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Deep learning the physics of heavy-ion collisions at the CBM experiment with PointNet

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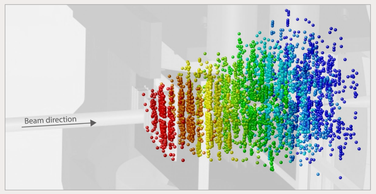
HIC experimental data as point clouds

- Point clouds are set of data points in space.
- Experimental data naturally have point cloud structure.
- Point clouds can be represented as 2D array.
  - each row= a point in the point cloud
  - each column =a dimension of the point cloud



x_1	y_1	z_1
x_2	y_2	z_2
⋮	⋮	⋮
x_n	y_n	z_n

Fig 1. (Left) Visualisation of the hits in different detector planes for a collision event in the CBM detector. (Right) Representation of the point cloud of hits as an array.

PointNet: Deep Learning for point clouds

- PointNet based models learn directly from point clouds.
  - respects the order invariance of point clouds
  - direct processing of experimental data
    - less processing time ⇒**ideal online algorithm**
  - optimal algorithm for higher dimensional data
- Major components of PointNet:
  - 1D Conv to extract per point features
  - average pooling to extract global feature of an event from per point feature maps

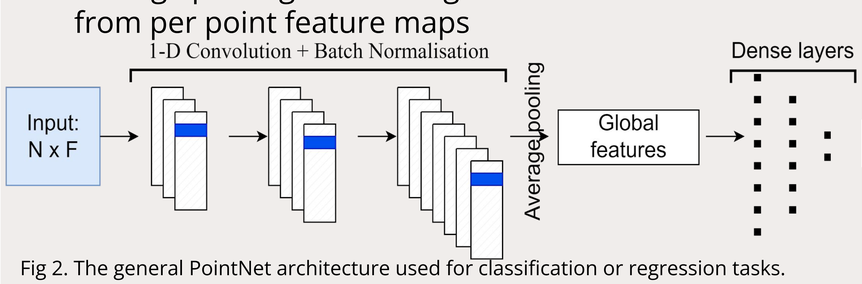


Fig 2. The general PointNet architecture used for classification or regression tasks.

The training data

- A realistic, "experiment like" data is generated using UrQMD & CbmRoot.
  - models trained on reconstructed tracks/ hits

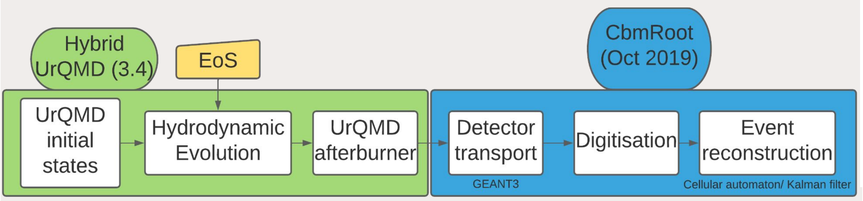


Fig 3. The general data preparation pipeline.

PointNet based centrality meter

- The impact parameter (b) of collision is not measurable directly.
- experiments model track multiplicity using Glauber MC
  - collision centrality is defined as percentiles of track multiplicity distribution
  - expected mean and variance of b for a centrality bin is calculated
  - **event-by-event b is not available**
- We propose to use PointNet based models for b reconstruction at CBM.

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Pointnet models

- models trained on different type of detector output

01	M-hits	(x,y,z) of all Hits in MVD
02	S-hits	(x,y,z) of all hits in STS
03	MS-tracks	(x,y,z,dx/dz,dy/dz,q/P) tracks from MVD+ STS
04	HT-combi	Hits from MVD and tracks from MVD+STS
05	Polyfit (non-ML baseline)	Third order polynomial fit to multiplicity- b curve

Fig 4. Different PointNet models developed in this study. MVD and STS are the Micro Vertex Detector and Silicon Tracking System of The CBM detector respectively.

Performance of the models

- DL models outperform conventional methods
  - **excellent resolution and accuracy** across b=2-14 fm
  - better performance than polyfit when underlying physics changes
- **provides event-by-event b** directly from experimental data
  - fast enough to be usable in online event selection
  - **~ 1000 events/s** on one GPU

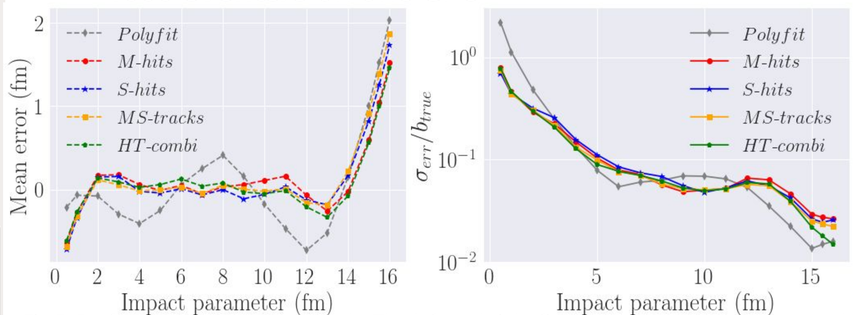

Fig 5. Performance of the DL models. The left and right figures show the mean error and relative precision of the models respectively.

PointNet based Equation of State meter

- HIC experiments trace the QCD phase diagram:
  - identify regions of different types of transition
  - search for critical point
- Comparisons of model simulations of event averaged observables are used in experiments to identify the type of QCD transition.
- We propose to use PointNet based models to classify different types of QCD transition at CBM.

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PointNet models

- models classify a phase transition from crossover
- trained on 3 types of input

01	UrQMD output	• 4-momentum of all particles • Ideal detector
02	UrQMD output with CBM acceptance	• 4-momentum of all particles • 2- 25° acceptance cut
03	UrQMD + CbmRoot	• Reconstructed tracks from digitised STS hits • Realistic simulation

Fig 6. The three types of input to train the models.

Test results and model performance

- accuracy decreases with increase in experimental effects
- accuracy on the event by event data:
  - ideal case: 77.2%, realistic case: 62.4%
- accuracy improves for multi-event point clouds
  - with 40 events: **97% accuracy** for UrQMD+CbmRoot
  - work over a wide range of centralities
  - outperform conventional methods (e.g. v_2, $\langle p_t \rangle$ etc.)
  - immune to changes in theoretical model parameters

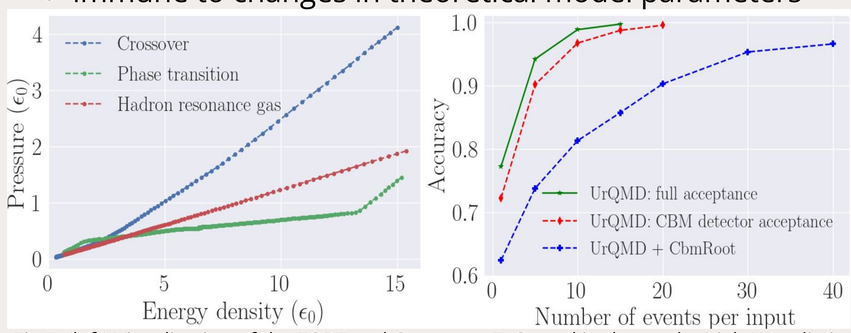

Fig 7. (left) Visualisation of the FOPT and Crossover EoS used int he study. (right) Prediction accuracy as a function of number of events combined to form the input point cloud.

References

1. Omana Kuttan, M., et al. Physics Letters B, 811, 135872. (link)
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3. Omana Kuttan, M., et al . Journal of High Energy Physics, 2021(10), 1-25. (link)