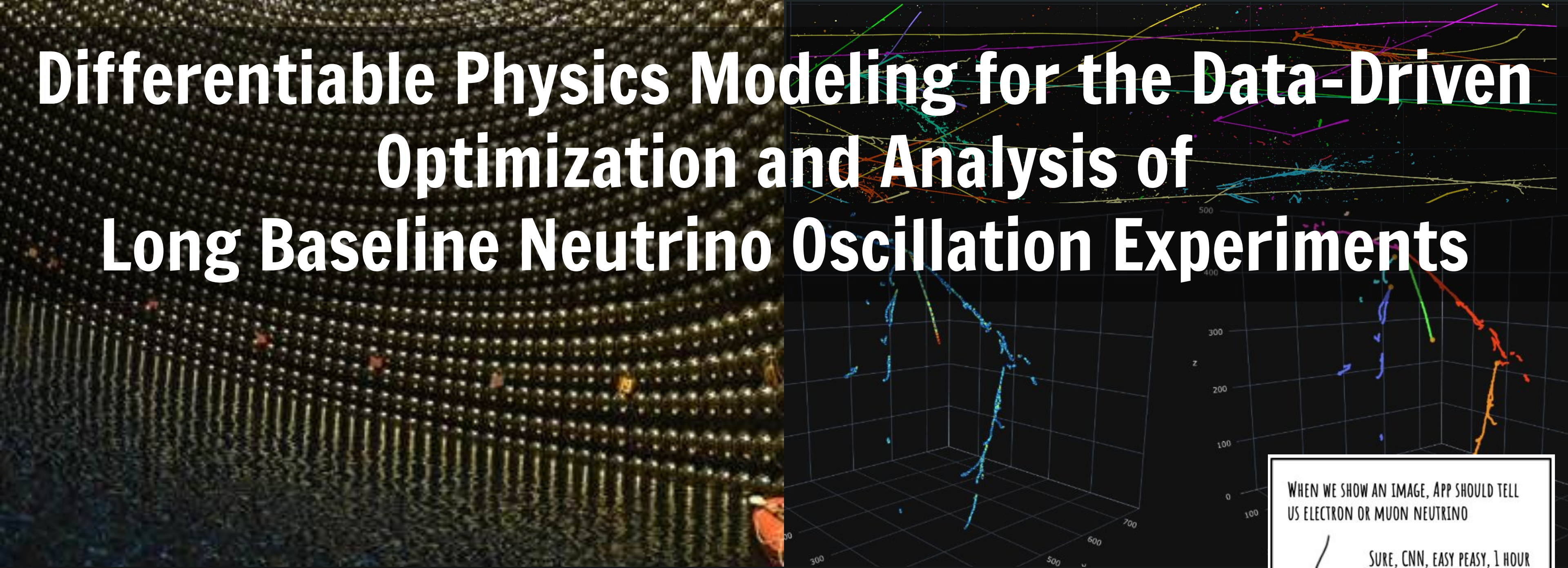


Differentiable Physics Modeling for the Data-Driven Optimization and Analysis of Long Baseline Neutrino Oscillation Experiments

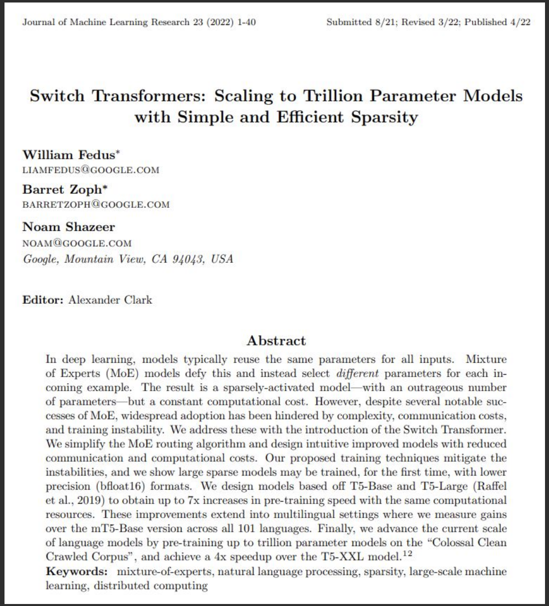
US-JAPAN SCIENCE AND TECHNOLOGY COOPERATION PROGRAM
COLLABORATION KICK-OFF MEETING, AUGUST 7/8TH, 2023

Patrick de Perio — KAVLI IPMU

Kazuhiro Terao — SLAC

(Physics) Model Optimization

Success of AI is through gradient-based optimization that works for millions, billions, or even trillions of parameters.



Journal of Machine Learning Research 23 (2022) 1-40 Submitted 8/21; Revised 3/22; Published 4/22

Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity

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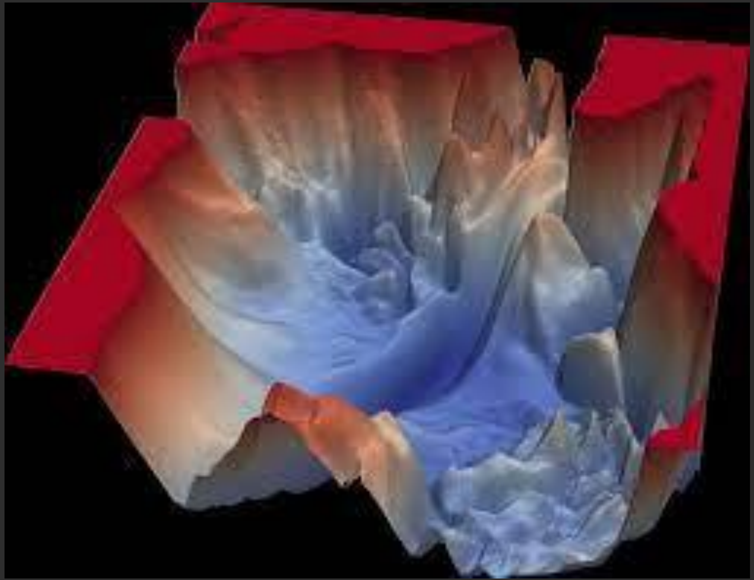
Editor: Alexander Clark

Abstract

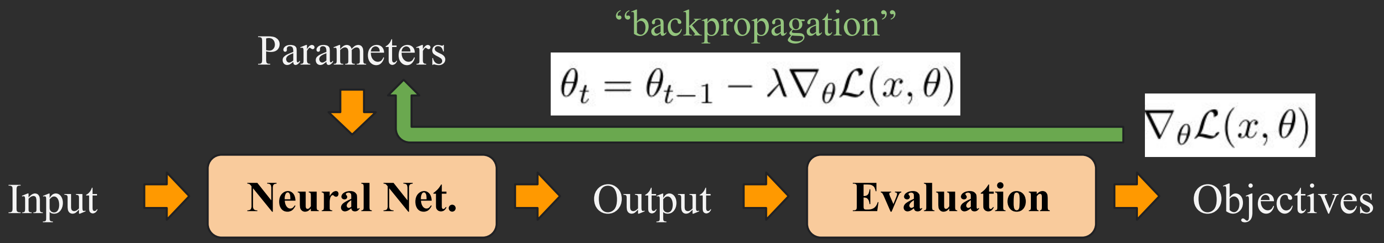
In deep learning, models typically reuse the same parameters for all inputs. Mixture of Experts (MoE) models defy this and instead select *different* parameters for each incoming example. The result is a sparsely-activated model—with an outrageous number of parameters—but a constant computational cost. However, despite several notable successes of MoE, widespread adoption has been hindered by complexity, communication costs, and training instability. We address these with the introduction of the Switch Transformer. We simplify the MoE routing algorithm and design intuitive improved models with reduced communication and computational costs. Our proposed training techniques mitigate the instabilities, and we show large sparse models may be trained, for the first time, with lower precision (bfloat16) formats. We design models based off T5-Base and T5-Large (Raffel et al., 2019) to obtain up to 7x increases in pre-training speed with the same computational resources. These improvements extend into multilingual settings where we measure gains over the mT5-Base version across all 101 languages. Finally, we advance the current scale of language models by pre-training up to trillion parameter models on the "Colossal Clean Crawled Corpus", and achieve a 4x speedup over the T5-XXL model.[12]

Keywords: mixture-of-experts, natural language processing, sparsity, large-scale machine learning, distributed computing



"To deal with hyper-planes in a 14-dimensional space, visualize a 3-D space and say "fourteen" to yourself very loudly. Everyone does it." - Geoffrey Hinton

Gradient-based Optimization



Differentiable Physics Models

"backpropagation"

$$\theta_t = \theta_{t-1} - \lambda \nabla_\theta \mathcal{L}(x, \theta)$$

Parameters

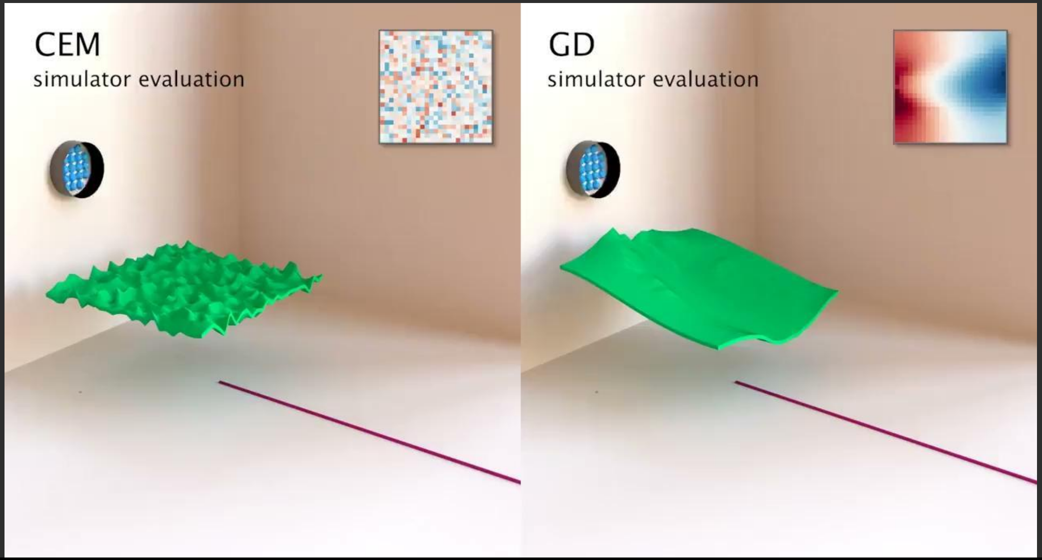
$$\nabla_\theta \mathcal{L}(x, \theta)$$

Input → **Physics Sim.** → Output → **Evaluation** → Objectives

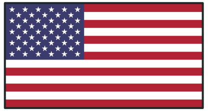
x → Program → $f_\theta(x)$

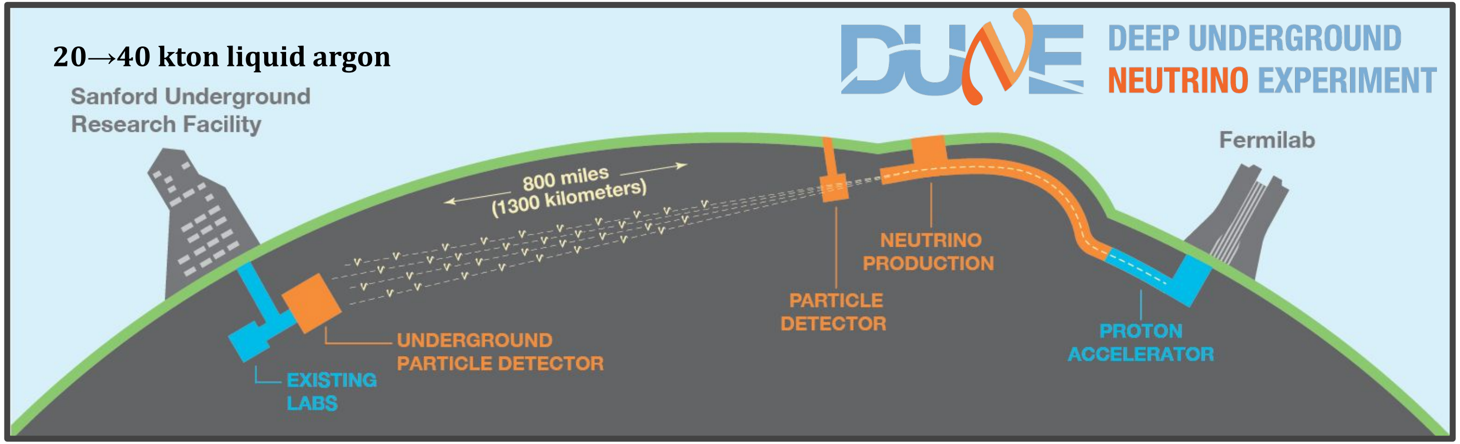
θ → Program → $\nabla_\theta f_\theta(x)$

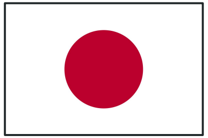
Physical Design using Differentiable Learned Simulators (DeepMind 2202.00728)

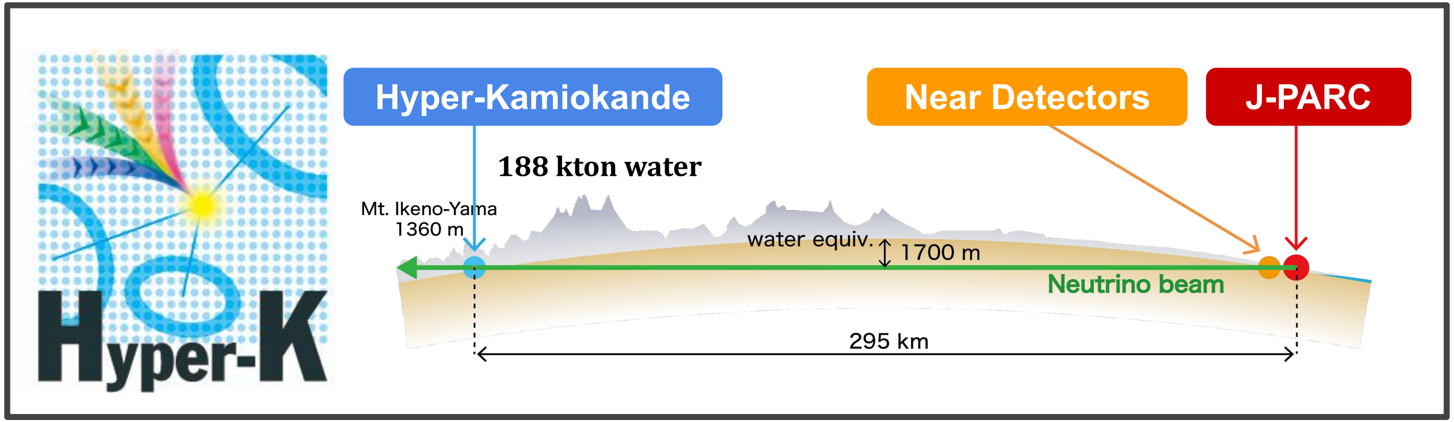


Future Neutrino Oscillation Experiments





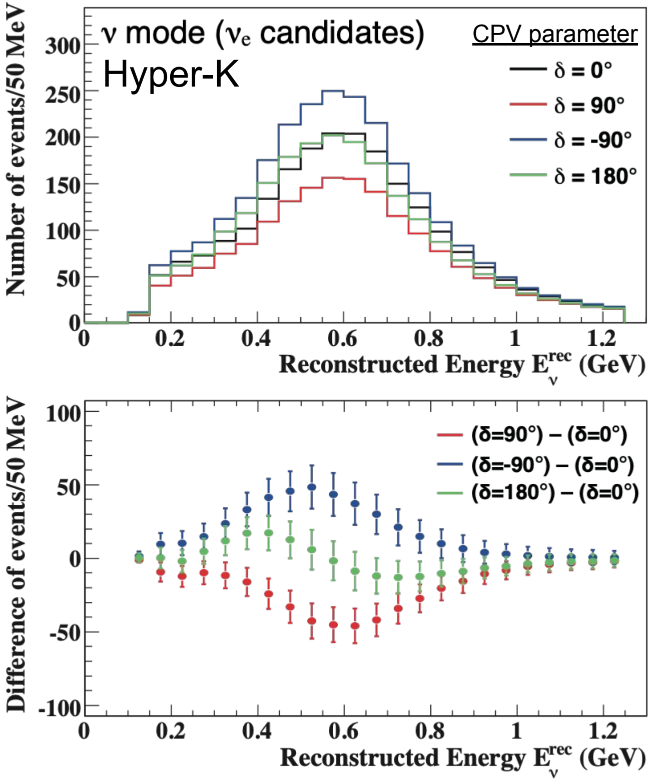


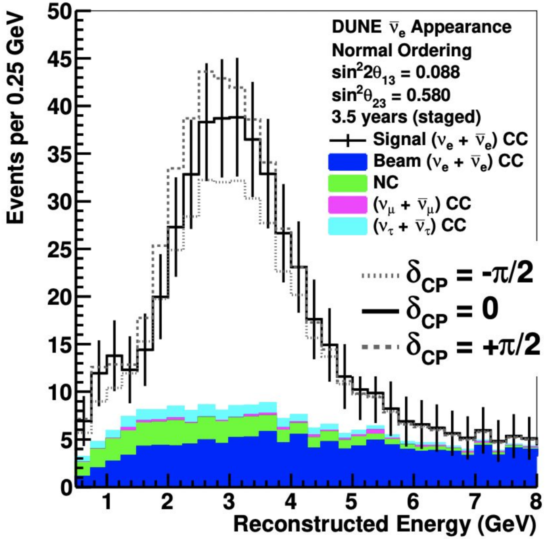


Unprecedented Statistical Precision

Event rates for different assumptions of true δ_{CP}

- DUNE and Hyper-K aim to collect 1000s of ν_e and $\bar{\nu}_e$ appearance events
  - Can measure CP violation (CPV) with ~3% statistical uncertainty!



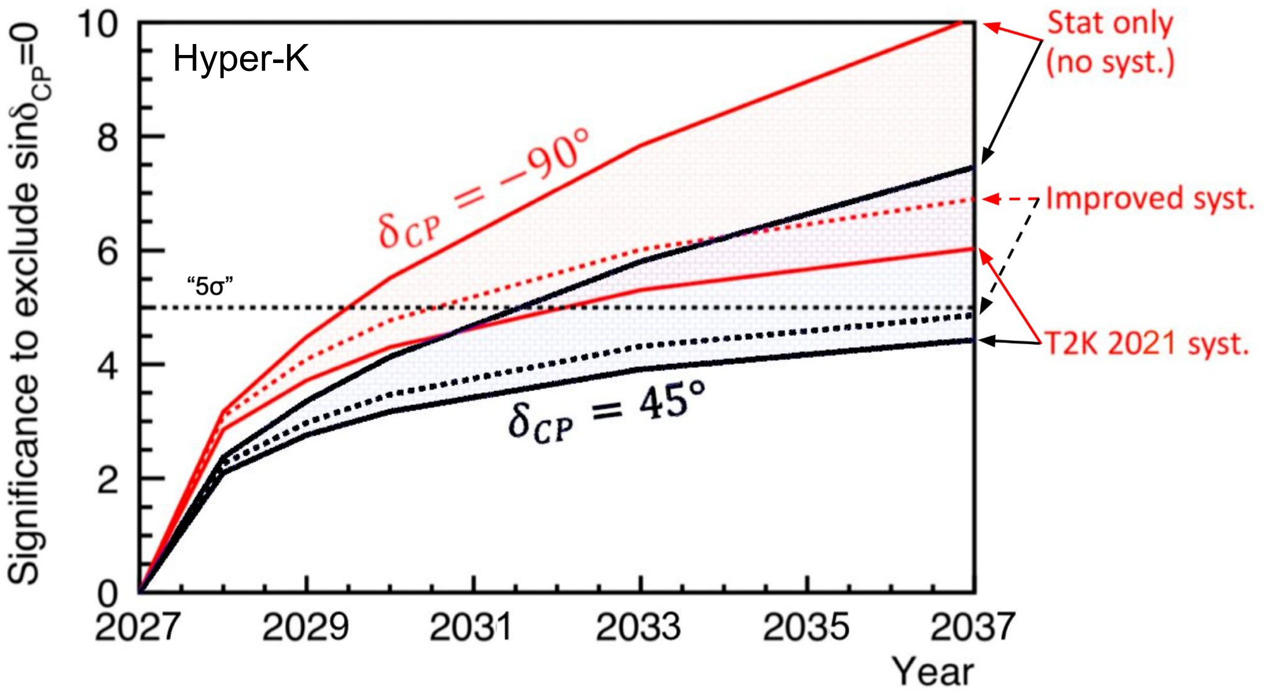


- Controlling systematics becomes critical!

CP Violation Discovery Potential

- Improved understanding of systematic errors is required for a robust and timely discovery of CPV

- Controlling systematics becomes critical!



Current Neutrino Oscillation Systematic Error Budget

- Breakdown of current (T2K) state-of-the-art understanding
  - φ: Beam neutrino flux
  - σ: Neutrino interaction cross-sections
  - ND: Near detector
  - SK (FD): Super-K (far detector)
  - NC: Neutral current

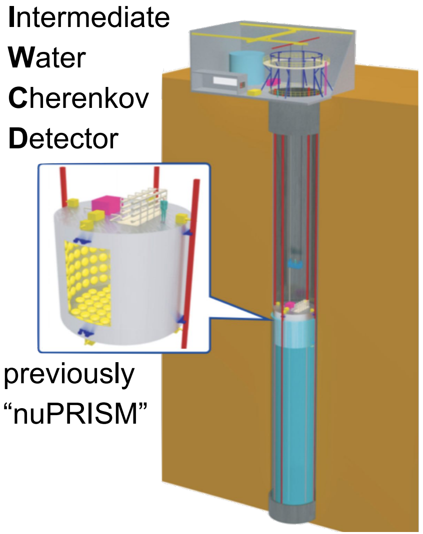
- Need reduction on all fronts

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

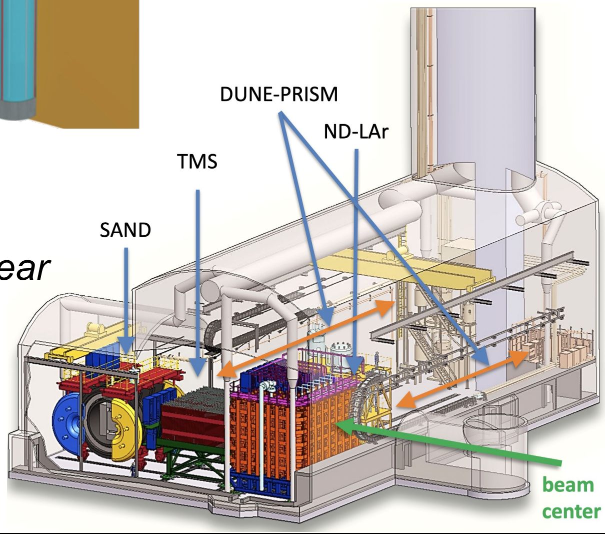
Error Source	% Error for CPV search
$\varphi + \sigma$ (ND constrained)	2.7
$\varphi + \sigma$ (ND unconstrained)	1.2
Nucleon removal energy	3.6
SK π re-interactions	1.6
$\sigma(\nu_e)$, $\sigma(\bar{\nu}_e)$	3.0
NC γ + other	1.5
SK detector (FD)	1.5
Total	**6.0**

Need to reduce to <3%

Novel Beam-Spanning (PRISM) Near Detectors



- New NDs aim to mitigate most systematic errors
- Then detector systematics (of ND too) become especially important



DUNE Near Detector

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

Error Source	% Error for CPV search
$\varphi + \sigma$ (ND constrained)	2.7
$\varphi + \sigma$ (ND unconstrained)	1.2
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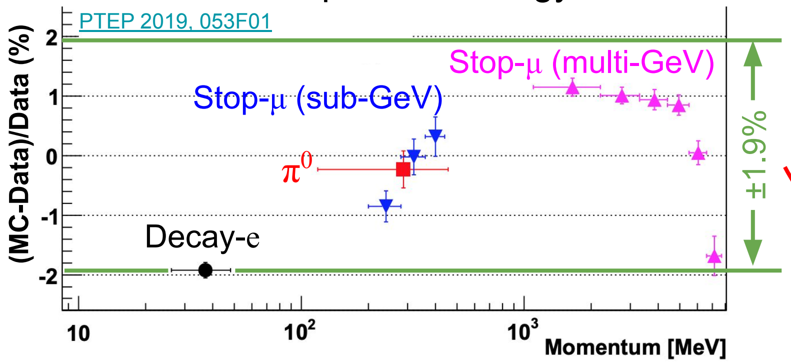
NC γ + other	1.5
SK detector (FD)	1.5
Total	**6.0**

Need to reduce to <3%

T2K-SK Water Cherenkov Detector Systematics



Aiming for 0.5% in Hyper-K

Systematic errors in event selection and energy scale assigned from data/MC discrepancies in cosmic ray and atmospheric ν data

"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%

Traditional Paradigm of Detector Physics Modeling

Geometry

Cherenkov physics

Water properties (light scattering, absorption)

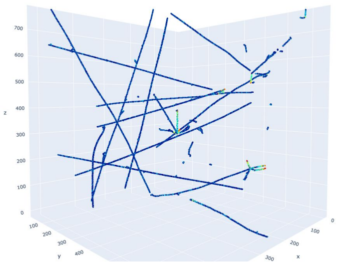
PMT and wall reflectivity

Residual magnetic fields

PMT+electronics response

- **Limitations**
  - Lack of “end-to-end” optimization
  - Some models are not even optimizable (e.g. look-up tables)
  - Same physics, two separate software (i.e. simulation & calibration)

- **Goals** toward “detector systematics @ <1% level”
  - Automation + fast compute that can scale for HK/DUNE
  - Accurate model optimized directly to minimize data/MC disagreement



Simulation Input (true dE/dX)

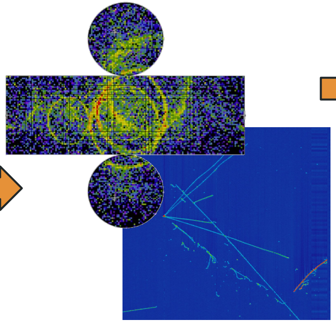
Detector Simulation

$$\mathcal{R}_{\text{ICARUS}} = \frac{A_B}{1+k_B\cdot(dE/dx)/\mathscr{E}}$$

$$Q = Q_0 \exp(-v_{\text{drift}}t/\tau)$$

$$\sigma_t^2(t) \simeq \sigma_t^2(0) + \left(\frac{2D_L}{v_d^2}\right)t$$

...

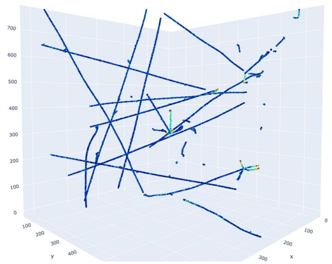


Detector Output (ADC)

Reconstruction

Detector physics model parameters

Calibration

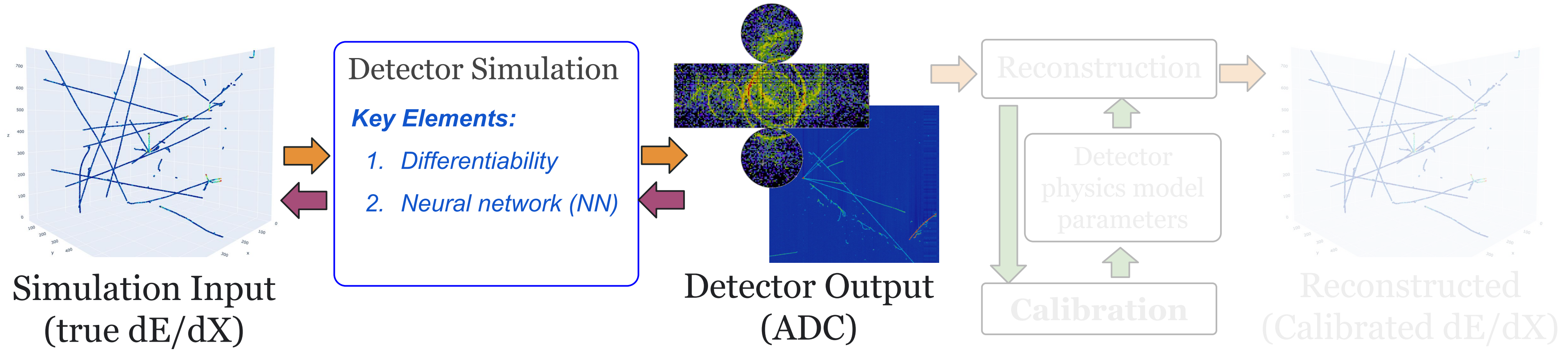


Reconstructed (Calibrated dE/dX)

Automation of Physics Model Tuning

Research Proposal: differentiable detector physics simulator (DDSim)

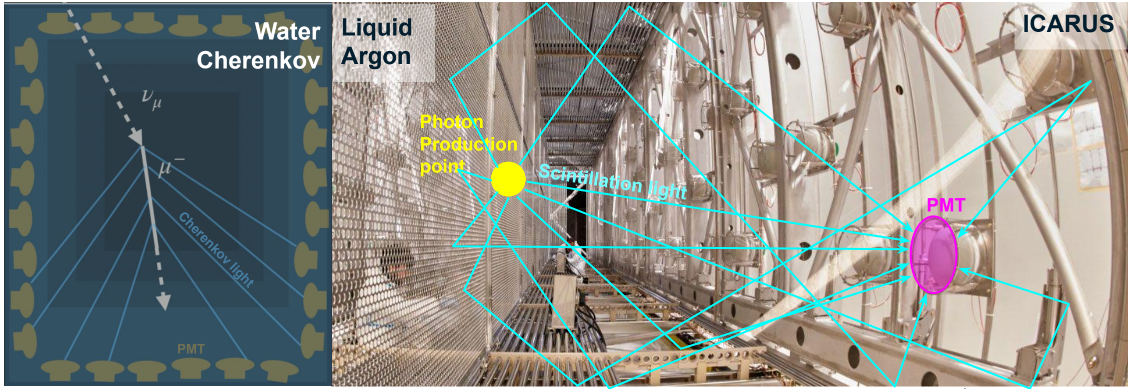
- **"End-to-end"**: gradient-based optimization using control (calibration) dataset
- **Interpretable**: analytical physics models for well understood physics
- **Flexible**: neural representation to incorporate complex features in real data
- **Fast**: utilization of modern computing accelerators (e.g. GPUs)



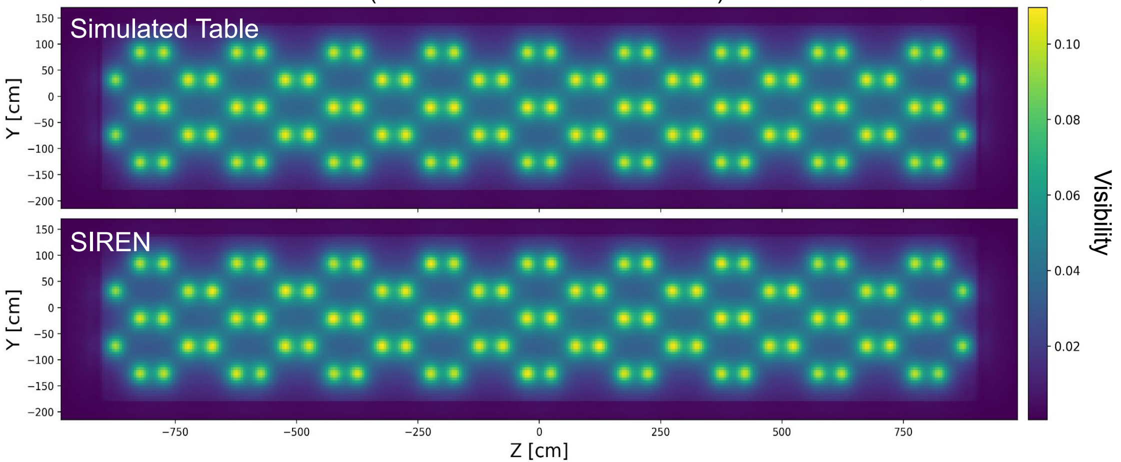
SIREN as a DDSim for Optical Detectors

- LAr “Visibility Map” (or light scattering table for WC) derived from massive photon MC, encoded in a multi-dimensional table … **but static & not scalable**

- Candidate: “SIREN”
  - Implicitly represents a continuous function in space
  - Designed to learn the gradient surface = enables applications using gradient-based optimization



Probability of detecting photon produced at given position
(2D slice of 3D voxelized volume)

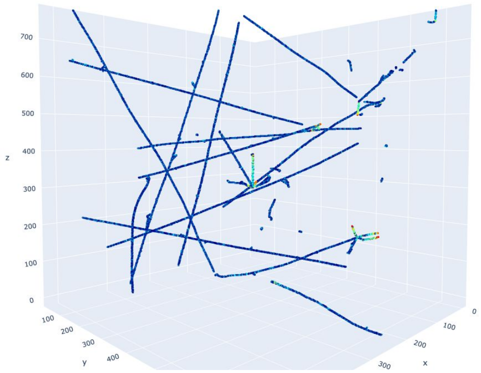


Detector Inverse Solver (DIS) using a differentiable simulator

A novel application enabled with a DDSim

G (X|Y, θ_G)

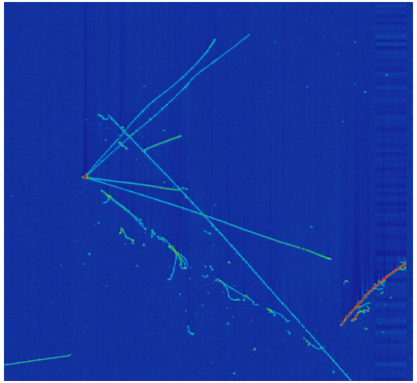
Inverse Image Solver (DIS)



$$\mathcal{L}_{\text{inv}} = |G(\mathbf{Y}) - \mathbf{X}|^2$$

and / or

$$\mathcal{L}_{\text{cc}} = |F(G(\mathbf{Y})) - \mathbf{Y}|^2$$



$\mathbf{X} \in \mathcal{D}_I$

Input domain of detector simulator (inaccessible)

F (Y|X, θ_F)

Differentiable Detector Simulator (DDSim)

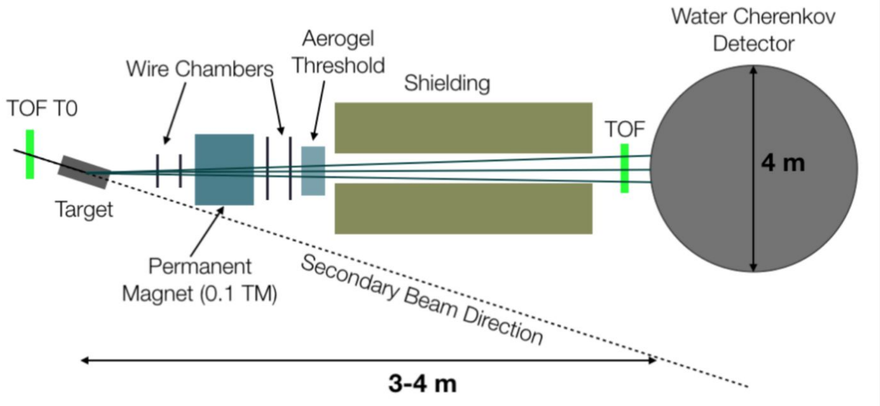
$\mathbf{Y} \in \mathcal{D}_O$

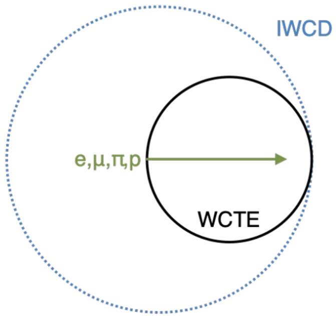
Output domain of detector simulator (e.g. real data)

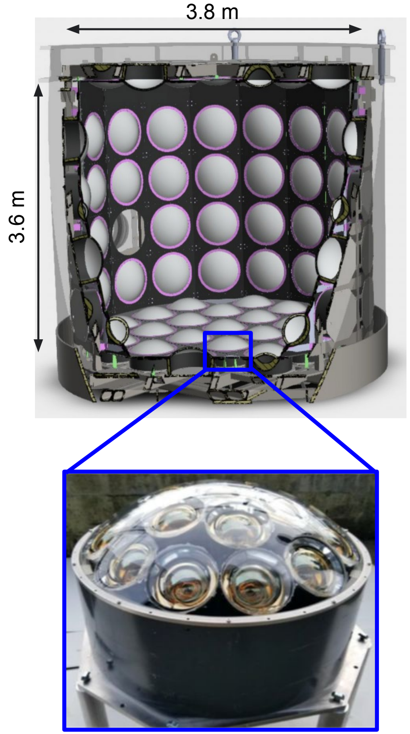
Enables near-far comparison of neutrino events at the event-by-event level for the first time

The Water Cherenkov Test Experiment (WCTE)

- Prototype for IWCD at CERN in 2024
- Well-understood $p, e, \pi^{\pm}, \mu^{\pm}$ particle beam from 140-1200 MeV/c
  - Control samples to constrain neutrino experiment modeling:
    - Detector response: Cherenkov light emission; $\pi^{\pm}$ interactions
    - Neutrino flux & interactions: lepton scattering and hadron production
  - Immediate impact to existing experiments (T2K, Super-K)
- Demonstration of these new ML simulation and calibration techniques for WC, and optimization towards Hyper-K/IWCD







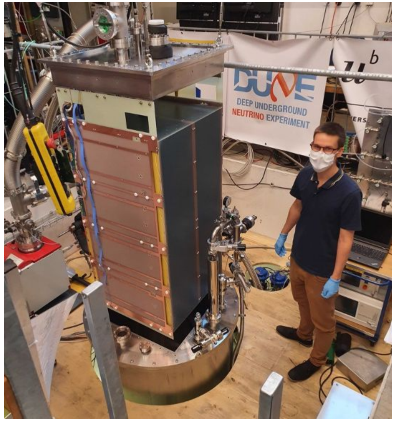
~102 mPMT modules
x19, 3” PMTs each

ArgonCube 2x2

- Prototype for ND-LAr (LArTPC component of DUNE Near Detector) at Fermilab
  - 2x2 array of 0.7x0.7x1.2 m^3 modules deployed in NuMI beam with elements of MINERvA
  - Installation and operation in NuMI anticipated in summer 2023

- NuMI provides an intense source of neutrinos & muons

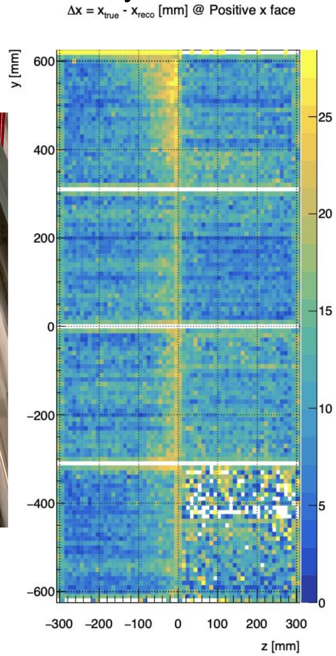
- Demonstration of these new ML simulation and calibration techniques for LArTPCs, and optimization towards DUNE
  - AI/ML reconstruction already under development
  - SIREN optical model developed



1st module testing at Bern

Module at Fermilab

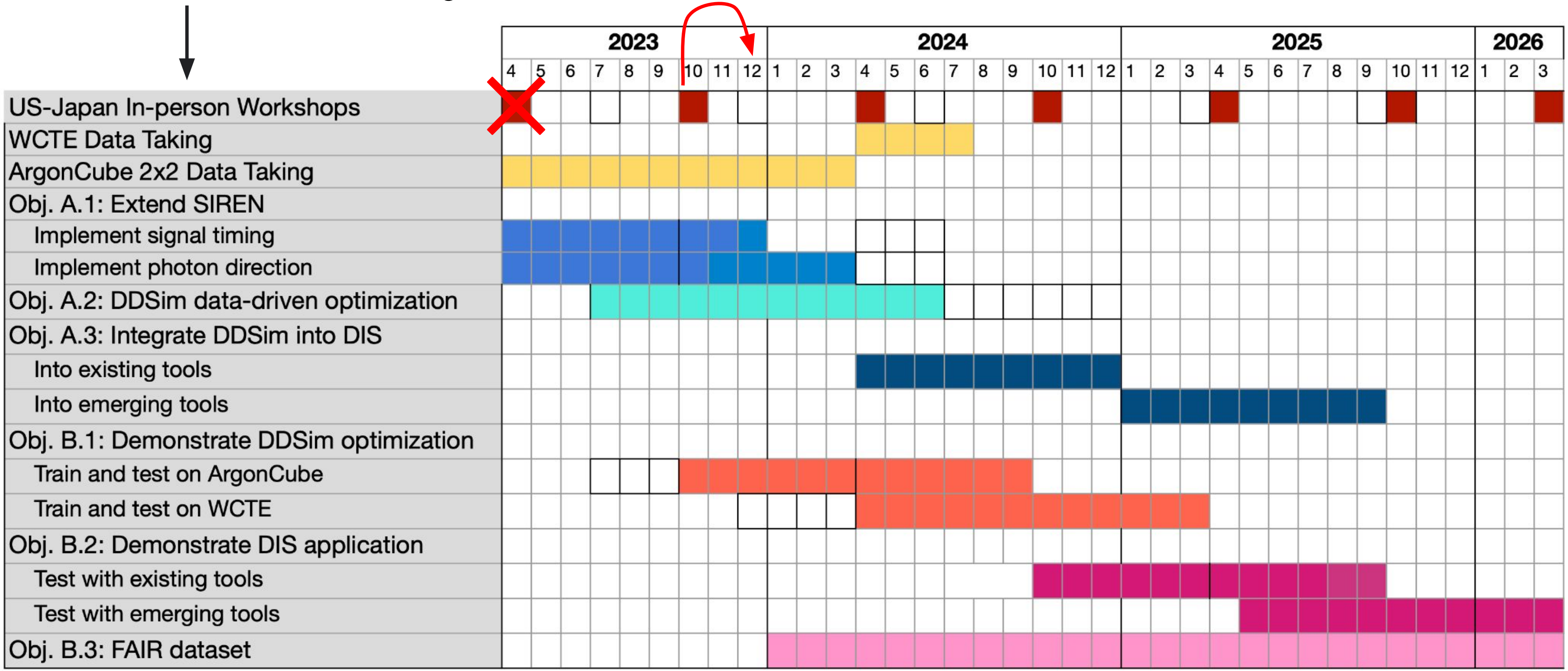
Field uniformity study at SLAC



Research Schedule

Tasks to be fleshed out and assigned

Move to December @ SLAC?



In-person Workshop at SLAC

- Japan-side budget allows e.g. 4 people travel for 2 weeks, this fiscal year (FY)
  - Project will be reviewed then budget decided for the following 2 FYs
- Hack-a-thon-like format with code sprints
  - Tasks to be defined as we ramp up these coming months
- Candidate dates to be decided this meeting, then poll will follow
  - Sep. 25 - Oct. 6 (too soon?)
  - Not Oct. 9 - 13 (JPS-APS Hawaii)
  - Not Oct. 23 - 27 (HK CM)
  - Not Nov. 6 - 10 (T2K CM)
  - Not Nov. 27 - Dec. 1 (SK CM)
  - Dec. 4 - 15?
  - Early next year?

Collaboration Name?

- Urgent in case we want to include in mailing list name, GitHub name, etc.
- Any ideas?
  - Differentiable Signal Propagation Project (DSPP)
  - …

Meeting Agenda

Monday, 7 August

18:00 → 20:00 **Day 1: https://ipmu.zoom.us/j/94250009765**

- 18:00 **Project overview: Differentiable physics modeling**
  Speakers: Kazuhiro Terao (SLAC) , Patrick de Perio (Kavli IPMU)
- 18:30 **Questions/Discussion**
- 18:40 **LArTPC: differentiable neural implicit representation for physics modeling**
  Speaker: Patrick Tsang (SLAC)
  2023-08-07 SIREN U...
- 19:10 **Questions/discussion**
- 19:20 **Water Cherenkov applications/challenges**
  Speaker: Ka Ming Tsui (Kavli IPMU)
- 19:50 **Questions/**

Tuesday, 8 August

17:00 → 19:00 **Day 2: https://ipmu.zoom.us/j/97884442440**

- 17:00 **Alternative methods for signal propagation**
- 17:30 **Questions/Discussion**
- 17:40 **Brainstorming Session**
  Speakers: Kazuhiro Terao (SLAC) , Patrick de Perio (Kavli IPMU)

Summary

- Next generation long-baseline neutrino oscillation experiments will require unprecedented precision understanding of their detectors

- Existing simulation, calibration, and reconstruction analysis pipelines are becoming a limiting factor in this endeavor

- Proposed novel machine learning algorithms to solve these modeling and computational issues
  - Common tools to be shared between US-Japan
  - Seed for community-wide effort

- Meeting notes (feel free to contribute): https://docs.google.com/document/d/1aw6Yv7exMGs7tk4SyKdBMq-r3j7zVS58mYJjLiUT3hw/edit?usp=sharing

References

- [Project Abstract]
- [Project Proposal]
- [Project Plan (for KEK)]

Appendix

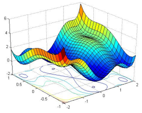
How: Differentiable Detector Physics Simulator (DDSim)

Gradient-based optimization

Yann LeCun
January 5, 2018

OK, Deep Learning has outlived its usefulness as a buzz-phrase.
Deep Learning est mort. Vive Differentiable Programming!

Approximated gradient



Input
x

physics model
parameters
θ

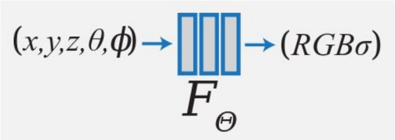
Output
$F(x|\theta)$

Optimization
target
$L(F(x|\theta), y)$

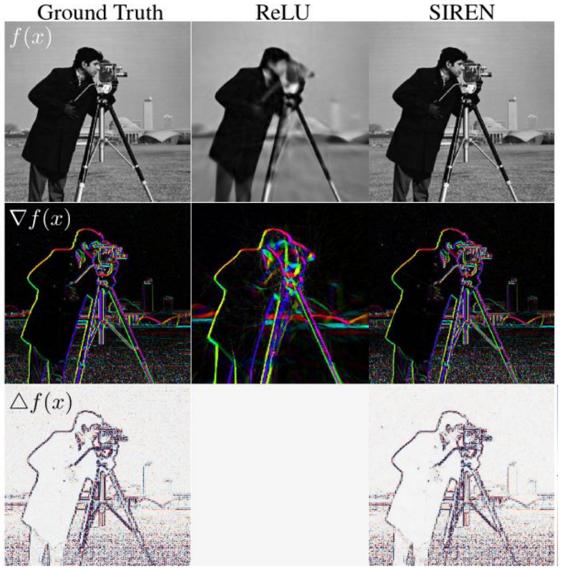
Exact gradient

Neural differentiable surrogate for optical detectors

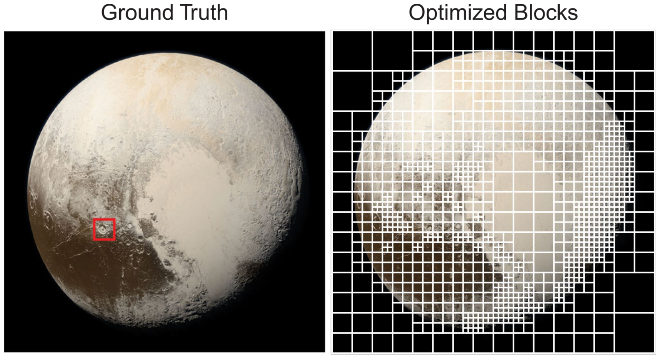
Differentiable Neural Scene Representation



NeRF: breakthrough on high resolution image representation by a very simple neural network



SIREN: success of learning the 1st and 2nd order derivatives

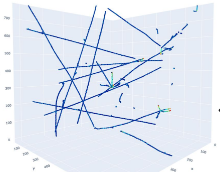


ACORN: scalable version of SIREN by adding spatial feature compression (essentially a learnable kd-tree)

... only a few examples

AD-Enabled Detector Physics Simulator

- Enable **Automatic Differentiation** (AD):
  - Same physics formula, now differentiable
  - Backed-up by a large AI/ML research community
  - Speed up by enabling co-processors (GPUs/TPUs)

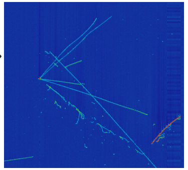


Detector Simulation

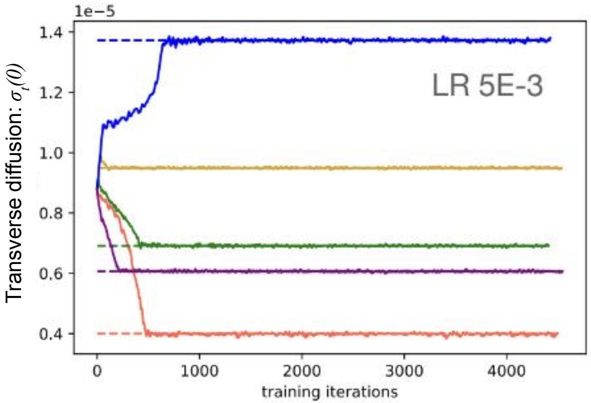
$$\mathscr{R}_{\text{ICARUS}} = \frac{A_B}{1 + k_B \cdot (dE/dx)/\mathscr{E}}$$

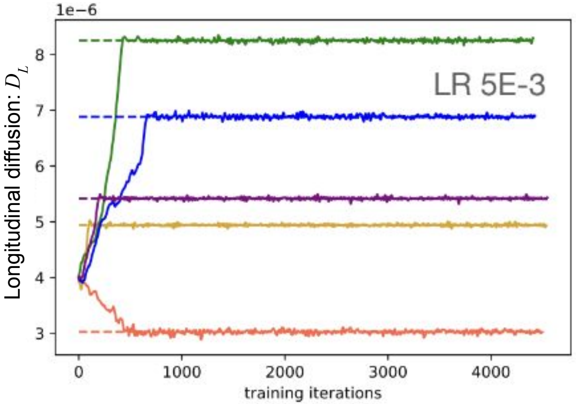
$$Q = Q_0 \exp(-v_{\text{drift}} t/\tau)$$

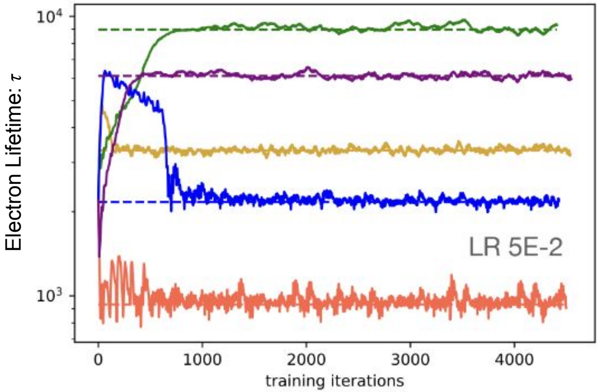
$$\sigma_t^2(t) \simeq \sigma_t^2(0) + \left(\frac{2D_L}{v_d^2}\right) t$$



- Successful demonstration for LArTPC imaging detector
  - End-to-end: simultaneous optimization of multiple detector physics parameters
  - On-going study: the robustness of the fits, modeling of poorly understood physics (e.g. electric field)



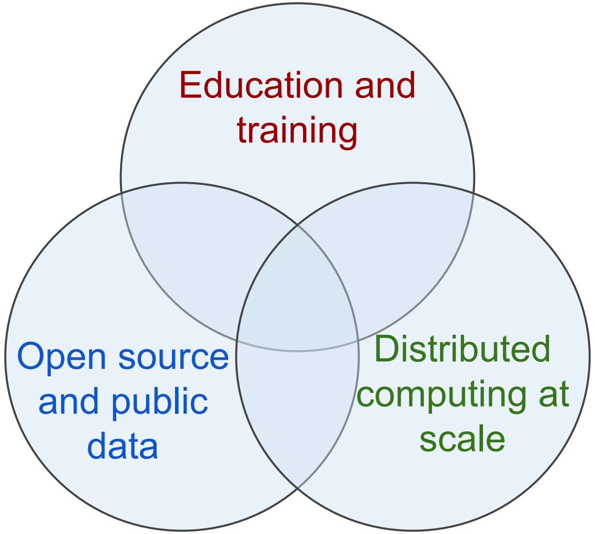




Data Reconstruction in Experimental Particle Physics

Cross-domain HEP AI ecosystem

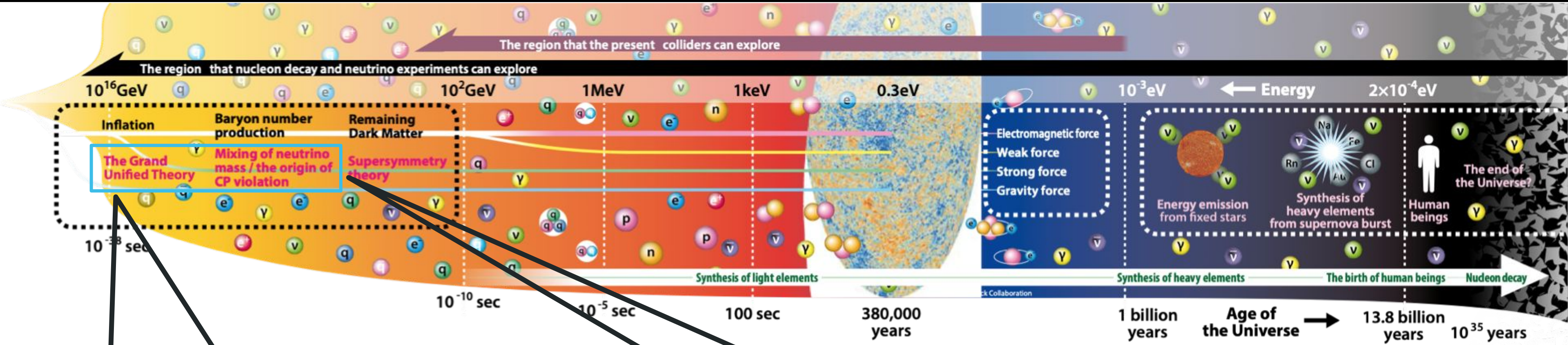
ML is a "solution pattern" v.s. a domain-specific "hard-coded" solution. It's **naturally reusable across domains including software tools** supported by a large community of researchers.

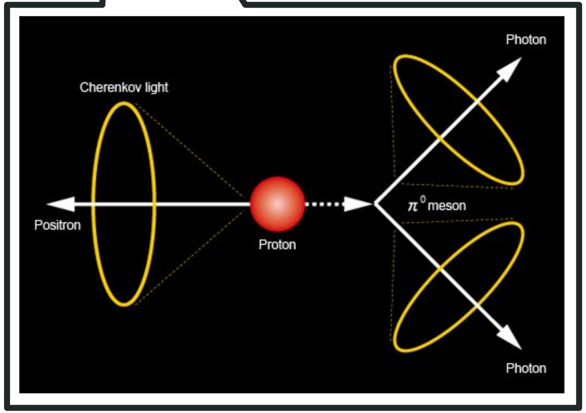


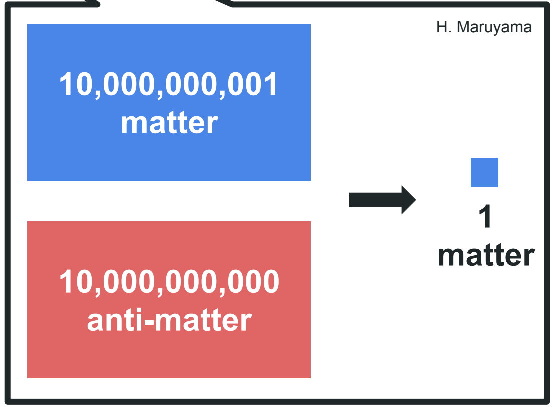
HEP Ecosystem for AI research

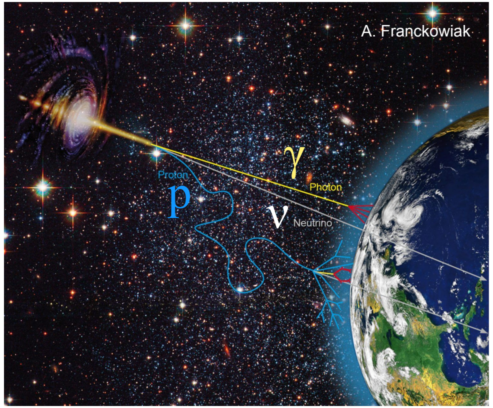
- Accessible **education and training** at all levels
- **Reusable software tools** to unlock modern compute accelerators and networking (distributed ML)
- **Public datasets** with documentation and performance metrics for transparent, reproducible science
- Artificial Intelligence and Technology Office (AITO)
  - Federated, equitable, responsible, trustworthy AI
  - **AI is an accelerator**. It is coming. Don't avoid. **Participate to make sure the use is good.**

Evolution of the Universe









Proton Decay → GUTs

Matter - Antimatter Asymmetry

Multi-messenger astronomy

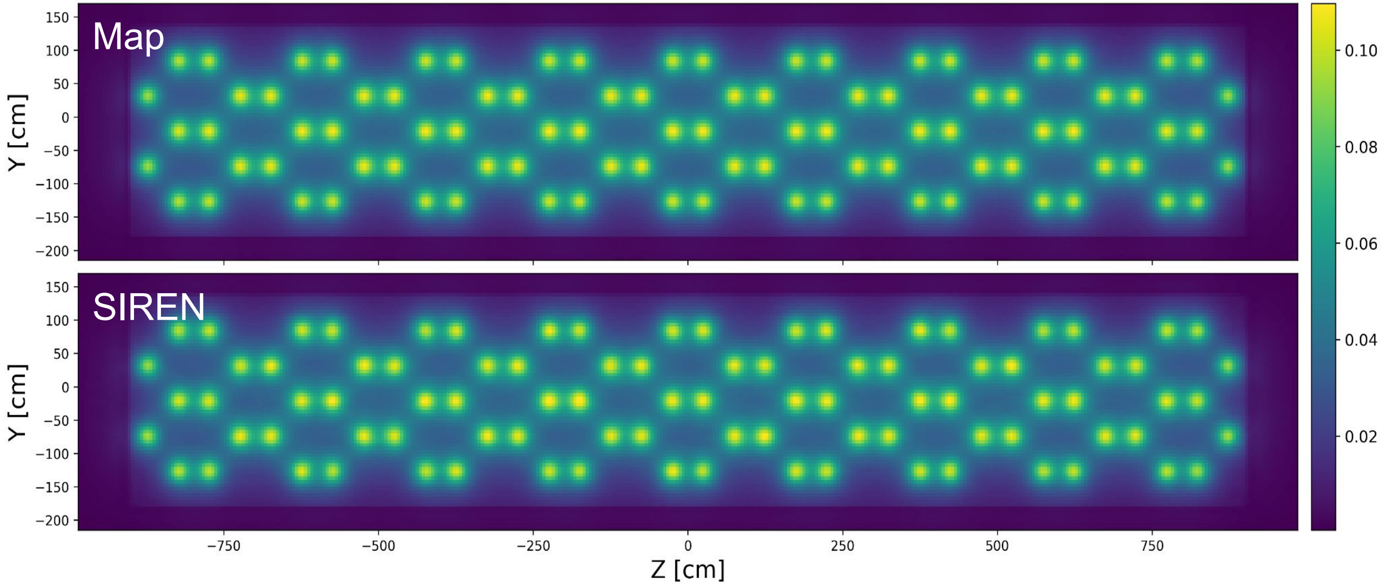
SIREN as a DDSim for Optical Detectors

- Example: “Visibility Map” (or light scattering table for WC) derived from massive photon simulations, encoded in a multi-dimensional table
- **Issues**: “static” and not scalable

- SIREN is an implicit representation of a continuous function in space
  - Can be seen as a trade-off between an analytical function and a table

Probability of detecting photon produced at given position
(2D slice of 3D voxelized volume)

arXiv:2211.01505



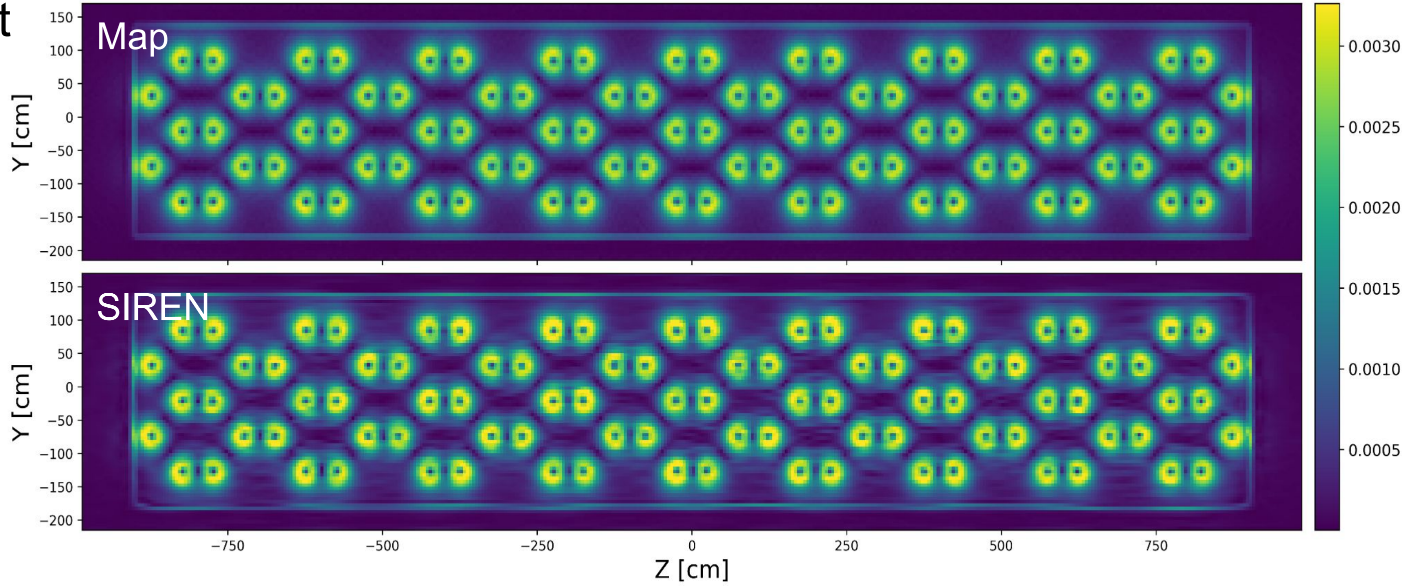
SIREN as a DDSim for Optical Detectors

- SIREN is designed to represent (learn) the gradient surface hence “differentiable”
- Can be optimized directly by minimizing “a data/MC discrepancy” with control samples

- SIREN is an implicit representation of a continuous function in space
    - Can be seen as a trade-off between an analytical function and a table

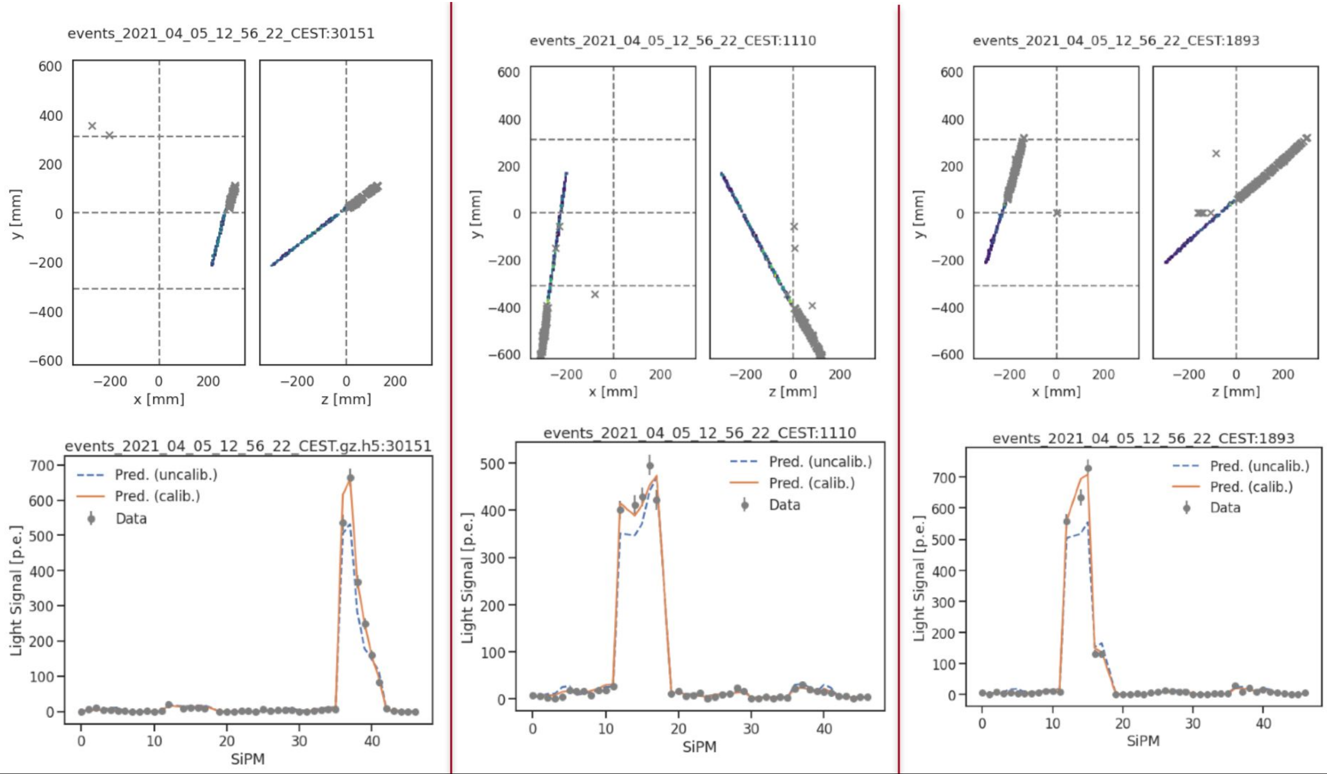
Derivative of previous slide
(2D slice of 3D voxelized volume)

arXiv:2211.01505



SIREN as a DDSim for Optical Detectors

- Preliminary demonstration on real DUNE ND prototype data strongly promising
- Optimized as a simulator + applied in reconstruction (inverse solver)



ML for Detector Physics Modeling

SIREN as a differentiable surrogate for optical detectors

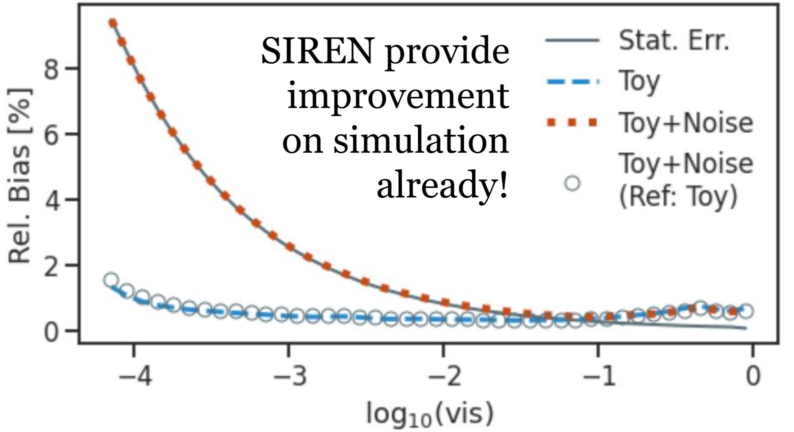
Differentiable Neural Scene Representation

SIREN for LArTPC detectors

- Designed as an implicit representation of a continuous function in space (suited to "visibility", "E-field", etc.)
  - Can be seen as a trade-off between an analytical function and a table
- "Differentiable" implies we can directly optimize against "data v.s. simulation discrepancy" given control samples

SIREN trained on "Toy + Noise" successfully learned the underlying analytical function shape (simulation)

$$\text{Relative Bias} = \frac{\left|\langle \text{P.E.} \rangle_{\text{true}} - \langle \text{P.E.} \rangle_{\text{pred.}}\right|}{\langle \text{P.E.} \rangle_{\text{true}} + \langle \text{P.E.} \rangle_{\text{pred.}}}$$

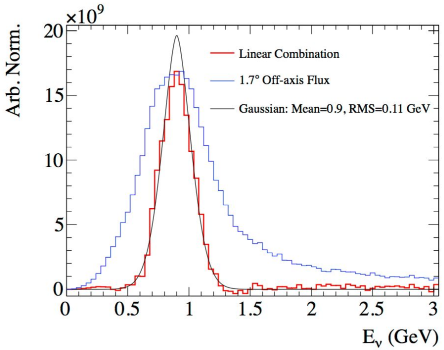


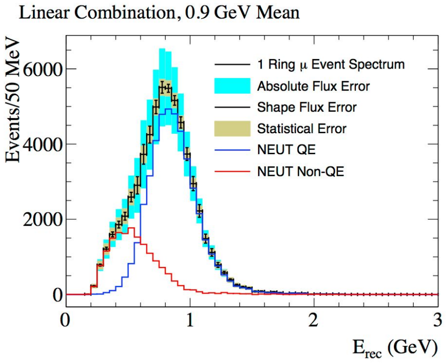
The NuPRISM Concept

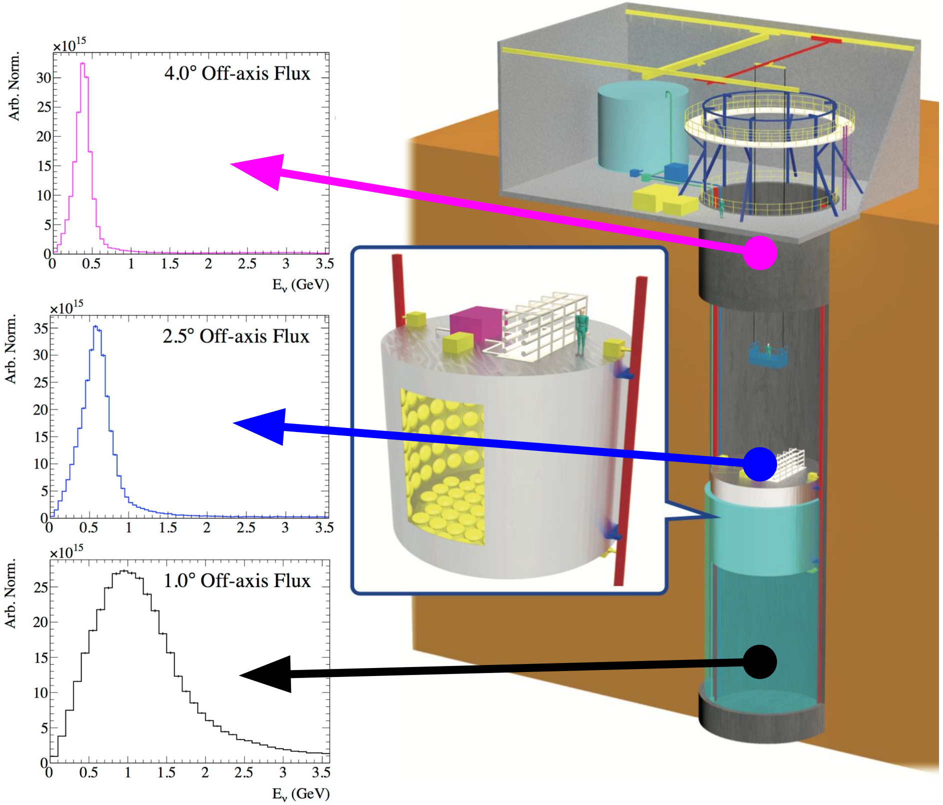
Neutrino energy spectrum depends on **off-axis angle to the neutrino beam source**

Moving IWCD vertically → varying off-axis angle → measurements with differing energy spectra

Linear combinations of measurements at off-axis angles can mimic **a monochromatic beam**, or the far-detector spectrum

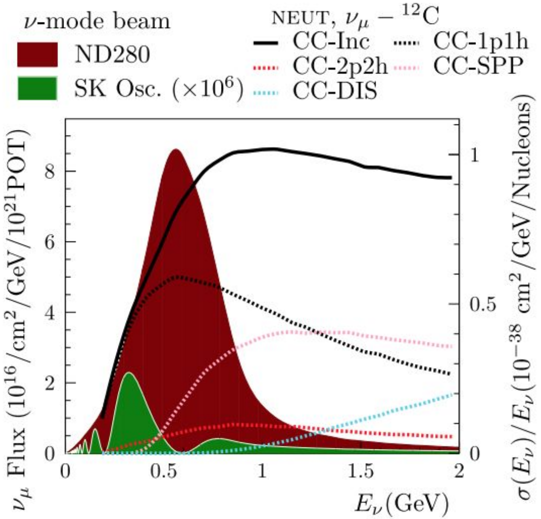






The Need for a New Near Detector

Imperfect extrapolation of neutrino flux & cross-section from near detector to Super-K



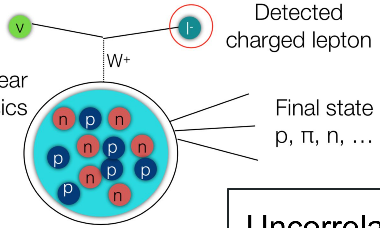
Differing energy spectra between near and far detectors

T2K: Phys. Rev. D 103, 112008 (2021)

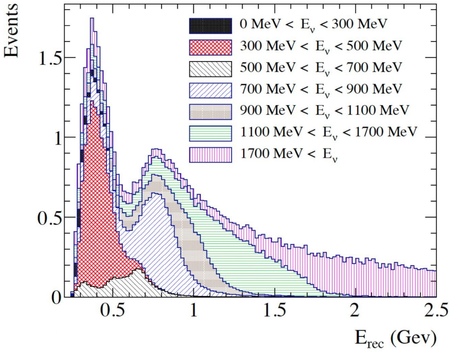
Error Source	% Error for CPV search
φ + σ (ND constrained)	2.7
φ + σ (ND unconstrained)	1.2
Nucleon removal energy	3.6
SK π re-interactions	1.6
$\sigma(\nu_e)$, $\sigma(\bar{\nu}_e)$	3.0
NC γ + other	1.5
SK detector	1.5
Total	**6.0**

Need to reduce to <3% for Hyper-K

The Need for a New Near Detector



Uncorrelated processes between near detector and Super-K
(Non-QE scattering, pion production, multi-nucleon knockout, etc.)



Large energy reconstruction errors

T2K: Phys. Rev. D 103, 112008 (2021)

Error Source	% Error for CPV search
$\varphi + \sigma$ (ND constrained)	2.7
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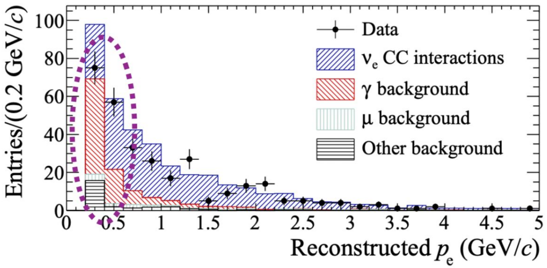
Need to reduce to <3% for Hyper-K

The Need for a New Near Detector

T2K: Phys. Rev. Lett. 113, 241803 (2014)



Difficult ν_e ($\bar{\nu}_e$) measurement at near detector (mostly ν_μ ($\bar{\nu}_\mu$) beam and γ backgrounds)

T2K: Phys. Rev. D 103, 112008 (2021)

Error Source	% Error for CPV search
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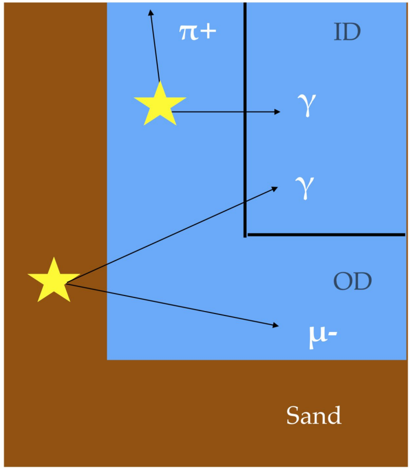
NC γ + other	1.5
SK detector	1.5
Total	**6.0**

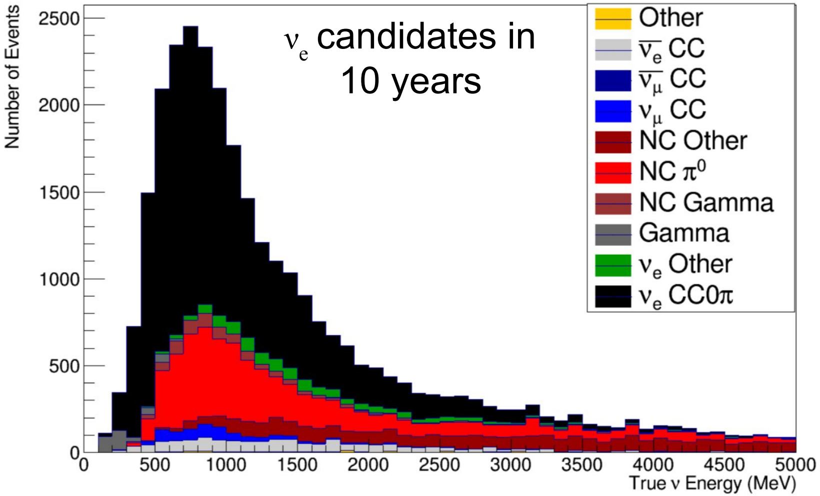
Need to reduce to <3% for Hyper-K

IWCD Measurement of ν_e ($\bar{\nu}_e$)

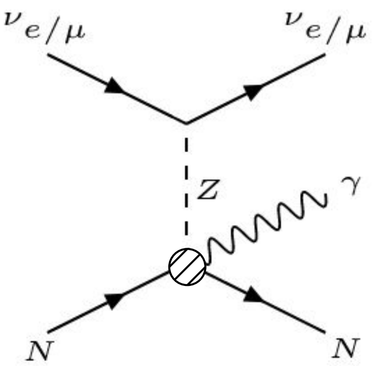
Constrain $\frac{\sigma(\nu_e)/\sigma(\nu_\mu)}{\sigma(\bar{\nu}_e)/\sigma(\bar{\nu}_\mu)}$ using **1% ν_e ($\bar{\nu}_e$) contamination in beam**

γ background mostly mitigated by water Cherenkov active shielding





The Need for a New Near Detector



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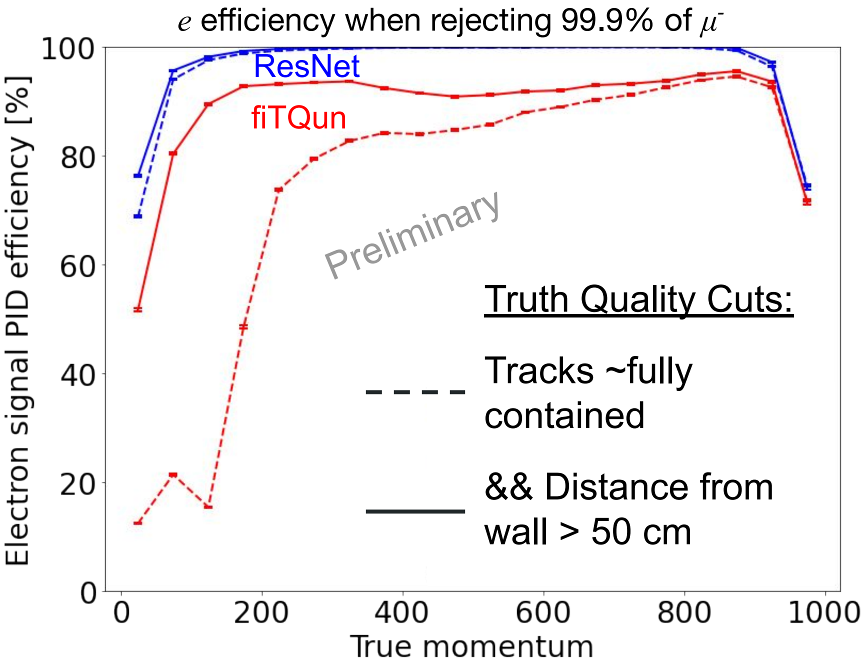
$\sigma(\nu_e)$, $\sigma(\bar{\nu}_e)$	3.0
NC γ + other	1.5
SK detector	1.5
Total	**6.0**

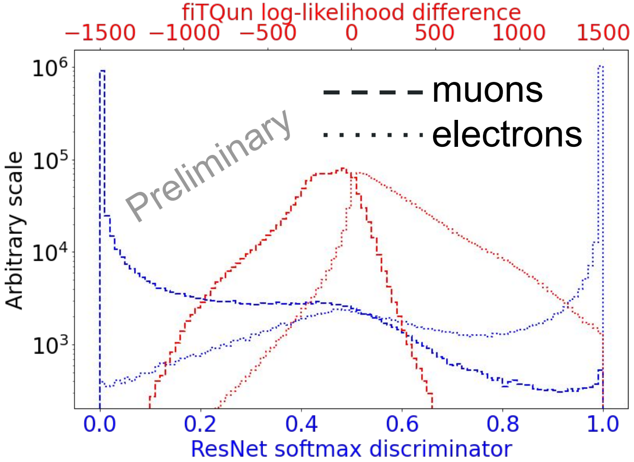
Neutral current backgrounds lacking data driven constraints

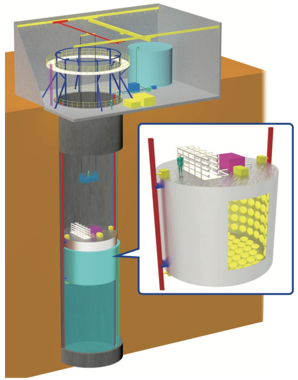
Need to reduce to <3% for Hyper-K

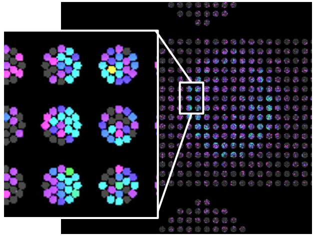
e / μ Classification in IWCD



- Constrain $\frac{\sigma(\nu_e)/\sigma(\nu_\mu)}{\sigma(\bar{\nu}_e)/\sigma(\bar{\nu}_\mu)}$ using **1% intrinsic ν_e ($\bar{\nu}_e$) in beam**
- Need >~1000 in μ rejection (>99.9%)
- Can be achieved in IWCD with ML
- Factor 10^5 speedup

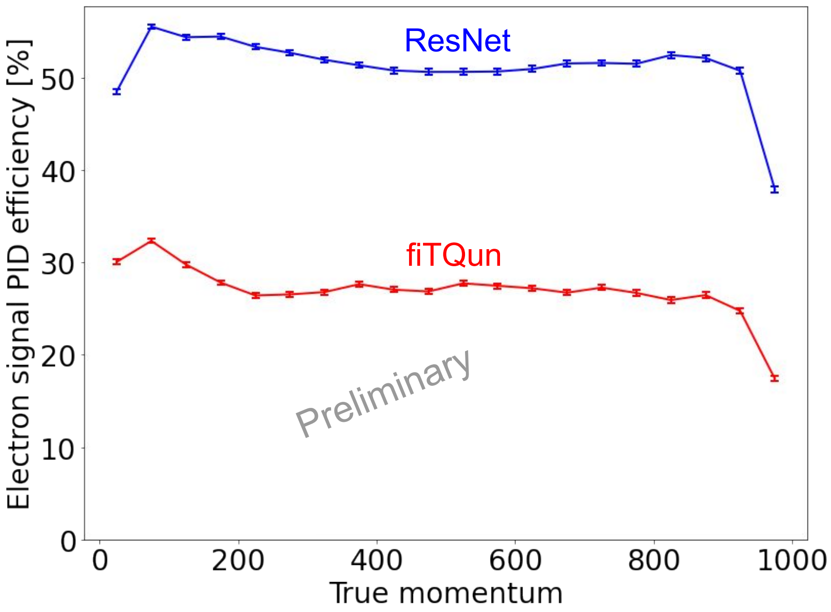




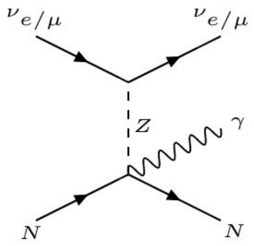


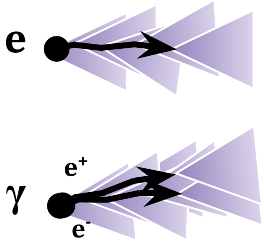
Gamma (γ) Identification

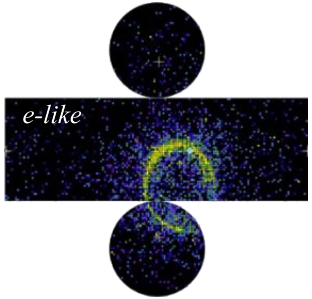
e efficiency when rejecting 80% of γ



- Need data driven constraints on γ backgrounds

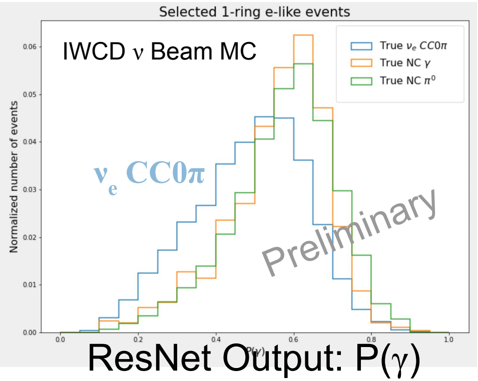






- γ and e almost indistinguishable in water Cherenkov detectors
  - Potential discrimination shown for the first time

- ML shows promise with at least statistical separation



Detector Modeling Uncertainties

- The fundamental ν–Ar interaction is the same in the ND and FD, so some detector error cancelation is possible
  - Ionization, recombination, drift velocity may be similar provided that the detector conditions are similar (e.g. E-field, Ar purity, etc.)
- However, there are several important differences
  - ND pixel readout vs FD wire or strip readout
  - Large pileup at ND (10's of events per spill)
  - Geometry: ND has smaller active volume, dead regions within the active volume, shorter drifts (less diffusion)
  - Different calibration strategies (e.g. ND has plentiful muons; FD has ~5,000/day and will rely more on calibration systems)
- Currently, a conservative assumption of uncorrelated ND/FD energy response uncertainties for each particle type is assumed
  - Estimated from calorimetric approaches (Minerva + NOvA) and LAr-TPCs (LArIAT, MicroBooNE, ArgoNeuT)
- Other uncertainties include fiducial volume size and energy resolution(s), and selection uncertainties on the muon identification and hadronic energy containment

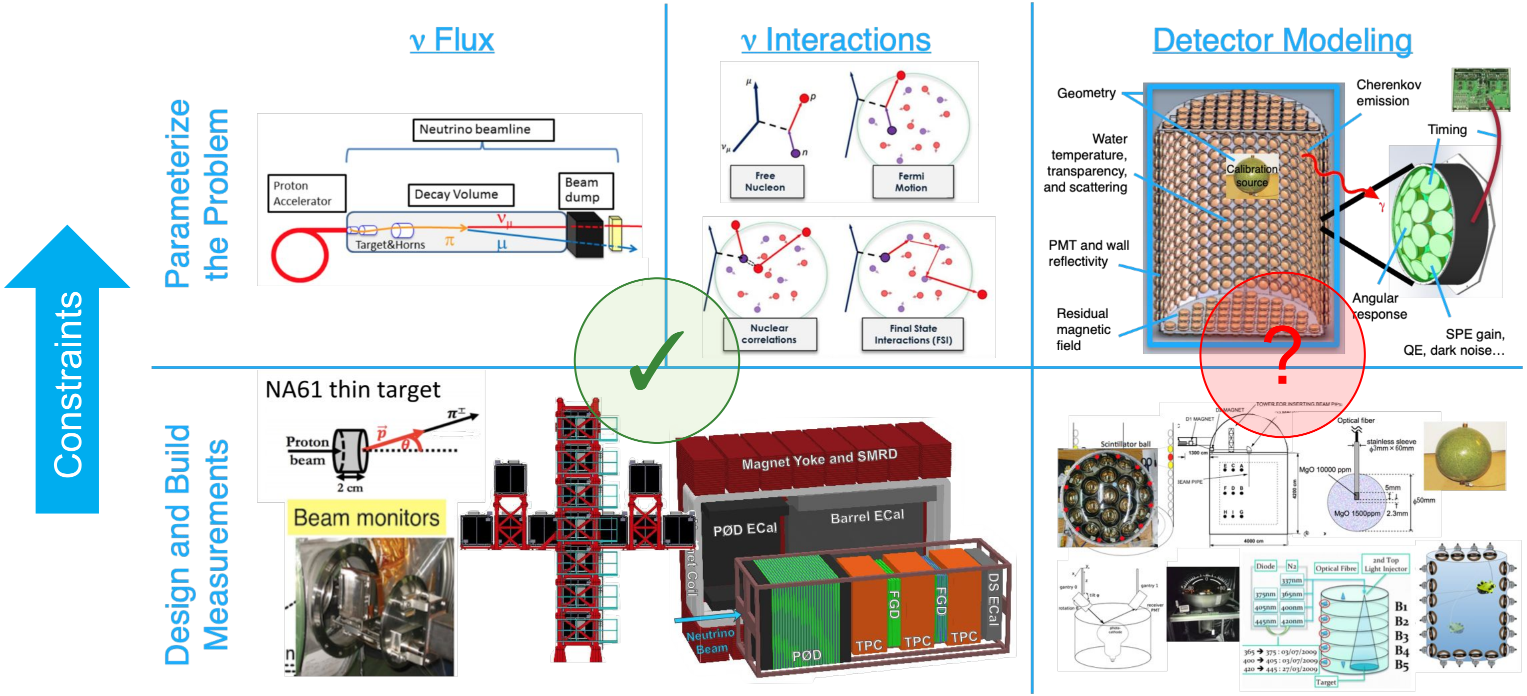
$$E'_{rec} = E_{rec} \times (p_0 + p_1\sqrt{E_{rec}} + \frac{p_2}{\sqrt{E_{rec}}})$$

Particle type	Allowed variation		
	p_0	p_1	p_2
all (except muons)	2%	1%	2%
μ (range)	2%	2%	2%
μ (curvature)	1%	1%	1%
p, $\pi^{\pm}$	5%	5%	5%
e, γ, π^0	2.5%	2.5%	2.5%
n	20%	30%	30%

Eur. Phys. J. C 80, 978 (2020)

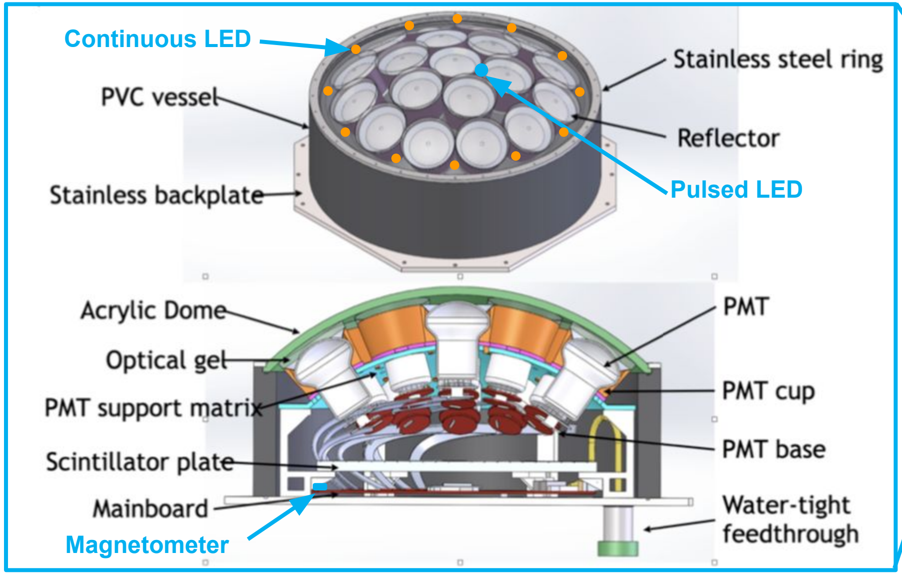
Constrained Modeling of the Experiment

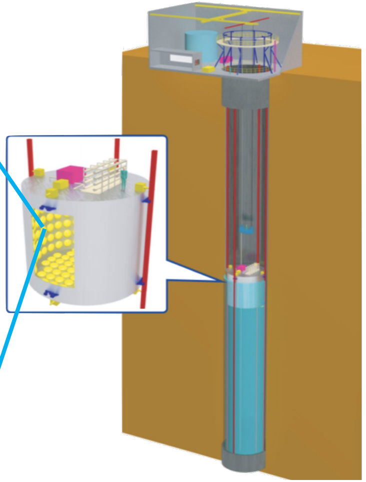
- A coherent method exists for constraining (degenerate) fundamental physics parameters of the neutrino flux and interactions with measurements
- This still needs to be developed for detector physics parameters



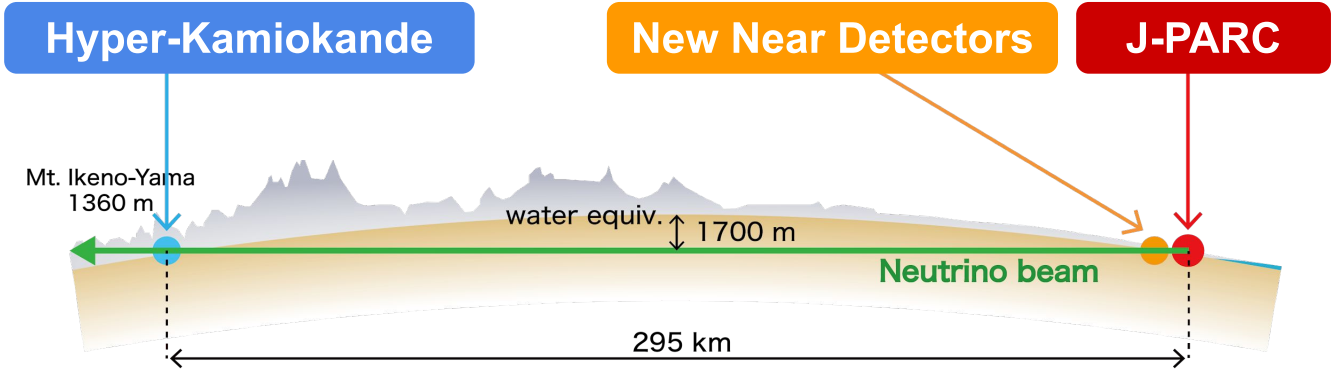
IWCD & Hyper-K Photosensor Development

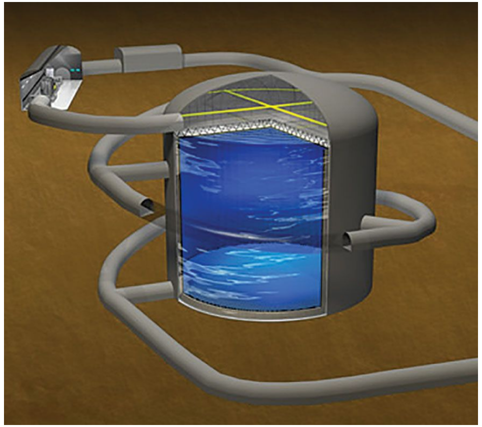
- Multi-PMT (mPMT): 19 x 3" diameter PMTs in a water-tight vessel with HV and electronics
- Pulsed and continuous LEDs for calibration:
    - PMT timing
    - Water properties
    - Detector geometry
- Sensors for magnetic field monitoring





Overview: Next Generation Experiment



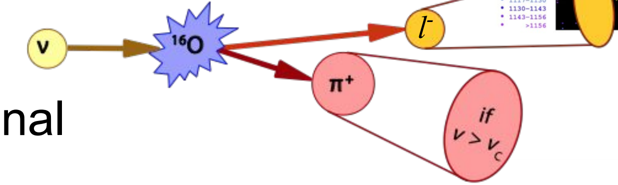


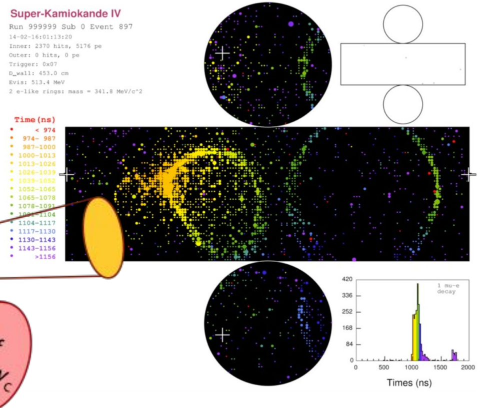
- Bigger and more sensitive than ever
  - Fiducial mass 8x Super-K
  - J-PARC beam 2.5x more powerful
    - → Neutrino rates 20x T2K
- Precise systematic understanding becomes critical to the % level
  - New near detectors and photon detectors
  - New calibration and event reconstruction techniques
  - New supporting external data from auxiliary experiments

T2K-SK Multi-Ring Datasets for Future Analyses

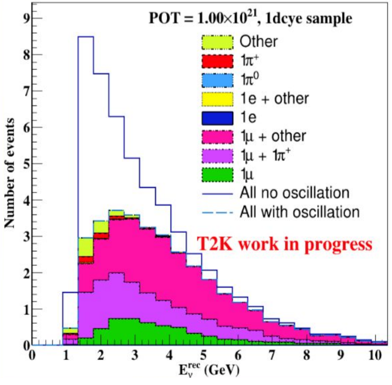
- Second dominant interaction channel: resonant 1π production
- Expected to improve oscillation parameter measurements
  - E.g. ~12% increase in ν_e signal statistics
- New BDT pushing the limits of traditional likelihood reconstruction algorithm

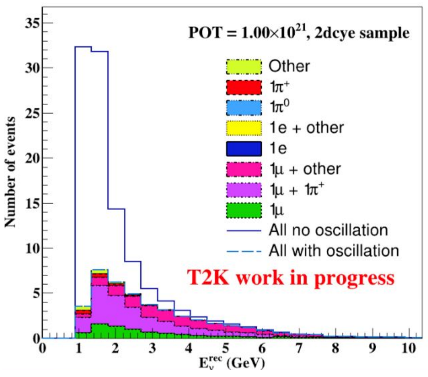
$$\overset{(-)}{\nu}_l\, p \rightarrow l^{\mp} p \pi^{\pm}$$
$$\overset{(-)}{\nu}_l\, n \rightarrow l^{\mp} n \pi^{\pm}$$



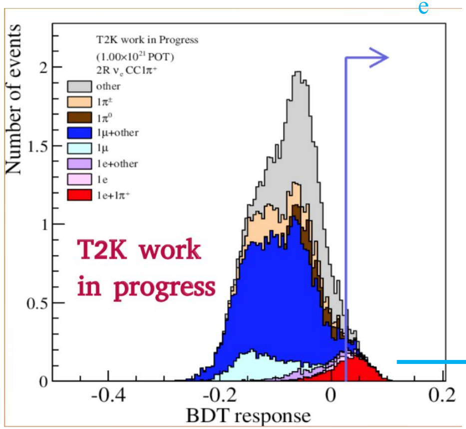


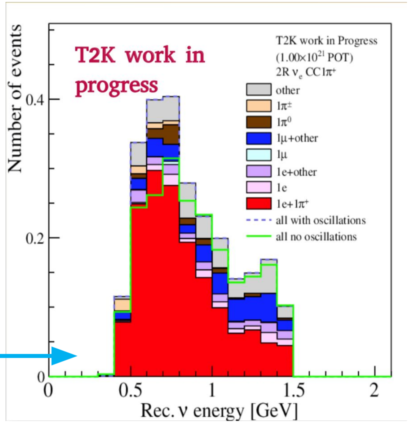
ν_μ CC1π^+





ν_e CC1π^+

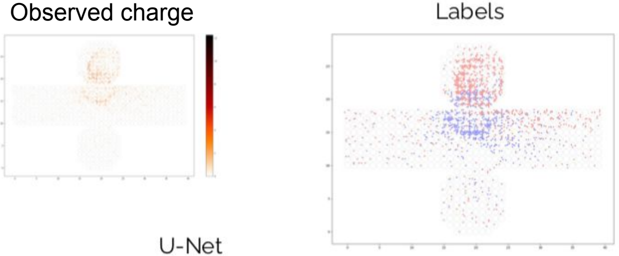




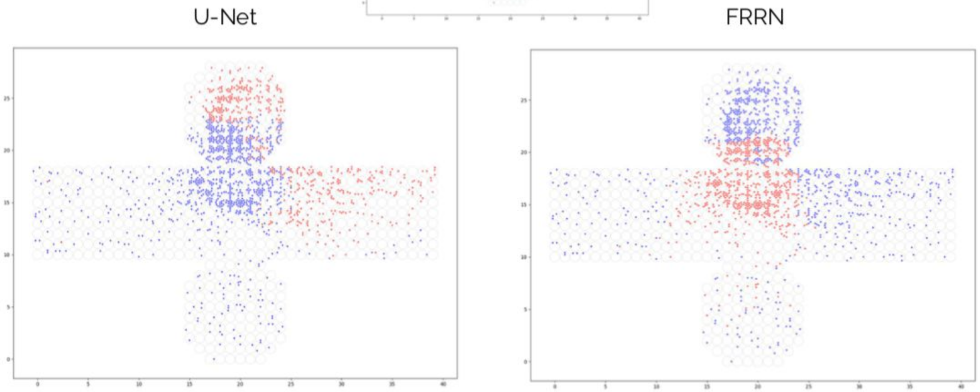
Multi-Ring Reconstruction in the Further Future

- More machine learning: panoptic segmentation
- Towards improving multi-ring & multi-GeV event classification and reconstruction
  - ν mass ordering, ν_τ appearance, δ_{CP}

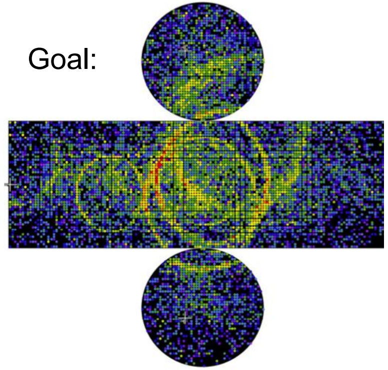
(a) image (b) semantic segmentation

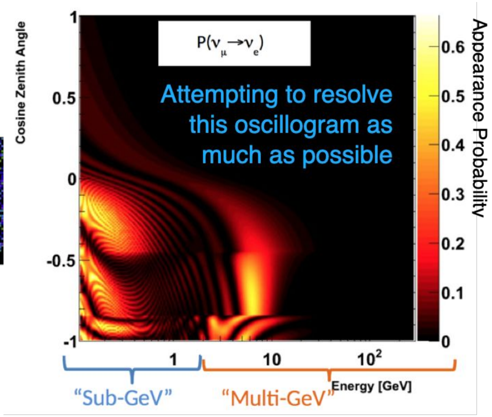


First attempt on π^0 decay events in IWCD: ~80% accuracy



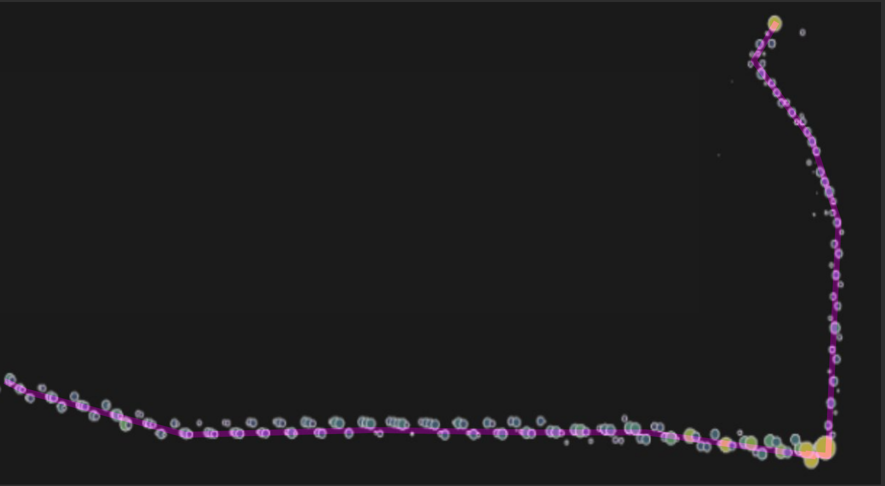
Goal:





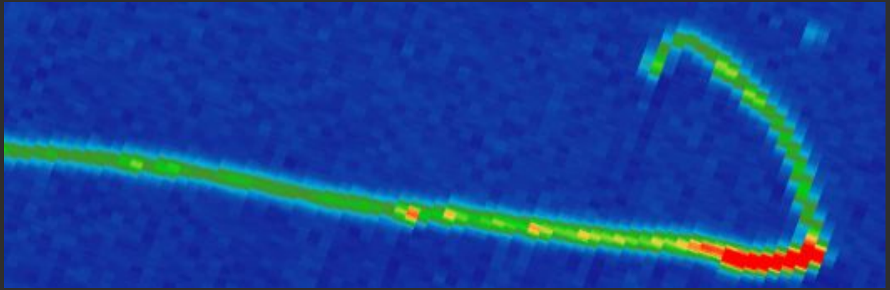
Differentiable Physics Models

Modeling Detector Physics

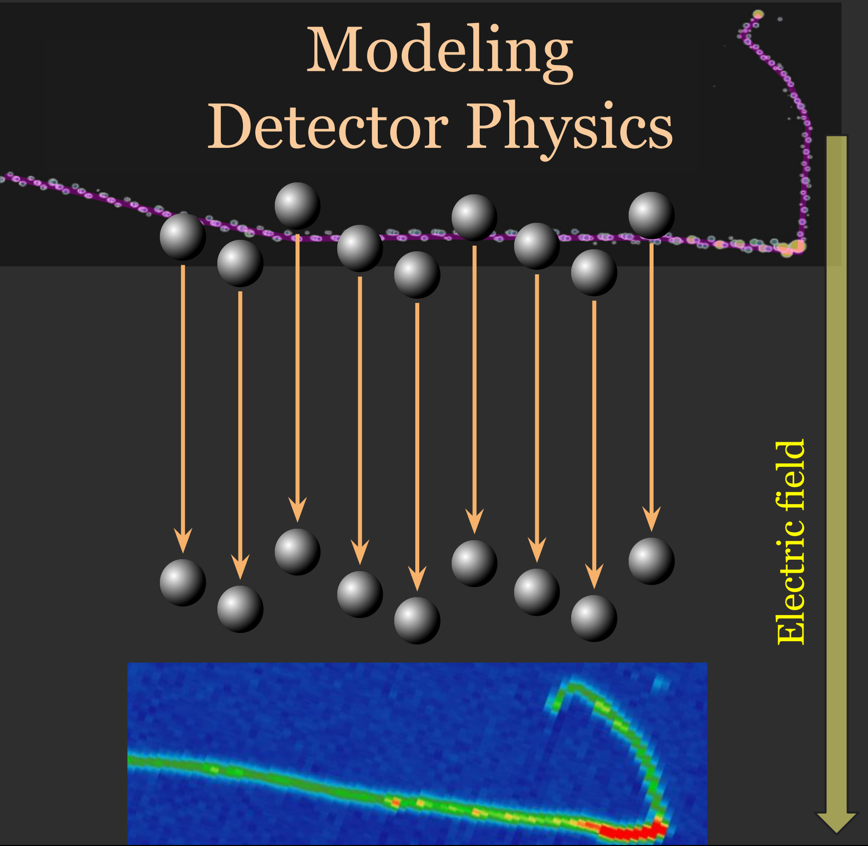


Example: Liquid Argon TPC

Objective: given a calibration dataset (i.e. images of particle trajectories with approximated dE/dX values), "fit" the detector physics parameters



Differentiable Physics Models



Example: Liquid Argon TPC

- Charged particle ionize electrons
- Electrons drifts under E-field
- Signal diffuse and attenuated

Detector Simulation

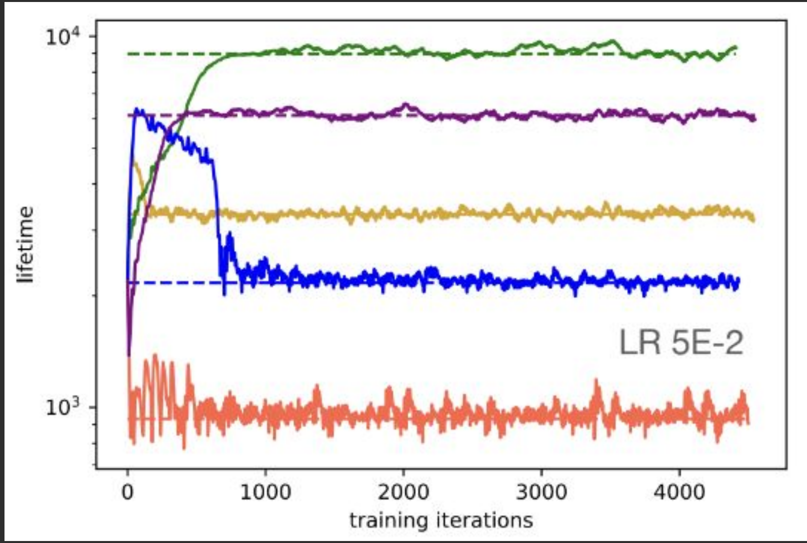
$$\mathscr{R}_{\mathrm{ICARUS}} = \frac{A_B}{1 + k_B \cdot (dE/dx)/\mathscr{E}}$$

$$Q = Q_0 \exp(-v_{\mathrm{drift}} t/\tau)$$

$$\sigma_t^2(t) \simeq \sigma_t^2(0) + \left(\frac{2D_L}{v_d^2}\right) t$$

...

Differentiable Physics Models



Optimizing the "lifetime" physics parameter directly from calibration dataset

Example: Liquid Argon TPC

- Charged particle ionize electrons
- Electrons drifts under E-field
- Signal diffuse and attenuated

Detector Simulation

$$\mathscr{R}_{\mathrm{ICARUS}} = \frac{A_B}{1 + k_B \cdot (dE/dx)/\mathscr{E}}$$

$$\boxed{Q = Q_0 \exp(-v_{\mathrm{drift}} t/\tau)}$$

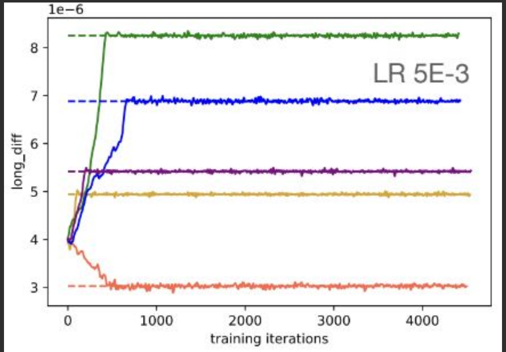
$$\sigma_t^2(t) \simeq \sigma_t^2(0) + \left(\frac{2D_L}{v_d^2}\right) t$$

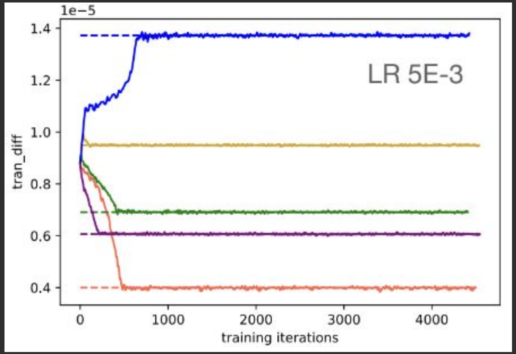
...

Differentiable Physics Models

Diffusion during the drift

$$\sigma_t^2(t) \simeq \sigma_t^2(0) + \left(\frac{2D_L}{v_d^2}\right) t$$

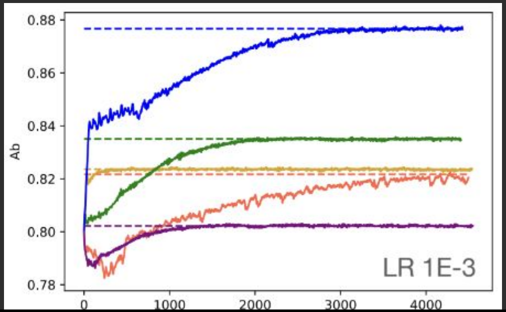


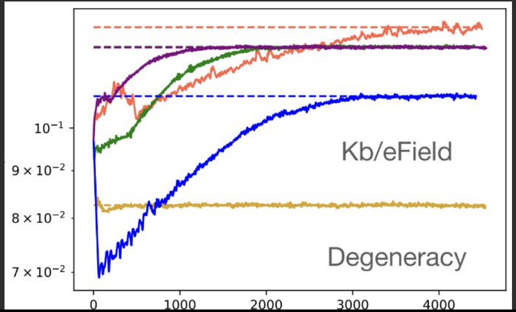


Work credit due (from left):
ML/Math: Youssef N., Sean G., Daniel R.
neutrino: Yifan C., Roberto S.

Ionization (signal) yield

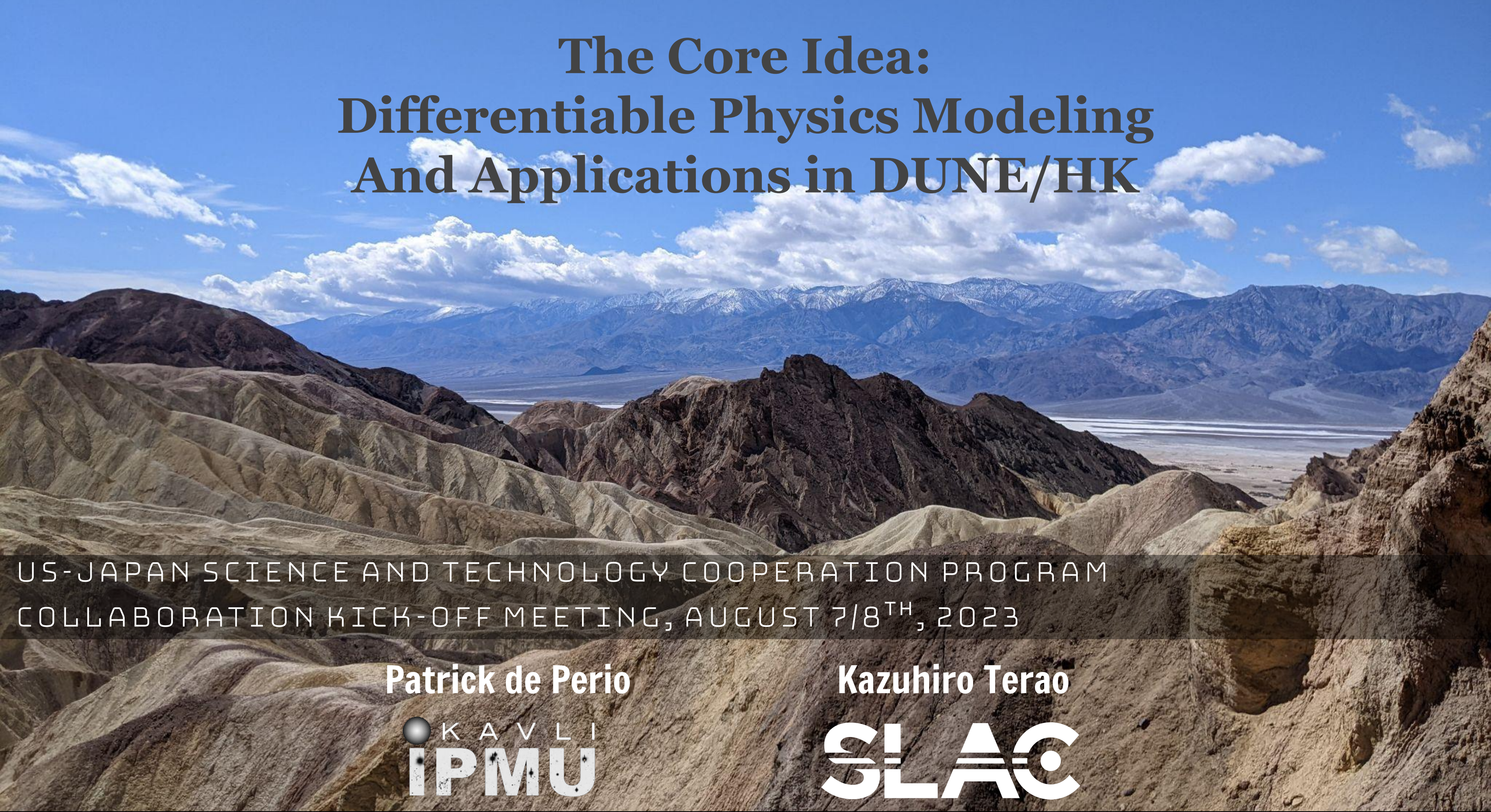
$$\mathscr{R}_{\mathrm{ICARUS}} = \frac{A_B}{1 + k_B \cdot (dE/dx)/\mathscr{E}}$$





Lots of applications

- Simultaneous multi-parameter fit
- Inter-parameter dependency study
- Automation of calibration workflow
- Inverse imaging (i.e. reconstruction)



The Core Idea: Differentiable Physics Modeling And Applications in DUNE/HK

US-JAPAN SCIENCE AND TECHNOLOGY COOPERATION PROGRAM
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