The application of machine learning in the holographic QCD

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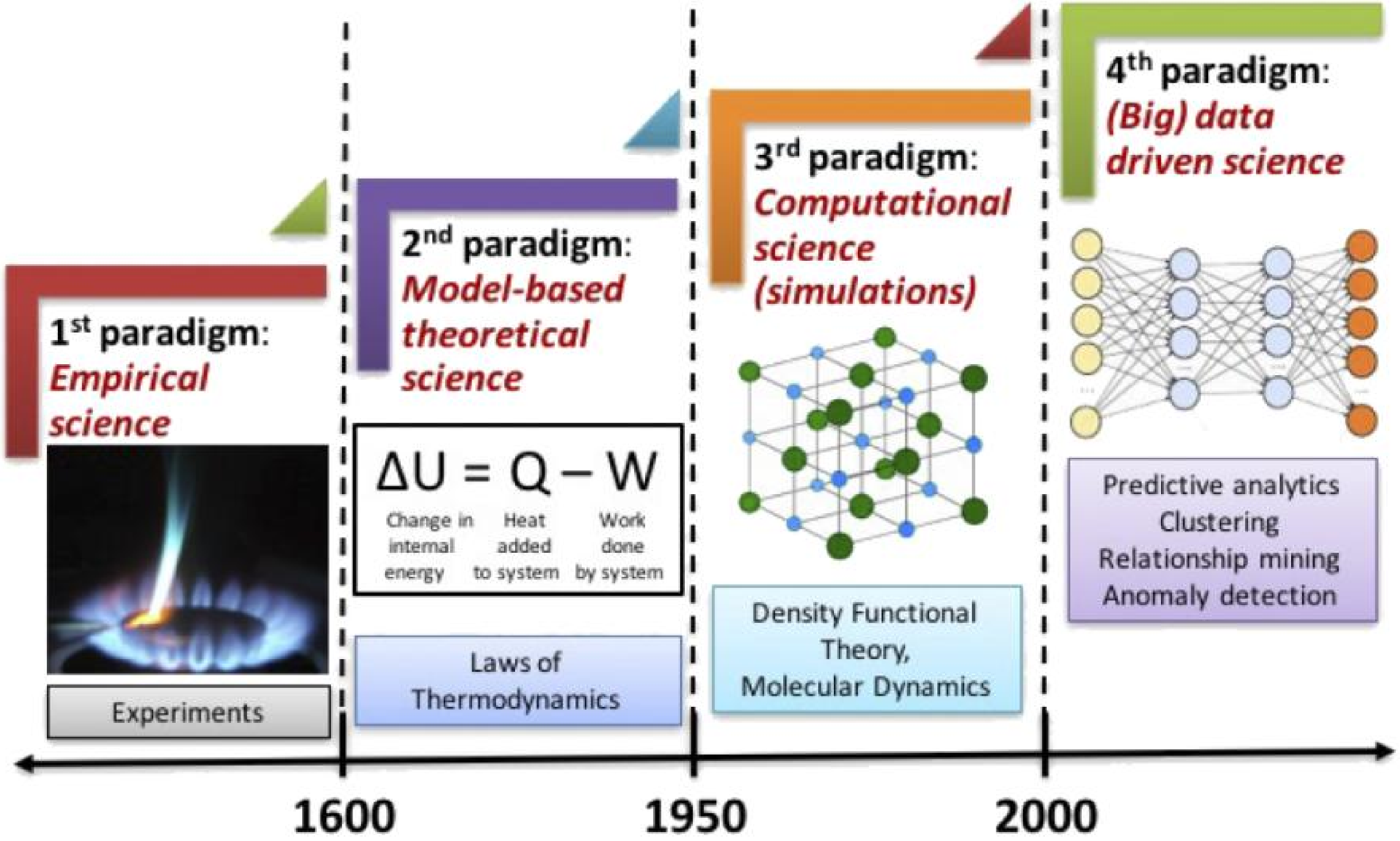
Affiliation: University of South China（南华大学）

Content

- **Motivation**
- **Machine learning and EMD model**
- **Bayesian inference and EMD model**
- **Kolmogorov-Arnold networks in a holographic model**
- **Inverse problem of holographic glueball with neural network**
- **Summary**

The Fourth Paradigm, Data-intensive Scientific Discovery

T. Hey, S. Tansley, and K. Tolle, (ed.)



The four paradigms of science: empirical, theoretical, computational, and data-driven.

Recent works about holographic QCD and machine learning

Koji Hashimoto,Sotaro Sugishita, Akinori Tanaka, Akio Tomiya, Deep learning and the AdS/CFT correspondence, Phys.Rev.D 98 (2018) 4, 046019

1、K. Li, **Y. Ling**, P. Liu and M. H. Wu, Phys. Rev. D 107 (2023) no.6, 066021.
2、K. Hashimoto, K. Ohashi and T. Sumimoto, PTEP 2023, no.3, 033B01 (2023).
3、Y. K. Yan, S. F. Wu, **X. H. Ge** and **Y. Tian**, Phys. Rev. D 102, no.10, 101902.
4、Byoungjoon Ahn, Hyun-Sik Jeong, **Keun-Young Kim**, Kwan Yun, arXiv: 2406.07395.
5、**Rong-Gen Cai**, **Song He**, **Li Li**, Hong-An Zeng, arXiv:2406.12772
……

Machine learning holographic black hole from lattice QCD equation of state
Xun Chen, Mei Huang, Phys.Rev.D 109 (2024) 5, L051902
ArXiv: 2401.06417

Flavor dependent Critical endpoint from holographic QCD through machine learning
Xun Chen, Mei Huang, (under review)
ArXiv: 2405.06179

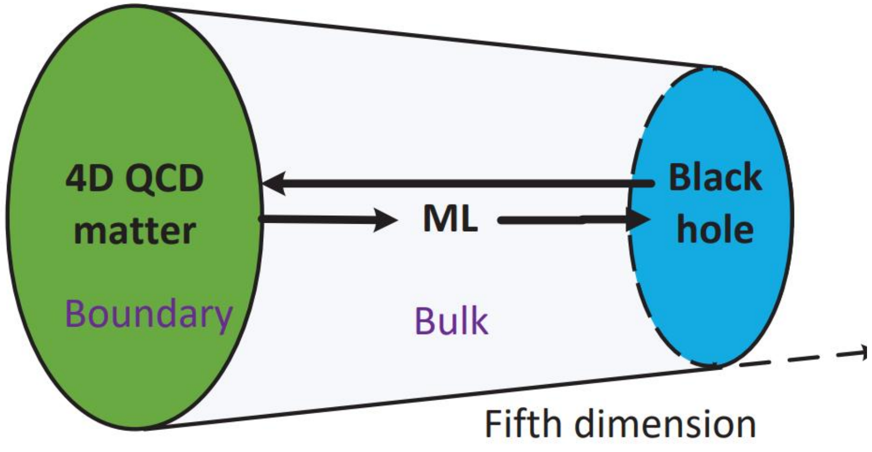


Figure 1. The sketch of holographic QCD and machine learning.

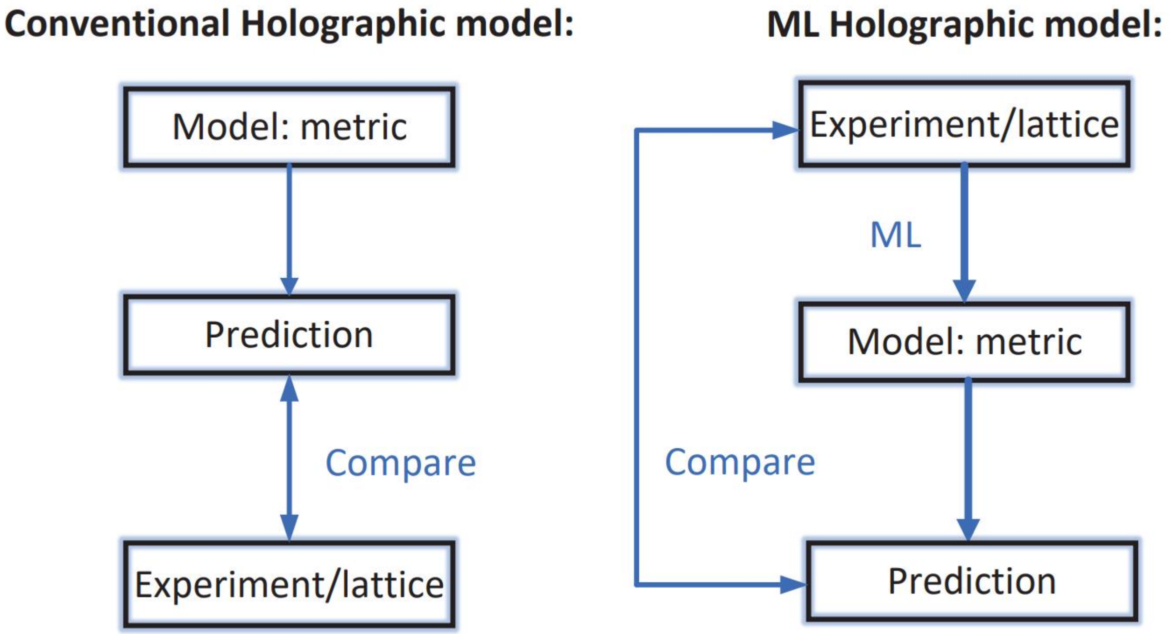


Figure 2. The difference between ML holographic model and the traditional holographic method.

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 $\quad\quad$ F is the tensor of gauge field

Metric ansatz:

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

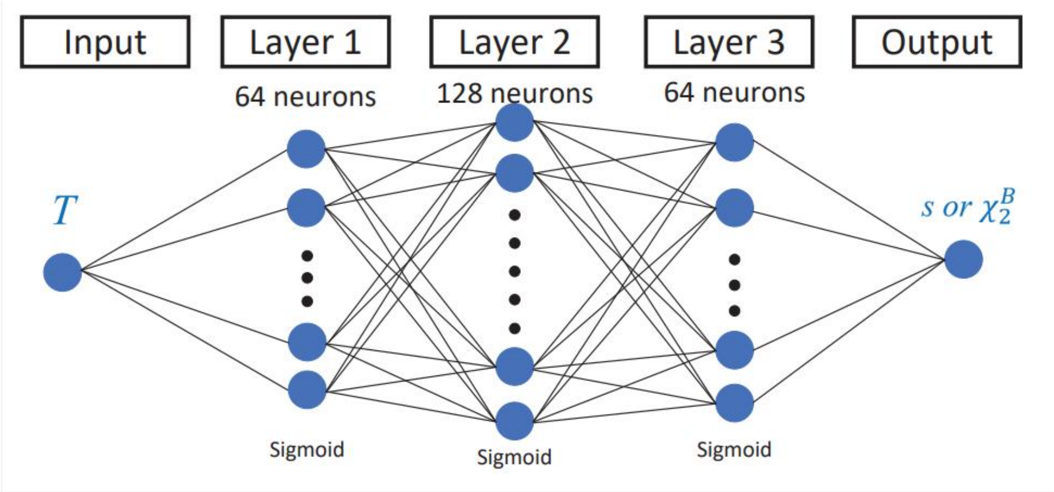
$$A(z) = d\ln\left(az^2+1\right) + d\ln(bz^4+1),\ f(z) = e^{cz^2 - A(z) + k}$$

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

Learning progress

First step：

2+1 flavor



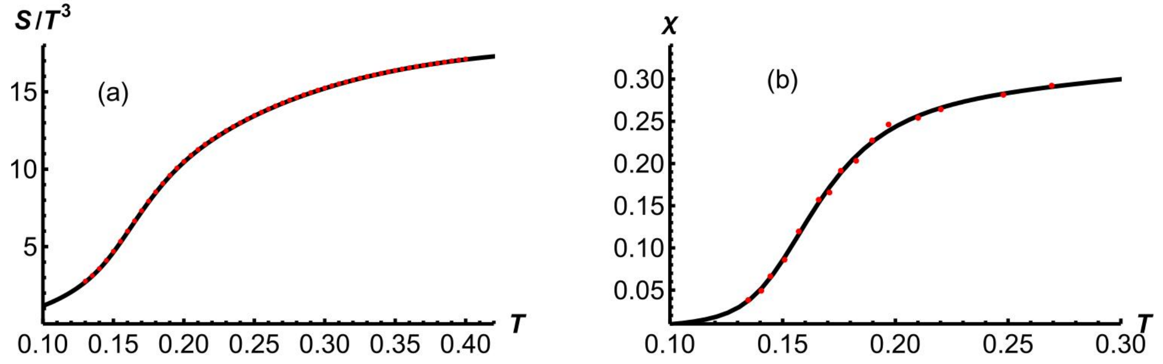


FIG. 1. (a) The entropy as a function of temperature. (b) The baryon susceptibility as a function of temperature. The dots are the results from the lattice and the black line is the prediction of the neural network. The unit of T is GeV.

We use ”TensorFlow” to build a neural network model for regression tasks.

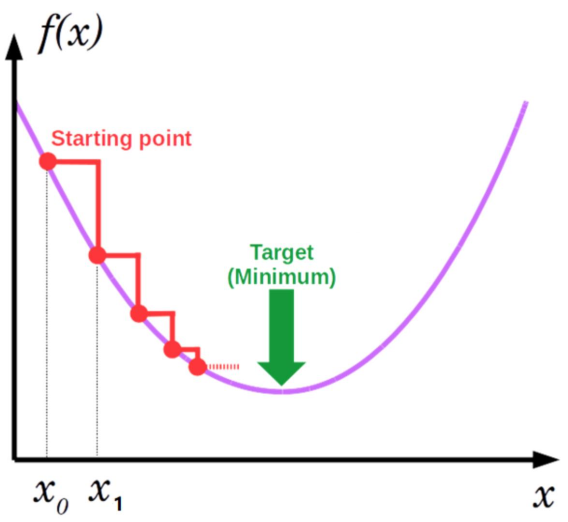
Activation function： Sigmoid

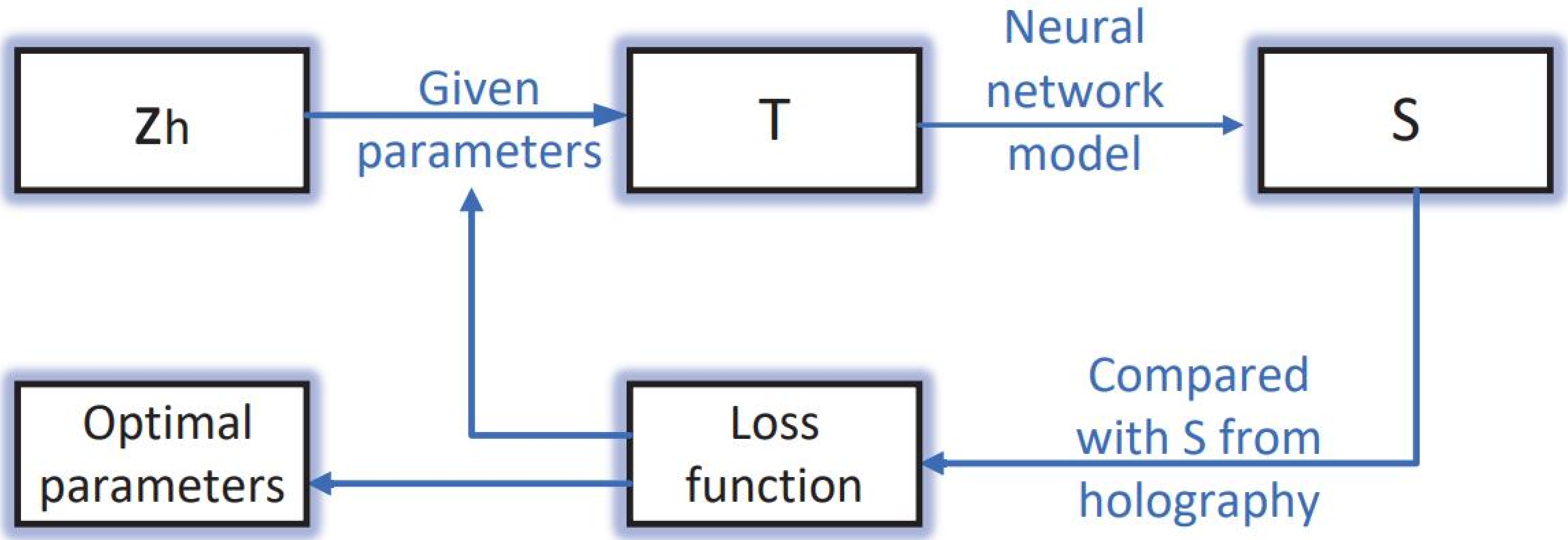
Optimizer: Adam

Learning progress

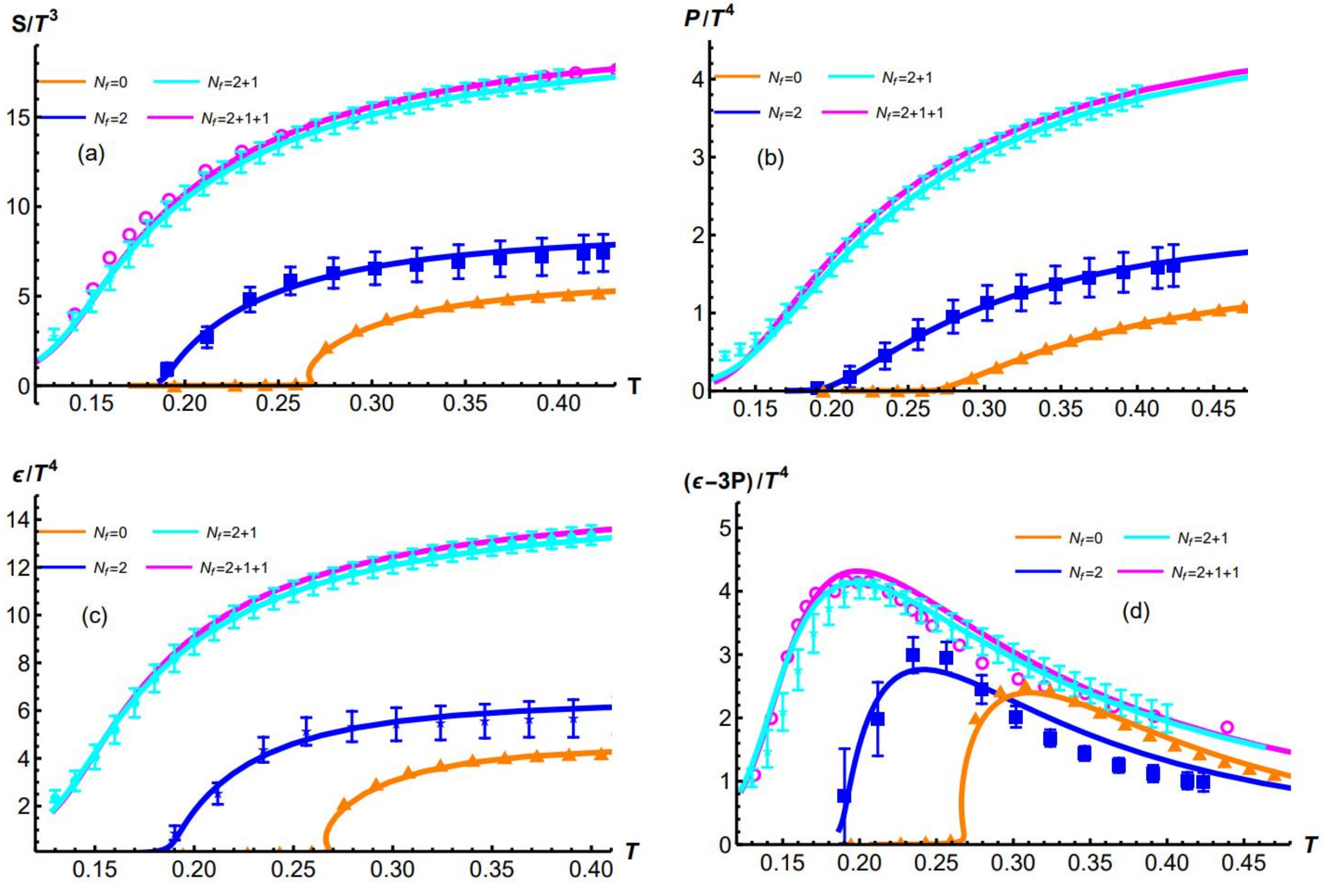
Second step：

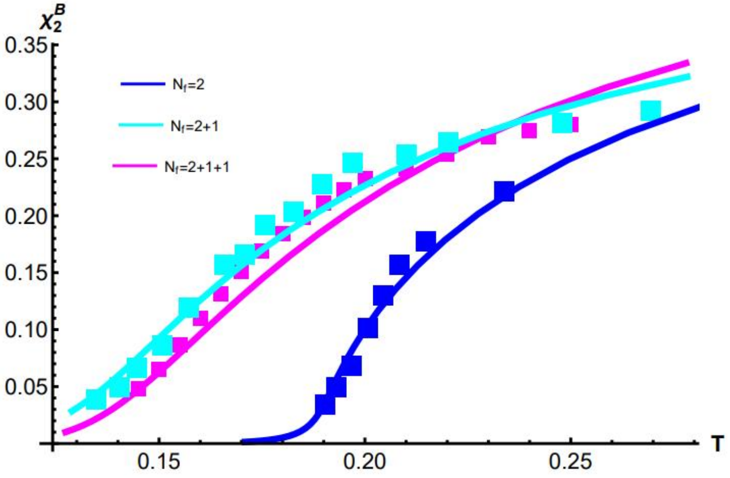
Gradient descent algorithm

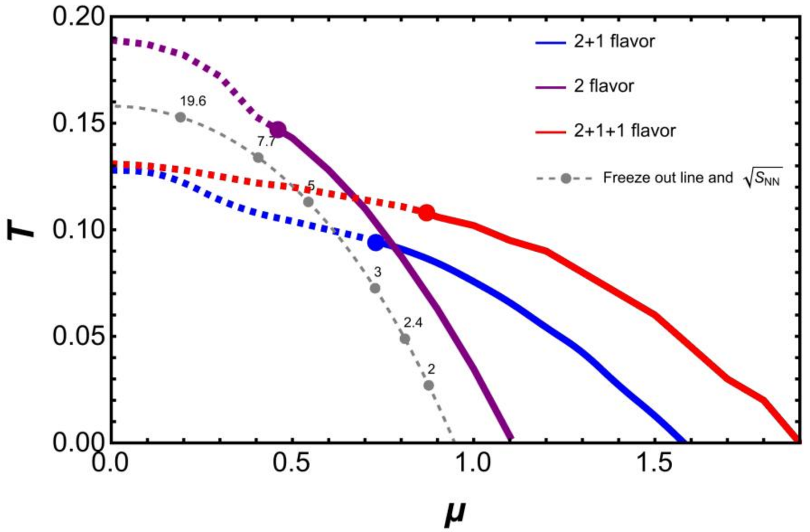




Results


S/T^3
P/T^4
ϵ/T^4
(ϵ−3P)/T^4
N_f=0
N_f=2+1
N_f=2
N_f=2+1+1
(a)
(b)
(c)
(d)
T

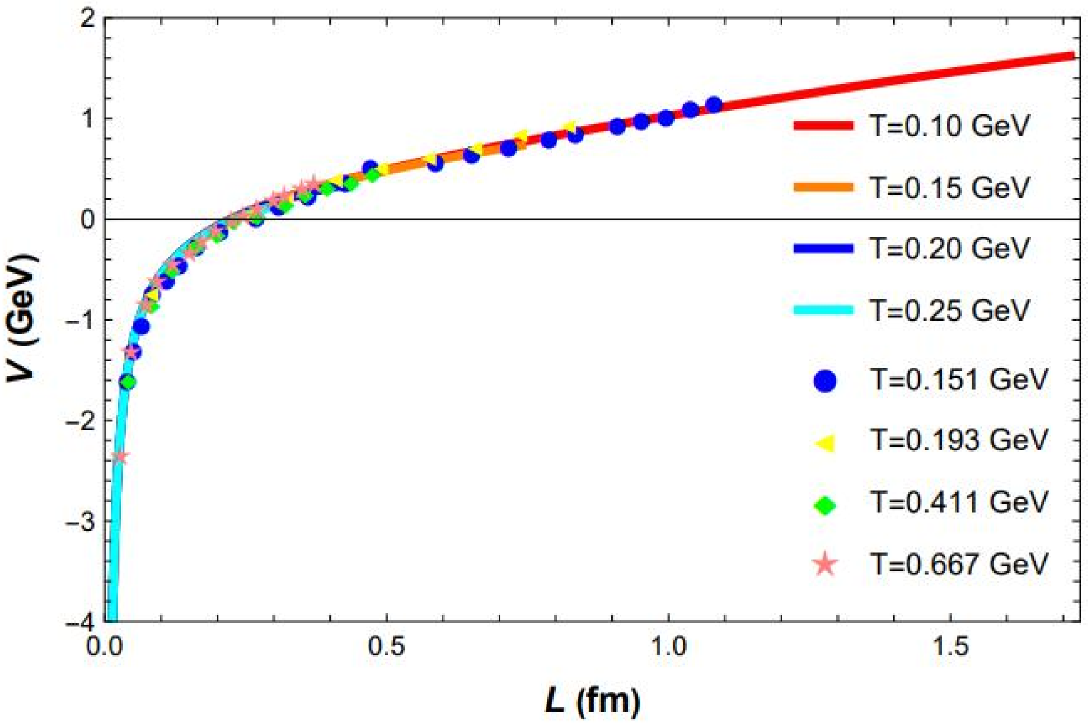

χ_2^B
N_f=2
N_f=2+1
N_f=2+1+1
T

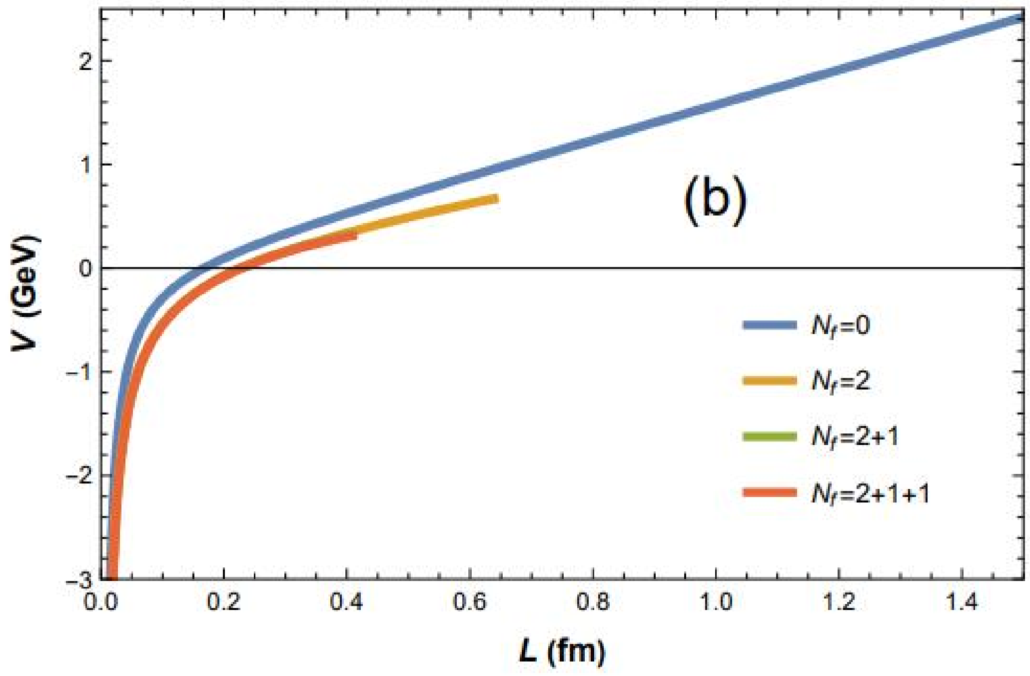

2+1 flavor
2 flavor
2+1+1 flavor
Freeze out line and √S_NN
19.6
7.7
5
3
2.4
2
T
μ

Potential energy of heavy quarkonium in flavor-dependent systems from a holographic model

Phys.Rev.D 110 (2024) 4, 046014 • e-Print: 2406.04650

Xi Guo, Xun Chen, Dong Xiang, Miguel Angel Martin Contreras, Xiao-Hua Li



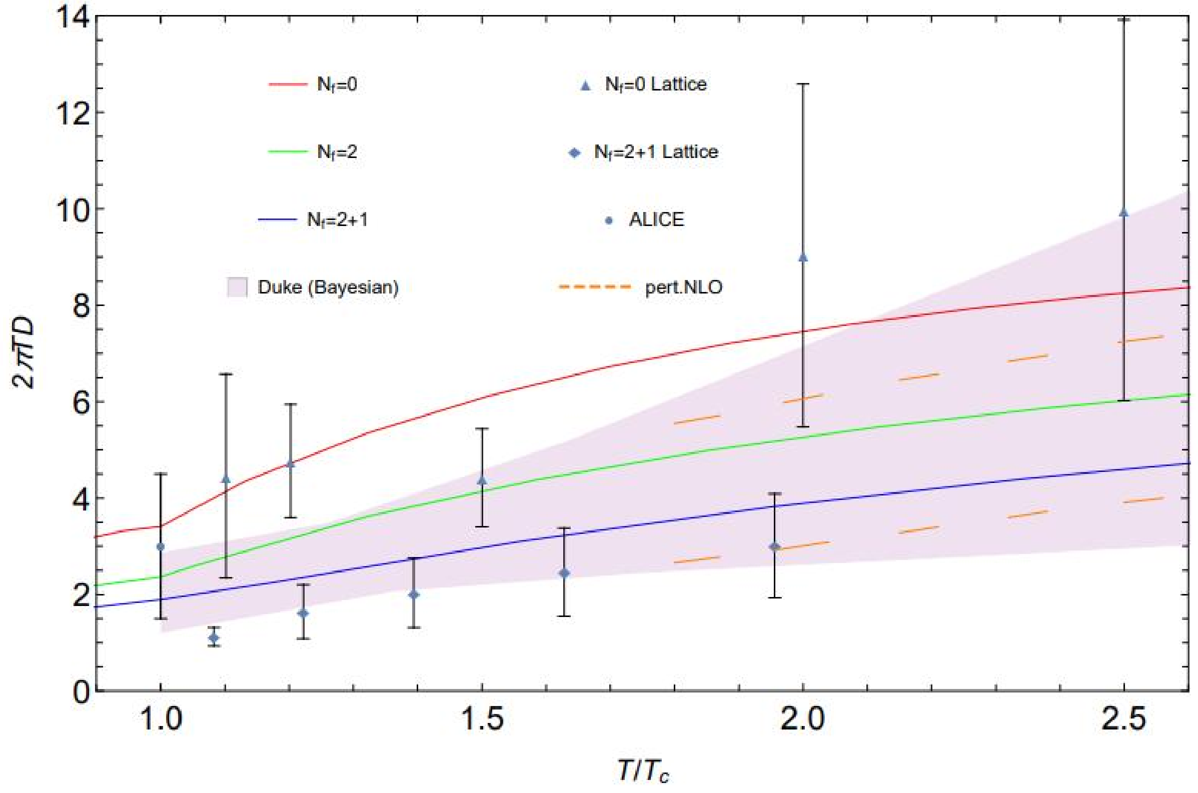


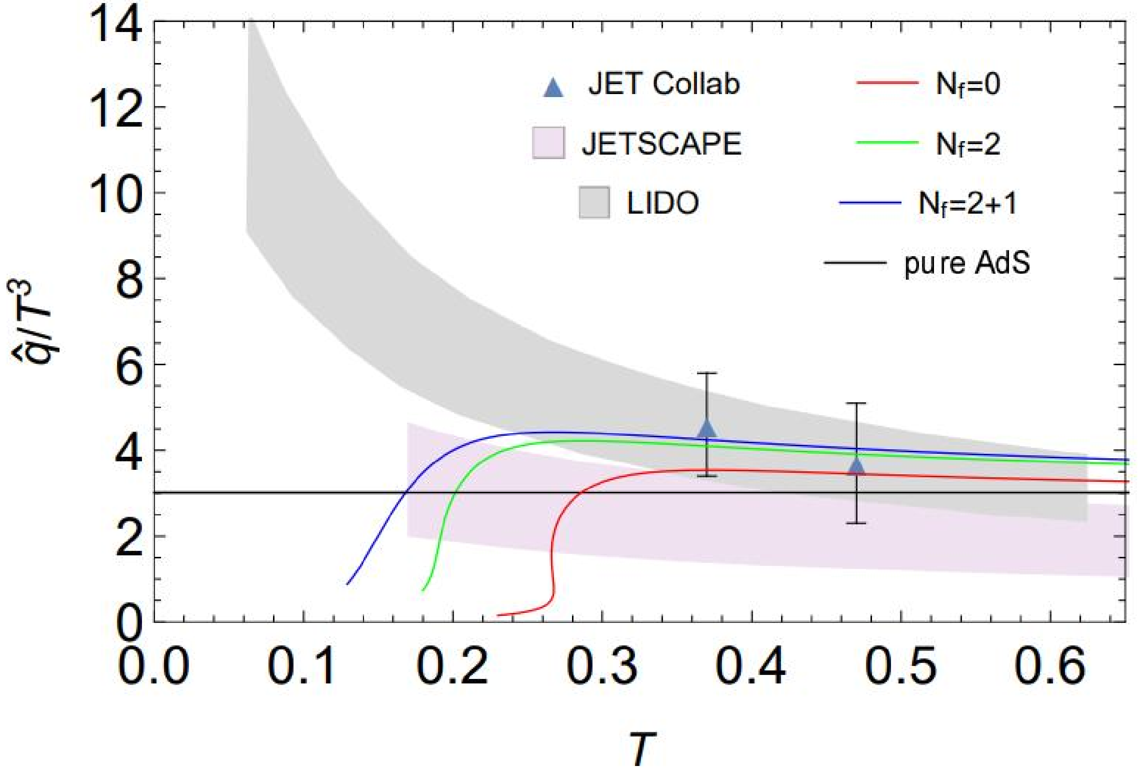
Lattice, arXiv:2110.11659

Exploring Transport Properties of Quark-Gluon Plasma with a Machine-Learning assisted Holographic Approach

e-Print: 2404.18217 (PRD under review)

Bing Chen, Xun Chen, Xiaohua Li, Zhou-Run Zhu, Kai Zhou

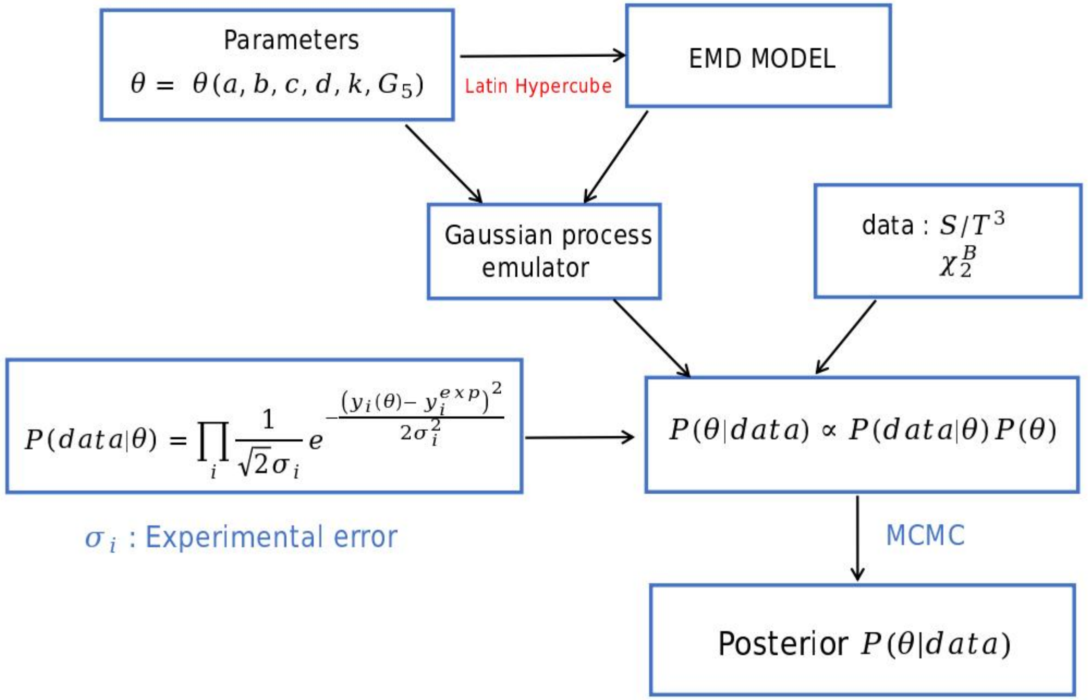




Bayesian Inference of the Critical Endpoint in 2+1-Flavor System from Holography

In preparation,

Xun Chen, Liqiang Zhu, Hanzhong Zhang, Kai Zhou, and Mei Huang



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

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

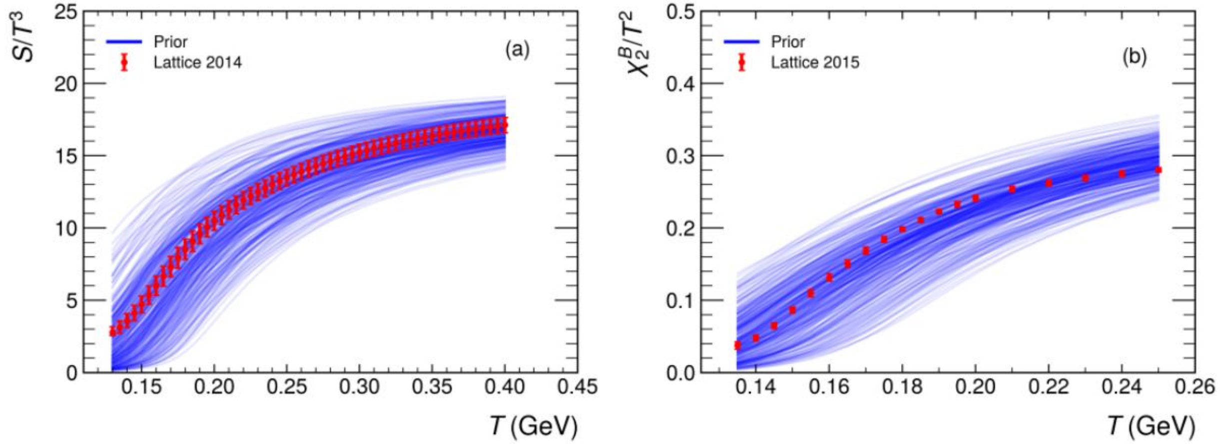
$$s = \frac{e^{3A(z_h)}}{4G_5 z_h^3}. \qquad \chi_2^B = \frac{1}{T^2}\frac{\partial\rho}{\partial\mu}.$$

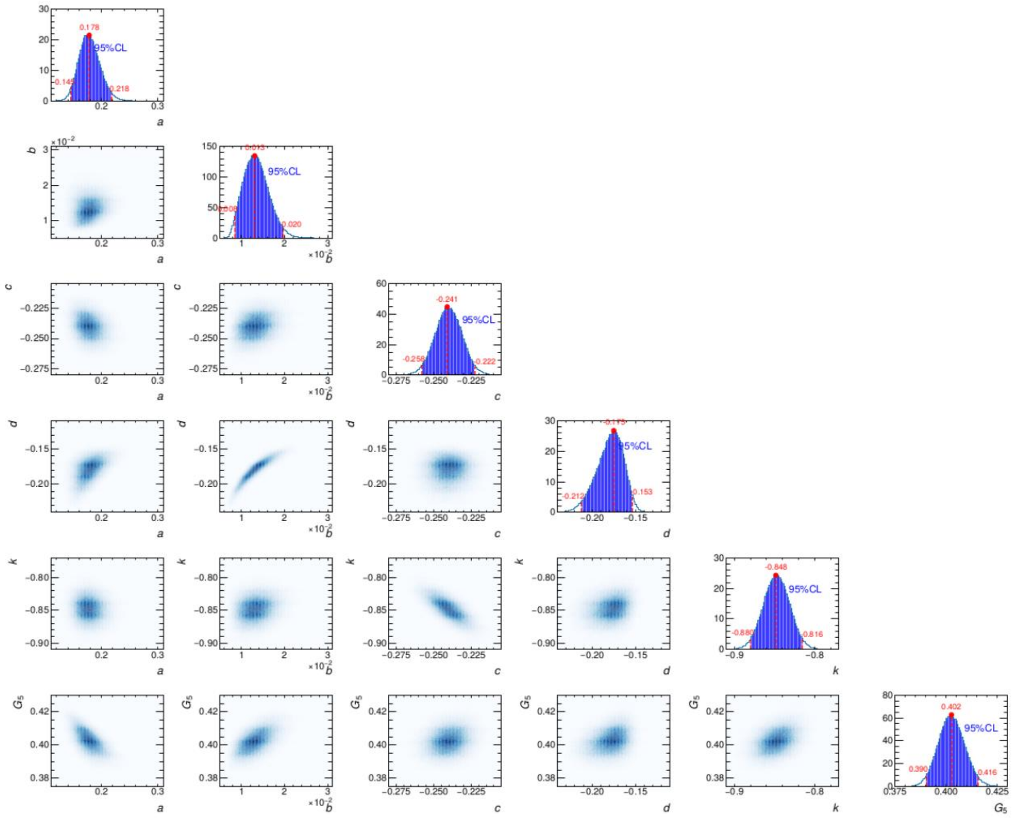
Mauricio Hippert, Joaquin Grefa, T. Andrew Manning, Jorge Noronha, Jacquelyn Noronha-Hostler, Phys.Rev.D 110 (2024) 9, 094006

Bayesian Inference of the Critical Endpoint in 2+1-Flavor System from Holography

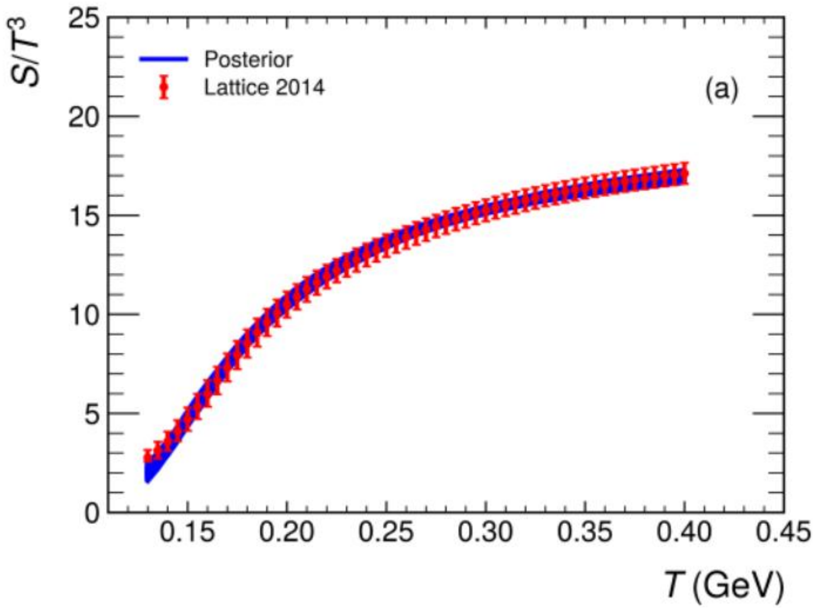
Prior		
Parameter	min	max
a	0.110	0.310
b	0.005	0.031
c	-0.280	-0.205
d	-0.240	-0.110
k	-0.910	-0.770
G_5	0.375	0.430

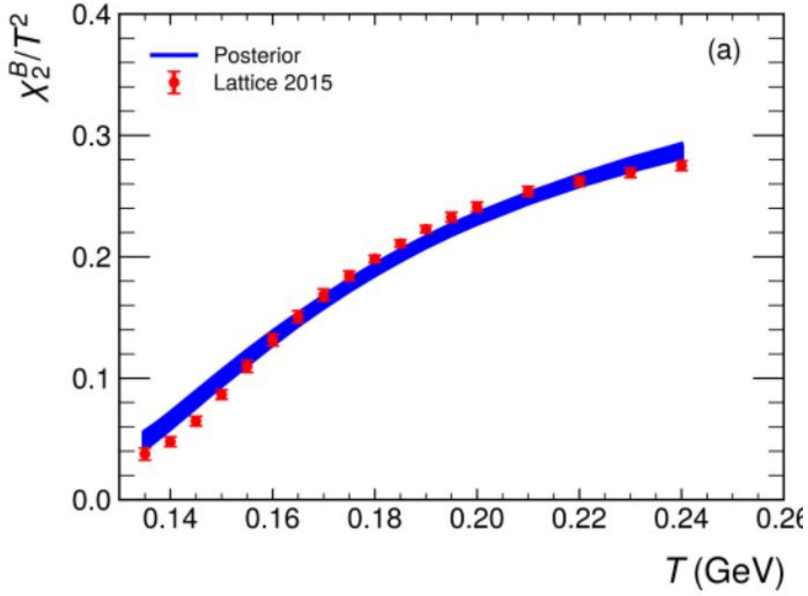
Posterior 95% CL			
Parameter	min	max	MAP
a	0.145	0.218	0.178
b	0.008	0.020	0.013
c	-0.258	-0.222	-0.241
d	-0.212	-0.153	-0.175
k	-0.880	-0.816	-0.848
G_5	0.390	0.416	0.402

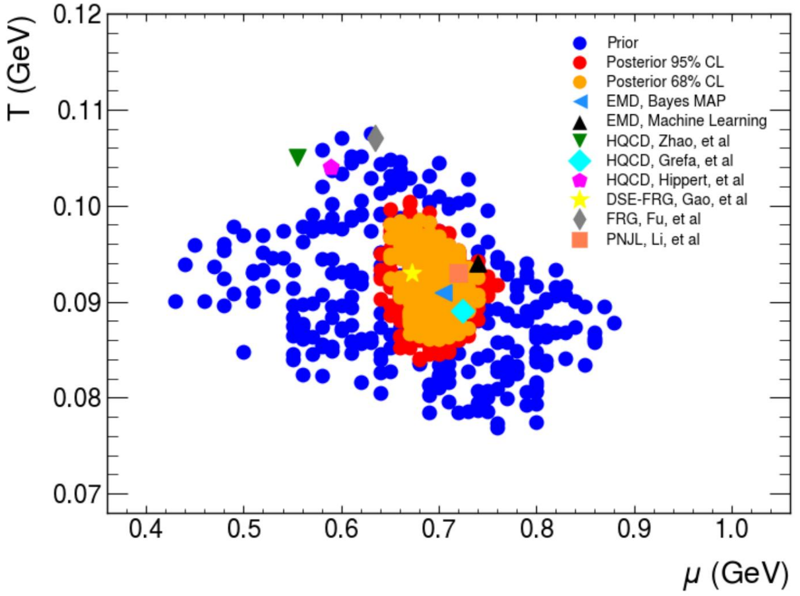




Bayesian Inference of the Critical Endpoint in 2+1-Flavor System from Holography







Multi-Layer Perceptrons (MLP) and Kolmogorov-Arnold Networks (KAN)

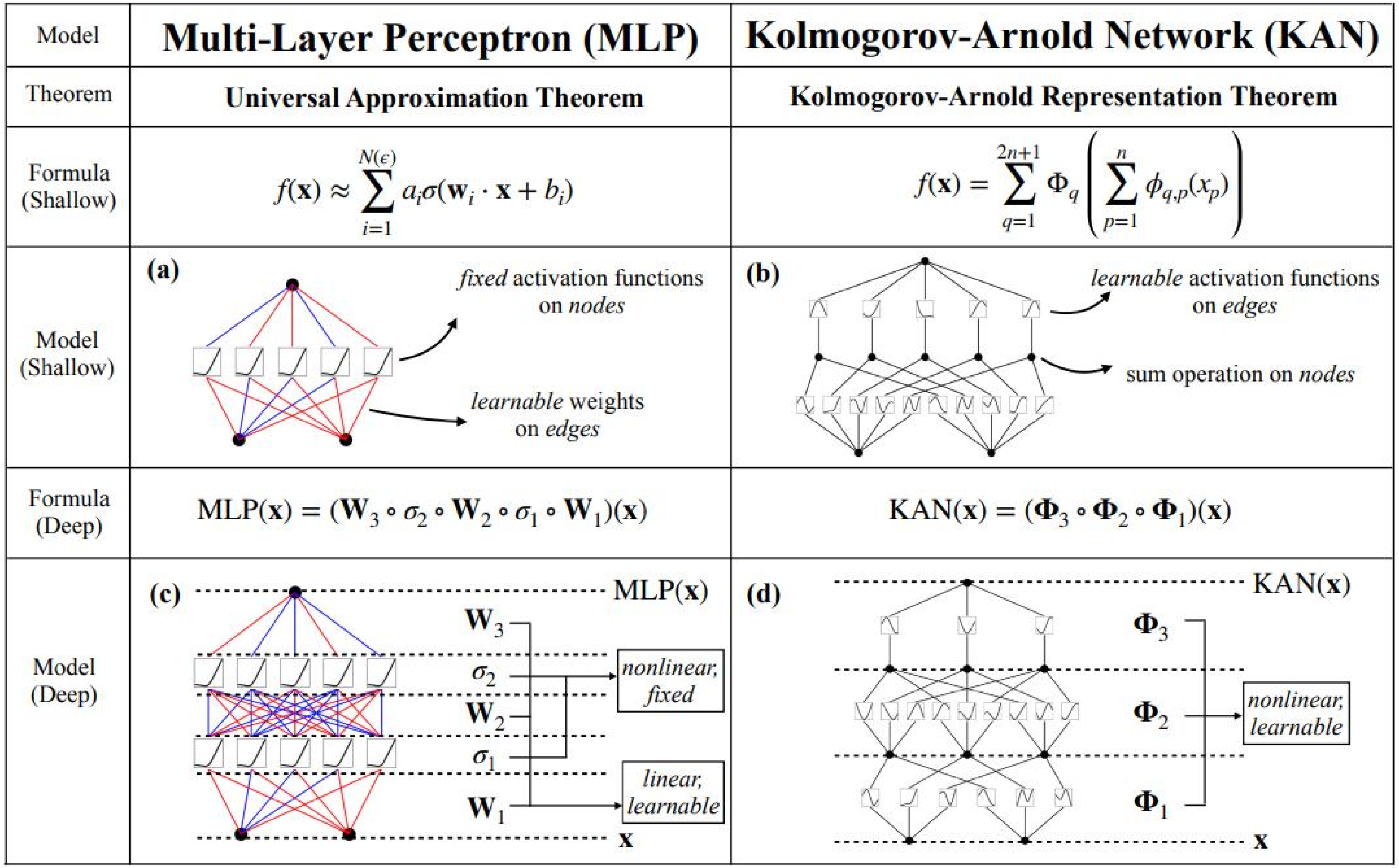
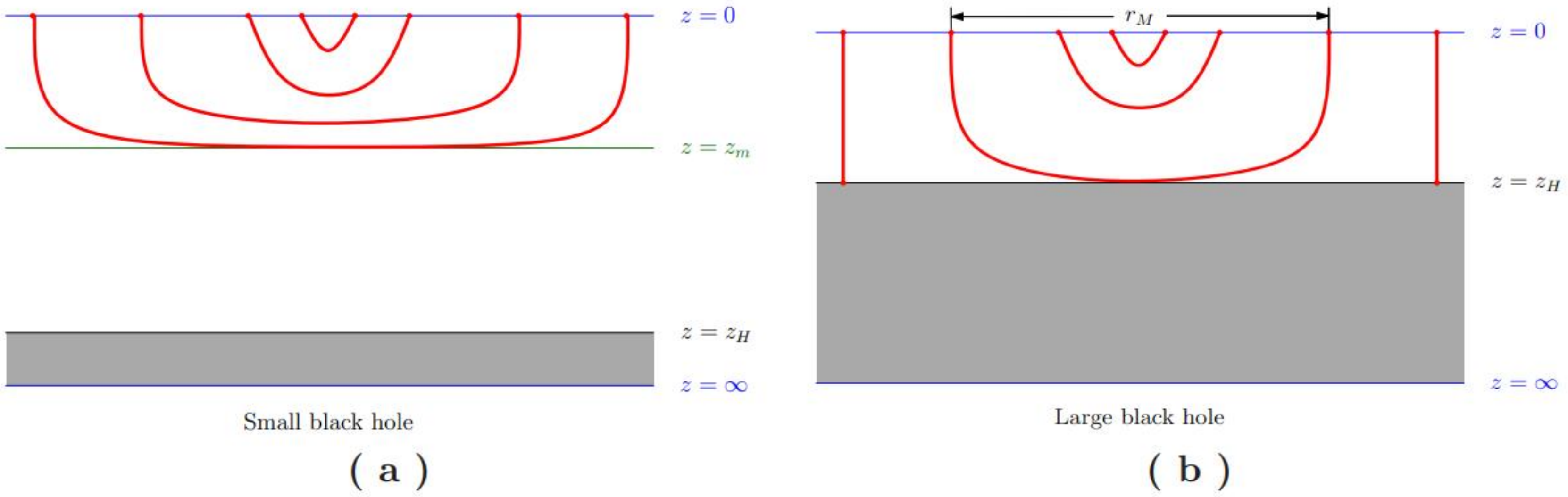


Figure 0.1: Multi-Layer Perceptrons (MLPs) vs. Kolmogorov-Arnold Networks (KANs)

Ziming Liu, et. al.
Arxiv: 2404.19756

Holographic heavy-quark potential



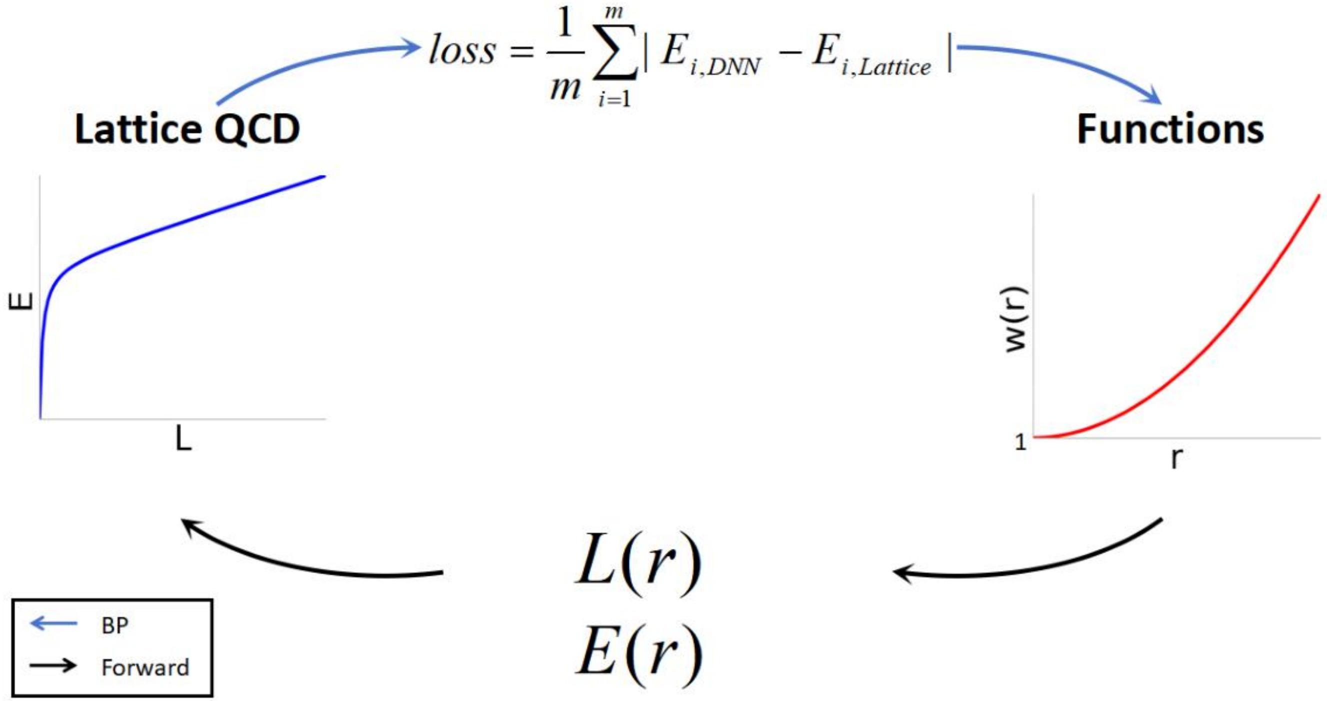
Andreev-Zakharov model
JHEP 04 (2007) 100

$$ds^2 = w(r)\frac{1}{r^2}\left[f(r)dt^2 + d\vec{x}^2 + f^{-1}(r)dr^2\right],$$

$$f(r) = 1 - \left(\frac{1}{r_h^4} + q^2 r_h^2\right) r^4 + q^2 r^6.$$

$$w(r) = 1.0e^{0.45r^2}$$

Neural Network Modeling of Heavy-Quark Potential from Holography
arXiv:2408.03784 (under review)
Ouyang Luo, **Xun Chen**, Fu-Peng Li, Xiao-hua Li, Kai Zhou



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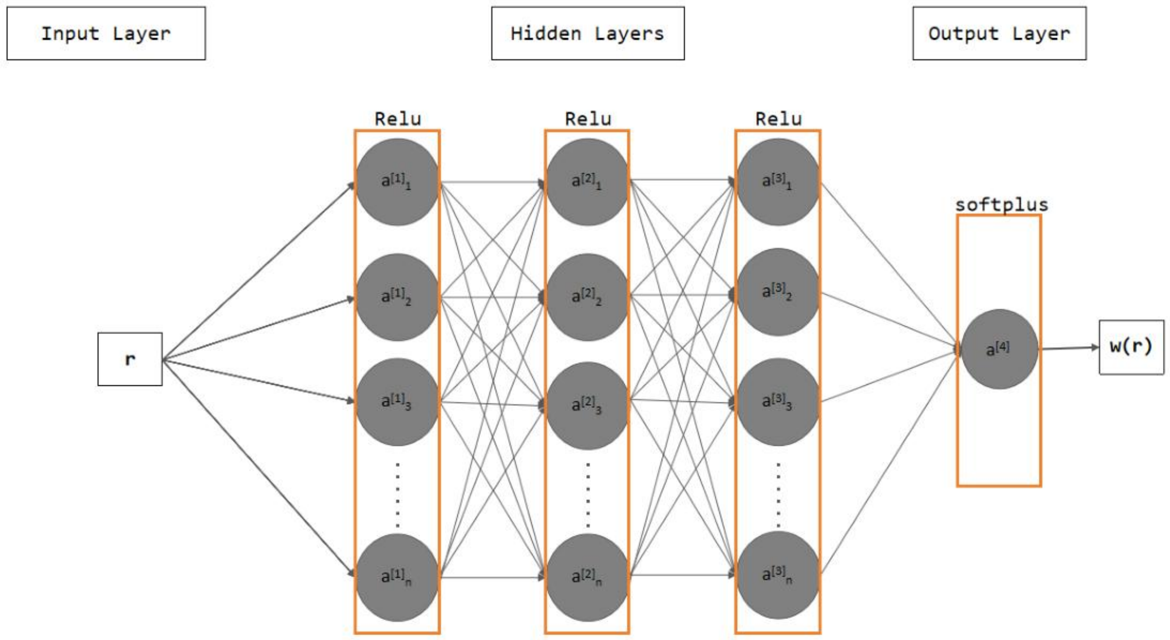
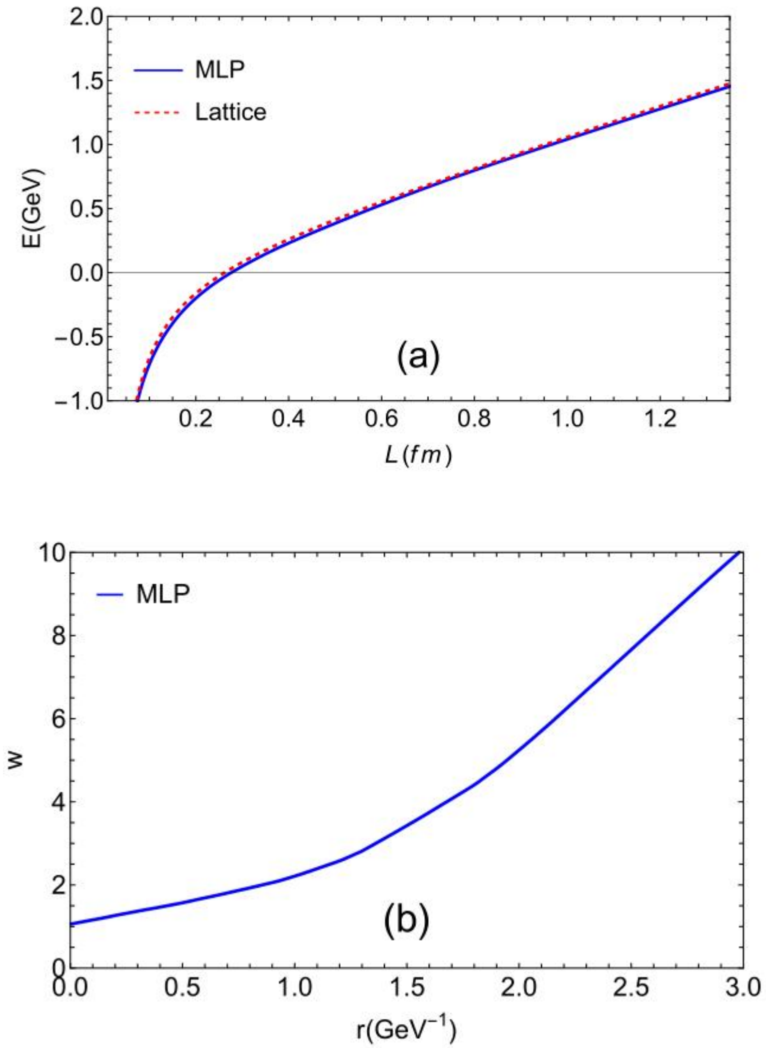
arXiv:2408.03784 (under review)

Ouyang Luo, **Xun Chen**, Fu-Peng Li, Xiao-hua Li, Kai Zhou





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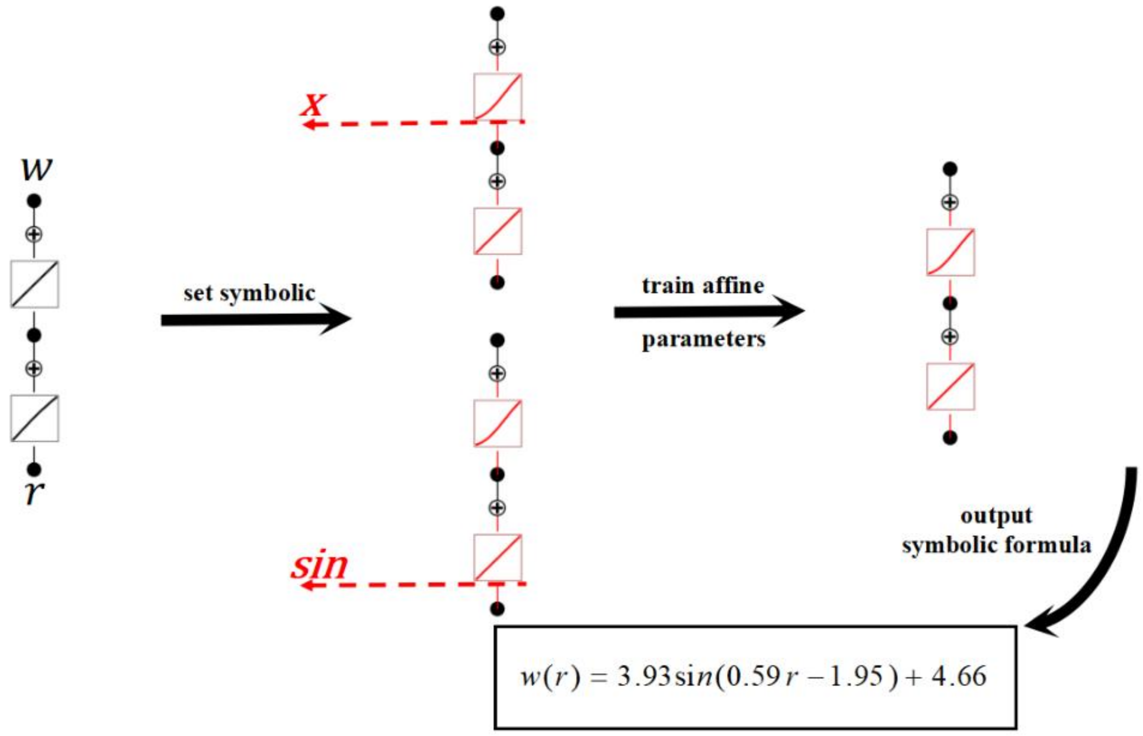
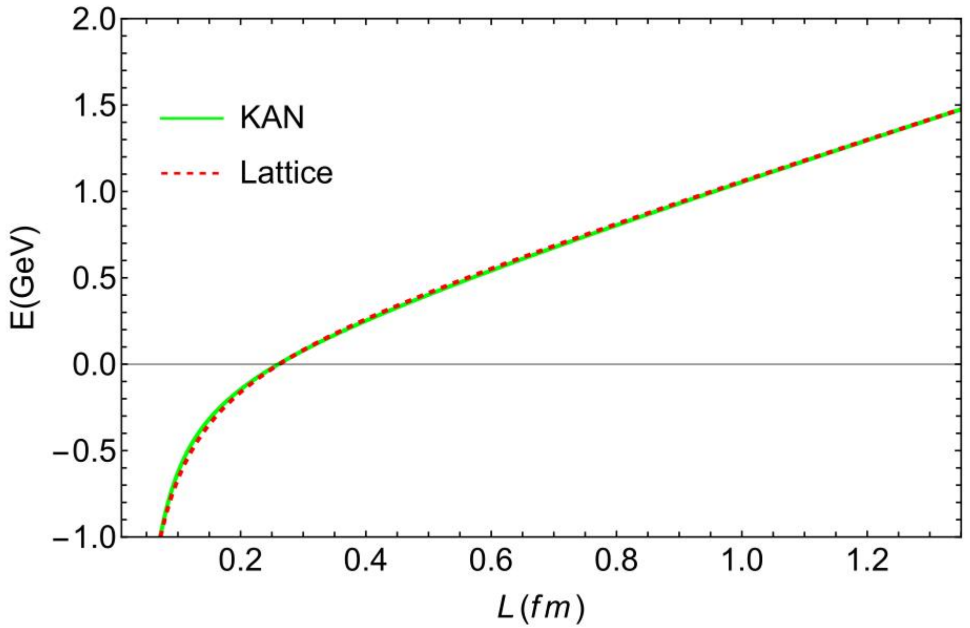
arXiv:2408.03784 (under review)

Ouyang Luo, **Xun Chen**, Fu-Peng Li, Xiao-hua Li, Kai Zhou





Holographic glueball spectrum and neural network

Dynamical holographic QCD model for glueball and light meson spectra

Danning Li, Mei Huang, JHEP 11 (2013) 088

Background
$$S_G = \frac{1}{16\pi G_5}\int d^5x\sqrt{g_s}e^{-2\Phi}\left(R_s + 4\partial_M\Phi\partial^M\Phi - V_G^s(\Phi)\right).$$

$$ds^2 = b_s^2(z)(dz^2 + \eta_{\mu\nu}dx^\mu dx^\nu), \quad b_s(z) \equiv e^{A_s(z)}.$$

The scalar glueball $S_{\mathscr{G}} = \int d^5x\sqrt{g_s}\frac{1}{2}e^{-\Phi}\left[\partial_M\mathscr{G}\partial^M\mathscr{G} + M^2_{\mathscr{G},5}\mathscr{G}^2\right].$ EoM $-\mathscr{G}_n'' + V_{\mathscr{G}}\mathscr{G}_n = m^2_{\mathscr{G},n}\mathscr{G}_n,$

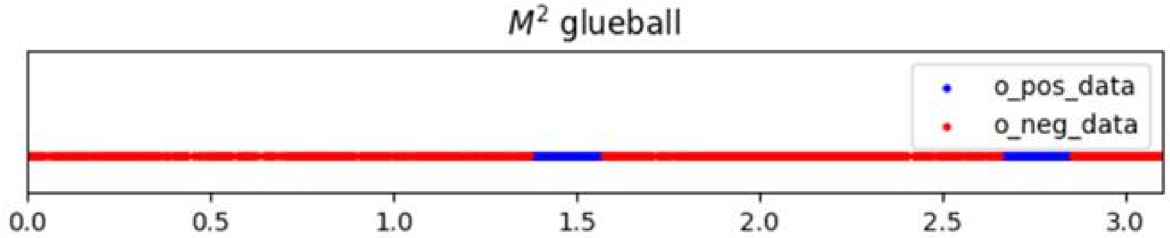
$n(0^{++})$	$\Phi = \mu_{G^2}^4 z^4$	
	$\mu_{G^2} = 650$	$\mu_{G^2} = 800$
0	1450	1784
1	3083	3795
2	4297	5289
3	5388	6632

$n(0^{++})$	$\Phi = \mu_G^2 z^2$		
	$\mu_G = 900$	$\mu_G = 1000$	$\mu_G = 1100$
0	1434	1593	1752
1	2356	2618	2880
2	2980	3311	3642
3	3489	3877	4264

Holographic glueball spectrum and neural network

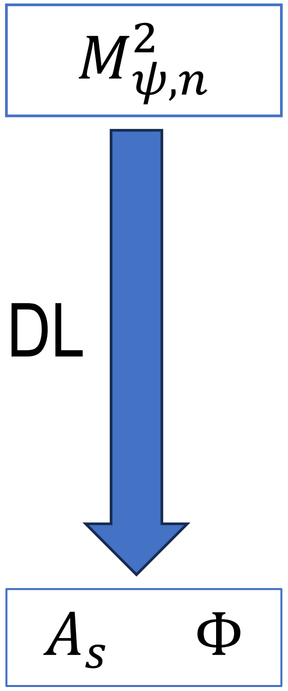
Jia-Jie Jiang, **Xun Chen**, Mei Huang, in preparation

Deep Learning and AdS/QCD, Phys.Rev.D 102 (2020) 2, 026020



$n(0^{++})$	Lat1
	$N_c = 3$
1	1475(30)(65)
2	2755(70)(120)
3	3370(100)(150)
4	3990(210)(180)

$n(0^{++})$	Lat1	This Work	error
0	1.475	1.538	4.26%
1	2.755	2.710	1.62%
2	3.370	3.520	4.44%
3	3.990	4.219	5.75%

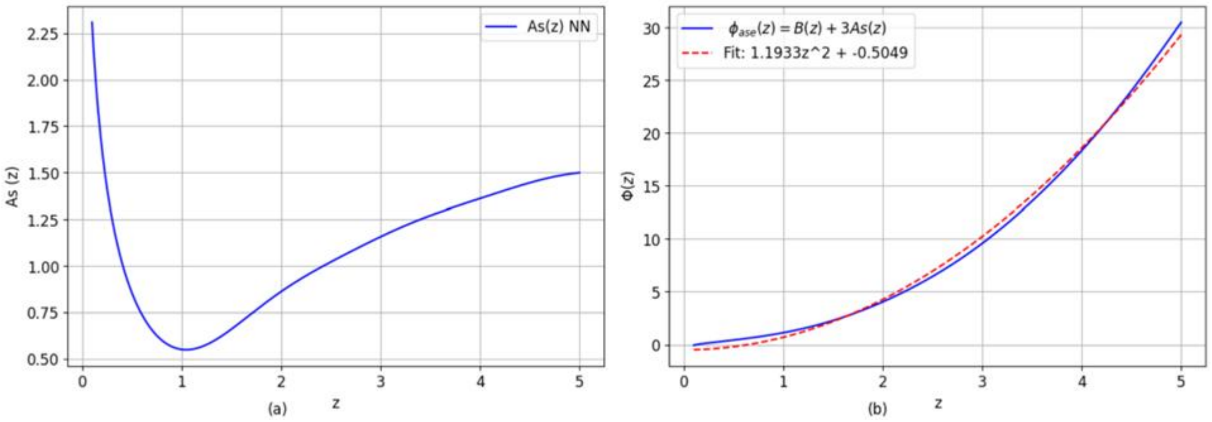


Inverse problem

The Equation of motion for ψ has the form of

$$-e^{-(3As-\Phi)}\partial_z(e^{3As-\Phi}\partial_z\psi_n) = M^2_{\psi,n}\psi_n$$

$$-A_s''-\frac{4}{3}\Phi' A_s' + A_s'^2 + \frac{2}{3}\Phi'' = 0$$



Summary

- By inputting the equation of state and baryon number susceptibility into the model, we construct the holographic model with machine learning. We calculated the results of heavy-quark potential and transport properties.

- Bayesian inference can also assist us in constructing the model by incorporating the error bars obtained from lattice data.

- Attempting to construct the holographic model using the MLP and KAN methods, based on the heavy-quark potential derived from lattice QCD.

- By inputting mass spectrum information, we aim to construct an effective holographic model.

Outlook

Can we construct a holographic model with NN which can describe all the results?