
- NOvA also has trained a network using singularly simulated particles for ND analyses → no contextual information
- Also developing a network designed for neutron identification using these samples



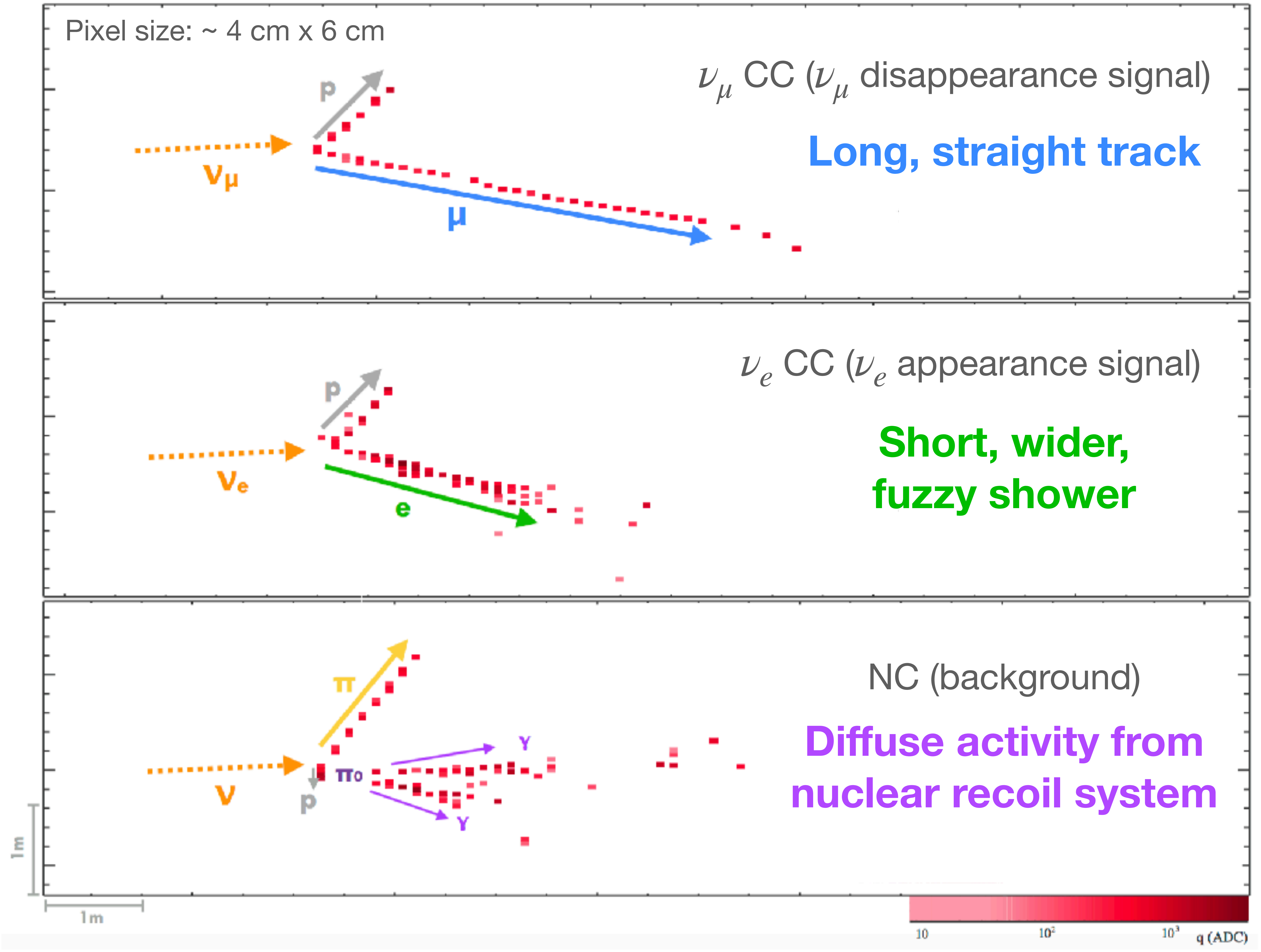
Improved ProngCVN

Akshay Chatla, DAE 2022

- Modifies ProngCVN (modified MobileNetv2) architecture by adding Squeeze-Excite block for channel attention
- Trained on a combined sample of neutrino and antineutrino mode
- Shows good performance for particle classification

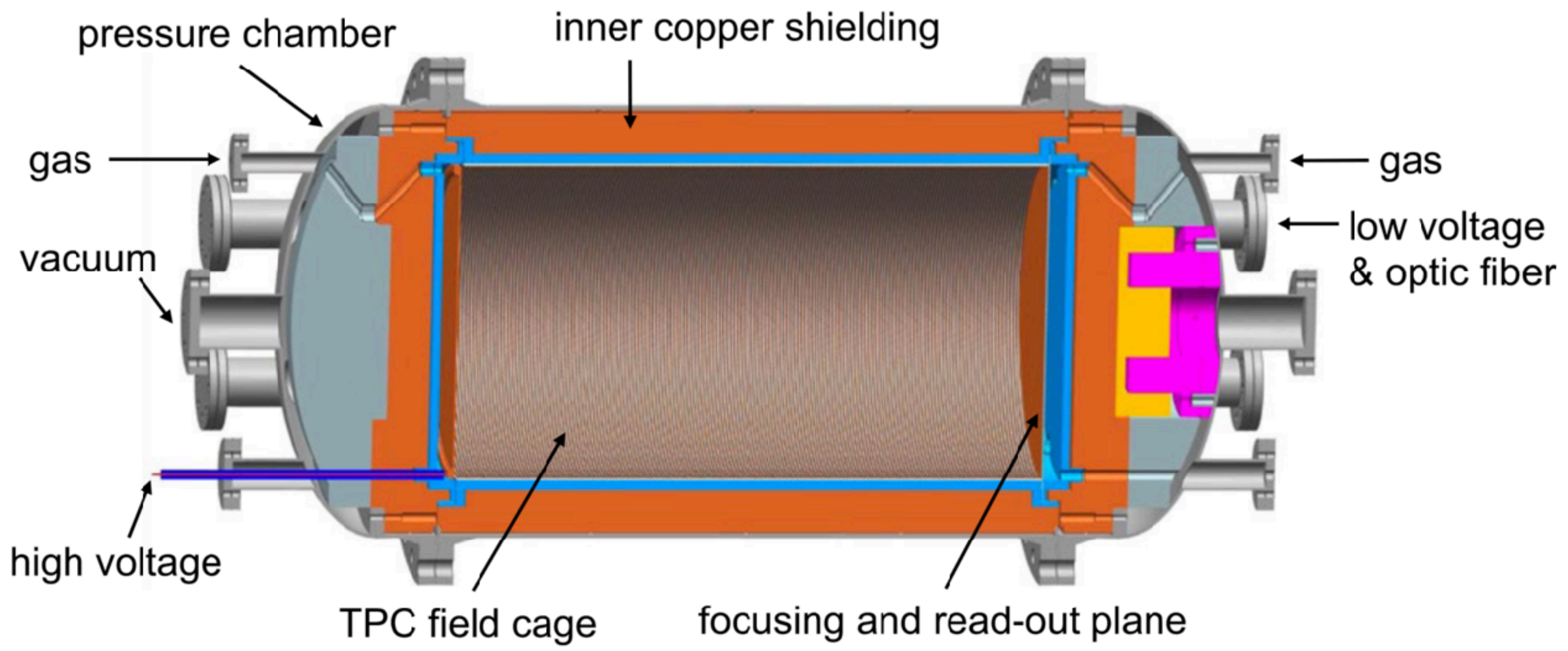


Event Topology



J. Inst. **11**, P09001 (2016)

NvDEx-100

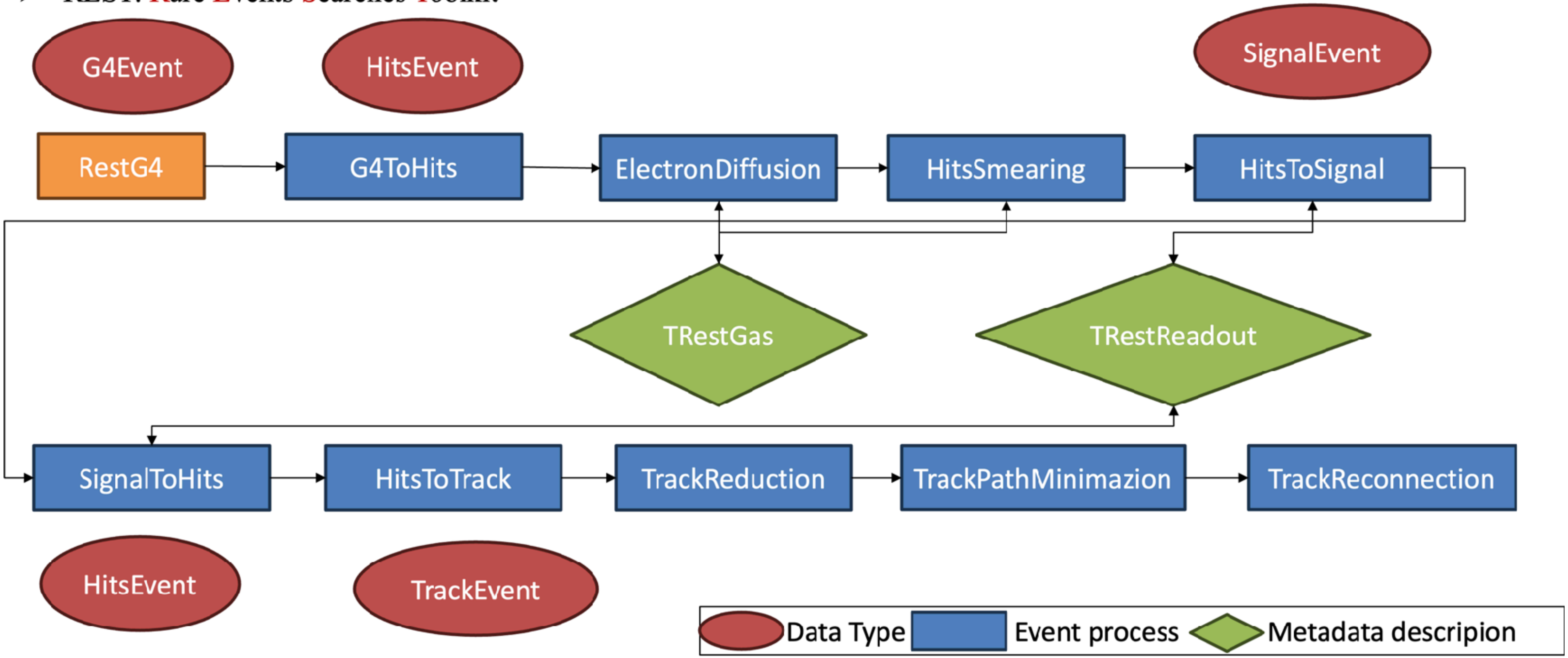


- 100 kg SeF_6 gas at 10 atm in the sensitive volume
- Barrel part length: 160 cm, pressure vessel inner diameter: 120 cm
- Tightness requirement for poisonous SeF_6: < 0.05 ppm in environment

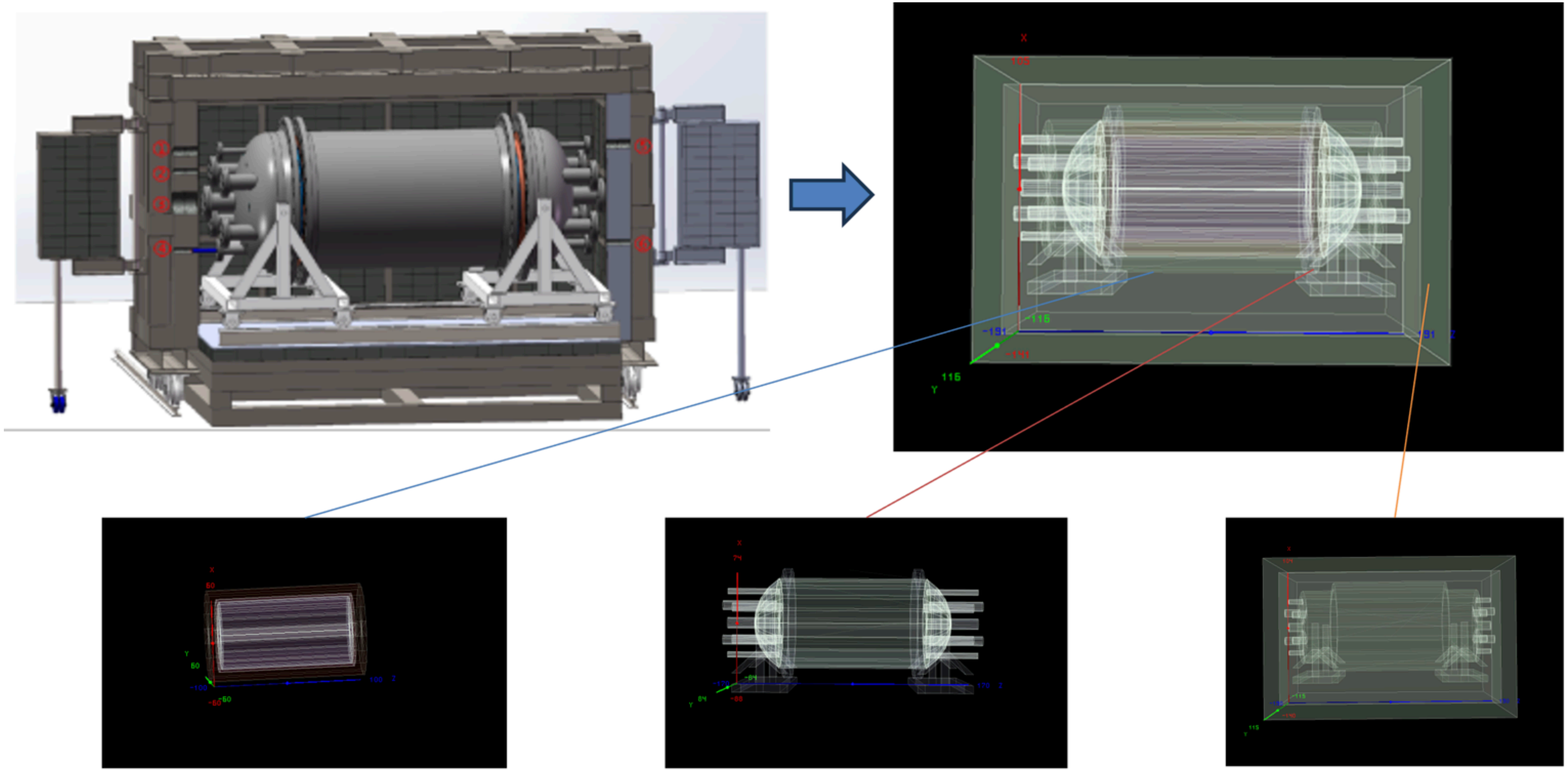
Simulation Framework

全流程模拟：信号和本底产生、电子径迹和能量沉积、正负离子产生和漂移、Topmetal-S芯片响应信号、径迹重建、事例鉴别等

➢ REST: Rare Events Searches Toolkit

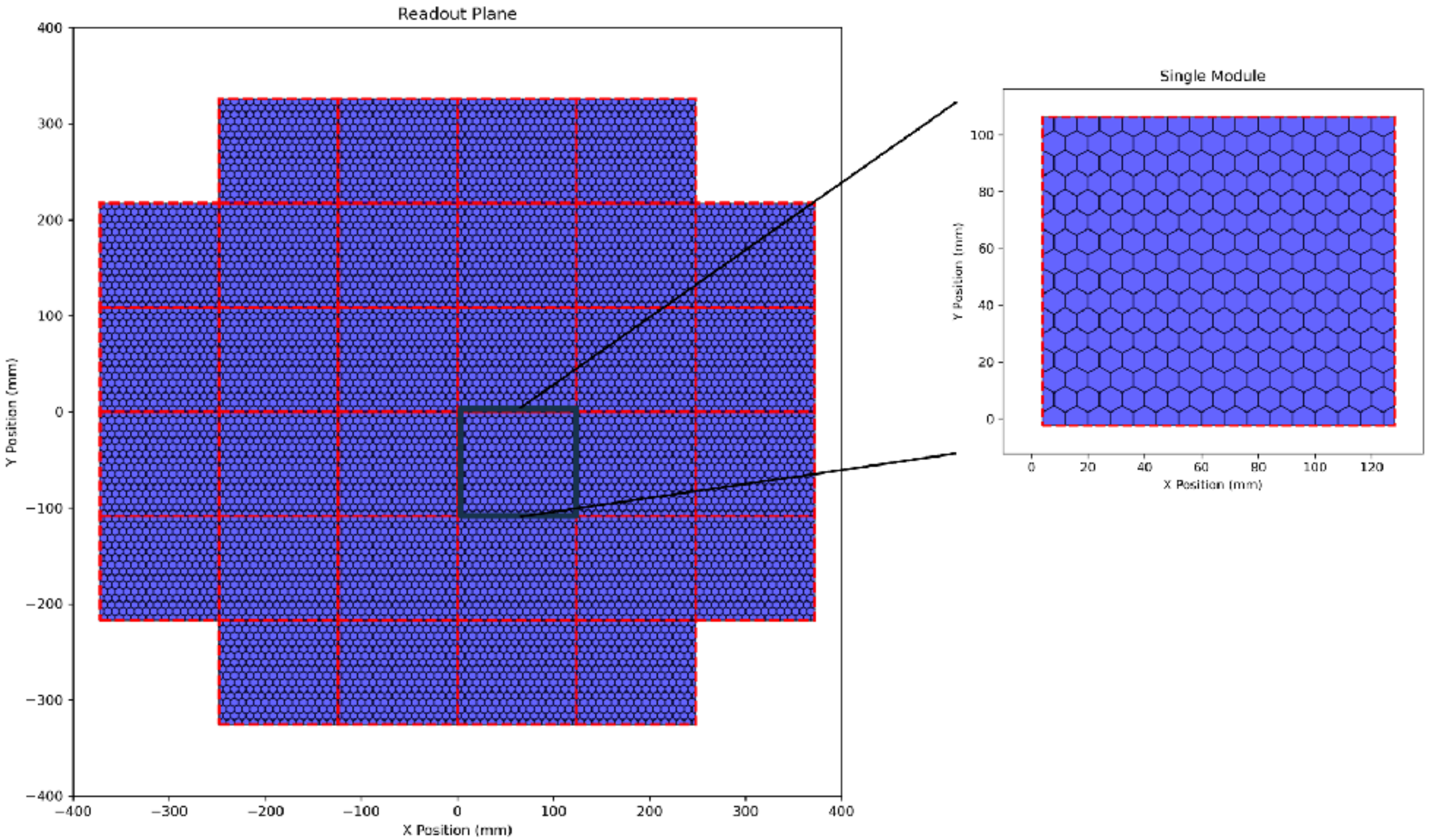


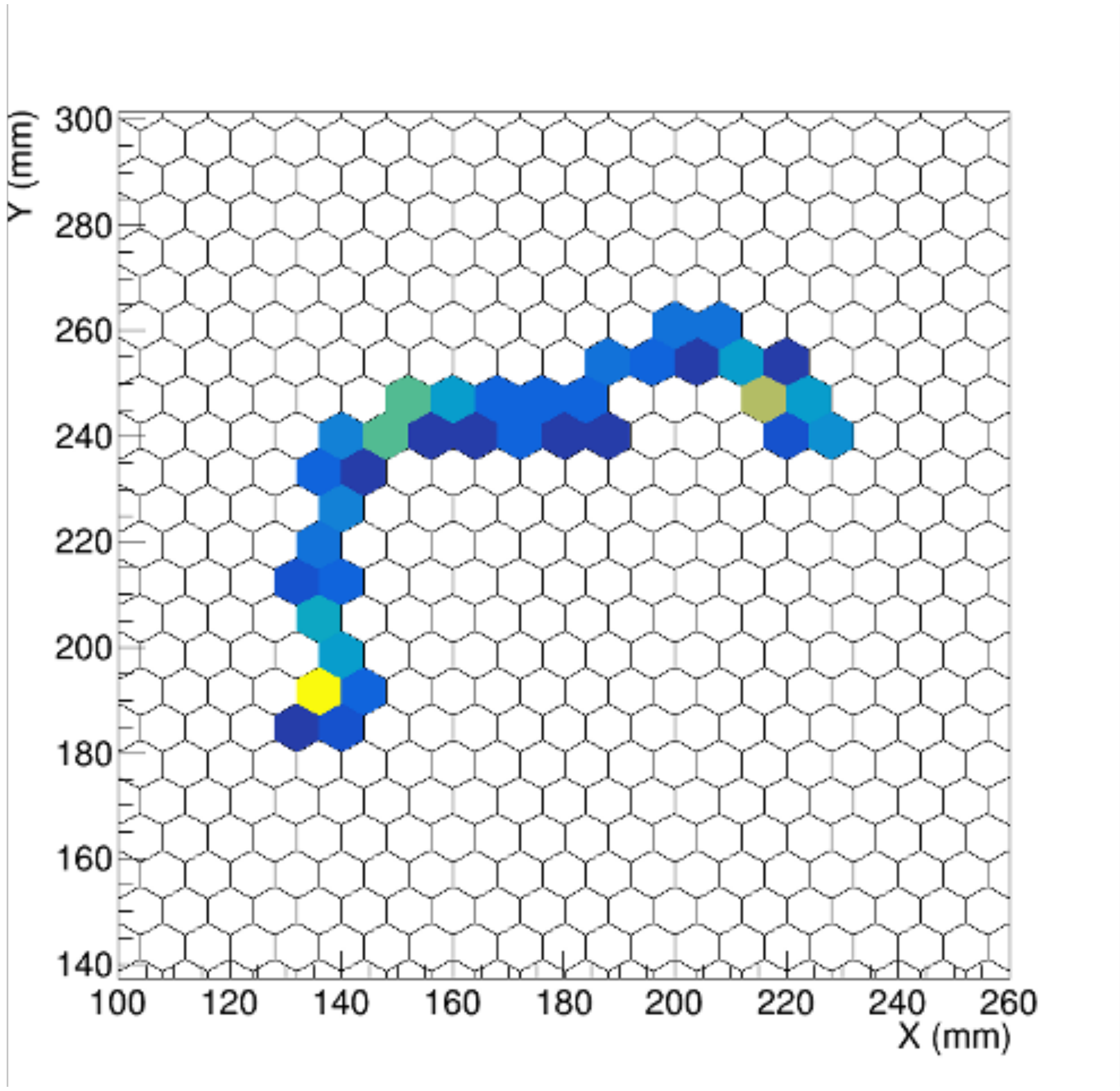
Simulation Framework



气体与铜屏蔽体　　　　罐体，管道与支架　　　　外屏蔽体

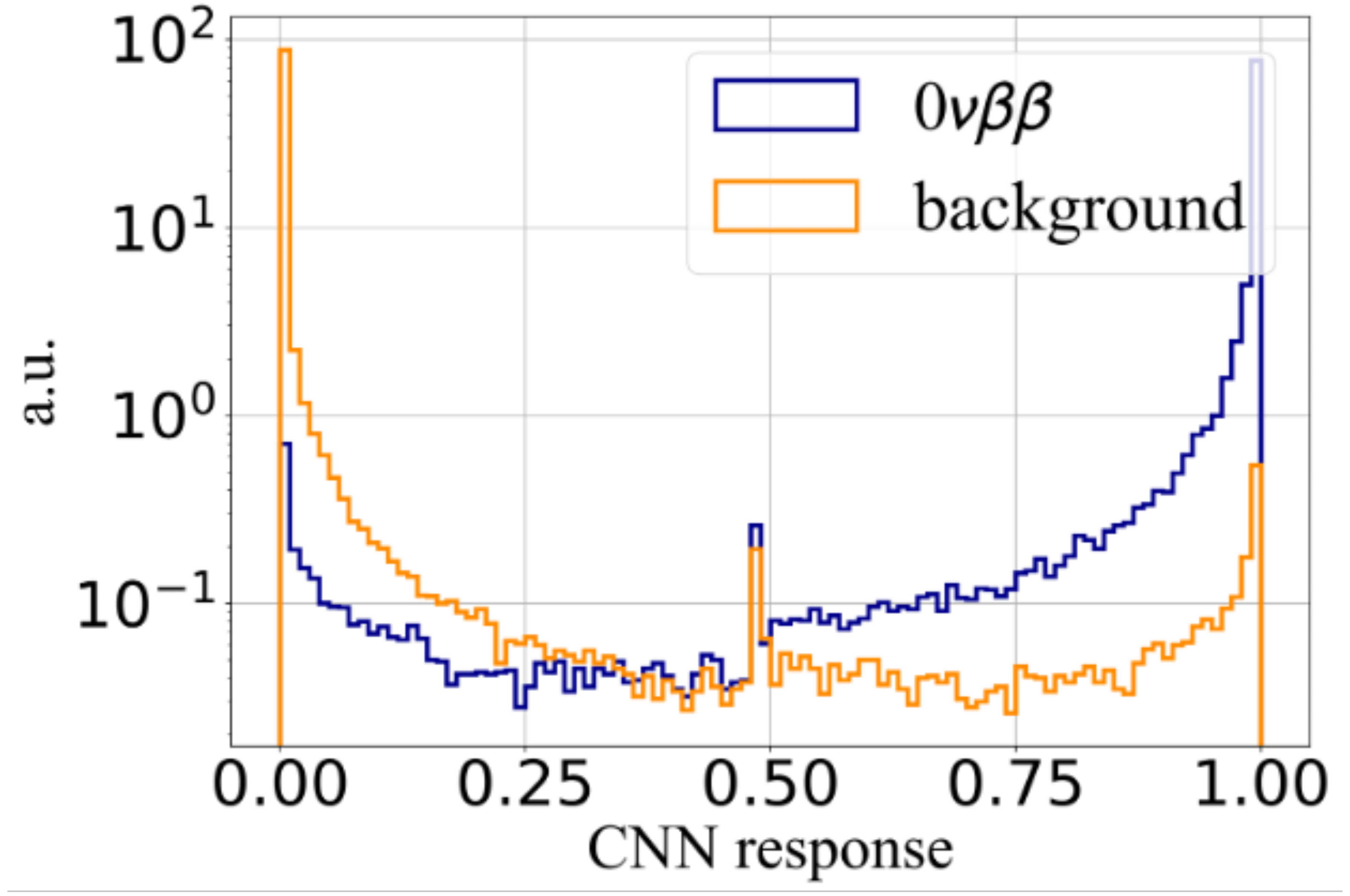
Simulation Framework

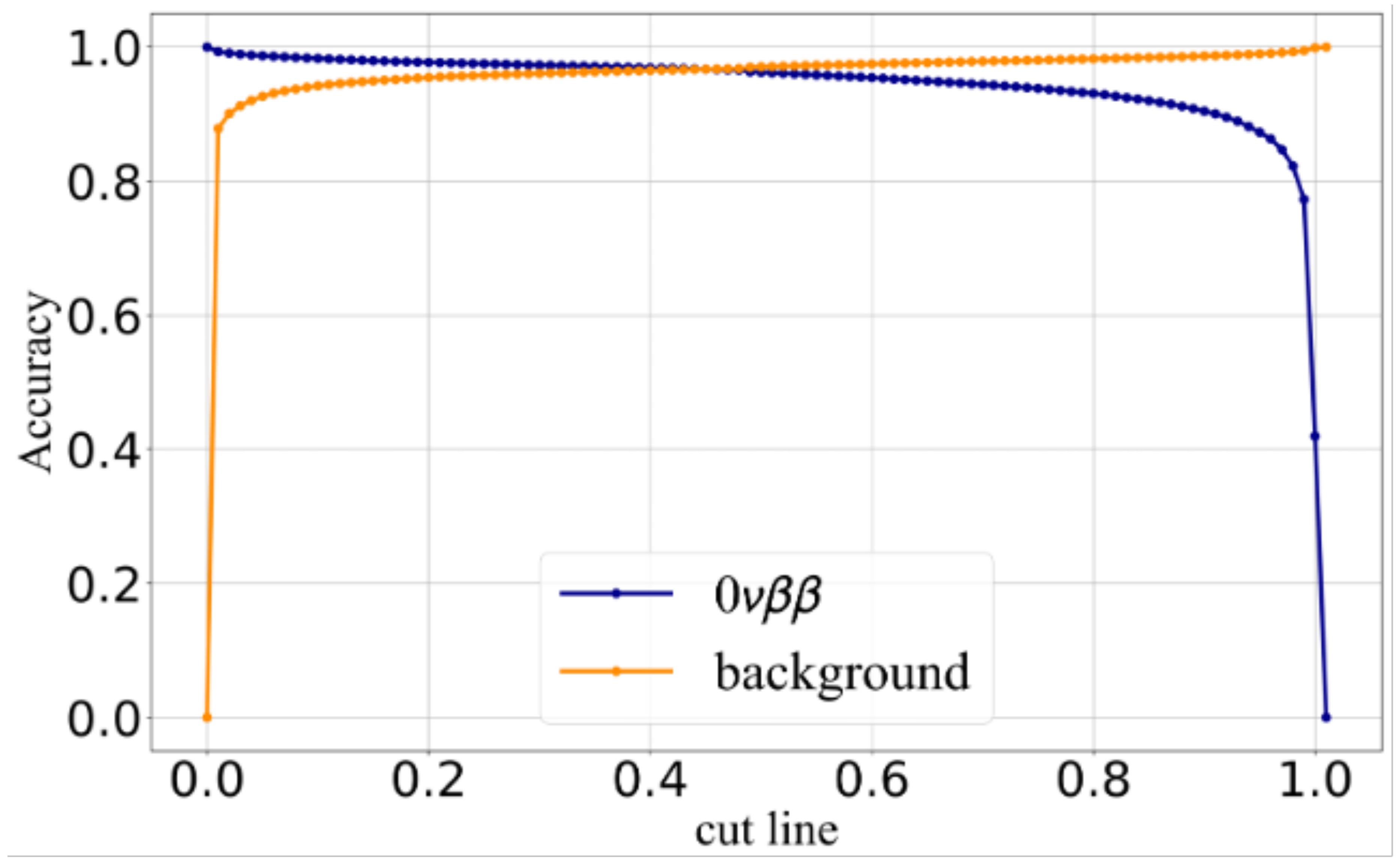




读出平面：32个模块，每个模块有16x16共256个正六边形像素，相邻像素中心间距8 mm，总共8192个像素

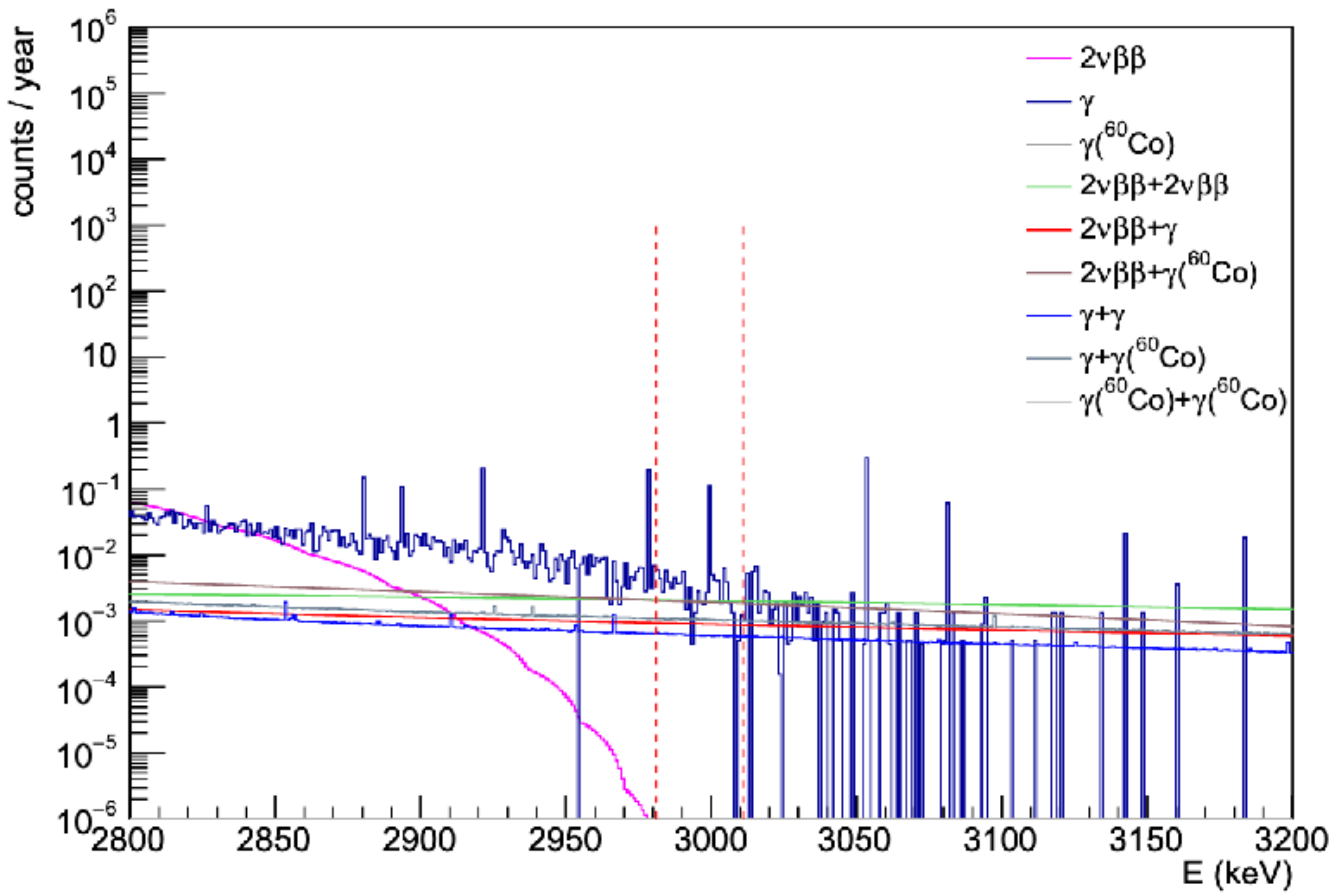
Simulation Framework

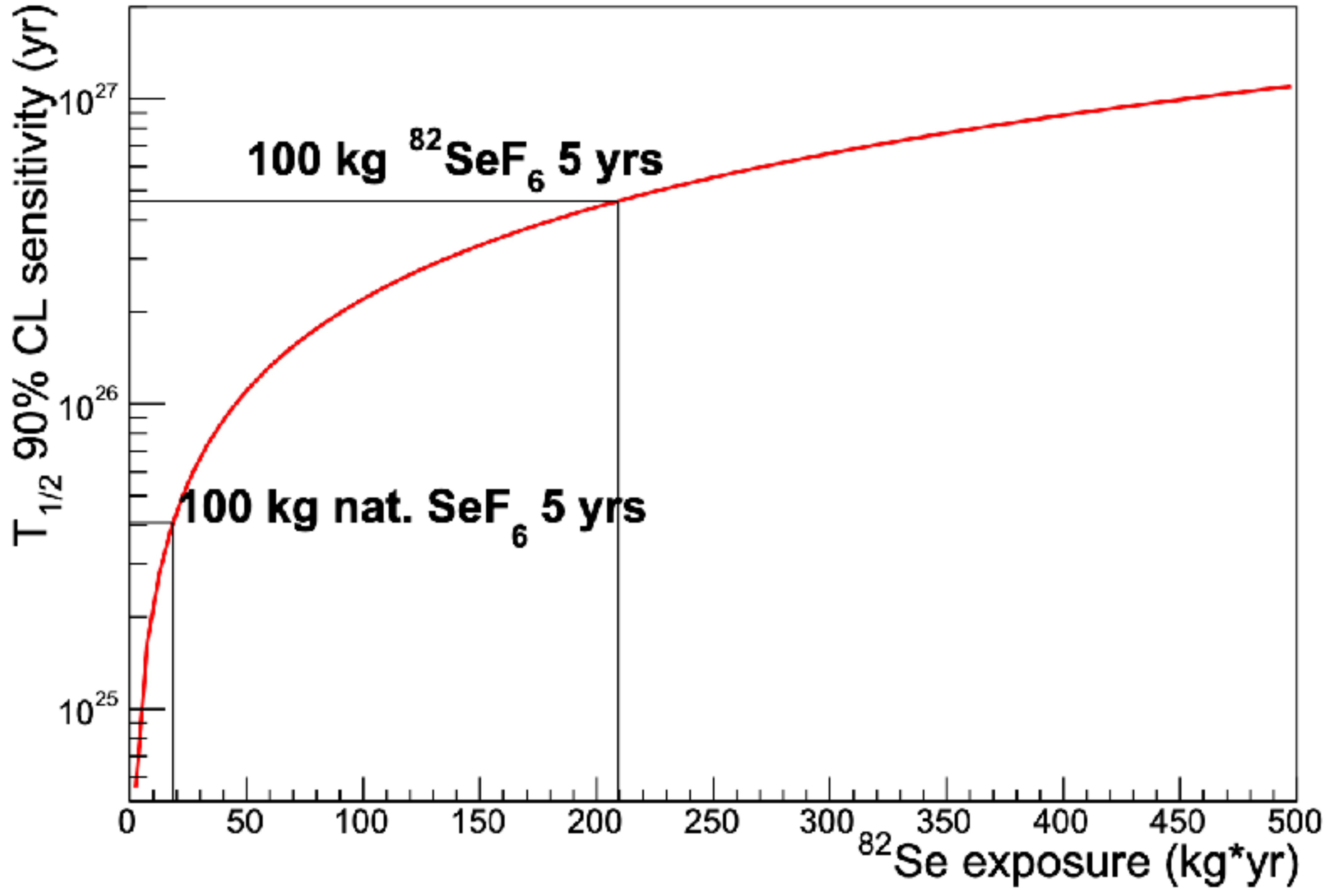




- 利用信号、本底事件不同的几何特征，使用卷积神经网络进行信号本底鉴别
- 0vββ信号与β本底事例的CNN响应值分布差别很大
- 在保证信号90%的挑选效率时，可以排除98.6%的本底事例

Sensitivity Estimation





- Dominant background is natural radiation γ
  - 0.4 evts/yr in ROI before suppression using event topology information

- 100 kg natural SeF_6 (3.7 kg Se), 5 years
  - $T_{1/2} > 4 \times 10^{25}$ yr (90% CL)
- 100 kg enriched $^{82}SeF_6$, 5 years
  - $T_{1/2} > 4 \times 10^{26}$ yr (90% CL)