Machine Learning for Hyper-Kamiokande's Water-Cherenkov Detectors

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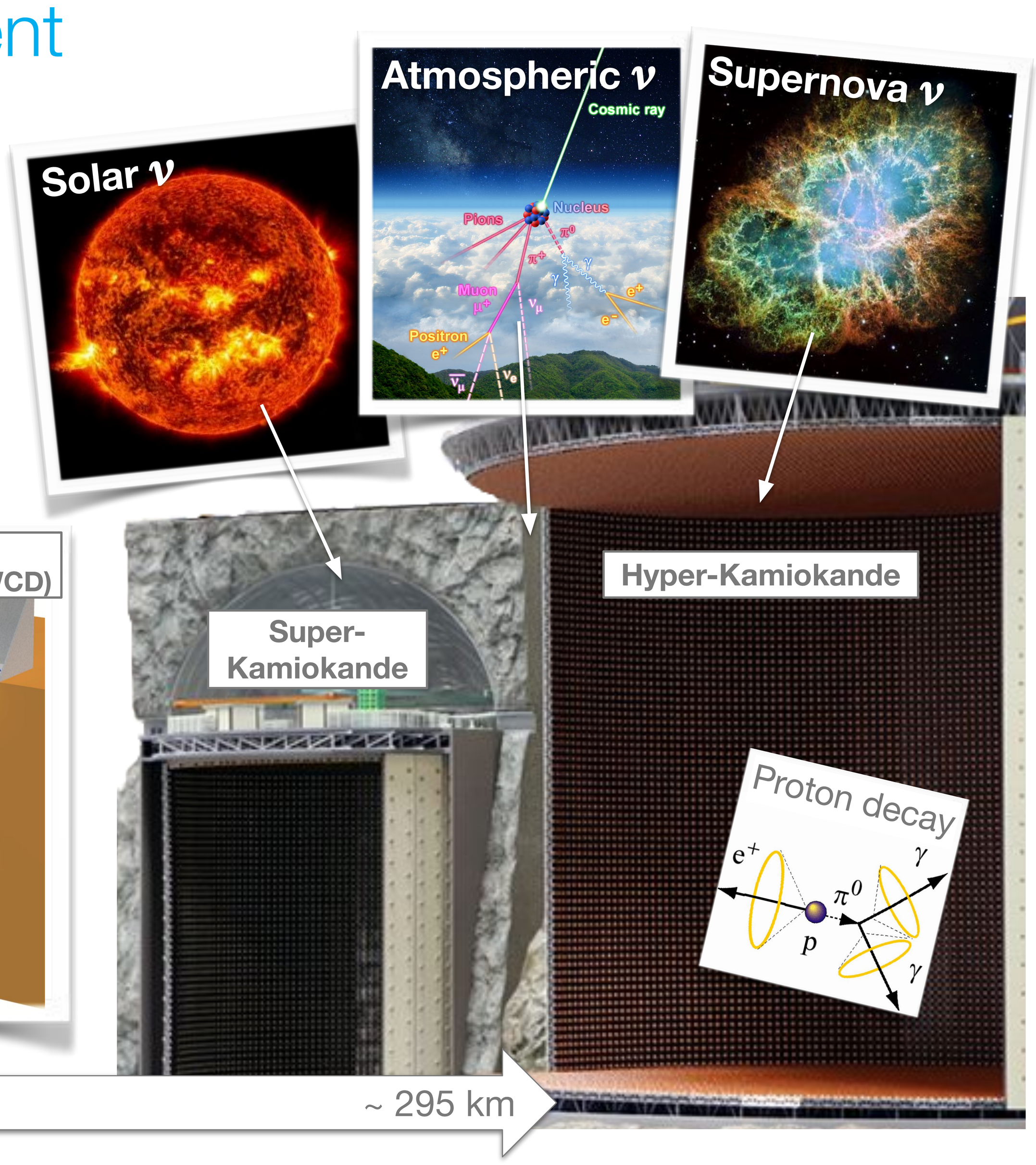
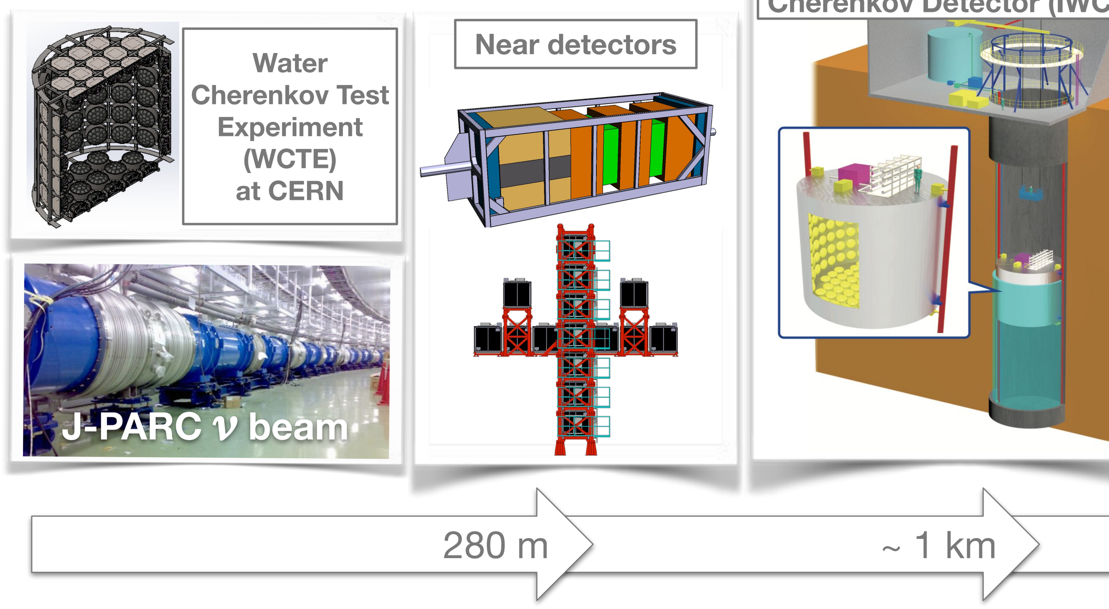
The Hyper-Kamiokande Experiment

The Hyper-Kamiokande (Hyper-K) experiment is a next-generation neutrino experiment

- The water-Cherenkov far-detector, currently under construction near Kamioka, Japan and is ~8x larger than Super-Kamiokande
- The experiment will observe neutrinos from astrophysical and terrestrial sources, as well as search for nucleon decay

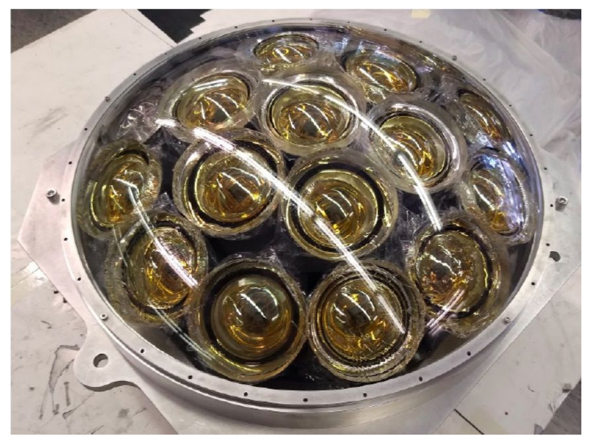


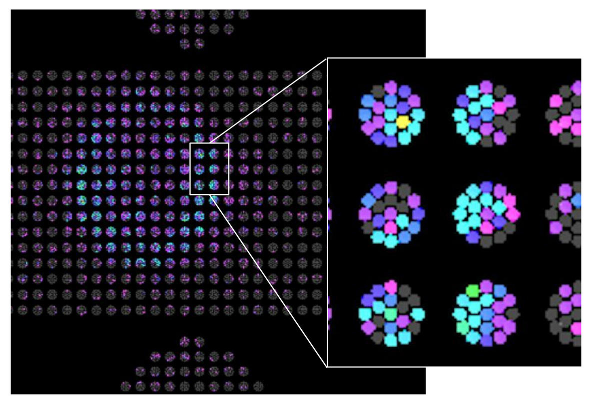


The Intermediate Water Cherenkov Detector

The Intermediate Water Cherenkov Detectors (IWCD) is planned to be built ~ 1 km from the J-PARC neutrino beam, to measure the un-oscillated beam flux and interaction cross-sections

- Development is being led by the TRIUMF and Canadian Hyper-K members, with 5.4M CAD CFI-IF funding for IWCD approved
- The 6m tall, 8m diameter tank is surrounded by ~ 500 multi-PMT modules (mPMTs) around the barrel and two end-caps
- Each mPMT contains 19 individual 8cm PMTs, providing greater position and direction granularity and improved timing resolution
- The detector can move vertically in a ~ 50 m tall pit to measure the beam at different angles providing different ν energy fluxes
- IWCD data consists of the charge and time of hits observed in the 19 PMTs in each mPMT module





Reconstruction in WC Detectors

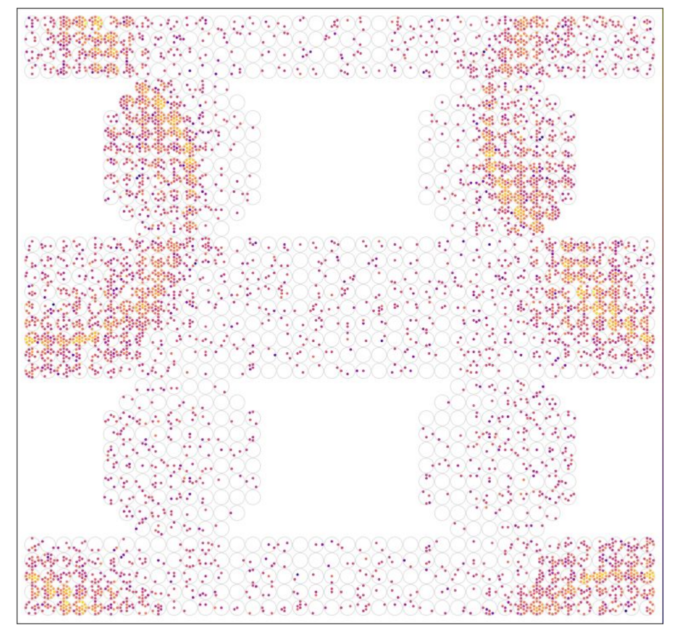
The traditional likelihood method (fiTQun) used for reconstruction in Super-K, Hyper-K and IWCD is reaching the limits of achievable precision

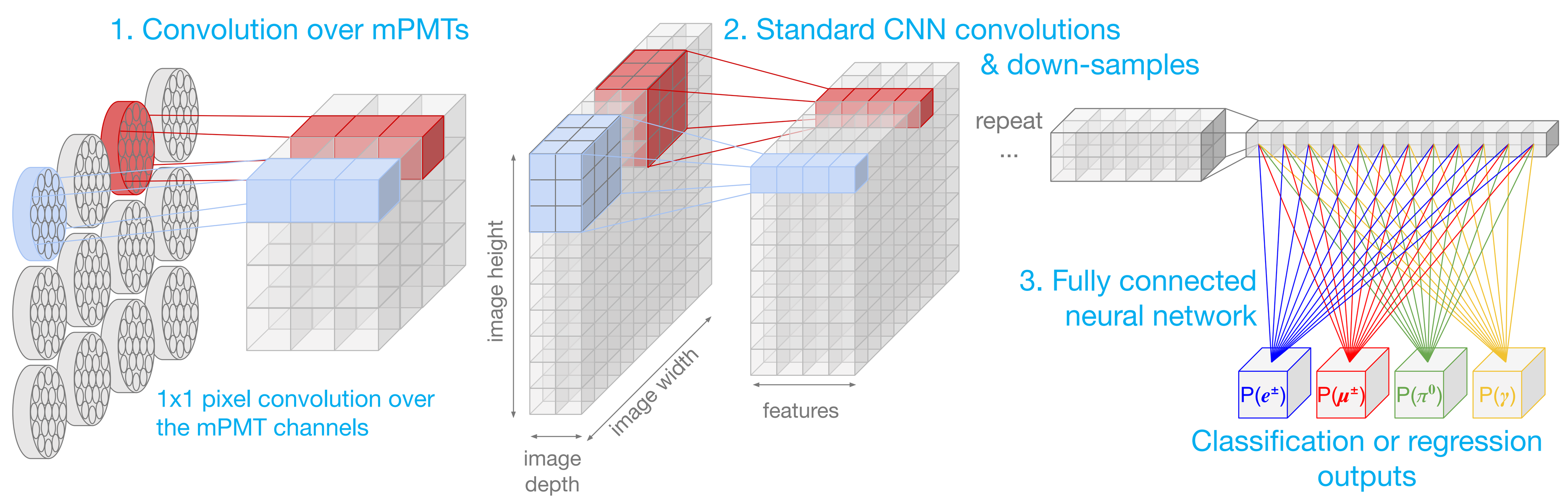
- Hyper-K requires improved reconstruction of particles in complex multi-ring event topologies
- Computation time is a limiting factor in larger detectors or when greater precision requirements need complex models with fewer approximations
- Machine learning (ML) approaches can use all information without physics approximations, in a fraction of the computation time

ResNet CNN Architecture

The cylindrical detector geometry into a 2D image for use with a CNN architecture based on ResNet.

- A double-cover of the detector surface is used, duplicating the data from two viewpoints to mitigate gaps from unwrapping detector walls.
- An initial 1×1 convolution is applied over the channels (PMTs) of the multi-PMT modules.
- Data augmentation is applied by reflecting the tank about its axes to provide more training data.

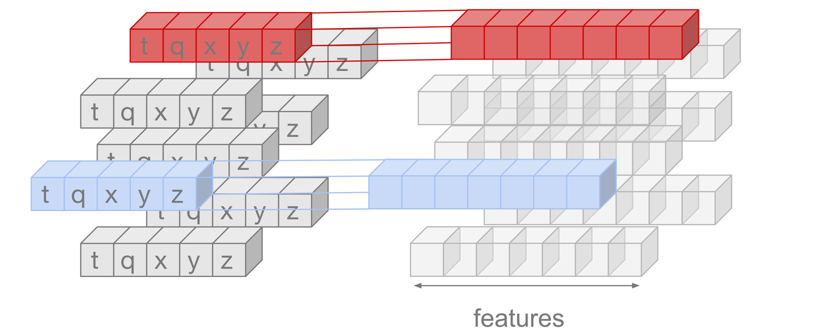




PointNet Architecture

The PointNet architecture acts on a point cloud instead of a 2D image, using the full 3D detector geometry.

- Each point is a PMT hit with charge, time and position.
- The majority of layers involve 1×1 convolutions on points (PMTs)
- Information passes between points by applying arbitrary learned transformations
- A single downsample leads to the fully connected network

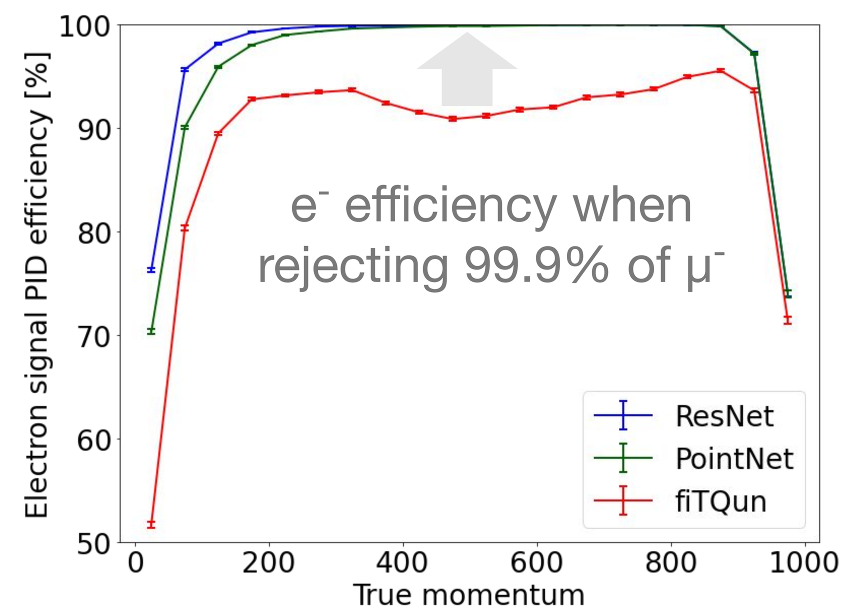


PointNet layer (1×1 convolution on point cloud)

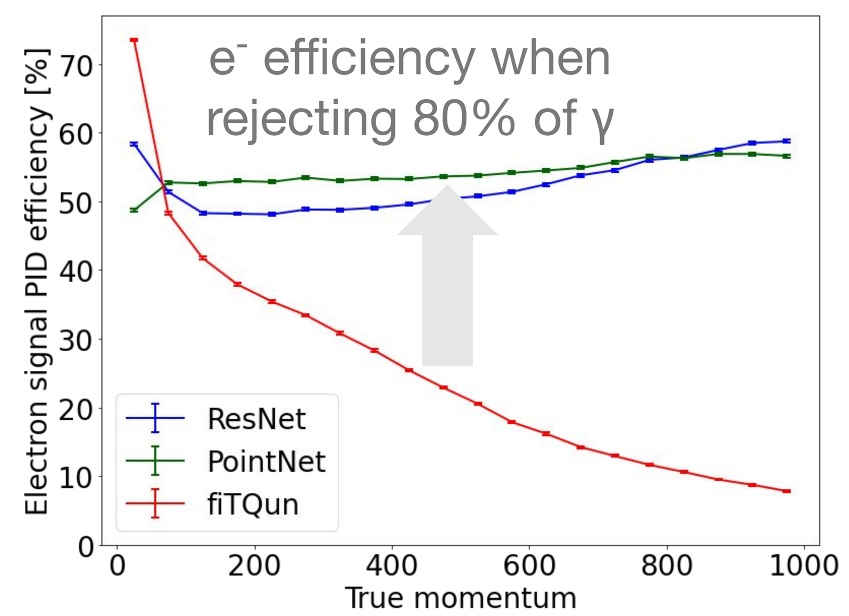
Classification

Particle identification with ML significantly outperforms fiTQun.

- Improved e⁻ vs μ⁻ PID important for high background rate in IWCD

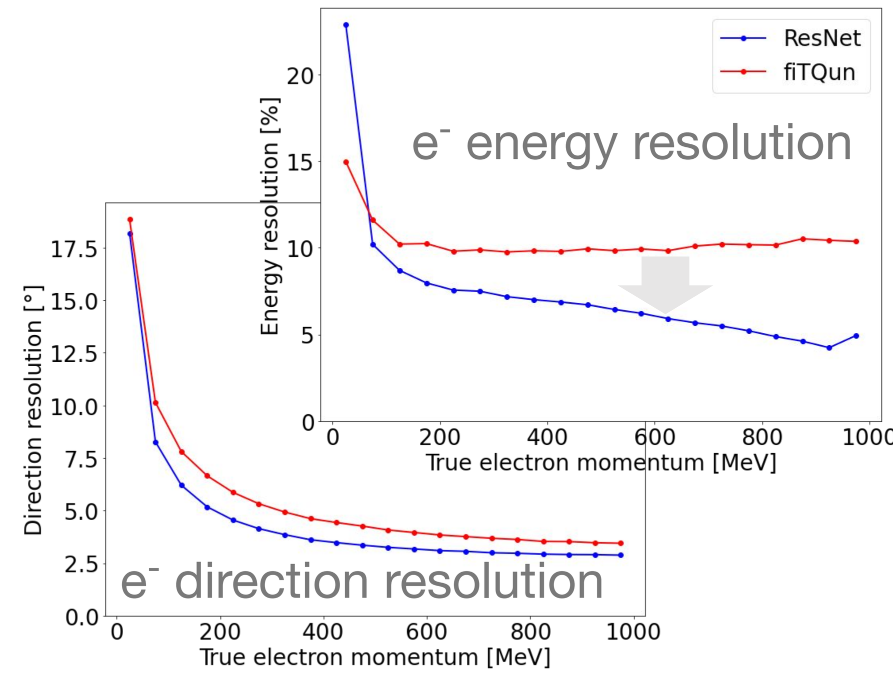


- Statistical separation of e⁻ vs γ enables new measurements

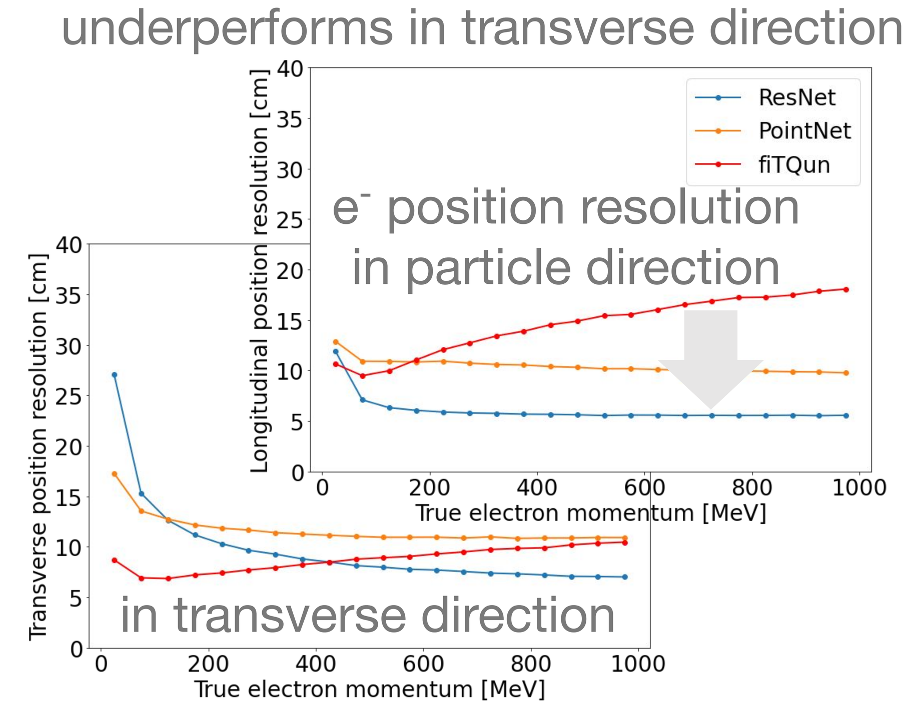


Regression

- Reconstructing energy and direction with ResNet outperforms fiTQun

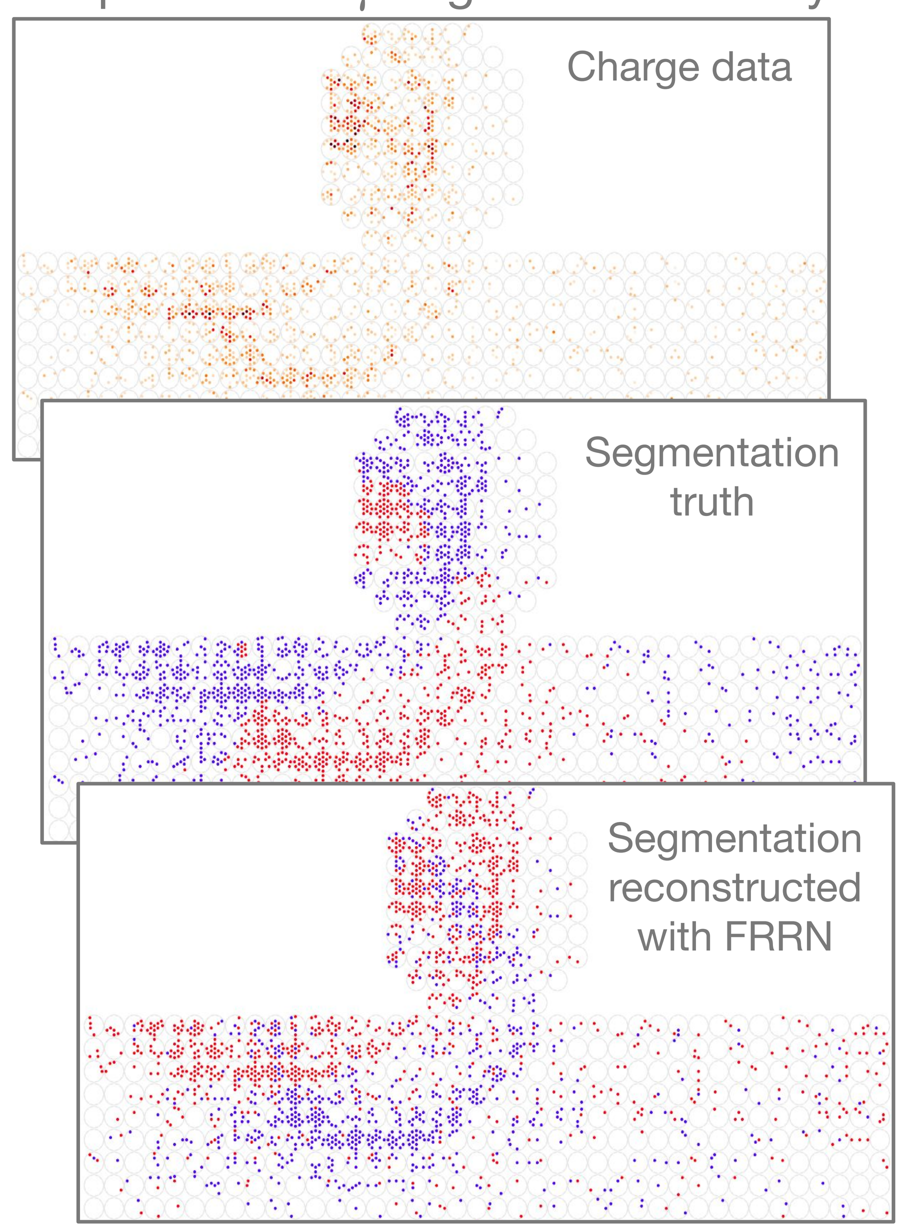


- ResNet position reconstruction improved in particle direction but underperforms in transverse direction



Segmentation

- CNN architecture adapted to segment image pixels, trained to separate two γ rings from π^0 decay.



Discovery, accelerated