dN/dx Reconstruction with Machine Learning for Drift Chamber

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On behalf of the CEPC DC Working Group

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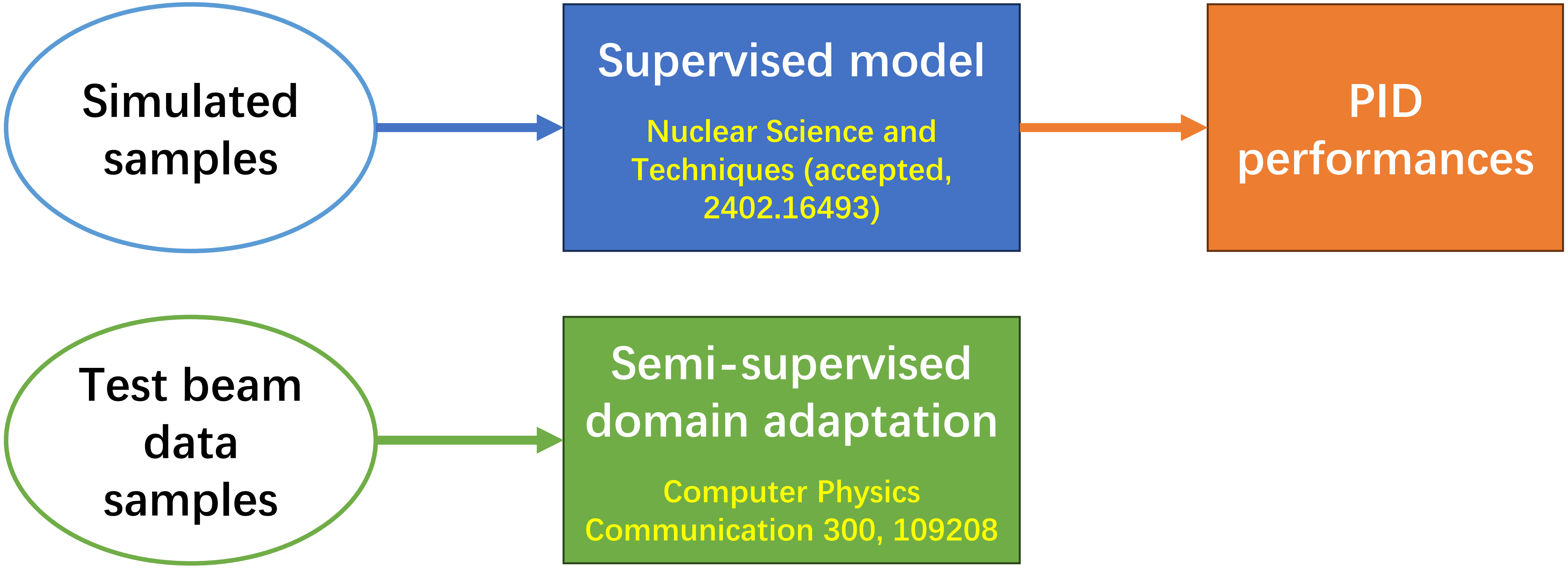
Quantum Computing and Machine Learning Workshop 2024

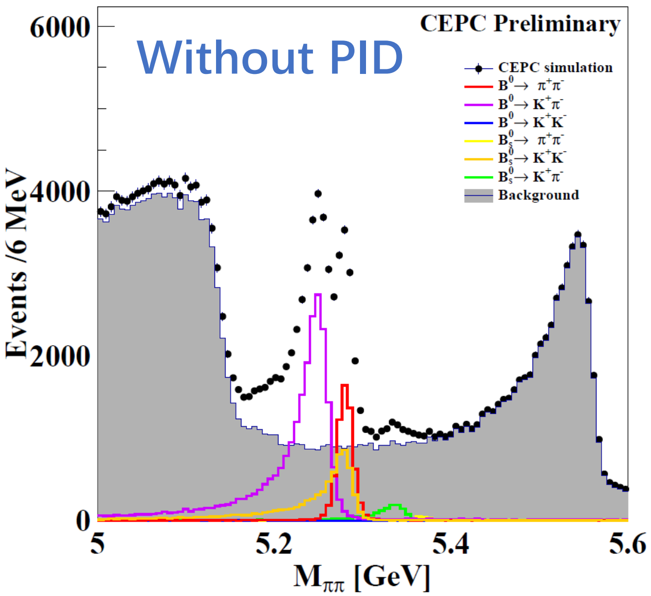
ML algorithms for dN/dx reconstruction



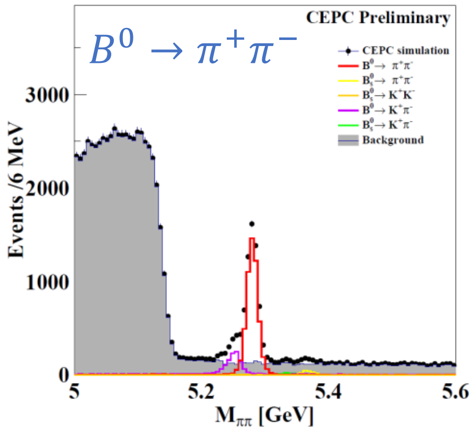
Motivation: Particle identification

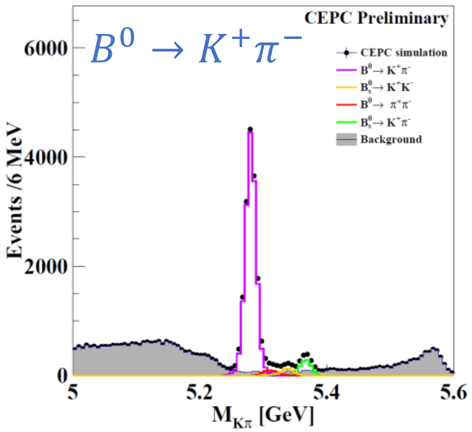
- **PID is essential for high energy physics experiments**
  - Suppressing combinatorics
  - Distinguishing between same topology final-states
  - Adding valuable additional information for flavor tagging of jets
  - …

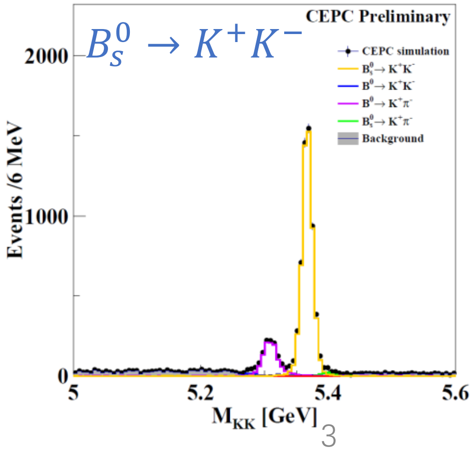
Benchmark channel:
$B^0_{(s)} \to h^+h'^-$



With PID

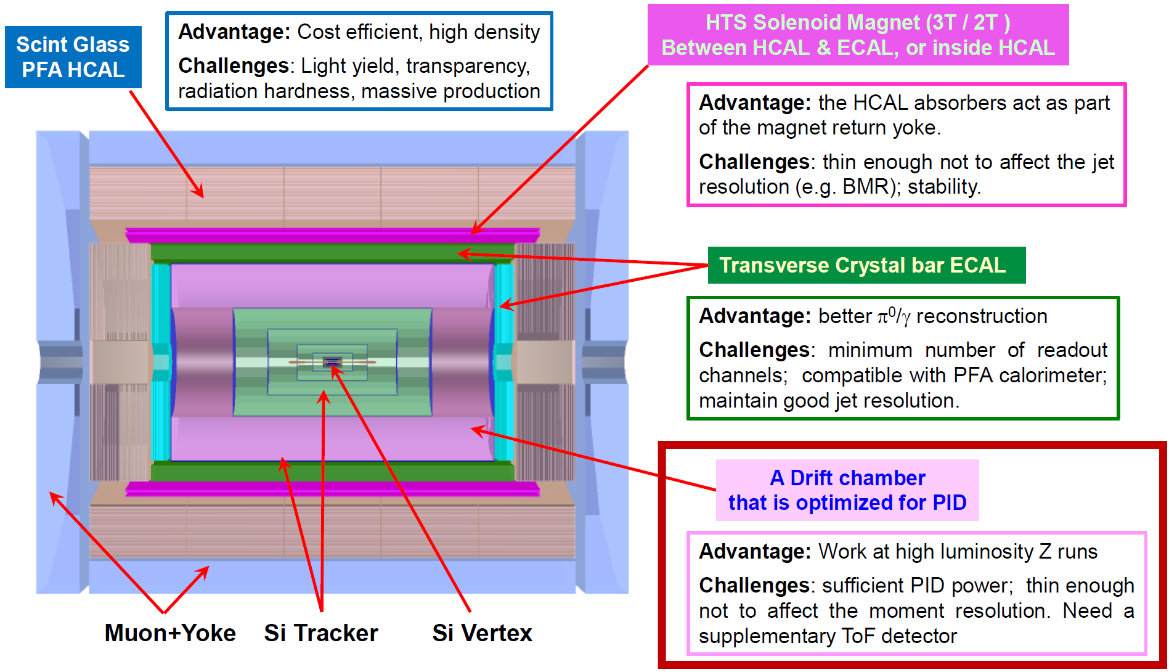






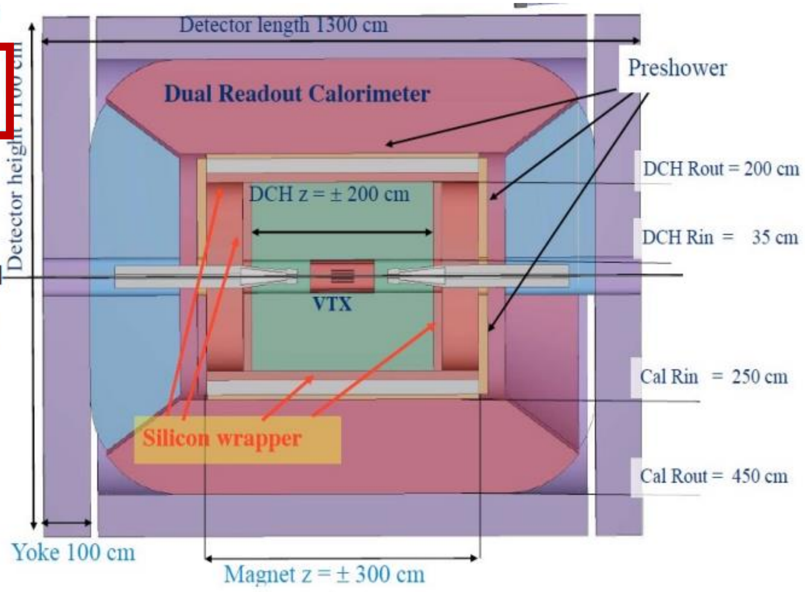
Drift chamber for next-gen experiments

CEPC 4th Concept



IDEA for FCC-ee

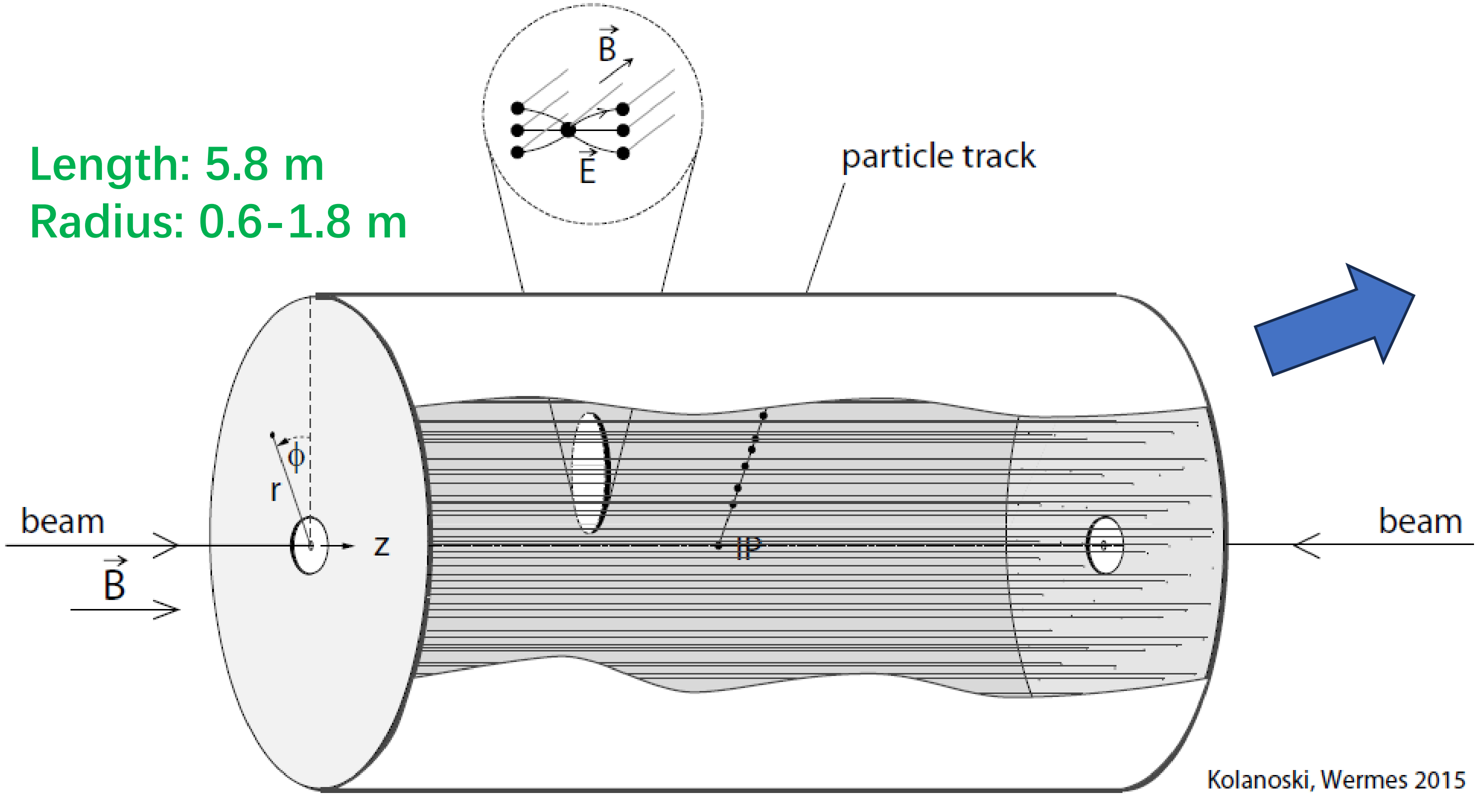
- a silicon pixel vertex detector
- a large-volume extremely-light **drift chamber**
- surrounded by a layer of silicon micro-strip detectors
- a thin low-mass superconducting solenoid coil
- a preshower detector based on **μ-WELL technology**
- a dual read-out calorimeter
- muon chambers inside the magnet return yoke, based on **μ-WELL technology**



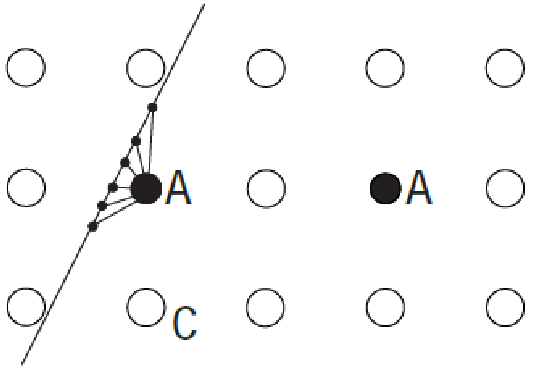
- Flavor physics studies in high luminosity Z-pole run requires high performance PID up to tens of GeV/c. Traditional technique, i.e., dE/dx, cannot meet such requirement.
- **Cluster counting (dN/dx) in drift chamber is a breaking through PID technique, which is proposed in both CEPC and FCC-ee**

Ionization measurement in drift chamber

Length: 5.8 m
Radius: 0.6-1.8 m

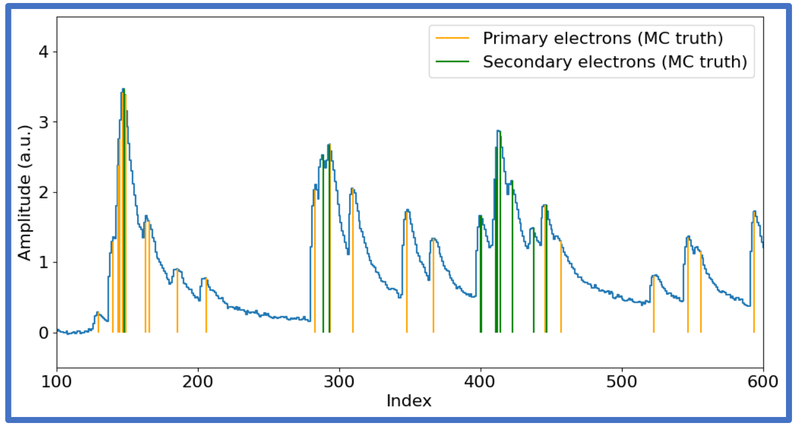


Kolanoski, Wermes 2015

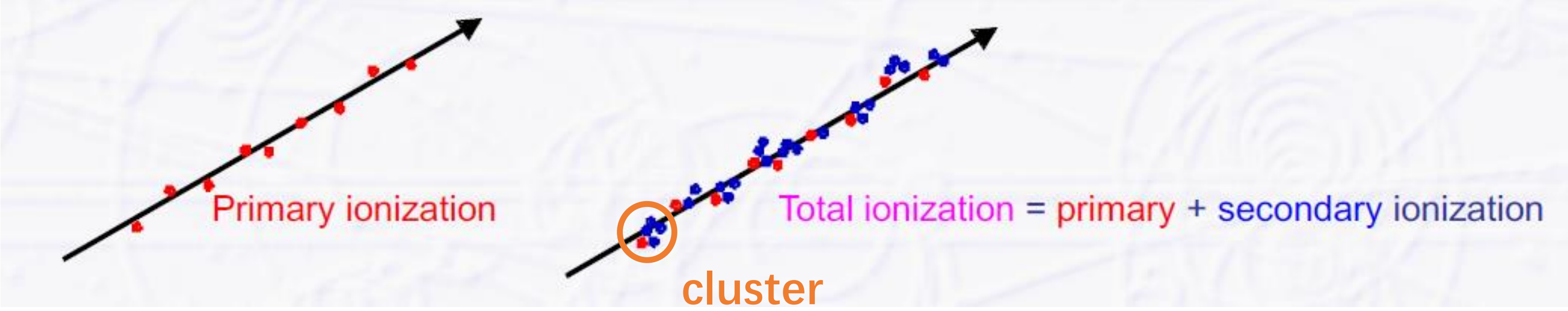


Cell size: 1.8x1.8 cm^2

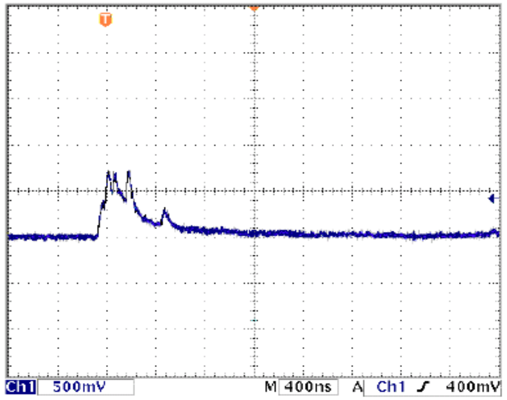
~15 clusters/cm for 90% He + 10% iC_4H_{10}



Induced current waveform in 1D timing



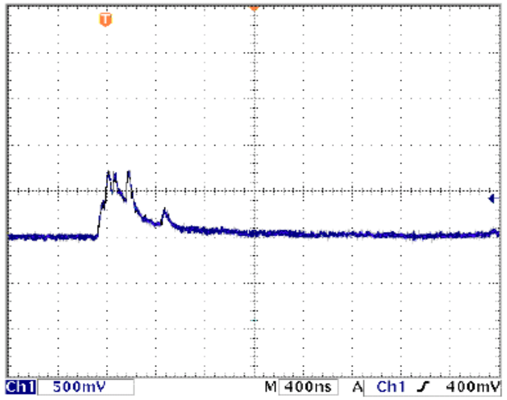
dE/dx and dN/dx measurements



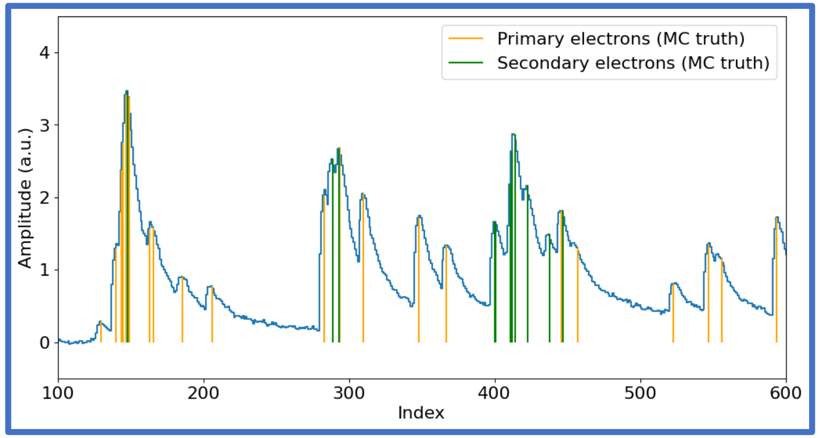
dE/dx (traditional method):

- **Method:** Total energy loss measurement by integrating the waveform
- **Characteristics:**
    - Landau distributed ➔ Loss ~30% statistics due to truncation
    - Large fluctuation from many sources

dE/dx and dN/dx measurements



High bandwidth & sampling rate electronics



dE/dx (traditional method):

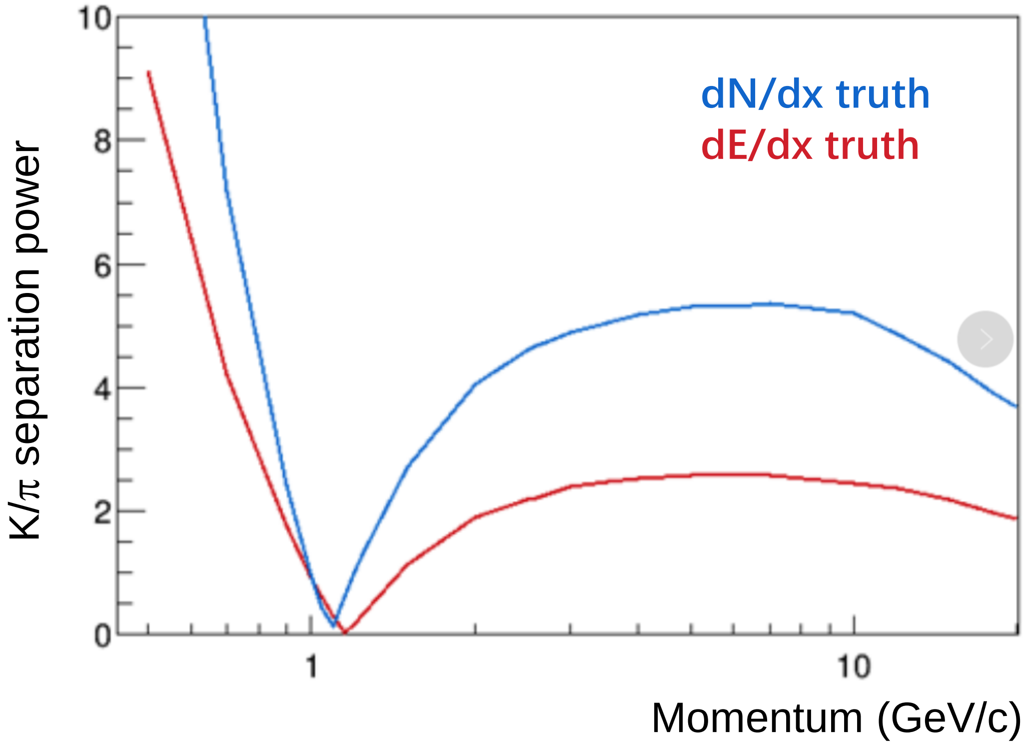
- **Method:** Total energy loss measurement by integrating the waveform
- **Characteristics:**
  - Landau distributed ➔ Loss ~30% statistics due to truncation
  - Large fluctuation from many sources

dN/dx ("ideal" method):

- **Method:** Number of ionization cluster measurement (require fast electronics)
- **Characteristics:**
  - Poisson distributed
  - Small fluctuation (resolution potentially improved by a factor of 2)

Particle separation power

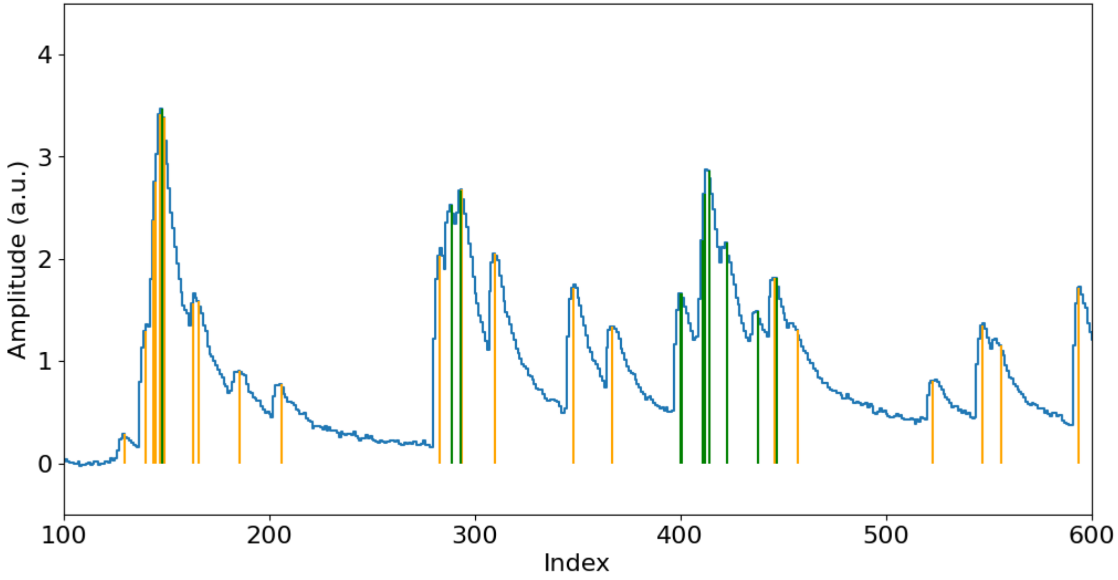
- **Important for physics:**
  - $\text{separation power} = \frac{\text{separation}}{\text{resolution}} = \frac{|\mu_A - \mu_B|}{(\sigma_A + \sigma_B)/2}$
- **Typical K/π separation power:**
  - dE/dx: > 2σ up to 2…20 GeV/c
  - dN/dx: > 3σ up to 2…20 GeV/c



dN/dx has much better PID power than dE/dx

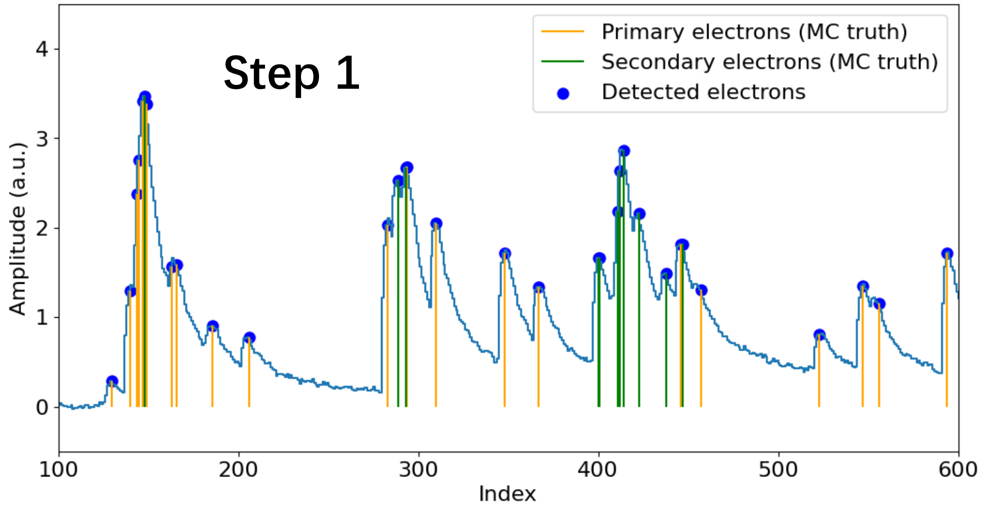
What is dN/dx reconstruction?

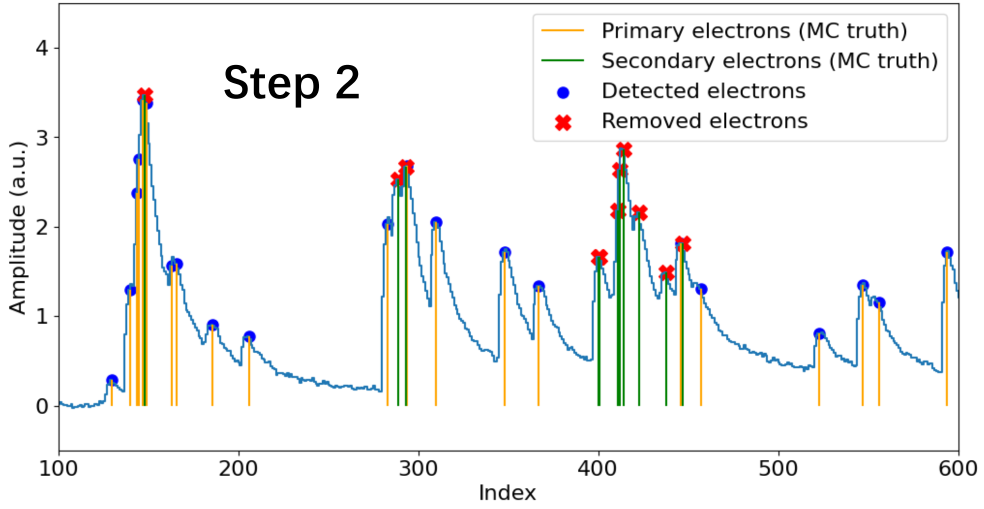
Orange lines: Primary electrons (MC truth)
Green lines: Secondary electrons (MC truth)



GOAL: Determine the number of **primary electrons** in the waveform

dN/dx reconstruction (II)

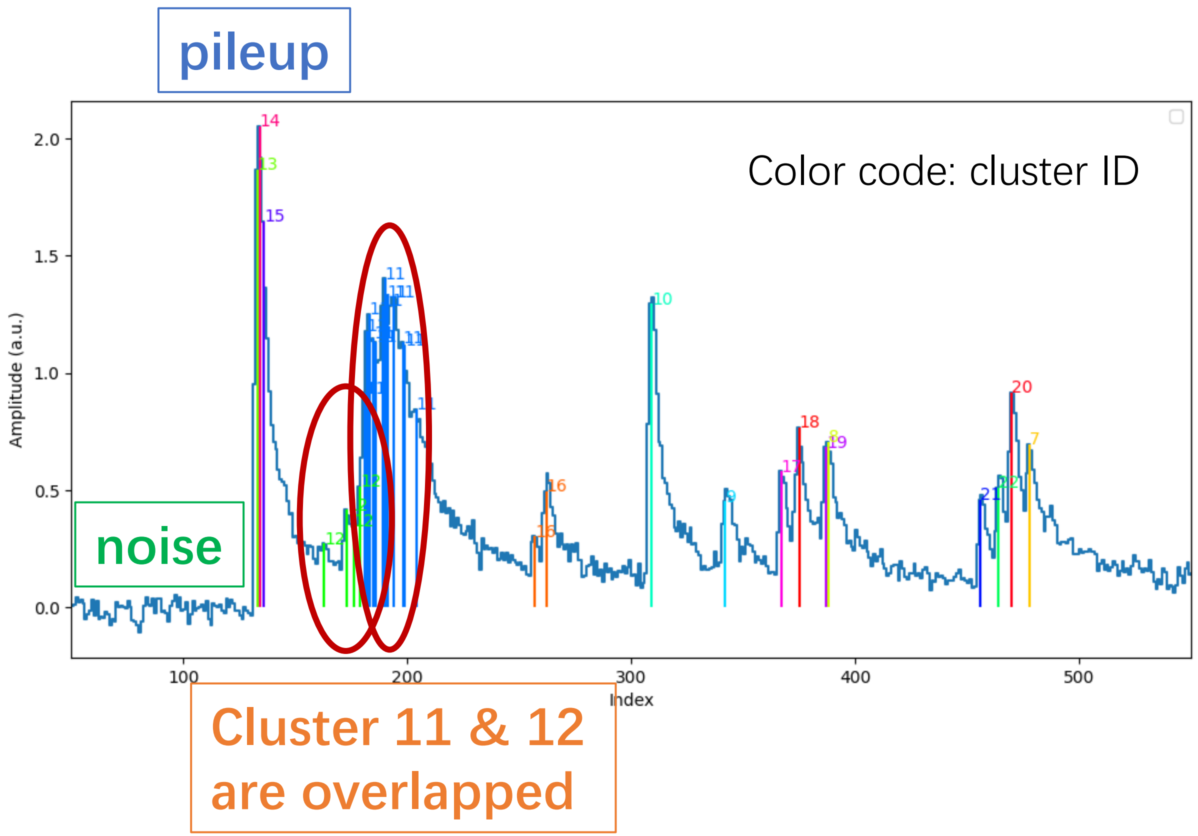




2-step algorithm

- **Peak finding:**
  - Detect peaks from both primary and secondary electrons
- **Clusterization:**
  - Remove secondary electrons from the detected peaks in step 1

dN/dx reconstruction is challenging



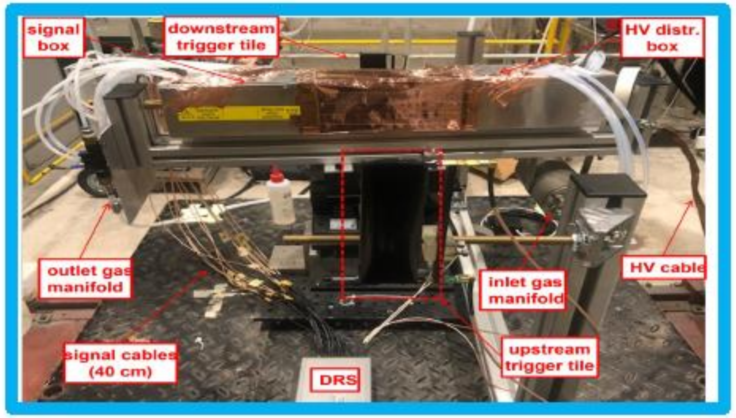
- Highly piled-up ➔ Difficult to efficiently detect pile-ups
- Noisy ➔ Filtering could (significantly) lose efficiency
- Overlapping between clusters ➔ Difficult to set a simple “cut” for clusterization

Solution: Deep learning

Software package and data samples

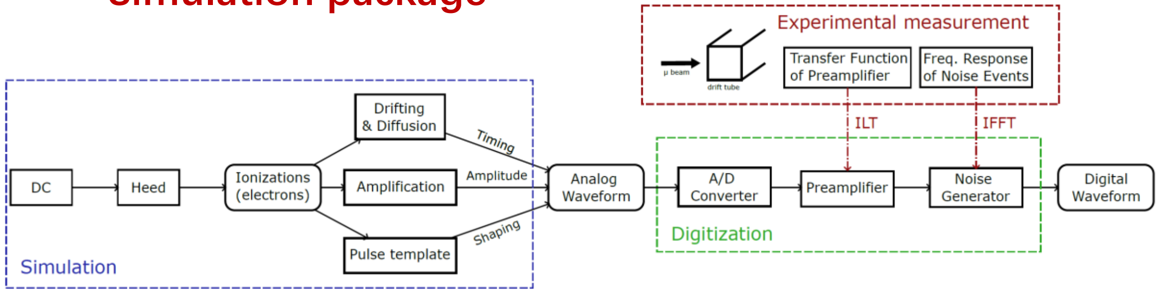
- **Simulation package**
  - Garfield++-based simulation + data-driven digitization
- **Data samples**
  - Simulated samples
    - 0-20 GeV/c pions and kaons
  - Experimental samples
    - 180 GeV/c muons from CERN/H8 beam

Test beam at CERN

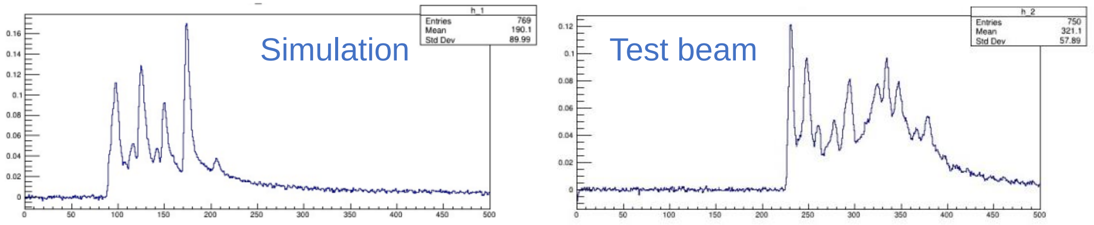


From INFN group leaded by Franco Grancagnolo and Nicola De Filippis

Simulation package

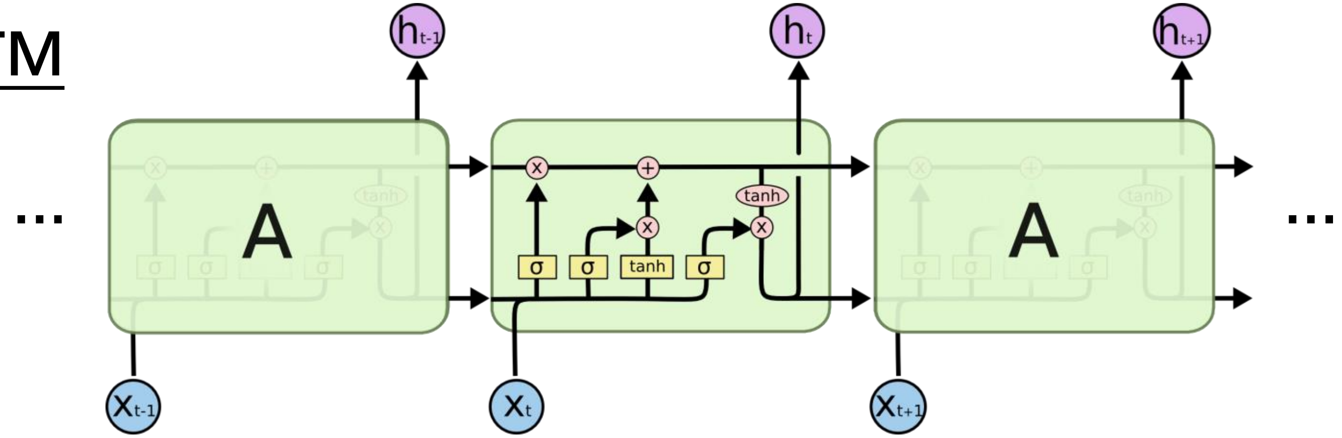


Tuned MC is comparable to data



Supervised model for simulated samples

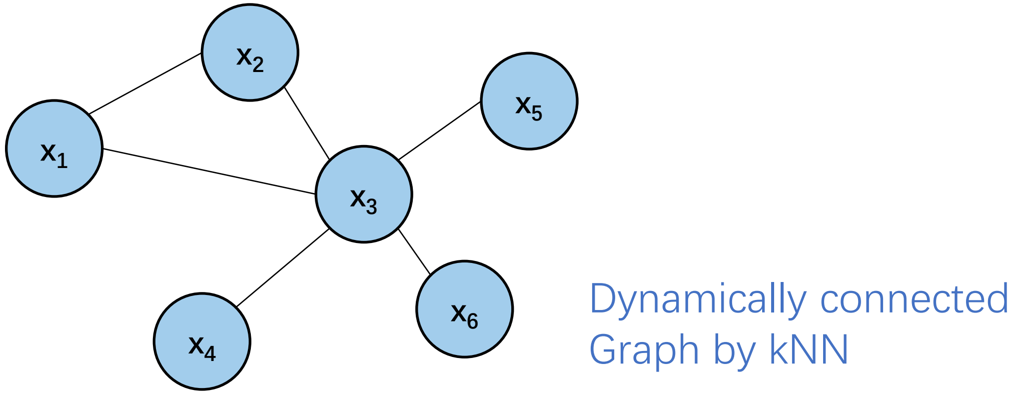
LSTM



LSTM-based peak finding:

- Can efficiently handle time-sequence
- Waveform slices as the LSTM input
- Binary classification of signals and noises

DGCNN

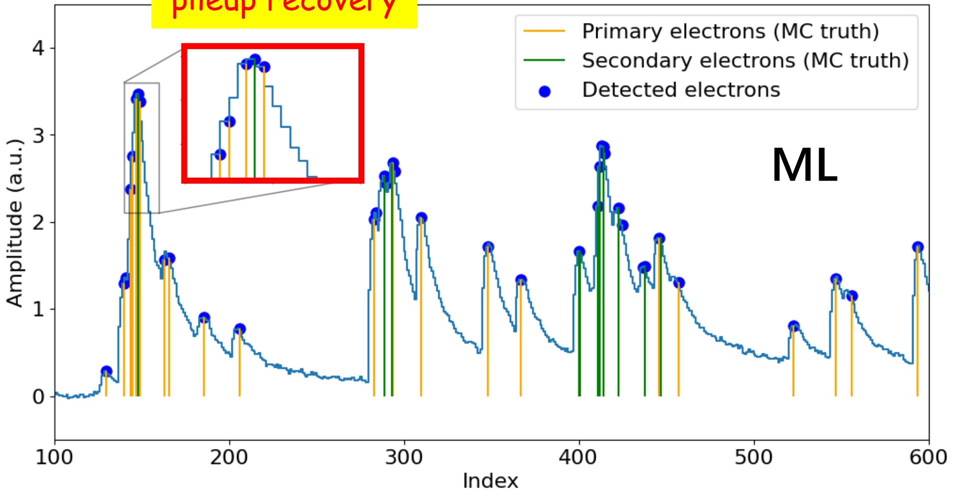


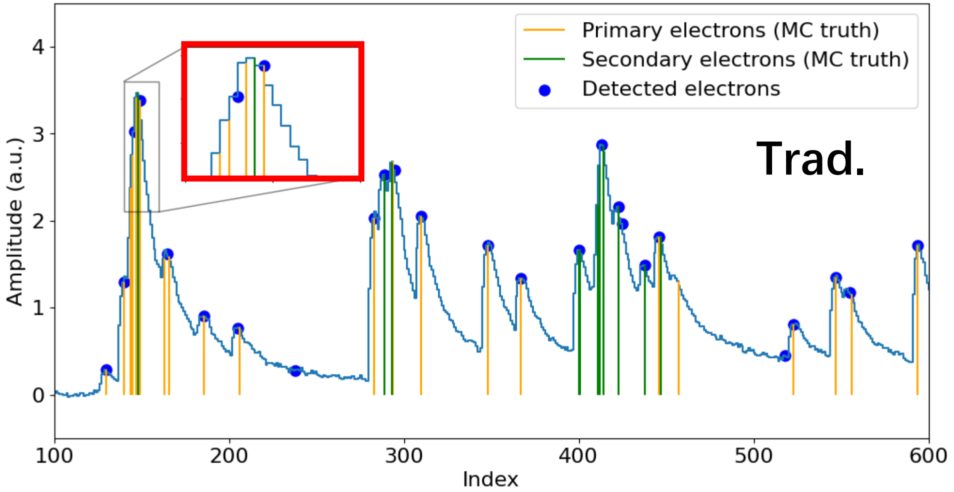
DGCNN-based clusterization:

- Incorporate local information to learn global properties
- Detected timings from the peak-finding as the DGCNN input
- Binary node classification of primary and secondary electrons

Peak finding results

More efficient pileup recovery





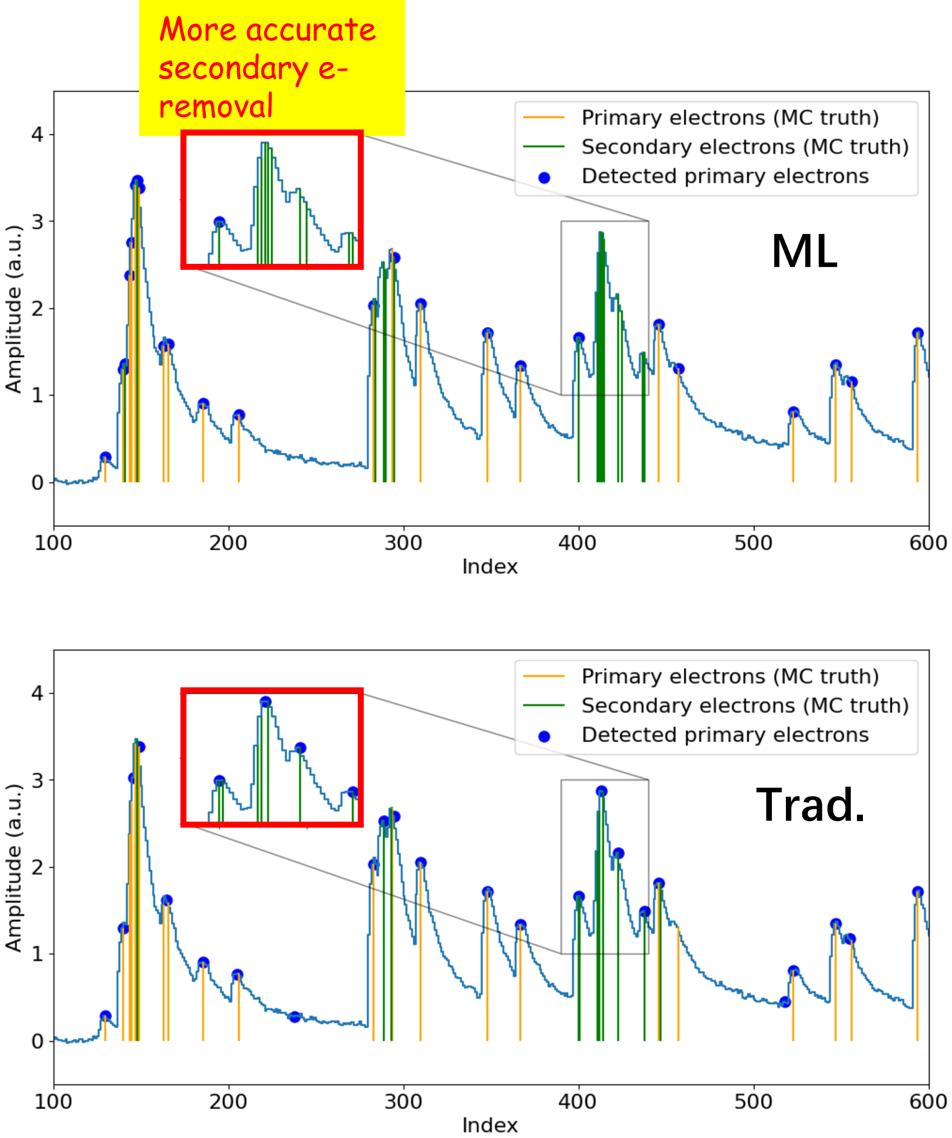
Traditional peak-finding: second derivative

Table 2. The purity and efficiency comparison between LSTM-based algorithm and traditional D2 algorithm for peak-finding.

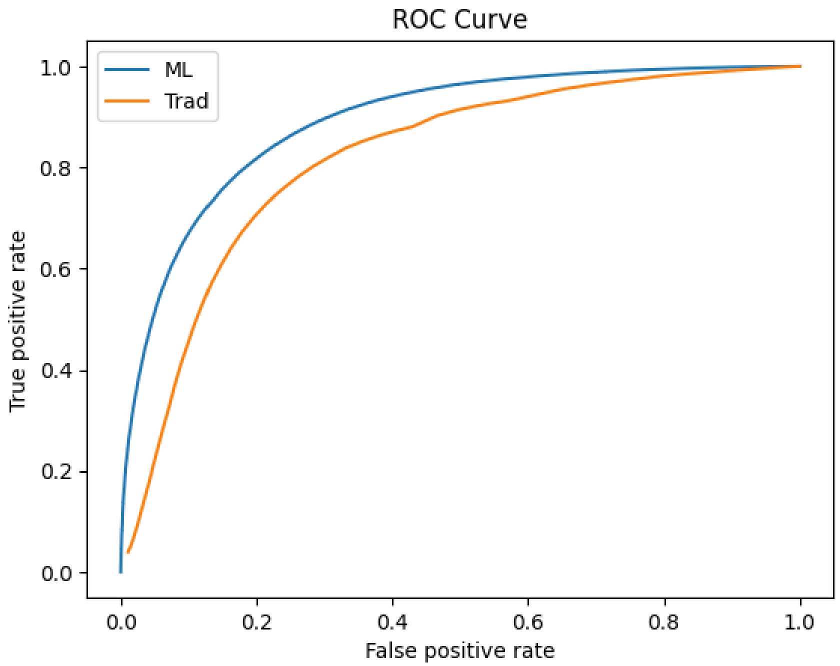
	Purity	Efficiency
LSTM algorithm	0.8986	0.8820
D2 algorithm	0.8986	0.6827

- The LSTM-based model is more powerful than the traditional derivative-based algorithm, especially for the pileup recovery

Clusterization results



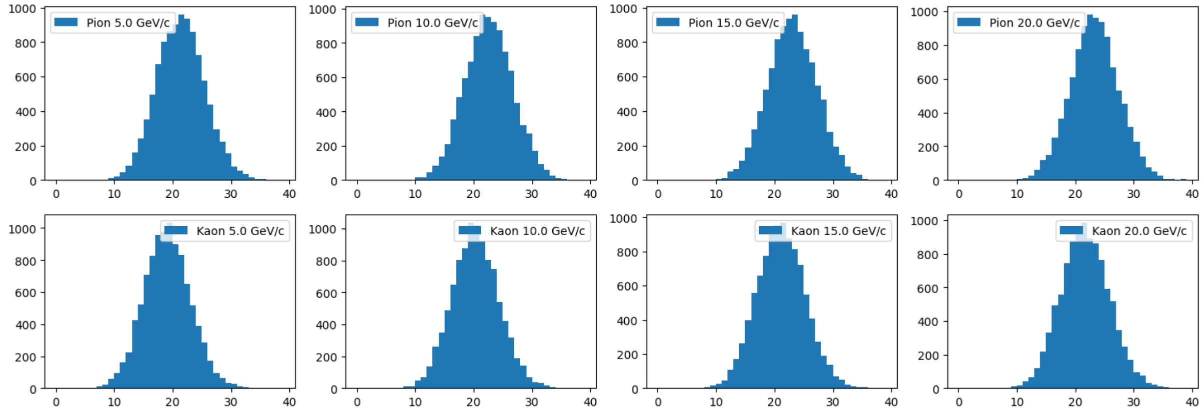
Traditional clusterization: adjacent-peak merge



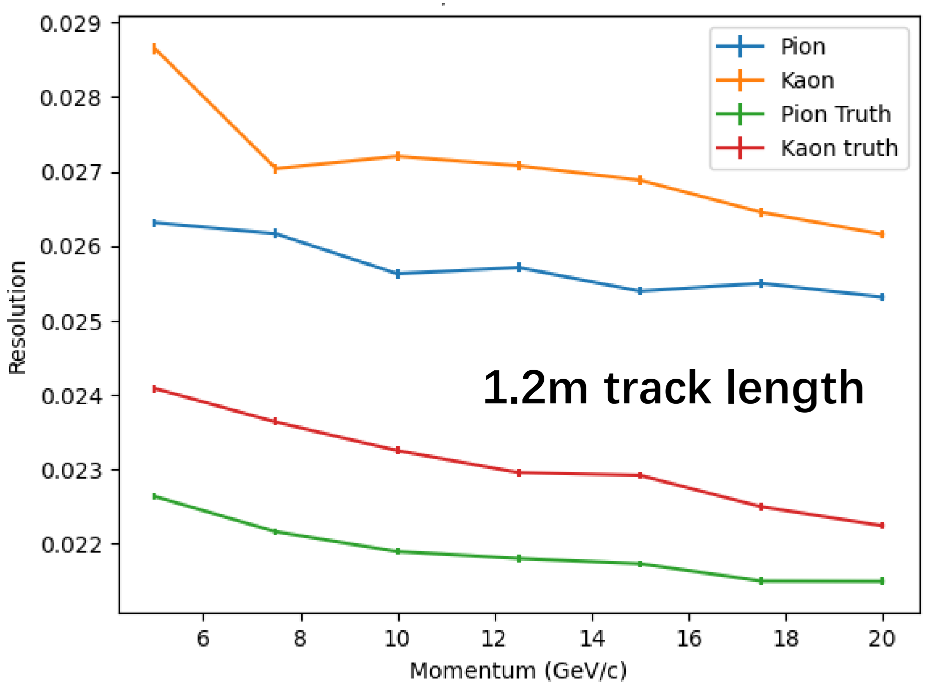
- The DGCNN-based model is more powerful than the traditional peak-merge algorithm, as it can remove the secondary electrons more accurate

PID performances with supervised models

Reconstructed # of clusters distributions



dN/dx resolution

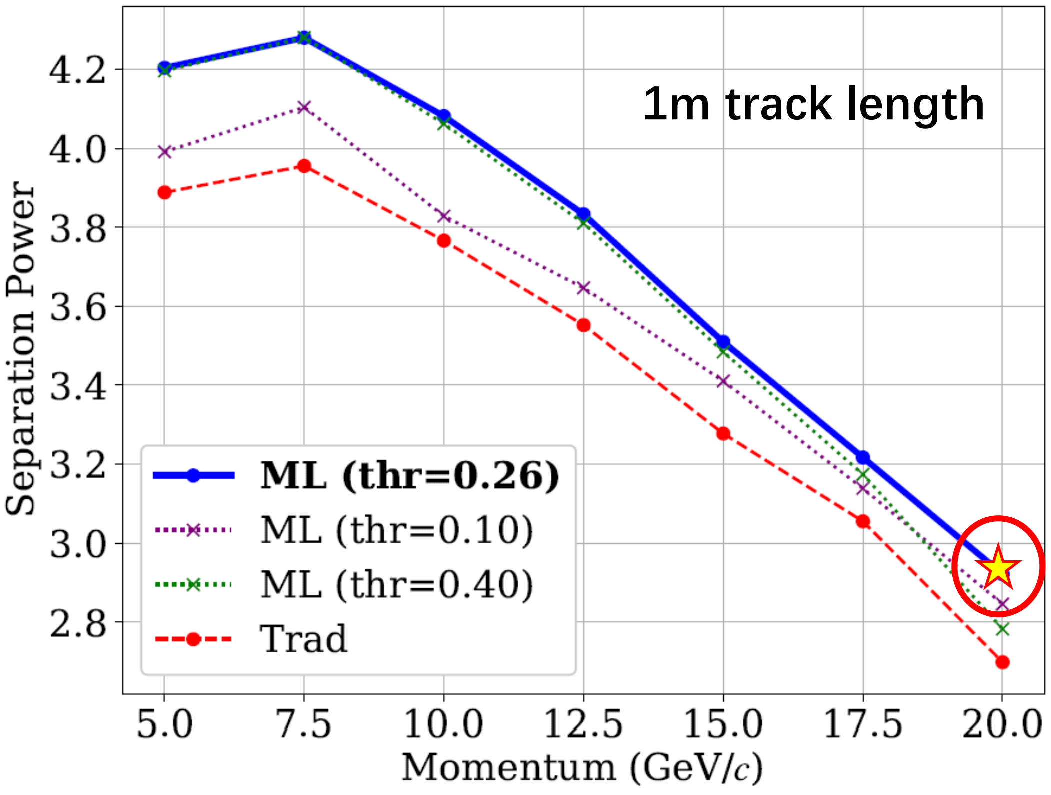


The reconstructed n_{cls} distributions are very well Gaussian-like

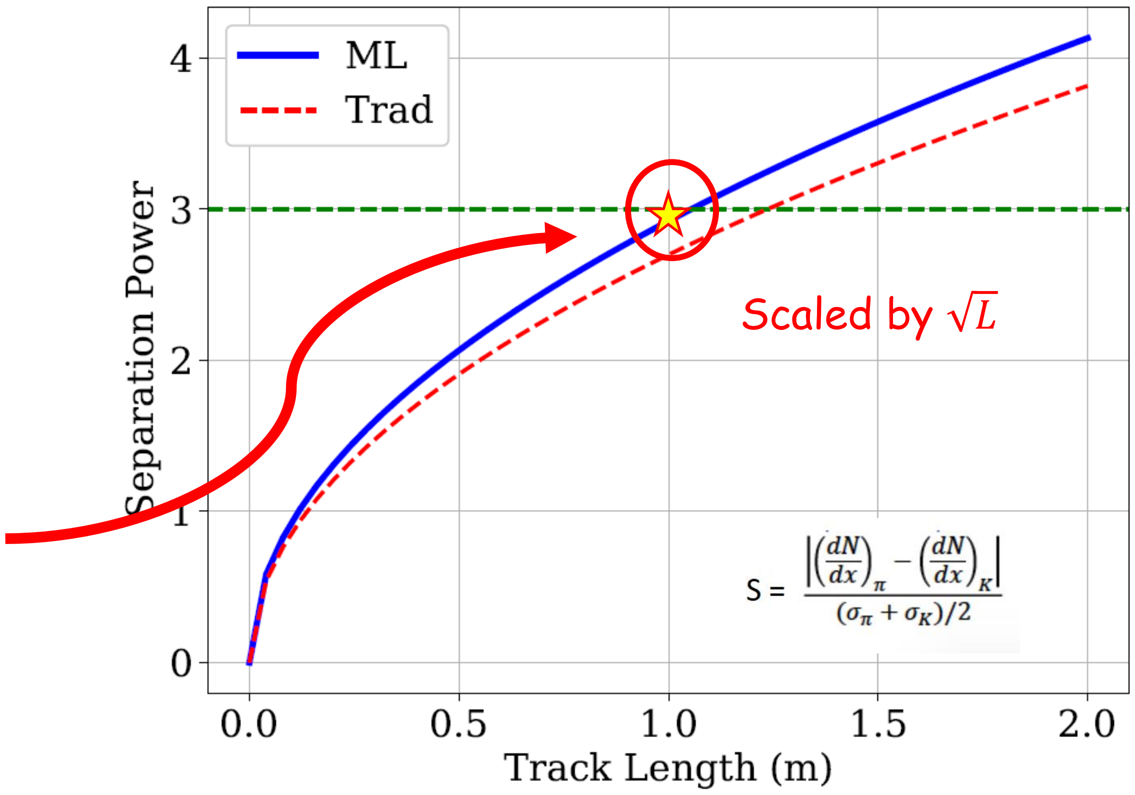
dN/dx resolutions for high momenta pions/kaons are < 3%， which are much better than typical dE/dx ~5%

PID performances with supervised models (II)

K/π separation power vs. momentum



K/π separation power @ 20 GeV/c

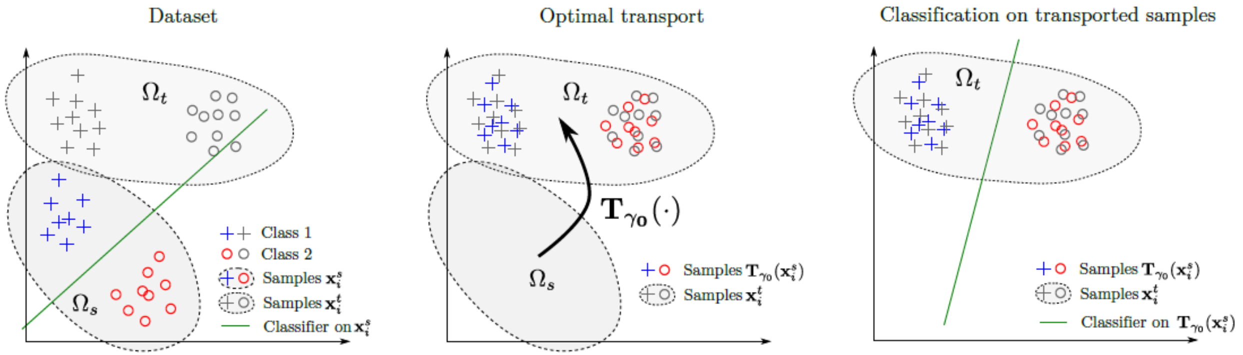


~10% improvement for ML (equivalent to a detector with 20% larger radius)

Could achieve 3σ for 1m track length. For 1.2m track length (current CEPC baseline), the separation is 3.2σ

Domain adaptation for test beam data

- **Challenges for real data**
  - Imperfect simulation
  - Incomplete labels in real data
- **Solution: Domain adaptation**
  - Transfer knowledge between simulation and real data



Align data/MC samples with Optimal Transport

Loss for labeled samples in source domain

$$\min_{f,g}\left[\sum_{i=1}^{m} L_s\left(y_i^s, f(g(x_i^s))\right) + \boxed{\frac{1}{m_l}\sum_{i=1}^{m_l} L_t\left(y_i^{t,l}, f\left(g(x_i^{t,l})\right)\right)} + \min_{\gamma\in\Delta}\sum_{i,j}^{m}\gamma_{ij}\left(\alpha\|g(x_i^s)-g(x_j^t)\|^2 + \lambda_t L_t\left(y_i^s, f\left(g(x_j^t)\right)\right)\right)\right]$$

Loss for labeled samples in target domain (THIS WORK)

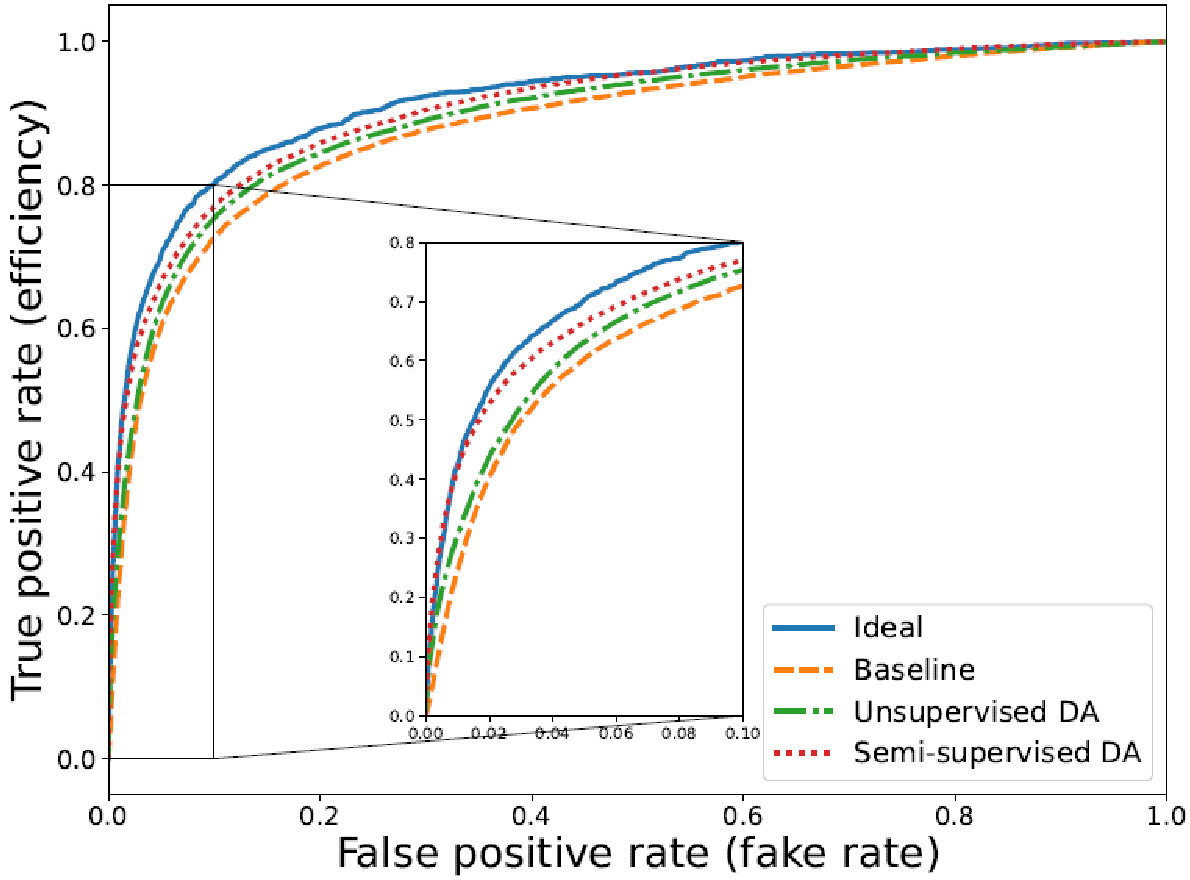
Cost of feature differences between source and target

Cost of 'label' differences between source and target

Cost of joint feature-label distribution for OT

Semi-supervised domain adaptation

Model validation by pseudo data



Numeric experiment with pseudo data in 2 domains
(simulation domain & data domain)

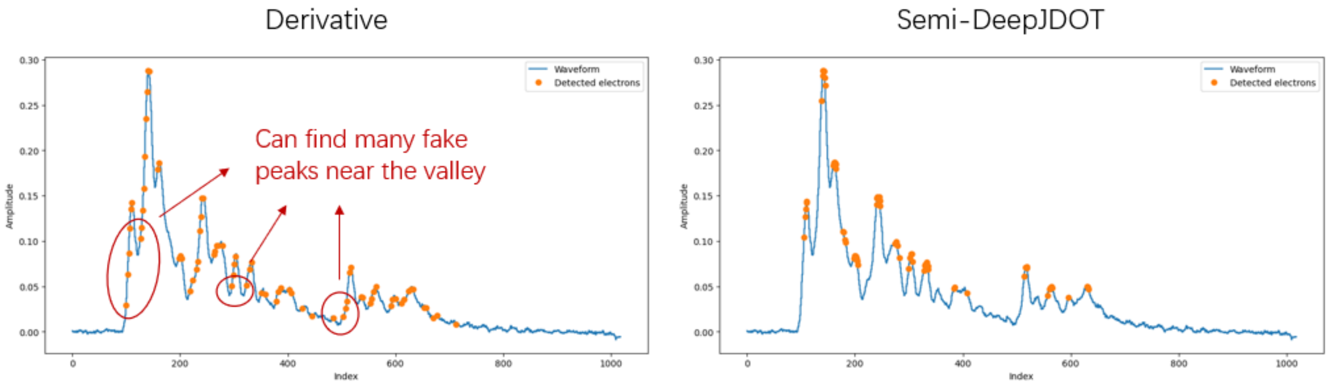
Model	AUC	pAUC (FPR<0.1)
Ideal	0.926	0.812
Baseline	0.878	0.749
Unsupervised DA	0.895	0.769
Semi-supervised DA	0.912	0.793

Improve
Improve

- **Note:**
  - Ideal = Supervised model in data domain
  - Baseline = Supervised model in sim. domain
  - Unsupervised DA = Baseline + OT
  - Semi-supervised DA = Baseline + OT + semi-supervised setup
- **The OT and the semi-supervised loss improve the results, and the performance of the semi-supervised DA model is very close to the ideal model**

Peak finding for test beam data

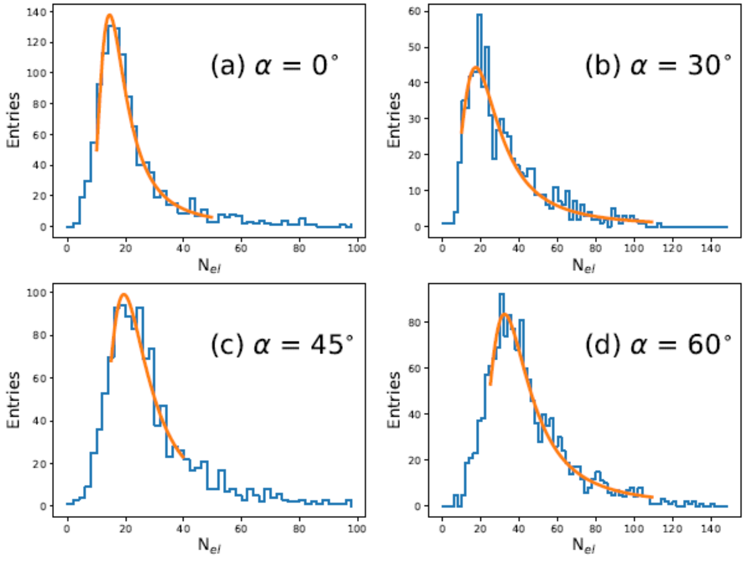
Single-waveform results between derivative alg. and DL alg.

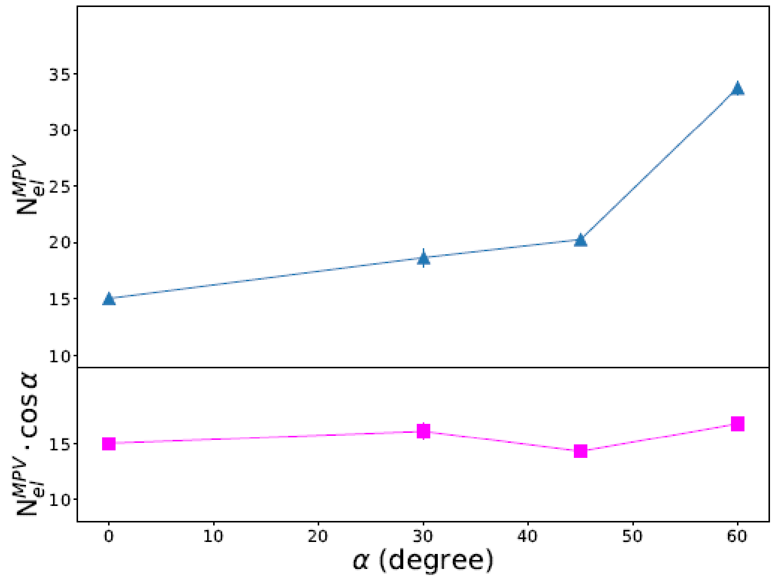


Note: Require similar efficiency for both cases

DL algorithm is more powerful to discriminate signals and noises

Multi-waveform results for samples in different angles





Scale w.r.t. track length

The algorithm is stable w.r.t. track length

Conclusion

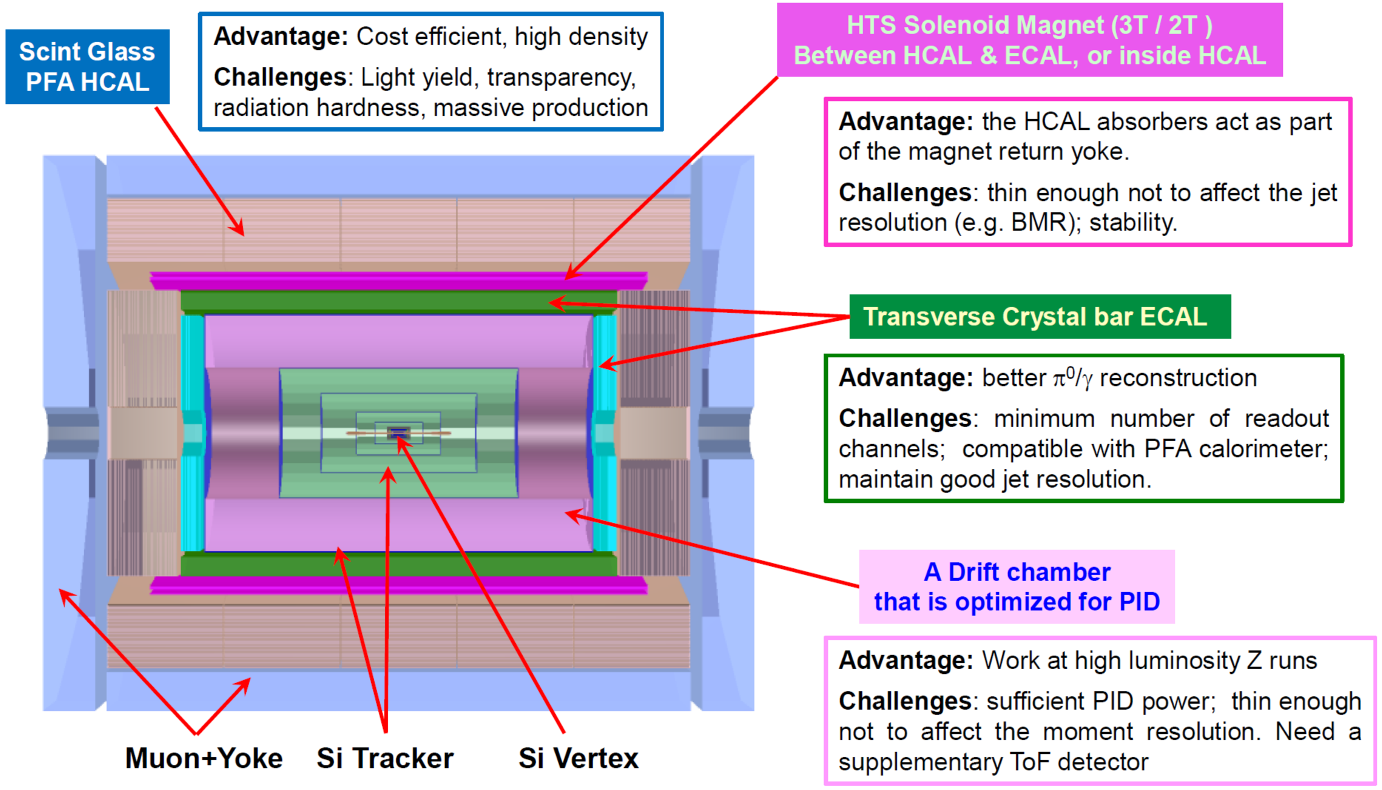
- **Two machine learning algorithms are developed for dN/dx reconstruction. In principle, the method can be applied to similar feature extraction tasks in signal processing.**
- **The supervised model has 10% improvement on K/pi separation w.r.t. traditional algorithm. The situation could be similar for the semi-supervised domain adaptation model.**
- **When studied with the full-simulation samples using a supervised model, the PID performance achieves < 3% K/pi resolution and > 3.2σ K/pi separation for 1.2m track length.**
- **When studied with the test beam samples, the semi-supervised domain adaptation model successfully transfer information from simulation and achieve stable performances.**

Thank you!

Backup

Drift chamber with PID capability

The CEPC 4th concept



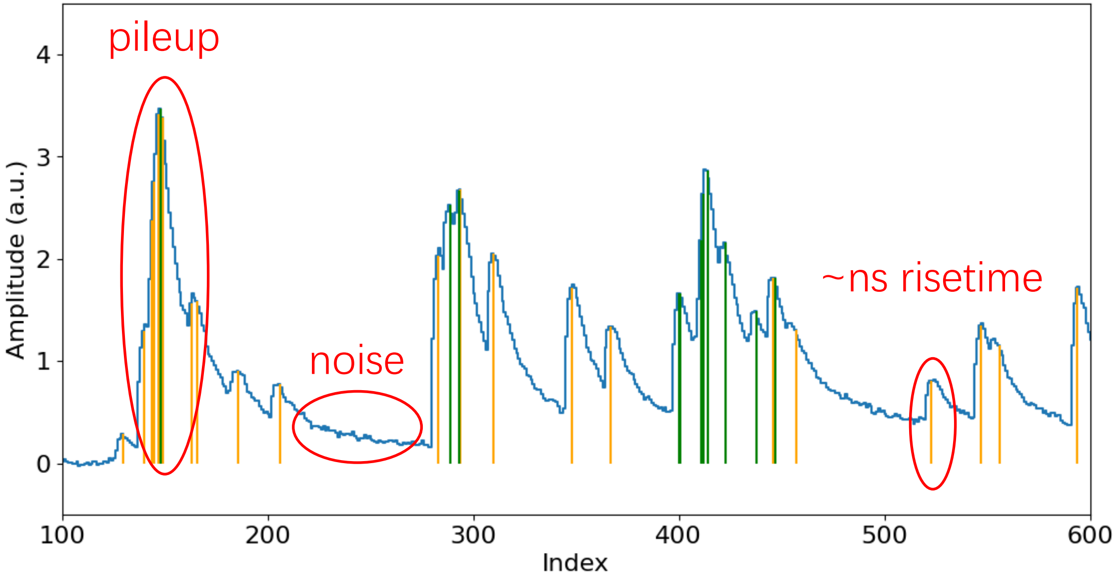
A drift chamber with cluster counting (dN/dx) is one of the gaseous detector options

Key parameters:

- Full length: 5800 mm
- Barrel coverage: |cosθ| < 0.85
- Radius: 600 – 1800 mm
- Support: 8x8 carbon fiber frame
- Endcap: 20 mm Al plate
- Gas mixture: 90/10 He/iC_4H_{10}

Challenges of dN/dx measurement

Orange lines: Primary electrons (MC truth)
Green lines: Secondary electrons (MC truth)



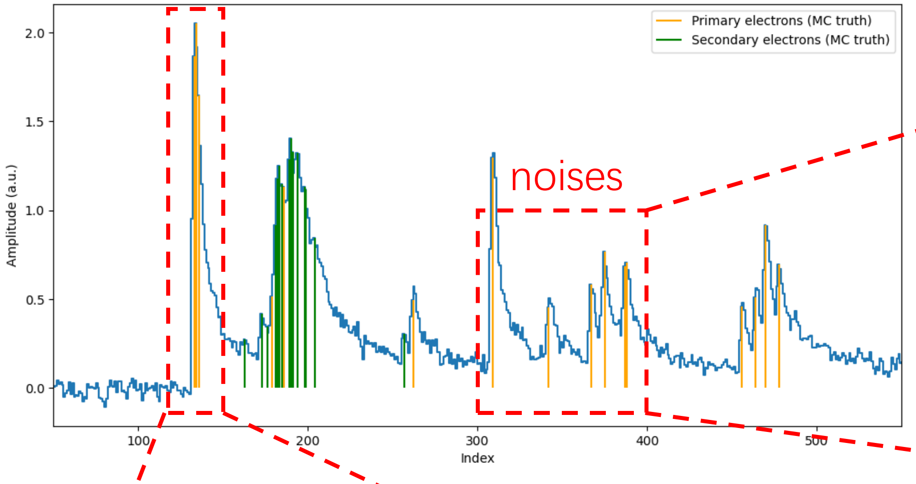
- **Single pulse risetime ~ns, require fast electronics**
  - Bandwidth > 1 GHz
  - Gain > 10
  - Sampling rate > 1.5 GS/s
  - Bit resolution > 12 bit

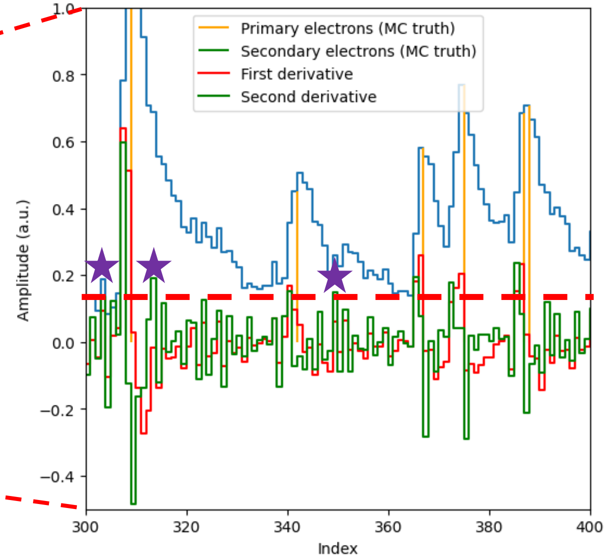
- **Signals are superimposed with noises and are heavily piled-up in some regions, require sophisticated reconstruction algorithm**

Traditional peak finding

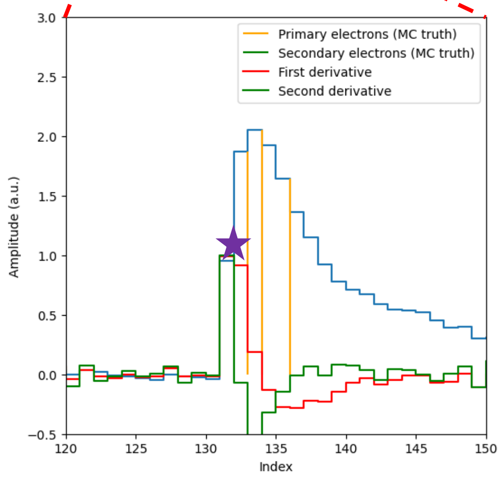
pileup signals

noises





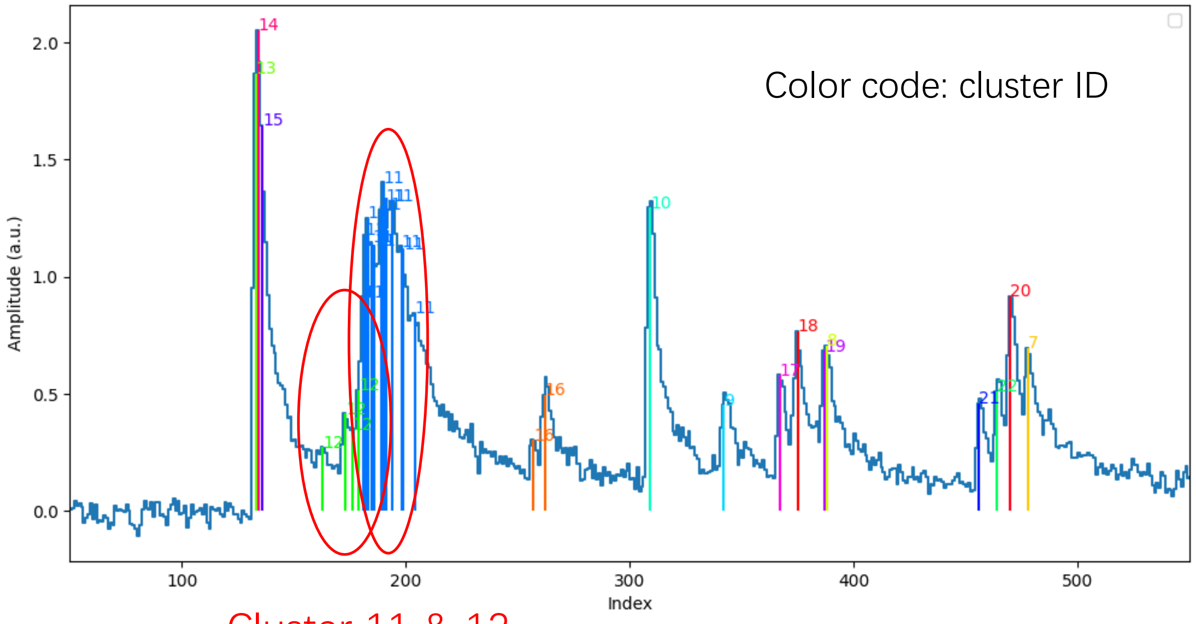
Some noises can also pass the threshold



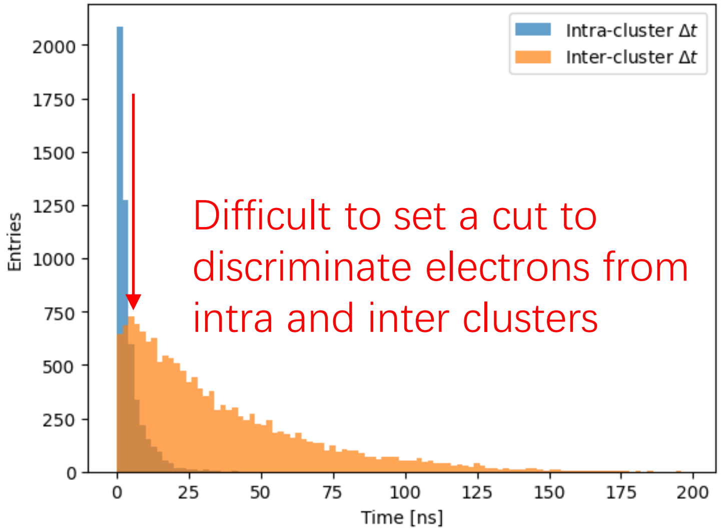
Only 1 out of 3 signals is detected

- **Derivative-based peak finding**
  - Take first and secondary derivatives
  - Require threshold passing
- **Challenges**
  - Noises can pollute the signal
  - Signals are highly piled up

Traditional clusterization



Cluster 11 & 12
are overlapped



- **Timing-based clusterization**
  - Merge adjacent peaks
- **Challenges**
  - Electrons from different clusters can overlap

Additional plots for domain adaptation

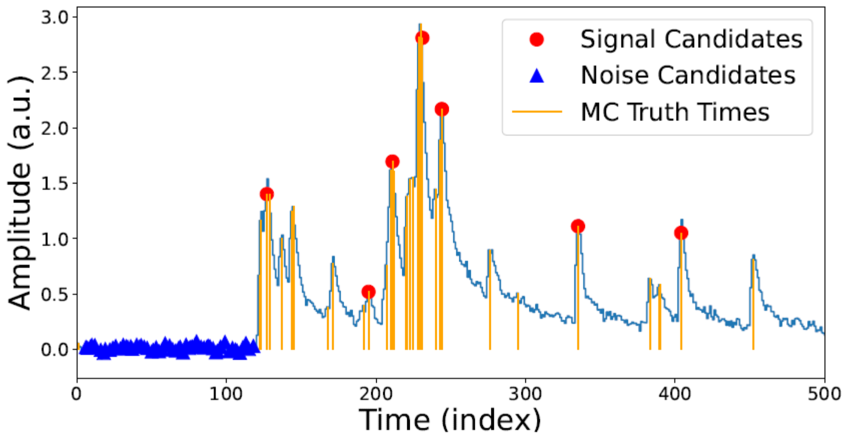


Figure 1: An example of simulated waveform. The blue histogram is the waveform. The red solid circles are the signal peaks selected by the CWT algorithm. The blue solid triangles are the noise peaks selected by requiring the 3 RMS requirement. The orange lines indicate the electron signal times from MC truth information.

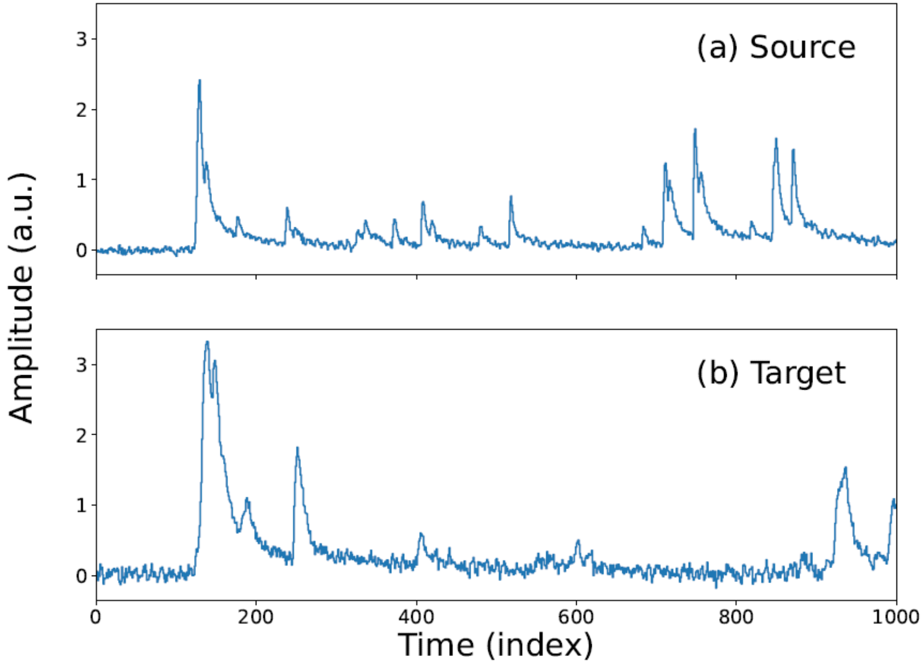


Figure 4: Waveform examples from the source sample (a) and the target sample (b). The source waveforms are generated with a noise level of 10% and a pulse risetime of 2 ns, while the target waveforms with a noise level of 20% and a pulse risetime of 4 ns.