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Conference Report

Deep Learning Based Impact Parameter Determination for the CBM Experiment

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Abstract: In this talk we presented a novel technique, based on Deep Learning, to determine the impact parameter of nuclear collisions at the CBM experiment. PointNet based Deep Learning models are trained on UrQMD followed by CBMRoot simulations of Au+Au collisions at 10 *A*GeV to reconstruct the impact parameter of collisions from raw experimental data such as hits of the particles in the detector planes, tracks reconstructed from the hits or their combinations. The PointNet models can perform fast, accurate, event-by-event impact parameter determination in heavy ion collision experiments. They are shown to outperform a simple model which maps the track multiplicity to the impact parameter. While conventional methods for centrality classification merely provide an expected impact parameter distribution for a given centrality class, the PointNet models predict the impact parameter from 2–14 fm on an event-by-event basis with a mean error of −0.33 to 0.22 fm.

Keywords: heavy ion collisions; deep learning; PointNet; centrality; CBM detector; impact parameter

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1. Introduction

The phase structure of strongly interacting matter is studied in the laboratory via relativistic heavy ion collision experiments. The upcoming Compressed Baryonic Matter (CBM) experiment at the Facility for Antiproton and Ion Research (FAIR) at GSI (Darmstadt) will study high energy nucleus-nucleus collisions with beam energies from 2 to 10 *A*GeV at the SIS-100 accelerator and up to 40 *A*GeV at the SIS-300 accelerator [1–3]. The CBM detector will measure up to 1000 charged particles per collision and will operate at a maximum interaction rate of 10 MHz. This produces about 1 Tbytes/s of raw data that needs to be processed online to select interesting events for permanent storage and further analyses. These unique experimental requirements call for development of novel analysis techniques that can make ultra fast analyses of experimental data in realtime.

The impact parameter is an essential quantity for event selection and all subsequent analyses in heavy ion collisions. However, experiments cannot directly measure the impact parameter of the collision. Instead, final state observables such as charged particle multiplicity and energy deposited by spectator fragments are used to define centrality classes based on the predictions of a theoretical model. The likely impact parameter distribution of a centrality class is then estimated from this theoretical model. The CBM experiment uses a Monte Carlo Glauber (MC-Glauber) model [4] to calculate the charged particle multiplicity and spectator energy. Centrality classes are defined from percentiles of these observables which is then used for a broad grouping of events. The main disadvantage of this technique is that this model cannot determine the impact parameter on an event-by-event basis. However, an accurate impact parameter determination is necessary for studies on the event-by-event fluctuations which are one of the crucial probes to search for a possible critical point or a phase transition [5–7].

Machine learning techniques are widely used in high energy physics, both in experiments and theory to develop models that can replace conventional analysis techniques [8–30]. Naturally, such techniques have also been proposed as tool for impact parameter determination in [31–36]. However, previous studies were using shallow neural networks or other traditional Machine Learning algorithms with simplified experimental constraints based on detector acceptance and event selection. Moreover, the features used in these studies were often not readily available in an experiment during data taking. Therefore alternate ML algorithms, in particular Deep Learning (DL) [37] techniques that can learn from raw experimental outputs of realistic detector simulations can be extremely useful for all experimental heavy ion collision programs.

In this proceedings, we summarise the results and performance of PointNet based Deep Learning models for impact parameter determination. A detailed description of the models and discussions on their performance can be found in [38].

2. Data Preparation

The CBM detector comprises of several sub detector systems each designed for specific tasks. A Silicon Tracking System (STS) [39,40] together with Micro Vertex Detector (MVD) [40] is placed in a dipole magnet next to the target. The STS performs track and momentum reconstruction of charged particles while the MVD is designed to reconstruct open charm decays. The present study used data only from these sub detectors to train the DL models. Other sub systems in CBM include a Ring Imaging CHerenkov detector [41], Transition Radiation Detector, Time Of Flight (TOF) detector and Projectile Spectator Detector (PSD) but have not been considered for the task at hand.

For the following, the UrQMD model [42,43] was used as event generator to generate Au+Au collision events at 10 AGeV. To simulate a realistic detector output and incorporate weak and electromagnetic interactions of hadrons, the generated UrQMD events were fed as input to CbmRoot [44] simulation framework which performed transport of all UrQMD generated particles through the CBM detector geometry using Geant3 [45]. The standard CbmRoot macros were then used for detector response simulation and event reconstruction. These simulations do not contain any realistic background of hits from other sources like event pile-up, hits originating from delta rays or from beam halo interactions.

3. PointNet Models

The PointNet [46] is a DL architecture optimised to learn from point cloud data. The detector output in heavy ion collisions are the tracks or hits of the final state particles. Individual events can therefore be efficiently represented as pointclouds where each point is defined by the attributes of a track or hit in given event. Using the pointcloud as input, the PointNet architecture was trained to regress the impact parameter of the collision events. Four different DL models were trained using 10^5 Au + Au collisions at 10 AGeV with impact parameters sampled from a uniform b-distribution. The *M-hits* and *S-hits* models developed in the study used the hits of particles in MVD and STS detectors respectively. The model *MS-tracks* used the tracks reconstructed from the hits in MVD and STS detectors while the model *HT-combi* used combination of MVD hits and reconstructed tracks as input features. More details of these PointNet models are tabulated in Table 1.

Table 1. Properties of the PointNet models developed in the study. The number of parameters (# param.) refers to the total number of parameters of the Neural Network. The first dimension of the input is defined by the maximum number of tracks or hits expected in an event while the second dimension is the number of input features considered for each point in the pointcloud. e.g., The *M-hits* is expected to have up to 1995 hits where 3 features (x, y, z) of each hit is used for training.

Model	Input Features	# Param.	Input Dimensions
M-hits	x, y, z of hits in all MVD planes	3×10^6	1995×3
S-hits	x, y, z of hits in all STS planes	3×10^6	9820×3
MS-tracks	x, y, z, dx/dz, dy/dz, q/P of tracks in first and last planes	6×10^6	560×12
HT-combi	combination of features of *M-hits* and *MS-tracks*	10×10^6	1995×3, 560×12

4. Results

The DL models were trained with 75,000 events of the training dataset while the remaining 25,000 events were used as a validation sample for testing the generalisation ability of the model to unseen data. The models were trained using the *Adam* optimiser with the Mean Square Error (MSE) of the impact parameter as the loss function. The values of the Mean Absolute Error (MAE), coefficient of determination (R^2) and Mean Squared Error for the validation data were used to choose the best model for further analyses. Upon training, all the models converged to similar values of R^2, MSE and MAE. All the models had an R^2 of about 0.98, MSE of 0.39–0.47 fm and MAE of 0.49–0.54 fm.

The DL models can take advantage of the huge computational capability on Graphics Processing Units (GPU). On a Nvidia Geforce RTX 2080 Ti with a graphics processing memory of 12 GB, the *MS-tracks* model was found to be the fastest in its decision making with a processing speed of about 1092 events/s. The *S-hits* was the slowest with a speed of 159 events/s. However, it should be noted that the present network structure and complexity are not optimised for speed. Therefore, the processing speed can be further scaled up by reducing the model complexity or by redesigning the network structure to optimally utilize the available computational resources.

Figures 2–4 in [38] illustrate the performance of the PointNet models in comparison to a simple polynomial fit (*Polyfit*) to the track multiplicity vs. impact parameter relation. The DL models were shown to be more accurate and precise than the *Polyfit* model. The predictions of the *MS-tracks* for different impact parameters is illustrated in Figure 1 (left). It can be seen that the distributions of DL predicted impact parameters have their mean close to the true impact parameter. The precision in predictions are quantified by the spread of these distributions, which is small and has quickly diminishing tails as evident from the figure. The mean of the predicted distribution of impact parameters, using different PointNet models and the *Polyfit* model, are compared in Figure 1 (right). The error bars show the standard deviation of these distributions. For impact parameters from 2–14 fm, the PointNet models have a mean error between -0.33 to 0.22 fm while it is between -0.7 and 0.4 fm for the polyfit model. It can be seen that the spread of the distributions are also larger for *Polyfit* in comparison to the Dl models, especially for most central events. For events below 2 fm, the simple model had a relative precision ((σ_{pred}/ true b)$\times$ 100%) reaching up to 200% while this was less than 80% for the DL models with the values being less than 50% for events with 1 fm or above. Moreover, in Figure 5 in [38], it was also shown that the DL models are robust to small changes in the physics of the underlying event generator model.

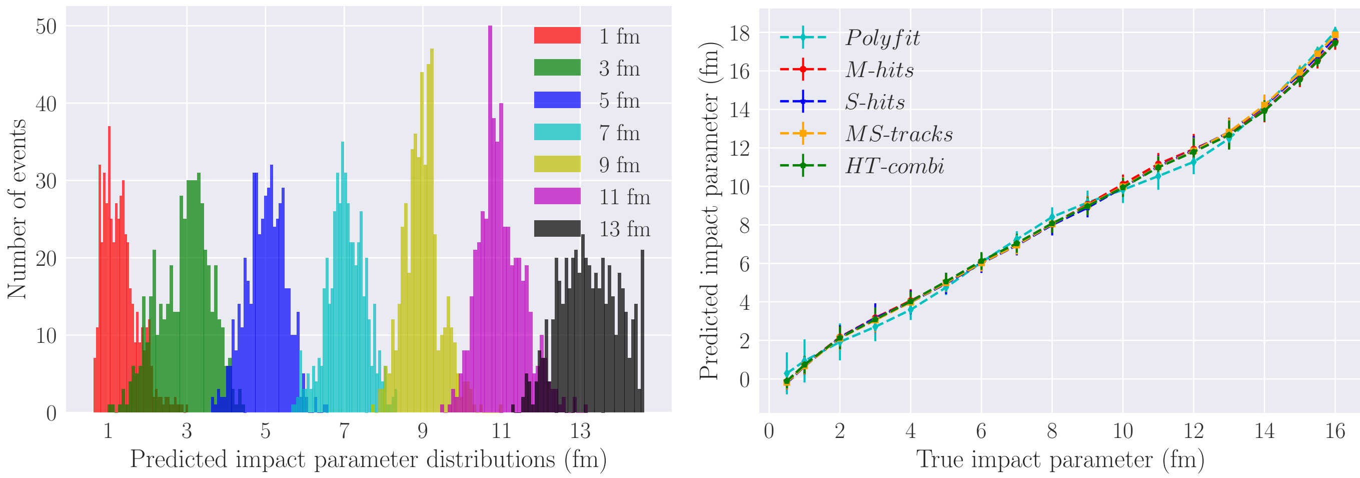

Figure 1. **(left)** Distribution of the predicted impact parameters using *MS-tracks*. 500 events of a given fixed impact parameter were used to generate each distribution in the figure. (**right**) Mean of the predictions for different DL models and the *Polyfit* model compared to the true impact parameter. 500 events each for different impact parameters from 0.5–16 fm were used to calculate the mean of the predictions. The error bars denote the standard deviation of the predictions around the mean.

5. Conclusions

The PointNet based models can be used for accurate impact parameter determination at the CBM experiment. The fact that these models can reconstruct the impact parameter from experimental outputs such as tracks or hits of final state particles and their processing speed make them ideal to be used for online event selection. Unlike the polynomial fit or other conventional techniques for centrality determination which fails for most central collisions, the DL models are reliable over most range of impact parameters. The tracks or hits in detector planes are the basic information available in any collision experiment. Therefore these PointNet models can also be easily developed for application in any other fixed target or collider experiment.

The conventional methods of centrality classification cannot perform impact parameter determination on an event-by-event basis. Only a theoretical estimate of the impact parameter distribution is known for a given centrality class. The definition of centrality classes from percentiles of parameters such as track multiplicity or spectator energy can only perform a broad grouping of events. The accuracy of such a classification is limited by the uncertainty in the particles produced or the spectator energy for a given impact parameter. However, by using Deep Learning models, we can develop models which can learn other unknown correlations in the data to make an accurate impact parameter determination.

The impact parameter of heavy ion collision is a highly model dependent parameter. All methods including the DL models and MC- Glauber model will have a bias in the predictions from the choice of theoretical model. However, for the DL models, such bias can be studied and minimised by combining data from multiple event generators for the training. This can force the DL algorithm to look for alternate, model independent correlations in the data to determine impact parameter. However, that is beyond the scope of this study. In future, it would also be interesting to investigate if the DL models developed in the study can be trained for other tasks in the experiment by using tracks or hits as input feature eg. in identifying a QCD phase transition or regressing other observables, like collective flow and particle multiplicities.

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