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

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 \(\log \frac{s_{NN}}{s_0}\) 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: adam, Loss function: mse
- Max epoch: 100
  Batch Size: 32, callback = 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