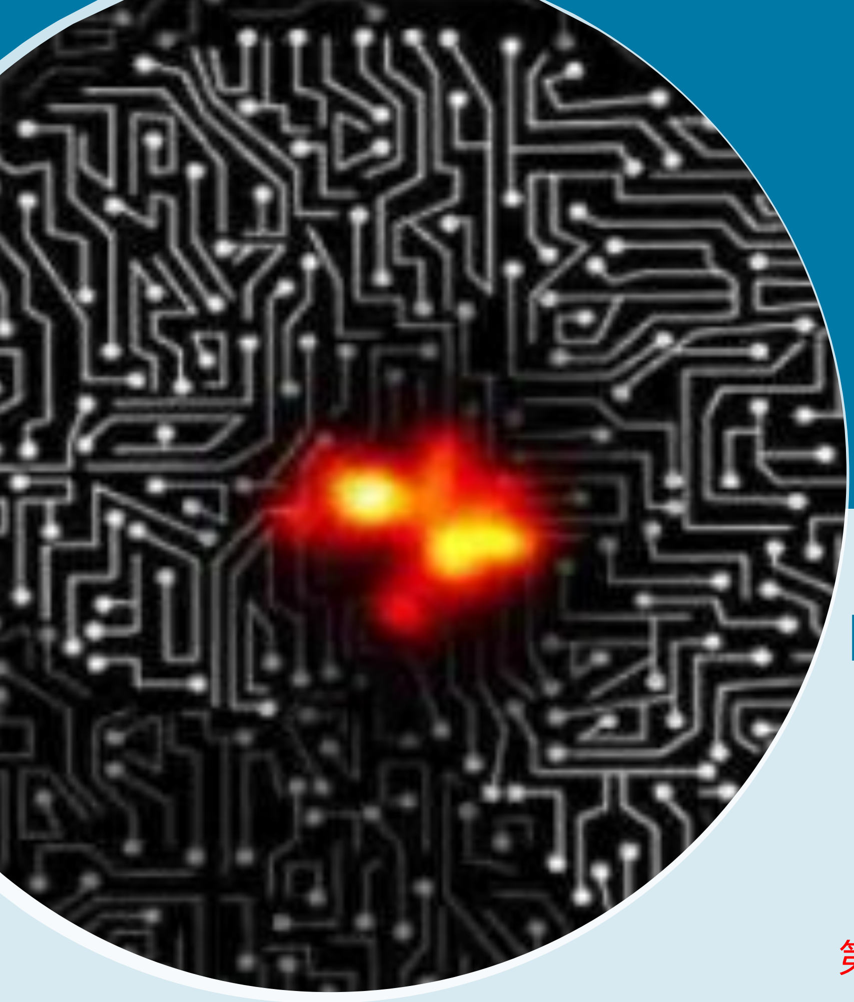


香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

Machine Learning in High Energy Nuclear Physics

Kai Zhou (CUHK-Shenzhen)

第二十届全国中高能核物理大会, 上海, 2025

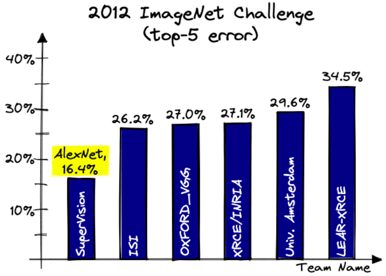
Overview : Nuclear Physics meets Machine Learning

- **2012** : Discovery of Higgs boson

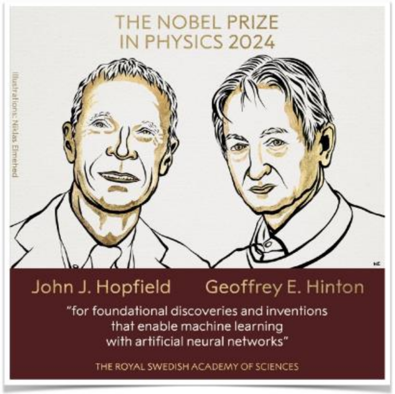

The New York Times
Physicists Find Elusive Particle Seen as Key to Universe

- AlexNet - Birth of Deep Learning

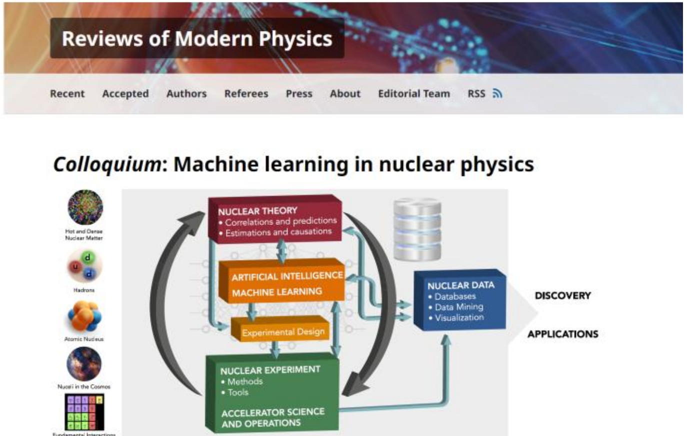

The New York Times
Chatbots › OpenAI Unveils GPT-4 What GPT-4 Can and Can't Do Funding Frenzy Escalates How C
Scientists See Promise in Deep-Learning Programs
Give this article



- **2024** : Nobel Prize in Physics



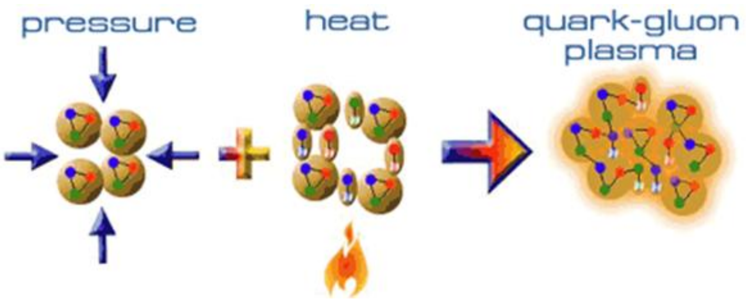
- ML4Physics, AI4Science

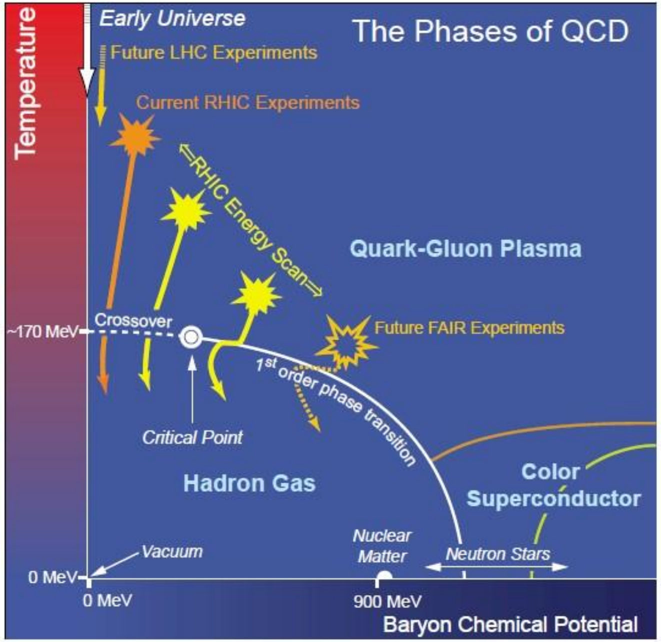


Overview : Golden Age of QCD matter in extreme

- **Phases** of matter : solid, liquid, gas, plasma

- Matter in extreme conditions reveals its **constituents** :
  nuclear matter → quark matter





To study **the most elementary particle matter** :

- **Nuclear Collisions** : heat & compress matter

- **Lattice Field Theory / fQCD / Effective models**

- **Neutron Star** : dense matter, astronomy constraints

Fig: arXiv:1804.04649

Initial Stage

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

$$p^\mu \partial_\mu f + F \cdot \partial_p f = C$$

Final State

Impact parameter
Nuclear structure

Bulk Matter properties:
Phase Transition
EOS
Shear/Bulk viscosities
Hard Probes

Event Generation
Final observables

Outline: Initial state + Bulk matter + Generative model

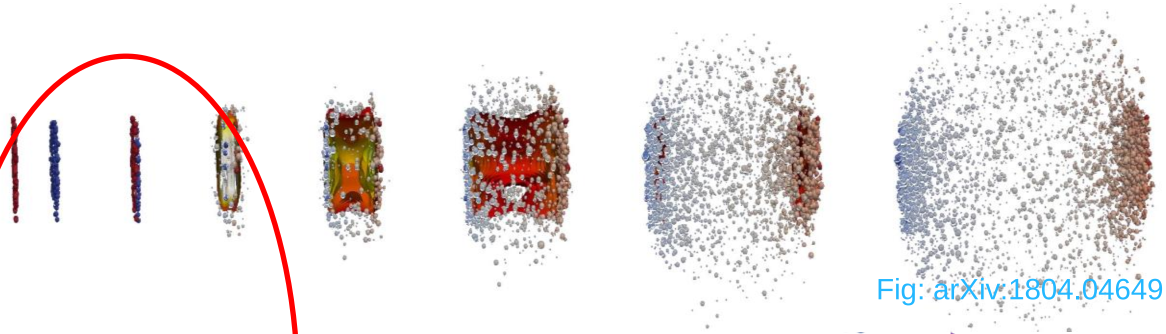


Fig: arXiv:1804.04649

Initial Stage

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$$p^\mu \partial_\mu f + F \cdot \partial_p f = C$$

Final State

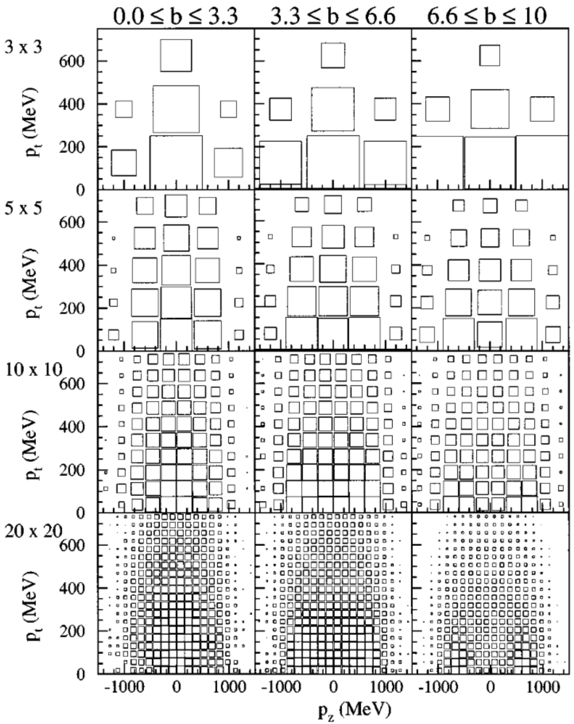
Impact parameter
Nuclear structure

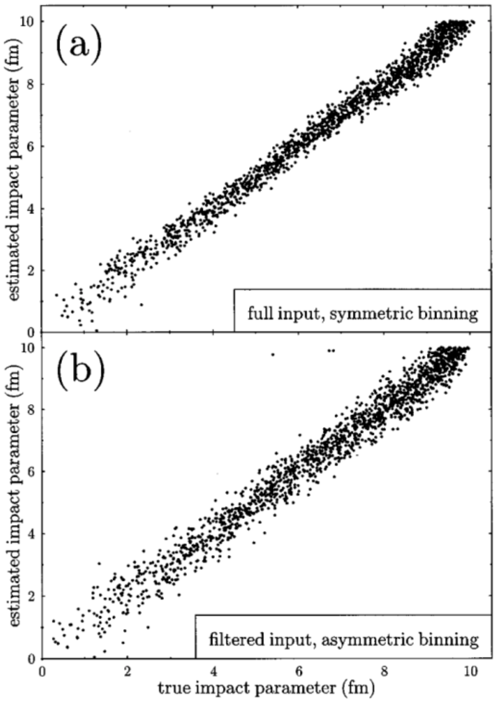
Bulk Matter properties:
Phase Transition
EOS
Shear/Bulk viscosities
Hard Probes

Event Generation
Final observables

impact parameter determination – early attempts

Simple DNN
Trained on
QMD data
Input 5X5



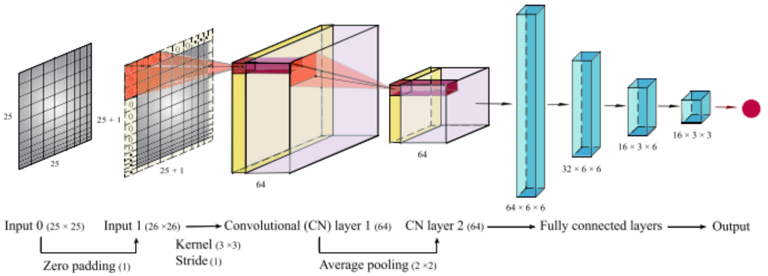


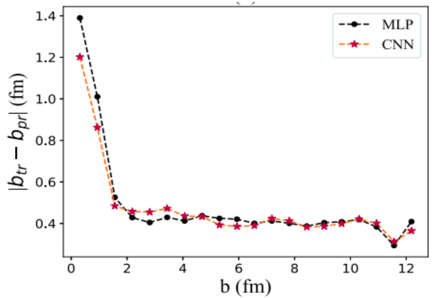
S. A. Bass, A. Bischoff, J. A. Maruhn, H. Stöcker, and W. Greiner, Phys. Rev. C 53, 2358 (1996)

Further developments for impact parameter/centrality regression

P. Xiang, Y. Zhao, X. Huang,
Chi. Phys. C 53, 2358 (2022)

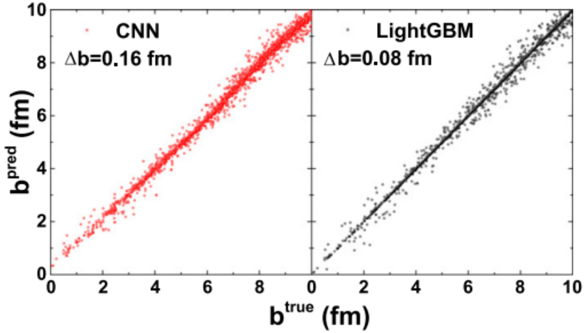
MLP and **CNN**
(on AMPT event)

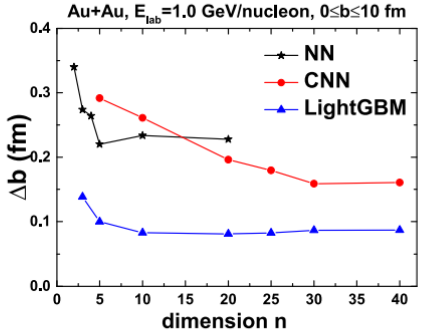




F. Li, Y. Wang, H. Lue, P. Li,
Q. Li, F. Liu, **JPG** 47, 115104 (2020)

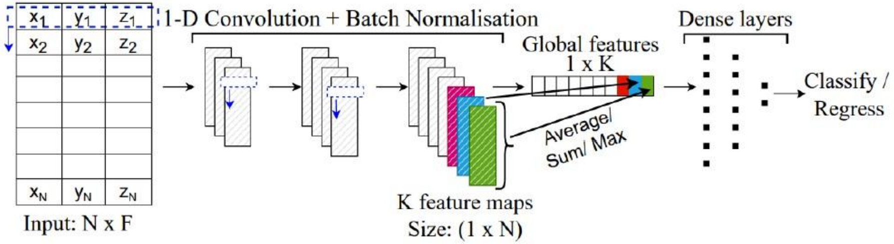
CNN and **LightGBM**
(on UrQMD event)

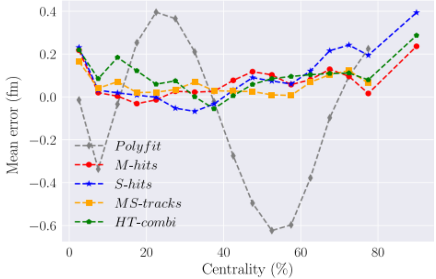




M. OK, J. S, K. Z, H. S,
PLB 811,135872 (2020)

PointCloud Network
(on UrQMD + CBMRoot event)
End-to-end b estimation





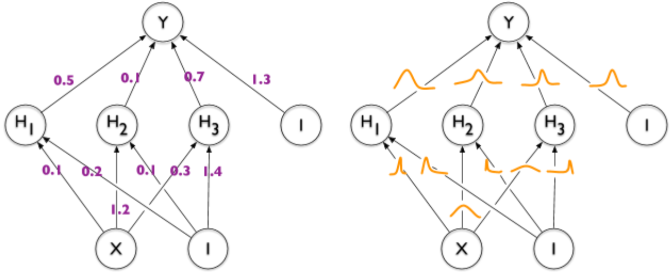
Manjunath O.K. and Kai Zhou, etc. *Phys.Lett.B* 811 (2020) 135872; JHEP10(2021)184.

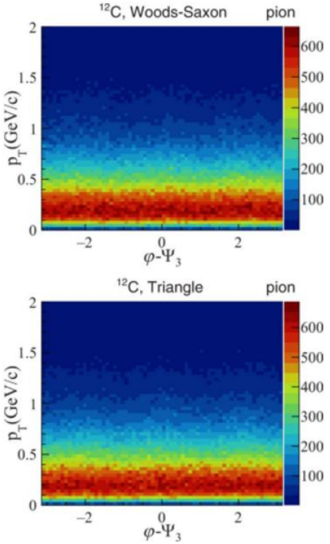
Initial clustering structure identification in HICs with BNN

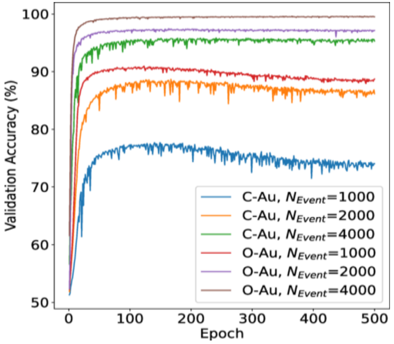
PHYSICAL REVIEW C **104**, 044902 (2021)

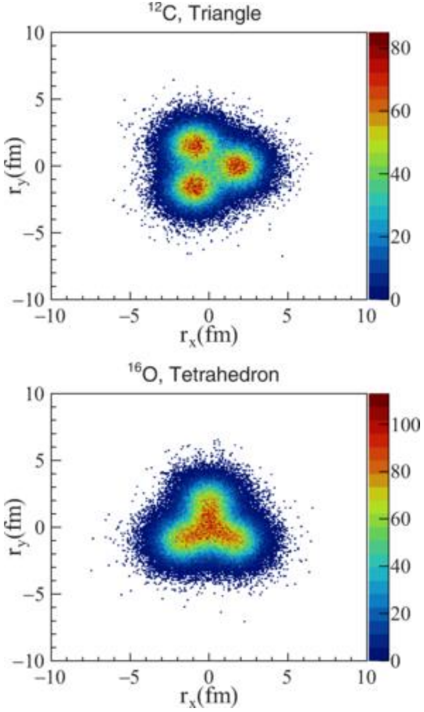
Machine-learning-based identification for initial clustering structure in relativistic heavy-ion collisions

Junjie He (何俊杰)[1,2] Wan-Bing He (何万兵)[3,*] Yu-Gang Ma (马余刚)[3,†] and Song Zhang (张松)[3]









Bayesian CNN

on AMPT events (multiple-event basis)

Charged pions (phi, pT) from 12C/16O + 197Au collisions at 200 GeV

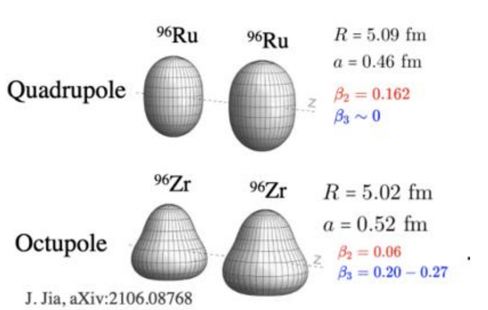
Multiple event basis

Bayesian Imaging for Nuclear Structure in Isobar Collisions

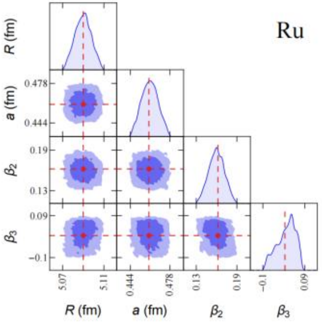
- Nuclear Structure imaging for single system ? (caveat: model dependent)

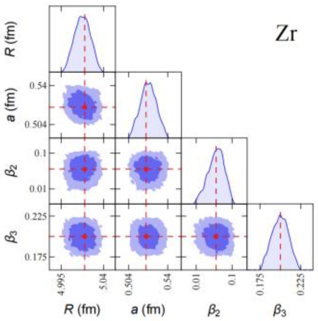
- Simultaneous inference for isobar systems with ratio?
- **Bayesian Inference:** Gaussian Process emulator + PCA dim reduction + MCMC

Data: MC-Glauber + Matching (linear response approximation)

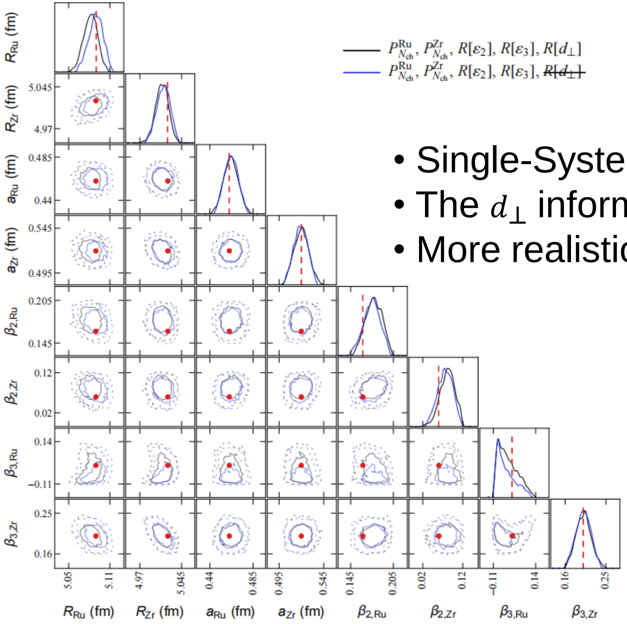


$$\boldsymbol{y}_{\mathrm{Ru}} \equiv \{P_a^{\mathrm{Ru}}, \varepsilon_{2,a}^{\mathrm{Ru}}, \varepsilon_{3,a}^{\mathrm{Ru}}, d_{\perp,a}^{\mathrm{Ru}}\}_{a=1,\cdots,40}$$





Single system works good



- Single-System Multiplicity makes it possible
- The $d_\perp$ information is redundant
- More realistic analysis with AMPT in progress

$$\boldsymbol{y}_{\mathrm{r},2} \equiv \{P_a^{\mathrm{Ru}}, P_a^{\mathrm{Zr}}, R_{\varepsilon_2,a}, R_{\varepsilon_3,a}, R_{d_\perp,a}\}_{a=1,\cdots,40}$$

Y.Cheng, S.Shi, Y. Ma, H. S., K. Zhou,
Phys. Rev. C 107 (2023) 064909

Outline: Initial state + Bulk matter + Generative model

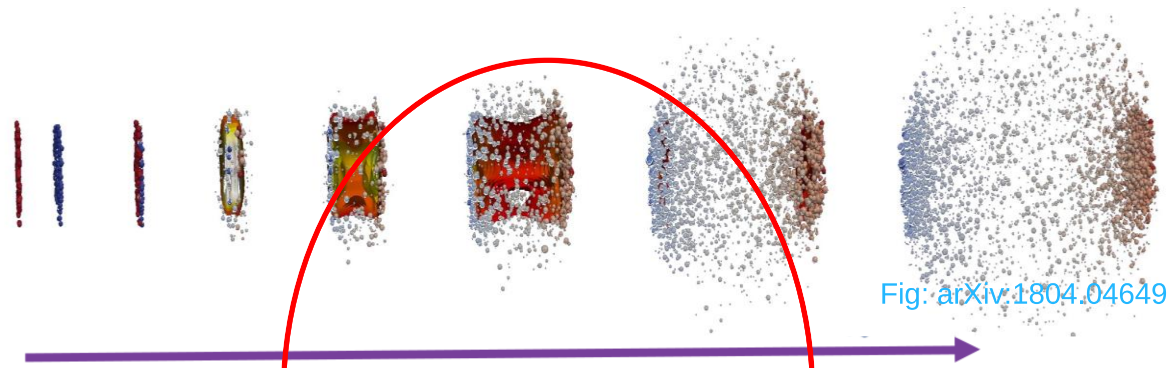


Fig: arXiv:1804.04649

Initial Stage

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

$$p^\mu \partial_\mu f + F \cdot \partial_p f = C$$

Final State

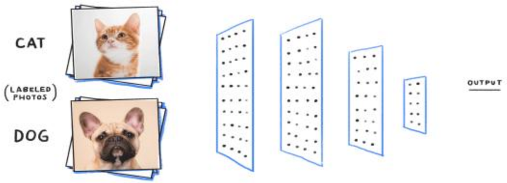
Impact parameter
Nuclear structure

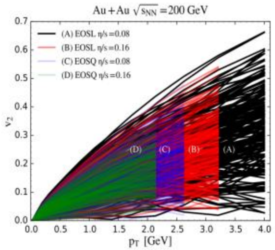
<u>Bulk Matter properties</u>:
Phase Transition
EOS
Shear/Bulk viscosities
Hard Probes

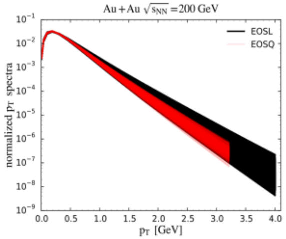
Event Generation
Final observables

QCD Transition: direct inverse mapping with Data driven supervised learning

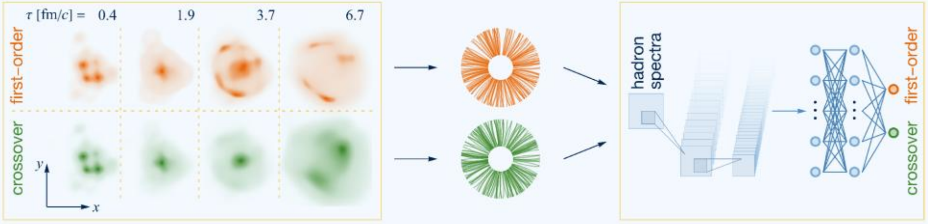
Data-driven
Inverse Mapping





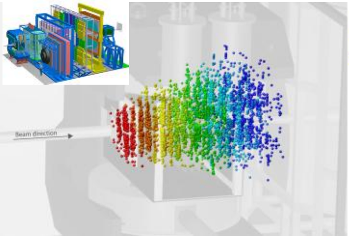


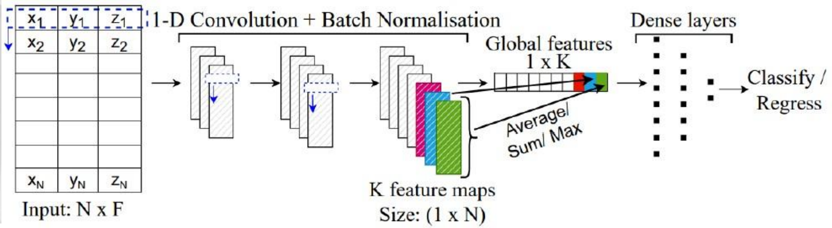
Physics Simulation
provide the Prior



(a) quark gluon plasma (b) hadrons (c) CNN for classification

Conclusion : Information of early dynamics can **survive** to the end of hydrodynamics and encoded within the final state raw spectra, immune to other uncertainties, **with deep CNN we can decode it back.** L. Pang, K. Zhou, N. Su, H. Stoecker, H. Petersen, X. Wang, **Nature Commu.**9 (2018), no.1, 210





- **Collision Centrality Regression**
  M. OK, J. S, K. Zhou, H. S, **Phys.Lett.B** 811 (2020) 135872
- **EoS Classification**
  M. OK, K. Zhou, J. S, H. S, **JHEP** 10(2021) 184
- **Small/ Large-system Identification**
  S.Guo, H. Wang, K. Zhou, **G. Ma**, **Phy.Rev.C 110 (2024)2**

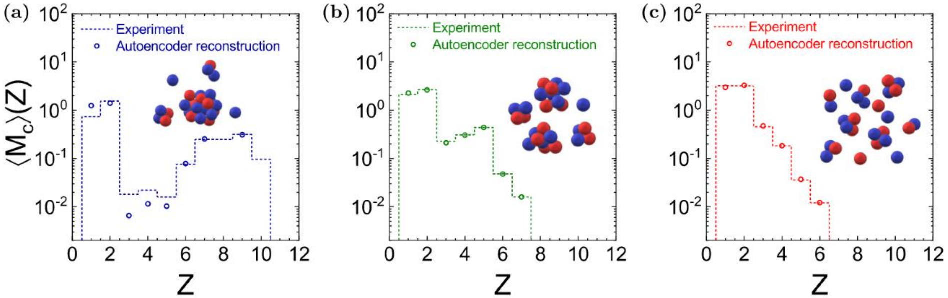
Manjunath O.K. and Kai Zhou, etc. *Phys.Lett.B* 811 (2020) 135872; JHEP10(2021)184.

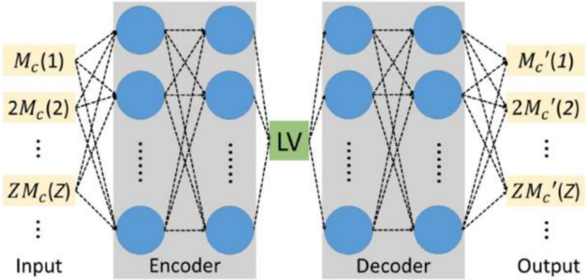
Nuclear liquid-gas phase transition recognition from autoencoder

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]





EbE charge-weighted charge multiplicity distribution of quasi-projectile as input →

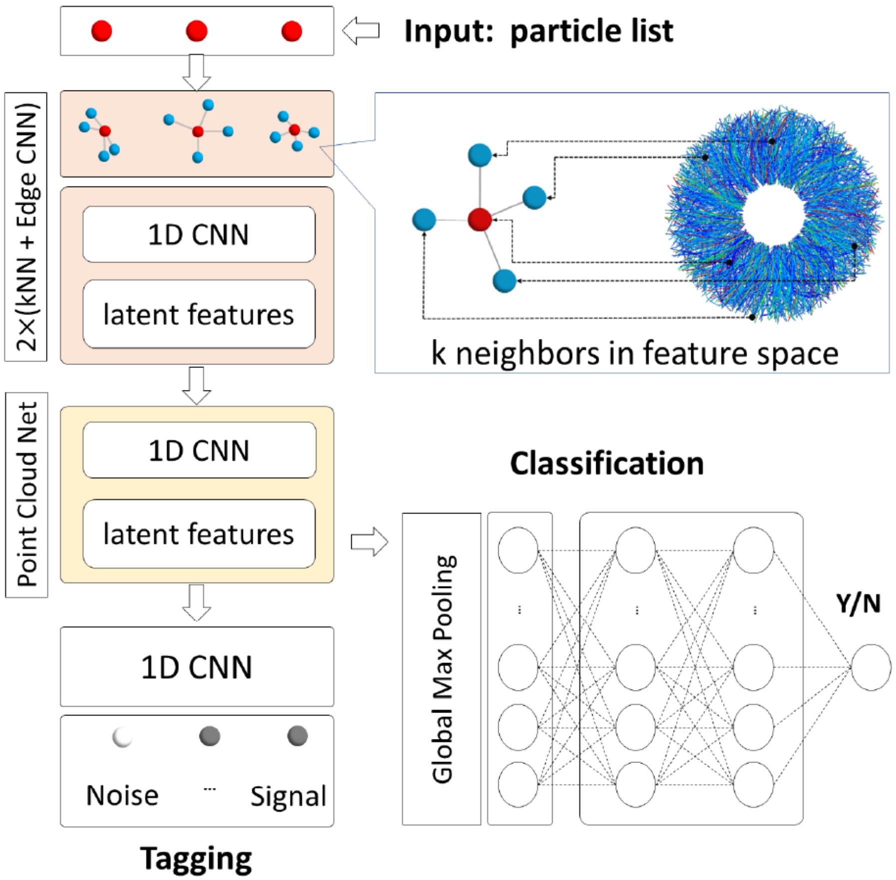
Autoencoder + confusion scheme
(on NIMROD experiment)

Modern dynamical edge CNN + PCN for self similarity searching

dynamical edge convolution network followed by a point cloud net is used to identify self-similarity and critical fluctuations in HIC

Repeating the **KNN** and **edge convolution** blocks twice helps to find long-range multi-particle correlations that are the key to searching for critical fluctuations.

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



Bayesian (Statistical) Inference of hot matter EoS from HIC data

PRL **114,** 202301 (2015) PHYSICAL REVIEW LETTERS week ending 22 MAY 2015

Constraining the Equation of State of Superhadronic Matter from Heavy-Ion Collisions

Scott Pratt,[1] Evan Sangaline,[1] Paul Sorensen,[2] and Hui Wang[2]
[1]*Department of Physics and Astronomy and National Superconducting Cyclotron Laboratory Michigan State University, East Lansing, Michigan 48824, USA*
[2]*Brookhaven National Laboratory, Upton, New York 11973, USA*

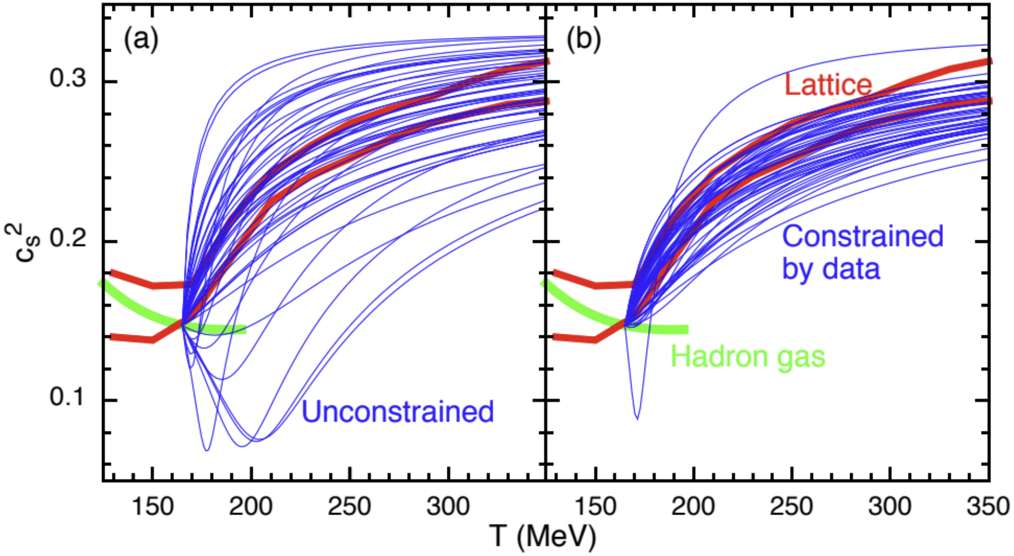
(Received 19 January 2015; published 19 May 2015)

$$c_s^2(\epsilon) = c_s^2(\epsilon_h) + \left(\frac{1}{3} - c_s^2(\epsilon_h)\right)\frac{X_0 x + x^2}{X_0 x + x^2 + X'^2},$$
$$X_0 = X' R c_s(\epsilon)\sqrt{12}, \quad x \equiv \ln \epsilon/\epsilon_h,$$

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

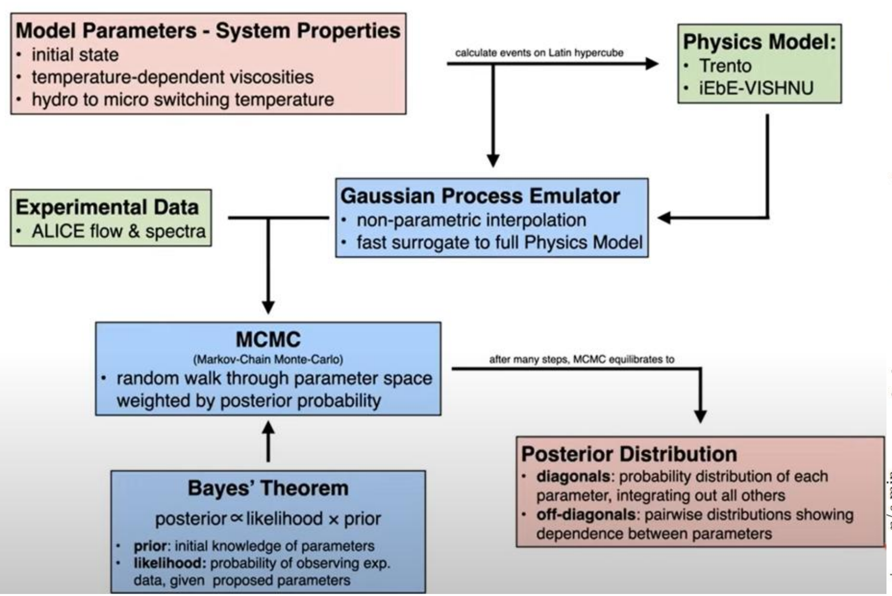
14 model parameters

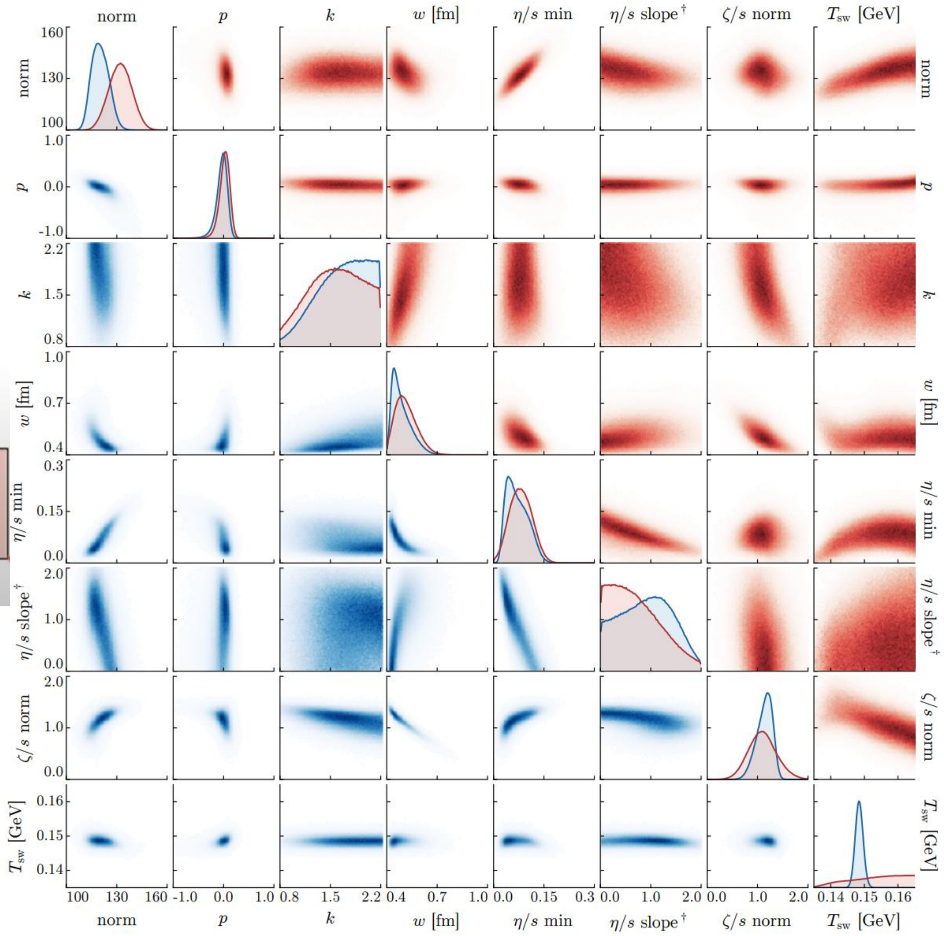
speed of sound squared slightly <u>softer</u> than lattice EoS
<u>**But significantly overlap**</u>



Bayesian (Statistical) global fit on HICs – Shear and Bulk viscosities

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen





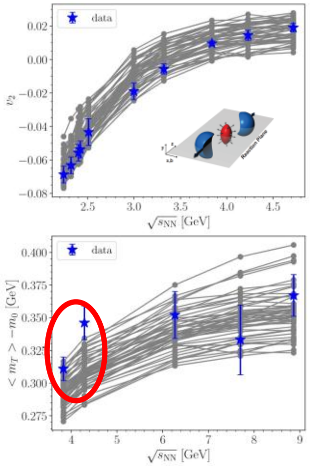
Trento + IEBE-VishNew + UrQMD

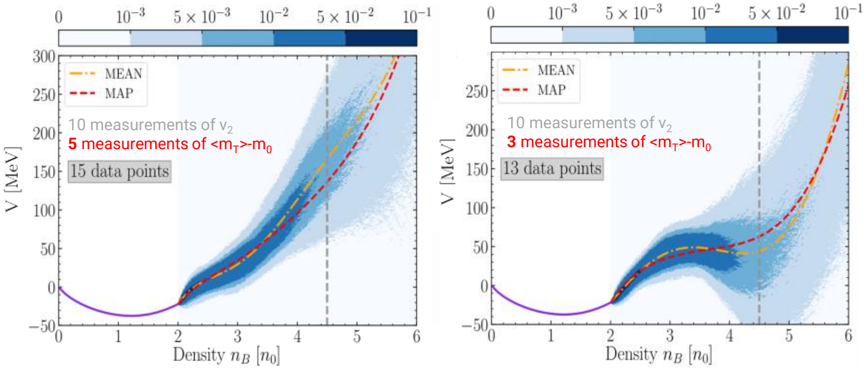
J. Bernhard, J. Morel, S. Bass, **Nat. Phy.** 15, 1113 (2019)

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; … …

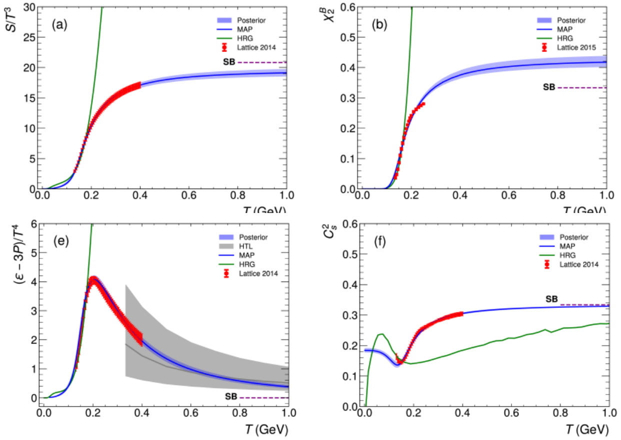
Bayesian Inference Dense Matter EoS from HIC and Holography





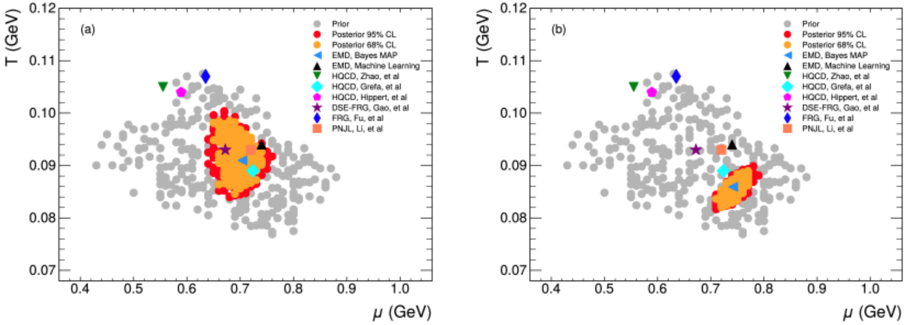
- Comprehensive Bayesian inference necessary for unambiguous solution
- Tension between data-data or model (**UrQMD**)-data
- Next-gen experiments will provide immense amount of high precision data

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



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

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



- Critical endpoint from **holography (EMD)** via Bayesian Inference

L. Zhu, X. Chen, K. Zhou, H. Zhang, M, Huang, **arXiv:2501.15810**

Incompressibility K from Bayesian Inference with low-energy HIC

Bayesian inference of nuclear incompressibility from proton elliptic flow in central Au+Au collisions at 400 MeV/nucleon

J. M. Wang (汪金梅),[1,2] X. G. Deng (邓先概),[1,2,*] W. J. Xie (谢文杰),[3] B. A. Li (李宝安),[4,†] and Y. G. Ma (马余刚)[1,2,‡]

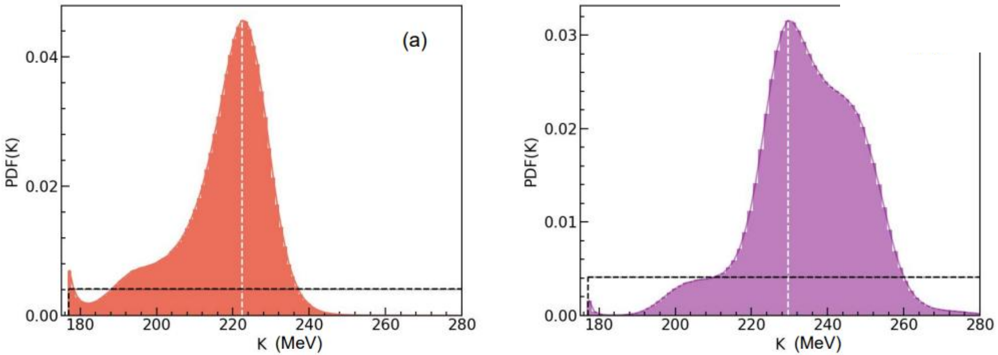


FIG. 5. Without considering the MDI: the posterior PDFs of K. Left: using only the observable $-v_2(y_0)$, right: using the two observables $-v_2(y_0)$ and $-v_2(u_{t0})$.

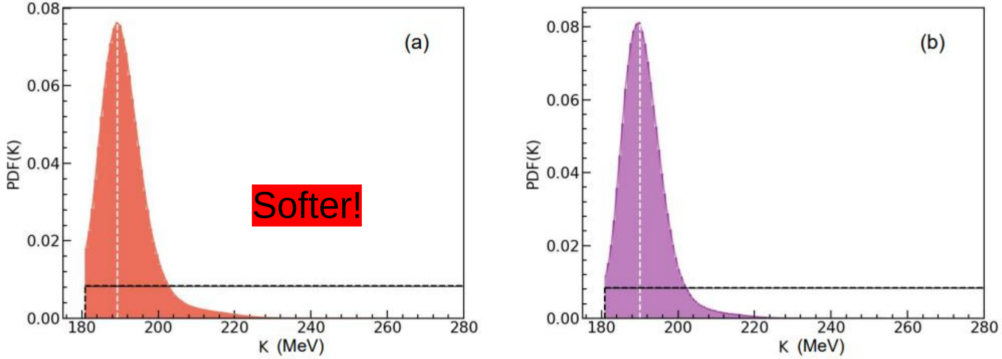


FIG. 7. Considering the MDI: the posterior PDFs of K. Left: observable only $-v_2(y_0)$, right: observables $-v_2(y_0)$ and $-v_2(u_{t0})$.

arXiv:2406.07051

IQMD simulation of
proton v2 Au+Au at E=400 MeV/Nucleon

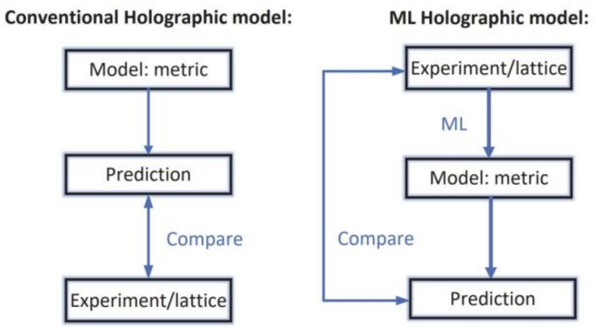
MDI: momentum dependent Interaction

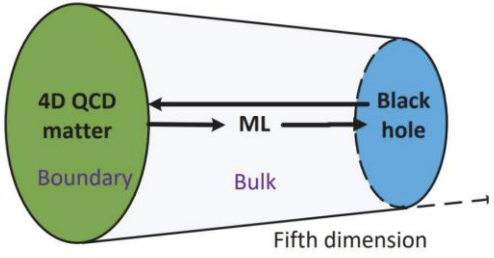
$$E/A = \frac{\alpha}{2}\frac{\rho}{\rho_0} + \frac{\beta}{\gamma+1}\left(\frac{\rho}{\rho_0}\right)^{\gamma} + \frac{3}{10m}\left(\frac{3\pi^2\hbar^3\rho}{2}\right)^{2/3} + \frac{1}{2}t_4\frac{\rho}{\rho_0}\int f(\vec{p})\ln^2\left[1+t_5\left(\vec{p}-\langle\vec{p}'\rangle\right)^2\right]d^3p, \quad (1)$$

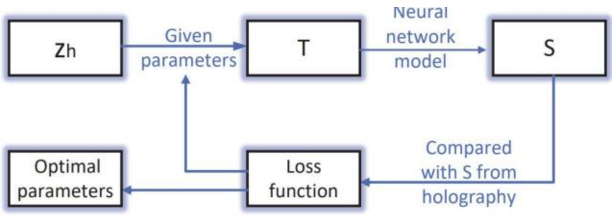
$$P = \rho^2\frac{\partial E/A}{\partial\rho} = \frac{\alpha}{2}\frac{\rho^2}{\rho_0} + \frac{\beta\gamma\rho}{\gamma+1}\left(\frac{\rho}{\rho_0}\right)^{\gamma} + \frac{1}{5m}\left(\frac{3}{2}\pi^2\hbar^3\right)^{\frac{2}{3}}\rho^{\frac{5}{3}} + \frac{t_4}{2}\frac{\rho^2}{\rho_0}\ln^2\left(1+t_5P_F^2\right), \quad (2)$$

$$K = 9\rho^2\frac{\partial^2 E/A}{\partial\rho^2}\Big|_{\rho_0} = -\frac{3}{5m}\left(\frac{3\pi^2\hbar^3\rho_0}{2}\right)^{2/3} + \frac{9\beta\gamma(\gamma-1)}{\gamma+1} + \ln\left(1+t_5P_F^2\right)\frac{6t_4t_5P_F^2}{1+t_5P_F^2}, \quad (3)$$

ML Holography (EMD model) with lattice QCD reference







Einstein-Maxwell-Dilation model

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

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

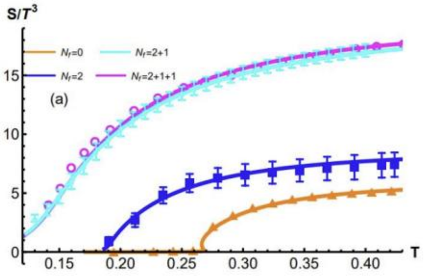
Non-conformal

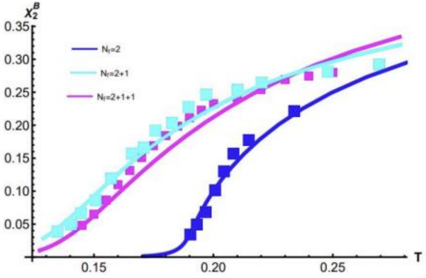
ϕ is dilaton F is the tensor of gauge field

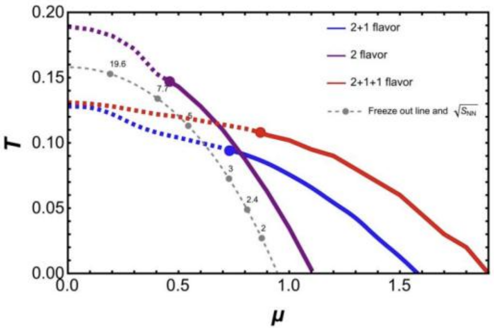
Metric ansatz: $$ds^2 = \frac{e^{2A(z)}}{z^2}\left[-g(z)dt^2 + \frac{dz^2}{g(z)} + d\vec{x}^2\right]$$

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

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



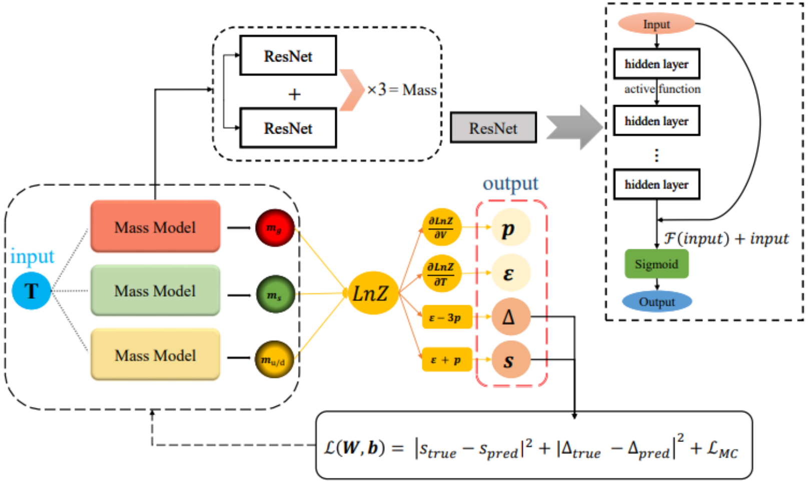


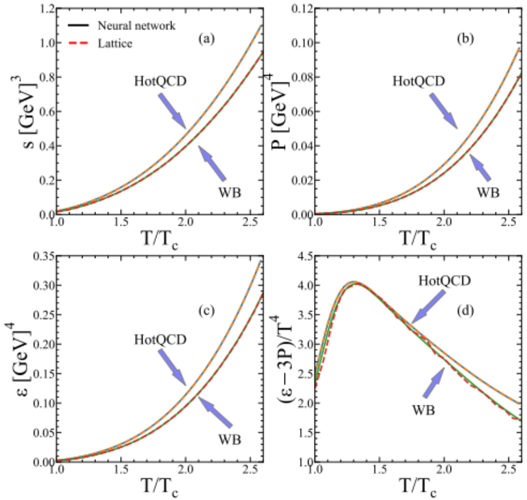


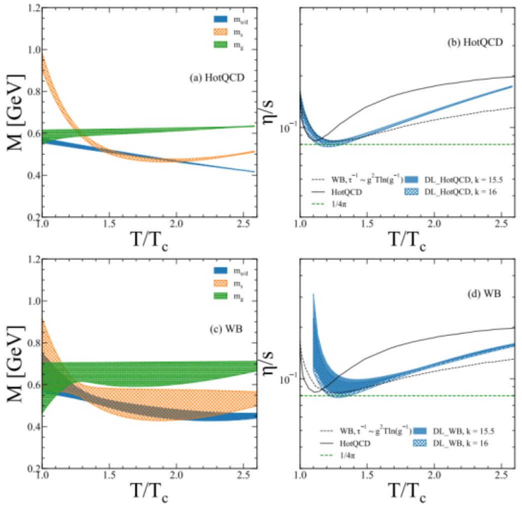
X. Chen, M. Huang, **Phys.Rev.D** 109 (2024) L051902; **JHEP**02 (2025)123

Quasi-particle analysis of lQCD thermodynamics

香 港 中 文 大 學 (深 圳)
The Chinese University of Hong Kong, Shenzhen







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

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

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

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

$$\chi_i^B = \left.\frac{\partial P(T, \hat{\mu}_B)/T^4}{\partial \hat{\mu}_B^i}\right|_{\hat{\mu}_B = 0}, \hat{\mu}_B = \mu_B/T.$$

$$\mathcal{L}(\theta_1, \theta_2, \theta_3) = |s_{NN} - s_{input}| + \left|\frac{\Delta_{NN} - \Delta_{input}}{T}\right| + |\chi^B_{2,NN} - \chi^B_{2,input}| + |\chi^B_{4,NN} - \chi^B_{4,input}| + \mathcal{L}_{MC}$$

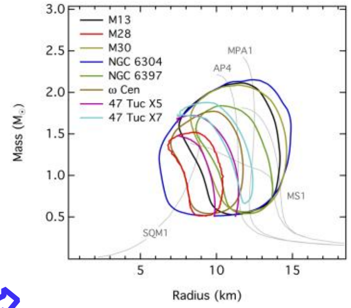
F. Li, H. Lue, L. Pang and G. Qin, **Phys. Lett. B** 2023, arXiv:2211.07994

Recently generalized to finite baryon chemical potential (use lQCD res with Taylor expansion) → **arXiv:2501.10012**

Dense matter EoS from Neutron Star obs - AutoDiff

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

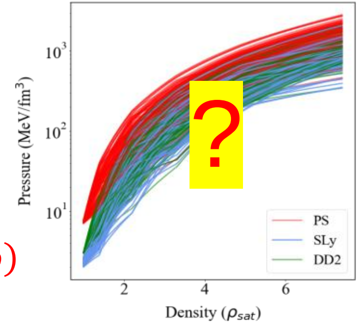
Noisy/Limited NS Observables to EoS ?



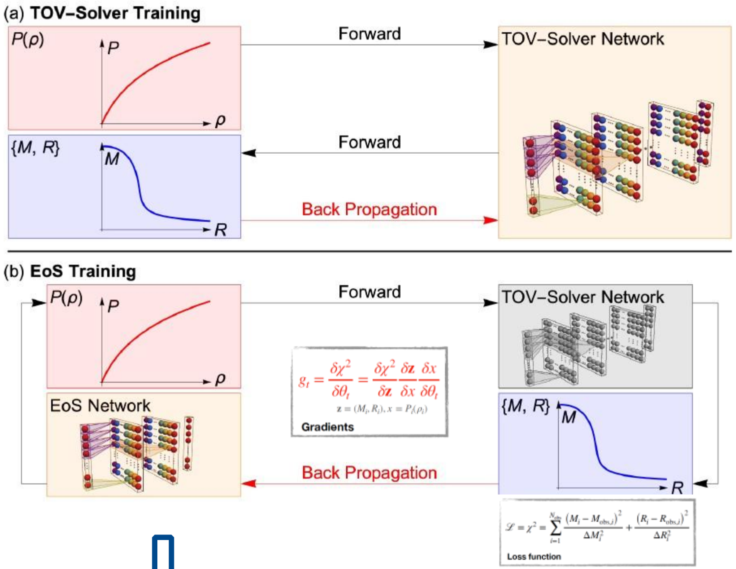
TOV eqs

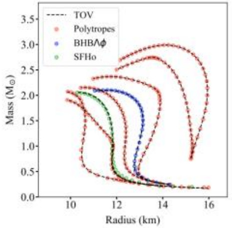
$$\frac{dP}{dr} = -\frac{G}{r^2}\left(\rho + \frac{P}{c^2}\right)\left(m + 4\pi r^3 \frac{P}{c^2}\right)\left(1 - \frac{2Gm}{c^2 r}\right)^{-1}$$

$$M = m(R) = \int_0^R 4\pi r^2 \rho \, dr$$

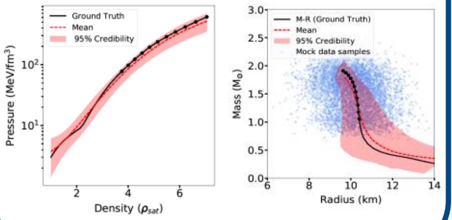


$P(\rho)$

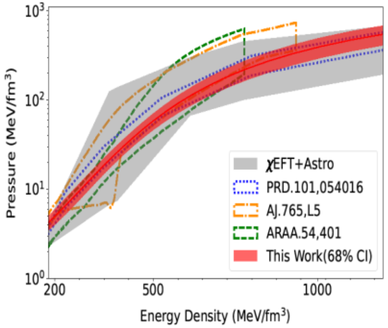


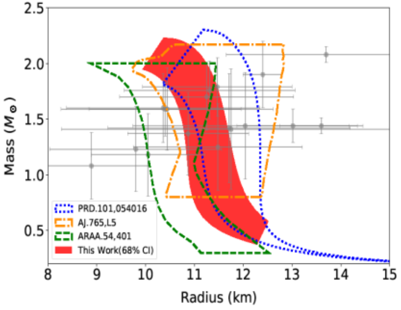


Mock Test



S. S, L. W, S. S, H. S, K. Z,
JCAP 98(2022)071;
PRD107(2023)083028



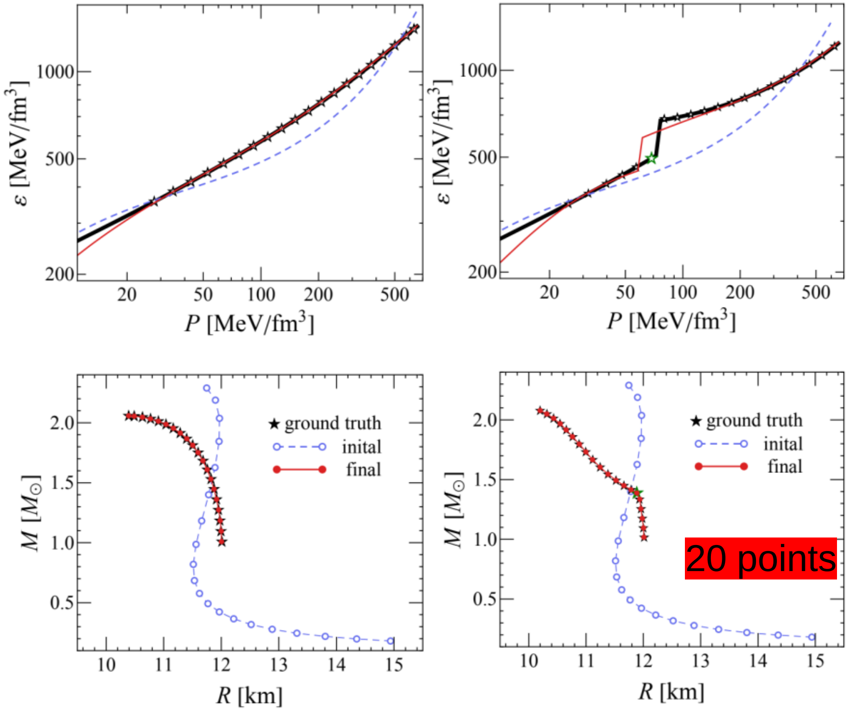


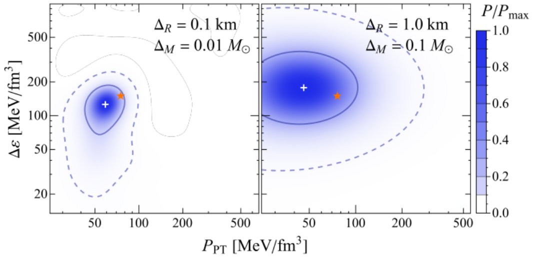
First-order phase transition reconstruction from NS obs. via auto-diff

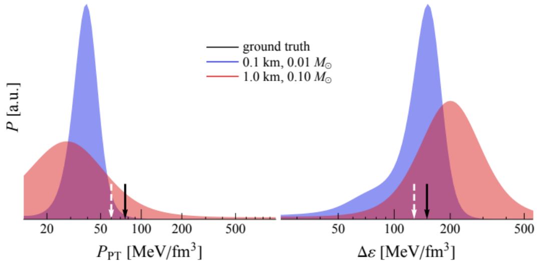
Linear response analysis get the gradients! Then use DNN :

We parameterize the inverse speed of sound squared containing both regular parts and Dirac-δ functions corresponding to possible first-order phase transitions,

We adopt SFHo as the baseline EoS and introduce a PT with latent heat $\Delta\varepsilon = 150$ MeV/fm^3 at pressure $P_{\rm PT} = 76$ MeV/fm^3. Above the PT point, we take the stiffest (causal) limit that $c_s = 1$. We employ twenty

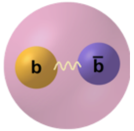


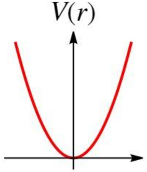




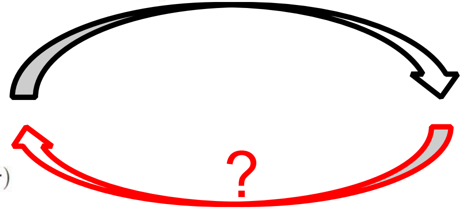
R. Li, S. Han, Z. Lin, L. Wang, K. Zhou, S. Shi, **arXiv:2501.15819, PRD 2025**

HQ Potential by Inversing Shroedinger Eq. on lattice data

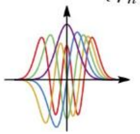




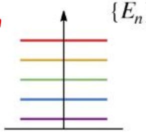
$$\hat{H}\psi_n = -\frac{\nabla^2}{2m_\mu}\psi_n + V(r)\psi_n = E_n\psi_n$$



$\{\psi_n(r)\}$



$\{E_n\}$

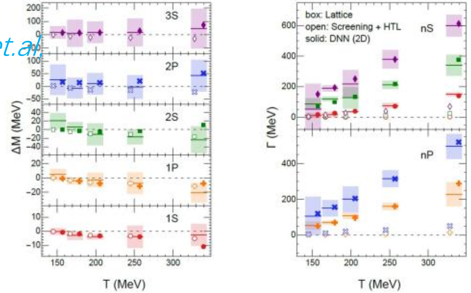


$$V(T,r) = V_R(T,r) + i \cdot V_I(T,r)$$

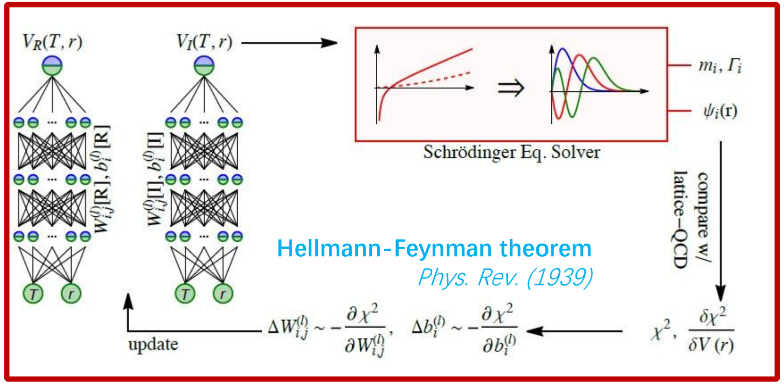
$$\begin{cases} \mathrm{Re}[E_n] = m - 2m_b \\ \mathrm{Im}[E_n] = -\Gamma \end{cases}$$

New lQCD results cannot be explained by Perturbative HTL-inspired potentials !

R. Larsen, et.al PRD(2019), PLB(2020), PRD(2020)

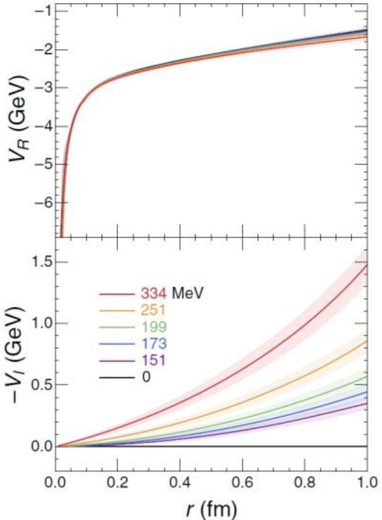


How to extract effective potential given limited spectroscopy ? →

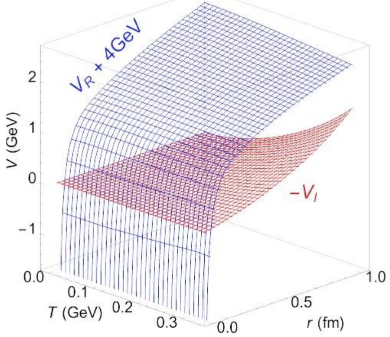


Hellmann-Feynman theorem
Phys. Rev. (1939)

⇨



Chi2-per-data=16.5/30



S.S, K. Z, J.Z, S.M., P. Z, **Phys. Rev. D 105 (2022) 1, 1**

Outline: Initial state + Bulk matter + Generative model

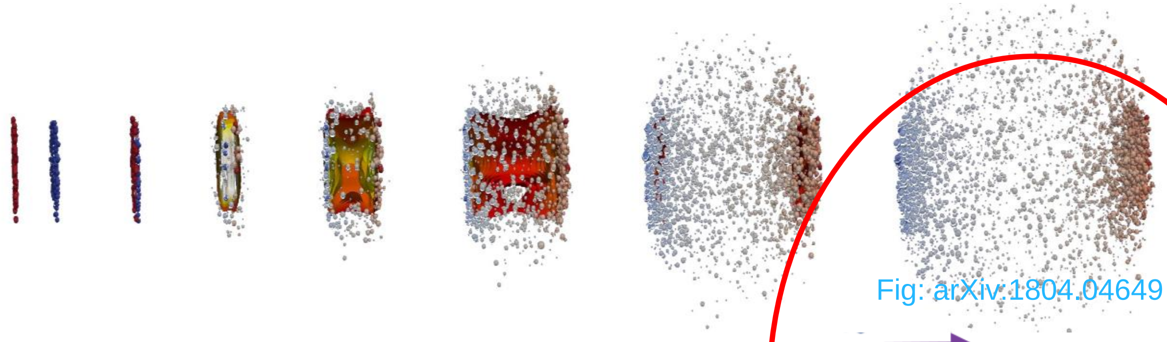


Fig: arXiv:1804.04649

Initial Stage

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

$$p^\mu \partial_\mu f + F \cdot \partial_p f = C$$

Final State

Impact parameter
Nuclear structure

Bulk Matter properties:
Phase Transition
EOS
Shear/Bulk viscosities
Hard Probes

Event Generation
Final observables

Discriminative / Generative model

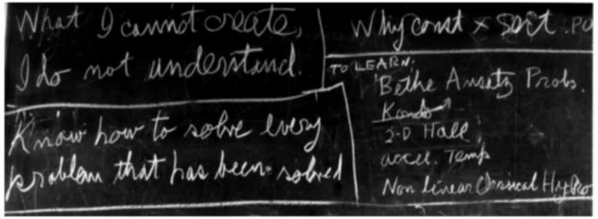
- Discriminative Learning : **prediction**

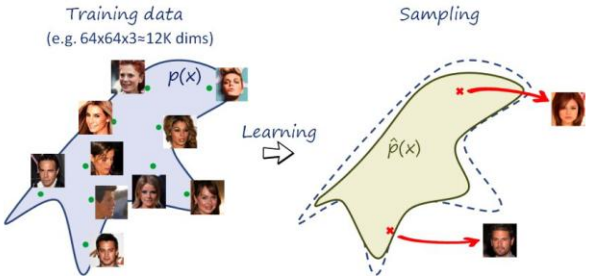
  function fitting $y = f(x)$

  conditional probability $p_\theta(y|x) \to p(y|x)$

- Generative Modelling : **understand**

  Joint probability distribution $p_\theta(x, y) \to p(x, y)$





"What I can not create, I do not understand"

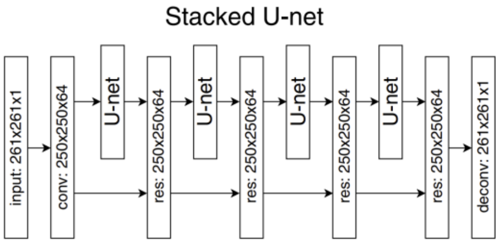
U-net Emulator for relativistic hydrodynamics

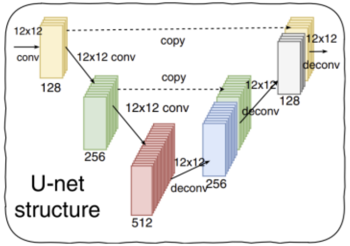
PHYSICAL REVIEW RESEARCH **3**, 023256 (2021)

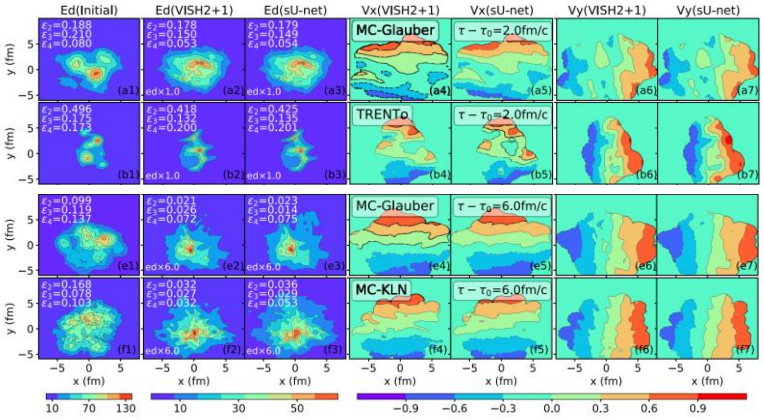
Applications of deep learning to relativistic hydrodynamics

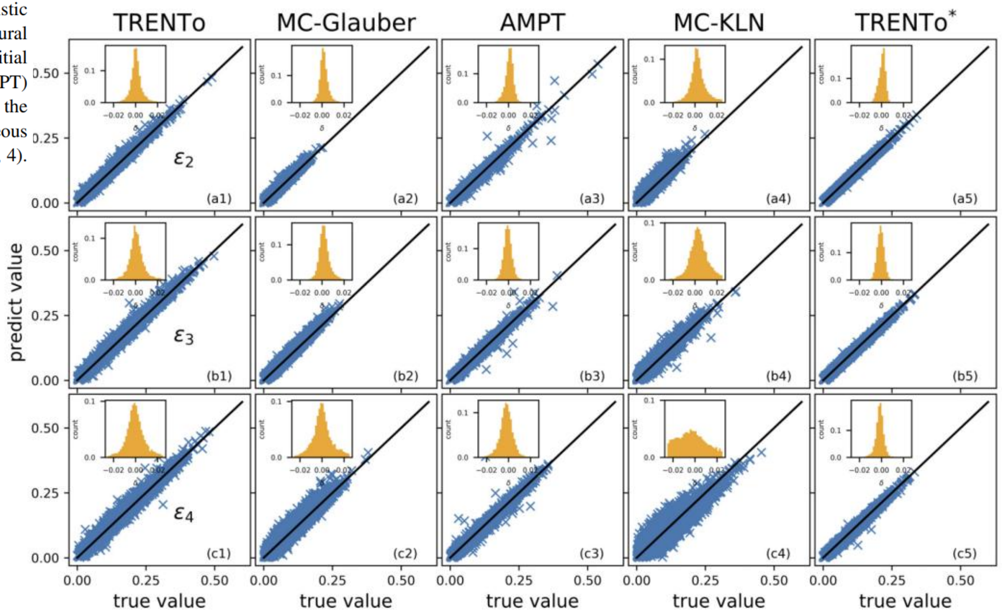
Hengfeng Huang,[1,2] Bowen Xiao,[3] Ziming Liu,[1] Zeming Wu,[1,2] Yadong Mu,[3,4] and Huichao Song[1,2,5]

tic heavy-ion collisions. Using 10 000 initial and final profiles generated from (2+1)-dimensional relativistic hydrodynamics VISH2+1 with Monte Carlo Glauber (MC-Glauber) initial conditions, we train a deep neural network based on the stacked U-net, and use it to predict the final profiles associated with various initial conditions, including MC-Glauber, MC Kharzeev-Levin-Nardi (MC-KLN), a multiphase transport (AMPT) model, and the reduced thickness event-by-event nuclear topology (TRENTo) model. A comparison with the VISH2+1 results shows that the network predictions can nicely capture the magnitude and inhomogeneous structures of the final profiles, and creditably describe the related eccentricity distributions $P(\varepsilon_n)$ ($n = 2, 3, 4$).









香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

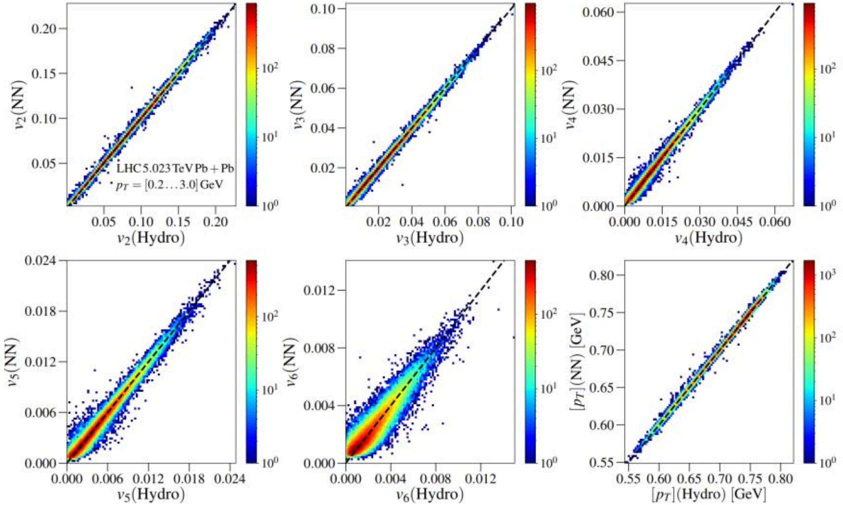
PHYSICAL REVIEW C **108**, 034905 (2023)

Deep learning for flow observables in ultrarelativistic heavy-ion collisions

H. Hirvonen, K. J. Eskola, and H. Niemi

As an input, the DenseNet model uses discretized initial energy density in the transverse-coordinate (x, y) plane calculated from the EKRT model with a grid size 269×269 and a resolution of 0.07 fm. The DenseNet model is trained to reproduce a set of final state p_T integrated observables v_n, average transverse momentum $[p_T]$, and charged particle multiplicity $dN_{ch}/d\eta$ for each event. The input energy density is normalized in such a

Block	Output size	Layers
Convolution	134x134x64	7x7 conv, stride 2
Pooling	67x67x64	3x3 max pool, stride 2
Dense Block	67x67x256	[1x1 conv, 3x3 conv] x 6
Transition Layer	67x67x128	1x1 conv
	33x33x128	2x2 average pooling, stride 2
Dense Block	33x33x512	[1x1 conv, 3x3 conv] x 12
Transition Layer	33x33x256	1x1 conv
	16x16x256	2x2 average pooling, stride 2
Dense Block	16x16x896	[1x1 conv, 3x3 conv] x 20
Transition Layer	16x16x448	1x1 conv
	8x8x448	2x2 average pooling, stride 2
Dense Block	8x8x1216	[1x1 conv, 3x3 conv] x 24
Output Layer	1x1x1216	8x8 global average pooling
	N_{out}	Fully connected layer with ReLU activation



10^7 events using the neural network, which takes around 20 h with the GPU. This is a very substantial difference compared to doing full hydrodynamic simulations using CPU, which would take about 5×10^6 CPU hours.

Similar study for intermediate energies with IBUU +DNN emulation see: **B. Li, etc., arXiv:2406.18421**

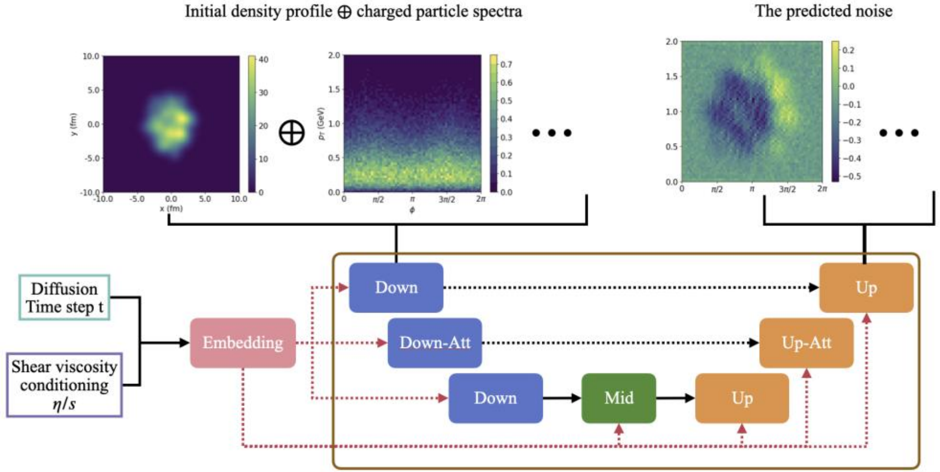
Generative diffusion model to heavy-ion collisions

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

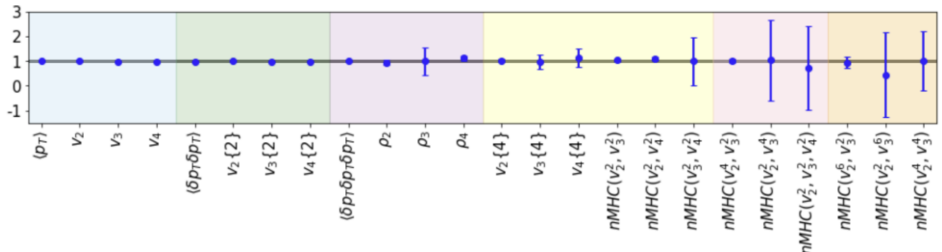
An end-to-end generative diffusion model for heavy-ion collisions

arXiv:2410.13069

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



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



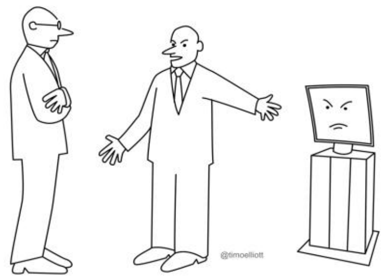
tor. We carried out (2+1)D minimum bias simulations of Pb-Pb collisions at 5.02 TeV, choosing the shear viscosity η/s to be one of three distinct values: 0.0, 0.1, and 0.2. For each value of η/s, we generate 12,000 pairs of initial entropy density profiles and final particle spectra, corresponding to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

Point Cloud Diffusion Model for HICs – AI clone of full event generation

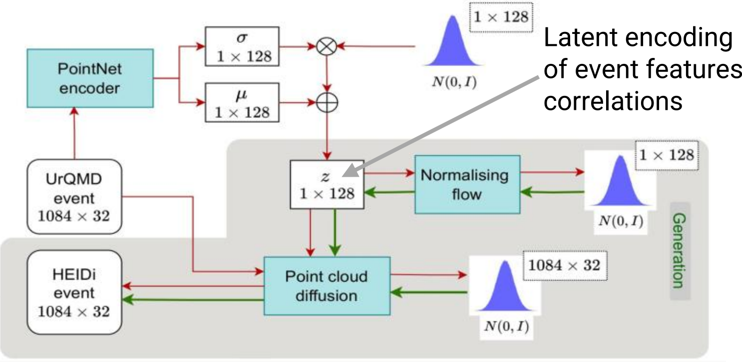


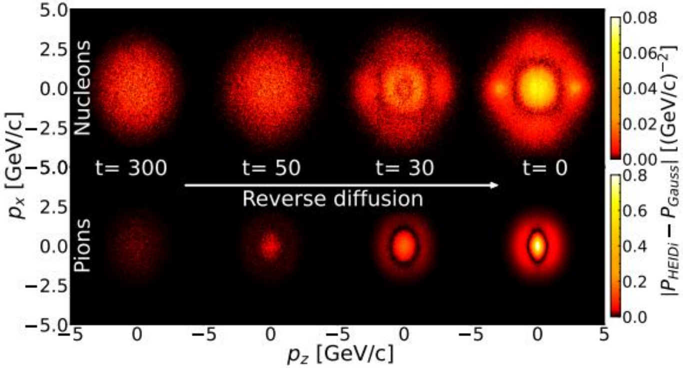
His decisions aren't any better than yours — but they're WAY faster...

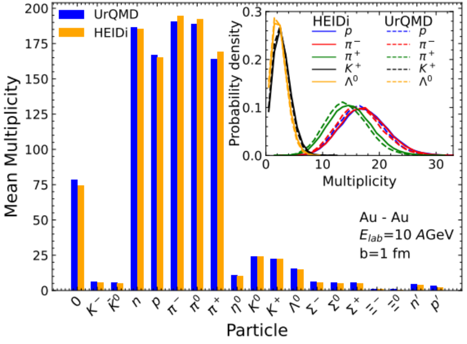
- 18k UrQMD simulation events for central Au-Au@10 AGeV collisions

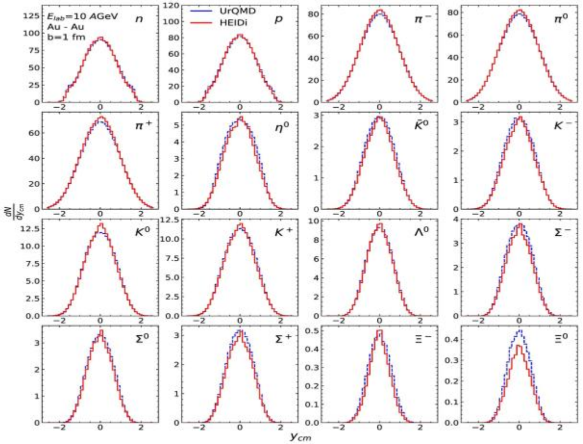
- HEIDi:
  Heavy-ion Events through Intelligent Diffusion

PointNet encoder + Normalizing flow decoder + **Pointcloud** diffusion →









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

What's the future? – Generative AI and LLM maybe the future

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

Should artificial intelligence be interpretable to humans?

Matthew D. Schwartz

Nature Reviews Physics **4**, 741–742 (2022) | Cite this article

Machine vs. Biological intelligence

- Biological intelligence grows by a factor of 2 in one million years
- Machine intelligence grows by a factor of 10 in 1 year
- **Factor of 10^6 difference in *exponent***

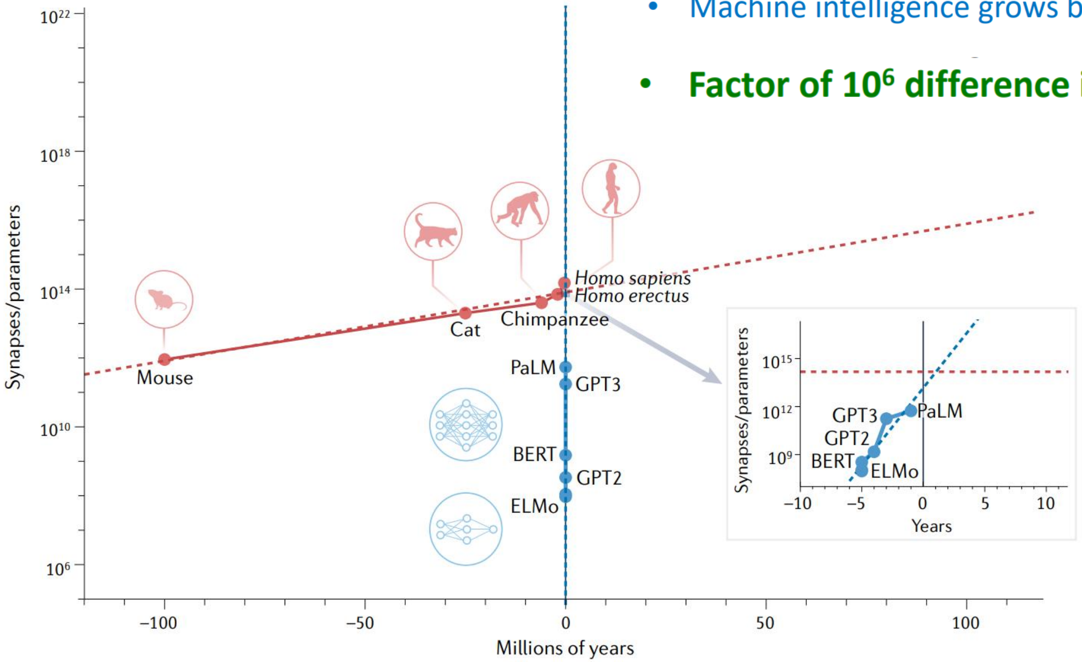


Fig. 1 | The evolution of biological and artificial intelligence takes place on dramatically different timescales. Any hope of interpreting and understanding AI will exponentially fade. Some example data points are highlighted in the evolution of biological (red) and artificial (blue) intelligence. The dashed lines represent the linear regression to these points. The acronyms in the figure are: Pathways Language Model (PaLM), Embeddings from Language Model (ELMo), Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT).

Chat-GPT

↓

Chat-GPh.T?
Chat-GPh.D?

Summary: Machine Learning and HENP

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

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

Nature Review Physics (2025)

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

Progress in Particle and Nuclear Physics 135 (2024) 104084

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

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Review

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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

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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]

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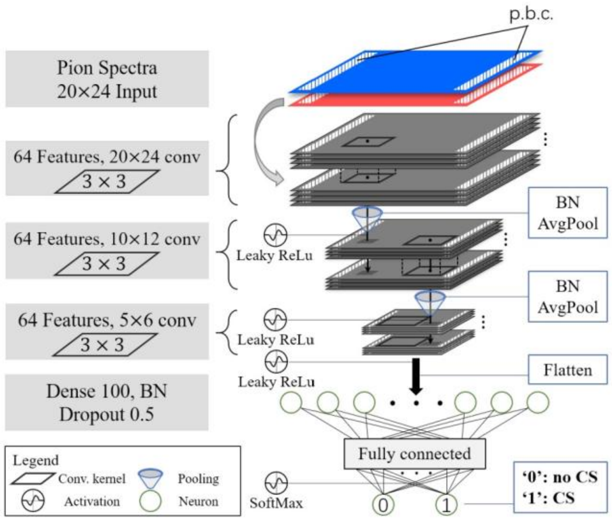
Abstract

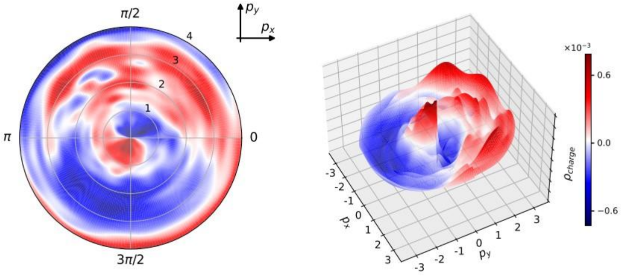
Although seemingly disparate, high-energy nuclear physics (HENP) and machine learning (ML) have begun to merge last few years, yielding interesting results. It is worthy to raise the profile of utilizing this novel mindset from ML in H to help interested readers see the breadth of activities around this intersection. The aim of this mini-review is to infor community of the current status and present an overview of the application of ML to HENP. From different aspects and examples, we examine how scientific questions involving HENP can be answered using ML.

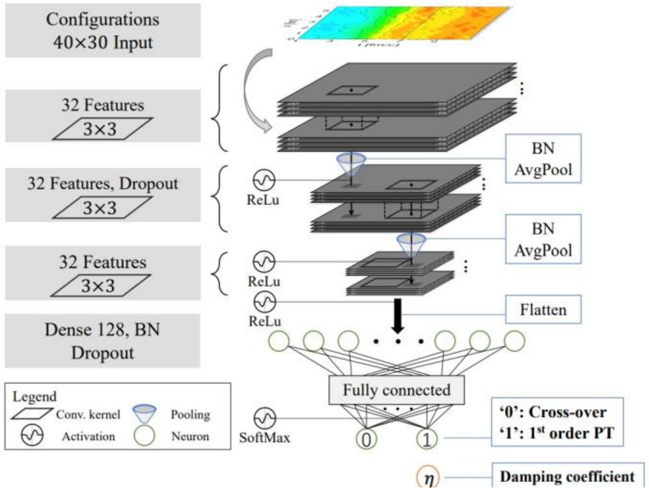
Keywords Heavy-ion collisions · Machine learning · Initial state · Bulk properties · Medium effects · Hard probes · Observables

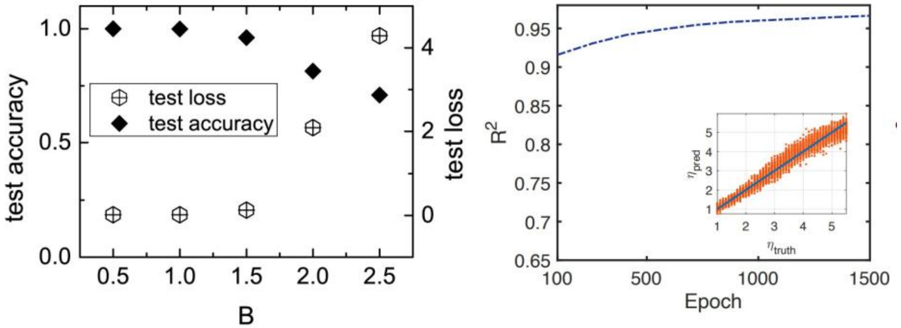
Thanks!

CNN to detect CME, and regress stochastic dynamics in HICs









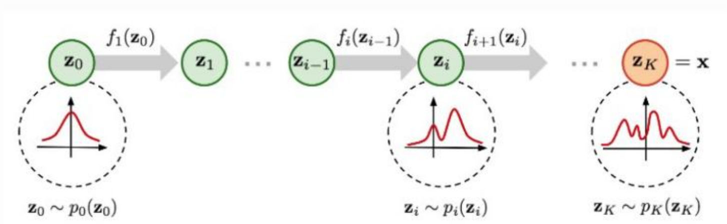
Y. Zhao, L. Wang, K. Zhou, X. Huang, PRC 106, L051901(Letter)

L. Jiang, L. Wang, K. Zhou, PRD 103, 116023

Flow based generative model (given unnormalized distribution)

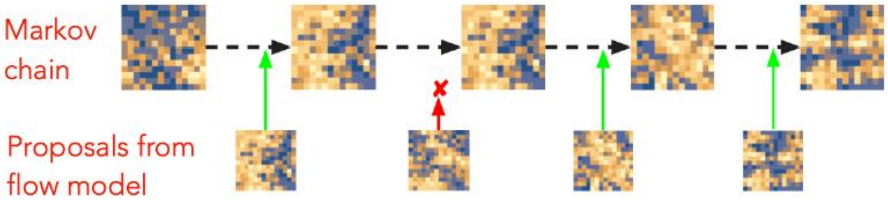
A series **(Flow)** of invertible/bijective transformations for p(z)

<u>compose several invertible transformations to form the flow :</u>



$$p_i(\mathbf{z}_i) = p_{i-1}(f_i^{-1}(\mathbf{z}_i))|\det J_{f_i^{-1}}| = p_{i-1}(\mathbf{z}_{i-1})|\det J_{f_i}|^{-1}$$

$$\rightarrow \log p(\mathbf{x}) = \log p_0(f^{-1}(\mathbf{x})) + \sum_{i=1}^{K} \log|\det J_{f_i^{-1}}| = \log p_0(\mathbf{z}_0) - \sum_{i=1}^{K} \log|\det J_{f_i}|$$

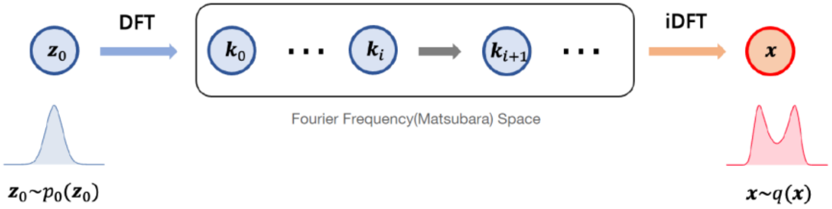


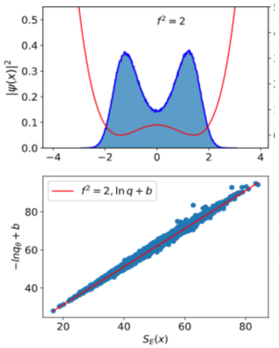
Albergo +, 1904.12072; Boyda +, 2008.05456; Favoni +, 2012.12901; Abbott +, 2208.03832; Abbott +, 2211.07541; Abbott +, 2305.02402; Bulgarelli+ 2412.00200 (SU(3)); Abbott +, arXiv:2502.00263

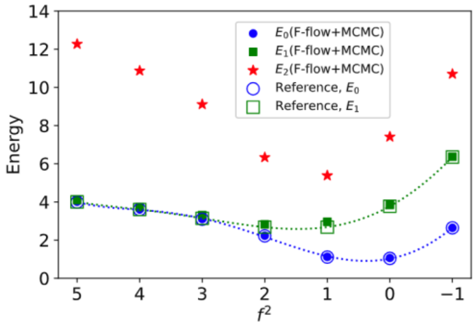
K.C, G. K., S. R., D. R., P. S., **Nature Reviews Physics** 5, 526-535 (2023)

Fourier Flow Model

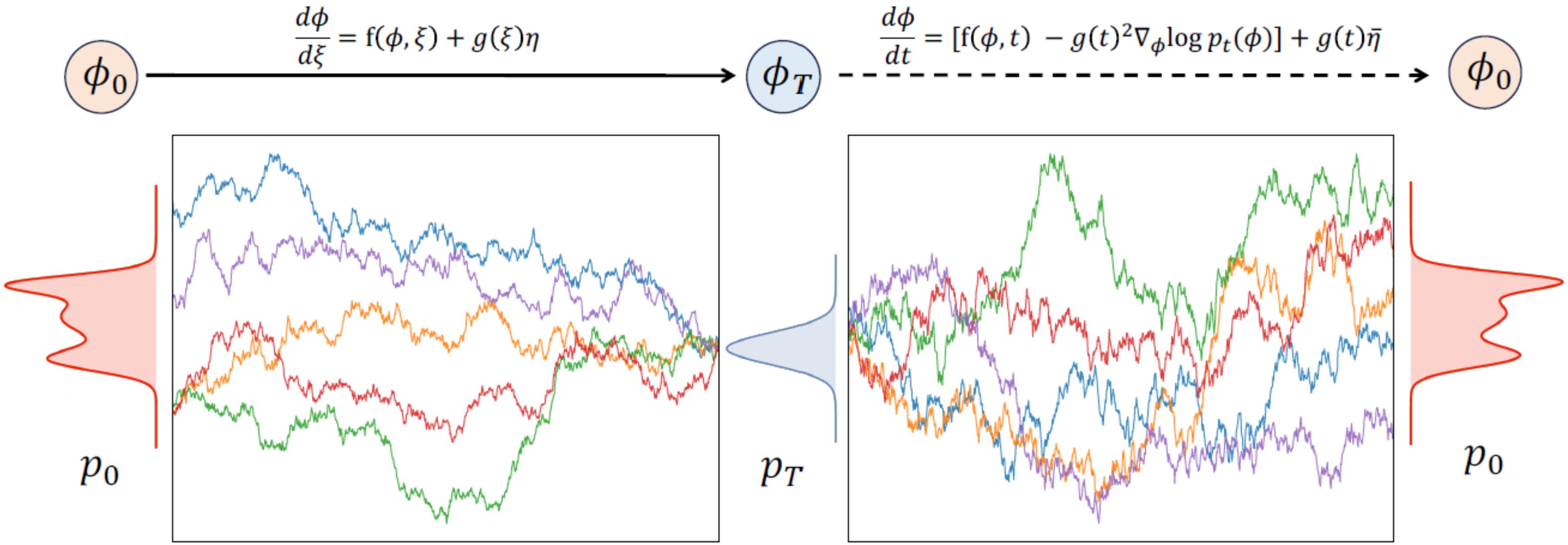
S.Chen, O. Savchuk, S. Zheng, B. Chen, H. Stoecker, L. Wang, K. Zhou, **PRD107, 056001(2023)**







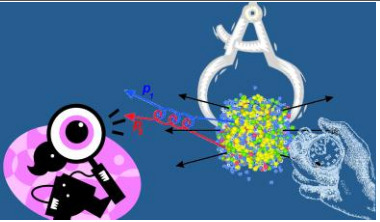
Diffusion Model on lattice QFT configurations



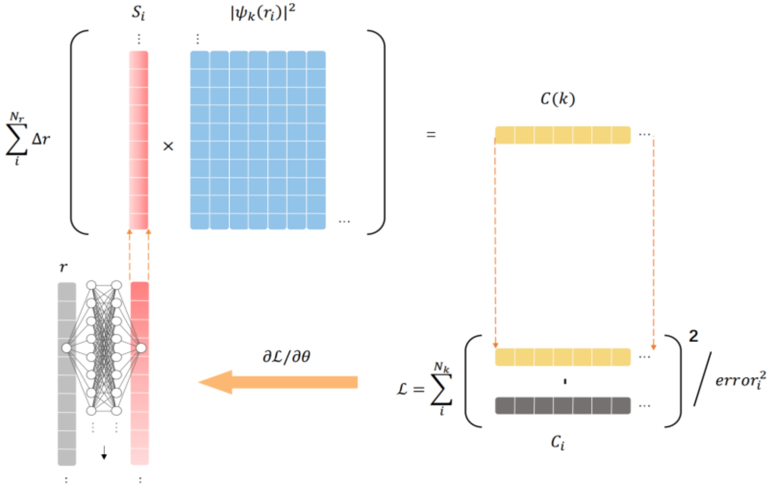
L. Wang, G. Arts, K. Zhou, JHEP 05 (2024) 060
L. Wang, G. Arts, K. Zhou, arXiv:2311.03578 (NeurIPS 2023 workshop "ML&Physical Sciences")
G. A, D. E. H, L. W, K. Z, arXiv:2410:21212 (NeurIPS 2024 workshop "ML&Physical Sciences) → **Best Physics for AI Paper Award !**
Q. Zhu, G. Aarts, W. Wang, K. Zhou, L. Wang, arXiv:2410.19602 (NeurIPS 2024 workshop "ML&Physical Sciences)

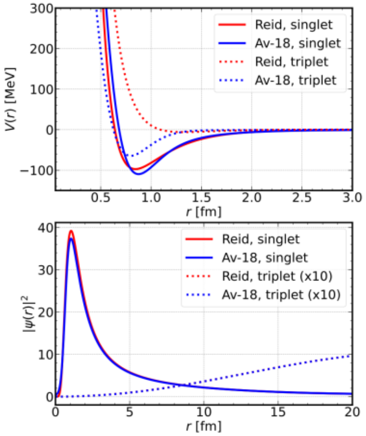
Hadron emission source reconstruction via femtoscopy

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen



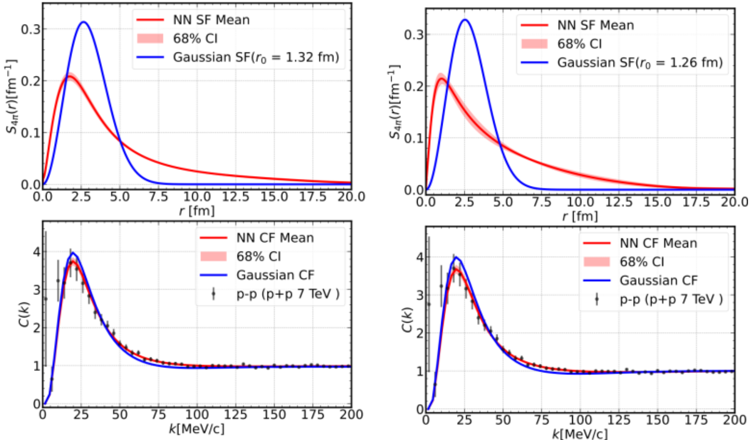
$$C(k) = \int S(\mathbf{r}) \mid \psi_k(\mathbf{r}) \mid^2 \mathrm{d}^3 r,$$





Learning Hadron Emitting Sources with Deep Neural Networks

Lingxiao Wang[1] and Jiaxing Zhao[2,3,*]



arXiv:2411.16343