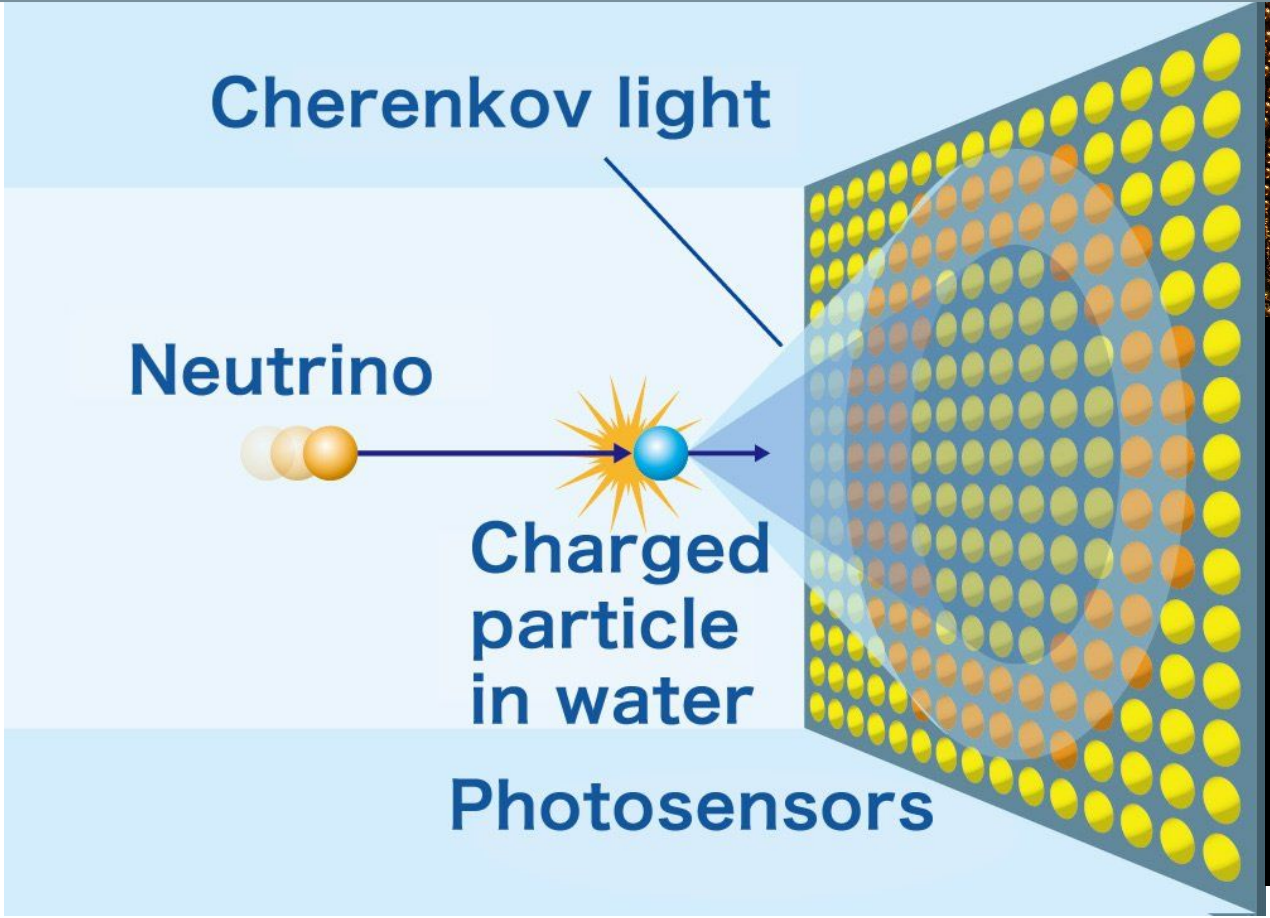
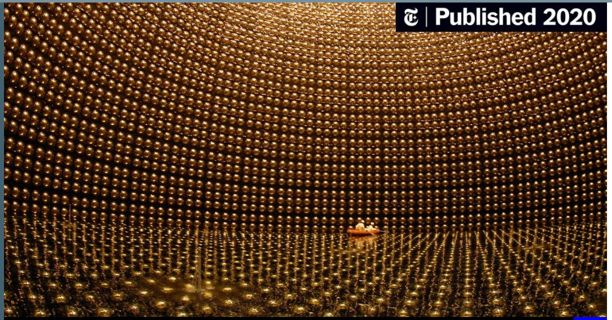
Deep Learning for Water Cherenkov Detectors

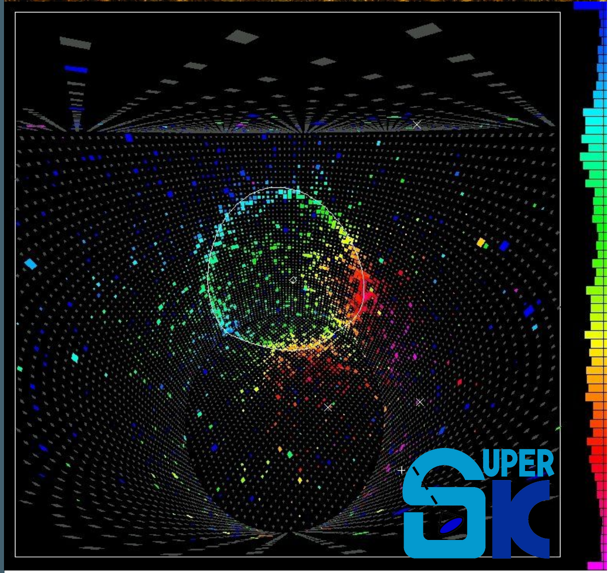
Junjie Xia

Neutrino Physics and Machine Learning, Aug 23 2023
Online/Boston, MA, US

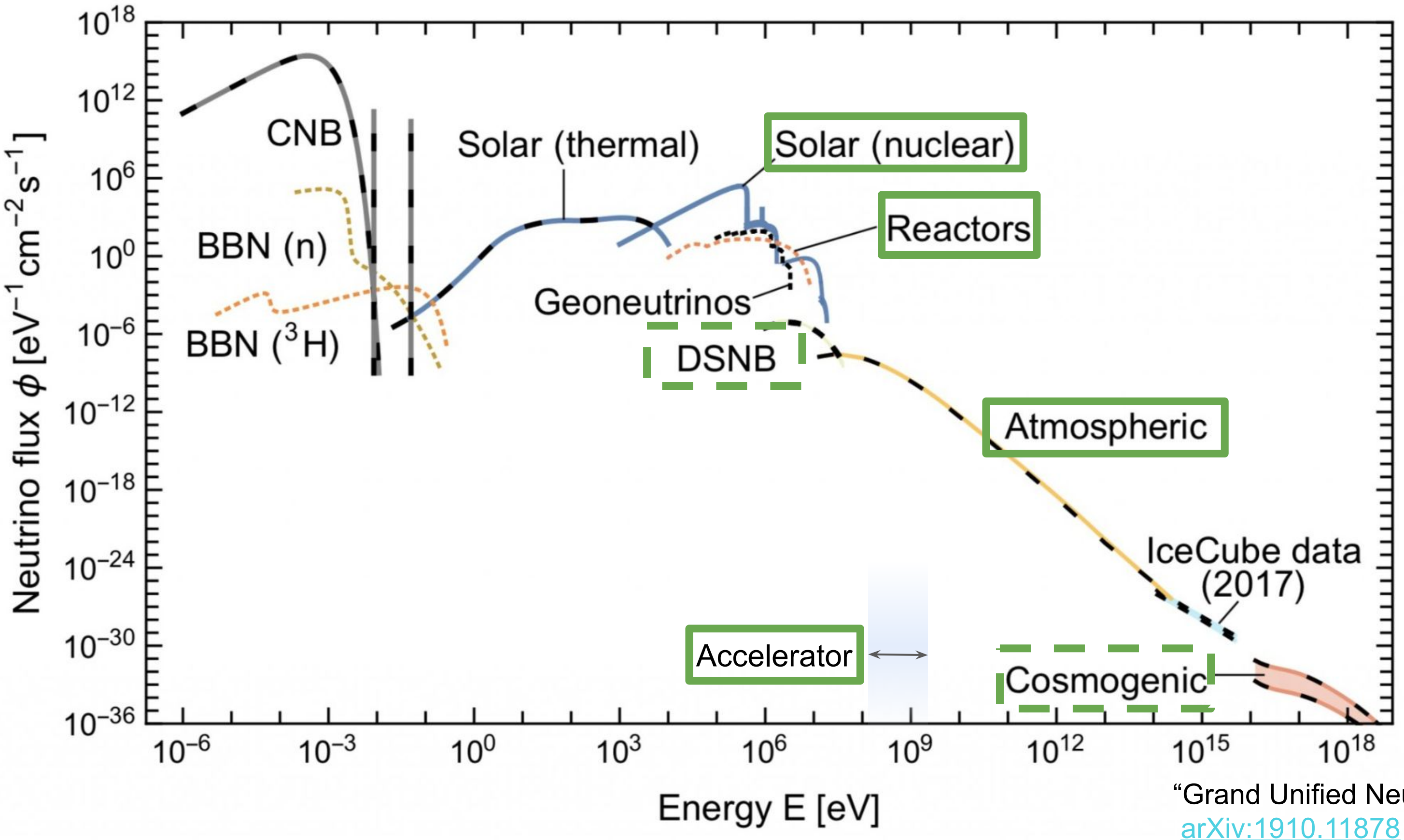
Water Cherenkov Detector Principle





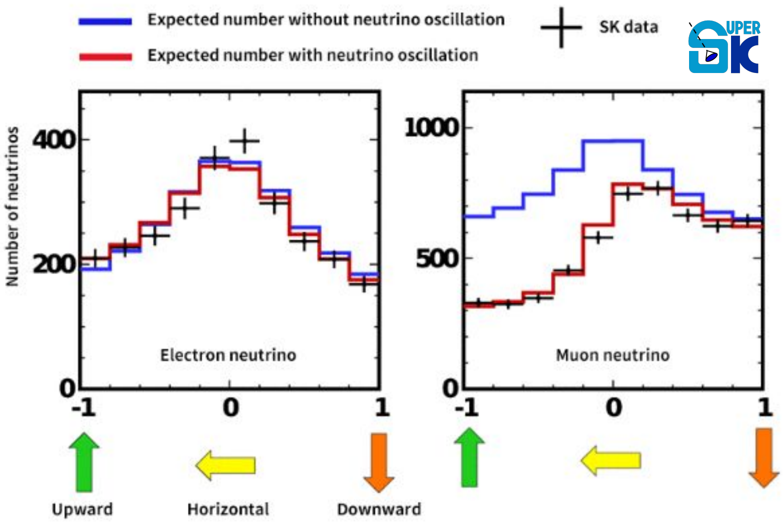


PhysicsOpenLab.org

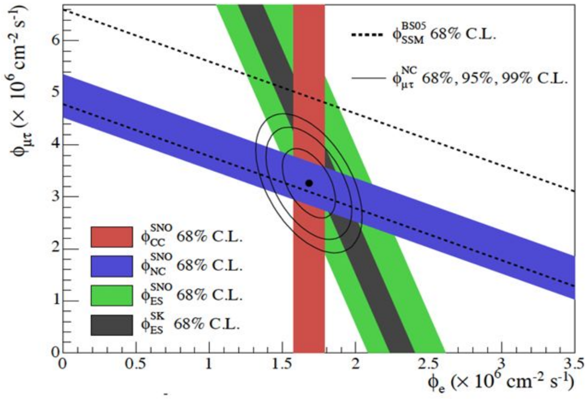


"Grand Unified Neutrino Spectrum"
arXiv:1910.11878

The Standard Neutrino Oscillations



SNO, arXiv:1602.02469

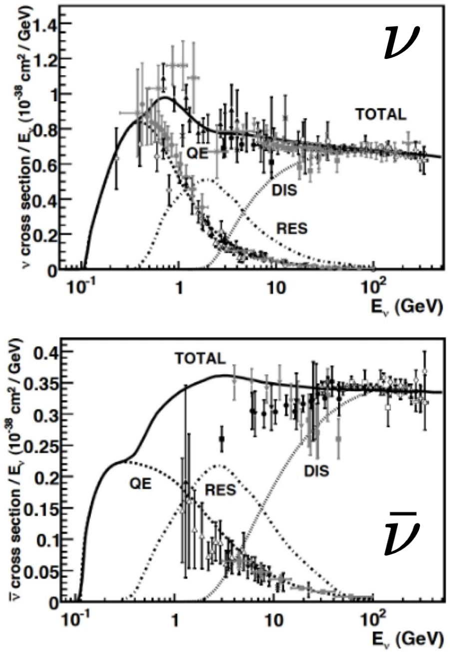


Open questions:

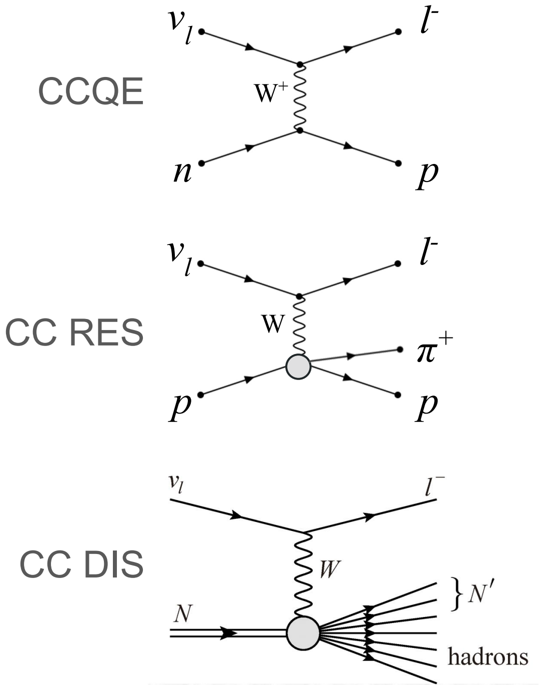
- The value of leptonic δ_{CP}
- Mass Ordering (MO), i.e. is Δm^2_{32} > 0 (Normal) or < 0 (Inverted)?
- What's θ_{23} octant (> or < π/4) ?

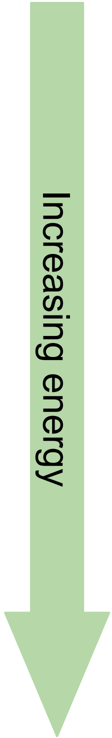
- hint for leptogenesis
- neutrino feature (Dirac or Majorana via 0νββ)
- GUTs

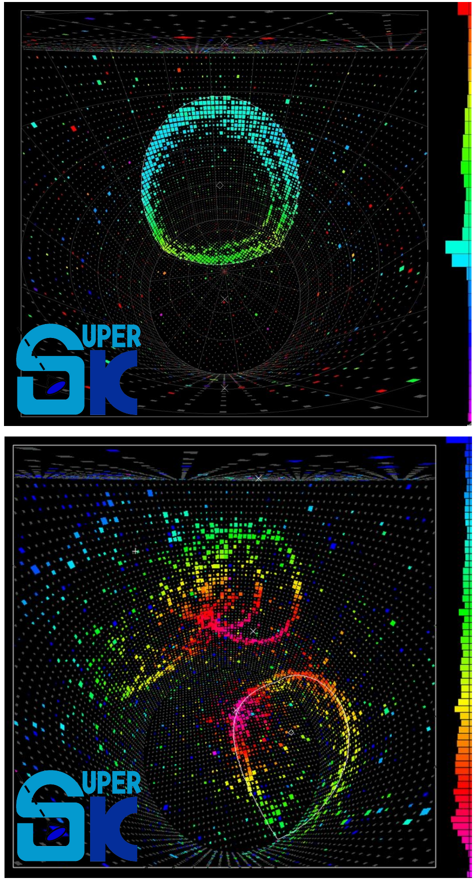
Neutrino Interactions



J. Formaggio and G. Zeller,
arXiv:1305.7513v1



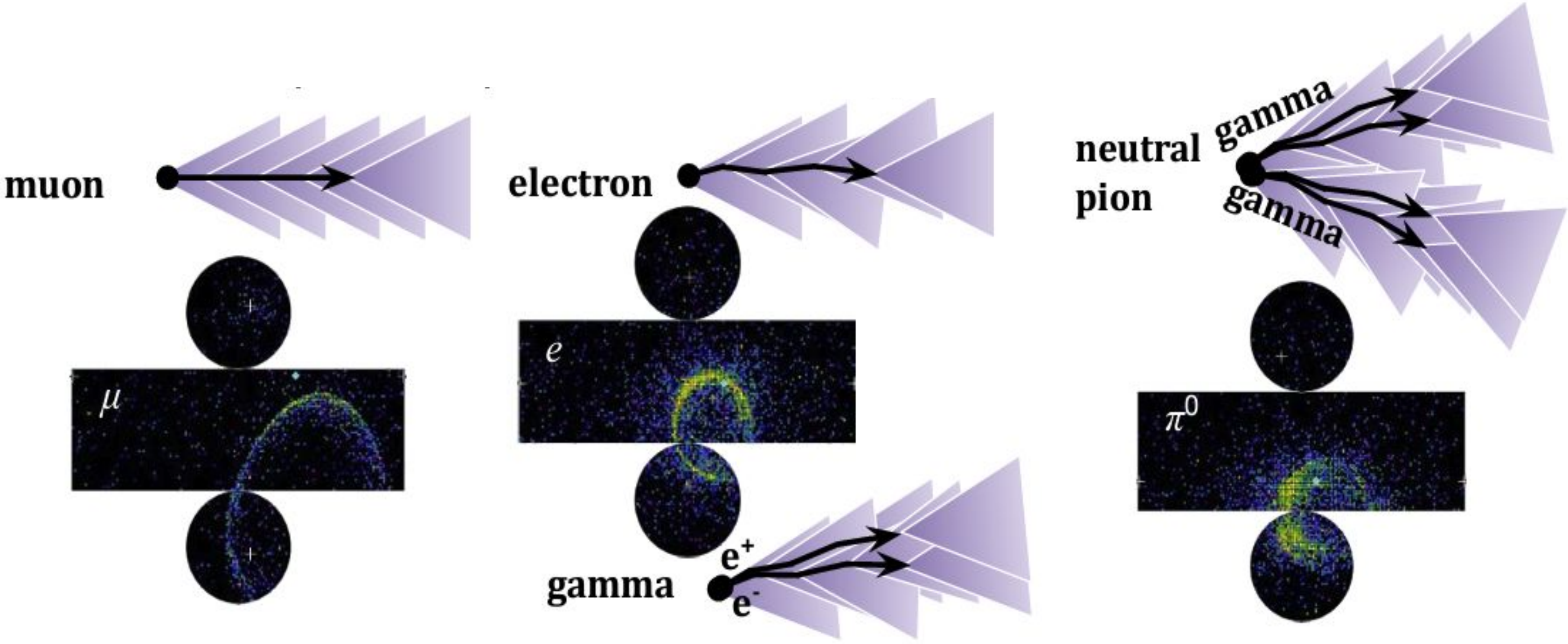




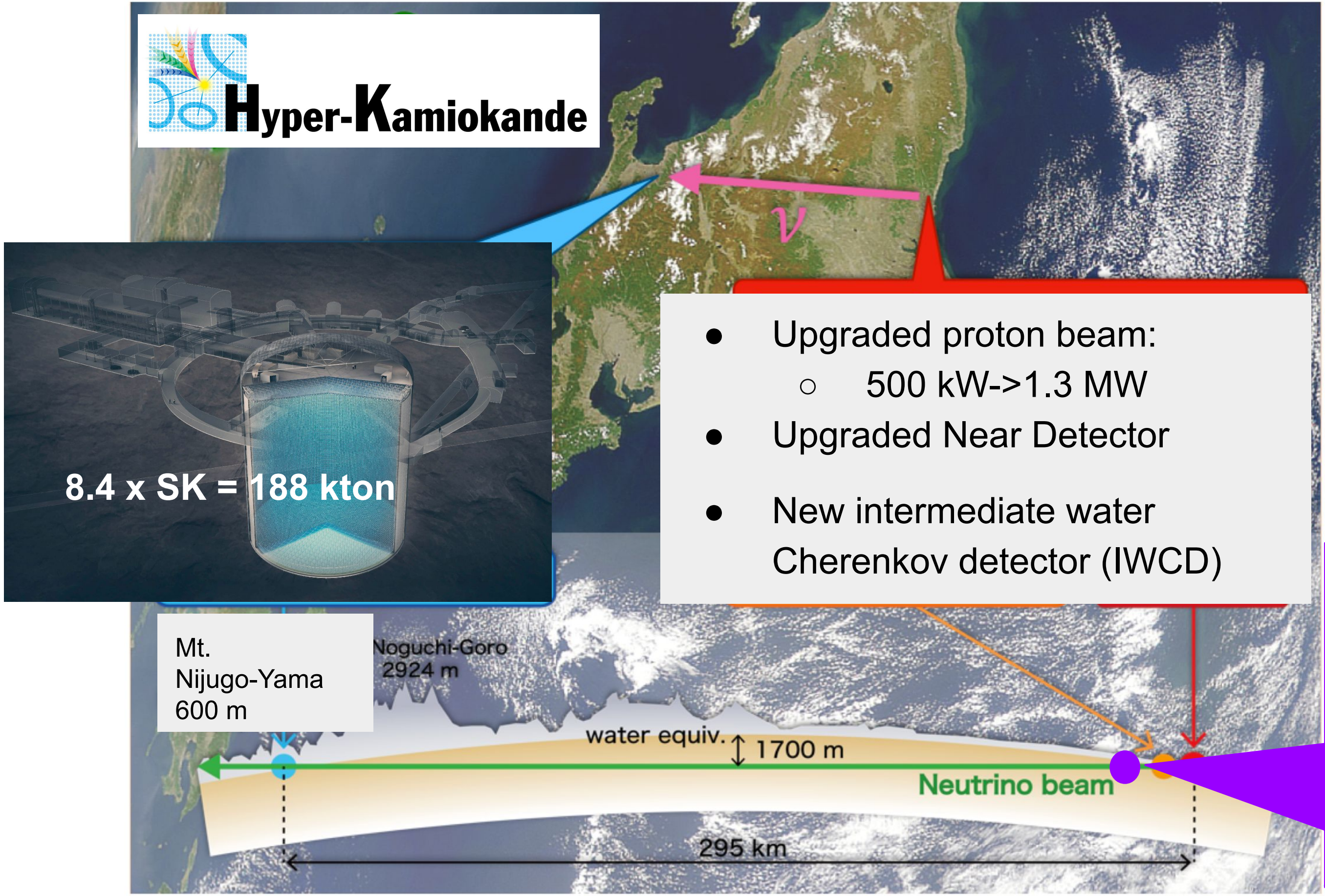
In water Cherenkov detectors, neutrino flavor is known by the outgoing lepton flavor in charged current (CC) interactions.

Event Topology in Water Cherenkov Detectors

Different particles have different types of rings

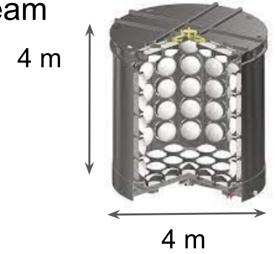


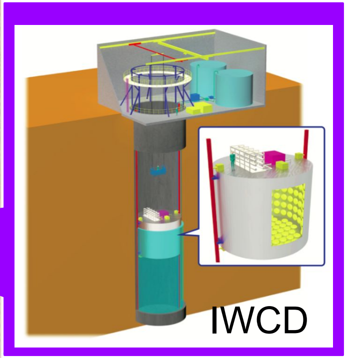
The Current and Next Generation Water Cherenkov Experiments



- Upgraded proton beam:
  - 500 kW->1.3 MW
- Upgraded Near Detector
- New intermediate water Cherenkov detector (IWCD)

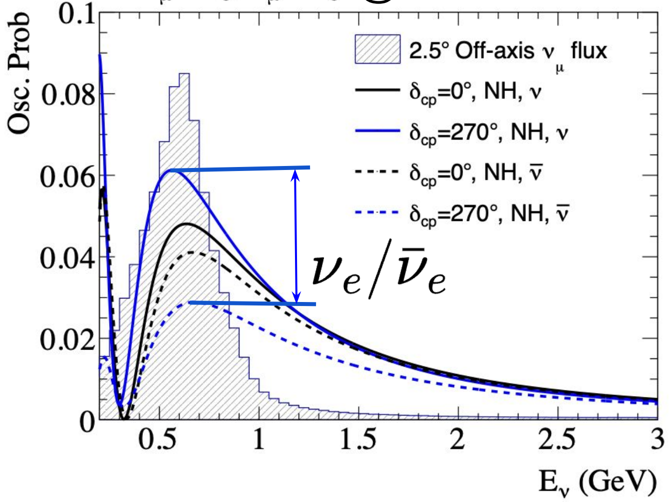
Water Cherenkov Test Experiment (WCTE) @ CERN
- Starting in 2024
- multi-PMT modules (mPMT)
- Tagged lepton/hadron beam



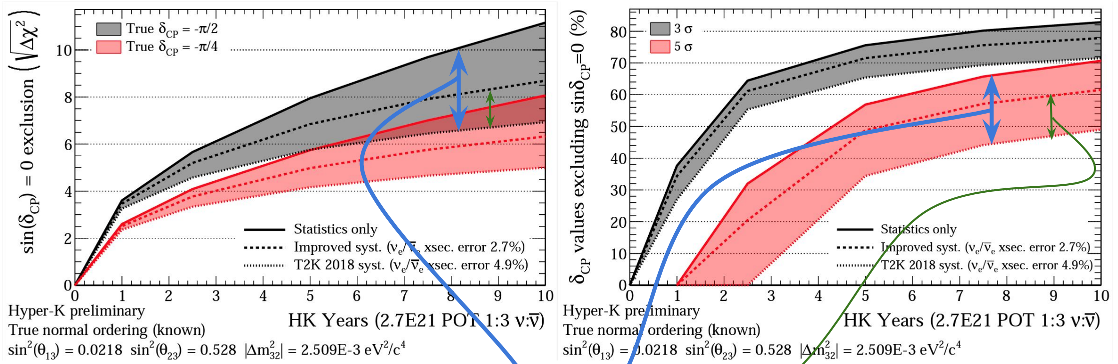


Potential for CP-Violation Discovery in Hyper-K

$\nu_\mu \rightarrow \nu_e, \bar{\nu}_\mu \rightarrow \bar{\nu}_e$ @T2K



Exclusion of $\sin(\delta_{CP})$ = 0 @ Hyper-K



Impact of T2K systematics

Improvements of systematics

Need < 3% for Hyper-K

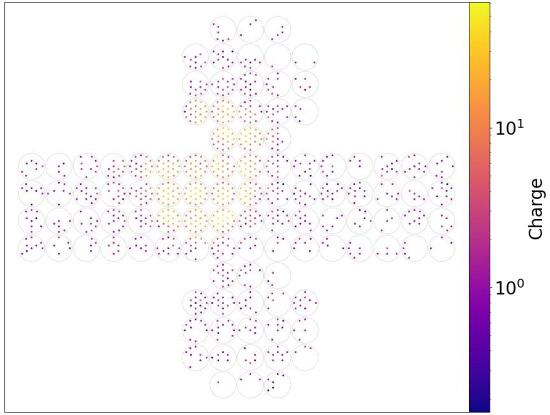
Fractional uncertainties from the LO error sources in T2K (%)

Phys. Rev. D 103, 112008 (2021)

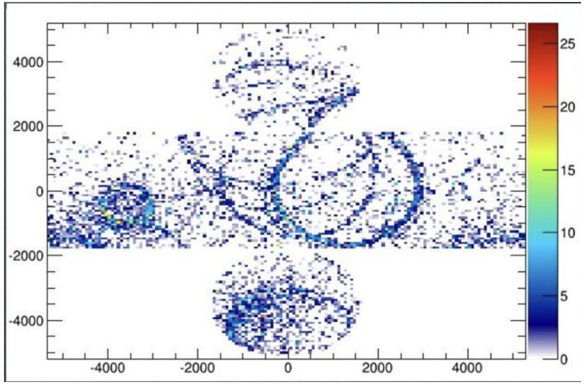
Flux+cross section	Nucleon removal energy	SK detector	π reinteraction	$\frac{\sigma(\nu_e)/\sigma(\nu_\mu)}{\sigma(\bar{\nu}_e)/\sigma(\bar{\nu}_\mu)}$	Bkg (NCγ,etc)	Total
2.7	3.6	1.5	1.6	3.0	1.5	6.0

Tasks to be Completed

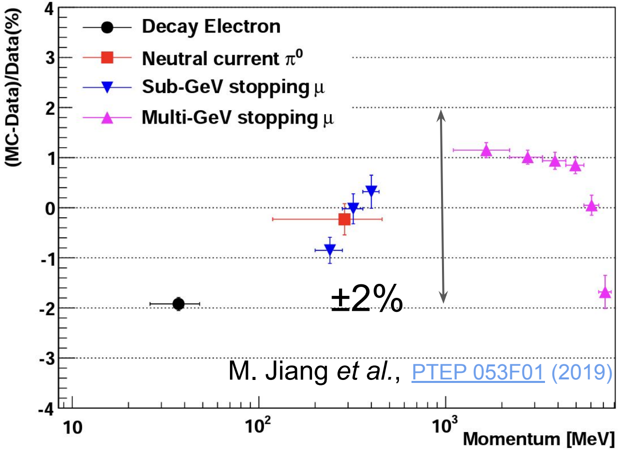
Better signal/background discrimination



Accurate and efficient reconstruction



Robust physics inference



M. Jiang *et al.*, PTEP 053F01 (2019)

The state-of-the-art

FiTQun is the event reconstruction algorithm used in SK and T2K based on the “maximum-likelihood” method.

The core of this process is to, given the PMT signal information, find among many competing event hypotheses **x** the one that maximizes the likelihood over all PMTs:

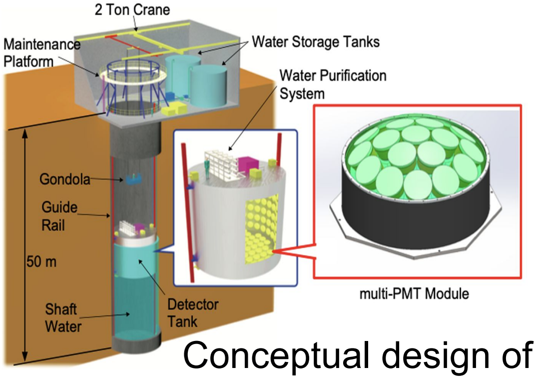
$$\boxed{L(x)} = \underbrace{\prod_{j}^{unhit} P_j(unhit \mid x) \prod_{i}^{hit} \{1 - P_i(unhit \mid x)\}} \underbrace{f_q(q_i \mid x) f_t(t_i \mid x)}$$

Combined likelihood function of all PMTs for event hypothesis **x**

Probabilities of a single photosensor registering hits from this event; *i* and *j* iterates through the hit/unhit PMTs respectively.

Comparing observed charge q and time t to the predictions by hypothesis **x**.

Improving e/μ classification

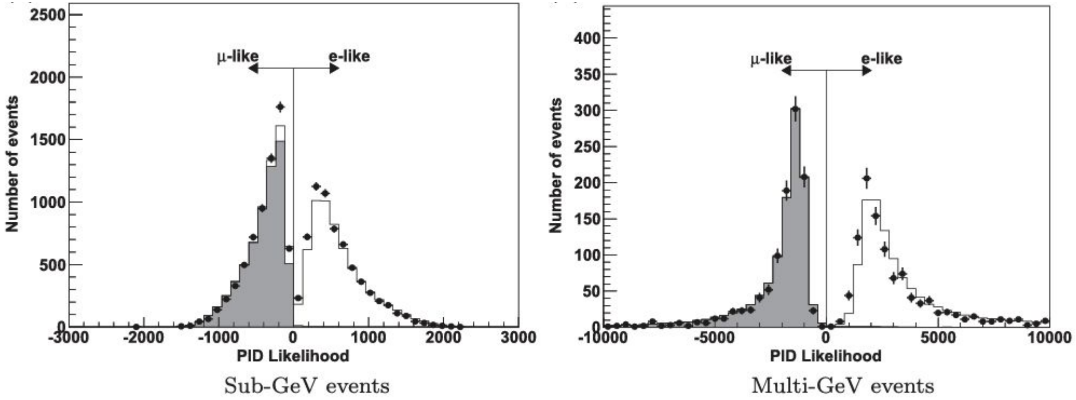


Conceptual design of IWCD

- ~300t water tank
- ~750 m from beam target
- ~400 mPMT modules

- Constraining $\frac{\sigma(\nu_e)/\sigma(\nu_\mu)}{\sigma(\bar{\nu}_e)/\sigma(\bar{\nu}_\mu)}$ with the < 1% intrinsic $\nu_e(\bar{\nu}_e)$ in the $\nu_\mu(\bar{\nu}_\mu)$ beam before oscillation.
- FiTQun can achieve > 99% Particle-IDentification (PID) accuracy in single-ring e/μ.
- Need > 99.9% efficiency in μ rejection.

fiTQun PID performance with atmospheric ν



M. Jiang *et al.*, PTEP 053F01 (2019)

ResNet-18 for e/μ classification

- Using ResNet-18 architecture (K. He et al. arXiv:1512.03385)
- Currently each mPMT is mapped to one channel of depth = 19 (for the PMT charge)
- The inclusion of PMT timing is in progress

N. Prouse, NuFact22

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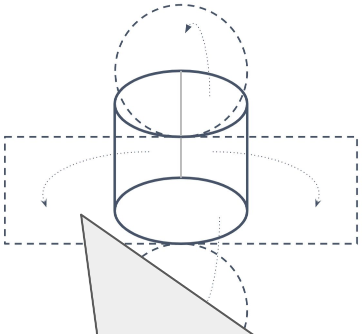
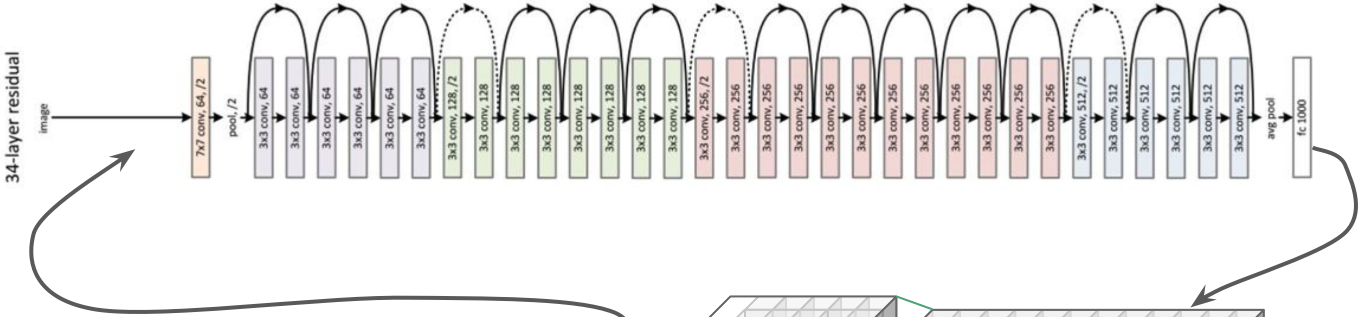
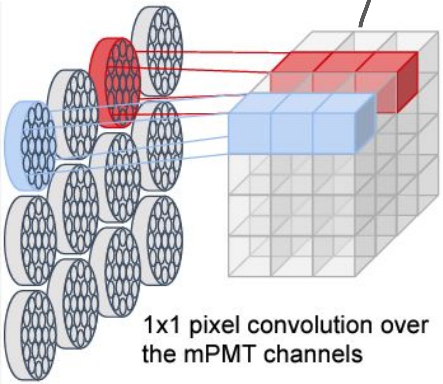
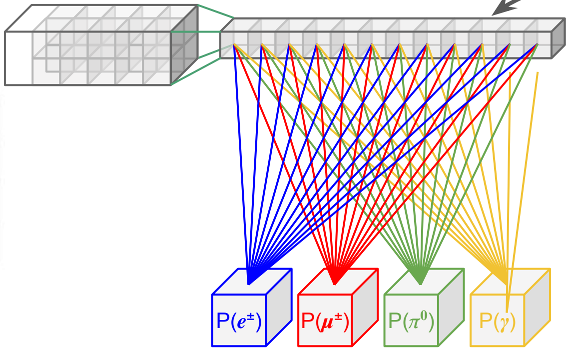




19 8cm PMTs in each mPMT module

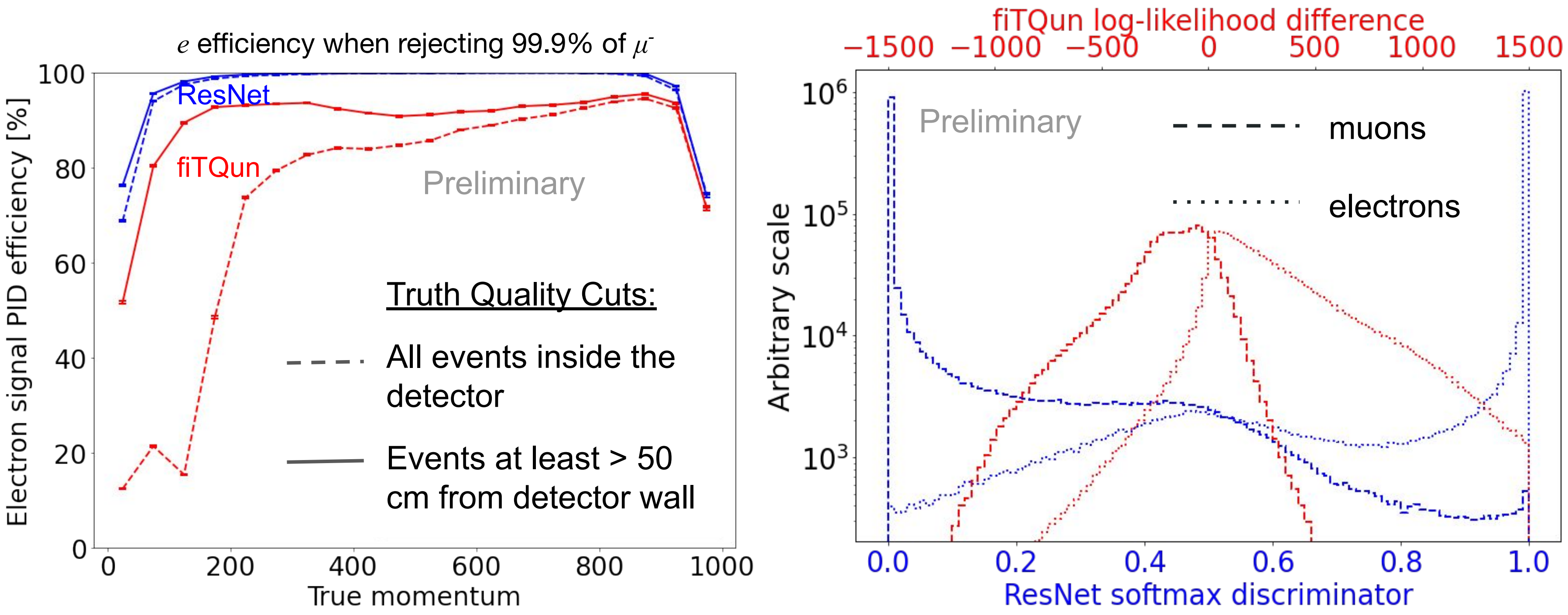


1x1 pixel convolution over the mPMT channels



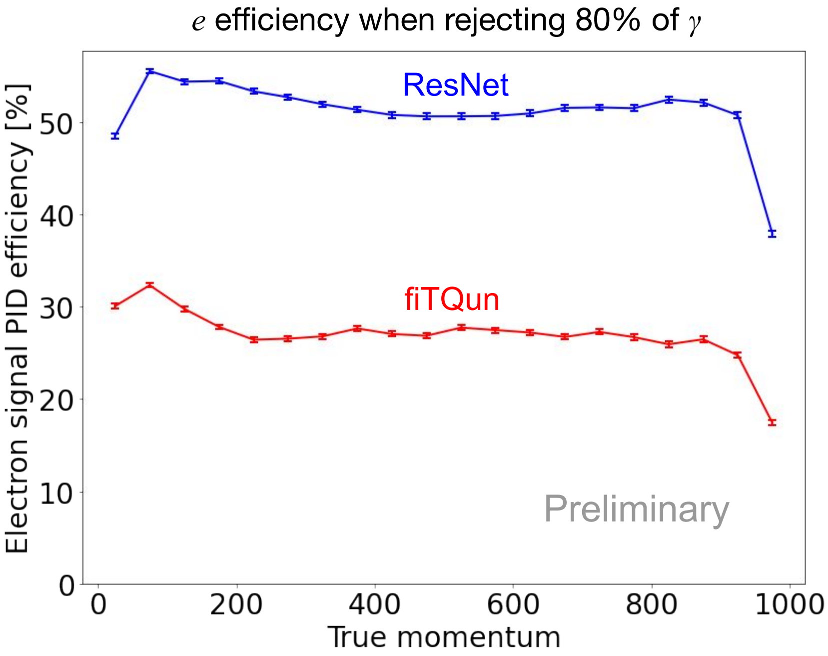
“Softmax discriminators” for PID likelihoods

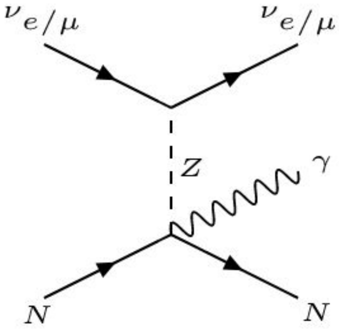
Performances of single-ring (SR) e/μ classification in IWCD



**fiTQun is not optimized for IWCD environment yet*

Separation of SR e/γ events in IWCD





A more challenging background since electron and gamma events appear almost identical in water.

Minute difference from the gamma initial track before the pair production of e^+e^-.

DL shows greater potential to achieve a better background rejection rate.

fiTQun is not optimized for IWCD environment yet

SR Event Reconstruction with ResNet-18

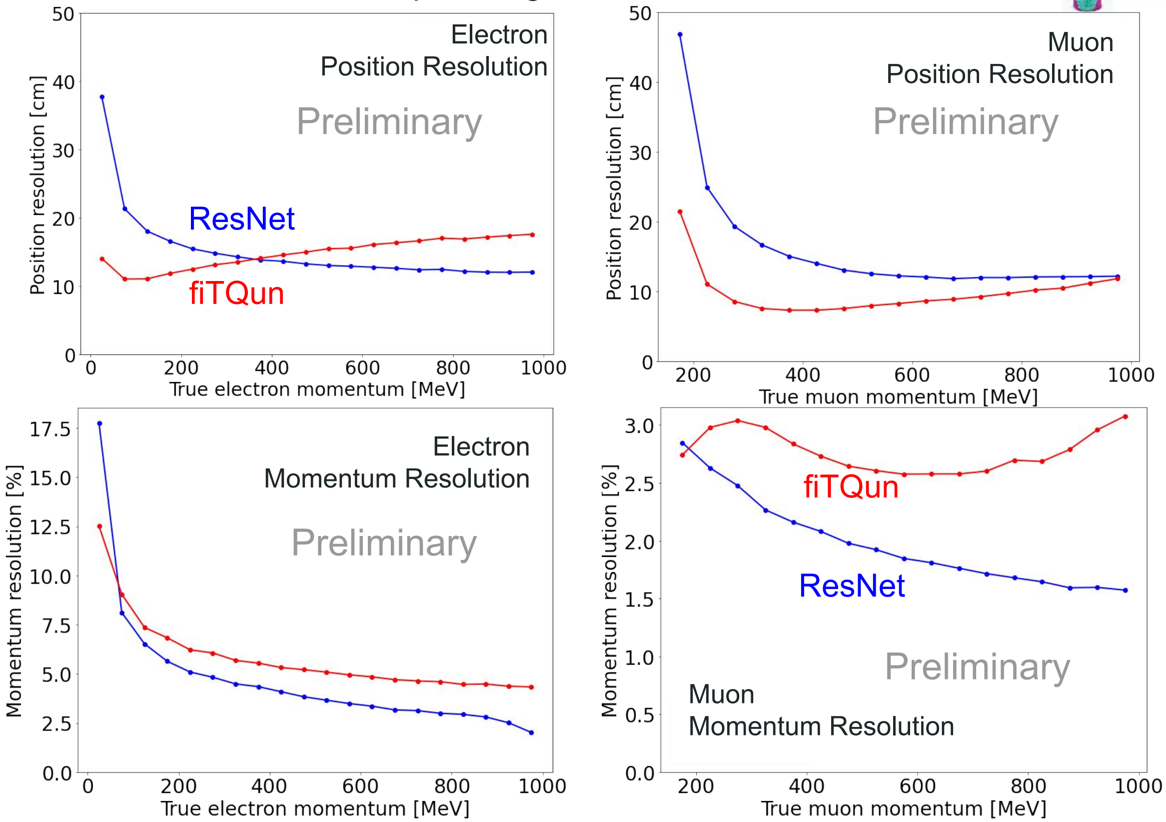
Output particle reconstructed quantities instead of PID in the last layer of the same ResNet.

So far only using the charge information of each PMT hit.

Including the timing is expected to further improve the reconstruction performance of ResNet.

**fiTQun is not optimized for IWCD environment yet*

SR "particle gun" events in IWCD

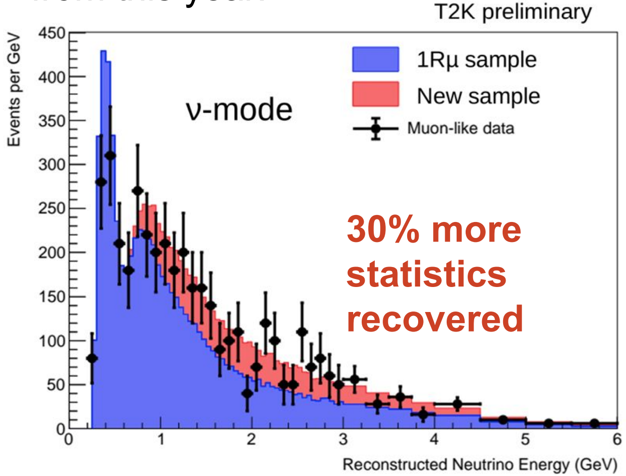


Multi-Ring (MR) Events

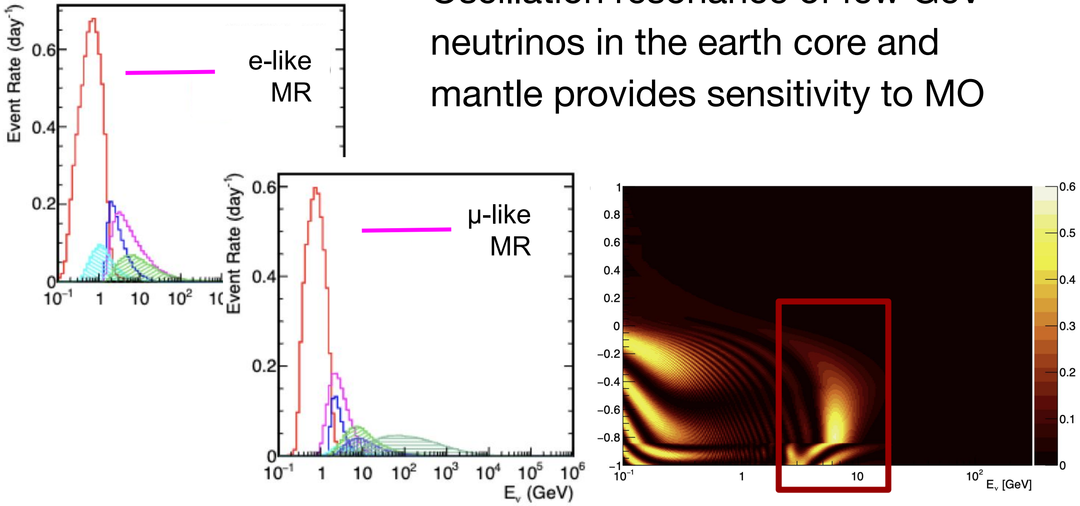
Multi-ring events are critical to neutrino oscillation analyses.

They usually have one or more $\pi^0/\pi^\pm$ in the intermediate and/or final event topology.

The T2K oscillation analysis will include multi-ring samples starting from this year!



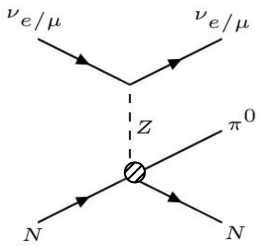
Oscillation resonance of few GeV neutrinos in the earth core and mantle provides sensitivity to MO

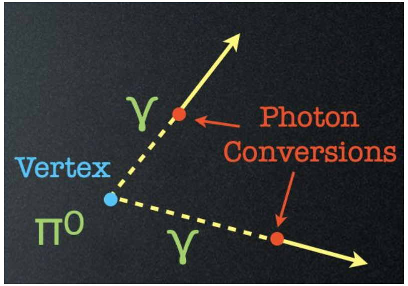


Oscillation analysis with SK atmospheric neutrinos

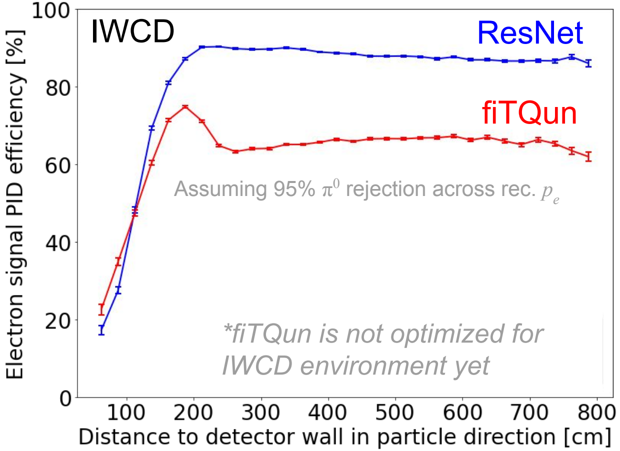
“Single-vertex” MR Events

NCπ^0 background





M. Wilking [Aspen Winter Workshop]



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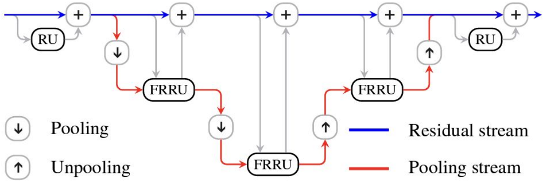
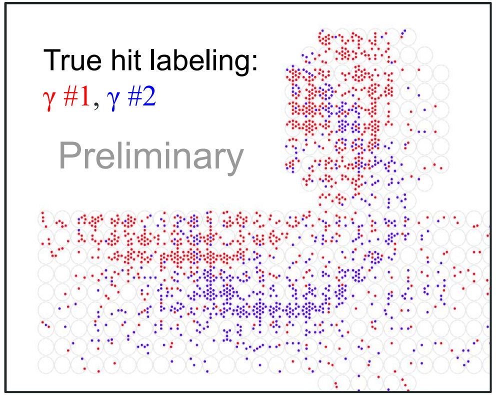
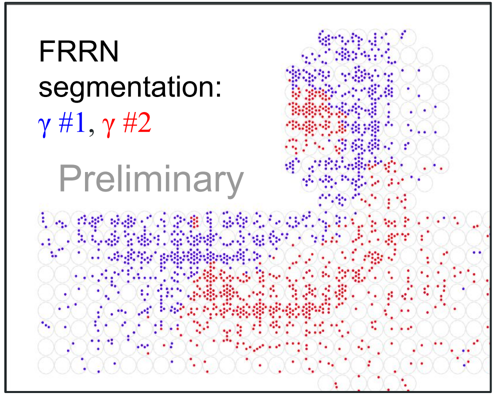
Panoptic segmentation for the two gamma rings using full-resolution residual networks (FRRN).

T. Pohlen et al., [2017]

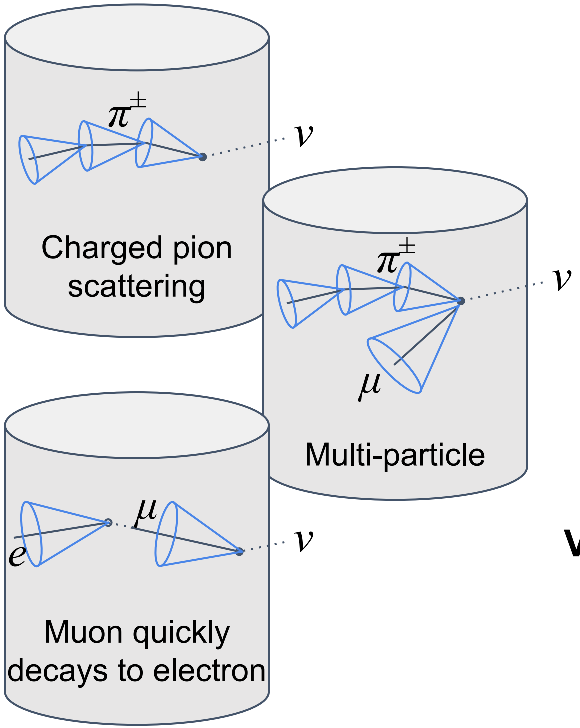


The features at all resolution levels can be propagated directly to the loss.





Multi-vertex MR Events



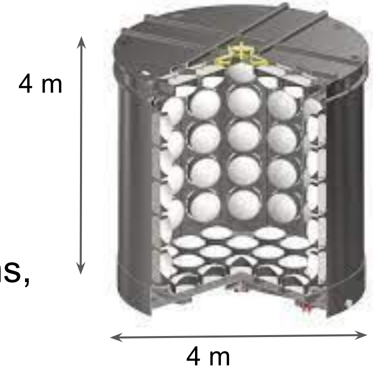
M. Jiang *et al.*, PTEP 053F01 (2019)

True number of rings	fiTQun reconstruction		
	1R	2R	$\geq$ 3R
True 1R	95.0%	4.64%	0.41%
True 2R	27.8%	66.7%	5.56%
True $\geq$3R	7.04%	25.5%	67.5%

Many challenges exist:

- Pion re-interaction rate uncertainties
- Pile-up and saturation of multi-rings
- Similar Cherenkov rings, e.g. $\pi^{\pm}$ vs. $\mu^{\pm}$
- Computing efficiency [O(min)->O(ms)]

Water Cherenkov Test Experiment (WCTE)



Various studies ongoing:

- NN including Boosted Decision Trees (BDT), ResNet, PointNet, and more.
- WCTE with 0.1~1.2 GeV tagged e/μ/π/p beams, starting in 2024, will help achieving better reconstruction and understanding of these particles' detection in water.

CNN-based Cherenkov Ring Generator

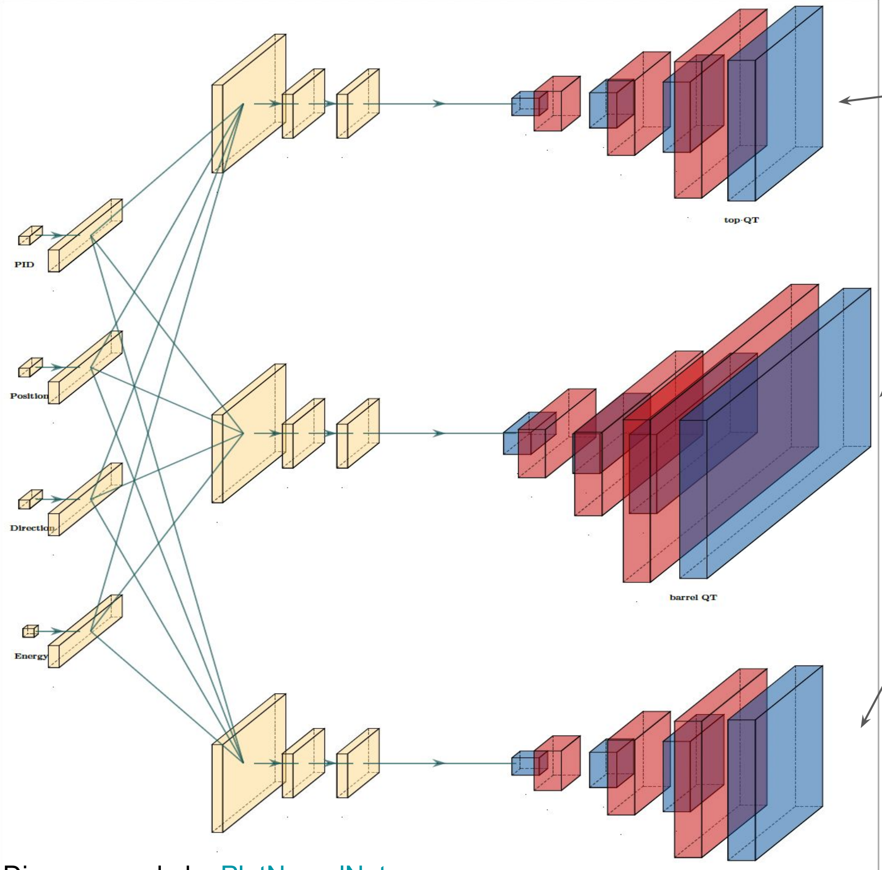
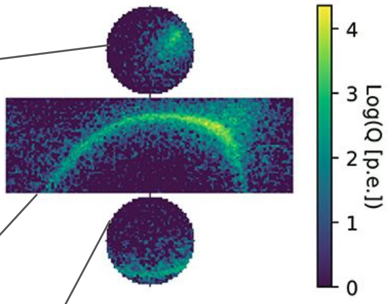


Diagram made by PlotNeuralNet



arXiv:2202.01276

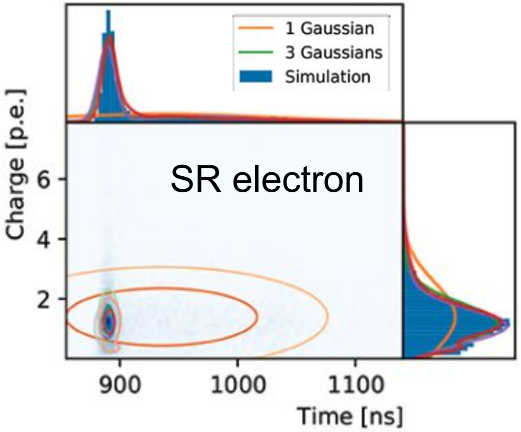
Cylindrical detector separated into three parts: top, barrel, and bottom.

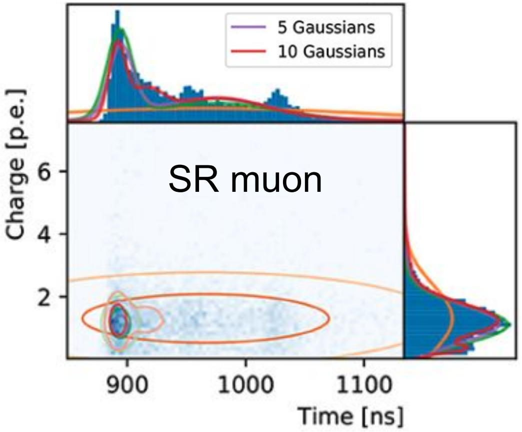
- Generating WC detector responses (Q&T correlated) to a particle of given particle type, energy, position, and direction.
- Loss designed based on the fiTQun likelihood with substantially more flexibility, and can be trained on the "physics MC".

CNN-based Cherenkov Ring Generator

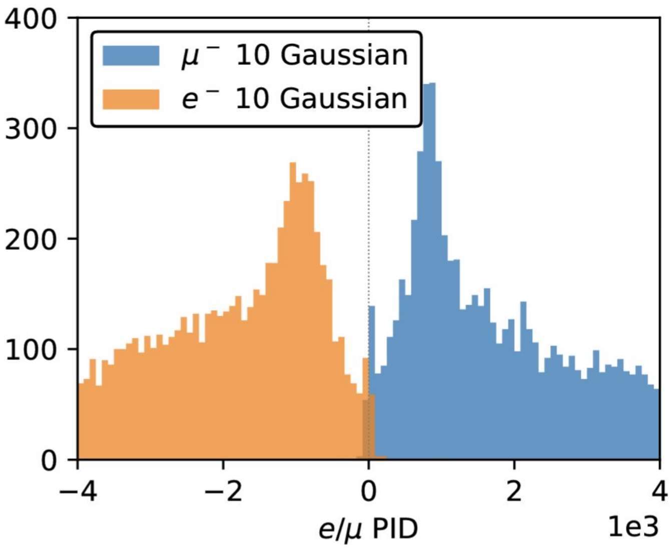
The charge and timing likelihood functions of each PMT hit are not always simple Gaussians due to various factors including electronics, multi-PE hits, scattered photons, and more.

AI/DL techniques allow more flexibilities in modeling individual PMT's responses and help achieving better representation with finer details.





arXiv:2202.01276

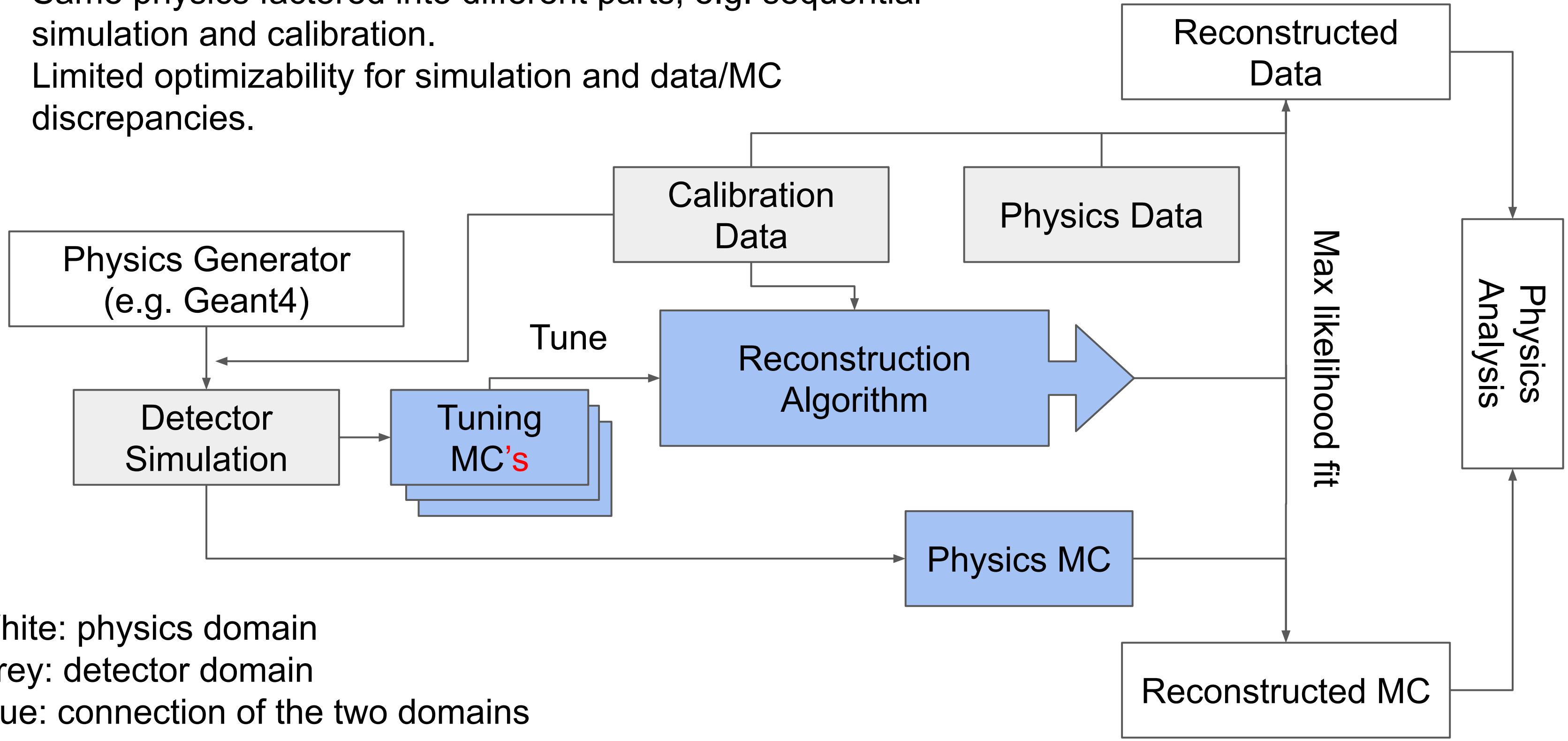


Demonstration of the PID likelihoods given by a trained CNN for single ring events uniformly generated inside the WC detector. Pile-up of events around the boundary comes from the events near detector walls.

Towards a robust physics inference

A conventional analysis pipeline

- Same physics factored into different parts, e.g. sequential simulation and calibration.
- Limited optimizability for simulation and data/MC discrepancies.

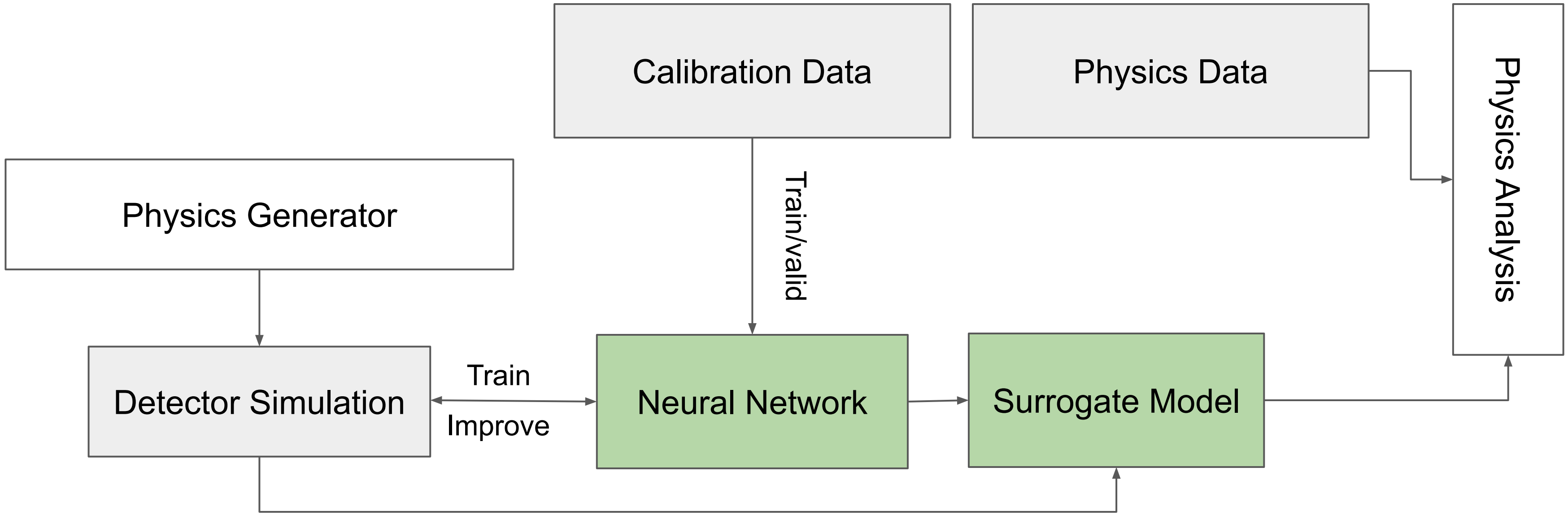


White: physics domain
Grey: detector domain
Blue: connection of the two domains

Towards a robust physics inference

AI/DL-based analysis pipeline

- Optimizing the simulation as a whole with calibration data
- Explainable with well-understood physics while good approximation to complex features in real data with NN



US-Japan Science and Technology Cooperation Program

See P. Tsang's talk!

Enabling New Machine Learning Techniques for the Data-Driven Physics Modeling and Analysis of Long Baseline Neutrino Oscillation Experiments

K.Terao, SLAC (Principal Investigator, the U.S.)
P. de Perio, IPMU (Principal Investigator, Japan)
P. Tsang, SLAC (Co-Investigator)
H. Tanaka, SLAC (Co-Investigator)
Z. Zhang, SLAC (Co-Investigator)
Y. Nashed, SLAC (Co-Investigator)
M. Wilking, SLAC (Co-Investigator)

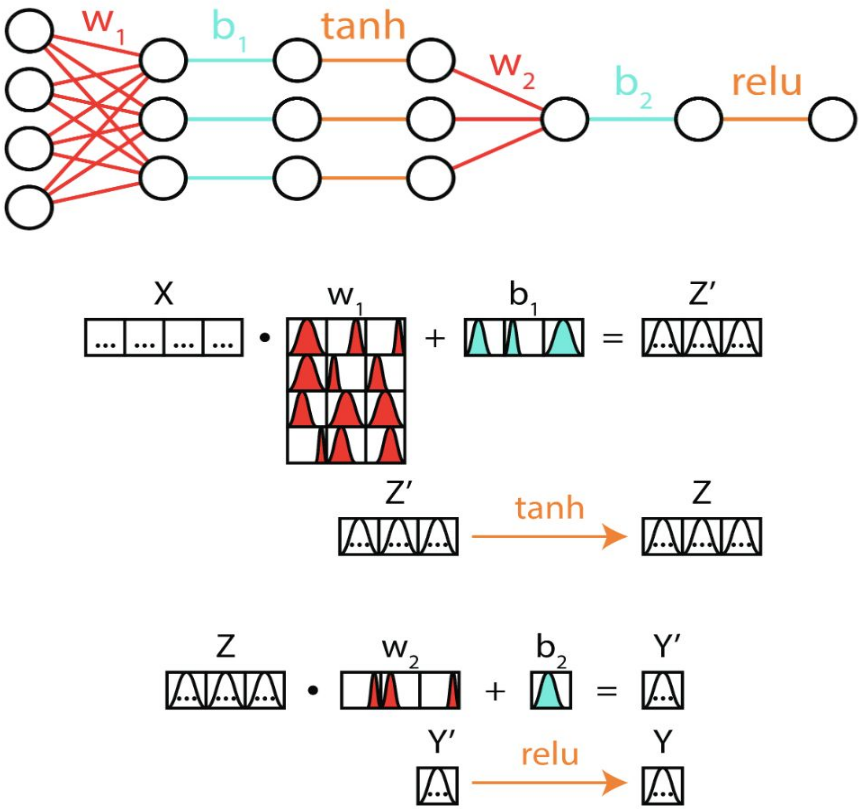
SLAC

DUNE DEEP UNDERGROUND NEUTRINO EXPERIMENT

Hyper-K

IPMU INSTITUTE FOR THE PHYSICS AND MATHEMATICS OF THE UNIVERSE

Towards a robust physics inference



Work in progress by J. Potel, ILANCE

Systematic error estimation is a popular and critical subject in the scientific applications of AI/DL techniques.

Exploring new ideas to improve the current working example of Cherenkov ring generator (arXiv:2202.01276).

Implementation of Bayesian Neural Network (BNN) is under investigation.

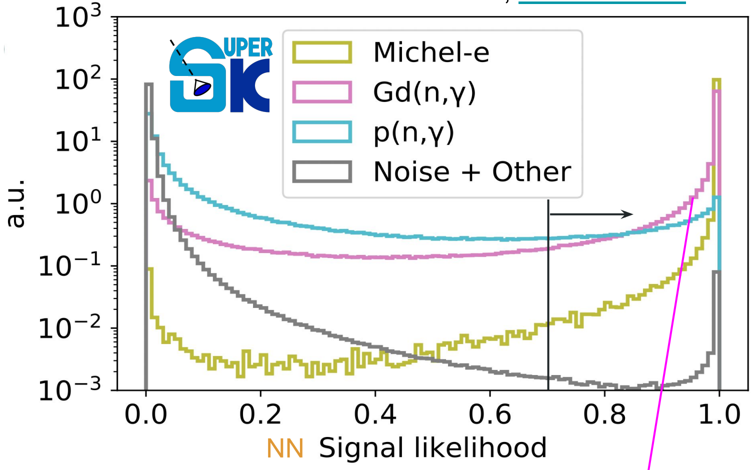
Other applications of DL - neutron classification

Neutrons freed from an Inverse Beta Decay (IBD) will be captured by a proton or Oxygen nucleus in ~200 μs after thermalization, releasing a ~2.2 MeV γ.

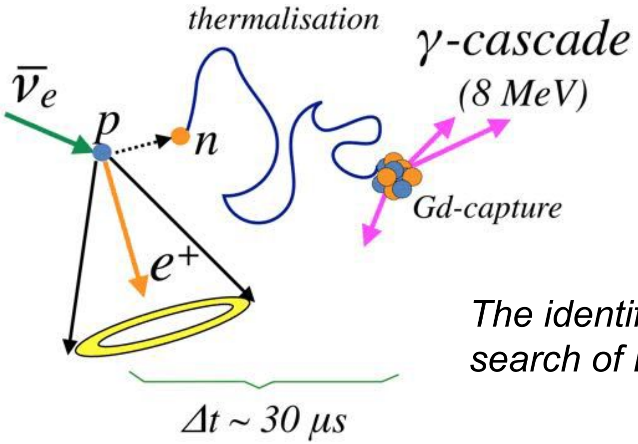
The same neutron capture with Gadolinium nucleus is much faster (~30 μs) and stronger signals (~8 MeV γ).

Detection threshold of SK is ~4 MeV.

S. Han, Neutrino 2022



80% efficiency and 98% purity of Gd(n,γ) achieved by NN in SK.

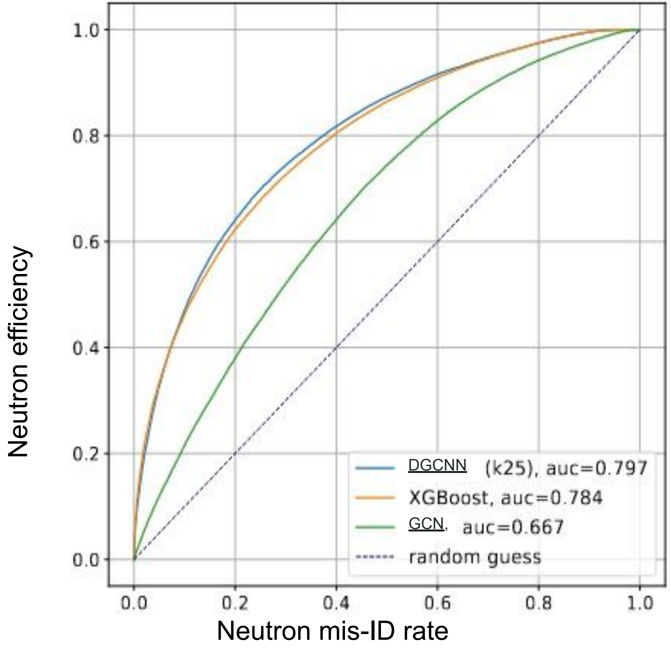


The identification of IBD via neutron capture is a key to the search of Diffusive Supernova Neutrino Background (DSNB).

Other applications of DL - neutron classification

IWCD Neutron Tagging, arXiv:2206.12954

Various studies of different NN architectures ongoing for improving neutron capture detection efficiency with Gd-loaded IWCD simulation.



Dynamic Graph Convolutional Neural Network (DGCNN, arXiv:1801.07829) and BDT (XGBoost, T. Chen and C. Guestrin) can achieve similar results and outperform Graph Convolutional Network (GCN, arXiv:1609.02907).

The dynamic grouping of the nearest pair of nodes in DGCNN allows the model to learn non-local feature in a graph, while the feature engineering of XGBoost provides great level of model interpretability.

Summary and Outlook

- Neutrino physics with water Cherenkov detectors is entering the era of high precision:
  - Systematic uncertainties will become the dominant limits to achieve new discoveries.

- To better constrain the systematics, various deep learning techniques are under development and show great potential:
  - New methods also enable new studies such data-driven physics modelling

- Simultaneously, fiTQun is being improved and generalized as well:
  - More fair comparisons around the corner!

- Software frameworks for DL is in place, welcoming application to all physics topics and further architecture development

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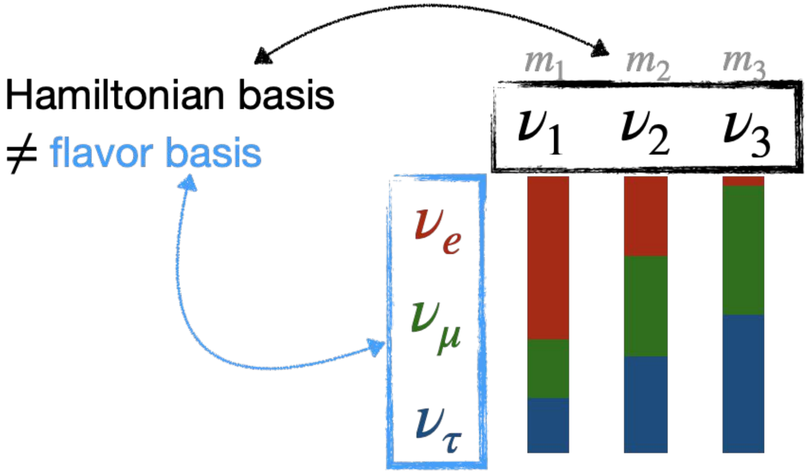
Appendix

The Standard Neutrino Oscillations



Propagation of Hamiltonian (mass) state and detection in the weak interaction eigenstate causes flavor change -> **Neutrino Oscillation**

Oscillation probability is related to:

- $\Delta m^2_{ij} \cdot L/E_\nu$, where $\Delta m^2_{ij} \equiv m_i^2 - m_j^2$ and $i, j = 1, 2, 3$
- The mixing (PMNS) of the Hamiltonian eigenvectors

$$\begin{bmatrix} \nu_e \\ \nu_\mu \\ \nu_\tau \end{bmatrix} = \boxed{\begin{bmatrix} 1 & 0 & 0 \\ 0 & c_{23} & s_{23} \\ 0 & -s_{23} & c_{23} \end{bmatrix} \begin{bmatrix} c_{13} & 0 & s_{13}e^{-i\delta_{\mathrm{CP}}} \\ 0 & 1 & 0 \\ -s_{13}e^{i\delta_{\mathrm{CP}}} & 0 & c_{13} \end{bmatrix} \begin{bmatrix} c_{12} & s_{12} & 0 \\ -s_{12} & c_{12} & 0 \\ 0 & 0 & 1 \end{bmatrix}} \begin{bmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{bmatrix}$$

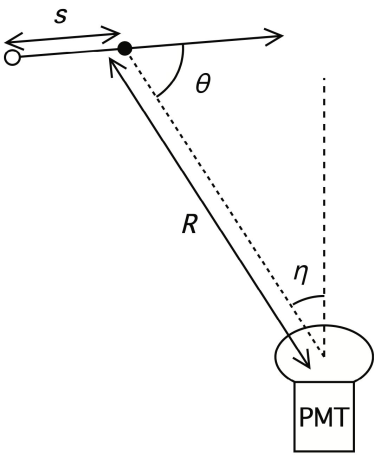
FiTQun reconstruction algorithm

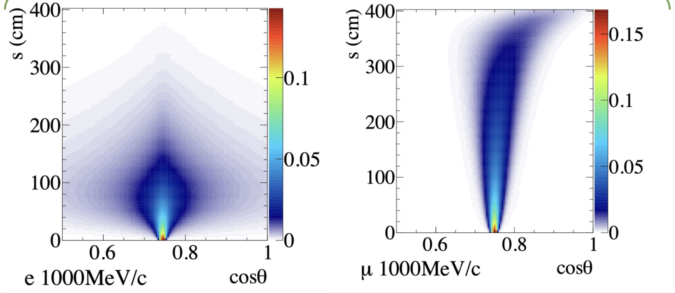
P. de Perio, NNN22

$$L(\mathbf{x}) = \prod_{j}^{\text{unhit}} P_j(\text{unhit}|\mu_j) \prod_{i}^{\text{hit}} \{1 - P_i(\text{unhit}|\mu_i)\} f_q(q_i|\mu_i) f_t(t_i|\mathbf{x})$$

- In practice, "predicted charge" is first calculated: $\mu = \mu^{dir} + \mu^{sct}$ which is used in the likelihood evaluation, where the direct light contribution is:

$$\mu^{\text{dir}} = \underbrace{\boxed{\Phi(p)}}_{\text{Light yield}} \overbrace{\boxed{\int ds}}^{\text{Integral over track length}} \underbrace{\boxed{g(p, s, \cos\theta)}}_{\text{Cherenkov emission profile}} \overbrace{\boxed{\Omega(R)}}^{\text{PMT solid angle}} \underbrace{\boxed{T(R)}}_{\text{Light Attenuation}} \overbrace{\boxed{\epsilon(\eta)}}^{\text{PMT angular response}}$$





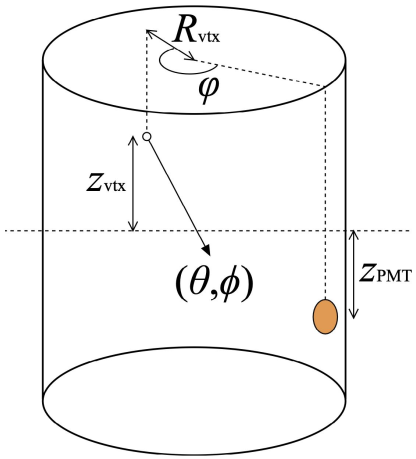
- Particle ID information encoded here and extracted from likelihood comparison of different hypotheses

FiTQun reconstruction algorithm

P. de Perio, NNN22

$$L(\mathbf{x}) = \prod_j^{\text{unhit}} P_j(\text{unhit}|\mu_j) \prod_i^{\text{hit}} \{1 - P_i(\text{unhit}|\mu_i)\} f_q(q_i|\mu_i) f_t(t_i|\mathbf{x})$$

- In practice, “predicted charge” is first calculated: $\mu = \mu^{dir} + \mu^{sct}$ which is used in the likelihood evaluation, where the direct light contribution is:



$$\mu^{\text{sct}} = \Phi(p) \int ds \, \frac{1}{4\pi} \rho(p,s) \Omega(R) T(R) \epsilon(\eta) A(s)$$

$$\rho(p,s) \equiv \int g(p,s,\cos\theta) \, d\Omega$$

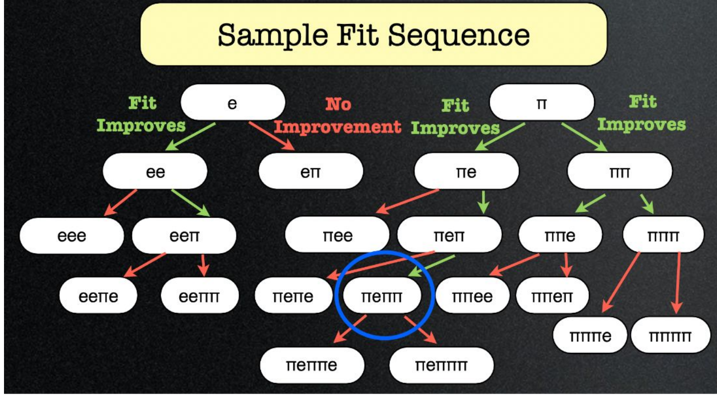
$$A(s) = A(x_{\text{PMT}}, z_{\text{vtx}}, R_{\text{vtx}}, \varphi, \theta, \phi) \equiv \frac{d\mu^{\text{sct}}}{d\mu^{\text{iso,dir}}}$$

- Assuming direction-averaged Cherenkov profile
- Scattering table derived from uniformly distributed, isotropic low energy electrons

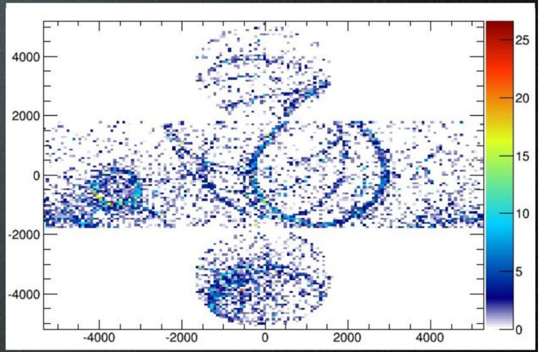
FiTQun reconstruction algorithm

M. Wilking, [DUNE Module of Opportunity Workshop]

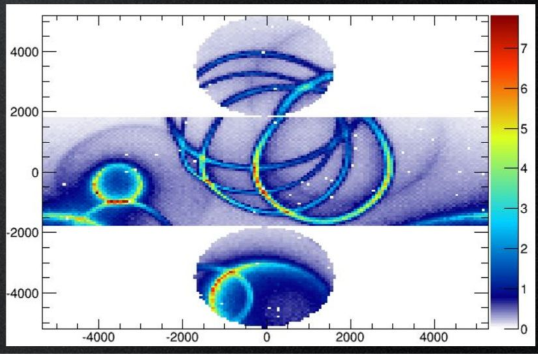
- FiTQun can currently reconstruct up to 6 rings in a staged approach
  - Each step sequentially adds a “track-like” (π^+) or “shower-like” (e) ring
  - The chain terminates when adding a ring does not sufficiently improve the fit
- Ring counting & PID are significantly improved



Hit Charge Distribution



Reconstructed “Mean” Charge



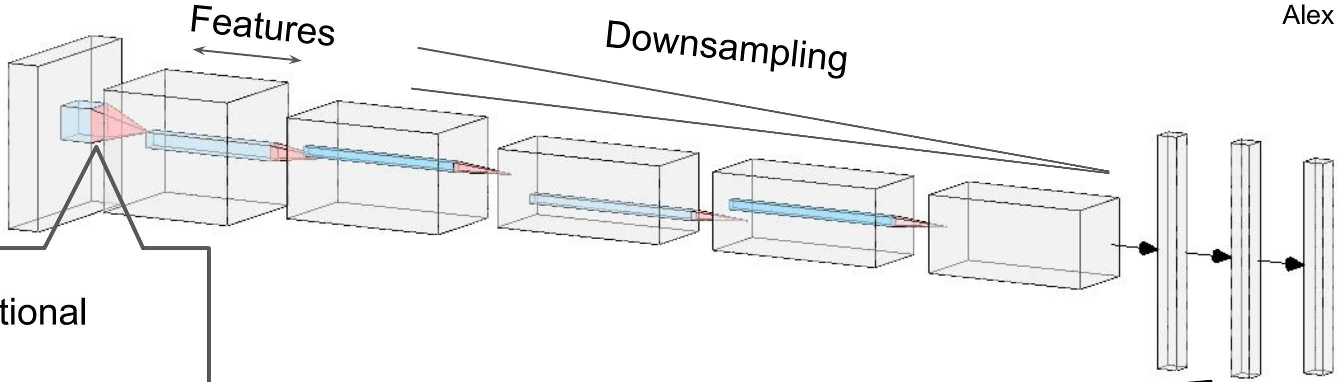
Computing Time Improvement

P. de Perio, NNN22

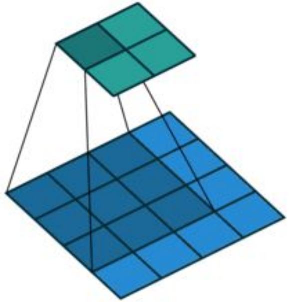
- Growing MC (and data) sample sizes in high precision era
- Event reconstruction becoming a computing time limiting factor
  - Especially in systematic error studies varying a large number of detector parameters
- fiTQun: ~90 seconds per event on CPU (for e, μ, $\pi0$ hypotheses in IWCD)
  - Multi-ring events >~5 minutes
- ResNet: ~6 ms per event on GPU (for classification and e, μ regression)
- Factor of 10^5 speed-up
  - But actual throughput will depend on how many GPUs you can afford
- Assuming the size and cost of the small CPU and GPU clusters at IPMU:
  ~ 5000x more throughput with the $ spent on GPUs instead

Convolutional Neural Network (CNN)

Diagram tool by
Alex Lenail, NN-SVG



Convolutional
kernel



Vincent Dumoulin, Francesco Visin
(arXiv:1603.07285)

Fully connected layers

$$\mathbf{x}_{i+1} = \sigma(\mathbf{w}_i \mathbf{x}_i + \mathbf{b}_i)$$

Non-linear
activation function

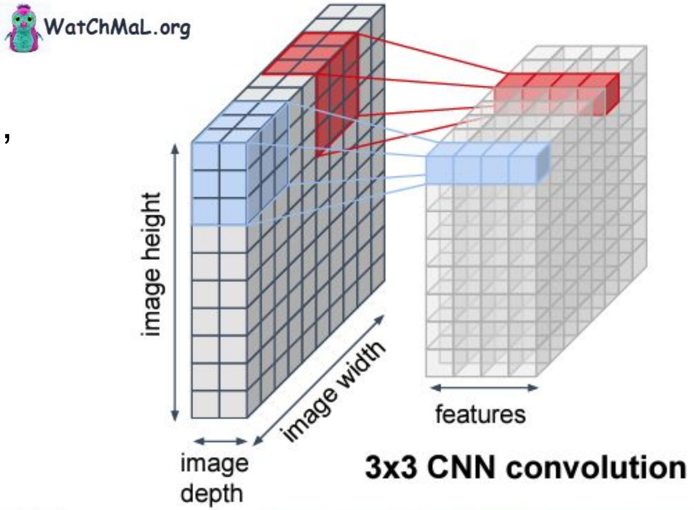
Multiplicative
weights

Additive
biases

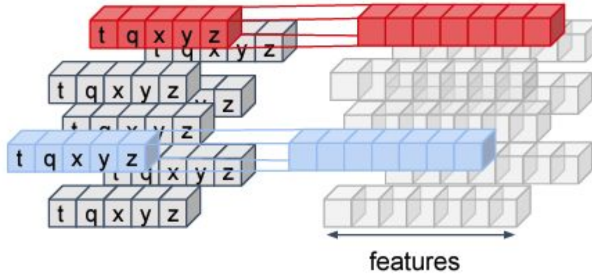
PointNet

PointNet designed to work on ‘point clouds’ rather than images of pixels

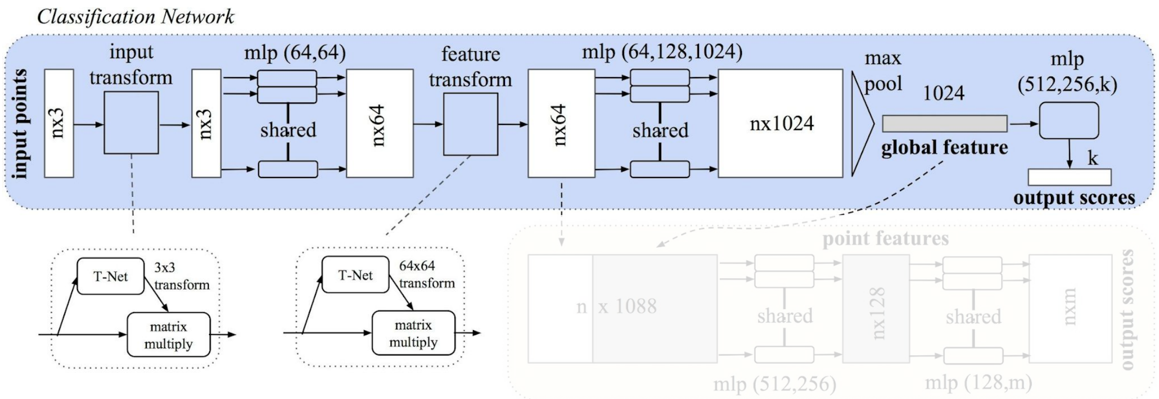
- Each hit PMT is a ‘point’ with time, charge & position, not fixed to grid
- Convolution-like operations act on each point’s charge, time and position
- Learn global transformations applied to all points
- Single pooling layer from all points to 1D array
- Can apply to any detector geometry



3x3 CNN convolution



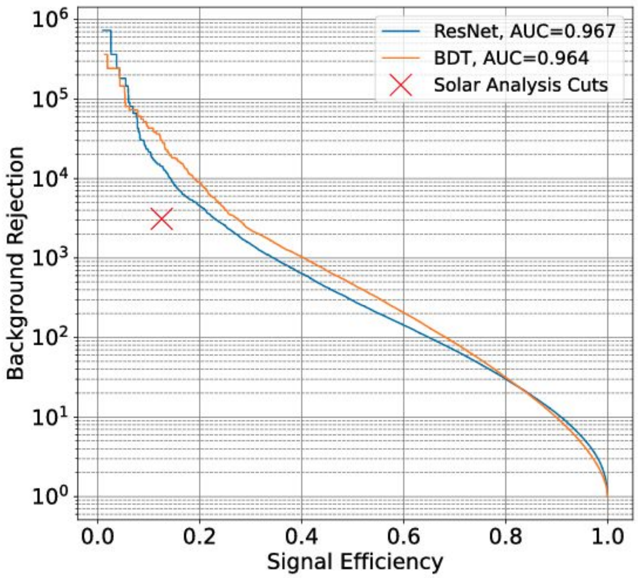
PointNet MLP (1x1 convolution on point cloud)



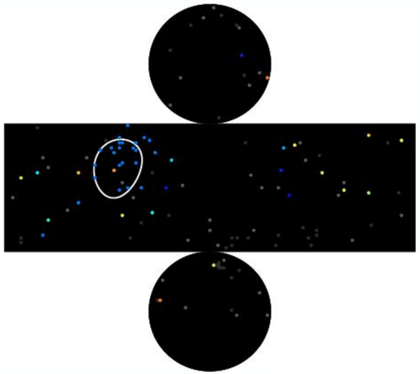
Other applications of DL - solar neutrino classification

A. Yankelevich, NuFact22

Object: reduce radioactive background noise in low energy (a few MeV) solar neutrino events at SK.



1/FPR vs Signal Efficiency. All events 2.49 MeV < E_{kin} < 3.49 MeV.



Sparse hits of low energy events are challenging for ResNet to extract features.

Performance also susceptible to noise model.

BDT trained on the reconstructed variables used in SK's solar neutrino analyses outperform the traditional selection cuts 6x better.

The Water Cherenkov Test Experiment (WCTE)

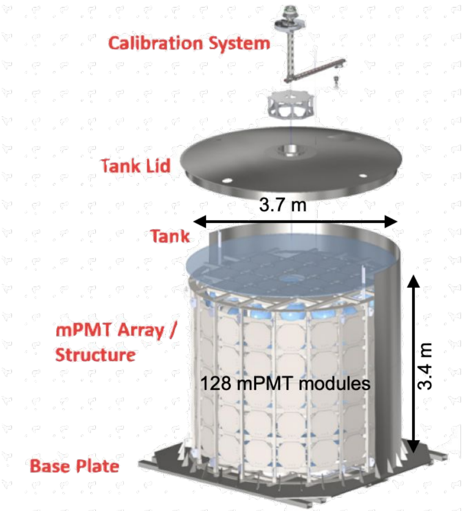
Prototype detector for beam test at **CERN in 2024**

mPMT pilot run and test-bed for precision calibration and AI/DL

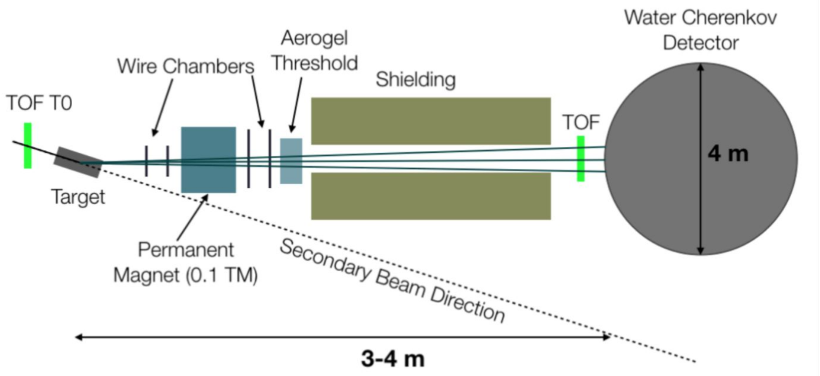
Opportunity to improve systems prior to IWCD and Hyper-K

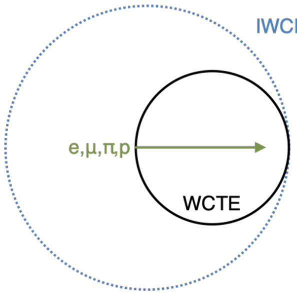
Control samples to constrain neutrino experiment modeling

Immediate impact to existing experiments (T2K, Super-K)



p, e, $\pi^{\pm}$, $\mu^{\pm}$ (potentially tagged-γ) particle beam from 140-1200 MeV/c





CERN SPSC Proposal; Hadron production EOI