PointNet for event characterization at the CBM experiment

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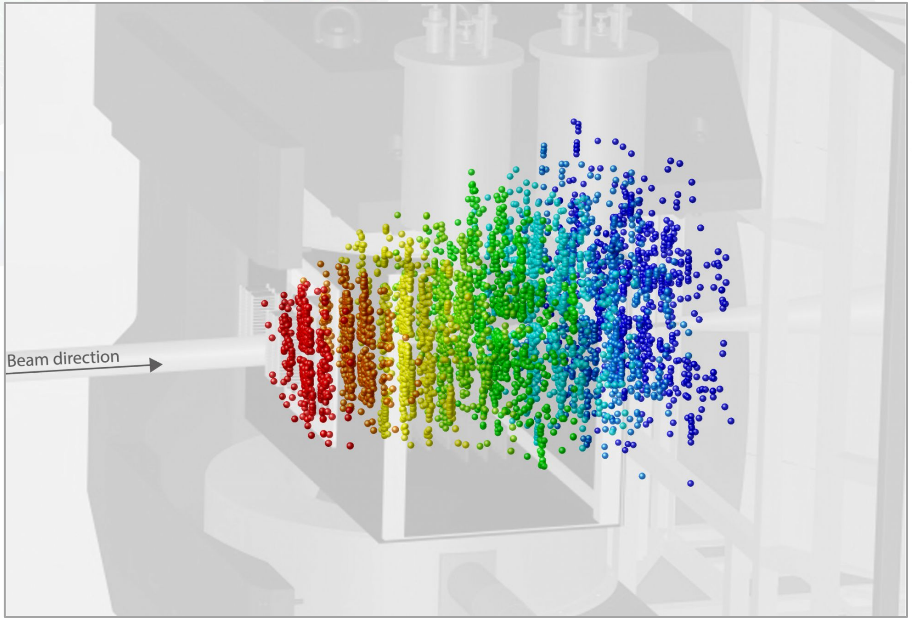
Experimental data as point clouds

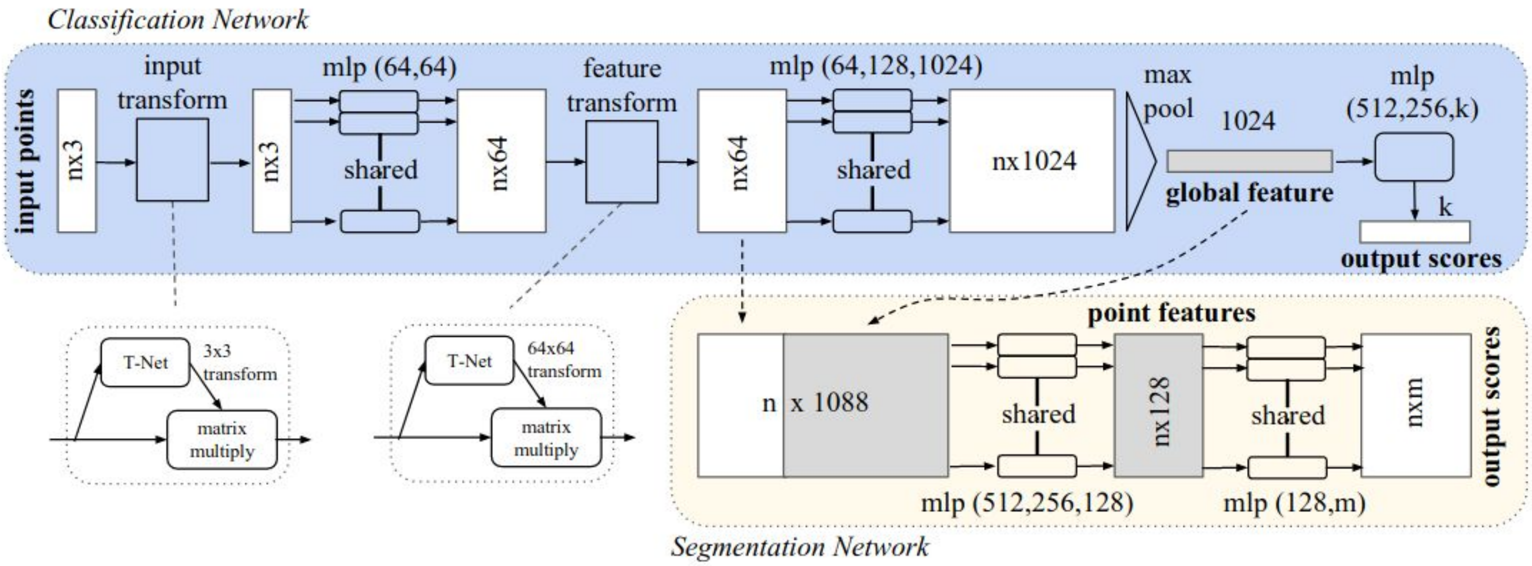
- Point cloud: set of data points in space
  - No ordering
  - $\{(x_1,y_1,z_1), (x_2,y_2,z_2),\ldots(x_n,y_n,z_n)\}$
  - Not limited to 3 dimensions
- Electronically collected data often has point cloud structure
  - Data from sensors, detectors etc.



DL models operating on Point clouds ➡

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

PointNet: Deep Learning for point clouds



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”

$F=\{f_1, f_2...f_m\}$

where $f_i(\{x_1,...,x_n\}) \approx g(h_i(x_1),...,h_i(x_n))$

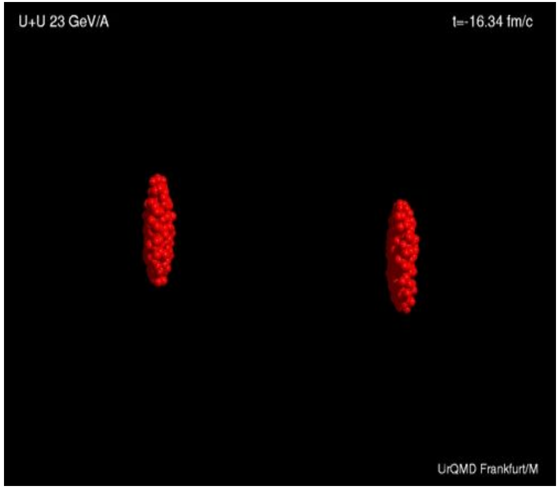
h~ MLP with shared weights/ 1D CNN

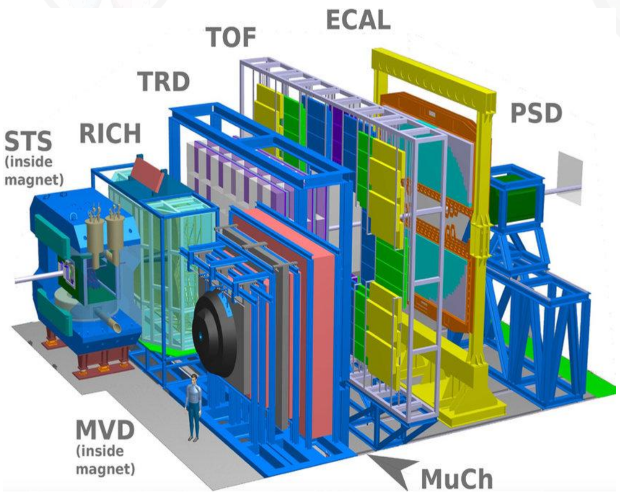
g=symmetric function (maxpool, avgpool, sumpool etc.)

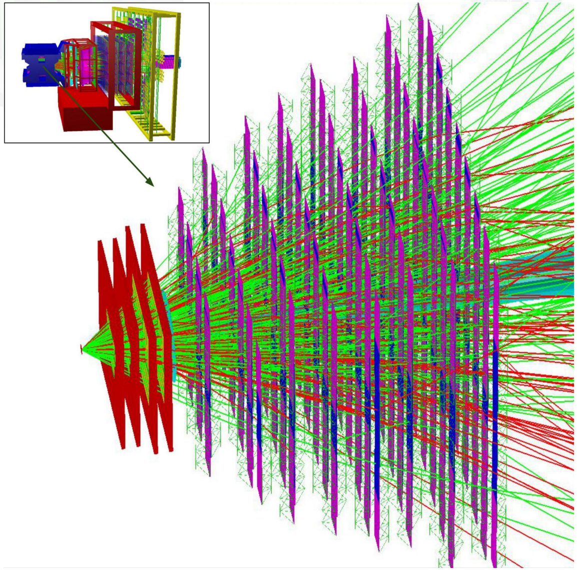
The CBM experiment: challenges and goals

- Explores QCD phase diagram at highest baryon densities through Heavy-ion collisions
  - EoS of highly compressed baryonic matter
  - the deconfinement phase transition
  - Search for critical point

- Upto 45 AGeV collisions
- 10^7 collisions/ Second
- 1000 tracks per collision
- 1 TBytes/Second raw data

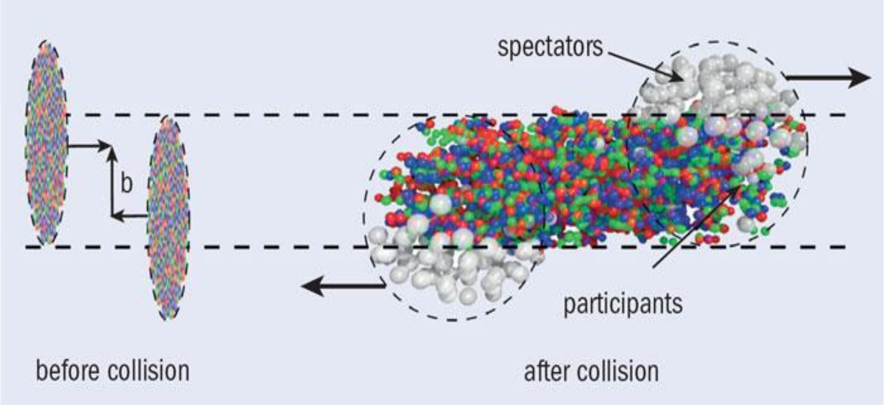






Centrality determination at CBM

- Impact parameter ‘b’: not experimentally measurable
  - Glauber MC
  - Percentiles of N_{chg}, E_{spect} are mapped to collision centrality
  - Only a ‘likely’ distribution for b in a centrality bin is known

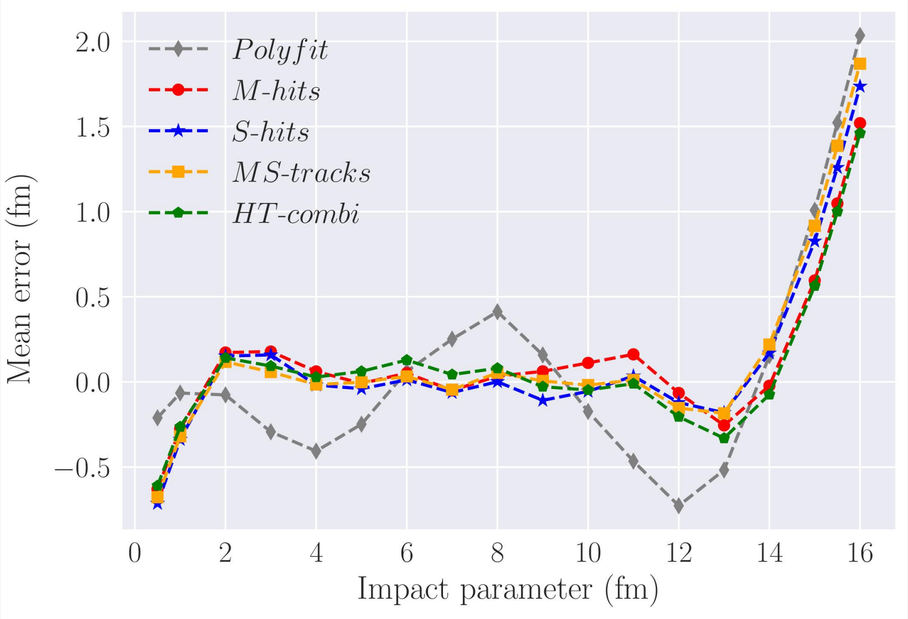


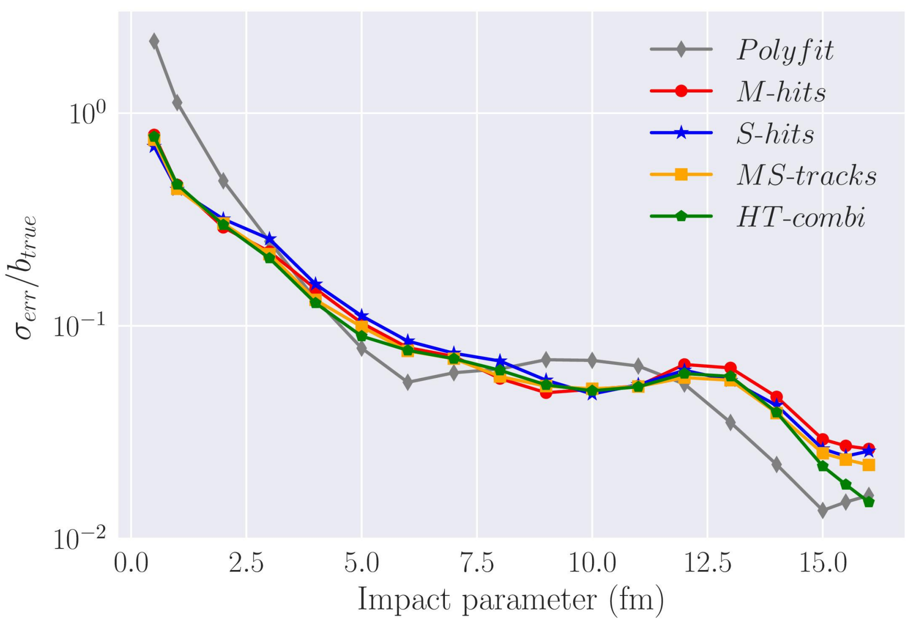
Our solution: PointNet based ‘b’ meter
- Event-by event
- Works on direct experimental output
- Online event characterisation

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

PointNet centrality meter

- mean error -0.3 - 0.2 fm for b= 2- 14 fm
- Polyfit: highly fluctuating

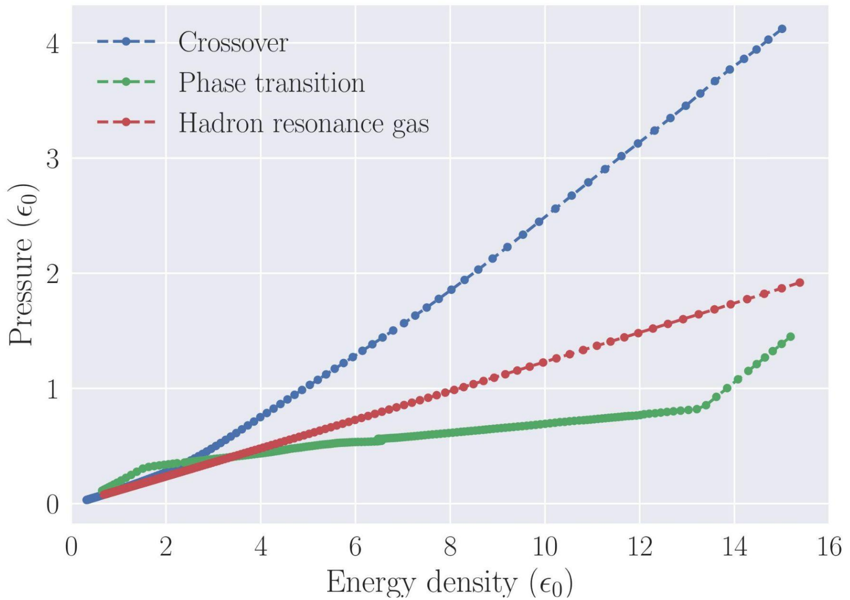




- Quantifies precision in predictions
- Polyfit fails for central events!
- Similar precision for b>3 fm

EoS classification with PointNet

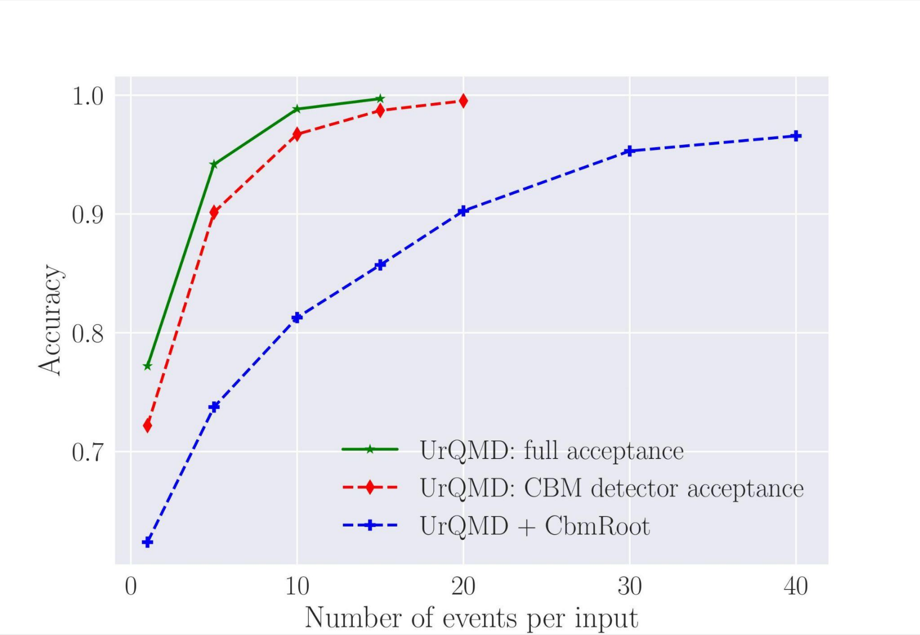
- Essential input to fluid dynamics evolution
  - pressure of the medium for any given energy and net baryon number densities
- Incorporates the QCD transition
  - Pressure gradients drives the evolution
- Not directly accessible experimentally
  - Comparisons with model calculations
  - Bayesian fit to different obervables



Our solution: PointNet EoS classifier

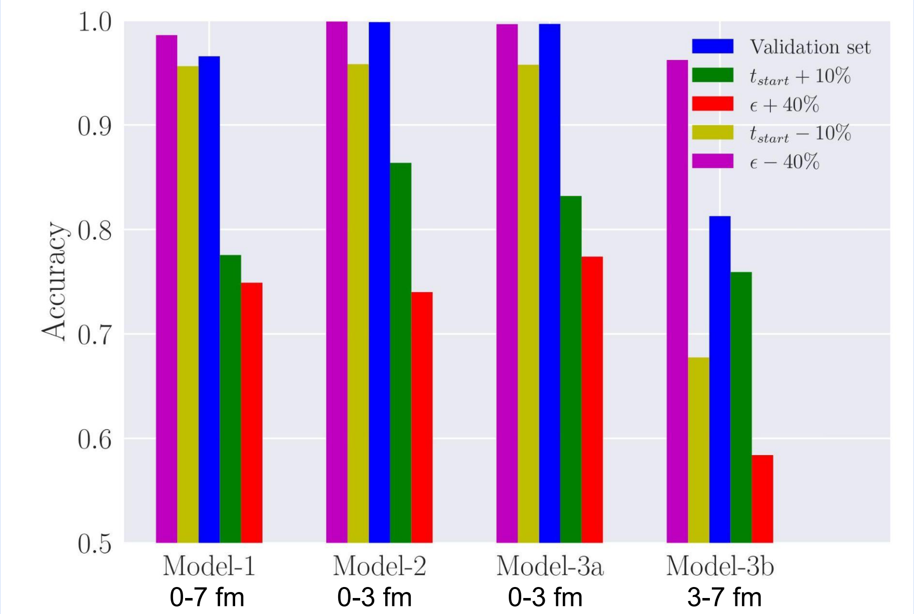
- We use:
  - **First Order Phase transition:** Maxwell construction between a bag model quark gluon EoS and a gas of pions and nucleons
  - **Crossover:** Chiral Mean Field hadron-quark EoS

PointNet EoS meter



- Decrease in performance with increase in experimental effects
- Performance improves when events are combined

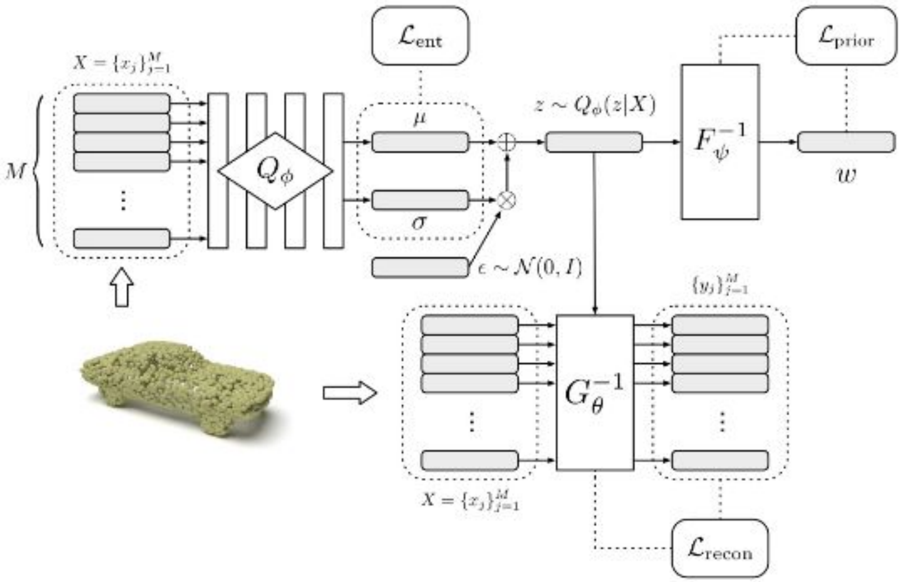
- Models tested for t_{start}∓10% and ε∓40% from training value
- Decrease in accuracy with t_{start}+10% or ε+40% : underlying physics limitation



In progress: Generative modelling of Heavy-ion collisions

- HIC simulations are computationally expensive/ time consuming
- Experiments often rely on model simulations for analyses

- Generative modelling of Point cloud:
  - Invertible NN based on continuous normalising flows
- DL simulation of a collision event
  - Each point: a particle (E, p_x, p_y, p_z)
  - 2 stage generation
    - A. Generates the particle multiplicities
    - B. Generates the momentum 4 vector for each particle



Summary

- The DL models outperforms conventional methods for impact parameter determination
  - Event by event
  - Reconstructs ‘b’ from hits/ tracks
  - *Phys.Lett.B* 811 (2020) 135872, *Particles* 2021, 4(1), 47-52
- PointNet based DL models are an efficient tool for identifying phase transition at CBM
  - Accuracy upto 99.8%
  - Online algorithm- Works with direct experimental data
  - *Journal of High Energy Physics* 2021 (10), 1-25
- Ongoing works on Generative modelling of HIC
  - Generates collision event as point cloud
  - Invertible NN based on normalising flows