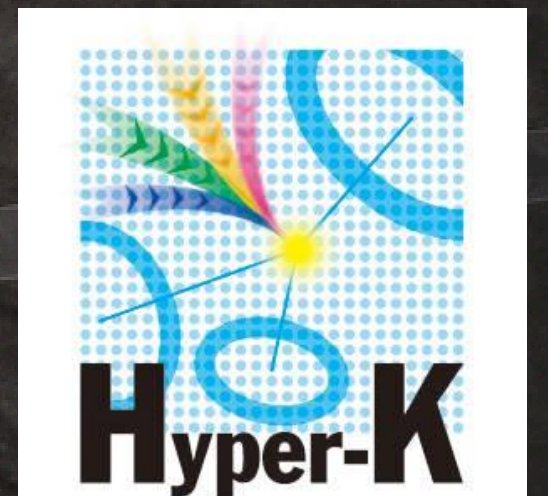


IMPROVING EVENT RECONSTRUCTION IN HYPER KAMIOKANDE WITH MACHINE LEARNING

OCTOBER 27TH 2025 - ANDREW ATTA

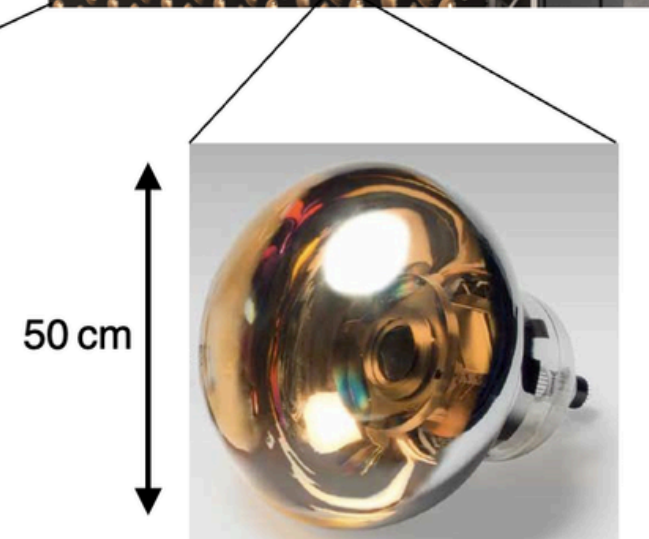
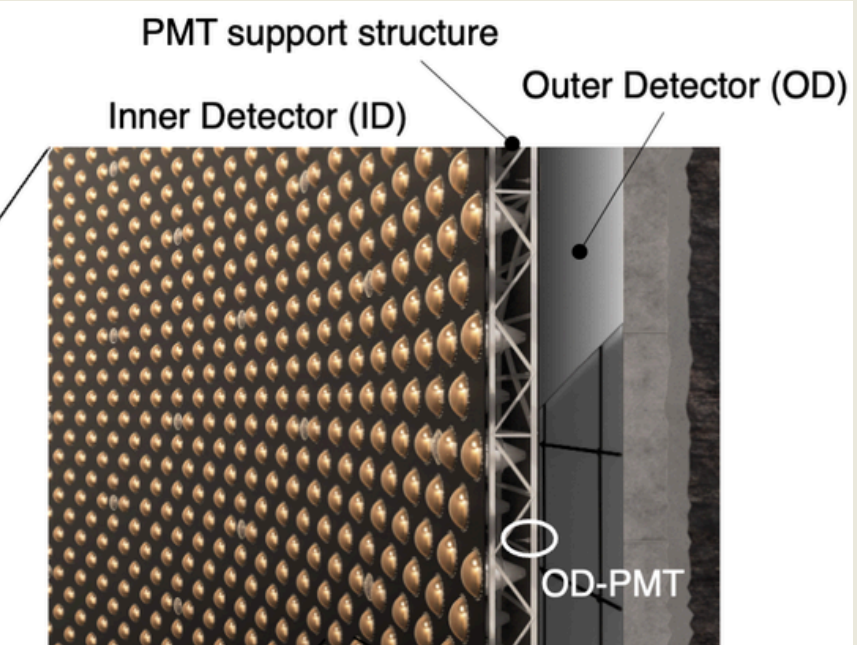
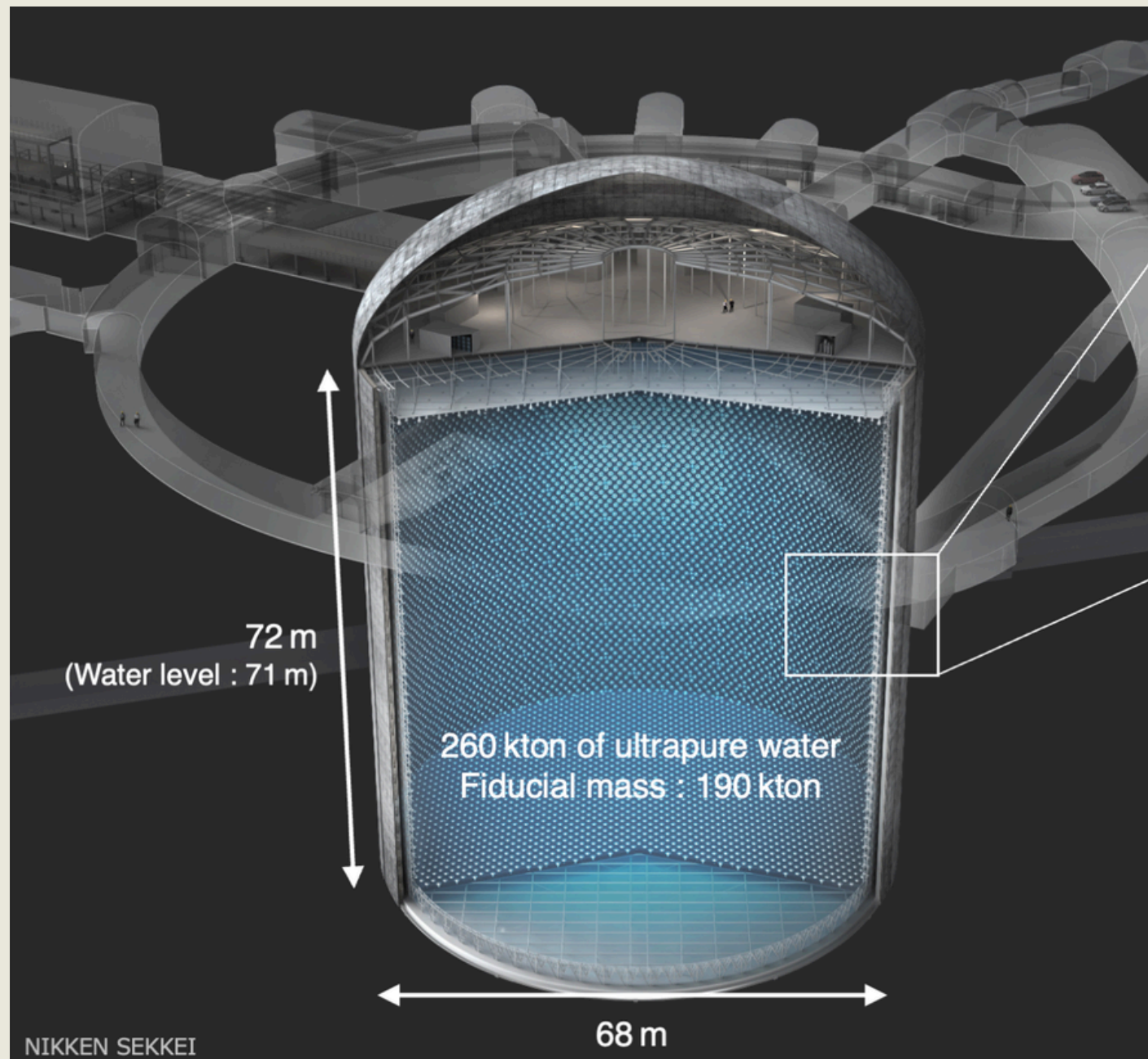


WatChMaL

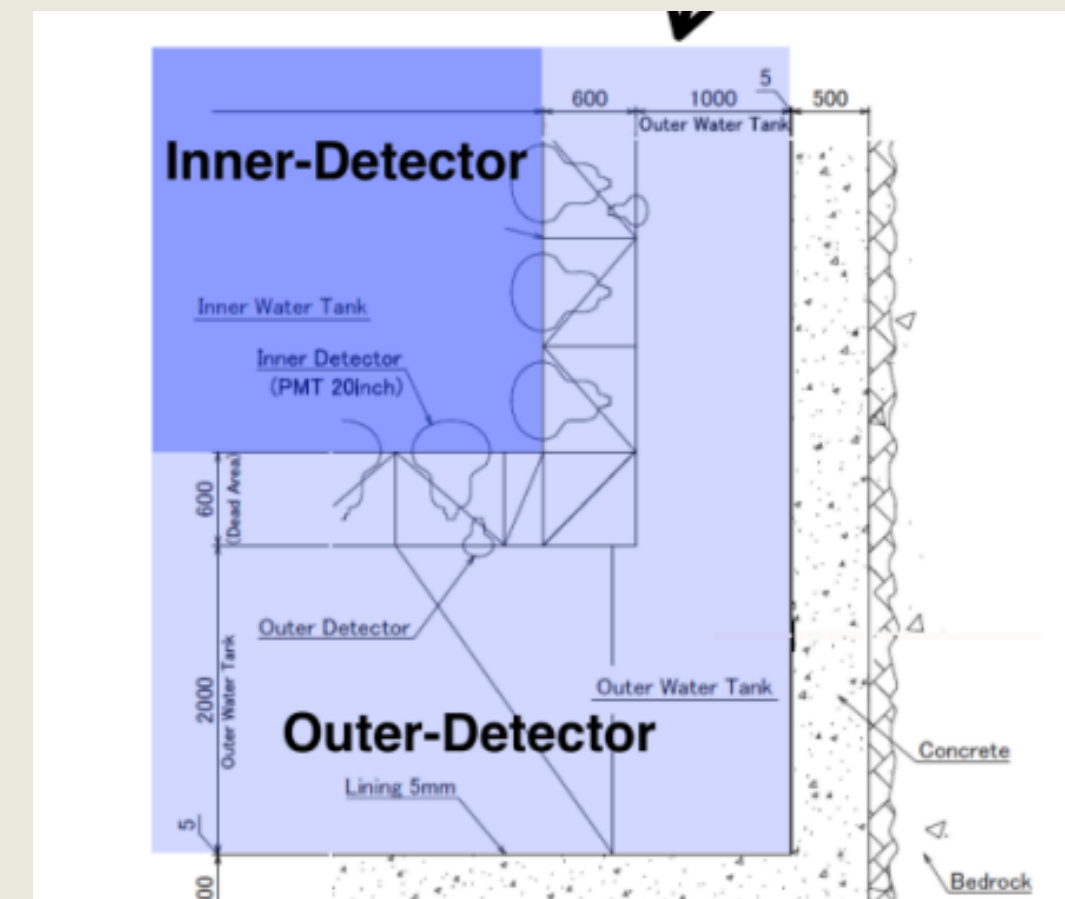
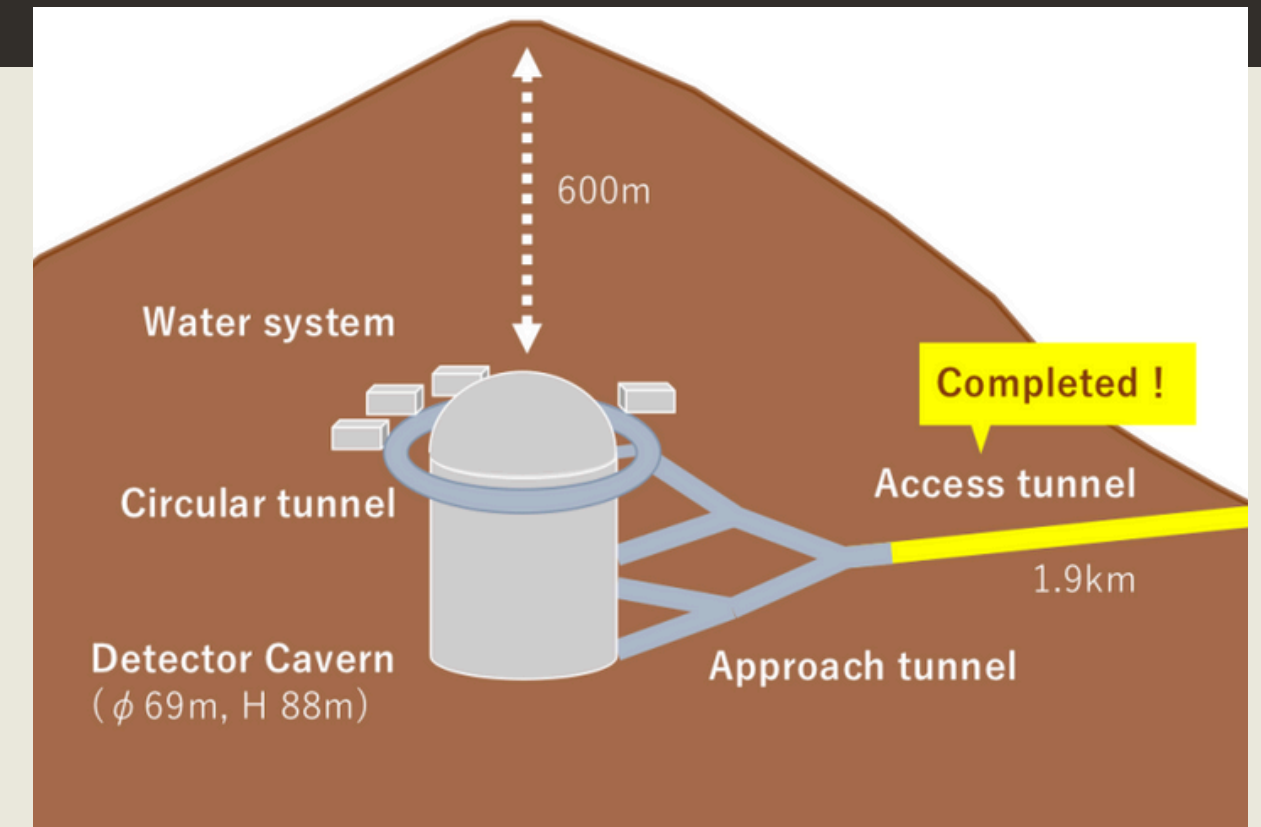


MONASH University

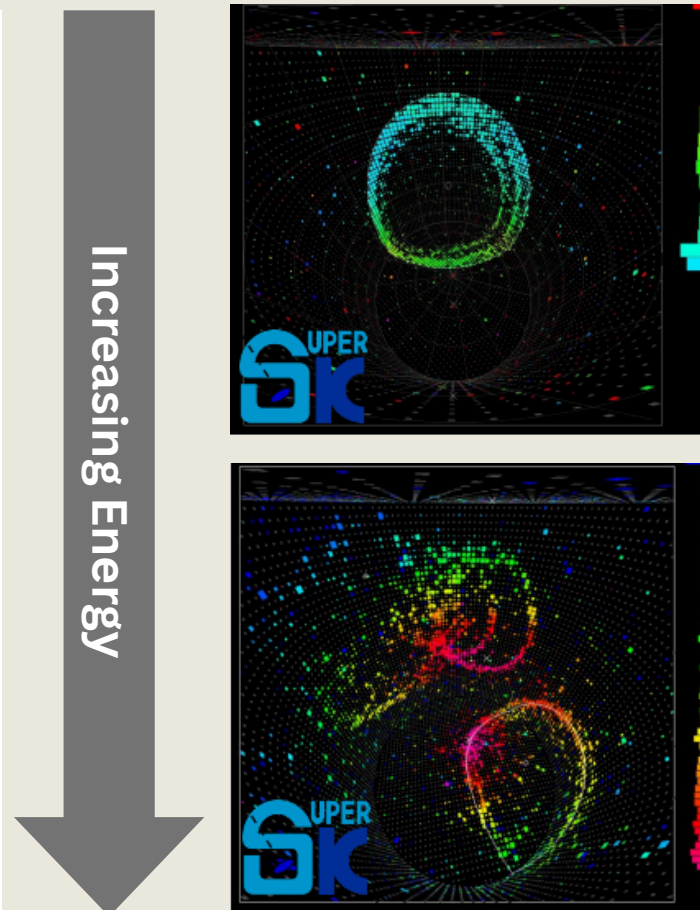
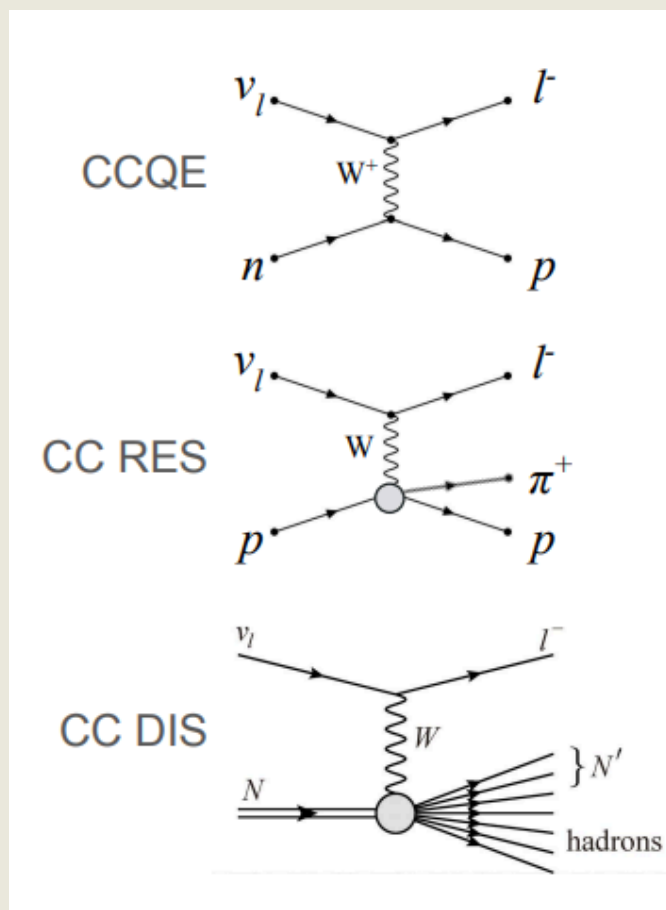
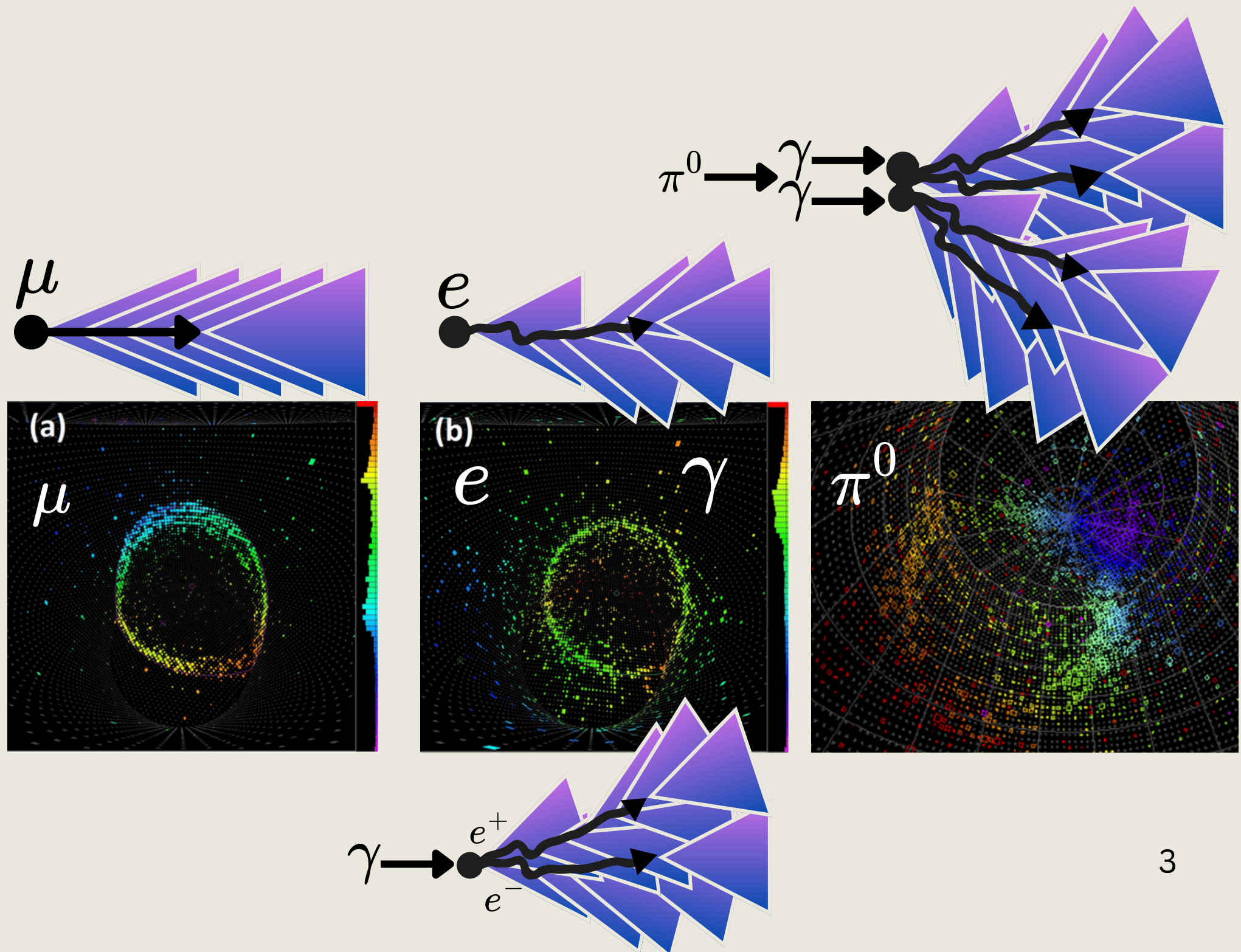
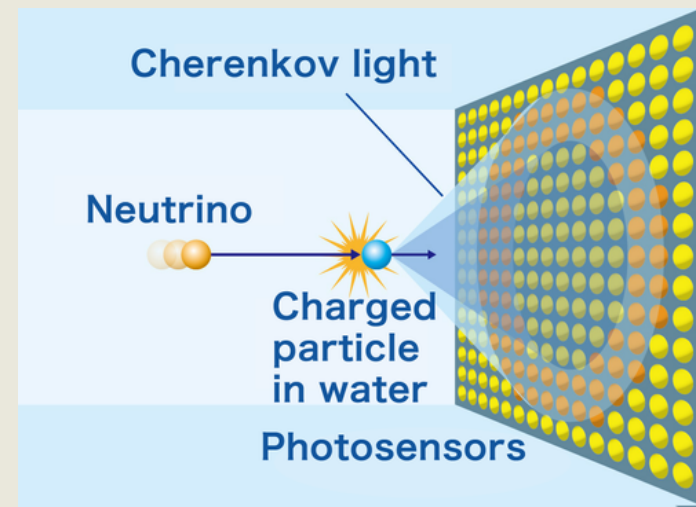
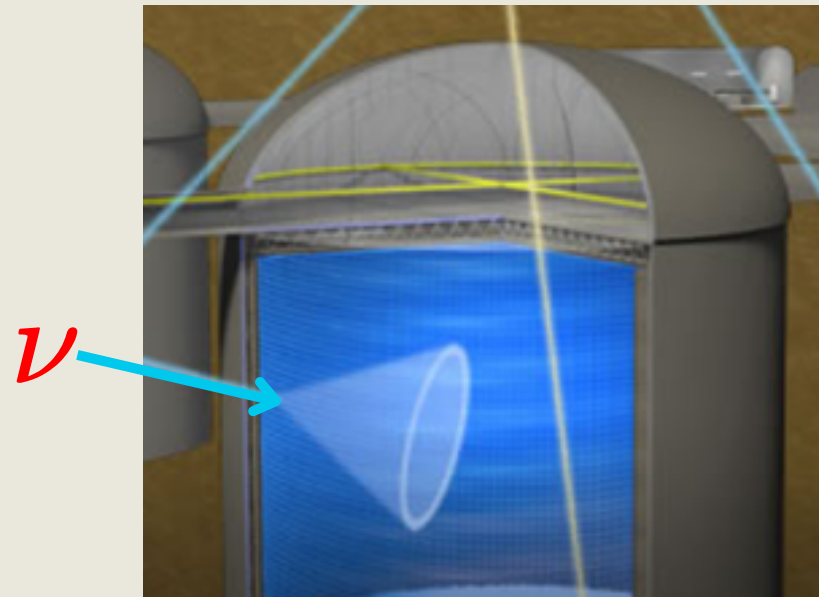
HYPER KAMIOKANDE



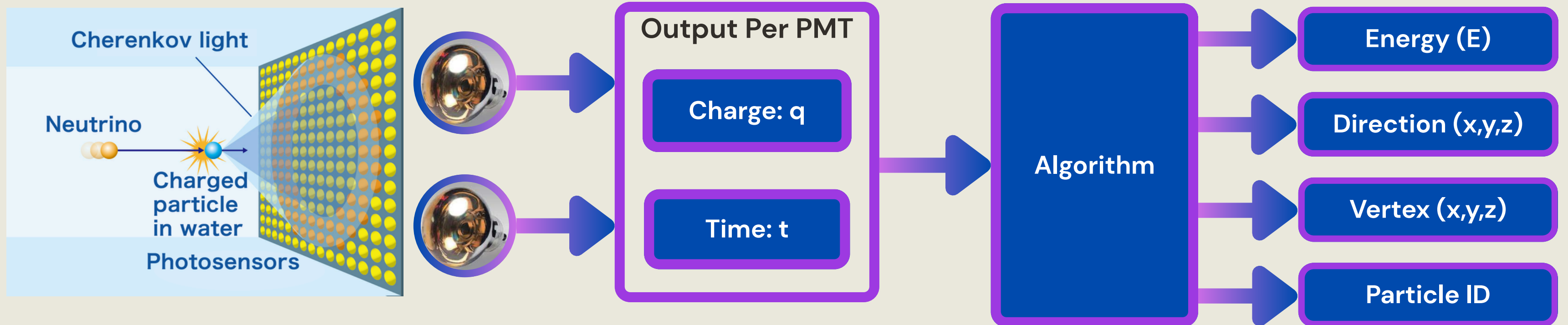
©Hamamatsu Photonics K.K.
New ultrasensitive ID-PMT



EVENT TYPOLOGY



EVENT RECONSTRUCTION



TRADITIONAL EVENT RECONSTRUCTION

- In Super-Kamiokande event reconstruction is handled through an algorithm known as **fiTQun**
 - Maximum likelihood estimator:

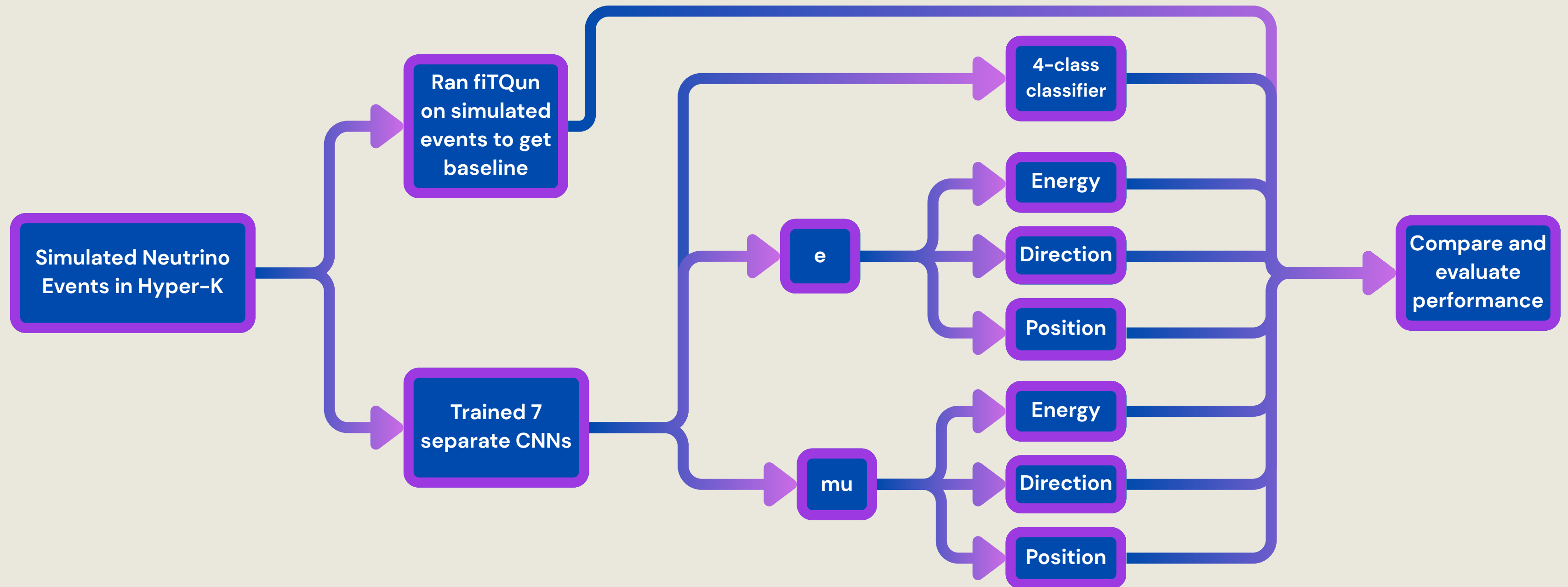
The diagram illustrates the fiTQun maximum likelihood estimator formula. The formula is
$$L(\mathbf{x}) = \prod_j^{unhit} P_j(unhit|\mathbf{x}) \prod_i^{hit} P_i(hit|\mathbf{x}) f_q(q_i|\mathbf{x}) f_t(t_i|\mathbf{x})$$
. Above the formula, four boxes point down to the terms: 'fit parameters (7D)' points to $\mathbf{x}$, 'Unhit Probability' points to $P_j(unhit|\mathbf{x})$, 'Hit Probability' points to $P_i(hit|\mathbf{x})$, and 'charge of ith PMT' and 'time of ith PMT' point to $f_q(q_i|\mathbf{x})$ and $f_t(t_i|\mathbf{x})$ respectively. Below the formula, three boxes point up to the terms: 'Unhit Probability' points to $P_j(unhit|\mathbf{x})$, 'PMT hit charge pdf' points to $f_q(q_i|\mathbf{x})$, and 'PMT hit time pdf' points to $f_t(t_i|\mathbf{x})$.

$$\mathbf{x} = (x, y, z, t, p, \theta, \phi)$$

- Does so for multiple different particle hypotheses, then takes a ratio between each to pick the most likely event hypothesis
- Robust and has shown great success in Super-K
- Starting to see the upper limit of performance

NEURAL NETWORKS TO THE RESCUE

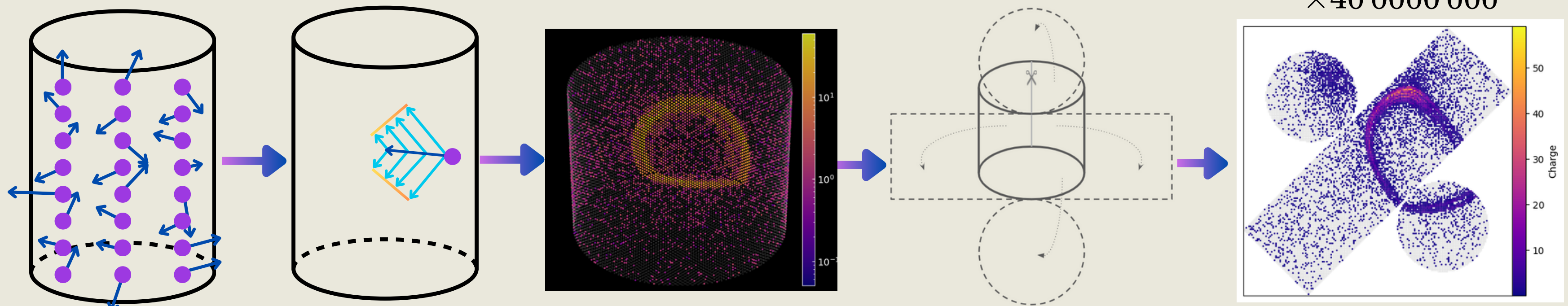
- In recent years there has been a push to adopt machine learning based inference techniques
- 1M events can be processed by fiTQun in 100,000 CPU hours
- Same 1M events can be processed by ML in less than 100 CPU hours or **10 GPU minutes**
- Proven on other water Cherenkov detectors



SIMULATING THE DATA

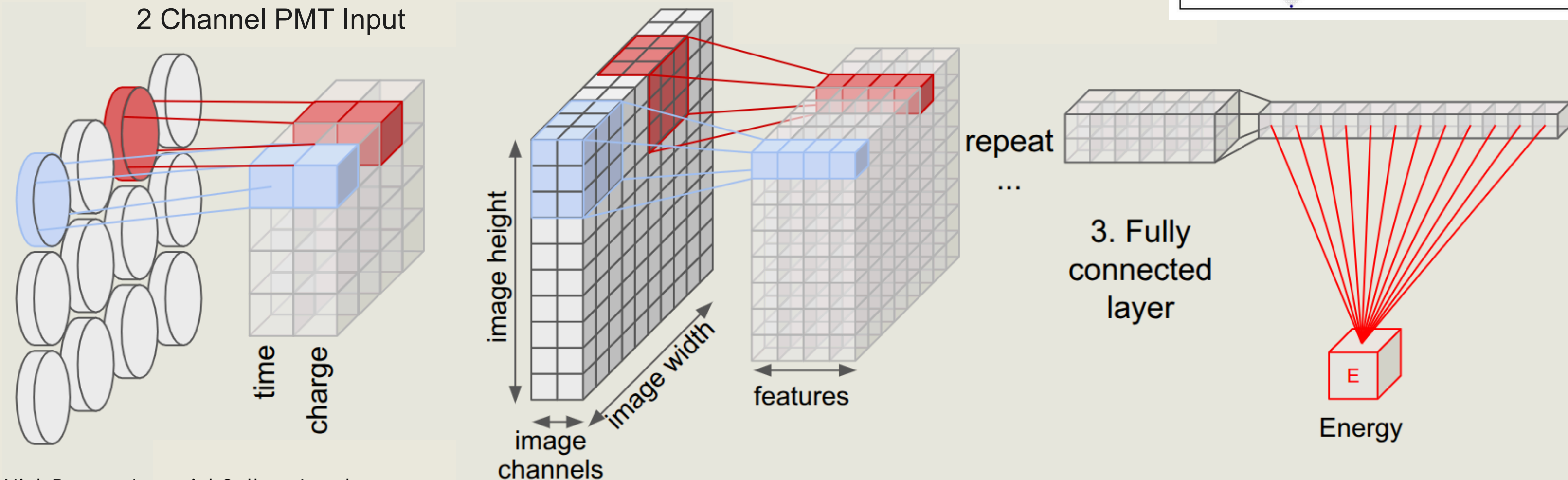
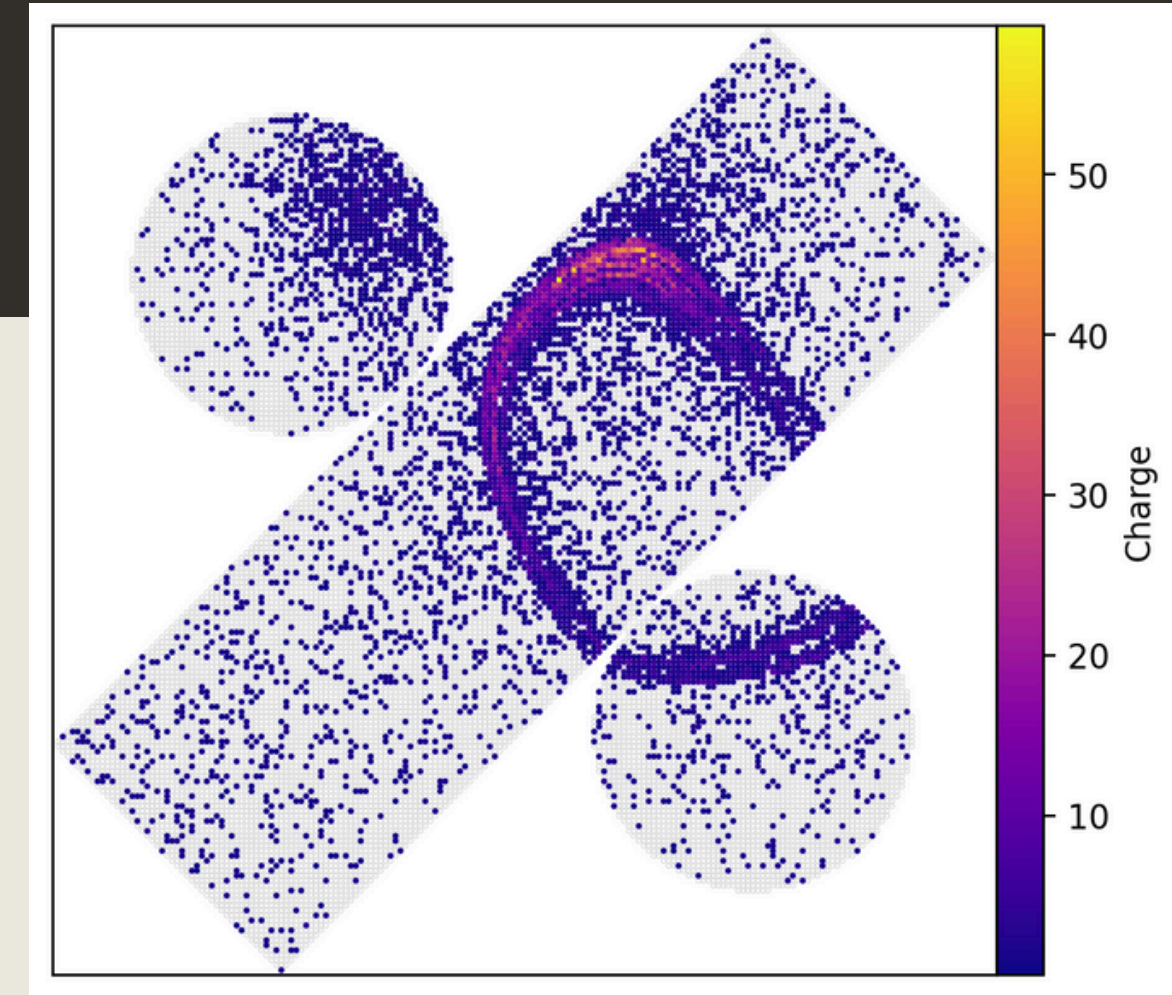
- Simulated the tank and Cherenkov producing process in WCSim - a Geant4 based tool designed for SK and HK
- total of 40 million events - 10 million electrons, muons, gamma rays, and neutral pions
- Uniform energy distribution of 0-2GeV kinetic energy **above** Cherenkov threshold for that particular particle
- Uniform initial position in tank
- Isotropic direction distribution
- Only **fully contained** events kept
- Muon decay disabled in muon events

Cuts	FC and nhits>200
Energy	0-2GeV
PID	μ, e, γ, π^0
Muon Decay?	no decay
Training Split	96:2:2
Training Set	~8,569,149
Validation Set	~178,449
Testing Set	~178,595

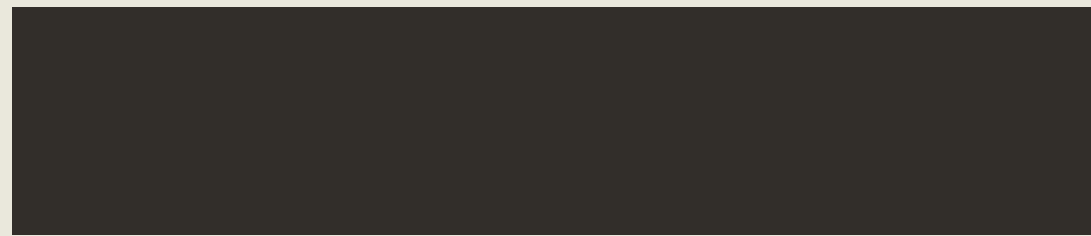


THE MODELS IN QUESTION

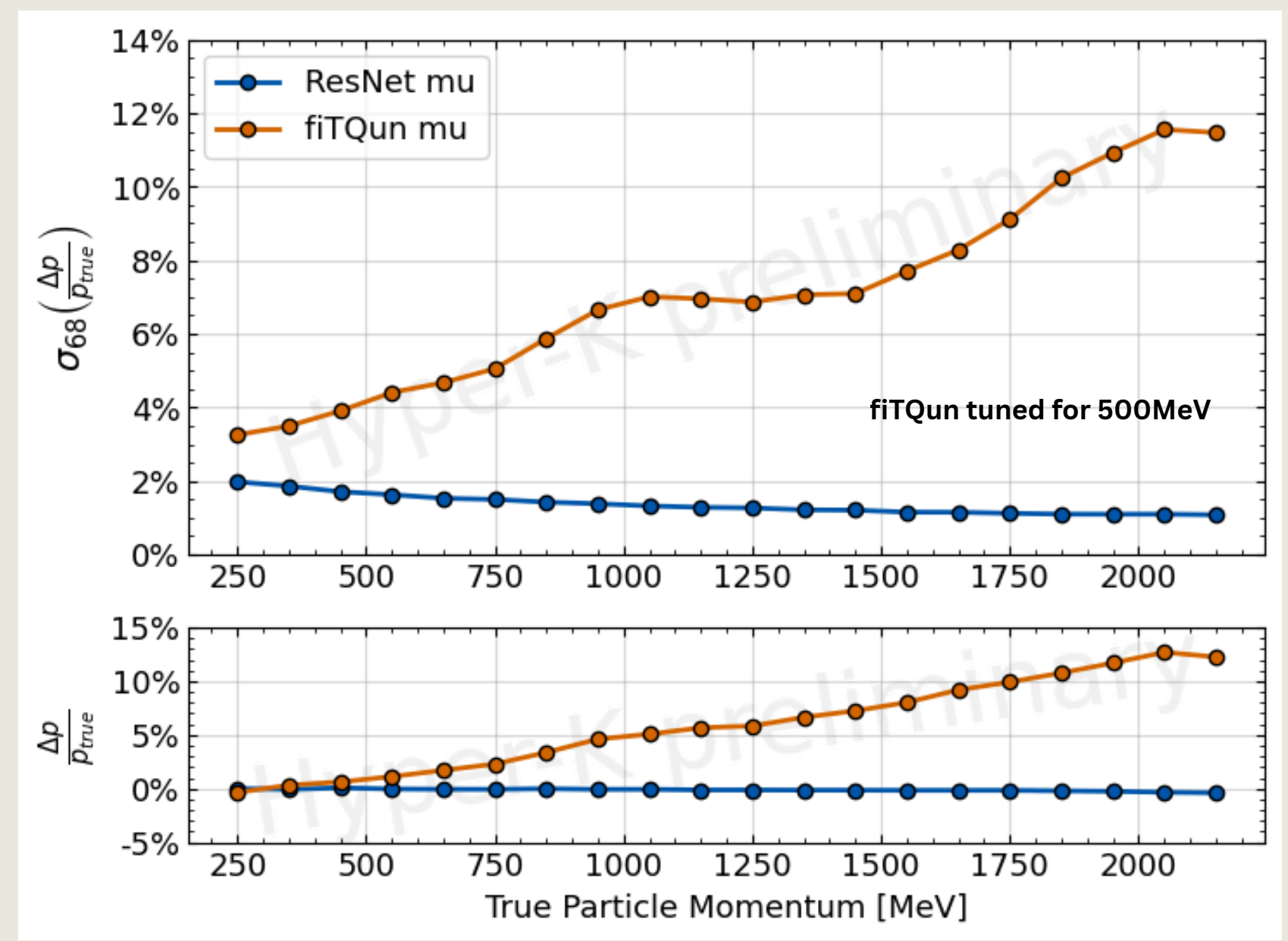
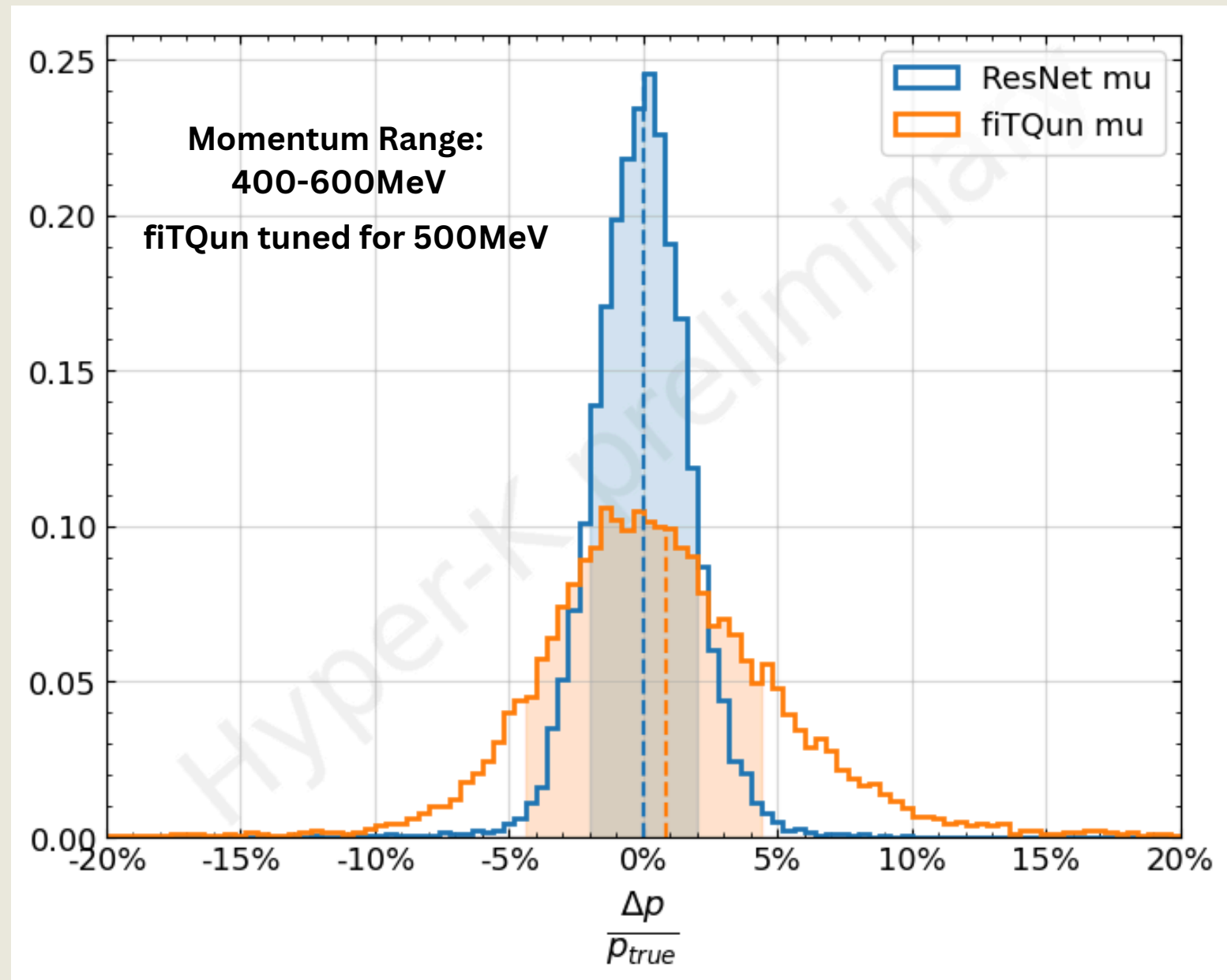
- Each used model used **ResNet-152** as a base and used the WatChMaL (**Water Cherenkov Machine Learning**) framework
- Depending on parameter being reconstructed, the input/outputs look different and the loss function is different but the core is still the same
- **7 models in total**
 - 4-class classifier
 - muon regressors - direction, position, energy
 - electron regressors - direction, position, energy



MUON REGRESSION



MOMENTUM RECONSTRUCTION



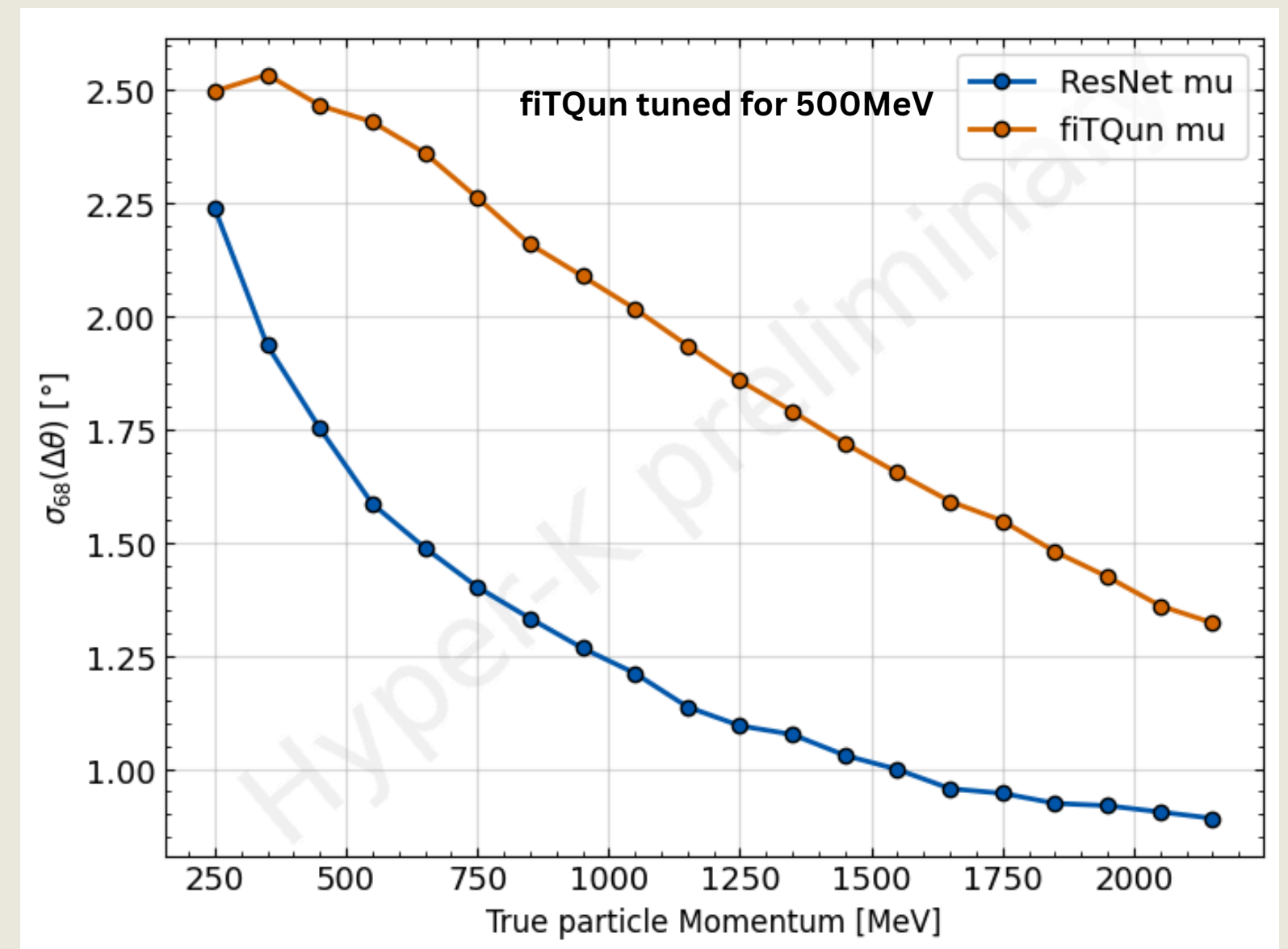
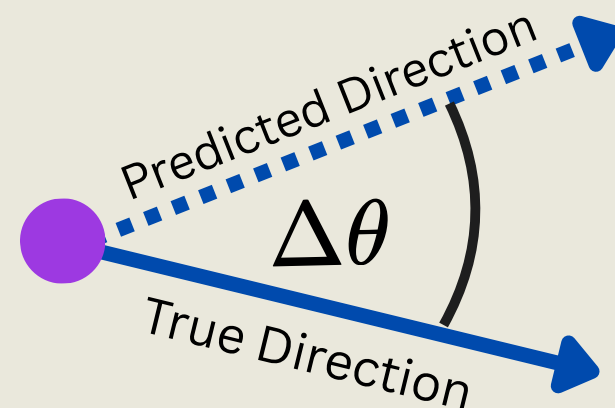
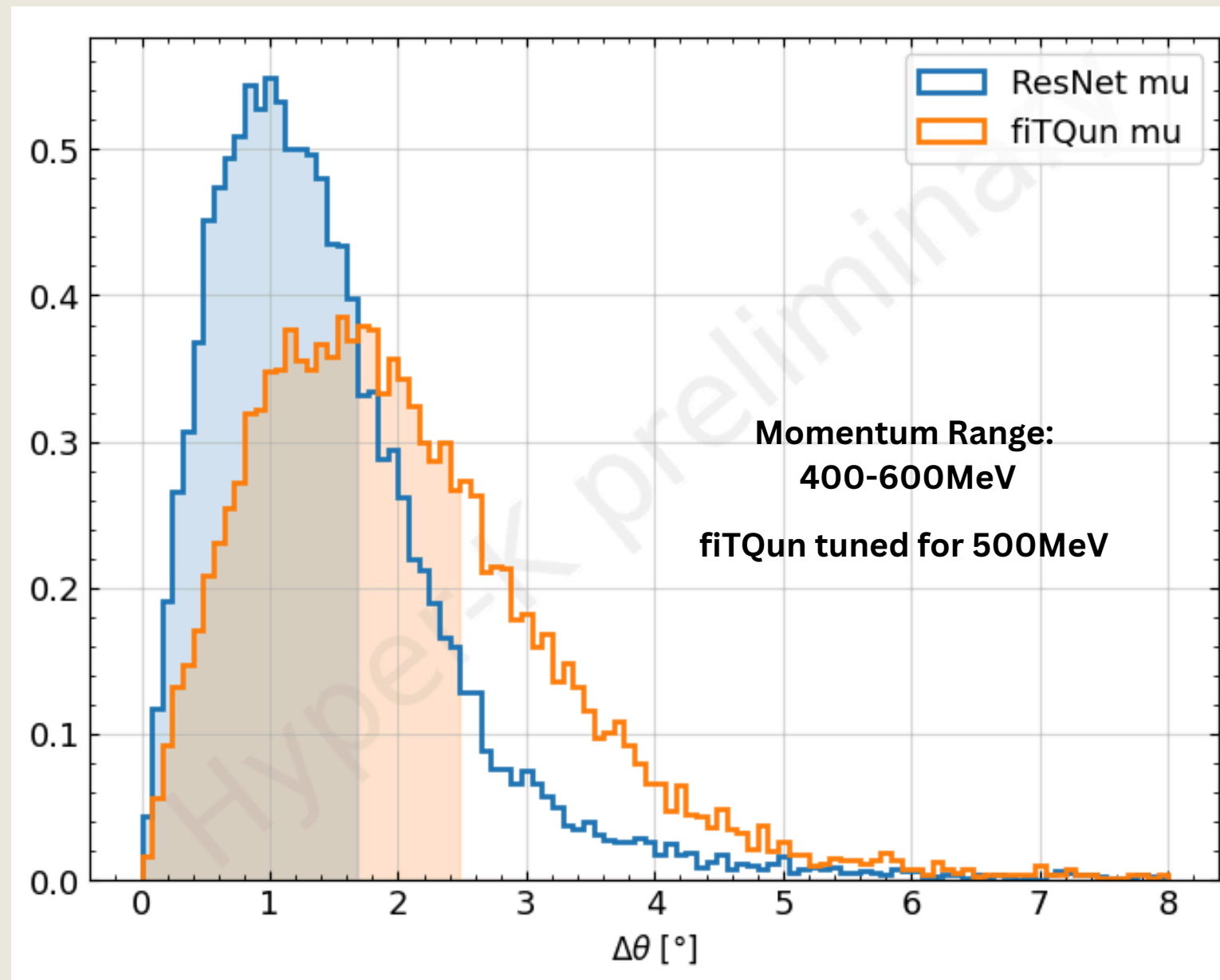
$$\frac{\Delta p}{p_{true}} = \frac{\text{True } p - \text{Predicted } p}{\text{True } p} \times 100$$

$$\sigma_{68} \left(\frac{\Delta p}{p_{true}} \right) = \begin{matrix} \text{absolute fractional momentum residual} \\ \text{below which 68\% of events fall under.} \\ \text{Analogous to 1 standard deviation} \end{matrix}$$

The version of fiTQun I compare results to does not include scattered light despite MC including it

400-600MeV	ResNet	fiTQun
Average $\sigma_{68} \left(\frac{\Delta p}{p_{true}} \right)$	1.67%	4.15%
Average $\frac{\Delta p}{p_{true}}$	0.02%	0.87%

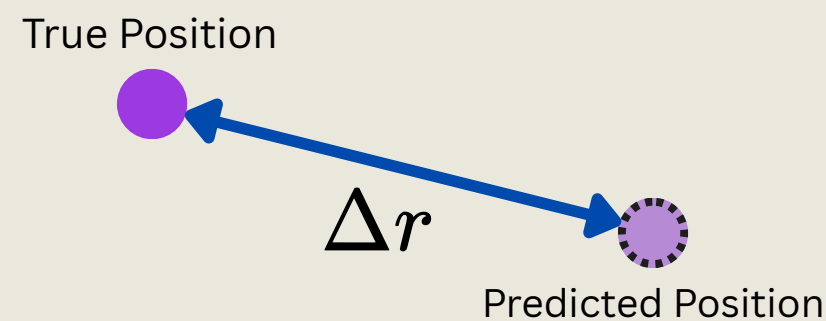
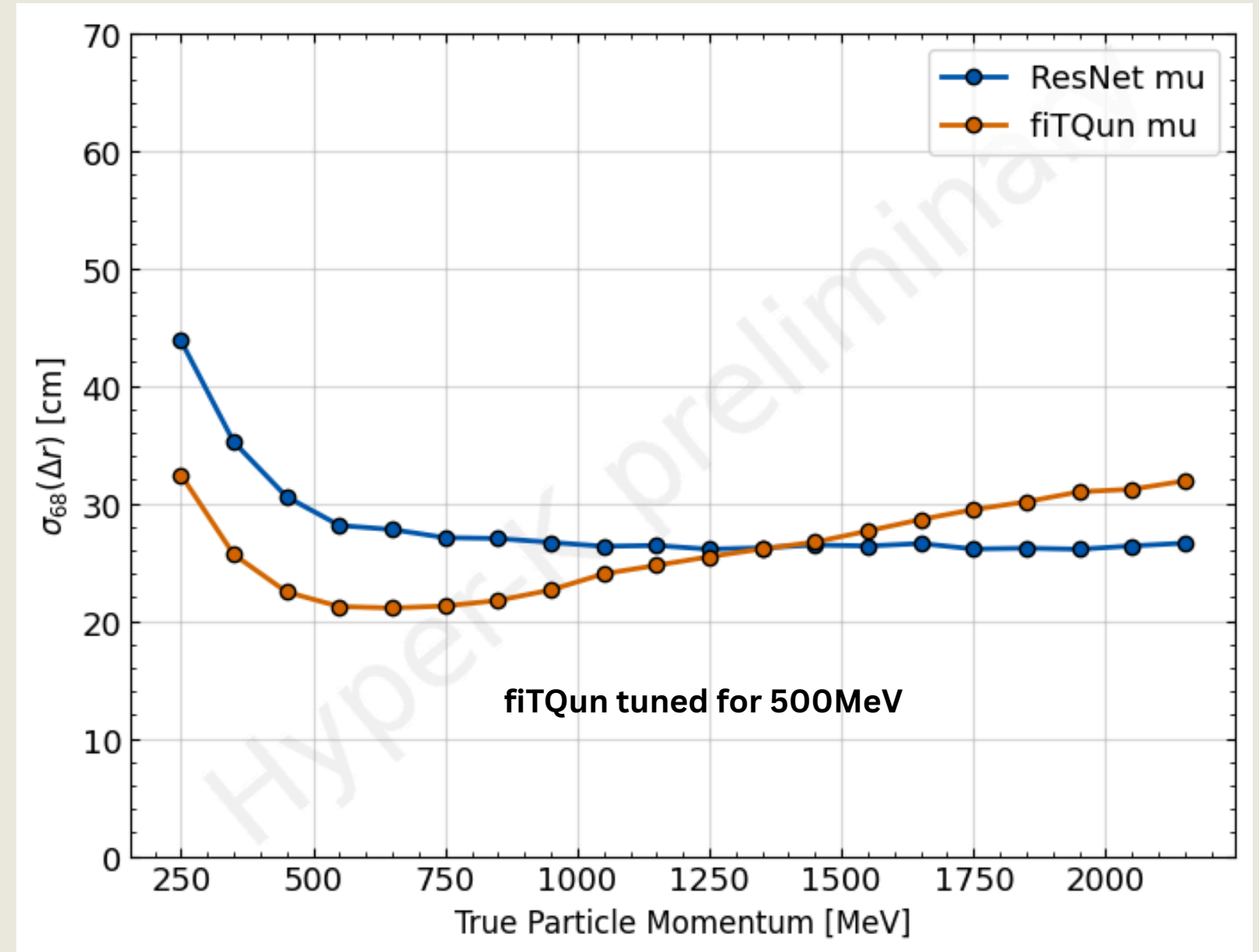
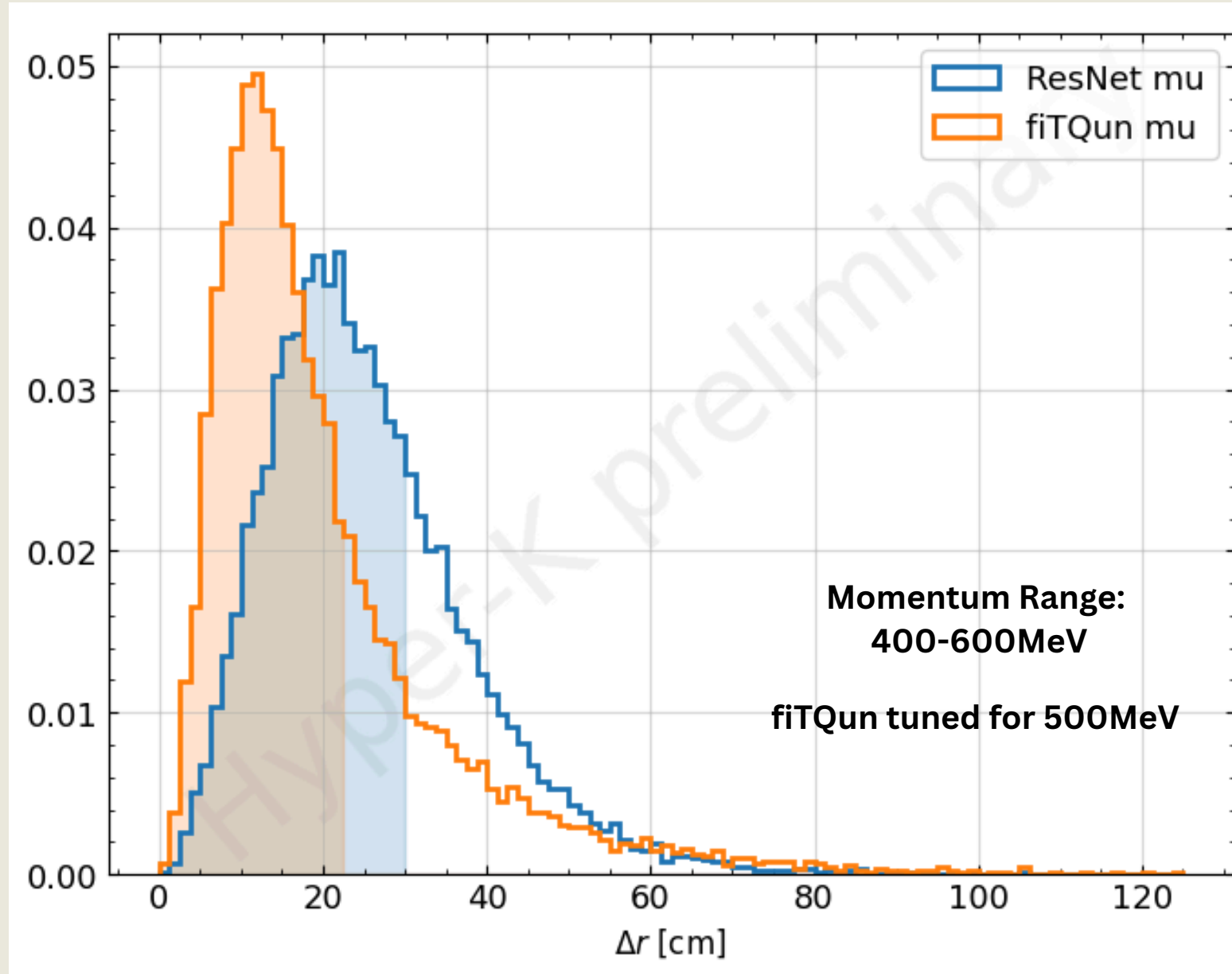
DIRECTION RECONSTRUCTION



	ResNet	fiTQun
Average $\sigma_{68}(\Delta\theta)$	1.66°	2.45°

$\sigma_{68}(\Delta\theta)$ = opening angle residual below which 68% of events fall under

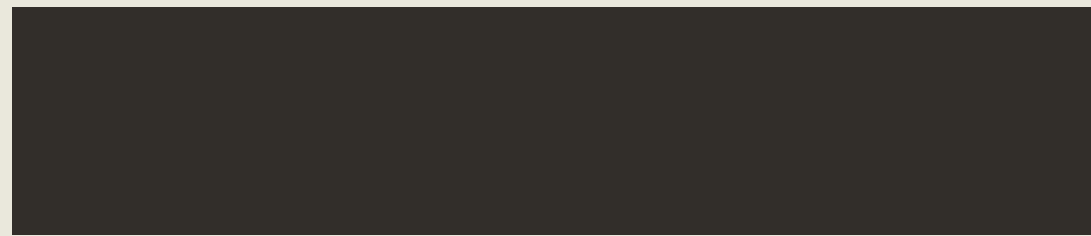
POSITION RECONSTRUCTION



	ResNet	fiTQun
Average $\sigma_{68}(\Delta r)$	29.4 cm	21.7 cm

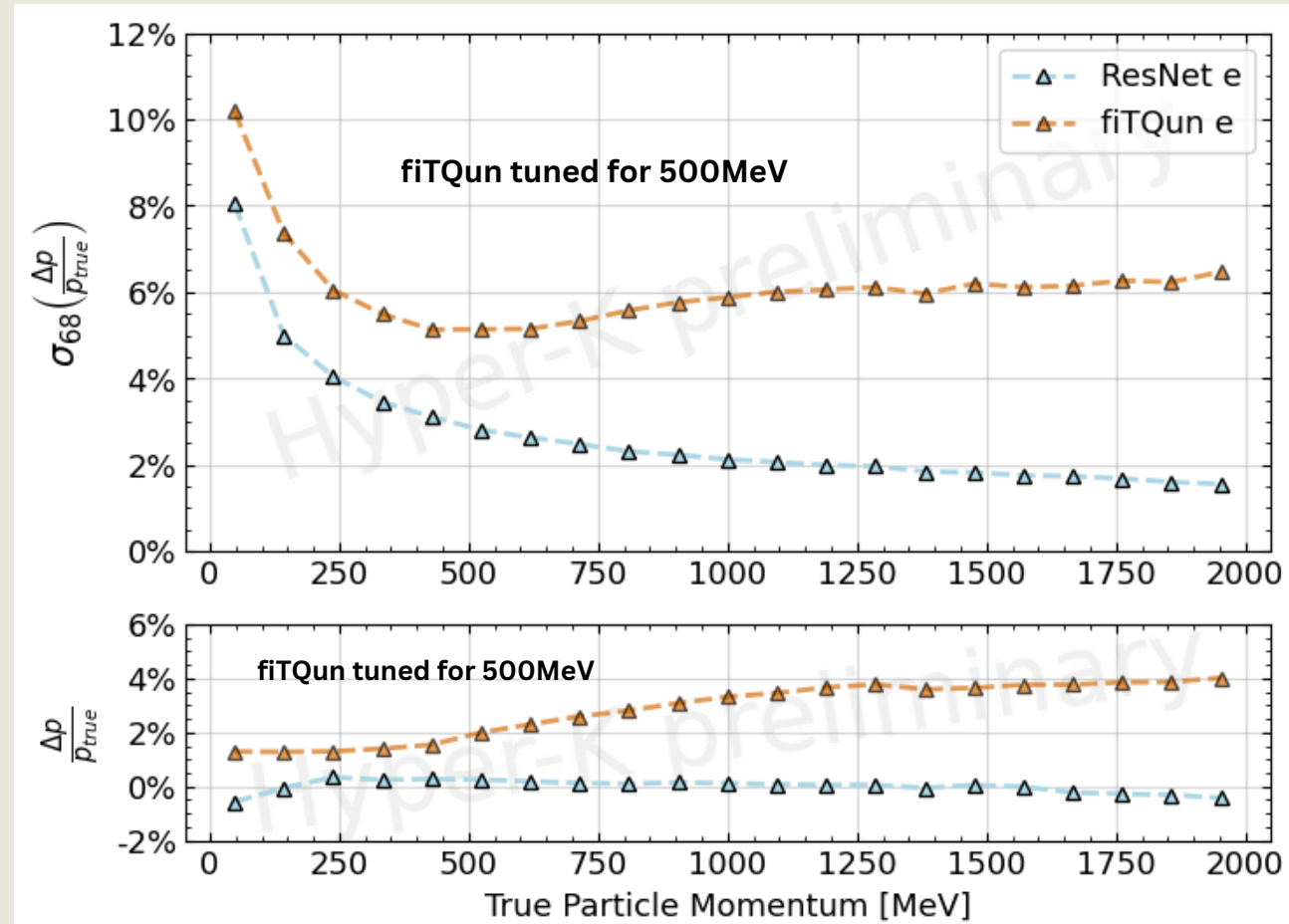
$\sigma_{68}(\Delta r)$ = 3D distance residual below which 68% of events fall under

ELECTRON REGRESSION

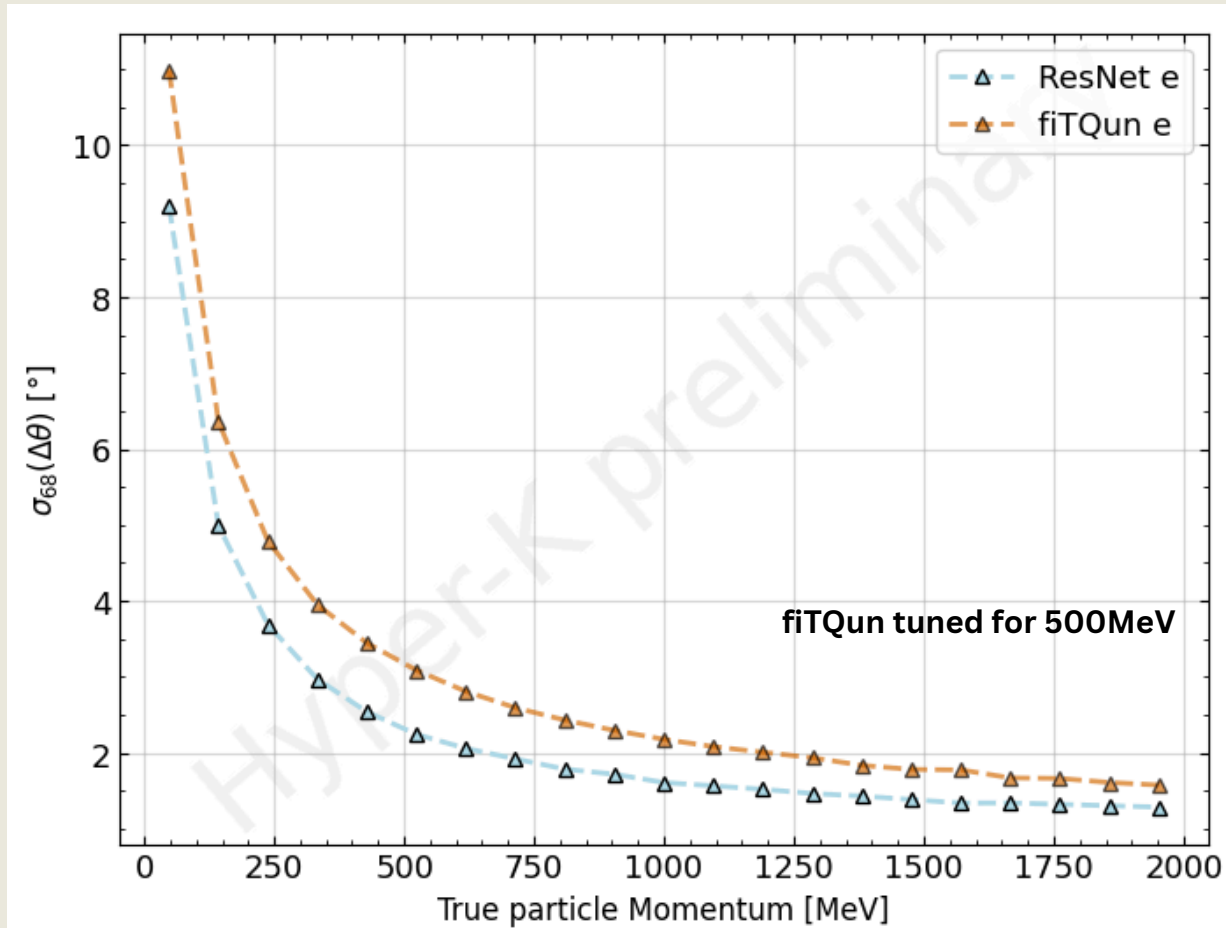


ELECTRON RECONSTRUCTION

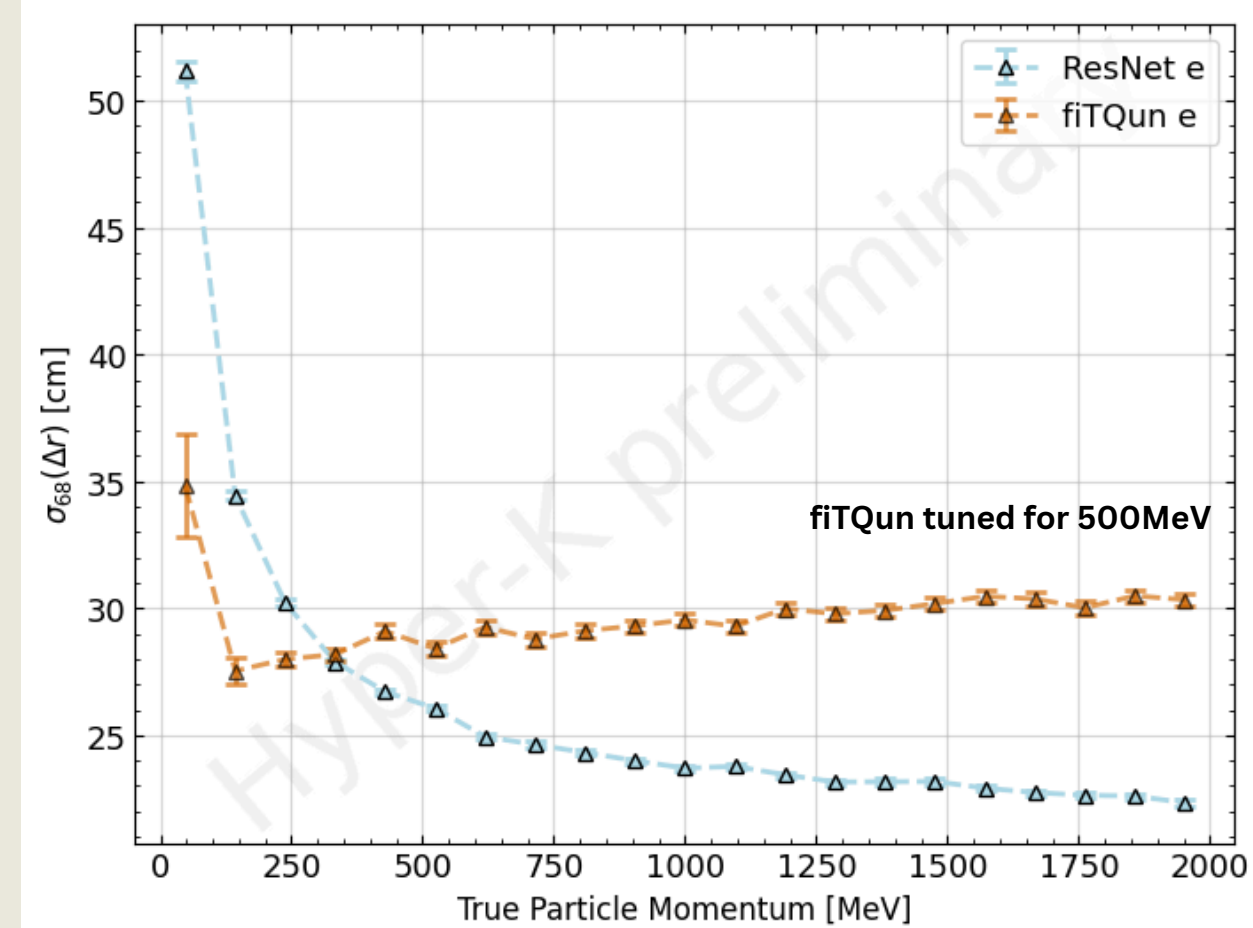
Momentum



Direction

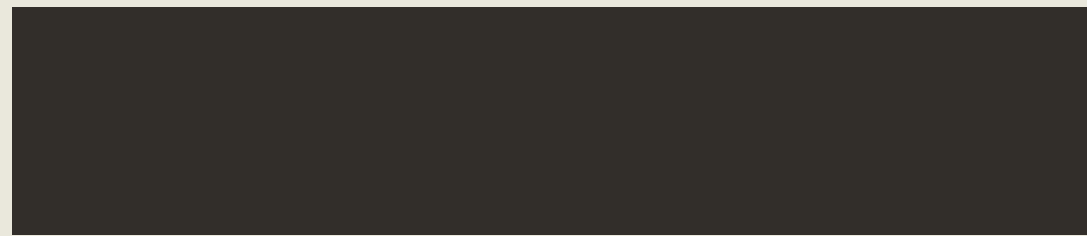


Position

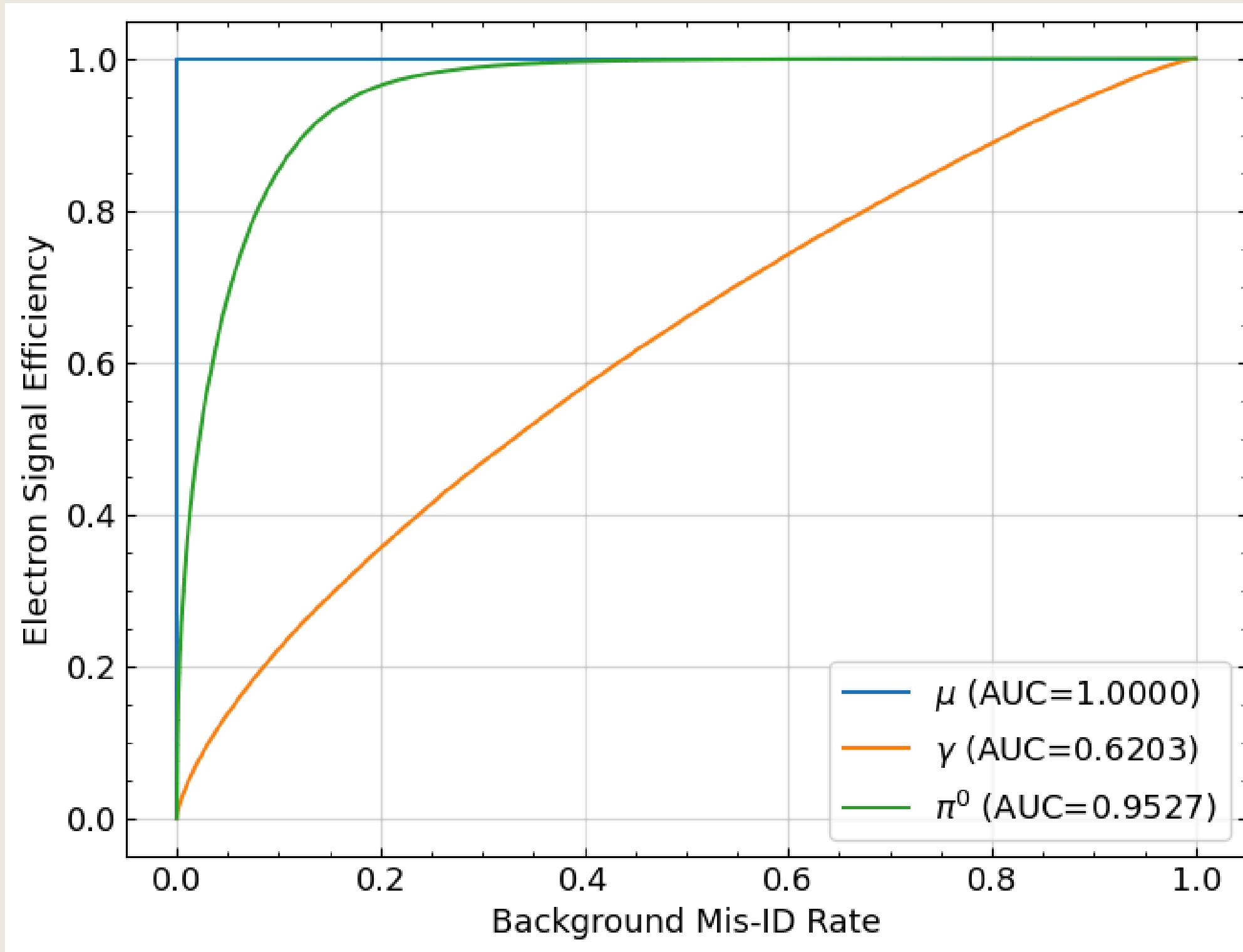


400-600MeV	ResNet	fiTQun
Average $\sigma_{68} \left(\frac{\Delta p}{p_{true}} \right)$	2.91%	5.11%
Average $\frac{\Delta p}{p_{true}}$	0.26%	1.84%
Average $\sigma_{68} (\Delta r)$	26.1 cm	28.71
Average $\sigma_{68} (\Delta \theta)$	2.33°	3.20°

CLASSIFICATION



CLASSIFICATION



True Particle	Predicted Particle			
	γ	e	μ	π^0
γ	114,400	68,800	800	15,100
e	82,700	101,200	1,500	13,000
μ	200	700	195,500	100
π^0	22,000	13,200	400	162,500

Discriminators defined as:

$$D_{e/\mu} = P_e + P_\gamma + P_{\pi^0} = 1 - P_\mu$$

$$D_{e/\pi^0} = \frac{P_e + P_\gamma}{P_e + P_\gamma + P_{\pi^0}} = 1 - \frac{P_{\pi^0}}{P_e + P_\gamma + P_{\pi^0}}$$

$$D_{e/\gamma} = \frac{P_e}{P_e + P_\gamma} = 1 - \frac{P_\gamma}{P_e + P_\gamma}$$

CONCLUSIONS

- HK is a next generation neutrino detector that expects to see massively increased statistics
- Traditional reconstruction techniques are no longer fast enough, machine learning techniques are arising to fill the gap
- We've shown that CNNs like ResNet can achieve as good, if not better, reconstruction than traditional techniques while being orders of magnitude faster to compute

If you'd like to discuss anything with me further, I will be showing off a poster
Or feel free to email me at andrew.atta1@monash.edu

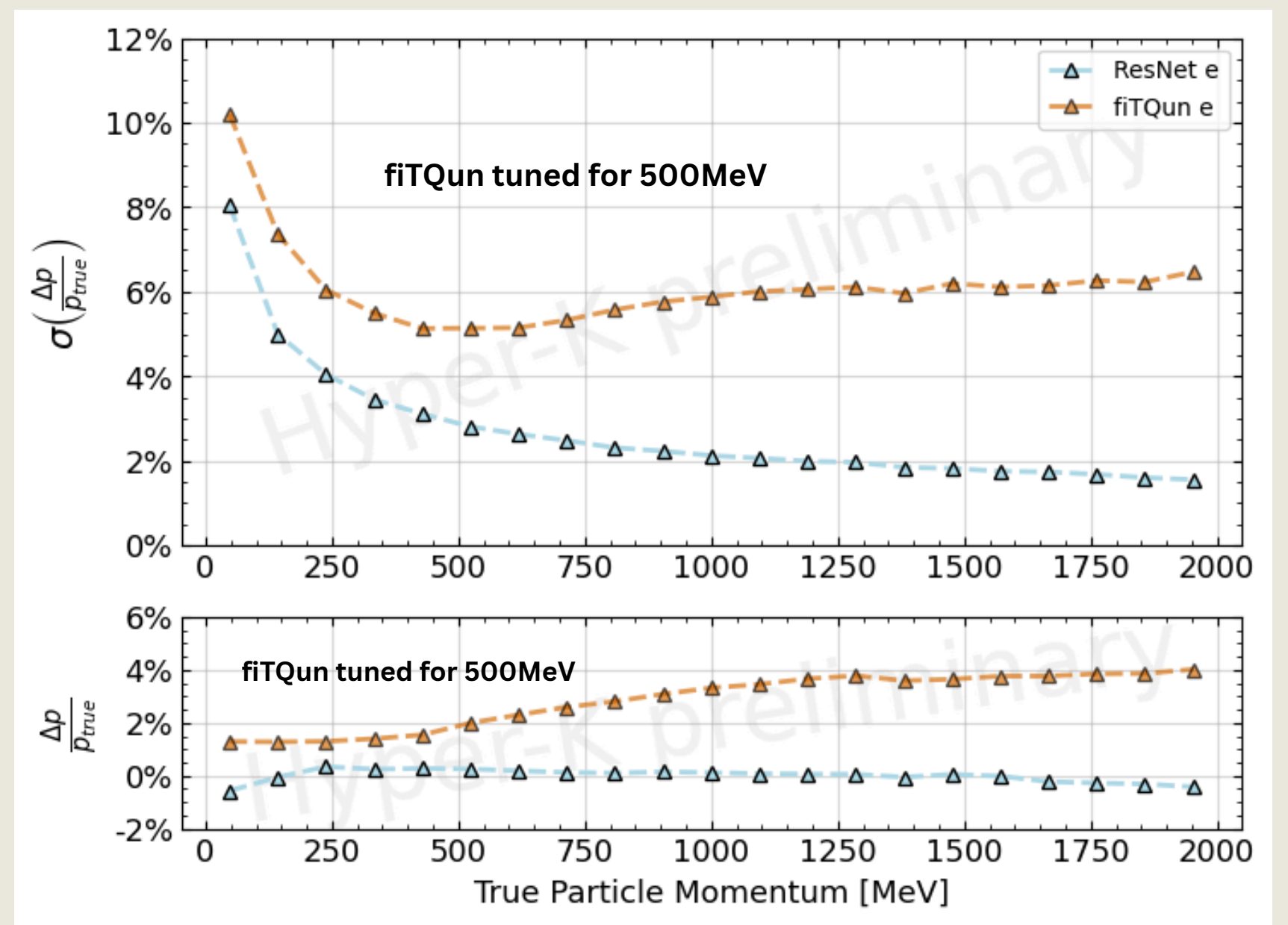
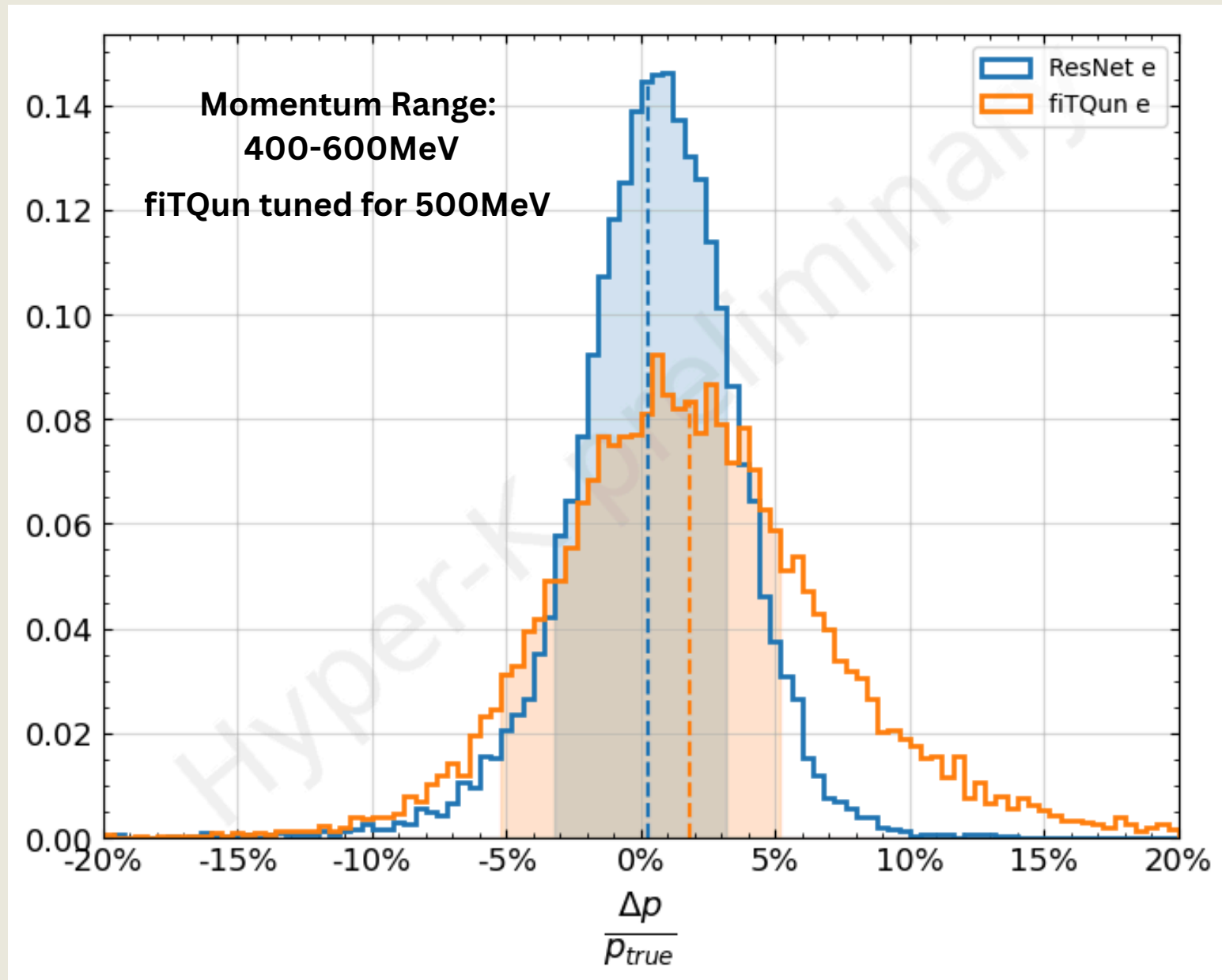
THANKS :)



APPENDIX



ELECTRON MOMENTUM RECONSTRUCTION

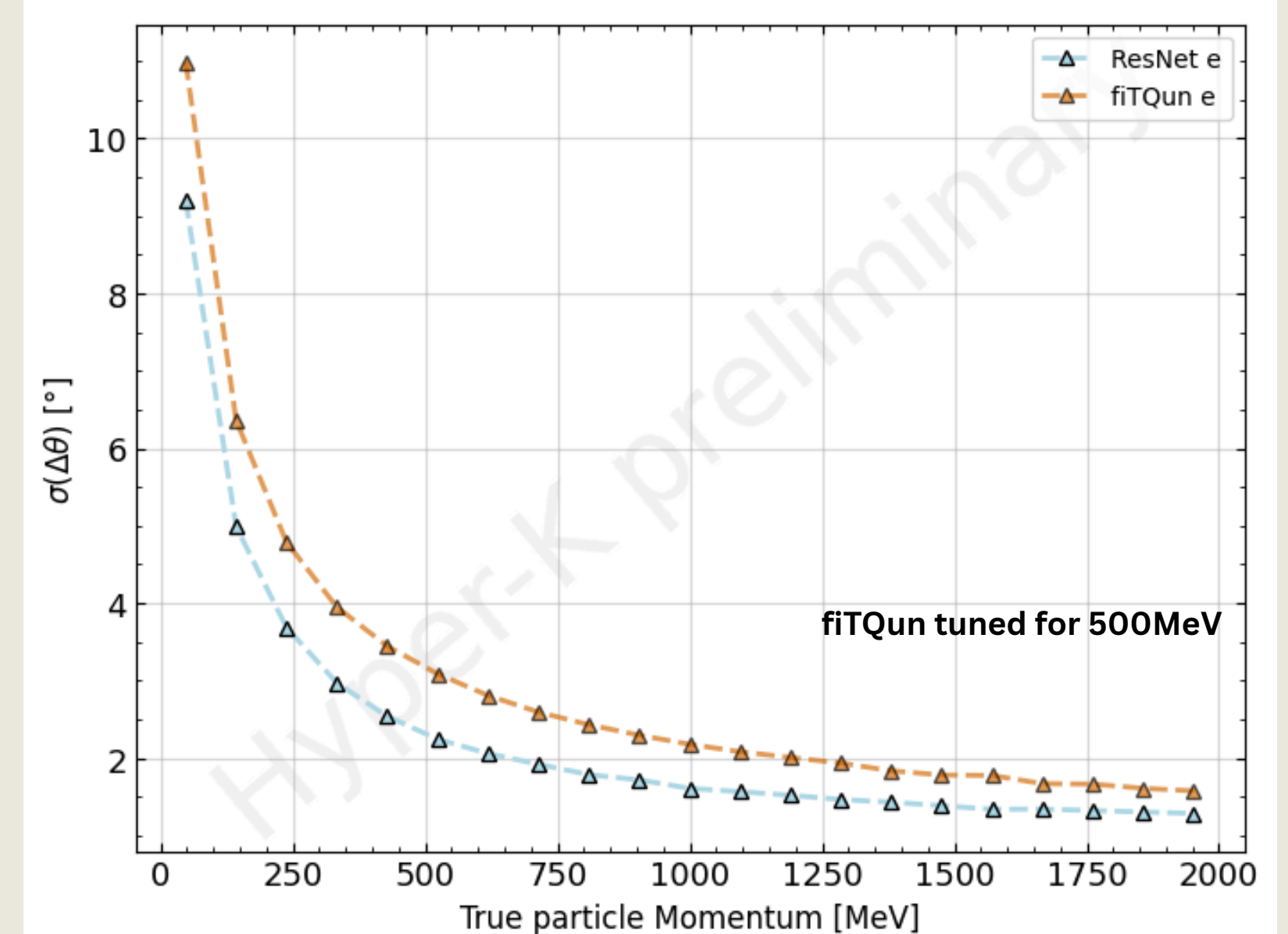
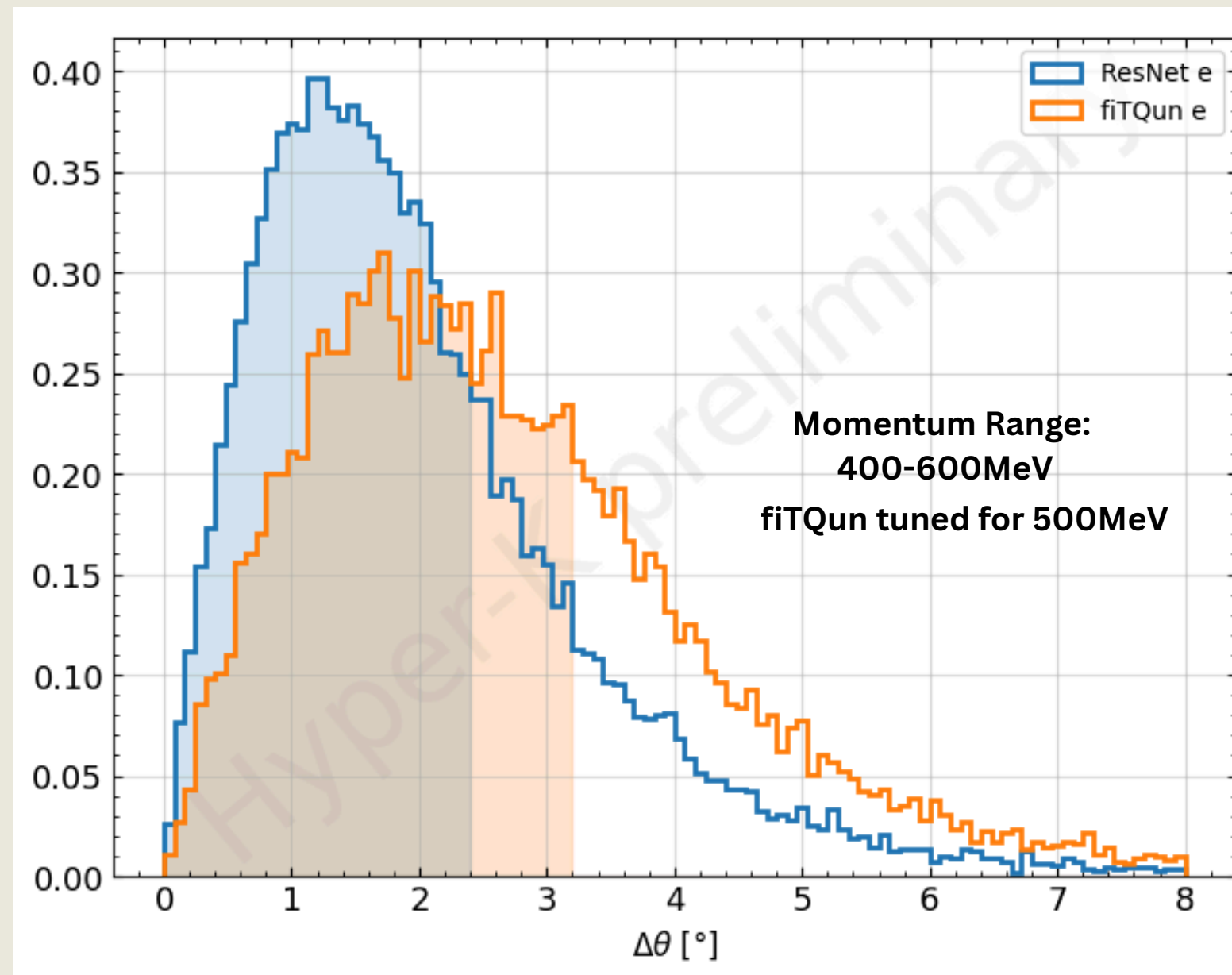


$$\frac{\Delta p}{p_{true}} = \frac{\text{True p} - \text{Predicted p}}{\text{True p}} \times 100$$

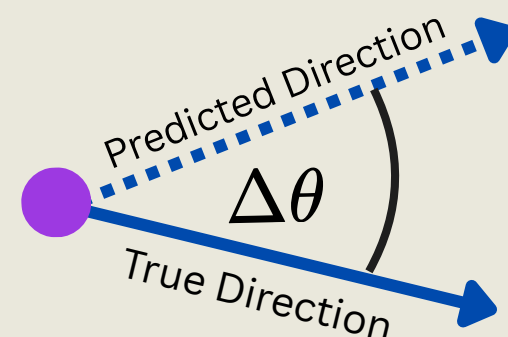
$$\sigma\left(\frac{\Delta p}{p_{true}}\right) = \text{absolute fractional momentum residual below which 68\% of events fall under. Analogous to 1 standard deviation}$$

	ResNet	fiTQun
Average $\sigma\left(\frac{\Delta p}{p_{true}}\right)$	2.91%	5.11%
Average $\frac{\Delta p}{p_{true}}$	0.26%	1.84%

ELECTRON DIRECTION RECONSTRUCTION

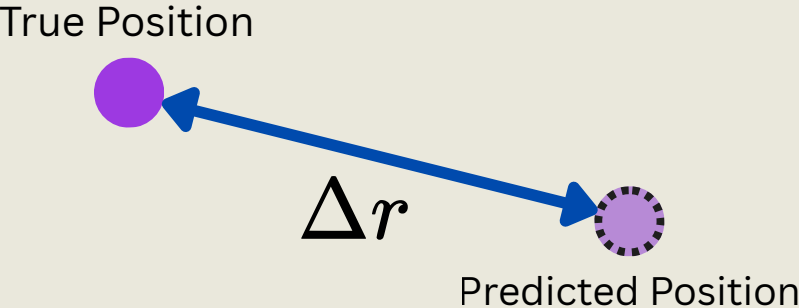
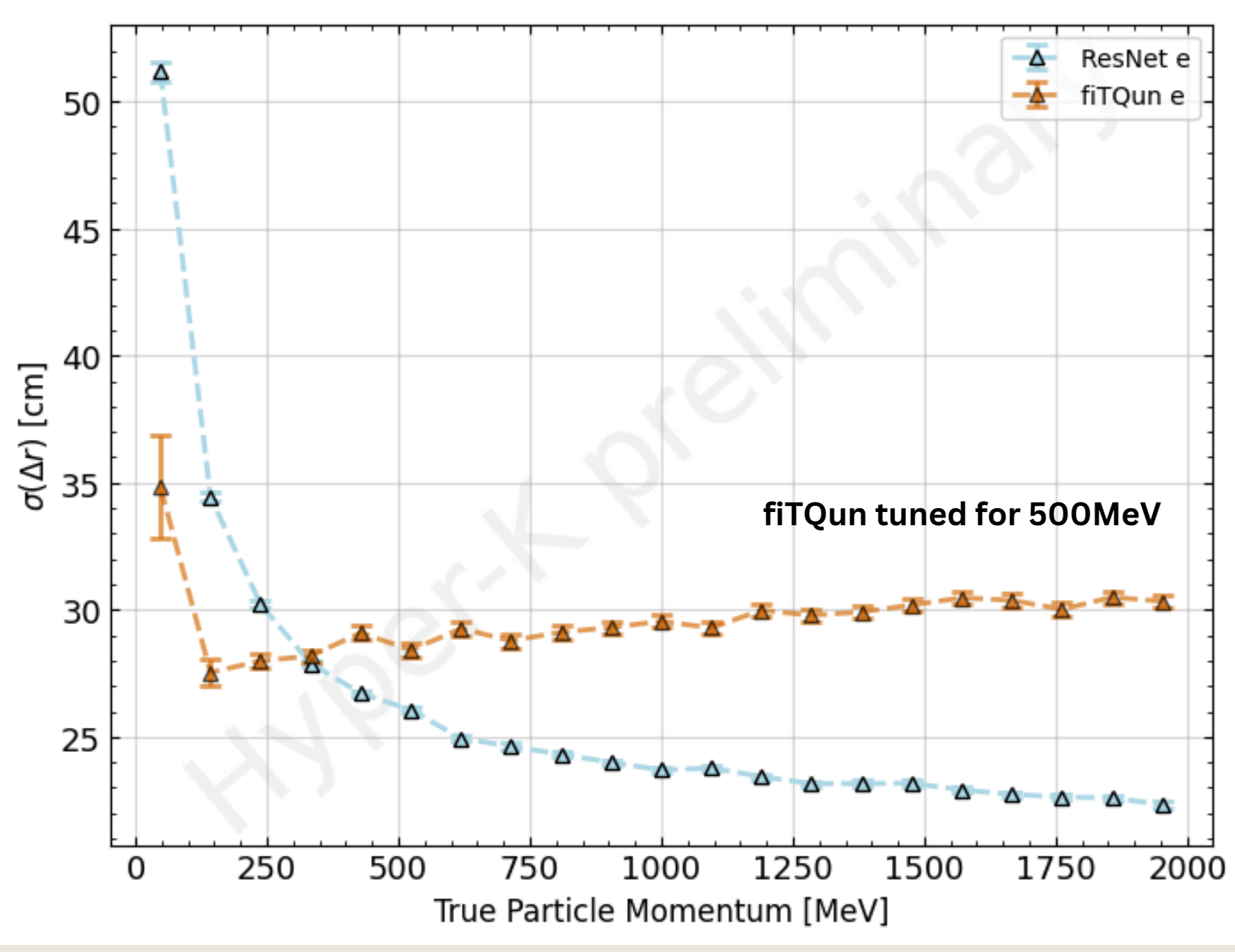
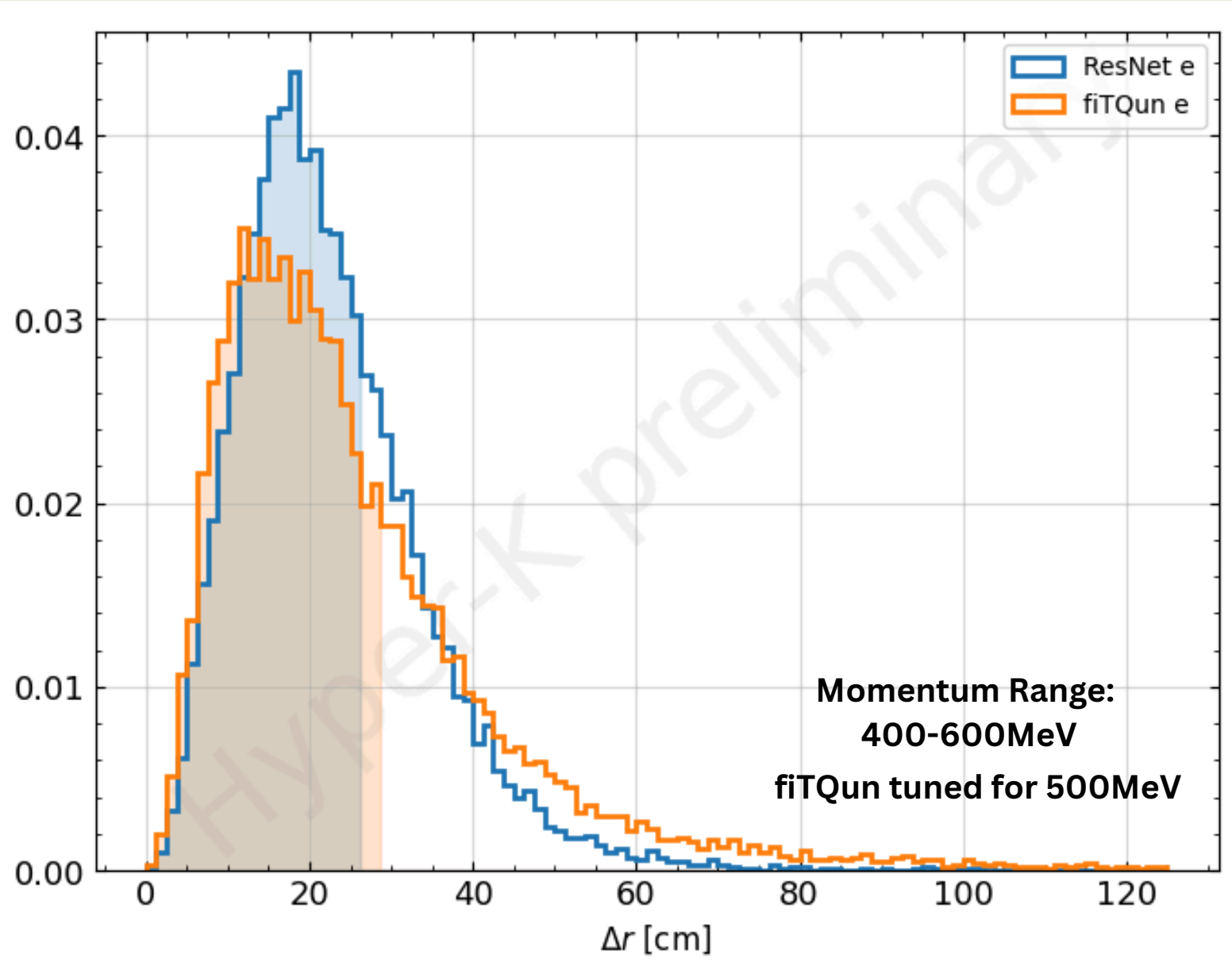


	ResNet	fiTQun
Average $\sigma(\Delta\theta)$	2.33°	3.20°



$\sigma(\Delta\theta)$ = opening angle residual below which 68% of events fall under

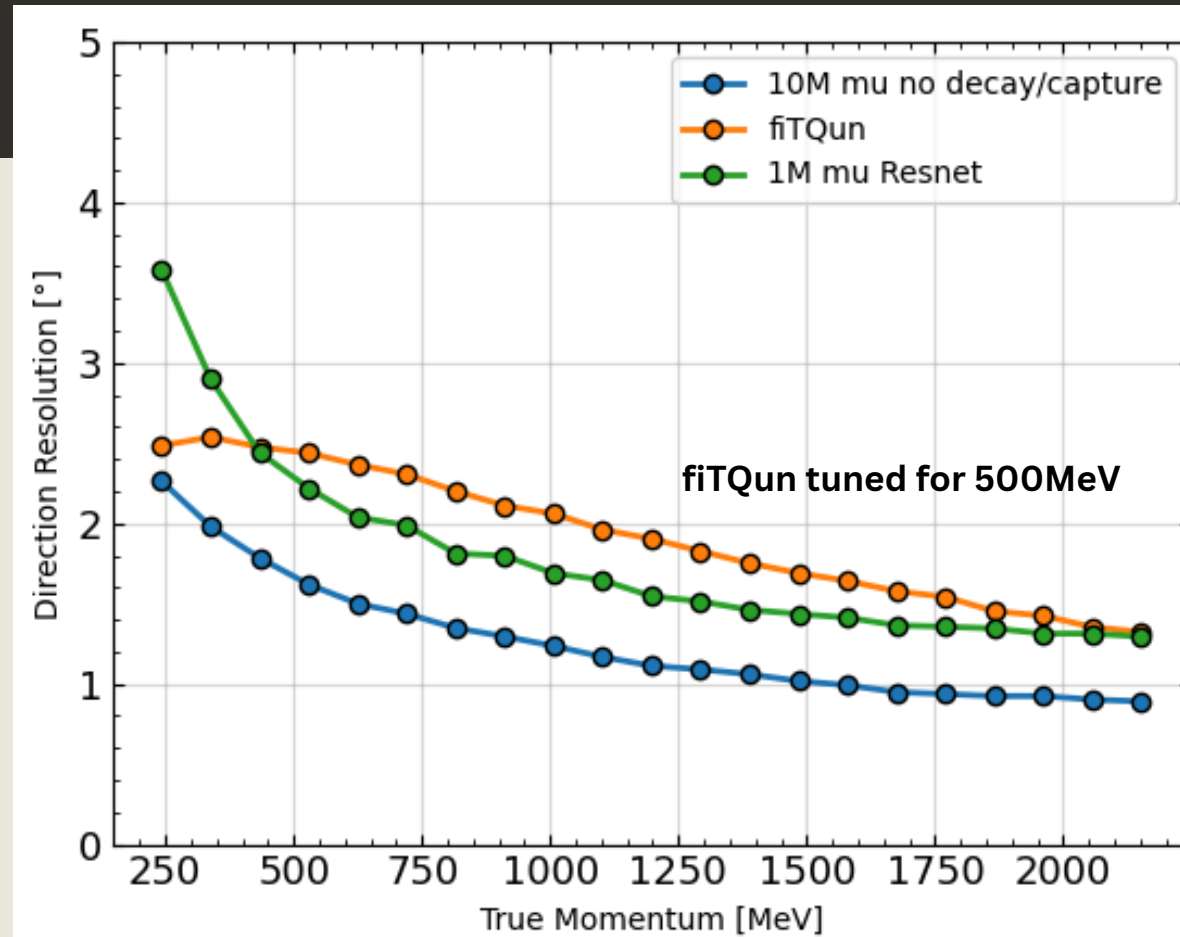
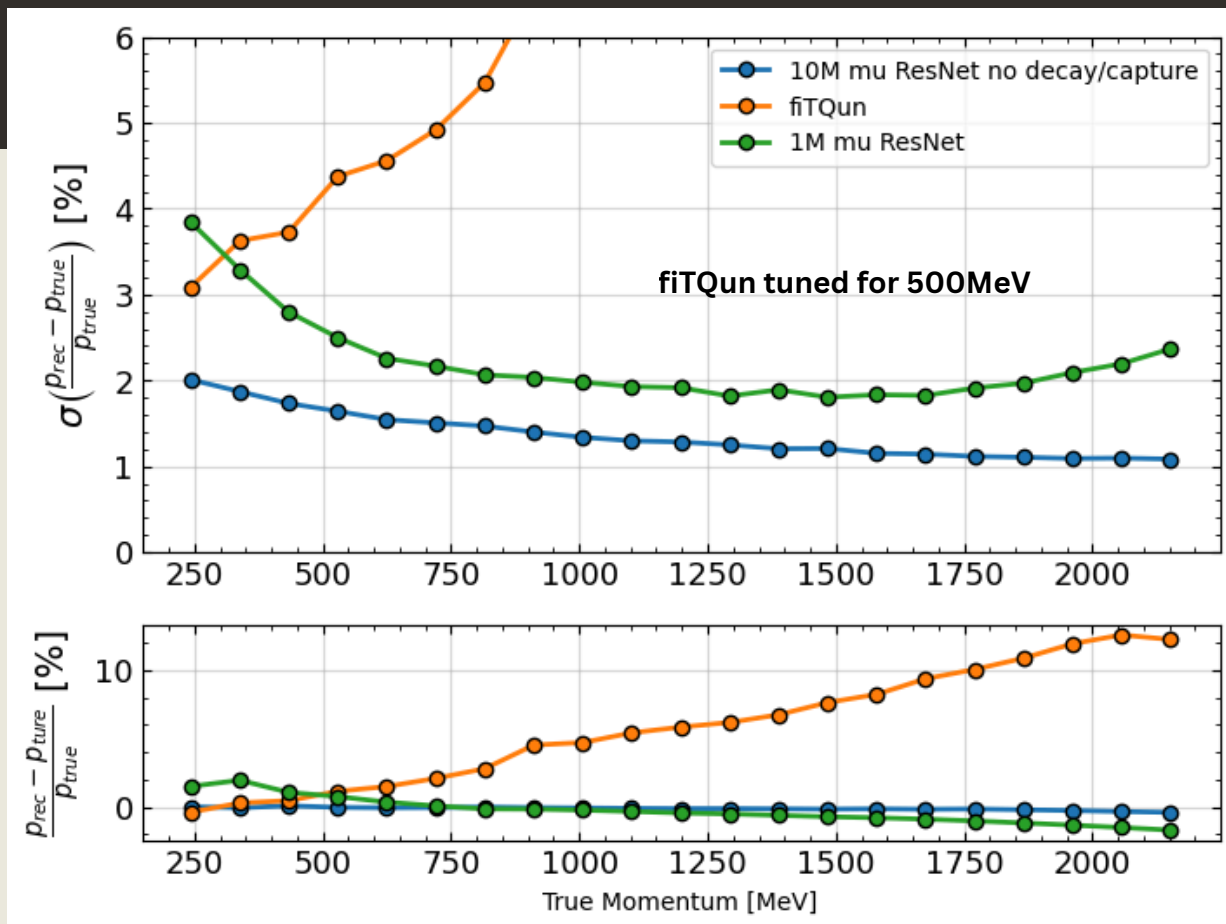
ELECTRON POSITION RECONSTRUCTION



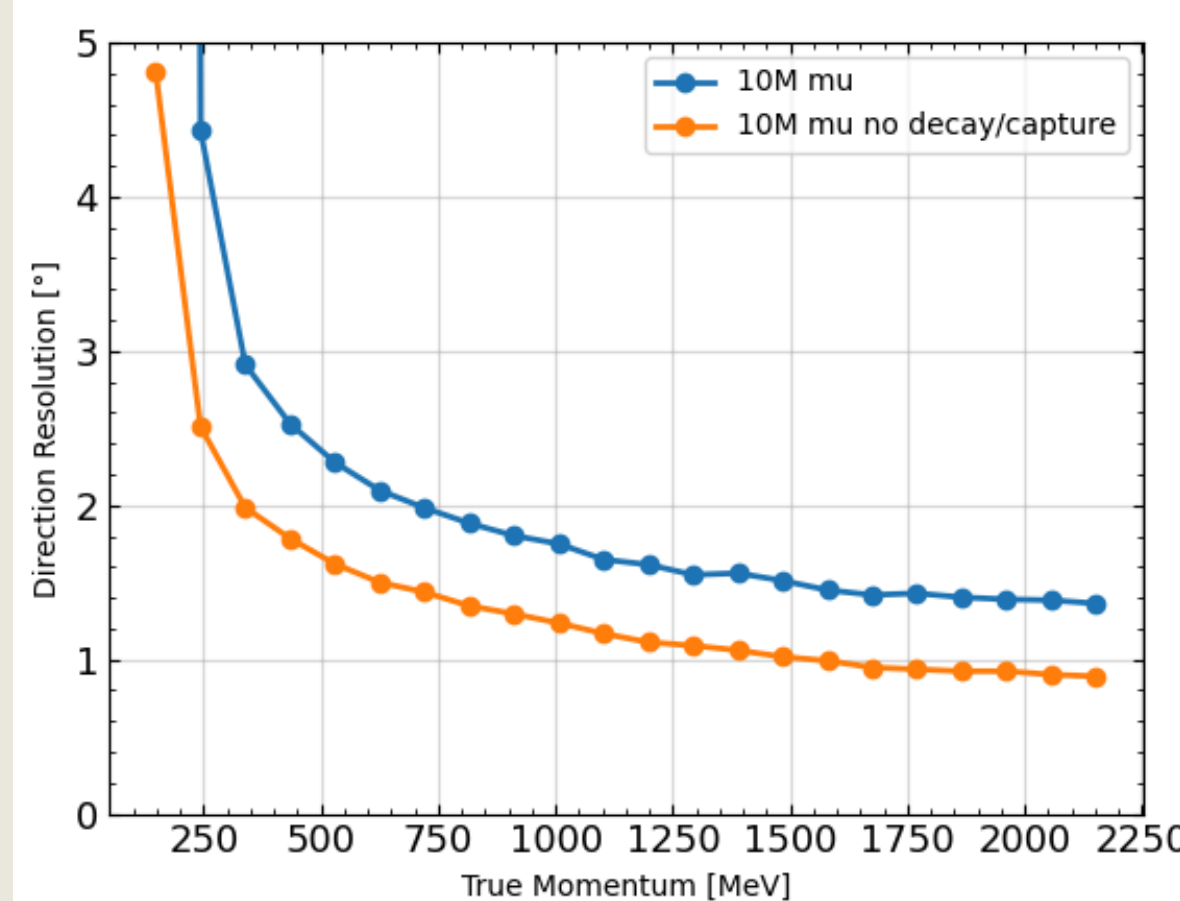
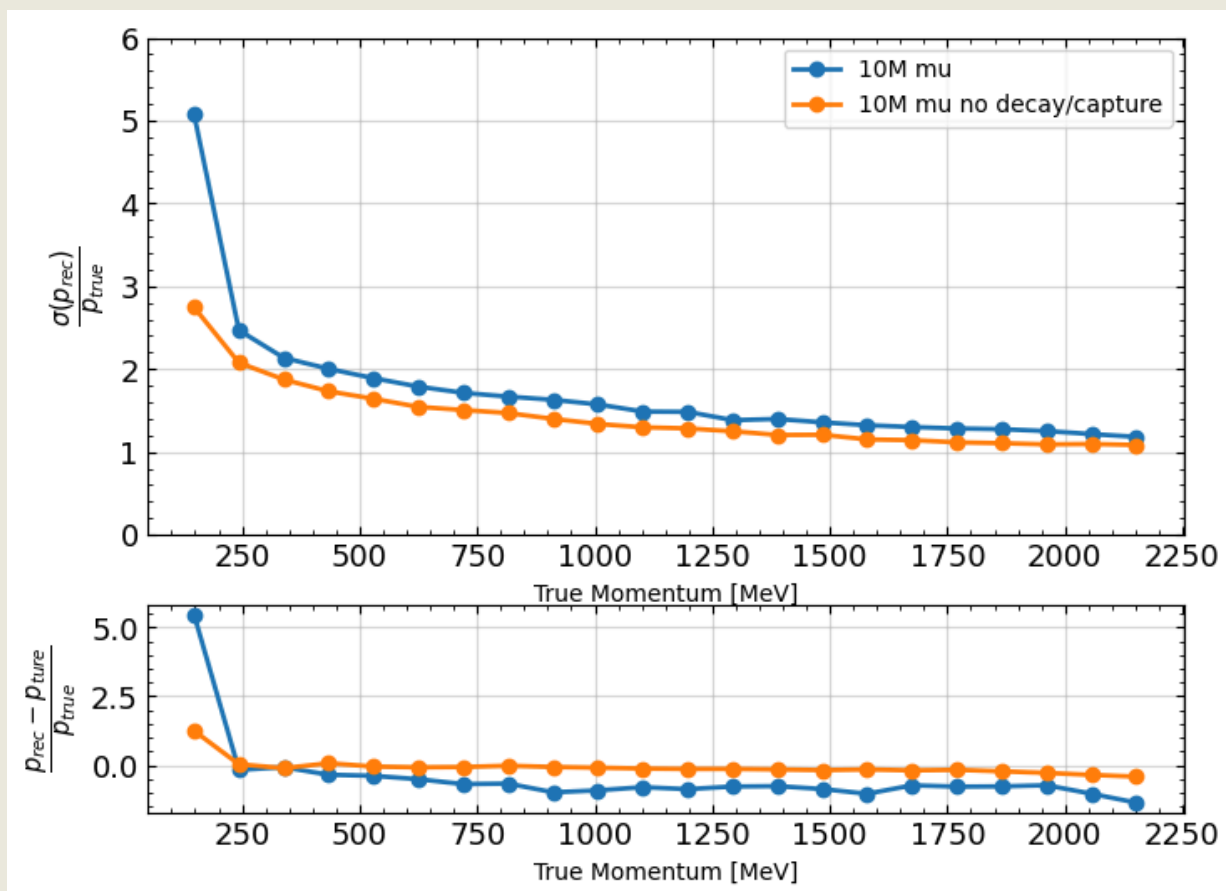
	ResNet	fiTQun
Average $\sigma(\Delta r)$	26.1 cm	28.71

$\sigma(\Delta r) =$ 3D distance residual below which 68% of events fall under

A NOTE ON SCALABILITY



- Going from 700,000 $\rightarrow$ 9,600,00 Training events does not improve momentum or direction reconstruction much
- In fact, benefit is likely caused by removing decay muons and junk events arising from incorrect trigger timestamping in muon capture events



TRAINING NETWORKS

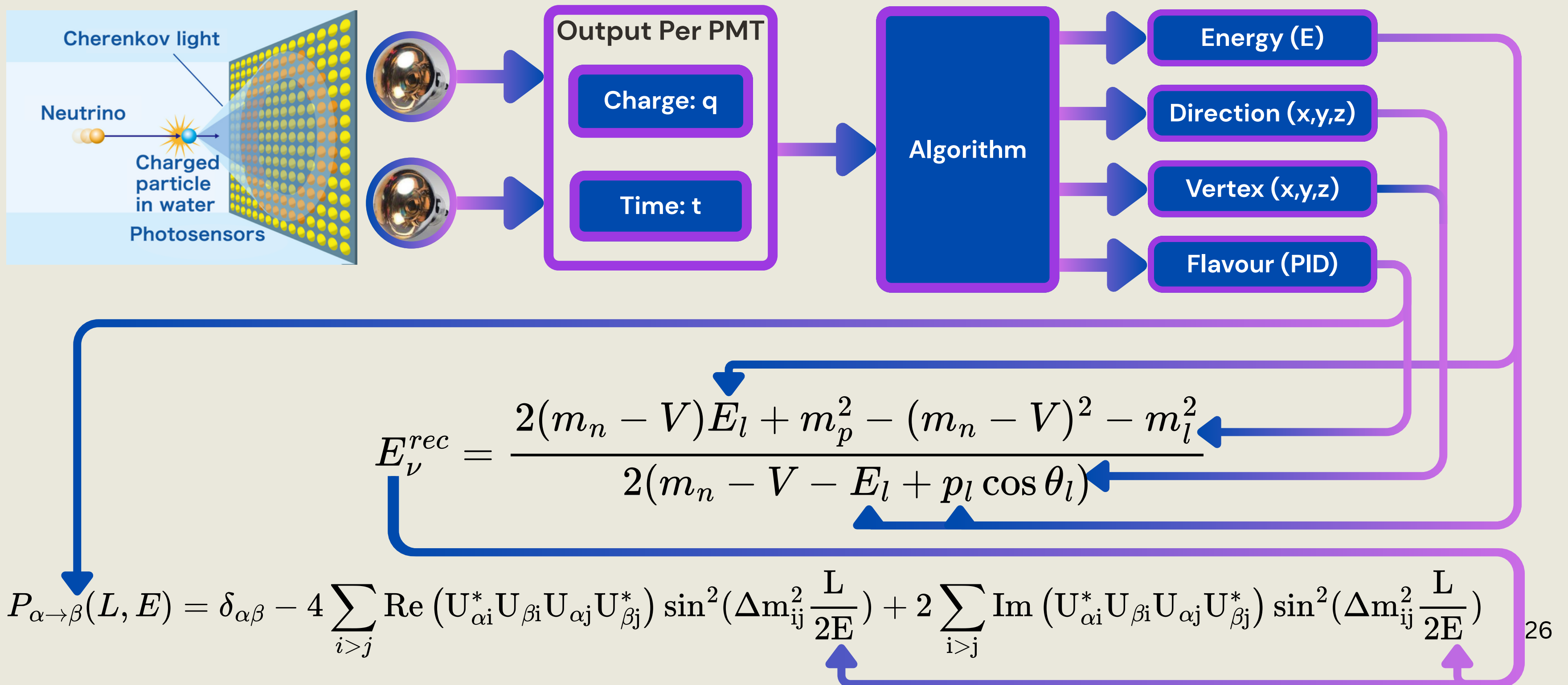
- Trained 7 networks
 - 6 Regression Networks
 - Three Muon Regressors for energy, position, direction - 10 million events
 - Three Electron Regressors for energy, position, direction - 10 million events
 - Trained for 20 epochs each, batch size=512, AdamW optimiser, learning rate=1e-3 - 1e-6 (cosine annealing LR every 2.5 epochs)
 - Trained on fully contained events only
 - Used Huber Loss function. Relative Huber loss for momentum reconstruction
 - One Classification Network
 - 4-class classifier for PID - γ vs. e vs. μ vs. π^0
 - Same config as above (besides loss function)
- All used ResNet-152 architecture using **WatChMaL**
- 190x189 input images with two channels - PMT hit time and charge
 - Input channels scale by dividing hit charges by 10 and hit times 1350 (readout window)
- Trained on 4 A100 GPUs for 20 epochs for regression networks and 8 epochs for classification network

Cuts	FC and nhits>200
Energy	0-2GeV
PID	μ , e , γ , π^0
Muon Decay?	no decay
Training Split	96:2:2
Training Set	~8,569,149
Validation Set	~178,449
Testing Set	~178,595

PERFORMANCE SUMMARY

	400–600MeV	ResNet	fiTQun
μ	Average $\sigma \left(\frac{\Delta p}{p_{true}} \right)$	1.67%	4.15%
	Average $\frac{\Delta p}{p_{true}}$	0.02%	0.87%
	Average $\sigma (\Delta r)$	29.4 cm	21.7 cm
	Average $\sigma (\Delta \theta)$	1.66°	2.45°
e	Average $\sigma \left(\frac{\Delta p}{p_{true}} \right)$	2.91%	5.11%
	Average $\frac{\Delta p}{p_{true}}$	0.26%	1.84%
	Average $\sigma (\Delta r)$	26.1 cm	28.71
	Average $\sigma (\Delta \theta)$	2.33°	3.20°

EVENT RECONSTRUCTION BUT REAL THIS TIME



FULL OSCILLATION EXPRESSION

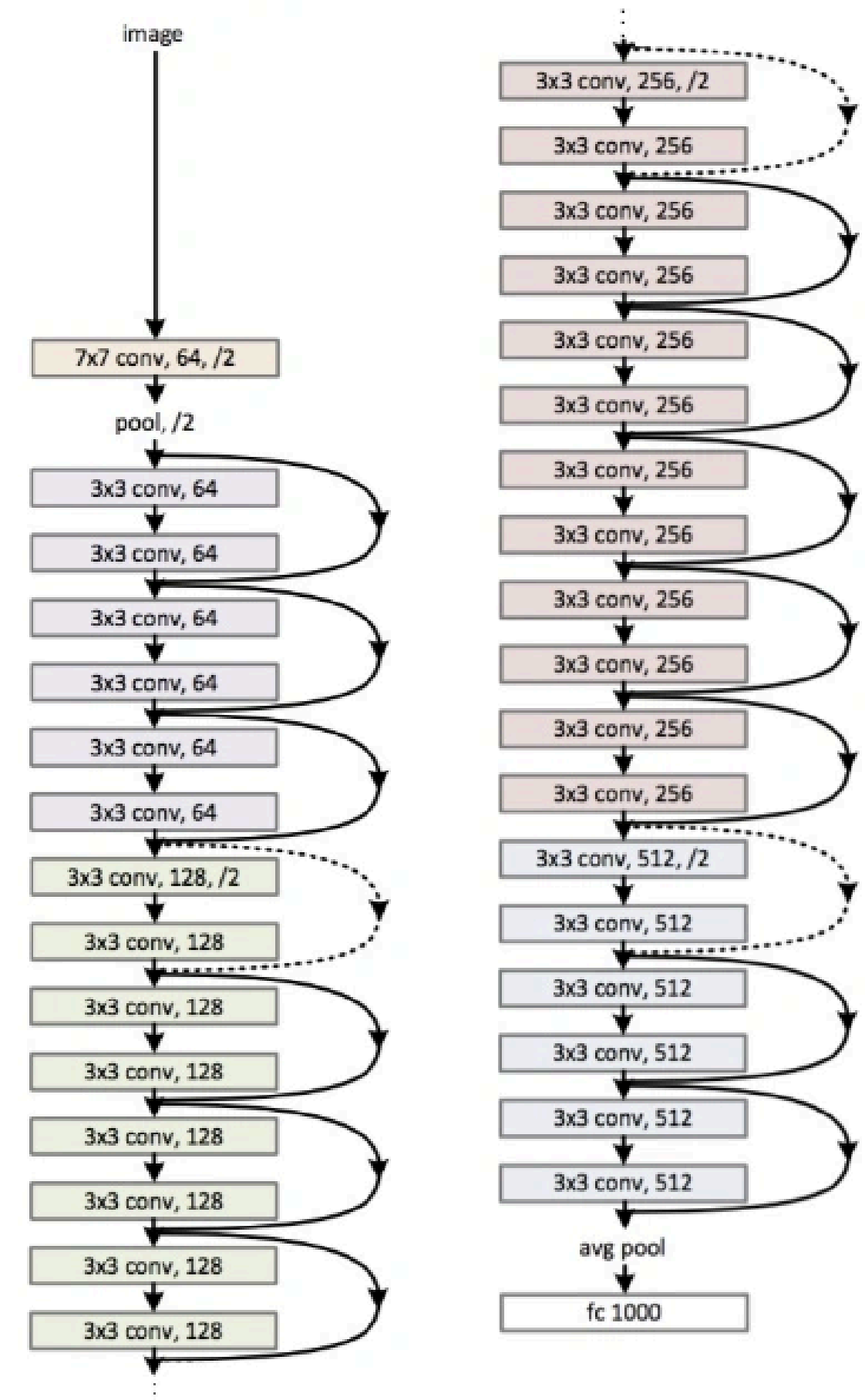
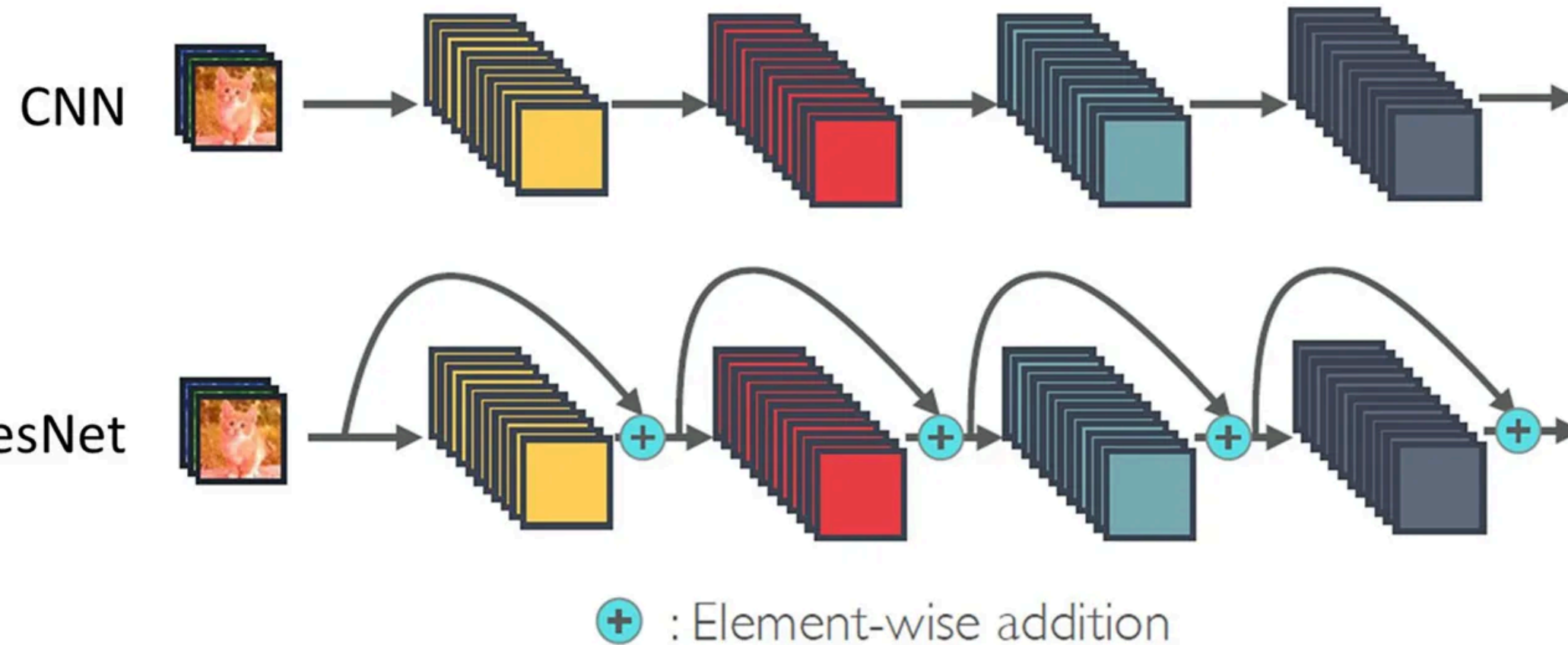
$$\begin{aligned}
 P(\nu_\mu \rightarrow \nu_e) = & 4c_{13}^2 s_{13}^2 s_{23}^2 \cdot \sin^2 \Delta_{31} \\
 & + 8c_{13}^2 s_{12} s_{13} s_{23} (c_{12} c_{23} \cos \delta_{CP} - s_{12} s_{13} s_{23}) \cdot \cos \Delta_{32} \cdot \sin \Delta_{31} \cdot \sin \Delta_{21} \\
 & \mp 8c_{13}^2 c_{12} c_{23} s_{12} s_{13} s_{23} \sin \delta_{CP} \cdot \sin \Delta_{32} \cdot \sin \Delta_{31} \cdot \sin \Delta_{21} \\
 & + 4s_{12}^2 c_{13}^2 (c_{12}^2 c_{23}^2 + s_{12}^2 s_{23}^2 s_{13}^2 - 2c_{12} c_{23} s_{12} s_{23} s_{13} \cos \delta_{CP}) \cdot \sin^2 \Delta_{21} \\
 & \mp 8c_{13}^2 s_{13}^2 s_{23}^2 \cdot \frac{aL}{4E_\nu} (1 - 2s_{13}^2) \cdot \cos \Delta_{32} \cdot \sin \Delta_{31} \\
 & \pm 8c_{13}^2 s_{13}^2 s_{23}^2 \cdot \frac{a}{\Delta m_{31}^2} (1 - 2s_{13}^2) \cdot \sin^2 \Delta_{31},
 \end{aligned}$$

$$c_{ij} = \cos \theta_{ij}, \quad s_{ij} = \sin \theta_{ij} \quad \Delta_{ij} = \frac{\Delta m_{ij}^2 L}{4E_\nu} \quad \Delta m_{ij}^2 = m_i^2 - m_j^2$$

$$a = 2\sqrt{2}G_F n_e E_\nu$$

Fermi Coupling Constant
 electron density
 Neutrino Energy

RESNET



LOSS FUNCTION

$$\text{Huber} = \frac{1}{n} \sum_{i=1}^n \frac{1}{2} (y_i - \hat{y}_i)^2 \quad |y_i - \hat{y}_i| \leq \delta$$
$$\text{Huber} = \frac{1}{n} \sum_{i=1}^n \delta \left(|y_i - \hat{y}_i| - \frac{1}{2} \delta \right) \quad |y_i - \hat{y}_i| > \delta$$

