

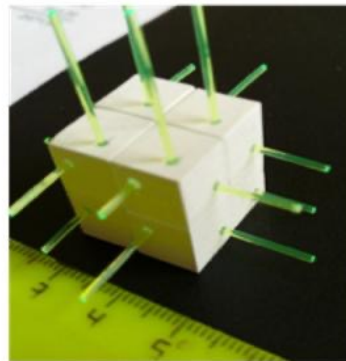
DEEP LEARNING METHODS FOR NEUTRINO EVENT RECONSTRUCTION

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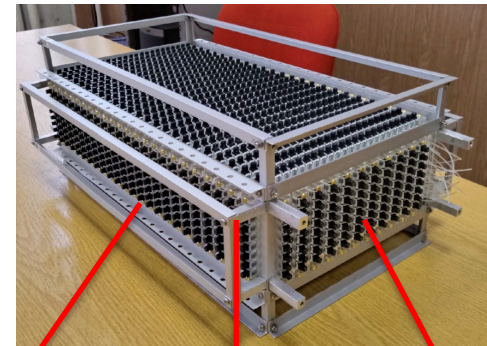
Joint Annual Meeting of the
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7 September 2023

The physics case

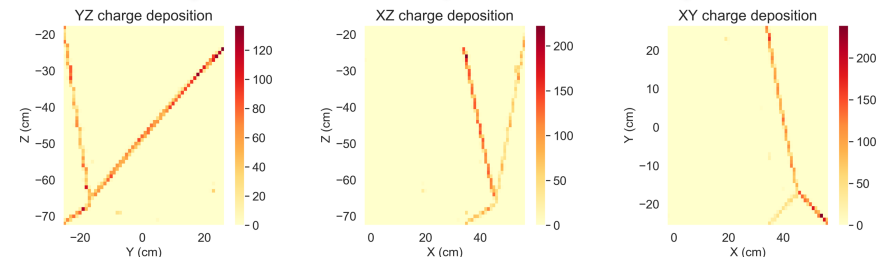
- Goal: develop an **analysis strategy** that **does not depend on the neutrino interaction model** for 3D granularity detectors.
- Case study: a detector concept **analogous** to the **SuperFGD detector from the T2K experiment**.
 - Part of the upgrade of the near detector (ND280) of the T2K experiment in Japan.
 - Full-active fine-grained scintillator (FGD) with three views.
 - 2M optically independent cubes, 1 cm³ per cube.
 - Spatial localization of scintillation light.



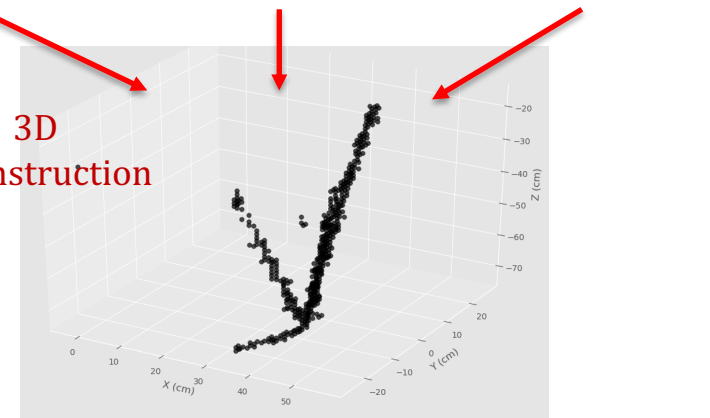
JINST 13 (2018) 02, P02006
NIM A936 (2019) 136-138



2D
projections

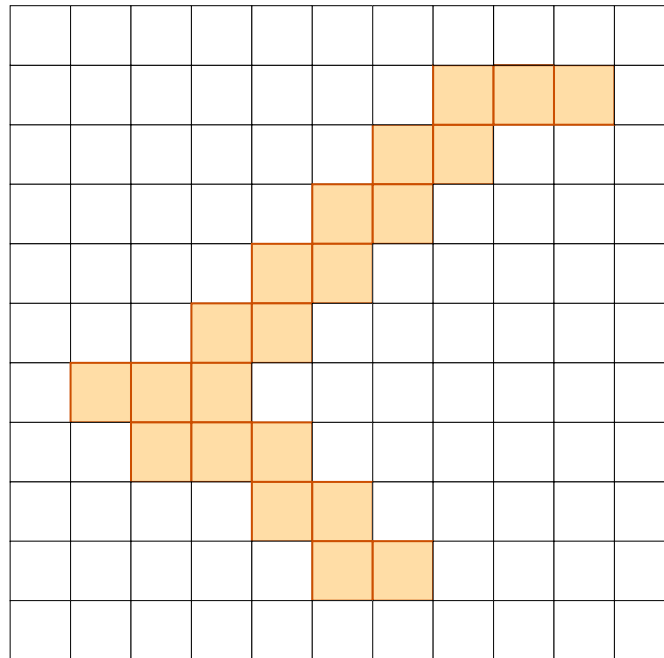


3D
reconstruction



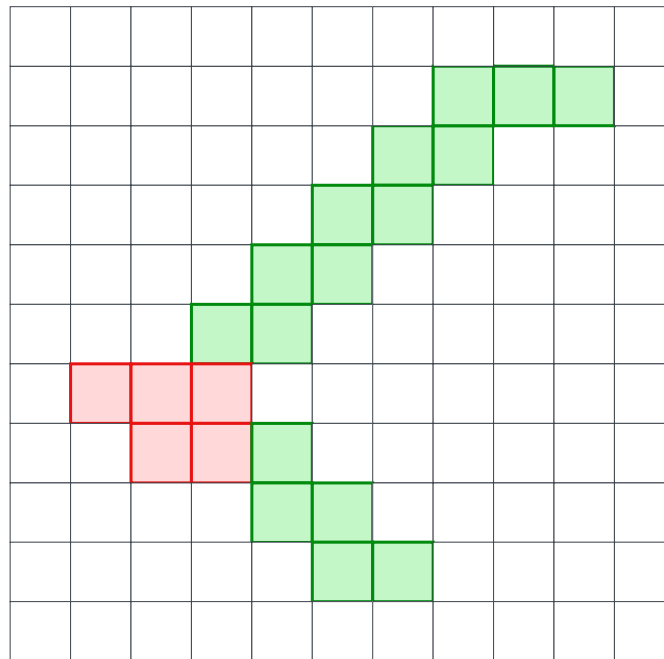
Reconstruction approach

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



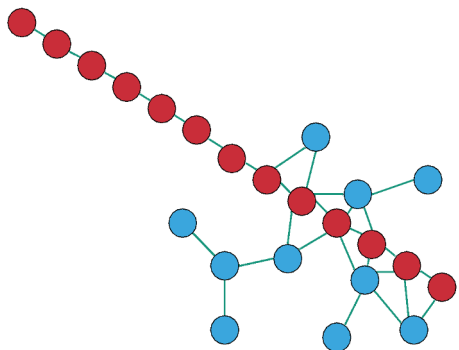
Reconstruction approach

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

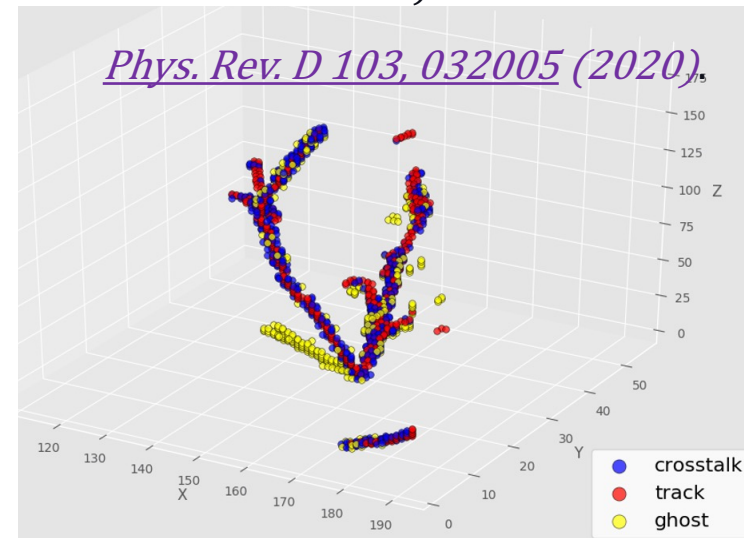


Hit identification: noise and ambiguity rejection

- **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](https://arxiv.org/abs/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).

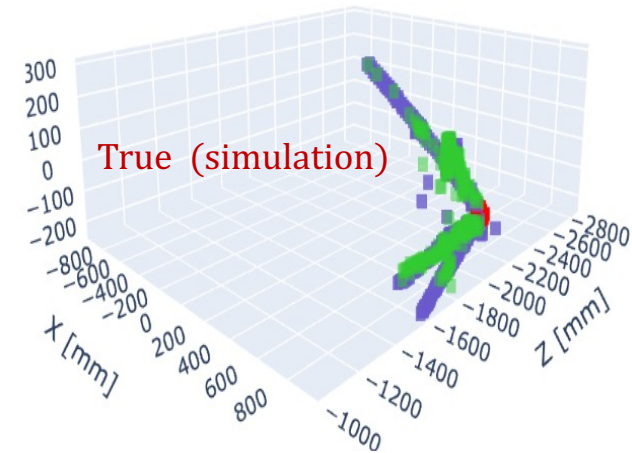


		GENIE Training		
		Track	xTalk	Ghost
GENIE Testing	Efficiency	94%	94%	88%
	Purity	96%	91%	92%
Pgun* Testing	Efficiency	95%	94%	85%
	Purity	98%	89%	92%



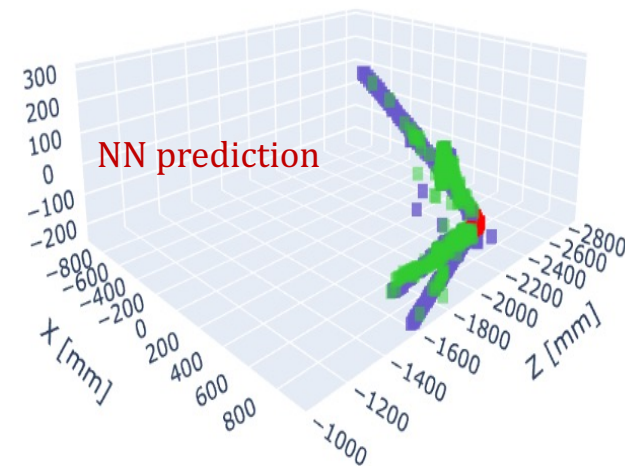
Hit identification: single vs multi-particle hits

- 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:

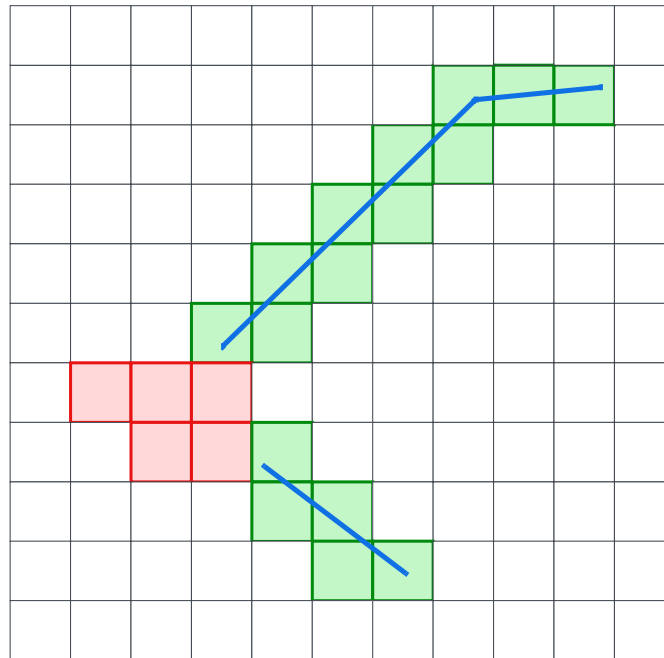
	True multi-particle	True single-particle	True other
Pred. multi-particle	0.7777	0.1511	0.0711
Pred. single-particle	0.0055	0.9654	0.0291
Pred. other	0.0079	0.0479	0.9442



- 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.

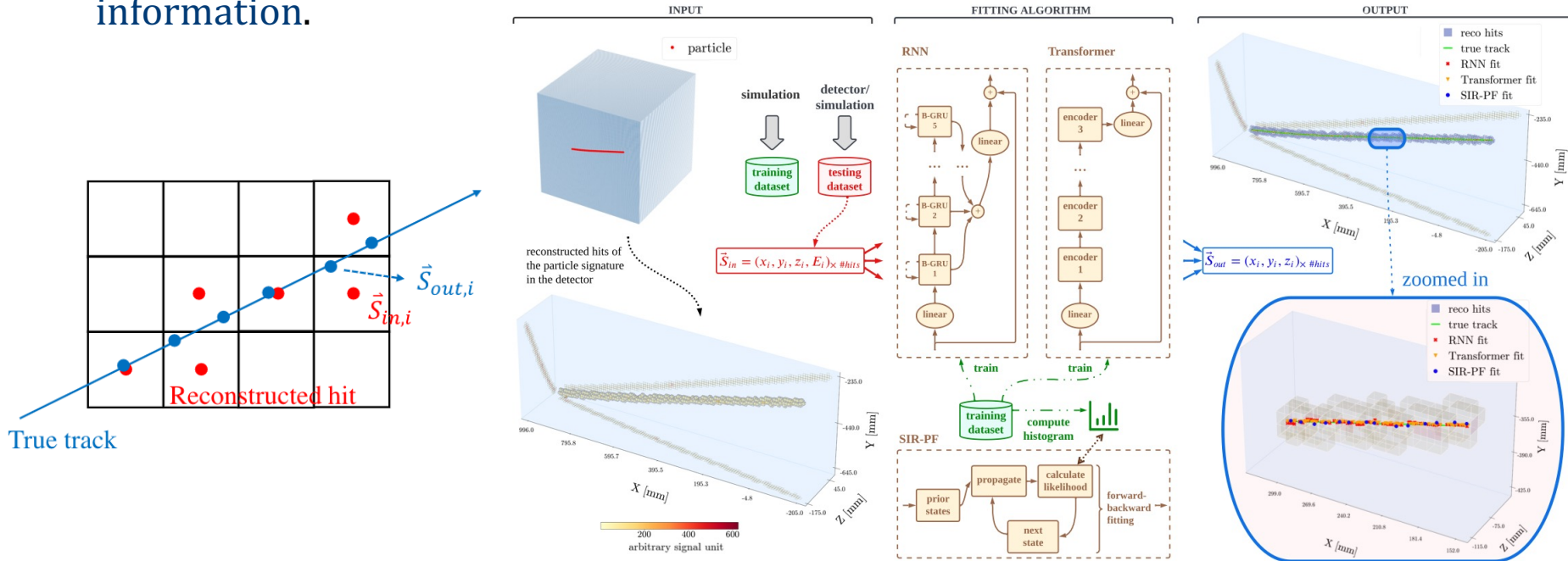
Reconstruction approach

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



Fitting of the particle trajectory

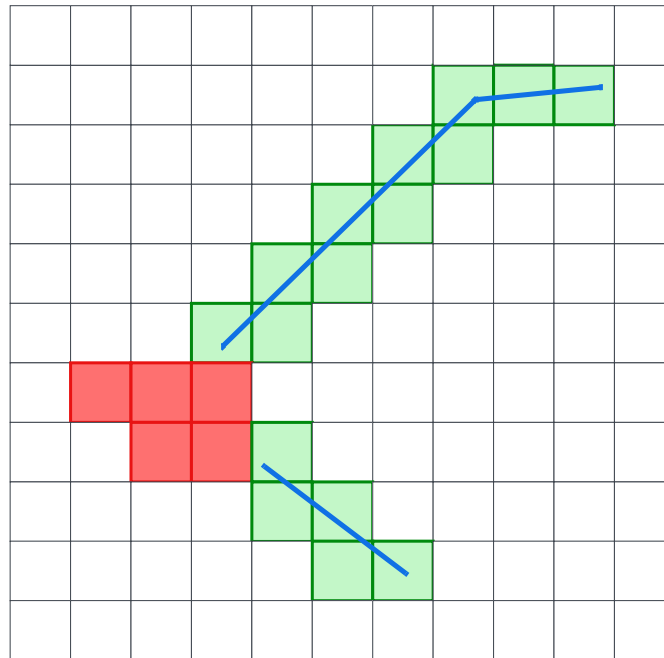
- The next step is to **predict the trajectory of particles** based on single-particle hit information.



- 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).

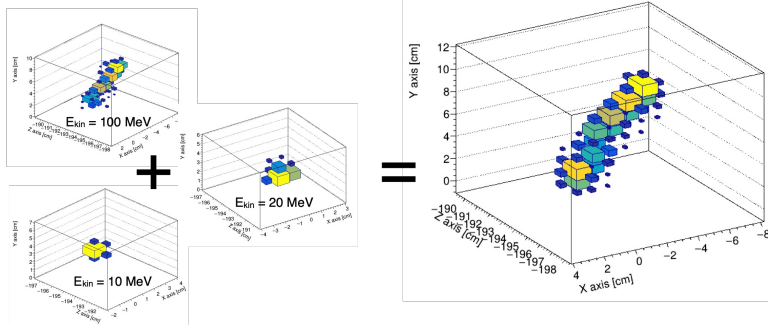
Reconstruction approach

- 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.

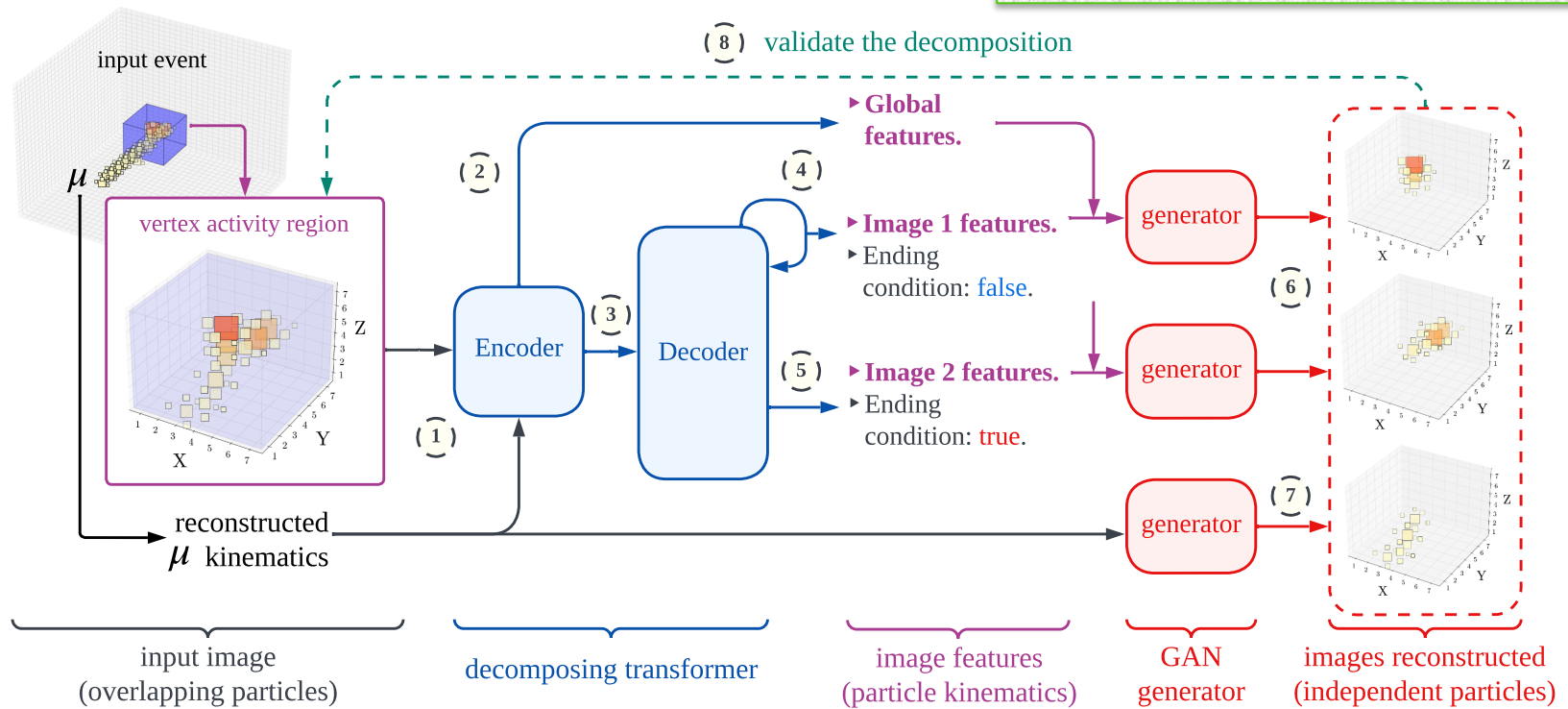


- The fitting method is **highly computationally expensive**.
 - Requires a large number of combinations of parameters to be simulated.
 - **Unfeasible in practice.**

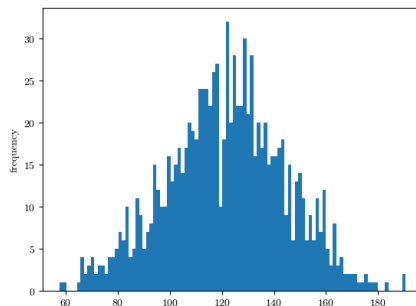
- **Advantages:**
 - Studying systematics directly from single-particle data (e.g., beam test)
 - Allowing to set confidence intervals on the fitted VA parameters.

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

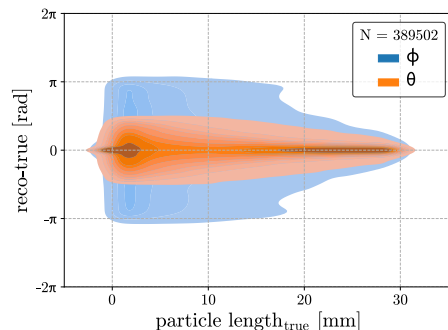
VA fitting transformer results

- **Number of protons:**

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

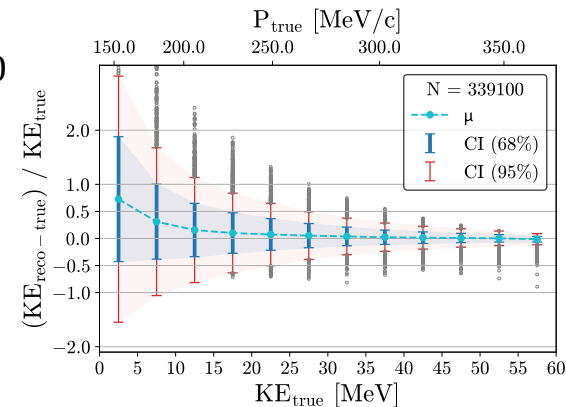
- **Direction (in spherical coordinates):**

- Isotropic testing events.
- Symmetric results for both θ and Φ .
- Better results for longer particles (as expected).



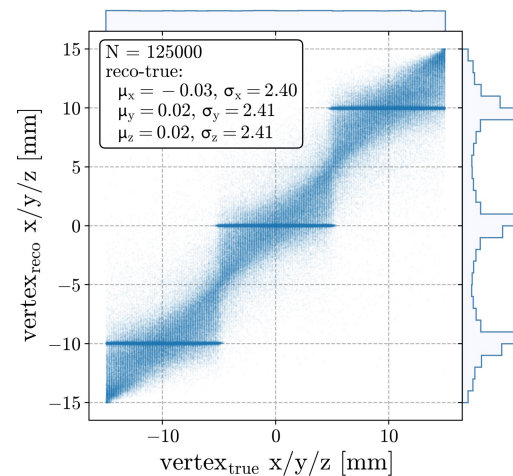
- **Kinetic energy:**

- 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 $\sim 11\%$).



- **Vertex position:**

- Testing protons starting randomly within a $3 \times 3 \times 3$ 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).



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**.

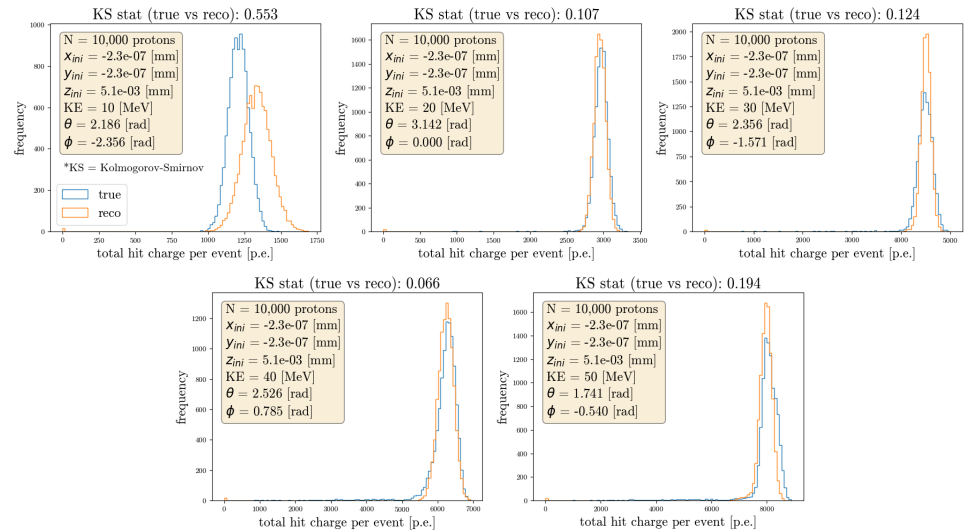
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Validating the GAN generator

- Five distinct batches of samples, each with fixed initial physics parameters.
 - 10K protons each.
- We generated five batches of protons with the NN using the same physics parameters.
 - 10K protons each too.
- Allows us to understand whether the network is catching the stochasticity of the simulation.



XY charge projection

	Number of protons	Initial KE [MeV]	Initial position [cm]	θ [rad]	ϕ [rad]
Testing sample 1	10K	10	$\begin{pmatrix} -2.3e^{-7} \\ -2.3e^{-7} \\ -5.1e^{-3} \end{pmatrix}$	2.186	-2.356
Testing sample 2	10K	20	$\begin{pmatrix} -2.3e^{-7} \\ -2.3e^{-7} \\ -5.1e^{-3} \end{pmatrix}$	3.142	0.000
Testing sample 3	10K	30	$\begin{pmatrix} -2.3e^{-7} \\ -2.3e^{-7} \\ -5.1e^{-3} \end{pmatrix}$	2.356	-1.571
Testing sample 4	10K	40	$\begin{pmatrix} -2.3e^{-7} \\ -2.3e^{-7} \\ -5.1e^{-3} \end{pmatrix}$	2.526	0.785
Testing sample 5	10K	50	$\begin{pmatrix} -2.3e^{-7} \\ -2.3e^{-7} \\ -5.1e^{-3} \end{pmatrix}$	1.741	-0.540

