Understanding $p_T$-dependent flow fluctuations from initial geometry


1 Introduction

Flow vectors reflect the hydrodynamic response of the quark-gluon plasma to the initial geometry. Defining

$$ E\frac{dN}{dp_T} = \frac{1}{2\pi} N(p_T, y) \sum_{n=m} \langle V_n[p_T, y] e^{-i n \phi} \rangle, $$

we can approximate relations of the form

$$ V_\ell(p) \approx \kappa(p) \epsilon_\ell, $$

where the eccentricities $\epsilon_\ell$ characterize the initial geometry. To understand $p_T$-dependent flow fluctuations, we generalize (1) to multiple linear and nonlinear terms (1).

2 Mapping hydrodynamic response

- Eccentricities from cumulant-generating function of the transverse (entropy) density $\rho(x)$ [1]:

$$ W_k(\ell) \equiv \ln \left( \sum_{n,m} W_{n,m} k e^{-\epsilon_{n,m}} \right) \equiv \sum_{n,m} W_{n,m} (W_{n,m})^{k/2}. $$

- Differential flow, $V_r(p_T)$, can be predicted by $\epsilon_\ell$:

$$ V_2(p_T) \approx \epsilon_2 c_2 + \epsilon_3 c_3 + \epsilon_4 c_4 + \epsilon_5 c_5 + \epsilon_6 c_6 + \epsilon_7 c_7 + \epsilon_8 c_8 + \epsilon_9 c_9 + \epsilon_{10} c_{10} + \epsilon_{11} c_{11} + \epsilon_{12} c_{12}, $$

$$ V_3(p_T) \approx \epsilon_2 c_3 + \epsilon_3 c_4 + \epsilon_4 c_5 + \epsilon_5 c_6 + \epsilon_6 c_7 + \epsilon_7 c_8 + \epsilon_8 c_9 + \epsilon_9 c_{10} + \epsilon_{10} c_{11} + \epsilon_{11} c_{12}, $$

$$ V_4(p_T) \approx \epsilon_2 c_4 + \epsilon_3 c_5 + \epsilon_4 c_6 + \epsilon_5 c_7 + \epsilon_6 c_8 + \epsilon_7 c_9 + \epsilon_8 c_{10} + \epsilon_9 c_{11} + \epsilon_{10} c_{12}, $$

- Correlation between $V_r(p_T)$ and estimator $\Rightarrow$ performance!

2.1 Results

We test the estimators above within a hybrid hydrodynamic model, using TgENTo + MUSIC + ISS + UrQMD, with parameters for Pb + Pb collisions at $\sqrt{s_NN} = 5.02$ TeV and oversampled events [2].

3 Principal Component Analysis

Principal component analysis (PCA) provides a natural, concise visualization of $p_T$-dependent two-particle correlations [3]. It isolates linearly uncorrelated modes of flow fluctuations.

The subleading PCA mode can be dominated by multiplicity fluctuations. We redefine this PCA observable to reveal fluctuations of the initial geometry.

3.1 Standard definition [3]

- Diagonalization of the covariance matrix [3]:

$$ V_{n,m} \equiv \langle N(p_T) N(p_T) V_n[p_T] V_m[p_T] \rangle. $$

- PCA modes defined from $V_{n,m} \equiv \sqrt{\lambda_n} \psi_n(p_T)/\langle N \rangle$:

$$ V_{n,m} \equiv \sum_{k=0}^{k=n} \langle N(p_T) \rangle \langle N(p_T) \rangle V_{n,m}(p_T)/V_{n,m}(p_T). $$

- Eigenvalues are strongly ordered $\Rightarrow$ truncation at $k = 2$.

- PCA of multiplicity fluctuations from $n = 0$.

3.2 Multiplicity fluctuations [5]

- $\langle \Delta N(p_T) \Delta N(p_T) \rangle$ not compensated by Eq. (4).

- Redundancy between $V_{2,0}^{(2)}$, $V_{2,0}^{(3)}$, and $V_{2,0}^{(4)}$ [5].

- See results from CMS data in Figure 3.

- Multiplicity fluctuations not predicted by the “mapping”.

3.3 New prescription [5]

- Diagonalization of refined covariance matrix [5]:

$$ V_{n,m} \equiv \langle V_n[p_T] V_m[p_T] \rangle. $$

- Most of the information is in the first PCA modes:

$$ V_{n,m} \equiv \sum_{k=0}^{k=n} \langle V_{n,m} \rangle V_{n,m}(p_T)/V_{n,m}(p_T). $$

- Alternatively, one might use $V_{n,m}^{(2)}(p_T)/(N(p_T) N(p_T))$ [5].

- Predictions for these observables are shown in Figure 1, along with estimates from predictors (2) and (3).

4 Final Remarks

- Generalization of $V_2 \propto \epsilon_2$, with $p_T$ dependence and multiple terms. [1].

- Eccentricities of higher order $m \Rightarrow$ smaller scales.

- The standard subleading PCA mode can be dominated by multiplicity fluctuations [5].

- We can understand how $p_T$-dependent flow fluctuations arise from initial geometry fluctuations.

- For $V_2$, the refined subleading PCA mode is dominated by nonlinear response.

- For $V_2$, the refined subleading PCA mode is sensitive to higher-order eccentricities.

- Promising probe of small-scale structure.

References


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