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

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 \(\equiv\) 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
  - input: \(N \times F\)

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

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.

PointNet models
- models trained on different type of detector output
  - M-hits
  - S-hits
  - MS-tracks
  - HT-combi
  - Polyfit (non-ML baseline)

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
  - \(\sim 1000\) events/s on one GPU

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.

Test results and model performance
- accuracy decreases with increase in experimental effects
  - 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. \(v_{2} < p_{t}\) etc.)
  - immune to changes in theoretical model parameters

Performance of the EoS
- PointNet models classify a phase transition from crossover trained on 3 types of input
  - models classify a phase transition from crossover trained on 3 types of input
    - 01 UrQMD output
    - 02 UrQMD output with CBM acceptance
    - 03 UrQMD + CbmRoot
- reconstruction of events (e.g. 4-momentum of all particles)
- Realistic simulation

Comparisons of model simulations of event averaged observables
- UrQMD output with CBM
- UrQMD output
- UrQMD + CbmRoot
- polyfit

References

Figures:
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.
2. The general PointNet architecture used for classification or regression tasks.
3. The general data preparation pipeline.
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.
5. Performance of the DL models. The left and right figures show the mean error and relative precision of the models respectively.
6. The three types of input to train the models.
7. (left) Visualisation of the FOPT and Crossover EoS used in the study. (right) Prediction accuracy as a function of number of events combined to form the input point cloud.