Improving Tracking Performance with Cluster Counting in Drift Chambers

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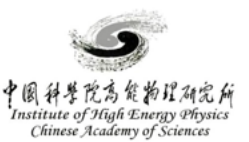
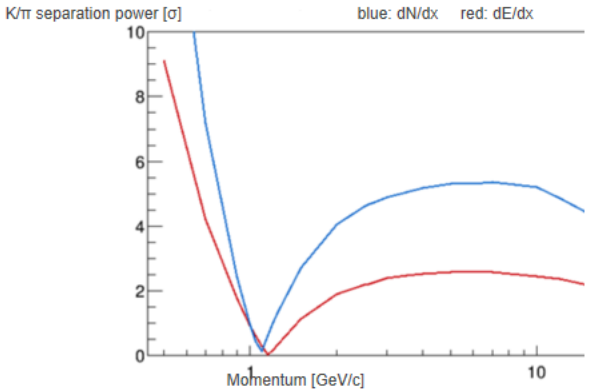


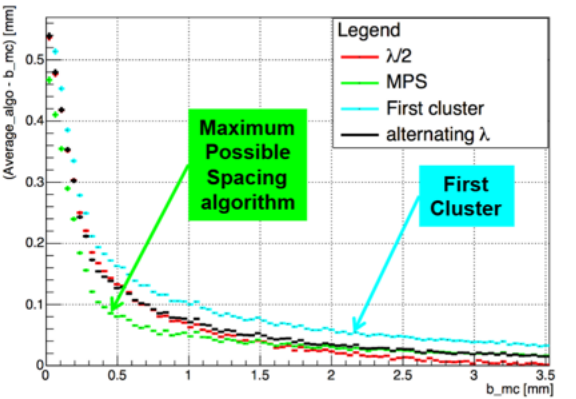
From cluster counting (dN/dx) for PID to its tracking potential

dN/dx improves PID and provides timing information



G. Zhao's study:
dN/dx gives stronger K/π separation than dE/dx across the 2–20 GeV/c range

Earlier simulations demonstrate the potential of cluster timing to improve position measurements

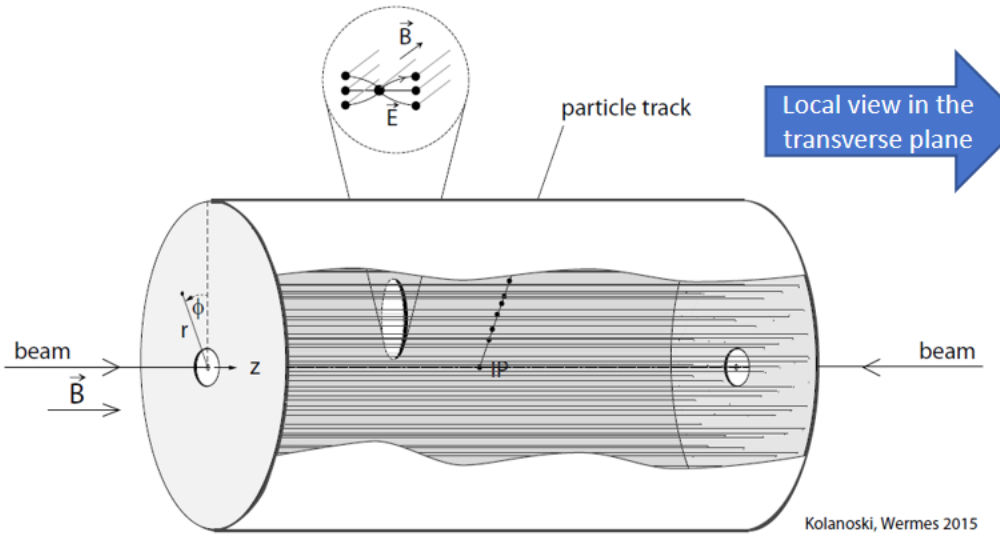


Simulations presented by F. Grancagnolo:
About 20% better average single-hit resolution for a 1 cm He/isobutane cell.

This work explores how to exploit the additional timing information to improve drift-distance reconstruction and tracking performance.

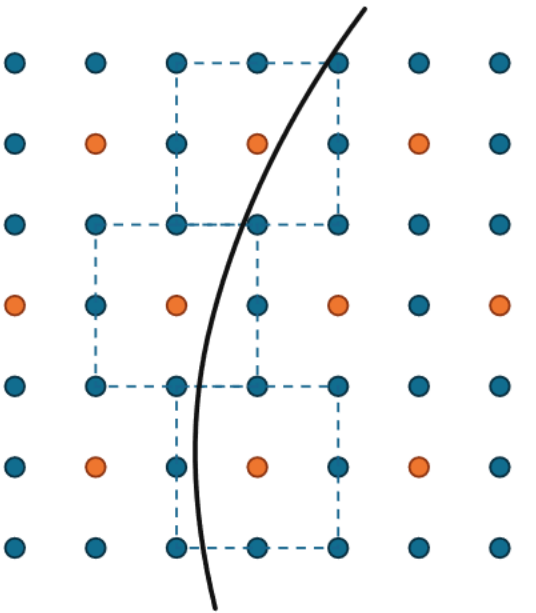
Sources: G. Zhao, CHEP 2024, slide 8; F. Grancagnolo, HKIAS 2022, slide 13.

Track measurement in a drift chamber

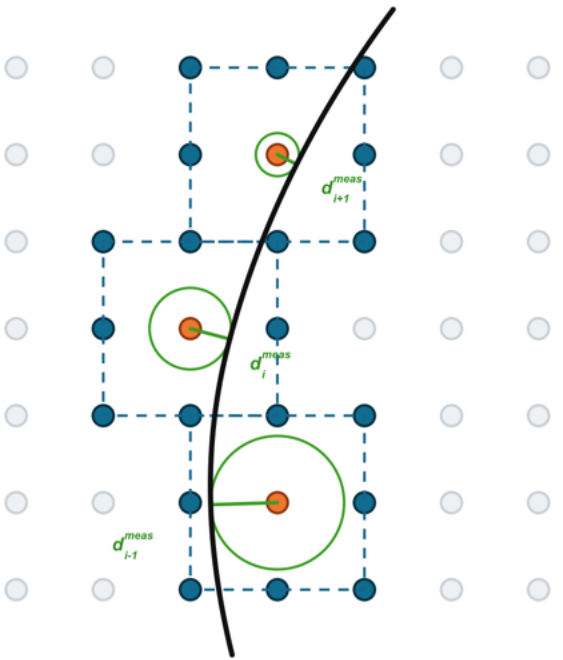


A track passing through the DC

Local view in the transverse plane



Track fitting



Measured distance

$$d_i^{meas} = d(T)$$

Distance of Closest Approach (DOCA) for a candidate helix

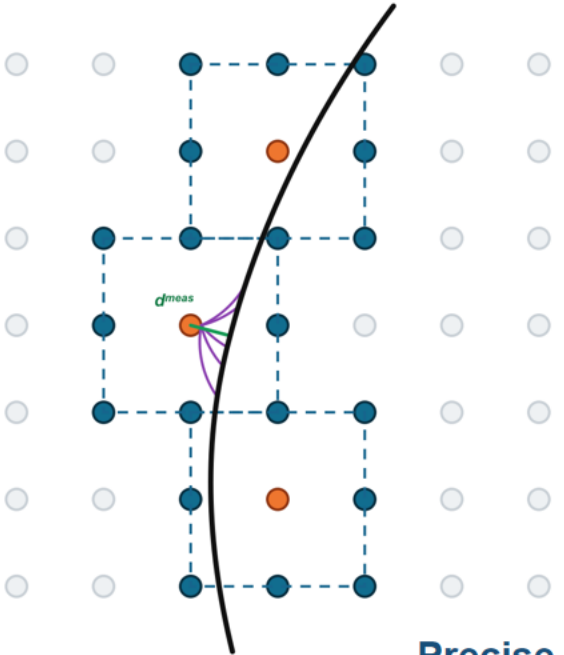
$$d_i^{DOCA} = f_i(h)$$

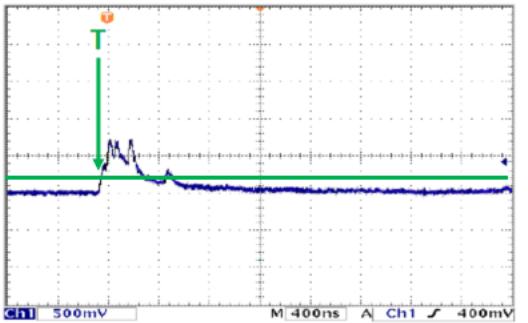
Track-fit objective

$$\chi^2 = \sum_i \frac{\left(d_i^{meas} - d_i^{DOCA}\right)^2}{\sigma_i^2}$$

Bias or resolution loss in d_i^{meas} propagates into the fitted track parameters and momentum resolution.

Conventional time measurement



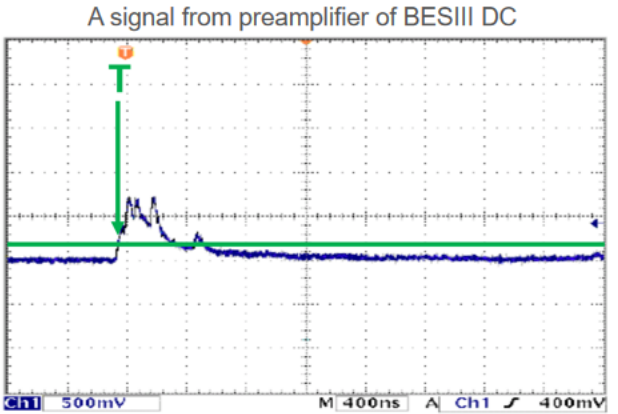


- Earliest threshold-reaching time of signal is recorded
- T is converted to drift distance d^{meas} using X-T relation
- d^{meas} is approximately the smallest distance from the sense wire to the track

Precise track fitting requires precise measurement of d^{meas}

From threshold timing to full-waveform reconstruction

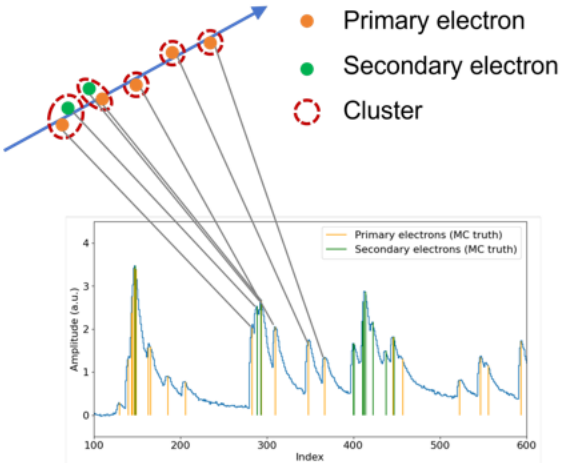
Conventional method



t_0 → X-T relation → d^{meas}

Only the earliest threshold-reaching time of the signal is used for DOCA reconstruction.

Cluster counting method

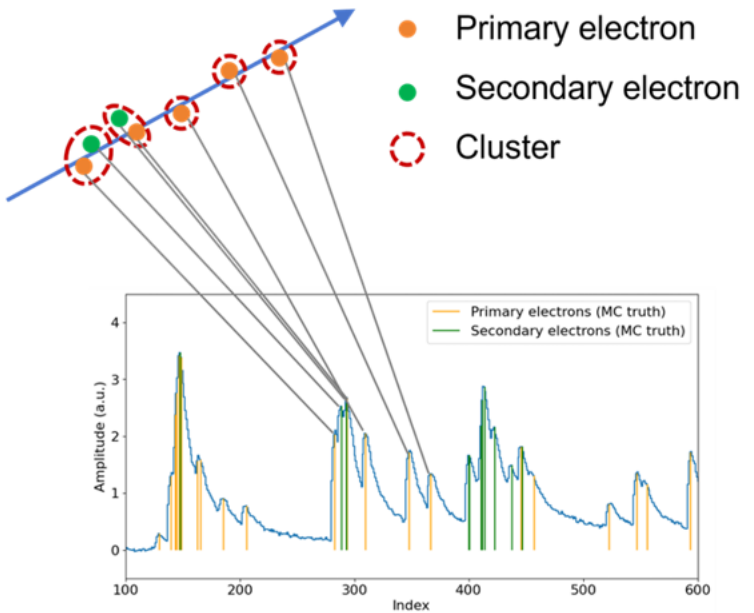


$t_0, t_1, t_2 \ldots$ → Complex relation → d^{meas}

More information is available for DOCA reconstruction.

Machine learning for cluster counting method

One signal contains many electron arrival times



Simulated waveform; colored markers indicate MC-truth electron arrivals.

More information

Use multiple arrival times t_0 , t_1 , t_2 , …

Complex relation

Their relation to the drift distance depends on the combined timing pattern.

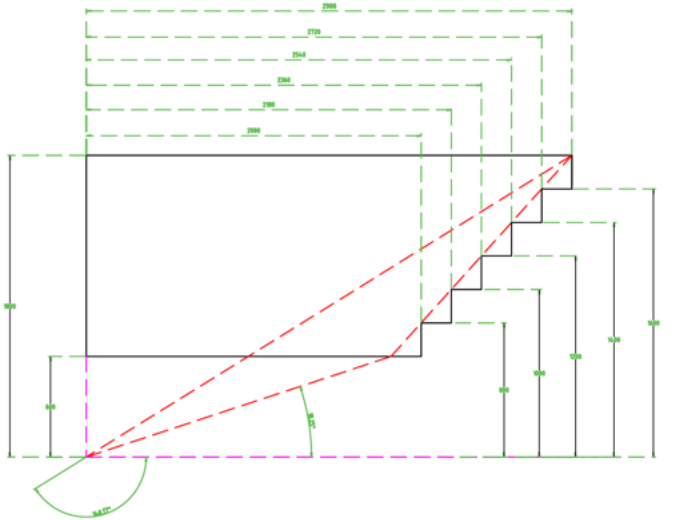
Our approach

A Transformer learns from the electron timing sequence.

The complex waveform-to-DOCA relation motivates a machine-learning reconstruction method.

CEPC drift chamber

Schematic layout of one-fourth of the CEPC drift chamber



Source: Z. Tian et al., *Nucl. Sci. Tech.* (2025), Fig. 2, https://doi.org/10.1007/s41365-025-01670-y.

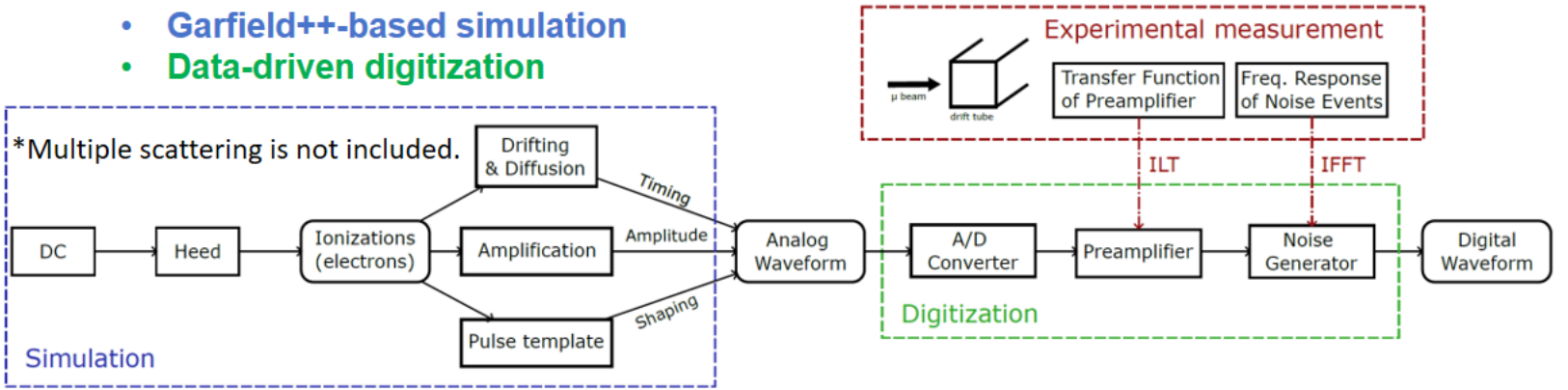
A drift chamber with cluster counting is one of the gaseous detector options

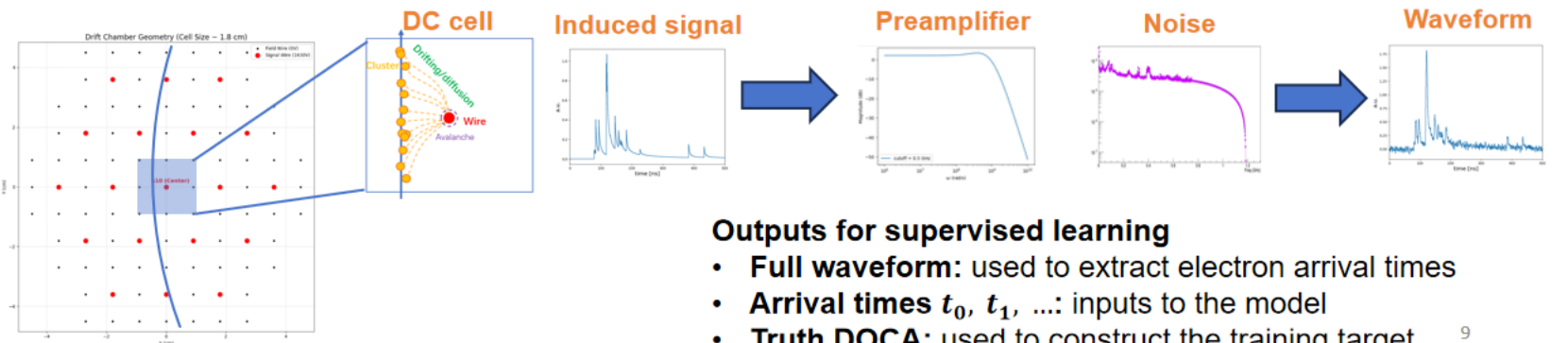
Parameters	Configuration
Gas mixture	90/10 He/iC_4H_{10}
Detector grid	50 layers × 19 columns
Cell size	1.8 cm
Magnetic field	B_z = 3.0 T

This study uses simulated data based on this CEPC drift-chamber design.

Full Simulation

- **Garfield++-based simulation**
- **Data-driven digitization**





Outputs for supervised learning

- **Full waveform:** used to extract electron arrival times
- **Arrival times t_0, t_1, ...:** inputs to the model
- **Truth DOCA:** used to construct the training target

Data samples

Particle Pion **Momentum range** 1–25 GeV/c

Model development

Training	Validation	Preliminary test
7,200	**800**	**2,000**
tracks		

Performance scan

10 fixed momentum points

2, 4, …, 20 GeV/c

10,000 events per point

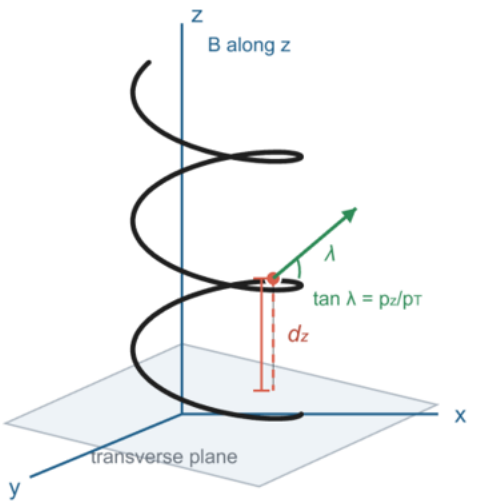
100,000 events in total

The development split supports training and preliminary checks.
Final tracking performance uses the separate fixed-momentum scan.

2D track model

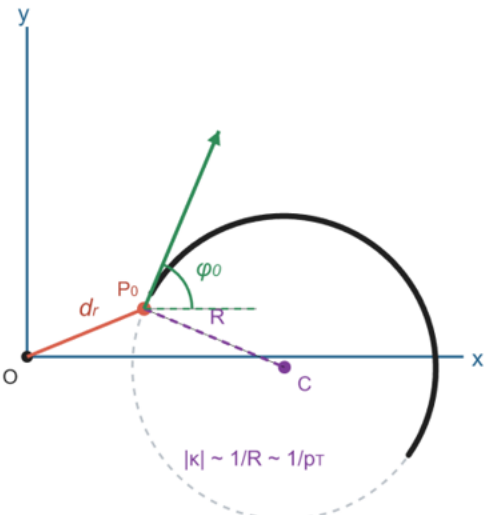
As a first step, we use a simplified 2D track model in the transverse plane.
The transverse fit retains three parameters: d_r, φ_0 and κ.

3D helical track



project onto x–y plane

2D transverse track

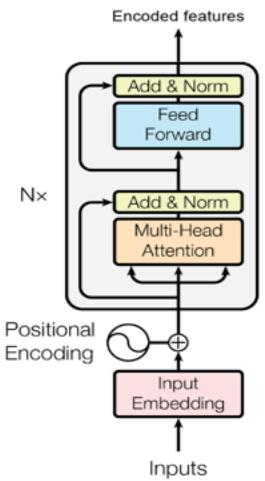


Five helix parameters
(d_r, φ_0, κ, d_z, tan λ)

Three parameters retained
(d_r, φ_0, κ)

Transformer architecture with attention pooling

Arrival-time sequence $t_0, t_1, \ldots, t_{23}$ → **Input embedding + Transformer encoder** → **Attention pooling** h_{pool} → **Concatenate** $[h_{pool}, \alpha, d_{baseline}^{meas}]$ → **Residual regression** → Δd^{pred}



The encoder learns correlations among the electron arrival times.

$$a_i = softmax(q^T h_i)$$

$$h_{pool} = \sum_i a_i h_i$$

Global inputs

Track angle α

Baseline distance $d_{baseline}^{meas}$

Predicted residual correction

$$d_{ML}^{meas} = d_{baseline}^{meas} + \Delta d^{pred}$$

Attention pooling assigns a learned weight to each valid arrival-time candidate.

Source: Adapted from Vaswani et al., *Attention Is All You Need*, NeurIPS 30 (2017), Fig. 1.

Model inputs and learning target

Model inputs

Electron arrival times

$t_0, t_1, \ldots, t_{23}$ (truth value)

Baseline drift distance

$$d_{baseline}^{meas} = d)t_0($$

Track angle

α (truth value)

Target and Loss

Residual target

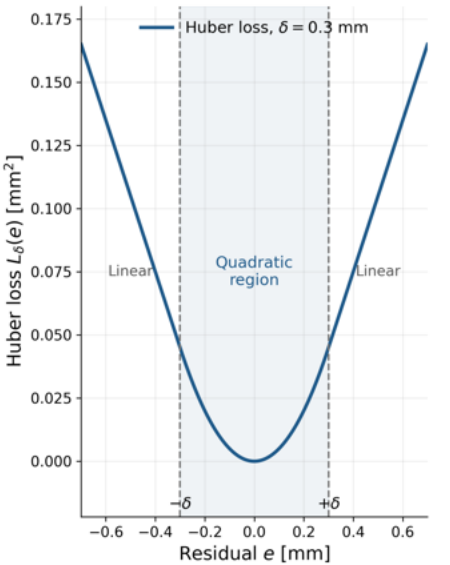
$$\Delta d = d^{DOCA} - d_{baseline}^{meas}$$

Model prediction

$$\Delta d^{pred}$$

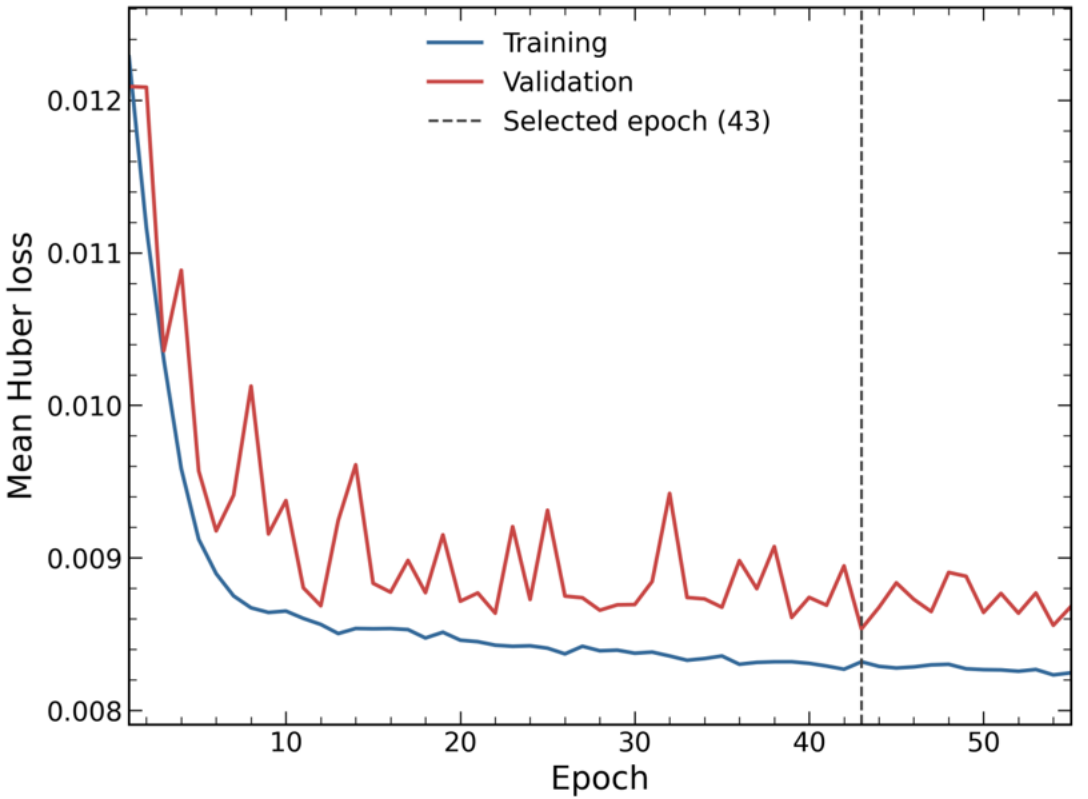
Loss function

$$\mathbf{Huber}(\Delta d^{pred} - \Delta d, \delta = 0.3\ \mathbf{mm})$$



The model learns a residual correction to the conventional X-T estimate from multiple electron arrival times.

Model training



Training setup

7,200 training tracks
800 validation tracks

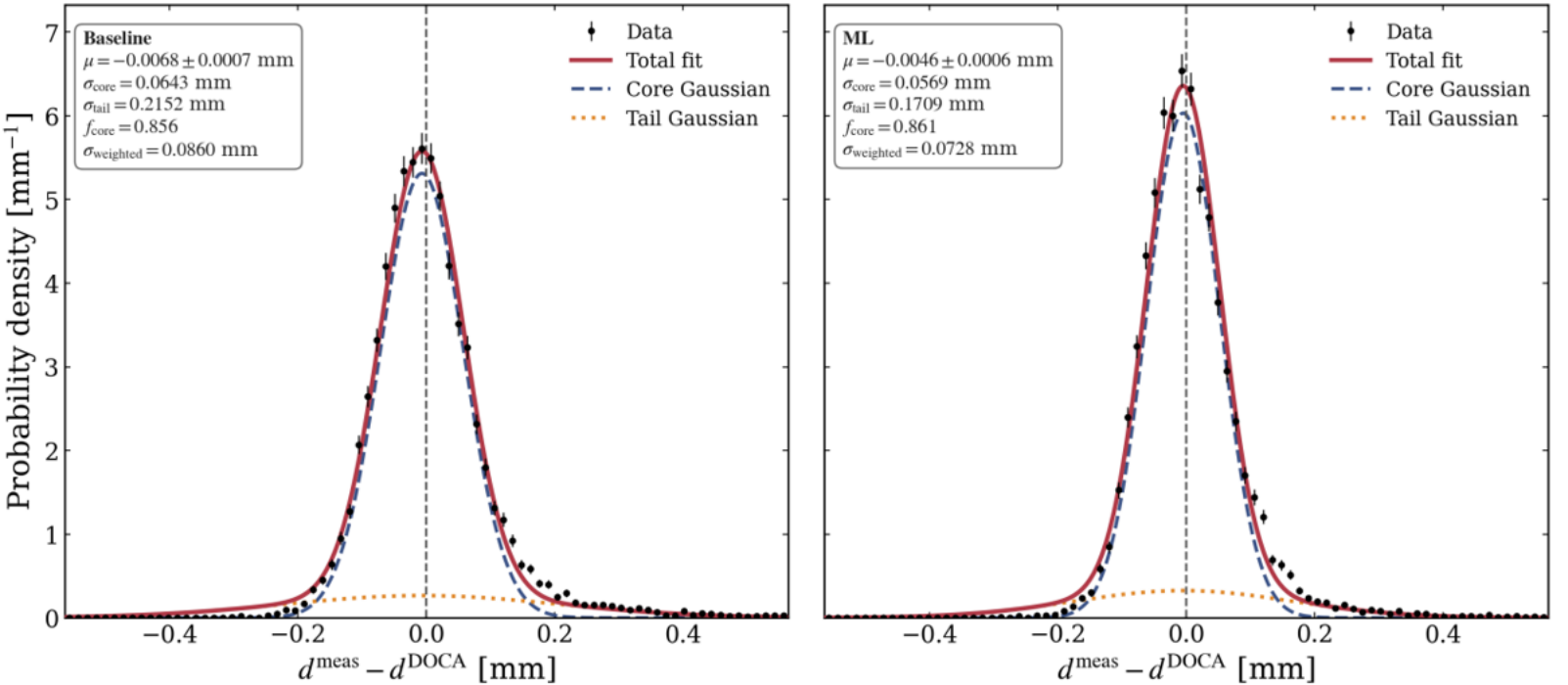
Loss

Huber loss, $\delta = 0.3$ mm

Checkpoint

Epoch 43

Drift-distance residual distribution

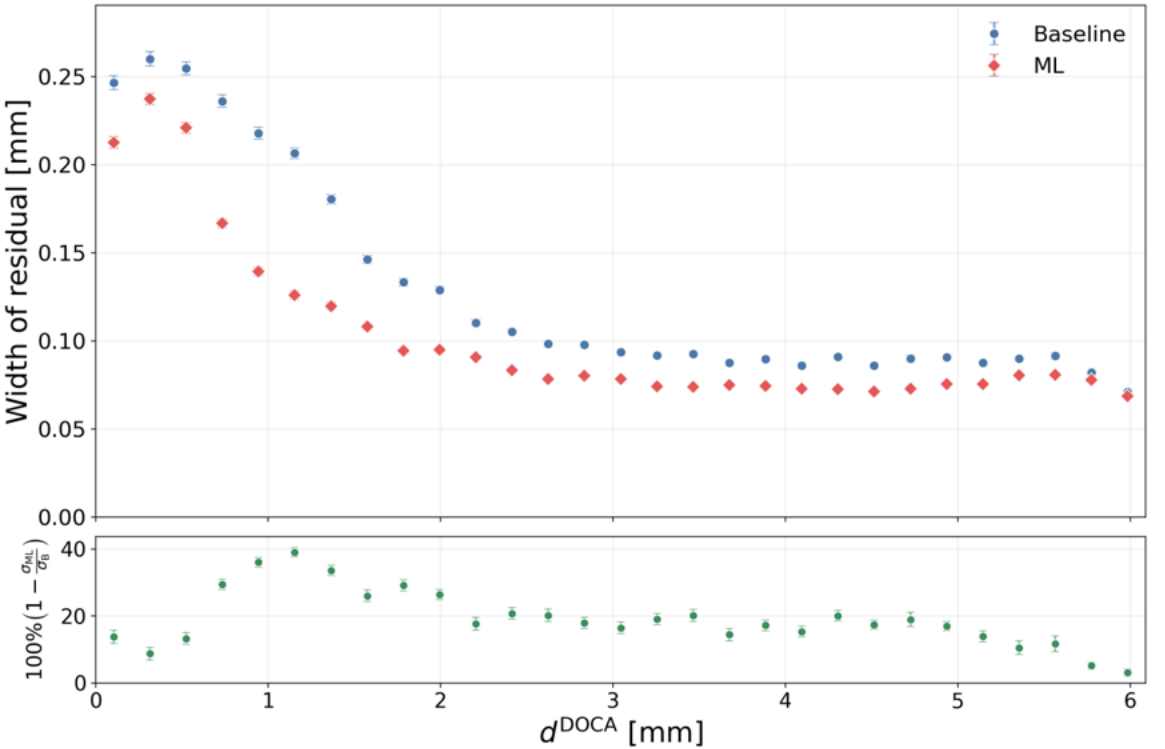


Double-Gaussian width

$$\sigma_{weighted} = f_{core}\sigma_{core} + (1 - f_{core})\sigma_{tail}$$

At $d^{DOCA} \approx 4$ mm ,weighted residual width improves from 0.0860 to 0.0728 mm (15.3%).

Improvement of spatial resolution



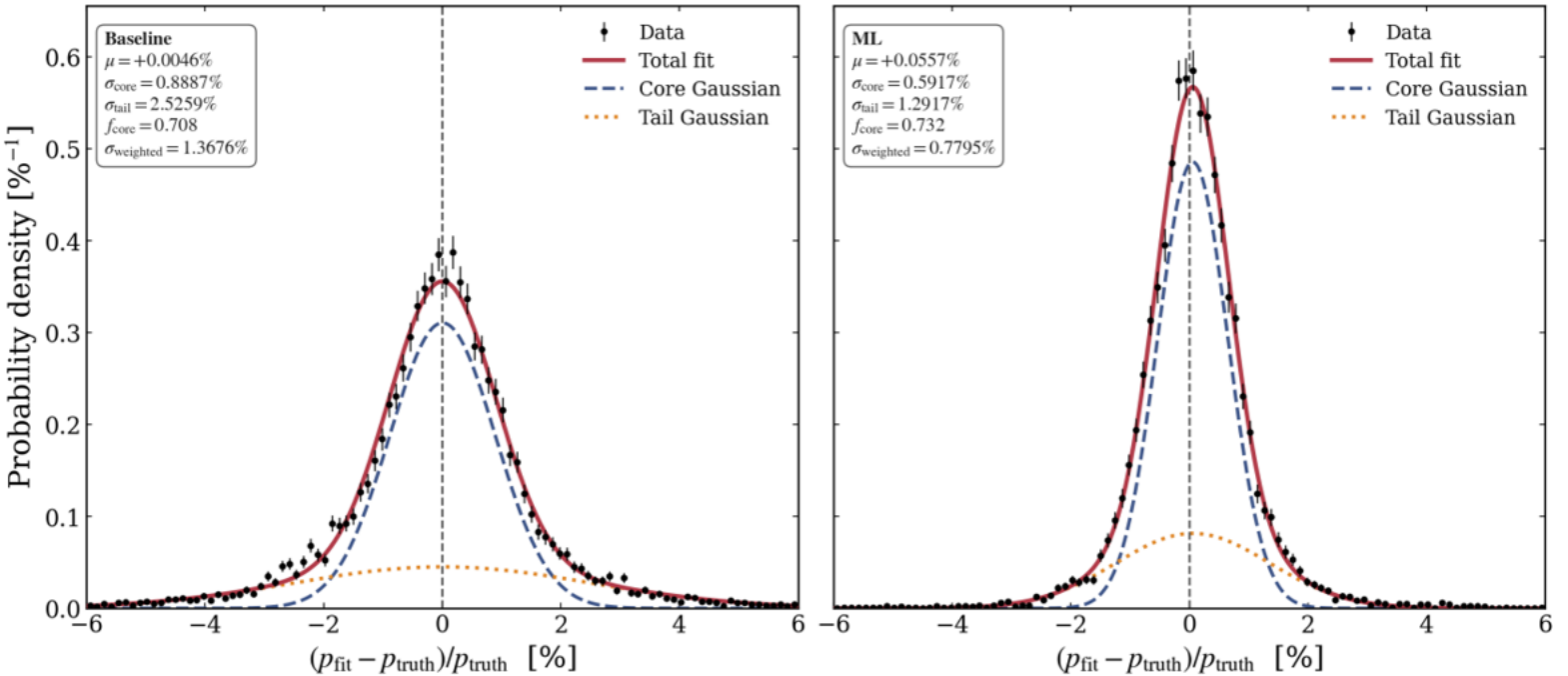
ML improves the fitted residual width across the entire DOCA range.

Average relative improvement

≈20%

The largest gains occur at intermediate DOCA.

Improvement on momentum resolution

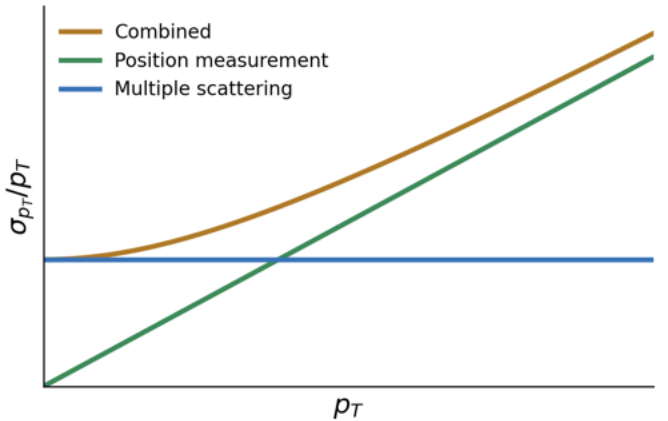


$$r_p = \frac{p_{\text{fit}} - p_{\text{truth}}}{p_{\text{truth}}}, \qquad \frac{\sigma_p}{p} \equiv \sigma_{\text{weighted}}(r_p)$$

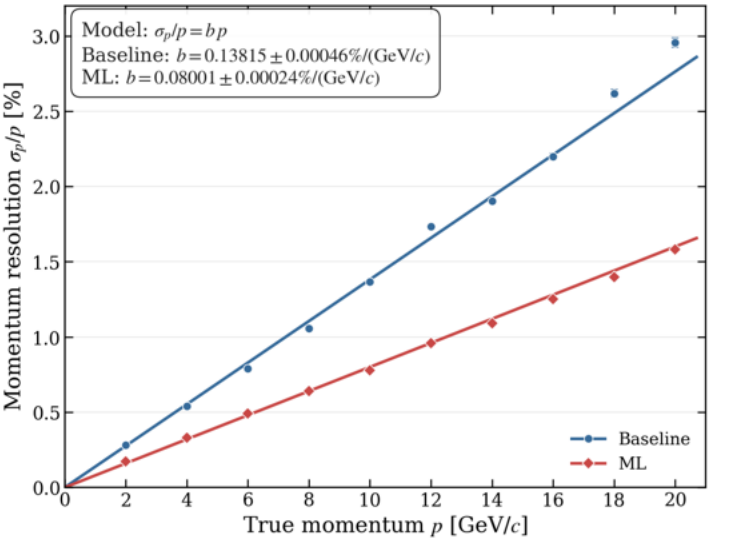
At 10 GeV/c, the momentum resolution improves from 1.3676% to 0.7795% (43.0%).

Improvement on momentum resolution

$$\frac{\sigma_{p_T}}{p_T} = ap_T \oplus \frac{b}{\sqrt{\sin\theta}}$$



Since multiple scattering is not included, b=0.

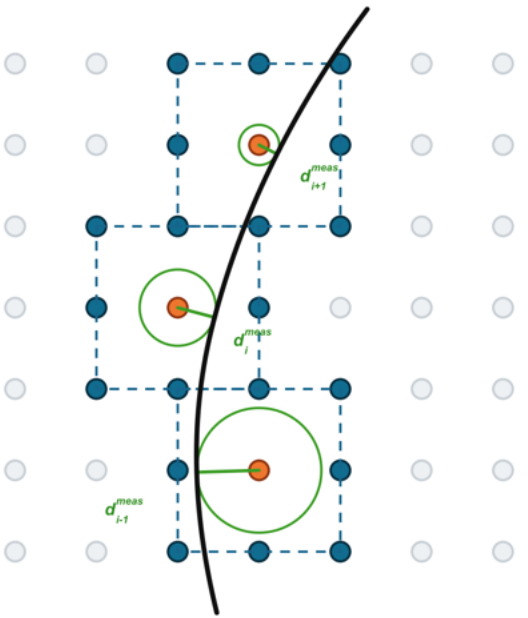


Fitted slope: 0.13631 → 0.07936 %/(GeV/c)

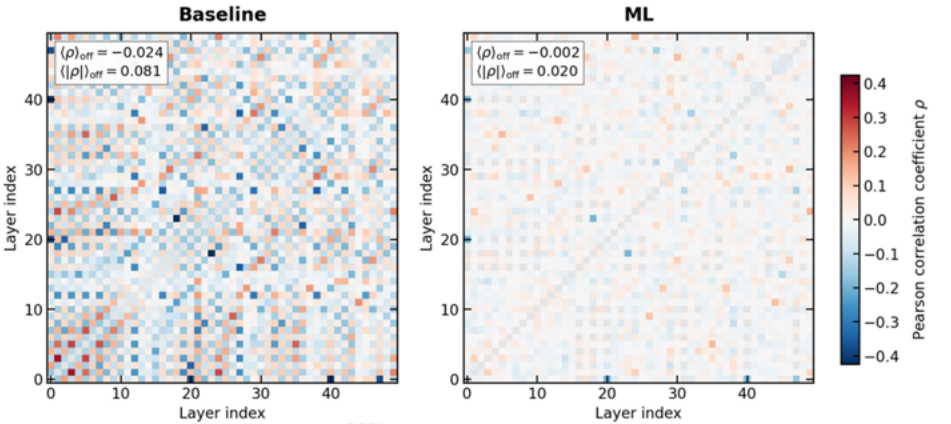
ML-corrected drift distances reduces the measurement contribution to momentum resolution by 41.8%.

Why drift distance and momentum improvements differ

Drift distance σ_d: ≈20% improvement **Momentum σ_p /p: ≈40% improvement**



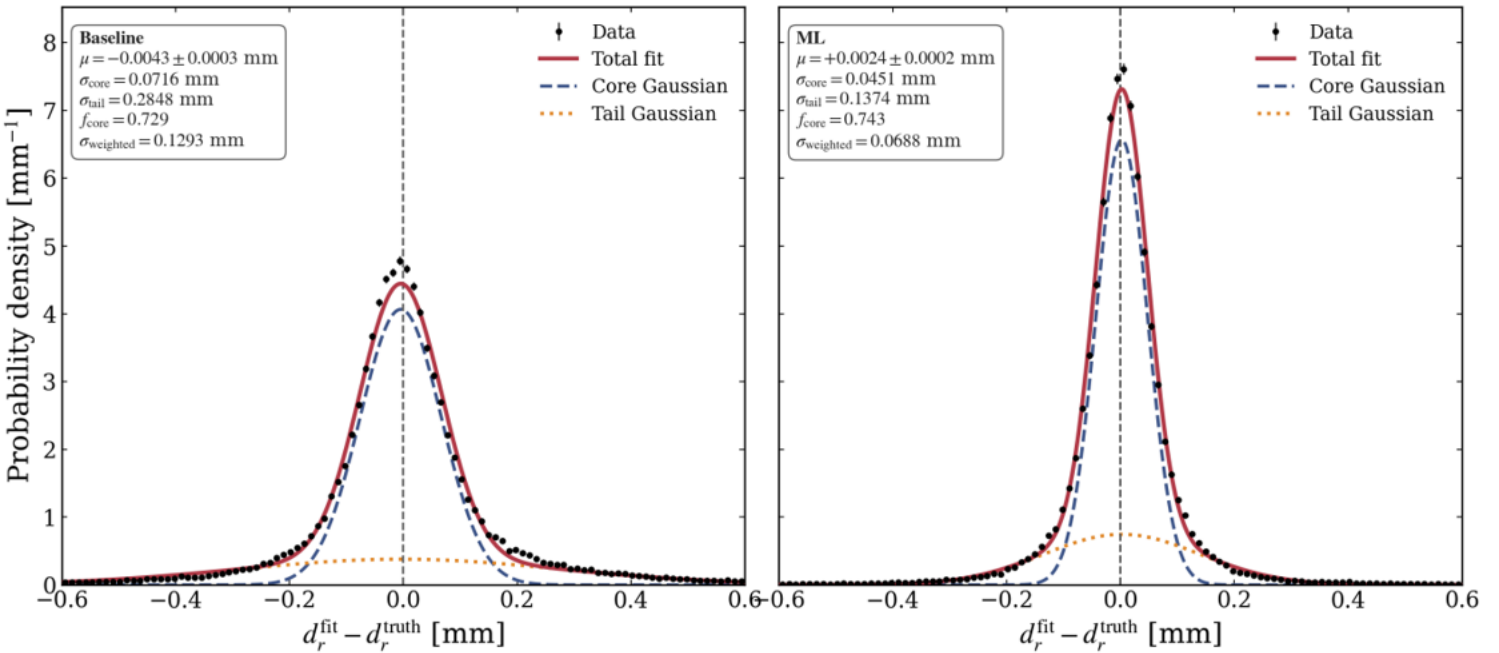
$$\rho_{ij} = \frac{\mathrm{Cov}(\epsilon_i, \epsilon_j)}{\sigma_{\epsilon_i}\sigma_{\epsilon_j}}, \epsilon_i = d_i^{meas} - d_i^{DOCA}$$



Signed hit residual: $\Delta d = d^{\mathrm{meas}} - d^{\mathrm{DOCA}}$. Diagonal self-correlations are masked.

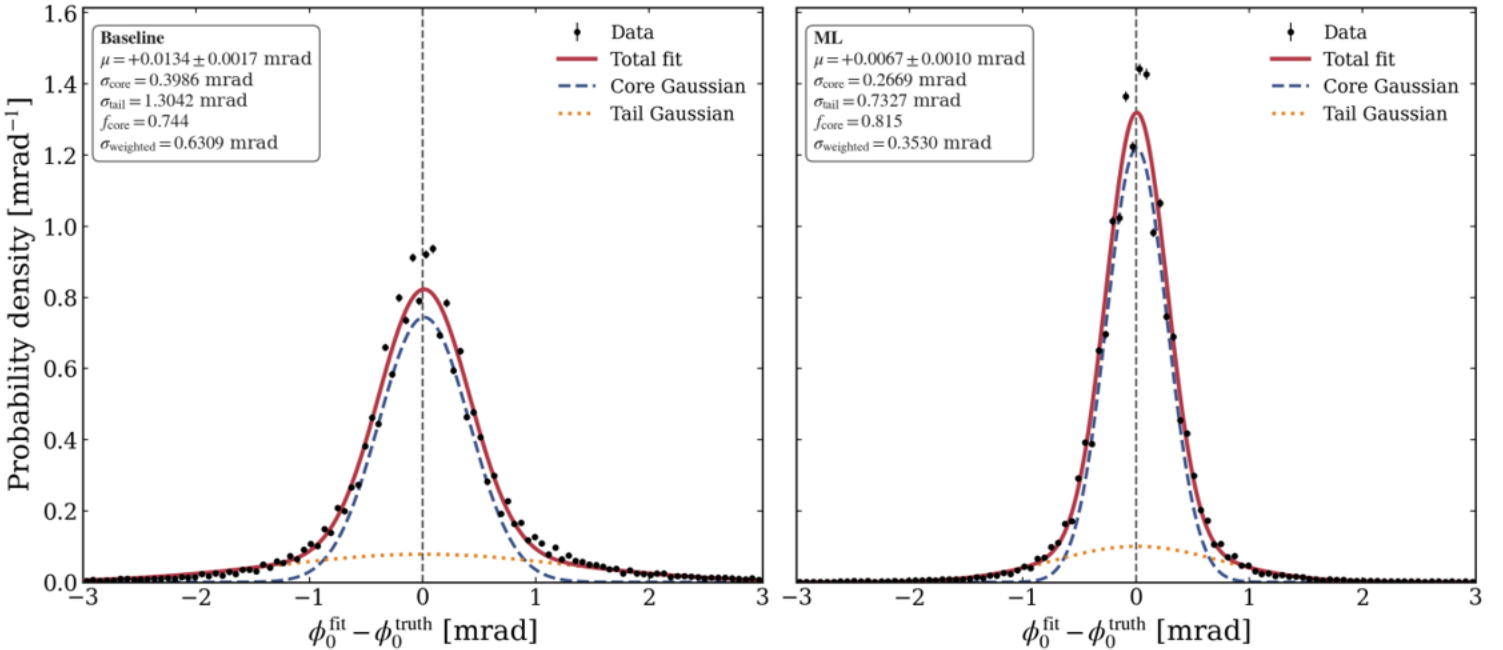
ML reduces the mean absolute inter-layer correlation from 0.0806 to 0.0199 (−75.3%).

Track-parameter residual: d_r



The Transformer reduces the weighted d_r residual width from 0.1293 to 0.0688 mm (46.8%).

Track-parameter residual: ϕ_0



The Transformer reduces the weighted ϕ_0 residual width from 0.6309 to 0.3530 mrad (44.1%).

Conclusions and outlook

Conclusions

- Full-waveform readout provides multiple electron arrival times beyond the first threshold crossing.
- A Transformer with attention pooling learns a residual correction to the conventional x-t drift-distance estimate.
- The improved drift-distance measurement significantly improves the resolution of momentum and other fitted track parameters.

Outlook

- Replace truth-level electron arrival times with timing candidates extracted from waveforms using a peak-finding algorithm.
- Include multiple Coulomb scattering in the simulation and track reconstruction.
- Extend the current 2D track reconstruction to full 3D tracking.
- Further understand the track level improvement beyond expectations.

These results demonstrate the potential of cluster-counting technique on tracking.