

AI Research in Neutrinos in Japan

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FAIRS-Japan @ KMI
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Overview

Highlighting progress since
[FAIRS 2024](#):

- Reconstruction
- Surrogate Models
- Simulation
- Domain Adaptation

Past workshops on Neutrino
Physics Machine Learning (NPML):

2020 ([Remote](#)),

2023 ([Tufts](#)),

2024 ([Zurich](#))



This time focusing on Japanese
program-relevant efforts and
their integration into a complete
AI/ML analysis (with some bias
towards Hyper-K).

NPML:

2025 ([UTokyo-IPMU](#)),

2026 ([UC Irvine](#))

[2027 June 14-18 (Valencia)]



Supernovae

Solar
The Sun in Neutrinos
Super-K, 1500 days

Proton decay
 e^+ , π^0 , p , γ

Hyper-K (FD)
71m
68m

Atmosphere
COSMIC RAY
AIR NUCLEUS
PION
MUON
ELECTRON
2 muon-neutrinos
1 electron-neutrino

Accelerator

J-PARC
ND280
Neutrinos
295km

IWCD

FUKUI
GIFU
TOYAMA
NAGANO
TOKYO

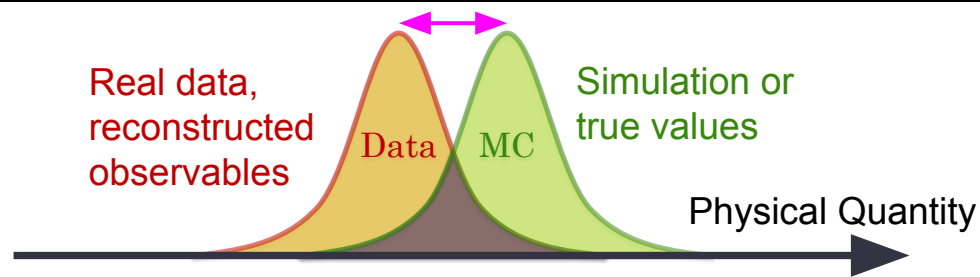
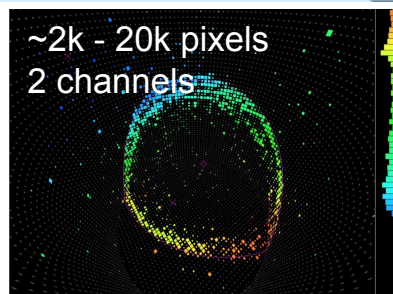
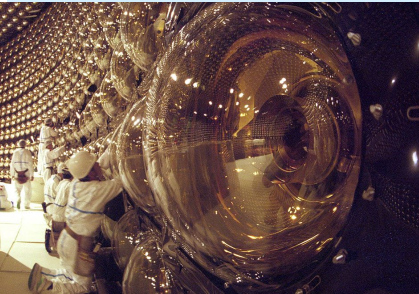
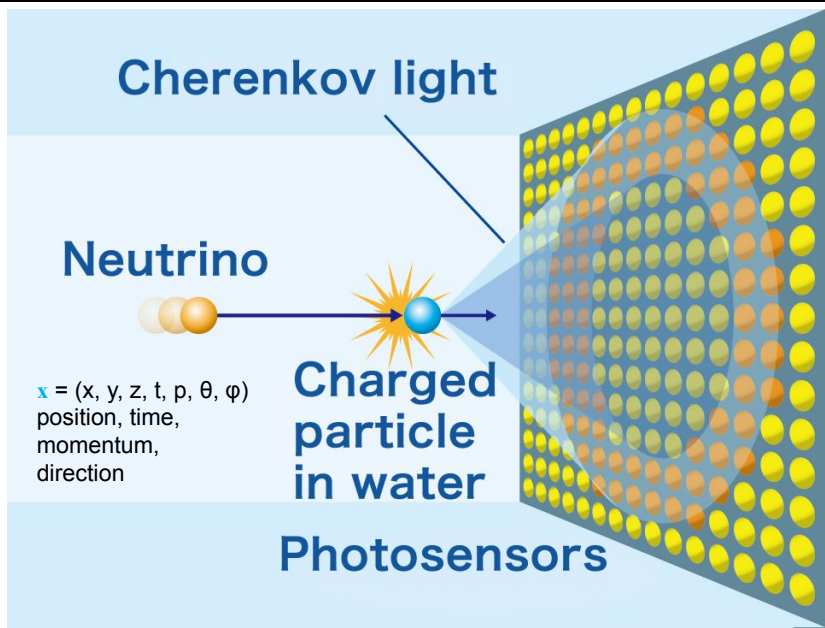


23 countries
104 institutes
~660 people



Operation start
in JFY2028

Systematics Limited - Approaching Precision Physics



Domain shift: Difference between data and simulation (systematic uncertainty caused by imperfections in detector modeling)

→ AI-based neutrino event simulation & reconstruction
How can systematic uncertainties arising from domain shift be estimated and reduced?

Error Source	% Error
Flux and interactions	3.0
Other interactions	5.0
Detector modeling	1.5
Total	6.0

Error Level	Time to 5 σ Discovery
Current baseline	10 years
Target Improvement	5 years

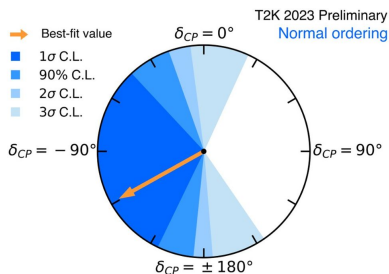
Hyper-K target: systematic uncertainty <3%

→ *improving sensitivity to CP-violation discovery*

A Critical Physics Target: CP Violation (δ_{CP}) in Neutrinos

- Potential source of matter-antimatter asymmetry in the universe (leptogenesis)
- Hyper-K: 10 years to reach 5σ discovery potential at current systematic error understanding
- **Systematic errors must be improved**
 - New and upgraded near detectors
 - *Improved analysis tools (AI/ML)*

Conservation of CP symmetry excluded at 90% CL



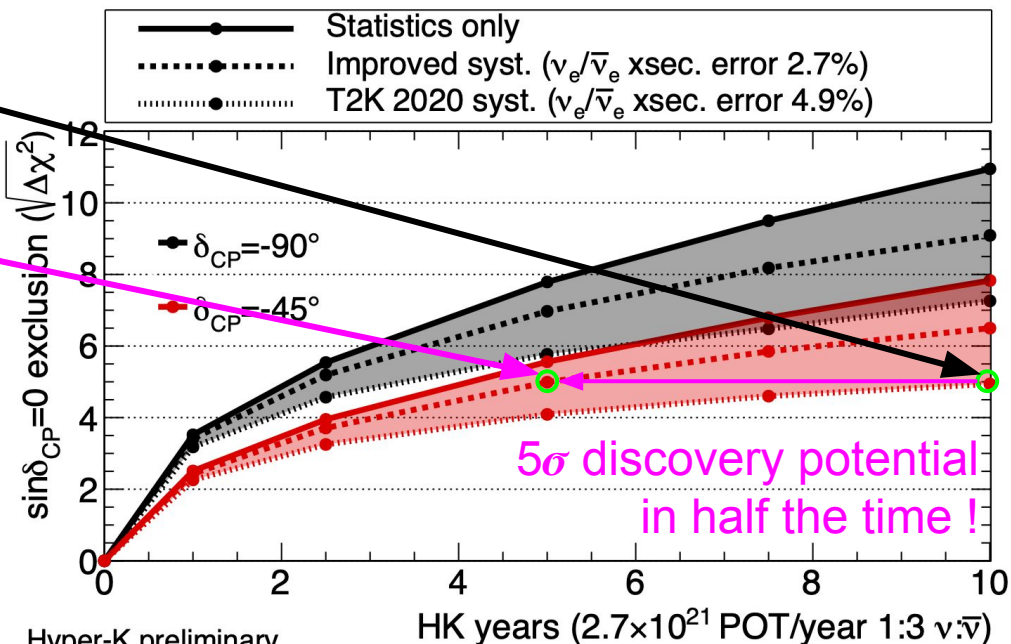
Latest T2K Result

Far detector systematic uncertainty

Sample	OA22	New results
ν -mode 1R μ	3.4%	3.2%
ν -mode 1Re	5.2%	4.9%
ν -mode MR	4.9%	3.9%
ν -mode 1Re+d.e.	14.3%	6.3%
$\bar{\nu}$ -mode 1R μ	3.9%	5.0%
$\bar{\nu}$ -mode 1Re	5.8%	6.7%

C. Giganti @ Neutrino 2024
D. Carabadjac @ ICHEP 2024

To HK



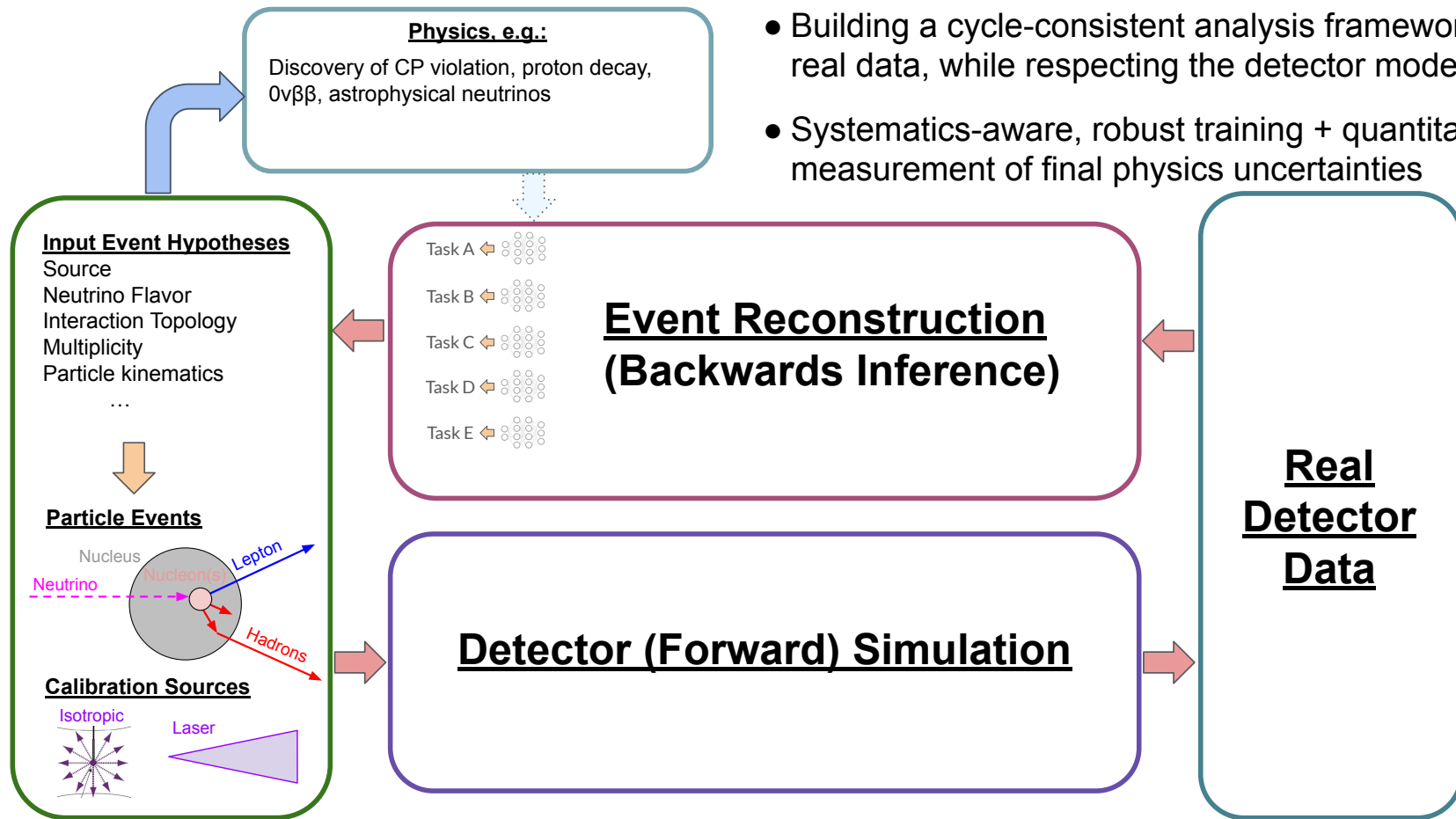
Hyper-K preliminary

True normal ordering (known)

$$\sin^2 \theta_{13} = 0.0218 \pm 0.0007, \sin^2 \theta_{23} = 0.528, \Delta m_{32}^2 = 2.509 \times 10^{-3} \text{ eV}^2/c^4$$

Analysis Overview

- Building a cycle-consistent analysis framework to train on real data, while respecting the detector model
- Systematics-aware, robust training + quantitative measurement of final physics uncertainties



Analysis Overview

Physics, e.g.:

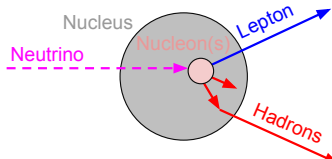
Discovery of CP violation, proton decay, $0\nu\beta\beta$, astrophysical neutrinos

- Building a cycle-consistent analysis framework to train on real data, while respecting the detector model
- Systematics-aware, robust training + quantitative measurement of final physics uncertainties

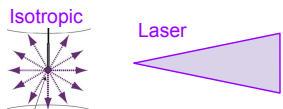
Input Event Hypotheses

Source
Neutrino Flavor
Interaction Topology
Multiplicity
Particle kinematics
...

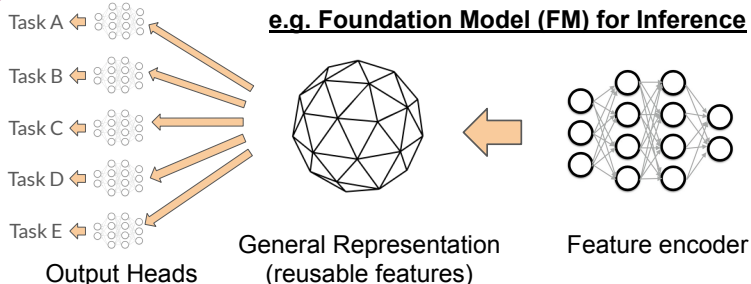
Particle Events



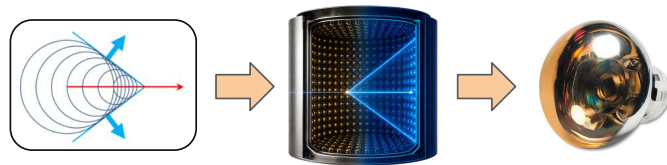
Calibration Sources



e.g. Foundation Model (FM) for Inference

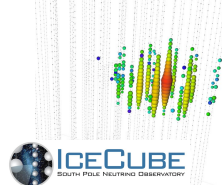
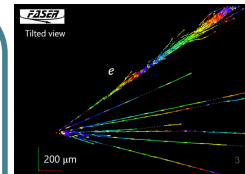
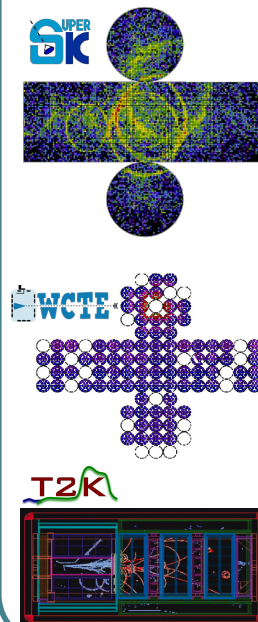


Differentiable Detector Simulation (DDSim)

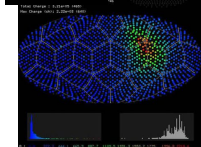


Analytic physics plus constrained neural **surrogates**

Detector Data



ICECUBE
SOUTH POLE NEUTRINO OBSERVATORY



Event Reconstruction

The background is a complex, abstract pattern of glowing circuit lines in shades of blue, purple, and red. These lines radiate from a central, semi-transparent grey square, creating a starburst or network-like effect. The overall aesthetic is high-tech and digital.

Event Reconstruction References

Model zoo of AI/ML efforts for Japan:

- Hyper-K: [ICHEP2026](#) - ResNet (CNN), (CLS)GAT (GNN), ViT, Transformer, U-Net
- Super-K: [NPML2026](#) cosmic μ , [arXiv:2609.25681](#) proton decay - CNN
 - *[arXiv:2609.00611](#) - "Panda" Hierarchical Attention + Self-Distillation (SSL)
- T2K (SuperFGD): [NPML2025](#) - Transformer (SSL)
- KamLAND: [NPML2025](#) - ViT
- IceCube: [NPML2025](#) - Transformer

(Apologies if anyone missed; please contact if so!)

*KEK-DOE U.S.-Japan Science and Technology Cooperation Program in High Energy Physics

CNNs and Vision Transformers (ViT)

Explored in Super-K, Hyper-K, and [KamLAND](#)

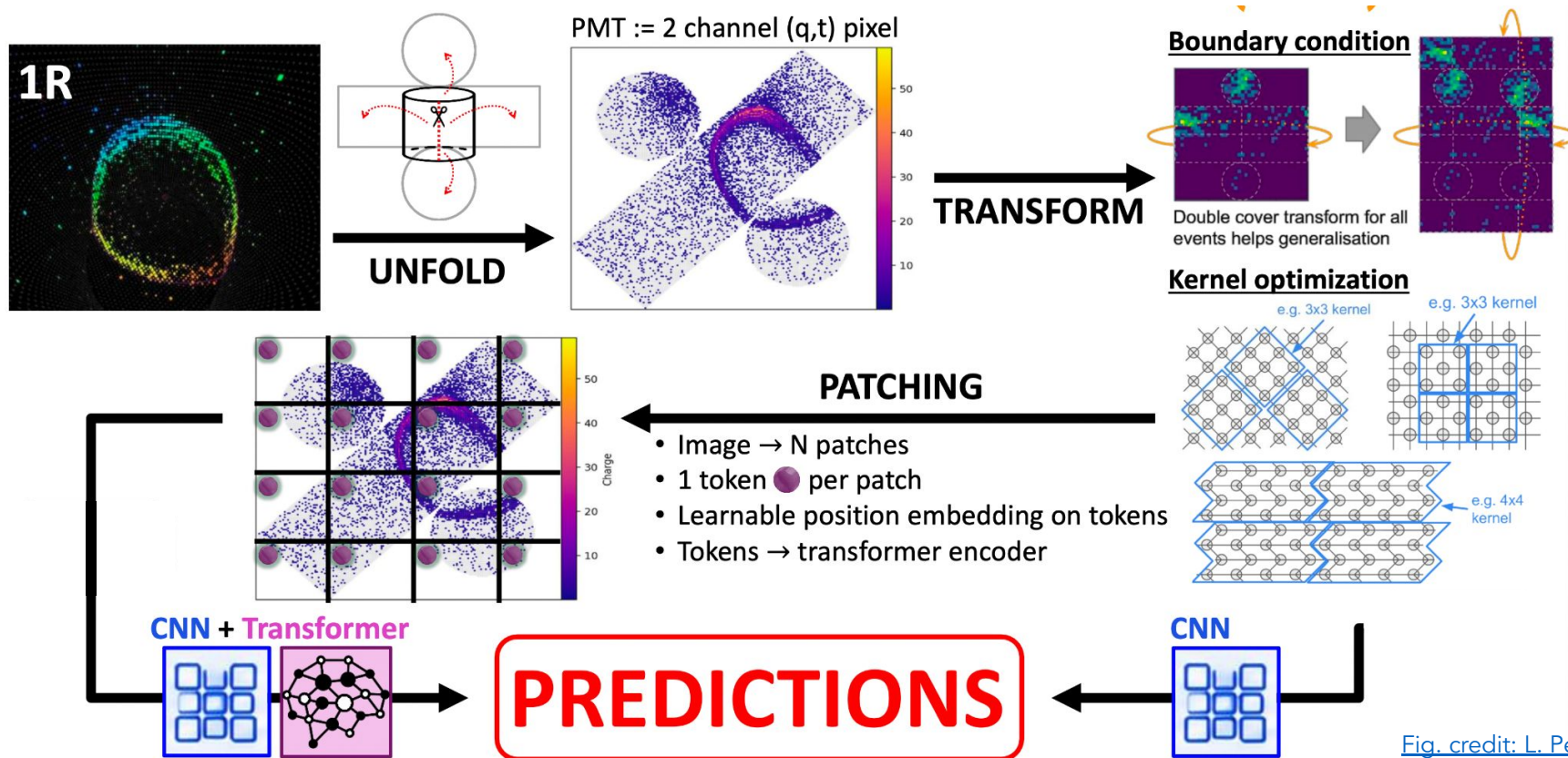
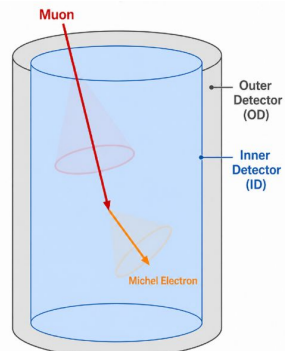


Fig. credit: L. Perisse

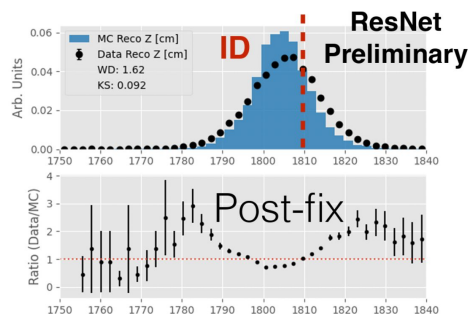
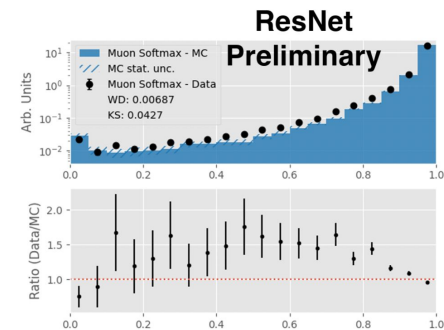
Recent Super-K Data Applications with CNN

Begun confronting past ~8 years of model development with real data

Cosmic ray muons ([NPML2026](#))



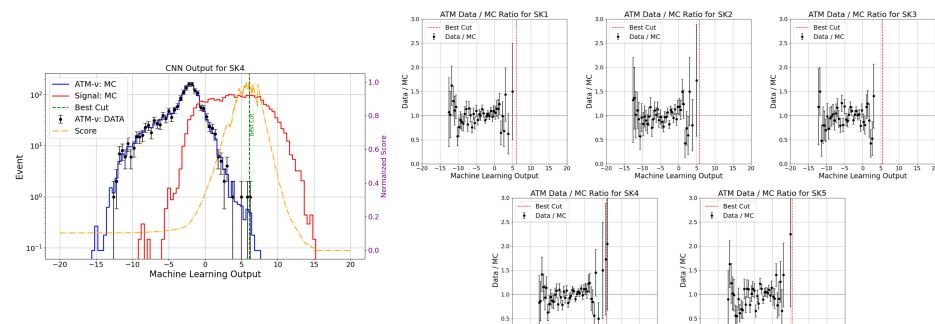
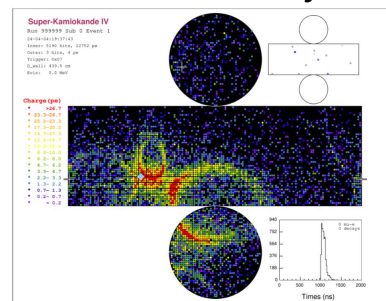
- Muon/electron classification and regression from supervised CNN showing shift from data
 - Simulation used for training likely not perfectly tuned to this detector period



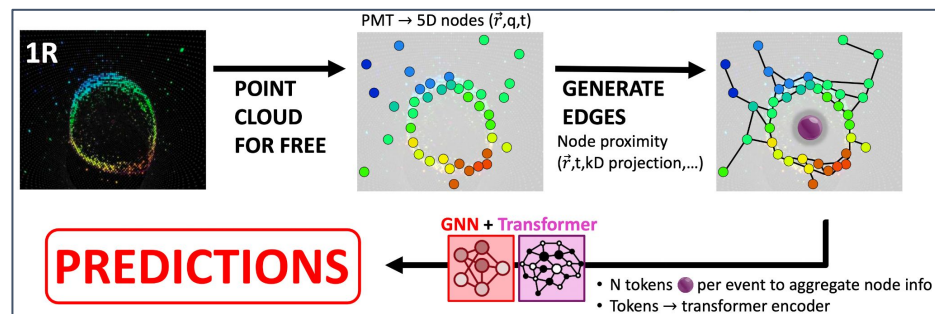
Proton Decay Search ([arXiv:2609.25681](#))

Trinucleon decay: $^{16}\text{O}(\text{ppp}) \rightarrow ^{13}\text{C}\pi^+\pi^+\text{e}^+$

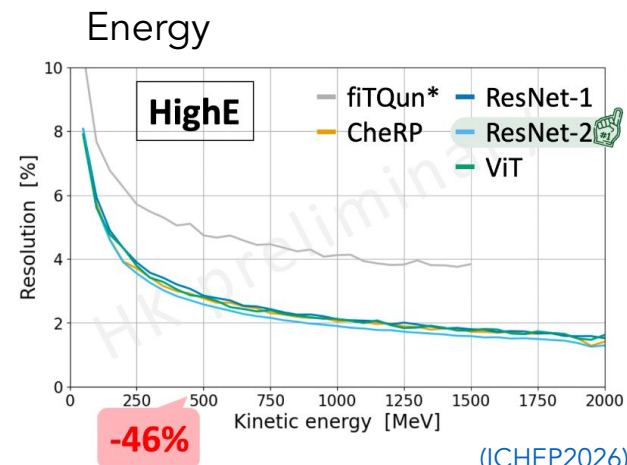
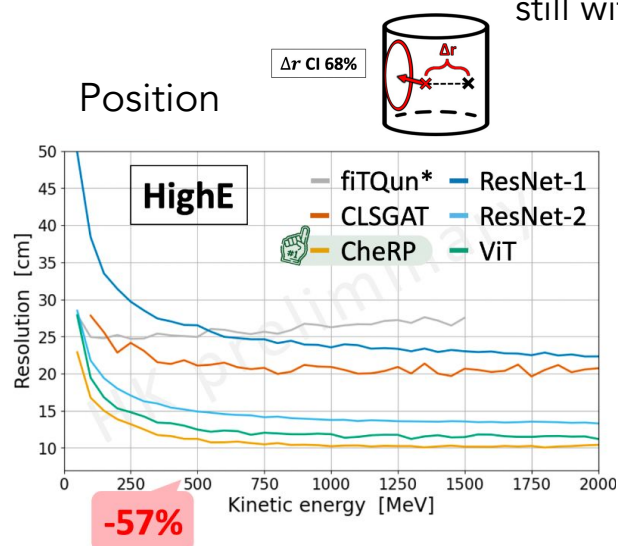
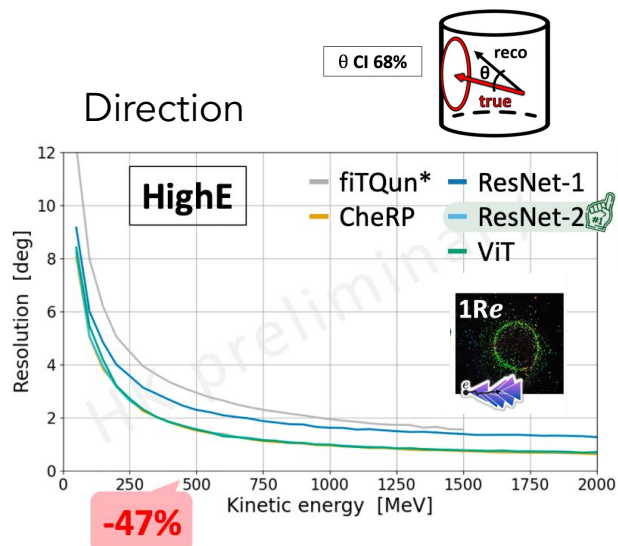
- Signal/background classifier
- CNN re-trained across detector periods obtains good data/MC agreement



+GNNs and Hyper-K Benchmarks

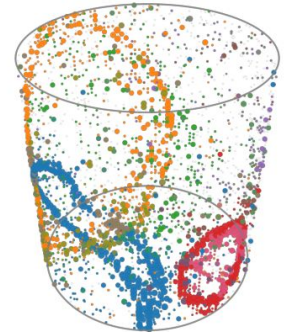
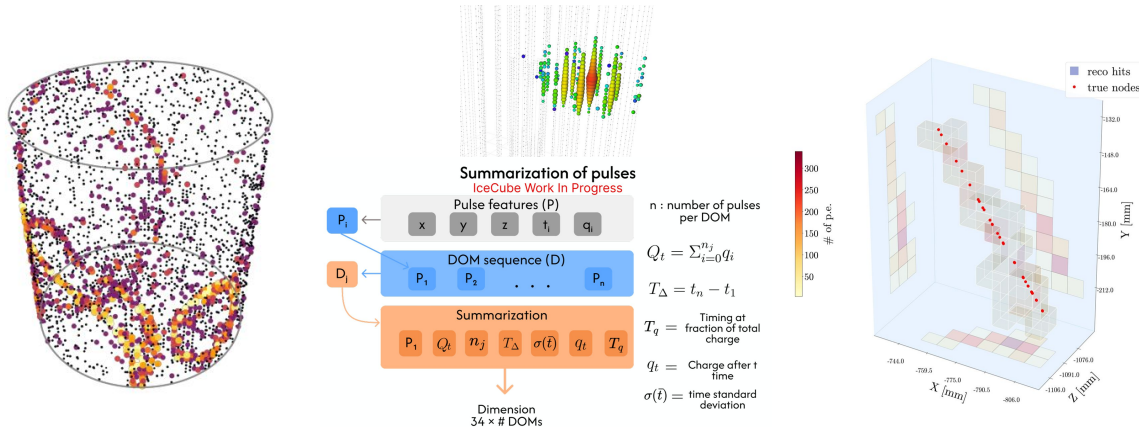


- Benchmarking regression performance from many independently developed models on a common dataset
 - Previously scattered effort across multiple groups producing own datasets
 - *fiTQun traditional likelihood-based fitter still with preliminary tuning for Hyper-K



Transformers

	<u>Hyper-K</u> <u>(ICHEP2026)</u> "CheRP" on prev. slide	<u>IceCube</u> <u>(NPML2025)</u>	<u>T2K SuperFGD</u> <u>(NPML2025)</u>	<u>Panda</u> (for Water Cherenkov) <u>(arXiv:2609.00611)</u>
Input	Unordered hit PMTs	DOM pulse summaries	Ordered reconstructed track nodes	3D detector points
Architecture	Perceiver / latent Set Transformer	Global multi-task Transformer	Dense sequence Transformer	Hierarchical Point Transformer



IceCube: ATtention for High-Energy Neutrino Alerts (ATHENA)

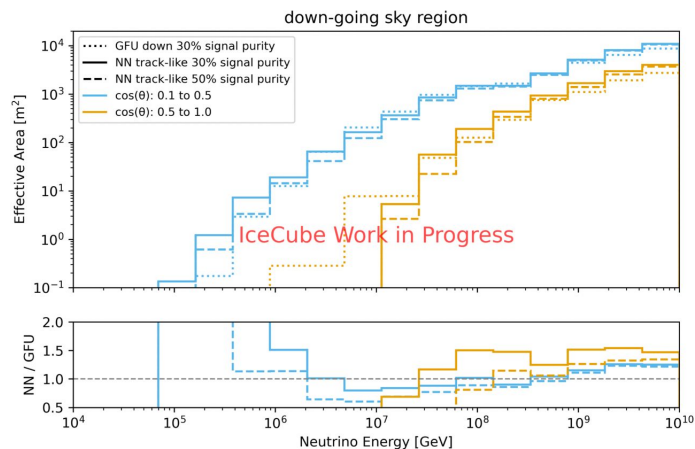
- Transformer-based model to reconstruct high-energy neutrinos
- Multi-task model reconstructs
 - Energy (at entrance and deposited)
 - Direction
 - Position
 - Topology (starting and trackness)
- Goal:
 - Build a new event selection with robust directional reconstruction for neutrino alerts
 - Increasing number of neutrino candidates for multi messenger observations
 - Opens up the Southern sky for IceCube alerts!
 - Naturally also expands to cascades

Resulting effective area comparison

down-going region

- Increase in number of signal events of ~ 200% — 300% However this number is quite dependent on the astrophysical flux assumed.
- Angular distance median is slightly worse.
- ~20% of the events are also present in the GFU selection

	This work	GFU
Median	0.34	0.25
90th	1.70	2.17

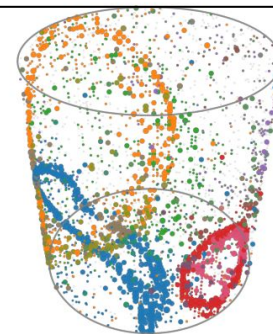
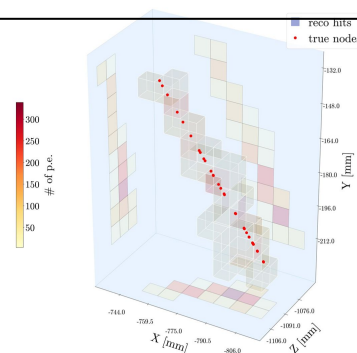


(NPML2025)

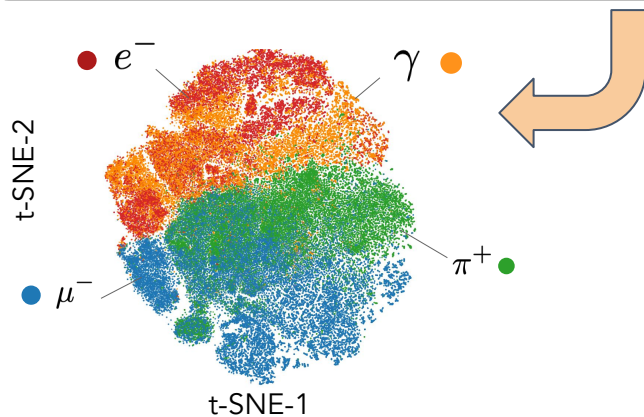
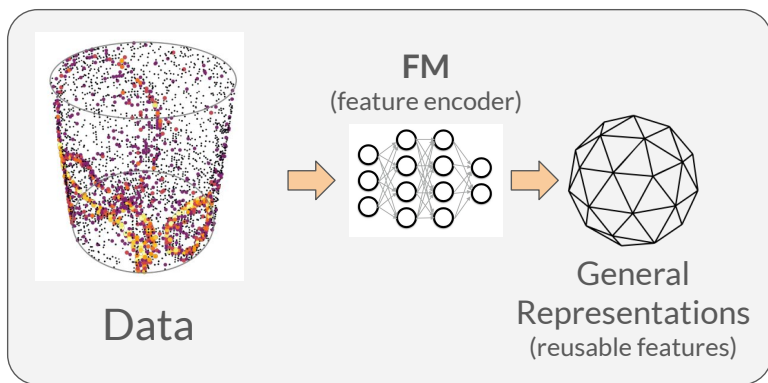
Transformers with Self-Supervision (SSL)

	<u>Hyper-K</u> (ICHEP2026) "CheRP" on prev. slide	<u>IceCube</u> (NPML2025)	<u>T2K SuperFGD</u> (NPML2025)	<u>Panda</u> (for Water Cherenkov) (arXiv:2609.00611)
Input	Unordered hit PMTs	DOM pulse summaries	Ordered reconstructed track nodes	3D detector points
Architecture	Perceiver / latent Set Transformer	Global multi-task Transformer	Dense sequence Transformer	Hierarchical Point Transformer
Training	Supervised	Supervised multi-task	Masked-feature SSL → PID	Self-distillation SSL → downstream tasks

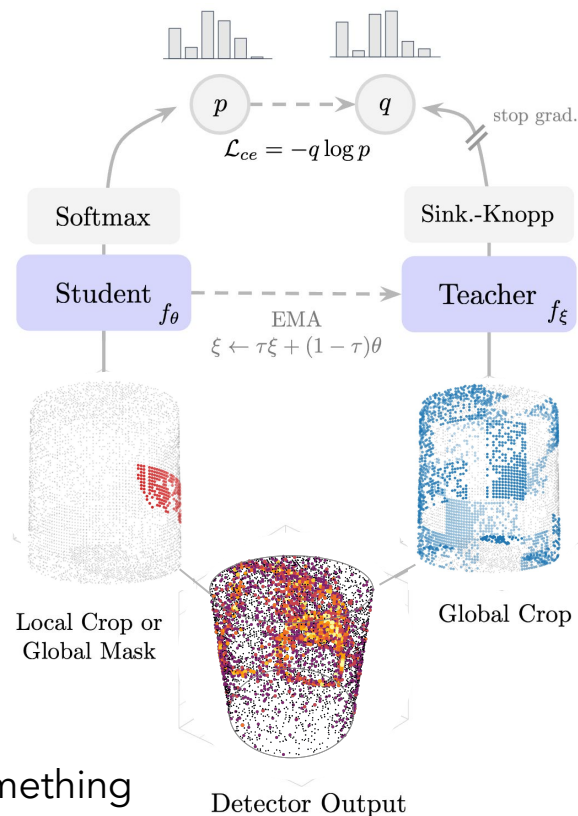
Pre-training on real detector data to mitigate domain shift and establish automation of continuous learning from sensors



Foundation Model



Clustering in representation space shows something physical after pre-training without truth labels



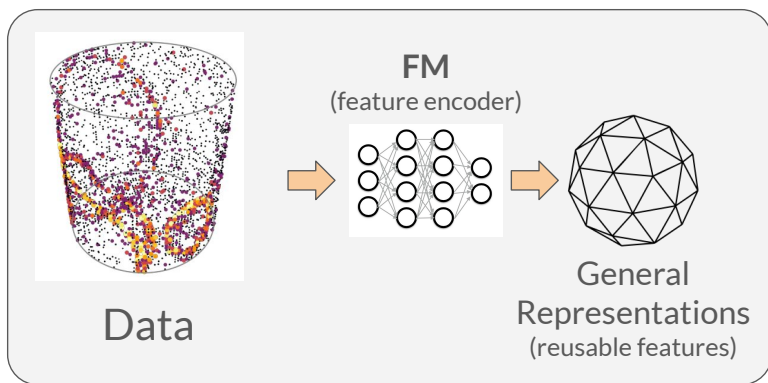
Panda
(for Water Cherenkov)
([arXiv:2609.00611](https://arxiv.org/abs/2609.00611))

3D detector points

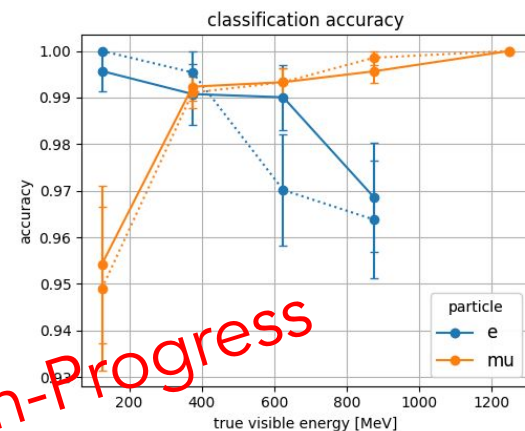
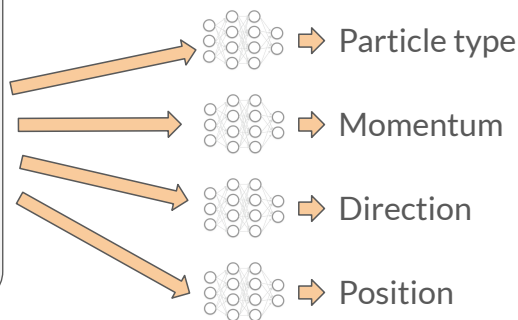
Hierarchical Point Transformer

Self-distillation SSL $\rightarrow$ downstream tasks

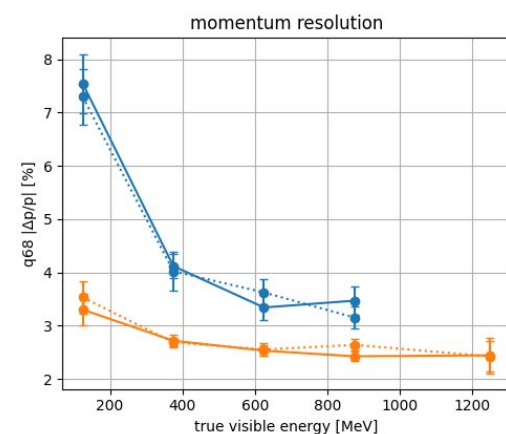
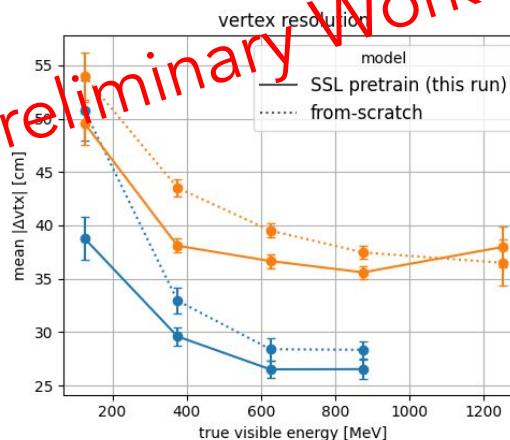
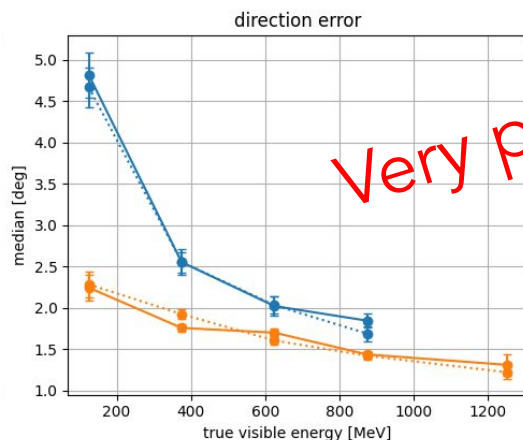
Foundation Model → Fine-Tuning



Multiple fine-tune task heads



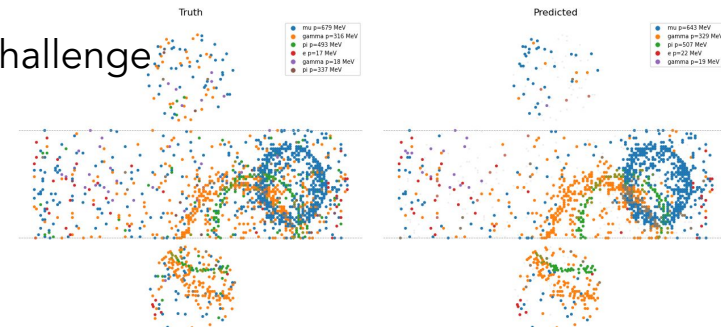
Very preliminary Work-in-Progress



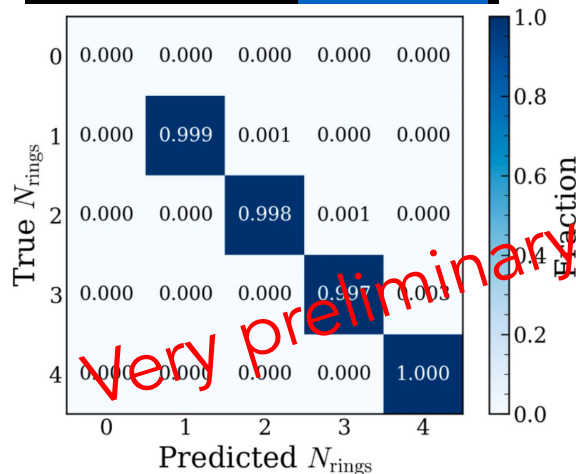
Performance approaching previous supervised benchmarks

Particle Instance Identification (Ring Counting)

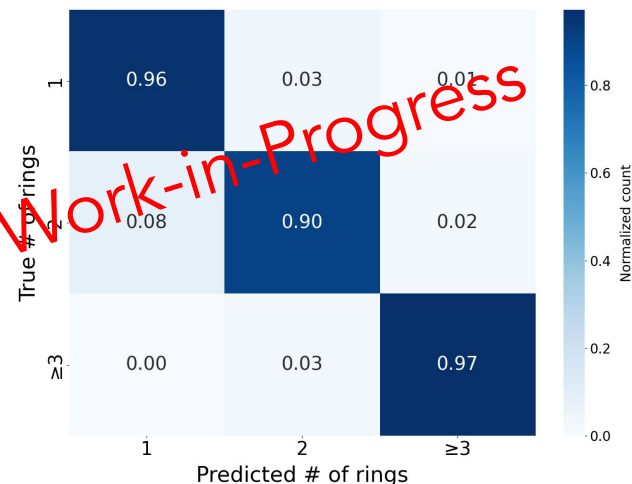
- Multi-ring separation and reconstruction major remaining challenge
- Very preliminary fine-tuned head of Panda FM already comparable to collaboration tools
 - Plus the reconstruction of each ring with ML



Sparse U-Net encoder +
Attention head (ICHEP2026)



Panda (arXiv:2609.00611)



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%

fiTQun on fully contained atmospherics
(not apples to apples) ([arXiv:1901.03230](https://arxiv.org/abs/1901.03230))

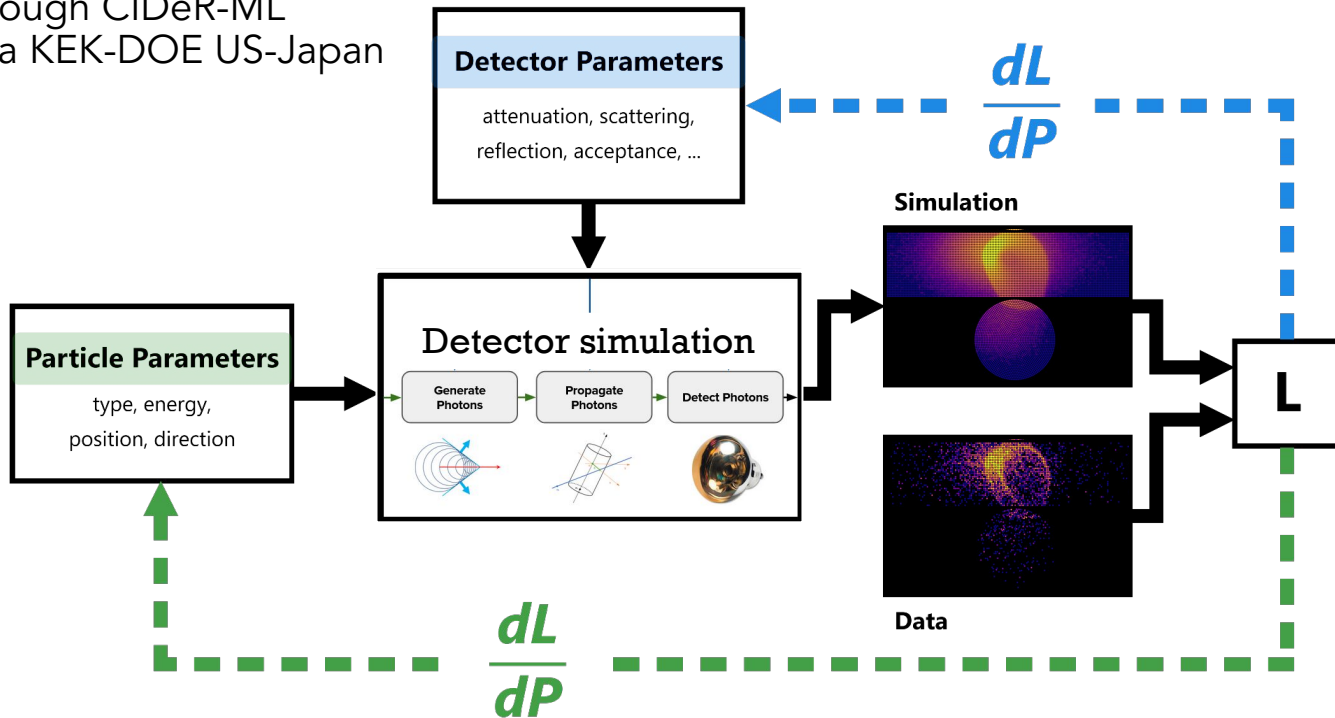
Warning: each tested on different data sets

The background is a complex, abstract pattern of glowing circuit lines in shades of blue, purple, and yellow, set against a dark, starry space-like background. A large, solid grey square is positioned in the center of the image, acting as a focal point. The circuit lines radiate outwards from this central square, creating a sense of connectivity and flow.

Simulation

Differentiable Detector Simulator (DDSim)

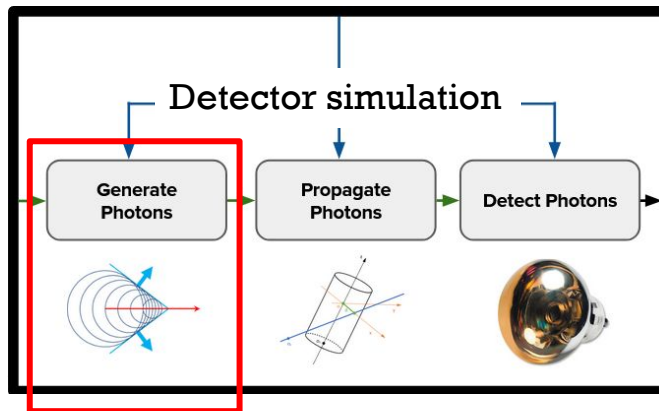
- Write detector simulation with differentiable models for each physics process
 - Exploring two methods: neural surrogates & analytical auto-differentiable programming
- Enables end-to-end pipeline that allows gradient-based optimization with ML tools
- Developed through CIDEr-ML collaboration, a KEK-DOE US-Japan project



Neural Surrogate Model

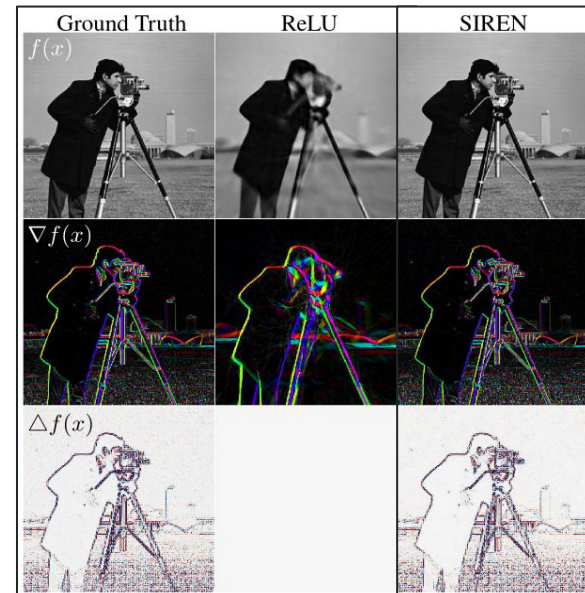
(NPML 2025)

- Write detector simulation with differentiable models for each physics process
- Replace lookup tables with surrogate model
 - Cherenkov light production
 - Optical photon propagation and detection



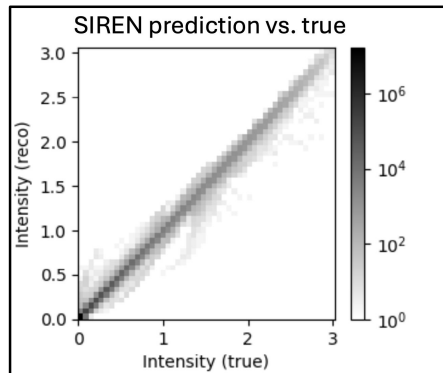
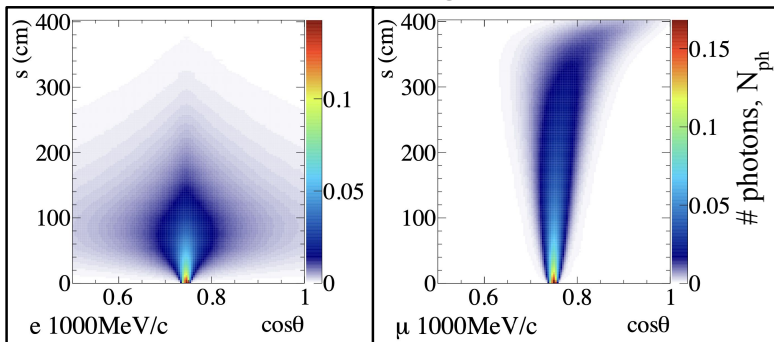
SIREN

Sinusoidal Representation Network



Can better represent underlying distributions and their derivative compared to other networks

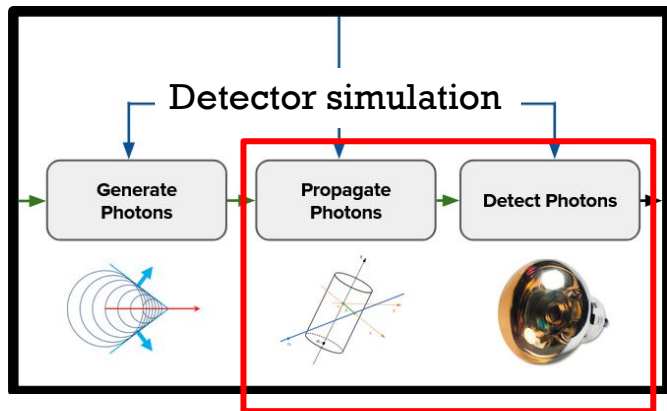
Cherenkov Light Profiles



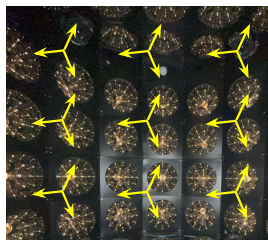
Neural Surrogate Model

(NPML 2025)

- Write detector simulation with differentiable models for each physics process
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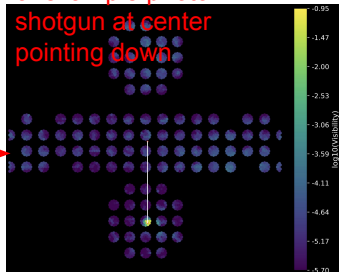


Pre-tune MC photon gun

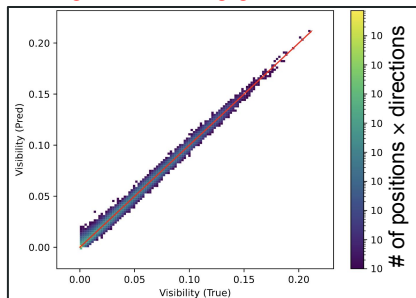


$\text{vis}(\vec{x}, \vec{d})$

SIREN prediction of example photon shotgun at center pointing down

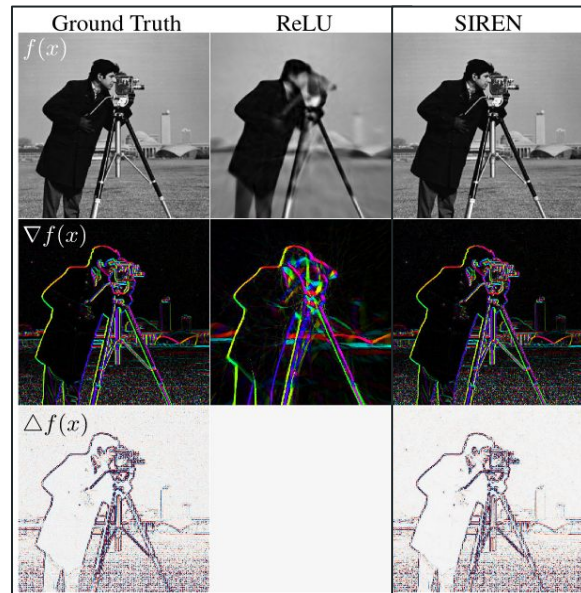


Surrogate modeling goodness



SIREN

Sinusoidal Representation Network

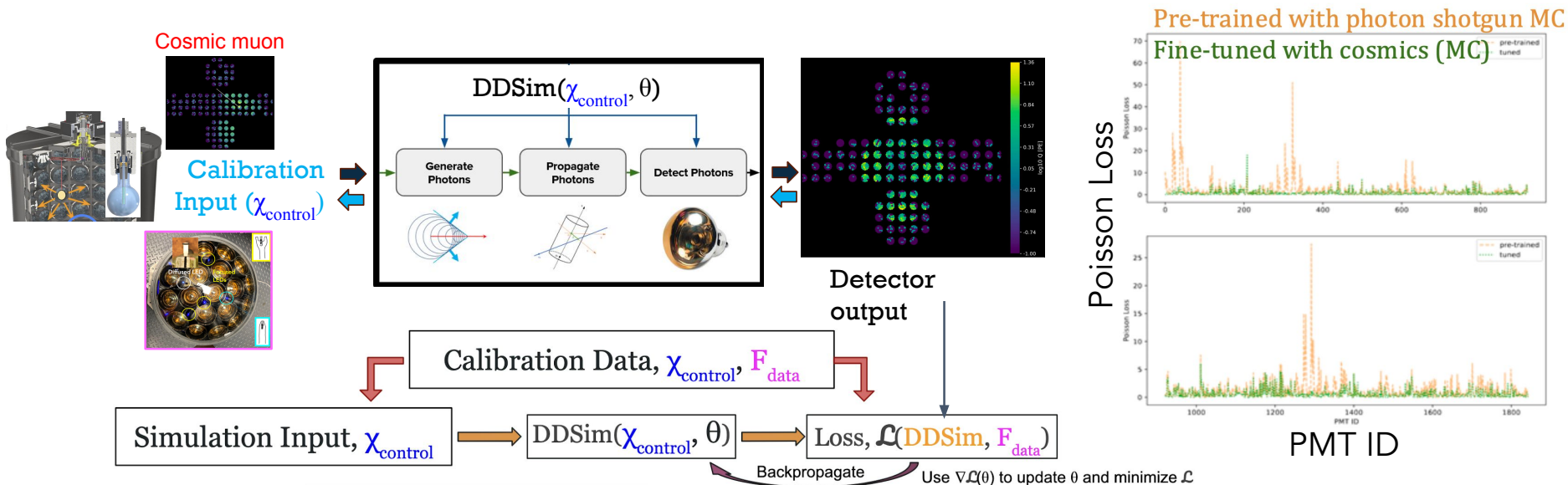


Can better represent underlying distributions and their derivative compared to other networks

Calibration with Neural Surrogates

(NPML 2025)

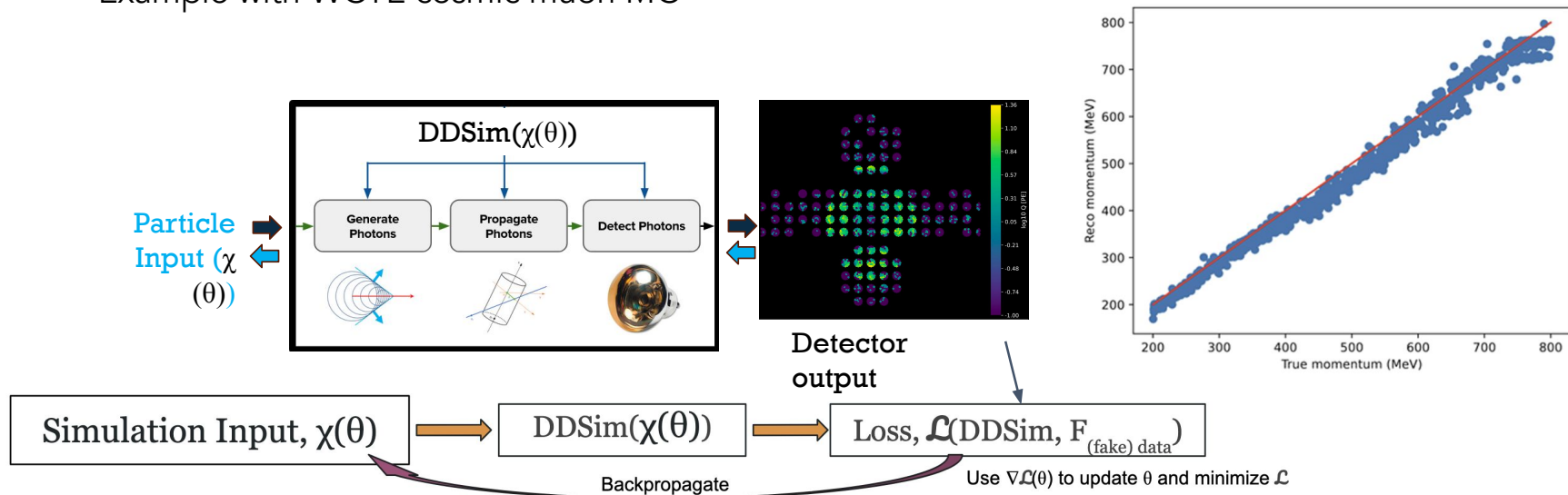
- Enabled end-to-end pipeline that allows gradient-based optimization with ML tools
- Calibration = Optimization (fine-tuning) of DDSim parameters, θ
 - Example loss reduction with fine-tuning using WCTE cosmic muon MC (real data coming soon)



Reconstruction with Neural Surrogates

(NPML 2025)

- Enabled end-to-end pipeline that allows gradient-based optimization with ML tools
- Reconstruction = Optimization of input particle track parameters, θ
 - Example with WCTE cosmic muon MC



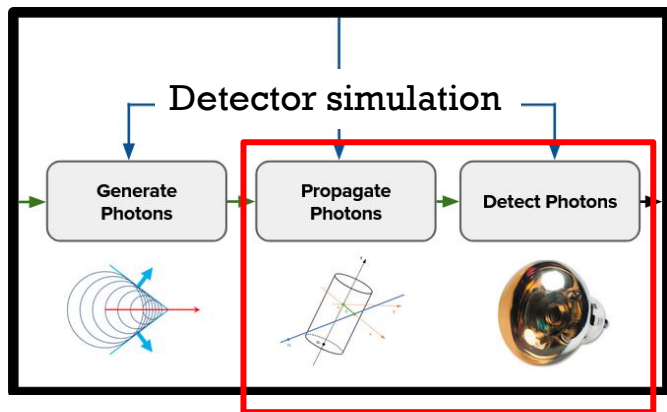
Work-in-Progress

2.7% momentum resolution (assuming fixed position & direction, bias-corrected, but charge only)
Comparable to previous benchmarks

Analytical DDSim

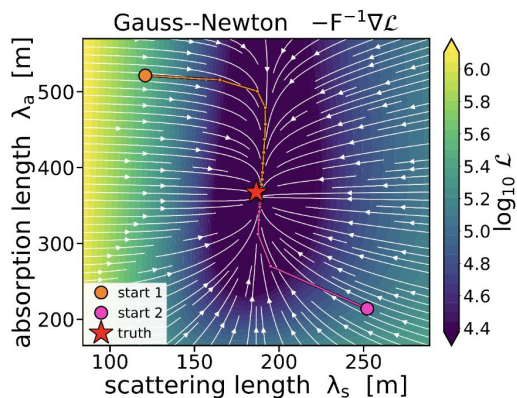
[arXiv:2602.24129](https://arxiv.org/abs/2602.24129)

- Write detector simulation with differentiable models for each physics process
- Alternatively, re-write physical processes/models in automatic-differentiable language

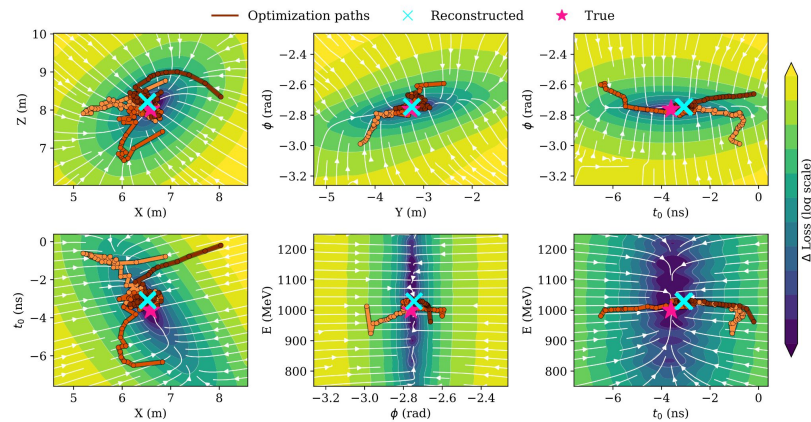


LUC₁D 

Light-based Unified Calibration and tracking Differentiable simulation



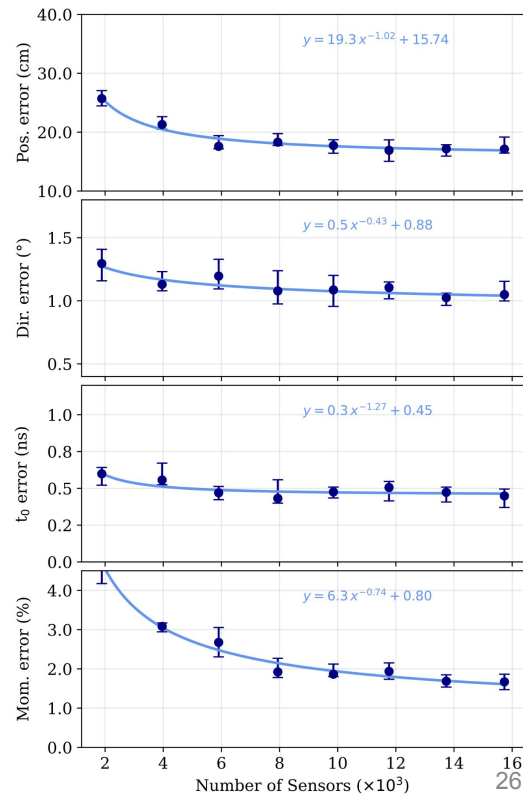
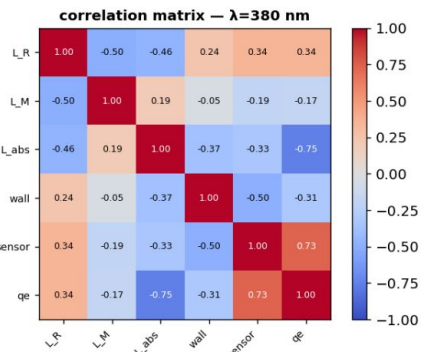
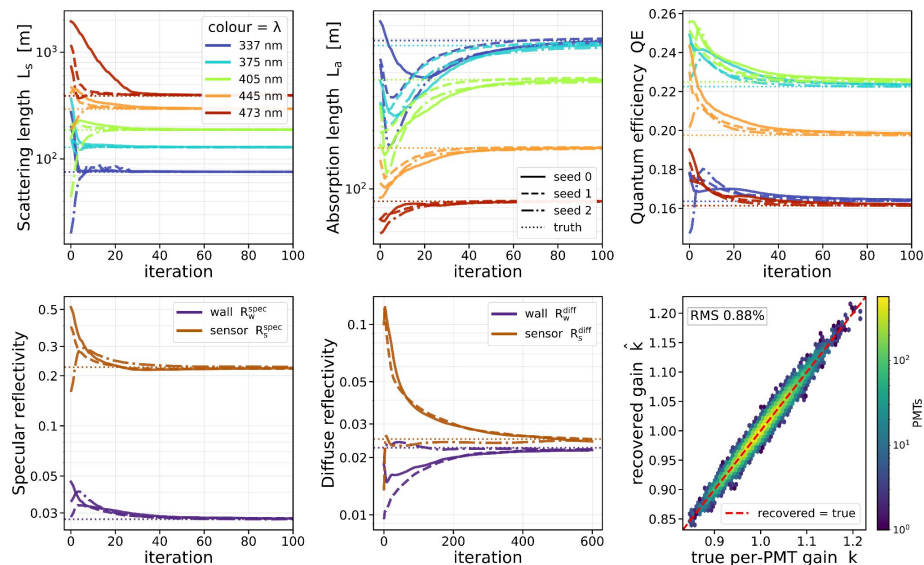
Gradients of detector parameters and track parameters well-behaved



Analytical DDSim: Calib & Reco

(arXiv:2602.24129)

- Enabled end-to-end pipeline that allows gradient-based optimization with ML tools
- Demonstrated calibration of water Cherenkov detector parameters using multiple calibration sources, including correlations
- Demonstrated single track reconstruction and detector optimization, with performance comparable to previous benchmarks

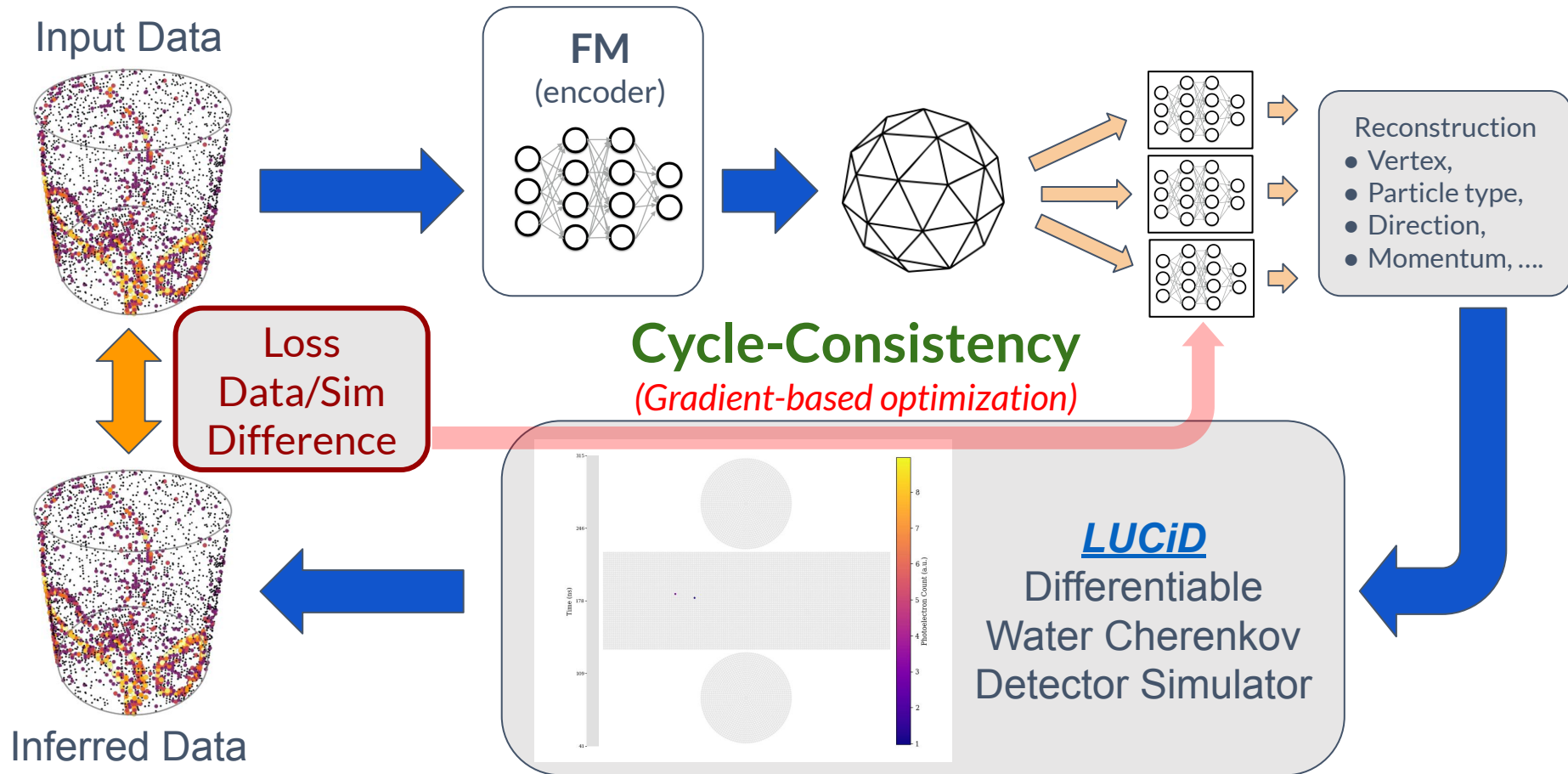


*KEK-DOE U.S.-Japan Science and Technology Cooperation Program in High Energy Physics & Ozaki Exchange Program

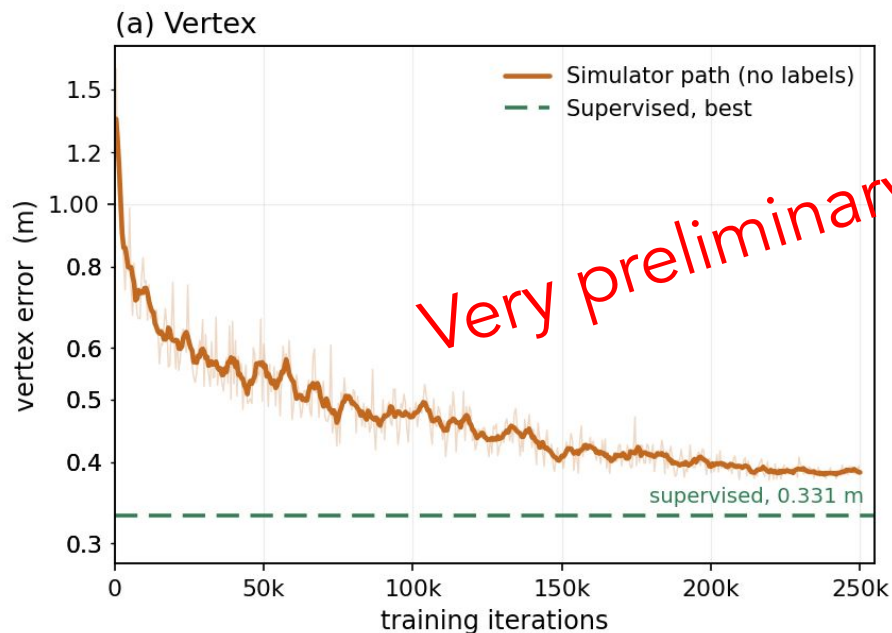
Cycle-Consistency

The background of the slide is a complex, abstract pattern. It features a dense network of glowing blue and purple lines that resemble circuit board traces or data paths. These lines are set against a dark, textured background that looks like a starry night sky or a nebula. In the center of the image, there is a solid, light-blue square. The overall aesthetic is high-tech and futuristic.

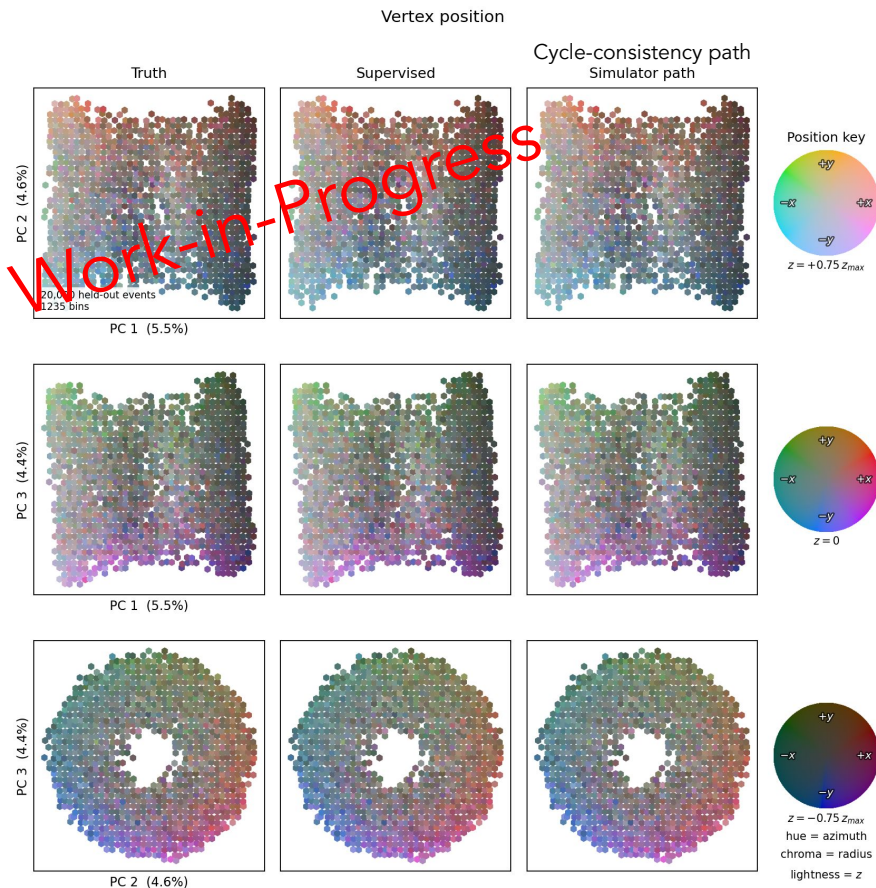
Fine-tuning w/o Labels: Differentiable Detector Simulator



Fine-tuning w/o Labels: Vertex Reconstruction @ WC

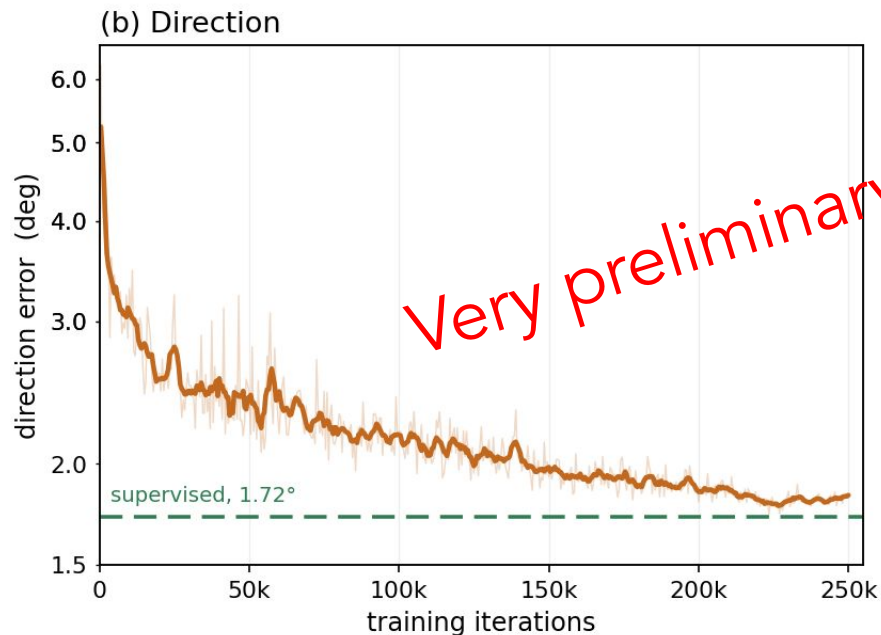


Work Credit:
O. Alterkait (Tufts)

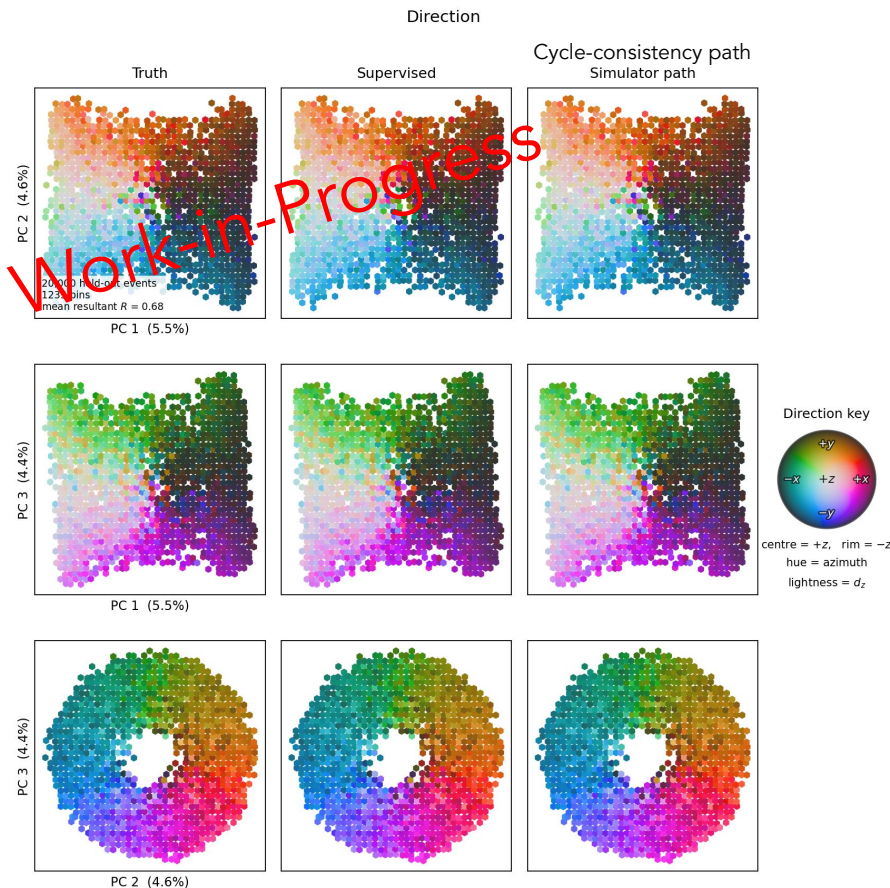


percentages: fraction of feature variance (PCA is unsupervised)

Fine-tuning w/o Labels: Direction Reconstruction @ WC

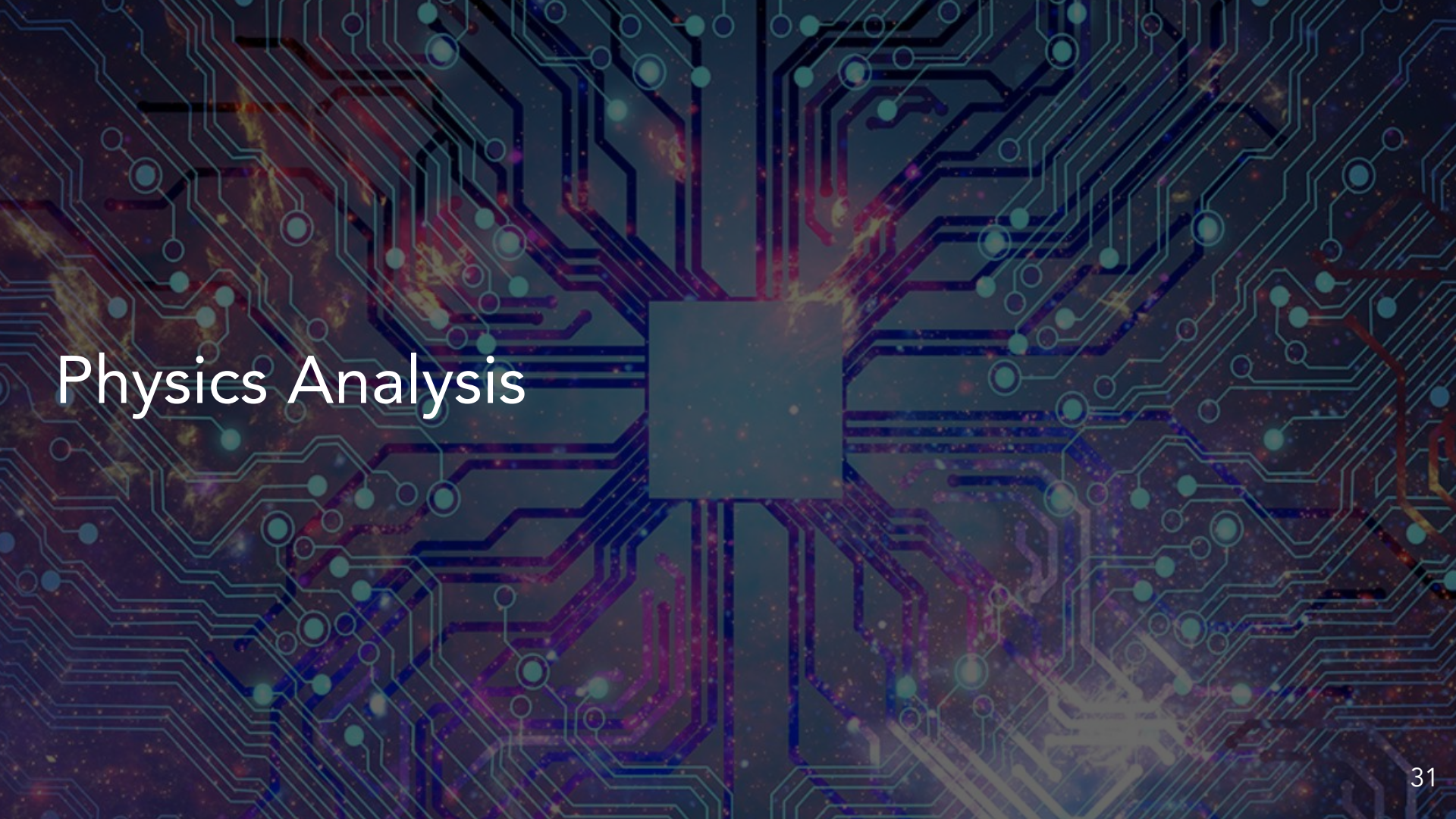


Work Credit:
O. Alterkait (Tufts)

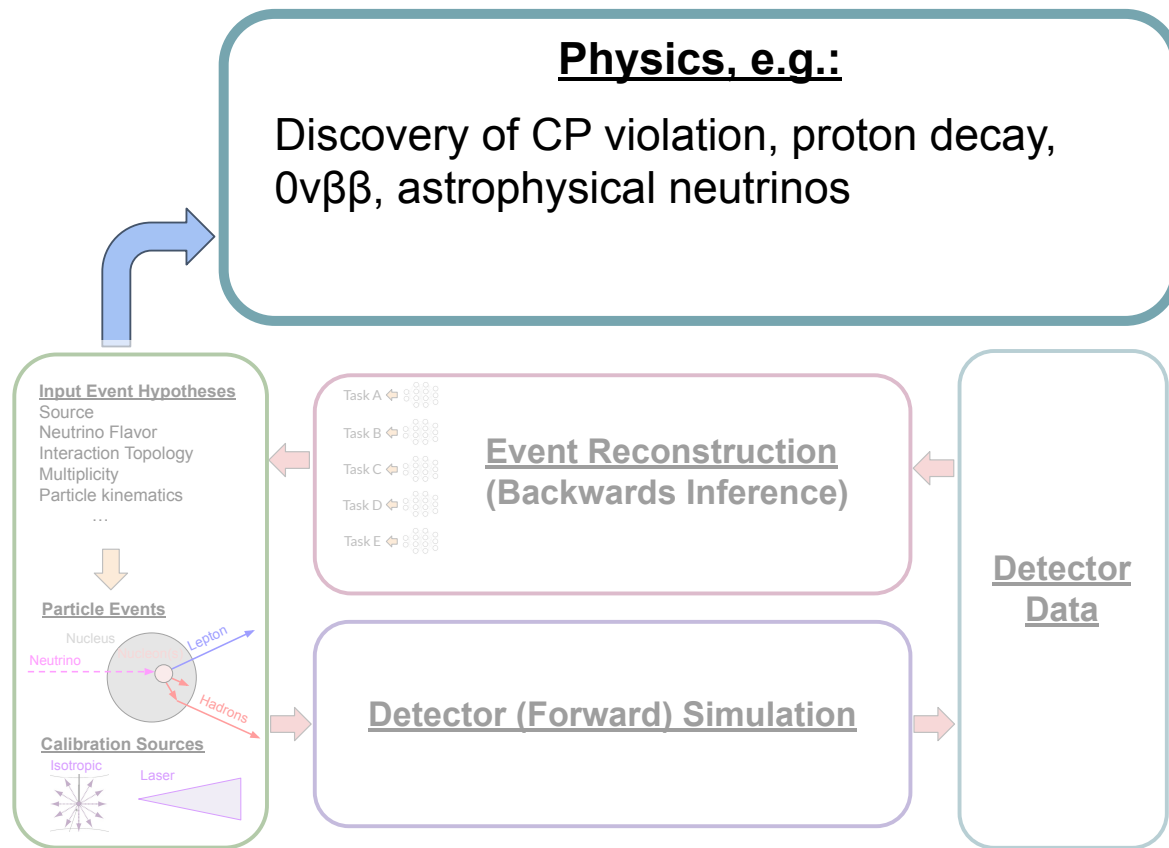


percentages: fraction of feature variance (PCA is unsupervised)

Physics Analysis

The background is a complex, abstract composition. It features a dense network of glowing blue and purple circuit-like lines that branch out from a central, solid grey square. These lines are set against a dark, textured backdrop that resembles a cosmic or nebula-like environment, with hints of yellow and orange light. Small, glowing blue circles are scattered throughout the circuitry, adding to the digital and scientific aesthetic.

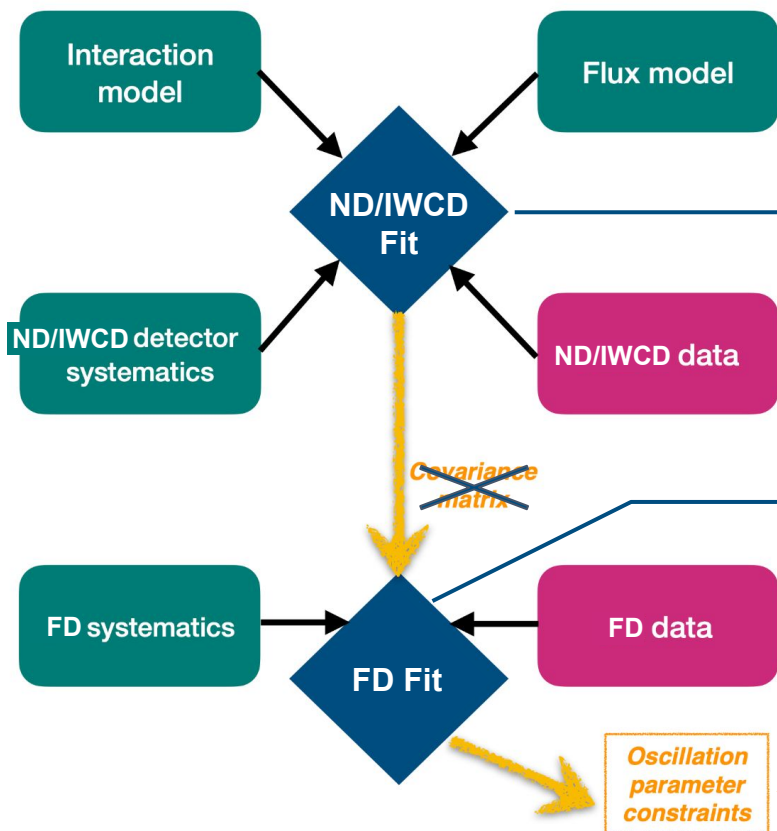
Efforts also to improve physics (e.g. neutrino oscillation) analysis with ML, which can reduce information bottleneck and couple directly to FM output



Normalizing Flows (NFs) as Likelihood Surrogates

External cross section measurements

External hadron production measurements, INGRID data



Modeling neutrino flux and interaction systematics from long-baseline near detector fit ([arXiv:2607.03477](https://arxiv.org/abs/2607.03477))

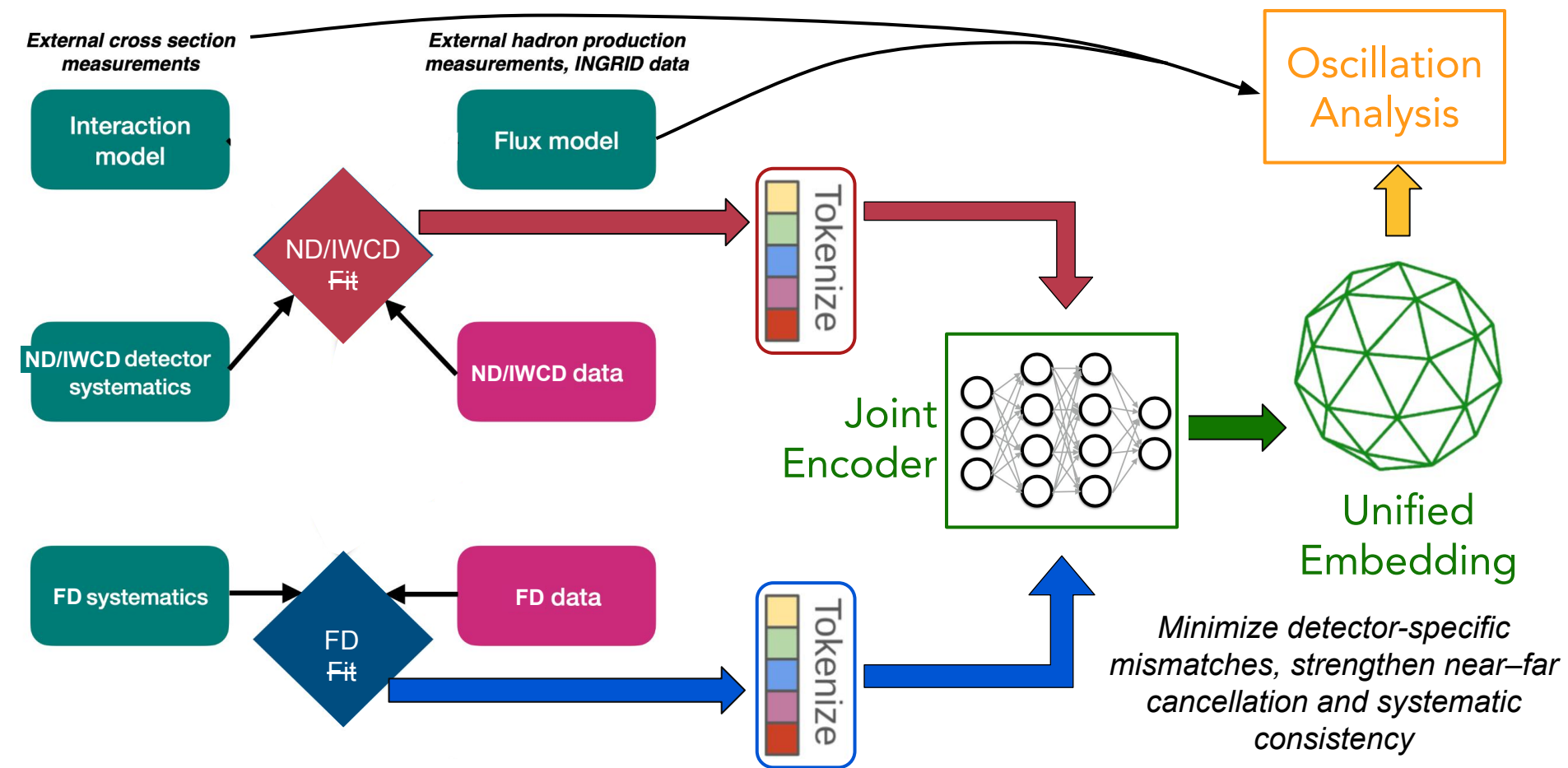
$$p(\theta | D) \propto \pi(\theta) \int d\eta q_{\text{ND}}(\eta) \prod_i \int dE_{\nu,i} q_{\text{det}}(\hat{x}_i | E_{\nu,i}, \eta) p(E_{\nu,i} | \theta, \eta).^*$$

Modeling PDF of reconstructed observables given true neutrino energy ([NPML2026](https://arxiv.org/abs/2607.03477))

*Note: Joint likelihood with NFs not yet implemented

Future: Cross-Modal Foundation Model

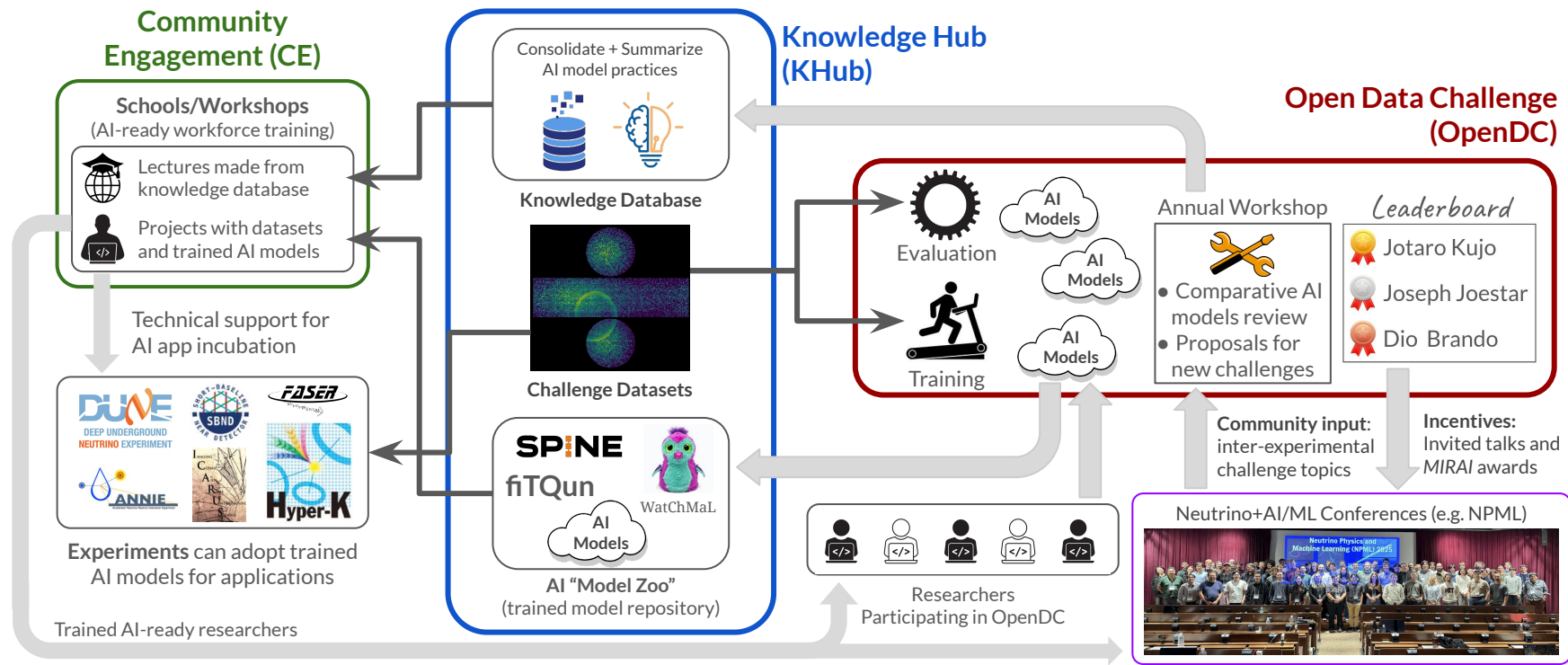
Ref. K. Terao



The background is a complex, abstract pattern of glowing circuit lines in shades of blue, purple, and yellow, set against a dark, starry space-like background. A large, solid grey square is positioned in the center, acting as a focal point where the circuit lines converge and radiate outwards.

Community

Development Of Resilient AI EcosysteM for Oscillating Neutrinos (another US-Japan project)



See more detail in [K. Terao talk on Wednesday](#)

Summary

- Lots of work in simulation, reconstruction, domain adaptation, and analysis
 - Deep learning and foundation models with self-supervision, neural surrogates and differentiable simulation
 - Growing applications to real data
- Building a new open ecosystem for AI/ML research in neutrino

Appendix

Systematics Limited - Approaching Precision Physics



- New near detectors (NDs) aim to mitigate most flux and interaction systematics

Need to reduce to <3% for Hyper-K



"T2K 2021 syst.": [Phys. Rev. D 103, 112008](#)

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

- Then, efficiently and effectively mitigating detector systematics (of NDs too) become critical to quickly achieve target physics sensitivity