Imperial College London

Enhancing Event Reconstruction with Machine Learning for Water Cherenkov Detectors of Hyper-Kamiokande

ICHEP 2024, Prague

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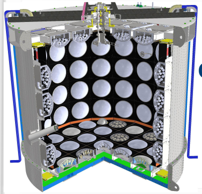
20th July 2024

The Hyper-Kamiokande Experiment

Hyper-Kamiokande (Hyper-K) is a world-leading neutrino experiment, building on success of Super-Kamiokande & T2K.

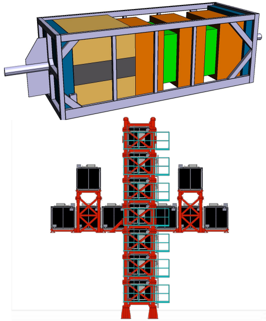
Broad & ambitious physics programme covering many neutrino sources as well as proton decay measurements.

Water Cherenkov (WC) detector technology provides huge target mass with excellent particle ID and reconstruction capabilities.

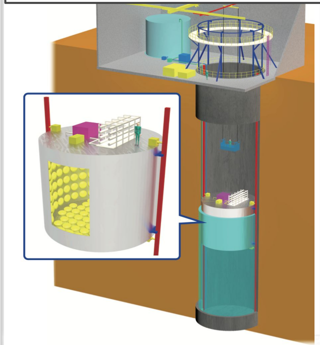


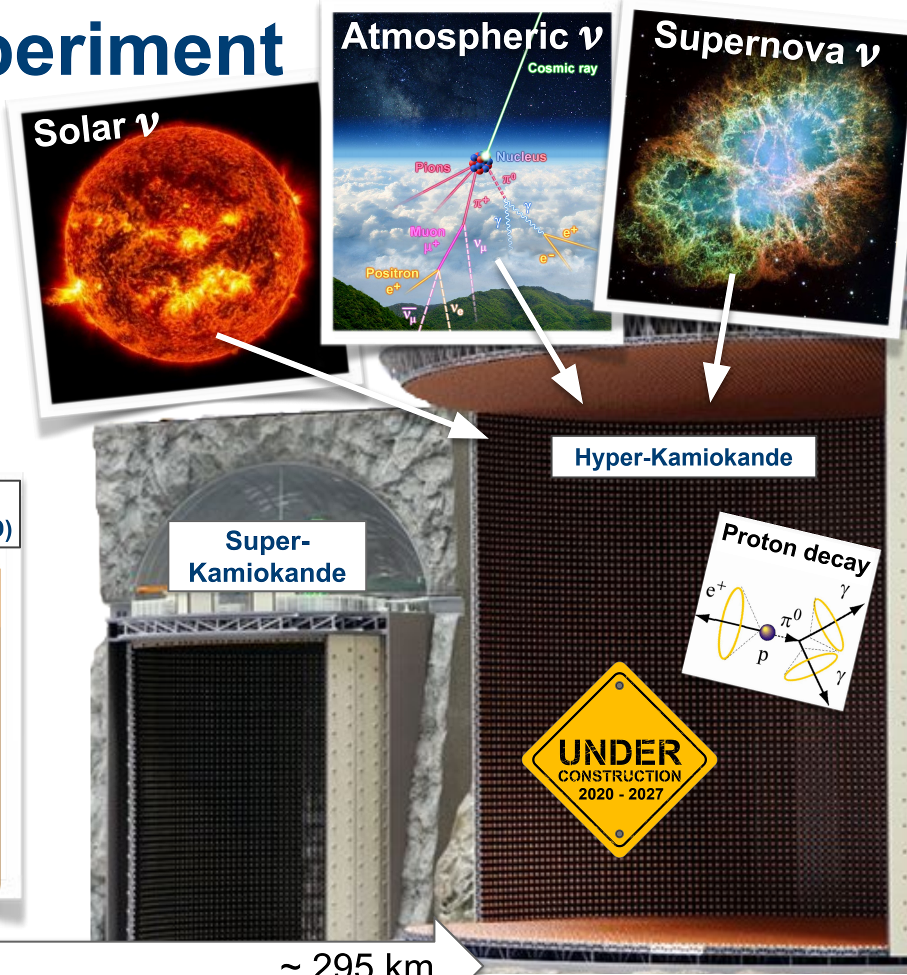
Also the **Water Cherenkov Test Experiment (WCTE)** at CERN

Near detectors



Intermediate Water Cherenkov Detector (IWCD)

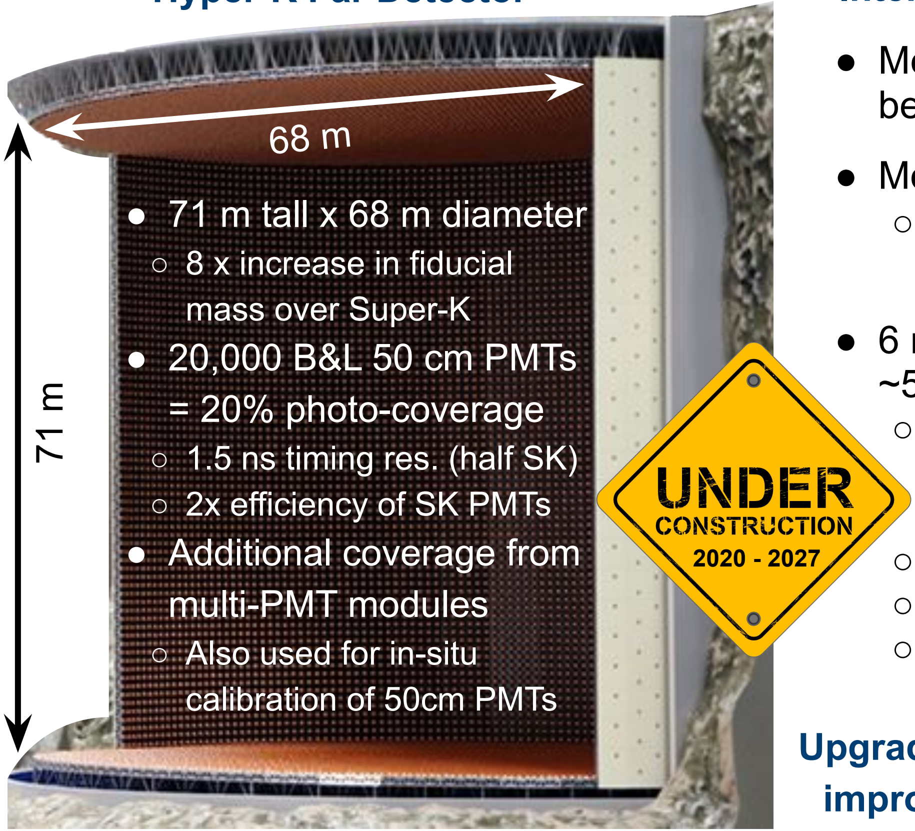




280 m → ~ 1 km → ~ 295 km

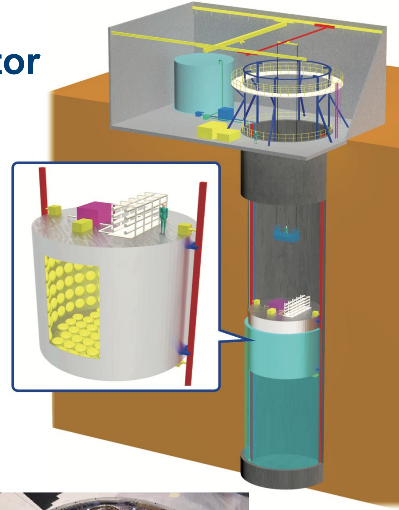
Hyper-K's Water Cherenkov Detectors

Hyper-K Far Detector

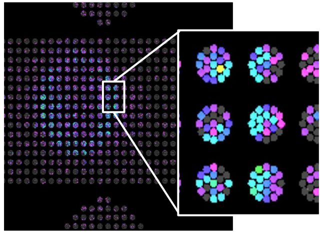


- 71 m tall x 68 m diameter
  - 8 x increase in fiducial mass over Super-K
- 20,000 B&L 50 cm PMTs = 20% photo-coverage
  - 1.5 ns timing res. (half SK)
  - 2x efficiency of SK PMTs
- Additional coverage from multi-PMT modules
  - Also used for in-situ calibration of 50cm PMTs

Intermediate Water Cherenkov Detector



- Measures ν flux and cross-section of beam at ~1 km from source
- Moves vertically in ~50 m tall pit
  - spans off-axis angles of ν beam for different ν energy spectra
- 6 m tall x 8 m diameter tank with ~500 multi-PMT modules (mPMTs)
  - 8 cm PMTs:
    - Better position resolution
    - 1 ns timing resolution
  - Additional directionality information
  - mPMTs will also be used for WCTE
  - Also being produced for portion of far detector photo-coverage

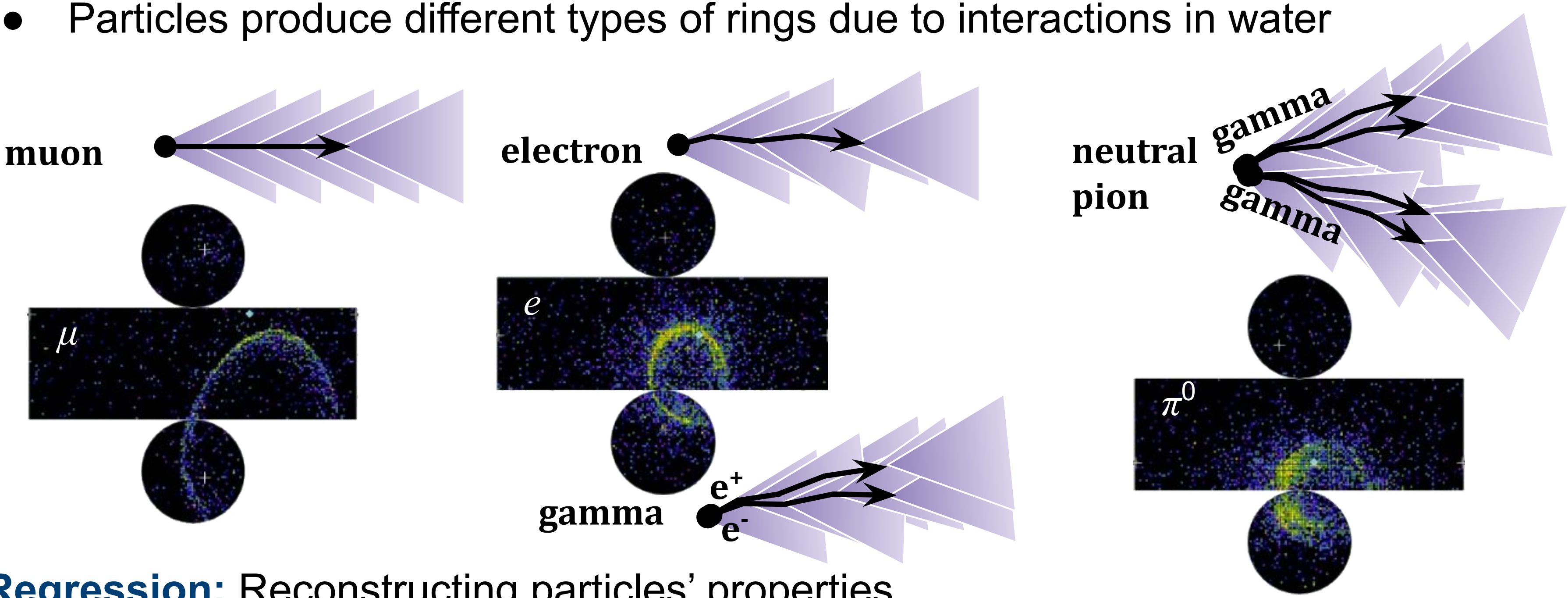


Upgraded detector technologies need improved data analysis techniques

Reconstruction in Water Cherenkov Detectors

Classification: Particle type identification (PID)

- Particles produce different types of rings due to interactions in water



Regression: Reconstructing particles' properties

- Location and time of PMT hits allow triangulating particle's position and direction
- Amount of charge observed at PMTs gives estimate of particle's energy

Machine Learning Reconstruction for WC

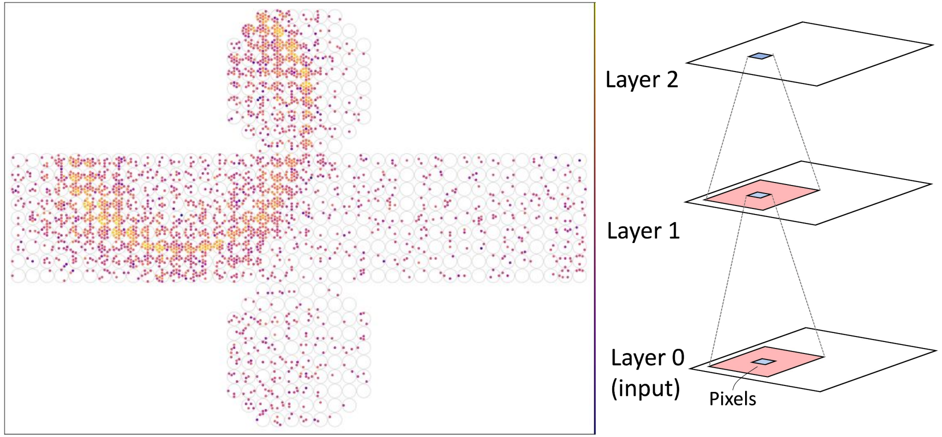
Reaching limit of traditional maximum-likelihood reconstruction methods (**fiTQun**)

- Improved resolutions require more complex algorithms with fewer approximations
- Computation time is limiting factor: **1M events in fiTQun = 10,000s CPU-hours**

Machine Learning (ML) and deep neural networks have potential to push reconstruction further

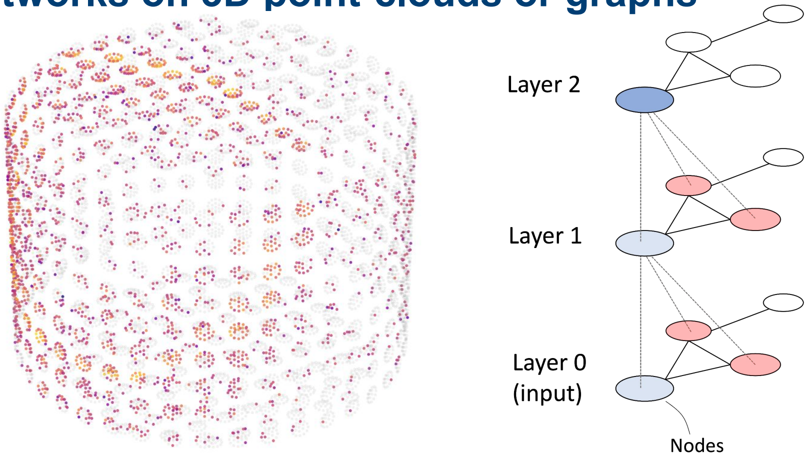
- Potential to use all information without detector model approximations
- Very fast once network is trained: **1M events with CNN < 100 CPU-hours or < 1 GPU-hour**

Networks on 2D image-like data



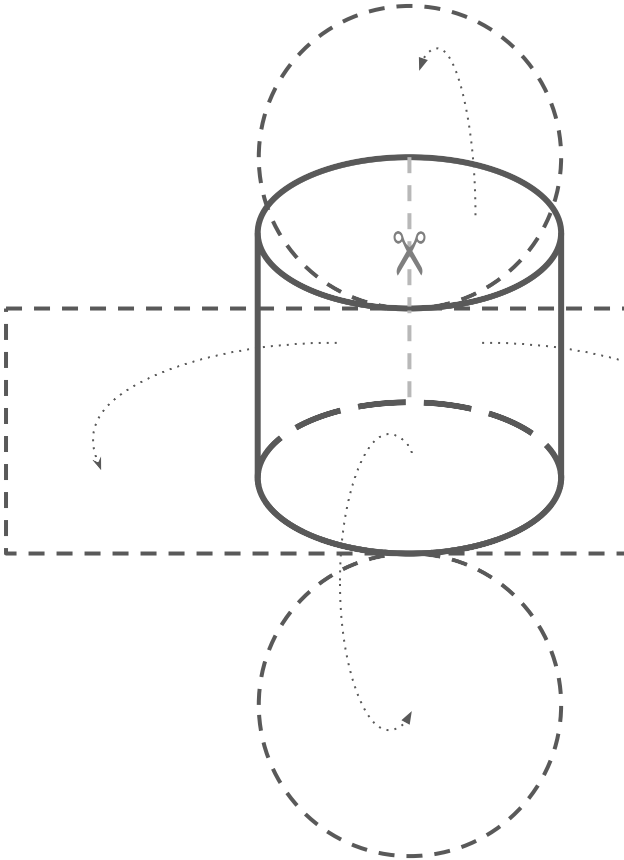
- Fast and well understood CNN-based networks
- Leverage extensive progress in computer vision

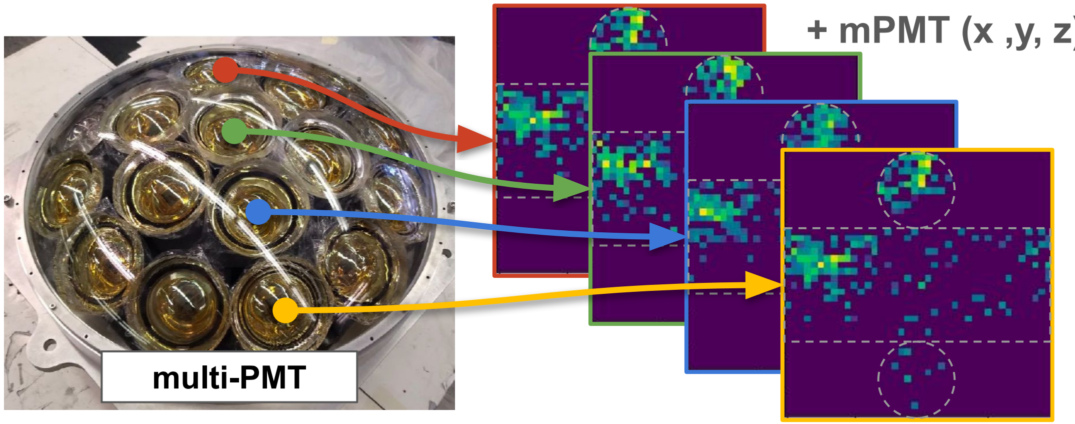
Networks on 3D point-clouds or graphs

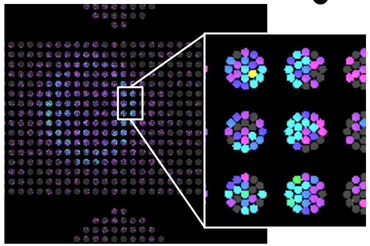


- Retain physical 3D detector geometry
- More complex and challenging to explore

Image-like data for IWCD with mPMTs



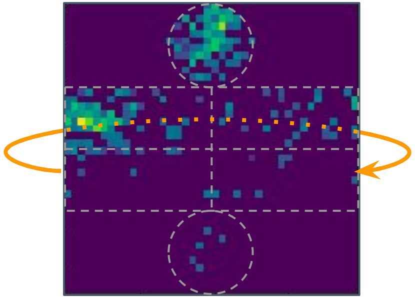


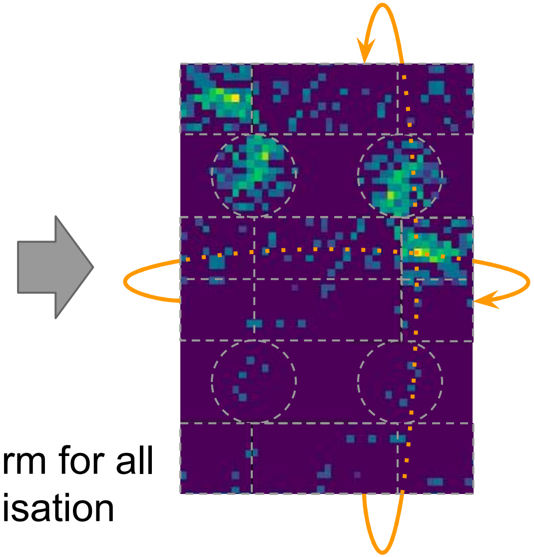


Full cylinder is unwrapped onto flat image

- One pixel per multi-PMT
- 41 channels per pixel:
  - 19 charge (at each of the 19 PMTs per mPMT)
  - 19 time (first hit time of each PMT is digitized)
  - (x, y, z) positional encoding of mPMT location helps network learn geometric information
- Tried other topological mappings with less success

Data Transformations and Augmentation





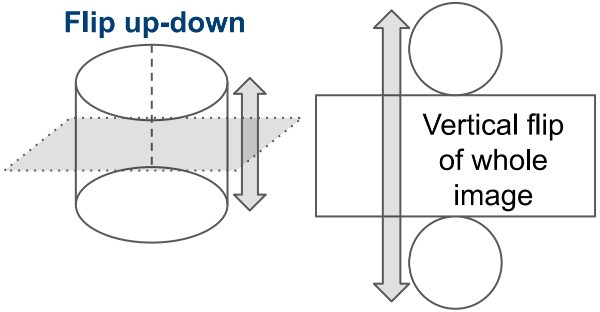
Double cover transform for all events helps generalisation

Rearranging and duplicating the geometrical surface has several advantages

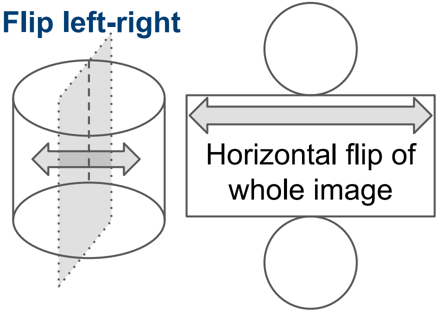
- Less dependence on choice of slice along barrel to unwrap cylinder
- All segments appear exactly twice, with minimal blank space
- Circular boundary conditions in both directions

Applying random transformations using detector symmetry effectively increases dataset

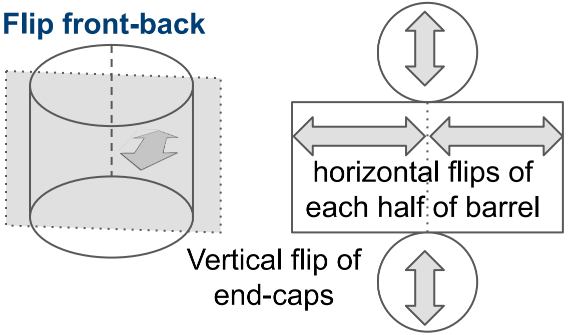
Flip up-down



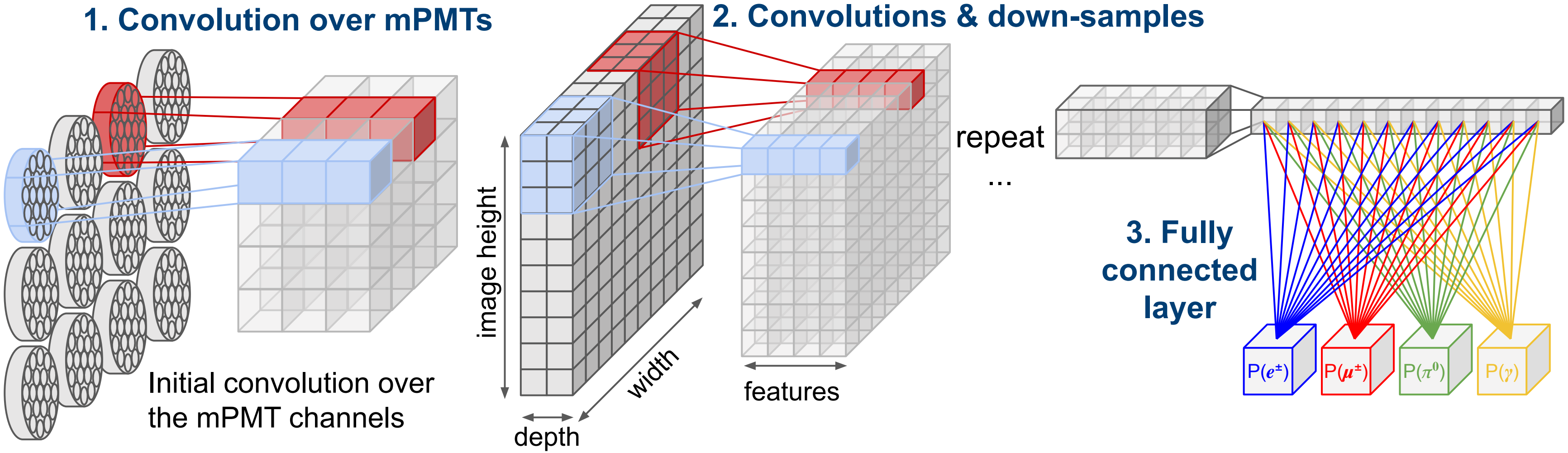
Flip left-right



Flip front-back



ResNet event reconstruction for IWCD with mPMTs



Convolutional Neural Network based on ResNet-50

- Initial 7x7 convolution with downsampling replaced by convolution over mPMT features
- Circular padding applied on each convolution to exploit cyclic boundary conditions

Simulated for IWCD 3M each of e, μ, π^0, γ (with γ to e^+/e^- pair conversion at initial position)

- Uniform random position, isotropic directions, uniform energy 0 to 1 GeV above Cherenkov threshold
- 1.5M of each particle for training, 0.3M for validation, 1.2M for final evaluation

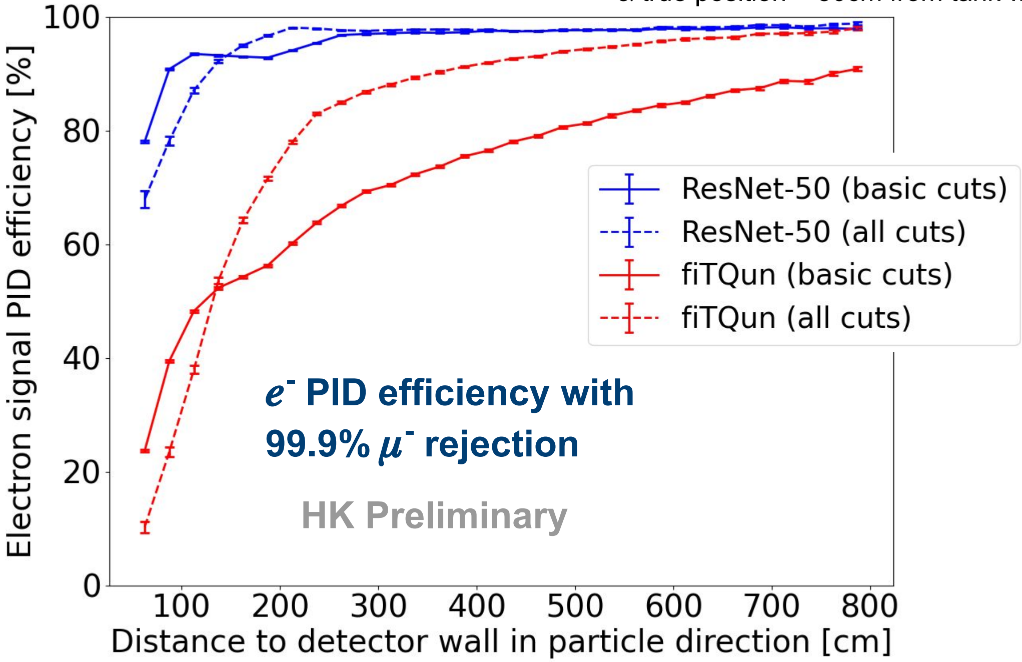
Trained separate models for each task for ~ 12 hours on 4 x A100 GPUs

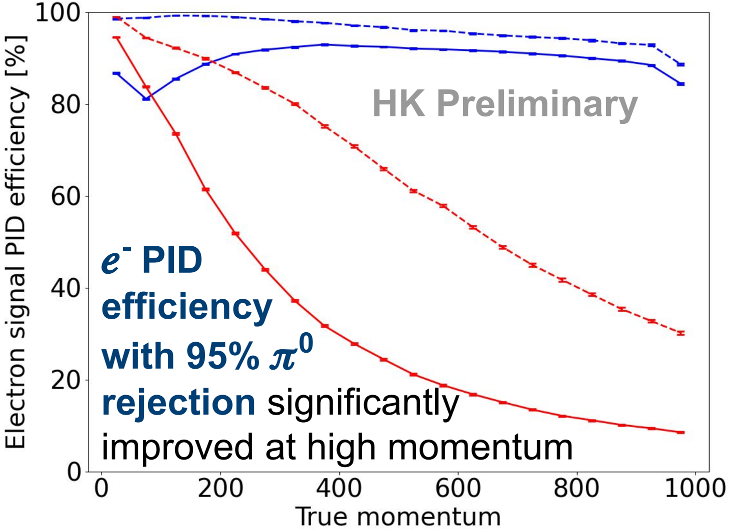
- Single 4-class network for PID classification of e, μ, π^0, γ
- Six networks for position, direction and energy of e and μ

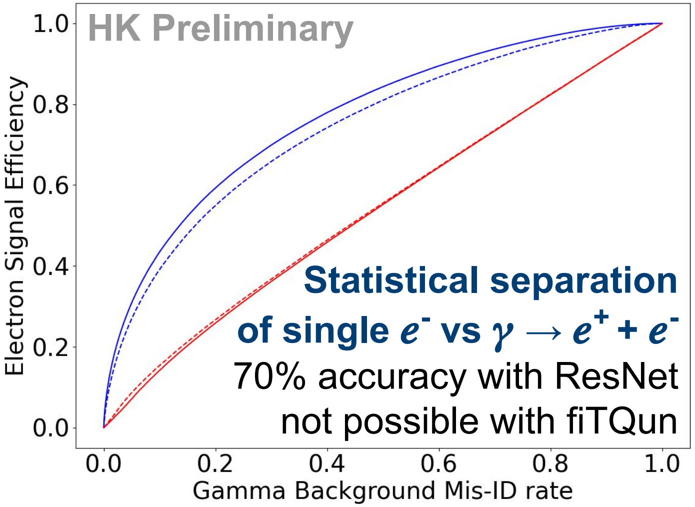
PID results

Basic cuts: > 25 hits
& fully contained event

All cuts: basic cuts
& fiTQun fit converges
& true position > 50cm from tank wall





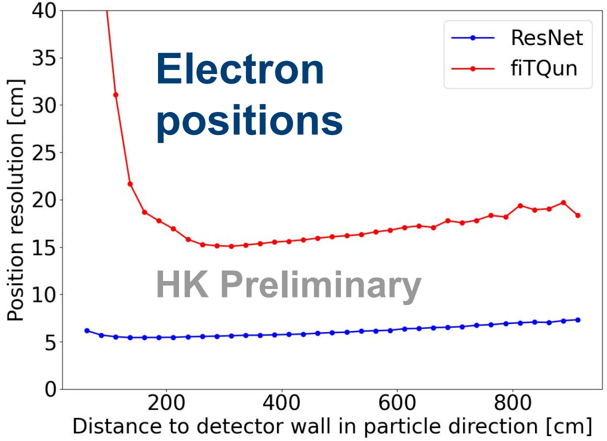


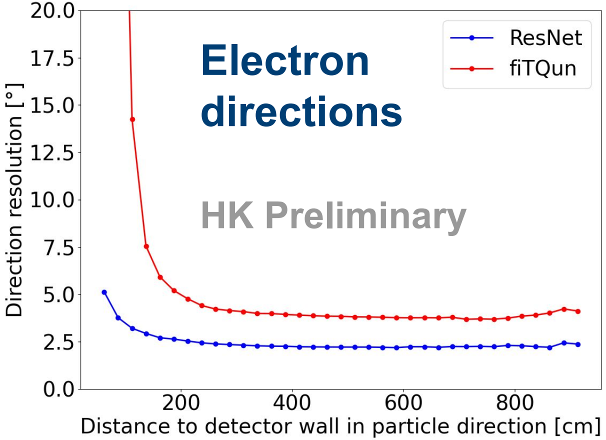
ResNet performing better, particularly where fiTQun's likelihood model approximations fail close to detector wall

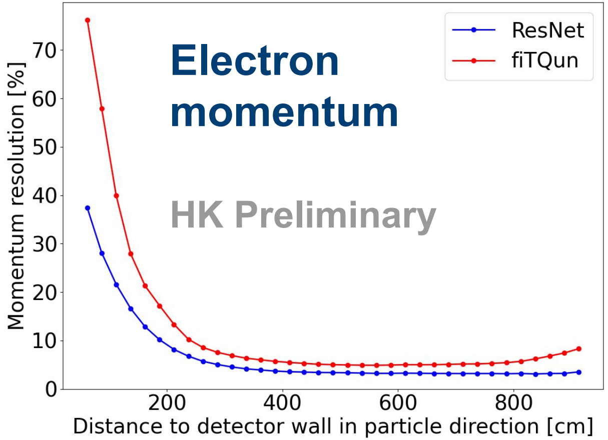
Regression results

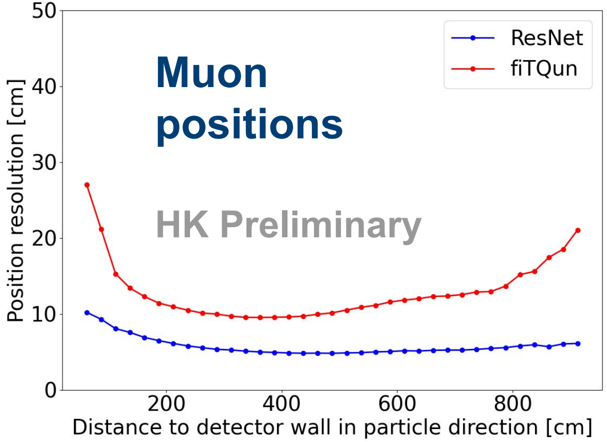
Basic cuts: > 25 hits & fully contained event

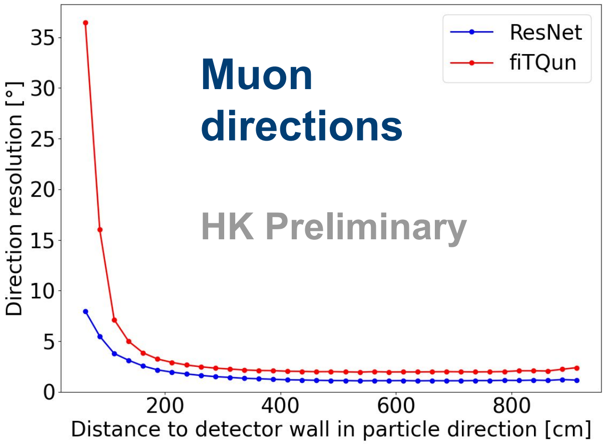
Reconstruction resolutions all reduced by 40 - 70%

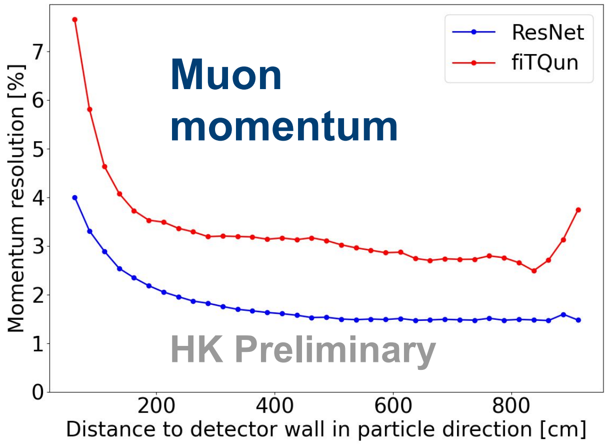




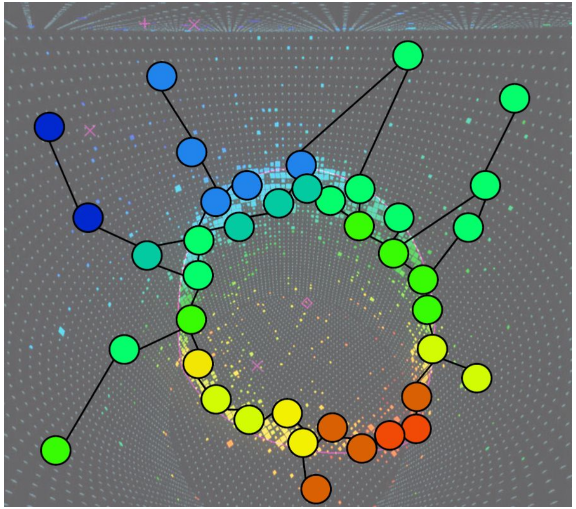


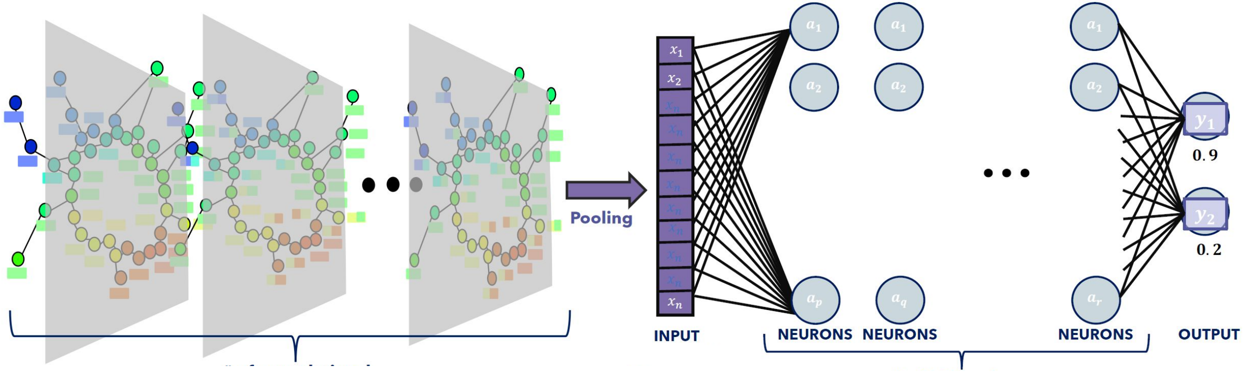






GRANT: Graph Network for Hyper-K Far Detector





Graph convolutional layers

Fully connected layers

Features at each node (hit PMT)

- PMT hit charge
- PMT hit time
- PMT location

Nearest neighbour graph

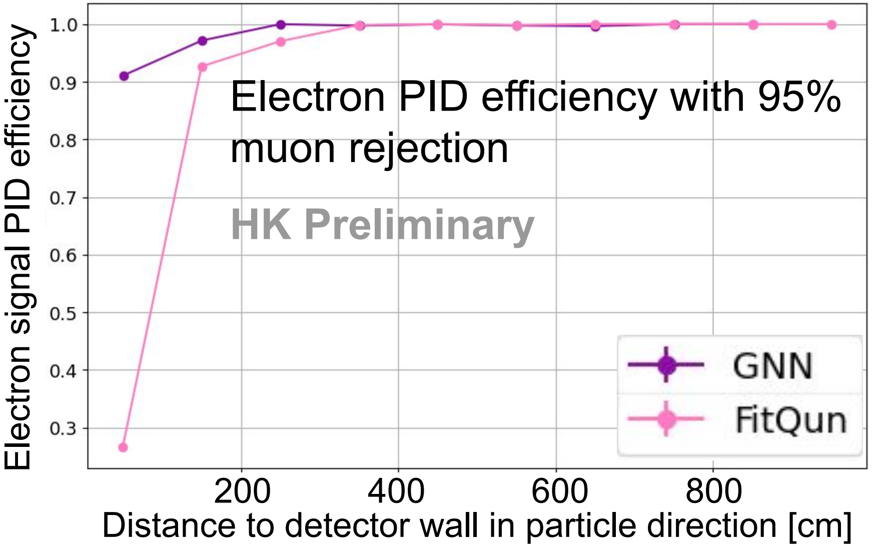
- Physical proximity of PMTs
- or charge, time proximity
- or both

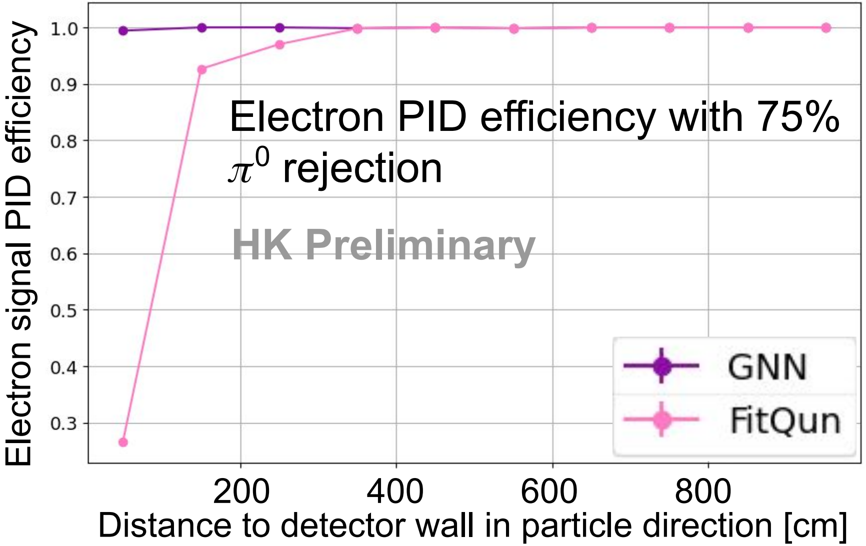
ResGatedGraphConv

- Graph convolution: aggregates information from neighbouring nodes
- Gate mechanism: adaptively controls amount of information passed between nodes
- Residual connection: Adds original node information to updated information for enhanced gradient propagation

Pooling layer followed by fully connected network provides 1D array of output features (PID variables, reconstructed quantities)

GRANT GNN Results



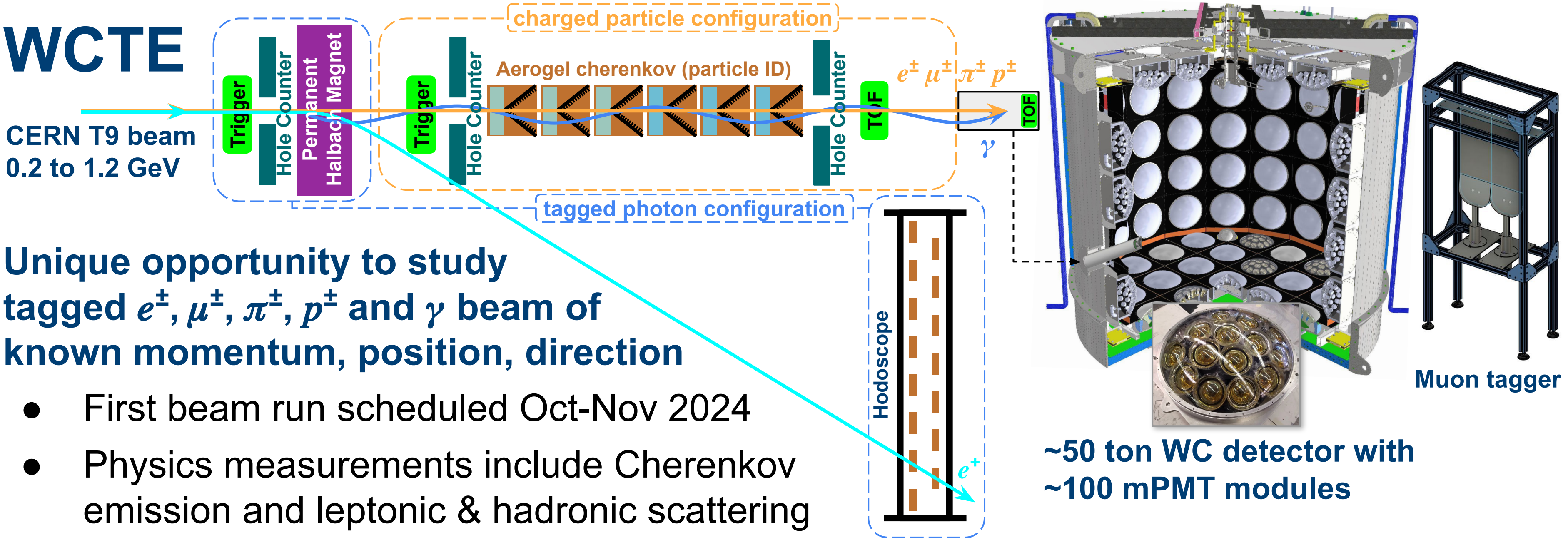


Energy reconstruction	**500 MeV electrons**	**500 MeV muons**
GRANT GNN	5.5% resolution, 1.5% bias	2.5% resolution, 0.5% bias
fiTQun	7.0% resolution, 0% bias	6.0% resolution, 0% bias

Traditional method (fiTQun) tuned to MC to avoid / correct for bias, need to investigate bias source in GRANT

Vertex position reconstruction is not performing well in GRANT, under further investigation

WCTE



Unique opportunity to study tagged $e^{\pm}$, $\mu^{\pm}$, $\pi^{\pm}$, $p^{\pm}$ and γ beam of known momentum, position, direction

- First beam run scheduled Oct-Nov 2024
- Physics measurements include Cherenkov emission and leptonic & hadronic scattering
- Main purpose is to develop new hardware, techniques and measurements to reduce interaction physics and detector systematic uncertainties in future ν experiments
- ResNet and GRANT both adapted to WCTE Detector geometry with ResNet currently showing comparable performance to IWCD on simulated MC samples
- Potential to demonstrate and validate ML-based reconstruction for WC detectors on real data in real-world experimental conditions

Summary

Hyper-Kamiokande, the next-generation water Cherenkov neutrino detector experiment has begun construction to start operation in 2027

- Both the far detector and IWCD will require new techniques to improve reconstruction, suppress backgrounds and reduce systematics

Machine learning can avoid the likelihood model approximations of traditional methods

- CNN and GNN architectures already outperforming traditional methods
  - 40 - 70% improvement in IWCD position, direction and energy resolutions
  - New analyses made possible from new e / γ discrimination capability
- Additional benefit of huge increase in speed of reconstruction

WCTE provides unique opportunity to demonstrate ML methods with real-world data

- First data taking with beam scheduled Oct - Nov this year

Appendix

ResNet event reconstruction for IWCD

Trained models on simulated IWCD data

- Generated 3M each of e, μ, π^0, γ (with conversion γ to e^+/e^- pair at initial position)
  - Uniform random initial position in entire detector, isotropic random initial directions
  - Uniform random energy 0 to 1 GeV above Cherenkov threshold for given particle type
- Split into training, validation and test sets
  - Training: 1.5M of each particle for training
  - Validation: 0.3M of each particle to monitor training and to choose the best trained model
  - Testing: 1.2M of each particle; enough stats to compare small differences between models e.g. differences in e vs mu performance around 99.9% accuracy
- Trained each model for ~ 12 hours on 4 x A100 GPUs

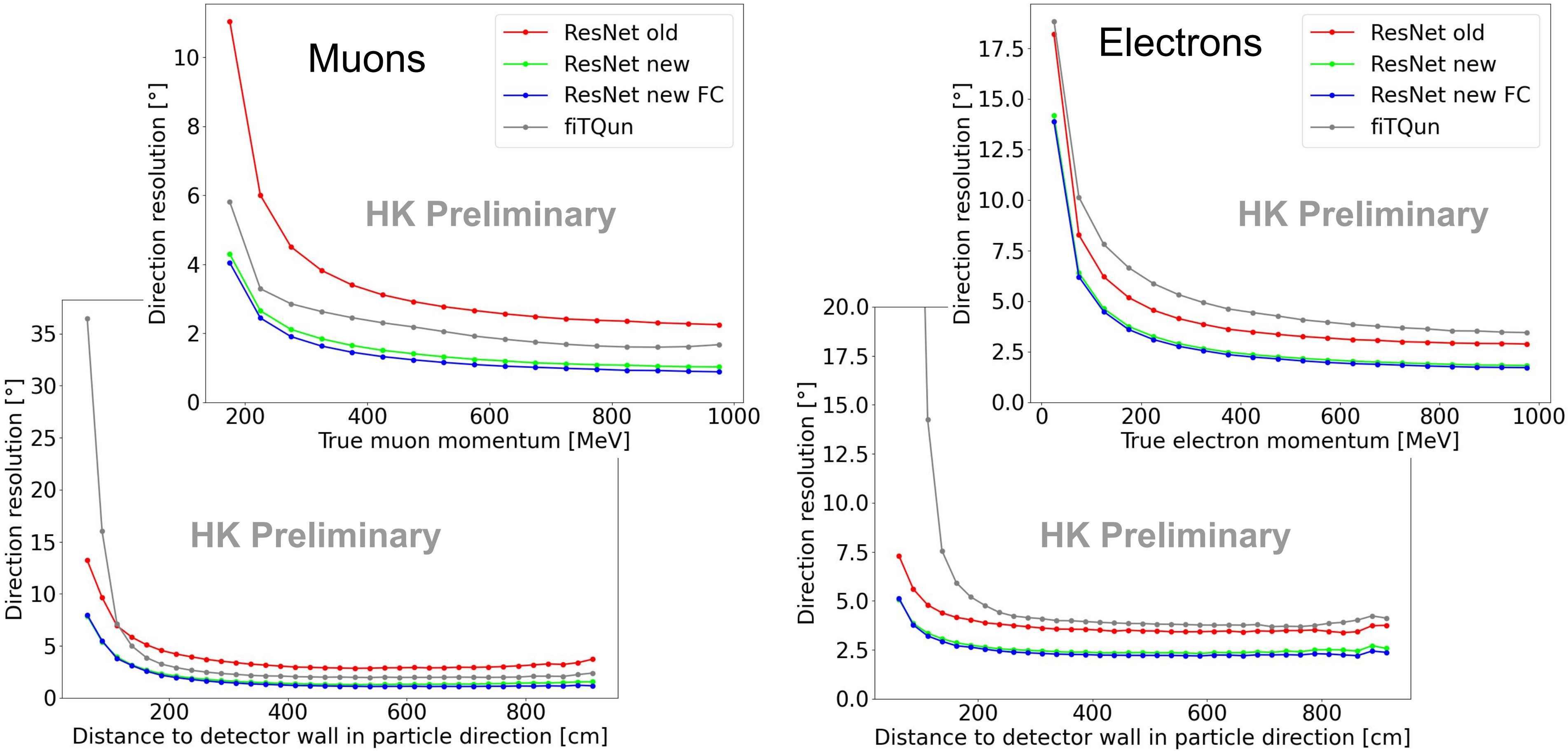
Classification

- Single 4-class network for PID classification of e, μ, π^0, γ
- Cross-entropy loss, batch size=1024, Adam optimiser, learning rate=0.002

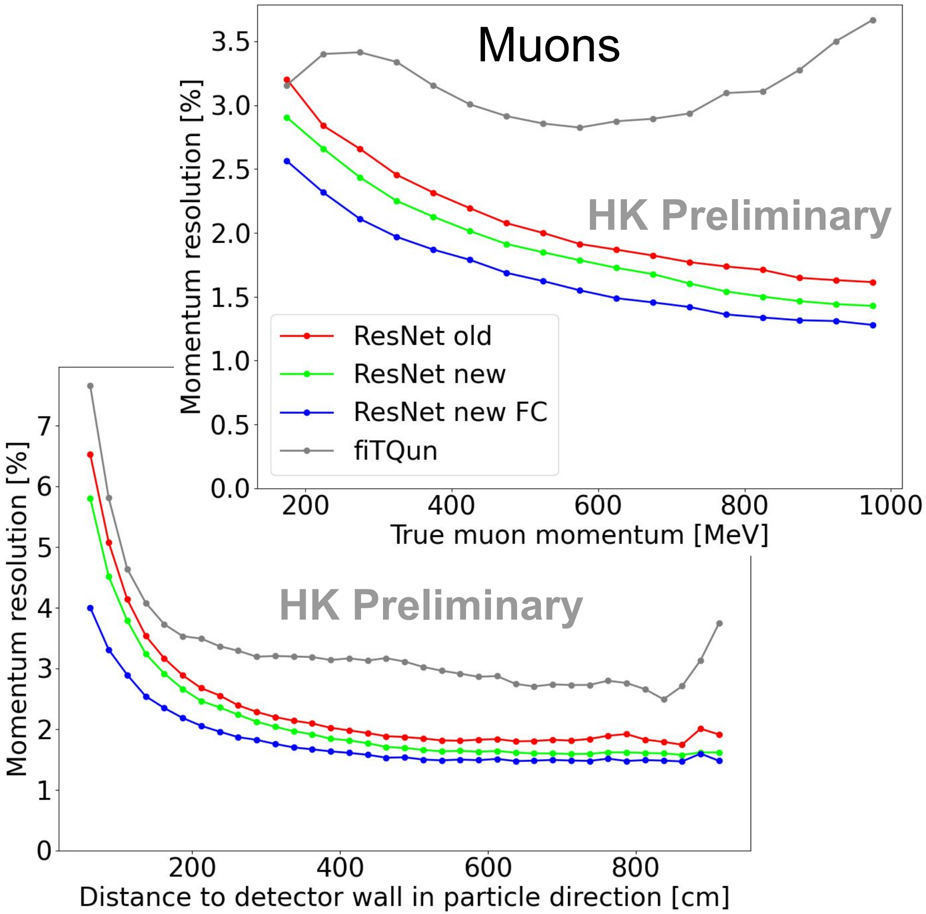
Regression

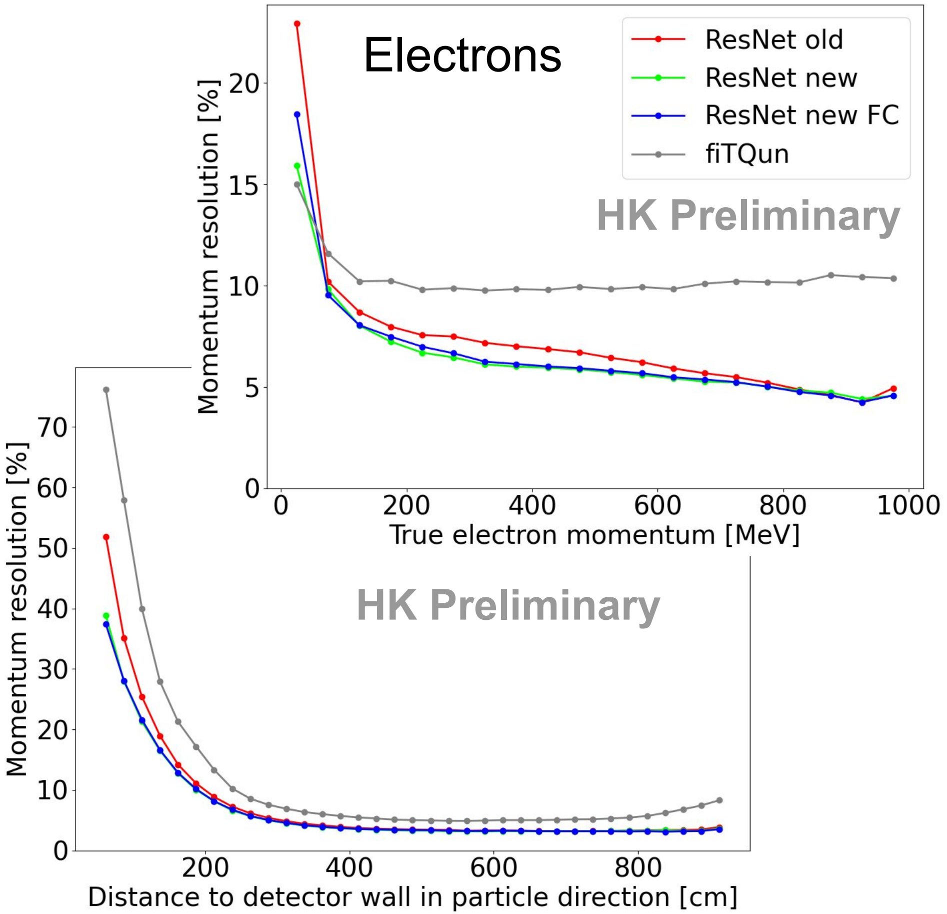
- Six separate networks for position, direction and energy of e and μ
- Huber loss with delta=0.1, batch size=1024, Adam optimiser, learning rate=0.002

Direction reconstruction

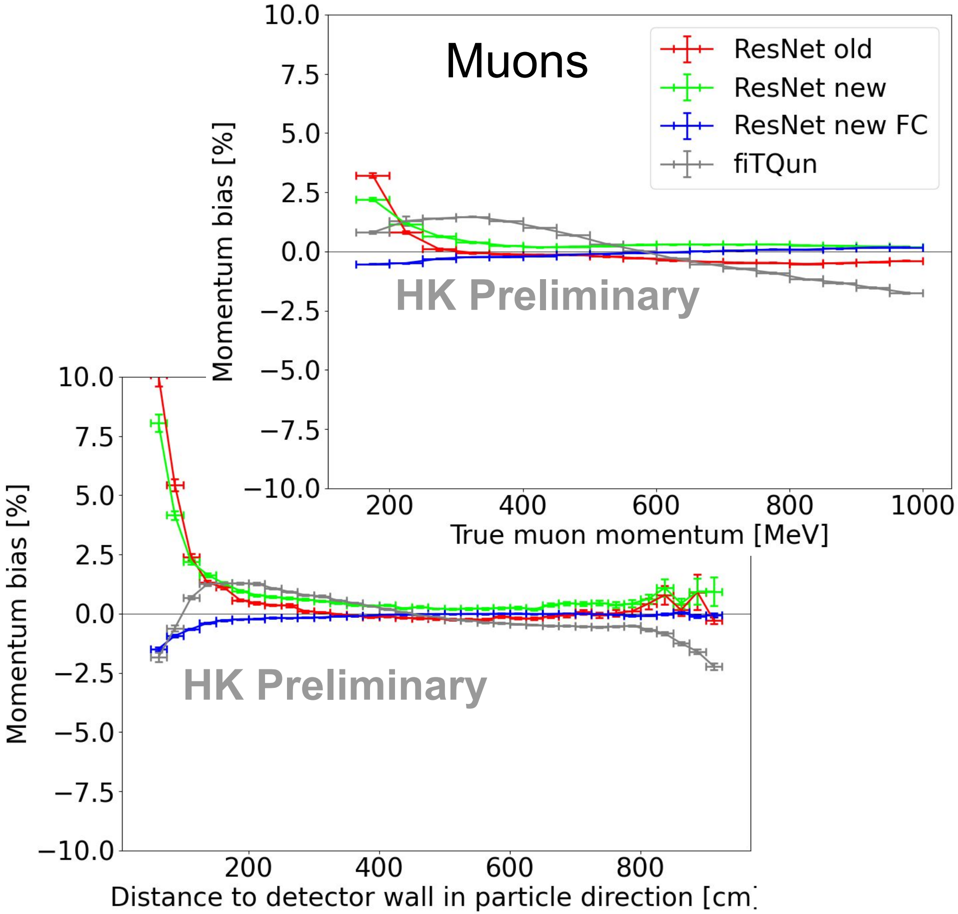


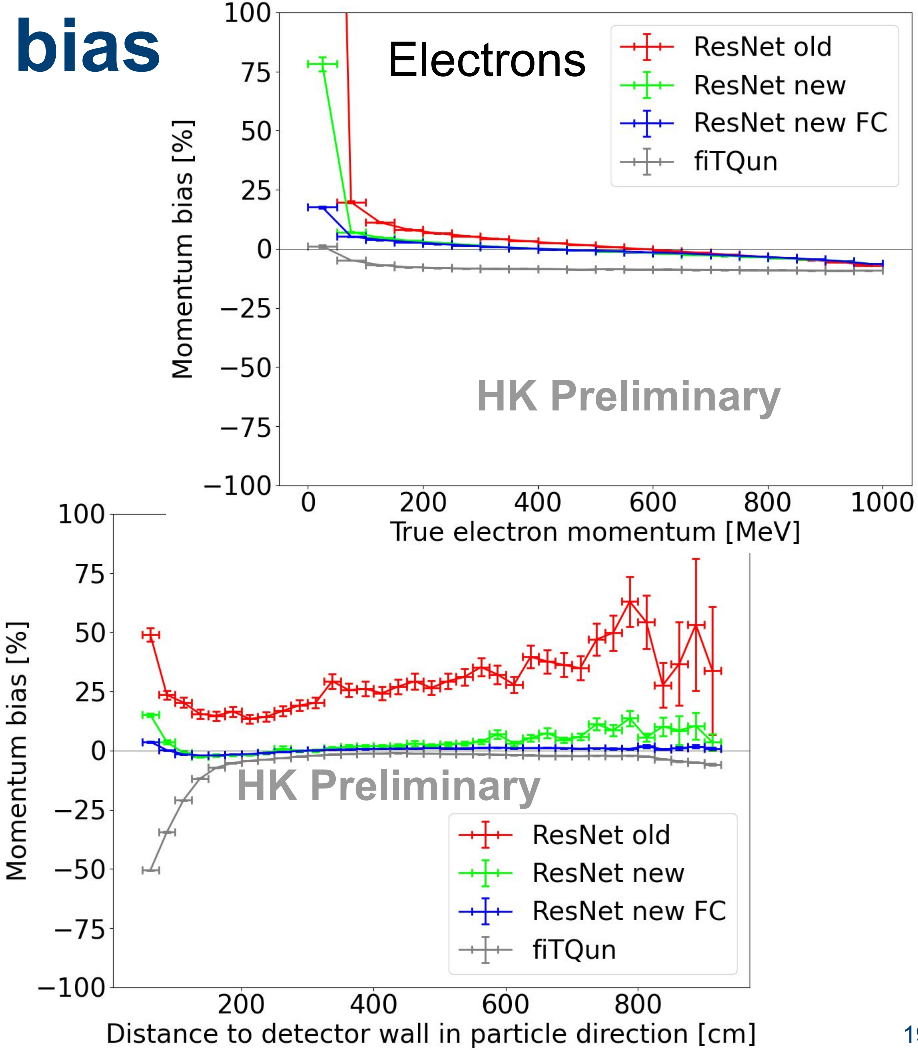
Momentum reconstruction resolution



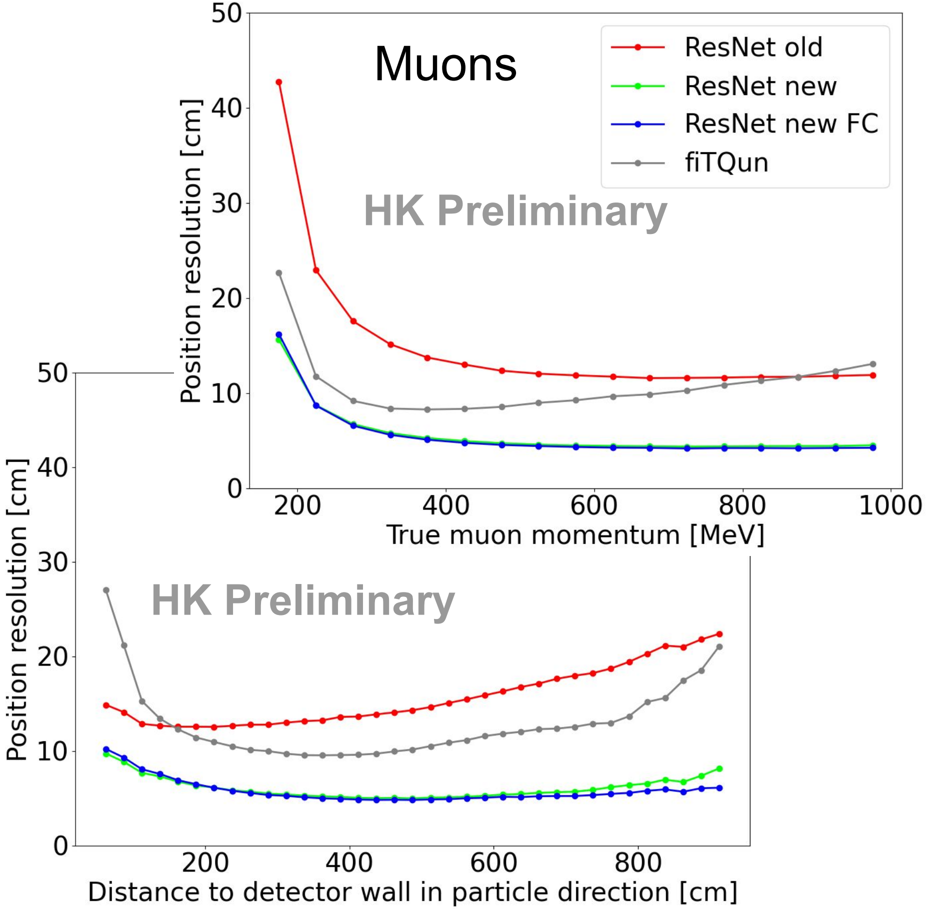


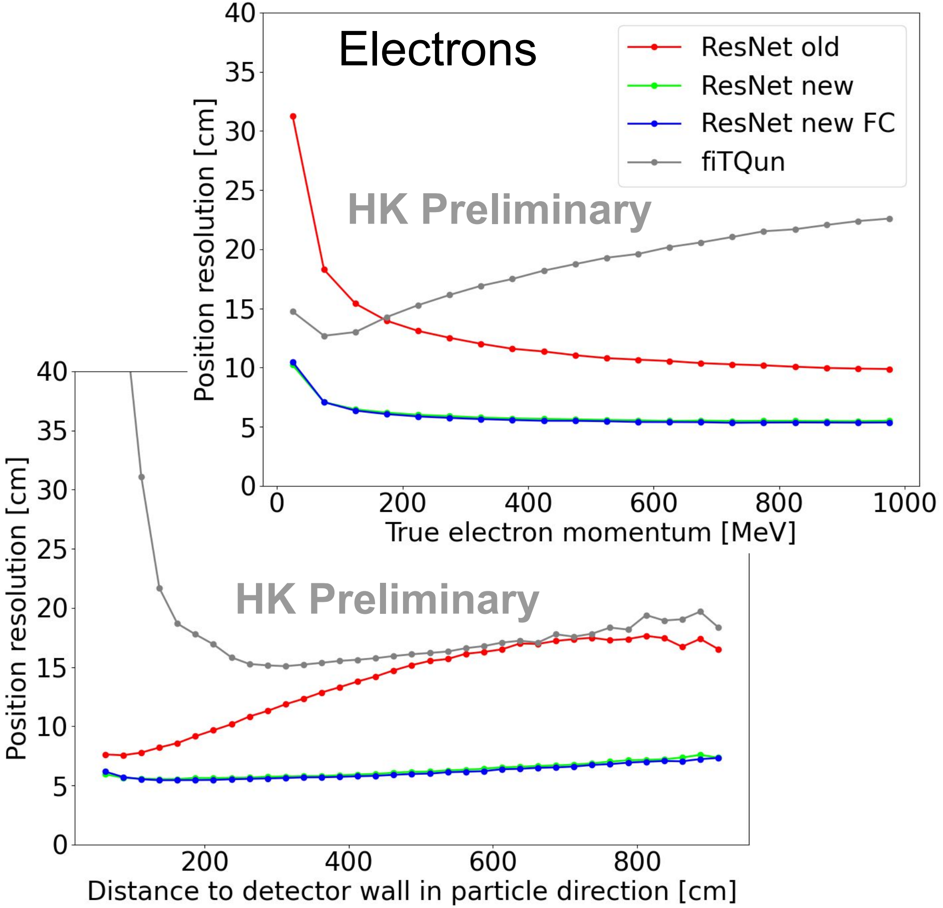
Momentum reconstruction bias



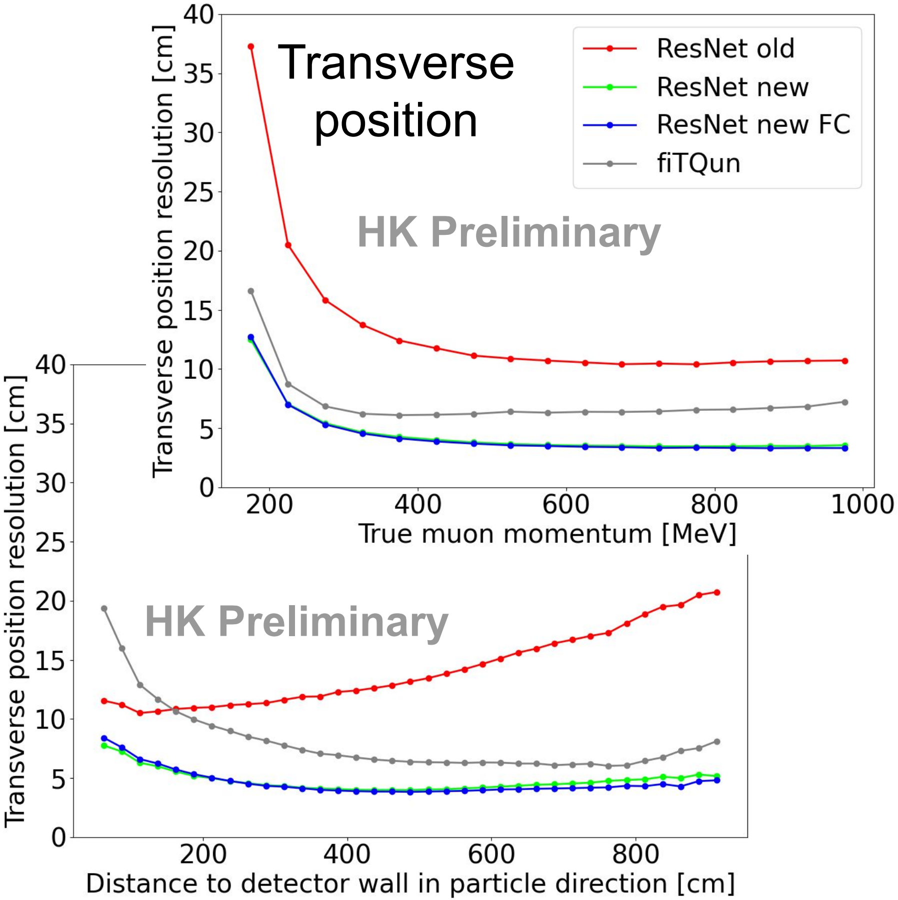


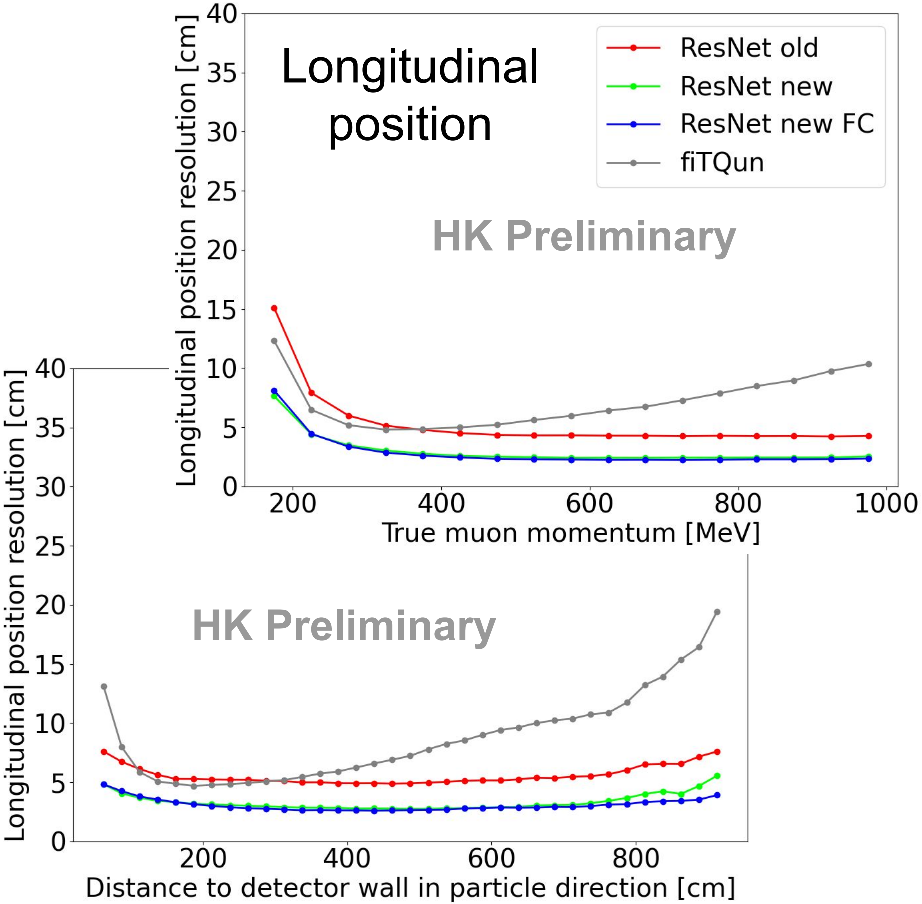
3D position reconstruction



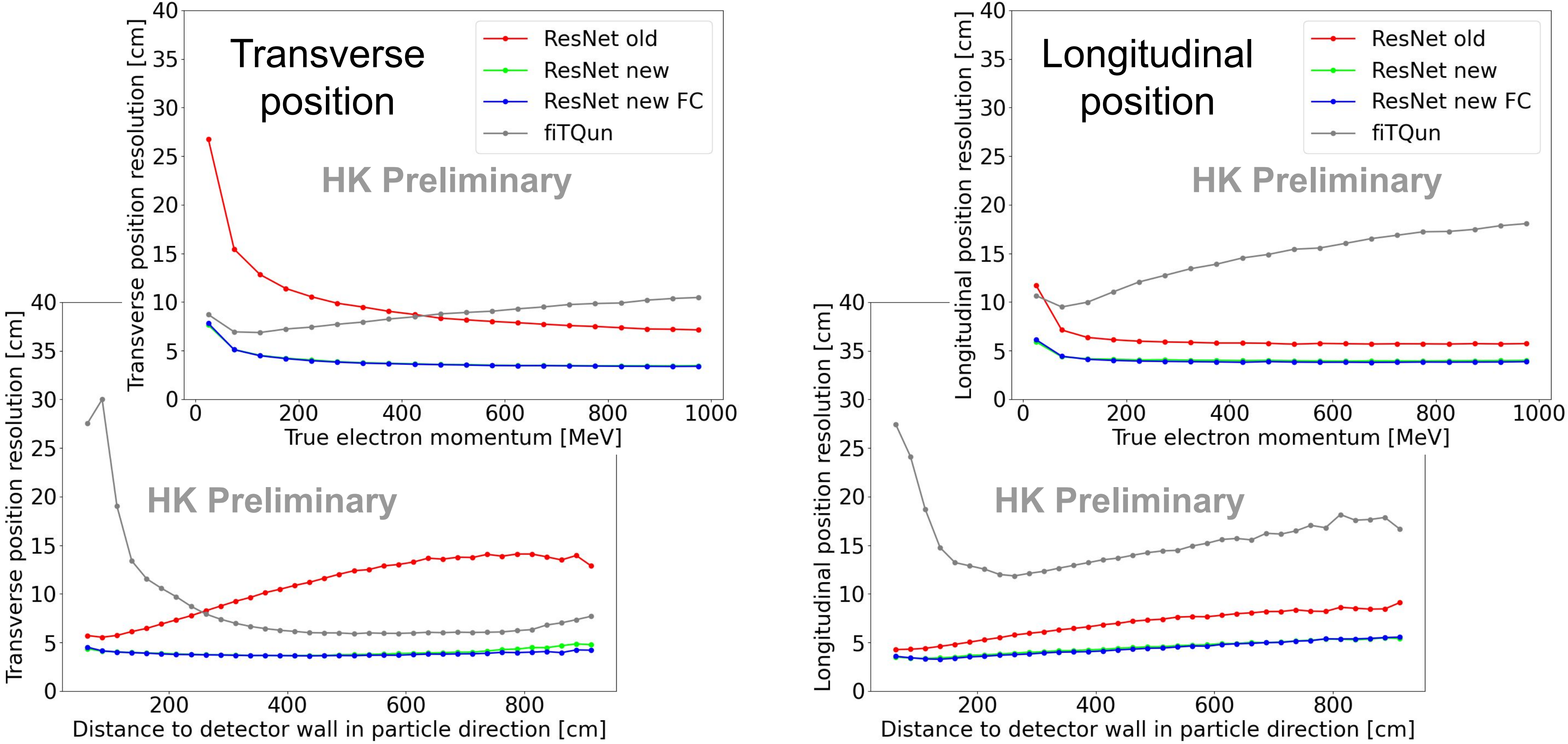


Muon position reconstruction (longitudinal & transverse)





Electron position reconstruction (longitudinal & transverse)



IWCD Regression summary

- Position, direction and energy for both muons and electrons
- Separate training run for each particle / quantity
- Trained for 12 hours in each configuration - # epochs varied by training set size
    - Trained each model on one Narval GPU node (4 x A100 40 GB GPUs) for 12 hours
    - Electron dataset is much larger (from large e/gamma separation dataset)
    - FC cuts also reduce dataset size
    - Could maybe benefit from larger muon dataset to match electrons

	All electrons	FC electrons	All muons	FC muons
# events	7,361,250	6,550,175	1,455,729	809,418
Trained # epochs	18	20	90	160

- For comparison, “ResNet old” refers to results with:
    - No double cover, no augmentations, no hit timing information, no feature scaling
    - Polar and azimuth angles for direction reconstruction
    - 20 epochs for all cases

IWCD Regression summary

Muon	ResNet	fiTQun
3D position resolution [cm]	**5.36**	11.05
Transverse position resolution [cm]	**4.27**	7.40
Longitudinal position resolution [cm]	**2.84**	7.13
Longitudinal position mean bias [cm]	**-0.16**	8.35
Direction resolution [°]	**1.37**	2.29
Momentum resolution [%]	**1.70**	3.18
Momentum mean bias [%]	**-0.12**	0.17
Electron	**ResNet**	**fiTQun**
3D position resolution [cm]	**5.81**	18.31
Transverse position resolution [cm]	**3.81**	8.62
Longitudinal position resolution [cm]	**3.97**	14.47
Longitudinal position mean bias [cm]	**-0.04**	2.39
Direction resolution [°]	**2.57**	5.25
Momentum resolution [%]	**6.65**	10.51
Momentum mean bias [%]	**0.21**	-7.85

Resolutions defined as 68th percentile of 3D distance between true and reco positions, angle between true and reco directions, residual of |reco - true| energy, etc.

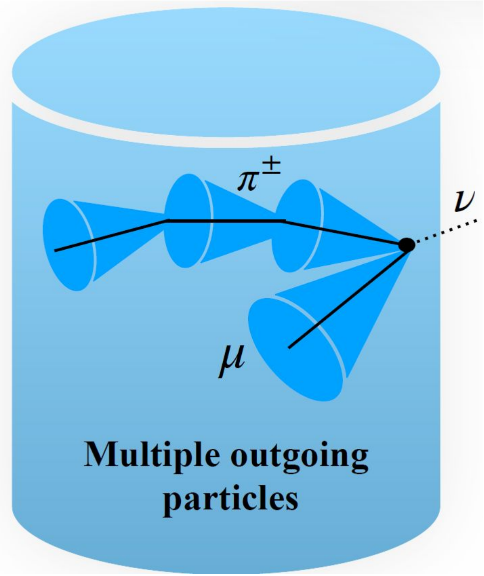
Biases defined as mean of (reco - true) values

ResNet for pile-up identification in IWCD

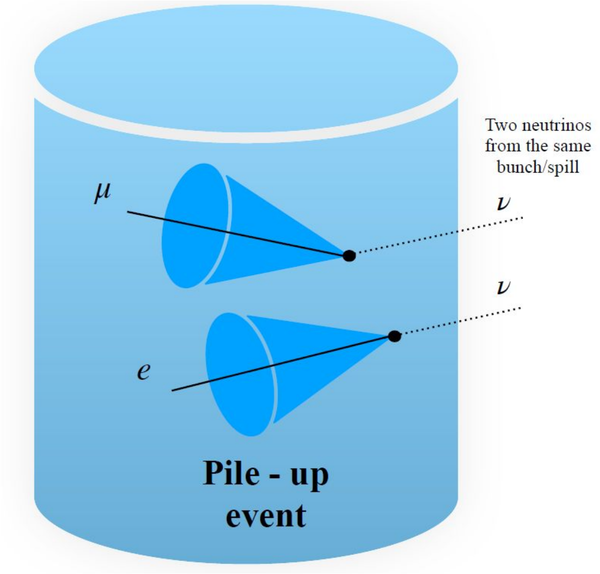
Study of single-vertex vs multi-vertex classification

- IWCD will see multi-vertex pile-up events due to close proximity to neutrino beam
- Trained network to classify multi-track events as single or multiple vertices
- Trained on particle gun events with 2+ particles from a single vertex or from two vertices
- Tested on samples using realistic neutrino interactions generated by GENIE or NEUT

Single-vertex multi-track event



Pile-up event



Pile-up training and testing samples

For all events:

- Each vertex is a random uniform position in the tank, random initial time from Gaussian with width of 25ns

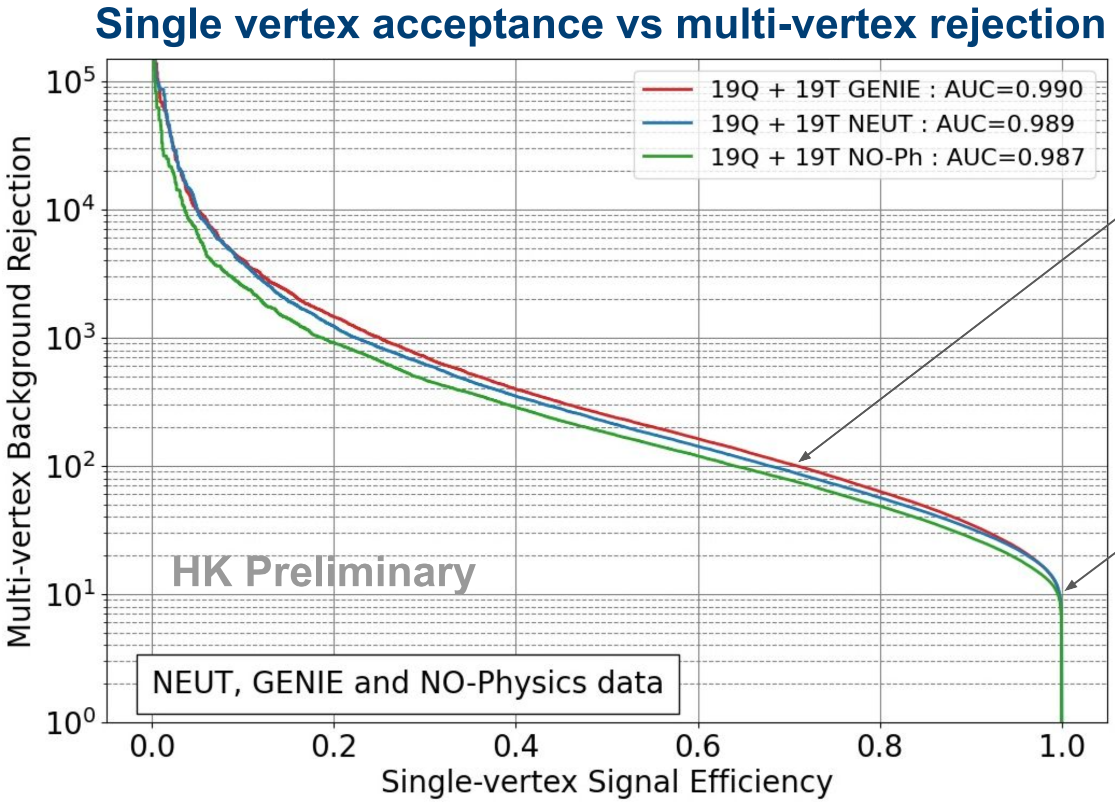
For training:

- 2.5M events each for single or multi-vertex
  - For single-vertex all particles start at the same vertex (position and time)
  - For multi-vertex particles randomly split between two vertices
- 2 to 5 particles simulated per event, with ‘unbiased’ distributions to avoid model bias
  - Each particle randomly chosen from electron, muon, neutral and charged pions
  - Each particle has random isotropic direction
  - Total energy of all particles uniformly distributed from 0 to 2 GeV

For testing:

- Number, type, energies, direction of particles determined by neutrino interaction MC
- ~1M events produced using each of NEUT and GENIE
  - For single-vertex take a single neutrino interaction
  - For multi-vertex take two neutrino interactions

Pile-up results

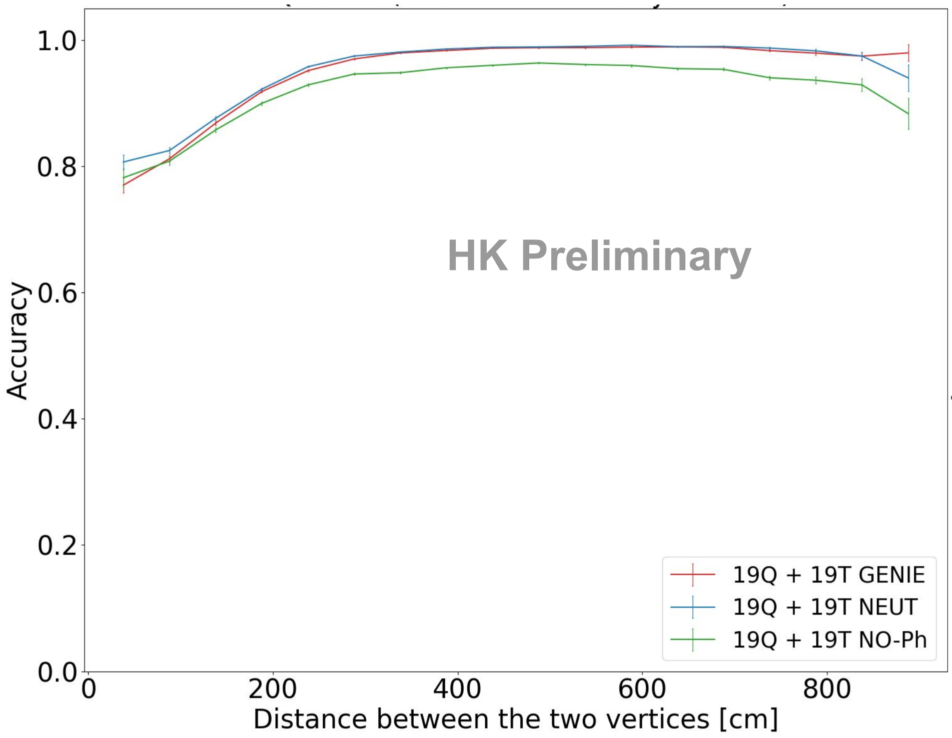


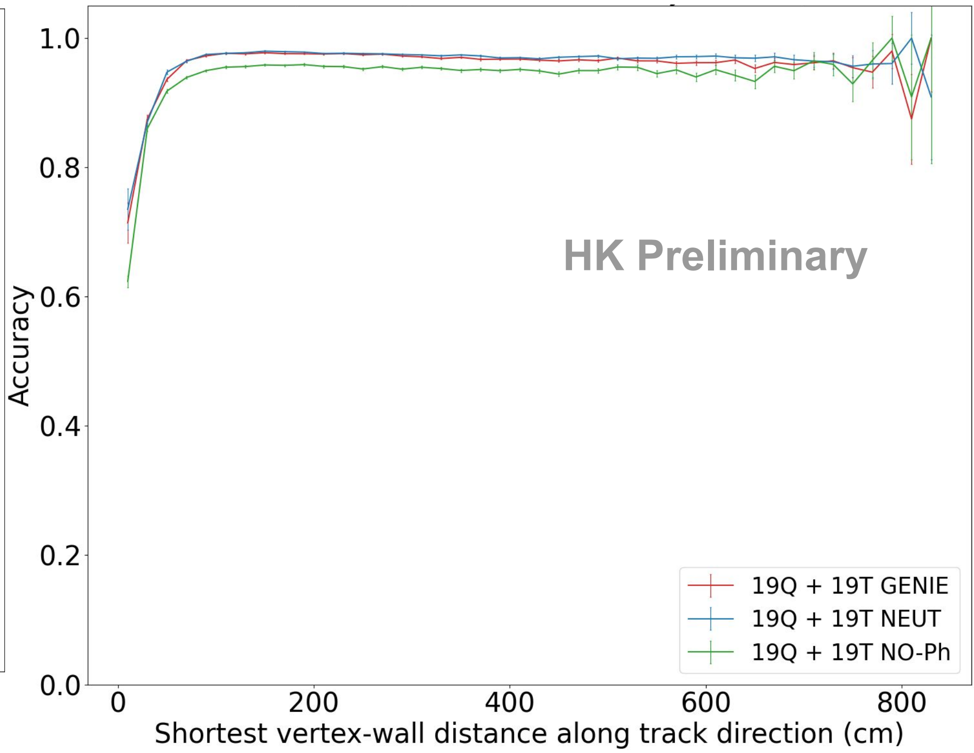
~70% of single vertex events accepted with 99% of multi-vertex events rejected

~99% of single vertex events accepted with 90% of multi-vertex events rejected

Working nicely with NEUT/GENIE MC events after training with particle gun MC

Pile-up results

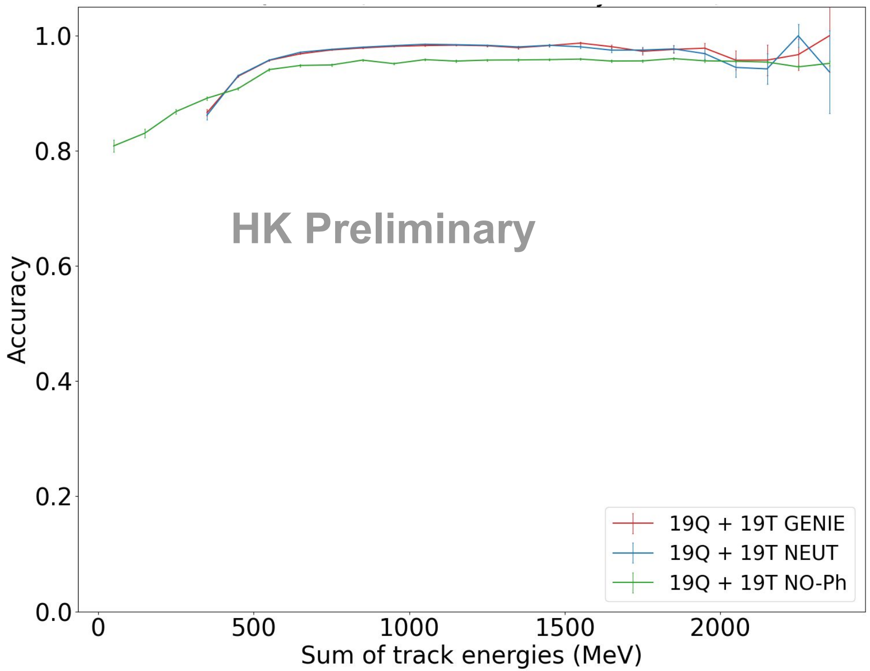




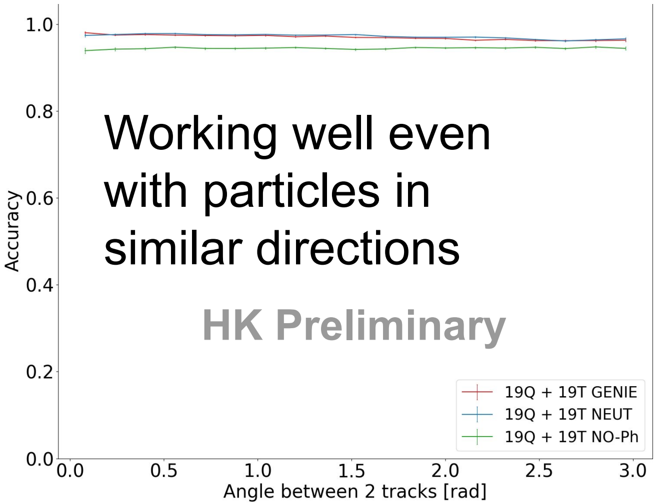
Some degradation of performance when vertices close to each other in space

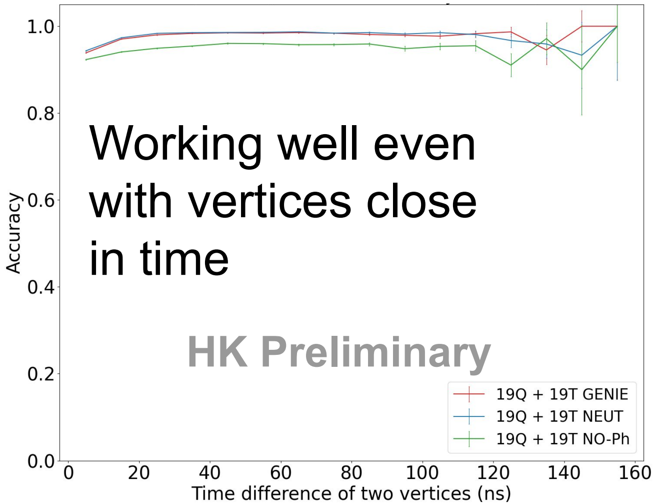
Degradation of performance for particles with small towall distance

Pile-up results



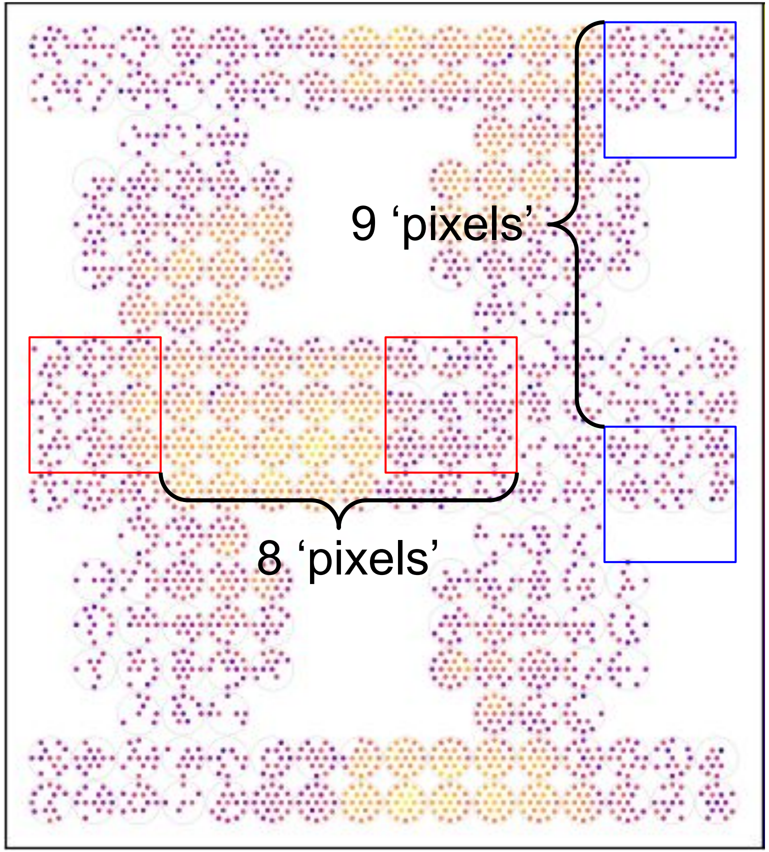
Some degradation of performance at lower energies





Problem with WCTE in ResNet for regression

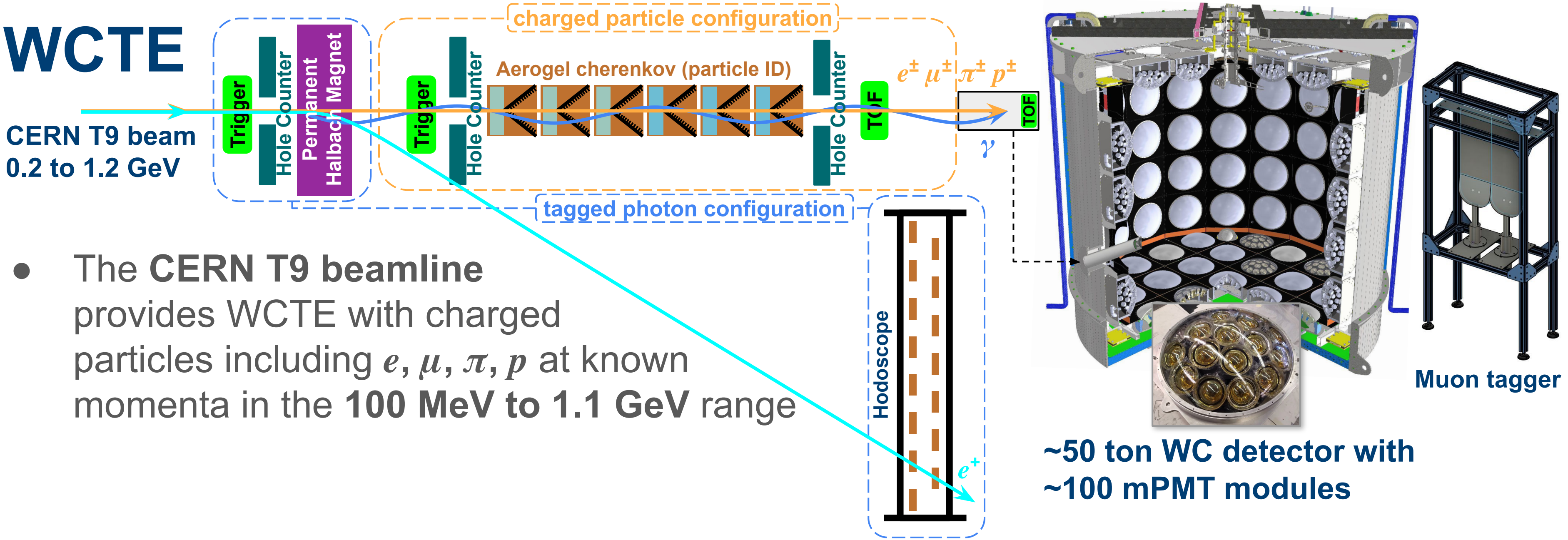
- **Problem:** 16 columns + circular boundaries + CNN translation invariance = identical network output after 180° rotation of detector about its axis
  - Network learns locations on tank from pattern of filled/unfilled pixels
  - But translations equivalent to 180° tank rotation have same pattern so network output is identical for a 180° rotated event
  - Need to break symmetry for network to learn position and directon
- ResNet performs 3x3 convolutions and maxpools with a stride of 2
  - Considering the downsampling, the translation invariance is only unbroken for translations by number of pixels equal to powers of 2
- WCTE has 16 columns
  - Horizontal 180° rotation of the tank about its axis in 3D is the same as translating the 2D double-cover image by 8 pixels
  - So the network cannot distinguish between any event and the equivalent with the tank rotated by 180°
  - Vertical 180° rotation is equivalent to 9 pixel translation so the invariance is broken due to the stride of 2
- IWCD has 40 columns so didn't see this problem
  - After 2 downsamples, the a 20-pixel translation for 180° tank rotation becomes a 5-pixel translation
  - With stride of 2, there is translation invariance of only even number of pixels
  - So it can learn the difference between an event and the equivalent event rotated by 180°



Problem with WCTE in ResNet for regression

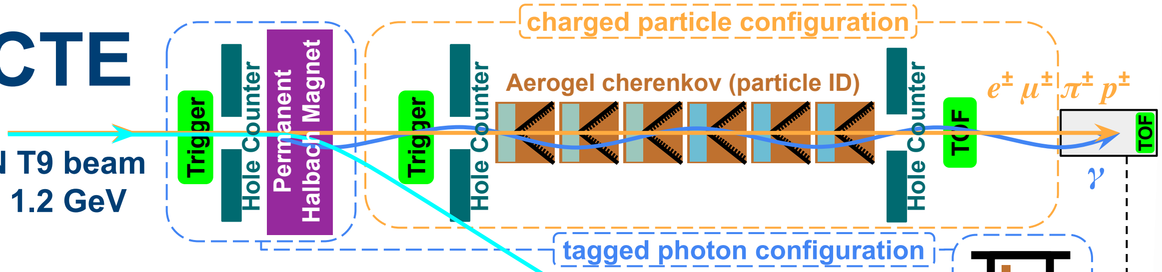
- **Problem:** 16 columns + circular boundaries + CNN translation invariance = identical network output after 180° rotation of detector about its axis
- Solve problem with Positional encoding: provide geometrical information as extra channels
  - Each mPMT pixel now has 41 channels of data instead of 38
    - 19 charge channels + 19 time channels = 38
    - + 3 channels for x, y, z position of the middle of the mPMT
  - Also added option to provide channels for mPMT orientation
- Adding the mPMT position channels allowed it to successfully learn particle position and direction
  - Takes longer to converge, but once it does the performance is improved
  - No benefit seemed to come from also adding orientation, only position seemed to help
  - Also tried one-hot encoding channels of mPMT locations for network to learn 3D geometry
    - Same eventual performance within statistical errors, but slower to train

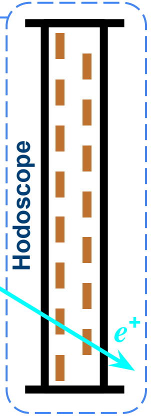
WCTE

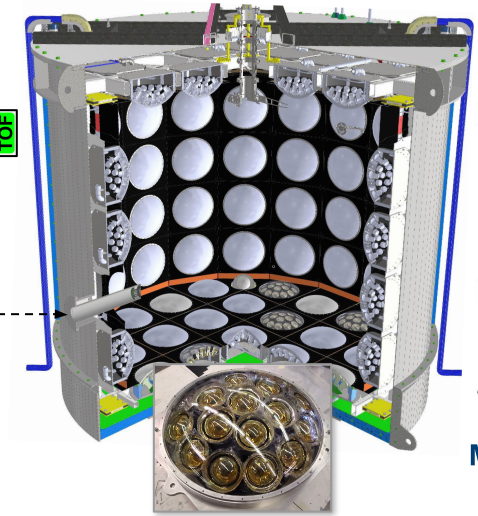


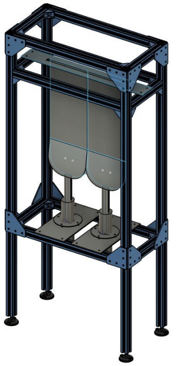
- The **CERN T9 beamline** provides WCTE with charged particles including e, μ, π, p at known momenta in the **100 MeV to 1.1 GeV** range
- The **charged particle configuration** includes **Aerogel Cherenkov counters** with different refractive indices chosen for each beam momentum, for tagging of electrons and muons through their Cherenkov threshold; **Time of Flight** (TOF) detectors with 100 ps timing resolution provide identification of the heavier hadrons (p, π, K, etc.)

WCTE





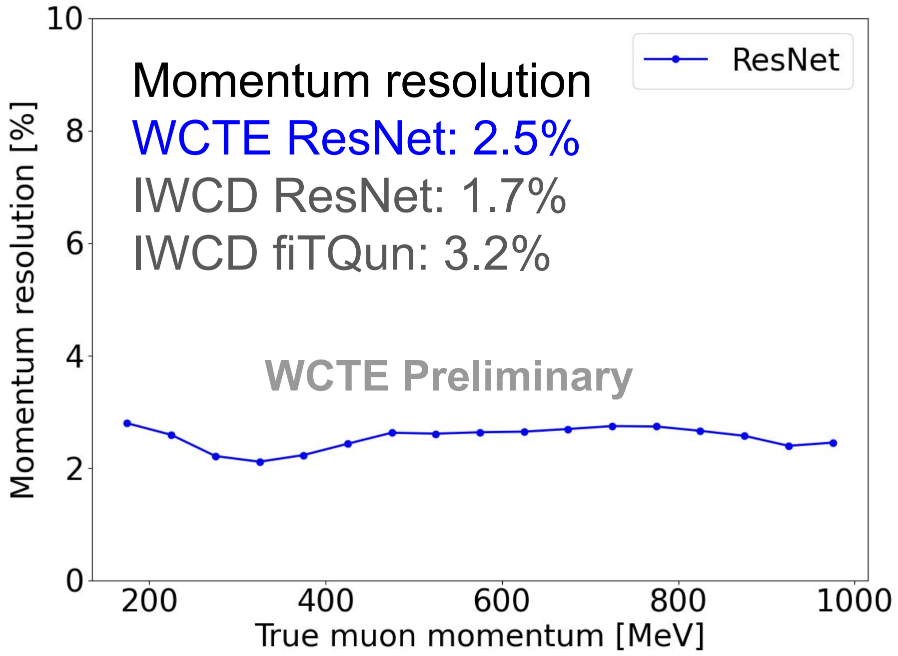


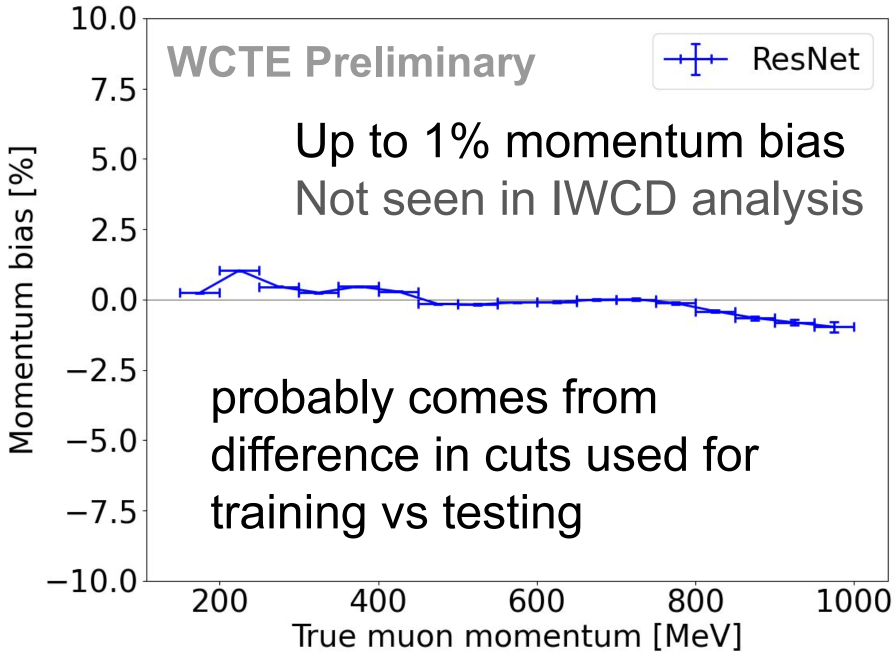


- The **tagged photon configuration** includes a **1 Tesla permanent magnet** to deflect positrons while bremsstrahlung photons continue towards the water-Cherenkov detector
- A **hodoscope** measures the deflected positron's energy to determine the photon's energy
- July 2023 beam test successfully demonstrated capability of both beam monitor configurations
- Data taking is scheduled for 6 weeks Oct-Nov 2024 with additional beamtime expected in 2025

WCTE Muon momentum reconstruction

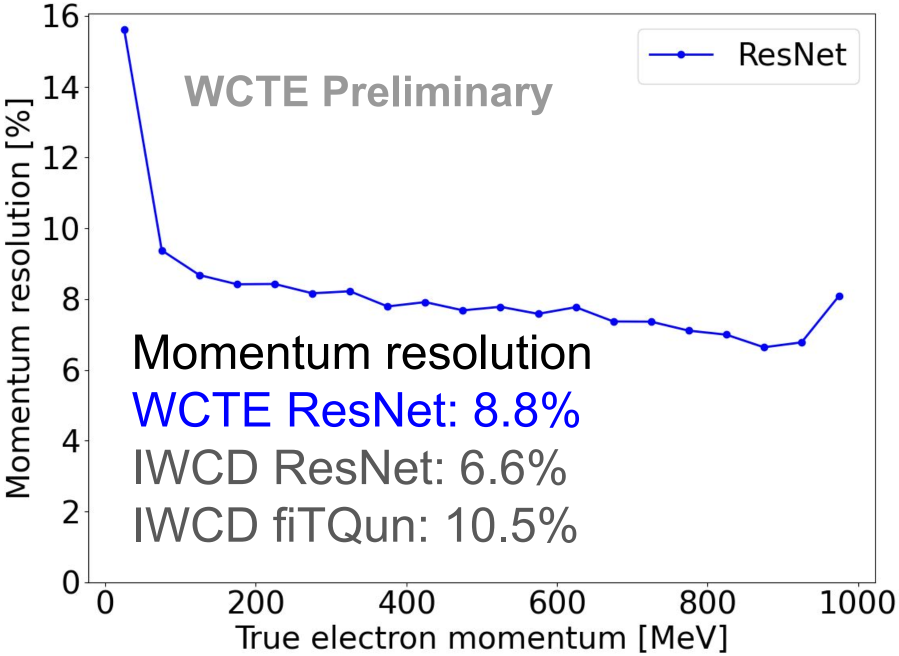
- Trained on true fully contained events with > 10 hits
- Test on fully contained events with > 25 hits and towall > 1 m

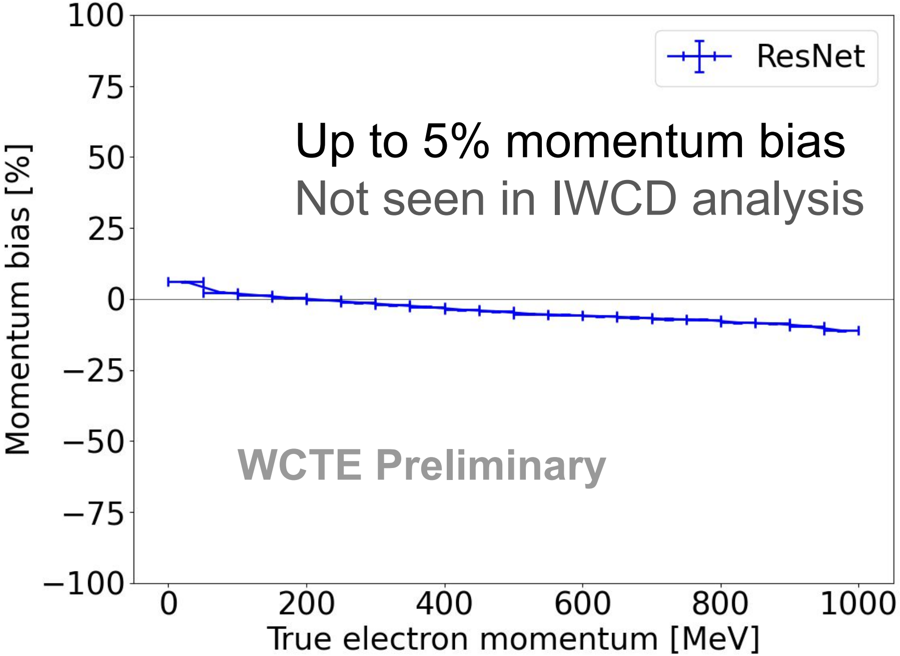




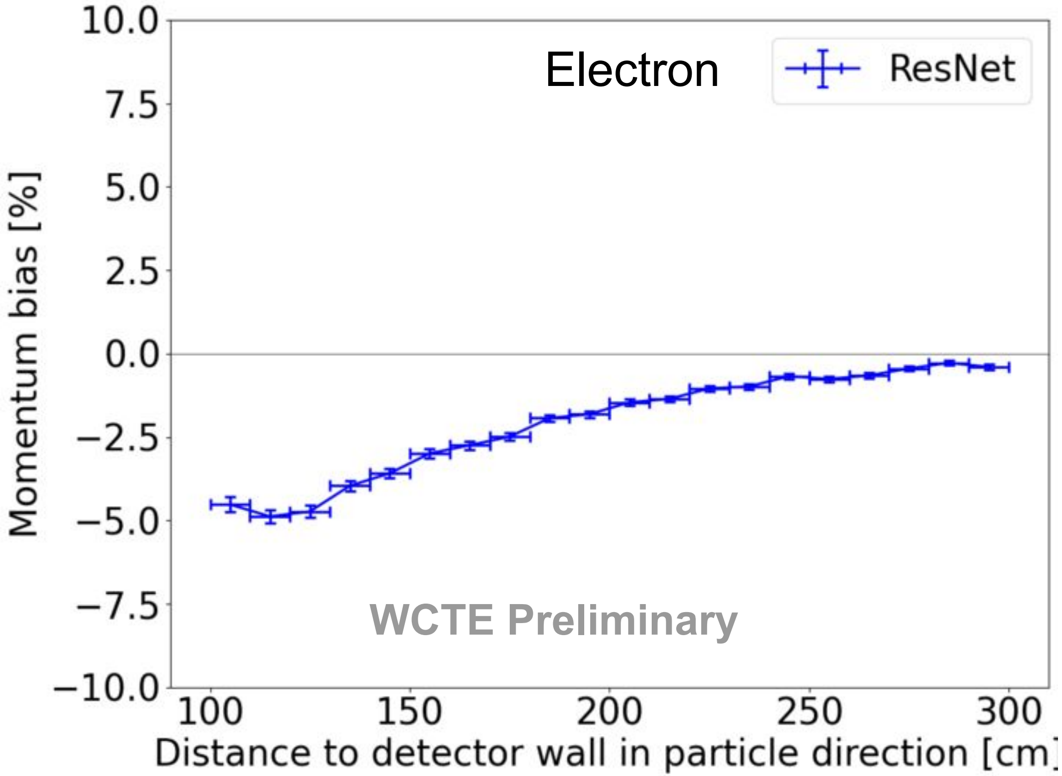
WCTE Electron momentum reconstruction

- Trained on true fully contained events with > 10 hits
- Test on fully contained events with > 25 hits and towall > 1 m



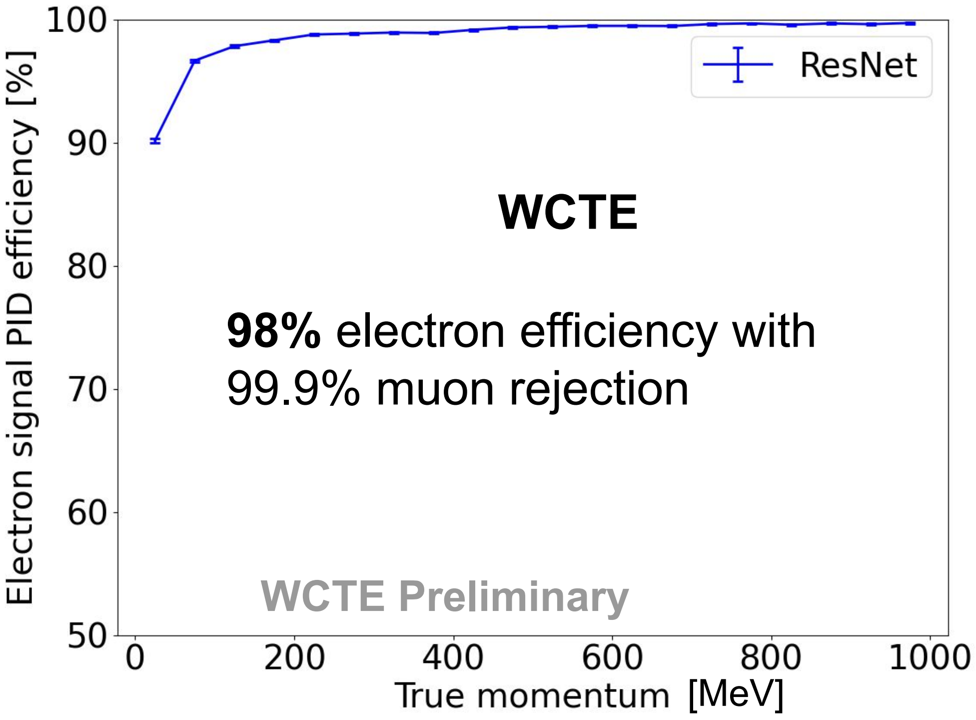


WCTE Momentum bias against to wall distance

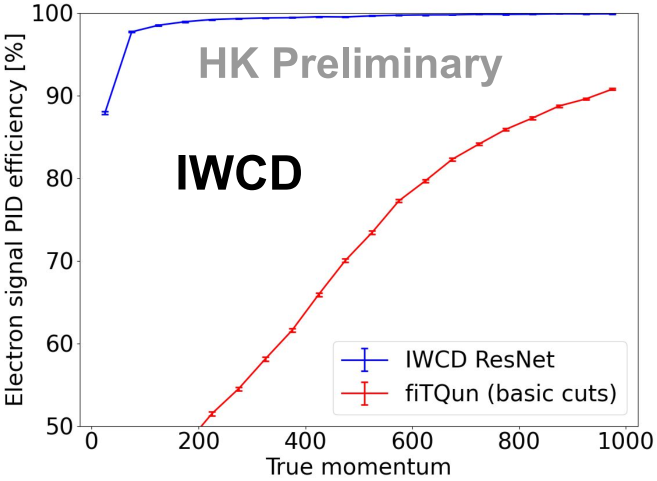


Trained using ALL events with >10 hits
Tested on FC events with >25 hits, towall > 1m

WCTE Electron / muon PID



98% electron efficiency with
99.9% muon rejection



99% electron efficiency with
99.9% muon rejection

fiTQun performs poorly without additional cuts on towall, dwall, etc.

Trained using ALL events with >10 hits
Tested on FC events with >25 hits, towall > 1m

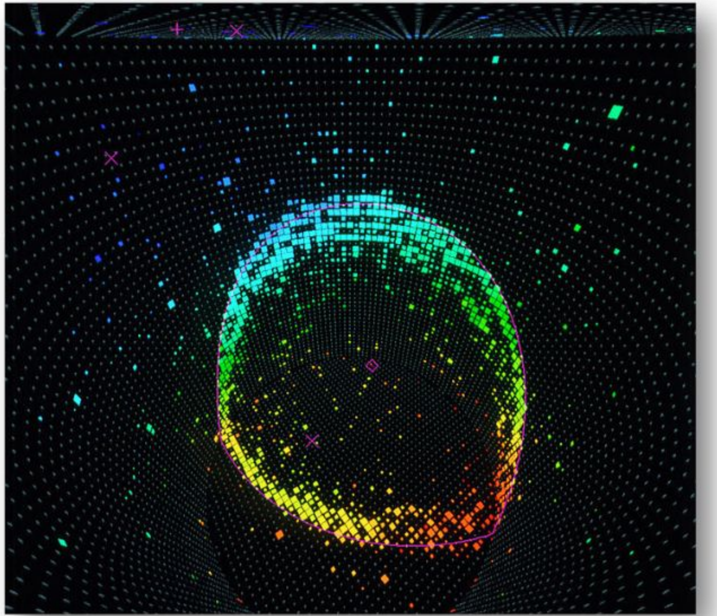
WCTE Reconstruction summary

Muon	WCTE ResNet	IWCD ResNet	IWCD fiTQun
3D position resolution [cm]	**6.46**	5.36	11.05
Transverse position resolution [cm]	**5.67**	4.27	7.40
Longitudinal position resolution [cm]	**2.69**	2.84	7.13
Longitudinal position mean bias [cm]	**0.17**	-0.16	8.35
Direction resolution [°]	**2.17**	1.37	2.29
Momentum resolution [%]	**2.48**	1.70	3.18
Momentum mean bias [%]	**0.21**	-0.12	0.17
Electron	**WCTE ResNet**	**ResNet**	**fiTQun**
3D position resolution [cm]	**6.83**	5.81	18.31
Transverse position resolution [cm]	**4.96**	3.81	8.62
Longitudinal position resolution [cm]	**4.17**	3.97	14.47
Longitudinal position mean bias [cm]	**0.63**	-0.04	2.39
Direction resolution [°]	**4.12**	2.57	5.25
Momentum resolution [%]	**8.80**	6.65	10.51
Momentum mean bias [%]	**-2.00**	0.21	-7.85

WCTE ResNet performance almost as good as IWCD ResNet and better than IWCD fiTQun

Direction resolution most significantly reduced compared to IWCD, probably due to lower granularity of PMTs to resolve particle direction

2 GRANT : Machine Learning based algorithm for reconstruction



Events at high energy

- **Large number of PMTs** triggered (around **3000 hit** PMTs for e- event at 500 MeV).
- For each PMT, **5 distinct pieces of data** are collected: Position (x, y, z), Charge, Time
- **Result**: **MASSIVE DATASET**
- These events exhibit a distinctive **geometrical shape (like a ring).** Our goal is to identify patterns using the 5 pieces of information from each hit PMT.
- **Graphs are an excellent tool for this purpose!** 😊

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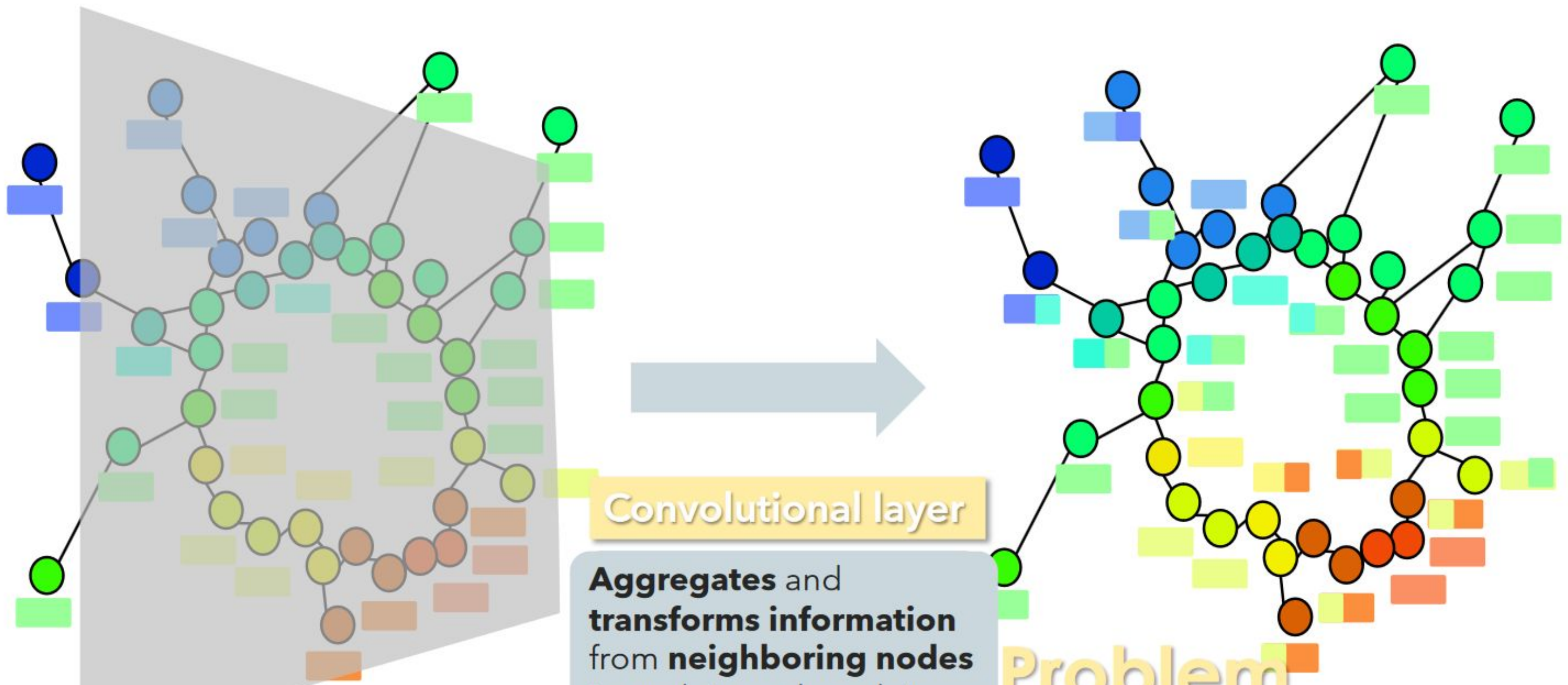
2 GRANT : Machine Learning based algorithm for reconstruction



Aggregates and **transforms information** from **neighboring nodes** to update each node's feature. **Reflecting local graph structures**

Problem dependant !

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2 GRANT : Machine Learning based algorithm for reconstruction

Convolutional layer

ResGatedGraphConv.

Main Features

- Graph Convolution: Aggregates information from neighboring nodes to update each node. (graph-based learning)
- Gate Mechanism: Uses a weight (between 0 and 1) to control the amount of information that is passed from one node to another. (adaptive control of information flow)
- Residual Connection: Adds the original node information to its updated information, facilitating gradient propagation. (enhanced gradient propagation)

- It's a neural network layer designed to **work with data** structured as graphs.
- It combines elements of graph **convolution, gating mechanisms**, and **residual connections.**

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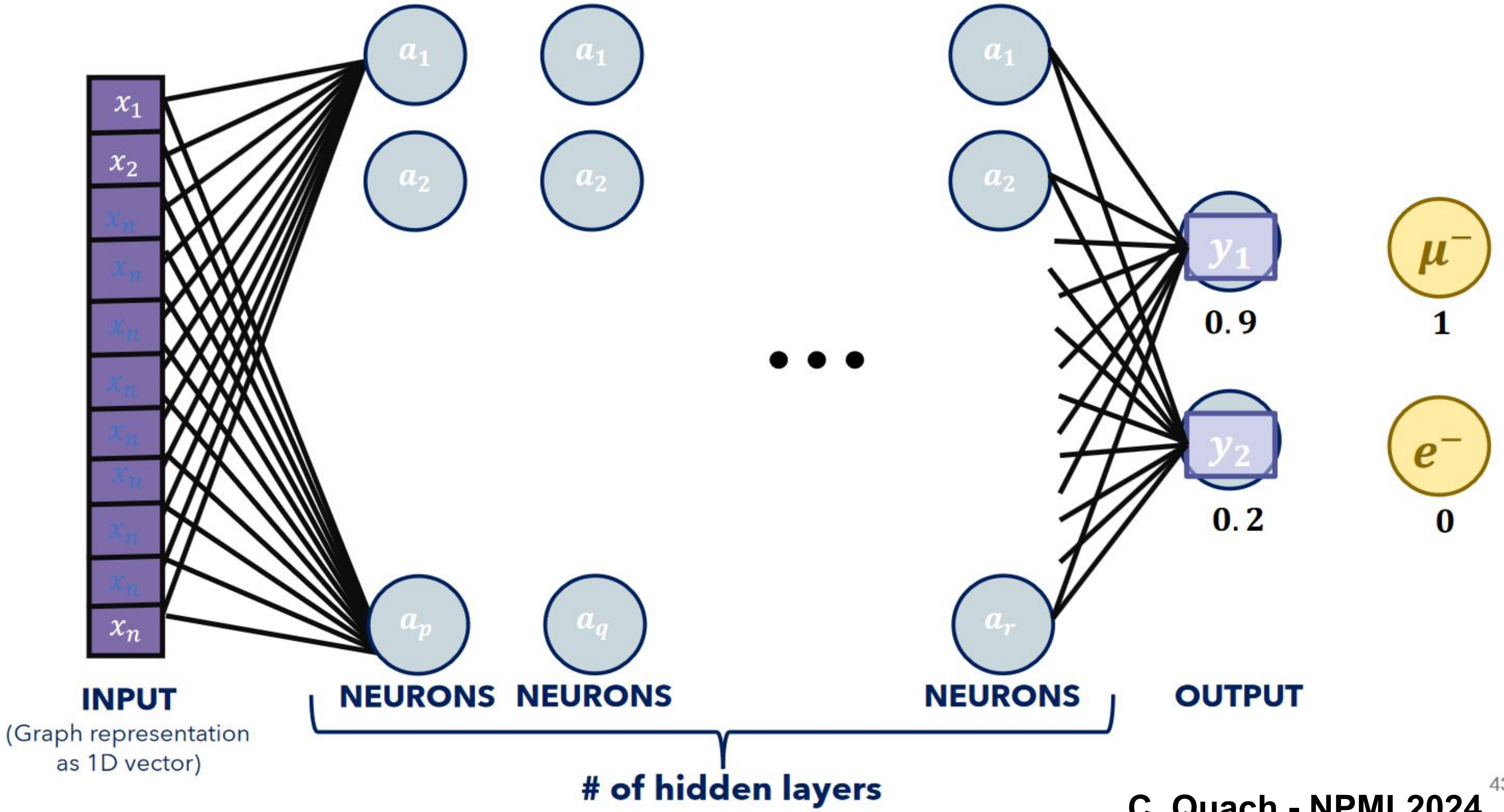
2 GRANT : Machine Learning based algorithm for reconstruction



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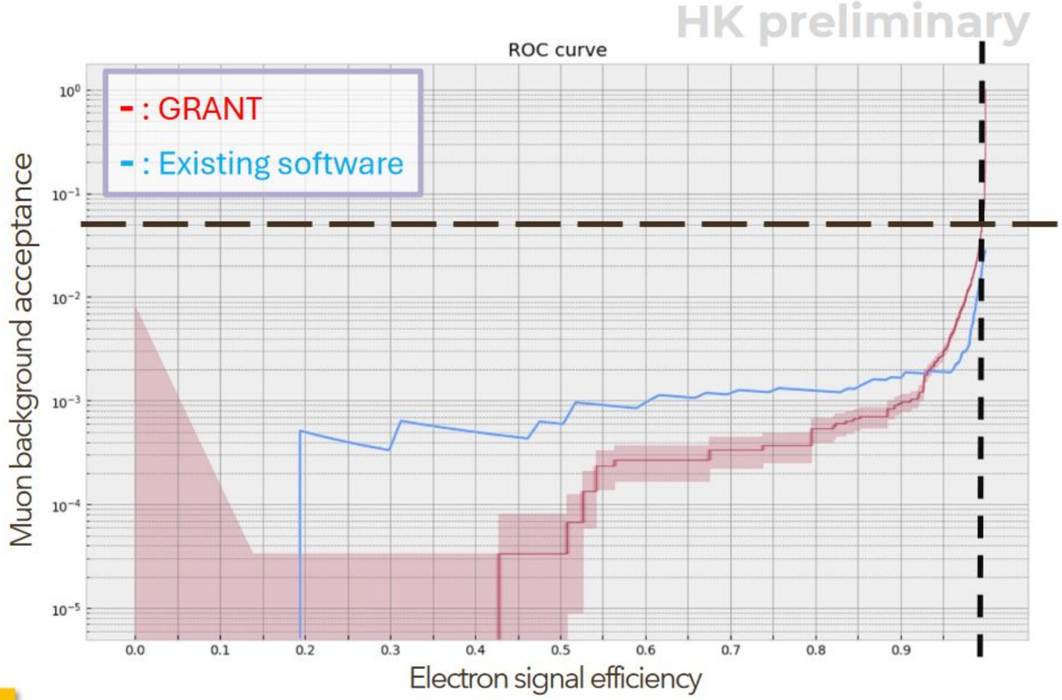
3 Performance comparation: GRANT vs existing software

a) e/mu   b) e/pi0   c) e/gamma   d) Energy   e) Vertex

Roc curve



GRANT :
99% efficiency at
5% bg acceptance

Existing software :
99% efficiency at
5% bg acceptance

0.1 s per event (GRANT)
1min30 (Existing software)

52

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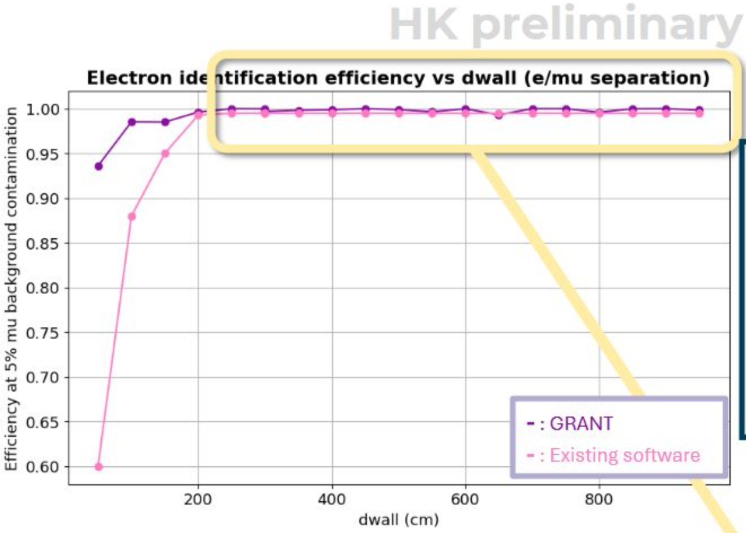
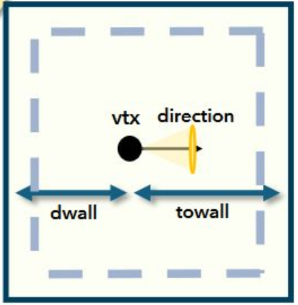
3 Performance comparation: GRANT vs existing software

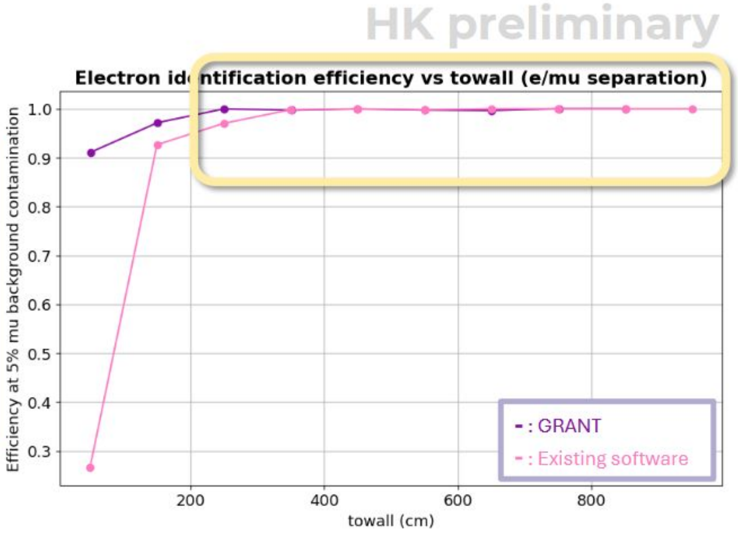
a) e/mu b) e/pi0 c) e/gamma d) Energy e) Vertex

dwall





towall



After 2 m, efficiency above 99.4% !

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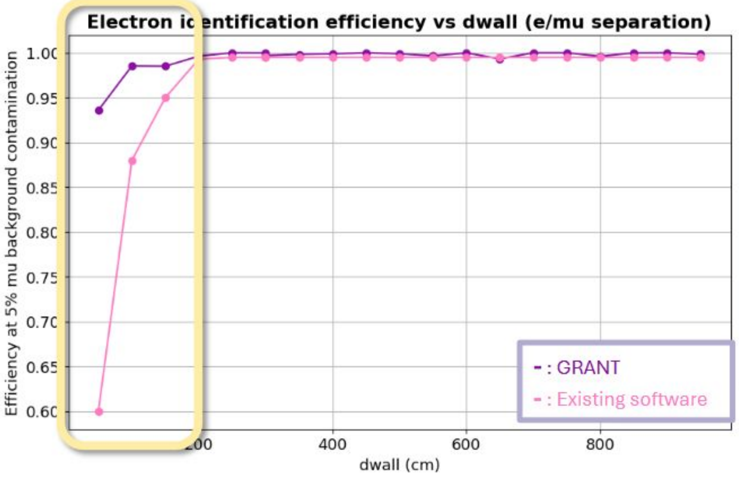
3 Performance comparation: GRANT vs existing software

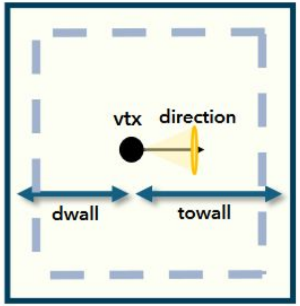
a) e/mu b) e/pi0 c) e/gamma d) Energy e) Vertex

dwall

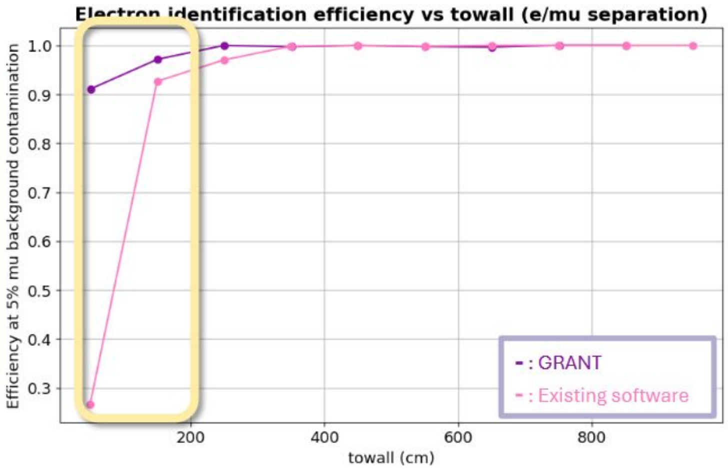
towall

HK preliminary





HK preliminary



For events close to the wall : GNN > existing software => potentially increase FV

55

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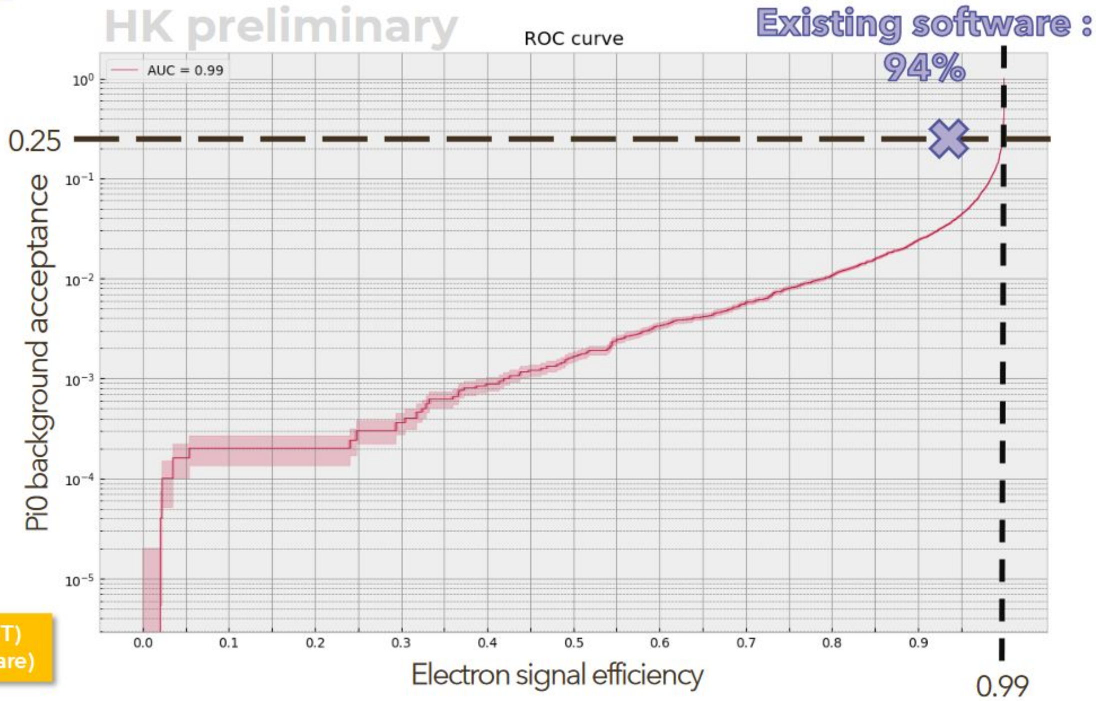
3 Performance comparation: GRANT vs existing software

a) e/mu | b) e/pi0 | c) Energy | d) Vertex | e) Direction

Roc curve



GNN : 99% efficiency at 25% bg acceptance

Existing software : 94% efficiency at 25% bg acceptance

0.1 s per event (GRANT)
1min30 (Existing software)

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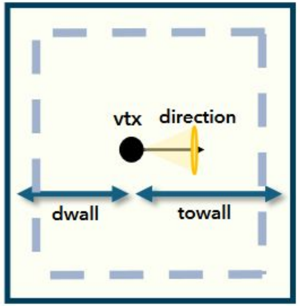
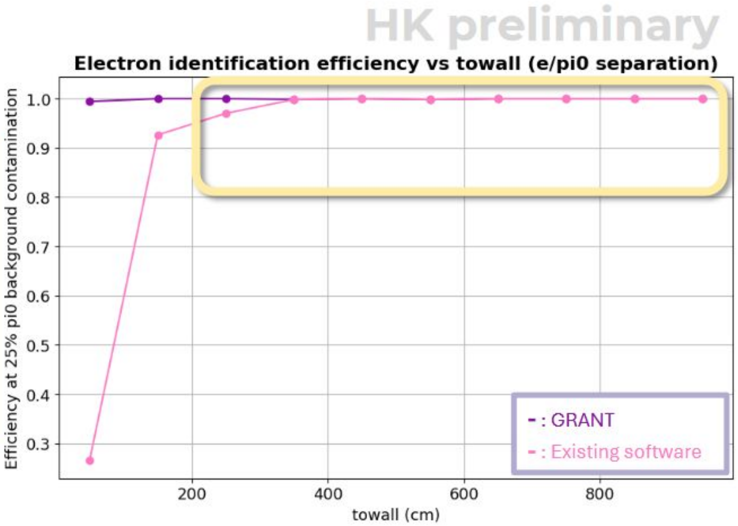
3 Performance comparation: GRANT vs existing software

a) e/mu   **b) e/pi0**   c) Energy   d) Vertex   e) Direction

dwall



towall



After 2 m, efficiency above 99% !

60

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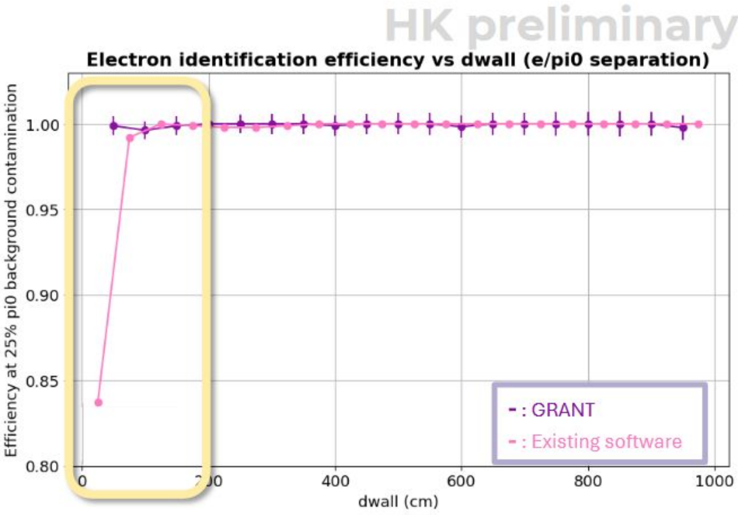
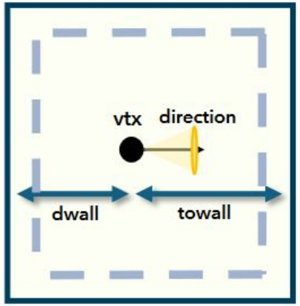
3 Performance comparation: GRANT vs existing software

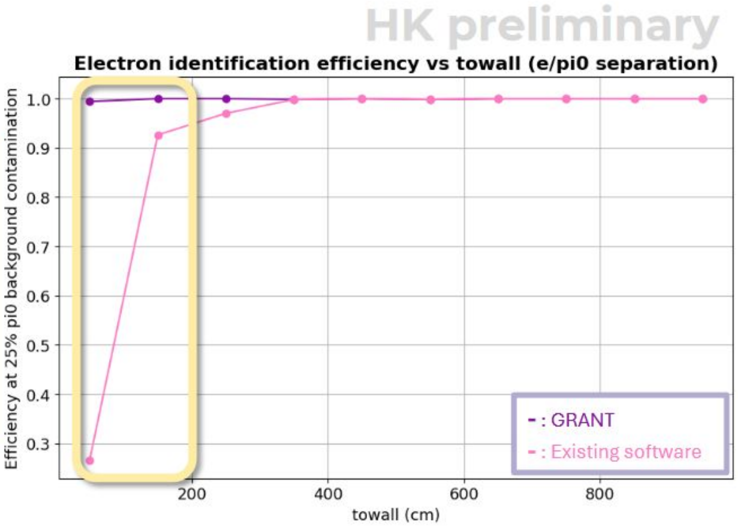
a) e/mu | b) e/pi0 | c) Energy | d) Vertex | e) Direction

dwall





towall



For events close to the wall : GNN > Existing software => potentially increase FV

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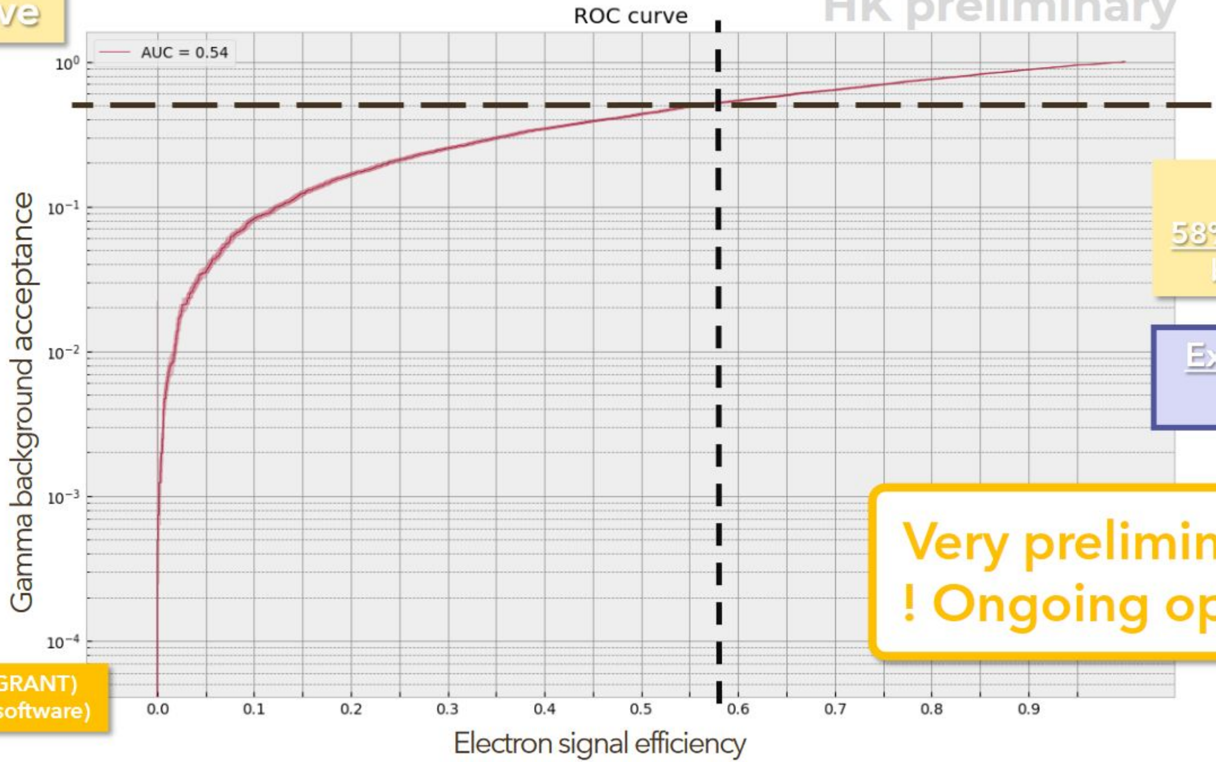
3 Performance comparation: GRANT vs existing software

a) e/mu b) e/pi0 **c) e/gamma** d) Energy e) Vertex

Roc curve



GRANT :
58% efficiency at 50% bg acceptance...

Existing software :
Not done

Very preliminary results ! Ongoing optimization

0.1 s per event (GRANT)
1min30 (Existing software)

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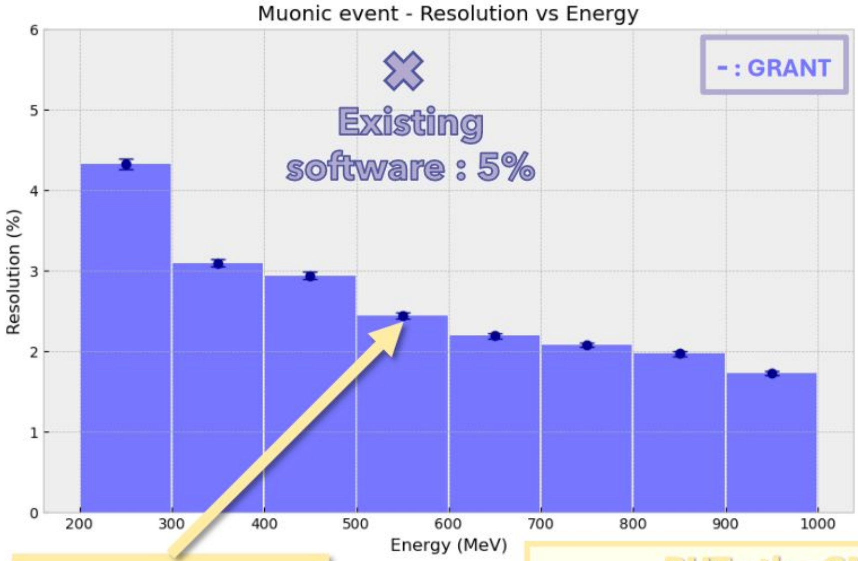
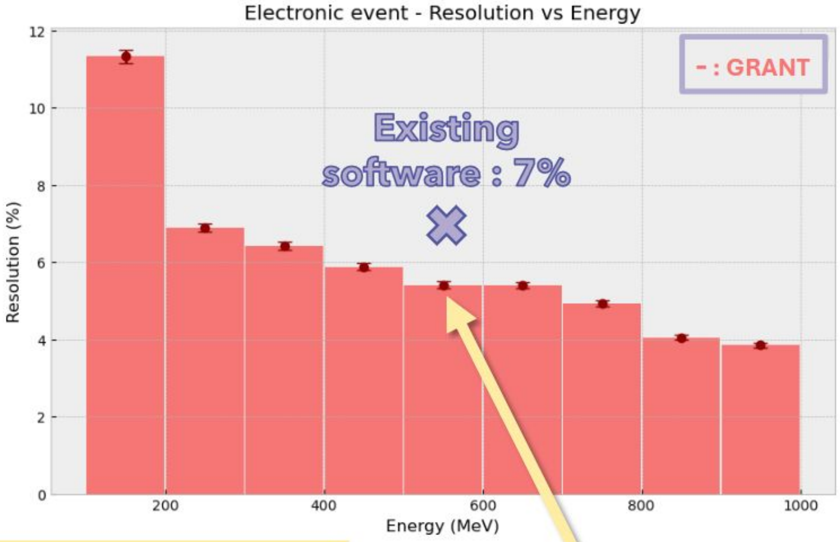
3 Performance comparation: GRANT vs existing software

a) e/mu   b) e/pi0   c) e/gamma   d) Energy   e) Vertex

Muon



Electron



GNN : 2.5% at 500 MeV,

0.06 s per event (GRANT)
1min30 (Existing software)

BUT : the GNN has a biais ☹
(1.5% electron, 0.5% muon at 500 MeV)

Existing software : 0% biais !

GNN : 5.5% at 500 MeV,

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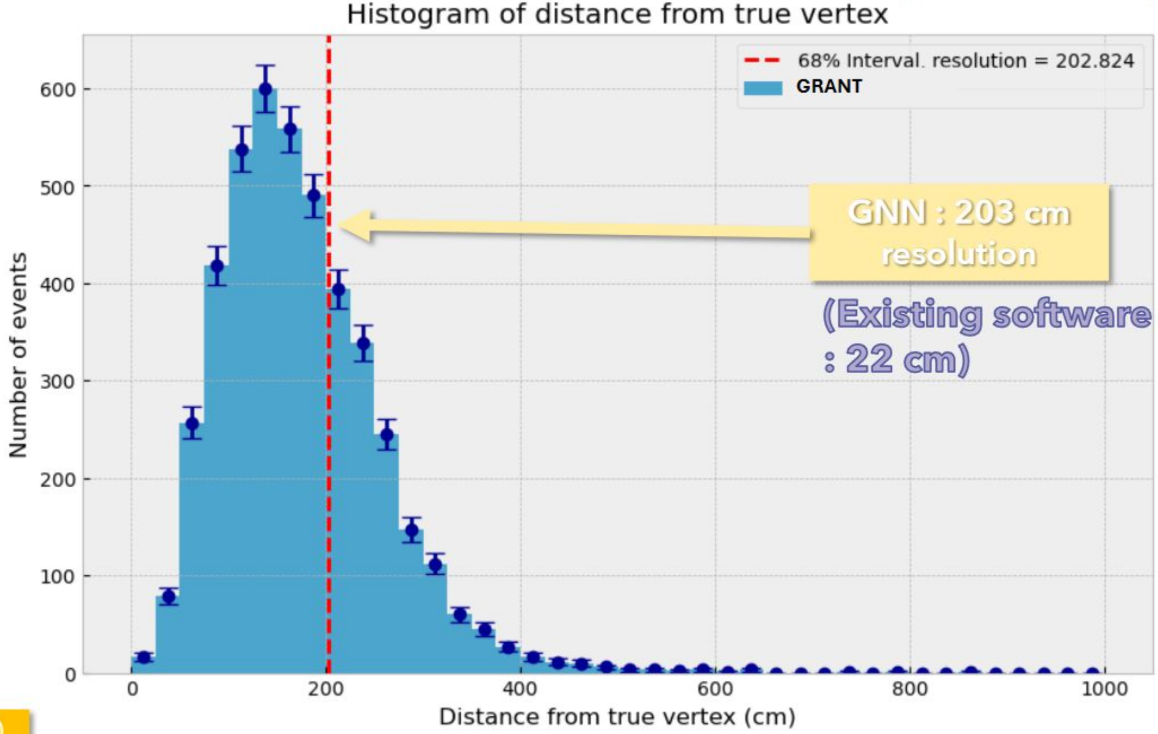
Performance comparation: GRANT vs existing software

3

a) e/mu b) e/pi0 c) e/gamma d) Energy **e) Vertex**

Electron

HK preliminary



GNN : 203 cm resolution

(Existing software : 22 cm)

0.07 s per event (GRANT)
1min30 (Existing software)

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3 Performance comparation: GRANT vs existing software

a) e/mu b) e/pi0 c) e/gamma d) Energy e) Vertex

	GRANT	Existing software
e/mu	**99%** **electron efficiency** at 5% muon bg acceptance,	**99%** **electron efficiency** at 5% muon bg acceptance,
e/pi0	**99%** **electron efficiency** at 25% pi0 bg acceptance	**94%** **electron efficiency** at 25% pi0 bg acceptance
e/gamma	**58%** **efficiency** at 50% bg acceptance… **[Fixed energy]**	None
Energy reconstruction for e & mu (1D)	**Electron : 5.5% resolution** at 500 MeV, **energy bias at ~1.5%** **Muon : 2.5% resolution** at 500 MeV, **energy bias at ~0.5%**	**Electron : 7% resolution** at 500 MeV, **energy bias at ~0%** **Muon : 6% resolution** at 500 MeV, **energy bias at ~0%**
Vertex reconstruction for e & mu (3D)	**Electron :** 203 cm **Muon:** None	**Electron :** 22 cm **Muon :** 28 cm

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Traditional reconstruction method

fiTQun: Likelihood-based reconstruction for higher energies

- Originally developed for Super-K detector
  - Based on algorithm of MiniBooNE: https://arxiv.org/abs/0902.2222
- Uses full information of unhit PMTs + time & charge of hit PMTs:

$$\underbrace{L}_{\text{Likelihood to maximise}}(\underbrace{\mathbf{x}}_{\text{Candidate event hypothesis}}) = \prod_{j}^{unhit} \underbrace{P_j\left(unhit|\mathbf{x}\right)}_{\text{Probability of no hit at PMT}} \prod_{i}^{hit} \underbrace{P_i\left(hit|\mathbf{x}\right)}_{\text{Probability of hit at PMT}} \underbrace{f_q\left(q_i|\mathbf{x}\right)}_{\text{Hit charge probability density}} \underbrace{f_t\left(t_i|\mathbf{x}\right)}_{\text{Hit time probability density}}$$

- Probabilities calculated based on direct + scattered + reflected light
- Likelihood ratios used to distinguish particle types and single-ring / multi-ring event topology hypotheses

Topological map to square

$$X_{\pm} = W(\rho, z)\frac{\pi \pm \phi}{2\pi}$$

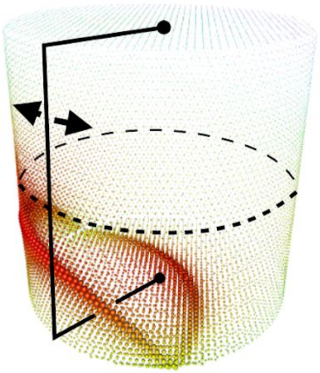
$$W(\rho, z) = \sqrt{\frac{\rho^2 + 2Rz + RH}{R^2 + RH}}$$

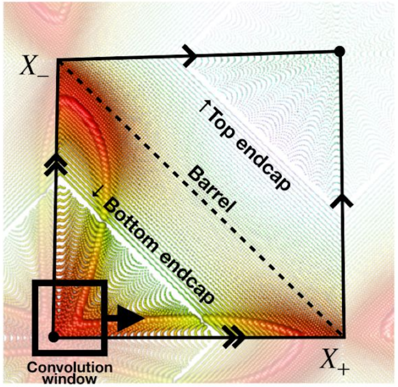
Solve differential eq. for constant Jacobian

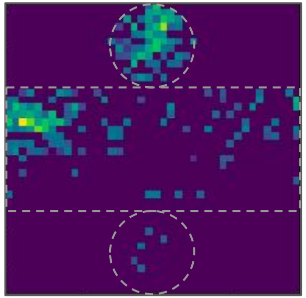
$$\mathrm{d}X_+\mathrm{d}X_- = \left|\frac{\partial(X_+, X_-)}{\partial(\rho, \phi)}\right| \mathrm{d}\rho\,\mathrm{d}\phi$$

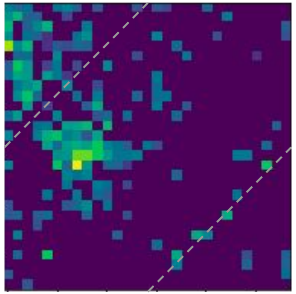
Alternative map onto square with boundary conditions preserving topology of cylinder

- Cut open along barrel to centre of end caps (solid line)
- Deform onto square, keeping density of PMTs constant
- Place mPMTs onto nearest pixel
- Use boundary conditions identifying edges of square (indicated by arrows)
  - Pad image with copy of pixels from the corresponding edge



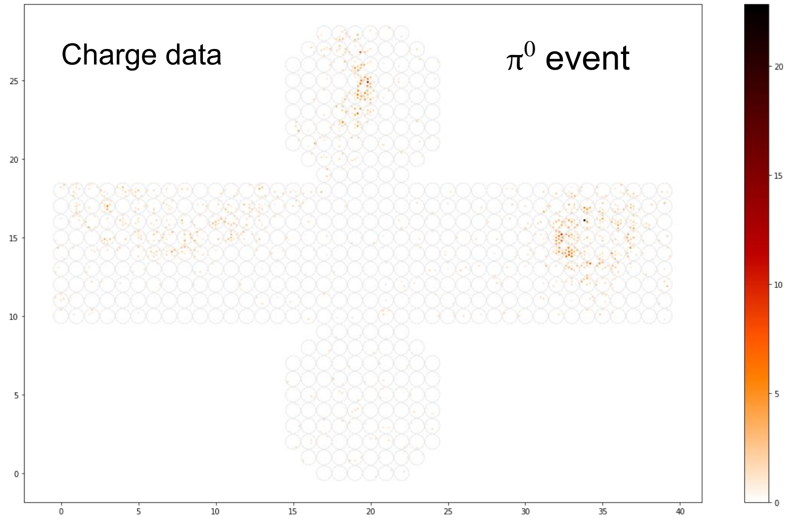


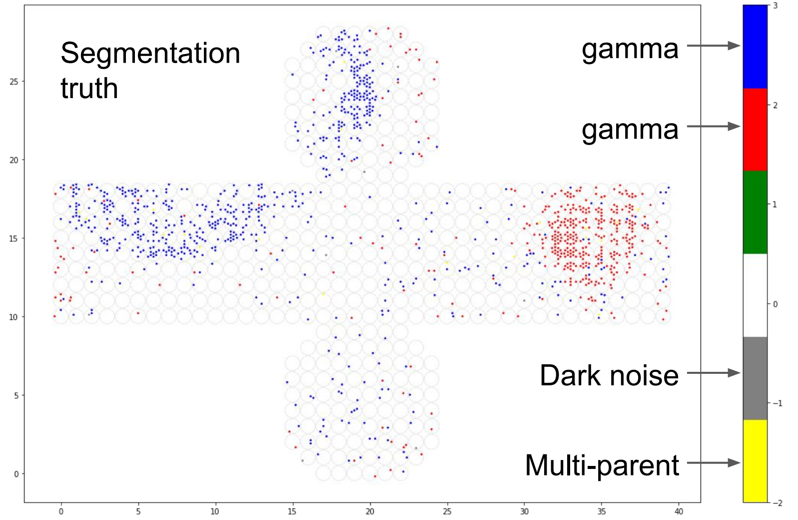




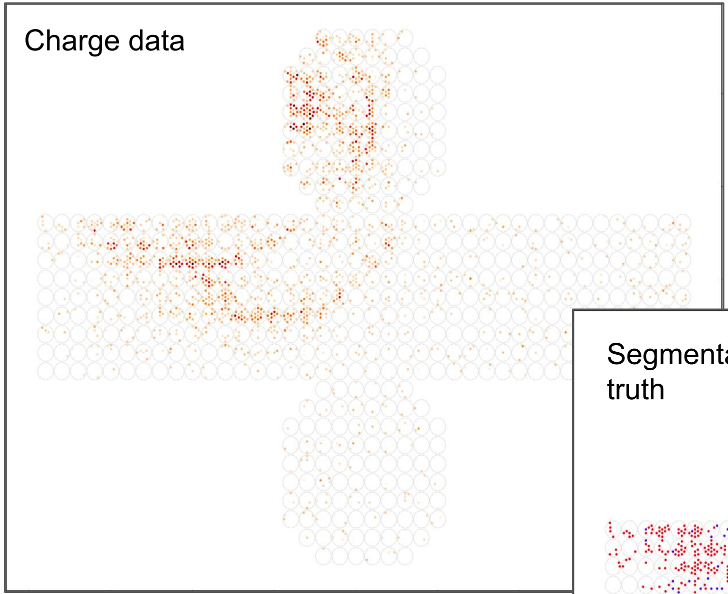
Segmentation networks

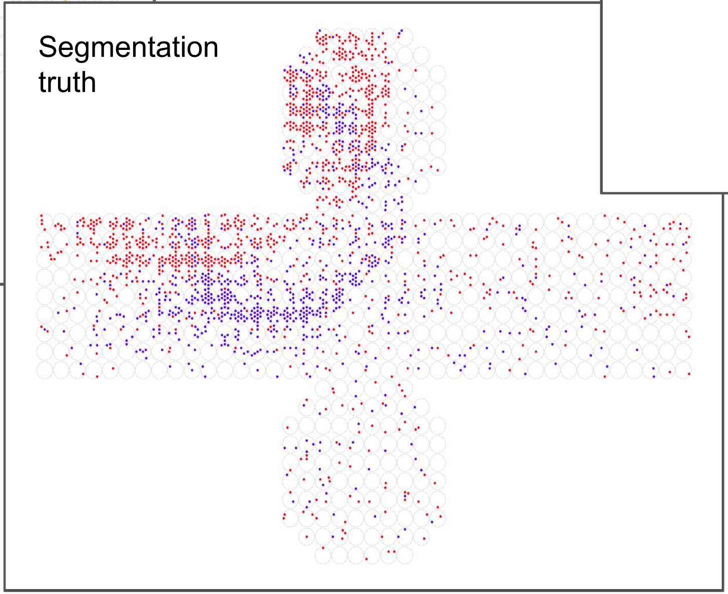
- Classification networks can be extended to perform segmentation
  - Deconvolutions and upsampling reverse convolutions and downsampling
  - Provides output value for each pixel
  - Currently using U-Net and FRRN
- Starting development with π^0 events
  - π^0 decay to produce two γ rings
  - Higher energy π^0 have overlapping rings

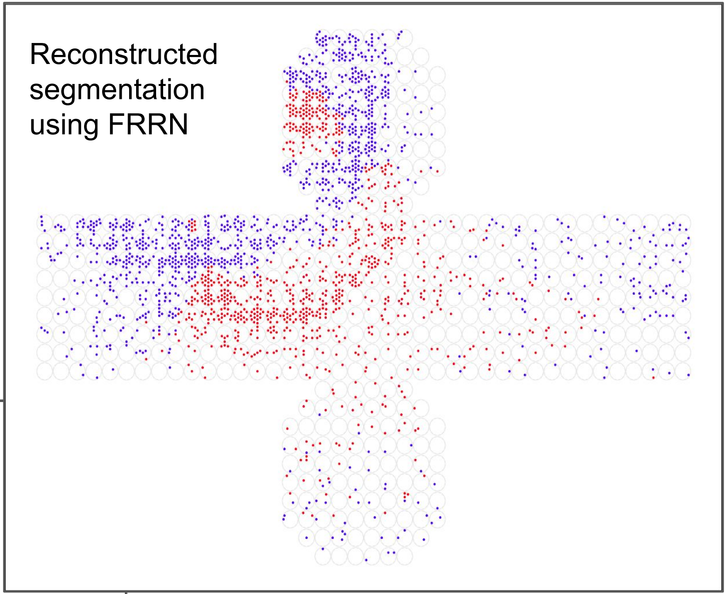




Segmentation results

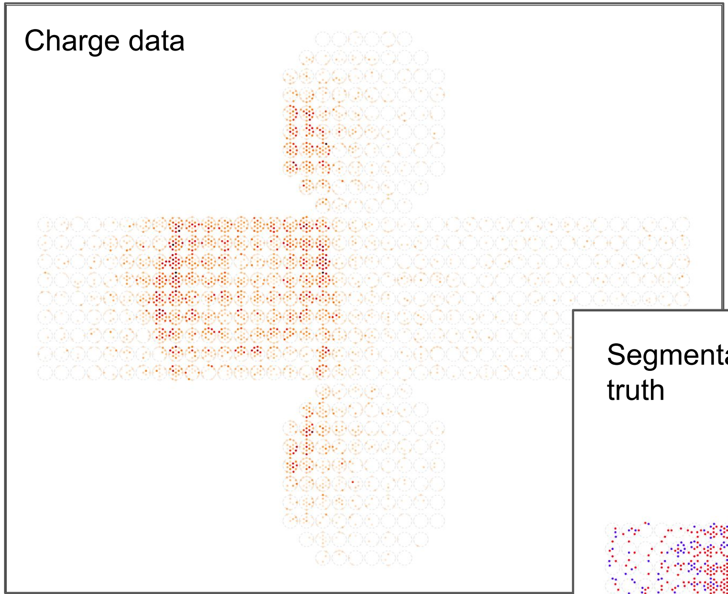


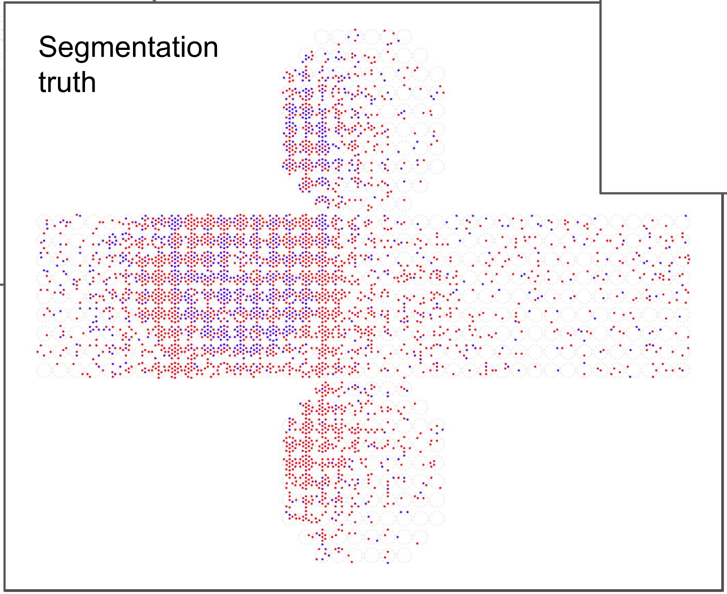


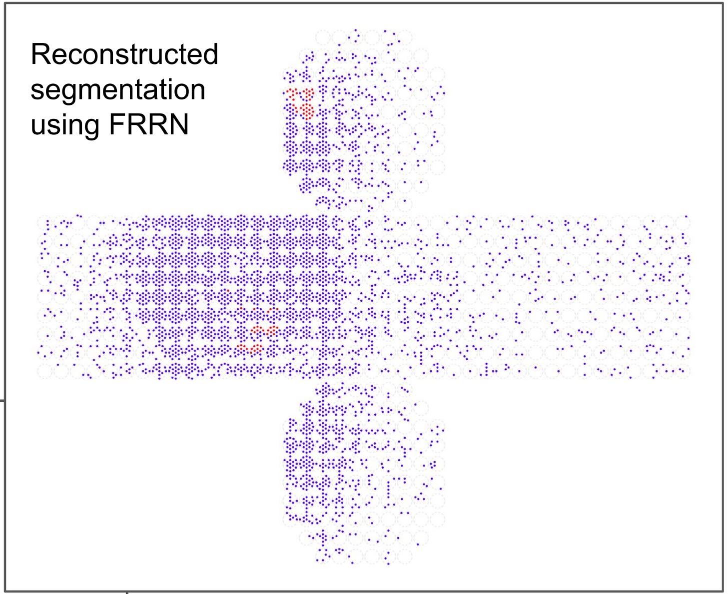


Works well with separated or partially overlapping rings

Segmentation results







Poor reconstruction with some more overlapping rings