

Conditional Flow based generative model of Jet induced hydro response

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Introduction

- In high-energy heavy-ion collisions, jets traverse the quark-gluon plasma (QGP), depositing energy into the medium and inducing Mach-cone-like excitations. 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 gamma-jet events from Pb+Pb collisions (5.02 TeV, 0 10% centrality), we demonstrated that the energy-momentum of gamma and jet, along with jet initial positions can predict the Mach-cone's leading edge and maintain a particle spectrum within the same order of magnitude as actual data.

Flow-based generative model

The structure of the flow model is illustrated. We need to swap the data transformation positions between the two layers of the RealNVP model.

Initial data and Generative results

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

• We rotate the gamma ϕ into the $\phi = 0$ direction



The concise structure of adjacent two layers is:



${\bf RealNVP} \ {\bf method}$

The real-valued non-volume-preserving (realNVP) method is a popular method in flow modle because it has a concise structure and can easily calculate it's transformation determinate.



- 0
- The transverse label is ϕ from $[0, 2\pi]$
- The vertical label is η from [-2.7, 2.7]
- We use the γ and jet's P^{μ} and leading parton position in transverse plane as the initial condition to predict the particle spectra of hydro response.
- We compress each particle spectra of hydro response about $\frac{dN}{d\eta d\phi}$ into 20 numbers.

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





The distribution transition formula of inverse direction is:

$$\mathbf{z}_{1:d} = \mathbf{x}_{1:d}$$
(1)
$$\mathbf{z}_{d+1:D} = (\mathbf{x}_{d+1:D} - t(\mathbf{x}_{1:d})) \odot \exp(-s(\mathbf{x}_{1:d}))$$
(2)

The math relationship between Q(z) and q(x) is: $Q(x|\theta) = q(z) \prod_{l=1}^{L} |\det T_l^{-1}|$. The Jacobi matrix of $\left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}}\right)$ is:

$$\mathbf{J} = \begin{bmatrix} \mathbf{I}_{d \times d} & \mathbf{0} \\ \frac{\partial \mathbf{z}_{d+1:D}}{\partial \mathbf{x}_{1:d}} & \operatorname{diag}(\exp(-s(\mathbf{z}_{1:d}))) \end{bmatrix}$$

(3)

(5)

(6)

The K-L divergence loss function

$$\mathcal{L}(\theta) = \sum_{x \in \mathcal{X}} \left\{ P_{data}(x) \log\left(\frac{P_{data}(x)}{Q(x|\theta)}\right) \right\}$$
(4)

Our goal is to make the distribution of $P_{data}(x)$ and $Q(x|\theta)$

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

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 have the same direction in η , but in ϕ , they are back-to-back. We compared the $\Delta \eta$ and $\Delta \phi$ distributions between the brightest and darkest points of all real and generated events. V is the "fireball radius" that we extracted from the photo.



as close as possible.Because $P_{data}(x)$ is is independent of neural network. So, the part $\sum_{x \in \mathcal{X}} P_{data}(x) \log P_{data}(x)$ can be neglected. We can only calculate the part $\mathcal{L}(\theta) = -\log Q(x|\theta)$ because the $P_{data}(x)$ is inpendent to θ .



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