AI and Machine Learning Applications at the Near Detector of the T2K Experiment

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for the T2K collaboration & ND280 AI/ML working group

EPS-HEP Marseille, 07/07/2025
↳T16 - AI for HEP

Overview

- The T2K experiment and its Near Detector
- The AI/ML working group
- Overview of the group activities:

1. SFGD Momentum reconstruction and PID with a BDT (TMVA)
2. Global ND280 PID with BDT (XGBoost)
3. Identify EM shower with PointNet
4. 2D+3D CNN for e/γ classification
5. Other projects using ND280 data (Omnifold, Normalizing Flows)
6. PID in the SFGD with a Transformer

The T2K experiment & its Near Detector

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particle accelerator to
create neutrino beam

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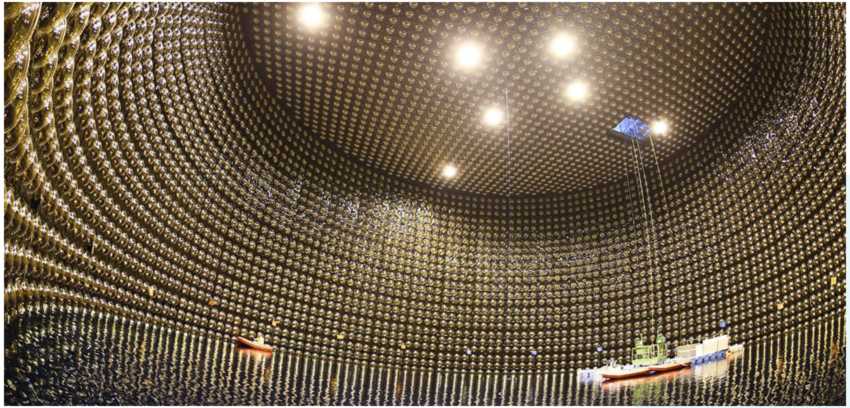
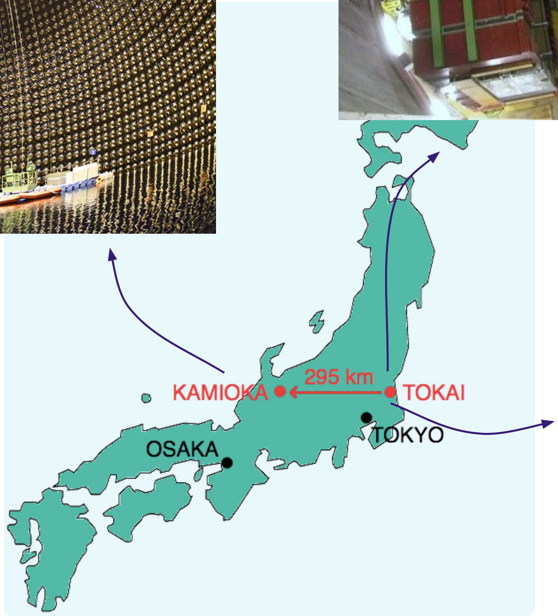
near detector: ND280

particle accelerator to create neutrino beam

The T2K experiment & its Near Detector



far detector: Super-Kamiokande

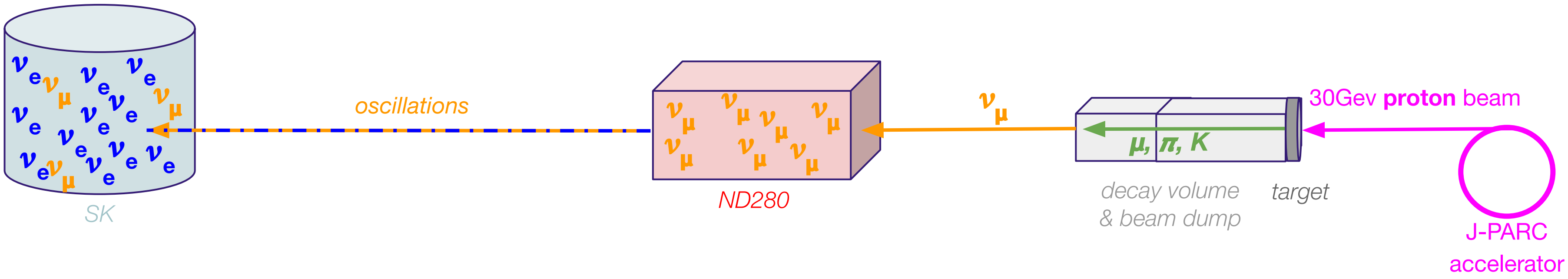


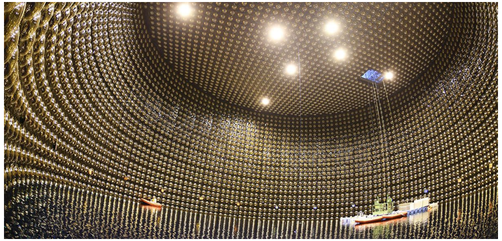
near detector: ND280

particle accelerator to create neutrino beam

The T2K experiment & its Near Detector

goal: measure neutrino oscillation parameters





Super-Kamiokande

295km

ND280

280m

neutrino beam

The T2K experiment & its Near Detector

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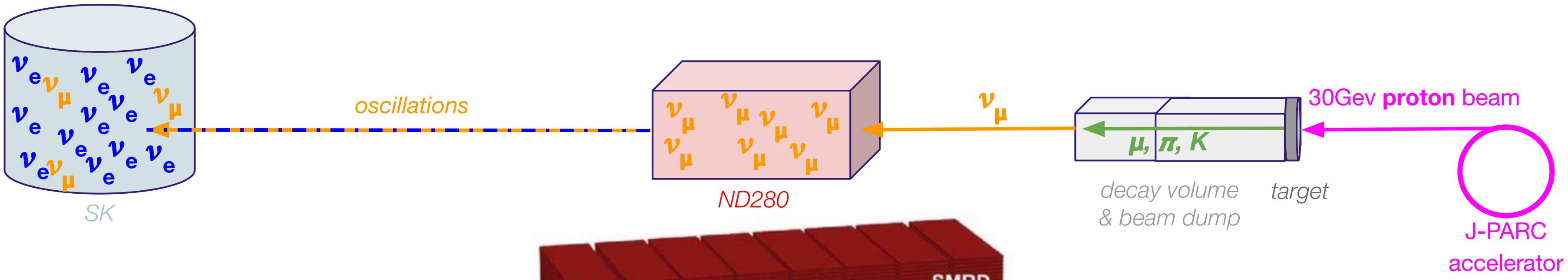
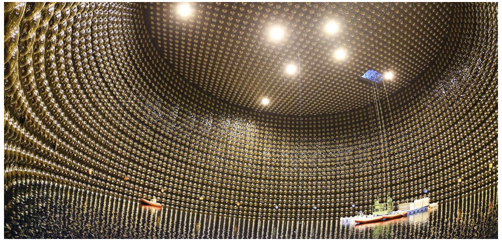
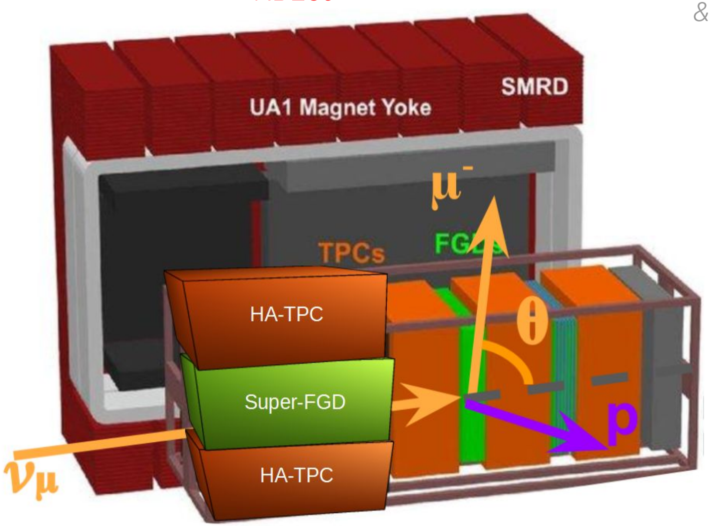




Super-Kamiokande



neutrino beam

The T2K experiment & its Near Detector

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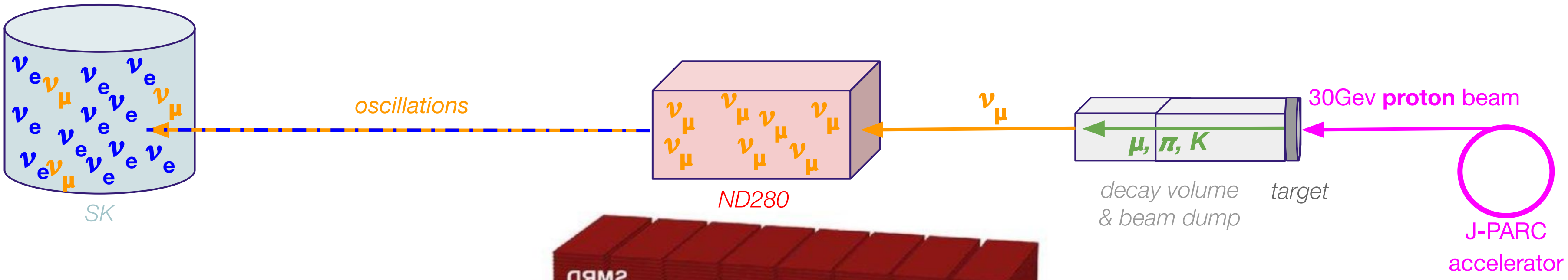

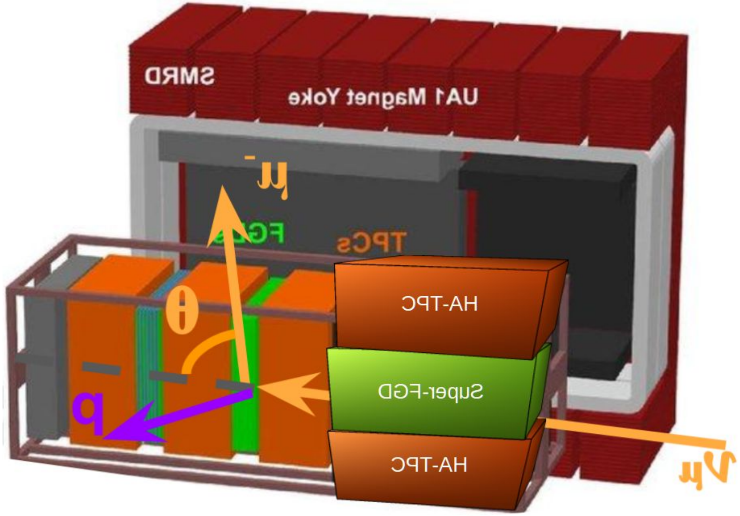

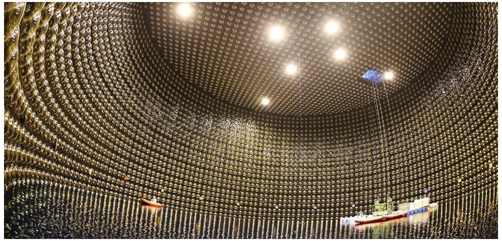

Super-Kamiokande

neutrino beam

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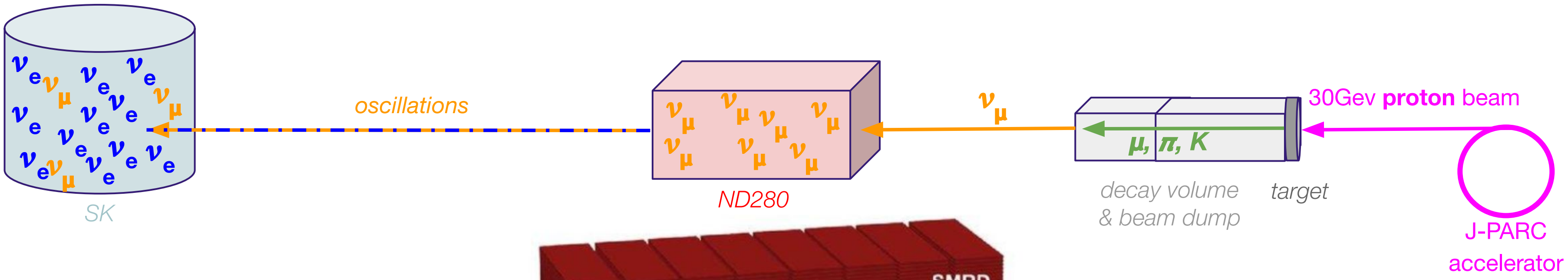

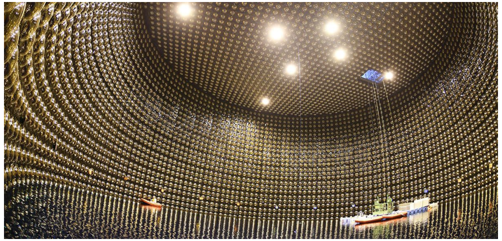

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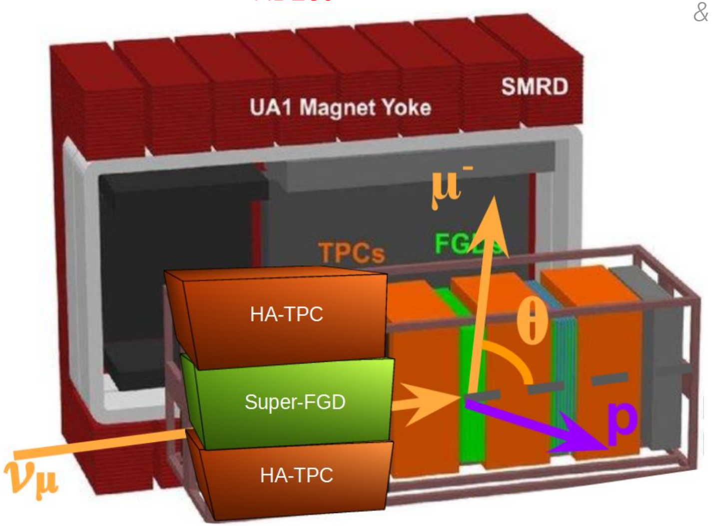
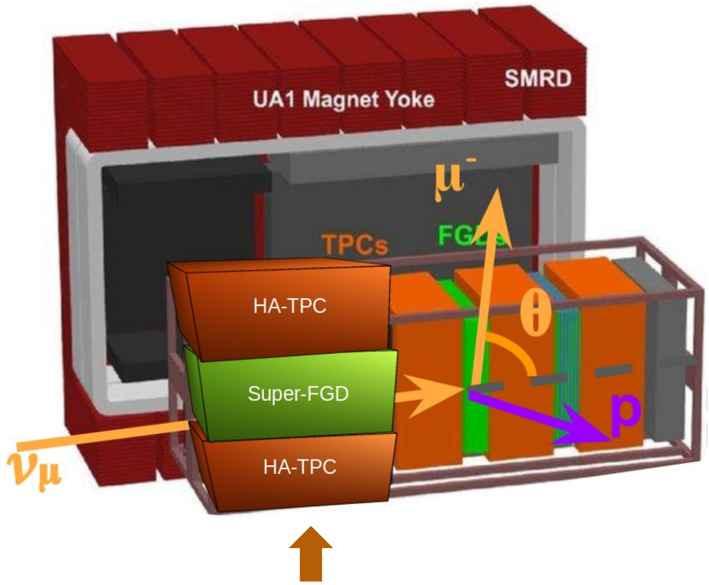
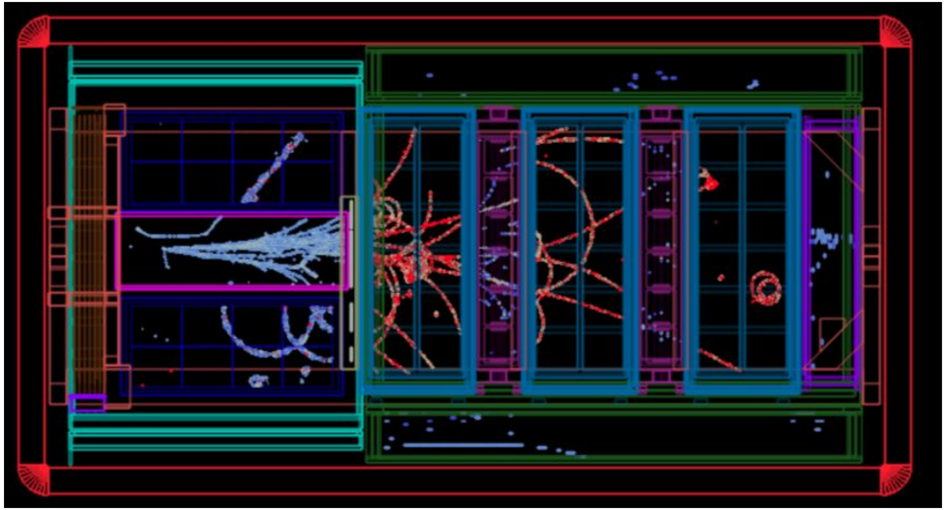


neutrino beam

The T2K experiment & its Near Detector

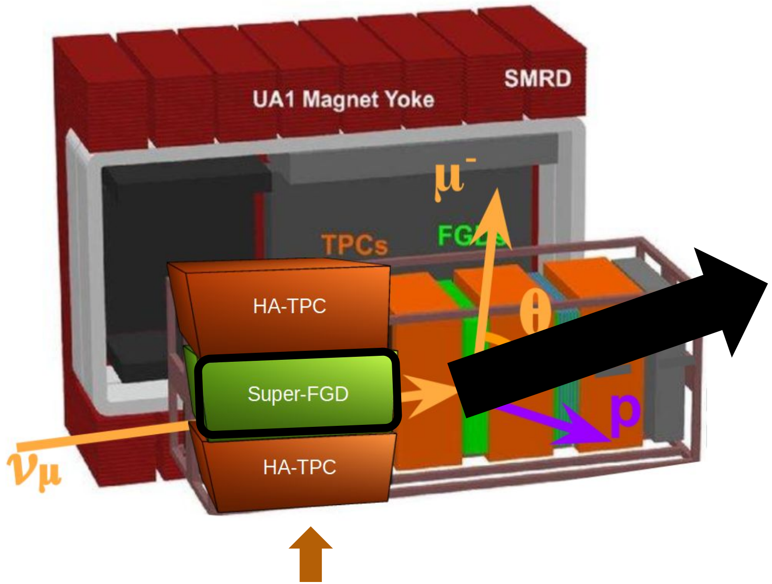




ND280 Upgrade installed last year!

& data taking since end of 2024

The T2K experiment & its Near Detector



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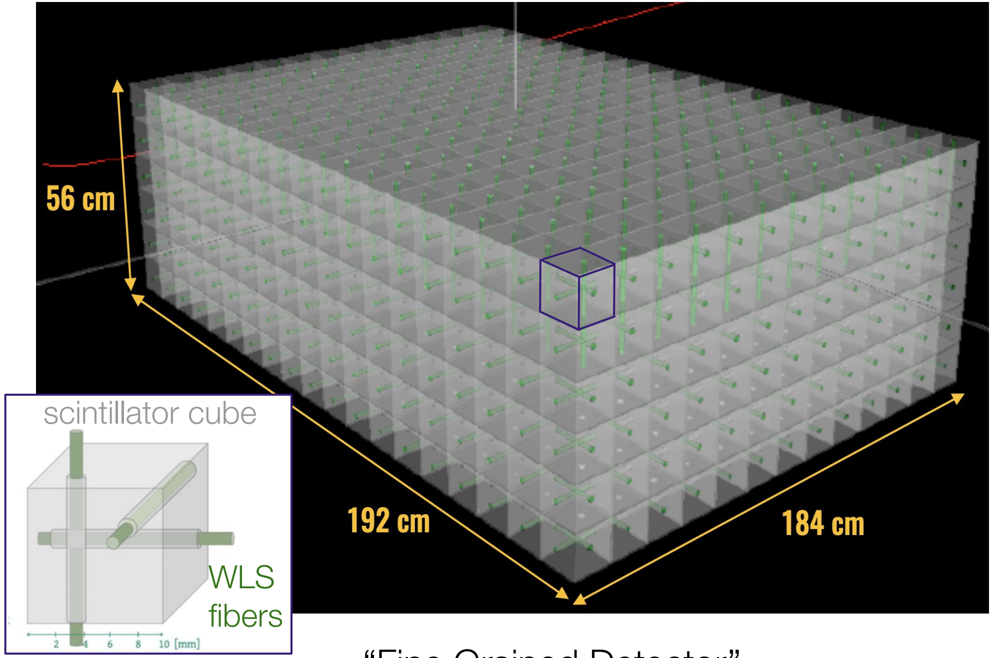
The Super-FGD: a Scintillator Detector



~2M cubes

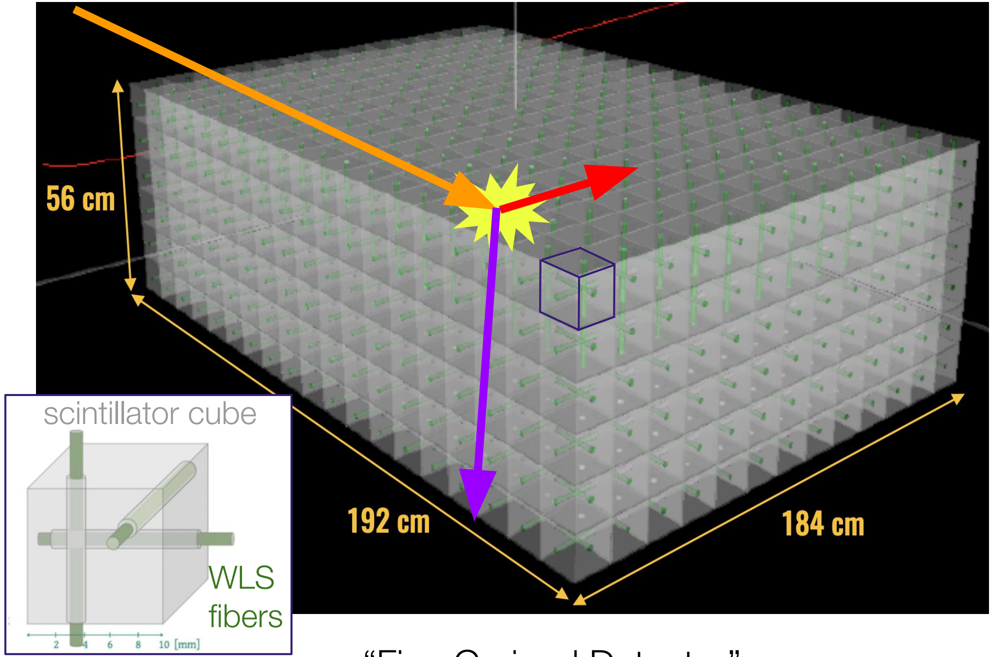
"Fine Grained Detector"

The T2K experiment & its Near Detector

New detector technology

⇒ need new tools to identify the particle types (PID) from neutrino interaction using charge deposition in the detector

The Super-FGD: a Scintillator Detector



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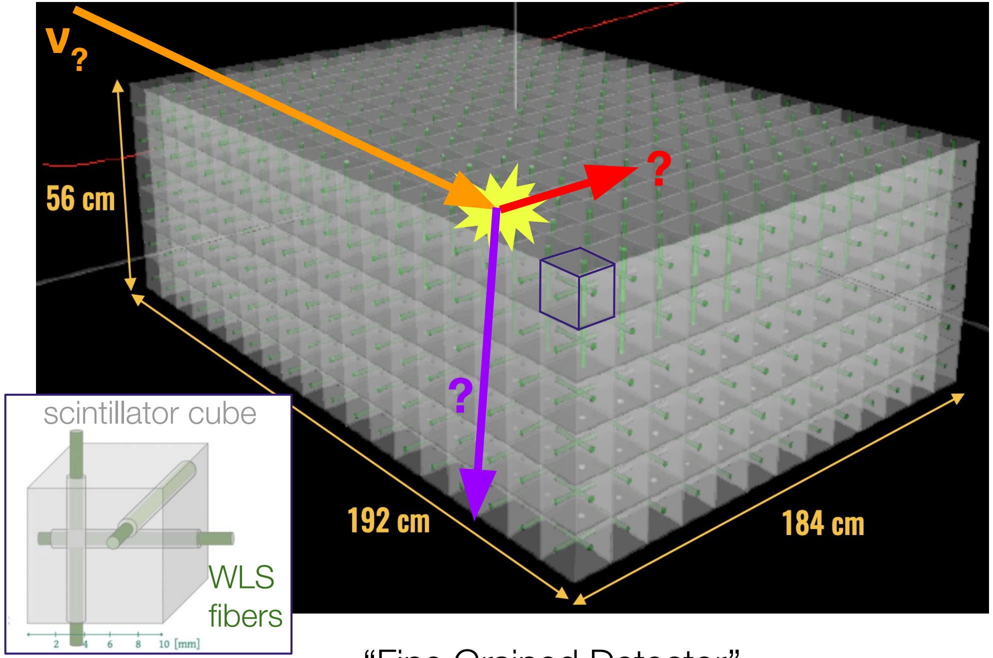

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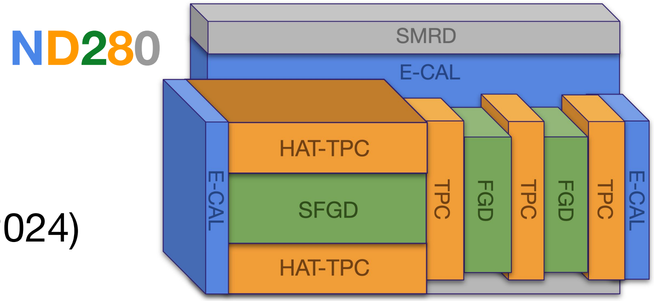
"Fine Grained Detector"

The ND280 AI/ML working group



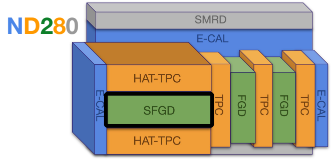
- Recent working group dedicated to AI/ML methods (since Nov. 2024)
- Convener is Saúl Alonso Monsalve (ETH Zurich)
- ~ 10 active analysers
- In different part of the experiment, various task focused around the Near Detector:

★ ***reconstruction***: vertex activity, track fitting, momentum reco → 3 projects

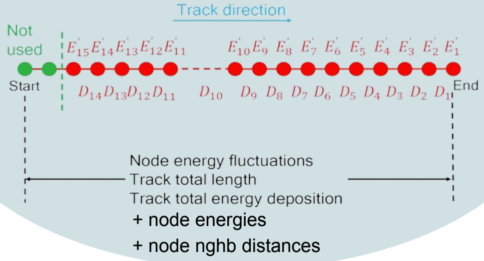
★ ***analysis***: PIDs, unfolding, modelling posterior systematics → 7 projects

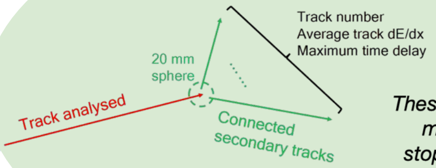
★ ***simulation***: cross-section sampling → 1 project

1. SFGD Momentum reconstruction & PID with BDT (TMVA)



Inputs: Primary track params (5) & secondary tracks params (3)





These parameters are mainly used for stopping track PID.

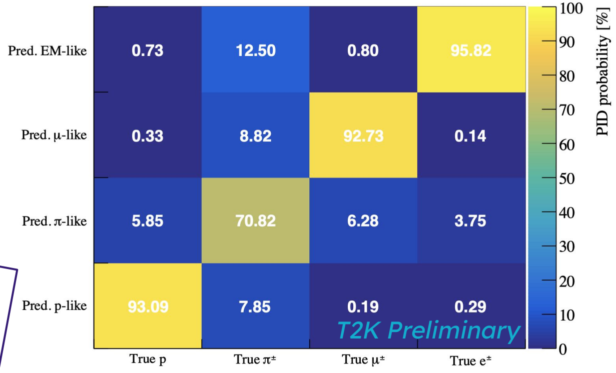
BDT HP: 5 to tune (done by hand):

Hyperparameter	Value
Decision tree number M	2000
Division point number K at each node	20
Decision tree maximum depth D_{max}	3
Shrinkage ν	0.05
Stochastic boosting fraction f	0.5

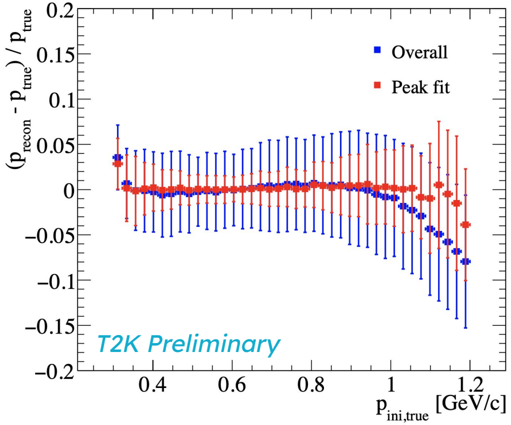
same for regression & classification

Training:
- on particle-gun MC data (i.e. 1 particle /event): p, $\pi^{\pm}$, $\mu^{\pm}$, $e^{\pm}$ with 2M/type
- distinct classifiers & momentum regressors

Test: classification results



momentum resolution:



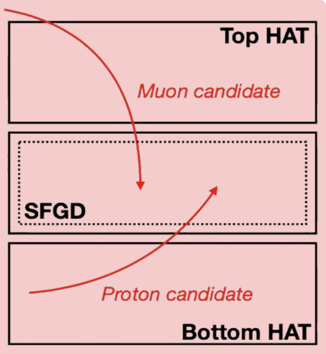
Currently in use in official T2K analysis software

work of Xingyu Zhao

1. SFGD Momentum reconstruction & PID with BDT (TMVA)

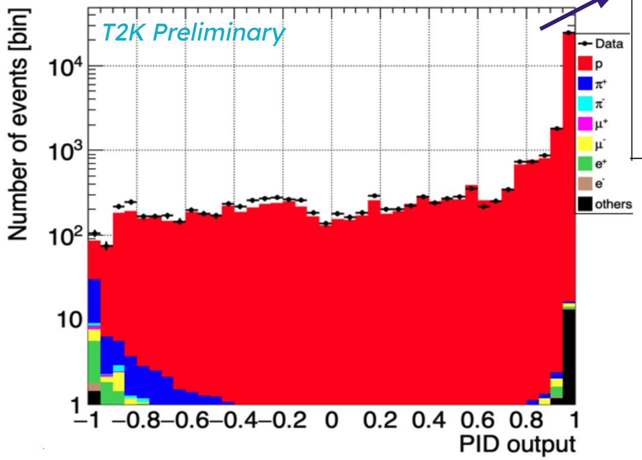
BDT Systematics:

- for real application, apply BDT to MC & data ⇒ check if have similar performances!
- If not → need to evaluate the difference
- Propage this difference as systematic source in the analysis
- Evaluation of systematics: **use stopping control sample**



stopping control sample

PID efficiency:

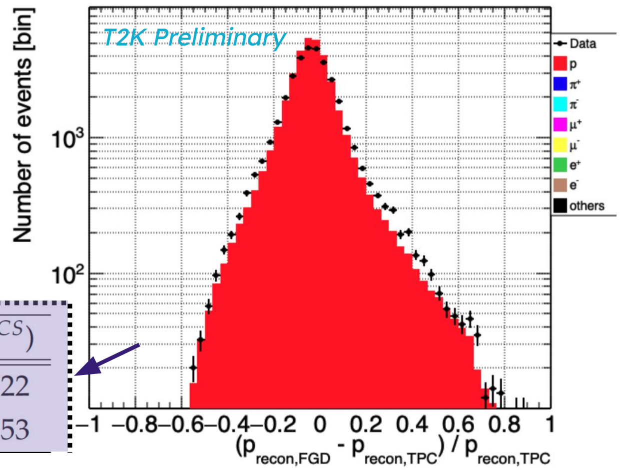


Control Sample	Data / MC
Proton	0.99 ± 0.00
Pion (π^+)	$\mathbf{2.17 \pm 0.06}$
Muon (μ^-)	1.32 ± 0.05
Electron / Positron	1.41 ± 0.15

those values are propagated as systematics

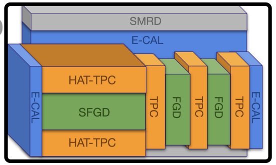
Control Sample	Data / MC (r^{CS})
Proton	1.2034 ± 0.0222
Muon (μ^-)	0.8840 ± 0.0153

Momentum resolution:



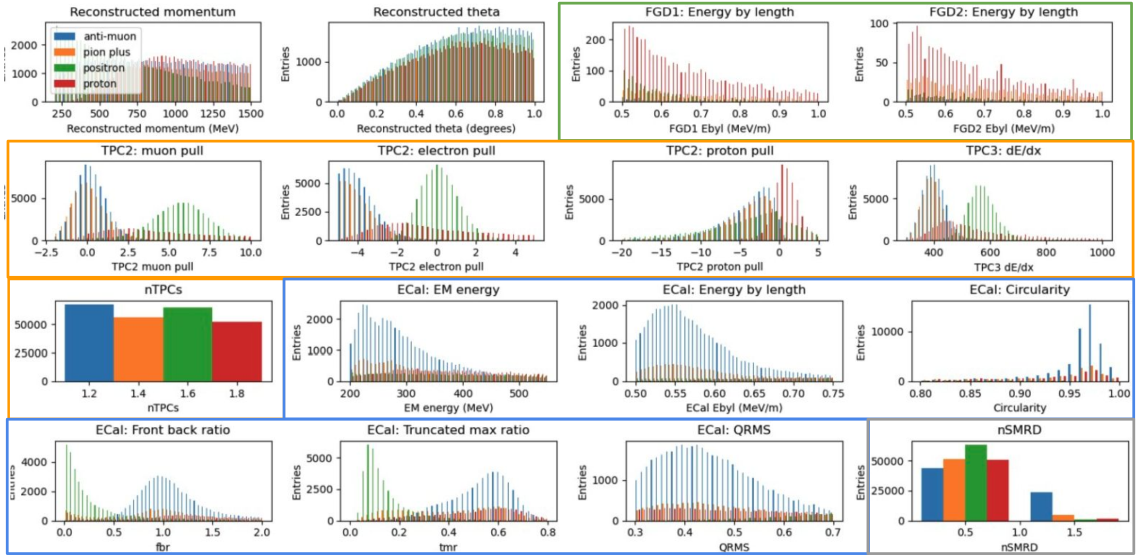
2. Global ND280 PID with BDT (XGBoost)

ND280

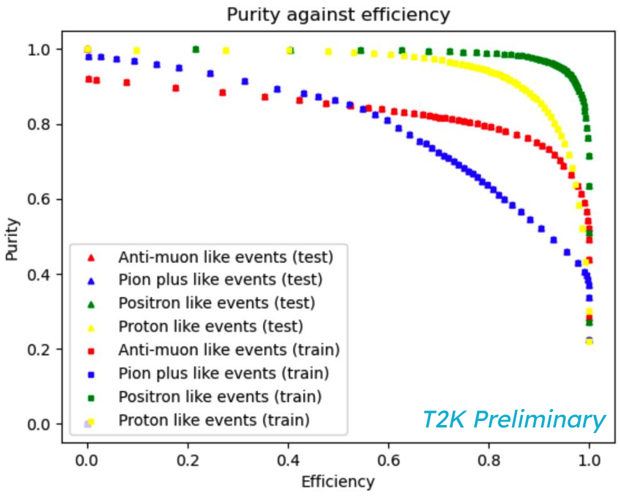


Goal: use inputs from many ND280 sub-detectors to get a global PID tool

Inputs: 16 variables from 4 of ND280 sub-detectors

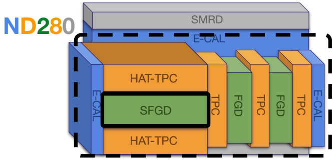


Results:

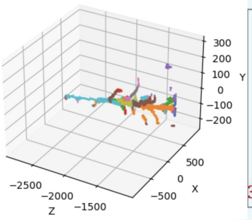


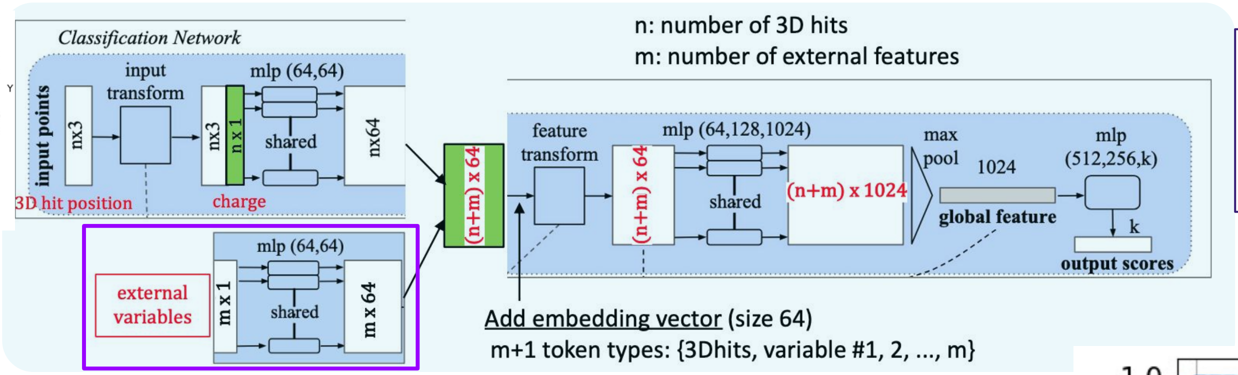
Training: - on particle-gun MC data: p, π^+, μ^+, e^+ with 250k events
- HPO

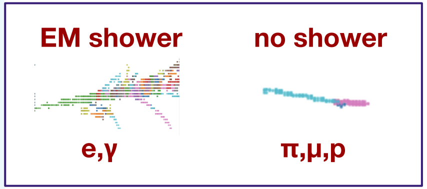
3. Identify EM shower in SFGD: PointNet



Architecture: PointNet (DNN for 3D point cloud data) with modifications







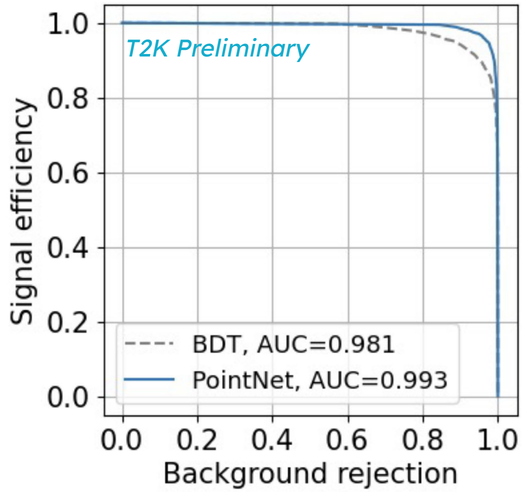
Goal: distinguish EM shower-like (e,γ) particle from non EM ones (μ,π,p)

Training data: pgun MC data of e^-, μ^- with 8000 patterns +data augmentation

External features: adding global feature of the event increase performances!
will be tested: add all BDT variables as external features

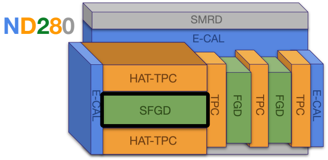
- SFGD variables (similar to BDT)
- TPC/HAT/ECAL variables
- size of the shower

Results:

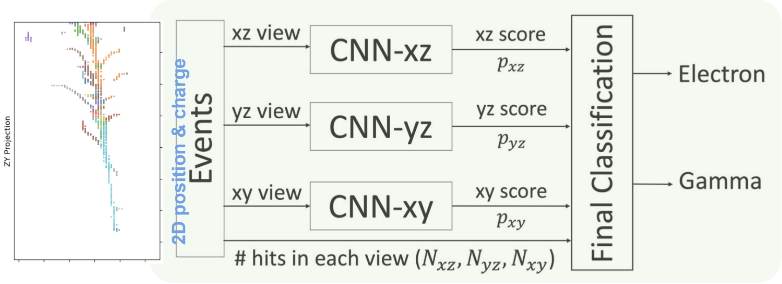


work of Hikaru Tanigawa

4. 2D+3D CNN for e/γ classification

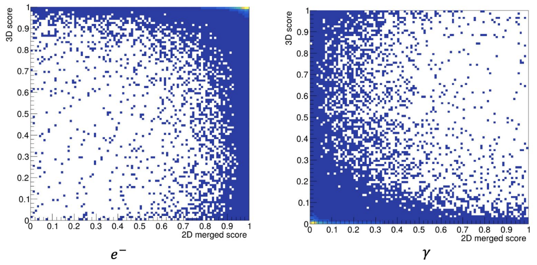


Architecture: experimental combination of 2D CNNs + sparse 3D CNN
ResNet50 SSCNN



& Sparse Submanifold convolutional network

$$\Rightarrow (final\ score) = \frac{(2D\ score) + (3D\ score)}{2}$$



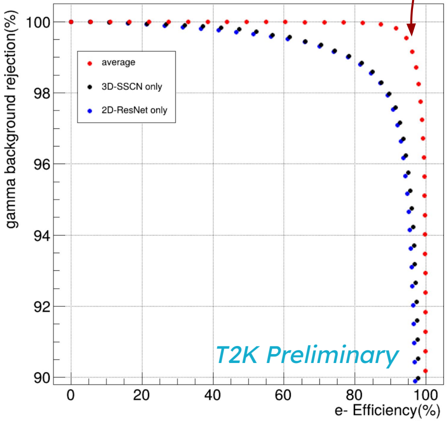
2D vs 3D scores: not much correlations

Training: pgun MC data of e⁻ and γ with 400k training event

Results:

model	e^- efficiency	γ rejection
3D-SSCN	95.5	95.3
3D-ResNet	94.9	95.8
2D-ResNet	95.3	94.4
3DSS+3DRes	96.1	96.4
3DSS+2DRes	**98.3**	**97.9**

T2K Preliminary



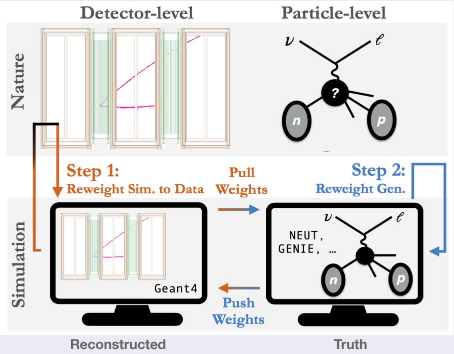
e/γ events looks similar because of $\gamma \rightarrow e^+e^-$ creating similar shower of particles
⇒ **challenge to distinguish them**

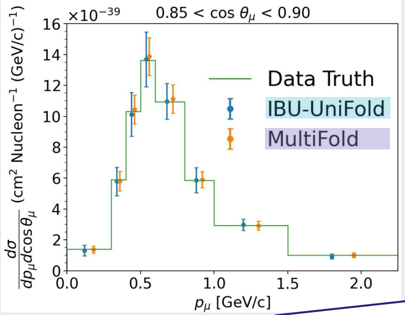
5. Other projects using ND280 data (Omnifold, Normalizing Flows)

Omnifold:

work of Roger Huang

unbinned method to unfold ND280 data faster

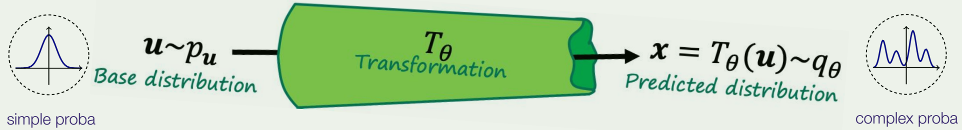




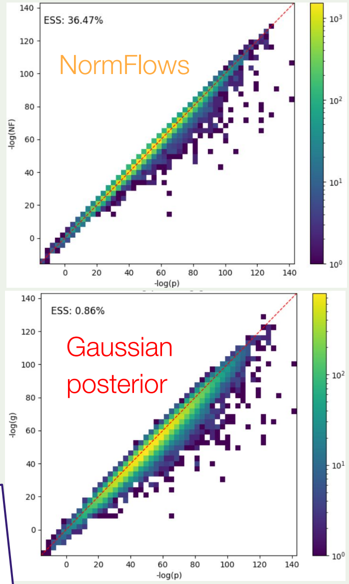
Discussions to incorporate these in T2K softwares

Normalizing flows:

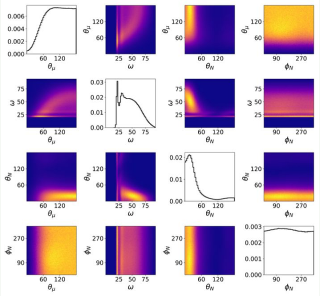
work of Mathias El Baz

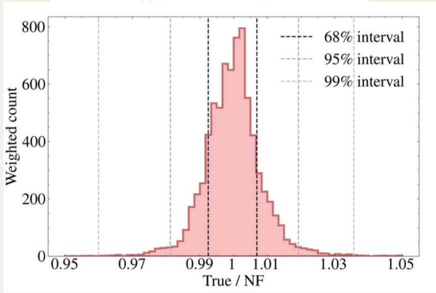


Modeling posterior systematics

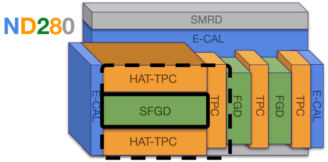


Efficient CCQE cross-section sampling



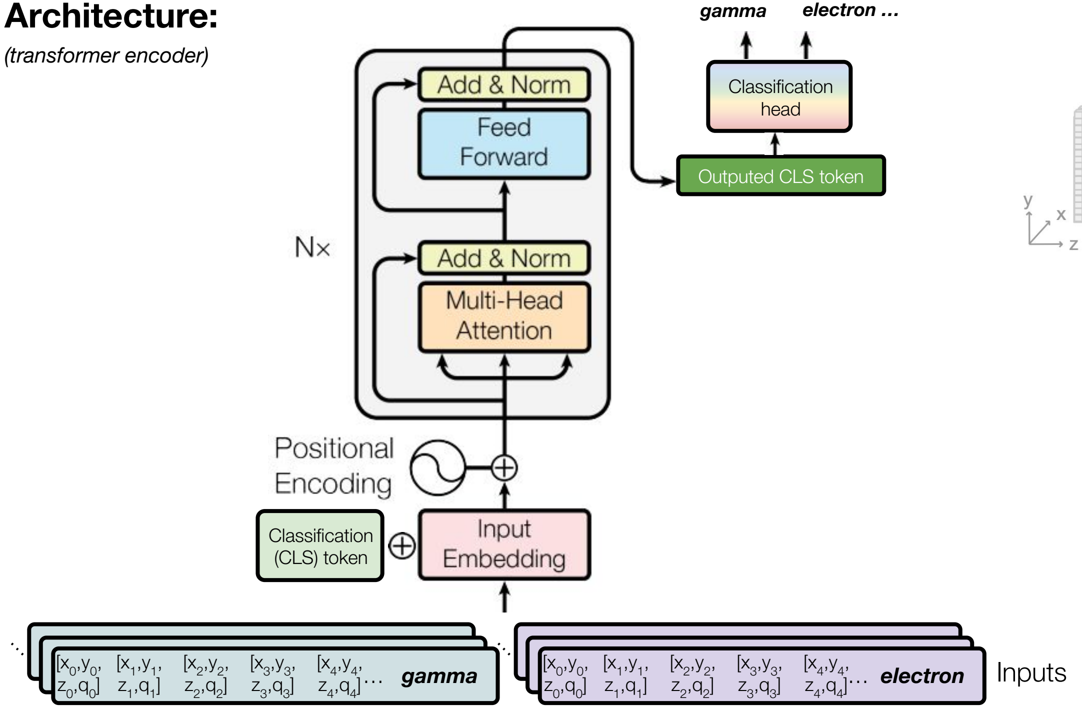


6. PID in the SFGD with a Transformer



Architecture:

(transformer encoder)



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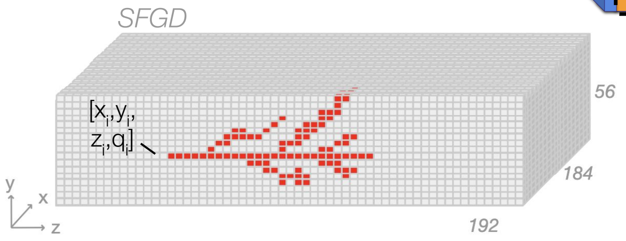

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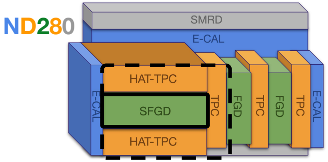

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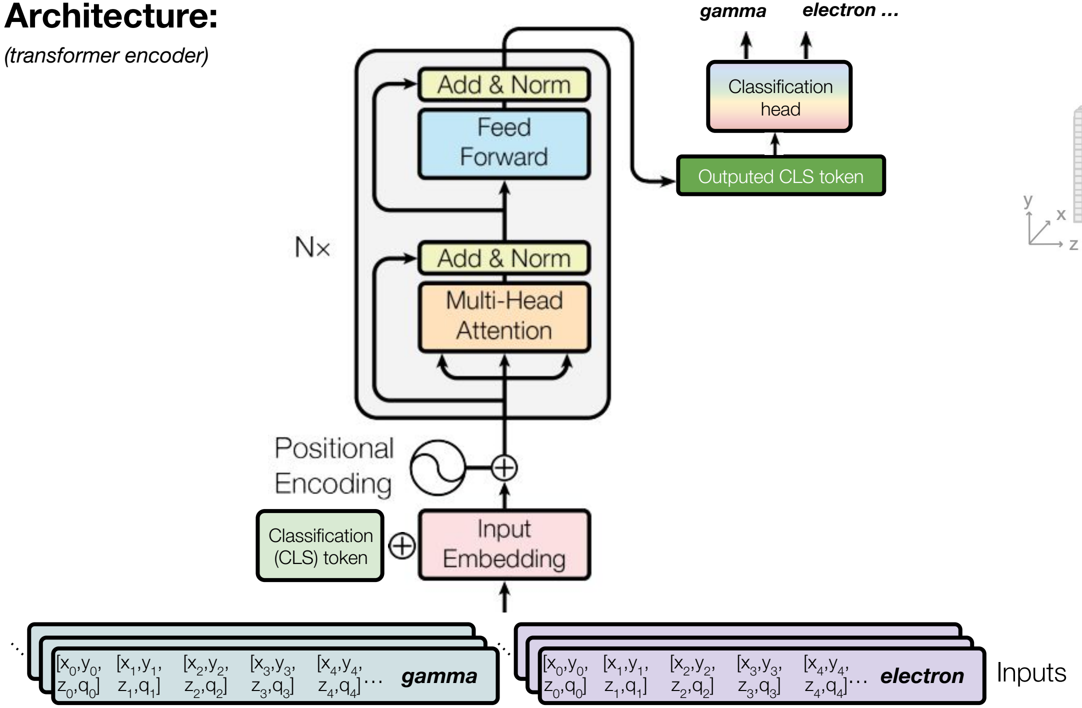

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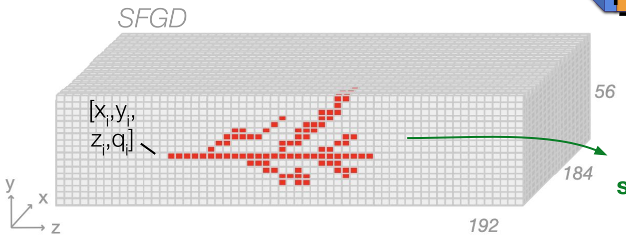

Too long sequences of hits: use Vision Transformer principle

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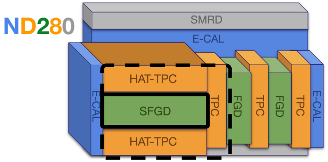

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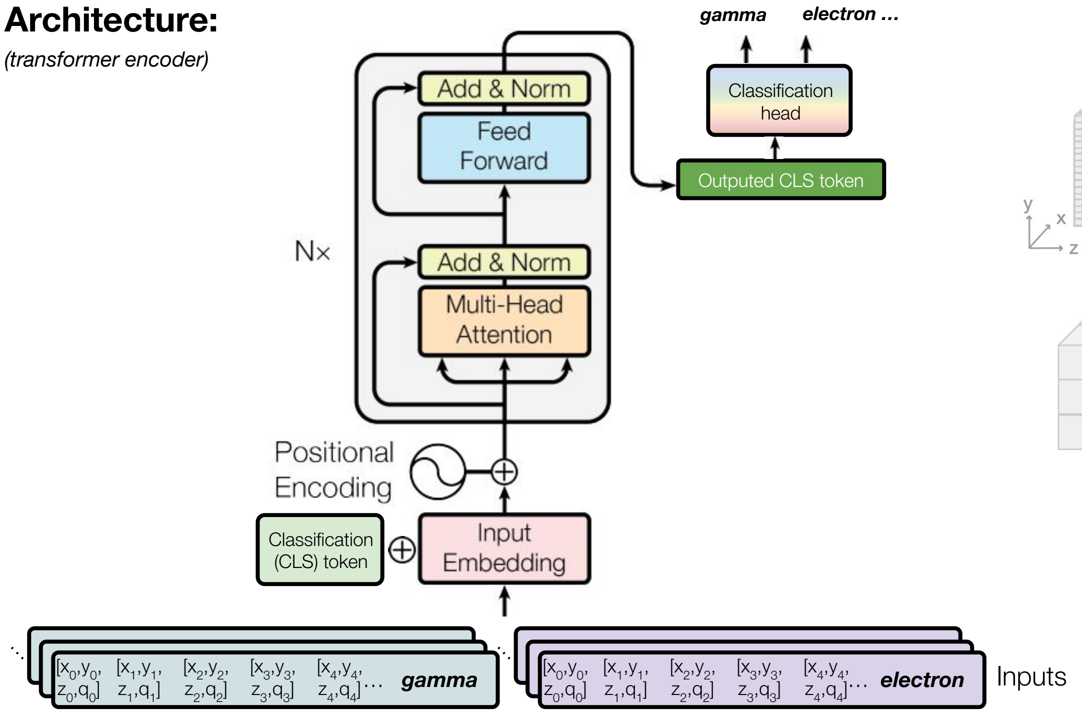

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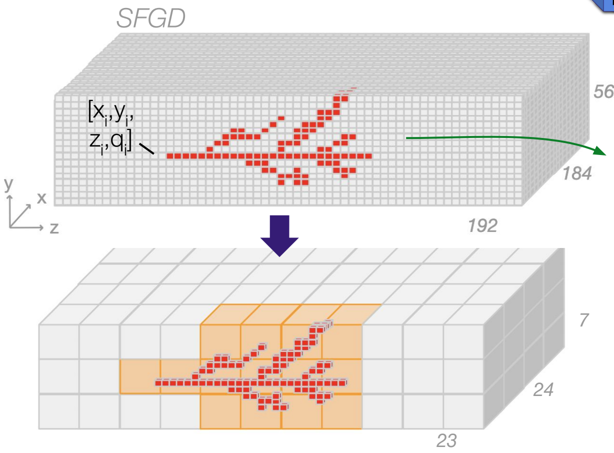

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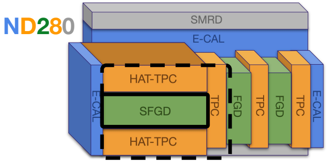

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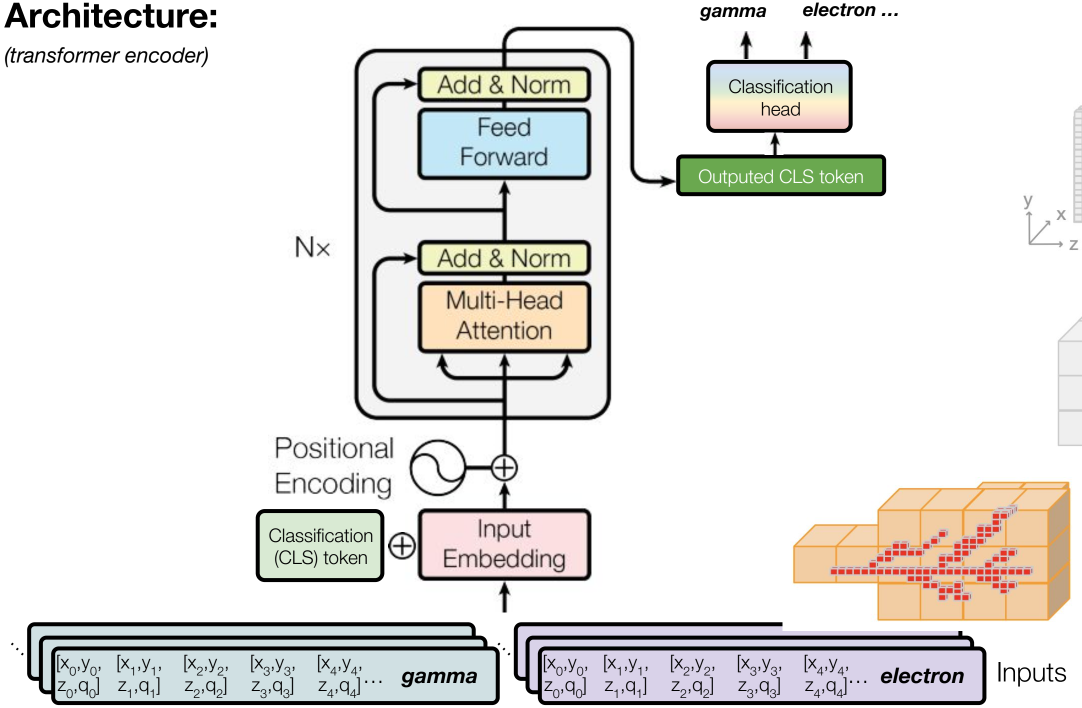

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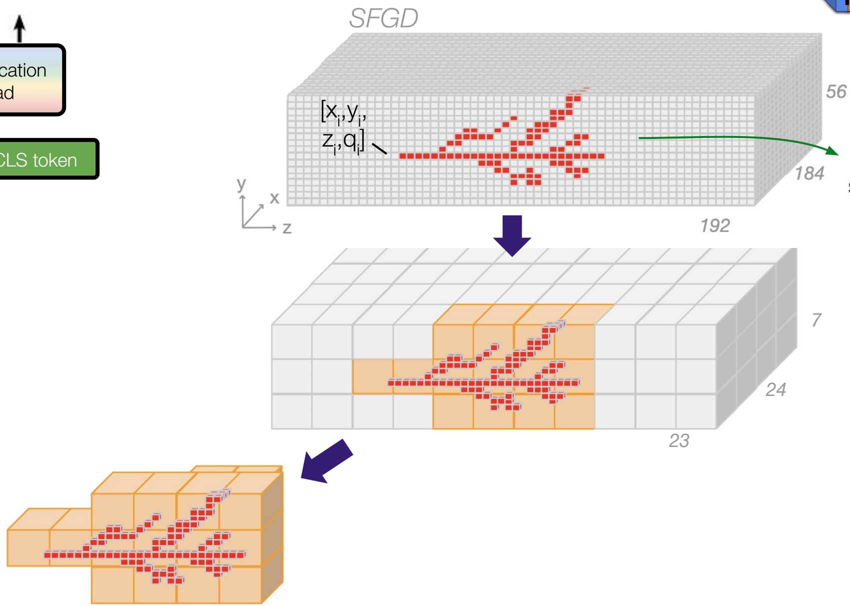

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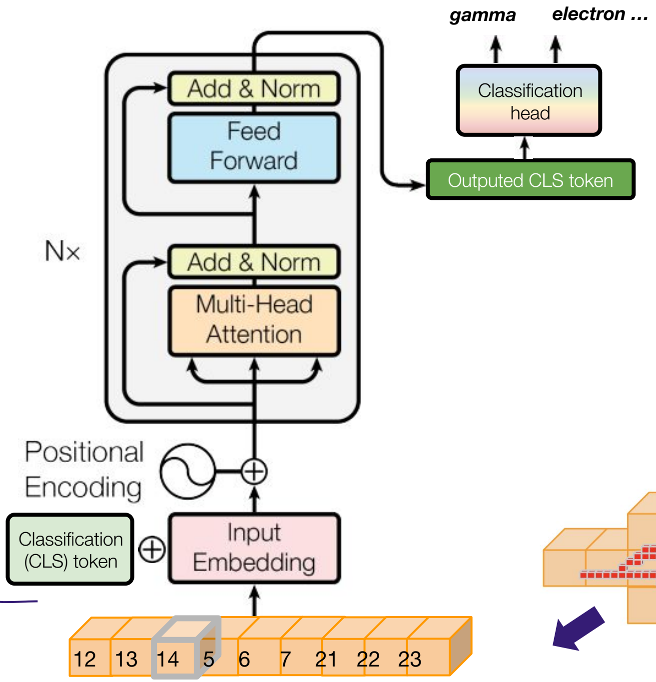
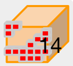
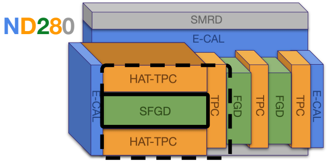


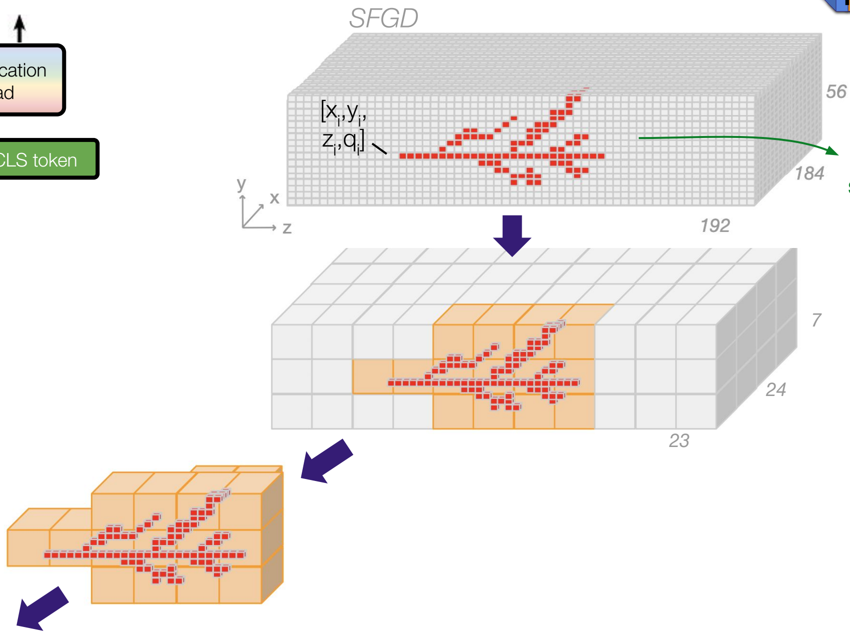
positional encoding of the parent cubes in the parent grid

each parent cube holds the info of its child voxels: relative positions & charge



Inputs:



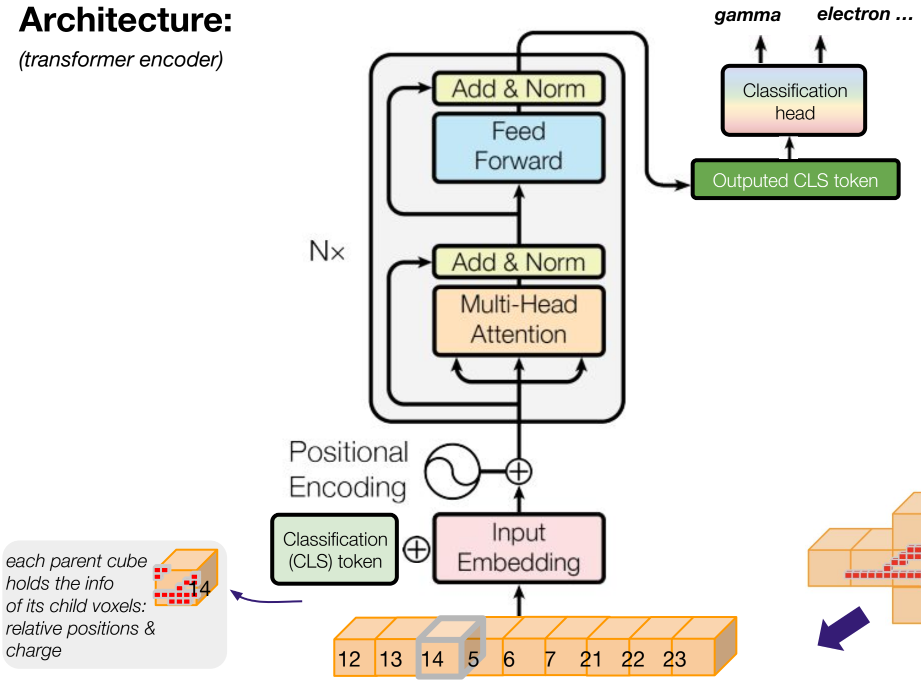


Too long sequences of hits: use Vision Transformer principle

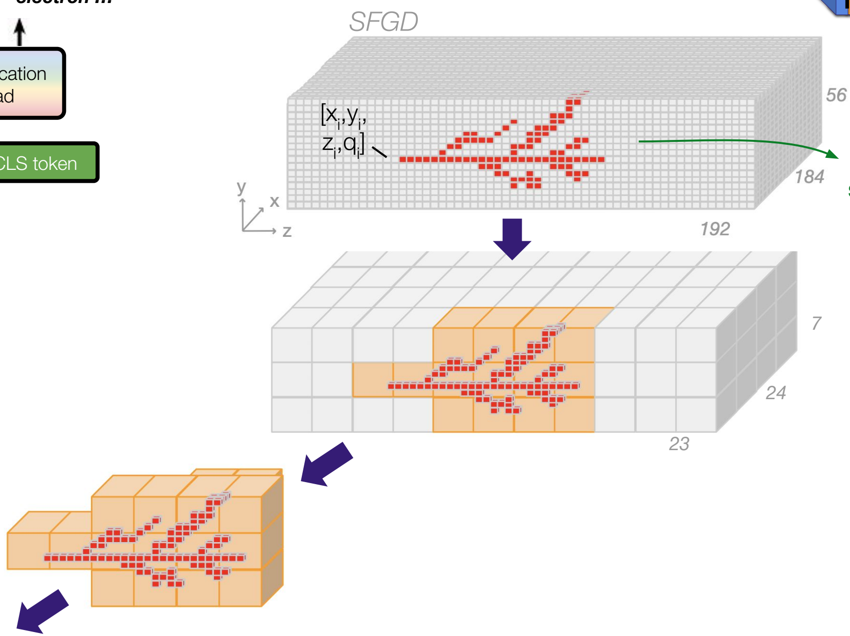
6. PID in the SFGD with a Transformer

Architecture:

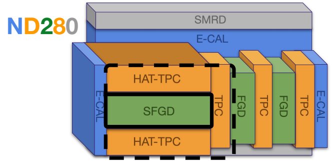
(transformer encoder)



Inputs:



Too long sequences of hits: use Vision Transformer principle

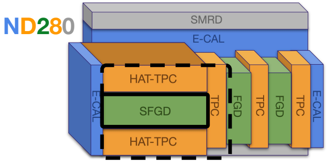


Training: - particle-gun MC data: e^-, γ, π^-, μ^-

- either along 1 direction or isotropic

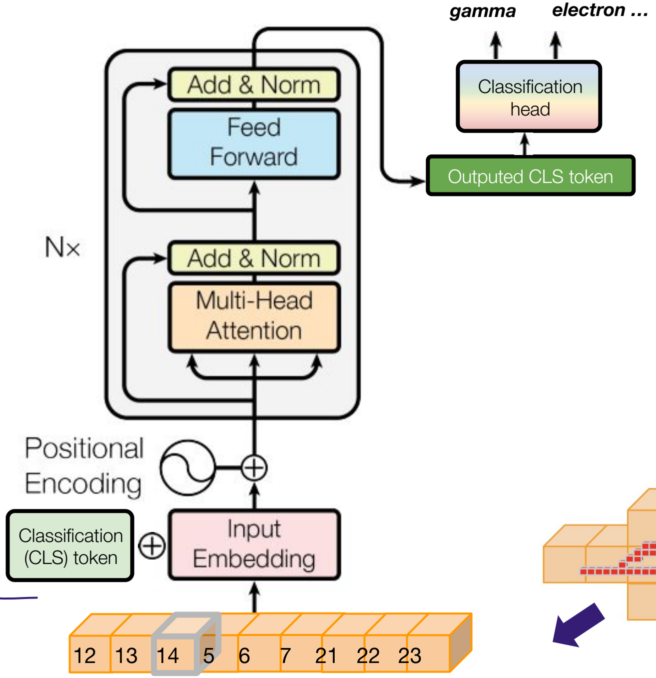
'z-pgun' *'iso-pgun'*

6. PID in the SFGD with a Transformer



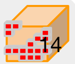
Architecture:

(transformer encoder)

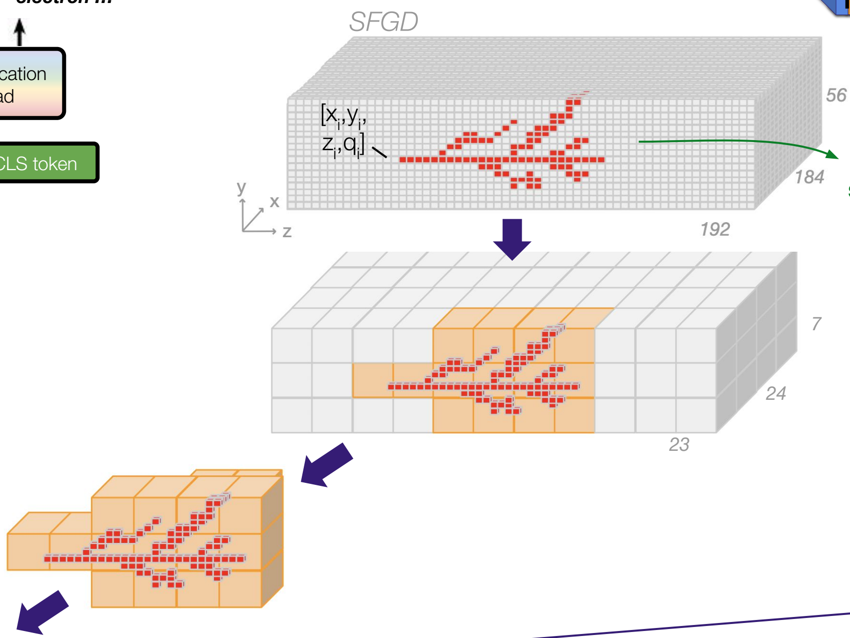


positional encoding of the parent cubes in the parent grid

each parent cube holds the info of its child voxels: relative positions & charge



Inputs:



Too long sequences of hits: use Vision Transformer principle

- architecture converted in C++ (*Libtorch*)
- saved weights from training to be loaded in C++

➡ 1rst complex ML model implemented in analysis soft!

Training: - particle-gun MC data: e^-, γ, π^-, μ^-

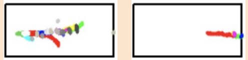
- either along 1 direction or isotropic

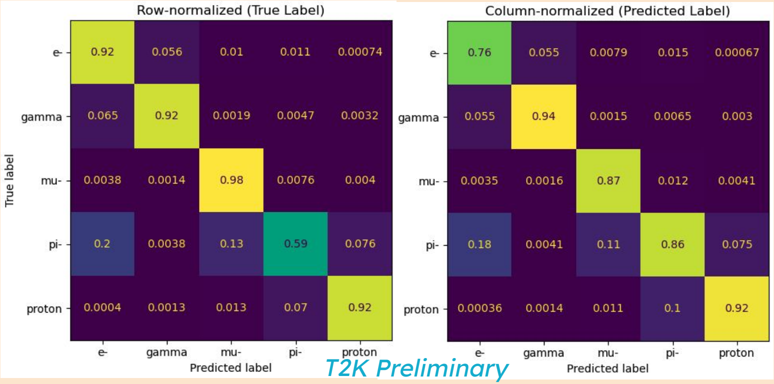
'z-pgun' *'iso-pgun'*

6. PID in the SFGD with a Transformer

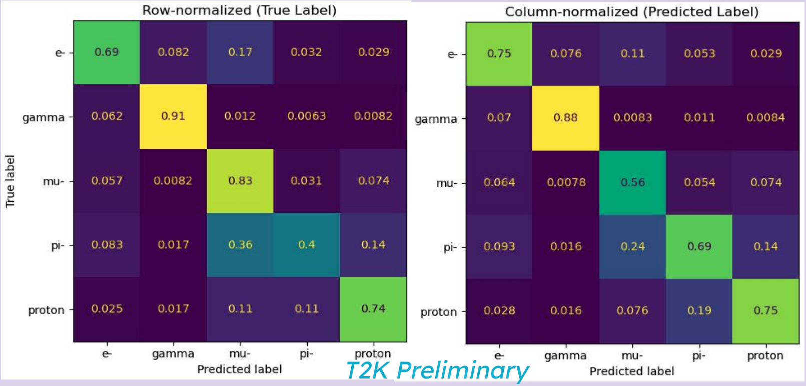
Test:

☺ ***z-pgun*** *(train&test)*



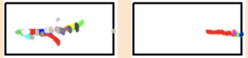


😐 ***iso-pgun*** *(train&test)*

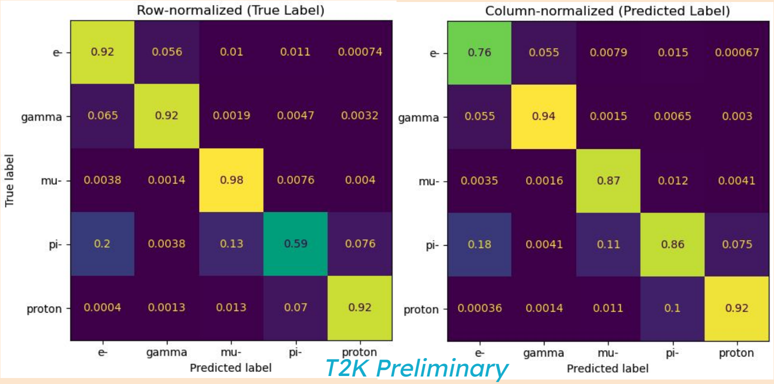


6. PID in the SFGD with a Transformer

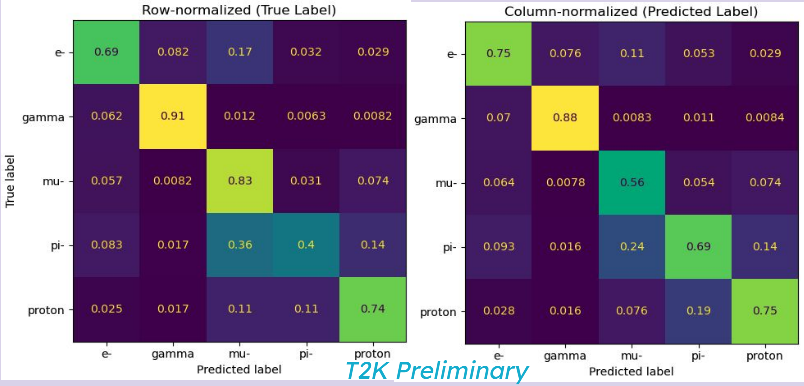
☺ ***z-pgun*** *(train&test)*



Test:



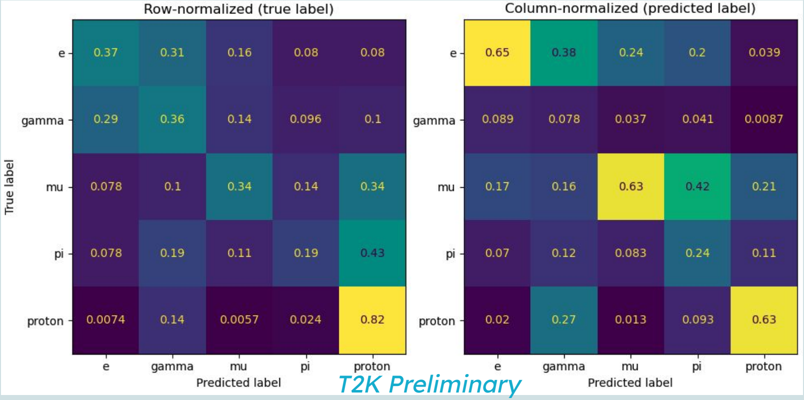
😐 ***iso-pgun*** *(train&test)*



Test on neutrino interactions:

(iso-pgun training)

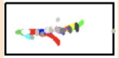
☹



6. PID in the SFGD with a Transformer

Test:

☺ ***z-pgun*** *(train&test)*



Row-normalized (True Label)

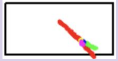
True label \ Predicted label	e-	gamma	mu-	pi-	proton
e-	0.92	0.056	0.01	0.011	0.00074
gamma	0.065	0.92	0.0019	0.0047	0.0032
mu-	0.0038	0.0014	0.98	0.0076	0.004
pi-	0.2	0.0038	0.13	0.59	0.076
proton	0.0004	0.0013	0.013	0.07	0.92

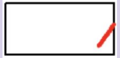
Column-normalized (Predicted Label)

True label \ Predicted label	e-	gamma	mu-	pi-	proton
e-	0.76	0.055	0.0079	0.015	0.00067
gamma	0.055	0.94	0.0015	0.0065	0.003
mu-	0.0035	0.0016	0.87	0.012	0.0041
pi-	0.18	0.0041	0.11	0.86	0.075
proton	0.00036	0.0014	0.011	0.1	0.92

T2K Preliminary

☺ ***iso-pgun*** *(train&test)*





Row-normalized (True Label)

True label \ Predicted label	e-	gamma	mu-	pi-	proton
e-	0.69	0.082	0.17	0.032	0.029
gamma	0.062	0.91	0.012	0.0063	0.0082
mu-	0.057	0.0082	0.83	0.031	0.074
pi-	0.083	0.017	0.36	0.4	0.14
proton	0.025	0.017	0.11	0.11	0.74

Column-normalized (Predicted Label)

True label \ Predicted label	e-	gamma	mu-	pi-	proton
e-	0.75	0.076	0.11	0.053	0.029
gamma	0.07	0.88	0.0083	0.011	0.0084
mu-	0.064	0.0078	0.56	0.054	0.074
pi-	0.093	0.016	0.24	0.69	0.14
proton	0.028	0.016	0.076	0.19	0.75

T2K Preliminary

Test on neutrino interactions:

(iso-pgun training)

☹

Row-normalized (true label)

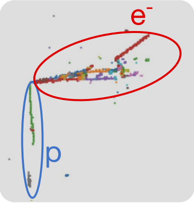
True label \ Predicted label	e	gamma	mu	pi	proton
e	0.37	0.31	0.16	0.08	0.08
gamma	0.29	0.36	0.14	0.096	0.1
mu	0.078	0.1	0.34	0.14	0.34
pi	0.078	0.19	0.11	0.19	0.43
proton	0.0074	0.14	0.0057	0.024	0.82

Column-normalized (predicted label)

True label \ Predicted label	e	gamma	mu	pi	proton
e	0.65	0.38	0.24	0.2	0.039
gamma	0.089	0.078	0.037	0.041	0.0087
mu	0.17	0.16	0.63	0.42	0.21
pi	0.07	0.12	0.083	0.24	0.11
proton	0.02	0.27	0.013	0.093	0.63

T2K Preliminary

On-going improvements:



- refine pattern recognition before PID (if bad, then model cannot succeed)
- use time of each hits
- add e^+, π^+, μ^+ to training
- add extra token to the input sequence:
  total nhits
  total charge
  pulls from nghb detectors (HAT/TPCs)

Summary

- Increasing number of ML projects at T2K ND
- In all stages of the experiment: more project in the analysis part, then reconstruction then simulation
- Methods are starting to be used in the official software (BDT, Transformer), paving the way for the other ones
- Challenges to come:
  - more friendly integration possibilities for these methods
  - strategy for systematic propagation

Thank you!

Back-up

3. Identify EM shower in SFGD: PointNet

External features:

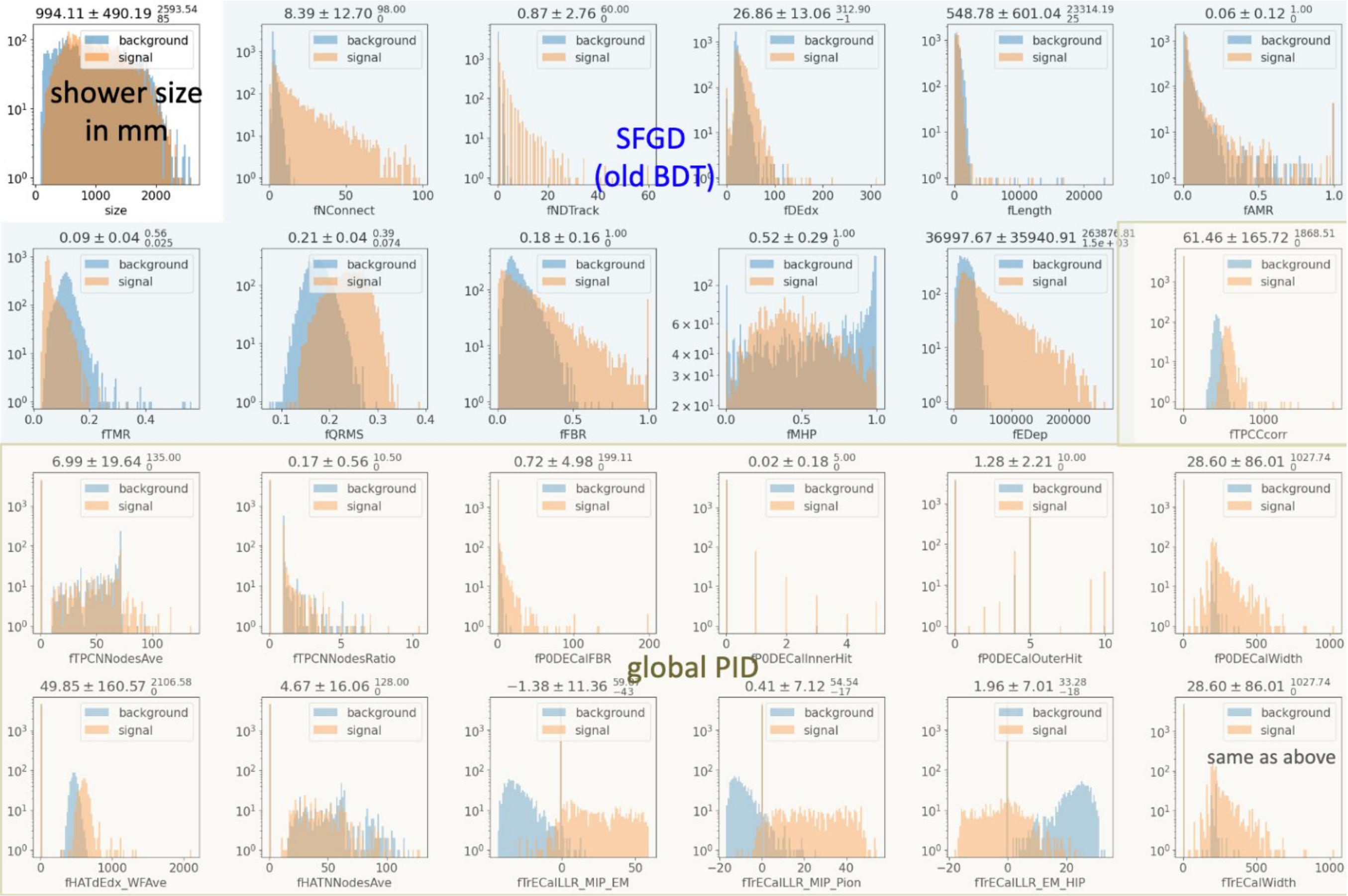
shower size
- added by HT

SFGD features: 10
- from old BDT

nonSFG features: 13
- from global PID
- mostly empty for the contained cones
  - 85-90% are “0”

Distributes in wide range

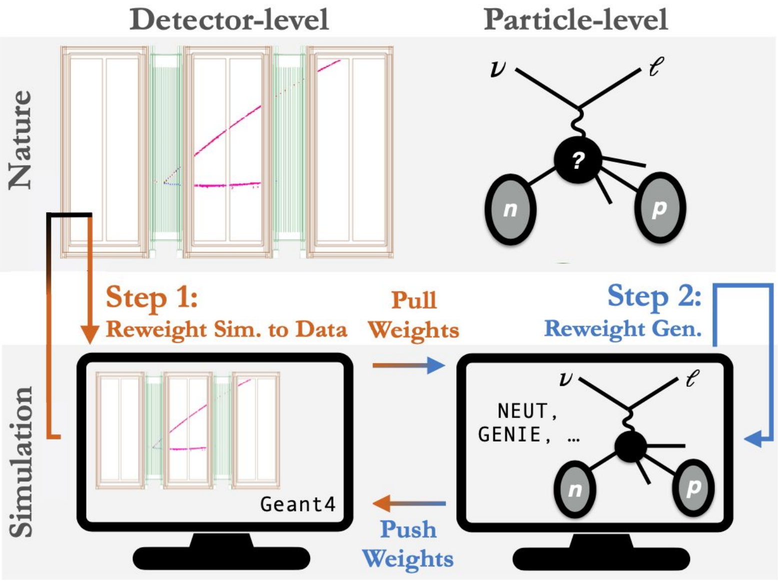
→ Need scaling



Unfolding of ND280 data: Omnifold

ref. https://arxiv.org/pdf/2504.06857v1

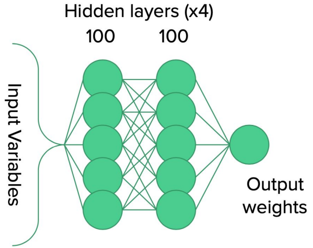
Working principle:



Reconstructed

Truth

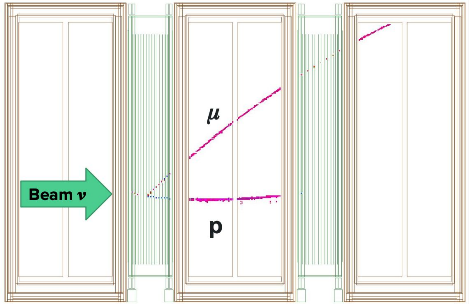
Archi:



1NVIDIA A100 on a NERSC Perlmutter node: takes < 30 min to run 15 OmniFold iterations on one set of data/MC

Data:

- 1.2M simulated ND280 evts ≃ 20k measured evts
- with π^+ and leading p kinematics



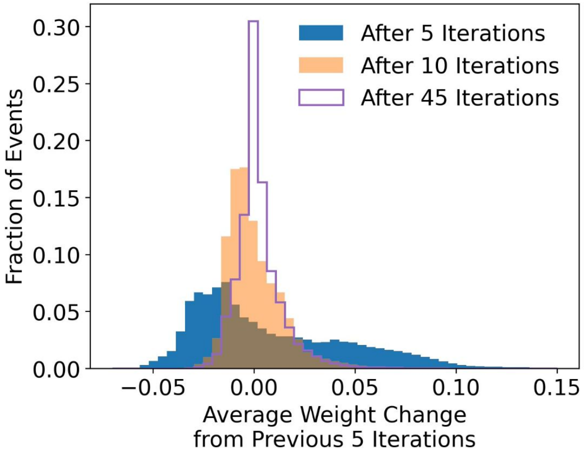
- *for test:* create fake dataset with a BeRPA-based modification to the true interaction rates

Inputs:

- kinematic observables (p_μ, $\cos\theta_\mu$, p_p, δp_T, $\delta\alpha_T$, $\delta\phi_T$)
- detector sample ID
- interaction topology (CC0π0p, CC0π1p, CC0πNp, CC1π, CCother)

Unfolding of ND280 data: Omnifold

Test:



Comparision with conventional-like unfoldings:

- not straightforward since Omnifold is unbinned
- use Omnifold in a way that it is mathematically equivalent to IBU (Iterative Bayesian Unfolding): inputs limited to bin indices

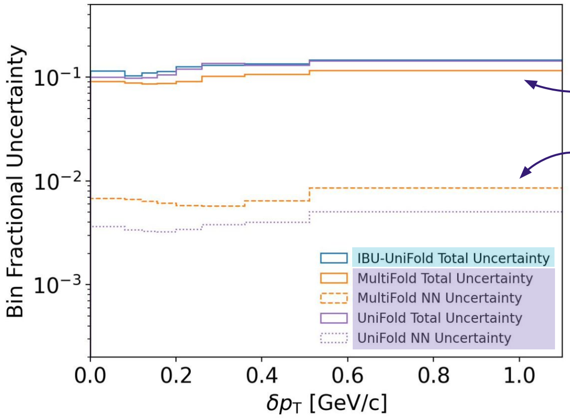
conventional-like method: IBU-UniFold, Binned UniFold

Omnifold variations (inputs choice): UniFold, MultiFold, OmniFold

Method	χ^2 (p_μ, cos θ_μ) DoF=58	χ^2 δp_T DoF=8	χ^2 $\delta\alpha_T$ DoF=8	χ^2 $\delta\phi_T$ DoF=8
Prior	298.2	2.3	5.9	4.9
IBU-UniFold	2.1	0.2	0.4	0.1
Binned UniFold	21.4	1.4	0.9	0.5
UniFold	27.1	1.1	0.6	1.1
MultiFold	3.1	0.3	0.2	0.3
OmniFold	10.0	0.8	1.1	0.4

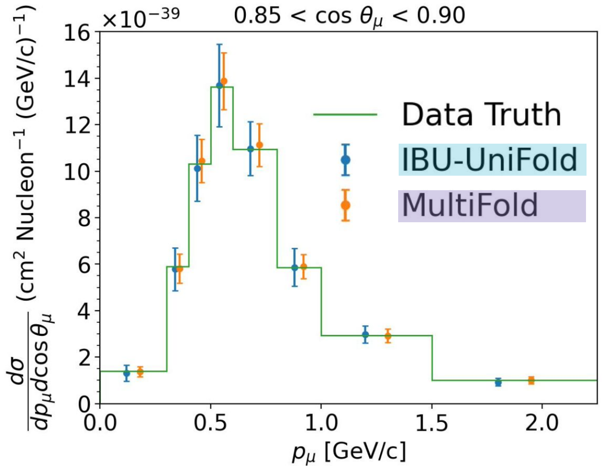
Method	Triangular Discriminator (p_μ, cos θ_μ)	δp_T	$\delta\alpha_T$	$\delta\phi_T$
Prior	545.6	27.5	31.2	26.7
IBU-UniFold	17.1	1.9	3.4	0.8
Binned UniFold	29.9	2.8	6.0	1.9
UniFold	17.3	5.7	5.8	1.7
MultiFold	2.7	0.7	0.6	0.6
OmniFold	9.4	1.7	3.0	2.1

Uncertainties:



total

from NN stochasticness



ref. https://arxiv.org/pdf/2312.02045

Modeling posterior systematic: Normalizing Flows

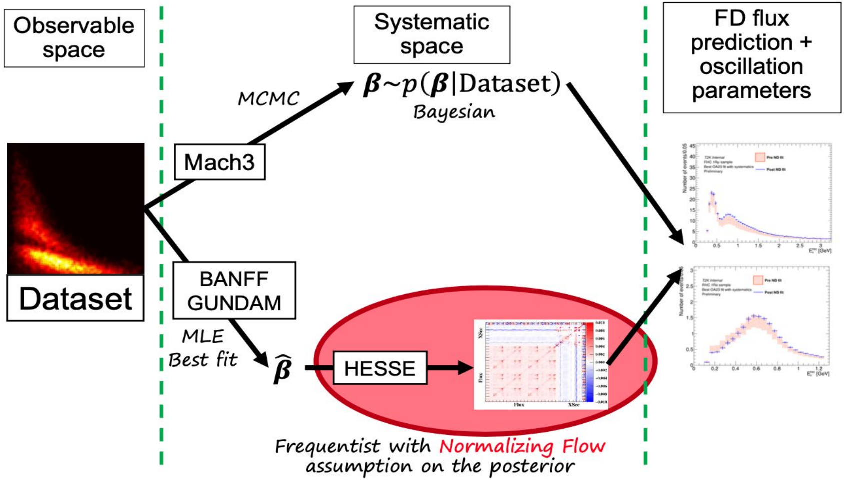
ND fit is a constrain on systematic uncertainties using ND280 observations

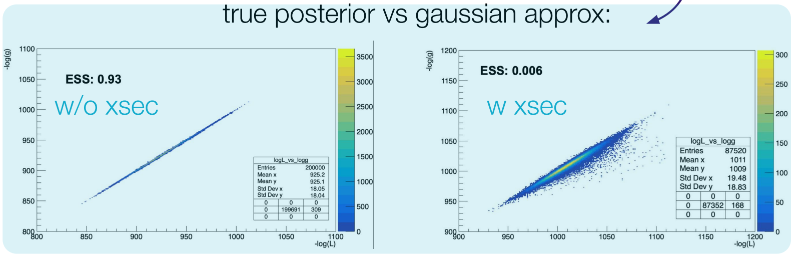
Context: ND280 likelihood of systematics depends on >700 variables (from flux, detector and xsec uncertainties)

Goal: Learn the posterior probability distribution of neutrino flux binned in neutrino energy

Conventional methods:

- Semi-frequentist (*GUNDAM*): gaussian assumption on the posterior, get best-fit params from MLE
  + analytical
  - miss xsec non-gaussianities
- Bayesian (*Mach3*): sample from the posterior using MCMC
  + capture non-gaussianties
  - pt cloud estimation (not analytical)





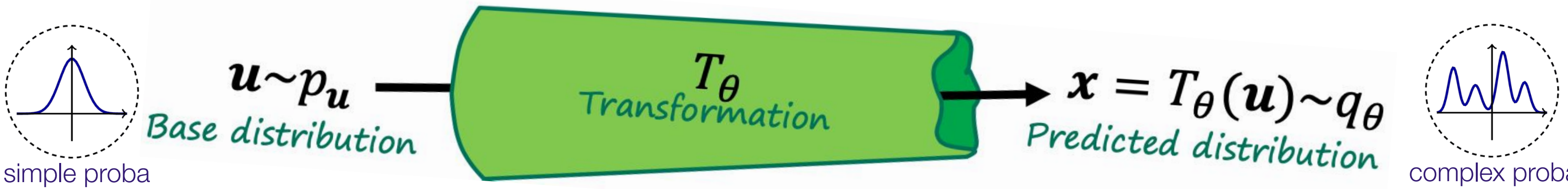
Where ML comes in:

replace *GUNDAM* gaussian approximation by something more complex to capture non-gaussianities in xsec params

ref. https://arxiv.org/pdf/2312.02045

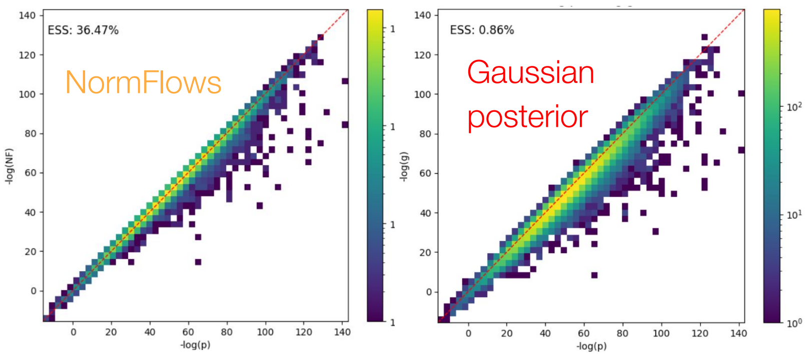
Modeling posterior systematic: Normalizing Flows

NormFlows:

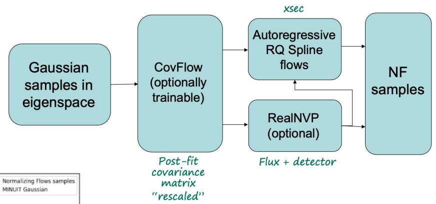


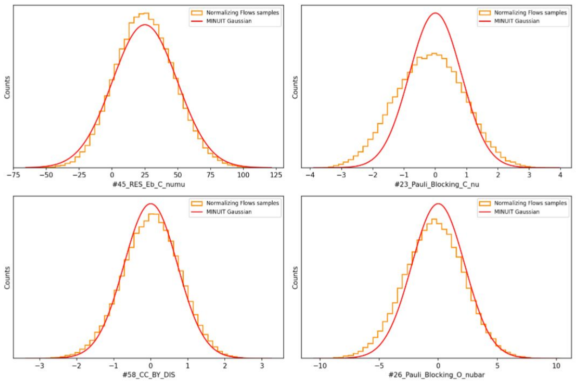
↳ straighforward to: sample $\boldsymbol{x} = T_\theta(\boldsymbol{u}) \sim q_\theta$ with $\boldsymbol{u} \sim p_{\boldsymbol{u}}$ & evaluate the proba $q_\theta(\boldsymbol{x}) = p_{\boldsymbol{u}}(\boldsymbol{u}) \,|\det\left(J_{T_\theta}(\boldsymbol{u})\right)|^{-1}$

Test: on full sets of systematics (OA 2022 config) to learn the 59 xsec probas conditioned on the 652 flux + detector systematics



Archi: 5 RQ-NSF splines, MANN-parametrized flows





Fast method:
10M sample /day
vs ?

ref. https://arxiv.org/pdf/2502.14452

CCQE cross-section sampling: Normalizing Flows

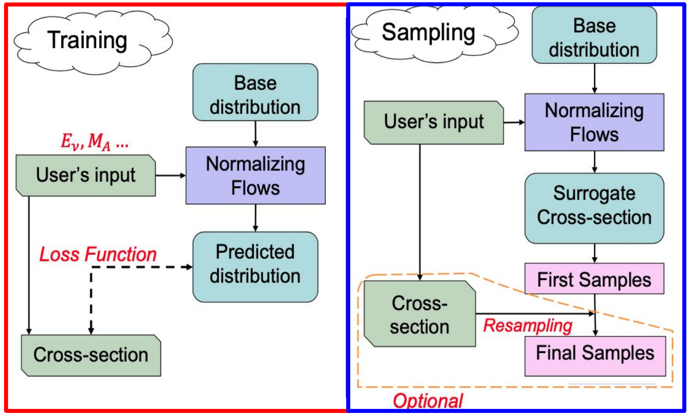
Goal: efficient MC sampling for CCQE exclusive cross-section of neutrino-nucleus (^{12}C)

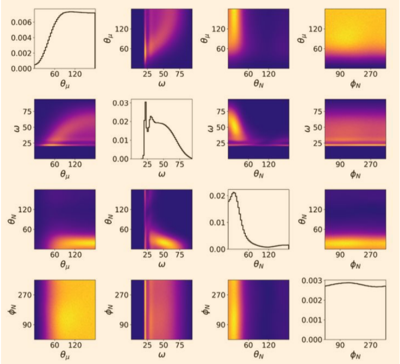
Conventional method:
use sophisticated nuclear models $\frac{d^6\sigma}{dE_\nu d\omega d\Omega_\mu d\Omega_N} \propto L^{\mu\nu} W_{\mu\nu}$ → long computations

ML method: same Normalizing Flow architecture as project 5
(slightly different loss function derived from KLD)

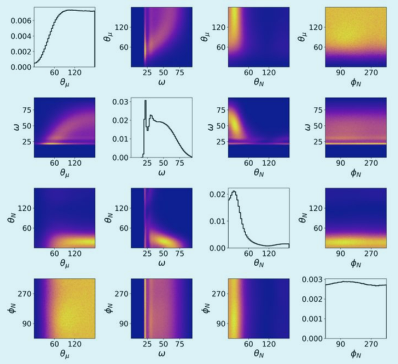
Train: to model 1p1h i.e. $p(\theta_\mu, \omega, \theta_N, \phi_N \mid E_\nu, \alpha)$ on 2 shells for many E_ν

Test: sample e.g for (600 MeV, 1s shell)

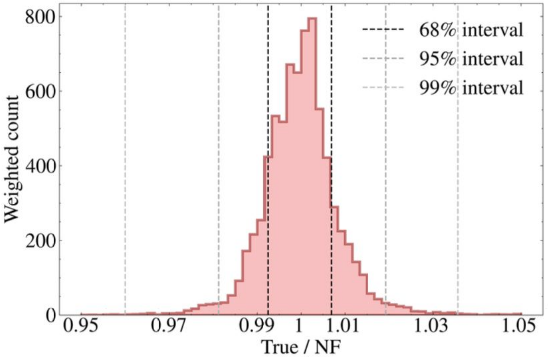




true



surrogate



Fast method:
1M sample /25min/GPU
vs 1 day/CPU

Next:
2p2h will be more complicated because higher dimension