KEK-PH, 18 Feb 2025

Recent Results in MLPhys.

Koji Hashimoto (Kyoto U)

"Machine-learning emergent spacetime from linear response in future tabletop quantum gravity experiments" 2411.16052
w/ K.Matsuo, M. Murata, G.Ogiwara (Saitama Tech), D.Takeda (Kyoto)
"Spacetime-emergent ring toward tabletop quantum gravity experiments" 2211.13863
w/ D.Takeda, K.Tanaka, S.Yonezawa (Kyoto)
"Deriving dilaton potential in improved holographic QCD from chiral condensate" 2209.04638
"Deriving dilaton potential in improved holographic QCD from meson spectrum" 2108.08091
w/ K.Ohashi (Keio), T.Sumimoto (Osaka u)
"Neural ODE and Holographic QCD" 2006.00712
w/ H.Y.Hu, Y.Z.You (UCSD)
"Deep Learning and AdS/QCD" 2005.02636
w/ T. Akutagawa, T. Sumimoto (Osaka u)
"Deep Boltzmann Machine and AdS/CFT" 1903.04951
"Deep Learning and Holographic QCD" 1809.10536
w/ S. Sugishita (Kentucky), A. Tanaka, A. Tomiya (RIKEN)
"Deep Learning and AdS/CFT" 1802.08313
w/ S. Sugishita (Kentucky), A. Tanaka, A. Tomiya (RIKEN)

MLPhYs

Foundation of "Machine Learning Physics"

Resolution of fundamental problems in physics via unification of theoretical methods of Machine learning and Physics

Physics

The most precise testing ground in natural science
Multi-hierarchical problems and collaborative mathematics

Machine Learning

Explosive field of computational science
Social and technological innovation

Machine Learning Physics

Discovering new laws, pioneering new materials

Solving fundamental problems in physics by integrating theoretical methods in machine learning and in physics

MLPhys in 2024.

AI Phys

AI comp. phys. : Spin MC by transformer

AI particle phys. : Jet recogn. by transformer

AI cond-mat phys. : Wave fn. of superconductors

AI molc. dyn. : Siml. of quasicrystals

Phys AI

Stat-mech AI： Wetting transition in deep NN

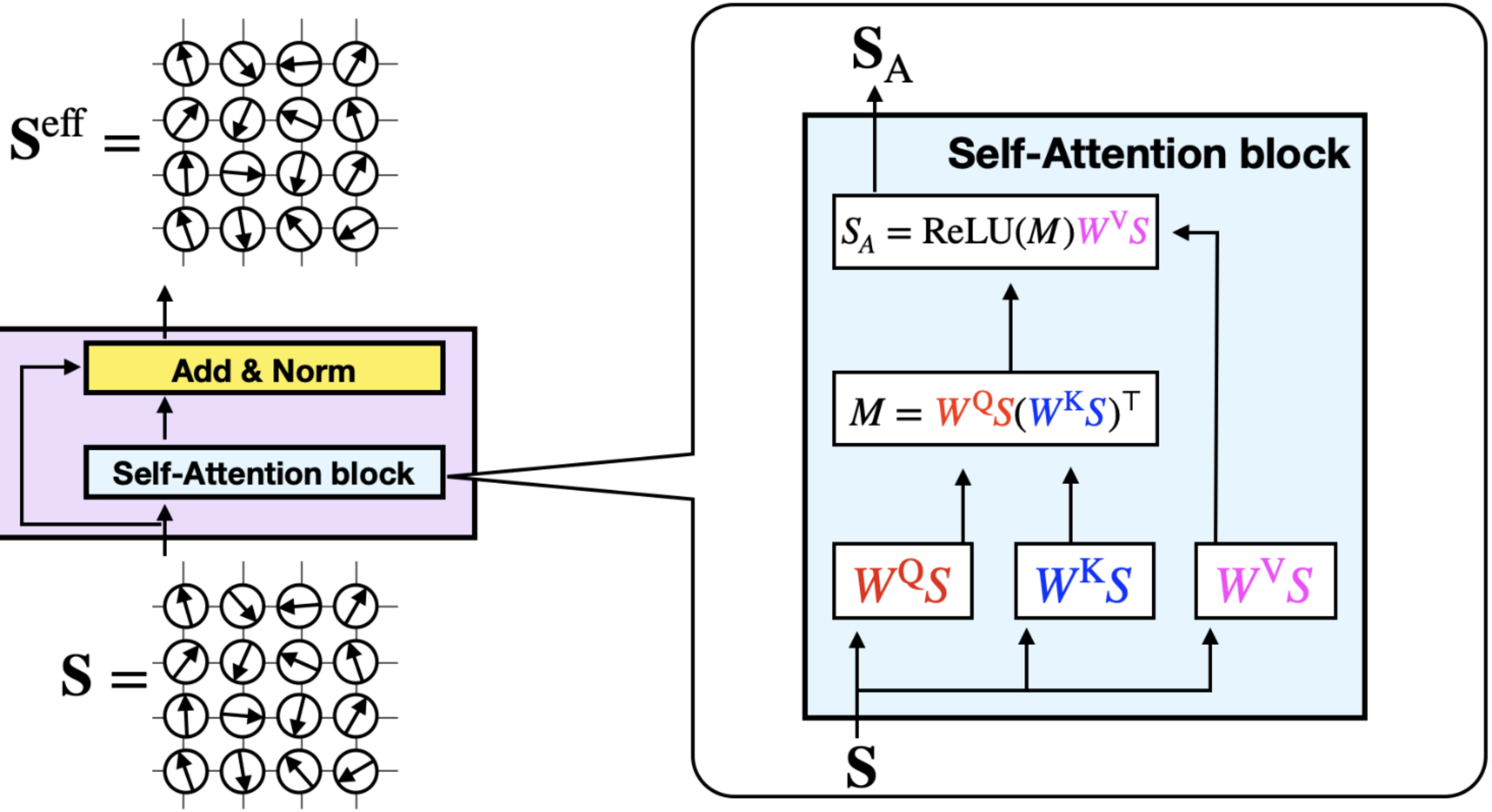
Path-integral AI： Difusion models via QM

Gravity AI： Symmetry in neurons

AI comp. phys. : Spin MC by transformer

[Tomiya Nagai *PoS* LATTICE2023 (2024) 001]

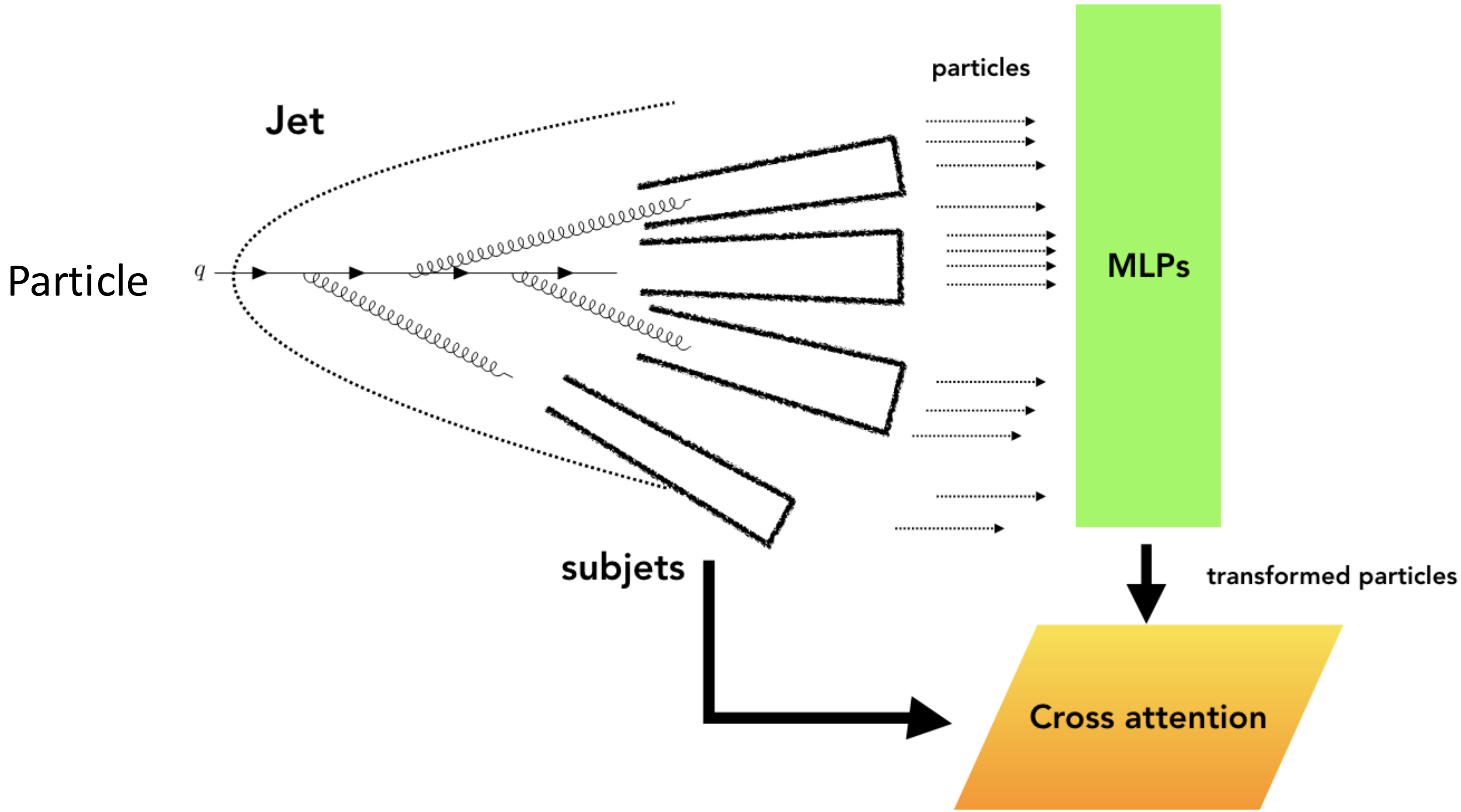
Attention mechanism describes nonlocality



AI particle phys. : Jet recogn. by transformer

[Hammad, Nojiri, JHEP 06(2024)176, JHEP 03 (2024) 114]

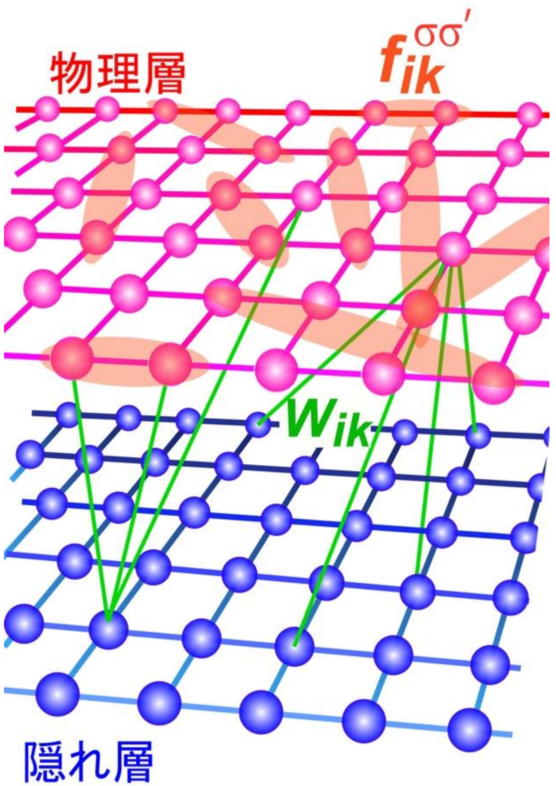
Cross-attention learns
Physical energy scales

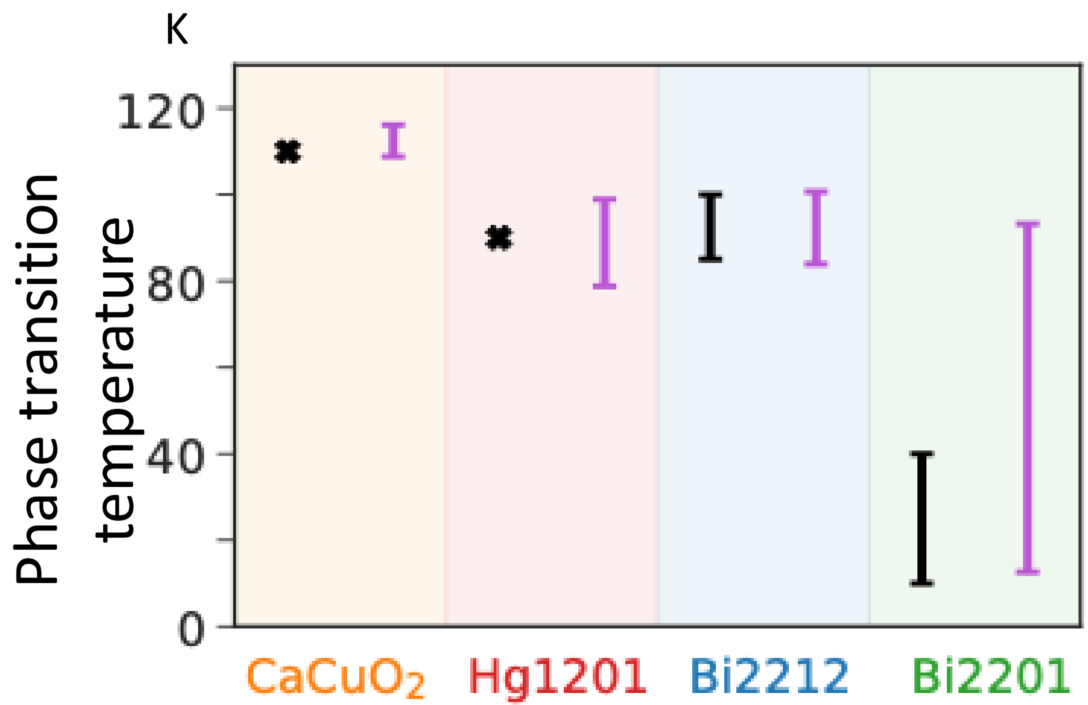


AI cond-mat phys. : Wave fn. of superconductors

Quantum many-body wave functions by Boltzmann machine

[Schmid Morée Kaneko Yamaji Imada, Phys. Rev. X 13, 041036 (2023)]





Exp. vs. AI

AI molc. dyn. : Siml. of quasicrystals

[Nagai et al., Phys.Rev. Lett. 102, 041124 (2024)]

Higher-dim. structure
learned by Machine

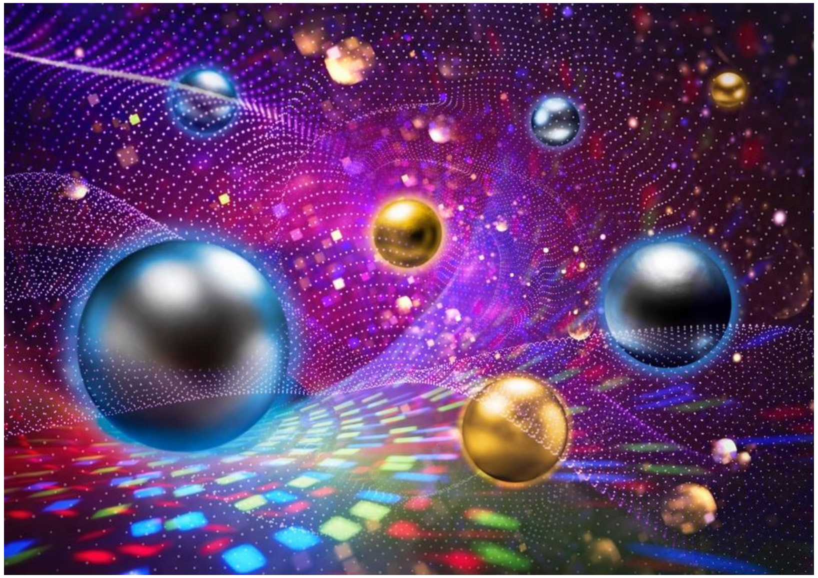
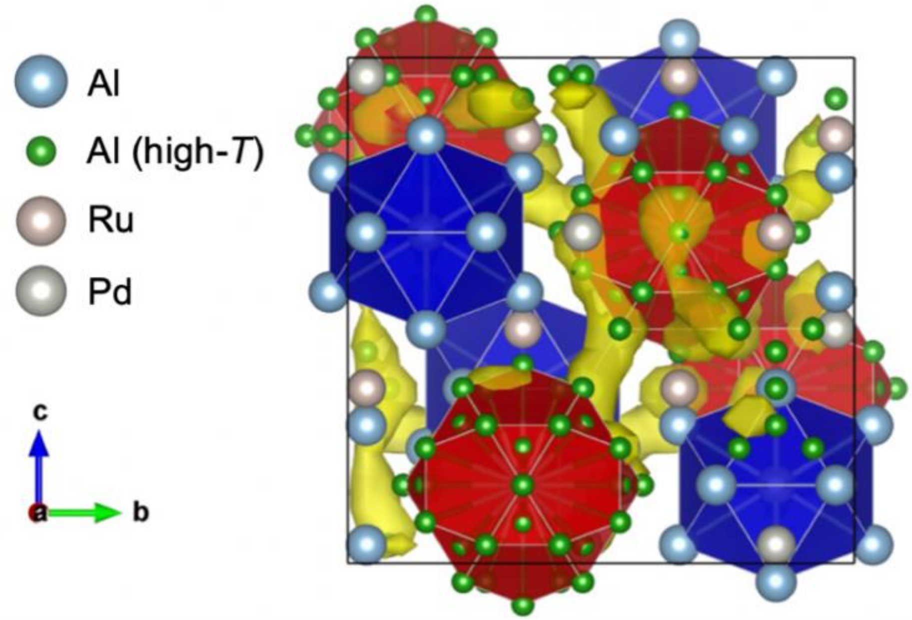


Image of higher-dimensional atoms affecting the 3-dim. world
Credit: UTokyo ITC/Shinichiro Kinoshita

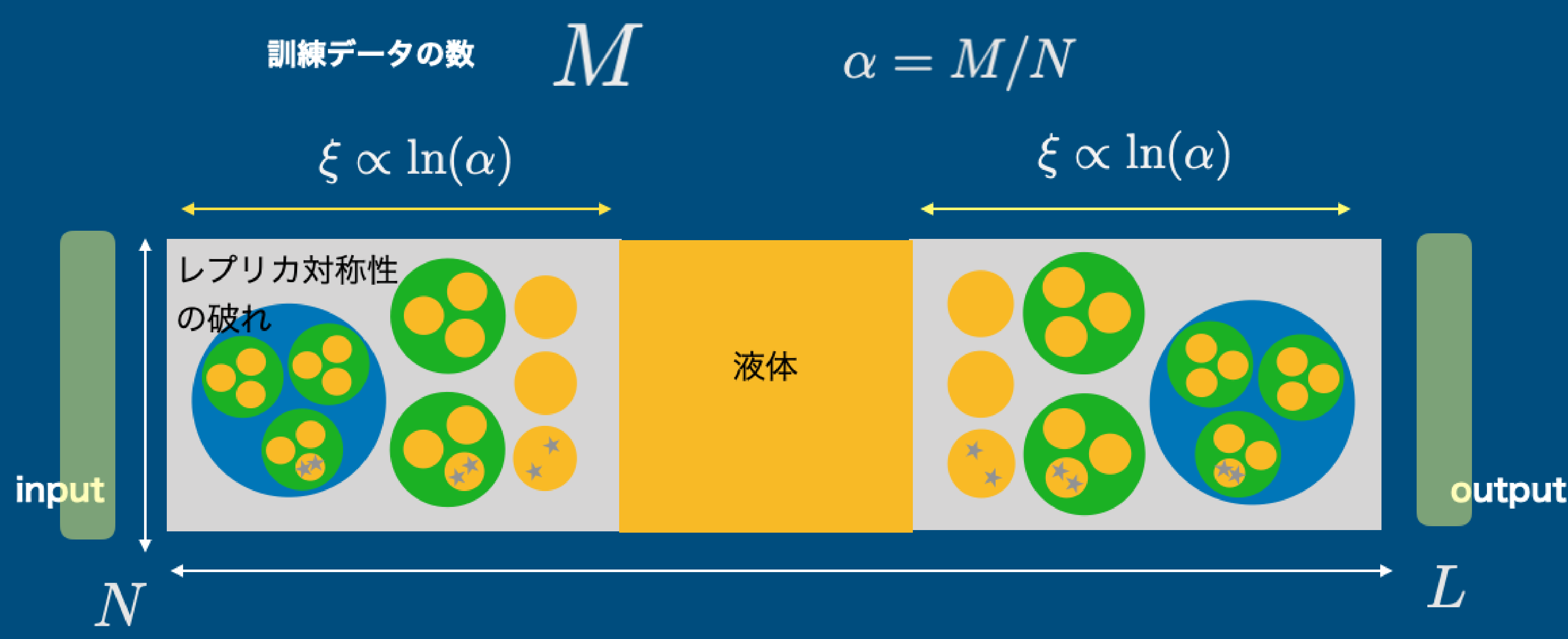


Alminium atoms floating through high-dim. paths

Stat-mech AI：Wetting transition in deep NN

Inside deep NN is liuquid

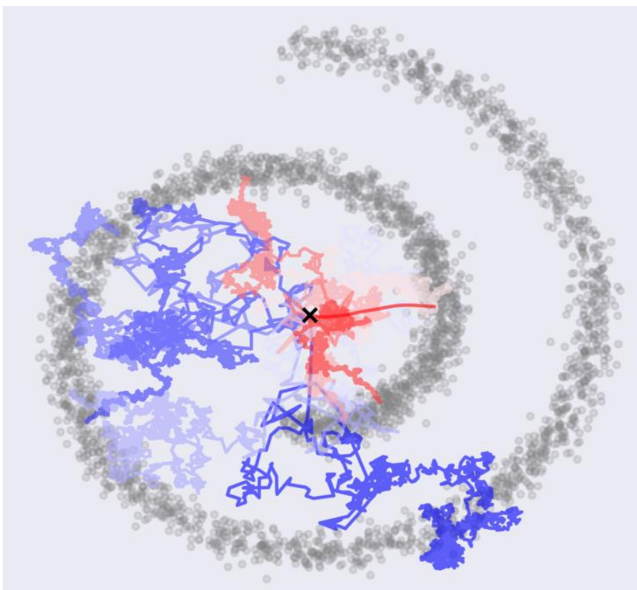
[Yoshino, Phys. Rev. Research, 5, 033068 (2023), SciPostPhys. Core 2, 005 (2020).]

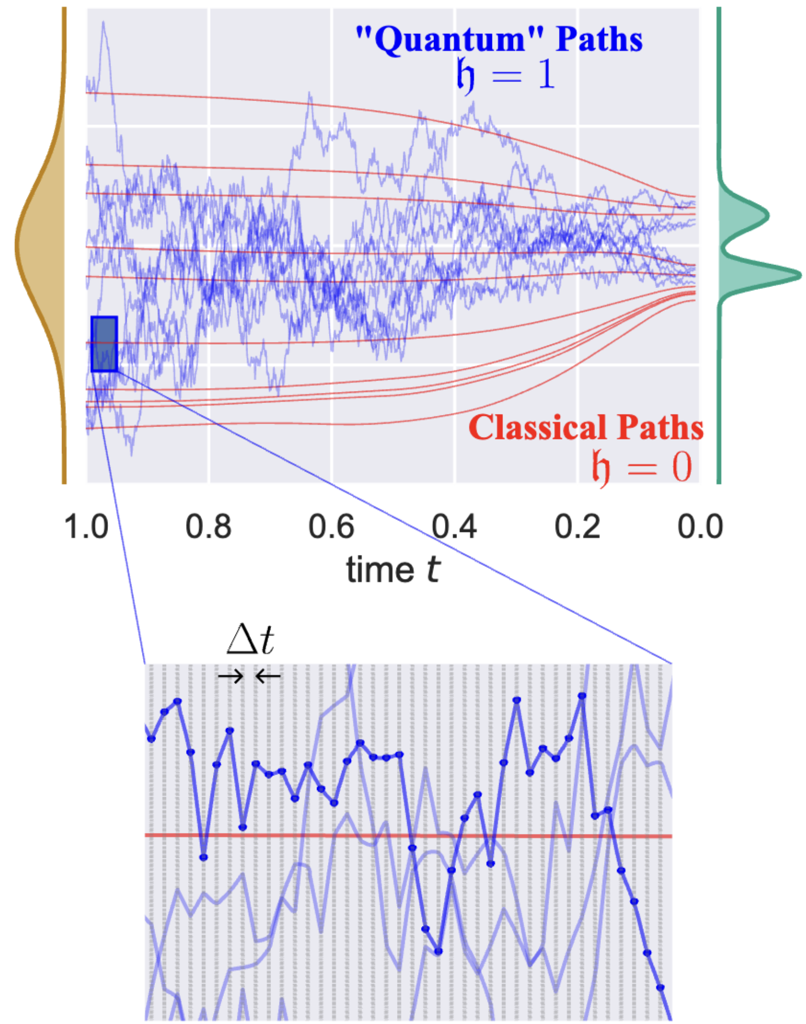


Path-integral AI：Difusion models via QM

[Hirono Tanaka Fukushima ICML 2024, arXiv:2403.11262]

Diffusion model for generative AI is rewritten by path-integral

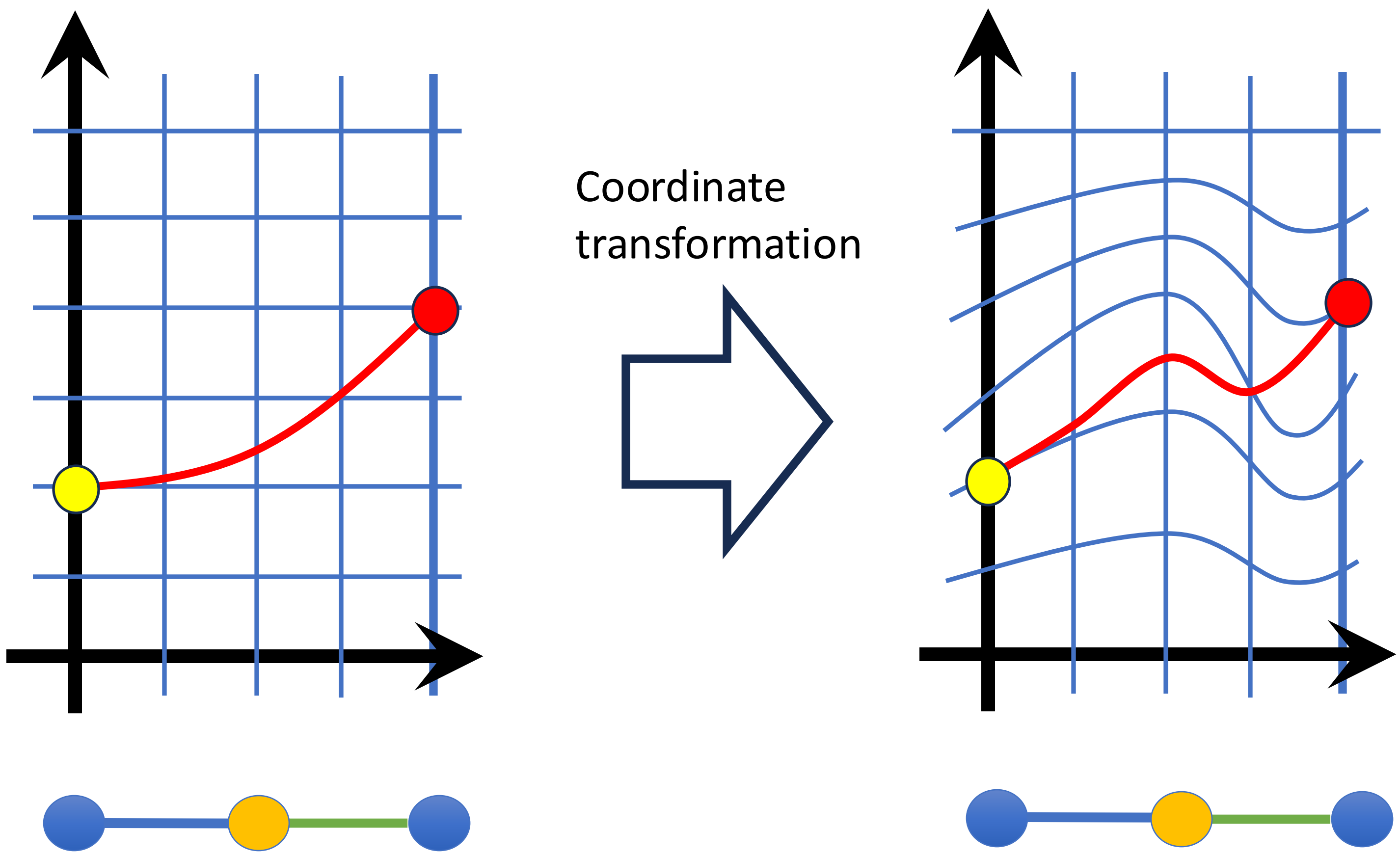




Gravity AI：Symmetry in neurons

[Hashimoto, Hirono, Sannai, Mach. Learn.: Sci. Technol. 5 025079 (2024)]

Gravitational symmetry
in transformers and neural ODEs

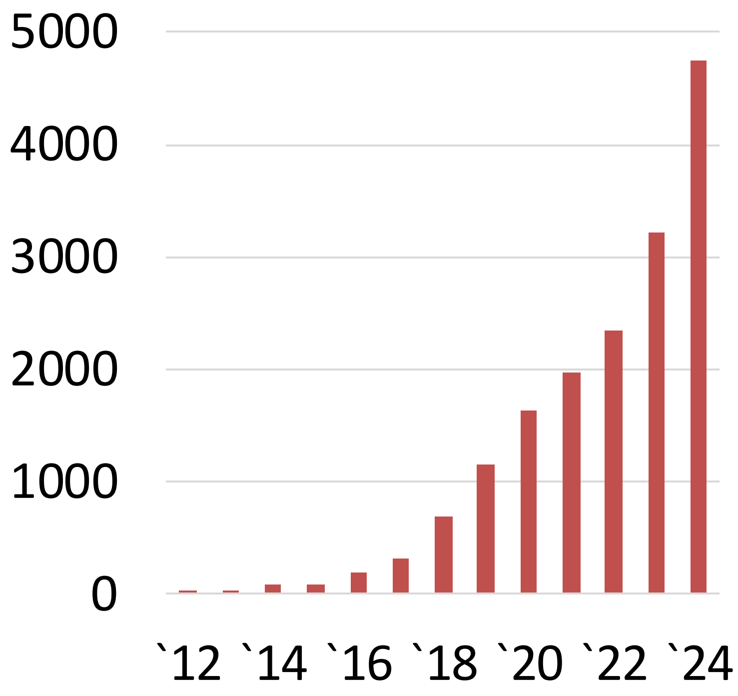


Expanding research field in the world

arXiv papers of MLPhys

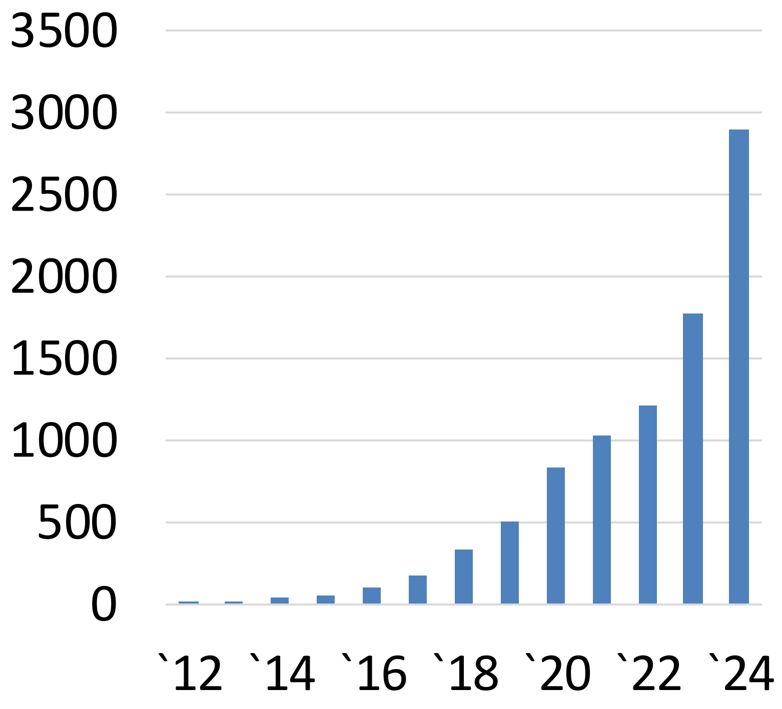
Phys category

(abstract includes “machine (deep) learning”)



CS category

(abstract includes “physics” and “learning”)



AdS/CFT by ML

1. Why and how? 6 pages

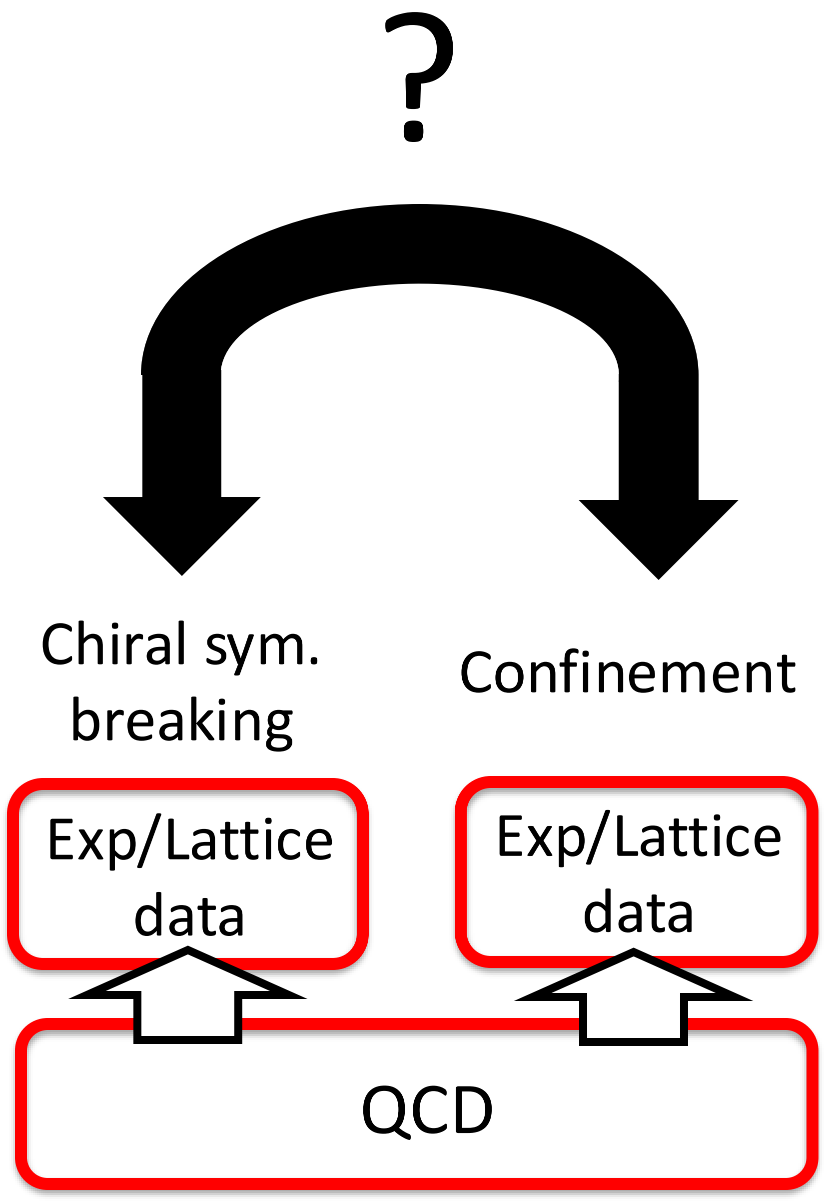
   1809.10536, 1903.04951

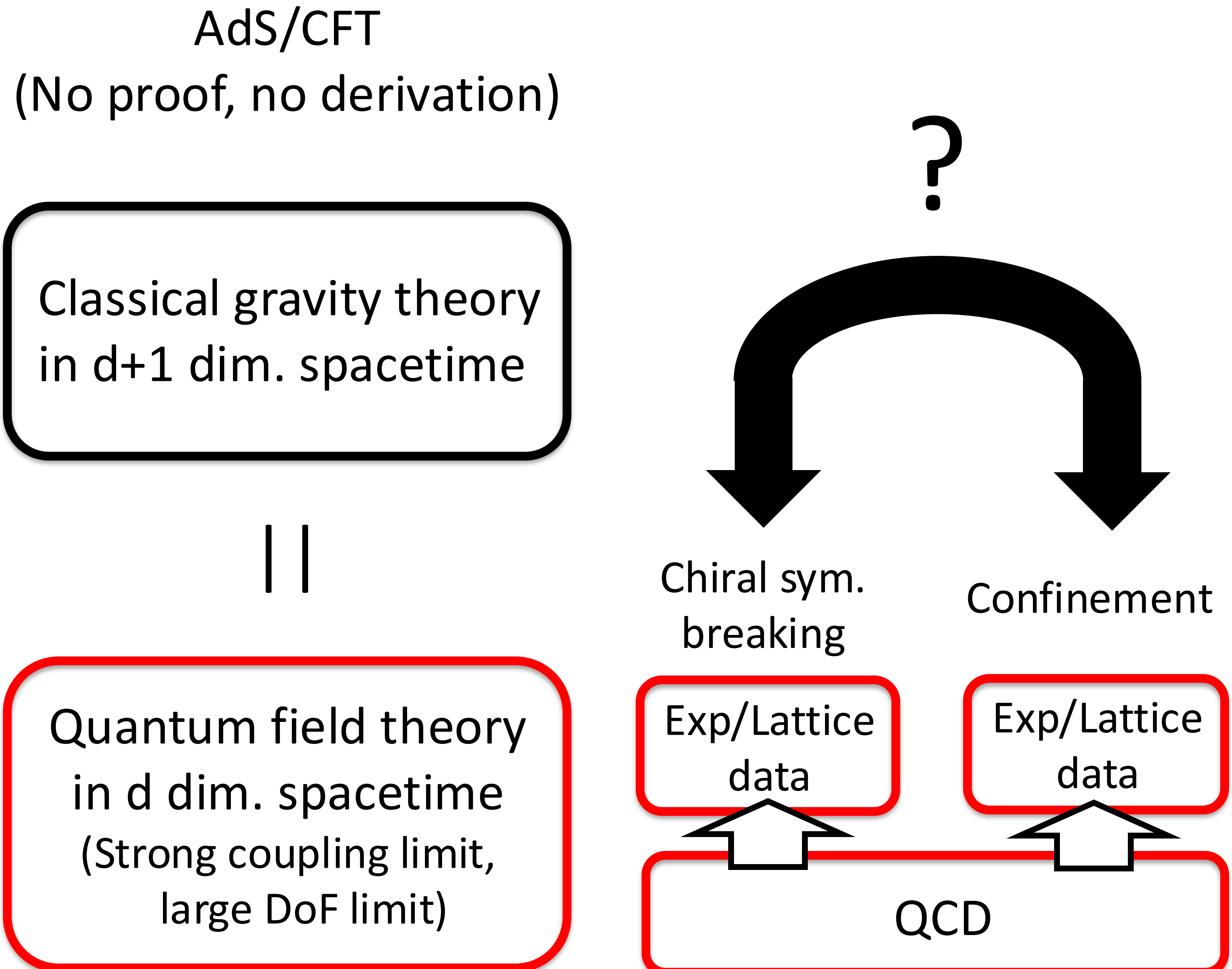
2. Space emergent from data 4 pages

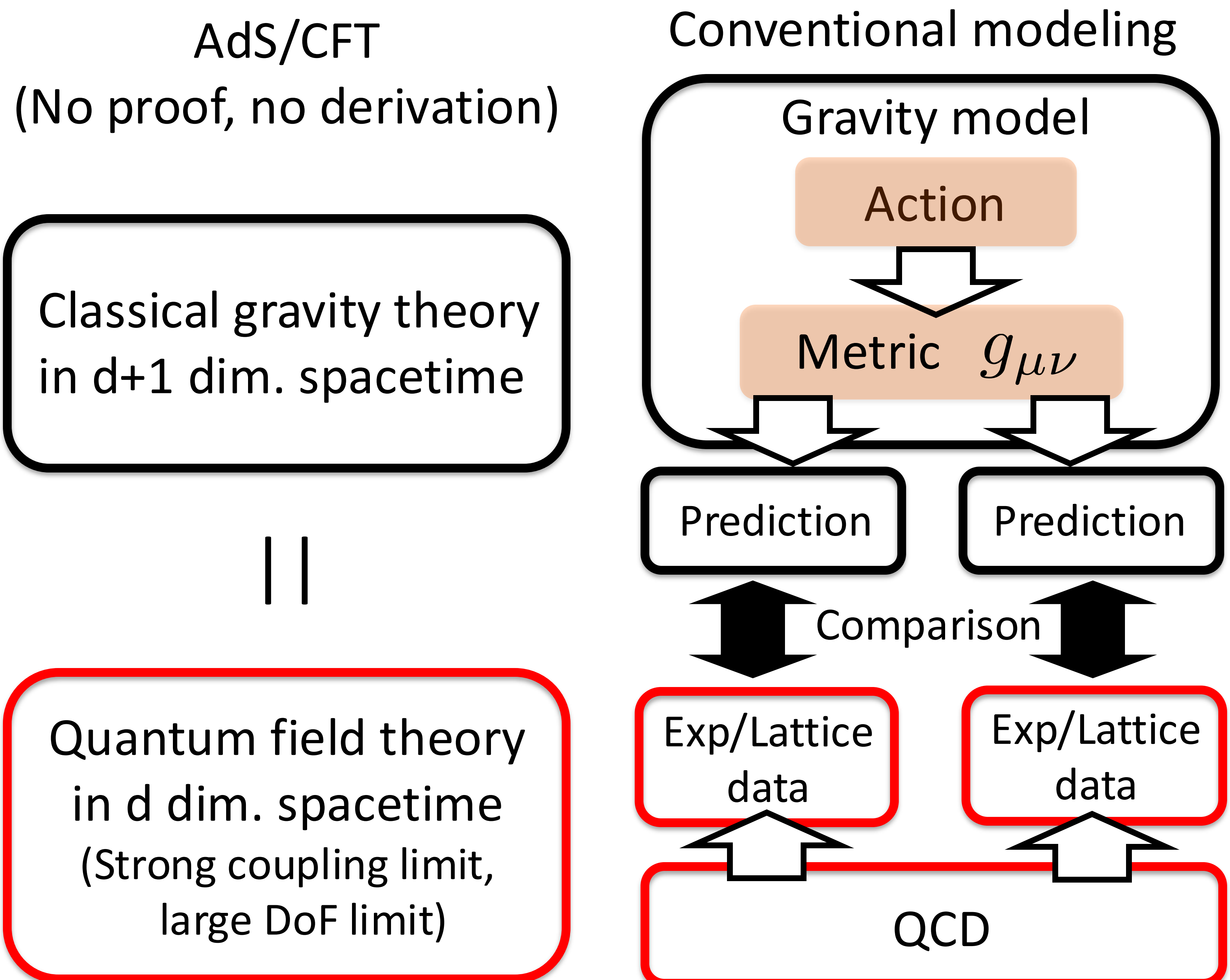
   2005.02636 (1802.08313, 1809.10536, 2006.00712, 2411.16052)

3. Prediction by learned gravity 5 pages

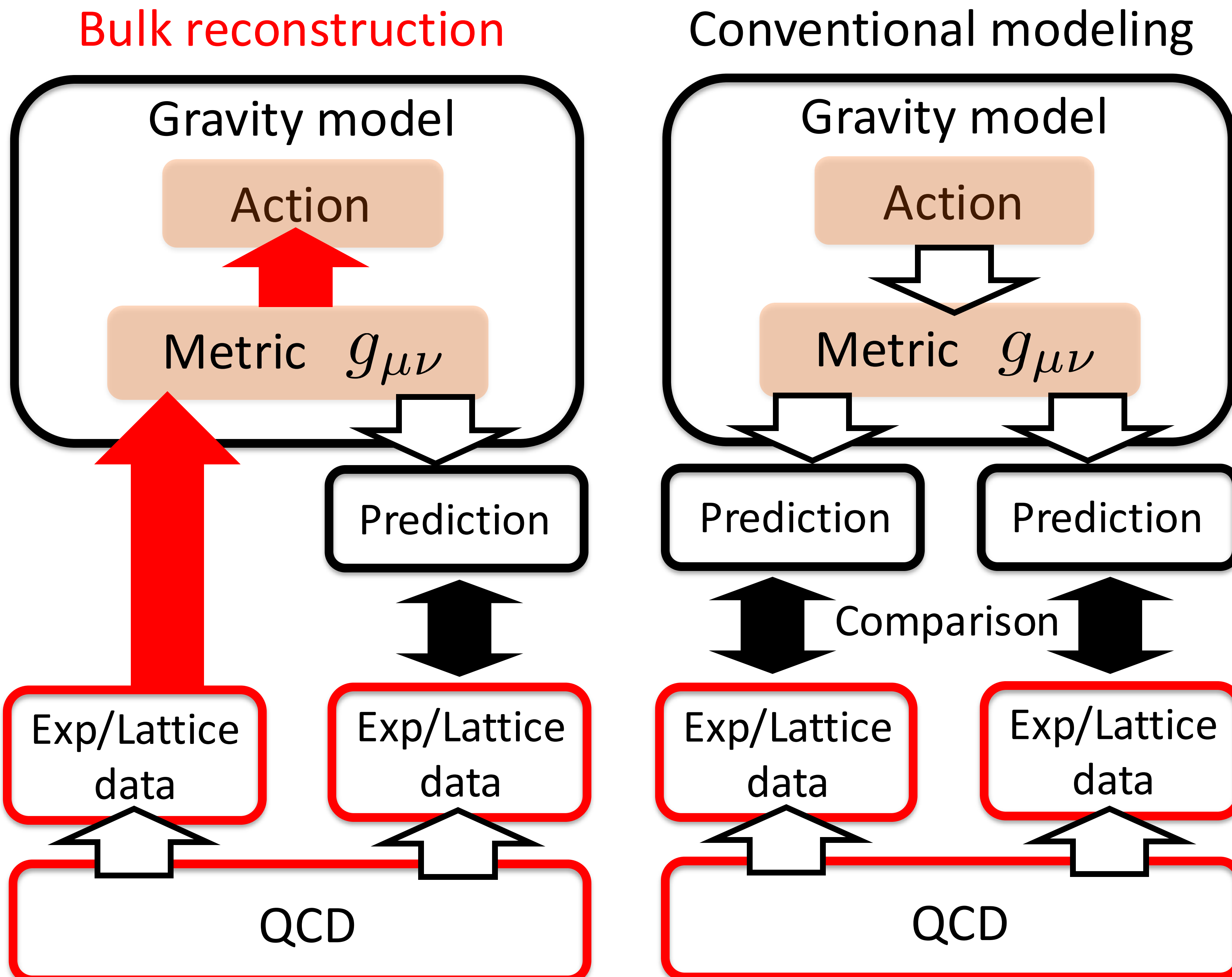
   2108.08091, 2209.04638


?
Chiral sym.
breaking
Confinement
Exp/Lattice
data
Exp/Lattice
data
QCD


AdS/CFT
(No proof, no derivation)
Classical gravity theory
in d+1 dim. spacetime
||
Quantum field theory
in d dim. spacetime
(Strong coupling limit,
large DoF limit)
?
Chiral sym.
breaking
Confinement
Exp/Lattice
data
Exp/Lattice
data
QCD



AdS/CFT
(No proof, no derivation)
Classical gravity theory in d+1 dim. spacetime
||
Quantum field theory in d dim. spacetime
(Strong coupling limit, large DoF limit)
Conventional modeling
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Prediction
Comparison
Exp/Lattice data
Exp/Lattice data
QCD


Bulk reconstruction
Conventional modeling
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Exp/Lattice data
QCD
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Prediction
Comparison
Exp/Lattice data
Exp/Lattice data
QCD

Comparison of solvers

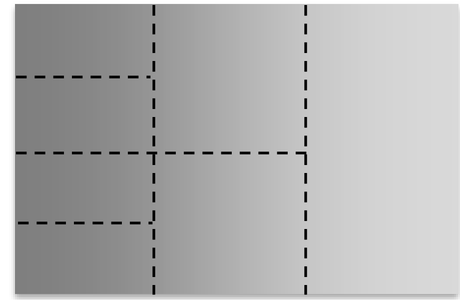
Reconstruction method	No gravity action	Lattice input	Exp. input
Holographic renormalization [deHaro Solodukhin Skenderis 00]		✓	
Entanglement, Complexity [Hammersley 07] [Bilson 08]… [KH Watanabe 21]	✓		
Correlators [Hammersley 06] [Hubeny Liu Rangamani 06]	✓		✓
AdS/DL [KH Tanaka Tomiya Sugishita 18]	✓	✓	✓
Wilson loop [KH 20]	✓	✓	

Emergent spacetime as a neural network

Quantum gravity in (d+1)-dim.

General spacetime

Anti de Sitter spacetime



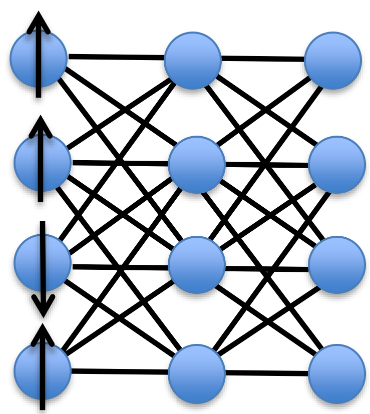
'tHooft `93
Susskind `94
Maldacena `97

||

|| ?

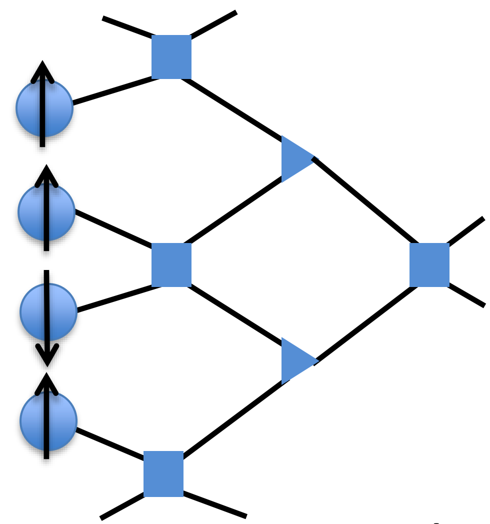
|| Swingle `10

Quantum mechanics in d-dim.



Neural network

Carleo, Troyer `17



Tensor network

AdS/CFT by ML

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   2108.08091, 2209.04638

② Space emergent from data

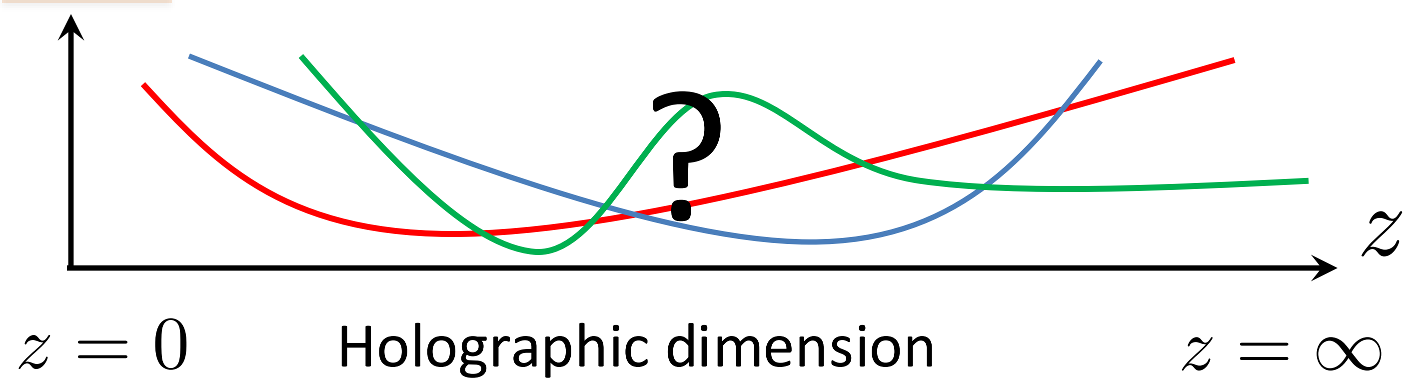
holographic QCD model for meson spectra

[Karch, Kaz, Son, Stephanov `06]

Vector meson spectra are eigenvalues $\omega^2 = m_n^2$ of normalizable solutions of the differential eq:

$$\frac{\partial}{\partial z}\left(e^{-B(z)}\frac{\partial}{\partial z}v_n(z)\right) + \omega^2 e^{-B(z)}v_n(z) = 0$$

$B(z)$: metric in the emergent dimension



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Model : Classical 5-d gauge theory in unknown dilaton gravity b.g.

$$S = \int d^4x dz\, e^{-\Phi}\sqrt{-g}\,(F_{MN})^2$$

Dilaton $\Phi(z)$, metric $ds^2 = e^{2A(z)}\left(dz^2 + \eta_{\mu\nu}dx^\mu dx^\nu\right)$

AdS boundary ($z \sim 0$) : $B(z) \equiv \Phi(z) - A(z) \sim \log z$

Solve EoM for the gauge field $A_\mu(z, x^\mu) = v_n(z)\rho_\mu(x^\mu)$

② Space emergent from data

Bring the bulk EoM to neural network

2005.02636

Bulk EoM $$\frac{\partial}{\partial z}\left(e^{-B(z)}\frac{\partial}{\partial z}v_n(z)\right)+m_n^2e^{-B(z)}v_n(z)=0$$

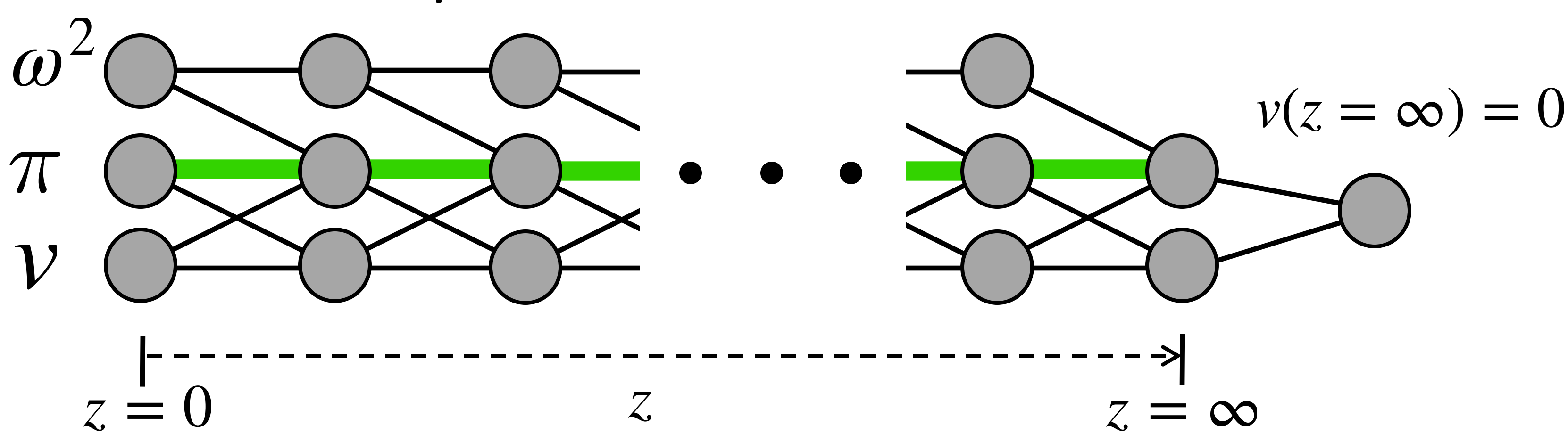
⇩

Discretization
Hamilton form

$$\begin{cases} v_n(z+\Delta z)=v_n(z)+\Delta z\,\pi_n(z) \\ \pi_n(z+\Delta z)=\pi_n(z)+\Delta z\left(B'(z)\pi_n(z)-\omega^2 v_n(z)\right) \end{cases}$$

⇩

Neural-Network representation



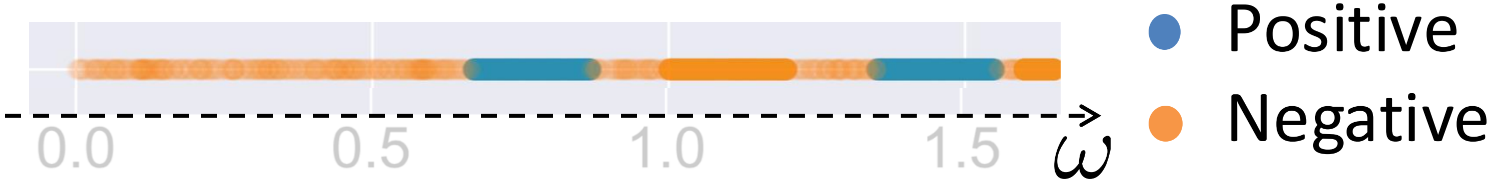
② Space emergent from data

Training with QCD data: hadron spectra

2005.02636

Data : PDG data for rho meson mass

$$m_\rho^{(1)} = 0.77 \text{ GeV}, \, m_\rho^{(2)} = 1.45 \text{ GeV}$$

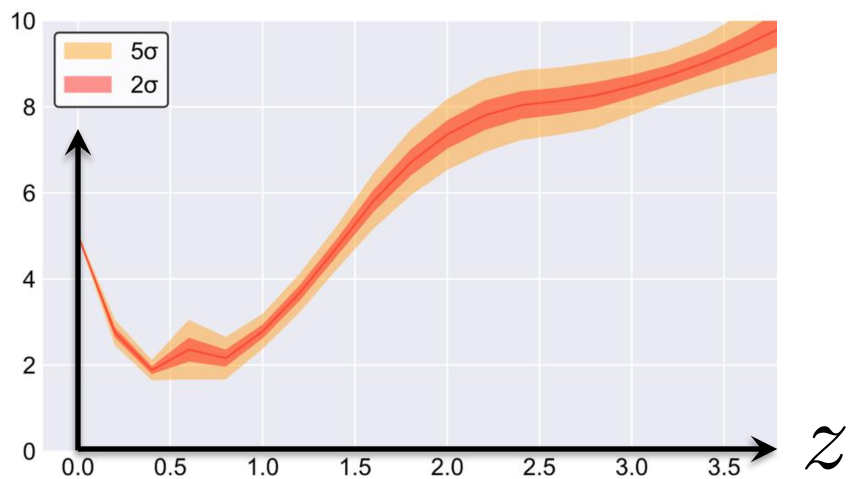


Machine learning with the interpretable NN

Learned result :

Emergent metric

$$B'(z) = \Phi'(z) - A'(z)$$



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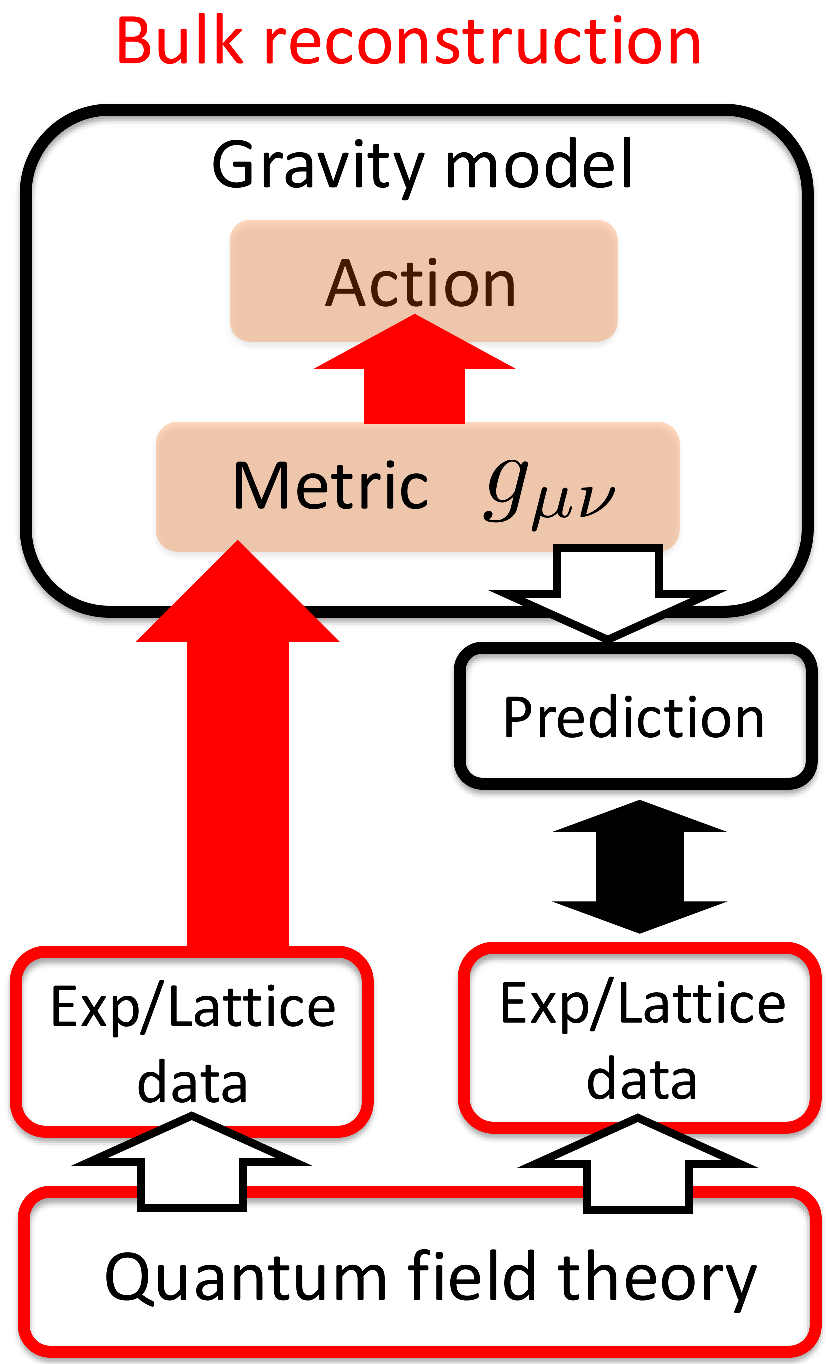
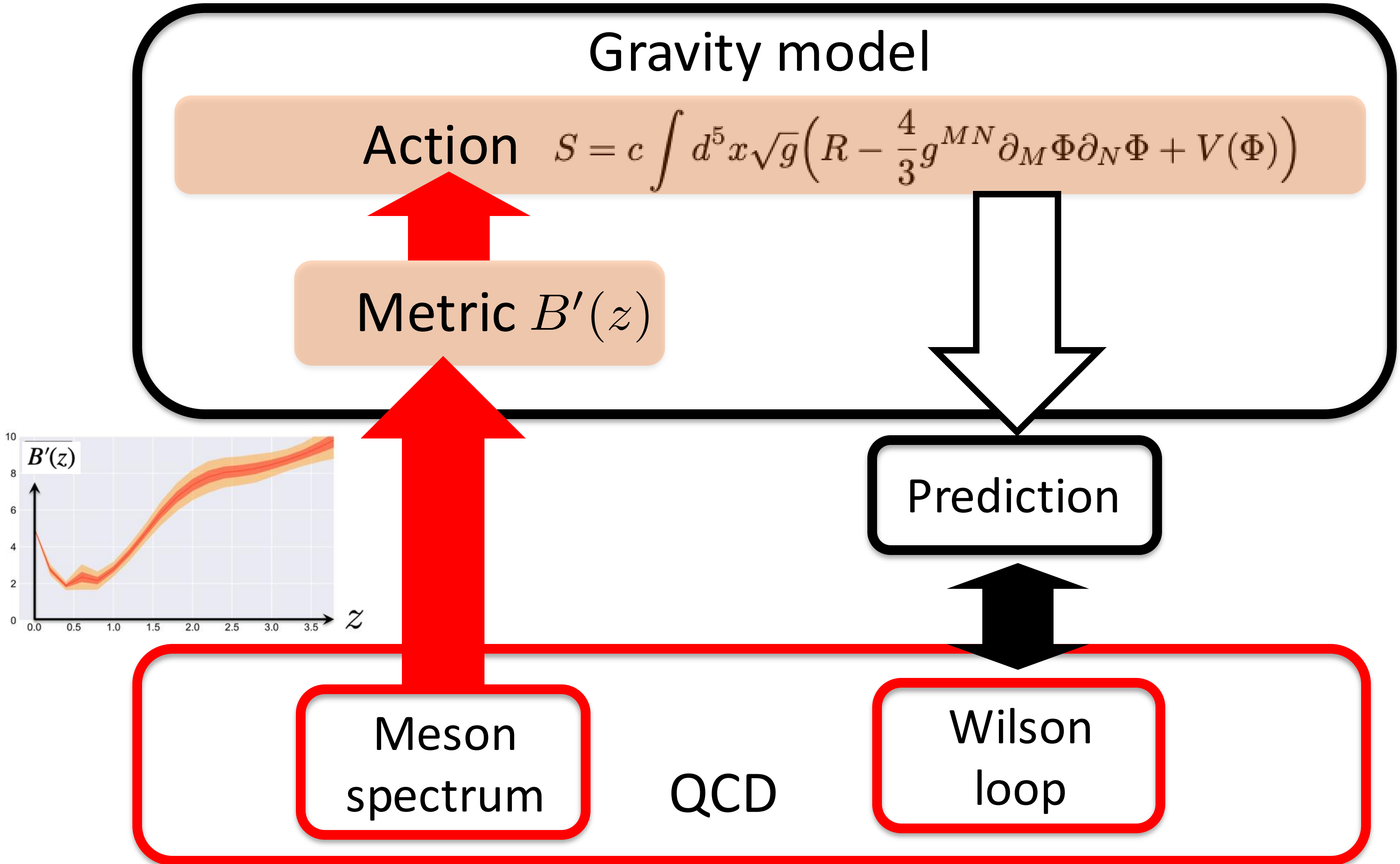


Bulk reconstruction
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Exp/Lattice data
Exp/Lattice data
Quantum field theory

③ Prediction by learned gravity

Two independent information of metric



③ Prediction by learned gravity

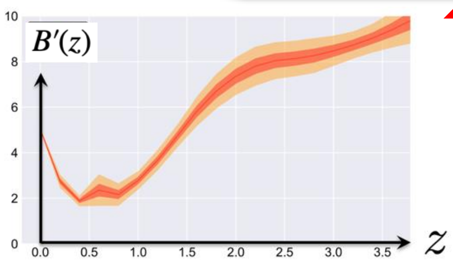
Reconstructing the dilaton potential

Gravity model

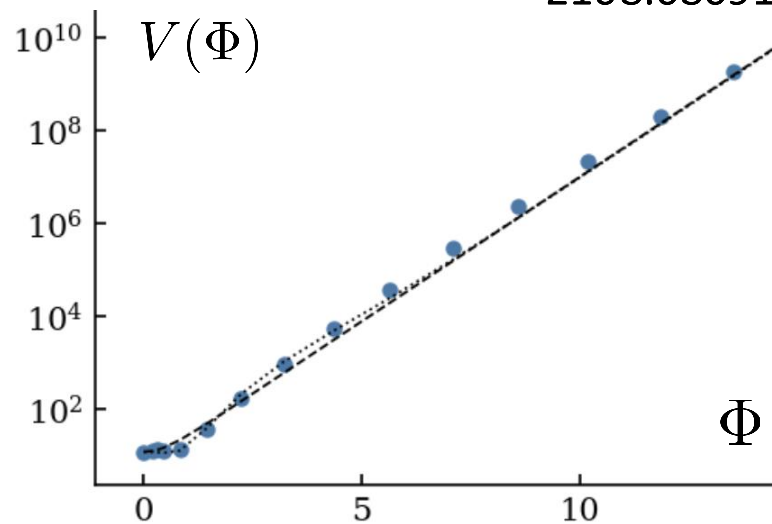
Action $S = c\int d^5x\sqrt{g}\left(R - \frac{4}{3}g^{MN}\partial_M\Phi\partial_N\Phi + V(\Phi)\right)$

Metric $B'(z)$

Meson spectrum



2108.08091



------ $V = 12\cosh(1.433\Phi)$

.... $V = 12\cosh(1.430\Phi) - 16.778\Phi^2 + 5.943\Phi^4$

Cf. [Gubser, Nellore, 0804.0434]

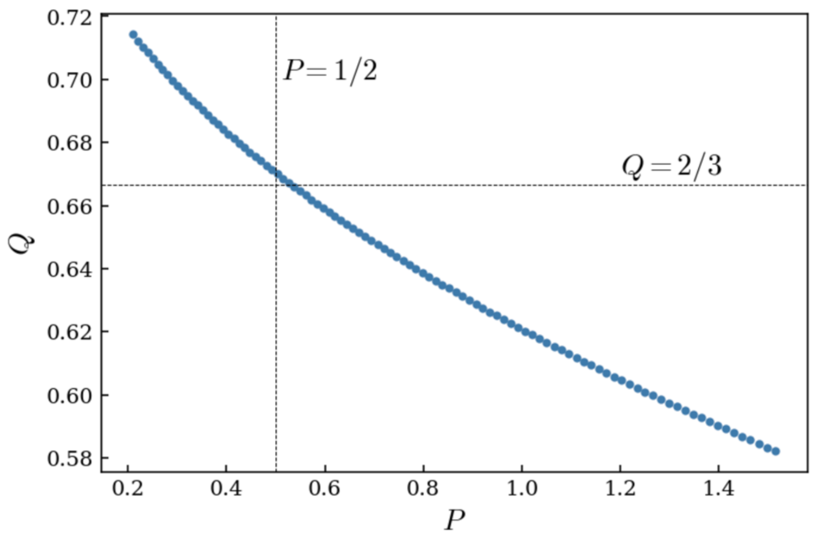
③ Prediction by learned gravity

It's a nice dilaton potential !

Gravity model

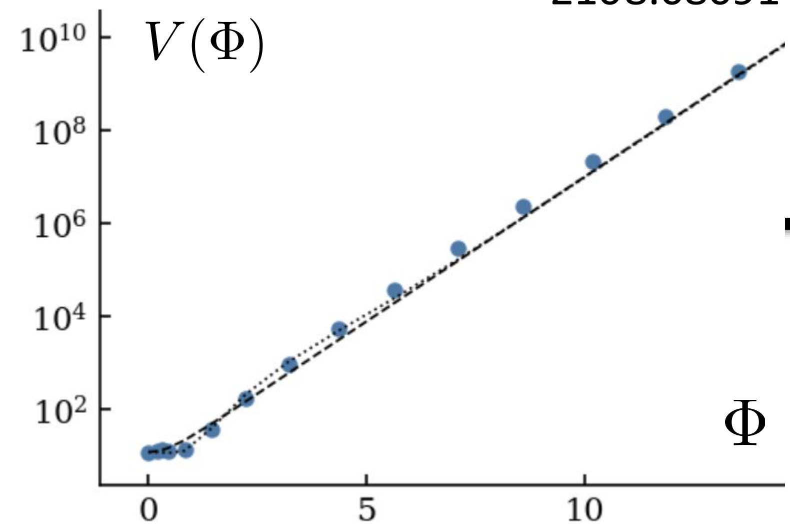
Action $S = c\int d^5x\sqrt{g}\left(R - \frac{4}{3}g^{MN}\partial_M\Phi\partial_N\Phi + V(\Phi)\right)$

2108.08091



Fit the asymptotic part by $V(\Phi) \sim e^{2Q\Phi}\Phi^P$ for different values of dilaton initial cond.

Cf. [Gursoy, Kiritsis, 0707.1324]
[Gursoy, Kiritsis, Nitti, 0707.1349]



------ $V = 12\cosh(1.433\Phi)$

.... $V = 12\cosh(1.430\Phi) - 16.778\Phi^2 + 5.943\Phi^4$

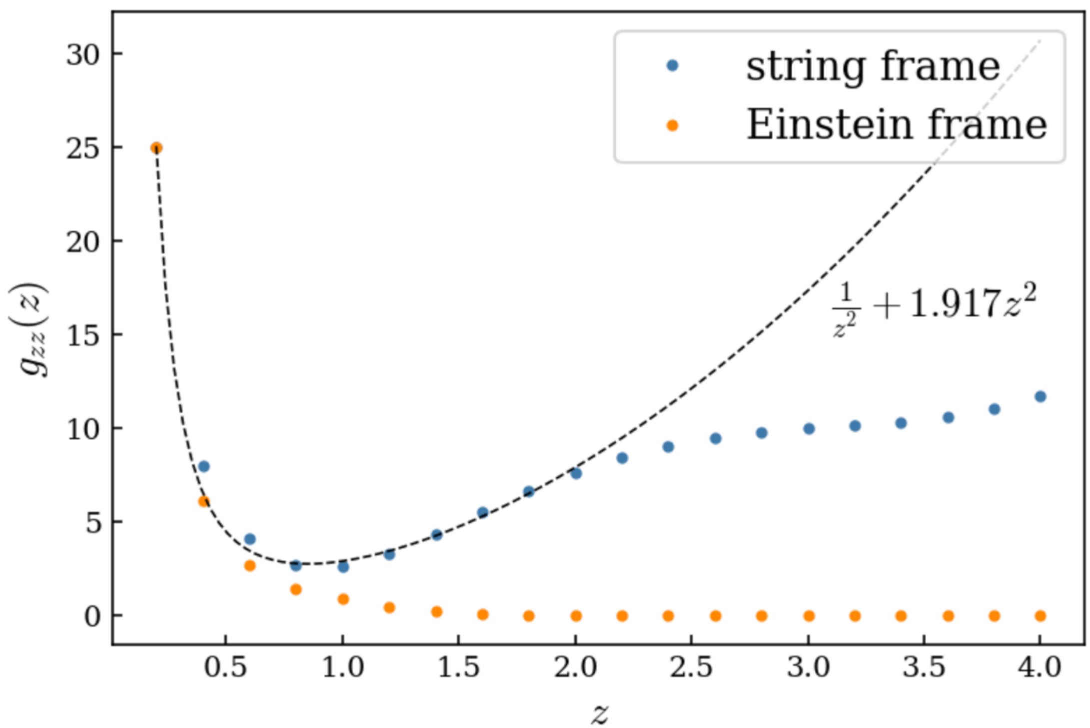
Cf. [Gubser, Nellore, 0804.0434]

③ Prediction by learned gravity

Bulk string metric has a bottom

Gravity model

Action $S = c\int d^5x\sqrt{g}\left(R - \frac{4}{3}g^{MN}\partial_M\Phi\partial_N\Phi + V(\Phi)\right)$



Prediction

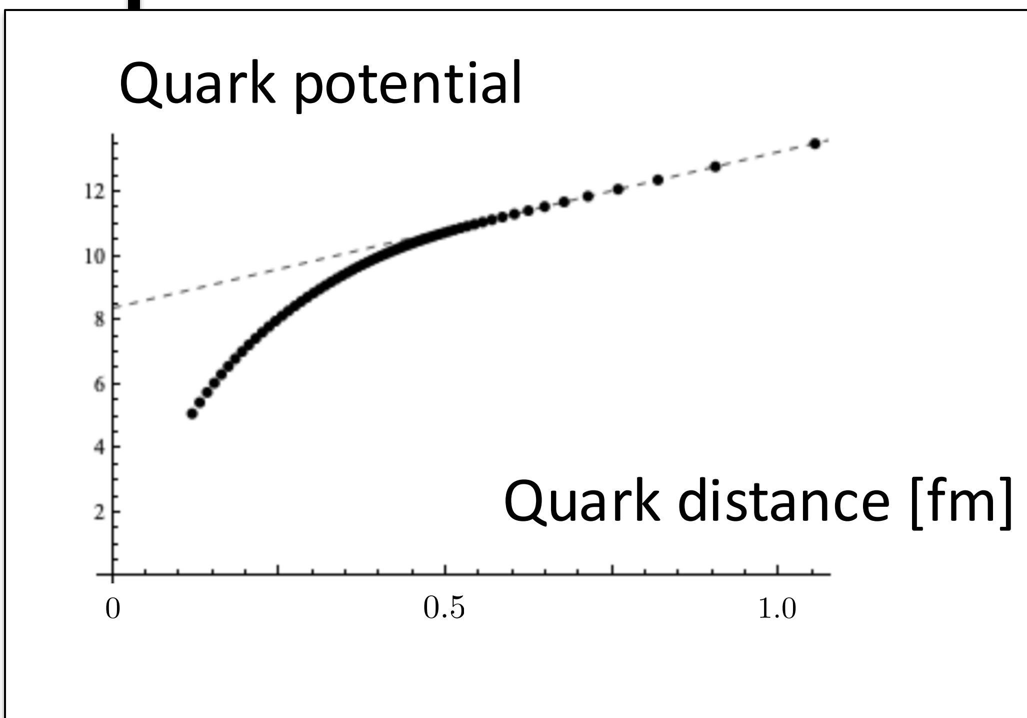
Wilson loop

③ Prediction by learned gravity

Prediction of string breaking

Gravity model

Action $S = c \int d^5x \sqrt{g} \left(R - \frac{4}{3} g^{MN} \partial_M \Phi \partial_N \Phi + V(\Phi) \right)$



Prediction

Wilson loop

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