

Classifying the QCD transition at the CBM experiment with Deep Learning

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The study of QCD matter

Conjunctured QCD phase diagram

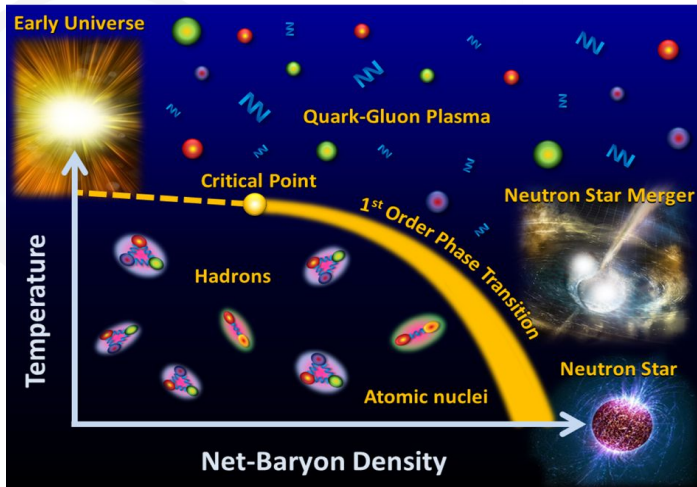
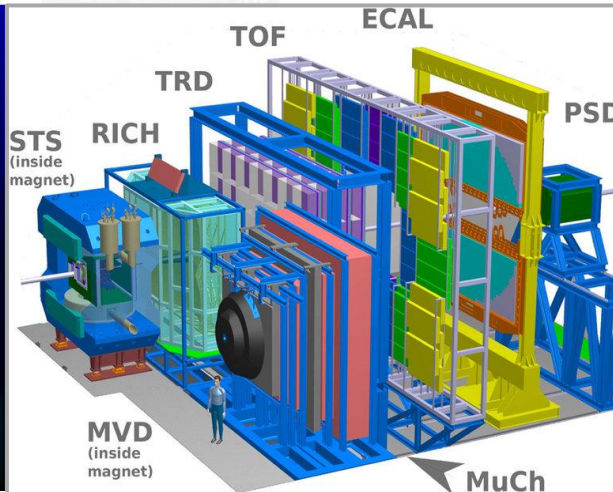


Fig: Senger, Peter. "Astrophysics in the Laboratory—The CBM Experiment at FAIR." *Particles* 3.2 (2020): 320-335.

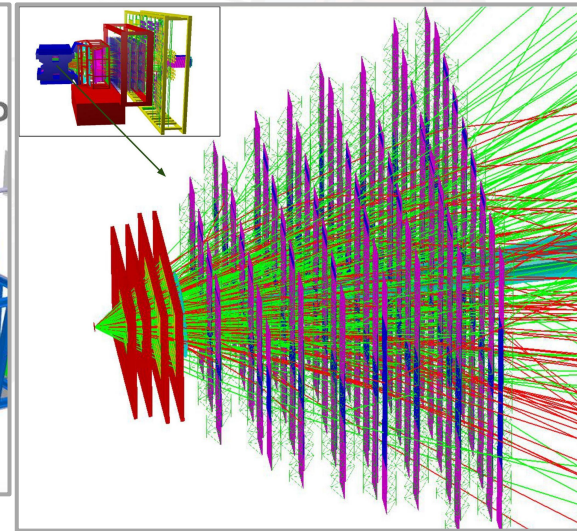
- LQCD-> Smooth crossover at high temperature and small densities
- Is there a phase transition?
- If so, where is the critical point?

The CBM Detector



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

A simulated event in STS + MVD



- MVD -> 4 planes
Position resolution: $3.5-6 \mu\text{m}$
Secondary vertex resolution: $50 \mu\text{m}$
- STS-> 8 planes
Momentum resolution: 1 %

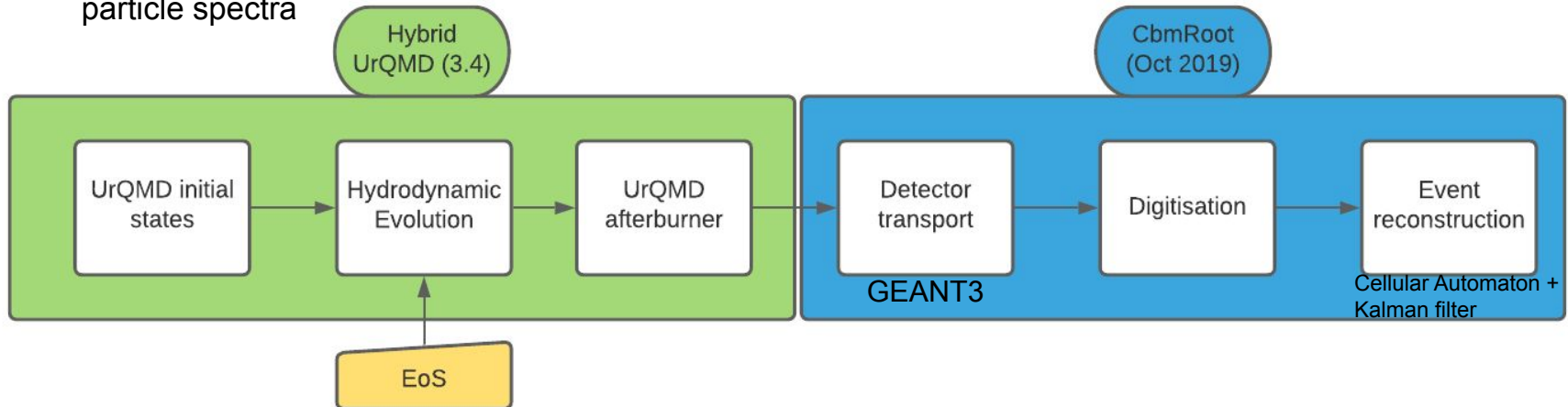
Data preparation

Previous works:

- Pure hydrodynamic study: Pang, L. G., Zhou, K., Su, N., Petersen, H., Stöcker, H., & Wang, X. N. (2018). *Nature communications*, 9(1), 1-6.
 - > 95% accuracy
- Hydrodynamics + afterburner: Du, Y. L., Zhou, K., Steinheimer, J., Pang, L. G., Motornenko, A., Zong, H. S., ... & Stöcker, H. (2020). *The European Physical Journal C*, 80(6), 1-17.
 - Finite particle spectra, hadronic rescattering, resonance decays
 - prediction accuracy depended on smoothness of the particle spectra

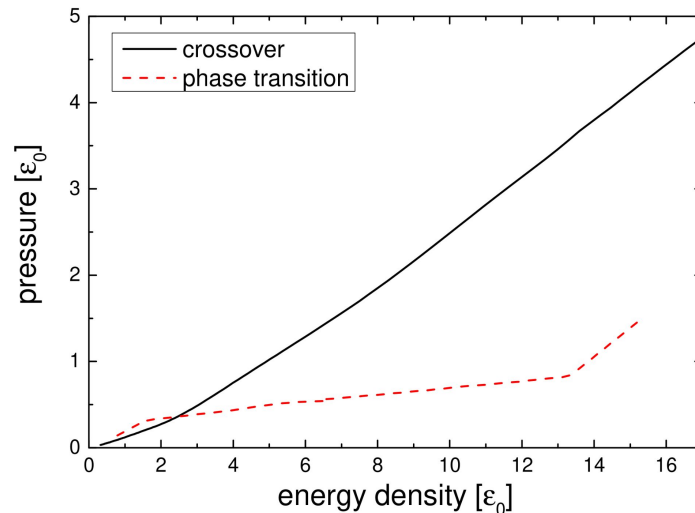
The Goal:

- Design a DL based EoS meter for CBM
 - increased uncertainties from electro-weak decays and detector effects
- Train on “experiment like” data
 - avoid biases from user defined selection criterias and analysis algorithms



The Equation of State

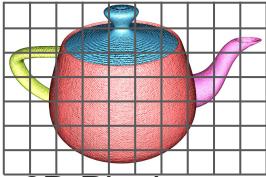
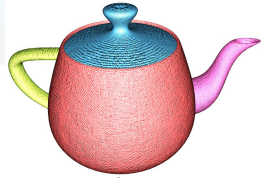
- Essential input to fluid dynamics evolution
- Provides the pressure of the medium for any given energy and net baryon number densities
- Incorporates the QCD transition
 - Pressure gradients drives the evolution
- We use:
 - Maxwell construction between a bag model quark gluon EoS and a gas of pions and nucleons :**First Order Phase transition**
 - Chiral Mean Field hadron-quark EoS :**Crossover**



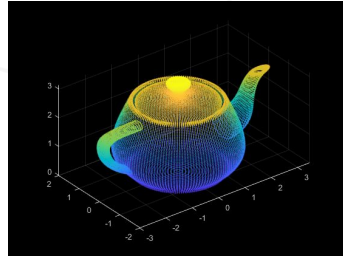
Representing the experimental data

- Experimental data: tracks or hits of particles

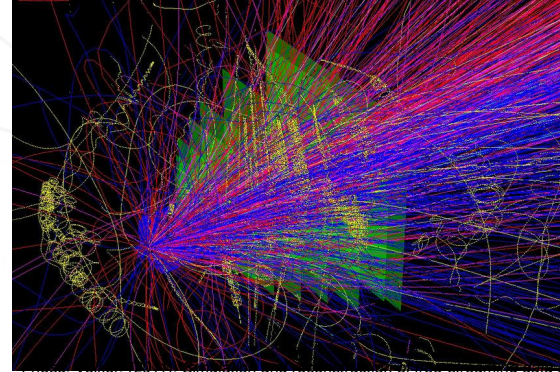
- Each particle is a point in a point cloud
- The order of input shouldn't affect the output



2D Pixel map



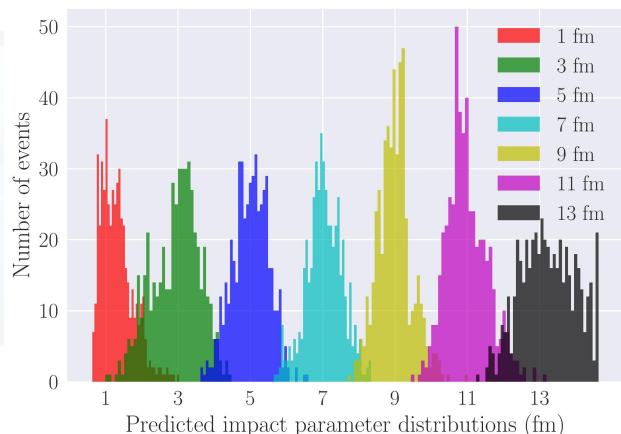
- 3D Voxels map
 - voluminous!
- Pointcloud: order invariant 2D array of (x,y,z) coordinates (or other point attributes) of each point
 - Efficient representation for higher dimensions



Prozor, Vukobratovic (2017). Simulation and reconstruction of free streaming data in CBM. *Journal of Physics: Conference Series*. 331. 032008. 10.1088/1742-6596/331/3/032008.

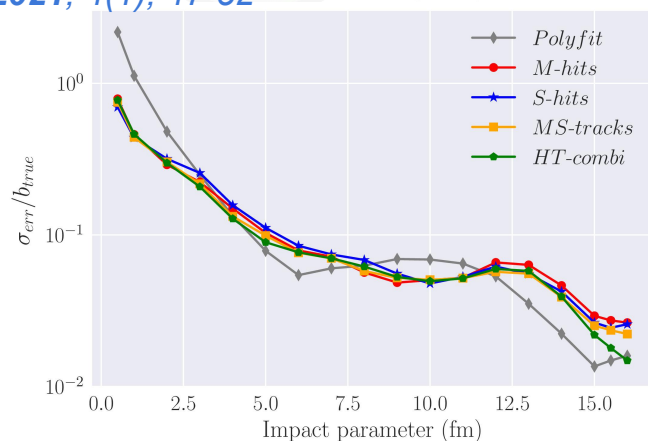
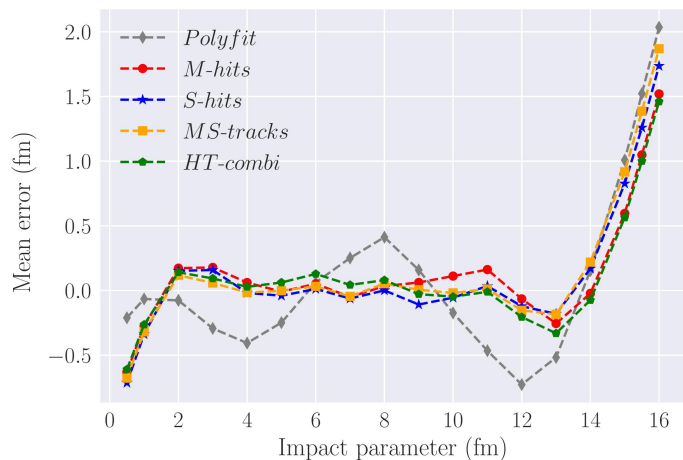
X1,y1,z1,.....
X2,y2,z2,.....
X3,y3,z3,.....
⋮
xn,yn,zn,.....

Learning the impact parameter from point cloud data



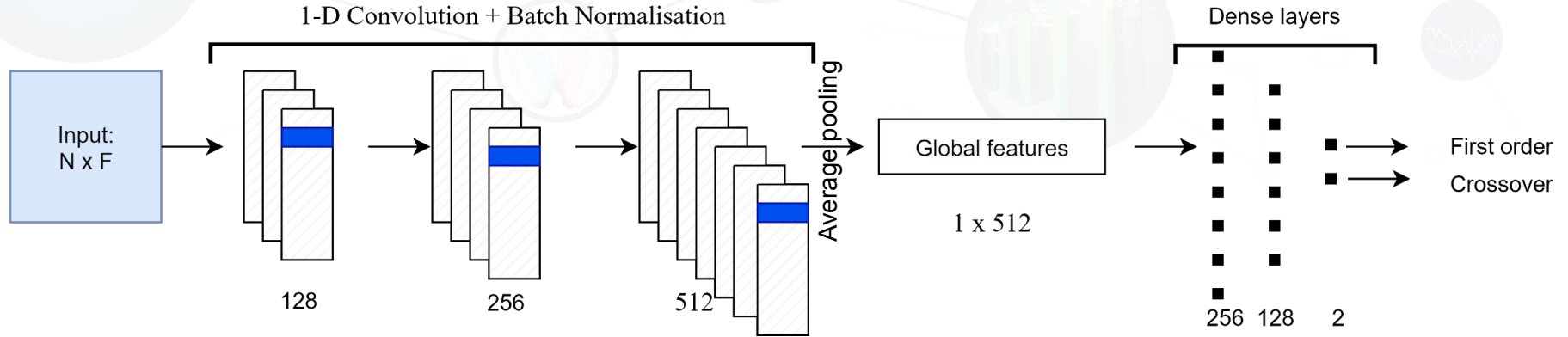
- PointNet based impact parameter determination
- mean error between -0.3 and 0.2 fm for b= 2- 14 fm

- *A fast centrality-meter for heavy-ion collisions at the CBM experiment*
[Phys.Lett.B 811 \(2020\) 135872](#)
- *Deep Learning based impact parameter determination for the CBM experiment*
[Particles 2021, 4\(1\), 47-52](#)



The PointNet model

- DL model to learn from point cloud
- Extracts order invariant global features



- ❑ N = No of particles
- ❑ F = No of features per particle

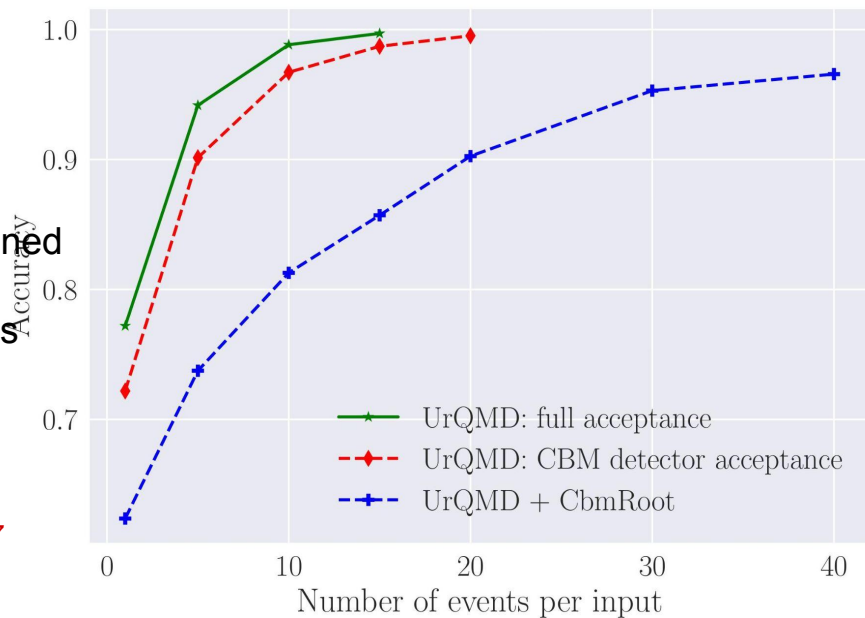
Training the models

- Au- Au Collisions at 10 AGeV
- 0-7 fm impact parameter (uniform)
- 60000 training samples (30000+ 30000) , 20000 validation samples (10000+ 10000)
- 3 Cases are considered
- All models used similar architecture, hyperparameters
- Differ in the input dimensions

01	UrQMD output	<ul style="list-style-type: none">• 4-momentum of all particles• Ideal case: 360° acceptance + 100% detector efficiency
02	UrQMD output with CBM acceptance	<ul style="list-style-type: none">• 4-momentum of all particles• 2- 25° acceptance cut
03	UrQMD + CbmRoot	<ul style="list-style-type: none">• Reconstructed tracks from the digitised hits in STS• Realistic simulation

Training results

- Decrease in performance with increase in experimental effects
- Accuracy on the event by event data:
 - UrQMD: 77.2%
 - UrQMD+ CBM acceptance: 72.2%
 - UrQMD+ CbmRoot: 62.4%
- Performance improves when events are combined
 - More uncertainties-> More events
 - UrQMD+ CbmRoot: 96.6% with 40 events
- Similar dependency found in *Du, Y. L., Zhou, K., Steinheimer, J., Pang, L. G., Motornenko, A., Zong, H. S., ... & Stöcker, H. (2020). The European Physical Journal C, 80(6), 1-17*
- Increasing the statistics reduces the stochasticity



Centrality dependence

- Can the performance improve with a centrality selection?

		Impact parameter	Validation Accuracy
1	Model-1	0-7 fm	96.6%
2	Model-2	0-3 fm	99.8%
3	Model-3a	0-3 fm	99.65%
4	Model-3b	3-7 fm	81.27%

- Accuracy increases when trained on events with $b < 3\text{fm}$
- Centrality selection improves accuracy but most data collected goes unused
 - Model 3 can solve this issue

- Trained on events with both $b=0-3\text{ fm}$ and $b=3-7\text{ fm}$
- Centrality classes are not mixed when combining events
- Additional input to network which identifies the class of input data

- All models used combinations of 40 events of STS tracks

Input parameters for Hydrodynamics evolution

- Several inputs to hydrodynamic simulation re not precisely known.
- A practical DL model should be immune against changes to these parameters

1. Starting time of hydrodynamic evolution:

$$t_{start} = 2R\sqrt{\frac{m}{E_{lab}}}$$

R=radius of nuclei

m=mass of nucleon

E_{lab} = kinetic energy in lab frame

2. Freeze-out energy density (ϵ) :

The hydrodynamic evolution happens in a cartesian grid $\Delta x=0.2$ fm , 200^3 cells

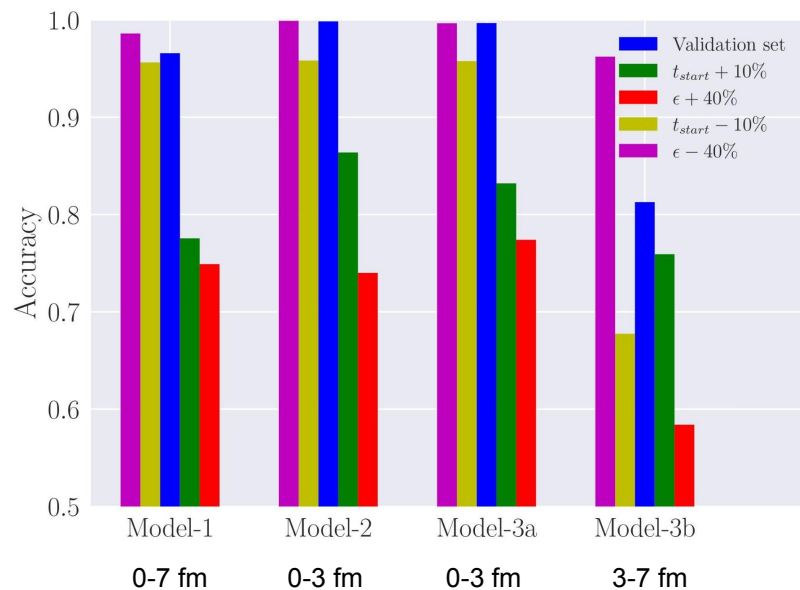
Hydrodynamic evolution stops when $\epsilon < 5\epsilon_0$ for all cells

Particlisation happens from the iso energy density hypersurface using Cooper-Frye formula

$$E \frac{dN}{d^3p} = \int_{\sigma} f(x, p) p^{\mu} d\sigma_{\mu}$$

$f(x, p)$ =boosted Fermi/ Bose distribution
 $d\sigma_{\mu}$ =freezeout hypersurface element

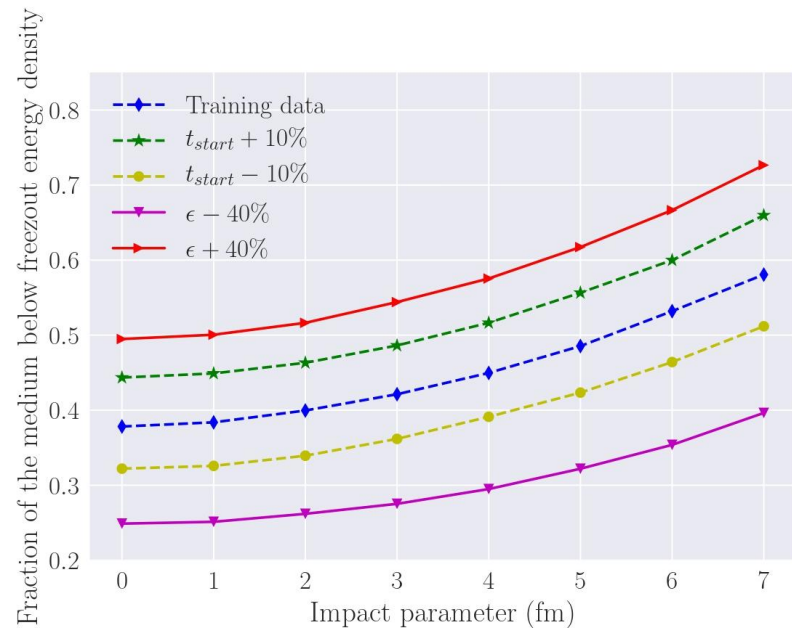
Dependence on t_{start} and ϵ



- Models tested for $t_{\text{start}} \pm 10\%$ and $\epsilon \pm 40\%$ from training value
- Decrease in t_{start} and ϵ doesn't affect the performance
- Increasing these parameters however causes considerable decrease in accuracy

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 $t_{\text{start}} - 10\%$
 - ~75% for $\epsilon - 40\%$
- Increasing t_{start} or ϵ decreases hydro duration
 - Small fraction of system experience hydro
 - For $b=0$:
 - ~55% for $t_{\text{start}} + 10\%$
 - ~50% for $\epsilon + 40\%$
- For peripheral events, decreasing t_{start} or ϵ could cause as less as ~25% of the medium to experience hydro



Summary

- PointNet based DL models are an efficient tool for identifying phase transition at CBM
 - Accuracy upto 99.8%
 - Online algorithm- Works with experimental data
- The performance of PointNet model is different conditions of experimental uncertainties and detector effects are demonstrated
 - >95% accuracy in a realistic experimental simulation with b 0-7 fm
- Best performance can be achieved with a centrality selection ($b=0-3$ fm)
 - Method to incorporate peripheral events is demonstrated
- Performance decrease due to increase in t_{start} or ε is merely the limitation caused by the underlying physics
- Any global event feature could be analysed with PointNet