

Challenges in Neutrino Physics

Where can we connect Physics Goals and AI-Driven Studies?

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Future of Artificial Intelligence Research for Science (FAIRS) in Japan

October 2026

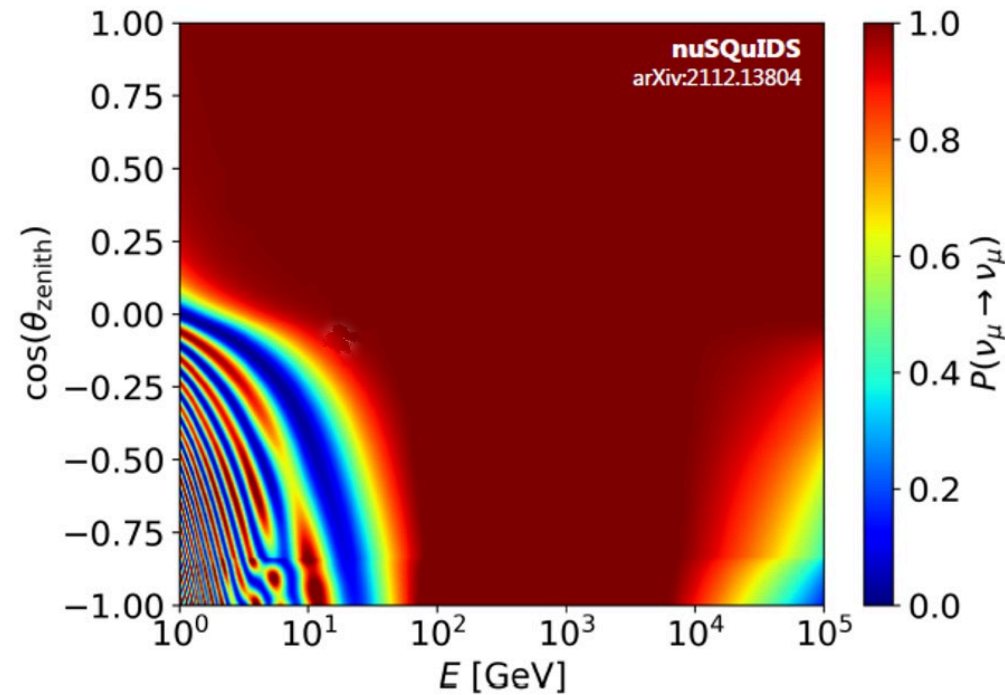
Fundamental Neutrino Properties

Fundamental neutrino properties

Astrophysical neutrinos

BSM neutrino physics and Cosmology

- **Neutrino mass ordering**
Normal or inverted ordering?
- **Leptonic CP violation**
Is CP symmetry broken?
- **Precision PMNS physics**
Mixing angles, unitarity tests
and global-fit consistency
- **Absolute mass scale**
- **Nature of neutrino mass**
Dirac or Majorana?



Astrophysical Neutrinos

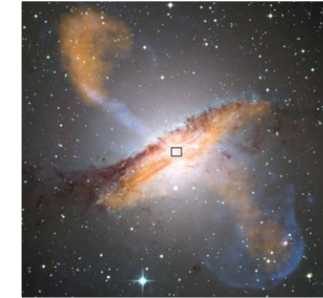
Fundamental neutrino properties

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BSM neutrino physics and Cosmology

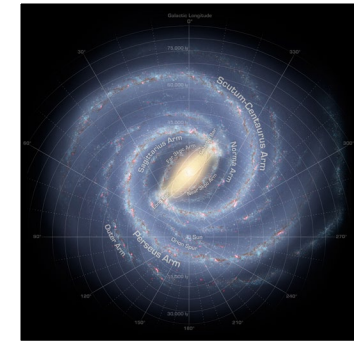
- **Origin of cosmic neutrinos**

Which Galactic and Extragalactic Sources Dominate at Different Energies, and How Are the Neutrinos Produced?



- **Connection to UHECRs**

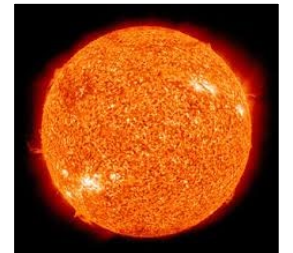
A common origin with UHECRs?



- **Multi-messenger astronomy**

Neutrinos, photons and gravitational waves to extract extreme environments

- AGN, TDEs, GRBs, magnetars, mergers



BSM Neutrino Physics and Cosmology

Fundamental neutrino properties

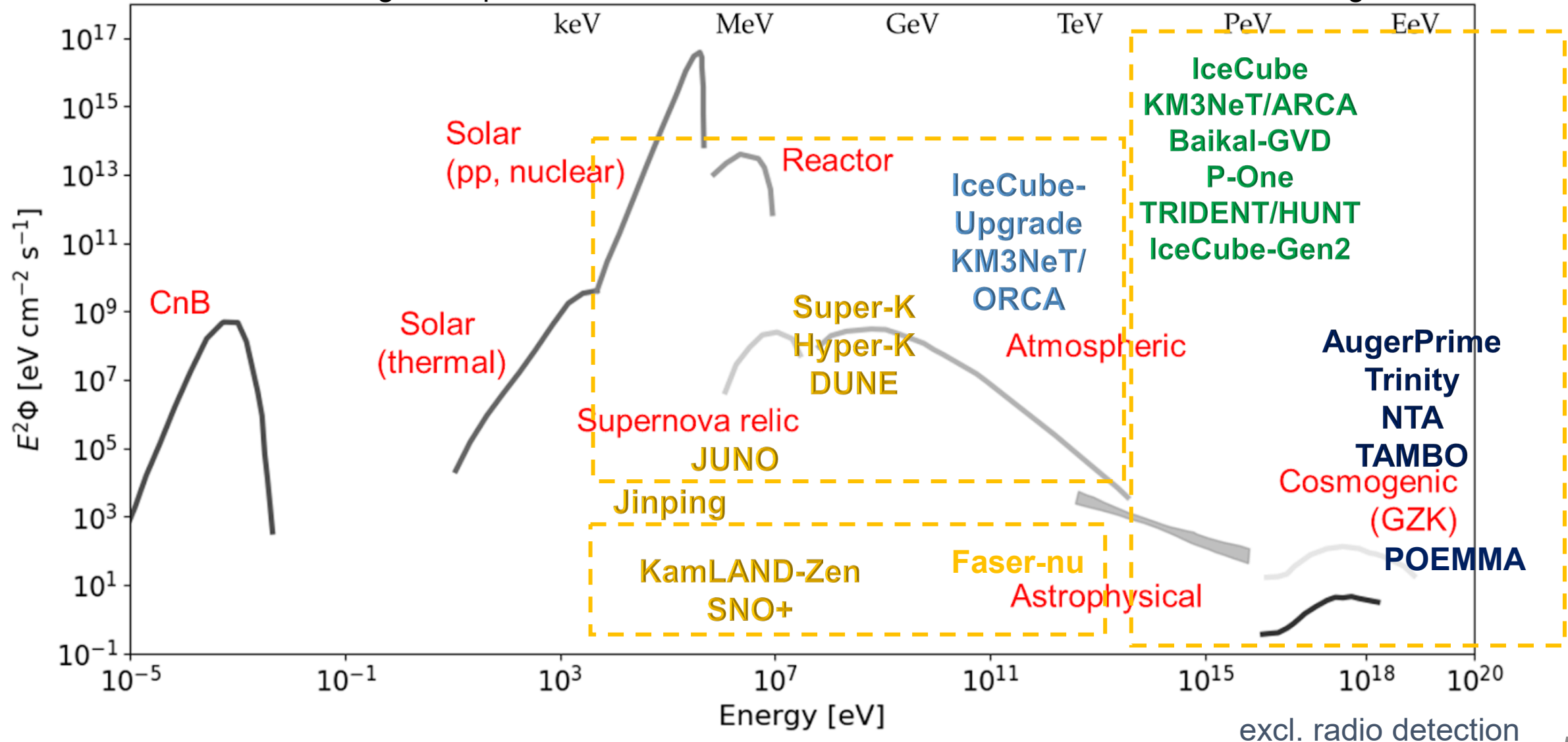
Astrophysical neutrinos

BSM neutrino physics and Cosmology

- Sterile neutrinos
- Non-standard interactions
- Heavy neutral leptons
- Neutrinos and dark matter
- Portals to hidden sectors
- **Neutrinos in the early universe**
Effective neutrino number;
big-bang nucleosynthesis
- **Cosmic neutrino background**

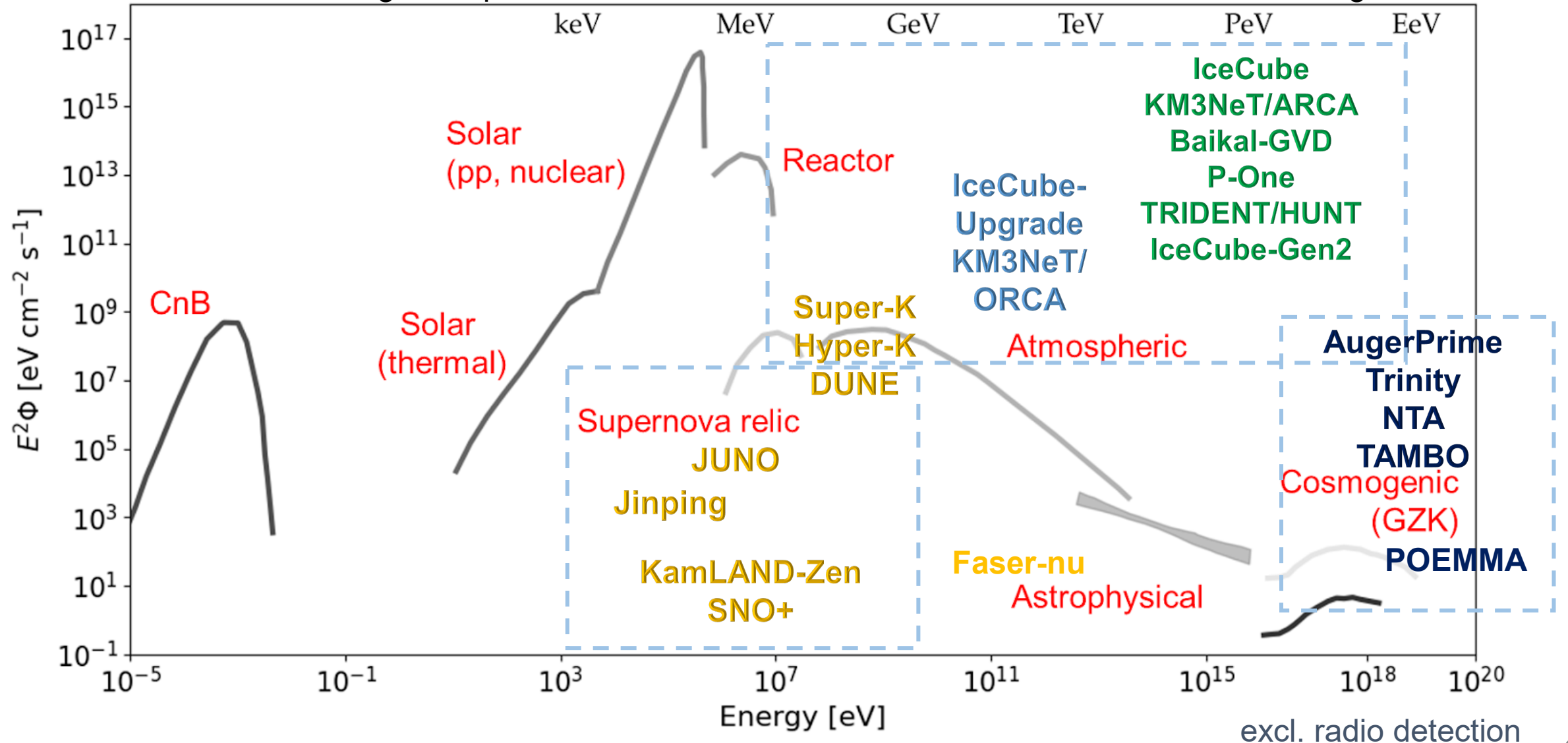
A Wide Energy Landscape

Different energies require different detectors, observables and reconstruction strategies

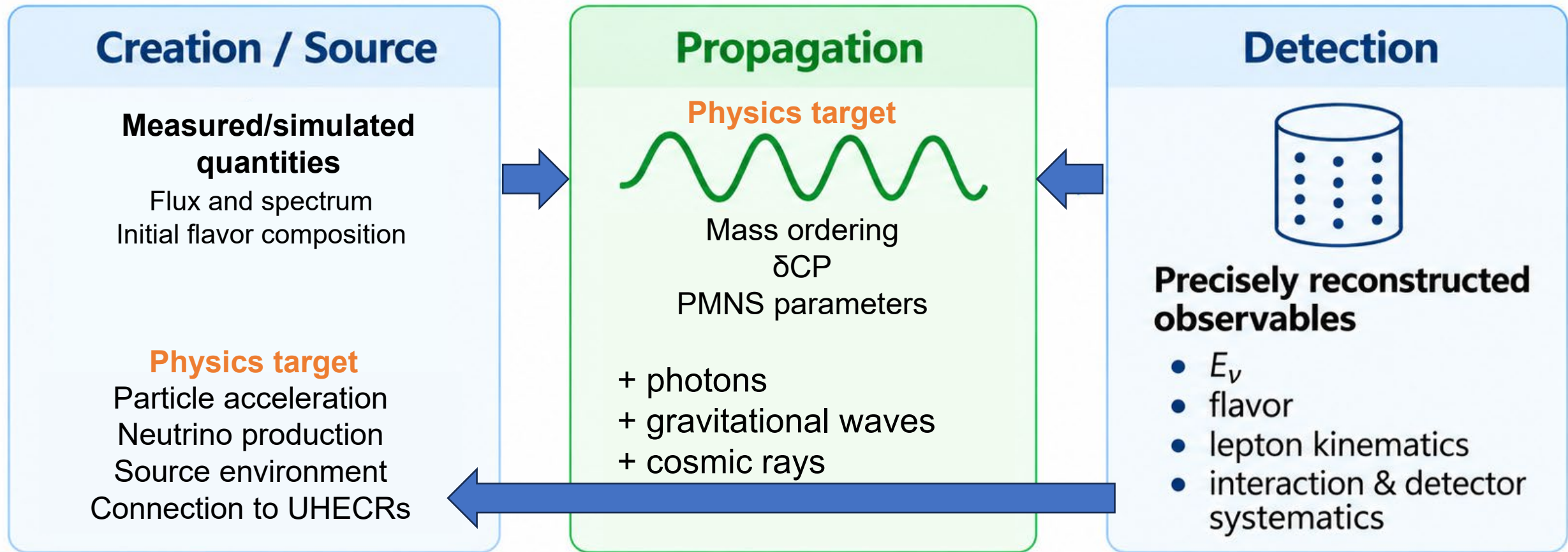


A Wide Energy Landscape

Different energies require different detectors, observables and reconstruction strategies



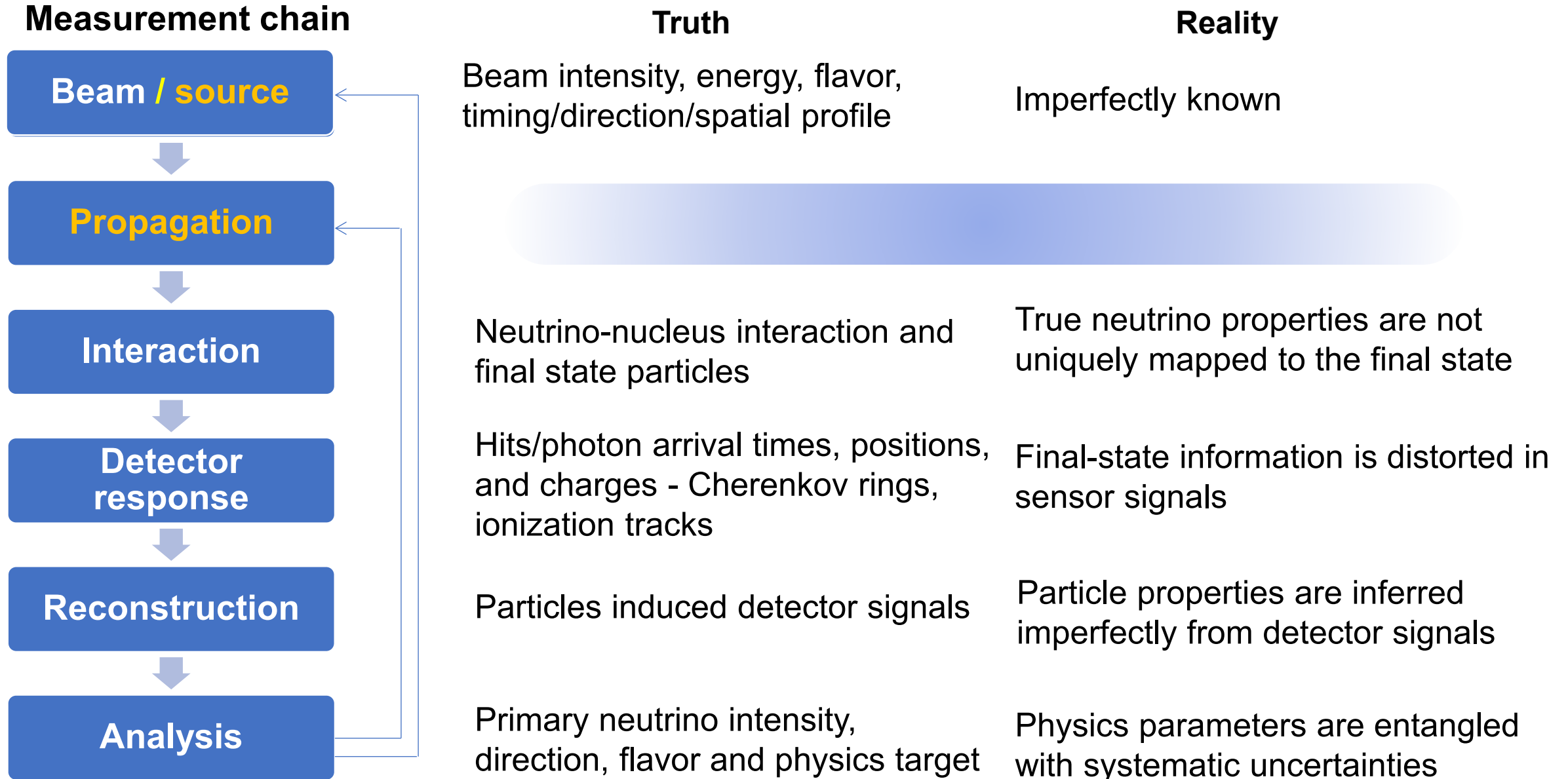
Isolate Propagation / Infer the Source



Control source + detection → isolate propagation physics

Measure the messengers → infer the source physics

Where Do We Lose Information?



Beam: Where Do We Lose Information?

Measurement chain

Beam / source

Truth

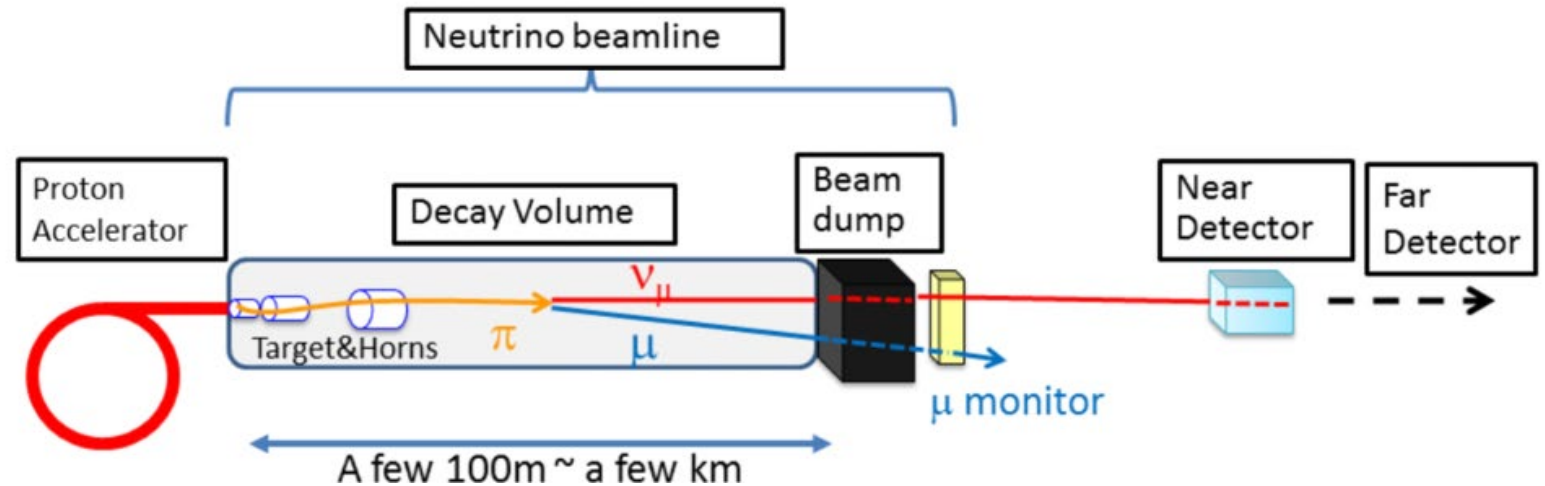
Beam intensity, energy, flavor,
timing/direction/spatial profile

Reality

imperfectly known

Sources of Information loss

- **Hadron-production uncertainty**
 π/K production after proton–target interactions is not perfectly known
- **Beam focusing, transport and stability**
Horn current, alignment, optics, and time-dependent variations affect the beam
- **Decay-kinematics ambiguity**
Decay kinematics are not fully measured
- **Incomplete beam monitoring**
Beam intensity and operating conditions cannot always be fully monitored or tagged



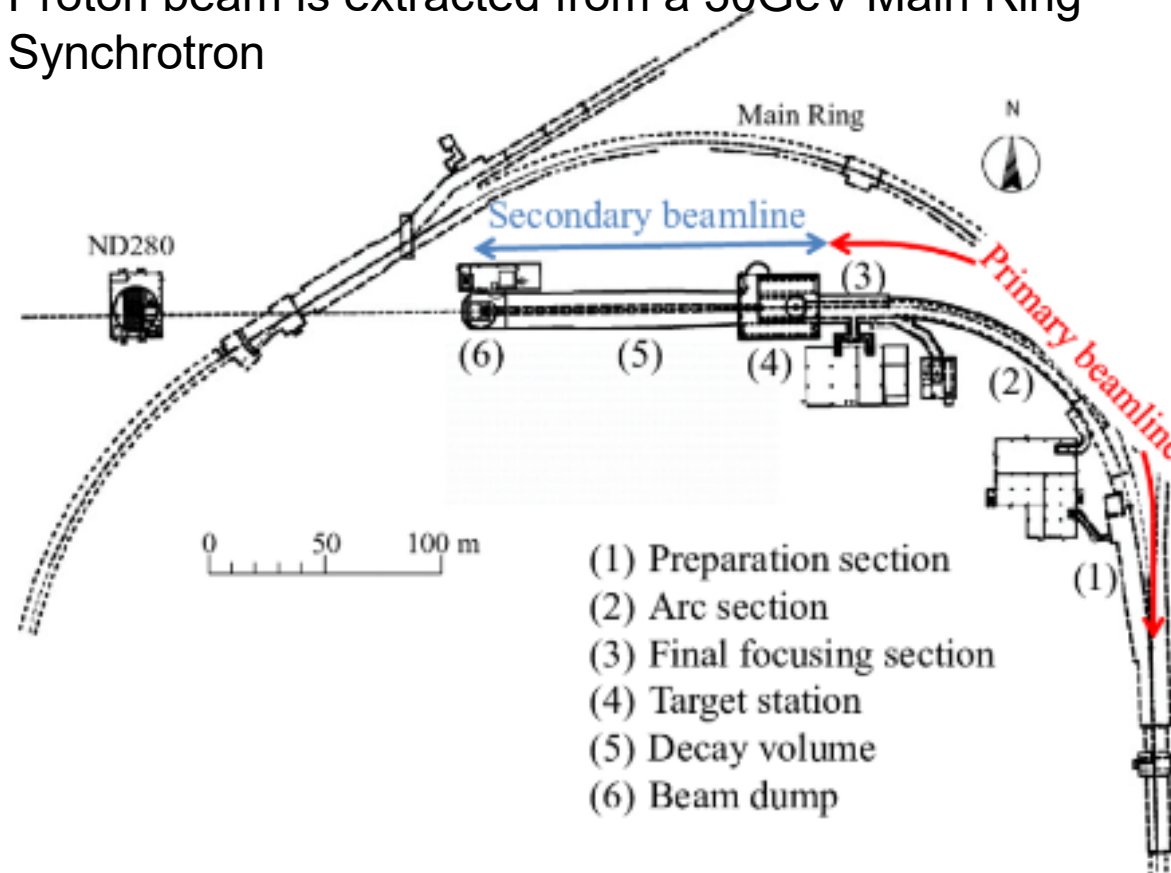
Physics impact

- event rate uncertainty
- energy-dependent flux uncertainty
- flavor uncertainty

Beam: Where Can AI Make a Difference?

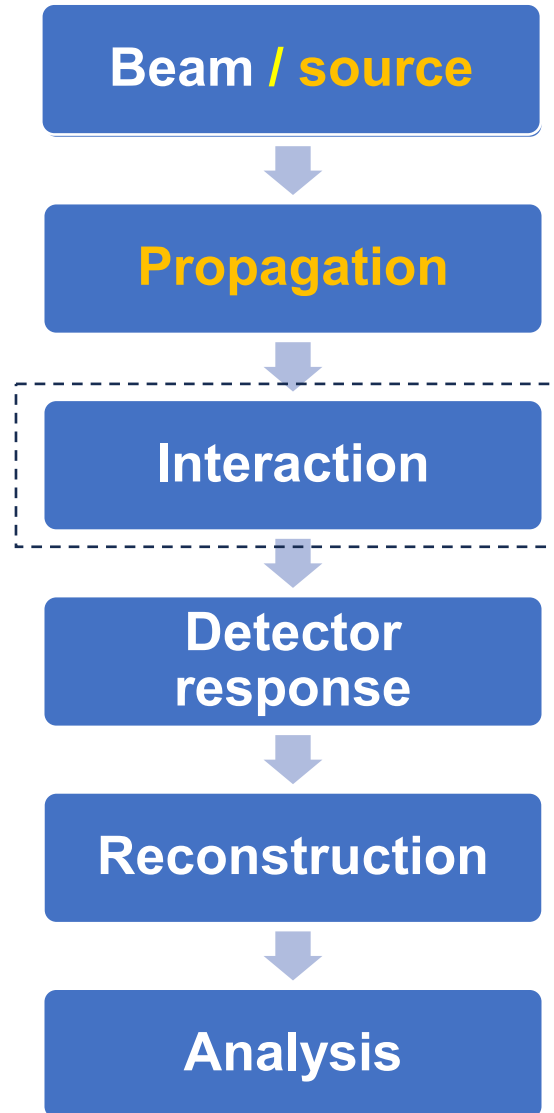
Beamline Monitoring to recover information at the source

Proton beam is extracted from a 30GeV Main Ring Synchrotron



- Hundreds of beam and environmental parameters
- Detect drifts and abnormal conditions
- Diagnose faults before they affect the neutrino flux
- Stabilize the input to physics inference

Measurement chain



Interaction: Where Do We Lose Information?

Measurement chain

Interaction

Truth

Neutrino-nucleus interaction
secondary particles

Reality

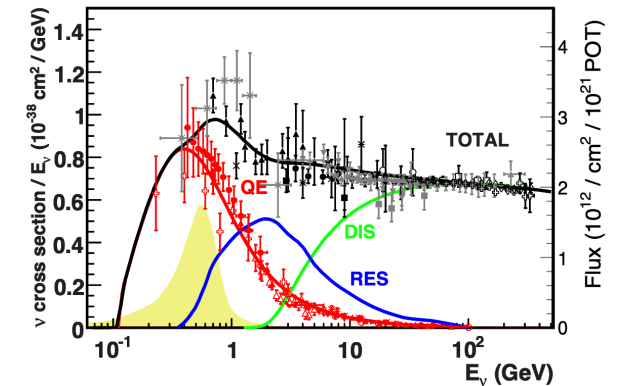
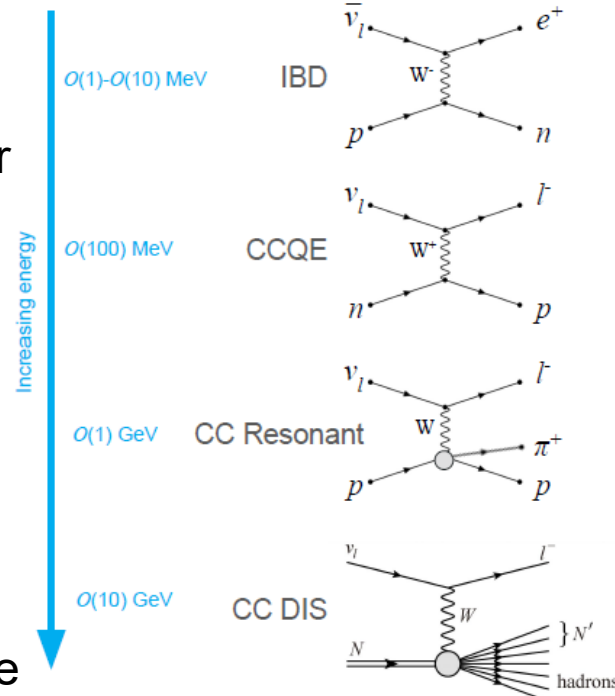
true neutrino properties and observed
final state mapping is not unique

Sources of loss

- **Topology degeneracy**
Different interactions can produce very similar observable final state
- **Generator / model dependence**
Imperfect generators; Inferred quantities depend on the model parameters

Model tuning

- **Initial nuclear-state effects:** Fermi motion and binding energy blur the initial kinematics
- **Multi-nucleon effects:** 2p2h involves multiple nucleons and complicates interpretation
- **Final-state interactions & invisible energy:**
Hadrons can scatter, be absorbed, or carry undetected energy



Physics impact

- biased E_ν reconstruction
- interaction-channel misidentification
- biased oscillation spectra
- cross-section systematics

Interaction: Where Can AI Make a Difference?

- **data → model parameters**

Infer correlated interaction parameters and uncertainties from data

Traditional: rerun GENIE for many parameter choices

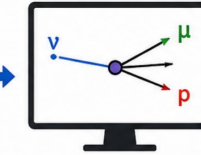
SBI: learn the parameter–data relation once

- **Fast tuning:** once trained, model parameters can be inferred in seconds
- **Pathology-Free:** Eliminates χ^2 grid-search issues

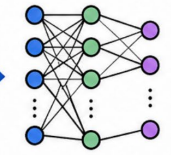
1. Physics Models



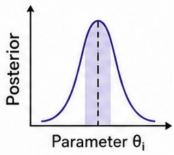
2. Simulate



3. Learn (ML)



4. Infer



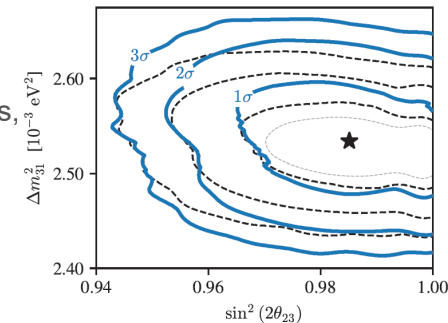
Example: Simulation-based inference for neutrino interaction model parameter tuning, arXiv:2510.07454

- **data → a physics-guided interaction model**

Use ND data to learn how neutrinos interact with nuclei

- **Less dependence on imperfect models:** avoids over-tuning a possibly wrong generator
- **Learn the interaction directly from data:** not just retuning preset model parameters
- **Built-in physics constraints:** structure functions $W_i(x, Q^2)$ make ND → FD extrapolation possible

Example: Machine learning neutrino-nucleus cross sections, PRD 112, 113005 (2025)



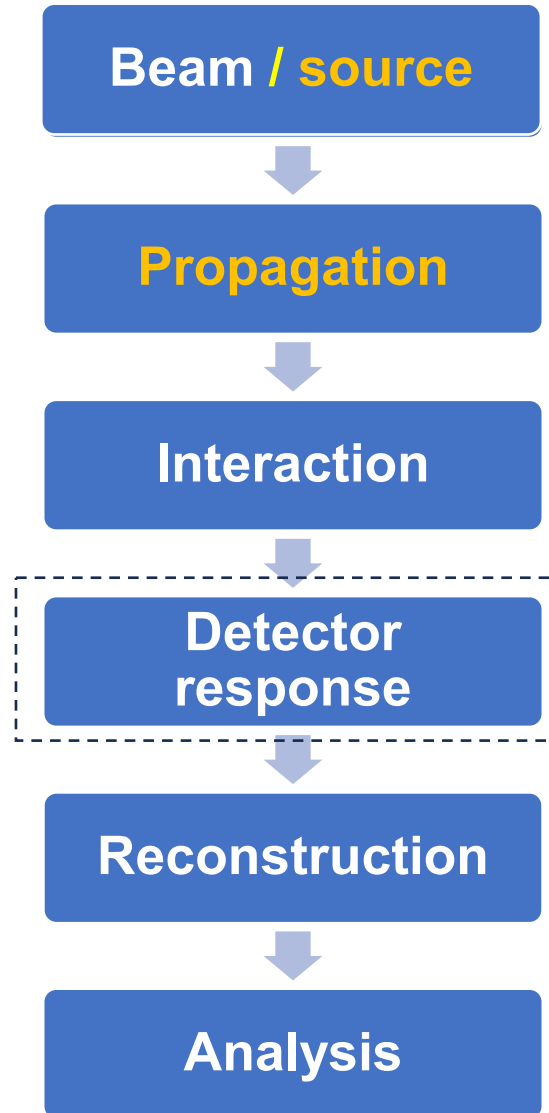
- **Emulate detailed model → fast surrogate**

Slow but accurate nuclear theory → train → fast ML surrogate

- **Keep detailed nuclear physics:** preserves shell and final-state kinematics
- **Generate efficiently:** avoids inefficient accept-reject sampling
- **Fast surrogate:** millions of events in minutes
- **Scalable:** promising for more complex 2p2h and pion-production channels

Example: Efficient Monte Carlo Event Generation for Neutrino-Nucleus Exclusive Cross Section, PRD 111, 113001 (2025)

Measurement chain



Detector: Where Do We Lose Information?

Measurement chain

Detector response

Truth

Hits/photon arrival times, positions, and charges - Cherenkov rings, ionization tracks

Reality

Final-state information is distorted in sensor signals

Sources of loss

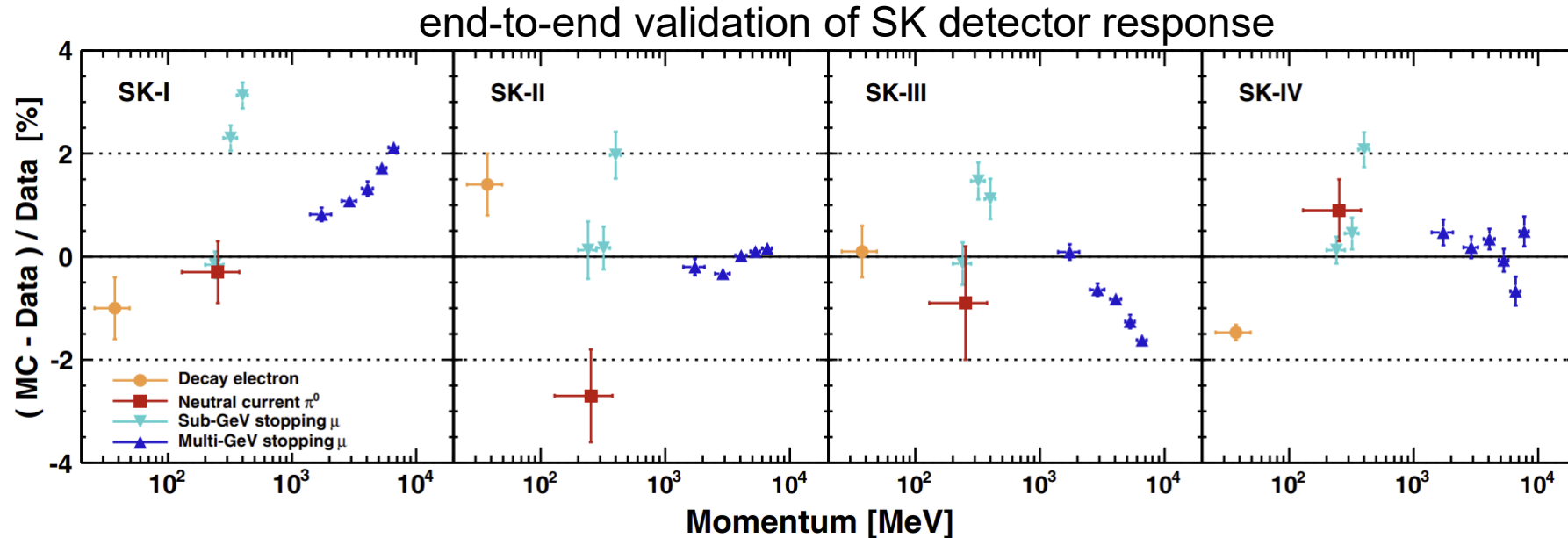
- **Limited detection / incomplete capture**
Thresholds, finite acceptance, partial containment, and dead channels can leave part of the event unobserved
- **Limited spatial / signal resolution**
Coarse granularity, sparse hits, and overlapping signatures reduce event detail
- **Response uncertainty / distortion**
Calibration drift, medium uncertainty, nonlinearity, and saturation distort the measured signal
- **Noise and background**
Detector noise and accidental activity contaminate the event information



Physics impact

- Loss of event information
- Degraded reconstruction resolution
- Reduced PID performance
- Increased detector systematics and bias

Why Detector Response Modeling Matters



NIM A 737, 253 (2014); Phys. Rev. D 97, 072001 (2018)

$\pm 2\%$ energy-scale uncertainties is estimated in Super-K and it **directly affects physics sensitivity and performance**

- Δm^2 uncertainty in T2K oscillation experiment
- Energy selection window and amount of BG in proton decay analysis

- Difficult to constrain each systematic independently
- Potential sources of detector systematics
 - PMT gain
 - QE uniformity
 - light attenuation in water
 - reflection light on detector wall
 - residual magnetic field
- Environment/time dependent

Detector: Where Can AI Make a Difference?

Goal: make the detector response more accurate, stable, and interpretable before reconstruction begins

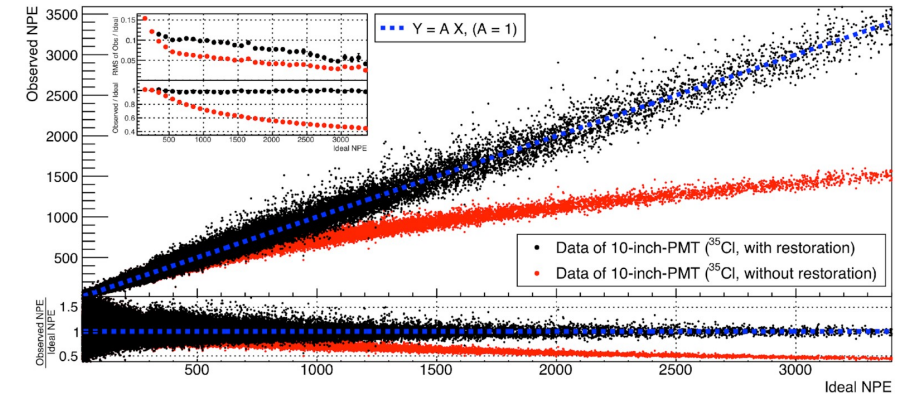
• Correction

Example: Restoring the saturation response of a PMT using pulse shape and artificial neural networks PTEP 5 053C01(2023)

Learn detector-response parameters from calibration or physics data such as timing, gain/charge response, optical properties, field distortions

Recover nonlinear PMT response

- PMT saturation reduces pulse area and distorts pulse shape
- ANN learns the correlation between waveform distortion and lost charge
- The inferred correction restores the PMT response toward linearity

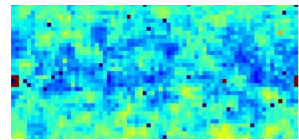


• Monitor

Detect abnormal detector states channel failures drifts noise / environmental changes

Example: Autoencoder-based anomaly detection system for online data quality monitoring of the CMS electromagnetic calorimeter. Comput. Softw. Big Sci., 8 11 (2024)

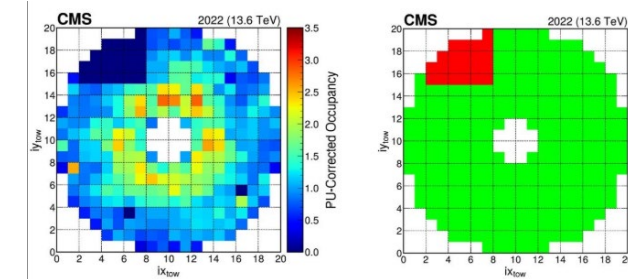
Introduced into Run 3 online DQM workflow



The autoencoder learns a compressed representation of normal detector patterns



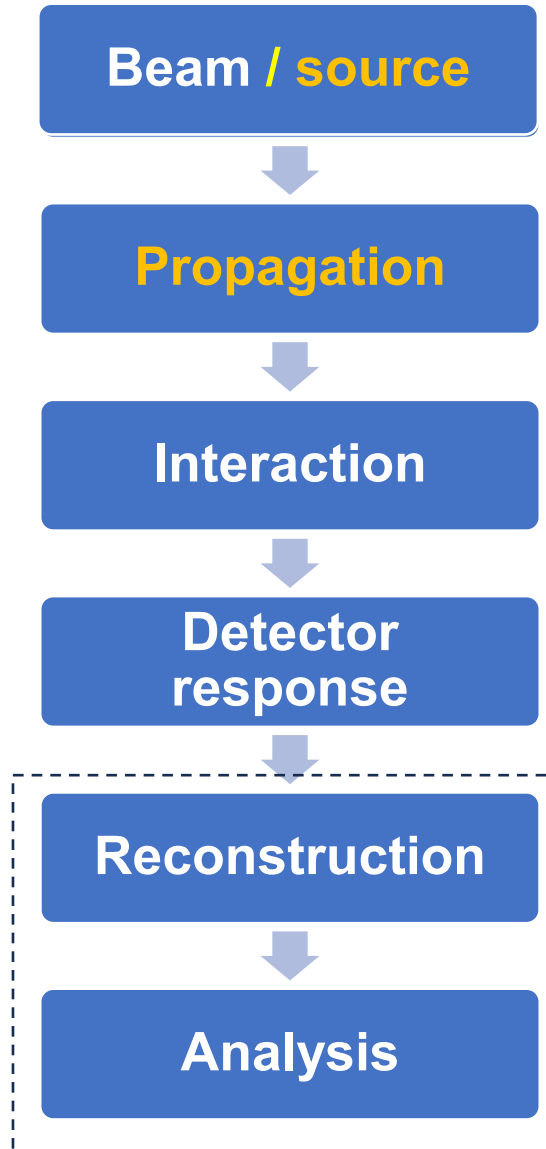
- detect deviations
- flag problematic channels
- support data-quality decisions



• Certify

Automate data-quality assessment good / suspicious / bad runs prioritize expert review

Measurement chain



Reco: Where Do We Lose Information?

Measurement chain

Truth

Reality

Reconstruction

Particles induced detector signals

Particle properties are inferred imperfectly from detector signals

Sources of loss

- **Lossy and simplified inference**

Rich detector information is compressed into a few variables, often using approximate likelihoods or hand-crafted features.

- **Non-unique inverse problem**

Different particle hypotheses can produce similar detector responses.

- **Topology and algorithmic ambiguities**

Tracks, cascades, overlapping signatures, or multi-particle events can be confused, and results may depend on initialization or model assumptions.

- **Incomplete uncertainty representation**

Point estimates often fail to capture the full posterior uncertainty.

- **Imperfect detector-response calibration**

Calibration errors propagate directly into reconstructed quantities.

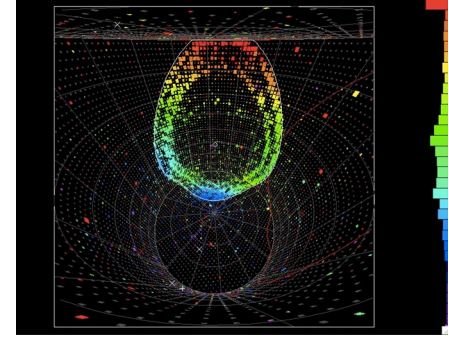


Physics impact

- resolution tails
- misclassification
- outliers
- event loss due to failed reconstruction

The Same Inverse Problem, Different Detector Modalities

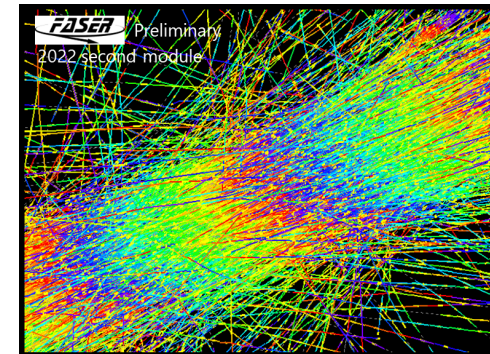
Water Cherenkov — overlap of multiple particle rings, fuzzy rings from particle scattering



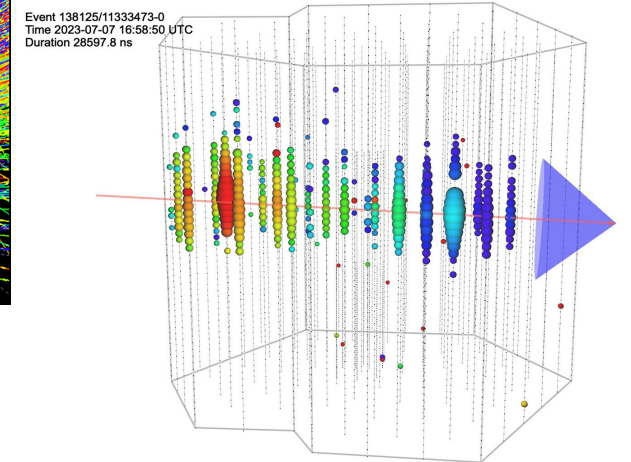
Scintillator detectors — pattern recognition with short-track hadrons, identification of electromagnetic showers, utilization of neutrons



Emulsion detectors — pattern recognition in a high pile-up environment



Neutrino Telescopes — sparse 3D light pattern: Directionality, flavour ID, CC/NC separation



Shared tasks: classification, regression, segmentation and topology recognition 20

Reco: Where Can AI Make a Difference?

- **Faster reconstruction** : Replace expensive likelihood fits
- **Better use of detector information** : Learn complex spatial and timing correlations
- **Multi-task reconstruction** : Energy, direction, vertex, PID, topology in one framework
- **Uncertainty-aware outputs** : Predict $p(\theta|x)$, not only a best-fit value
-

Reconstruction can not be independent from previous topics as “AI Learns What We Give It”

ML performance is only as reliable as the training model
Simulation–data mismatch can dominate ML systematics

- Detector-response mismodeling
- Interaction-model mismatch
- Calibration and operating-condition differences

Make simulation trustworthy

- Constrain detector response with calibration data
- Validate simulation–data differences
- Propagate remaining uncertainties

Make simulation scalable

- Replace expensive simulation steps with fast surrogates
- Generate large samples for systematic studies
- Validate surrogate errors against physics requirements

Analysis: Where Do We Lose Information?

Measurement chain

Analysis

Truth

Physics target and primary
neutrino intensity, direction, flavor

Reality

Physics parameters are entangled
with systematic uncertainties

Sources of loss

- **Event selection and hard categorization**
Cuts and discrete categories can discard borderline events and continuous classification information.
- **Lossy statistical compression**
Binning and simplified test statistics may fail to use the full event-level information.
- **Physics–systematics degeneracies and model mismatch**
Flux, cross-section, detector uncertainties, and simulation–data differences can bias or obscure physics inference.
- **Incomplete uncertainty propagation**
Reconstruction and modeling uncertainties may not be fully carried into the final fit.



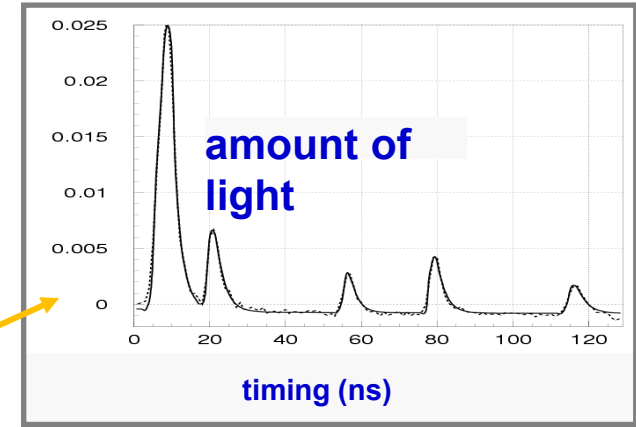
Physics impact

- Loss of statistical power
- Biased parameter inference
- Misestimated uncertainties
- Reduced physics sensitivity

Analysis: Where Can AI Make a Difference?

- **Keep more useful events**
Better signal/background separation without hard cuts
- **Preserve event-level information**
Use continuous scores and richer event representations
- **Infer physics more directly**
Exploit full event distributions and correlations
- **Search beyond predefined signatures**
Rare and unexpected topologies
- ...

IceCube: From Detector Signals to Physics



- Sparse 3D detector in Antarctic ice
- DOM positions, photon arrival times and charges

What the analysis needs

- Select neutrinos from backgrounds
- Reconstruct energy, direction and topology
- Estimate event-by-event uncertainty
- Use the outputs in physics analyses



IceCube Reconstruction: Different Ways to Represent the Same Event

Boosted decision trees / Random Forest being used from 2010

	CNN JINST 16 (2021) P07041	GNN JINST 17 (2022) P11003	Transformer arXiv:2604.19846, submitted to MLST
Input representation	Structured detector grid	Points linked as a graph	A set of measurement tokens
Information exchange	Local spatial patterns	Messages between linked neighbors	Learned attention between tokens
Main flexibility	Efficient use of regular structure	Irregular geometry and variable inputs	Flexible, long-range relationships
Design choice to test	Grid mapping and input summaries	Graph construction and aggregation	Input compression and computation

Complementary choices

The goal is not a newer architecture — it is better use of detector information

Galactic Neutrinos: Improved Physics Reach

diffuse neutrino emission from the Galactic plane [Science 380, 1338 \(2023\)](#)

AI gain came not only from better resolution, but from retaining more useful events

- 30 times as many events as precursor analysis

Bottleneck
Background rejection +
cascade directional
information

AI contribution

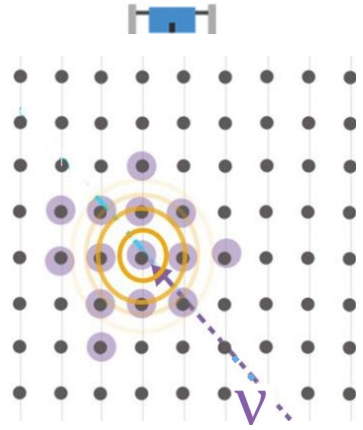
CNN/BDT selection +
improved reconstruction

Physics impact

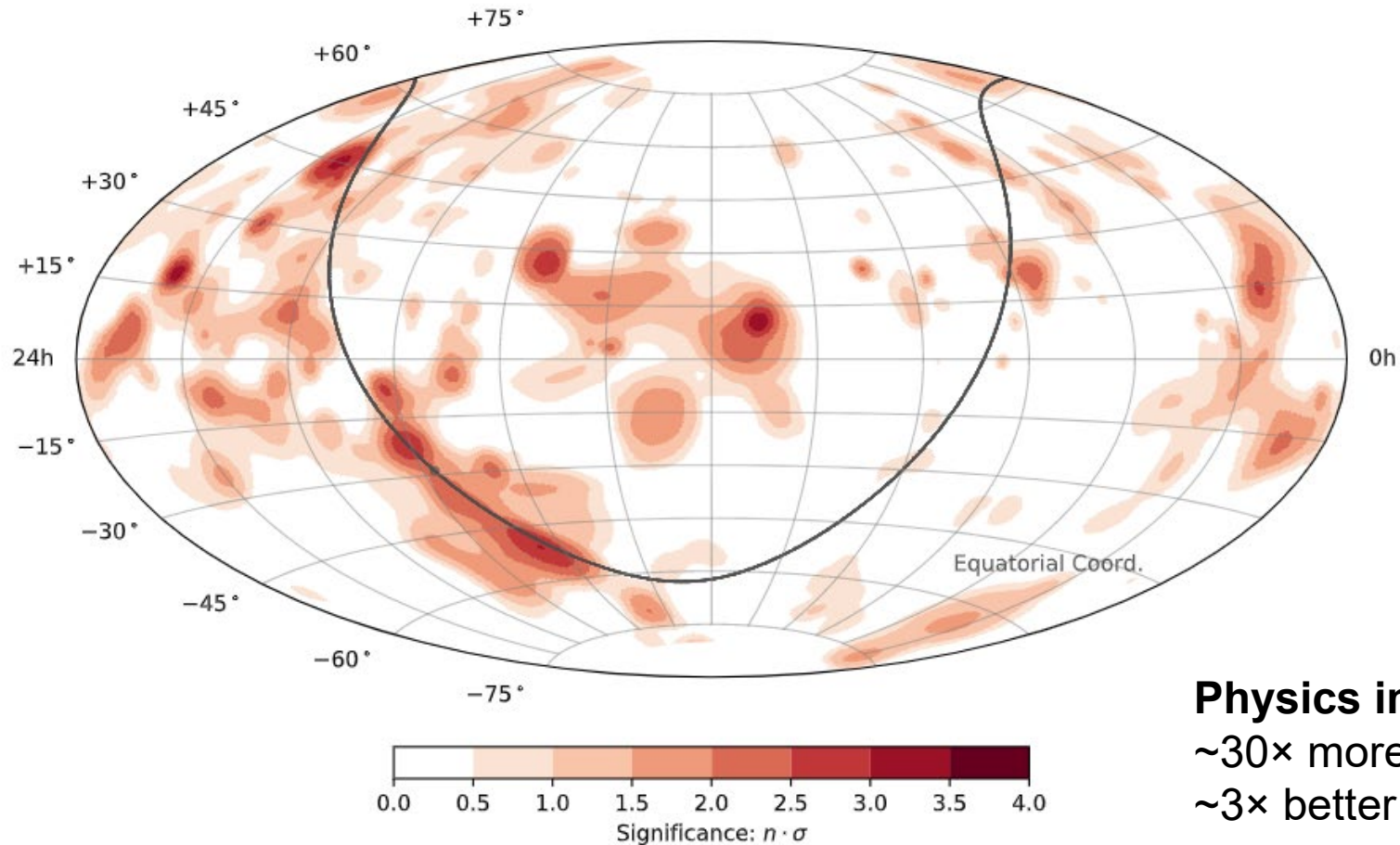
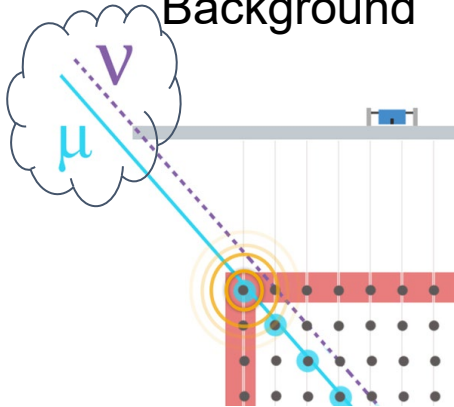
~30× more selected events

~3× better sensitivity

Cascades



Atmospheric
Background

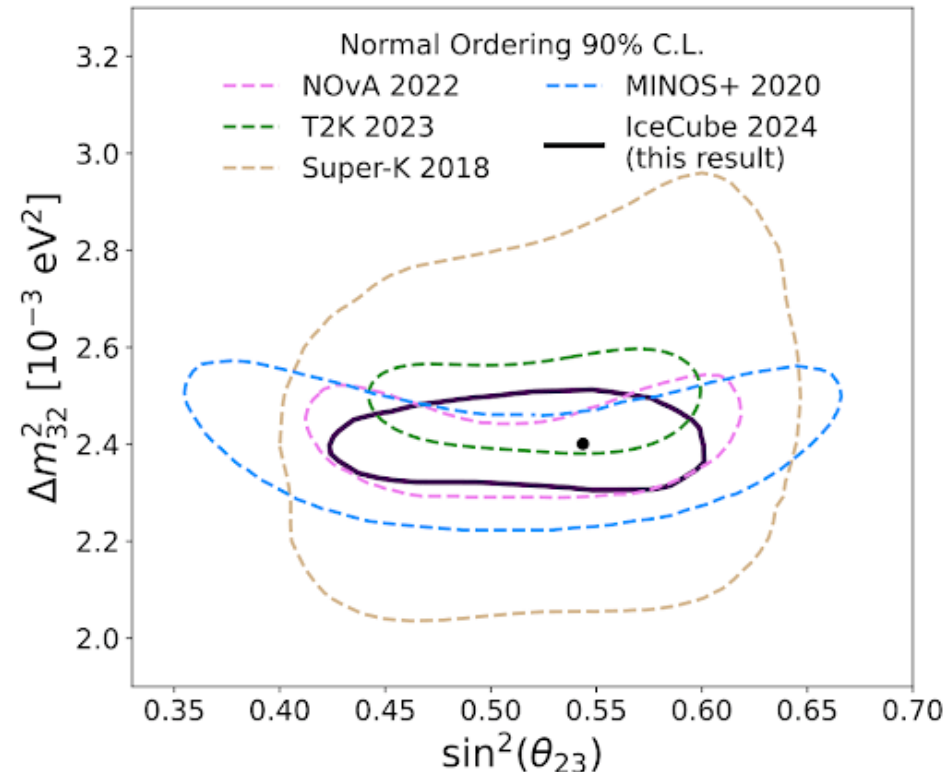


Neutrino oscillation parameters using convolutional neural networks

PRL 134, 091801 (2025). A GNN-based extension was under development

Quantitative Impact of CNN Reconstruction

- **~5,000× faster event processing**
Compared with conventional log-likelihood reconstruction
- **~7× larger analysis sample**
About seven times more neutrino events than the previous DeepCore analysis
- **<0.6% atmospheric-muon contamination**
917 background events out of 150,272 selected events, while maintaining high signal efficiency



Bottleneck

Large event sample +
multi-variable
reconstruction

AI contribution

- CNNs for energy, direction, vertex, PID
- muon rejection
- faster processing

Physics impact

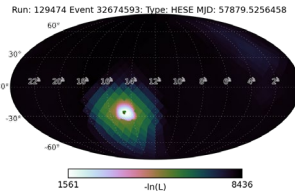
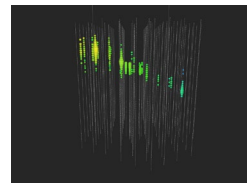
- ~150,000 neutrino candidates
- 99% purity

	$N_{\text{events}}(9.3\text{yrs})$
ν_μ CC	88306
ν_e CC	35296
ν_τ CC	8772
ν NC	16981
atm. μ	917
Total MC	150272
data	150257

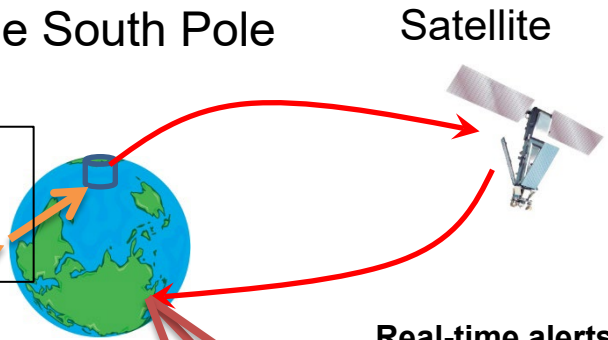
ATHENA: Toward Multi-Messenger Neutrino Astronomy

Goal: convert more detected neutrinos into useful multi-messenger alerts

IceCube: Rapid reconstruction of neutrino arrival directions (error circle), Energy, Cosmic-likeness at the South Pole



Bottleneck
Need fast, robust event information



energetic transient phenomena



photons and GW

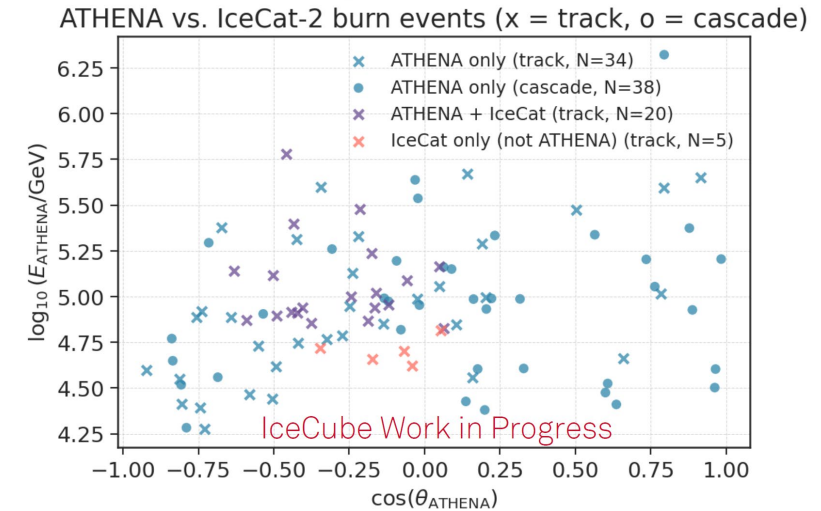
Physics impact

- more useful alert candidates
- improved Southern-sky coverage
- cascade alerts
- unified alert reconstruction

Alert!

Real-time alerts are issued to telescopes worldwide

within tens of seconds of detection.



AI contribution

Multi-task Transformer:

- energy
 - direction
 - position
 - topology
- event-level uncertainty**

Prospects: From Individual Examples to Shared Challenges

Different detectors, different data — many shared inference challenges

Shared AI efforts can accelerate neutrino physics

- Identify where information is lost — preserve it
- Control simulation–data mismatch
- Propagate uncertainties reliably
- Accelerate simulation and reconstruction
- Build transferable tools across experiments

Special Thanks to Contributors

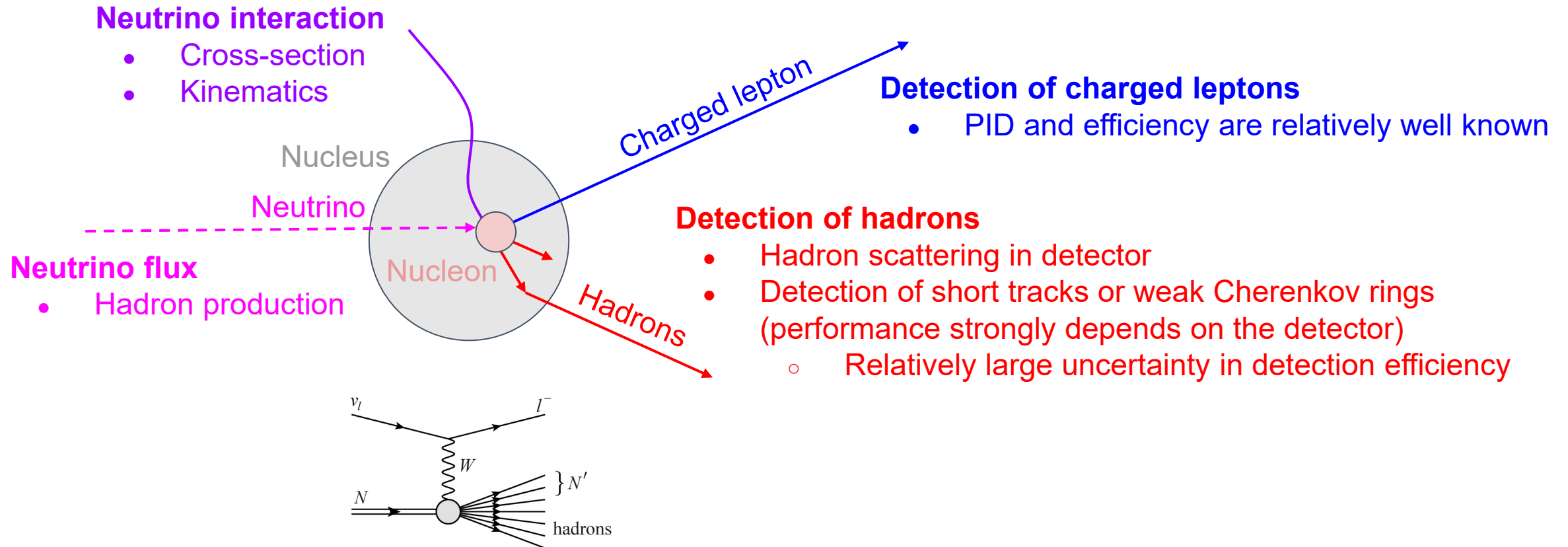
- Kimihiro Okumura (RCCN, UTokyo)
- Masaki Ishitsuka (TUS)
- Saul Alonso Monsalve (ETH Zurich)
- Yusuke Koshio (Okayama)
- Saki Fujita (IPMU, UTokyo)
- Seungho Han (Kyoto)
- Koun Choi (IBS, Korea)
- Callum Wilkinson (LBNL)
- Megan Friend (KEK)
- Ken Sakashita (KEK)
- Maximilian Meier (Chiba)
- Aya Ishihara (Chiba)
- Hideyoshi Ozaki (Tohoku)
- Tsutomu Fukuda (Nagoya)
- Tomoko Ariga (Kyushu)
- Akitaka Ariga (Chiba/Bern)

+ Kazu Terao and Patrick de Perio

Backup

Neutrino-Nucleus Interaction

- We cannot see neutrinos directly.
- Must infer neutrino properties (energy and type) from the products of an interaction.
- Challenges vary across experiments: different target nuclei and detection techniques.



Neutrino-Nucleus Interaction

- Neutrino interaction generators are not perfect
 - Many theoretical models and assumptions to determine the outgoing particles
- Challenges:
 - 1) Modeling large parameter space with limited control data
 - 2) Effective use of this model in physics (e.g. oscillation) analyses to mitigate parameter degeneracies and unknowns

Neutrino interaction

- Cross-section
- Kinematics

Nucleus

Neutrino

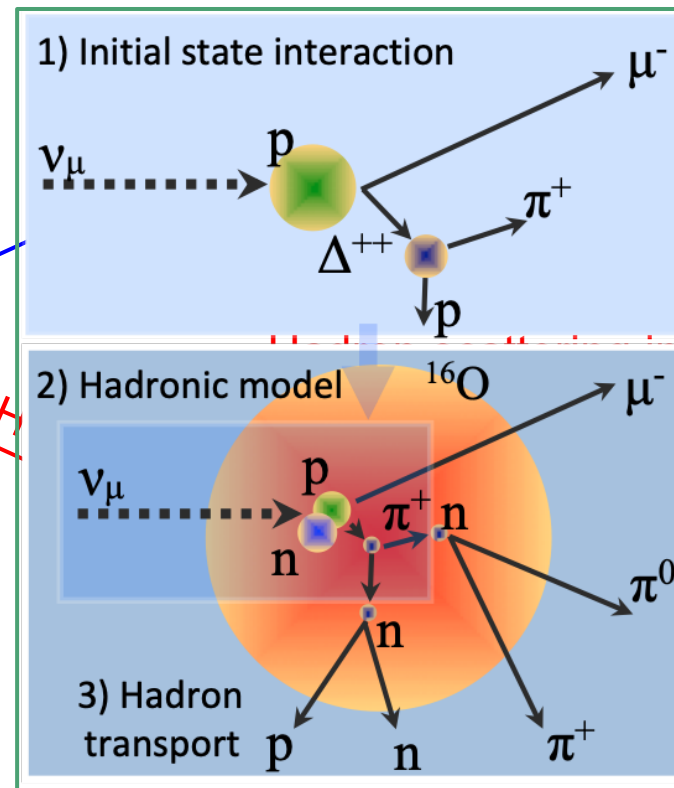
Neutrino flux

- Hadron production

Nuclear physics:

- Nucleon momentum (Fermi motion)
- Multi-nucleon correlations
- Hadron scattering in nucleus (FSI)

These depend on the target nucleus



of charged leptons

and efficiency are relatively well known

detector

tracks or weak Cherenkov rings

(efficiency depends on the detector)

the uncertainty in detection efficiency

Neutrino