PROCEEDINGS OF SCIENCE

Extraction of global event features in heavy-ion collision experiments using PointNet

Manjunath Omana Kuttan,[a,b,c,*] **Jan Steinheimer,**[a] **Kai Zhou,**[a] **Andreas Redelbach**[a,d] **and Horst Stoecker**[a,b,e]

[a] *Frankfurt Institute for Advanced Studies,*
Ruth-Moufang-Str. 1, D-60438 Frankfurt am Main, Germany
[b] *Institut für Theoretische Physik, Goethe Universität Frankfurt,*
Max-von-Laue-Str. 1, D-60438 Frankfurt am Main, Germany
[c] *Xidian-FIAS international Joint Research Center, Giersch Science Center,*
D-60438 Frankfurt am Main, Germany
[d] *Institut für Informatik, Goethe Universität Frankfurt,*
Max-von-Laue-Str. 1, D-60438 Frankfurt am Main, Germany
[e] *GSI Helmholtzzentrum für Schwerionenforschung GmbH,*
Planckstr. 1, D-64291 Darmstadt, Germany
E-mail: manjunath@fias.uni-frankfurt.de,
steinheimer@fias.uni-frankfurt.de, zhou@fias.uni-frankfurt.de,
redelbach@compeng.uni-frankfurt.de, stoecker@fias.uni-frankfurt.de

A Deep Learning based method to extract global event properties in heavy-ion collision experiments is introduced. The order invariant, point cloud representation of experimental data is chosen to train the models. The point clouds of hits recorded in detector planes or tracks reconstructed from these hits can be represented as a 2 dimensional array in which each row stores an arbitrary hit or track. The PointNet is a Deep Learning model that is designed to efficiently perform classification or regression tasks using such a representation of data. The PointNet based models are shown to accurately determine different properties of heavy-ion collisions by learning several global features of the input point cloud that can be mapped to a target property. In particular, we demonstrate that the PointNet based models can accurately determine the collision impact parameter on event-by-event basis, and classify the events based on the nature of the QCD transition as implemented in the hydrodynamic phase of the collision. These models outperform conventional analysis techniques and can work directly on free streaming detector output with extremely high event rates.

FAIR next generation scientists - 7th Edition Workshop (FAIRness2022)
23-27 May 2022
Paralia (Pieria, Greece)

*Speaker

PoS(FAIRness2022)040

1. Introduction

Heavy-ion collision experiments study the properties of strongly interacting matter in the laboratory [1]. Experiments reconstruct a collision event by measuring the position, momenta, charge and mass of the particles produced in the collision using a variety of particle detectors. However, the detection efficiency, dead time and the phase space coverage of detectors make these measurements noisy and incomplete. Moreover, the event reconstruction efficiency is ultimately limited by the position, momentum and time resolution of the detectors. Additional uncertainties are also introduced into the data by the algorithms used in processing the detector data. The final goal is then to trace back the physics embedded in the this partial, noisy information recorded by experiments by comparing different observables such as flow coefficients, baryon number fluctuations etc. with the predictions of theoretical models [2]. Although these observables are shown to be useful to study the properties and the dynamics of the matter produced in heavy-ion collisions, the experimental effects can significantly decrease the sensitivity of these observables. Therefore, it is interesting to explore new methods to analyse and characterise heavy-ion collision data.

In this work, we investigate Deep Learning (DL) methods that can be used to discover novel event features that can characterise heavy-ion collisions directly from experimental data such as hits and/or reconstructed tracks of particles. In particular, we discuss DL models based on the PointNet [3] architecture to extract novel global features of the collision events that can be used to accurately identify or distinguish different properties of heavy-ion collisions. We explain in detail, the model architecture, it's advantages compared to other DL models and finally present a couple of its use cases at the Compressed Baryonic Matter (CBM) [4] experiment.

2. Deep Learning heavy-ion collisions with PointNet

One of the main problems in training Deep Learning models using detector output is the sparse nature of the detector data. Consider a particle detector which records the coordinates of the particles crossing it. This hit information from an event can be stored as a 3 dimensional histogram of particle coordinates. The data is now a three dimensional array containing an "image-like" representation of the detector output. Convolution Neural Network (CNN) based algorithms are commonly used to train Neural Network models on "image-like" data [5, 6]. However, most of the bins in such a histogram will not contain any hit. Modern particle detectors which have excellent position resolution would further increase the size and sparsity of these arrays. Processing such extremely sparse arrays with CNNs would require huge amount of memory and computing power. Moreover, extending such a representation to accommodate more features of a hit such as the time of hit or the amplitude of the signal produced by the hit in the sensor would require additional dimensions to be added making it even more sparse. CNNs are not efficient in learning from sparse, high dimensional detector data.

An alternate representation of this data is as point clouds which are a collection of disordered points in space. A point cloud of the hits from an event is a dense representation of detector data in the form of an unordered list where each element is the set of coordinates of a hit. This can be stored in the form of a two dimensional array with each row storing a hit and each column recording an attribute of it (eg: x coordinate). This representation resolves the sparsity issue associated with an image-like representation as we store only the locations of hits but not the entire representation of the detector volume. Moreover, adding more features to a hit is possible by simply adding another column to this array. Thus, the point clouds are ideal for representing high dimensional data.

The lack of inherent order in the point cloud representation however makes it impossible to train CNN based DL models using point cloud data. The PointNet is a modification of regular CNN which is designed to respect the order invariance in the data allowing us to train DL models directly on the point cloud data. The PointNet model comprises of the following 2 components to achieve order invariance in the predictions unlike regular CNNs:

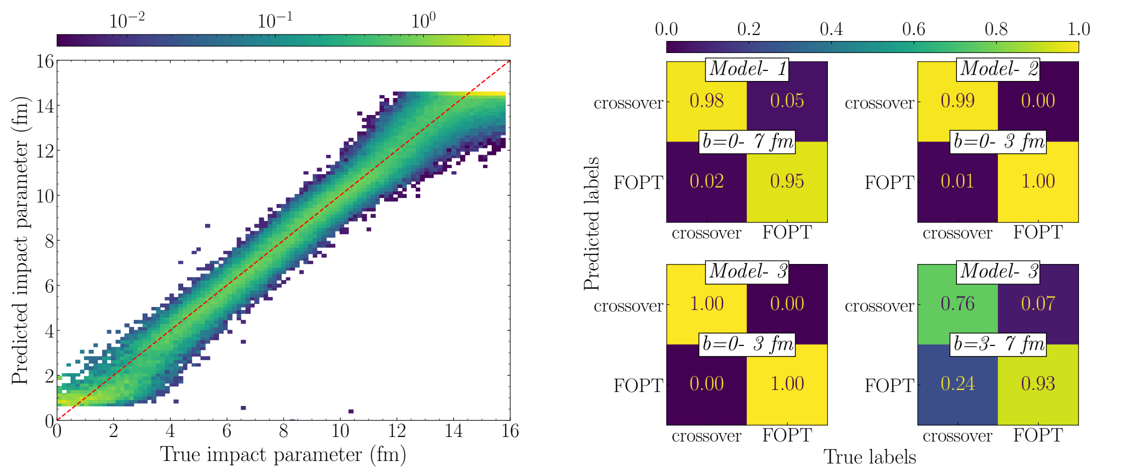
1. Convolution kernels with size $1 \times N$ where N is the number of columns in the input point cloud array. The advantage of using $1 \times N$ kernels is that it extracts only single point features as the kernel can only span one row at a time. Similar kernels are used in all hidden layers to ensure that the features extracted at the last convolution layer is still order invariant.

2. Symmetric functions to extract global features. The single point feature maps extracted by the $1 \times N$ kernels are converted into global feature maps of the entire point cloud by passing each feature map produced by the last convolution layer through an order invariant, symmetric function such as AveragePooling or MaxPooling. The output of these symmetric functions in the PointNet model can be interpreted as a global feature of the point cloud.

These global features are then passed through a fully connected neural network to classify or regress our target quantity. The original implementation of PointNet also includes "mini PointNets" which learn matrices that can transform the input point cloud or the feature point cloud in such a way to make PointNet respect the symmetries involved. The ability to extract order invariant, global event features that also respects the symmetries in the data directly from a dense representation of experimental data makes PointNet an ideal choice for training DL models on detector output. In the following sections, we discuss two different examples demonstrating the use of PointNet based models in heavy-ion collision experiments. For both the examples described below, we have trained DL models on UrQMD [7–9] and CbmRoot [10] simulations of Au-Au collisions at 10 AGeV.

2.1 Example 1: Event-by-event impact parameter determination

The impact parameter quantifies the centrality of a collision which is essential for experiments to analyse the data collected. However, experiments cannot measure the impact parameter of the collision directly and therefore perform only a broad classification of collision events into different centrality classes. In [11, 12], we have shown that PointNet based models can be used for accurate event-by-event impact parameter determination at the CBM experiment using the hits of charged particles in different detector planes and/or the tracks reconstructed from these hits. The Probability Density Functions (PDF) of the predictions of a PointNet model trained on the hits of charged particles of the CBM detector simulation is shown in figure 1a. The model provides fast, accurate impact parameter determination with a Mean Squared Error (MSE) of about 0.5 fm. With the use of this model, CBM experiment now has access to an event-by-event impact parameter directly from the hits recorded.



(a) PDF of the predictions for b as a function of true b **(b)** Confusion matrices of the predictions of EoS classifiers

Figure 1: Visualisation of the performance of PointNet based DL models for impact parameter determination (1a) and EoS classification (1b). The red dashed lines in 1a represents the y=x curve. In 1b, the numbers are normalised to have the sum of each column to be 1. The *Model 1* is trained on b= 0-7 fm while *Model 2* is trained on b= 0-3 fm and *Model 3* is trained on two different b classes (b= 0-3 fm, 3-7 fm). The performance of *Model 3* for the two different b classes are shown separately in the two matrices on the second row.

2.2 Example 2: Classifying the Equation of State (EoS)

One of the main goals of all heavy-ion collision experiments is the determination of the EoS of QCD matter. The EoS essentially governs the evolution of the hot, dense fireball created in the collision. It embeds the nature of the transition of hadronic matter to Quark Gluon Plasma in a collision and is a crucial input to different hydrodynamic models. We have shown in [13] that PointNet models can be used to distinguish the collision events produced by an EoS with a crossover transition from an EoS with a first order phase transition. The models were trained on the reconstructed tracks from the simulated CBM detector [10] where hybrid- UrQMD [9] events are used as input. The model achieved an accuracy of about 96% when trained on collision events with impact parameter (b) from 0 to 7 fm (*Model-1*). The model misclassified a phase transition as crossover in about 5% of the cases. However, when the model is trained on collision events with b=0-3 fm (*Model-2*), the classifier achieves an accuracy of about 99%. We have also shown that the model can be trained on data from two different impact parameter classes (b=0-3 fm and b=3-7 fm), with the class information of the data as additional input to the PointNet (*Model-3*). In this way the model can perform the EoS classification on peripheral or mid-central collision events without compromising on the accuracy for central collisions. The performance of these models are visualised in figure 1b. More details of the dependence of the models on impact parameter, experimental effects and simulation model parameters can be found in [13].

3. Conclusion

In this talk, it was shown how PointNet based DL models can be developed to perform different physics analyses directly on heavy-ion collision detector output. We discussed in detail the features of PointNet that can be utilised by heavy-ion collision experiments to extract global event features capable of characterising the collision. As a use case of our methods, we demonstrated how the CBM experiment can perform an accurate impact parameter determination and EoS classification using hits and/or reconstructed tracks from the detector. These methods can be easily extended for many more tasks and other experiments. The PointNet based models could be trained to determine other global event features such as the event plane angle, number of participant nucleons, flow coefficients etc., directly from detector level data. Once trained on appropriate data, these models can be deployed to analyse, characterise and select the incoming data in real time. In this way, heavy-ion collision experiments can significantly improve or extend their capabilities with the use of PointNet based models.

In future, it would be interesting to see the performance of these models in the presence of detector noise, event pileup and other experimental artifacts. It is also worthwhile to develop PointNet models that can be deployed on FPGA chips in real detectors. Such models could directly process raw, incoming data to perform event selection and characterisation. This can facilitate ultra fast processing of the data in high event rate experiments like the CBM. By training the models directly on raw detector signals, we can bypass the need for any pre-processing algorithms for event reconstruction during the online event selection. Deploying the models on FPGAs could also mitigate the requirements for dedicated high performance computing facilities for online event reconstruction and selection. The decisions can be made within the detector itself. It would also be possible to process each event or time-slice locally within different detector segments through "local PointNets" deployed in each FPGA. The models can then process the local data in parallel to denoise the signals, identify potential faults in the detector, compress the data, identify outliers etc., and feed this information to a "global PointNet" which can use it to perform online event selection, characterisation or physics analyses. However, several challenges need to be addressed before such sophisticated AI based real time analysis chains can be deployed in experiments. These include careful fine tuning of model architecture so that it is optimised for use in FPGA chips and designing proper protocols for communication and data flow between the detectors.

References

[1] H. Stoecker and W. Greiner, *High-Energy Heavy Ion Collisions: Probing the Equation of State of Highly Excited Hadronic Matter*, *Phys. Rept.* **137** (1986) 277.

[2] D.H. Rischke, Y. Pürsün, J.A. Maruhn, H. Stoecker and W. Greiner, *The Phase transition to the quark - gluon plasma and its effects on hydrodynamic flow*, *Acta Phys. Hung. A* **1** (1995) 309 [nucl-th/9505014].

[3] C.R. Qi, H. Su, K. Mo and L.J. Guibas, *Pointnet: Deep learning on point sets for 3d classification and segmentation*, in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 652–660, 2017.

[4] CBM collaboration, *The CBM experiment at FAIR*, *J. Phys. Conf. Ser.* **50** (2006) 357.

[5] L.-G. Pang, K. Zhou, N. Su, H. Petersen, H. Stöcker and X.-N. Wang, *An equation-of-state-meter of quantum chromodynamics transition from deep learning*, *Nature Commun.* **9** (2018) 210 [1612.04262].

[6] A. Kawęcka, W. Bryliński, M. Omana Kuttan, O. Linnyk, J. Pawlowski, K. Schmidt et al., *NA61/SHINE online noise filtering using machine learning methods*, *J. Phys. Conf. Ser.* **2438** (2023) 012104.

[7] S.A. Bass et al., *Microscopic models for ultrarelativistic heavy ion collisions*, *Prog. Part. Nucl. Phys.* **41** (1998) 255 [nucl-th/9803035].

[8] M. Bleicher et al., *Relativistic hadron hadron collisions in the ultrarelativistic quantum molecular dynamics model*, *J. Phys. G* **25** (1999) 1859 [hep-ph/9909407].

[9] H. Petersen, J. Steinheimer, G. Burau, M. Bleicher and H. Stöcker, *A Fully Integrated Transport Approach to Heavy Ion Reactions with an Intermediate Hydrodynamic Stage*, *Phys. Rev. C* **78** (2008) 044901 [0806.1695].

[10] https://subversion.gsi.de/cbmsoft/cbmroot/release/OCT19/, Accessed: 01-12-2019.

[11] M. Omana Kuttan, J. Steinheimer, K. Zhou, A. Redelbach and H. Stoecker, *A fast centrality-meter for heavy-ion collisions at the CBM experiment*, *Phys. Lett. B* **811** (2020) 135872 [2009.01584].

[12] M. Omana Kuttan, J. Steinheimer, K. Zhou, A. Redelbach and H. Stoecker, *Deep Learning Based Impact Parameter Determination for the CBM Experiment*, *Particles* **4** (2021) 47.

[13] M. Omana Kuttan, K. Zhou, J. Steinheimer, A. Redelbach and H. Stoecker, *An equation-of-state-meter for CBM using PointNet*, *JHEP* **21** (2020) 184 [2107.05590].