ATHIC2023

Looking for Mach cones in QGP using deep learning

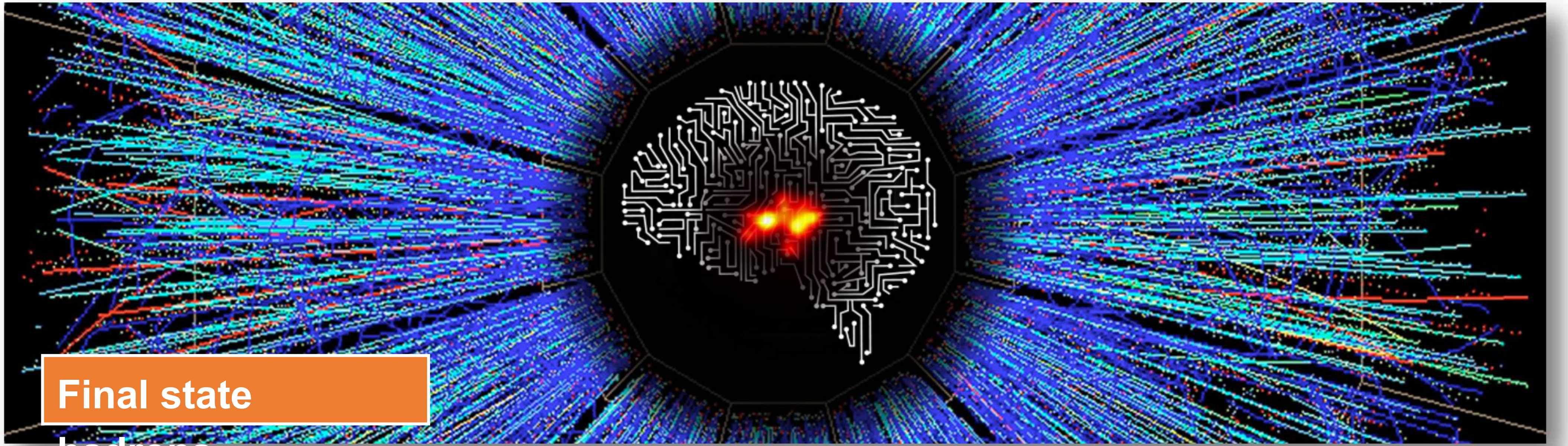
Long-Gang Pang
Central China Normal University

Deep learning assisted jet tomography for the study of Mach cones in QGP

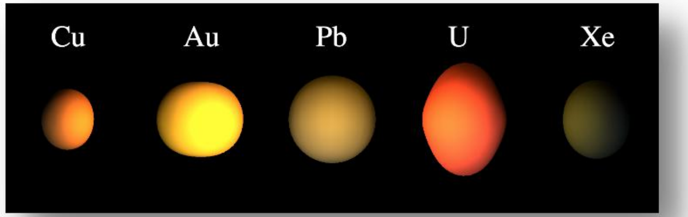
Zhong Yang[1], Yayun He[2,3], Wei Chen[4], Wei-Yao Ke[5,6,7], Long-Gang Pang[1a] and Xin-Nian Wang[1,5,6b]

The 9th Asian Triangle Heavy-Ion Conference (ATHIC 2023), Hiroshima, Japan

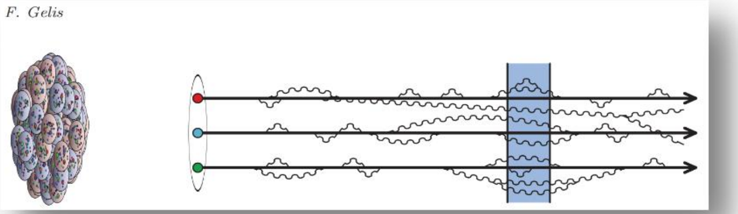
Deep Learning for inverse problem in HIC



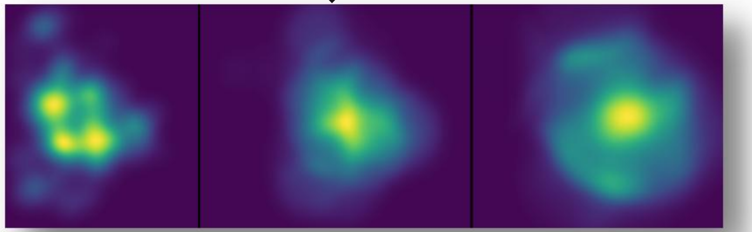
Non-linear mapping



（1）nuclear structure

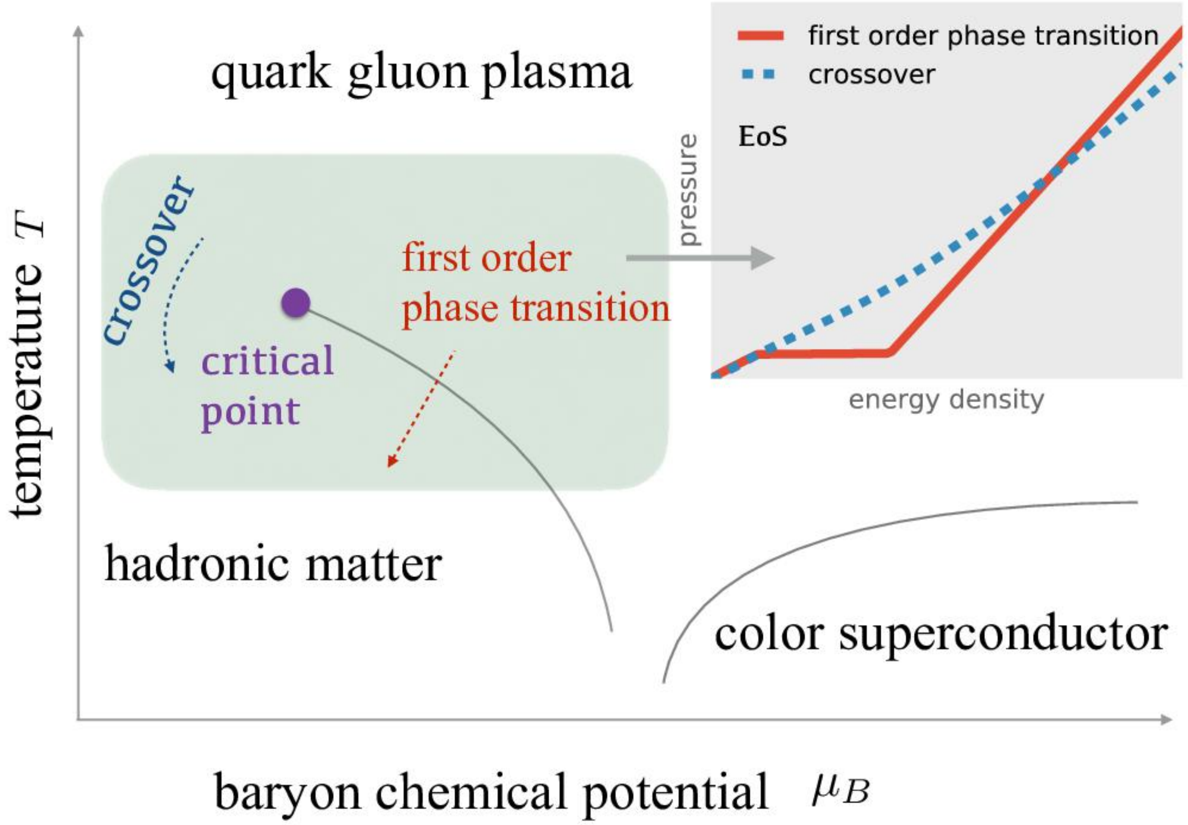


（2）initial parton distribution

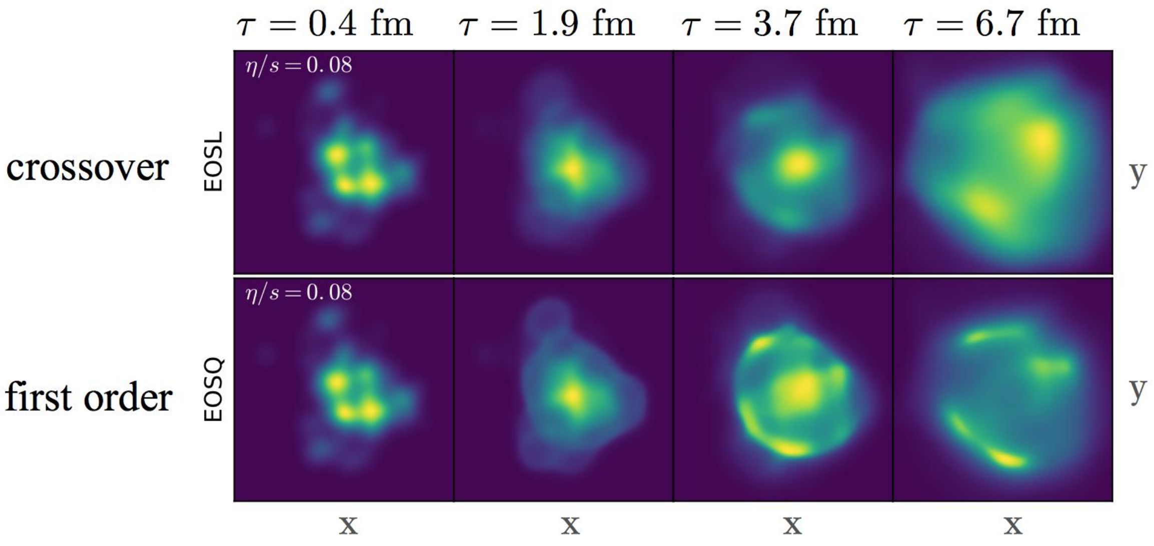


（3）QGP and phase transition

Deep Learning for Nuclear EoS and QCD transition



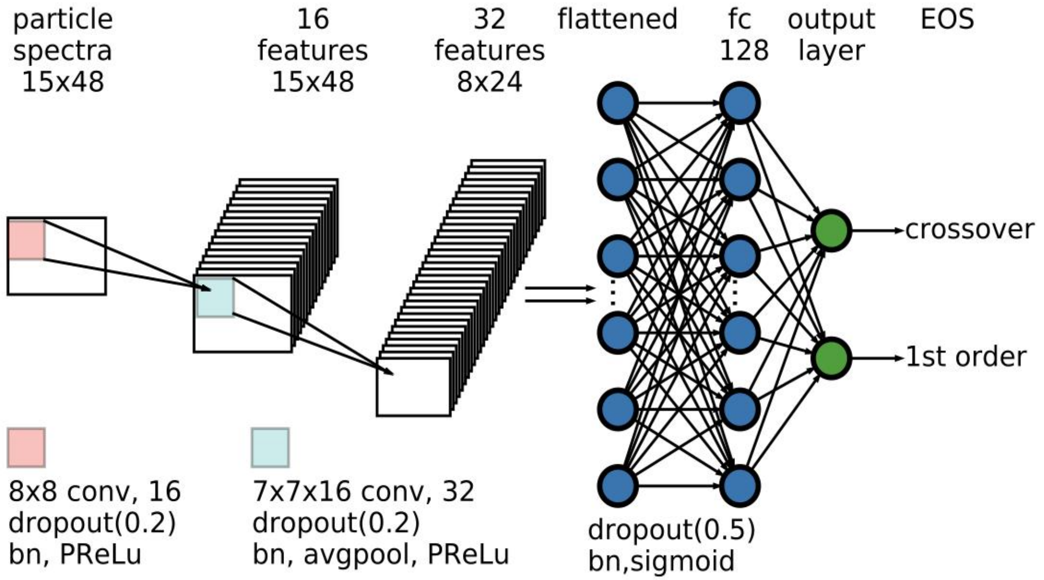
$$\nabla_\mu T^{\mu\nu} = 0$$



CLVisc 3+1D relativistic hydrodynamics

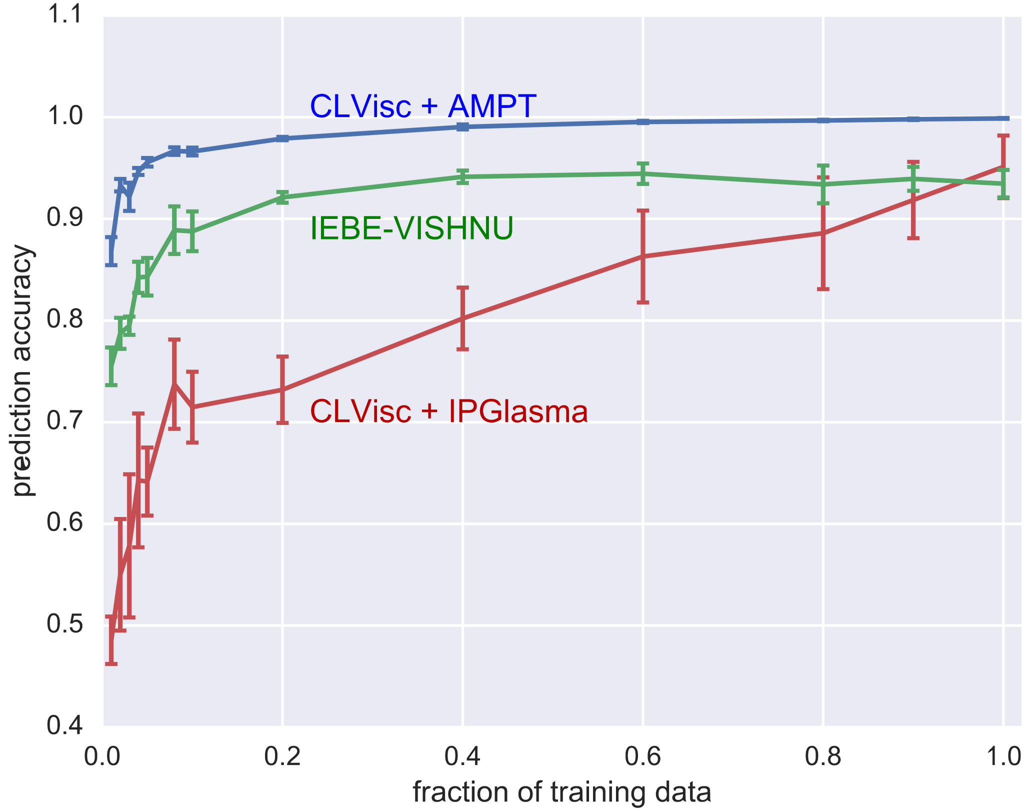
Nature Communications 2018, LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang.

Deep Learning for Nuclear EoS and QCD transition



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

cross entropy loss L2 regularization

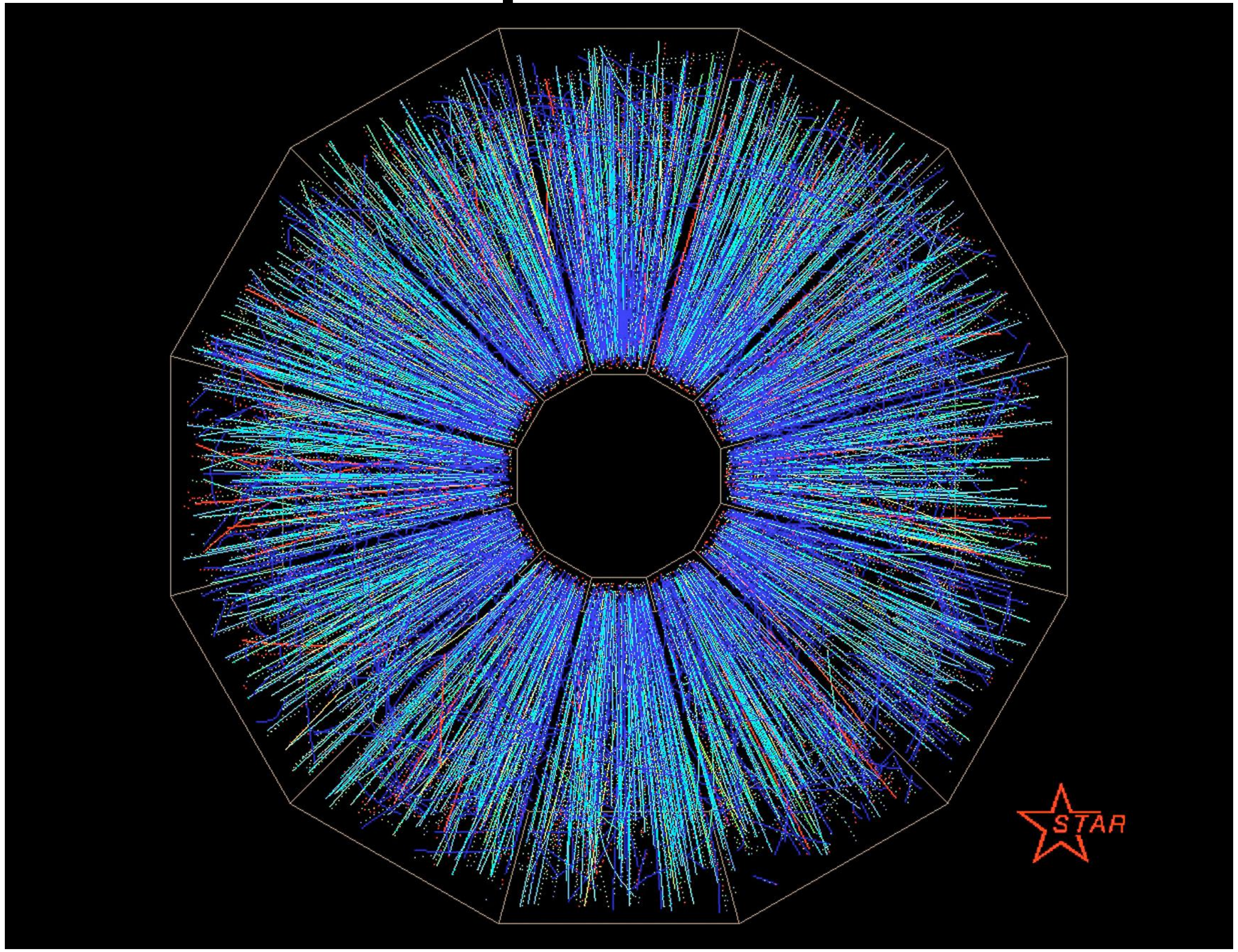


Nature Communications 2018, LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang.

Increasing list of ML for QCD EoS

- An equation-of-state-meter of quantum chromodynamics transition from deep learning, Long-Gang Pang, Kai Zhou, Nan Su, Hannah Petersen, Horst Stöcker, Xin-Nian Wang
- Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning, Yi-Lun Du, Kai Zhou, Jan Steinheimer, Long-Gang Pang, Anton Motornenko, Hong-Shi Zong, Xin-Nian Wang, Horst Stöcker
- A machine learning study to identify spinodal clumping in high energy nuclear collisions, Jan Steinheimer, LongGang Pang, Kai Zhou, Volker Koch, Jørgen Randrup, Horst Stoecker
- An equation-of-state-meter for CBM using PointNet, Manjunath Omana Kuttan, Kai Zhou, Jan Steinheimer, Andreas Redelbach, Horst Stoecker
- Classification of Equation of State in Relativistic Heavy-Ion Collisions Using Deep Learning, Yu. Kvasiuk, E. Zabrodin, L. Bravina, I. Didur, M. Frolov
- Neural network reconstruction of the dense matter equation of state from neutron star observables. Shriya Soma, Lingxiao Wang, Shuzhe Shi, Horst Stöcker, Kai Zhou
- Learning Langevin dynamics with QCD phase transition, Lingxiao Wang, Lijia Jiang, Kai Zhou
- Machine learning phase transitions of the three-dimensional Ising universality class, Xiaobing Li, Ranran Guo, Kangning Liu, Jia Zhao, Fen Long, Yu Zhou, Zhiming Li
- Extensive Studies of the Neutron Star Equation of State from the Deep Learning Inference with the Observational Data Augmentation, Yuki Fujimoto, Kenji Fukushima, Koichi Murase
- Nuclear liquid-gas phase transition with machine learning, Rui Wang, Yu-Gang Ma, R. Wada, Lie-Wen Chen, Wan-Bing He, Huan-Ling Liu, Kai-Jia Sun
- Machine learning spectral functions in lattice QCD, S.-Y. Chen, H.-T. Ding, F.-Y. Liu, G. Papp, C.-B. Yang
- Probing criticality with deep learning in relativistic heavy-ion collisions, Yige Huang, Long-Gang Pang, Xiaofeng Luo, Xin-Nian Wang
- Mapping out the thermodynamic stability of a QCD equation of state with a critical point using active learning, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta
- …

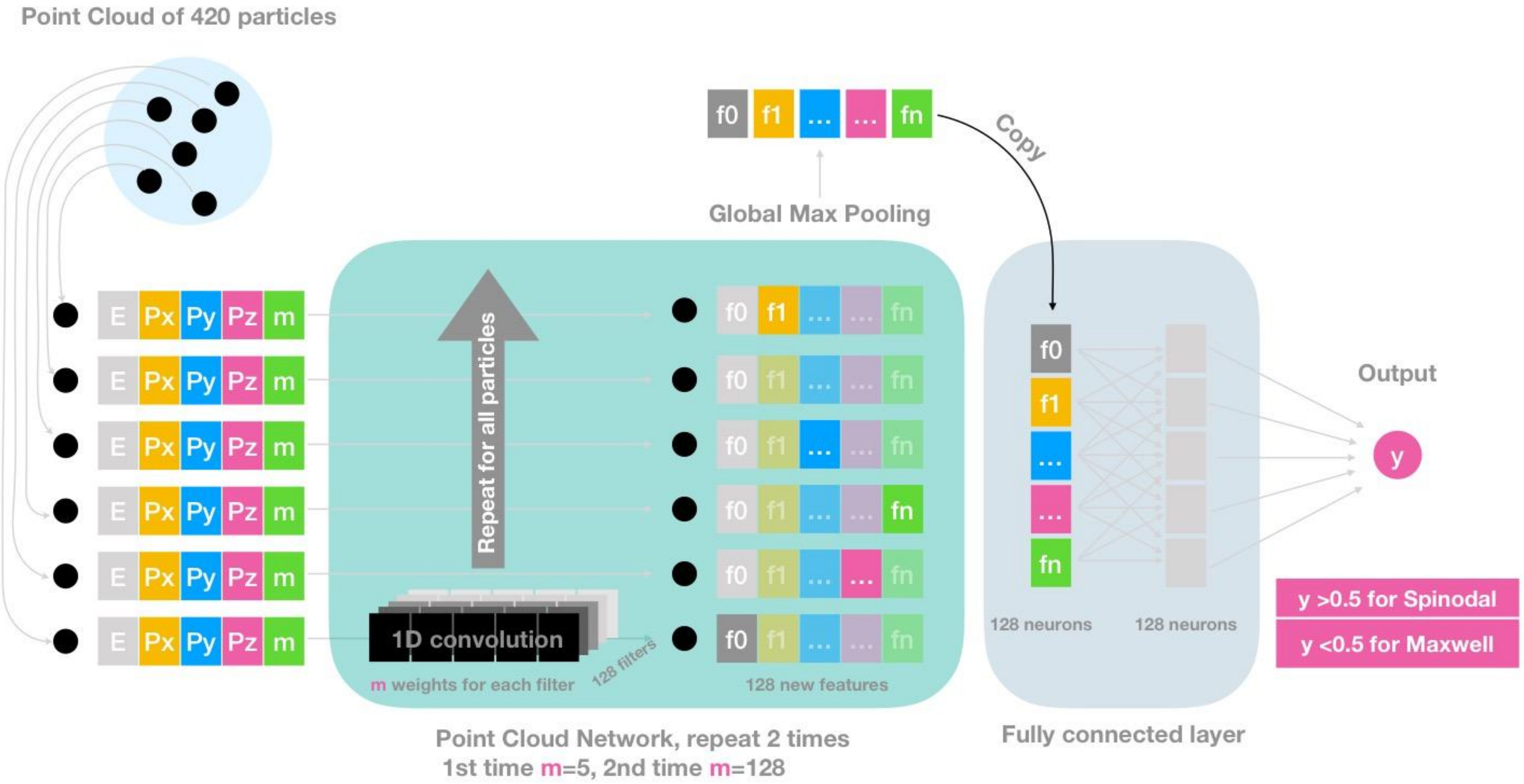
Data representation



- Images： histograms
  - (px， py) or (pt， phi)
  - (px， py， pz)
  - (pt， phi， eta)
- Point cloud： particle list

E	Px	Py	Pz	pid
6.84	1.07	4.5	6.83	211
68.92	0.75	0.64	68.91	2212
40.4	0.06	0.54	40	321
…				

Point Cloud Network for EoS classification



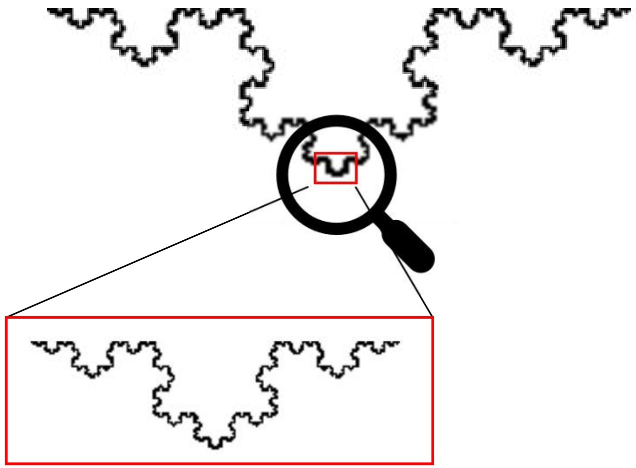
JHEP 12 (2019) 122, J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup

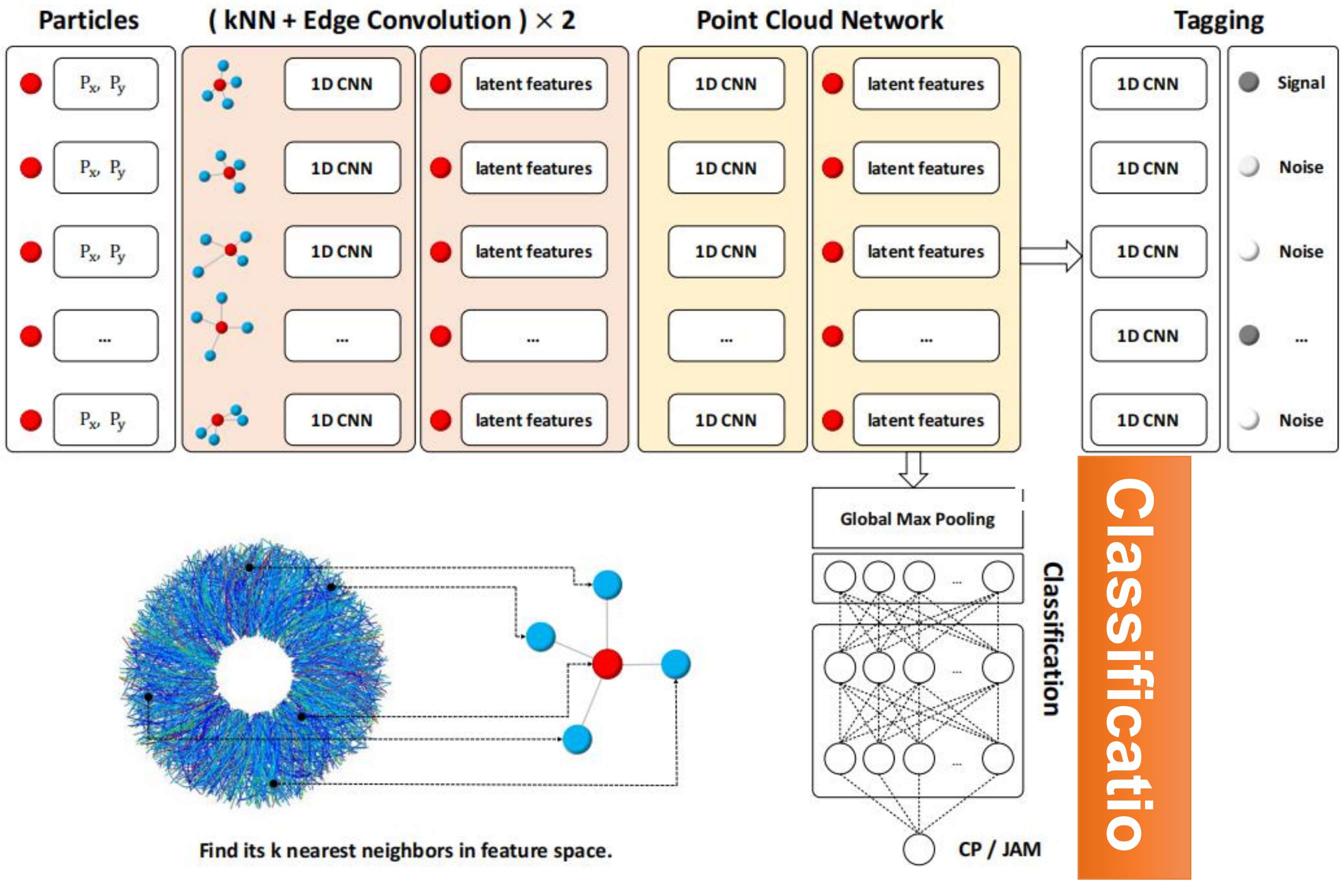
Looking for self-similarity in momentum space using DEC

Dynamical Edge Convolution Network

Tagging

Self-similarity in critical region



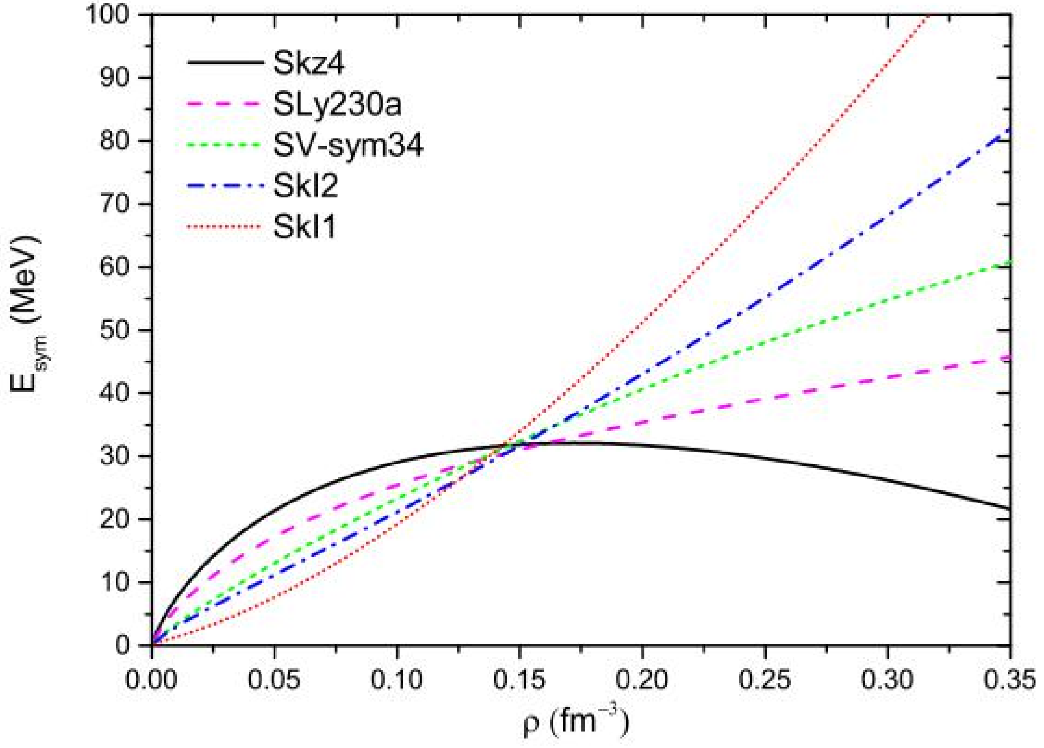


Classificatio

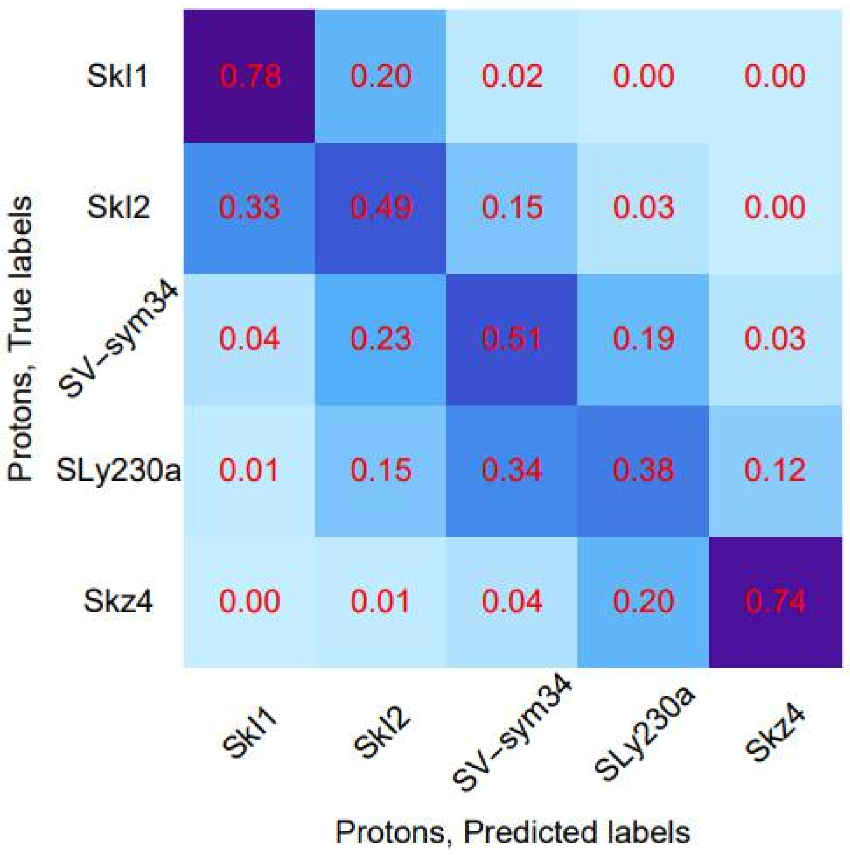
PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

Nuclear EoS at high density region

Skyrme potential + IMQMD



off-diagonal = misclassified



Phys.Lett.B 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. Lu, and K. Zhou

Active Learning for EoS with critical point

$$(\mu_{BC}, \alpha_{\text{diff}}, w, \rho) \mapsto P(T, \mu_B) \mapsto \{\text{acceptable, unstable, acausal}\}.$$

4 parameters from 3D Ising model | QCD EoS | Lables for classification

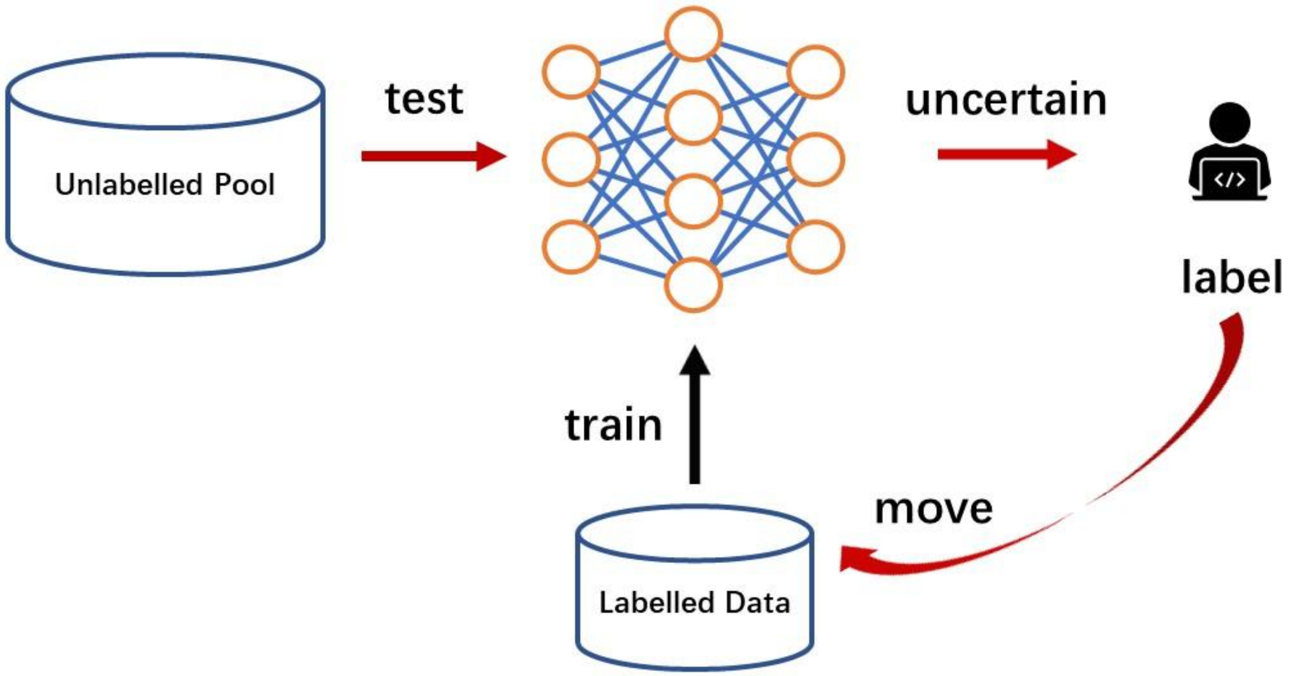
Acceptable = Stable + Causal

$$P, s, \varepsilon, n_B, \chi_2^B, \left(\frac{\partial S}{\partial T}\right)_{n_B} > 0\ ,$$

$$0 \leq c_s^2 \leq 1.$$

2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

Active Learning for EoS with critical point



2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

Deep Learning the mass of quasi partons from Lattice QCD EoS

Fermi-Dirac distributions,

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

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

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.

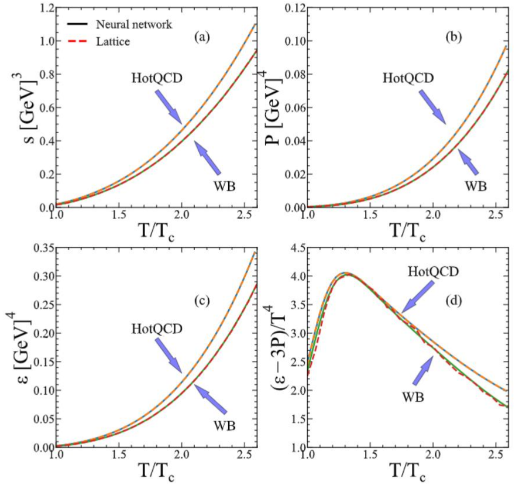
The resulting pressure and energy density are computed using the following statistical formulae,

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

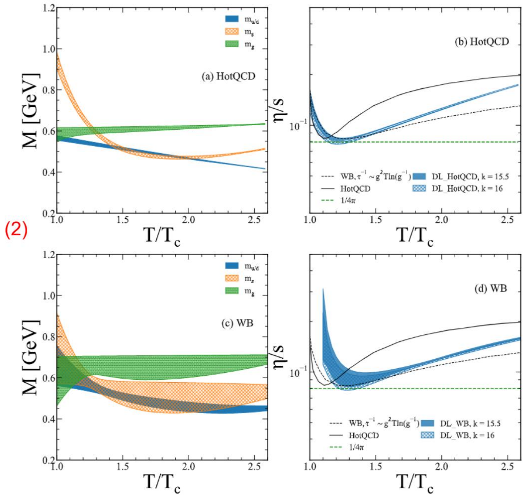
$$\epsilon(T) = \frac{T^2}{V}\left(\frac{\partial \ln Z(T)}{\partial T}\right)_V, \quad (6)$$

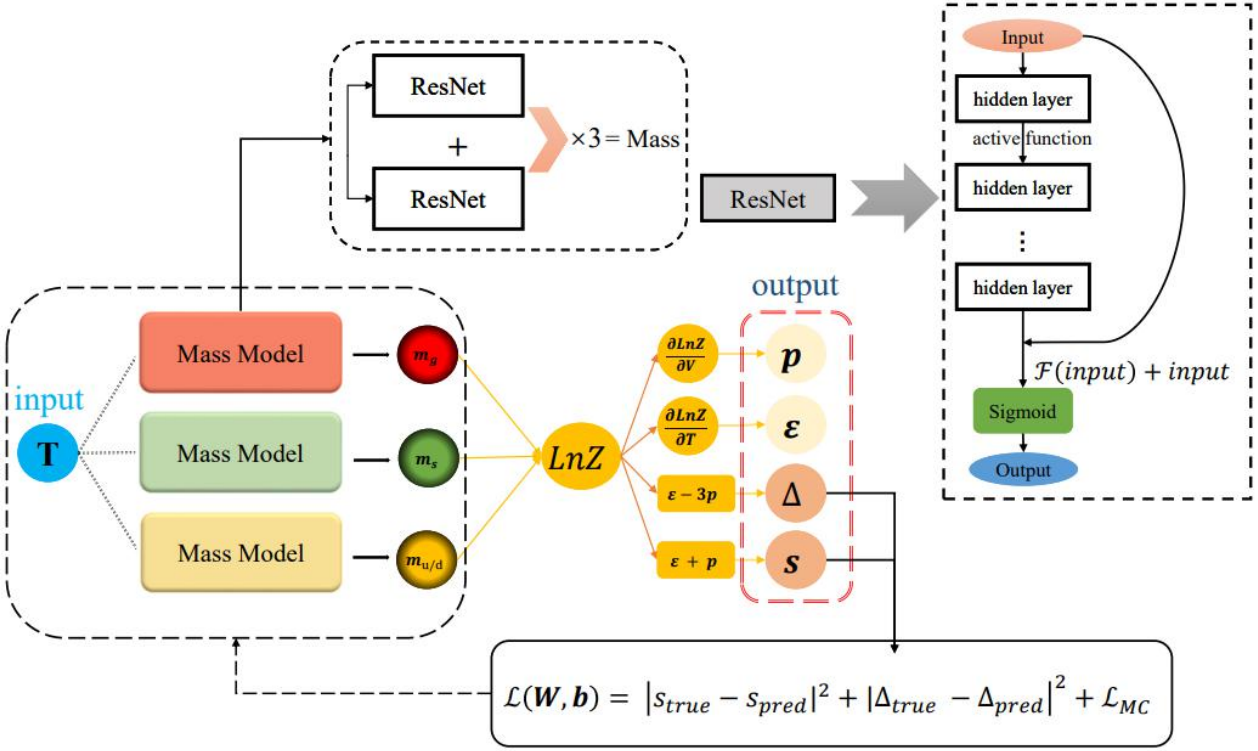
$$\ln Z(T) = \ln Z_g(T) + \ln Z_{u,d}(T) + \ln Z_s(T),$$

EoS



$m_{u/d}, m_s, m_g$ η/s

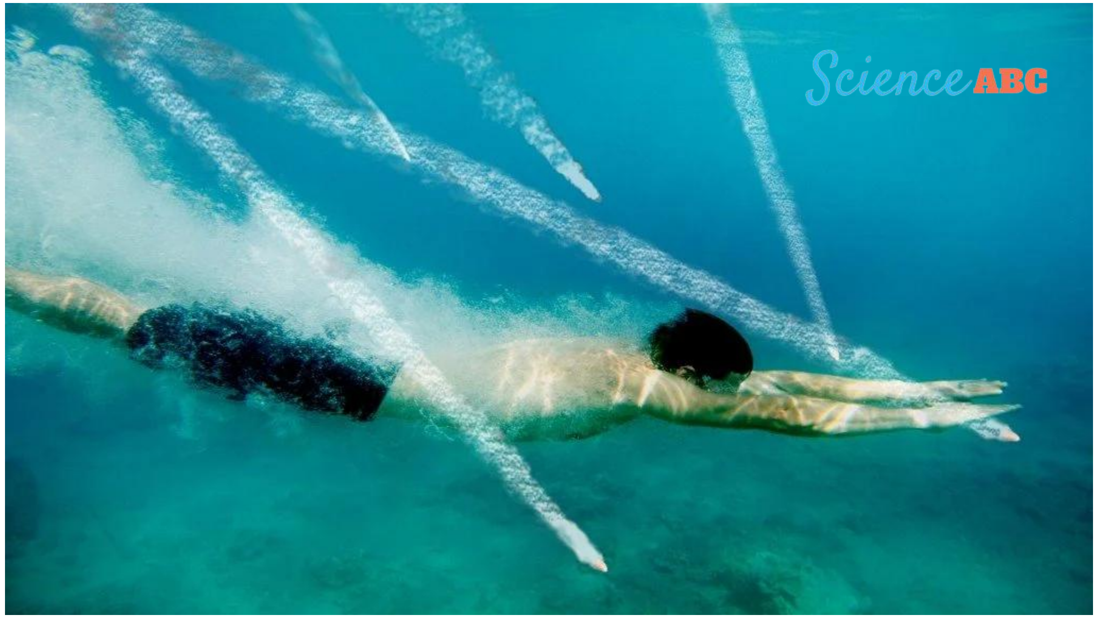


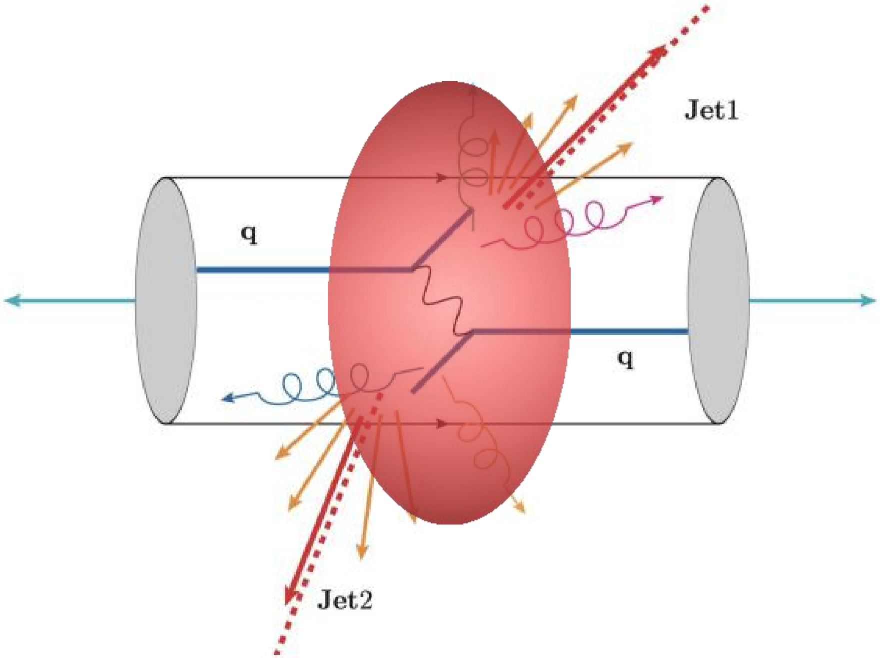


FuPeng Li, HongLiang Lu, LongGang Pang, GuangYou Qin, 2211.07994 [hep-ph]

Jet quenching as a probe

Can Being Underwater Protect You From Bullets?

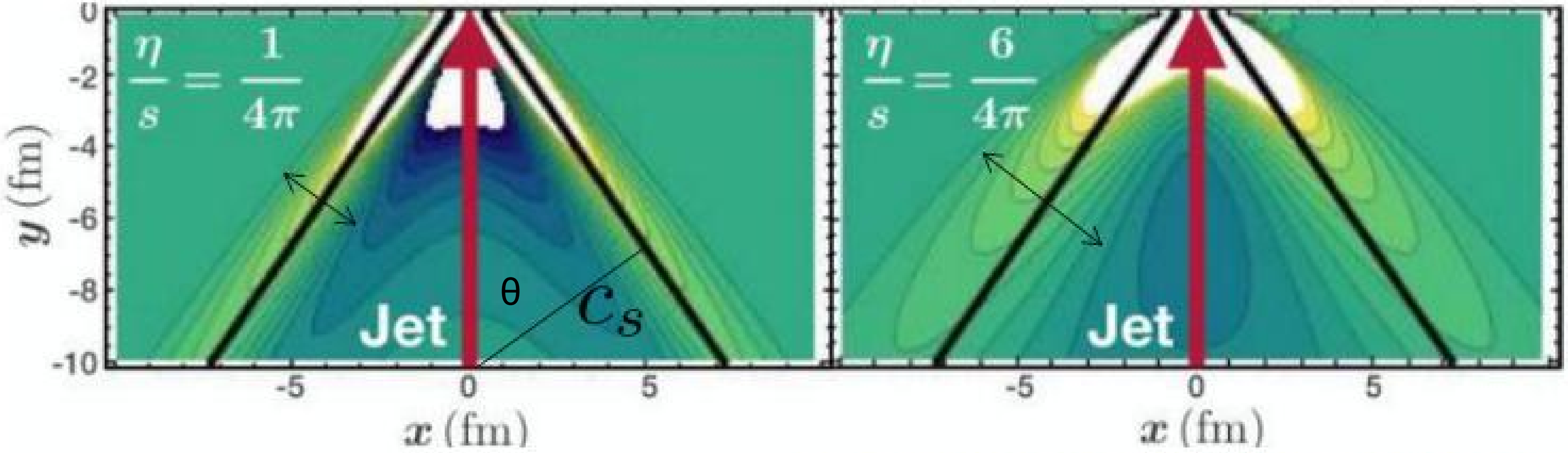




❝ *If the bullet is shot from an angle of 30 Degrees, then being underwater in the range of 3-5 feet (0.9-1.5 meters) can ensure safety from most guns.*

Energetic partons loss energy as they traverse QGP

Shape of the Mach Cone tells a lot



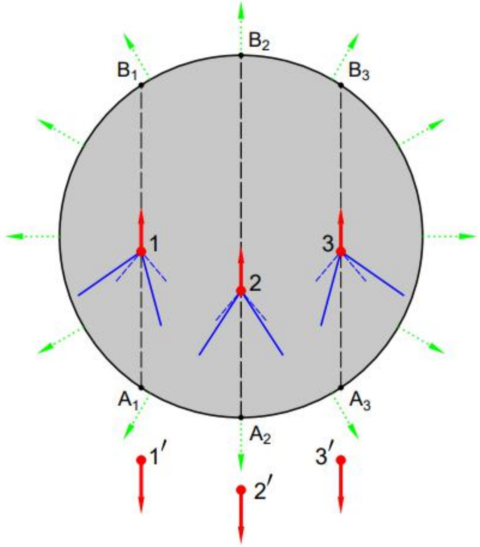
R.B.Neufeld. PRC79,054909(09')

The nuclear EoS：$c_s^2 = \frac{dP}{d\epsilon} = cos^2\,\theta$

The shear viscosity：the width of the wavefront

Mach Cone in nuclear droplet - difficulties

- Path Length dependence
  - Initial position: random
  - Propagating direction: random
- Shape twisting
  - Collective flow
  - Density gradients
- Motivation： if one can locate the initial jet production locations, it is possible to inference the QCD EoS and QGP transport coefficients using the shape modificationss

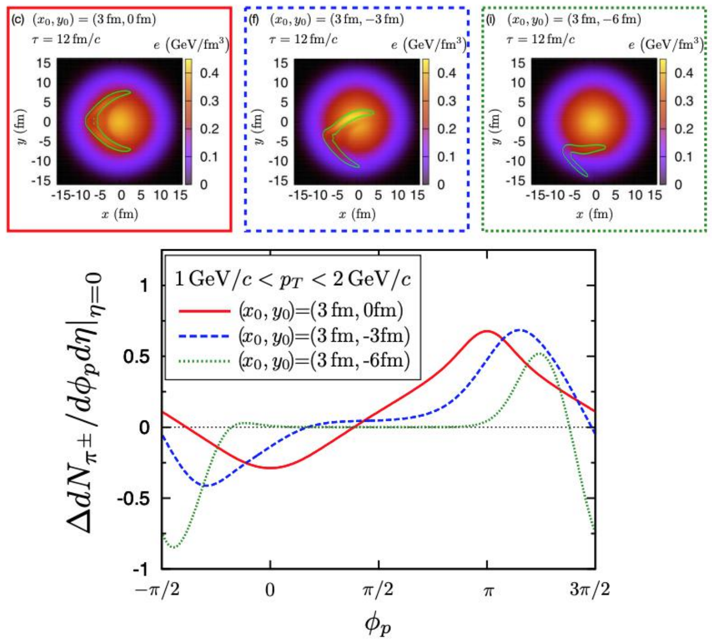


L.M. Satarov, H. Stoeck
I.N.Mishustin,
PLB 627 (2005) 64-70

Interplay with medium expansion

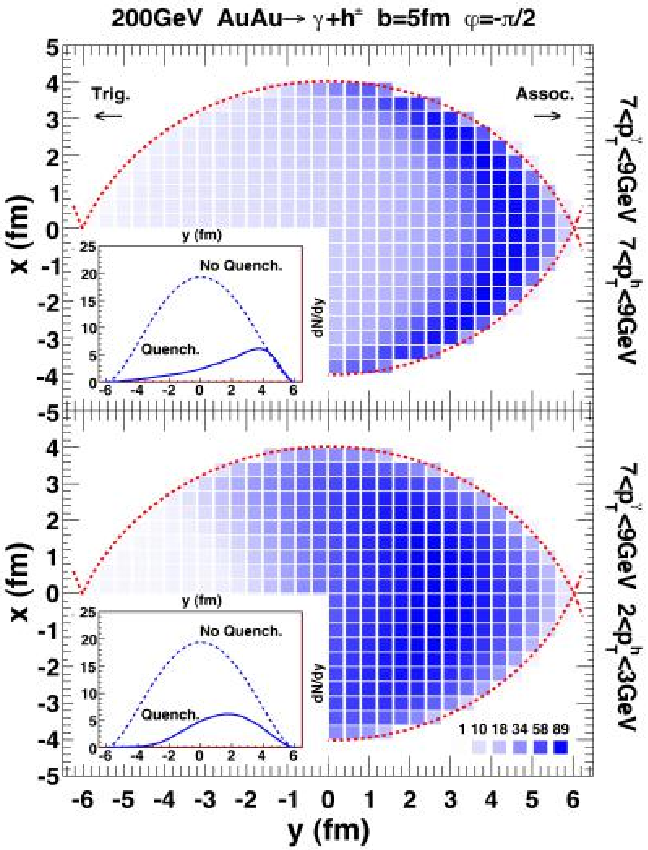
YT, Hirano, PRC 93, 054907 (2016)

Correlation with jet production point



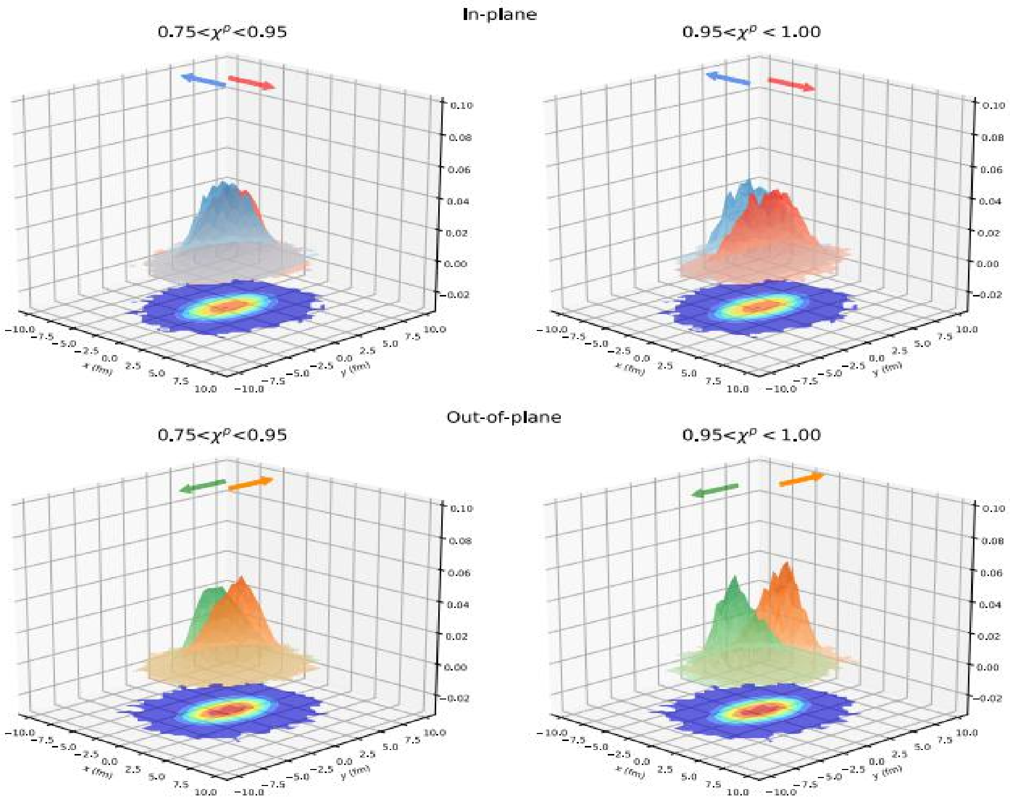
Yasuki, ATHIC2023

Longitudinal Location：Path Length



Short path length
Small energy loss

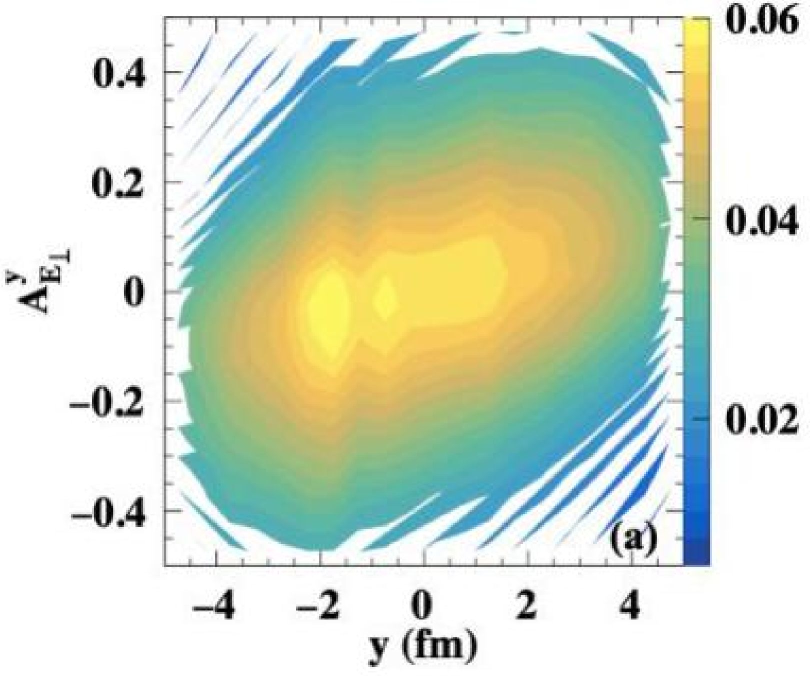
Long path length
Large energy loss

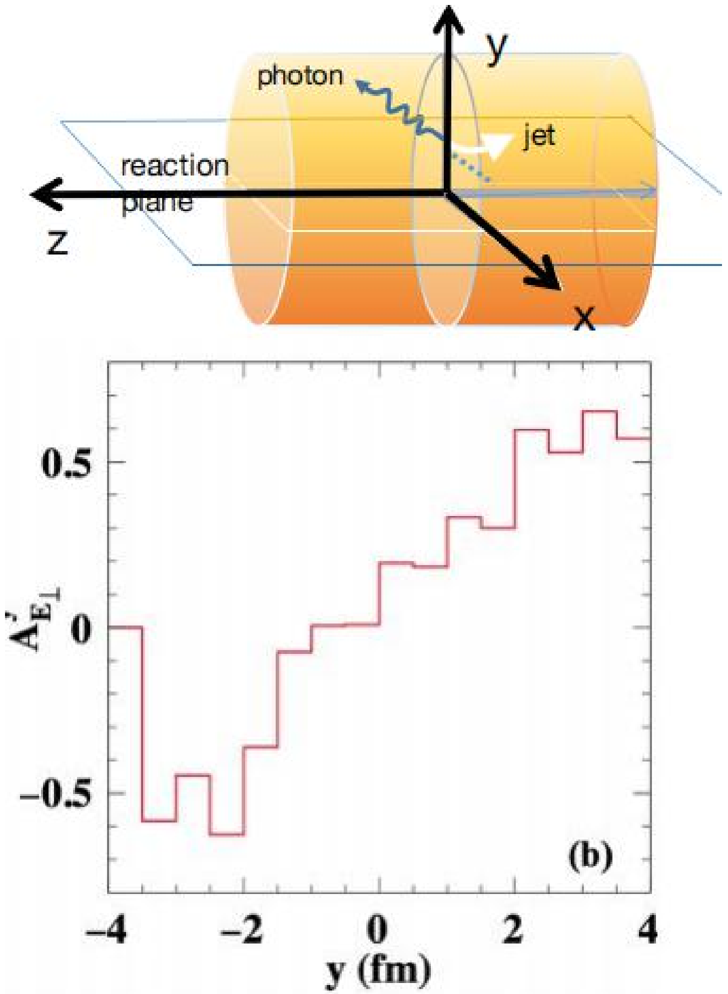


zhang, Owens, Wang and XNW, PRL 103, 032302, (2009) Yi-Lun Du, D. Pablos, K. Tywoniuk, PRL 2022

Transverse Location: Gradient Tomography

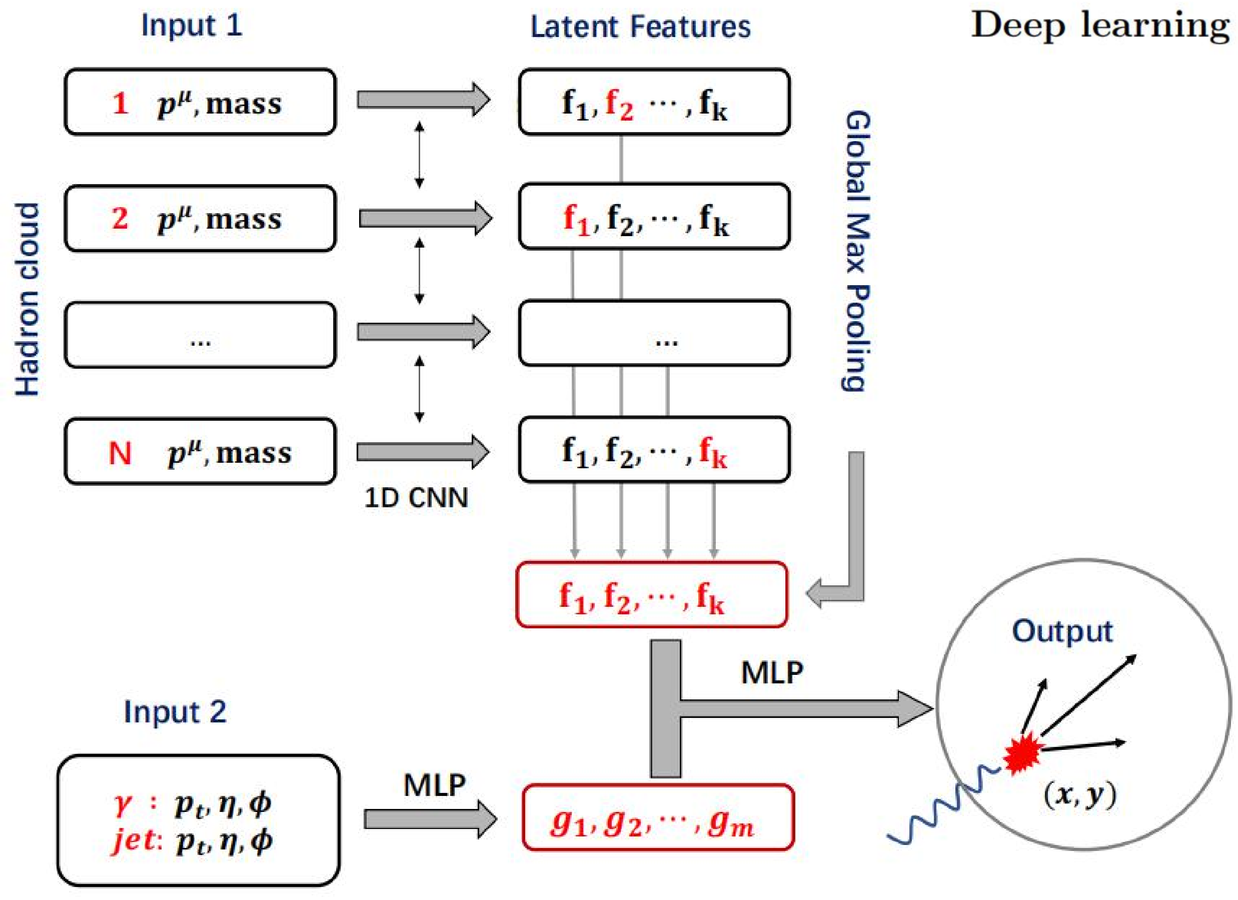
$$A_N^{\vec{n}} = \frac{d^3 r d^3 k f_a(\vec{k},\vec{r}) \mathrm{Sign}(\vec{k}\cdot\vec{n})}{\int d^3 r d^3 k f_a(\vec{k},\vec{r})}$$





He, Pang & Wang, PRL 125 (2020) 12, 122301

Deep Learning Assisted Jet tomography



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

Deep learning assisted jet tomography for the study of Mach cones in QGP

Zhong Yang[1], Yayun He[2,3], Wei Chen[4], Wei-Yao Ke[5,6,7], Long-Gang Pang[1a] and Xin-Nian Wang[1,5,6b]

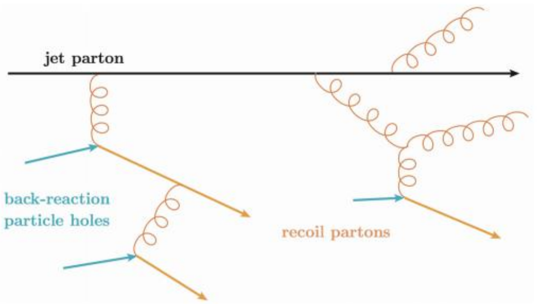
- γ-triggered jet event
- Point cloud network
- Input data：
  - 1. mass and 4-momentum of all hadrons in the jet cone whose $p_T > 2$ GeV
  - 2. γ and jet
- Objective：train the network using simulated data, to predict the initial jet production positions from final state output data

Training data: CoLBT-hydro: LBT + CLVisc

$$p_1\partial f_1 = -\int dp_2 dp_3 dp_4 (f_1 f_2 - f_3 f_4)\left|M_{12\to34}\right|^2 (2\pi)^4\delta^4(\sum_i p^i) + inelastic$$

Medium-induced gluon(HT):

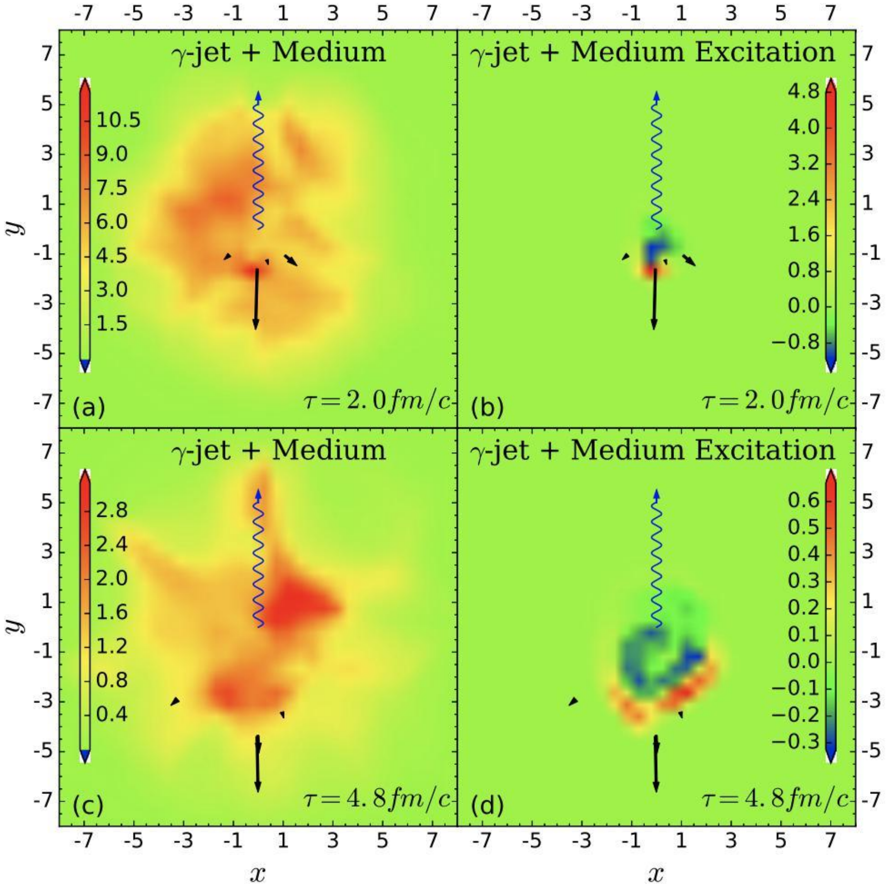
$$\frac{dN_g}{dz d^2k_\perp dt} \approx \frac{2C_A\alpha_s}{\pi k_\perp^4} P(z)\hat{q}(\hat{p}\cdot u) sin^2 \frac{k_\perp^2(t-t_0)}{4z(1-z)E}$$



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

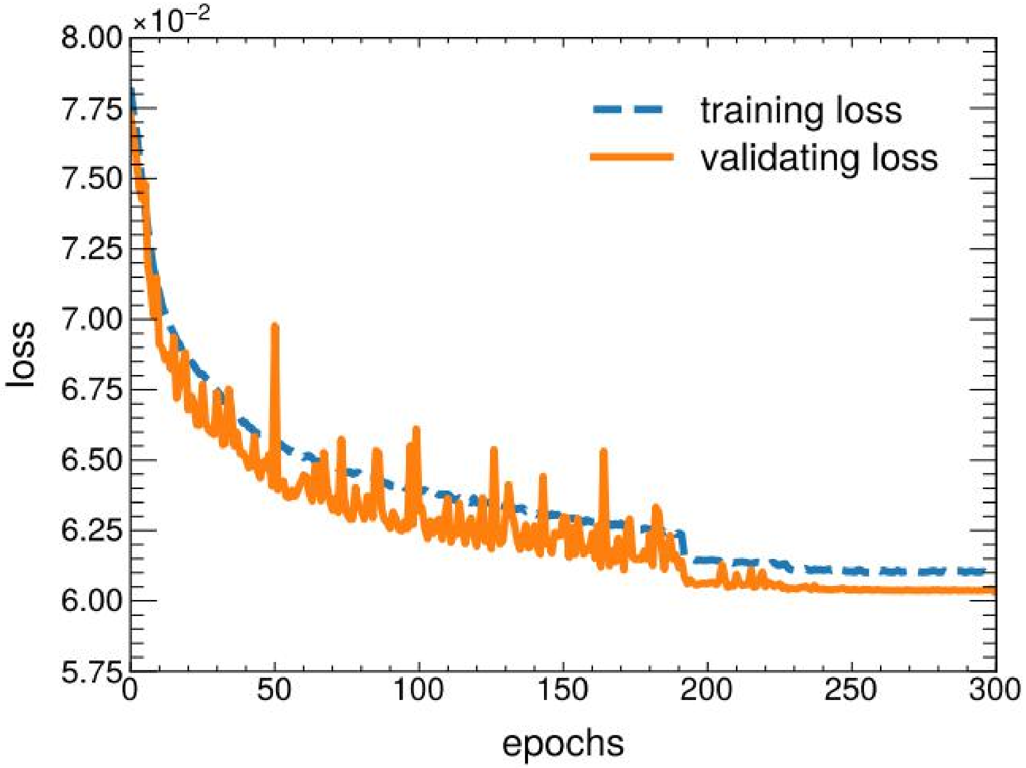
$$\partial_\mu T^{\mu\nu}(x) = j^\nu(x)$$

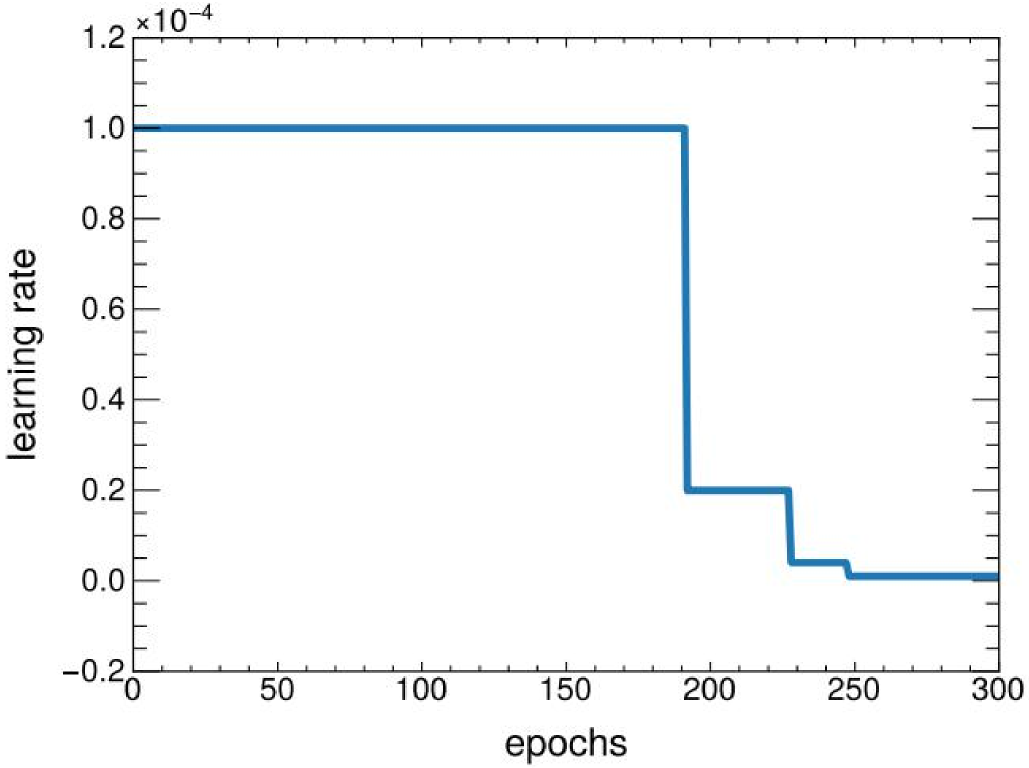
$$j^\nu = \sum_i p_i^\nu \delta^{(4)}(x-x_i)\theta(p^0_{cut} - p\cdot u)$$



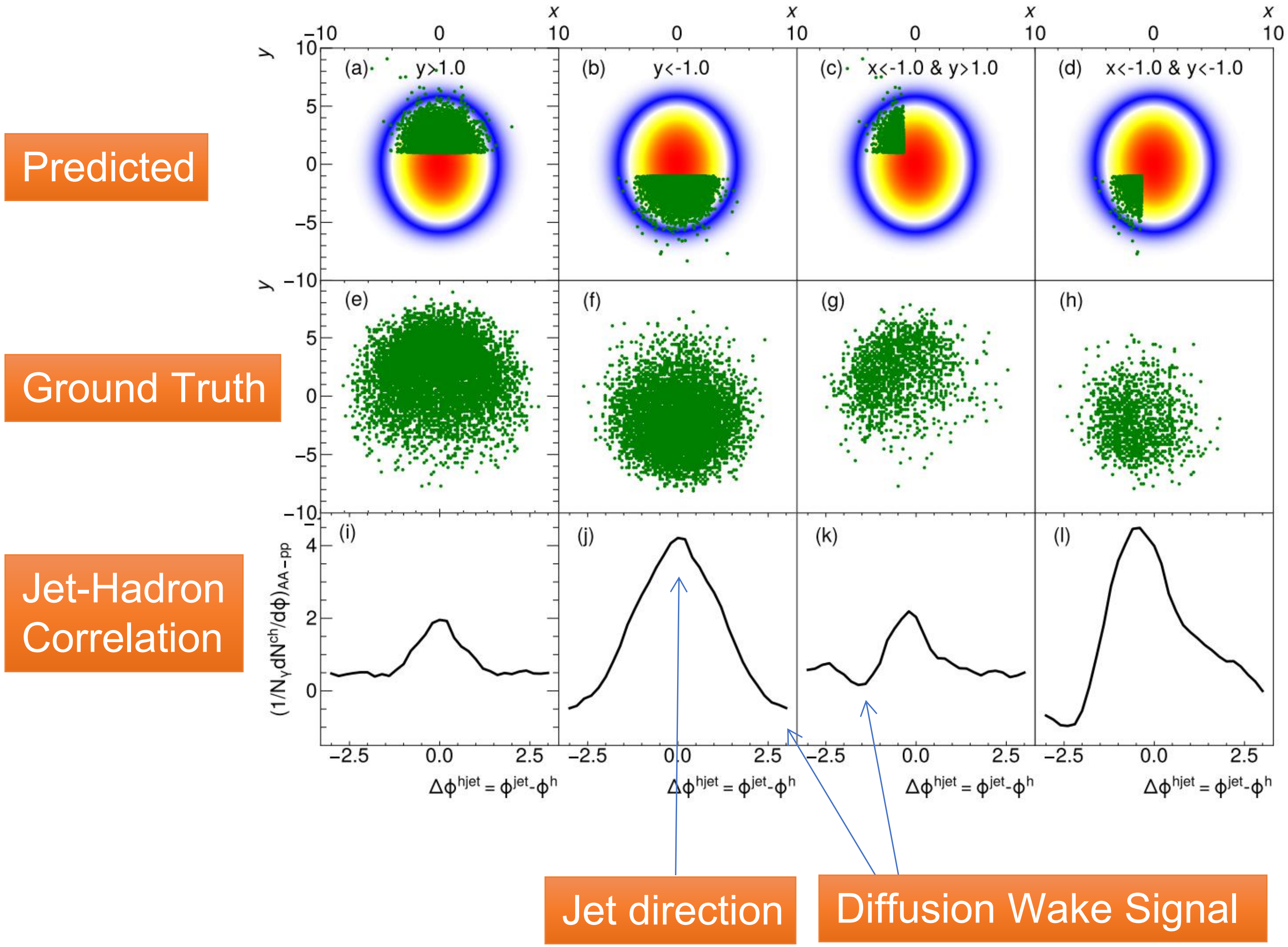
W. Chen, S.S Cao, T. Luo, L.G Pang, X.N Wang, PLB 2017

Training and validation loss



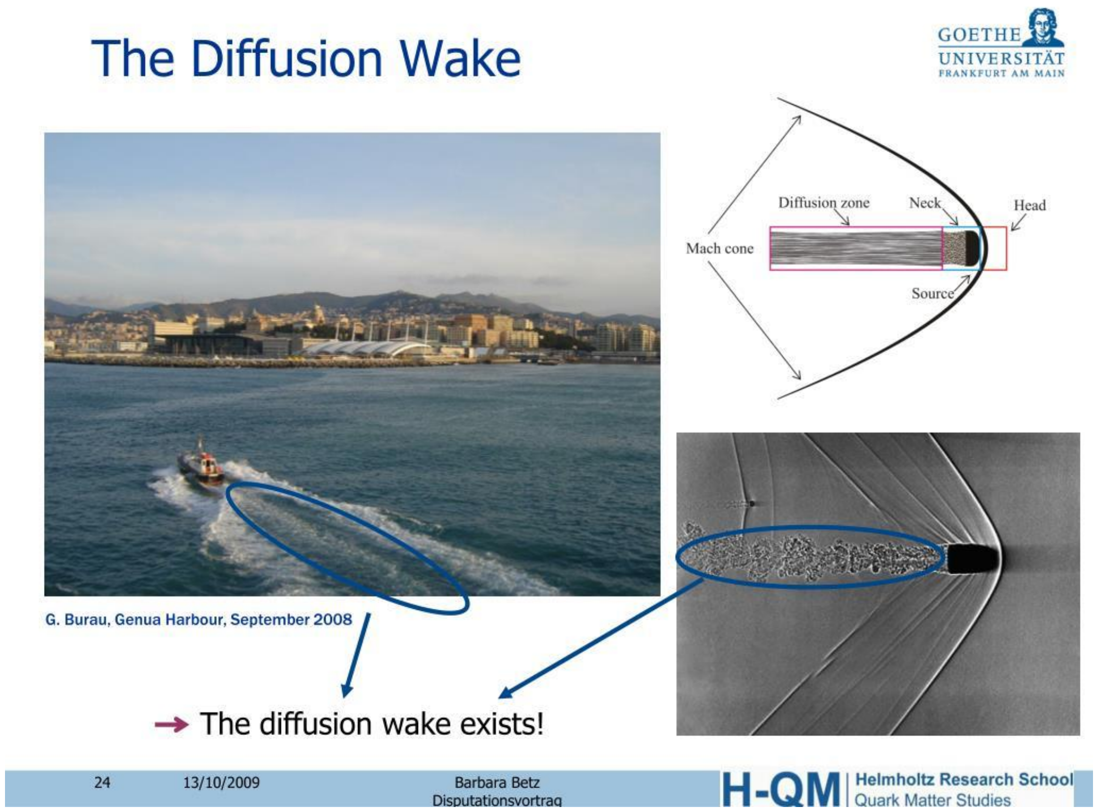


Jet position engineering



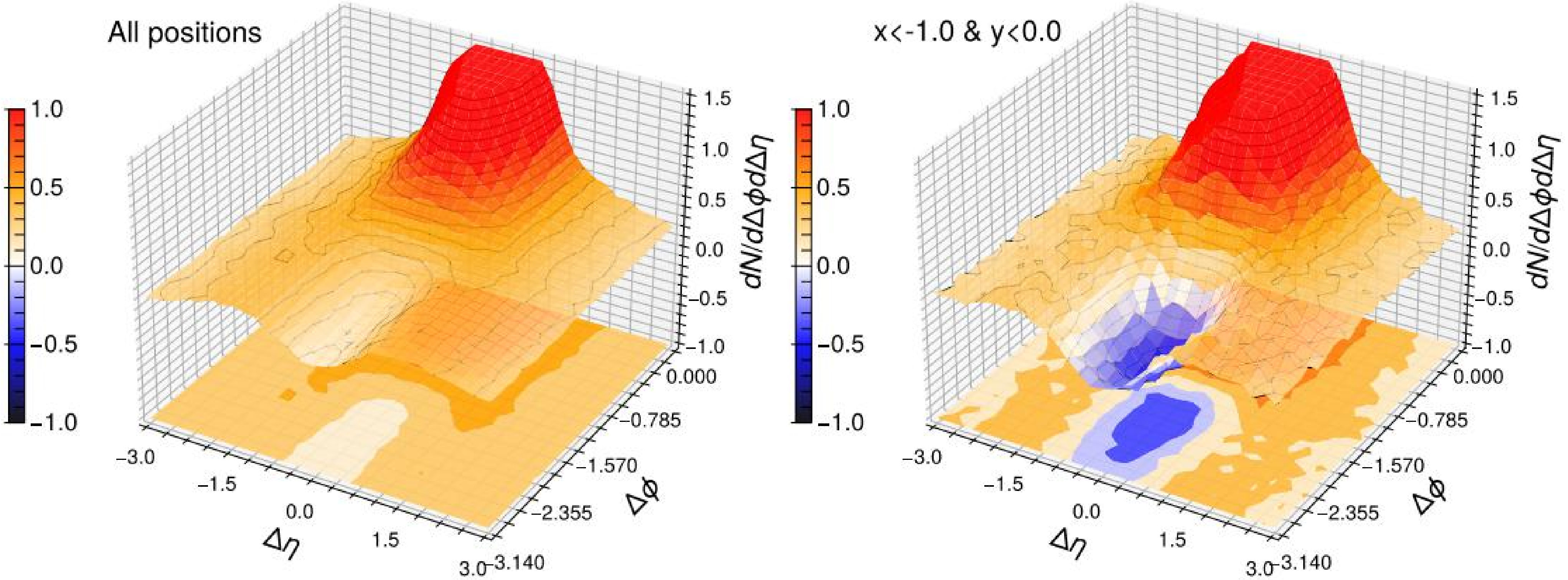
- 1. The prediction is not precise because of fluctuations
- 2. Network helps to select jets initiated from the same region
- 3. The location and the magnitude of the diffusion wake are different because of the path length dependence, the collective flow as well as the density gradient

Diffusion Wake Associated with Mach Cone



- Mach cone has the same direction as the jet, it is difficult to isolate hadrons from Mach Cone with hadrons from the jet
- The Signal of the Diffusion Wake behind the Mach Cone is less affected by the jets
- The effect of diffusion wake on particle azimuthal angular distribution is a better probe for looking for Mach cones in nuclear droplet

The enhancement of diffusion wake signal using jet position engineering



Summary

- Deep Learning is widely used to solve inverse problems in HIC
- The shape of Mach cones are sensitive to jets production positions and their propagating directions
- Deep learning assisted jet tomography helps to locate the jet production positions roughly
- The jet-hadron correlations have different shapes for jets from different regions in the transverse plane. It provides a novel probe for looking for Mach cones
- The present method brings new opportunities to study the QGP EoS and transport coefficients