Estimation of centrality in heavy-ion collision at $\sqrt{s} = 200$ GeV using deep learning

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Introduction

Lattice QCD predicted a phase transition to a new form of matter known as Quark Gluon Plasma (QGP) at extreme temperature and/or baryon density [1]. Due to its transient lifetime the direct detection of QGP is impossible, but one can study the properties of the QGP indirectly from various signatures proposed over the last few decades.

In heavy-ion collisions, centrality is a quantity of significance as it is related to the size and shape of the resulting medium created by the colliding nuclei in the overlap region. The impact parameter (b) between the two nuclei, which is the separation between their centres in a plane perpendicular to the beam axis, is generally used to quantify the centrality of a collision.

Various machine learning (ML) and deep learning (DL) models were used to predict impact parameter from intermediate to high energy heavy-ion collisions [2–6]. Xiang *et al.* [7] used a Deep Neural Network (DNN) model having four hidden layers with a considerable number of neurons to predict imapct parameter in Au+Au collisions at $\sqrt{s} = 200$ GeV in the range $2 \leq b \leq 12.5$ fm. One of the motivations of our study is to achieve greater accuracy in estimating impact parameter with minimum number of layers and nodes such that the computational resources could be minimized. In the present investigation an attempt has therefore been made to predict the impact parameter using a DNN model with minimum number of layers and nodes by simulating Au+Au collisions at $\sqrt{s} = 200$ GeV with the help of a multi-phase transport model.

A Multi-Phase Transport (AMPT) model is a Monte Carlo event generator generally used for simulating heavy-ion collisions at relativistic energies [8]. The AMPT model comprises of four components: initial conditions, patron interactions, hadronization, and hadron cascade. In the default version of AMPT model, hardronization process is implemented via the Lund string fragmentation scheme and in the string melting version, it is done by the quark coalescence model.

In this work, string melting version of the AMPT model (version 2.26t9b) is used to simulate Au+Au collisions at $\sqrt{s} = 200$ GeV with impact parameter in the range $0 \leq b \leq 14$ fm.

Methodology

Deep learning can predict the hidden correlation between the input data and the output target variable. The inputs for the present study are the event-by-event 2D histograms of p_T weighted $(\eta - \phi)$ spectra of charged hadrons with 30×30 bins. Charged hadrons with $|\eta| \leq 1$ and $\phi \in [0, 2\pi]$ are considered in the analysis.

The DNN model considered in this study consists of three dense layers with one input layer, one hidden layer and one output layer. The first two layers contain 16, 32 nodes respectively, whereas the final layer contains a single node. For the input and hidden layers, rectified linear unit (ReLU) activation function is used while in the output layer the linear activation function is considered. A dropout layer with a dropout rate 0.2 is implemented before the output layer in order to overcome the overfitting problem. Flatten function was also utilized to covert the 2D arrays to a single dimensional array which is fed to the final

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layer. The Adam optimization algorithm with learning rate 0.0001 is used for the training of the network. Mean-squared-error (MSE) is used as loss function and to check the performance of the model, Mean Absolute Error (MAE) metrics are used. The model is trained for 50 epochs.

Results and discussion

The AMPT model is used to generate 150K minimum biased Au+Au collisions at $\sqrt{s}$ = 200 GeV. Simulated events are randomly divided into train and test datasets of 120K and 30K events respectively. 20% of the test datasets were kept for the model validation. Fig. 1 shows the evolution of the training and the validation loss in terms of mean-squared-error as a function of the number of epochs. It is evident from the figure that both the losses decrease as the number epochs increases. Moreover, the training and validation loss are also seen to be close to each other from which it can be concluded that the model suitably learns hidden features from the training datasets and generalizes well in predicting the target variable using the validation dataset.

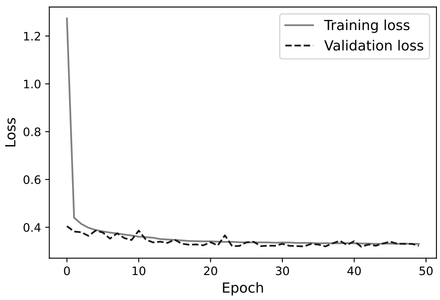

FIG. 1: Loss in terms of mean-squared-error as a function of the number of epochs.

The trained model is now used for prediction of impact parameter using the test dataset. Fig. 2 hows a correlation plot between the true and the predicted values of the impact parameter estimated using the DNN model. From the figure it is seen that the predicted impact parameters are nicely populated along the dashed line which corresponds to $b^{true} = b^{pred}$. The performance of the model has been quantified by determining the mean-absolute-error (MAE) in b given by the equation,

$$\triangle b = \frac{1}{N}\sum_{i=1}^{N} |b_i^{true} - b_i^{pred}|. \quad (1)$$

where, N is the number of events in the test dataset. The value of MAE calculated for the current DNN model is found to be 0.45 fm. As previously reported in ref. [7], the present investigation also shows a slight deterioration in performance for both in extreme central and ultra-peripheral collisions and therefore needs further investigation.

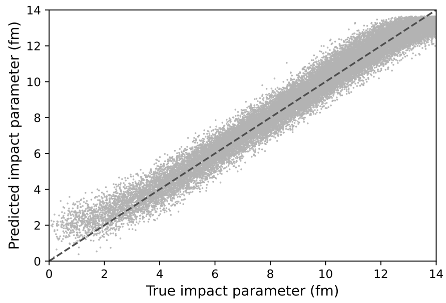

FIG. 2: Correlation plot between the true and predicted impact parameters.

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