

Angle measurement with sampling calorimeter

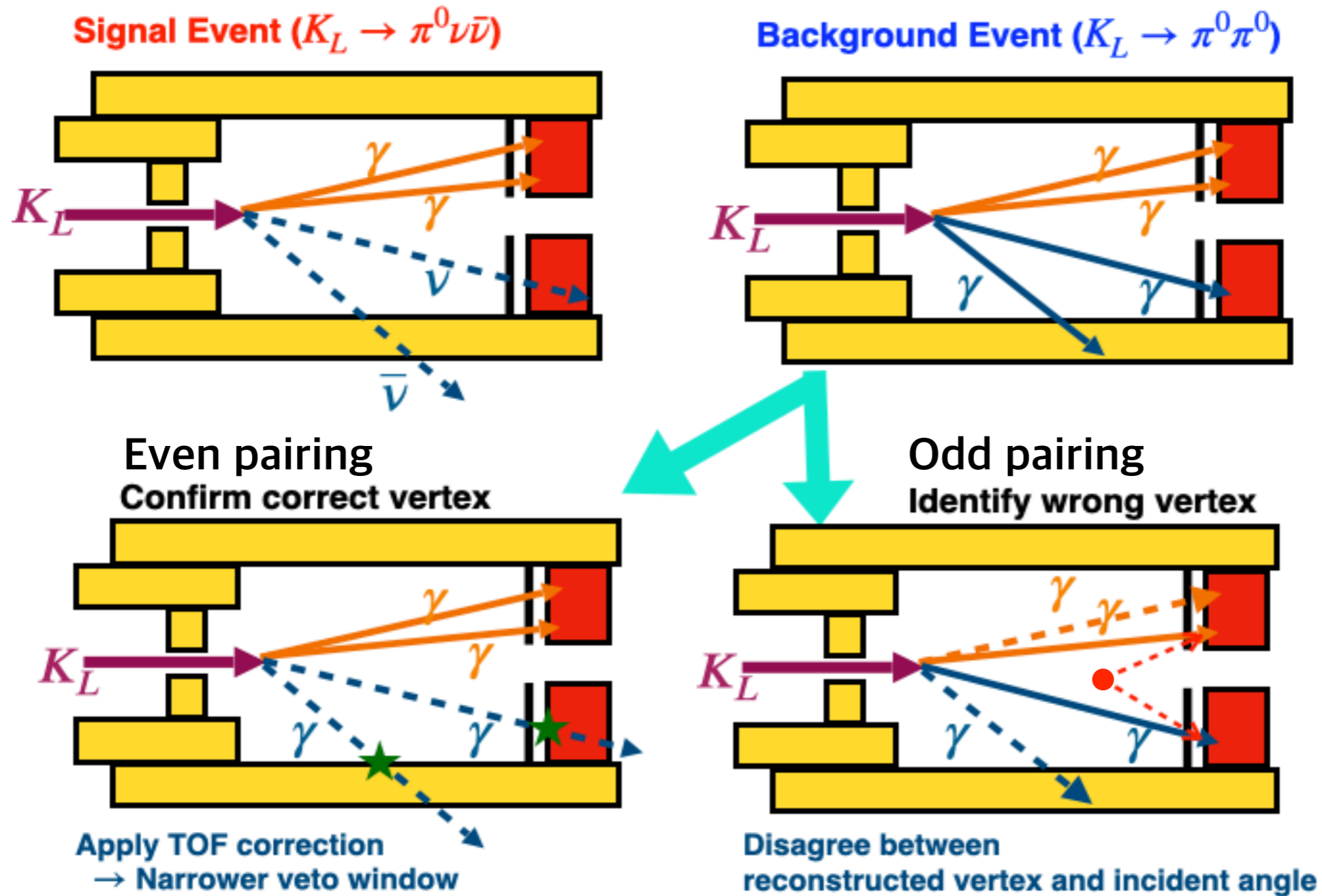
KOTO Collaboration meeting

YoungJun Kim

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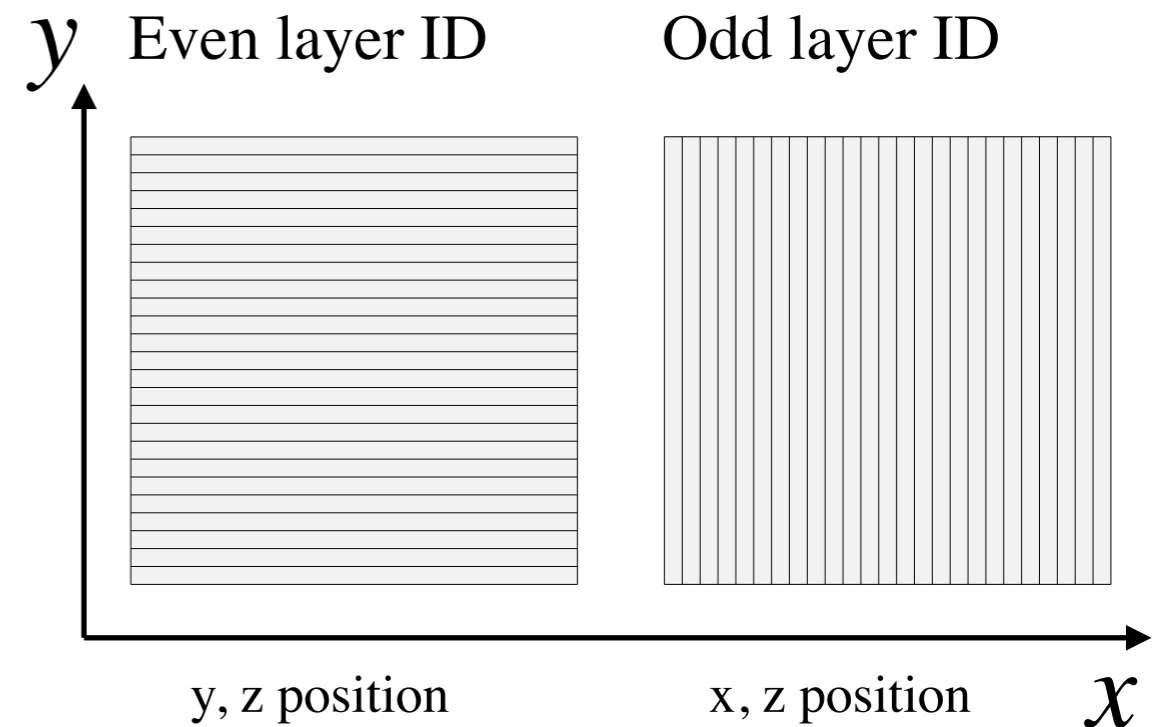
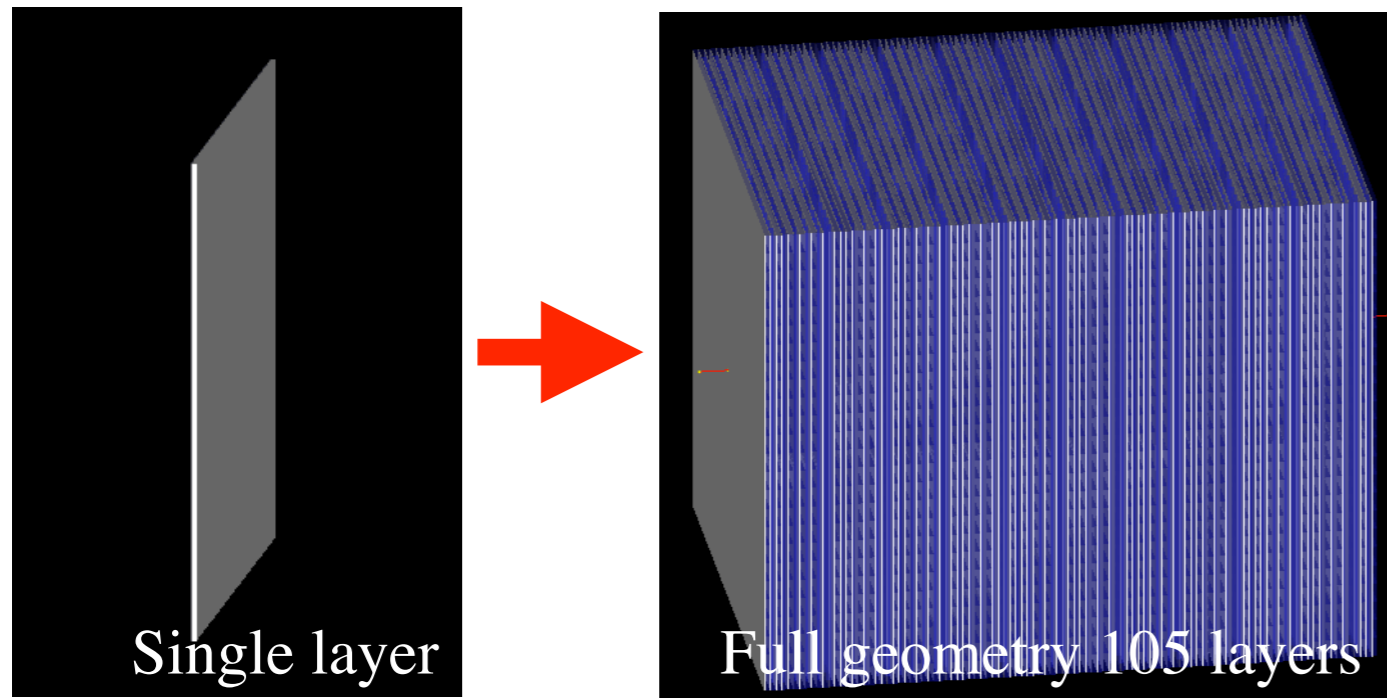
- Motivation
- Geometrical design
- Detector properties
 - Shower profile
 - Moliere radius, visible ratio
 - Accidental loss by backsplash particles
- Angle reconstruction with Machine Learning
 - Training setup optimization
 - Detector optimization and current achievement
 - Energy dependency
- Conclusion

Why do we need γ tracking?



- Two vertices from different observables
 - Rejection power for backgrounds
 - **To reduce accidental loss (at high beam rate) → narrow veto window**

Design of the Prototype Sampling Calorimeter



Single layer configuration:

Pb: 50 cm (l) \times 50 cm (w) \times 1 mm (t)

Scintillator: 50 cm (l) \times (2 cm (w) \times 25) \times 5 mm (t)

Radiation length: $0.19X_0$

In total 105 layers:

$$20X_0 = 0.19X_0 \times 105$$

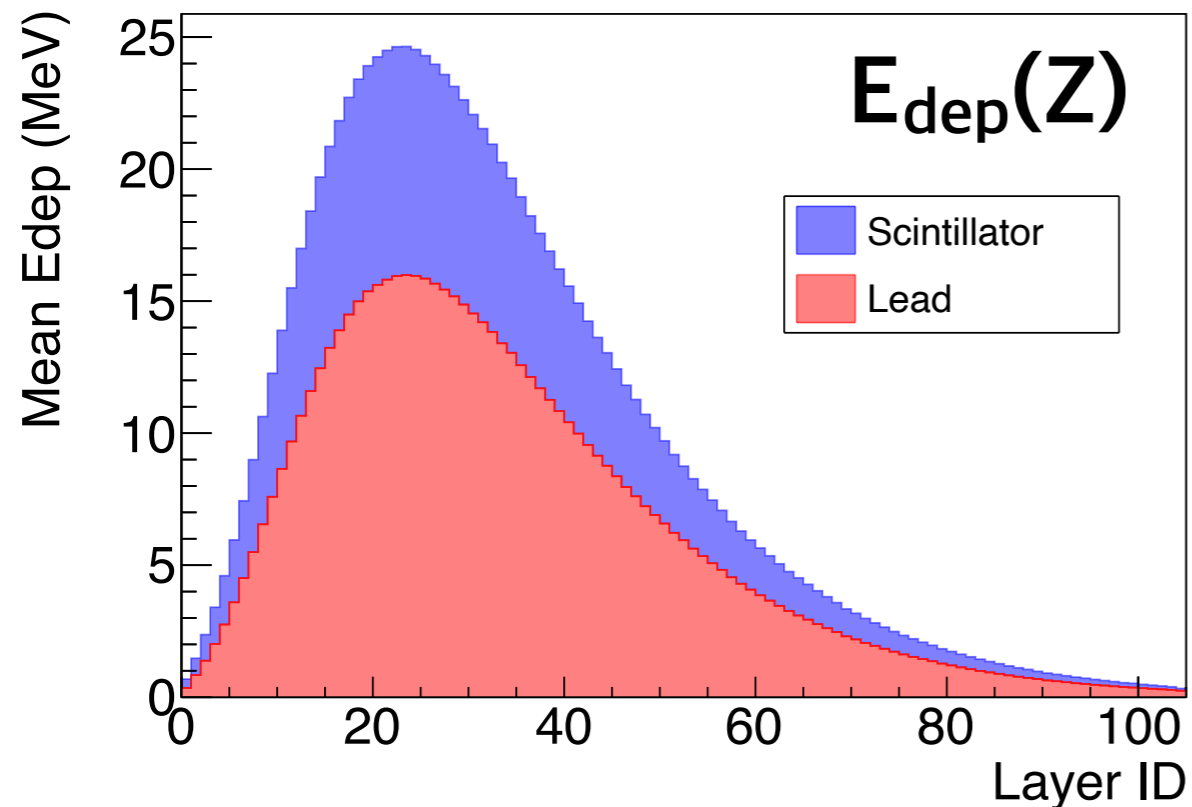
Alternatively aligned along x and y axis

→ Readout y, z position (even layer)

→ Readout x, z position (odd layer)

Shower Profile at 1 GeV photon

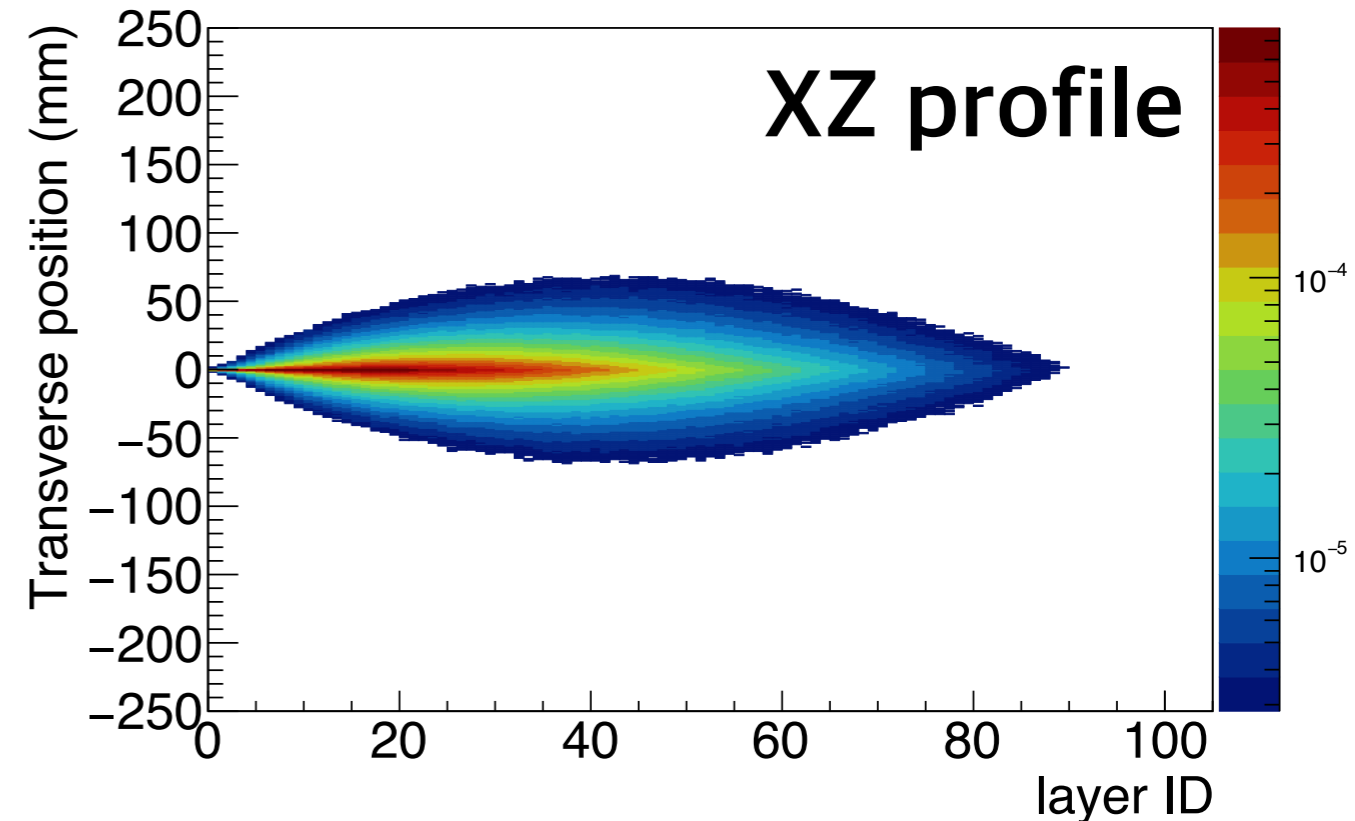
Longitudinal Profile



At 1 GeV photon

- Typical shower shape

2D Shower (Scintillator)



We will discuss relevant properties.

- Moliere radius
- Visible ratio

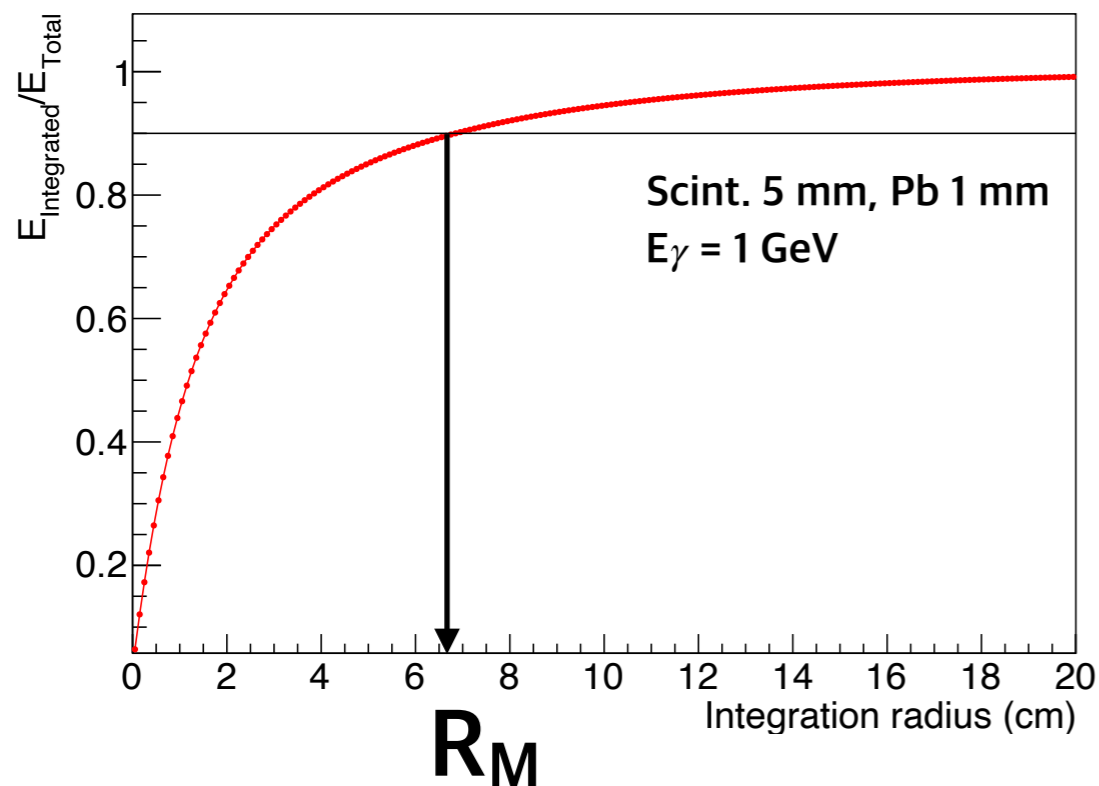
Moliere radius (R_M) and Visible ratio

- **Small Moliere radius** (separation of two photons)
- **Large visible ratio** (good energy resolution)

Moliere radius and visible ratio are studied with combinations of

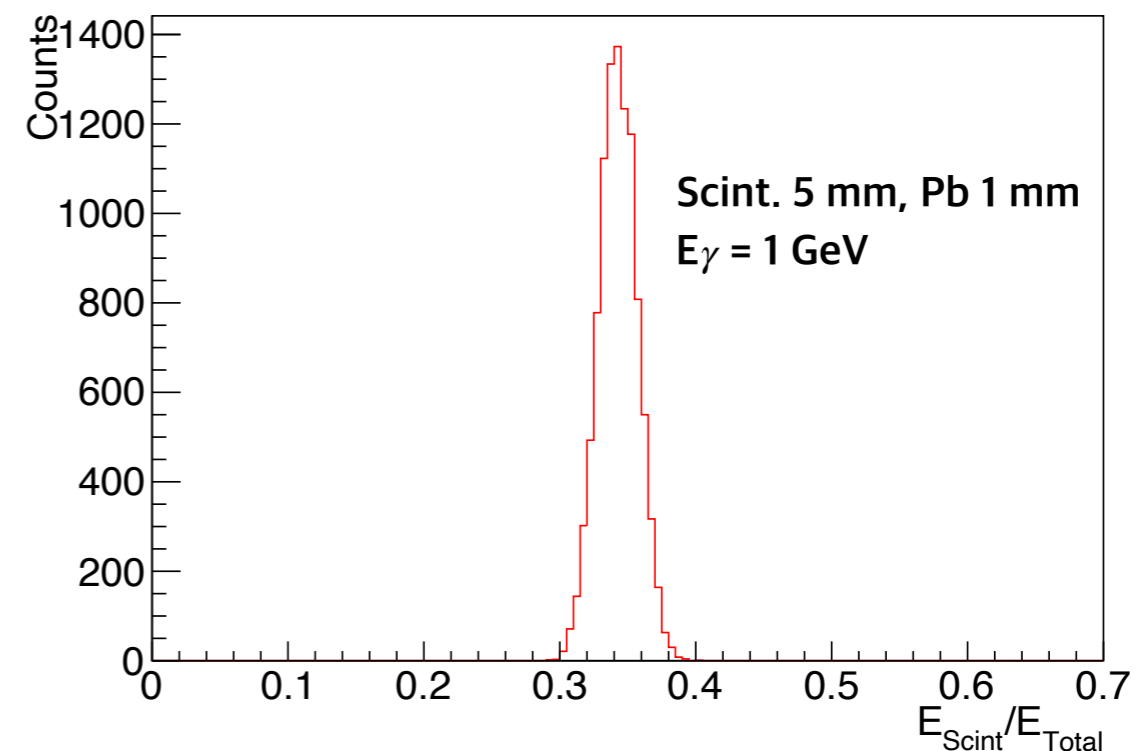
Scintillator \times Converter (Pb)
2.5, 5, 10, 15, 20 (mm) \times 0.5, 1, 2 (mm)

Moliere radius



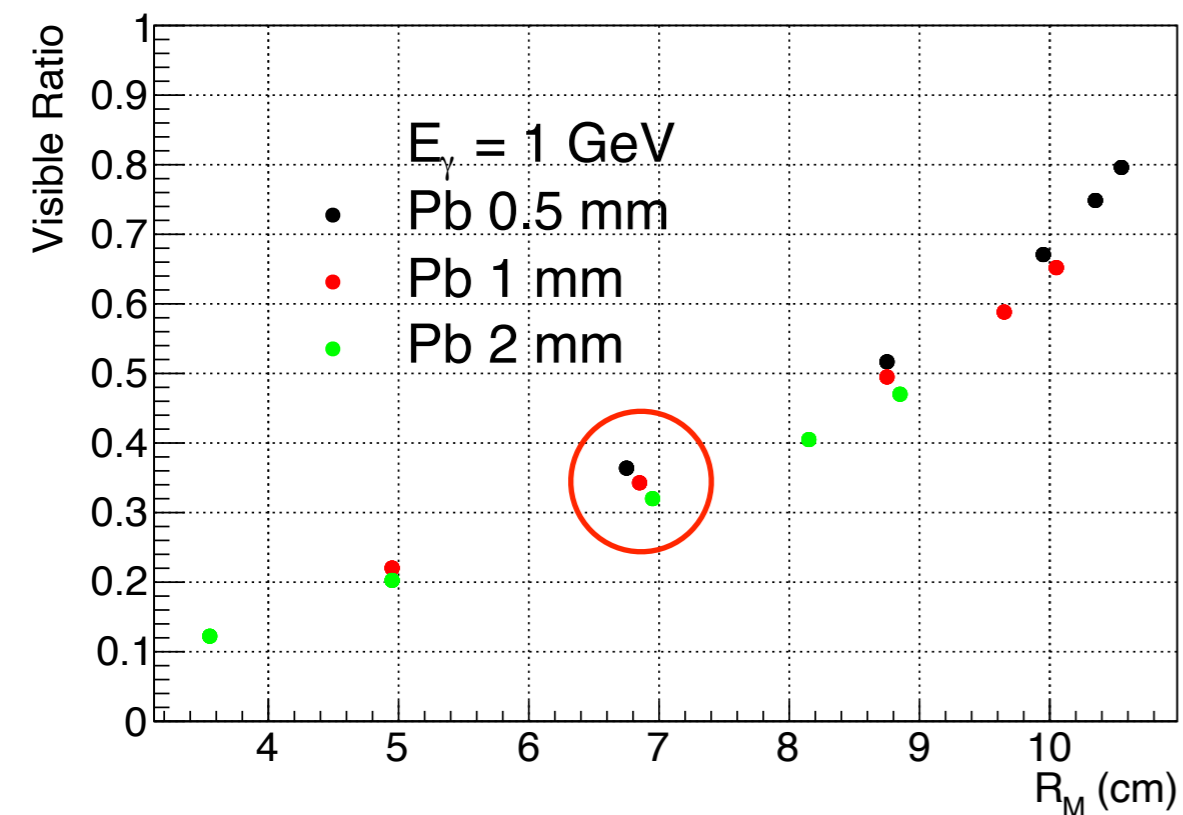
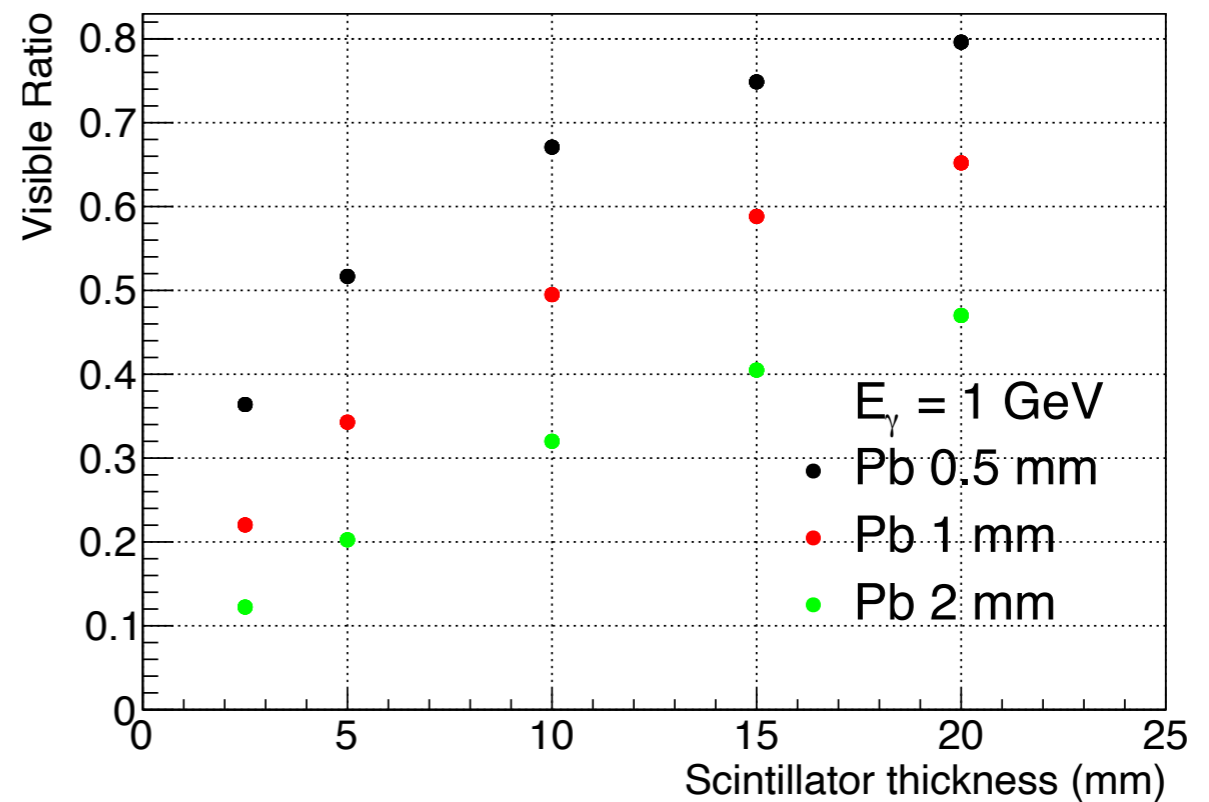
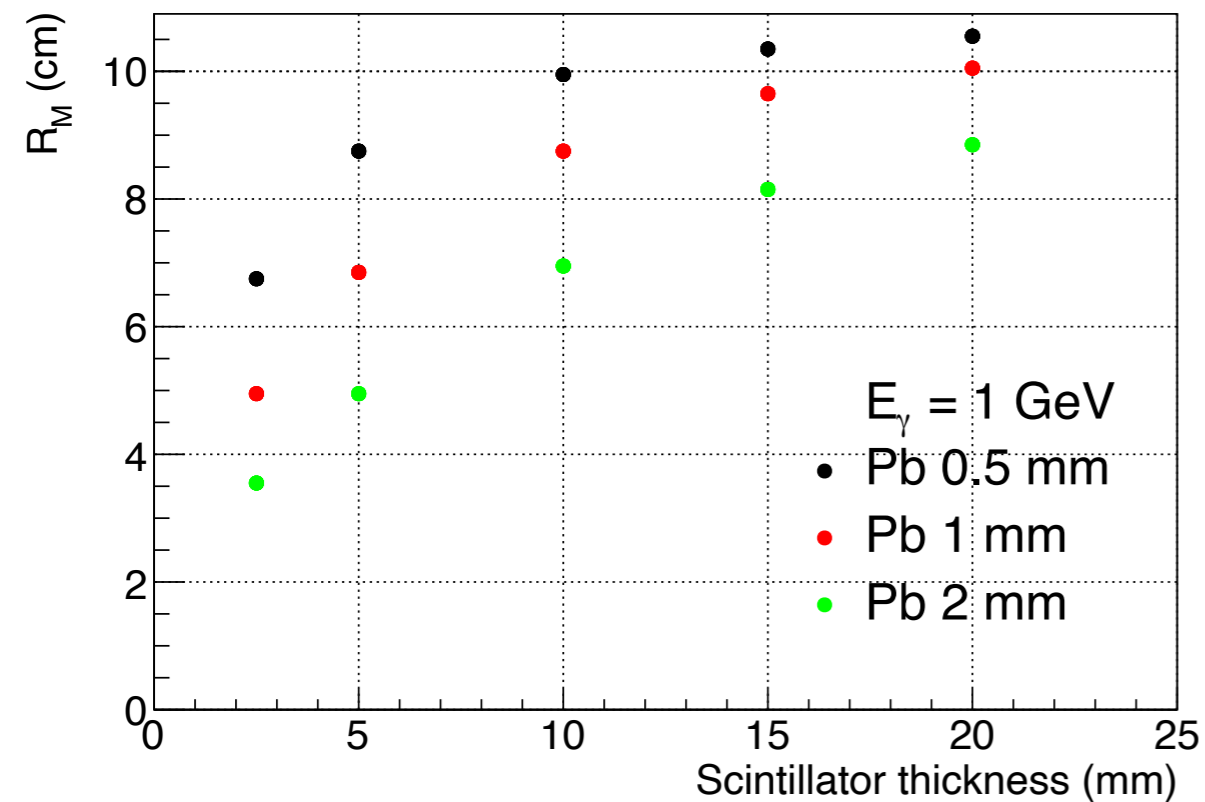
Radius of a cylinder containing on average **90%** energy deposit

visible ratio



Mean value of the ratio $E_{\text{scint}}/E_{\text{total}}$

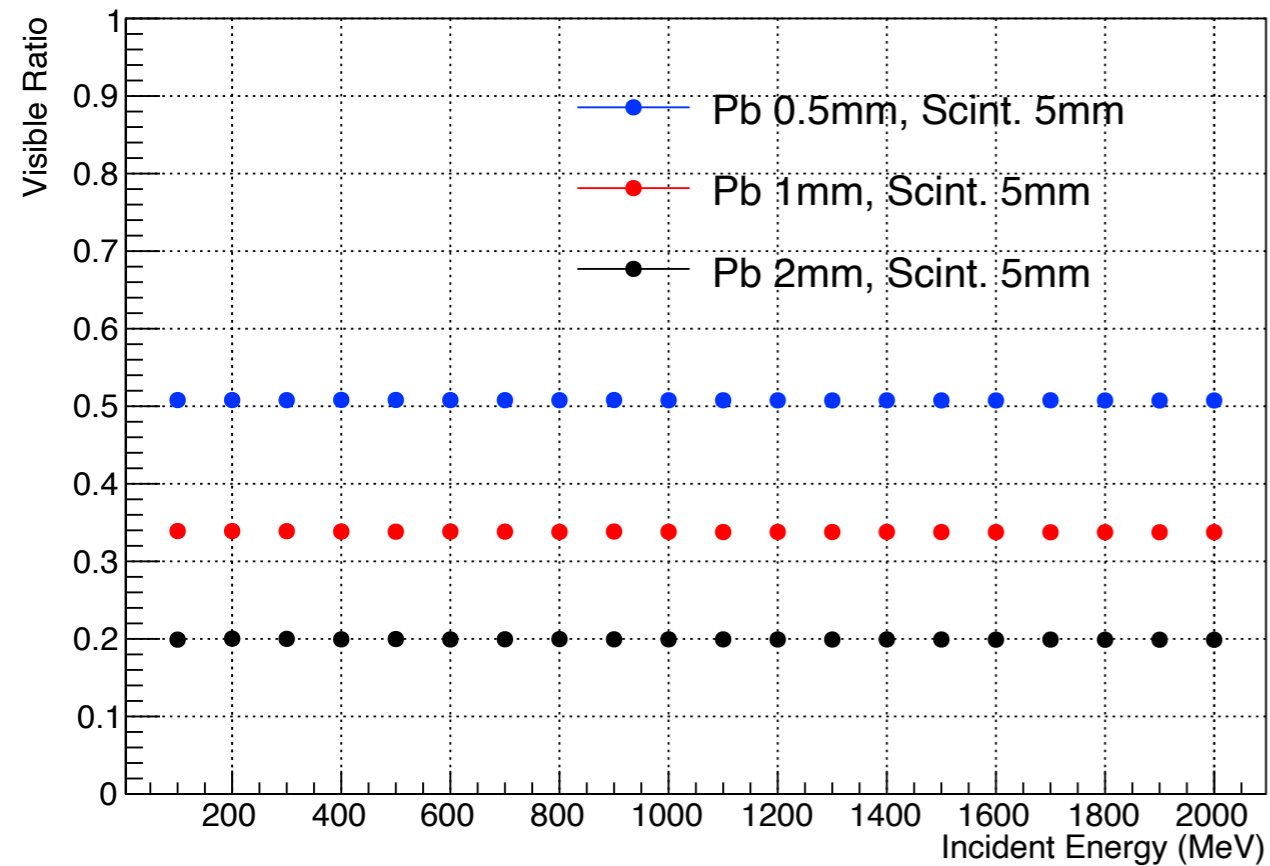
Moliere radius (R_M) and Visible ratio



- Moliere radius and visible ratio depend on ratio between amount of lead and scintillator.
- Strong correlation between Moliere radius and visible ratio
- We chose the configuration (1 mm, 5 mm).
(Pb, Scintillator)
- R_M : 7 cm, visible ratio: 34%

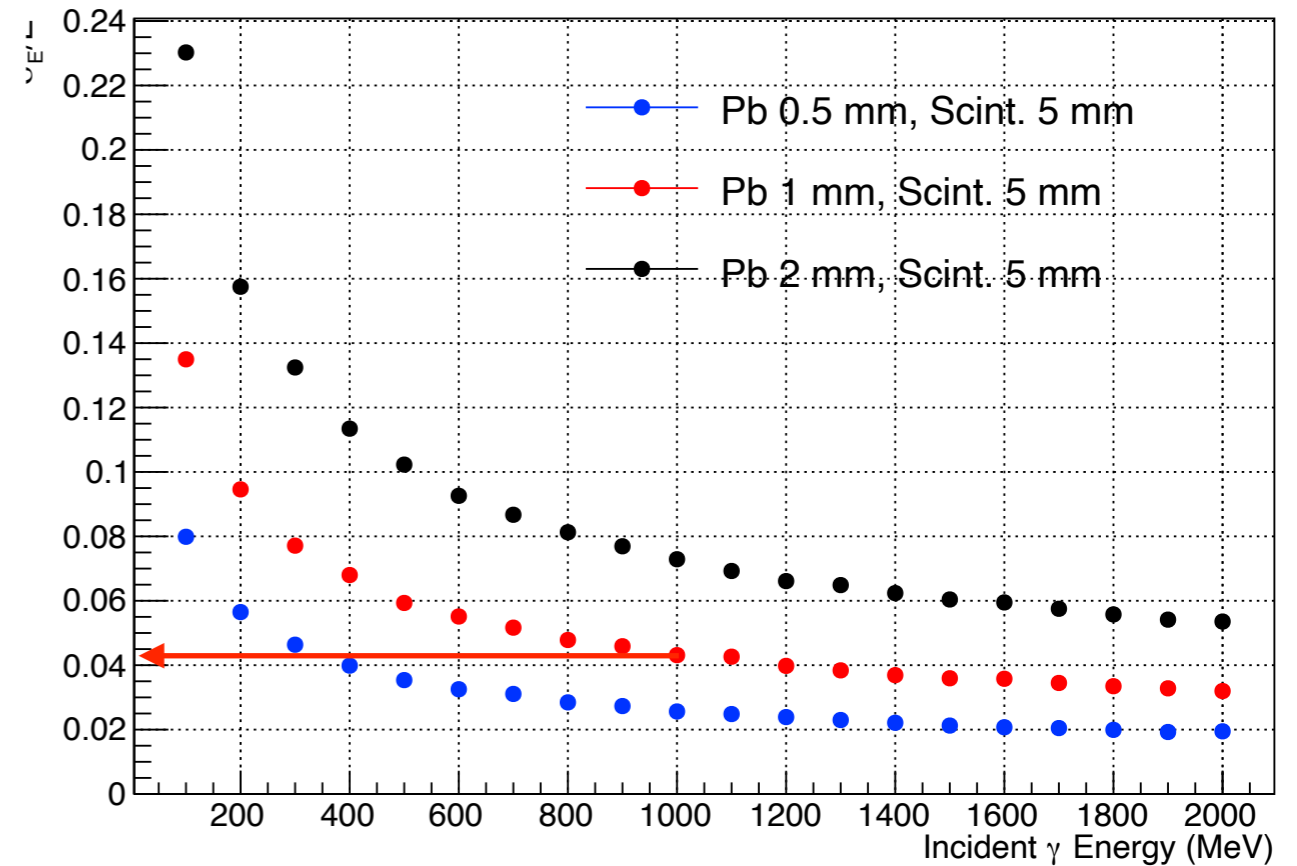
Energy Dependency

Visible ratio



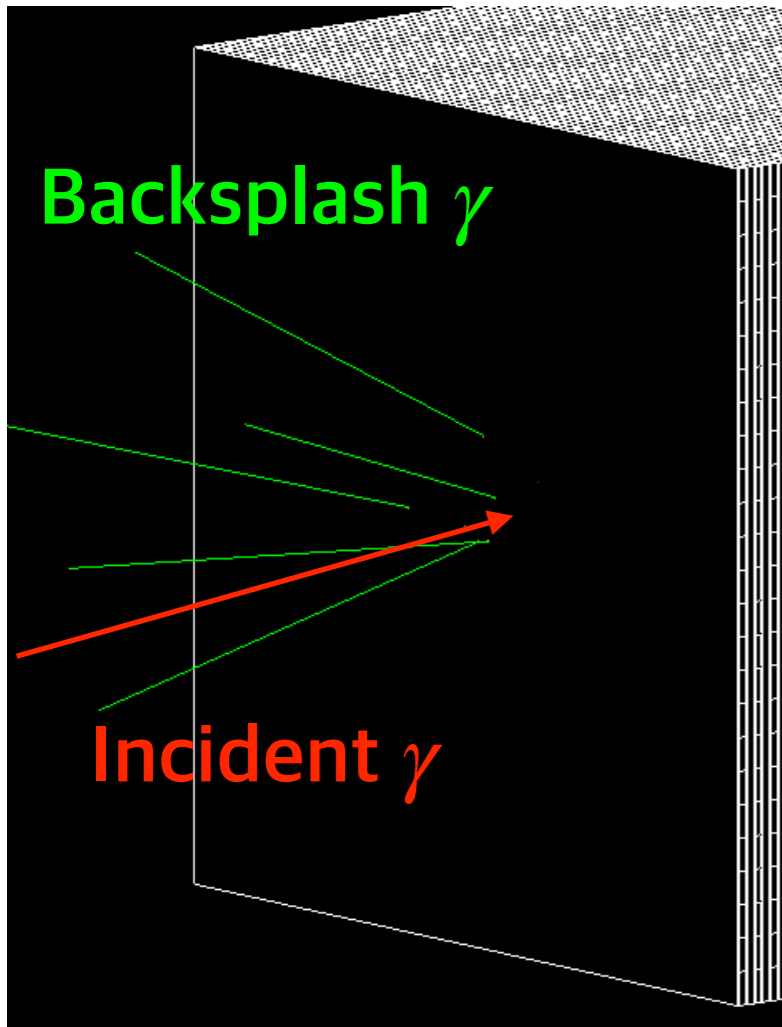
No energy dependency

Energy resolution



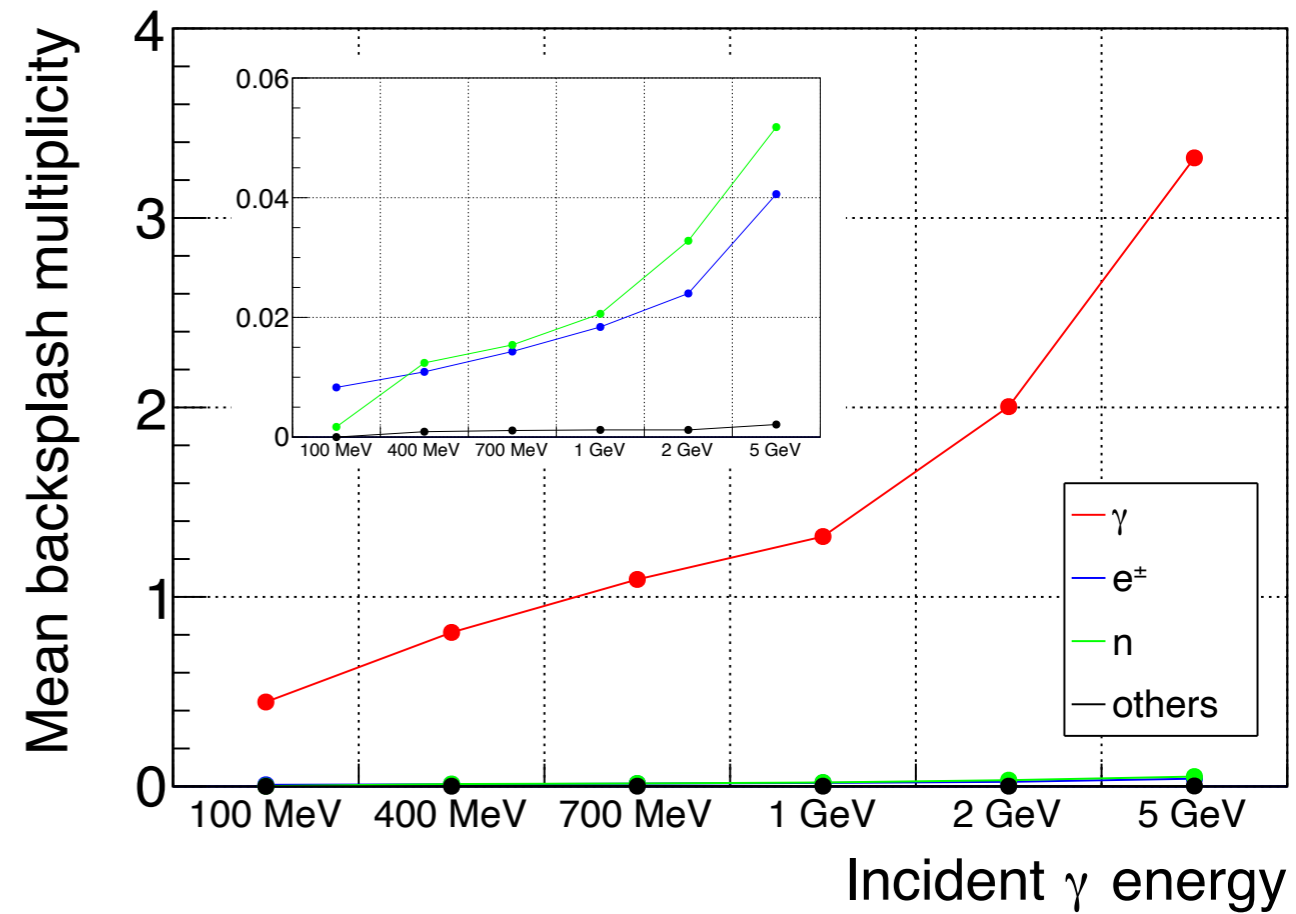
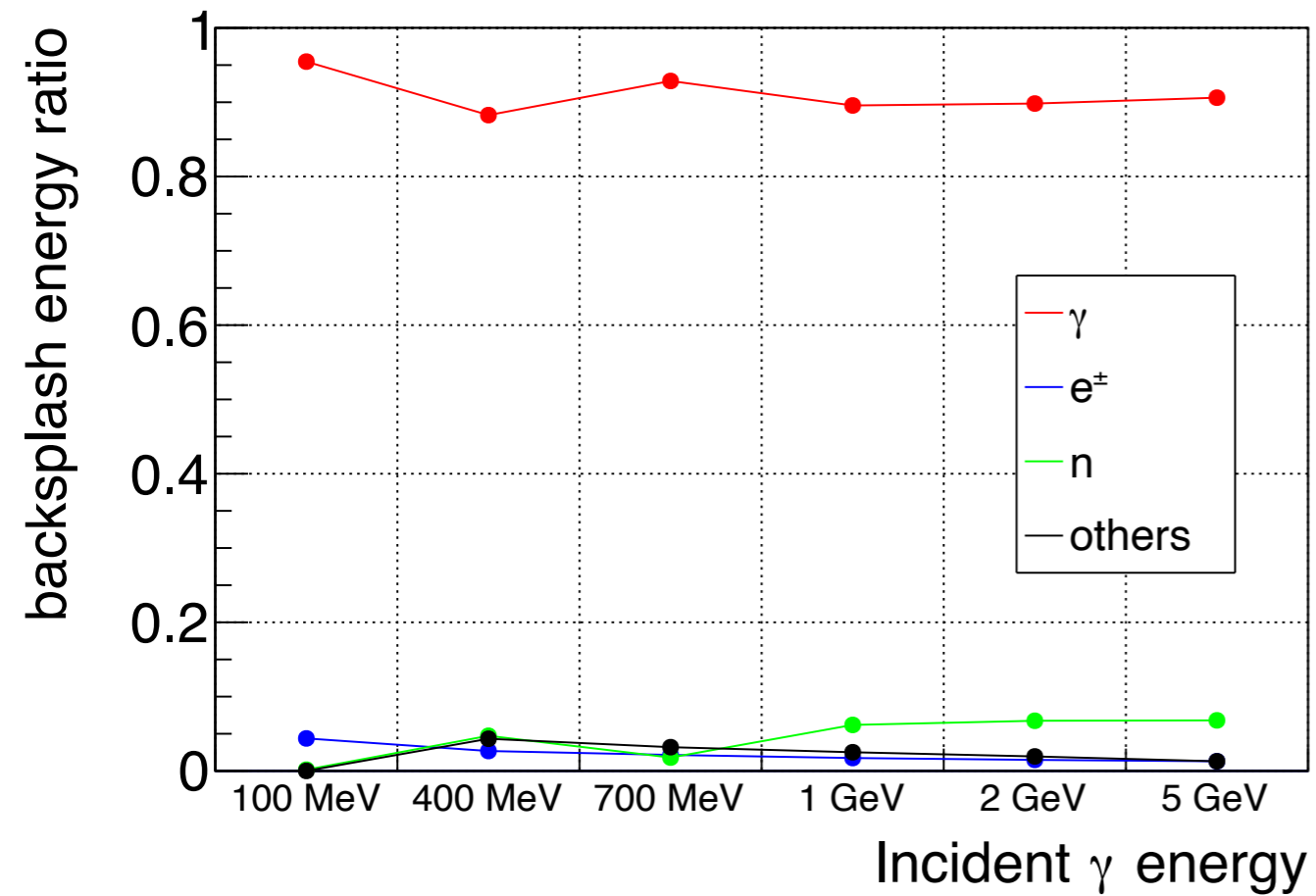
4% energy resolution at 1 GeV γ

Backsplash Events



- Backsplash particles: Outgoing particles through the incident surface
- Backsplash γ or e^{\pm} is one of the most significant sources of the event loss.
- **The event veto rate of a single gamma event is studied.**
 - Event veto rate: The fraction of the number of events with backplash particles

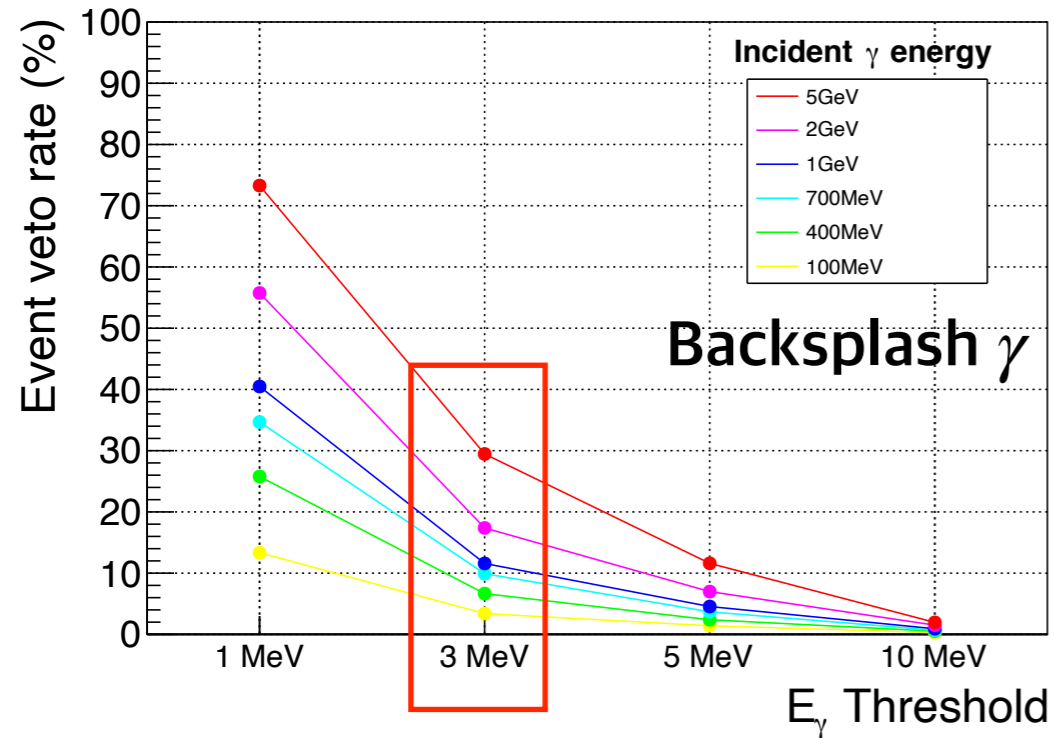
Backsplash Energy / Multiplicity



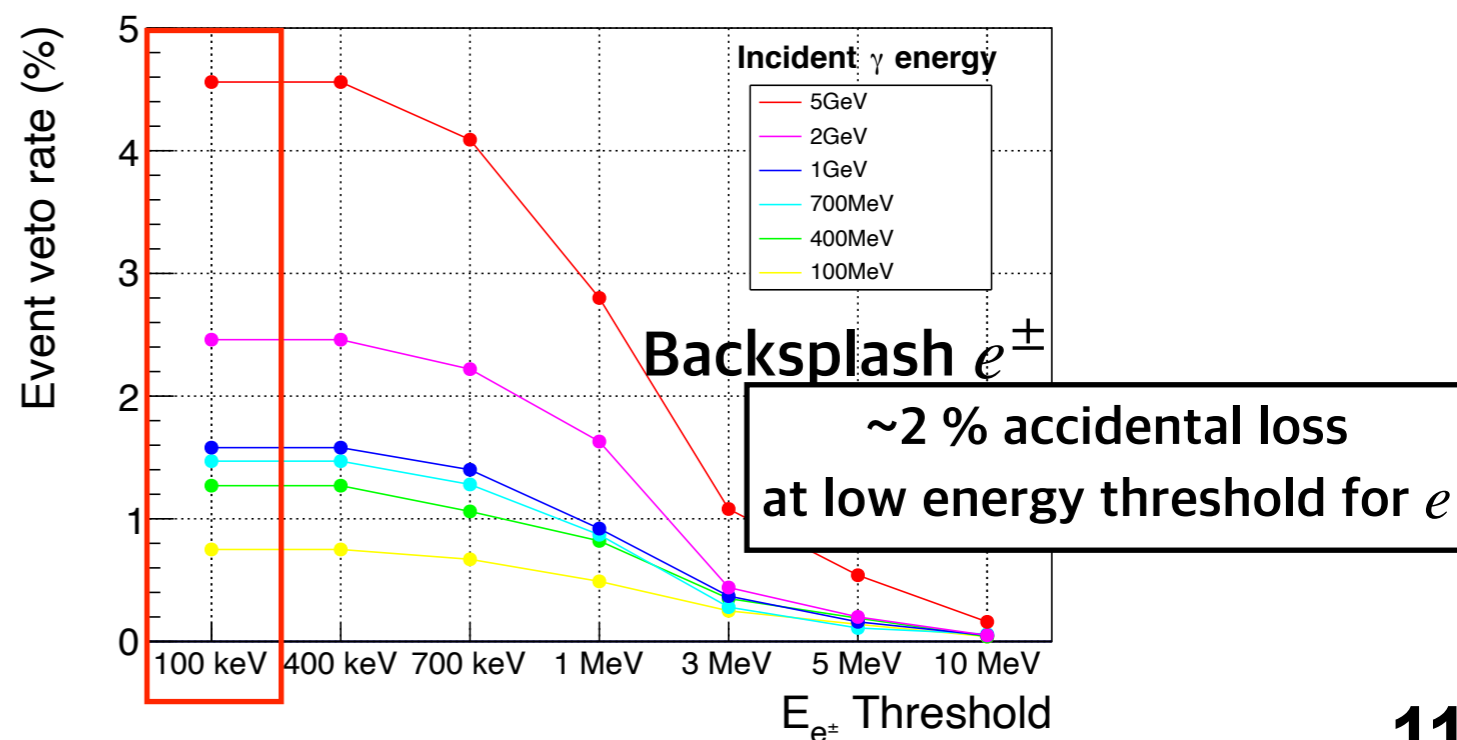
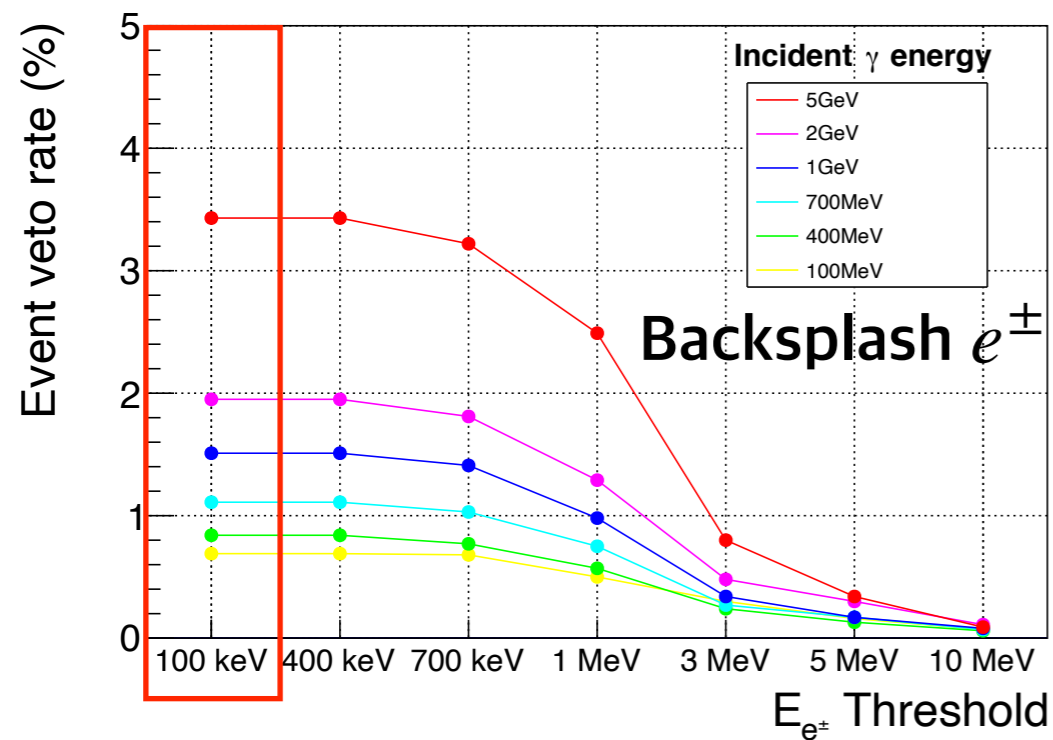
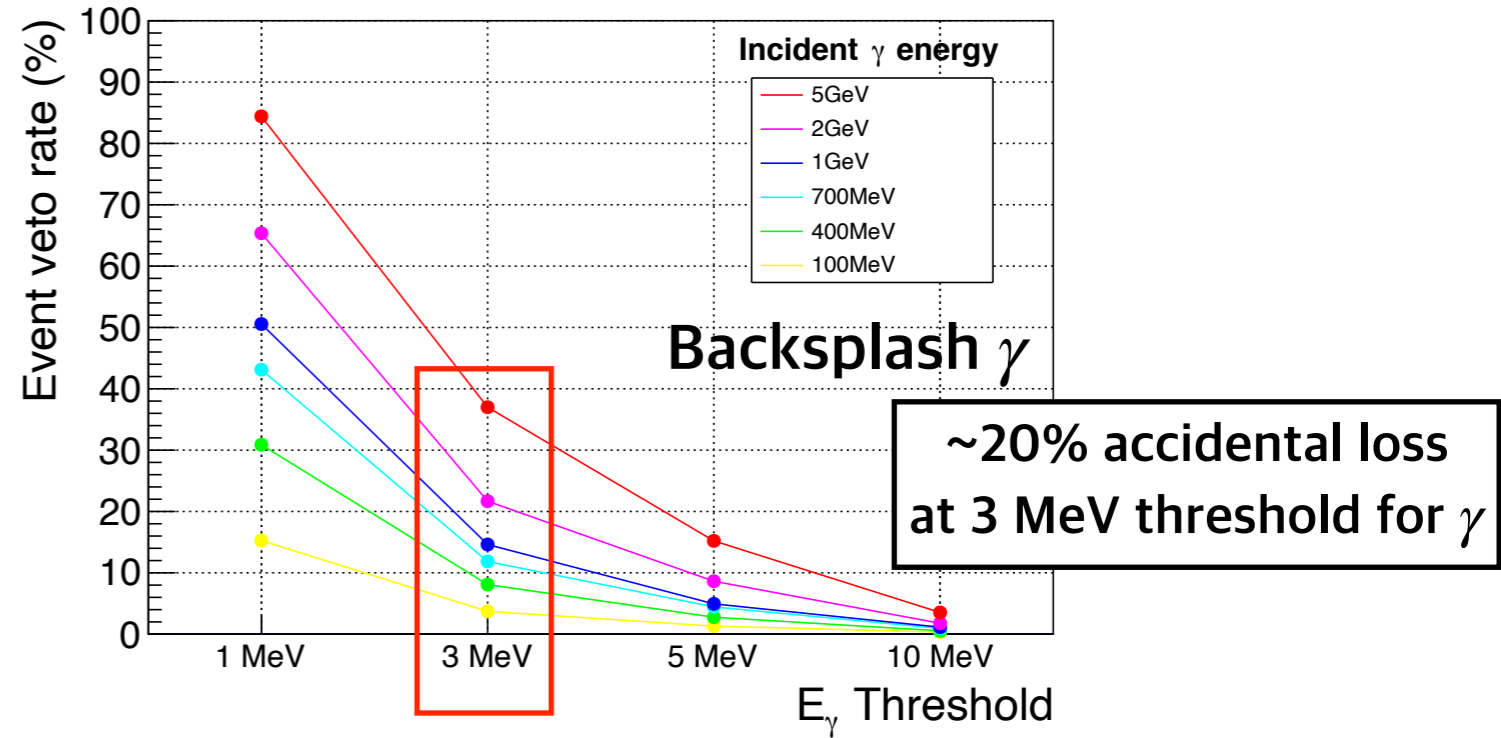
- Almost of backsplash particles are γ ($> 90\%$).

Event veto rate: $N_{\gamma/e^\pm} \geq 1$

Sampling Calorimeter



CsI Calorimeter



XGBoost: Machine Learning (ML) Toolkit

- We utilized a machine learning toolkit “XGBoost” to **reconstruct the incident angle of γ via the regressions process.**
 - XGBoost: Fast training, to prevent overtraining.
 - **arXiv:1603.02754**
- Co-working with Junlee Kim (Jeonbuk National Univ.)

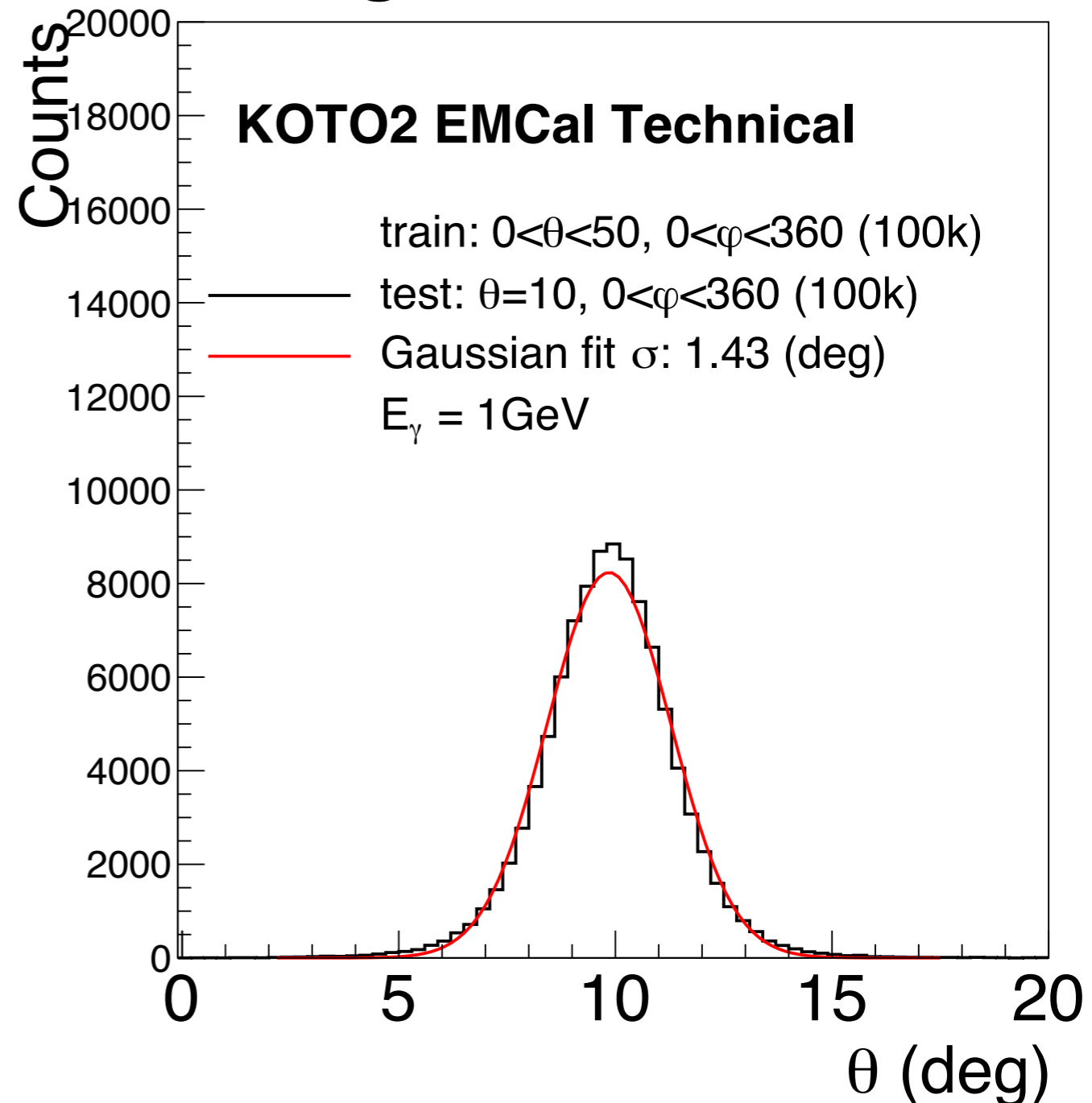
Angle Reconstruction via ML

- Input: detector responses (EM showers) from the Geant4
 - Deposit energy in each channel
- Output: the incident angle

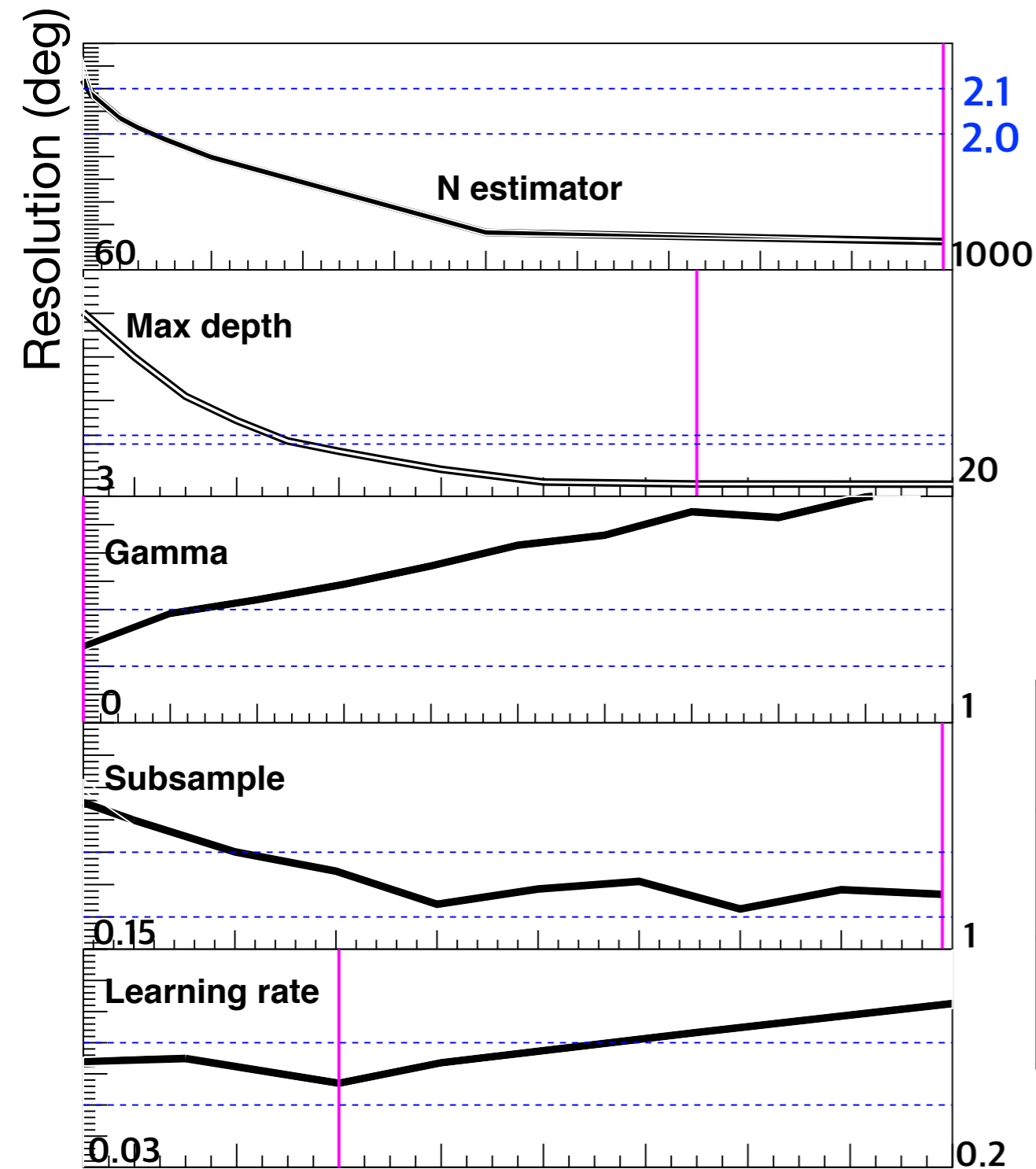
$$\theta = \text{atan} \left(\sqrt{(\Delta x / \Delta z)^2 + (\Delta y / \Delta z)^2} \right)$$

- Training
 - Training input: Detector responses + Target (true angle)
 - Training time: a few minutes to a few hours for 100k
- Reconstruction test
 - Test input: Detector responses
 - Test output: incident angle (prediction)
 - Test time: a few seconds for 100k

Angle Reconstruction



ML Parameters Setting



----- Y axis from 2.0 to 2.1

We scanned ML parameters from the default values.

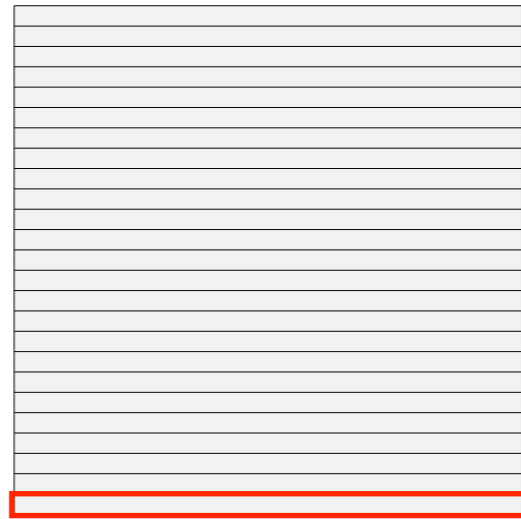
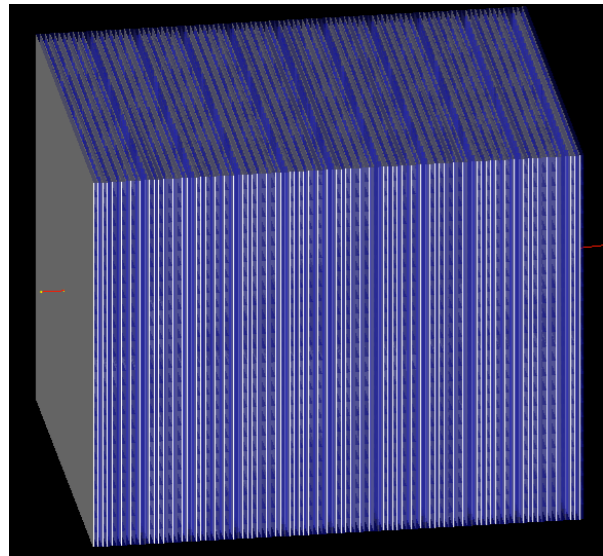
→ Finding a setup of the best angular resolution value

| Variable | N estimator | max depth | Gamma | Subsample | Learning rate |
|-----------------------|-------------|-----------|-------|-----------|---------------|
| Selected Value | 1000 | 15 | 0 | 1 | 0.08 |
| Default Value | 100 | 7 | 0 | 1 | 0.08 |

Detector Optimization: Scintillator Width

105 layers

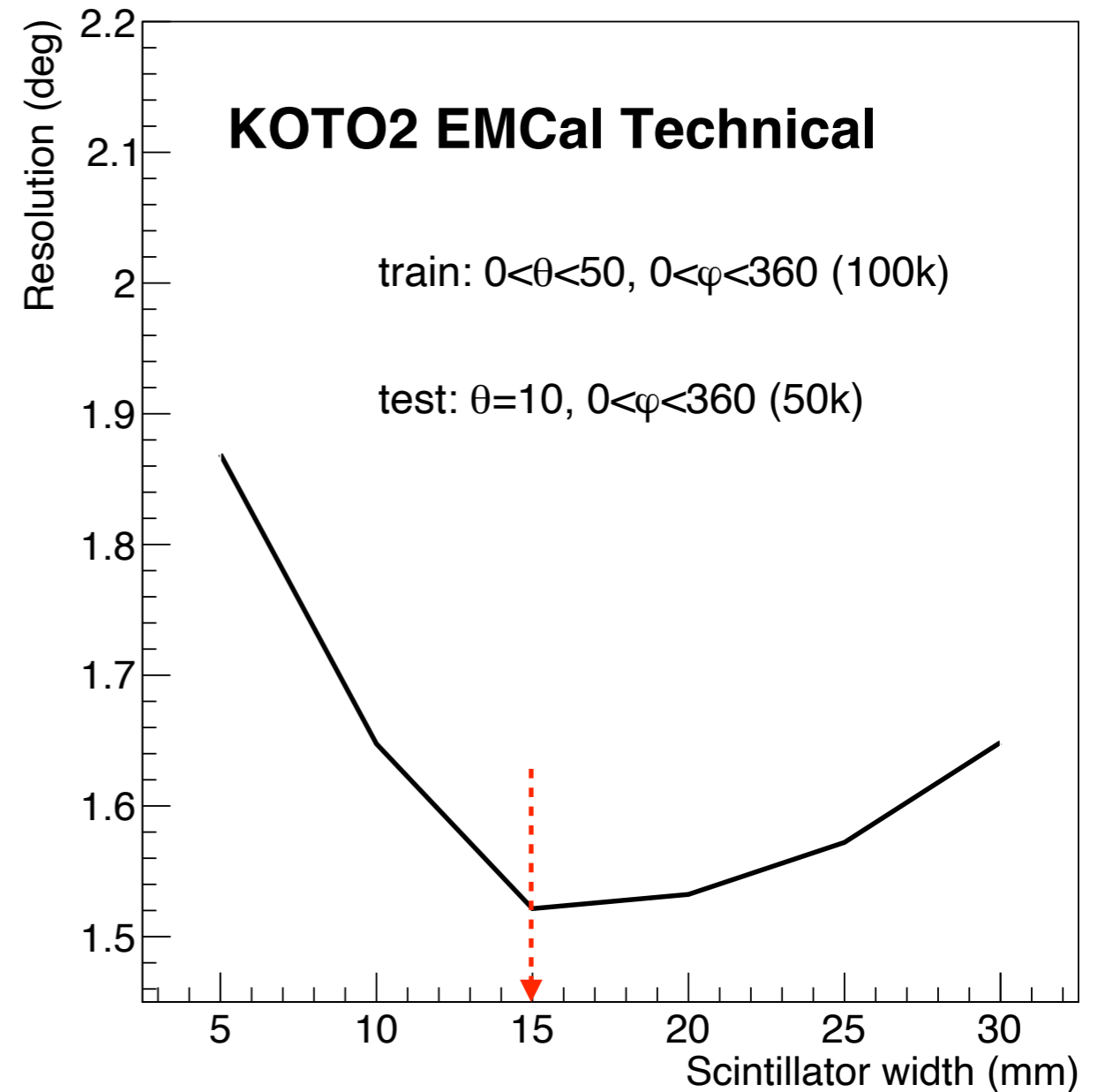
Single scintillator layer



Scintillator Segment

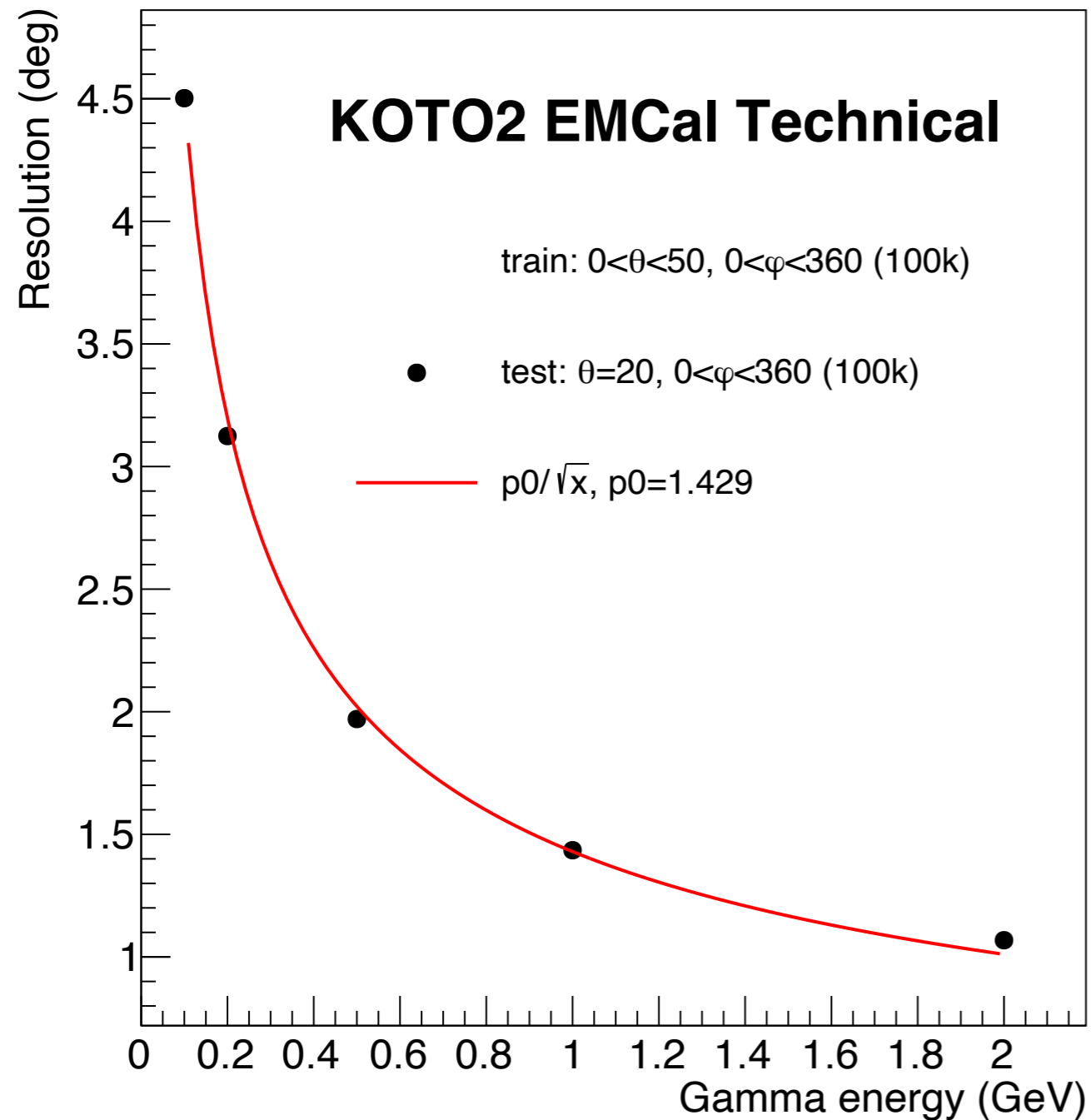


Scintillator width



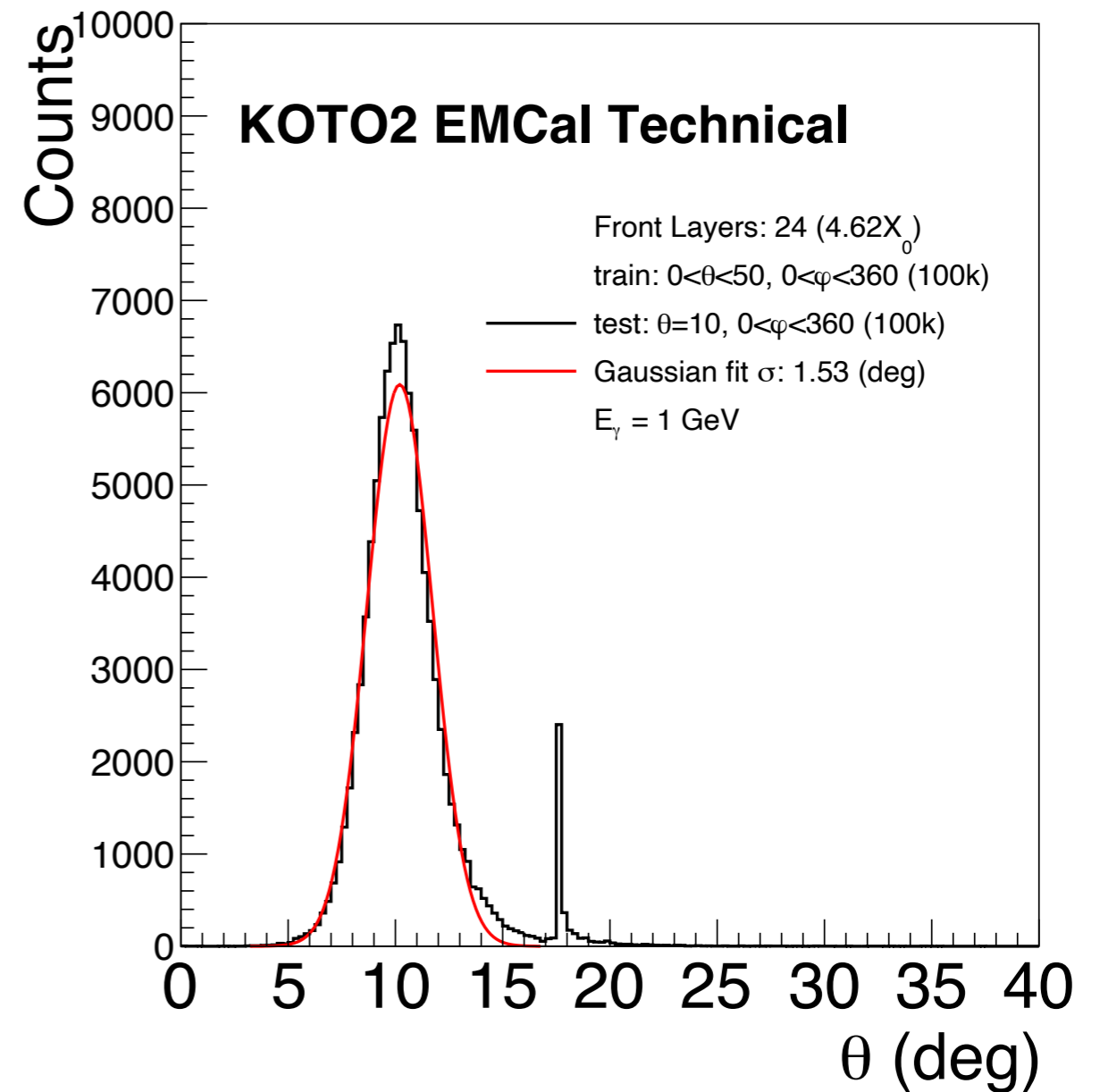
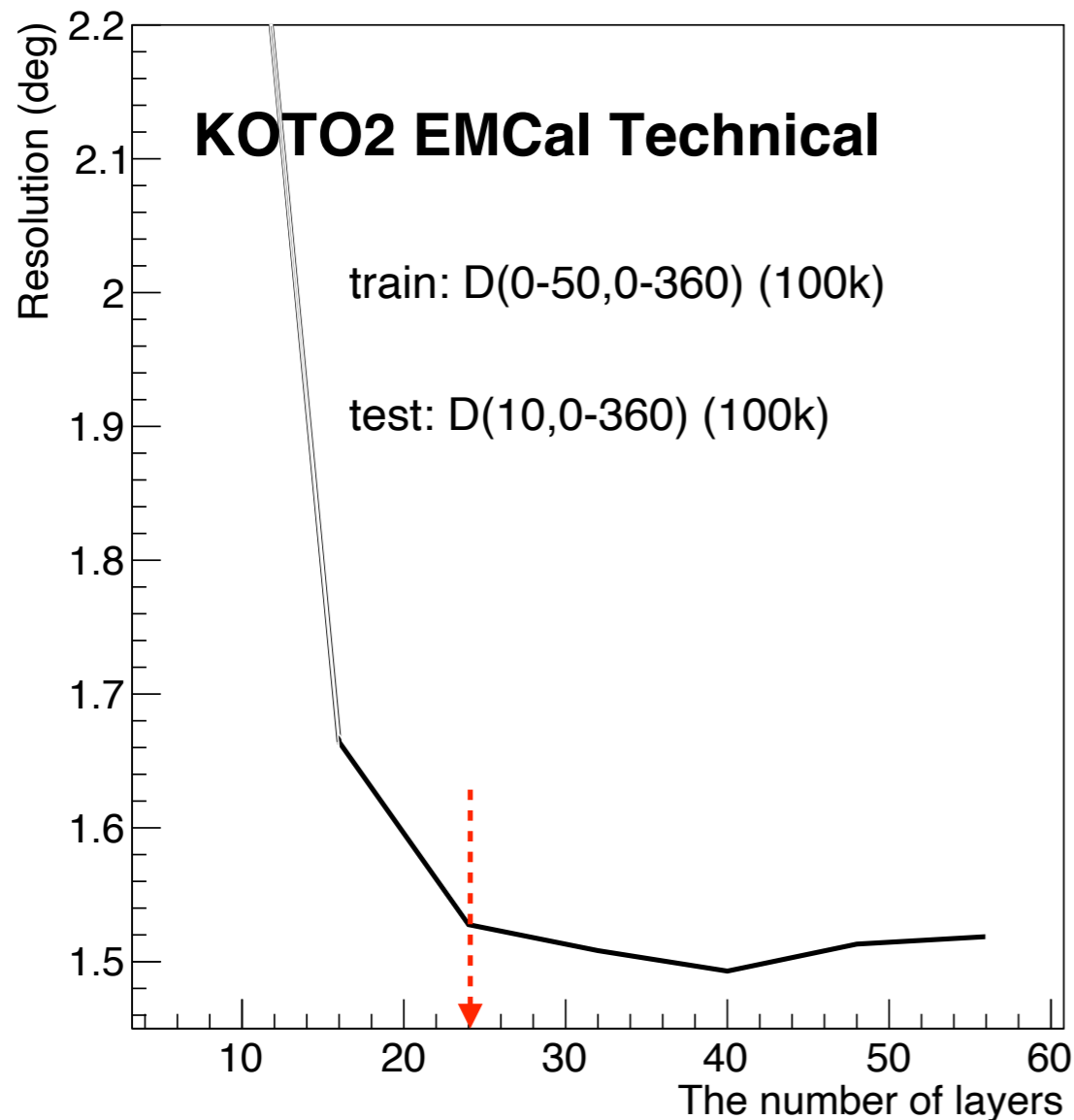
- Width of each segment: **15 mm** (from 20 mm) with 1.5° angular resolution.

Energy Dependency of ML Results



- The angular resolution is proportional to $1/\sqrt{E}$
- The angular resolution is estimated to be 1.4° at 1 GeV

Detector Optimization: The Number of Front Layers



- The angle reconstruction with only front part of the detector
- Front **24 layers** (total 105 layers) are enough to reconstruct the incident angle.
- Radiation length: **$4.6 X_0$** (total $20 X_0$) with **1.5°** angular resolution and **3%** inefficiency

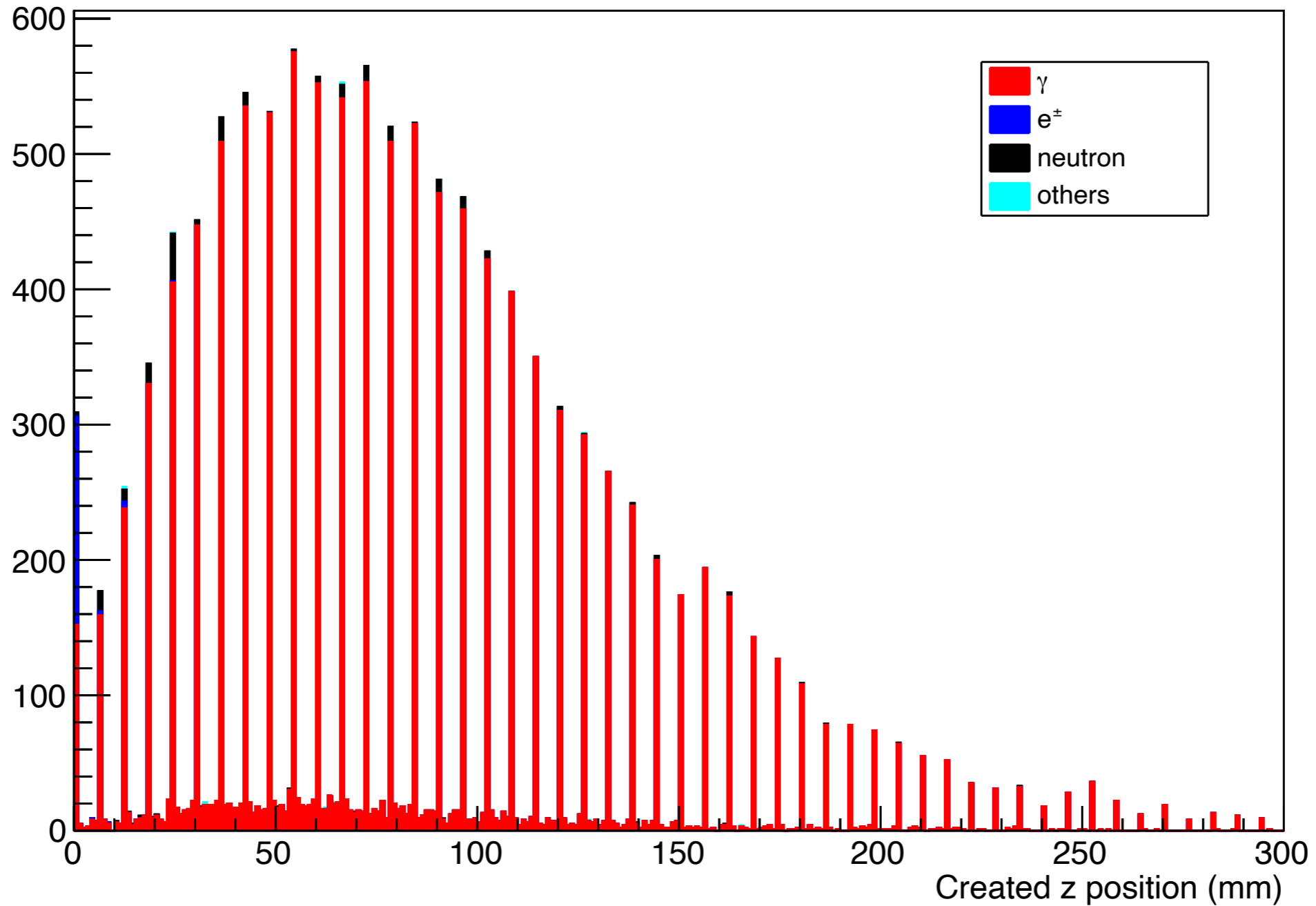
Conclusions

- We have been developing a sampling calorimeter for gamma tracking.
- We have checked several detector properties:
 - $R_M = 7$ cm, visible ratio = 34%, $\sigma_E/E = 4\%$ at 1 GeV
 - The sampling calorimeter is comparable with pure CsI for the accidental loss from backplash particles.
- Angle reconstruction and Detector optimization:
 - A machine learning toolkit XGBoost is utilized for this study.
 - We have determined training parameters of XGBoost setup.
 - We have improved a geometry of the gamma tracking detector with the training setup
 - **15 mm for scintillator width**
 - **24 layers ($4.6X_0$) from 105 layers ($20X_0$)**
 - We have achieved **1.5° angular resolution with 3% inefficiency**.
- Future plan:
 - Study with scintillating fiber + tungsten configuration
 - Hardware production and test

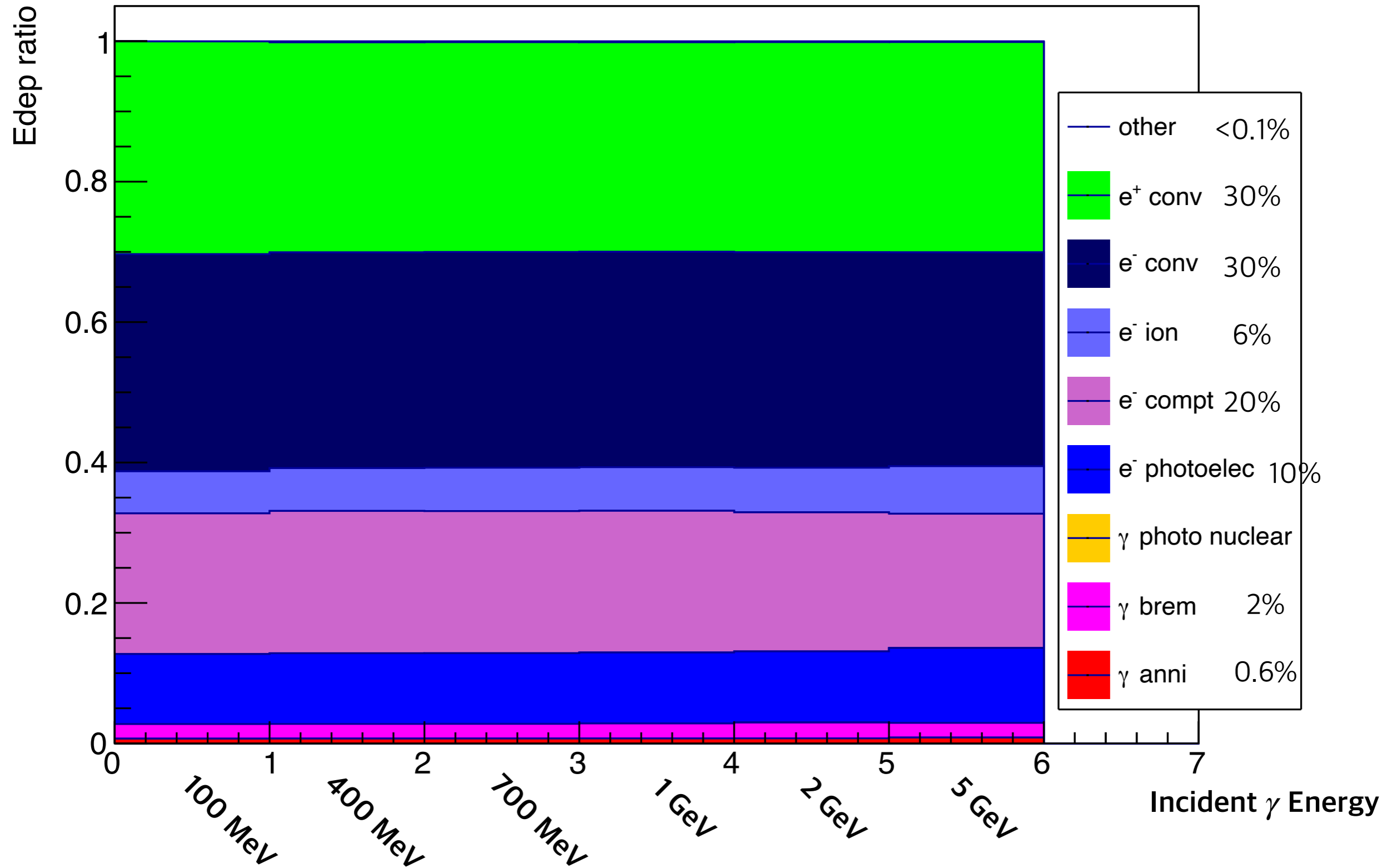
Backup

Creation position of backsplash particles

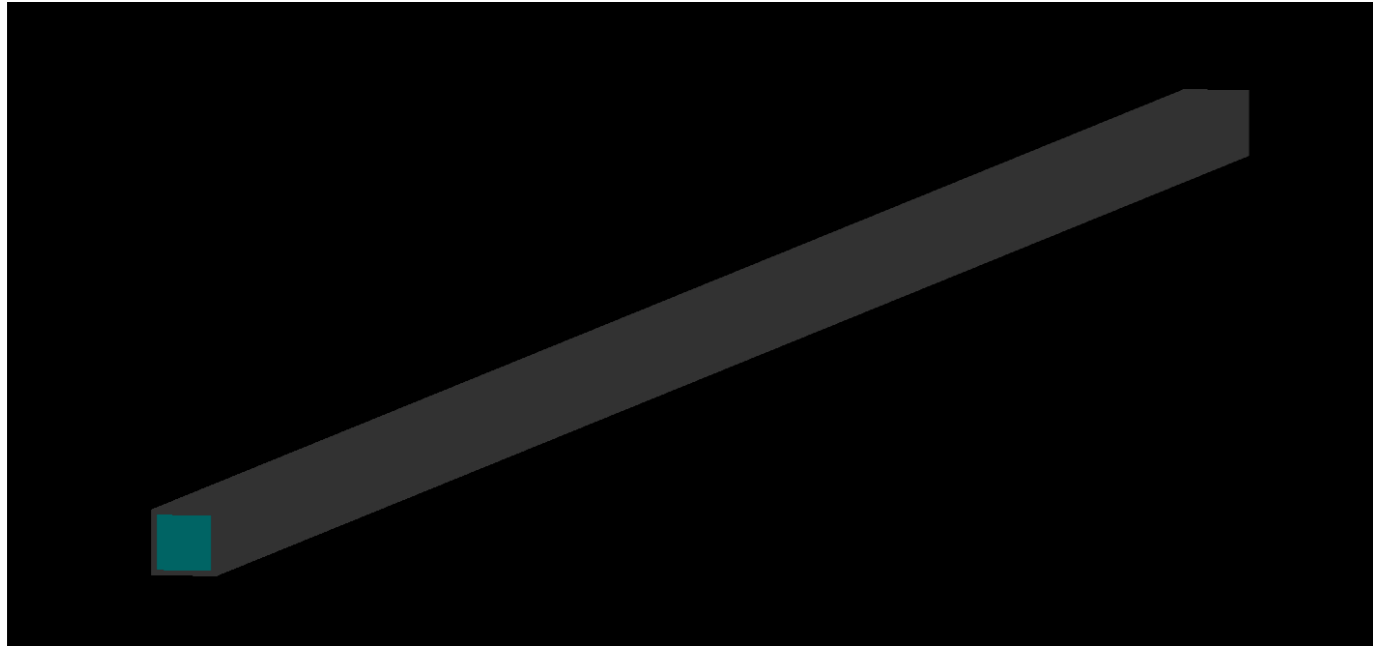
1 GeV Incident γ



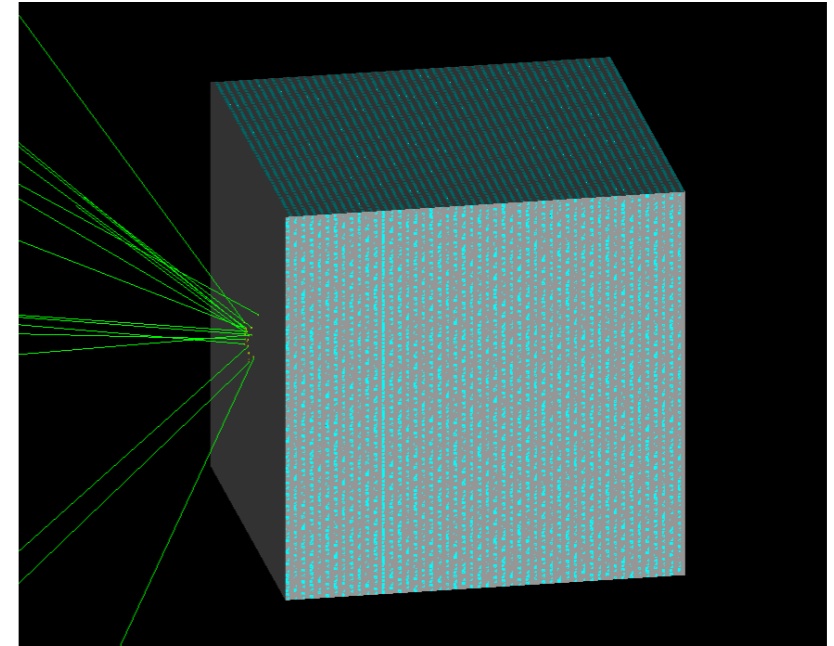
E_{dep} creation process



Pipe Type Design



Single segment



100 scintillators \times 100 layers

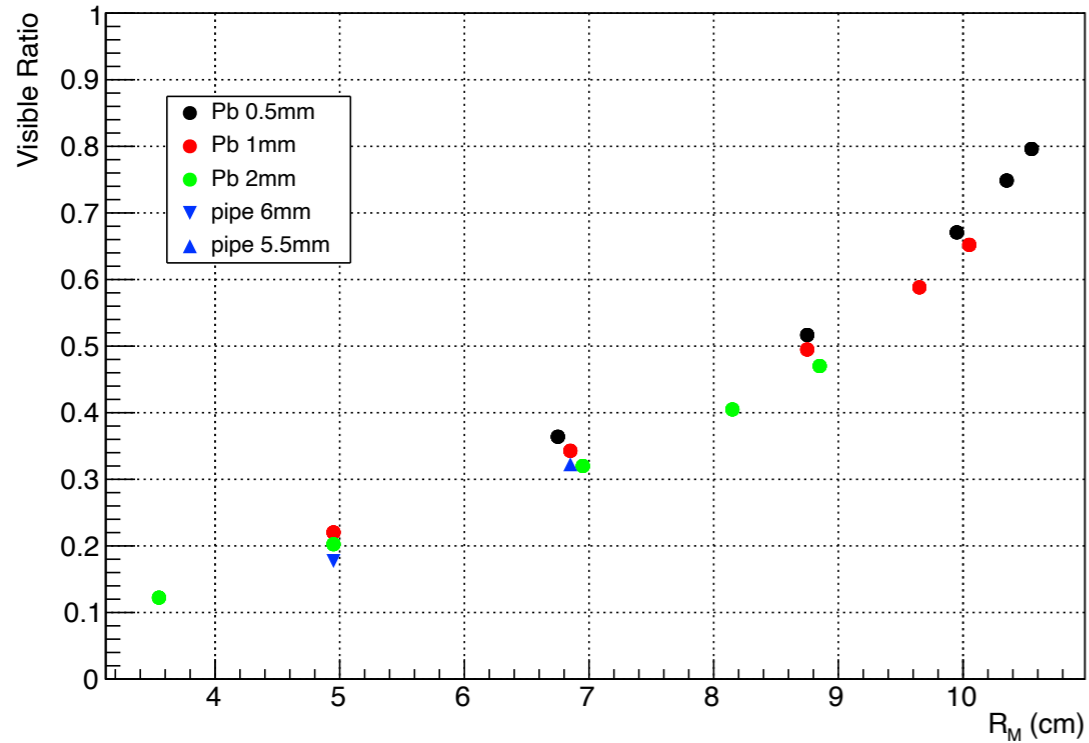
Design 1

Lead : 6 mm x 6 mm x 60 cm
Scintillator: 5 mm x 5 mm x 60 cm

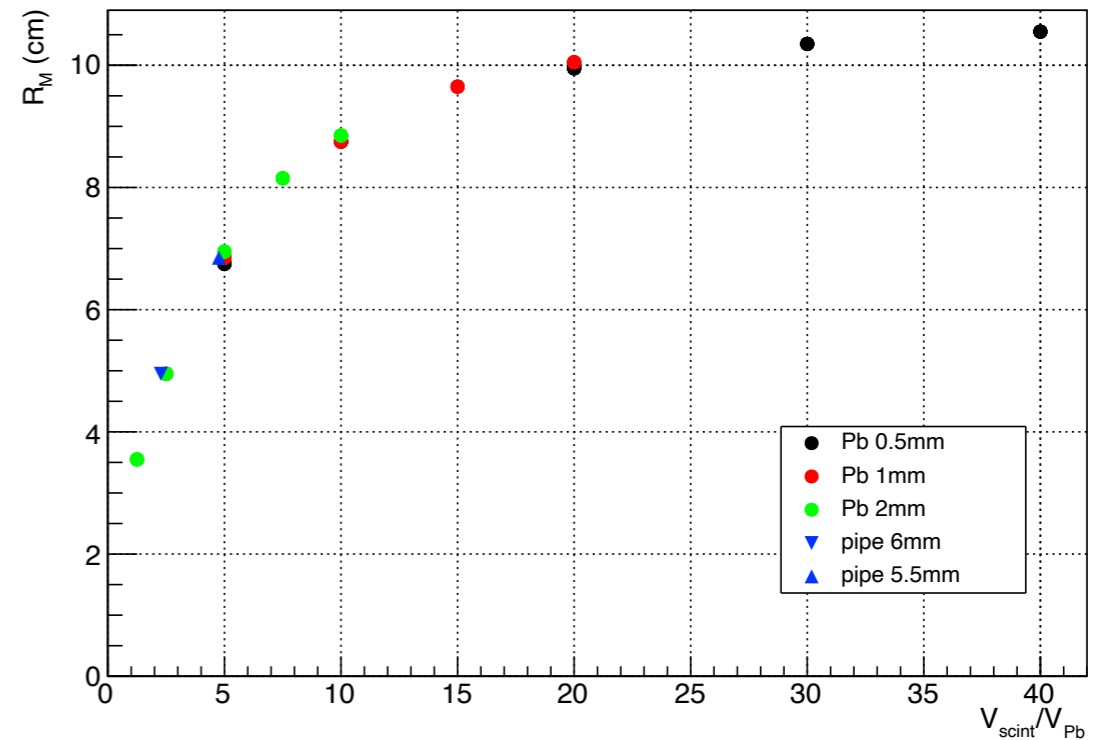
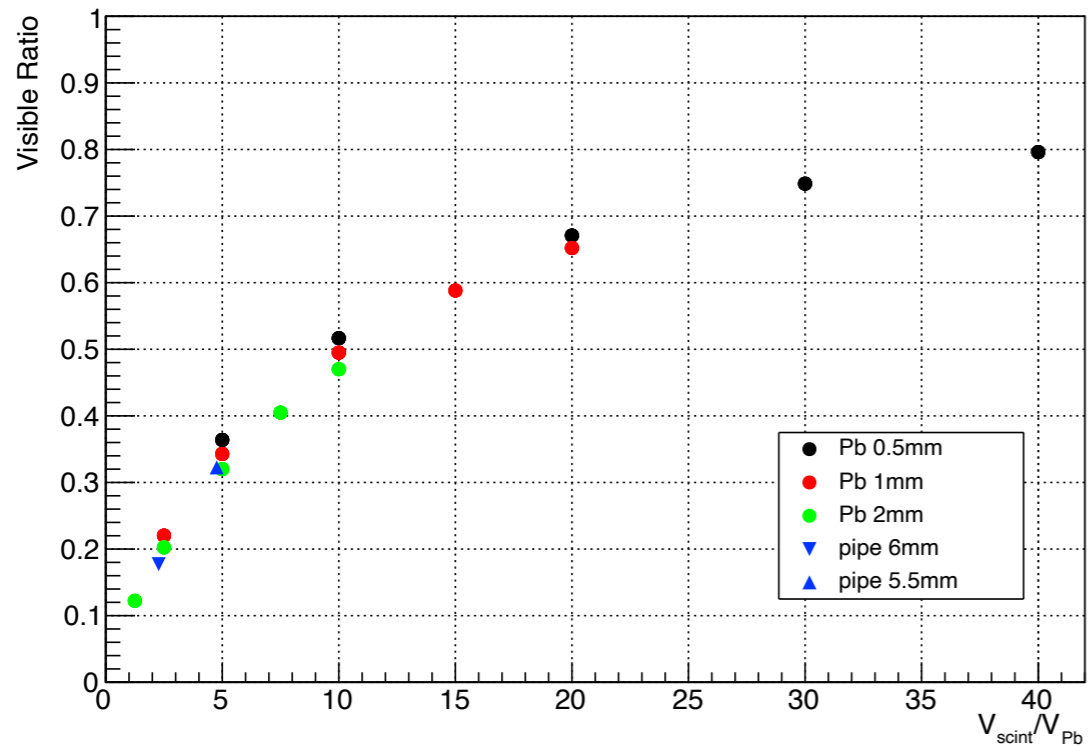
Design 2

Lead : 5.5 mm x 5.5 mm x 55 cm
Scintillator: 5 mm x 5 mm x 55 cm

Pipe Type and Volume Ratio Dependency

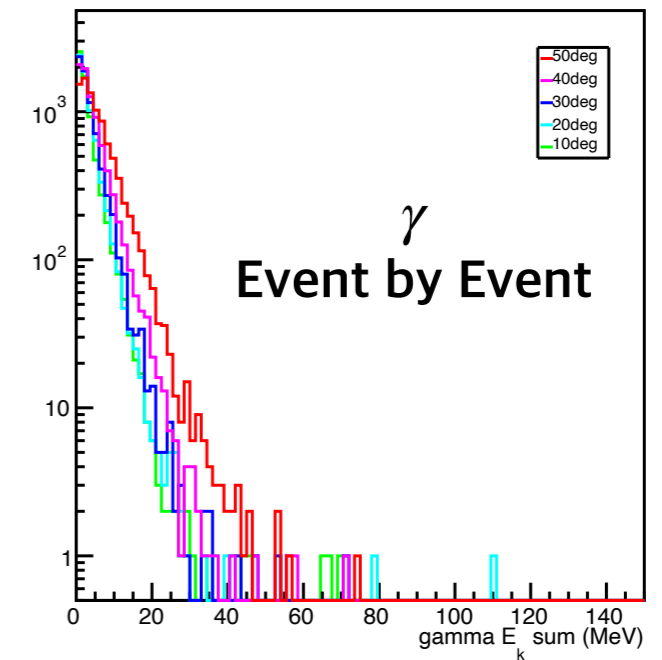
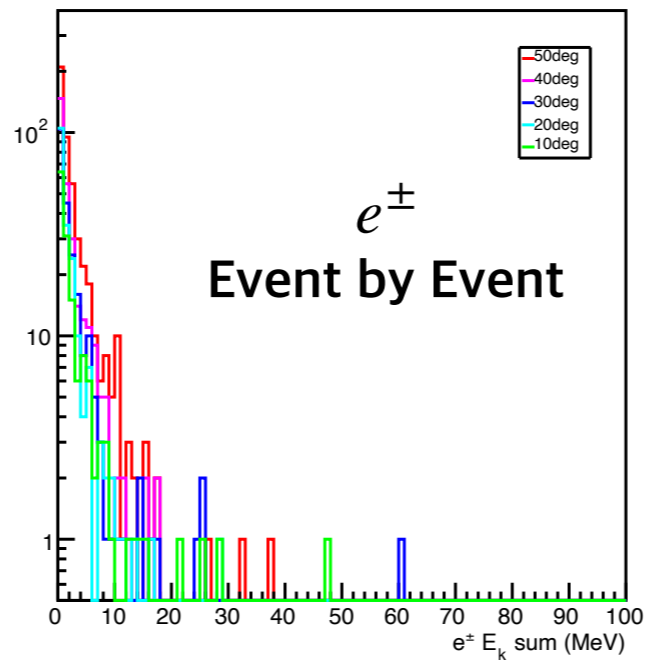
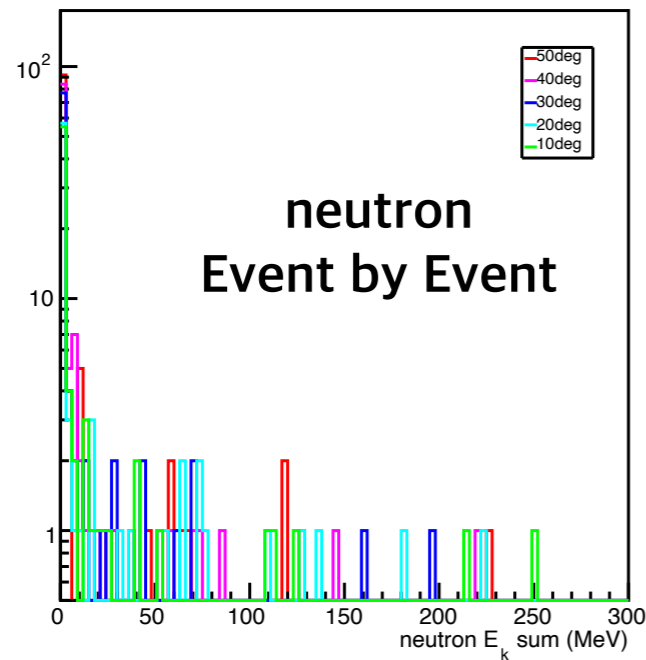
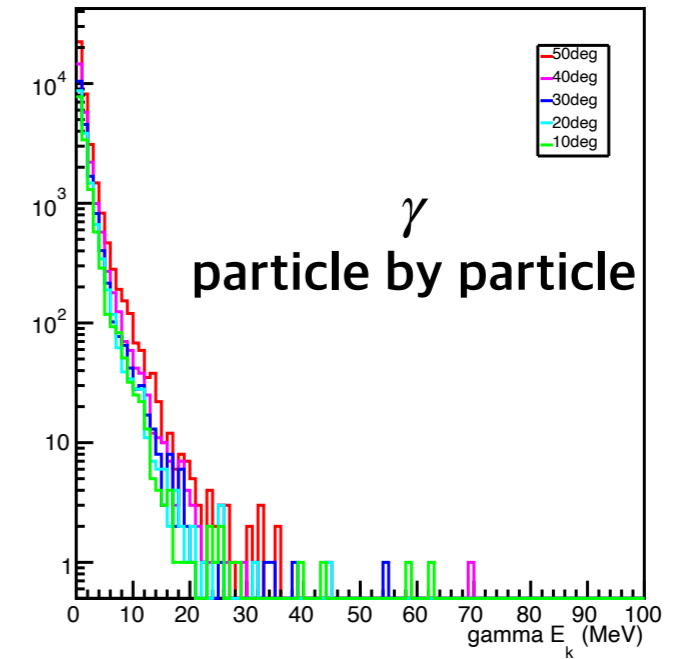
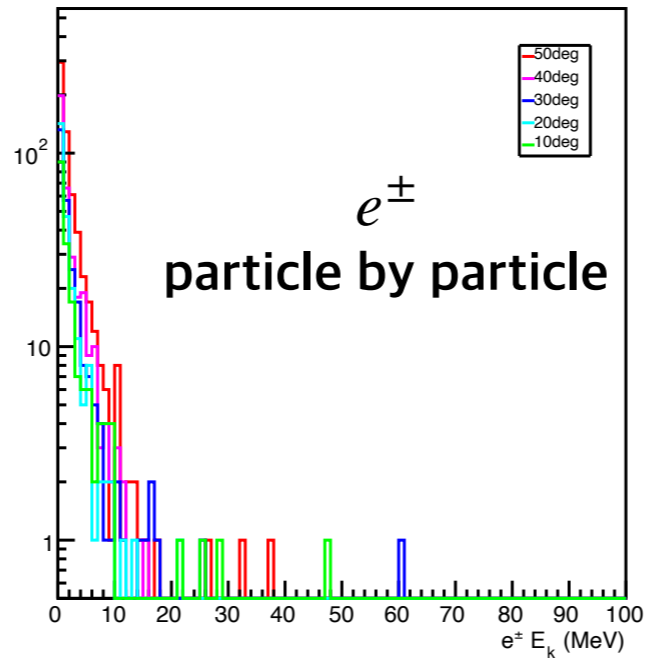
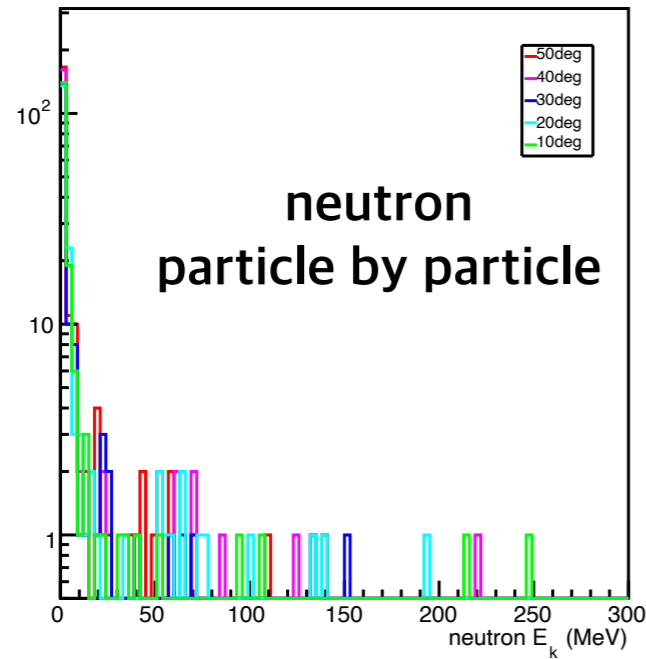


- There is no meaningful improvement in different geometrical configuration



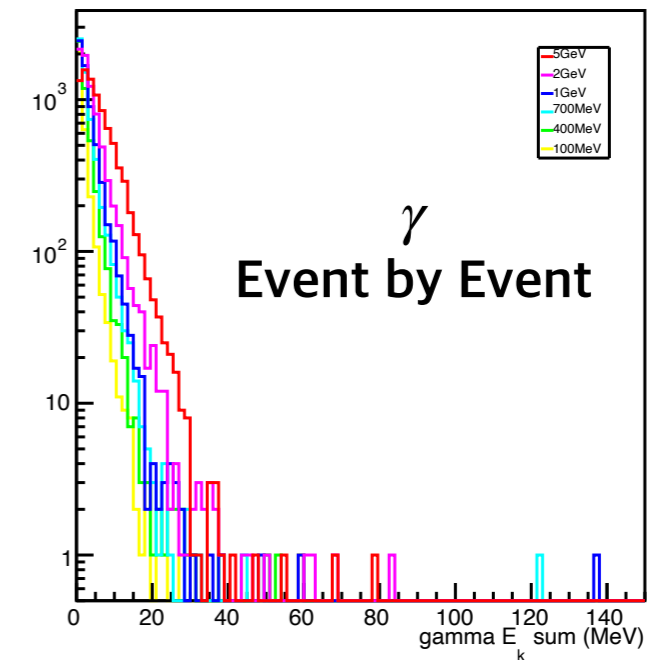
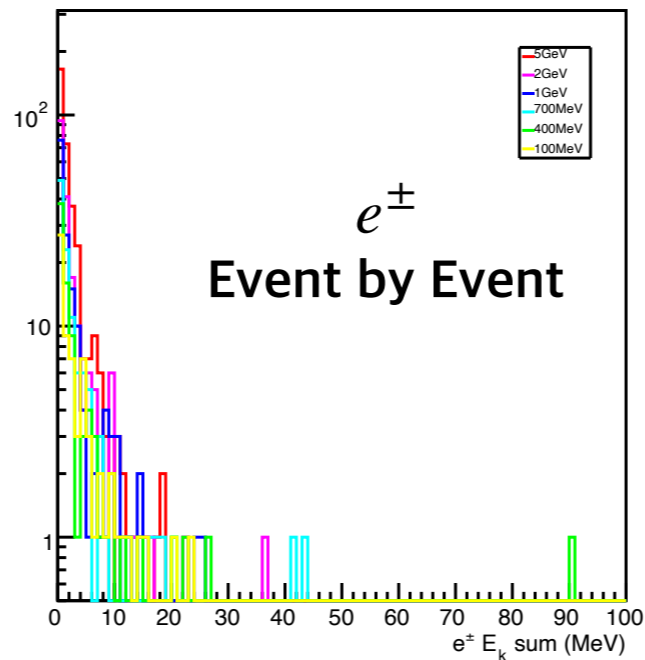
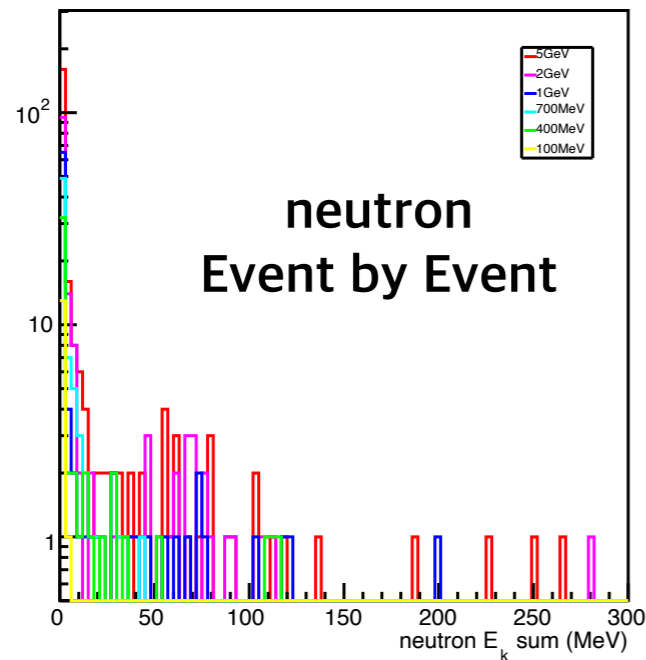
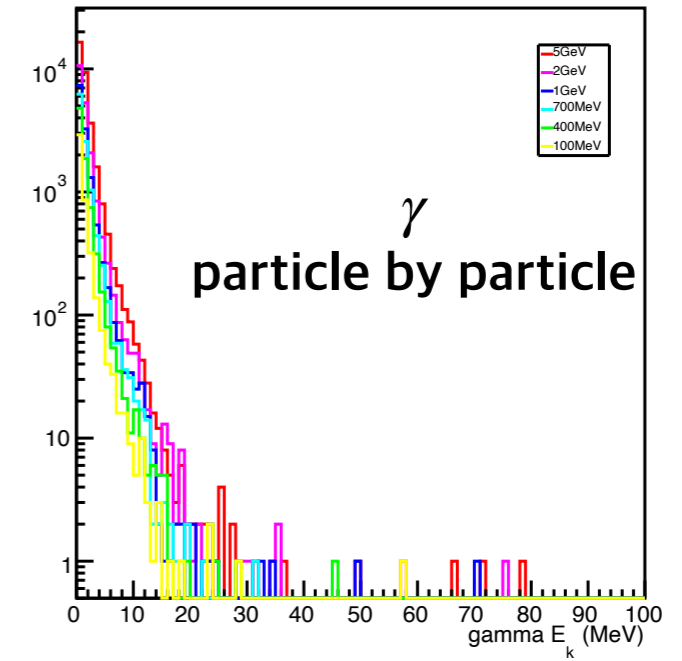
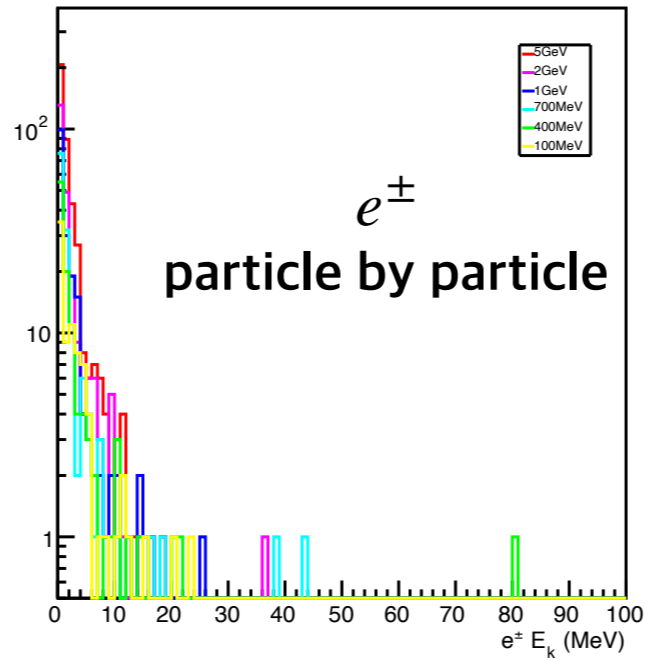
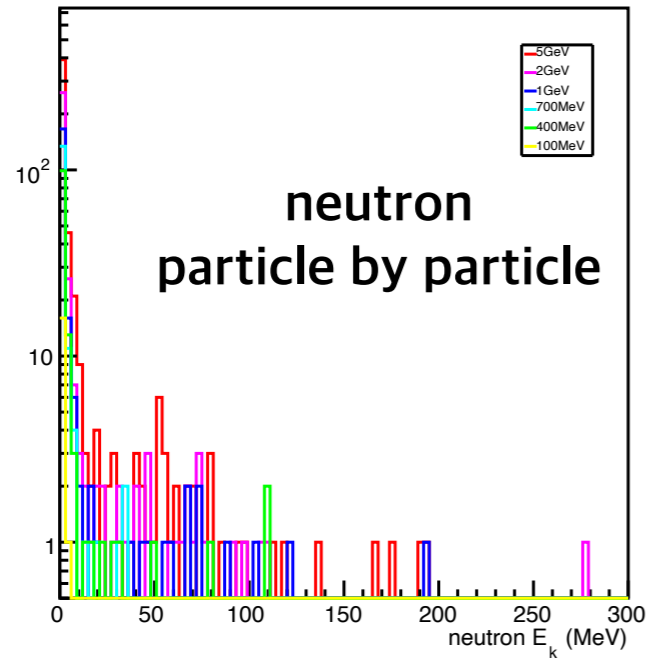
Backsplash particle energy distribution

1 GeV incident γ , incident angle dependence



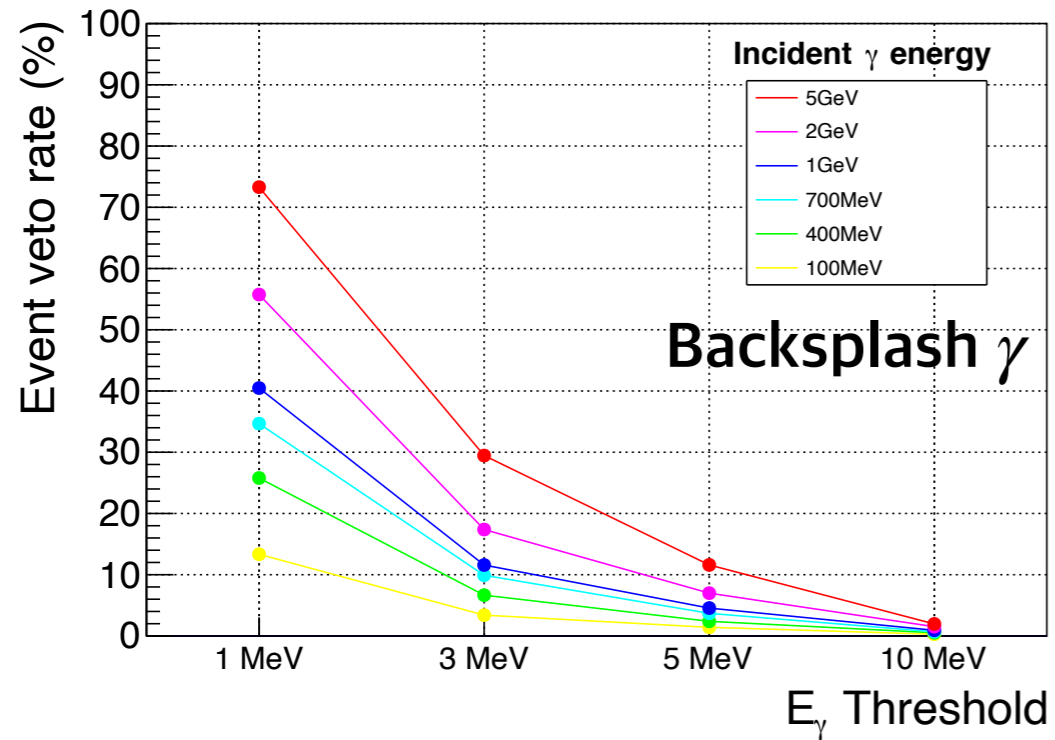
Backsplash particle energy distribution

Incident energy dependence

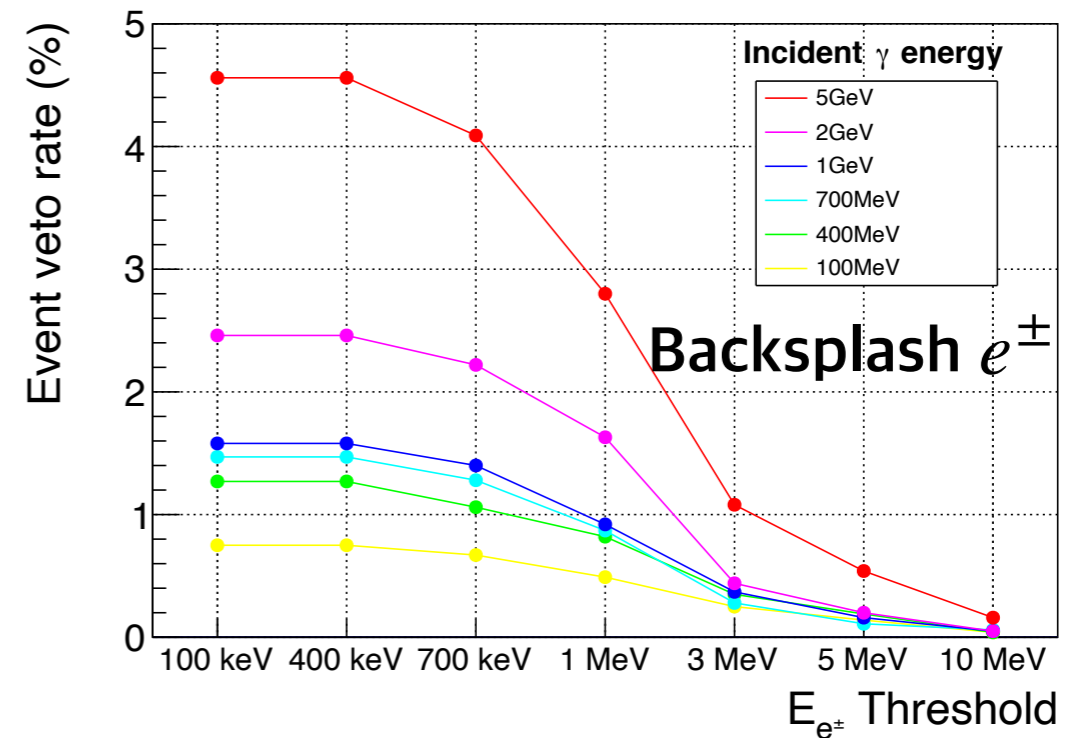
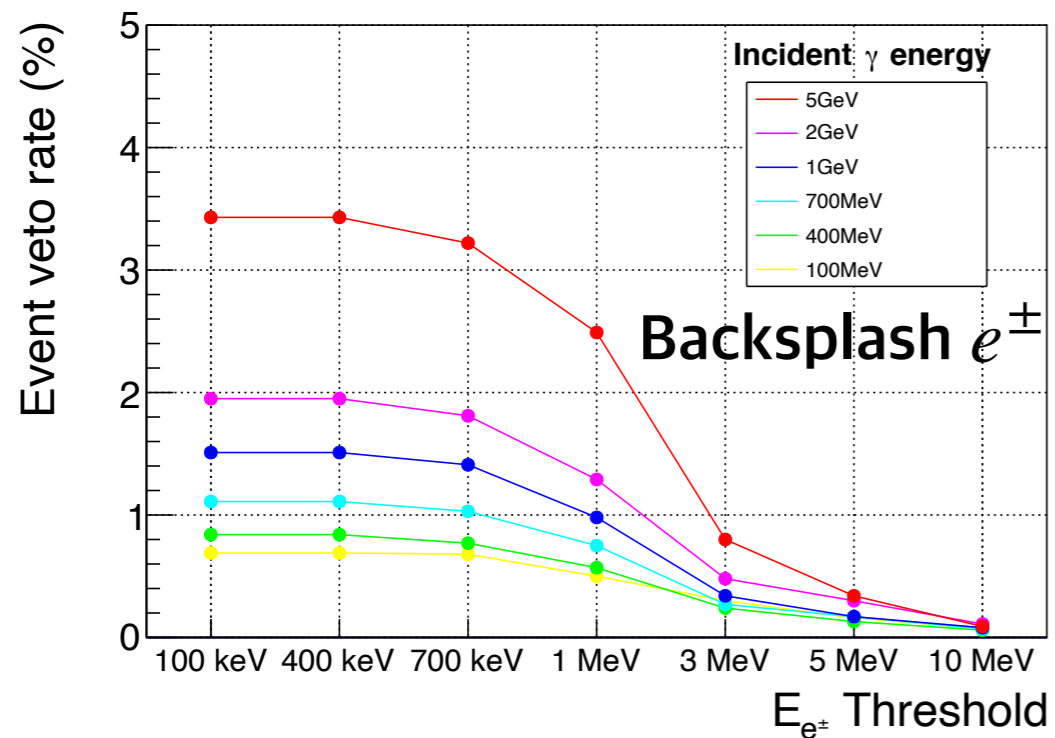
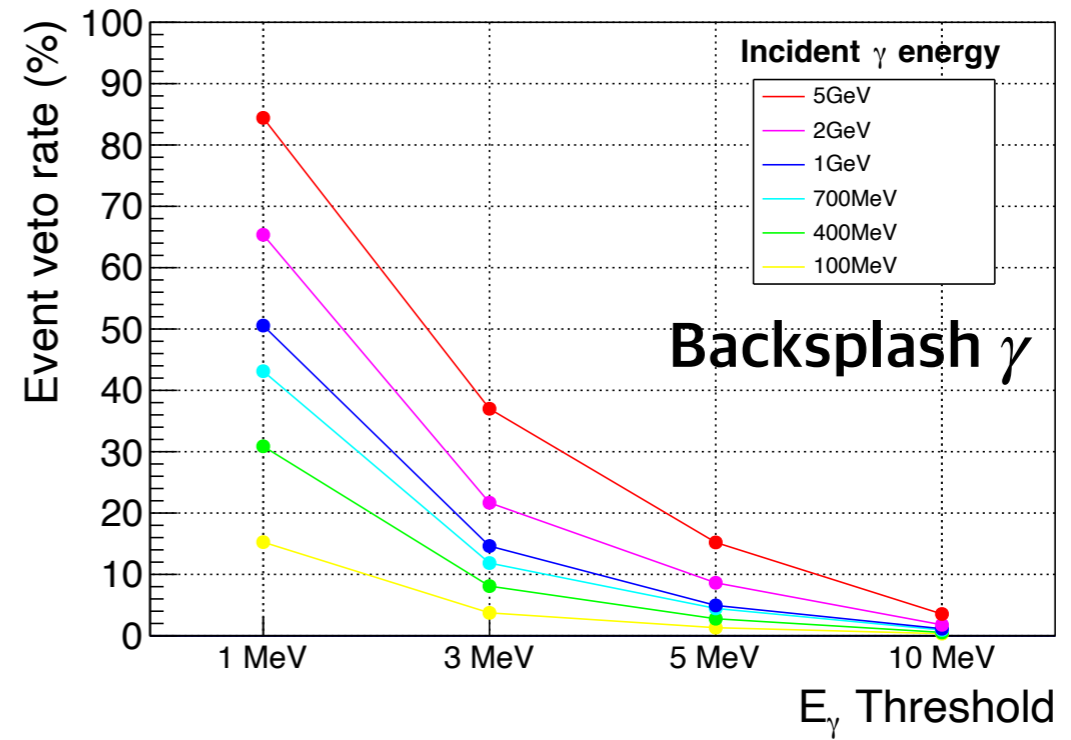


Event veto rate: $N_{\gamma/e^\pm} \geq 1$

Sampling Calorimeter

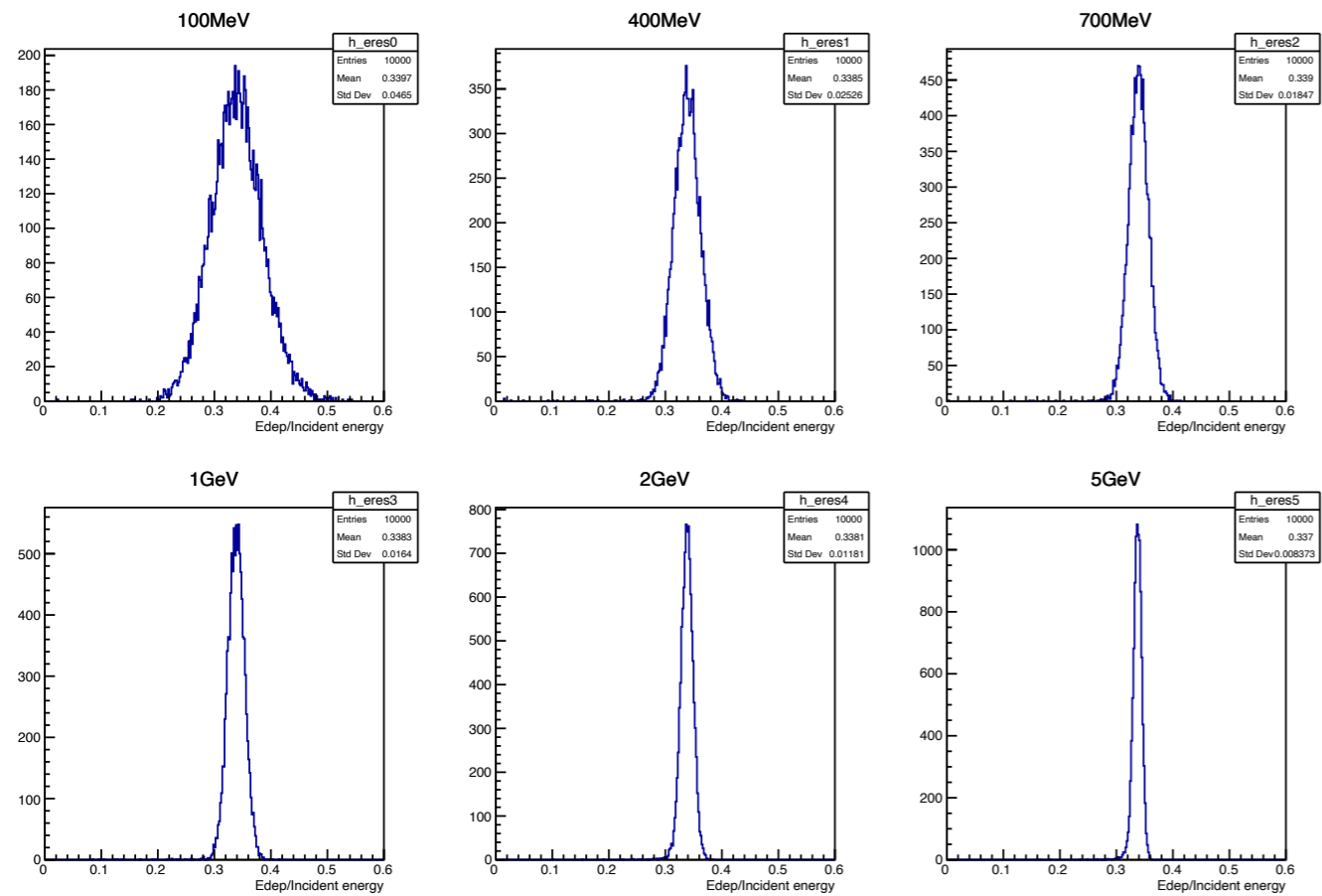


CsI Calorimeter

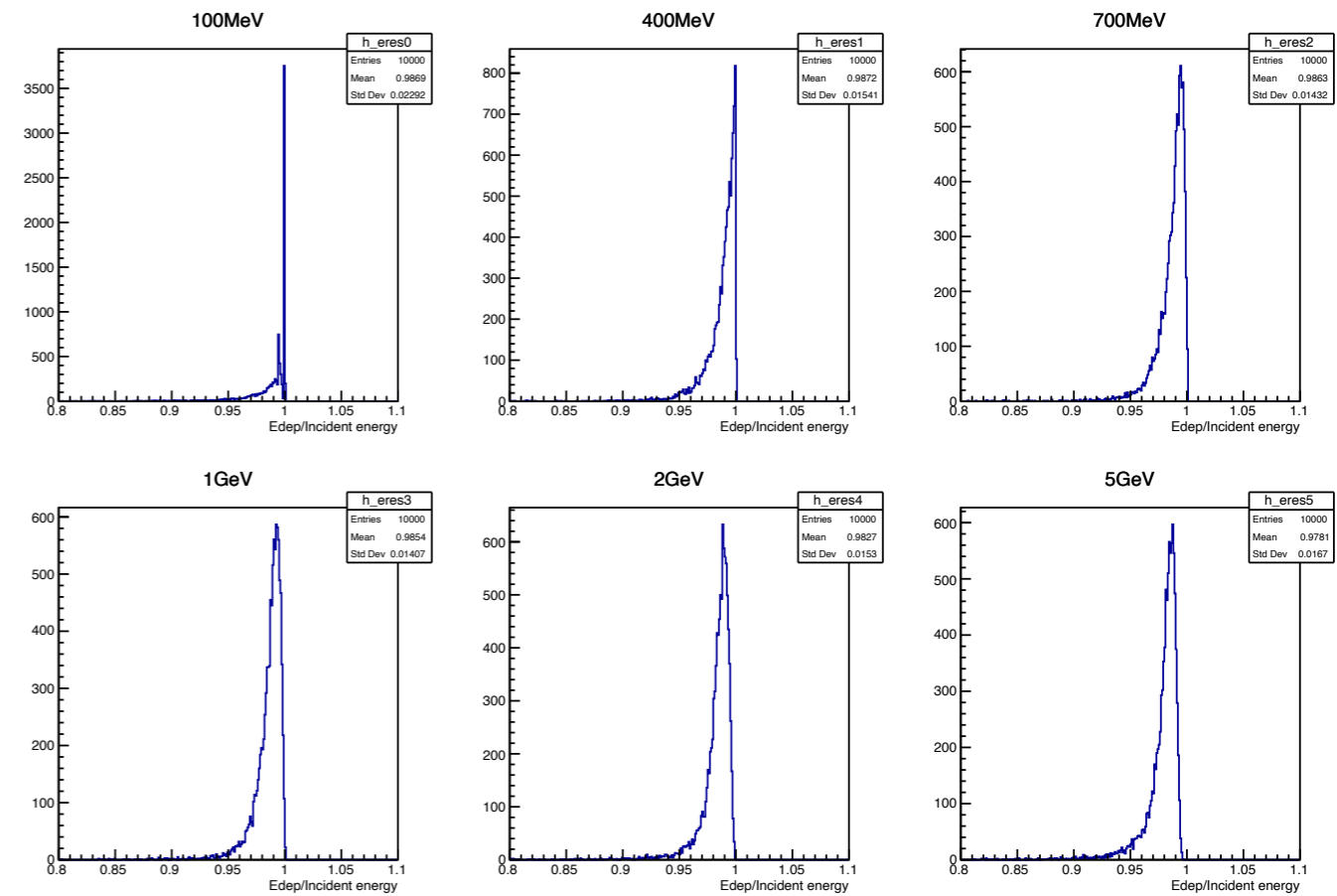


Energy deposit distribution

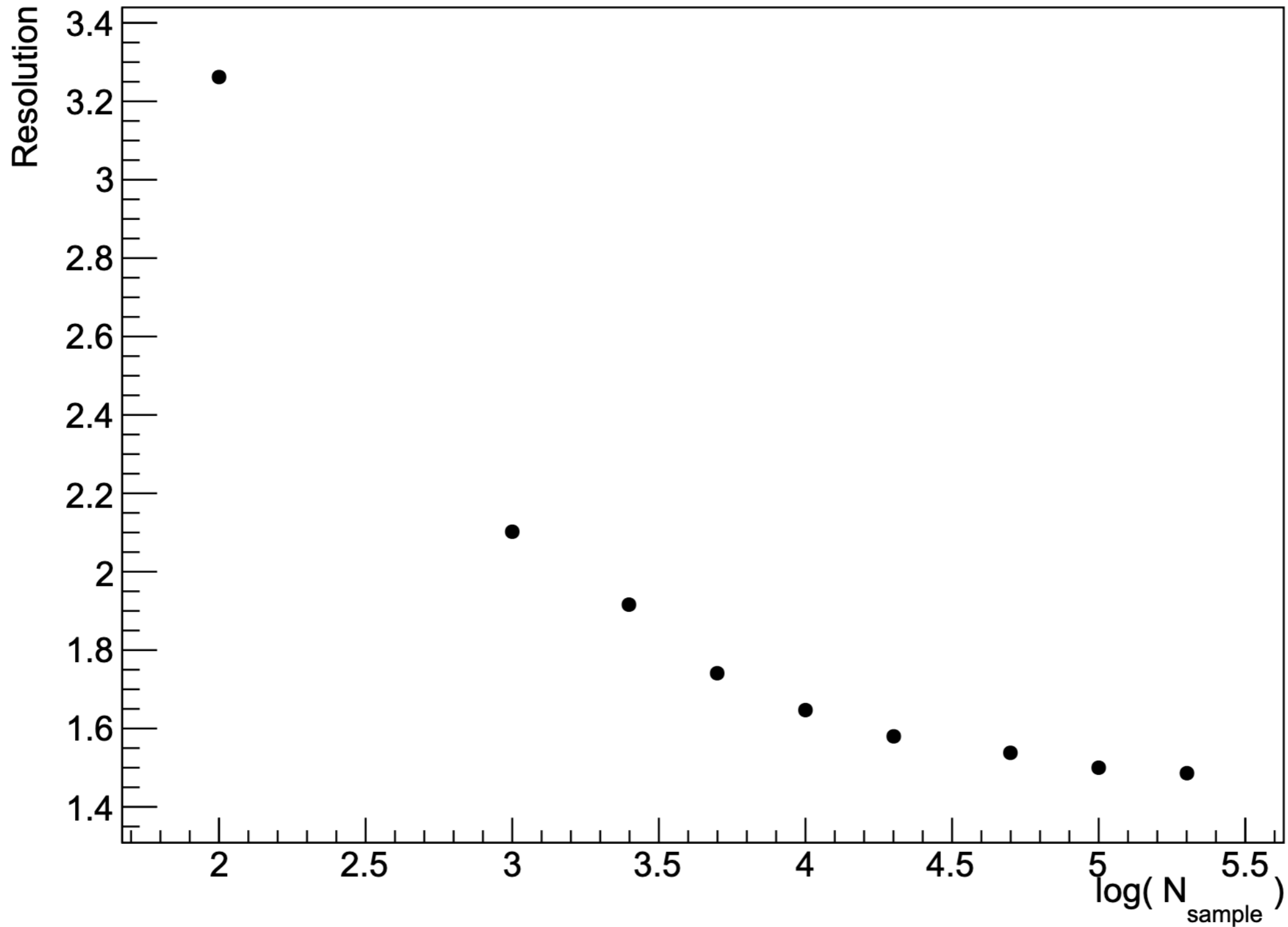
Sampling Detector



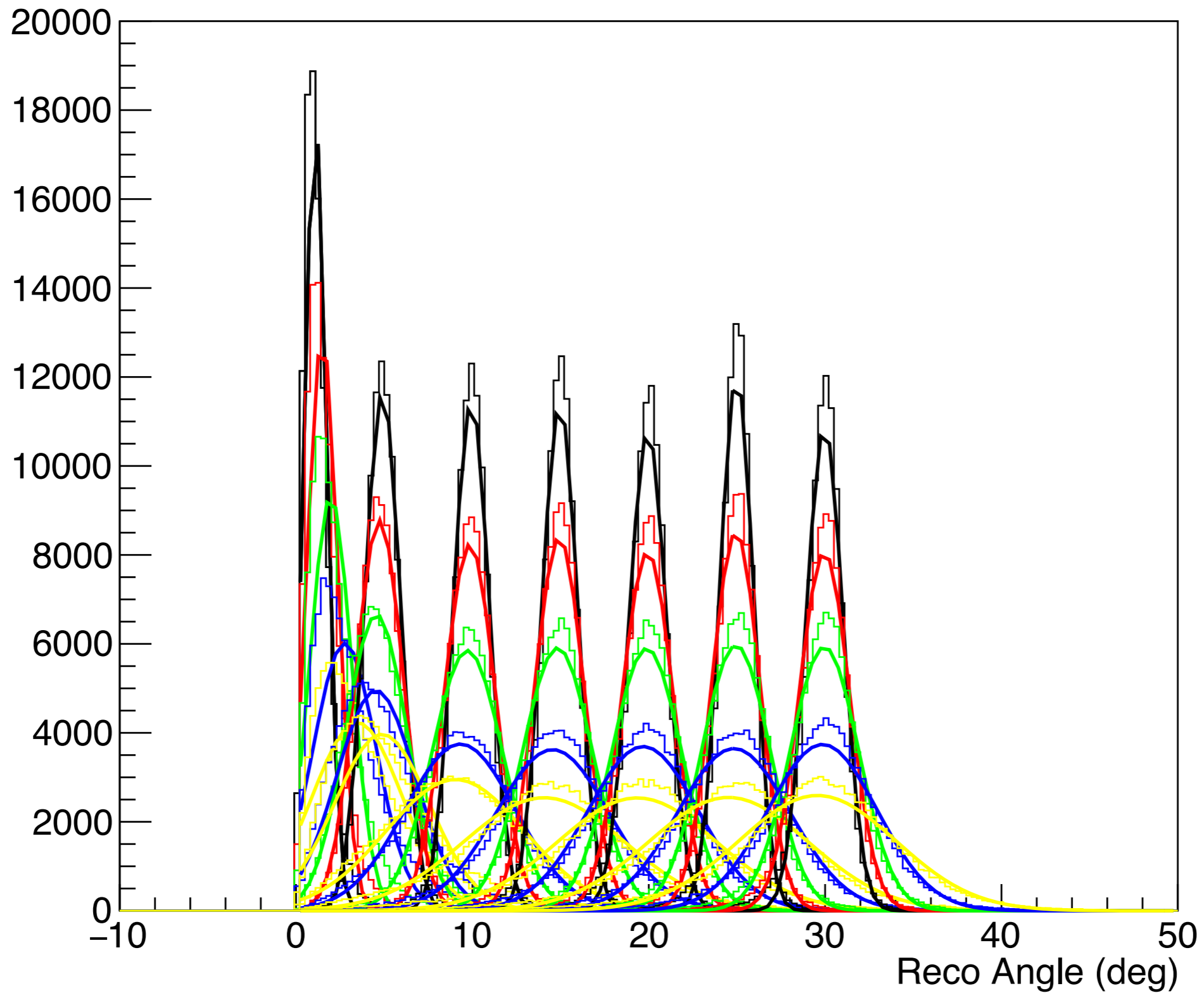
CsI Detector



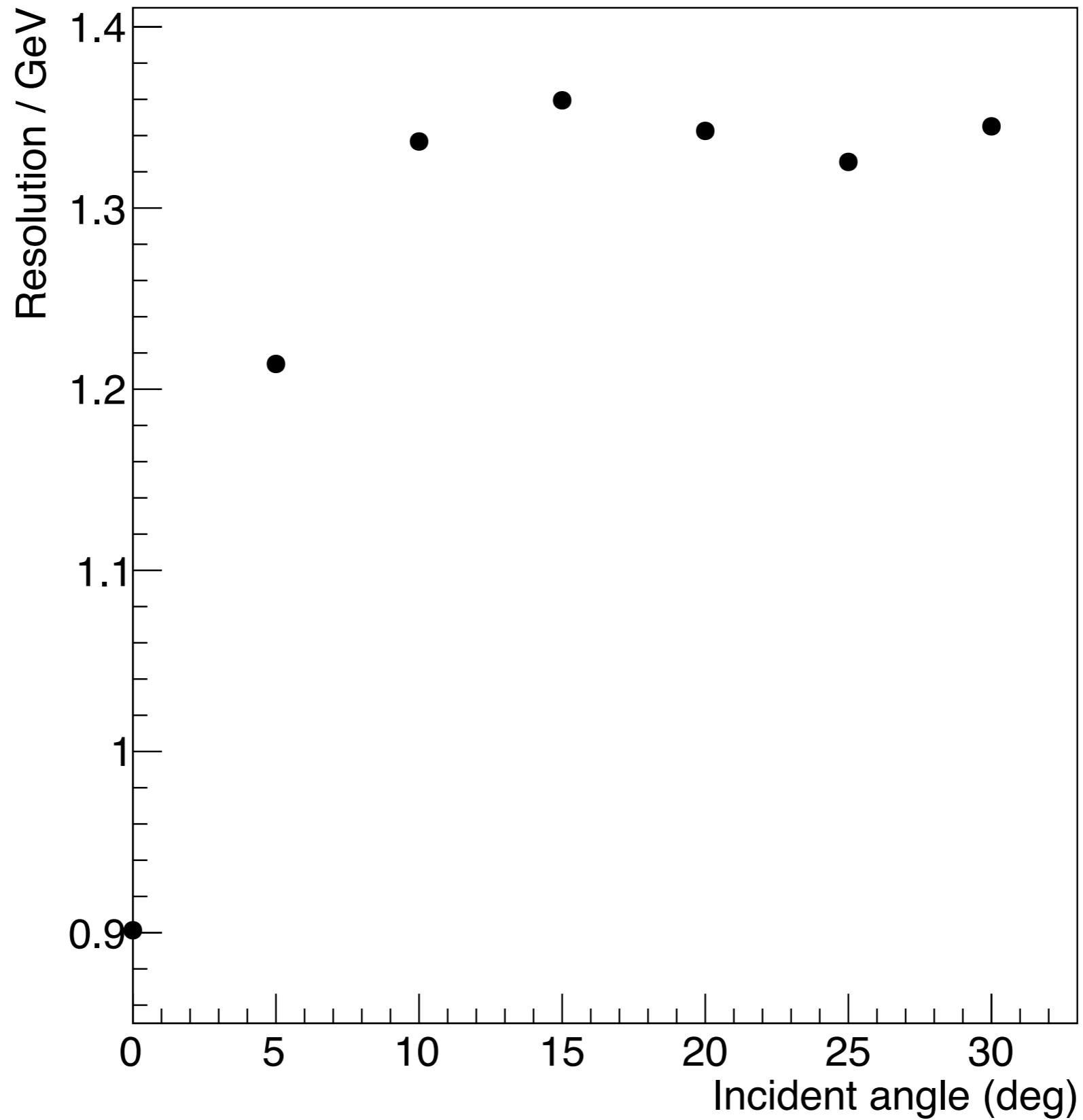
Number of training samples



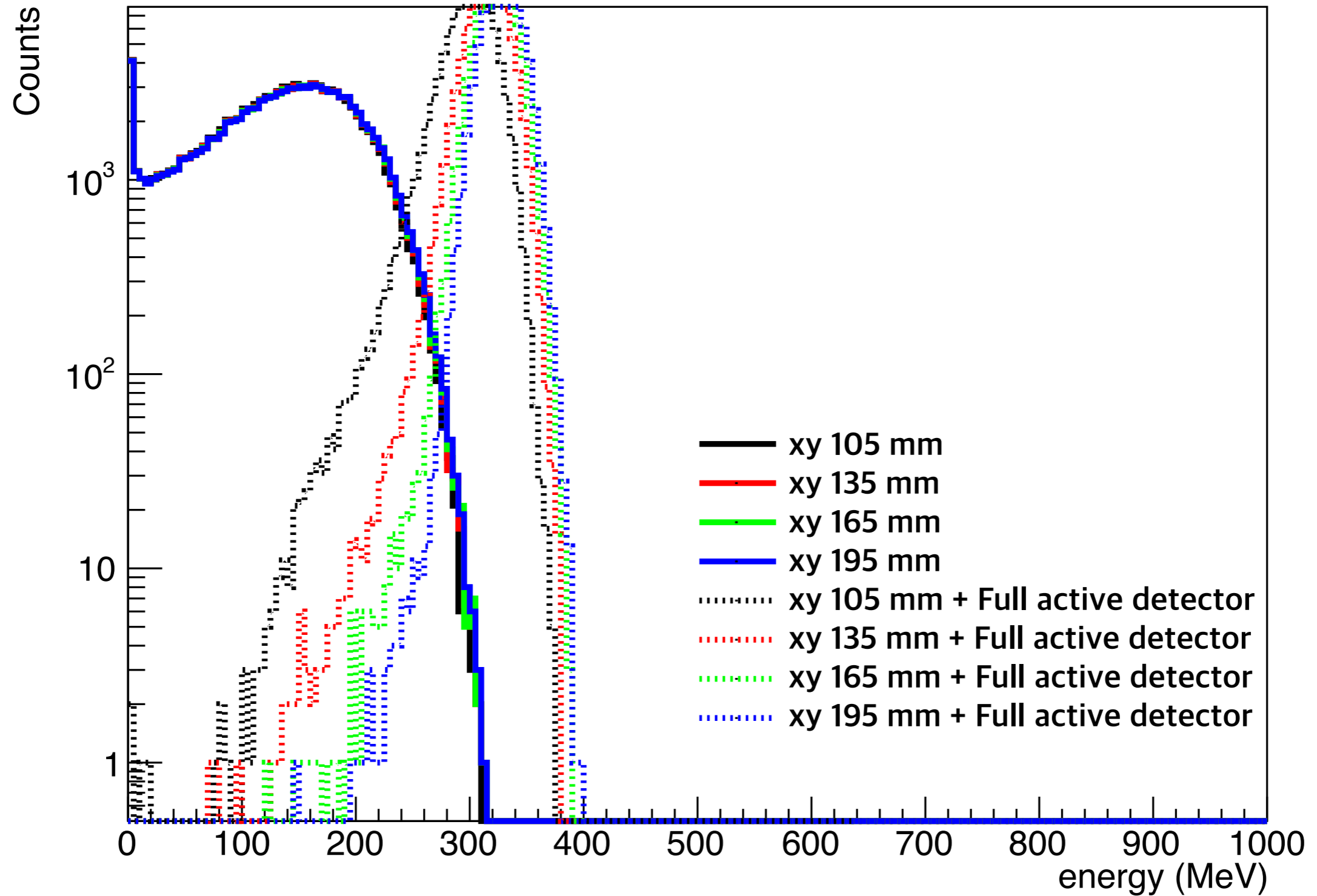
ML test at different E and angle



Angular resolution depending on incident angle and energy

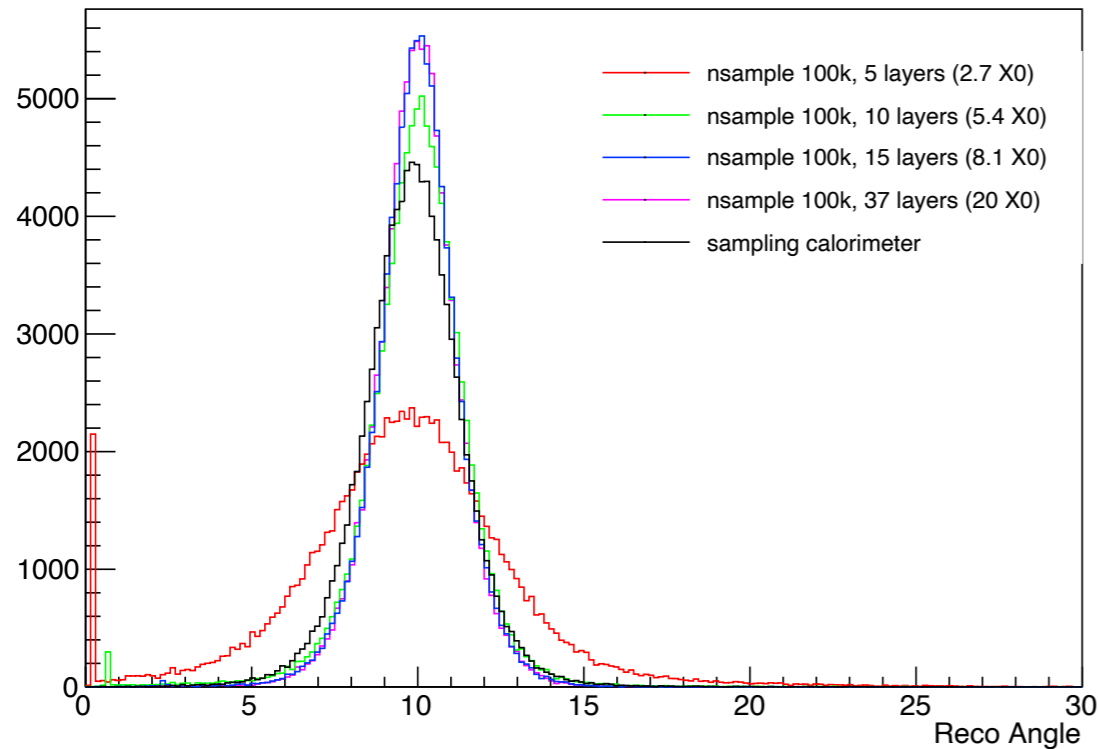


XY length reduction

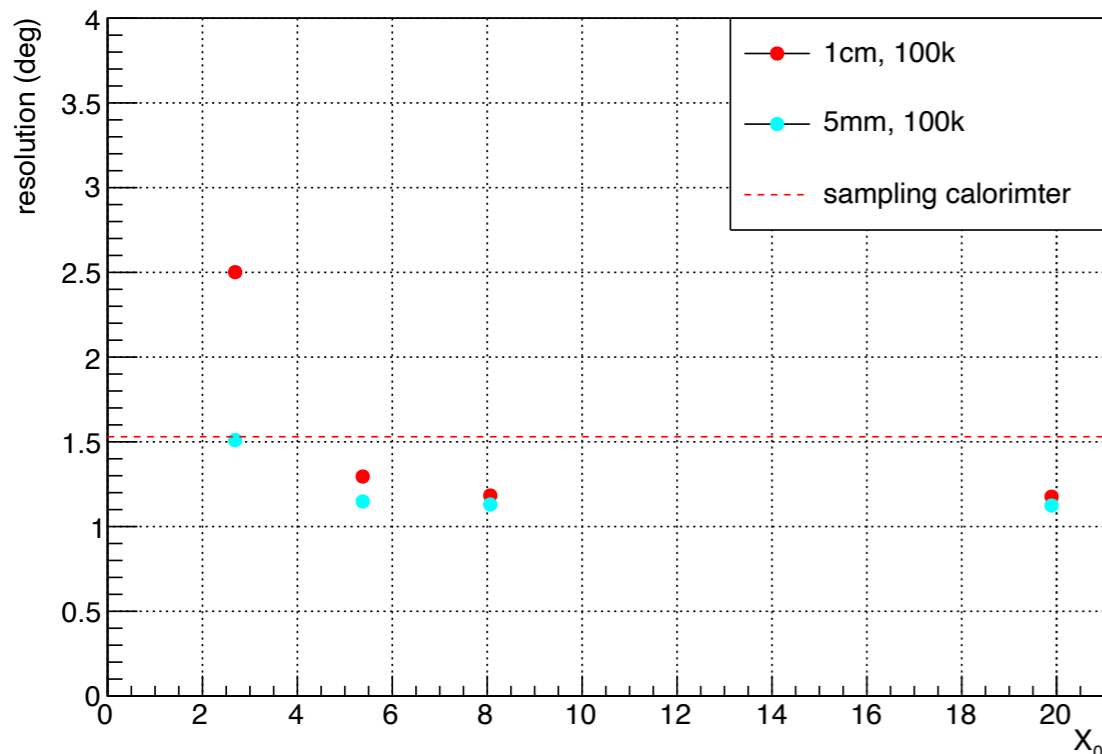
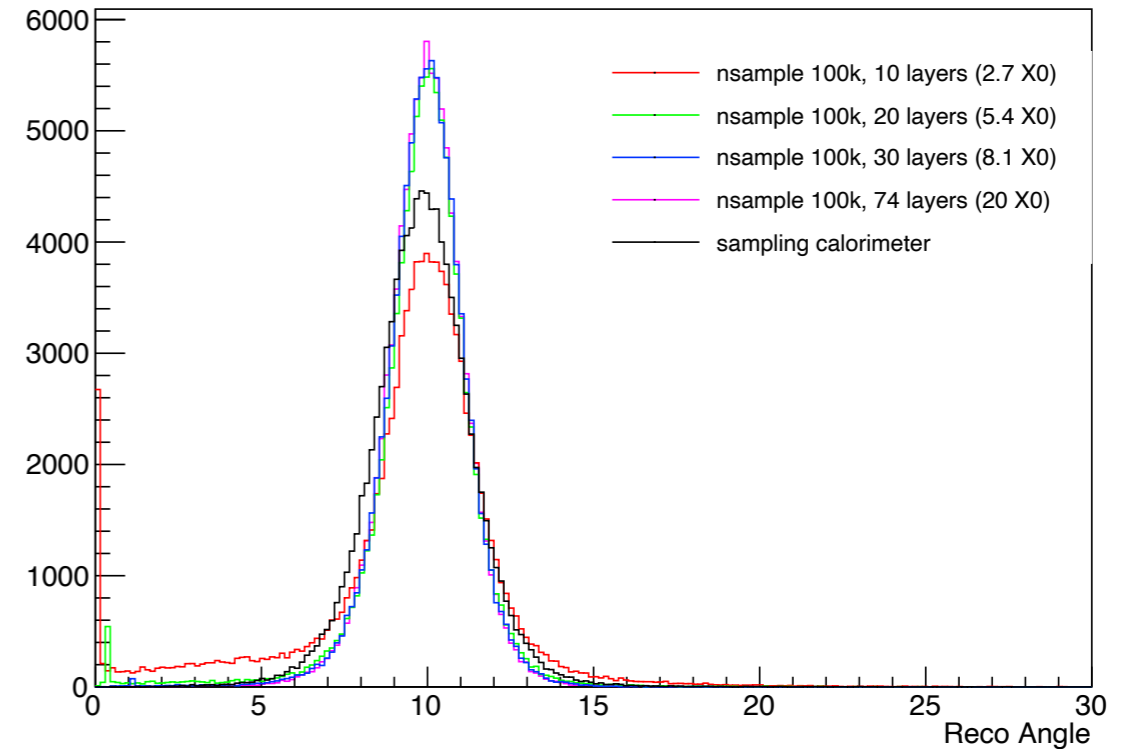


Full active CsI detector

1cm x 1cm x 50cm segment

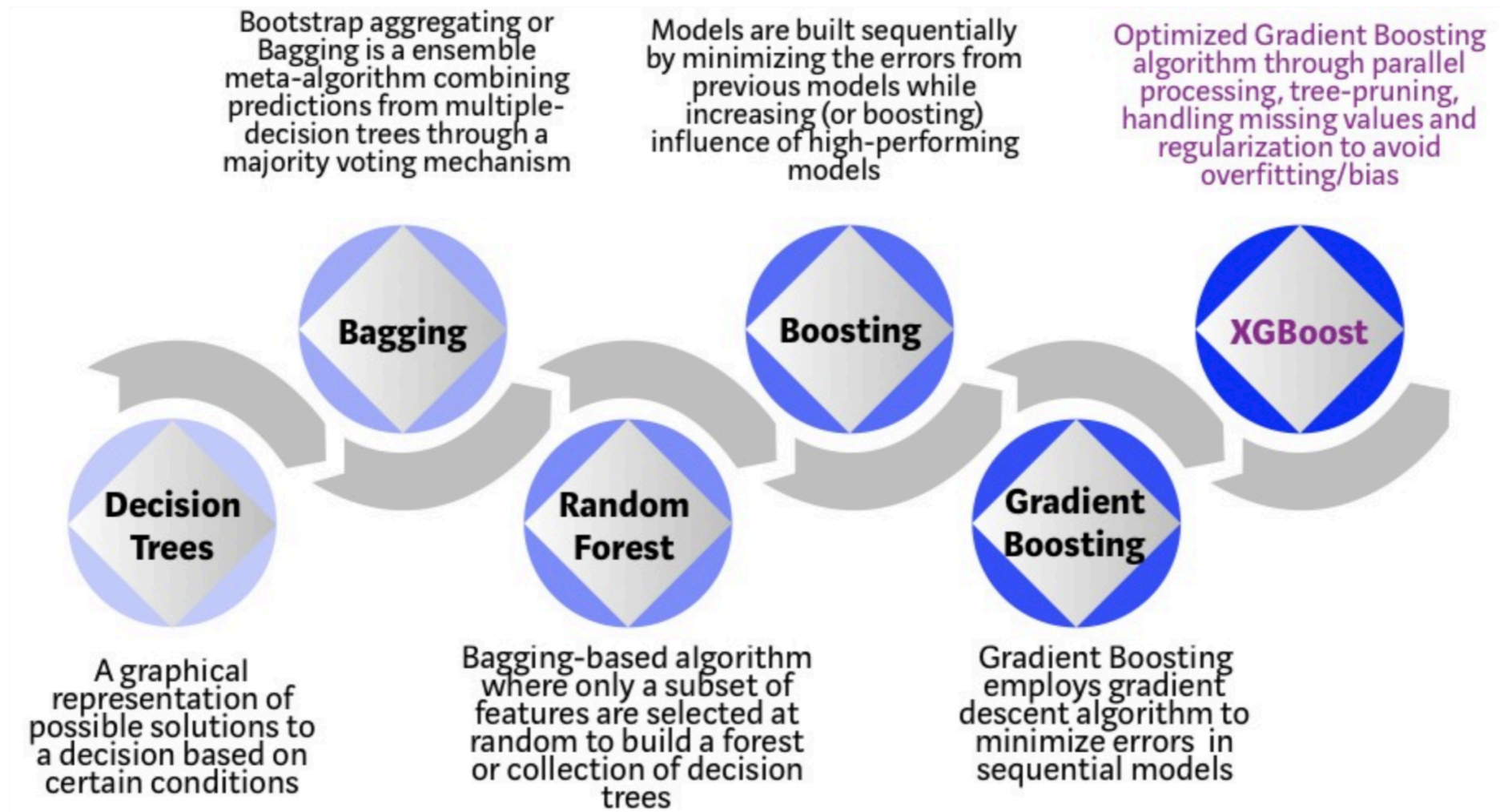


5mm x 5mm x 50cm segment



- Same studies are done with similar design of full active CsI detector.
- Fiber type segments are aligned along x and y axis.
- Angle reconstruction is studied with 5 mm and 1 cm segmentation.
- **1.1°** resolution with fine segmented full active detector
- **1.5°** resolution with sampling calorimeter at **1 GeV photon**

XGBoost: A scalable tree boosting system



arXiv:1603.02754 Table 1: Comparison of major tree boosting systems.

| System | exact greedy | approximate global | approximate local | out-of-core | sparsity aware | parallel |
|----------------|--------------|--------------------|-------------------|-------------|----------------|----------|
| XGBoost | yes | yes | yes | yes | yes | yes |
| pGBRT | no | no | yes | no | no | yes |
| Spark MLlib | no | yes | no | no | partially | yes |
| H2O | no | yes | no | no | partially | yes |
| scikit-learn | yes | no | no | no | no | no |
| R GBM | yes | no | no | no | partially | no |