# The application of machine learning in holographic QCD

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# Outline

1. Motivation
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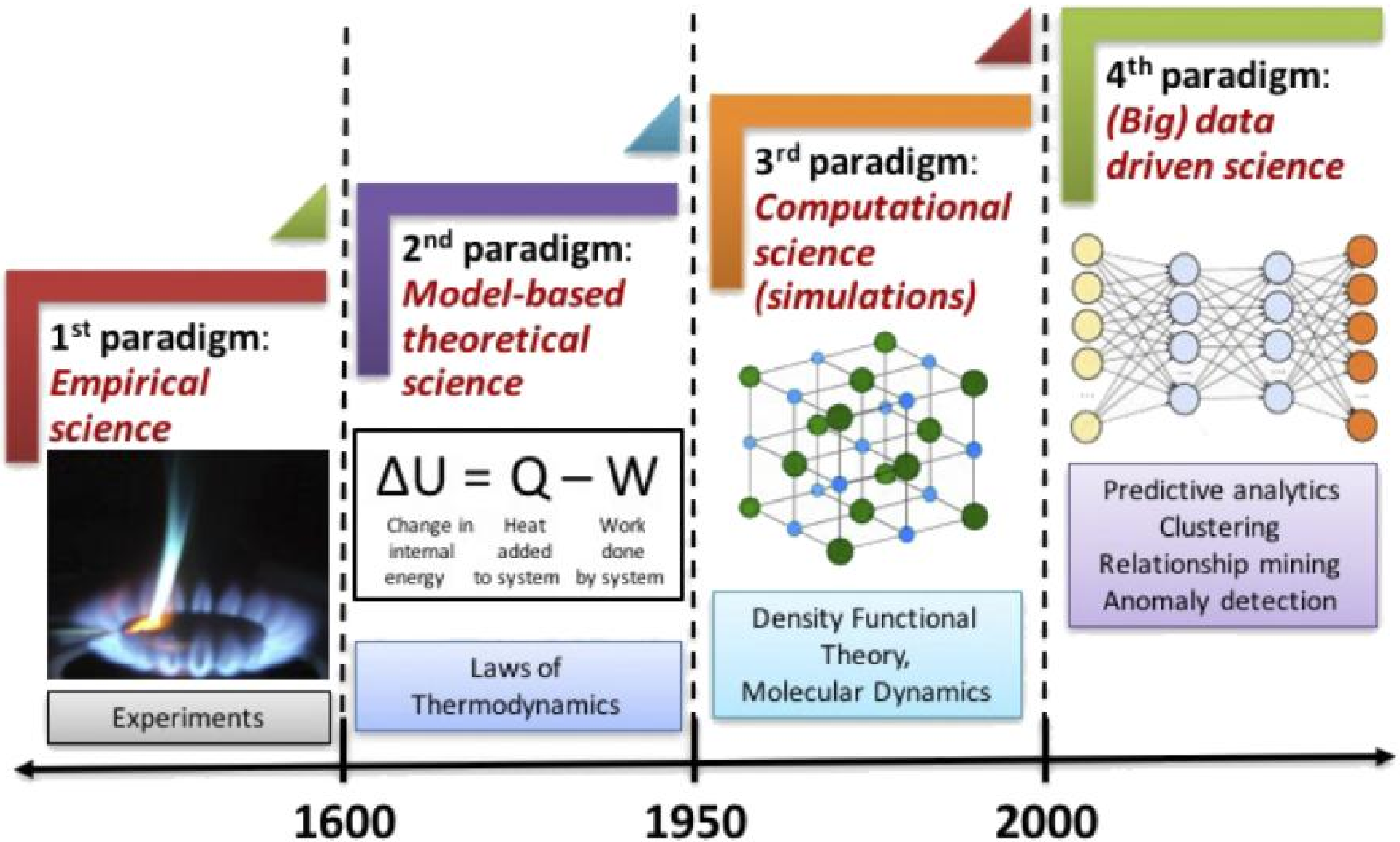
# Motivation

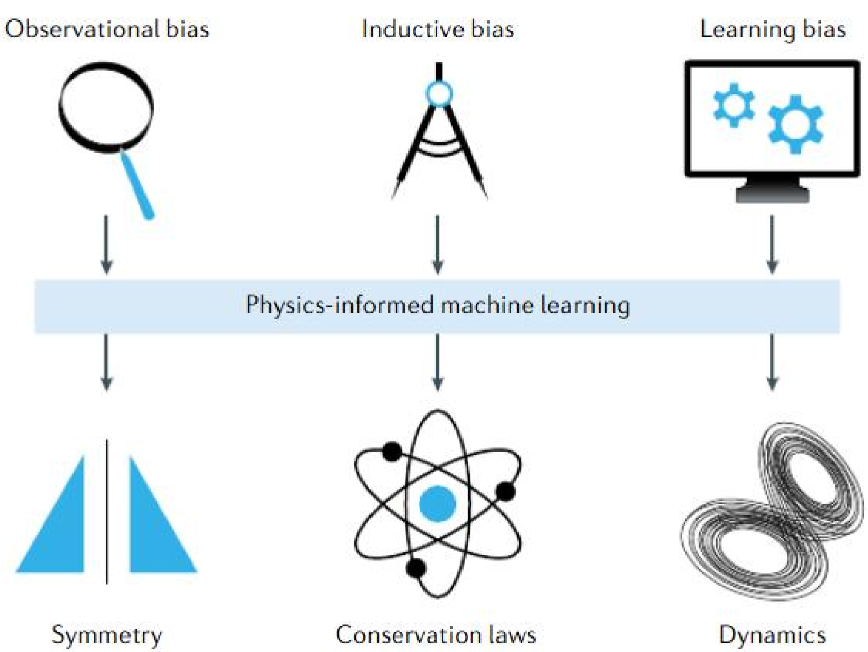


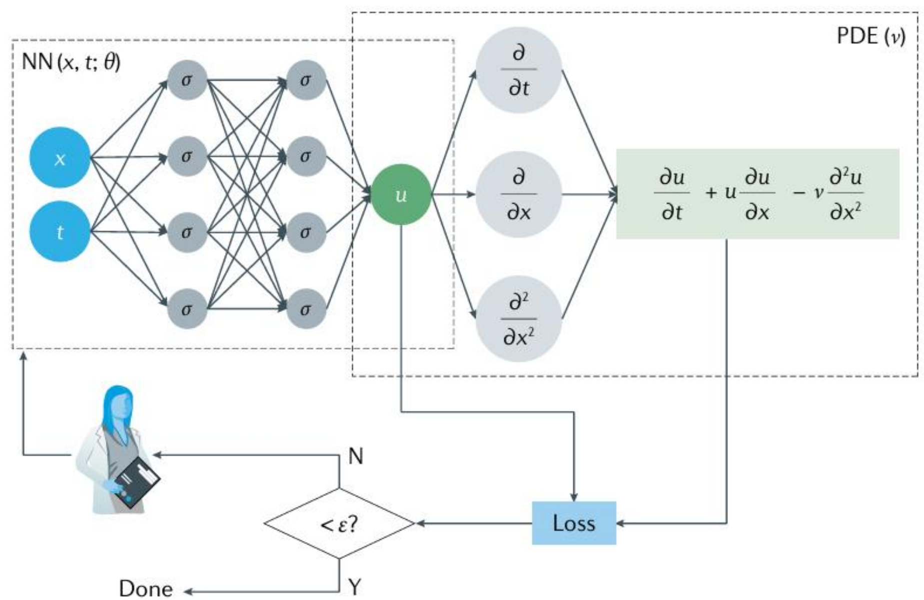

***The Fourth Paradigm, Data-intensive Scientific Discovery***

*Tony Hey, Communications in Computer and Information Science (CCIS), volume 317*

# Motivation

***Physics Informed Machine Learning***,
*George Em Karniadakis, Ioannis G. Kevrekidis, Sifan Wang and Liu Yang*
*Nature Reviews Physics volume 3, pages 422–440 (2021)*



# Application Ⅰ:

## Automatically dertermining the model parameters

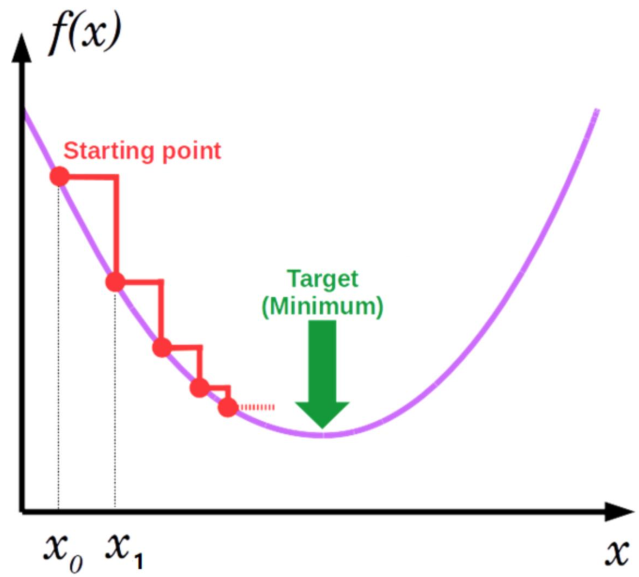
**Loss function:** $$f(x)=\frac{1}{N}\sum(y_{pre}-y_{\exp})^2$$

To minimize *f(x)*, parameters are updated as:

where: $w_{new}=w-\eta\cdot\nabla f(x)$

$\eta$ = learning rate (step size)

$\nabla f(x)$ = gradient at current point



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

***Xun Chen**, Mei Huang, Flavor dependent critical endpoint from holographic QCD through machine learning, JHEP 02 (2025) 123.*

## Einstein-Maxwell-Dilaton model (gravitational model)

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

$f(\phi)$ is the gauge kinetic function coupled with the Maxwell field. (derteming the dependent of chemical potential.)

$V(\phi)$ is the potential of the dilaton field. (Simulating the QCD properties at finite temperature.)

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

$f(\phi)$ and $V(\phi)$ are unknow function, which need to be fixed.

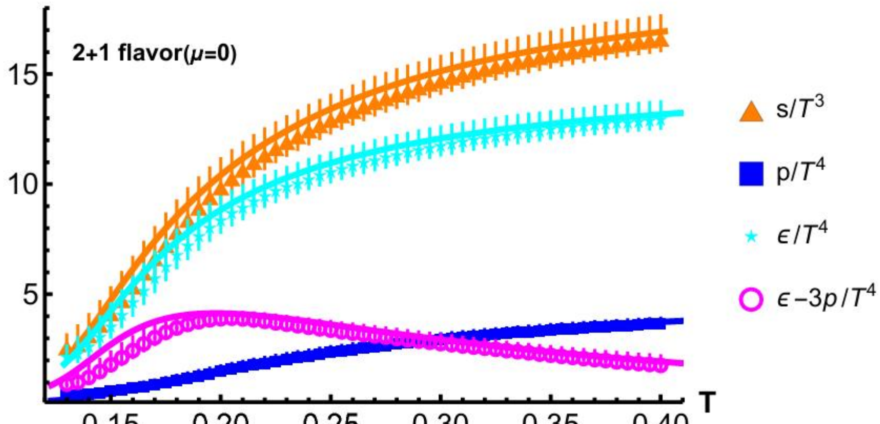
Equally, we assume the form of *A(z)* and *f(z):*

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

with undeterming parameters: *a,b,c,d,k*

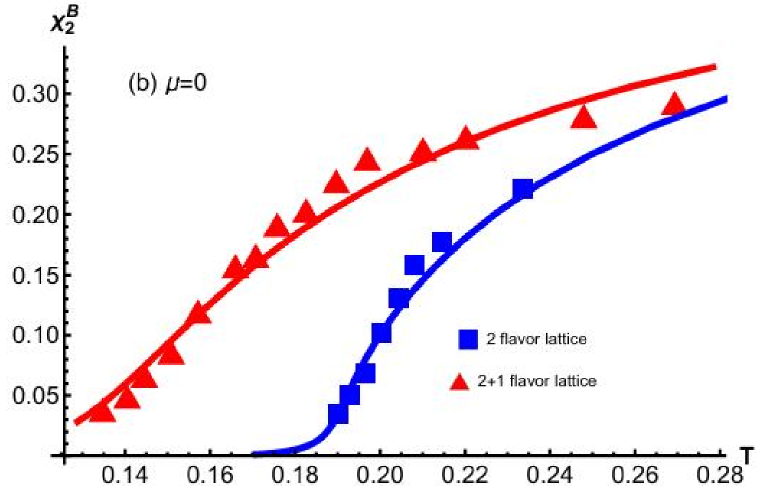
entropy: $s = \frac{e^{3A(z_h)}}{4G_5 z_h^3}.$ Baryon number susceptibility $\chi_2^B = \frac{1}{T^2}\frac{\partial\rho}{\partial\mu}.$

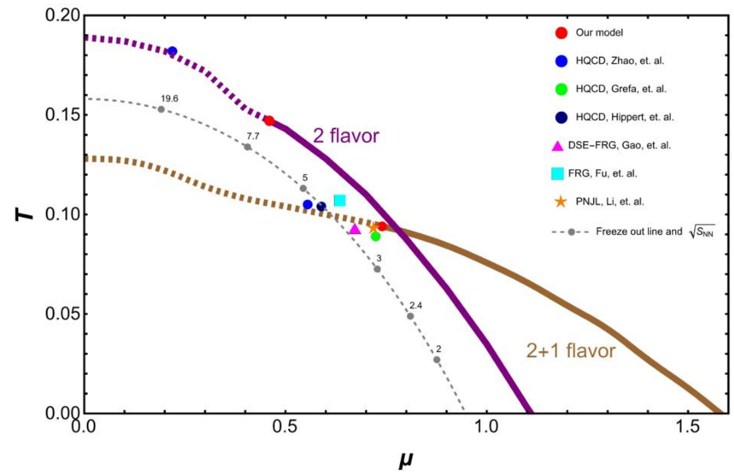
# QCD equation of state from lattice




| | $a$ | $b$ | $c$ | $d$ | $k$ | $G_5$ | $T_c$ |
|---|---|---|---|---|---|---|---|
| $N_f=0$ | 0 | 0.072 | 0 | -0.584 | 0 | 1.326 | 0.265 |
| $N_f=2$ | 0.067 | 0.023 | -0.377 | -0.382 | 0 | 0.885 | 0.189 |
| $N_f=2+1$ | 0.204 | 0.013 | -0.264 | -0.173 | -0.824 | 0.400 | 0.128 |

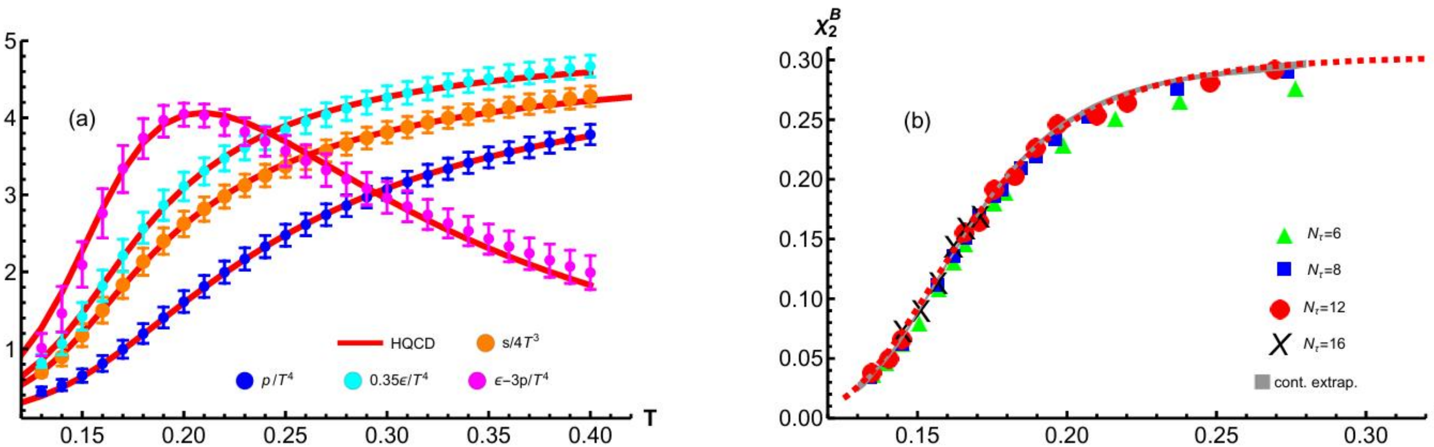
# Baryon number susceptibility

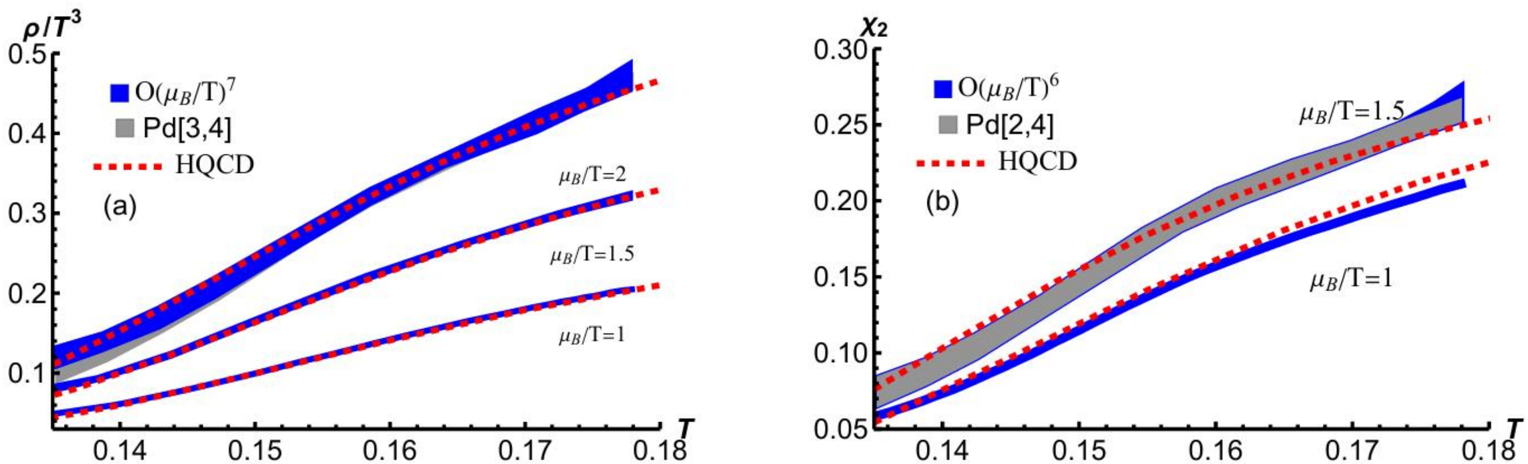


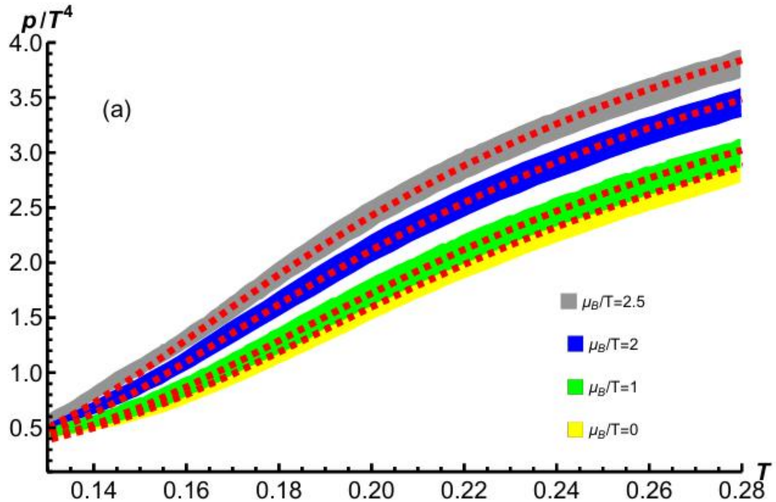



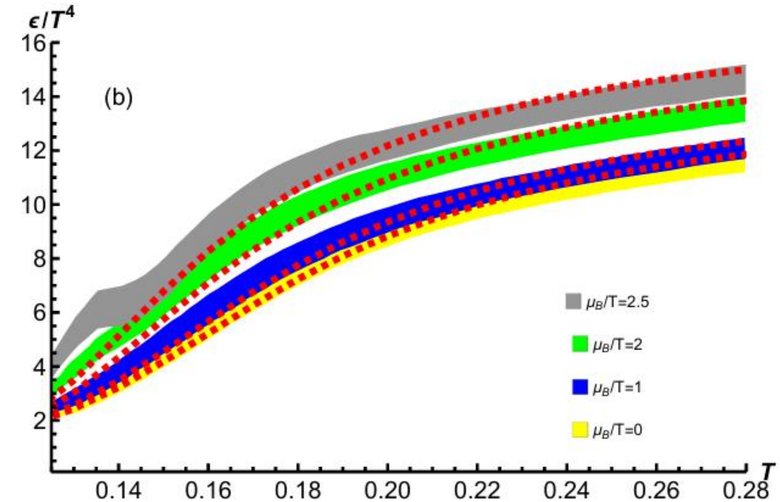
***Data-Driven Refinement of an Analytical Holographic Model for the QCD Phase Transition (In preparation)***

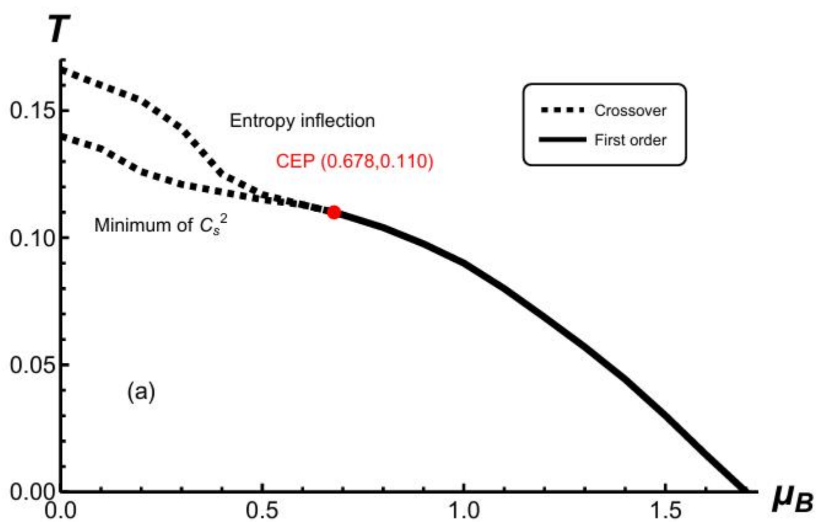
***Xun Chen**, Floriana Giannuzzi, Stefano Nicotri*

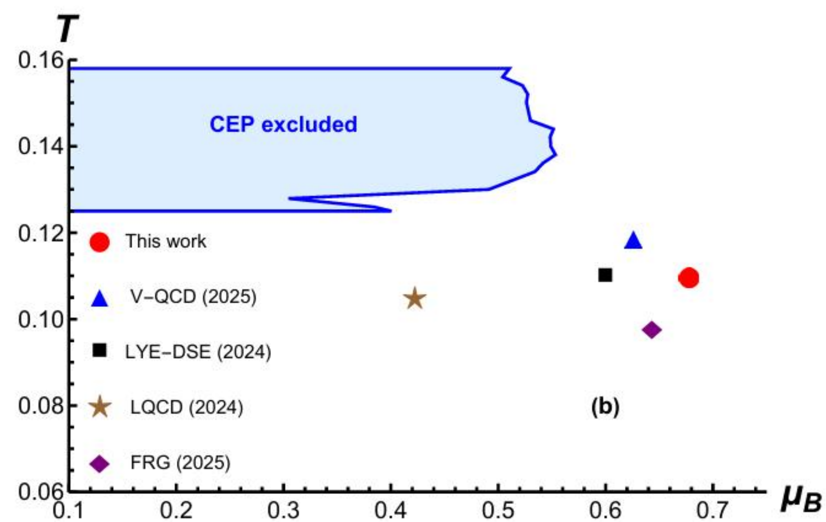



p/T^4
(a)
μB/T=2.5
μB/T=2
μB/T=1
μB/T=0
T


ϵ/T^4
(b)
μB/T=2.5
μB/T=2
μB/T=1
μB/T=0
T


T
Entropy inflection
CEP (0.678,0.110)
Minimum of Cs^2
Crossover
First order
(a)
μB


T
CEP excluded
This work
V−QCD (2025)
LYE−DSE (2024)
LQCD (2024)
FRG (2025)
(b)
μB

# Application II:

## Including the error bar in the model

***Bayesian Inference of the Critical Endpoint in 2+1-Flavor System from Holographic QCD****,*

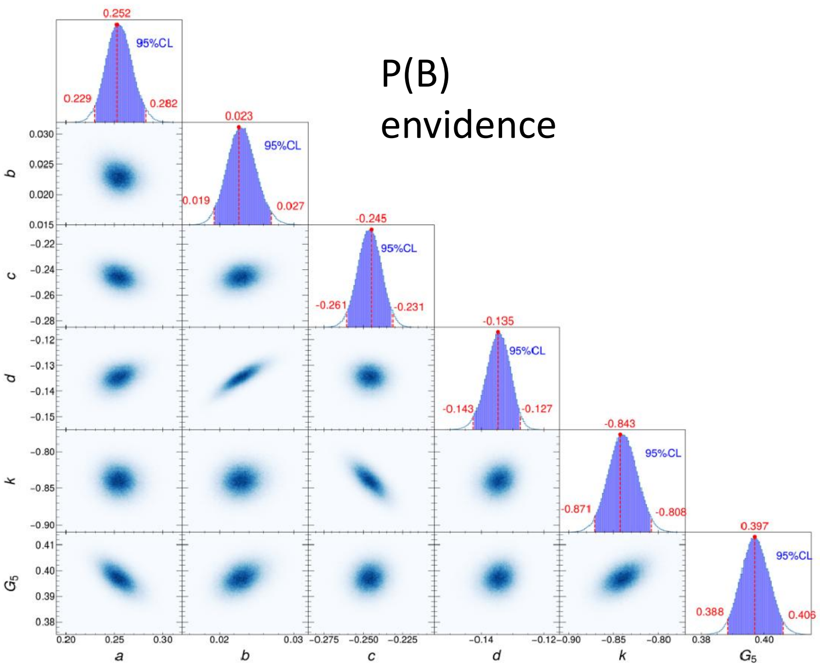
*Phys.Rev.D 112 (2025) 2, 026019*

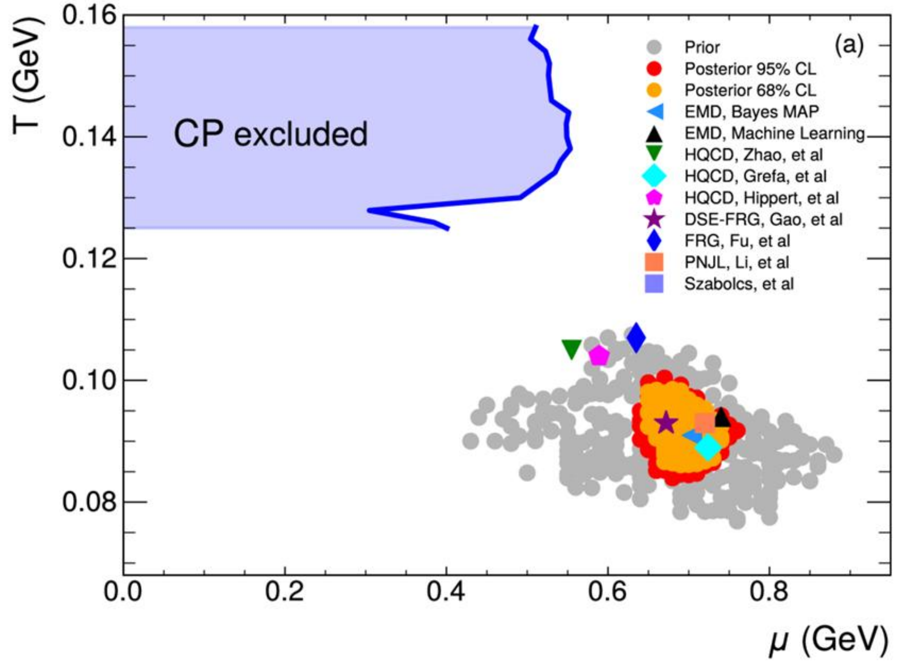
*Liqiang Zhu,* ***Xun Chen****, Kai Zhou, Hanzhong Zhang, Mei Huang,*

$$P(A|B) = \frac{P(B|A)\cdot P(A)}{P(B)}$$

*P(A) prior, P(B|A) likelihood , P(A|B) posterior*

P(B)
envidence

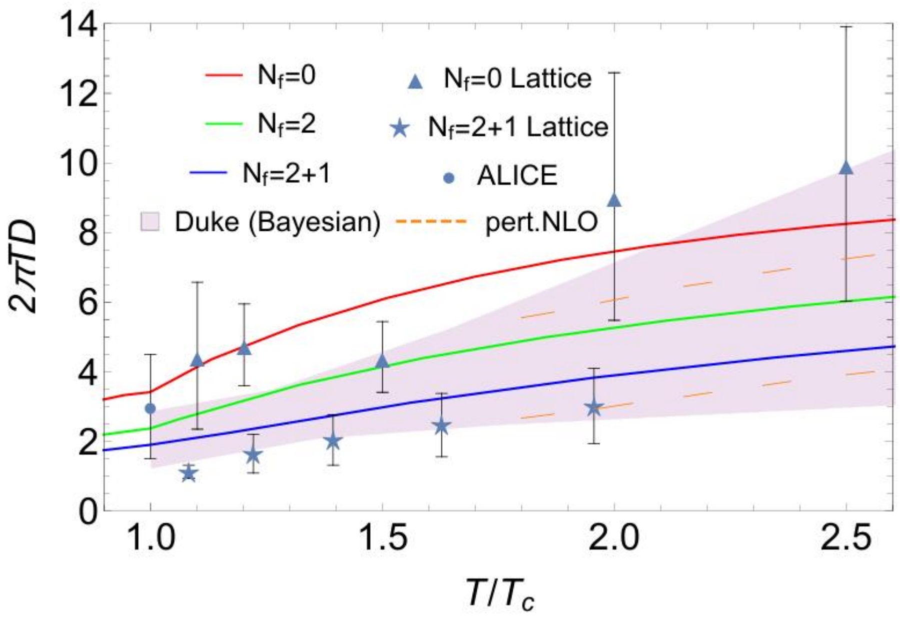


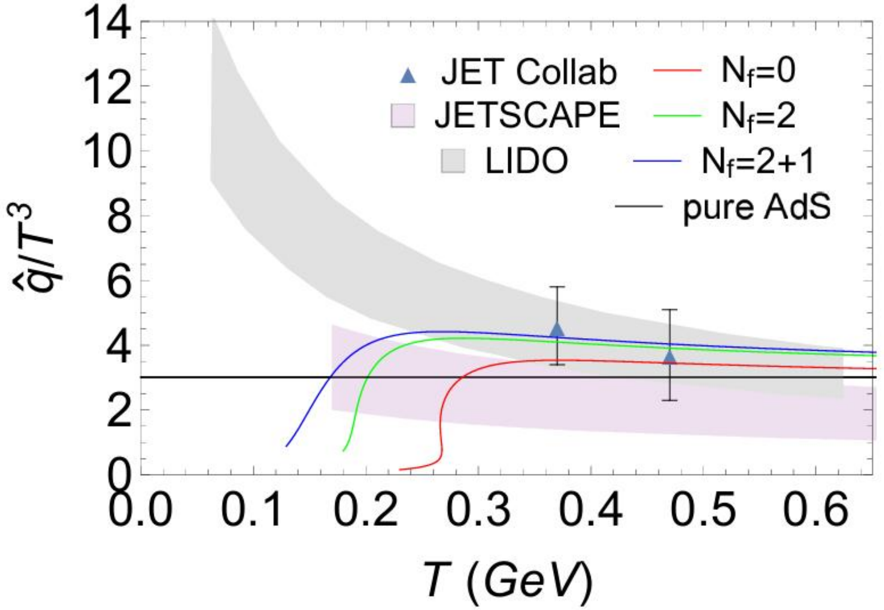



***Exploring transport properties of quark-gluon plasma in flavor-dependent systems with a holographic model***

*Phys.Rev.D 111 (2025) 8, 086033*

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



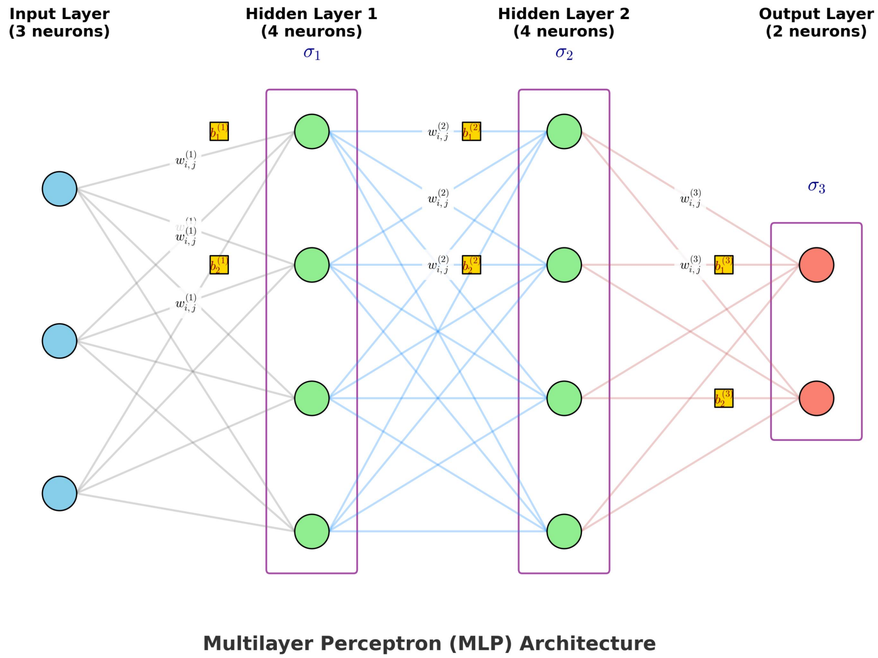



# Universal Approximation Theorem

$$f(x) = \sum_{i=1}^{N} \alpha_i \, \sigma(w_i x + b_i).$$

σ : activation function
w : weight
b : bias

When *N* is sufficiently large, *f(x)* can approximate any function arbitrarily closely.




***Data-Driven Einstein-Dilaton Model for Pure Yang-Mills Thermodynamics and Glueball Spectrum***

*Arxiv: 2507.06729*

***Xun Chen***, *Yidian Chen, Kai Zhou*

$$A(z) = d * \ln(az^2 + 1) + d * \ln(bz^4 + 1),$$

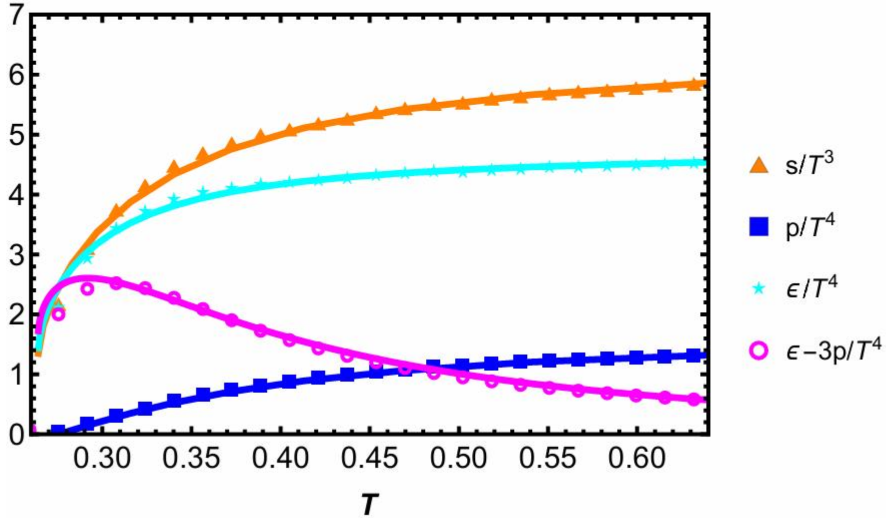
*A(z)* → Nueral network

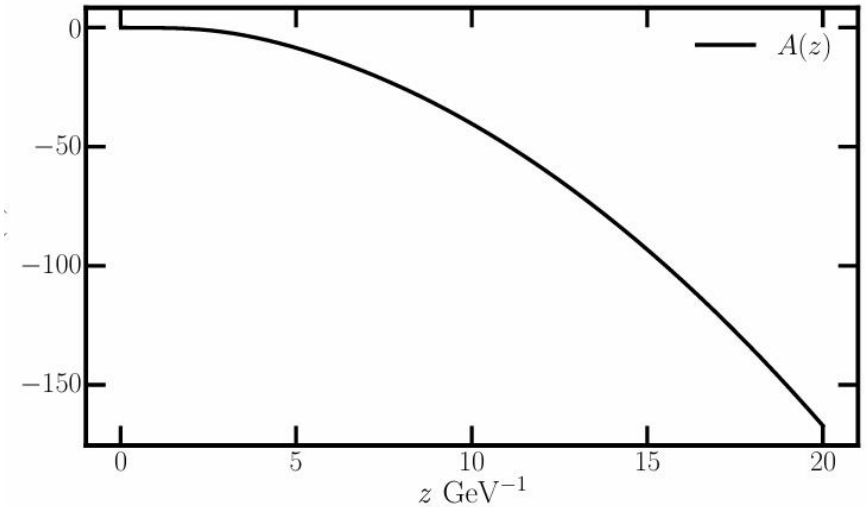
$$S_\psi = \int \mathrm{d}^5 x \sqrt{g_s}\, e^{-\Phi} \left[ \frac{1}{2} \partial_M \psi \partial^M \psi + \frac{1}{2} M_5^2 \psi^2 \right]$$

$$-\widetilde{\psi}_n'' + V_g(z) \widetilde{\psi}_n = m_n^2 \widetilde{\psi}_n,$$

*m_0* = 1.475GeV (groundstate) and
*m_1* = 2.775GeV (first excitedstate) from lattice QCD

Inverse problem




| State | Lat1 | Lat2 | Lat3 | Our model |
|---|---|---|---|---|
| $0^{++}$ | 1475(30)(65) | 1653(26) | 1730(50)(80) | 1791 |
| $0^{++*}$ | 2755(70)(120) | 2842(40) | 2670(180)(130) | 2751 |
| $0^{++**}$ | 3370(100)(150) | – | – | 3500 |
| $0^{++***}$ | 3990(210)(180) | – | – | 4122 |

# Application III: Can we get the analytical function from data with neural network?

*Multi-Layer Perceptrons (MLP) and Kolmogorov-Arnold Network (KAN)*

*Ziming Liu, et al, arXiv: 2404.19756*

Black box

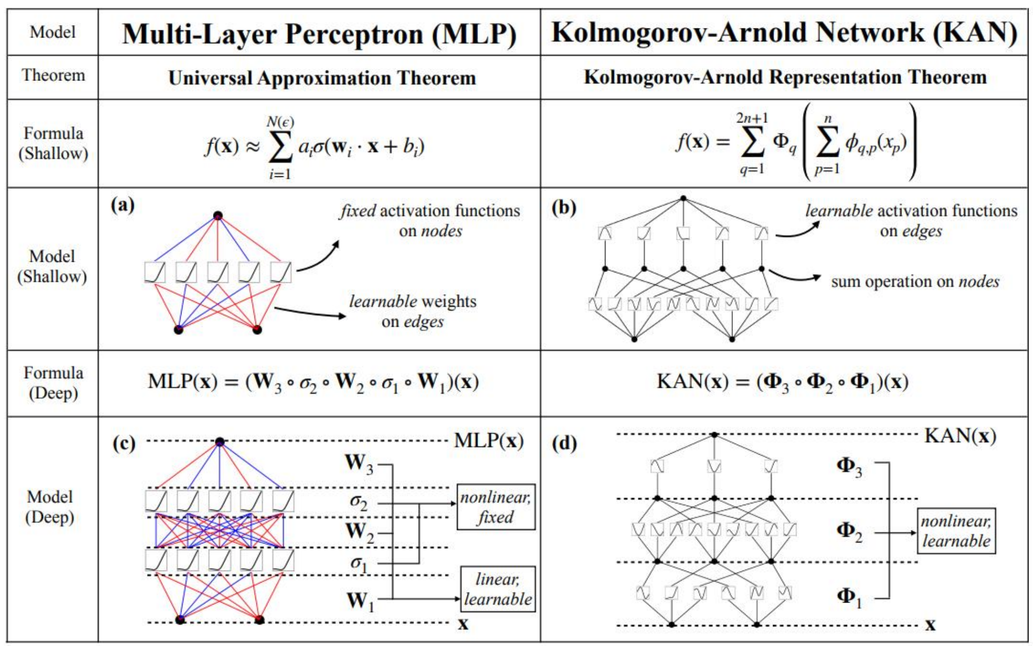



Figure 0.1: Multi-Layer Perceptrons (MLPs) vs. Kolmogorov-Arnold Networks (KANs)

Intrinsic Interpretability

# *Neural network modeling of heavy-quark potential from holography*

*Eur.Phys.J.C 85 (2025) 6, 637*

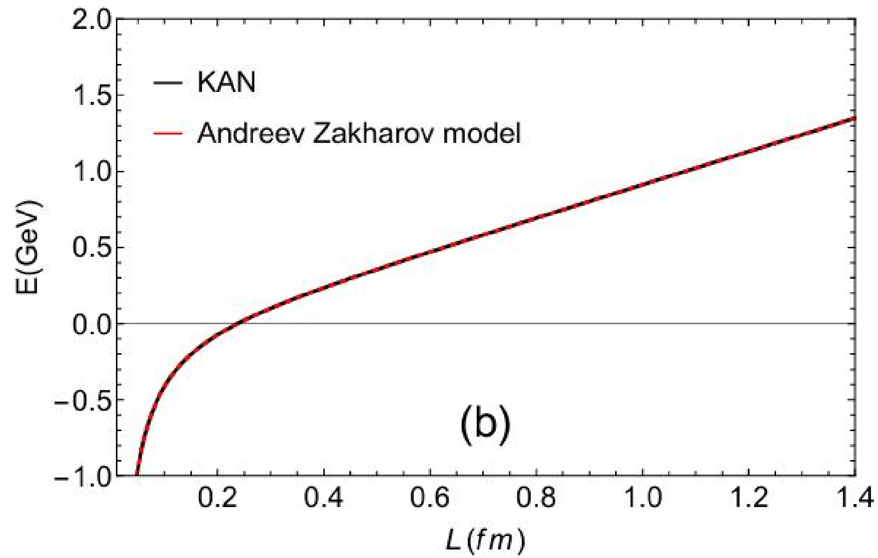
*Ou-Yang Luo, **Xun Chen**, Fu-Peng Li, Xiao-Hua Li, and Kai Zhou*

*Oleg Andreev, Valentin I. Zakharov, On Heavy-Quark Free Energies, Entropies, Polyakov Loop, and AdS/QCD, JHEP 04 (2007) 100*

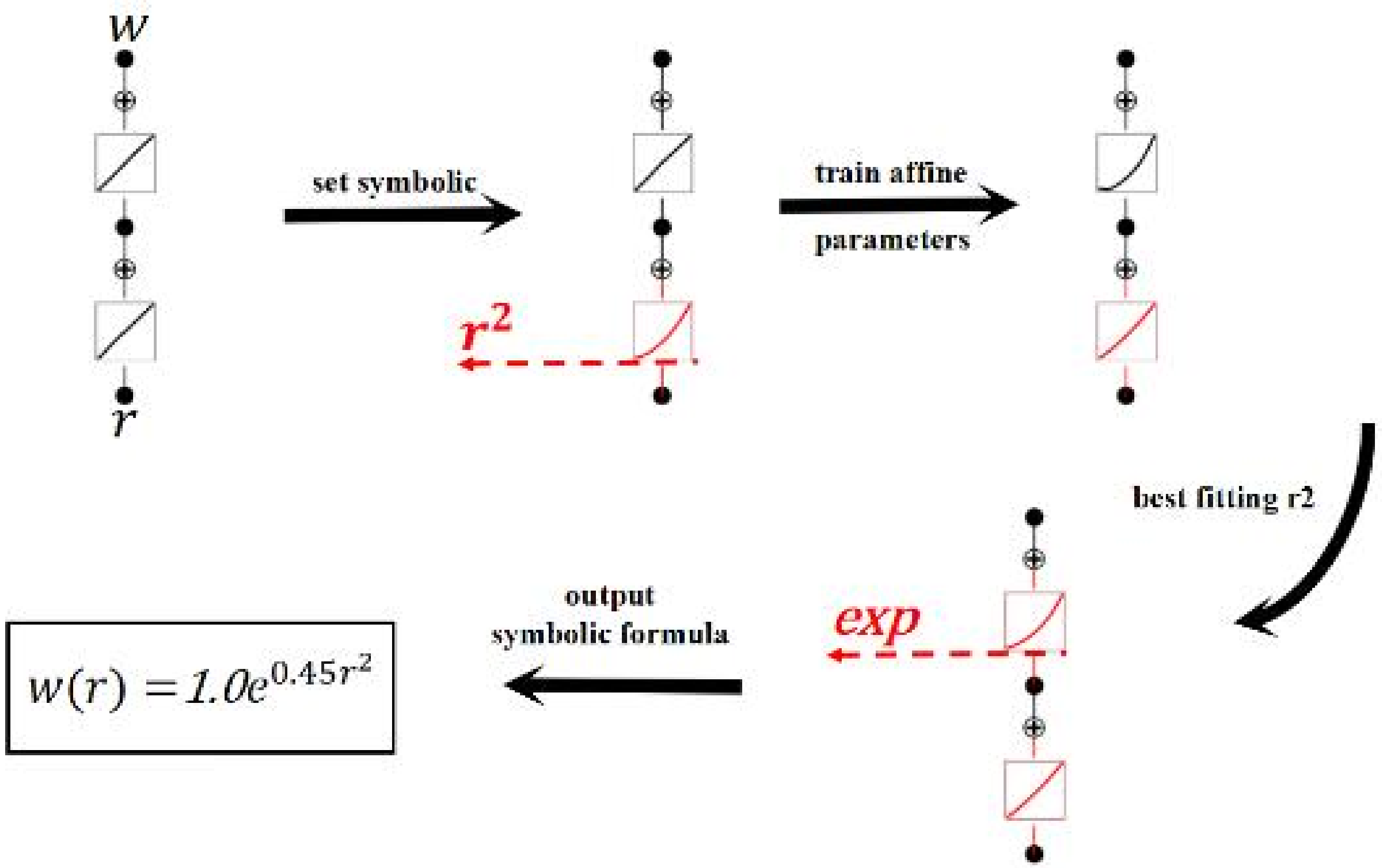
Deformed AdS-RN black hole

$$ds^2 = w(r)\frac{1}{r^2}\left[f(r)dt^2 + d\vec{x}^2 + f^{-1}(r)dr^2\right],$$
$$f(r) = 1 - \left(\frac{1}{r_h^4} + q^2 r_h^2\right) r^4 + q^2 r^6.$$

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



# Reproduce the Andreev-Zakharov model



# Summary

- Help us quickly determine the parameters of the model.

- Use neural networks to inversely obtain the numerical solutions of the model.

- By using KAN, we can further derive the analytical solution of the model.

With the help of machine learning, we aim to change the holographic model from qualitative study to precisely quantitative study.

# Advertisement

## 第四届全国核物理及核数据中的机器学习应用研讨会

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# Acknowledgement

**Thank you for your listening**

**Thanks to the organizers.**

Fundings：