Centrality determination in AuAu@4.5 AGeV with FHCal and forward hodoscope

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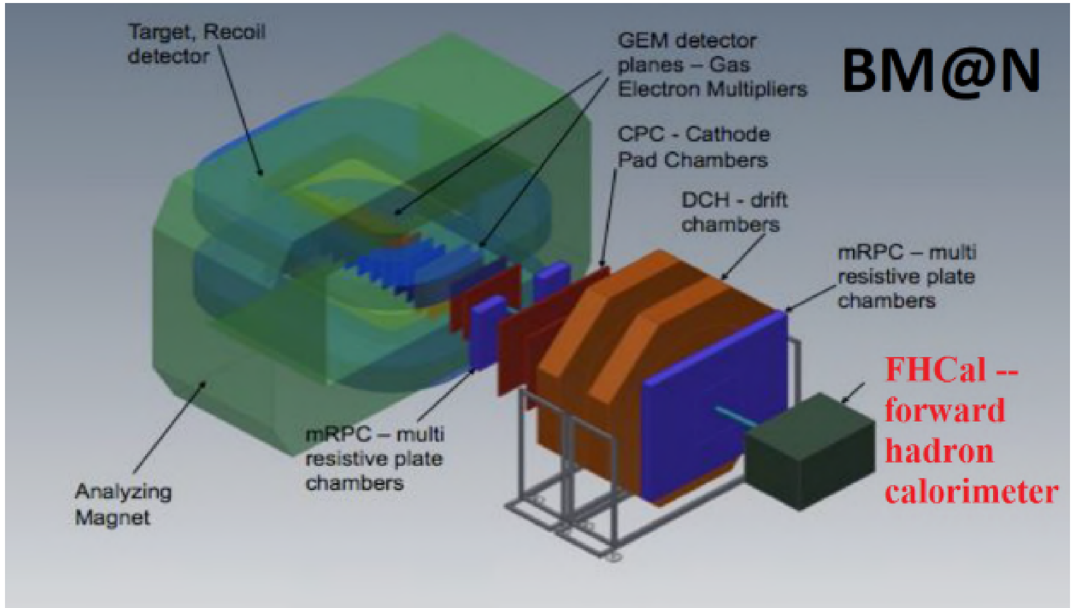
19.04.2021

Outline

- FHCal of BM@N centrality problem statement
- Supervised & Unsupervised ML approaches
- FHCal & forward hodoscope approach
- Application to the simulation files



Determination of centrality using hadron calorimeters by ML methods

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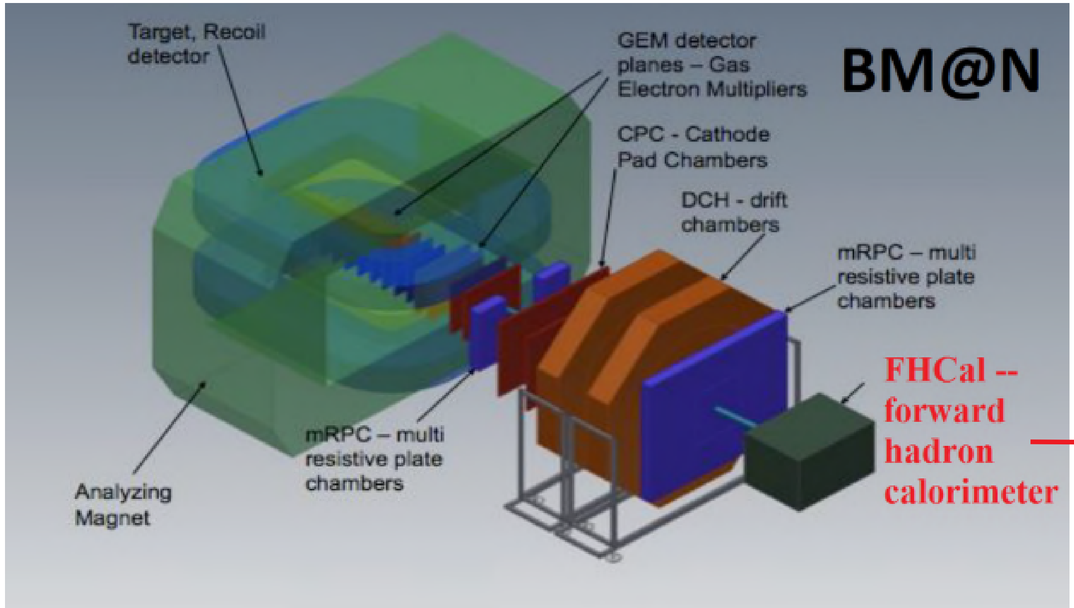
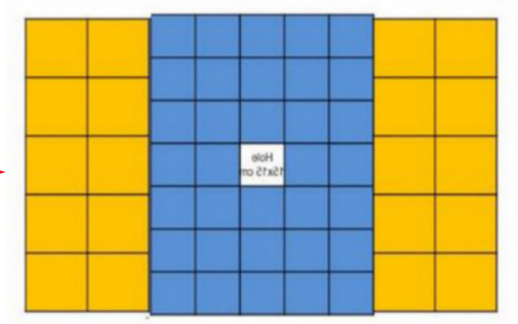
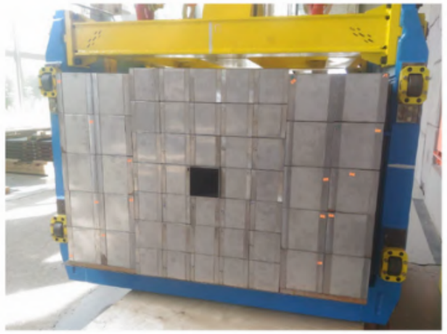
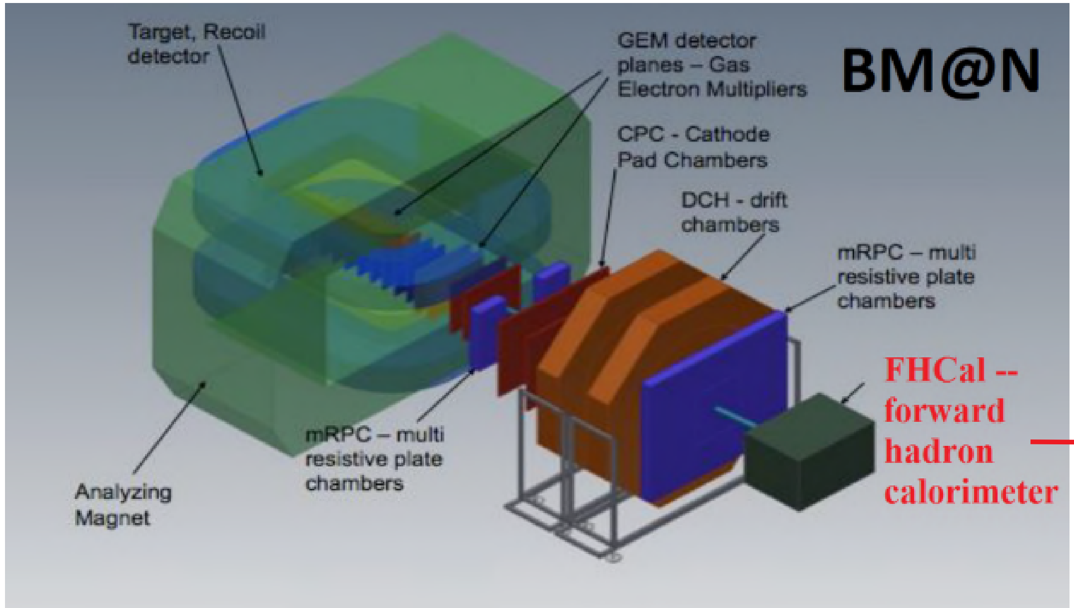






34 inner modules with sizes 15*15
+ 20 outer modules with sizes 20*20
Beam hole 15*15
Total weight – 17t



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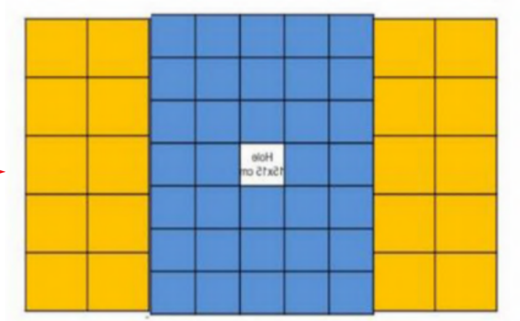

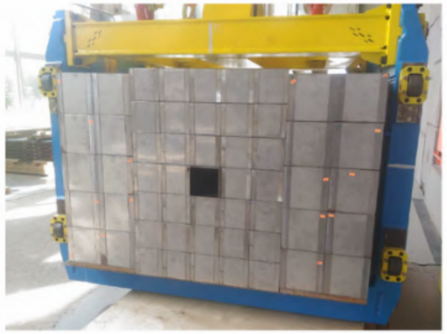

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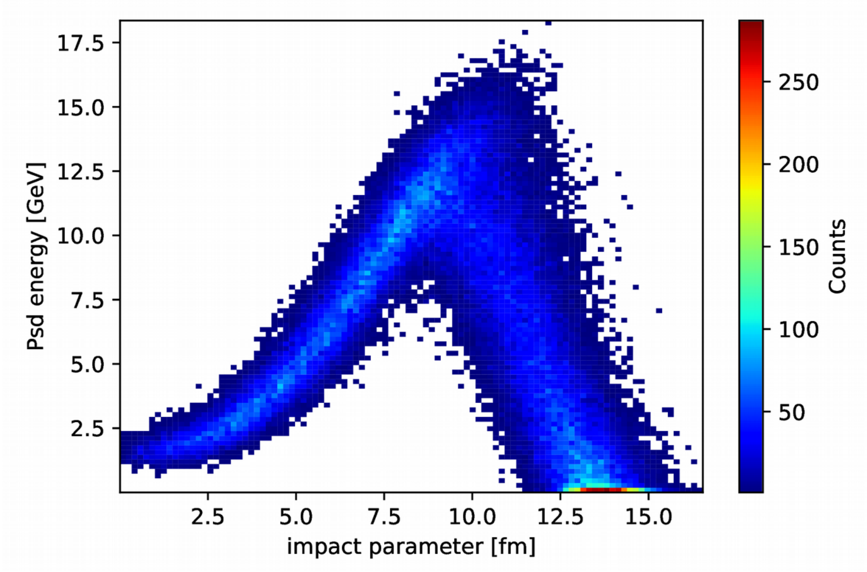
ambiguity



BM@N FHCal hole15cm DCMQGSM
AuAu 4.5AGeV 85k events

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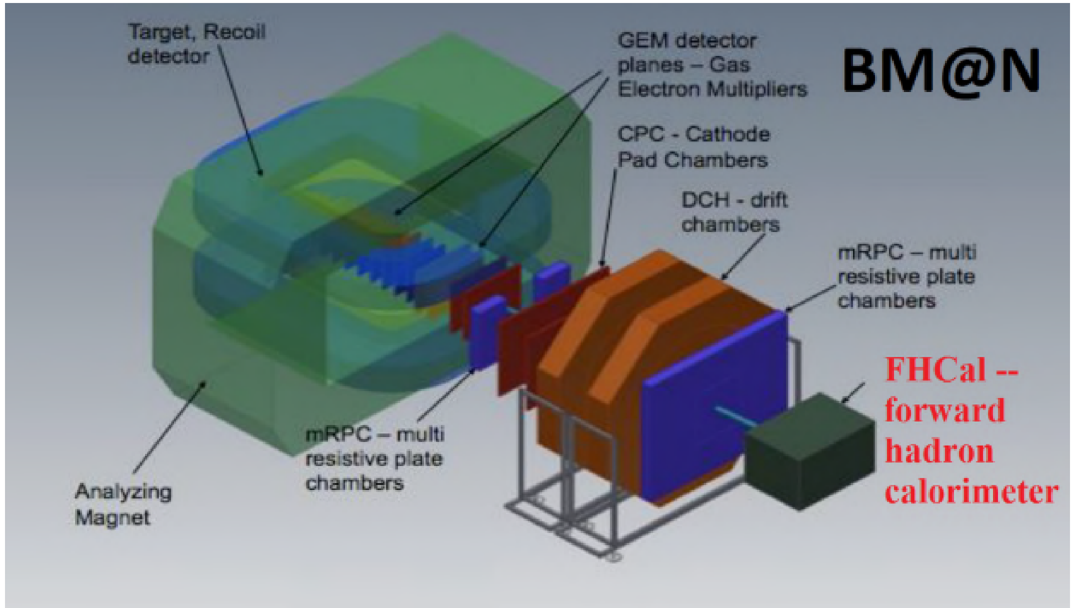

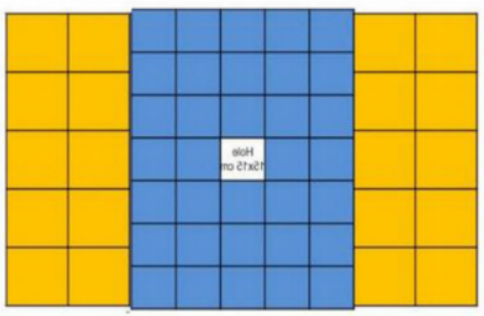

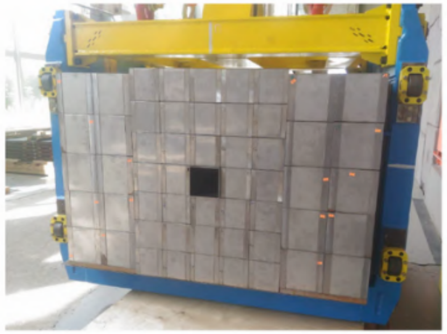

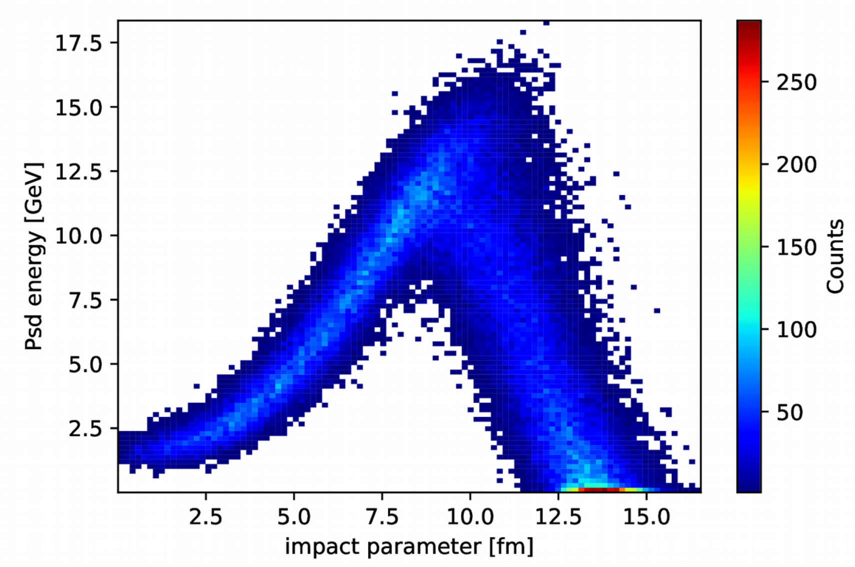

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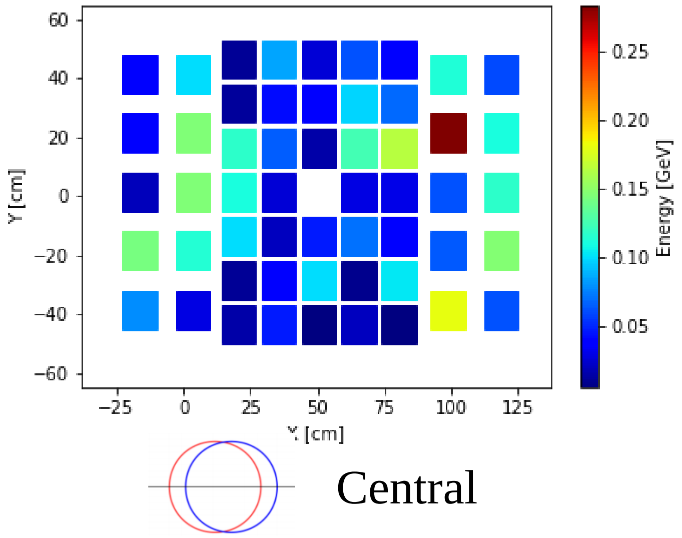
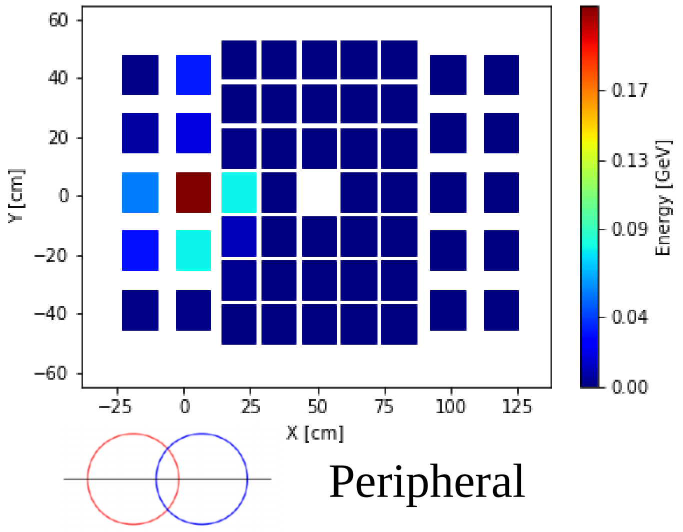
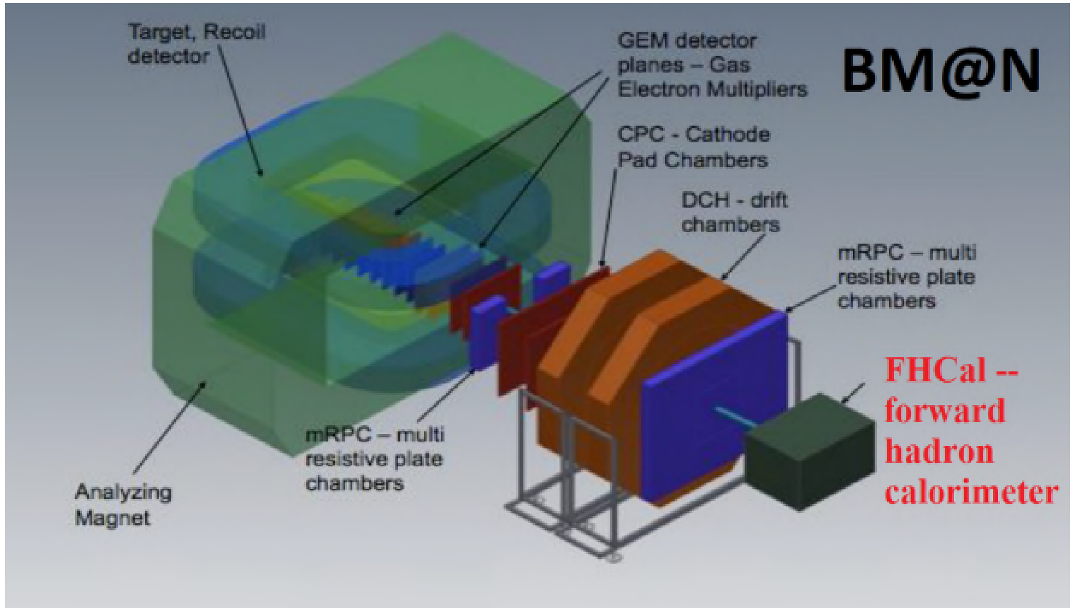
Calorimeter energy surface (single event)



Central



Peripheral



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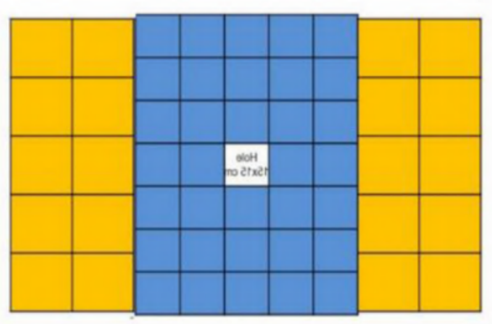
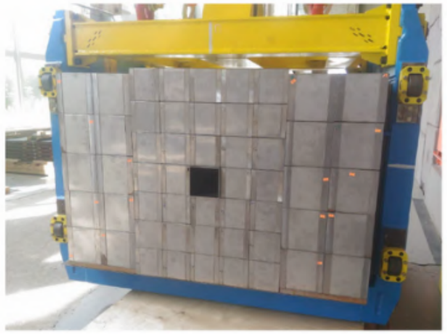




54 “pixels” to train ML algorithm

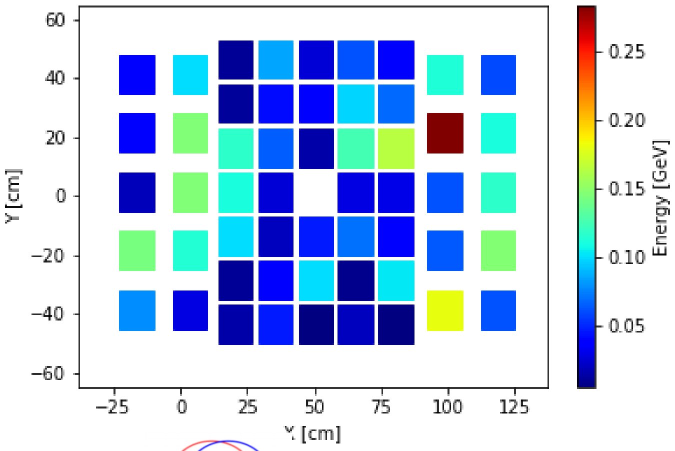
Use of simulation files:

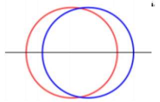
Input parameters – modules positions and energy depositions

Target variable – impact parameter

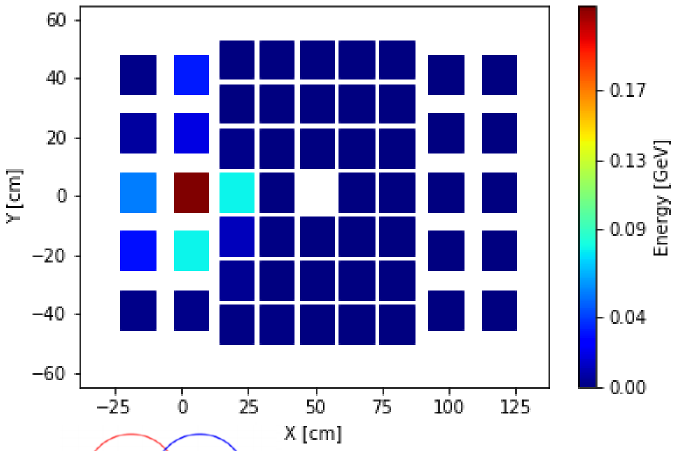
Expected result: online trigger for centrality estimation

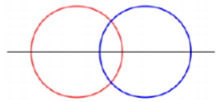
Calorimeter energy surface (single event)





Central





Peripheral

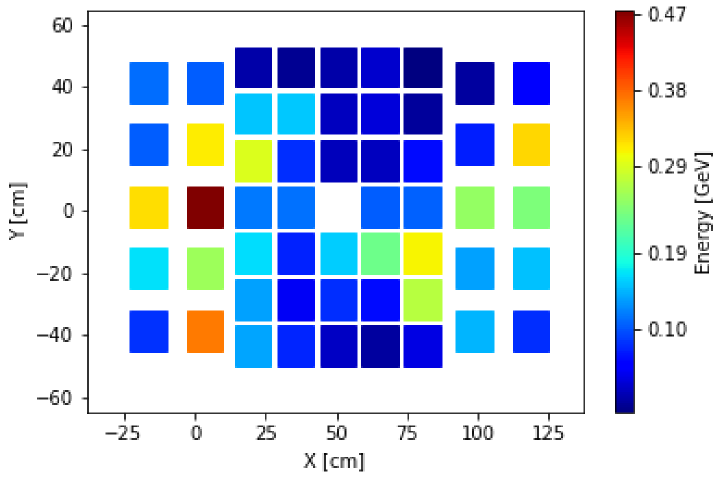
Supervised approach

1. Train-test split
2. Train the model:

Main goal:
Confirm approach capabilities.
Not to be used on real data.

Inputs:

- 1D arrays of energy depositions in calorimeter modules (Energy surface)



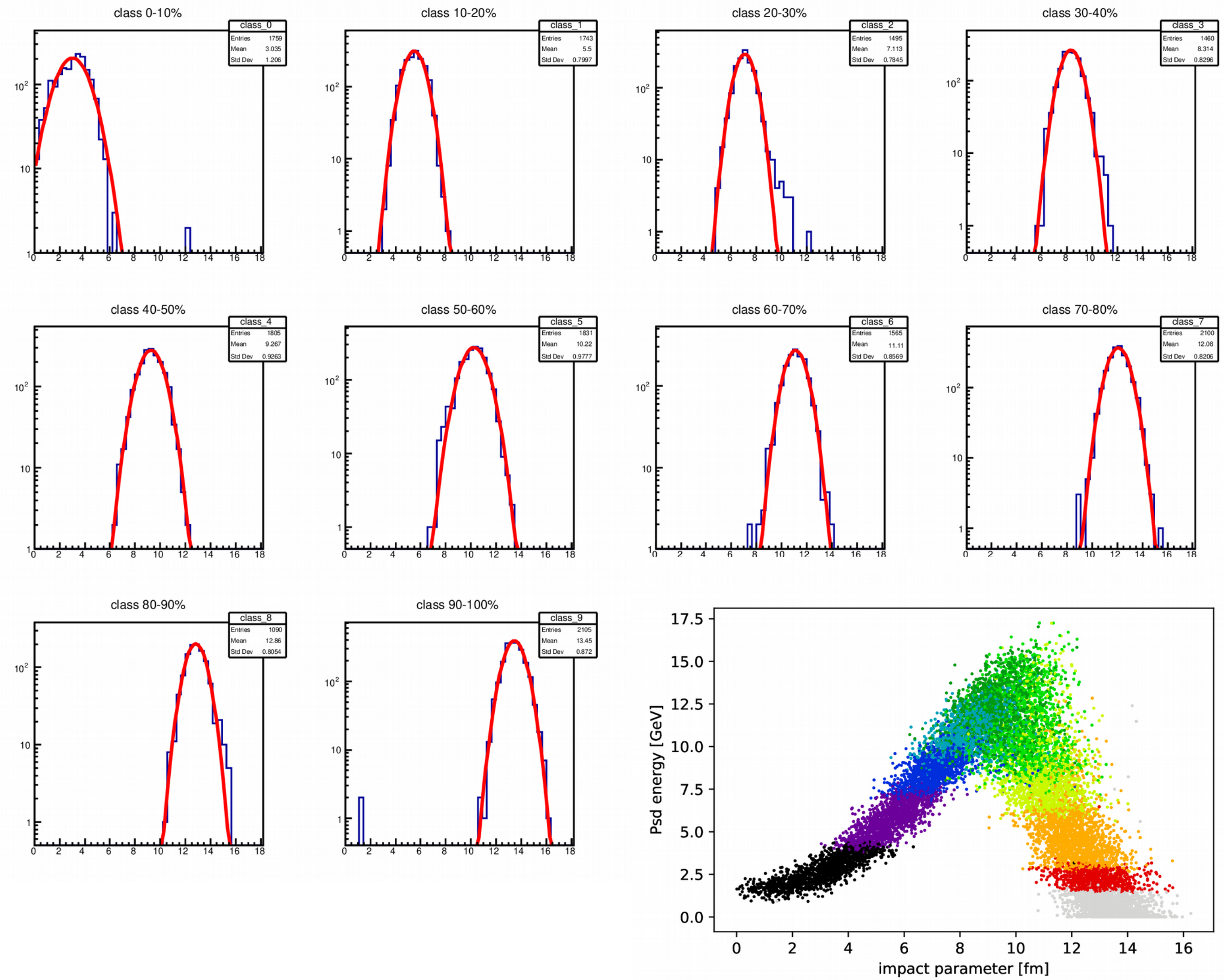
- Centrality class index (impact parameter label)

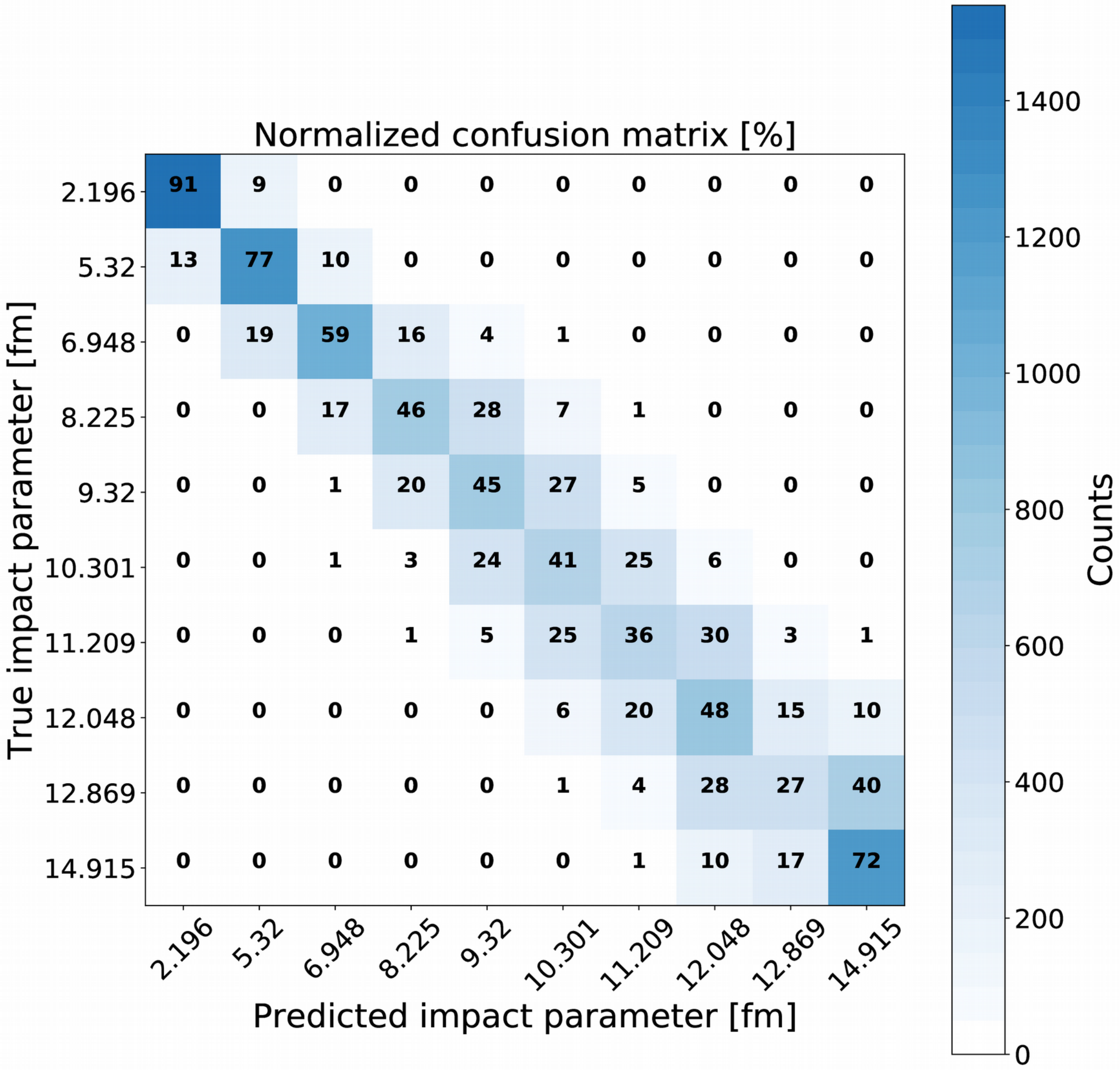
Model architecture:

dense_input: InputLayer → dense: Dense → dense_1: Dense → dense_2: Dense → dense_3: Dense → dense_4: Dense

3. Test model accuracy

AuAu 4.5AGeV DCMQGSM Supervised





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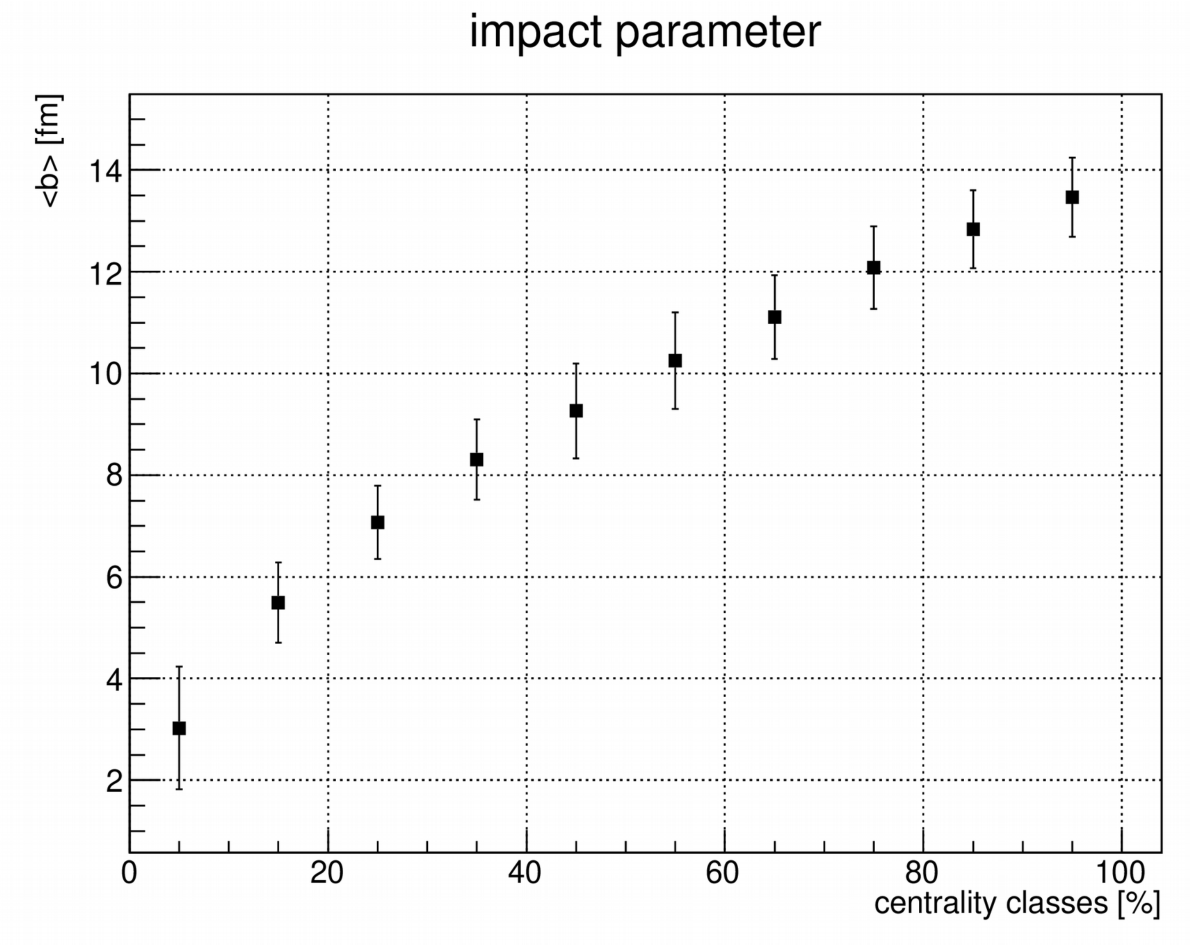
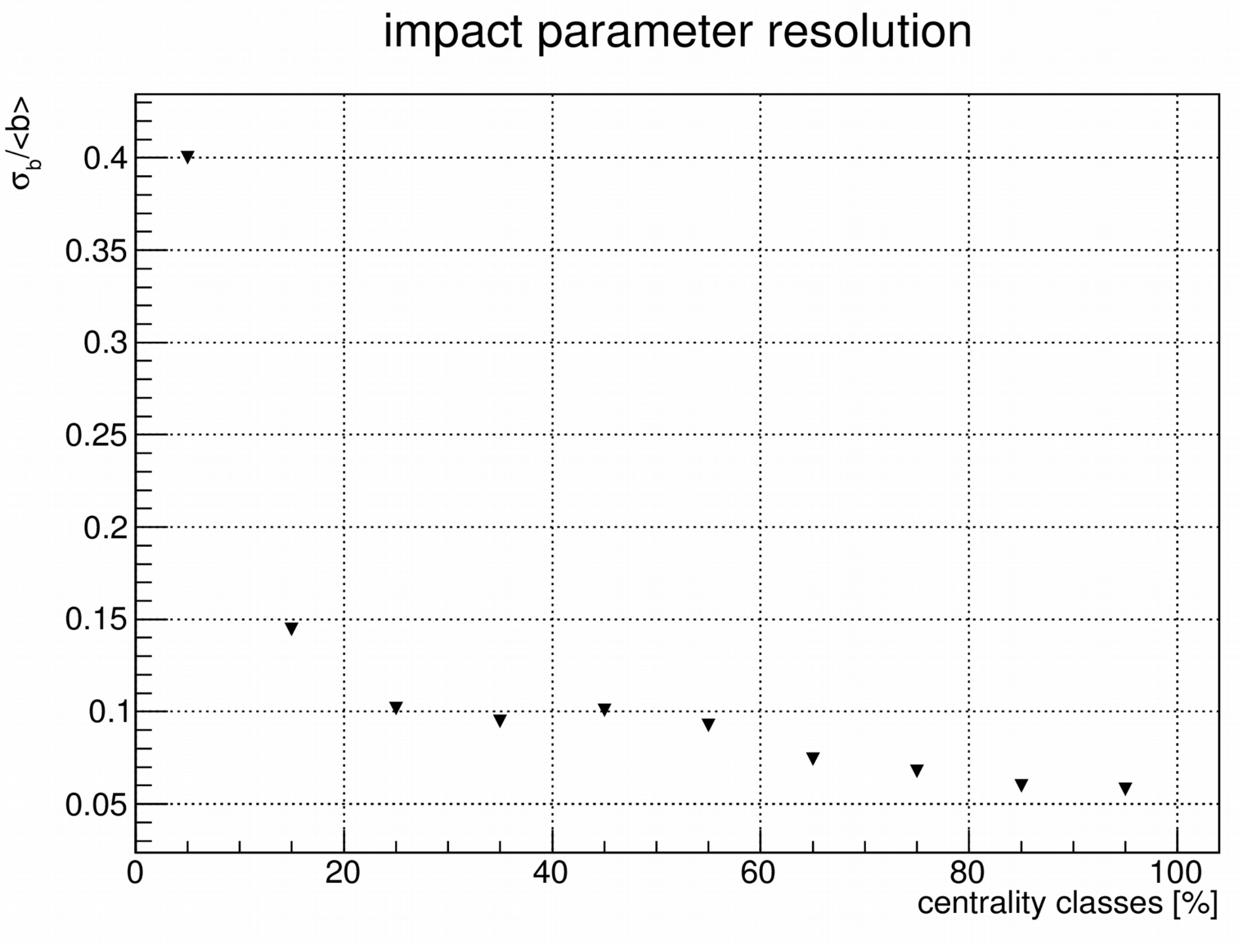
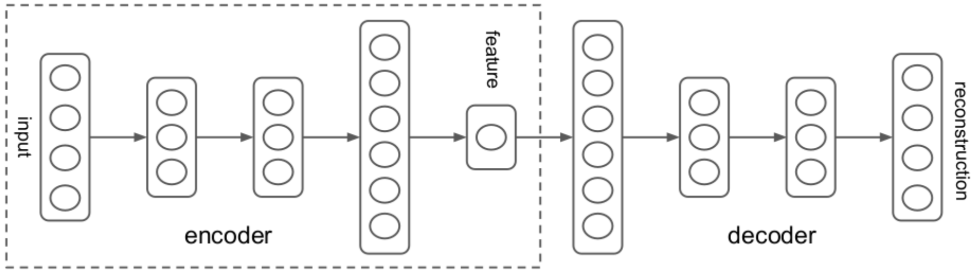




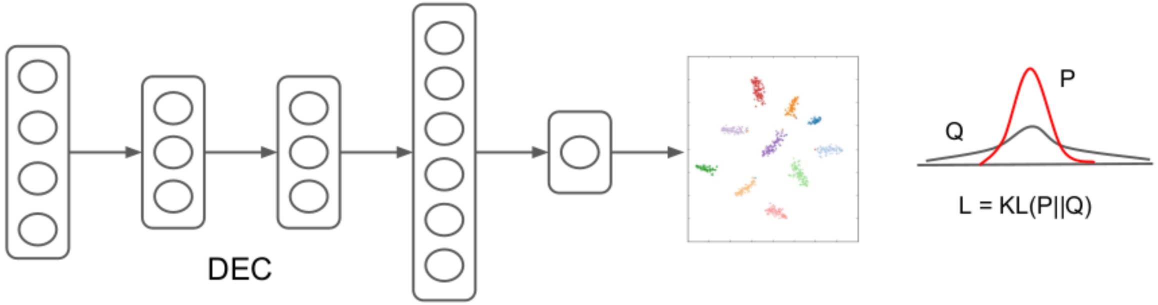
Unsupervised approach – Deep Embedded Clustering

1. Train autoencoder



2. Estimate cluster centroids: Encode data + TSNE + KMeans

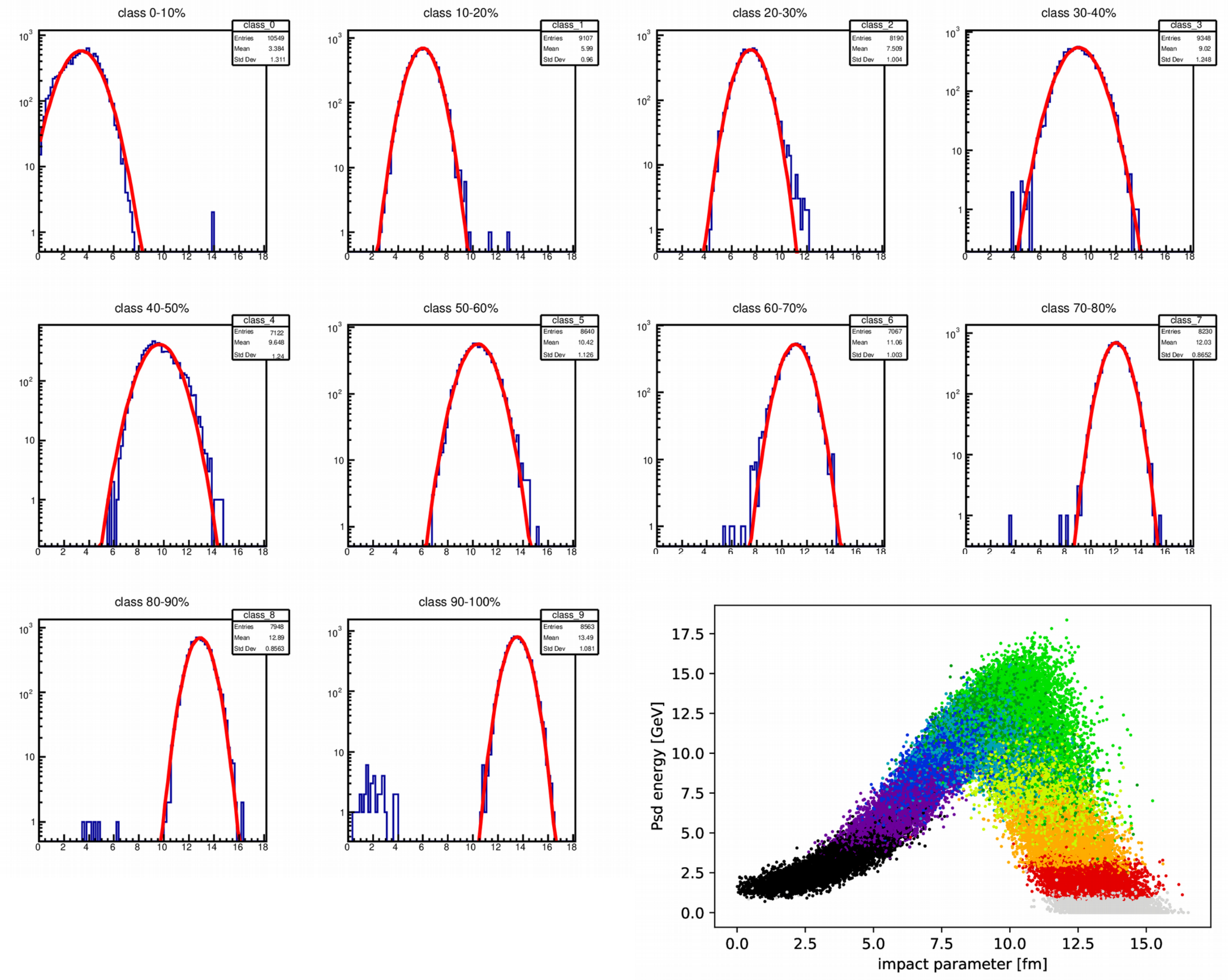
3. Deep Embedded Clustering (link):

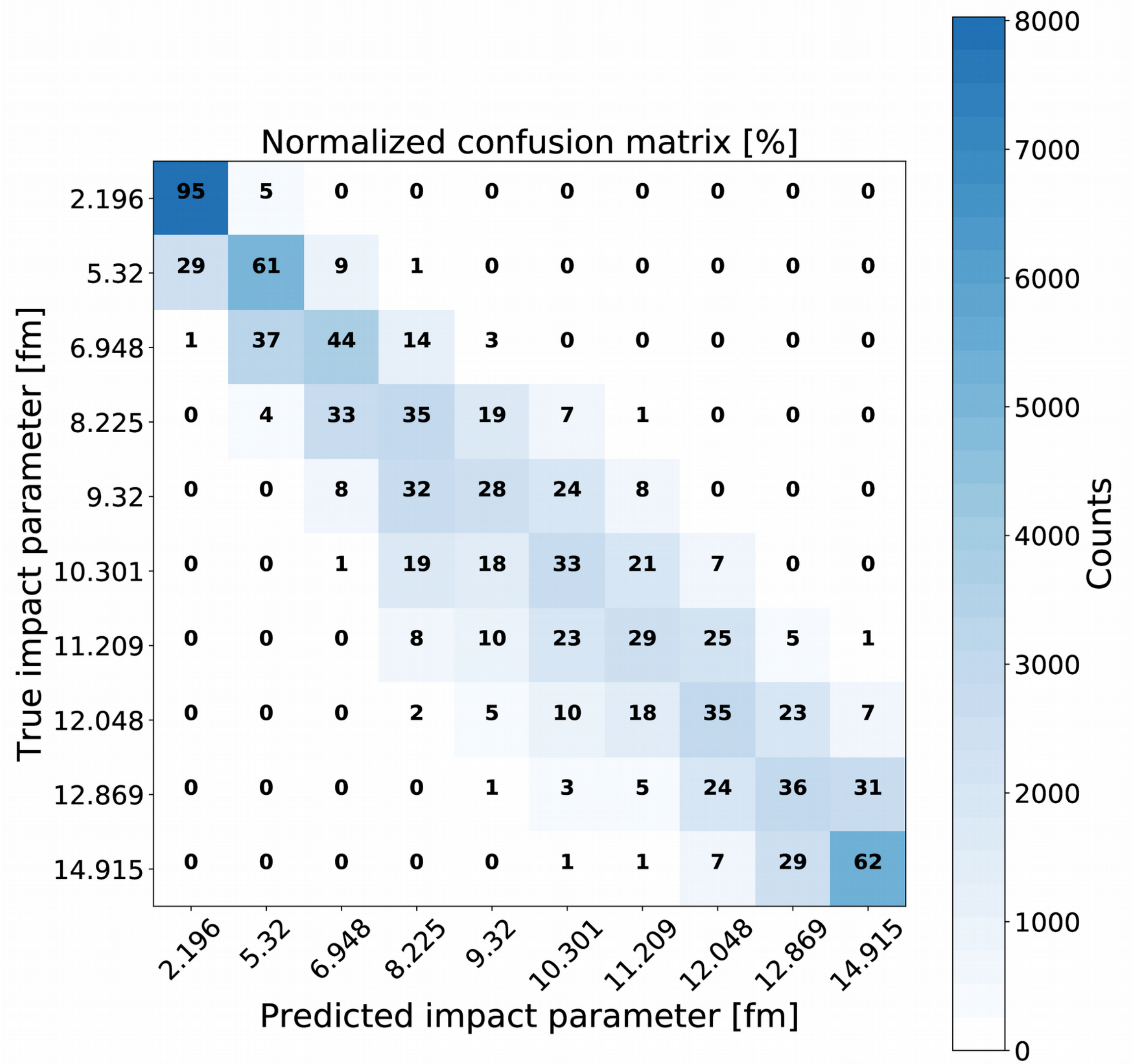


a) Soft clustering of encodded data by Student’s t-distribution

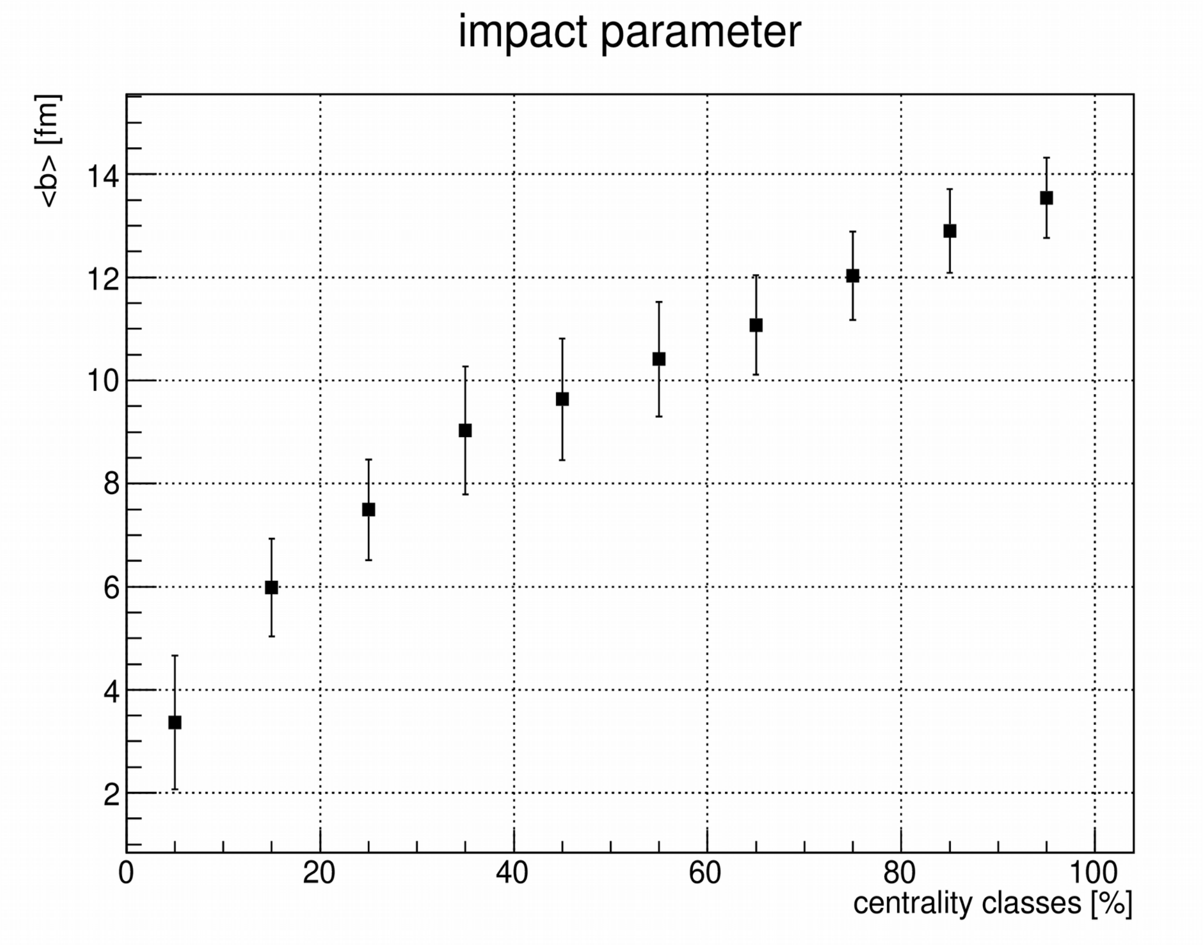
b) Iteratively strengthen predictions by approximating the obtained distribution **Q** to the auxiliary target distribution **P**

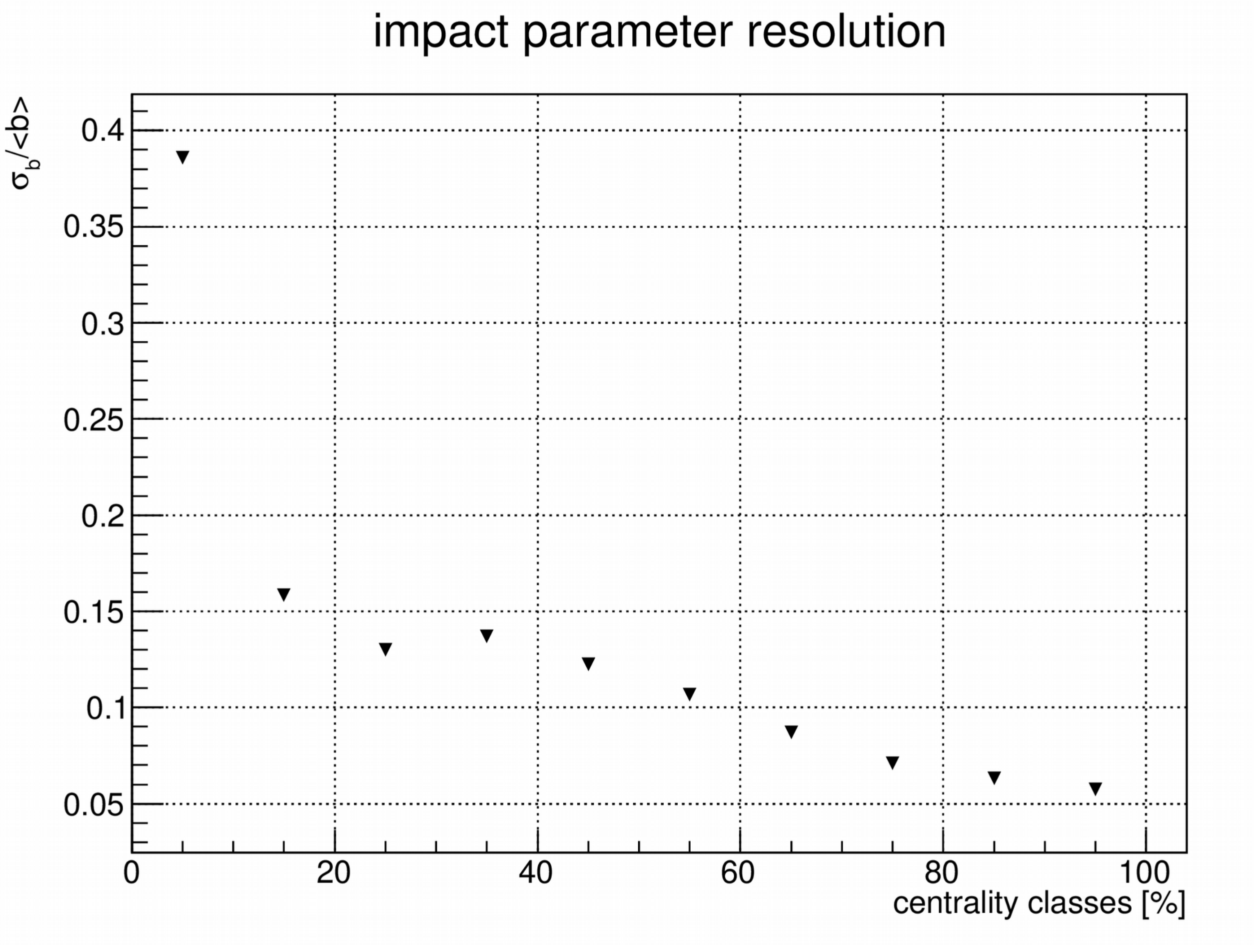
AuAu 4.5AGeV DCMQGSM Unsupervised



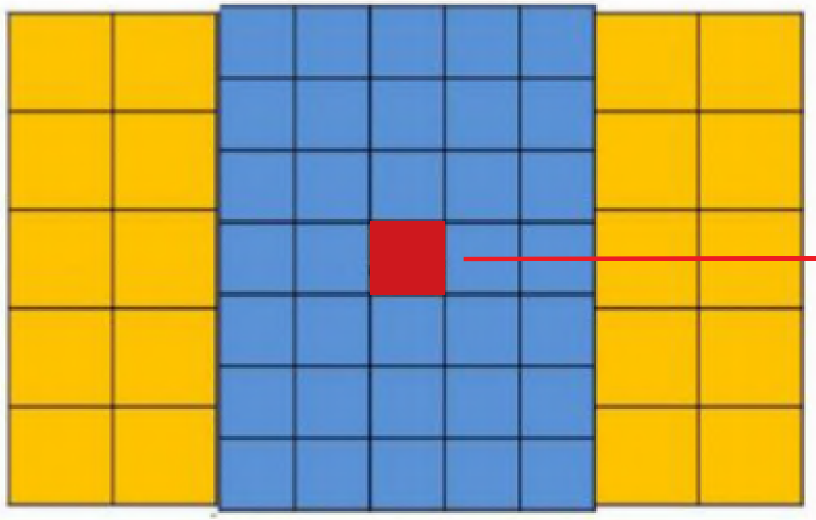


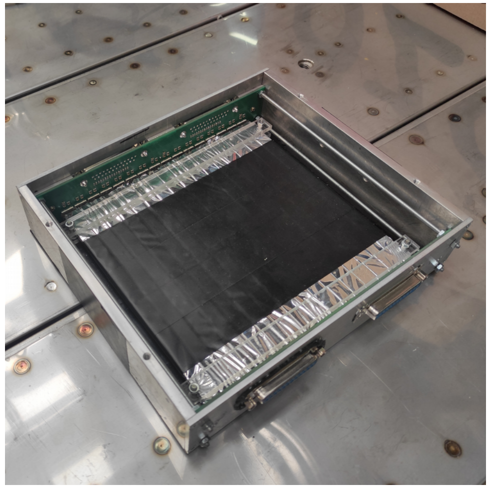
AuAu 4.5AGeV DCMQGSM Unsupervised



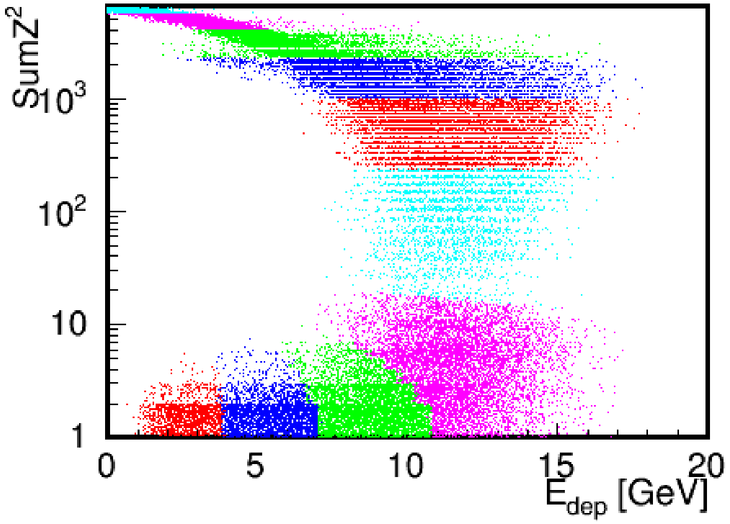


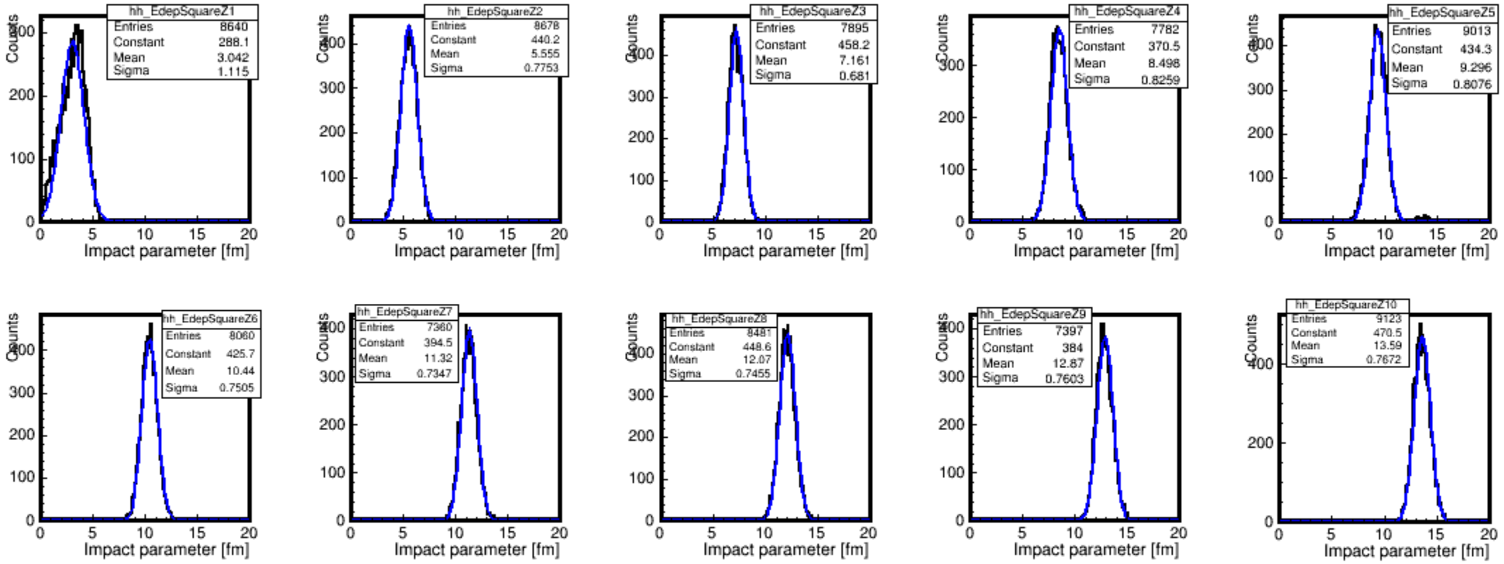
FHCal & forward hodoscope



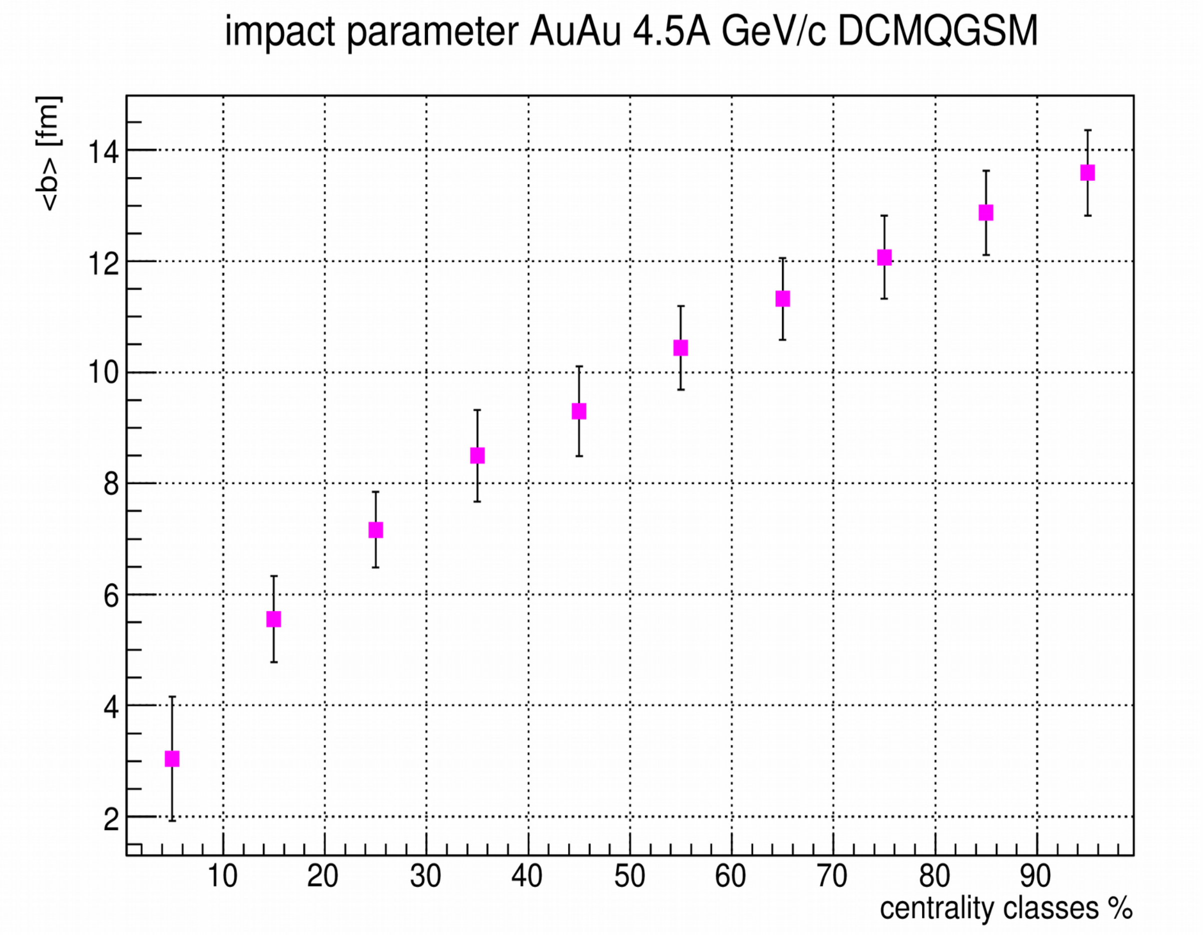


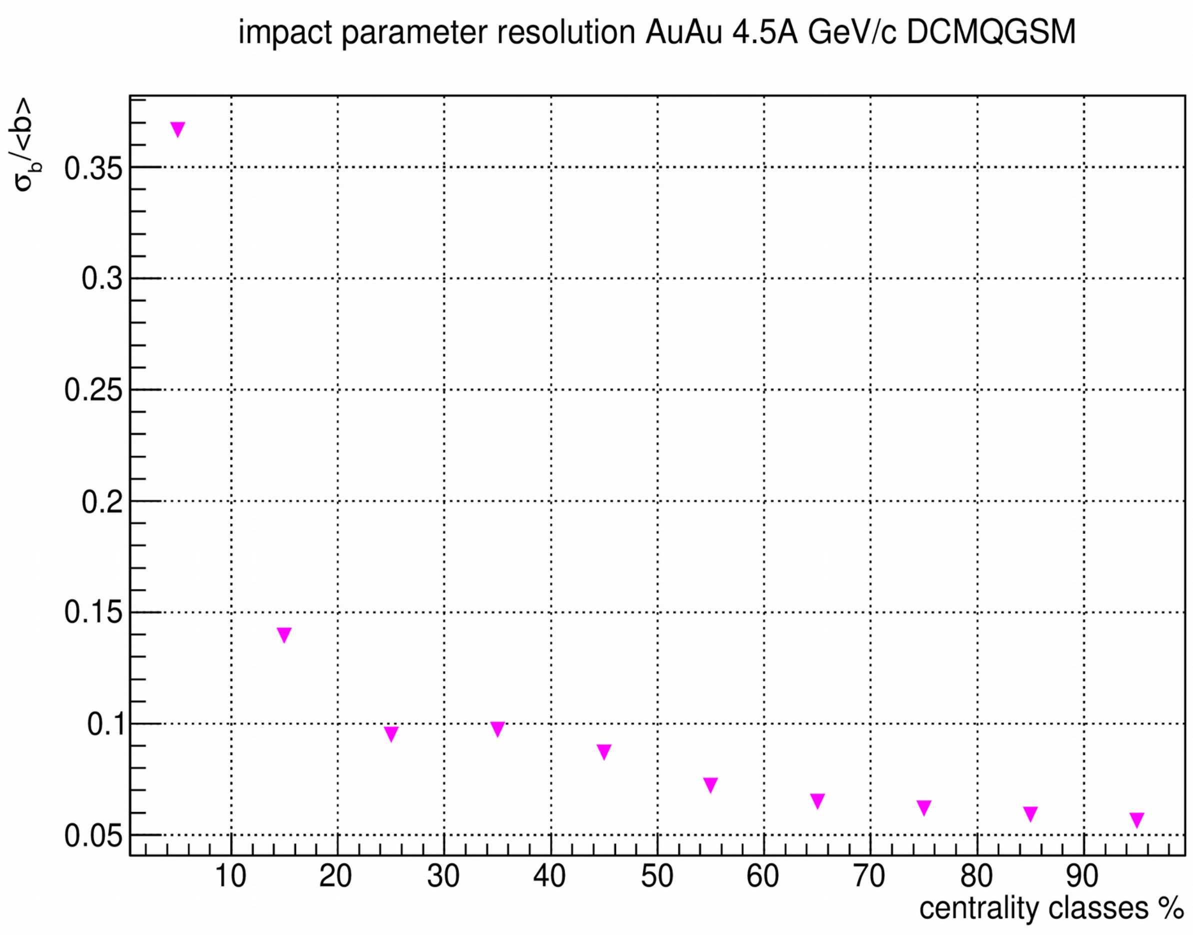
- Additional detector placed in the FHCal beamhole
- Measure charge of fragments at very forward rapidity region
- Online trigger for minbias/ centrality selection available



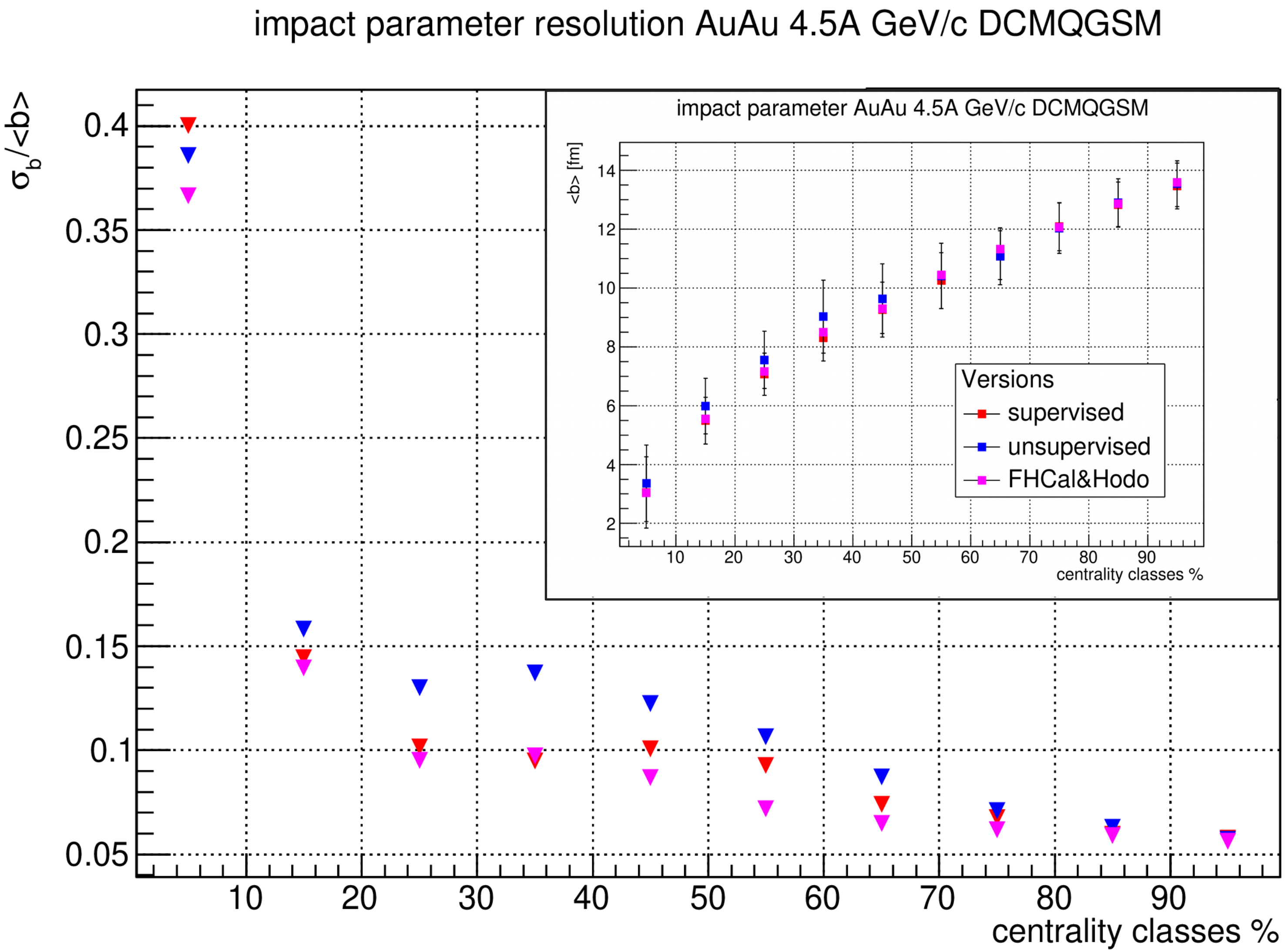


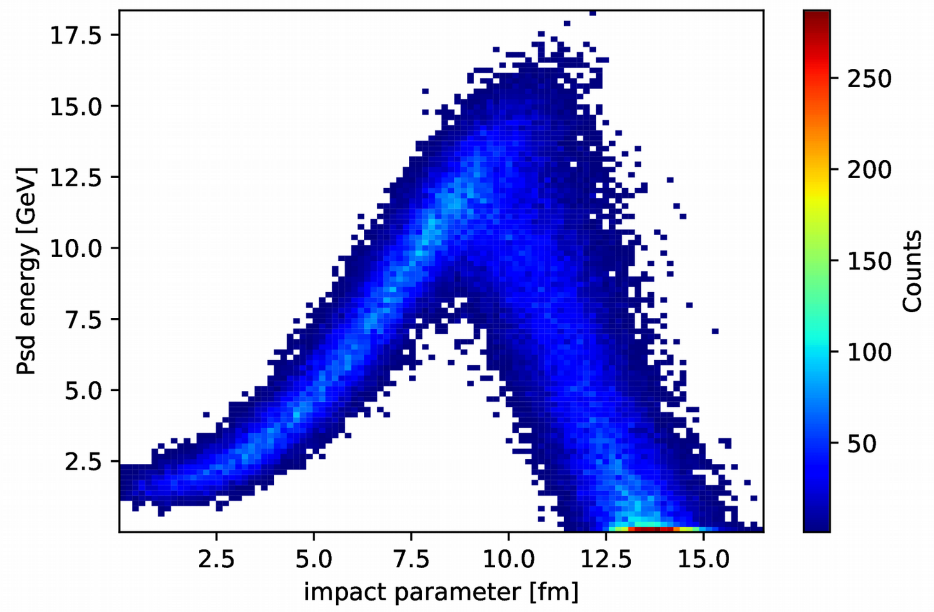
AuAu 4.5AGeV DCMQGSM FHCal&Hodo





Resolution: supervised, unsupervised, FHCal&Hodo





Conclusions

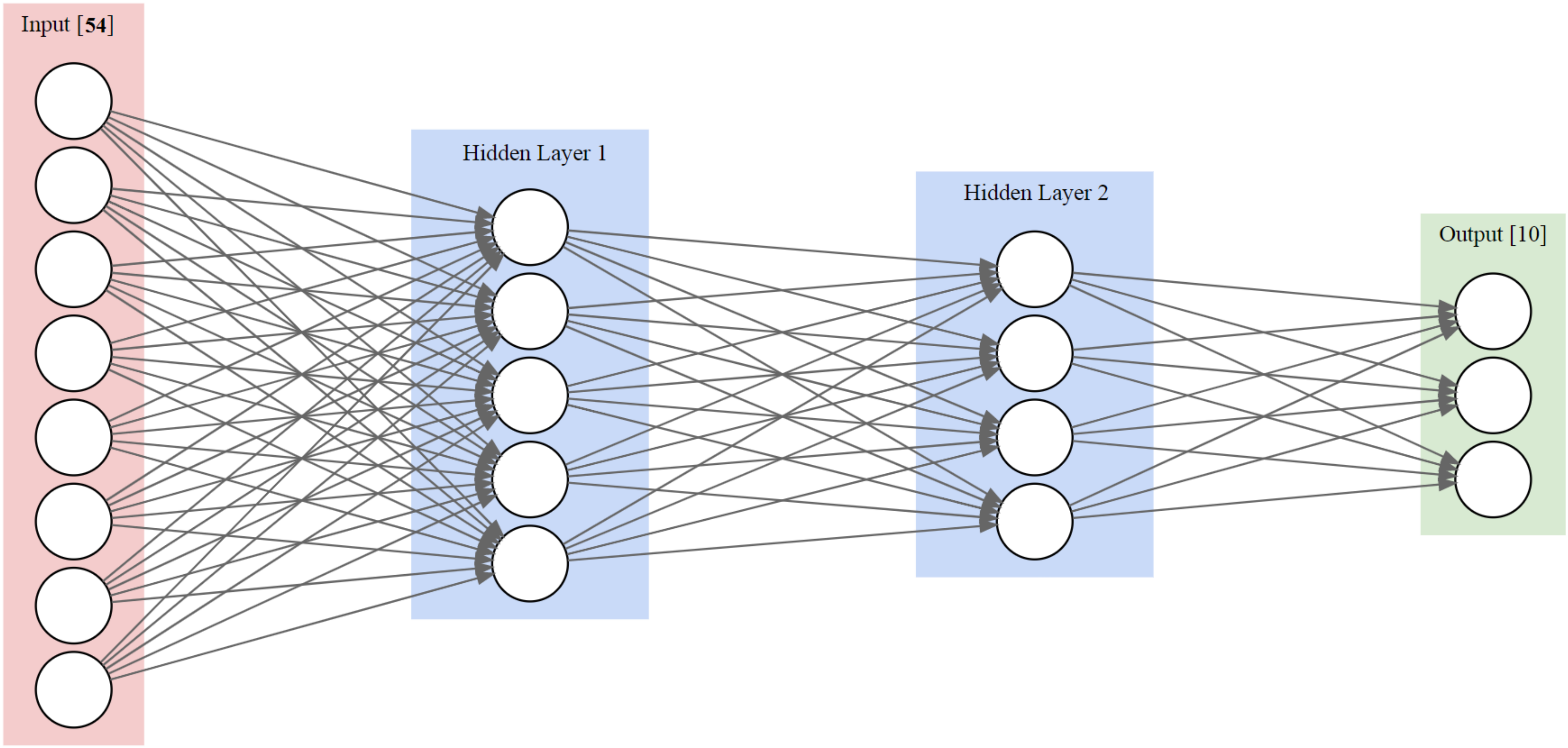
- Supervised&Unsupervised ML approaches are developped for centrality classes determination with forward hadron calorimeters with beam holes.
- Forward hodoscope is designed and manufactured to measure charge of fragments at very forward rapidity. A method for determining centrality using a front hodoscope and a calorimeter is presented.
- The results of applying the approaches to BM@N simulation data were shown. The centrality resolution and impact parameters determined by three methods are in a good agreement with each other.

Outlook

- Further improvement of methods will be carried out. Git repository: link

Thank you for your attention!

BACKUP


Input [54]
Hidden Layer 1
Hidden Layer 2
Output [10]

Machine Learning

Machine Learning

Supervised

Unsupervised

Machine Learning

Supervised

- Train-test split of the same data.
- Need target variable to train (data labeling).
- Model dependent: if ML-model is trained with one physical model, the spatial distributions of another model will hardly be reproduced. As well as real physical data.
- May serve as a reference for unsupervised ML.

Unsupervised

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Unsupervised

- Uses all available data and clusters them.
- No need of target variable.
- Model independent: one can take real physical data and cluster them. No need to use MC data first.
- How to check? Use secondary particles multiplicity distributions in centrality classes selected by ML-model.