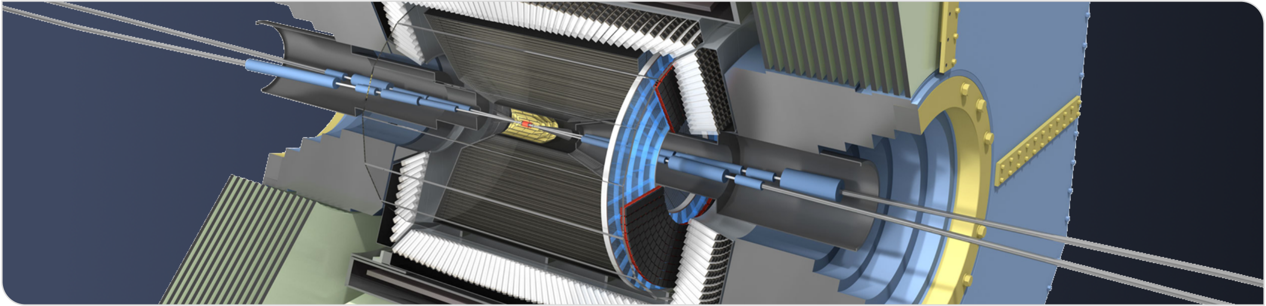
GNN-based Track and Vertex Finding

B2GM TRG

Lea Reuter, Philipp Dorwarth, Slavomira Stefkova, Torben Ferber | 7th October 2022



Project members: Machine Learning for Trigger

Karlsruhe Institute of Technology

KIT (ETP)

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P. Ecker, S. Stefkova, T. Ferber

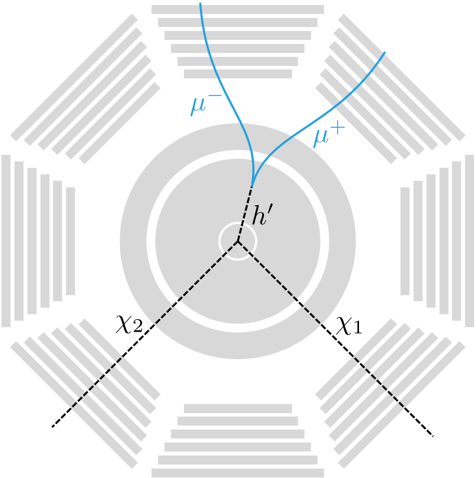
KIT (ITIV)

M. Neu, K. Unger, J. Becker

MPI (MPP)

E. Schmidt, F. Meggendorfer, C. Kiesling

Motivation



Searches for displaced vertices [a]

- Displaced vertices important signature in searches for new physics
- Example signal decay with dark photon A' and dark higgs h'

  $e^+e^- \to A'h',$
  $h' \to \mu^+\mu^-,$
  $A' \to \chi_1\chi_2,$
  $\chi_2 \to \chi_1 e^+ e^-$

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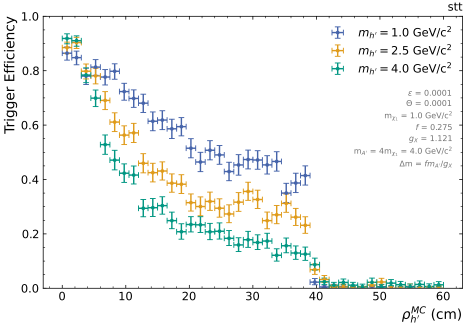
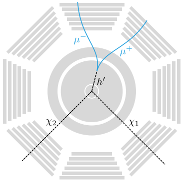
[a] Patrick Ecker : Search for Inelastic Dark Matter

Motivation



Credit: Patrick Ecker



Searches for displaced vertices

- Displaced vertices important signature in searches for new physics
- Example signal decay with dark photon A' and dark higgs h'

$$\begin{aligned} e^+e^- &\to A'h', \\ h' &\to \mu^+\mu^-, \\ A' &\to \chi_1\chi_2, \\ \chi_2 &\to \chi_1 e^+e^- \end{aligned}$$

Problem:

- Tracks with displacement larger than 40 cm are currently not triggered by **S**ingle **T**rack **T**rigger (stt)
- stt reconstruction efficiency decreases depending on displacement

Project Goal

- **Improve Track and Develop Vertex Finding using Graph Neural Networks (GNNs):**
  - Find events with displaced vertices (develop vertex finding)
  - Need to improve online L1 Trigger reconstruction

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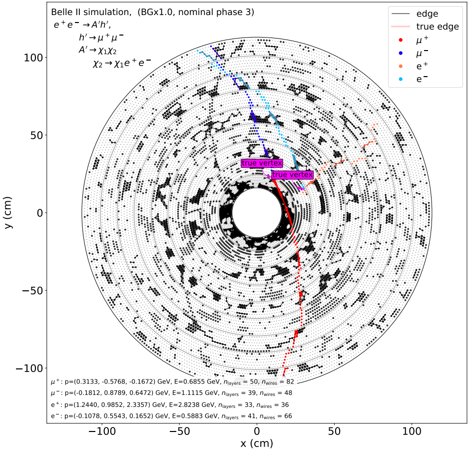
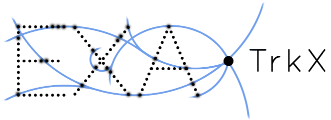
  - Find events with displaced vertices (develop vertex finding)
  - Need to improve online L1 Trigger reconstruction
- **Challenge:**
  - Tracks with low p_t (tracks curve)
  - Large occupancy due to beam-background hits (nominal phase 3)
  - Beam-background tracks (look like signal tracks)
  - Displaced vertices that are not pointing back to the interaction point

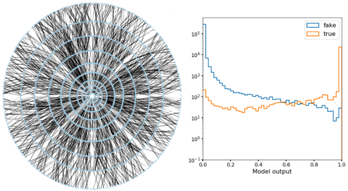


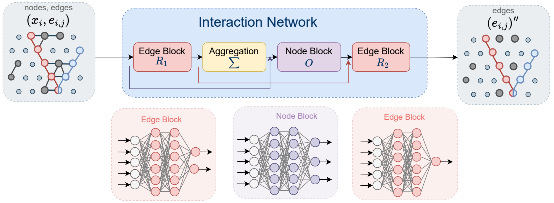
`/group/belle2/dataprod/BGOverlay/nominal_phase3/prerelease-05-00-00a/overlay/phase3/BGx1/`

Related Work: GNN Models for Real-Time Tracking

- Project Exa.TrkX: ATLAS, CMS, and DUNE experiments: Tracking with GNN models on FPGA-based real-time processing systems
- Graph Neural Networks for Charged Particle Tracking on FPGAs (arxiv:2112.02048)
- Greta Heine (ETP, IPE): Trackfinding on FPGAs for the PANDA Experiment





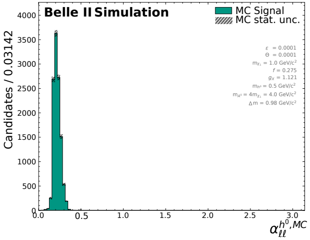


MC Simulated Samples

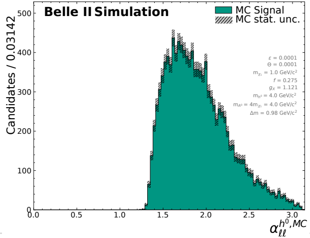
- Release:
  `feature/BII-9379-store-cdchit-relations-to-all-particle`
- Globaltags: `main_2022-01-27` and `patch_main_release-07`
- Starting with BGx0 and early-phase 3 BGx1
  `/group/belle2/dataprod/BGOverlay/early_phase3/release-05-01-15/overlay/phase31/BGx1/set0/`
- Signal samples:
  - Single displaced vertex samples
  - $e^+e^- \to A'h'$,
    $h' \to \mu^+\mu^-$,
    $A' \to \chi_1\chi_2$,
    $\chi_2 \to \chi_1 e^+e^-$ (outside of CDC)
  - on-shell (two-body)
  - $m(h)$ (0.5-4.0 GeV) in 0.1 GeV steps
- Background samples:
  - $e^+e^- \to e^+e^-$
  - $e^+e^- \to \mu^+\mu^-$

Distribution of opening angle $\alpha_{ll}^{h'}$

$m(h)$ =0.5 GeV

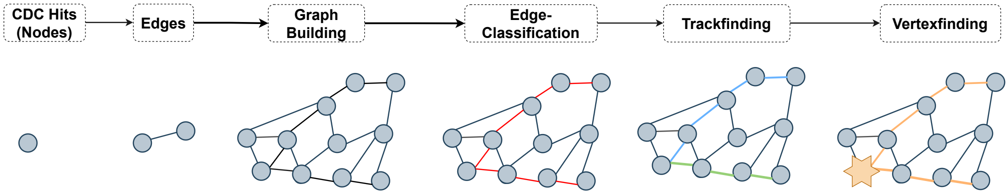


$m(h')$ =4.0 GeV



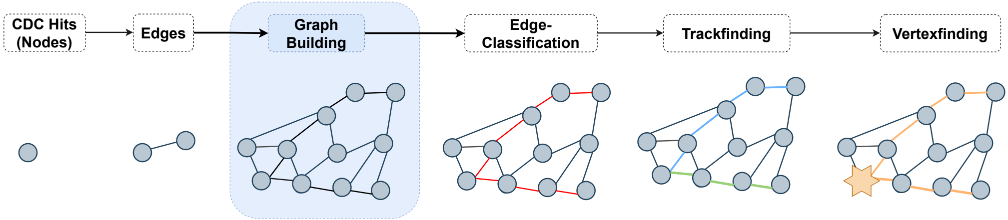
Approach with Graph Neural Networks

Variable number of CDC hits $\rightarrow$ utilize Graphs and Graph Neural Networks

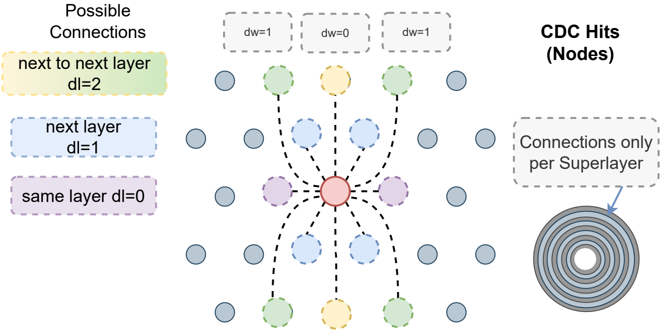


Approach with Graph Neural Networks: Graph Building

Variable number of CDC hits → utilize Graphs and Graph Neural Networks



Graph-Segment Building

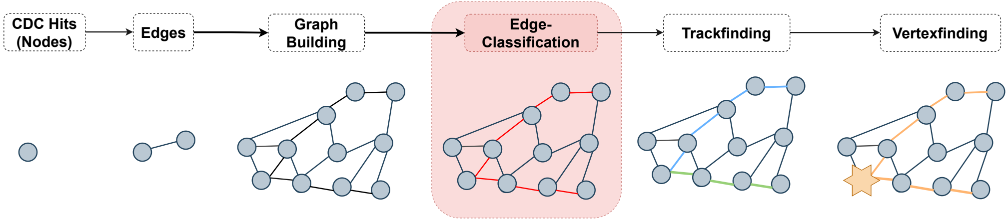


- Find trade-offs between purity, efficiency, graph size and timing
- Choice of graph building dependent on subsequent tasks
- Working together with ITIV (Department of Electrical Engineering Information Technology) at KIT for L1 Trigger graph building

→ Philipp Dorwarth is working on this and will show studies and results in upcoming trigger meetings

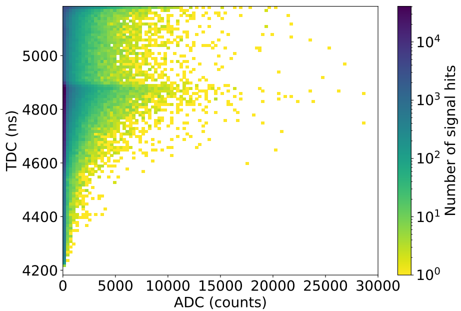
Approach with Graph Neural Networks: Edge Classification

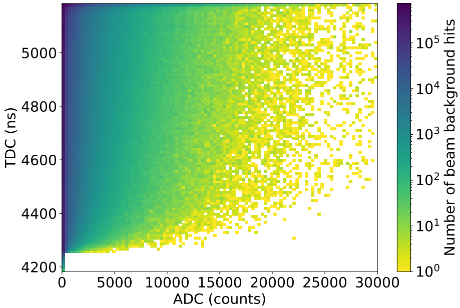
Classify True and False edges of the graph



Interaction Network: Graph Neural Networks for Charged Particle Tracking on FPGAs (arxiv:2112.02048)

GNN Input Feature Studies





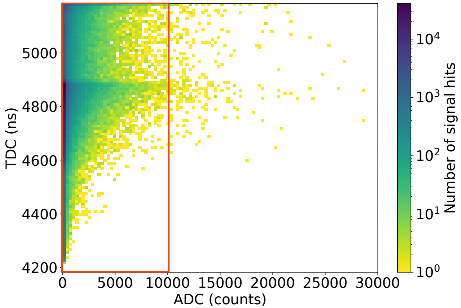
Testing discriminating input features:

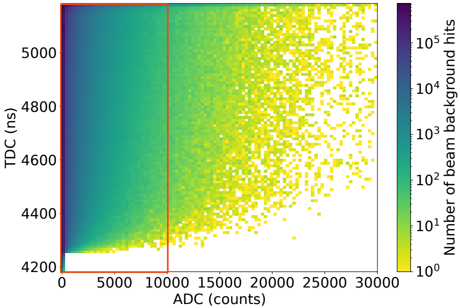
- Edges: $\Delta\rho$, $\Delta\phi$
- Nodes: ρ, ϕ, TDC, ADC

Additional inputs

- digitized timing information **TDC** (online available after LS1)
- digitized signal information **ADC** (online perhaps available for 2025)

GNN Input Feature Studies





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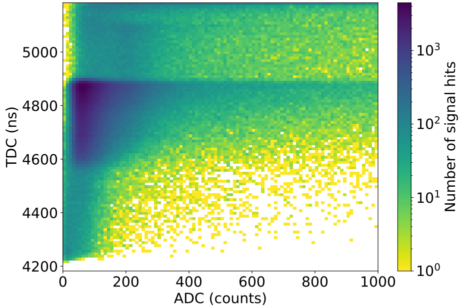

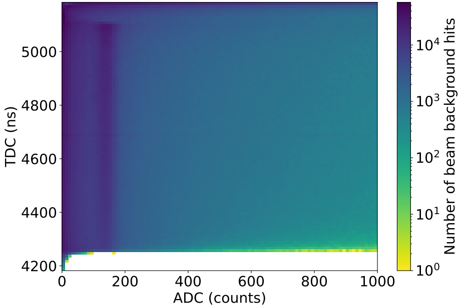

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$\rightarrow$ Currently working on data to MC comparison for ADC and TDC (see backup for initial comparison)!

Edge Classification GNN Evaluation

Determine binary threshold using maximal F_1 score:

- $purity = \frac{TP}{TP+FP}$
- $efficiency = \frac{TP}{TP+FN}$

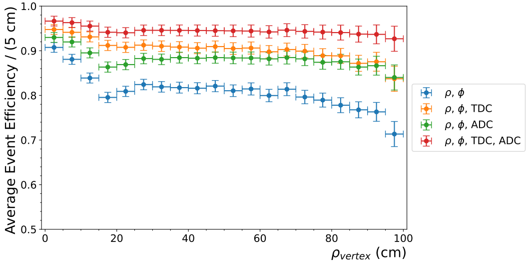
- $F_1 = 2 \cdot \frac{purity \cdot efficiency}{purity + efficiency} = \frac{TP}{TP+(FP+FN)/2}$

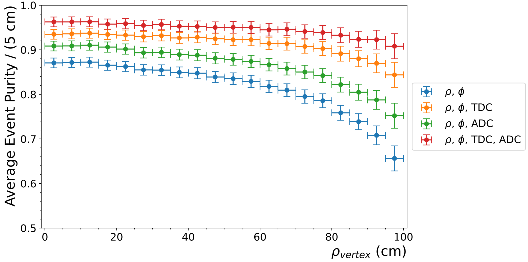
Using both TDC and ADC results in a

- Event classification efficiency of 94% and
- Event classification purity of 93%

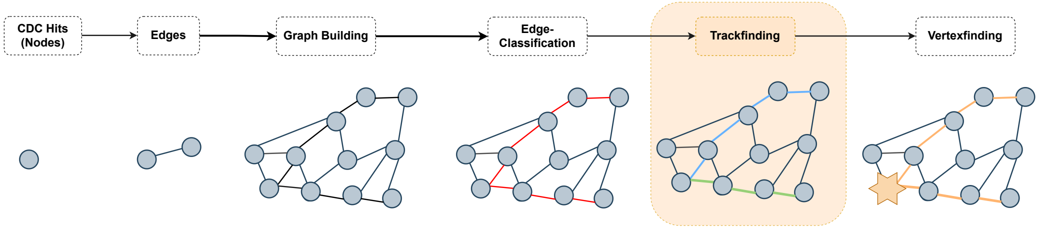
on signal with early-phase 3 beam-background

evaluated on 1000 samples per mass





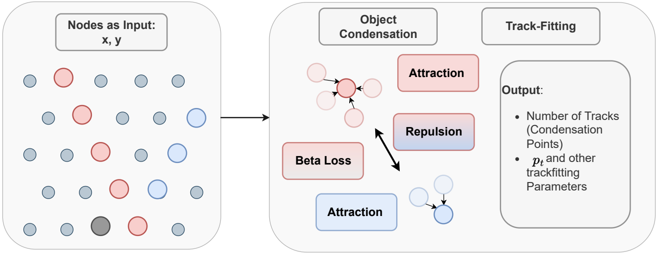
Approach with Graph Neural Networks: Trackfinding



Use **Object Condensation** (arXiv:2002.03605)
→ Based on Isabel Haide: Improving ECL Clustering with Object Condensation

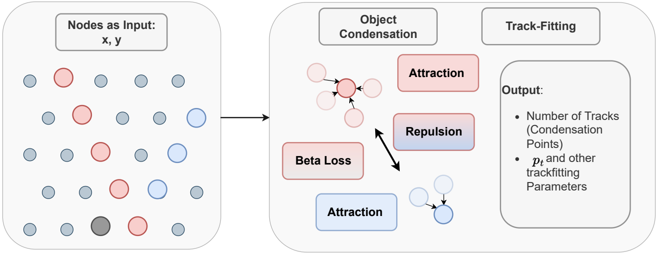
Object Condensation Trackfinding Approach

Karlsruhe Institute of Technology

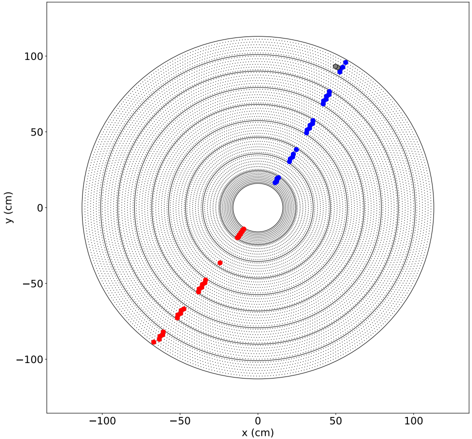


→ Use nodes as input to Object Condensation (arXiv:2002.03605)
→ **Goal:** predict track fitting parameters and find condensation points

Object Condensation Trackfinding Approach



Start with very simple case:
$e^+e^- \to \mu^+\mu^-$
no beam-background



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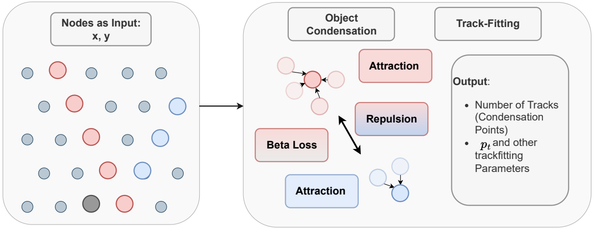
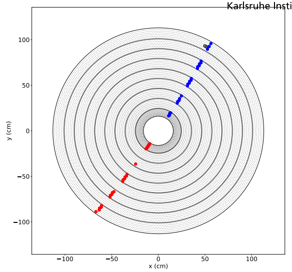
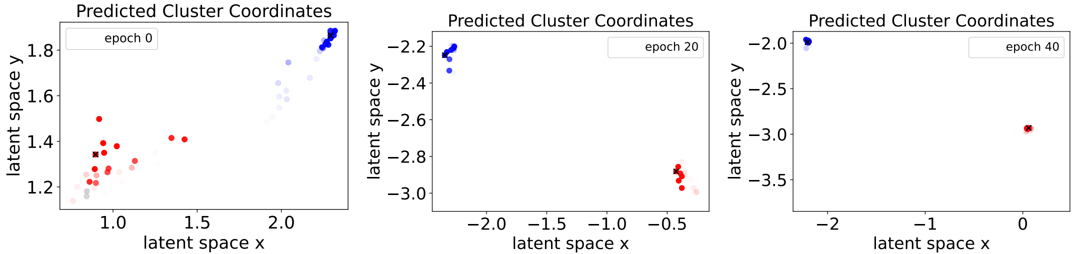
Object Condensation Trackfinding Approach

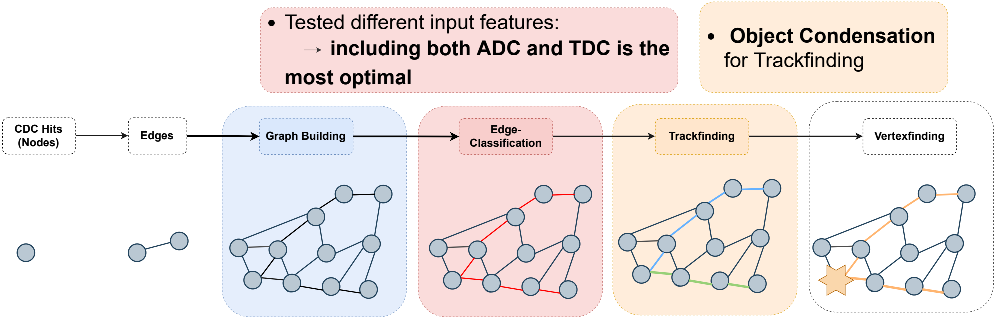






Summary and Outlook

- **Displaced vertices** relevant for new physics searches
- **L1 Trigger reconstruction** needs to be improved

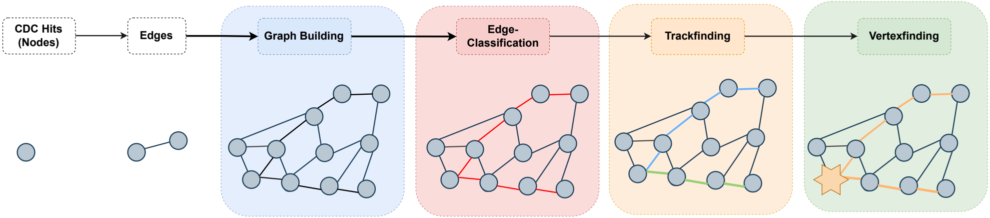


Summary and Outlook

- **Displaced vertices** relevant for new physics searches
- **L1 Trigger reconstruction** needs to be improved

- Tested different input features:
  → **including both ADC and TDC is the most optimal**

- **Object Condensation** for Trackfinding

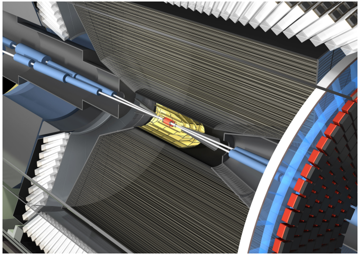


- Working together with **ITIV** for **online Graph Building** and **FPGA implementation**

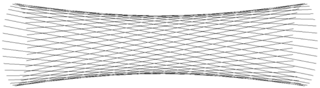
- **Data to MC Comparison** Study for ADC and TDC Input Features

- **Object Condensation** for Trackfitting and Vertex Finding to improve L1 Trigger Reconstruction

Central Drift Chamber (CDC)



(a) An axial wire layer - sense wires are parallel to the beamline

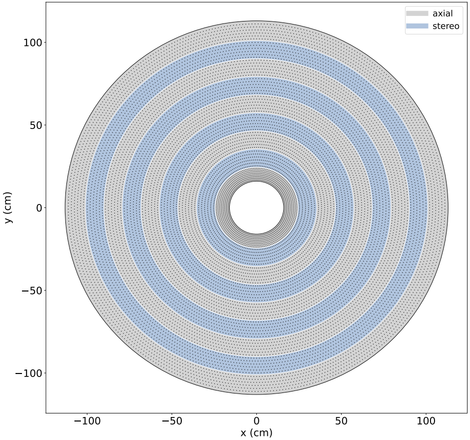


(b) A stereo wire layer - sense wires are skewed to the beamline (exaggerated)

- Sense wires are arranged around the beamline (z-axis) to measure charged particles
- z Information gathered from stereo layers
- Events with displacement $\rho > 16.0\,\text{cm}$ start within the CDC

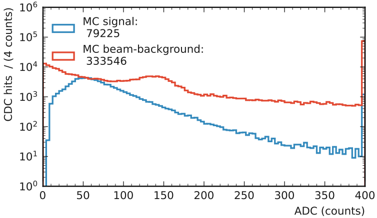
$\rightarrow$ Focus on track reconstruction using the CDC information

CDC x-y view

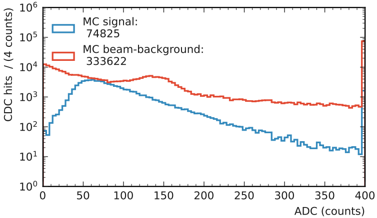


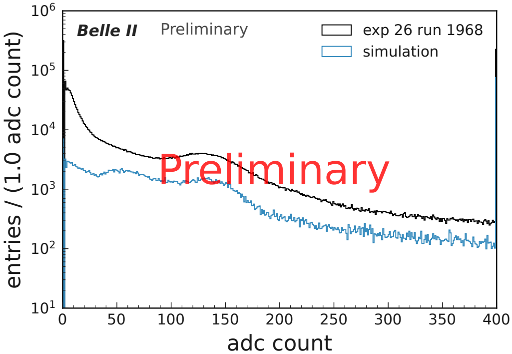
Preliminary Data to MC ADC Overlay

$e^+e^- \to A'h'$, $h' \to \mu^+\mu^-$, $m(h') = 2.0\,\mathrm{GeV}$
(run-independent early-phase 3)



$e^+e^- \to \mu^+\mu^-$ (run-independent early-phase 3)





Credit: Philipp Dorwarth, Work in Progress:

- MC ($e^+e^- \to \mu^+\mu^-$, run-independent early-phase 3) not skimmed (`hlt_mumu_tight_or_highm_calibskim`) and not calibrated
- Data (`hlt_mumu_tight_or_highm_calibskim`) only contains exp 26 run 1968

GNN Evaluation: F_1: Input Feature Studies

Karlsruhe Institute of Technology

Determine binary threshold using maximal F_1 score: $F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} = \frac{TP}{TP + (FP+FN)/2}$

input features: $[\rho, \phi]$

Confusion matrix

Actual \ Predicted	True	False	Row Sum
True	36784 TP: 14.68%	7465 FN: 2.98%	44249 TPR: 83.13% FNR: 16.87%
False	9826 FP: 3.92%	196459 TN: 78.42%	206285 TNR: 95.24% FPR: 4.76%
Column Sum	46610 PPV: 78.92% FDR: 21.08%	203924 NPV: 96.34% FOR: 3.66%	250534 ACC: 93.10% MISS: 6.90%

$F_1 = 0.81$

input features: $[\rho, \phi, TDC]$

Confusion matrix

Actual \ Predicted	True	False	Row Sum
True	41499 TP: 16.56%	3414 FN: 1.36%	44913 TPR: 92.40% FNR: 7.60%
False	5111 FP: 2.04%	200510 TN: 80.03%	205621 TNR: 97.51% FPR: 2.49%
Column Sum	46610 PPV: 89.03% FDR: 10.97%	203924 NPV: 98.33% FOR: 1.67%	250534 ACC: 96.60% MISS: 3.40%

$F_1 = 0.91$

input features: $[\rho, \phi, ADC]$

Confusion matrix

Actual \ Predicted	True	False	Row Sum
True	40465 TP: 16.15%	5993 FN: 2.39%	46458 TPR: 87.10% FNR: 12.90%
False	6145 FP: 2.45%	197931 TN: 79.00%	204076 TNR: 96.99% FPR: 3.01%
Column Sum	46610 PPV: 86.82% FDR: 13.18%	203924 NPV: 97.06% FOR: 2.94%	250534 ACC: 95.16% MISS: 4.84%

$F_1 = 0.87$

input features: $[\rho, \phi, TDC, ADC]$

Confusion matrix

Actual \ Predicted	True	False	Row Sum
True	43741 TP: 17.46%	2760 FN: 1.10%	46501 TPR: 94.06% FNR: 5.94%
False	2869 FP: 1.15%	201164 TN: 80.29%	204033 TNR: 98.59% FPR: 1.41%
Column Sum	46610 PPV: 93.84% FDR: 6.16%	203924 NPV: 98.65% FOR: 1.35%	250534 ACC: 97.75% MISS: 2.25%

$F_1 = 0.94$

GNN Evaluation per Mass