

Characterization of flavor dependence of Chiral Magnetic Effect with multiple correlators

Somdeep Dey

School of Physics
University of Hyderabad



The 10th Asian Triangle Heavy-Ion Conference
ATHIC - 2025

Chiral Magnetic Effect

- Chiral Magnetic Effect (CME) is a transport phenomenon arising from the interaction between quantum anomalies and strong magnetic fields in the relativistic nuclear collisions.
- CME in Quantum Chromodynamics a generation of electric current along an extremely strong magnetic field that is induced by the chirality imbalance of the quarks.
- Chirality imbalance + Magnetic Field \rightarrow Current

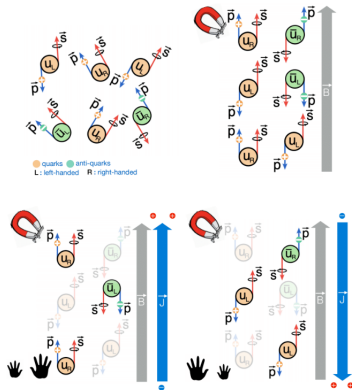


Figure: Chiral Magnetic Effect

Why flavor dependency?

- The current induced along the magnetic field is given by,

$$J_{CME} = N_C \left(\sum_f Q_f^2 \right) \frac{e^2}{2\pi^2} \mu_5 \vec{B} \quad (1)$$

$N_C \rightarrow 3$ (color number), $Q_f \rightarrow$ Charge of quark flavors

$\vec{B} \rightarrow$ Magnetic field, $\mu_5 \rightarrow$ Chiral chemical potential

- CME carries information about the quark number (N_f). Since CME current is dependent on the charge of quark flavors.

$$J_{CME} \approx \frac{2}{3} K (N_f = 3)$$

$$J_{CME} \approx \frac{5}{9} K (N_f = 2) \quad (2)$$

where, $K = \frac{N_C \mu_5 \vec{B}}{2\pi^2} e^2$.

Gamma Correlator

- Any observable designed to detect the CME will involve measuring the angles of the emitted particles. This could be measured by two particle azimuthal correlations.
- The observable Gamma correlator (γ) refers to the correlation between the azimuthal angles of two charge particles produced in RHIC.

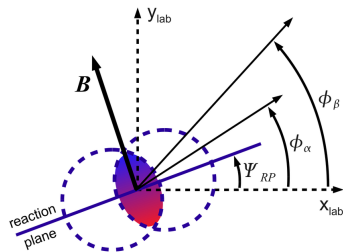


Figure: schematic diagram of HIC

$$\gamma = \langle \cos(\phi_\alpha + \phi_\beta - 2\psi_{RP}) \rangle \quad (3)$$

$\phi \rightarrow$ azimuthal angle of charge particles

$\psi_{RP} \rightarrow$ reaction plane angle

α and β are the combination of charges (+ +, - +, - +, - -)

$R_{\psi_2}(\Delta S)$ Correlator

$R_{\psi_2}(\Delta S)$ Correlator designed to suppress or separate back-ground contribution from genuine CME-driven charge separation.

$$R_{\psi_2}(\Delta S) = \frac{C_{\psi_2}(\Delta S)}{C_{\psi_2}^{\perp}(\Delta S)} \quad (4)$$

Where, $C_{\psi_2}(\Delta S)$ and $C_{\psi_2}^{\perp}(\Delta S)$ are the correlation functions designed to quantify charge-separation ΔS .

$$C_{\psi_2}(\Delta S) = \frac{N(\Delta S)}{N(\Delta S_{mix})} \quad (5) \quad C_{\psi_2}^{\perp}(\Delta S) = \frac{N(\Delta S^{\perp})}{N(\Delta S_{mix}^{\perp})} \quad (8)$$

$$\Delta S = \langle S_p \rangle - \langle S_n \rangle \quad (6) \quad \Delta S^{\perp} = \langle S_p^{\perp} \rangle - \langle S_n^{\perp} \rangle \quad (9)$$

$$\Delta S_{mix} = \langle S_{p_{mix}} \rangle - \langle S_{n_{mix}} \rangle \quad (7) \quad \Delta S_{mix}^{\perp} = \langle S_{p_{mix}}^{\perp} \rangle - \langle S_{n_{mix}}^{\perp} \rangle \quad (10)$$

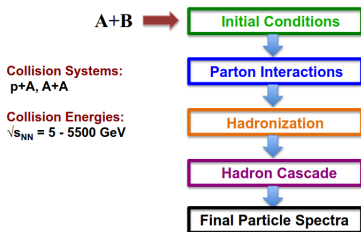
$$\langle S_p \rangle = \frac{1}{p} \sum_p \sin(\phi_p - \psi_2) \quad \langle S_p^{\perp} \rangle = \frac{1}{p} \sum_p \sin(\phi_p - \psi_2 - \frac{\pi}{2})$$

$$\langle S_n \rangle = \frac{1}{n} \sum_n \sin(\phi_n - \psi_2) \quad \langle S_n^{\perp} \rangle = \frac{1}{n} \sum_n \sin(\phi_n - \psi_2 - \frac{\pi}{2})$$

- $C_{\psi_2}(\Delta S)$ measures both CME and back-ground driven charge separation. $C_{\psi_2}^{\perp}(\Delta S)$ measures only background driven charge separation.
- $N(\Delta S) \rightarrow$ distribution of ΔS over events relative to ψ_2 .
- p and n are number of positive and negative charge particles respectively, $\phi \rightarrow$ azimuthal angle of charged particles; $\psi_2 \rightarrow$ second order event plane angle.
- For $C_{\psi_2}^{\perp}(\Delta S)$ calculation $\psi_2 \rightarrow \psi_2 + \frac{\pi}{2}$.
- we have used Particle Mixing Method to calculate ΔS_{mix} and select same number of particles irrespective of their charges.
- The correlator $R_{\psi_2}(\Delta S)$ gives a measure of charge separation \parallel to the $\vec{B}(\perp \psi_2)$ relative to the charge separation \perp to $\vec{B}(\parallel \psi_2)$.
- $R_{\psi_2}(\Delta S)$ is dominated by CME-driven charge separation result in **concave-shaped distributions** having width that reflects the magnitude of charge separation.
- **The stronger the CME driven charge separation narrower the $R_{\psi_2}(\Delta S)$ distribution.**

Introducing CME in AMPT

- A MultiPhase Transport Model (AMPT) has been extensively used to study RHIC, which provides individual particle information including position, momentum, energy etc.



- We have introduced CME in the AMPT model by switch p_y values for a fraction(f) of the downward $u(\bar{d})$ moving quarks with those of the upward moving $\bar{u}(d)$ quarks and introduce into the initial partonic states.

$$\text{where, } f = \frac{N_{\uparrow(\downarrow)}^{+(-)} - N_{\downarrow(\uparrow)}^{+(-)}}{N_{\uparrow(\downarrow)}^{+(-)} + N_{\downarrow(\uparrow)}^{+(-)}}$$

N → number of a given of quarks; + and - → positive and negative charges; \uparrow and \downarrow are the moving directions of quarks along the y axis respectively.

Effect of flavor dependence of CME for γ and $R_{\psi_2}(\Delta S)$ Correlators

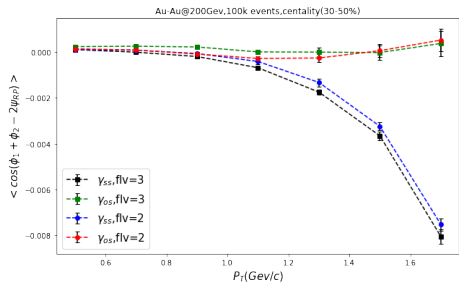


Figure: Gamma correlation vs P_T plot for Au-Au collision at 200 GeV for (30 – 50)% centrality

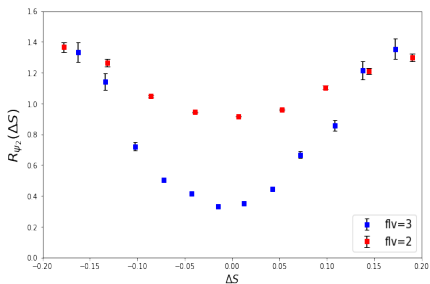


Figure: R_{ψ_2} vs ΔS plot for Au-Au collision at 200 GeV for (30 – 50)% centrality

Classification Model with ML Algorithm

- A classification model in machine learning is a predictive modeling approach used to categorize data into predefined classes or labels by learning patterns from labeled training data.

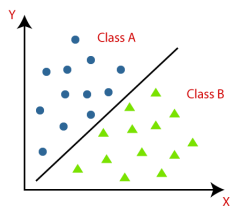
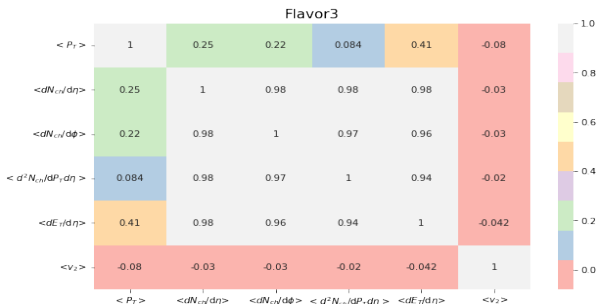
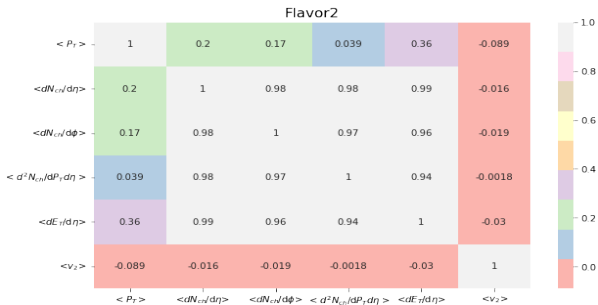


Figure: An example of classification

- Here we want to classify 2 flavor and 3 flavor CME.
- To train our model we need to find out best suited distributions.
- For that we have calculated correlation matrix for both flavors and distinguish them by observing their coefficients.
- we choose different observables like P_T , $dN_{ch}/d\eta$, $dN_{ch}/d\phi$, $d^2N_{ch}/dP_T d\eta$, $dE_T/d\eta$, V_2 as variables to construct correlation matrix.



Result:

- From Correlation Matrix we have figured out $dN_{ch}/d\eta$ vs P_T , $dN_{ch}/d\phi$ vs P_T , $dE_T/d\eta$ vs P_T , these three distributions are showing some differences and chosen as input to train our model.

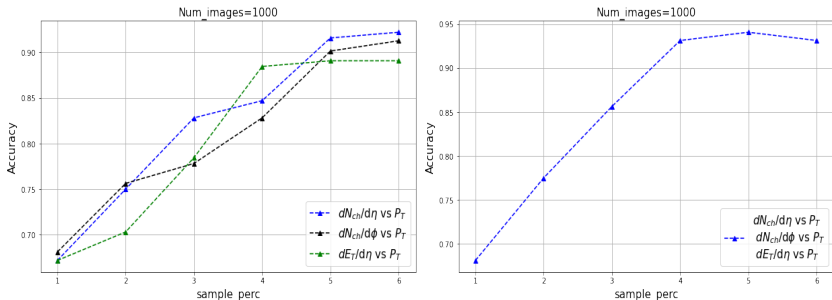


Fig: Accuracy Prediction with individual and all distribution

Summary

- At first we have introduced CME in AMPT.
- After that we have studied how γ and $R_{\psi_2}(\Delta S)$ correlators characterizes 2 flavor and 3 flavor CME.
- Then we have calculated correlation matrix with different observables to figure out best suited distributions to distinguish 2 flavor and 3 flavor CME.
- We have used those distributions as an input to train our neural network model(CNN) and make a prediction how accurately it can classify 2 flavor and 3 flavor CME.

References

- Ling Huang, Chun-Wang Ma and Guo-Liang Ma (PHYSICAL REVIEW C 97, 034909 (2018))
- L. Huang, C-W Ma and G-L Ma, Physical Review C 97 034909 (2018)
- N. Magdy et. al. Physical Review C 97 061901(R) (2018)
- Chiral Magnetic Effect(Phys. Rev. D 78, 074033 - 2008)
- Journal of Physics: Conference Series 612(2015) 012044
- Detecting the chiral magnetic effect via deep learning(Physical Review C 106,L051901(2022))
- Zhi-Lei She et al. Computer Physics Communications 274 108289 (2022)

Acknowledgement

- We acknowledge IoE research grant No. UH/RITE/PHY/SS/IoE-RC522020/01 for financial support.
- I have worked in collaboration with Dr. Abhisek Saha and Prof. Soma Sanyal in this project.

THANK YOU!