Application of Machine Learning methods for centrality determination in heavy ion reactions at the BM@N and MPD@NICA

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Outline

- BM@N and MPD@NICA centrality problem statement
- Proposed solution
- Supervised & Unsupervised ML approaches
- 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 cm$^2$
+ 20 outer modules with sizes 20*20 cm$^2$

*Beam hole 15*15 cm$^2*

Total weight – 17t
Determination of centrality using hadron calorimeters by ML methods

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Beam hole 15*15 cm$^2$
Total weight – 17t
Determination of centrality using hadron calorimeters by ML methods

BM@N FHCal hole15cm DCM-QGSM
AuAu 4.5AGeV 85k events

Calorimeter energy surface (single event)

Central

Peripheral
Determination of centrality using hadron calorimeters by ML methods

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
Supervised approach

1. Train-test split
2. Train the model:
   - Inputs:
     - 1D arrays of energy depositions in calorimeter modules (Energy surface)
     - Centrality class index (impact parameter label)
   - Model architecture:

3. Test model accuracy

Main goal:
Confirm approach capabilities.
Not to be used on real data.
AuAu 4.5AGeV DCM-QGSM Supervised
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 encoded 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 DCM-QGSM Unsupervised
Resolution: supervised, unsupervised

impact parameter resolution AuAu4.5AGeV DCM-QGSM

Normalized confusion matrix [%]

supervised

unsupervised

Versions
red: supervised
blue: unsupervised

centrality classes %

Predicted impact parameter [fm]

Counts
ML centrality method for MPD@NICA

MPD FHCal
2x44 modules 15*15 \(cm^2\)
Beam hole (15*15 \(cm^2\))
Total weight – 18t

Calorimeter energy surface (single event)

MPD FHCal hole 15cm DCM-QGSM
AuAu 11AGeV 100k events
AuAu 11AGeV DCM-QGSM Supervised
AuAu 11A GeV DCM-QGSM Unsupervised

Normalized confusion matrix [%]

Counts
Resolution: supervised, unsupervised

impact parameter resolution AuAu11AGeV DCM-QGSM
Conclusions

- Supervised & Unsupervised ML approaches are developed for centrality classes determination with forward hadron calorimeters with beam holes.

- The results of applying the approaches to BM@N and MPD@NICA simulation data with different collision energies were shown.

- The centrality resolution and impact parameters are shown for all centrality classes in each case.

Outlook

- Further improvement of methods will be carried out. Git repository: [link](#)

- The approaches will be tested to determine the centrality classes in the BM@N, NA61/SHINE@SPS, CBM@FAIR and MPD@NICA experiments.
Thank you for your attention!