

# Event-by-event jet-induced hydro response from Generative model

The Fourth National Conference on Machine Learning Applications in Nuclear Physics and Nuclear Data

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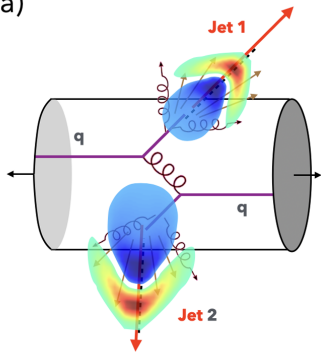




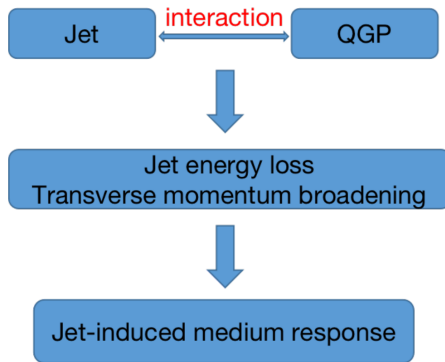
- Introduction
- Initial training datasets
- Generative model: Flow matching model
- 3D  $\frac{dN}{dp_T d\eta d\phi}$  results

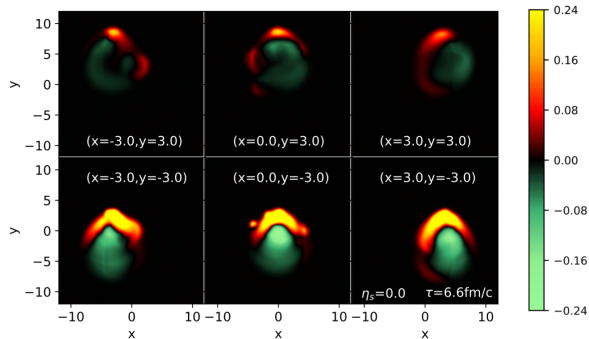
# Introduction

(a)

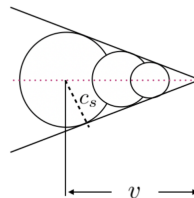


zhong y arXiv:2501.03419v3





zhong Y, et al. arXiv:2206.06393



马赫锥形成示意图

$$\sin \theta = \frac{c_s}{v}$$

$$c_s = \sqrt{\frac{dp}{d\epsilon}}$$



- **Large grid number:**  $200 \times 200 \times 100$  cells per timestep per event
- **High computational cost:** 7-10 minutes per event on A100 GPU (80GB VRAM)
- **Research goal:** Establish relationship between initial conditions and final particle spectra
  - Using generative models to bypass expensive hydrodynamic calculations

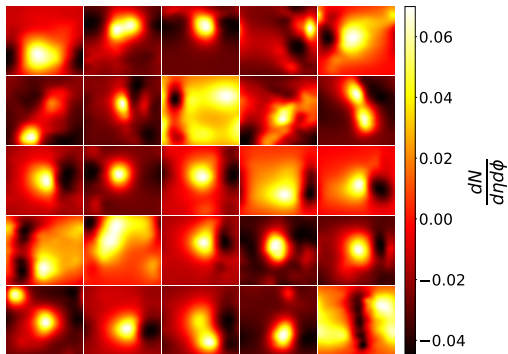
# Initial datasets



- **Source:** CoLBT-hydro model, 0 – 10%Pb+Pb,  $\sqrt{s_{\text{NN}}} = 5.02$  TeV The  $\gamma$   $p_T$  cut is  $100\text{GeV}$ , and the jet  $p_T$  cut is  $10\text{GeV}$ .
- **16,000 events** containing:
  - Initial parton showers and  $\gamma$  information
  - Final particle spectra  $\frac{dN}{p_T dp_T d\eta d\phi}$   
( $p_T \in [0, 4]$  GeV/c,  $\eta \in [-2.7, 2.7]$ ,  $\phi \in [0, 2\pi]$ )
  - 50 PCA features extracted from each 3D spectrum
- **Processing:**
  - Jet reconstruction with anti- $k_T$  algorithm (FASTJET)
  - Data rotation:  $\gamma$  at  $\phi = 0$ , jet at  $\phi = \pi$



## 25 2D distributions sampled from CoLBT training datasets



- **Axes:**  $\phi \in [0, 2\pi]$  (x),  $\eta \in [-2.7, 2.7]$  (y)
- **Bright positive region:** Mach cone front wake
- **Dark negative region:** Diffusion wake behind jet partons
- **Background subtracted:** Hydro without jet contribution removed

# Flow matching

Sora:



**Prompt:** Full body, anime art, Young woman practicing martial arts with steel gloves, Chinese dragon in the background, sky garden sanctuary, 4k

## Flow matching advantage

- Constructing a "continuous flow" from a simple distribution (such as Gaussian noise) to a complex data distribution
- Without relying on complex intermediate processes (like iterative denoising), enables fast training and sampling, as well as stable training.



## Differential Equation Foundation

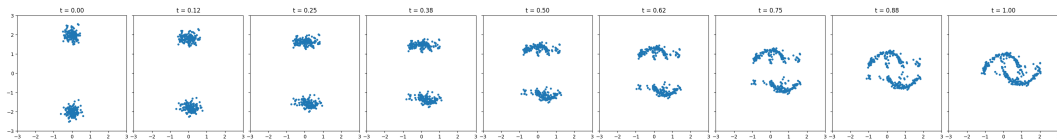
$$\frac{dx}{dt} = u(x, t)$$

Known initial condition  $x(t_0)$  and  $u(x, t)$  enables solution  $x(t)$

## Flow Matching Approach

- Neural network representation:  $u_\theta(x, t)$
- Known initial distribution:  $x \sim P_0$  at  $t = 0$
- Discrete evolution:

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



- Start: Sample  $(x_1, x_2)$  from bimodal Gaussian at  $t = 0$
- Apply iterative transformations using velocity field  $u_\theta(x, t)$
- Follow:  $x_{i+1} = x_i + \Delta t \cdot u_\theta(t_i, x_i)$
- End: Obtain sample from crescent distribution at  $t = 1.0$



- **Probability path:** Linear interpolation between distributions

$$x(t) = tx_1 + (1 - t)x_0$$

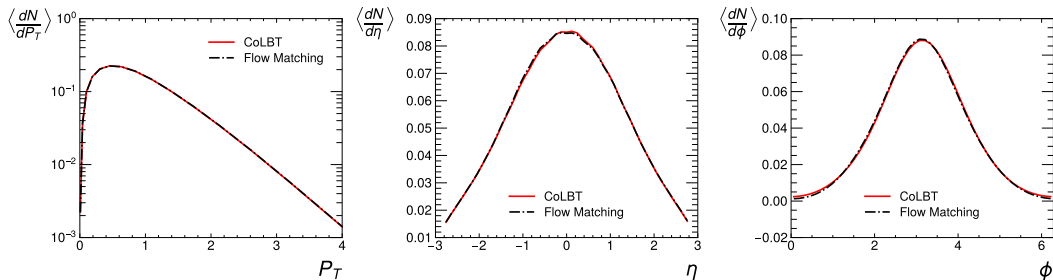
- **Time derivative:**

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

- **Loss function:** Difference between actual and predicted evolution

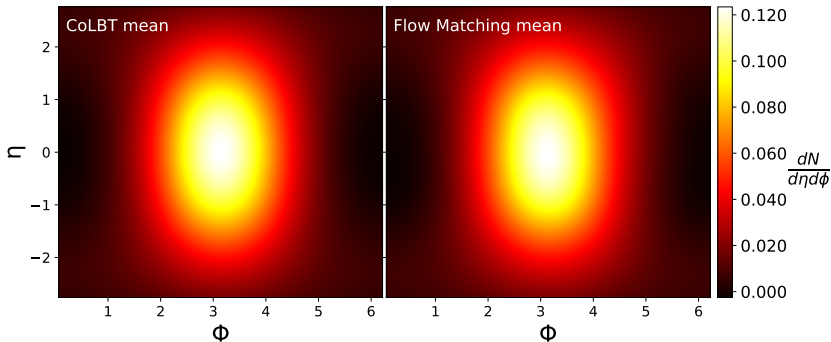
$$\mathcal{L}(\theta) = ||u_\theta(x, t) - (x_1 - x_0)||$$

# 3D Spectra Results

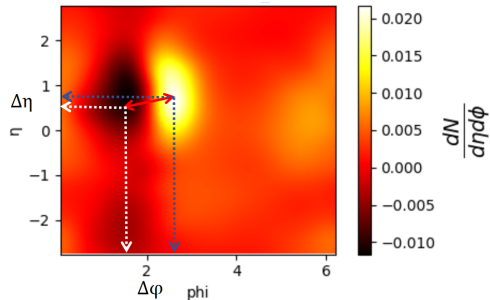
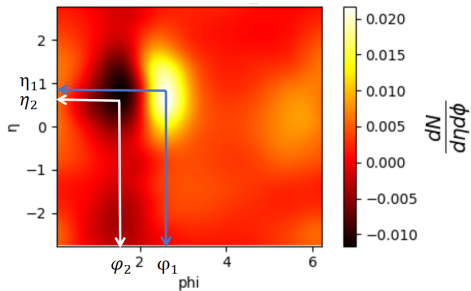


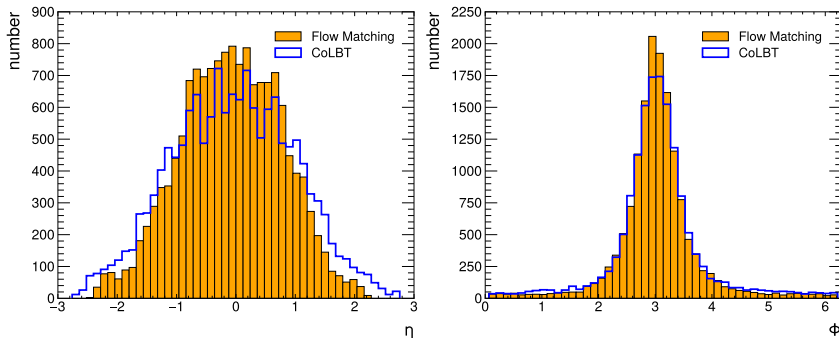
- **Left:**  $p_T$  distribution (integrated over  $\eta$  and  $\phi$ )
- **Middle:**  $\eta$  distribution (integrated over  $p_T$  and  $\phi$ )
- **Right:**  $\phi$  distribution (integrated over  $p_T$  and  $\eta$ )



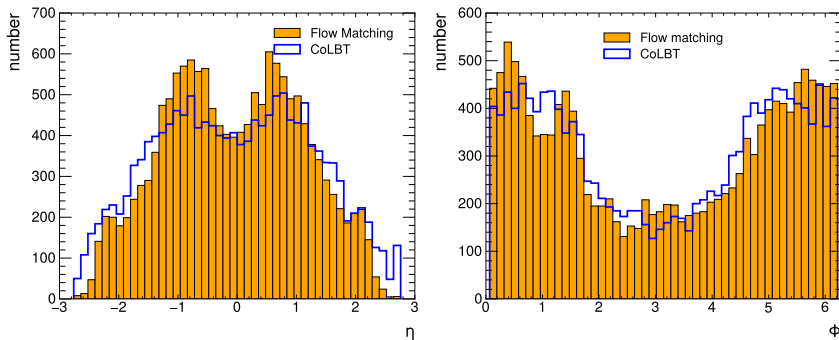


- **Left:** Average of all real events for  $\frac{dN}{d\eta d\phi}$
- **Right:** Average of all corresponding generated events

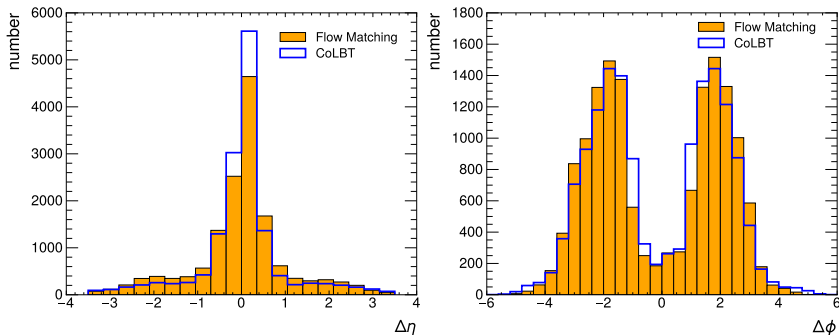




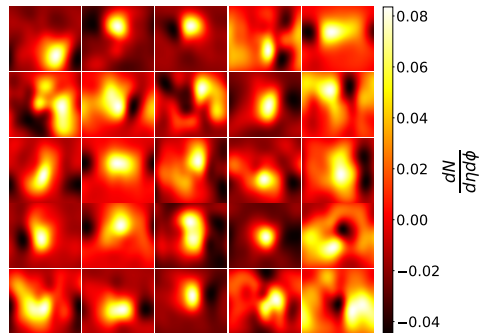
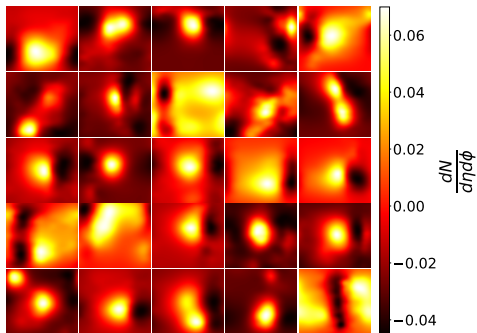
- **Left:** Statistical  $\eta$  values distribution at brightest points (Front wake)
- **Right:** Statistical  $\phi$  values distribution at brightest points



- **Left:** Statistical  $\eta$  values distribution at darkest points (Diffusion wake)
- **Right:** Statistical  $\phi$  values distribution at darkest points



- **Left:**  $\eta$ -direction difference between brightest (Front wake) and darkest (Diffusion wake) points
- **Right:**  $\phi$ -direction difference between these points



- **Left:** 25 randomly sampled real events
- **Right:** Corresponding generated events
- 2D  $\frac{dN}{d\eta d\phi}$  distributions from  $p_T \in [0, 4]$  GeV-integrated 3D spectra



- **Average Spectra:** Perfectly reproduces averaged particle spectra
- **Feature Distribution:** Accurately captures event-by-event location distributions of Front wake and diffusion wake
- **Fluctuation Stability:** Maintains particle spectrum within same order of magnitude under large fluctuations
- **Computational Efficiency:** 1 million events generated per second on NVIDIA RTX 4090 GPU vs. conventional CoLBT model on A100

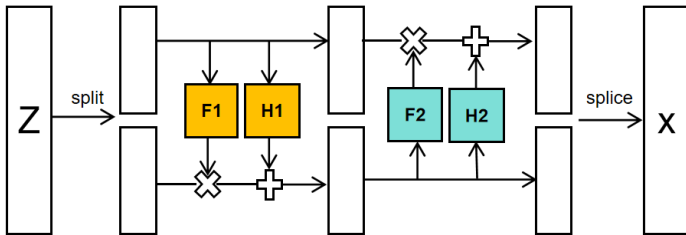


# Thank you



**Back up**

A little trick between two adjacent blocks of RealNVP:



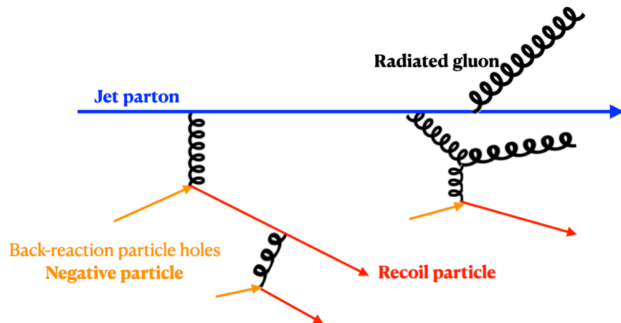
# CoLBT model

The jet transport through the QGP medium:

$$p_a \partial f_a = \int \prod_{i=b,c,d} \frac{d^3 p_i}{2E_i (2\pi)^3} \frac{\gamma_b}{2} (f_c f_d - f_a f_b) |M_{ab \rightarrow cd}|^2 \\ \times S_2(\hat{s}, \hat{t}, \hat{u}) (2\pi)^4 \delta^4(p_a + p_b - p_c - p_d) + \text{inelastic}, \quad (1)$$

- phase space distribution:  $f_i = (2\pi)^3 \delta^3(\vec{P} - \vec{P}_i) \delta(\vec{x} - \vec{x}_i - \vec{v}_i t)$  ( $i = a, c$ ).
- thermal parton distribution:  $f_i = 1/(e^{p \cdot u/T} \pm 1)$  ( $i = b, d$ )
- **Medium-induced gluons(High-twist)**[Wang, Guo 2001]

$$\frac{dN_g^a}{dz dk_{\perp}^2 dt} = \frac{2\alpha_s C_A \hat{q}_a(x) P_a(z) k_{\perp}^4}{\pi (k_{\perp}^2 + z^2 m^2)^4} \sin^2 \left( \frac{t - t_i}{2\tau_f} \right) \quad (2)$$



## LBT Tracked partons

- Jet shower partons
- Thermal recoil partons
- Radiated gluons
- Negative partons

**medium response = particle holes + soft partons**

CCNU-LBNL viscous hydrodynamic model: 3+1D viscous hydro evolution model



High-Energy Collision Characteristics (LHC Energy Region)

- Net baryon number is approximately zero, baryon number conservation can be neglected
- $\nabla_{\mu} N^{\mu} = 0$



## Energy-momentum conservation:

$$\nabla_{\mu} T^{\mu\nu} = 0$$

## Energy-momentum tensor composition:

$$T^{\mu\nu} = e u^{\mu} u^{\nu} - (P + \Pi) \Delta^{\mu\nu} + \pi^{\mu\nu}$$

$e$ : energy density

$u^{\mu}$ : fluid four-velocity

$P$ : thermodynamic pressure     $\Pi$ : bulk viscous pressure

$\pi^{\mu\nu}$ : shear viscous tensor

- Solves relativistic hydrodynamics with source terms:

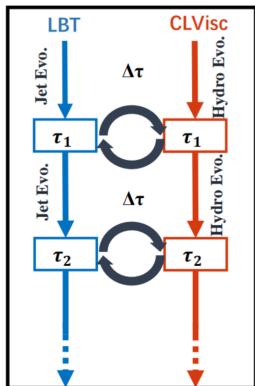
$$\nabla_\mu T^{\mu\nu} = j^\nu$$

- Source term implementation:

$$J^\nu = \sum_i \frac{\theta(p_{\text{cut}}^0 - p_i \cdot u) p_i^\nu / \Delta\tau}{\tau (2\pi)^{3/2} \sigma_r^2 \sigma_{\eta_s}} \exp \left[ -\frac{(\vec{x}_\perp - \vec{x}_{\perp,i})^2}{2\sigma_r^2} - \frac{(\eta_s - \eta_{si})^2}{2\sigma_{\eta_s}^2} \right]$$

- Gaussian deposition in transverse plane ( $\sigma_r$ ) and spacetime rapidity ( $\sigma_{\eta_s}$ )
- Cutoff condition:  $\theta(p_{\text{cut}}^0 - p_i \cdot u)$



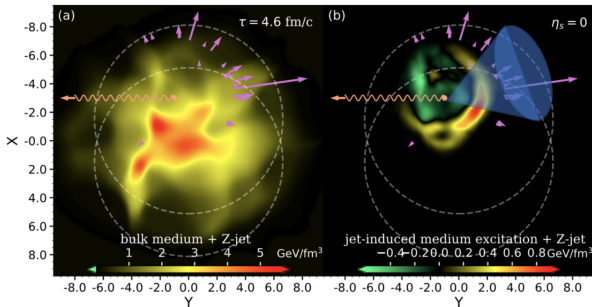


wei chen

- **Couples two complementary models:**
  - **LBT:** Energetic partons (jet showers and recoil) ( $E_{cut} > 2GeV$ )
  - **CLVisc:** Bulk/soft partons via hydrodynamics
- **Medium evolution with source terms:**

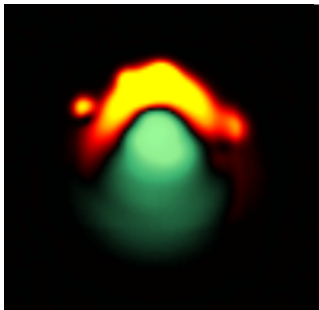
$$\nabla_{\mu} T^{\mu\nu} = j^{\nu}$$

- Energy-momentum deposition from partons
- Self-consistent QGP medium evolution



Chen, Yang, He, Ke, Pang and Wang, PRL 127 (2021) 8, 082301

- The CoLBT was runned twice with and without jet to subtract hydro background.
- The Mach-cone-like jet-induced medium response is clear in right panel.



Zhong Y, et al.  
arXiv:2206.02393

- **Soft hadron enhancement** along jet direction due to medium response
- **Similar effect** from medium-induced gluon radiation
- **Diffusion wake:** Distinct component of jet-induced response
  - Causes depletion of soft hadrons opposite to jet direction