Towards Realistic Hyperon Reconstruction using Deep Learning in the PANDA Experiment

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Outline

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

Motivation

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

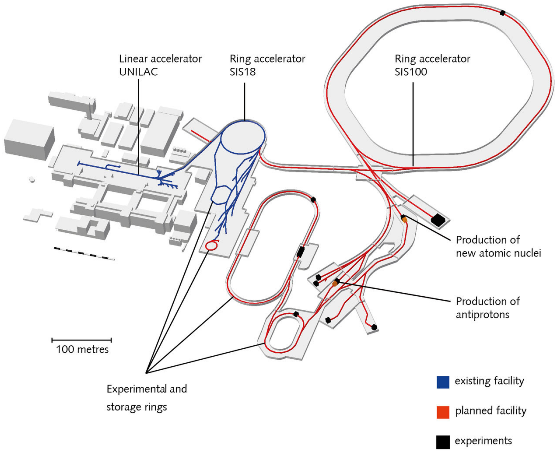
- Low momentum tracks, and
- with displaced vertices

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

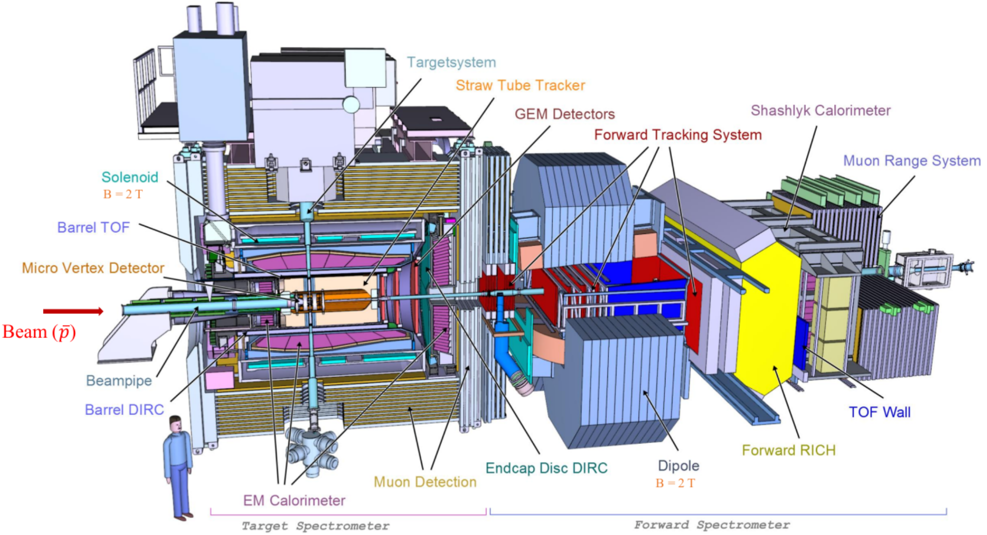
[1] A. Akram, *Towards Realistic Hyperon Reconstruction in PANDA: From Tracking with Machine Learning to Interactions with Residual Gas*, Doctoral Thesis, Uppsala University, Uppsala (2023)

PANDA Experiment at FAIR

- Future Facility for Antiproton and Ion Research (FAIR) in Darmstadt, Germany.
- PANDA is a 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).
- Interaction rate: up to 20 MHz.

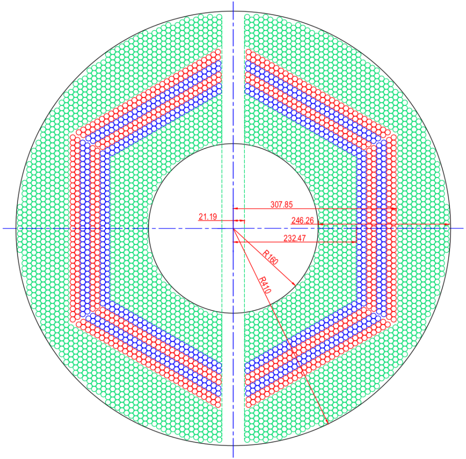


The PANDA Detector



Straw Tube Tracker (STT)

- 4224 straw tubes
- 15 - 19 axial layers (green)
- 8 skewed layers ($\pm 2.9°$) (red and blue)
- Radial coverage: 15 cm to 41.8 cm
- Longitudinal coverage: 150 cm
- The magnetic file is $\vec{B} = 2$ T (Solenoid)

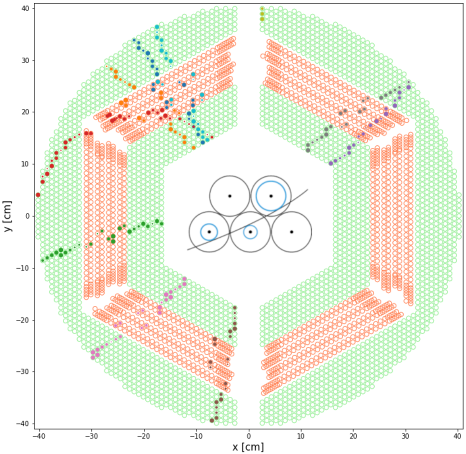


What is the Challenge?

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

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

$\Rightarrow$ Use deep learning for track reconstruction



How to Apply Deep Learning?

- Data Representation
  - Image Representation (Fixed Grid)
  - Point-cloud Representation (Hit Pairs, Hit Sequences, Hit Graphs)
- Deep Learning Tasks
  - Classification (Supervised Learning)
  - Clustering (Unsupervised Learning)
- Deep Learning Models
  - Depends on what we have decided above: DNNs, RNNs, CNNs, GNNs, etc.

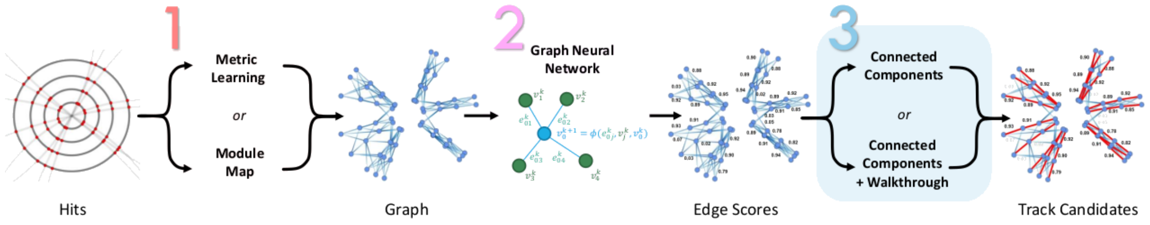
Strategy

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



[1] Image credited to Exa.TrkX-L2IT Collaboration.

Track Evaluation

Let's define the variables first:

- $N_{\textbf{particles}}$: # of generated particles in the detector
- $N_{\textbf{tracks}}$: # 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

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:

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

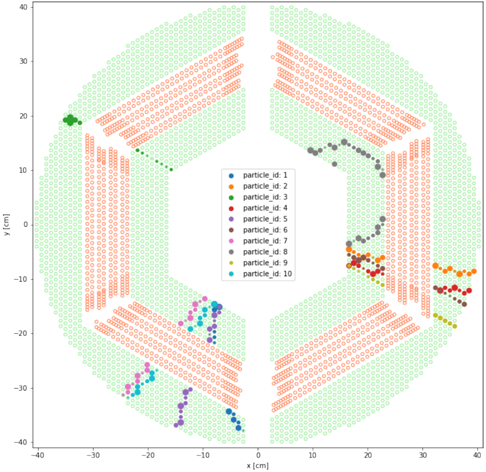
Track purity measures the accuracy of a reconstructed track in matching a particle:

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

Muon Reconstruction in STT

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
- DL and GDL pipelines for muons



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).

$\Rightarrow$ A clear increase in performance with Geometric Deep Learning!

Track Evaluation (II): Tracking Efficiencies vs Transverse Momentum

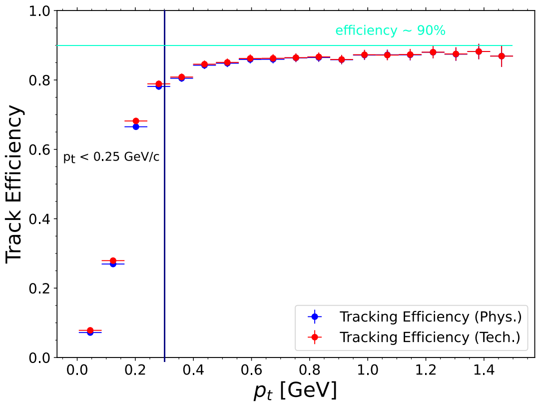


Figure: Deep Learning

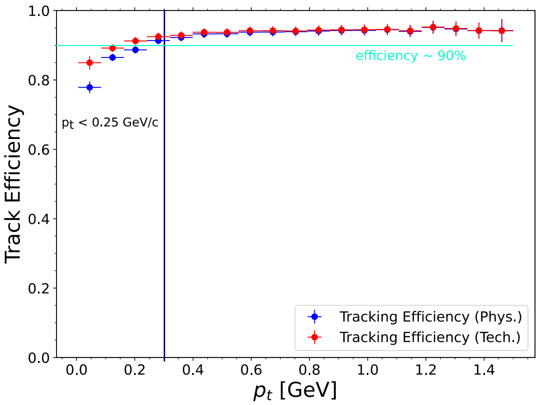


Figure: Geometric Deep Learning

Track Evaluation (II): Tracking Efficiencies vs Azimuthal Angle

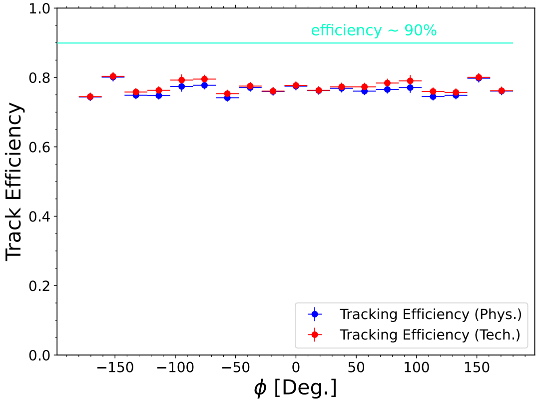


Figure: Deep Learning

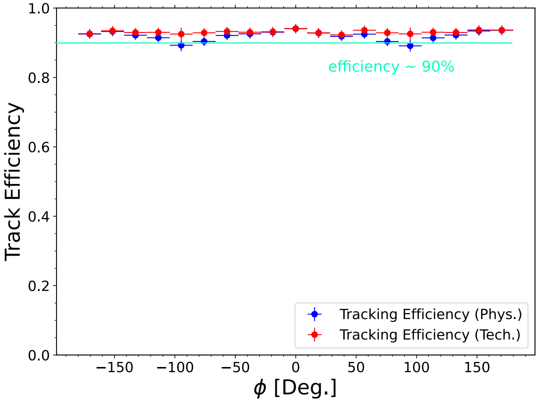


Figure: Geometric Deep Learning

Track Evaluation (II): Tracking Efficiencies vs Theta Angle

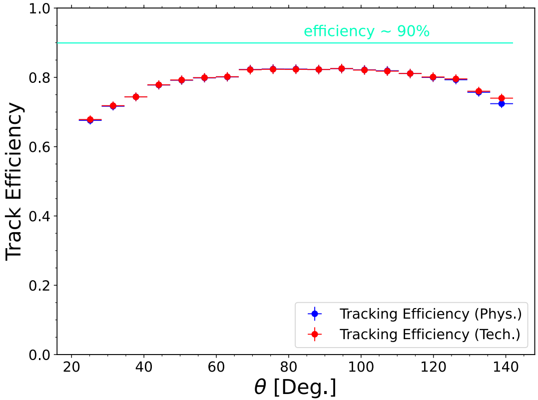


Figure: Deep Learning

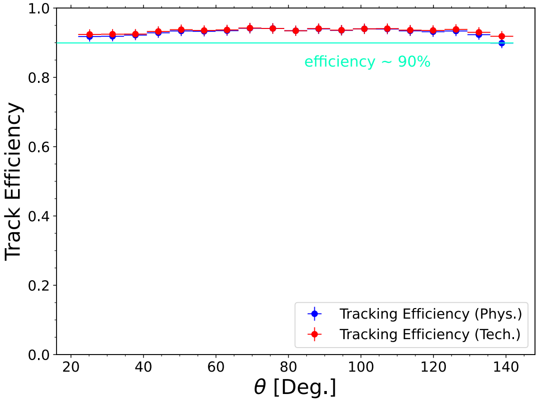
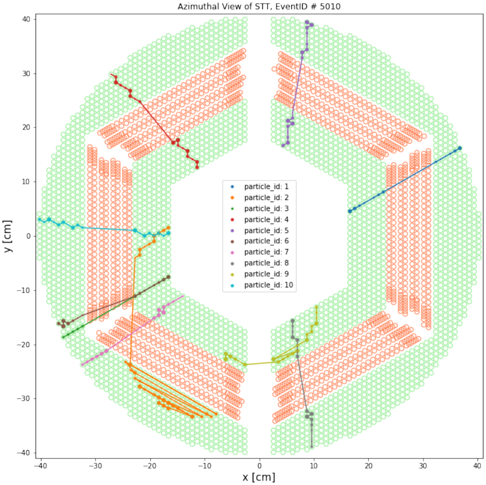
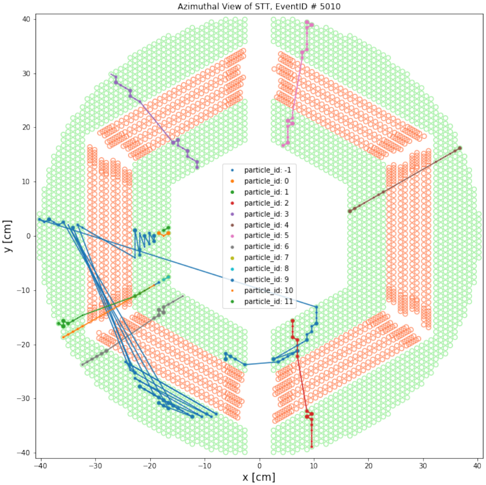


Figure: Geometric Deep Learning

Tracking Efficiency Loss

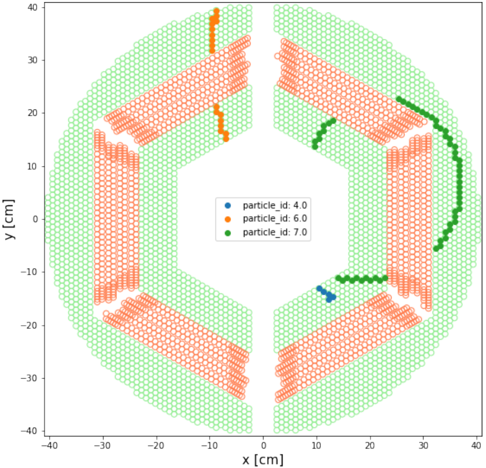




Hyperon Reconstruction in STT

Data Generation

- $\bar{p}p \rightarrow \bar{\Lambda}\Lambda \rightarrow \bar{p}\pi^{+}p\pi^{-}$ events simulated with EvtGen at $p_{beam} = 1.642$ GeV/c
- In total, 10^5 events are generated
- On average, three tracks per event $\rightarrow \bar{p}$ 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
- Same GDL pipeline as for muons



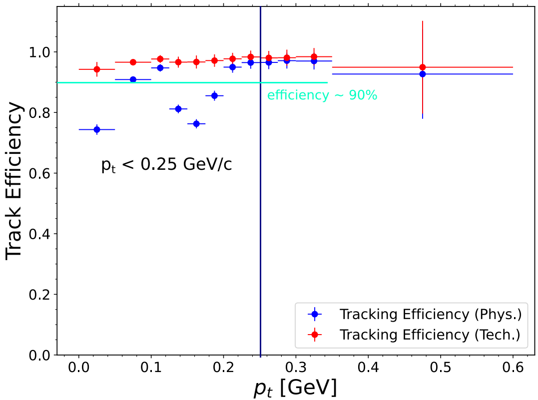
Track Evaluation (I)

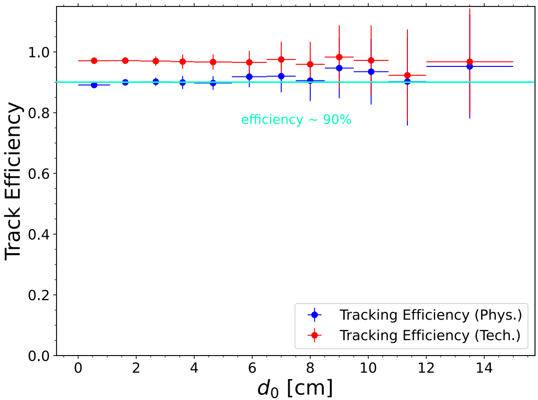
Using the criteria of $N_t \geq 7$, $N_r \geq 5$ and MF $> 50\%$, the results are

	$\epsilon_{phys.}$ [%]	$\epsilon_{tech.}$ [%]	GR [%]	CR [%]
Geometric Deep Learning	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)

END

Backup

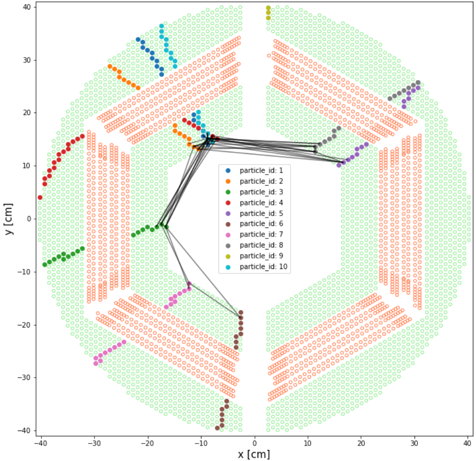
Pipeline: Graph Construction

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

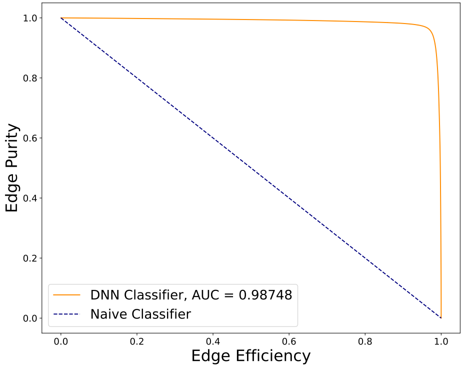


Figure: Deep Learning

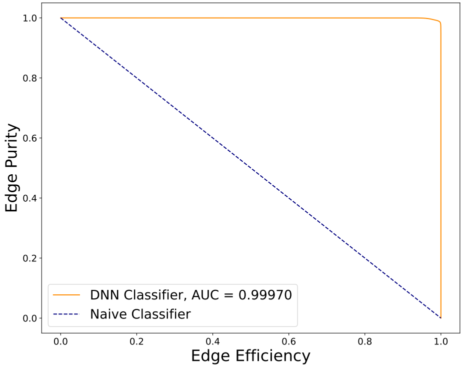


Figure: Geometric Deep Learning

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

Pipeline: Track Formation

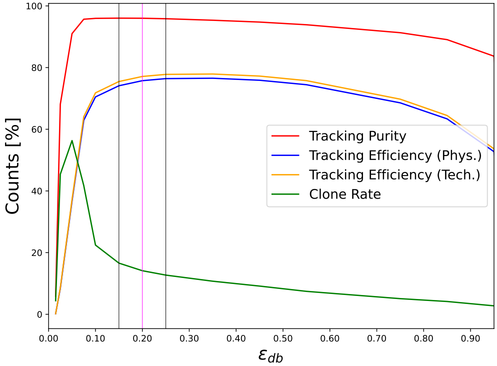


Figure: Deep Learning

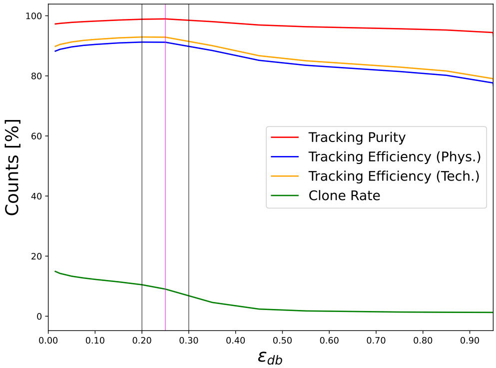


Figure: Geometric Deep Learning

$\Rightarrow$ Track Candidates: Cluster hits of weighted graphs using the DBSCAN

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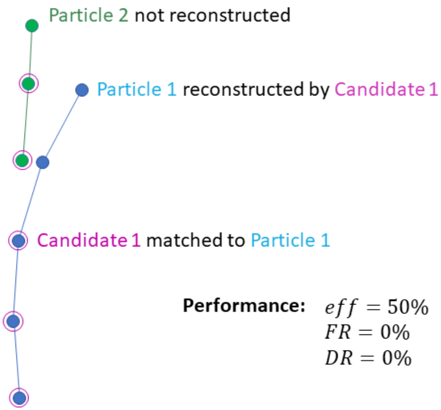
- Selected: # of particles/tracks within STT acceptance.
- Reconstructable: # of particles with # of hits > 7 STT hits (denoted N_t).
- Matched: # of particles (tracks) matched to a reconstructed track (particle).

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:

$$\epsilon_{\text{phys}} = \frac{N_{particles}(\text{selected, matched})}{N_{particles}(\text{selected})} \tag{4}$$

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

$$\epsilon_{\text{tech.}} = \frac{N_{particles}(\text{selected, reconstructable, matched})}{N_{particles}(\text{selected, reconstructable})} \tag{5}$$

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

$$\text{Purity} = \frac{N_{\text{tracks}}(\text{selected, matched})}{N_{\text{tracks}}(\text{selected})} \equiv 1 - \text{Ghost Rate} \tag{6}$$

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:

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