Drift Chamber Track Reconstruction with GNN and QC

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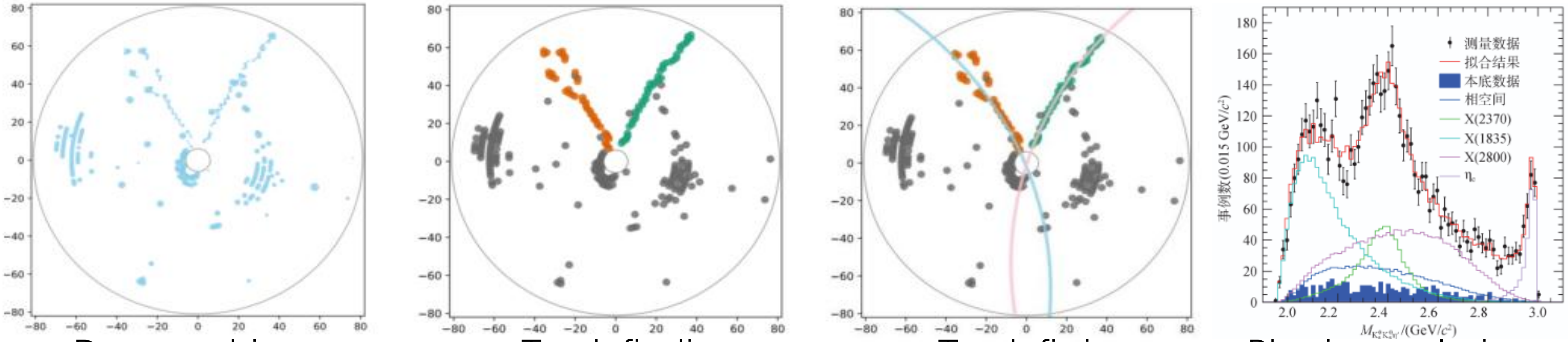
Outline

1. Introduction
2. Track Reconstruction
   - Graph Neural Network (GNN) + Object Condensation (OC)
   - Staged end to end tracking by DNN
   - Quantum Computing(QC)

From Detector Hits to Particle Tracks

- Charged particle leaves a sequence of discrete measurements, or **hits**
- Track reconstruction
  - **Which hits were produced by the same particle?**
  - **What was the trajectory and momentum of that particle?**
- DC tracking accuracy and precision directly determine physics performance
- Typical reconstruction chain



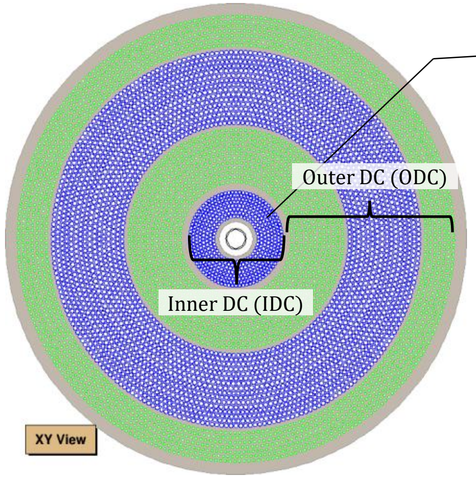
Detector hits | Track finding | Track fitting | Physics analysis

Tracking: Finding physical structure in a set of detector measurements

BESIII Tracking Detector - MDC

- Multi-layer Drift Chamber (MDC)
  - ✓ Provides precise position & momentum measurements
  - ✓ Enables dE/dx particle identification
  - ✓ Delivers fast trigger signals

MDC Parameter	Value
layers	43
$\sigma(p)/p$	0.5@1GeV/c
$\sigma(xy)$	$135\mu m$
Acceptance	93% @4π

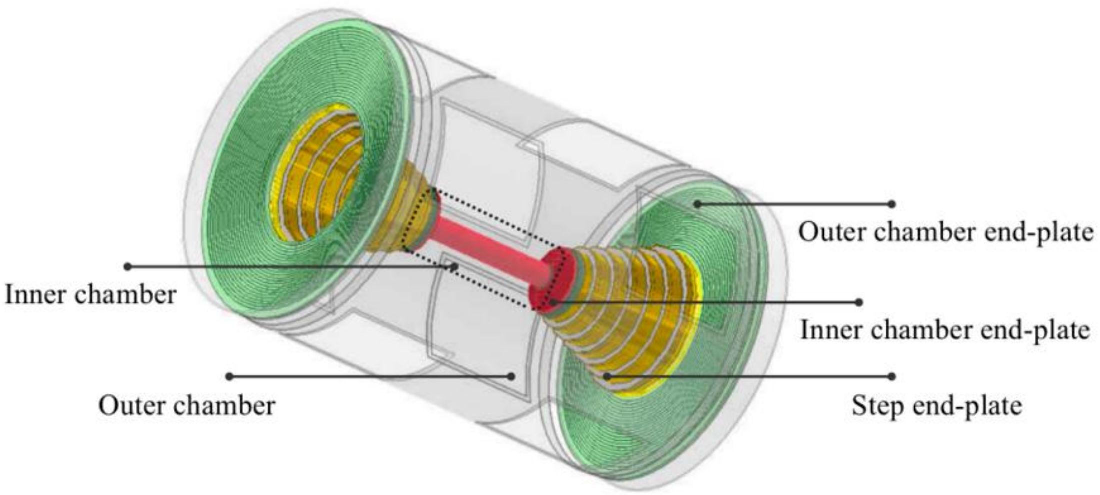


Inner Drift Chamber (IDC)

Outer Drift Chamber (ODC)

axial wires
stereo wires

MDC X-Y in view

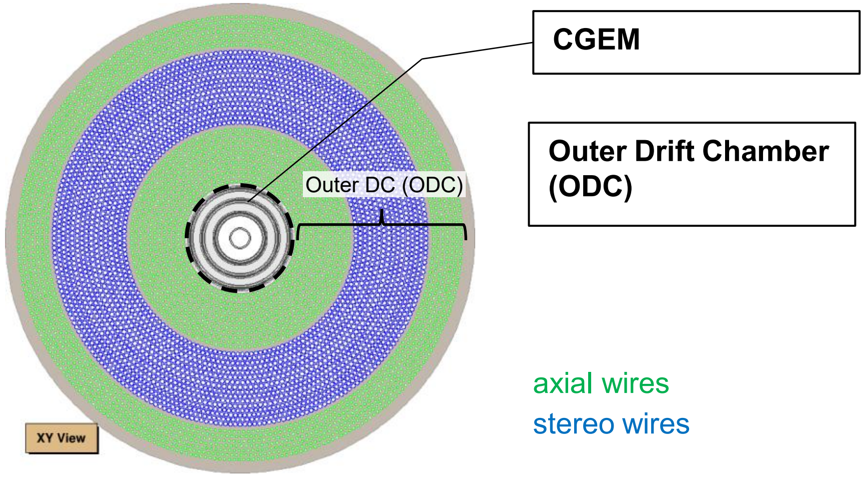


MDC in 3D view

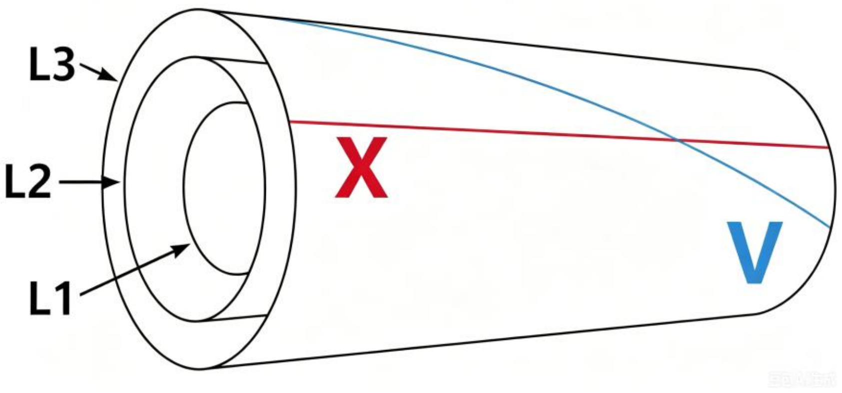
Detector Upgrade - CGEM+ODC

- Inner tracker - Cylindrical GEM detector (CGEM)
  - Beam-background resistant
  - High-rate capability
  - Better z resolution
  - Radiation-hard
- Outer tracker - Outer Drift Chamber (ODC)
  - Reuse MDC outer chamber
  - 35 layers

CGEM Parameter	Value
# layers	3
$\sigma(p)/p$	0.5@1GeV/c
$\sigma(\varphi)$	$130\sim150\mu m$ (charge + time)
$\sigma(z)$	$\sim300\mu m$

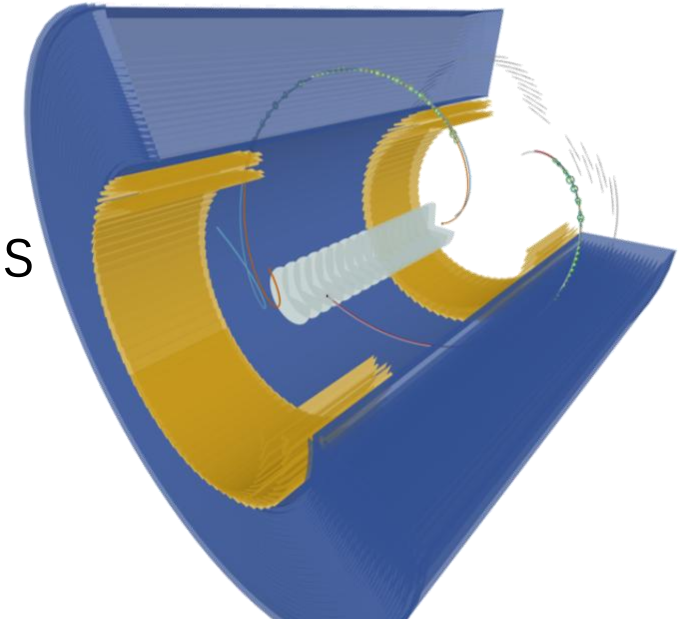


CGEM+ODC in X-Y view



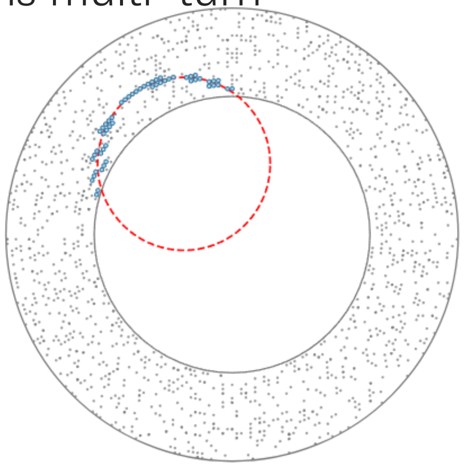
CGEM in 3D view

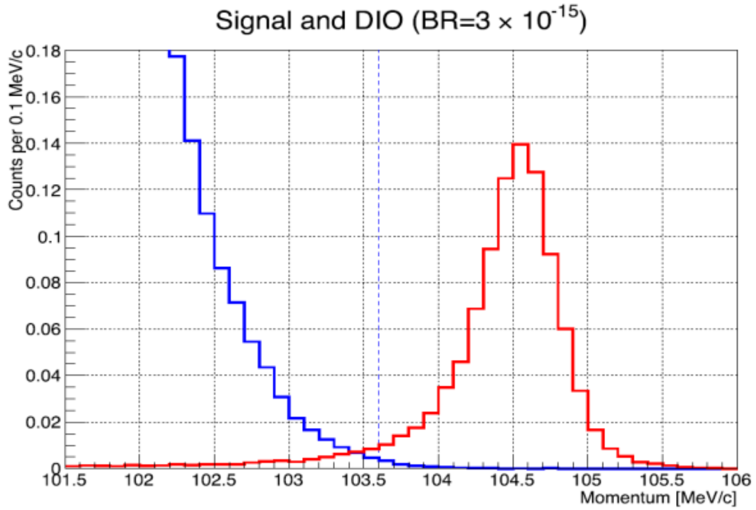
COMET Cylindrical Drift Chamber (CDC)



- COMET : search for $\mu^- \to e^-$ conversion
- CDC : primary tracking detector for signal electrons

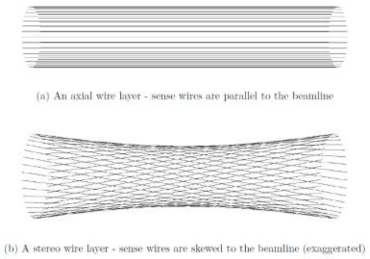
- Challenges of COMET CDC tracking
  - No vertex constraint
  - No seed from other-detector
  - All curled low momentum tracks and 1/3 is multi-turn
  - Overlapping hits from different turns
  - Bremsstrahlung -> kink
  - No direct measurements on Z
  - High momentum tail is danger
  - High occupancy

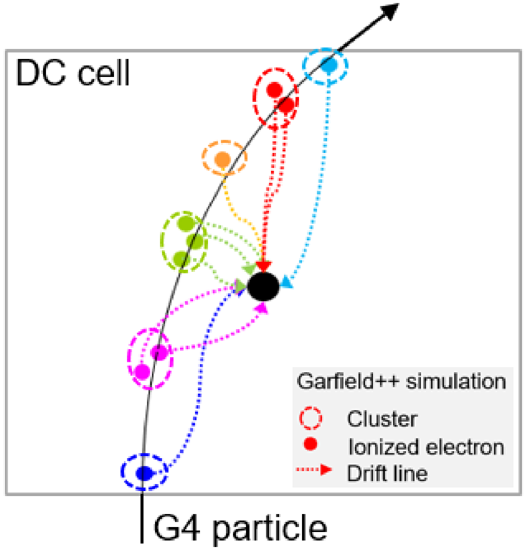


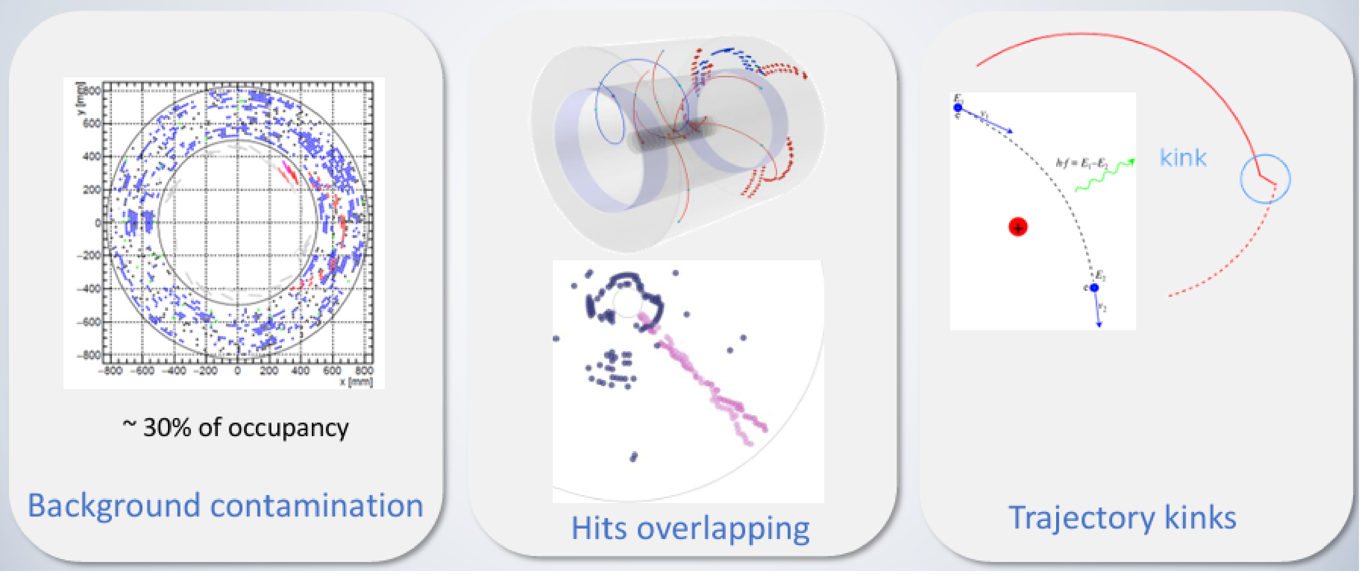


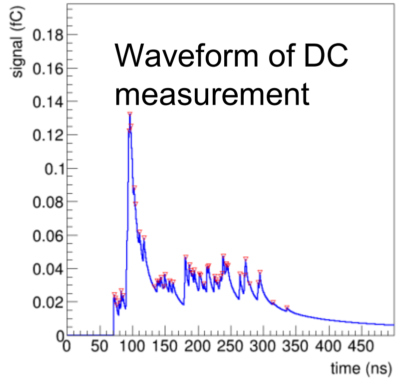
Tracking of drift chambers

- Drift chamber measure ionization electrons **drift** toward sense **wires**
- The challenges of drift chamber tracking
  - Detector noise and unrelated hits **contamination**
  - **Overlapping hits** nearby track/other turn's trajectories
  - Left right geometrical **ambiguities**
  - **Combined tracking** of two tracking detectors
  - **Manual tuning** tracking alg. parameter





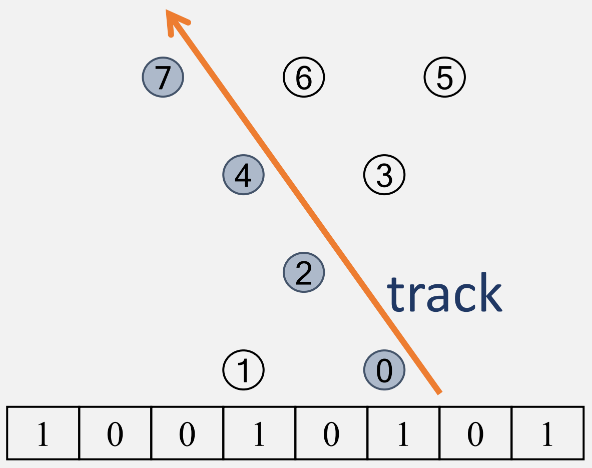




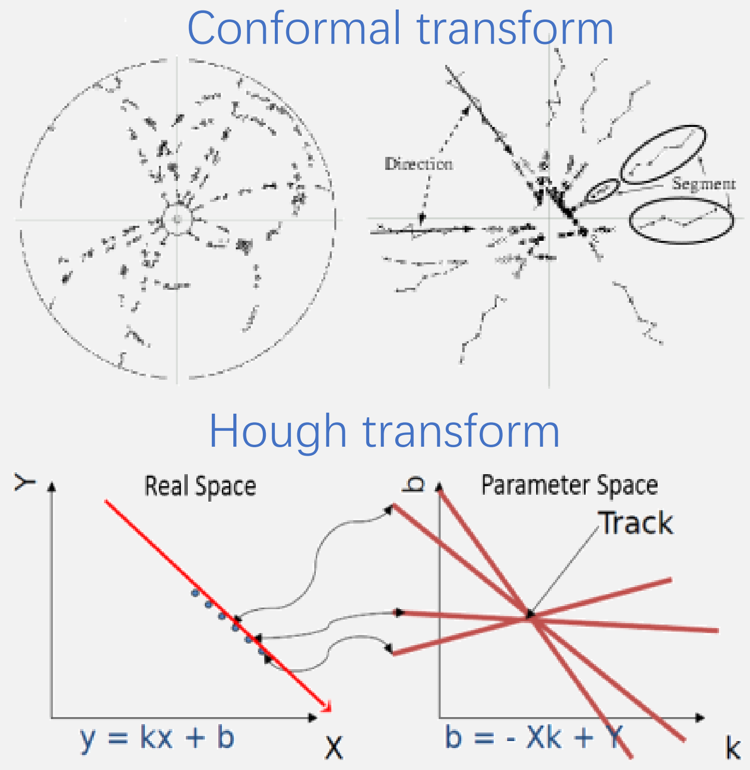
Multi-hits in one cell

Traditional tracking algorithms

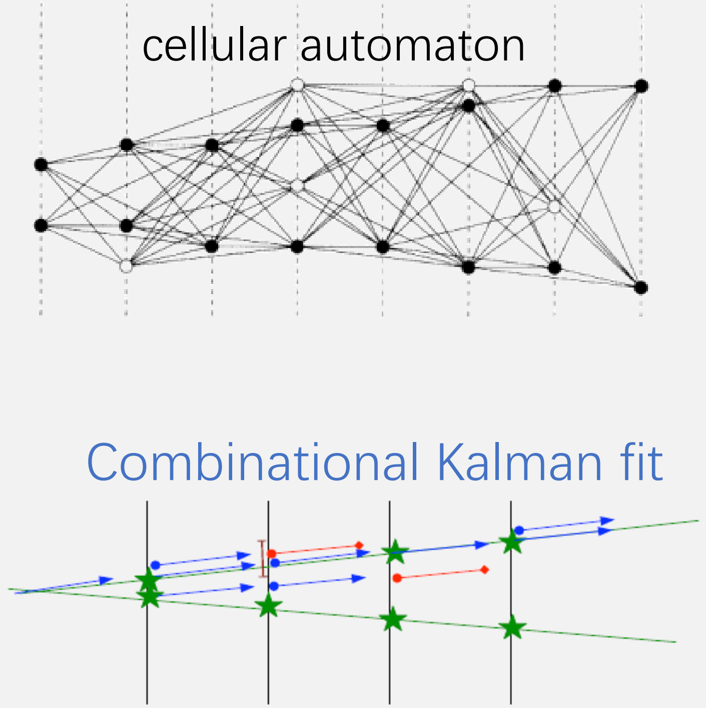
Template matching



Transformation

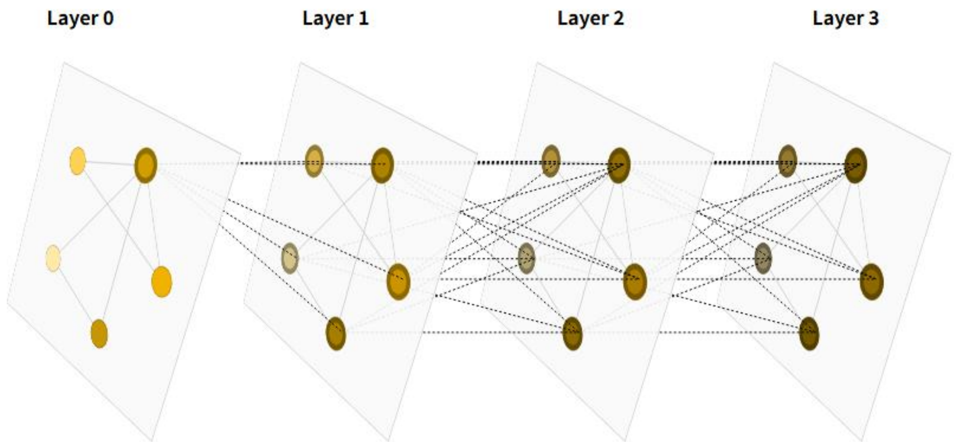


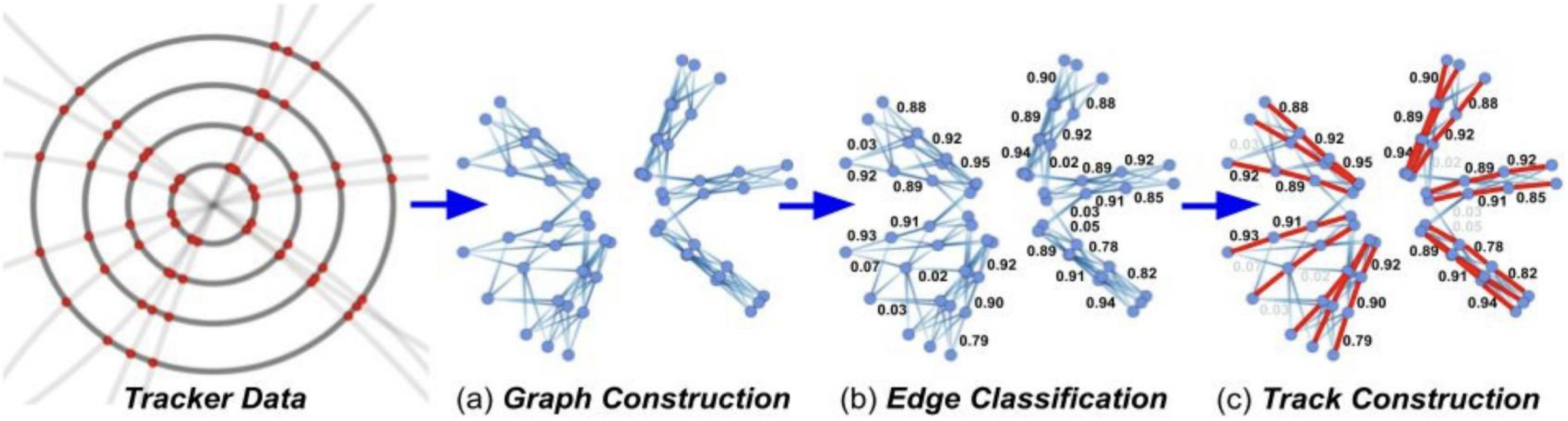
Combination optimization



GNN as representation learning for tracking

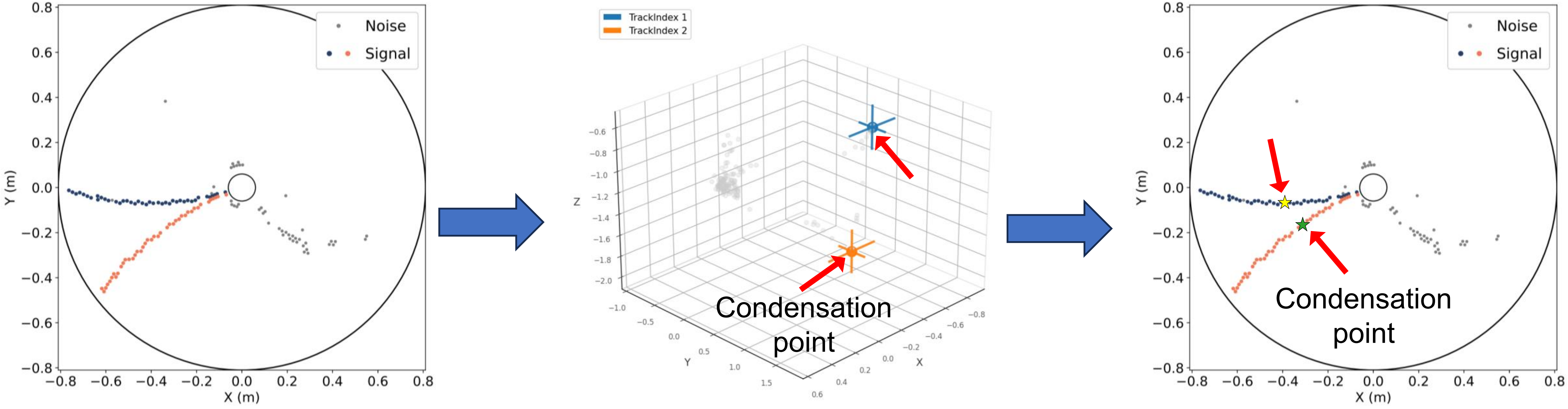
- Hit assignment problem by GNN:
  - Nodes/edges → hits; Edges/nodes → hit-hit associations
  - detector space vs latency space
- Pros
  - Permutation-invariant
  - Handle variable measurements
  - Global attention
  - High noise tolerance





Object condensation for end-to-end tracking

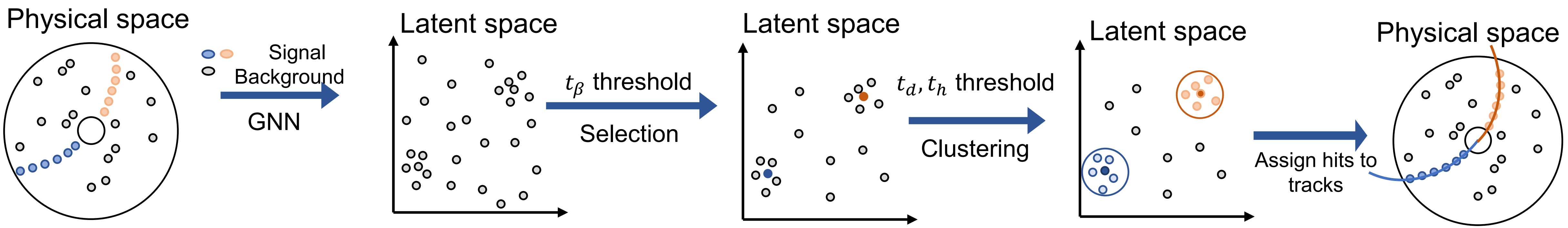
- GravNet+**Object Condensation**
  - **Attractive & Repulsive Potentials** → pull same-track hits together, push others apart
  - **Same-track hits** → cluster closely in latent space
  - **Each track** → condensed into a single condensation point



Physical space | Latent space | Physical space

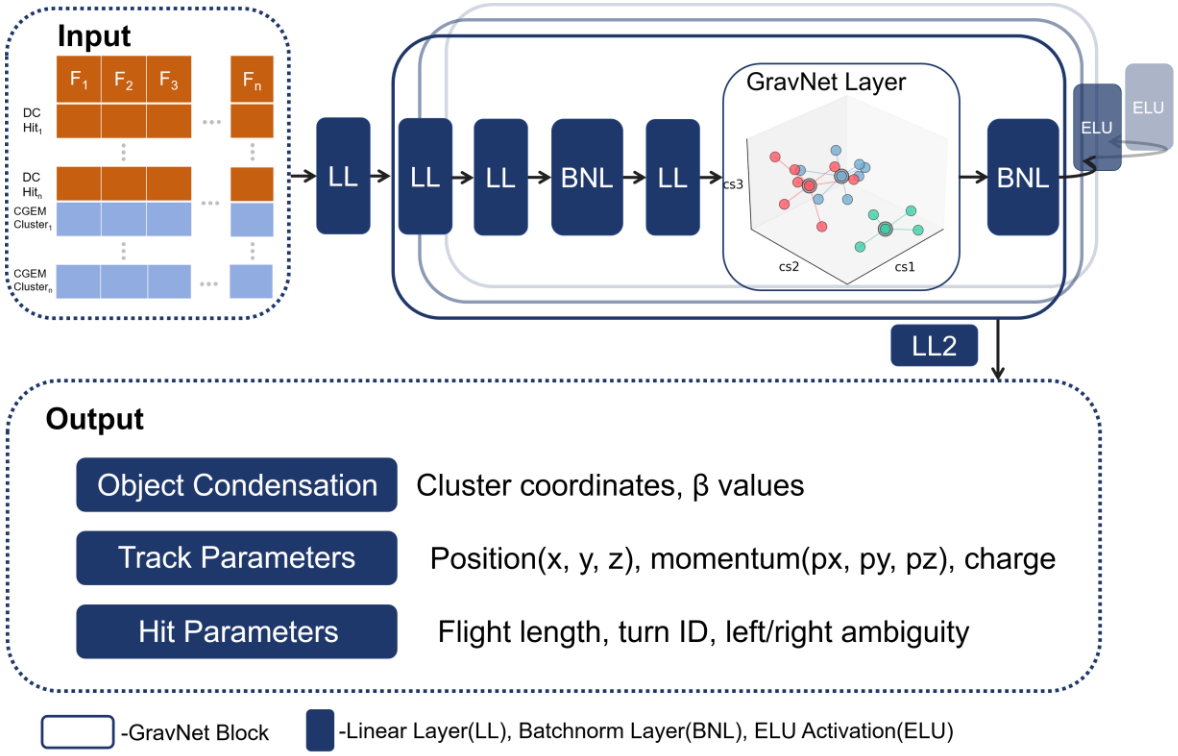
Post processing for hit assignment

- GNN embeds hits into latent space for track clustering, then:
  1. selects high-confidence condensation points as track seeds (t_β)
  2. assigns hits within their latent-space radius (t_d)
  3. separation between different tracks (t_h)
  4. decodes full track parameters



GNN Model for DC tracking

- Applied to BESIII arXiv:2602.14571 and COMET drift chamber tracking
- MDC or CGEM (CGEM clusters) + ODC combined tracking as input
- End to end solve
  - Cluster results
    - Latent coordinates
    - Wights
  - Track parameters
    - Position
    - Momentum
    - charge
  - Hits parameters
    - Hit flight length
    - Turn ID
    - Left right ambiguity



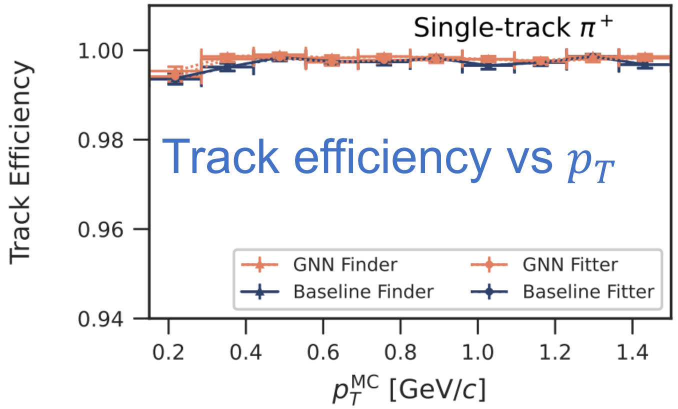
MDC high P_T track performance

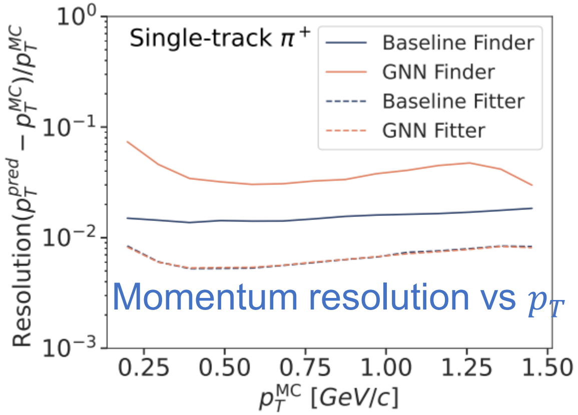
Track efficiency : better than baseline

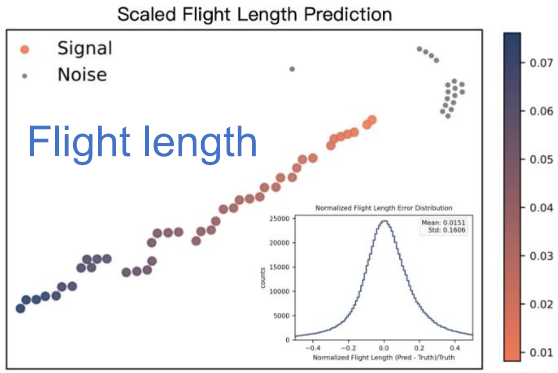
p_T resolution : comparable with baseline after fitting

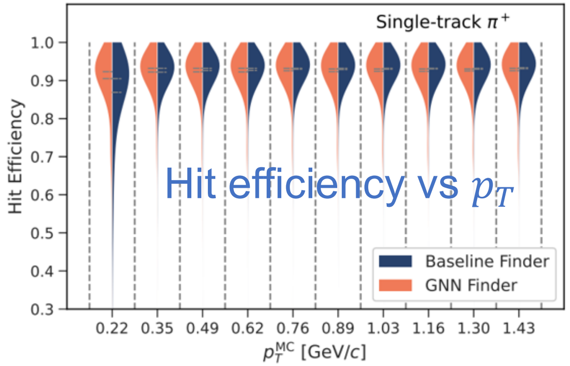
Processing time: 45ms / event for double-track

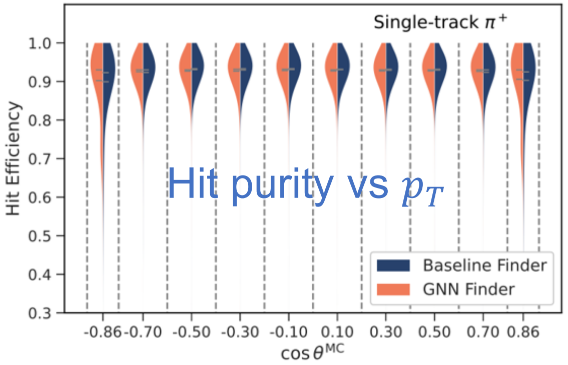
Innovations: first application of NN to predict hit-level flight length and left-right ambiguity

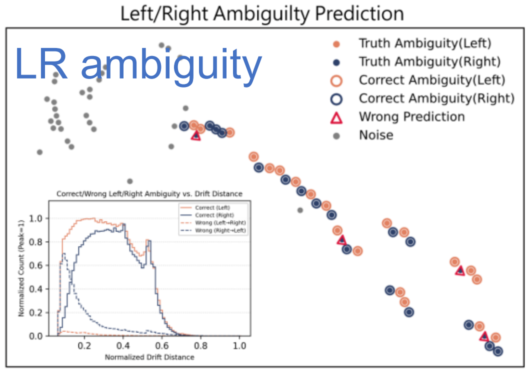






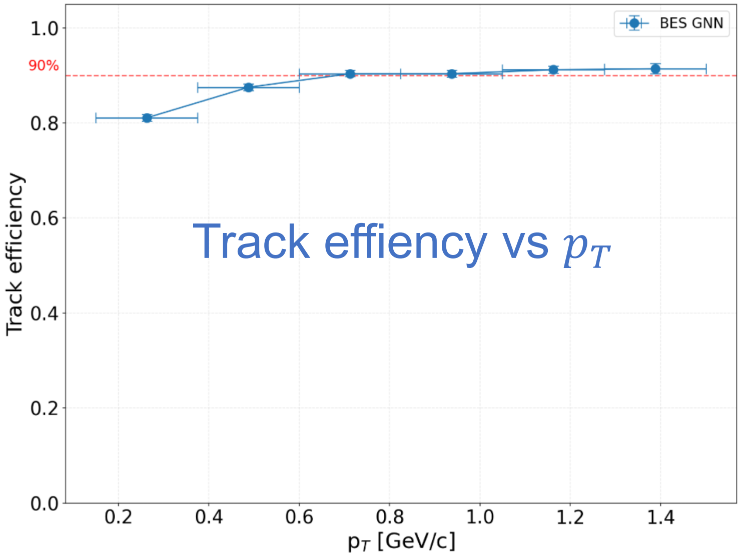


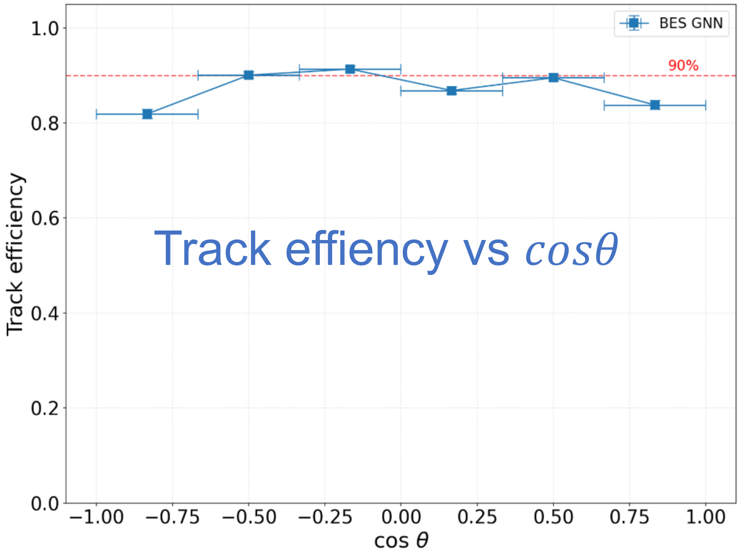


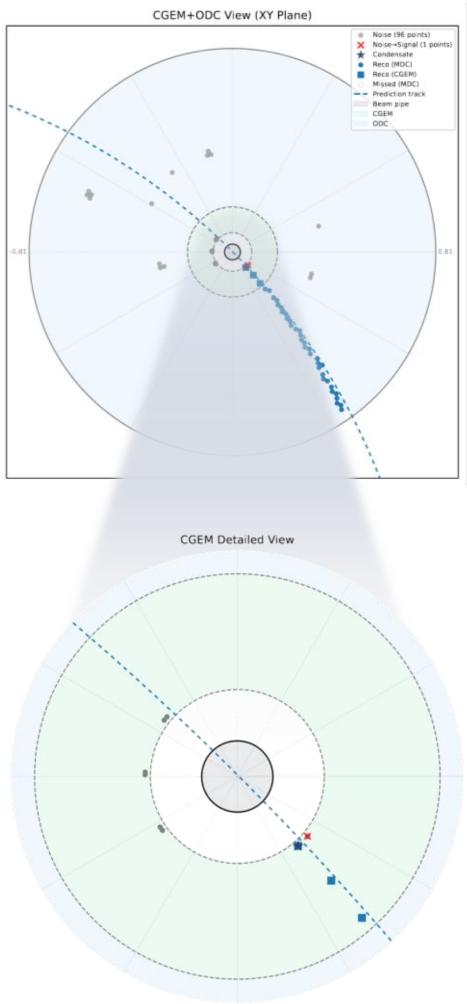


Combined tracking across detectors: CGEM & ODC

- CGEM clusters + ODC hits → Tracks
- **Track efficiency**: ~90% (p_T > 0.5 GeV/c)



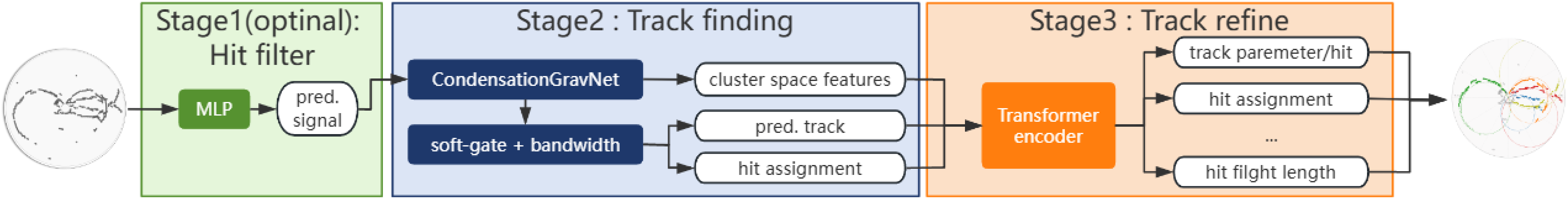




End-to-end joint reconstruction validated

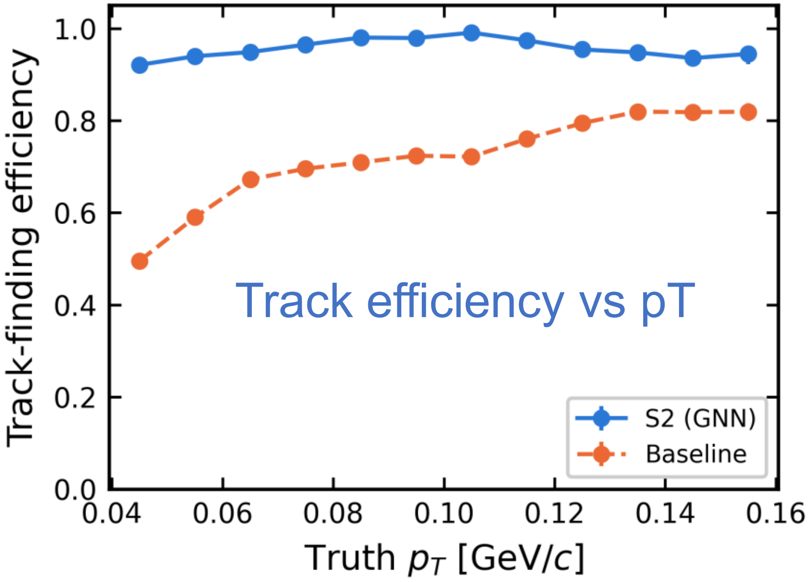
Towards end-to-end staged tracking via DNN

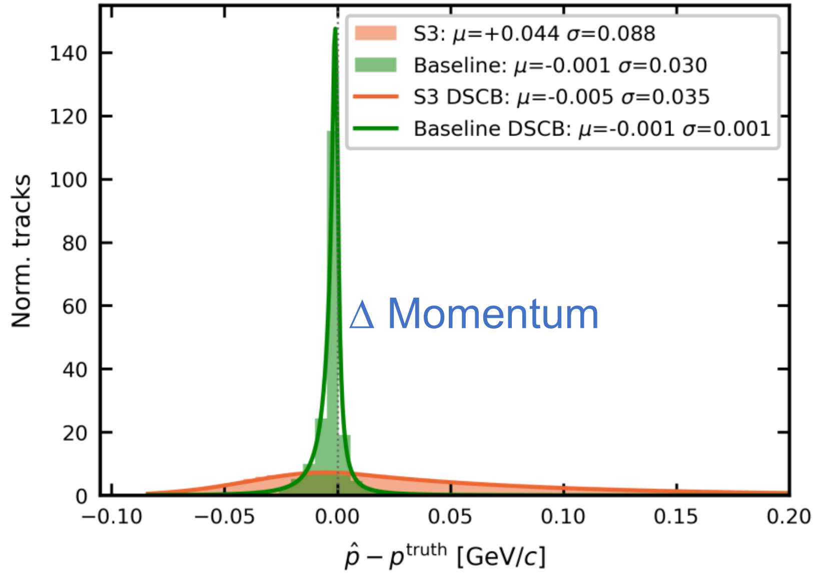
- Staged Tracking Pipeline
  1. **Hit Filtering** → cleaner input with fewer hits
  2. **Differentiable Clustering** → end-to-end learnable association
  3. **Track Refinement** → physics-guided smoothing

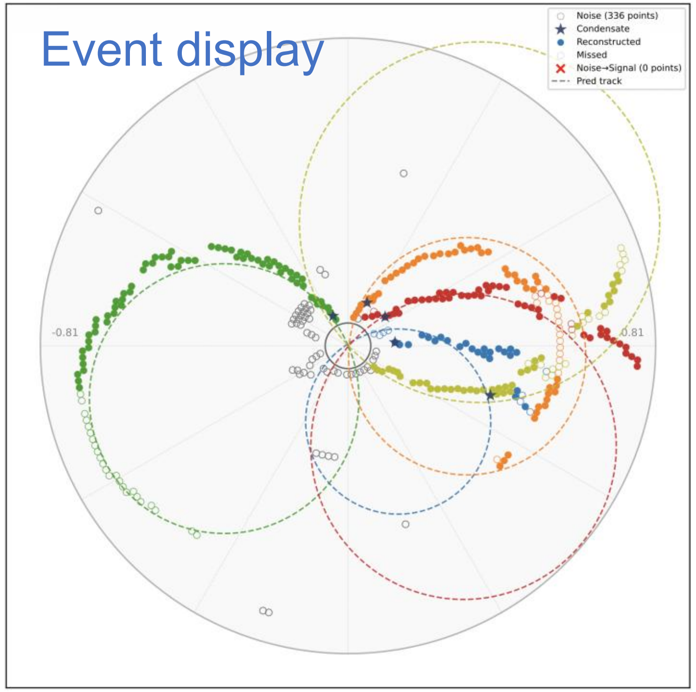


MDC low P_T performance with Staged Tracking

- Low-momentum track efficiency: ~20% improvement

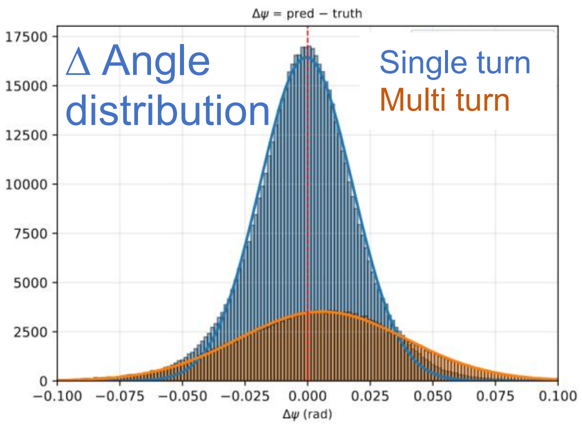




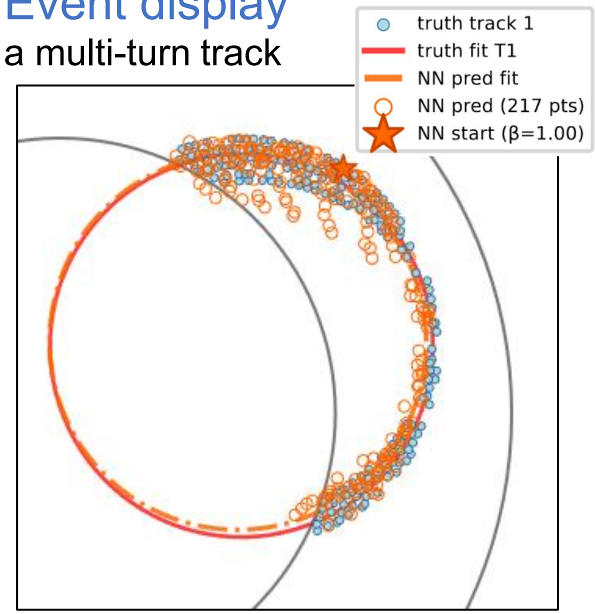


COMET CDC GNN tracking performance

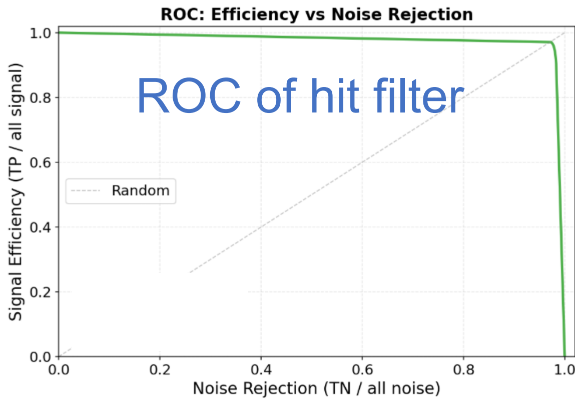
- 2-stage NN tracking performed on CDC
  - MLP hit filter + GNN tracking
- Performance
  - 96 hit efficiency with 98% noise reduction
  - 100% tracking efficiency
  - Momentum resolution ~5%

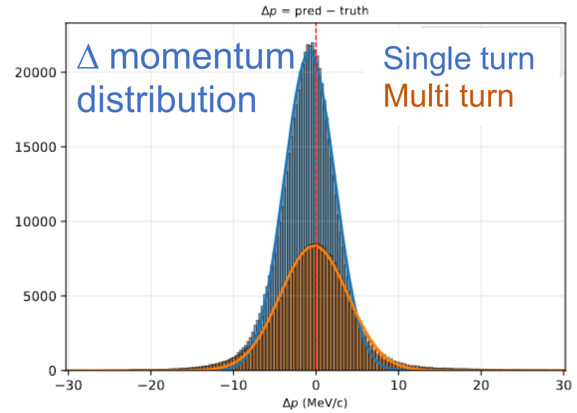


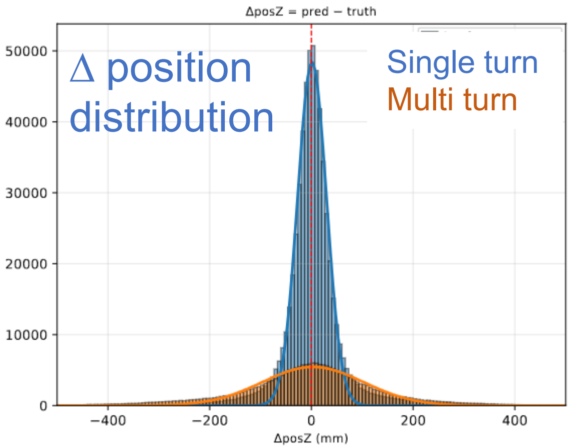
Event display
a multi-turn track

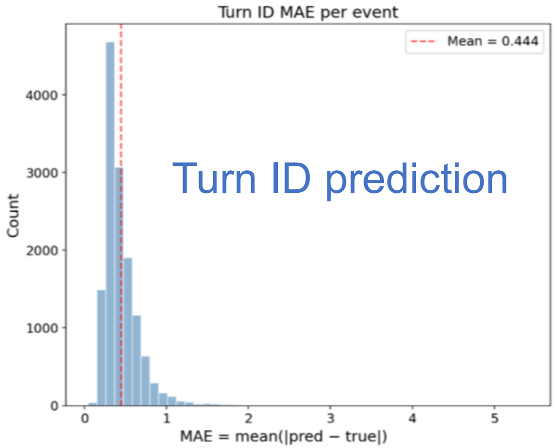


Demonstrating multi-turn tracking with GNN for the all-stereo DC









DC hit assignment with Quantum Computing

- A demonstration to solve hit assignment problem with QC

Hit candidates
Cell/hit candidates arranged in the φ direction

→ **Sliding windows**
window_size=6
overlap=2

→ **QUBO**
Build helix qubo
Get Q_win

→ **Solver**
BF / SA / QAOA
output bitstring

→ **Vote merge**
overlapping cell multi-window voting then combine track

Hits candidate: c0 c1 c2 c3 c4 c5 c6 c7 c8 c9 c10 c11 c12 c13

Track candidate windows:
window 0 → Q_win[0]
window 1 → Q_win[1]
window 2 → Q_win[2]

QUBO
$E(x)$

→ **Ising**
$x_i=(1-Z_i)/2$
$H = \Sigma h_i Z_i + \Sigma J_{ij} Z_i Z_j$

→ **QAOA Ansatz**
p layer cost + mixer
parameter γ, β

→ **Measure**
Bitstrings sampling
estimate energy

→ **Optimizer**
COBYLA / grid
Update parameter

DC hit assignment with Quantum Computing

- **BF(Brute Force)** guarantees the exact optimum by full enumeration (small-scale only)
- **SA(Simulated Annealing)** temperature-controlled random search to approximate low-energy solutions

	BF	SA	QAOA
Succ. rate gap<1%	100%	84%	99%
Gap median	0	0.0025	0.0000
Gap mean	0	0.0054	0.0009
Bit overlap	1.00	0.77	0.92
time/window	0.04s	0.08s	9.4s

Preliminary result

- **BF**: exact baseline (small windows, 84% success, 0.08s)
- **SA**: best cost-performance balance
- **QAOA p=1**: near-optimal (gap~0, bitoverlap=0.92)

- **QAOA p=1 achieves near-optimal CDC hit assignment, outperforming BF and SA,**

Summary

- We demonstrated
  - End-to-end GNN joint reconstruction (CGEM + CDC)
  - Low-p_T efficiency: **significantly improved**
  - All-stereo CDC tracking: **validated**
  - Performance: **better than baseline**
  - Hit-level ambiguity & flight length: **first NN-based solver**
  - CDC hit assignment: **QC solver applied**

Thanks for your attention!

Tracking Quality Metrics

Hit efficiency

$$\epsilon_{hits} = \frac{N_{hit}^{matched}}{N_{hit}^{detectable}}$$

$N_{hit}^{matched}$ is the number of hits on the track that match the truth, and $N_{hit}^{detectable}$ is the number of detectable hits on the truth track associated with this reconstructed track.

Hit purity

$$p_{hits} = \frac{N_{hit}^{matched}}{N_{hit}^{assigned}}$$

$N_{hit}^{assigned}$ is the number of hits on the reconstructed track.

Track criteria

$$p_{hits} > 50\%, N_{hit}^{matched} > 6$$

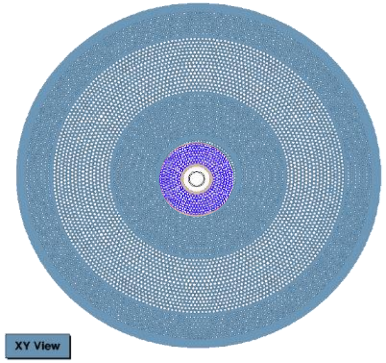
Track efficiency

$$\epsilon_{track} = \frac{N_{track}^{matched}}{N_{track}^{detectable}}$$

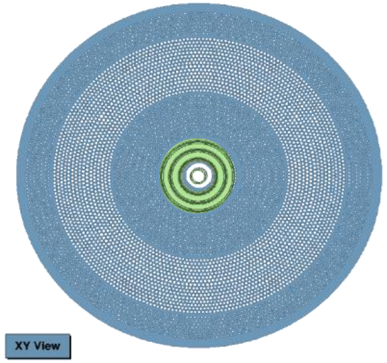
$N_{\mathrm{track}}^{matched}$ is the number of reconstructed tracks that match the truth, and $N_{track}^{detectable}$ is the number of detectable tracks in the sample.

Datasets

MDC
43 layers



CGEM(3 layers) + ODC(35 layers)



MDC Dataset, train:validation = 9:1

Event type	$P_T\ [GeV/c]$	$cos\theta$	Particle type	Number
high pt multi track	0.15 ~ 1.5	-0.93 ~ 0.93	$\pi^+\pi^-$	2×10^5
nearby track	0.15 ~ 1.5	-0.93 ~ 0.93	$\pi^+\pi^-$	2×10^5
non origin track	0.15 ~ 1.5	-0.93 ~ 0.93	$\pi^+\pi^-$	2×10^5
low pt multi track	0.04 ~ 0.16	-0.93 ~ 0.93	$\pi^+\pi^-\pi^+\pi^-p\bar{p}$	2×10^5

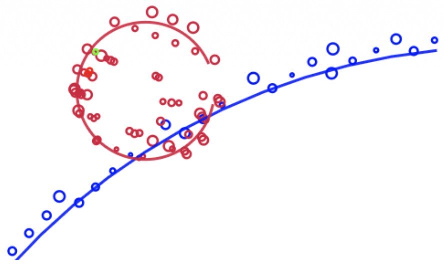
CGEM+ODC train: validation: test = 8:1:1

Event type	$P_T\ [GeV/c]$	$cos\theta$	$\phi\ [rad]$	Particle type	Number
Single-track	0.15~1.5	-0.93~0.93	0~2π	π^-	2×10^5

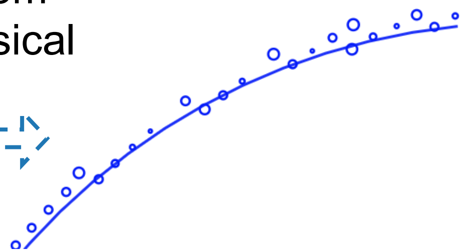
Monte Carlo full simulation of BESIII detectors
Mixed background from real data

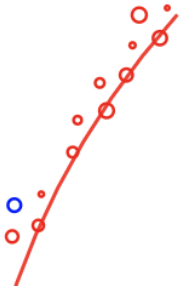
Data Preprocessing

Category	Example process	Action
Low quality	Tracks with < 6 hits	Remove
	conv, compt	Remove
Relabeling	Decay tracks > 7 turns	Label as noise
	Ionized hits	Label as signal
Track splitting	Multi-turns track	Split
	Detector edge bounces	Split by turn

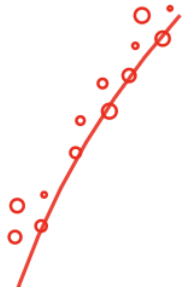


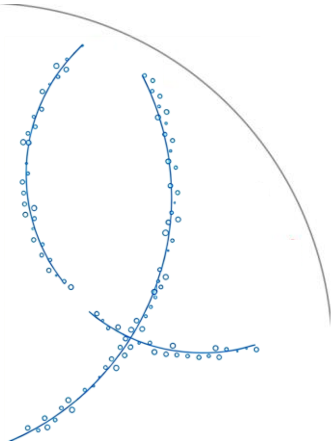
Remove hits from non-signal physical process



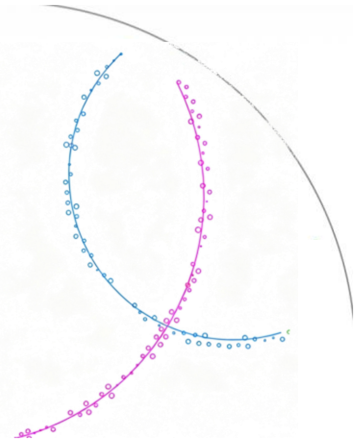


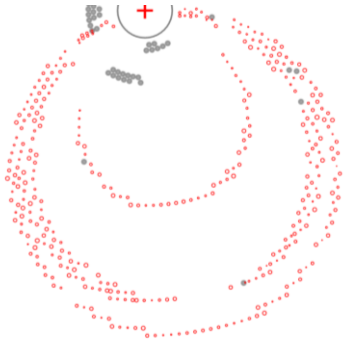
Reassign hits



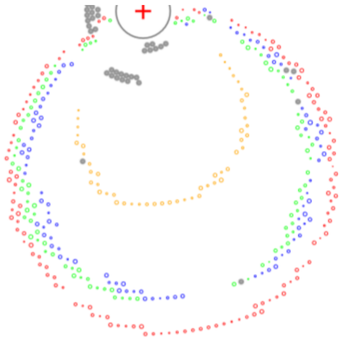


Detector edge bounces Split



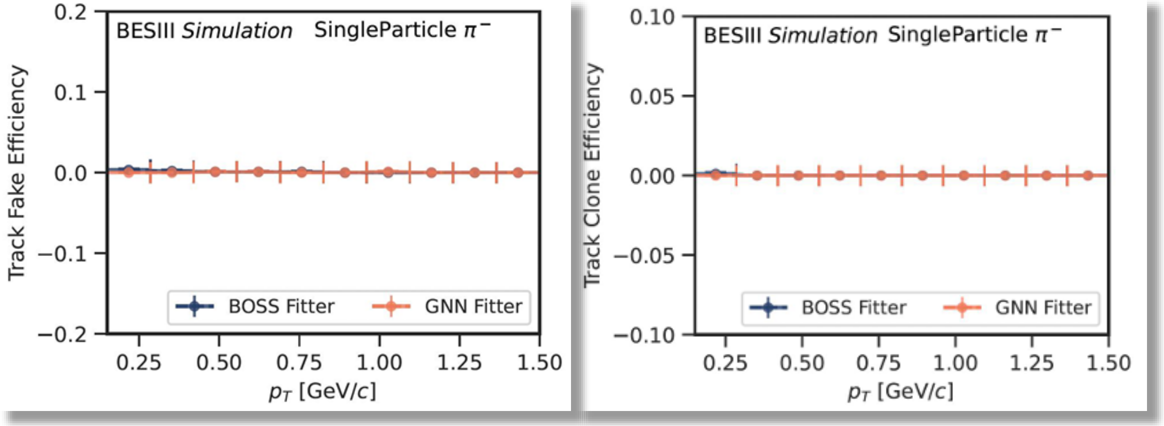


Multi-turns track Split by turn



Fake Track and Clone Track Rate

- GNN method of Fake and clone rate lower than baseline

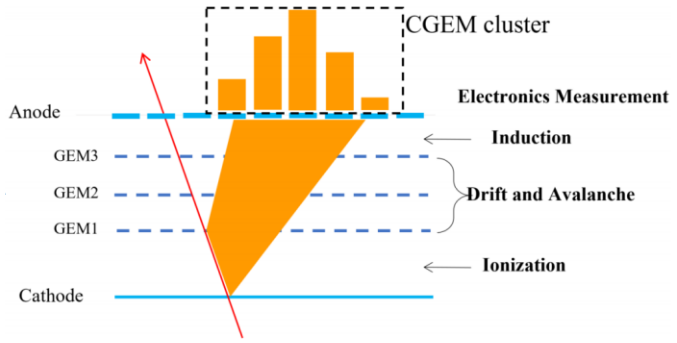


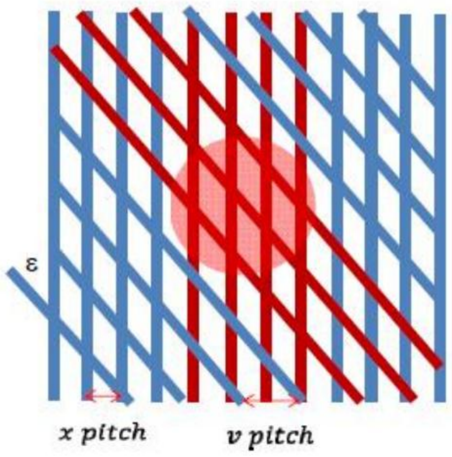
%		BOSS 方法	GNN 方法
克隆径迹率	寻迹	0.01 ± 0.01	0
	拟合	0.01 ± 0.01	0
假径迹率	寻迹	0.09 ± 0.03	0.07 ± 0.03
	拟合	0.08 ± 0.03	0.03 ± 0.02

Tracking of BESIII MDC

- Traditional tracking methods
  - Track finding: Pattern matching, Hough transform, etc.
  - Track fitting: Least-squares method, Kalman filter fitting, etc.

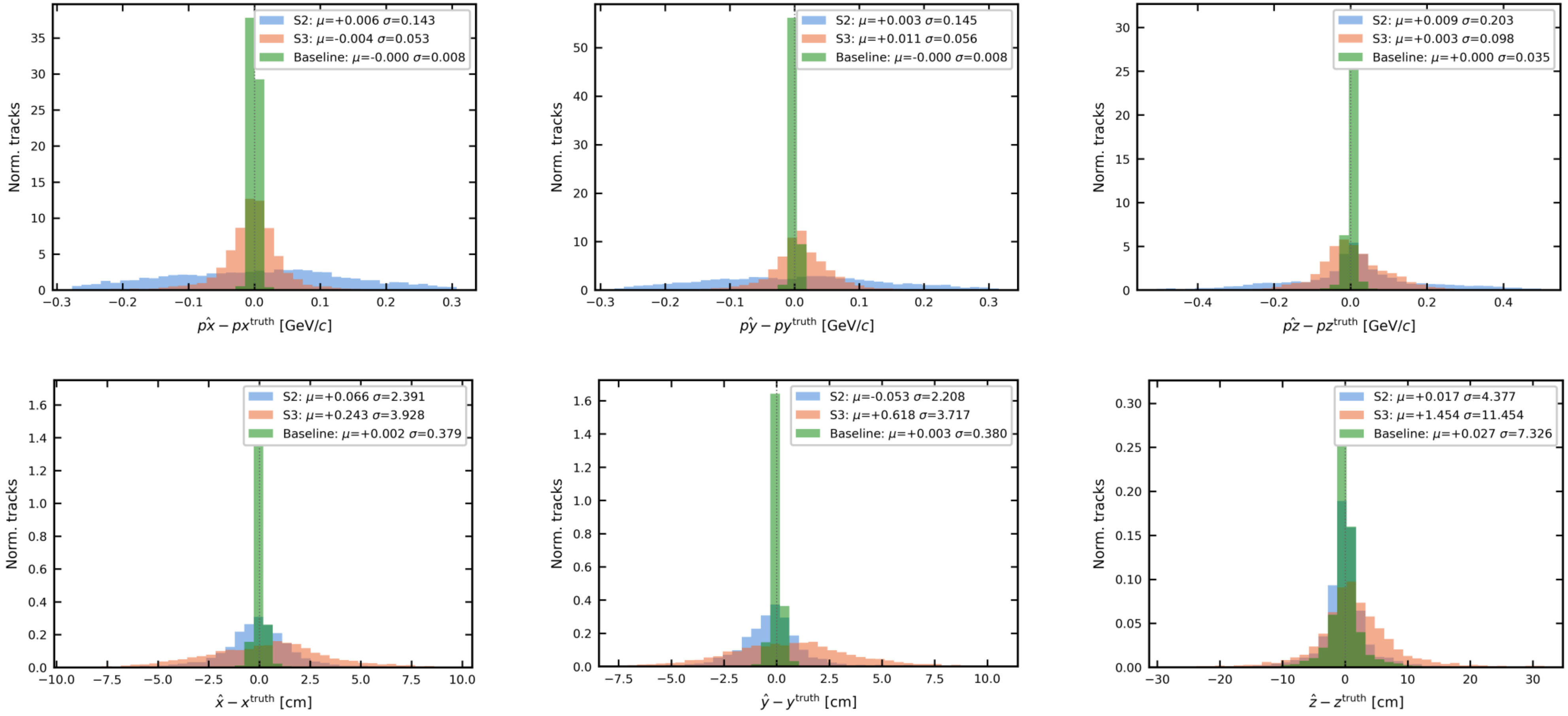
- Baseline method
  - Traditional track finding + GenFit fitting(Kalman)



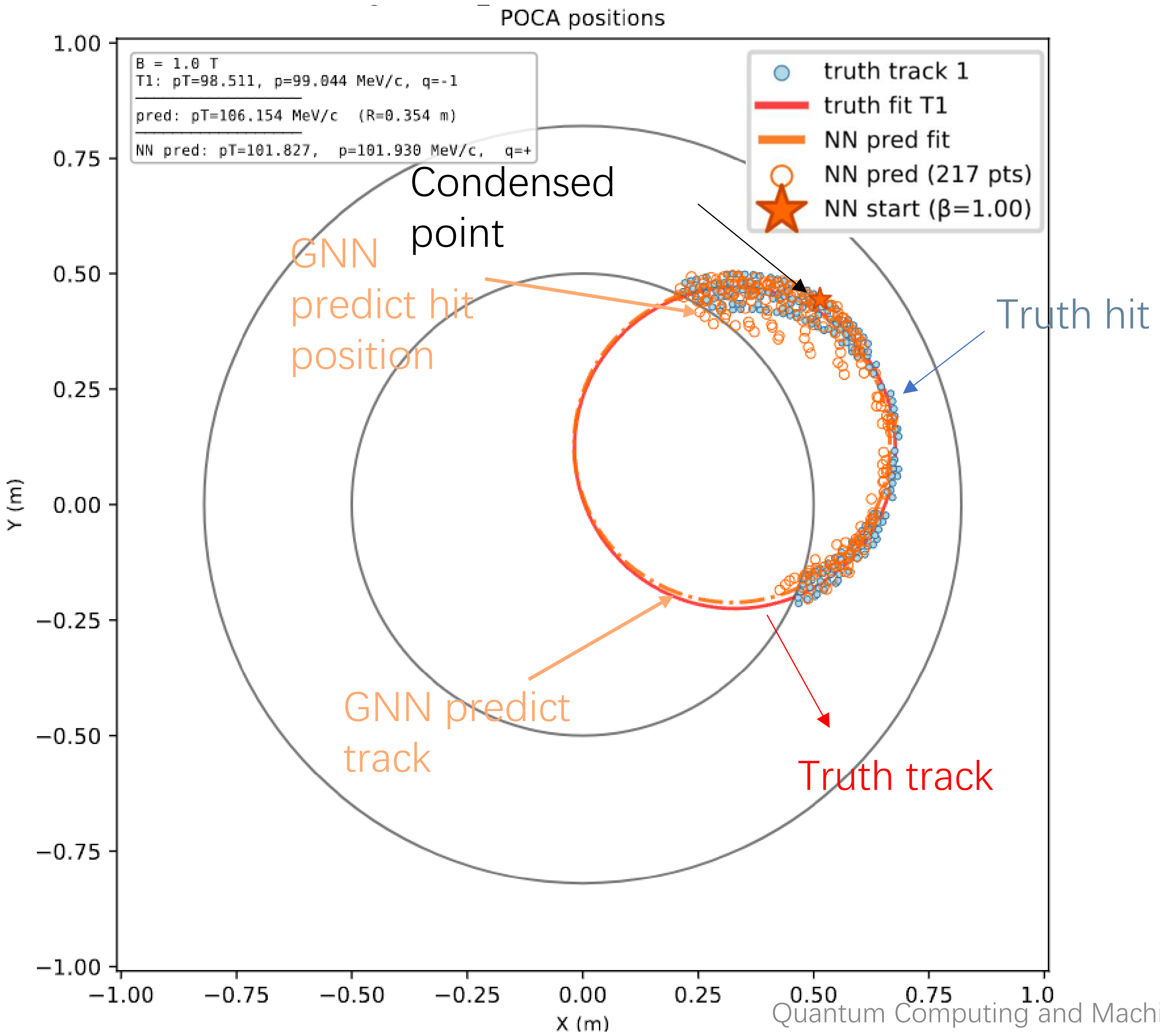


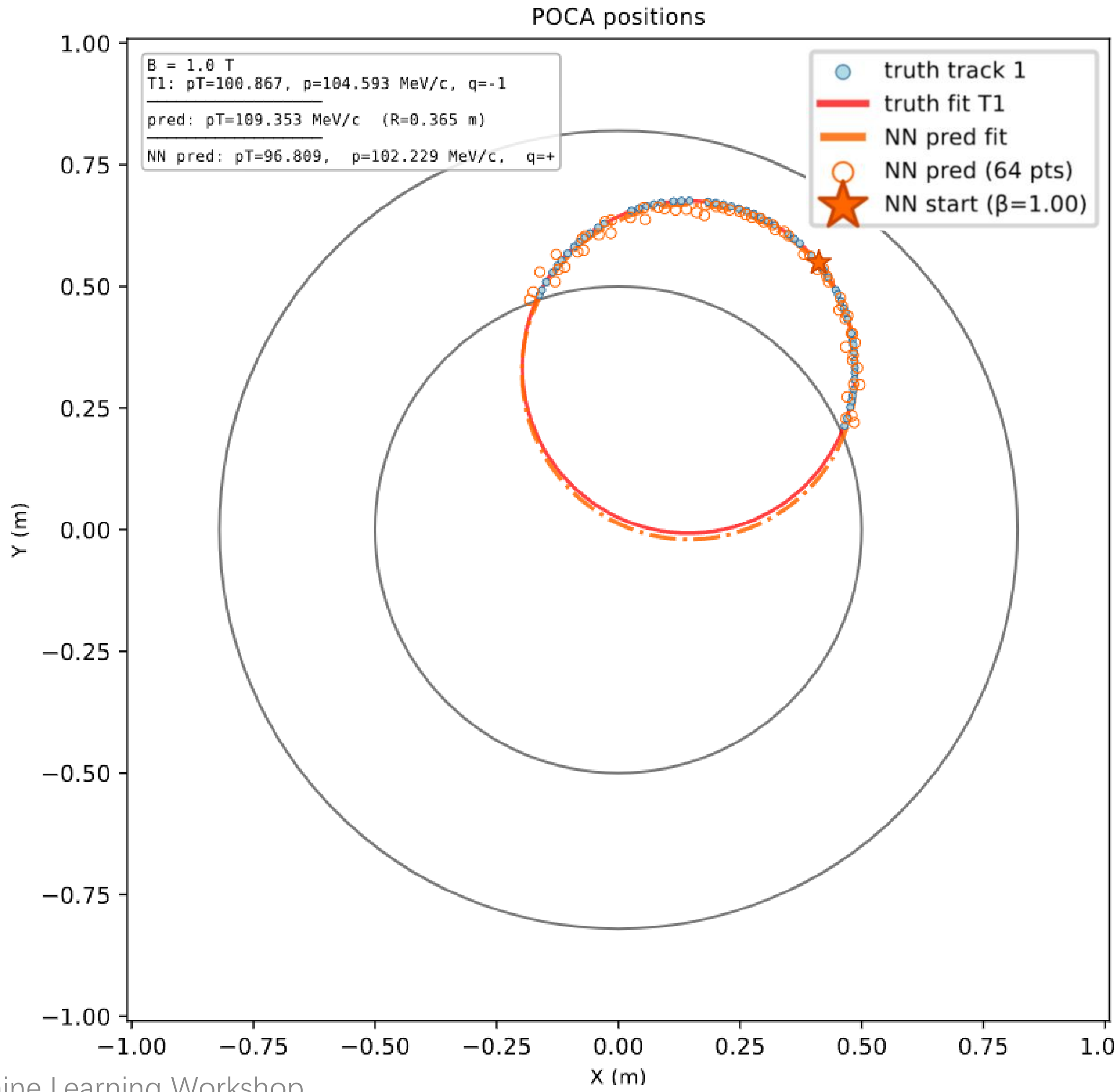
Performance

➢ Gap remains: NN vs. traditional (track parameters, e.g. low pt)

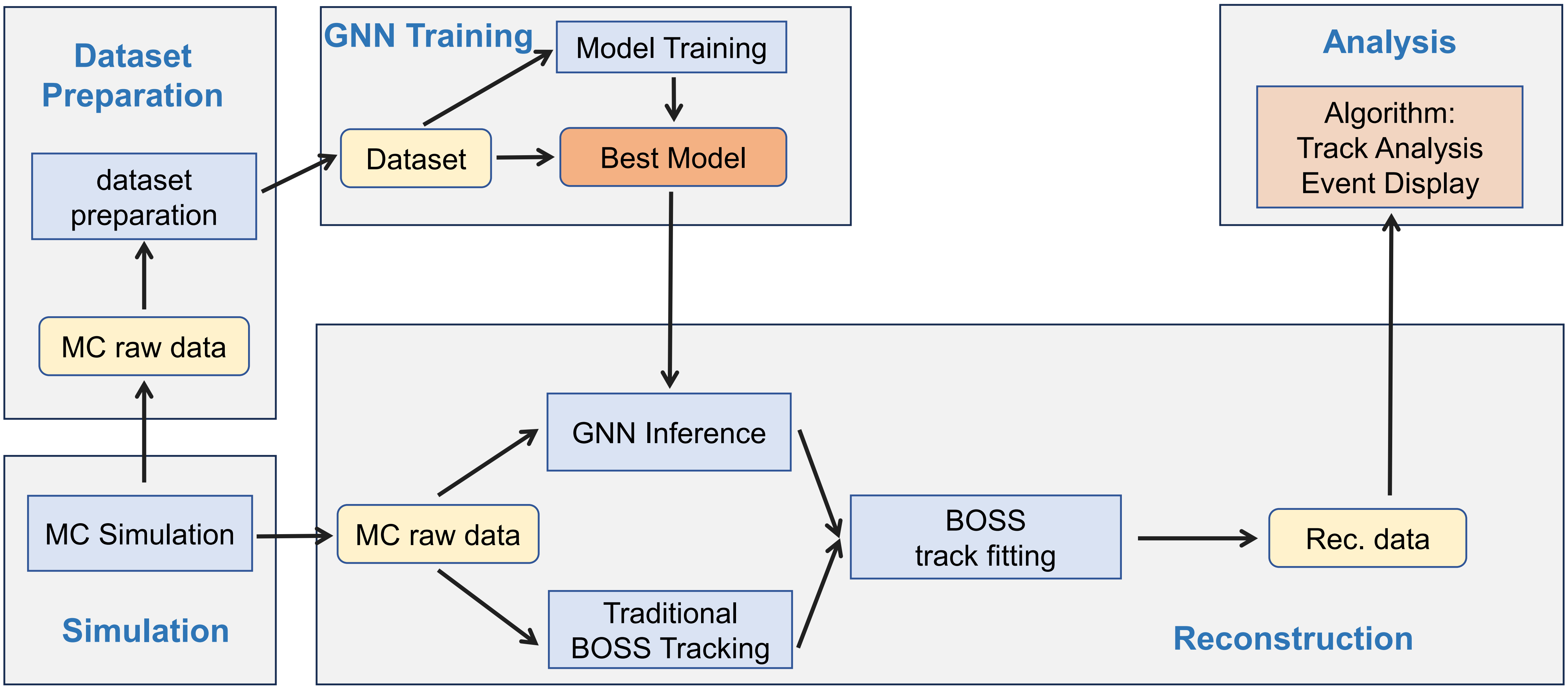


COMET CDC Event





Model Deploy



BF：Brute Force 暴力穷举

小窗口中直接枚举所有 bitstring，给出精确最优解。

输入 Q_win

窗口内 M 个变量

枚举 2^M 个状态

M=12 时只有 4096 个
每个都计算 E(x)

选择最小 E(x)

返回 exact optimum
作为 ground truth

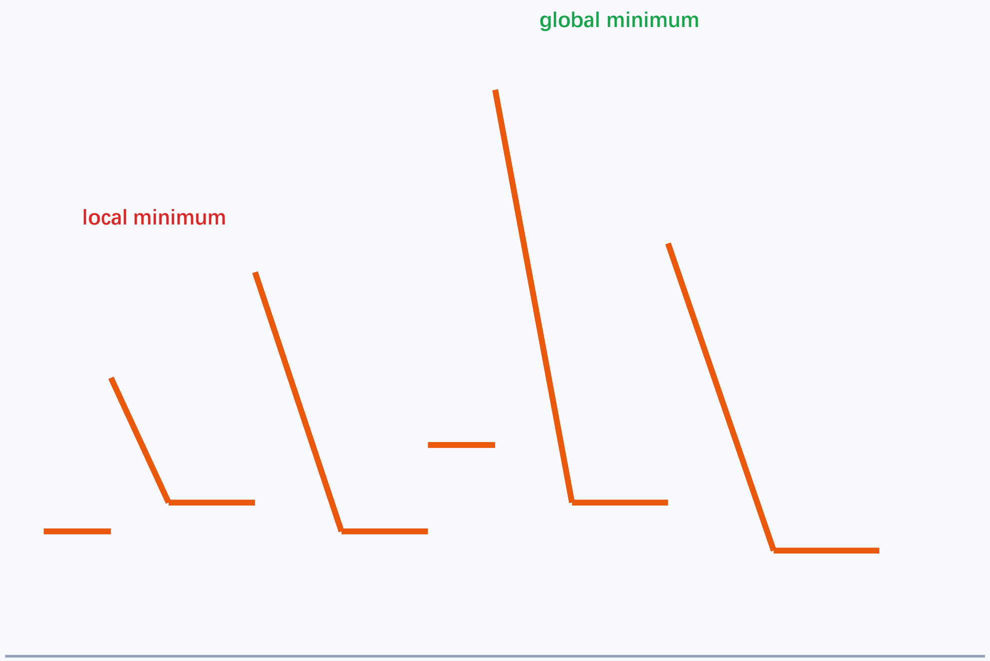
优点：最优性可证明。缺点：变量数增大时，2^M 指数爆炸。

0	0	0	0	0	0
0	0	0	0	0	1
0	0	0	0	1	0
...					
1	1	1	1	1	1

在当前 M≤12 的 Sliding QUBO 中，BF 是最快且最可靠的基准。

SA：Simulated Annealing 模拟退火

不枚举全空间，而是用带温度的随机搜索逼近低能量解。



Energy landscape

1. 随机初态

从一个 bitstring 开始

2. 随机翻转 bit

计算 ΔE

3. 接受/拒绝

更好必收；更差按概率收

4. 降低温度

高 T 探索，低 T 收敛

接受较差解的概率：$P = \exp(-\Delta E / T)$

SA 的价值：速度接近 BF，但不保证全局最优；适合较大窗口的经典近似基线。

QAOA：把 QUBO 转成量子线路求近似最优解

Hybrid quantum-classical loop：量子线路产生分布，经典优化器调整参数。

QUBO

$E(x)$

Ising

$x_i=(1-Z_i)/2$
$H = \Sigma h_i Z_i + \Sigma J_{ij} Z_i Z_j$

QAOA Ansatz

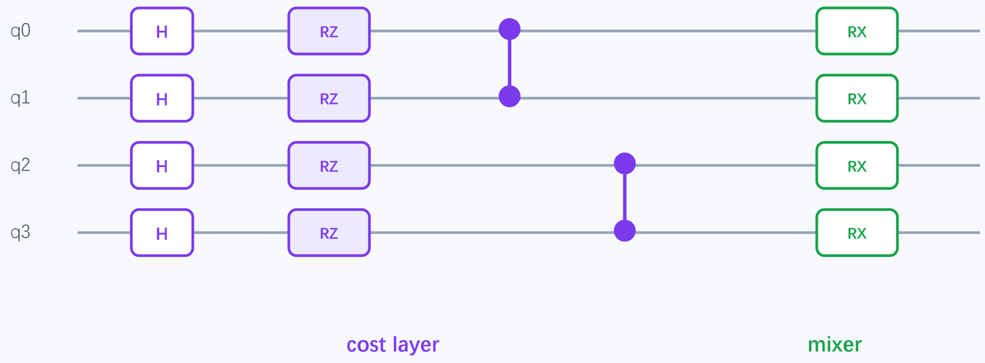
p 层 cost + mixer
参数 γ, β

Measure

采样 bitstrings
估计 energy

Optimizer

COBYLA / grid
更新参数



p=1

2 参数：γ_1, β_1
景观简单，实验质量最好

p=2

4 参数：$\gamma_1,\beta_1,\gamma_2,\beta_2$
更难优化，易陷入局部极小