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

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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


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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 \(\log\frac{s_{NN}}{s_0}\) 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
- Optimizer: \textit{adam}, Loss function: \textit{mse}
- Max epoch: 100
  - Batch Size: 32, callback = \textit{early_stopping}
- Training: \(2 \times 10^5\) events (~60 GB)
- Validation: 10% Events
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