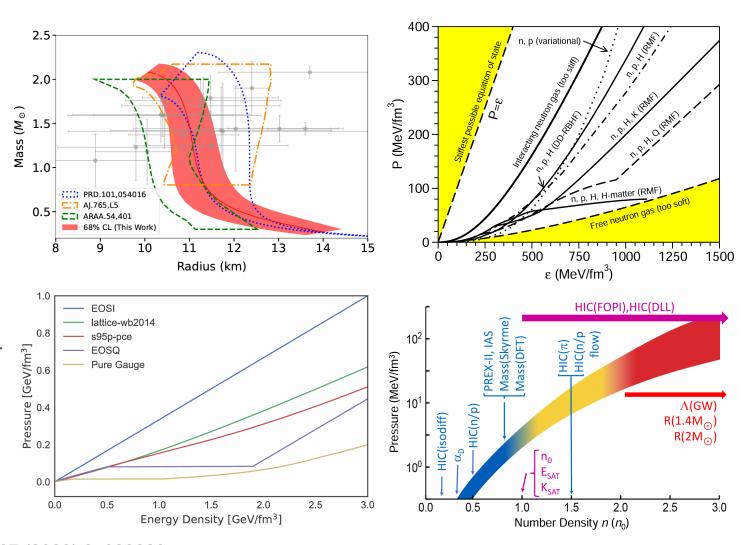


A Quasi-Parton Model by Physics Informed Neural Network

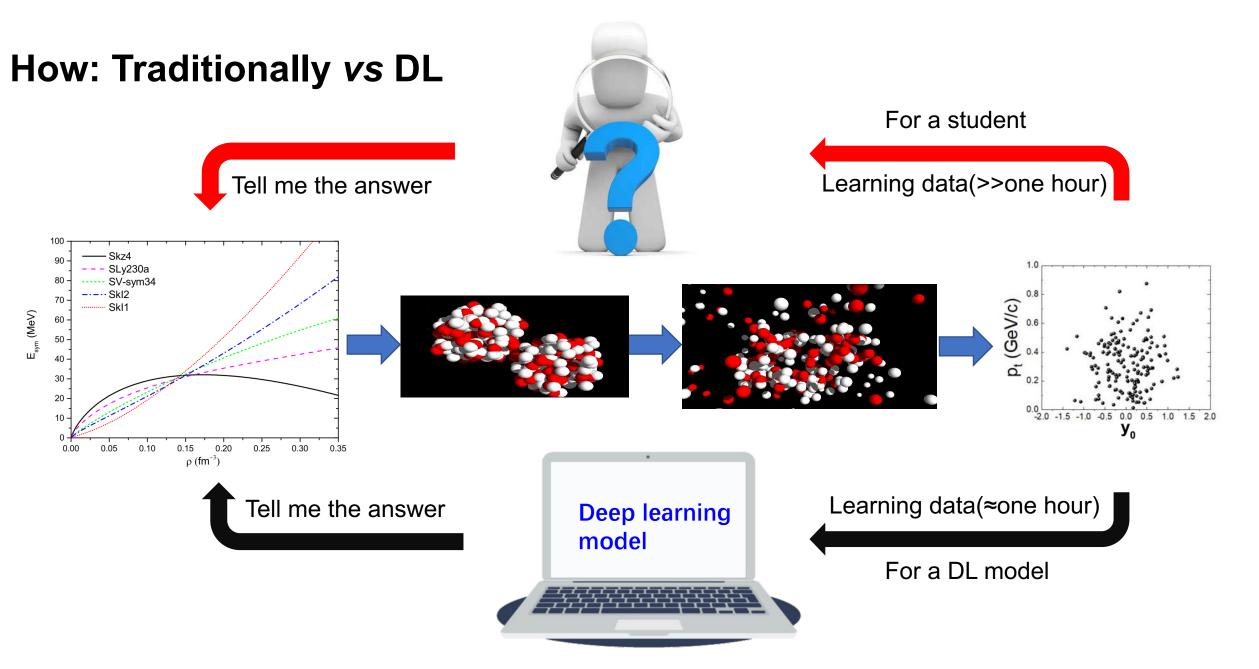
Fu-Peng Li(FDU)@Hengyang https://github.com/leefp29

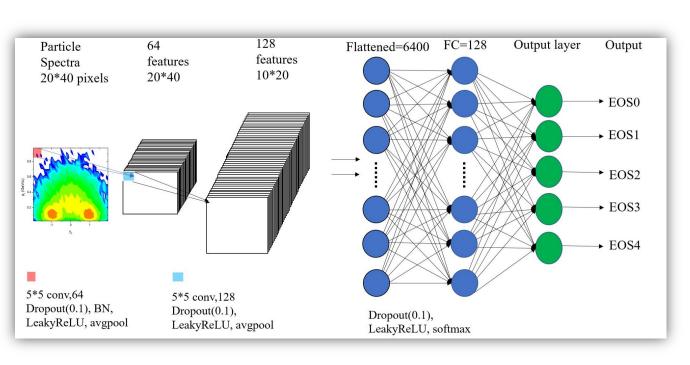
Nuclear EoS

- Crucial for understanding the evolution of early universe, neutron star and properties of QGP
- Also constrains many-body nuclear interactions and non-perturbative QCD
- One of the key physical objectives of heavyion collision experiments

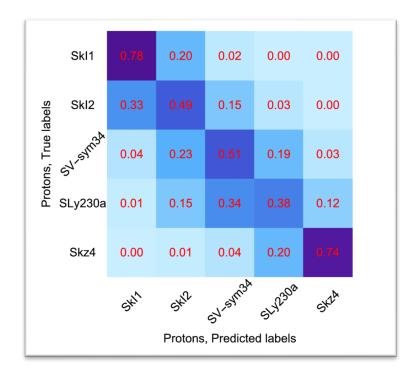


Shriya Soma, Lingxiao Wang, Shuzhe Shi. et al. Phys.Rev.D 107 (2023) 8, 083028 Tsang, C.Y., Tsang, M.B., Lynch, W.G. et al. Nat Astron 8, 328–336 (2024) Long-Gang Pang, Hannah Petersen, Xin-Nian Wang. Phys. Rev. C 97, 064918(2018) F. Weber, R. Negreiros, P. Rosenfield Prog.Part.Nucl. Phys.59:94-113,2007



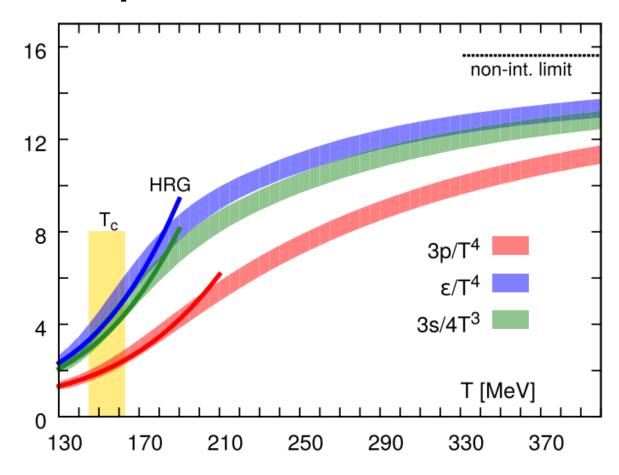


The confusion matrix for five-class classification task.



- ➤ The diagonal entries show the fraction of correctly classified testing data.
- ➤ The larger the value on the diagonal, the better the network will perform.

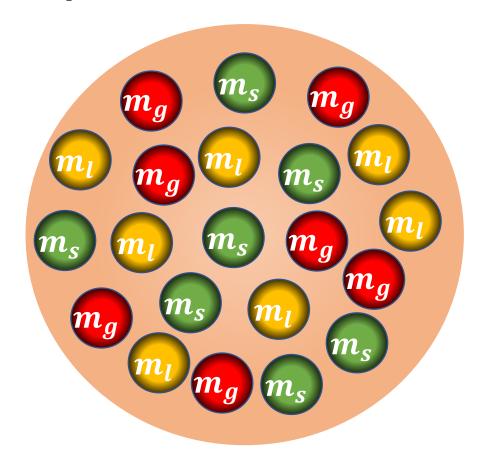
QCD equation of state

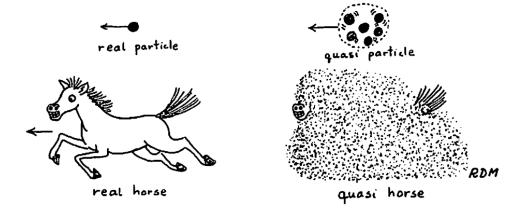


HRG model: the hot and dense QCD matter is considered as non-interaction hadrons.

- T < 200 MeV: QCD equation of state is well described by HRG.
- T > 200 MeV: nuclear matter transitions into the QGP phase.

Quasi-particle method





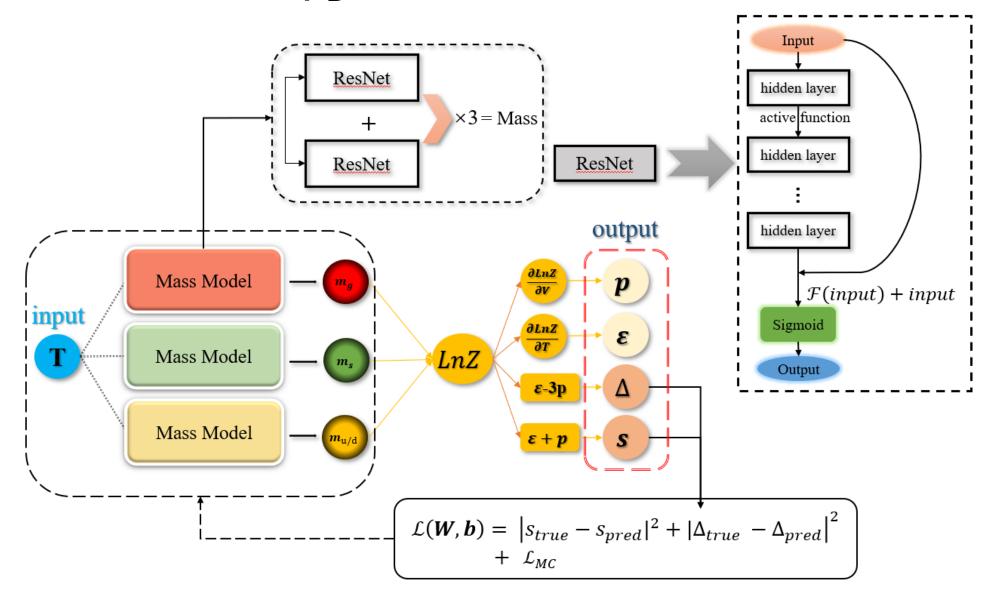
quasi particles of this particular system. Many different types of systems of interacting particles may be described in this manner, and in general we have

Sometimes this same equation is stated in a more powerful terminology coming from quantum field theory:

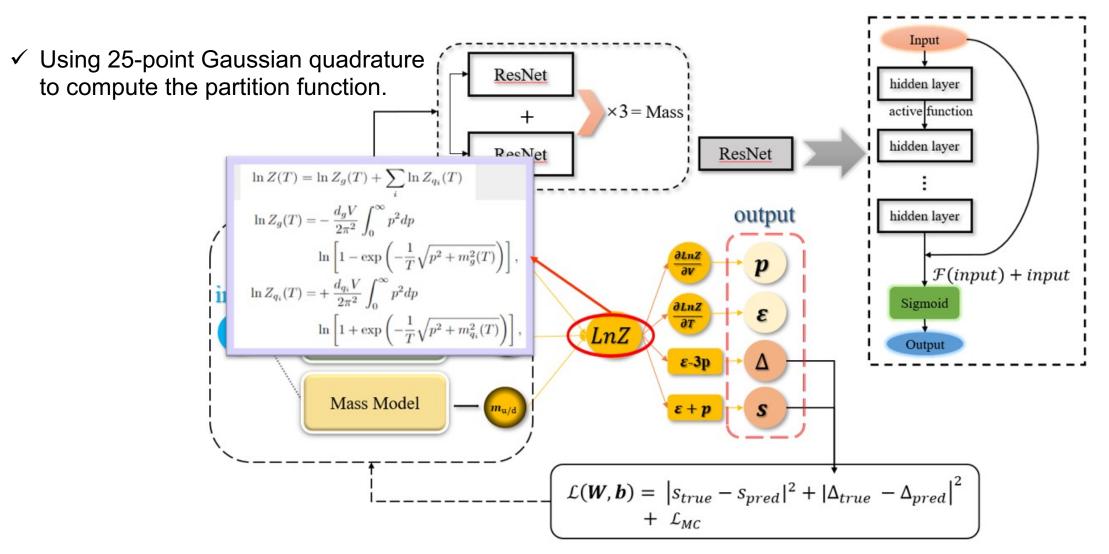
 We construct a weakly interacting quasi-parton-gas model, which is an effective theory for strongly coupled QGP.

$$H = T + V_{eff} = \frac{P^2}{2M_{real}} + V_{eff}$$
 $H = \frac{P^2}{2M_{quasi}}$

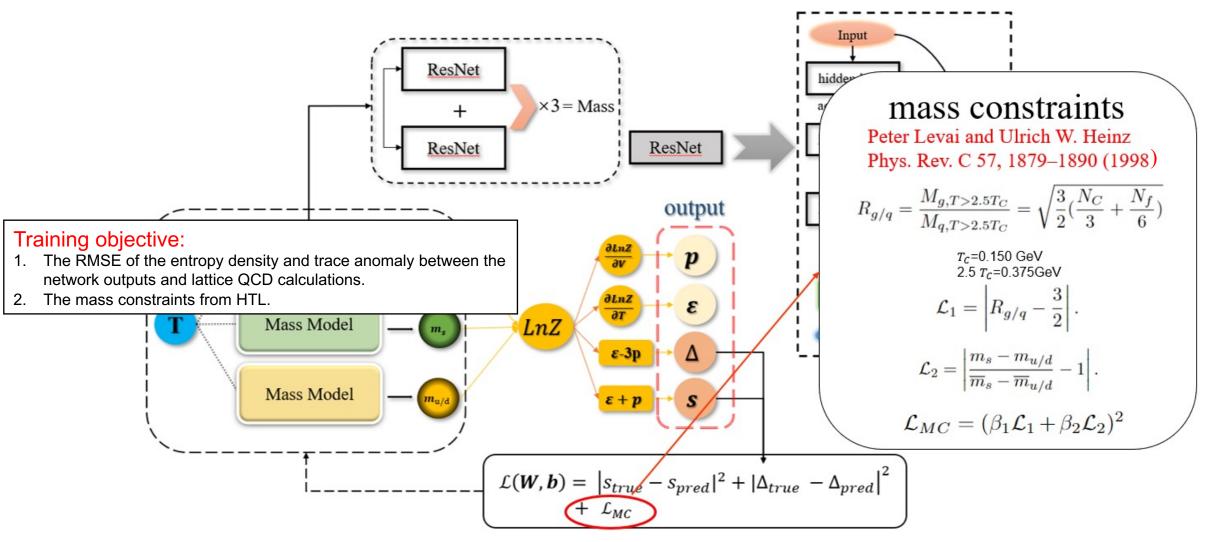
The framework of DNN: $\mu_B = 0$

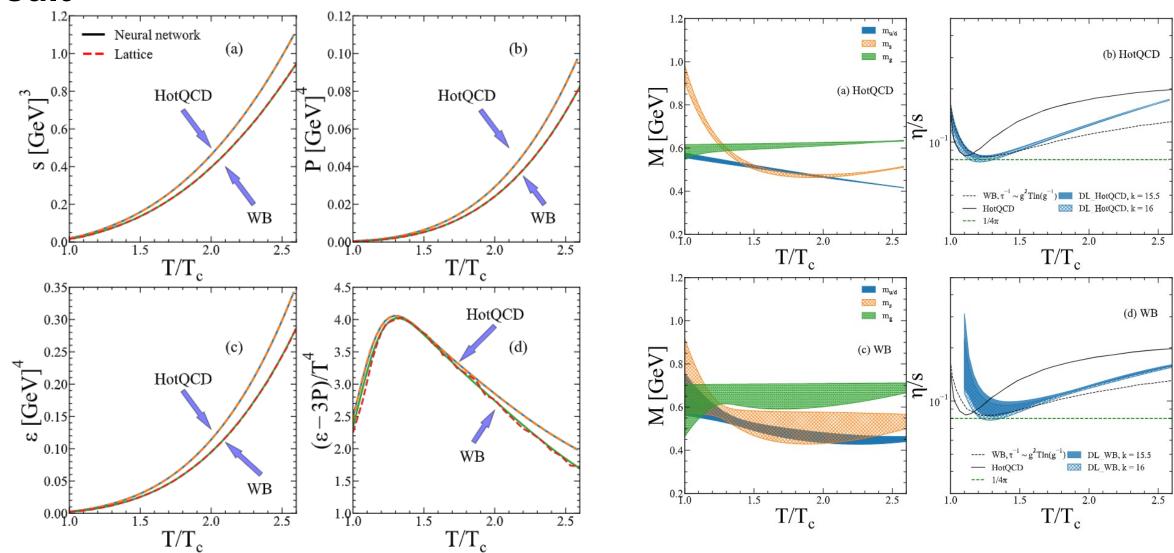


The framework of DNN



The framework of DNN





Result: Extended work

DLQPM (data-driven):

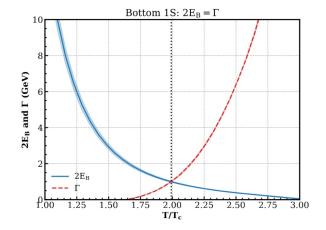
- ▶ Train ResNet on lattice-QCD EoS $(s, \varepsilon 3p)$ in $T/T_c \in [1, 3]$.
- ▶ Outputs quasi-parton masses $m_g(T), m_q(T)$.
- Infer $\alpha_s(T)$ via thermal-mass relations; then $m_{\rm D}(T) = T \sqrt{4\pi\alpha_s(T)\left(\frac{N_c}{3} + \frac{N_f}{6}\right)}$.

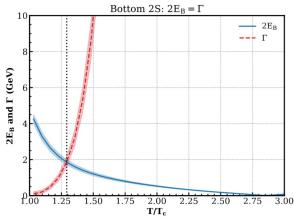
Radial Schrödinger (S-wave):

$$\Big[-\frac{1}{2\mu}\frac{d^2}{dr^2}+\frac{\ell(\ell+1)}{2\mu r^2}+\operatorname{Re}V(r,T)\Big]\psi_n=E_n(T)\psi_n,\quad \mu=\frac{m_Q}{2}.$$

Thermal width (first-order perturbation):

$$\Gamma_n(T) = -\int_0^\infty 4\pi r^2 |\psi_n(r)|^2 \operatorname{Im} V(r,T) dr.$$





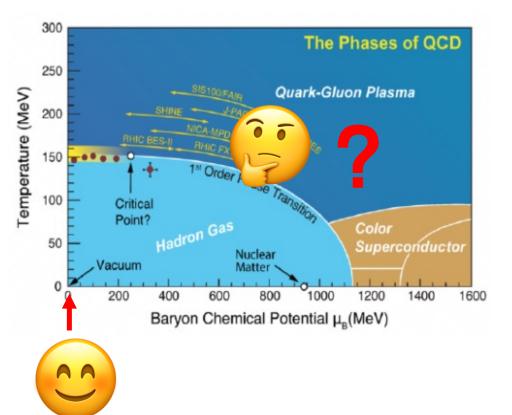
 $\Upsilon(1S)$: width criterion.

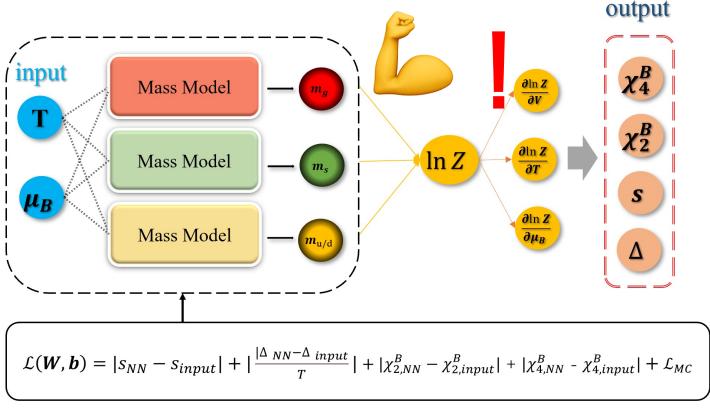
 $\Upsilon(2S)$: width criterion.

Method / Reference	Dissociation Temperatures T_d (in units of T_c)			
	$\Upsilon(1S)$	$\Upsilon(2S)$	J/ψ	$\psi(2S)$
This work: $(2E_B = \Gamma)$	1.99	1.29	1.30	≤ 1.00
This work: $(E_B = 3T)$	1.38	1.10	1.13	≤ 1.00
Mocsy and Petreczky [31]	2.00	1.20	1.20	≤1.00
Digal et al. [41]	2.31	1.10	1.10	< 1.00
Satz [42]	>4.00	1.60	2.10	1.12
Blaschke et al. [43]	2.25	1.05	1.20	<1.00
Rethika et al. [44]	0.77	0.82	1.47	1.62
Meng et al. [45]	5.81	1.56	2.06	1.13
Jamal et al. [33]	2.96	1.47	1.52	< 1.00
Agotiya et al. [46]	2.60	2.10	1.90	1.70

TABLE I: Comparison of the dissociation temperatures T_d for selected quarkonium states. The first two rows show the results of this work using the thermal width criterion $(2E_B = \Gamma)$ and the lower bound criterion $(E_B = 3T)$. The lower rows present representative theoretical predictions from the literature [31, 33, 41–46]. All temperatures are in units of the QCD critical temperature T_c .

The framework of DNN: $\mu_B > 0$





$$\begin{split} \ln Z_g(T,\mu_B) &= -\frac{d_g V}{2\pi^2} \int_0^\infty p^2 dp \ln \left[1 - \exp \left(-\frac{1}{T} \sqrt{p^2 + m_g^2(T,\mu_B)} \right) \right], \\ \ln Z_{q(\bar{q})_i}(T,\mu_B) &= +\frac{d_{q(\bar{q})_i} V}{2\pi^2} \int_0^\infty p^2 dp \ln \left[1 + \exp \left(-\frac{1}{T} (\sqrt{p^2 + m_{q(\bar{q})_i}^2(T,\mu_B)} - \mu_{q(\bar{q})_i} \right) \right], \end{split}$$

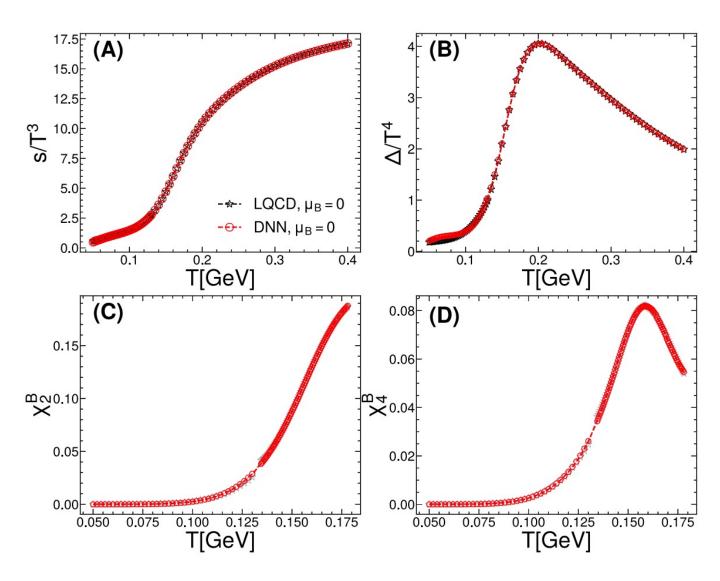
$$\mu_u = \frac{1}{3}\mu_B + \frac{2}{3}\mu_Q,$$

$$\mu_d = \frac{1}{3}\mu_B - \frac{1}{3}\mu_Q,$$

$$\mu_s = \frac{1}{3}\mu_B - \frac{1}{3}\mu_Q - \mu_S,$$

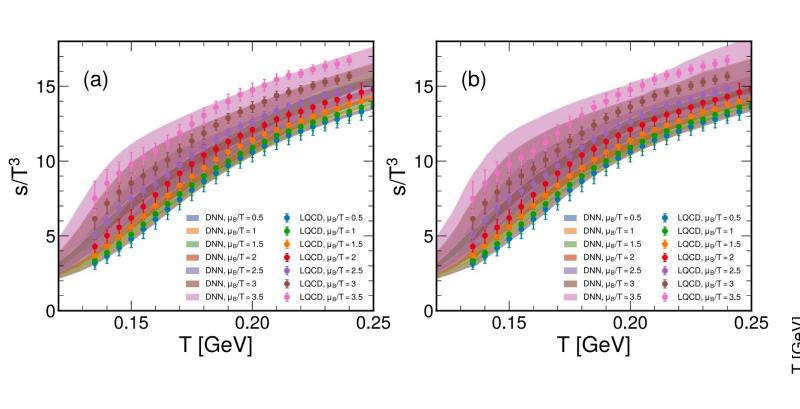
$$\chi_i^B = \frac{\partial P(T, \hat{\mu}_B)/T^4}{\partial \hat{\mu}_B^i} \bigg|_{\hat{\mu}_B = 0}, \hat{\mu}_B = \mu_B/T.$$

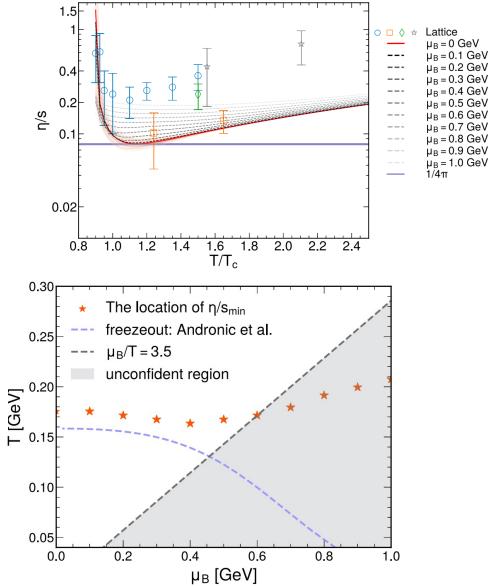
The training data&result



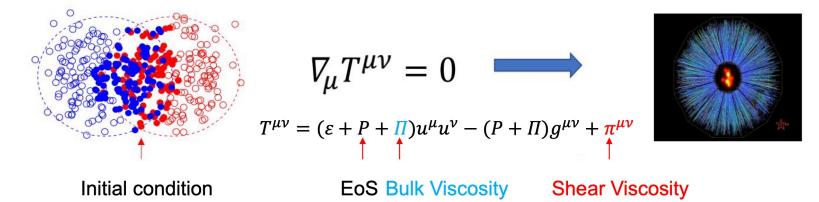
Training data:

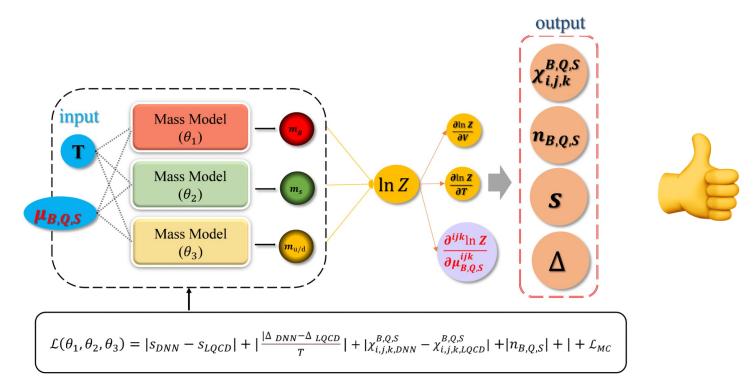
Phys Rev D 95, 054504 (2017) Phys Rev Lett 118, 182301 (2017) Phys Rev D 90, 094503 (2014)

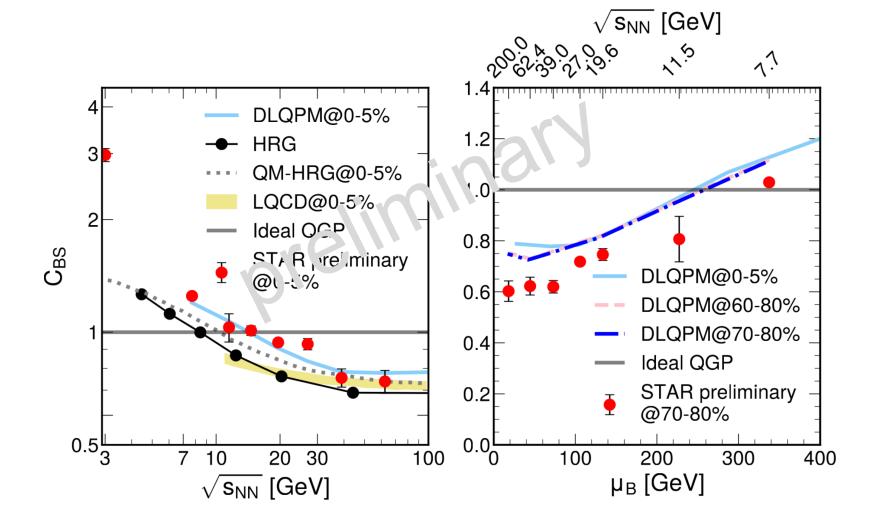


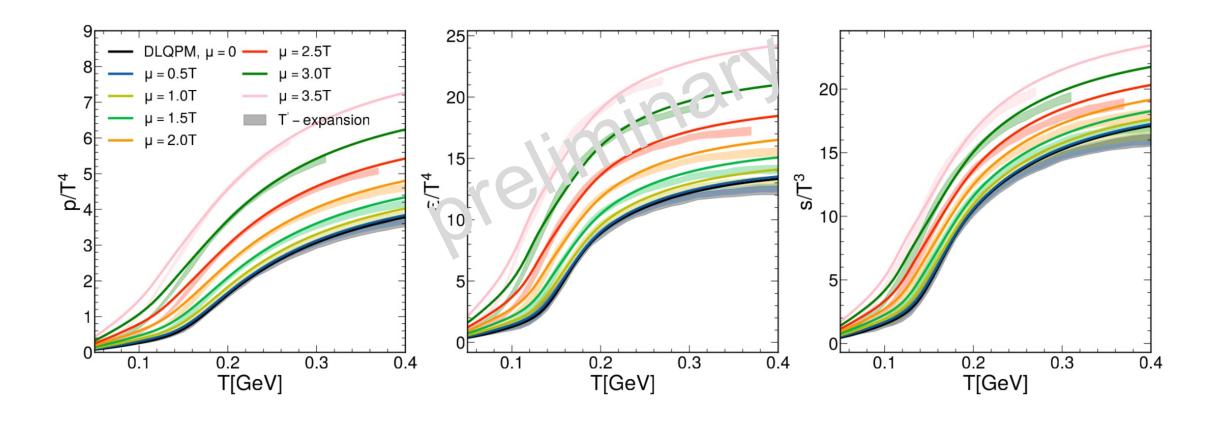


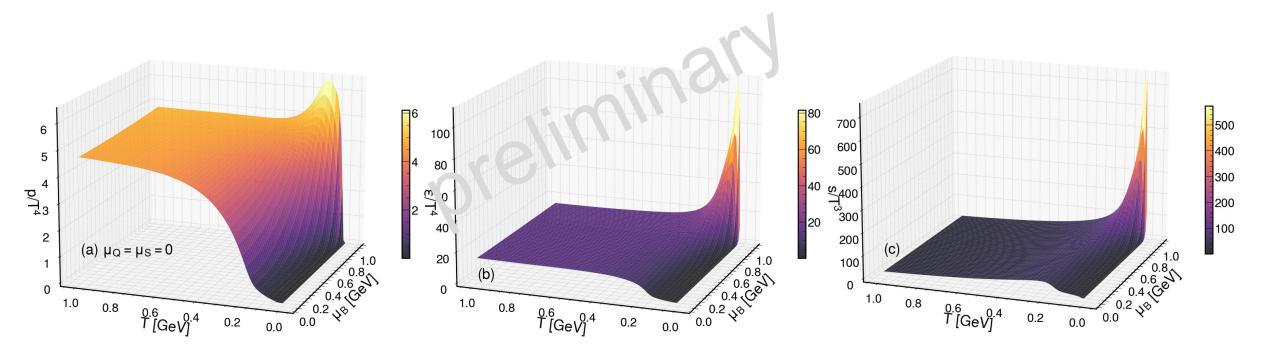
The framework of DNN: 4D DLQPM



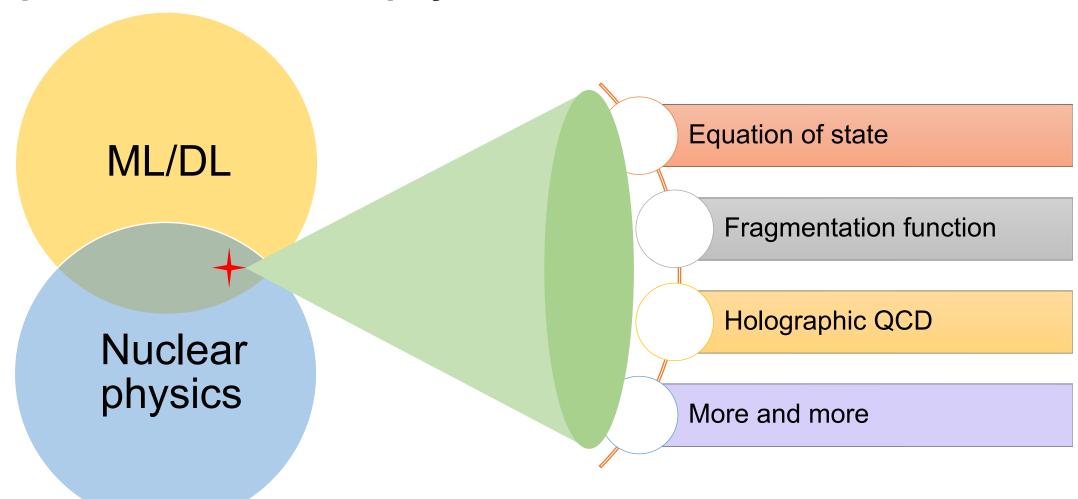








Inverse problems in nuclear physics



Reviews:

Exploring QCD matter in extreme conditions with Machine Learning(2024) Colloquium: Machine learning in nuclear physics(2022) Modern Machine Learning and Particle Physics(2021) Machine learning and the physical sciences (2019)

DL for Parton Fragmentation Functions

Framework of the neural networks

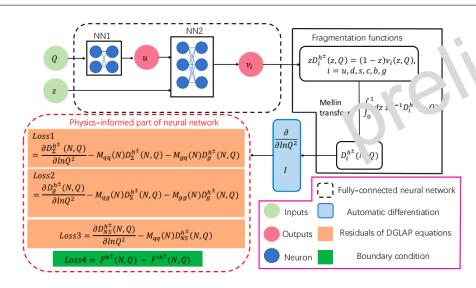
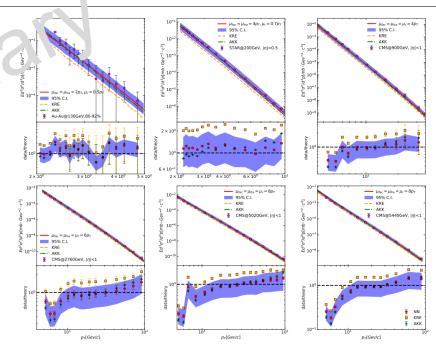


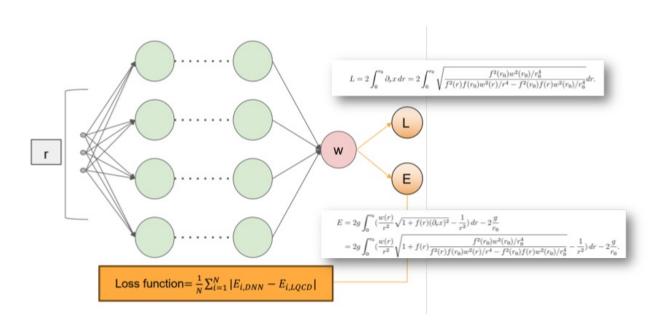
Figure 1. The neural network framework for FFs extractions.

Fitting hadron spectra in pp collisions



per panels: comparison of our NLO results for single-inclusive charged hadron production $pp \to h + X$, where $h = h^+ + h^-$, with data from the STAR, PHENIX and CMS data for various c.m.s energies \sqrt{s} . Also shown are the results obtained with the KRE and AKK parameterizations. Lower panels: data/theory comparison for our results and the KRE and AKK parameterizations.

DL for hQCD



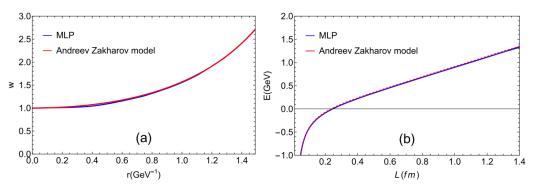


Fig. 3 a The comparison of w(r) from the MLP and the Andreev–Zakharov model. b The comparison of E(L) from Andreev–Zakharov model with E(L) from MLP at vanishing temperature and chemical potential

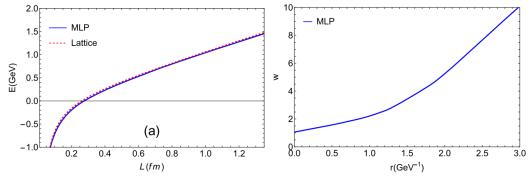
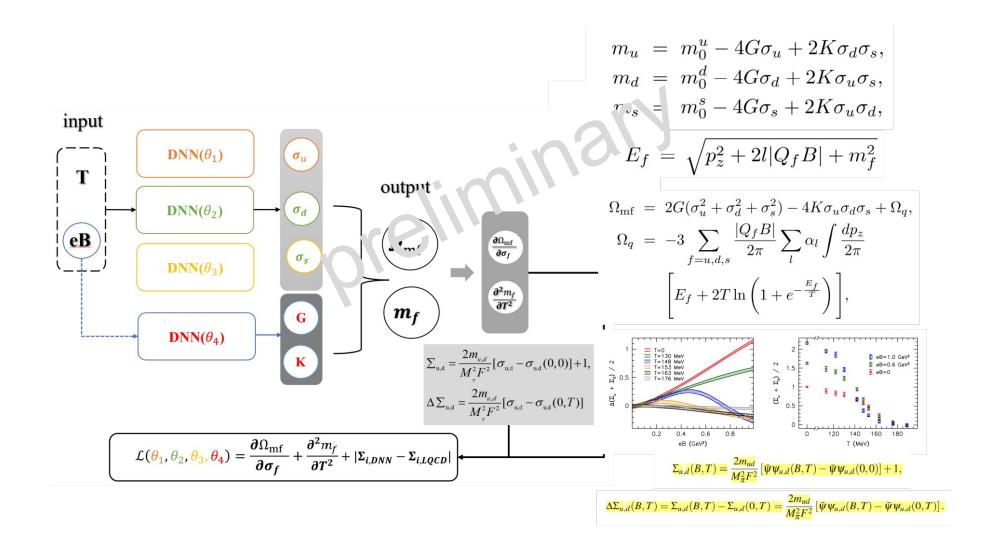


Fig. 4 a Comparison of lattice QCD results [108] with MLP performance on the training dataset, illustrating the relationship between L and E at vanishing temperature and chemical potential. **b** Reconstruction of the function w(r) from MLP, with g set to 0.176

DL for QCD in external magnetic fields



Summary

- Deep learning methods can be used for inverse problems in NP:
 - I. Identifying the nuclear equation of state
 - The DL model can assist us in mapping the relationship between final state observables and initial nuclear equation of state.
 - II. Reconstructing the QCD equation of state
 - We use three neural networks to represent the quasi-particles masses can well reproduce the lattice QCD EoS at zero chemical potential.
 - We can calculate the entropy density at finite baryon chemical potentials, which is consisted with Lattice QCD result using Taylor expansions.
 - The QCD equation of state at finite chemical potential can be used in relativistic hydrodynamics simulations to study the QCD matter produced in the BESII region.
 - III. Reconstructing the parton FFs, the metric of hQCD and ME.

Last but not least

for small x physics ML/DL provides us with promising for Quantum Computing methods and ideas for studying physics. for nuclear ab-initio calculation for QCD equation of state

Thank you for your attention!