Machine Learning for Nuclear Theory

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Central China Normal University

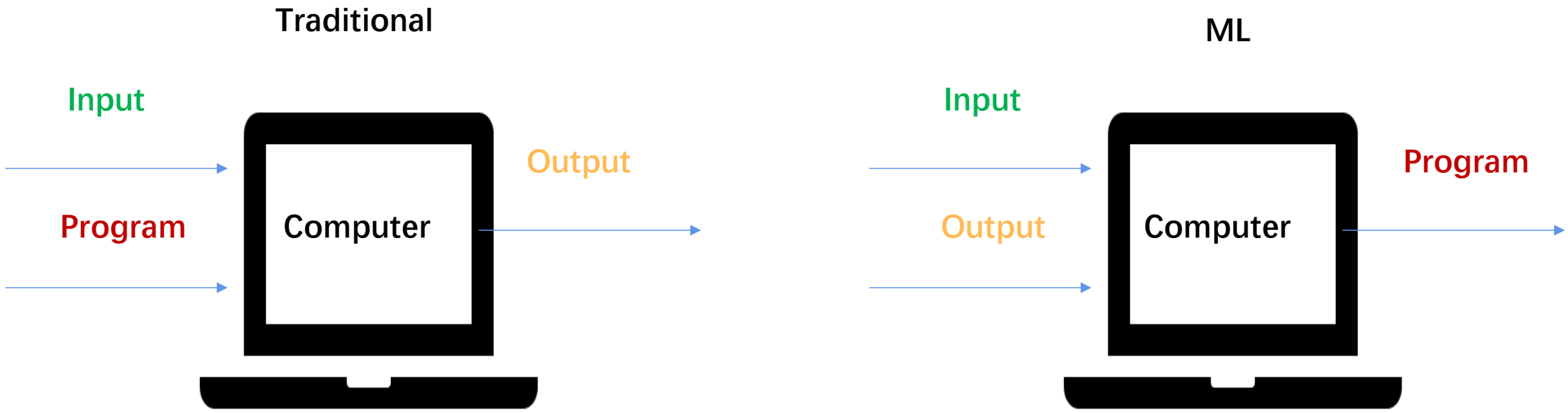
2025/5/18 WuHan

Inaugural Symposium of the CentralChina Center for Nuclear Theory(C3NT) on Frontiers in Nuclear Theory

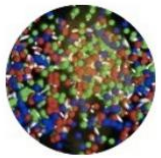
What is Machine Learning

The field of study that gives computers the ability to learn without being explicitly programmed.

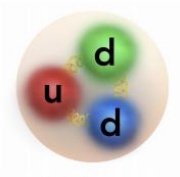
—Samuel 1959



ML for nuclear physics



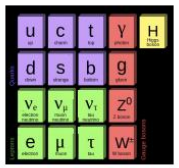
Hot and Dense Nuclear Matter



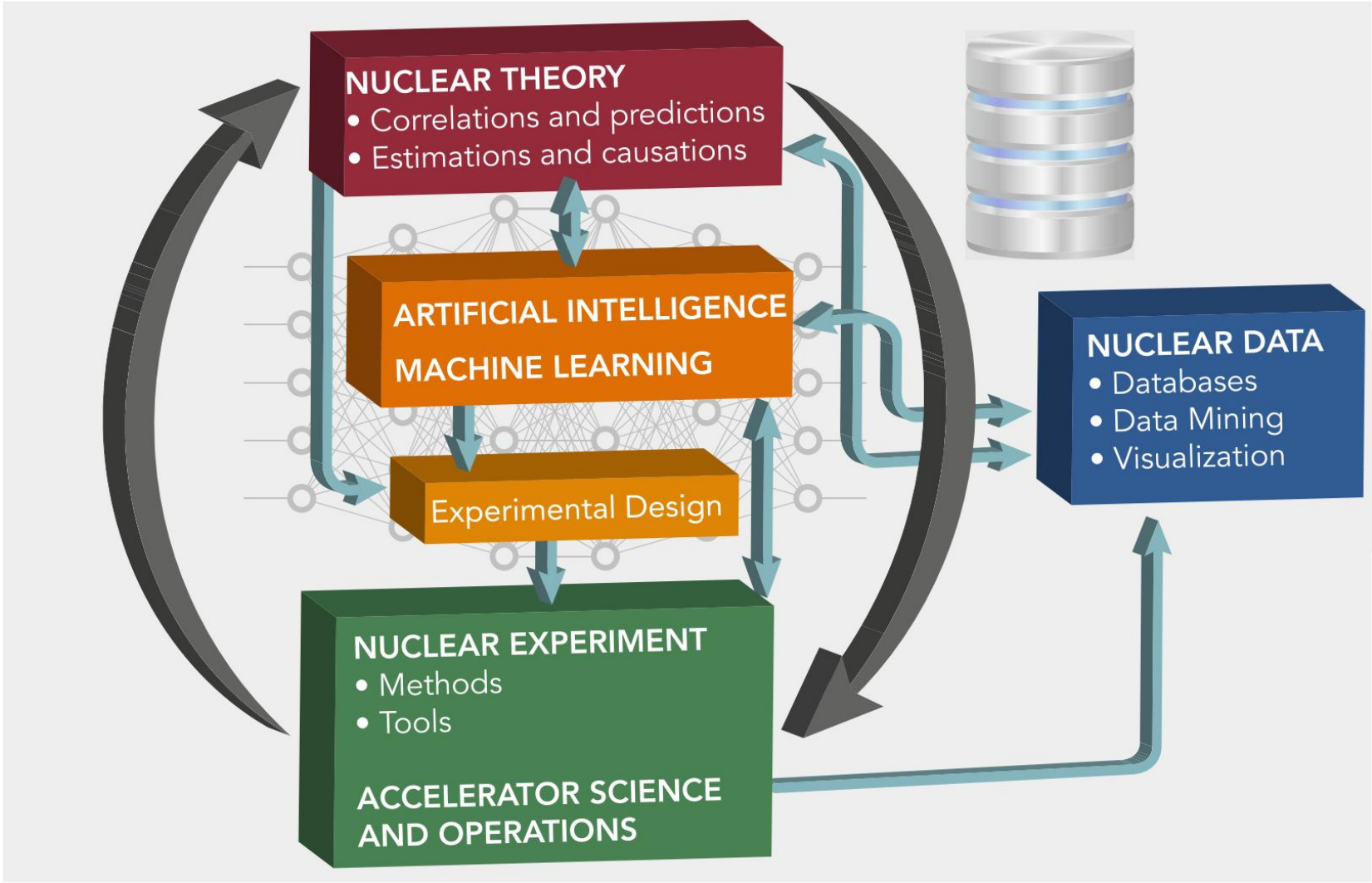
Hadrons

Atomic Nucleus

Nuceli in the Cosmos



Fundamental Interactions



RMP 94, 031003 (2022) Amber Boehnlein, et al.

ML for Nuclear mass and other properties

ANN: Gazula1992NPA, Athanassopoulos2004NPA, Bayram2014ANE, Zhang2017JPG, Ming2022NST, Yüksel2021IJMPE, Li2022PRC

BNN: Utama2016PRC, Niu2018PLB, Niu2019PRC, Niu2022PRCL, Rodriguez2019EPL, Rodriguez2019JPG

BGP: Neufcourt2018,2020PRC, Neufcourt2019PRL, Yüksel2024PRC

CNN: Yang2023PRC

LightGBM: Gao2021NST

KRR: Wu2020PRC, Wu2021PLB

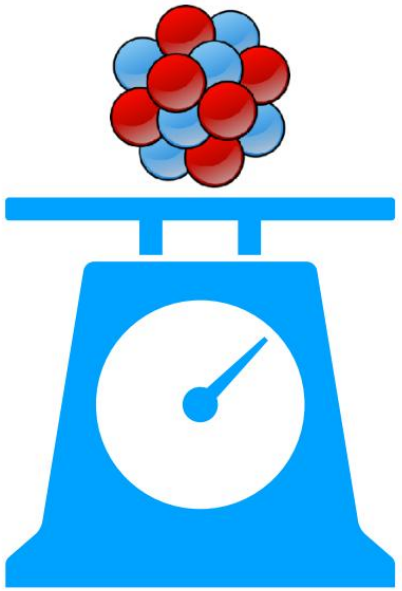
NBP: Liu2021PRC, Xie2024PRC

RBF: Wang2011PRC, Niu2013,2016PRC,2018SciB

SVM: Clark2006IJMPB

CLEAN: Morales2010PRC

... from Prof. PengWei Zhao's slides



RNN, GRU and LSTM Models:
Amir Jalili, Feng Pan, Ai Xi Chen, and Jerry P. Draayer, 2025

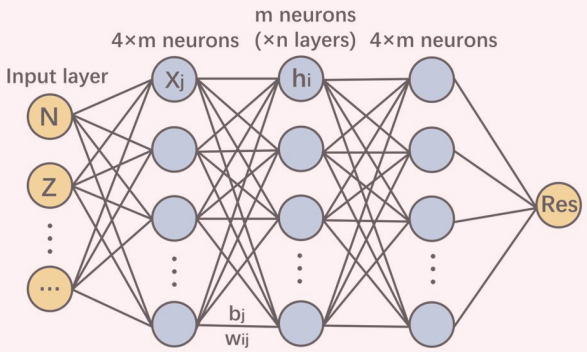
ML for Nuclear Charge Radius (Review)

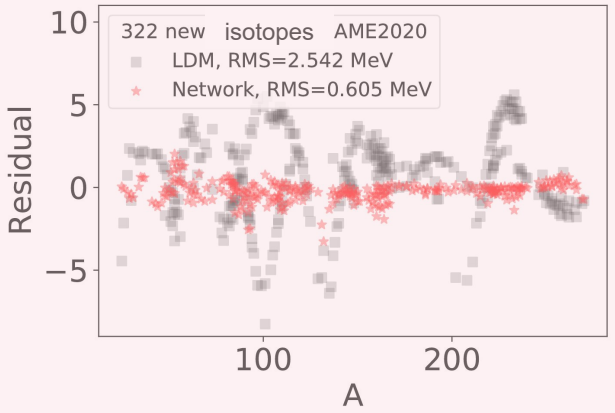
Dong Xiaoxu; Geng Lisheng

- Naive Bayesian
- kernel ridge regression
- ANN

Z, N → mass, charge radius, ...

ML for Nuclear mass



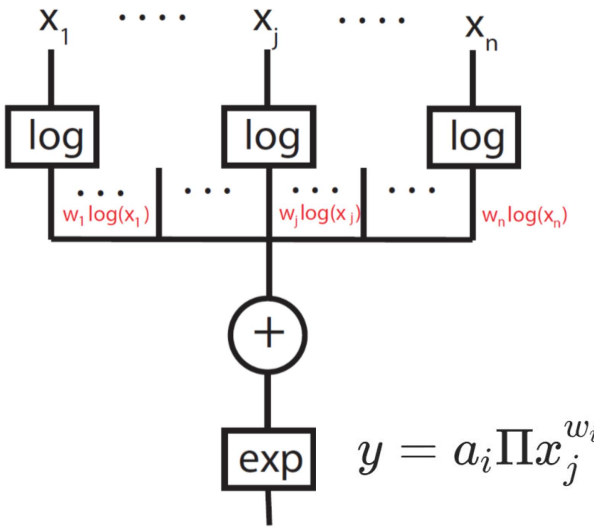


The Deep Neural Network

- 1 millions trainable parameters
- thought to be easy to overfit to training data
- in practice, it generalizes better than LDM

Li, Tong, Du, Pang, PRC 105 (2022) 6, 064306

Product-unit network



Babette D, Uwe J, Paulo S.A. F, John W. C. PLB 852(2024)138608

- complex valued x and w
- much fewer parameters
- better explanation

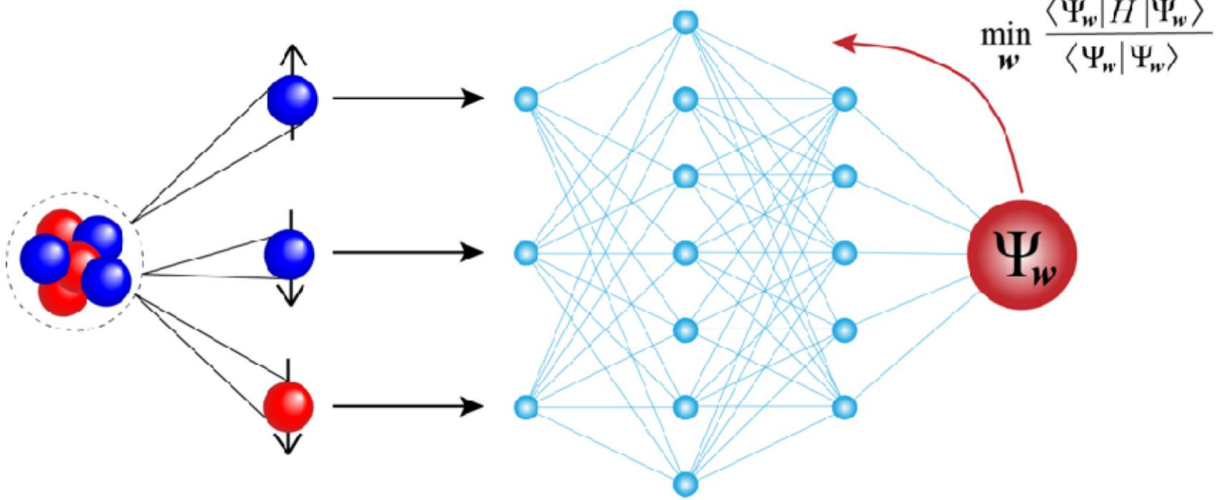
Ab initio calculations

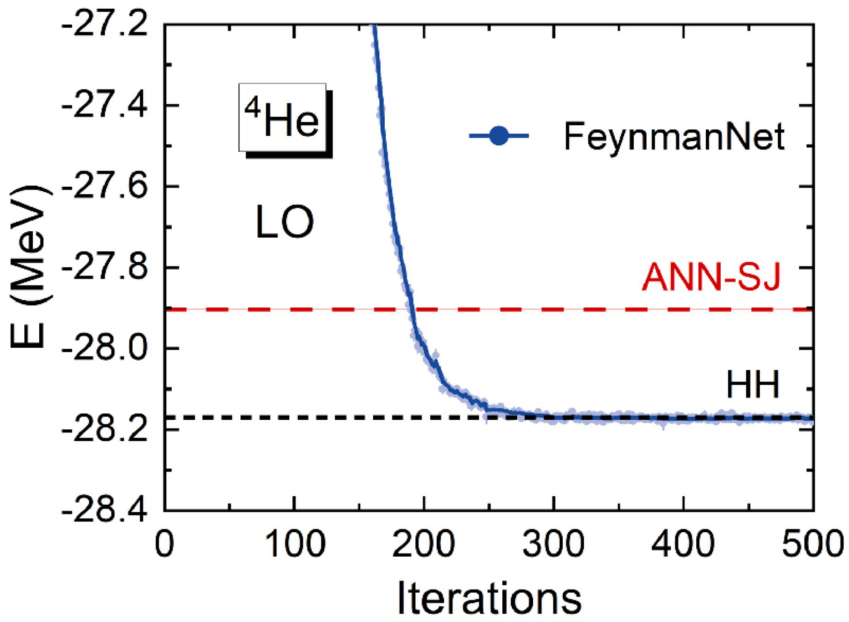
$$\hat{H} = \sum_{i=1}^{A} \frac{-\nabla_i^2}{2m_N} + \sum_{i<j} v_{ij} + \sum_{i<j<k} V_{ijk},$$

E_0: → ground state mass

Ψ_0: ground state wave function

Polynomial complexity





ANN-SJ: Adams, et al., PRL 127, 022502 (2021)
VMC-ANN: Alex Gnech, et al. Few Body Syst. 63 (2022) 1, 7
FeynmanNet: Yang, PWZ*, PRC 107, 034320 (2023)

Nuclear EDFT from machine learning

Nuclear energy density functionals from machine learning

X. H. Wu (吴鑫辉), Z. X. Ren (任政学), and P. W. Zhao (赵鹏巍)*

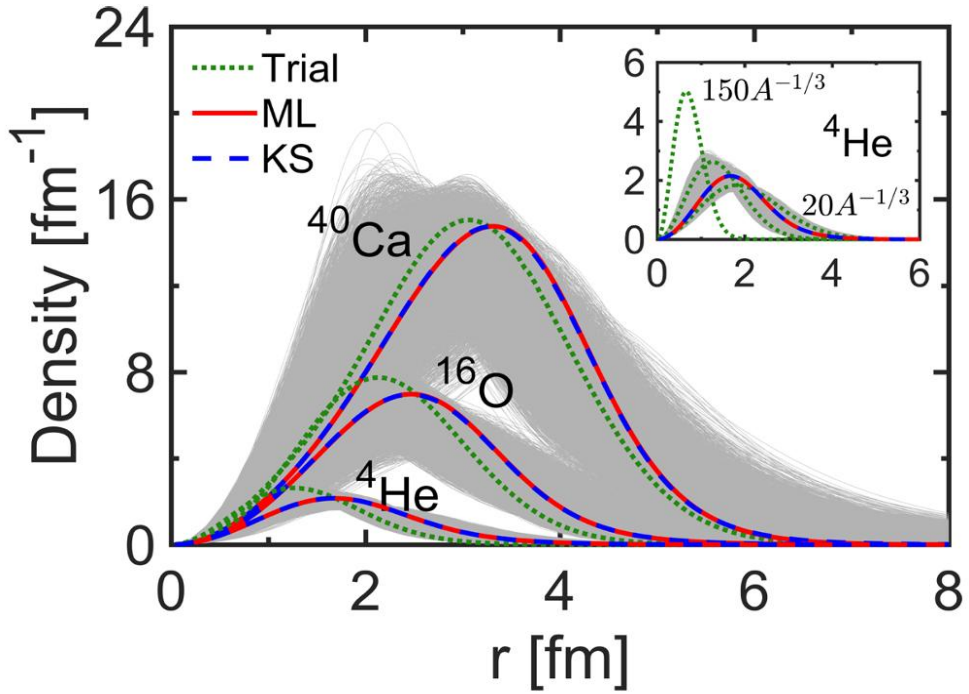
Kernel ridge regression: $\varrho(r) \rightarrow E_{kin}$

$$E_{\mathrm{kin}}^{\mathrm{ML}}[\rho(\boldsymbol{r})] = \sum_{i=1}^{m} \omega_i K(\rho_i, \rho).$$

$$K(\rho, \rho') = \exp[-||\rho(\boldsymbol{r}) - \rho'(\boldsymbol{r})||^2/(2AA'\sigma^2)].$$

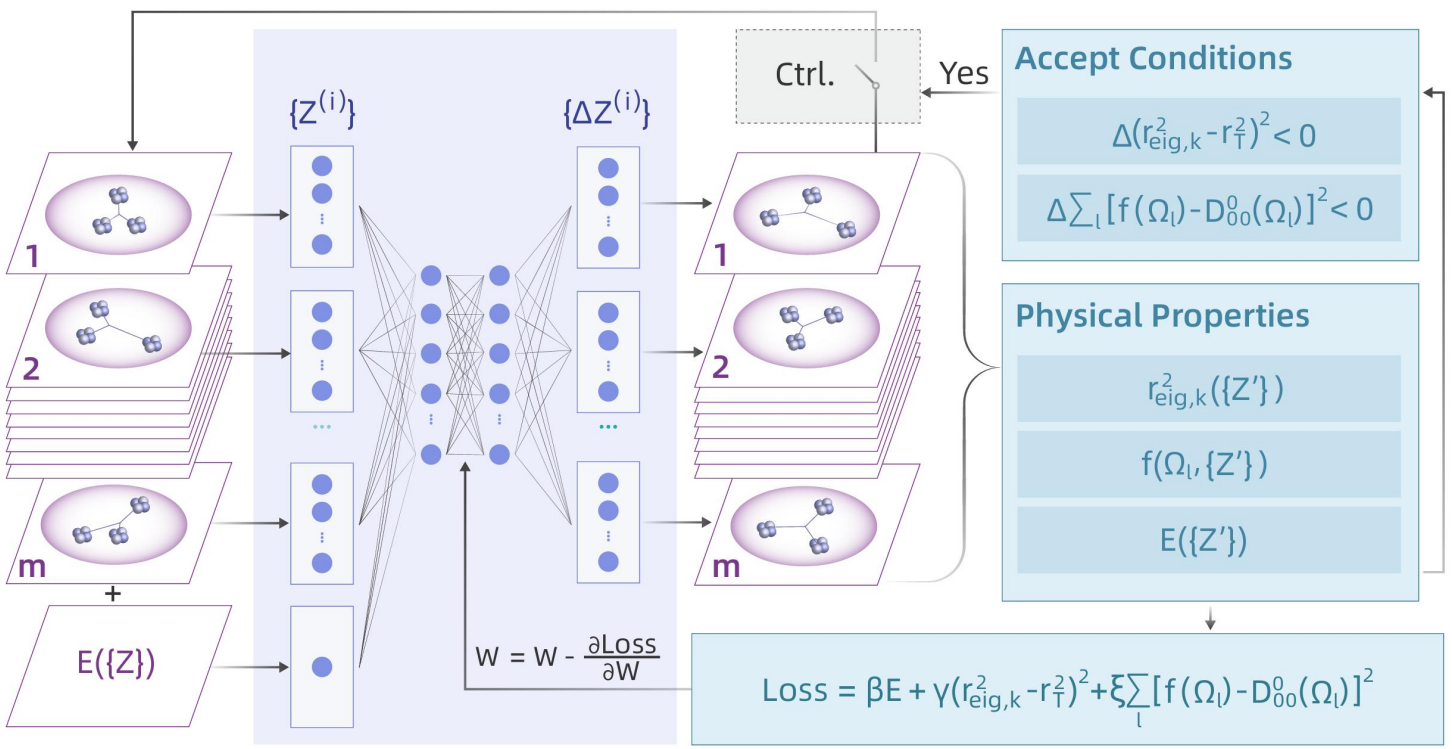
Loss function:

$$L(\boldsymbol{\omega}) = \sum_{i=1}^{m} \left(E_{\mathrm{kin}}^{\mathrm{ML}}[\rho_i] - E_{\mathrm{kin}}[\rho_i]\right)^2 + \lambda||\boldsymbol{\omega}||^2,$$



By learning the kinetic energy as a functional of the nucleon density alone, a robust and accurate orbital-free density functional for nuclei is established.

Control NN for 3-α breathing in C12



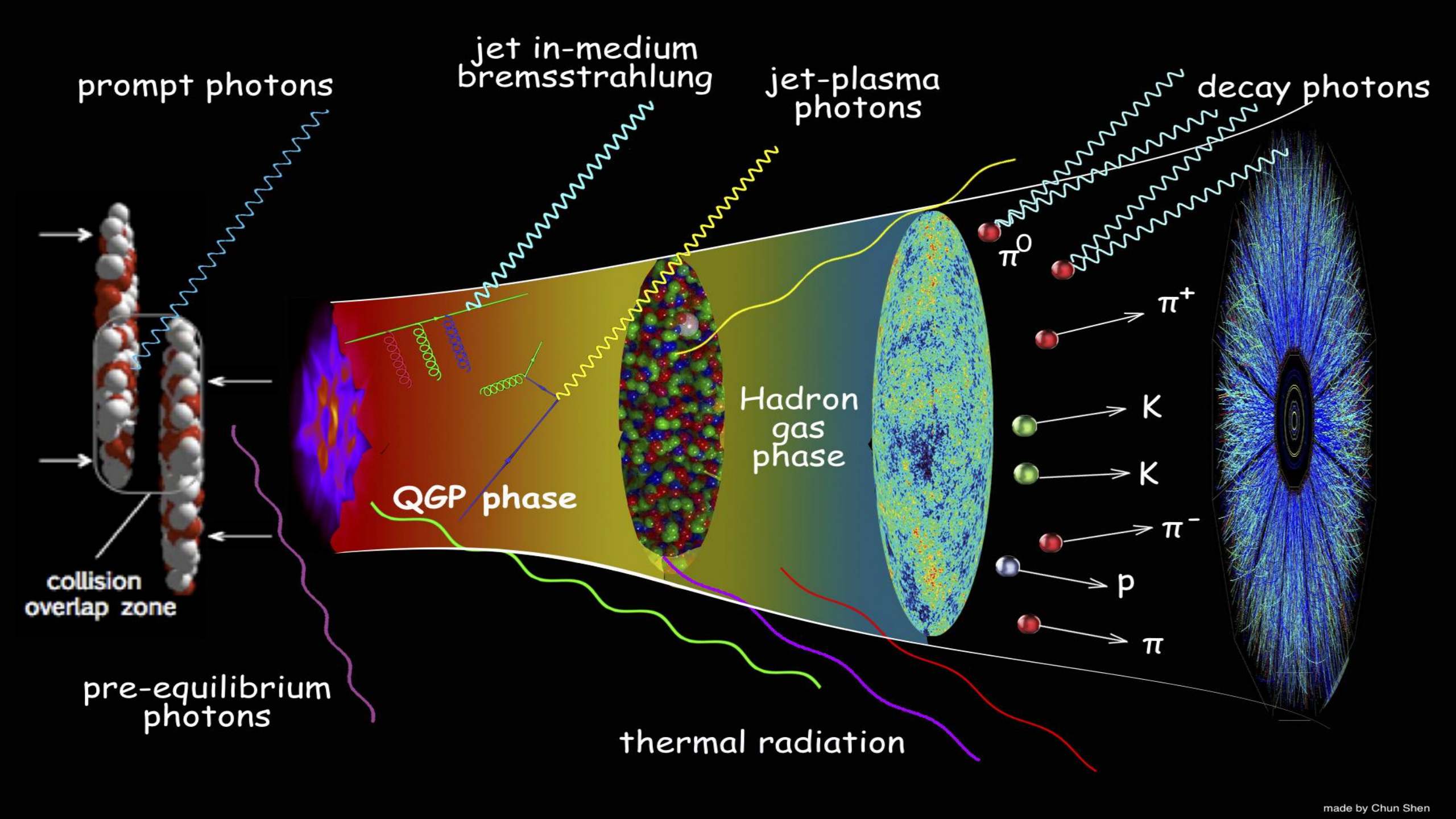
Evidence for Three-α Breathing Modes Uncovered by Control Neural Network

Zheng Cheng[1,2], Mengjiao Lyu[1,2,*], Takayuki Myo[3,4], Hisashi Horiuchi[4], Hiroshi Toki[4], Zhongzhou Ren[5,6], Masahiro Isaka[7], Mengyun Mao[1,2], Hiroki Takemoto[8], Niu Wan[9], Wenlong You[1,2], and Qing Zhao[10]

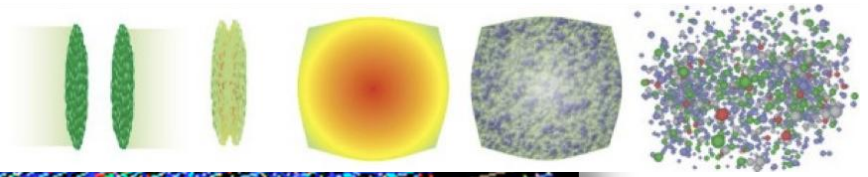
In each iteration, **a new basis set {Z'} is obtained and diagonalized to yield the new total intrinsic wave function** $\Psi(\{Z'\})$ and physical properties corresponding to each of the three constraints,

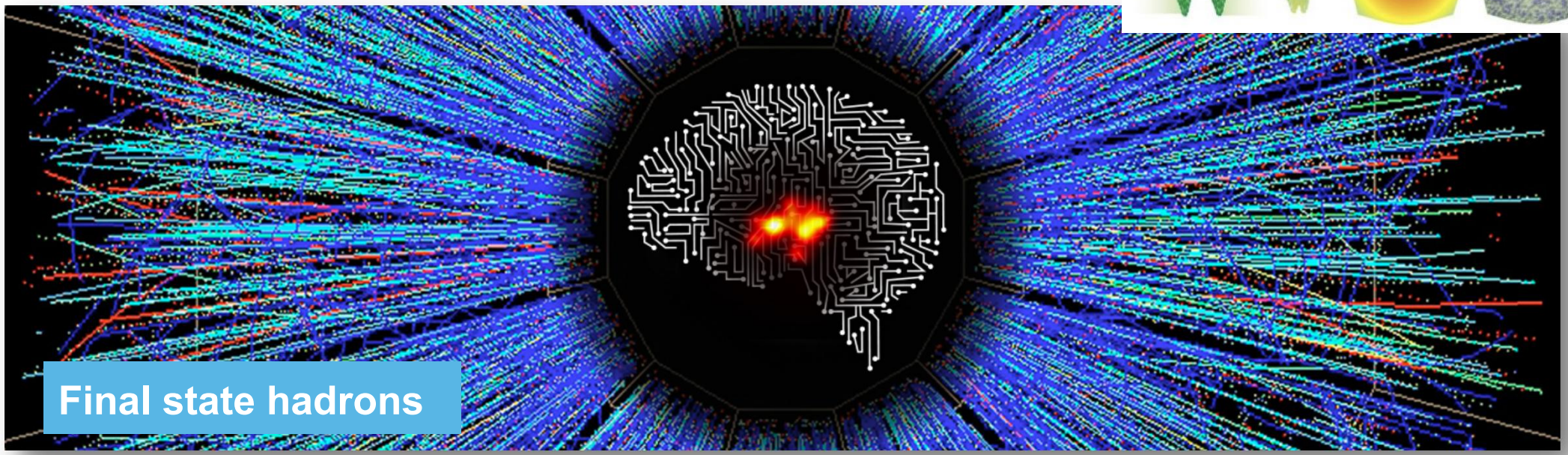
$$\mathrm{Loss} = \beta E + \gamma(r^2_{\mathrm{eig},k} - r^2_T)^2 + \xi \sum_{l=1}^{L}[f(\Omega_l) - D^J_{MK}(\Omega_l)]^2,$$

Constraints: (1) minimum eigen value (2) mean square radius (3) rotational symmetry

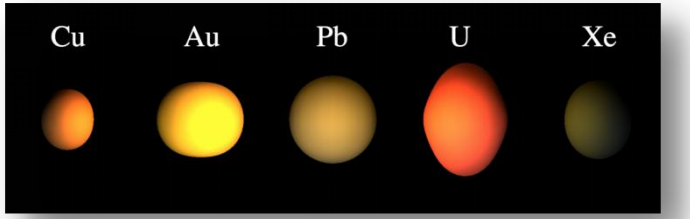

prompt photons
jet in-medium bremsstrahlung
jet-plasma photons
decay photons
collision overlap zone
QGP phase
Hadron gas phase
π^0
π^+
K
K
π^-
p
π
pre-equilibrium photons
thermal radiation
made by Chun Shen

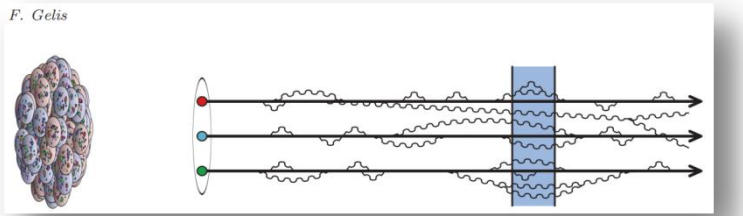
Inverse problems in HIC

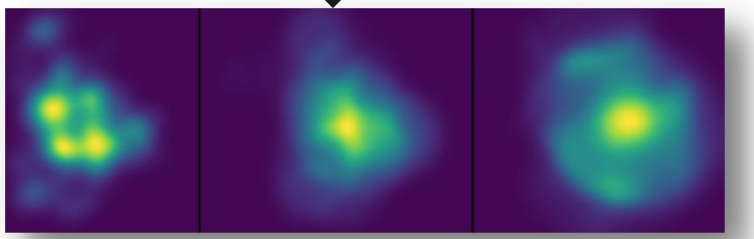




Non-linear mapping





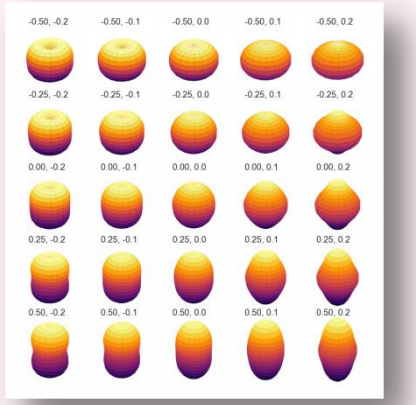


(1) Nuclear Structure

(2) Initial Parton Distribution

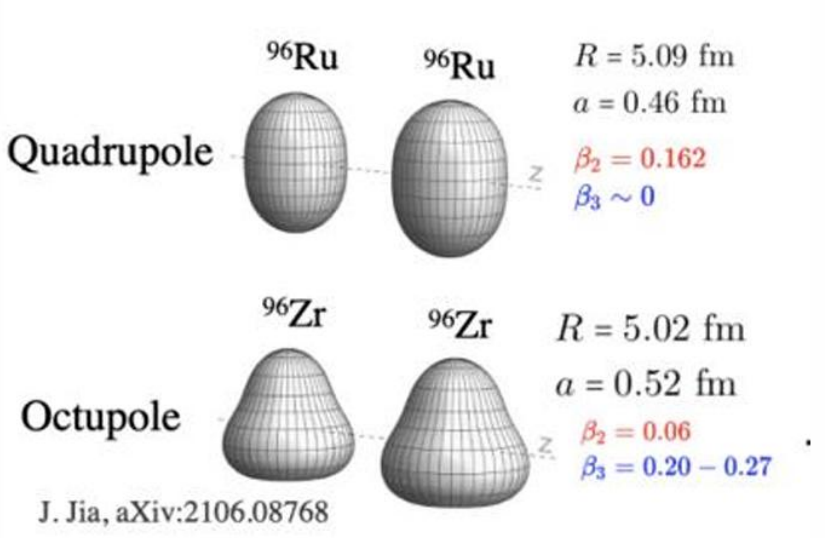
(3) QGP properties and EoS

Nuclear Structure using HICs and ML

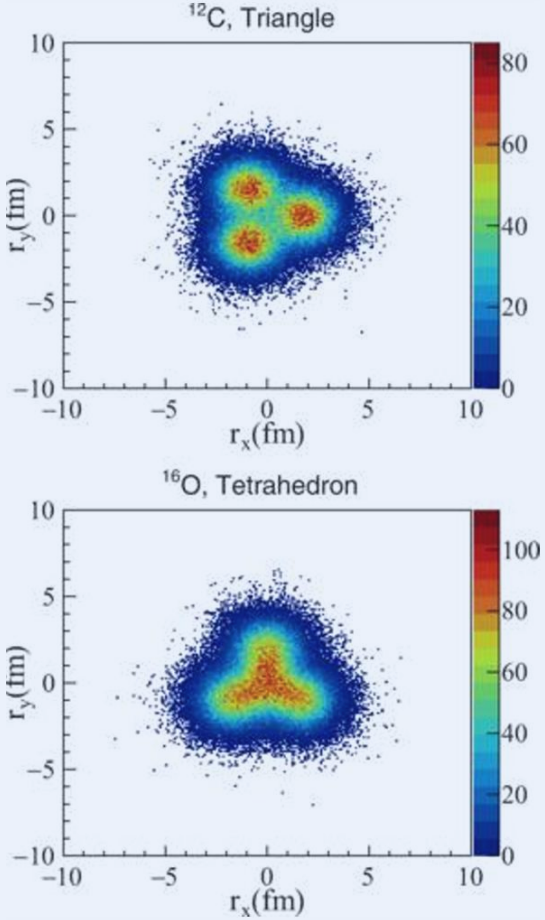


1. change β_2, β_4
2. A+A collision sim.
3. ML: final → initial nuclear deformation

LG. Pang, K. Zhou and X.-N. Wang, arXiv:1906.06429

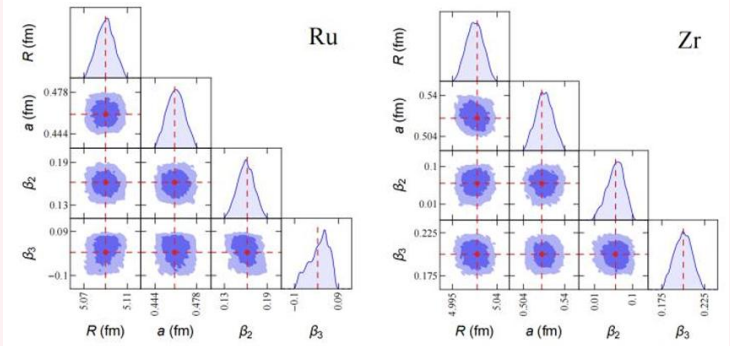


α cluster in C and O



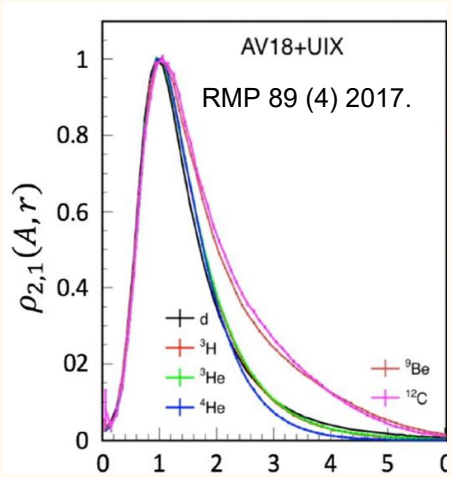
J He, W. He, Y.G. Ma, S. Zhan g, PRC104, 044902

$y_{\mathrm{Ru}} \equiv \{P_a^{\mathrm{Ru}}, \varepsilon_{2,a}^{\mathrm{Ru}}, \varepsilon_{3,a}^{\mathrm{Ru}}, d_{\perp,a}^{\mathrm{Ru}}\}_{a=1,\cdots,40}$



Single system works good

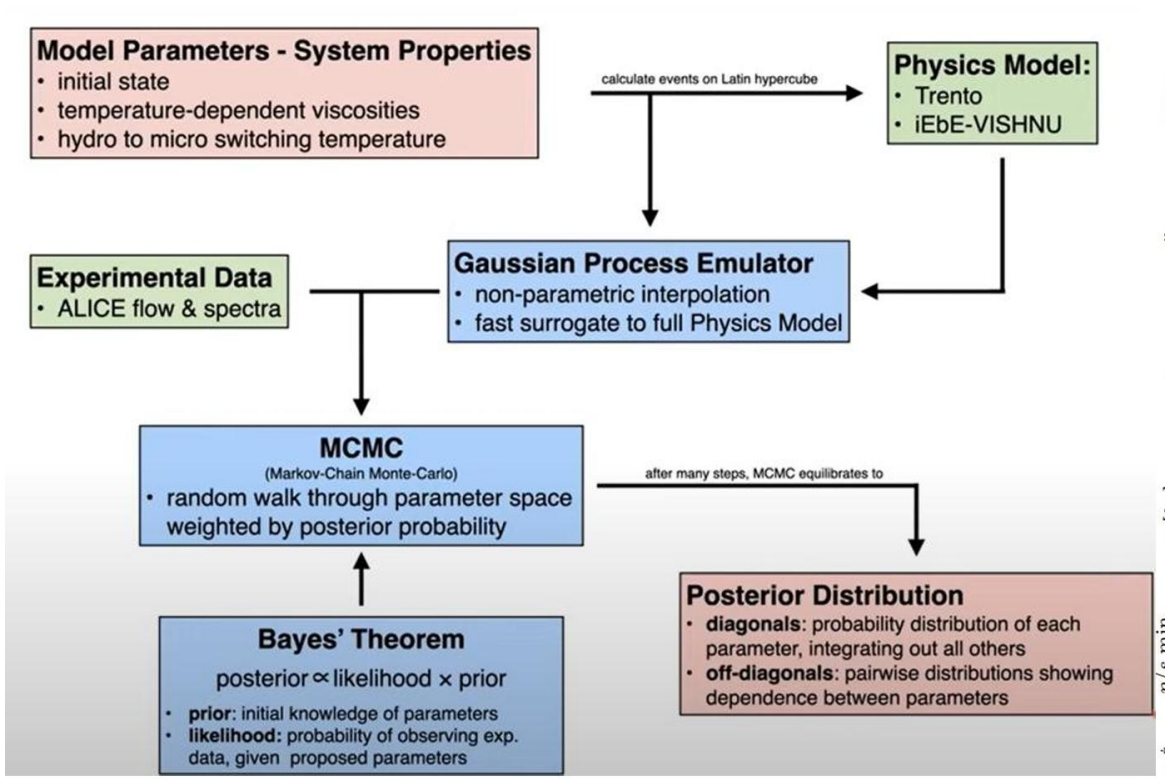
Y.Cheng, S.Shi, Y. Ma, H. S., K. Zhou, PRC107 (2023) 064909

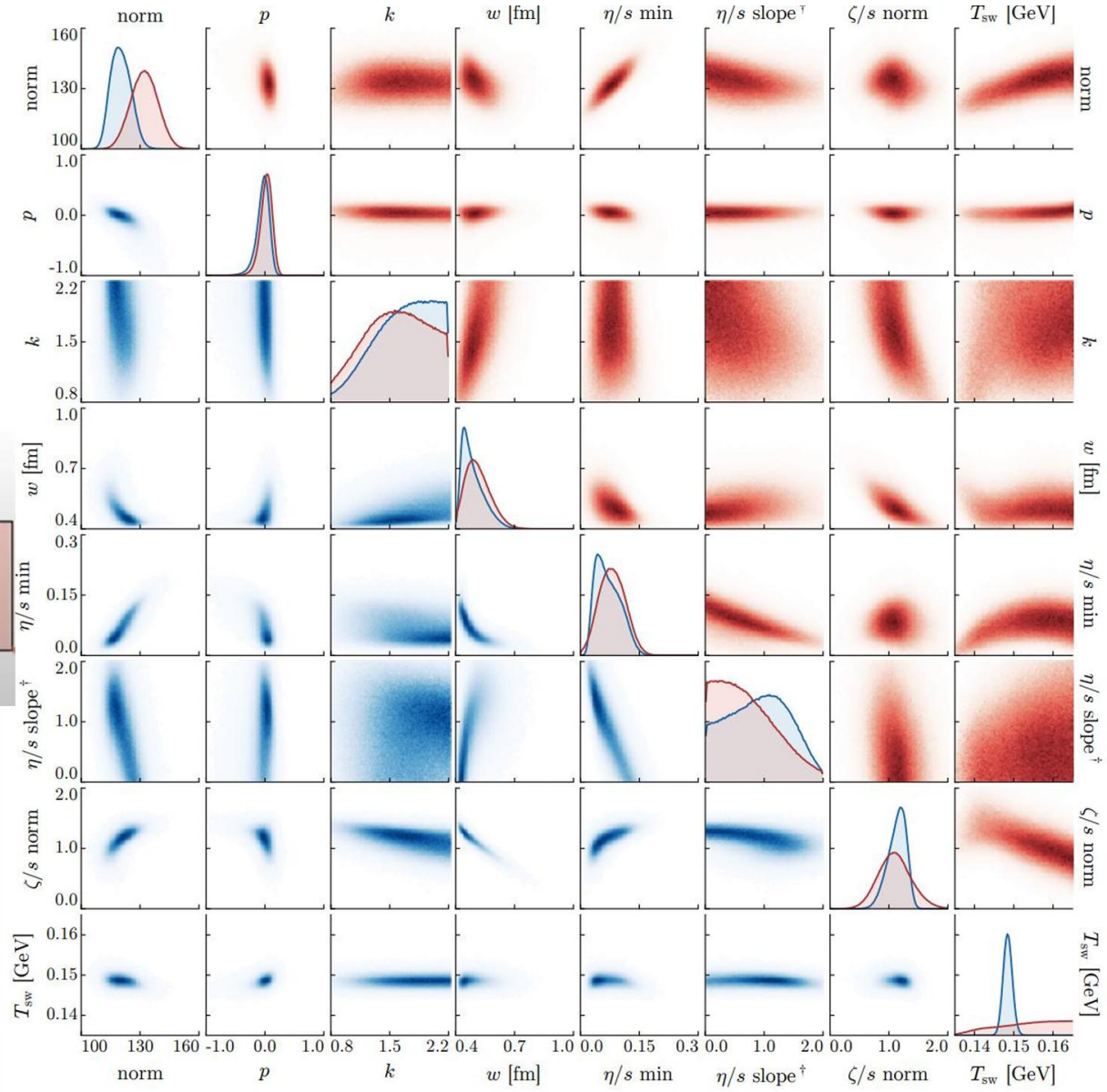


1. sample nucleons obeying both $\varrho(r)$ & $\varrho_{12}(\Delta r)$
2. do HIC simulations
3. Look for features that are sensitive to $\varrho_{12}(\Delta r)$

Y.J. Huang, Z. Meng, L.G. Pang, X.N. Wang, arXiv:2504.00790

Bayesian analysis of HICs





Trento + IEBE-VishNew + UrQMD

J. Bernhard, J. Morel, S. Bass, **Nat. Phy.** 15, 1113 (2019)

G. Nijs, W. Schee, U. Guersoy, R. Snellings, **PRC**103,054909;
JETSCAPE, **PRL**126,242301; U. Heinz+, 2302.14184 (VAH)
M. R. Heffernan, C. Gale, S. Jeon, J. Pauet, **PRC**109,065207;
... ...

Jet quenching/diffusion:

Y. He, L. Pang, X. Wang, **PRL** 122 (25) 252302
M. Xie, W. Ke, H. Zhang, X. Wang, **PRC108** (2023) L011901; ... ...

Bayesian analysis QCD EoS

$$c_s^2(\epsilon) = c_s^2(\epsilon_h) + \left(\frac{1}{3} - c_s^2(\epsilon_h)\right) \frac{X_0 x + x^2}{X_0 x + x^2 + X'^2} \tag{2.12}$$

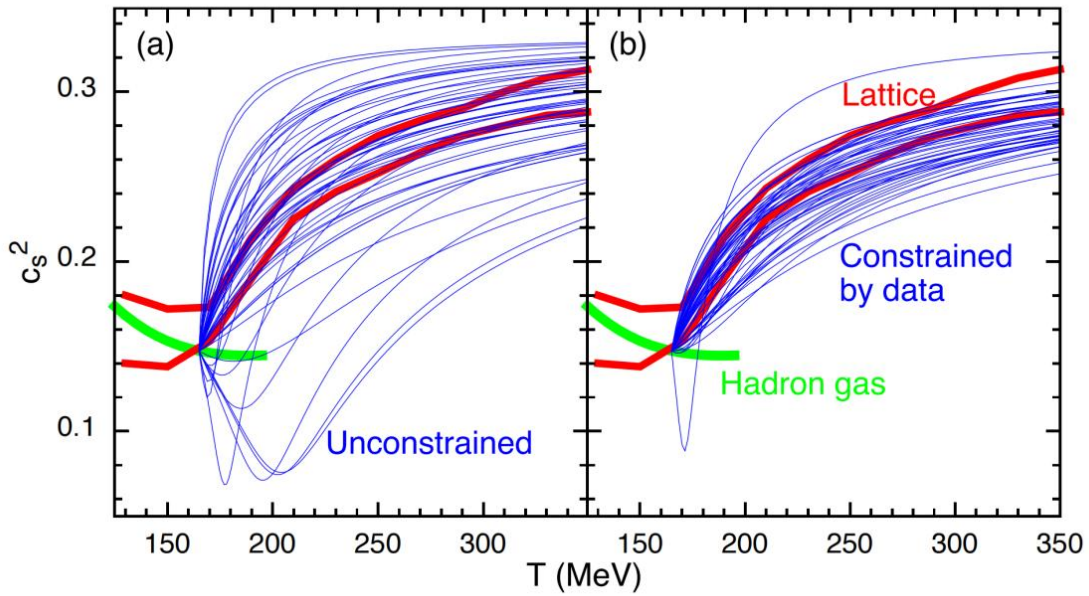
where $X_0 = \sqrt{12} R X' c_s(\epsilon_h)$, $x \equiv \ln \frac{\epsilon}{\epsilon_h}$, ϵ_h is the energy density at $T = 165$ MeV, R and X' are the two parameters in the EoS to be determined. Randomly choosing R and X' from the range $-0.9 < R < 2$ and $0.5 < X' < 5$ generate the

Likelihood:

$$P(D|\theta) = \Pi_i \exp\left(-(z_i(\theta) - z_{i,\exp})^2/2\right)$$

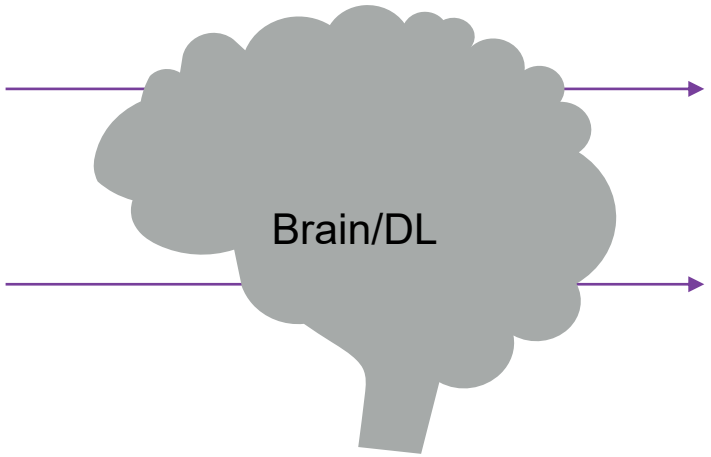
Posterior:

$$P(\theta \mid D) \propto P(D \mid \theta) P(\theta)$$



S. Pratt, E. Sangaline, P. Sorensen, H. Wang, PRL. 114 (2015) 202301.

DL for inverse/variational problems in HICs



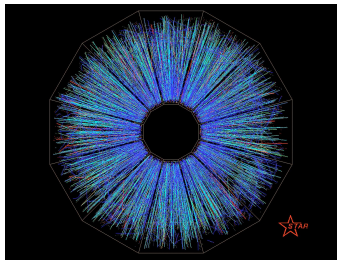
Dog

Cat

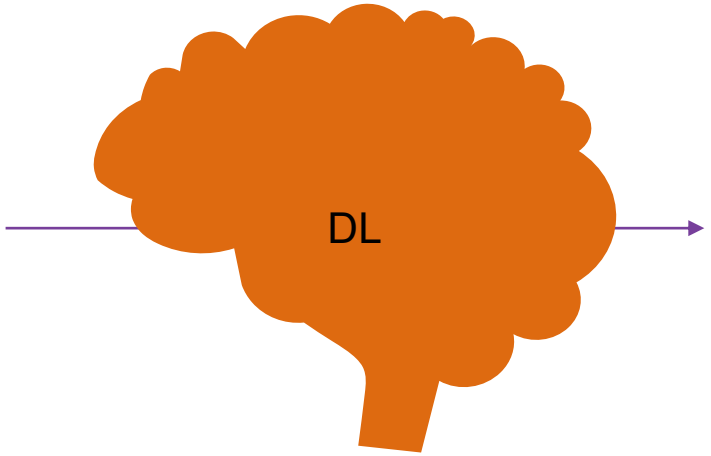
Human brains are not optimized for processing high-dimensional scientific data. Deep neural network can be trained:

(i) to identify optimal feature combinations

(ii) to represent variational functions



$\rho(p_T, \Phi)$

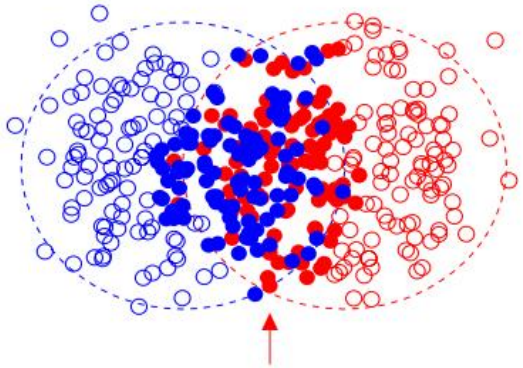


QCD phase structure/EoS,

Nuclear structure (deformation, nn SRC, neuteron skin, α clusters),

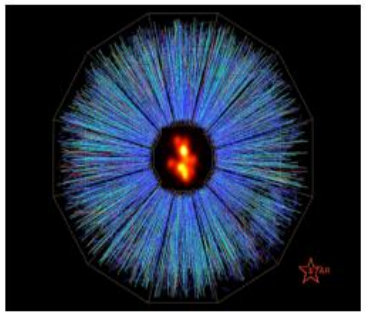
shear/bulk viscosity of QGP, CME ...

Theoretical model: relativistic hydro



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

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



Initial condition EoS Viscosity

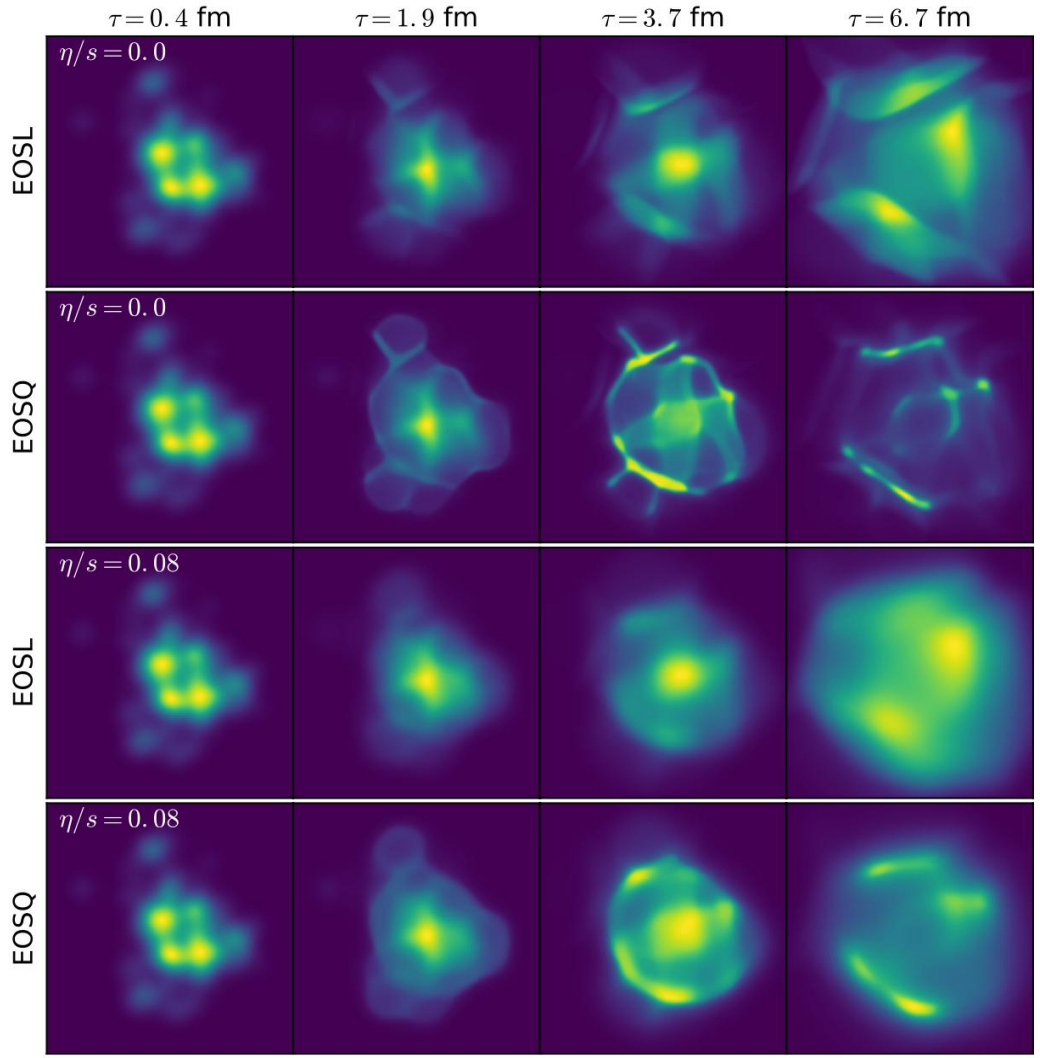
Name of CLVisc:

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

CLVisc for different EoS



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

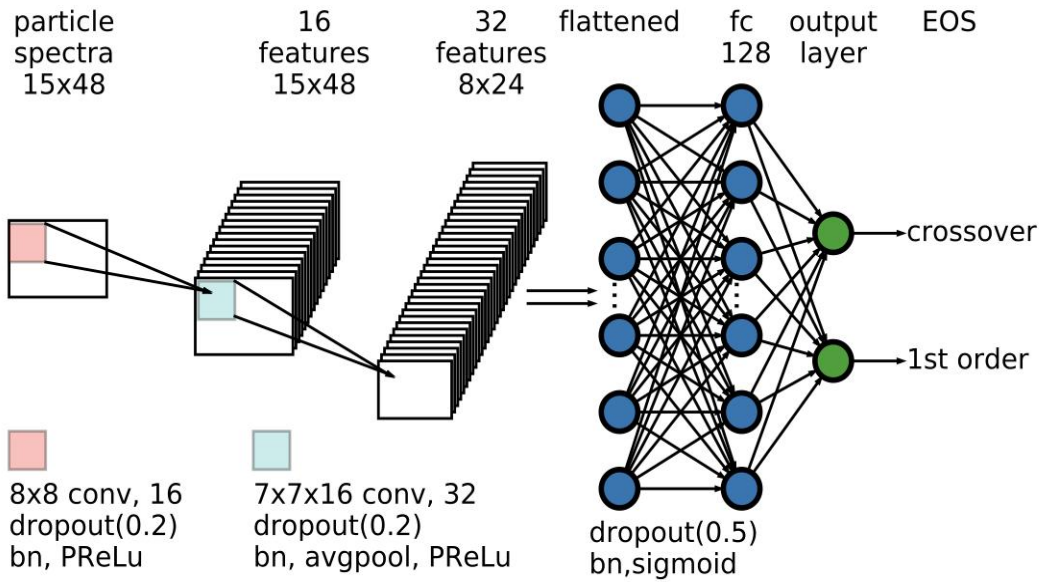
η/s = 0 (ideal hydro)
First order phase transition

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.

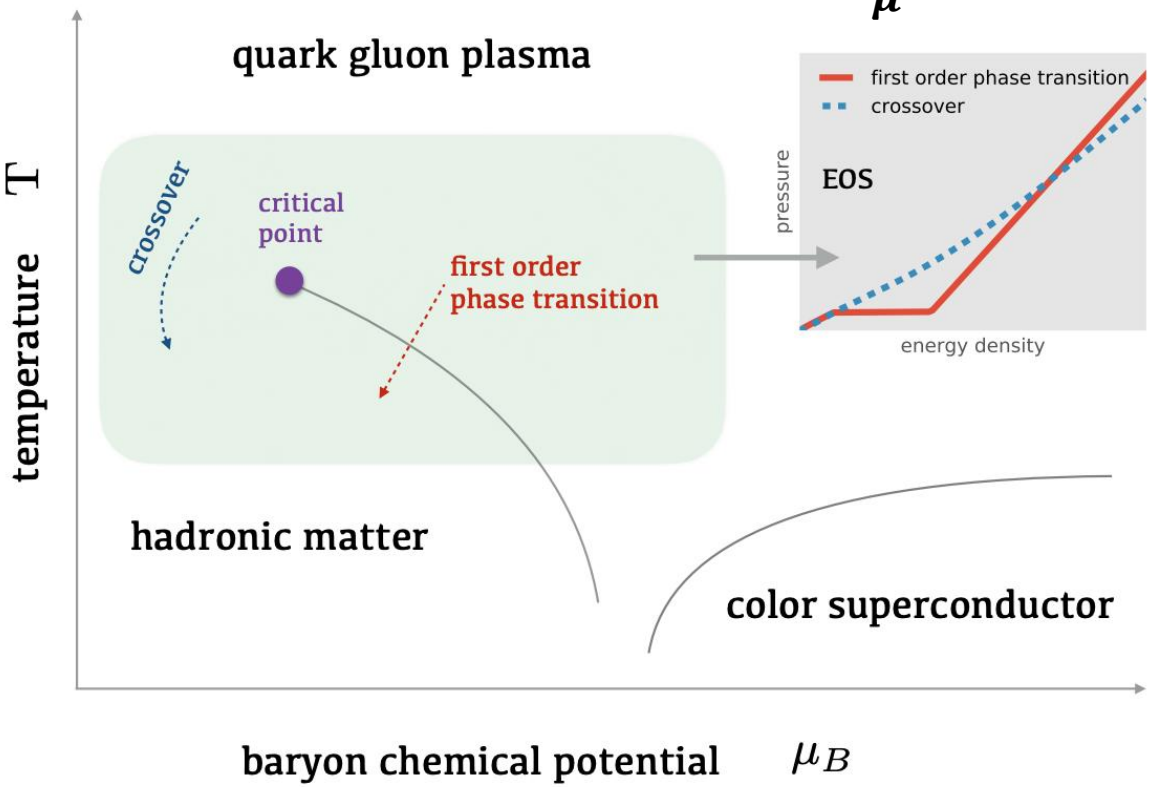
EoS for different phase transition types



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

cross entropy loss L2 regularization

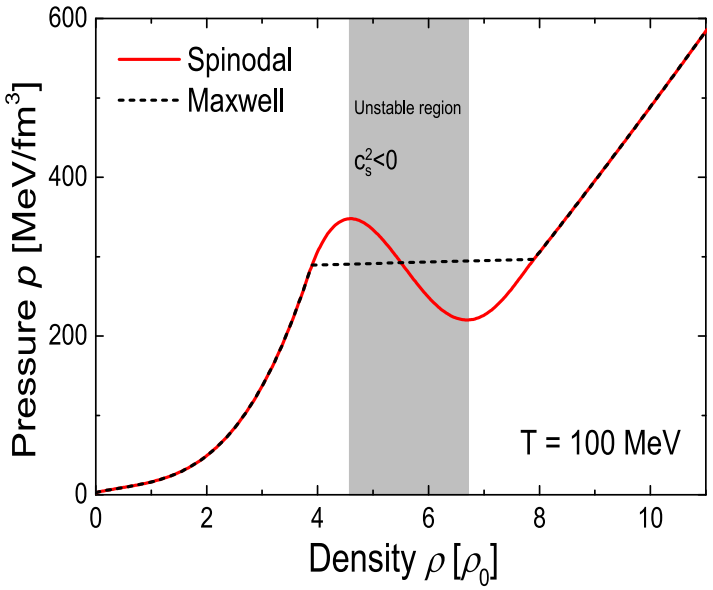
$$\nabla_\mu T^{\mu\nu} = 0$$

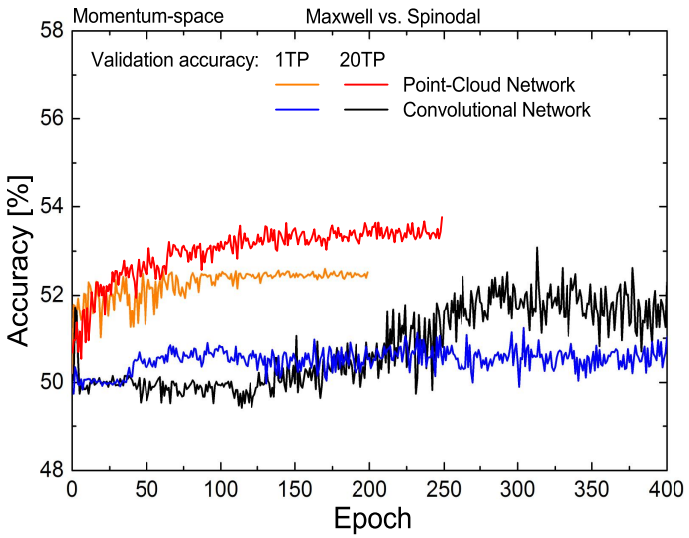


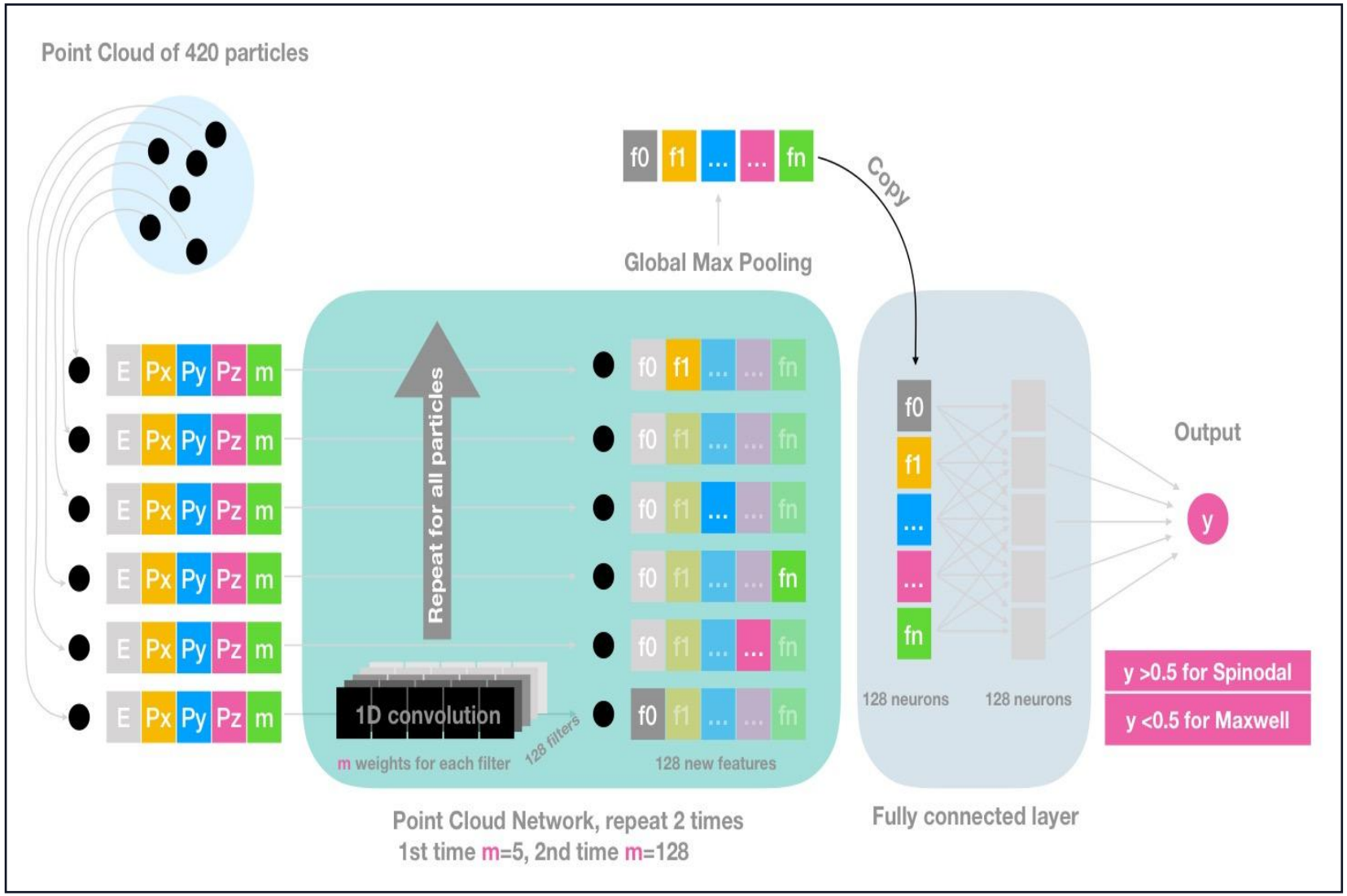
DL helps to decode the information of QCD phase transition in the QCD EoS (>93% accuracy).

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

Spinodal vs Maxwell 1st order phase transition

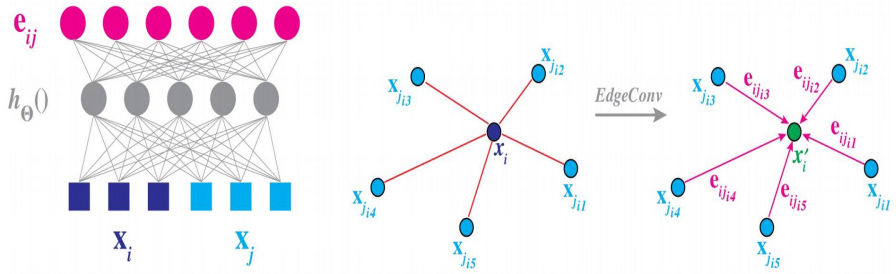


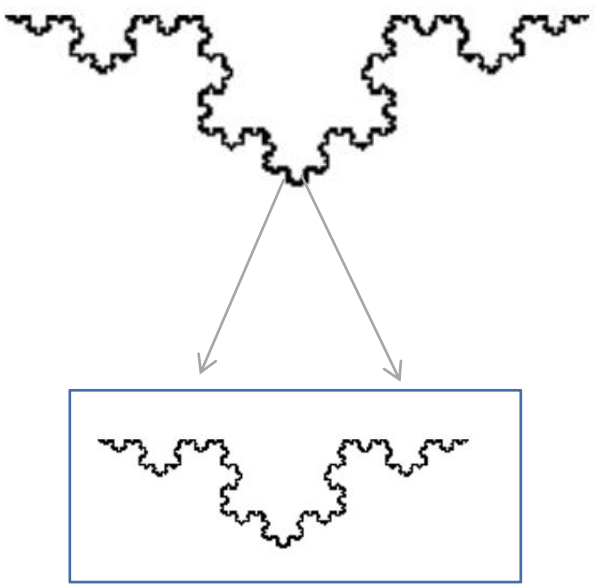




J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup, JHEP 12 (2019) 122

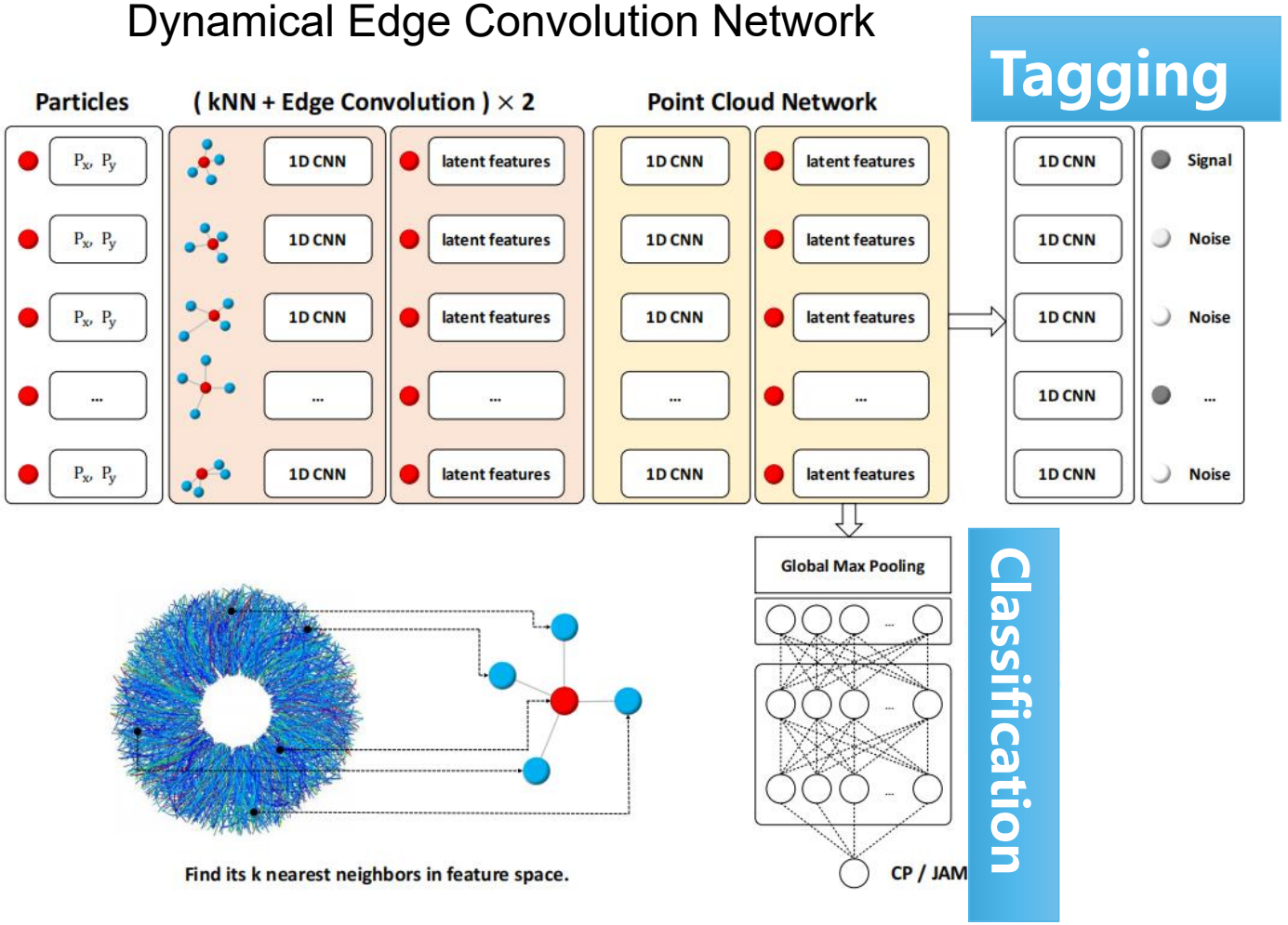
Looking for self similarity in momentum space





Self similarity, scaling invariance

Dynamical Edge Convolution Network



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

Active learning to map out unphysical EoS

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

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

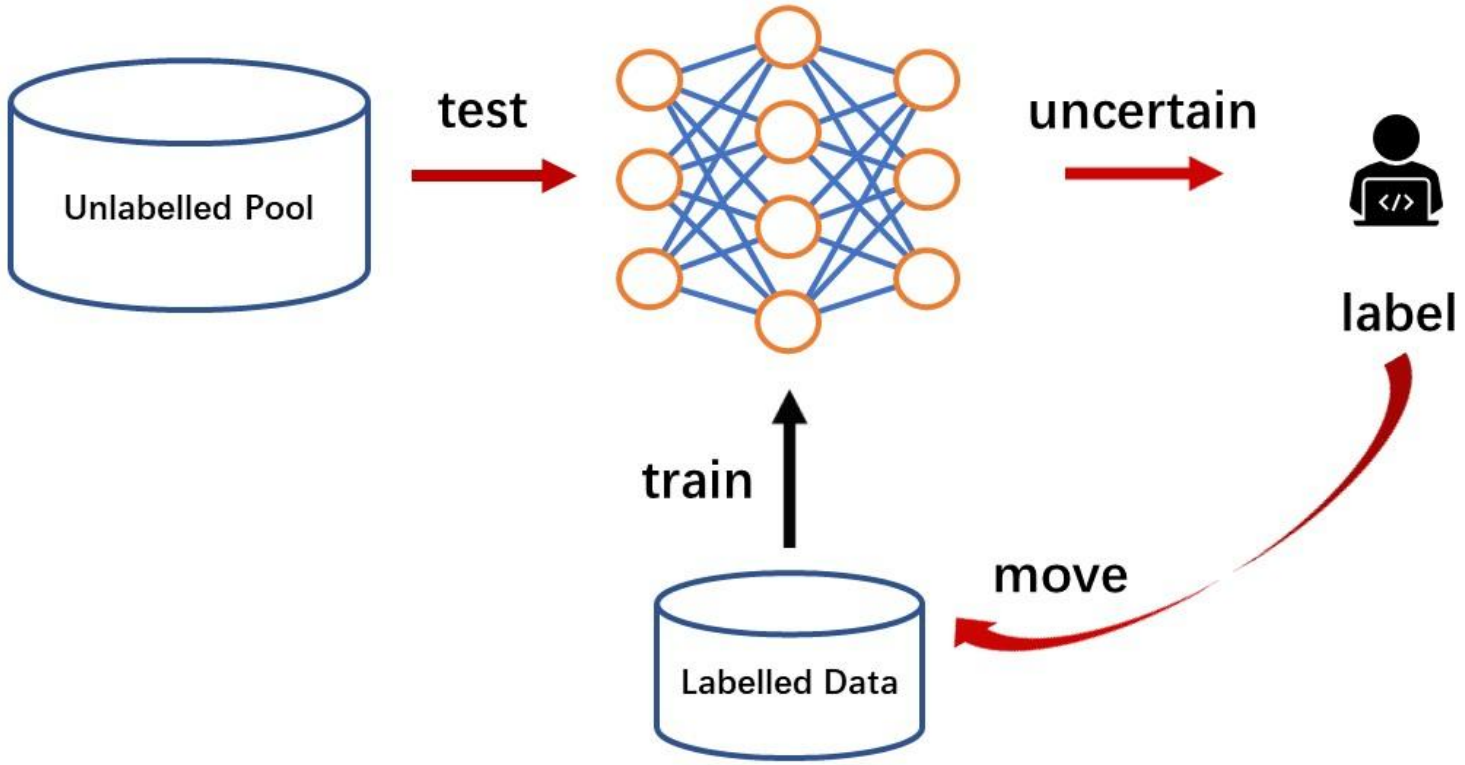
Acceptable = Stable + Causal

$$P, s, \varepsilon, n_B, \chi_2^B, \left(\frac{\partial S}{\partial T}\right)_{n_B} > 0\,, \qquad 0 \le c_s^2 \le 1.$$

D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta, PRC 107, 054911

Active learning

Achieve high performance with much fewer data (O(10^2))



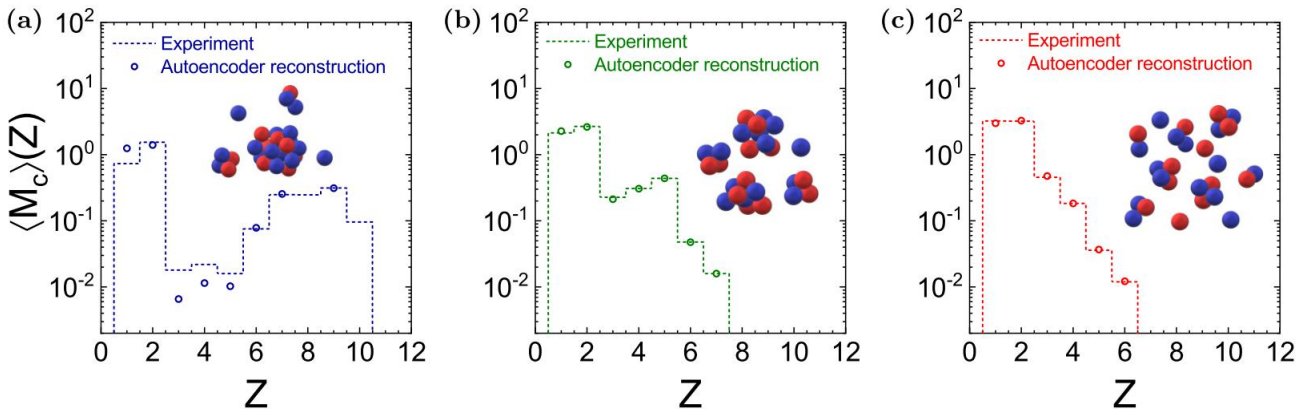
D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta, PRC 107, 054911

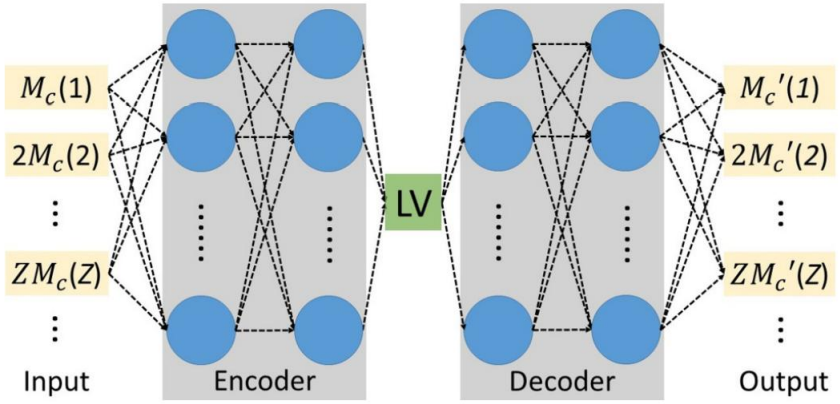
Auto Encoder for order parameter

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

Nuclear liquid-gas phase transition with machine learning

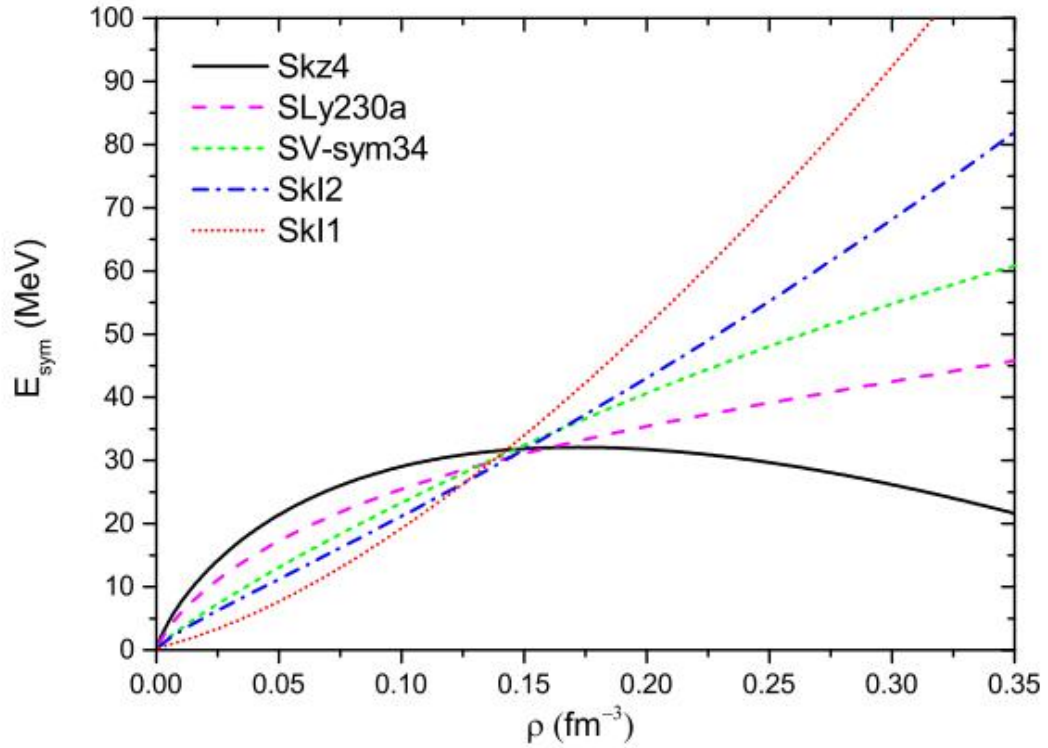
Rui Wang,[1,2,*] Yu-Gang Ma,[1,2,†] R. Wada,[3] Lie-Wen Chen,[4] Wan-Bing He,[1] Huan-Ling Liu,[2] and Kai-Jia Sun[3,5]



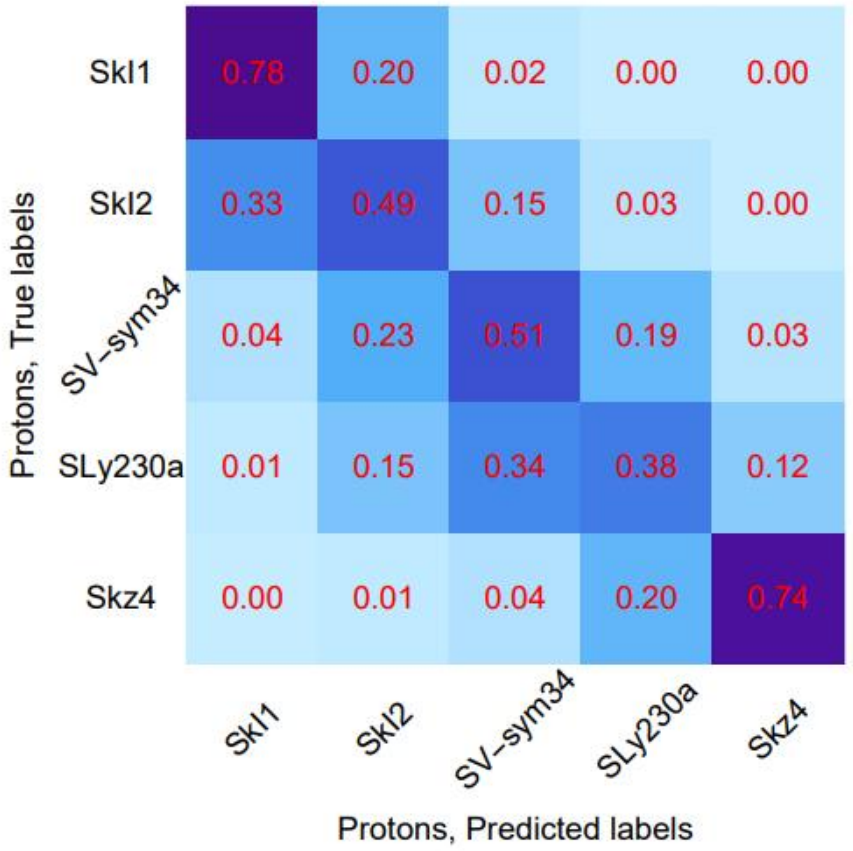


Nuclear EoS at high density region

Skyrme potential + IMQMD



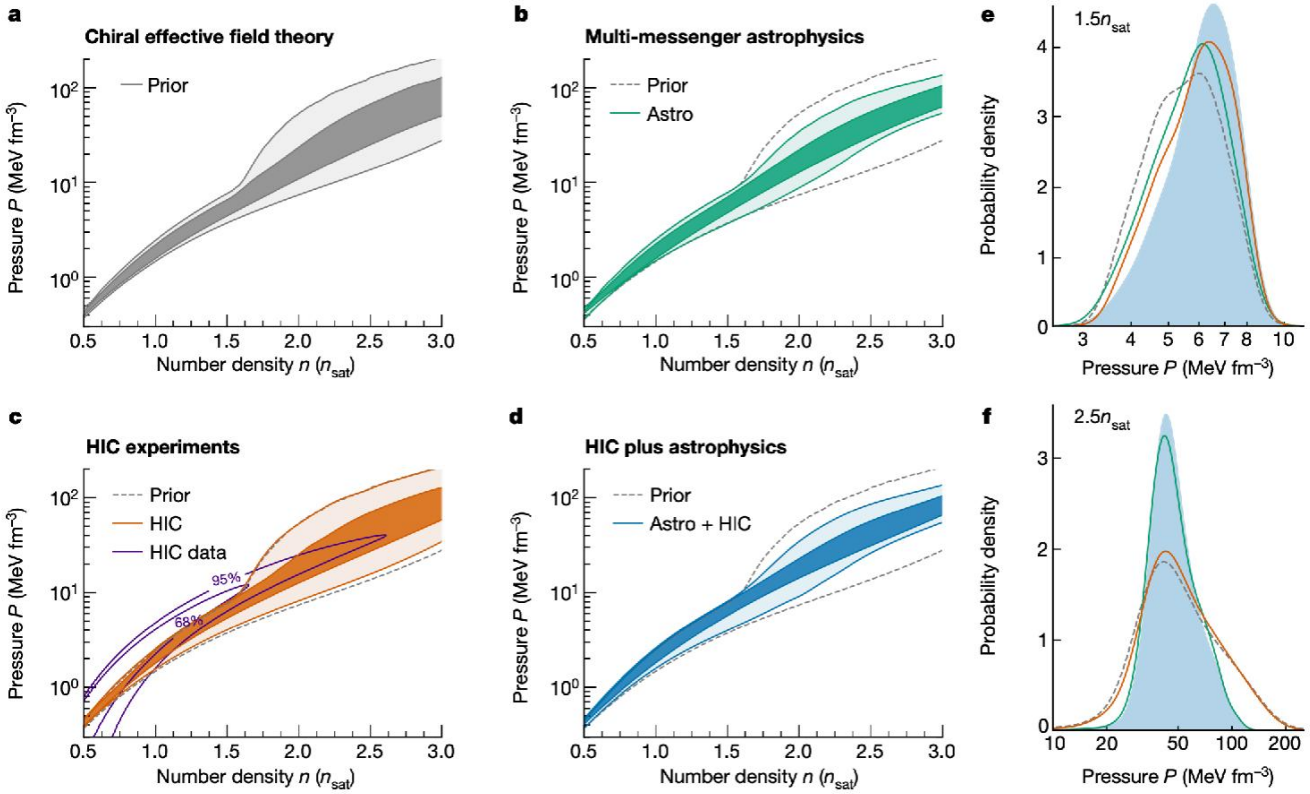
off-diagonal = misclassified

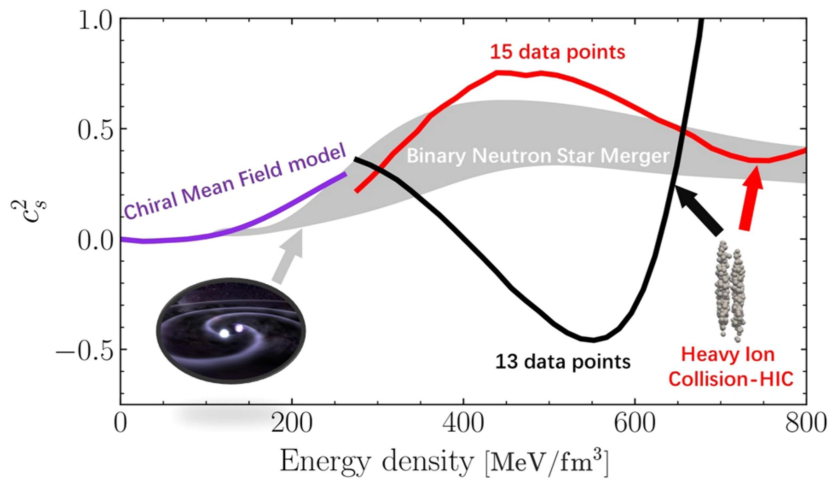


PLB 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

Bayesian analysis dense Nuclear EoS

through micro and macro collisions





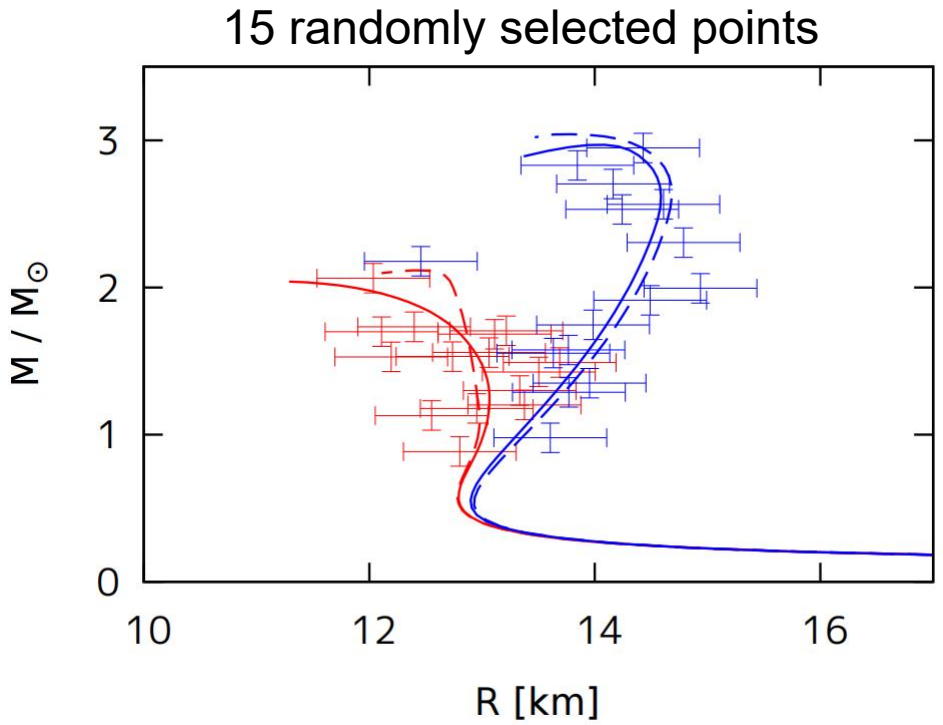
Left：Bayesian Inference Dense Matter EoS from HIC and astrophysics

Right：Bayesian Inference Dense Matter EoS from HIC using model (UrQMD) data comparison

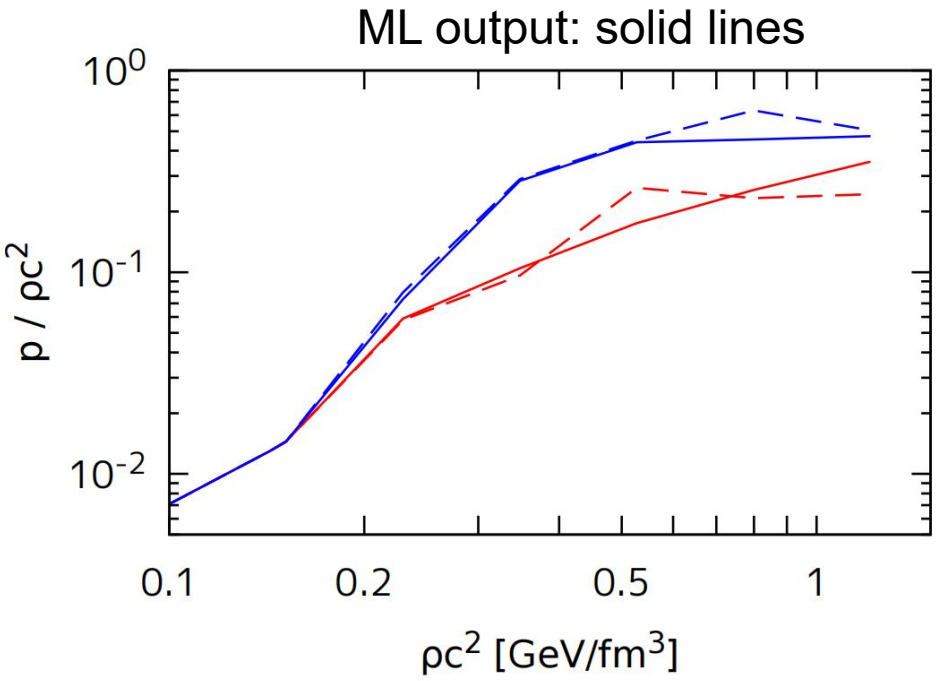
S. Huth et al., Nature 606, 276 (2022)

M.OK, J. Steinheimer, K. Zhou, H. Stoecker, PRL131,202303(2023)

TOV equation and nuclear EoS from DL



Network

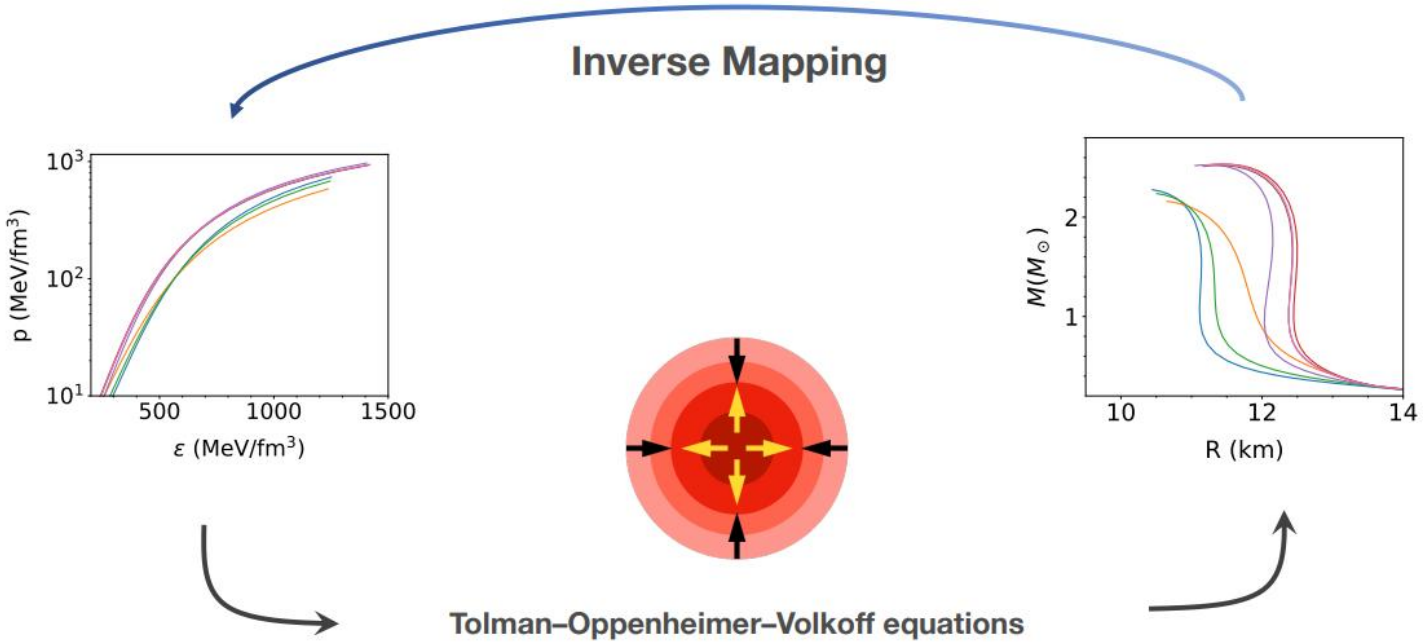


Yuki Fujimoto, Kenji Fukushima, and Koichi Murase, PRD 98 (2018) 2, 023019

TOV Equation and Nuclear EoS from DL

$$\frac{\mathrm{d}p}{\mathrm{d}r} = -G\frac{m(r)\varepsilon(r)}{r^2}\left(1+\frac{p(r)}{\varepsilon(r)}\right)\left(1+\frac{4\pi r^3 p(r)}{m(r)}\right)\left(1-\frac{2Gm(r)}{r}\right)^{-1},$$

$$\frac{\mathrm{d}m}{\mathrm{d}r} = 4\pi r^2 \varepsilon\,,$$



S. Soma, L. Wang, S. Shi, H. Stöcker, K. Zhou, PRD 107, (2023) 083028

Auto Differentiation: machine precision

- Forward Mode

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

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

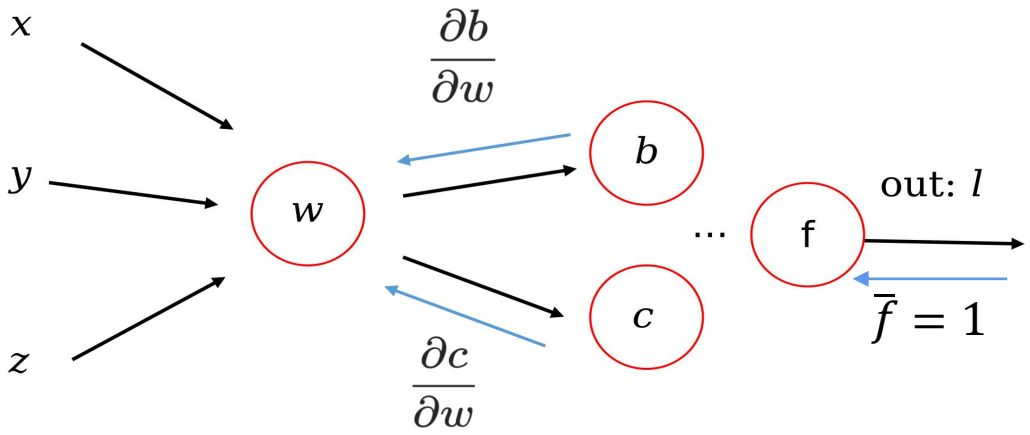
$$(x + \dot{x}\mathbf{d}) + (y + \dot{y}\mathbf{d}) = x + y + (\dot{x} + \dot{y})\mathbf{d}$$
$$(x + \dot{x}\mathbf{d}) - (y + \dot{y}\mathbf{d}) = x - y + (\dot{x} - \dot{y})\mathbf{d}$$
$$(x + \dot{x}\mathbf{d}) * (y + \dot{y}\mathbf{d}) = xy + (x\dot{y} + \dot{x}y)\mathbf{d}$$
$$\frac{1}{x + \dot{x}\mathbf{d}}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

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

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

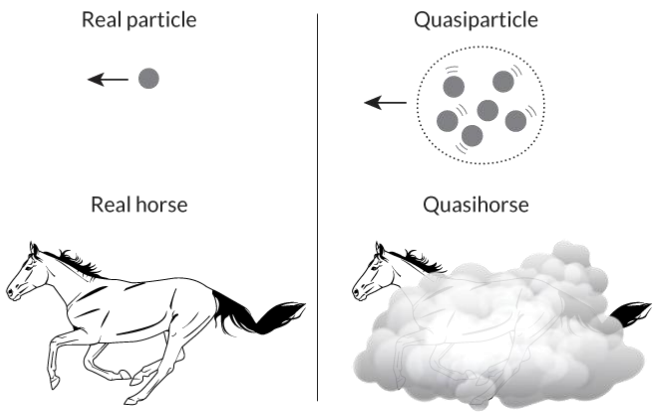
- Reverse Mode

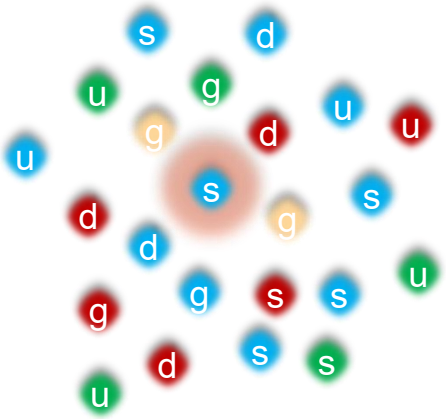
adjoint number: $\bar{w} = \frac{\partial l}{\partial w}$

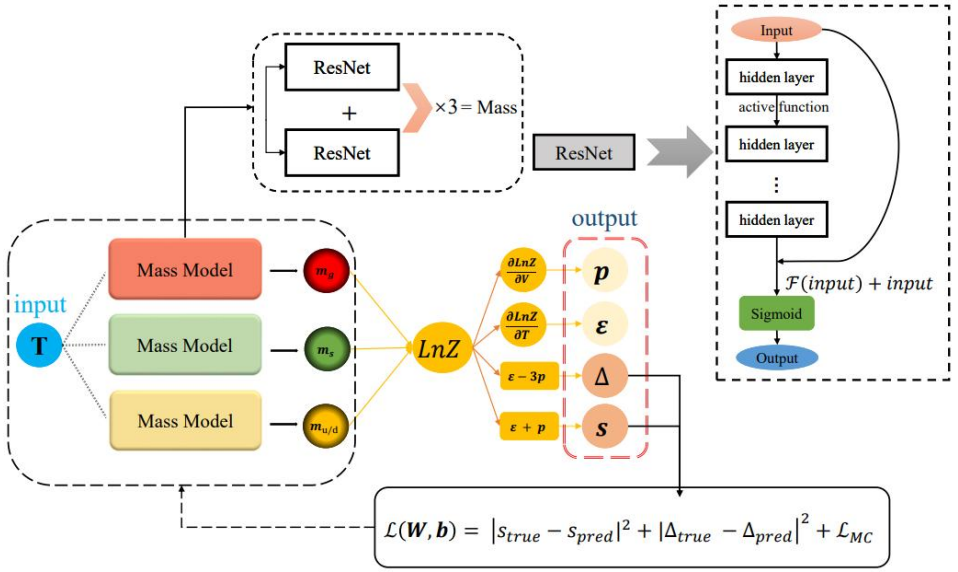


$$\text{step } 1 : \bar{w} = 0$$
$$\text{step } 2 : \bar{w} = \bar{w} + \bar{b}\frac{\partial b}{\partial w}$$
$$\text{step } 3 : \bar{w} = \bar{w} + \bar{c}\frac{\partial c}{\partial w}$$

Deep Learning Quasi Particle Model







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

Fermi-Dirac distributions,

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

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

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.

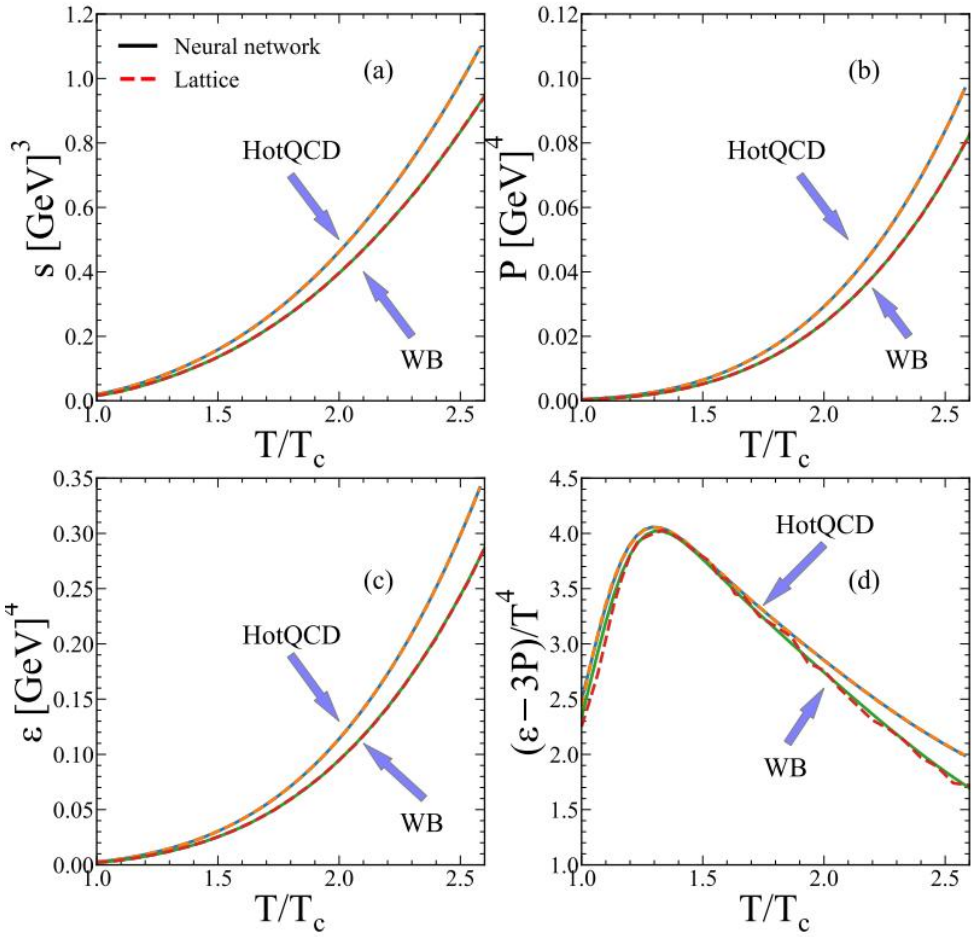
The resulting pressure and energy density are computed using the following statistical formulae,

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

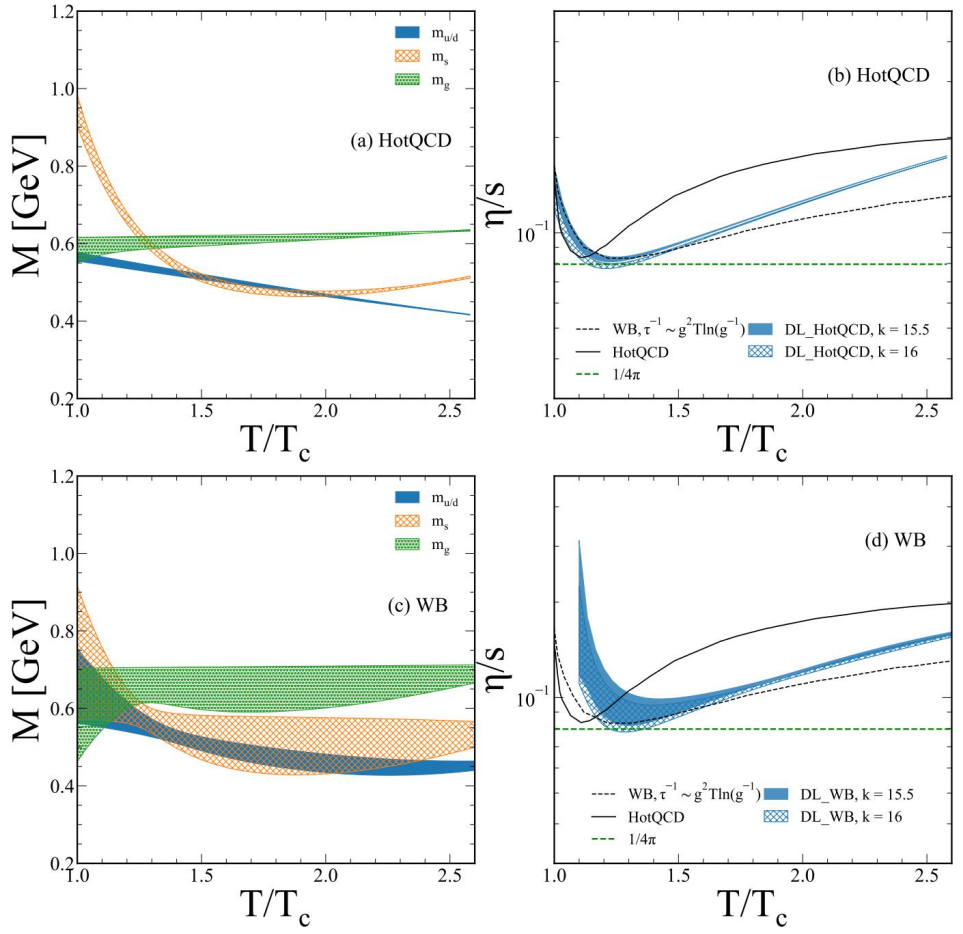
$$\epsilon(T) = \frac{T^2}{V}\left(\frac{\partial \ln Z(T)}{\partial T}\right)_V, \quad (6)$$

The learned quasi parton mass

EoS vs Lattice QCD

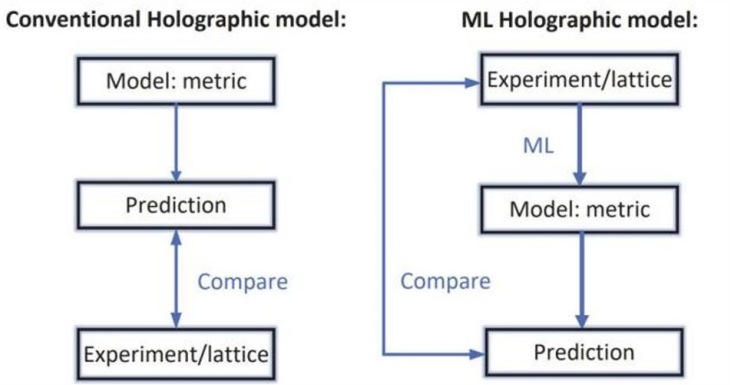


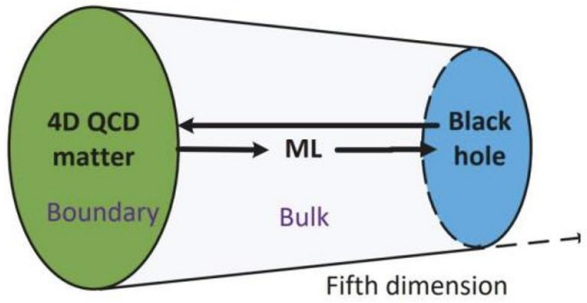
Learned Mass η/s

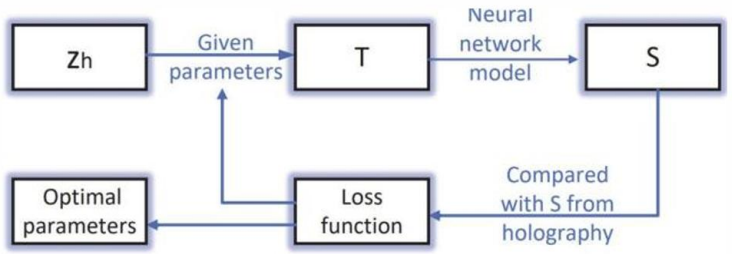


FuPeng Li, HL Lu, LG Pang, GY Qin, PLB 2023; Extend to finite μ_B, arXiv:2501.1001

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

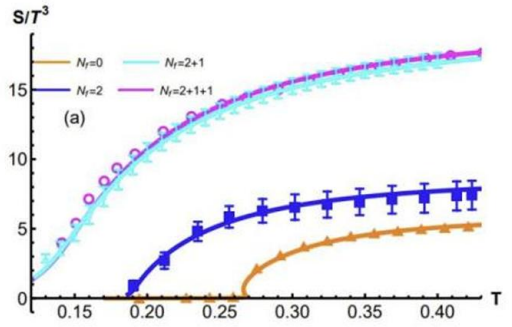
Non-conformal

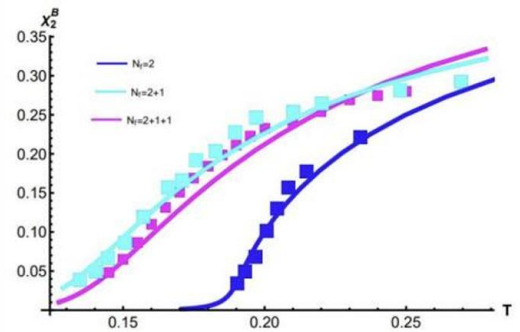
ϕ is dilaton F is the tensor of gauge field

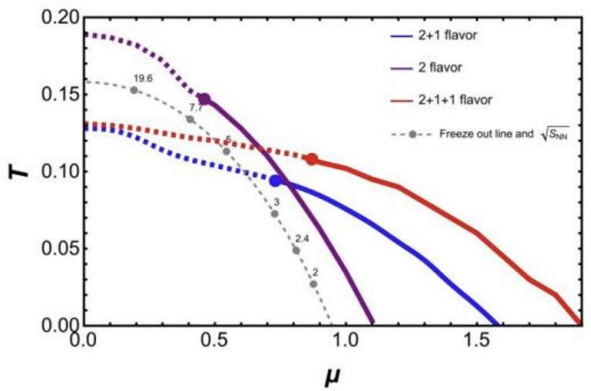
Metric ansatz: $$ds^2 = \frac{e^{2A(z)}}{z^2}\left[-g(z)dt^2 + \frac{dz^2}{g(z)} + d\vec{x}^2\right]$$

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

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







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

Stacked U-net for relativistic hydro

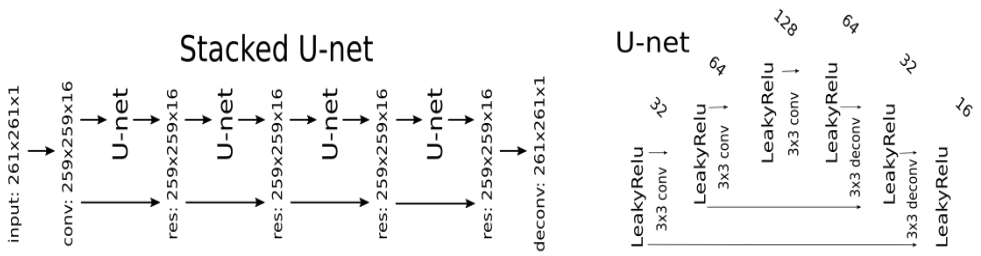
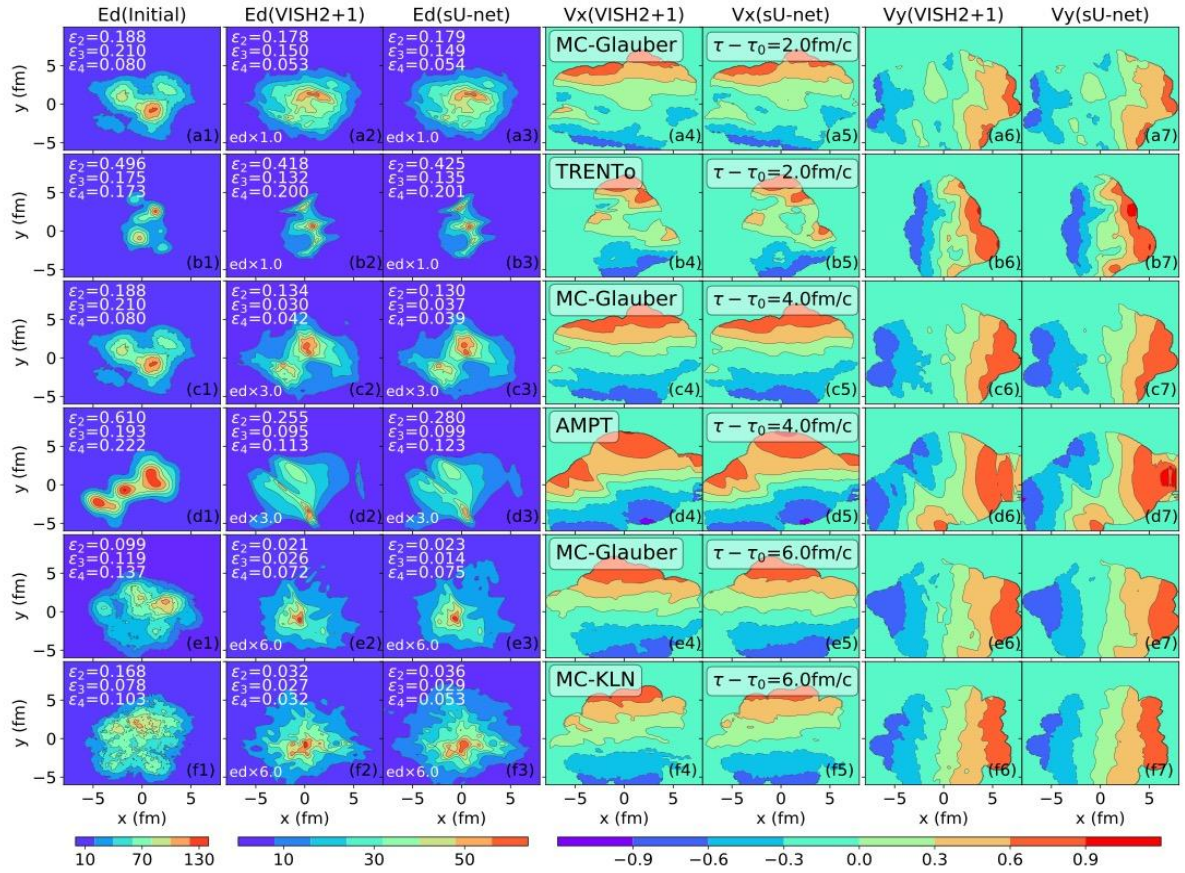


FIG. 1: An illustration of the encode-decode network, **stacked U-net**, which consists of the input and out layers and four residual U-net blocks. The right figure shows the U-net structure, and the depth of the hidden layer is written on the top of them.

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

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



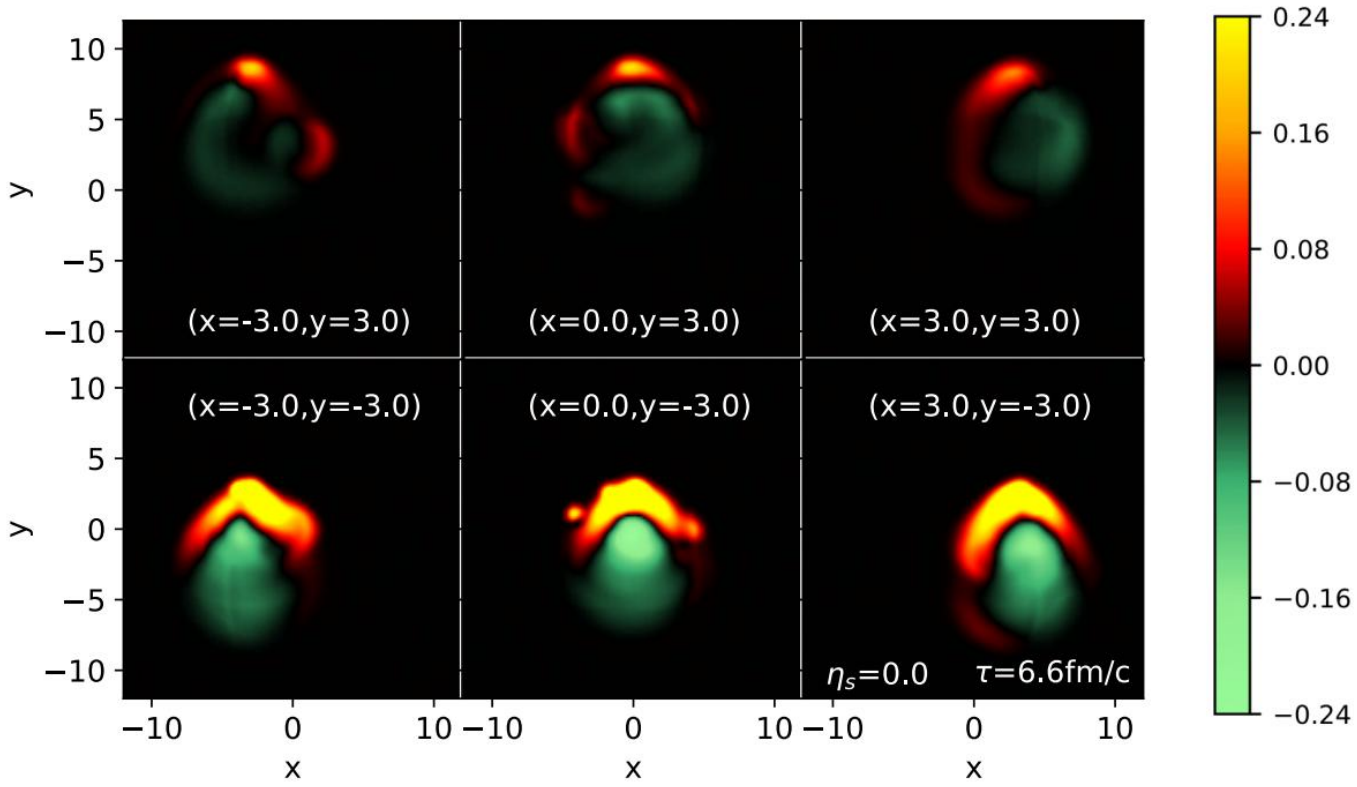
PRR. 3 (2021) 2, 023256, H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song

Medium response for nuclear EoS

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

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

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



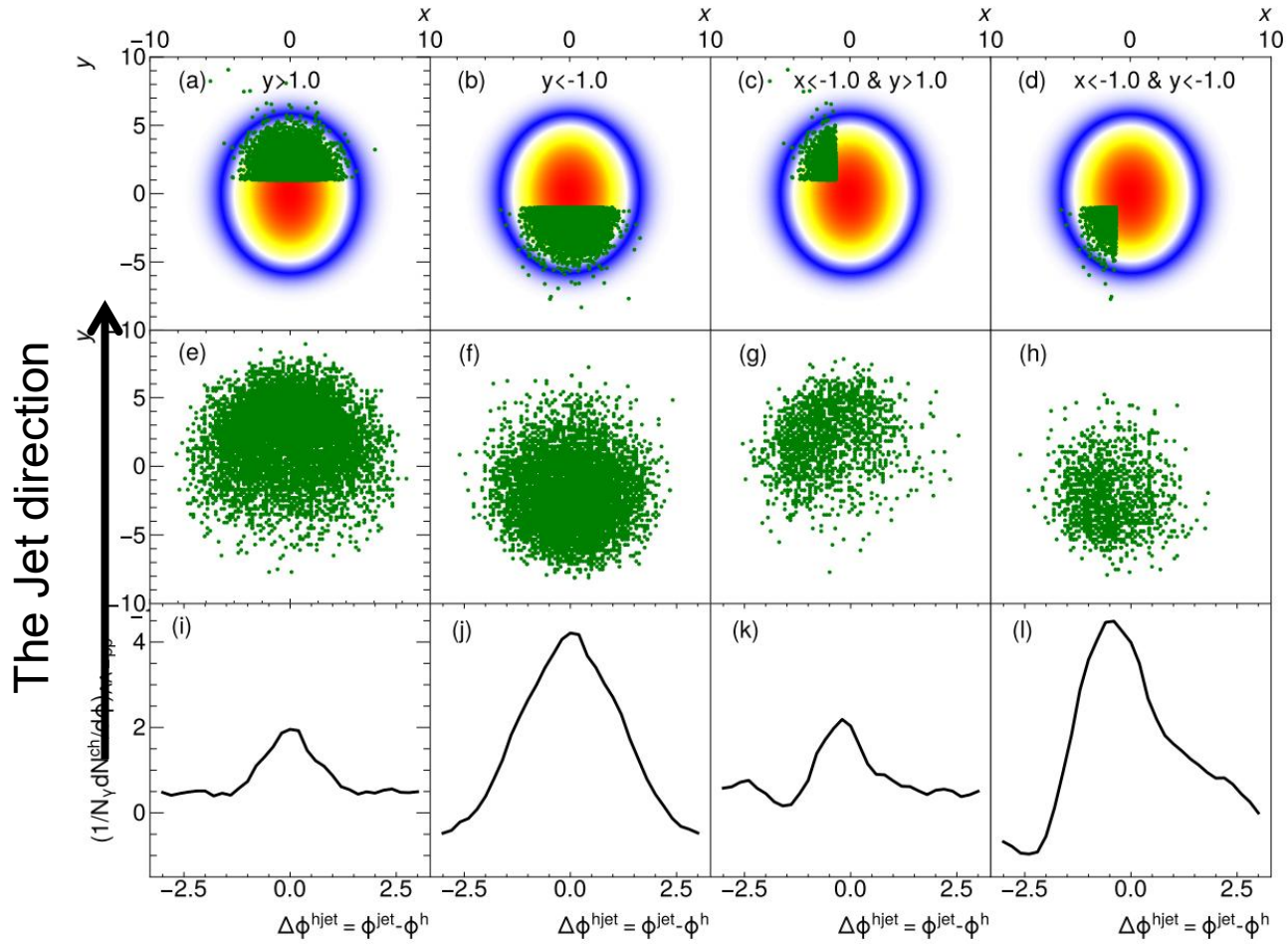
LBT: YY He, T Luo, XN Wang, Y Zhu,
PRC 91 (2015) 054908, PRC 97 (2018) 1, 019902

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

DL assisted jet tomography



Network predictions

True locations

Jet hadron correlation for selected events whose locations are constrained to specific regions using DL assisted jet tomography

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

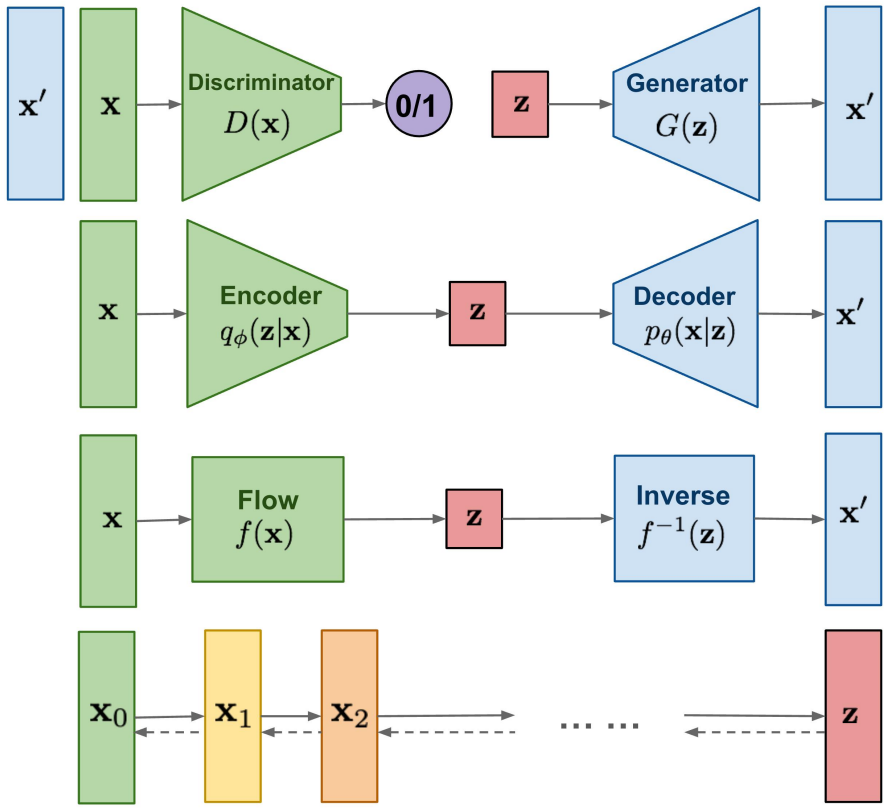
Generativive models: MC sampling

GAN: Adversarial training

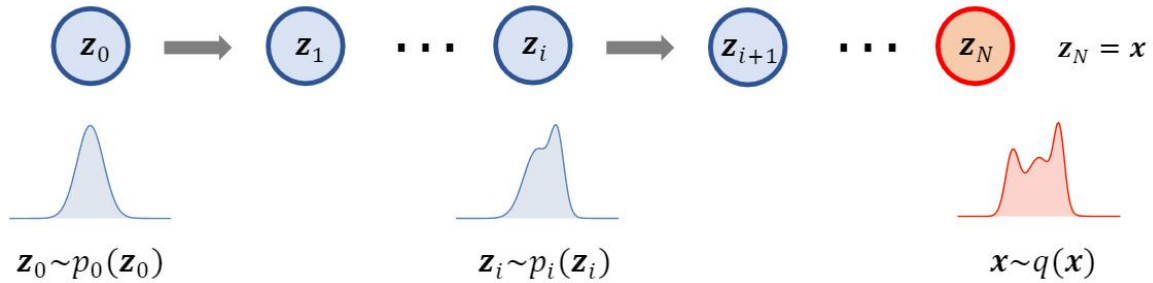
VAE: maximize variational lower bound

Flow-based models: Invertible transform of distributions

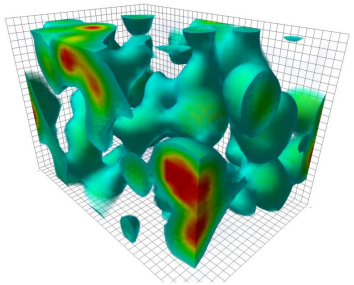
Diffusion models: Gradually add Gaussian noise and then reverse



Similar to Box Muller algorithm

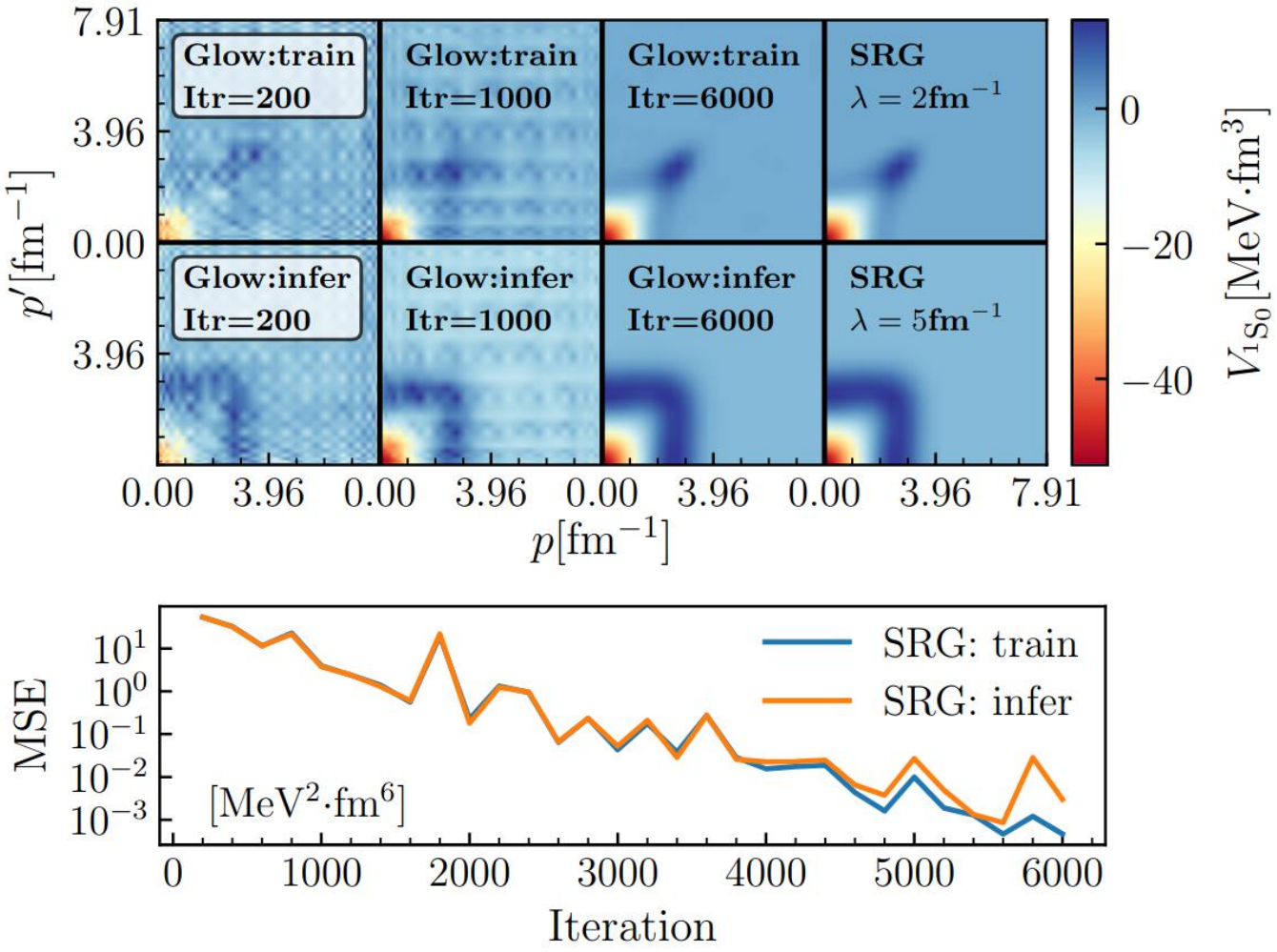


Samples Drawn from N-Dim Normal Distribution → Flow model or Diffusion models →



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

Learn NN interaction potential



train the **generative model on nucleon-nucleon potentials derived at second and third order in chiral effective field theory** and at three different choices of the resolution scale. We then show that the model can be used to generate samples of the nucleon-nucleon potential drawn from a continuous distribution in the resolution scale parameter space. The generated potentials are shown to produce high-quality nucleon-nucleon scattering phas

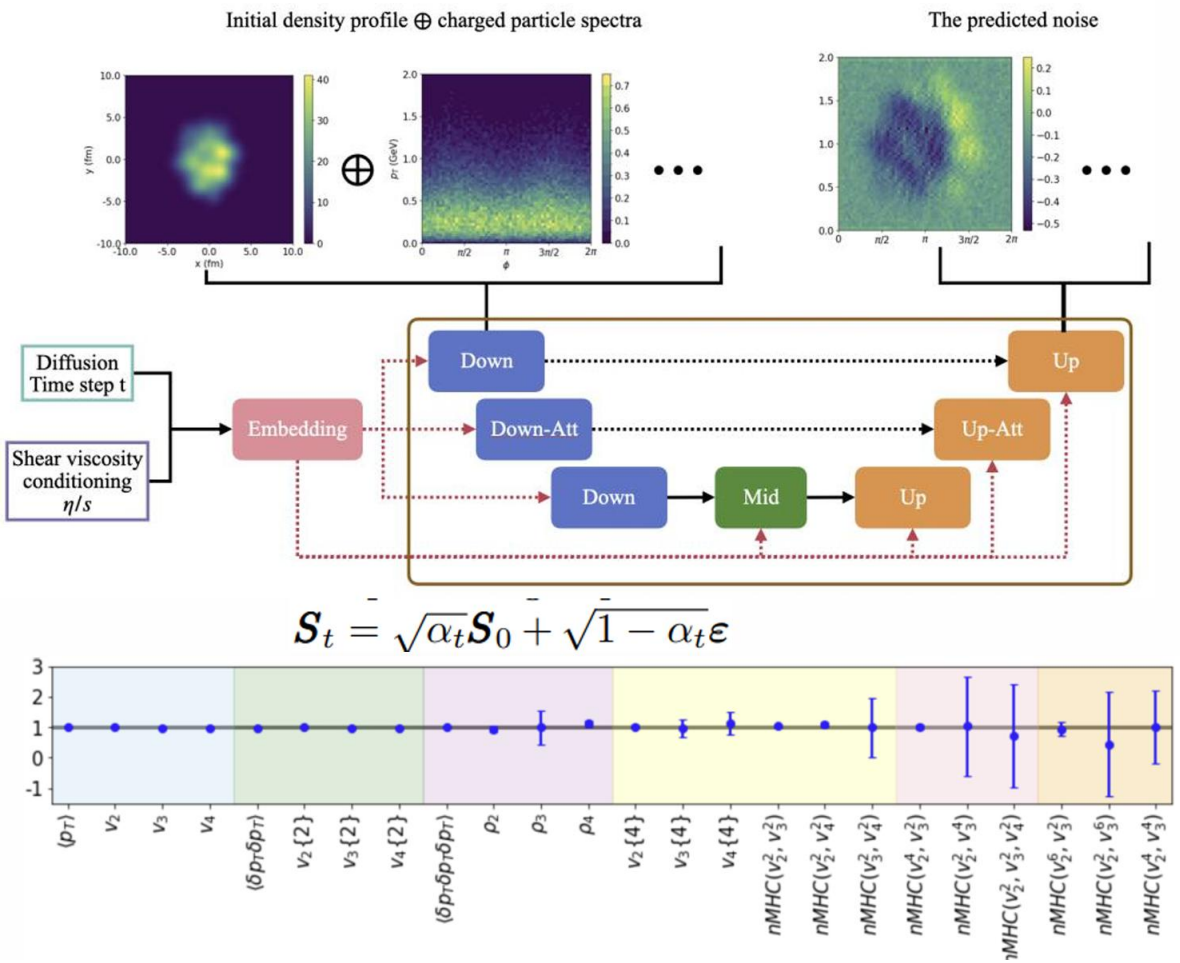
Wen P, Holt J.W., Li M, 2306.13007

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



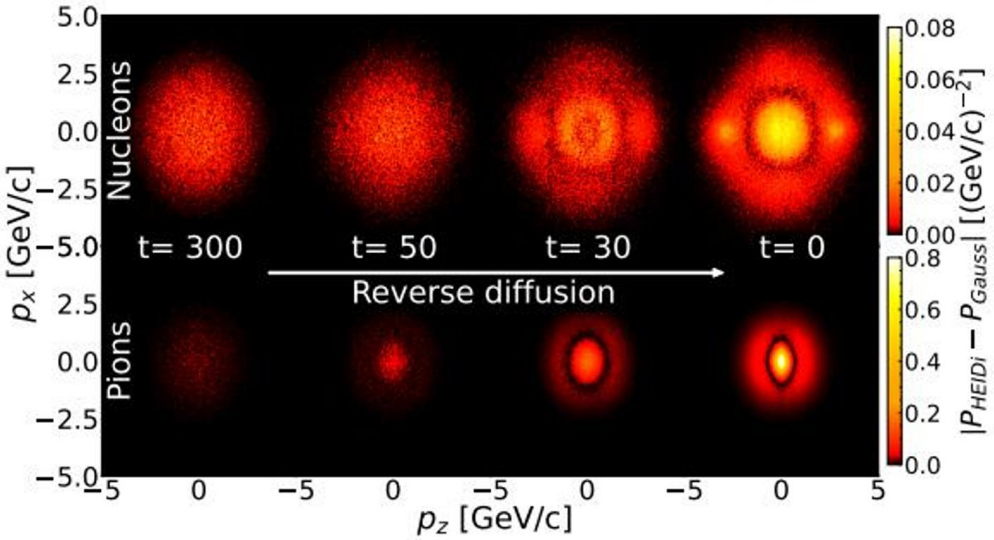
tor. We carried out (2+1)D minimum bias simulations of Pb-Pb collisions at 5.02 TeV, choosing the shear viscosity η/s to be one of three distinct values: 0.0, 0.1, and 0.2. For each value of η/s, we generate 12,000 pairs of initial entropy density profiles and final particle spectra corresponding to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

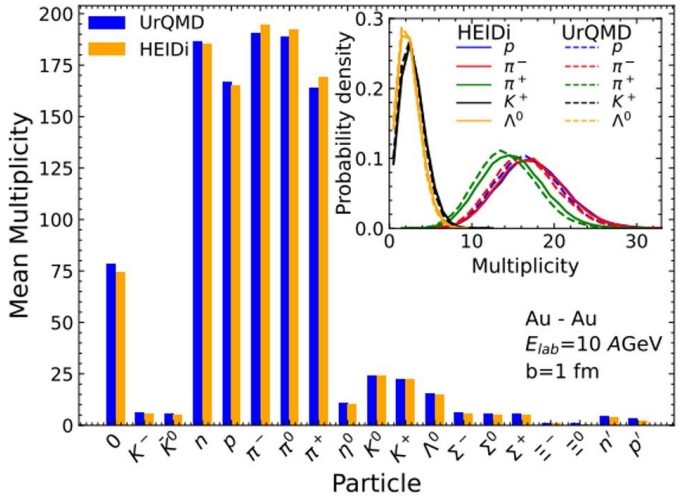
Considering that the spectra $\boldsymbol{S}_0$ depend on the initial entropy density profiles $\boldsymbol{I}$ and the shear viscosity η/s, we train a conditional reverse diffusion process $p(\boldsymbol{S}_0|\boldsymbol{I}, \eta/s)$ without modifying the forward process.

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





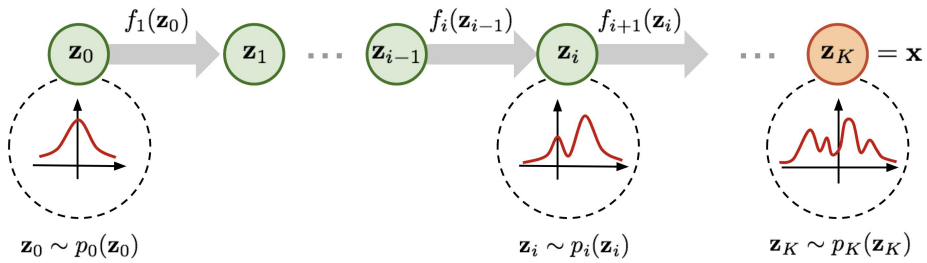
M. O.K, K. Z, J. S, H. S, arXiv: 2502.16330, arXiv:2412.10352

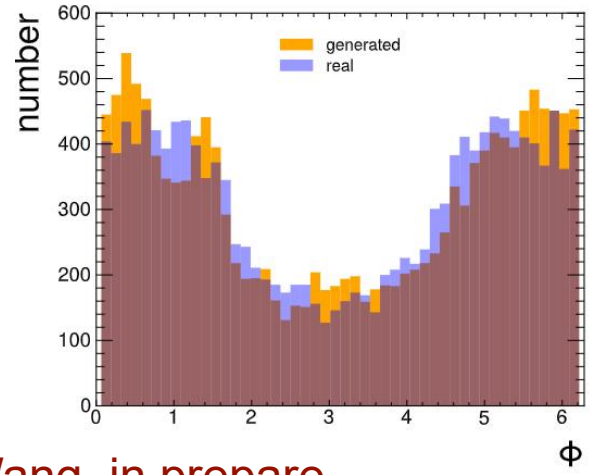
18k **UrQMD** simulation events for training

HEIDi:
Heavy-ion Events through Intelligent Diffusion

PointNet encoder + Normalizing flow decoder + Pointcloud diffusion

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





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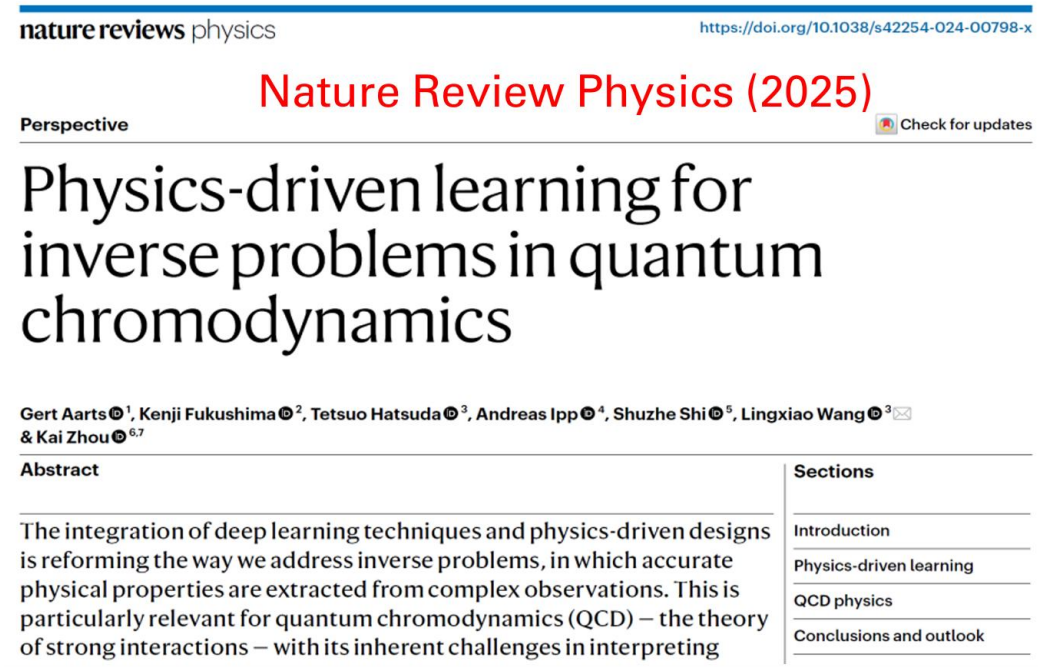
nature reviews physics

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

Nature Review Physics (2025)

Perspective

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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


Review Of Modern Physics (2022)

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Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang

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

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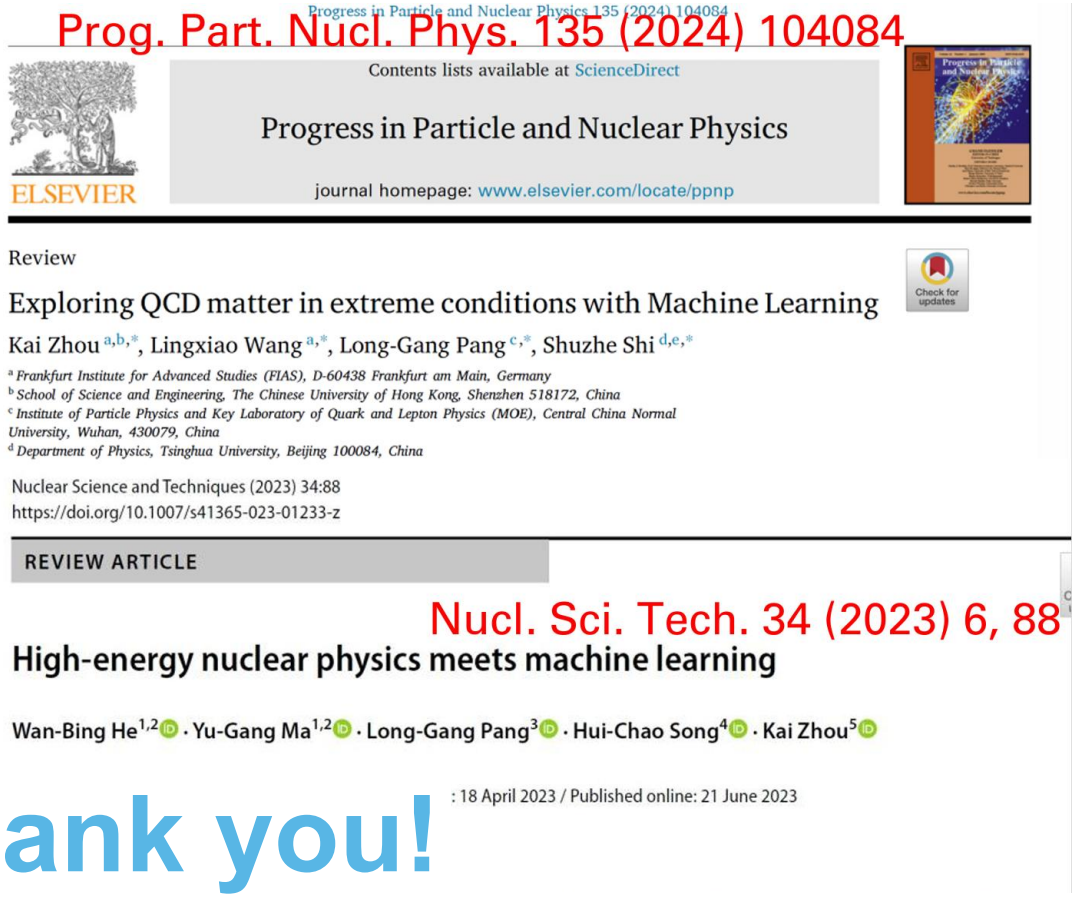
Progress in Particle and Nuclear Physics 135 (2024) 104084

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Review

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Exploring QCD matter in extreme conditions with Machine Learning

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

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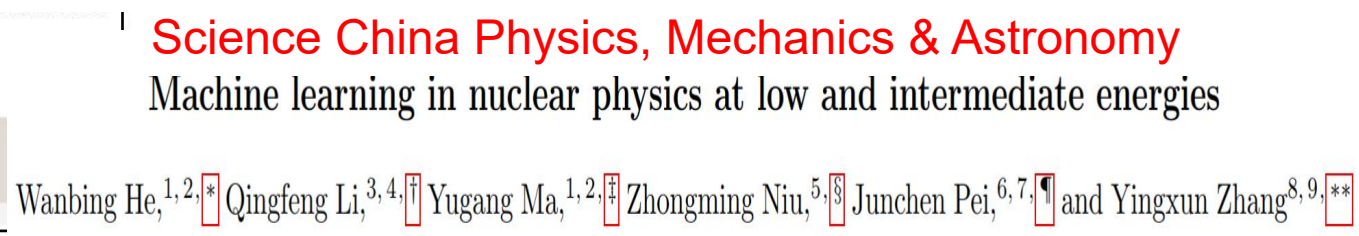
Nucl. Sci. Tech. 34 (2023) 6, 88

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

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,**]