Estimating elliptic flow coefficient in heavy-ion collisions using deep learning

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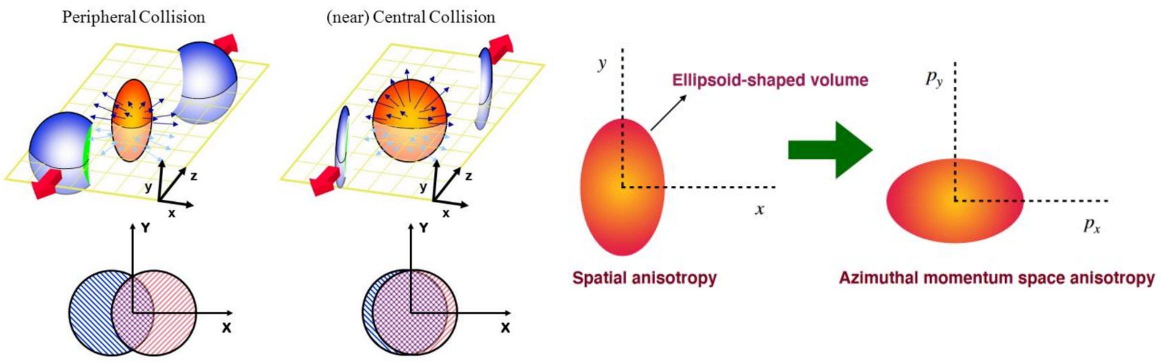
52nd International Symposium on Multiparticle Dynamics

21-26 Aug, 2023

Károly Róbert Campus of MATE in Gyöngyös, Hungary

1. Introduction

- Transverse collective flow is a crucial observable in studying the properties of quark-gluon plasma (QGP)
- Collective flow is anisotropic and depends on the equation of state and transport coefficients of the system
- Hydrodynamic response to the initial eccentricity of the system
- Anisotropic flow appears to be developed in the early partonic phase, evolves through relativistic hydrodynamics, and later gets influenced by hadronic rescatterings
- **First deep learning-based estimator for elliptic flow (v_2)**
- Machine learning model to learn from multiparticle production dynamics and its correlation to estimate any physical observable of interest



$$E\frac{d^3N}{dp^3} = \frac{d^3N}{p_{\mathrm{T}}dp_{\mathrm{T}}dyd\phi} = \frac{d^2N}{p_{\mathrm{T}}dp_{\mathrm{T}}dy}\frac{1}{2\pi}\left(1 + 2\sum_{n=1}^{\infty} v_n \cos[n(\phi - \psi_n)]\right)$$

$$v_n(p_{\mathrm{T}}, y) = \langle \cos(n(\phi - \psi_n)) \rangle$$

1. N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G. G. Barnaföldi, Phys.Rev.D 105, 114022 (2022).
2. N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G. G. Barnaföldi, Phys.Rev.D 107, 094001 (2023).

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2. Deep learning estimator

A multiphase transport model (AMPT)

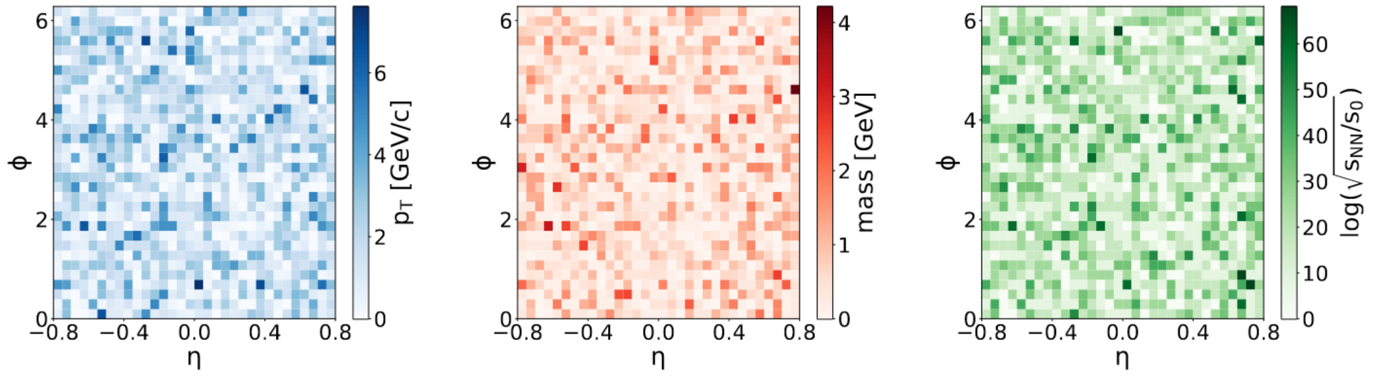
1. Initialization: Glauber MC with HIJING
2. Parton Cascade: Zhang's Parton Cascade
3. Hadronization: Quark Coalescence Model
4. Hadron Cascade: A Relativistic Transport Model

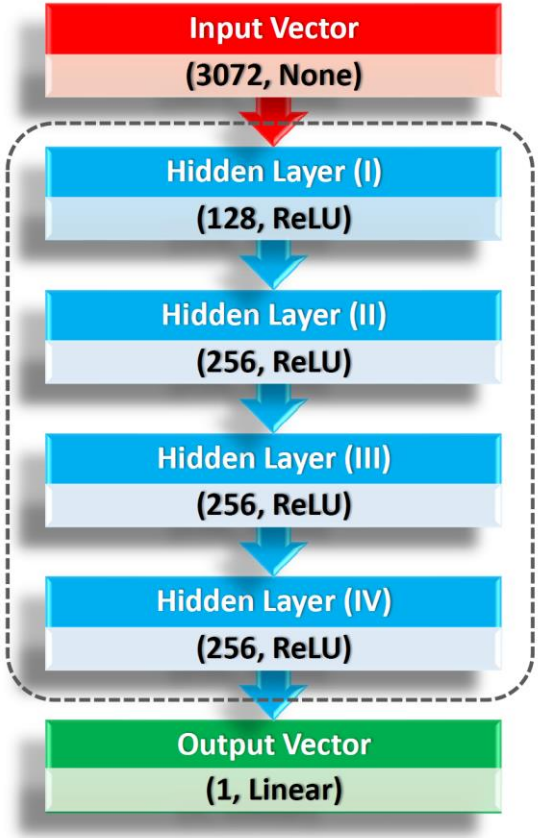
Input, output, and training

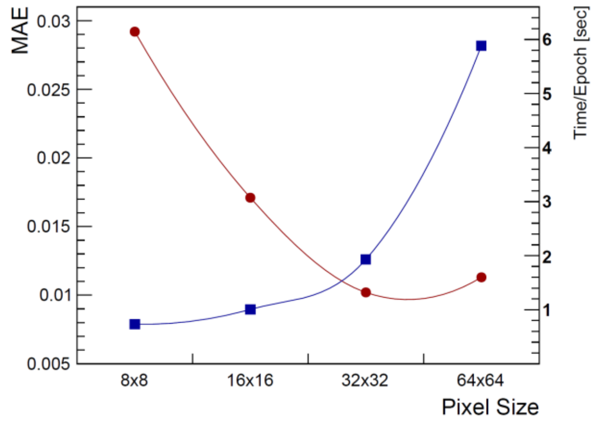
- Particle freezeout surface to elliptic flow mapping
- $(\eta - \phi)$ space as the primary input space
- p_T, mass, and $\log\sqrt{s_{NN}/s_0}$ weighted layers serve as the secondary input space
- Model trained on Pb-Pb, $\sqrt{s_{NN}}$ = 5.02 TeV (Minimum Bias)
- Feature size = $32 \times 32 \times 3 = 3072$ per event
- Increasing sparsity and model parameters with pixel size
- Optimzer: *adam* , Loss function: *mse*
- Max epoch: 100

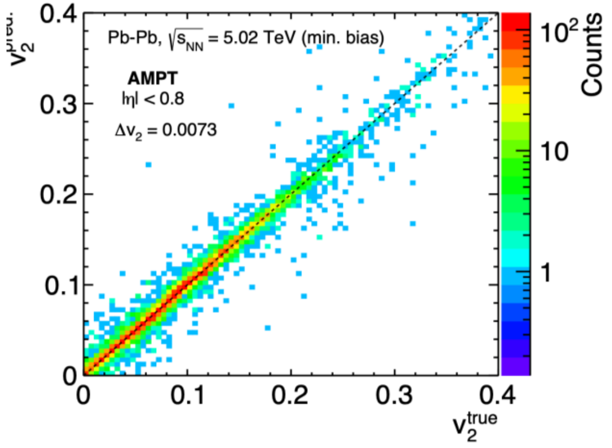
  Batch Size: 32, callback = *early_stopping*
- Training: 2×10^5 events (~60 GB)
- Validation: 10% Events

Pb-Pb collisions, $\sqrt{s_{\mathrm{NN}}} = 5.02$ TeV, AMPT simulation









3. Results

- Predictions are obtained for the collision centrality, energy, system size, particle mass, particle species, and transverse momentum dependence of elliptic flow
- The number-of-constituent-quark scaling behavior across different collision systems at different energies is also predicted by the DNN
- AMPT explains the data to a reasonable extent from low-p_T to intermediate-p_T but deviates for high-p_T

Summary

- DNN preserves the centrality, p_T, energy, and meson-baryon dependent behavior of elliptic flow
- Applicable to RHIC and LHC energies
- Faster and more efficient prediction as compared to the conventional methods