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

Challenges in Neutrino Physics

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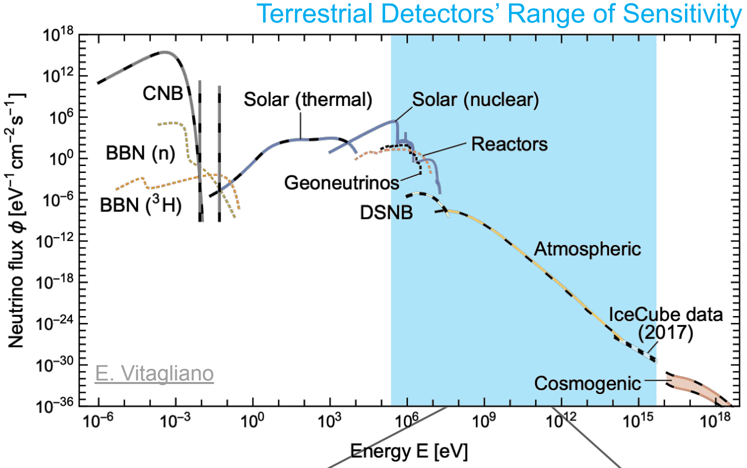
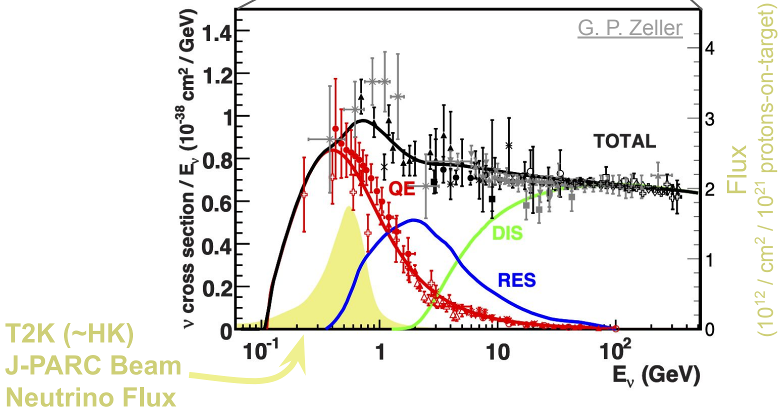
December 3-5, 2024

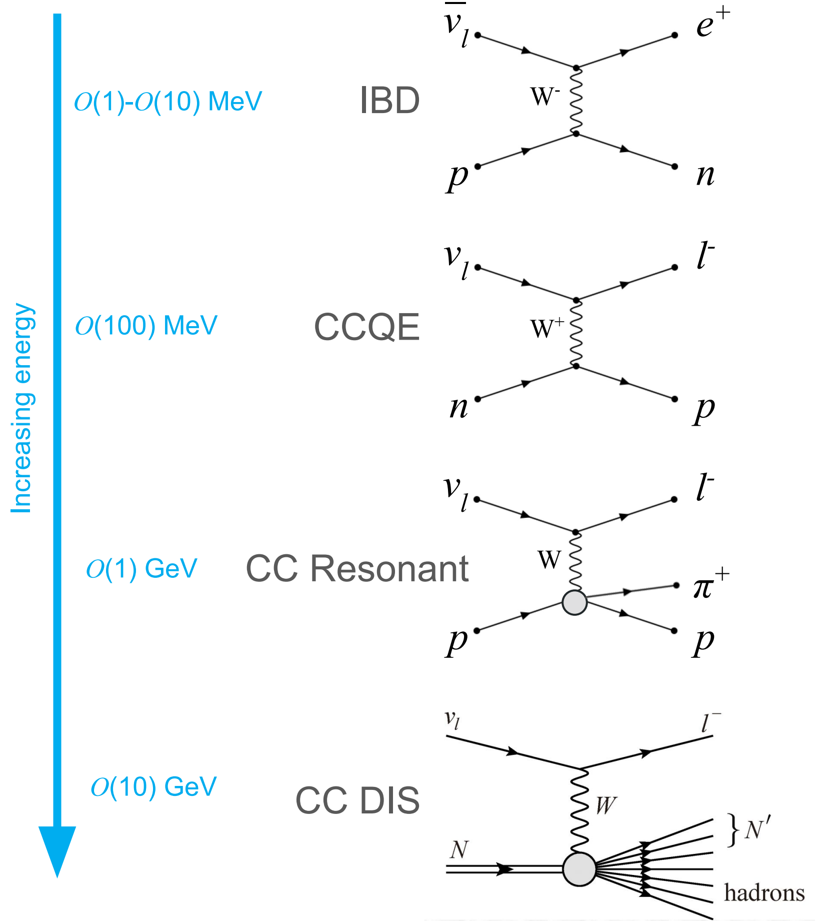
Impactful Research Areas in Neutrino Physics

- Introduction
- Beamline operations
- Neutrino-Nucleus interaction modeling
- Data reconstruction
- Weak signal, large background
- Data-simulation discrepancies
- Fast simulation/reconstruction
- Detector Hardware design and production

Neutrino Sources and Interactions

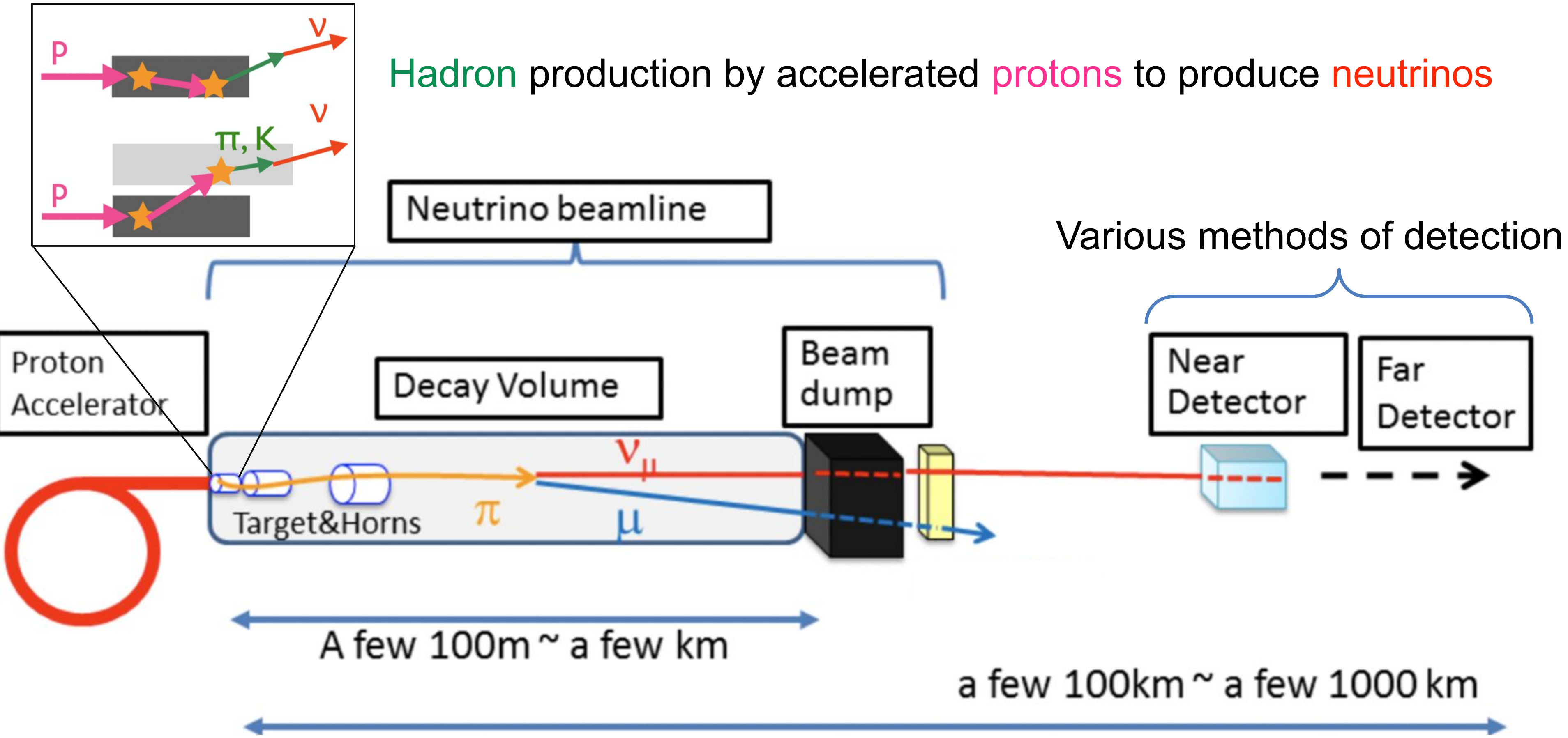






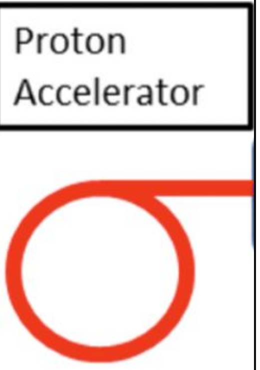
Beam Neutrino Production

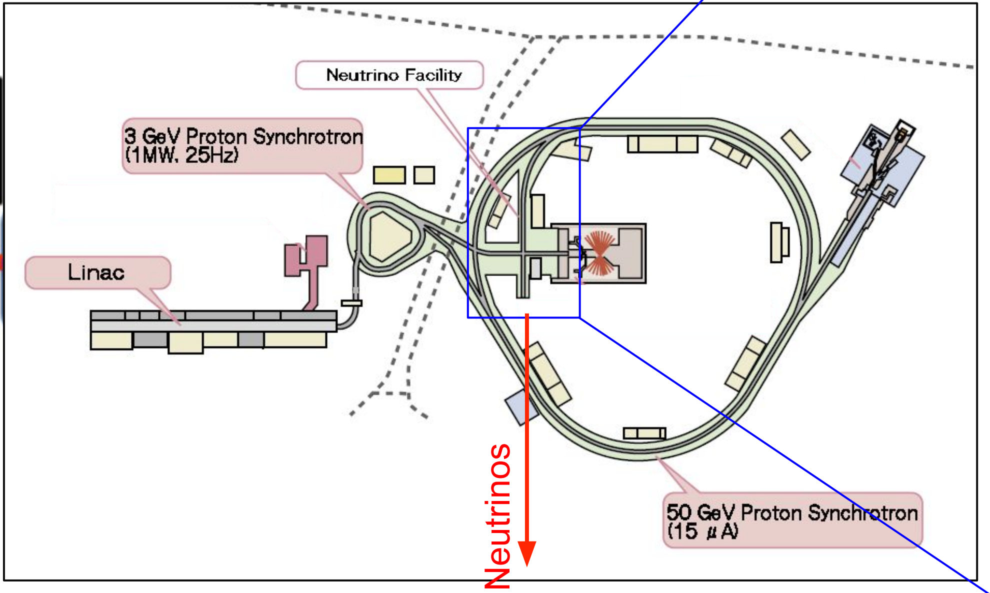
Hadron production by accelerated protons to produce neutrinos

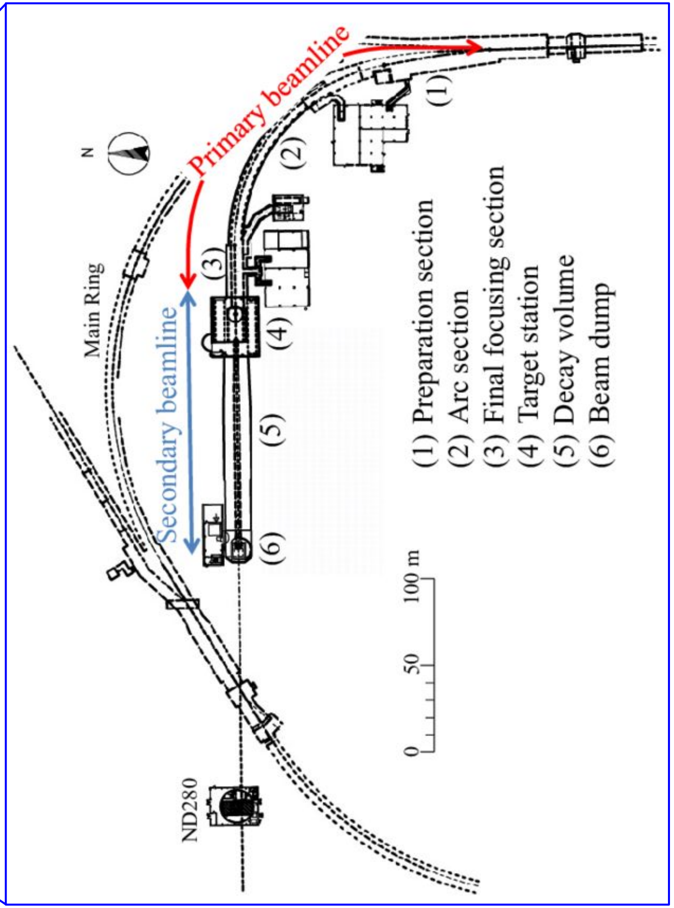


Accelerator and Neutrino Beamline Diagnostics

- Challenge: Efficient and safe operation, including during new operational conditions or to detect issues with aging equipment
- Informative monitoring, anomaly detection, quick diagnosis
  - Utilizing not only beam monitors, but also environmental data
    - 100s of parameters every ~second





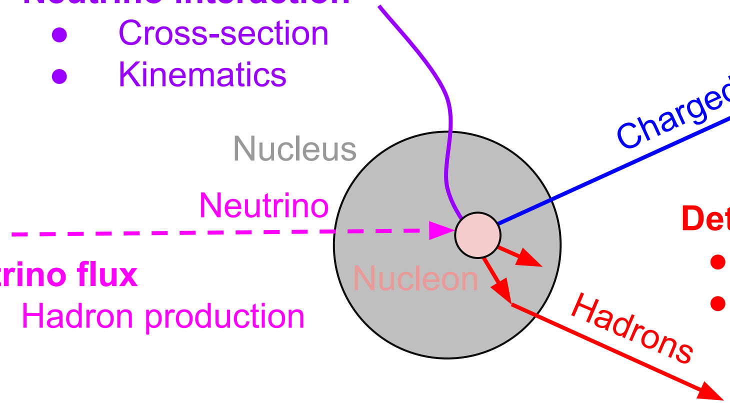


Neutrino-Nucleus Interaction

- 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.

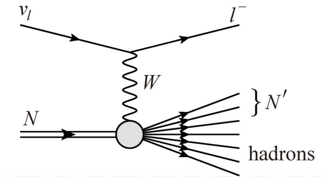
Neutrino interaction
- Cross-section
- Kinematics

Neutrino flux
- Hadron production



Detection of charged leptons
- PID and efficiency are relatively well known

Detection of hadrons
- Hadron scattering in detector
- Detection of short tracks or weak Cherenkov rings (performance strongly depends on the detector)
  - Relatively large uncertainty in detection efficiency

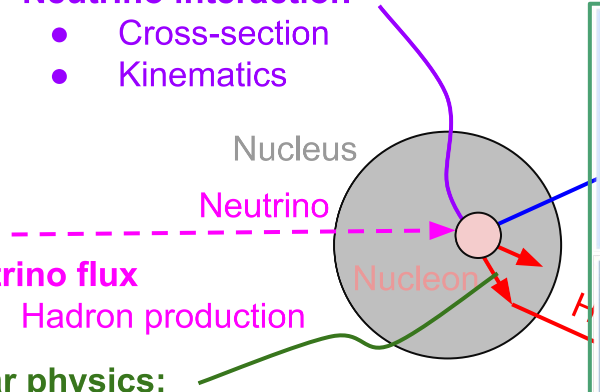


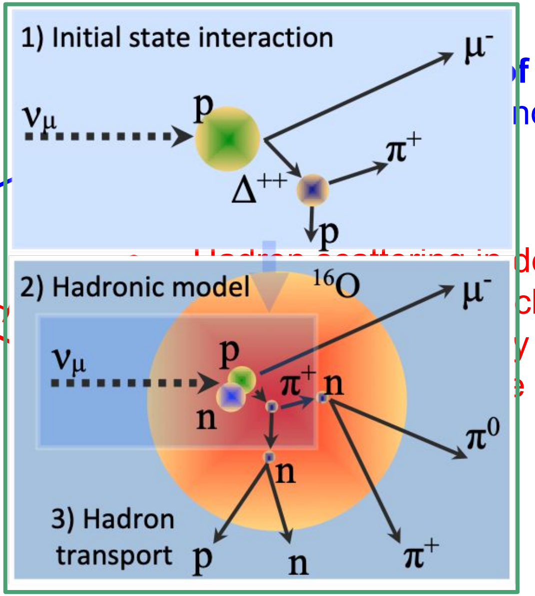
Neutrino-Nucleus Interaction

- 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





...f charged leptons
...nd efficiency are relatively well known

...detector
...cks or weak Cherenkov rings
...y depends on the detector)
...e uncertainty in detection efficiency

Neutrino flux
- Hadron production

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

These depend on the target nucleus

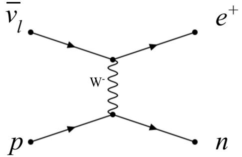
Event Topologies

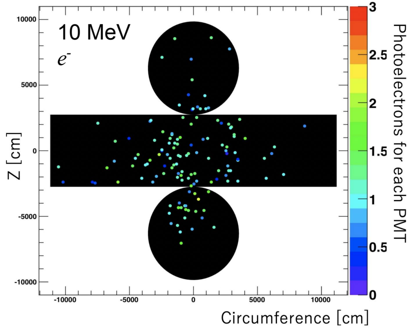
A rich problem for event reconstruction

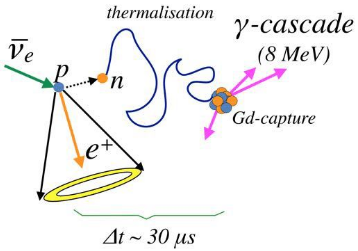
- Particle identification
  - Sig/bkg discrimination
- Kinematics determination
- Multi-particle separation

LowE

IBD

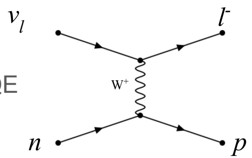


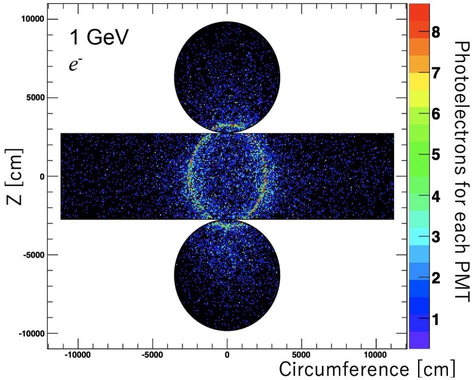




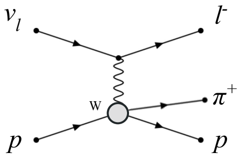
HighE

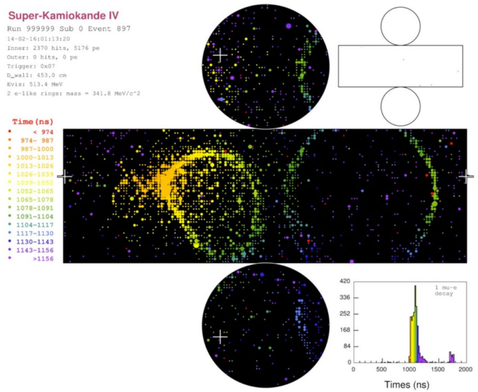
CCQE



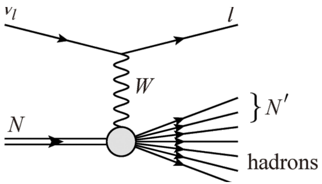


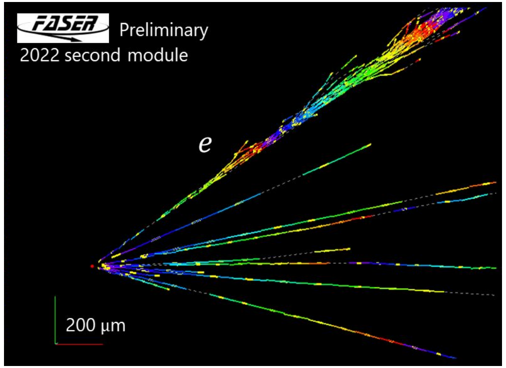
CC RES





CC DIS

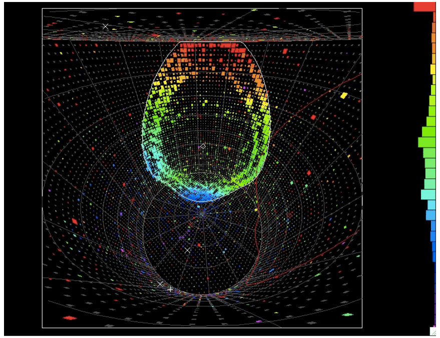


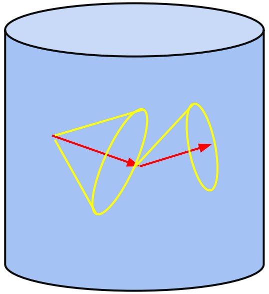


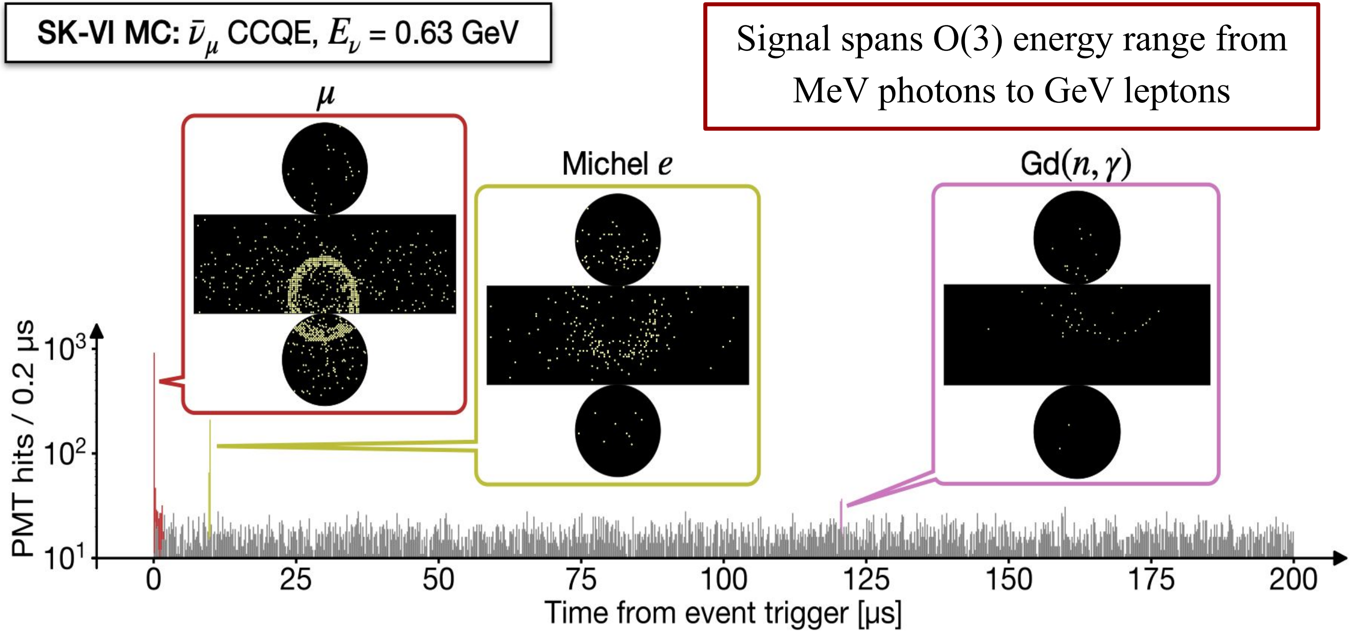
Data Reconstruction - Infer Neutrino Energy and Type

Hyper-K/SK = Beam Neutrino + Water Cherenkov Detectors

- Cherenkov rings to identify particles produced from a neutrino interaction.
- Critical challenge: overlap of multiple particle rings, fuzzy rings from scattering process.





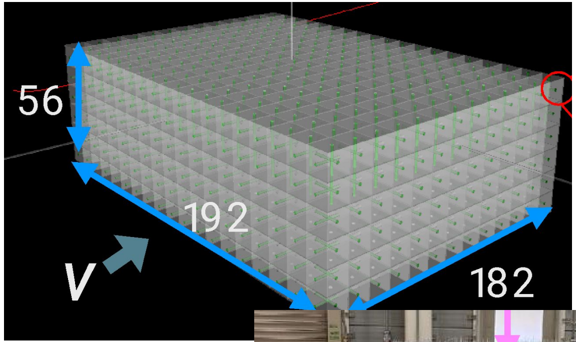


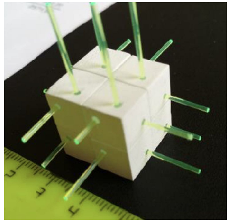
Signal spans O(3) energy range from MeV photons to GeV leptons

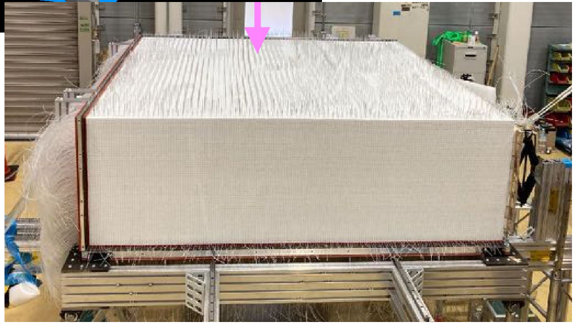
Data Reconstruction - Infer Neutrino Energy and Type

SuperFGD in T2K Near Detector Upgrade = Beam Neutrino + plastic scintillator detector

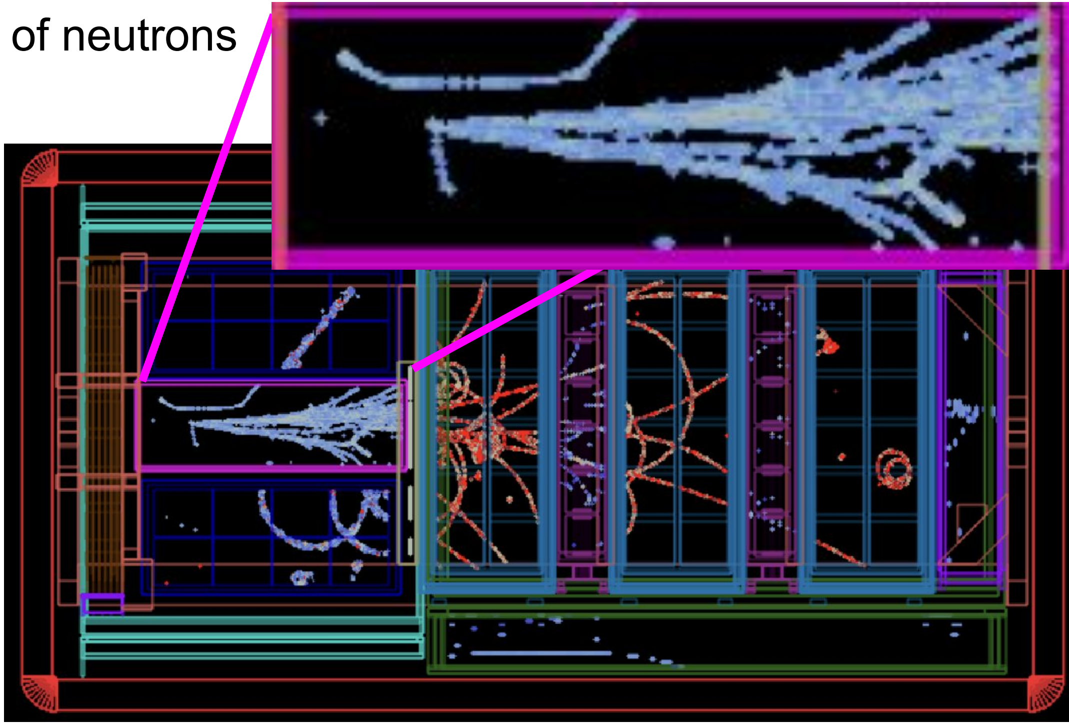
- Projection of particle trajectories to three 2D planes
- Critical challenge: pattern recognition with short-track hadrons, identification of electromagnetic showers, utilization of neutrons







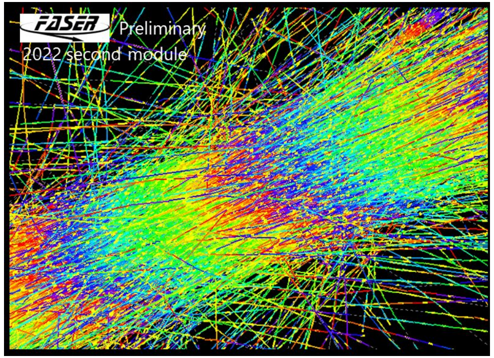
2 million
1cm^3 cubes,
~56k channels

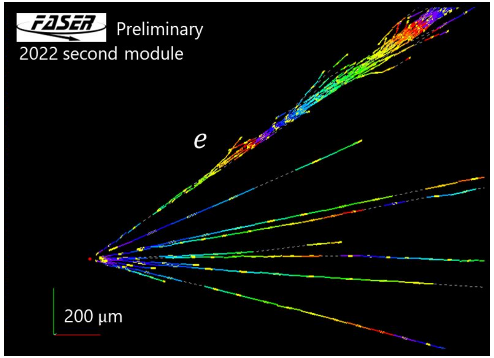


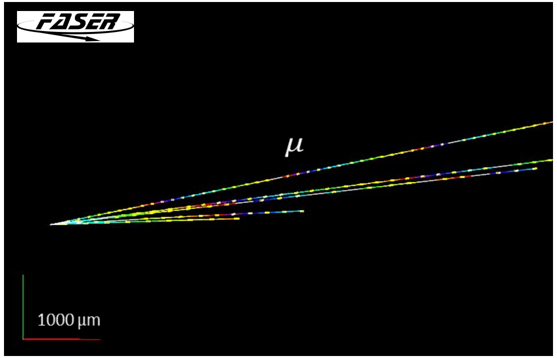
Data Reconstruction - Infer Neutrino Energy and Type

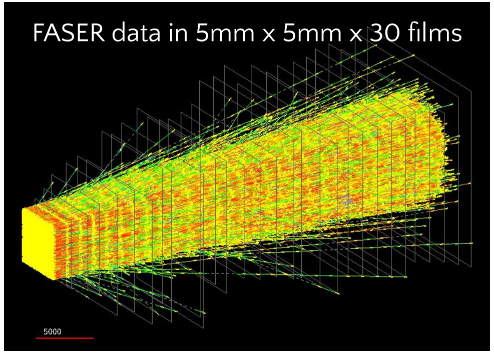
FASER = Beam Neutrino + Emulsion Detector

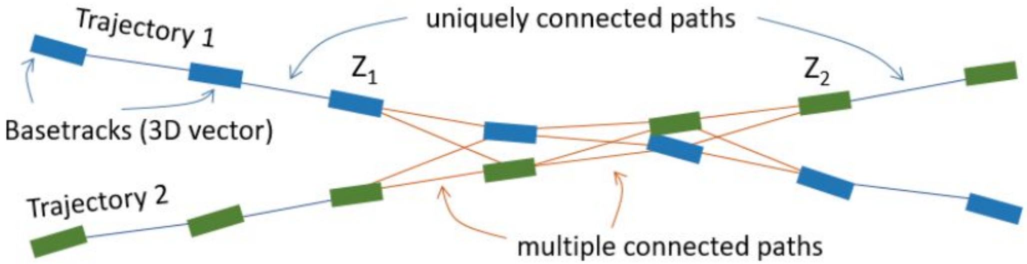
- Extremely detailed imaging of particle trajectories (energy deposition patterns)
- Critical challenge: pattern recognition in a high pile-up environment







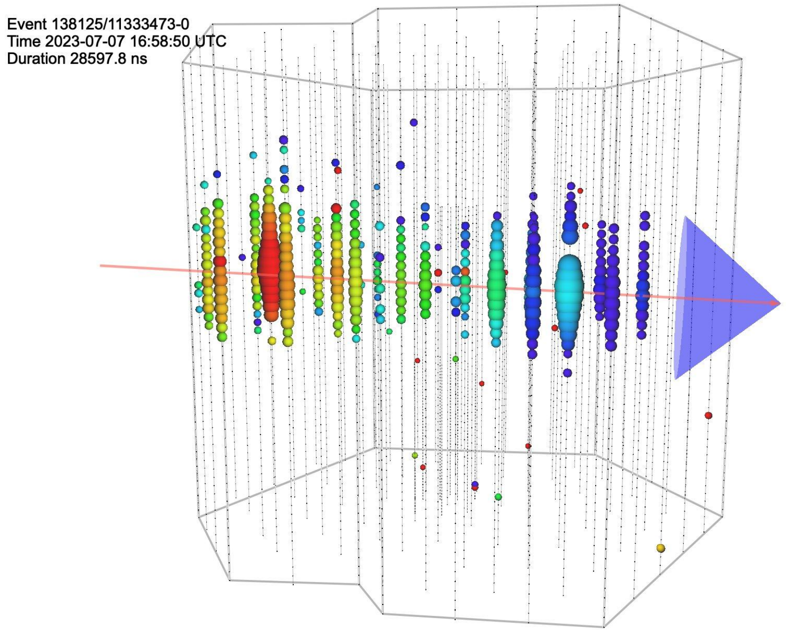


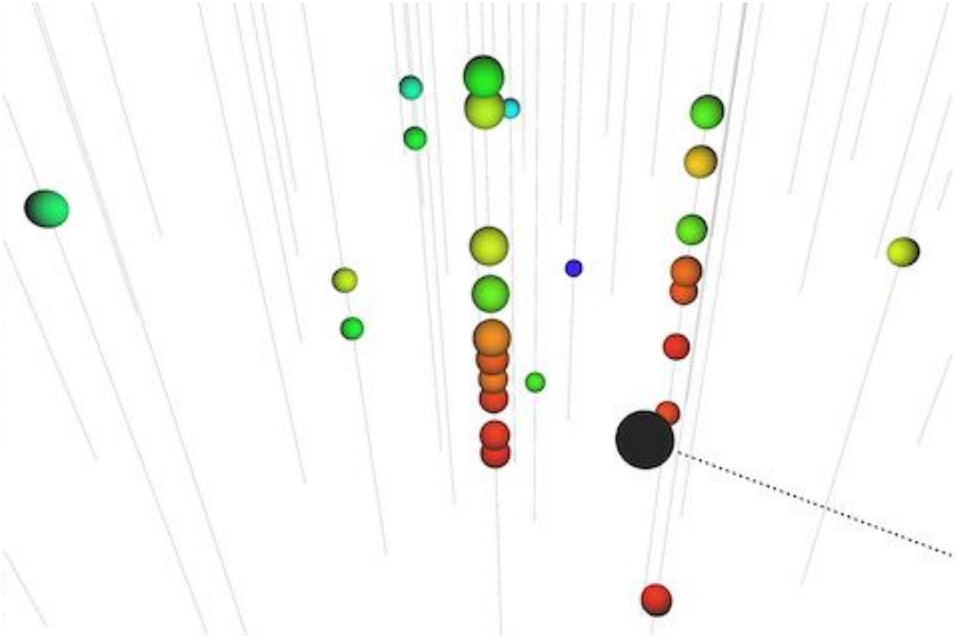


Data Reconstruction - Infer Neutrino Energy and Type

IceCube = Cosmic/Atmospheric Neutrino + Ice Cherenkov Detector

- Cherenkov lights detected along the particle trajectory. Color = signal timing.
- Critical challenge: Directionality, flavour ID, CC/NC separation



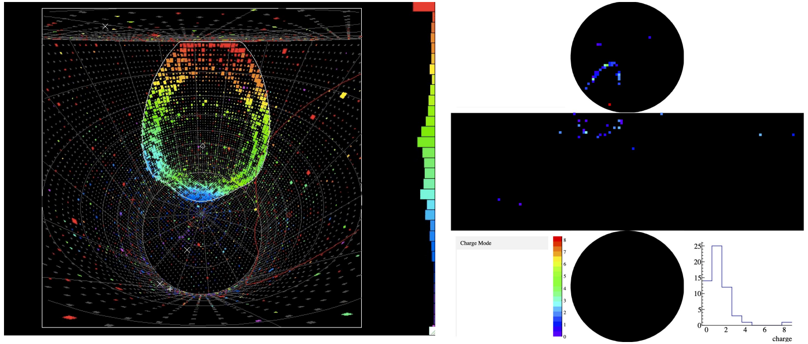


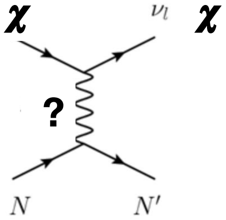
Exotic Physics Search

It requires a (sometimes fundamentally) different tools development from the main physics.

Critical challenge: effectively expand the physics scopes/capabilities of experiments

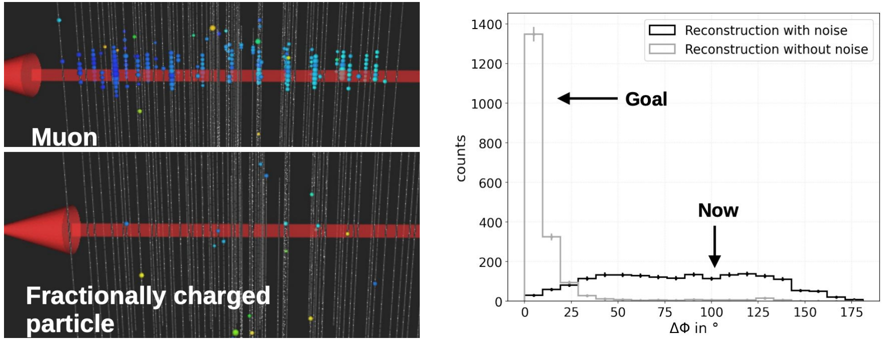
A proton ring in Water Cherenkov for BSM





Any BSM particle would interact NC-like, resulting in recoiled nucleon as a primary signal

Fractionally charged particles in Ice Cherenkov



Signal that produce spatially scattered hits but coincident in time is almost a direct opposite approach from the search of a main signal = high energy tracks/showers

Data-Simulation Discrepancies

Systematics

Geometry

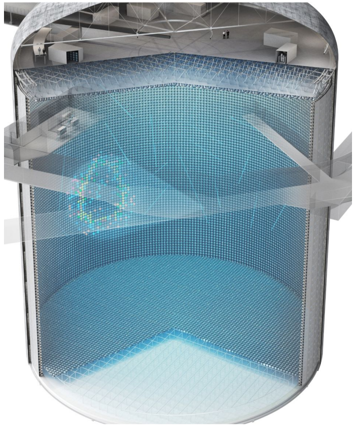
Cherenkov physics

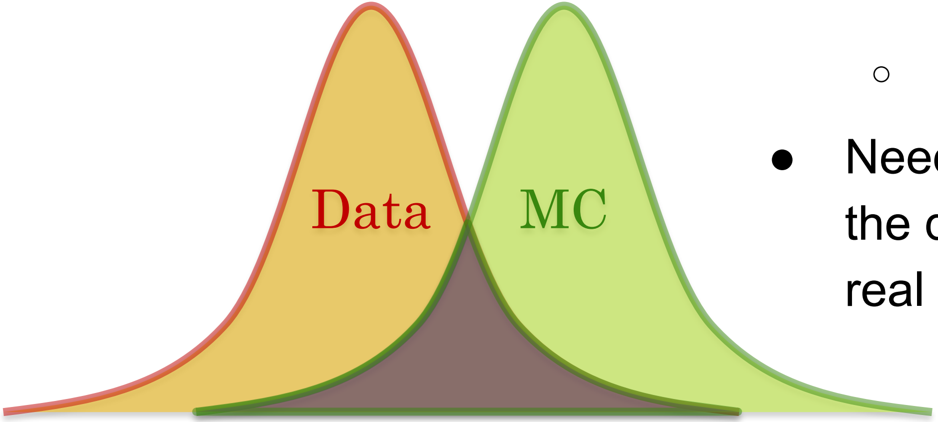
Water properties (light scattering, absorption)

PMT and wall reflectivity

Residual magnetic fields

PMT+electronics response



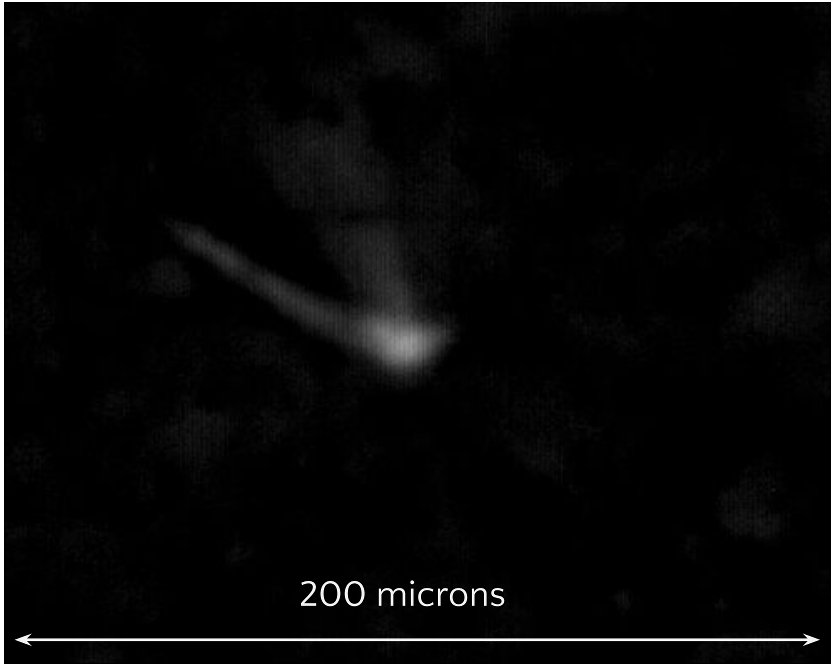


- Large and complex detectors are difficult to model accurately
  - Need substantial $O(10^9)$ events reconstructed MC to fully understand all systematics and their correlations
- Data-MC mismodeling (or domain shift) is becoming a limitation in physics measurements
  - Currently treated by inflating systematic errors, degrading precision and sensitivity
  - Exacerbated by upcoming high-statistics experiments
- Need a method to quickly and accurately model the detector, which can be directly optimized with real data to mitigate data-MC mismodeling

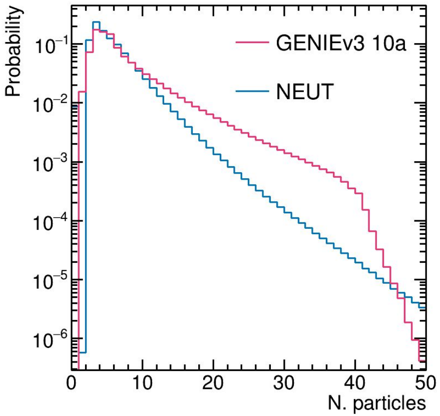
Fast Data Pipeline: Simulation and Reconstruction

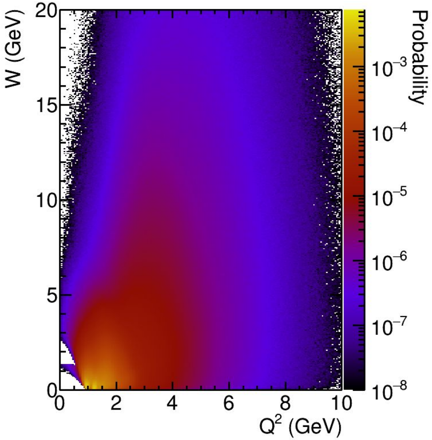
Experiments record every detail in data for high precision neutrino measurements

Critical Challenge: need to accelerate data processing speed by orders of magnitudes



The latest scanning system read-out for emulsion the data at a throughput of 48 Gbytes/sec



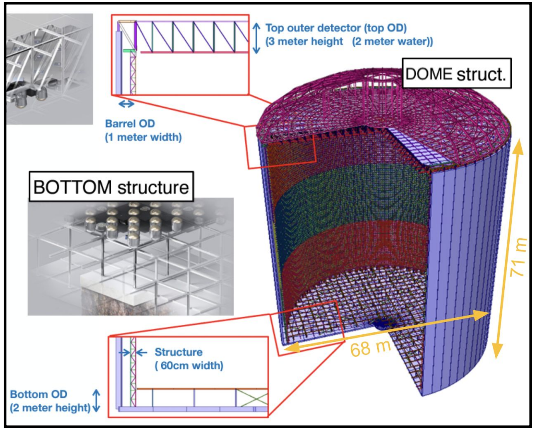


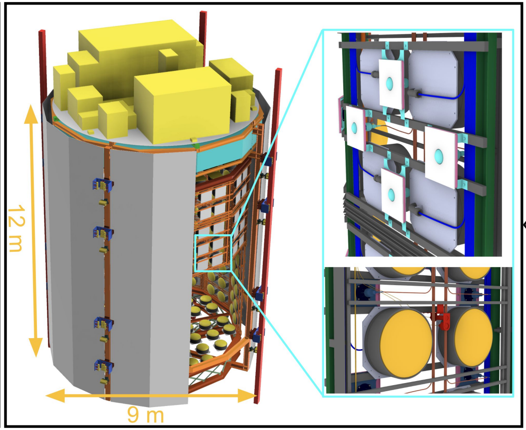
As discussed, neutrino event generators have significant differences (e.g. left plot), and each can have very narrow structures (e.g. right plot). In order to reweight events to fit data for high precision measurement, DUNE must deal with O(1E9) event statistics

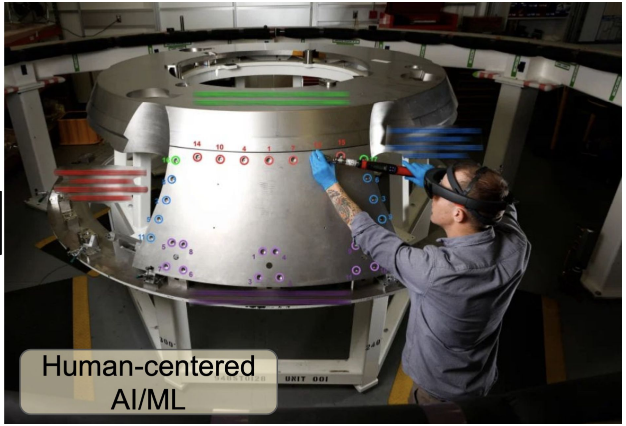
Figures/Words courtesy of Callum Wilkinson (LBNL)

Detector Hardware Design, Production, and Operation

- Challenge: Future experiments can suffer from poor documentation, communication breakdowns, and human errors that could compromise the quality and efficiency of the execution
  - Increasing project scale increases the chance of an error, introducing also several safety concerns
- Need systems that can effectively instruct workers and quickly detect errors (anomalies) and hazards to improve project outcomes and safety
  - Can this improve the detector design as well?
- Can dense manuals and log books be made more accessible to non-expert operators?







Un-summary of Challenges (for unconference)

- Introduced some of collected examples:
  - Fast diagnostics for safe operation of accelerator and neutrino beamline
  - Accurate and robust modeling of neutrino interactions
  - Fast and precise event reconstruction
    - Pile-up, complex topologies, non-standard signals
  - Mitigation of data-simulation discrepancies
  - Fast simulation and reconstruction for solutions to above
  - Streamline detector design optimization, safety during execution, and easing operational tasks
- However, there must be numerous applications beyond what is being considered or what has already been studied

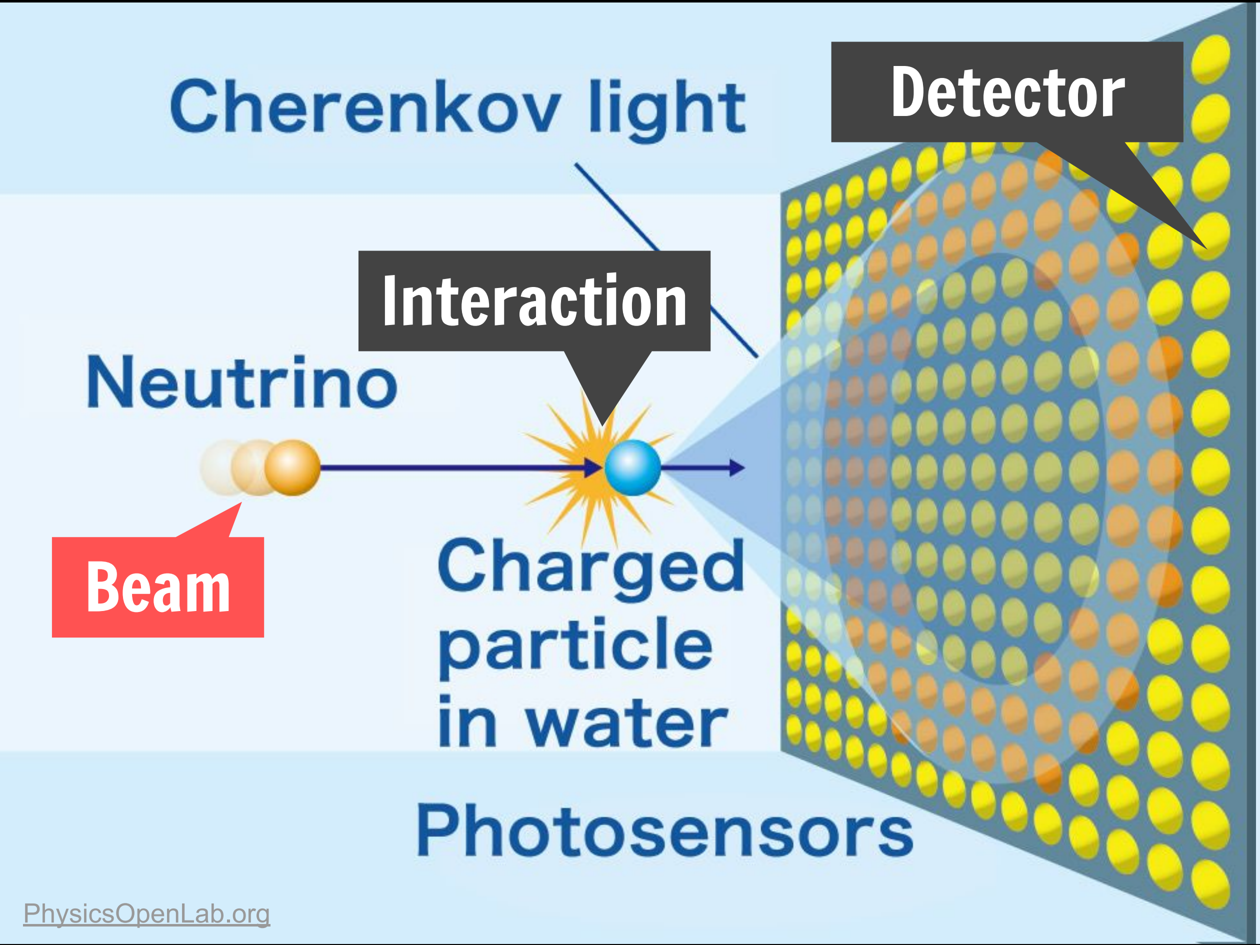
Special Thanks to Contributors

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

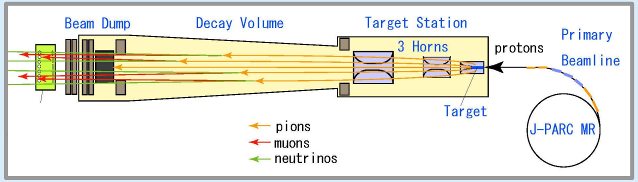
+ Kazu Terao and Patrick de Perio

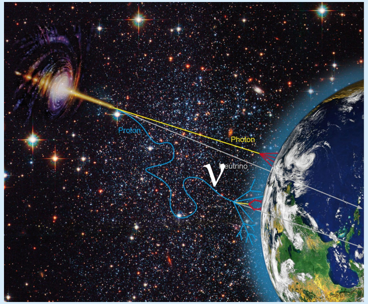
Appendix

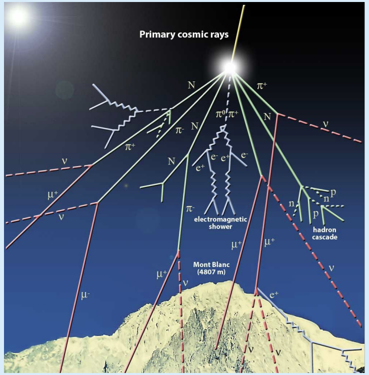
Neutrino Sources



PhysicsOpenLab.org







Neutrino-nucleus interaction modeling

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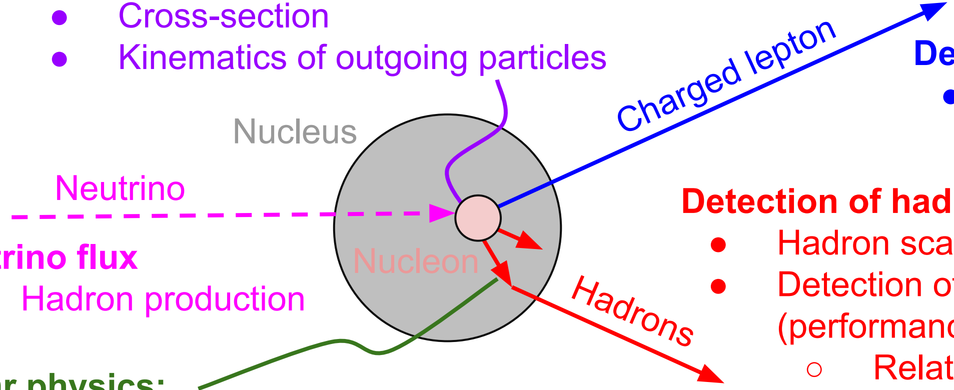
Challenges in neutrino-nucleus interaction model with AI/ML

- Production of various "not entirely unknown but inaccurate" information → degeneracy
    - Current measurements rely on certain models to suppress the degrees of freedom by the correlations
    - New models are often postulated → may or may not account for deviation of data from existing models
- Lack of controlled data for training (e.g. monochromatic energy neutrinos as calibration source)

Neutrino interaction
- Cross-section
- Kinematics of outgoing particles



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Neutrino flux
- Hadron production

Nuclear physics:
- Nucleon momentum (Fermi motion)
- Hadron scattering in nucleus (FSI)

These depend on the target nucleus

Possible approaches in experiments (e.g. neutrino oscillation measurement)
1. Precision measurement → "known x known = known"
2. Cancellation with same detectors → "unknown x unknown but known"

Current experiments take hybrid of these ↔ any new approach with AI/ML?

Water Cherenkov reconstruction

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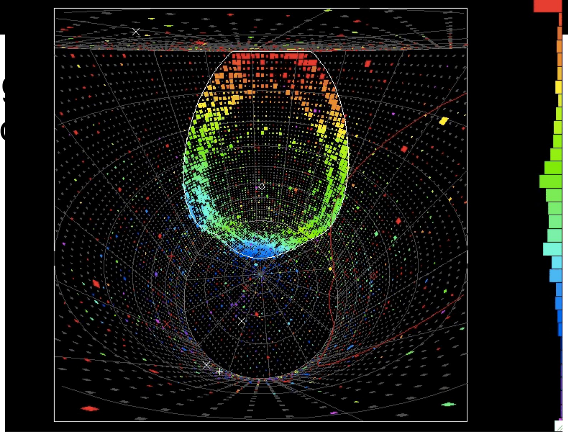
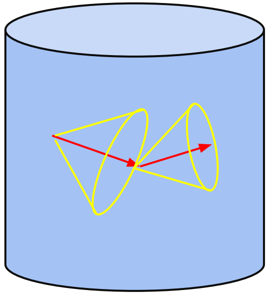
- Current reconstruction algorithms start from recognition of Cherenkov rin
  → Evaluate PID and momentum assuming each Cherenkov ring corresp



- AI/ML can reconstruct events beyond this assumption without complicated algorithms (and likely with better performance).
  - Identification of tau decay
  - Reconstruction of pions scattered in water
  - BG reduction in proton decay search
  - Muon spallation (BG in low energy physics) etc.

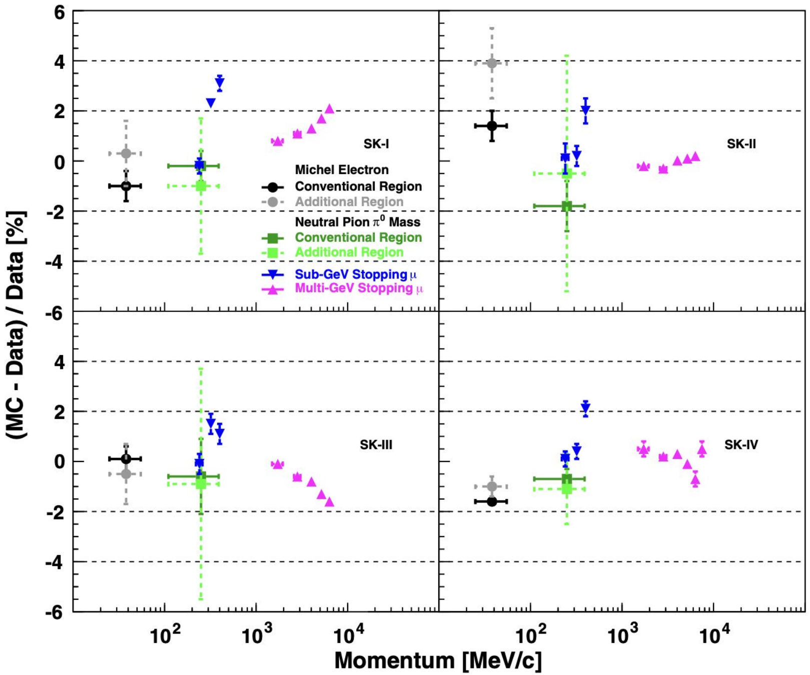
  Some of these studies are already ongoing.



- The challenges are not only to optimize the AI/ML for this but also to assess how the performance is affected due to the bias of MC simulation as it is not perfect.
  - It is not easy to understand what information AI/ML use to reconstruct.

Reduction of energy uncertainties due to detector systematics

- ±2% energy uncertainties is estimated in Super-K.
- Directly affected to physics sensitivities and performance.
  - Δm^2 uncertainty in T2K oscillation experiment.
  - Energy selection window and amount of BG in proton decay analysis.
- Potential sources of detector systematics
  - PMT gain, QE uniformity, light attenuation in water, reflection light on detector wall, residual magnetic field.
  - Difficult to measure each systematics.
- Possible to tune detector response by data-driven method using ML ?
  - Construct response model for each PMT and train using calibration data.



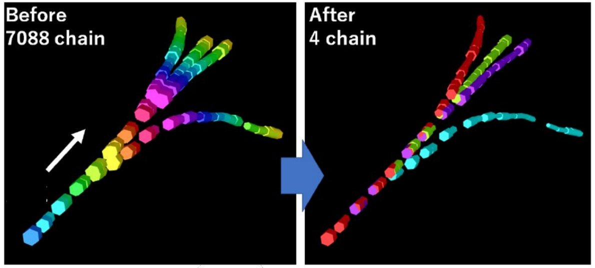
Nuclear Emulsion

The analysis of nuclear emulsion films in the research field of neutrino is performed using optical microscope images.

- **<u>Accelerator based neutrino experiments</u>**

  - Track reconstruction between emulsion films.
    : Likelihood-based connection using position, angle and blackness of tracks.
    Some advanced efforts involving track connection using graph theory are also being conducted.

  → Development of AI/ML based connection method that also takes into account info. on truck momentum and film noise components



Electron shower reconstruction

  - Energy reconstruction for electrons for high energy (> 1GeV) neutrino interactions.
    : Counting method of track segments of electron shower

  → Development of AI/ML based energy reconstruction with shower spread and track curvature (scattering)

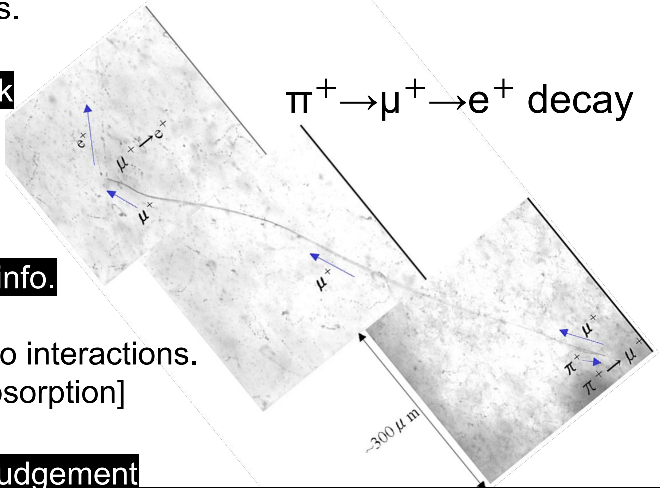
  - Identification of τ particle or charm particle decays and hadron interactions, and its momentum measurements.

  → Development of AI/ML based analysis methods with kinematical and topological info.

  - Identification of π stop/ μ stop in emulsion for low energy (a few 100MeV) neutrino interactions.
    : [$\pi^+ \to \mu^+ \to e^+$ decay], [$\pi^- \to$nuclear evaporation], [$\mu^+ \to e^+$ decay] and [$\mu^- \to$absorption] are judged by human eyes.

  → Development of AI/ML based image analysis of event topologies and automatic judgement

$\pi^+ \to \mu^+ \to e^+$ decay



Nuclear Emulsion

The analysis of nuclear emulsion films in the research field of neutrino is performed using optical microscope images.

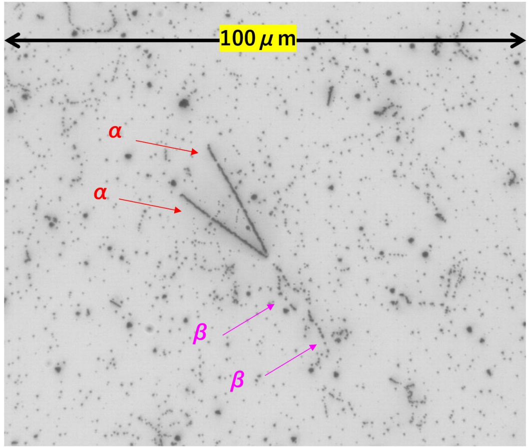
- **Other neutrino activities**

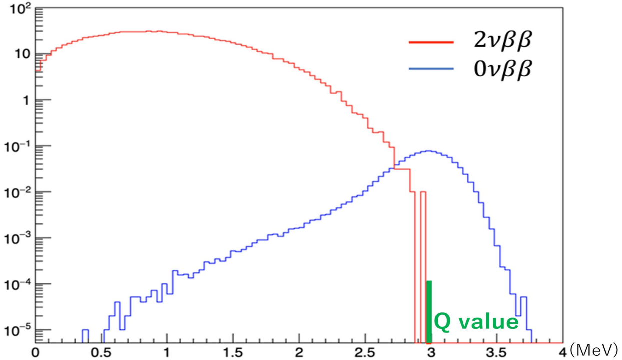
  - Track finding of α-particles from the crustal rocks with nuclear emulsions for precise geo-neutrino flux modeling
    : Alpha particles have short, dense, and straight tracks, making them well-suited for image analysis using AI/ML techniques.

    → A detection program for α-ray tracks was developed using the Yolo series, one of the object detection algorithms with ML.
    The performance evaluation of the detection efficiency, S/N, etc. is currently being carried out using image data in nuclear emulsion films.

  - Improvement of energy measurement accuracy in β-rays for neutrinoless double beta decay search with nuclear emulsions
    : Energy estimation by range measurement has an error of ~5%.

    → Development of an energy measurement method using AI/ML, incorporating bending information from multiple coulomb scattering and image analysis near the stopping point of the tracks





A simulation of energy reconstruction

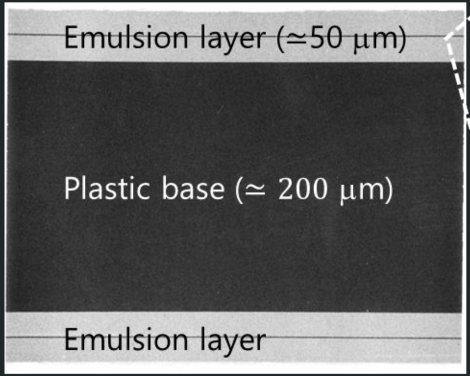
Emulsion detectors:
3D tracking device with 50 nm precision

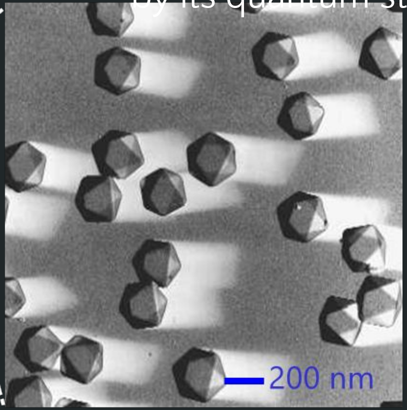
Tomoko Ariga, Aritaka Ariga

AgBr crystals = quantum sensors to record passages of charged particles by its quantum state

Emulsion film

Cross-sectional view

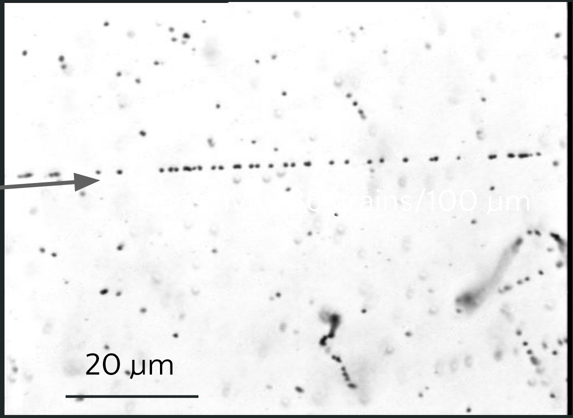


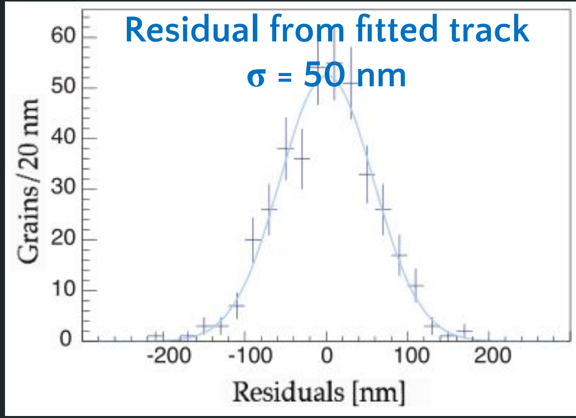


10^{14} sensors/film

or 10^{14} sensors/cm^3

10 GeV/c π beam





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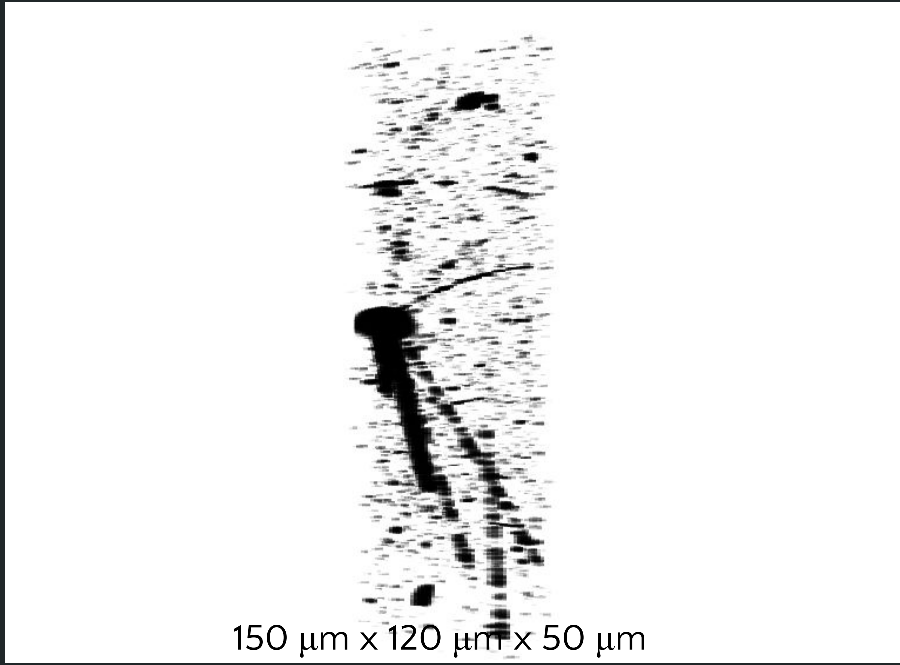
Emulsion raw data: 3D microscope images

Antiproton annihilation taken in AEgIS 2012

200 microns

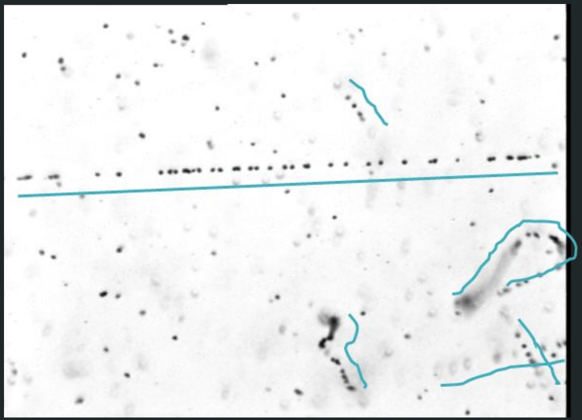


The latest scanning system read-out
the data at a throughput of 48 Gbytes/sec

Tomoko Ariga, Aritaka Ariga

Possible applications of the machine learning at raw image level

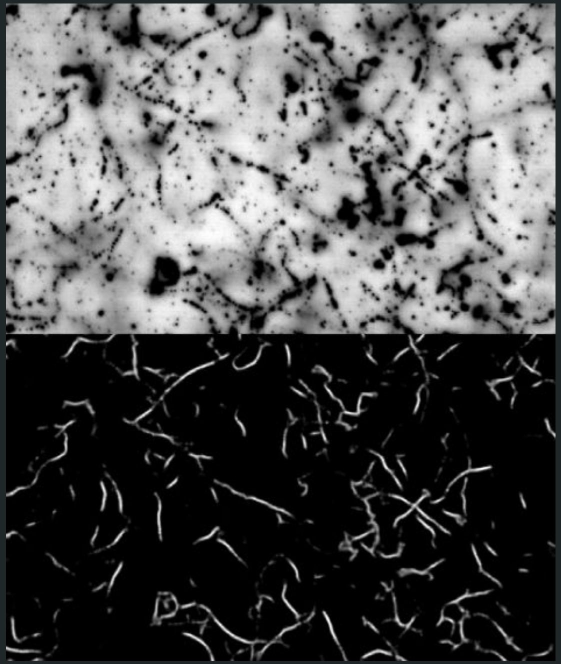
- Random noise (called fogs) contributes to fake tracks
- Separate particle trajectories from random noise (fogs)
- Challenges: tools for 3D images (e.g. 16 image stacks) are not matured or easy to use



Tracks are indicated by lines

Other dots are random noises (fogs)

- A trial to actively recognize trajectory by DNN, tried by Mykhailo Vladymyrov for β ray tracks (work in 2016 with U-NET)



Raw images

DNN output for particle passage

Significantly reduce fog contributions

Problem: Speed of inference was far too slow to process >1 Gvoxels/sec

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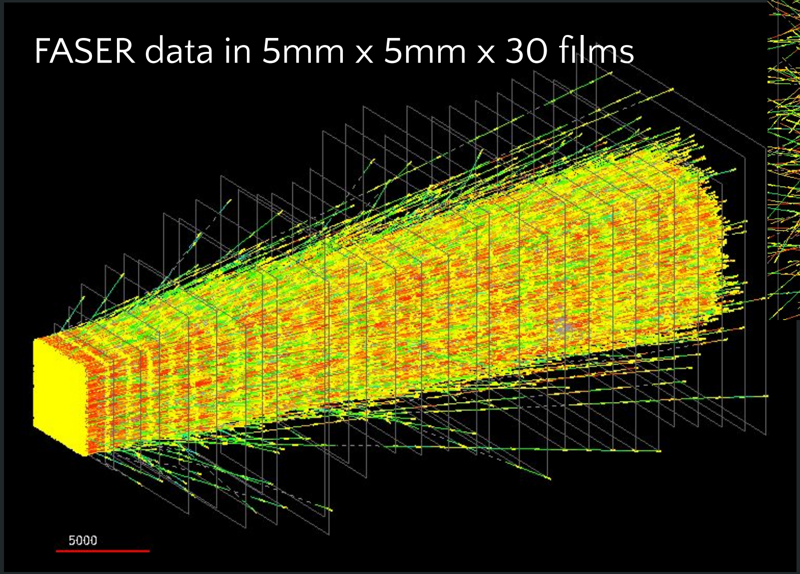
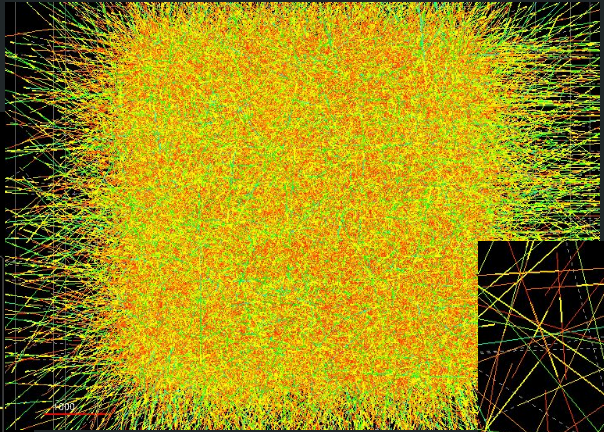
AI in reconstruction?



Beam view

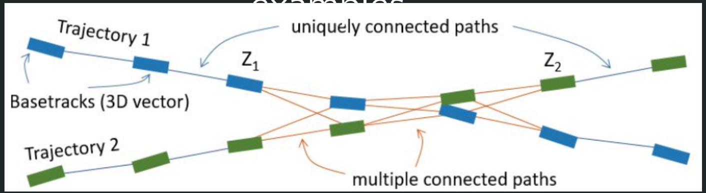


1000 μm

Beam view

5 μm

Reconstructed track examples



10.1007/JHEP01(2020)033

Emulsion detector = no timing information → Huge pile-up!
FASER emulsion data has high track density $\sim 5 \times 10^5/\mathrm{cm}^2$.
The reconstruction of tracks are challenging due to miss-connection.
AI could help reconstructing tracks with high quality.
Challenges: So many combinatorics→ efficient computing are needed, and it should be reliable.

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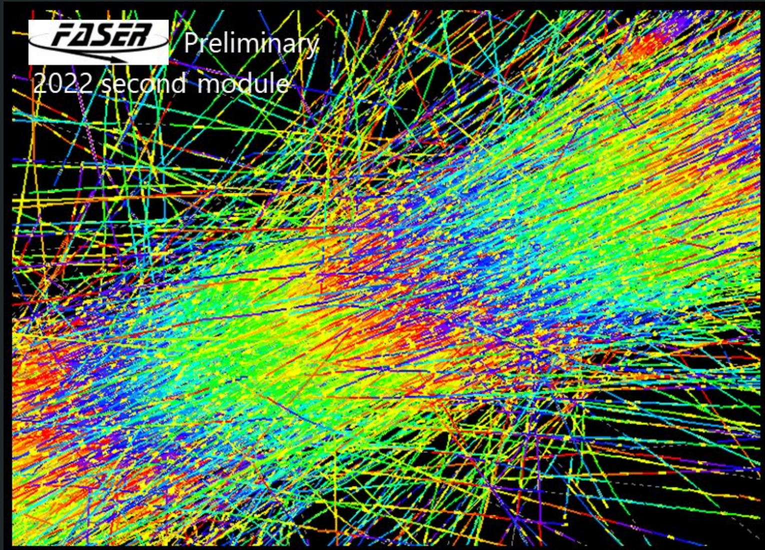
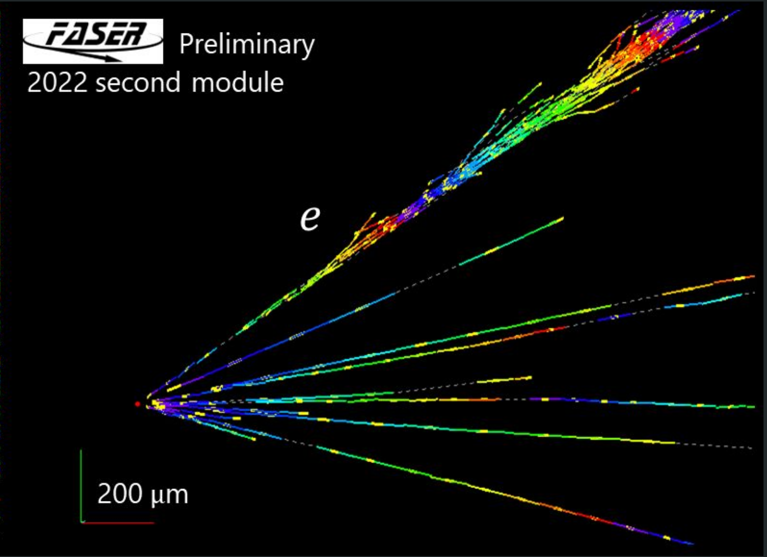
Vertex selection

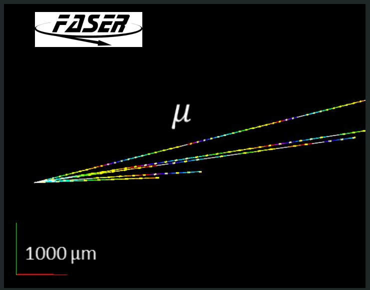
ν_e CC signal event with muon background tracks



ν_e CC signal event without muon background tracks



ν_μ CC signal event

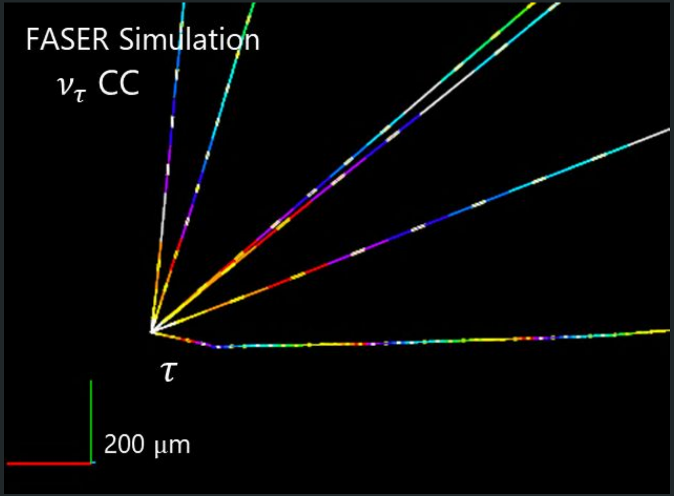


Background

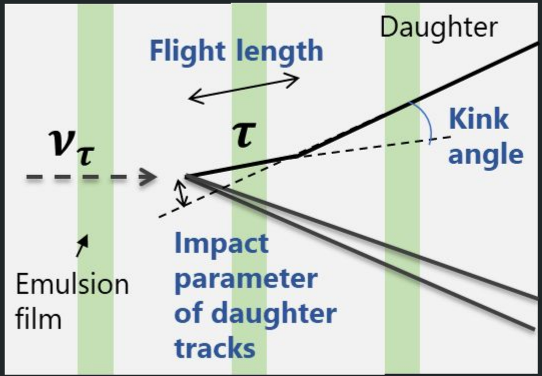
AI/ML could improve signal vertex selection by distinguishing them from background hadron interactions and fake vertices caused by parts of electromagnetic showers or broken tracks, especially in high track density environments.

Tomoko Ariga, Aritaka Ariga

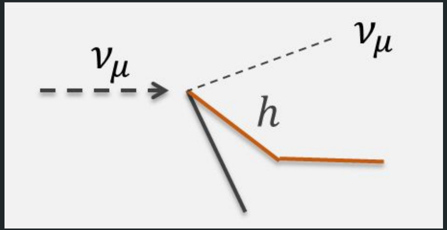
τ decay search and ν_τ event selection



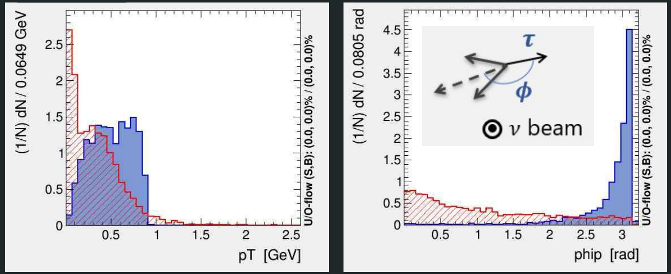
Signal event

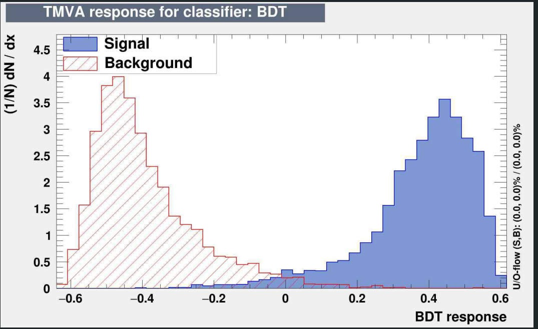


Main background



Example of input variables





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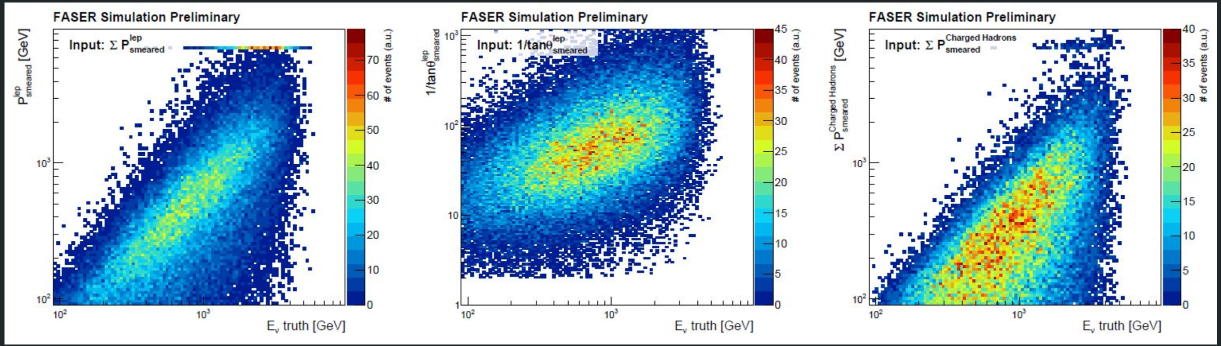
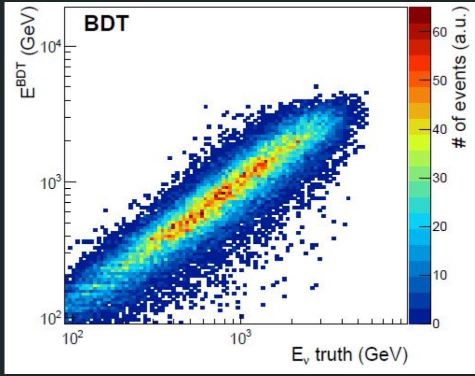
Neutrino energy reconstruction

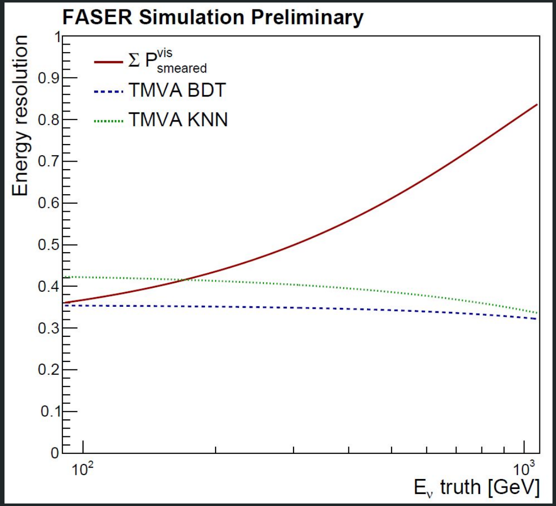
Jeremy Atkinson
at the 14th LHC students' poster session

Lepton momentum | $1/\tan\theta_{\mathrm{lepton}}$ | Sum of charged hadron momenta



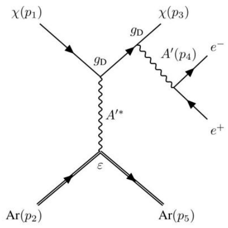
Will investigate different methods to improve the energy reconstruction performance

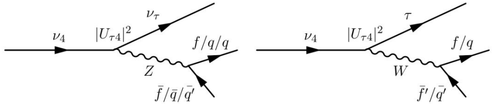




an example: BSM lepton jets

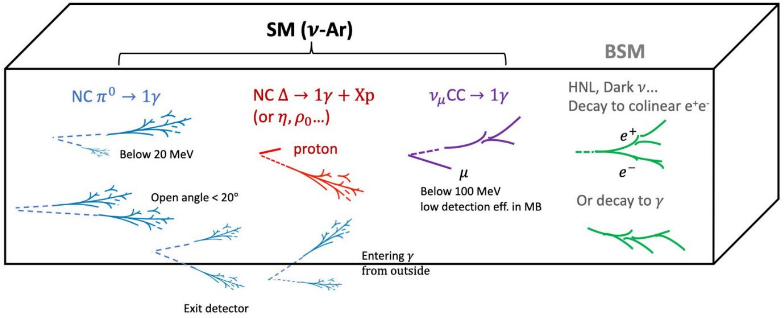
Koun Choi



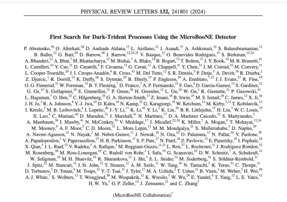


boosted DM-induced forwarded multiple particles (“jets”)

- **New inclusive single photon selection** has been developed with the aim to **cast a wide net** that will capture any potential single photon anomaly

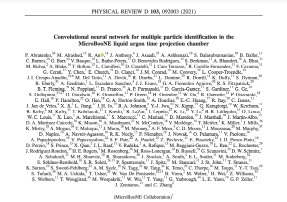


@Erin Yankel


PHYSICAL REVIEW LETTERS 132, 241801 (2024)

First Search for Dark-Trident Processes Using the MicroBooNE Detector

(MicroBooNE Collaboration)


PHYSICAL REVIEW D 103, 092003 (2021)

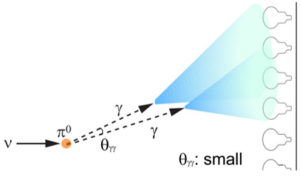
Convolutional neural network for multiple particle identification in the MicroBooNE liquid argon time projection chamber

(MicroBooNE Collaboration)

PHYSICAL REVIEW D 103, 092003 (2021)

PHYSICAL REVIEW LETTERS 132, 241801 (2024)

also useful for BSM @WCD, but not much has been done



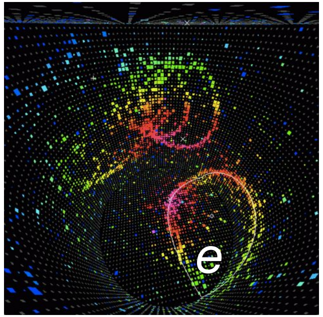
(b) Small opening angle

C.F. 2-ring pi0 sample also important for v osc physics

@L.Anthony

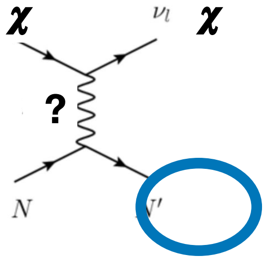
an example: protons in WCD

Koun Choi



ν osc analysis relies on accurate reconstruction & understanding of charged leptons and hadronic products from ν-p collision

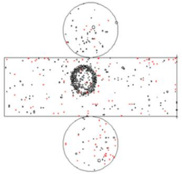
high Cherenkov threshold ~ few protons ~ not too much interest

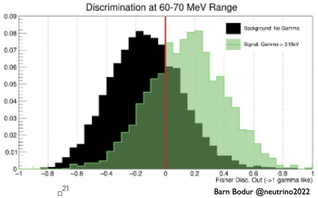


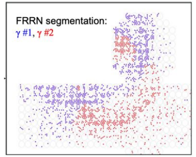
However, any BSM particle would interact NC-like, resulting in recoiled nucleon as a primary signal!

Event selections requires identification of faint proton ring (often in multi-ring image):

- proton
- proton + de-excitation
- proton among multiple rings
- …





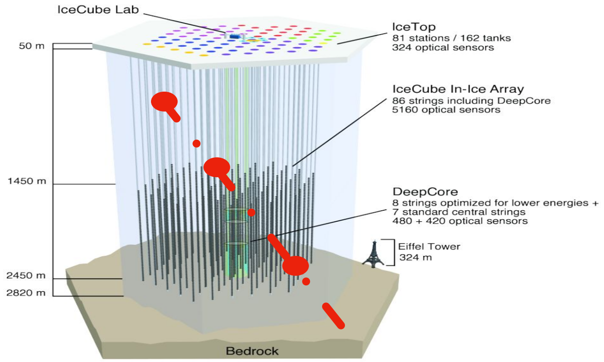


Barn Bodur @neutrino2022

Patrick de Perio, NNN22

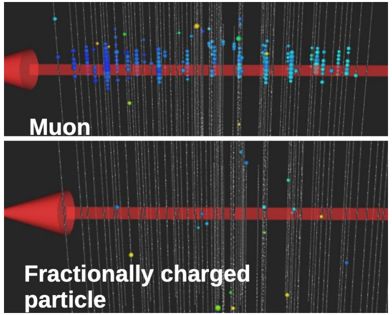
Koun Choi

an example: multiple scattering track



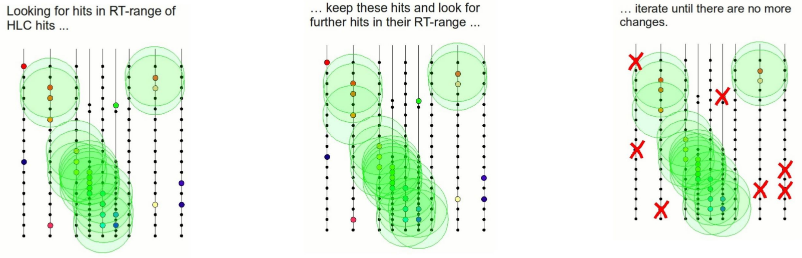
- arises from fractional charged particle, for example

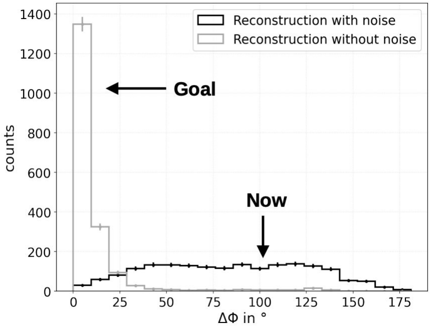
- challenge to collect simultaneous, multiple isolated hits
(low energy, spanning large area)
-> dedicated trigger system and reconstruction algorithm



@N.Schmeisser

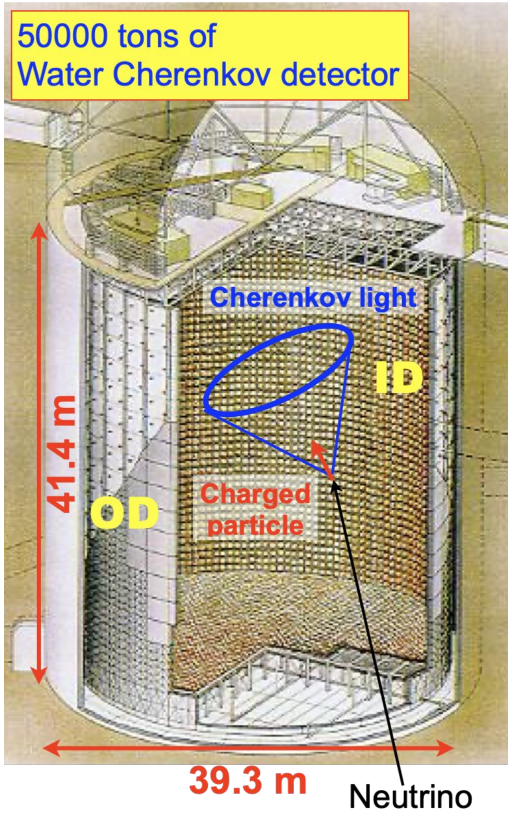
cleaning… cleaning…



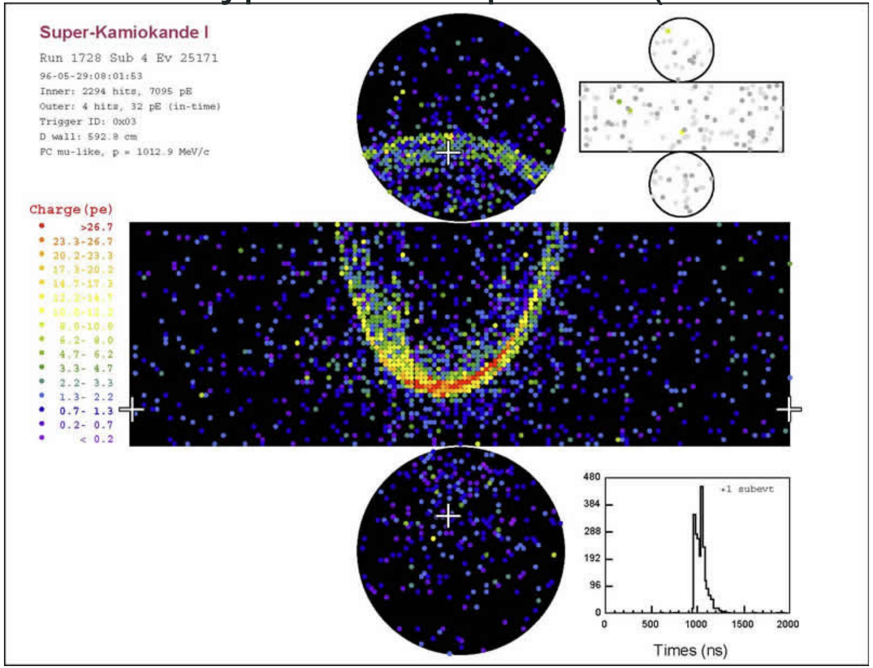


hard to get rid of BG with the existing reconstruction algorithms

Super-Kamiokande



Typical event pattern (1GeV muon)

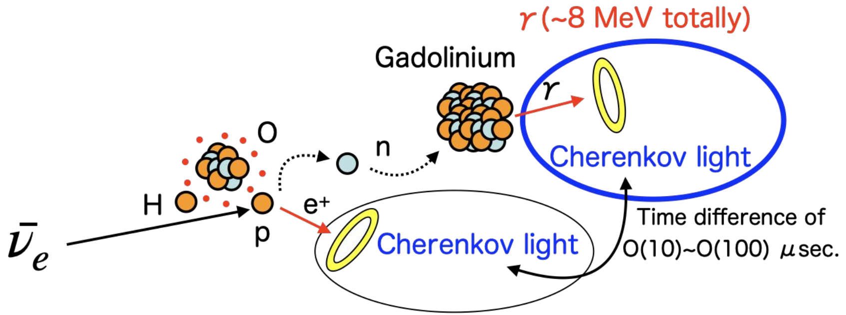


Not difficult so far, but recently the ML method becomes important, especially in SK-Gd.

SK-Gd running since 2020

S. Fujita, S. Han, Y. Koshio

Loaded Gadolinium into Super-K detector to enhance delayed neutron signal



J.Beacom and M.Vagins PRL 93 (2004) 171101

Neutron can be detected with delayed gamma-ray signal from capture on Gd

- 13 tons of Gadolinium sulfate was dissolved in 2020. (0.01% Gd mass conc.)
    - ~50% of neutrons are captured by Gadolinium
- Additional 26 tons was dissolved in 2022. (0.03% in total)
    - ~75% of neutrons are captured by Gadolinium

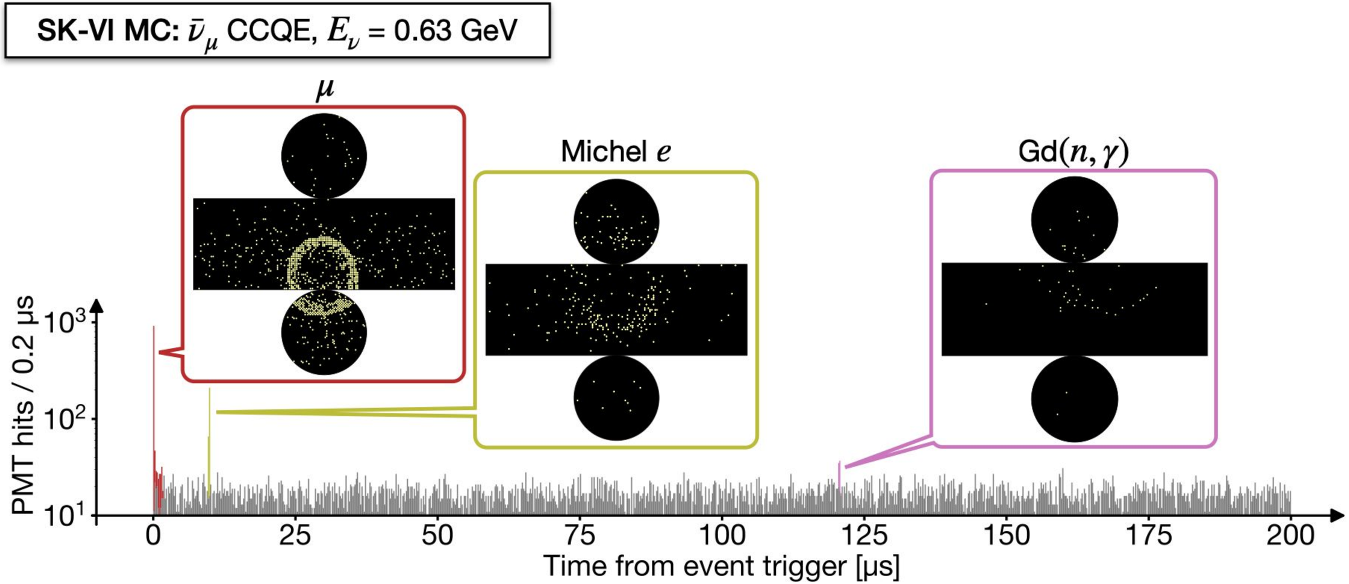
Uses of machine learning in SK analyses

Examples:

- **NN for neutron tagging (Topic 1)**
- **CNN for single-e vs. multi-γ classification (Topic 2)**
- **Transformer for muon track reconstruction (Topic 3)**
- BDT for reactor neutrino analysis
- BDT for solar neutrino analysis

Topic 1: Neutron tagging neutrino interactions @ Super-K

S. Fujita, S. Han, Y. Koshio

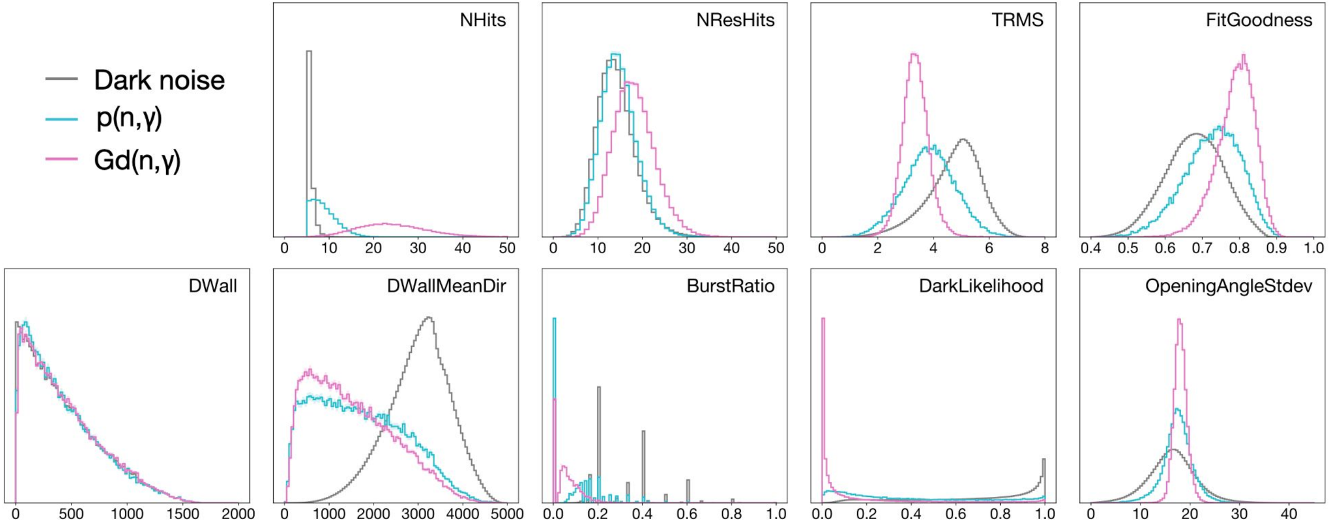


Helps neutrino event classification + neutrino energy reconstruction

→ Helps searches for rare phenomena + unknown neutrino properties

Topic 1: High-level features: Photon counts, PMT hit timing/angular correlation, etc.

S. Fujita, S. Han, Y. Koshio



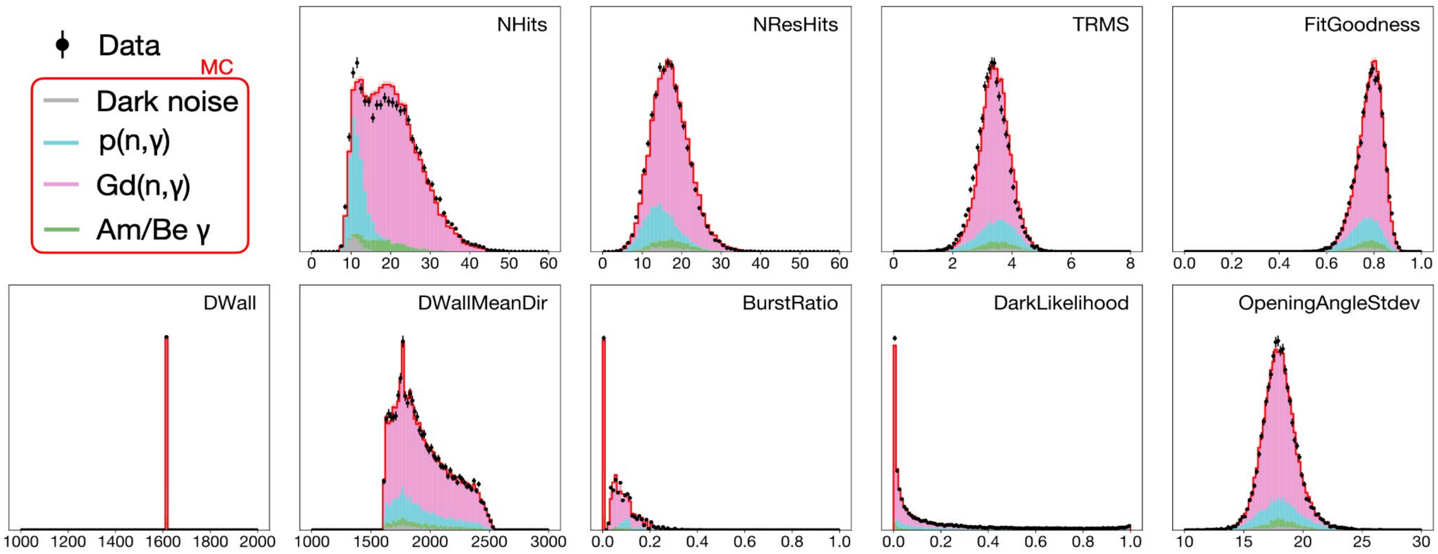
and more…

Signal features extracted from physics simulation

Noise features extracted from detector noise data

Topic 1: Training data vs. Test data

S. Fujita, S. Han, Y. Koshio



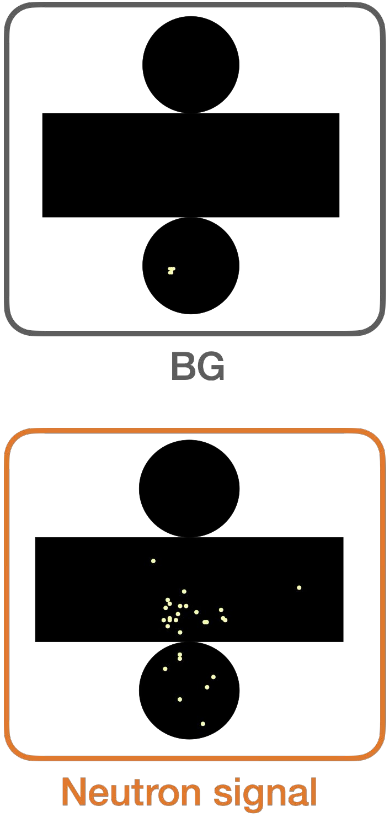
Difference btw simulation (training data) and calibration (test data) becomes a dominant source of uncertainty in model performance

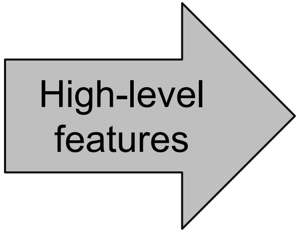
Feeding an ML model with good physics (training data) is our responsibility

Topic 1:

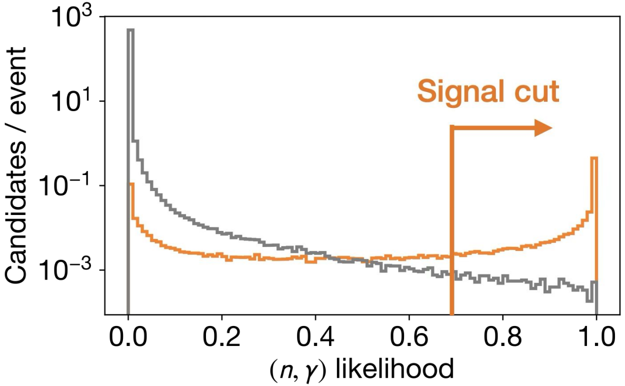
S. Fujita, S. Han, Y. Koshio

Default strategy: Binary classification with neural network





Only care about if it's signal or noise

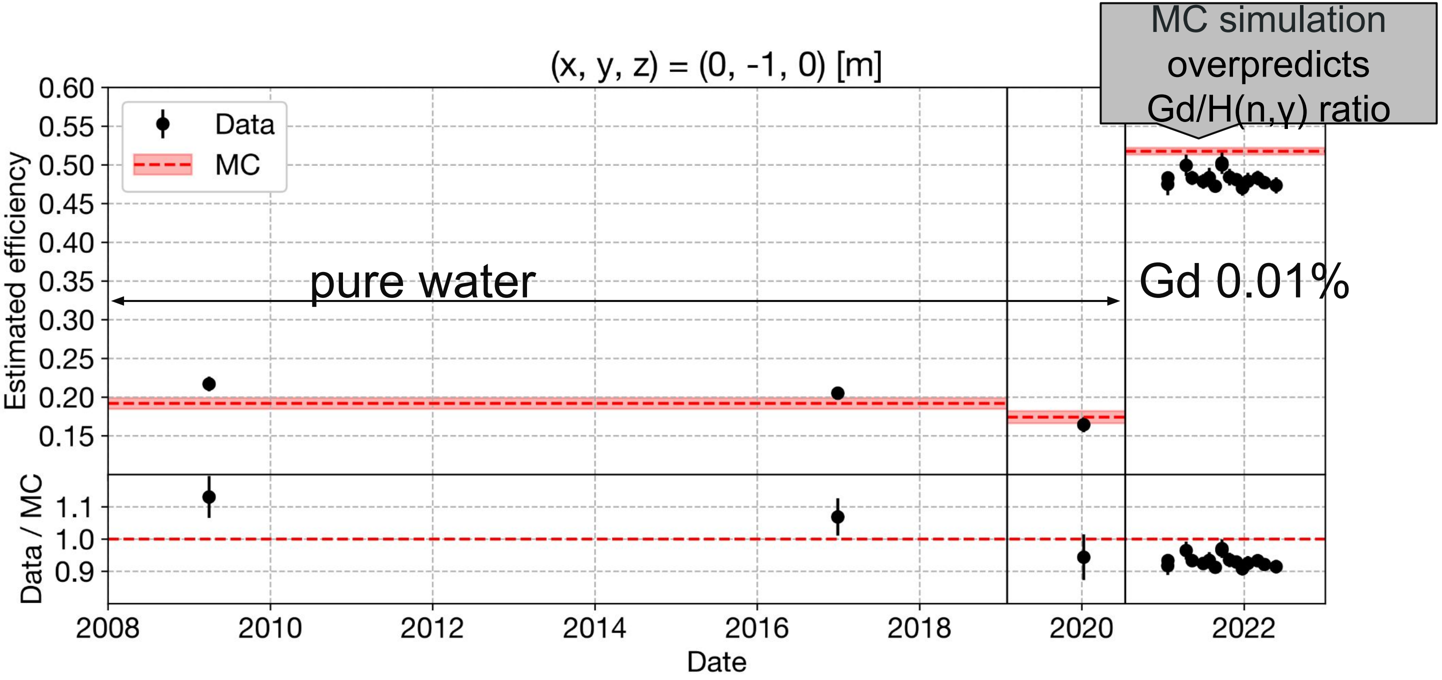


×1.5-2 higher recall (efficiency) compared to simple energy cuts

Topic 1:

S. Fujita, S. Han, Y. Koshio

Model performance on simulation/calibration data

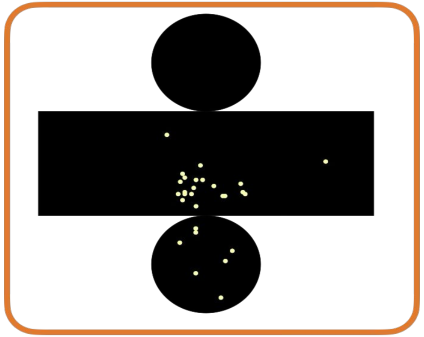


Model performance on train/test/validation data agrees within ~10%

Topic 1:

S. Fujita, S. Han, Y. Koshio

Future: Low-level features? Further tasks?



Neutron signal

Low-level (PMT hit) features:

- Charge
- Position (φ, z)
- Time

Further tasks on neutron signals:

- Vertex estimation?
  - Neutron kinetic energy regression?
- Nuclide (H/Gd) classification?

Topic 1:

S. Fujita, S. Han, Y. Koshio

What I would like to see happen

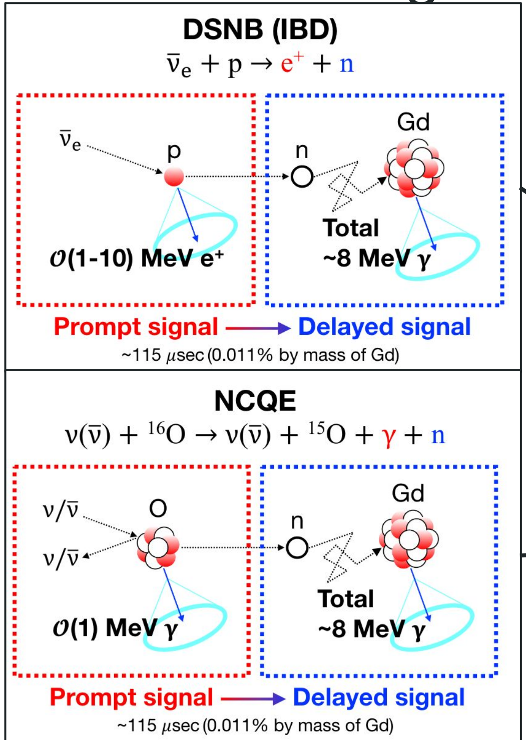
- One low-level ML model for all visible track reconstruction: e.g., e/μ/p/π/…
- Regressing neutrino properties using high-level features:
  Especially neutron multiplicity may be a good estimator
  for hadronic missing energy for multi-GeV neutrinos,
  which may be crucial for mass ordering sensitivity
- Getting how likely each neutrino event originates from a certain true topology:
  (e.g., 1 GeV ν_μ with Δ resonance, etc.)
  Can we use this likelihood information to test ν interaction models,
  or use it instead of reconstructed observables to bin events
  in ν oscillation analysis to maximize fit sensitivity?
- Any generative ML that makes simulation/reconstruction faster

Topic 2:

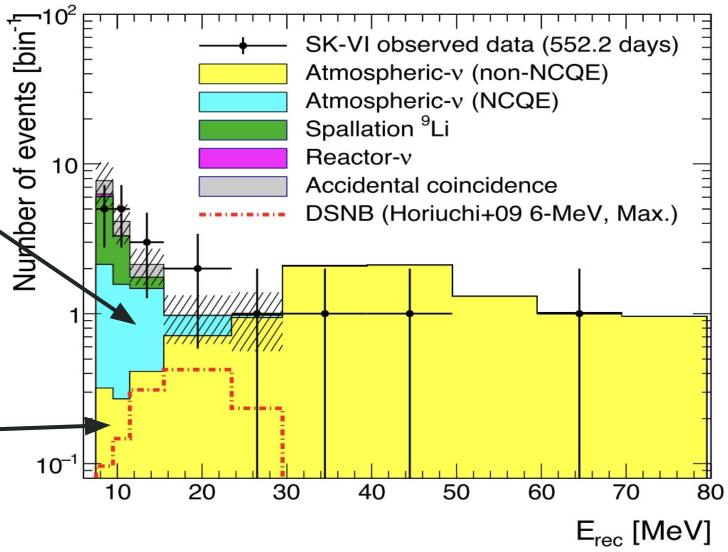
S. Fujita, S. Han, Y. Koshio

Electron vs. multi-γ event classification

- How can we reduce the atmospheric neutrino NCQE interaction background for the DSNB search?



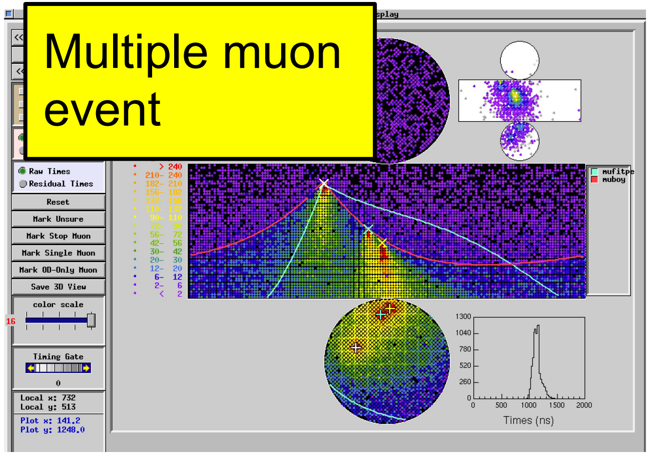
M. Harada et al 2023 ApJL 951 L27

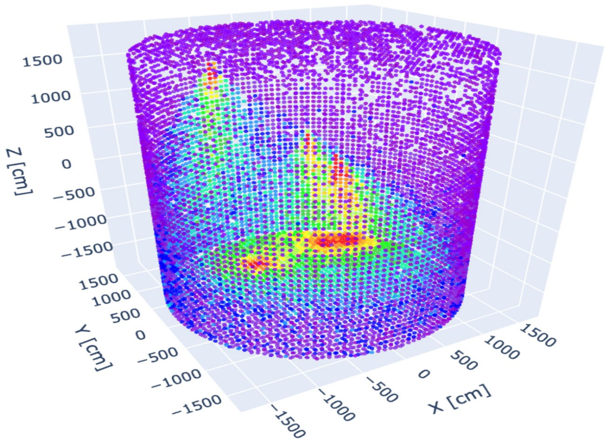


Topic 3: Muon track reconstruction

S. Fujita, S. Han, Y. Koshio

- Cosmic ray muons penetrate the detector at ~2Hz
  - **~90% single muons, ~10% multiple muons**
- Accurate reconstruction of muon tracks is essential for many analyses:
  - For studies of the **muons themselves**
  - For background reduction of **neutrino event searches**

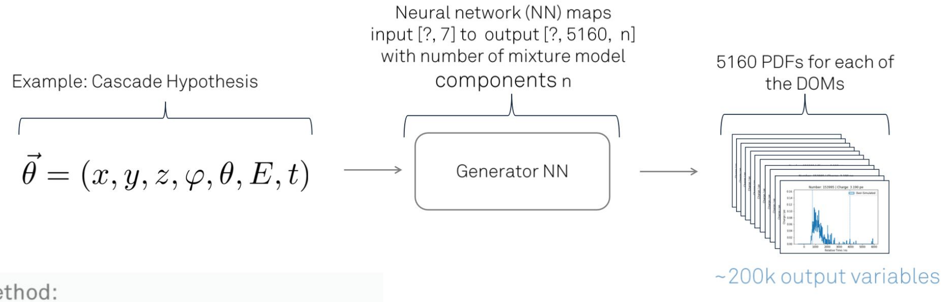


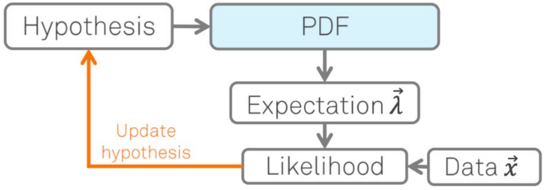


Neutrino cascade simulation and reconstruction

Event Generator (for IceCube)

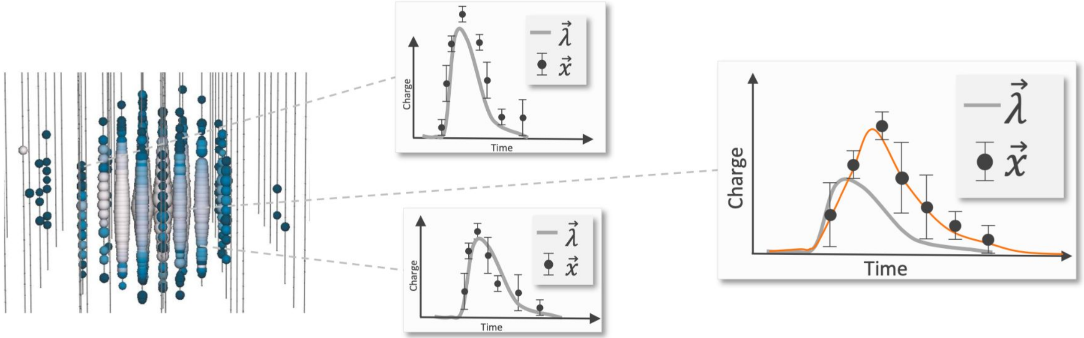
- Applicable in both reconstruction and simulations
- Domain knowledge can be directly incorporated into the model architechture





Hybrid reconstruction method:

- Combines maximum-likelihood estimation with deep learning
- Modeling of high-dimensional PDFs via generative model
- Exploits available information and symmetries
- **Robust and interpretable Deep Learning**



Not yet used in simulations, but promising way to approx. computationally expensive simulation steps!

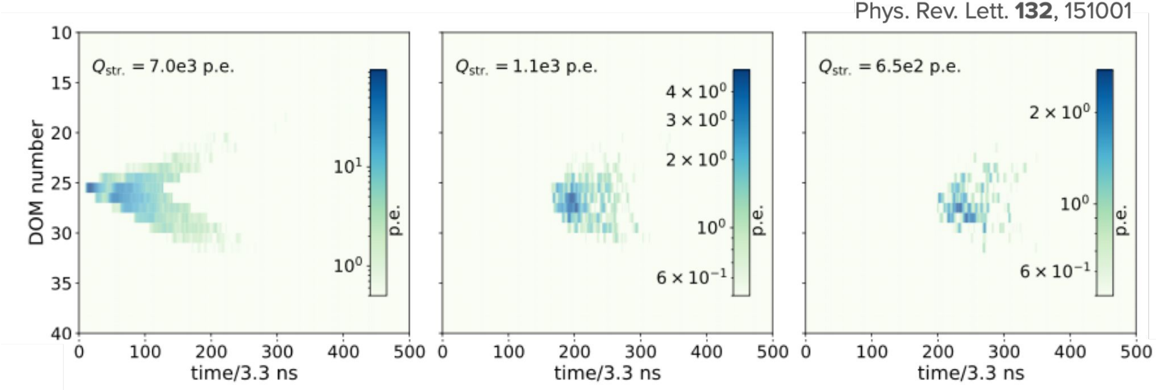
Credit: M. Huennefeld

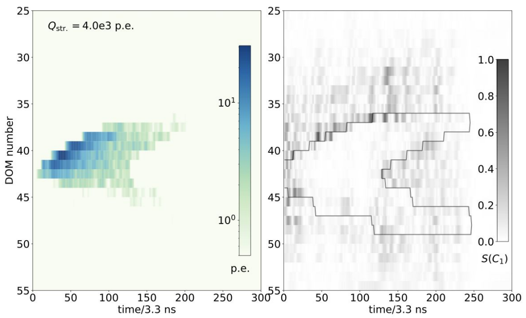
PID: Tau neutrino classification (IceCube)

Maximilian Meier

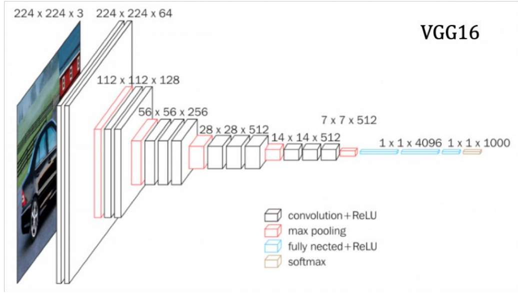
- Create images from PMT charge/time information
- Use standard tools (CNNs) in Computer vision to distinguish Tau neutrino signal from bkgs
- Tools to understand what information is used by NNs are critical. Example: saliency maps

Phys. Rev. Lett. **132**, 151001





https://arxiv.org/abs/1312.6034



Simonyan & Zisserman, 1409.1556