The 2nd China-Russia Joint Workshop on NICA Facility

Deep Learning for HIC: the nuclear EoS

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Sep. 9-12，ShanDong University

What is deep learning

Yann LeCun

Deep learning is constructing networks of parameterized functional modules & training them from examples using gradient-based optimization

DL: Neural Network with multi hidden layers

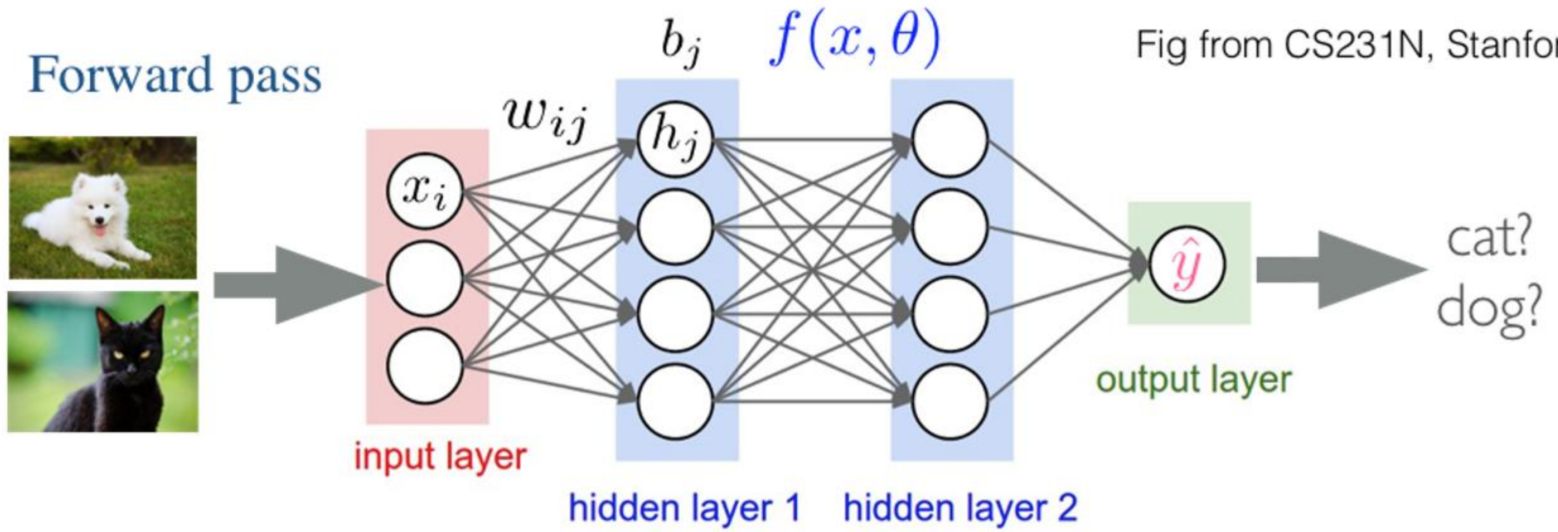


Fig from CS231N, Stanford

Linear operation

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

scaling, rotating, boosting, changing dimensions

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

(a) Sigmoid

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

(b) ReLU

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

(c) PReLU

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

How does the network learn

Input x

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

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

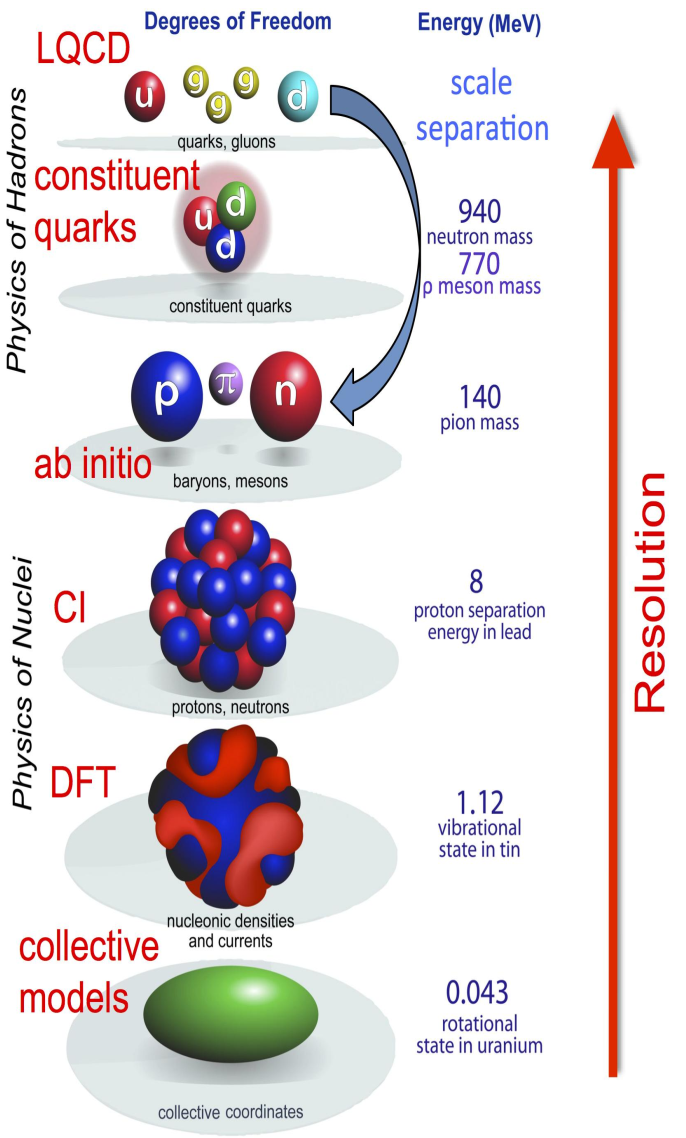
Loss(cost) function
$$L = \frac{1}{N}\sum_i (\hat{y}_i - y_i)^2$$

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

Back propagation

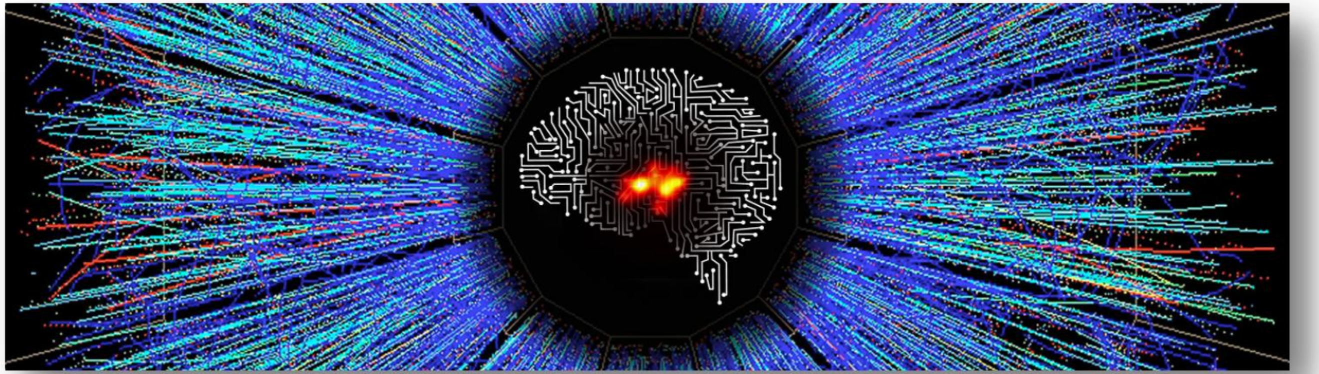
1. The network parameters are initialized with random numbers and the network make random guess
2. Compute the loss function L which is a functional of the network
3. Use auto-diff to compute the negative gradients of network parameters
4. Use SGD-like algorithms to update network parameters

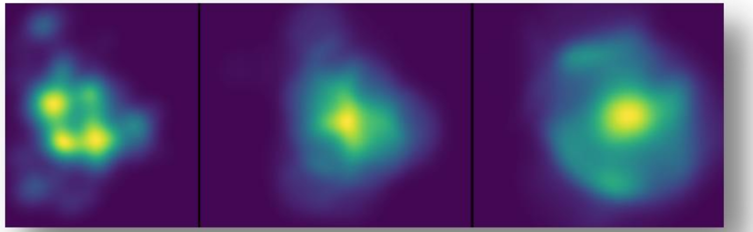
DL nuclear physics across energy scales

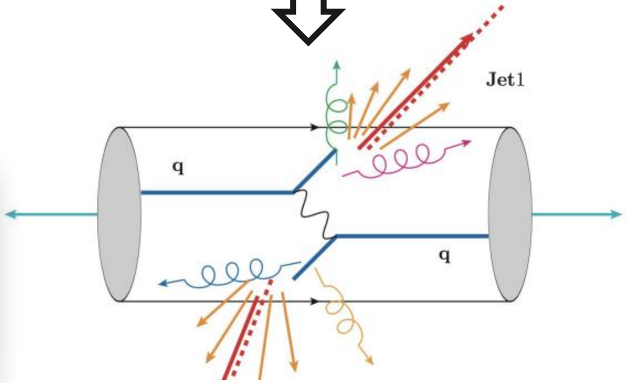


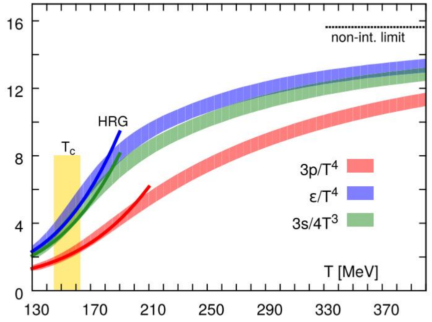
- **Deep generative models** (such as **normalizing flow** and the **diffusion model**) **have been used to sample Field Configureations in Lattice QCD**
- **Deep learning is widely used to solve inverse problems of HIC** to study the **EoS of hot QCD matter, the phase transition, the transport coefficients eta/s, the impact parameter, …**
- **Deep neural network is used to represent the many-body wave function of nucleus, to solve variational problems in ab initio calculations**
- **Deep learning is used to solve inverse problems of HIC to study the nuclear structure, for instance, the nuclear deformation, neutron skin, alpha cluster and short range correlation**
- …

Different approaches for nuclear EoS







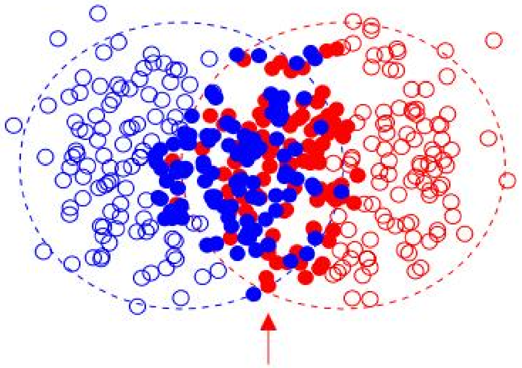


(1) Soft probe: low Pt < 3 GeV/C
hydrodynamics, transport model, ...

(2) Hard probe: Pt > 10 GeV
jet eloss, medium response

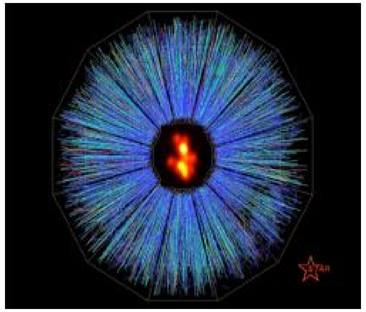
(3) Theoretical calculations
Lattice QCD, HRG, fRG, DSE, Quasi Parton Model, ...

Soft probe: 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

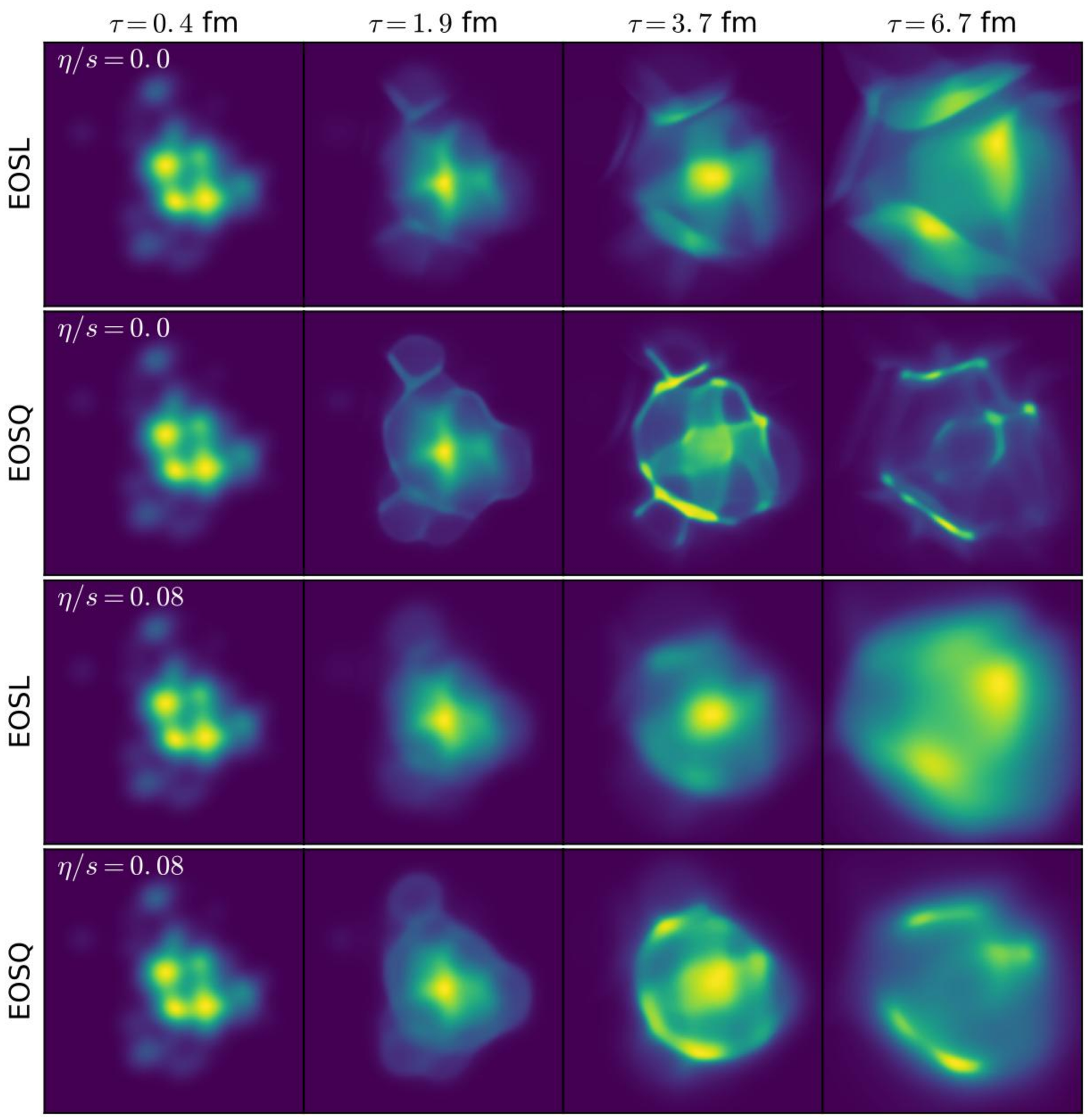
Name of CLVisc:

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: **60 times faster** for hydrodynamic evolution, **100 times faster** for hadronization

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



eta/s = 0
Lattice QCD EoS
(smooth cross over)

eta/s = 0
First order phase transition

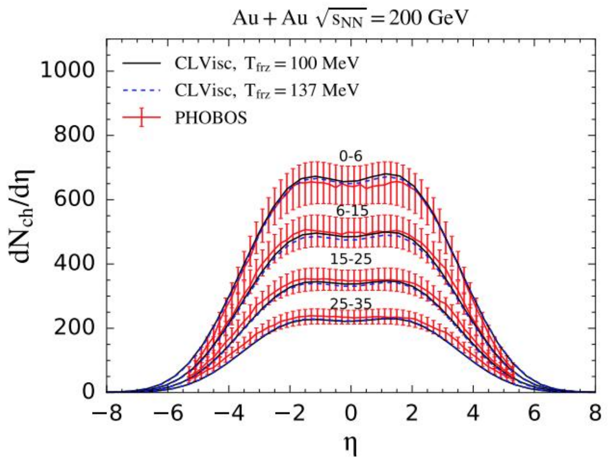
eta/s = 0.08
Lattice QCD EoS

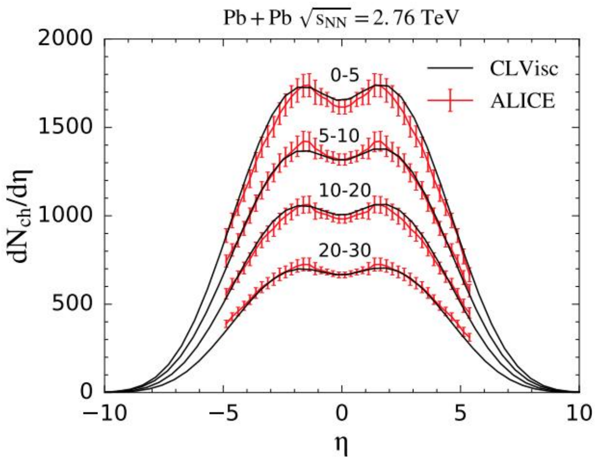
eta/s = 0.08
First order phase transition
eta/s: shear viscosity / entropy density

Will the effect of EoS survive the dynamical evolution and exist in the final state hadrons?

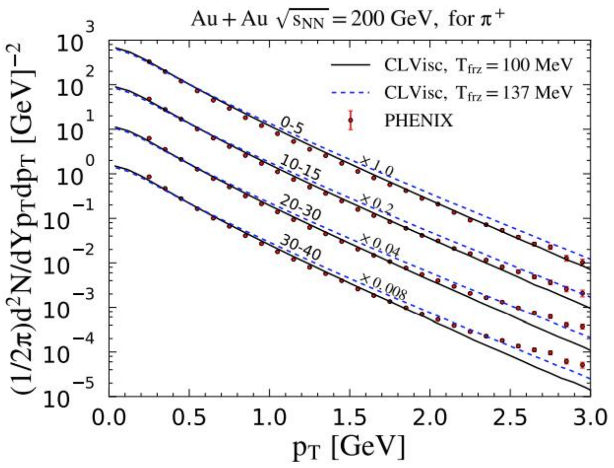
CLVisc for top RHIC and LHC energies

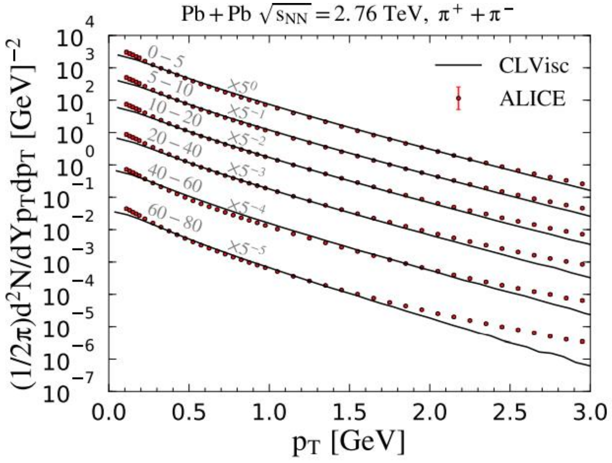
Longitudinal momentum distribution



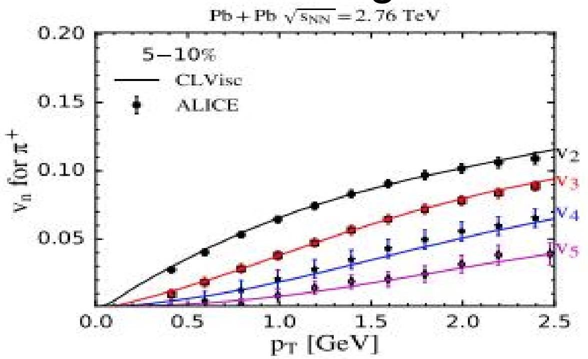


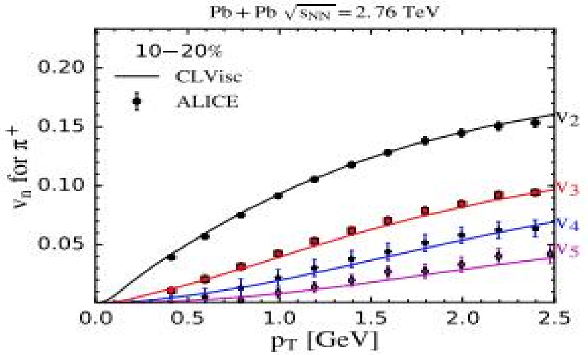
Transverse momentum distribution

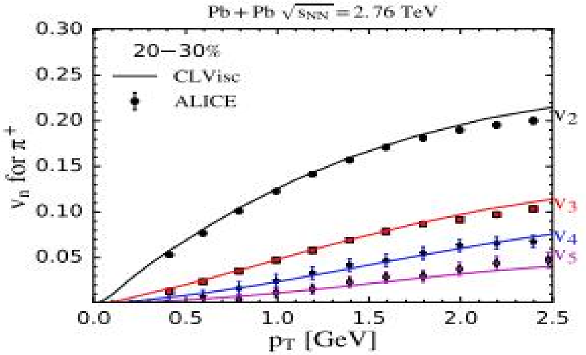




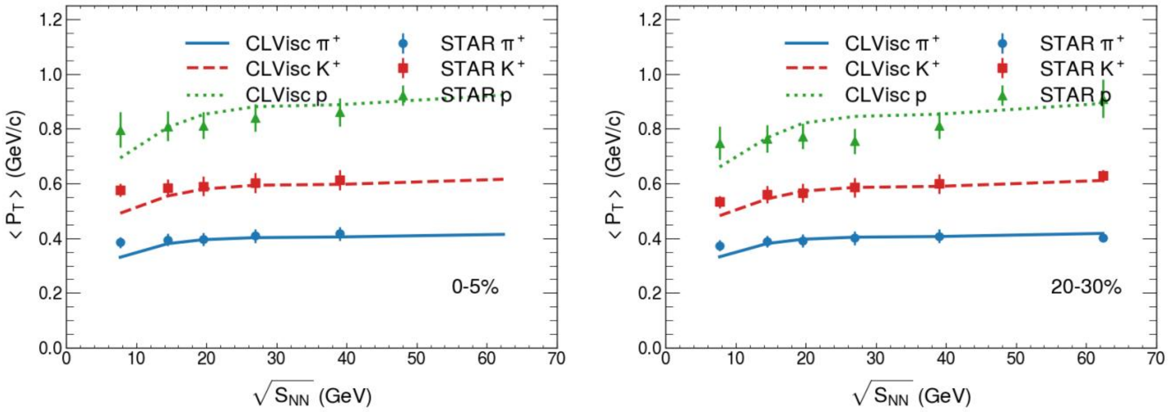
Fourier decomposition coef. for azimuthal angle

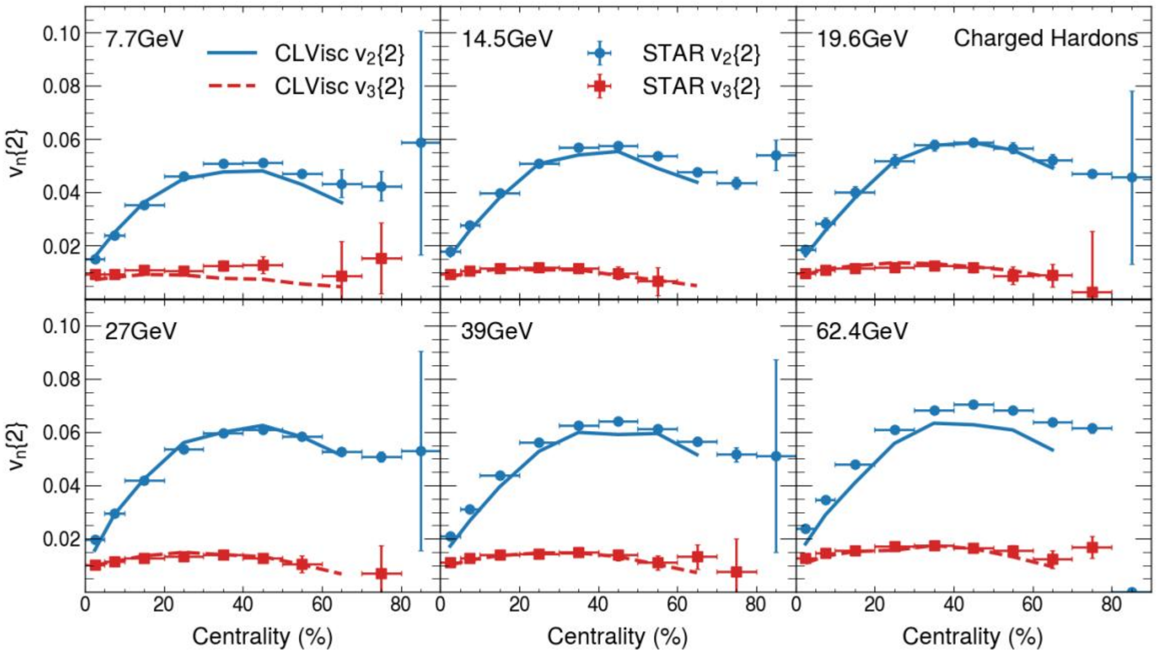






CLVisc for beam energy scan





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

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

$$\Delta^{\mu\nu}_{\alpha\beta} D\pi^{\alpha\beta} = -\frac{1}{\tau_\pi}\left(\pi^{\mu\nu} - \eta_v \sigma^{\mu\nu}\right) \tag{10}$$

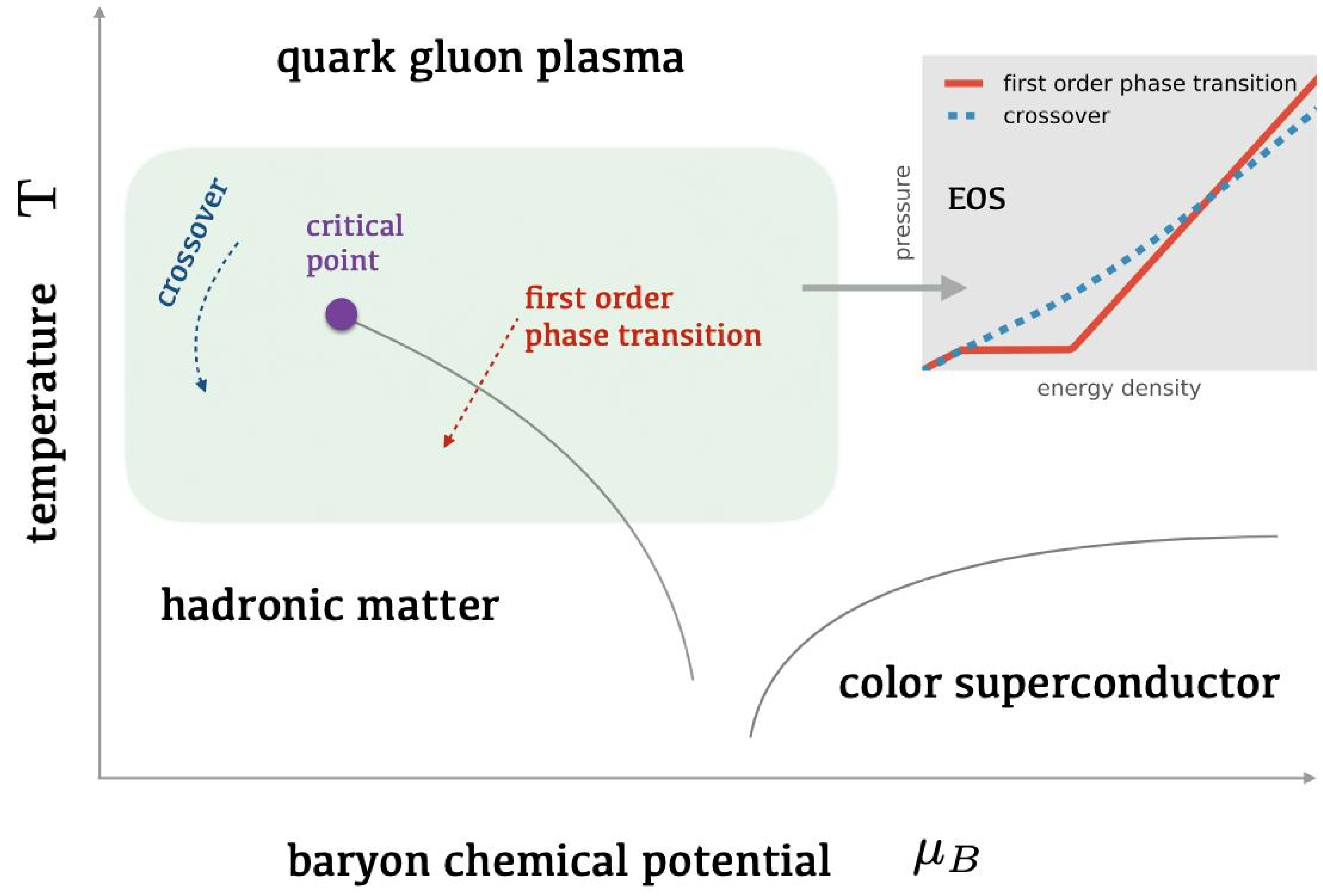
$$-\frac{4}{3}\pi^{\mu\nu}\theta - \frac{5}{7}\pi^{\alpha<\mu}\sigma_\alpha^{\nu>} + \frac{9}{70}\frac{4}{e+P}\pi_\alpha^{<\mu}\pi^{\nu>\alpha}\,,$$

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

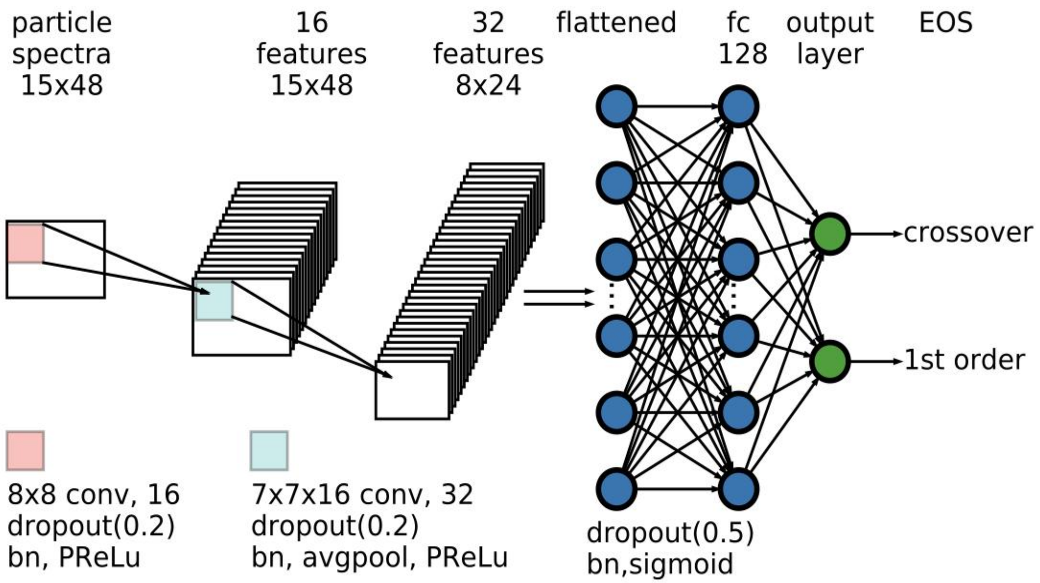
- + net baryon conservation
- + evolution of baryon diffusion current
- + extended to BES regions

XY Wu, GY Qin, LG Pang, XN Wang, PRC 105 (2022) 3, 034909

EoS for different phase transition types

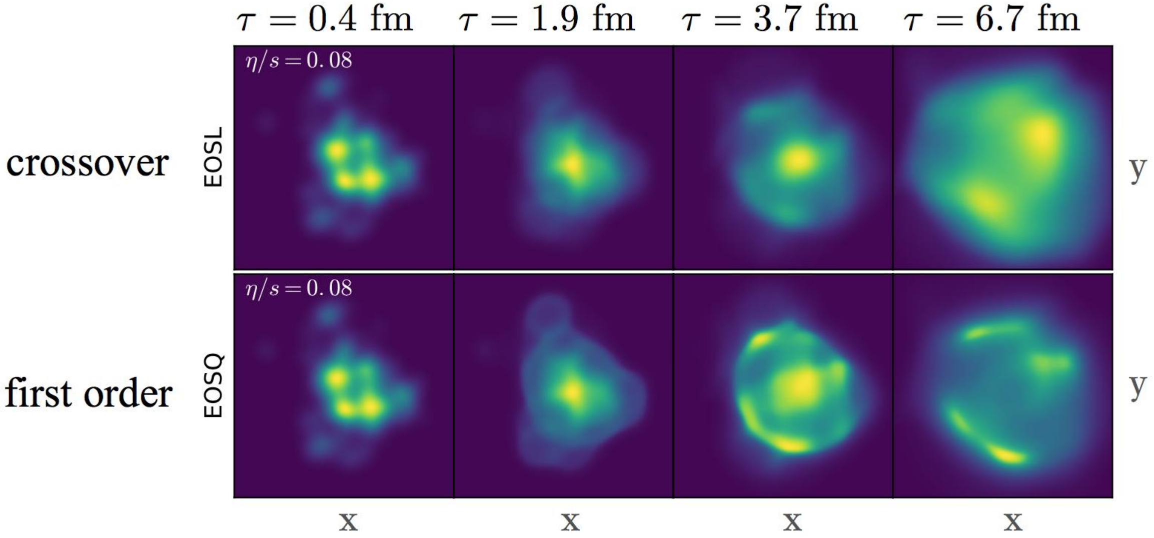


Determine nuclear phase transitions



$$l(\theta) = \underbrace{-\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]}_{\text{cross entropy loss}} + \underbrace{\lambda||\theta||_2^2}_{\text{L2 regularization}}$$

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

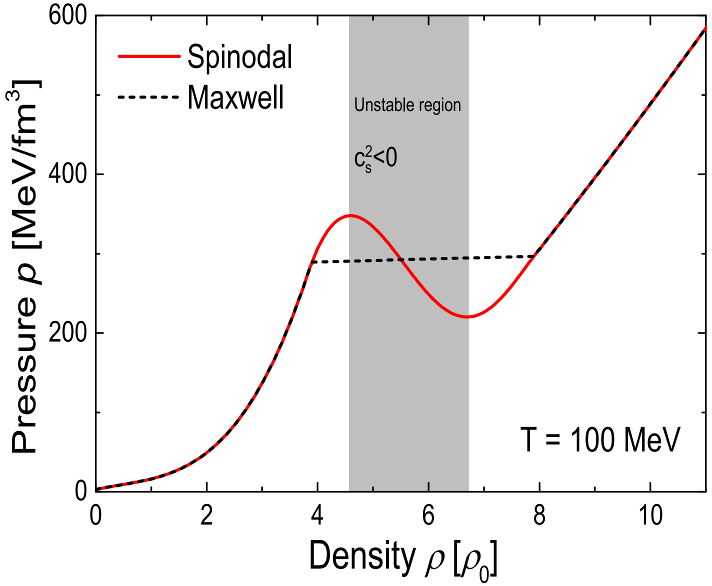


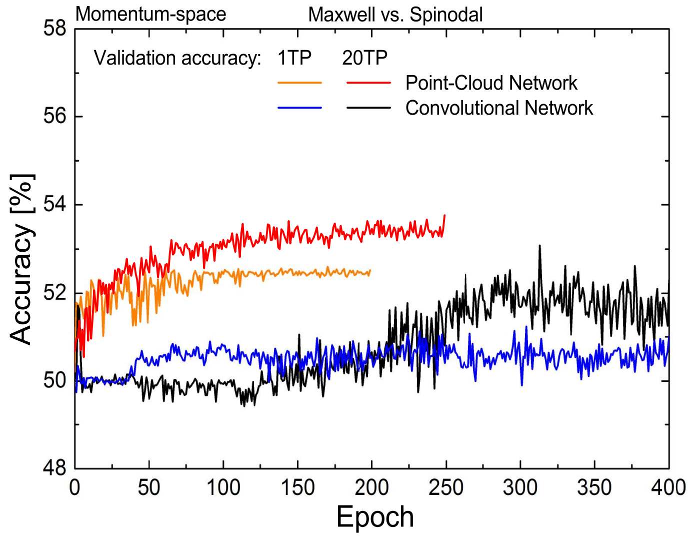
CLVisc 3+1D relativistic hydrodynamics

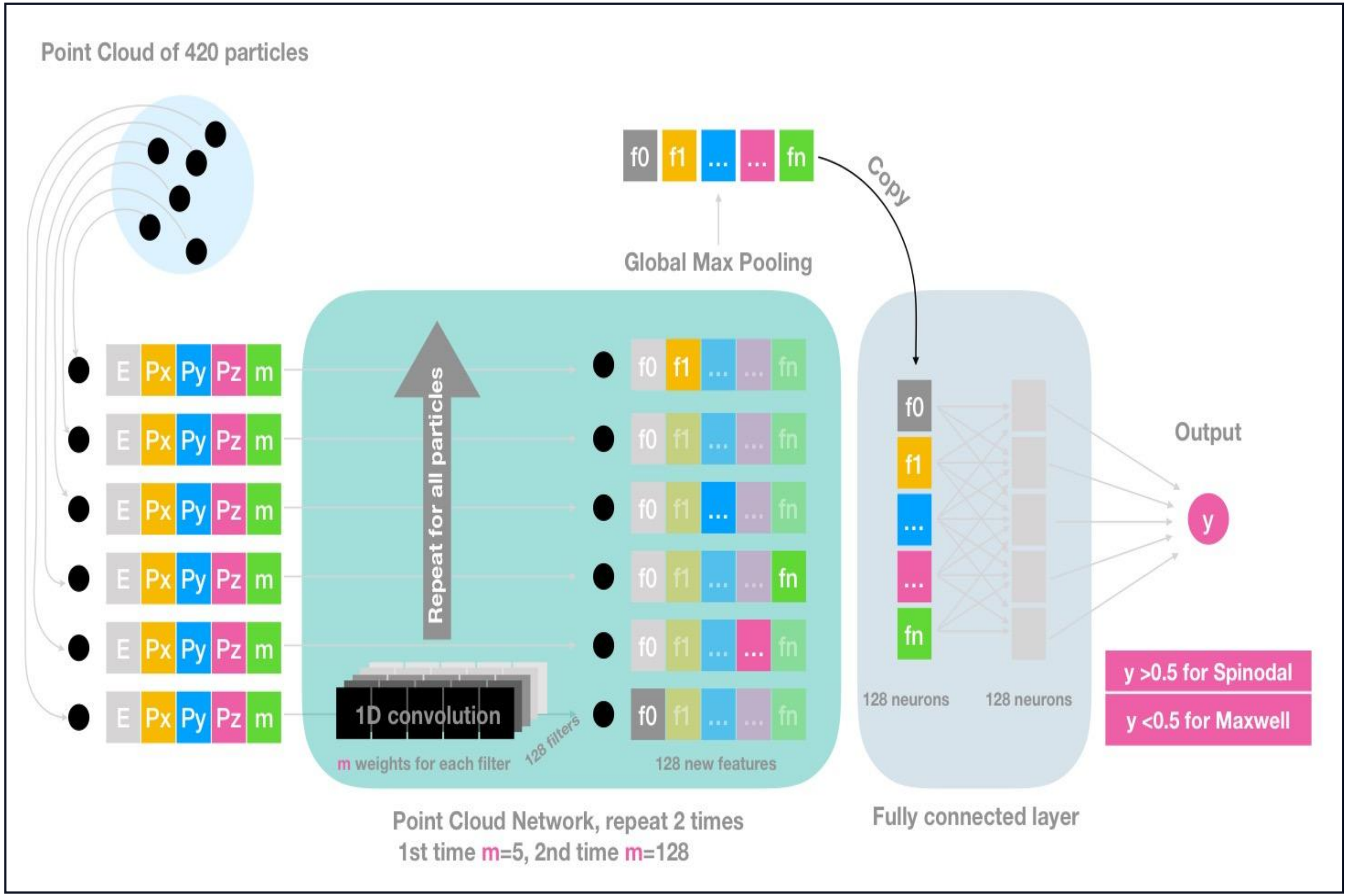
DL： 93% Classification Accuracy!

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

Capture more local correlations

Dynamical Edge Convolution Network

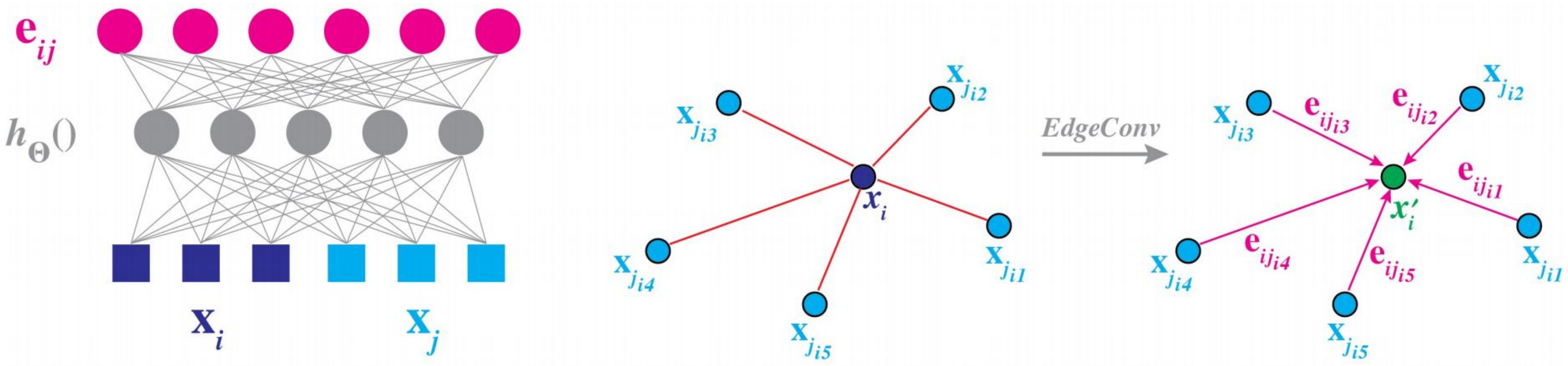
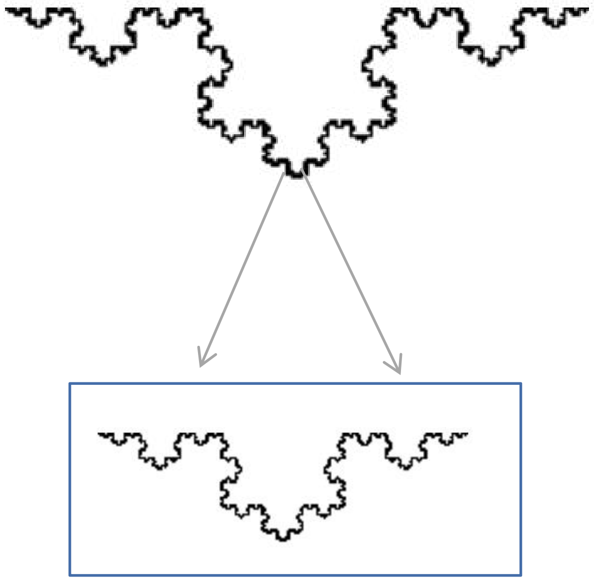


Fig. 2. **Left**: Computing an edge feature, $\mathbf{e}_{ij}$ (top), from a point pair, $\mathbf{x}_i$ and $\mathbf{x}_j$ (bottom). In this example, $h_\Theta()$ is instantiated using a fully connected layer, and the learnable parameters are its associated weights. **Right**: The EdgeConv operation. The output of EdgeConv is calculated by aggregating the edge features associated with all the edges emanating from each connected vertex.

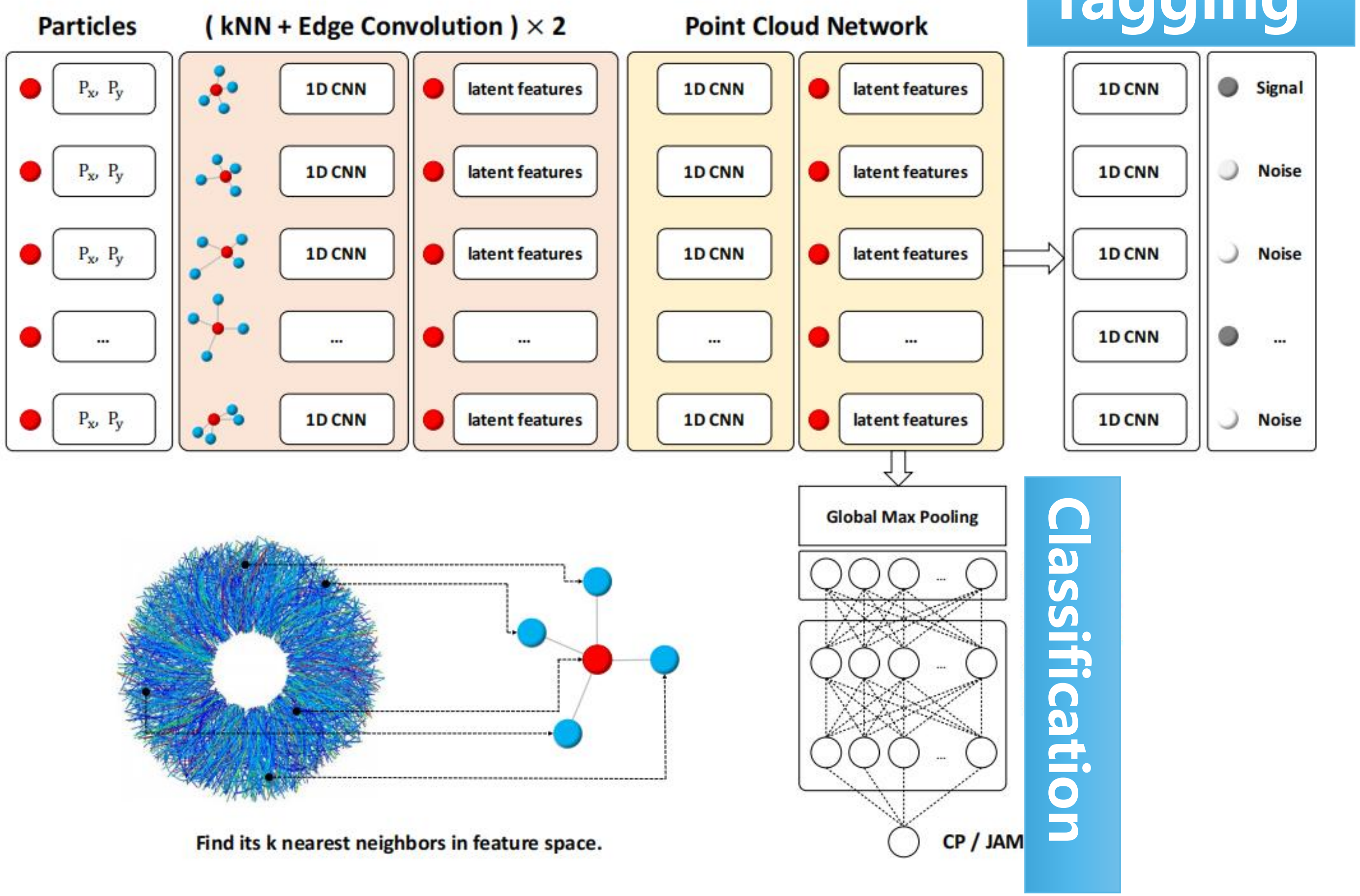
Looking for self similarity in momentum space



Self similarity, scaling invariance

Dynamical Edge Convolution Network

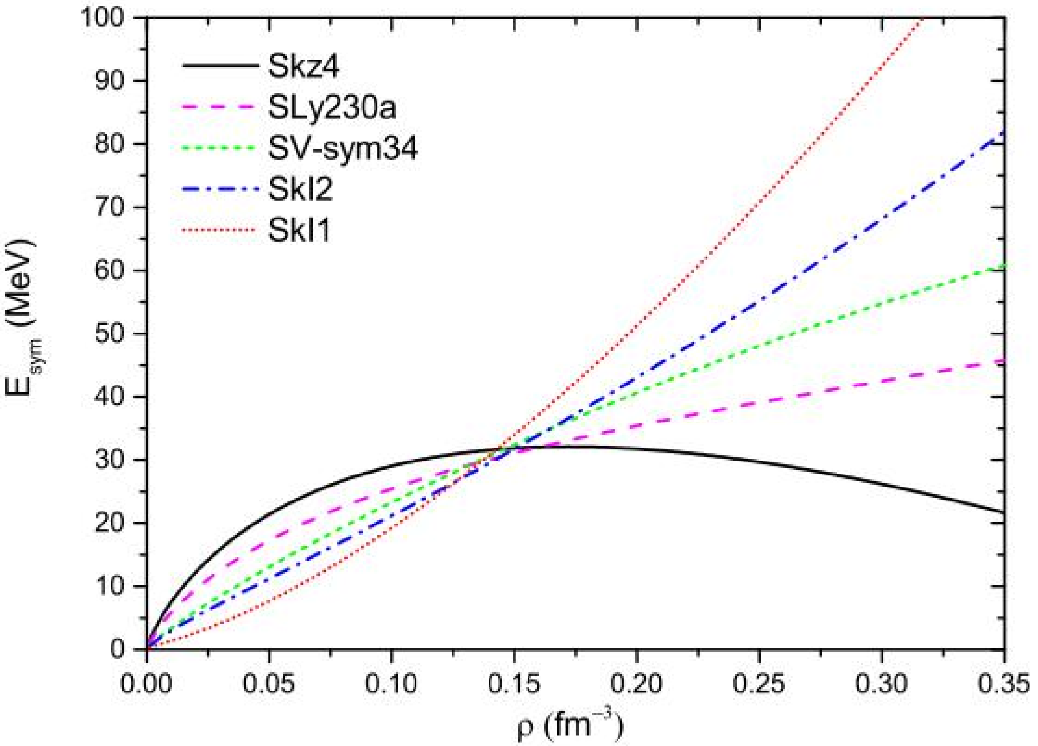
Tagging



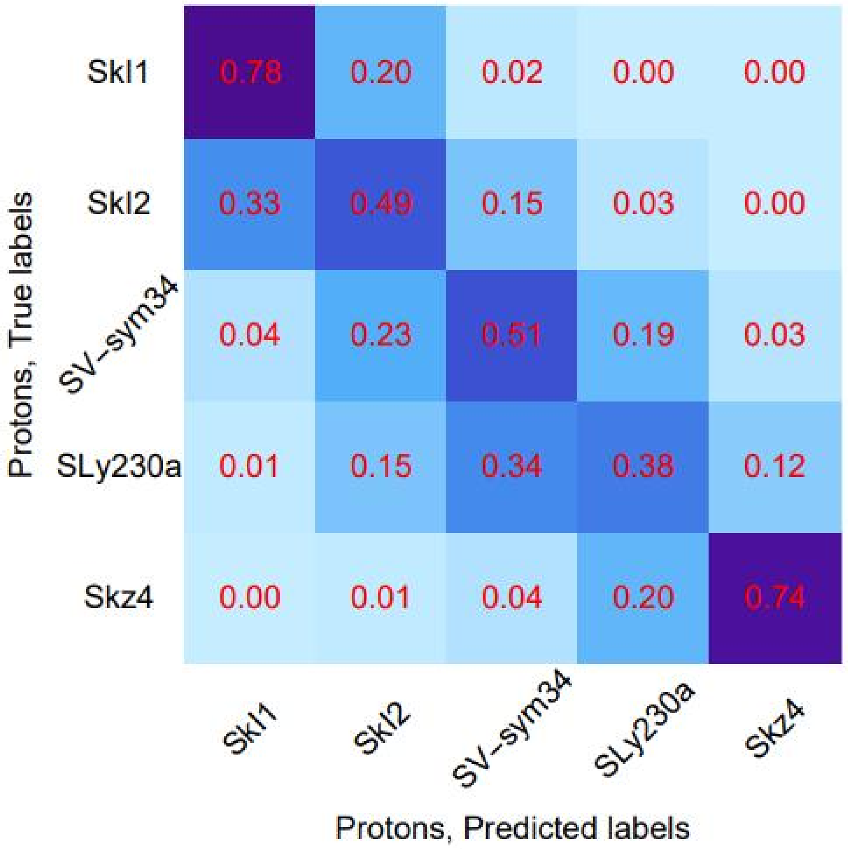
PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

Nuclear EoS at high density region

Skyrme potential + IMQMD



off-diagonal = misclassified



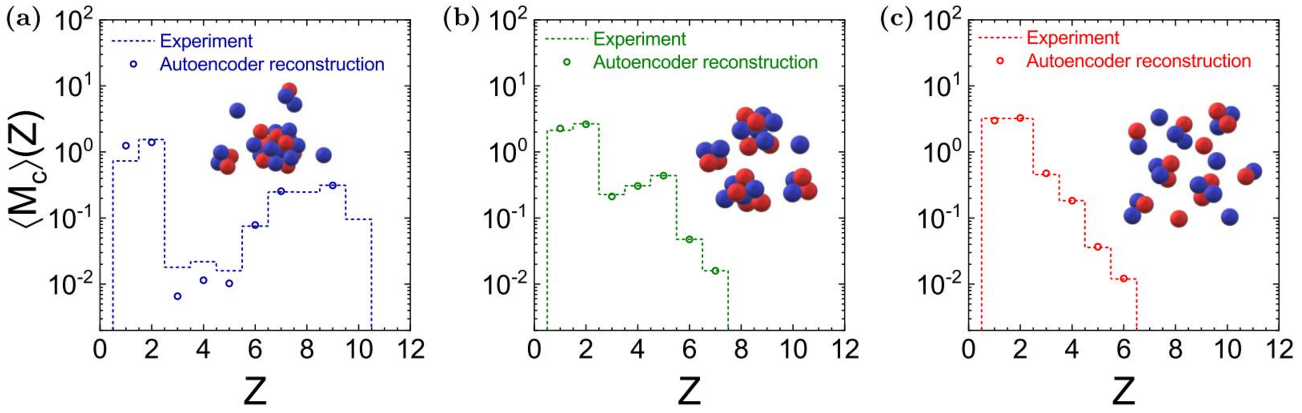
PLB 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

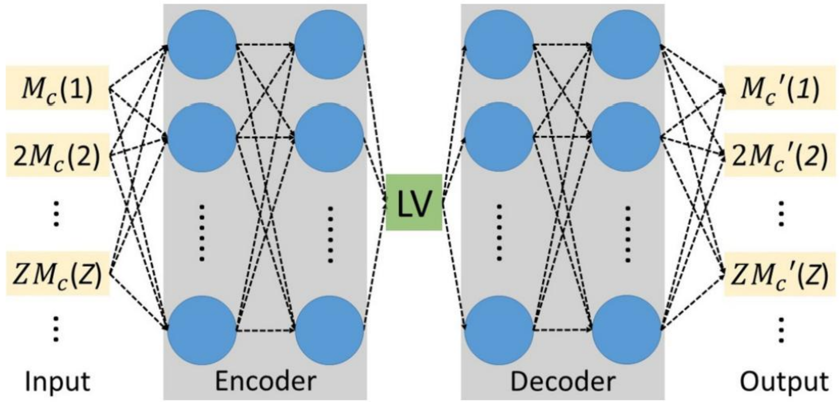
Auto Encoder for order parameter

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

Nuclear liquid-gas phase transition with machine learning

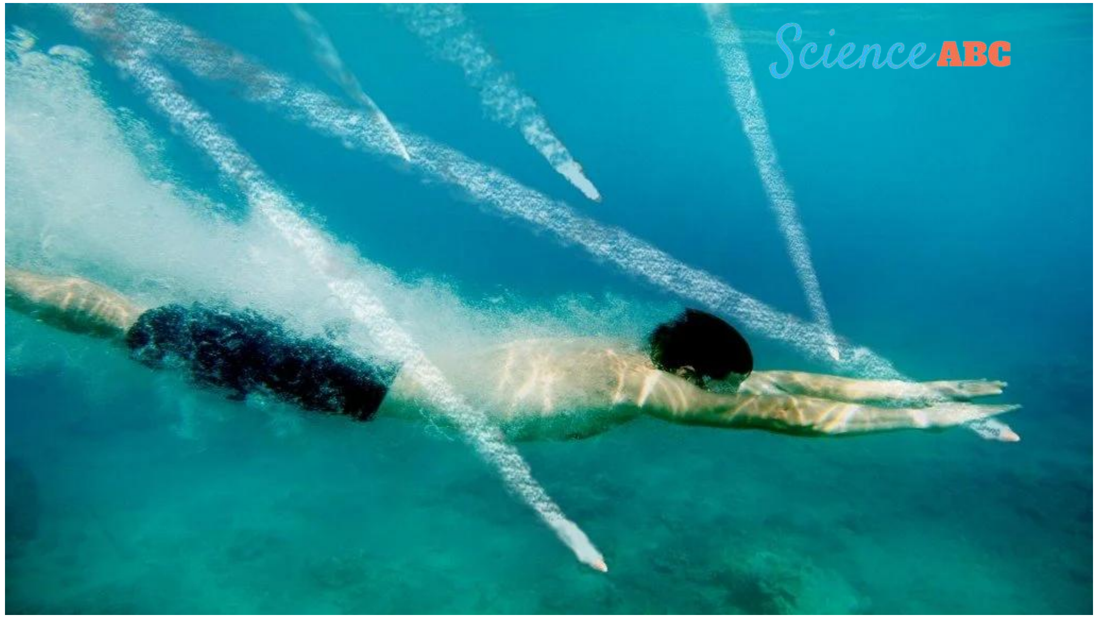
Rui Wang,[1,2,*] Yu-Gang Ma,[1,2,†] R. Wada,[3] Lie-Wen Chen,[4] Wan-Bing He,[1] Huan-Ling Liu,[2] and Kai-Jia Sun[3,5]



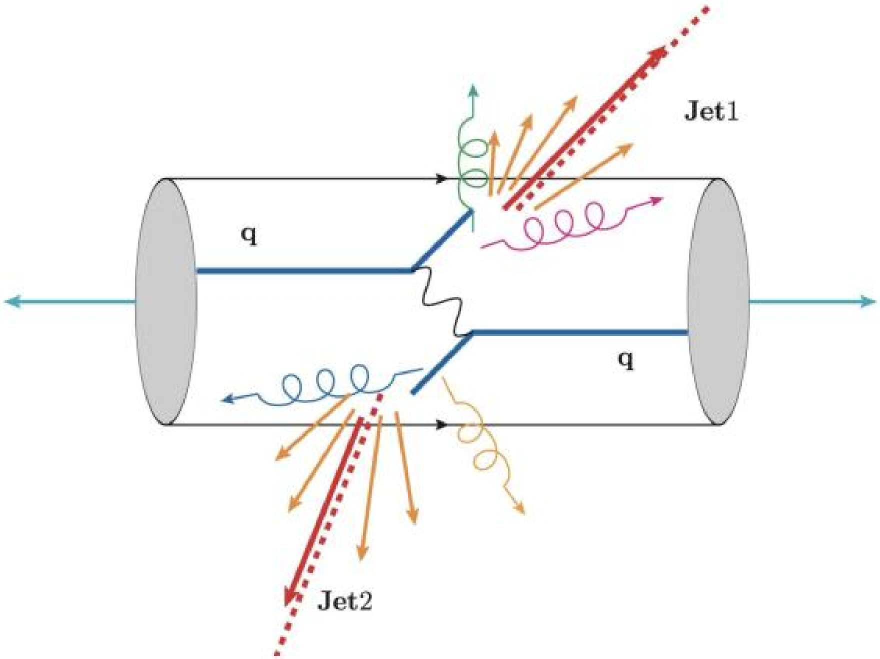


Hard probe: Jet eloss and medium response

Can Being Underwater Protect You From Bullets?

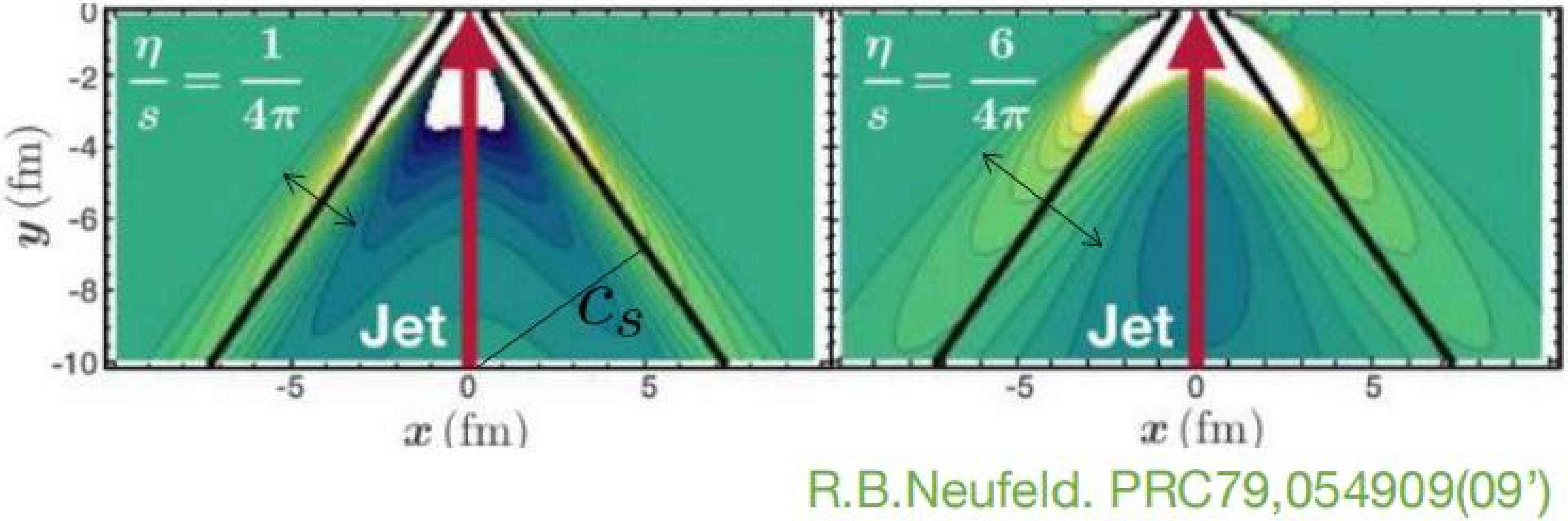


If the bullet is shot from an angle of 30 Degrees, then being underwater in the range of 3-5 feet (0.9-1.5 meters) can ensure safety from most guns.



Jet quenching in hot QGP

The nuclear EoS and Mach Cone

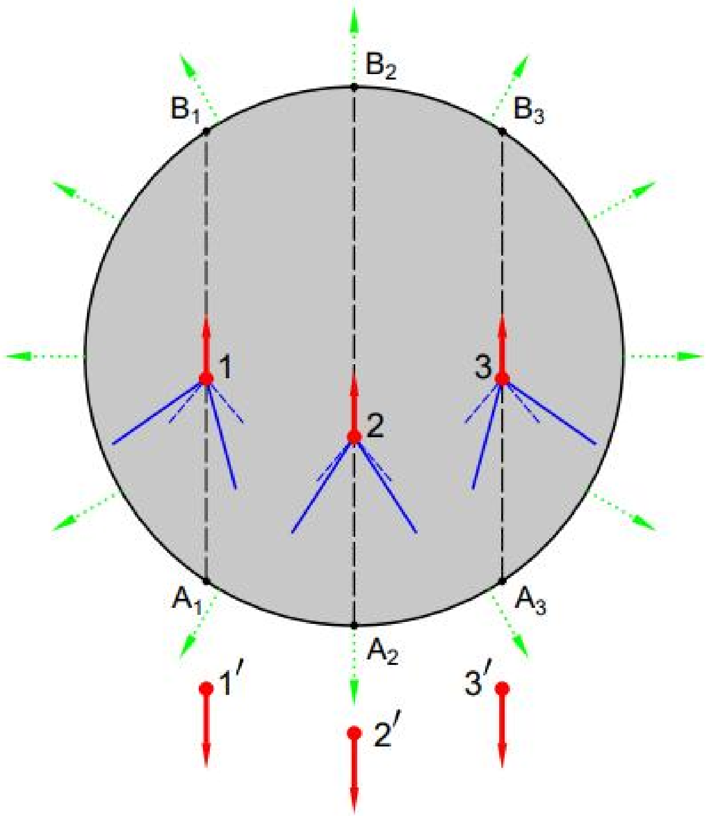


Nuclear EoS： $c_s^2 = \frac{dP}{d\epsilon} = \sin^2\theta$

Shear Viscosity： width of the shock wave

Difficulties in looking for Mach Cones in HIC

- **Random production locations** and **propagating directions** relative to collective flow
- Tilted by different **path length** and **collective flow**



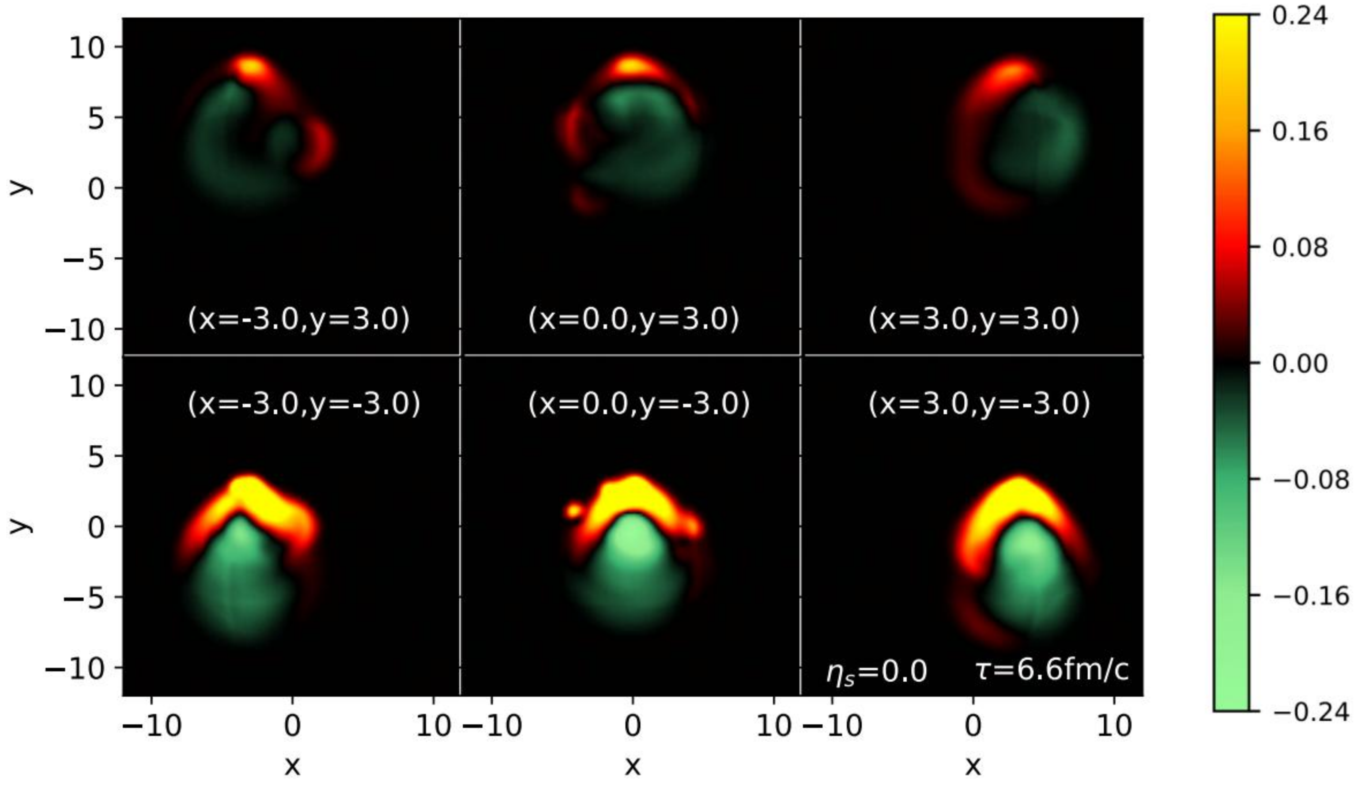
L.M. Satarov, H. Stoecker, I.N. Mishustin, PLB 627 (2005) 64-70

Training data: CoLBT(LBT + CLVisc)

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

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

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



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

CLVisc:

LG Pang, Q Wang, XN Wang, PRC 86 (2012) 024911

LG Pang, H Petersen, XN Wang, PRC 97 (2018) 6, 064918

XY Wu, GY Qin, LG Pang, XN Wang, PRC 105 (2022) 3, 034909

CoLBT:

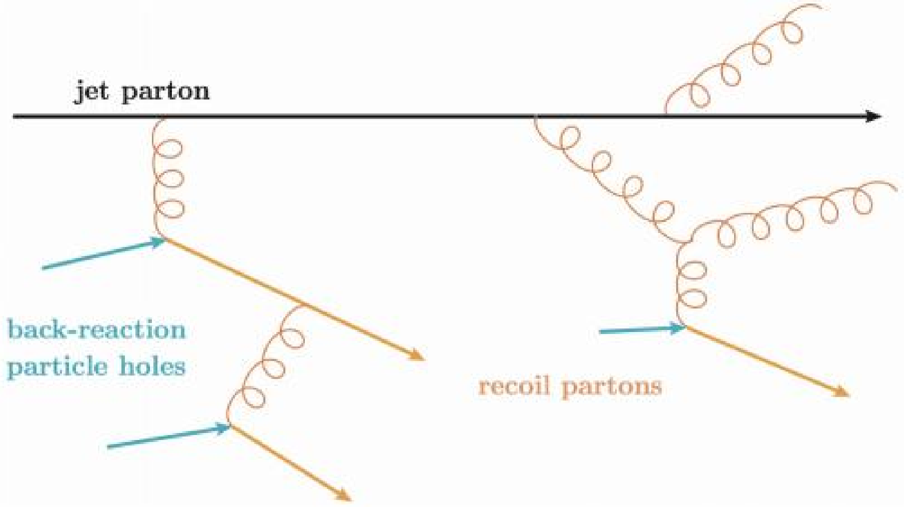
W Chen, T Luo, SS Cao, LG Pang, XN Wang, PLB 777 (2018) 86-90

LBT: Linear Boltzmann Transport

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

Medium-induced gluon(HT):

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

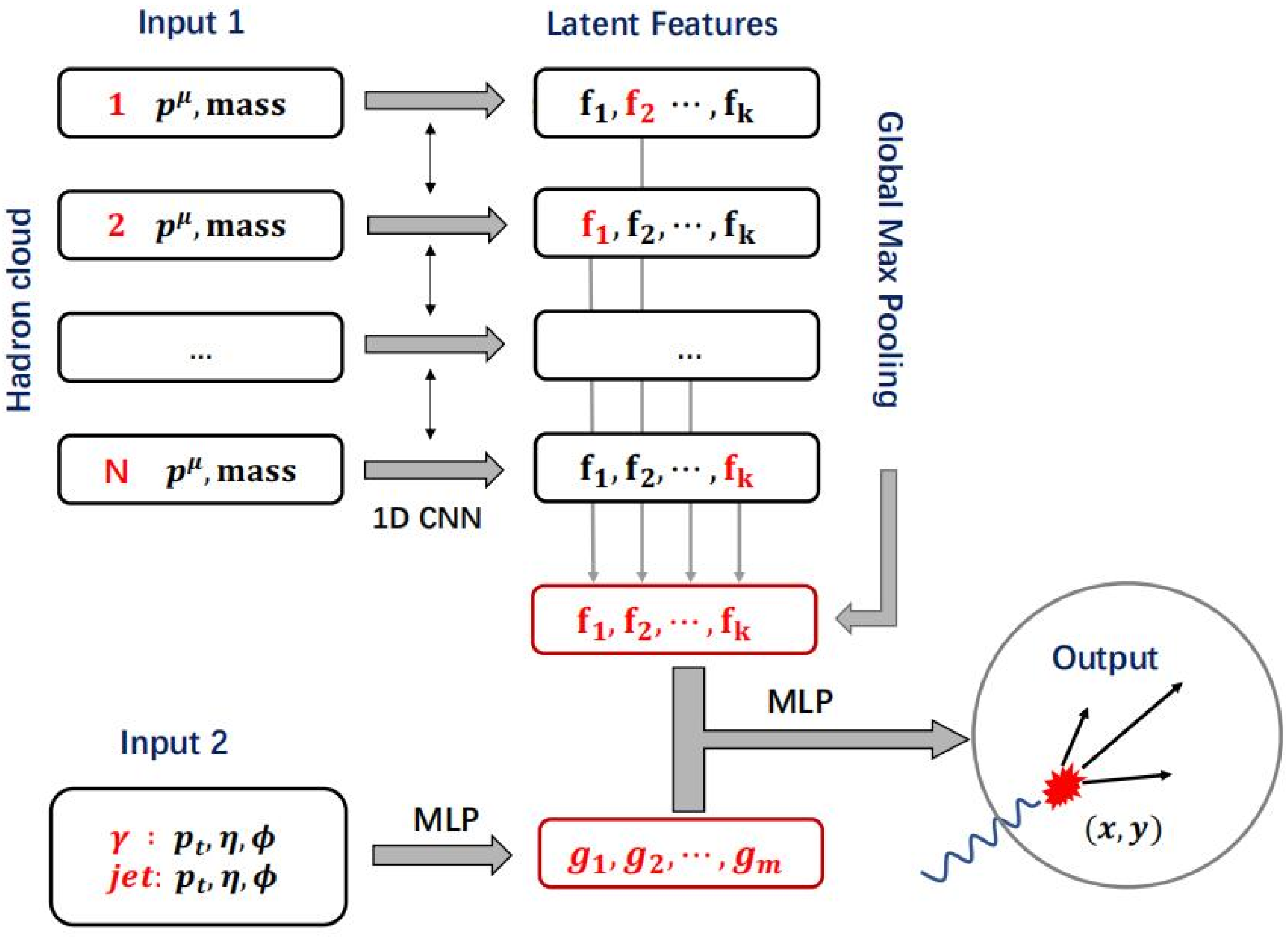


Tracked partons:

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

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

DL assisted jet tomography (gamma-jet)

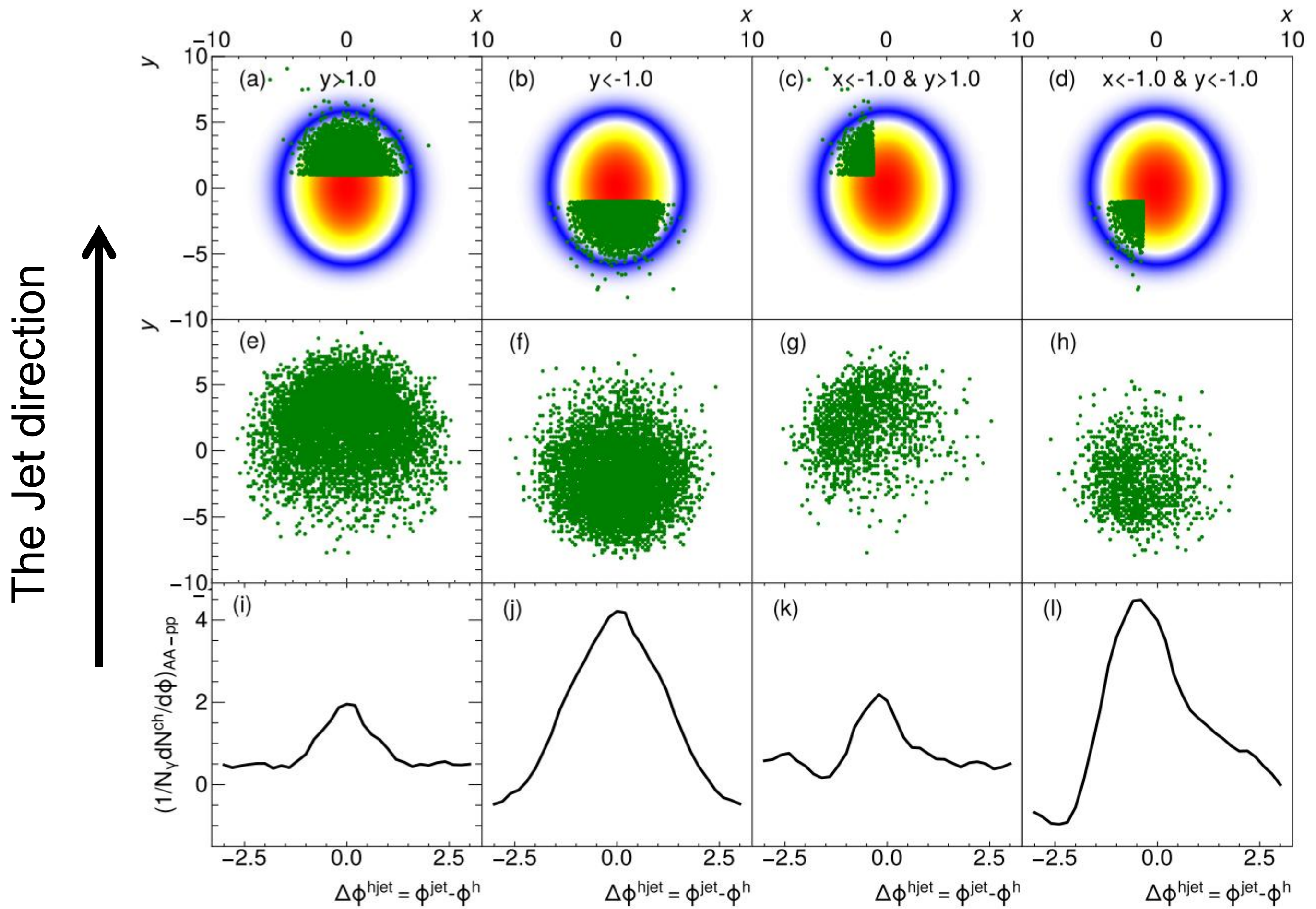


$ij \to kl$	$\lvert M\rvert^2_{ij\to kl}$	
$gg \to gg$	$\frac{9}{2} g_s^4 \left(3 - \frac{ut}{s^2} - \frac{us}{t^2} - \frac{st}{u^2}\right)$	(A-1)
$gg \to q\bar{q}$	$\frac{3}{8} g_s^4 \left(\frac{4}{9}\frac{t^2+u^2}{tu} - \frac{t^2+u^2}{s^2}\right)$	(A-2)
$gq \to gq$ $g\bar{q} \to g\bar{q}$	$g_s^4 \left(\frac{s^2+u^2}{t^2}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

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

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

DL assisted jet tomography



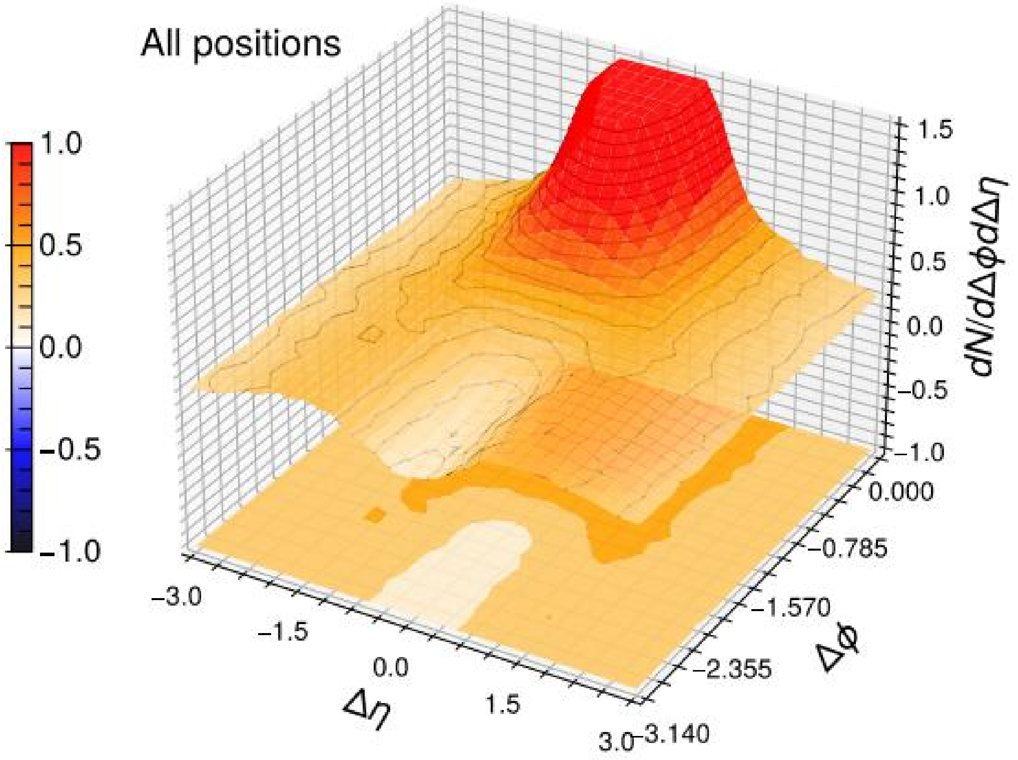
Network predictions

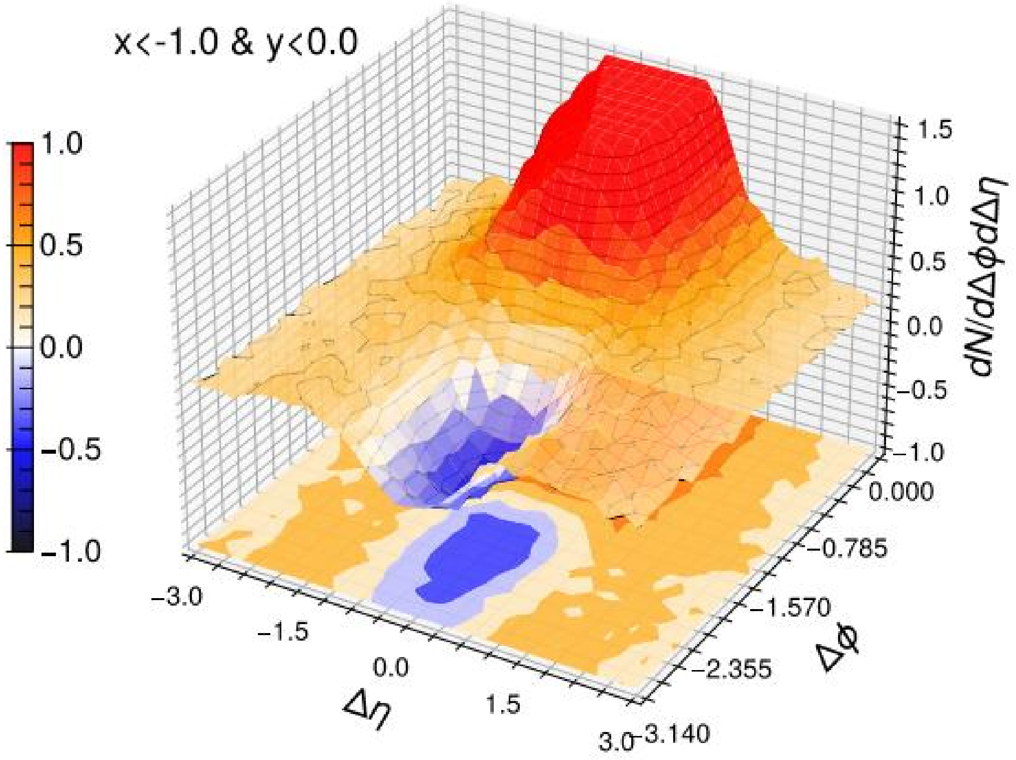
True locations

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

Enhance the Diffusion Wake signal

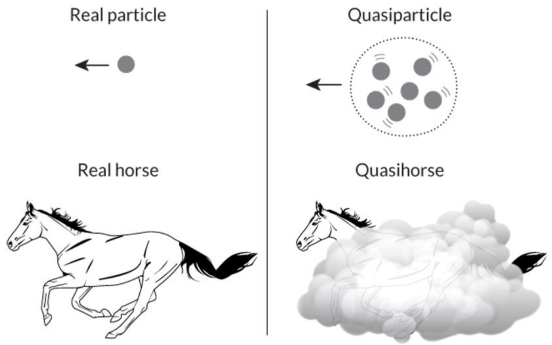


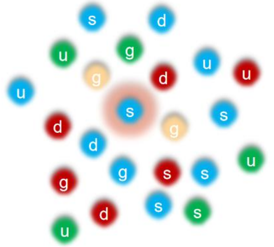


Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652

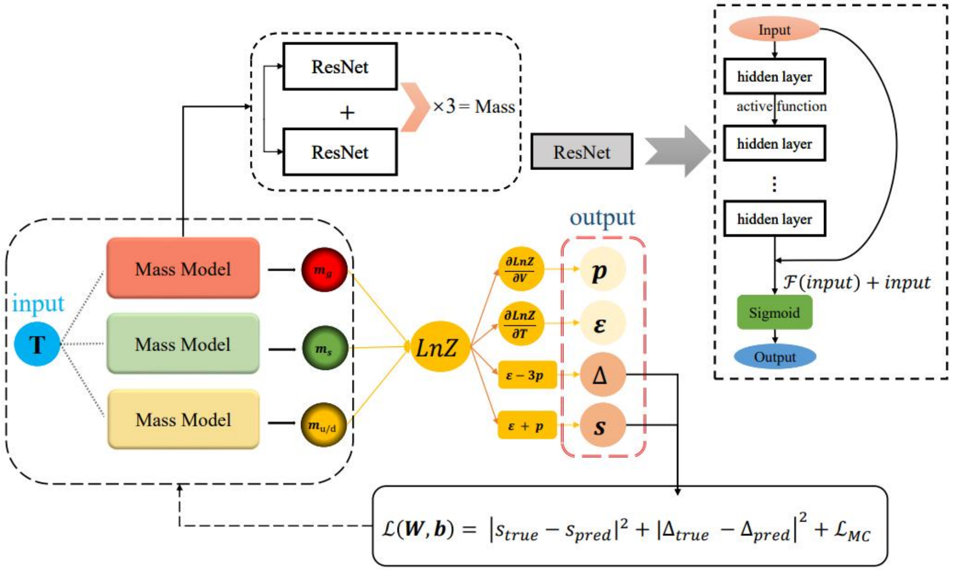
Z Yang, T Luo, W Chen, LG Pang, XN Wang, PRL 130 (2023) 5, 052301

Effective theory: DL For Quasi Particle Mass





screened, dressed, regularized, quasi particle



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

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

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.

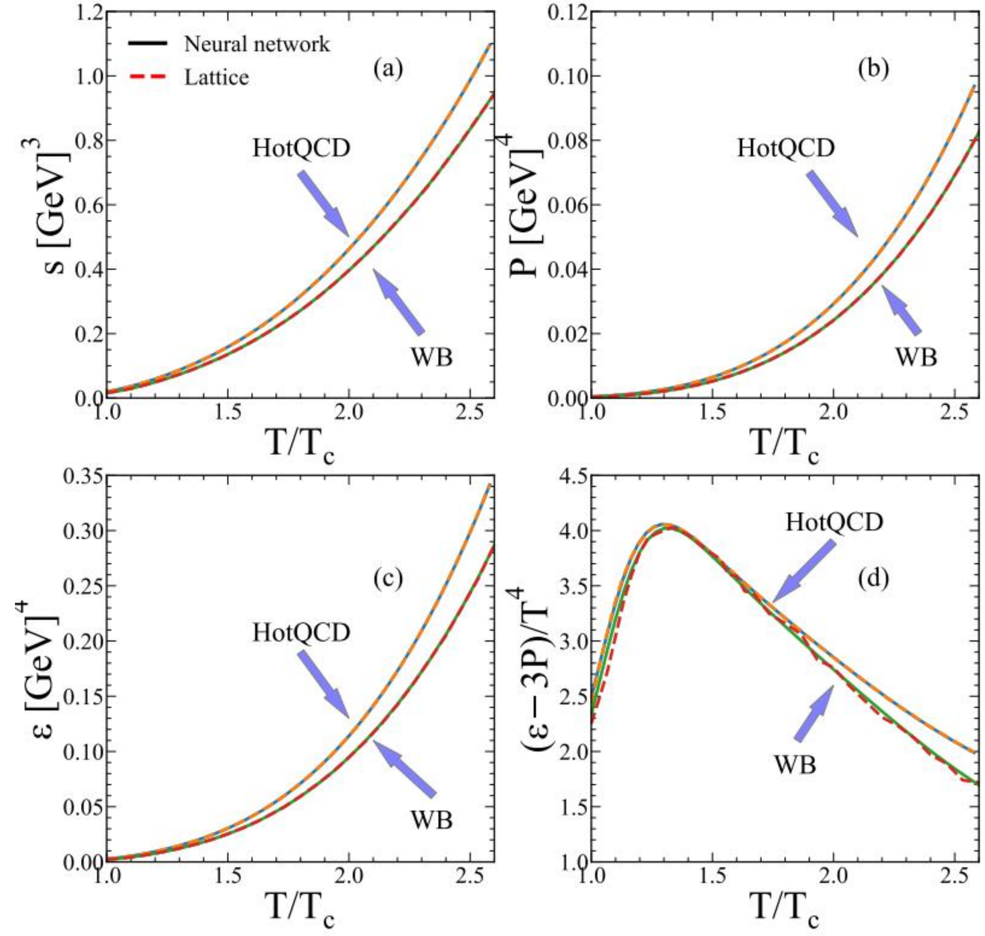
The resulting pressure and energy density are computed using the following statistical formulae,

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

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

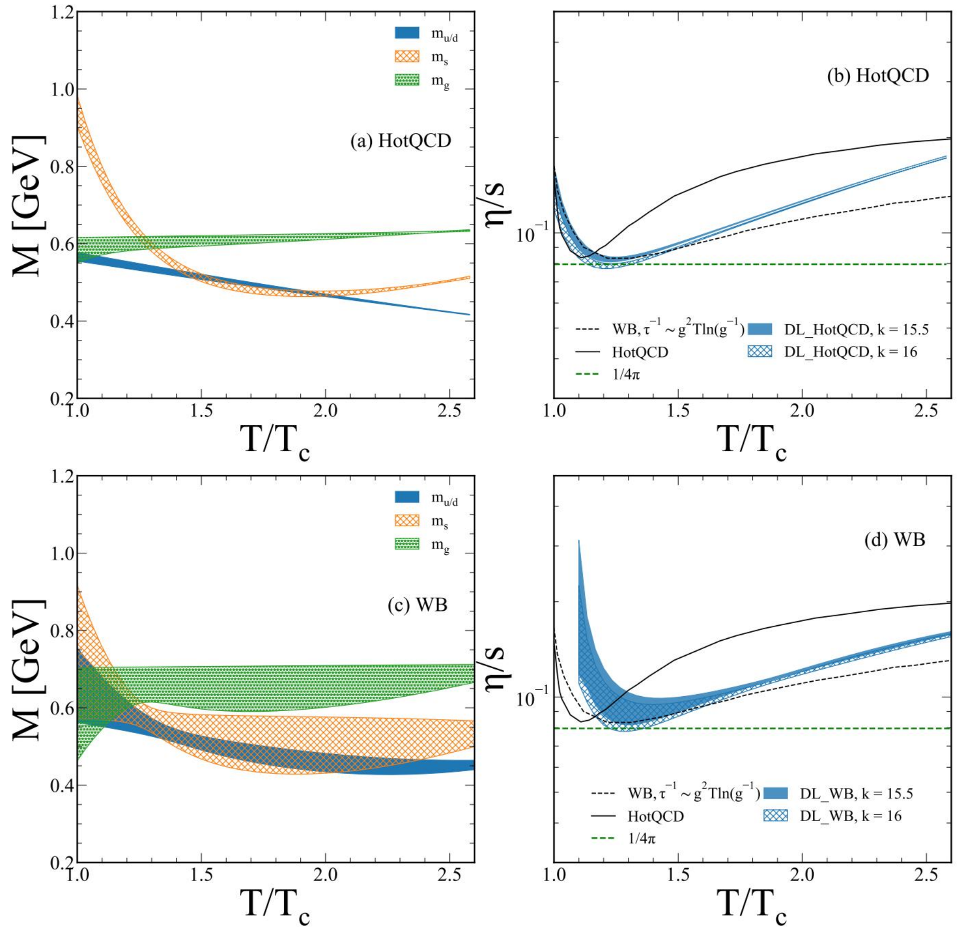
The learned quasi parton mass

EoS vs Lattice QCD



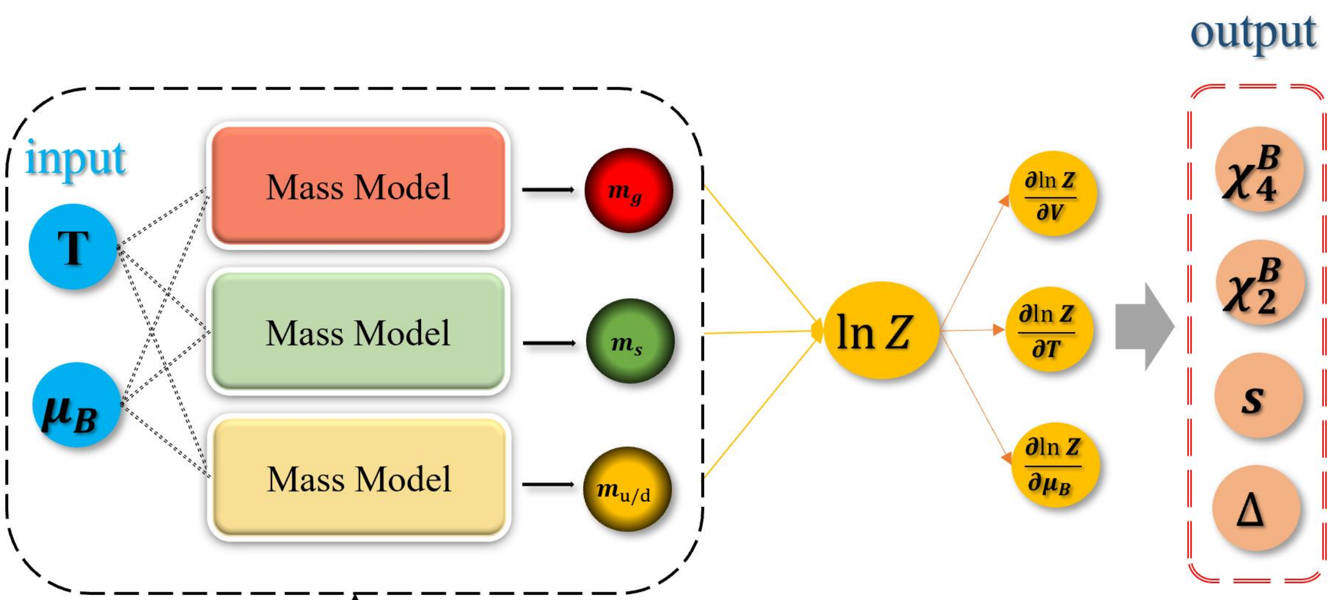
Learned Mass

η/s

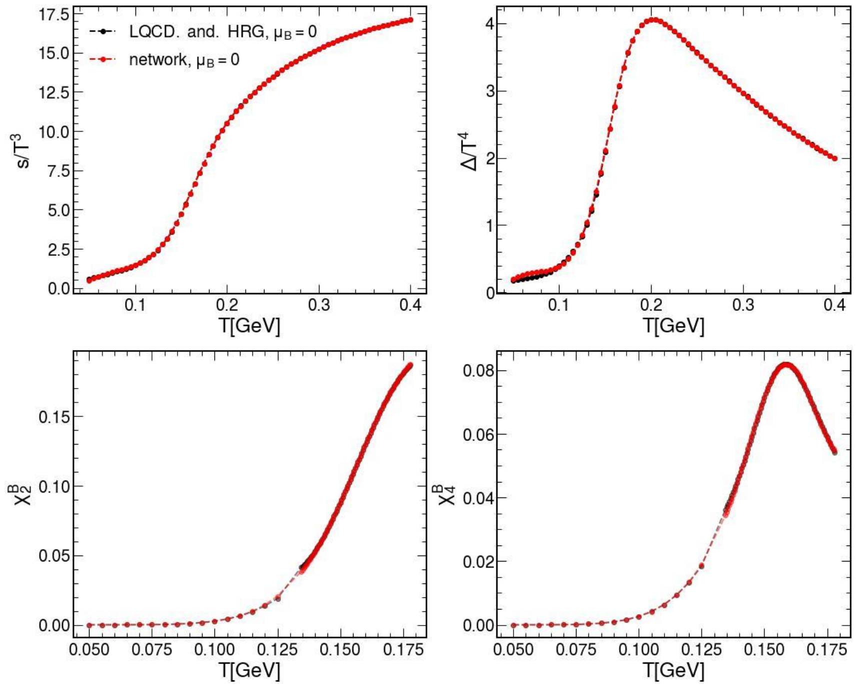


FuPeng Li, HL Lu, LG Pang, GY Qin, PLB 2023

Looking for CEP using Quasi Parton Model



$$\mathcal{L}(\boldsymbol{W}, \boldsymbol{b}) = |s_{NN} - s_{input}| + |\frac{\Delta_{NN} - \Delta_{input}}{T}| + |\chi^B_{2,NN} - \chi^B_{2,input}| + |\chi^B_{4,NN} - \chi^B_{4,input}| + \mathcal{L}_{MC}$$

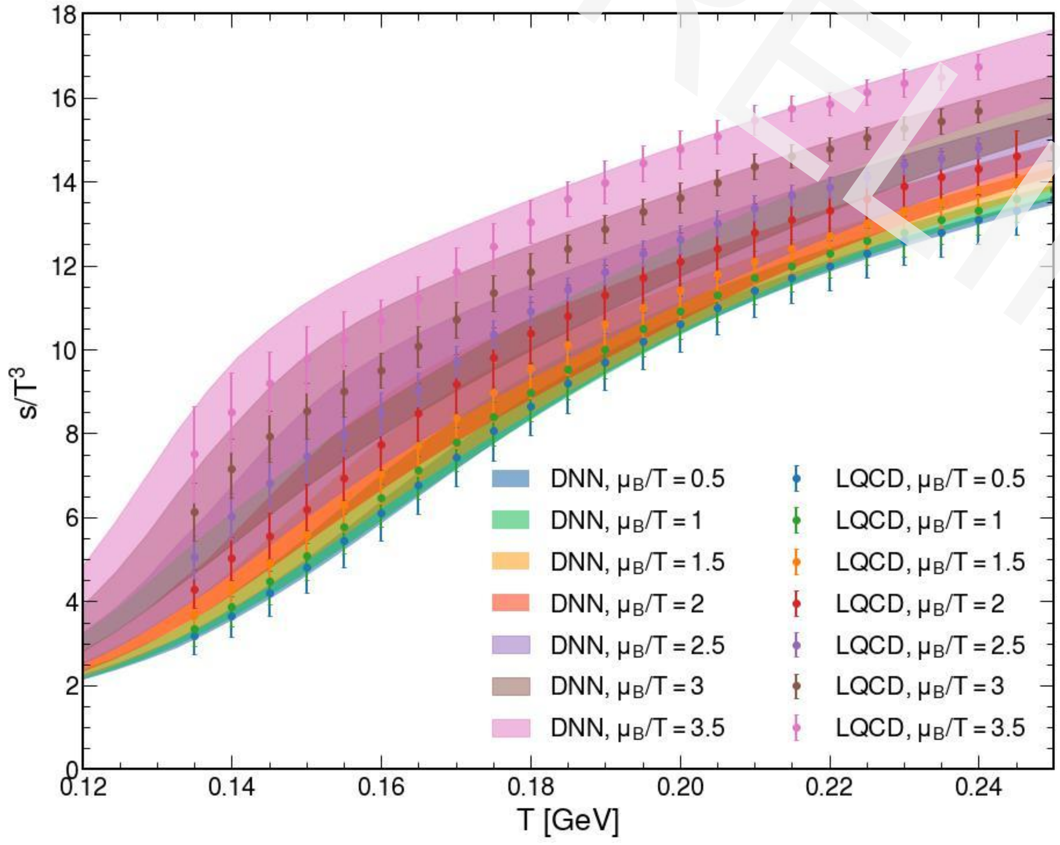


Model:
Deep learning Quasi Parton Model
Effective theory of strongly coupled QGP and nuclear matter at finite baryon density

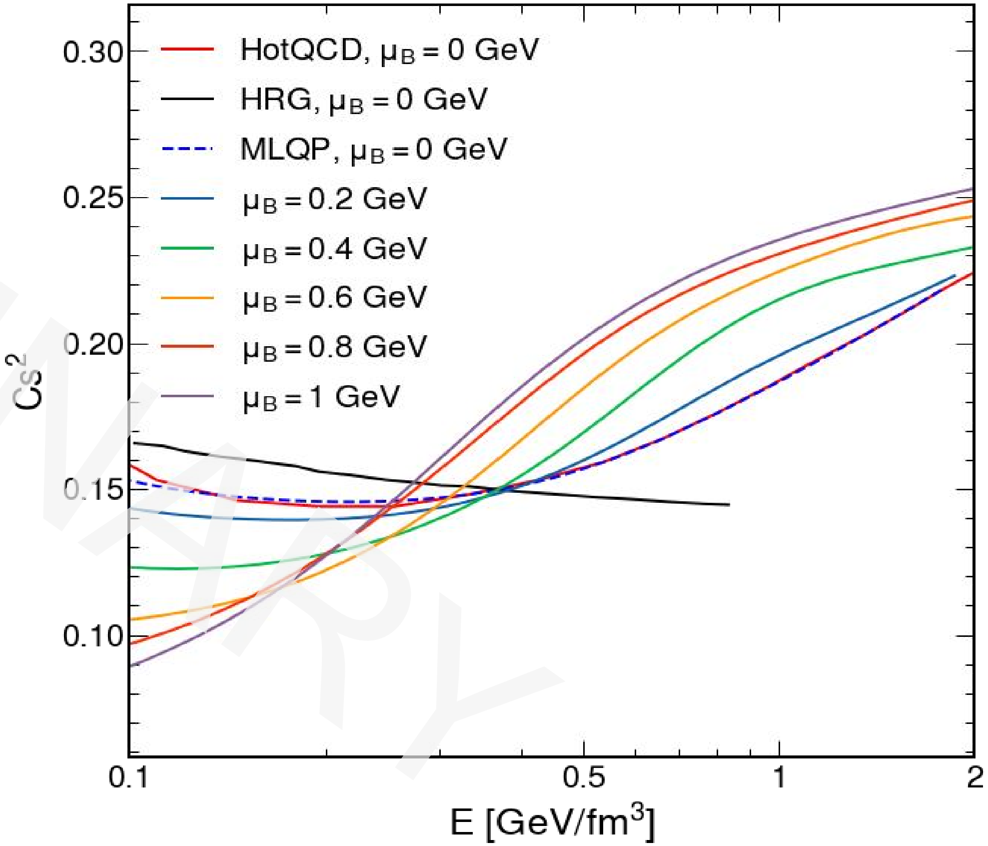
Training data: Lattice QCD + HRG
PRD 95, 054504 (2017)
PRL118, 182301 (2017)
PRD 90, 094503 (2014)

Predictions of DL quasi parton model

Entropy density

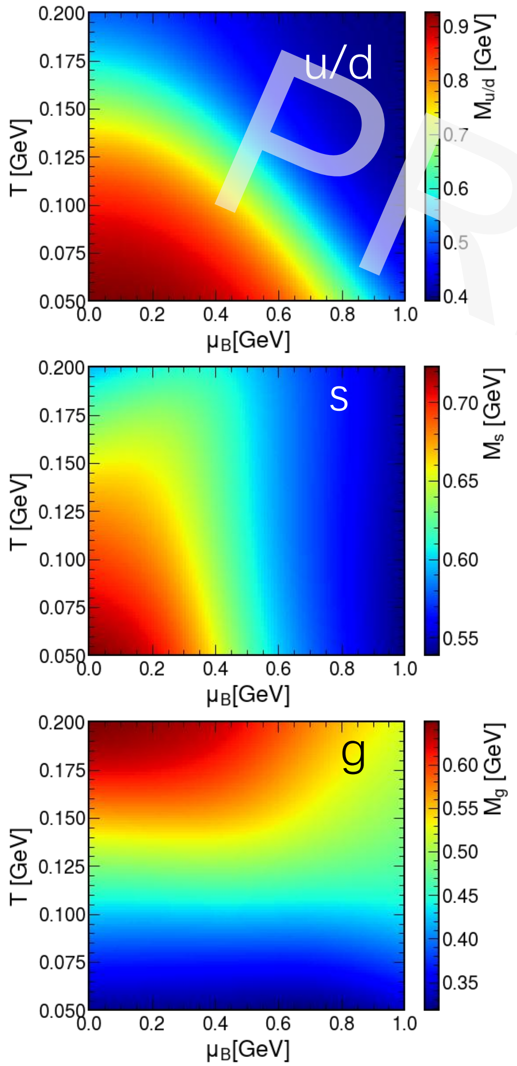


Speed of sound

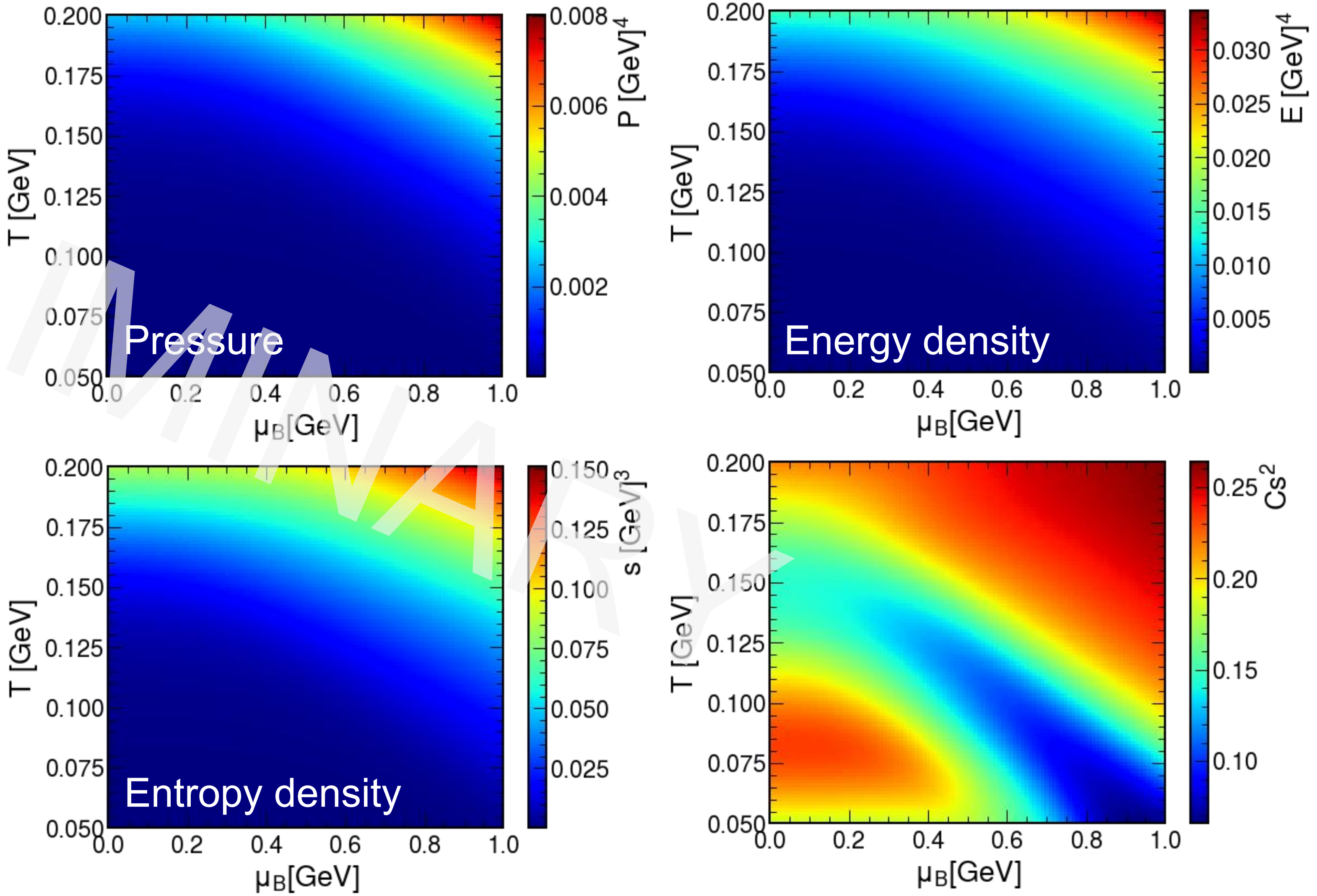


The learned Mass and EoS

Mass



EoS



Reviews

Colloquium: Machine learning in nuclear physics

Amber Boehnlein, Markus Diefenthaler, Nobuo Sato, Malachi Schram, Veronique Ziegler, Cristiano Fanel
Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostroumov,
Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang
Rev. Mod. Phys. **94**, 031003 – Published 8 September 2022

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

ABSTRACT

Advances in machine learning methods provide tools that have broad applicability in scientific resea
These techniques are being applied across the diversity of nuclear physics research topics, leading

High energy nuclear physics meets Machine Learning

#1

Wan-Bing He (Fudan U., Shanghai and Fudan U.), Yu-Gang Ma (Fudan U., Shanghai and Fudan U.), Long-Gang Pang, Huichao Song (CCNU, Wuhan, Inst. Part. Phys. and Hua-Zhong Normal U., LQLP and Peking U.), Kai Zhou (Frankfurt U., FIAS) (Mar 12, 2023)

e-Print: 2303.06752 [hep-ph]

Exploring QCD matter in extreme conditions with Machine Learning

Kai Zhou (Frankfurt U., FIAS), Lingxiao Wang (Frankfurt U., FIAS), Long-Gang Pang (CCNU, Wuhan, Inst. Part. Phys.), Shuzhe Shi (Stony Brook U.)

Mar 27, 2023

146 pages

e-Print: 2303.15136 [hep-ph]

HEPML-LivingReview

A Living Review of Machine Learning for Particle Physics

Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

download review

The purpose of this note is to collect references for modern machine learning as applied to particle physics. A minimal number of categories is chosen in order to be as useful as possible. Note that papers may be referenced in more than one category. The fact that a paper is listed in this document does not endorse or validate its content - that is for the community (and for peer-review) to decide. Furthermore, the classification here is a best attempt and may have flaws - please let us know if (a) we have missed a paper you think should be included, (b) a paper has been misclassified, or (c) a citation for a paper is not correct or if the journal information is now available. In order to be as useful as possible, this document will continue to evolve so please check back before you write your next paper. If you find this review helpful, please consider citing it using \cite{hepmllivingreview} in HEPML.bib.

- Reviews
  - Modern reviews
    - Jet Substructure at the Large Hadron Collider: A Review of Recent Advances in Theory and Machine Learning [DOI]
    - Deep Learning and its Application to LHC Physics [DOI]

Summary

- For soft probes, DL serves as an EoS-meter
- For hard probes, DL assisted jet tomography aids in the investigation of QCD EoS through Mach cones
- DL and auto-diff are widely used to represent unknown functions to construct effective theories of QCD EoS.
- DL quasi parton model are extended to finite muB region

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

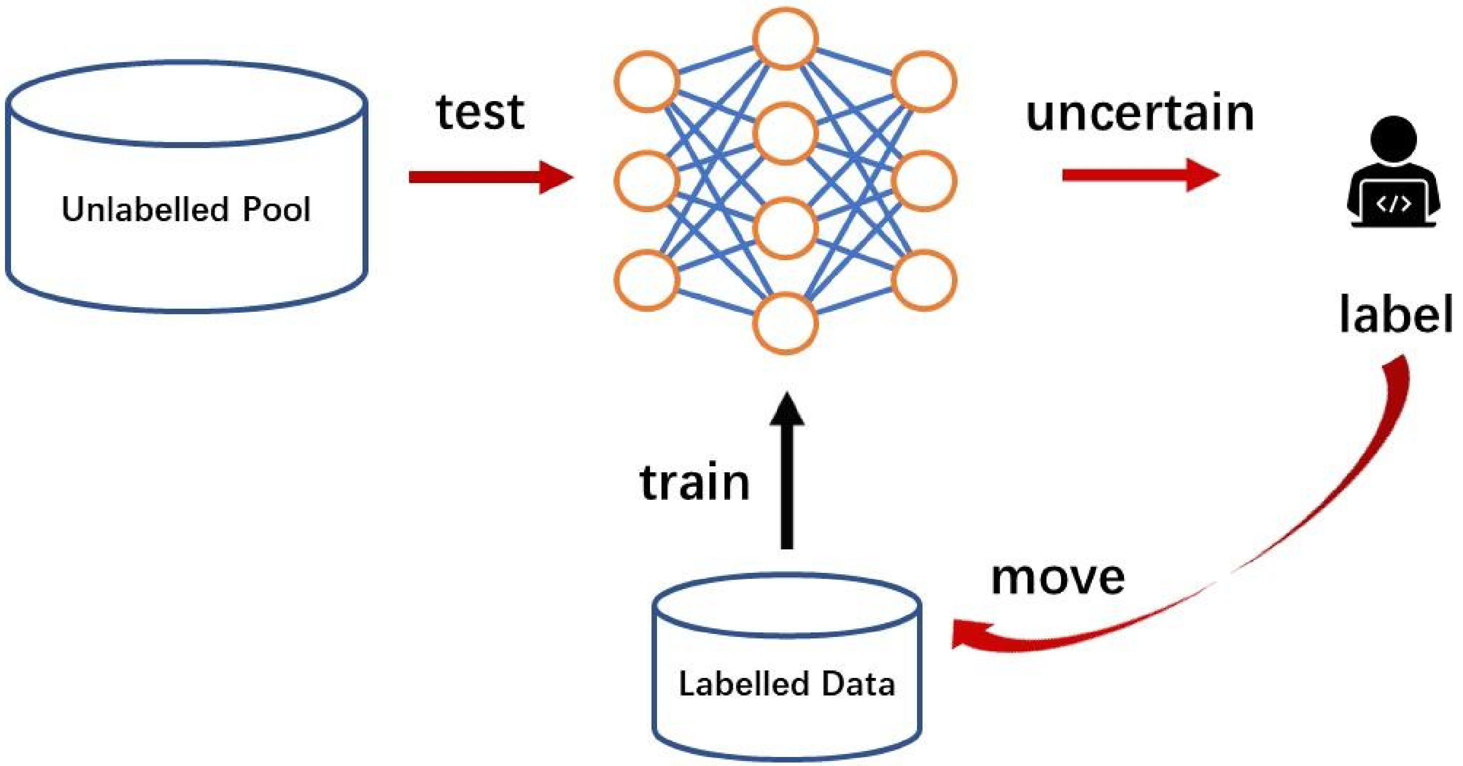
Acceptable = Stable + Causal

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

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

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

Active learning procedure



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

How does the network learn

Input x → Neural network $\hat{y} = f(x, \theta)$ → $\hat{y}$: Network prediction, y: True label

↓

Loss(cost) function

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

↓

Gradient decent

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

Back propagation

1. The network parameters are initialized with random numbers and the network make random guess
2. Compute the loss function L which is a functional of the network
3. Use auto-diff to compute the negative gradients of network parameters
4. Use SGD-like algorithms to update network parameters

What has been learned （Global interpretation）

shallow layers deep layers

Local interpretation

- **Ablation studies**： LIME or Prediction Difference Analysis. M. Tulio Ribeiro, et. al. “Why should I trust you?”
- **Class activation map**： map the deep layers to the input image， look for the most important region for decision making. BoLei Zhou, et. al. “Learning Deep Features for discriminative localization”
- **Layer-wise relevance propagation**： set the relavance of the output layer to 1， propagate the relevance to the input data, to look for the most important region for decision making.

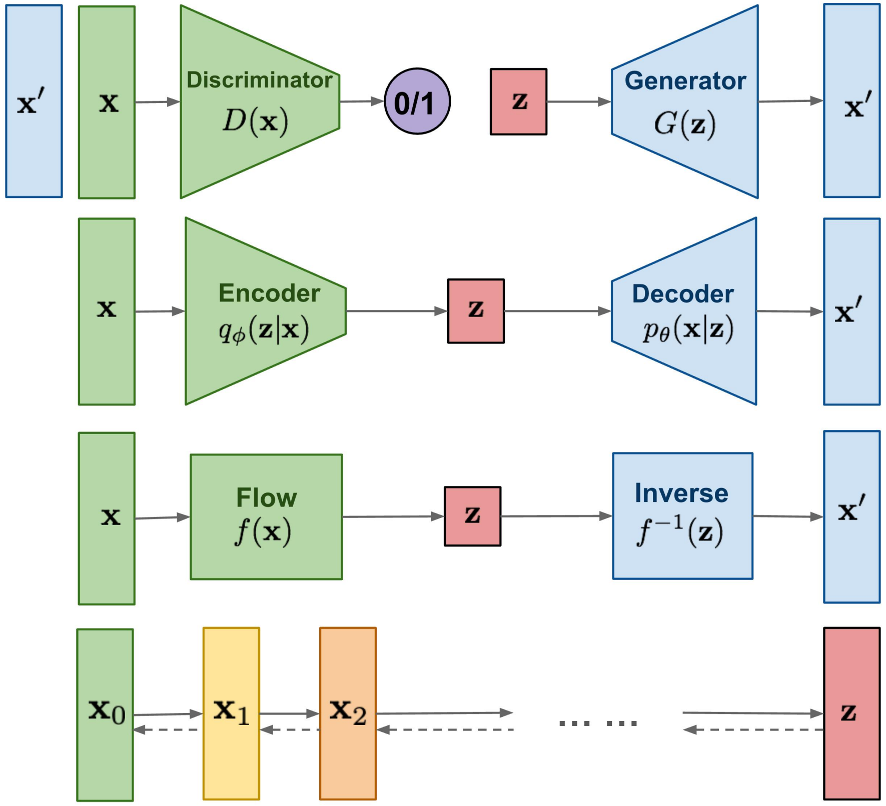
Generativive models： MC sampling

GAN: Adversarial training

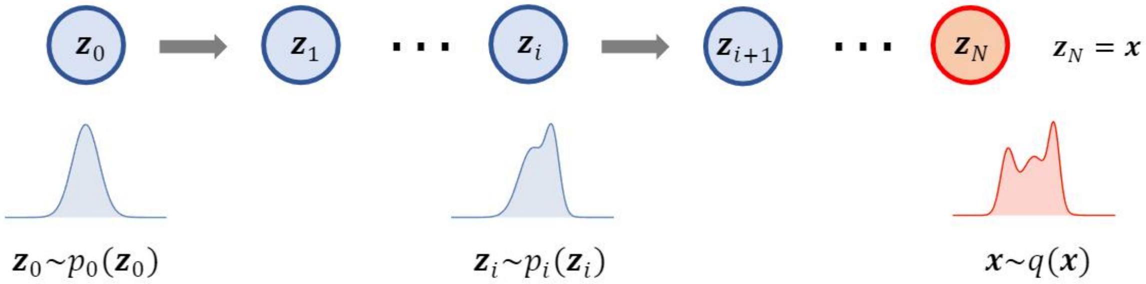
VAE: maximize variational lower bound

Flow-based models: Invertible transform of distributions

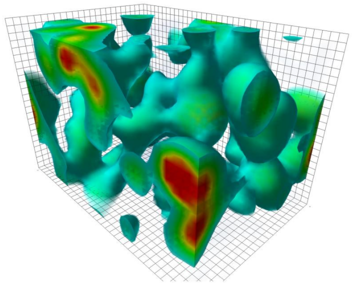
Diffusion models: Gradually add Gaussian noise and then reverse



Similar to Box Muller algorithm

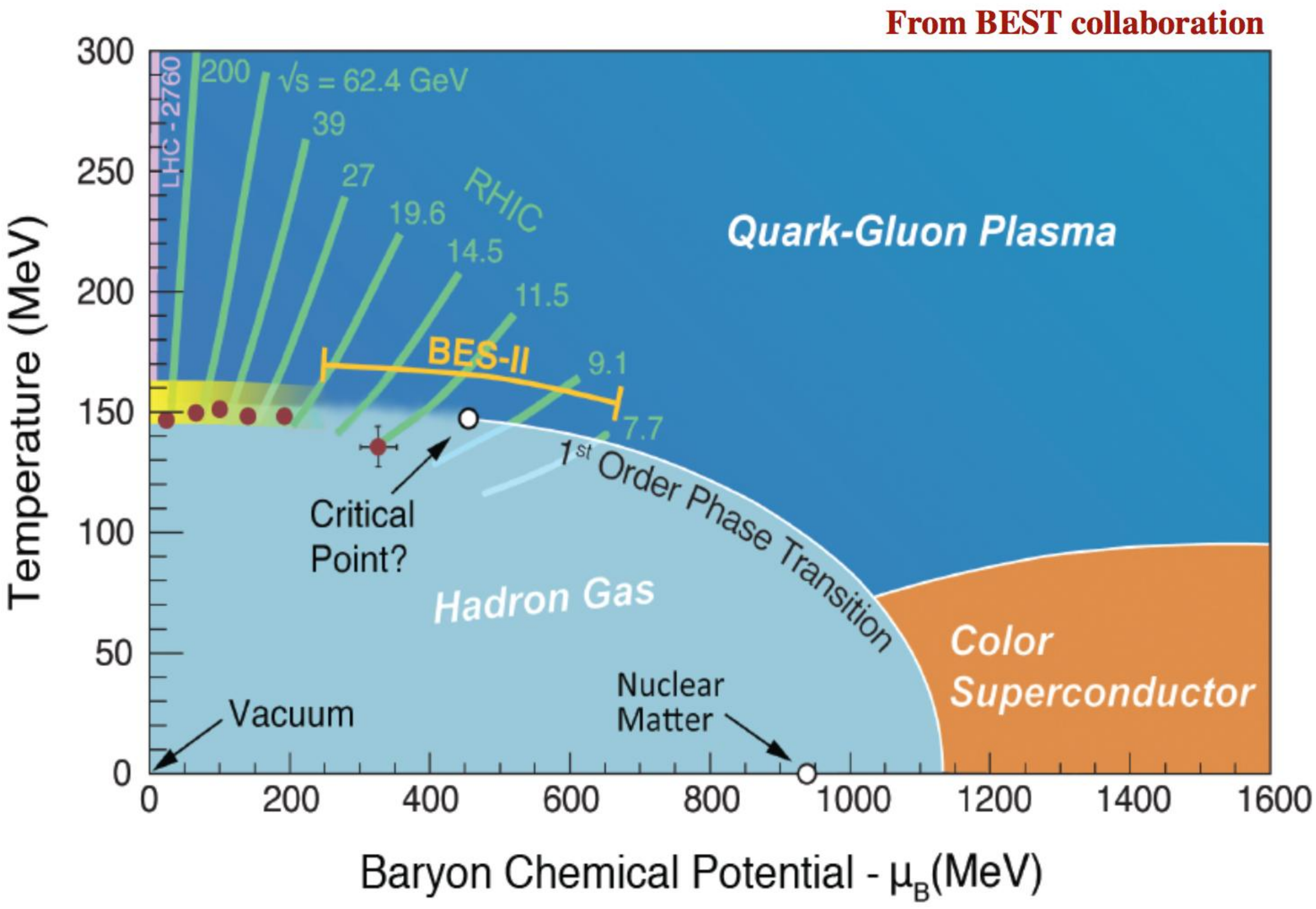


Samples Drawn from N-Dim Normal Distribution → Flow model or Diffusion models →

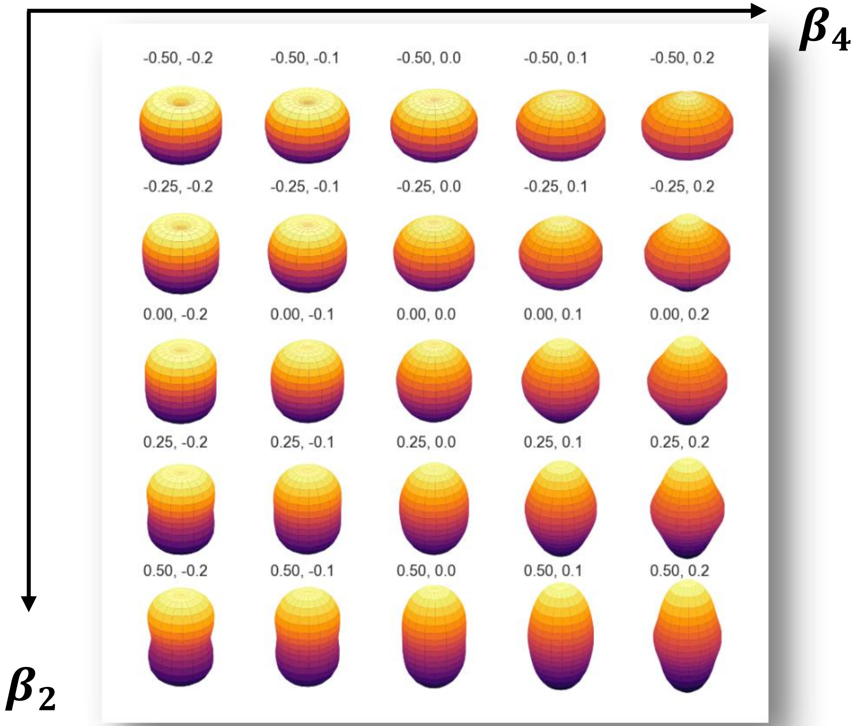


Flow-based generative models for Markov chain Monte Carlo in lattice field theory
Albergo, Kanwar, Shanahan 1904.1207

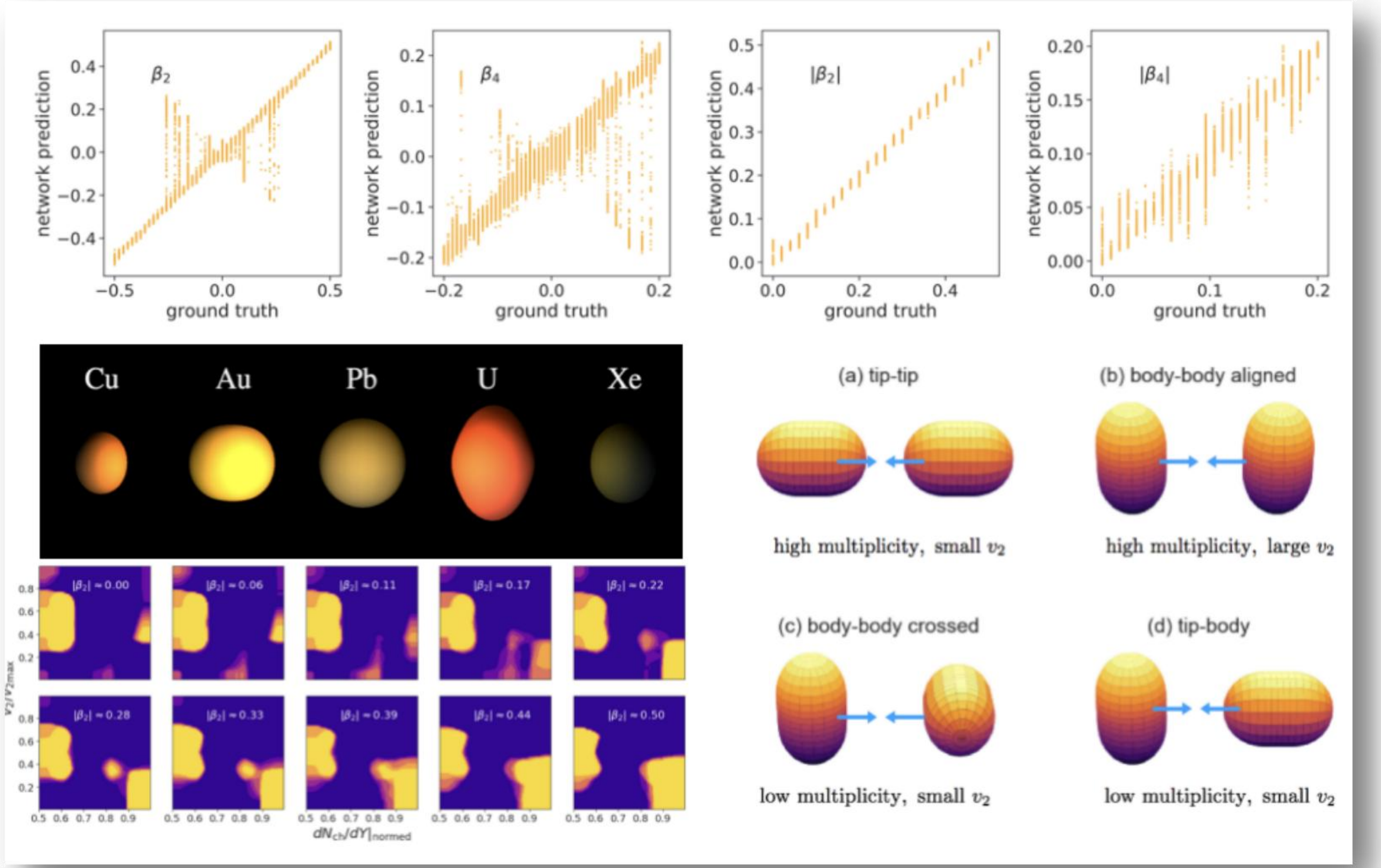
Explore QCD phase structure using HIC



Determining nuclear deformation



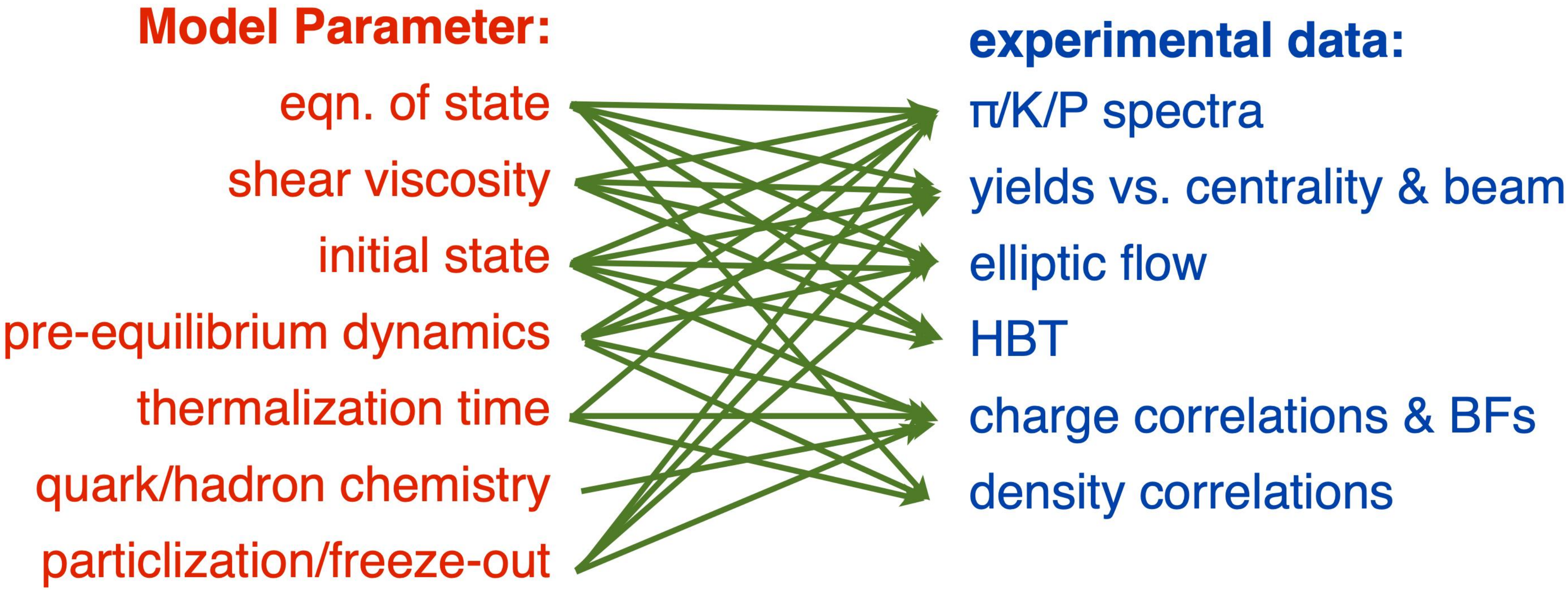
Data: Trento + Matching



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

Challenges

Fig from S. Bass QM2017 (Bayesian method)



(1) Multiple parameters entangle with multiple observables

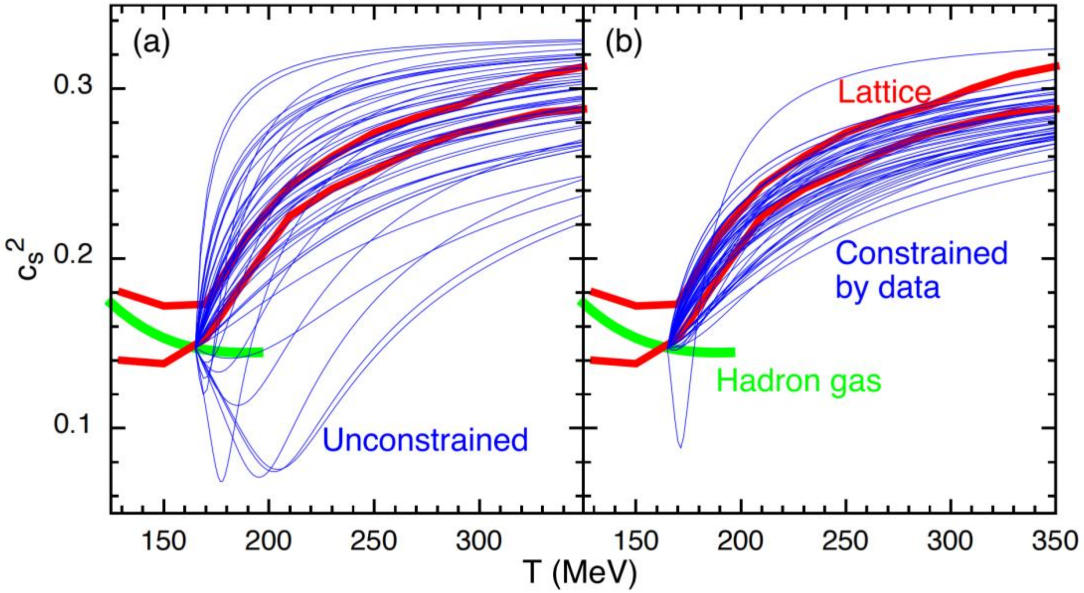
(2) Different parameter combinations describe the same data

Bayesian analysis QCD EoS

The c_s^2 is parameterized as a function of energy density in the following,

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

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 unconstrained EoS that varies in a large region between $c_s^2 = 0.05$ and $c_s^2 = 0.33$, as shown in Fig. 2.4-a. This corresponds to the a priori distribution of c_s^2 parameters together with other 12 parameters in the model $P(\theta)$.

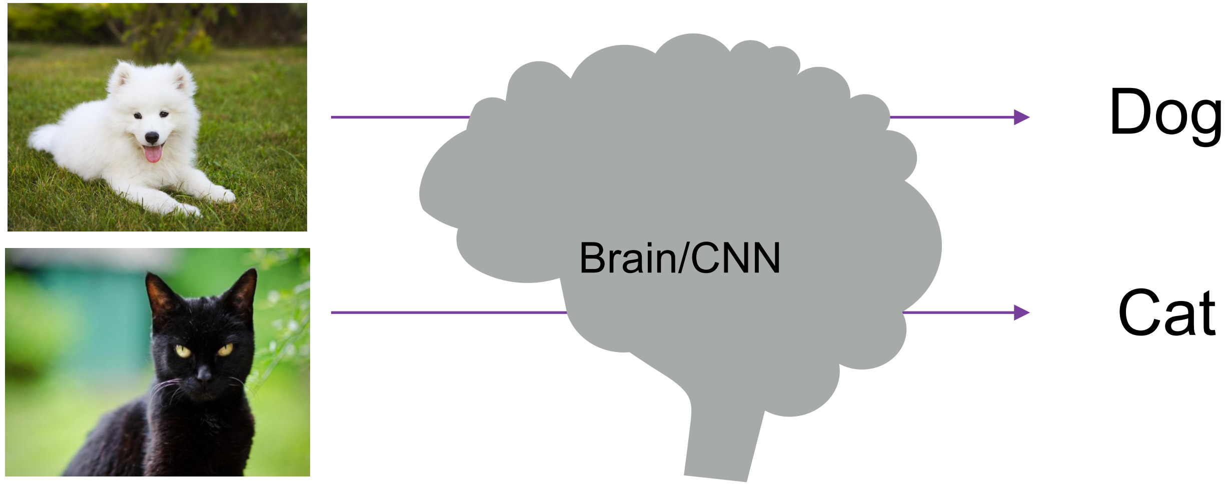


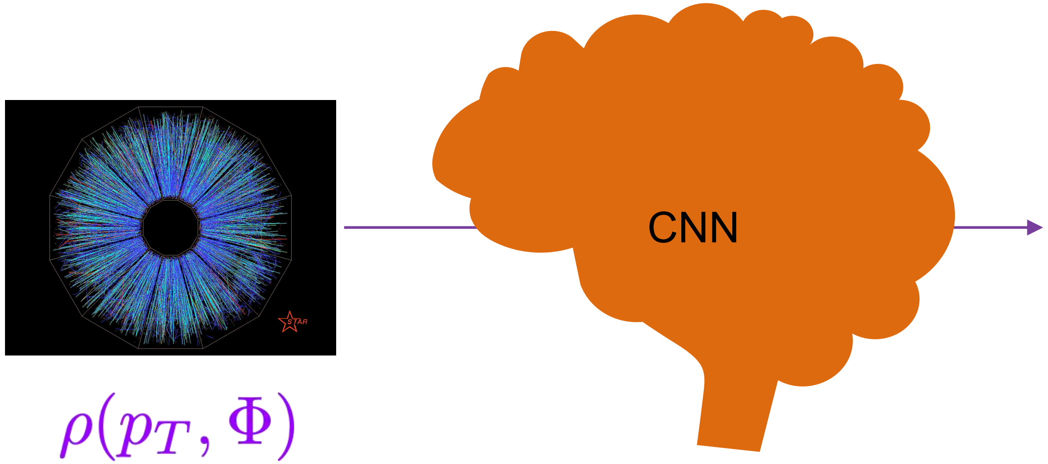
Likelihood: $$P(D|\theta) = \Pi_i \exp\left(-(z_i(\theta) - z_{i,\exp})^2/2\right)$$

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

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

Excellent pattern recognition of deep learning

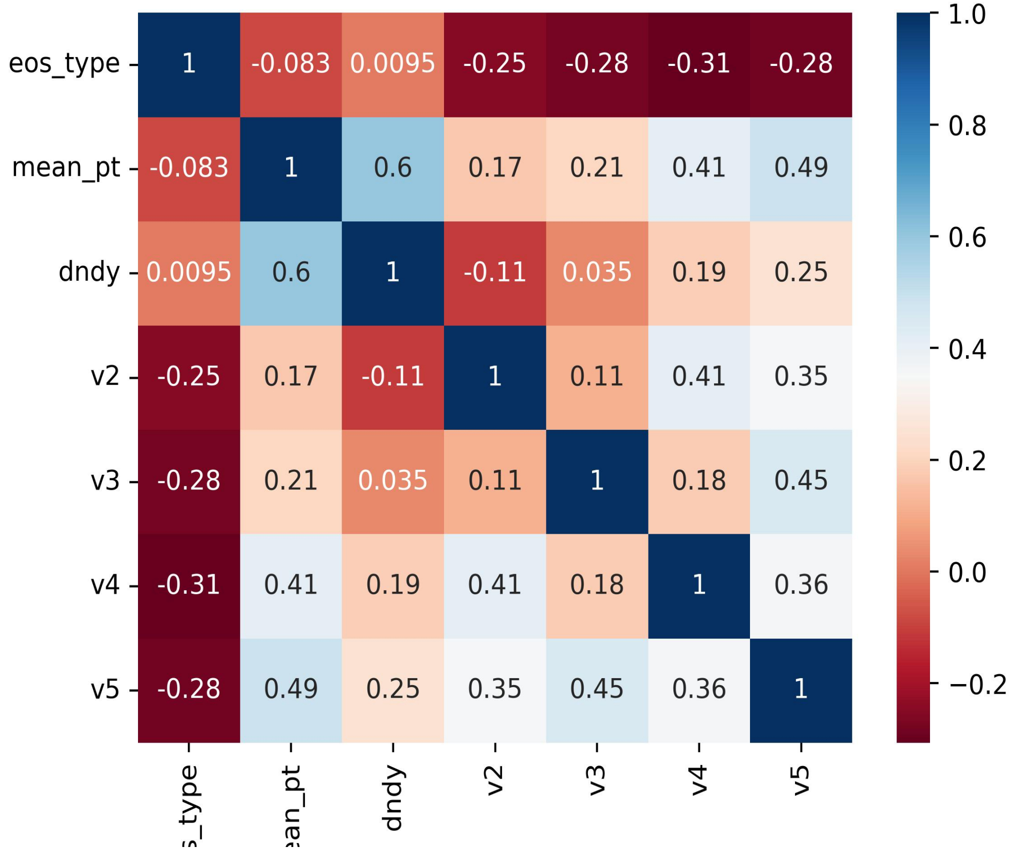


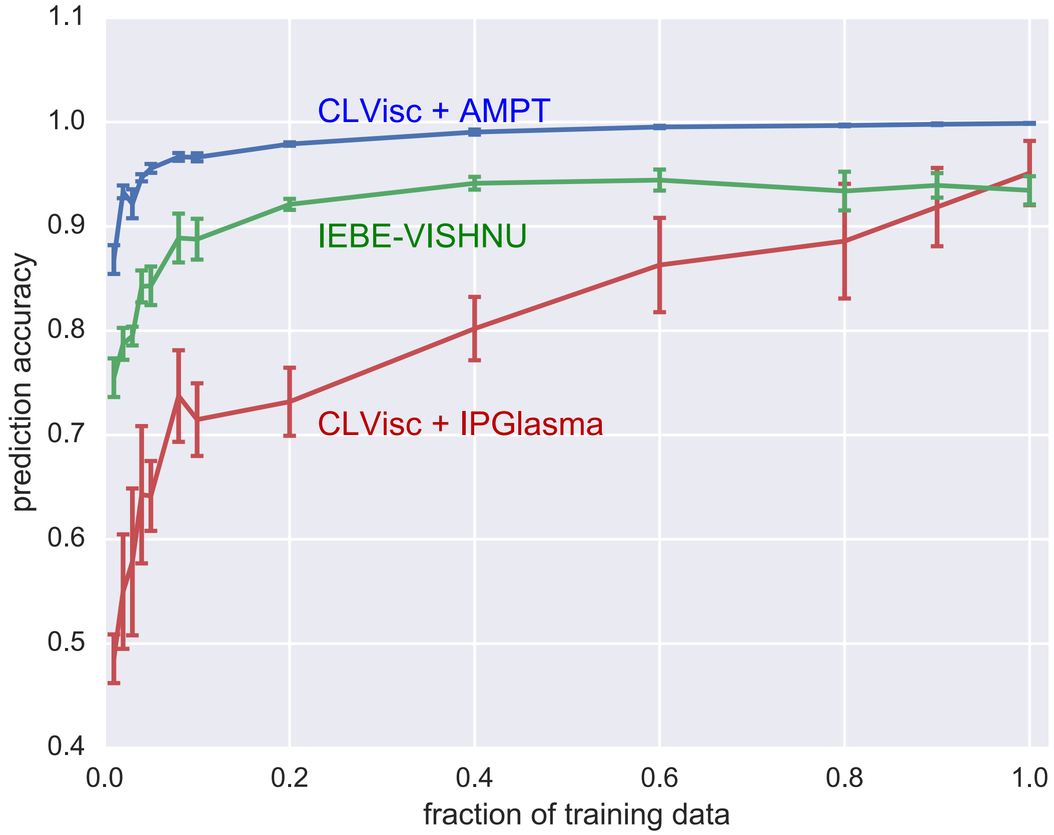


$\rho(p_T, \Phi)$

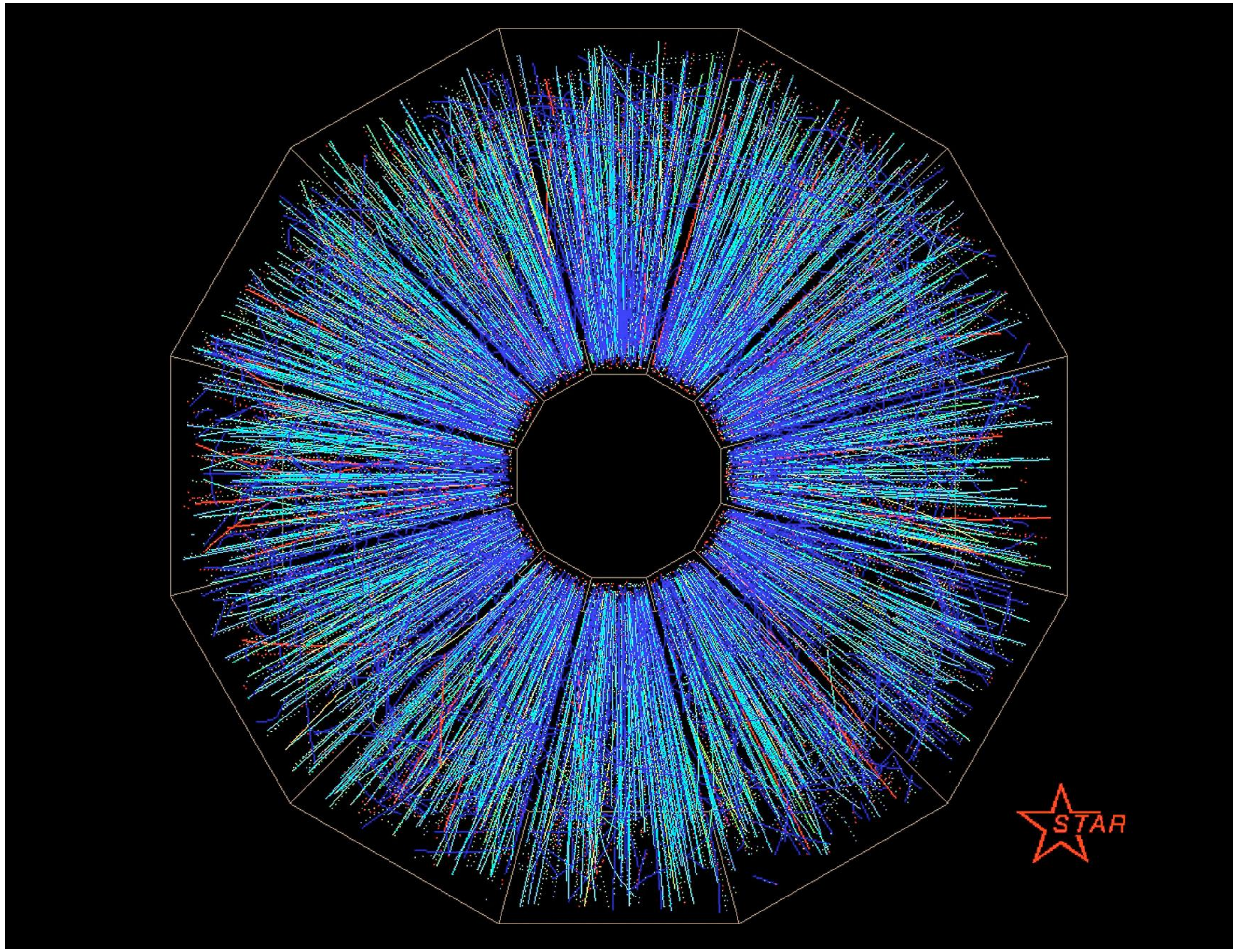
crossover or
1st order transition

DL with CNN for EoS classification





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
…				

Capture more local correlations

Dynamical Edge Convolution Network

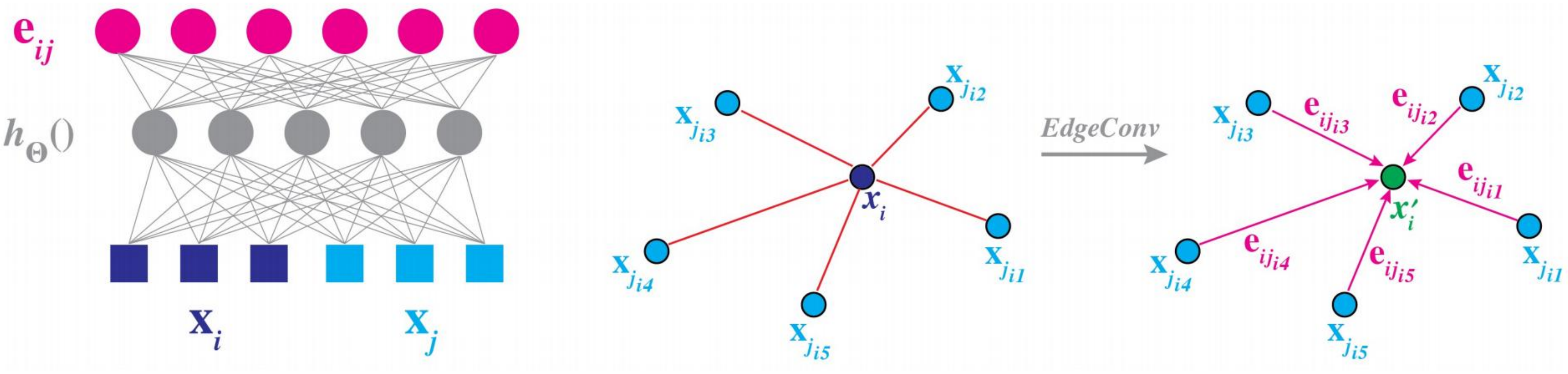
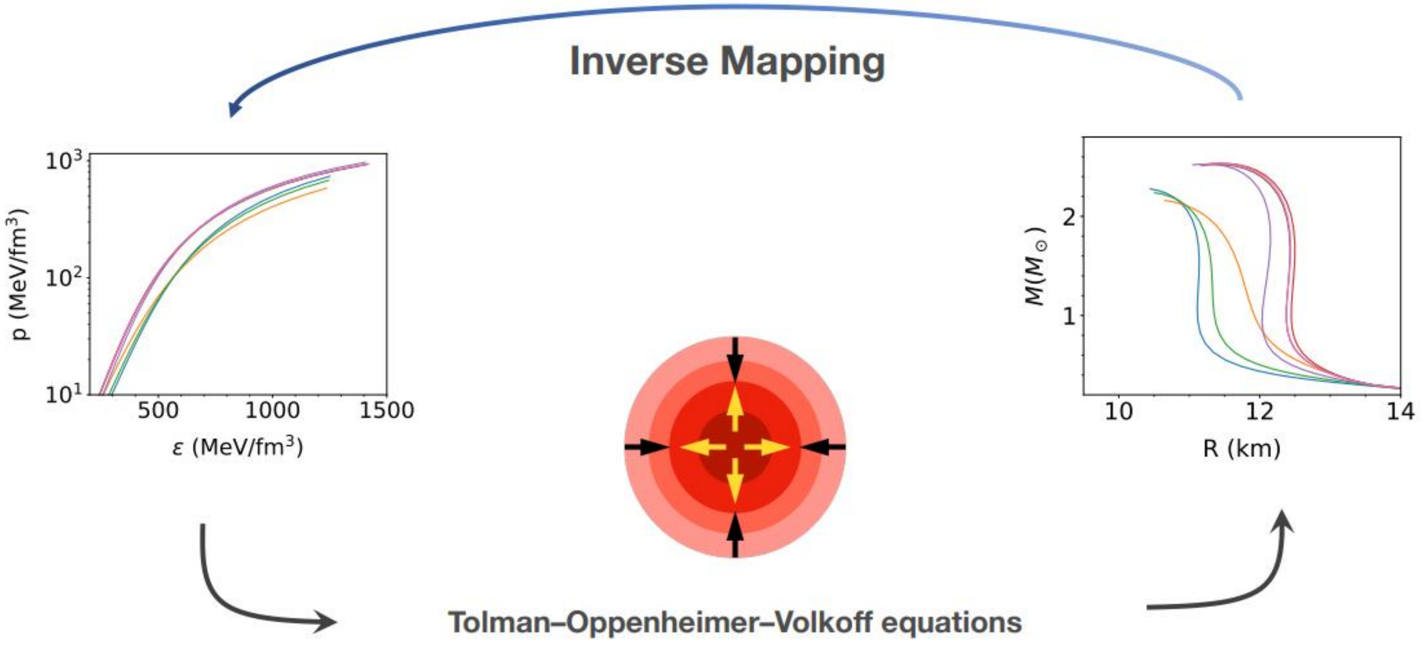


Fig. 2. **Left**: Computing an edge feature, $\mathbf{e}_{ij}$ (top), from a point pair, $\mathbf{x}_i$ and $\mathbf{x}_j$ (bottom). In this example, $h_\Theta()$ is instantiated using a fully connected layer, and the learnable parameters are its associated weights. **Right**: The EdgeConv operation. The output of EdgeConv is calculated by aggregating the edge features associated with all the edges emanating from each connected vertex.

TOV Equation and Nuclear EoS from DL

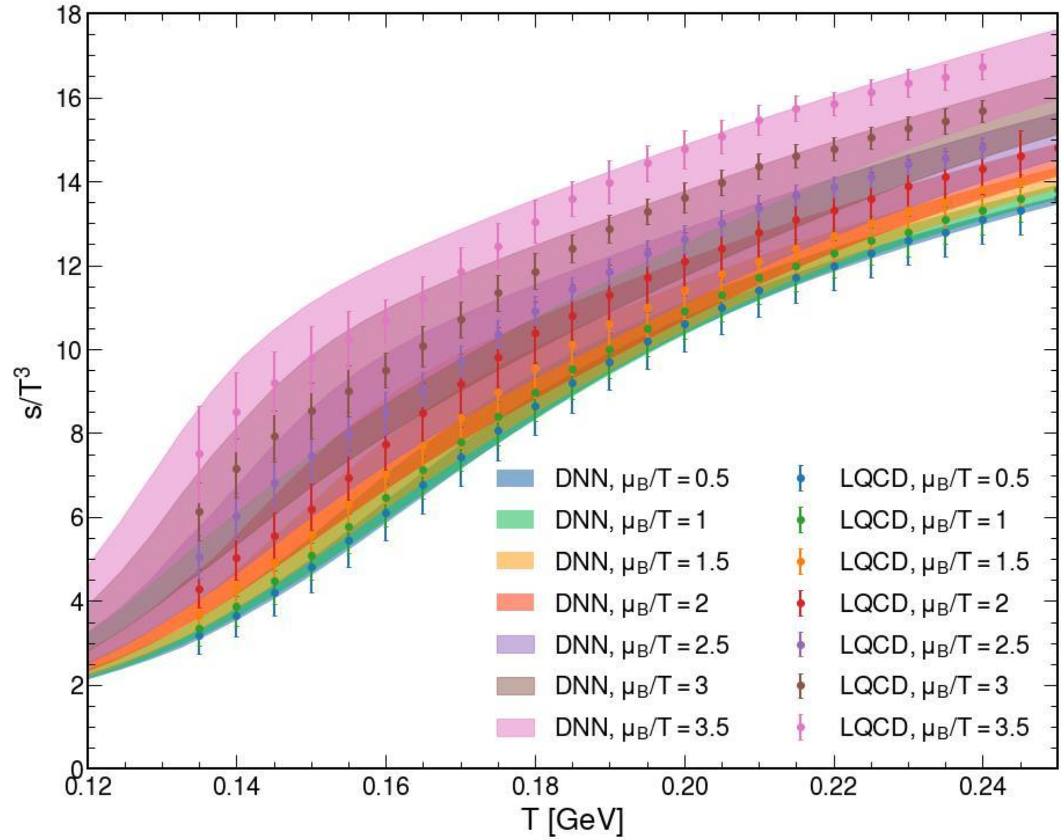
$$\frac{\mathrm{d}p}{\mathrm{d}r} = -G\frac{m(r)\varepsilon(r)}{r^2}\left(1+\frac{p(r)}{\varepsilon(r)}\right)\left(1+\frac{4\pi r^3 p(r)}{m(r)}\right)\left(1-\frac{2Gm(r)}{r}\right)^{-1},$$

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

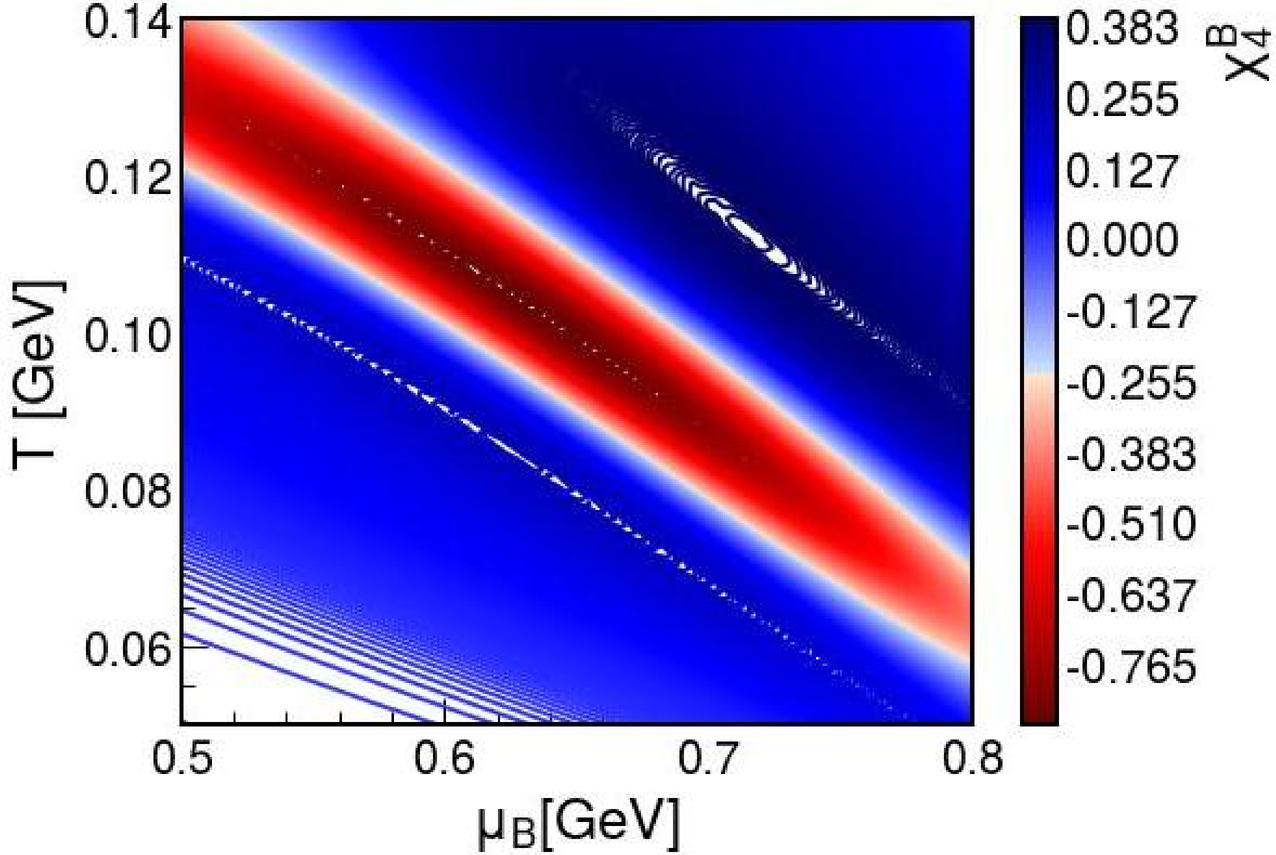


S. Soma, L. Wang, S. Shi, H. Stöcker, K. Zhou, PRD 107, (2023) 083028

method



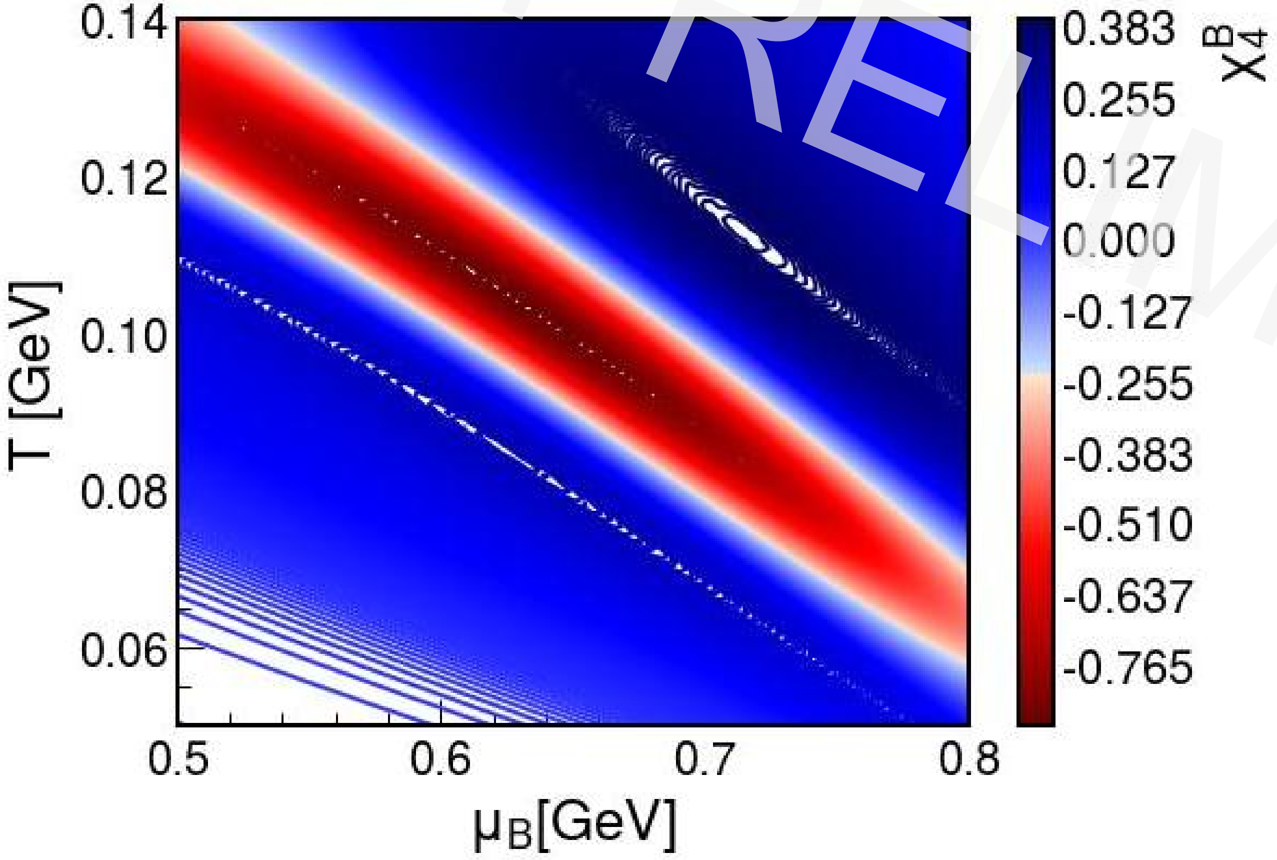
s/T^3
T [GeV]
DNN, μB/T = 0.5
DNN, μB/T = 1
DNN, μB/T = 1.5
DNN, μB/T = 2
DNN, μB/T = 2.5
DNN, μB/T = 3
DNN, μB/T = 3.5
LQCD, μB/T = 0.5
LQCD, μB/T = 1
LQCD, μB/T = 1.5
LQCD, μB/T = 2
LQCD, μB/T = 2.5
LQCD, μB/T = 3
LQCD, μB/T = 3.5



T [GeV]
μB[GeV]
χ4B
0.383
0.255
0.127
0.000
-0.127
-0.255
-0.383
-0.510
-0.637
-0.765

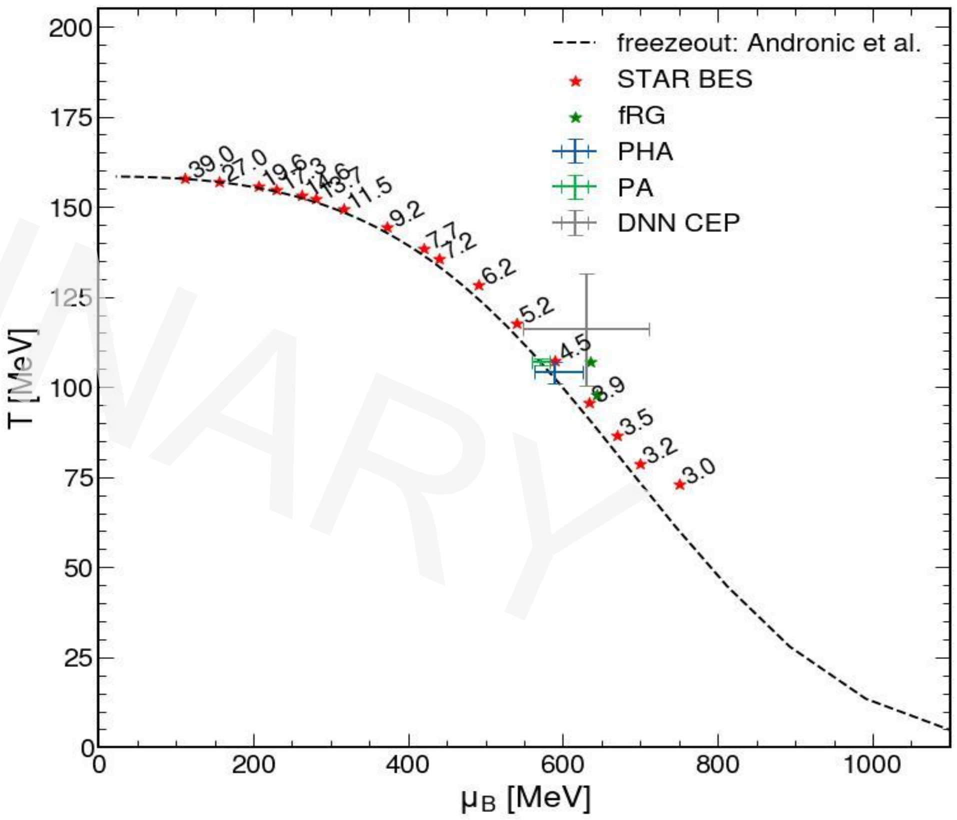
Predictions of DL quasi parton model

Susceptibility



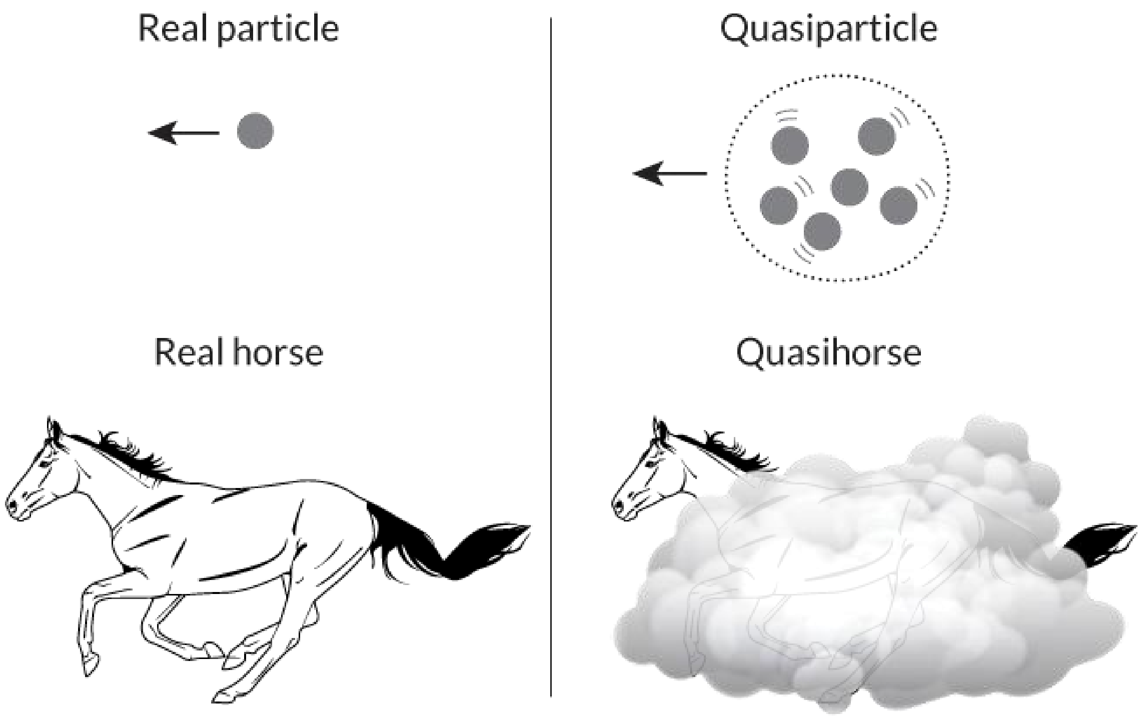
$$\chi_k^{\text{lattice}} = \partial^k (p/T^4)/\partial(\mu/T)^k.$$

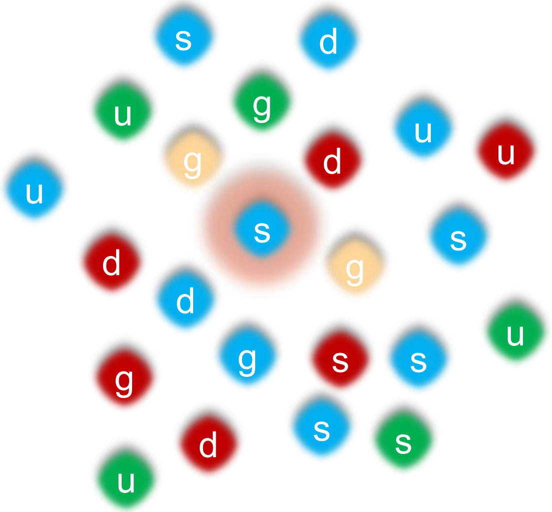
Location of CEP



$$(\mu_B, T) : (630.1 \pm 81.42, 115.9 \pm 15.46)\text{MeV},$$

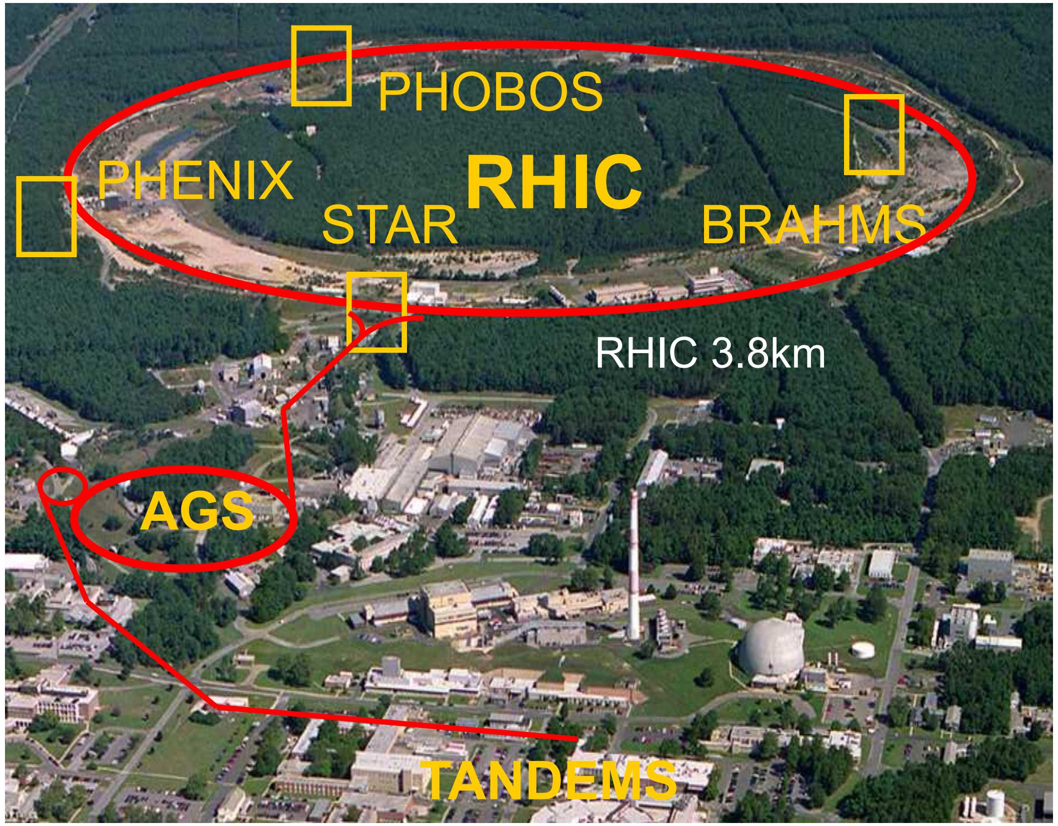
Effective theory: DL Quasi parton model

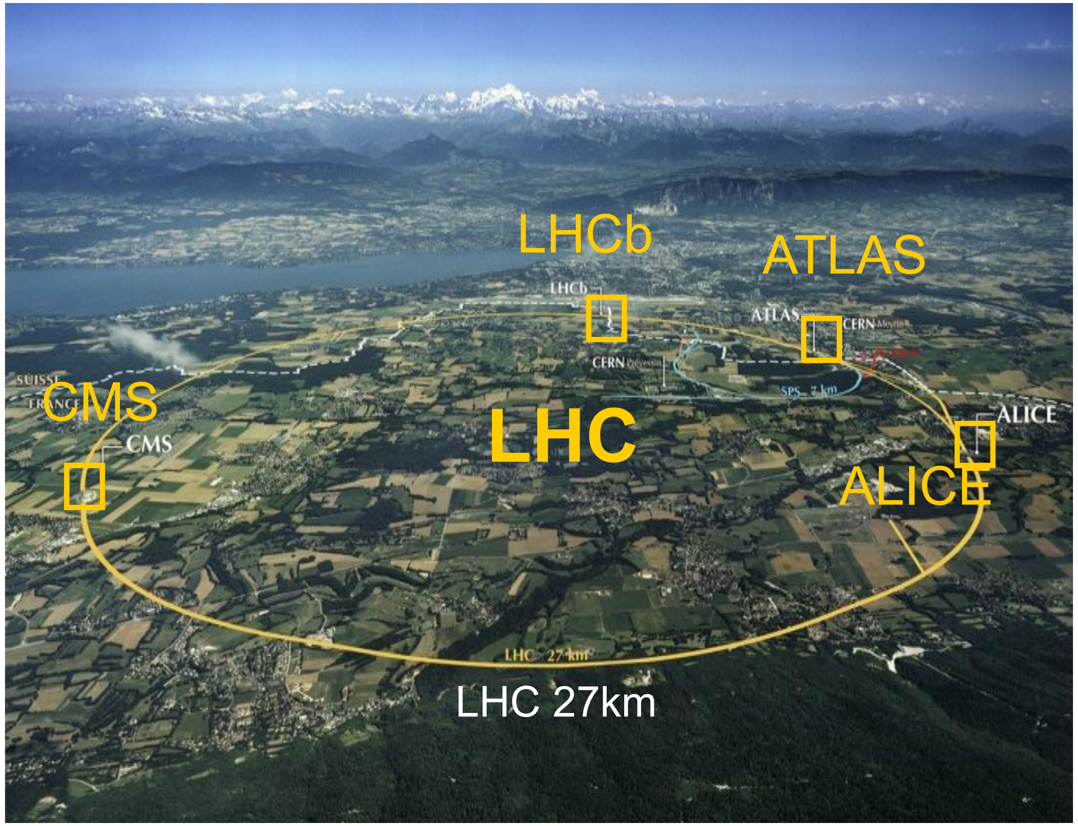




screened, dressed, regularized, quasi particle

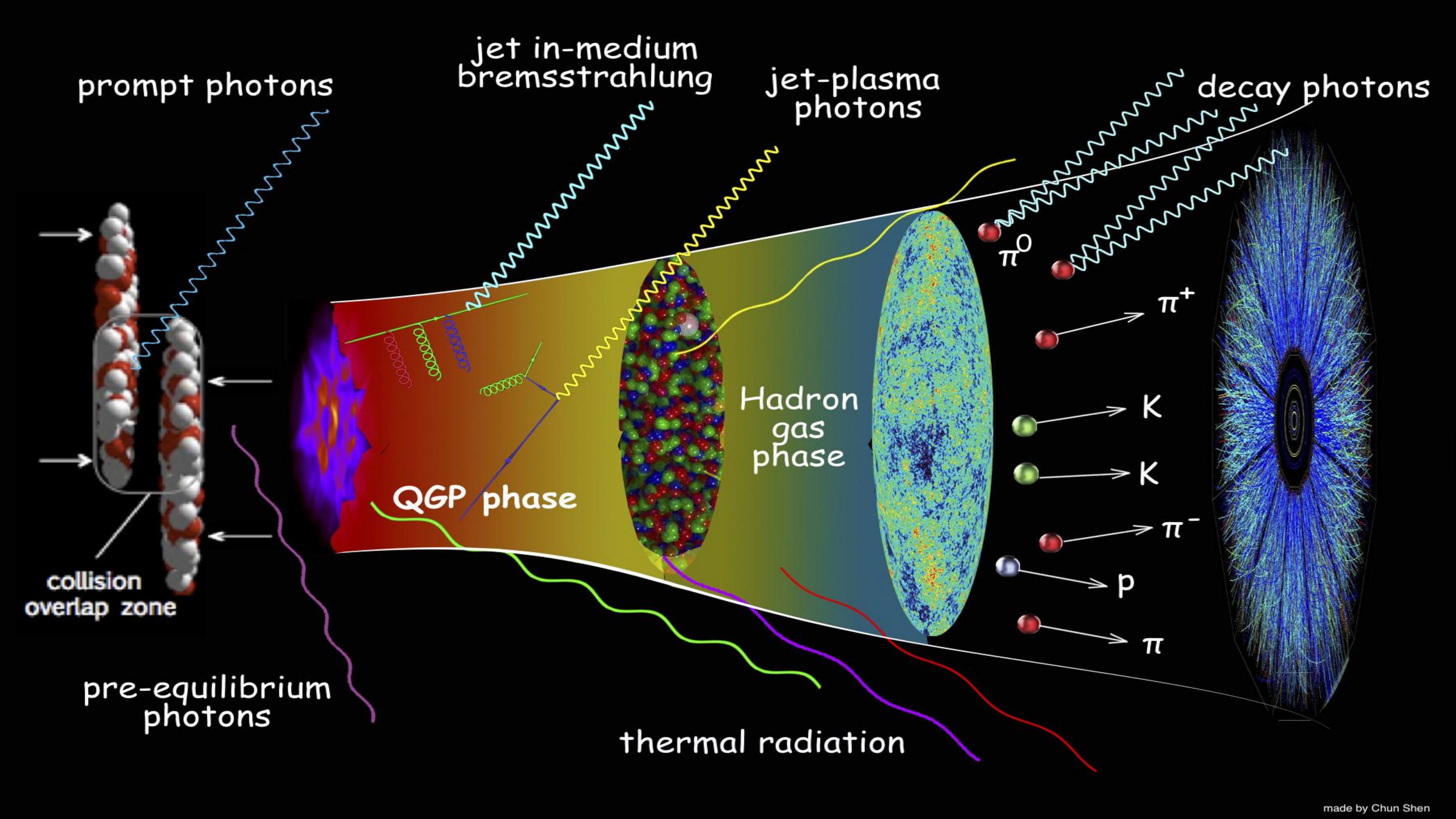
Nuclear Matter at extreme conditions





Au speed ～99.99% c

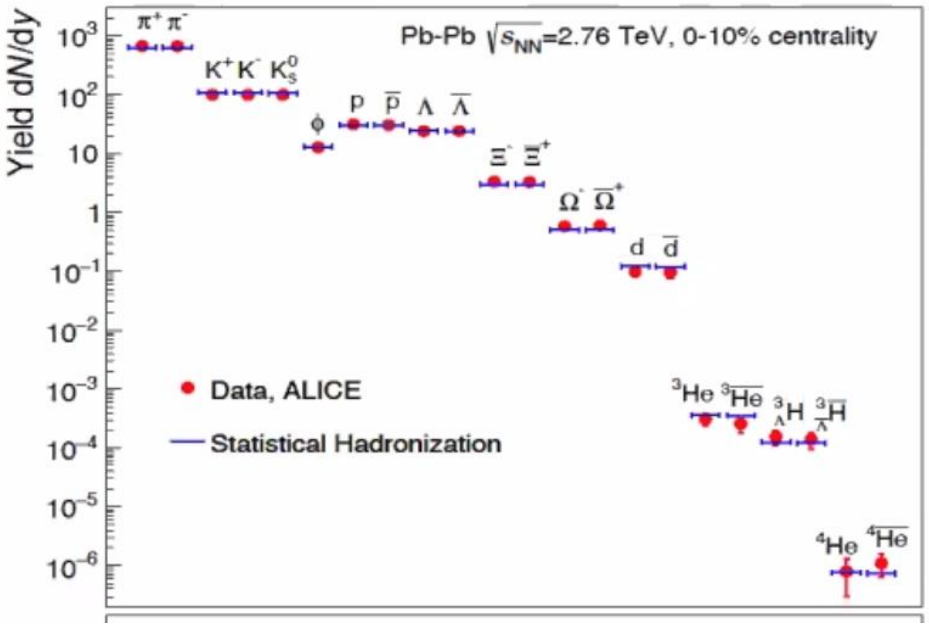
Pb speed～99.9999% c


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

How many hadrons are produced

statistical hadronization of (u,d,s) hadrons

A. Andronic, P. Braun-Munzinger, K. Redlich, J. Stachel, Nature 561 (2018) 321



Best fit:

$T_{CF} = 156.6 \pm 1.7$ MeV

$\mu_B = 0.7 \pm 3.8$ MeV

$V_{\Delta y=1} = 4175 \pm 380$ fm^3

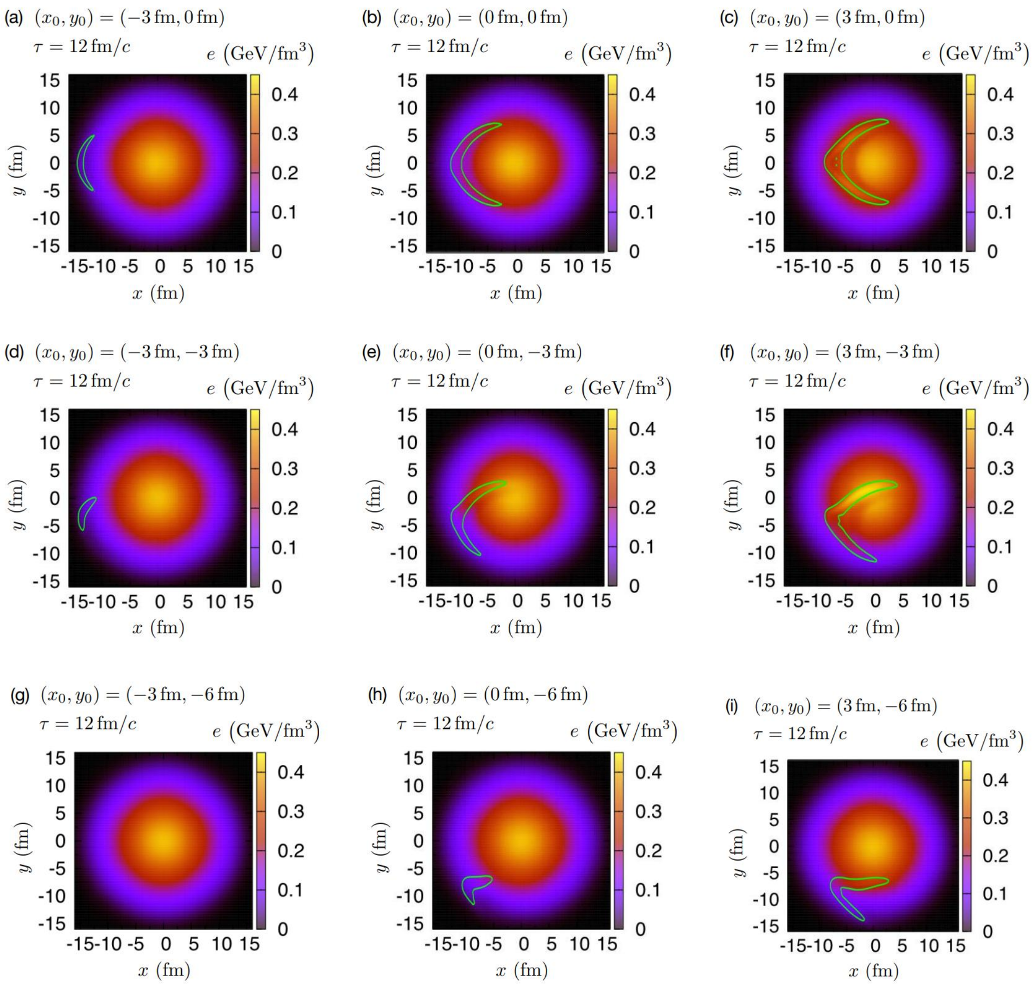
$\chi^2/N_{df} = 16.7/19$

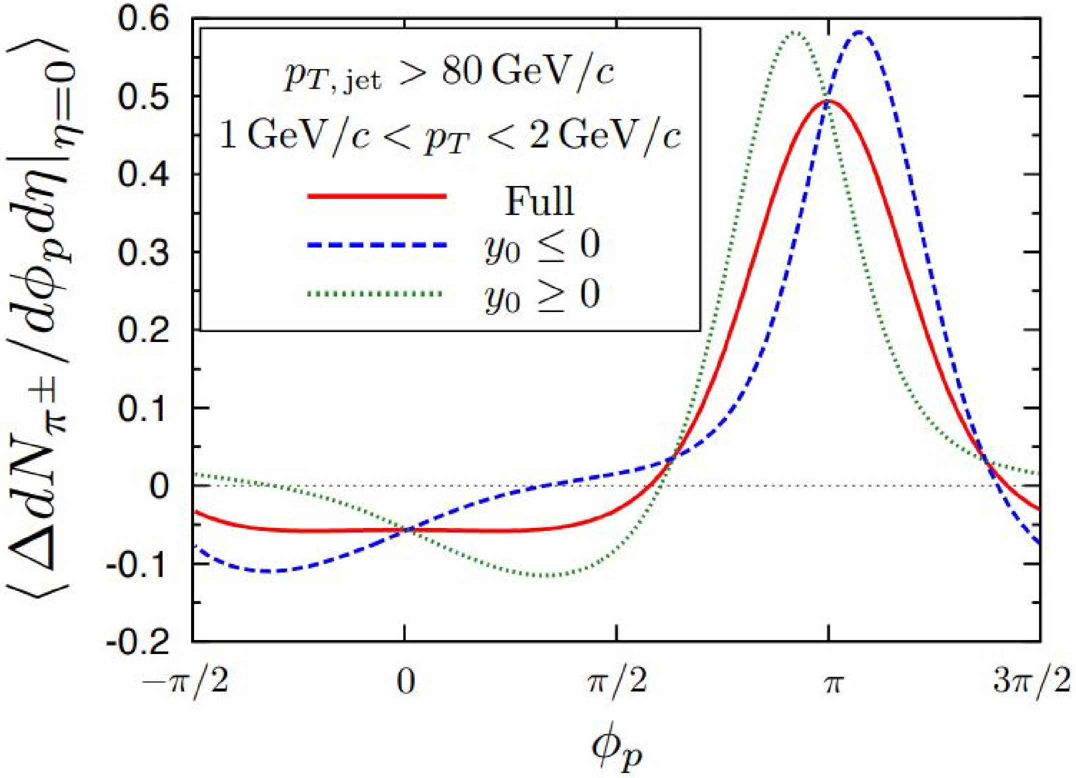
S-matrix treatment of inter-

$$n_i = (2s_i + 1)4\pi \int p^2 \left[e^{\left(\sqrt{p^2+m_i^2}-\mu_i\right)/T} \pm 1 \right]^{-1} dp$$

1. At LHC, equal amounts of matter and anti-matter are produced
2. At BES region, more protons than anti protons

If it is possible to locate the initial jets





Y Tachibana, T Hirano, PRC 93 (2016) 5, 054907