Improving Tracking Performance with Cluster Counting in Drift Chambers

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The CEPC physics programme demands precise tracking

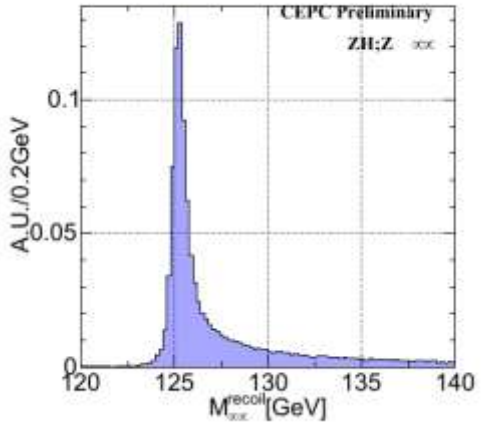
Tracking at the CEPC

01 **Tracking** is a fundamental requirement in HEP.

02 For future e^+e^- collider experiments such as CEPC, stringent **momentum resolution** requirements must be met.

03 A transparent gaseous tracker could provide not only **PID** but also **precise low-momentum tracking**.

04 For CEPC, a drift chamber serves as an **alternative gaseous tracker option**.

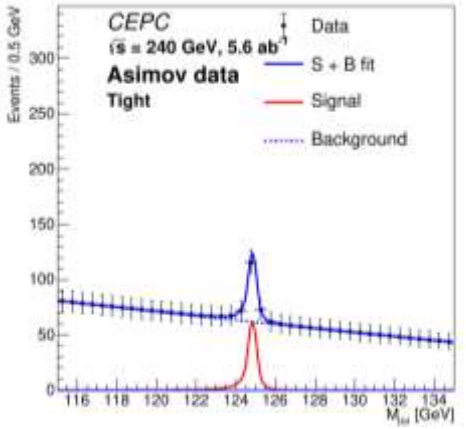


Higgs production[1]

$$e^+e^- \to ZH, Z \to \mu^+\mu^-$$

$$M^2_{recoil} = \left(\sqrt{s} - E_{\mu\mu}\right)^2 - \left|\vec{p}_{\mu\mu}\right|^2$$

Muon momentum controls the peak width.



Higgs decay [2]

$$e^+e^- \to ZH, H \to \mu^+\mu^-$$

$$M^2_{\mu\mu} = (p_{\mu^+} + p_{\mu^-})^2$$

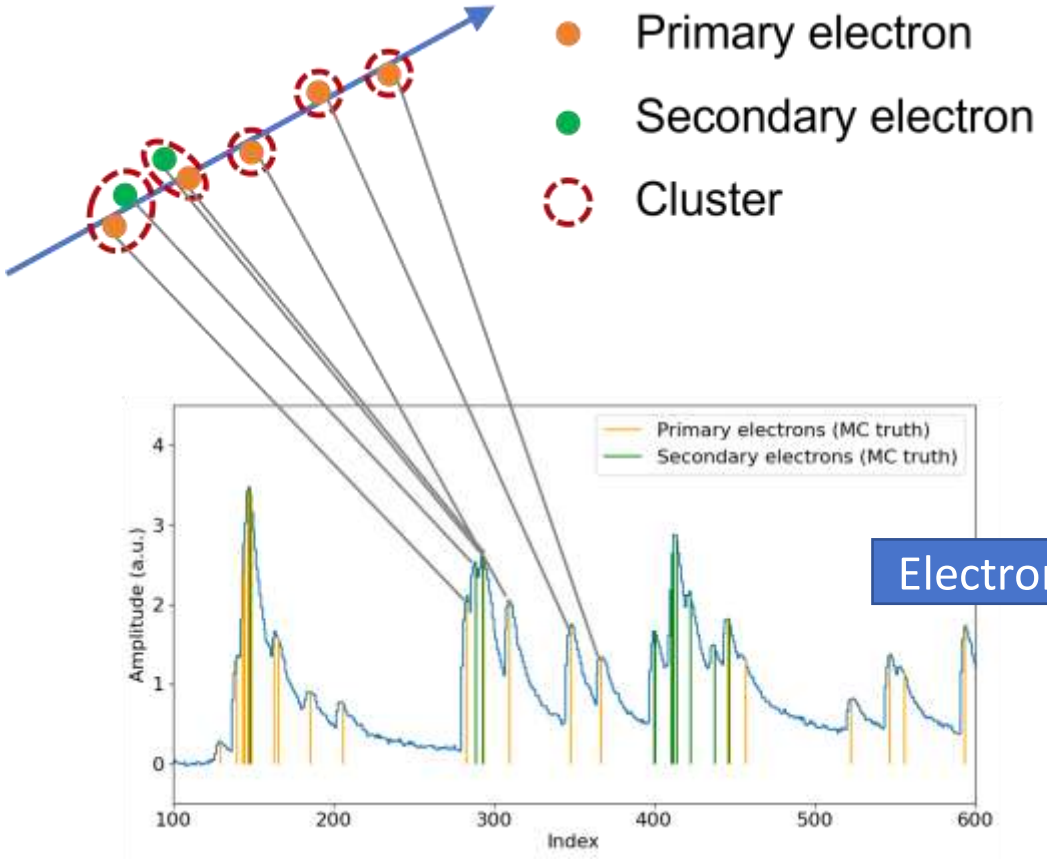
The narrow peak depends on momentum resolution.

Precise Higgs measurements require excellent track-momentum resolution.

[1] CEPC Study Group, CEPC CDR, Vol. 2, Fig. 10.9, arXiv:1811.10545 (2018).
[2] Q. Liu et al., Chin. Phys. C 47, 023001 (2023), arXiv:2211.07789, Fig. 7.

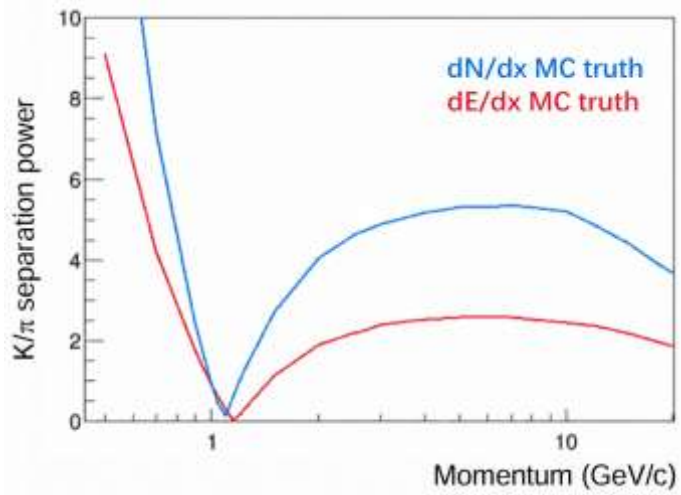
From cluster counting (dN/dx) for PID to its tracking potential

Fast waveform readout



Ionization-cluster counts

PID Cluster count per unit length gives dN/dx.



Electron arrival times

Drift-distance reconstruction

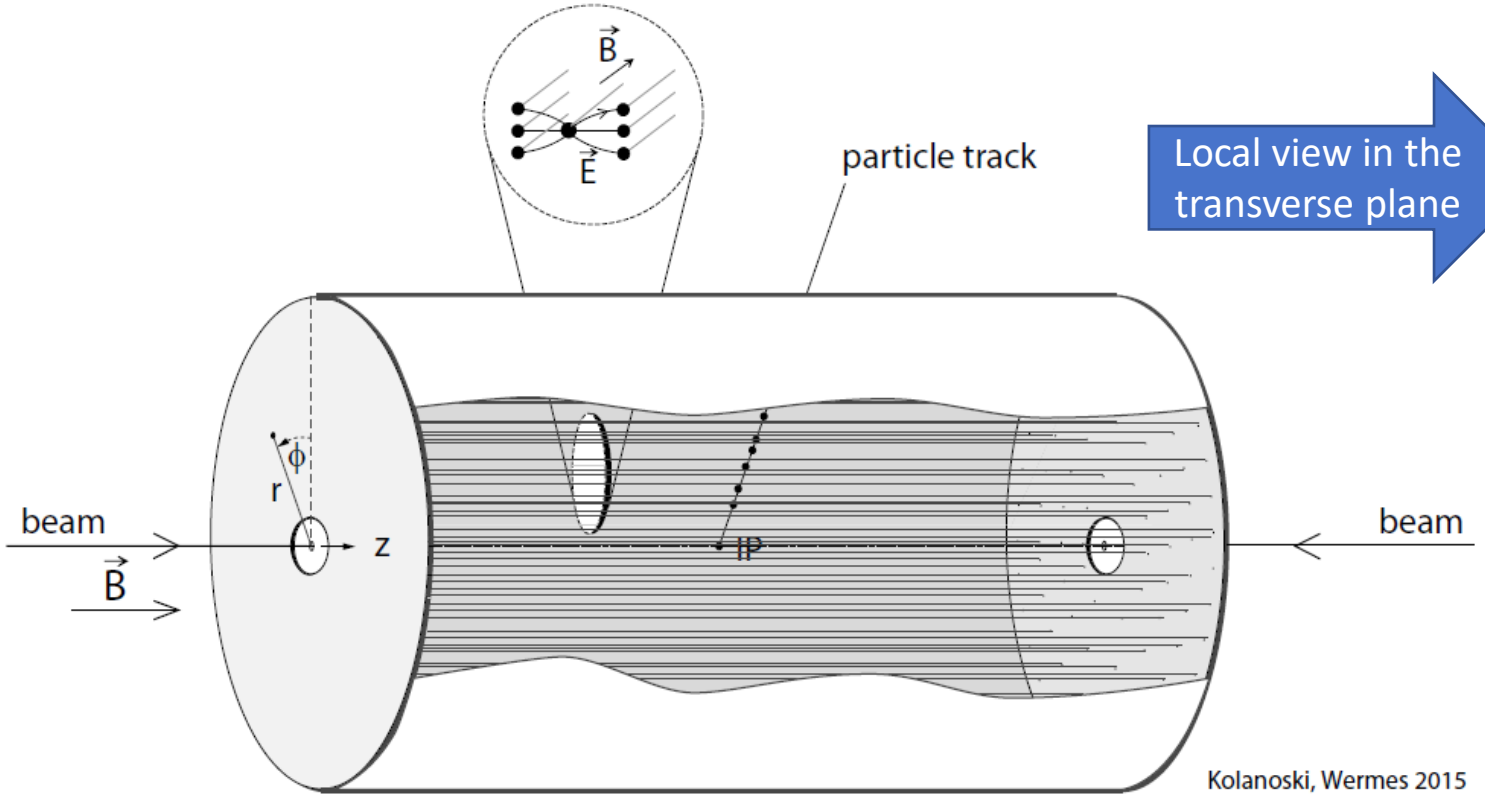
Peak times provide more information.

Conventional	**Cluster counting**
$D(t_0)$	$D(t_0, t_1, t_2, \dots)$

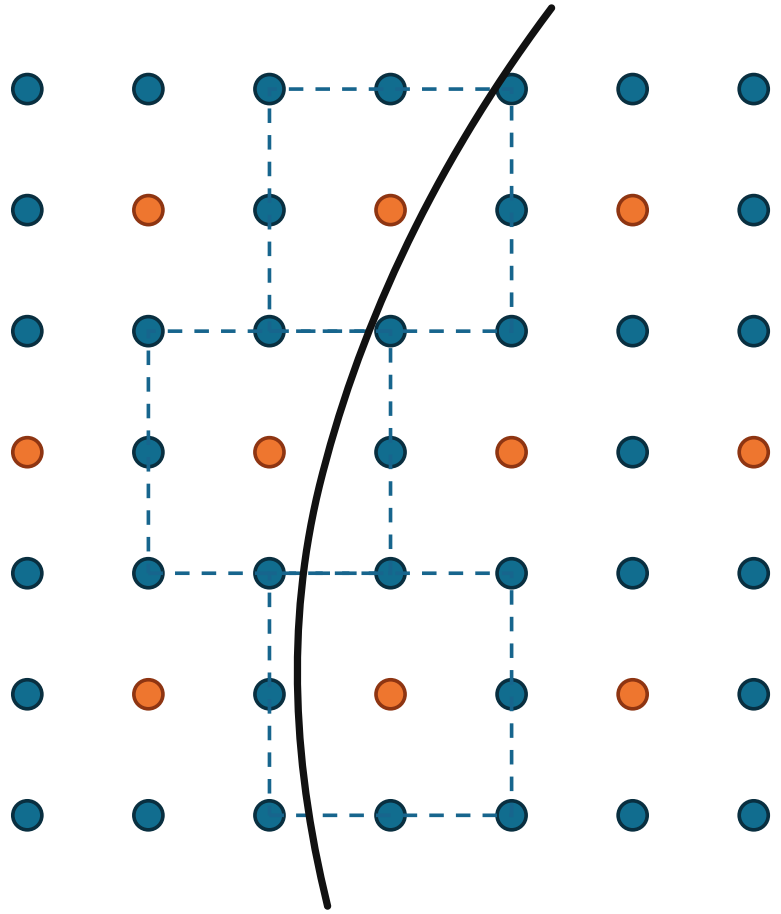
The waveform provides cluster counts for PID and timing information for position reconstruction.

Source: G. Zhao, CHEP 2024, slides 8–9.

Track measurement in a drift chamber

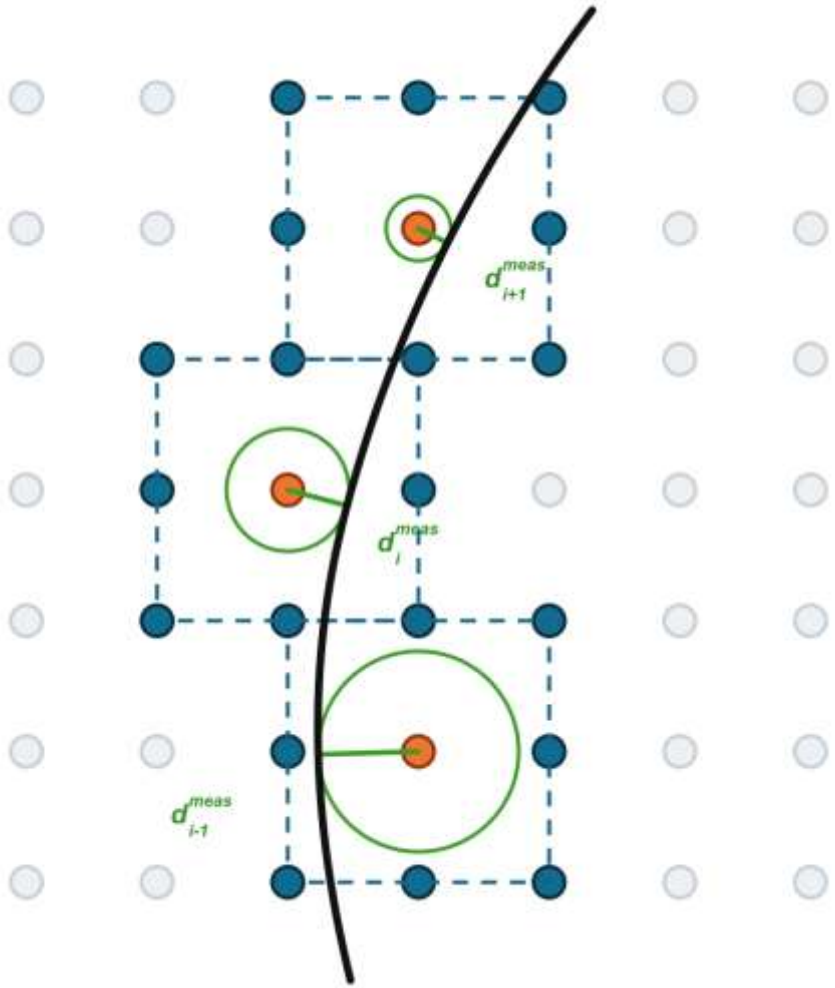


Local view in the transverse plane



A track passing through the DC

Track fitting



Measured distance

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

Distance of Closest Approach (DOCA) for a candidate helix

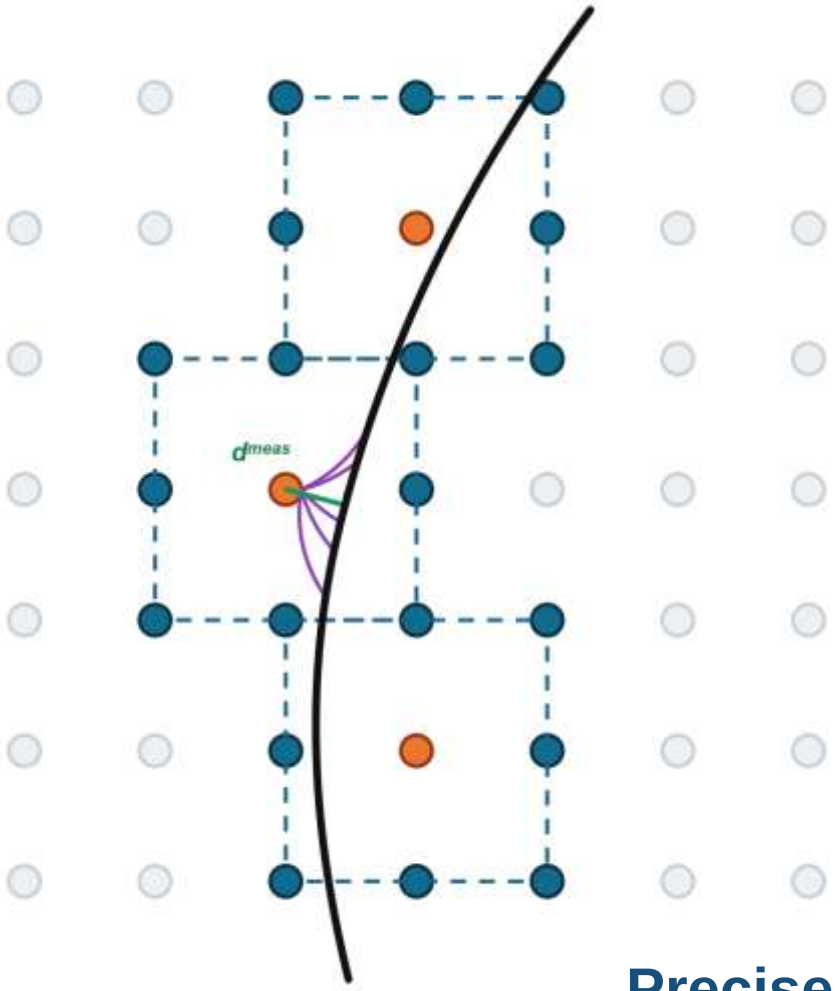
$$d_i^{DOCA} = f_i(h)$$

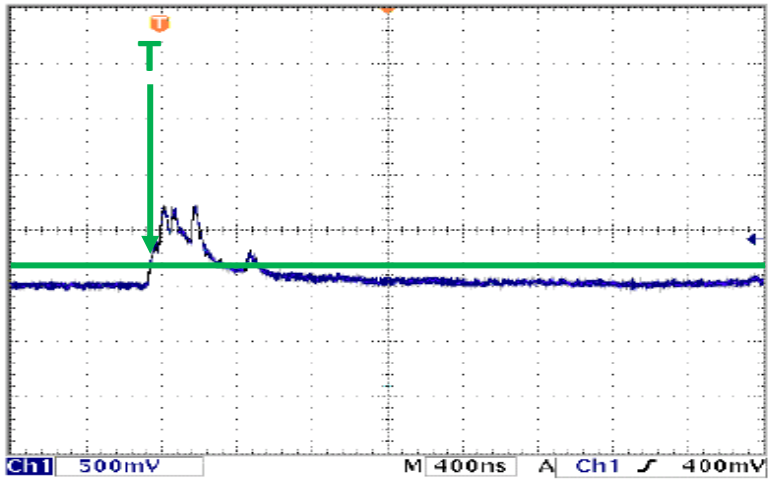
Track-fit objective

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

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

Conventional time measurement





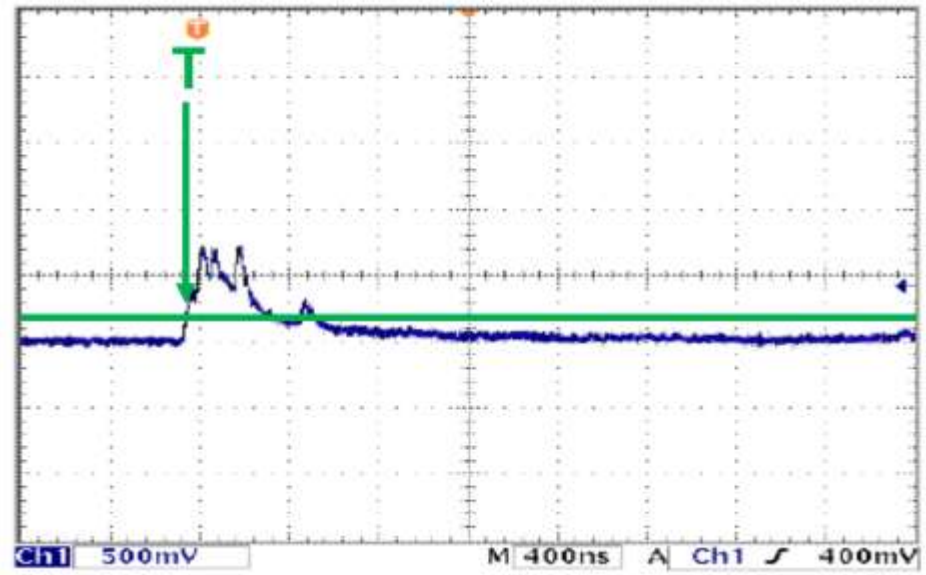
- Earliest threshold-reaching time of signal is recorded
- T is converted to drift distance d^{meas} using X-T relation
- d^{meas} is approximately the smallest distance from the sense wire to the track

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

From threshold timing to full-waveform reconstruction

Conventional method

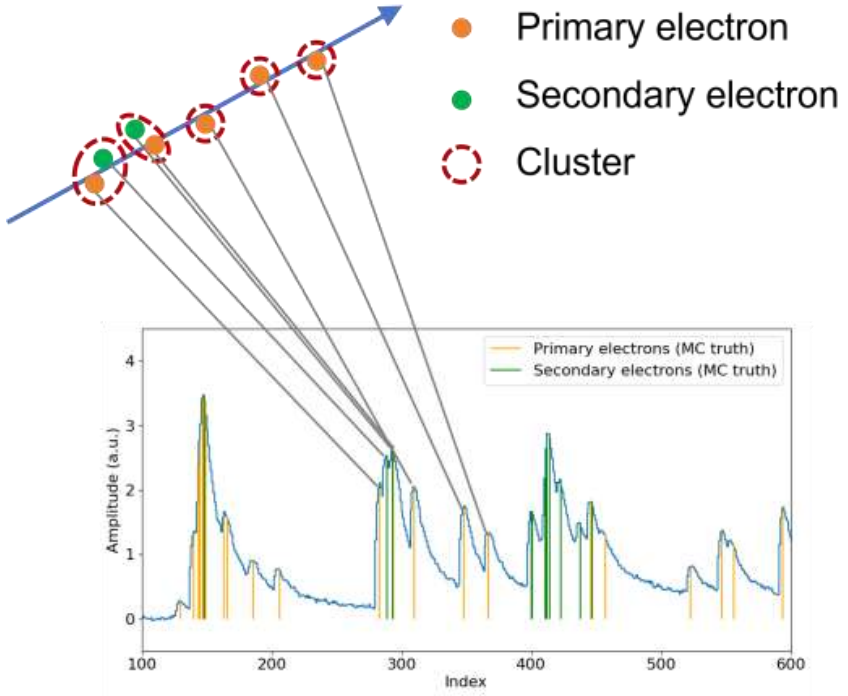
A signal from preamplifier of BESIII DC



t_0 ⟶ X-T relation ⟶ d^{meas}

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

Cluster counting method

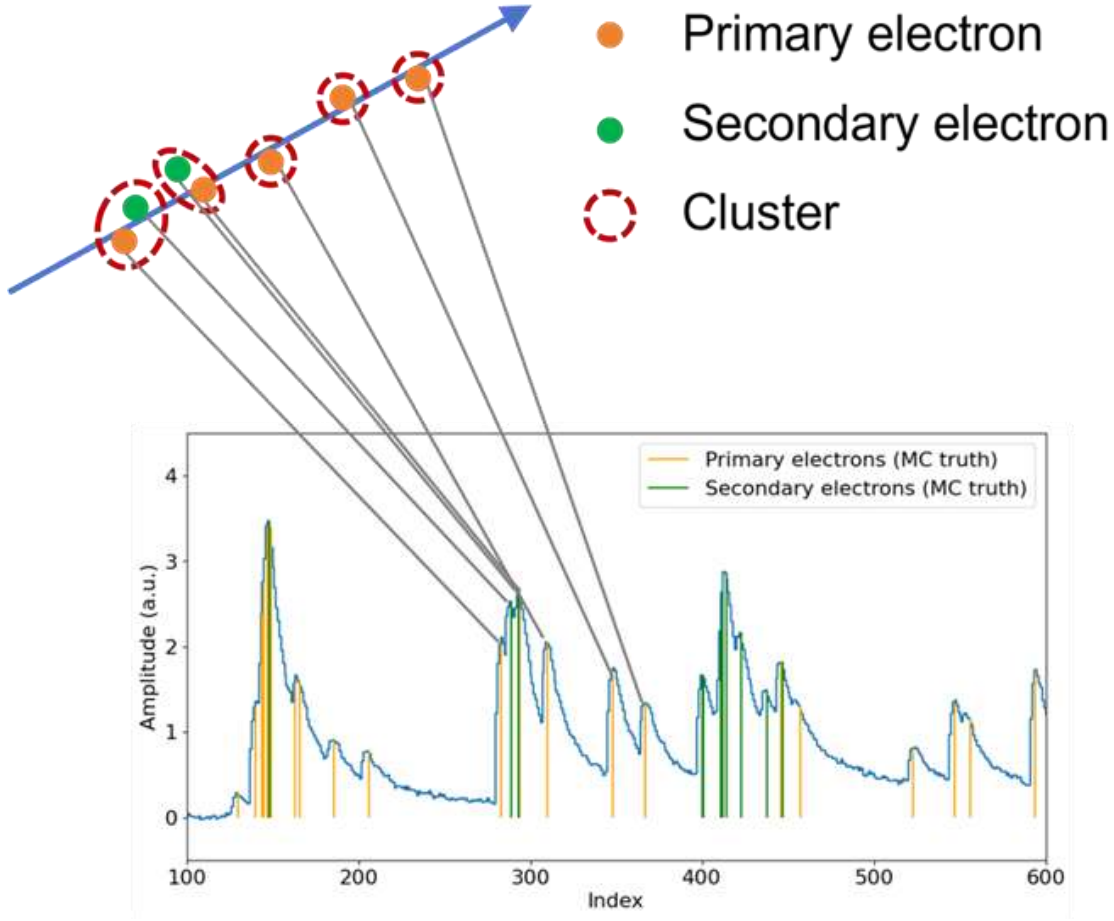


t_0, t_1, t_2 ... ⟶ Complex relation ⟶ d^{meas}

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.

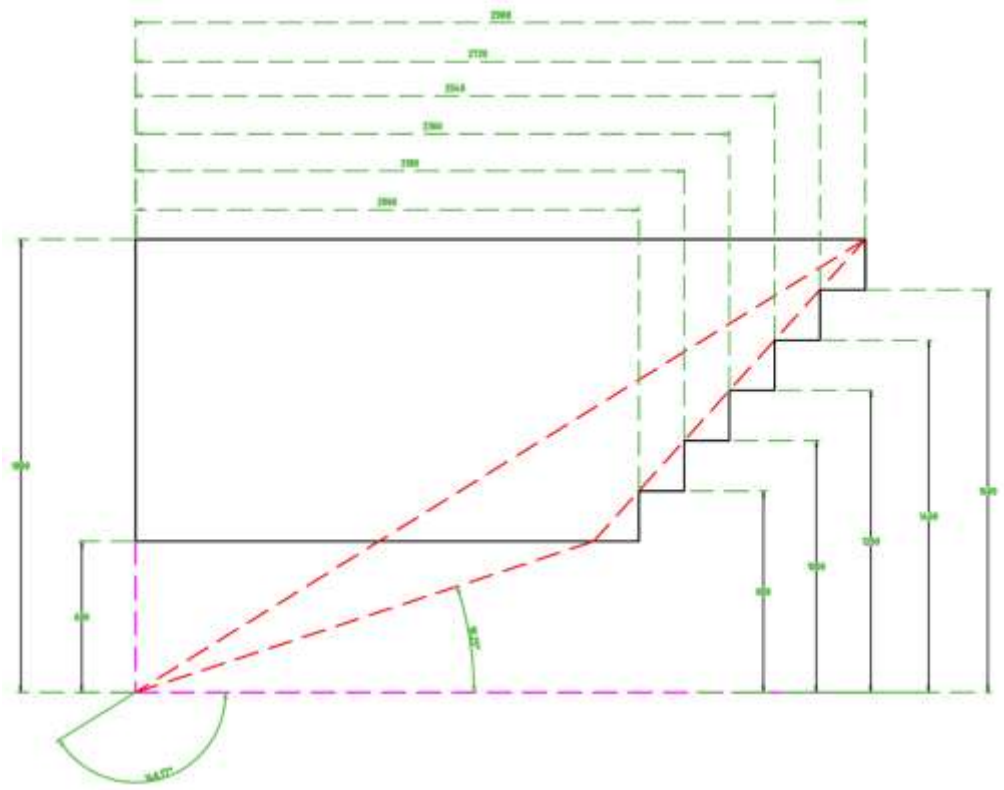
Our approach

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.

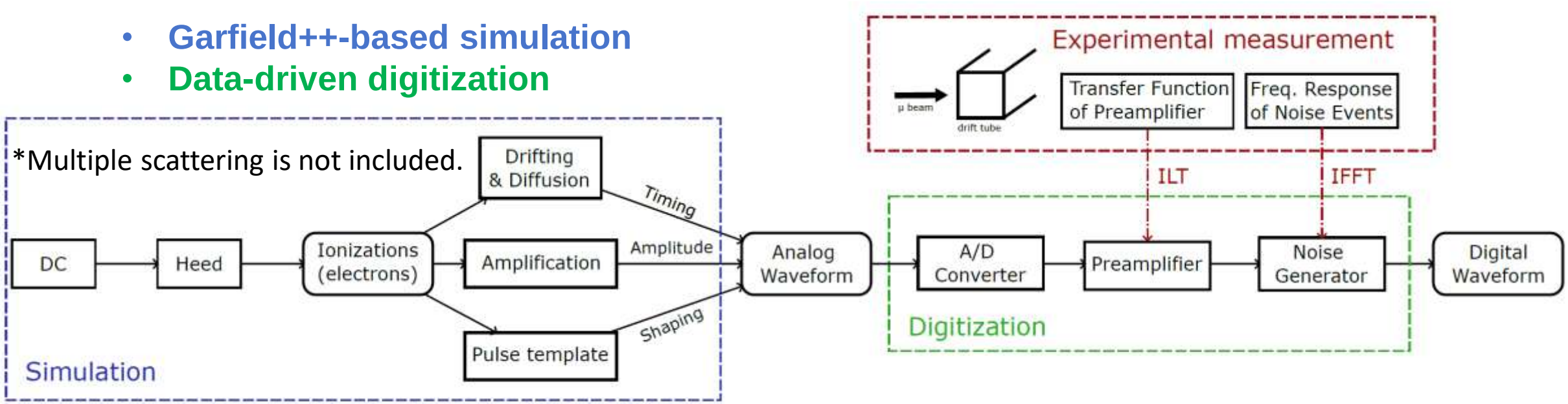
A drift chamber with cluster counting is one of the gaseous detector options

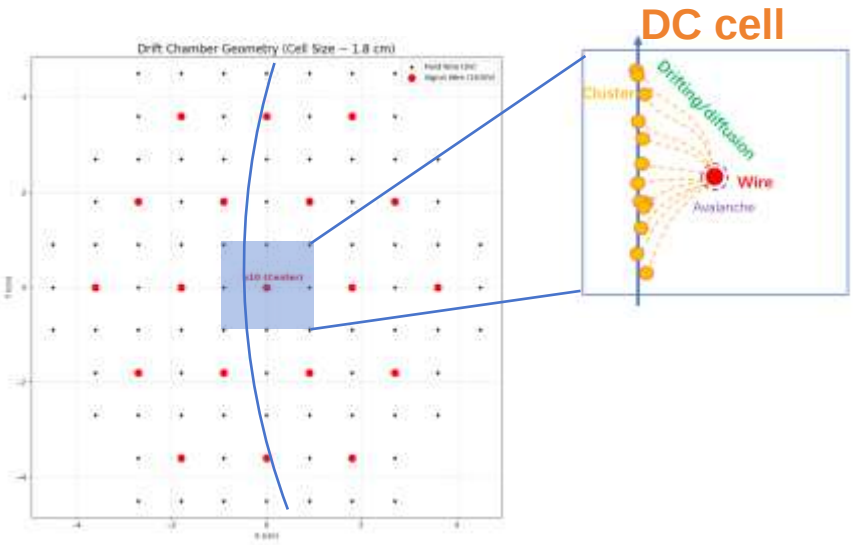
Parameters	Configuration
Gas mixture	90/10 He/iC_4H_{10}
Detector grid	50 layers × 19 columns
Cell size	1.8 cm
Magnetic field	B_z = 3.0 T

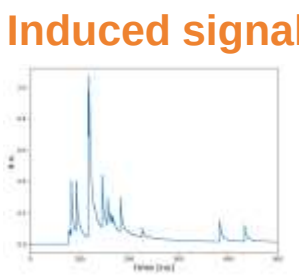
This study uses simulated data based on this CEPC drift-chamber design.

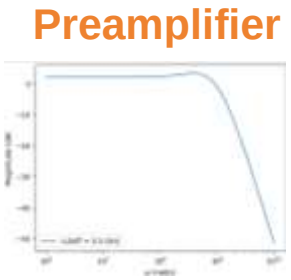
Full Simulation

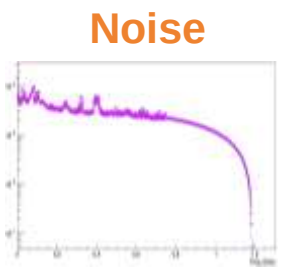
- **Garfield++-based simulation**
- **Data-driven digitization**

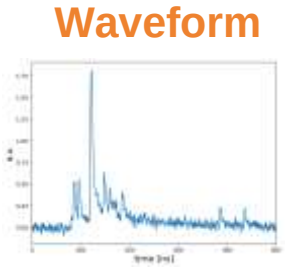












Outputs for supervised learning

- **Full waveform:** used to extract electron arrival times
- **Arrival times $t_0, t_1, \ldots$:** 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
7,200
tracks

Validation
800

Preliminary test
2,000

Performance scan

10 fixed momentum points

2, 4, …, 20 GeV/c

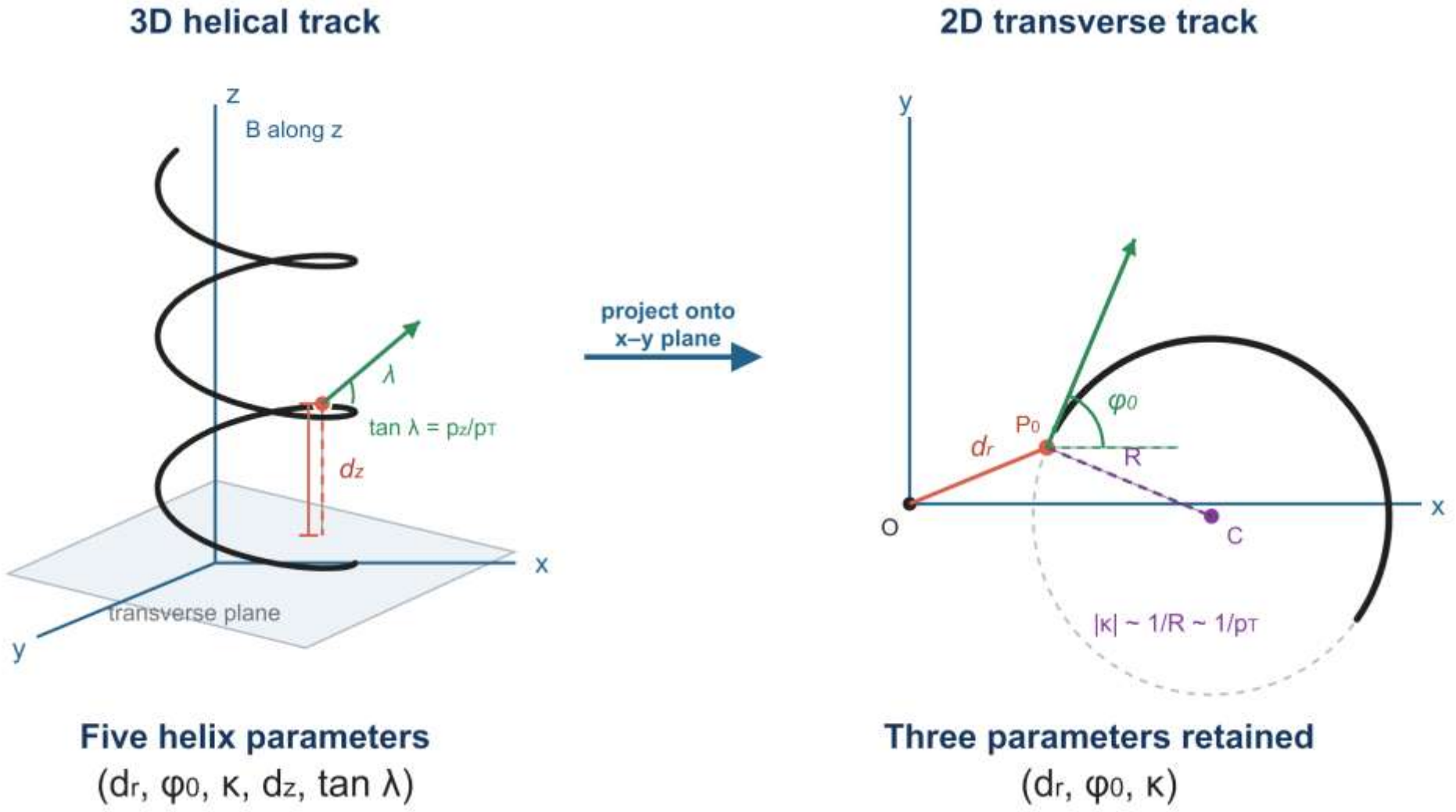
10,000 events per point

100,000 events in total

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

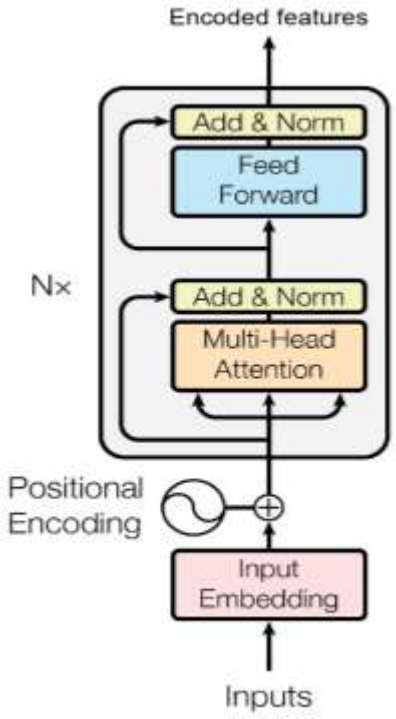
2D track model

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.



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

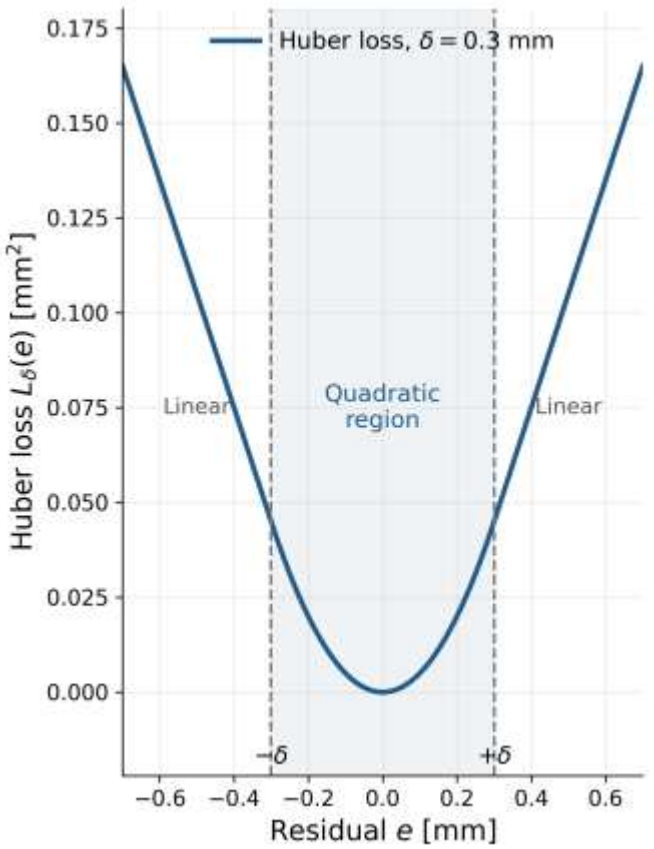
$$\Delta d = d^{DOCA} - d_{baseline}^{meas}$$

Model prediction

$$\Delta d^{pred}$$

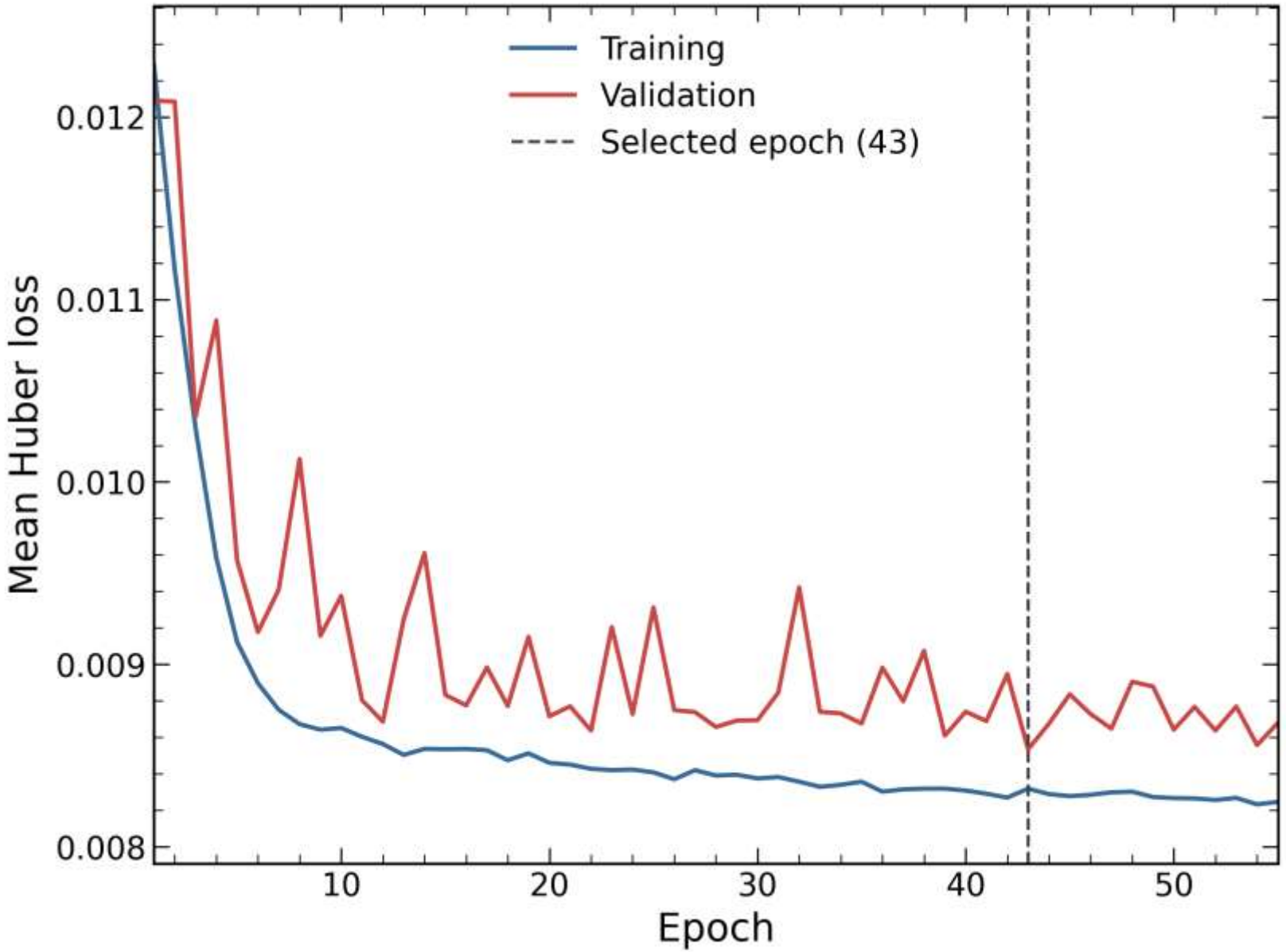
Loss function

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



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

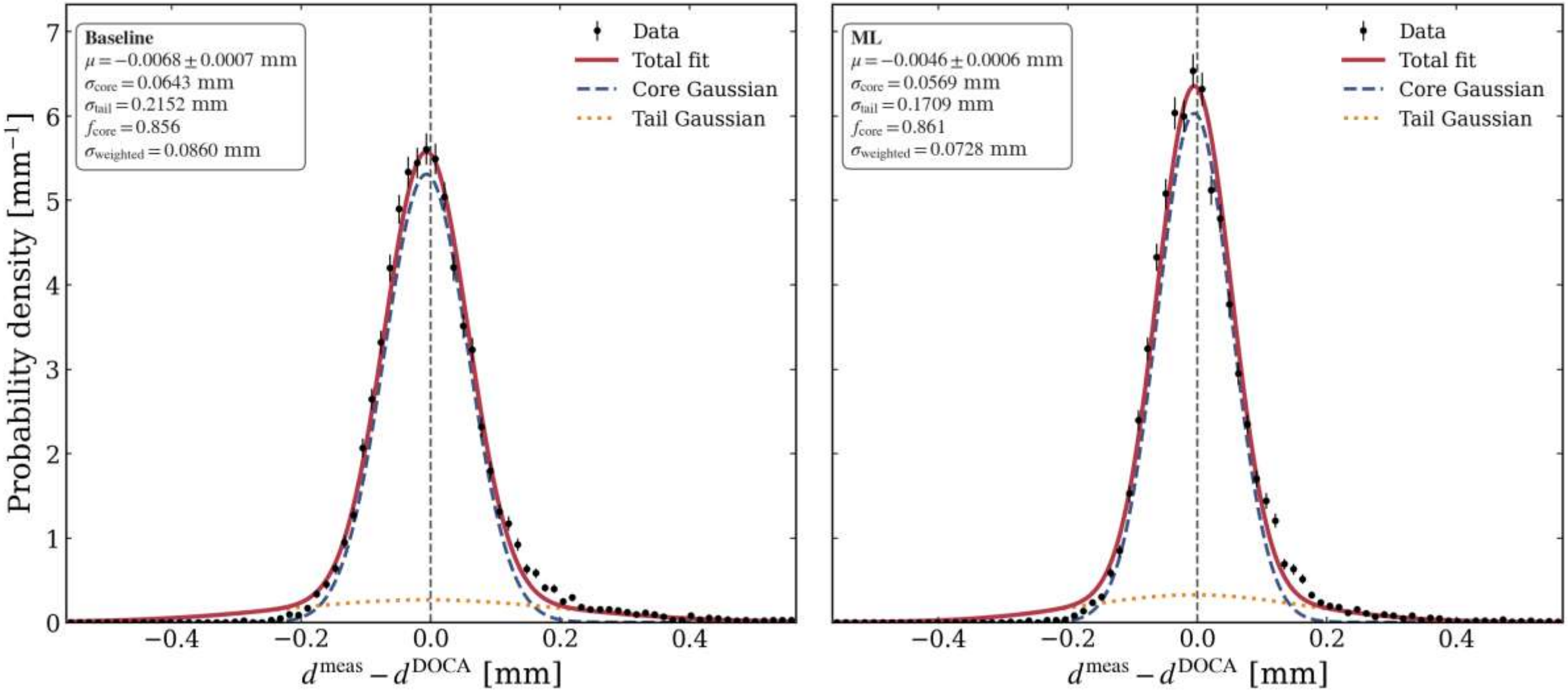
Loss

Huber loss, $\delta = 0.3$ mm

Checkpoint

Epoch 43

Drift-distance residual distribution

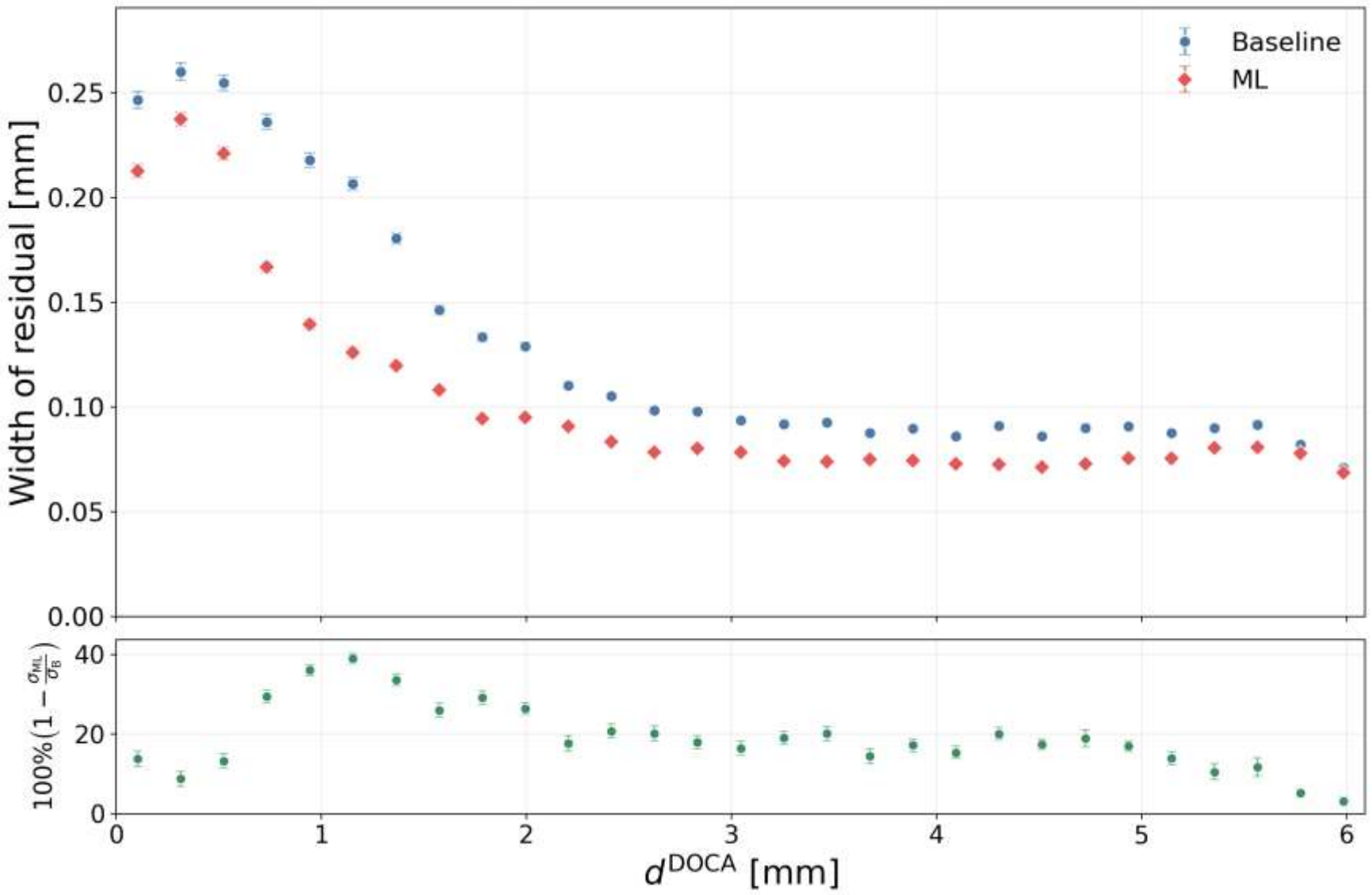


Double-Gaussian width

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

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

Improvement of spatial resolution



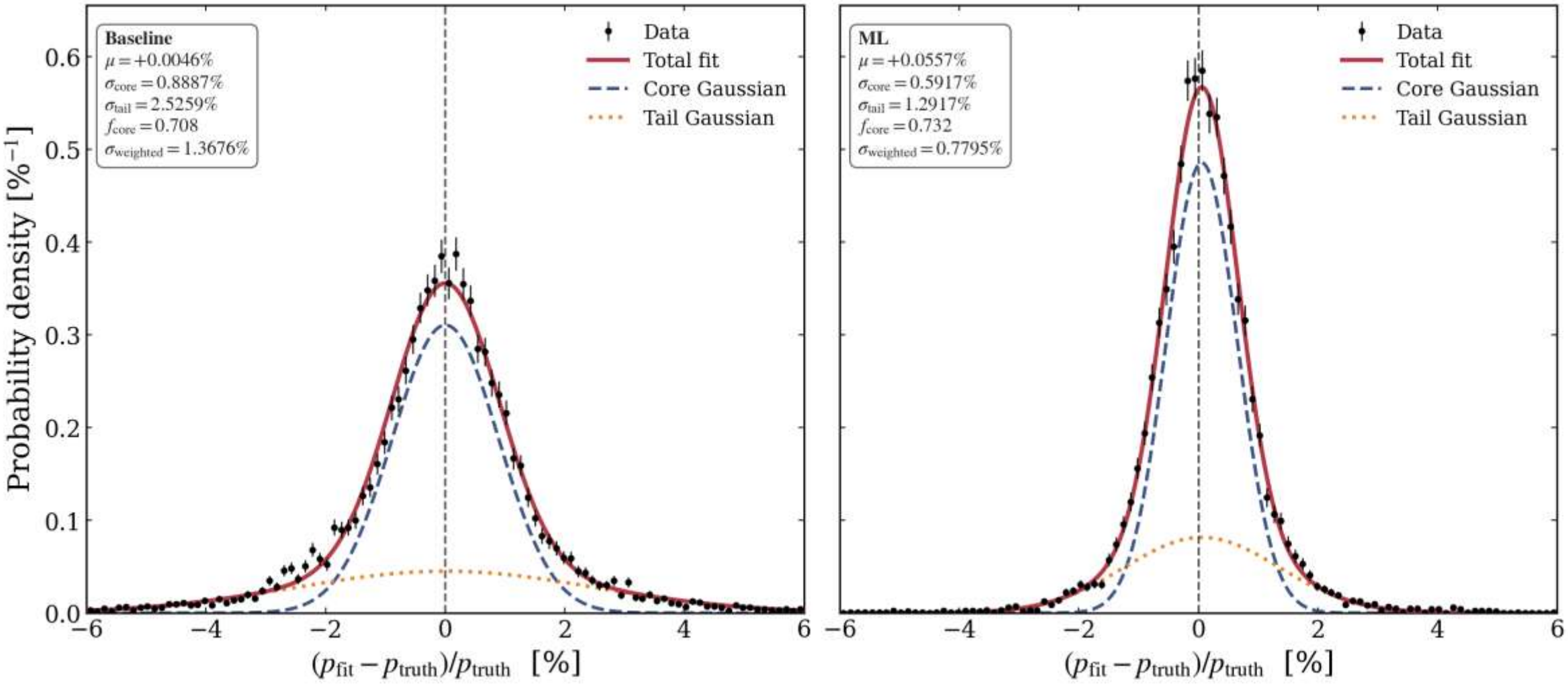
ML improves the fitted residual width across the entire DOCA range.

Average relative improvement

≈20%

The largest gains occur at intermediate DOCA.

Improvement on momentum resolution

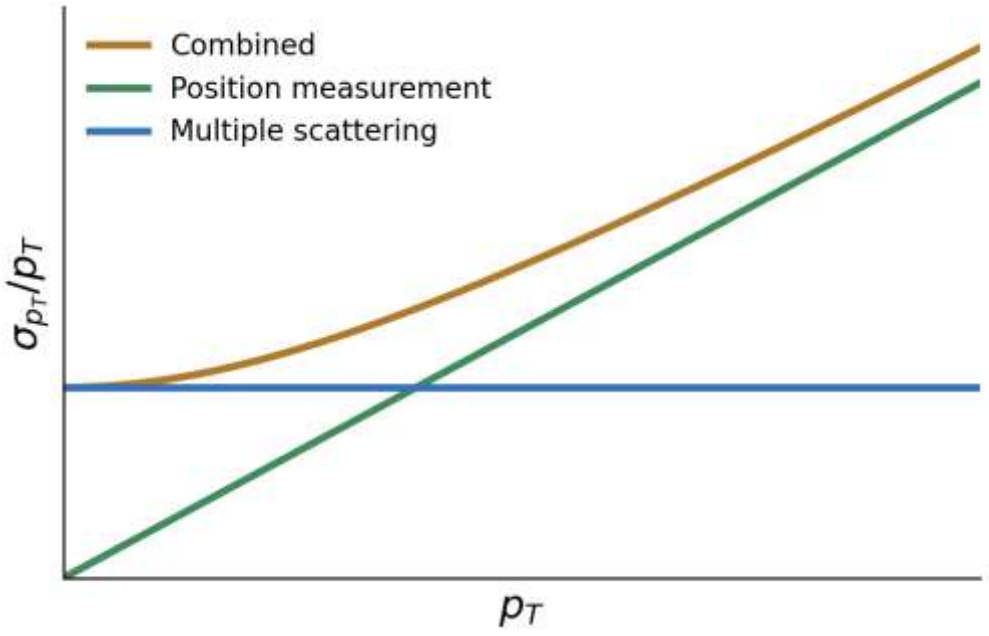


$$r_p = \frac{p_{\text{fit}} - p_{\text{truth}}}{p_{\text{truth}}}, \qquad \frac{\sigma_p}{p} \equiv \sigma_{\text{weighted}}(r_p)$$

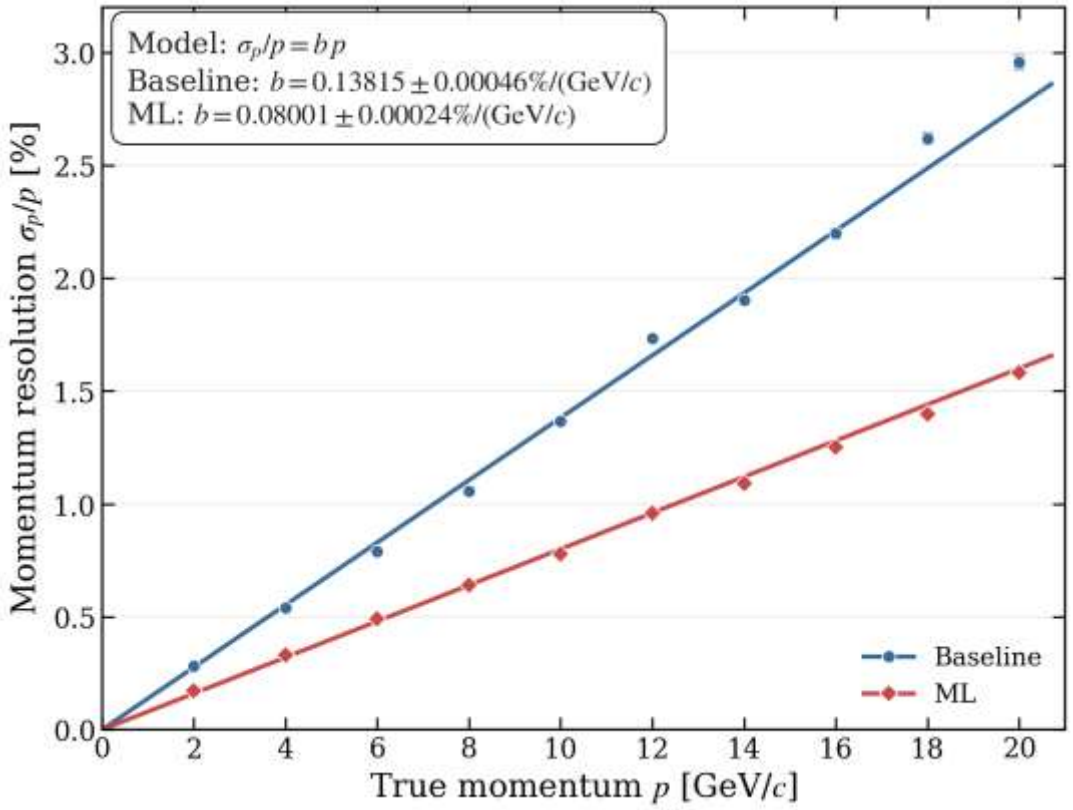
At 10 GeV/c, the momentum resolution improves from 1.3676% to 0.7795% (43.0%).

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.

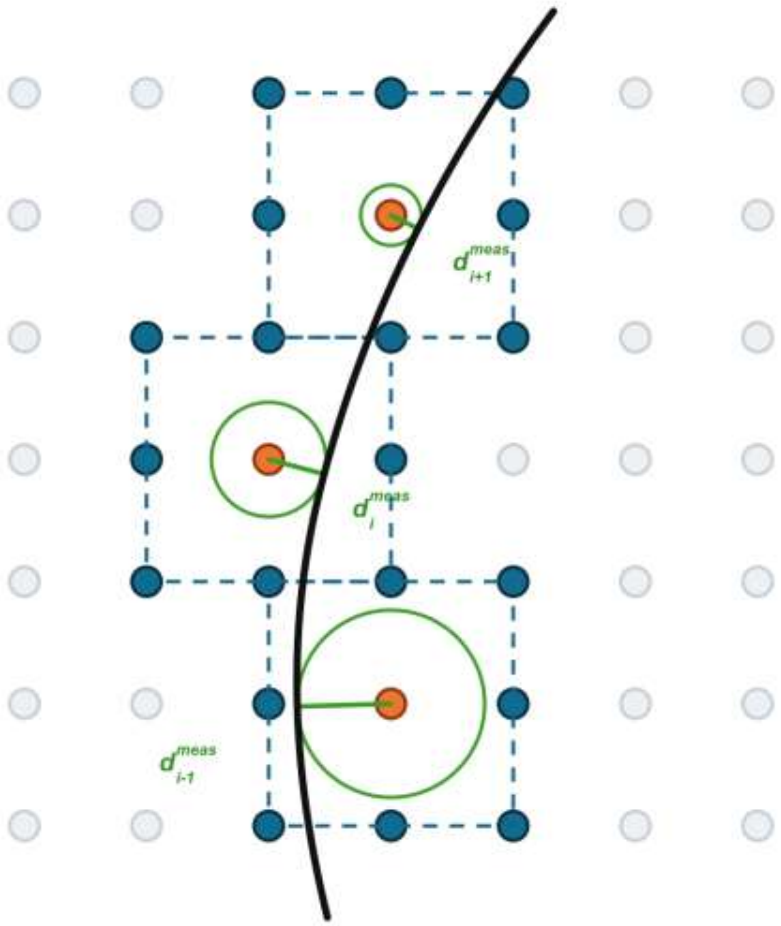


Fitted slope: 0.13631 → 0.07936 %/(GeV/c)

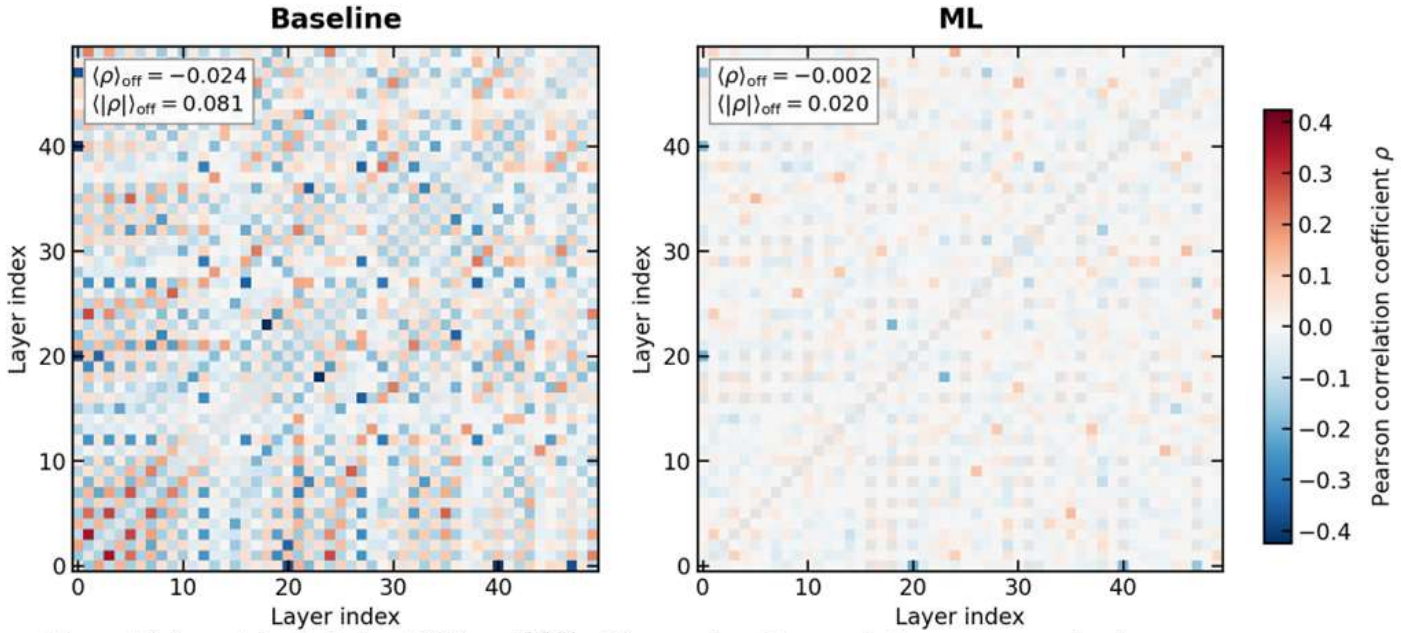
ML-corrected drift distances reduces the measurement contribution to momentum resolution by 41.8%.

Why drift distance and momentum improvements differ

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

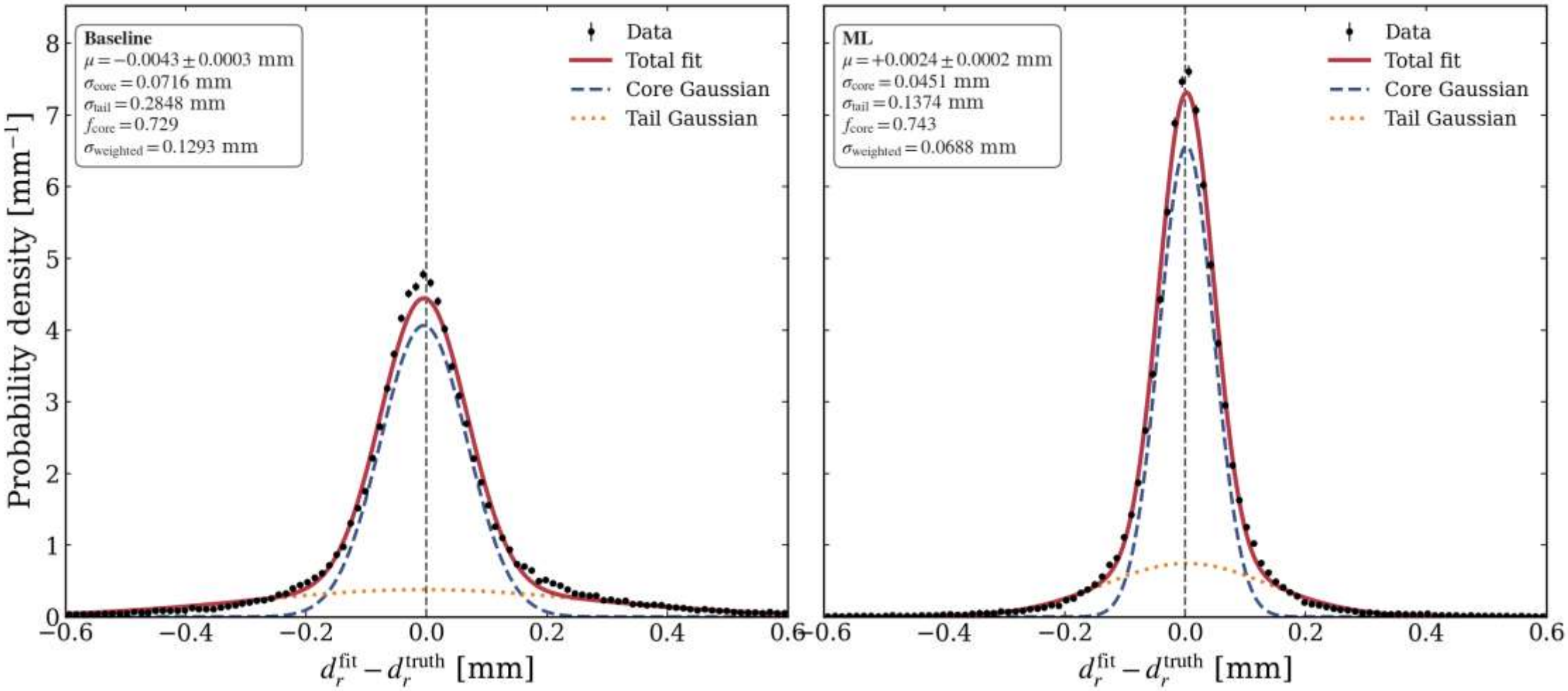


$$\rho_{ij} = \frac{\mathrm{Cov}(\epsilon_i,\epsilon_j)}{\sigma_{\epsilon_i}\sigma_{\epsilon_j}}, \epsilon_i = d_i^{meas} - d_i^{DOCA}$$



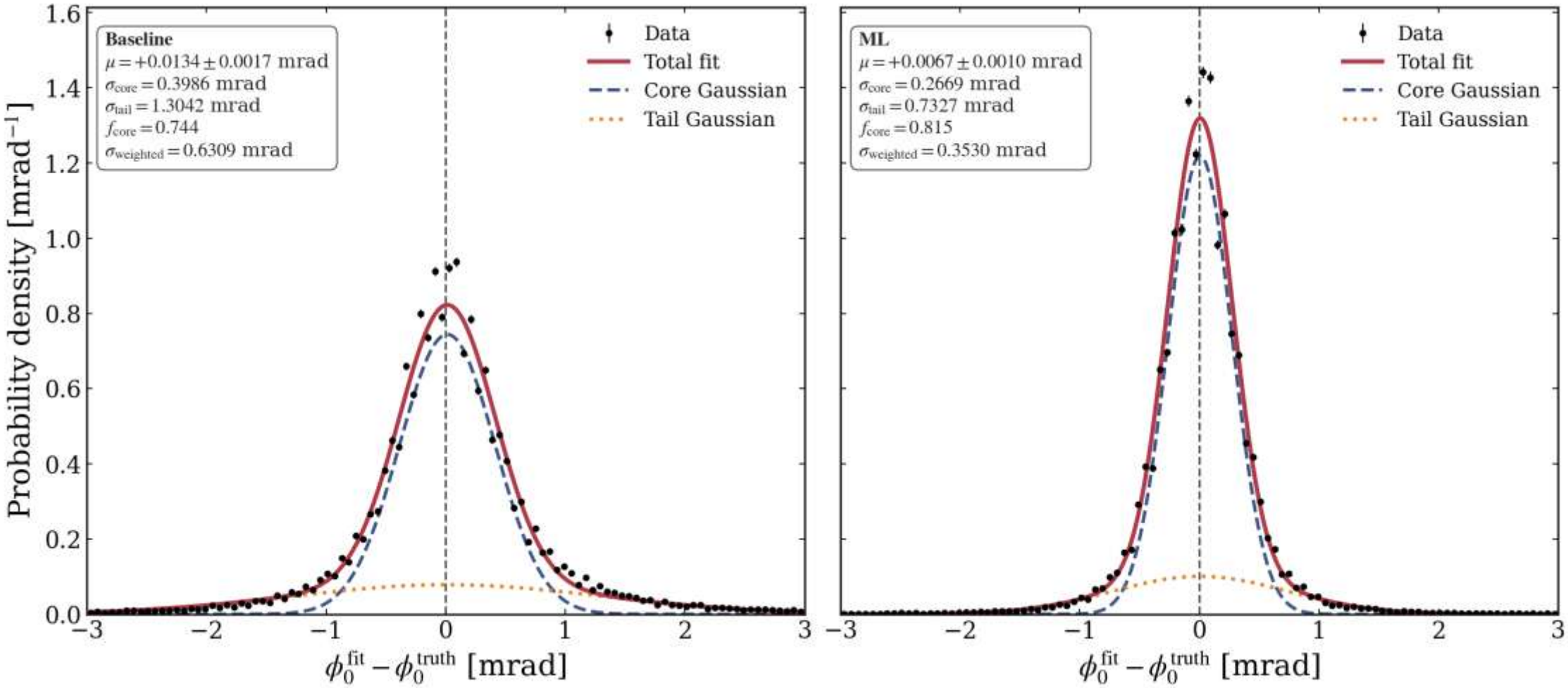
ML reduces the mean absolute inter-layer correlation from 0.0806 to 0.0199 (−75.3%).

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.