Machine Learning for NICA SPD Aerogel Reconstruction

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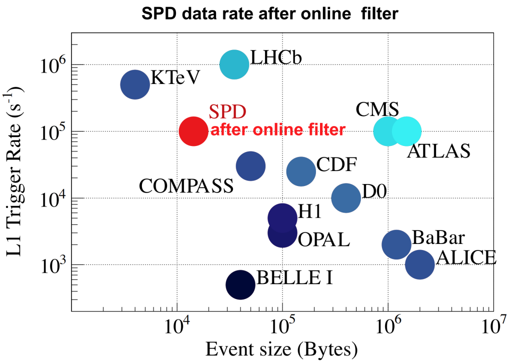
Introduction

- The experimental high-energy physics (HEP) objectives require searching for rare signals in background dominated environments
- Machine learning techniques can extract high-level representations from the input data and model complex relations
- This report concerns a case of machine learning application for aerogel reconstruction in the NICA SPD experiment

NICA SPD

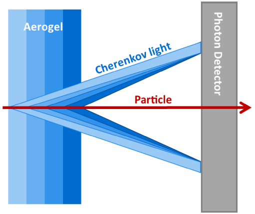
- A universal detector proposed by the SPD collaboration at NICA
- Study the Drell–Yan (DY) processes, J/Ψ production processes, elastic reactions, spin effects in one and two hadron production processes, polarization effects in heavy ion collisions, and more
- The SPD is a medium energy experiment, offering unique possibilities of beam operation and bridging the gap between the low-energy measurements, e.g. ANKE-COSY and the high-energy measurements, such as RHIC
- High luminosity up to 10^{32} cm^{-2}s^{-1} and free-flowing (triggerless) running mode

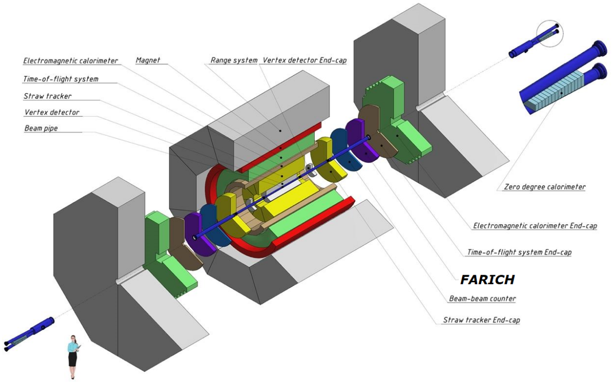


FARICH

Compact particle ID detector

- trade off between resolution and number of Cherenkov photons
- improve resolution with discrete focusing capability





https://nica.jinr.ru/projects/spd.php

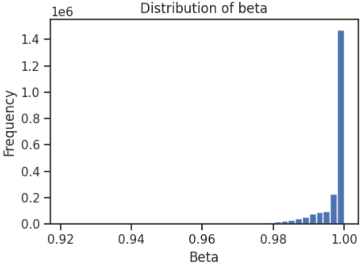
Dataset

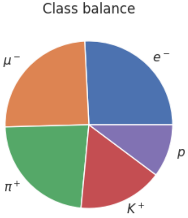
Provided input:

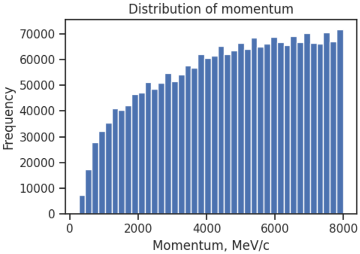
- Track parameters: x_p, y_p, z_p – coordinates of the particle when entering aerogel detector, θ_p, ϕ_p – polar angle and azimuth of the direction of travel;
- Photon hits: x_c, y_c, z_c – coordinates of triggered pixels in the photosensitive matrix.

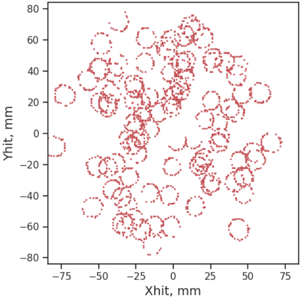
Expected output:

- PID statistics
- Particle type



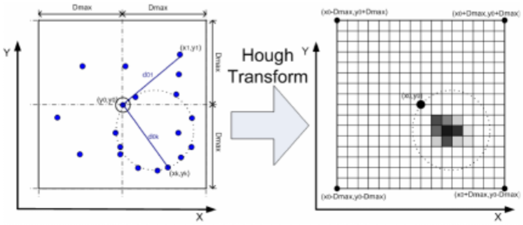






Baseline: Hough Transform

- Based on the RICH reconstruction from the CBM experiment at FAIR;
- Utilizes Hough transform for ellipses, more precisely the Taubin method;
- Outputs estimated parameters of the ellipse, such as a, b – semi-axes, x, y – center coordinates, and ϕ – angle of rotation;
- Does not account for refraction, does not use the information from the straw tracker, such as θ_p and ϕ_p.



Our Methods: Refraction Correction

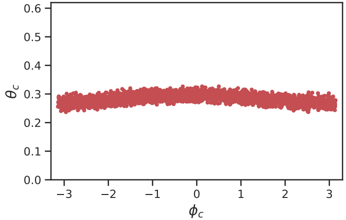
First order approximation

$$\alpha \approx \beta - (n-1)\tan\beta \tag{1}$$

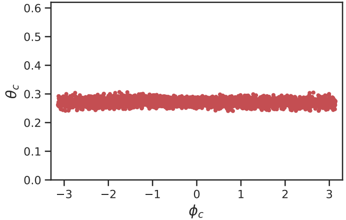
Or fixed-point iteration

$$\sin\alpha_{k+1} = \left(n\sqrt{1+\left(\frac{d}{r-h\tan\alpha_k}\right)^2}\right)^{-1} \tag{2}$$

θ_c before correction



θ_c after correction



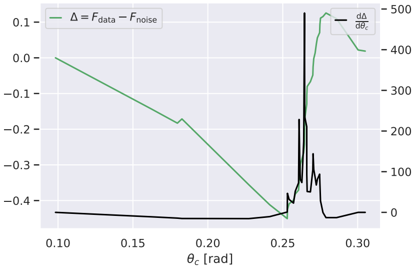
Algorithmic methods

Median:

- Compute θ_c distribution
- Take a median value $\hat{\theta}_c$

MLE:

- Compute θ_c distribution
- Drop unphysical velocities $\beta = v/c \geqslant 1$
- Construct eCDF F_{data}
- Take a numerical derivative and find its peak $\hat{\theta}_c = \arccos(1/n\hat{\beta})$



MLE example

Machine Learning Models

- Algorithmic models output $\hat{\theta}_c$ that can be converted to the rest mass of the particle using momentum p from the straw tracker
- The underlying task is regression
- The objective of RICH detector is to separate different particle types, in particular π/K separation
- ML end-to-end models are able to skip the intermediate step of computing $\hat{\theta}_c$
- Moreover, the regression task is not well suited for an ML model because of the significant value imbalance

We implement a neural classifier that incorporates both **hit coordinates** x_c, y_c and **momentum** p.

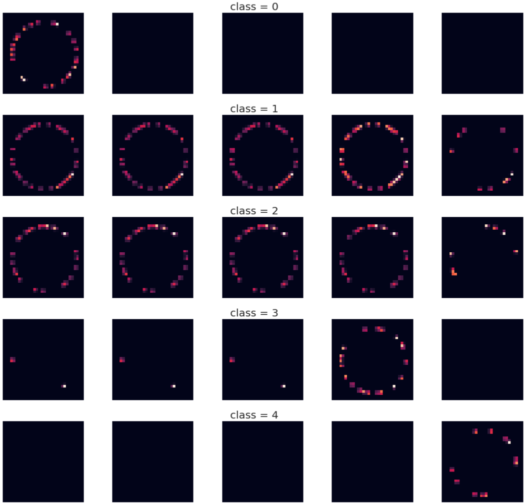
Data Transform

- Option 1: provide the value of p as an extra input channel / pathway
- Option 2: normalize the input using p

The non-linear dependence on p can be disentangled:

$$\cos\theta_c = \frac{1}{n}\sqrt{m_0^2/p^2 + 1} \tag{3}$$

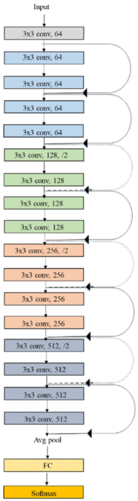
- Use (3) with N mass probes for each of the particle types in the data to transform θ_c into N mass probes
- Convert the probes to 2d images and stack into a tensor



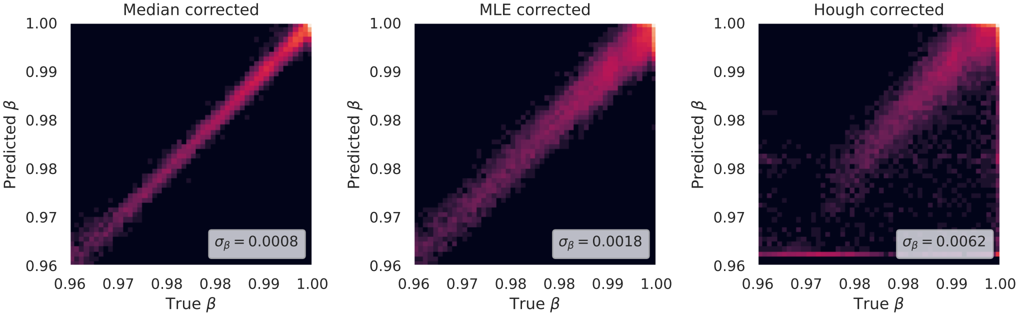
Input tensor example

Procedures: Learning

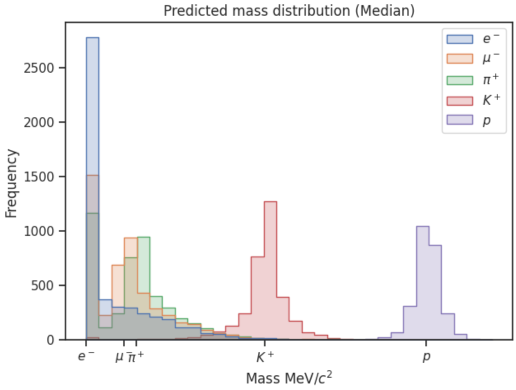
- ResNet-18 CNN architecture
  - Changed input conv, max pooling and classifier head to accommodate input and output data formats
- Input format for NN classifier: $5 \times 32 \times 32$ tensor
- Trained for 200000 samples with Adam optimizer, cosine annealing scheduler, a learning rate of $5 \cdot 10^{-4}$ and a batch size of 128
- Another model trained on π/K specifically for 400000 samples



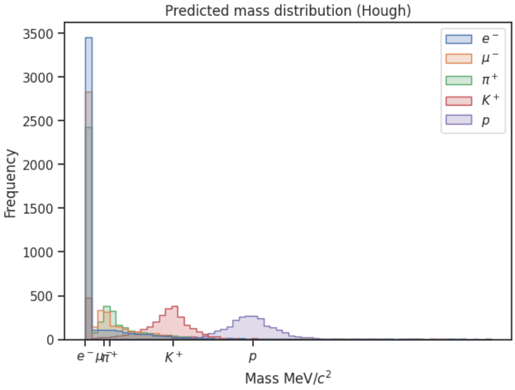
Results


Median corrected
MLE corrected
Hough corrected
Predicted β
True β
1.00
0.99
0.98
0.98
0.97
0.96
0.96 0.97 0.98 0.98 0.99 1.00
$\sigma_\beta = 0.0008$
$\sigma_\beta = 0.0018$
$\sigma_\beta = 0.0062$

Results



Predicted mass distribution (Median)
Frequency
0
500
1000
1500
2000
2500
e^-
μ^-
π^+
K^+
p
Mass MeV/c^2

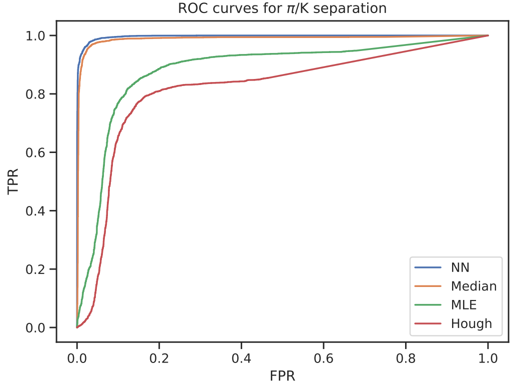


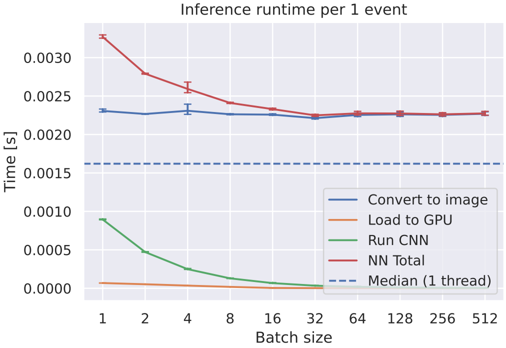
Predicted mass distribution (Hough)
Frequency
0
500
1000
1500
2000
2500
3000
3500
e^-
μ^-
π^+
K^+
p
Mass MeV/c^2

Results

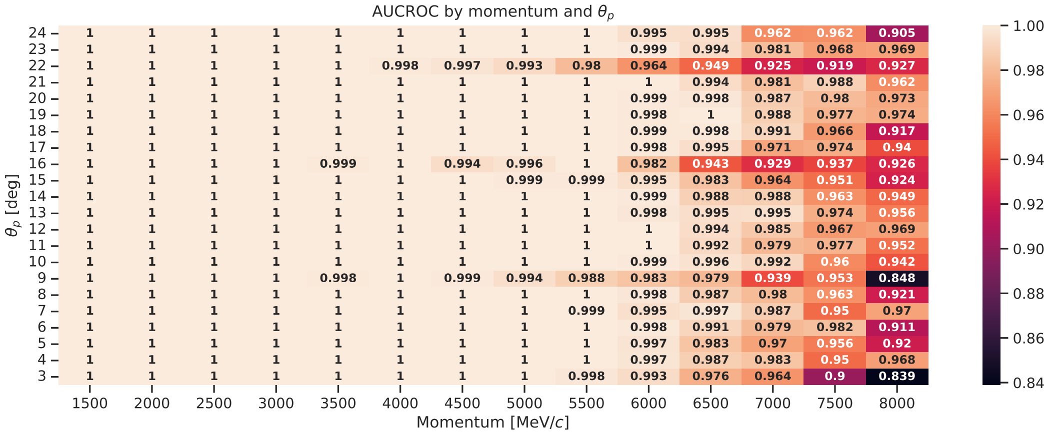
Method	$\mathbb{P}(\text{true } \pi, \text{ pred } K)$	$\mathbb{P}(\text{true } K, \text{ pred } \pi)$	π, K AUROC	Total accuracy	σ_β
NN	$\mathbf{0.016 \pm 0.005}$	$\mathbf{0.010 \pm 0.005}$	**0.997**	**0.65**	**N/A**
Median	0.06 ± 0.02	0.02 ± 0.02	0.989	0.64	0.0008
MLE	0.20 ± 0.02	0.12 ± 0.02	0.883	0.52	0.0018
Hough	0.13 ± 0.02	0.26 ± 0.02	0.817	0.49	0.0062

Results


ROC curves for π/K separation
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0
NN
Median
MLE
Hough


Inference runtime per 1 event
Time [s]
Batch size
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
1
2
4
8
16
32
64
128
256
512
Convert to image
Load to GPU
Run CNN
NN Total
Median (1 thread)

Results



Detailed NN performance

Conclusion and Future Plans

- NN model achieved good performance
- The real time use of ResNet-18 in the SPD DAQ is not possible because of the unavailability of GPUs
- Conversion to tensor is too slow regardless

Future steps

- Architecture optimization to run on CPU
  - knowledge distillation, pruning and quantization
- More efficient conversion or a different input format
- Multi-ring PID, automatic track-ring matching using ML