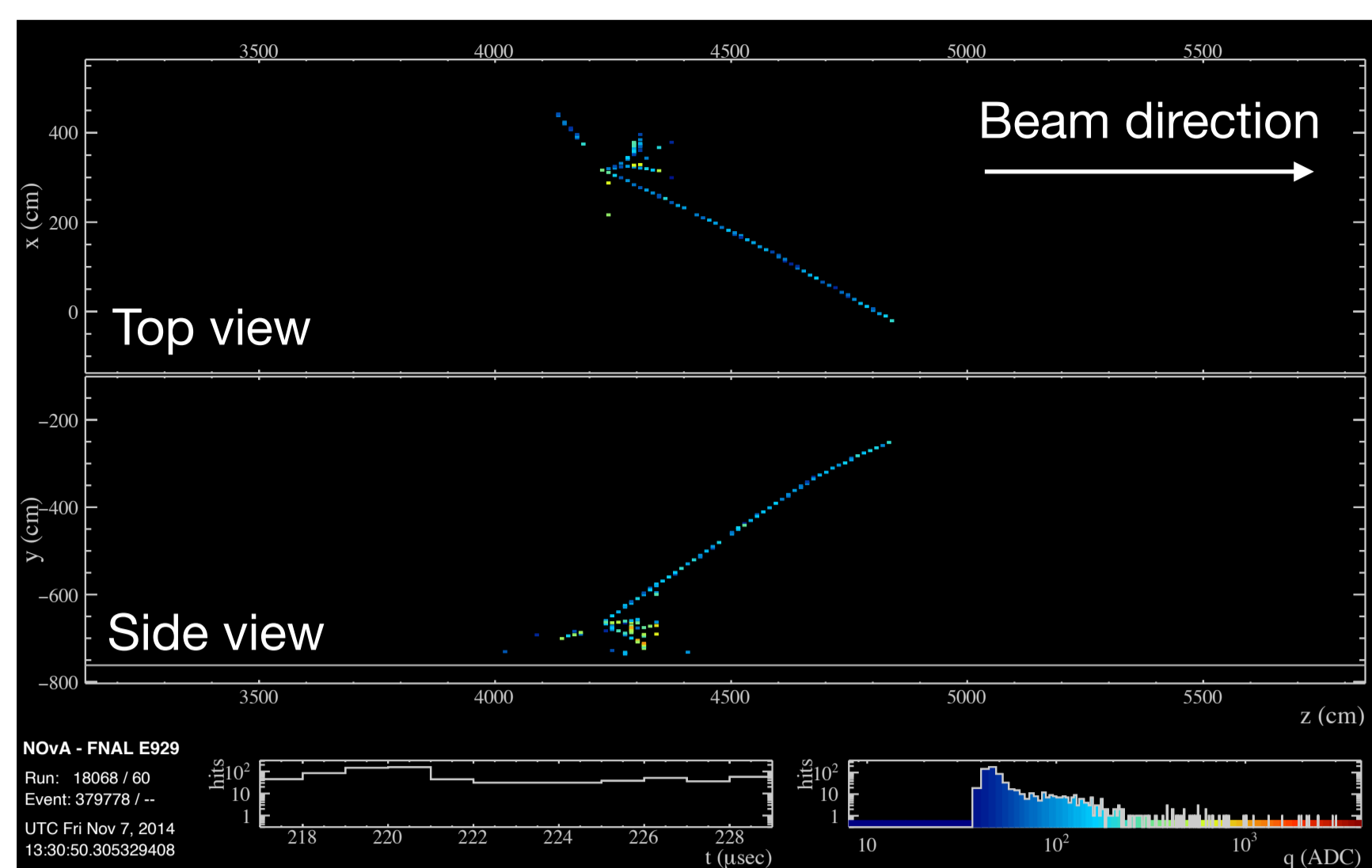


# RECENT ADVANCEMENTS IN MACHINE LEARNING TECHNIQUES UTILISED BY NOvA

Ashley Back<sup>1</sup>, Alexander Booth<sup>2</sup>, Erin Ewart<sup>1</sup>, Alexander Shmakov<sup>3</sup>, Wenjie Wu<sup>3</sup> & Alejandro Yankelevich<sup>3</sup> for the NOvA Collaboration



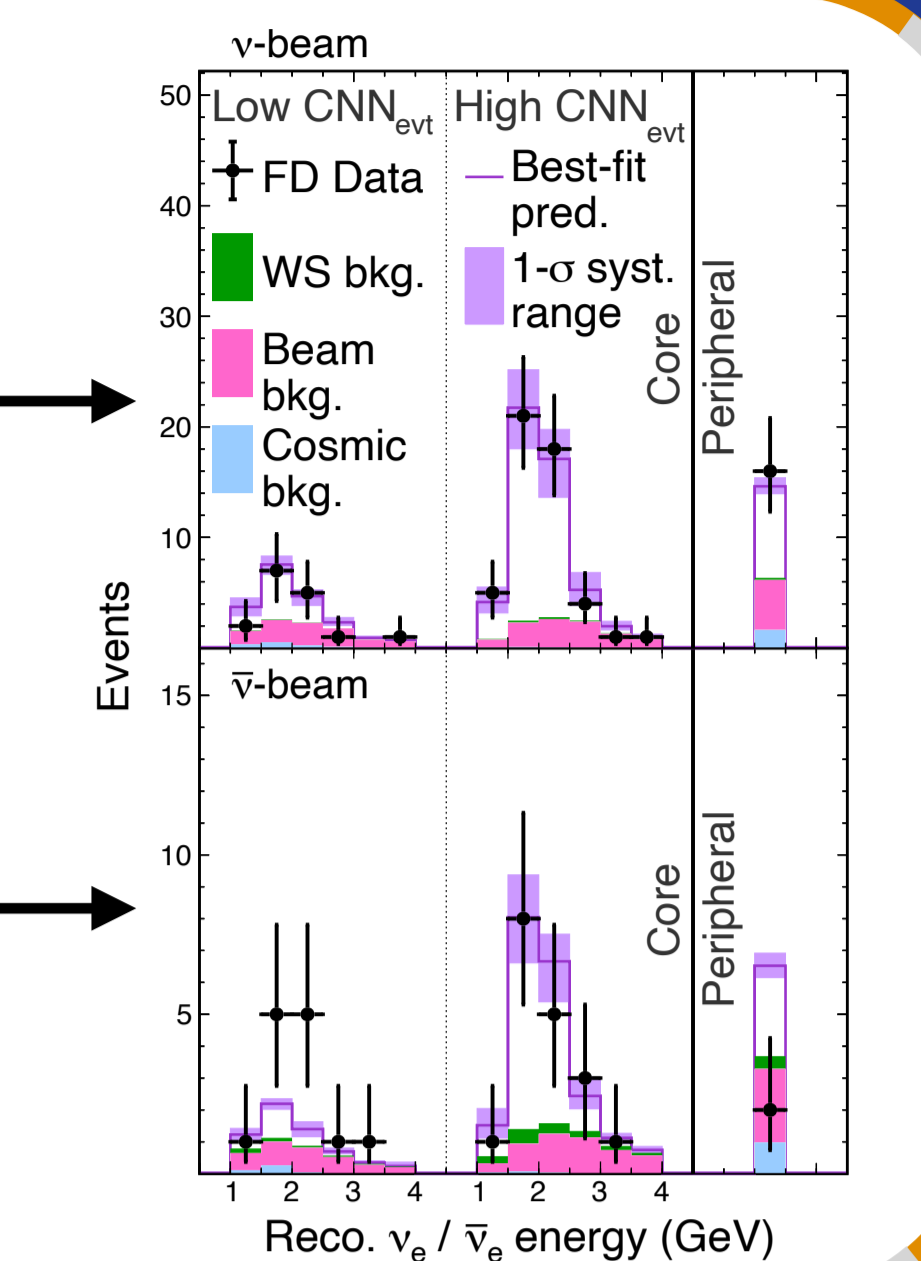
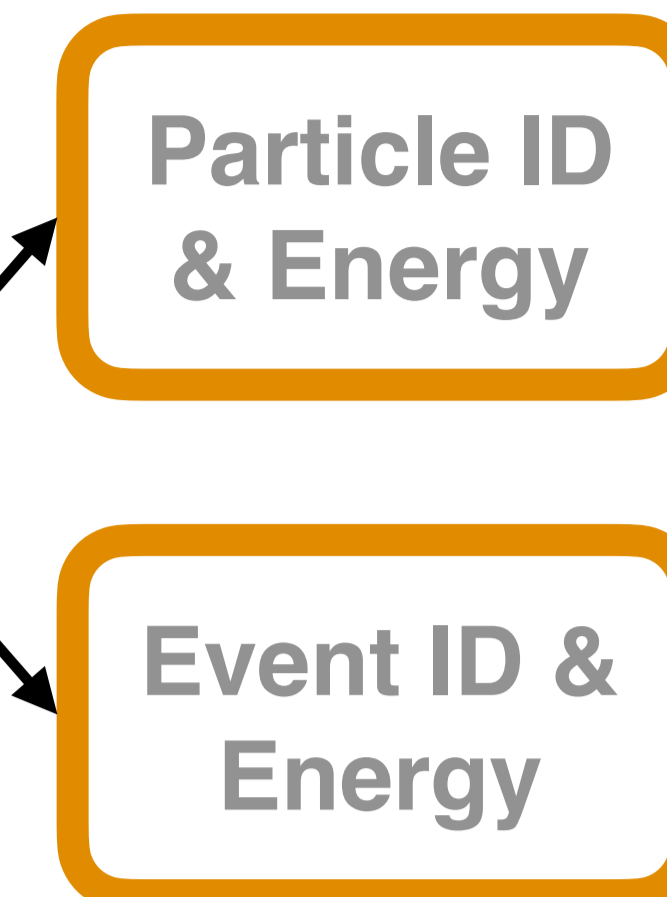
NOvA uses a variety of algorithms to reconstruct physics information - **machine learning contributes significantly**.

Detectors are naturally segmented - **pairs of pixel maps**.



Using CNNs to do particle ID **since 2017** (Phys.Rev.Lett. 118(2017)).

Focus now on **extending to vertex finding** and **improving robustness and interpretability** of ML techniques.

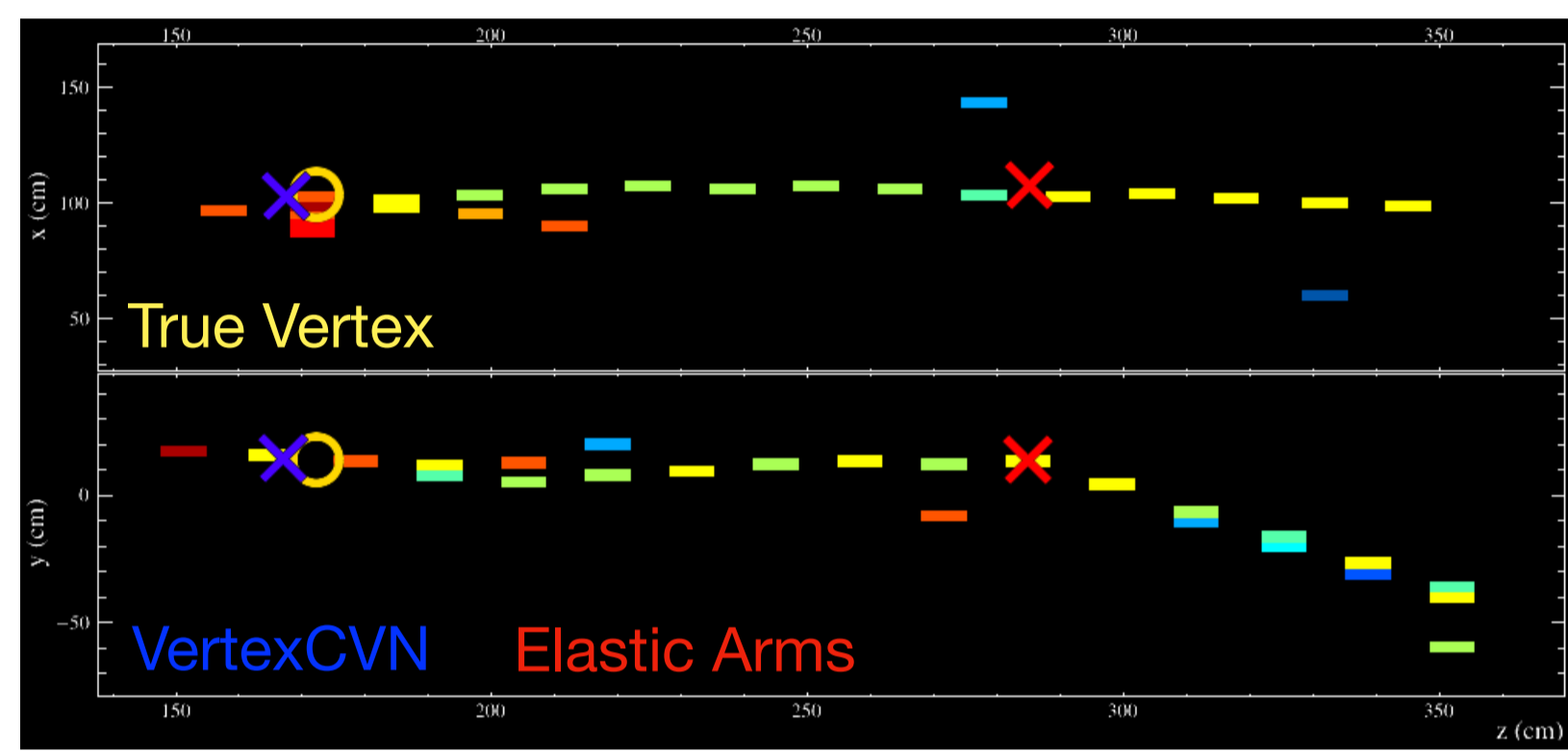


## VertexCVN

NOvA's first attempt to apply machine learning to estimate the position that a neutrino interacts with the detector medium.

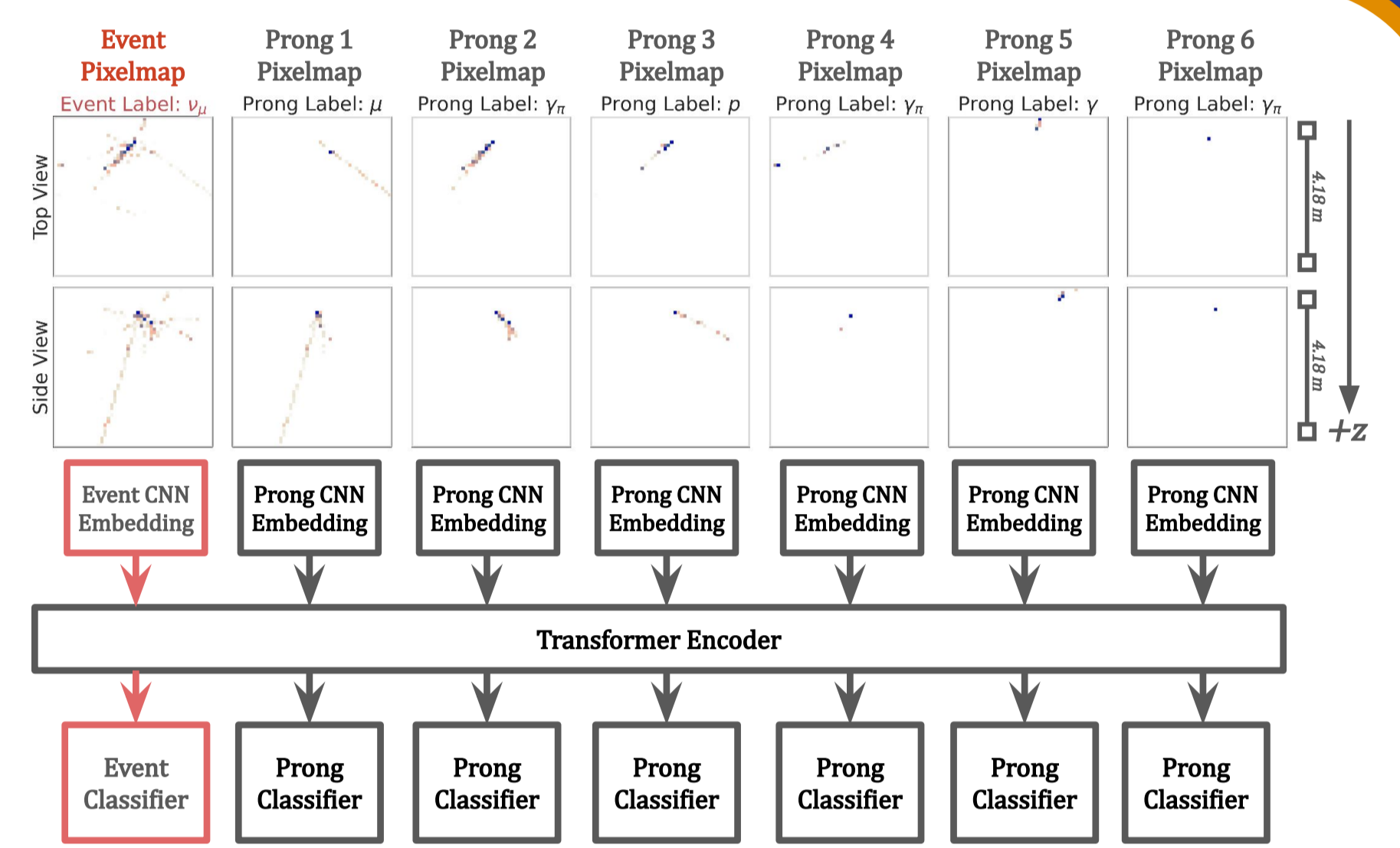
Developed to address several known failure modes of NOvA's existing algorithm "Elastic Arms".

- **Forward failure** - tendency for main prong to be split into two.
- **Backward failure** - tendency for multiple, small prongs to be combined into one.



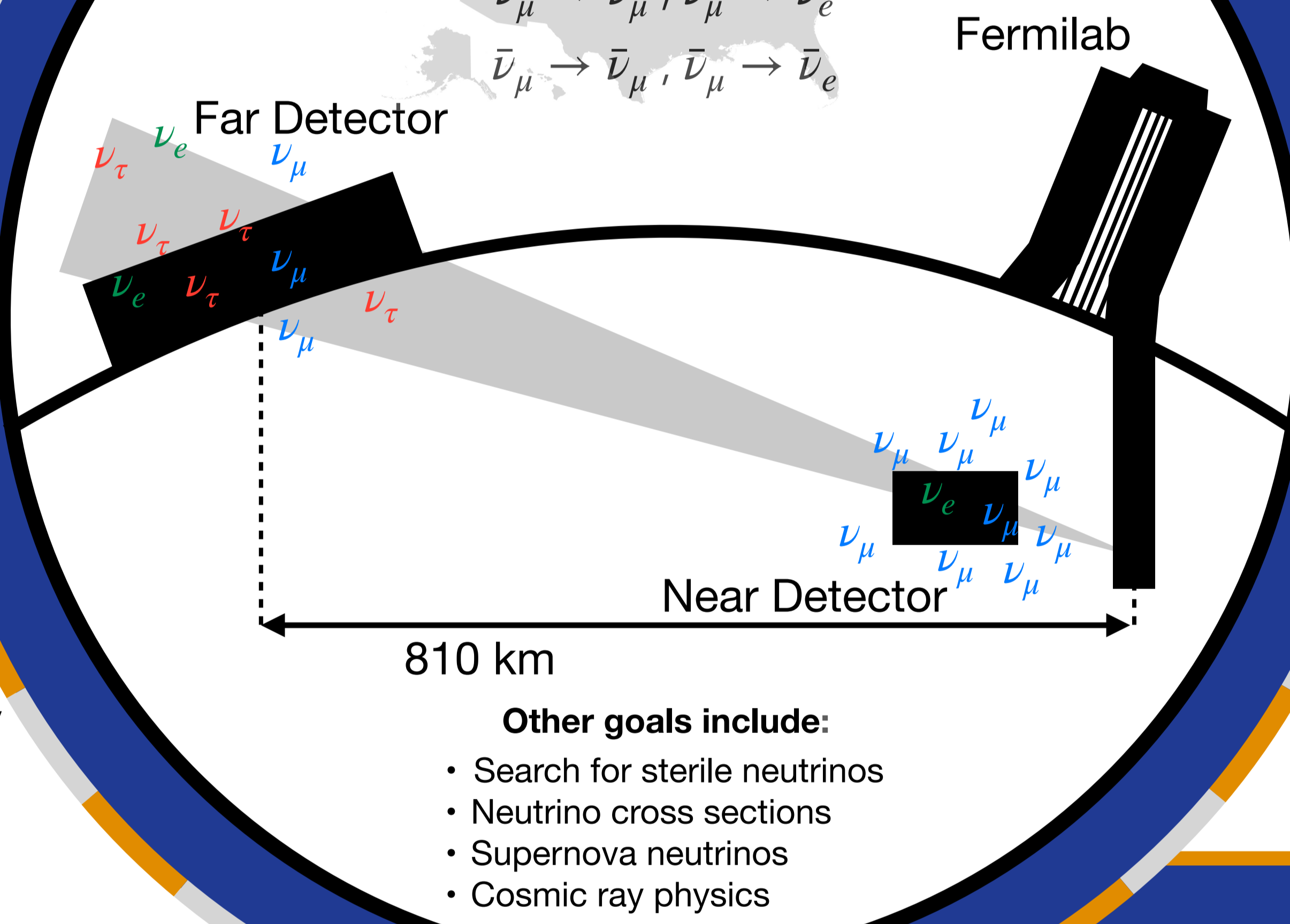
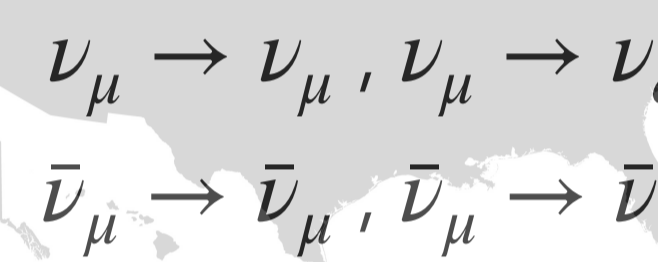
## TransformerCVN

NOvA's events contain **several particles**, each producing **sparse, high-dimensional spatial observations**.



A novel NN combining **spatial learning** enabled by **convolutions** with **contextual learning** enabled by **attention**.  
Joint approach **simultaneously classifies each event** and reconstructs every **individual particle's identity**.

NOvA's primary goal is to study 3 flavour neutrino oscillations via:



Other goals include:

- Search for sterile neutrinos
- Neutrino cross sections
- Supernova neutrinos
- Cosmic ray physics

## Architecture & Training

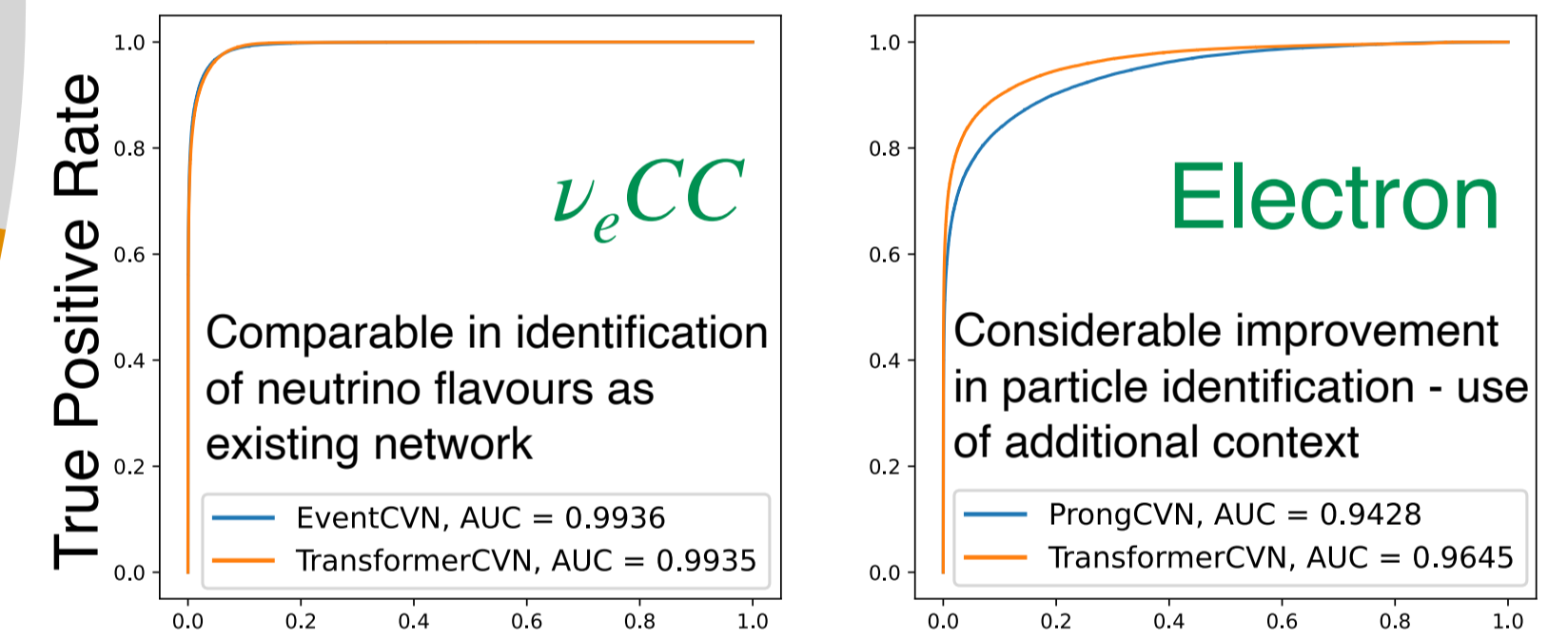
Uses a modified version of the network used by NOvA to do event classification **MobileNetv2** (arXiv:1801.04381):

- proven to do good feature extraction for NOvA.
- can use existing pixel maps as input.
- designed for fast inference on CPU.

Trained with **beam modes combined but separately** for **Near** (~18 million events) and **Far** (~26 million events) detectors.

Network converges within **first epoch**.

## Performance



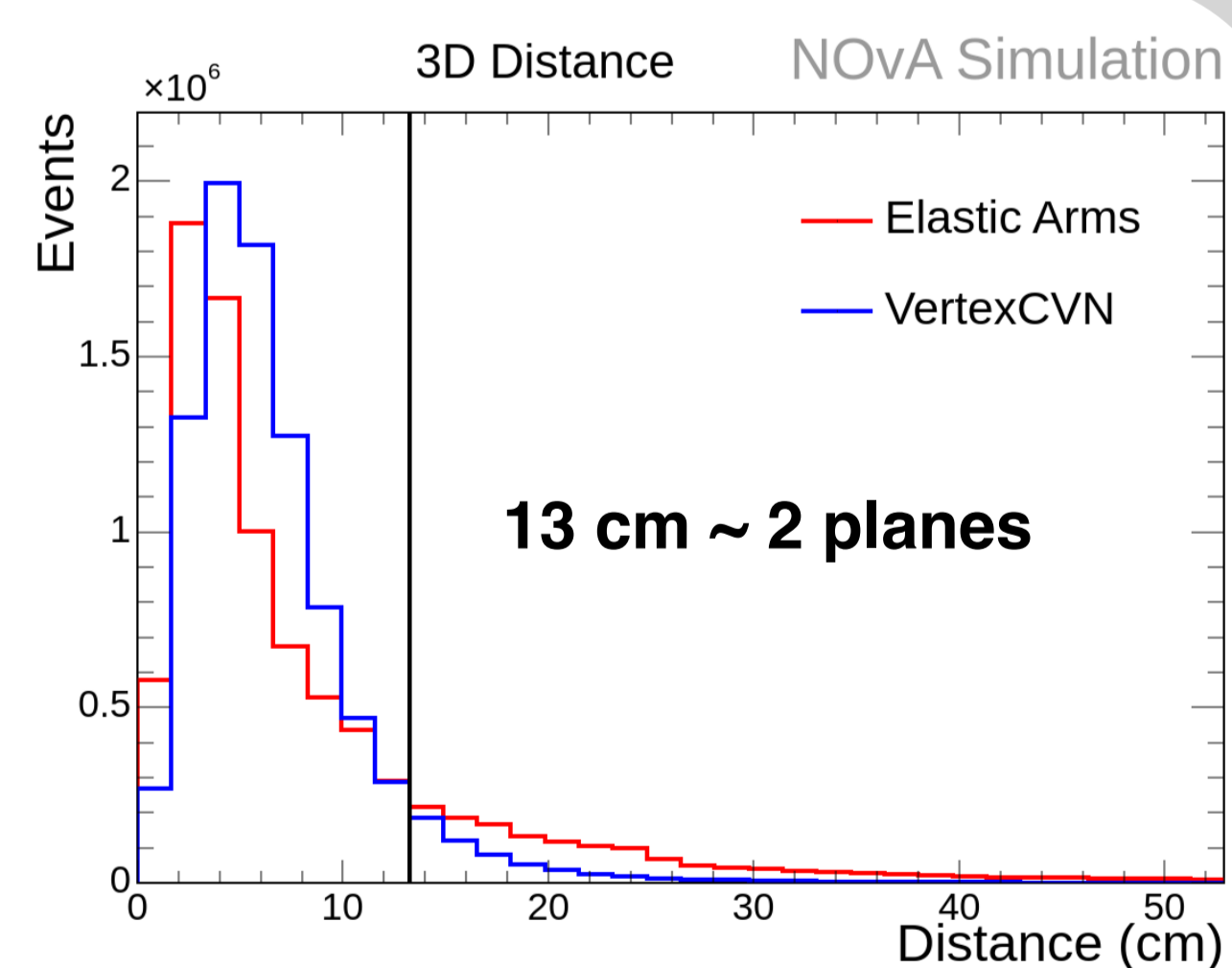
Classifies events with **90% accuracy** and improves identification of individual particles by **6%**.

## Results

VertexCVN is **more precise** than Elastic Arms but slightly **less accurate**.

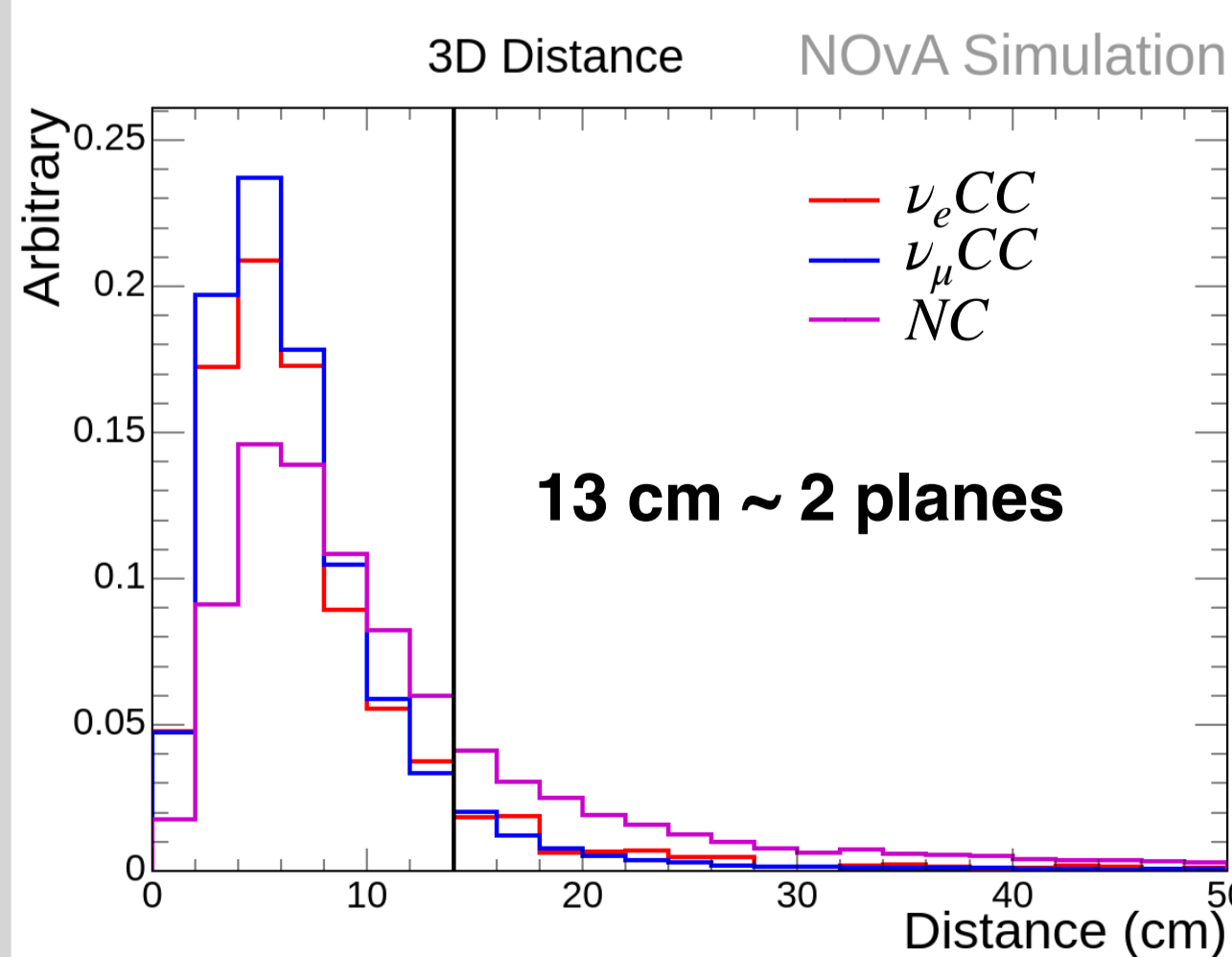
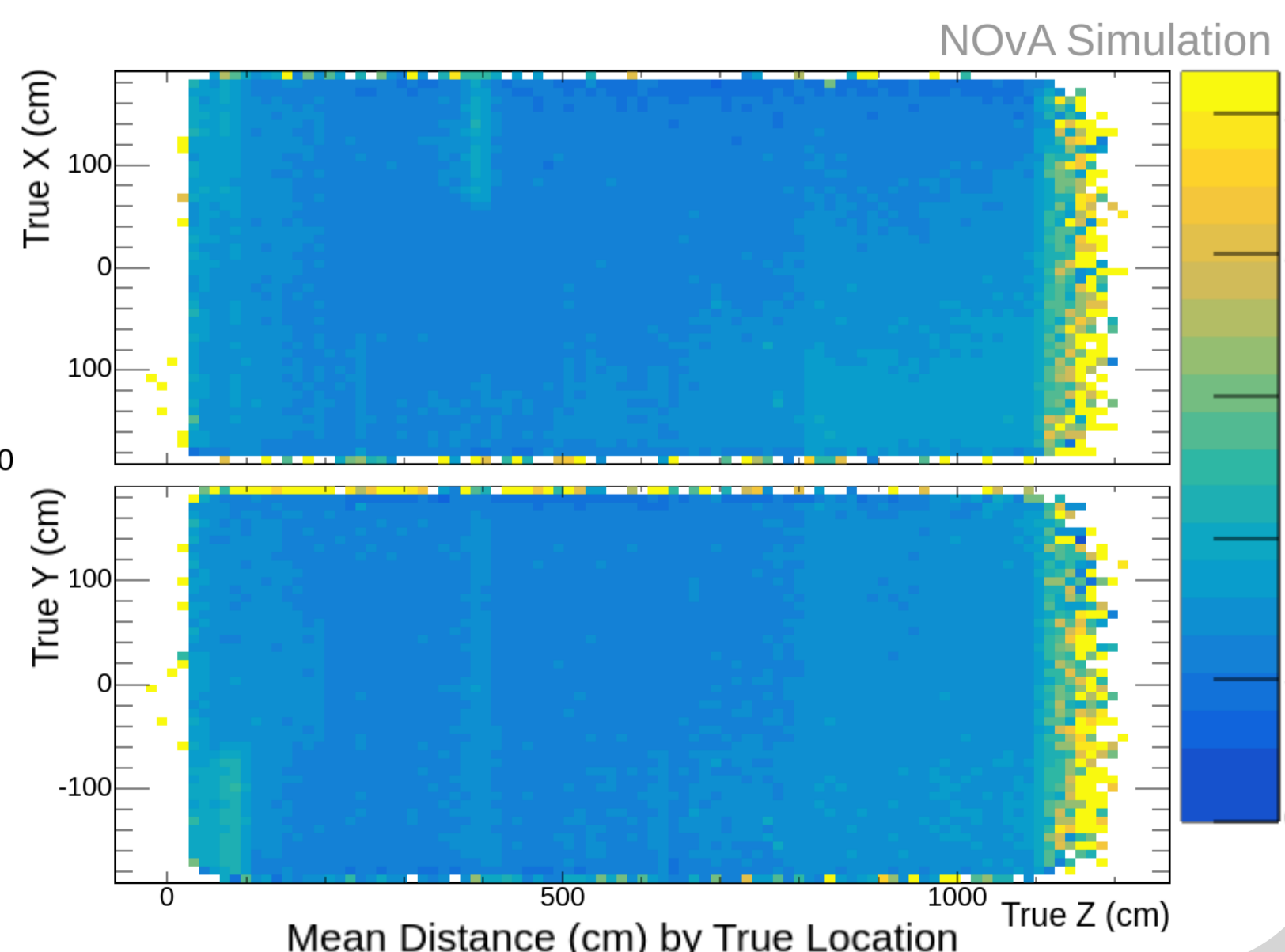
Relative performance has been studied for different types of neutrino interaction:

- more performant on  $\nu_e CC$  (even in ND where training sample population is small).
- less performant on  $NC$ .



13 cm ~ 2 planes

VertexCVN performance is **largely insensitive** to the true position of the vertex.



13 cm ~ 2 planes

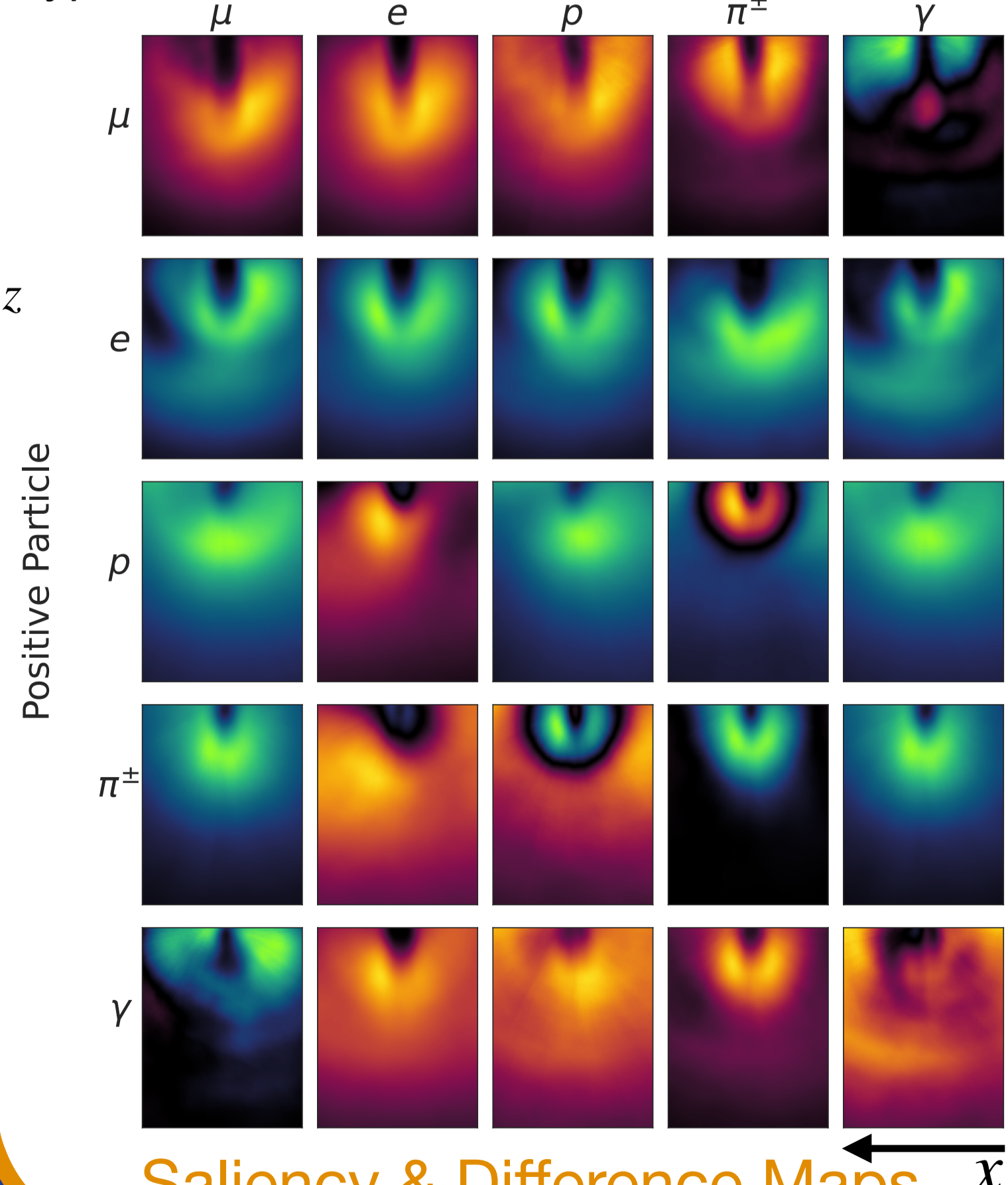
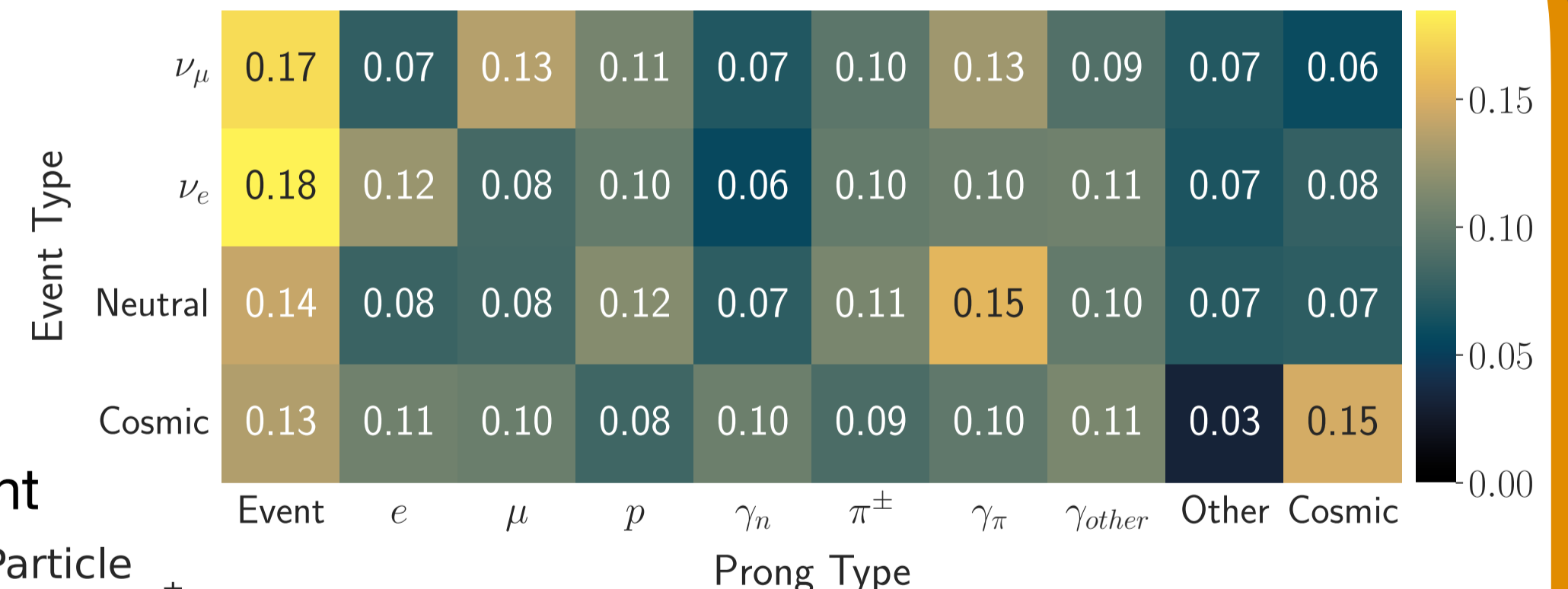
A manual scanning of events has shown:

- the **targeted failure modes** have been **eliminated**.
- two (minor) failure modes in total.

## Interpretability

Attention mechanism can be tracked throughout the network.

Build an interpretable understanding of the relationships between different particles and event types.



Elect to **aggregate** interpretation metrics across the full dataset to extract **consistent signals**.

**Attention:** relative importance of different types of prong for providing context necessary to make event-level prediction.

- Presence of electron prong impactful for  $\nu_e CC$ .
- $NC$  depends on photons from a neutral pion.

**Saliency:** the derivative of a network output with respect to the input pixel.

- **Diagonal:** saliency for a particular predicted class.
- **Off-diagonal:** pair-wise difference saliency maps computed as positive particle minus negative particle.

