Extraction of global event features at the CBM experiment using PointNet

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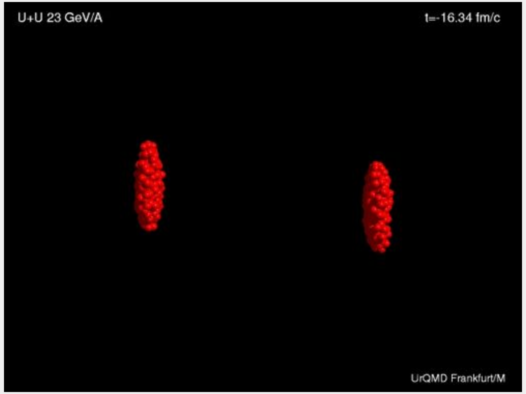
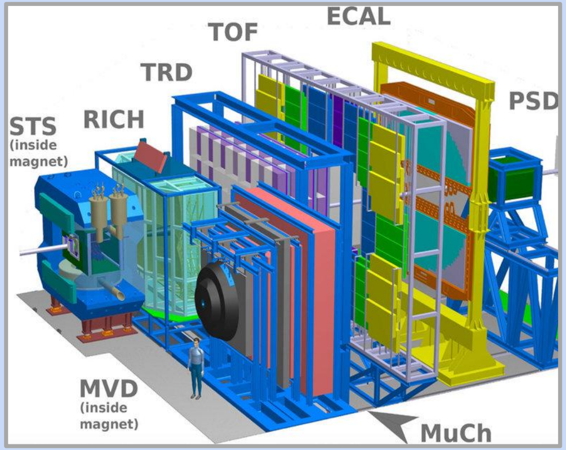
Heavy-ion Collisions: from experiments to theory

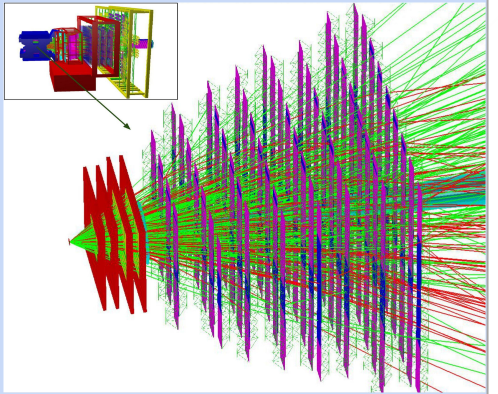
- Several established models for HIC
  - Microscopic cascade calculations
  - Hydrodynamics
  - Hybrid Micro+Macro models
- Inputs: ‘b’, EoS, etc.



- Next-gen experiments
  - High precision measurements
  - Unprecedented statistics
- Measure: Hits, tracks, etc.

The CBM Detector



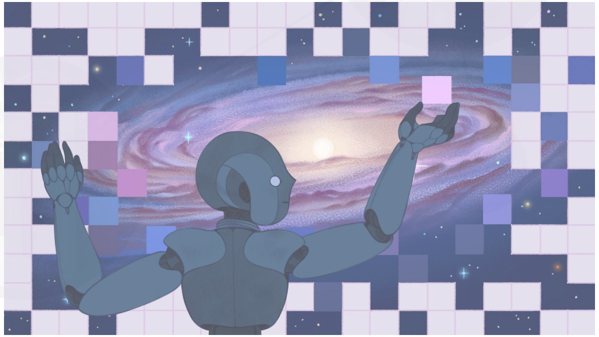


- Upto 45 AGeV collisions
- 10^7 collisions/ Second
- 1000 tracks per collision
- 1 TB/Second raw data

- How can we extract the theoretical quantities from the experimental data?
  - Conventional way: Large scale model simulations and preprocessing of data

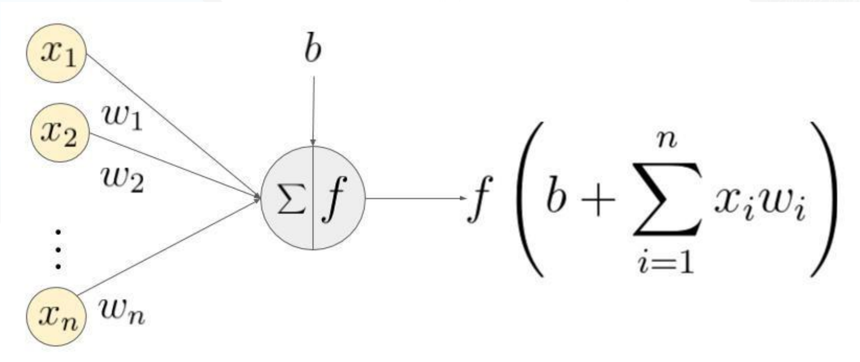
Artificial intelligence based data analysis for HIC ?

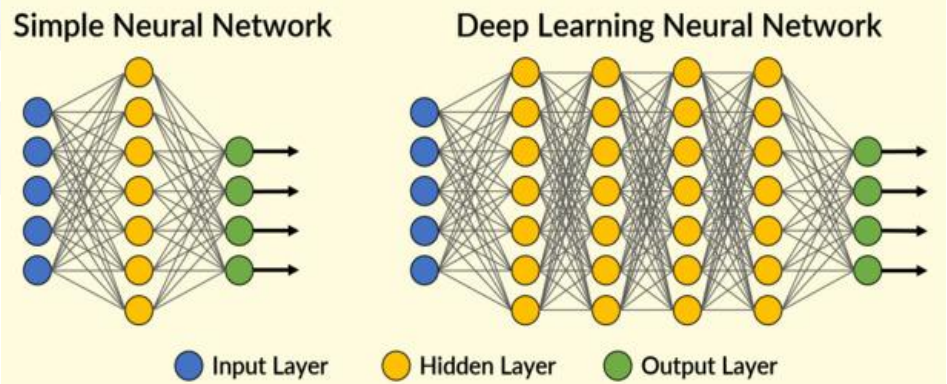
- DL/ML methods are widely used in High Energy Physics experiments
  - Data collection:
    - Calibration of detector
    - Filtering noise
    - Event separation
    - Event reconstruction
    - Particle identification
  - Analysis:
    - Reconstructing useful parameters from raw data
    - Search for new physics
    - Fast simulations
    - Build better analysis tools than conventional techniques

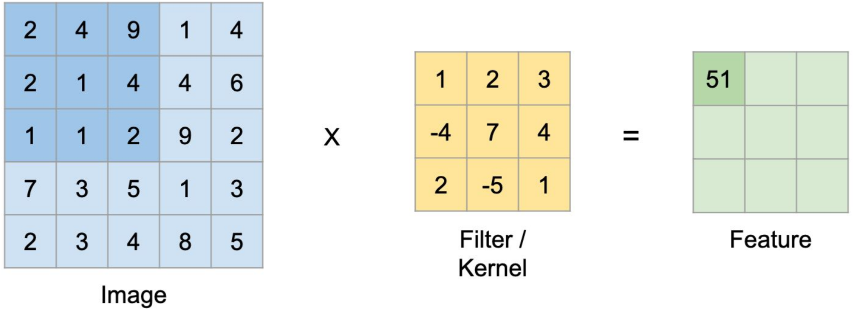


Can Deep Learning Methods be used to bridge the gap between theory and experiments in HIC?

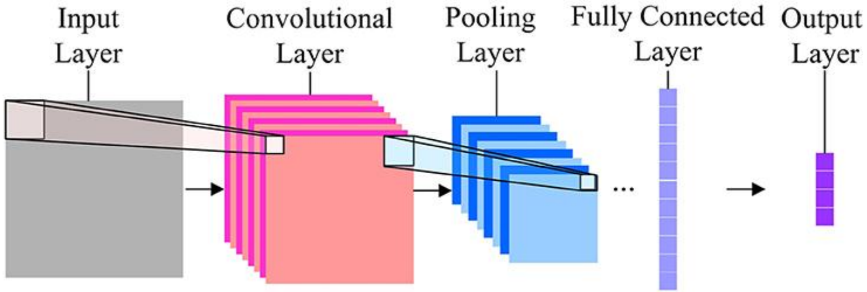
ML/ DL : A quick introduction







Convolution operation

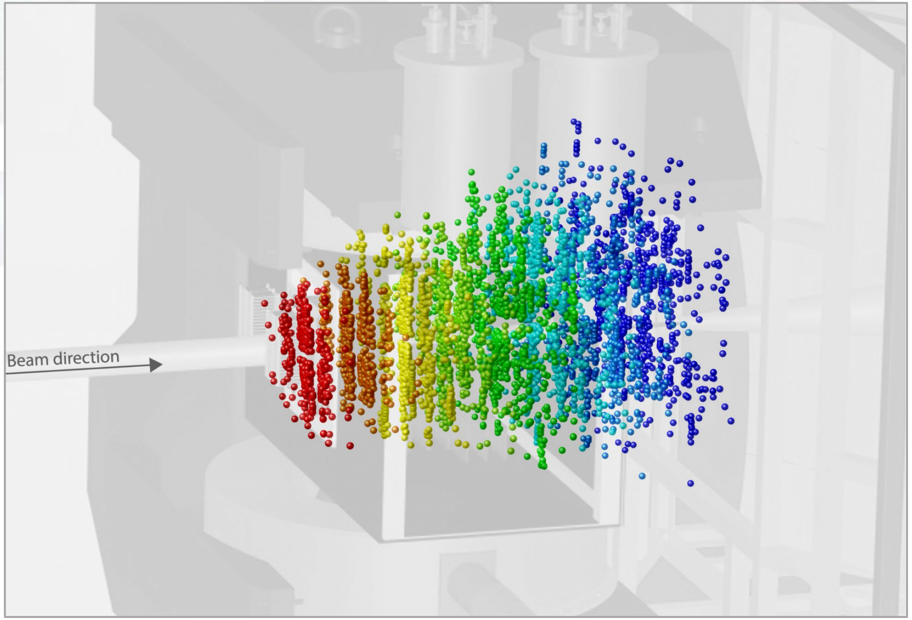


Convolution Neural Network

Experimental data as point clouds

- Point cloud: set of data points in space
  - No ordering
  - $\{(x_1,y_1,z_1), (x_2,y_2,z_2),...(x_n,y_n,z_n)\}$
  - Not limited to 3 dimensions

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

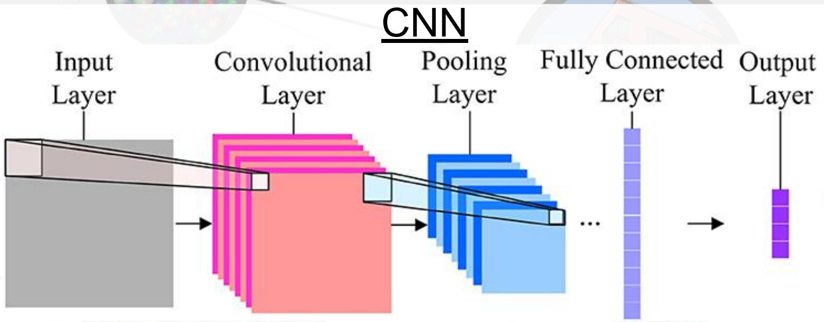


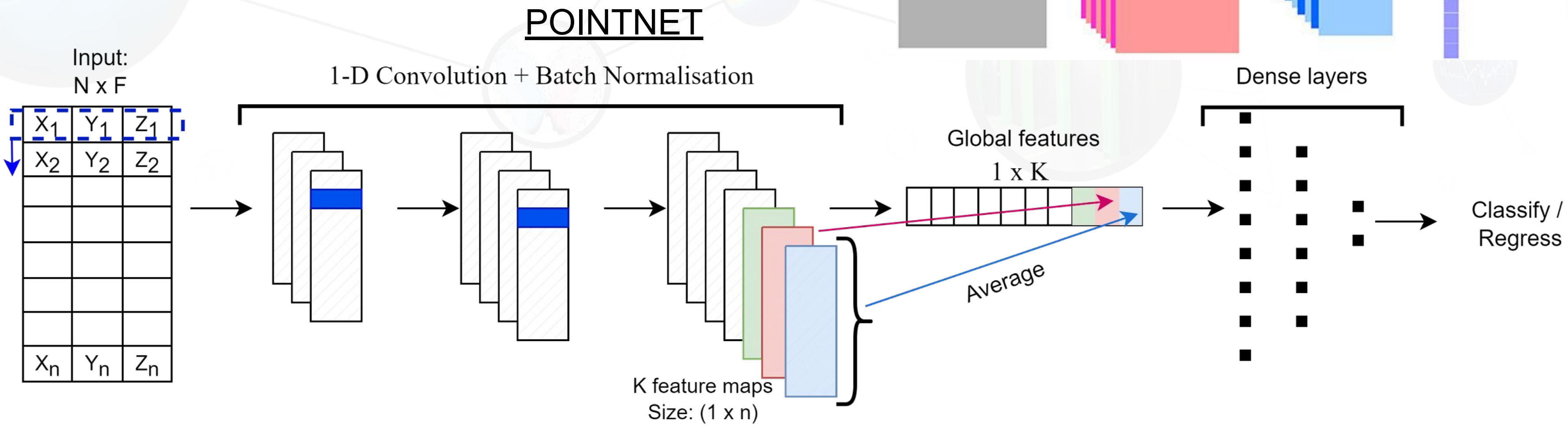
DL models operating on Point clouds ➡

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

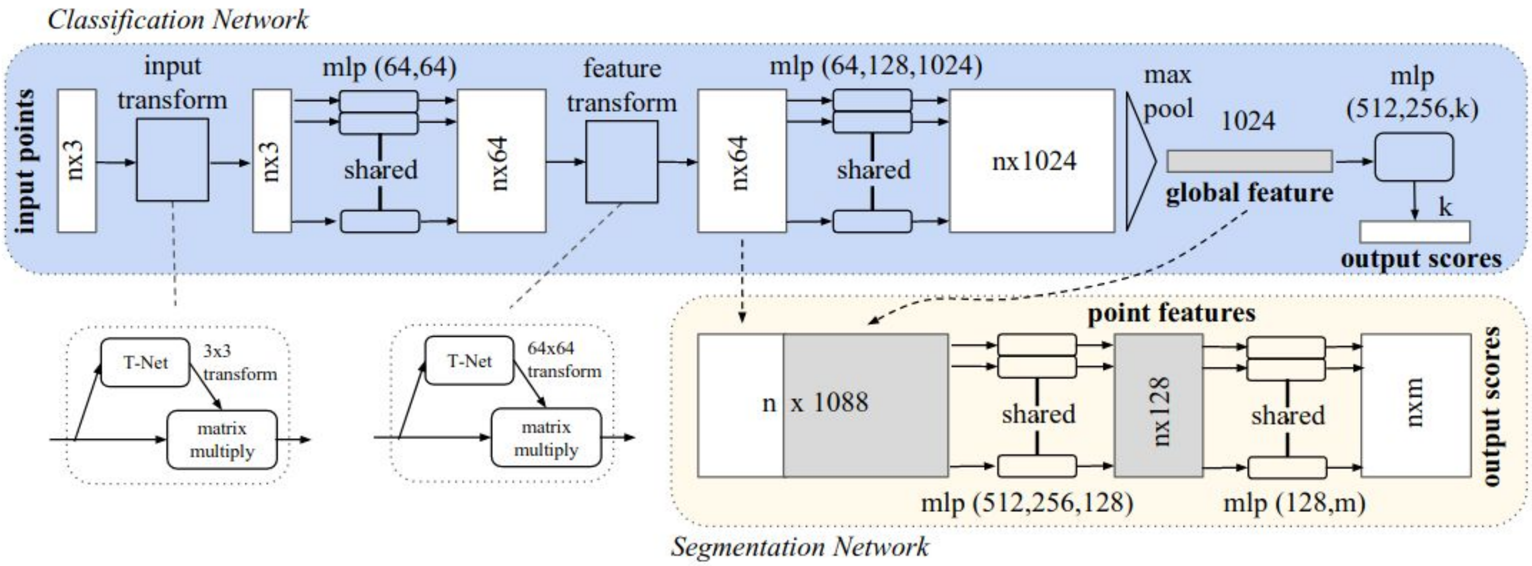
- Conventional CNNs extract spatially correlated features
- Point clouds are order invariant





- PointNet respects order invariance by :
  - A. extracting single particle features
  - B. Symmetric transformation of these features to global event features

PointNet: Detailed Structure



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”:

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

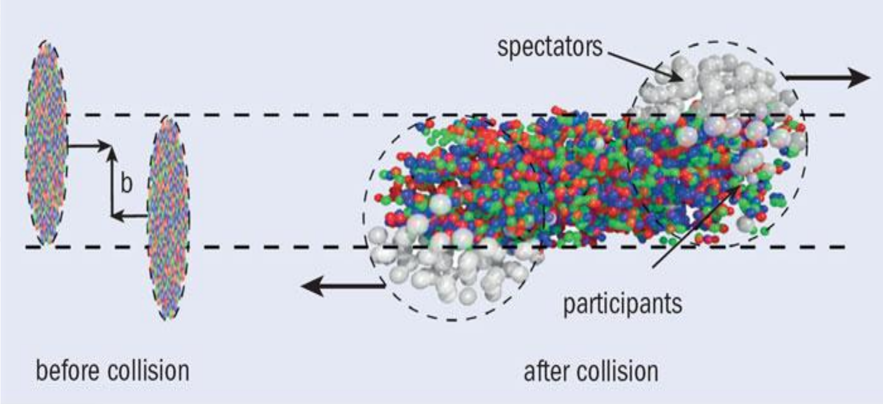
where $f_i(\{x_1,...,x_n\}) \approx g(h_i(x_1),...,h_i(x_n))$

h~ MLP with shared weights/ 1D CNN

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

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

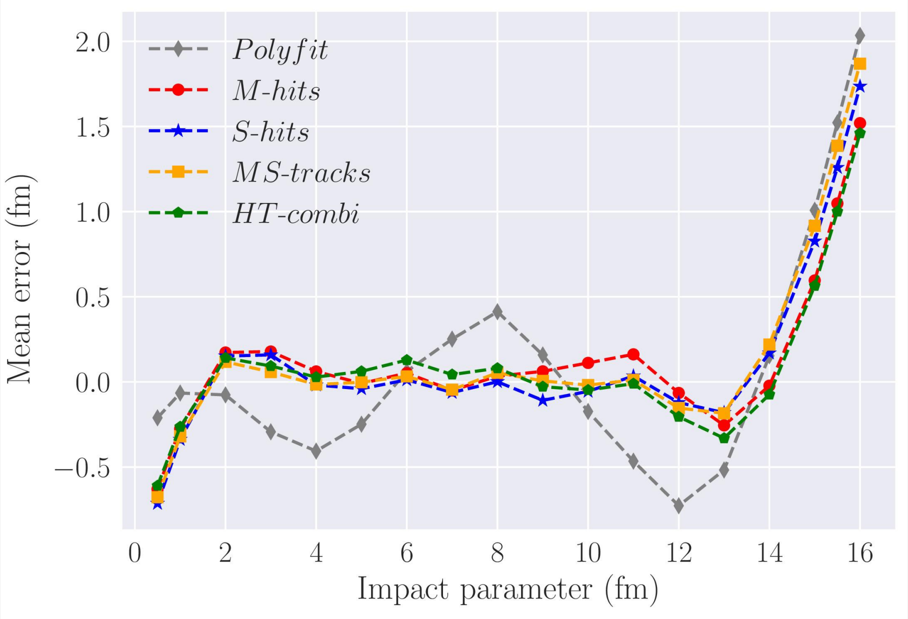


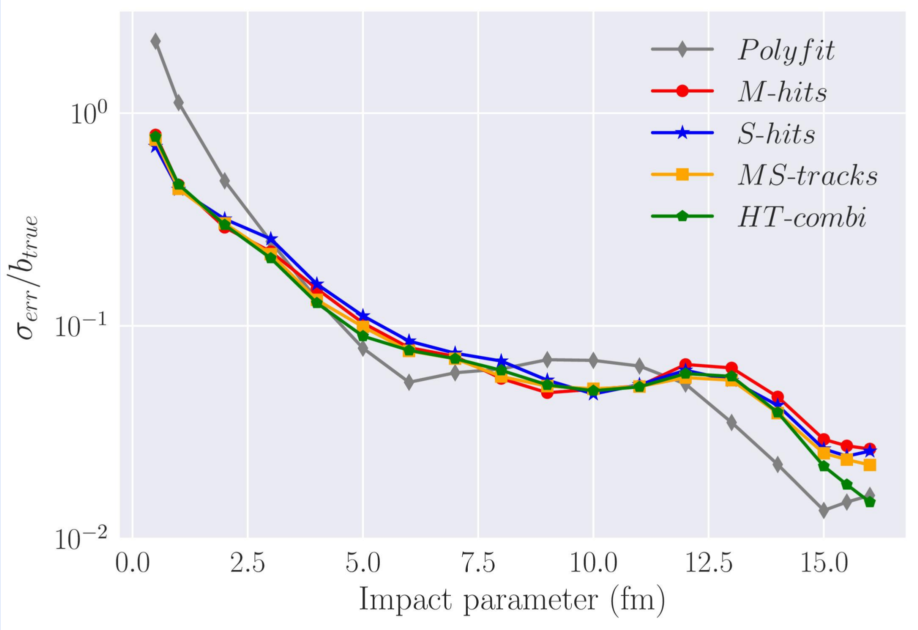
Our solution: PointNet based ‘b’ meter
- Event-by event
- Works on direct experimental output
- Online event characterisation

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

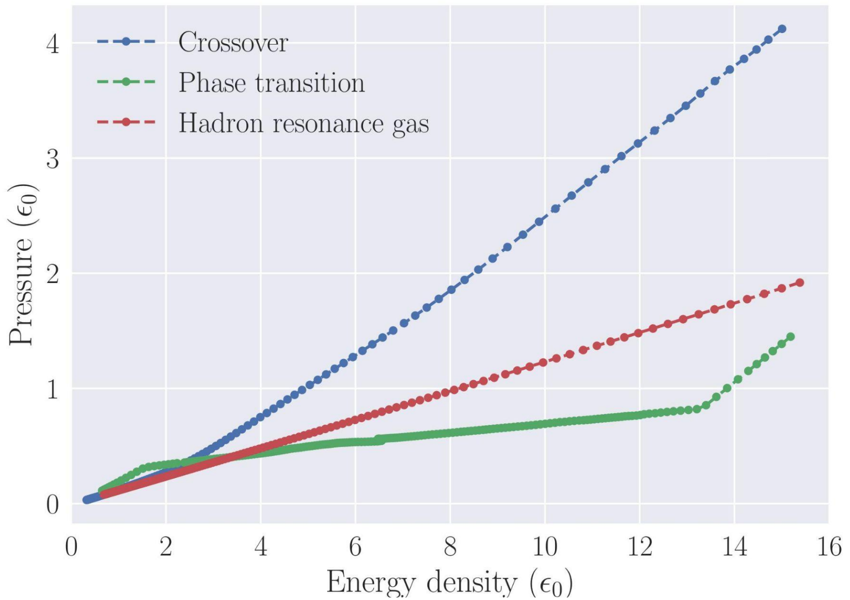




- Quantifies precision in predictions
- Polyfit fails for central events!
- Similar precision for b>3 fm

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
  - Multi-parameter fit to different observables

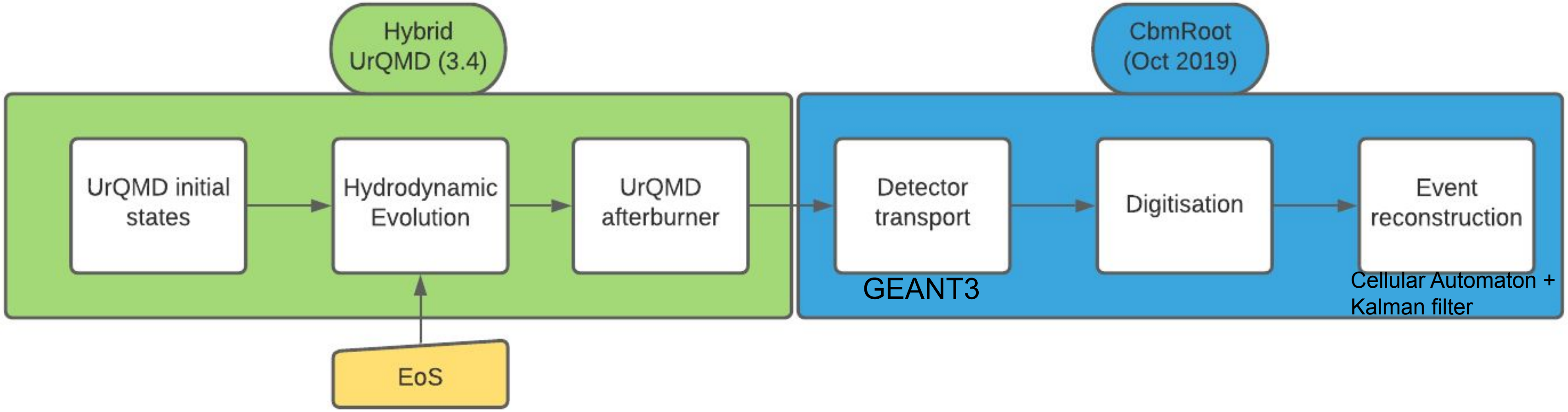


Our solution: PointNet EoS classifier

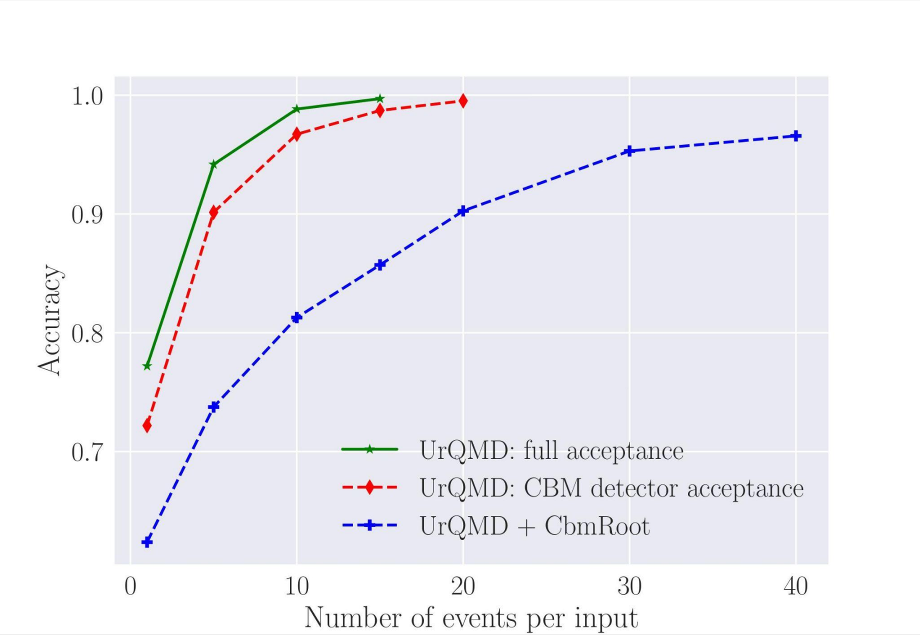
- We use:
  - **First Order Phase transition:** Maxwell construction between a bag model quark gluon EoS and a gas of pions and nucleons
  - **Crossover:** Chiral Mean Field hadron-quark EoS

Data preparation

- Design a DL based EoS meter for CBM experiment
  - increased uncertainties from electro-weak decays and other detector effects
- Raw experimental data as input
  - Minimises the biases from user defined selection criterias and other analysis algorithms

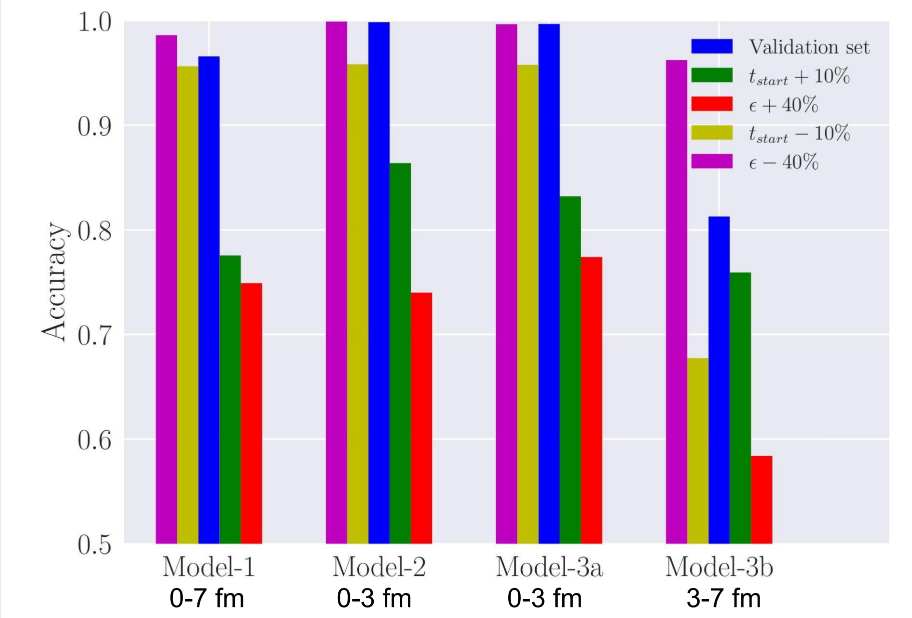


PointNet EoS meter



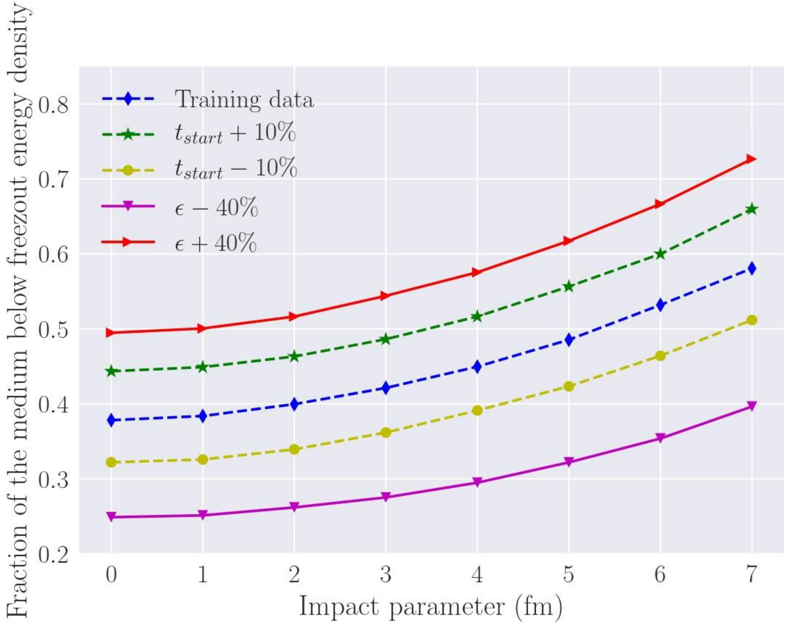
- Decrease in performance with increase in experimental effects
- Performance improves when events are combined

- 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



Reasons for dependence on centrality, t_{start} and ε

- For b=0, ~62% of the medium experiences hydro while it is ~42% for b=7
- Decrease in t_{start} or ε increases hydro duration
  - More part of system experience hydro
  - Even for b=0:
    - ~68% for t_{start}-10%
    - ~75% for ε -40%
- Increasing t_{start} or ε decreases hydro duration
  - Small fraction of system experience hydro
  - For b=0:
    - ~55% for t_{start}+10%
    - ~50% for ε +40%
- For peripheral events, decreasing t_{start} or ε could cause as less as ~25% of the medium to experience hydro



Summary

- PointNet based models are an excellent tool for DL based analysis in HIC experiments
- 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

- PointNet like models: not just for HIC or CBM but easily extendable to any detector based experiments

- Ongoing works on Generative modelling of HIC
    - Generates collision event as point cloud
    - Fast simulation of collision events