AI/ML helps solving challenges in neutrino experiments?

Junjie Xia

SLAC/Stanford University
junjiex@stanford.edu

April 25, 2025

My journey started in 2017

2017: Bachelor of Science in Astrophysics, UCLA

2017-2022: PhD student at ICRR/UTokyo

+ Super-Kamiokande (SK)
+ T2K
+ Hyper-Kamiokande

2022-2024: JSPS postdoc fellow at IPMU

+ WCTE
+ CIDeR-ML

2025~: Postdoc at SLAC/Stanford

How and when did Mark happen?

Back in 2017 when I just started my PhD…

The open questions for neutrinos

? The exact value of:

- CP violation phase δ_{CP}
- Mass ordering (MO)
- Mixing angle θ_{23}

? The absolute value of neutrino masses, and why

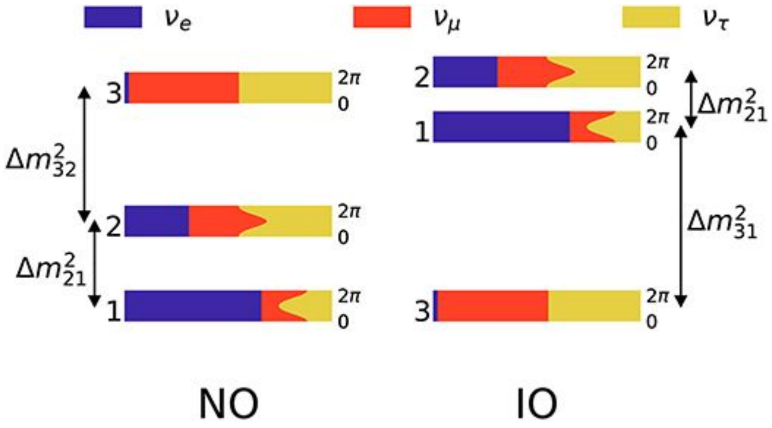
? The diffusive supernova neutrino background

? Coincidence of cosmic neutrinos and astrophysical events

…

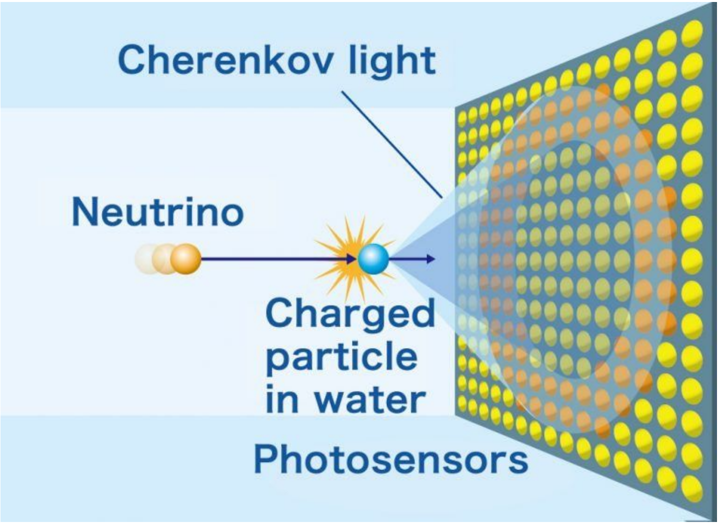
Is it two small and one big masses (Normal Ordering) or one small two big (Inverted Ordering)?

- Key constraints for various measurements including δ_{CP}, $0\nu\beta\beta$, etc.



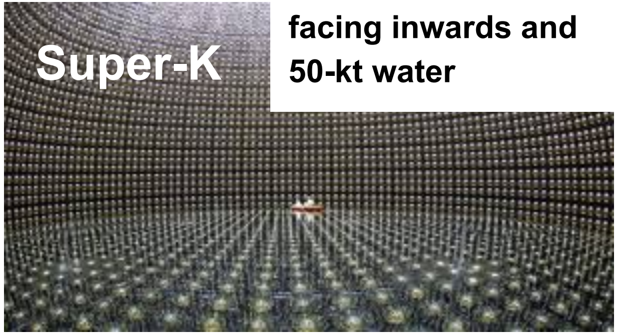
P.F.de Salas, S.Gariazzo, O.Mena, C.A.Ternes, M.Tortola, Front. Astron. Space Sci.,High-Energy and Astroparticle Physics Vol. 5 - 2018

Water Cherenkov detectors



https://physicsopenlab.org

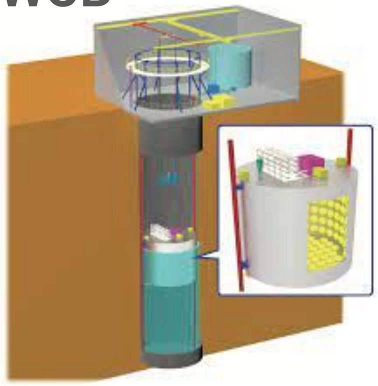
Proven reliable technique and already approved roadmap to the future experiments.



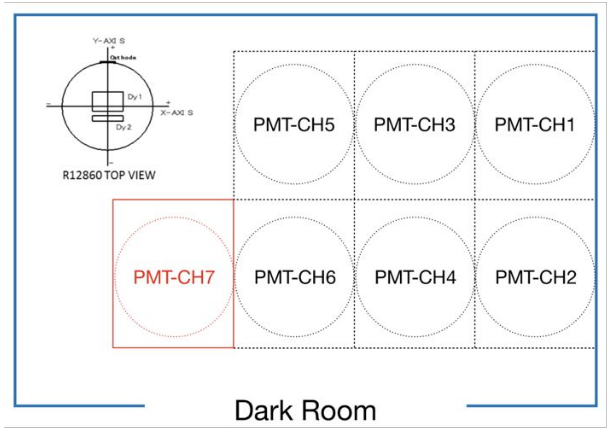
SK: ~11000 PMTs facing inwards and 50-kt water

WCTE

IWCD

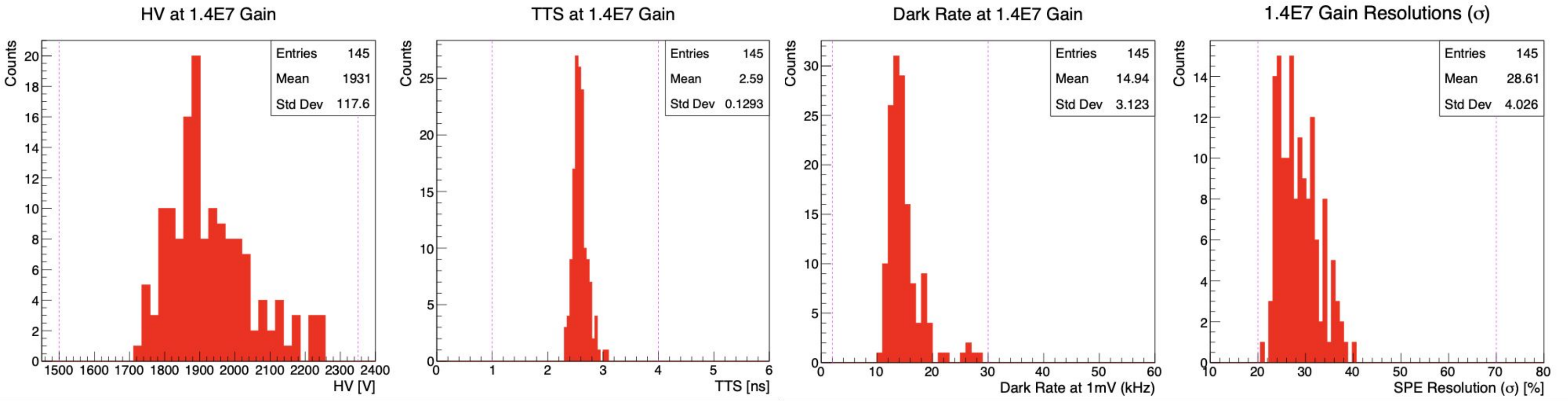


(Ex-situ) Calibration of SK/HK



- First batch production of ~150 HK Box&Line PMT prototypes
- First on-SK-site calibration of HK PMTs
- First HK PMT prototypes in running physics experiments

J.Xia et al., *JPS Conf. Proc.* 27, 012002 (2019)



(In-situ) Calibration of SK/HK

Geometry

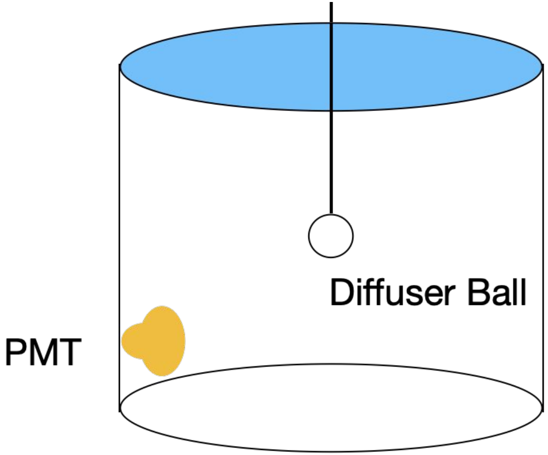
Cherenkov physics

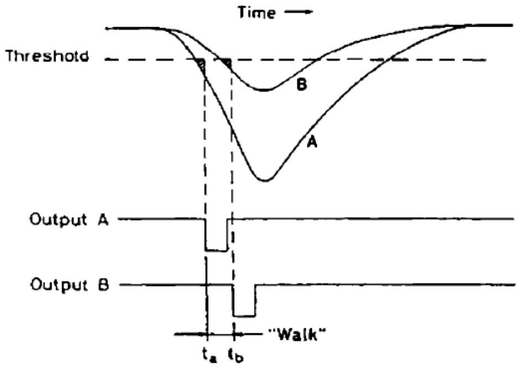
Water properties (light scattering, absorption)

PMT and wall reflectivity

Residual magnetic fields

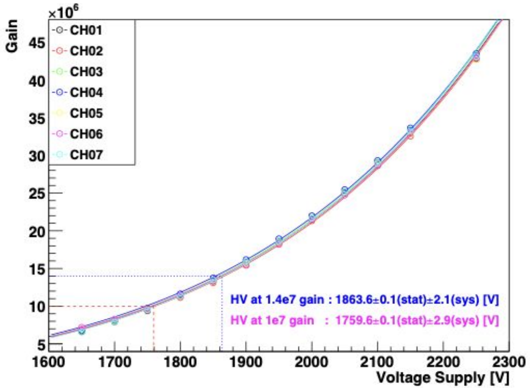
PMT+electronics response





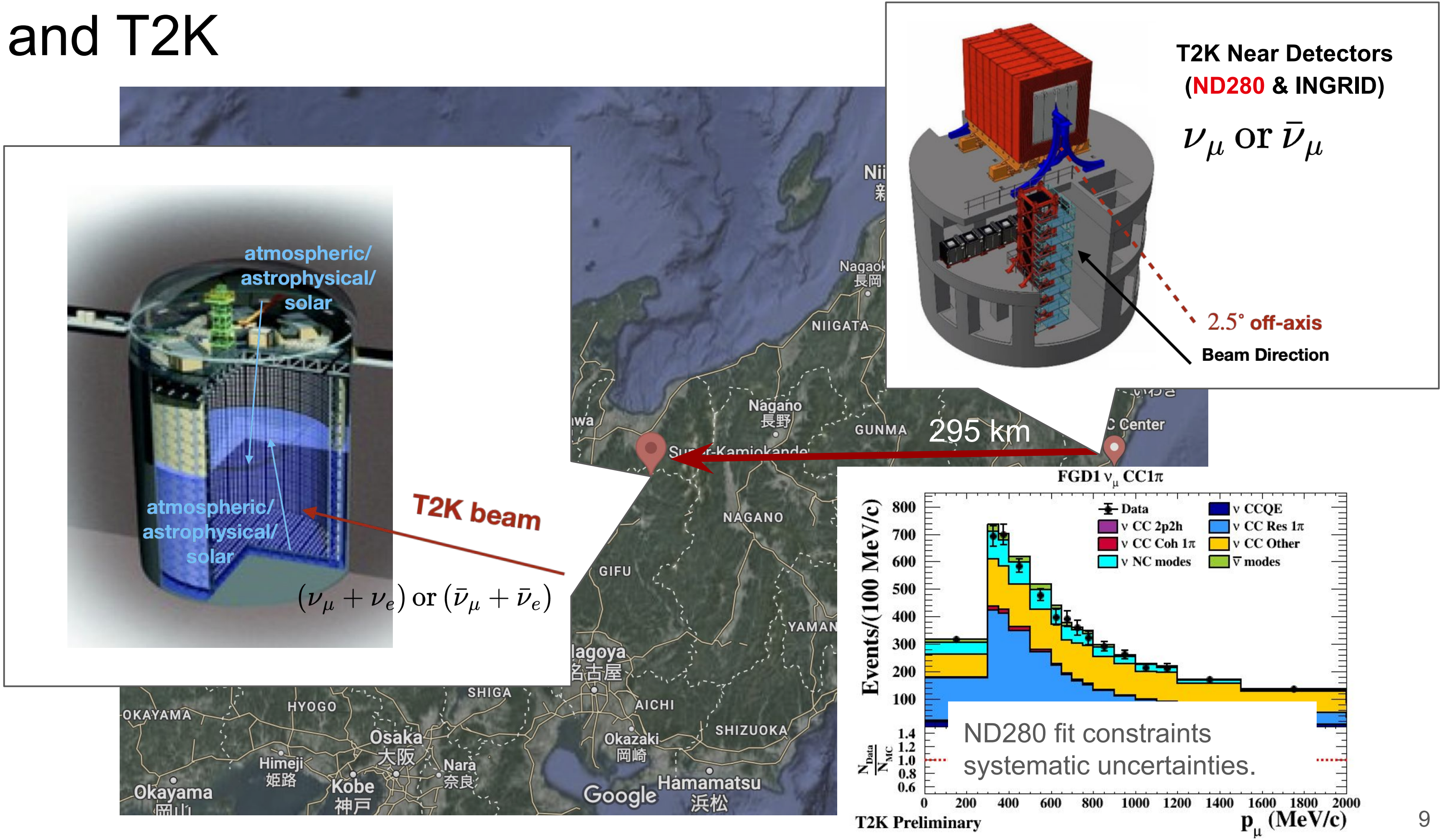
E.g. 2. A look-up table of the correlation between each PMT's charge and timing responses, i.e. correction of the "time walk" effect in the electronics.

E.g. 1. New PMT voltage supplies determined by a new calibration method.



By 2019, the SK detector was refurbished and ready for Gd loading

SK and T2K



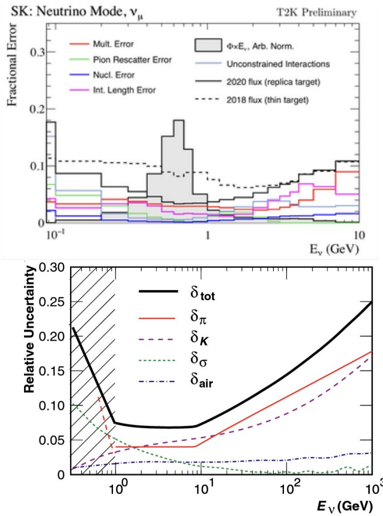
T2K Near Detectors
(ND280 & INGRID)
ν_μ or $\bar{\nu}_\mu$
2.5° off-axis
Beam Direction
atmospheric/
astrophysical/
solar
atmospheric/
astrophysical/
solar
T2K beam
$(\nu_\mu + \nu_e)$ or $(\bar{\nu}_\mu + \bar{\nu}_e)$
295 km
Super-Kamiokande
NIIGATA
Nagaoka
長岡
Nagano
長野
GUNMA
NAGANO
GIFU
YAMAN
Nagoya
名古屋
SHIGA
AICHI
SHIZUOKA
HYOGO
OKAYAMA
Osaka
大阪
Nara
奈良
Himeji
姫路
Kobe
神戸
Okayama
Okazaki
岡崎
Hamamatsu
浜松
Google
FGD1 ν_μ CC1π
Data
ν CCQE
ν CC 2p2h
ν CC Res 1π
ν CC Coh 1π
ν CC Other
ν NC modes
$\bar{\nu}$ modes
Events/(100 MeV/c)
N_{Data}/N_{MC}
p_μ (MeV/c)
T2K Preliminary
ND280 fit constraints
systematic uncertainties.

The SK-T2K Joint Fit

- SK and T2K are complementary in the sensitivity to δ_{CP} and MO. (The two experiments run almost independently of each other even though they share the same detector.)
  - Avoid bias from model dependence.
  - More statistics with coherent analysis models.

C. Bronner@Neutrino 2022
J. Xia@NOW2022

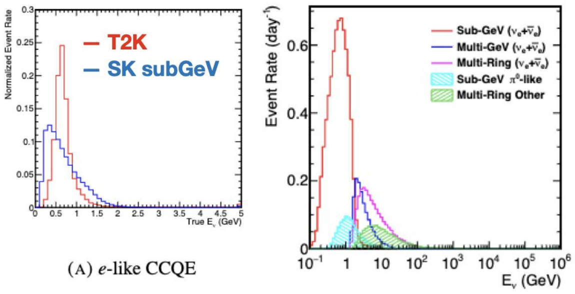
In a nutshell…



The beam and atmospheric **flux models** are not correlated.

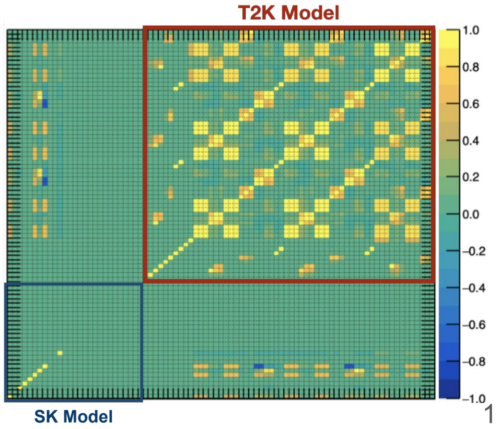
M. Honda, PHYSICAL REVIEW D 75, 043006 (2007)

T2K ND constraints on the **cross section** parameters of the neutrino samples of similar energy. The SK model is used without ND constraints for high energy samples.

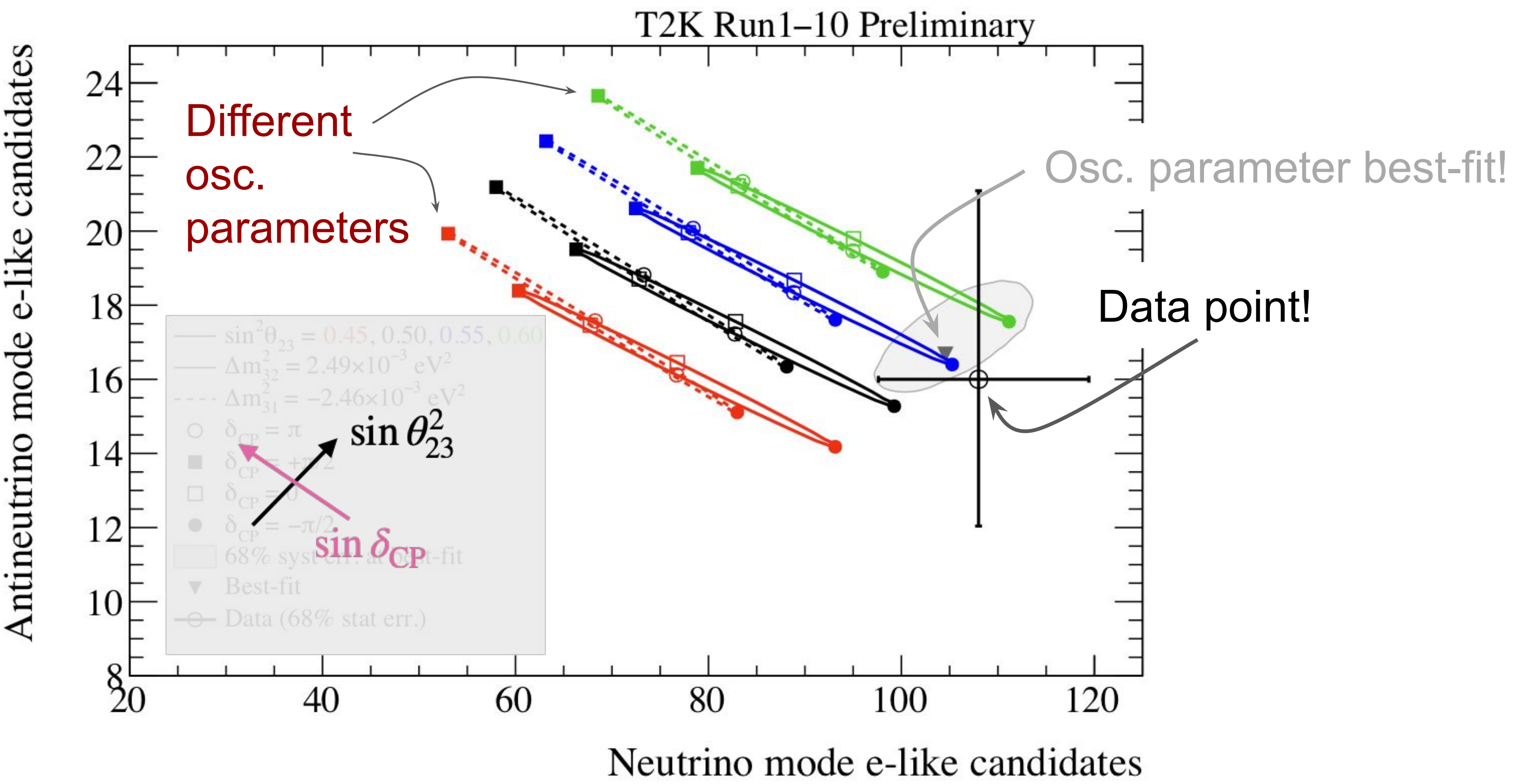


*a few ad-hoc systematics invented

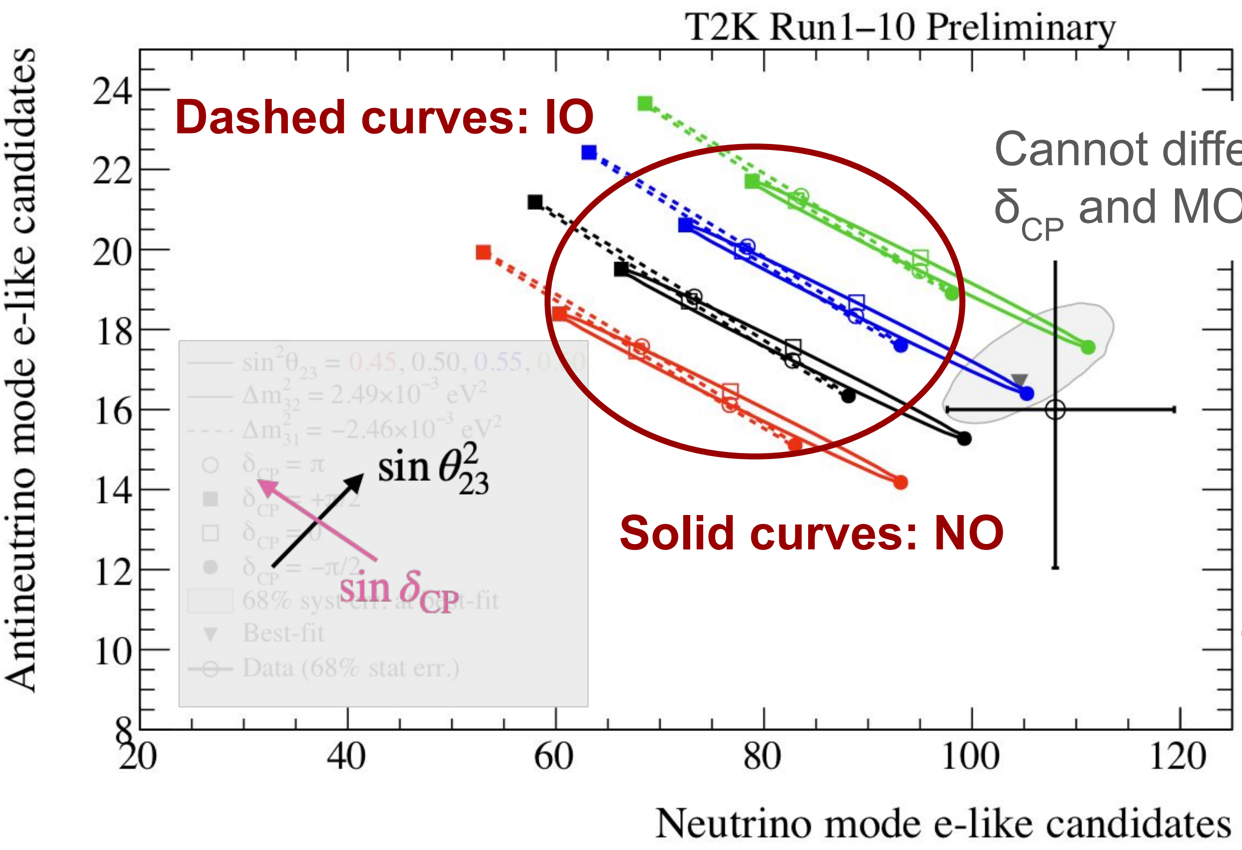
Correlated **detector systematic uncertainties** based on the existing ones from SK and T2K respectively.



SKT2K Joint Analysis breaking δ_{CP}-MO degeneracy



SKT2K Joint Analysis breaking δ_{CP}-MO degeneracy

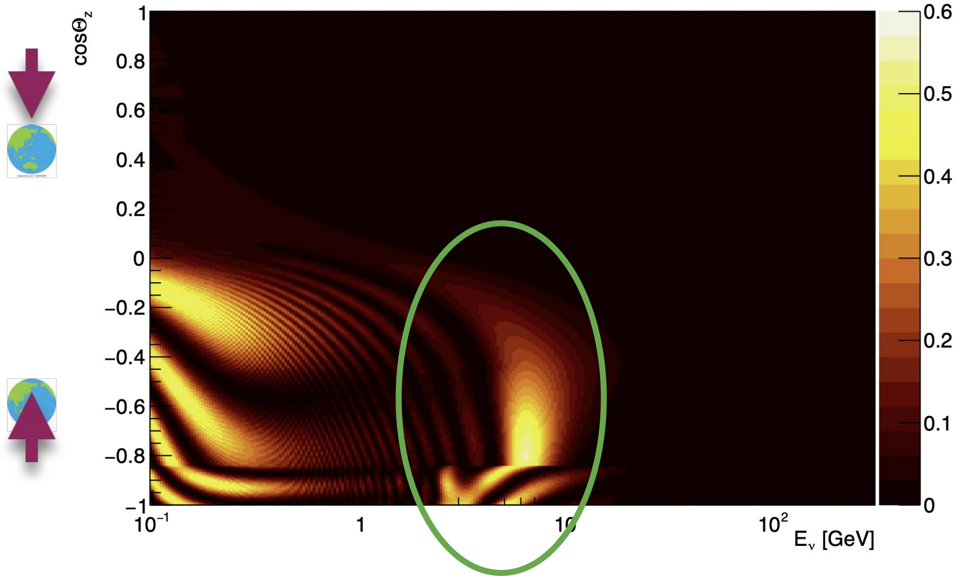


Cannot differentiate between δ_{CP} and MO!

T2K-only analysis suffers from the degeneracy!

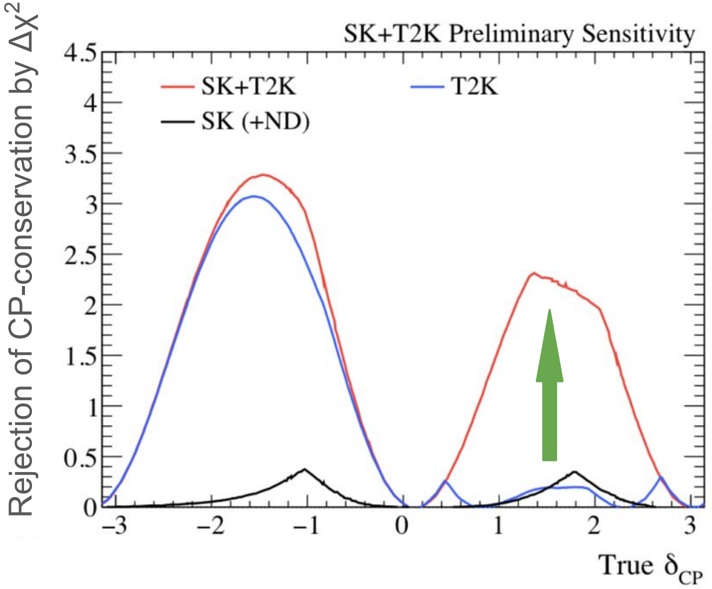
SKT2K Joint Analysis Breaking δ_{CP}-MO degeneracy

In SK atmospheric:



Oscillation resonance of few GeV neutrinos in the earth core and mantle provides sensitivity to MO: resonance in neutrinos if NO and anti-neutrinos if IO.

J. Xia@NOW2022

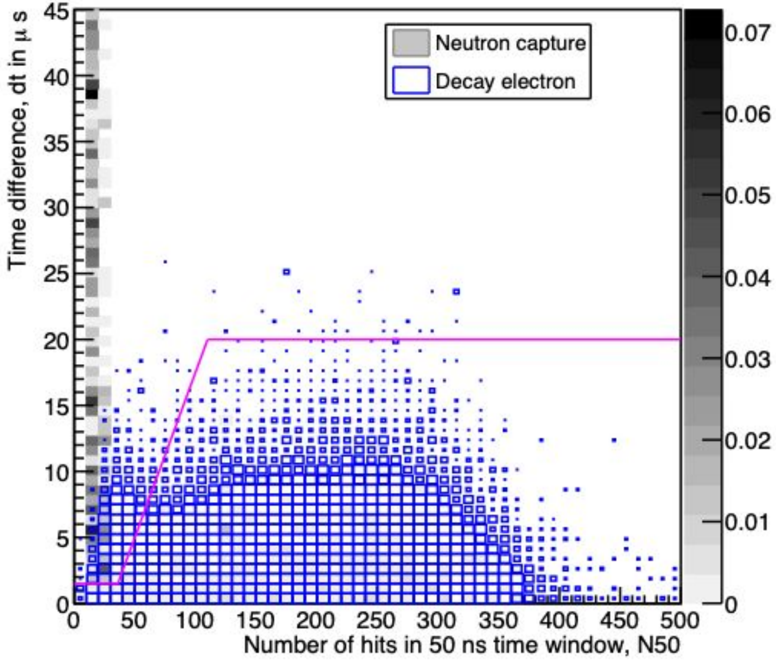


Sensitivity for rejecting the CP-conserved hypothesis at different true δ_{CP} values

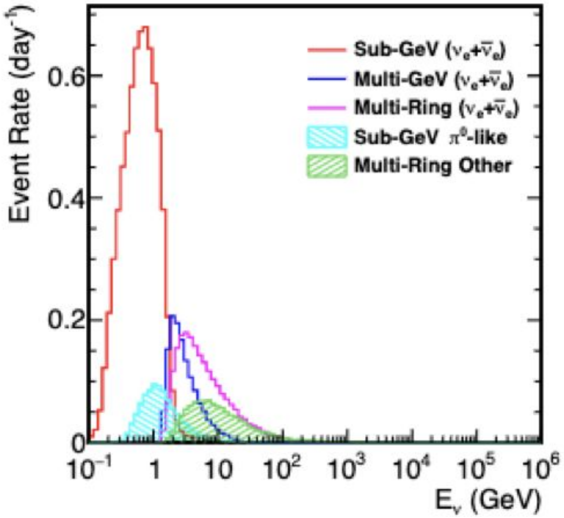
Truth: $\Delta m^2_{21} = 7.53 \times 10^{-5}\text{eV}^2, |\Delta m^2_{32,31}| = 2.509 \times 10^{-3}\text{eV}^2,$
$\sin^2\theta_{23} = 0.528, \sin^2\theta_{12} = 0.307, \sin^2\theta_{13} = 0.0218$

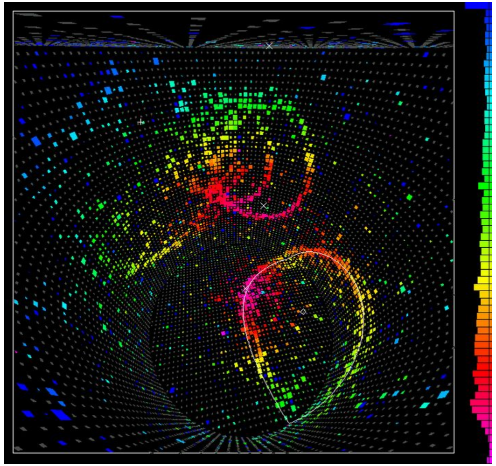
Gd in the T2K oscillation analysis

- Enhanced neutron tagging efficiency creates similar delayed secondary signals to those from Michel electrons
- Nudged the T2K sample selection criteria a bit to exclude these new candidates

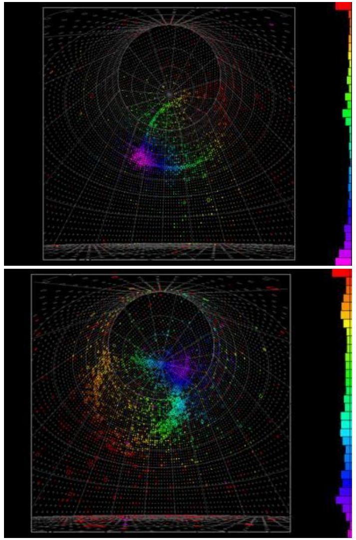


More rings more stats, yet more challenges





Higher ν energy



single-ring μ-like

single-ring e-like

- Differences in ring topology provide PID information
- PMT charge and timing information for ring reconstruction and energy deposition calculations (ν energy reconstruction if ν direction is known, e.g. ν_μ beam)

The state-of-the-art fitter: FiTQun

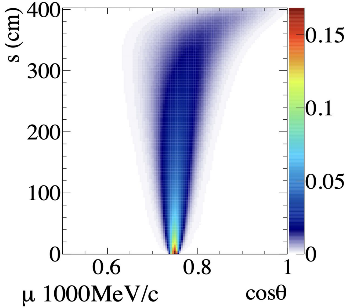
$$\boxed{L(x)} = \underbrace{\prod_{j}^{unhit} P_j(unhit\,|\,x) \prod_{i}^{hit} \{1 - P_i(unhit\,|\,x)\}}\, \underbrace{f_q(q_i\,|\,x) f_t(t_i\,|\,x)}$$

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**.

The infamous tuning:

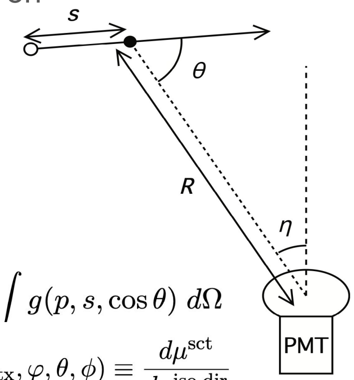


$$x \rightarrow \mu^{dir} + \mu^{sct}$$

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

$$\mu^{\text{dir}} = \Phi(p) \int ds\, g(p,s,\cos\theta) \Omega(R) T(R) \epsilon(\eta)$$

In practice the likelihood depends on PMT mean predicted hit charges.



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

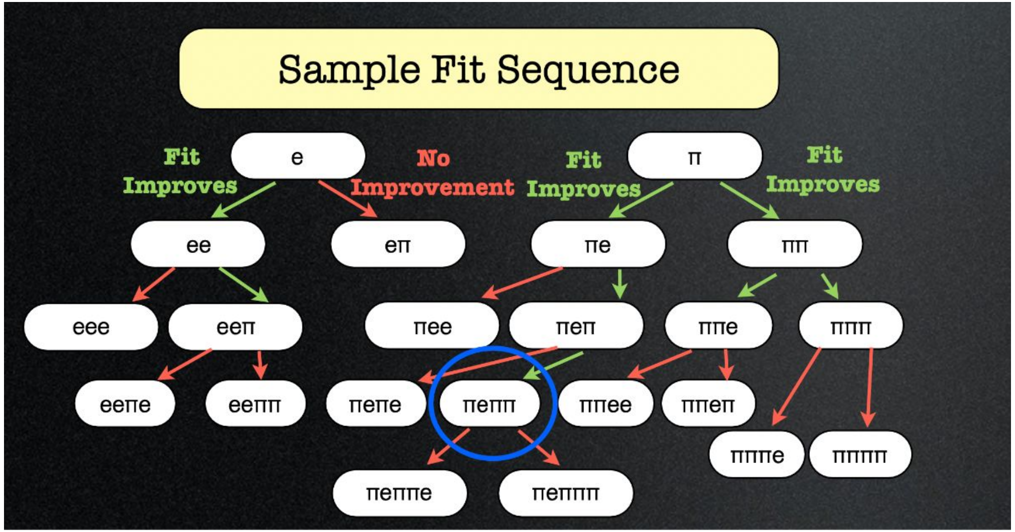
$$A(s) = A(x_{\text{PMT}}, z_{\text{vtx}}, R_{\text{vtx}}, \varphi, \theta, \phi) \equiv \frac{d\mu^{\text{sct}}}{d\mu^{\text{iso,dir}}}$$

The state-of-the-art fitter: FiTQun

PID in fiTQun:

M. Wilking

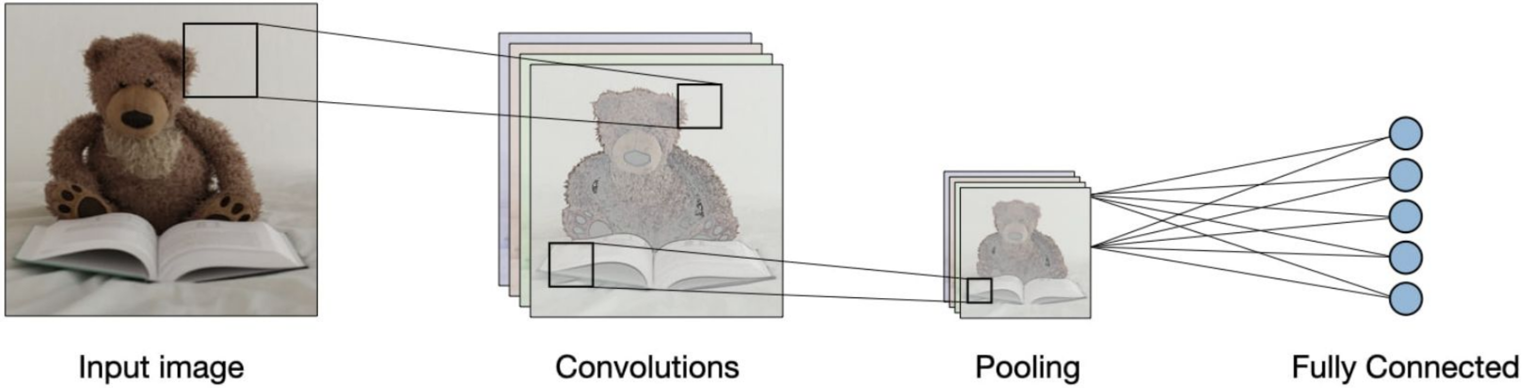
- FiTQun can currently reconstruct up to 6 rings in a staged approach
  - Each step sequentially adds a “track-like” (π^+) or “shower-like” (e) ring
  - The chain terminates when adding a ring does not sufficiently improve the fit



O(1) sec for single-ring events, and **O(1) min** for the multi-ring!

What is cnn and why it’s powerful

Usual architecture of a Convolutonal Neural Network



CNN is great at object detection and pattern recognition because:

- Hierarchical feature learning
- Translational invariance by the same filter

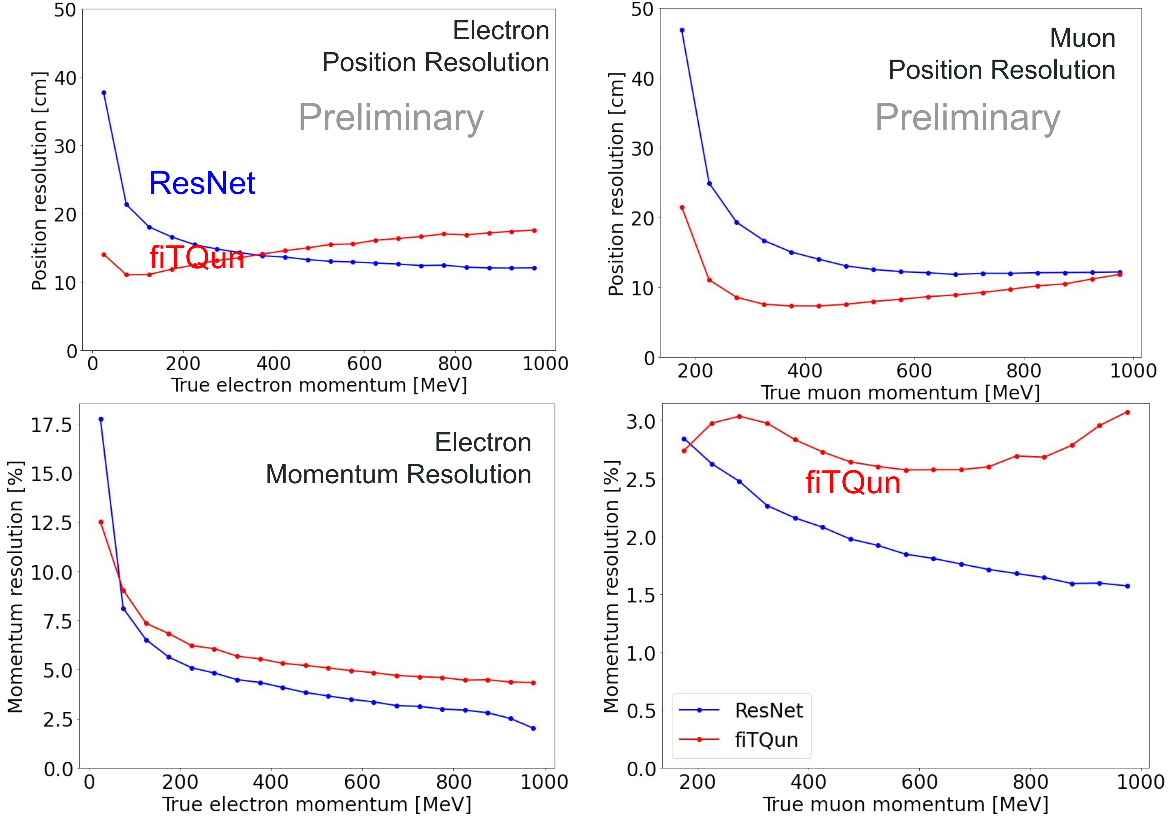
The exploration by WatChMaL
— mapping from detector domain to physics domain

Pioneer works in WatChMaL already shows that novel AI/ML techniques like ResNet can achieve similar reconstruction results as fiTQun.

**fiTQun is not tuned for IWCD environment yet*

Single "particle gun" events

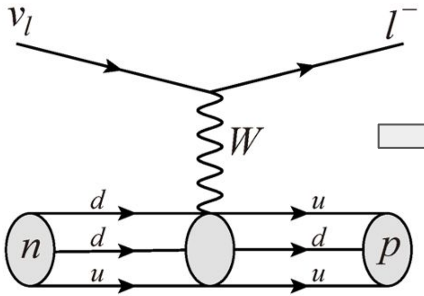
P. de Perio, NNN22



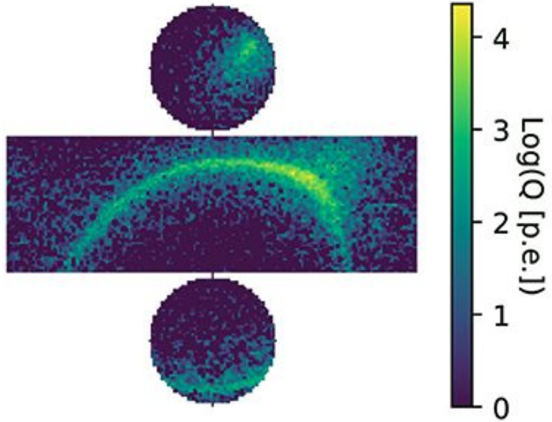
Neural Network for Cherenkov Ring Generation

Given physics input,
predict the detector output.

Ring Generation



Detector physics: photon scattering, attenuation, etc.



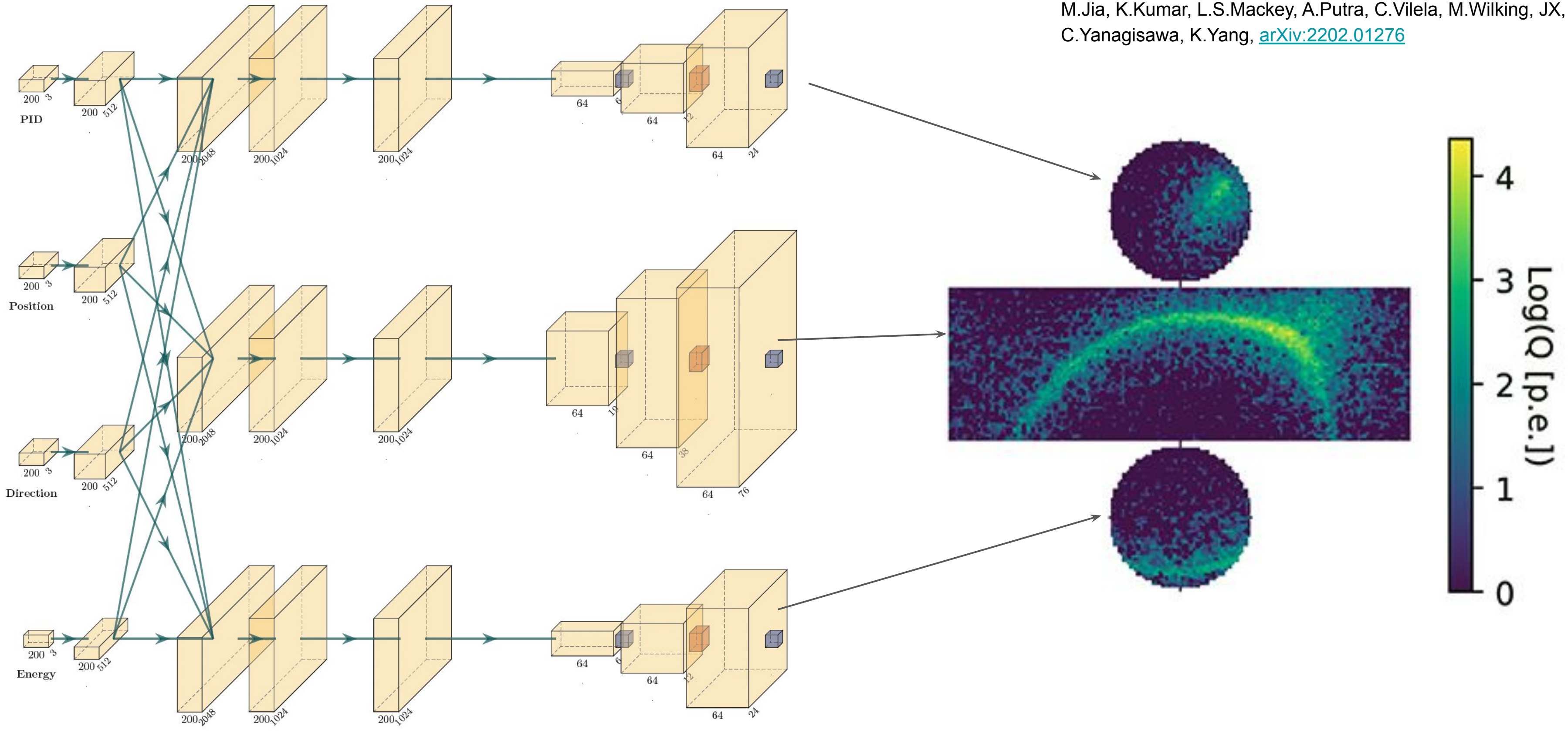
Particle physics:
- Particle types
- Particle energy
- Interaction position
- Outgoing direction

I have my doubts, but you're welcome to try

Detector outputs:
- Charge
- Timing

First attempt: a CNN-based Cherenkov Ring Generator

M.Jia, K.Kumar, L.S.Mackey, A.Putra, C.Vilela, M.Wilking, JX, C.Yanagisawa, K.Yang, arXiv:2202.01276

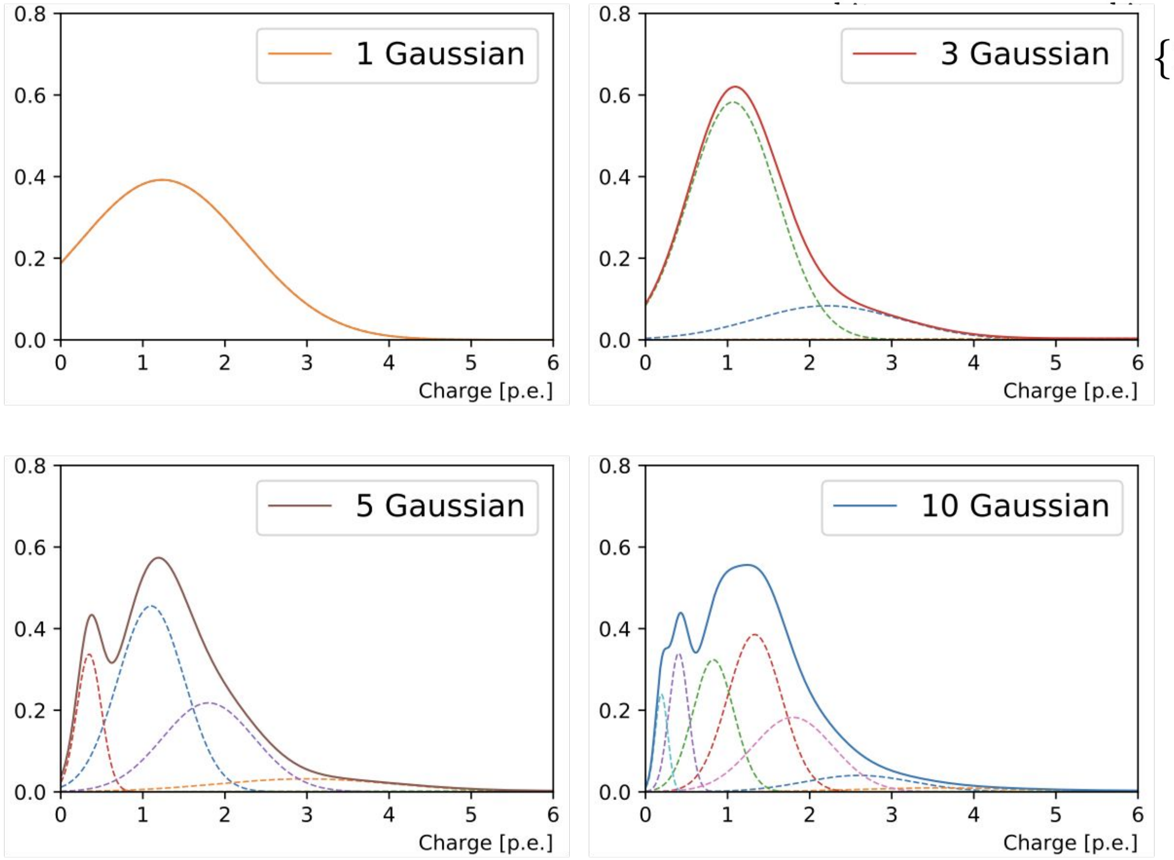


Fully connected layers

Convolutional layers

CNN-based Cherenkov Ring Generator

M.Jia, K.Kumar, L.S.Mackey, A.Putra, C.Vilela, M.Wilking, JX, C.Yanagisawa, K.Yang, [arXiv:2202.01276](https://arxiv.org/abs/2202.01276)

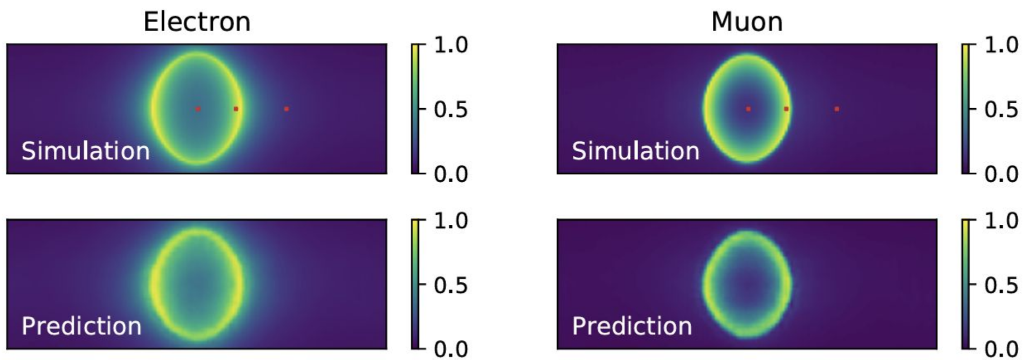


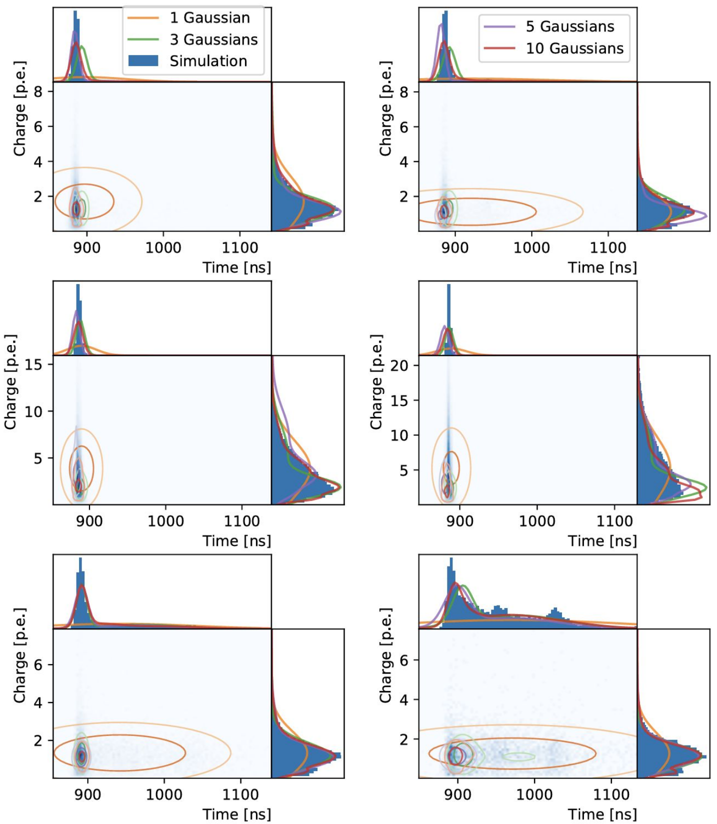
$$\{1 - P_i(\mathrm{unhit}|\mu_i)\}\boxed{f_q(q_i|\mu_i)}\boxed{f_t(t_i|\mathbf{x})}$$

Unlike fiTQun which only assumes gaussian-like PMT responses, the CNN based model is powerful enough to handle heavy likelihood computation like a multi-gaussian mixture.

First attempt: a CNN-based Cherenkov Ring Generator

M.Jia, K.Kumar, L.S.Mackey, A.Putra, C.Vilela, M.Wilking, JX, C.Yanagisawa, K.Yang, arXiv:2202.01276





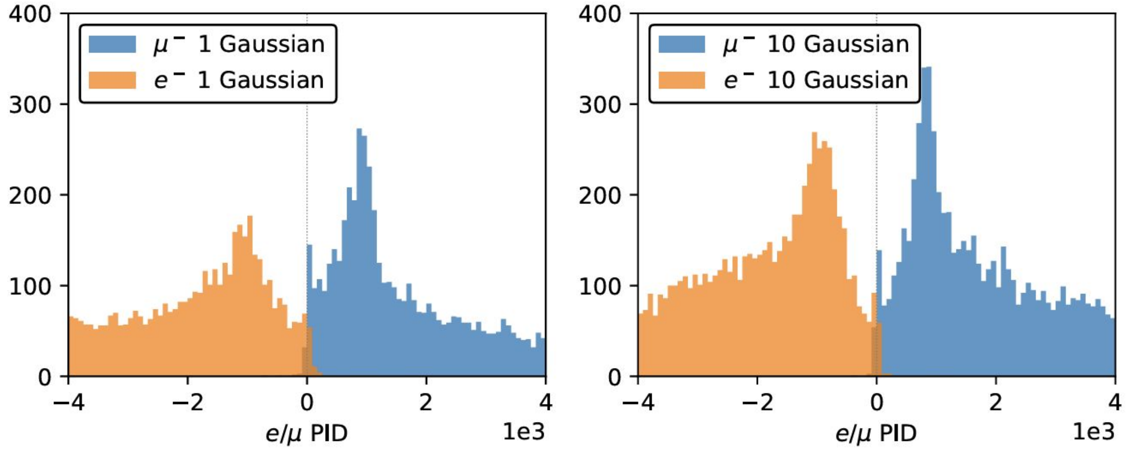
- More flexible likelihood model indeed capture the complex spatial-dependent PMT responses

- Generated good rings “by-eye”, but are “smeared” as compared to the input truth.

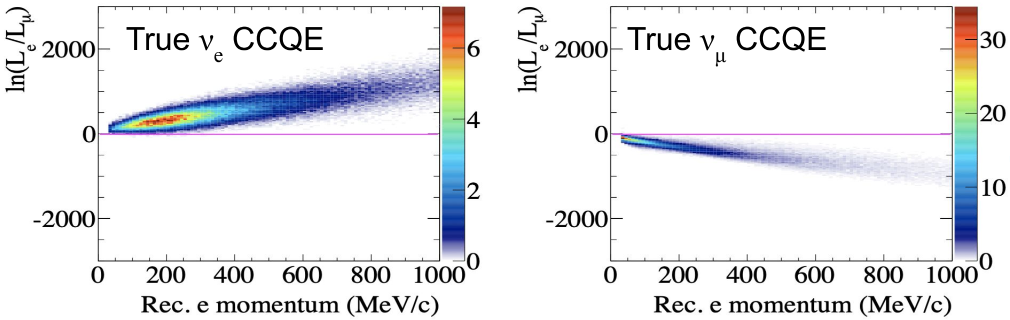
- Need a deterministic model for the PMT responses

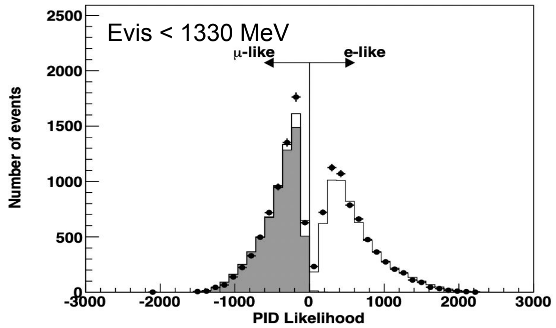
First attempt: a CNN-based Cherenkov Ring Generator

M.Jia, K.Kumar, L.S.Mackey, A.Putra, C.Vilela, M.Wilking, JX, C.Yanagisawa, K.Yang, [arXiv:2202.01276]



Not an apple-to-apple comparison, but here's the fiTQun PID performance





Challenges in Detector Calibration

Geometry

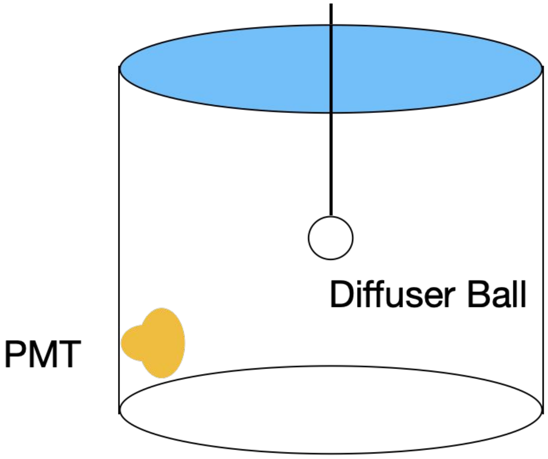
Cherenkov physics

Water properties (light scattering, absorption)

PMT and wall reflectivity

Residual magnetic fields

PMT+electronics response

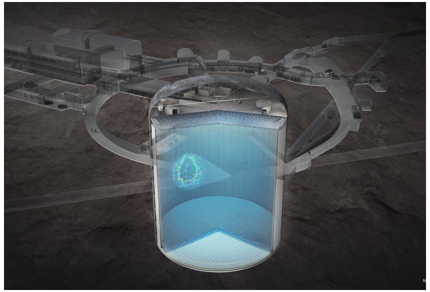


Lack of "end-to-end" optimization; some models are not even optimizable (e.g. look-up tables)

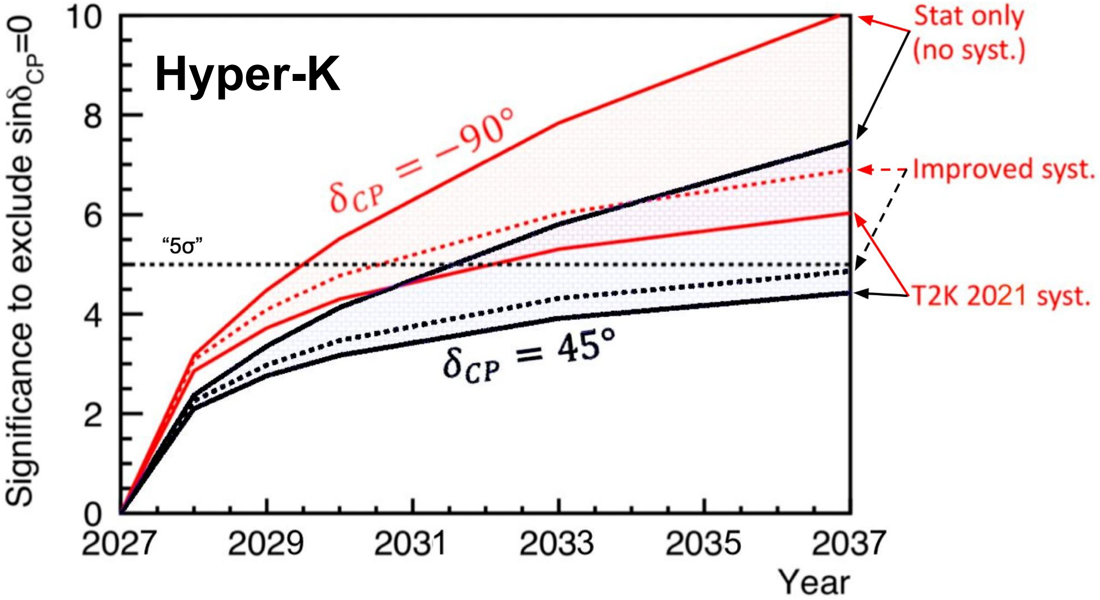
On the other hand:

- Only have a limited number of calibration sources
- These detector effects are usually degenerate to a single calibration source
- Impractical to tune many free parameters at once with the conventional calibration method

The Budget for Systematic Uncertainties



= 8 x SK



"T2K 2021 syst.": Phys. Rev. D 103, 112008

Error Source	% Error for CPV search
φ + σ (ND constrained)	2.7
φ + σ (ND unconstrained)	1.2
Nucleon removal energy	3.6
SK π re-interactions	1.6
$\sigma(\nu_e)$, $\sigma(\bar{\nu}_e)$	3.0
NC γ + other	1.5
SK detector (FD)	1.5
Total	**6.0**

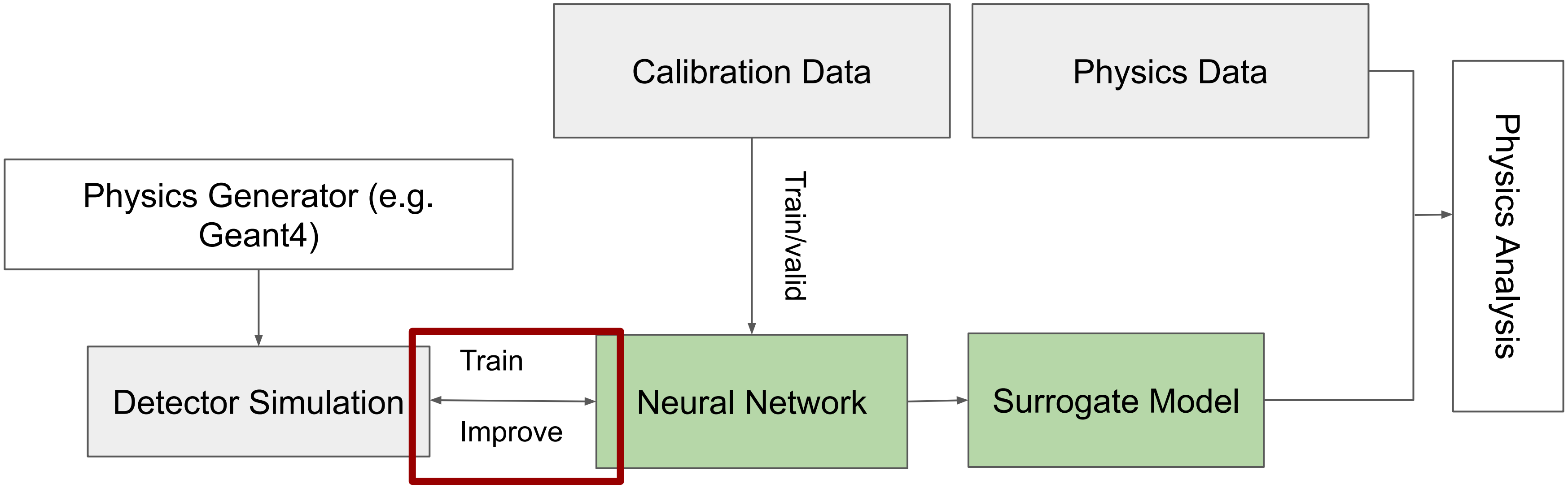
Need to reduce to <3%

Towards a robust physics inference

CIDeR-ML

- Optimizing the detector simulation input with calibration data, e.g. replacing fixed “look-up tables” with neural networks that can interpolate over the full phasespace.

- Minimal empirical assumptions

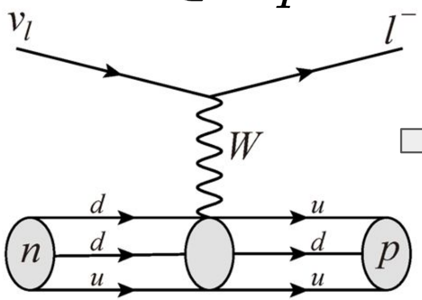


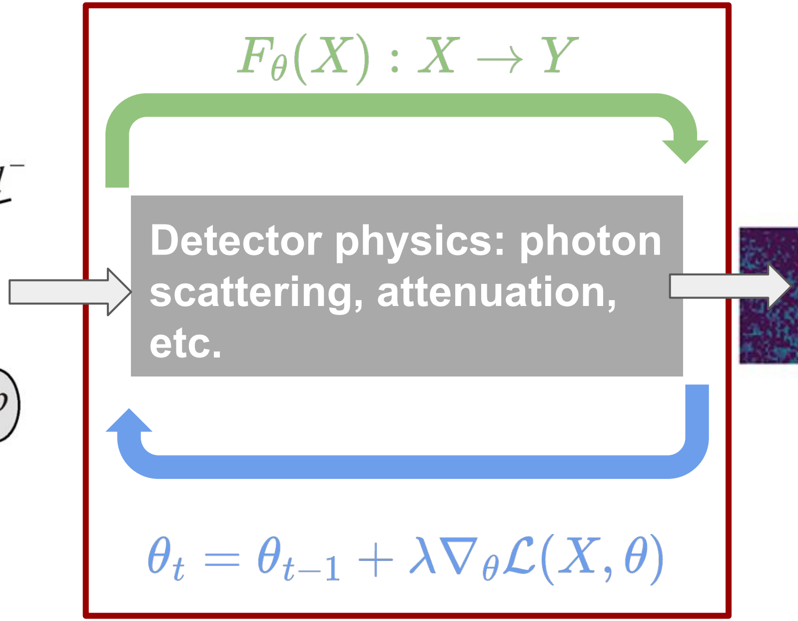
Optimization by gradient-descent

Differentiable detector simulator (DDSim)

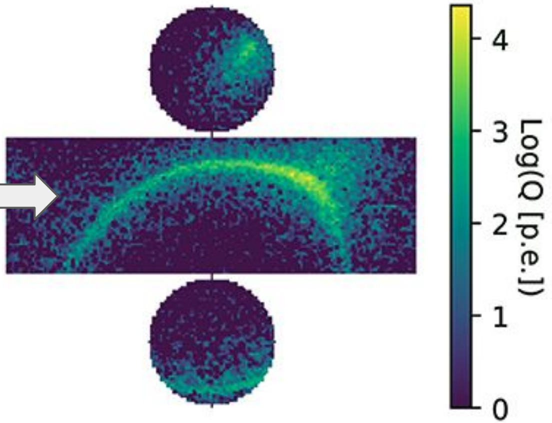
CIDeR-ML

$X \in \mathcal{D}_I$



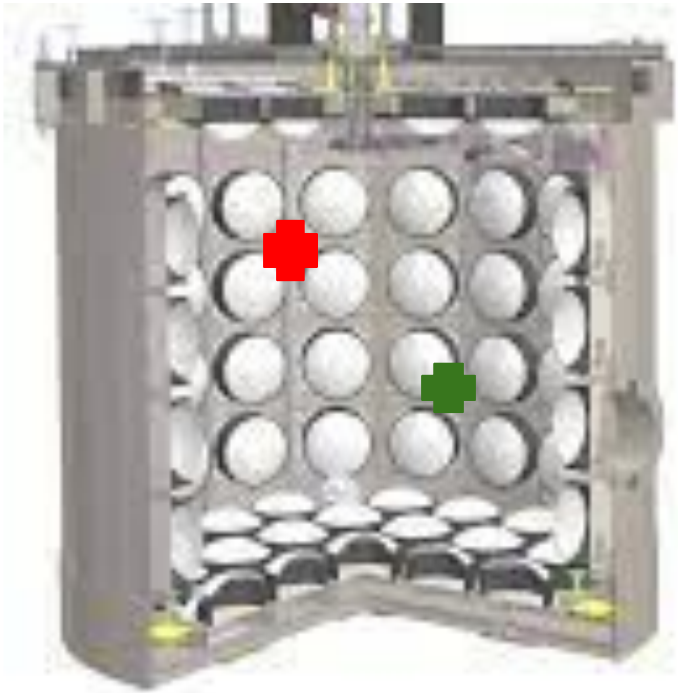


$Y \in \mathcal{D}_O$



In an end-to-end differentiable model *F*, one can achieve the gradient of the loss function related to the output states w.r.t the input and model parameters and optimize the latter's via chain rules.

Differentiable detector simulator (DDSim)



We would like to know the detector responses to optic photons generated and pointing anywhere in the detector.

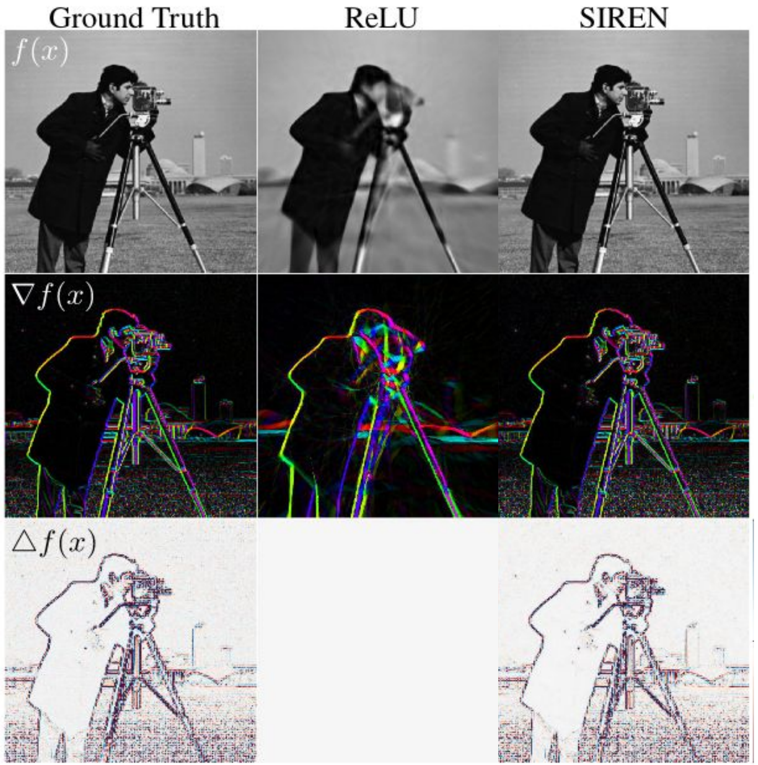
It is impractical to calibrate or simulate the responses with a large (infinite) number of position and directions.

With the differentiable model it is possible to interpolate the responses (assuming it is continuous) based on a few data points.

Differentiable detector simulator (DDSim)

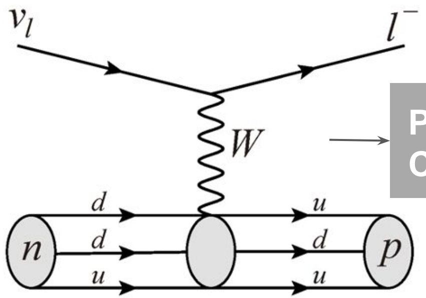
Implicit Neural Representations with Periodic Activation Functions (SIREN)

- A MultiLayer-Perceptron (MLP) architecture with sinusoidal activation functions.
- Good at representing sharp edges in images, e.g. the ring edge
- Smooth gradient surface and easy access to higher order derivatives



Validation using calibration data

CIDeR-ML

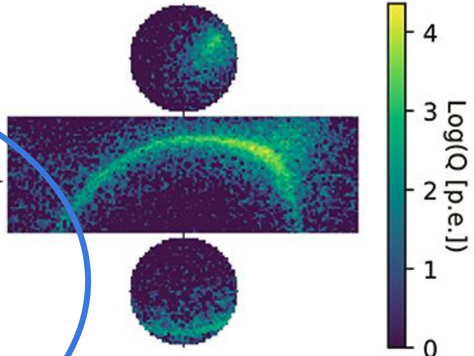


Optic photons

Physics SIREN:
Cherenkov radiation

Optical SIREN:
detector responses

Calibration sources to
verify the performance.



p: particle momentum
s: track length
PID: particle type

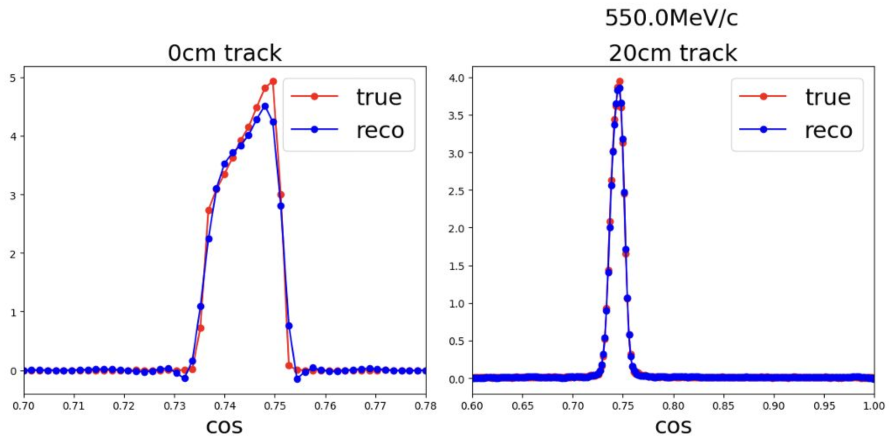
n: number of emitted photons
φ,*θ*: direction of photon
(x,y,z): vertex of photon emission

Q: PMT charge
T: PMT timing

Initial performance check

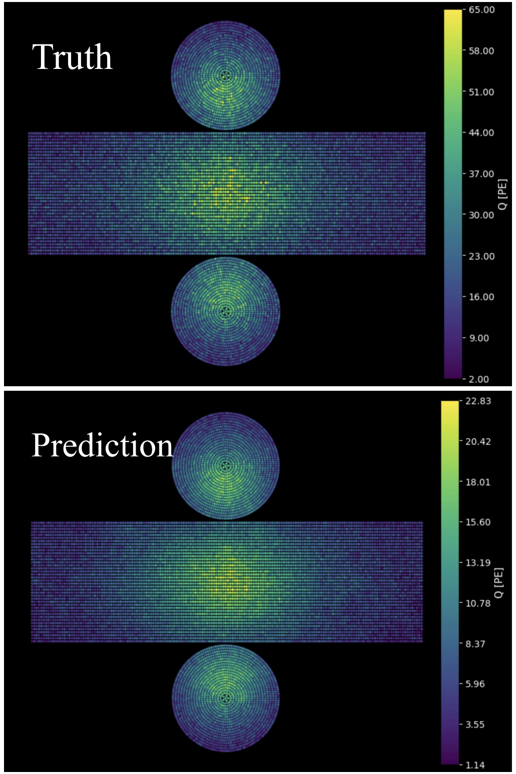
CIDeR-ML

Physics SIREN work in progress



SIREN models Cherenkov emission profile along particle trajectory given the initial particle momentum.

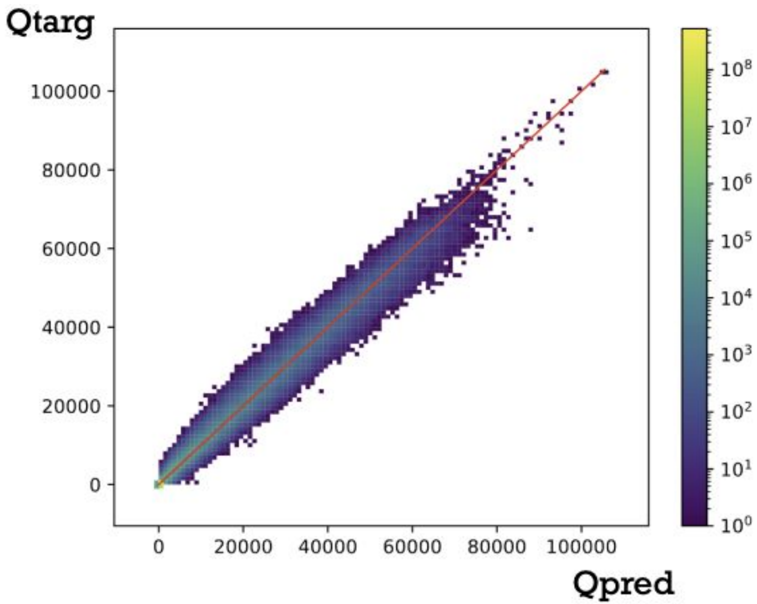
Optical SIREN work in progress



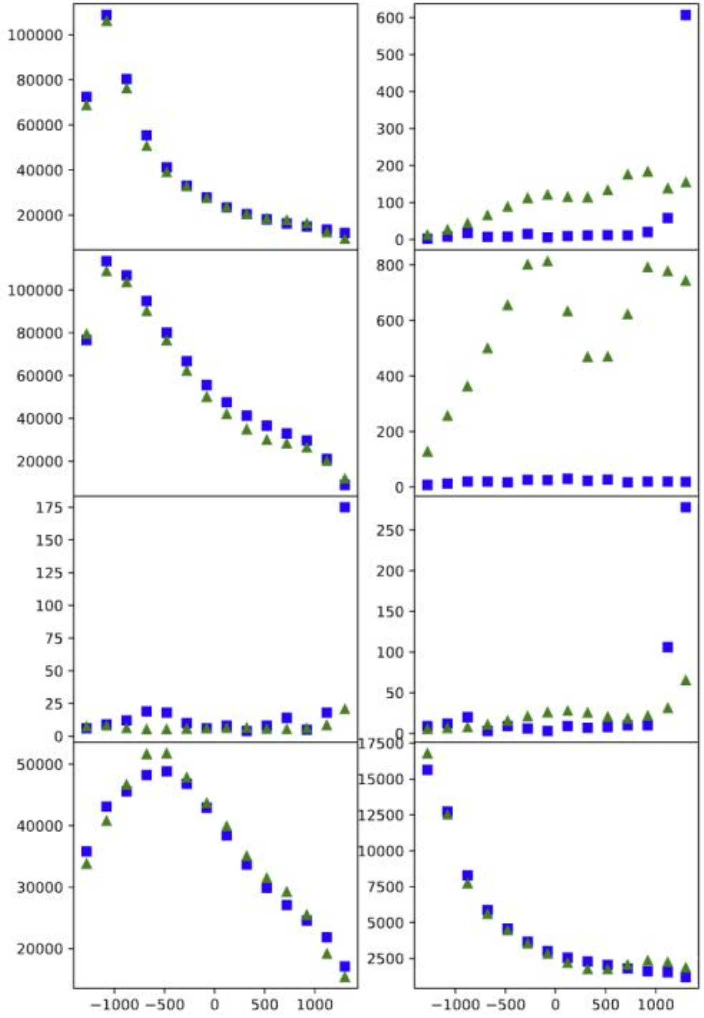
SIREN models detector hit responses to an isotropic optical photon source at any location.

Initial performance check

[CIDeR-ML](#)



Prediction
Target



Thanks so much for being an inspiring and supportive advisor, Mark!
Happy 60th birthday!