基于点云模型的高颗粒度 TPC dN/dx 重建方法的研究

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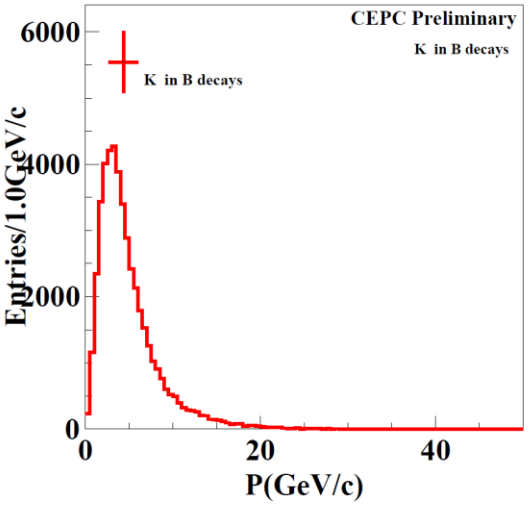
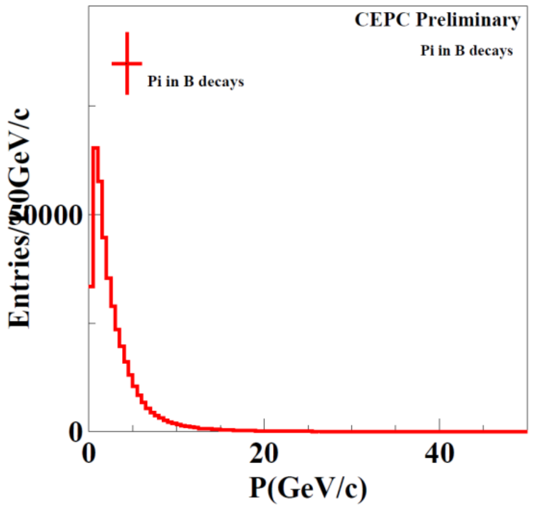
Motivation: Particle identification

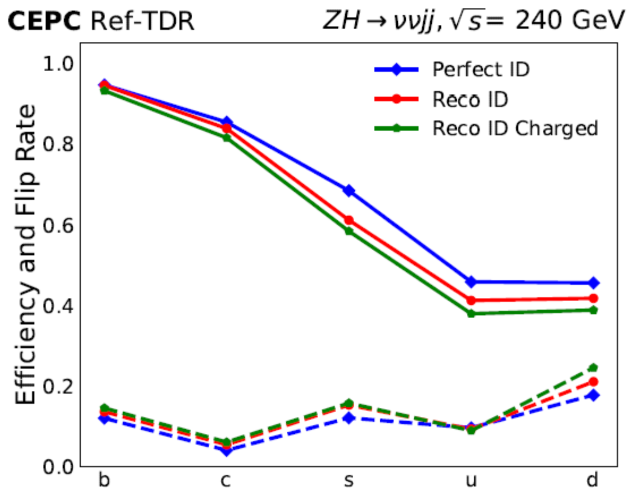
- **PID is essential for high-energy physics experiments. In the context of future e^+e^- 'Higgs factory' studies, PID has garnered significant attention:**
  - The Tera-Z at CEPC/FCC-ee offers vast flavor-physics opportunities, necessitating robust hadron identification across a broad momentum range.
- **There is a growing recognition of the performance gains that PID provides for jet-flavor tagging.**

K in B decays



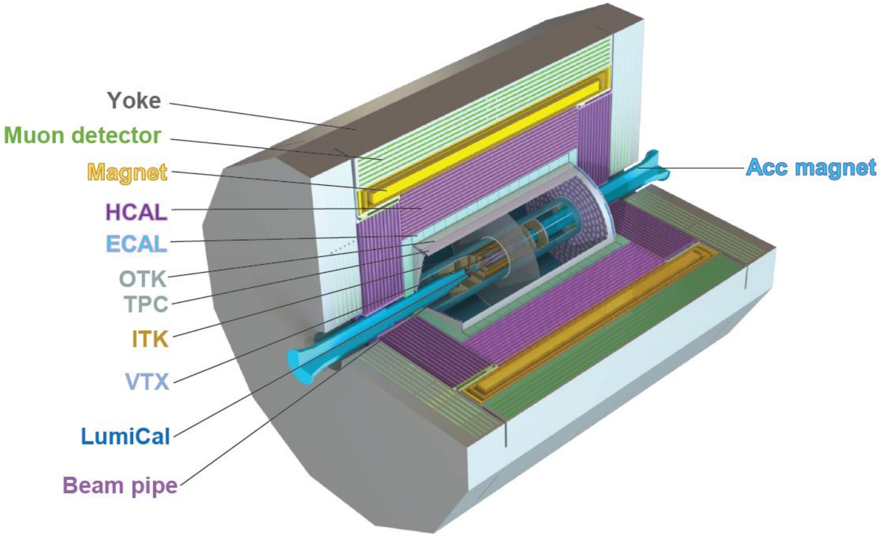
π in B decays



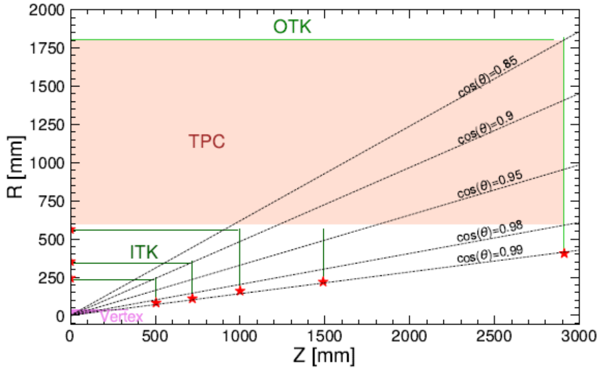


CEPC and AGORA detector

AGORA detector



Tracking system



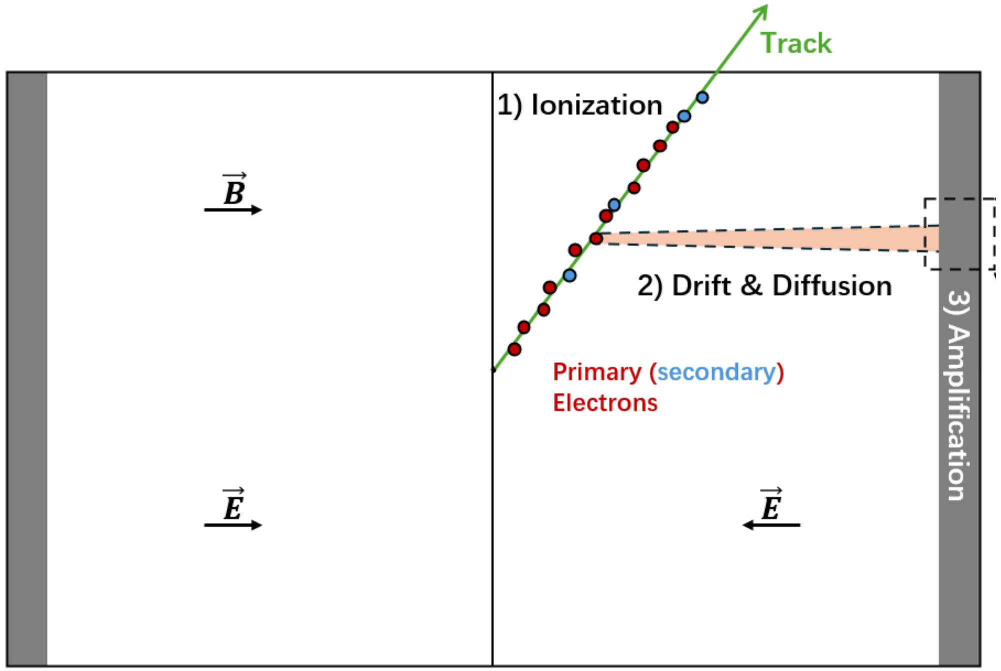
TPC parameters

Parameter	Value
Radial extension	0.6–1.8 m
Full length	5.8 m
Potential at cathode	−63,000 V
Gas mixture	$Ar{:}CF_4{:}iC_4H_{10}$ = 95:3:2
Drift velocity	8 cm/μs
Transverse diffusion	30 $\mu m/\sqrt{cm}$
Longitudinal diffusion	262 $\mu m/\sqrt{cm}$
Gas gain (MicroMegas)	2000
Pad size	500 × 500 μm^2
Total readout modules (per endcap)	244
Total readout channels (per endcap)	~33.5 M
Equivalent Noise Charge (per channel)	100 e^-
Power consumption	< 100 mW/cm^2

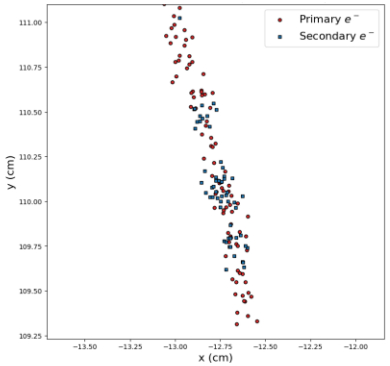
Table 1. Key parameters of the CEPC TPC.

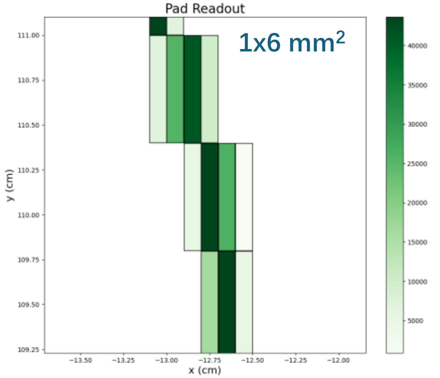
- **The CEPC is proposed as a future Higgs and Z factory, with a 100 km circumference that enables rich physics programs[1]**
  - Higgs physics, EW interactions, flavor physics, QCD and searches for new physics.
- **The CEPC detector, AGORA, features a large TPC positioned between silicon trackers for PID**
  - Low material budget (1.14 X_0): precise low-momentum tracking
  - **High granularity (500x500 um^2): accurate dN/dx measurements**

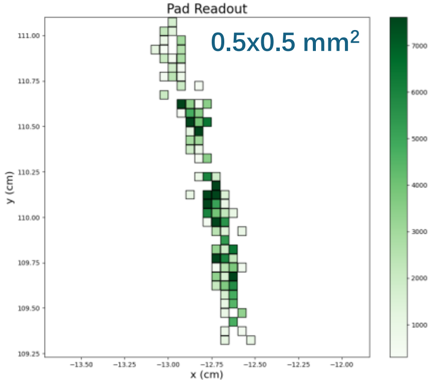
Ionization measurement in TPCs



Electrons at
the endcap







dE/dx (traditional method):

- **Method:** Total energy loss measurement by integrating the energies in large pads
- **Characteristics:**
  - Large fluctuations from energy measurements, amplification, secondary ionizations, etc

dN/dx or cluster counting ("ideal" method):

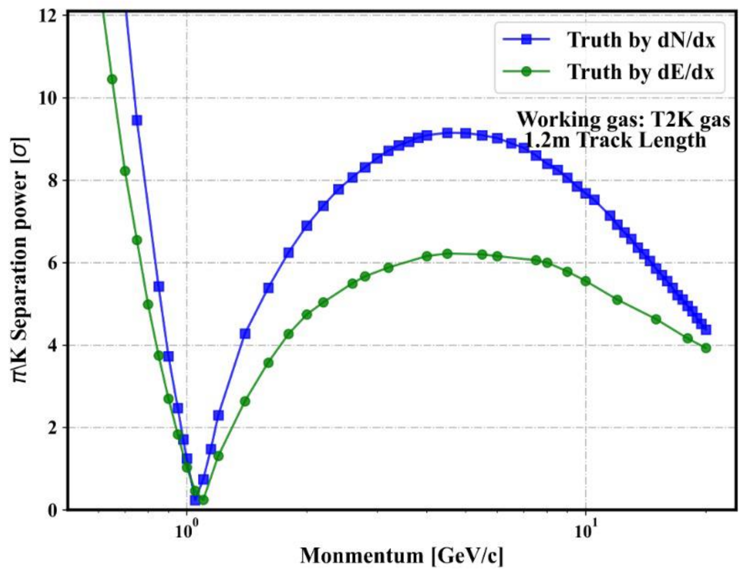
- **Method:** Number of primary ionization cluster measurement, **requiring high granularity readout**
- **Characteristics:**
  - **Small fluctuation (resolution potentially improved by a factor of 2)**

1. JINST 20 P11019
2. NIM A 1081 (2026) 170849

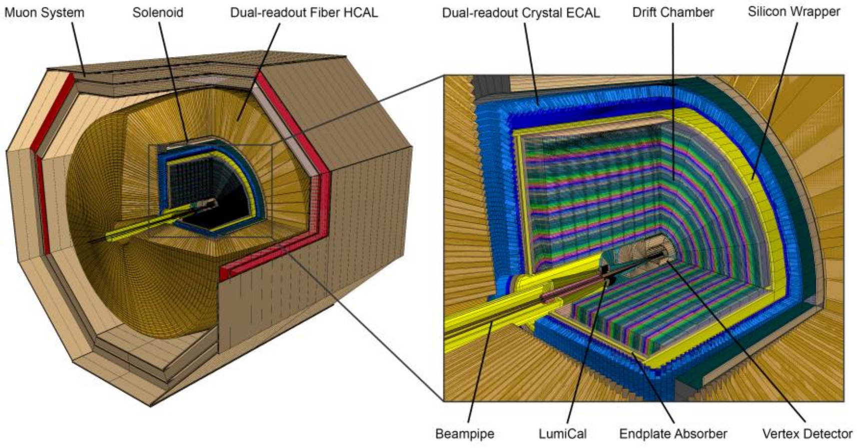
dN/dx is a powerful PID technique

- **dN/dx is much better than dE/dx**
  - Particle separation power: $\frac{\text{separation}}{\text{resolution}} = \frac{|\mu_A - \mu_B|}{\sqrt{\frac{\sigma_A^2 + \sigma_B^2}{2}}}$
- **Besides CEPC, dN/dx is also proposed in future detector designs**
  - FCC-ee: IDEA Drift Chamber[1] and Pixel TPC[2]

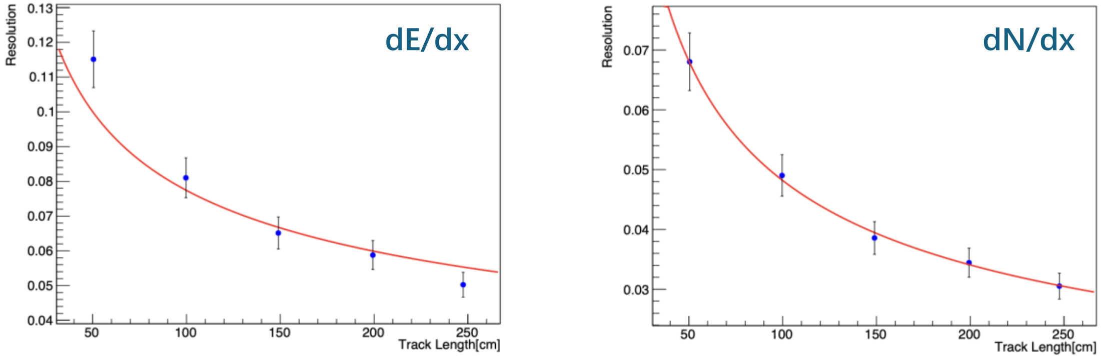
K/pi separation power



IDEA detector



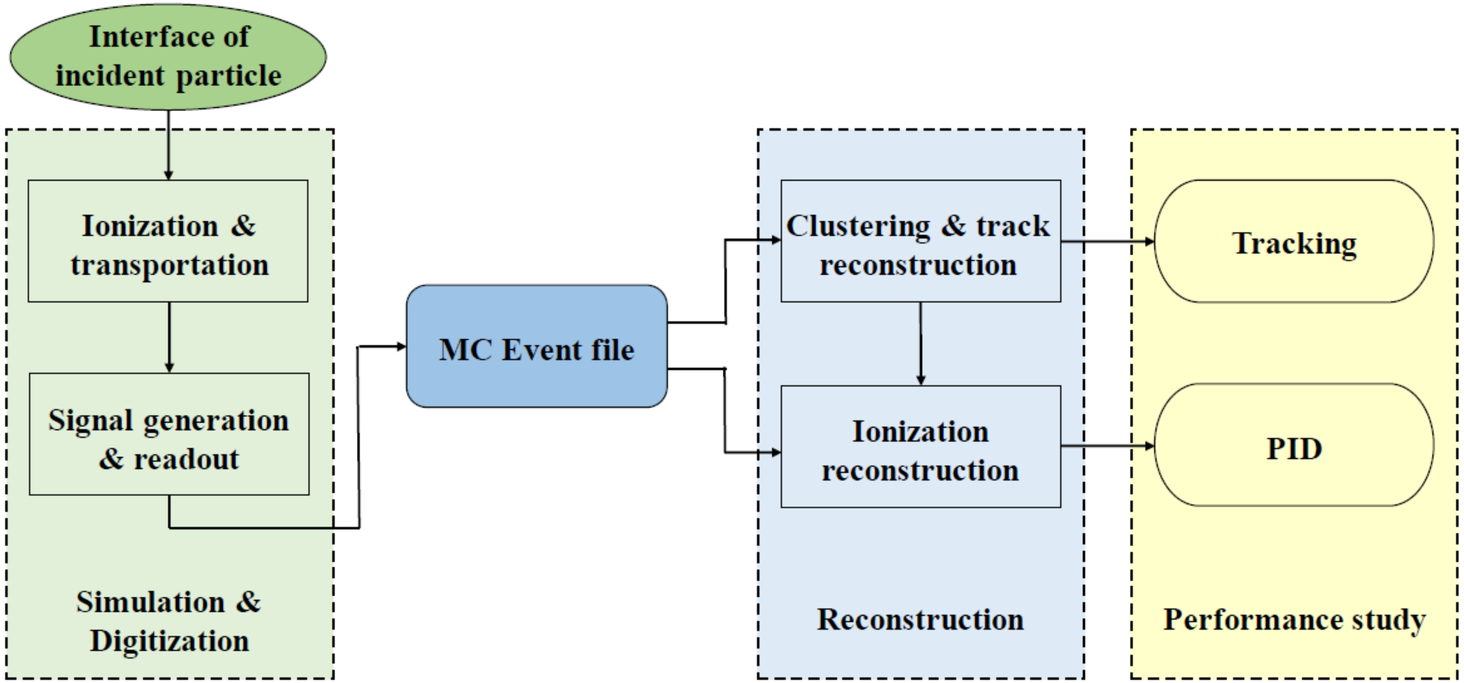
dE/dx and dN/dx resolution from beam tests (IDEA group)



Resolution improved by roughly a factor of 2

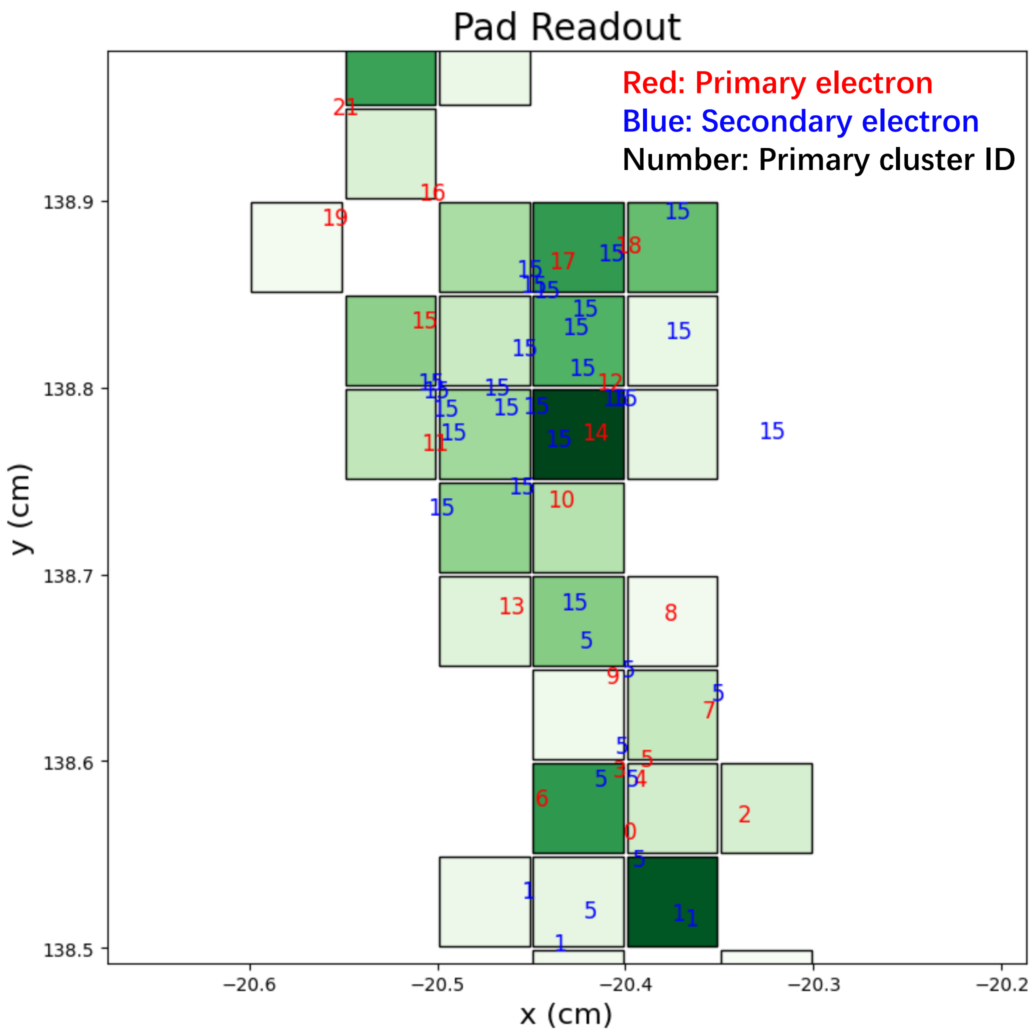
1. 2025 JINST 20 C08006
2. NIM A 952 (2020) 161978

TPC simulation framework



- **Precise simulation:**
  - Full geometry
  - Gas mixture: $Ar/CF_4/iC_4H_{10}$ (95:3:2)
  - Magnetic field: B = 3 T
  - Ionization: Heed
- **Data-driven digitization:**
  - Transport: Drift and diffusion
  - Amplification & readout (from experimental input[1, 2]):
    - Gas gain: ~2000; Noise: ~100e$^-$/ch.; Eff. width: ~100 um

dN/dx reconstruction: Definition



Readout information:

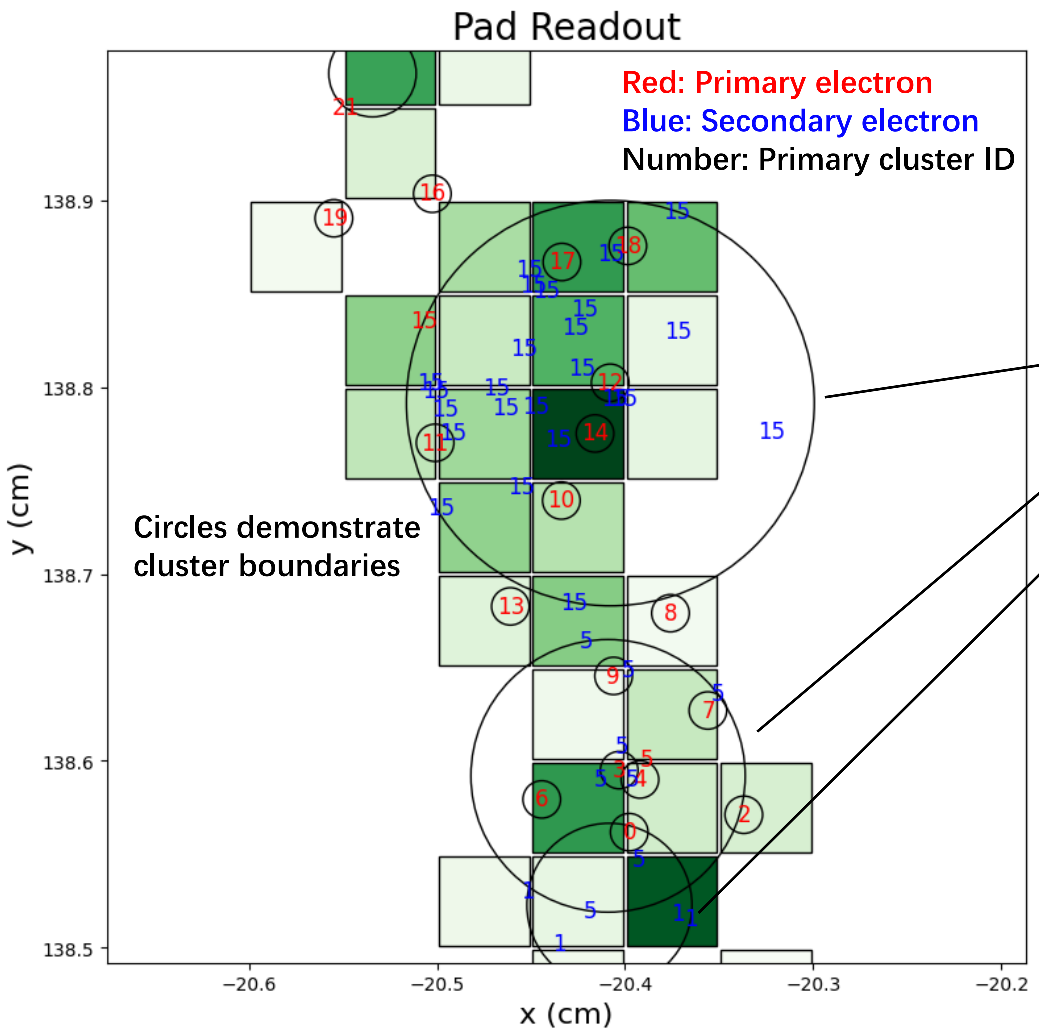
- Charge/timing in each pad

Reconstruction:

- Determine the number of primary electrons from 2D readout pads

  (or mitigating the impact of secondary electrons)

dN/dx reconstruction: Challenges



Cluster 1, 5, 15 overlap with other clusters

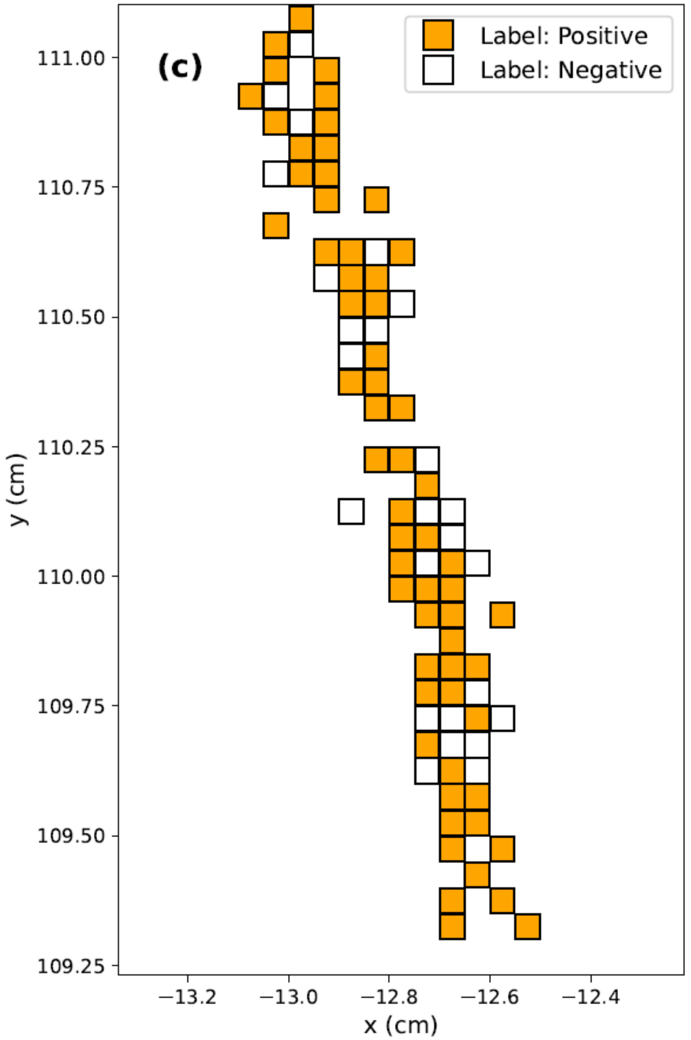
Challenges:

- Secondary electrons under transverse diffusion
  - Max. drift length 2.9m ➔ max. diffusion 550um ➔ Overlapped clusters ➔ Very difficult to use position locality for clustering

Solution:

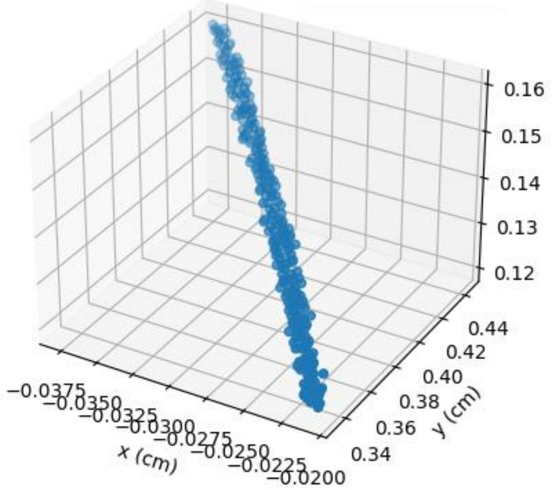
- Supervised learning for an efficient reconstruction algorithm

Supervised learning



- **Method: Supervised learning**
  - Pad labeling:
    - Positive: More than 1 primary e^-
    - Negative: No primary e^-
  - Perform binary classification

- **Data structure: Point cloud**
  - 2D position + 1D timing ➔ 3D spatial coordinates ➔ Point-cloud-based methods

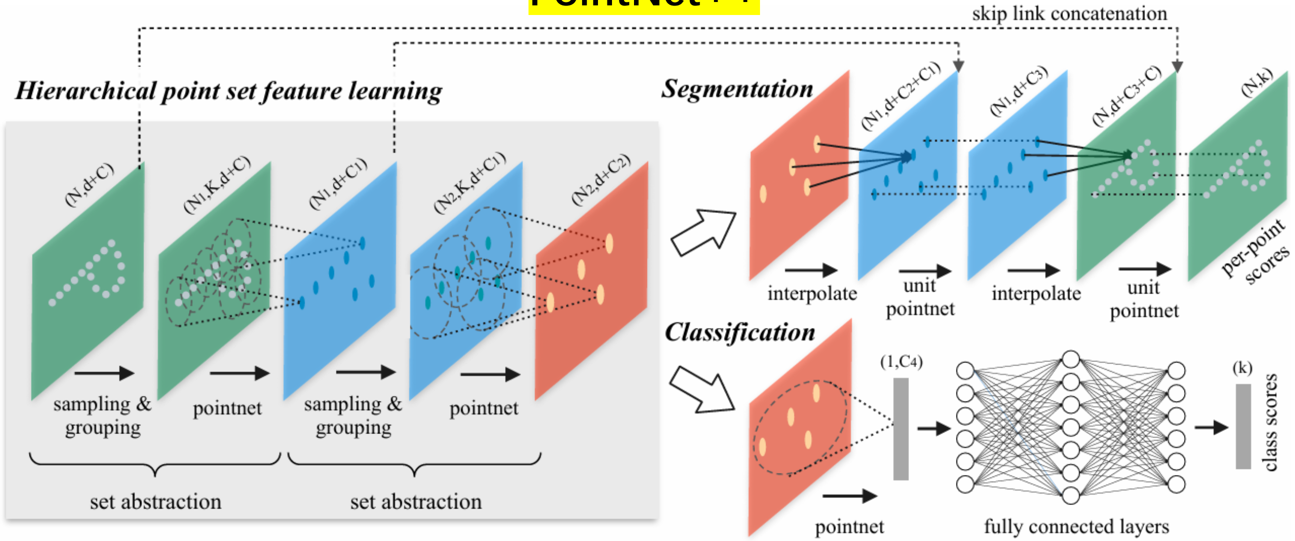


1. CR Qi, et. al., NIPS 2017
2. H. Zhao, et. al., IEEE/CVF 2021

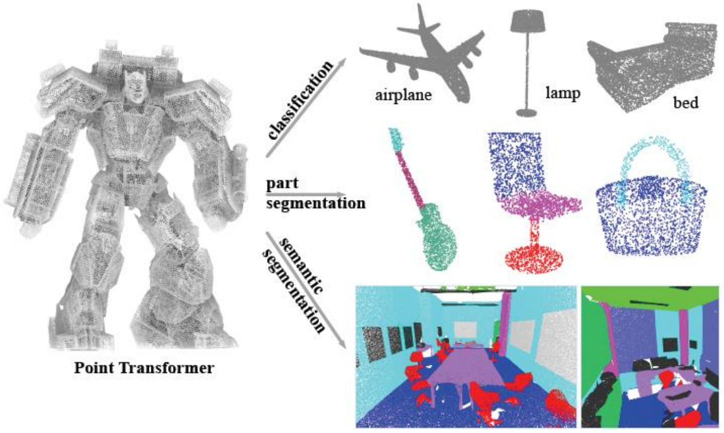
Point-based methods

- **PointNet++**[1]
  - Hierarchical structured: Encoder-decoder with skip links
  - Basic building block for feature aggregation: MLP + pooling

PointNet++

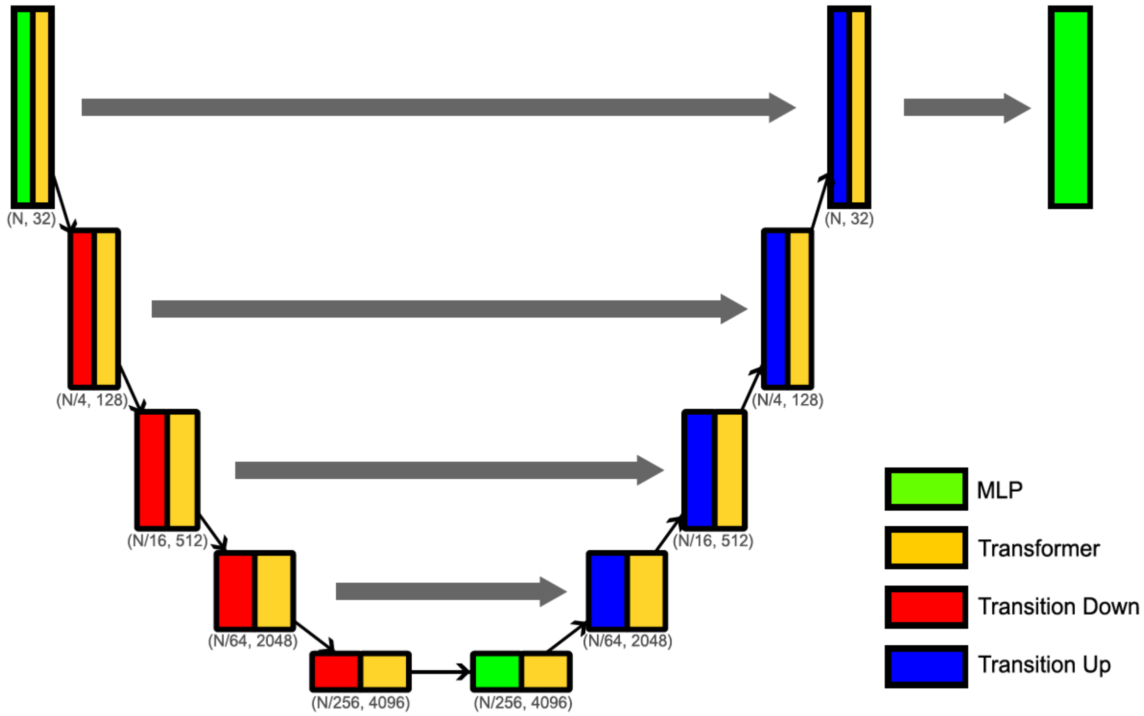


Point Transformer



- **Point Transformer**[2]
  - Replace the MLP + pooling with self-attention blocks

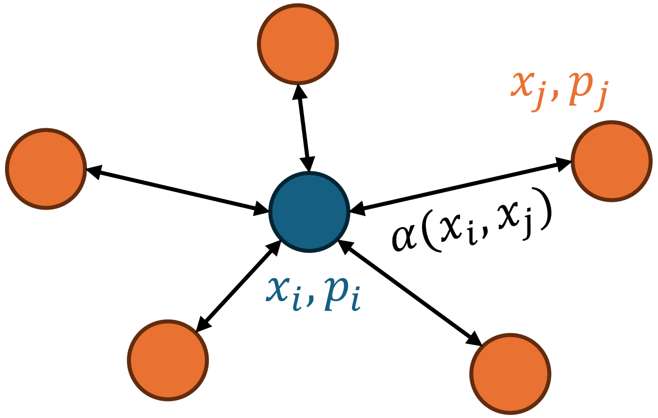
GraphPT: Point Transformer on Graphs



- **Design principles:**
  - PT built upon GNNs
  - Self-attention via message passing
- **Backbone structure:**
  - U-Net-based hierarchical architecture
    - Encoder-decoder with skips
    - MLP + softmax layer outputs [0, 1]

Our work: Guang Zhao, et. al., JHEP 04 (2026) 021

GraphPT: Point Transformer on Graphs

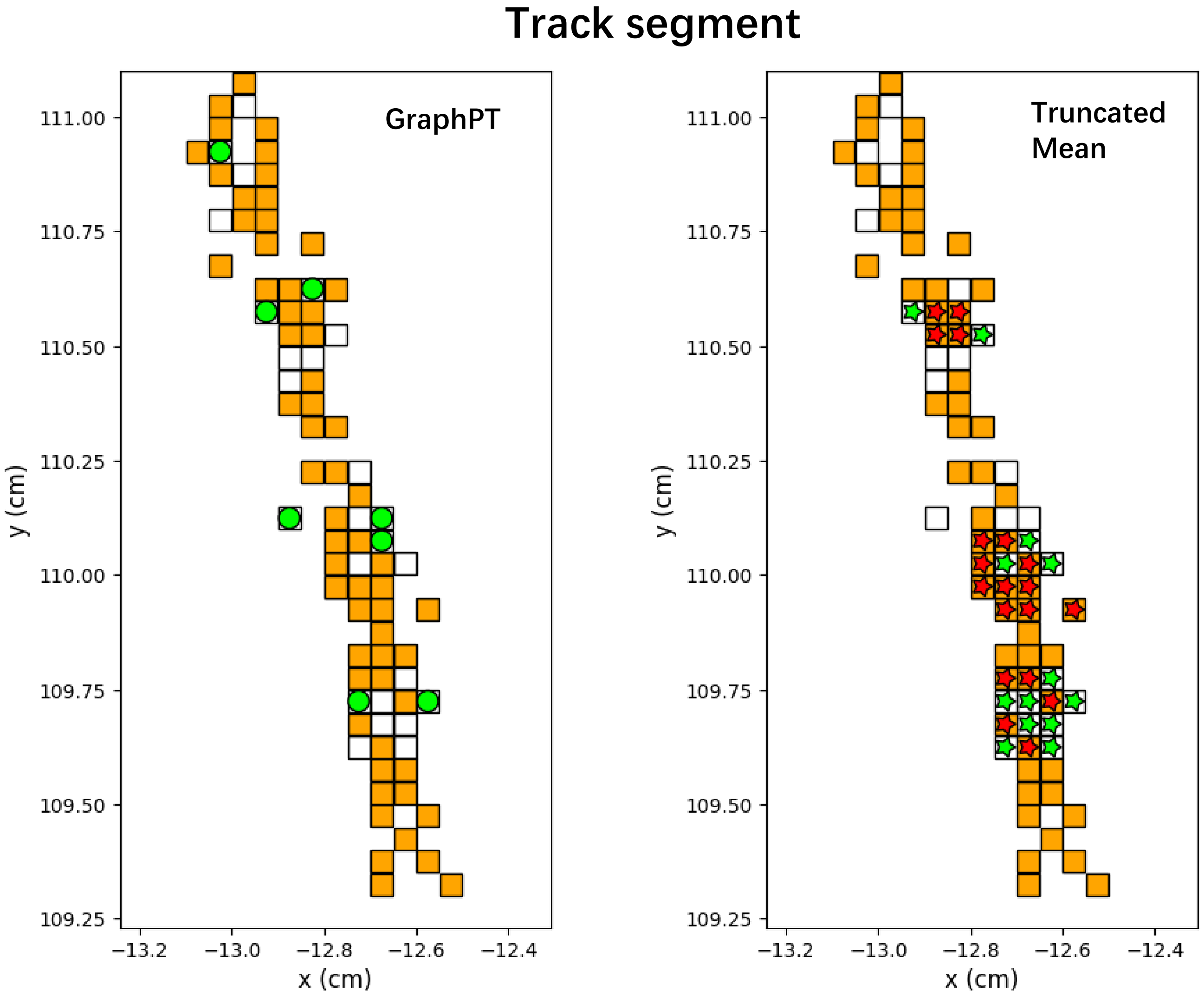


x: (Q, T)
p: 3D position

- **Self-attention mechanisms:**
  - Message-passing:
    - $x_i' = \beta(x_i) + \Sigma_{j \in N(i)} \alpha(x_i, x_j) \beta(x_j)$
  - Subtract operator (from PT):
    - $\alpha(x_i, x_j) = \mathrm{softmax}(\delta(\phi(x_i) - \psi(x_j) + \theta(p_i - p_j)))$
  - Multi-head dot-product operator (**this work**):
    - $\alpha(x_i, x_j) = \mathrm{softmax}\left(\frac{\phi(x_i)^{\mathrm{T}}(\psi(x_j) + \theta(p_i - p_j))}{\sqrt{d_{\mathrm{out}}}}\right)$

Our work: Guang Zhao, et. al., JHEP 04 (2026) 021

Classification for a track segment



Color code:

- Orange pad: Ground truth positive
- Write pad: Ground truth negative
- Green marker: True negative ☺
- Red marker: False negative ☹

Marker:

- Circle: Classified as negative by GraphPT
- Star: Classified as negative by Truncated Mean

Conclusions:

- Less false negative predictions by GraphPT
- Most signals are preserved, leading to higher signal efficiencies

Classification performance

- **Metrics:**
  - Accuracy = $\frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}}$
  - F1 score = $\mathbf{2} \times \frac{\boldsymbol{P \times R}}{\boldsymbol{P+R}}$, where $\boldsymbol{P} = \frac{\mathbf{TP}}{\mathbf{TP+FP}}$ and $\boldsymbol{R} = \frac{\mathbf{TP}}{\mathbf{TP+FN}}$

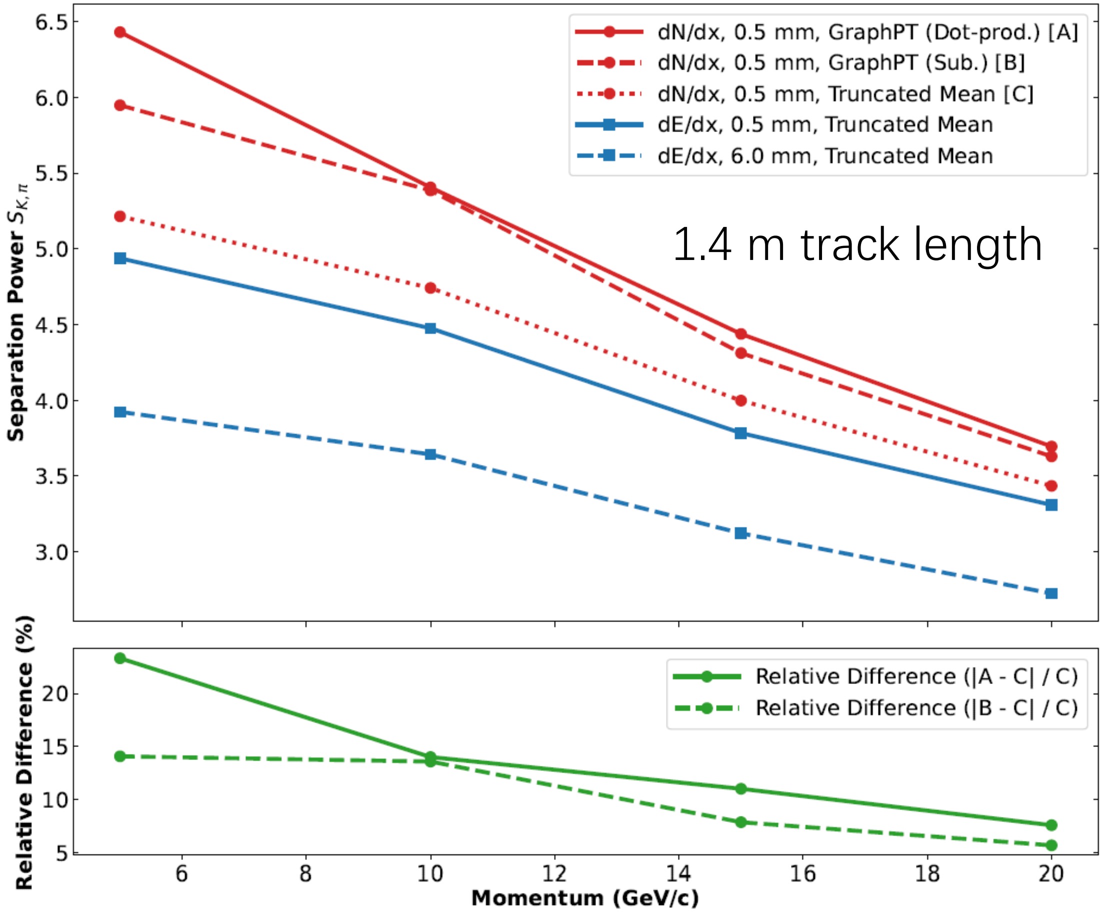
- **Conclusions:**
  - GraphPT has lower precision but much higher recall ➔ Much improved signal efficiency: **~60% improvement**
  - GraphPT has much better accuracy and F1 score: **~20% improvement**
  - The GraphPT with dot-product attention achieve the overall best classification power

Table 3. Classification metrics.

Method	Accuracy	Precision	Recall	F1-Score
Truncated Mean	0.601	0.743	0.574	0.648
GraphPT (Sub.)	0.698	0.689	0.960	0.802
GraphPT (Dot-prod.)	**0.707**	**0.702**	**0.941**	**0.804**

PID performances

K/π separation power



- ✓ **Metrics:**
  - ✓ K/π separation power within 5-20 GeV/c
- ✓ **dN/dx (vs. truncated mean):**
  - ✓ **GraphPT (sub.): 5-15% improvement**
  - ✓ **GraphPT (dot-prod.): 10-20% improvement**
- ✓ **Overall:**
  - ✓ All dN/dx results outperform dE/dx
  - ✓ Up to 50% improvement compared with traditional 6mm-pad dE/dx

Conclusions

- **dN/dx is novel technique offering robust PID for hadrons at momenta reaching tens of GeV/c.**
- **We have developed a reconstruction method based on point-cloud transformers, yielding significant performance gains over traditional approaches:**
  - Signal efficiency: ~60% improvement
  - Accuracy/F1 score: ~20% improvement
  - K/π separation power: ~10-20% improvement
- **The model can also be applied to other high-granularity 3D detector data.**
- **Future work will focus on refining simulations and advancing detector R&D to experimentally validate the dN/dx method.**

Backup

Baseline method: Truncated mean

- **Most used method:**
  - Reject measurements M_i with highest values ➔ most related to the secondaries
  - Calculate mean of remaining samples

Average over the lowest *n* measurements:

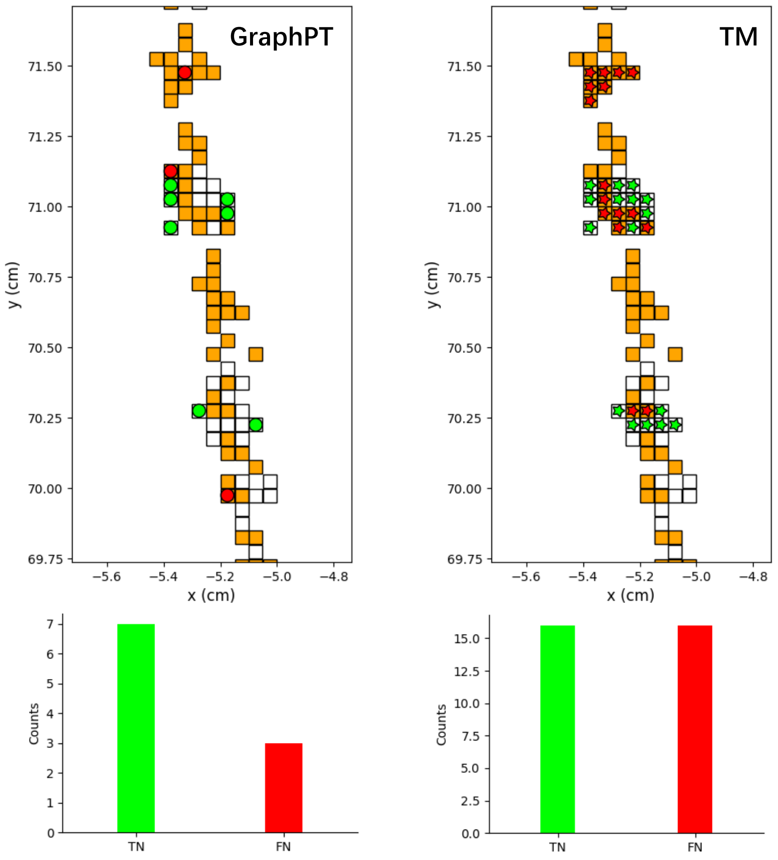
$$\langle M \rangle_\alpha = \frac{1}{n} \sum_{i=1}^{n} M_i$$

where $M_i \leq M_{i+1}$ for $i = 1, \dots, N-1$ and $\alpha = n/N$ is a fraction.

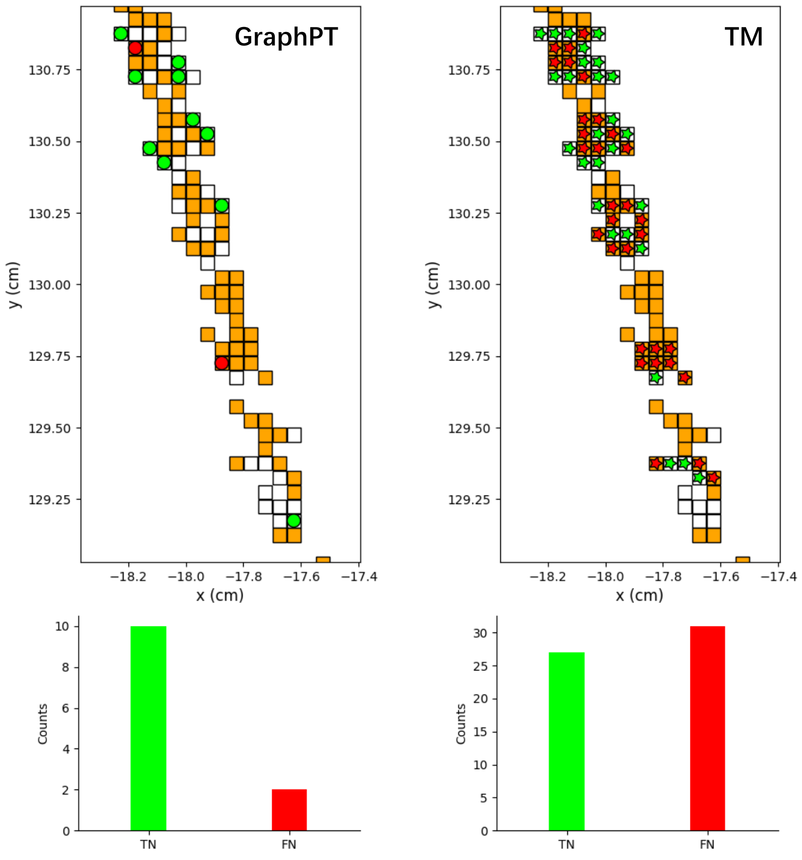
- **Measurement $\boldsymbol{M}$ refers to:**
  - **charge** for dE/dx
  - **number of activated pads** for dN/dx

Classification for more track segments

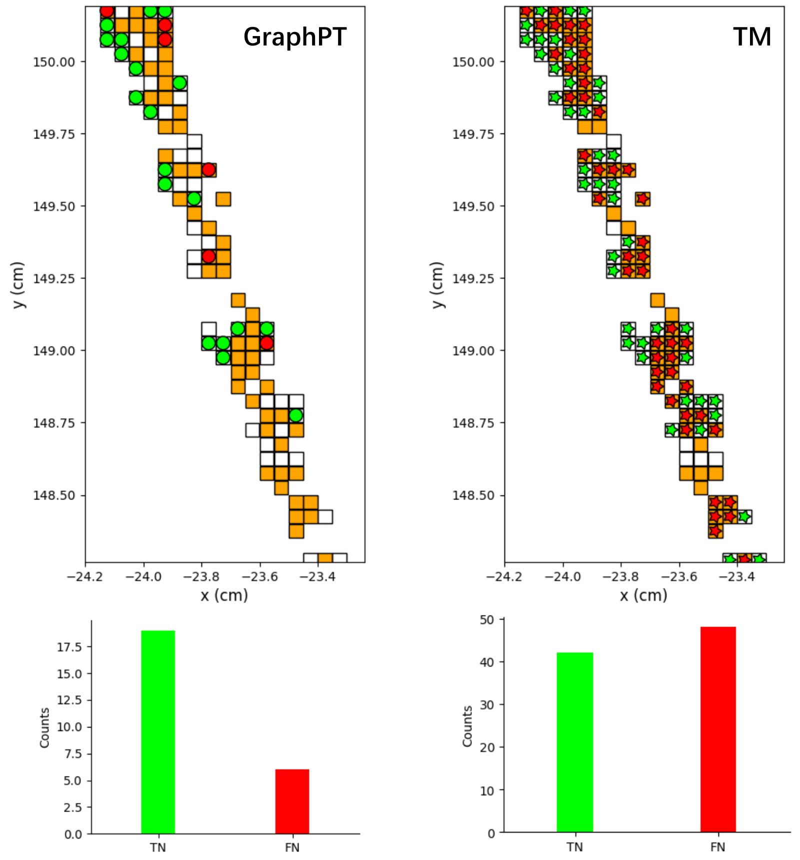
Track segment 2



Track segment 3

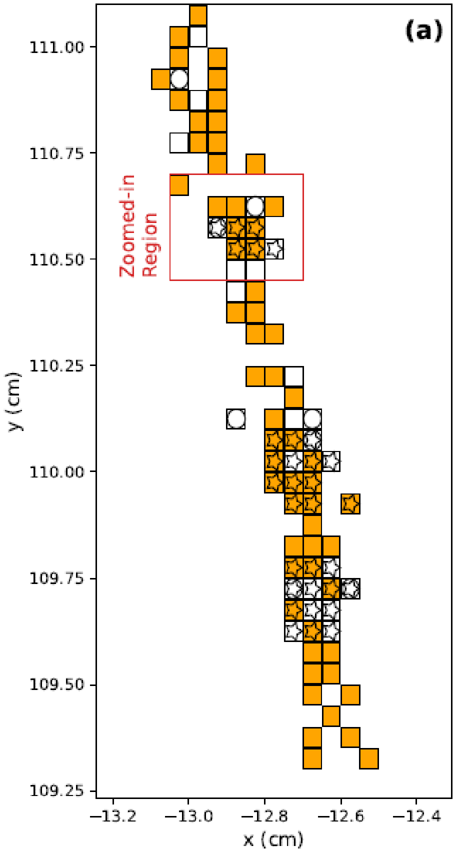


Track segment 4

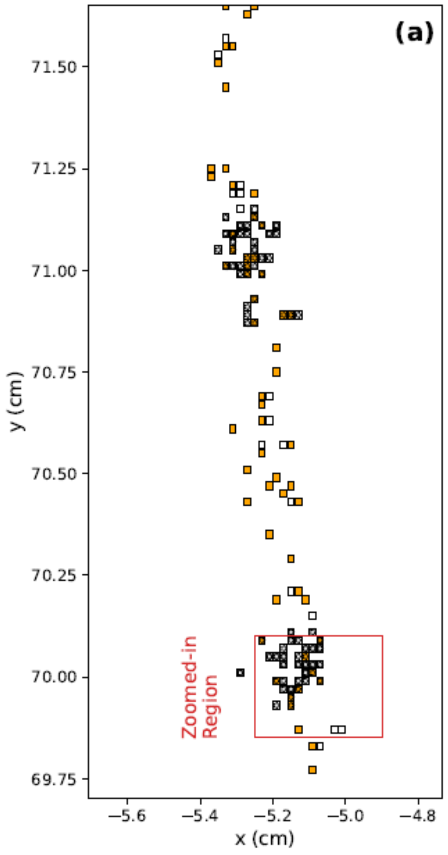


Validation using a 200x200 um^2 pad size

500x500 um^2



200x200 um^2

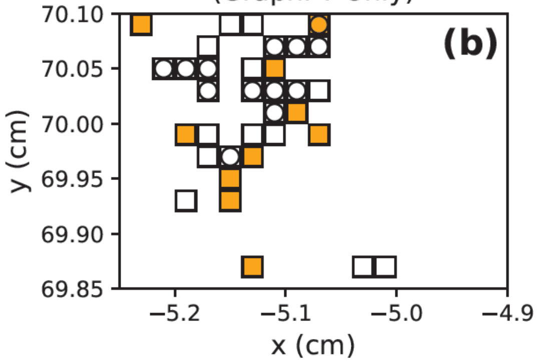


More challenging with a smaller pad size:

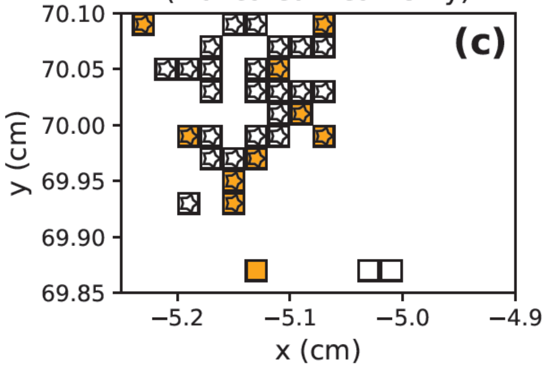
- Hits are sparser
- Secondary electrons are easier to be detected

Less false negative with ML

Zoomed-in Region (GraphPT Only)

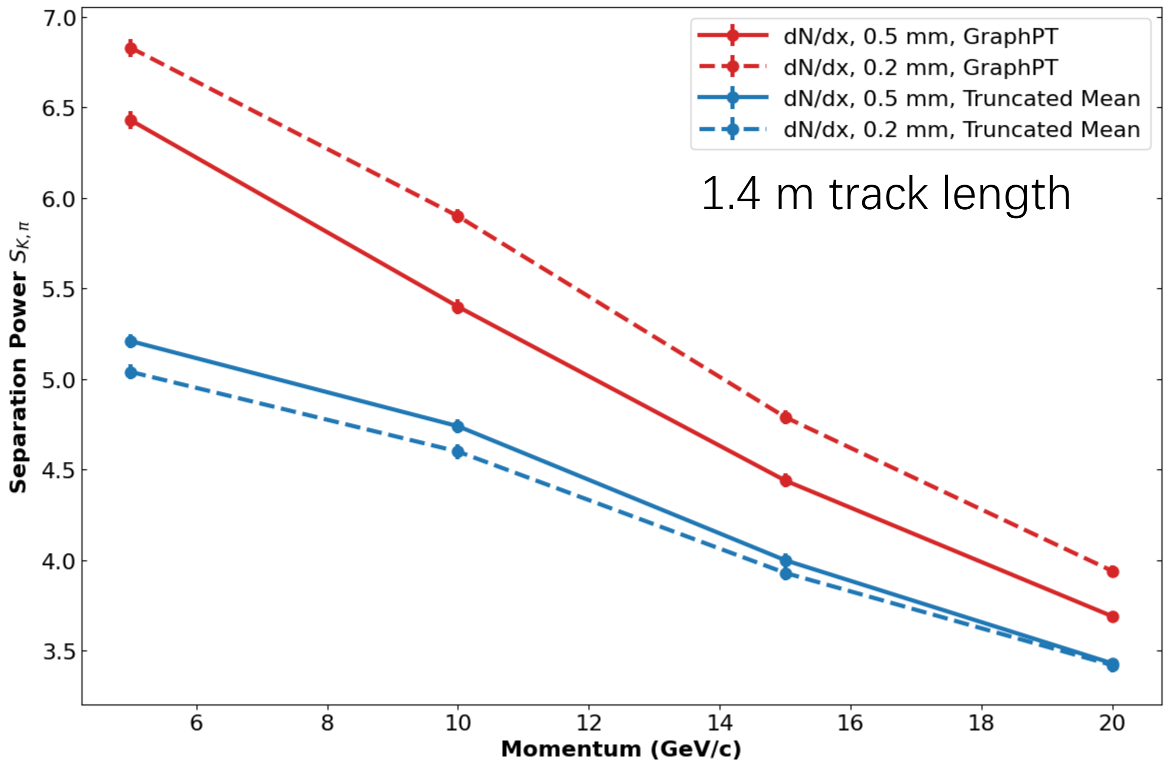


Zoomed-in Region (Truncated Mean Only)



Validation using a 200x200 um^2 pad size

K/π separation power



- ✓ **Compare to 500x500 um^2:**
  - ✓ **Truncated mean is slightly degraded due to reduced signal-to-noise ratio**
    - ➢ Noise level is the same (100e-/pad), but # of pads increases by a factor of 6.25
  - ✓ **ML is significantly improved by 35%-15%**
    - ➢ Information is exploited more effectively and more accurate suppression of secondaries