Sub GeV-Scale Particle Identification with PointNet in the Hyper-Kamiokande

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Hyper-Kamiokande

- Based in Gifu Prefecture, Japan
- A cylindrical water Cherenkov detector, the successor of Super-Kamiokande (Super-K) experiment
- Designed to be 8 times more fiducial volume than Super-K (220k tons), its current design has a diameter of 68 meters and a height of 71 meters
- Planned to house ~20,000 20-inch (50-cm) Photomultiplier tubes (PMT) and additional photo-coverage from multi-PMTs (mPMT) [1] in the inner detector (ID), and ~8,000 3-inch (8-cm) PMTs in the outer detector (OD)
- Research including neutrino oscillation and BSM physics (proton decay)

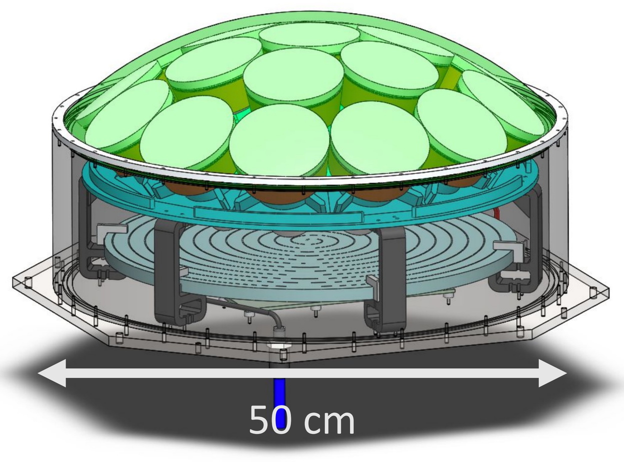
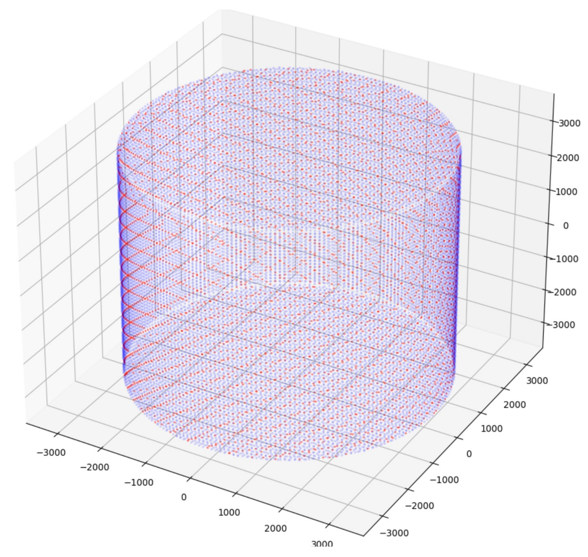


Fig 1: A CAD drawing of the multi-PMT module

Simulation Geometry

- Input data simulated using Geant4-based detector response simulation software WCSim
- The ID contains 18952 20-inch PMTs and 4716 mPMTs in the following pattern



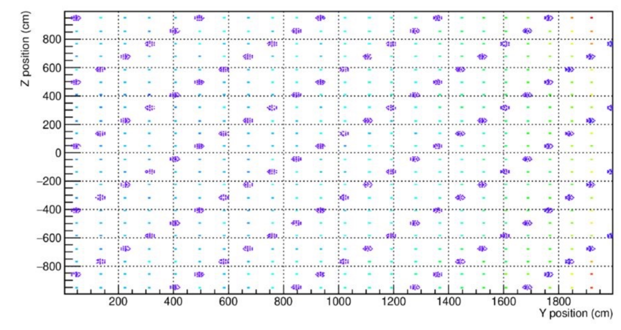


Fig 2: Schematic diagrams showing Hyper-K simulation geometry

FiTQun

- In Super- and Hyper-K, fiTQun reconstructs particle vertex, direction, momentum, etc. simultaneously by maximizing the likelihood function [2]

$$\underbrace{L(\mathbf{x})}_{\text{Fit parameters}} = \prod_j^{\text{unhit}} \underbrace{P_j(\text{unhit}|\mathbf{x})}_{\text{Unhit probability}} \prod_i^{\text{hit}} \{1 - \underbrace{P_i(\text{unhit}|\mathbf{x})}_{\text{Hit probability}}\} \underbrace{f_q(q_i|\mathbf{x})}_{\text{Charge likelihood}} \underbrace{f_t(t_i|\mathbf{x})}_{\text{Time likelihood}}$$

i-th PMT's charge, time

Simulated Data

- Electron and muon energy: uniformly distributed 0 to 1 GeV above their Cherenkov thresholds; π^0 energy: uniformly distributed 0 to 1 GeV above 4 times the electron Cherenkov threshold
- Initial locations of all particles: uniformly distributed in the tank
- Initial direction of all particles: isotropically distributed

PointNet

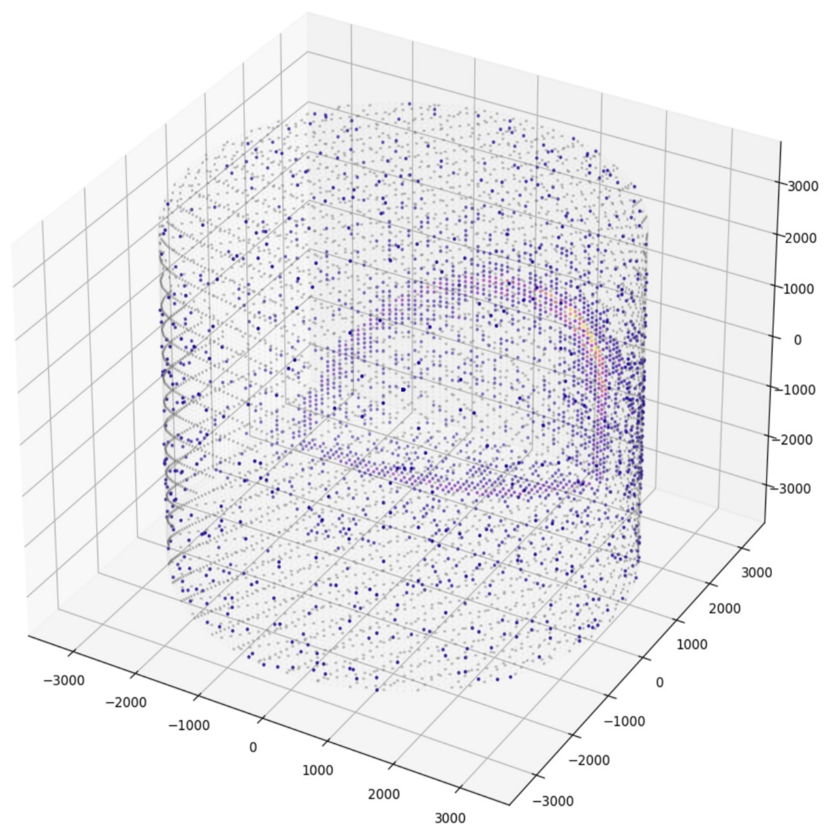
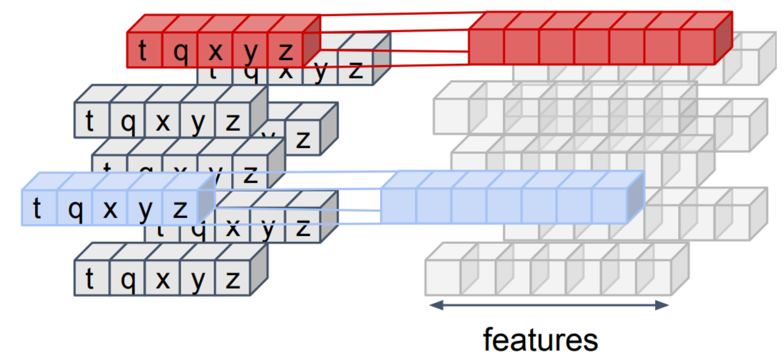


Fig 3: A Hyper-K event in the point cloud form

- A novel deep Neural Network (NN) that consumes point cloud (unordered point sets in 3D) [3], thus easy to adapt to other detector geometries
- For the application to Hyper-K reconstruction, each hit PMT is a point with PMT 3D position, time, charge (Fig. 3)
- PointNet learns symmetric functions on point clouds, as the order of points should be irrelevant
- Convolution-like operations act on each point's position, charge and time to linearly transform them, e.g., rotate all input vectors
- Feature transform allows global information to affect individual points
- Single down-sampling layer collapse all points for output



PointNet MLP (1x1 convolution on point cloud)

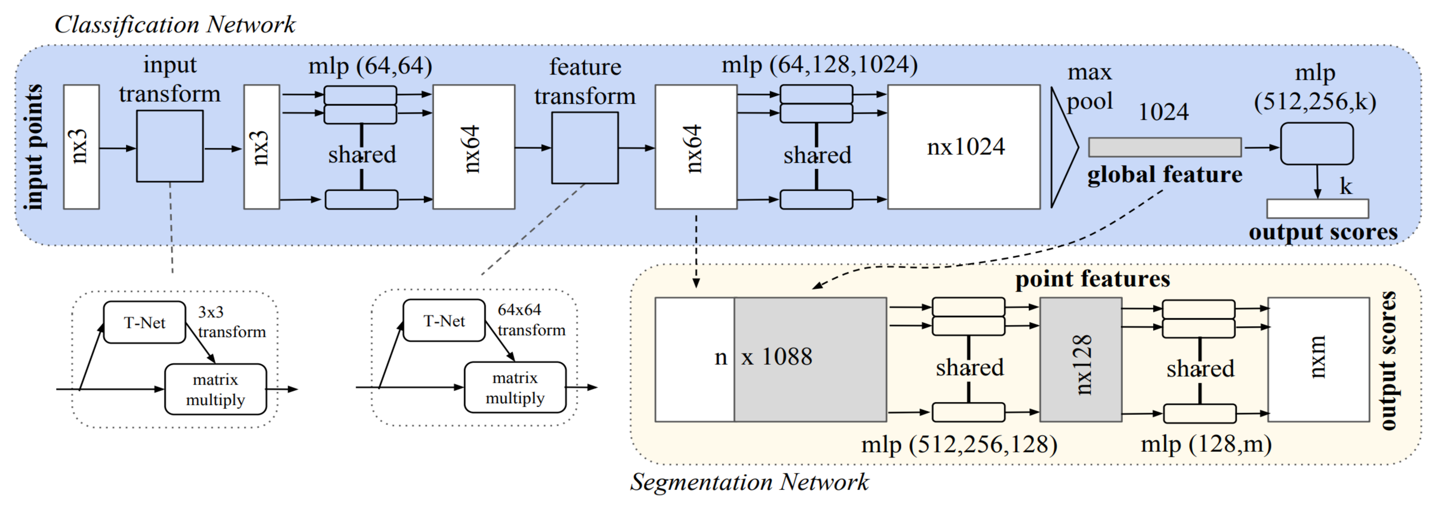
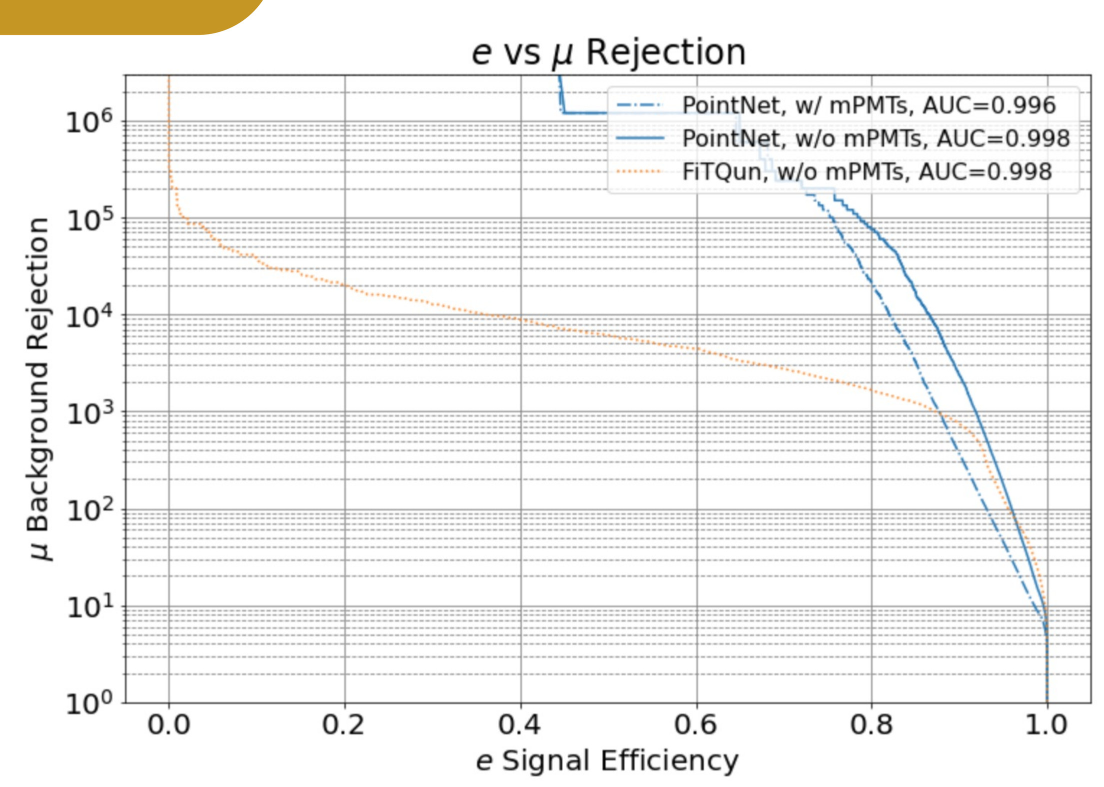
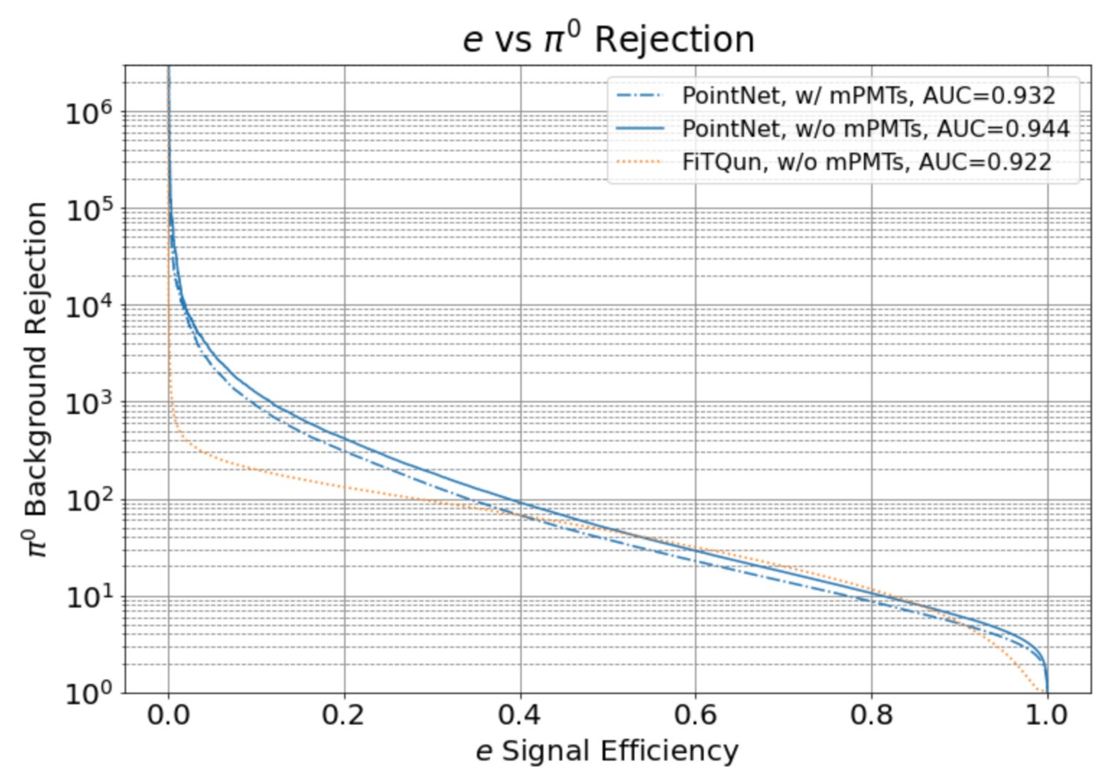


Fig 4: Schematic diagrams displaying the structure of the PointNet

Results





- Receiver Operating Characteristic (ROC) curve displays the trade-off between signal efficiency and background rejection rate with respect to different chosen threshold values
- Signal efficiency: AKA true positive rate, percentage of the signal correctly identified;
  Background rejection: AKA false positive rate, percentage of background falsely identified as signal
- Preliminary results show **that PointNet's performance is on par with fiTQun for electron/muon discrimination**
- **PointNet outperforms fiTQun for electron/ π^0 separation**
- A trained PointNet is **much faster** than fiTQun for PID
- A possible reason why PointNet performs better without mPMT signal is due to the naïve implementation in the PointNet model, where the 20-inch and 3-inch PMT signals are treated identically. By adapting the network to allow the PMT types to be treated differently, it is hoped that the performance will improve
- Currently conducting studies on the efficacy of electron/gamma separation using both tools

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[2] Jiang M, et al. Atmospheric neutrino oscillation analysis with improved event reconstruction in Super-Kamiokande IV. 2019.
[3] Qi CR, Su H, Mo K, Guibas LJ. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. 2017.