数值相对论流体与机器学习

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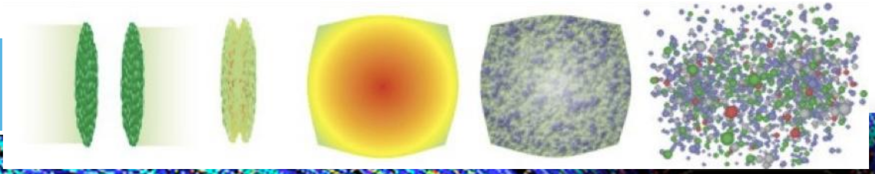
Central China Normal University
2025/8/13 复旦大学

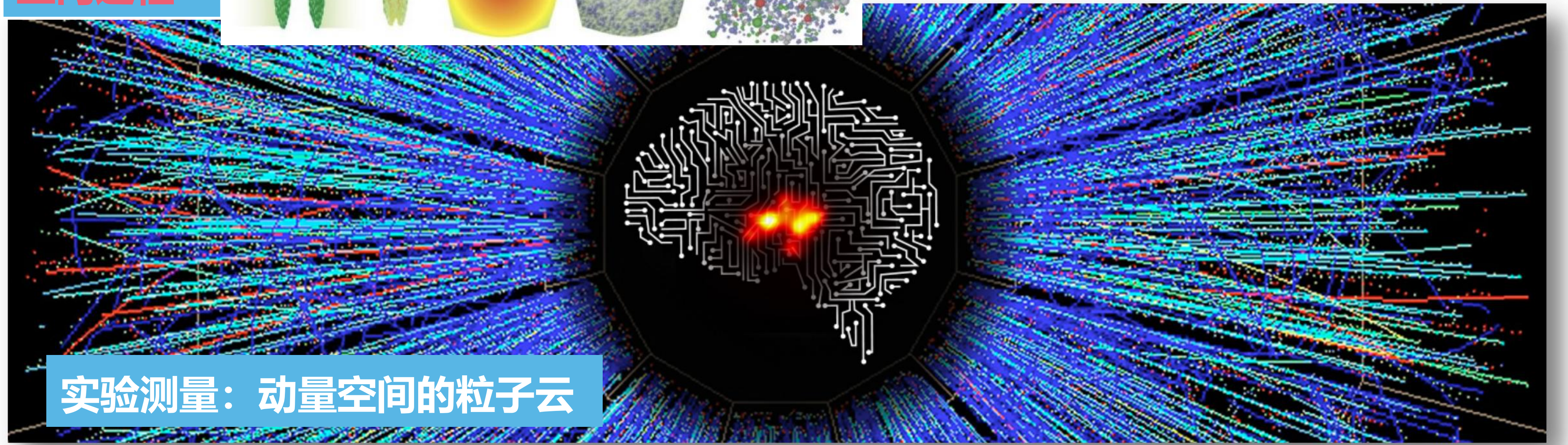
“极端等离子体：从夸克-胶子到聚变能”研讨会

重离子碰撞：典型的反问题

QGP 寿命：$10^{-23}s$

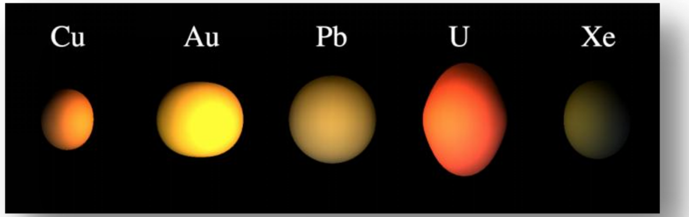
正向过程

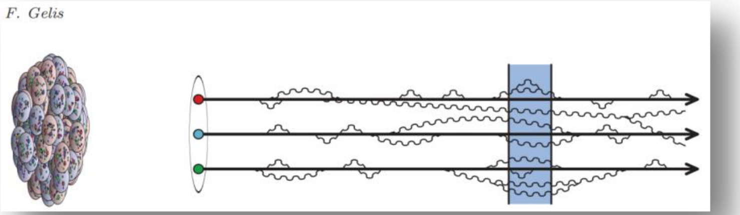


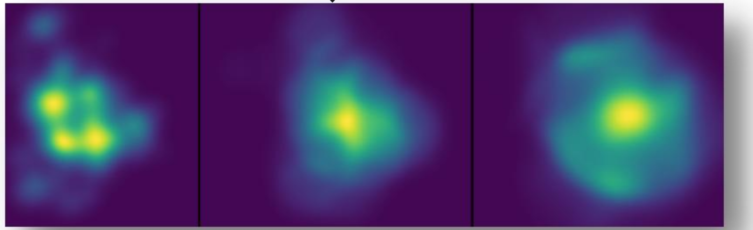


实验测量：动量空间的粒子云

反向过程

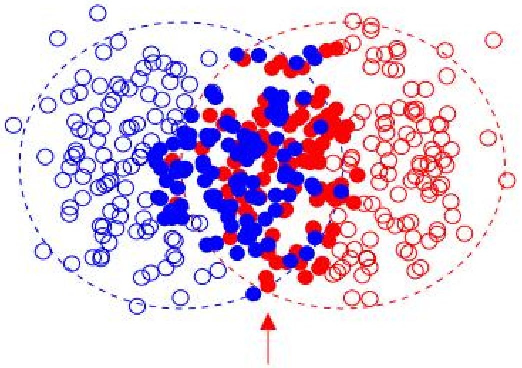




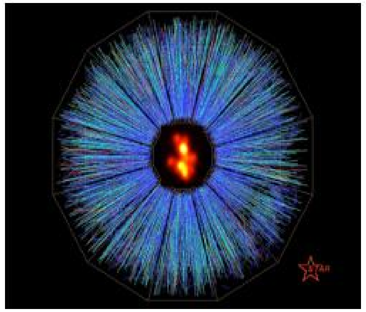


（1）Nuclear Structure　　（2）Initial Parton Distribution　　（3）QGP properties and EoS

理论模型之一：相对论流体



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



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

Initial condition　　EoS　Bulk Viscosity　　Shear Viscosity

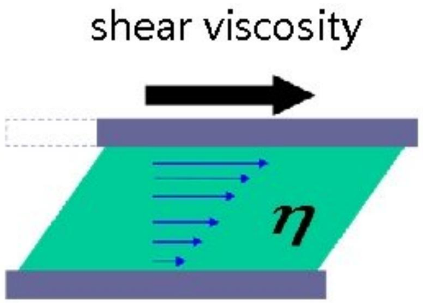
CLVisc:

1. CCNU-LBNL Viscous Hydro, CCNU = Central China Normal University
2. A 3+1D viscous hydro parallized on GPU using OpenCL

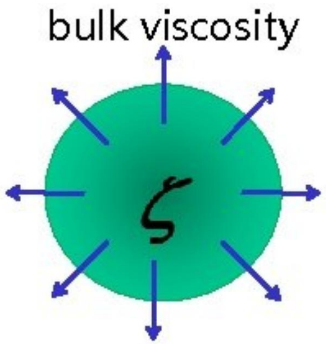
Purpose: Describe the non-equilibrium space-time evolution of hot QCD matter
Feature: **100 times faster** than using a single core CPU.

L.G. Pang, Q. Wang and X. N. Wang, PRC 86 (2012) 024911
L.G. Pang, B.W. Xiao, Y. Hatta, X.N.Wang, PRD 2015
L.G. Pang，H.Petersen, XN Wang, PRC97(2018)no.6,064918

粘滞流体



resistance to flow gradients



resistance to expansion

credit：HuiChao Song

一阶粘滞：数值不稳定

$$\Pi = -\zeta\theta - \tau_\Pi \left[u^\lambda \nabla_\lambda \Pi + \frac{4}{3}\Pi\theta \right]$$

$$\pi^{\mu\nu} = \eta_v \sigma^{\mu\nu} - \tau_\pi \left[\Delta^\mu_\alpha \Delta^\nu_\beta u^\lambda \nabla_\lambda \pi^{\alpha\beta} + \frac{4}{3}\pi^{\mu\nu}\theta \right]$$

$$-\lambda_1 \pi^{\langle\mu}_\lambda \pi^{\nu\rangle\lambda} - \lambda_2 \pi^{\langle\mu}_\lambda \Omega^{\nu\rangle\lambda} - \lambda_3 \Omega^{\langle\mu}_\lambda \Omega^{\nu\rangle\lambda},$$

Expansion rate: $\theta \equiv \nabla_\mu u^\mu,$

Shear viscous tensor: $\sigma^{\mu\nu} \equiv 2\nabla^{\langle\mu} u^{\nu\rangle} \equiv 2\Delta^{\mu\nu\alpha\beta}\nabla_\alpha u_\beta,$

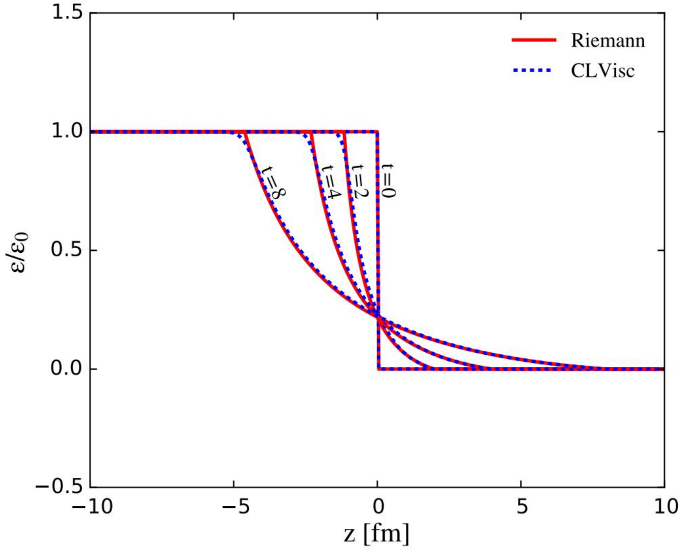
Vorticity tensor: $\Omega^{\mu\nu} \equiv \frac{1}{2}\Delta^{\mu\alpha}\Delta^{\nu\beta}(\nabla_\alpha u_\beta - \nabla_\beta u_\alpha),$

Double projection operator: $\Delta^{\mu\nu\alpha\beta} \equiv \frac{1}{2}(\Delta^{\mu\alpha}\Delta^{\nu\beta} + \Delta^{\mu\beta}\Delta^{\nu\alpha}) - \frac{1}{3}\Delta^{\mu\nu}\Delta^{\alpha\beta},$

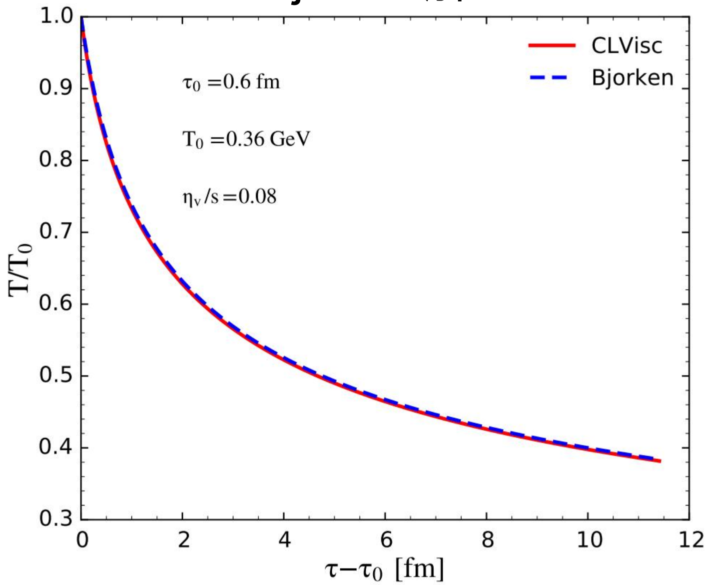
Projection operator: $\Delta^{\mu\nu} = g^{\mu\nu} - u^\mu u^\nu$

相对论流体的解析解

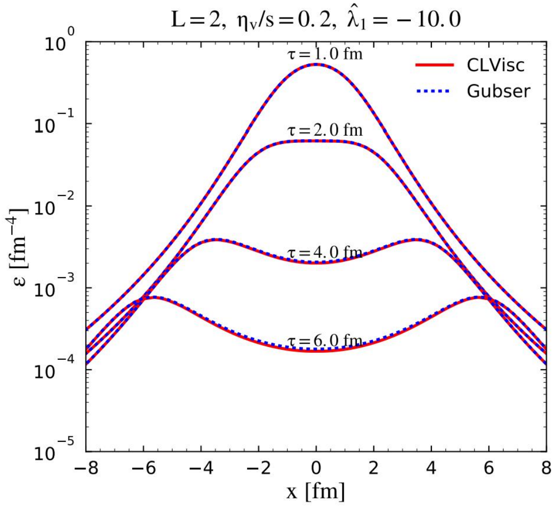
Riemann解

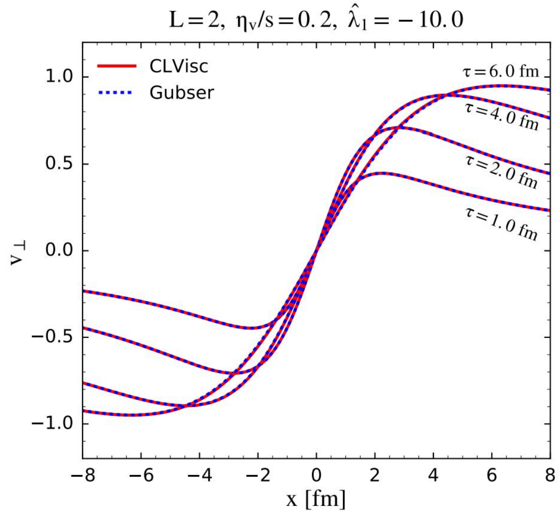


Bjorken解



粘滞 Gubser 解





相对论流体的解析解一般有 **Riemann解，Bjorken解，Gubser 解**;
为数值相对论流体提供重要参考!

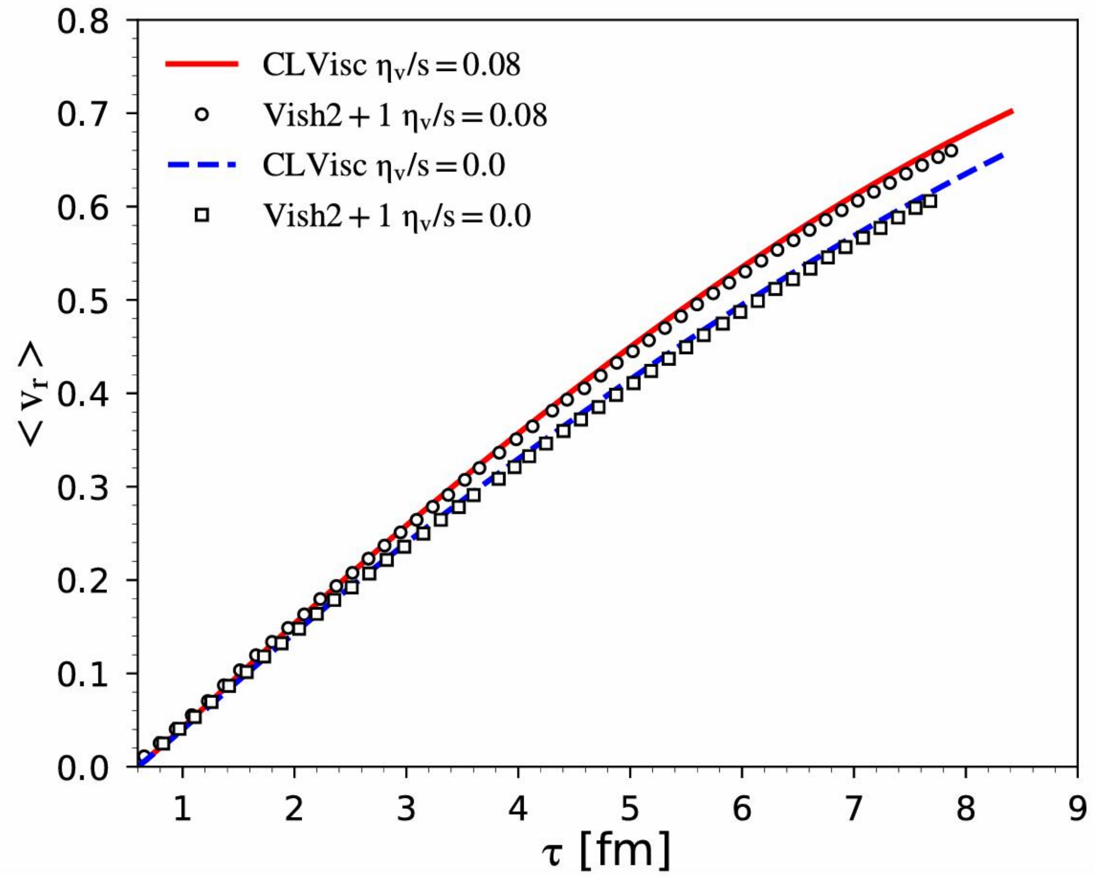
解析解构造方法:

1. 选择某种时空度规
2. 做对称性假设：假设能量密度分布均匀
3. 得到流速 $u^{\mu} = (1,0,0,0)$
4. 反变换回平直时空，得到非零流速

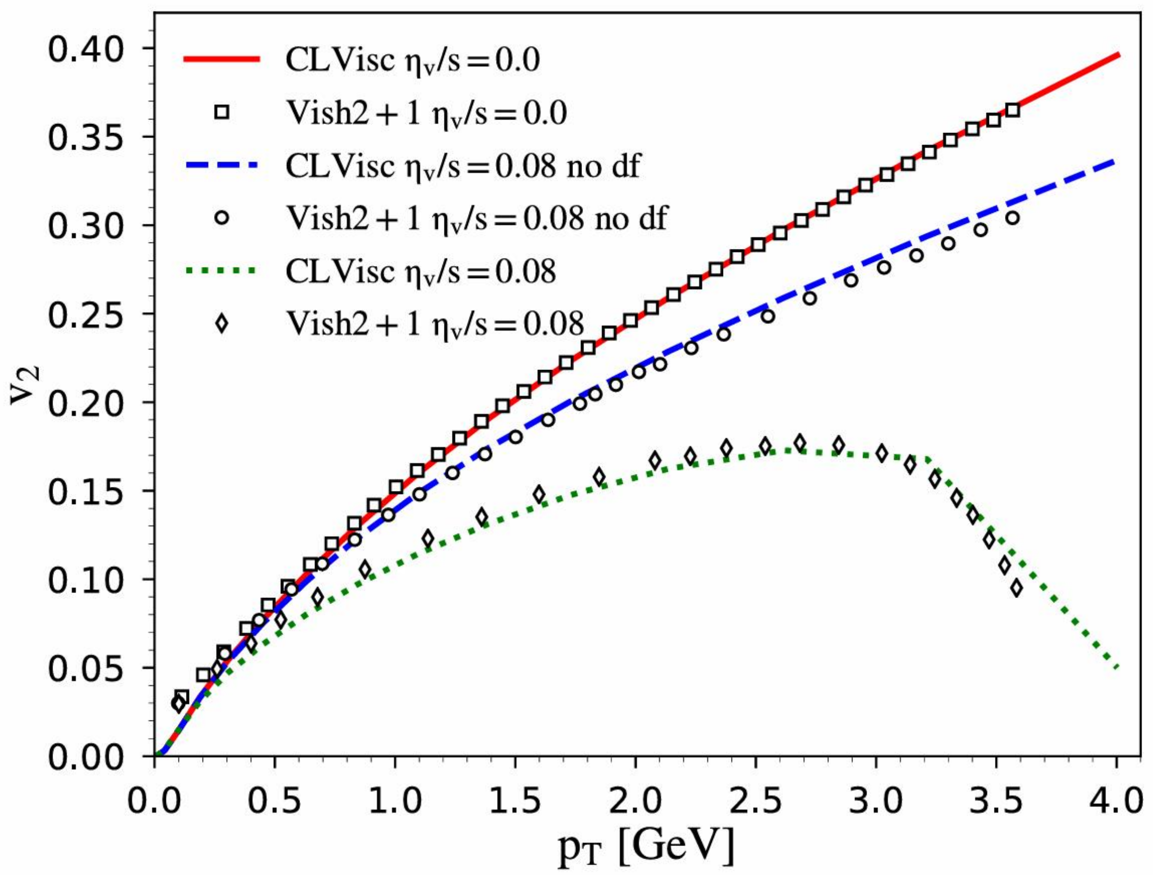
L.G. Pang，H.Petersen, XN Wang, PRC97(2018)no.6,064918

不同相对论流体力学结果的对比

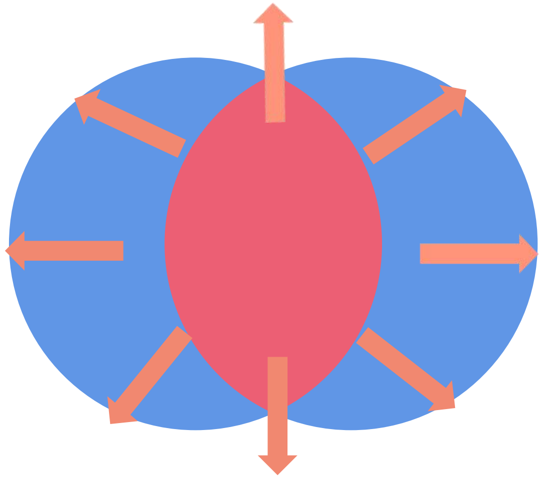
平均径向流速



椭圆流

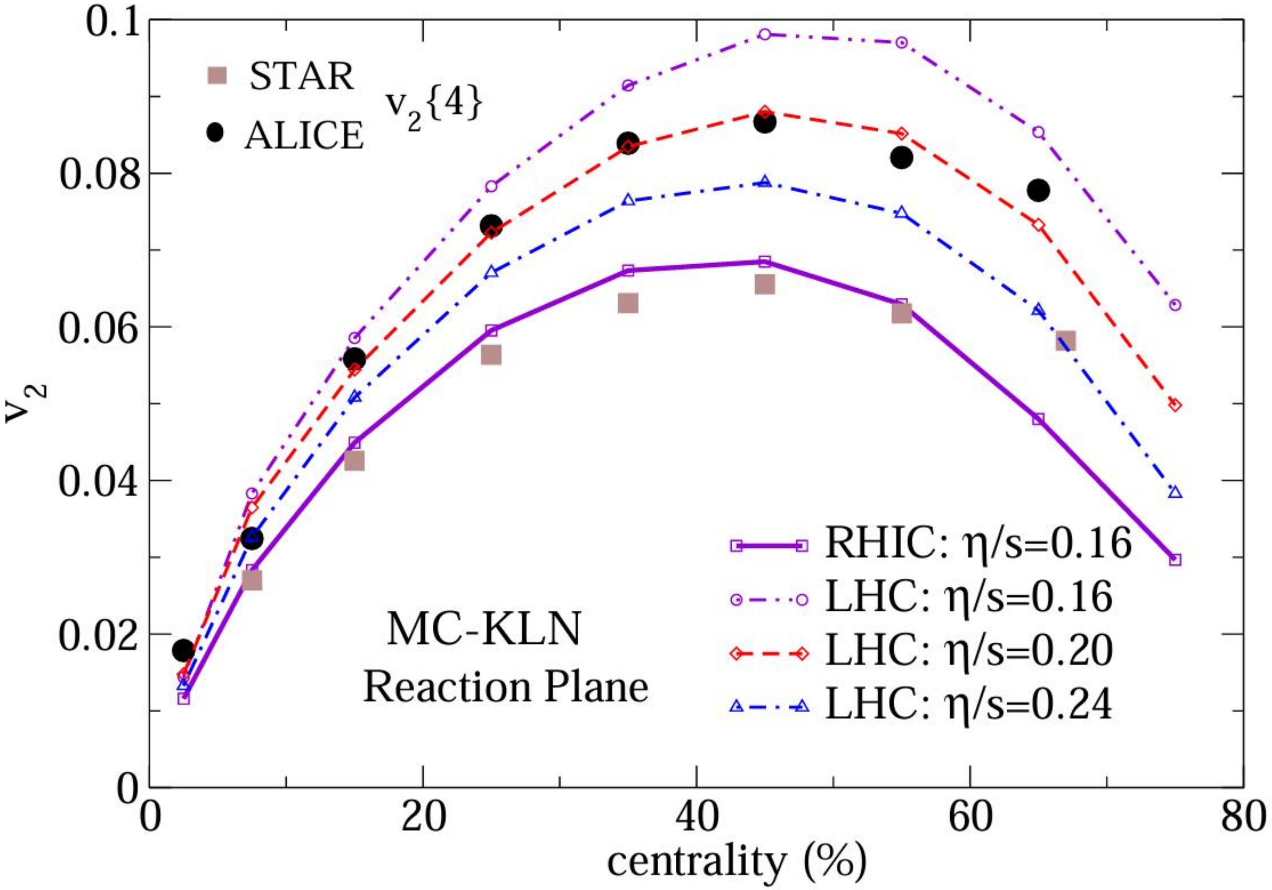


剪切粘滞的效应：VISHNU

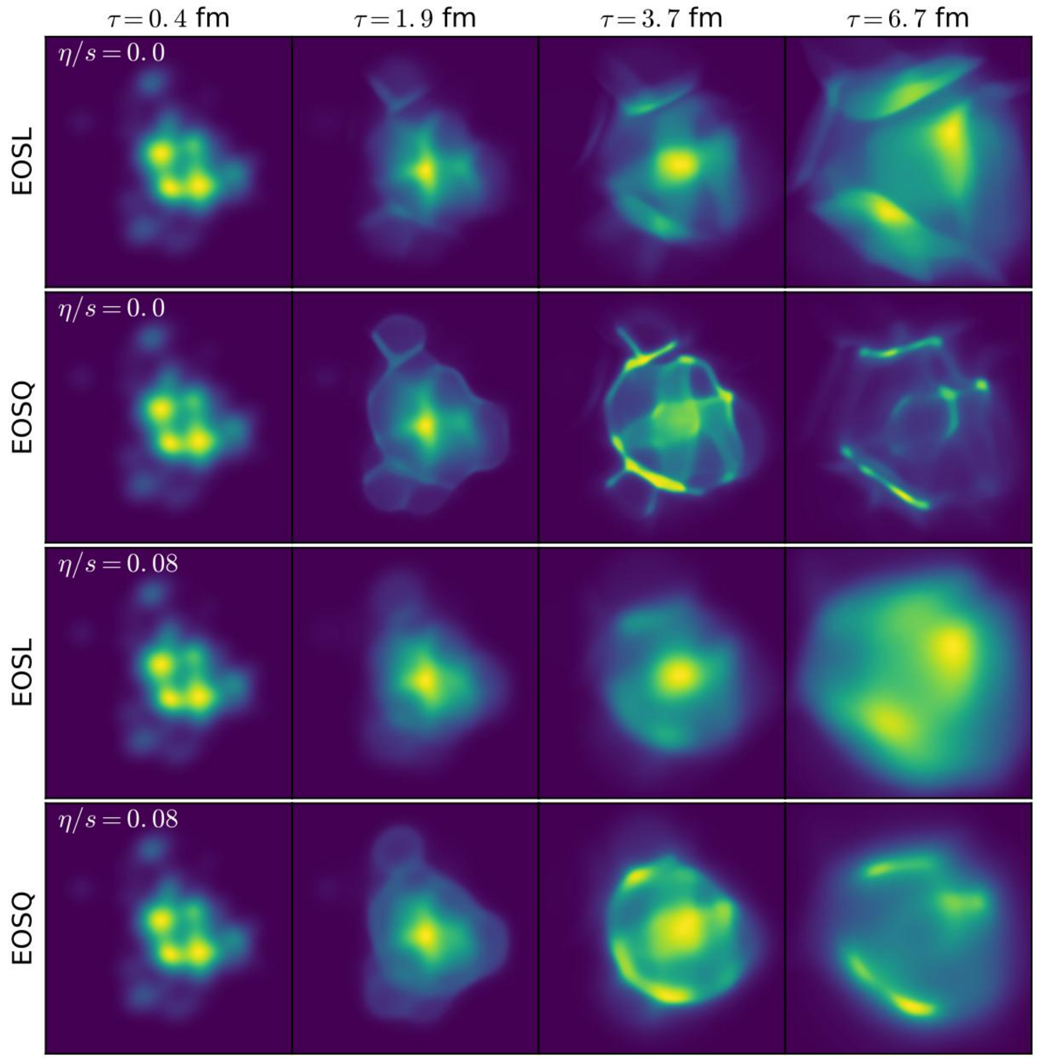


流体力学膨胀将几何各向异性转化为动量空间各向异性，剪切粘滞压低各向异性流

Huichao Song，VISHNU 2+1D hydro, 2008



CLVisc for different EoS and η/s



η/s = 0 (shear viscosity over entropy density)
Lattice QCD EoS (smooth cross over)

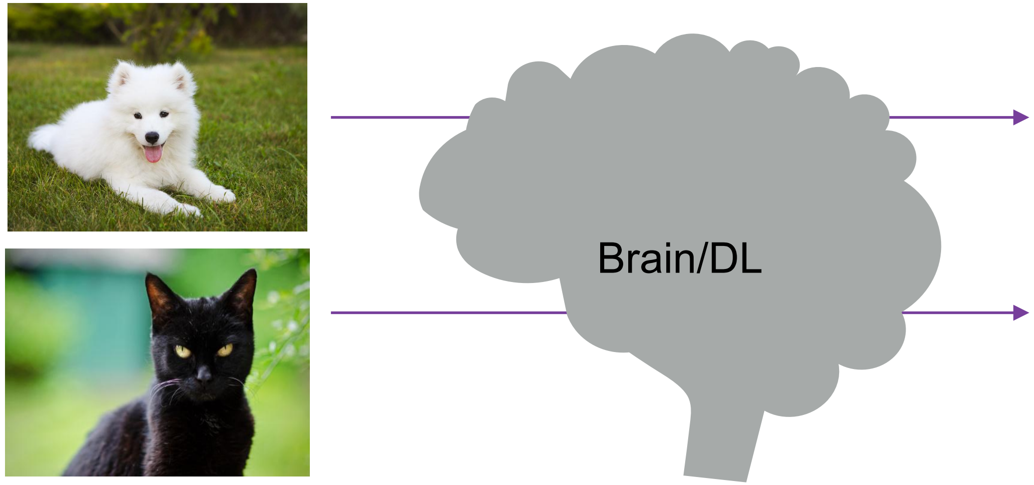
η/s = 0 (ideal hydro)
First order phase transition

η/s = 0.08 (viscous hydro)
Lattice QCD EoS (smooth cross over)

η/s = 0.08
First order phase transition

It is unknown **whether the information of EoS survives the complex dynamical evolution of HICs** and exists in each single event of the final state output.

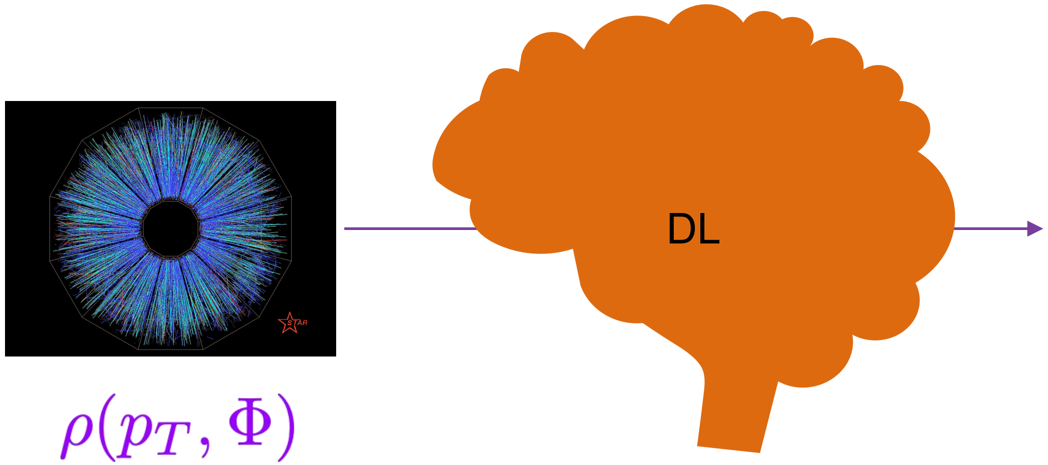
DL for inverse/variational problems in HICs



Human brains are not optimized for processing high-dimensional scientific data. Deep neural network can be trained:

(i) to identify optimal feature combinations

(ii) to represent variational functions

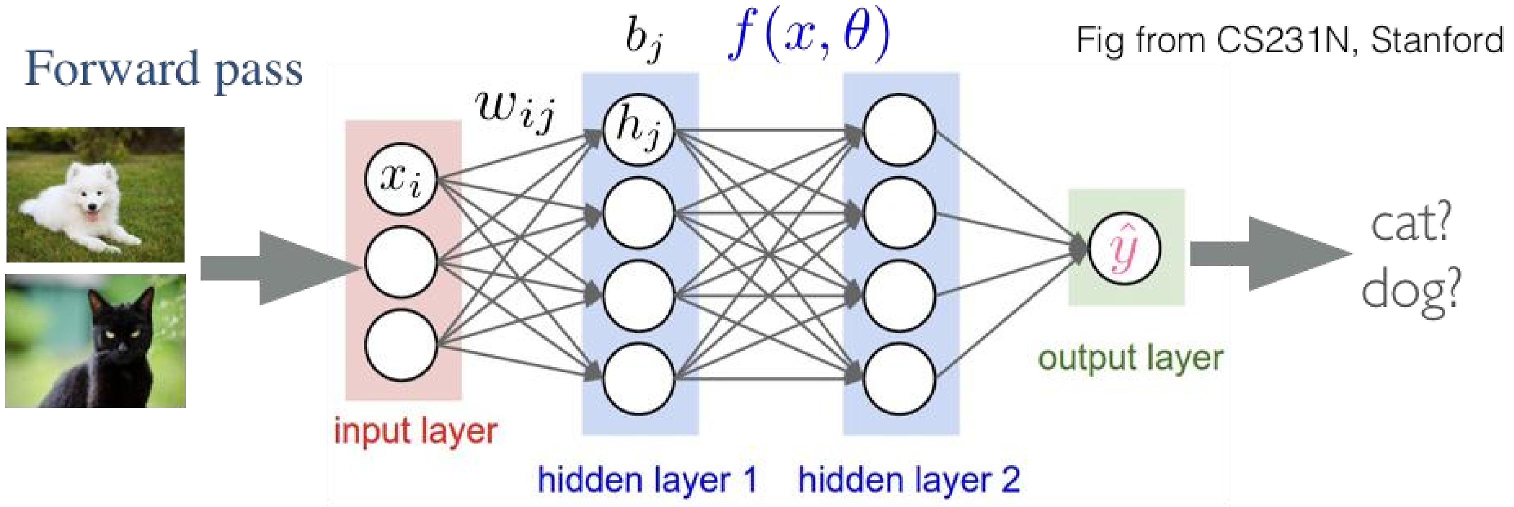


$\rho(p_T, \Phi)$

Lattce QCD EoS (crossover)

EOSQ (First order phase transition)

深度神经网络



Linear operation

$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

scaling, rotating, boosting, changing dimensions

Non-linear activation function $h_j = \sigma(z_j)$

(a) Sigmoid

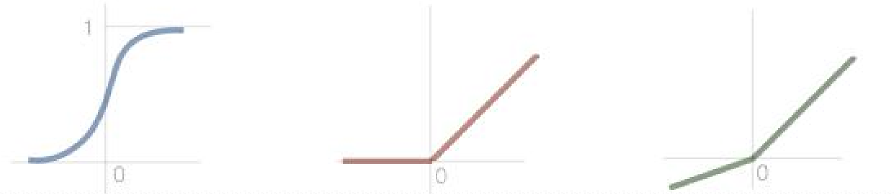
$$\sigma(z) = \frac{1}{1+\exp(-z)}$$

(b) ReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ 0, & z \le 0 \end{cases}$$

(c) PReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ az, & z \le 0 \end{cases}$$



混乱大脑：

一开始，神经网络的可训练参数（连接权重和偏置）被**初始化为随机数，神经网络做出随机预测。**

必须**训练网络，逐渐调节神经网络参数**，才能慢慢做出正确预测。

训练过程：误差后传与随机梯度下降

Input x

Neural network
$\hat{y} = f(x, \theta)$

$\hat{y}$: Network prediction
y: True label

Loss(cost) function
$$L = \frac{1}{N}\sum_i (\hat{y}_i - y_i)^2$$

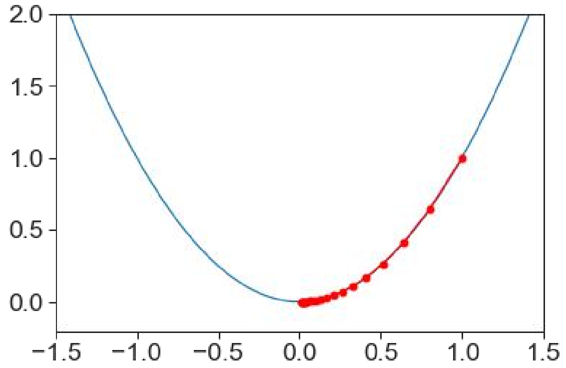
Gradient decent
$$\theta = \theta - \epsilon \frac{\partial L}{\partial \theta}$$

Back pro

1. Initially θ are random numbers and network makes random predictions
2. Using network prediction to compute loss L, which is a functional of $f(x, \theta)$
3. The gradients $\partial L / \partial \theta$ are computed through auto-differentiation
4. Trainable parameters θ are updated using stochastic gradient descent (SGD)

举例：1维梯度下降

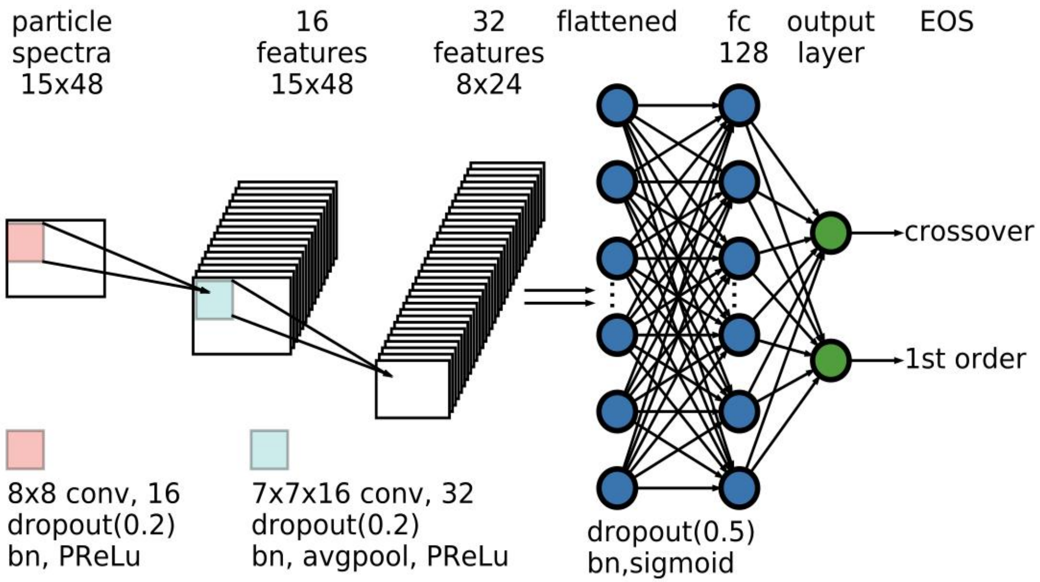
$$\mathrm{L}(\theta) = \theta^2$$



θ

$$\frac{\partial L}{\partial \theta} = 2\theta$$

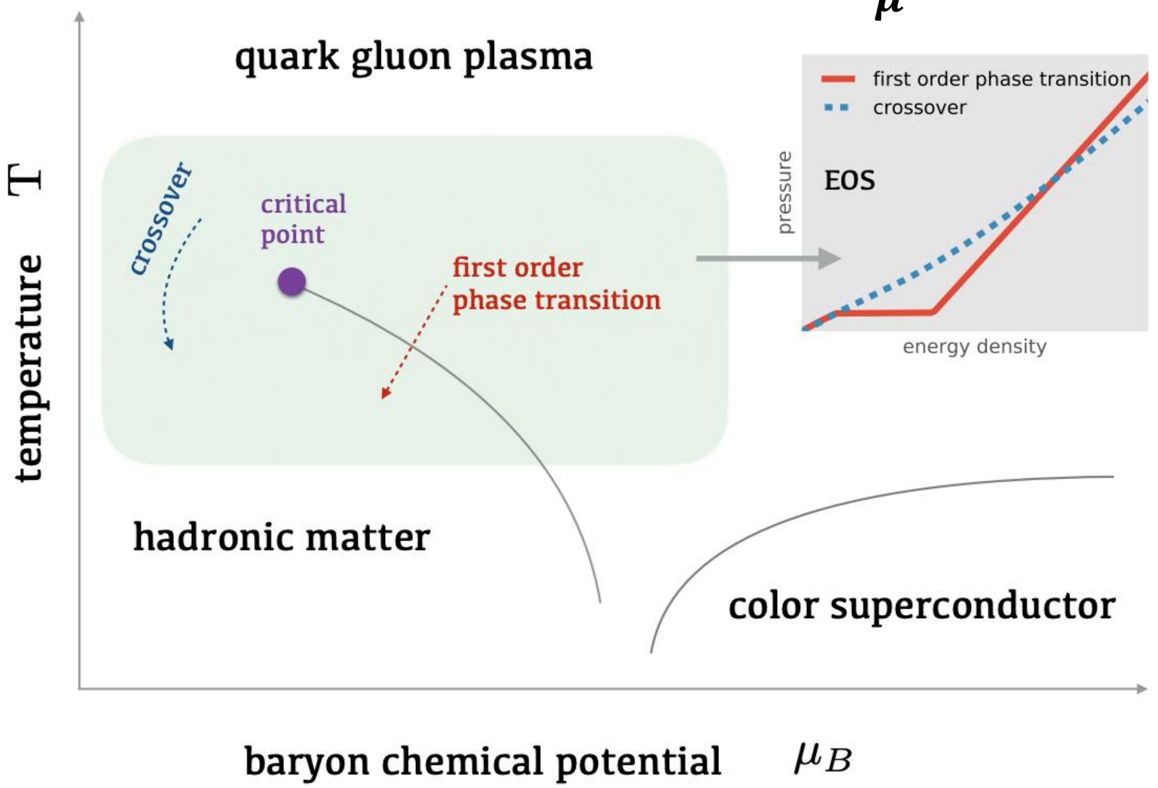
EoS for different phase transition types



$$l(\theta) = \boxed{-\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]} + \boxed{\lambda||\theta||_2^2}$$

cross entropy loss L2 regularization

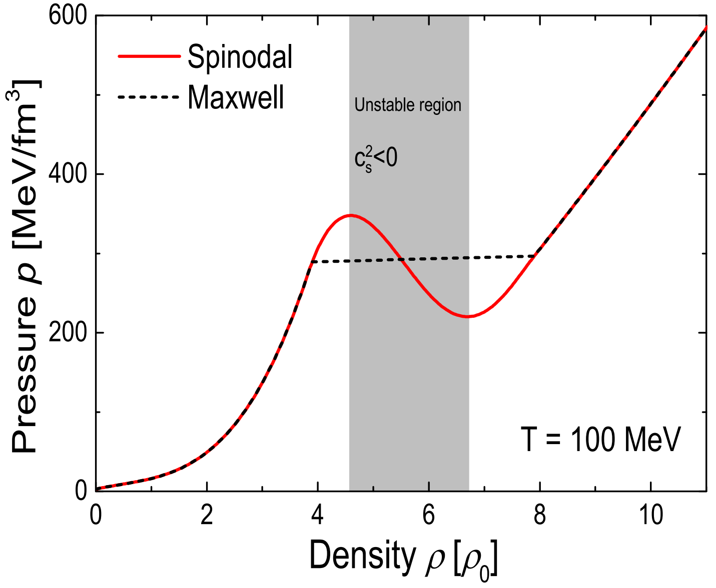
$$\nabla_\mu T^{\mu\nu} = 0$$

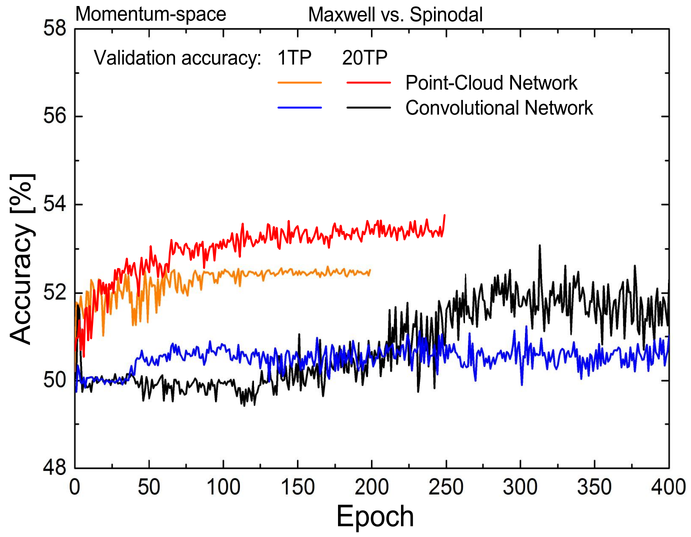


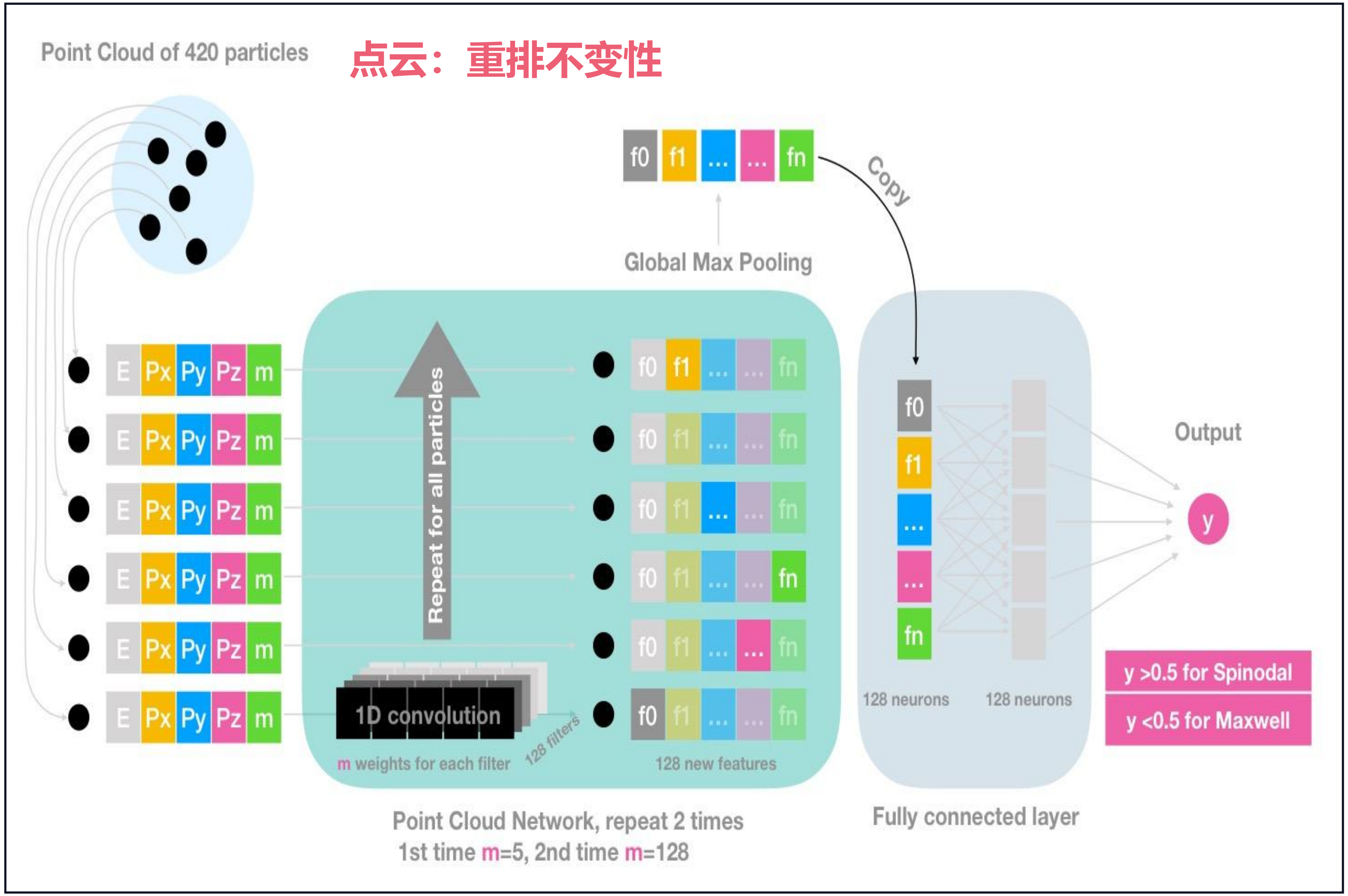
DL helps to decode the information of QCD phase transition in the QCD EoS (>93% accuracy).

Nature Communications 2018, **LG. Pang**, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang.

Spinodal vs Maxwell 1st order phase transition

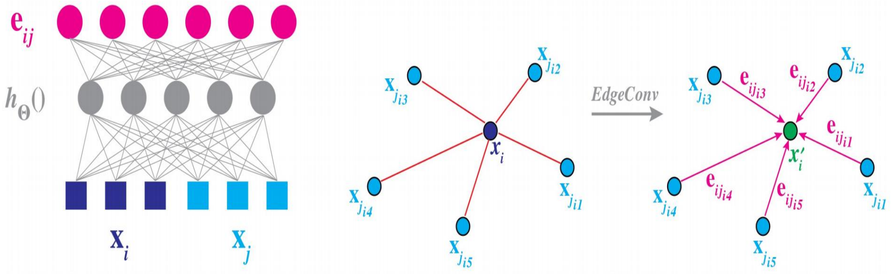


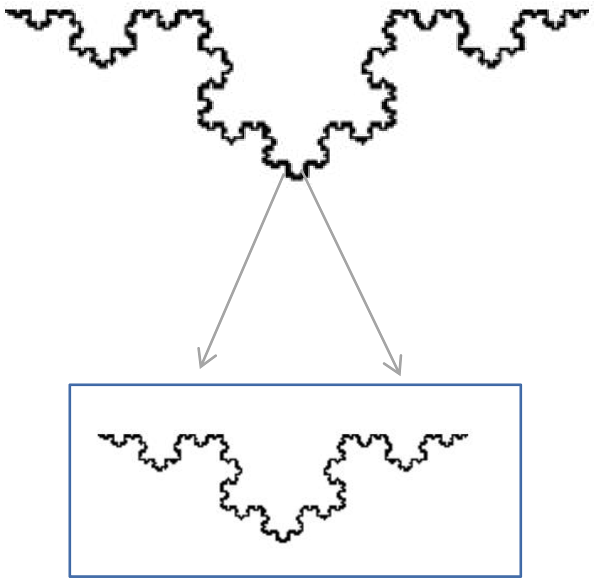




J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup，JHEP 12 (2019) 122

Looking for self similarity in momentum space



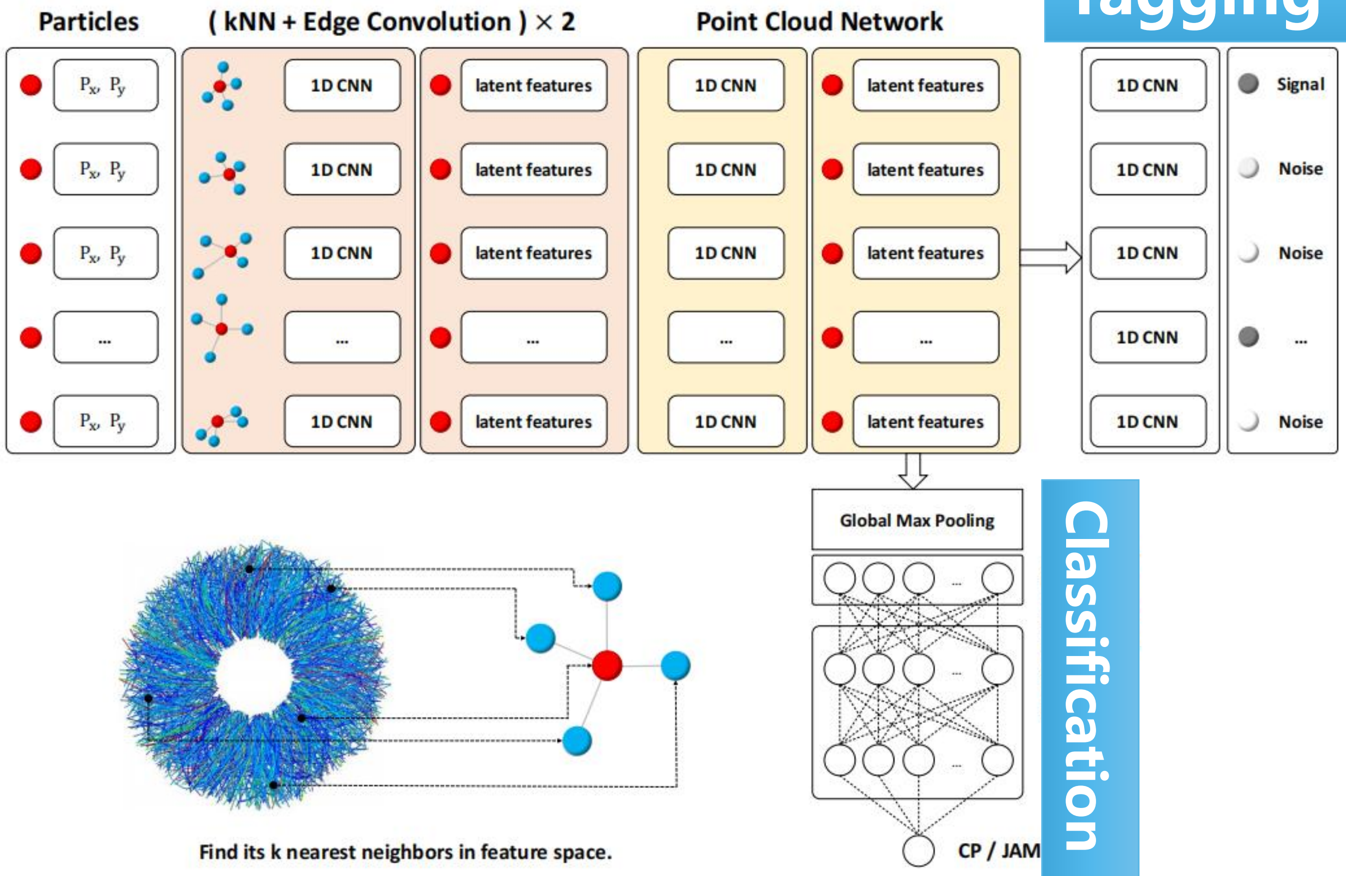


Self similarity, scaling invariance

捕捉局域关联与长程关联

Dynamical Edge Convolution Network

Tagging



Classification

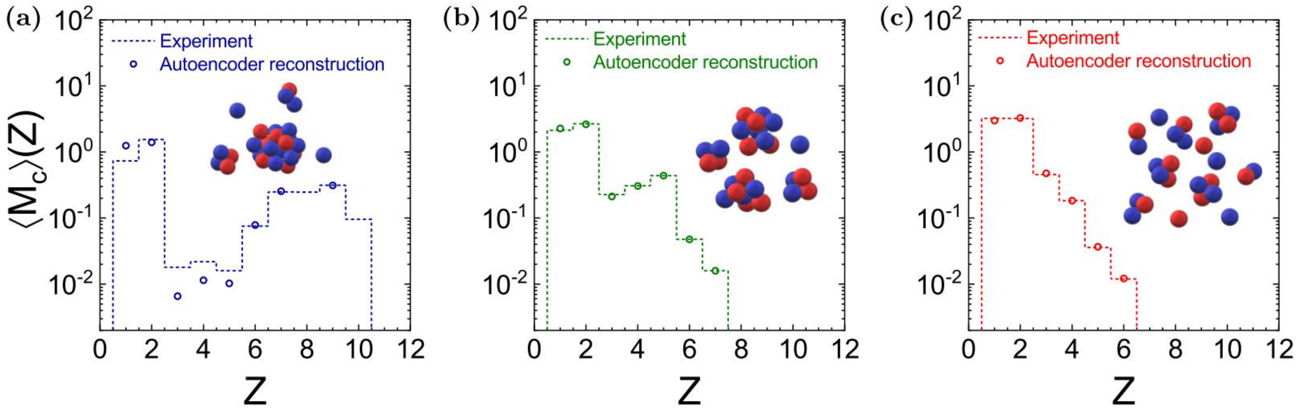
PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

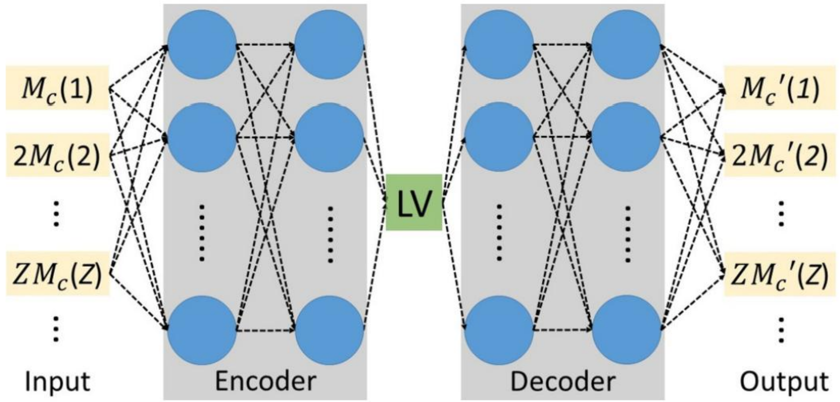
Auto Encoder for order parameter

PHYSICAL REVIEW RESEARCH **2**, 043202 (2020)

Nuclear liquid-gas phase transition with machine learning

Rui Wang,[1,2,*] Yu-Gang Ma,[1,2,†] R. Wada,[3] Lie-Wen Chen,[4] Wan-Bing He,[1] Huan-Ling Liu,[2] and Kai-Jia Sun[3,5]

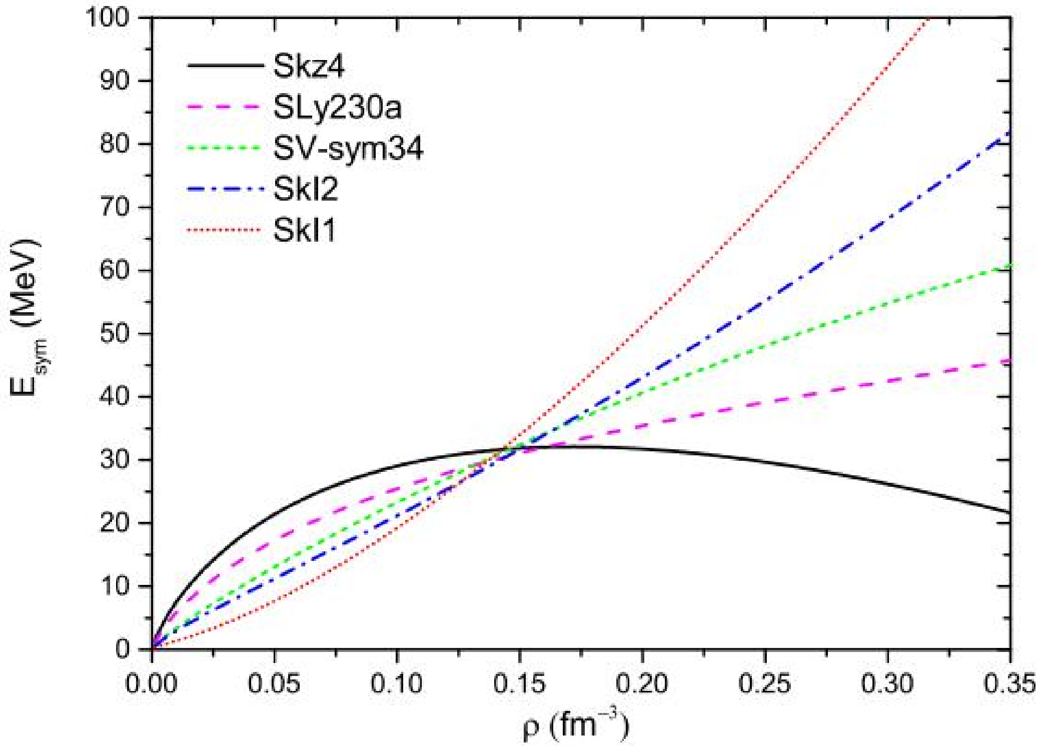


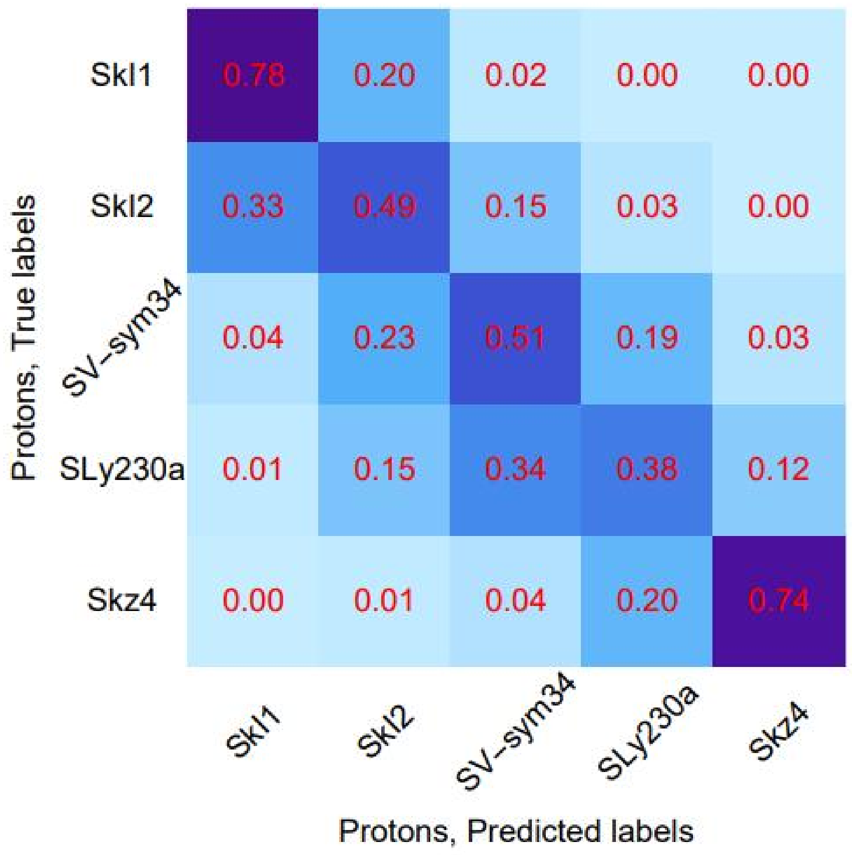


Nuclear EoS at high density region

Skyrme potential + IMQMD

off-diagonal = misclassified

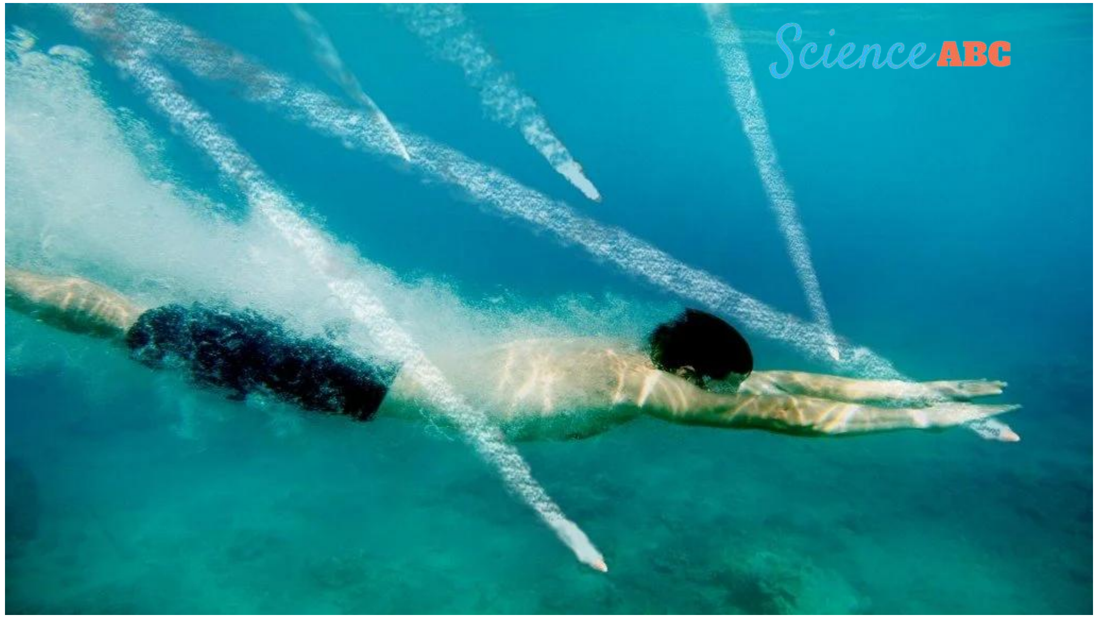




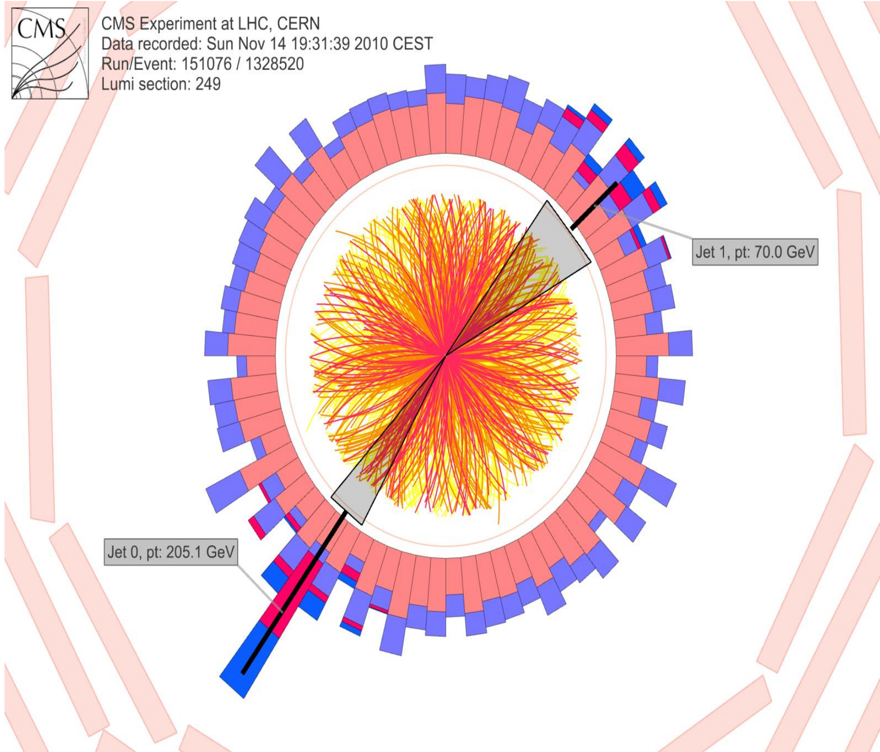
PLB 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

Jet eloss and medium response

Can Being Underwater Protect You From Bullets?

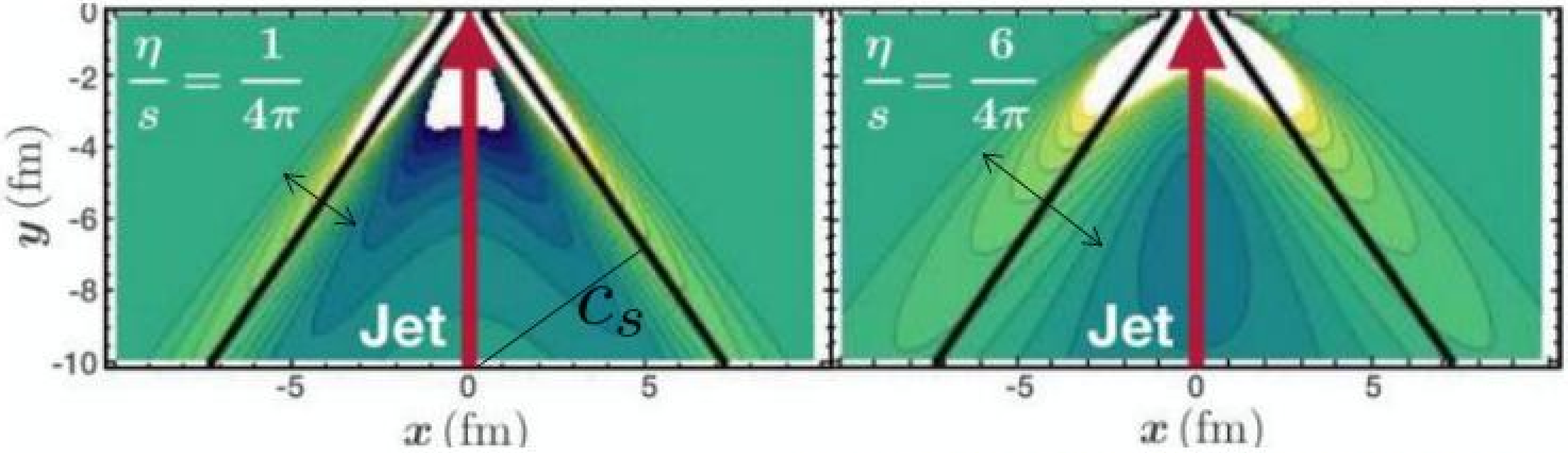


If the bullet is shot from an angle of 30 Degrees, then being underwater in the range of 3-5 feet (0.9-1.5 meters) can ensure safety from most guns.



Jet quenching in hot QGP

The nuclear EoS and Mach Cone



R.B.Neufeld. PRC79,054909(09')

Nuclear EoS： $c_s^2 = \frac{dP}{d\epsilon} = \sin^2\theta$

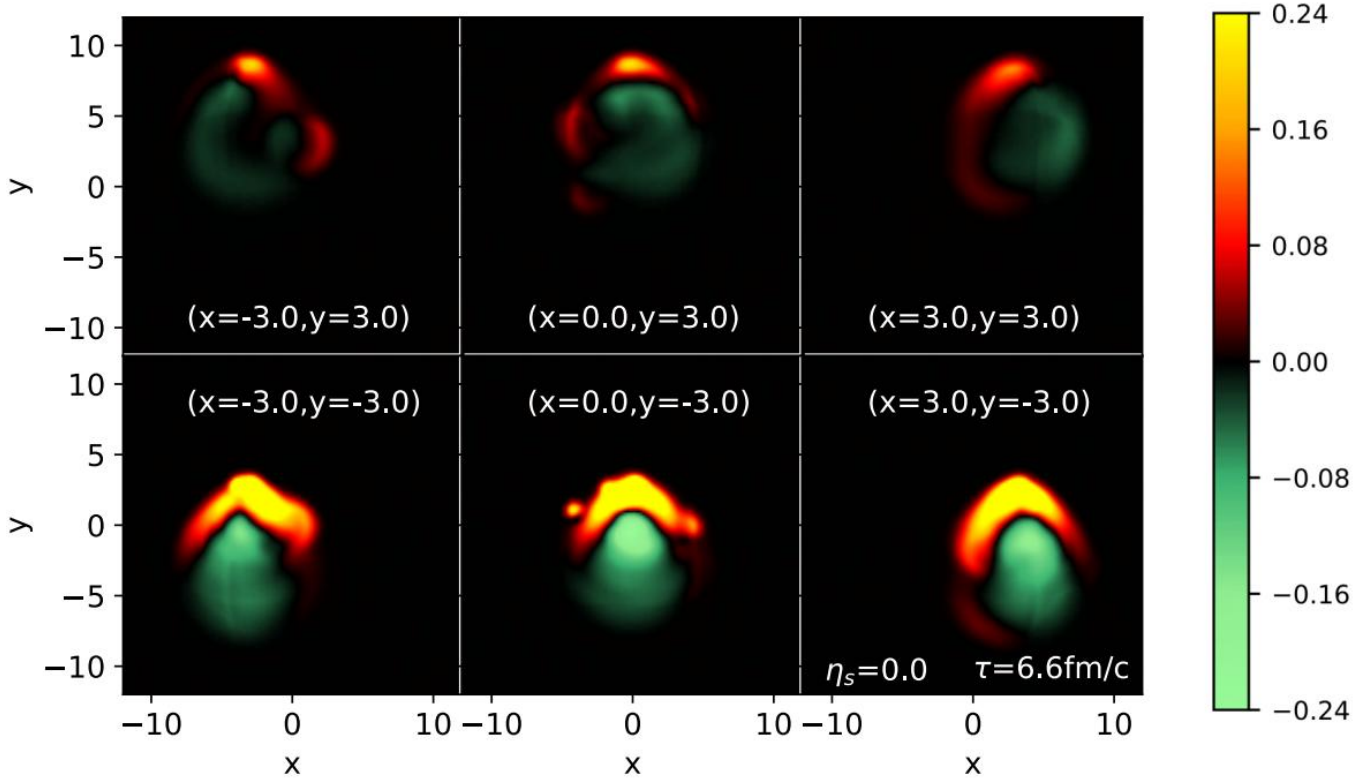
Shear Viscosity： width of the shock wave

Medium response for nuclear EoS

$$p\partial f(p) = -C(p) \quad (p\cdot u > p^0_{cut})$$

$$\partial_\mu T^{\mu\nu}(x) = j^\nu(x)$$

$$j^\nu = \sum_i p_i^\nu \delta^{(4)}(x - x_i)\theta(p^0_{cut} - p\cdot u)$$



LBT: YY He, T Luo, XN Wang, Y Zhu,
PRC 91 (2015) 054908, PRC 97 (2018) 1, 019902

CLVisc:
LG Pang, Q Wang, XN Wang, PRC 86 (2012) 024911
LG Pang, H Petersen, XN Wang, PRC 97 (2018) 6, 064918
XY Wu, GY Qin, LG Pang, XN Wang,PRC 105 (2022) 3, 034909

CoLBT:

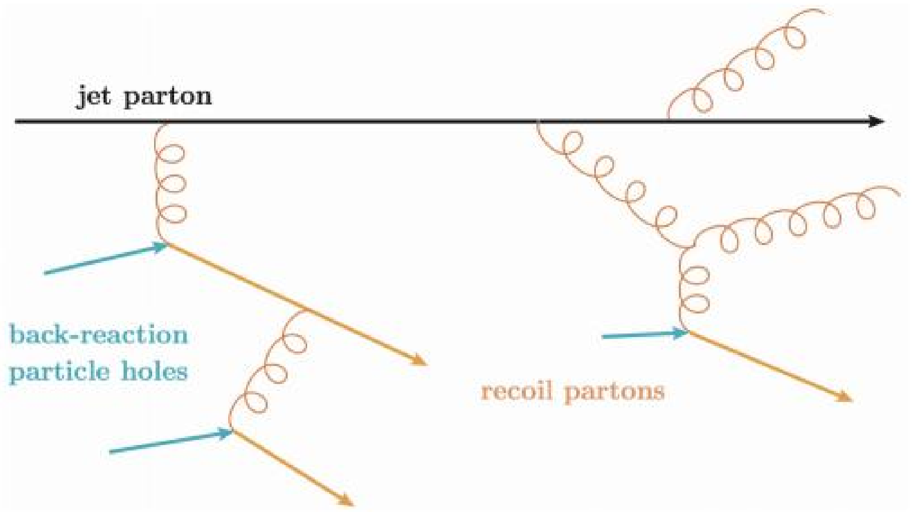
W Chen, T Luo, SS Cao, LG Pang, XN Wang,
PLB 777 (2018) 86-90

LBT: Linear Boltzmann Transport

$$p_1 \partial f_1 = -\int dp_2 dp_3 dp_4 (f_1 f_2 - f_3 f_4) \left| M_{12\to 34} \right|^2 (2\pi)^4 \delta^4 (\sum_i p^i) + inelastic$$

Medium-induced gluon(HT):

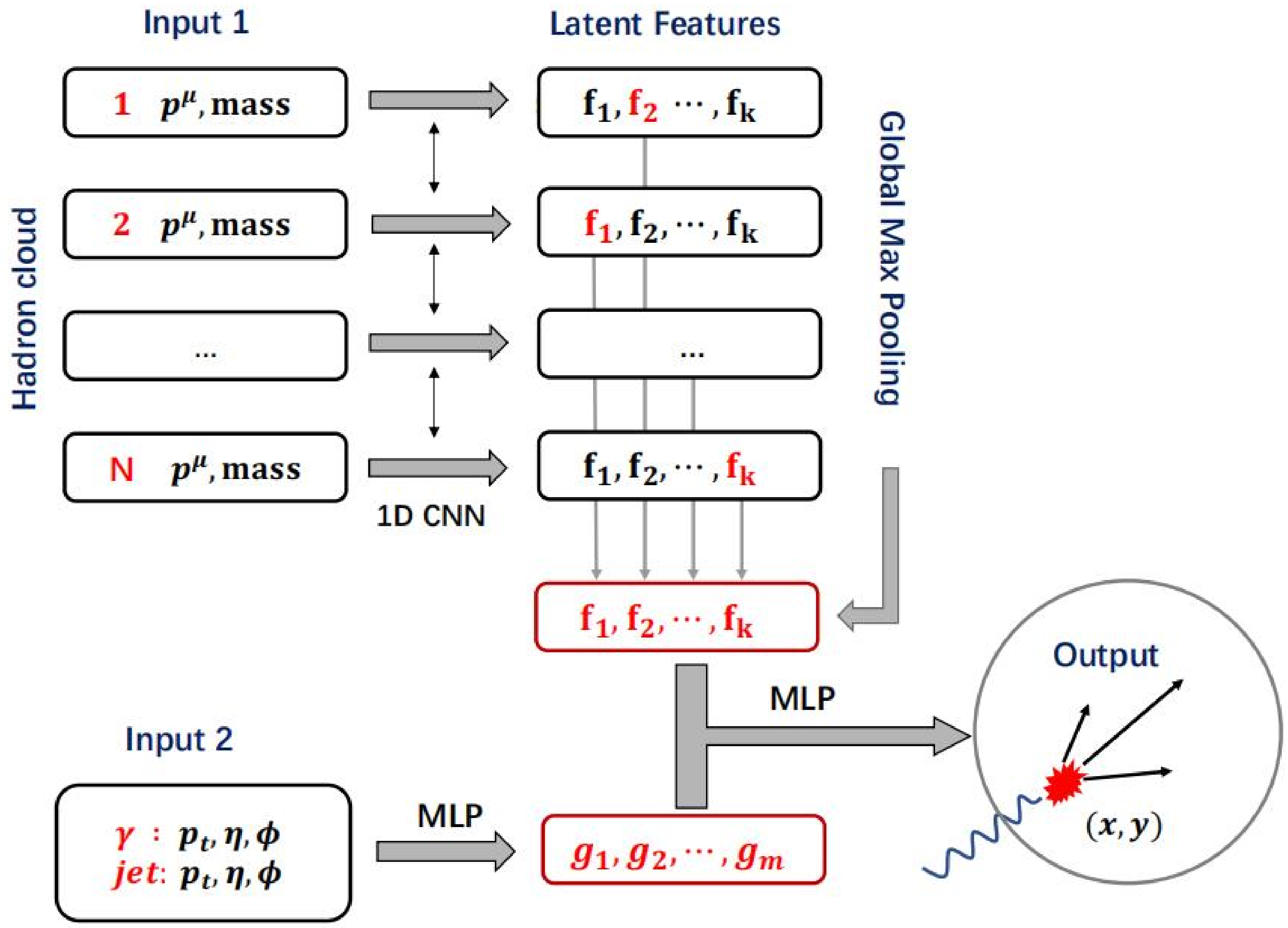
$$\frac{dN_g}{dz d^2 k_\perp dt} \approx \frac{2 C_A \alpha_s}{\pi k_\perp^4} P(z) \hat{q} (\hat{p} \cdot u) sin^2 \frac{k_\perp^2 (t - t_0)}{4z(1-z)E}$$



Tracked partons:
- Jet shower partons
- Thermal recoil partons
- Radiated gluons
- Negative partons(Back reaction induced by energy-momentum conservation)

YY He, T Luo, XN Wang, Y Zhu, PRC 91 (2015) 054908, PRC 97 (2018) 1, 019902

DL assisted jet tomography (gamma-jet)

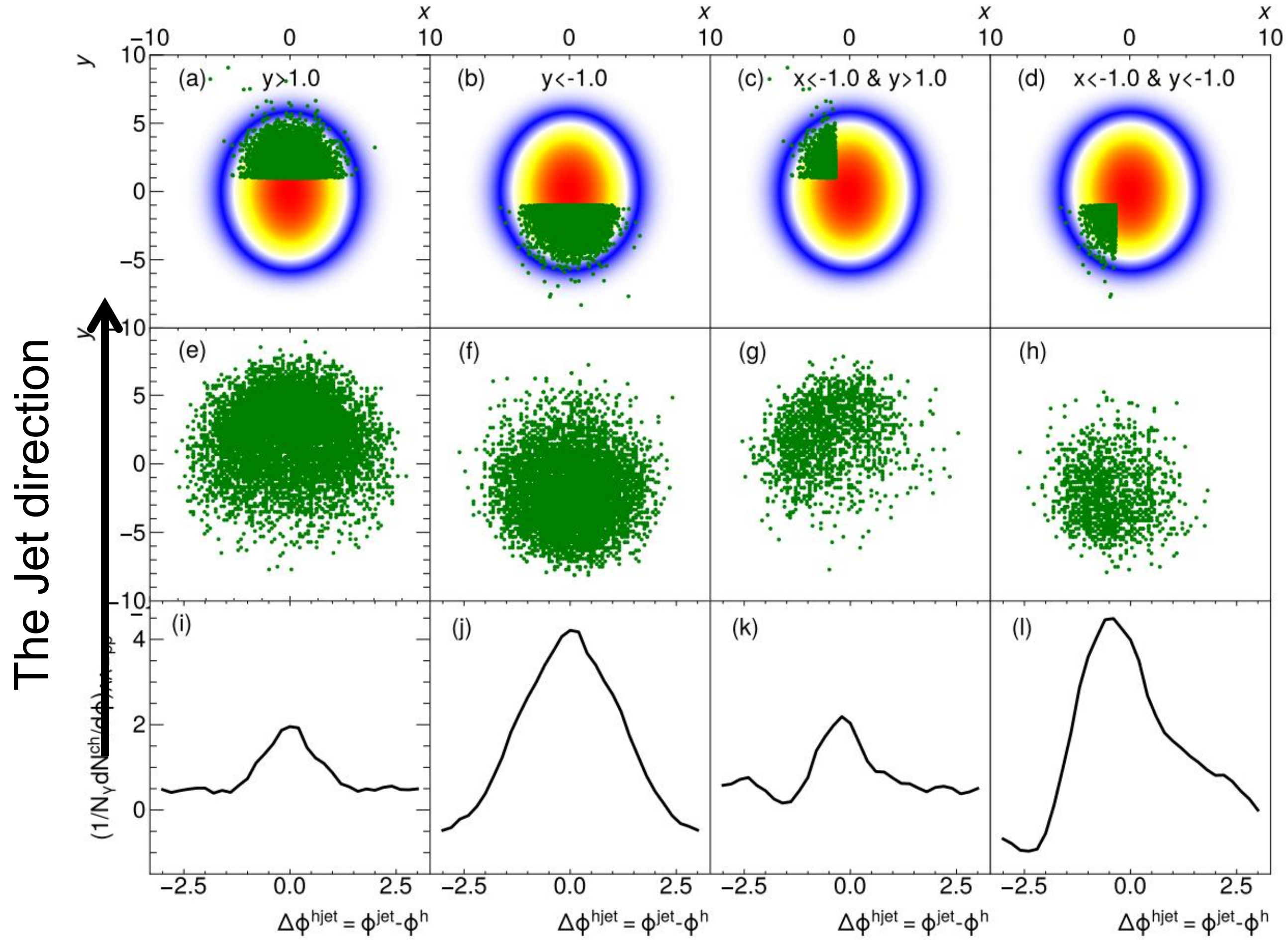


$ij \to kl$	$\lvert M\rvert^2_{ij\to kl}$	
$gg \to gg$	$\frac{9}{2}g_s^4\left(3-\frac{ut}{s^2}-\frac{us}{t^2}-\frac{st}{u^2}\right)$	(A-1)
$gg \to q\bar{q}$	$\frac{3}{8}g_s^4\left(\frac{4}{9}\frac{t^2+u^2}{tu}-\frac{t^2+u^2}{s^2}\right)$	(A-2)
$gq \to gq$ $g\bar{q} \to g\bar{q}$	$g_s^4\left(\frac{s^2+u^2}{t^2}-\frac{4}{9}\frac{s^2+u^2}{su}\right)$	(A-3)
$q_iq_j \to q_iq_j$ $q_i\bar{q}_j \to q_i\bar{q}_j$ $\bar{q}_iq_j \to \bar{q}_iq_j$ $\bar{q}_i\bar{q}_j \to \bar{q}_i\bar{q}_j$	$\frac{4}{9}g_s^4\frac{s^2+u^2}{t^2}, \quad i \neq j$	(A-4)
$q_iq_i \to q_iq_i$ $\bar{q}_i\bar{q}_i \to \bar{q}_i\bar{q}_i$	$\frac{4}{9}g_s^4\left(\frac{s^2+u^2}{t^2}+\frac{s^2+t^2}{u^2}-\frac{2}{3}\frac{s^2}{tu}\right)$	(A-5)
$q_i\bar{q}_i \to q_j\bar{q}_j$	$\frac{4}{9}g_s^4\frac{t^2+u^2}{s^2}$	(A-6)
$q_i\bar{q}_i \to q_i\bar{q}_i$	$\frac{4}{9}g_s^4\left(\frac{s^2+u^2}{t^2}+\frac{t^2+u^2}{s^2}-\frac{2}{3}\frac{u^2}{st}\right)$	(A-7)
$q\bar{q} \to gg$	$\frac{8}{3}g_s^4\left(\frac{4}{9}\frac{t^2+u^2}{tu}-\frac{t^2+u^2}{s^2}\right)$	(A-8)

$$(x_i^{\text{net}}, y_i^{\text{net}}) = f(\{\vec{p}\}_i, \theta),$$

Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652

DL assisted jet tomography



神经网络预测

真实产生位置

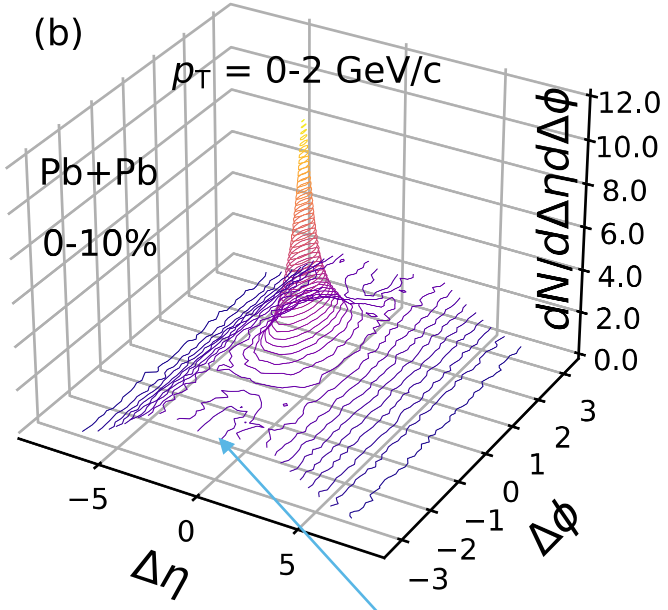
使用深度学习辅助的喷注层析，
扩散尾流的信号被大大增强

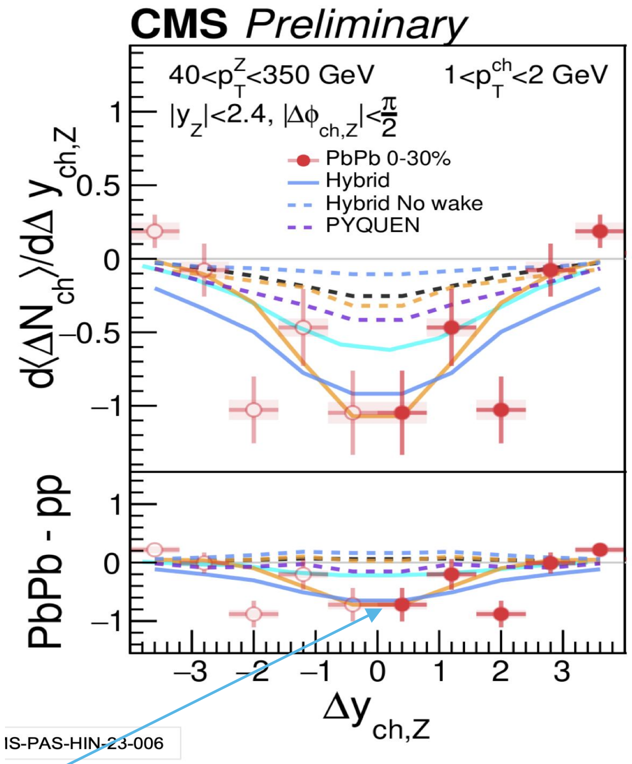
Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652
Z Yang, T Luo, W Chen, LG Pang, XN Wang, PRL 130 (2023) 5, 052301

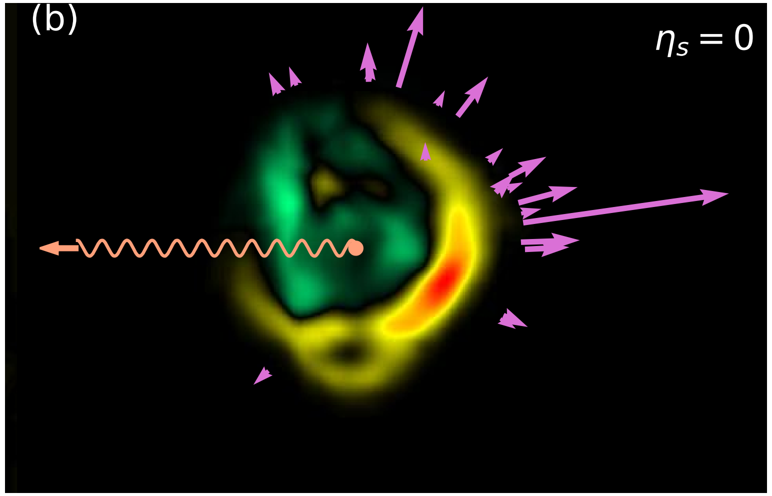
Jet induced sound wave in QGP

- **扩散尾流（Diffusion Wake, DF）：流体动力学中的普遍现象，伴随高速物体诱导的马赫尾迹。**
- **影响：扩散尾流导致软强子产额在喷流反方向压低**

g-triggered-jet-hadron correlation







扩散尾迹

我们使用相对论流体力学 CLVisc 和线性玻尔兹曼输运模型 LBT 以及 CoLBT 预测的扩散尾迹首次在LHC的Pb+Pb碰撞中被CMS实验观测到！

Z Yang, T. Luo, W. Chen, LG Pang，XN Wang, PRL, 130 (2023) , 052301

Auto Differentiation: machine precision

- Forward Mode

Introduce dual numbers: $x \to x + \dot{x}\mathbf{d}$

where $\mathbf{d}^2 = 0$

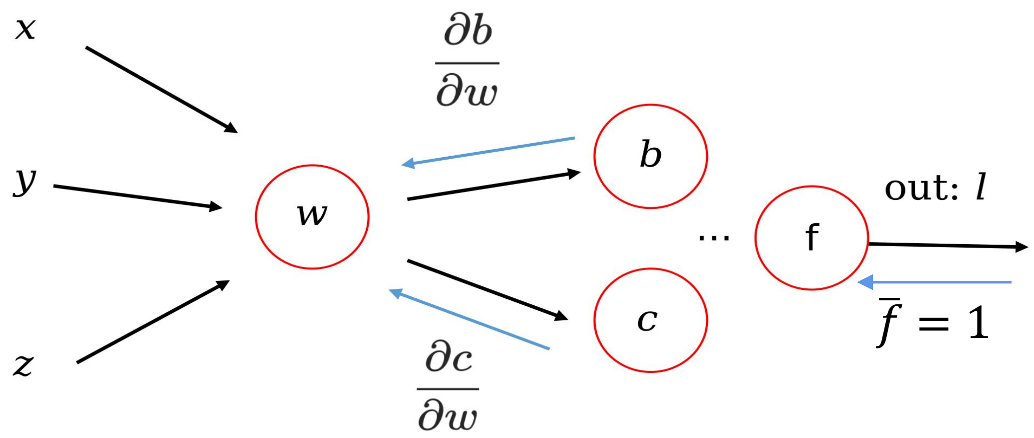
$$(x + \dot{x}\mathbf{d}) + (y + \dot{y}\mathbf{d}) = x + y + (\dot{x} + \dot{y})\mathbf{d}$$
$$(x + \dot{x}\mathbf{d}) - (y + \dot{y}\mathbf{d}) = x - y + (\dot{x} - \dot{y})\mathbf{d}$$
$$(x + \dot{x}\mathbf{d}) * (y + \dot{y}\mathbf{d}) = xy + (x\dot{y} + \dot{x}y)\mathbf{d}$$
$$\frac{1}{x + \dot{x}\mathbf{d}} = \frac{1}{x} - \frac{\dot{x}}{x^2}\mathbf{d} \qquad (x \neq 0)$$

Forward mode for $R^1 \to R^n$

Reverse mode for $R^n \to R^1$

- Reverse Mode

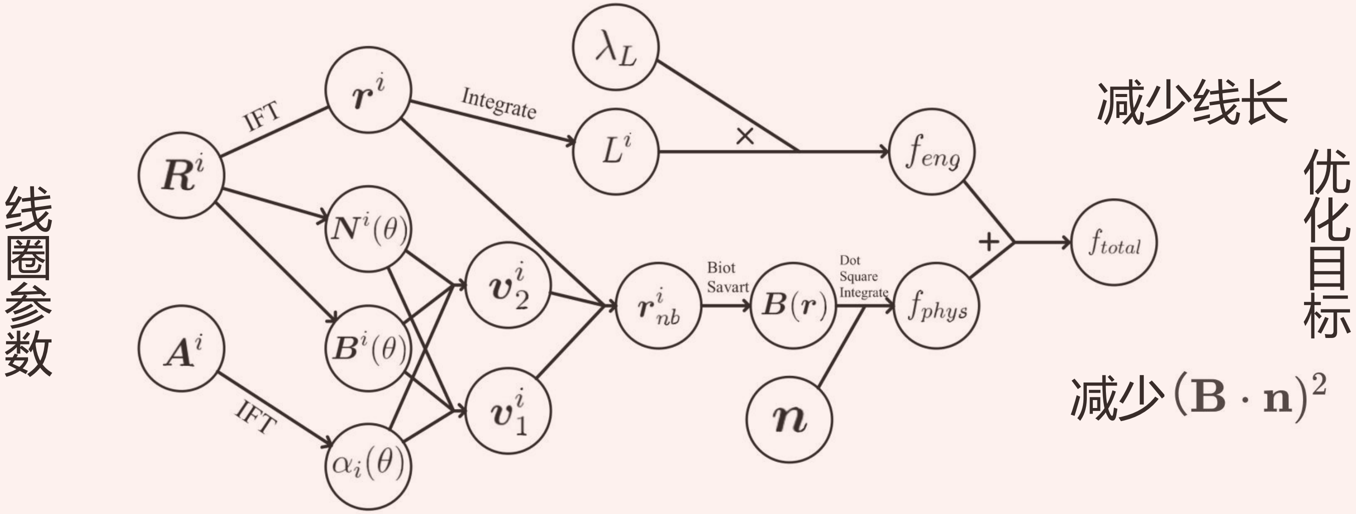
adjoint number: $\bar{w} = \frac{\partial l}{\partial w}$

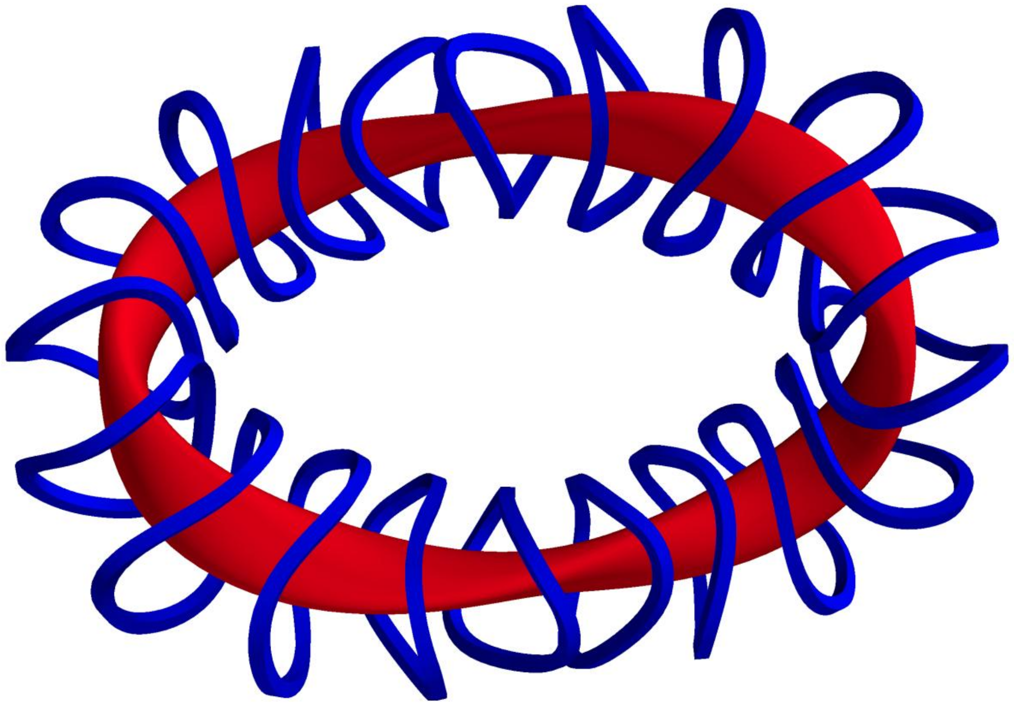


$$\text{step } 1: \bar{w} = 0$$
$$\text{step } 2: \bar{w} = \bar{w} + \bar{b}\frac{\partial b}{\partial w}$$
$$\text{step } 3: \bar{w} = \bar{w} + \bar{c}\frac{\partial c}{\partial w}$$

自动微分应用于仿星器的设计

$$\boldsymbol{B}(\boldsymbol{r}) = \sum_{i=1}^{N_c}\sum_{n=1}^{N_1}\sum_{b=1}^{N_2} \frac{\mu_0 I^i_{n,b}}{4\pi}\oint \frac{d\boldsymbol{l}^i_{n,b}\times(\boldsymbol{r}-\boldsymbol{r}^i_{n,b})}{|\boldsymbol{r}-\boldsymbol{r}^i_{n,b}|^3}.$$

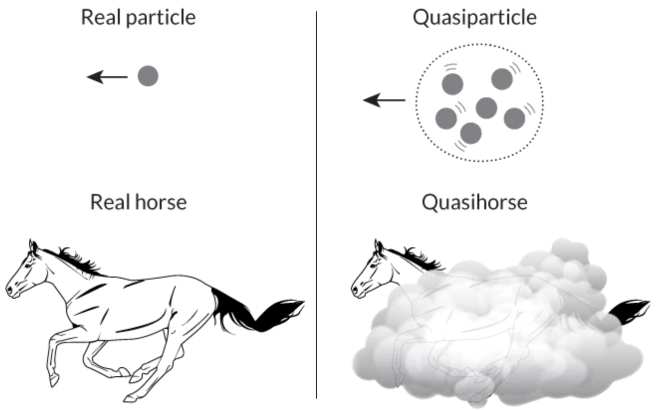


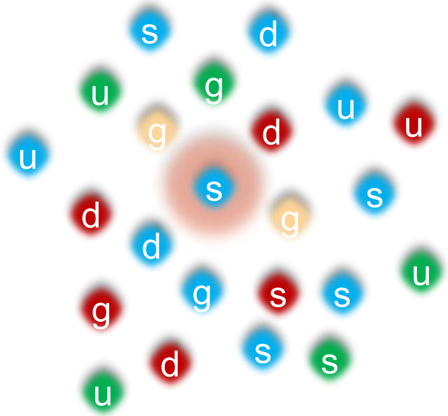


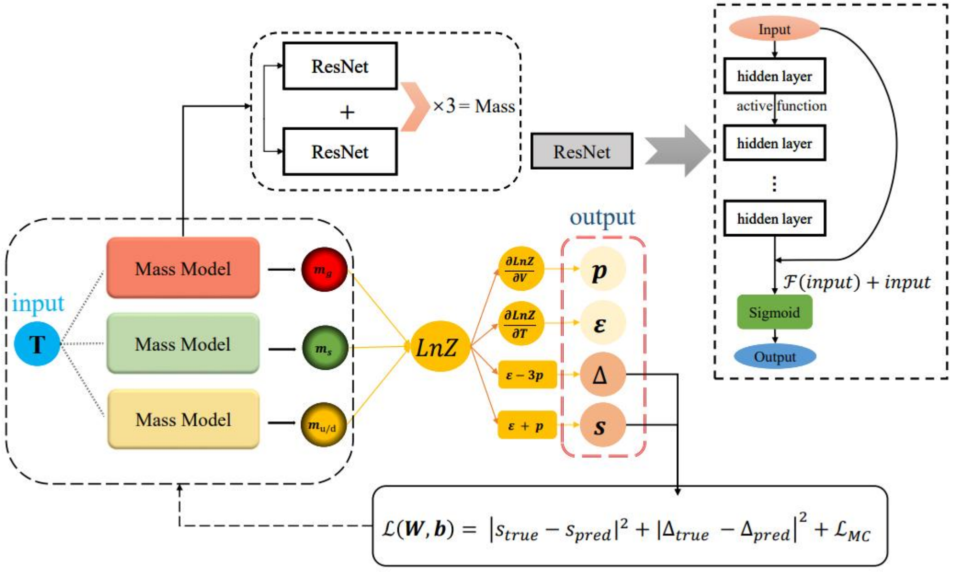
N McGreivy N，SR Hudson ，CX Zhu. 2020，arXiv:2009.00196

右图蓝色表示线圈，红色表示等离子体；线圈通电后产生的磁场要把等离子体约束在仿星器腔内。R，A 对应线圈参数，通过复杂的逆傅里叶变换(IFT),积分(Integrate)和比奥萨伐尔公式，获得磁场 B(r)。
优化目标：（1）工程目标，减小线长 (2) 物理目标，让磁场方向尽量垂直于外表面法向

Deep Learning Quasi Particle Model







$$\ln Z(T) = \ln Z_g(T) + \ln Z_{u,d}(T) + \ln Z_s(T),$$

Fermi-Dirac distributions,

$$\ln Z_g(T) = -\frac{16V}{2\pi^2}\int_0^\infty p^2 dp \; \ln\left[1 - \exp\left(-\frac{1}{T}\sqrt{p^2 + m_g^2(T)}\right)\right], \tag{2}$$

$$\ln Z_{q_i}(T) = +\frac{12V}{2\pi^2}\int_0^\infty p^2 dp \; \ln\left[1 + \exp\left(-\frac{1}{T}\sqrt{p^2 + m_{q_i}^2(T)}\right)\right], \tag{3}$$

quarks, $m_s(T, \theta_2)$ for strange quark and $m_g(T, \theta_3)$ for gluons, where θ_1, θ_2 and θ_3 are the parameters in DNN shown in Fig. 1.

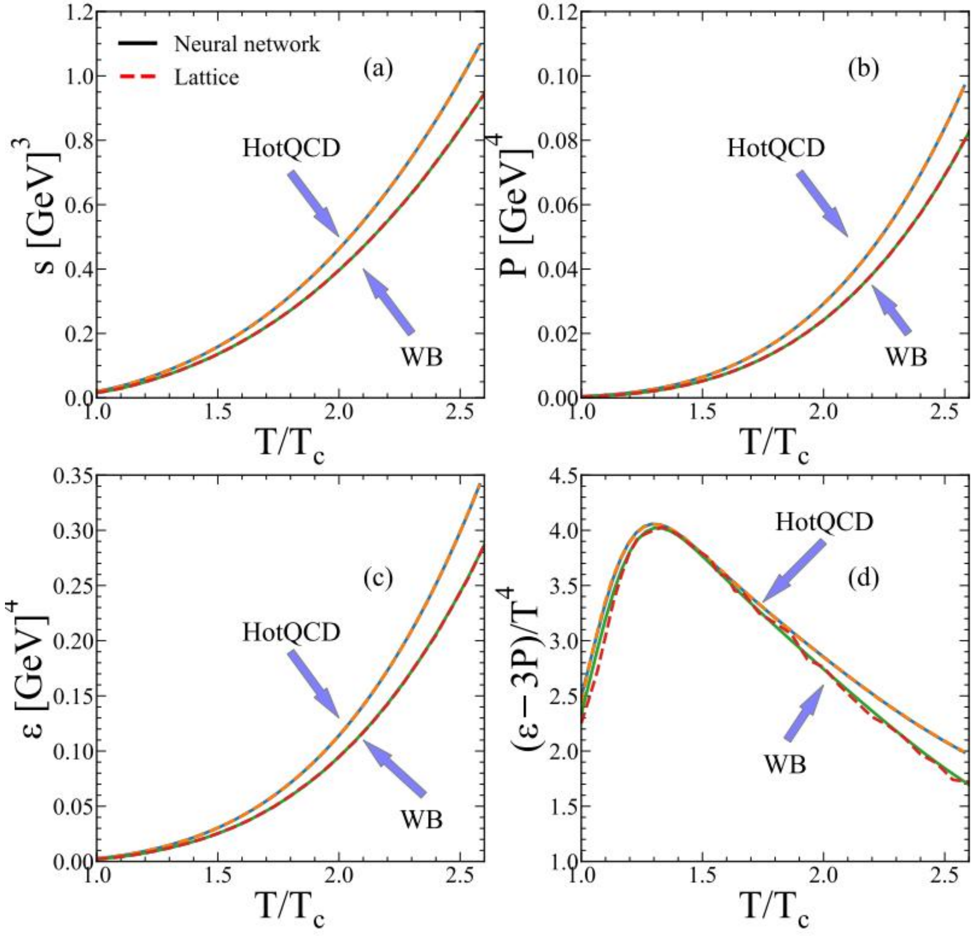
The resulting pressure and energy density are computed using the following statistical formulae,

$$P(T) = T\left(\frac{\partial \ln Z(T)}{\partial V}\right)_T, \tag{5}$$

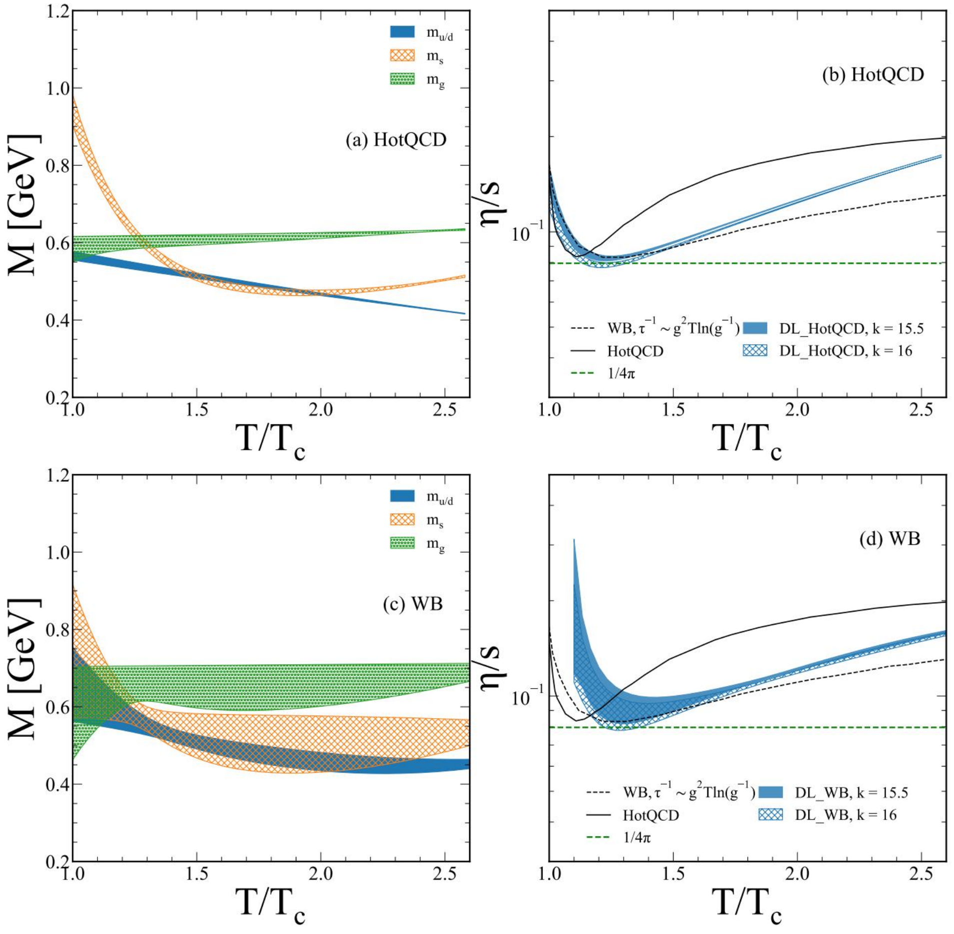
$$\epsilon(T) = \frac{T^2}{V}\left(\frac{\partial \ln Z(T)}{\partial T}\right)_V, \tag{6}$$

The learned quasi parton mass

EoS vs Lattice QCD

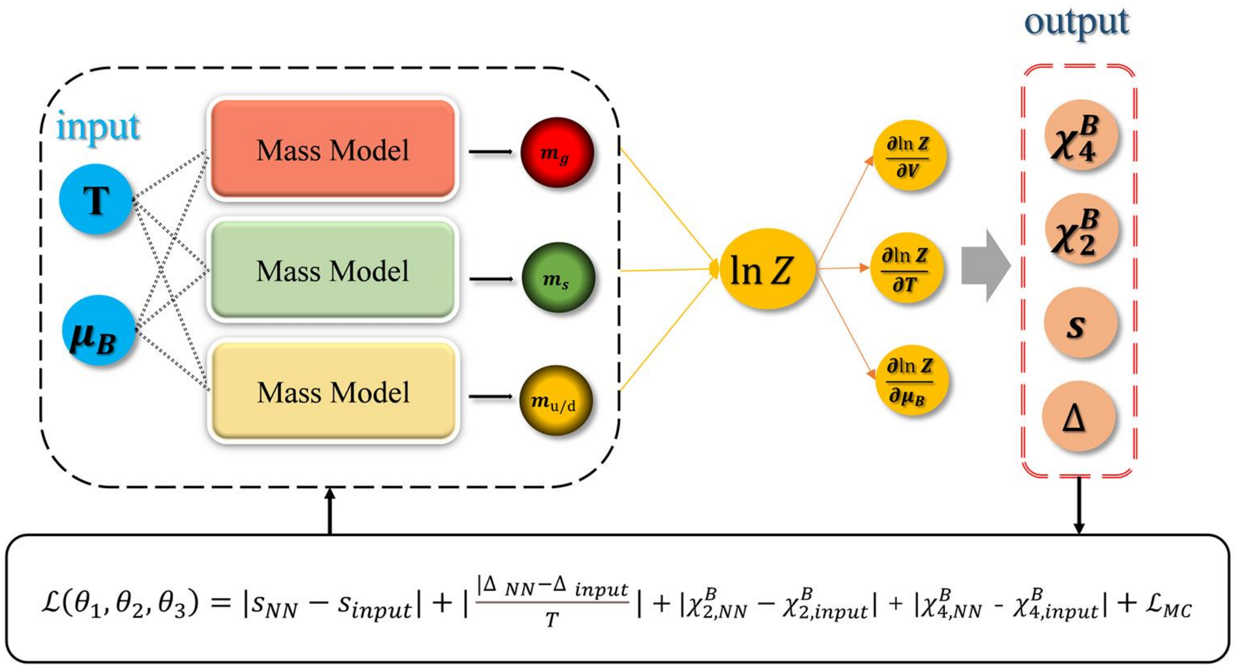


Learned Mass η/s

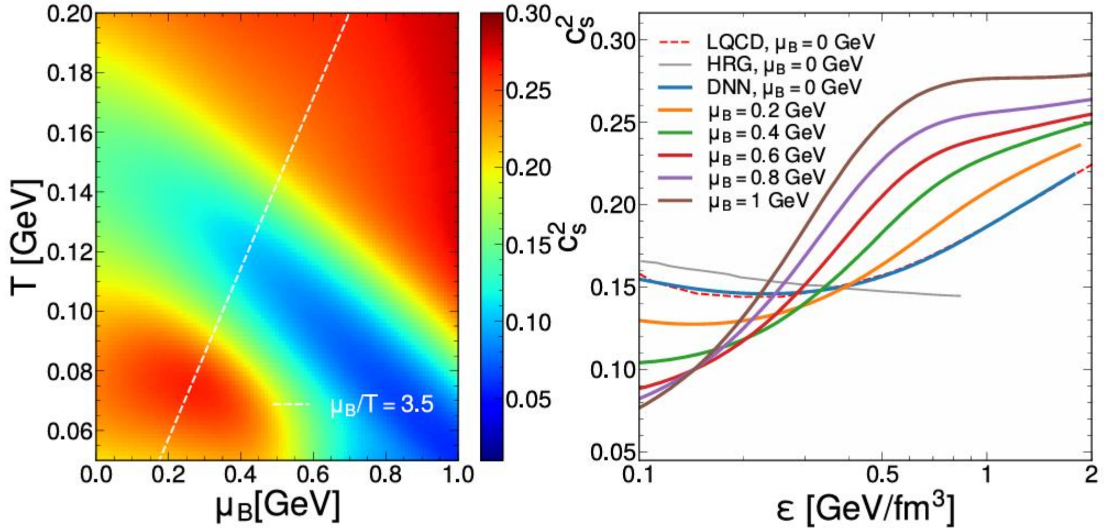


FuPeng Li, HL Lu, LG Pang, GY Qin, PLB 2023

准粒子模型扩展到2维:$m(T,\mu_B)$

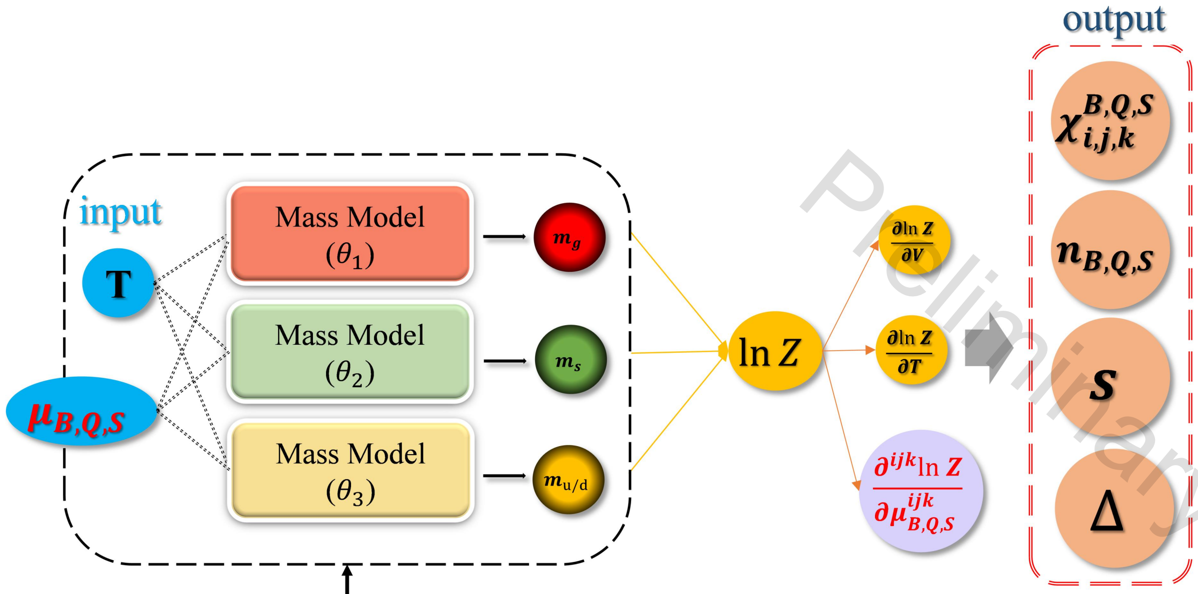


Equation Of State



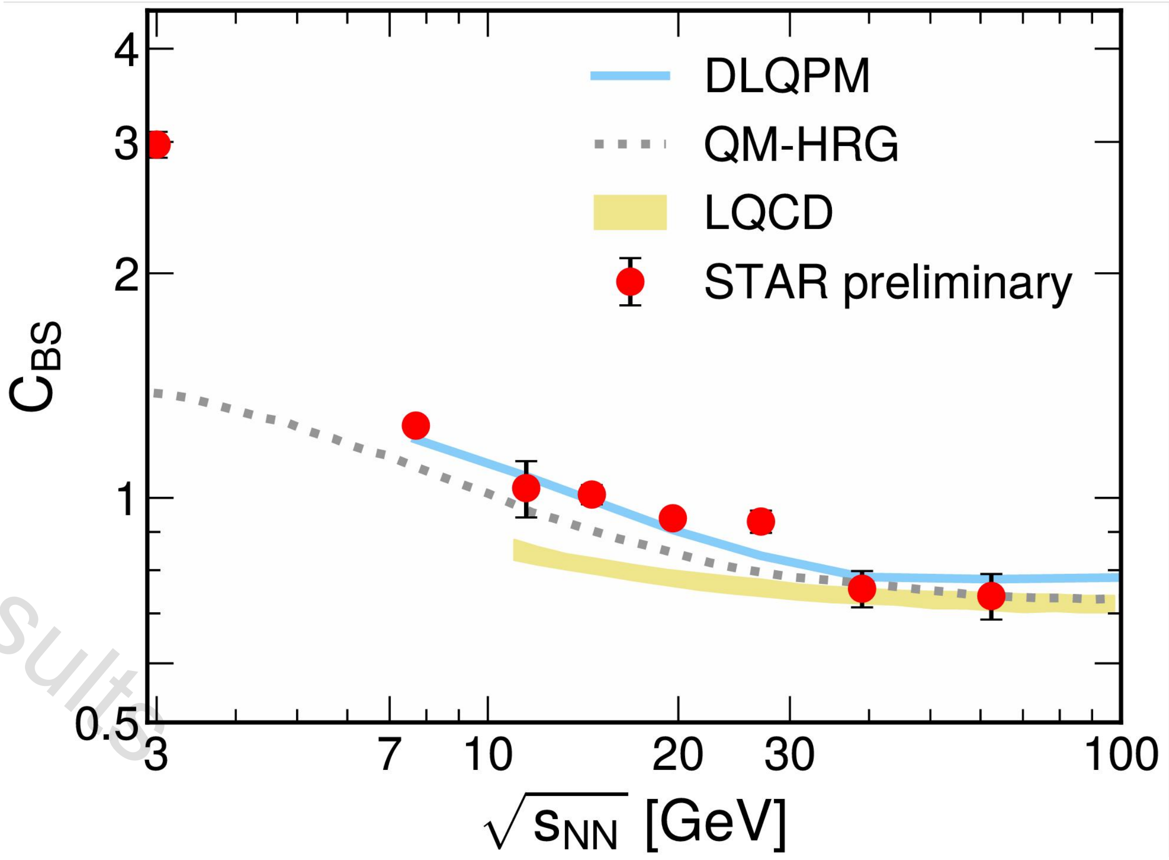
FP Li, LG Pang, GY Qin. PLB 868 (2025) 139692

准粒子模型扩展到4维: $m(T, \mu_B, \mu_Q, \mu_S)$



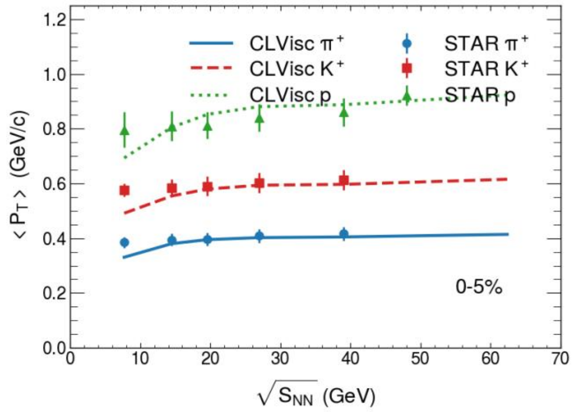
$$\mathcal{L}(\theta_1, \theta_2, \theta_3) = |s_{DNN} - s_{LQCD}| + |\frac{|\Delta_{DNN} - \Delta_{LQCD}}{T}| + |\chi^{B,Q,S}_{i,j,k,DNN} - \chi^{B,Q,S}_{i,j,k,LQCD}| + |n_{B,Q,S}| + | + \mathcal{L}_{MC}$$

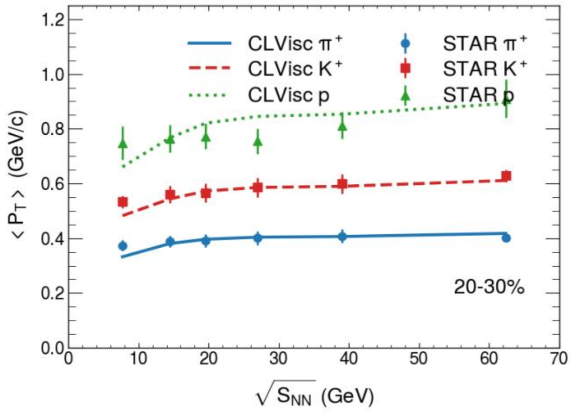
重子-奇异关联

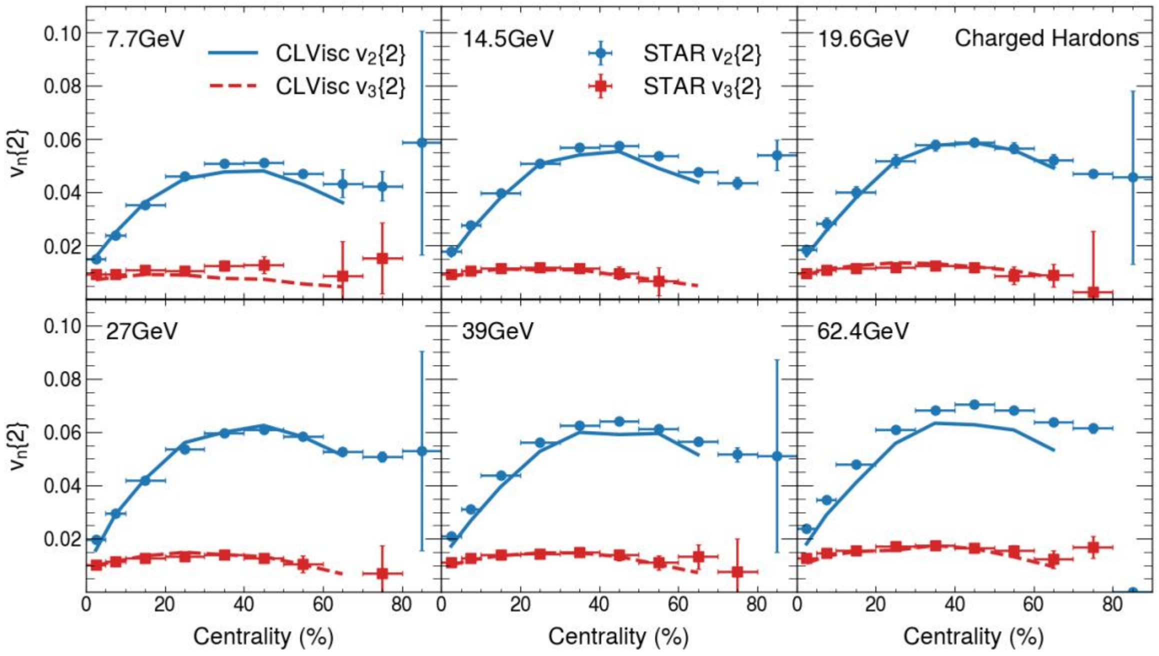


FP Li, LG Pang, GY Qin. in prepare

继续扩展CLVisc







$$\nabla_\mu T^{\mu\nu} = 0\,, \qquad T^{\mu\nu} = eU^\mu U^\nu - P\Delta^{\mu\nu} + \pi^{\mu\nu}\,,$$

$$\boxed{\nabla_\mu J^\mu = 0\,, \qquad J^\mu = nU^\mu + V^\mu\,,}$$

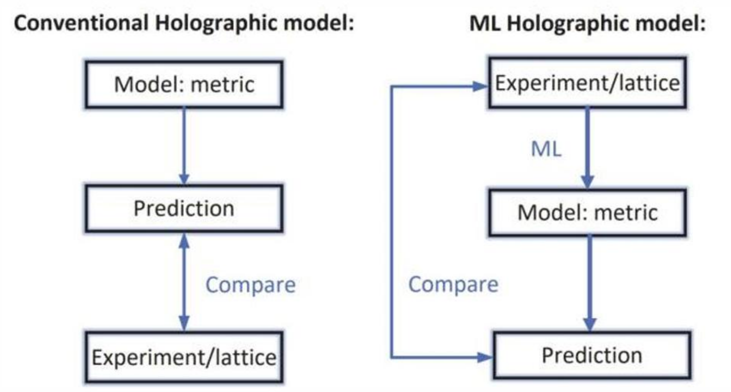
$$\Delta^{\mu\nu}_{\alpha\beta} D\pi^{\alpha\beta} = -\frac{1}{\tau_\pi}\left(\pi^{\mu\nu} - \eta_v \sigma^{\mu\nu}\right) - \frac{4}{3}\pi^{\mu\nu}\theta - \frac{5}{7}\pi^{\alpha<\mu}\sigma^{\nu>}_\alpha + \frac{9}{70}\frac{4}{e+P}\pi^{<\mu}_\alpha \pi^{\nu>\alpha}\,, \tag{10}$$

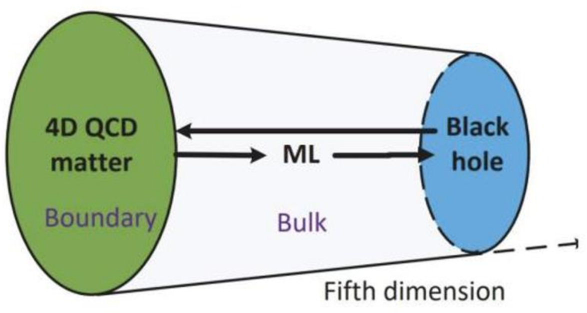
$$\boxed{\Delta^{\mu\nu} DV_\nu = -\frac{1}{\tau_V}\left(V^\mu - \kappa_B \nabla^\mu \frac{\mu_B}{T}\right) - V^\mu\theta - \frac{3}{10}V_\nu \sigma^{\mu\nu}\,, \quad (11)}$$

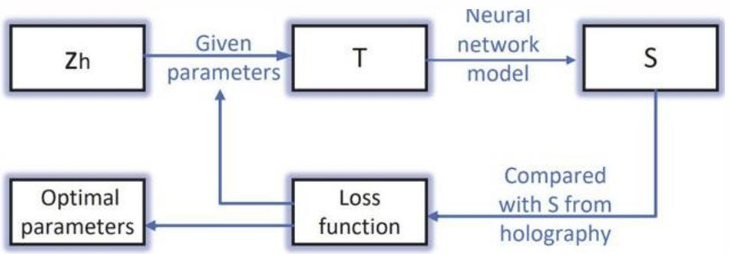
- 加入了净重子数守恒方程
- 添加了净重子扩散流满足的驰豫方程
- 新代码可以描述中低能核碰撞 （BES 能区）
- 未来：自洽的四维状态方程与输运系数

XY Wu, 秦广友，庞龙刚，王新年，PRC 105 (2022) 3, 034909

DL for holographic model using PINN







Einstein-Maxwell-Dilation model

O. DeWolfe, S. S. Gubser, and C. Rosen, Phys. Rev. D 83, 086005 (2011), arXiv:1012.1864.

Action: $$S_b = \frac{1}{16\pi G_5}\int d^5x\left[\sqrt{-g}R - \frac{f(\phi)}{4}F^2 - \frac{1}{2}\partial_\mu\phi\partial^\mu\phi - V(\phi)\right]$$

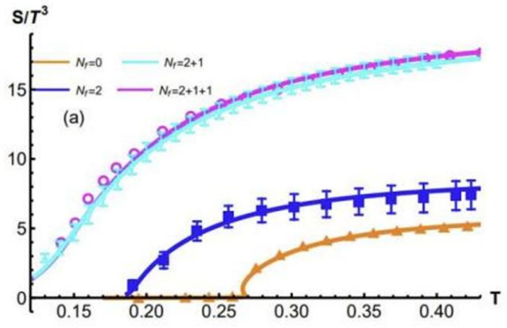
Non-conformal

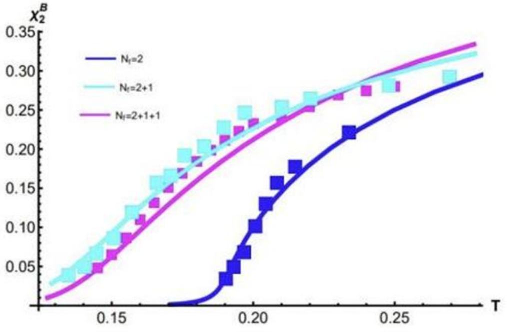
ϕ is dilaton $\quad$ F is the tensor of gauge field

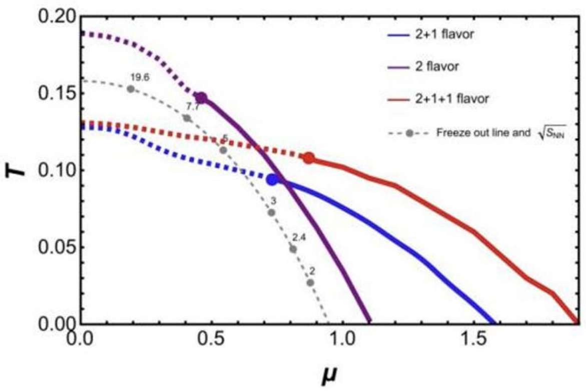
Metric ansatz: $$ds^2 = \frac{e^{2A(z)}}{z^2}\left[-g(z)dt^2 + \frac{dz^2}{g(z)} + d\vec{x}^2\right]$$

$$A(z) = d\ln(az^2+1) + d\ln(bz^4+1),\ f(z) = e^{cz^2 - A(z) + k}$$

$$s = \frac{e^{3A(z_h)}}{4G_5 z_h^3}. \qquad \chi_2^B = \frac{1}{T^2}\frac{\partial\rho}{\partial\mu}.$$







X. Chen, M. Huang, **Phys.Rev.D** 109 (2024) L051902; **JHEP**02 (2025)123

Stacked U-net for relativistic hydro

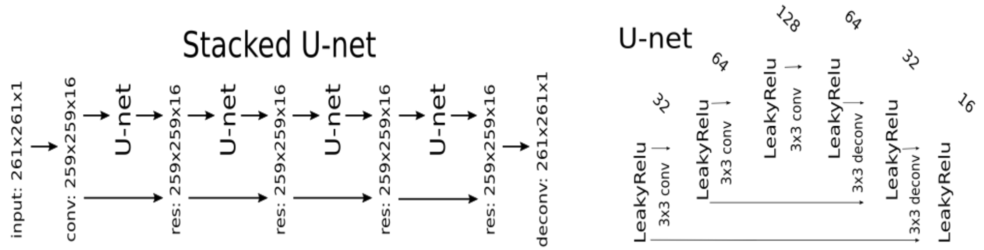
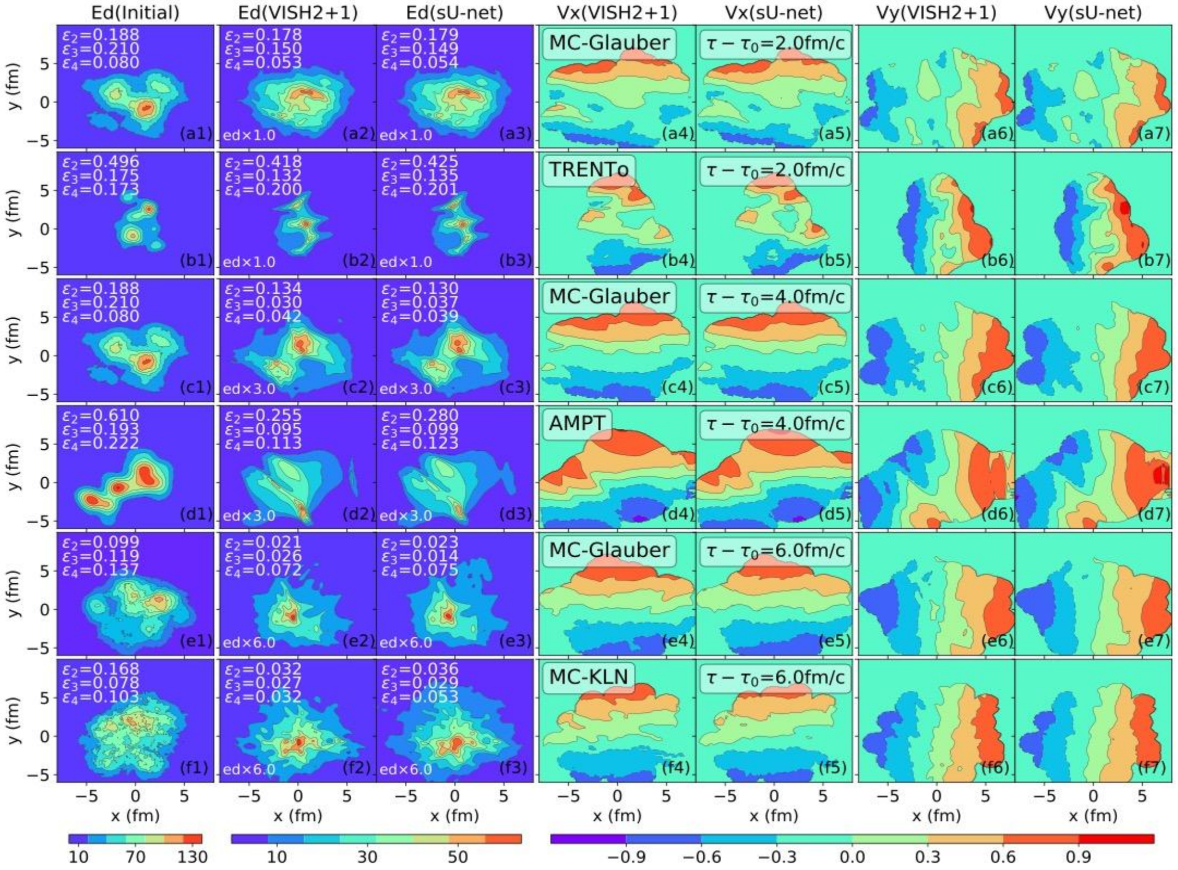


FIG. 1: An illustration of the encode-decode network, **stacked U-net**, which consists of the input and out layers and four residual U-net blocks. The right figure shows the U-net structure, and the depth of the hidden layer is written on the top of them.

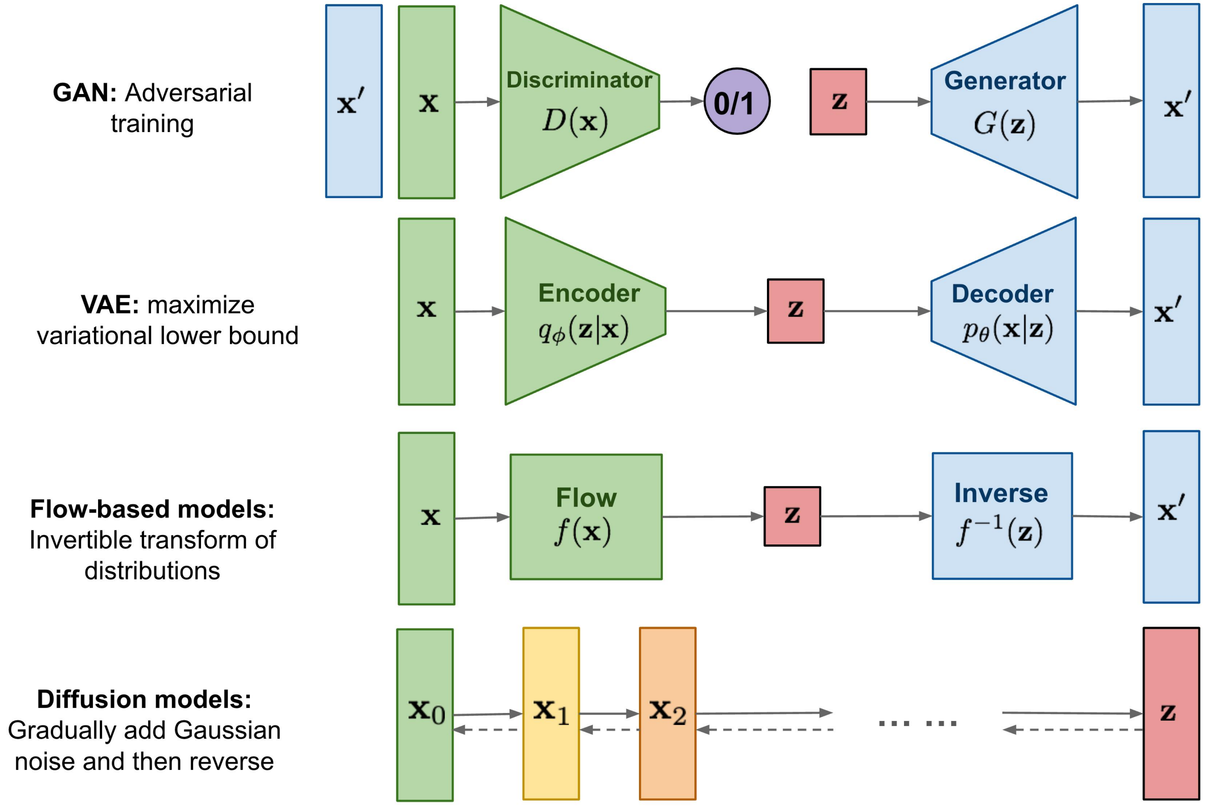
The expansion of quark gluon plasma is learned in the image translation task using stacked UNET.

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

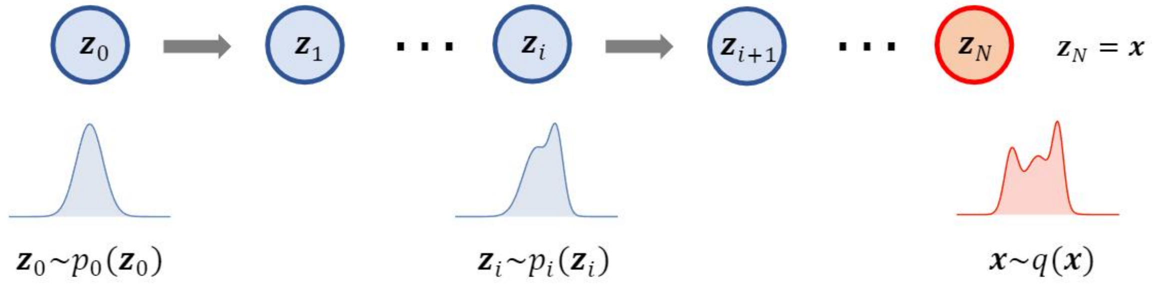


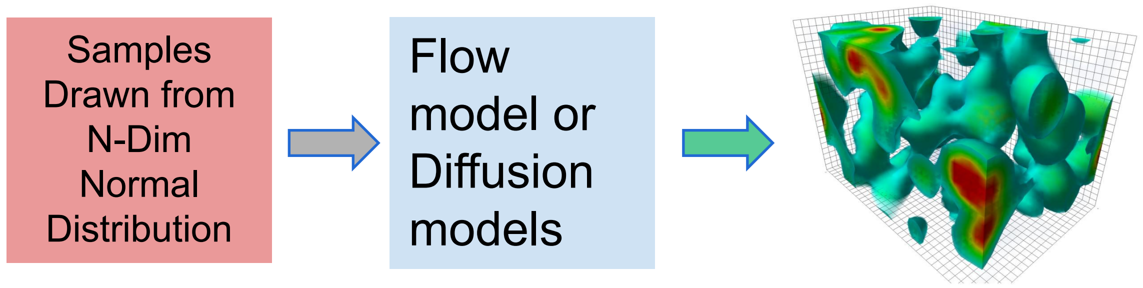
PRR. 3 (2021) 2, 023256, H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song

Generativive models： MC sampling



Similar to Box Muller algorithm





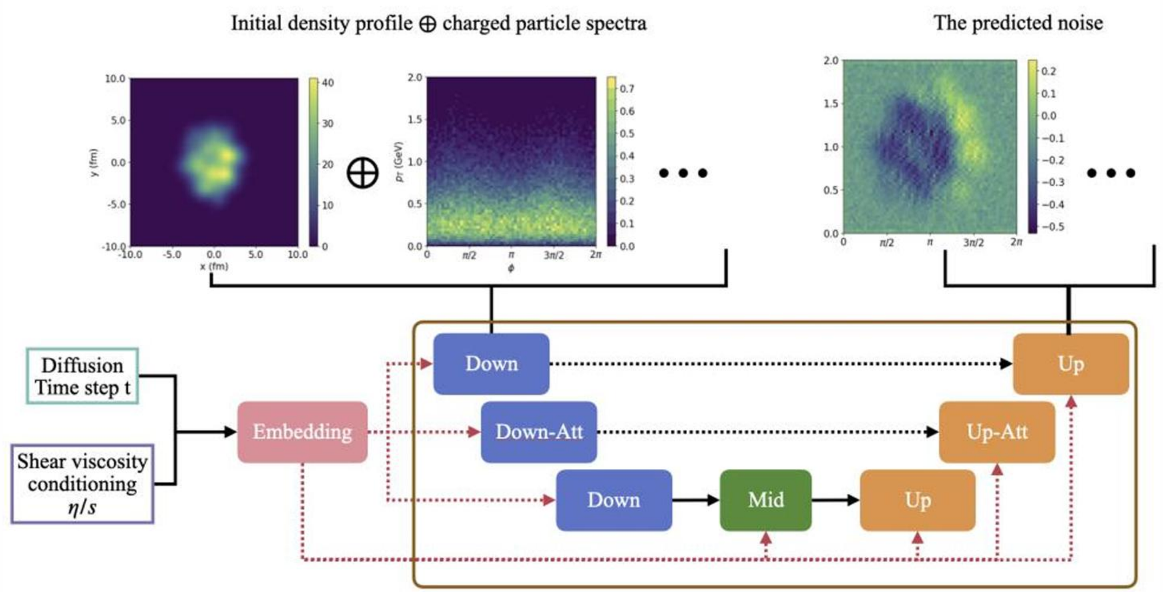
Flow-based generative models for Markov chain Monte Carlo in lattice field theory
Albergo, Kanwar, Shanahan 1904.1207

Generative model for HICs

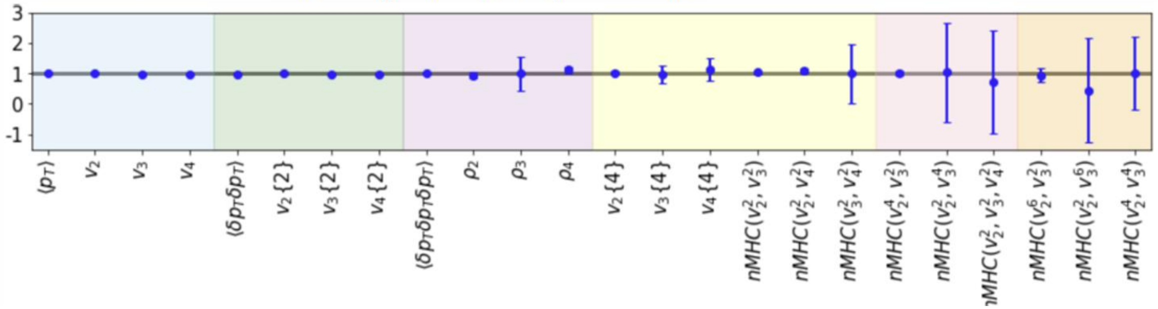
An end-to-end generative diffusion model for heavy-ion collisions

Jing-An Sun,[1,2] Li Yan,[1,3] Charles Gale,[2] and Sangyong Jeon[2]

arXiv:2410.13069



$$\boldsymbol{S}_t = \sqrt{\bar{\alpha}_t}\boldsymbol{S}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\varepsilon}$$



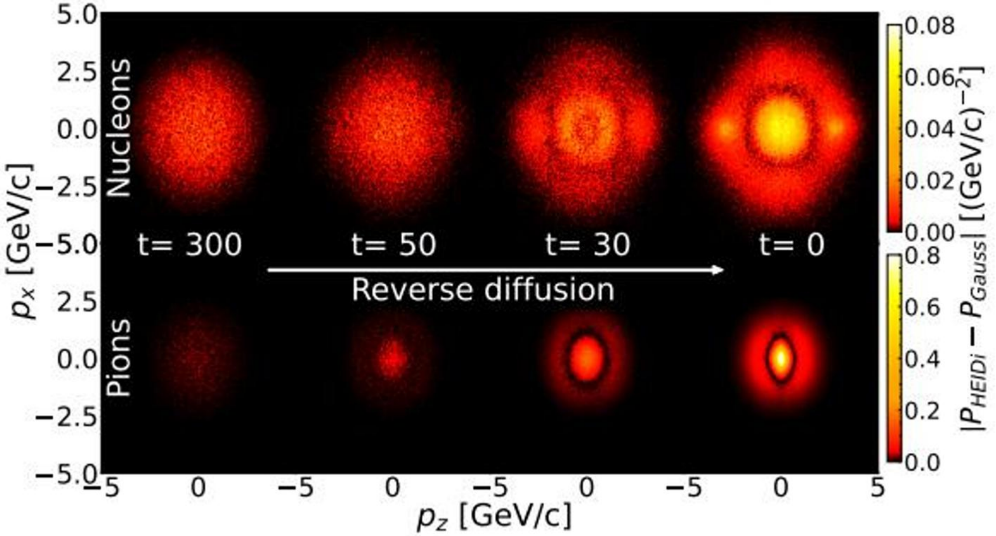
tor. We carried out (2+1)D minimum bias simulations of Pb-Pb collisions at 5.02 TeV, choosing the shear viscosity η/s to be one of three distinct values: 0.0, 0.1, and 0.2. For each value of η/s, we generate 12,000 pairs of initial entropy density profiles and final particle spectra corresponding to 12,000 simulated events, as the training dataset. 70% of the total events are used for training and the rest are used for validation.

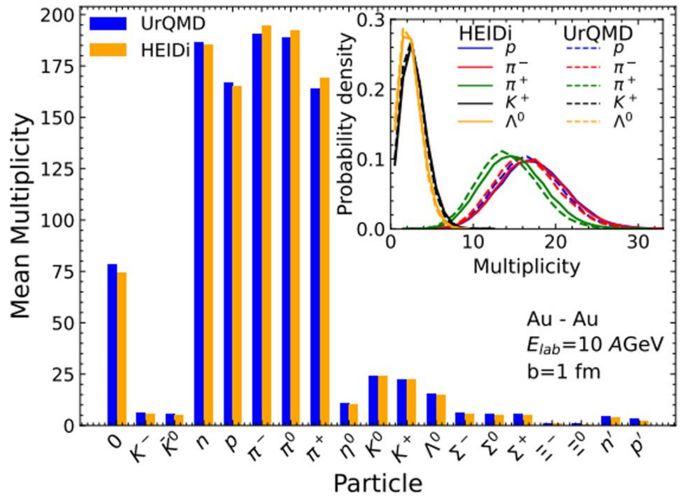
Considering that the spectra $\boldsymbol{S}_0$ depend on the initial entropy density profiles $\boldsymbol{I}$ and the shear viscosity η/s, we train a conditional reverse diffusion process $p(\boldsymbol{S}_0|\boldsymbol{I}, \eta/s)$ without modifying the forward process.

one single central collision event in just 10^{-1} seconds on a GeForce GTX 4090 GPU.

ble precision, as the traditional numerical simulation of hydrodynamics for one central event typically takes approximately 120 minutes (10^4 seconds) on a single CPU.

Generative model for HICs





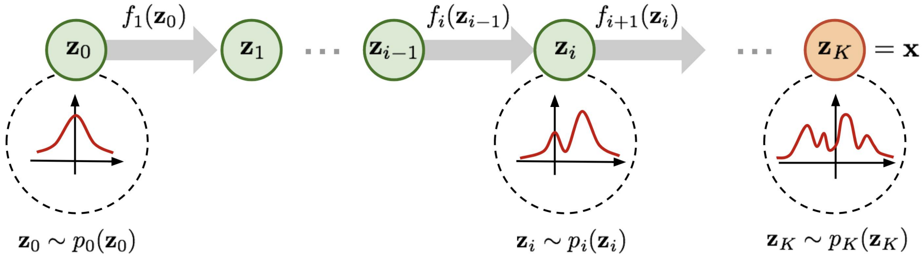
18k **UrQMD** simulation events for training

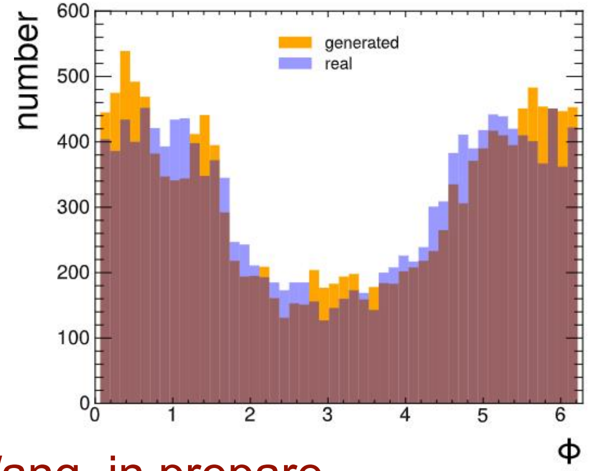
HEIDi:
Heavy-ion Events through Intelligent Diffusion

PointNet encoder +
Normalizing flow decoder +
Pointcloud diffusion

M. O.K, K. Z, J. S, H. S, arXiv: 2502.16330, arXiv:2412.10352

credit: https://lilianweng.github.io/





Event-by-event jet eloss and medium response

Flow model and flow matching are used to learn the high dimensional distribution for faster medium response sampler

K.Y. Wu, Z. Yang, L.G. Pang and X.N. Wang, in prepare

Review articles

Nature Review Physics (2025)

nature reviews physics https://doi.org/10.1038/s42254-024-00798-x

Perspective | Check for updates

Physics-driven learning for inverse problems in quantum chromodynamics

Gert Aarts[1], Kenji Fukushima[2], Tetsuo Hatsuda[3], Andreas Ipp[4], Shuzhe Shi[5], Lingxiao Wang[3] & Kai Zhou[6,7]

Abstract

The integration of deep learning techniques and physics-driven designs is reforming the way we address inverse problems, in which accurate physical properties are extracted from complex observations. This is particularly relevant for quantum chromodynamics (QCD) – the theory of strong interactions – with its inherent challenges in interpreting

Sections

Prog. Part. Nucl. Phys. 135 (2024) 104084

Progress in Particle and Nuclear Physics 135 (2024) 104084

Contents lists available at ScienceDirect

Progress in Particle and Nuclear Physics

journal homepage: www.elsevier.com/locate/ppnp

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Review | Check for updates

Exploring QCD matter in extreme conditions with Machine Learning

Kai Zhou[a,b,*], Lingxiao Wang[a,*], Long-Gang Pang[c,*], Shuzhe Shi[d,e,*]

[a] Frankfurt Institute for Advanced Studies (FIAS), D-60438 Frankfurt am Main, Germany
[b] School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen 518172, China
[c] Institute of Particle Physics and Key Laboratory of Quark and Lepton Physics (MOE), Central China Normal University, Wuhan, 430079, China
[d] Department of Physics, Tsinghua University, Beijing 100084, China

Nuclear Science and Techniques (2023) 34:88
https://doi.org/10.1007/s41365-023-01233-z

REVIEW ARTICLE

Nucl. Sci. Tech. 34 (2023) 6, 88

High-energy nuclear physics meets machine learning

Wan-Bing He[1,2] · Yu-Gang Ma[1,2] · Long-Gang Pang[3] · Hui-Chao Song[4] · Kai Zhou[5]

: 18 April 2023 / Published online: 21 June 2023

Review Of Modern Physics (2022)

Colloquium: Machine learning in nuclear physics

Amber Boehnlein, Markus Diefenthaler, Nobuo Sato, Malachi Schram, Veronique Ziegler, Cristiano Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostro Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang

Rev. Mod. Phys. **94**, 031003 – Published 8 September 2022

Article | References | No Citing Articles | PDF | HTML | Export Citation

Thank you!

Science China Physics, Mechanics & Astronomy

Machine learning in nuclear physics at low and intermediate energies

Wanbing He,[1,2,*] Qingfeng Li,[3,4,†] Yugang Ma,[1,2,‡] Zhongming Niu,[5,§] Junchen Pei,[6,7,¶] and Yingxun Zhang[8,9,**]