ATHIC 2025

Application of *machine learning* and *quantum computation* in high energy physics

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non-perturbative field theory calculation

“first principle” microscopic theory: quantum field theory $L \leftrightarrow H$

non-perturbative lattice QFT: thermodynamics, transport

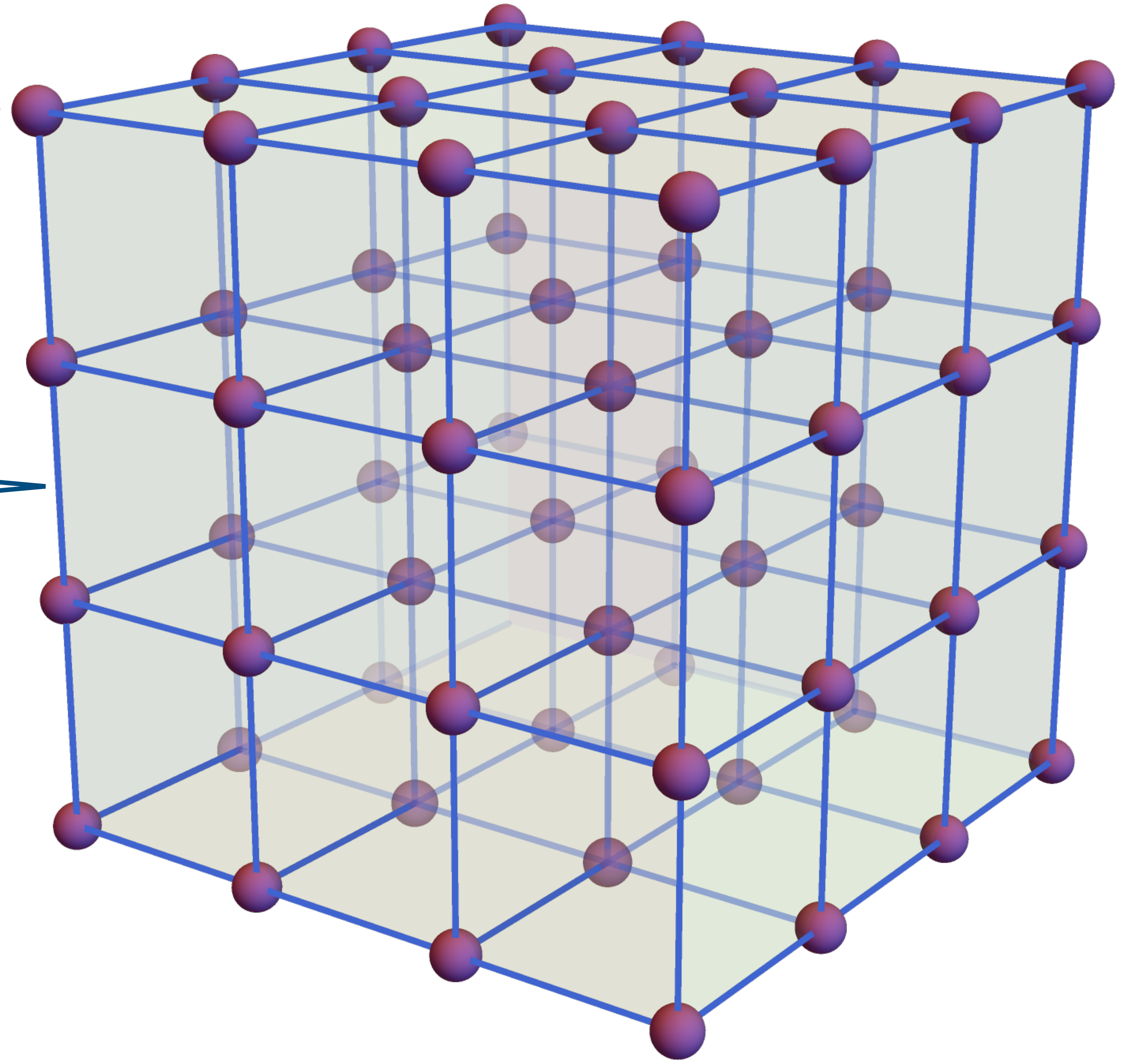
quantum simulation/computation of lattice QFT

fermion field

$$\prod_{\vec{x}} \left(\prod_{\text{spin,charge}} \otimes \left\{ \begin{array}{c} \text{occupied} \\ \overline{} \\ \overline{} \\ \text{unoccupied} \end{array} \right. \right)^{\text{color, flavor}}_{(\vec{x})}$$

gauge field

$$\prod_{(\vec{x},\vec{x}+d\vec{x})} \left(\prod_{\text{spin}} \otimes \left\{ \begin{array}{c} \vdots \\ \equiv \\ \equiv \\ \vdots \end{array} \right. \right)^{N_c^2-1}_{(\vec{x},\vec{x}+d\vec{x})}$$



field operators

$$\{\hat{\psi}_n^\dagger, \hat{\psi}_m\} = \delta_{n,m}\,, \quad \{\hat{\psi}_n, \hat{\psi}_m\} = \{\hat{\psi}_n^\dagger, \hat{\psi}_m^\dagger\} = 0\,,$$

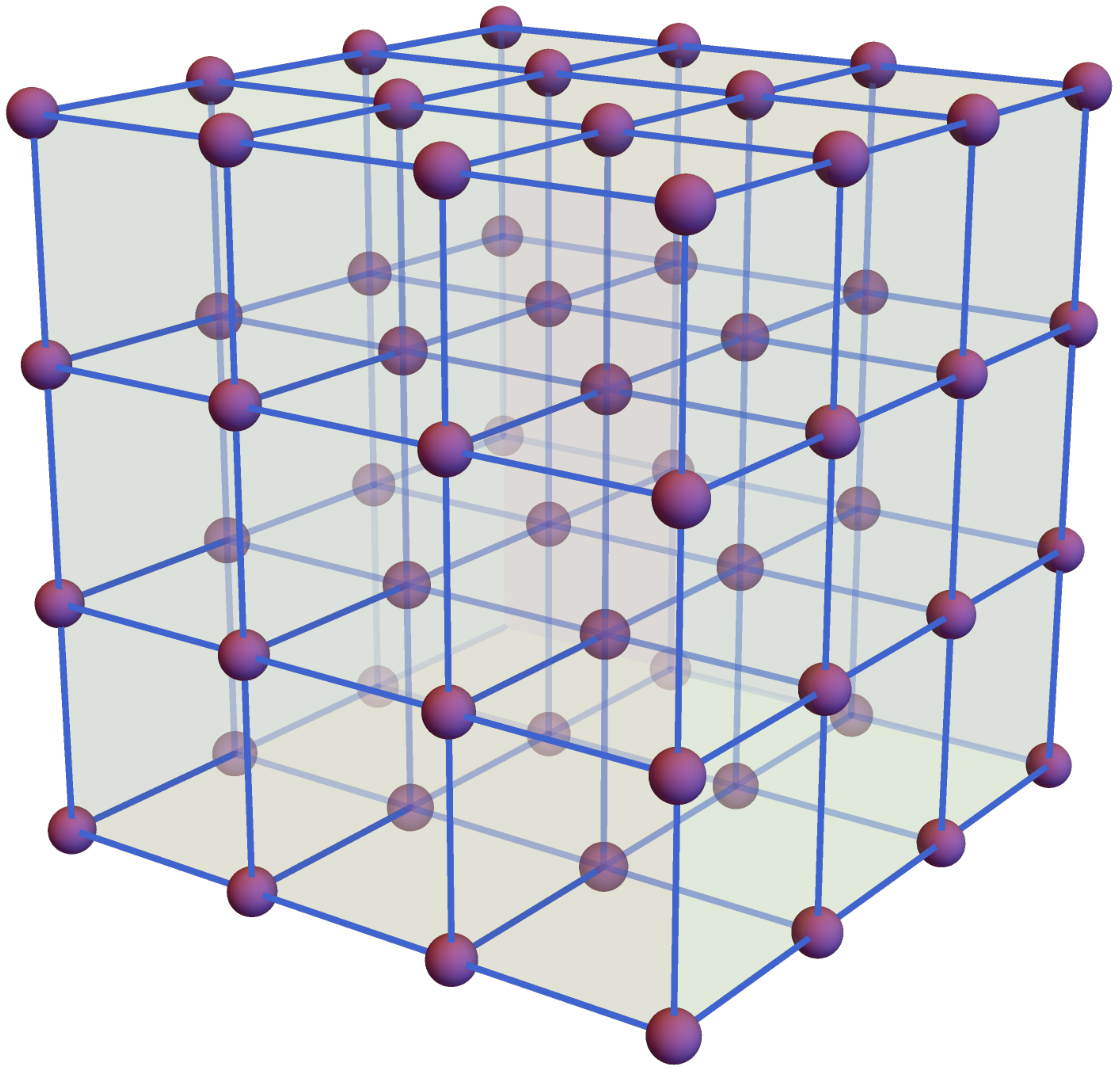
$$[\hat{\Pi}_n, \hat{A}_m] = \delta_{n,m}\,, \quad [\hat{\Pi}_n, \hat{\Pi}_m] = [\hat{A}_n, \hat{A}_m] = 0\,.$$

indices: spin, charge, color, flavor, $\vec{x}$, $\cdots$

[Jordan, Wigner, Z.Phys.47,631(1928)]
[Shaw, Lougovski, Stryker, Wieber, Quantum 4, 306]

quantum simulation/computation of lattice QFT

	classical hardware	quantum hardware
field configurations:	vectors	qubit-states
field operators:	matrices	gates



hadron structure

Reviews:
[C. W. Bauer et al., PRX Quantum 4, 027001 (2023)]
[Bauer, Davoudi, Klco, Savage, Nature Rev. Phys. 5, 420 (2023)]

$$\hat{H}|\Psi_{\rm vac}\rangle = E_{\rm gnd}|\Psi_{\rm vac}\rangle$$

$$\hat{H}|\Psi_{\rm meson}\rangle = E_{\rm 1st}|\Psi_{\rm meson}\rangle$$

[Li, Guo, Lai, Liu, Wang, Xing, Zhang, Zhu (QuNu Collaboration), PRD.105.L111502, PRD.109.036025, Sci.ChinaPhys.Mech.Astron.66,281011]

thermal properties

$$\langle O\rangle = {\rm tr}\left(\hat{O}\, e^{-\beta(\hat{H}-\mu\hat{Q})}\right)/Z$$

[Hidaka, Yamamoto, 2409.17349]
[Hayata, Hidaka, JHEP09(2023)126, JHEP07(2024)106]
[Ebner, Muller, Schafer, Seidl, Yao, PRD.109.014504]
[Yao, PRD.108.L031504]
[Czajka, Kang, Ma, Zhao, JHEP08,209]
[Ikeda, Kharzeev, Meyer, ***SS***, PRD.108.L091501]

real-time evolution

$$\partial_t|\Psi(t)\rangle = -i\hat{H}|\Psi(t)\rangle$$

$$\partial_t\hat{\rho}(t) = -i[\hat{H},\hat{\rho}(t)]$$

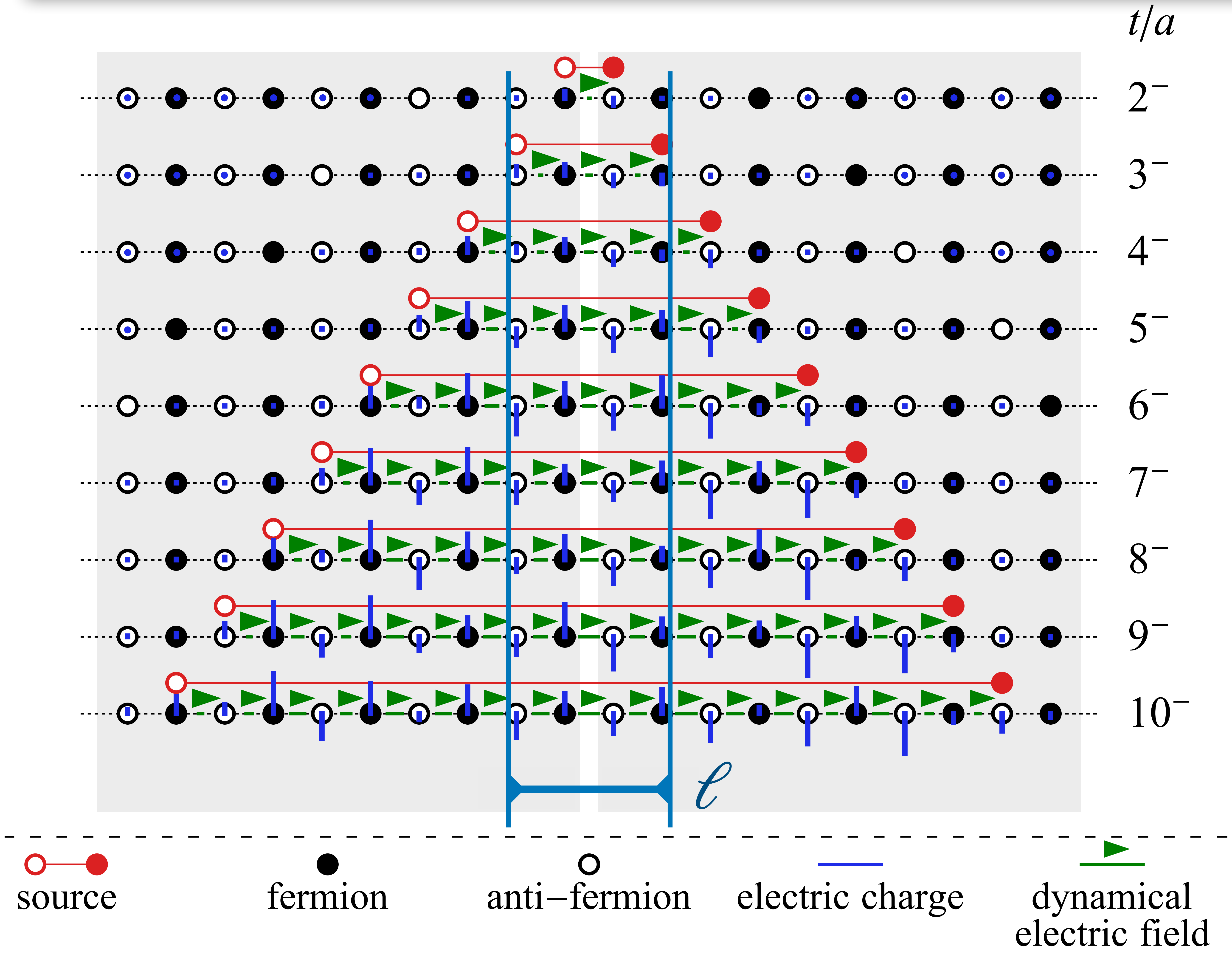
$$O(t) = {\rm tr}\left(\hat{O}\,\hat{\rho}(t)\right)$$

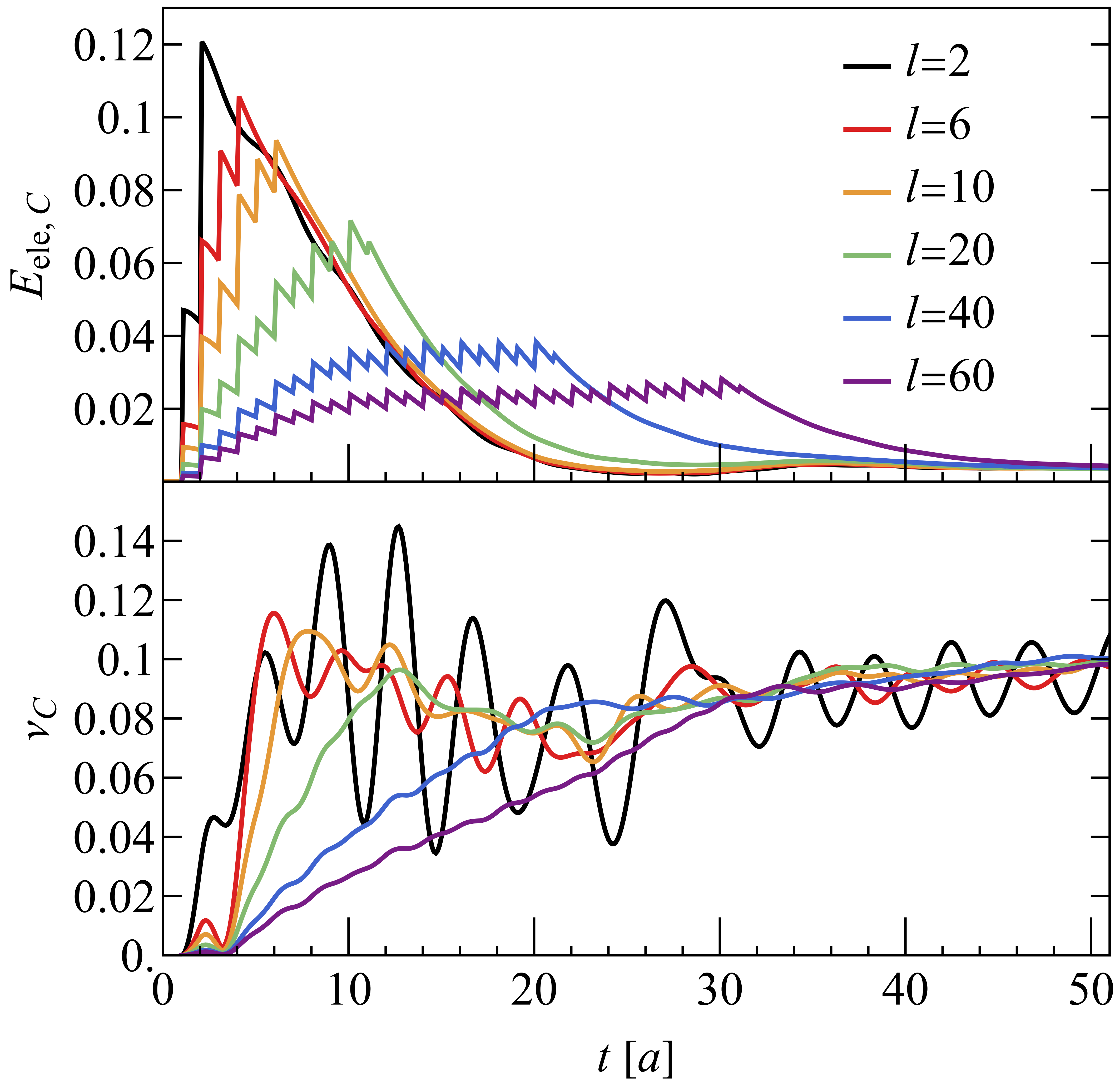
[de Jong, Lee, Mulligan, Ploskon, Ringer, Yao, PRD.106.054508]
[Farrell, Illa, Ciavarella, Savage, **PRX** Quantum.5.020315; PRD.109.114501]
[Florio, PRD.109.L071501]
[Ikeda, Kang, Kharzeev, Qian, Zhao, JHEP10(2024)031]
[Shile Chen, ***SS***, Li Yan, 2412.00662]
[Lee, Mulligan, Ringer, Yao, PRD.108.094518]
[Ikeda, Kharzeev, ***SS***, PRD.108.074001]
[Wu, Du, Zhao, Vary, PRD.110.056044]
[Ikeda, Kharzeev, Kikuchi, PRD.103.L071502]
[Kharzeev, Kikuchi, PRRes.023342]
[Florio, Frenklakh, Ikeda, Kharzeev, Korepin, ***SS***, Yu, **PRL**.131.021902; PRD.110.094029]

thermal hadron production in hard collisions

Schwinger model: w/ source

$$H(t) = \int \left(\frac{E^2}{2} - \bar{\psi}(i\gamma^1 \partial_x - g\gamma^1 A - m)\psi - j^1_{\text{ext}}(t) A \right) \mathrm{d}x \,.$$

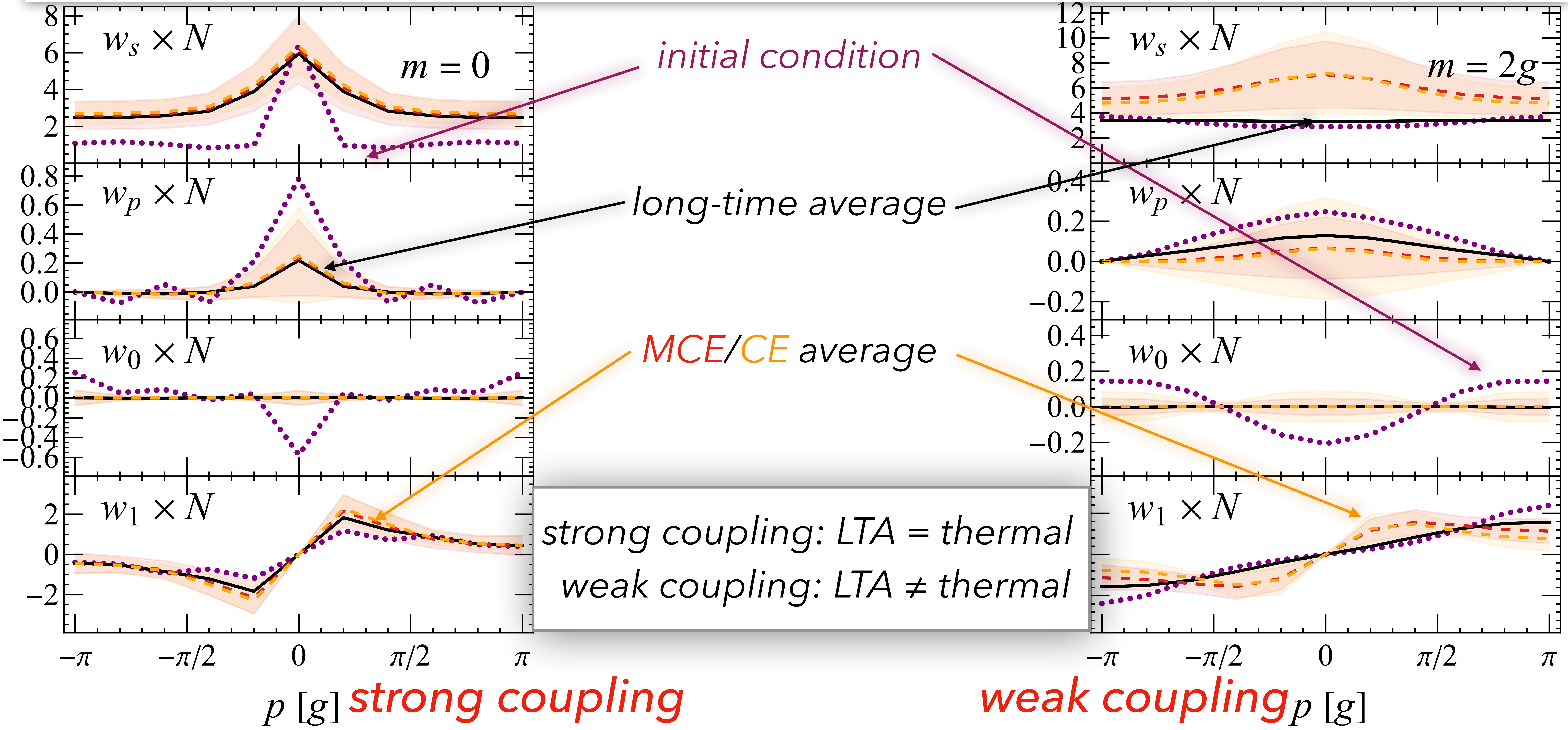




[Florio, Frenklakh, Ikeda, Kharzeev, Korepin, ***SS***, Yu, PhysRevLett.131.021902; PhysRevD.110.094029]

isolated quantum system: thermalization of quantum distribution function

Schwinger model: $H(t) = \int \left(\frac{E^2}{2} - \bar{\psi}(i\gamma^1 \partial_x - g\gamma^1 A - m)\psi \right) \mathrm{d}x \,.$ $\hat{W}_{\alpha\beta}(t,z,p) = \int \bar{\psi}_\alpha(z_+) U(z_+, z_-) \psi_\beta(z_-) \, e^{i\frac{py}{\hbar}} \, \mathrm{d}y$



strong coupling: LTA = thermal

weak coupling: LTA ≠ thermal

strong coupling **weak coupling**

isolated quantum system: thermalization of quantum distribution function

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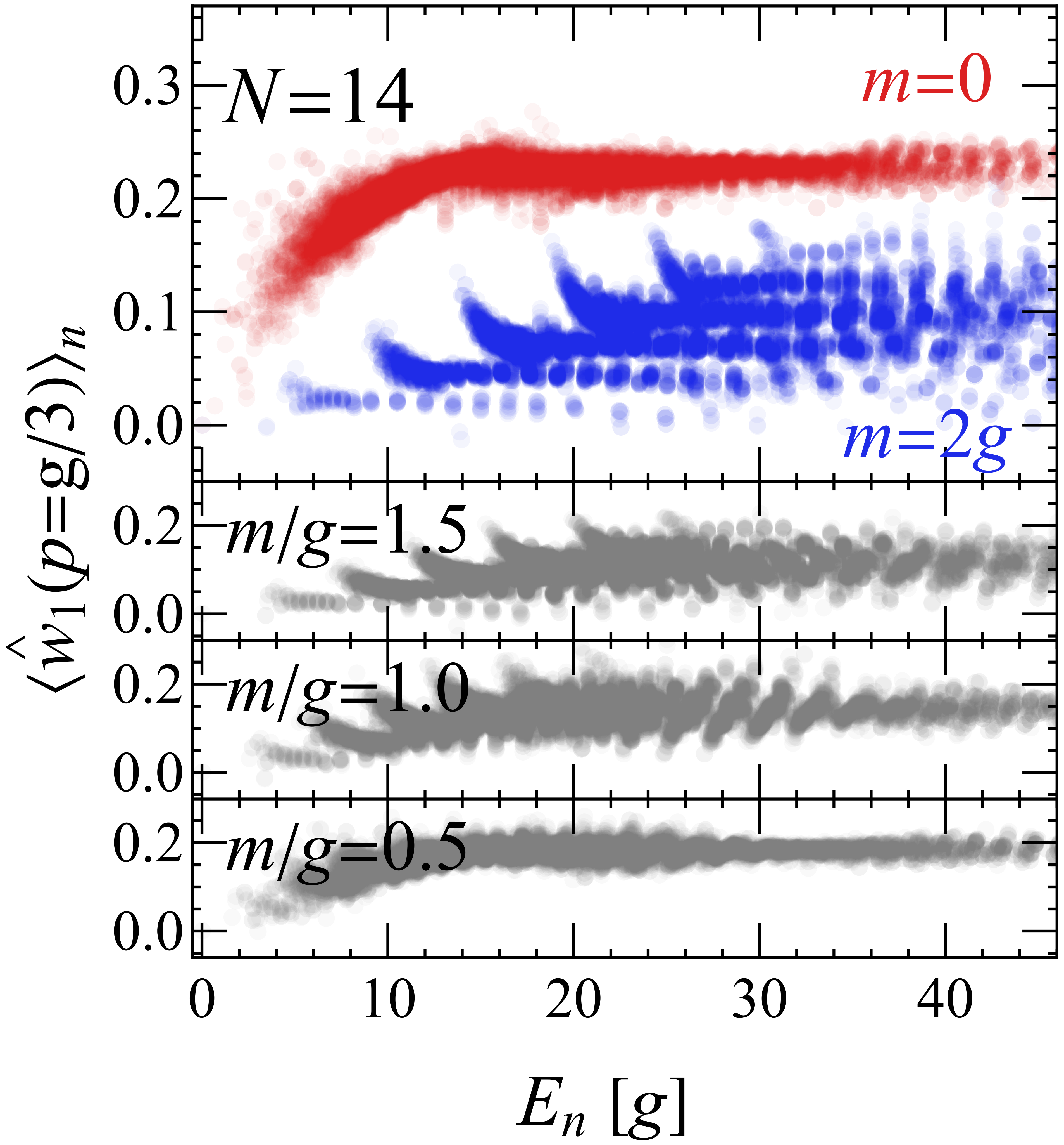


eigenstate thermalization hypothesis

$$\langle n|\hat{O}|n\rangle \approx f_O(E_n)$$

$$\sum_n p_n \langle n|\hat{O}|n\rangle \approx f_O\Big(\sum_n p_n E_n\Big)$$

general pure state: $|c_n|^2$

thermal: $e^{-\beta E_n}/Z$

$$\langle O\rangle_{PS} \approx \langle O\rangle_{th}$$

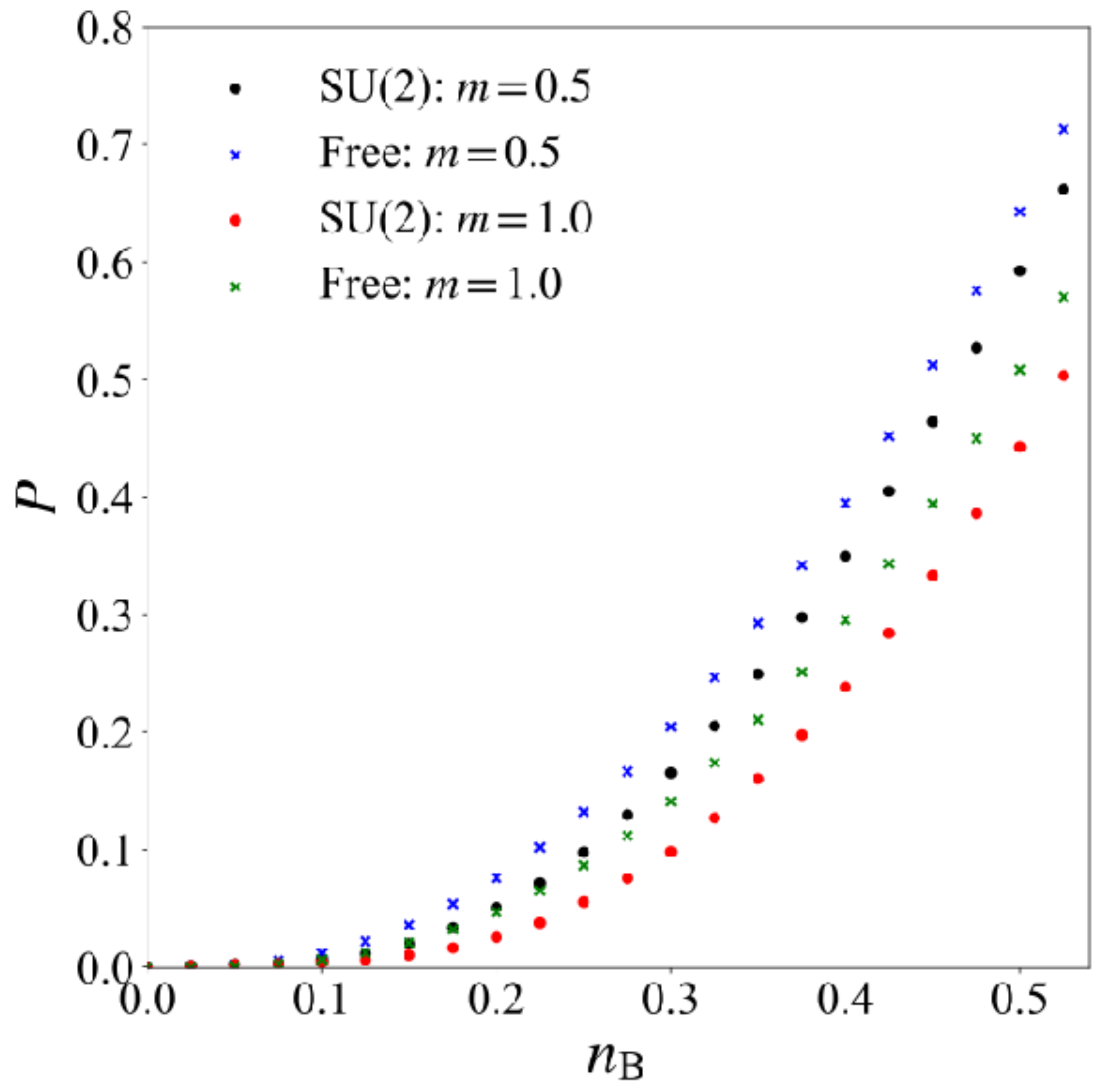
if $\langle E\rangle_{PS} = \langle E\rangle_{th}$

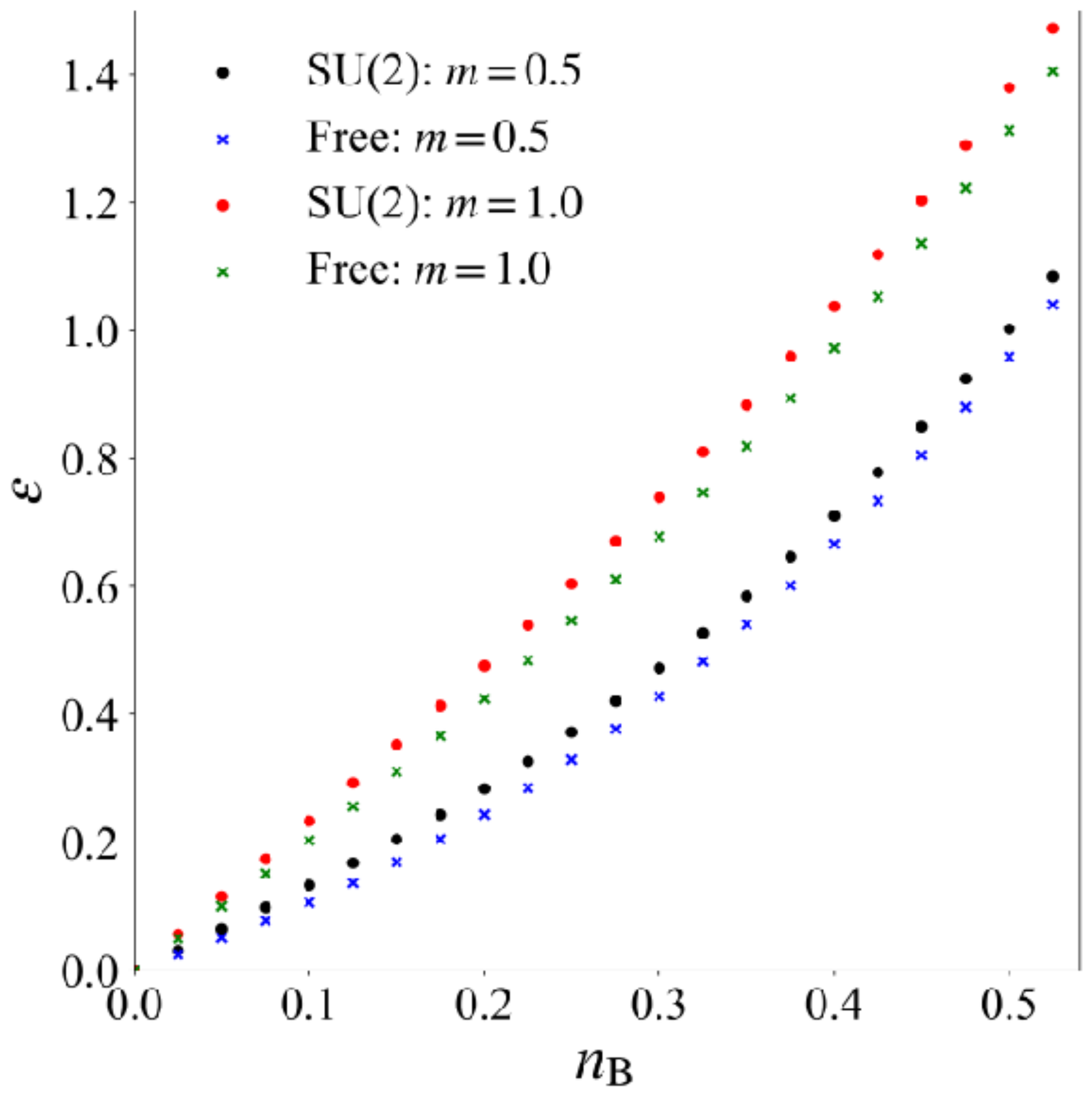
band structure caused by quasi-particles

[Shile Chen, ***SS***, Li Yan, 2412.00662]

zero-T high-μ EOS

SU(2) non-Abelian gauge theory in 1+1D



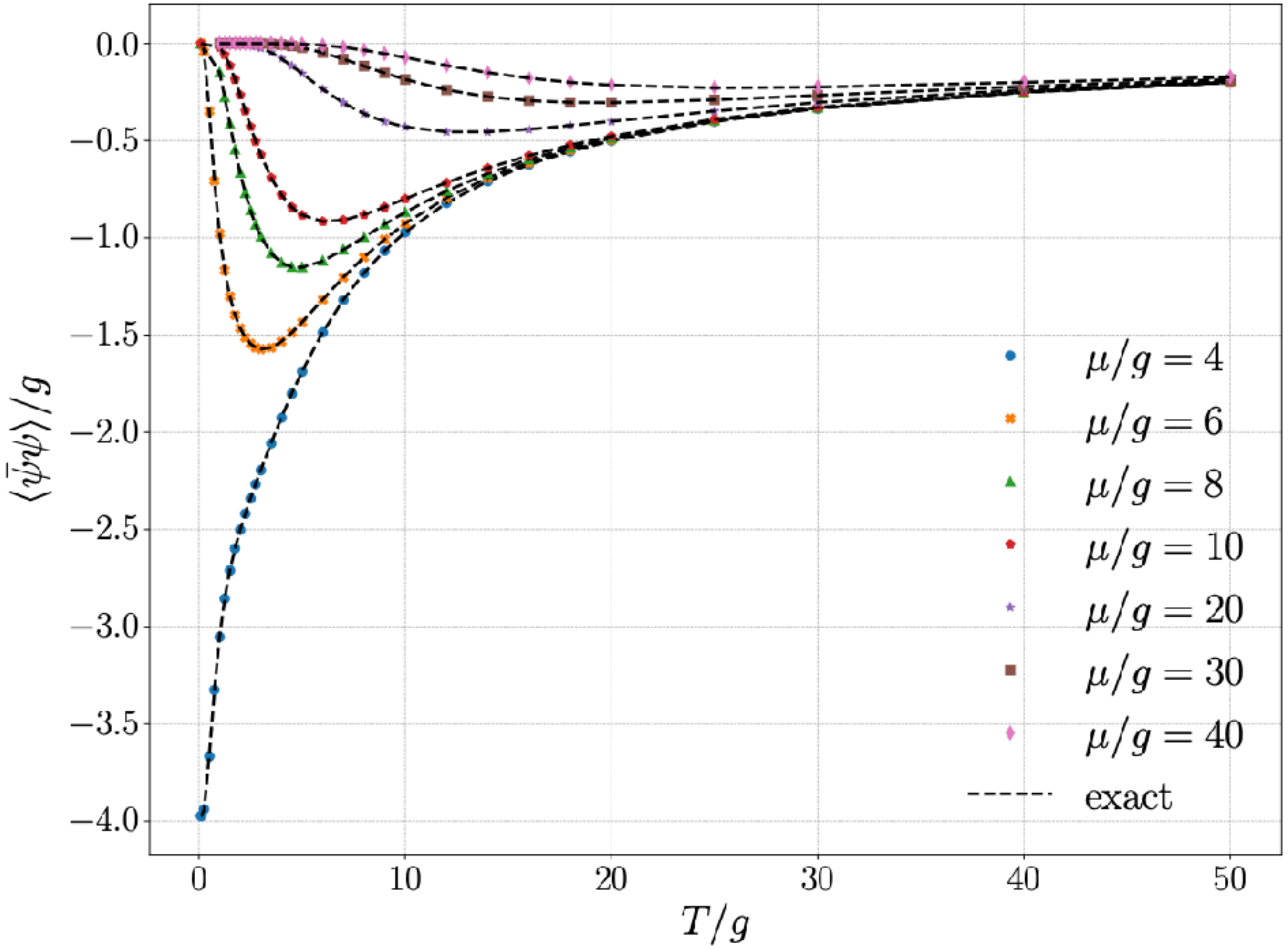


No first-order phase transition? b/c 1+1D?

[Hidaka, Yamamoto, 2409.17349; Hayata, Hidaka, JHEP07(2024)106]

finite T, μ on real Quantum Computer

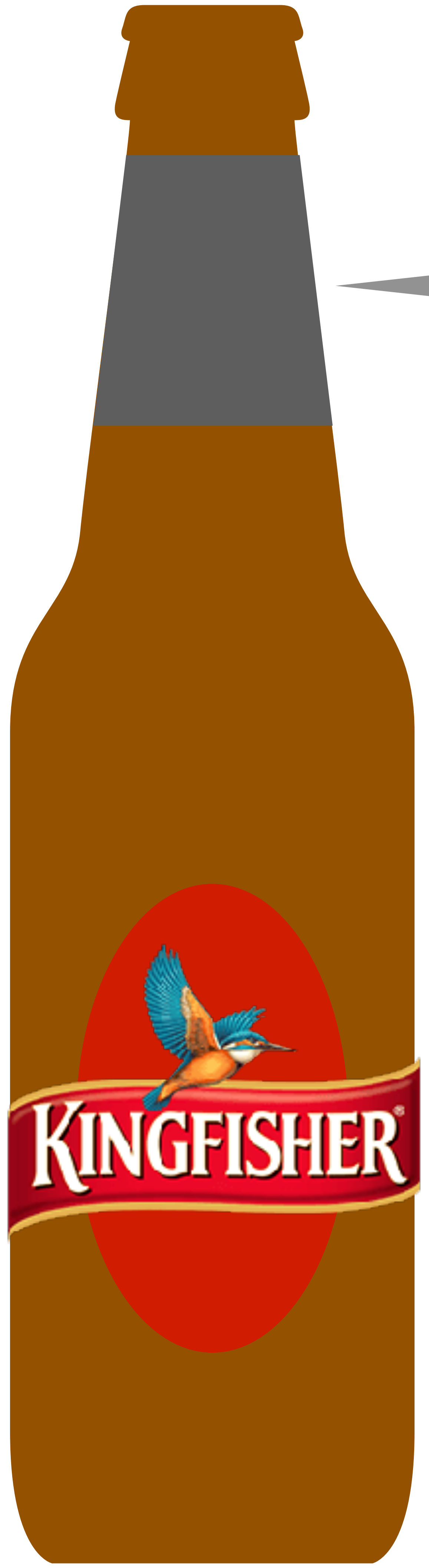
SU(2) non-Abelian gauge theory in 1+1D

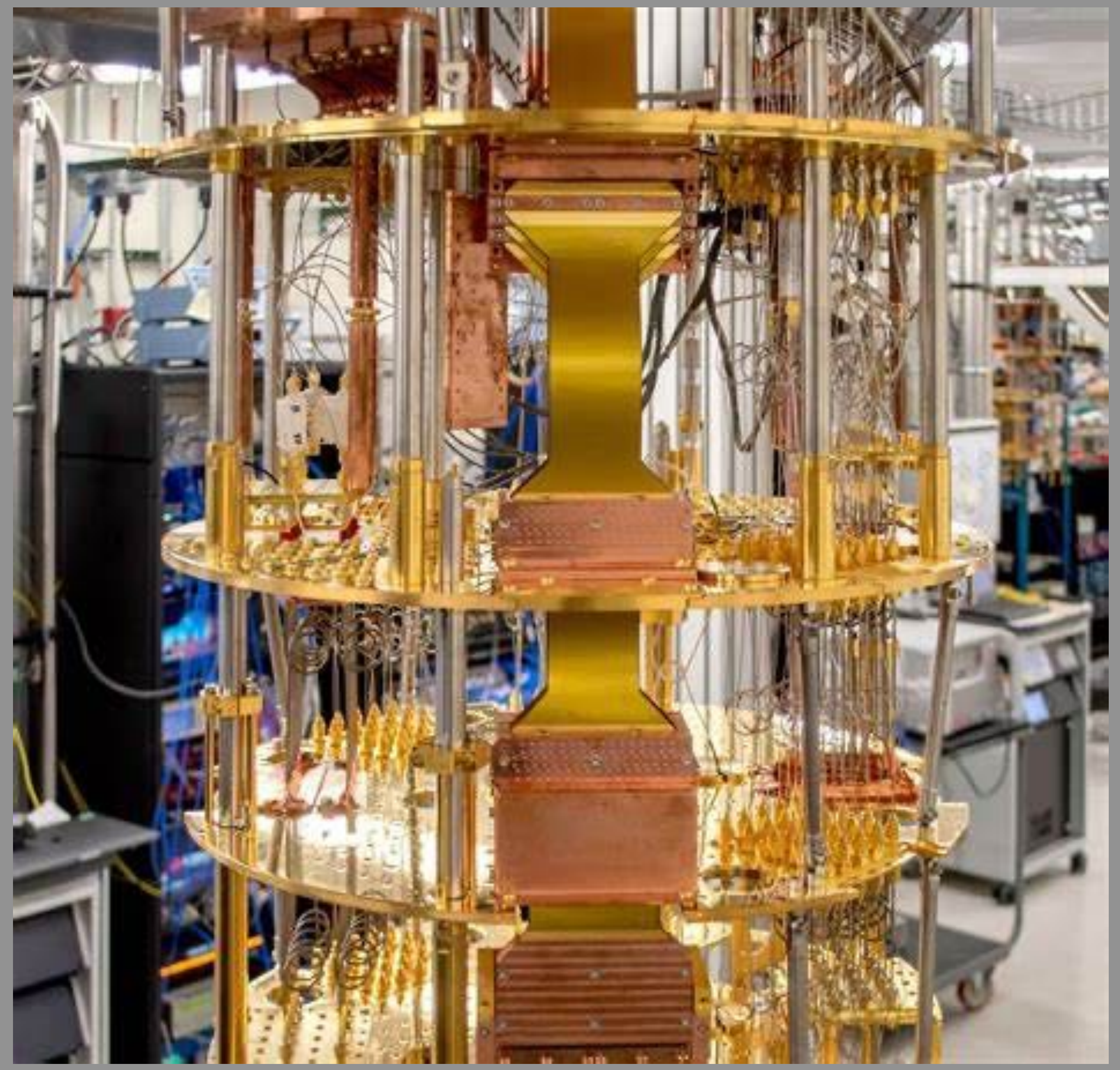


Chiral condensate at finite T, μ using real Quantum Computers!

[Zhang, Guo, Wang, Xing (QuNu Collaboration), 2411.18869]

Quantum Computation: Status





Noise in QCs!

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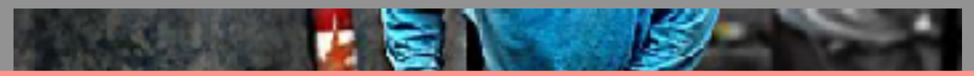
Quantum Computation: Status

Noise in QCs!



Tool(s) to assist Lattice QCD calculation?

Machine Learning!

thermal properties

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[Hidaka, Yamamoto, 2409.17349]
[Hayata, Hidaka, JHEP09(2023)126, JHEP07(2024)106]
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[Florio, Frenklakh, Ikeda, Kharzeev, Korepin, ***SS***, Yu, PRL.131.021902; PRD.110.094029]

Machine Learning assisted Lattice QFT calculation

Lattice calculation

$$Z = \mathrm{tr}(e^{-\beta H[\Psi,\Pi]}) = \int \mathscr{D}\Psi\, e^{-S[\Psi,\dot{\Psi}]}$$

sample $\Psi(\tau) \sim P[\Psi(t)] \propto e^{-\beta L[\Psi,\dot{\Psi}]}$.

expensive to sample uncorrelated configurations $\Psi(\tau)$!

ML: approximate $P[\Psi(t)] \approx P_{\mathrm{ML}}[\Psi(t)]$,

sample $\Psi(\tau) \sim P_{\mathrm{ML}}[\Psi(t)]$

•VAEs and GANs

D. Giataganas, et al., New J. Phys. 24, 043040 (2022).
K. Zhou, et al., Phys. Rev. D 100, 011501 (2019).
J. M. Pawlowski and J. M. Urban, MLST 1, 045011 (2020).
J. Singh, et al., SciPost Phys. 11, 043 (2021).

• Diffusion Models

Wang, Aarts, Zhou, JHEP 05 (2024) 060; 2412.13704

• Autoregressive models

D. Wu, et al., Phys. Rev. Lett. 122, 080602 (2019).
L. Wang, et al., CPL 39, 120502 (2022).
P. Białas, P. Korcyl, and T. Stebel, CPC 281, 108502 (2022).

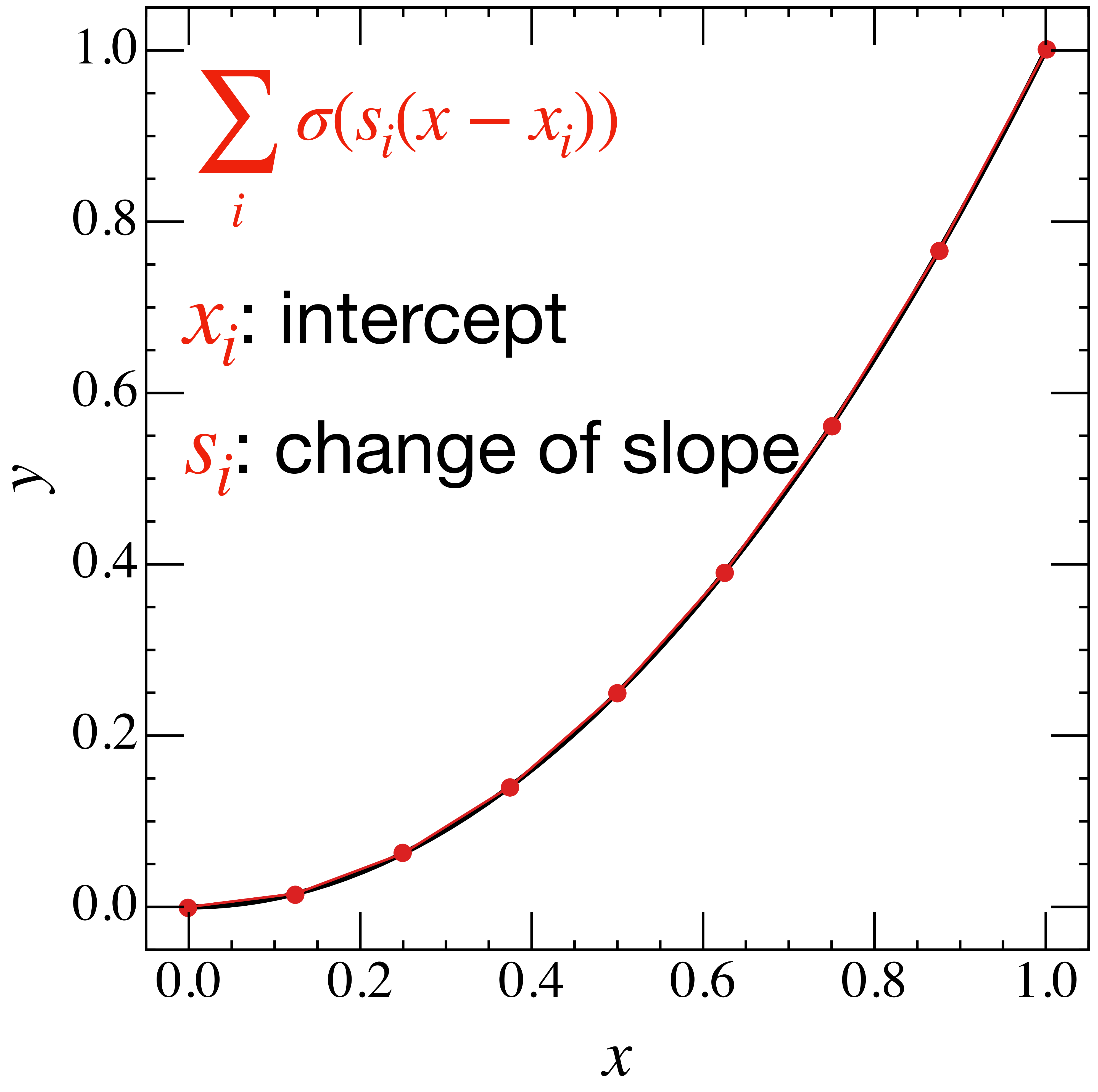
•Flow-based models

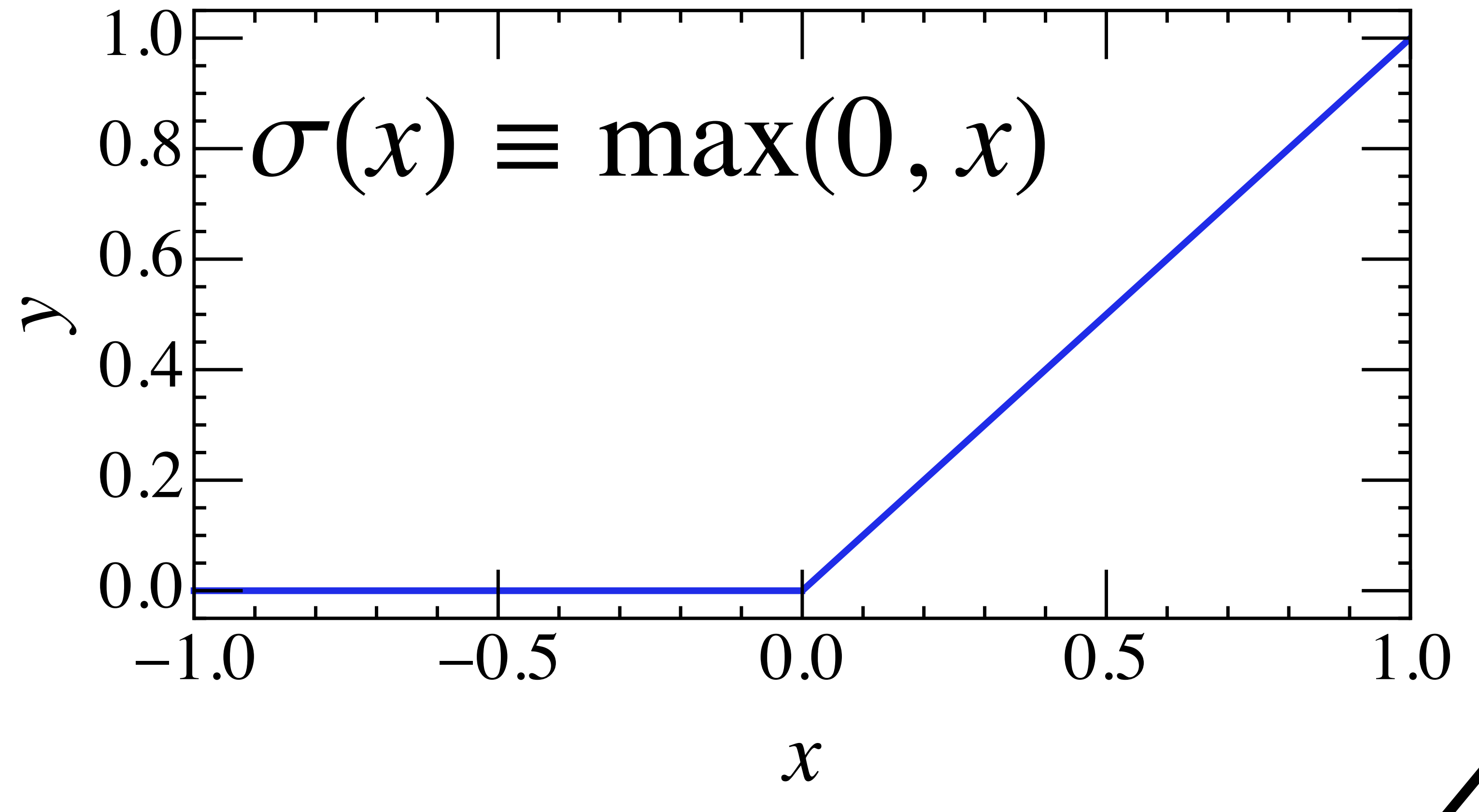
M. S. Albergo, et al., Phys. Rev. D 100, 034515 (2019).
G. Kanwar, et al., Phys. Rev. Lett. 125, 121601 (2020).
K. A. Nicoli, et al., Phys. Rev. Lett. 126, 032001 (2021).
L. Del Debbio, et al., Phys. Rev. D 104, 094507 (2021).
M. Caselle, et al., JHEP 2022, 15 (2022).
R. Abbott et al., Phys. Rev. D 106, 074506 (2022).
A. Singha, et al., Phys. Rev. D 107, 014512 (2023).
S. Chen, et al., Phys. Rev. D 107, 056001(2023).

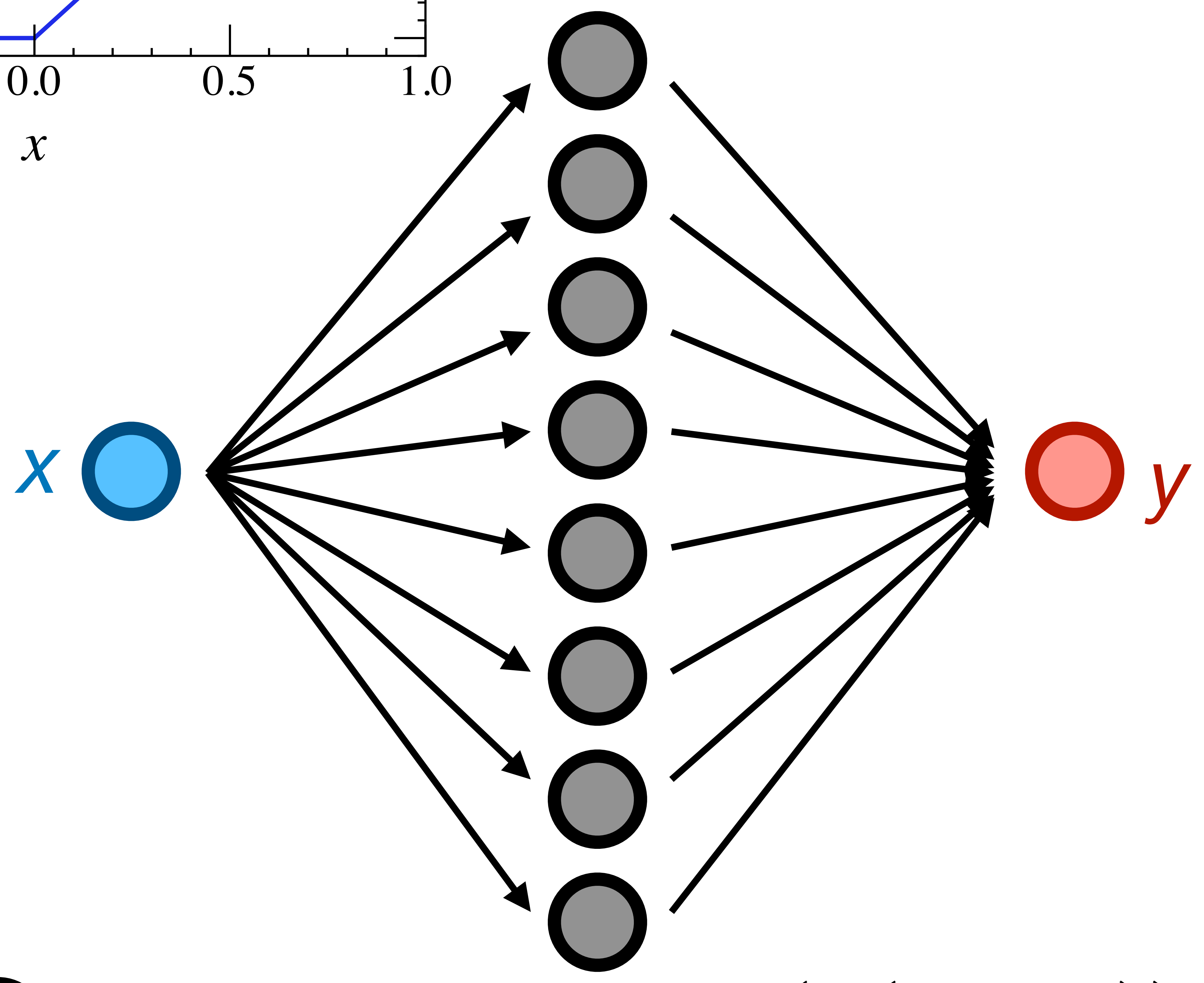
Review

K. Cranmer, G. Kanwar, S. Racanière, D. J. Rezende, and P. E. Shanahan, Advances in Machine-Learning-Based Sampling Motivated by Lattice Quatum Chromodynamics, Nat. Rev. Phys. 1 (2023).

--- a general parameterization scheme to approximate continuous functions.

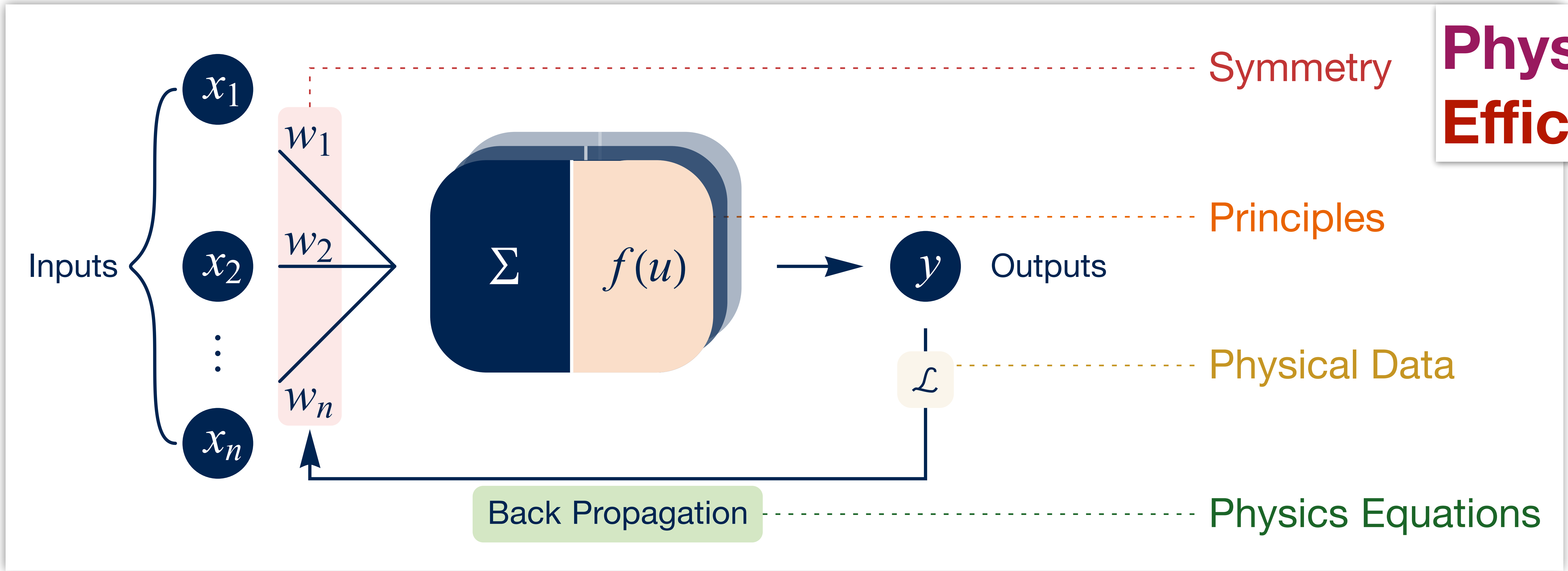






each ● represents one of $\sigma(s_i(x - x_i))$

inverse problem solver — physics-driven learning



Physics Knowledge in Design

Efficiency & Reliability

nature reviews physics
https://doi.org/10.1038/s42254-024-00798-x
Perspective
Check for updates

Physics-driven learning for inverse problems in quantum chromodynamics

Gert Aarts[1], Kenji Fukushima[2], Tetsuo Hatsuda[3], Andreas Ipp[4], Shuzhe Shi[5], Lingxiao Wang[3] & Kai Zhou[6,7]

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Review

Exploring QCD matter in extreme conditions with Machine Learning

Kai Zhou [a,b,*], Lingxiao Wang [a,*], Long-Gang Pang [c,*], Shuzhe Shi [d,e,*]

inverse problem solver — physics-driven learning

HIC observed particles → 1st-order phase transition

Pang, Zhou, Su, Petersen, Stocker, Wang, Nat.Comm. 9 (2018)1,210

Neutron Star Mass-Radius → EoS

Fujimoto, Fukushima, Murase, PhysRevD.98,023019

Soma, Wang, ***SS***, Stöcker, Zhou, PRD.107.083028; JCAP 98(2020)071

Energy spectrum → potential

SS, Zhou, Zhao, Mukherjee, Zhuang, PhysRevD.105.014017

imaginary time correlation → spectral function

Wang, ***SS***, Zhou, PRD.106.L051502; Com.Phys.Comm. (2022) 108547

femtoscopy → hadron interaction

Wang, Zhao, 2411.16343

lattice EoS → quasi particle properties

Li, Lu, Pang, Qin, Phys.Lett.B 844(2023)138088

Other Reviews:

Ma, Pang, Wang, Zhou, Chin.Phys.Lett.40.112101

He, Ma, Pang, Song, Zhou, Nucl.Sci.Tech.34,6,88

Pang, Int.J.Mod.Phys.E 33, 06, 2430009

Boehnlein et al, Rev.Mod.Phys.94.031003

Physics Knowledge in Design

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summary

- Quantum Computation / Simulation:
  - real-time
  - finite temperature
- Machine Learning:
  - inverse problems
  - classification