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A Deep Learning Based Estimator for Elliptic Flow in Heavy Ion Collisions

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Deep learning (DL)-based models are the most widely used machine learning models which have been applied to solve numerous problems in high-energy particle physics. The ability of the DL models to learn unique patterns and correlations from data to map highly complex nonlinear functions is a matter of interest. Such features of the DL model could be used to explore the hidden physics laws that govern particle production, anisotropic flow, and spectra in heavy-ion collisions. This work sheds light on the possible use of the DL techniques, such as the feed-forward deep neural network (DNN) based estimator, to predict the elliptic flow (v_2) in heavy-ion collisions at RHIC and LHC energies. A novel method is used to process the track-level information as input to the DNN model. The model is trained with Pb-Pb collisions at $\sqrt{s_{\mathrm{NN}}}$ = 5.02 TeV minimum bias simulated events with AMPT event generator. The trained model is successfully applied to estimate the centrality dependence of v_2 for both LHC and RHIC energies. The proposed model is quite successful in predicting the transverse momentum (p_{T}) dependence of v_2 as well. A noise sensitivity test is performed to estimate the systematic uncertainty of this method. The results of the DNN estimator are compared to both simulation and experiment, which concludes the robustness and prediction accuracy of the model.

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1. Introduction

In the quest to produce a hot and dense state of strongly interacting matter, known as the quark-gluon plasma (QGP), ultra-relativistic heavy-ion collisions have been investigated for decades. Direct probes to study the QGP are not available as it is extremely short-lived. Out of the many indirect probes to explore its signatures, the study of azimuthal anisotropy has played a pivotal role [1]. Azimuthal anisotropies in particle production with respect to collision symmetry planes are often referred to as anisotropic flow. They are believed to arise from the initial geometry of the collision coupled with energy density fluctuations and effects from hadronic rescatterings [2]. The anisotropic flow of different orders could be expressed as the Fourier coefficients of particle azimuthal momentum distribution, given as,

$$\frac{dN}{d\phi} = \frac{1}{2\pi}\left(1 + 2\sum_{n=1}^{\infty} v_n \cos[n(\phi - \psi_n)]\right) \tag{1}$$

Here, v_n is the n$^{\text{th}}$-order flow coefficient, ϕ and ψ_n are the azimuthal and n$^{\text{th}}$ harmonic symmetry plane angles, respectively [3]. The second-order flow coefficient, v_2, known as the elliptic flow, has the largest contribution to the overall azimuthal anisotropy of the medium. For the first time, we have used a feed-forward deep neural network (DNN) model based on the deep learning framework to estimate the elliptic flow coefficient from various final state particle kinematic information [4]. The proposed estimator is seen to learn the centrality and transverse momentum (p_{T}) dependence of elliptic flow and could be applied to RHIC and LHC energies. For this work, heavy-ion collisions are simulated with a multiphase transport model [5] with string melting mode (AMPT version 2.26t9b), and the settings used in this work are the same as reported in Refs. [6–8].

2. Deep learning estimator

Deep learning (DL) models are quite popular in the high-energy physics community and have been in use since the early 1980s [9, 10]. The ability of the DL models to capture unique patterns and correlations from data to map highly complex nonlinear functions is a matter of interest [11]. This work uses binned ($\eta - \phi$) space containing all the charged particles produced in an event as the primary input. Additional information to the model is provided by adding the p_{T}, mass and $\log(\sqrt{s_{\text{NN}}/s_0})$ weighted layers, which serve as the secondary input layers to the model [4]. Each ($\eta - \phi$) space contains 32×32 bins. Figure 1 shows the input space in color for one minimum bias Pb-Pb collision at $\sqrt{s_{\text{NN}}} = 5.02$ TeV from AMPT model. For the DNN regression model, all charged particles having transverse momentum, $0.2 < p_{\text{T}} < 5.0$ GeV/c, in pseudorapidity, $|\eta| < 0.8$ are considered for training. The model takes $32 \times 32 \times 3 = 3072$ number of input bins from the three layers of ($\eta - \phi$) space. The bins are normalized with *L2-Norm* to make a meaningful representation for the training algorithm and keep the model's weights small. It also helps in faster convergence of the regression estimator.

The proposed DNN model has one input layer with 128 nodes followed by three hidden layers of 256 nodes each. The final output layer has one node as the target observable v_2. All the layers are fully connected dense layers. The first four layers have ReLU activation, whereas the final layer is linearly activated. Here, the activation function is crucial as it introduces nonlinearity to the

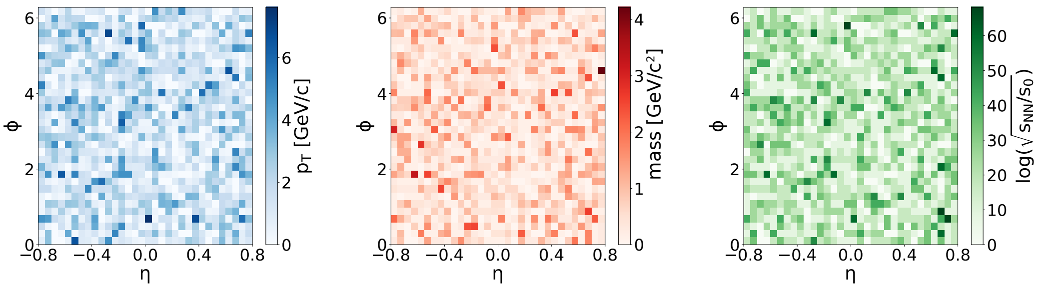

Figure 1: (Color online) Three different input layers of the (η−ϕ) space with 32 × 32 bins each showing one minimum bias event of Pb-Pb collision at $\sqrt{s_{\rm NN}}$ = 5.02 TeV from AMPT model. The $p_{\rm T}$, mass and log($\sqrt{s_{\rm NN}/s_0}$) weighted plots are shown in blue, red and green colours respectively. [Fig. 1 of Ref. [4]]

network, thus helping the model map nonlinear functions. The network is trained with minimum bias events of Pb-Pb collisions at $\sqrt{s_{\rm NN}}$ = 5.02 TeV from AMPT model. The *adam* optimizer is used with a mean-squared error (MSE) loss function for the training. Training is allowed up to 60 epochs with a fixed batch size of 32. An early stopping callback with a maximum patience level of 10 epochs is used to reduce overfitting. When subjected to a noise sensitivity test by adding uncorrelated noise to the feature space, the estimator performs quite accurately. This exercise estimates the method's systematic uncertainty by taking the mean-absolute-error (MAE) for a given centrality bin.

The deep learning model is built with KERAS v2.6.0 [12] deep learning API with TensorFlow v2.6.0 [13] backend in PYTHON. Scikit-Learn framework [14] is also found to be helpful in this work.

3. Results and discussions

The fully trained model is now applied to predict the centrality dependence of $v_2(p_{\rm T})$ for Pb-Pb collision at $\sqrt{s_{\rm NN}}$ = 5.02, and 2.76 TeV and Au-Au collisions at $\sqrt{s_{\rm NN}}$ = 200 GeV, as shown in Fig. 2. The solid red band shows the quadratic sum of statistical and systematic uncertainties in the upper panels. In contrast, in the bottom panels, these are shown separately in the solid and dashed red bands for statistical and systematic uncertainties, respectively. The bottom ratio plots clearly show the goodness of agreement between the true values from AMPT and the DNN predictions. Training the model with minimum bias Pb-Pb collisions at $\sqrt{s_{\rm NN}}$ = 5.02 TeV helps the model learn the physical correlations for a larger and more complex system. Thus, it preserves the correlations to accurately predict the centrality evolution of v_2, even at different collision energies.

Figure 3 shows the transverse momentum dependence of v_2 for (30-40)% central Pb-Pb collisions at $\sqrt{s_{\rm NN}}$ = 5.02 TeV. Both AMPT and DNN show similar trends as compared to the ALICE results. However, quantitatively, they slightly over-predict the v_2 values. The DNN predictions agree with the AMPT values over the entire range of $p_{\rm T}$ shown in the plot. The bottom ratio plot depicts the goodness of the prediction as the DNN to AMPT ratio stays close to unity. Here, we can conclude that the proposed DNN model can also learn and preserve the $p_{\rm T}$ dependence of v_2.

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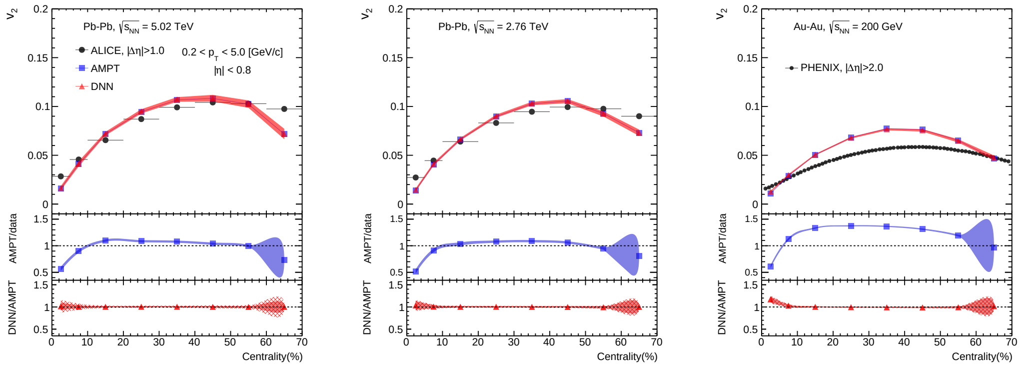

Figure 2: (Color online) Centrality dependence of $v_2(p_T)$ for Pb-Pb collision at $\sqrt{s_{NN}}$ = 5.02, and 2.76 TeV and Au-Au collisions at $\sqrt{s_{NN}}$ = 200 GeV. The true values from AMPT and the predictions from DNN are shown in blue and red markers, respectively. Experimental data from ALICE [15] and PHENIX [16] are added for comparison. [Fig. 6 of Ref. [4]]

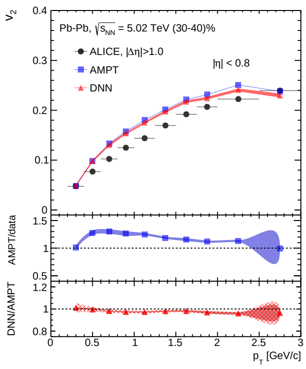

Figure 3: (Color online) Transverse momentum dependence of v_2 for (30-40)% central Pb-Pb collisions at $\sqrt{s_{NN}}$ = 5.02 TeV. The true values from AMPT and the predictions from DNN are shown in blue and red markers, respectively. Results from ALICE [15] are added for comparison. [Fig. 8 of Ref. [4]]

4. Summary

This article explores the possibilities of using a DNN-based estimator for elliptic flow in heavy-ion collisions at RHIC and LHC energies. The model is trained with final state particle kinematic information, and is shown to learn and preserve the physical correlations from data to predict the elliptic flow's centrality, energy, and transverse momentum dependence. The model is further subjected to an imperfect simulation data set with added uncorrelated noise and is shown to perform steadily and accurately. The results of the estimator are compared with simulation and experiment.

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