DEEP LEARNING IN VOXELISED NEUTRINO DETECTORS

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Neutrino Physics and Machine Learning (NPML 2023)

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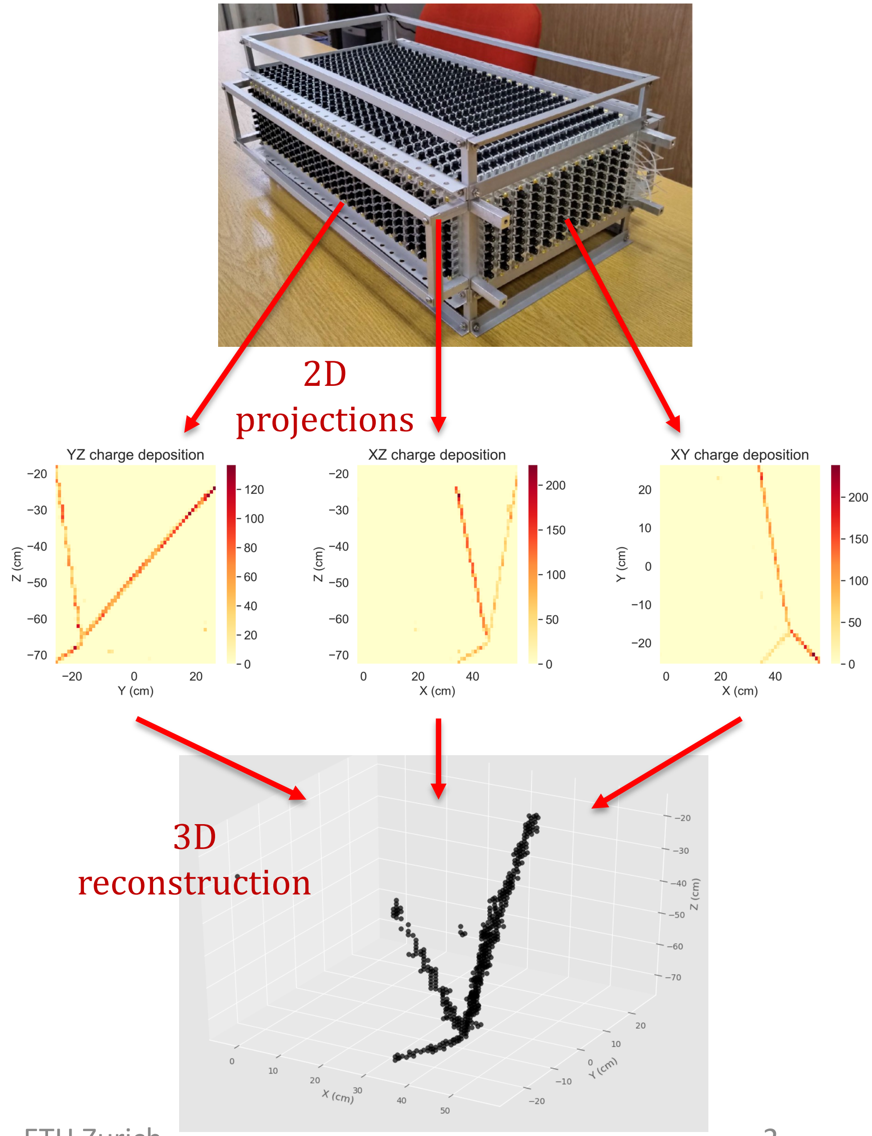
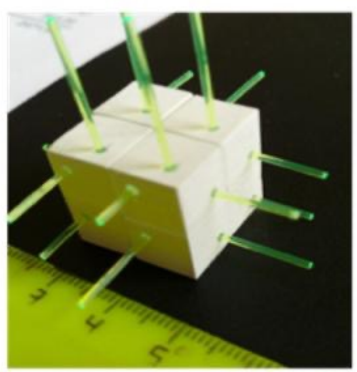
The physics case

- Goal: develop an analysis strategy that does not depend on the neutrino interaction model for 3D granularity detectors.

- Case study: a detector concept analogous to the SuperFGD detector from the T2K experiment.
  - Part of the upgrade of the near detector (ND280) of the T2K experiment in Japan.
  - Full-active fine-grained scintillator (FGD) with three views.
  - 2M optically independent cubes, 1 cm^3 per cube.
  - Spatial localisation of scintillation light.





JINST 13 (2018) 02, P02006
NIM A936 (2019) 136-138

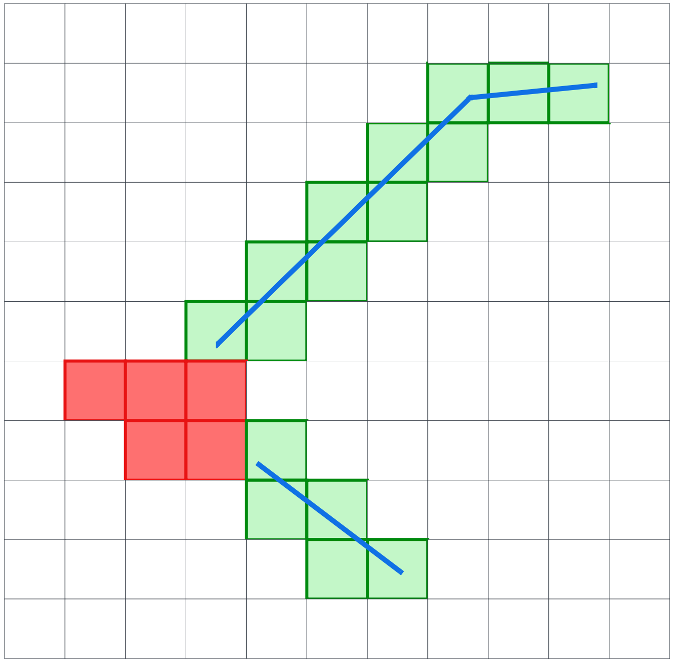
Reconstruction approach

- Goal: develop an analysis strategy that does not depend on the neutrino interaction model:

  a) Algorithms to reject noise and identify single vs multi-primary-particle hits.

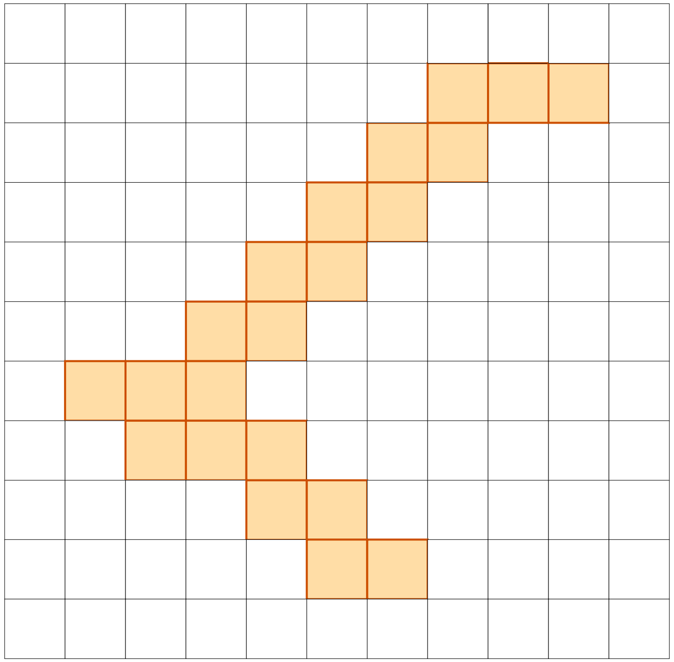
  b) Algorithms to fit the trajectory of single-particle objects.

  c) Algorithms to understand the activity at the vertex of neutrino interactions.



Approach

a) Hit identification.
b) Particle trajectory fitting.
c) Vertex activity fitting.



Approach

a) **Hit identification.**
b) Particle trajectory fitting.
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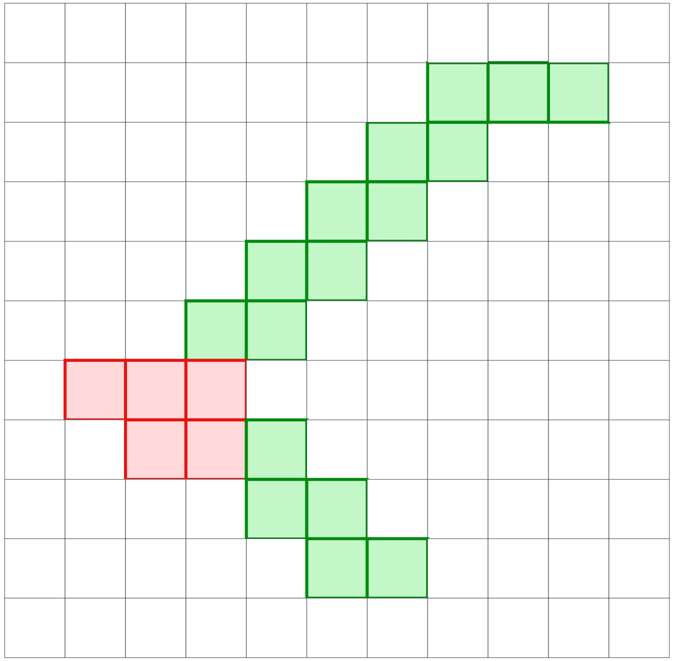
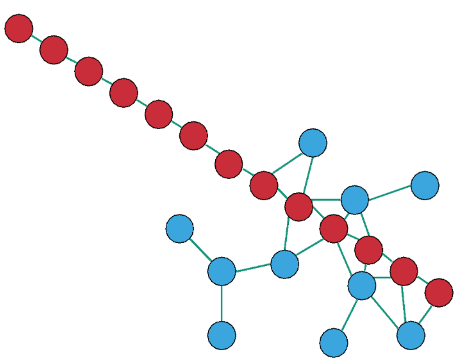


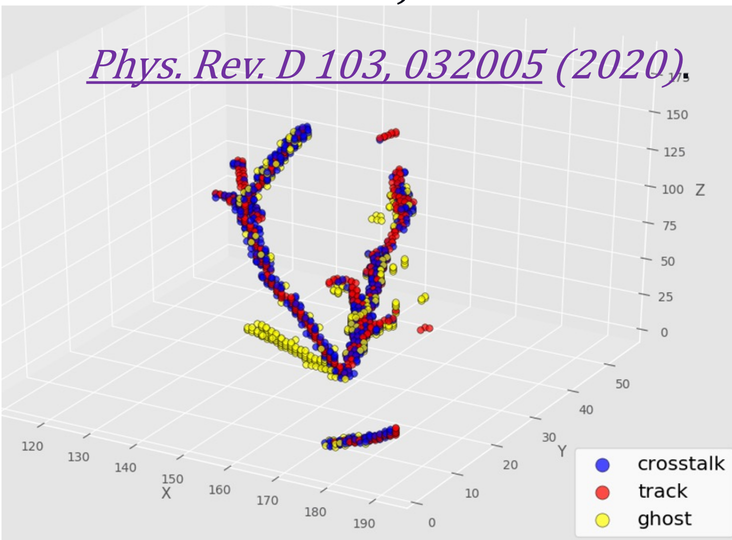
Hit identification: noise and ambiguity rejection

- Non-physical voxels appear due to a lack of information during the 2D to 3D reconstruction, called ghost voxels.
- Cubes with a real deposition but where no track has passed through it, called crosstalk voxels.
- Approach: use Graph Neural Networks (GNNs) to identify those voxels:
  - Example of variables representing each hit: number of photoelectrons deposited in each plane, multiplicity in each plane, etc.
  - The algorithm chosen was GraphSAGE (*arXiv:1706.02216*).
  - In GraphSAGE, each node neighbourhood defines a computation graph (in our example, each voxel is connected to other voxels within a 1.75 cm radius).



		GENIE Training		
GENIE Testing		Track	xTalk	Ghost
	Efficiency	94%	94%	88%
	Purity	96%	91%	92%
Pgun* Testing		Track	xTalk	Ghost
	Efficiency	95%	94%	85%
	Purity	98%	89%	92%

Phys. Rev. D 103, 032005 (2020).



Hit identification: single vs multi-particle hits

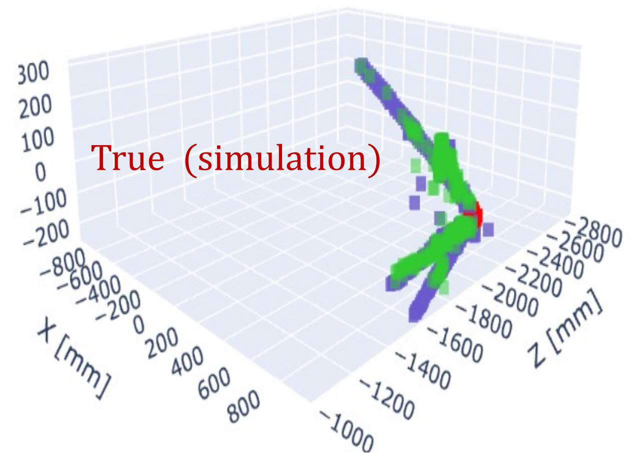
- Classify each individual hit as:
  - **Single-particle hit**: only one particle passes through the hit cube.
  - **Multiple-particle hit**: at least two different particles pass through the hit cube.
  - **Other**: crosstalk or ghost.

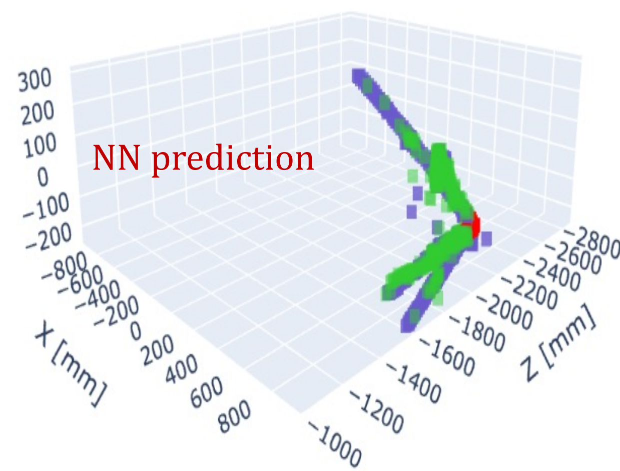
- Using a submanifold sparse U-Net-based neural network architecture (https://arxiv.org/abs/1706.01307).
  - More computationally efficient than standard CNNs.

- Efficiencies:

	True multi-particle	True single-particle	True other
Pred. multi-particle	**0.7777**	0.1511	0.0711
Pred. single-particle	0.0055	**0.9654**	0.0291
Pred. other	0.0079	0.0479	**0.9442**

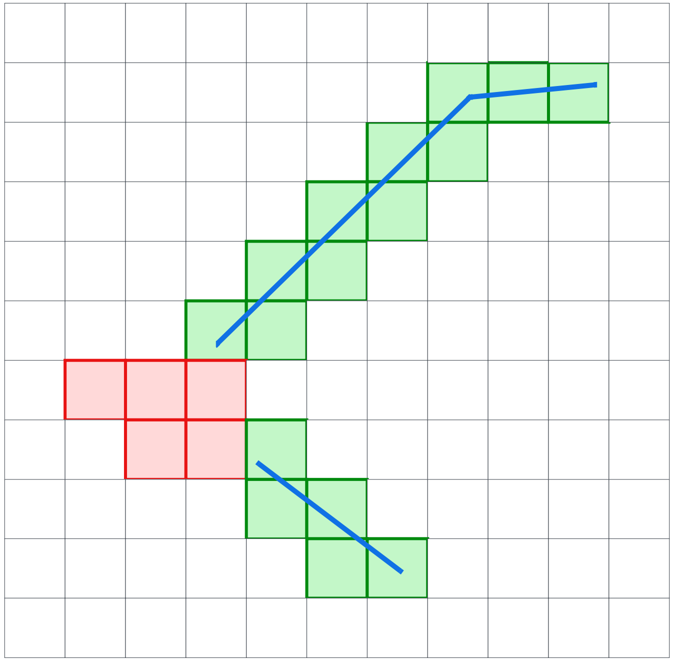
- Excellent single-particle isolation accuracy allows running a further NN-based track trajectory fitting on single particles, relying on detailed MC simulations of single particles.





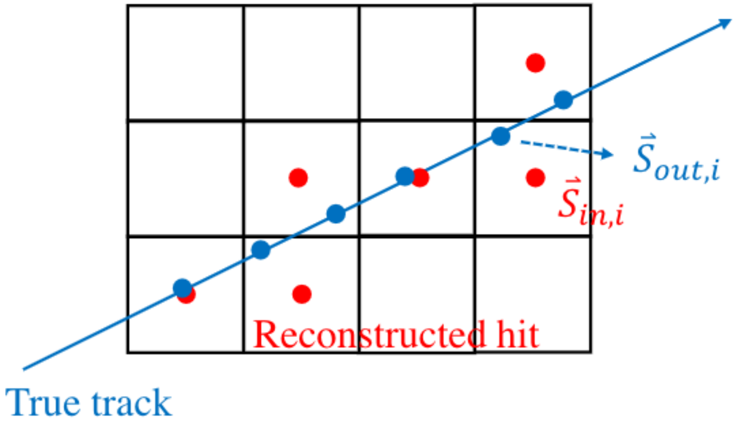
Approach

a) Hit identification.
b) Particle trajectory fitting.
c) Vertex activity fitting.



Fitting of the particle trajectory

- The next step is to predict the trajectory of particles based on single-particle hit information.
- For each state, we consider the 3D position and energy deposition of the hit.

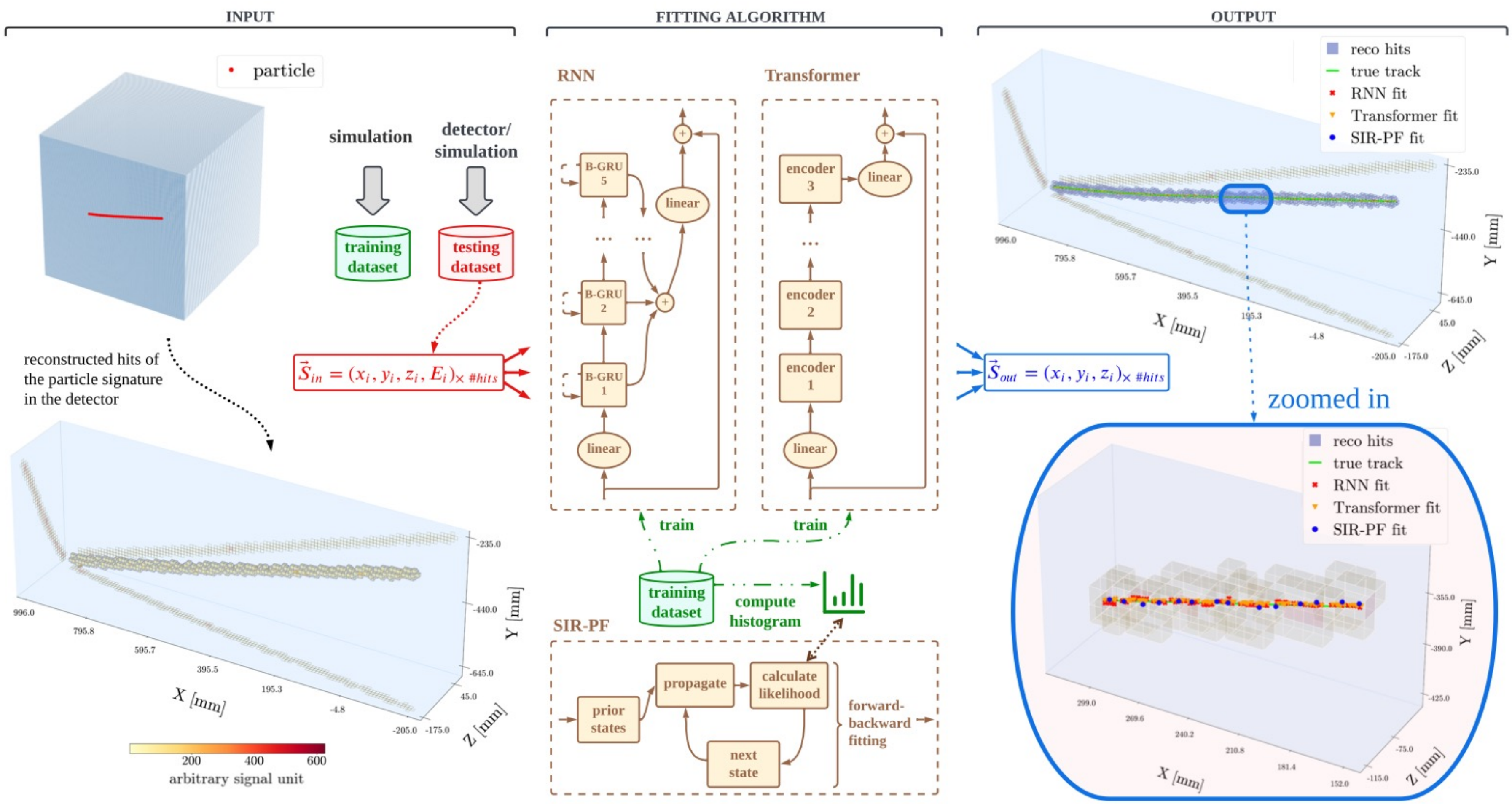


- Input hit state: $\vec{S}_{in,i} = (x_i, y_i, z_i, E_i), i = 1, \cdots, N$.
- Output node state: $\vec{S}_{out,i} = (x_i, y_i, z_i, E_i), i = 1, \cdots, N$.
- Use neural network to construct the map:

$$\{\vec{S}_{in,i}\} \rightarrow \{\vec{S}_{out,i}\}$$

- Implemented a recurrent neural network (RNN), a Transformer (encoder), and a sequential-importance-resampling particle filter (SIR-PF).
  - We treat each particle as a sequence of hits, benefiting from the success of RNN and Transformer in Natural Language Processing (NLP).

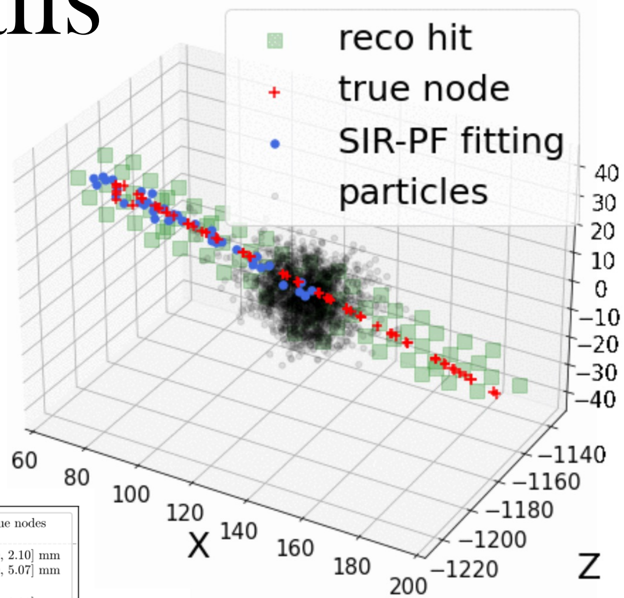
Workflow

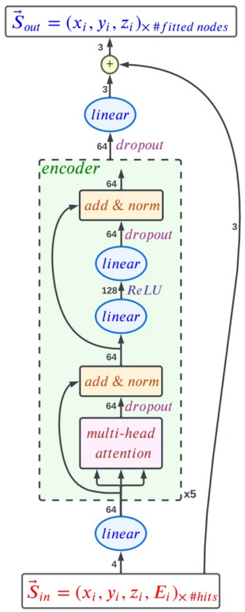


INPUT
FITTING ALGORITHM
OUTPUT
particle
simulation
detector/ simulation
training dataset
testing dataset
reconstructed hits of the particle signature in the detector
$\vec{S}_{in} = (x_i, y_i, z_i, E_i)_{\times \#hits}$
X [mm]
Y [mm]
Z [mm]
arbitrary signal unit
RNN
Transformer
B-GRU 5
B-GRU 2
B-GRU 1
linear
encoder 3
encoder 2
encoder 1
train
training dataset
compute histogram
SIR-PF
prior states
propagate
calculate likelihood
next state
forward-backward fitting
$\vec{S}_{out} = (x_i, y_i, z_i)_{\times \#hits}$
reco hits
true track
RNN fit
Transformer fit
SIR-PF fit
zoomed in

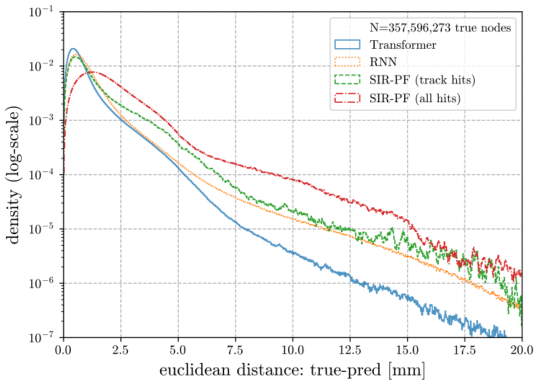
Details

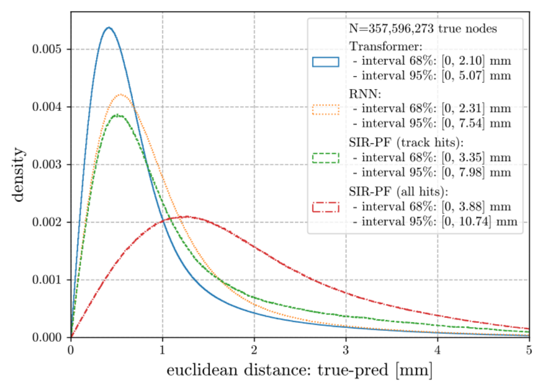
- Each algorithm outputs the fitted 3D trajectory point for each input hit.
  - SIR-PF: first reconstructed hit used as prior (average of forward and backward filterings), sample propagation through the following 15 hits. The likelihood relies on a precomputed 5-dimensional histogram.
  - RNN: five bi-directional GRU layers, 50 hidden units each.
  - Transformer: 5 encoder layers, 8 heads, hidden size of 64.



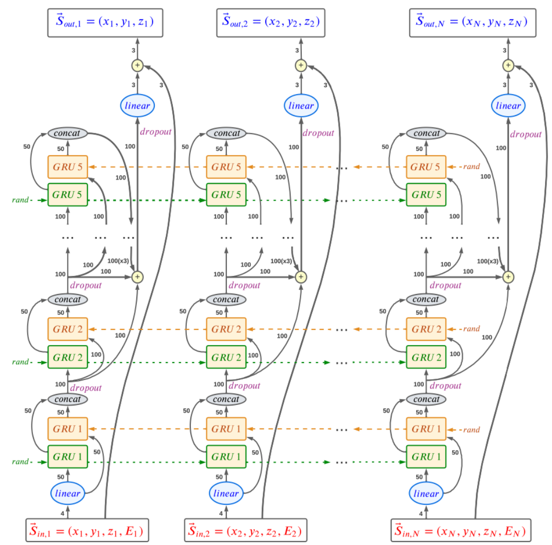


- Main results ([Commun. Phys 6, 119 (2023)]()):





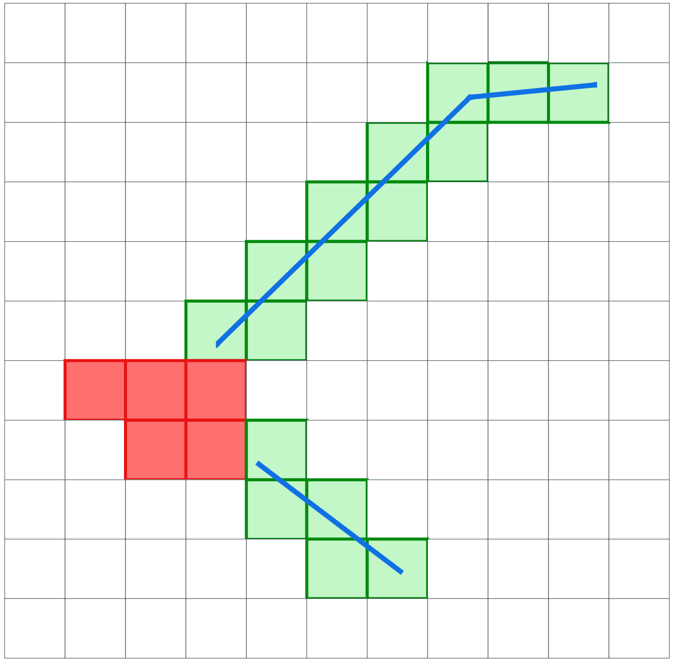
>30% better transformer resolution compared to the SIR-PF



- The improved trajectory fitting significantly improves the charge reconstruction, PID by range, and momentum by curvature.

Approach

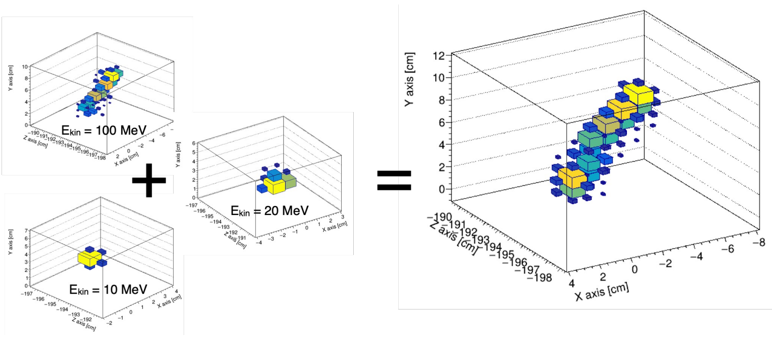
a) Hit identification.
b) Particle trajectory fitting.
c) Vertex activity fitting.



Vertex activity: standard fitting method

- Vertex activity (VA): particles releasing their energy in the proximity of the neutrino interaction vertex but that do not show visible tracks from where the kinematics can be reconstructed.
  - A “blob” of scintillation light is observed.

- Standard VA fitting method:
  - Goal: build the neutrino VA in forward folding from the sum of single particle reconstructed objects.
    - Particle information to reconstruct: # of particles (mostly protons), energy, direction, vertex position.
  - Method: likelihood fitting.
    1. Simulating any possible combination of the VA parameters and build VA.
    2. Finding the VA 3D image (e.g. SFGD hits) that “best fits” the data and find the “best-fit” parameters.

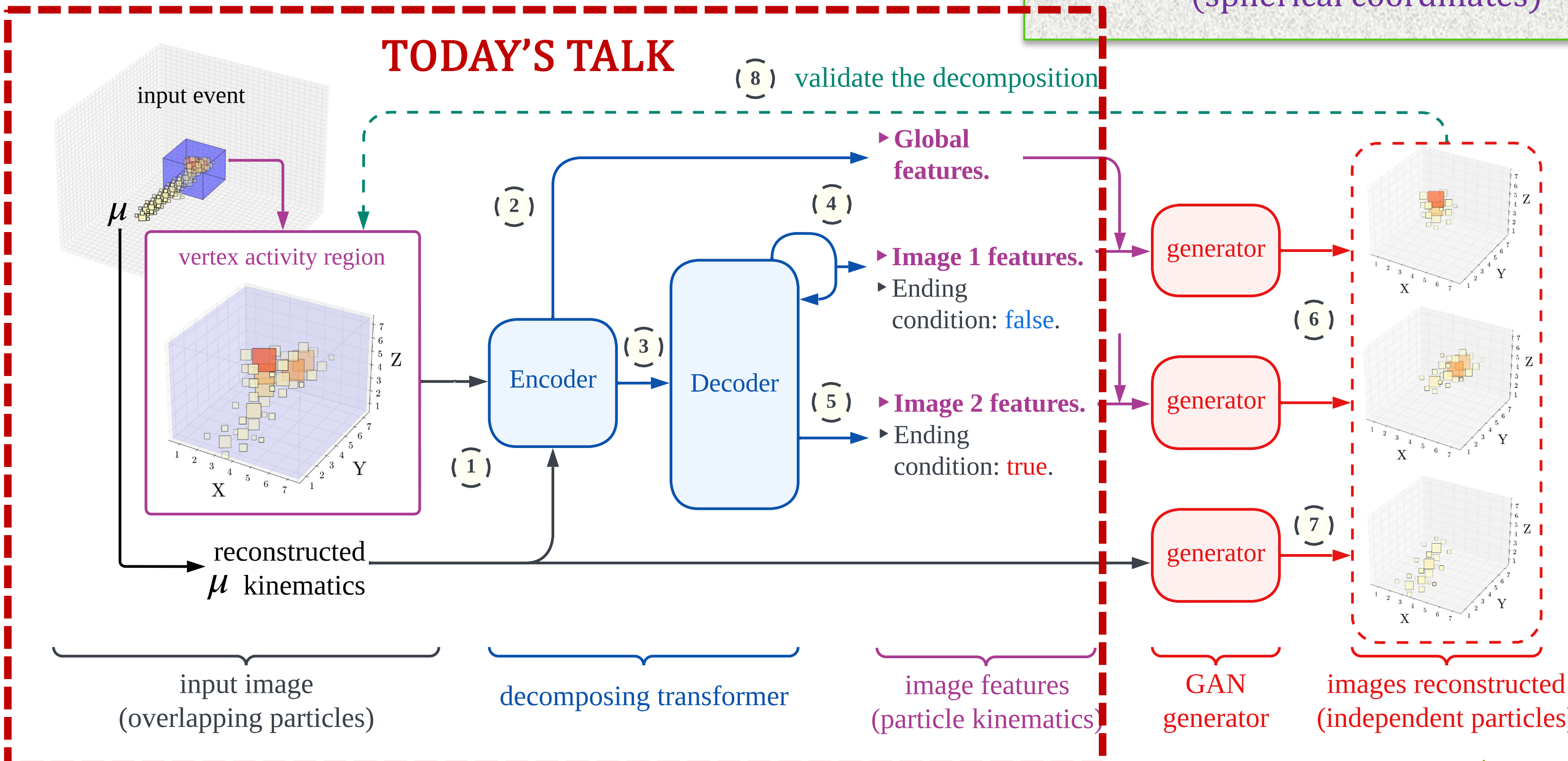


- The fitting method is highly computationally expensive.
  - Requires a large number of combinations of parameters to be simulated.
  - Unfeasible in practice.

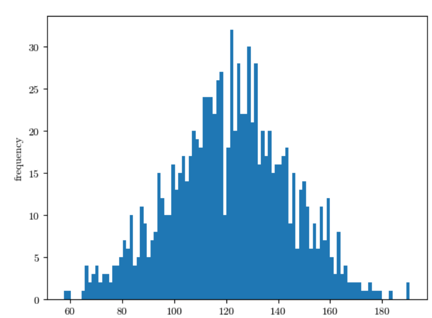
- Advantages:
  - Studying systematics directly from single-particle data (e.g., beam test)
  - Allowing to set confidence intervals on the fitted VA parameters.

Alternative: deep-learning approach

- Transformer output:
  - Vertex x, y, z position.
  - Kinetic energy of each particle.
  - Direction of each particle (spherical coordinates)



Select the combination that minimises/maximises a target metric (WORK IN PROGRESS)

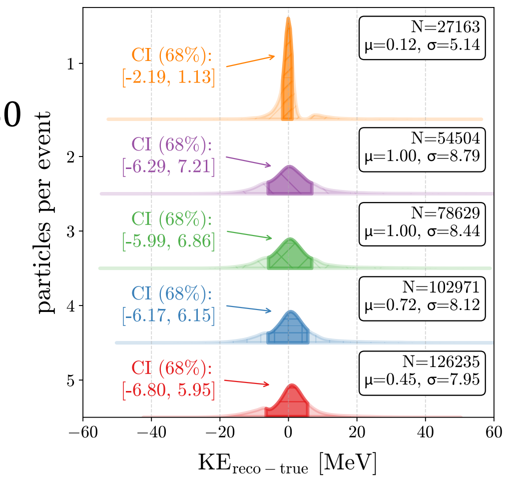


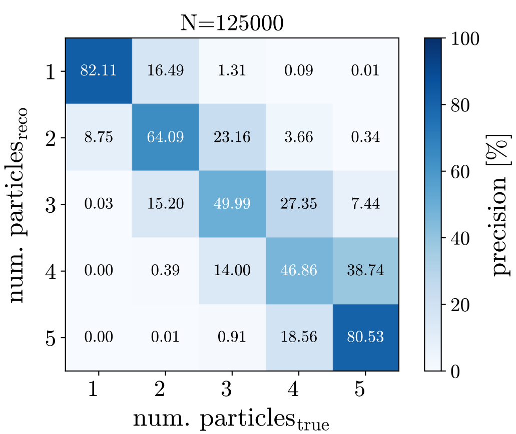
run the GAN multiple times per particle

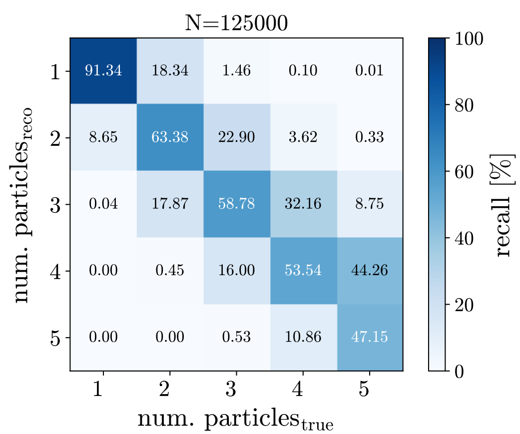
VA fitting transformer results (I)

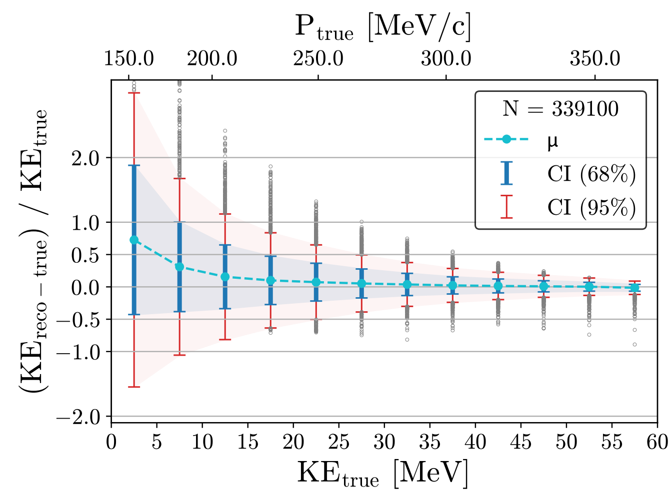
- Number of protons:
  - Testing on events with 1-5 protons.
  - The algorithm predicts the correct number of particles in each event with ~65% acc.
  - It predicts the correct number of particles with 98% acc. assuming an error of ± 1 particle.
  - Missed protons have on average a KE ≤ 10 MeV.

- Kinetic energy:
  - Testing events with protons of a KE up to 60 MeV (uniform distribution).
  - Better resolution for high-energy events.
  - Standard deviation ~7 MeV on average (resolution ~11%).



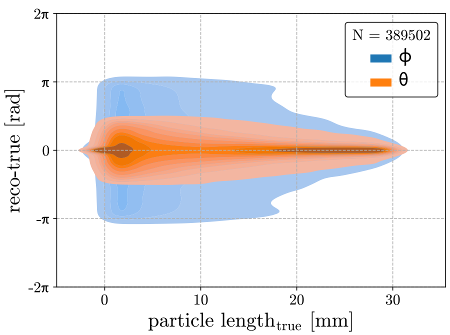


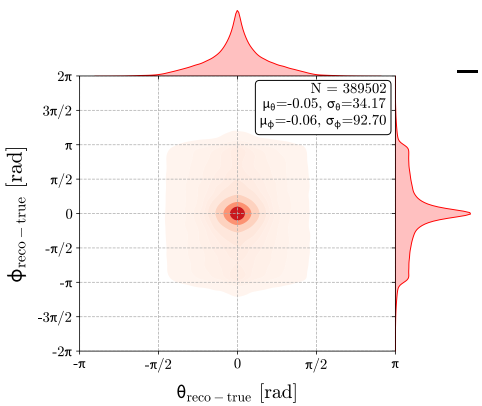




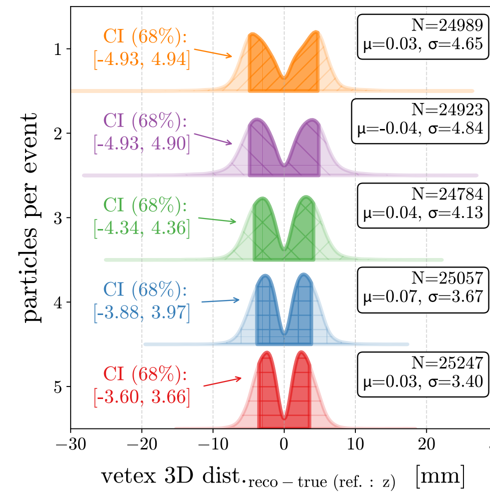
VA fitting transformer results (II)

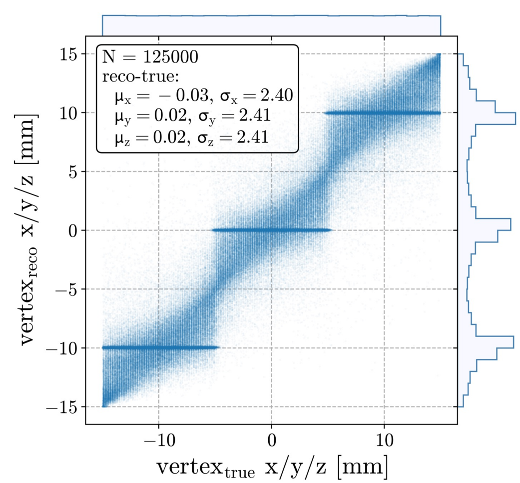
- Direction (in spherical coordinates):
  - Isotropic testing events.
  - Symmetric results for both θ and Φ.
  - Better results for longer particles (as expected).





- Vertex position:
  - Testing protons starting randomly within a 3x3x3 cube area.
  - Always guessing the right cube (>98% of the cases).
  - 3D average distance between true and reco vertex of ~4 mm (~2.4 mm per coordinate).





- The GAN-based fitting allows us to improve the reconstructed kinematics (e.g., 11% KE resolution improvement).
  - Work in progress!

Summary

- Deep learning could be a key tool for event reconstruction in voxelised detectors.
  - In particular, in detectors that provide fine details of the interaction but are hard to analyse using traditional methods.

- Successful application to different problems, such as:
  - Hit identification.
  - Track fitting.
  - Vertex activity understanding.

- The developed strategy allows us to attack the problem of systematic uncertainties and use the details of MC detector simulations more confidently.

- Future work requires an extensive validation of the methods and application to experimental data.

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