Time-of-Flight Estimation using Machine Learning Techniques

Konrad Helms

ML4Jets, November 6, 2023

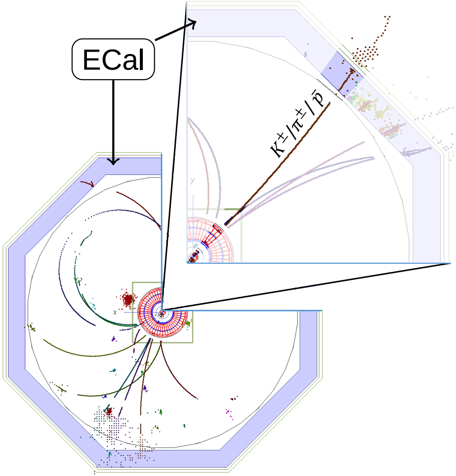
DESY.
GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN IN PUBLICA COMMODA SEIT 1737
HELMHOLTZ

Time-of-Flight and Particle Identification

- time-of-flight (TOF) estimation for hadron showers $\Rightarrow$ particle identification
- for $p \lesssim \mathcal{O}(10\,\text{GeV})$: $\pi^\pm$ vs. $K^\pm$ vs. $\overset{(-)}{p}$
- particle identified by electric charge &

$$m_0 = \frac{p \cdot \text{TOF}}{\ell_\text{track}} \sqrt{1 - \left(\frac{\ell_\text{track}}{(\text{TOF} \cdot c)}\right)^2}$$

- case study: International Linear Collider + International Large Detector

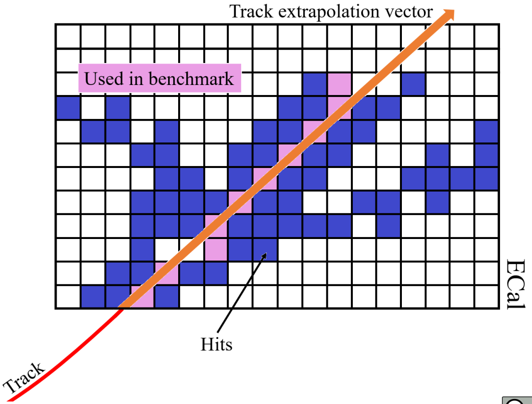


Benchmark Time-of-Flight Estimator

- select hits closest to track extrapolation into ECal in first 10 layers
- correct measured hit time by travel time to detection position, assuming velocity *c*

$$t_{\text{corrected},i} = t_i - \frac{\mathrm{d}(\text{ECal}, (x, y, z)_i)}{c}$$

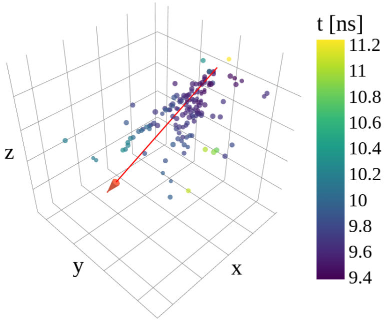
$$\text{TOF} = \frac{1}{n_{\text{hits}}} \sum_{i=1}^{n_{\text{hits}}} t_{\text{corrected},i}$$



Dataset

- 5D point cloud $\oplus$ track information:

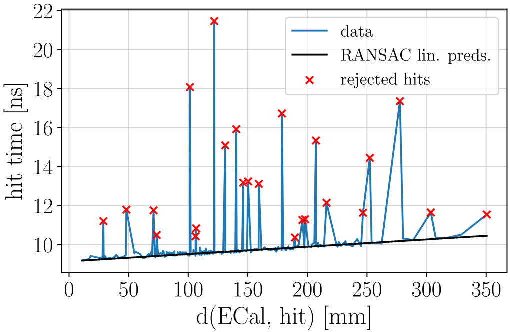
$$\{\underbrace{[x,y,z,e,t]_i}_{\text{coordinates, per hit}} \oplus \underbrace{[\ell_{\text{track}}, p, p_{\text{T}}, p_x, p_y, p_z, x_{\text{ECal}}, y_{\text{ECal}}, z_{\text{ECal}}]}_{\text{reconstructed track information, per shower}} \mid i = 1 \ldots n_{\text{hits}}\} \times n_{\text{showers}}$$

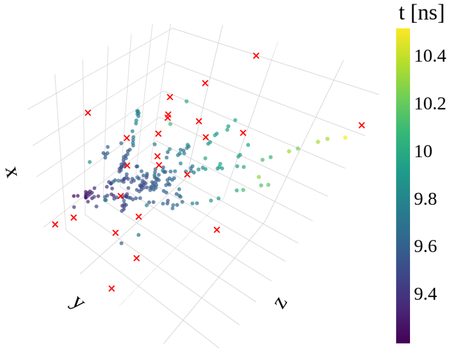


- assume hit time resolution ± 50 ps in ECal
- define distances using 3D euclidean metric + two extra channels: $(x,y,z)^{\text{T}} \oplus (e,t)$
- order hits by distance to ECal entry point d(ECal, hit)

RANSAC

- outliers in space and time
- random sample consensus (RANSAC) algorithm used for outlier rejection
- fit affine function: t vs. d(ECal, hit)
- if $(t_i -$ RANSAC pred.$_i) \leq 0.5\,$ns: keep hit, else: reject



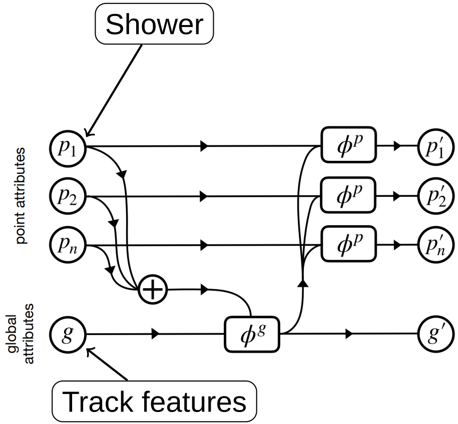


EPiC Regression

- 3 equivariant point cloud (EPiC) layers from

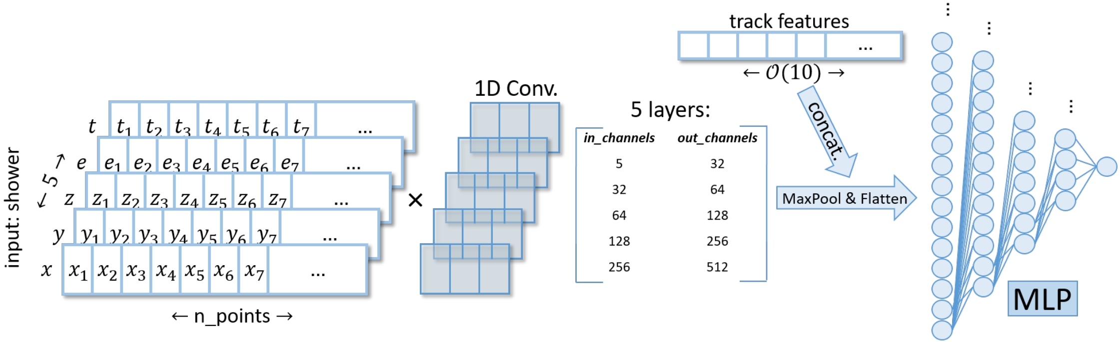
EPiC-GAN: arXiv:2301.08128
E. Buhmann, G. Kasieczka, J. Thaler

  for encoding of input
- connect global with local information
- 4 layer MLP for TOF regression based on encoded input

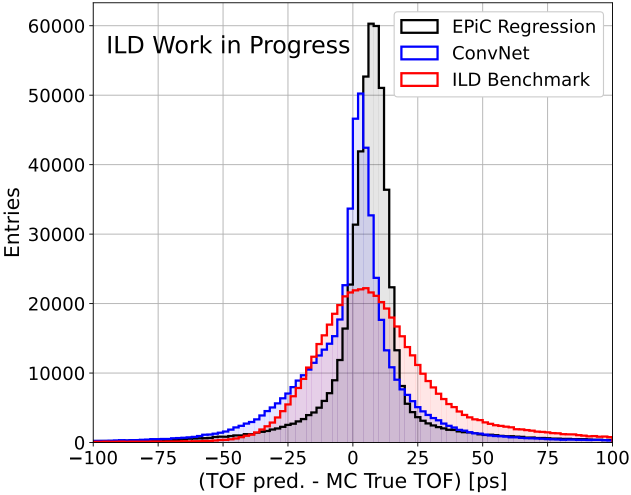


Simpler: ConvNet

- 1D convolutions along x, y, z, e, t for encoding of input
- relies on ordering $\Rightarrow$ kernels move along shower development direction
- 4 layer MLP for TOF regression



Results



- EPiC regression & ConvNet beat ILD benchmark
- smaller RMS90, less biased

Network	RMS90	μ_{90}
Benchmark	23.62 ± 0.02	9.73 ± 0.03
EPiC	15.00 ± 0.02	6.17 ± 0.01
ConvNet	18.18 ± 0.02	-0.48 ± 0.02

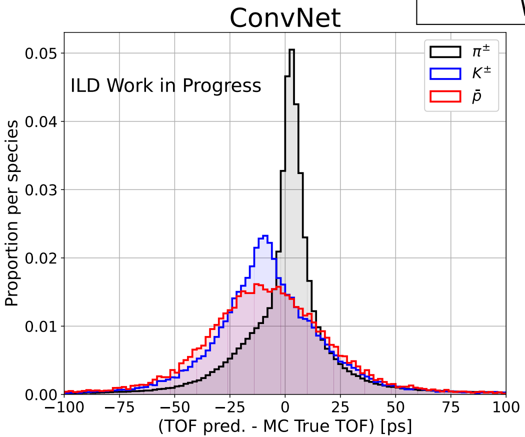
A Closer Look at the Results

An Exemplary Look at ConvNet

analytic:

$$\mathrm{TOF} = \sqrt{\left(\frac{m_\pi \ell_{\mathrm{track}}}{p}\right)^2 + \left(\frac{\ell_{\mathrm{track}}}{c}\right)^2}$$

type	m [MeV]	%
$\pi^\pm$	140	85
$K^\pm$	490	10
$\overset{(-)}{p}$	940	5



- TOF prediction performance dominates for $\pi^\pm$
- network learned $\pi^\pm$ mass? — no!
- mass-ordering does not follow order of distributions
- **hypothesis:**

  network learned at least two different mass classes and predicted TOF based on that

Hypothesis

type	m [MeV]	%
$\pi^\pm$	140	85
$K^\pm$	490	10
$\overset{(-)}{p}$	940	5

> 'mass classes':

1. well-learned $m_1 \simeq m_{\pi^\pm}$
2. approximate $m_2 \simeq m_p$

> $\{ [x, y, z, e, t]_i \oplus [\ell_{\text{track}}, p, p_T, p_x, p_y, p_z, x_{\text{ECal}}, y_{\text{ECal}}, z_{\text{ECal}}] \mid i = 1 \dots n_{\text{hits}} \} \times n_{\text{showers}}$

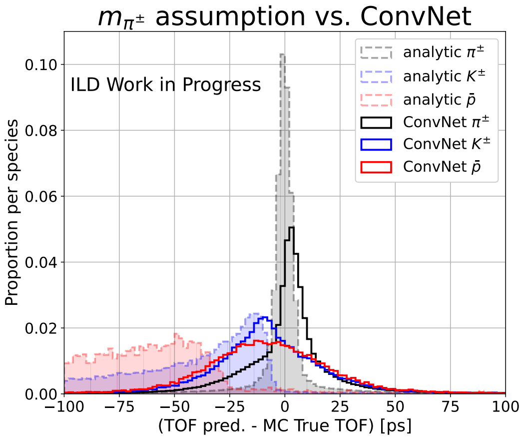
> what the network does:

1. rough TOF estimate, based hit times
2. estimates corresponding mass class: $m_{1,2} = \frac{p \cdot \text{TOF}}{\ell_{\text{track}}} \sqrt{1 - \left(\frac{\ell_{\text{track}}}{(\text{TOF} \cdot c)} \right)^2}$
3. corrects rough TOF estimate, based on: $\text{TOF} = \sqrt{\left(\frac{m_{1,2}\ell_{\text{track}}}{p} \right)^2 + \left(\frac{\ell_{\text{track}}}{c} \right)^2}$

Testing the Hypothesis — Mass Class 1

Assuming all Particles are $\pi^{\pm}$

type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5



- analytic:

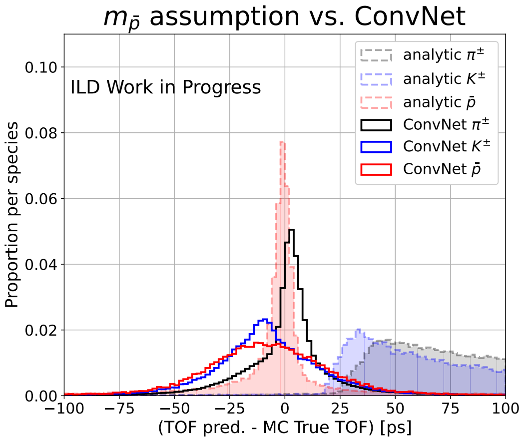
$$\text{TOF} = \sqrt{\left(\frac{m_{\pi}\ell_{\text{track}}}{p}\right)^2 + \left(\frac{\ell_{\text{track}}}{c}\right)^2}$$

- ConvNet $\pi^{\pm}$, $K^{\pm}$ distributions roughly match analytic predictions for $\pi^{\pm}$, $K^{\pm}$ in **both** cases assuming $m_{\pi^{\pm}}$

Testing the Hypothesis — Mass Class 2

Assuming all Particles are $\overset{(-)}{p}$

type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5



- analytic:

$$\mathrm{TOF} = \sqrt{\left(\frac{m_p \ell_{\mathrm{track}}}{p}\right)^2 + \left(\frac{\ell_{\mathrm{track}}}{c}\right)^2}$$

- ConvNet prediction for $\overset{(-)}{p}$ wide but approximates analytic prediction for $\overset{(-)}{p}$, assuming $m_{\overset{(-)}{p}}$
- low $\overset{(-)}{p}$ abundance $\Rightarrow$ difficult to learn $m_{\overset{(-)}{p}}$
- ConvNet has understood, that ≥ 2 mass classes exist

Summary & Outlook

Summary:

- idea: build a TOF regression network

$\Downarrow$

- predict TOF

$\Downarrow$

- use TOF + p + ℓ_{track} for particle identification

EPiC Regression, ConvNet

Outlook:

- continue to understand what the networks are doing
- no hyperparameter optimisation yet
- prevent internal particle identification

  ⋮

- skip TOF regression, classify $\pi^{\pm}$ vs. $K^{\pm}$ vs. $\overset{(-)}{p}$ directly

Thank you!

Contact

Deutsches Elektronen-
Synchrotron DESY

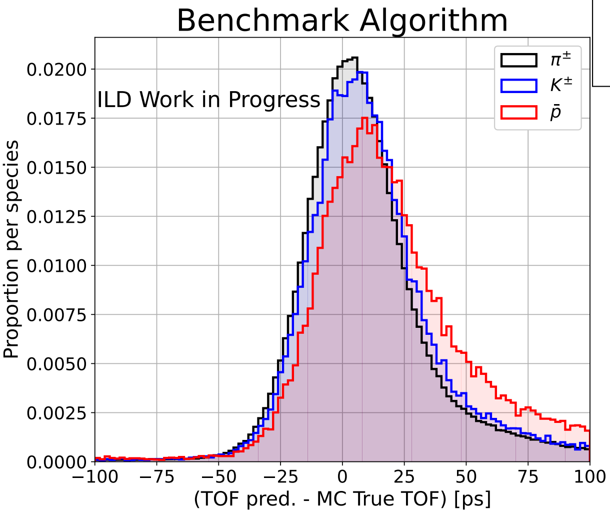
www.desy.de

Konrad Helms
0009-0008-7200-7670
DESY FTX / Georg-August-Universität Göttingen
konrad.helms@desy.de

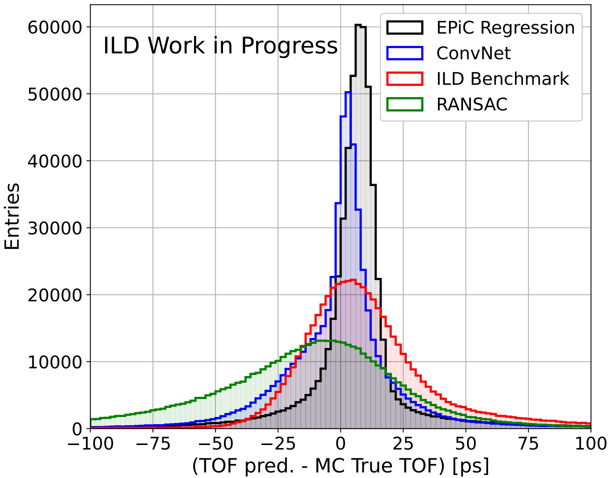
Backup

A Closer Look at the Benchmark Algorithm

type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5



Performance Comparison to RANSAC



Testing the Hypothesis #1

Assuming all Particles are $\pi^{\pm}$

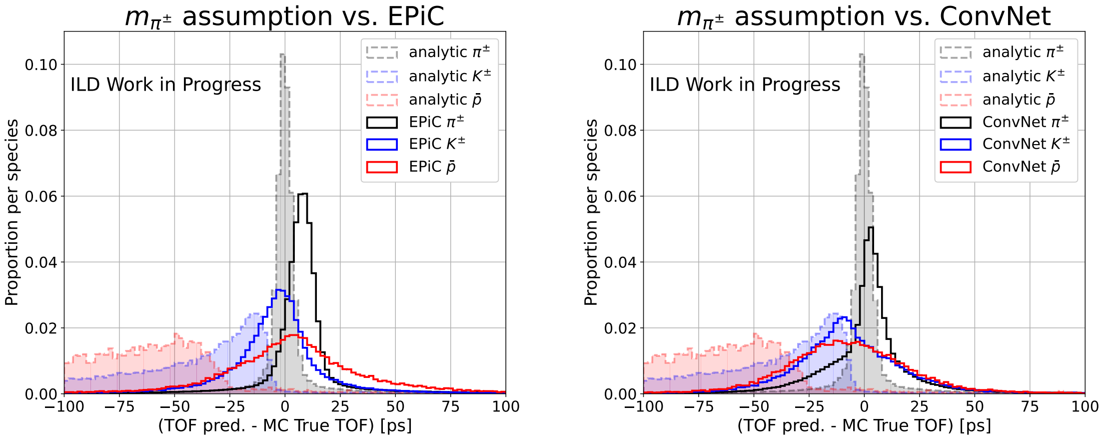
analytic:

$$\text{TOF} = \sqrt{\left(\frac{m_\pi \ell_{\text{track}}}{p}\right)^2 + \left(\frac{\ell_{\text{track}}}{c}\right)^2}$$

$m_{\pi^\pm} \simeq 140\,\text{MeV}$

$m_{K^\pm} \simeq 490\,\text{MeV}$

$m_{\overset{(-)}{p}} \simeq 940\,\text{MeV}$



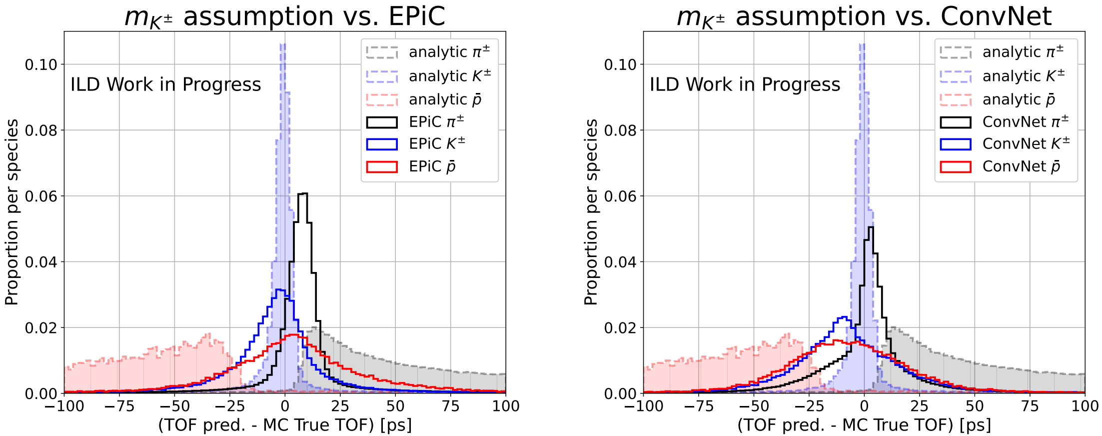
Testing the Hypothesis #2

Assuming all Particles are $K^{\pm}$

analytic:

$$\mathrm{TOF} = \sqrt{\left(\frac{m_K \ell_{\mathrm{track}}}{p}\right)^2 + \left(\frac{\ell_{\mathrm{track}}}{c}\right)^2}$$

$m_{\pi^{\pm}} \simeq 140$ MeV
$m_{K^{\pm}} \simeq 490$ MeV
$m_{\overset{(-)}{p}} \simeq 940$ MeV



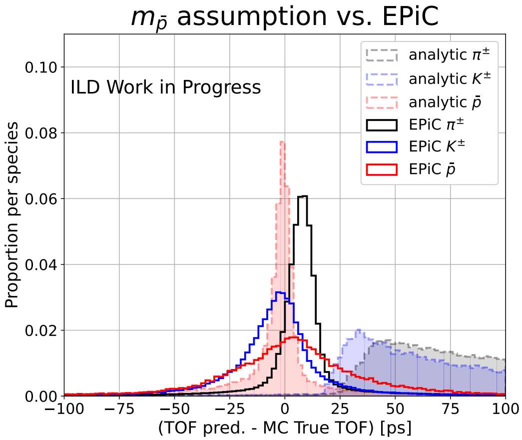
Testing the Hypothesis #3

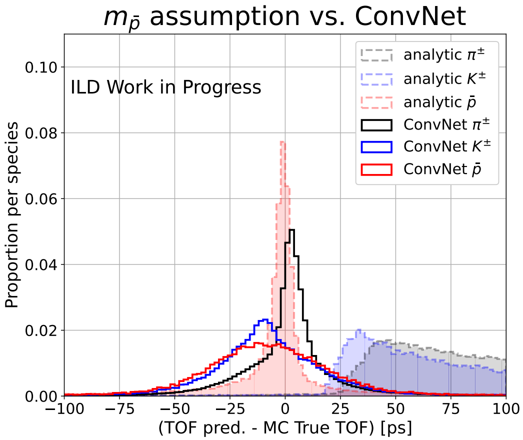
Assuming all Particles are $\overset{(-)}{p}$

analytic:

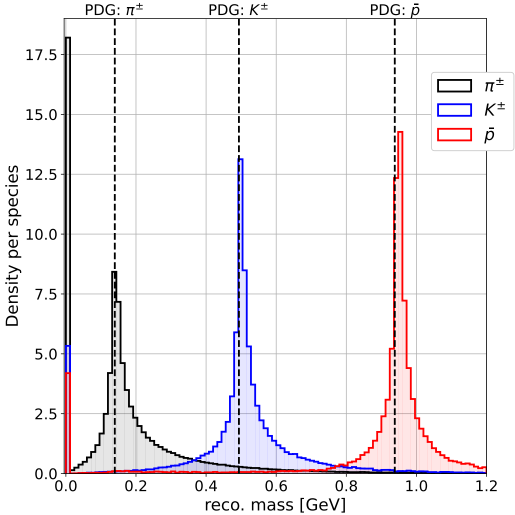
$$\text{TOF} = \sqrt{\left(\frac{m_p \ell_{\text{track}}}{p}\right)^2 + \left(\frac{\ell_{\text{track}}}{c}\right)^2}$$

$m_{\pi^\pm} \simeq 140\,\text{MeV}$
$m_{K^\pm} \simeq 490\,\text{MeV}$
$m_{\overset{(-)}{p}} \simeq 940\,\text{MeV}$





Reconstructing the Masses - Benchmark Algorithm

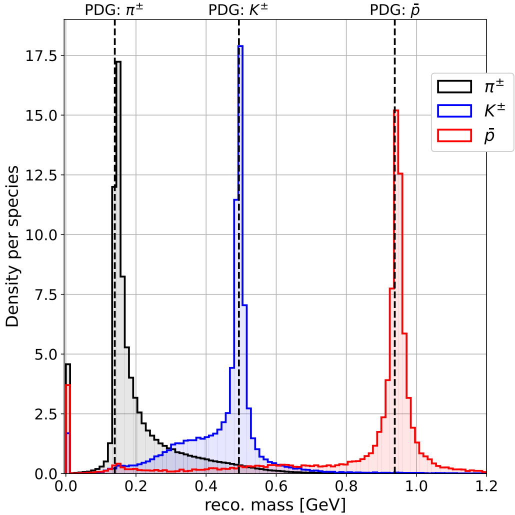


type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5

1. predict TOF
2. use ℓ_{track} and p to calculate

$$m_{\text{reco.}} = \frac{p \cdot \text{TOF}_{\text{pred.}}}{\ell_{\text{track}}} \sqrt{1 - \left(\frac{\ell_{\text{track}}}{(\text{TOF}_{\text{pred.}} \cdot c)} \right)^2}$$

Reconstructing the Masses - EPiC Regression

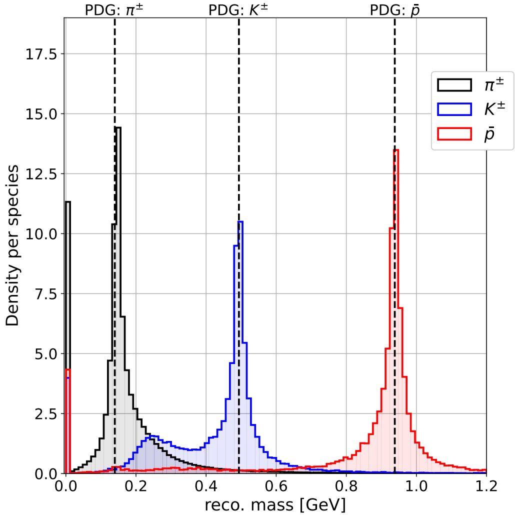


type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5

1. predict TOF
2. use ℓ_{track} and p to calculate

$$m_{\text{reco.}} = \frac{p \cdot \text{TOF}_{\text{pred.}}}{\ell_{\text{track}}} \sqrt{1 - \left(\frac{\ell_{\text{track}}}{(\text{TOF}_{\text{pred.}} \cdot c)} \right)^2}$$

Reconstructing the Masses - ConvNet

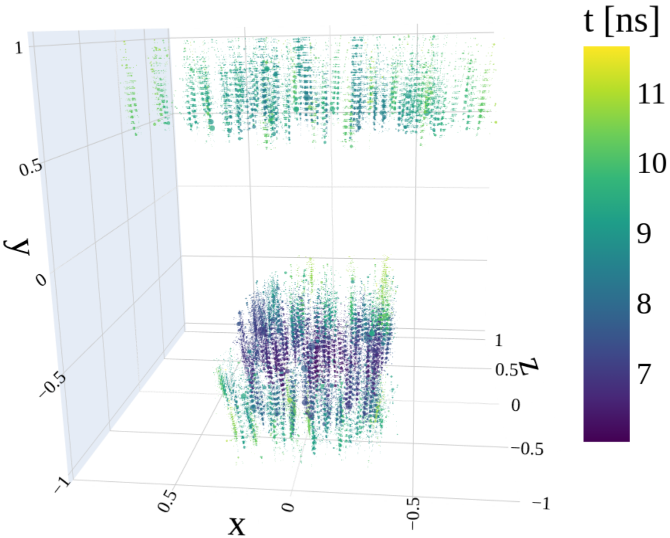


type	m [MeV]	%
$\pi^{\pm}$	140	85
$K^{\pm}$	490	10
$\overset{(-)}{p}$	940	5

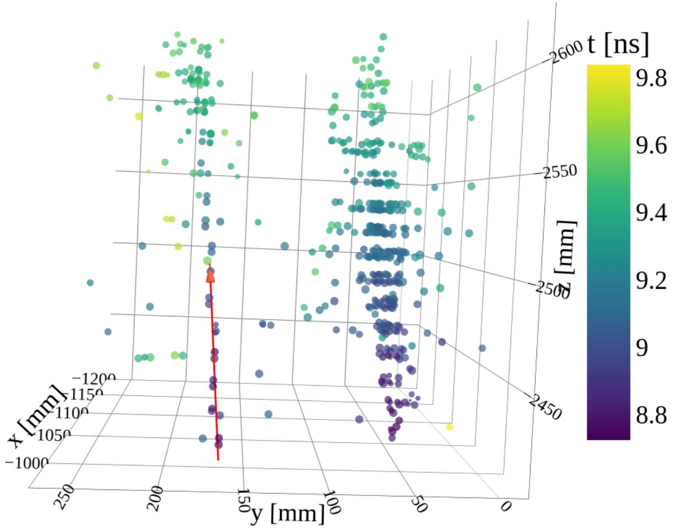
1. predict TOF
2. use ℓ_{track} and p to calculate

$$m_{\text{reco.}} = \frac{p \cdot \text{TOF}_{\text{pred.}}}{\ell_{\text{track}}} \sqrt{1 - \left(\frac{\ell_{\text{track}}}{(\text{TOF}_{\text{pred.}} \cdot c)} \right)^2}$$

Network Input - Boxed, Biased



Problems



t [ns]
9.8
9.6
9.4
9.2
9
8.8
2600
2550
2500
2450
z [mm]
−1200
−1150
−1100
−1050
−1000
x [mm]
250
200
150
100
50
0
y [mm]