Event-by-event jet-induced hydro response from machine learning

Kai-Yi Wu[1], Zhong Yang[1,2], Long-Gang Pang[1] and Xin-Nian Wang[1]
[1] *Key Laboratory of Quark & Lepton Physics (MOE) and Institute of Particle Physics*
Central China Normal University, Wuhan 430079, China
[2] *Department of Physics and Astronomy, Vanderbilt University, Nashville, TN*

Introduction

- In high-energy heavy-ion collisions, jets traverse the quark-gluon plasma (QGP), depositing energy into the medium and inducing medium response. This modifies jet structure, impacting observables such as jet shape and fragmentation function.
- Simulating jet-induced medium response requires a model that accurately captures the evolution of hard and soft partons, along with significant computational resources for full-scale simulations. So using a generative neural network trained on γ-jet events from Pb+Pb collisions (5.02 TeV, $0-10\%$ centrality), we demonstrated that the energy-momentum of γ and jet, along with jet initial positions can predict the Mach-cone's location and maintain a particle spectrum within the same order of magnitude as actual data.

Flow matching model

First, Consider a simple differential equation:

$$\frac{dx}{dt} = u(x,t) \tag{1}$$

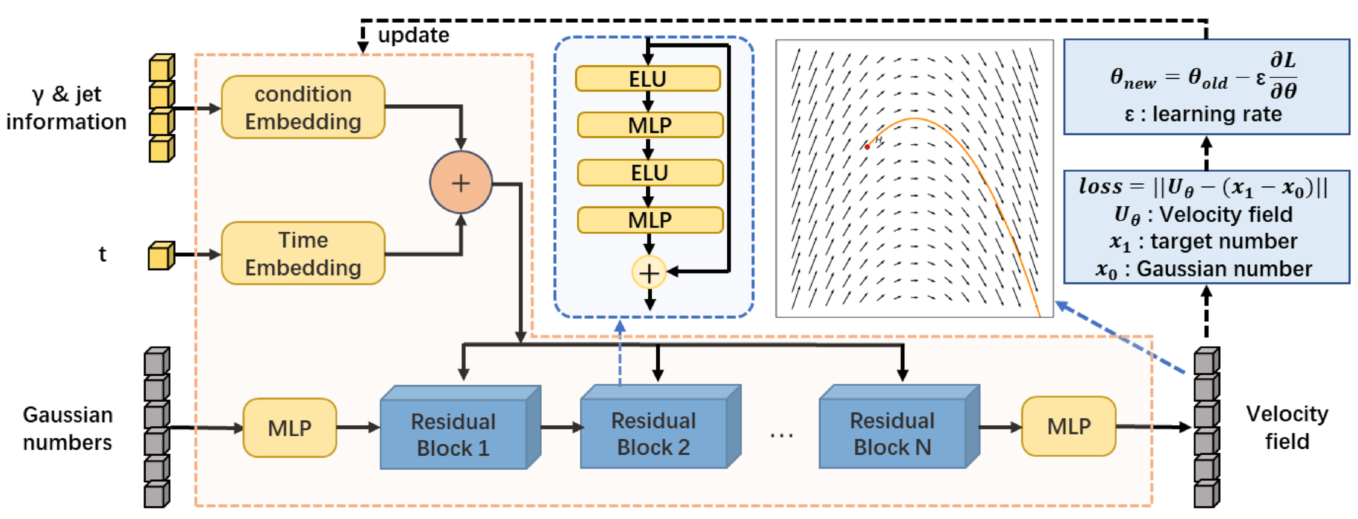
If we know the initial condition of $x(t=t_0)$ and the time evolution relationship $u(x,t)$, we can calculate the final solution $x(t)$ of the above function.

Flow matching method consider the problem in the same way. We can consider transforming a distribution p_0 to another distribution p_1 just like the above case. At $t=0$, x satisfies $x_0 \sim p_0$ distribution. When t=1, x satisfies $x_1 \sim p_1$ distribution. In this way, we only need to learn the time evolution relationship $u_\theta(x,t)$ by our neural network because we have already known the initial condition distribution $x_0 \sim p_0$. The we can solve differential equations just by employing a straightforward finite difference approximation.

$$\frac{x_{i+1}-x_i}{\Delta t} = u(t_i, x_i) \Rightarrow x_{i+1} = x_i + \Delta t \cdot u(t_i, x_i) \tag{2}$$

Consequently, the final distribution function can be obtained through a multi-step iterative solution of the differential equations. Of course there are many methods to solve the ODE such as the Euler discretization method and the Runge-Kutta method. Things become so simple and clear. Actually, the transformation capability of the Flow Matching method is pretty powerful and efficient.

Flow matching Loss function

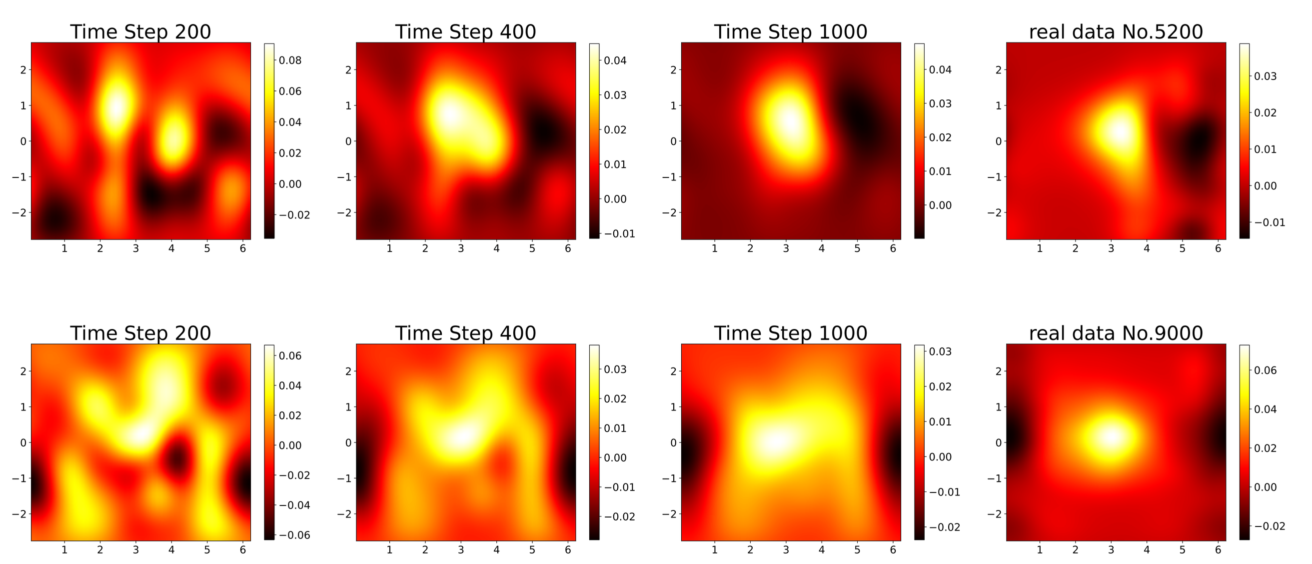


Flow matching assumes that the probability path follows a linear interpolation between distributions like:

$$x(t) = tx_1 + (1-t)x_0 \tag{3}$$

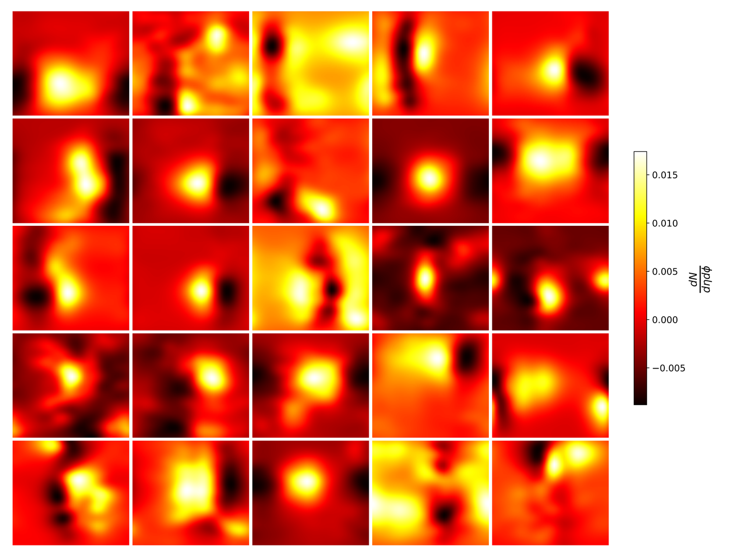
$$\frac{dx}{dt} = x_1 - x_0 \tag{4}$$

Here the $u_\theta(x,t)$ is the output of the neural network and the x_0 and x_1 is our training data. We use the conditional information γ-jet initial (P_T, η, ϕ) and jet initial position(x,y) spliced with some Gaussion numbers as the x_0. And we use the features extracted by PCA from the 3D particle spectra $\frac{dN}{dP_T d\eta d\phi}$ as x_1.



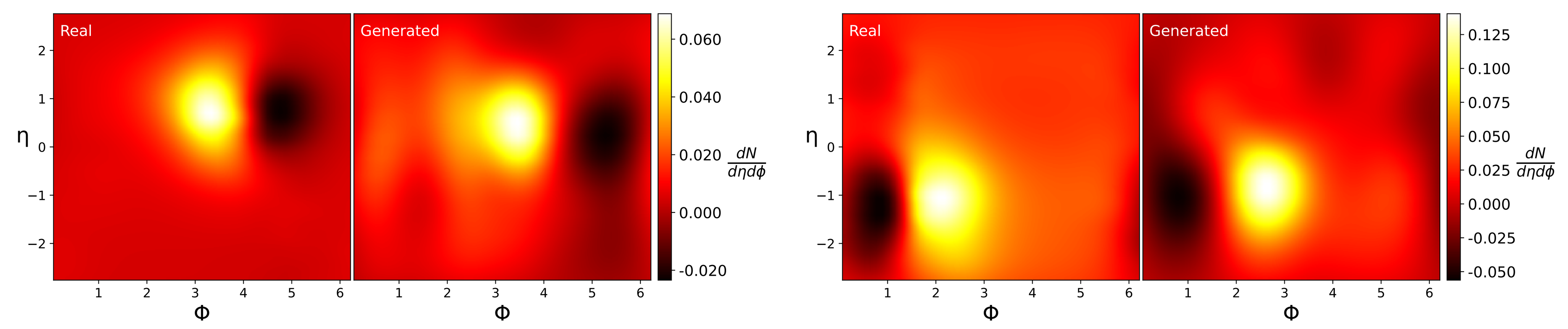
Initial data and Generative results

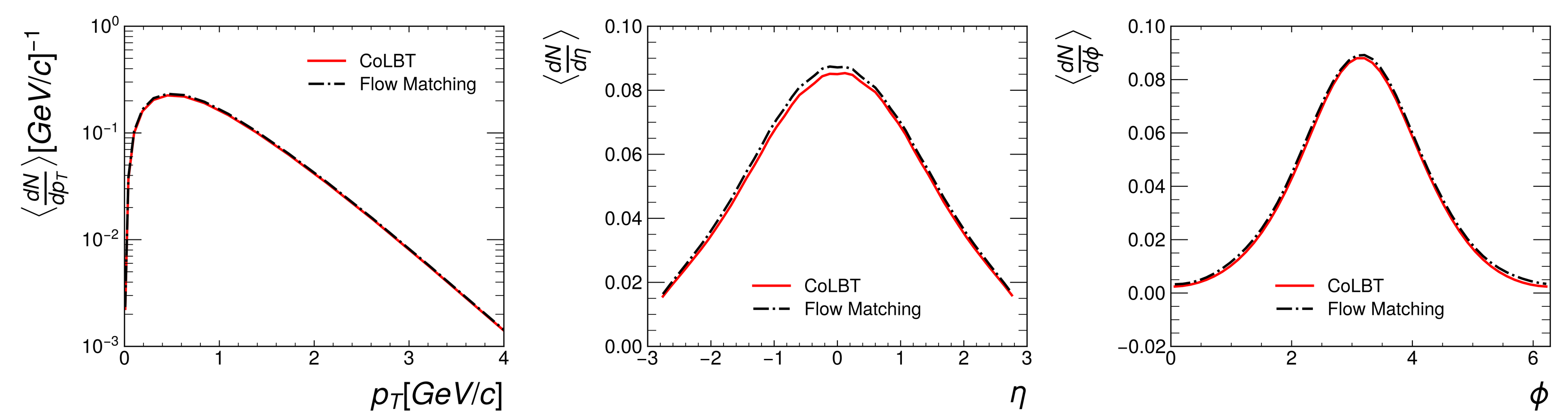
The initial data(γ - jet events) are showed below.



- We rotate the gamma ϕ into the $\phi=0$ direction, with up to three jets and medium-response particle spectra rotating correspondingly.
- The transverse label is ϕ from $[0, 2\pi]$ and The vertical label is η from $[-2.7, 2.7]$
- We use the γ and up to three jet's p^μ and jet's position(x,y) in transverse plane as the initial condition to predict the particle spectra of hydro response.
- We compress each particle spectra of hydro response about $\frac{dN}{dP_T d\eta d\phi}$ into 50 numbers.

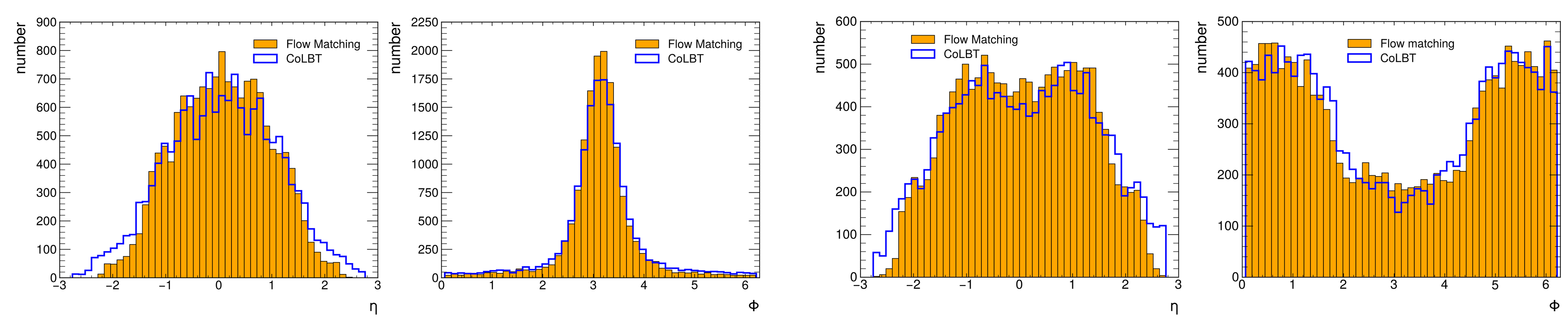
Here is a comparison between the means of the real data and the generated data:



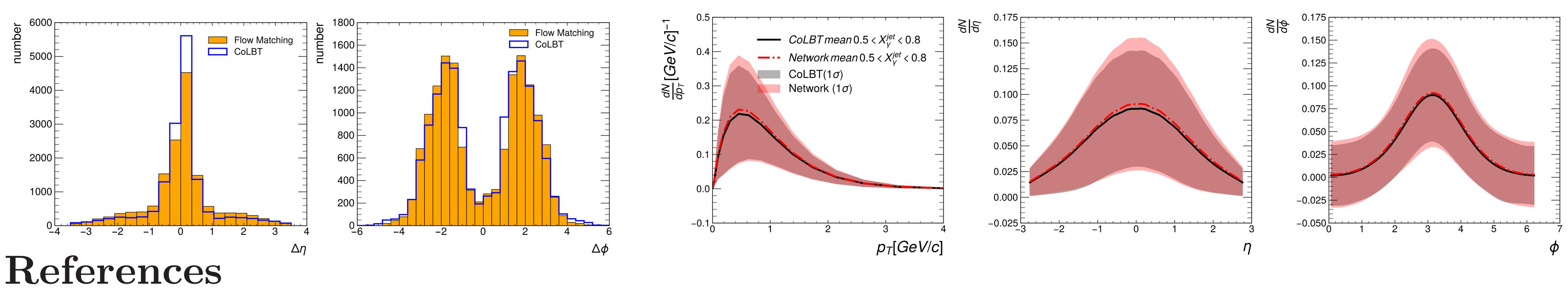


Results - η & ϕ, $\Delta\eta$ & $\Delta\phi$ comparison

For all events, we analyze the η and ϕ coordinates of the lightest and darkest points, then compare the η and ϕ distributions of the real data with those of the generated data.



The jet and diffusion wake are aligned in pseudorapidity (η), yet they are oriented back-to-back in azimuthal angle (ϕ). We compared the $\Delta\eta$ and $\Delta\phi$ distributions between the brightest and darkest points of all real and generated events.



References

[1] Z. Yang, T. Luo, W. Chen, L. Pang and X. N. Wang. 3D Structure of Jet-Induced Diffusion Wake in an Expanding Quark-Gluon Plasma, *Phys. Rev. Lett.* **130**, 052301 (2023).

[2] L.-G. Pang, H. Petersen and X.-N. Wang, Pseudorapidity distribution and decorrelation of anisotropic flow within the open-computing-language implementation clvisc hydrodynamics, Physical Review C 97 (2018)

[3] Yaron Lipman, Ricky T. Q. Chen, Heli Ben-Hamu, Maximilian Nickel, and Matt Le. Flow matching for generative modeling. 2023.