Towards Realistic Hyperon Reconstruction using Deep Learning in the Straw Tube Tracker

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Outline

- Motivation
- PANDA Experiment at FAIR
- Towards Realistic Hyperon Reconstruction:
  - Muon Reconstruction
  - Hyperon Reconstruction
- Track Evaluation
- Conclusions and Outlook

Motivation

How well can machine learning be used for the purpose of track reconstruction? Most importantly, reconstructing

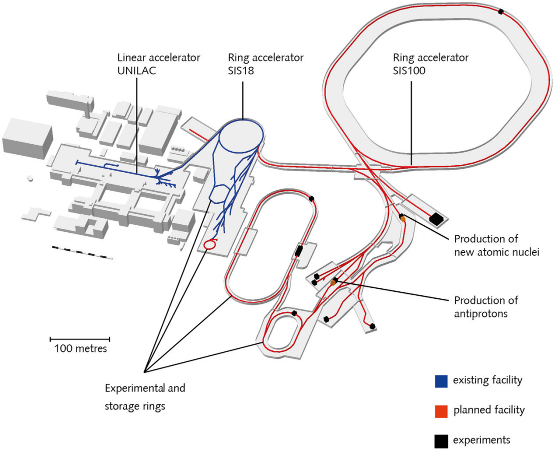
- Low momentum tracks, and
- with displaced vertices

These questions are answered in Part II of my doctoral thesis [1].

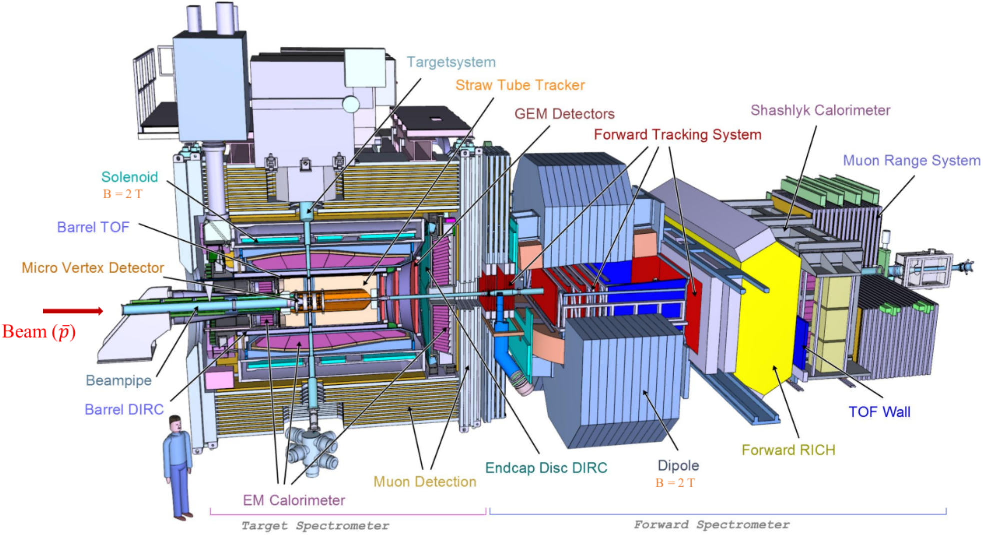
[1] A. Akram, *Towards Realistic Hyperon Reconstruction in PANDA: From Tracking with Machine Learning to Interactions with Residual Gas*, Doctoral Thesis, Uppsala University, Uppsala (2023)

PANDA Experiment at FAIR

- PANDA is general-purpose fixed target experiment with almost 4π coverage.
- Antiproton beam: 1.5 GeV/c to 15 GeV/c from High Energy Storage Ring (HESR).
- The interaction rate up to 20 MHz.

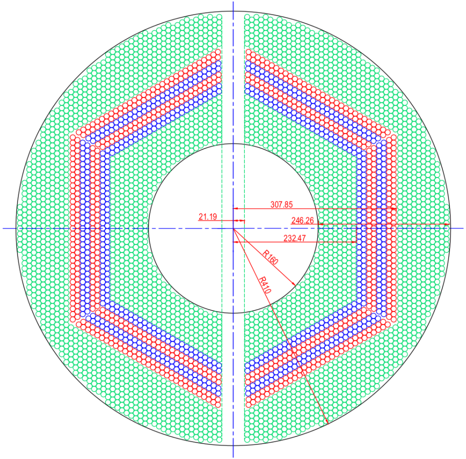


The PANDA Detector



Straw Tube Tracker (STT)

- 4224 straw tubes
- 15 - 19 axial layers (green)
- 8 skewed layers ($\pm 2.9^\circ$) (red and blue)
- Radial coverage: 15 cm to 41.8 cm

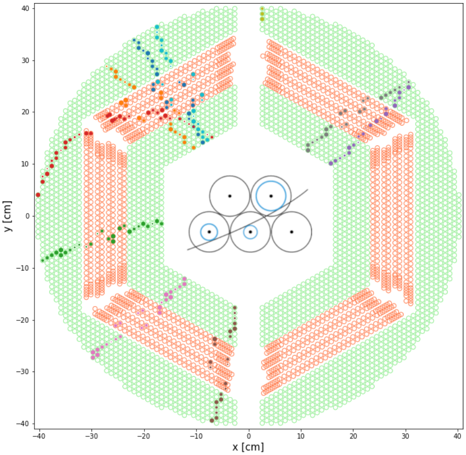


What is the challenge?

Focus on the $r\phi$-plane of the STT detector:

- Detector geometry:
  - straight and skewed tubes
  - hexagonal arrangement of straw tubes
- Track topology:
  - spiraling
  - overlapping
  - crossing

⇒ Use deep learning for track reconstruction



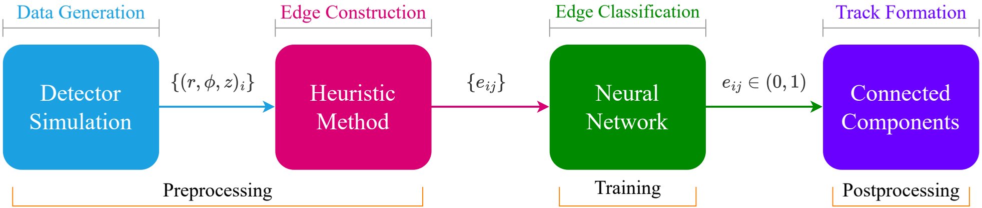
Strategy

The strategy is to use two pipelines:

- Deep Learning (DL) pipeline
  - A standard approach, tested on **muons** ($\mu^{\pm}$)
- Geometric Deep Learning (GDL) pipeline
  - A more elaborate approach was first tested with **muons** ($\mu^{\pm}$) and then with **hyperons**

$\Rightarrow$ Track evaluation

The Pipeline



$\Rightarrow$ Pipelines only differ in ***Edge Construction*** and ***Edge Classification*** stages.

Track Evaluation (I)

Let's define the variables first:

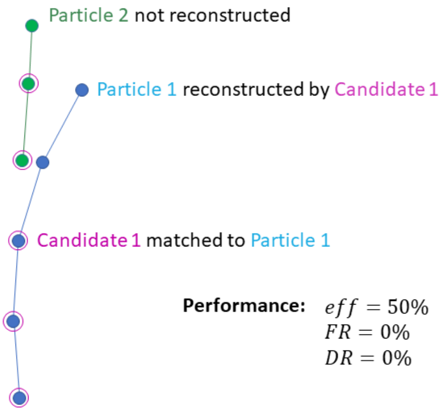
- $N_{\mathbf{particles}}$: # of generated particles in the detector
- $N_{\mathbf{tracks}}$: # of reconstructed tracks containing at least 5 or 6 hits (denoted N_r)
- Selected: # of particles/tracks within STT acceptance.
- Reconstructable: # of particles with # of hits $>$ 7 STT hits (denoted N_t).
- Matched: # of particles (tracks) matched to a reconstructed track (particle).

Track Evaluation (II)

A particle is **matched** to a reconstructed track if more than

- 50% of the hits in the reconstructed track belong to the same true particle, and
- 50% of the hits in the matched true particle are found in the reconstructed tracks.

This is known as a two-way matching scheme with a matching fraction (MF) > 50%.



Track Evaluation (III)

ϵ_{phys} is the efficiency considering both detector and algorithm:

$$\epsilon_{\text{phys}} = \frac{N_{particles}(\text{selected, matched})}{N_{particles}(\text{selected})} \tag{1}$$

$\epsilon_{\text{tech.}}$ is the efficiency of algorithm itself:

$$\epsilon_{\text{tech.}} = \frac{N_{particles}(\text{selected, reconstructable, matched})}{N_{particles}(\text{selected, reconstructable})} \tag{2}$$

Track purity measures the accuracy of a reconstructed track in matching a particle:

$$\text{Purity} = \frac{N_{\text{tracks}}(\text{selected, matched})}{N_{\text{tracks}}(\text{selected})} \equiv 1 - \text{Ghost Rate} \tag{3}$$

Track Evaluation (IV)

The transverse momentum (p_t), lab polar angle of the track (θ), and azimuthal angle of the track (ϕ) are defined as follows:

$$p_t = \sqrt{p_x^2 + p_y^2}$$
$$\theta = \tan^{-1}(p_t, p_z)$$
$$\phi = \tan^{-1}(p_y, p_x)$$

and the radial distance (d_0) between the interaction point and the decay vertex:

$$d_0 = \sqrt{v_x^2 + v_y^2}$$

Muon Reconstruction in STT

Pipeline: Data Generation

- Five $\mu^+\mu^-$ pairs per event using a *Box Generator*
- 100 MeV/c – 1.5 GeV/c
- In total, 10^5 events are generated
- Track reconstruction in $r\phi$-plane of STT, restricted to straight sections

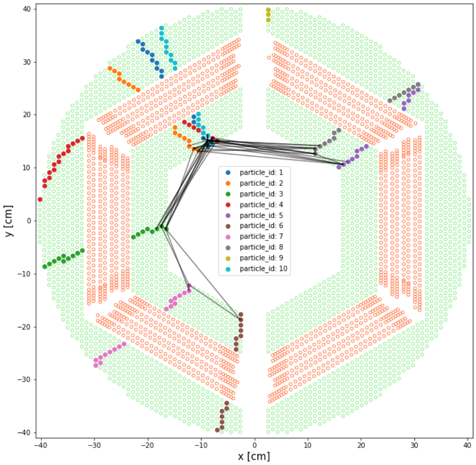
Pipeline: Graph Construction

Graph representation of tracks (*i.e.* a hit graph) in terms of nodes and edges:

- *node*: hit position of a particle
- *edge*: a connection between two hits

A heuristic method for layer-wise edge construction in adjacent sectors:

- *input graphs*: contain True & False edges
- *ground truth*: contain only True edges



Pipeline: Edge Classification (I)

Train a neural network on hit graphs to predict edges. There were two main differences:

- Deep Learning: directed graphs, classification with a dense network
- Geometric Deep Learning: bi-directed graphs, classification with interaction network

The output of the neural network in terms of edge score/probability.

Pipeline: Edge Classification (II)

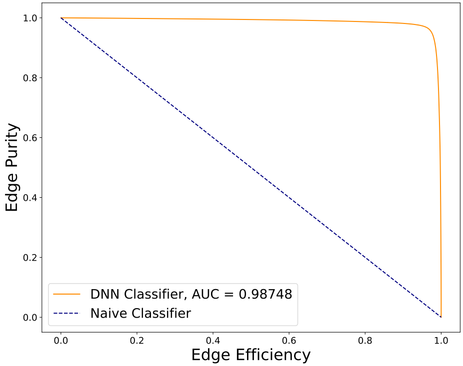


Figure: Deep Learning

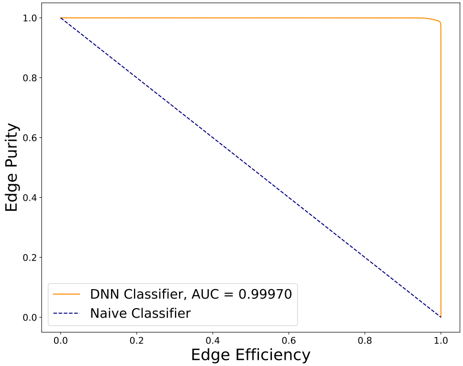


Figure: Geometric Deep Learning

⇒ Predicted Graphs: Weighted graphs with edge score/probability.

Pipeline: Track Formation

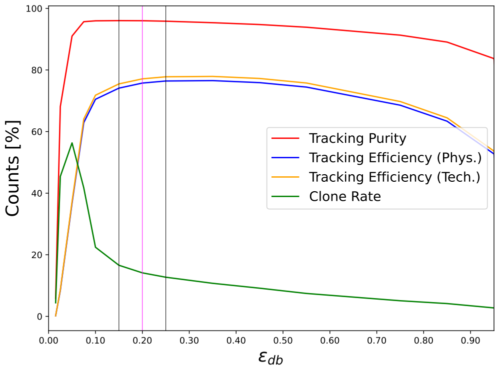


Figure: Deep Learning

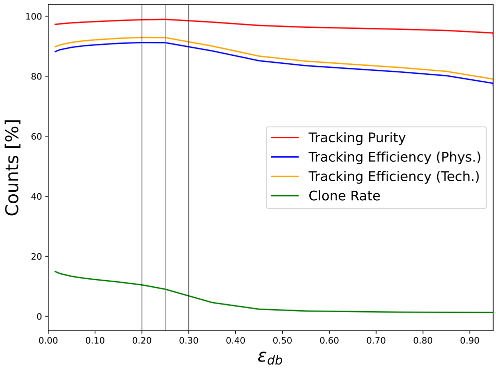


Figure: Geometric Deep Learning

⇒ Track Candidates: Cluster hits of weighted graphs using the DBSCAN

Track Evaluation (I)

Using the criteria of $N_t \geq 7$, $N_r \geq 5$ and MF $> 50\%$, the results are

	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
Deep Learning	76.3 ± 0.3	77.2 ± 0.3	3.64 ± 0.33	17.2 ± 0.1
Geometric Deep Learning	91.0 ± 0.3	92.6 ± 0.3	1.25 ± 0.32	11.5 ± 0.1

Table: Tracking efficiencies, ghost rate (GR), clone rate (CR).

⇒ A clear increase in performance with Geometric Deep Learning!

Track Evaluation (II): Tracking Efficiencies vs Transverse Momentum

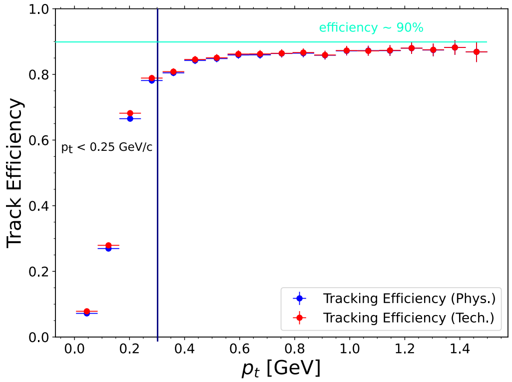


Figure: Deep Learning

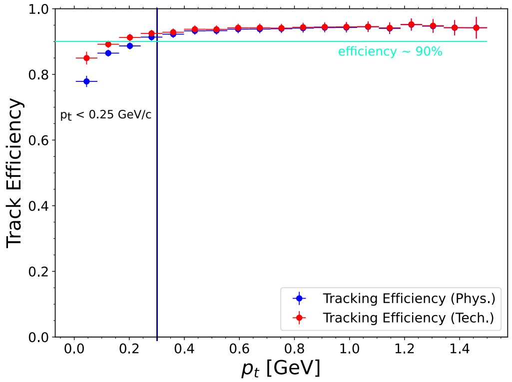


Figure: Geometric Deep Learning

Track Evaluation (II): Tracking Efficiencies vs Azimuthal Angle

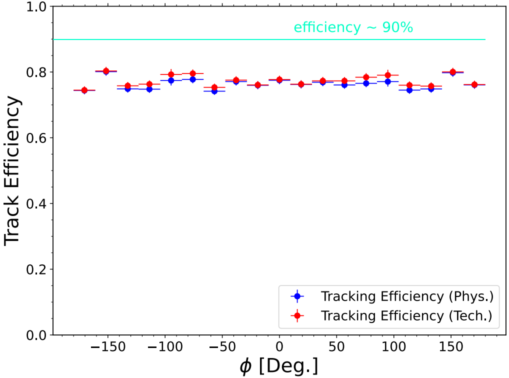


Figure: Deep Learning

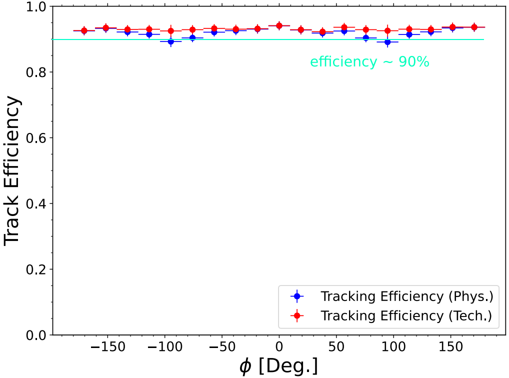


Figure: Geometric Deep Learning

Track Evaluation (II): Tracking Efficiencies vs Theta Angle

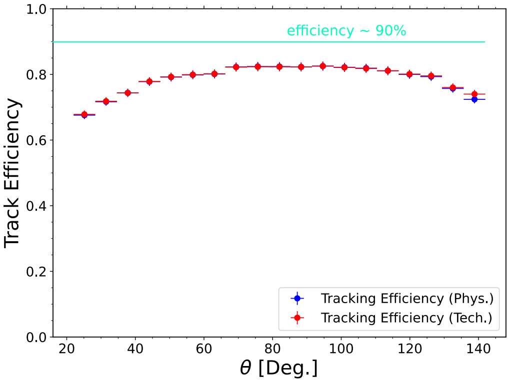


Figure: Deep Learning

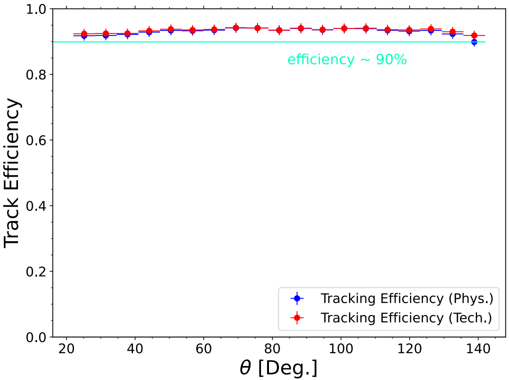
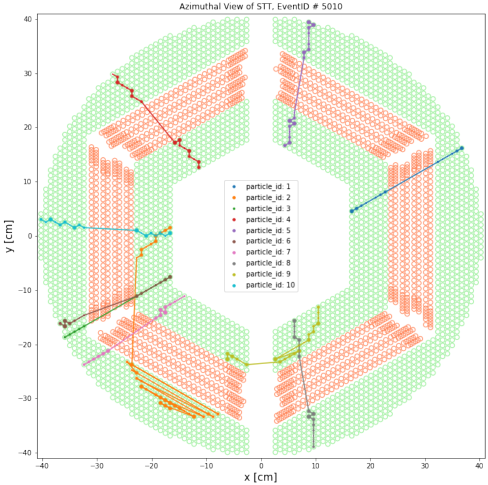
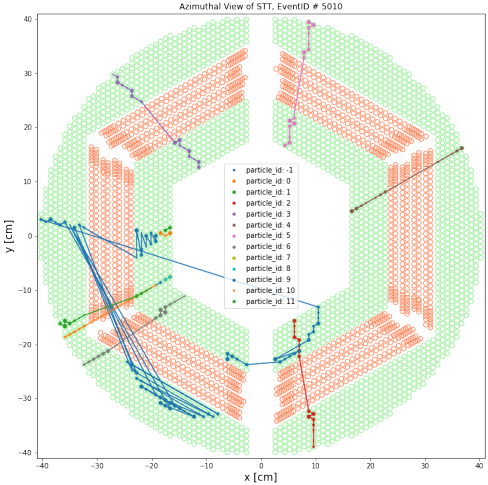


Figure: Geometric Deep Learning

Tracking Efficiency Loss

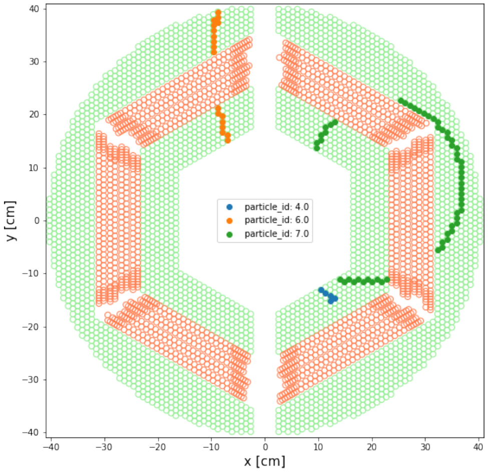




Hyperon Reconstruction in STT

The Pipeline

- Same GDL pipeline as for muons
- 10^5 $\bar{p}p \to \bar{\Lambda}\Lambda \to \bar{p}\pi^+ p\pi^-$ events simulated at $p_{beam} = 1.642$ GeV/c
- 3 tracks per event on average $\to \bar{p}$ emitted at small angles, escapes STT
- Final state particles are
  - low p_t hadrons such as $p, \bar{p}$ and $\pi^\pm$
  - with secondary decay vertices



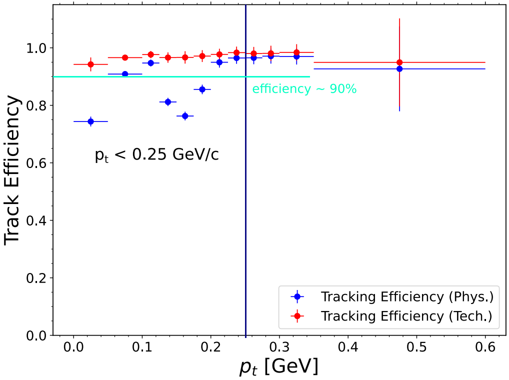
Track Evaluation (I)

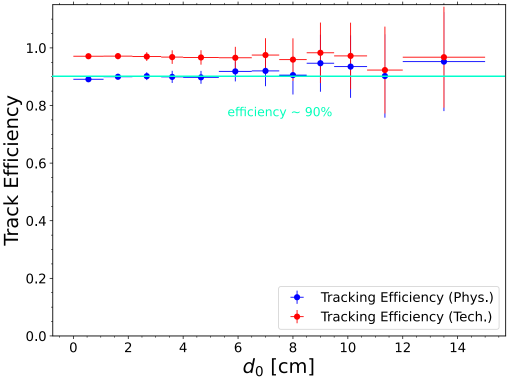
The same evaluation criteria used for muons are used for hyperons. The results are

N_t	N_r	MF [%]	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
7	5	> 50	89.6 ± 0.5	97.1 ± 0.6	0.5 ± 0.6	4.9 ± 0.1

Table: Tracking efficiencies, ghost rate (GR), clone rate (CR).

Track Evaluation (II)





Conclusions

- Interaction Network (GDL) is proven to be better than the Dense Network (DL).
- Pion track efficiency $> 95\%$ for $p_t > 0.05$ GeV/c
- Proton track efficiency $> 95\%$ for $p_t > 0.1$ GeV/c.
- Track efficiency $> 90\%$ in the full vertex position range considered *i.e.* up to $d_0 = 14$ cm.

Heavier hyperons, Ξ^- and Ω^-, decay into Λ hyperons with $d_0 < 15$ cm [1].

[1] J. Regina, Time for Hyperons: Development of Software Tools for Reconstructing Hyperons at PANDA and HADES, Doctoral Thesis, Uppsala University, Uppsala (2021)

Outlook (I)

The loss in efficiencies can be improved by using:

- A new method for building Ground Truth, especially for events with spiraling tracks
- A different track build method than DBSCAN to account for intersecting tracks
- Include MVD and GEM signals for more data

Will help increase tracking efficiency and decrease clone rate.

Outlook (II)

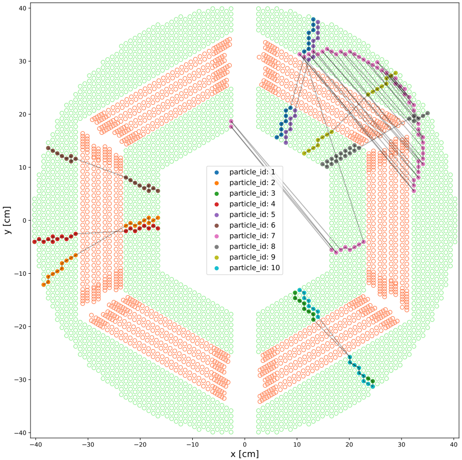


Figure: Current Ground Truth

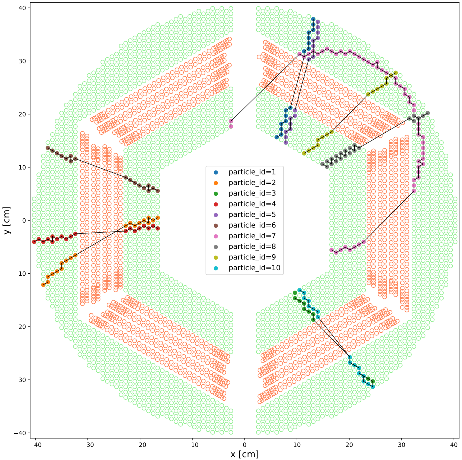


Figure: Future Ground Truth

END

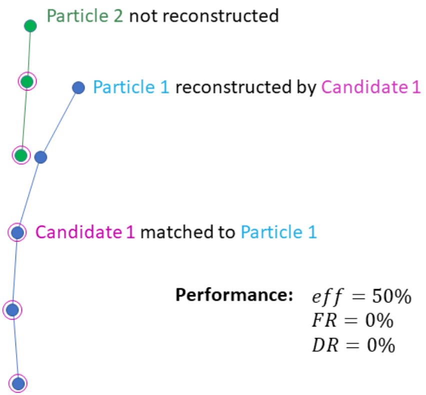
Backup

ATLAS Track Evaluation: Matching

A particle is **matched** to a reconstructed track if more than

- 50% of the hits in the reconstructed track belong to the same true particle, and
- 50% of the hits in the matched true particle is found in the reconstructed tracks.

This is a two-way matching scheme with a matching fraction (MF) $> 50\%$.



PANDA Track Evaluation: Matching

PANDA uses a similar matching scheme as of ATLAS scheme used in this work.

Particles **matched** to a reconstructed track

- Fully Purely Found, MF $= 100\%$
- Fully Impurely Found, MF $> 70\%$

Tracks **matched** to a true particle

- Partially Purely Found, MF $= 100\%$
- Partially Impurely Found, MF $> 70\%$

Deep Learning: Summary of Results

N_t	N_r	MF [%]	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
7	5	> 50	76.3 ± 0.272	77.2 ± 0.278	3.64 ± 0.329	17.2 ± 0.107
7	5	75	58.2 ± 0.225	58.6 ± 0.230	12.0 ± 0.307	27.4 ± 0.141
7	5	95	53.5 ± 0.213	53.8 ± 0.216	14.8 ± 0.300	29.7 ± 0.148
7	6	> 50	75.5 ± 0.270	76.8 ± 0.278	3.78 ± 0.337	13.9 ± 0.098
7	6	75	57.7 ± 0.224	58.6 ± 0.230	12.6 ± 0.314	24.5 ± 0.135
7	6	95	53.0 ± 0.211	53.8 ± 0.216	15.2 ± 0.307	27.1 ± 0.144

Table: Tracking efficiencies, ghost rate (GR), clone rate (CR) for $\mu^{\pm}$.

Geometric Deep Learning: Summary of Results

N_t	N_r	MF [%]	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
7	5	> 50	92.0 ± 0.312	93.0 ± 0.319	1.34 ± 0.315	14.1 ± 0.090
7	5	75	81.7 ± 0.286	82.4 ± 0.292	3.56 ± 0.310	21.3 ± 0.115
7	5	95	74.8 ± 0.268	75.4 ± 0.274	5.78 ± 0.304	25.5 ± 0.127
7	6	> 50	91.0 ± 0.309	92.6 ± 0.318	1.25 ± 0.322	11.5 ± 0.082
7	6	75	81.0 ± 0.284	82.4 ± 0.292	3.23 ± 0.317	19.1 ± 0.110
7	6	95	74.1 ± 0.267	75.4 ± 0.274	5.28 ± 0.312	23.6 ± 0.124

Table: Tracking efficiencies, ghost rate (GR), clone rate (CR) for $\mu^{\pm}$.

Geometric Deep Learning: Summary of Results

N_t	N_r	MF [%]	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
7	5	> 50	89.6 ± 0.548	97.1 ± 0.620	0.46 ± 0.609	4.88 ± 0.098
7	5	75	84.3 ± 0.524	91.1 ± 0.591	2.05 ± 0.601	8.97 ± 0.135
7	5	95	79.4 ± 0.502	85.7 ± 0.565	3.45 ± 0.595	12.7 ± 0.163
7	6	> 50	87.1 ± 0.536	96.5 ± 0.617	0.44 ± 0.621	3.79 ± 0.087
7	6	75	82.2 ± 0.514	91.1 ± 0.591	1.87 ± 0.614	7.71 ± 0.127
7	6	95	77.5 ± 0.493	85.7 ± 0.565	3.26 ± 0.608	11.5 ± 0.158

Table: Tracking efficiencies, ghost rate (GR), clone rate (CR) for hyperons.