PointNet for fast event characterisation in heavy-ion collision experiments

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PointNet: Deep Learning for point clouds

- **Experimental data has inherent point cloud structure**
  - pointclouds: collection of points in space
    - $x_1 \ y_1 \ z_1$
    - $x_2 \ y_2 \ z_2$
    - $\vdots \ \vdots \ \vdots$
    - $x_n \ y_n \ z_n$

- Point clouds are represented as 2D array.
  - each row = a point in the point cloud
  - each column = a dimension of the point cloud

- PointNet based models learn directly from point clouds.
  - respects the order invariance of point clouds
  - direct processing of experimental data

- Advantages:
  - less processing time ⇒ ideal online algorithm
  - optimal for higher dimensional data

- We consider the CBM experiment as a use case
  - Au-Au collisions
  - 10 AGeV

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PointNet based centrality meter

- Trained on simulated hits/tracks to **reconstruct impact parameter $b$**

![Image](image1.png)

**Fig 3.** The mean error in $b$-predictions for different DL models and Polyfit baseline.

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PointNet based Equation of State meter

- Trained on simulated tracks to **classify phase transition events from crossover**

![Image](image2.png)

**Fig 4.** Classification accuracy for PointNet models with different experimental effects.
The PointNet architecture

- Point cloud: set of data points in space
  - No ordering
  - \{(x_1, y_1, z_1), (x_2, y_2, z_2), ... (x_n, y_n, z_n)\}

- Electronically collected data often has point cloud structure
  - Data from sensors, detectors etc.

**DL models operating on Point clouds**

1. Works on free-streaming experimental data
2. Minimal preprocessing
3. No loss of information from histogram binning
4. Online physics analyses

**Major components of PointNet:**
- 1D Conv to extract per point features
- **symmetric operations** to convert per point feature maps to global event features

A point cloud is given by set of points “X”:

\[ X = \{x_1, x_2, x_3, ... x_n\} \]

PointNet learns a set of functions “F”:

\[ F = \{f_1, f_2, ..., f_m\} \text{, where } f_i((x_1, ..., x_n)) \approx g(h_i(x_1), ..., h_i(x_n)), \]

\[ h = \text{1D CNN, } g = \text{AvgPooling} \]
Impact parameter reconstruction with PointNet

- Impact parameter ‘b’: not experimentally measurable
  - Glauber MC
  - Only a ‘likely’ distribution for b in a centrality bin is known

Our solution: PointNet based ‘b’ meter
- Event-by event
- Works on direct experimental output
- Online event characterisation

- DL models outperform conventional methods
- excellent resolution and accuracy across b=2-14 fm
- provides event-by-event b directly from experimental readout
- fast enough to be usable in online event selection
  - ~ 1000 events/s on one GPU

Particles 4.1 (2021): 47-52

Polyfit (non-ML baseline)

- Hits in MVD
- hits in STS
- tracks in MVD+ STS
- MVD hits + tracks from MVD+STS
- polynomial fit to $N_{\text{ch}}$ vs. b
EoS classification with PointNet

- Essential input to fluid dynamics evolution
  - pressure of the medium for any given energy and net baryon number densities

- Incorporates the QCD transition
  - Pressure gradients drives the evolution

- Not directly accessible experimentally

Our solution: **PointNet EoS classifier**

- We use:
  - **First Order Phase transition**: Maxwell construction between a bag model quark gluon EoS and a gas of pions and nucleons
  - **Crossover**: Chiral Mean Field hadron-quark EoS

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**UrQMD output**

- 4-momentum of all particles
- Ideal detector

**UrQMD output with CBM acceptance**

- 4-momentum of all particles
- 2-25° acceptance cut

**UrQMD + CbmRoot**

- Reconstructed tracks from digitised STS hits
- Realistic simulation

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- accuracy on e-b-e data:
  - ideal case (01): 77.2%
  - realistic case (03): 62.4%

- accuracy improves for multi-event point clouds

- with 40 events: **97% accuracy** for case 03

- work over a wide range of centralities

- outperform conventional methods (e.g. v2)