Status of ECAL reconstruction and π/γ separation

Andrei Maltsev (JINR, Dubna)

SPD Physics & MC meeting

09.11.2022

Requirements on ECAL design from physics analyses

Prompt photons:

- interested in p_T > 3-4 GeV, high background from π^0, η, etc.
- Requirement: energy resolution at high (> 5 GeV) energies, π/γ separation

Charmonia (χ_{c1}, χ_{c2}):

- need to separate χ_{c1}, χ_{c2} from decay into $J/\psi\ \gamma$
- Requirement: energy resolution at low (< 1 GeV) energies

Online polarizability measurement:

- measure azimuthal asymmetry of π^0 production
- Requirement: energy and position resolution, π/γ separation

Algorithm of reconstruction in ECAL

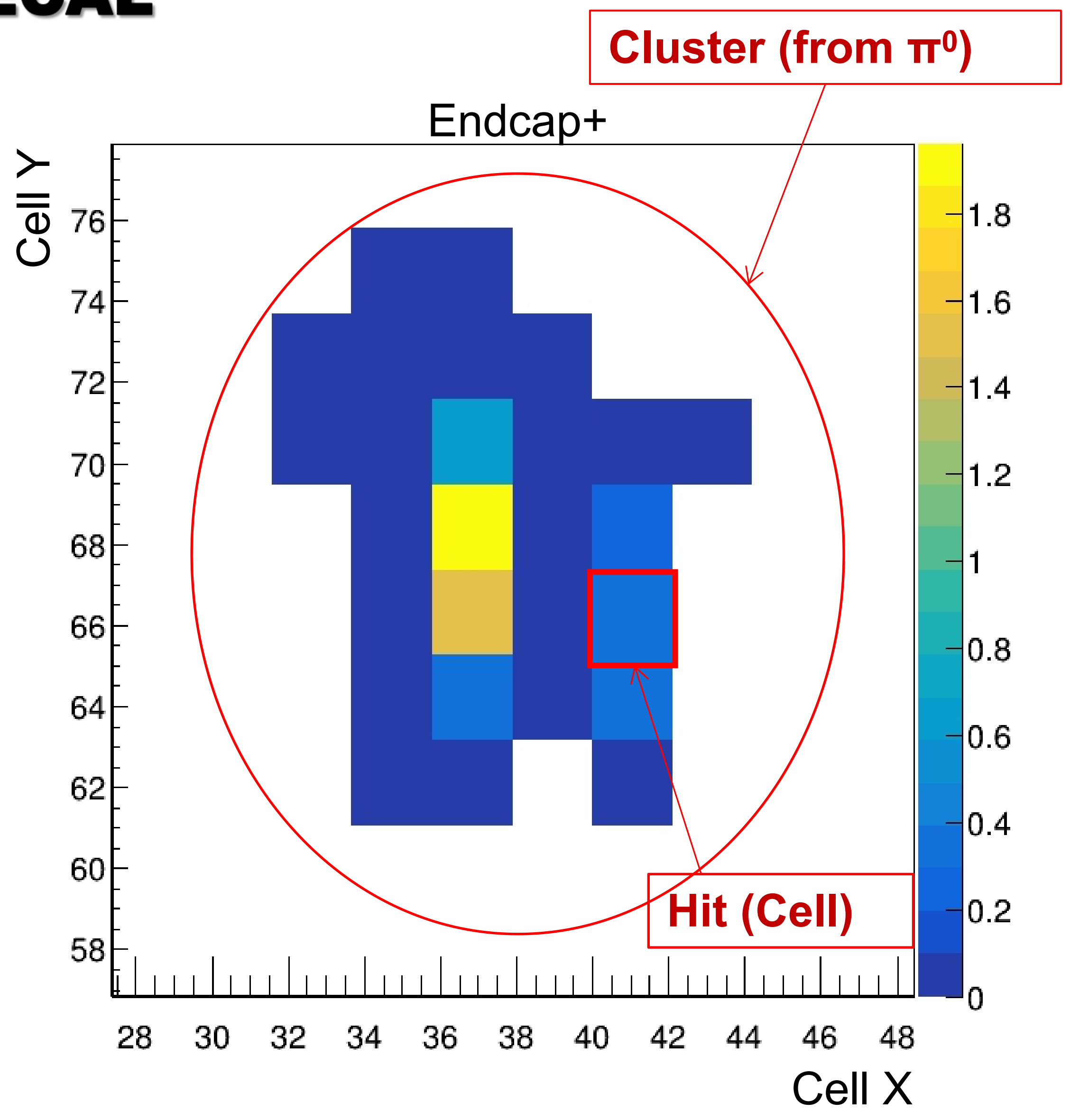
1) per-cell energy calibration: energy deposition in scintillator layers → energy deposition in the entire cell

2) clustering: identifying groups of neighboring cells

3) reconstruction: get particle position and energy from cluster

3*) π/γ ID: based on cluster shape analysis

In future, it is possible to merge (2) and (3) in a fast reconstruction algorithm based on convolutional neural network



Part 1: ECAL reconstruction

- Change of approach: previously: second/third-degree polynomials, angular dependence of the parameter

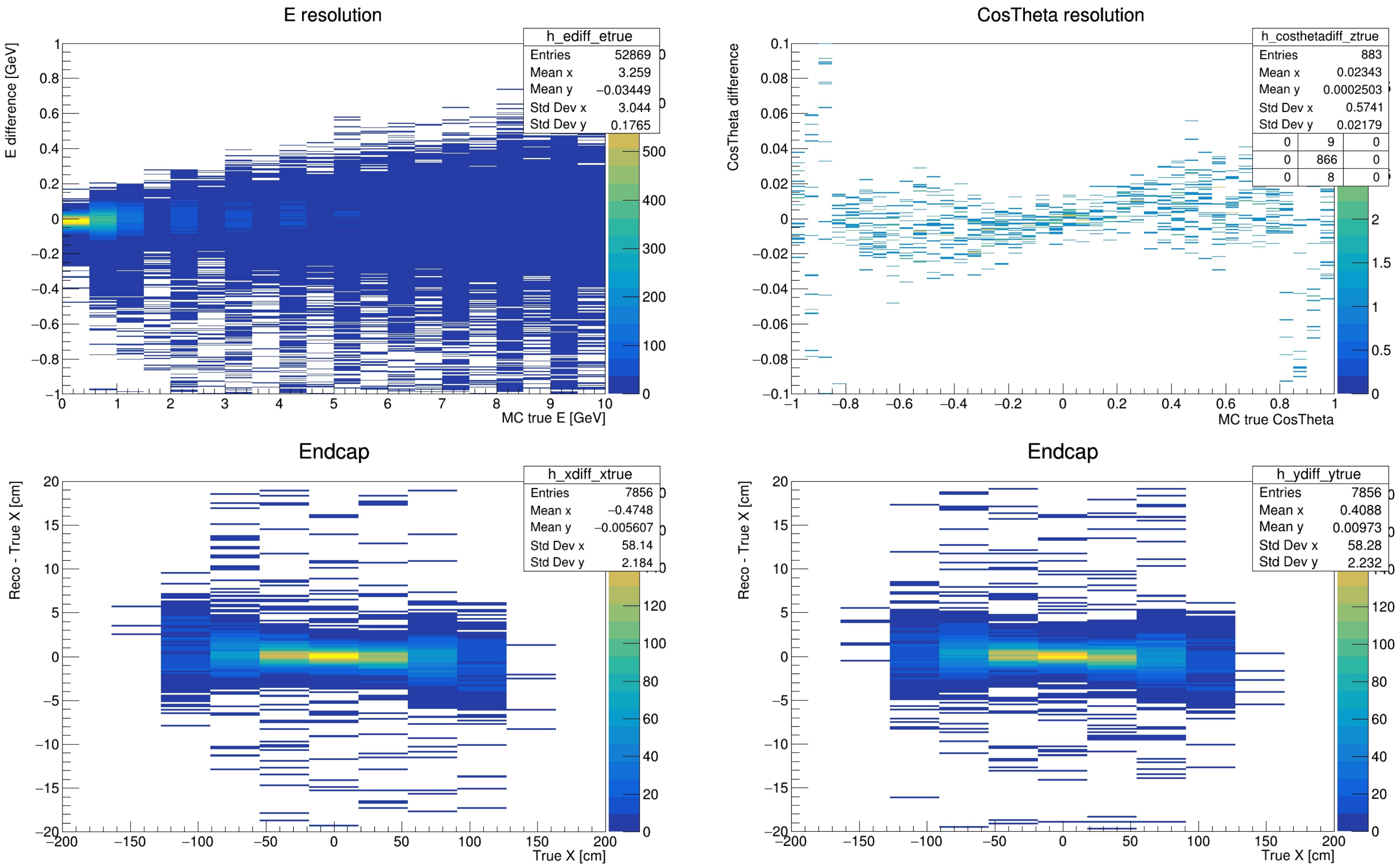
$$\epsilon_{loss} = a(\alpha) + b(\alpha)E + c(\alpha)E^2$$

a,b,c: second-degree polynomial

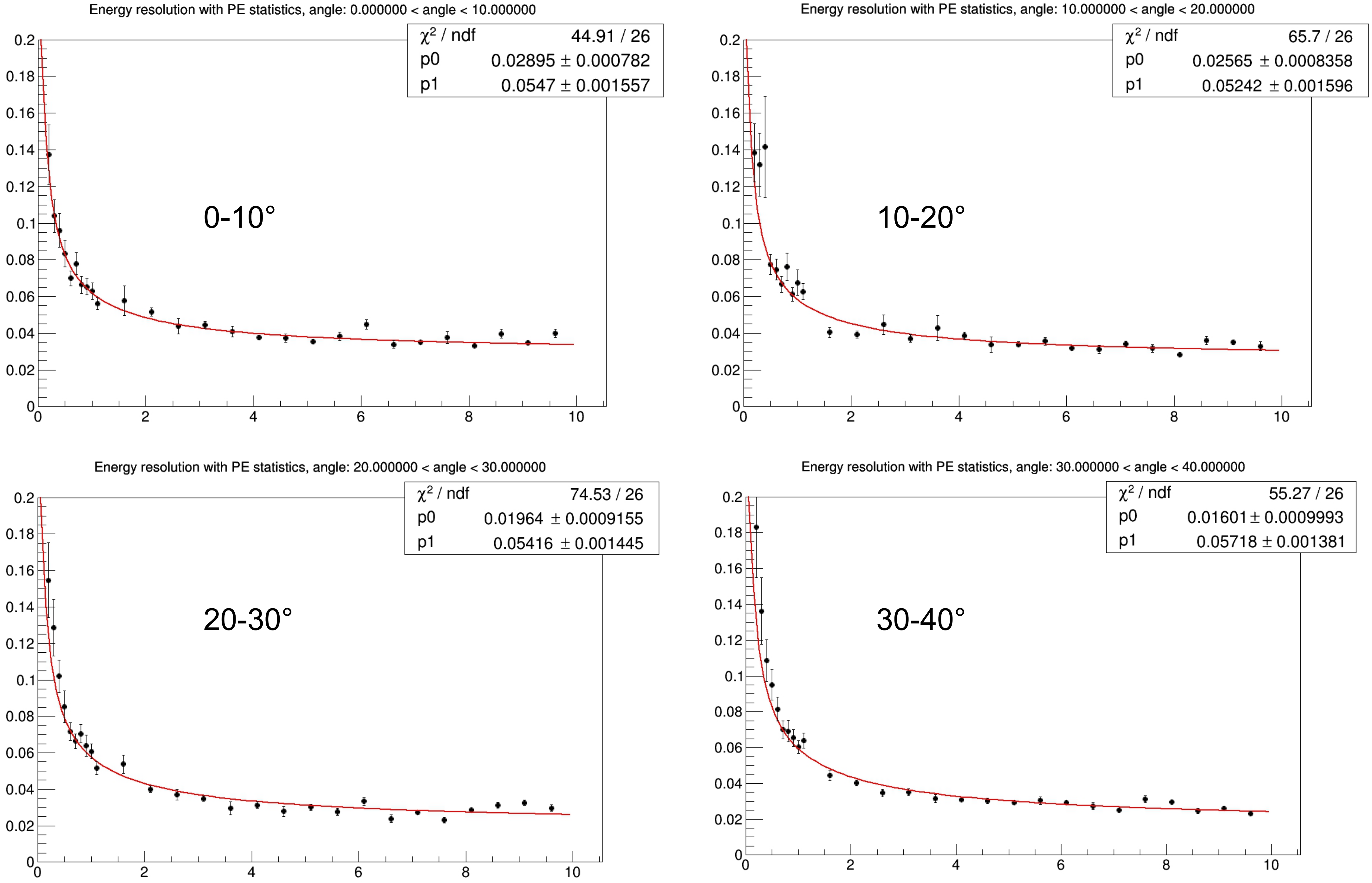
- Now: correctly taking into account the shower depth and its dependence on γ energy:

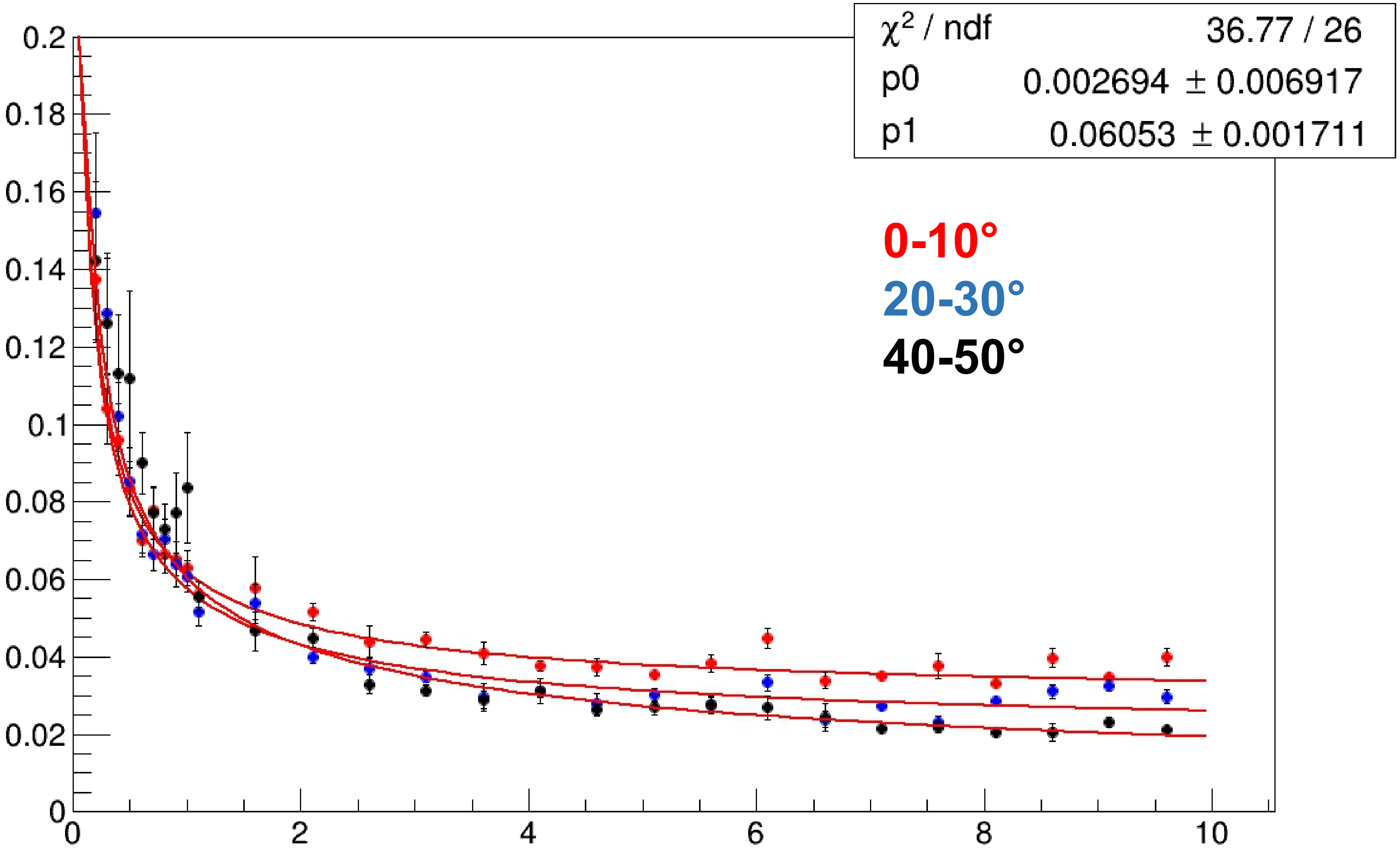
$$\epsilon_{loss} = a(\alpha) + b(\alpha)\ln(E/\mathrm{MeV})$$

a,b: linear functions



- Previous corrections: ~10% effect on γ energy
- Now: ~1% effect
- Best way to reconstruct clusters: using empirical energy- and angle-dependent approach, or machine learning approach?

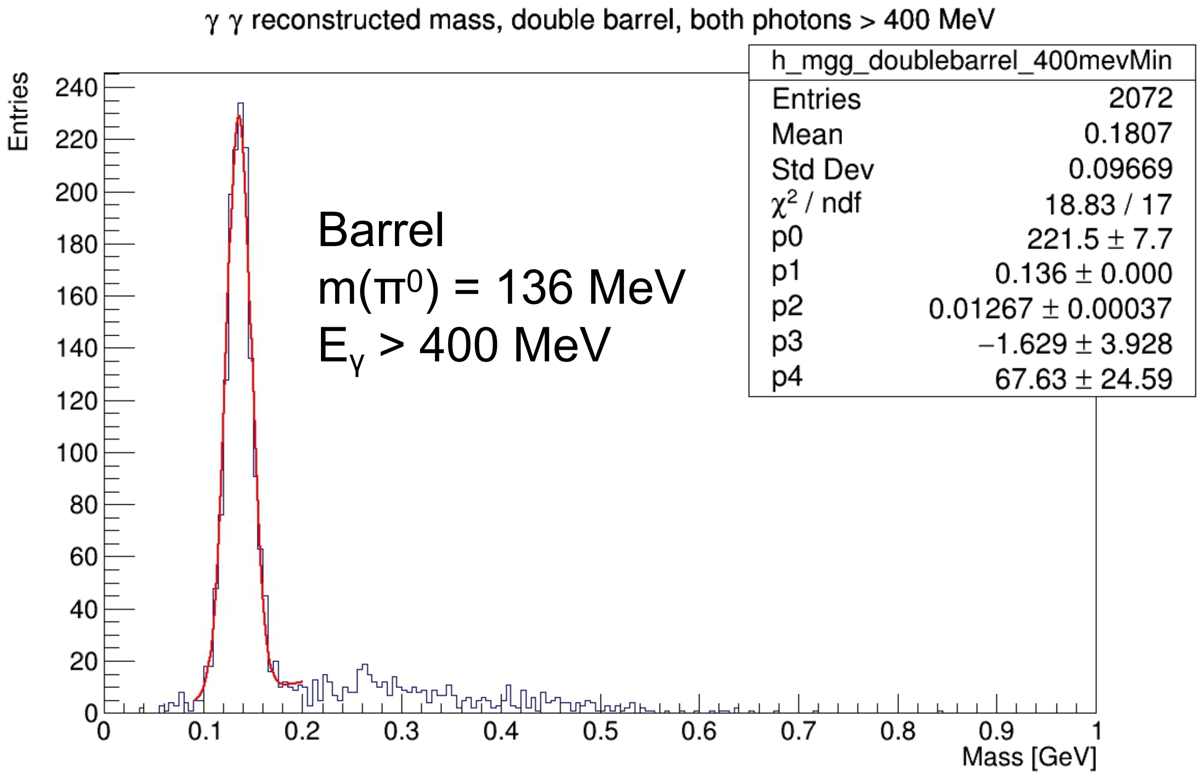

Energy resolution with PE statistics, angle: 0.000000 < angle < 10.000000
χ² / ndf 44.91 / 26
p0 0.02895 ± 0.000782
p1 0.0547 ± 0.001557
0-10°
Energy resolution with PE statistics, angle: 10.000000 < angle < 20.000000
χ² / ndf 65.7 / 26
p0 0.02565 ± 0.0008358
p1 0.05242 ± 0.001596
10-20°
Energy resolution with PE statistics, angle: 20.000000 < angle < 30.000000
χ² / ndf 74.53 / 26
p0 0.01964 ± 0.0009155
p1 0.05416 ± 0.001445
20-30°
Energy resolution with PE statistics, angle: 30.000000 < angle < 40.000000
χ² / ndf 55.27 / 26
p0 0.01601 ± 0.0009993
p1 0.05718 ± 0.001381
30-40°

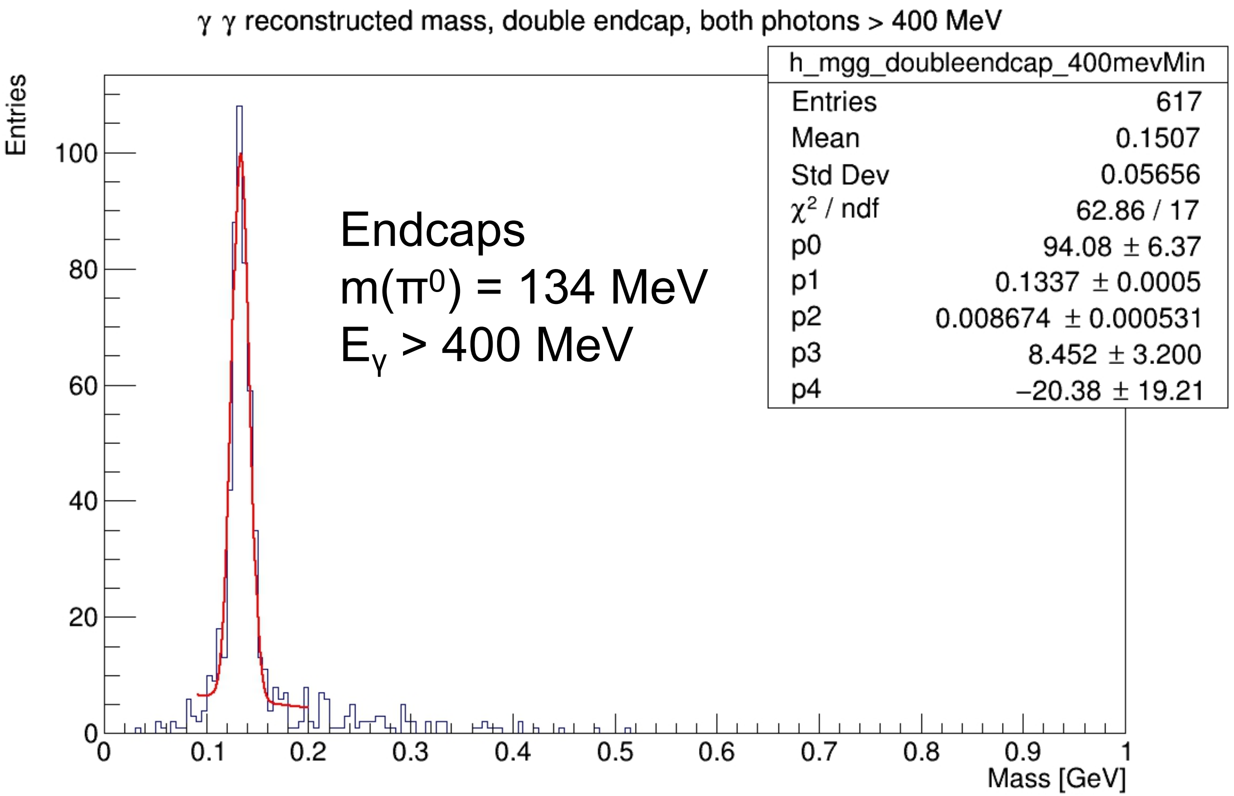


χ² / ndf 36.77 / 26
p0 0.002694 ± 0.006917
p1 0.06053 ± 0.001711
0-10°
20-30°
40-50°
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
2
4
6
8
10

π0 mass

- 1% effect for both barrel and endcap for E_γ > 400 MeV

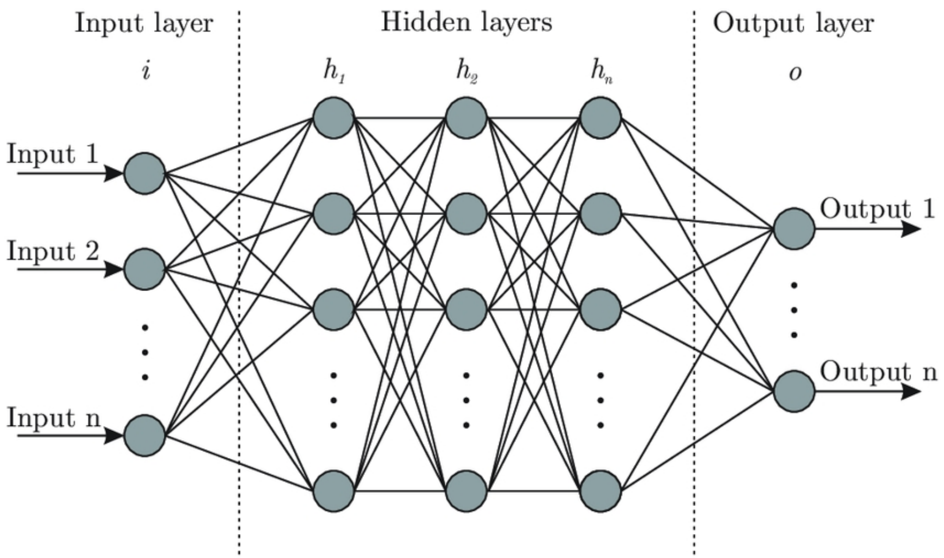




Part 2: π/γ separation

Attempt at using a more complex NN

Inspired by the work of Dimitrije Maletic (thanks!) and https://cds.cern.ch/record/2042173



$O_i = f(W_{i0} + \sum_{j=1}^{N} W_{ij} O_j)$ → weighted sum + bias for each node

- f: **ReLU** $f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$ sigmoid for output: $f(x) = \frac{1}{1+e^{-x}}$

- **Dropout** (p=0.1),
- **batchnorm** for each layer (before activation)

- Binary cross entropy loss **(BCE)**:

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

- Optimizer: **Adam**

(stochastic gradient descent +
adaptive moment estimation)
(lr = 0.001, β_1 = 0.9, β_2 = 0.999, ε=1e-8

2 hidden layers, 64 neurons each

Inputs

Variables describing moments

$$|x_{cog}|_{25} = \left| \frac{\sum_{i=1}^{25} E_i X_i^{rel}}{S_{25}} \right|$$

$$|y_{cog}|_{25} = \left| \frac{\sum_{i=1}^{25} E_i Y_i^{rel}}{S_{25}} \right|$$

$$r2 = < r^2 > = S_{XX} + S_{YY} = \frac{\sum_{i=1}^{N} e_i((x_i - x_c)^2 + (y_i - y_c)^2)}{\sum_{i=1}^{N} e_i}$$

$$S_{XX} = \frac{\sum_{i=1}^{N} e_i(x_i - x_c)^2}{\sum_{i=1}^{N} e_i}, \quad S_{YY} = \frac{\sum_{i=1}^{N} e_i(y_i - y_c)^2}{\sum_{i=1}^{N} e_i},$$

$$S_{XY} = S_{YX} = \frac{\sum_{i=1}^{N} e_i(x_i - x_c)(y_i - y_c)}{\sum_{i=1}^{N} e_i},$$

$$r2r4 = 1 - \frac{< r^2 >^2}{< r^4 >}$$

$$\kappa = \sqrt{1 - 4\frac{S_{XX}S_{YY} - S_{XY}^2}{(S_{XX} + S_{YY})^2}} = \sqrt{1 - 4\frac{\det S}{\mathrm{Tr}^2 S}}$$

Energy distribution

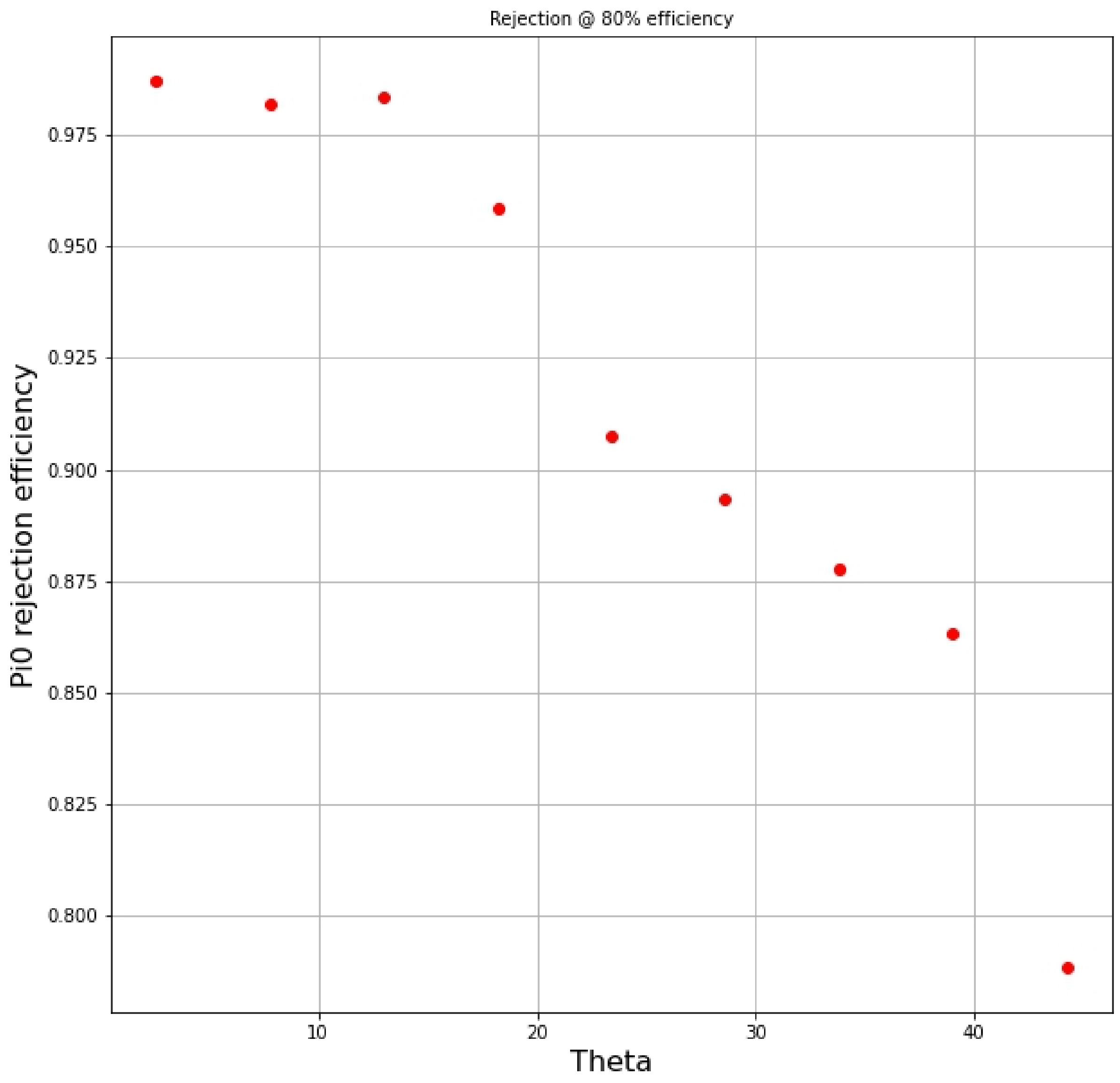
$$\frac{S_1}{S_9} \qquad \frac{S_9 - S_1}{S_{25} - S_1} \qquad \frac{M_2 + S_1}{S_4} \qquad \frac{S_6}{S_9} \qquad \frac{M_2 + S_1}{S_9}$$

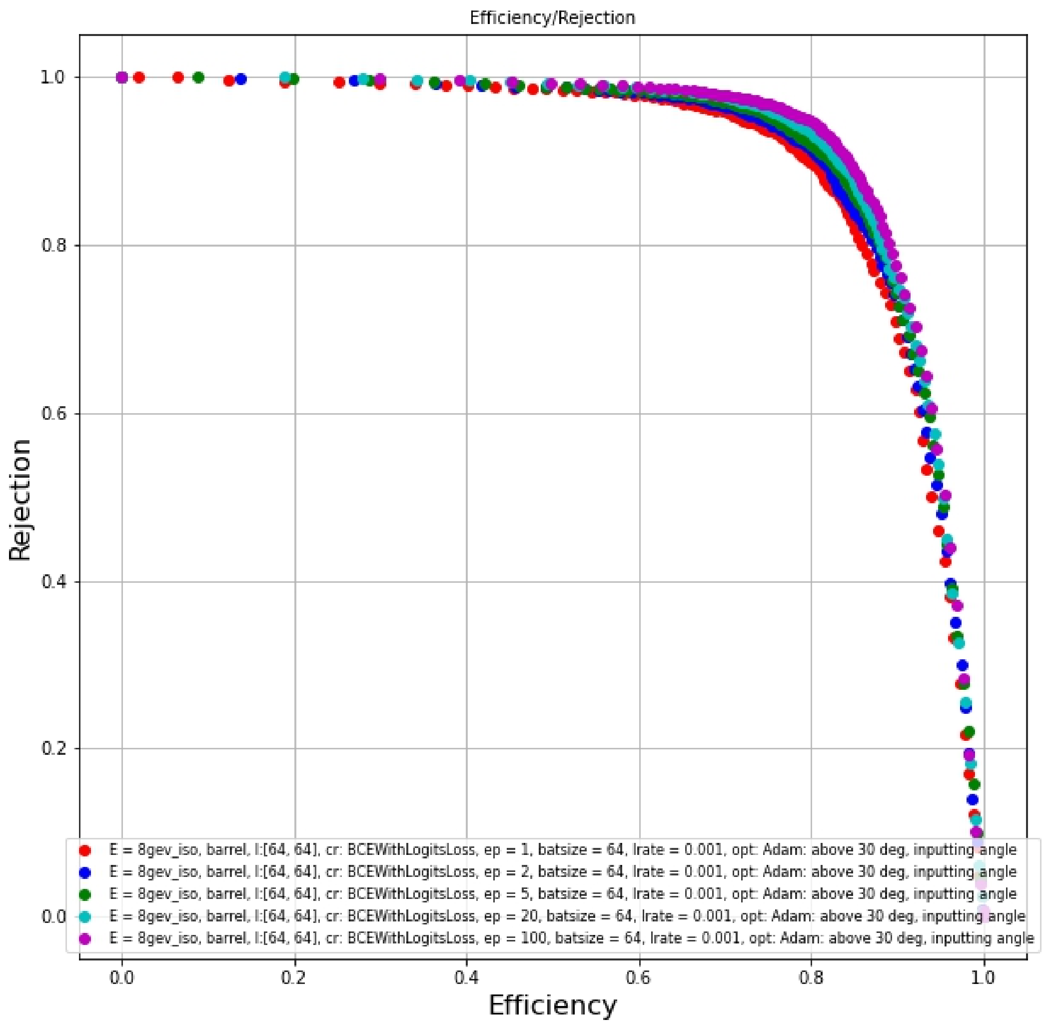
Angle θ as an input variable
(improves separation at high energies)
Total energy

X,Y ~ θ,φ
S_1, M_2 - 1st and 2nd largest energies
S_9, S_{25} - energy in 3x3, 5x5 region
S_6 - maximum energy in 3x2 region containing S_1 and M_2

14 inputs
Dataset: 2/3 → train, 1/3 → test

Results (barrel)





- ~98% π^0 rejection (at 80% γ efficiency) at small angles
- ~80% for larger angles

Implementation of the model in SPDROOT

- Two options:
- 1) add the implementation to the SpdEcalRCMaker
- 2) create a separate class (SpdJob) in the processing chain (reusability!)

Next steps

- produce a database of γ/π0 events for further studies → empirical corrections or machine learning approach
- extend the class SpdEcalRCMaker to add a flag on π^0/γ into the reconstructed particle class, or create a separate class for π/γ separation