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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
- Point clouds are 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. A point cloud of hits in detector planes

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

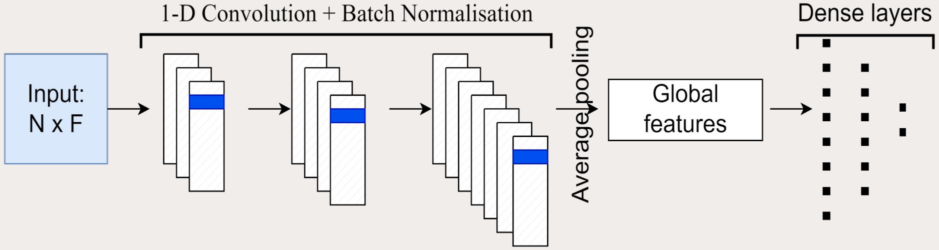


Fig 2. The general PointNet architecture used for classification or regression tasks.

- 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

PointNet based centrality meter

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

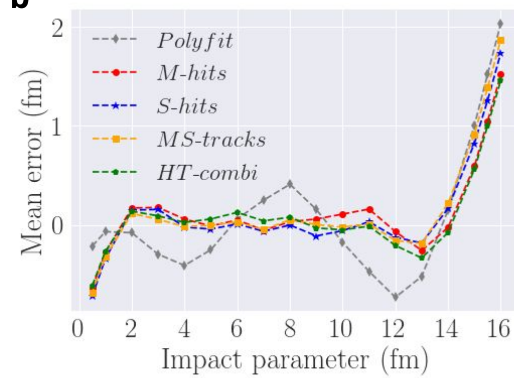


Fig 3. The mean error in b-predictions for different DL models and Polyfit baseline.

PointNet based Equation of State meter

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

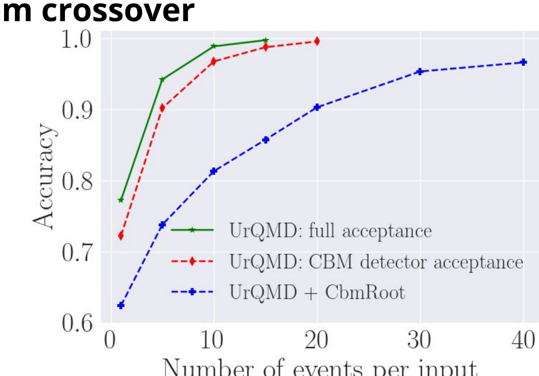
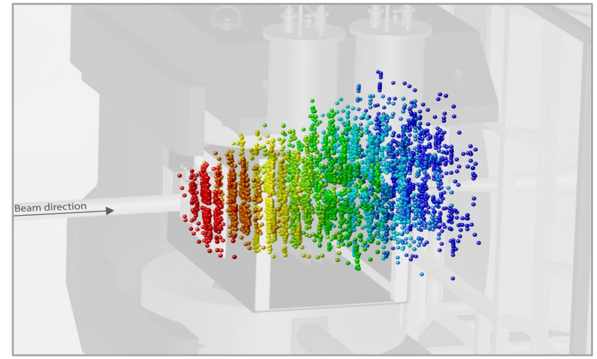


Fig 4. classification accuracy for PointNet models with different experimental effects

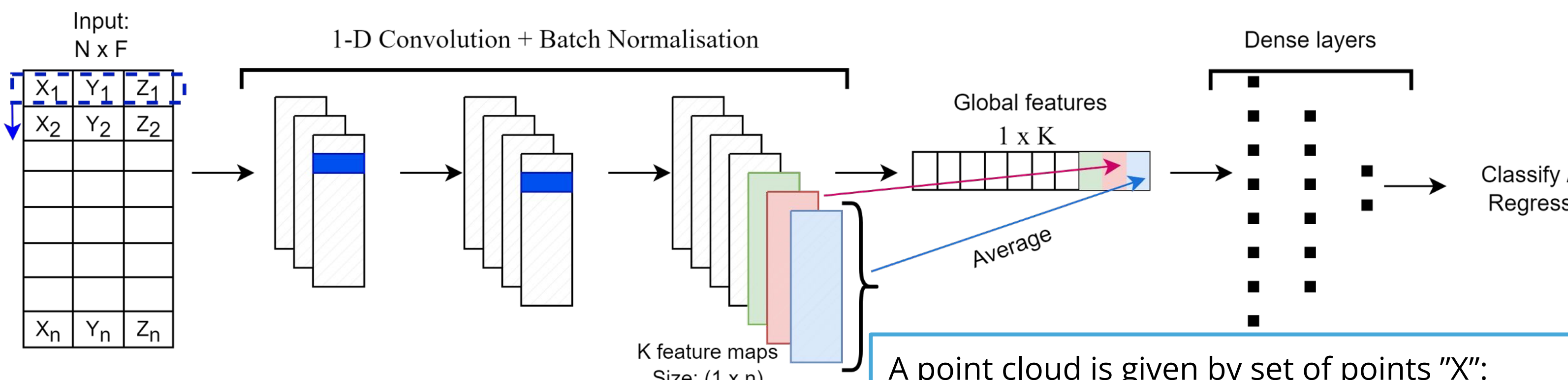
The PointNet architecture

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

$X=\{x_1, x_2, x_3, \ldots x_n\}$

PointNet learns a set of functions "F":

$F=\{f_1, f_2 .. f_m\}$, where $f_i(\{x_1,\ldots,x_n\}) \approx g(h_i(x_1),\ldots,h_i(x_n))$,

h= 1D CNN, g=AvgPooling

Impact parameter reconstruction with PointNet

SCAN ME
(or click here)

__Physics Letters B 811 (2020): 135872__

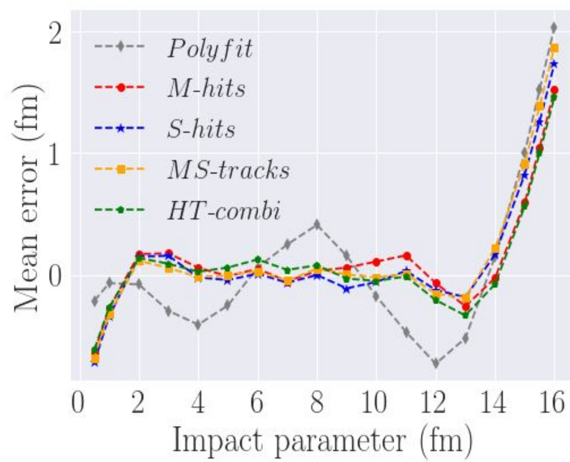
__Particles 4.1 (2021): 47-52__

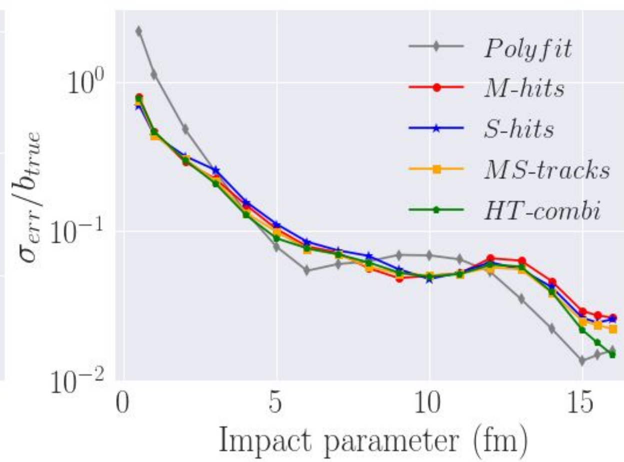
- Impact parameter ‘b’: not experimentally measurable
  - Glauber MC
    - Only a ‘likely’ distribution for b in a centrality bin is known

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

01	**M-hits**	Hits in MVD
02	**S-hits**	hits in STS
03	**MS-tracks**	tracks in MVD+ STS
04	**HT-combi**	MVD hits + tracks from MVD+STS
05	**Polyfit (non-ML baseline)**	polynomial fit to N_{chg} vs. b

- 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**





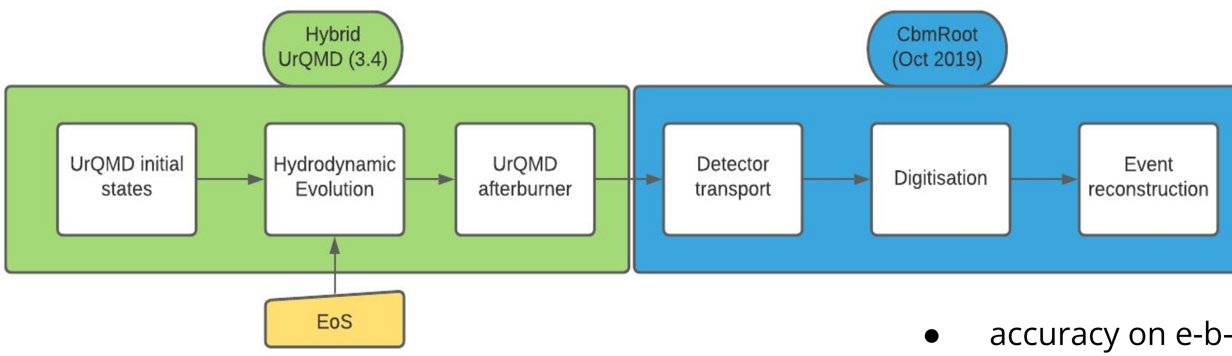
EoS classification with PointNet

- 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**

JHEP 2021.10 (2021): 1-25.

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



SCAN ME
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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

- 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)