

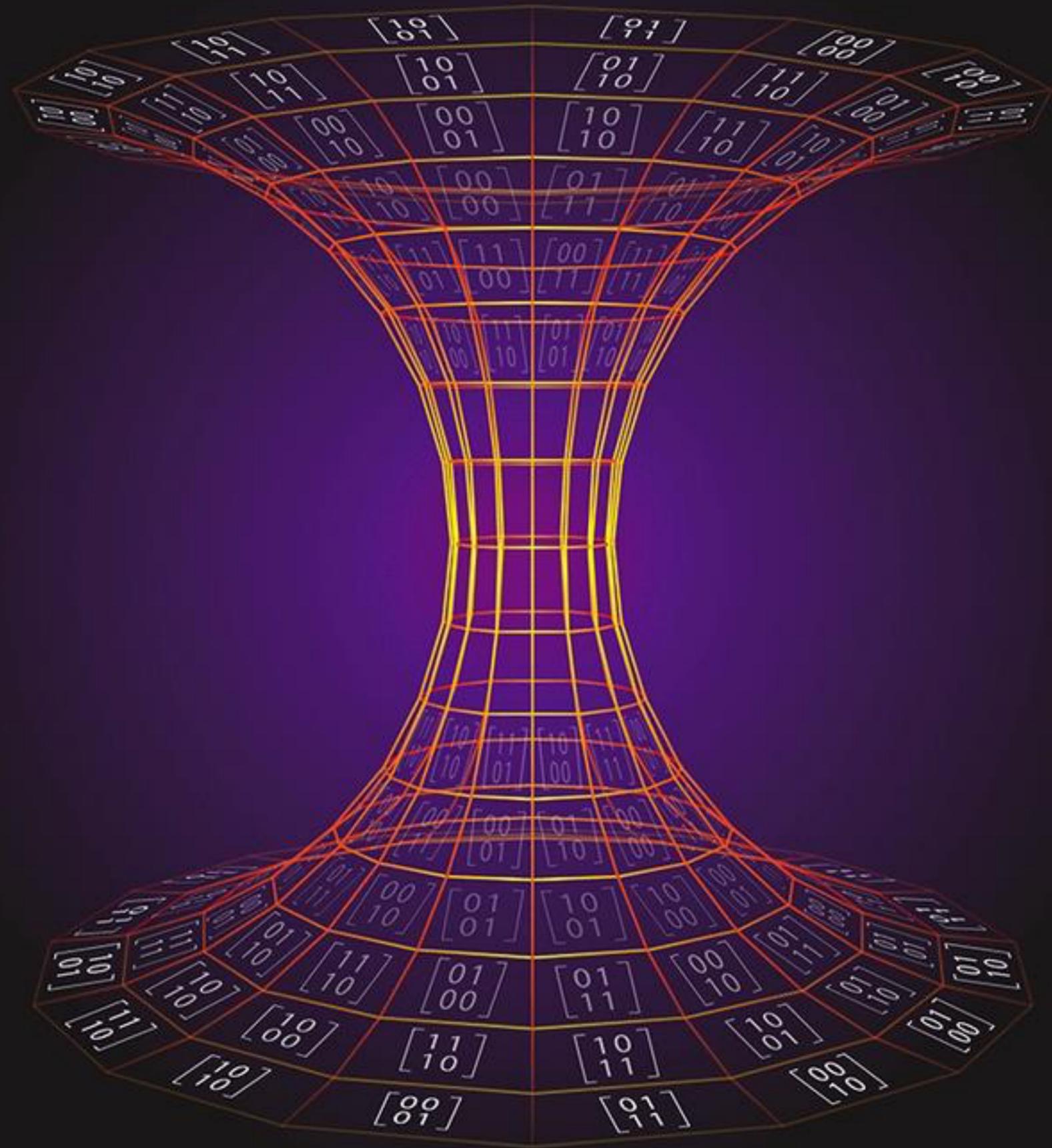
New Computational Methods for Matrix Models

Enrico Rinaldi

(Main) | Quantinum (London) > + (Visitor) | RIKEN [RQC] >

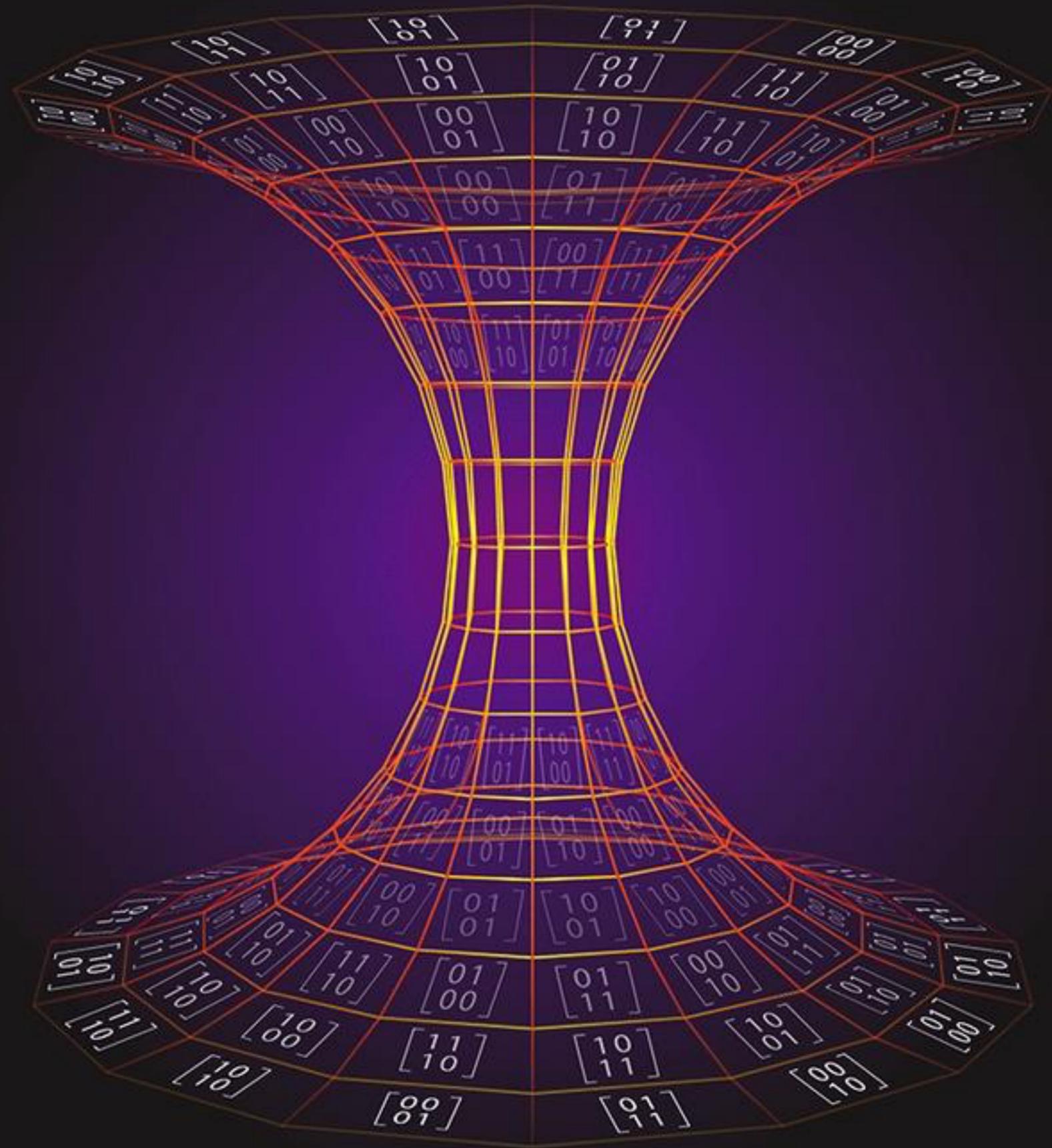
2025-12-03 Matrix Model for Superstring/M-theory (YITP) @ Kyoto

Outline

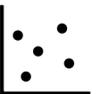
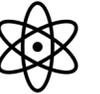


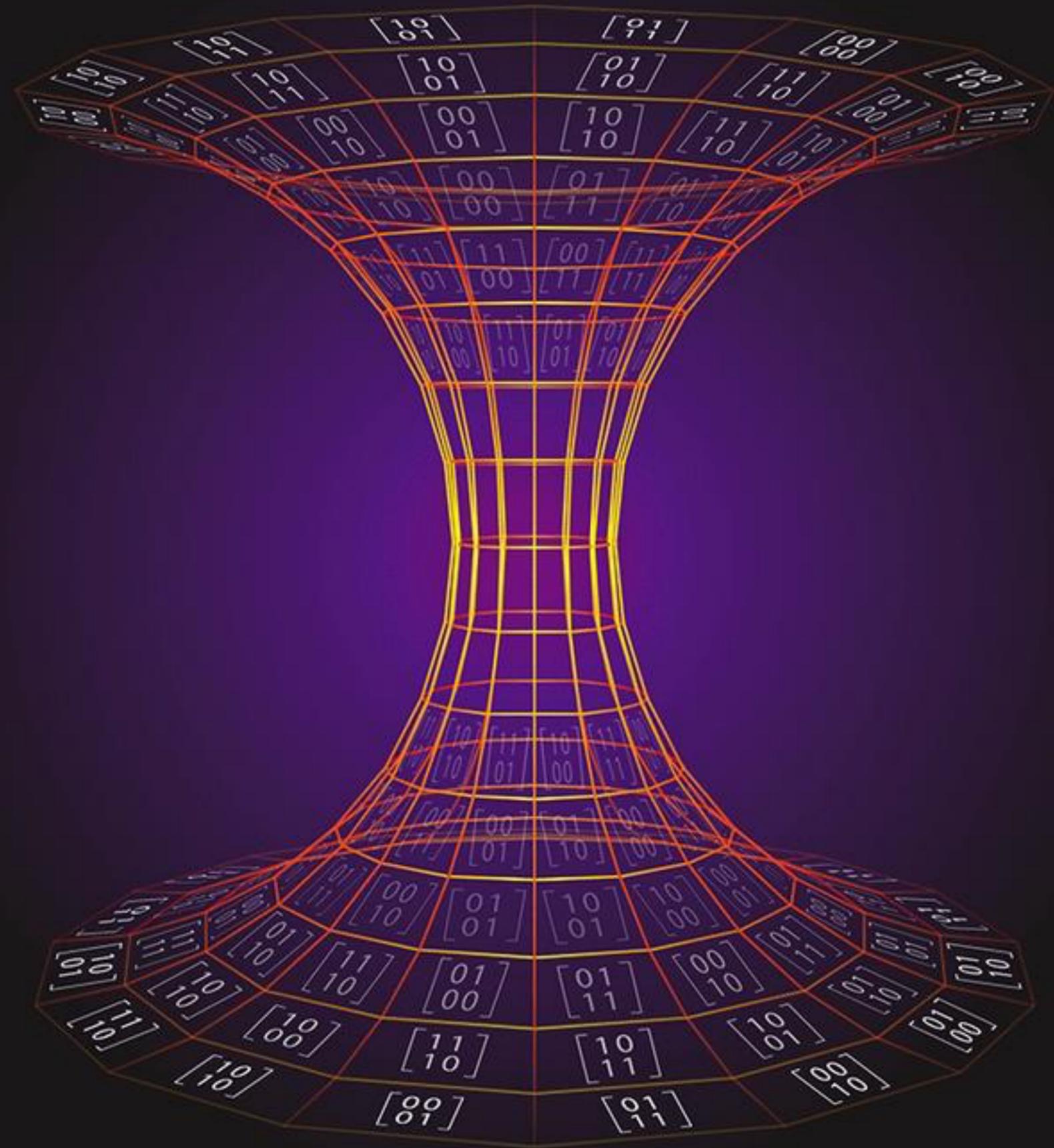
Outline

- Introduction 

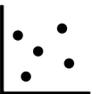
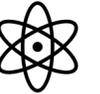


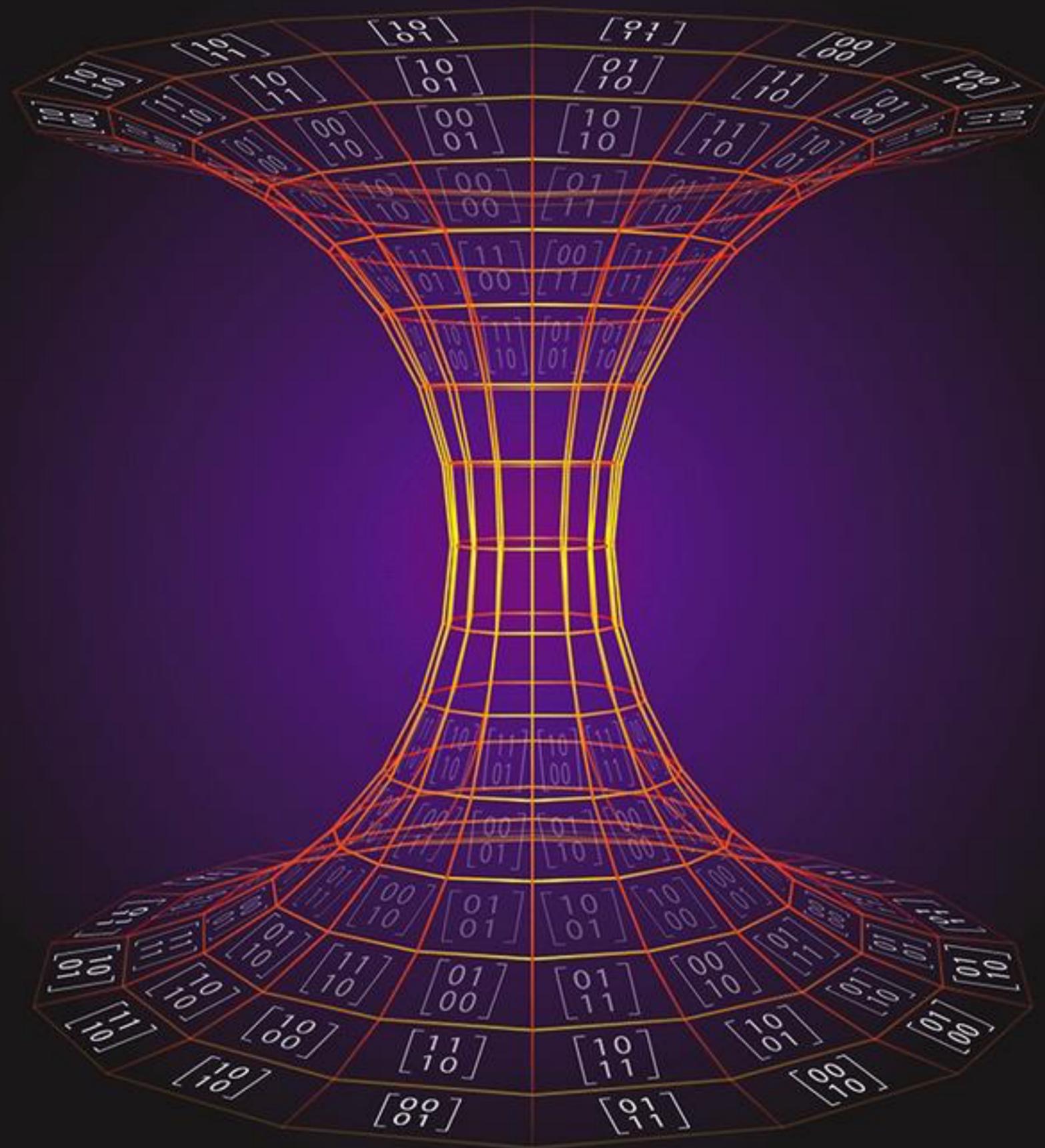
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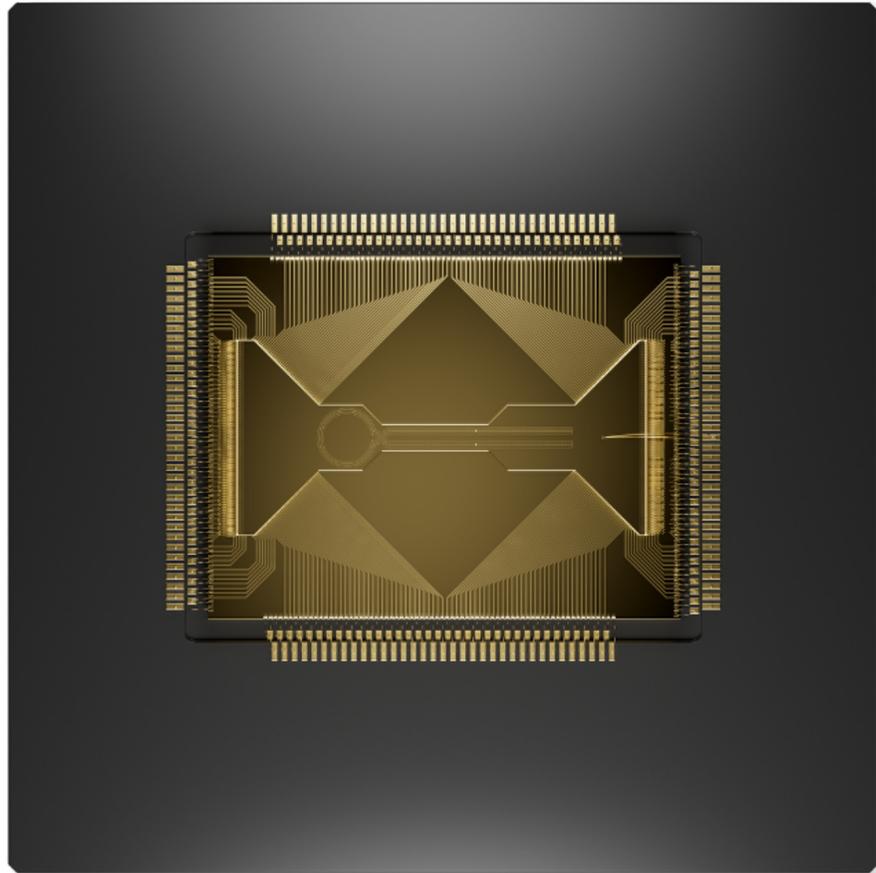
- Introduction 
- **Numerical techniques for matrix quantum mechanics:**
 - Path integral Monte Carlo 
 - Truncated Hamiltonian 
 - Quantum Computing 
 - Tensor Networks 

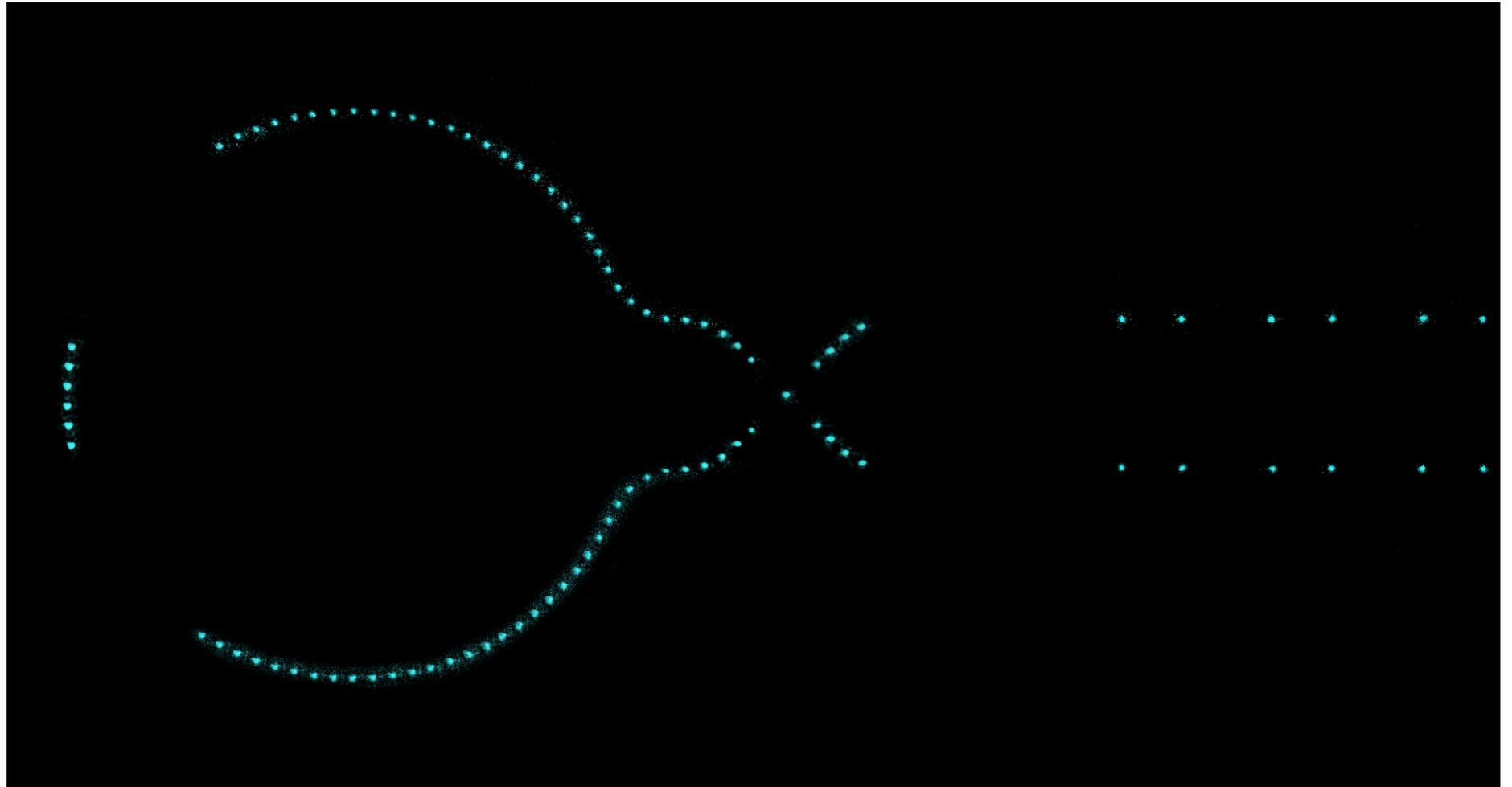
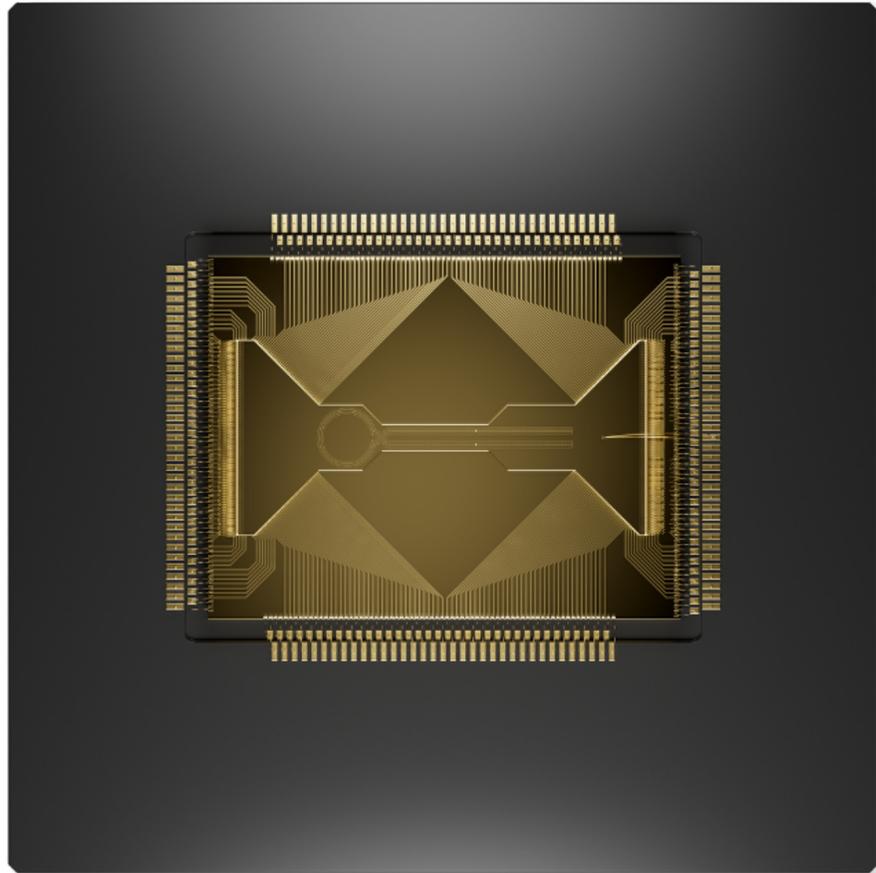


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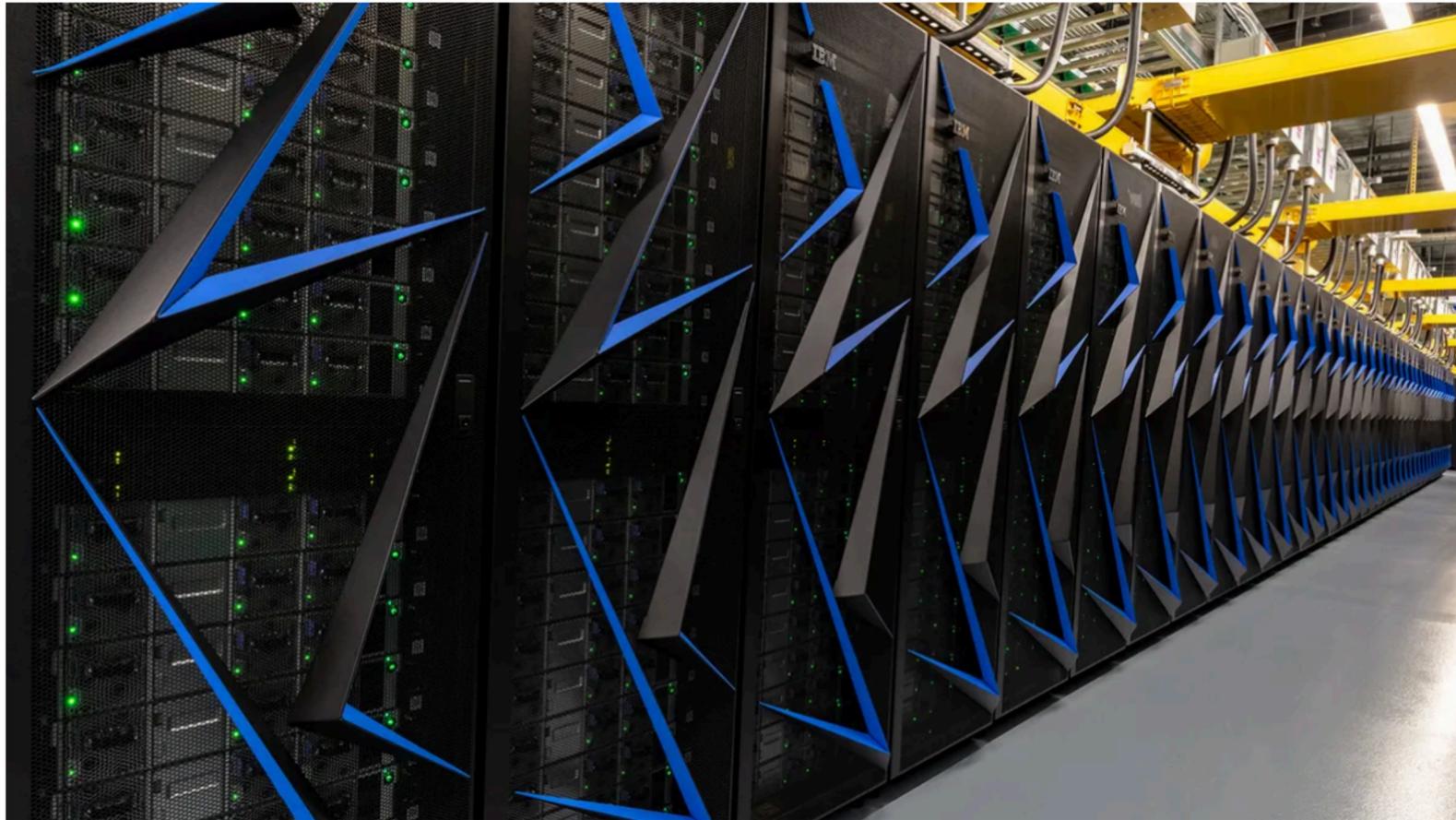
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- Conclusions and challenges







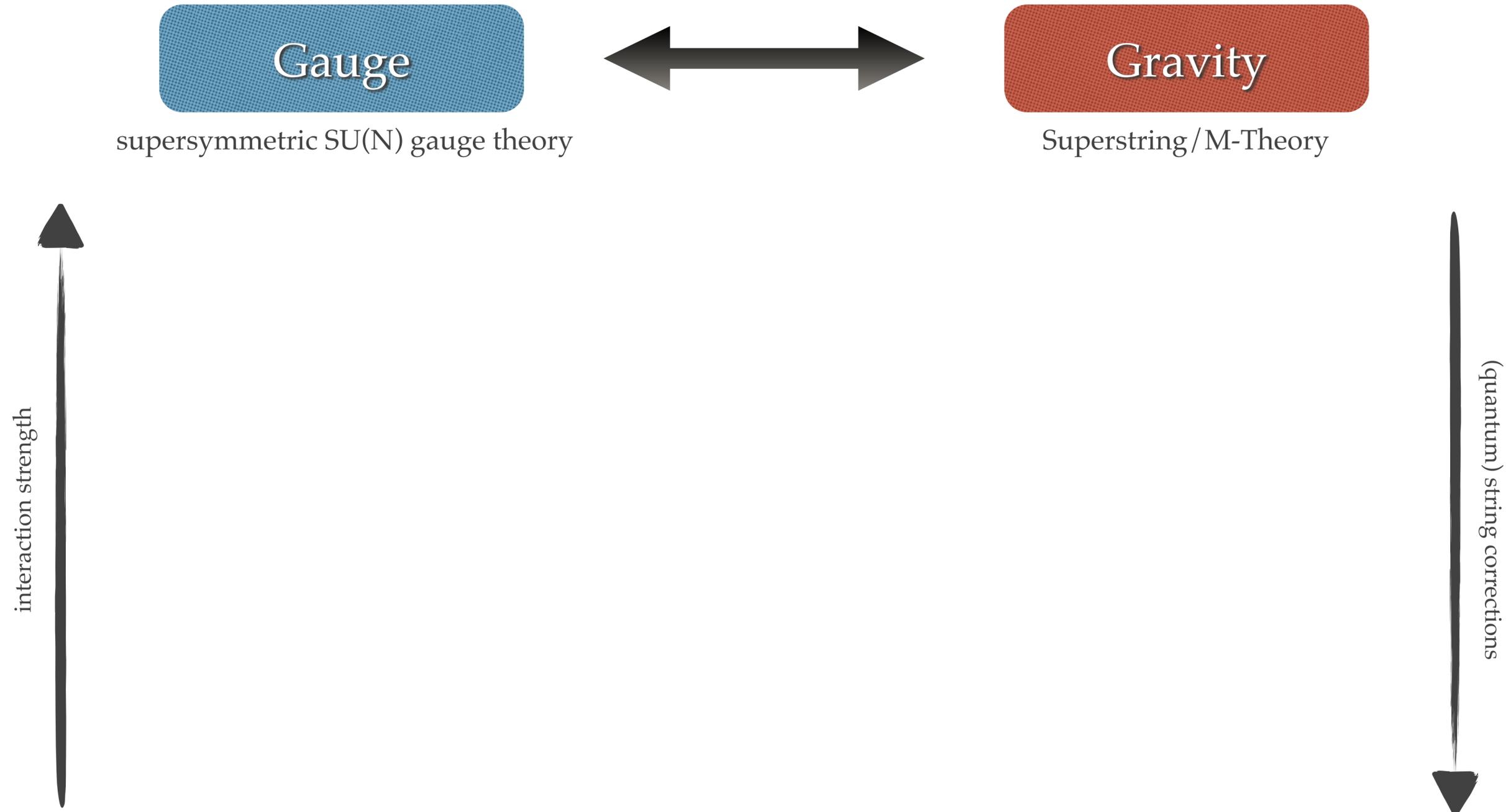
Summit @ ORNL



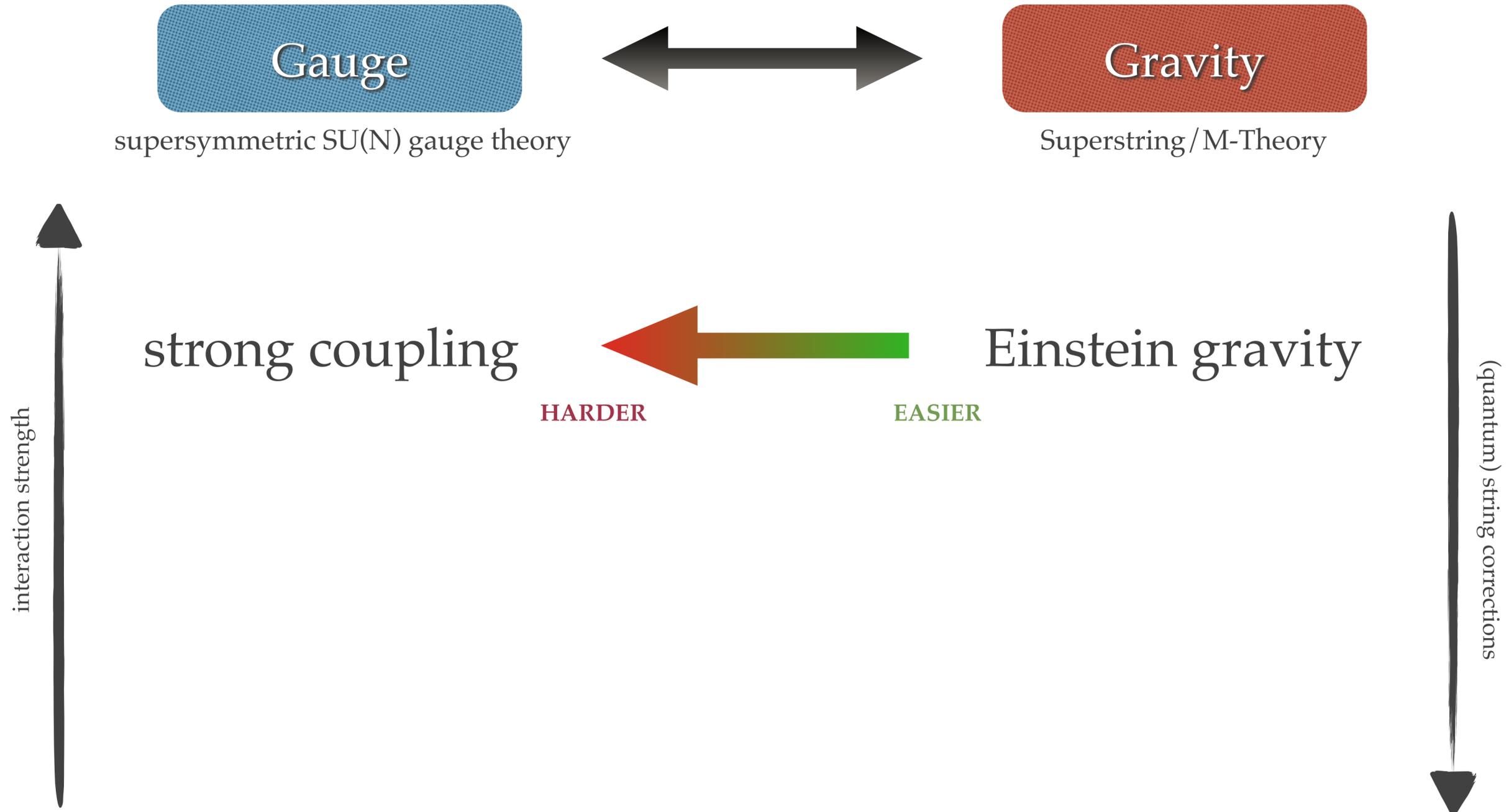
Fugaku @ R-CCS



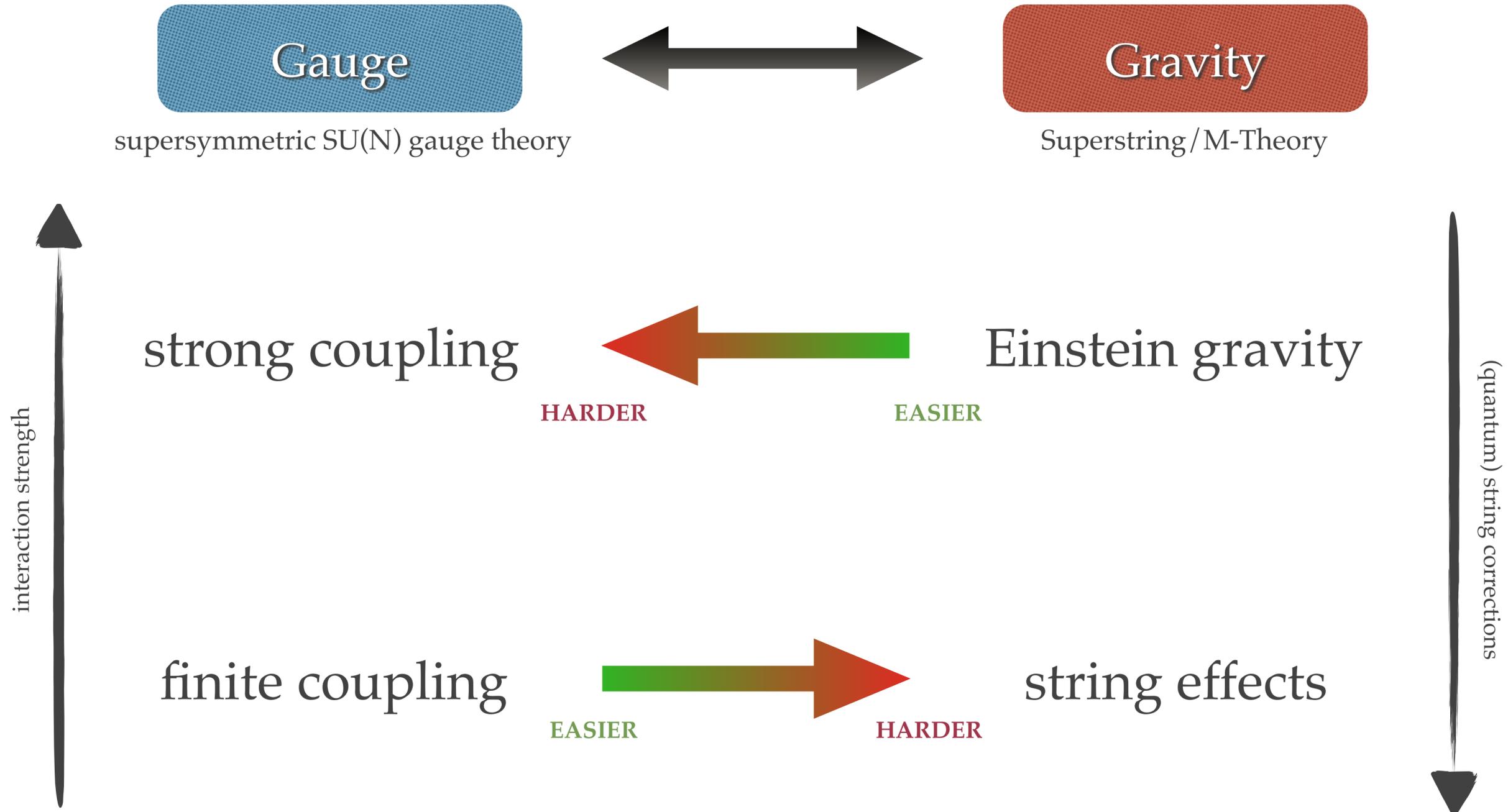
GAUGE/GRAVITY DUALITY



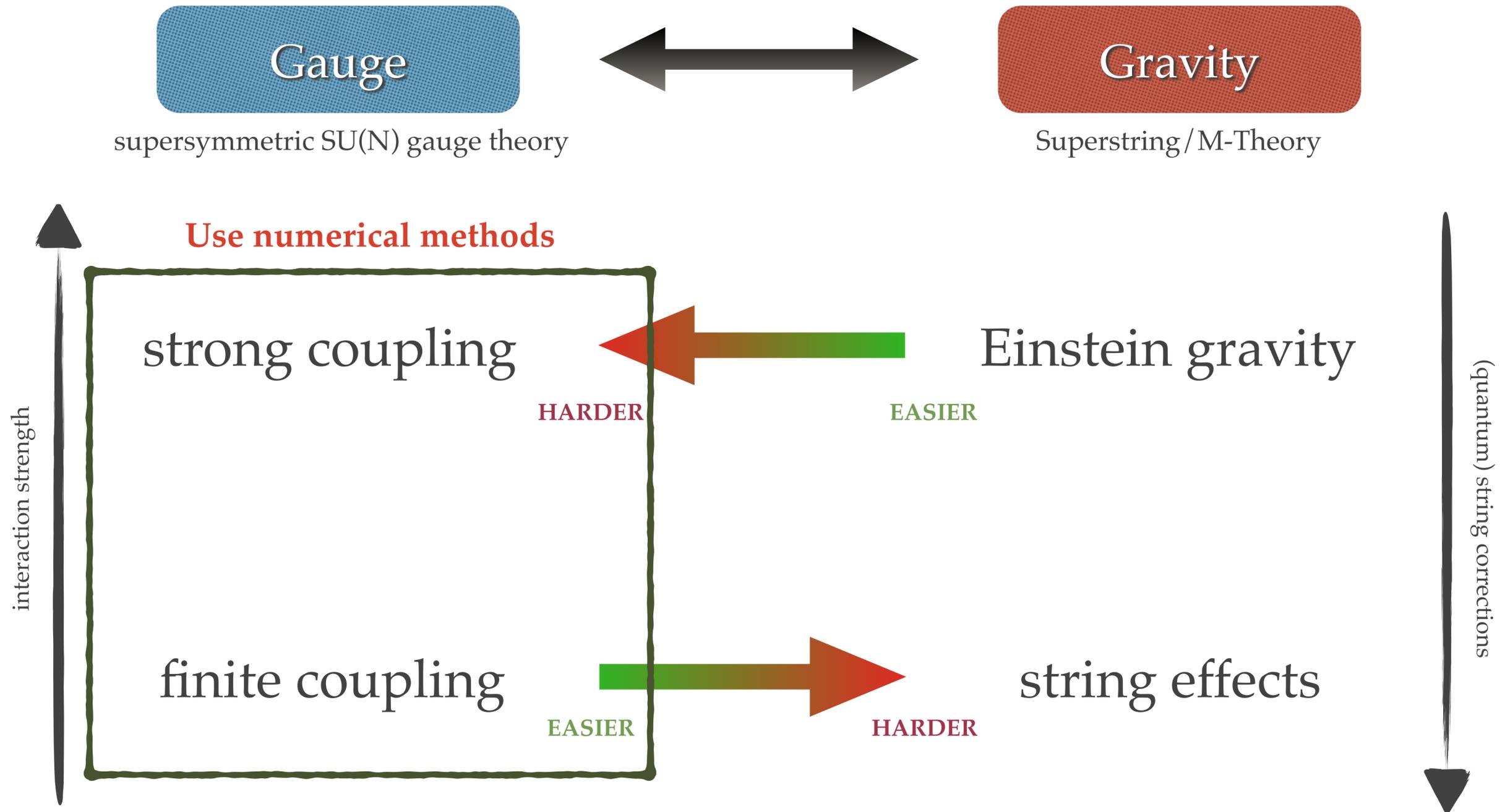
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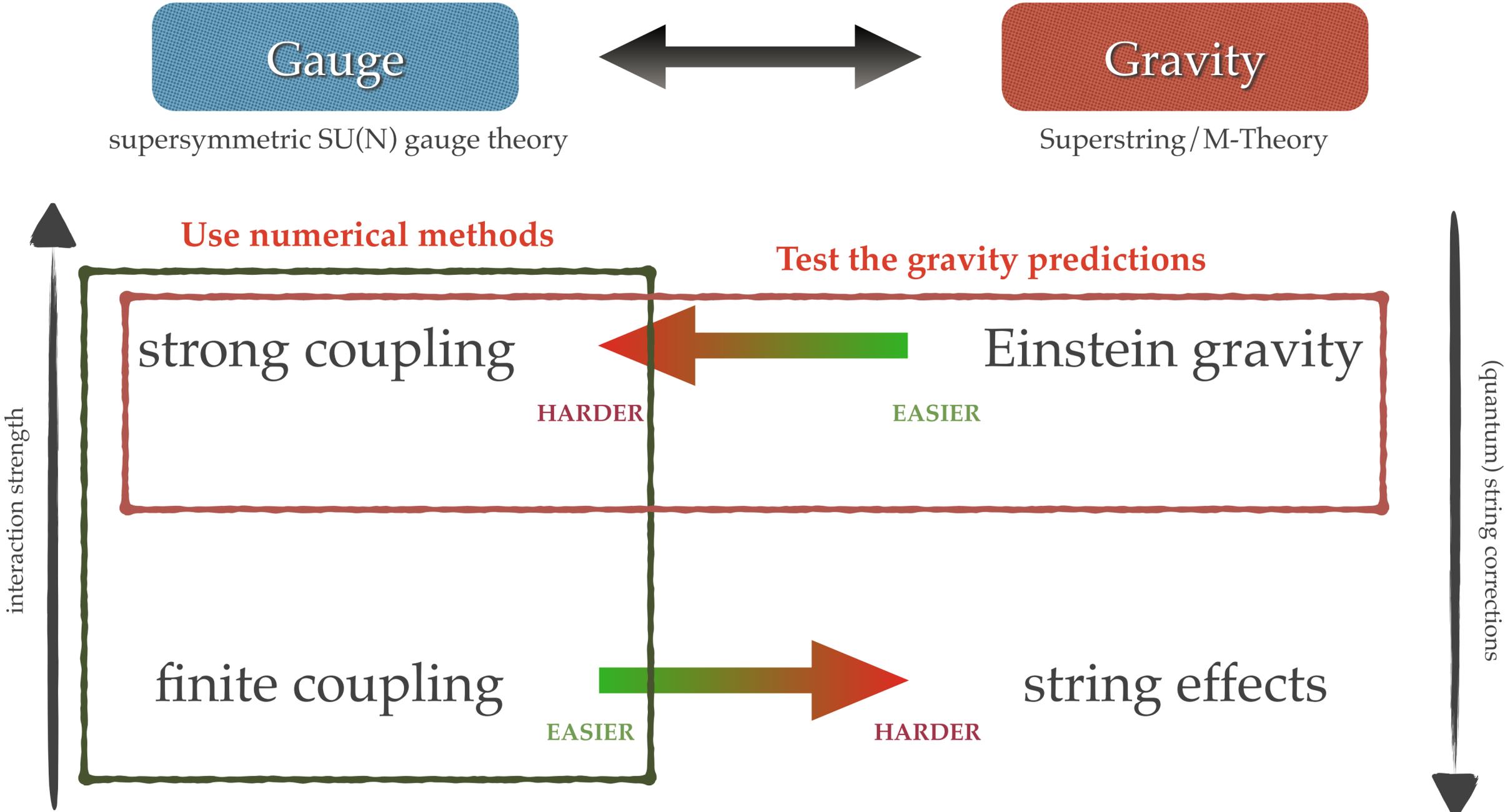
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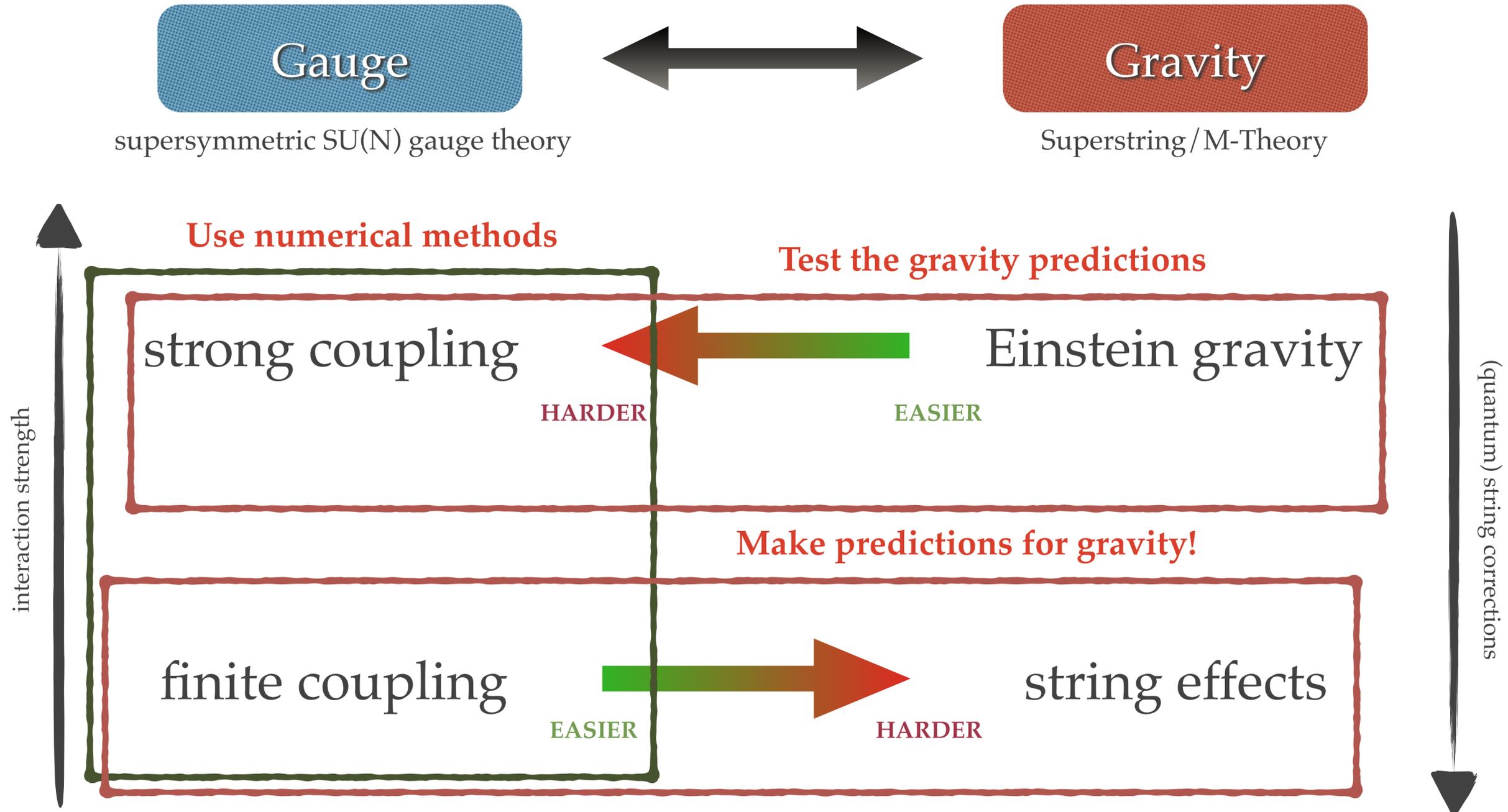
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Matrix Quantum Mechanics

Interpretation

$$L = \frac{1}{2g_{YM}^2} \text{Tr} \left\{ (D_t X_M)^2 + [X_M, X_{M'}]^2 + i\bar{\psi}^\alpha D_t \psi^\beta + \bar{\psi}^\alpha \gamma_{\alpha\beta}^M [X_M, \psi^\beta] \right\}$$

$$S = \int_0^{1/T} dt L$$

$$\lambda = g_{YM}^2 N \quad \text{'t Hooft coupling}$$

obtained from $\mathcal{N}=1$ U(N) SYM in (9+1)d via dimensional reduction to (0+1)d
or equivalently from $\mathcal{N}=4$ U(N) SYM in (3+1)d: it is maximally supersymmetric

$X_M, M = 1, \dots, 9$ ($N \times N$) \rightarrow hermitian scalars

$\psi^\alpha, \alpha = 1, \dots, 16$ ($N \times N$) \rightarrow adjoint fermions

$D_t \cdot = \partial_t \cdot - i[A_t, \cdot]$ \rightarrow gauge covariant derivative

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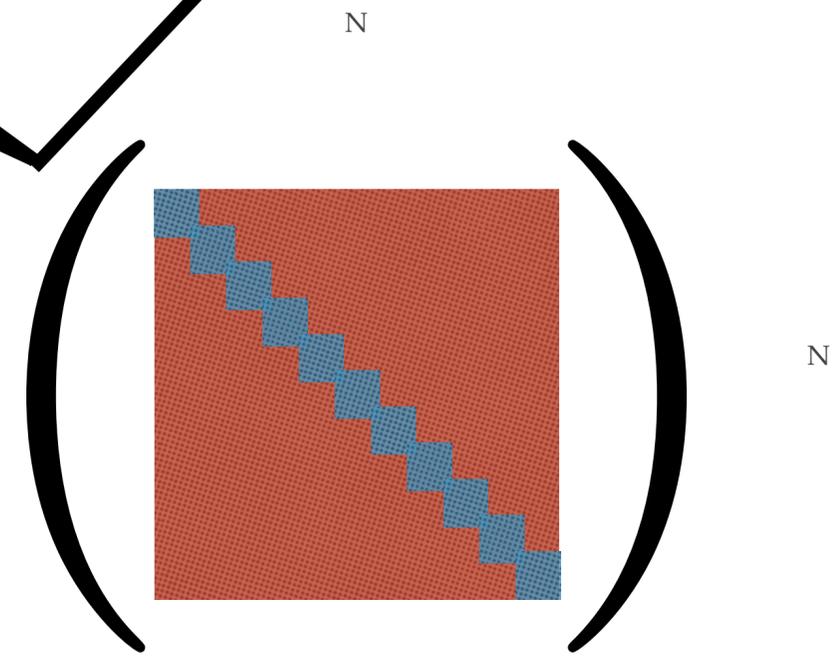
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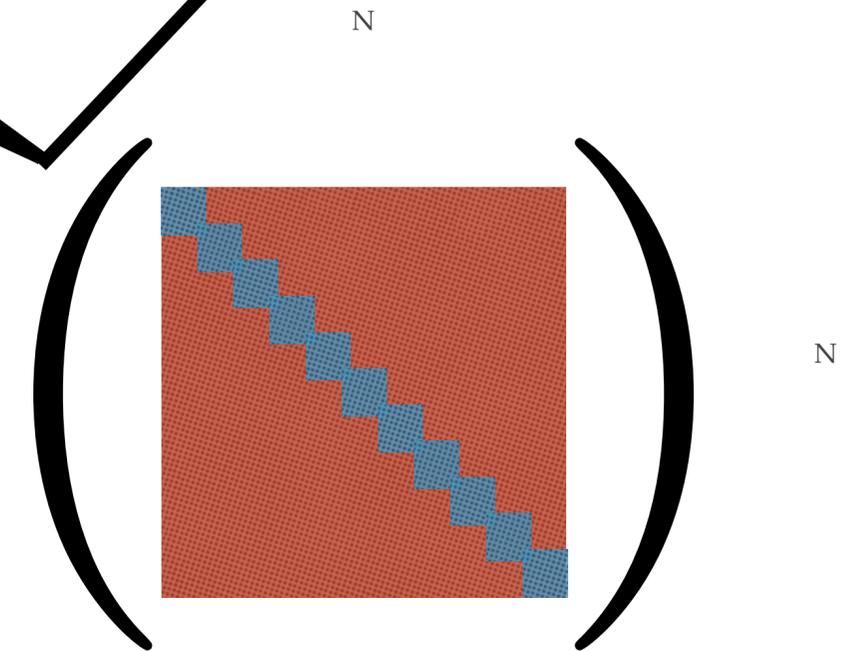
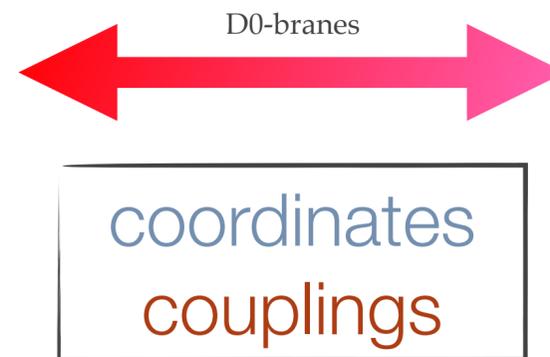
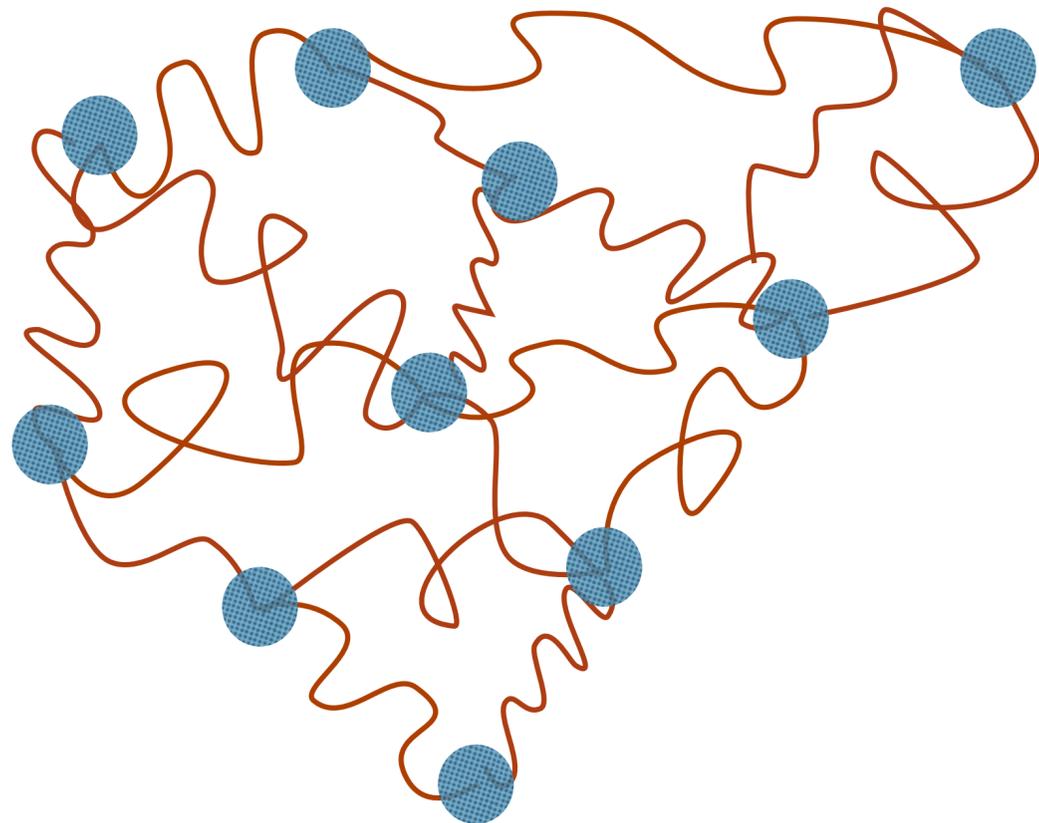
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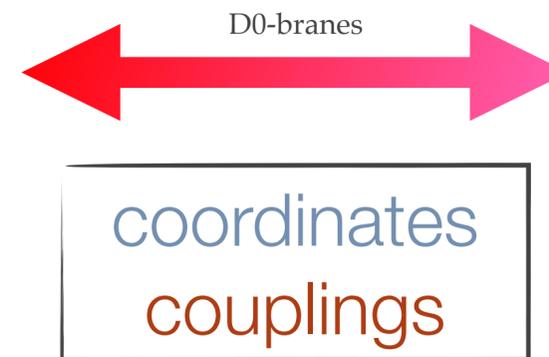
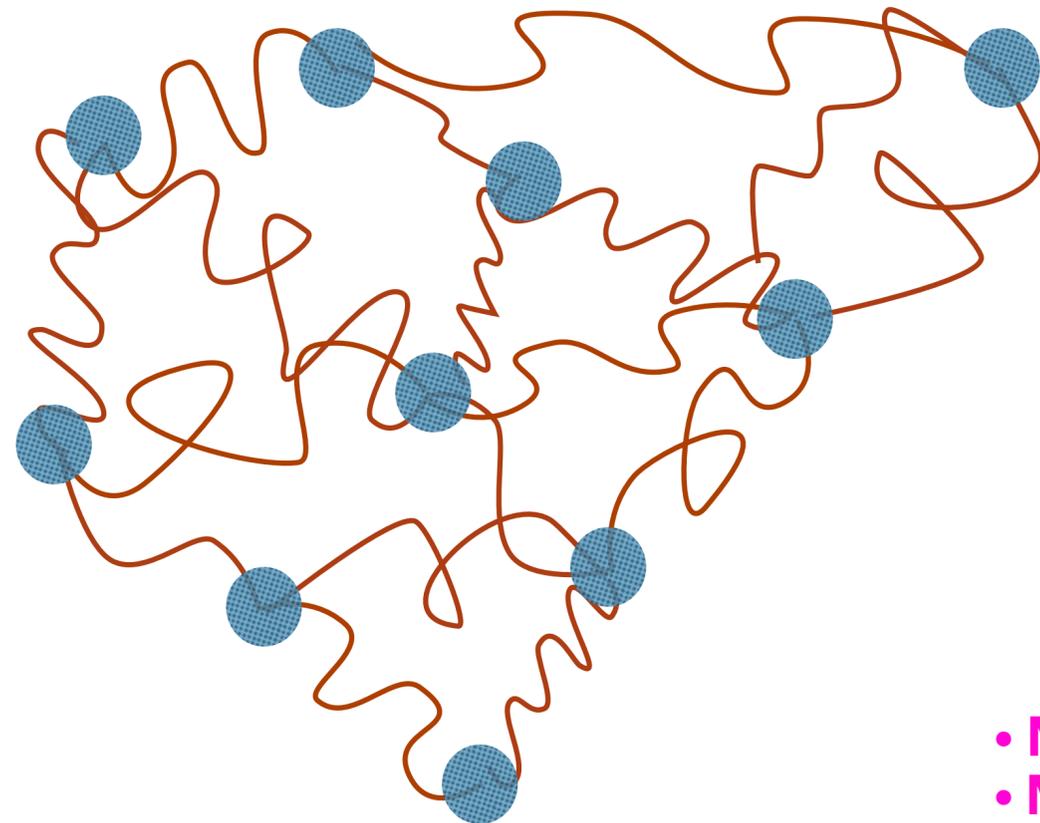
$$L = \frac{1}{2g_{YM}^2} \text{Tr} \left\{ (D_t X_M)^2 + [X_M, X_{M'}]^2 + i\bar{\psi}^\alpha D_t \psi^\beta + \bar{\psi}^\alpha \gamma_{\alpha\beta}^M [X_M, \psi^\beta] \right\}$$



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- Matrix regularization of 11D supermembrane [De Wit, Hope, Nicolai, 1988]
- Matrix model of M-theory [BFSS, 1996]
- Dual to type IIA black 0-brane near 't Hooft limit [IMSY, 1998]

Previous results

A long history

[Agnastopoulos et al. arxiv:0707:4454]

[Catteral, Wiseman arxiv:0803.4273]

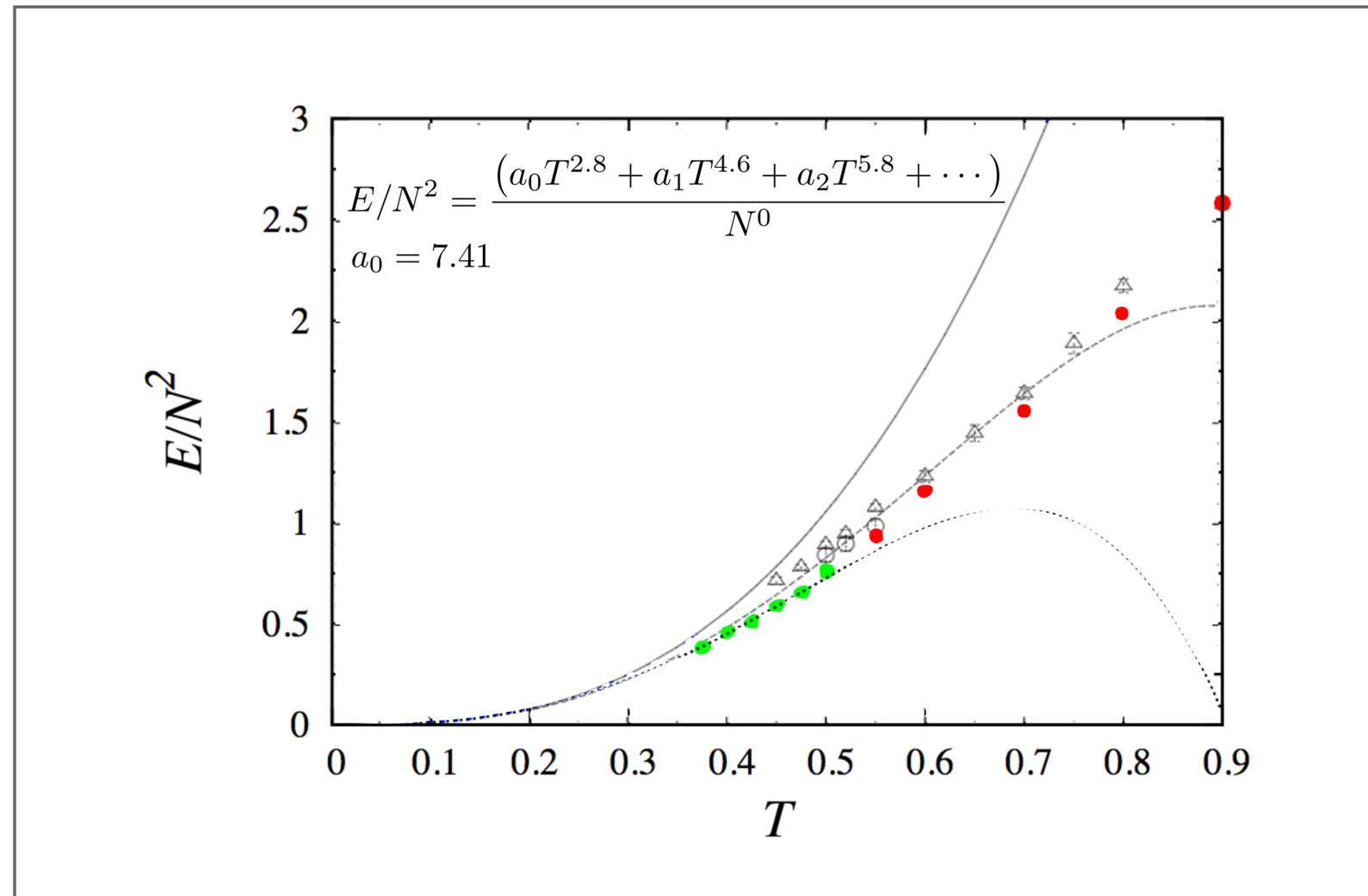
[Hanada et al. arxiv:0811.3102]

[Hanada et al. arxiv:1311.5603]

[Kadoh, Kamata arxiv:1503.08499]

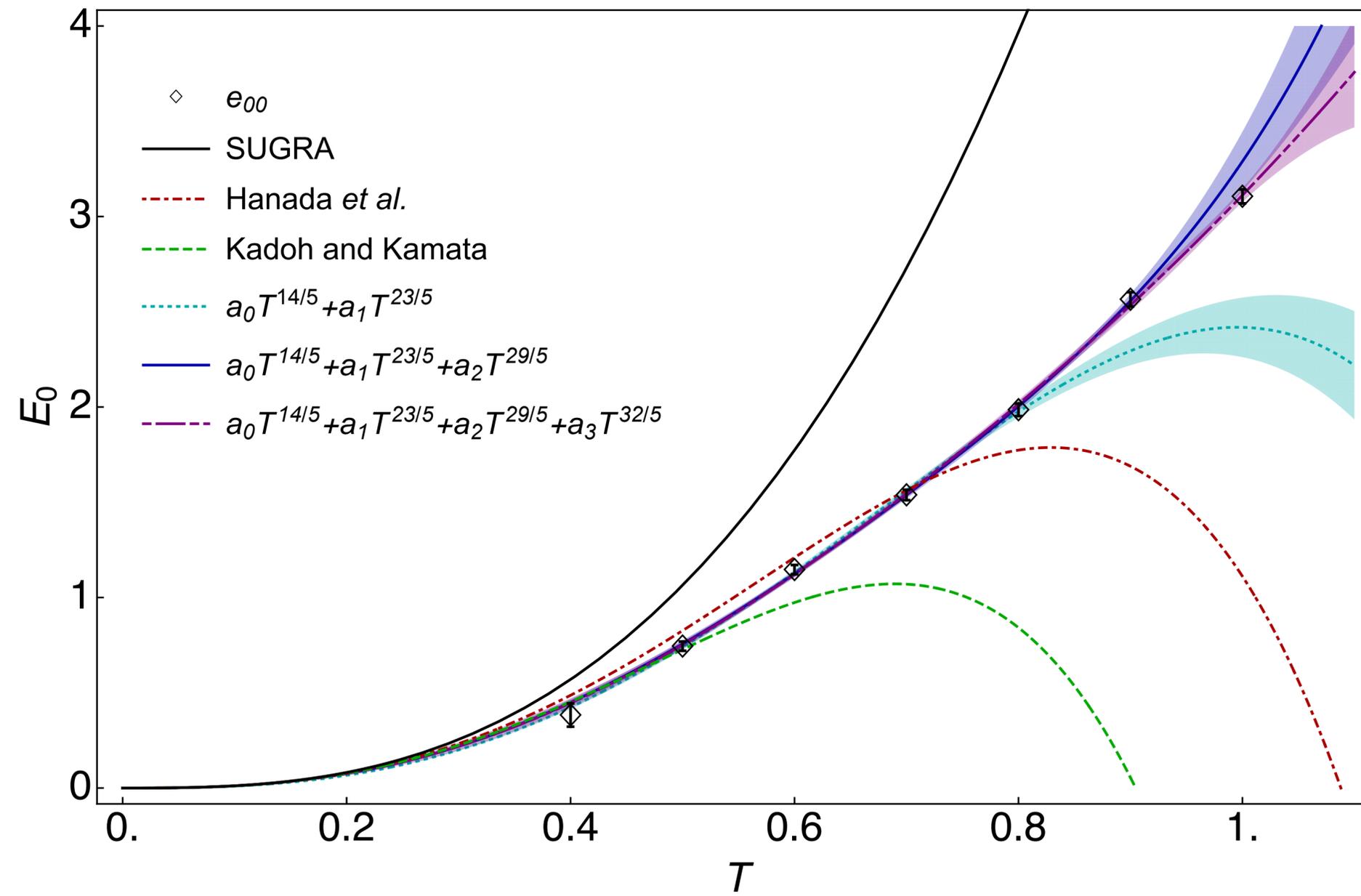
[Filev, O'Connor arxiv:1506.01366]

- * Different cutoff regulator
- * Different discretizations
- * **Finite N**
- * Finite cutoff
- * Qualitative agreement
- * Not enough precision for quantitative predictions



TEST OF DUALITY IN BFSS

$$\frac{E}{N^2} = a_0 T^{2.8} + a_1 T^{4.6} + a_2 T^{5.8}$$

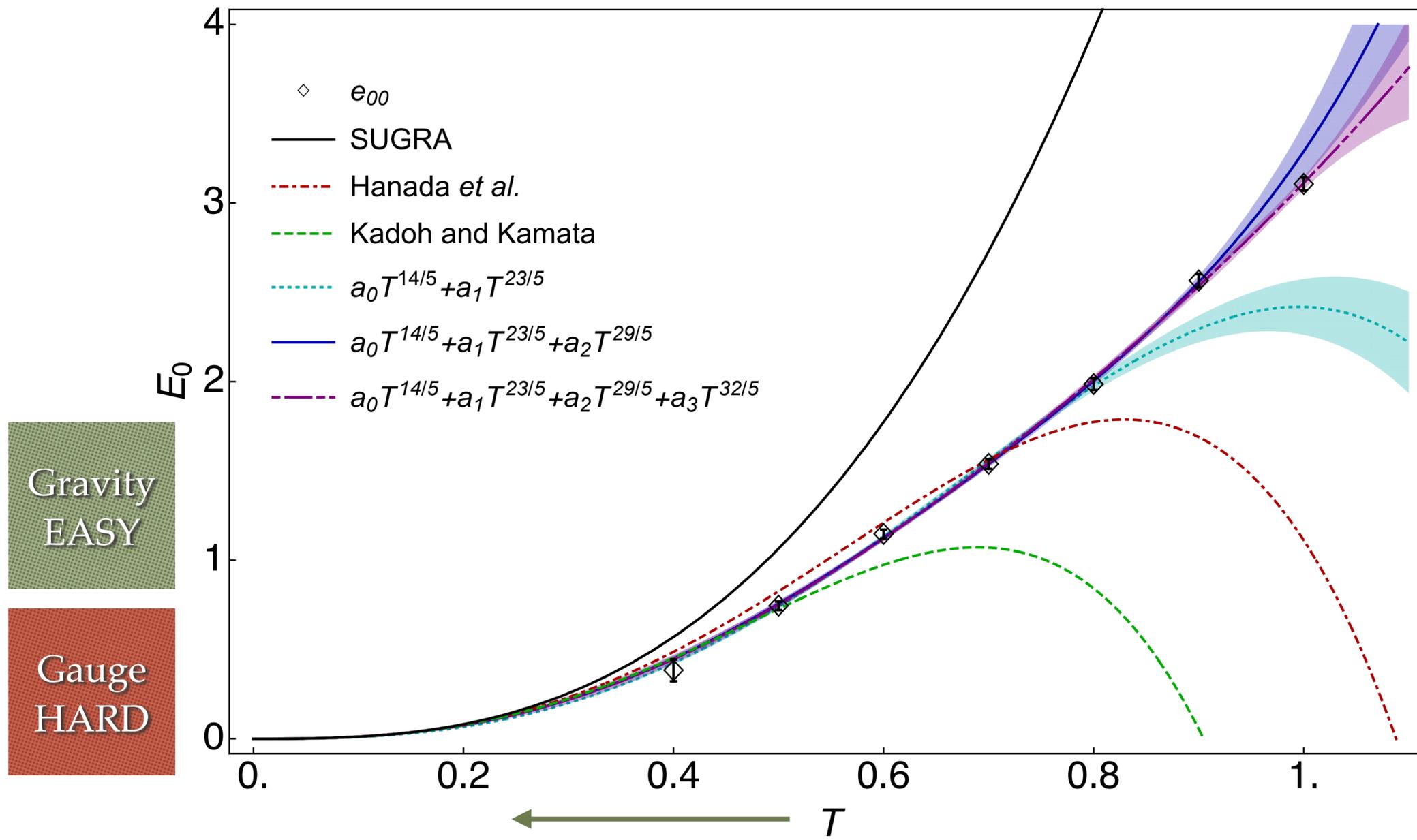


TEST OF DUALITY IN BFSS

$$\frac{E}{N^2} = a_0 T^{2.8} + a_1 T^{4.6} + a_2 T^{5.8}$$

$$a_0 = 7.41$$

Supergravity



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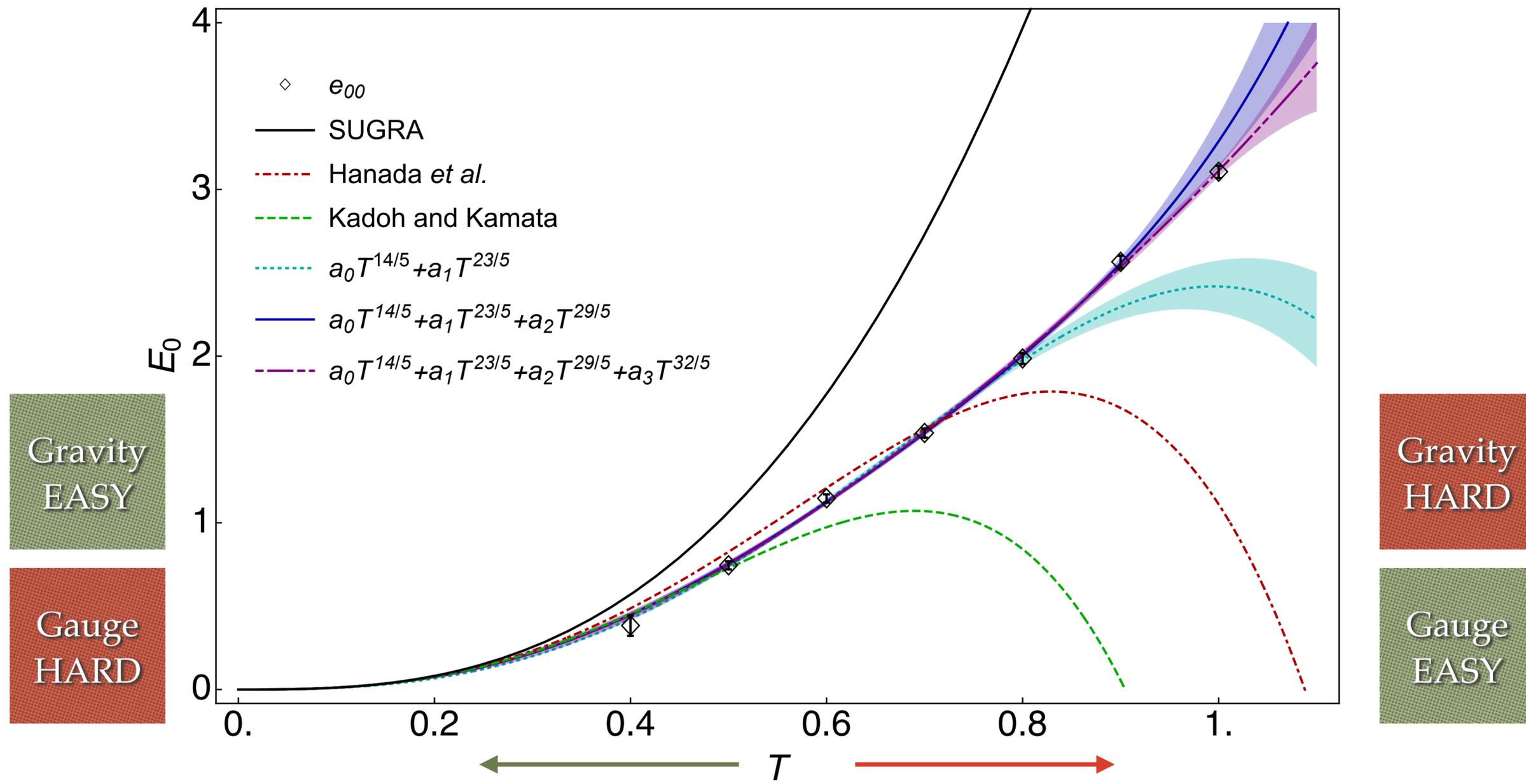
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$$a_1 = ? \quad a_2 = ?$$

String effects



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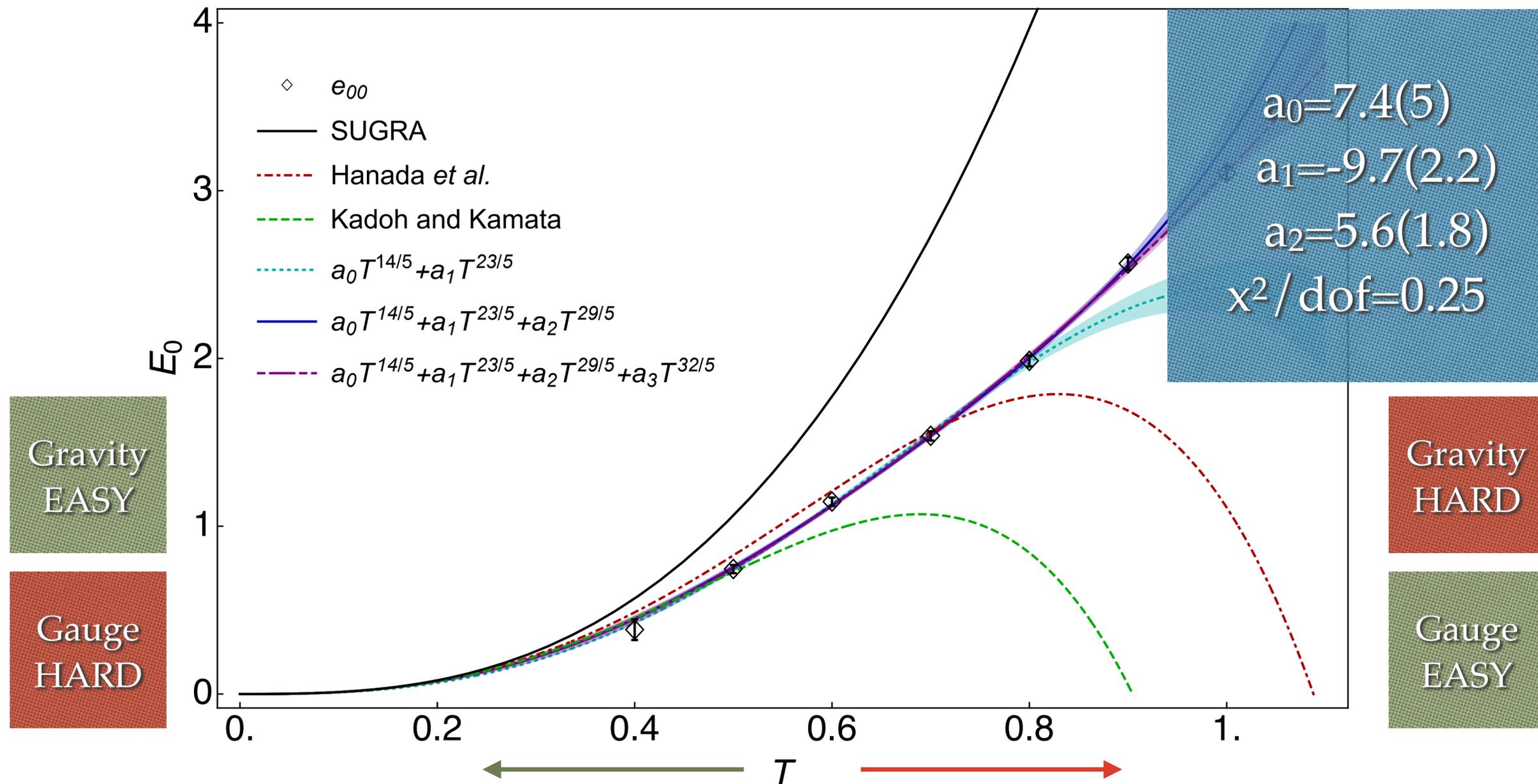
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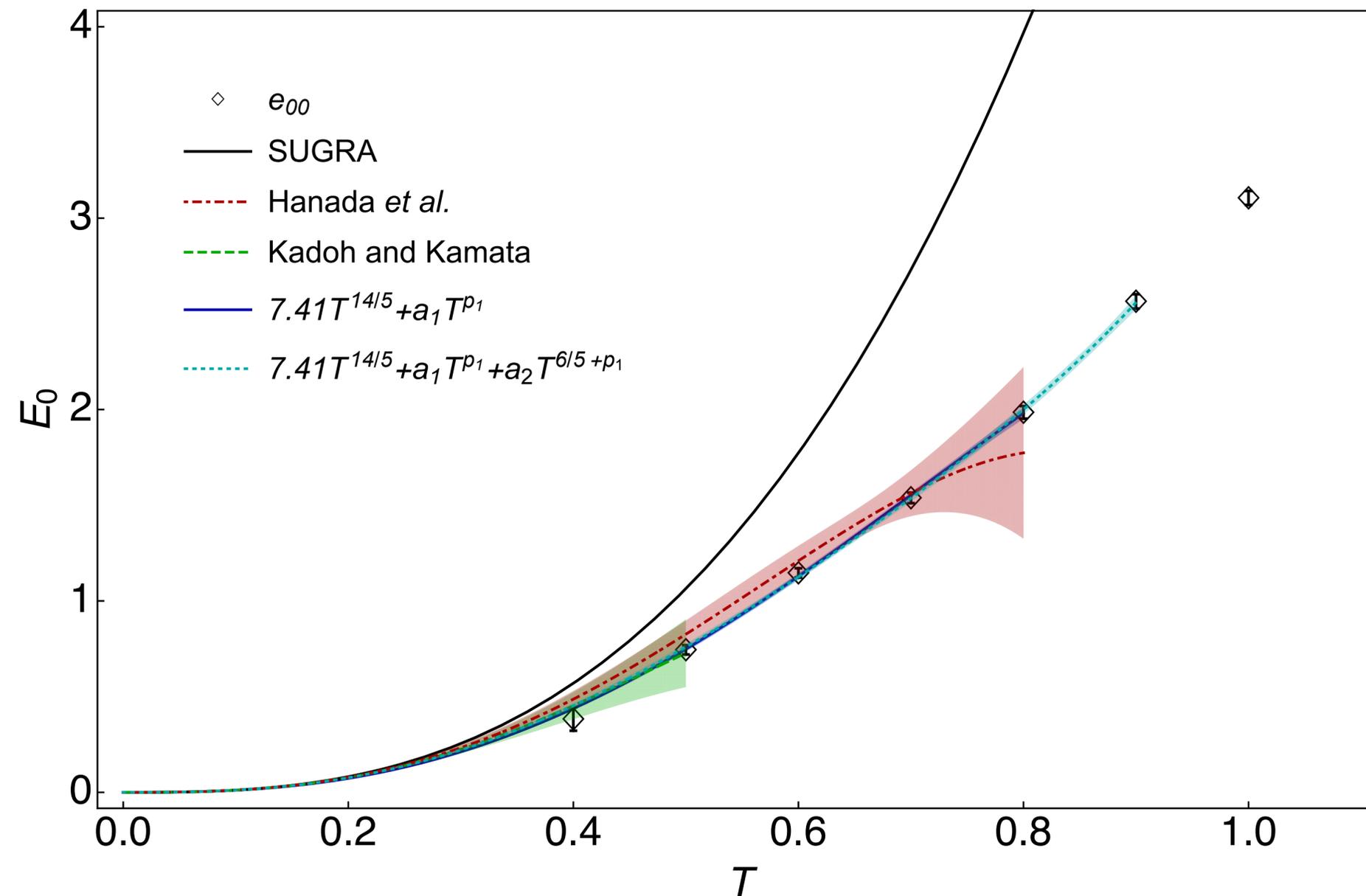
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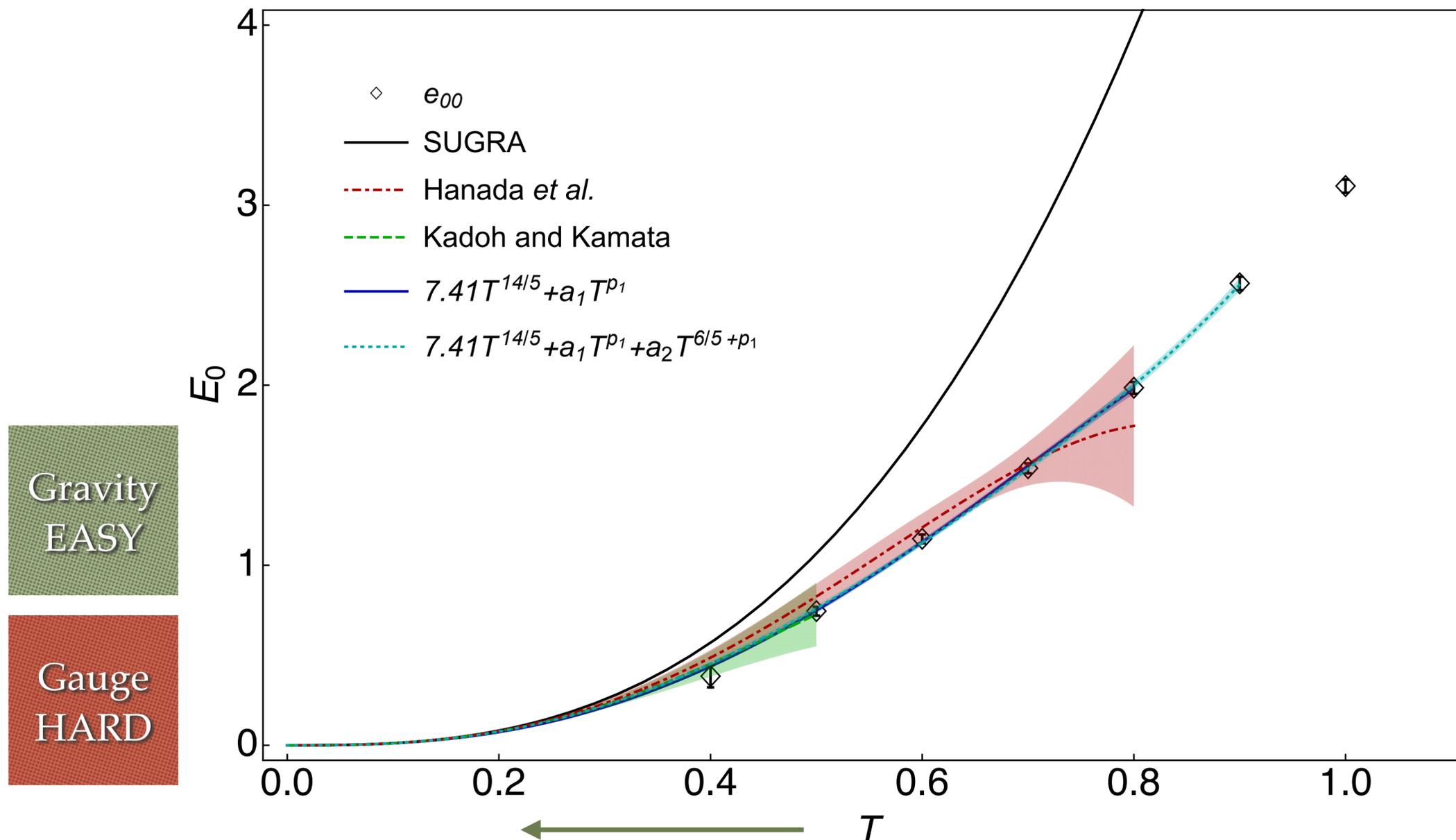
TEST STRING EFFECTS

$$\frac{E}{N^2} = a_0 T^{2.8} + a_1 T^{p_1} + a_2 T^{p_1+6/5}$$



TEST STRING EFFECTS

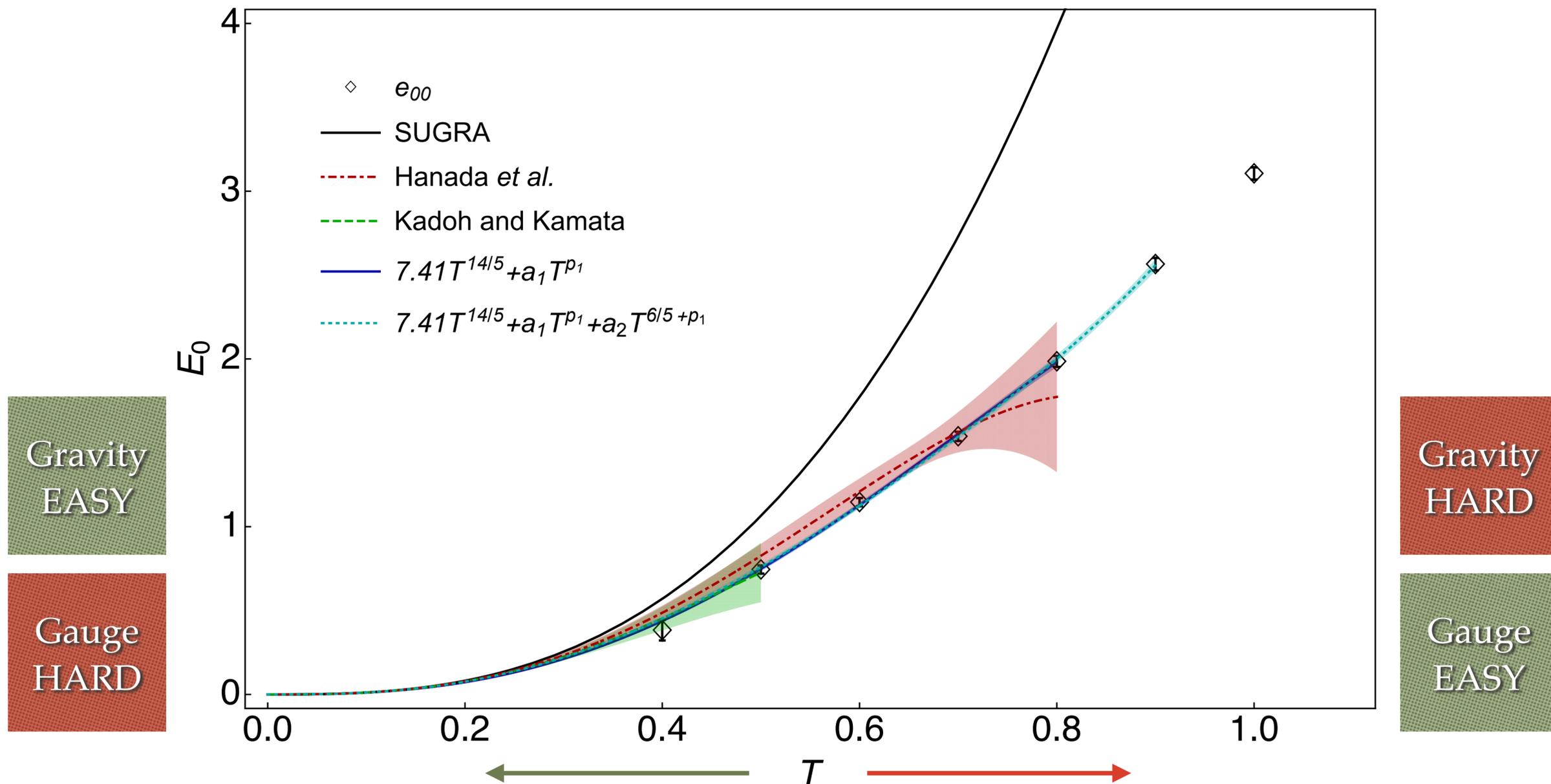
$$\frac{E}{N^2} = a_0 T^{2.8} + a_1 T^{p_1} + a_2 T^{p_1+6/5} \quad \longrightarrow \quad a_0 = 7.41 \quad \text{Supergravity}$$



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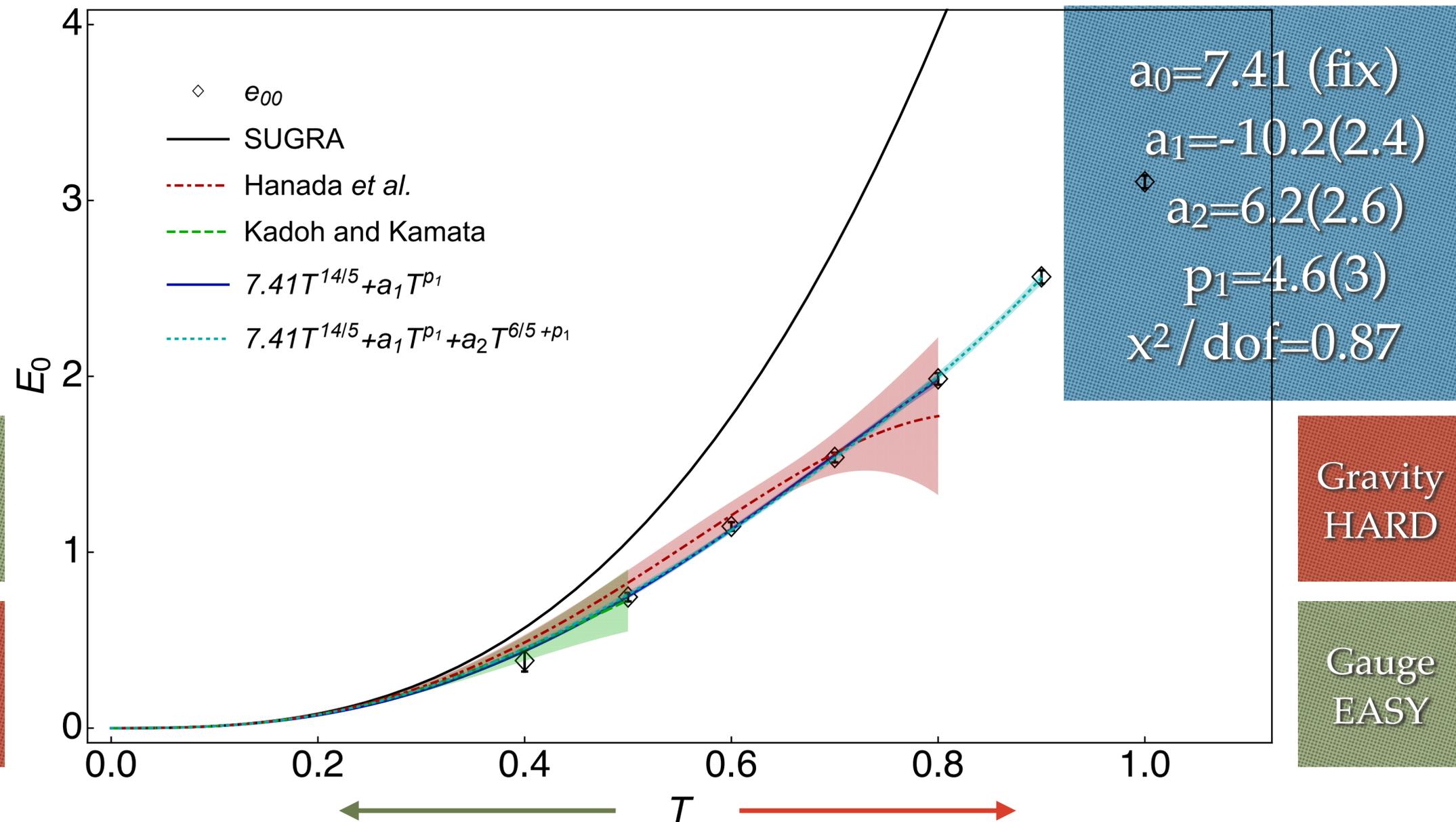


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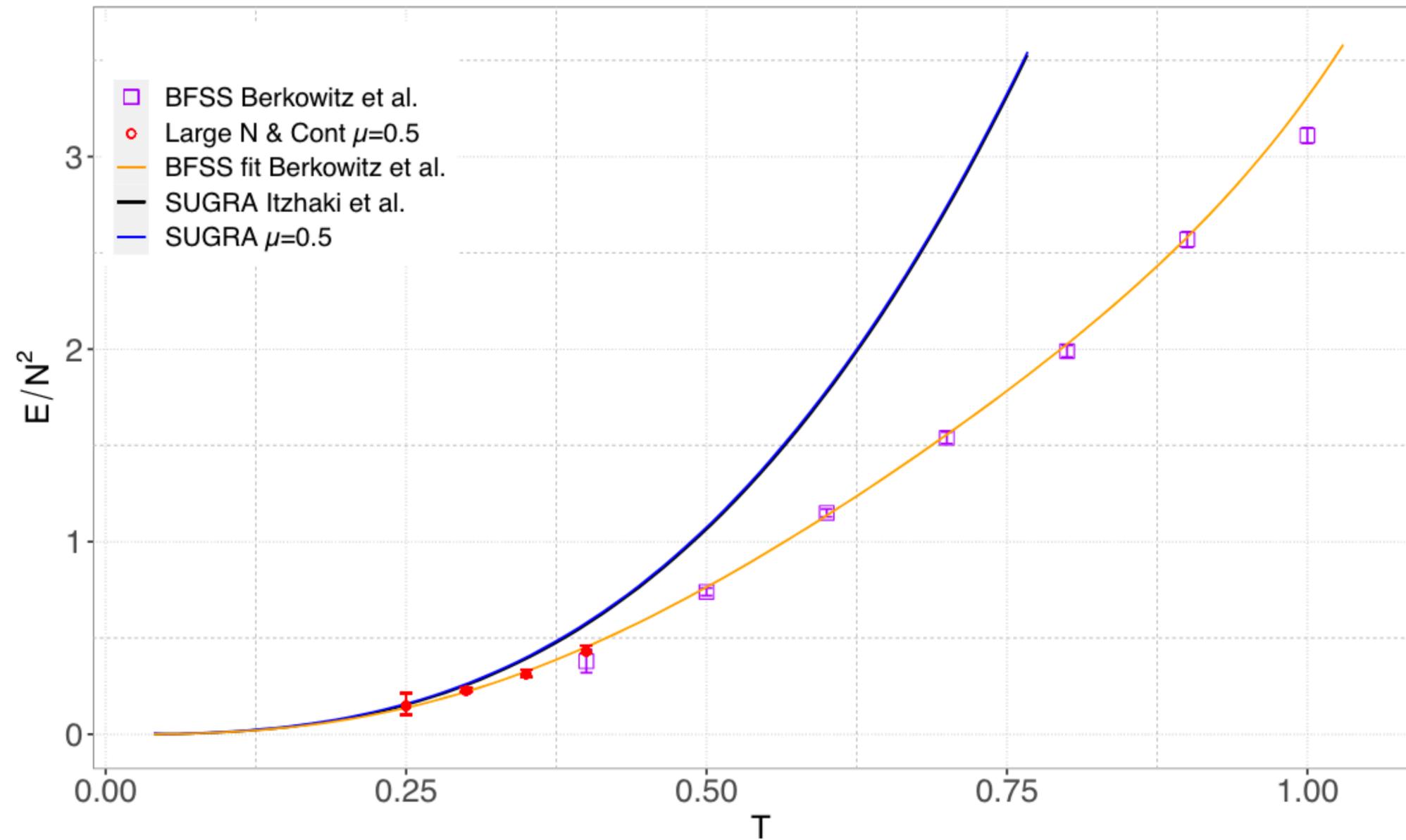
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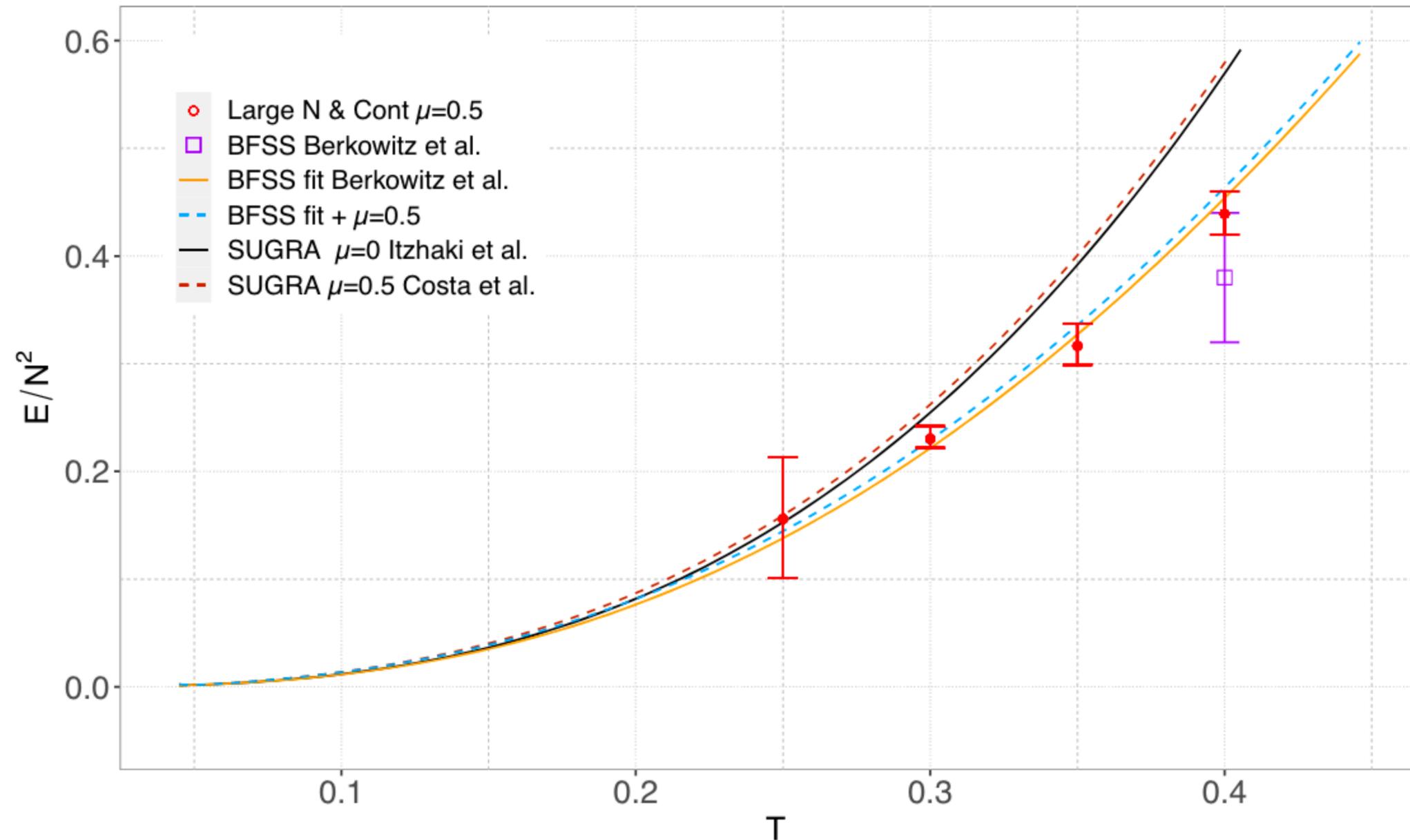
State-of-the-art results

6 years later...



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6 years later...



New Directions

★HPC simulations using Path Integral-based methods on discrete grids: Monte Carlo sampling of quantum mechanical paths.

→ Challenges:

- ▶ Sign problem → paths are not weighted with a standard probability distribution (*i.e.* chem. pot., time evolution)
- ▶ Wave function → physics applications require knowledge of entanglement (*i.e.* information paradox, geometry)



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Quantum Computers
→ Represent the entire wave function using quantum bits (qubits)



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Quantum Computers

→ Represent the entire wave function using quantum bits (qubits)

Deep Learning

→ Represent the real and imaginary part of the complex wave function using generative models

Quantum Computing

arxiv:2303.11534

- Juan Maldacena is not immune to the quantum “hype” 😊
- He estimates the number of qubits and gates to describe the evolution of a black hole:

$$n_q \sim N^2 \left[8 + 9 \log_2 \left(\frac{\lambda^{1/3}}{\omega} \right) \right] \sim 7,000, \quad \text{for } N = 16, \quad \frac{\lambda^{1/3}}{\omega} \sim 4$$

A simple quantum system that describes a black hole

Juan Maldacena

Institute for Advanced Study, Princeton, NJ 08540, USA

Abstract

During the past decades, theorists have been studying quantum mechanical systems that are believed to describe black holes. We review one of the simplest examples. It involves a collection of interacting oscillators and Majorana fermions. It is conjectured to describe a black hole in an emergent universe governed by Einstein equations. Based on previous numerical computations, we make an estimate of the necessary number of qubits necessary to see some black hole features.

Numerical Methods for MQM

Prototypes

Bosonic Model

$$\hat{H}_{B2} = \text{Tr} \left(\frac{1}{2} \hat{P}_I^2 + \frac{m^2}{2} \hat{X}_I^2 - \frac{g^2}{4} [\hat{X}_I, \hat{X}_J]^2 \right)$$

Physical states are invariant under SU(N) Gauge Symmetry

Supersymmetric Model

$$\begin{aligned} \hat{H} = & \hat{H}_{B2} + \\ & + \text{Tr} \left(\frac{g}{2} \hat{\xi} \left[-\hat{X}_1 - i\hat{X}_2, \hat{\xi} \right] + \frac{g}{2} \hat{\xi}^\dagger \left[-\hat{X}_1 + i\hat{X}_2, \hat{\xi}^\dagger \right] + \frac{3\mu}{2} \hat{\xi}^\dagger \hat{\xi} \right) \\ & - (N^2 - 1) \mu \end{aligned}$$

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$$\hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

\hat{X}_I^α → bosonic degrees of freedom
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Supersymmetric Model

$$\hat{H} = \hat{H}_{B2} + \text{Tr} \left(\underbrace{\frac{g}{2} \hat{\xi} [-\hat{X}_1 - i\hat{X}_2, \hat{\xi}] + \frac{g}{2} \hat{\xi}^\dagger [-\hat{X}_1 + i\hat{X}_2, \hat{\xi}^\dagger]}_{\text{FERM.-BOS. INTERACTION}} + \frac{3\mu}{2} \hat{\xi}^\dagger \hat{\xi} \right) - (N^2 - 1) \mu$$

$$\hat{\xi} = \sum_{\alpha=1}^{N^2-1} \hat{\xi}^\alpha \tau_\alpha \quad \hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

$\hat{\xi}^\alpha$ → fermionic degrees of freedom

Numerical Methods for MQM

Prototypes

Bosonic Model

$$\hat{H}_{B2} = \text{Tr} \left(\underbrace{\frac{1}{2} \hat{P}_I^2 + \frac{m^2}{2} \hat{X}_I^2}_{\text{FREE}} - \underbrace{\frac{g^2}{4} [\hat{X}_I, \hat{X}_J]^2}_{\text{BOS. INTERACTION}} \right)$$

Physical states are invariant under SU(N) Gauge Symmetry

$$\hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

\hat{X}_I^α → bosonic degrees of freedom
 τ_α → generators of SU(N) group

Supersymmetric Model

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$$- (N^2 - 1) \mu$$

ZERO EN.

$$\hat{\xi} = \sum_{\alpha=1}^{N^2-1} \hat{\xi}^\alpha \tau_\alpha \quad \hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

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Numerical Methods for MQM

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Bosonic Model

Supersymmetric Model

$$\hat{H}_{B2} = \text{Tr} \left(\underbrace{\frac{1}{2} \hat{P}_I^2 + \frac{m^2}{2} \hat{X}_I^2}_{\text{FREE}} \underbrace{- \frac{g^2}{4} [\hat{X}_I, \hat{X}_J]^2}_{\text{BOS. INTERACTION}} \right) \quad \Bigg| \quad \hat{H} = \hat{H}_{B2} + \underbrace{\left(\hat{X}_1 - i\hat{X}_2, \hat{\xi} \right) + \frac{g}{2} \hat{\xi}^\dagger \left[-\hat{X}_1 + i\hat{X}_2, \hat{\xi}^\dagger \right] + \frac{3\mu}{2} \hat{\xi}^\dagger \hat{\xi}}_{\text{FERM.-BOS. INTERACTION}}$$

Physical states are invariant under SU(N) Gauge

Challenge: numerical methods on quantum computers have a limited number of qubits!

$$\hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

$$\hat{\xi} = \sum_{\alpha=1}^{N^2-1} \hat{\xi}^\alpha \tau_\alpha \quad \hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

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Numerical Methods for MQM

Prototype: small-scale system

Bosonic Model

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Numerical Methods for MQM

Prototype: small-scale system

Bosonic Model

Example: N=2, D=2

$$\hat{H}_B = \text{Tr} \left(\underbrace{\left(\frac{1}{2} \hat{P}_I^2 + \frac{m^2}{2} \hat{X}_I^2 \right)}_{\text{FREE}} \underbrace{- \frac{g^2}{4} \left[\hat{X}_I, \hat{X}_J \right]^2}_{\text{BOS. INTERACTION}} \right)$$

$$\hat{H}_B = \sum_{\alpha, I} \left(\frac{1}{2} \hat{P}_{I\alpha}^2 + \frac{m^2}{2} \hat{X}_{I\alpha}^2 \right) + \frac{g^2}{4} \sum_{\gamma, I, J} \left(\sum_{\alpha, \beta} f_{\alpha\beta\gamma} \hat{X}_I^\alpha \hat{X}_J^\beta \right)^2 \quad I = 1, 2 \quad \alpha = 1, 2, 3$$

Physical states are invariant under SU(N) Gauge Symmetry

$$\hat{X}_I = \sum_{\alpha=1}^{N^2-1} \hat{X}_I^\alpha \tau_\alpha \quad I = 1, \dots, D$$

1	2	3	I = 1
4	5	6	I = 2

\hat{X}_I^α → bosonic degrees of freedom
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Numerical Methods for MQM

Prototype: small-scale system

Bosonic Model

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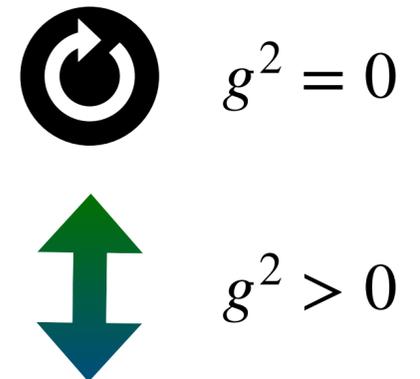
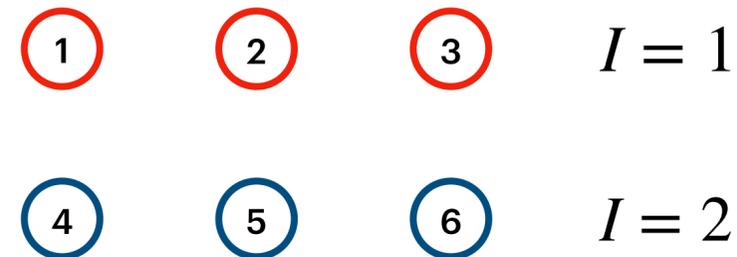
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SYMMETRIES

Physical states are invariant under SU(N) Gauge Symmetry

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Numerical Methods for MQM

Prototype: small-scale system

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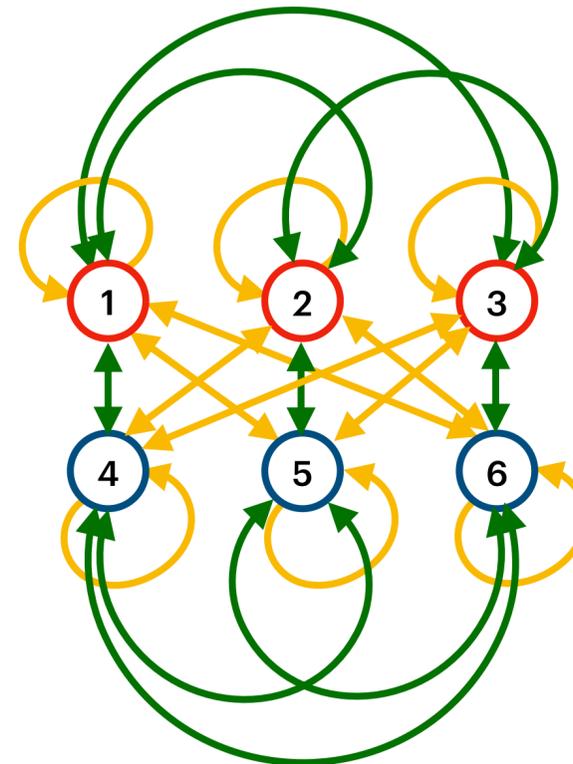
$I = 1, 2$ $\alpha = 1, 2, 3$

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 τ_α → generators of SU(N) group



$I = 1$

$I = 2$



$g^2 = 0$



$g^2 > 0$

Numerical Methods for MQM

Prototype: small-scale system

Bosonic Model

Example: N=2, D=2

$$\hat{H}_B = \text{Tr} \left(\underbrace{\left(\frac{1}{2} \hat{P}_I^2 + \frac{m^2}{2} \hat{X}_I^2 \right)}_{\text{FREE}} - \underbrace{\frac{g^2}{4} \left[\hat{X}_I, \hat{X}_J \right]^2}_{\text{BOS. INTERACTION}} \right)$$

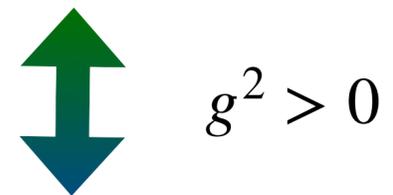
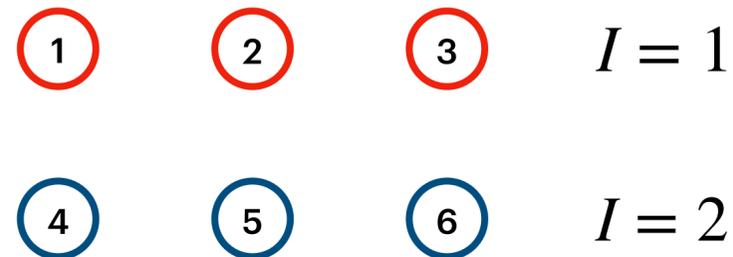
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SYMMETRIES

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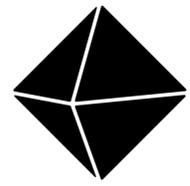
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$|\text{VACUUM}\rangle = \left(\otimes_{I,\alpha} |0\rangle_{I\alpha} \right) \rightarrow_{g^2 > 0}$

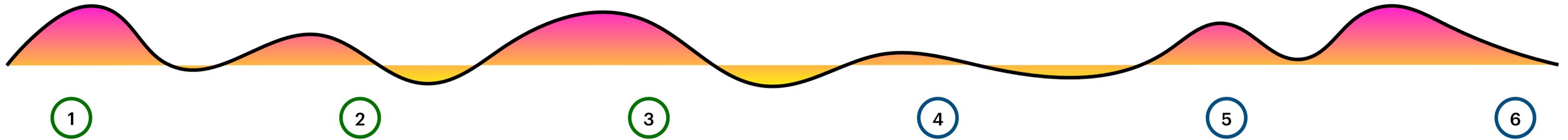
$|\text{Ground State}\rangle = (???)$



Hilbert space regularization

Truncation in Fock space

$$|\text{VACUUM}\rangle = \left(\otimes_{I,\alpha} |0\rangle_{I\alpha} \right) \xrightarrow{g^2 > 0} |\text{Ground State}\rangle = (???)$$

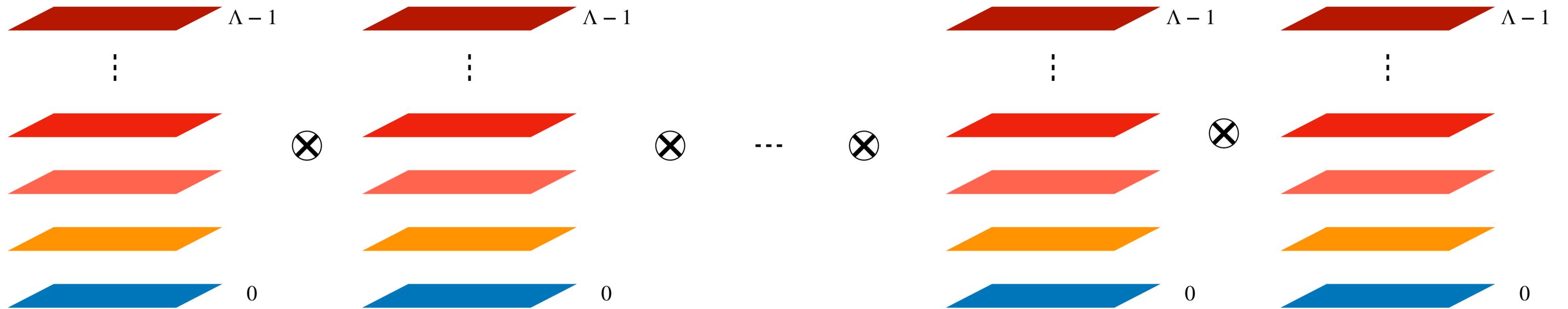
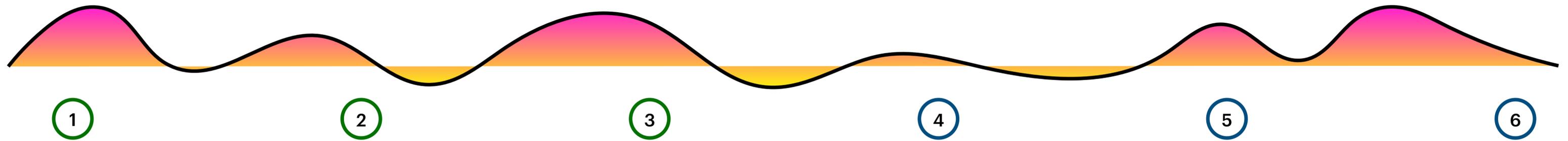




Hilbert space regularization

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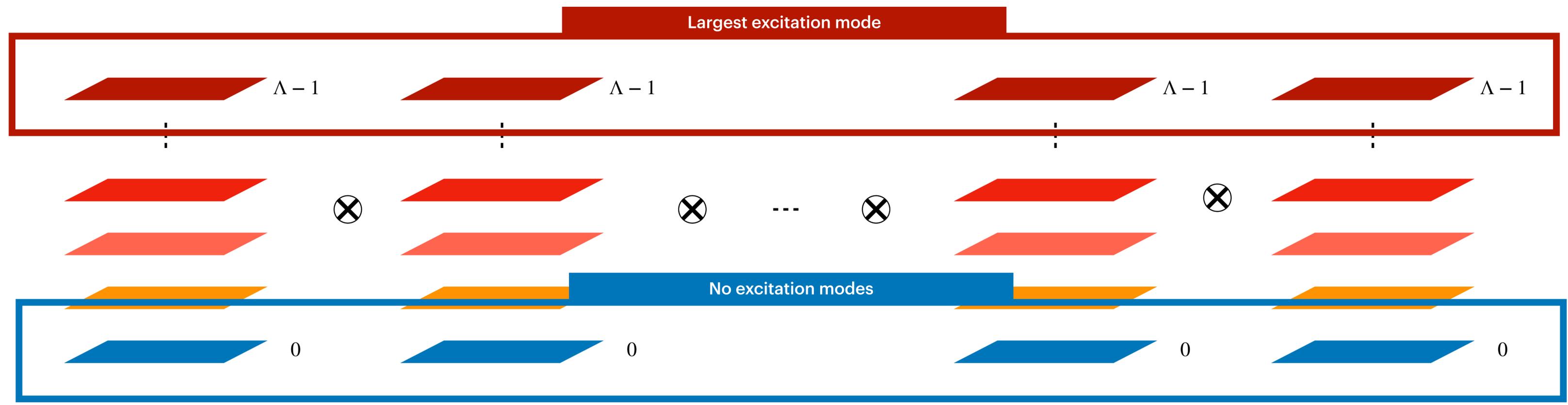
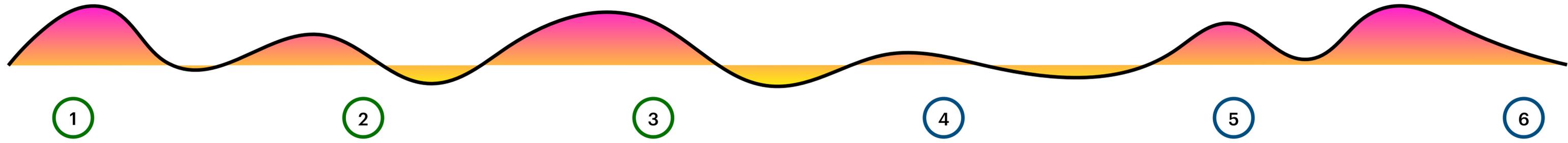




Hilbert space regularization

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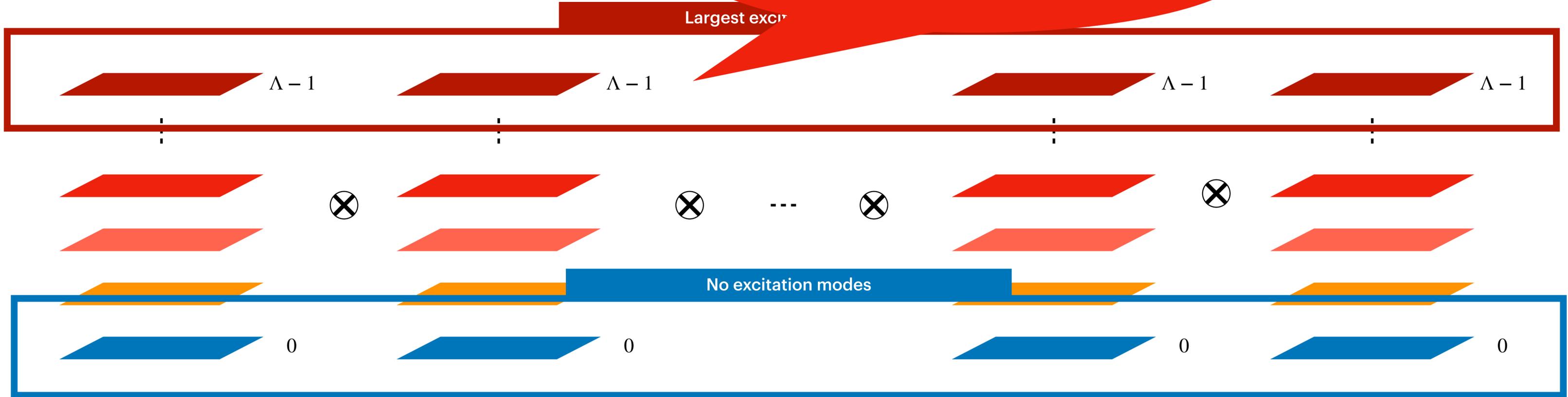
Hilbert space regularization

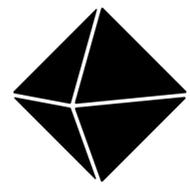
Truncation in Fock space

$$|\text{VACUUM}\rangle = \left(\otimes_{I,\alpha} |0\rangle_{I\alpha} \right) \xrightarrow{g^2 > 0} |\text{Ground State}\rangle = (???)$$



Challenge: physical results are at $\Lambda = \infty$!

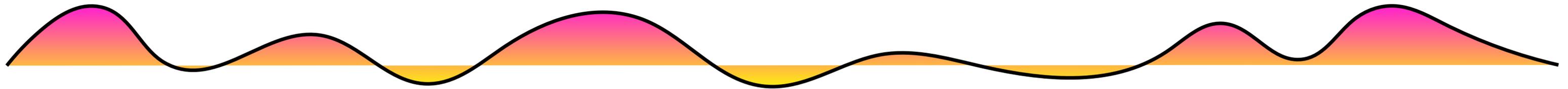


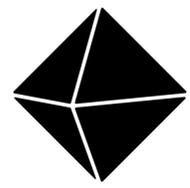


Hilbert space regularization

Truncation in the coordinate basis

$$\hat{x}|x\rangle = x|x\rangle$$

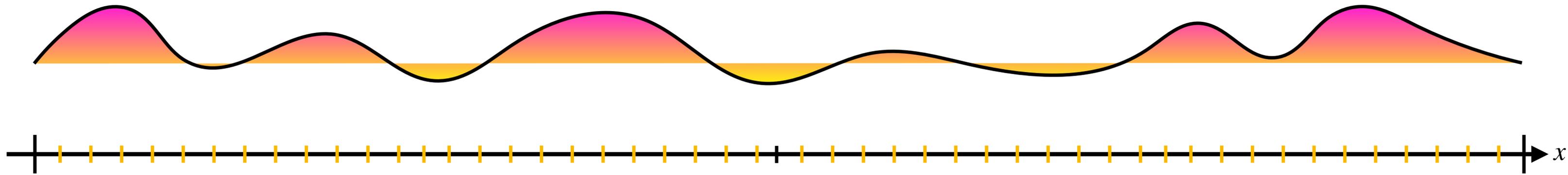


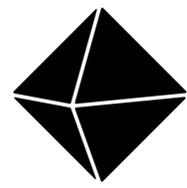


Hilbert space regularization

Truncation in the coordinate basis

$$\hat{x}|x\rangle = x|x\rangle$$

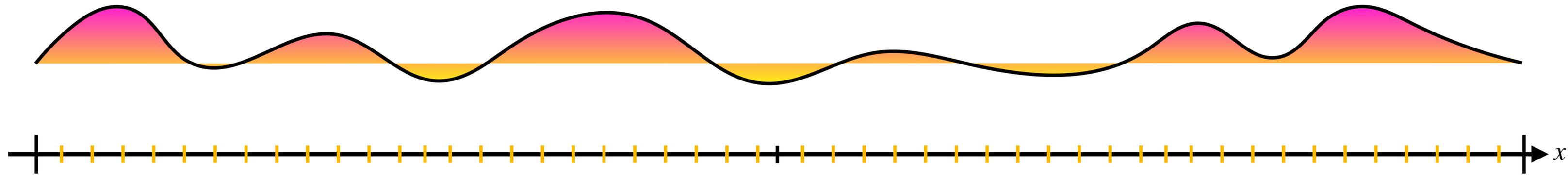




Hilbert space regularization

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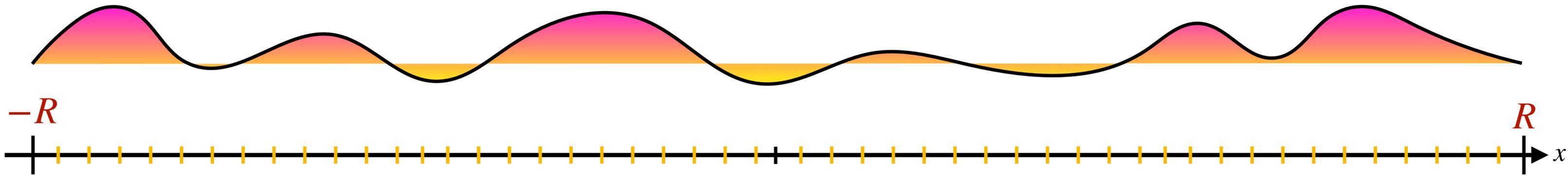
$$x(n) = -R + na_{\text{dig}}, \quad a_{\text{dig}} = \frac{2R}{\Lambda - 1}, \quad n = 0, 1, \dots, \Lambda - 1$$



Hilbert space regularization

Truncation in the coordinate basis

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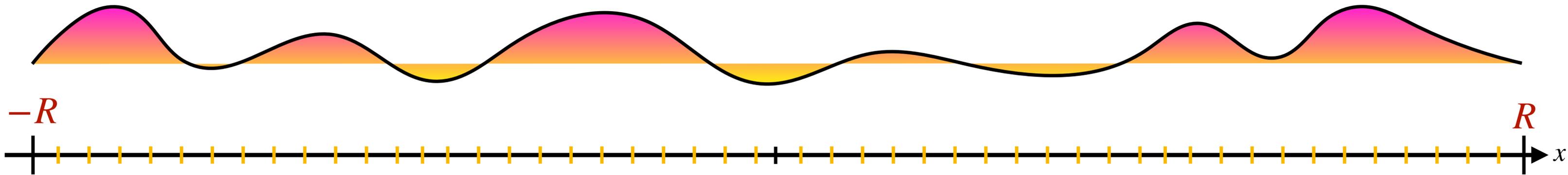
$$x(n) = -R + na_{\text{dig}}, \quad a_{\text{dig}} = \frac{2R}{\Lambda - 1}, \quad n = 0, 1, \dots, \Lambda - 1$$

- R is the “infrared” cutoff $\rightarrow \infty$

Hilbert space regularization

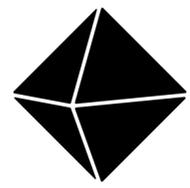
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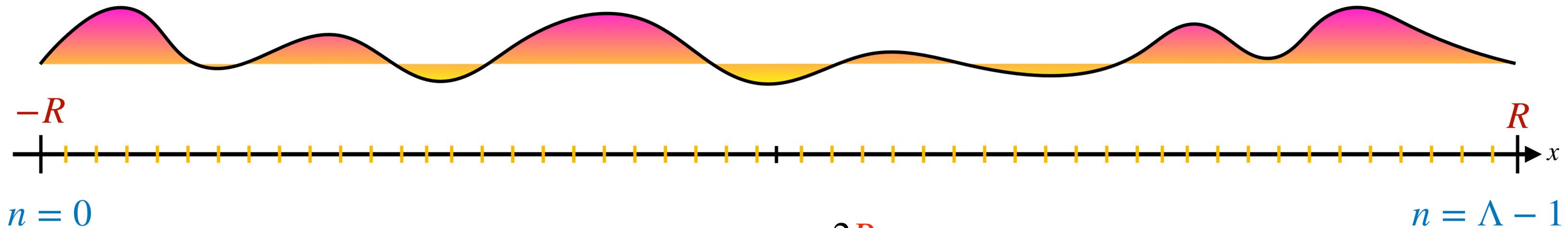
- R is the “infrared” cutoff $\rightarrow \infty$
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Hilbert space regularization

Truncation in the coordinate basis

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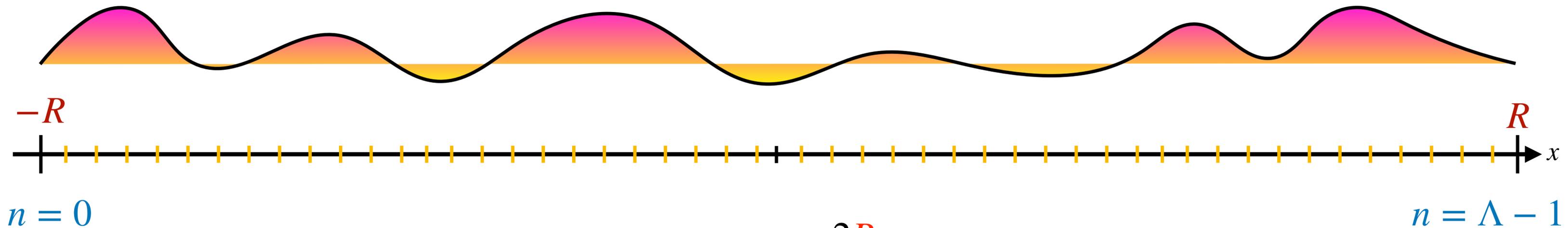
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Hilbert space regularization

Truncation in the coordinate basis

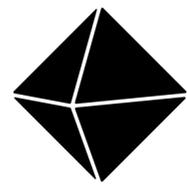
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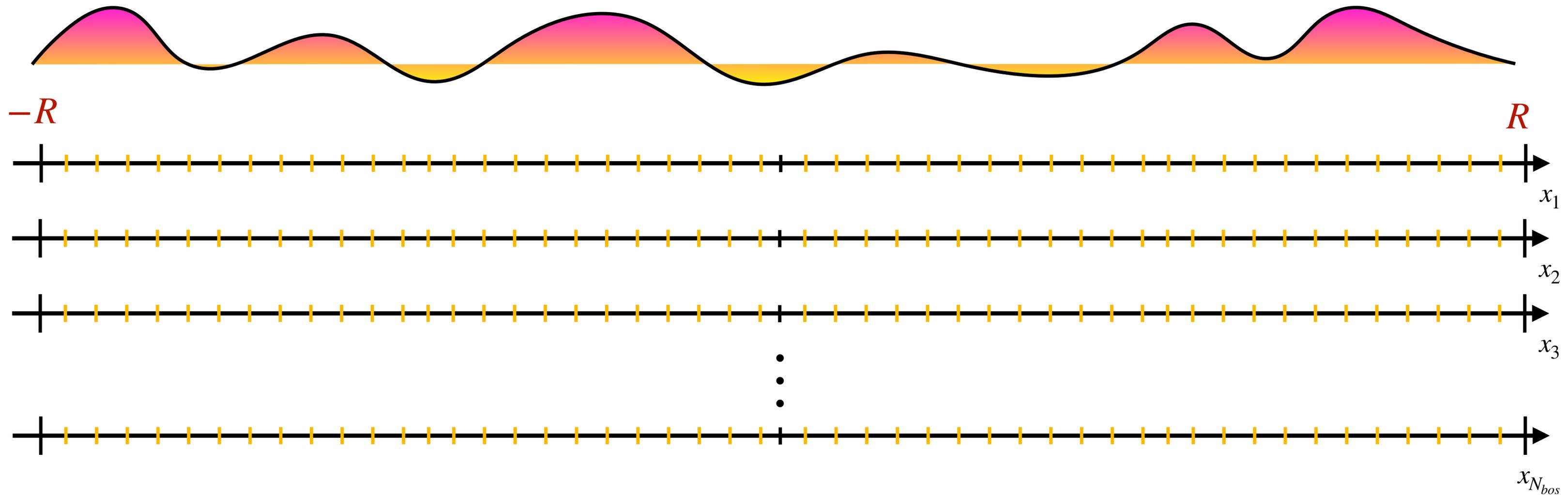
Note: can extend this to many bosons $N_{\text{bos}} > 1$!



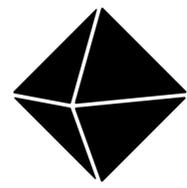
Hilbert space regularization

Truncation in the coordinate basis

$$\hat{x}|x\rangle = x|x\rangle$$



$$x_i(n_i) = -R + n_i a_{\text{dig}}, \quad a_{\text{dig}} = \frac{2R}{\Lambda - 1}, \quad n_i = 0, 1, \dots, \Lambda - 1, \quad i = 0, 1, \dots, N_{bos}$$



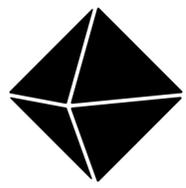
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Universal Framework

General paradigm across MQM and LGT

- Digitizing matrix elements or fields on lattices is a general strategy that makes these systems amenable to quantum computing algorithms

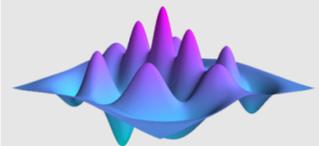
- Any Hamiltonian $\hat{H} = \frac{1}{2} \sum_a \hat{p}_a^2 + V(\hat{x})$ can be studied in this framework

- “**Space**” and “**Time**” resources can be easily computed for time evolution algorithms

	Number of qubits	# T gates in $V(\hat{x})$ term	# T gates in \hat{p}^2 term
Scalar QFT	$V_{\text{lattice}} Q$	$V_{\text{lattice}} \binom{Q}{4}$	$V_{\text{lattice}} Q(Q-1)$
Matrix Model	$dN^2 Q$	$d(d-1)N^4 Q^4$	$dN^2 Q(Q-1)$
Orbifold YM	$2dN^2 V_{\text{lattice}} Q$	$d^2 V_{\text{lattice}} N^4 Q^4$	$N^2 d V_{\text{lattice}} Q(Q-1)$

Space

Time

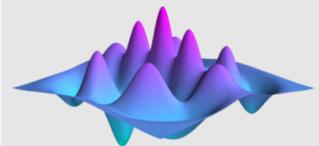


QuTiP

Quantum Toolbox in Python

Results

Small-scale: $N=2$, $D=2$, $\Lambda \rightarrow \infty$



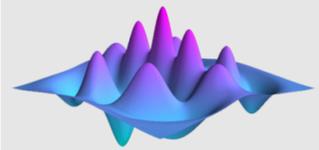
QuTiP

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- **Benchmark:** compute the lowest states via exact diagonalization



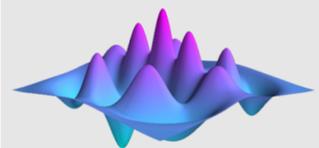
QuTiP

Quantum Toolbox in Python

Results

Small-scale: $N=2$, $D=2$, $\Lambda \rightarrow \infty$

- **Benchmark**: compute the lowest states via exact diagonalization
- Study the **convergence** to $\Lambda \rightarrow \infty$



QuTiP

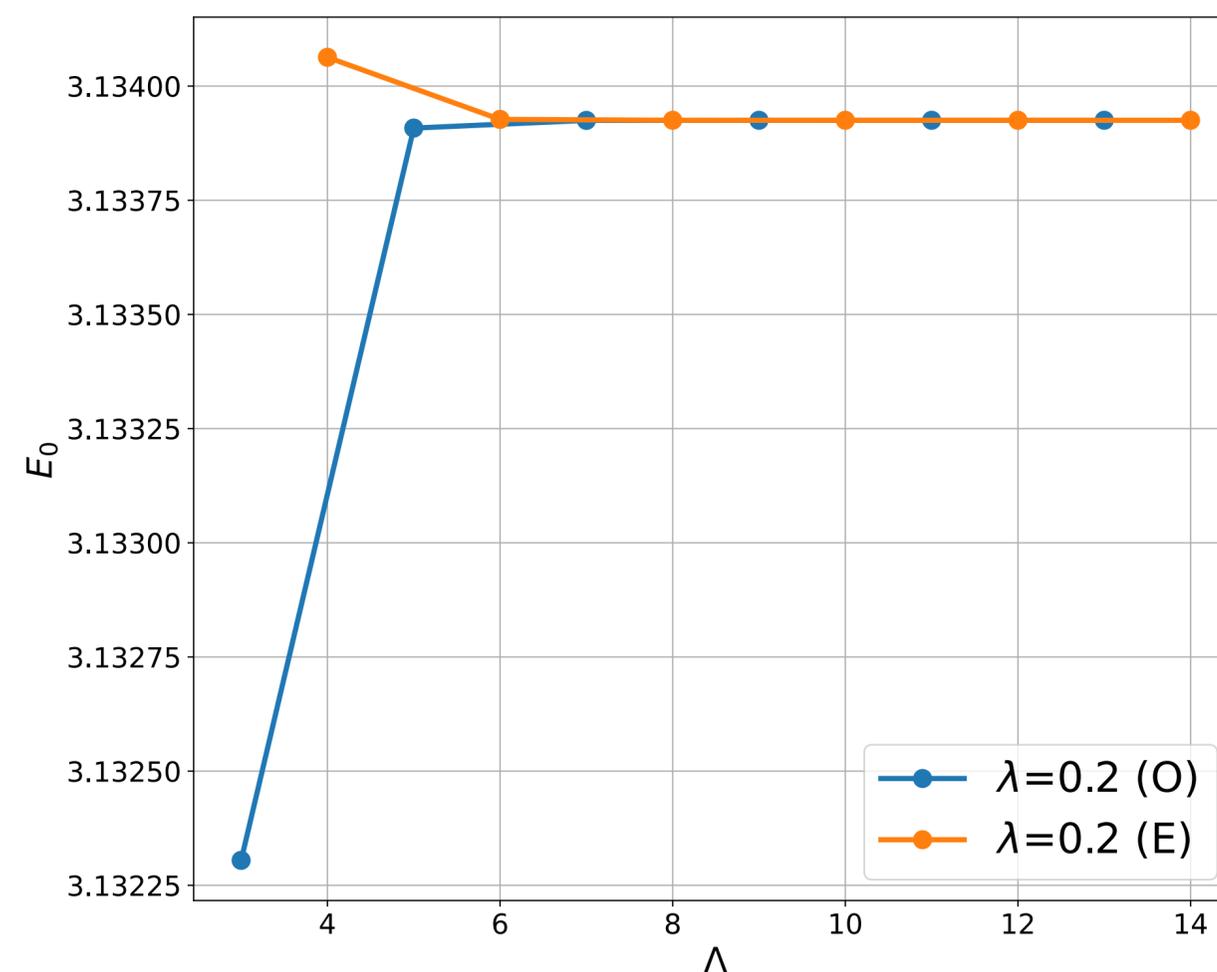
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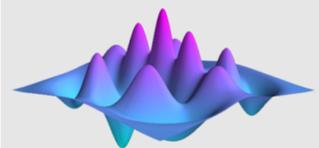
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$$E_0 = \langle E_0 | \hat{H} | E_0 \rangle$$





QuTiP

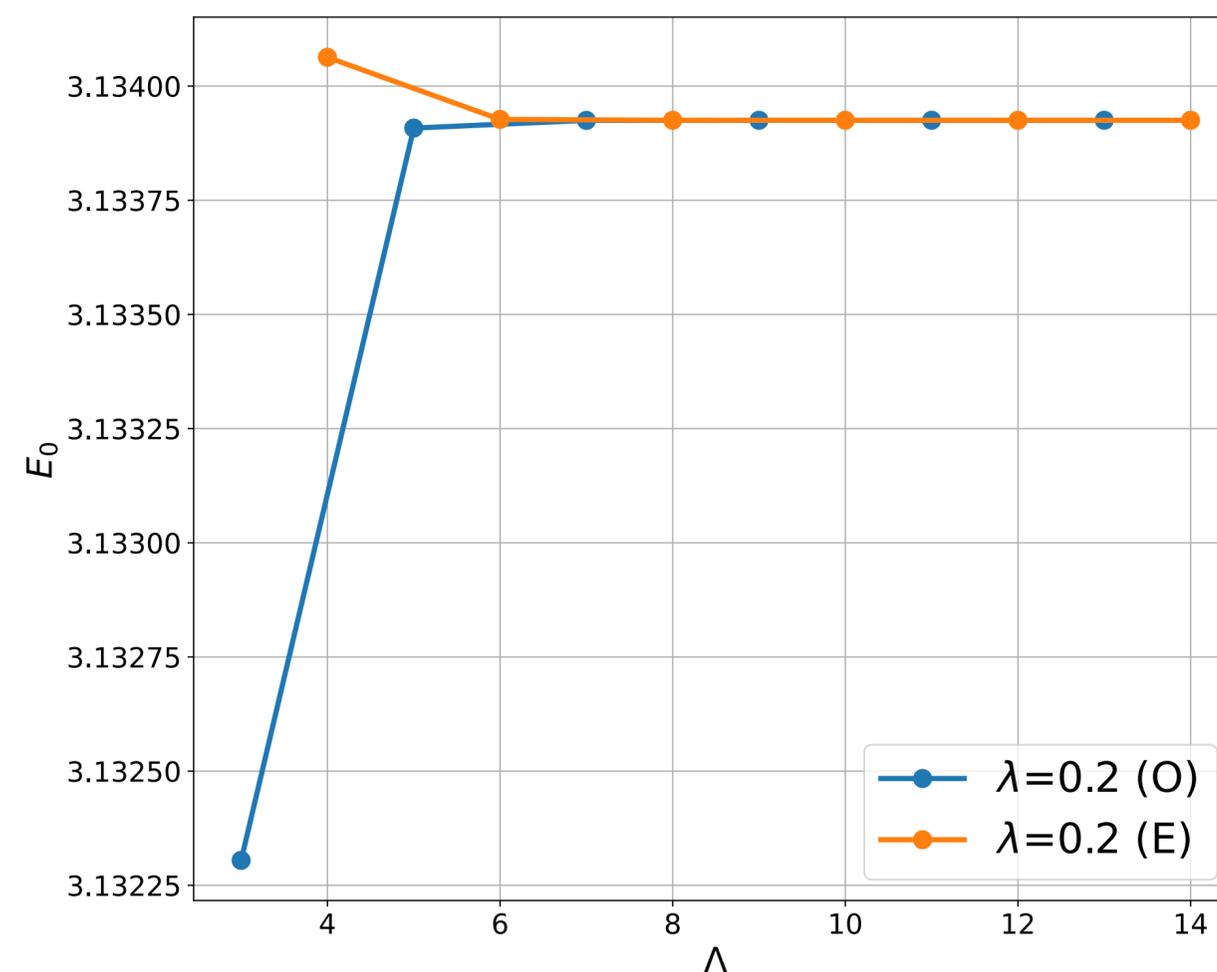
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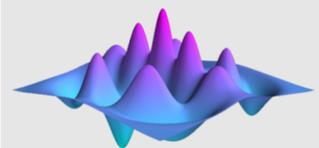
Results

Small-scale: $N=2$, $D=2$, $\Lambda \rightarrow \infty$

- **Benchmark:** compute the lowest states via exact diagonalization
- Study the **convergence** to $\Lambda \rightarrow \infty$
- Study the effects of different couplings

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QuTiP

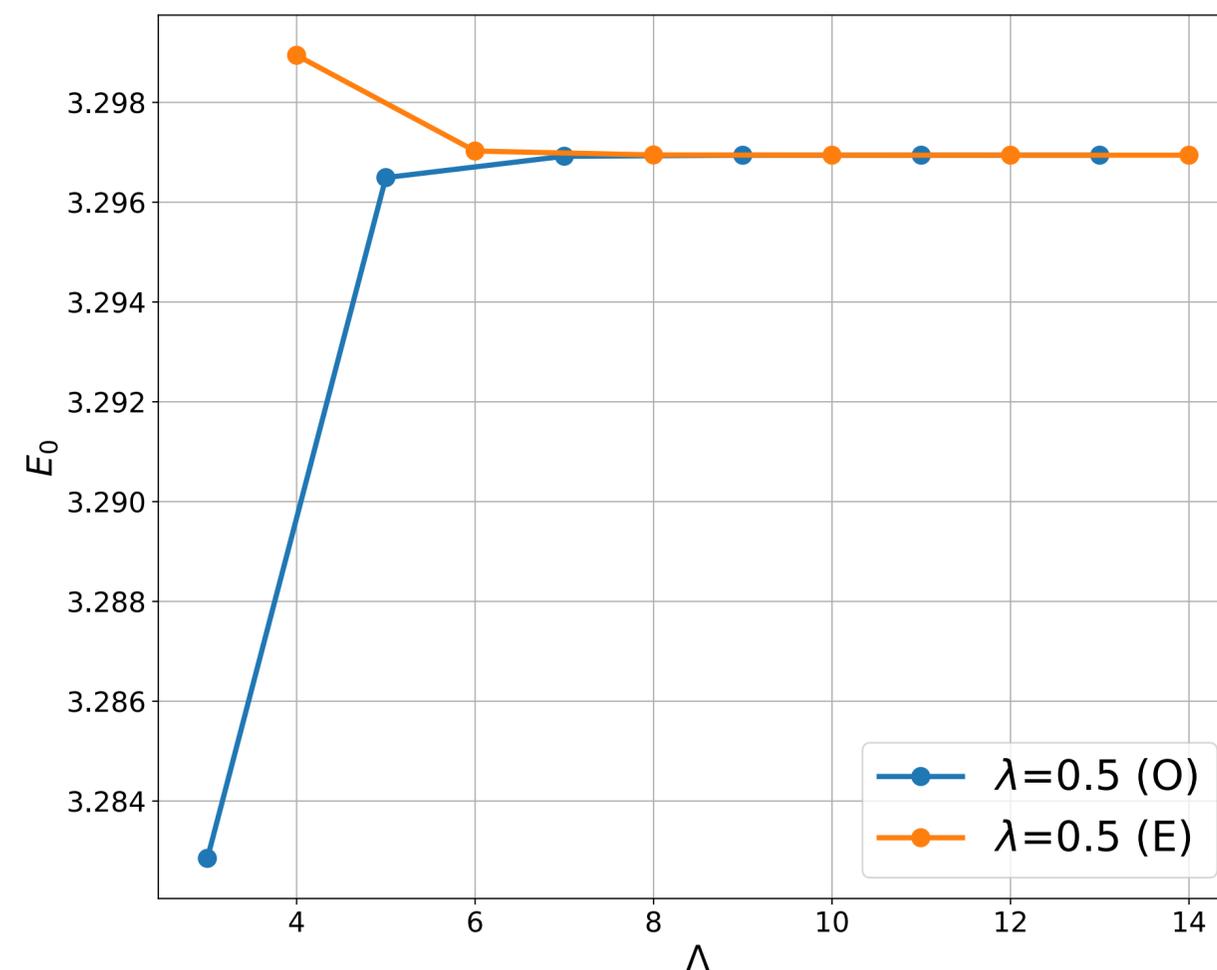
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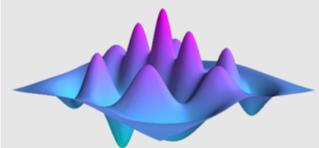
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- Study the **convergence** to $\Lambda \rightarrow \infty$
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$$E_0 = \langle E_0 | \hat{H} | E_0 \rangle$$





QuTiP

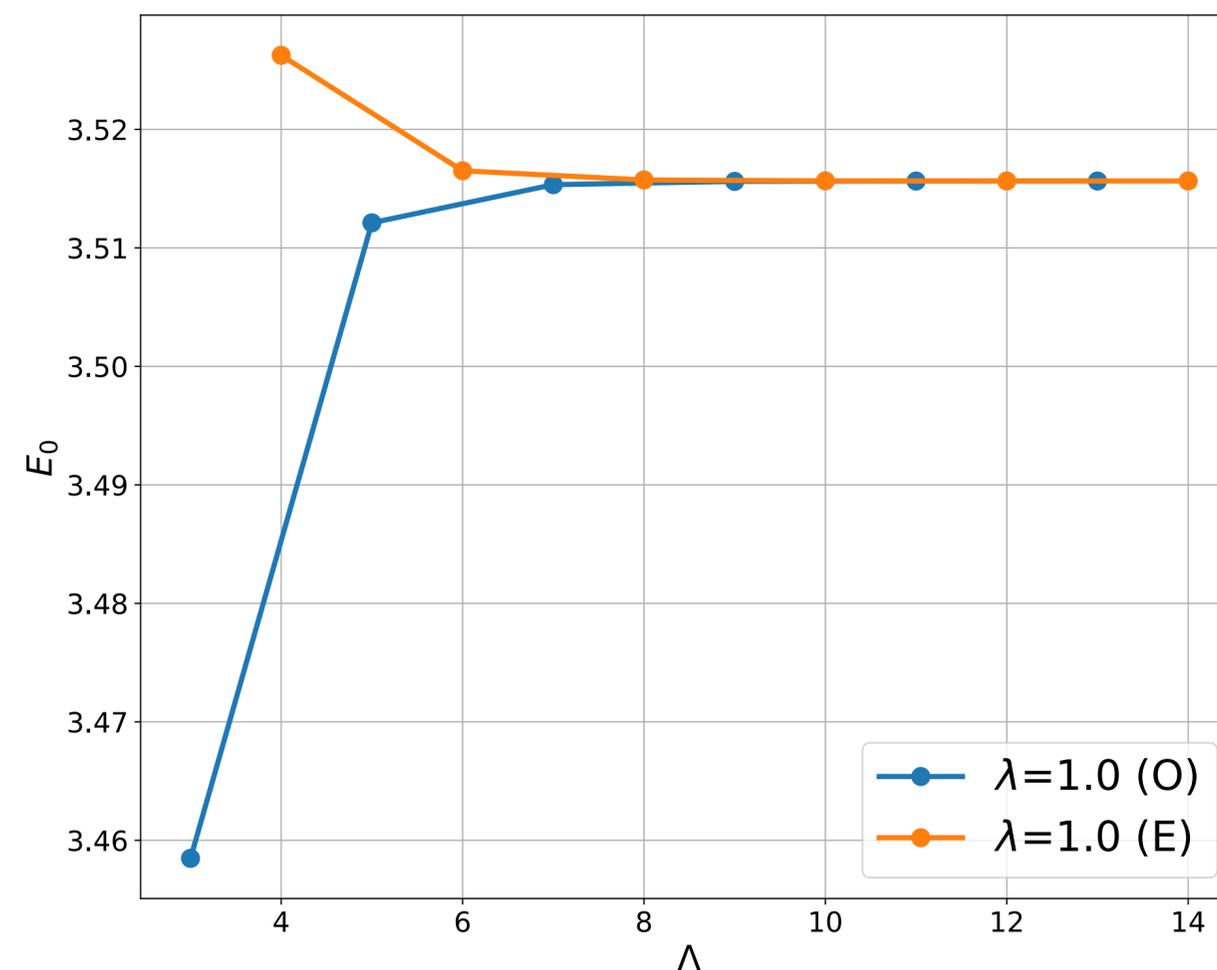
Quantum Toolbox in Python

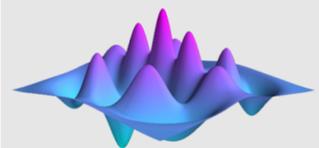
Results

Small-scale: $N=2$, $D=2$, $\Lambda \rightarrow \infty$

- **Benchmark:** compute the lowest states via exact diagonalization
- Study the **convergence** to $\Lambda \rightarrow \infty$
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QuTiP

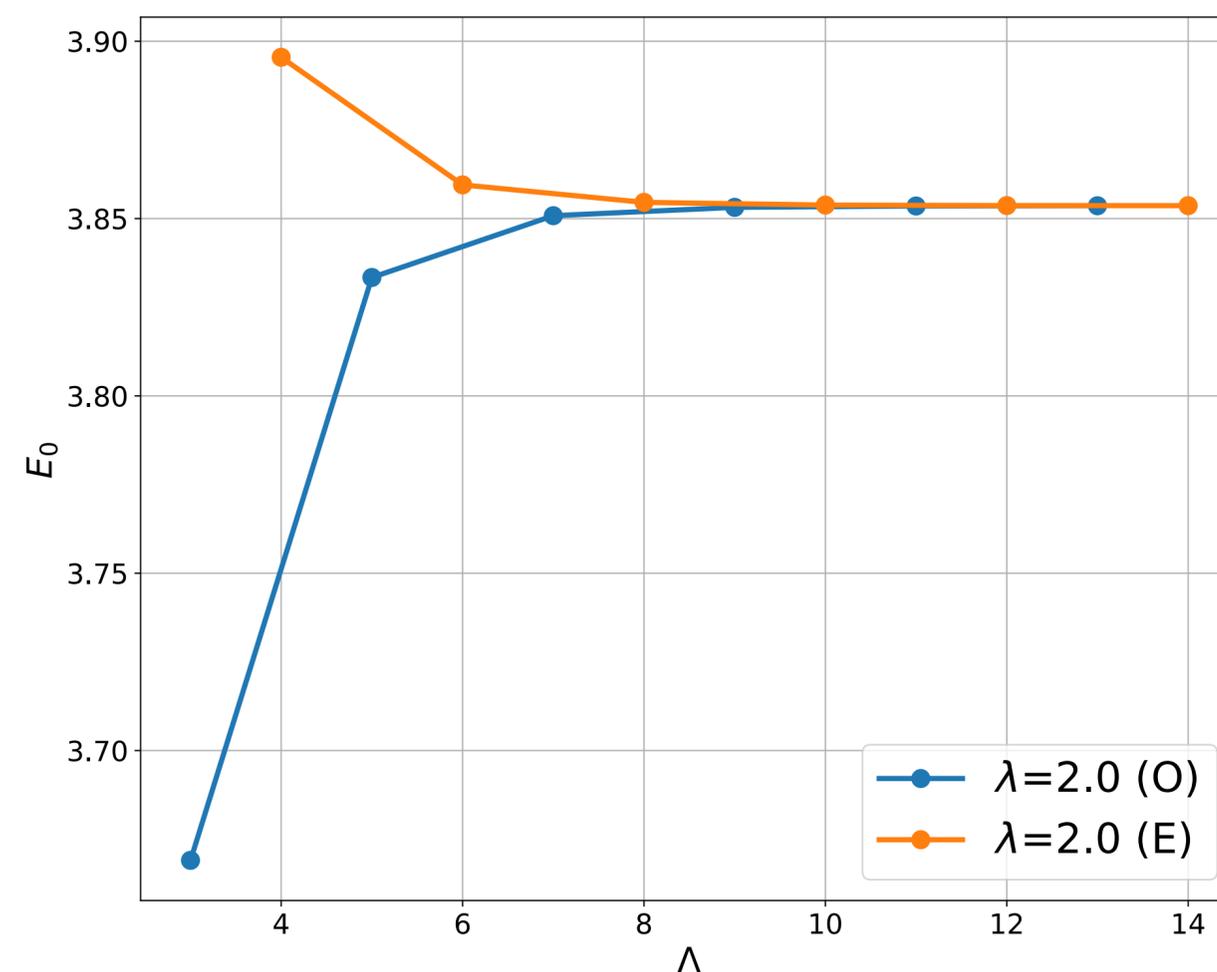
Quantum Toolbox in Python

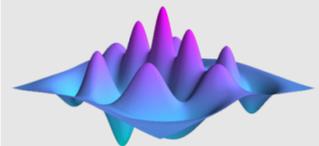
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QuTiP

Quantum Toolbox in Python

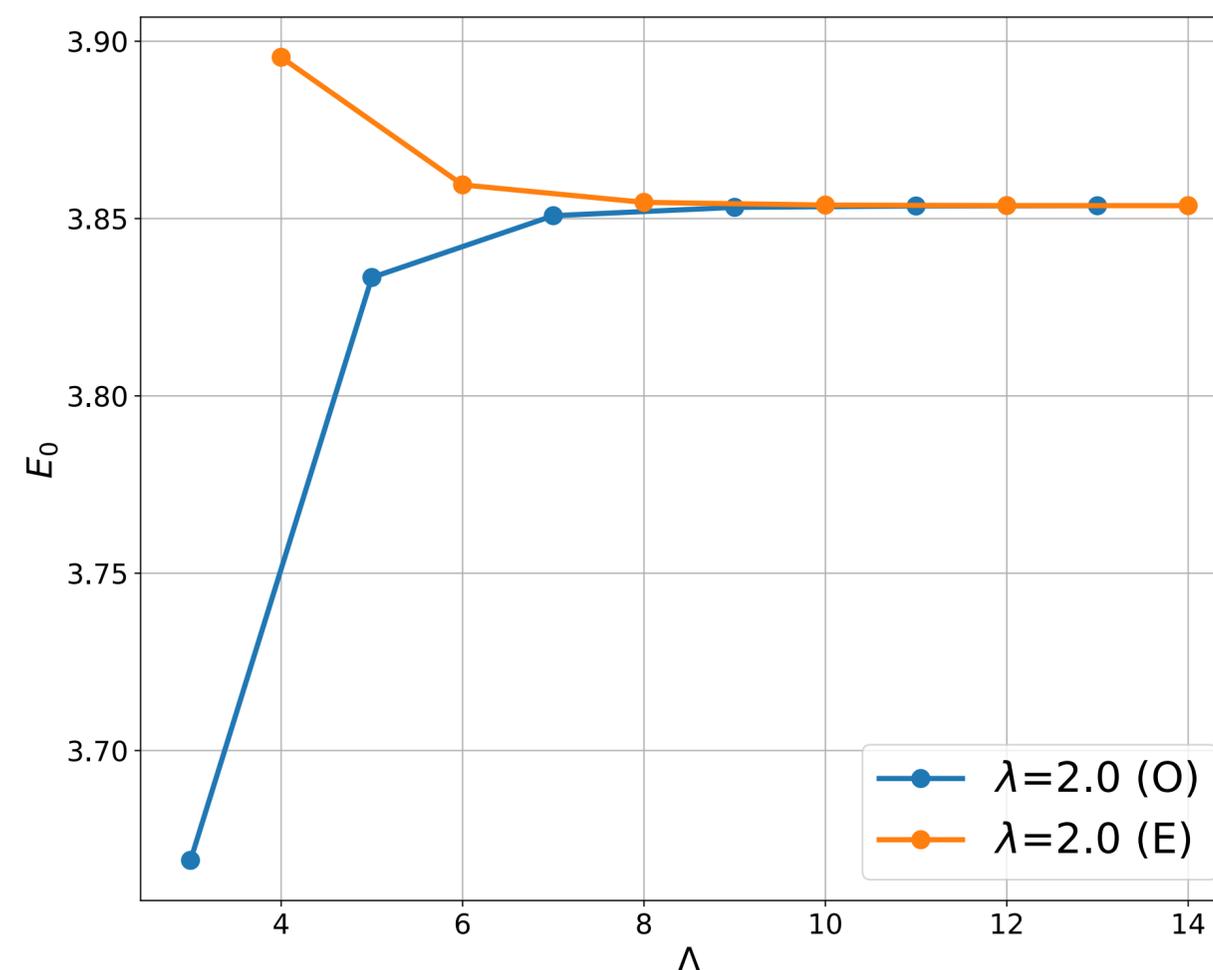
Results

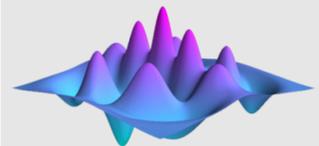
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$$\hat{G}_\alpha = i \sum_{\beta, \gamma, I} f_{\alpha\beta\gamma} \hat{a}_{I\beta}^\dagger \hat{a}_{I\gamma} \longrightarrow \hat{G}_\alpha \left(\bigotimes_{I,\beta} |0\rangle_{I\beta} \right) = 0$$





QuTiP

Quantum Toolbox in Python

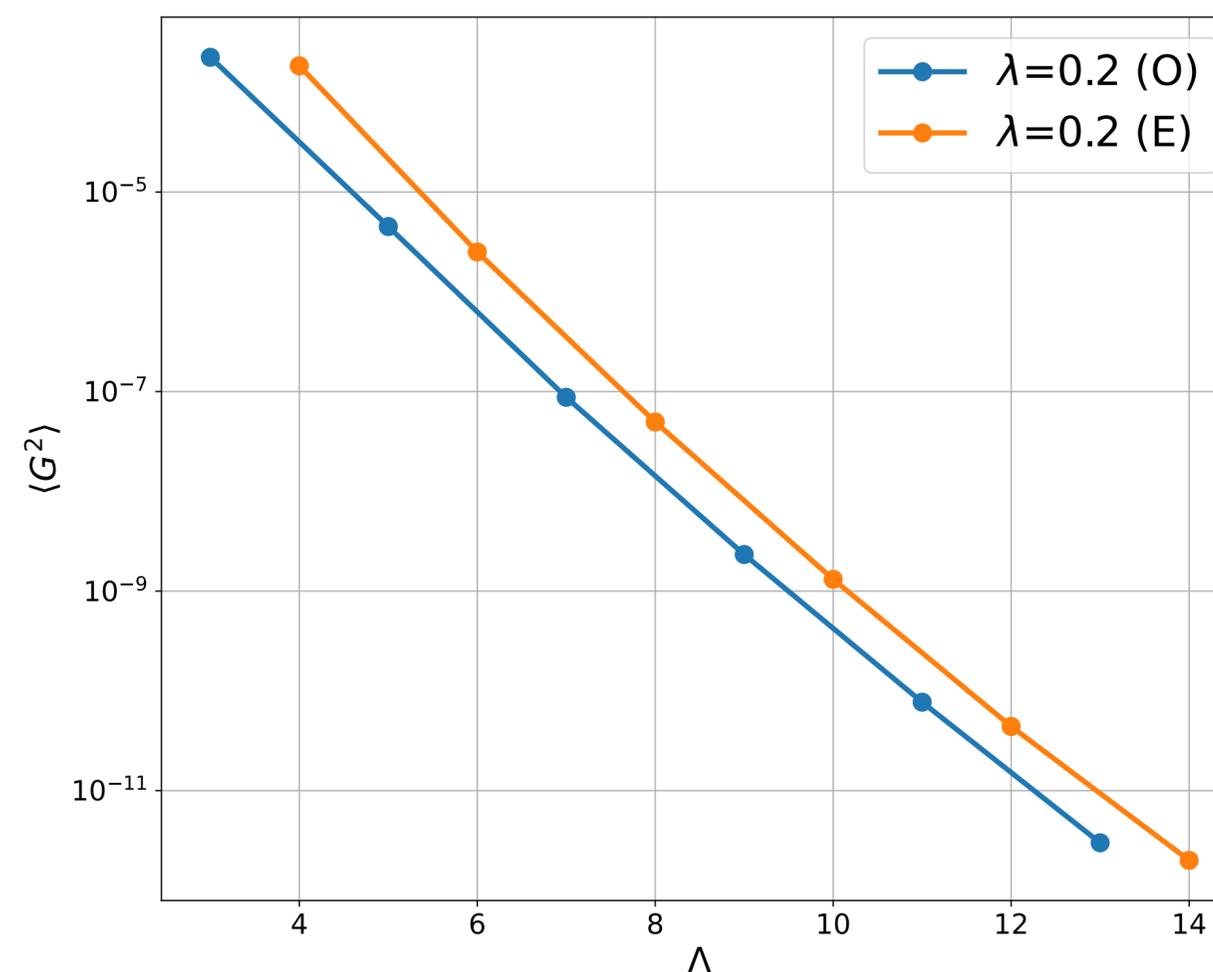
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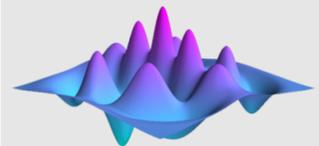
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QuTiP

Quantum Toolbox in Python

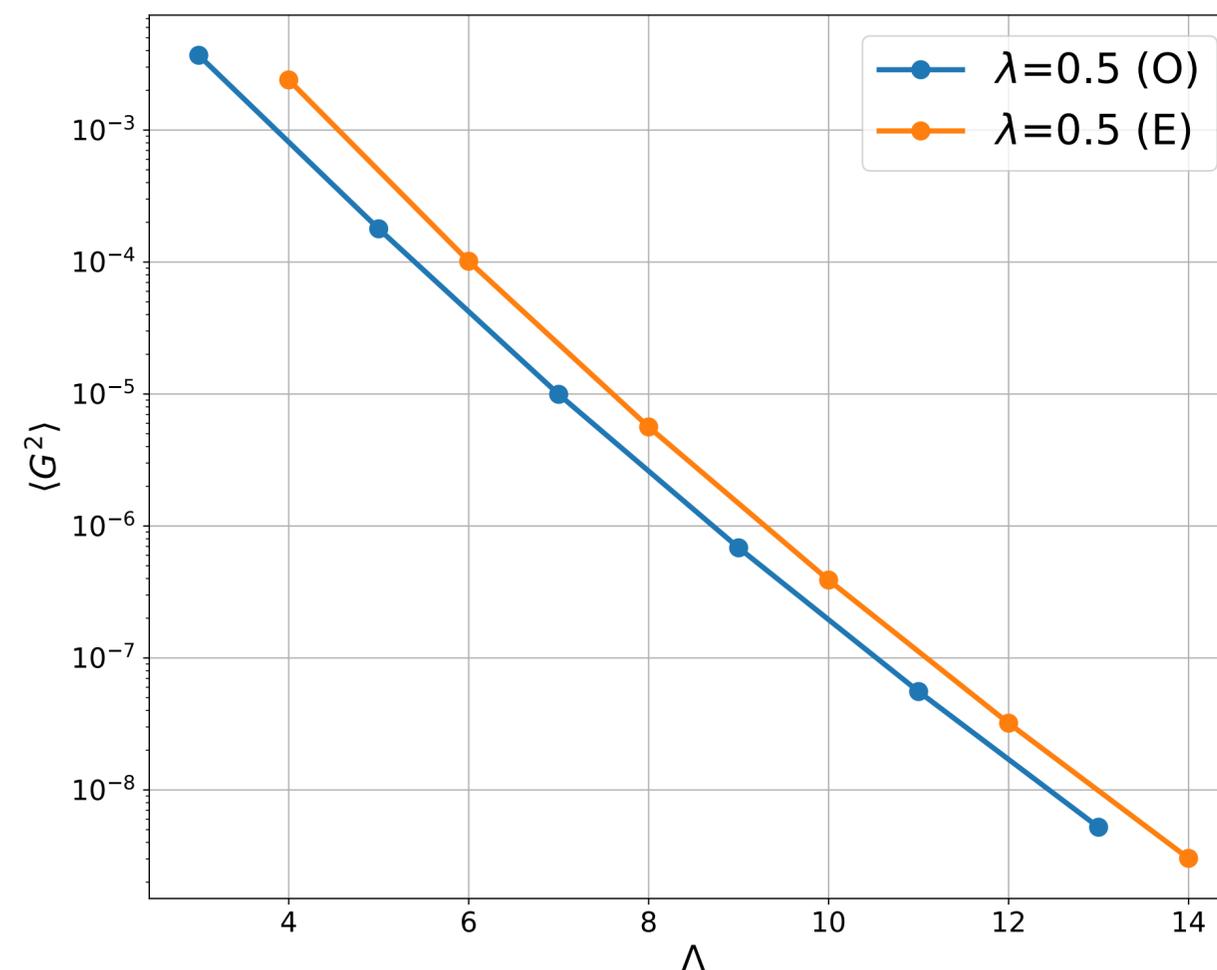
Results

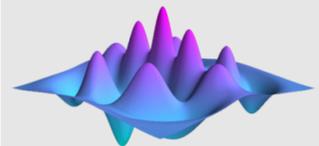
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QuTiP

Quantum Toolbox in Python

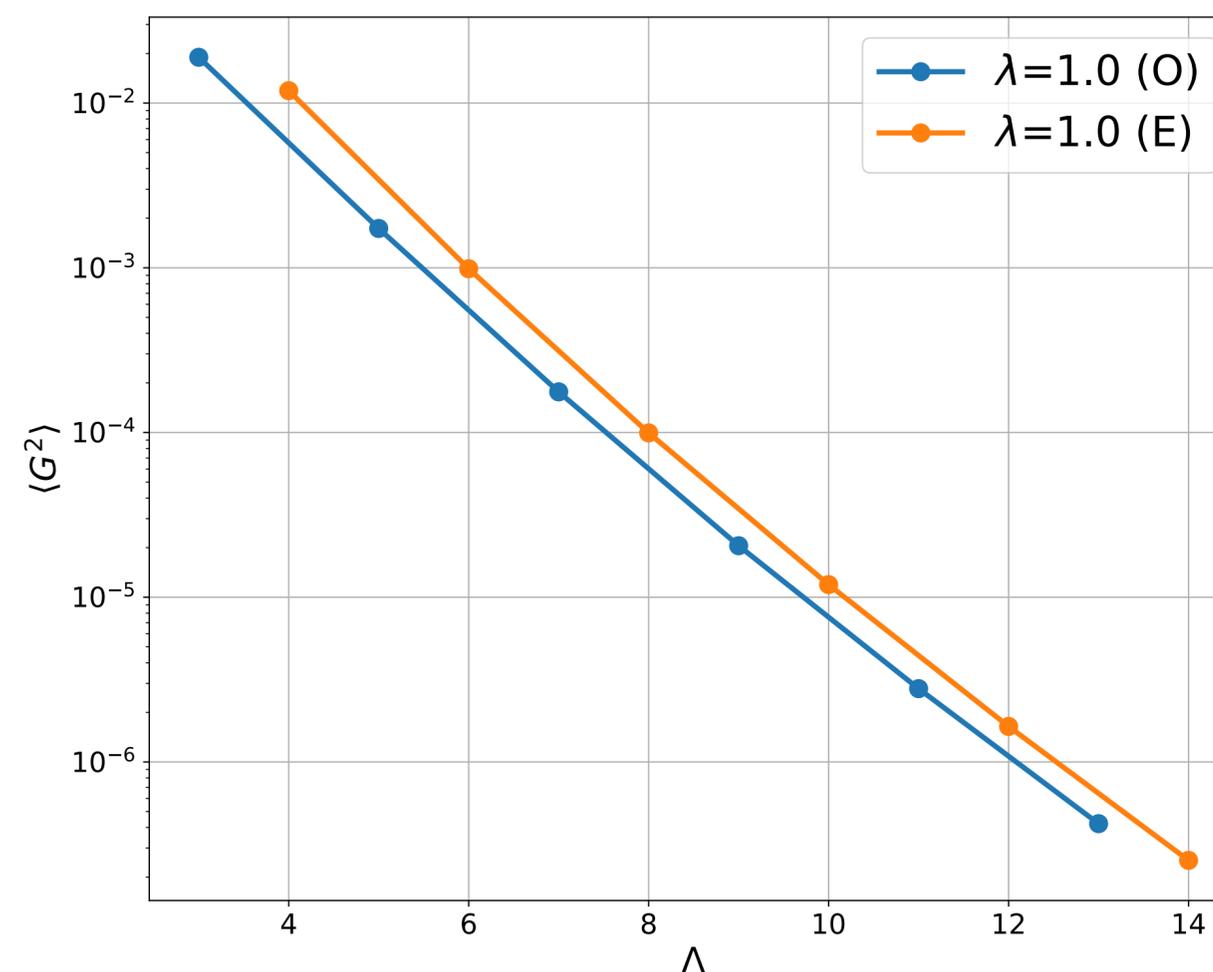
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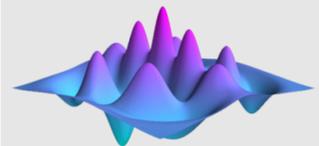
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QuTiP

Quantum Toolbox in Python

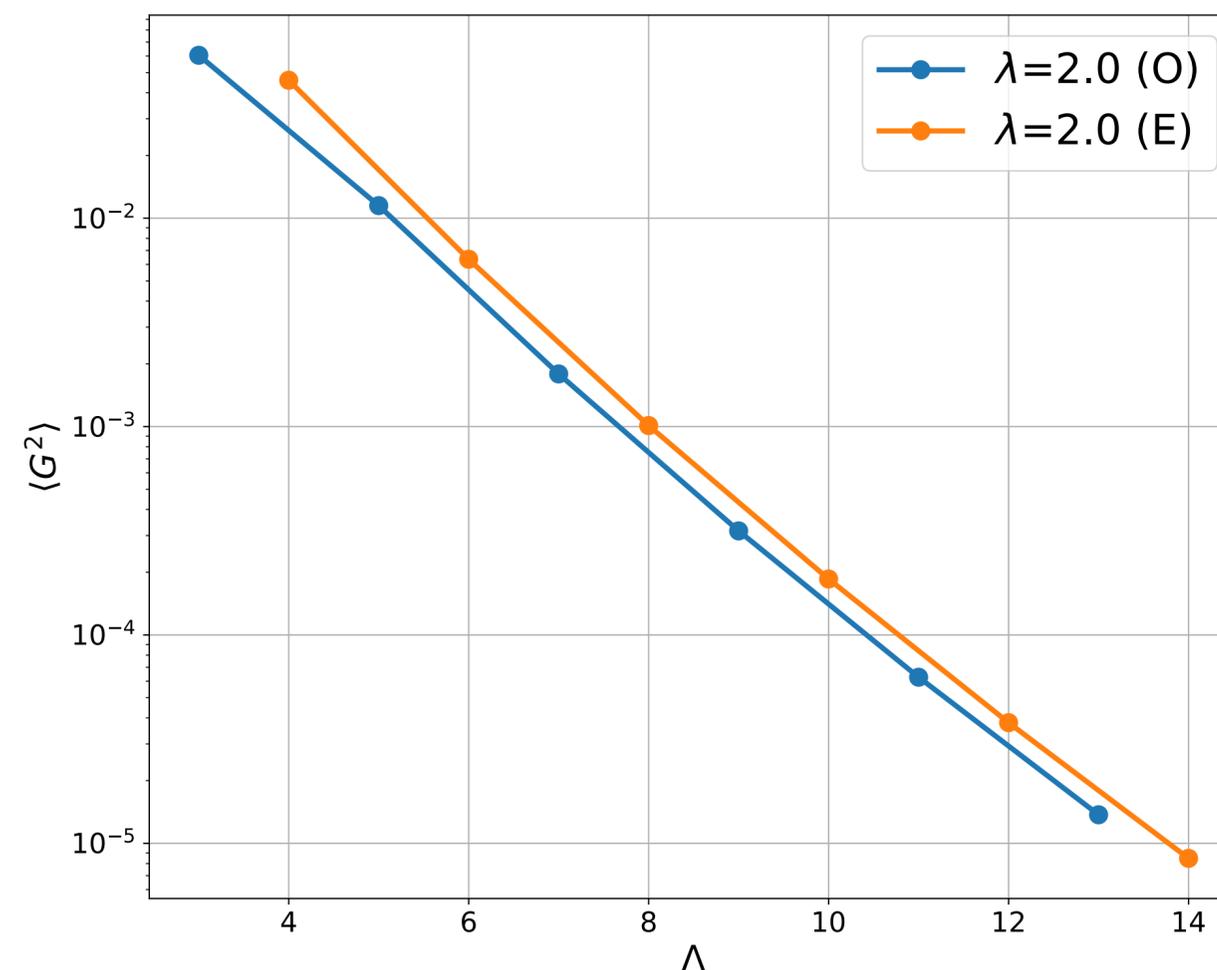
Results

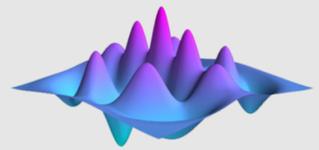
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QuTiP

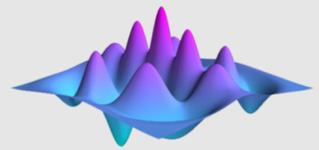
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QuTiP

Quantum Toolbox in Python

Results

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- **Benchmark**: compute the lowest states via exact diagonalization
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$$\hat{H}' = \hat{H} + c \sum \hat{G}_\alpha^2$$

$$\hat{G}_\alpha = i \sum_{\beta, \gamma, I} f_{\alpha\beta\gamma} \hat{a}_{I\beta}^\dagger \hat{a}_{I\gamma} \longrightarrow \hat{G}_\alpha \left(\otimes_{I,\beta} |0\rangle_{I\beta} \right) = 0$$

- Study a perturbed Hamiltonian with gauge penalty: **increase energy iff not singlet**



Results

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

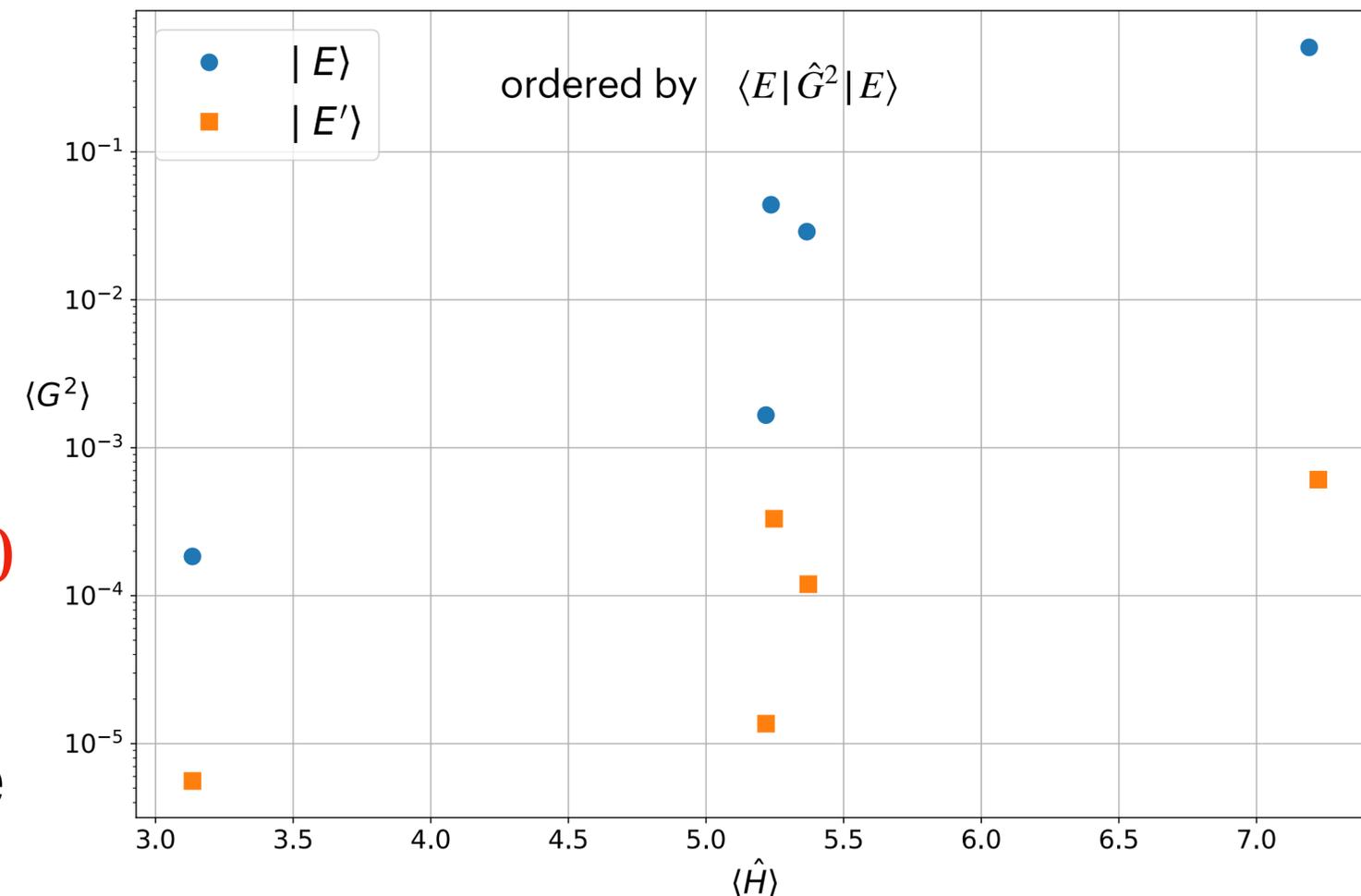
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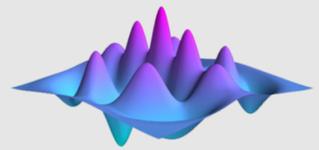
$$\hat{H}' = \hat{H} + c \sum \hat{G}_\alpha^2$$

$c = \Lambda = 4 \quad \lambda = 0.2$

$$\hat{G}_\alpha = i \sum_{\beta, \gamma, I} f_{\alpha\beta\gamma} \hat{a}_{I\beta}^\dagger \hat{a}_{I\gamma} \longrightarrow \hat{G}_\alpha \left(\bigotimes_{I, \beta} |0\rangle_{I\beta} \right) = 0$$

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QuTiP

Quantum Toolbox in Python

Results

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

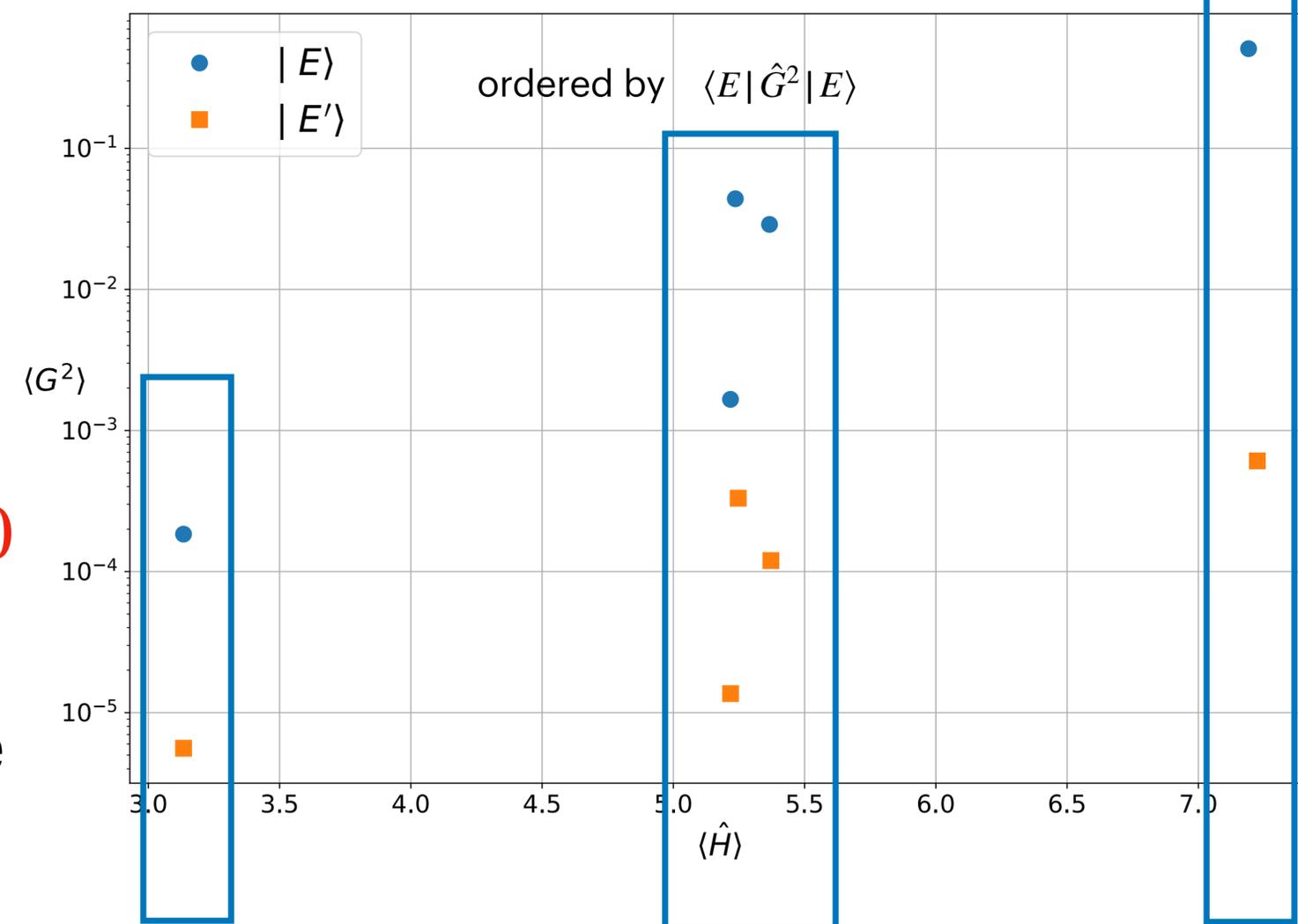
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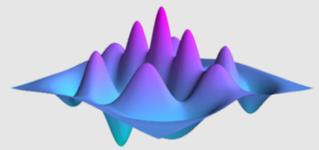
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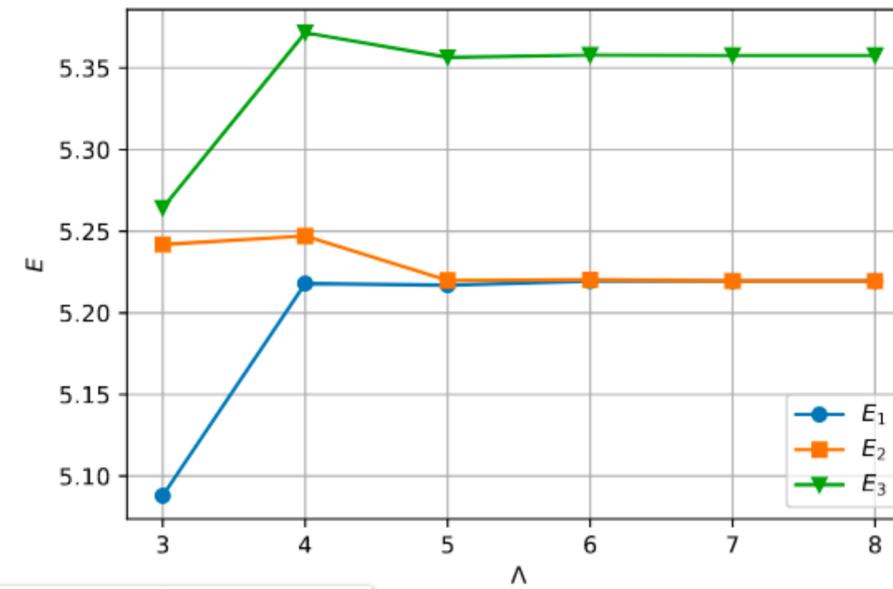
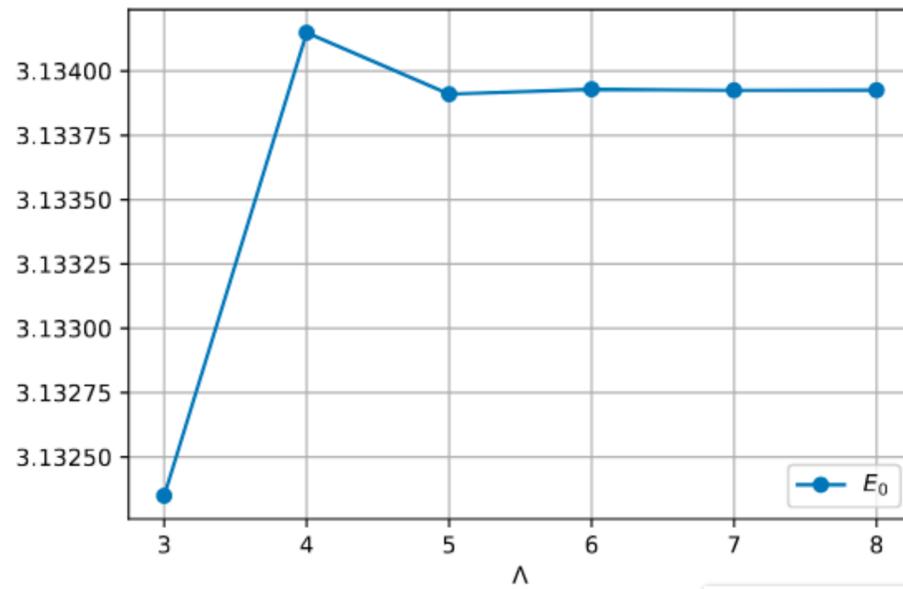


QuTiP

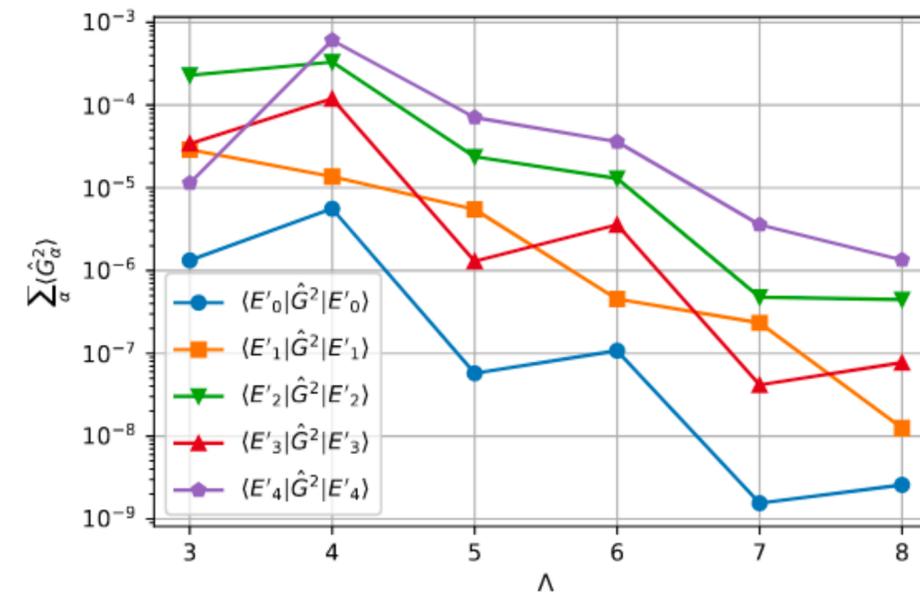
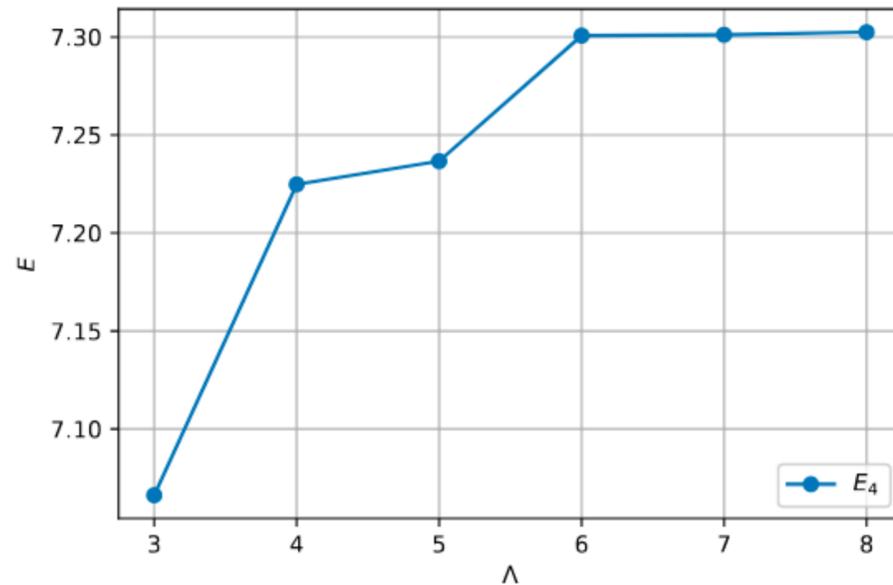
Quantum Toolbox in Python

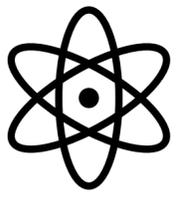
Excited states

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$



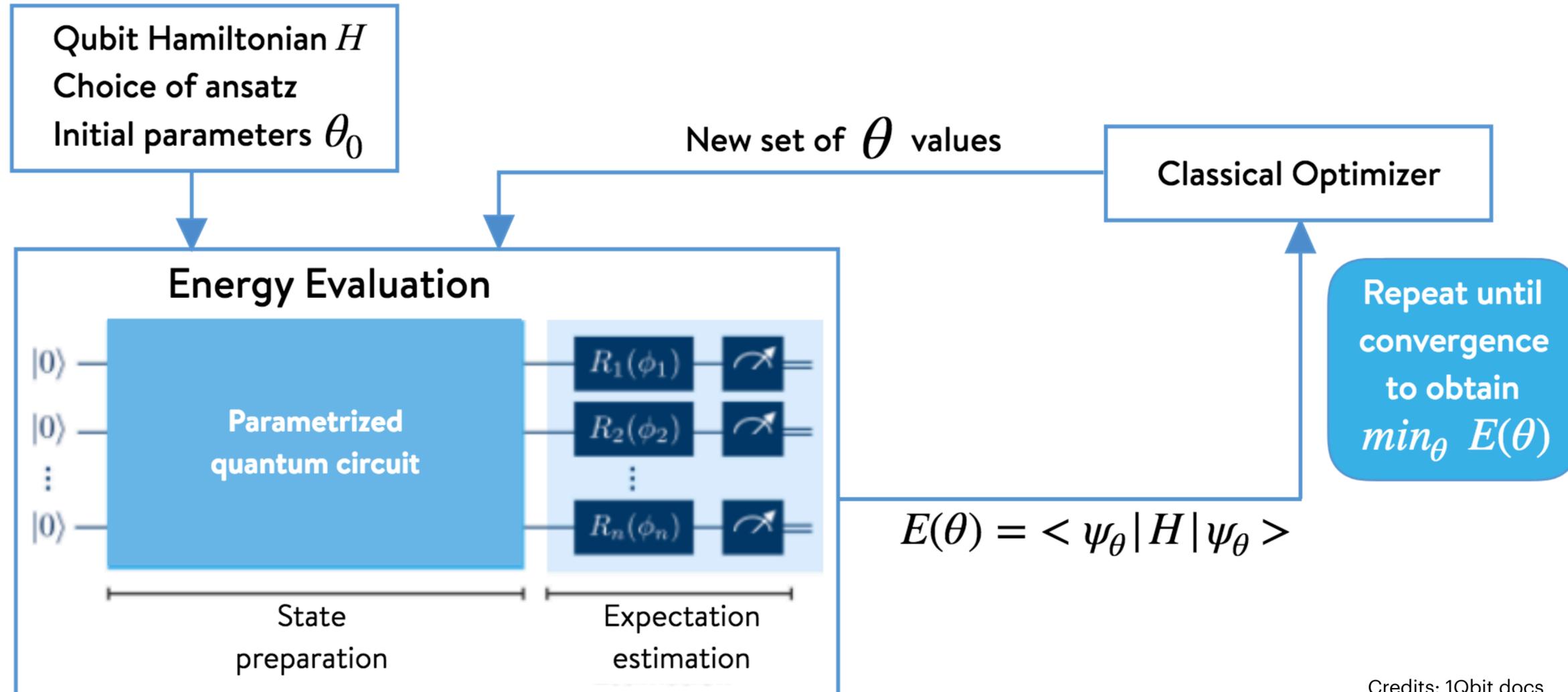
$$c = \Lambda, m^2 = 1, \lambda = g^2 N = 0.2$$

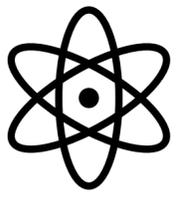




Quantum Computing

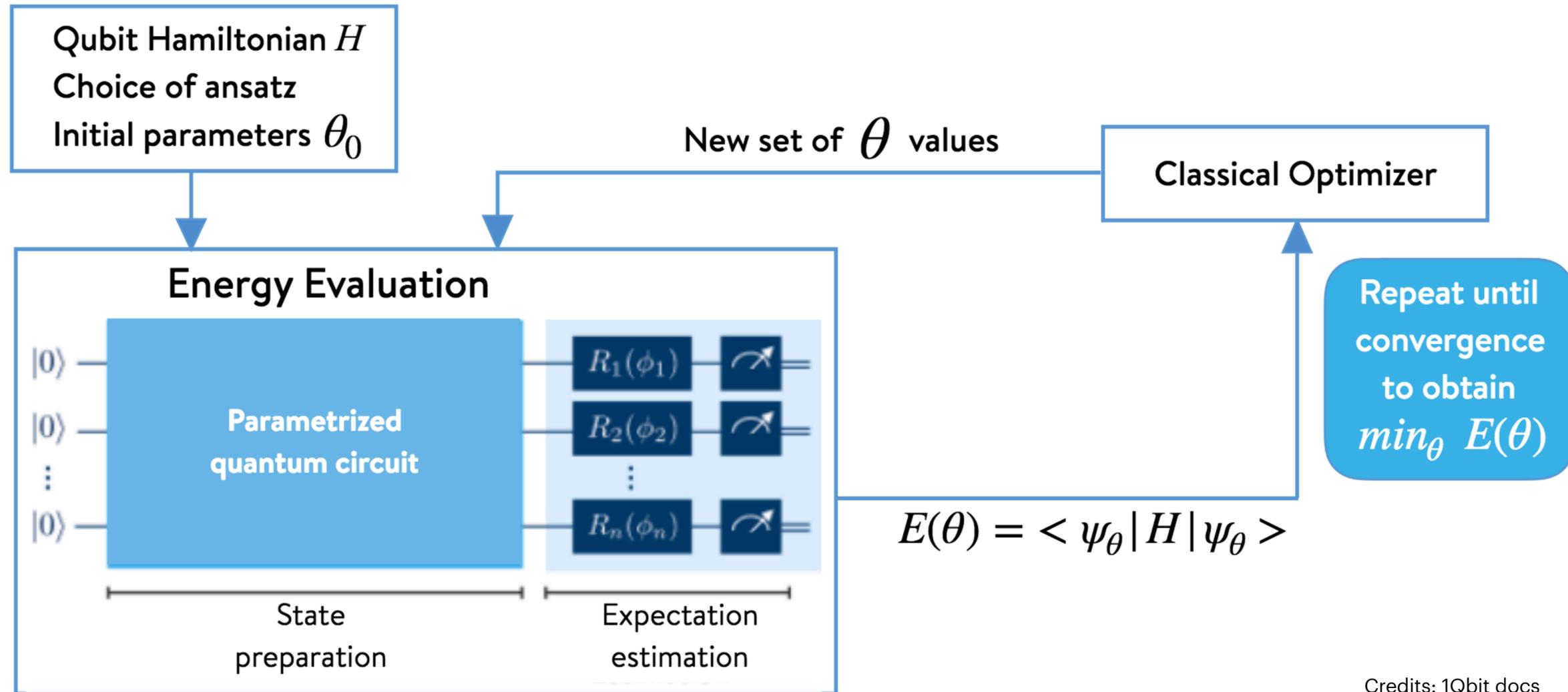
Variational Quantum Eigensolver - VQE





Quantum Computing

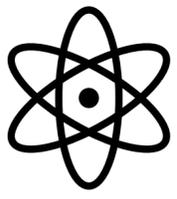
Variational Quantum Eigensolver - VQE



PQC \rightarrow Variational Ansatz for $|\phi\rangle$

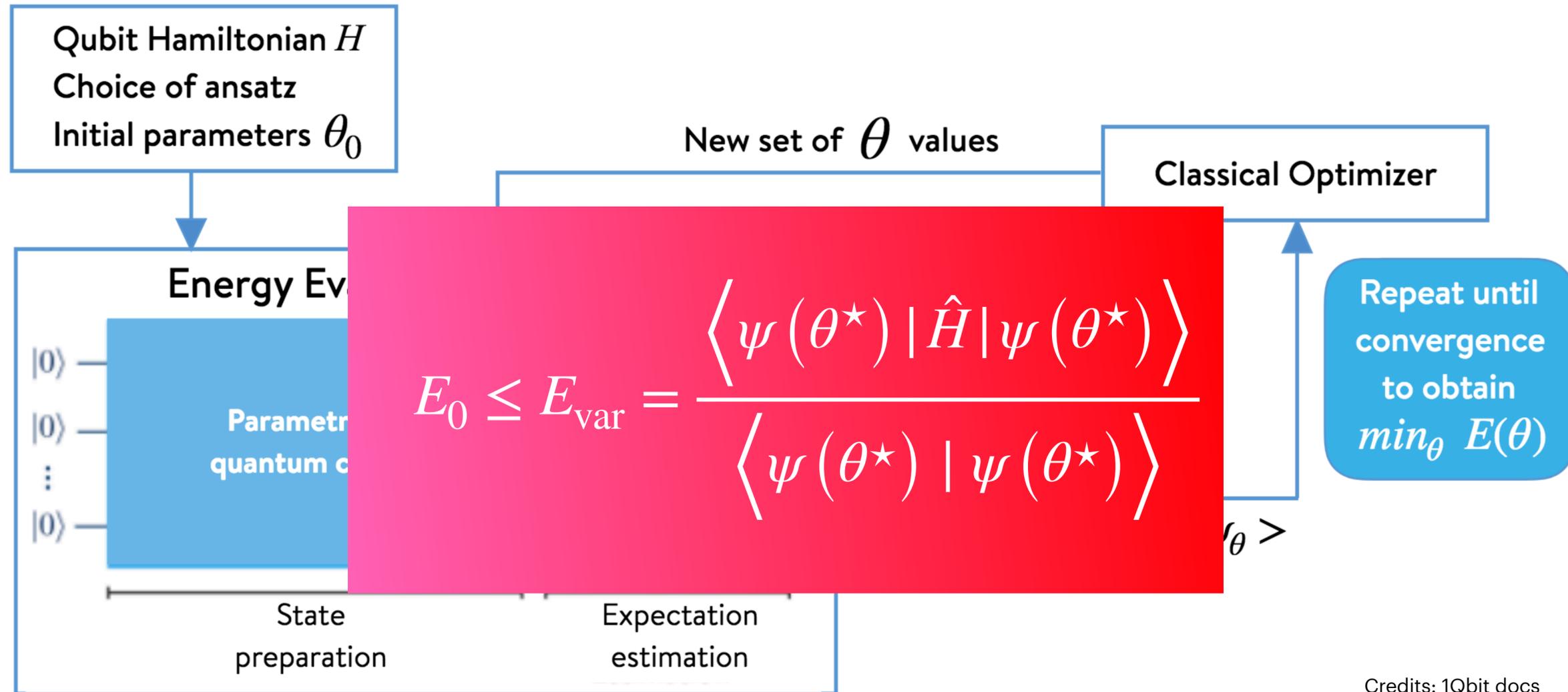
Evaluation of cost function $\rightarrow E(\theta)$

Optimize parameters $\rightarrow \theta^*$



Quantum Computing

Variational Quantum Eigensolver - VQE



PQC \rightarrow Variational Ansatz for $|\Phi\rangle$

Evaluation of cost function $\rightarrow E(\theta)$

Optimize parameters $\rightarrow \theta^*$



VQE details

Small-scale: $N=2$, $D=2$

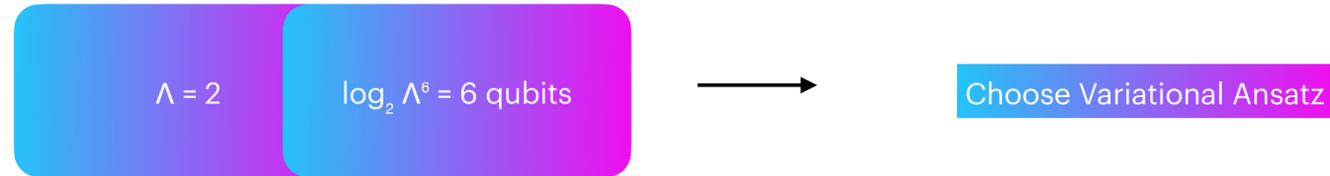
$$\Lambda = 2$$

$$\log_2 \Lambda^6 = 6 \text{ qubits}$$



VQE details

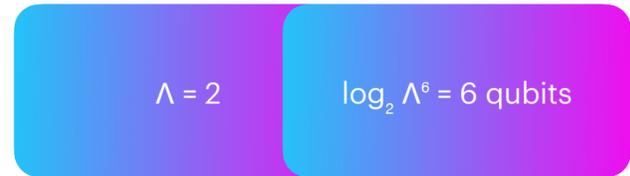
Small-scale: N=2, D=2





VQE details

Small-scale: $N=2$, $D=2$



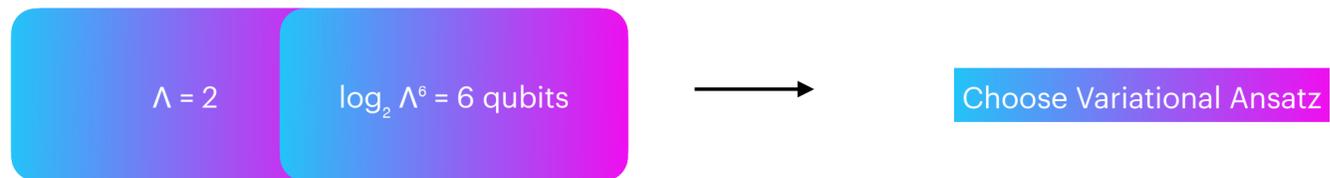
Choose Variational Ansatz

PQC \rightarrow Variational Ansatz for $|\Phi\rangle$

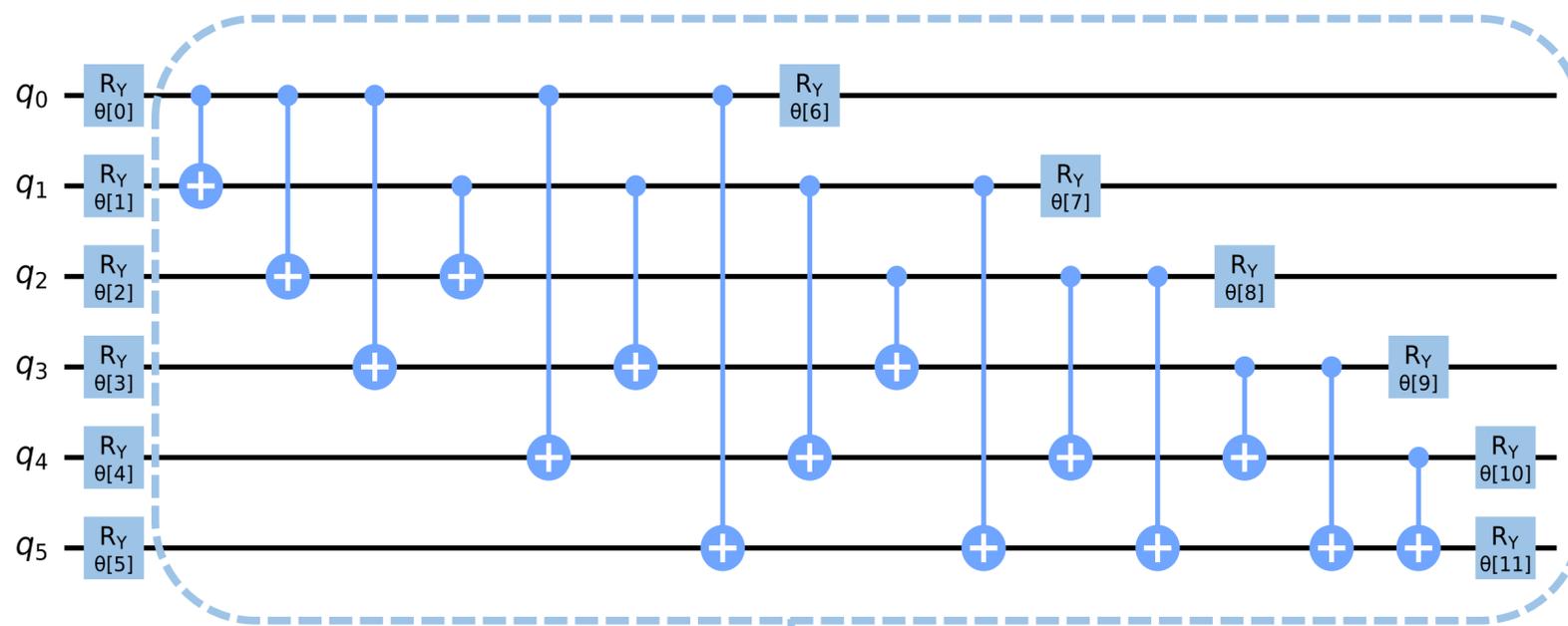


VQE details

Small-scale: N=2, D=2



PQC \rightarrow Variational Ansatz for $|\Phi\rangle$ depth = 1
parameters = 12

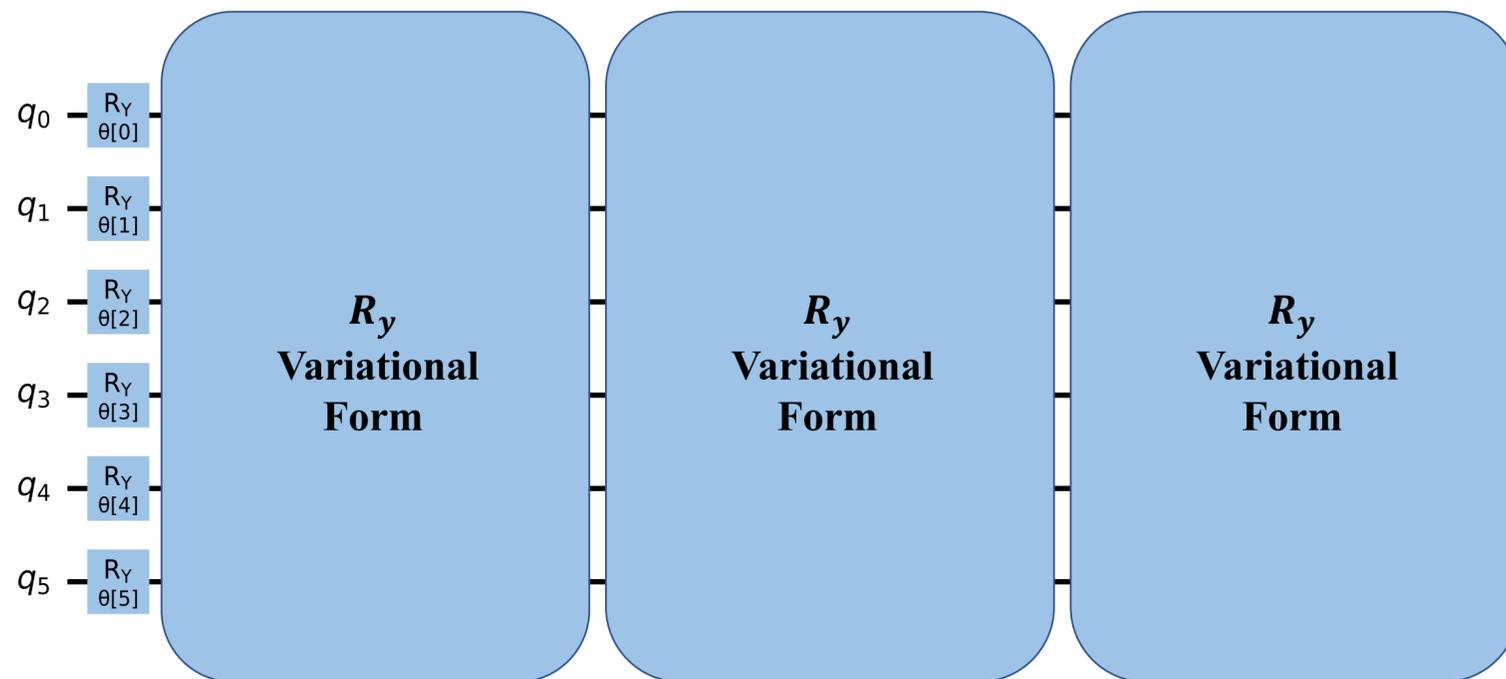
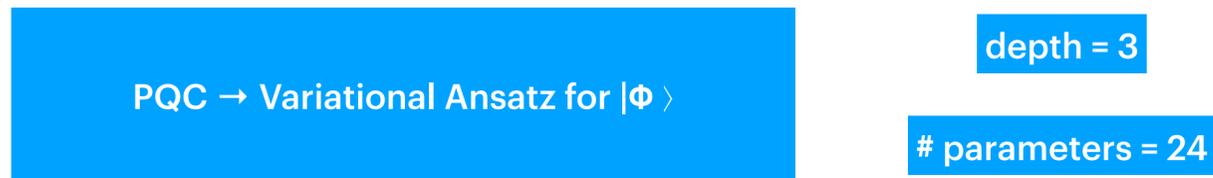
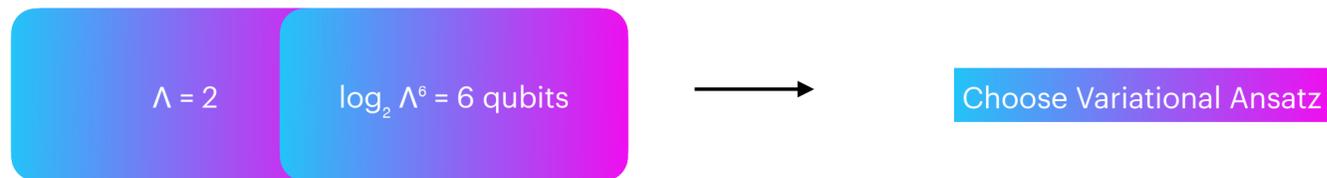


R_y Variational Form



VQE details

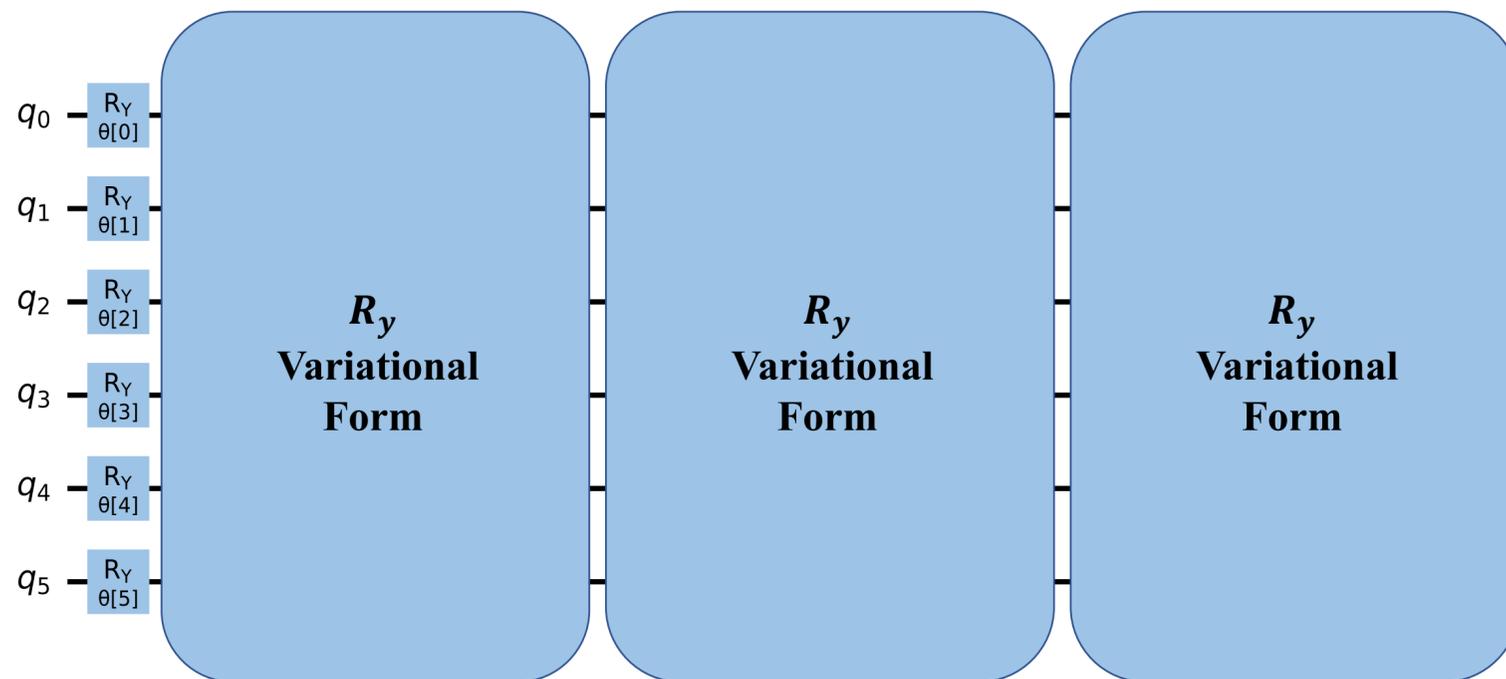
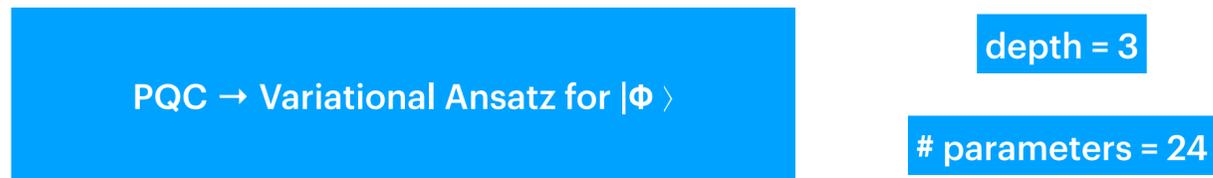
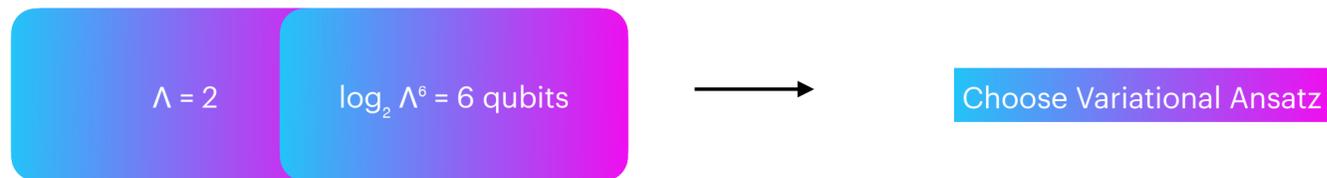
Small-scale: N=2, D=2





VQE details

Small-scale: $N=2, D=2$

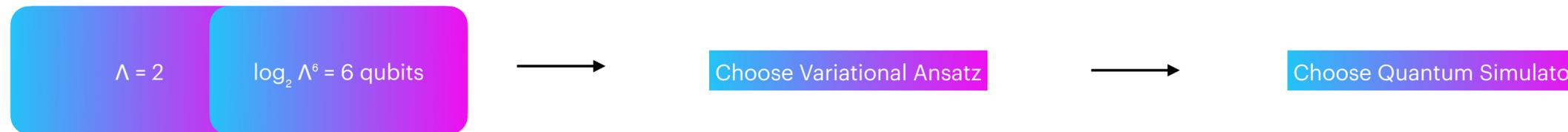


Run each multiple instances of PQC from different initial points



VQE details

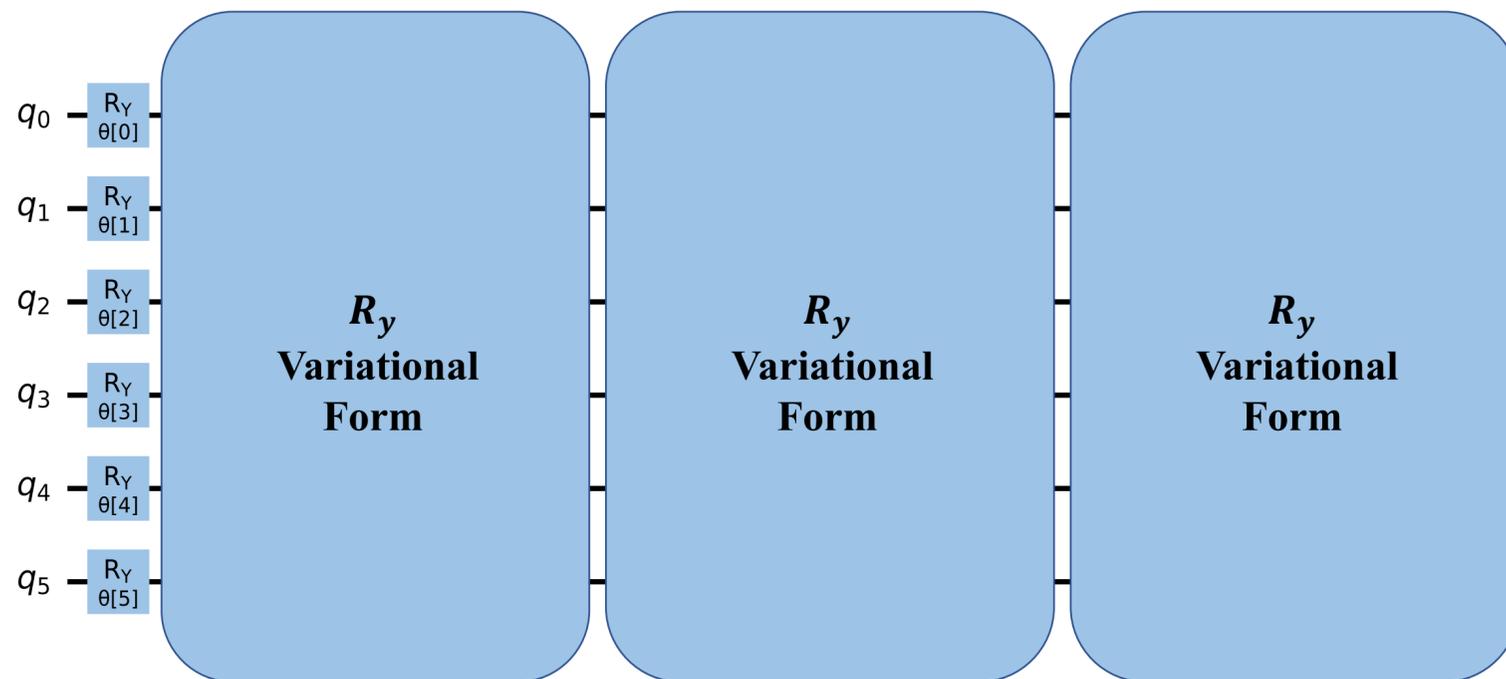
Small-scale: N=2, D=2



PQC → Variational Ansatz for $|\Phi\rangle$

depth = 3

parameters = 24

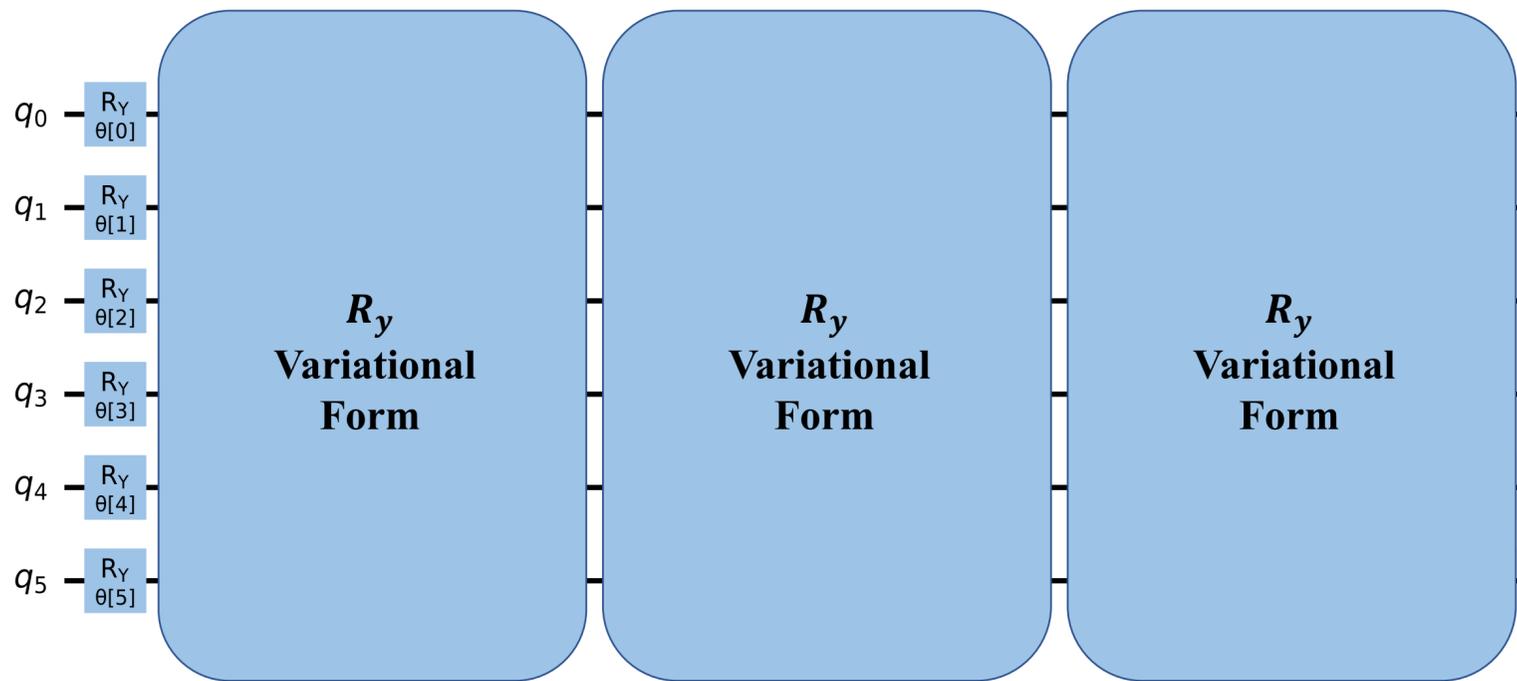
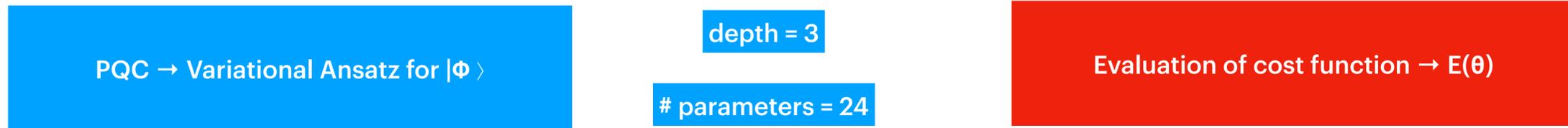
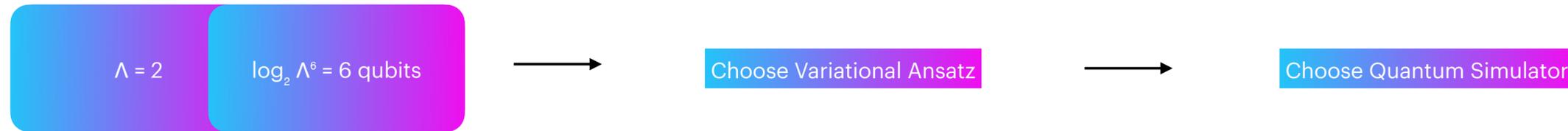


Run each multiple instances of PQC from different initial points



VQE details

Small-scale: N=2, D=2



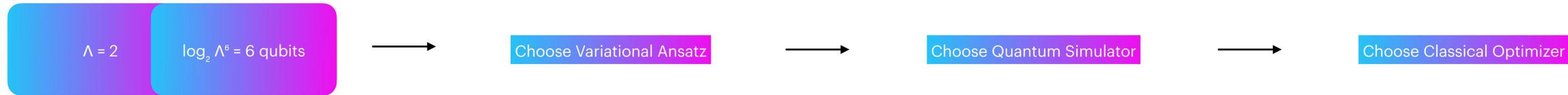
• Statevector simulator

Run each multiple instances of PQC from different initial points



VQE details

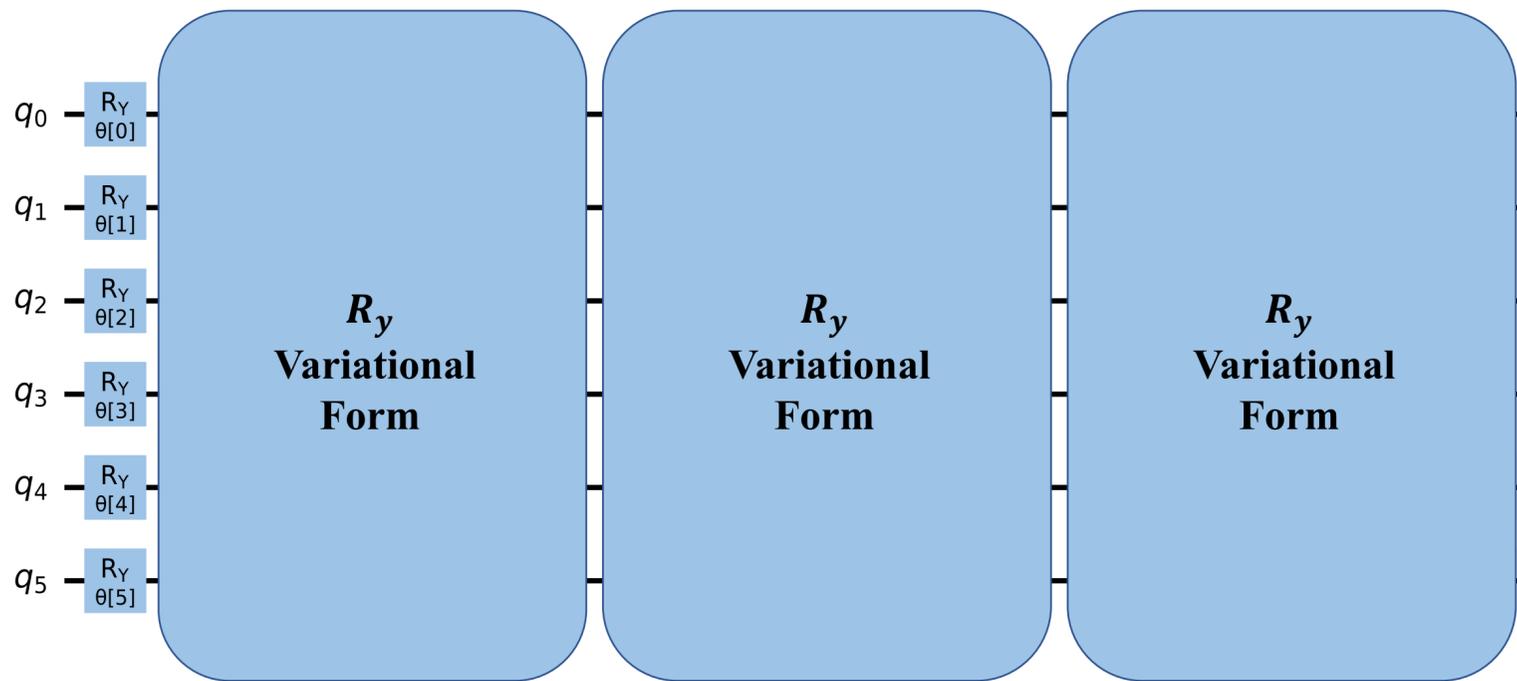
Small-scale: N=2, D=2



PQC → Variational Ansatz for $|\Phi\rangle$

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parameters = 24

Evaluation of cost function → $E(\theta)$



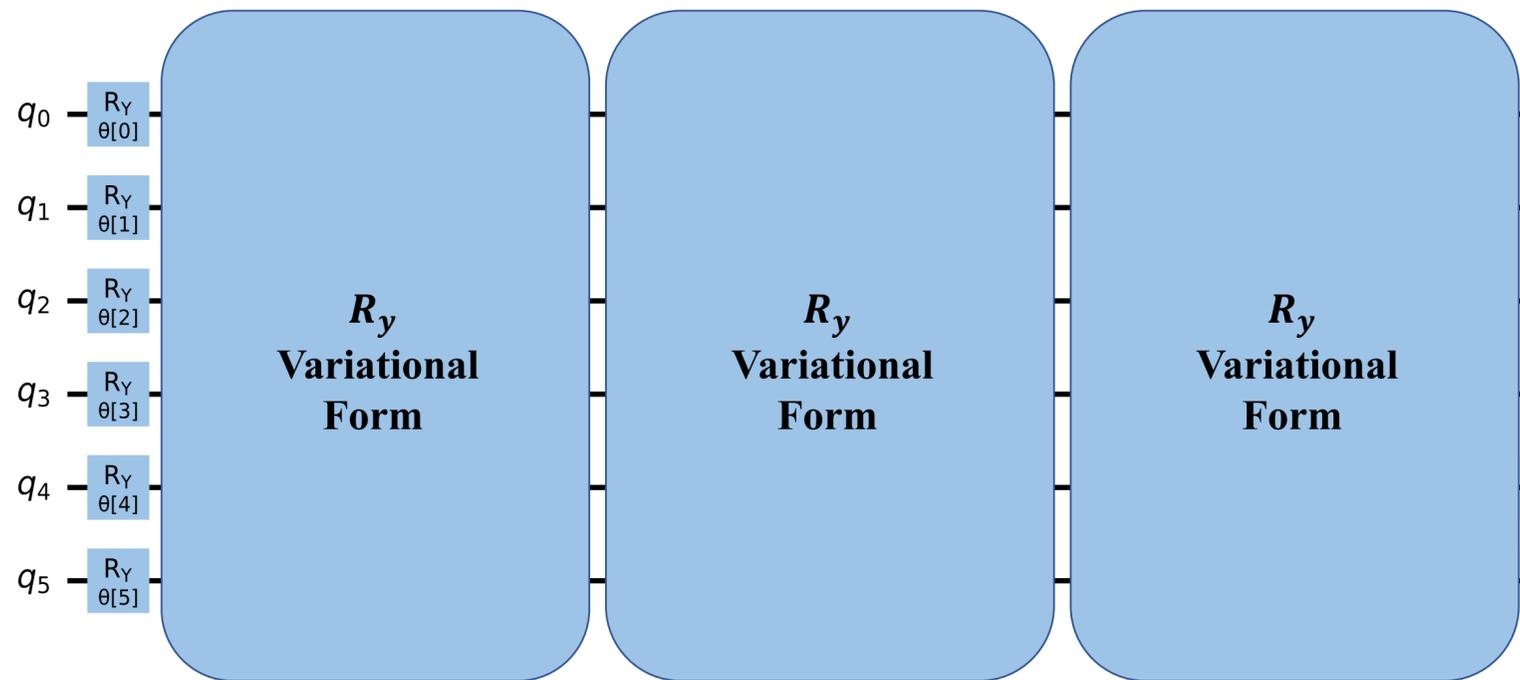
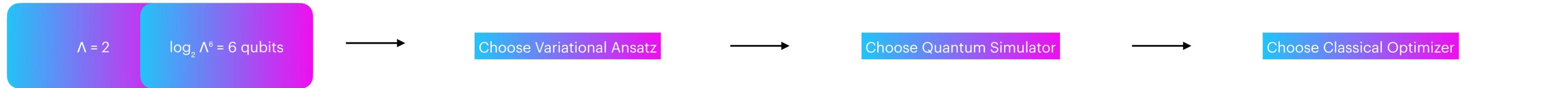
• Statevector simulator

Run each multiple instances of PQC from different initial points



VQE details

Small-scale: N=2, D=2



• Statevector simulator

- Least Squares Programming optimizer (SLSQP)
- Constrained Optimization By Linear Approximation optimizer (COBYLA)
- Limited-memory BFGS Bound optimizer (L-BFGS-B)
- Nelder-Mead

Run each optimizer with a max. number of iterations

Run each multiple instances of PQC from different initial points



Qubitization of MQM

Small-scale: $N=2$, $D=2$, $\Lambda \rightarrow \infty$





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$

$\Lambda = 4$

$\Lambda = 8$





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$

Each boson is 1 qubit

$\Lambda = 4$

$\Lambda = 8$





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$

Each boson is 1 qubit

$\log_2 \Lambda^6 = 6$ qubits

$\Lambda = 4$

$\Lambda = 8$





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$

Each boson is 1 qubit

$\log_2 \Lambda^6 = 6$ qubits

$\Lambda = 4$

Each boson is 2 qubits

$\log_2 \Lambda^6 = 12$ qubits

$\Lambda = 8$





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$

Each boson is 1 qubit

$\log_2 \Lambda^6 = 6$ qubits

$\Lambda = 4$

Each boson is 2 qubits

$\log_2 \Lambda^6 = 12$ qubits

$\Lambda = 8$

Each boson is 3 qubits

$\log_2 \Lambda^6 = 18$ qubits





Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$	Each boson is 1 qubit	$\log_2 \Lambda^6 = 6$ qubits
$\Lambda = 4$	Each boson is 2 qubits	$\log_2 \Lambda^6 = 12$ qubits



$\Lambda = 8$

Each boson is 3 qubits



$\log_2 \Lambda^6 = 18$ qubits

limited resources



Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

$\Lambda = 2$	Each boson is 1 qubit	$\log_2 \Lambda^6 = 6$ qubits
$\Lambda = 4$	Each boson is 2 qubits	$\log_2 \Lambda^6 = 12$ qubits



$\Lambda = 8$

Each boson is 3 qubits

$\log_2 \Lambda^6 = 18$ qubits



limited resources

$$\hat{H}_B = \sum_{\alpha, I} \left(\frac{1}{2} \hat{P}_{I\alpha}^2 + \frac{m^2}{2} \hat{X}_{I\alpha}^2 \right) + \frac{g^2}{4} \sum_{\gamma, I, J} \left(\sum_{\alpha, \beta} f_{\alpha\beta\gamma} \hat{X}_I^\alpha \hat{X}_J^\beta \right)^2 \quad I = 1, 2 \quad \alpha = 1, 2, 3$$

Build matrix Hamiltonian which gets mapped to qubits



Qubitization of MQM

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

Truncation Level

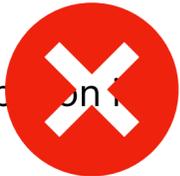
Rewrite $X_i \rightarrow a_i$
Annihilation operator for site "i"

$\Lambda = 2$	Each boson is 1 qubit	$\log_2 \Lambda^6 = 6$ qubits
$\Lambda = 4$	Each boson is 2 qubits	$\log_2 \Lambda^6 = 12$ qubits



$\Lambda = 8$	Each boson is 3 qubits	$\log_2 \Lambda^6 = 18$ qubits
---------------	------------------------	--------------------------------

limited resources



$$\hat{a}_i = \hat{I}_1 \otimes \dots \otimes \hat{I}_{i-1} \otimes \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \otimes \hat{I}_{i+1} \otimes \dots \otimes \hat{I}_6$$

$$\hat{a}_i = \hat{I}_1 \otimes \dots \otimes \hat{I}_{i-1} \otimes \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & \sqrt{2} & 0 \\ 0 & 0 & 0 & \sqrt{3} \\ 0 & 0 & 0 & 0 \end{pmatrix} \otimes \hat{I}_{i+1} \otimes \dots \otimes \hat{I}_6$$

$$\hat{H}_B = \sum_{\alpha, I} \left(\frac{1}{2} \hat{P}_{I\alpha}^2 + \frac{m^2}{2} \hat{X}_{I\alpha}^2 \right) + \frac{g^2}{4} \sum_{\gamma, I, J} \left(\sum_{\alpha, \beta} f_{\alpha\beta\gamma} \hat{X}_I^\alpha \hat{X}_J^\beta \right)^2 \quad I = 1, 2 \quad \alpha = 1, 2, 3$$

Build matrix Hamiltonian which gets mapped to qubits



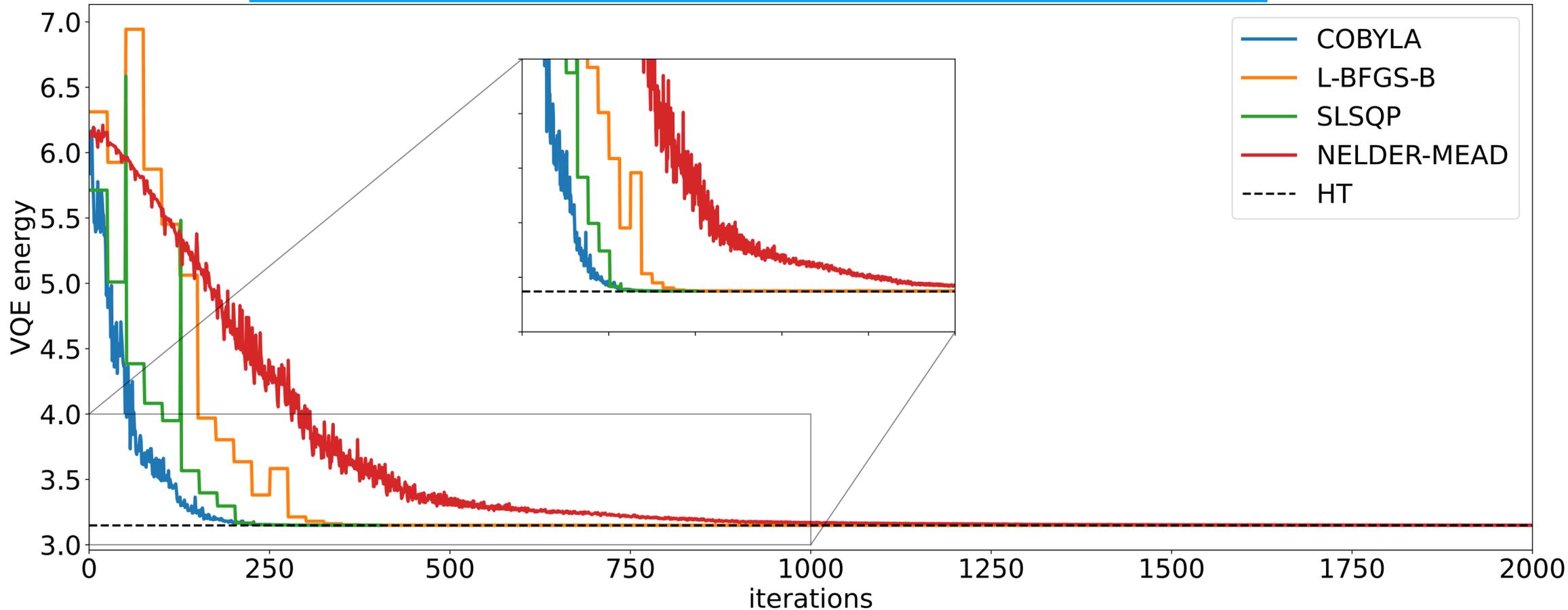
Results

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

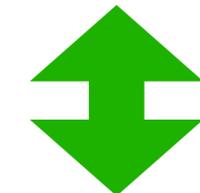
$\Lambda = 2$ $\log_2 \Lambda^6 = 6$ qubits

Optimizer	Var. form: R_y				Var. form: $R_y R_z$			
	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.
COBYLA	3.149370	4.147156	3.159740	0.099739	3.149157	3.150034	3.149862	0.000202
L-BFGS-B	3.149268	4.150000	3.159886	0.100012	3.149375	4.148751	3.159925	0.099882
SLSQP	3.149397	4.150000	3.164968	0.111340	3.149377	4.149946	3.164980	0.111349
NELDER-MEAD	3.148972	3.195922	3.150774	0.005065	3.149516	4.149891	3.171468	0.140469

PQC with y rotation gates: depth = 3 → 24 parameters | Best out of 100 runs



Best VQE (100 runs): $E_0 = 3.148972$



Exact Diagonalization: $E_0 = 3.14808$



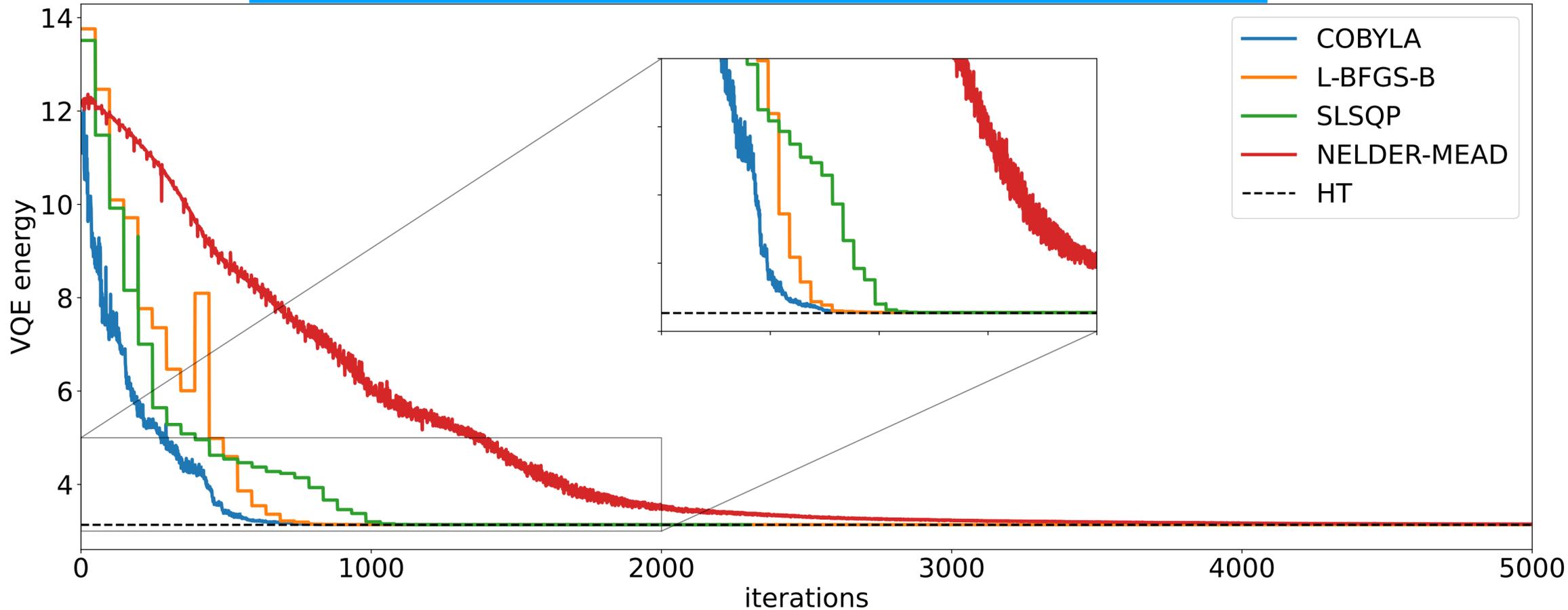
Results

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

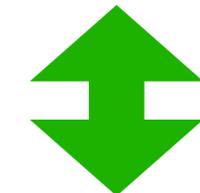
$\Lambda = 4$ $\log_2 \Lambda^6 = 12$ qubits

Optimizer	Var. form: R_y				Var. form: $R_y R_z$			
	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.
COBYLA	3.137059	4.769101	3.251414	0.347646	3.137237	4.782013	3.378628	0.472015
L-BFGS-B	3.137059	5.769553	3.283462	0.434162	3.137050	4.286367	3.243110	0.307549
SLSQP	3.137060	5.769554	3.327706	0.471957	3.137059	4.232419	3.236925	0.290855
NELDER-MEAD	3.137471	5.713976	3.492673	0.478810	3.273614	6.443055	4.428032	0.758732

PQC with y rotation gates: depth = 3 → 36 parameters | Best out of 100 runs



Best VQE (100 runs): $E_0 = 3.137$



Exact Diagonalization: $E_0 = 3.13406$

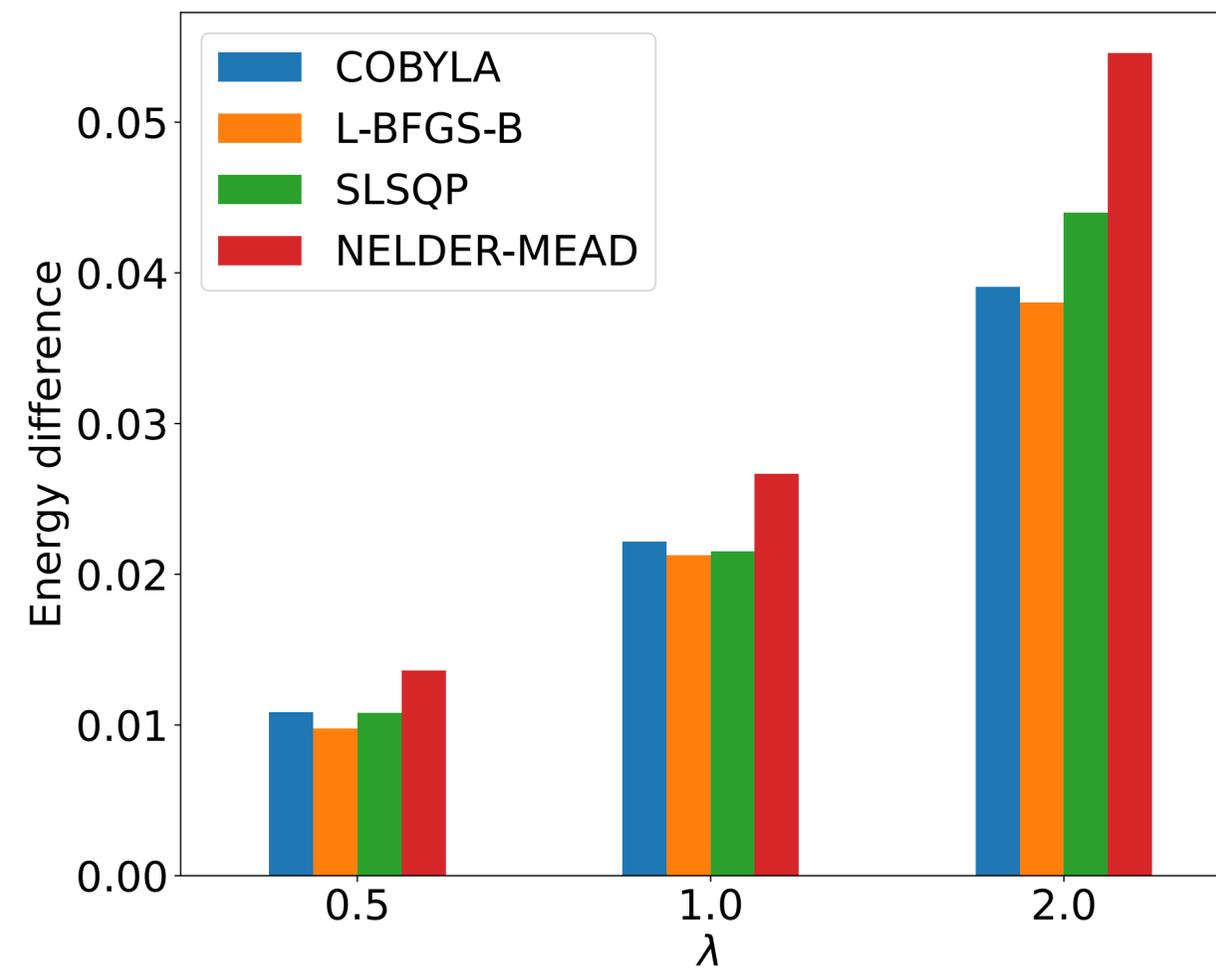
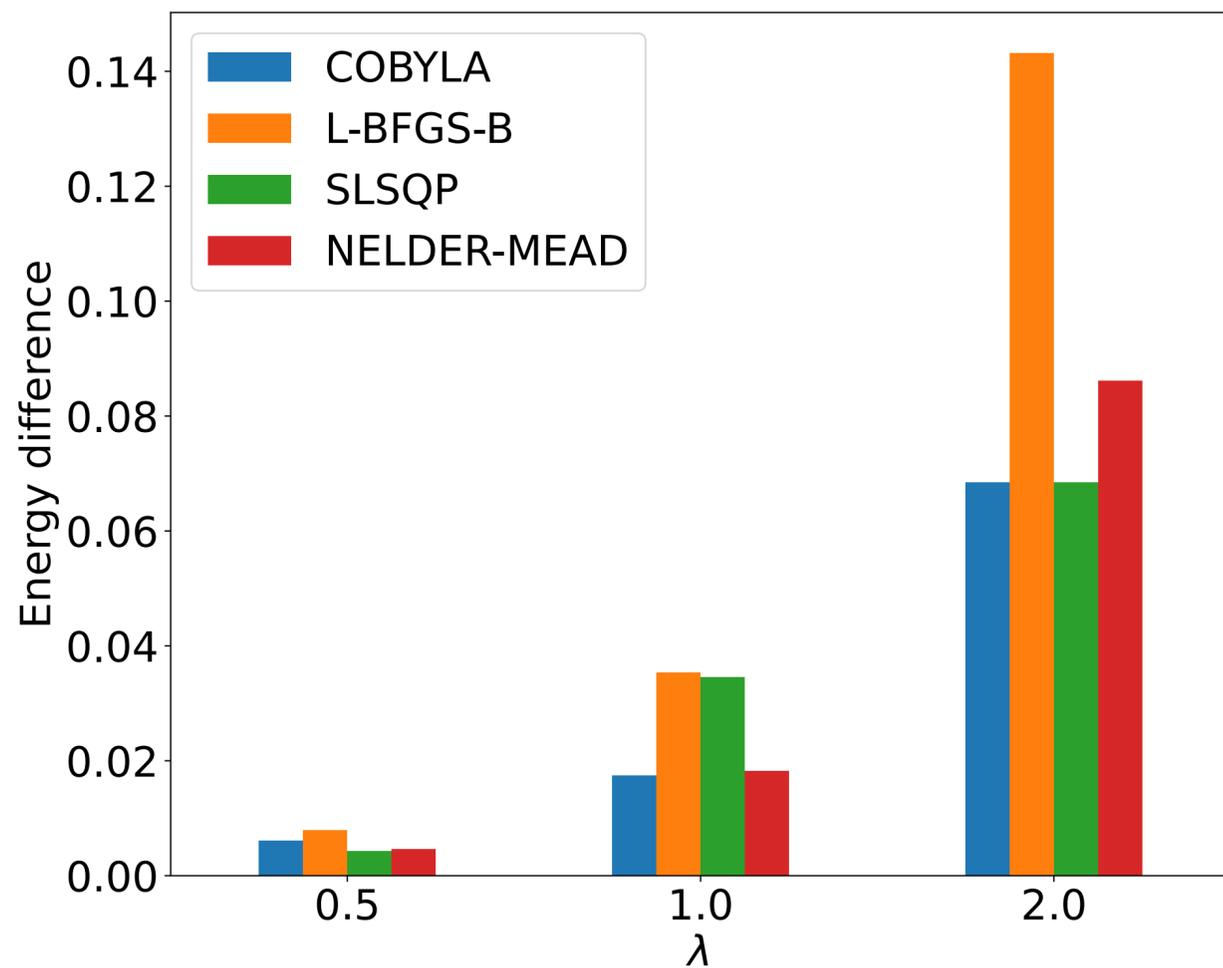


Results

Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

$\Lambda = 2$ $\log_2 \Lambda^6 = 6$ qubits

$\Lambda = 4$ $\log_2 \Lambda^6 = 12$ qubits



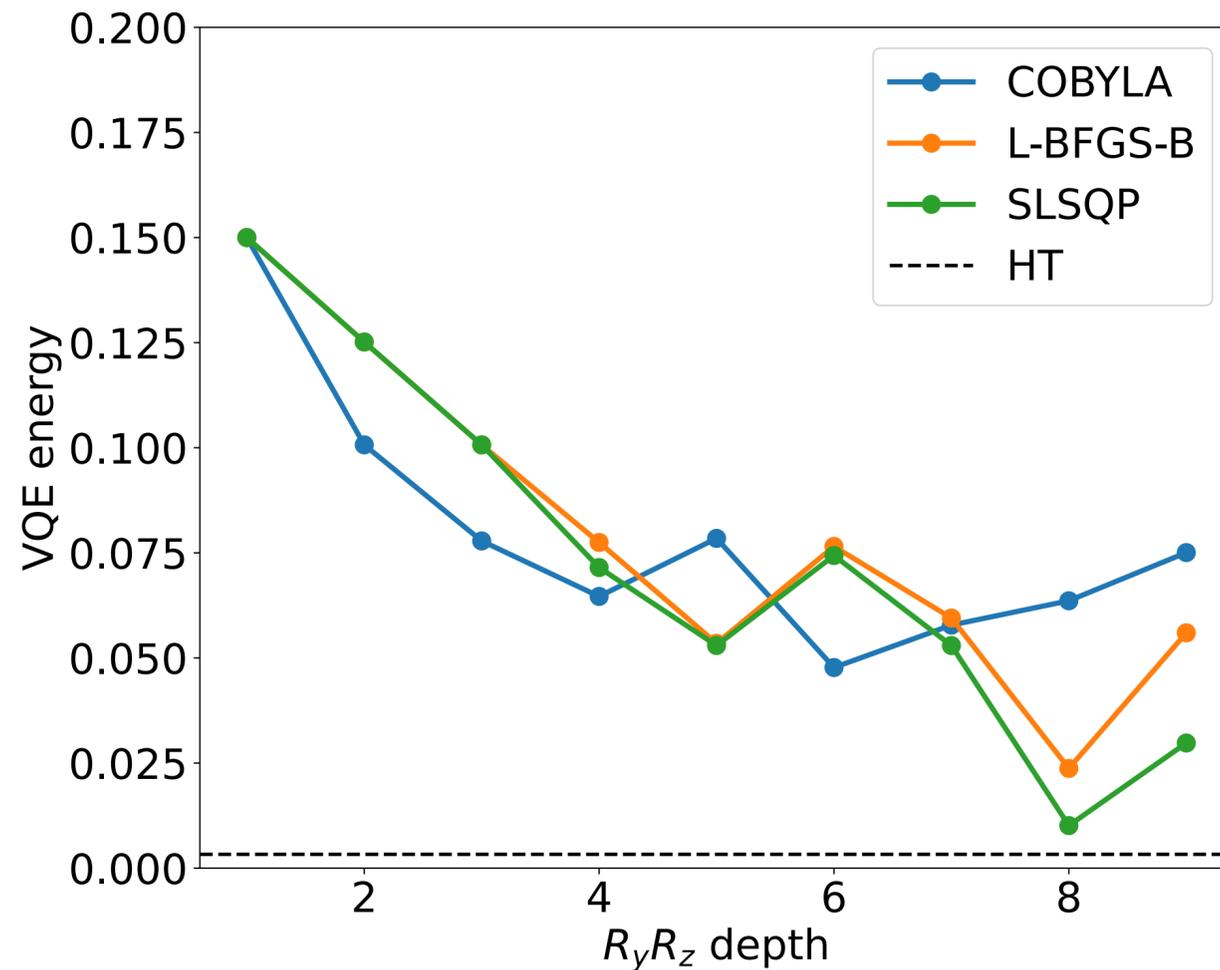
PQC with y rotation gates: depth = 3 | Best out of 100 runs



Results

Supersymmetric N=2 D=2 at large coupling

$\Lambda = 2$ $\log_2 \Lambda^6 = 9$ qubits

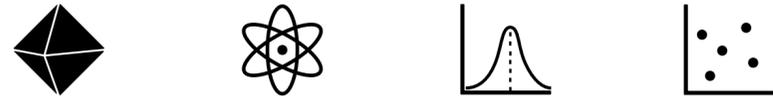


λ	depth = 5				depth = 9	HT (exact)
	COBYLA	L-BFGS-B	SLSQP	NELDER-MEAD	Best	
0.5	0.088492	0.139702	0.134517	0.406003	0.02744	0.01690
1.0	0.135800	0.219268	0.308781	0.752459	0.07900	0.04829
2.0	0.387977	0.622704	0.522396	1.271939	0.17688	0.08385

Computational Resources

How hard is it?

Bosonic Model

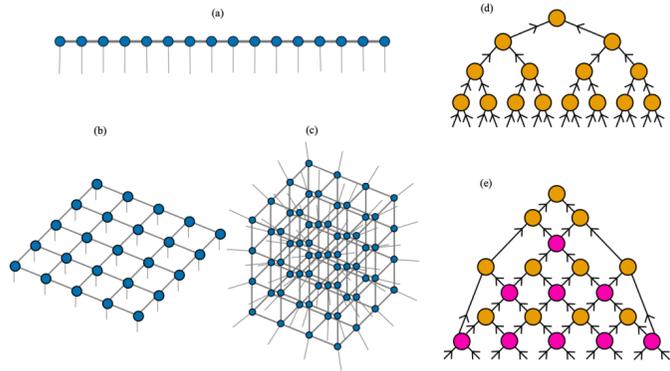


D=2	HT	VQE	DL	MC
N=2	✓	$\Lambda = 2,4$	✓	✓
N=3	!!	✗	✓	✓
N>3	✗	✗	✓	✓

Supersymmetric Model



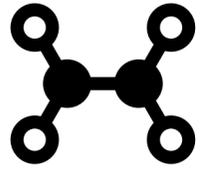
D=2	HT	VQE	DL	MC
N=2	✓	$\Lambda = 2$	✓	✓
N=3	!!	✗	✓	✓
N>3	✗	✗	✓	✓



Tensor Network Methods

Quick Introduction

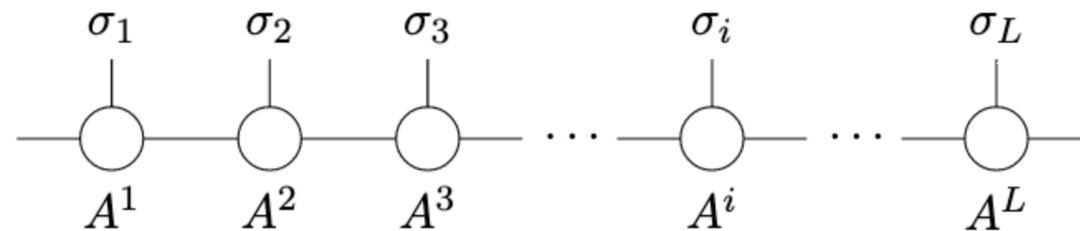
- In **quantum many-body systems**, TN are used as a parsimonious representation of the amplitudes of the wave function
- TN elements can be optimized to compress correlated wave functions
- Algorithms based on TN allow for **representing ground states** and for **time-evolving arbitrary states**
- TN with finite computational resources are **inherently approximate**
- In quantum computing, TN are the **leading “classical” simulation methods**



Matrix Product States

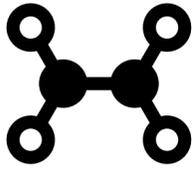
Ingredients

$$|\psi\rangle = \sum_{\{\sigma_i, \alpha_i\}} A_{\alpha_0 \alpha_1}^{1, \sigma_1} A_{\alpha_1 \alpha_2}^{2, \sigma_2} \cdots A_{\alpha_{L-2} \alpha_{L-1}}^{L-1, \sigma_{L-1}} A_{\alpha_{L-1} \alpha_0}^{L, \sigma_L} |\sigma_1 \sigma_2 \cdots \sigma_{L-1} \sigma_L\rangle,$$



- L sites \rightarrow total number of bosons ($\sim N^2 D$)
- Sites are d dimensional \rightarrow dimension of each bosonic Hilbert space Λ
- D is the *bond dimension* \rightarrow computational cost of DMRG:

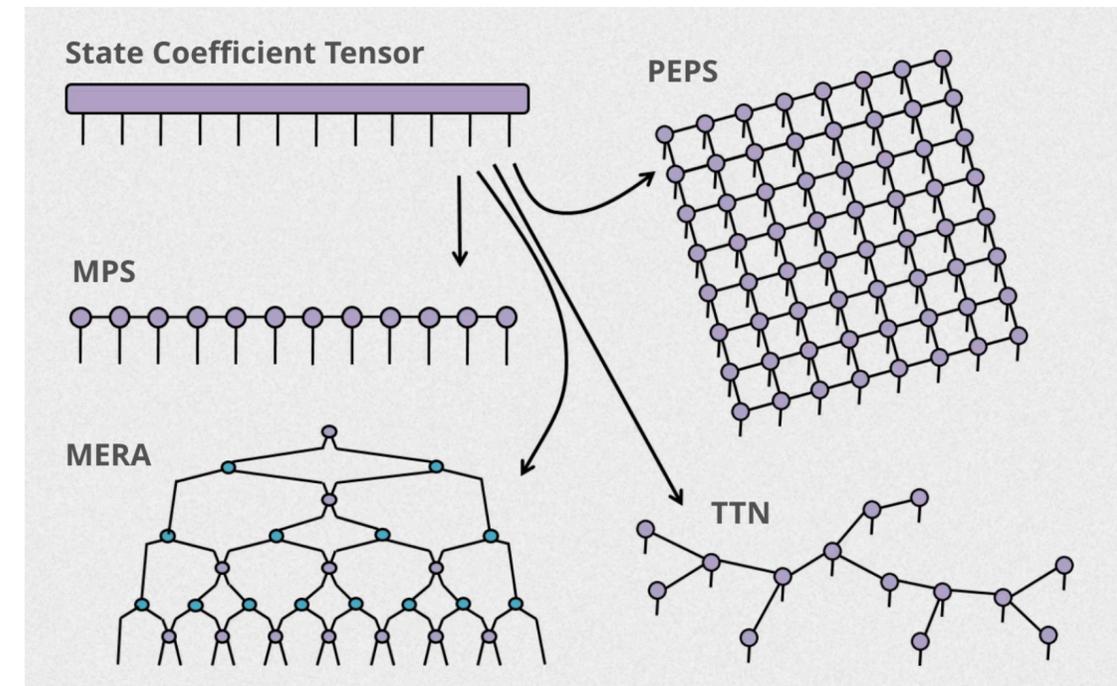
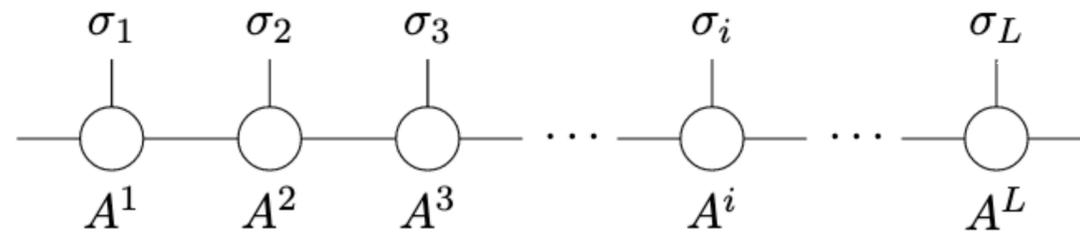
$$\mathcal{O}(2LD_{\max}^3 \chi d + 2LD_{\max}^2 \chi^2 d^2 + LD_{\max}^3 \chi d^2)$$



Matrix Product States

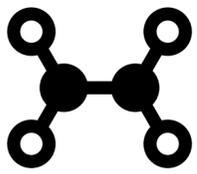
Ingredients

$$|\psi\rangle = \sum_{\{\sigma_i, \alpha_i\}} A_{\alpha_0 \alpha_1}^{1, \sigma_1} A_{\alpha_1 \alpha_2}^{2, \sigma_2} \cdots A_{\alpha_{L-2} \alpha_{L-1}}^{L-1, \sigma_{L-1}} A_{\alpha_{L-1} \alpha_0}^{L, \sigma_L} |\sigma_1 \sigma_2 \cdots \sigma_{L-1} \sigma_L\rangle,$$



- L sites \rightarrow total number of bosons ($\sim N^2 D$)
- Sites are d dimensional \rightarrow dimension of each bosonic Hilbert space Λ
- D is the *bond dimension* \rightarrow computational cost of DMRG:

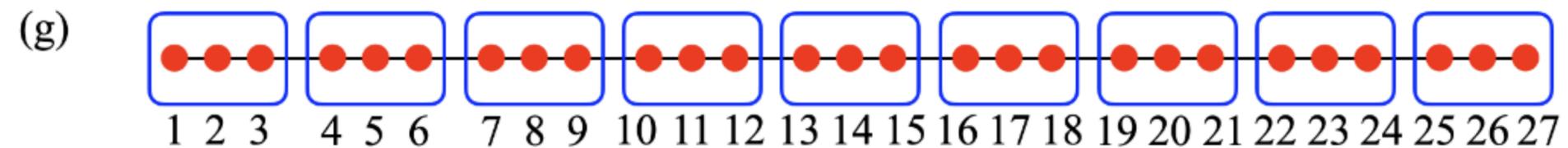
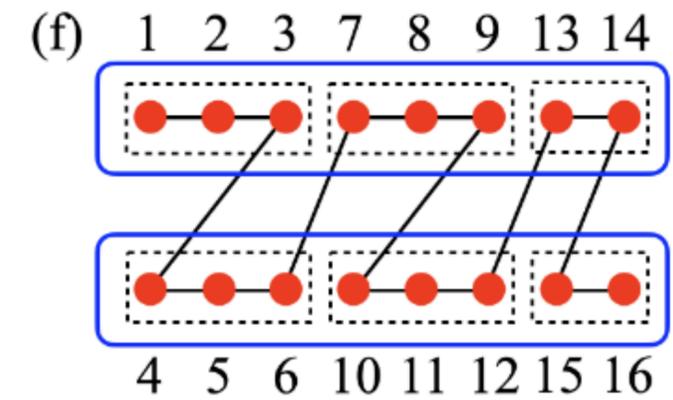
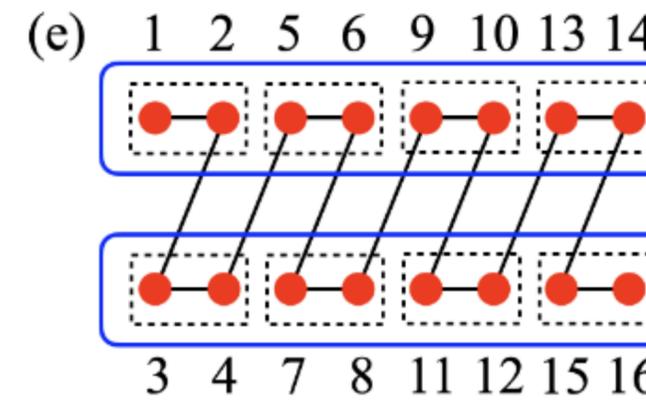
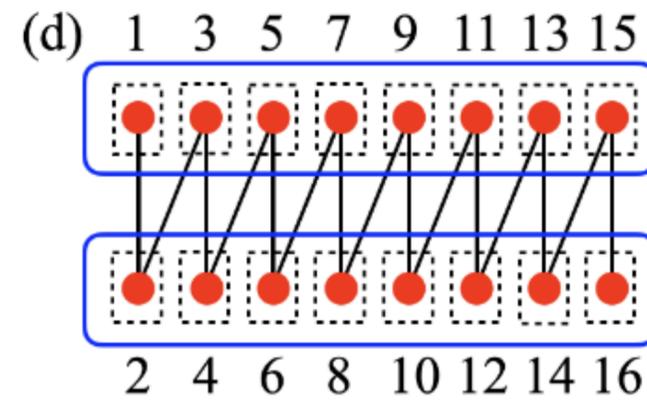
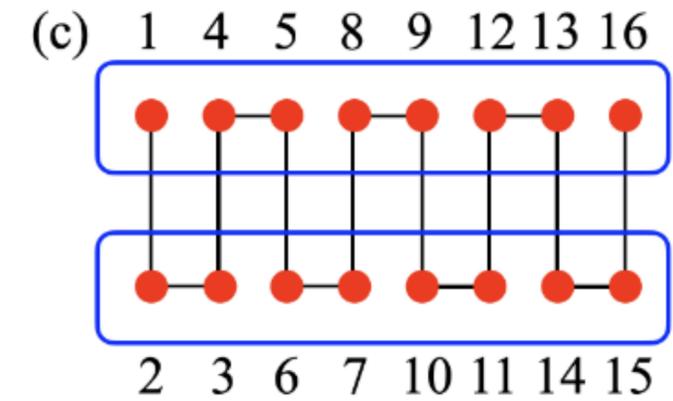
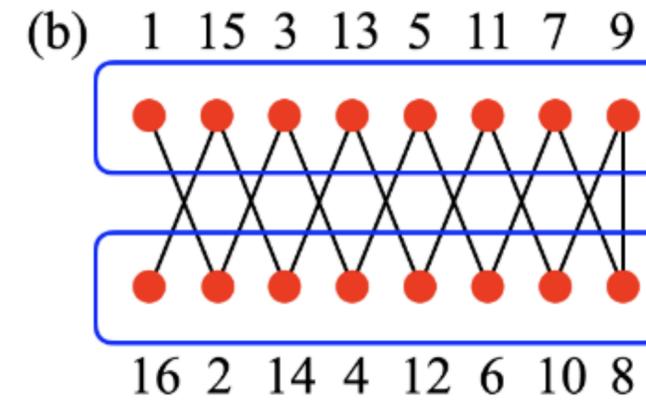
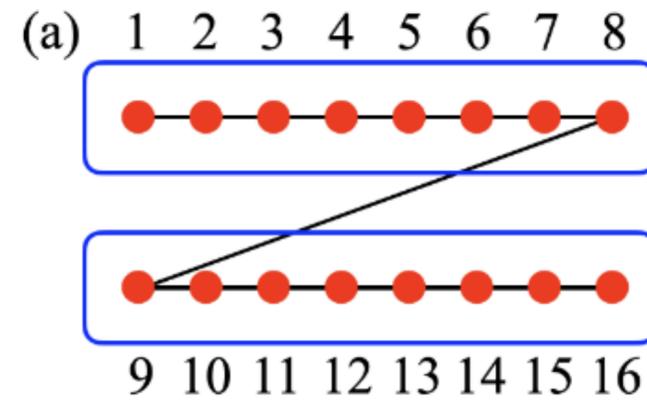
$$\mathcal{O}(2LD_{\max}^3 \chi d + 2LD_{\max}^2 \chi^2 d^2 + LD_{\max}^3 \chi d^2)$$

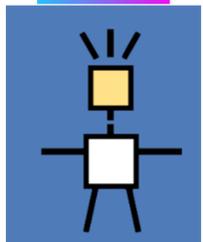


Matrix Product States Layouts

SU(3), D=2

SU(2), D=9

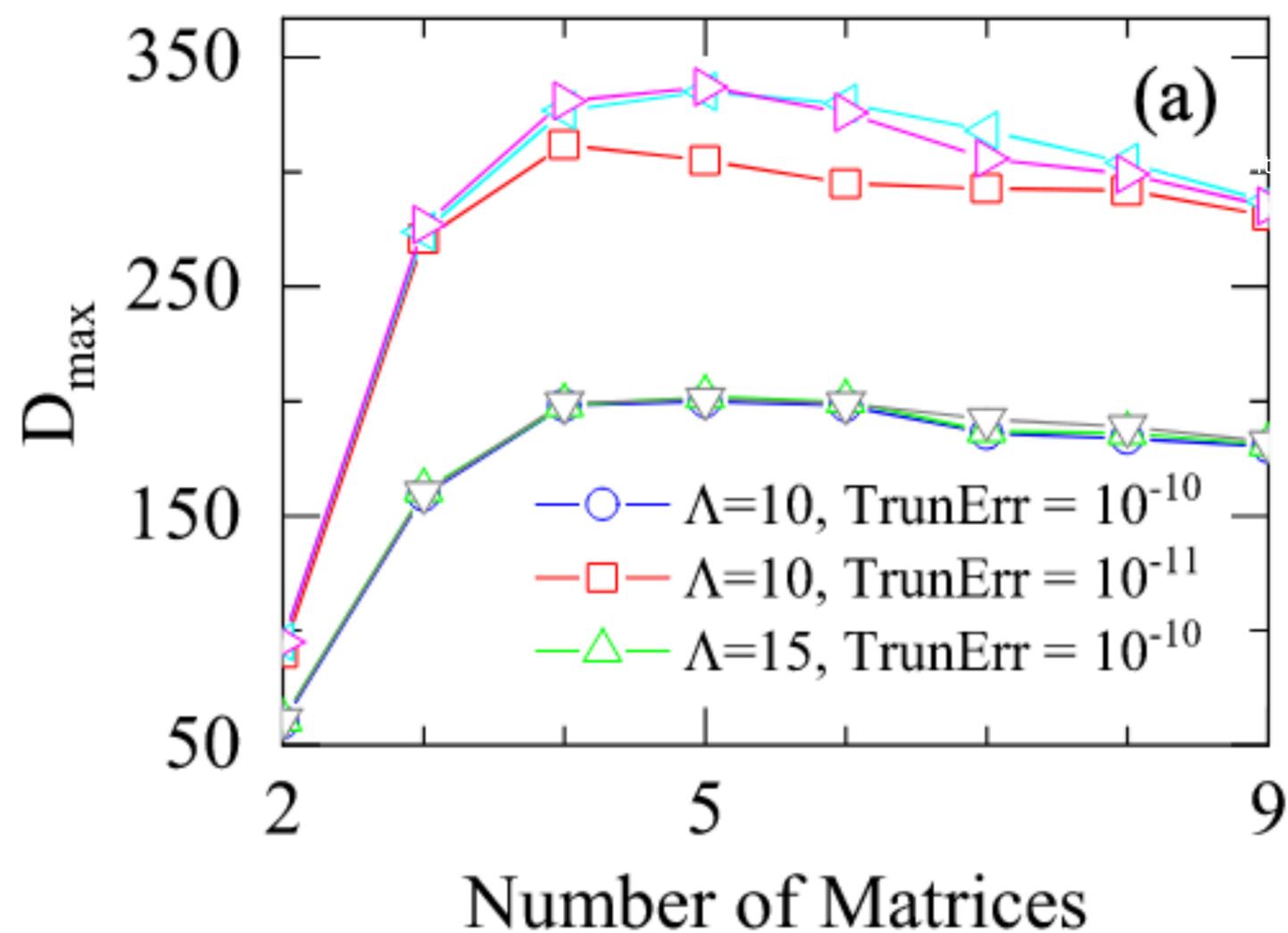




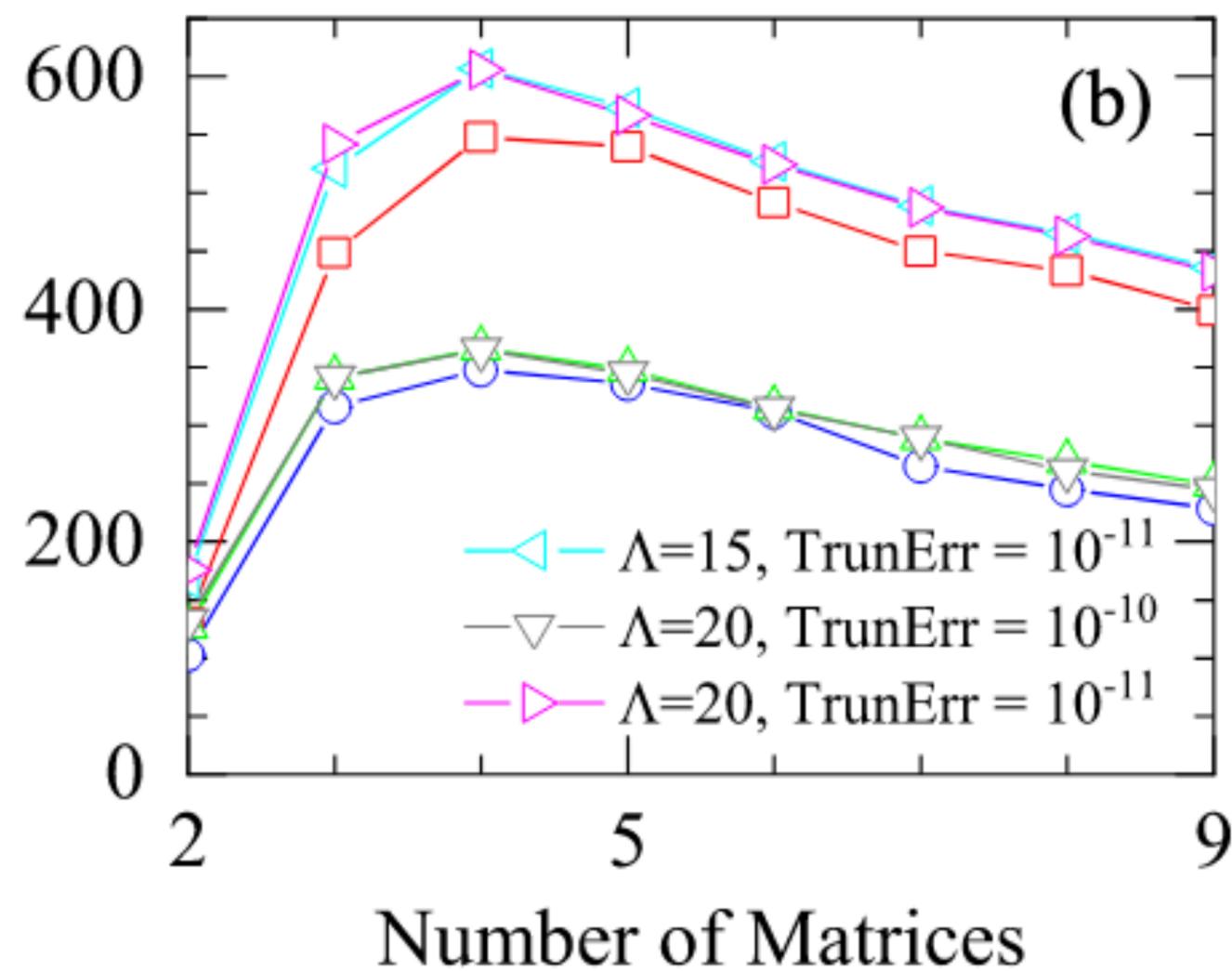
Results

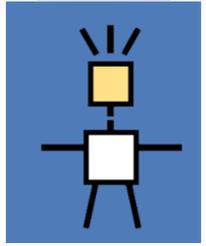
SU(2), D Matrices (Bosonic)

$g=0.5$



$g=1.0$



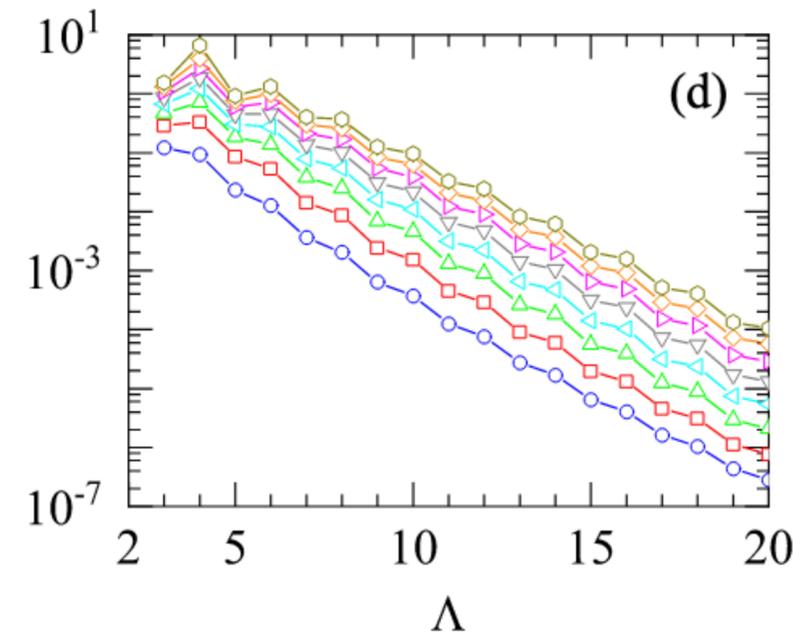
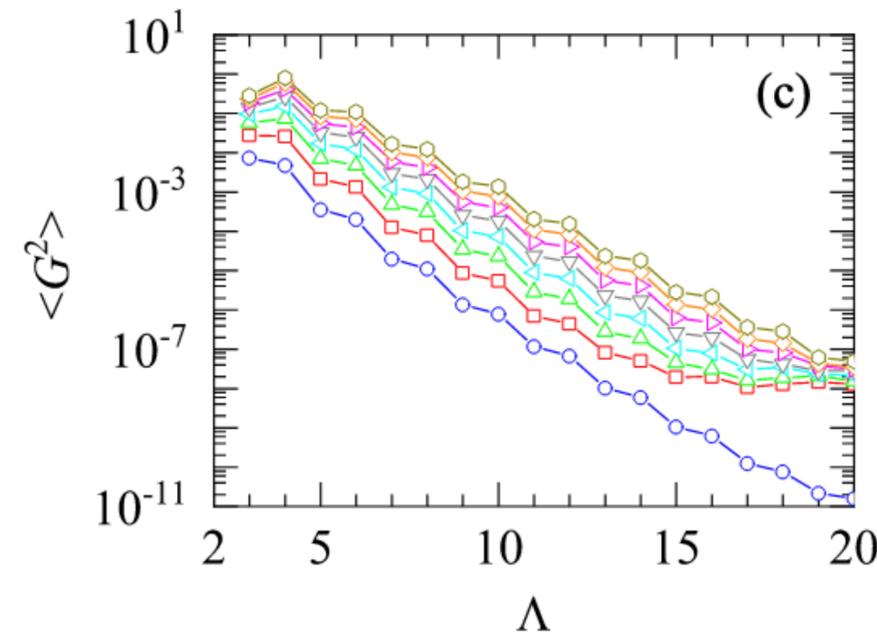
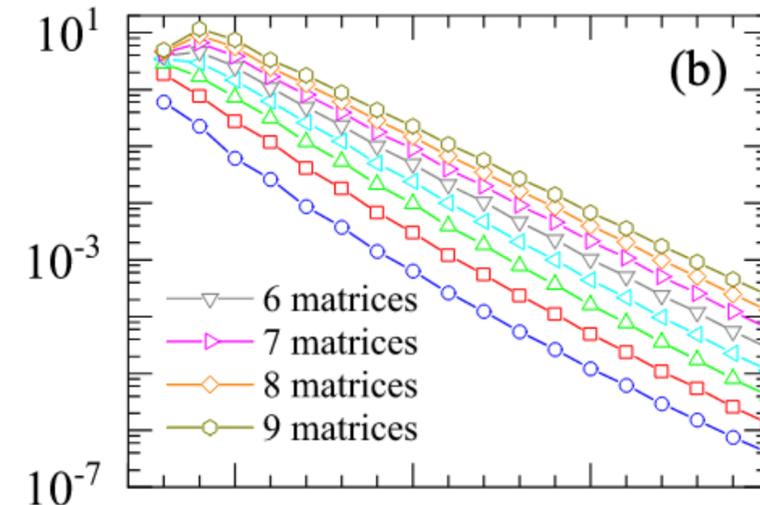
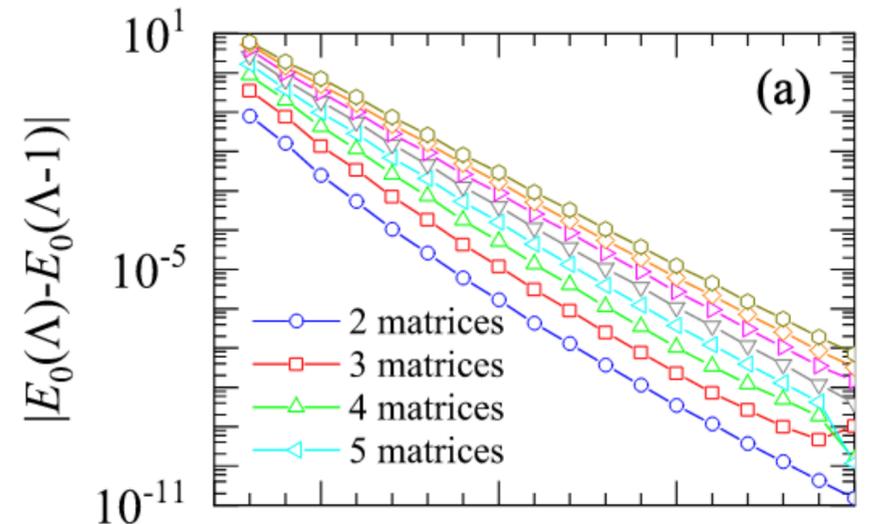


Results

SU(2), D Matrices (Bosonic), $\Lambda \rightarrow \infty$

$g=0.5$

$g=1.0$

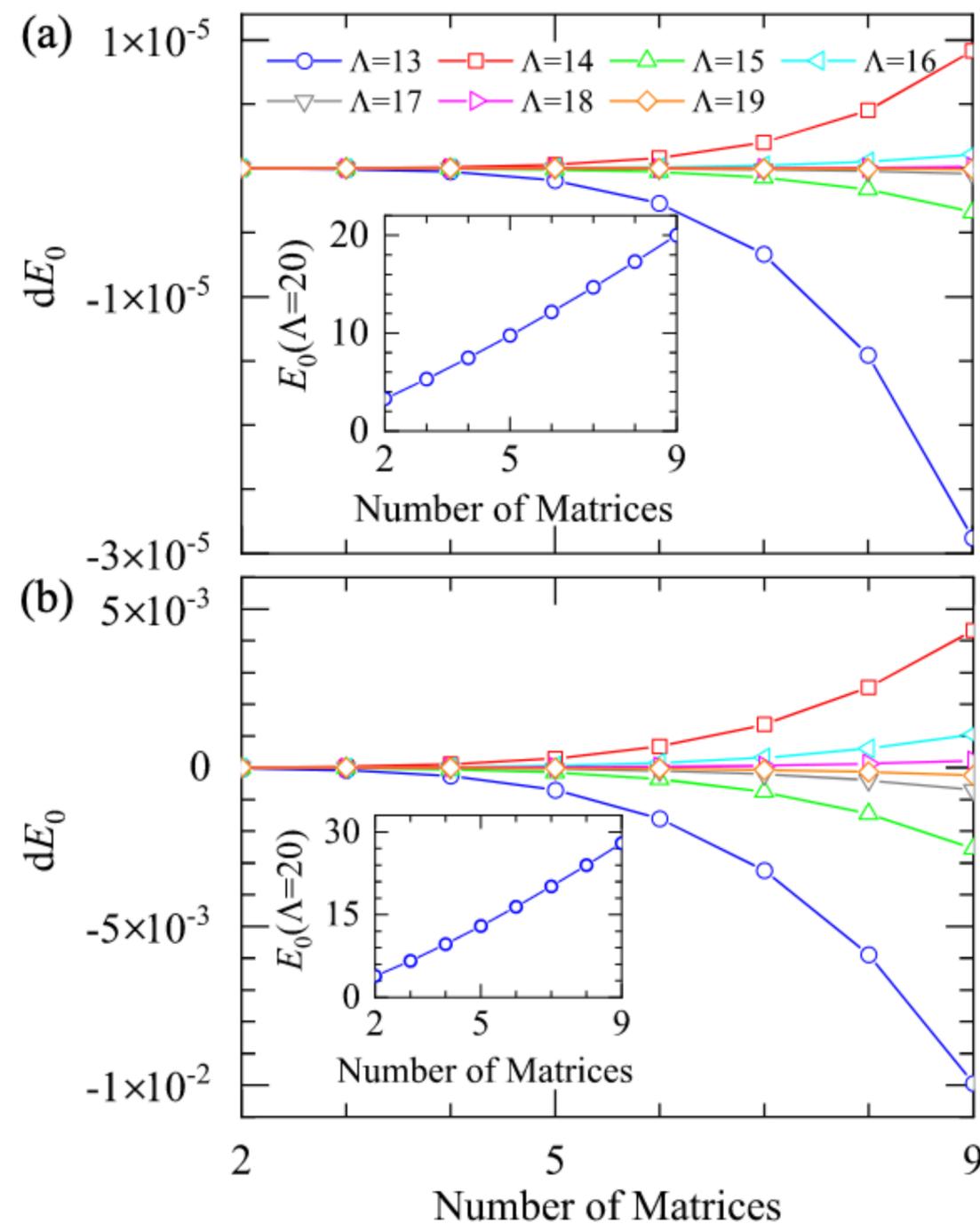


Ground state energy

Gauge invariance violation

Results

SU(2), D Matrices (Bosonic), $\Lambda \rightarrow \infty$



Energy convergence

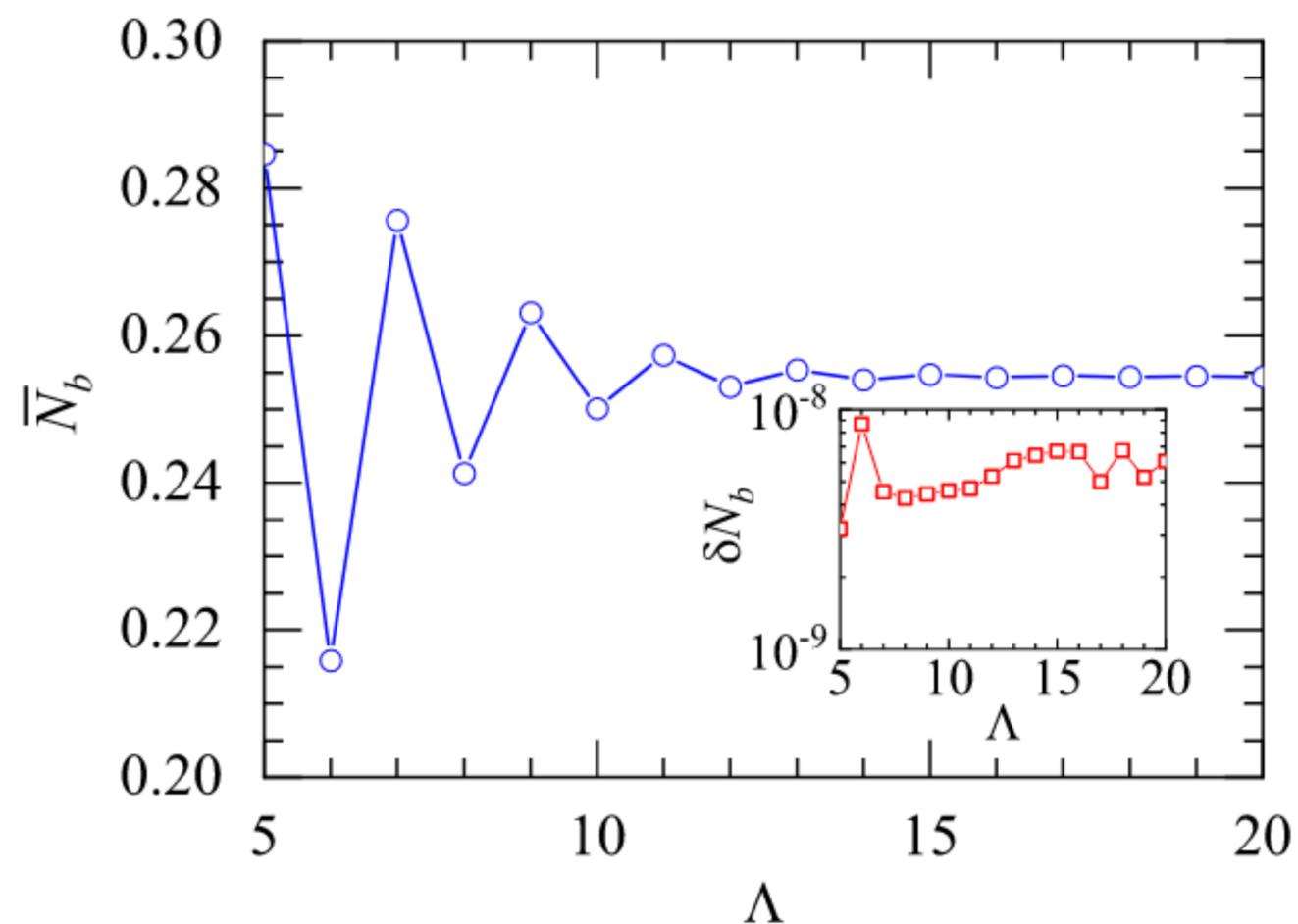
$g=0.5$

$g=1.0$

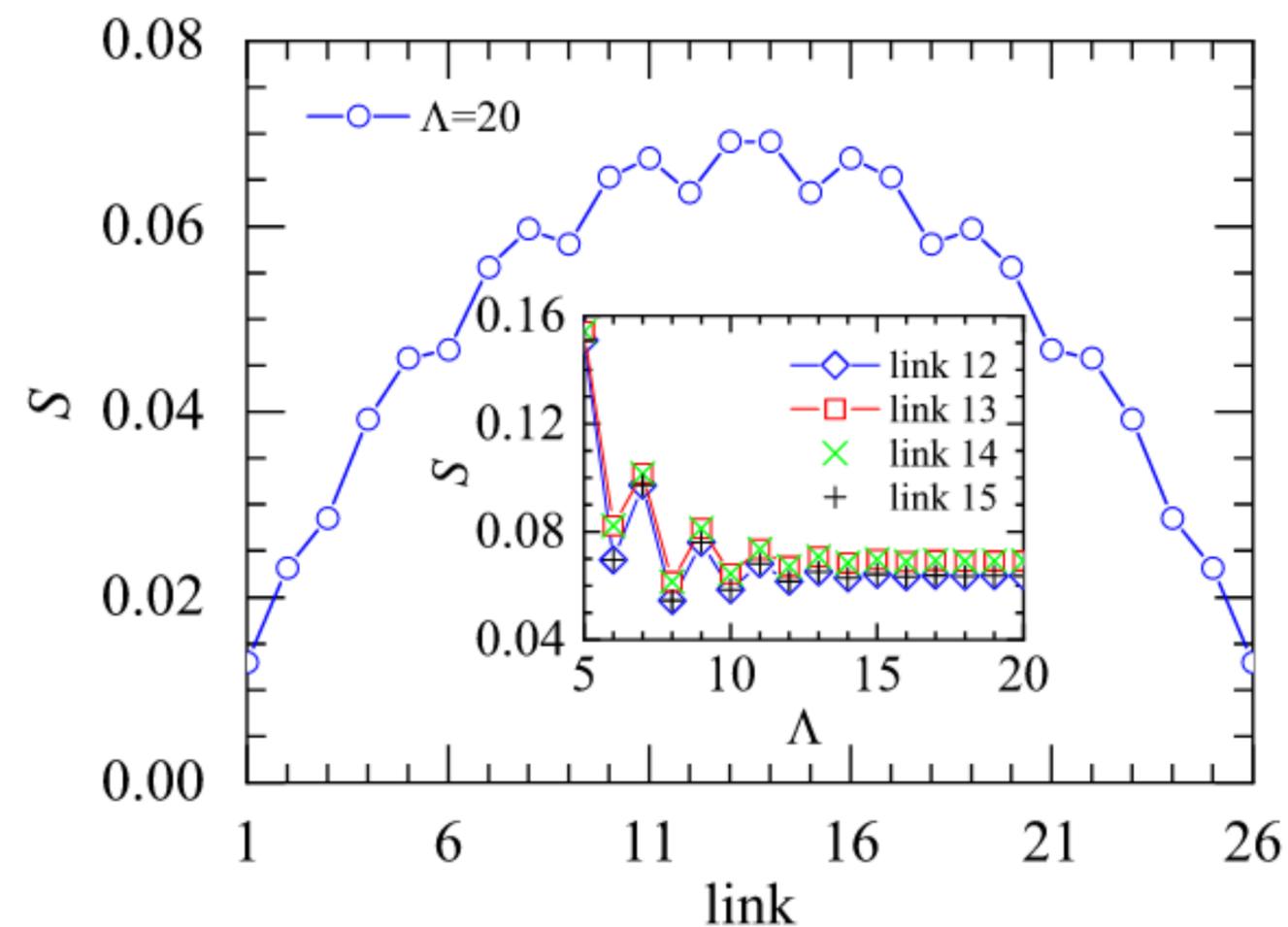
Results

SU(2), 9 Matrices (Bosonic BFSS)

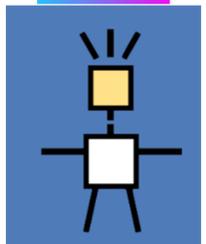
$m=1.0$ $g=1.0$



Average boson occupation number



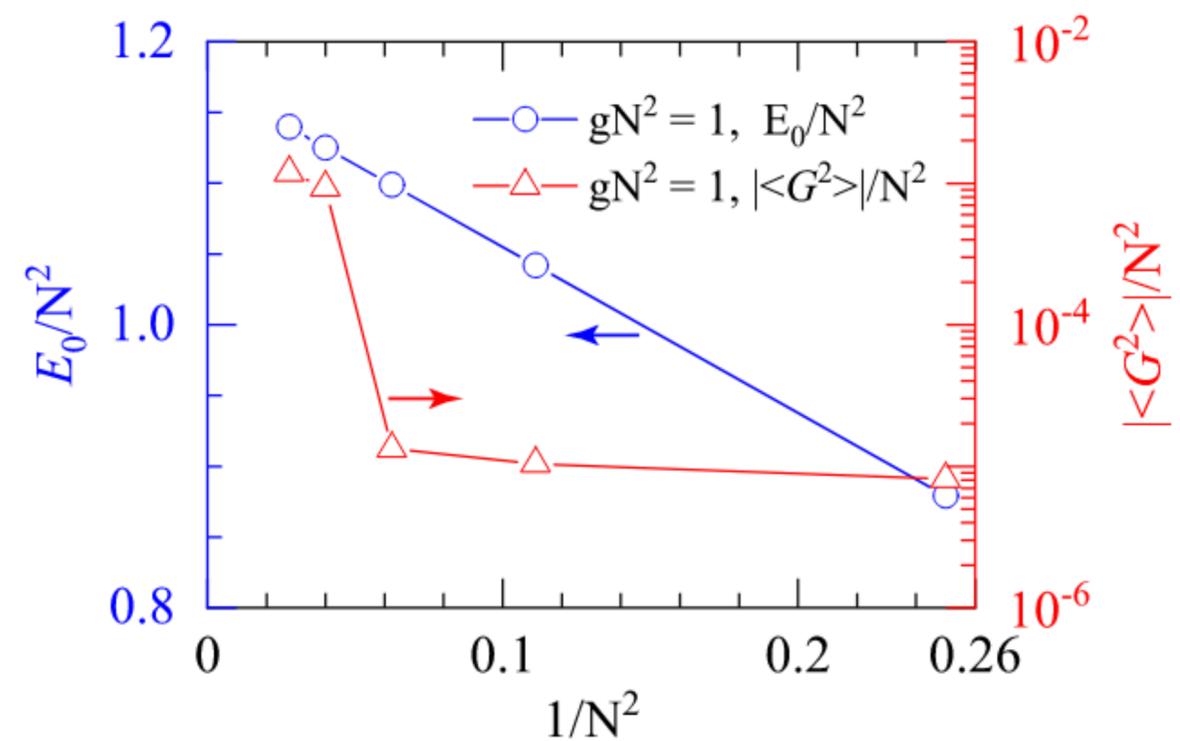
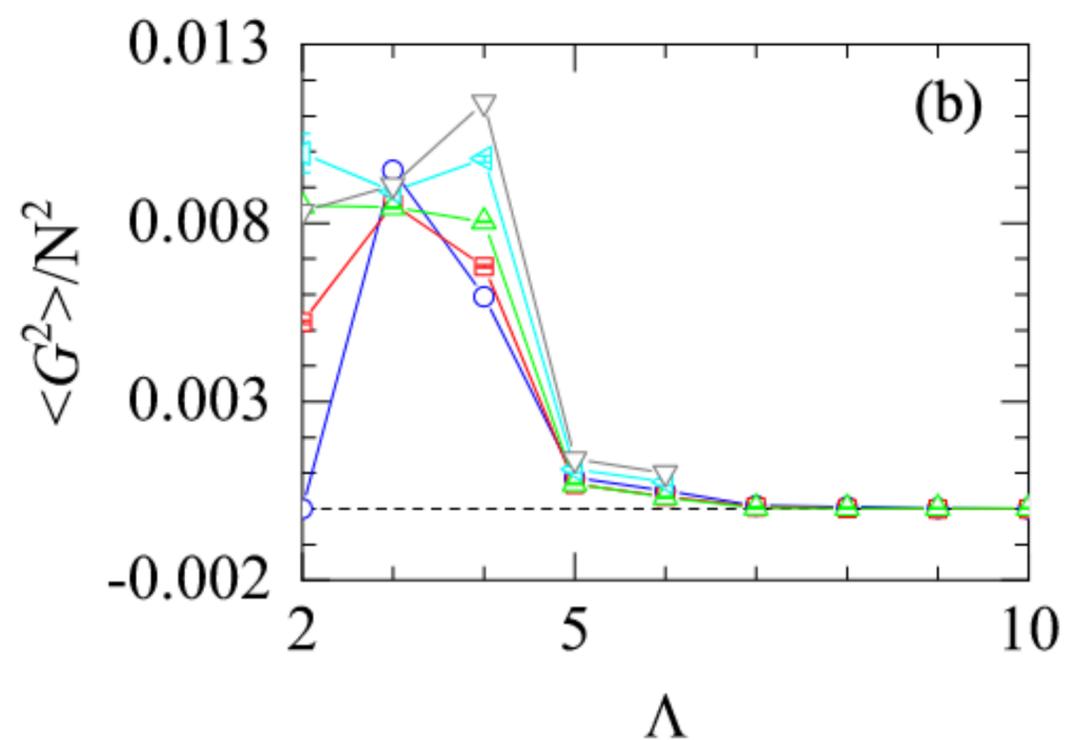
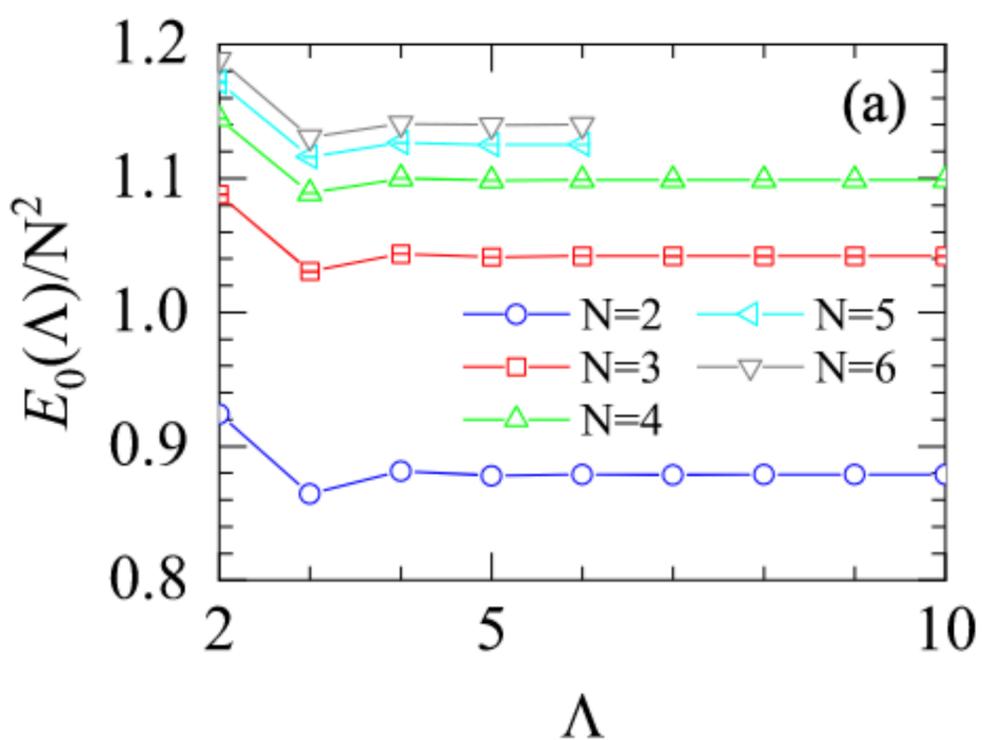
Entanglement Entropy

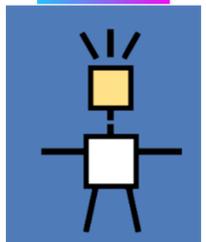


Results

SU(N), 2 Matrices (Bosonic)

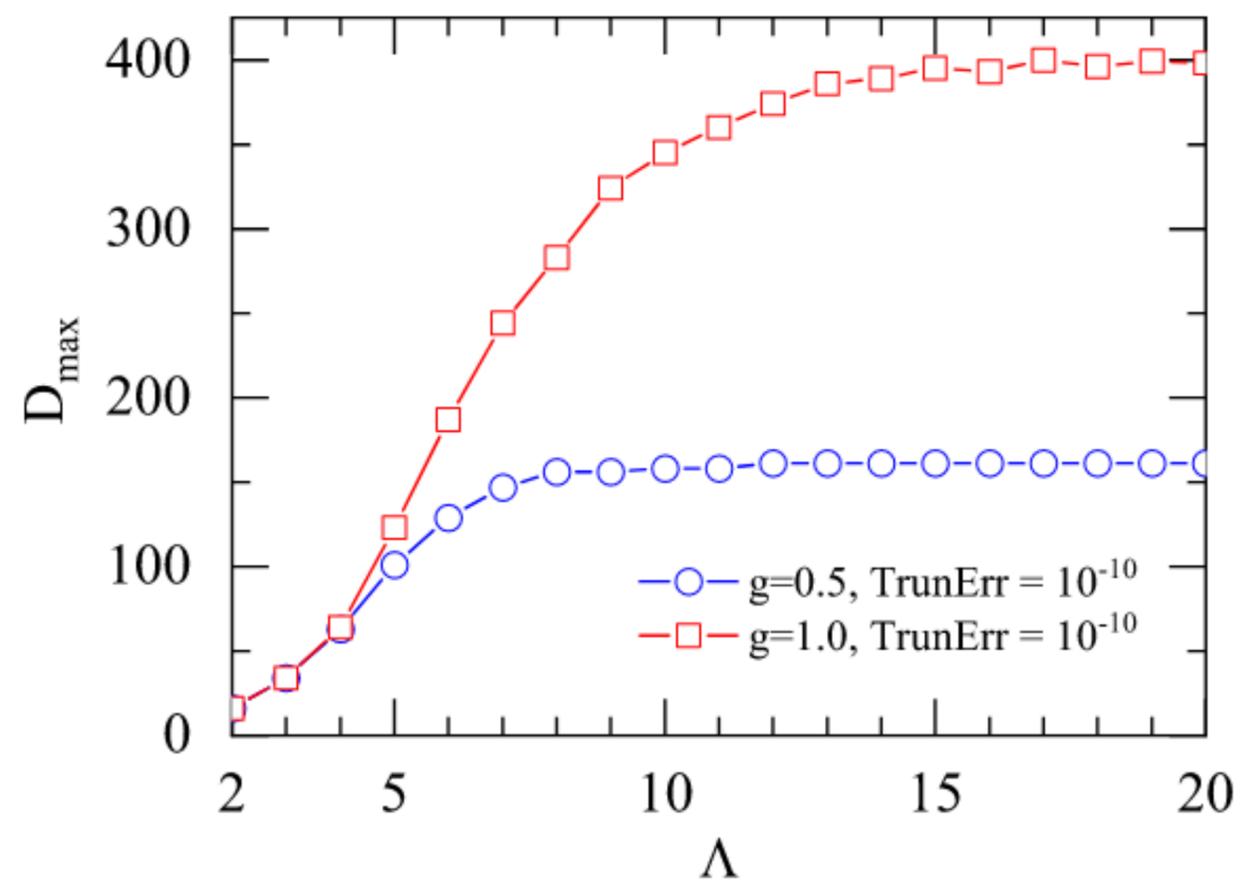
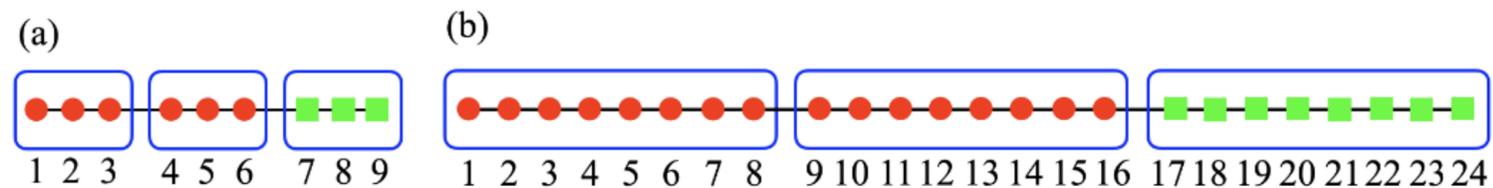
$$g^2 N = 1.0$$

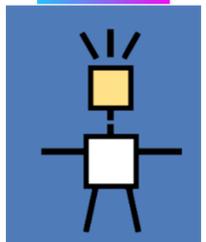




Results

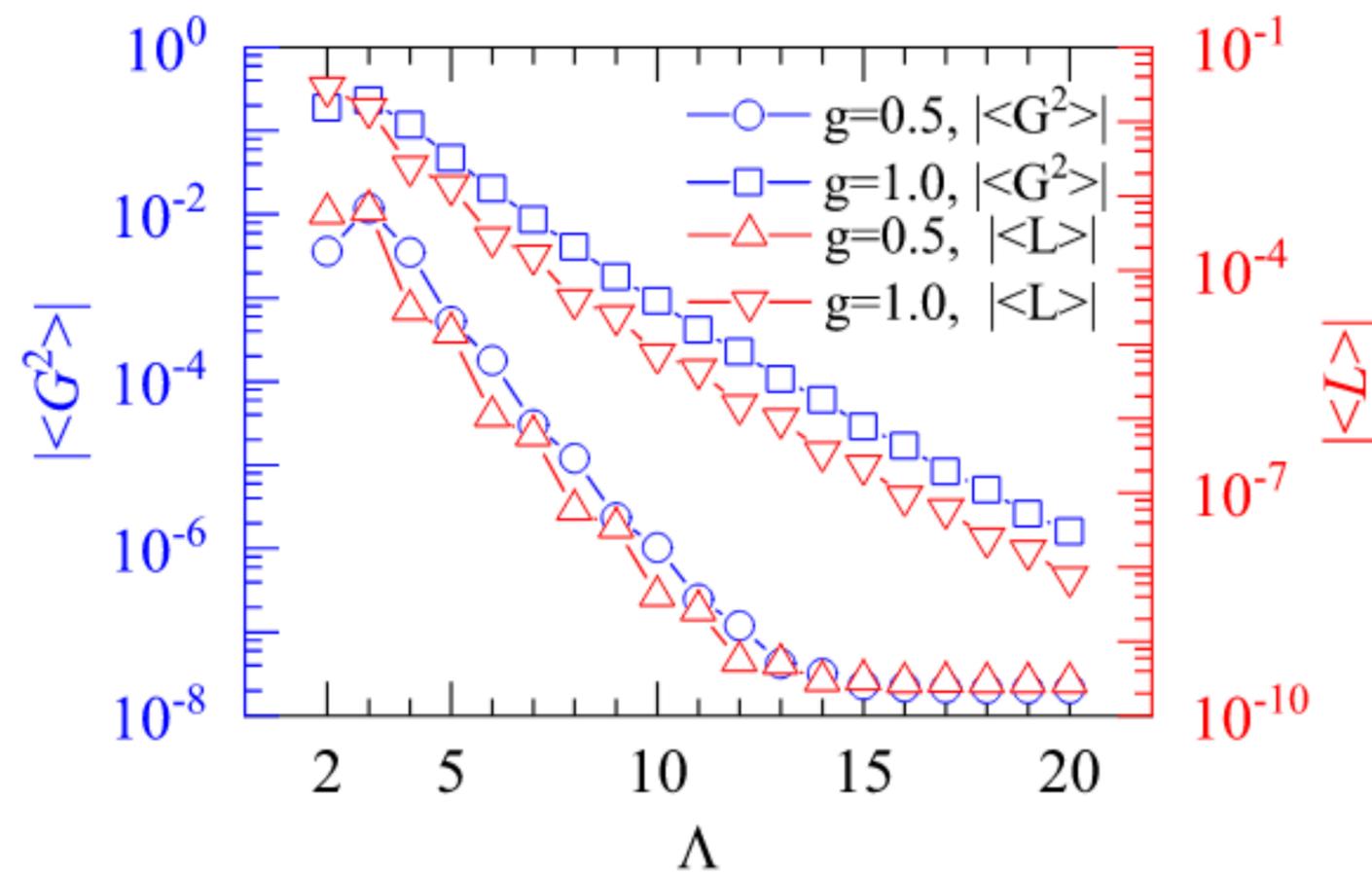
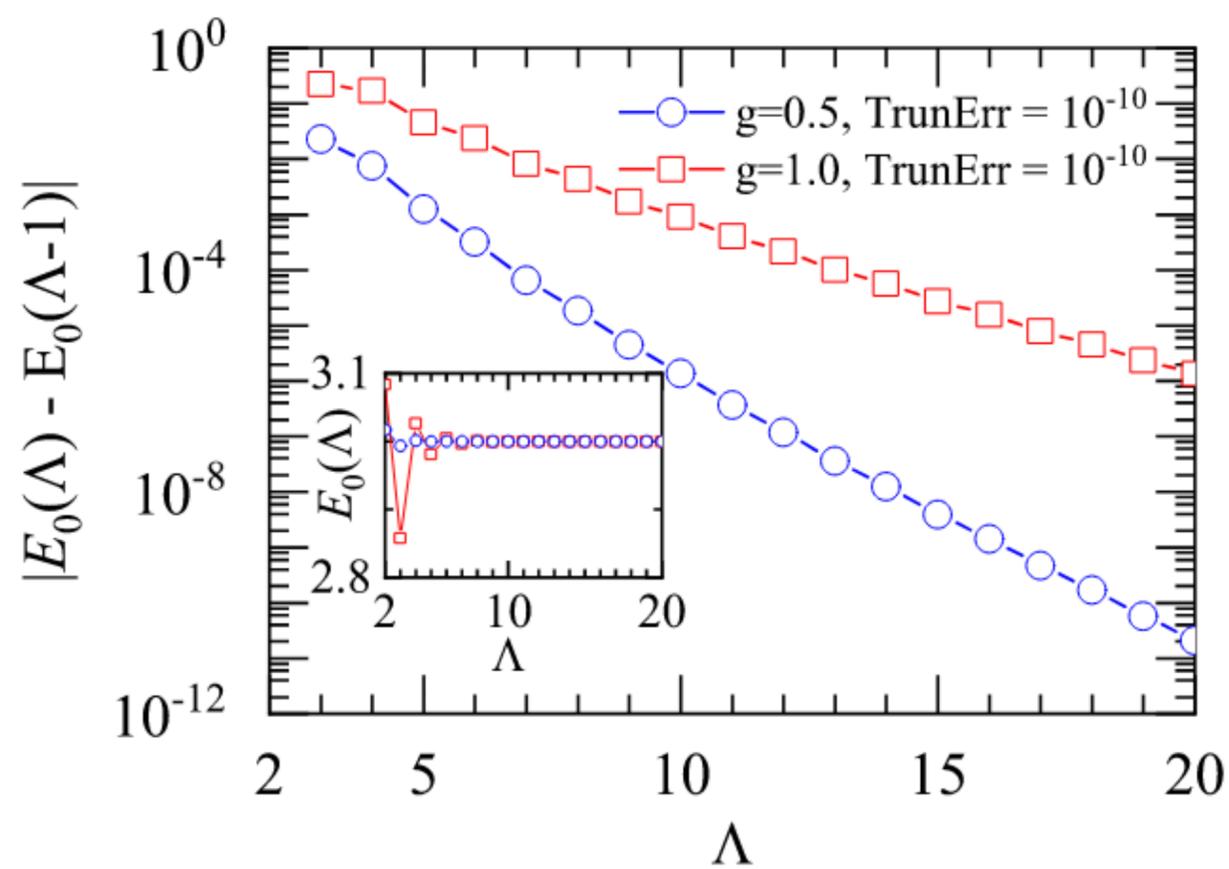
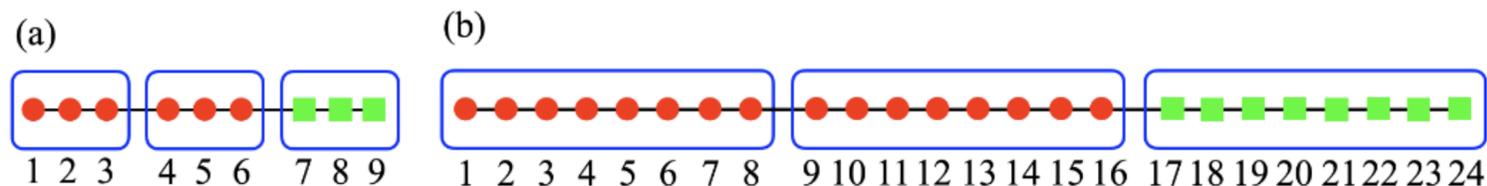
SU(2), 2 Matrices (SUSY)





Results

SU(2), 2 Matrices (SUSY)

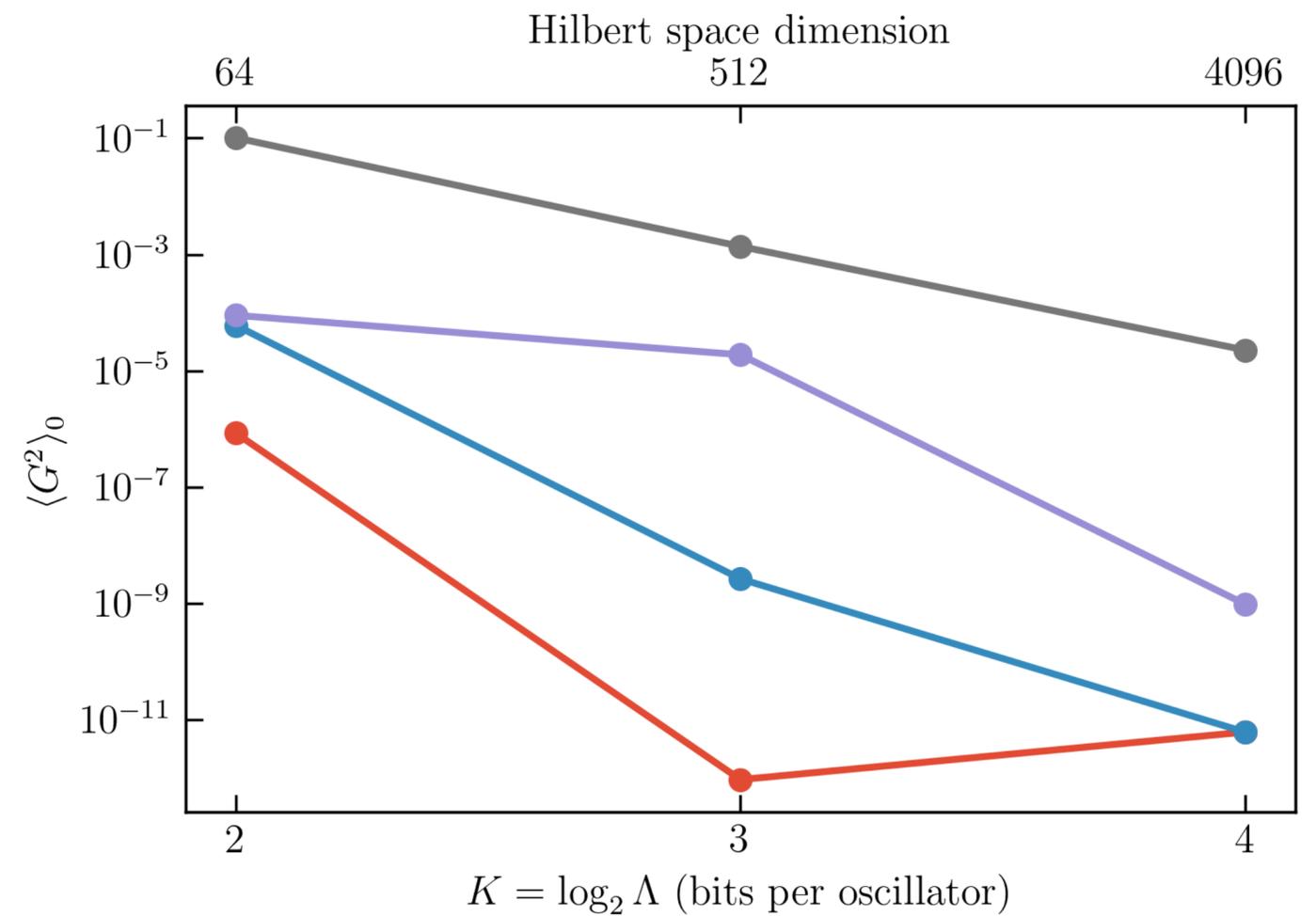
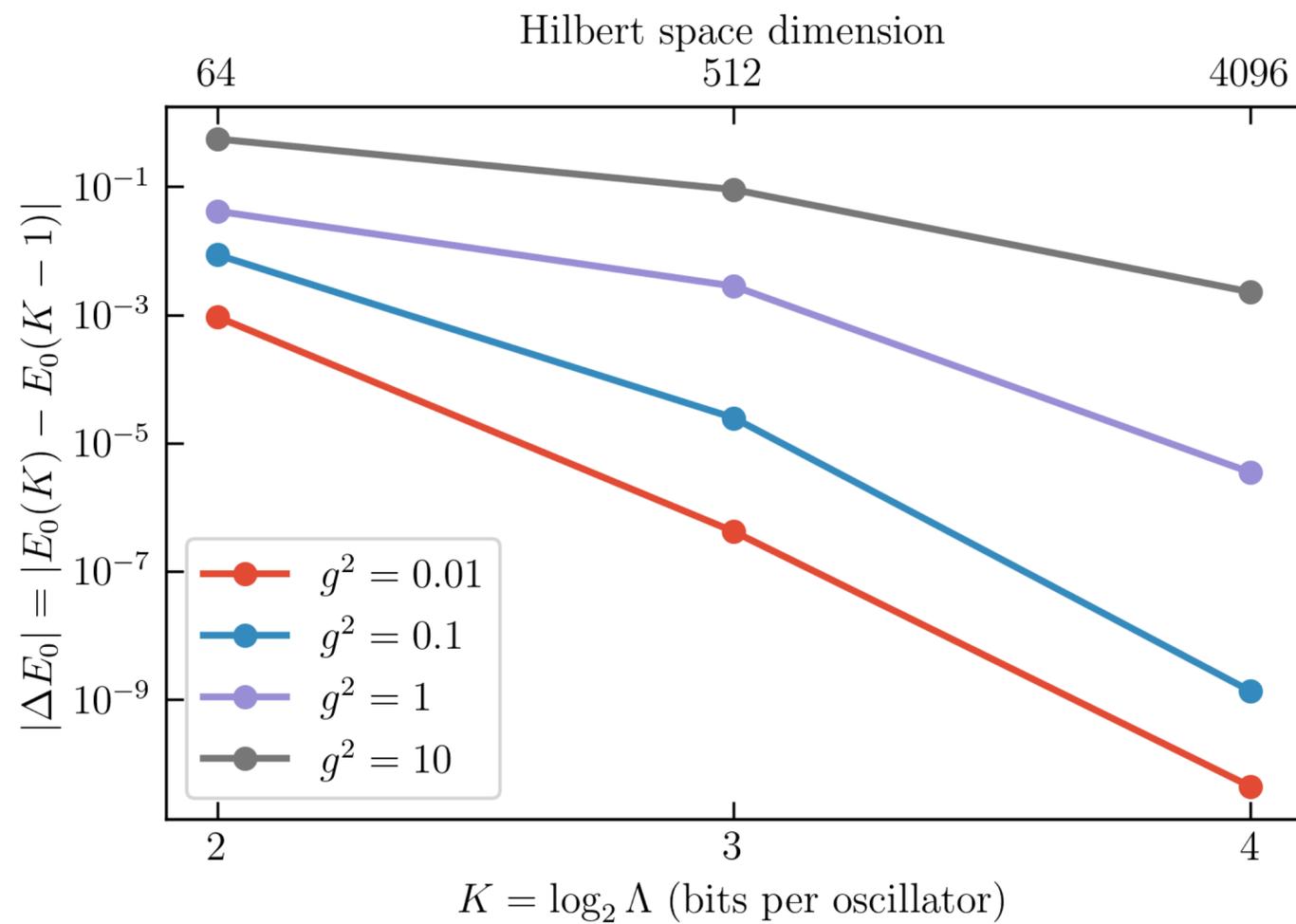


Conclusions and outlook

- ✓ Quantum simulations may be used for addressing **Quantum Gravity** problems, using the holographic duality
- ◆ **Hybrid quantum-classical algorithms** can be used on current quantum hardware to study small-size matrix models. Difficult to scale.
- ◆ **Tensor Network methods** allow an efficient representation of the ground state of matrix models up to larger N and number of matrices.
- ➔ Study **dynamics** of D0-brane bunches in “small” systems: black hole formation
- ➔ Study **entanglement entropy** of matrix ground states in different “configurations”
- ➔ Use matrix models to **benchmark** how quantum computers improve with time

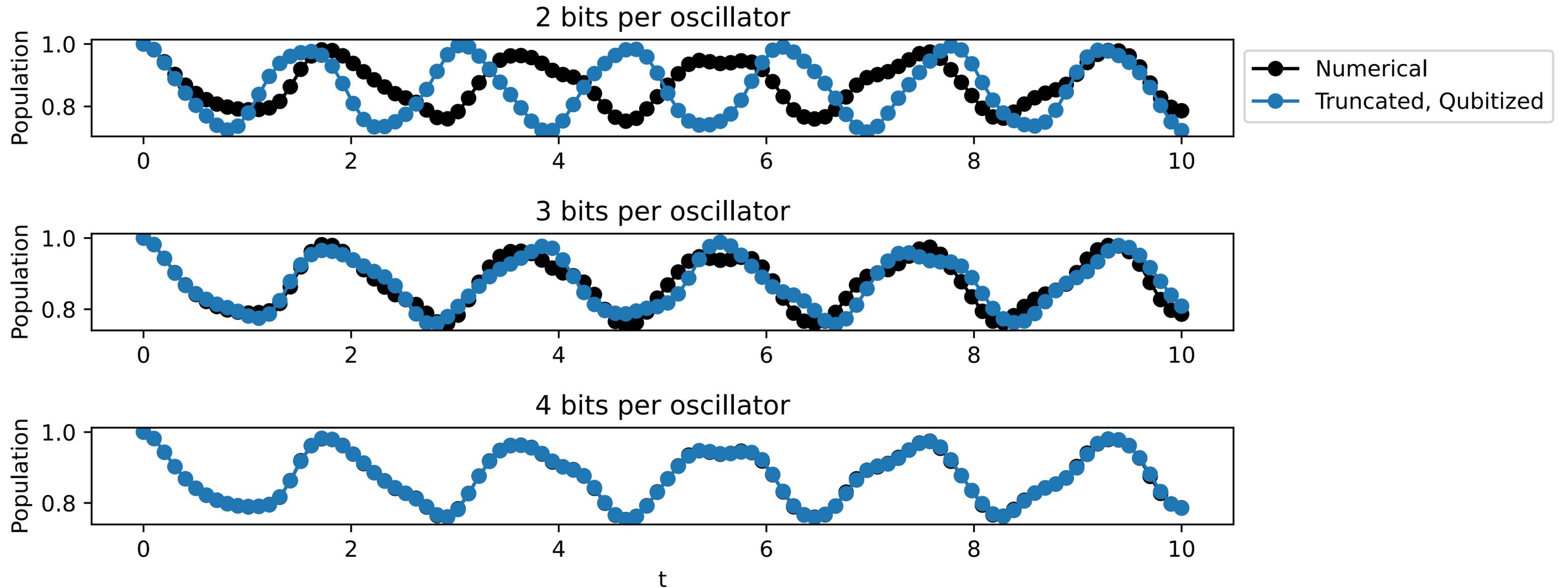
Time Evolution

Of SU(2) 1 Matrix model on Quantum Computers



Time Evolution

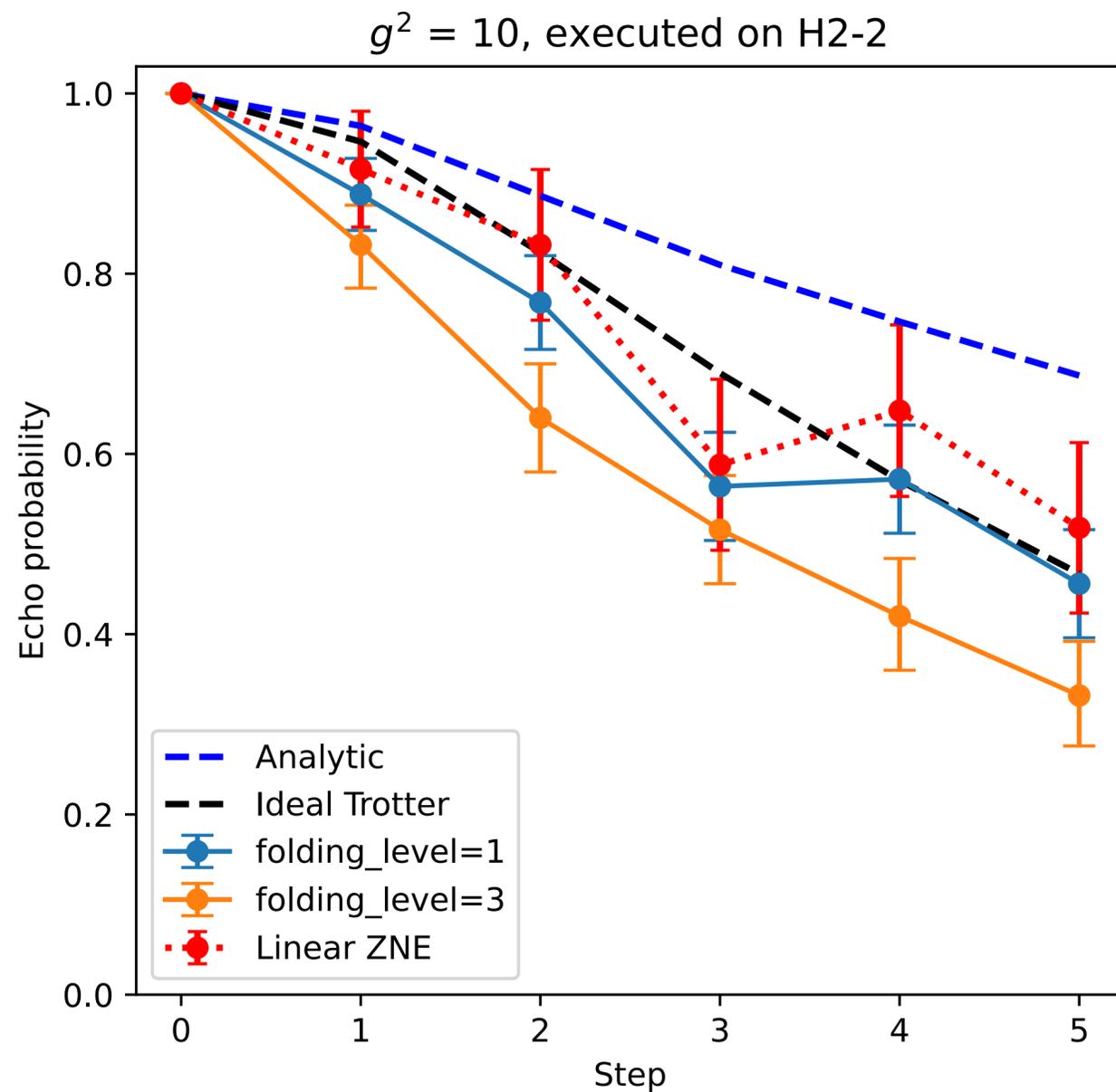
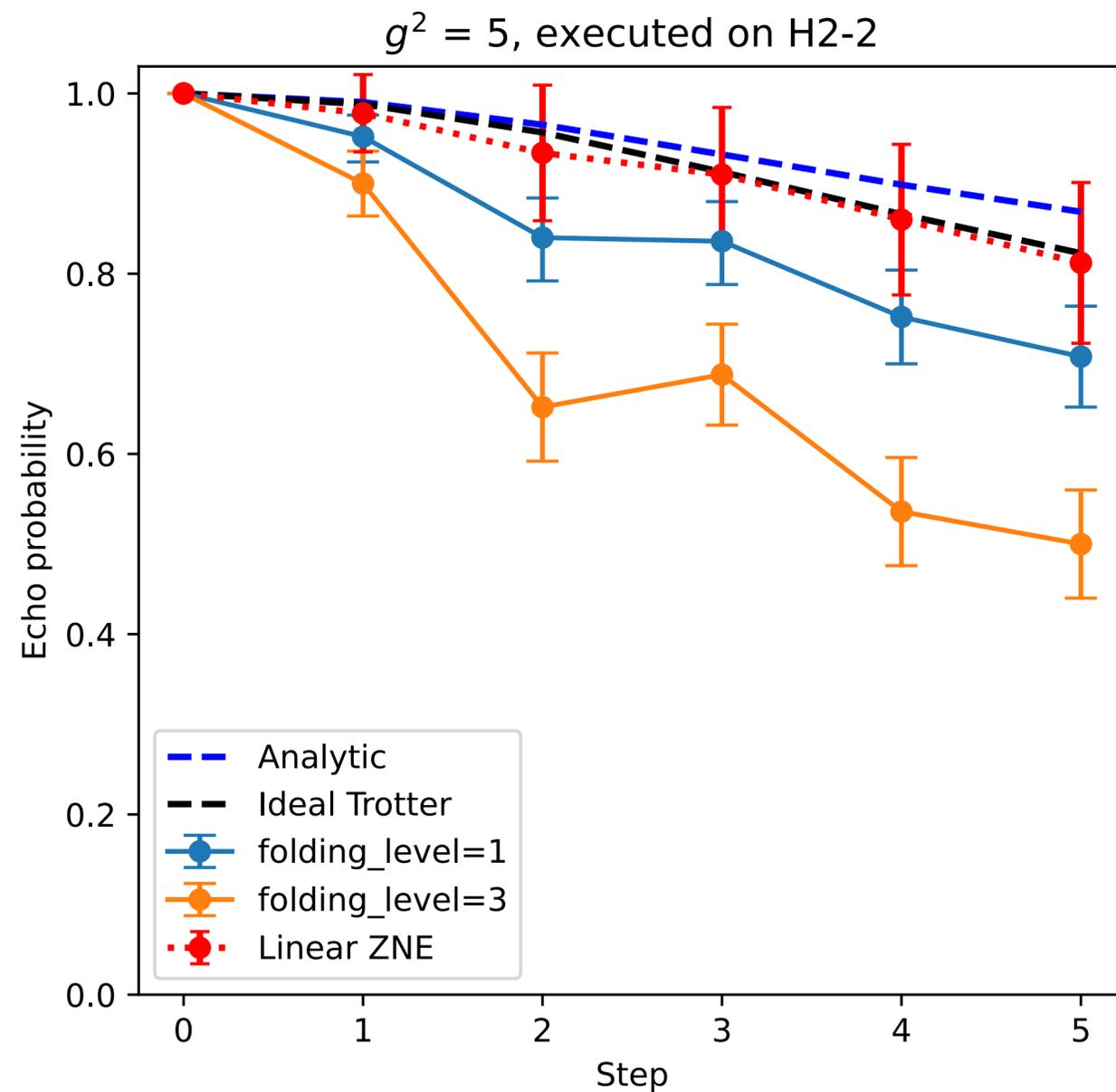
Of SU(2) 1 Matrix model on Quantum Computers



Time Evolution Of SU(2) 1 Matrix model on Quantum Computers

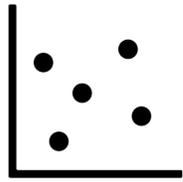
$\log_2 \Lambda^3 = 6$ qubits

$|\langle 0 | e^{-i\hat{H}t} | 0 \rangle|^2$



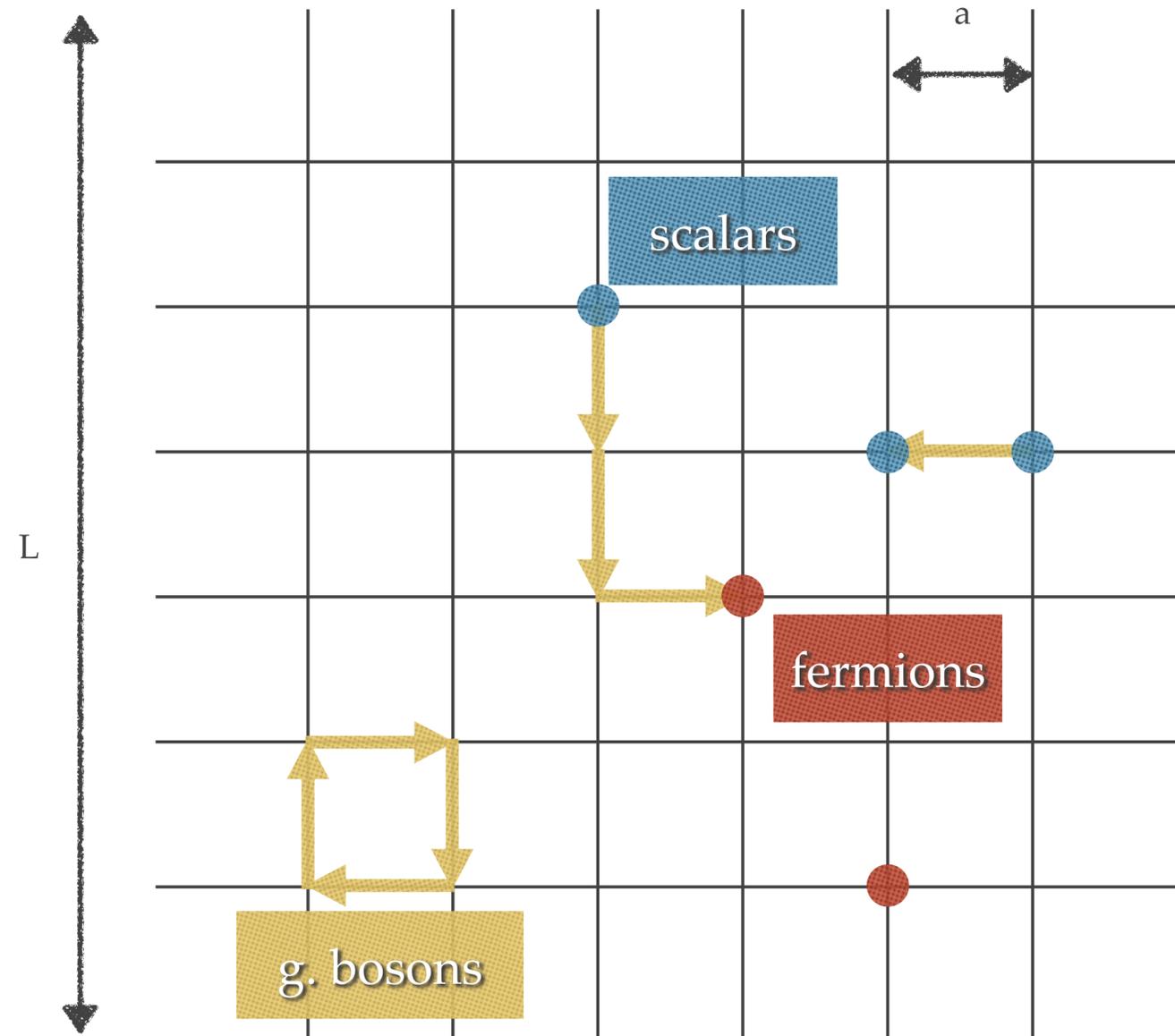
In preparation

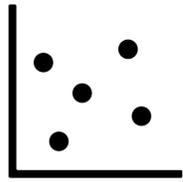
Questions?



Path Integral Monte Carlo

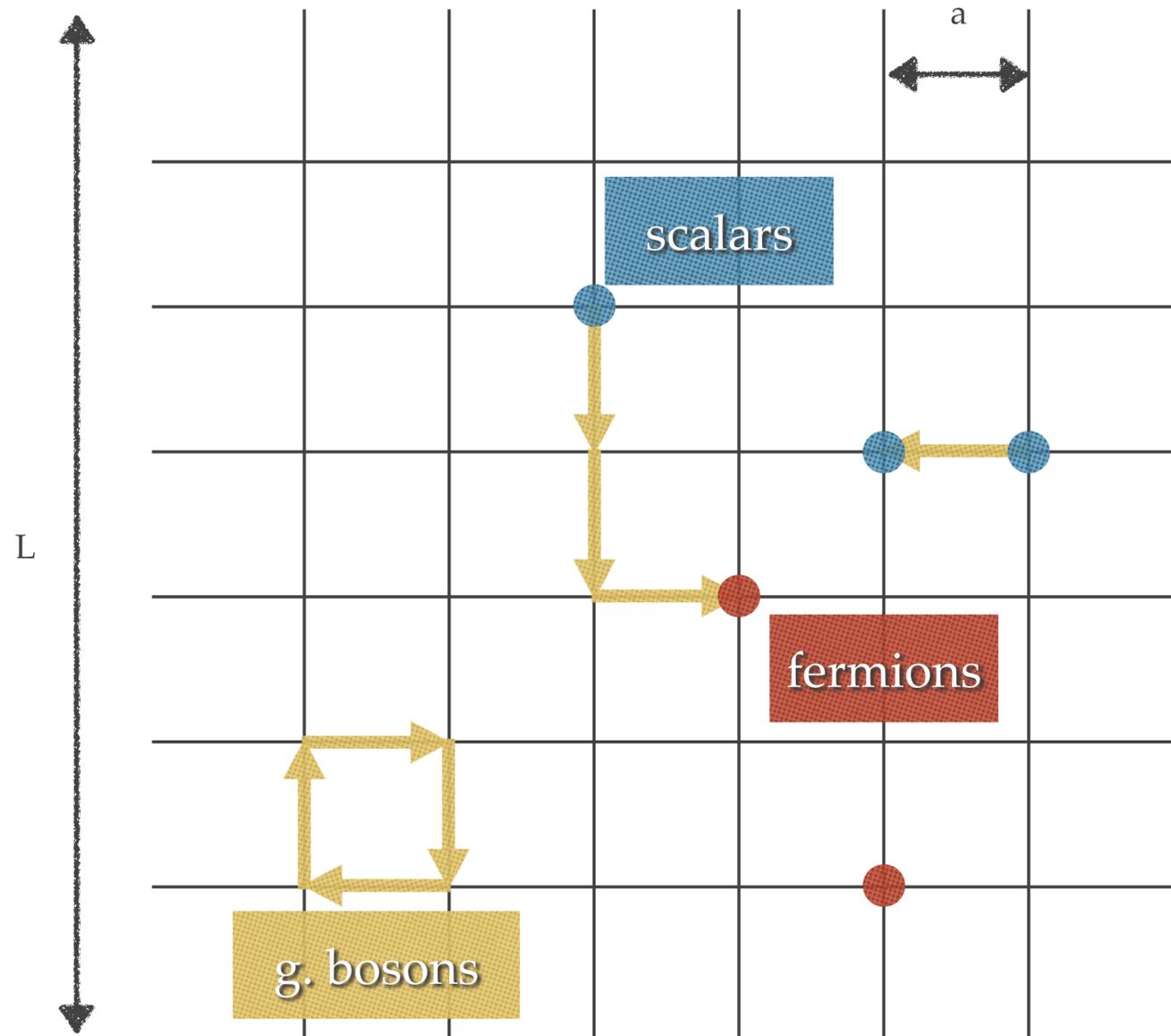
Lattice Gauge Theory Primer



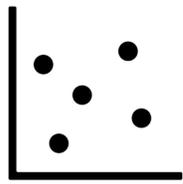


Path Integral Monte Carlo

Lattice Gauge Theory Primer

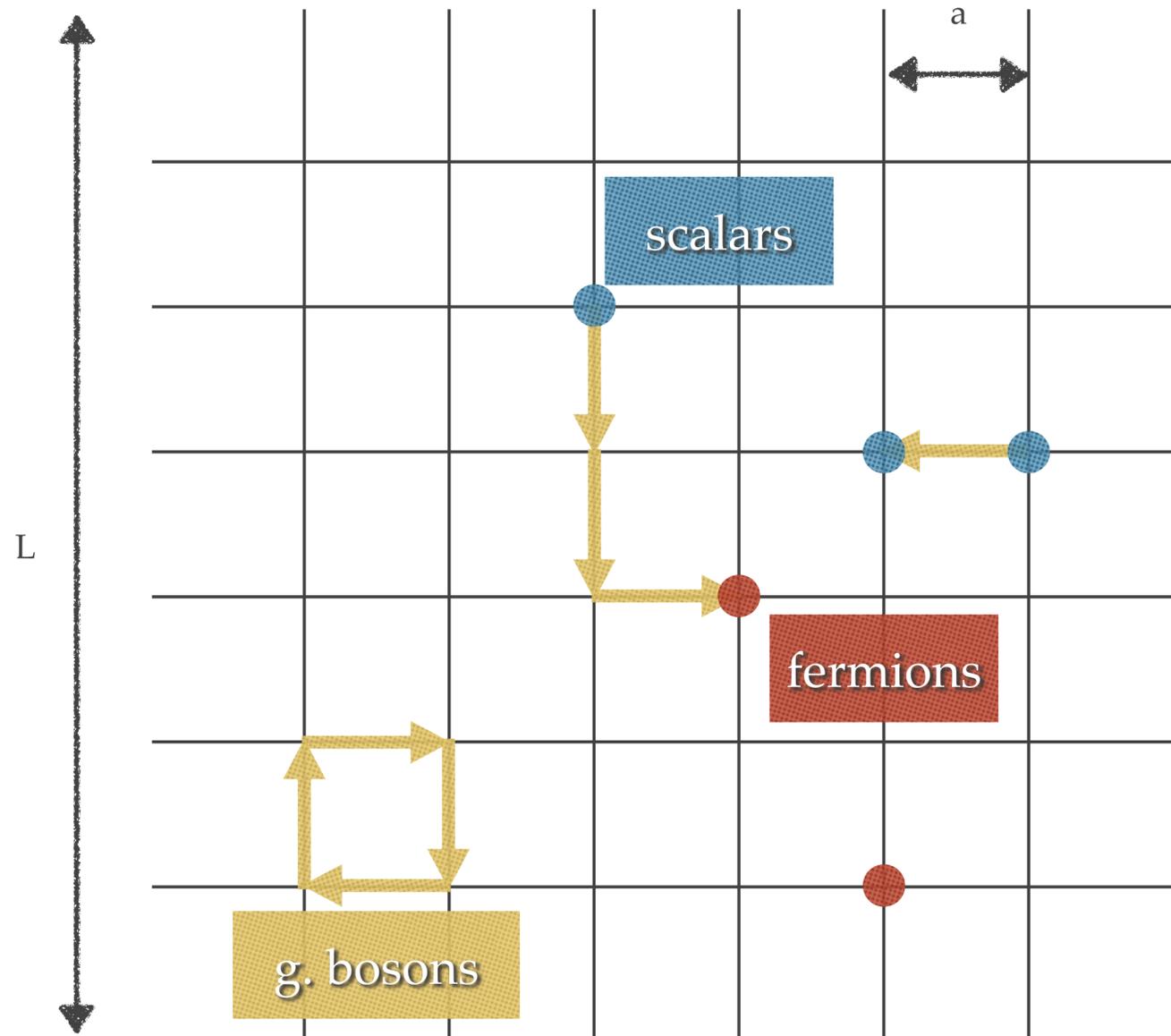


- Discretize space and time
 - lattice spacing “a”
 - lattice size “L”

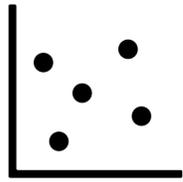


Path Integral Monte Carlo

Lattice Gauge Theory Primer

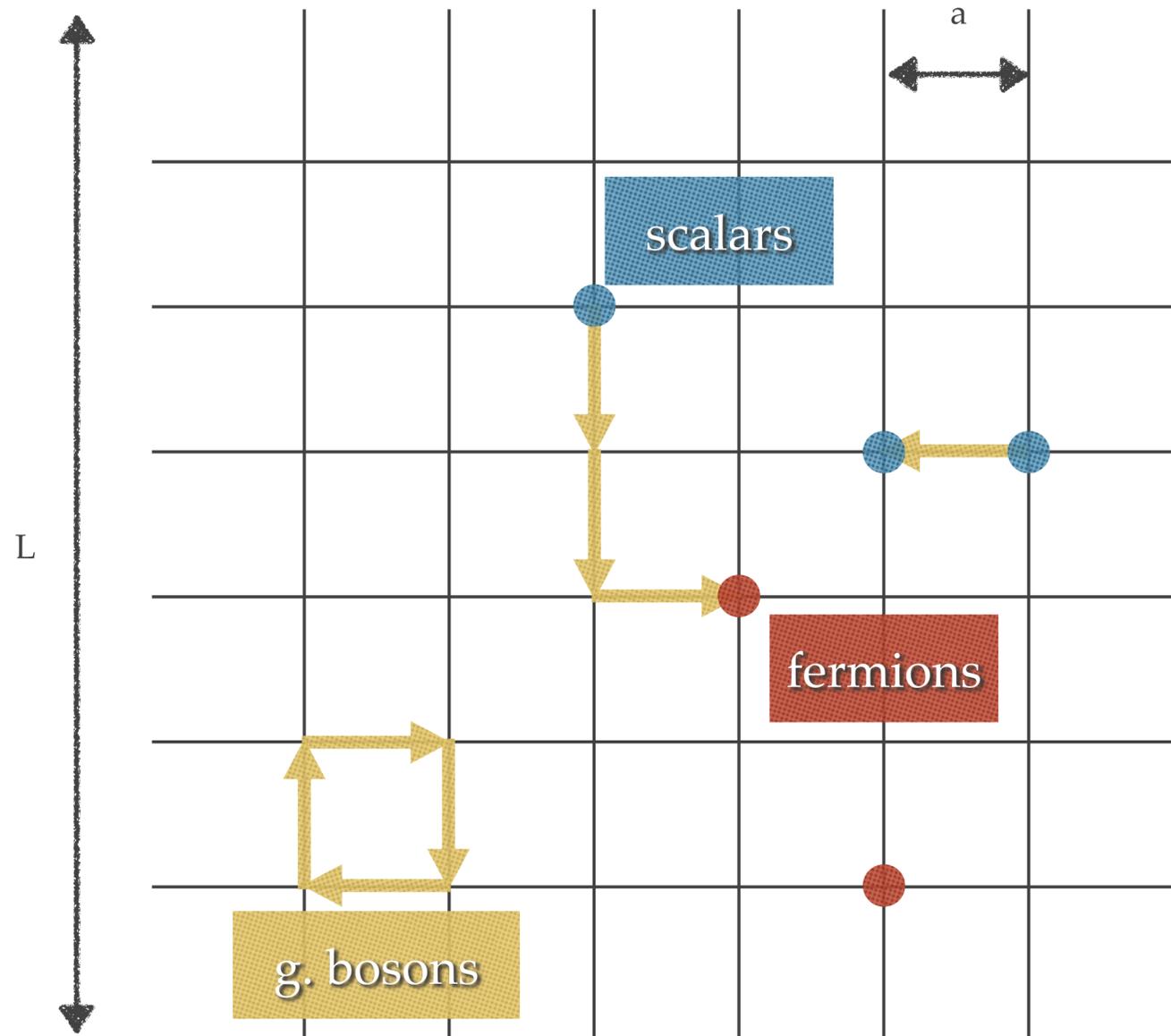


- Discretize space and time
 - lattice spacing “a”
 - lattice size “L”
- Keep all d.o.f. of the theory
 - not a model!
 - no simplifications

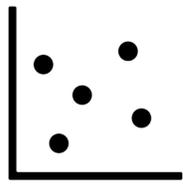


Path Integral Monte Carlo

Lattice Gauge Theory Primer

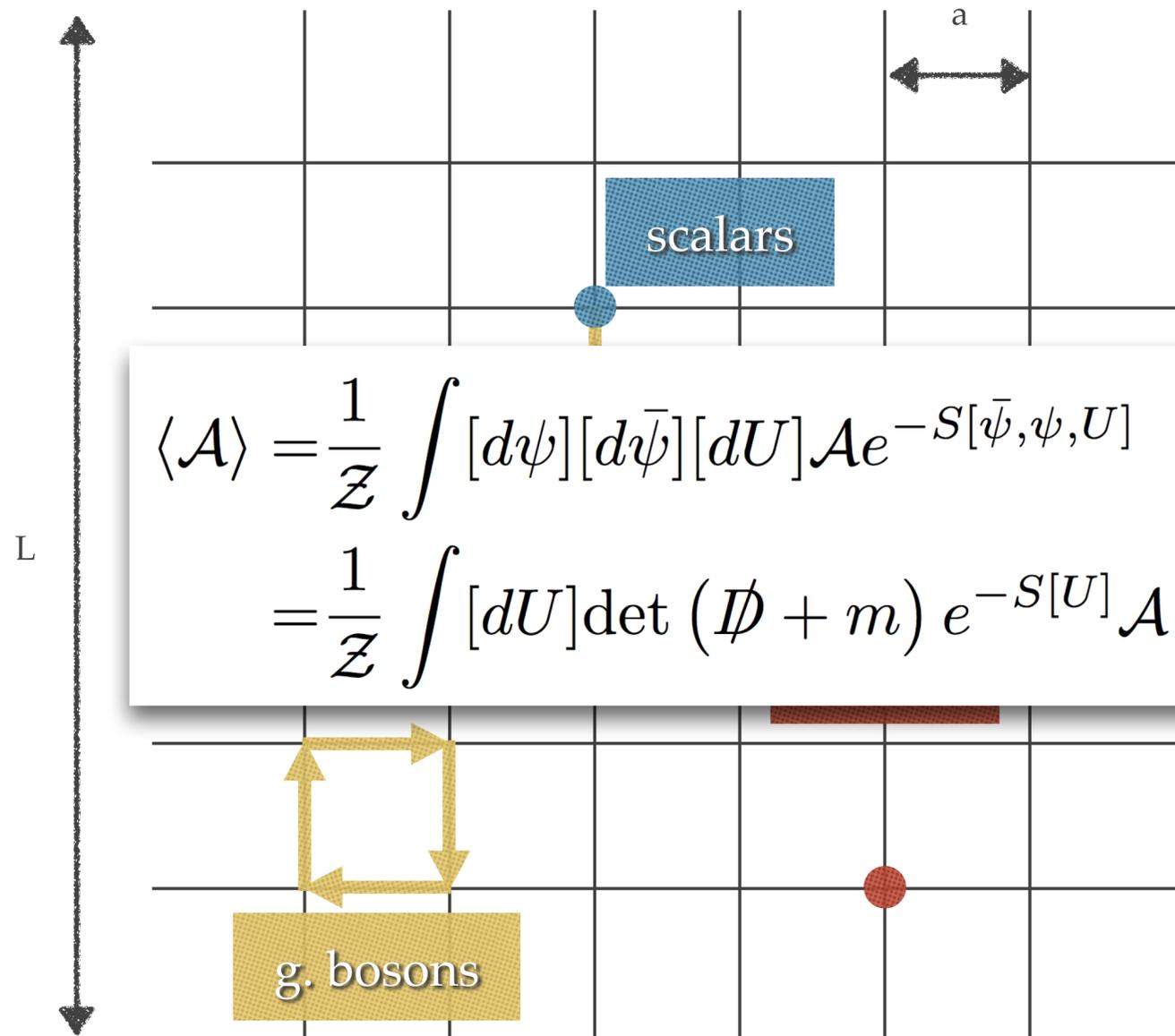


- Discretize space and time
 - lattice spacing “ a ”
 - lattice size “ L ”
- Keep all d.o.f. of the theory
 - not a model!
 - no simplifications
- Amenable to numerical methods
 - Monte Carlo sampling
 - use supercomputers

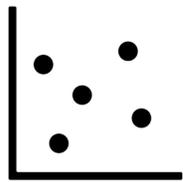


Path Integral Monte Carlo

Lattice Gauge Theory Primer

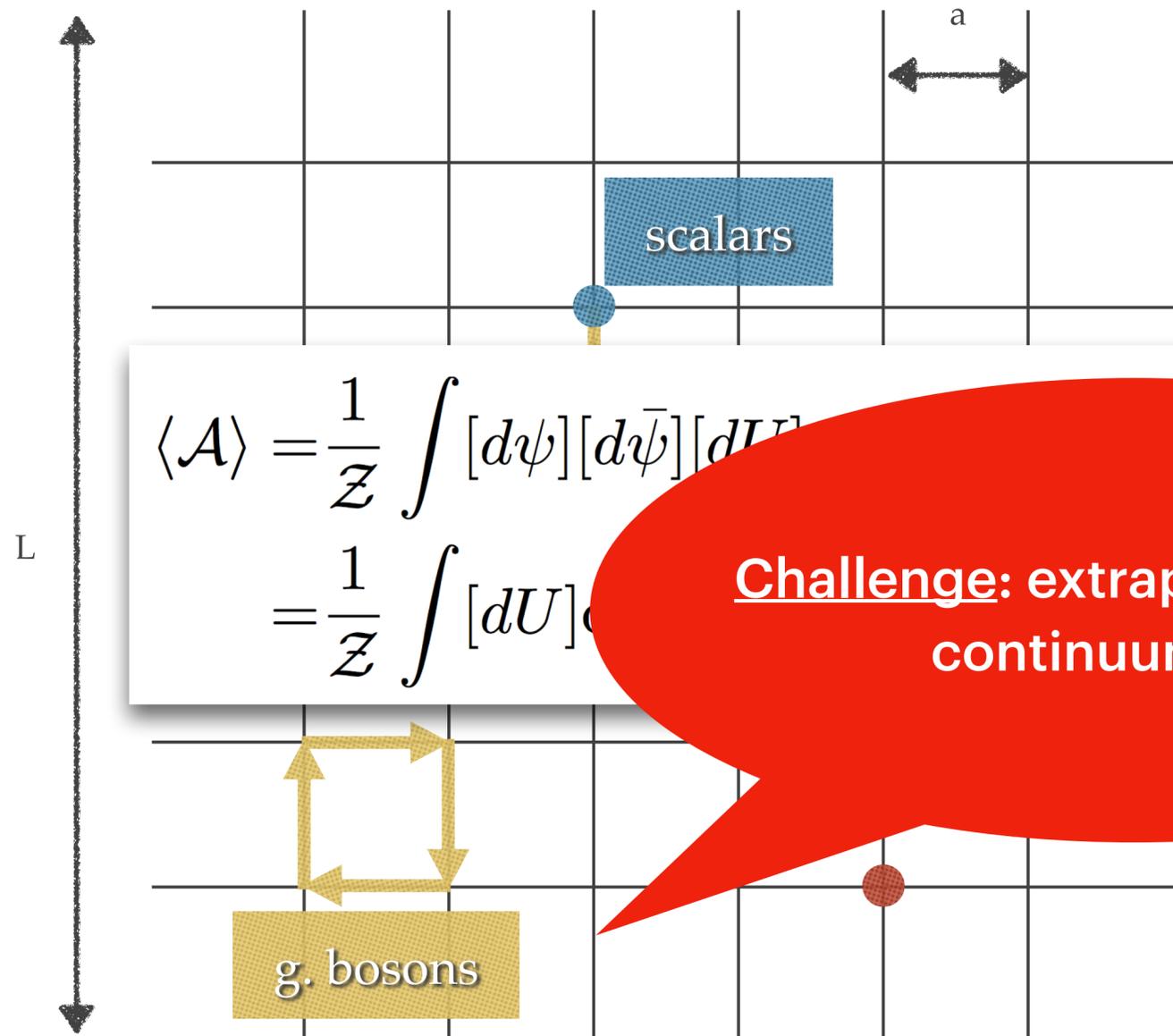


- Discretize space and time
 - lattice spacing “a”
 - lattice size “L”
- Keep all d.o.f. of the theory
 - not a model!
 - no simplifications
- Amenable to numerical methods
 - Monte Carlo sampling
 - use supercomputers
- Precisely quantifiable and improvable errors
 - Systematic
 - Statistical



Path Integral Monte Carlo

Lattice Gauge Theory Primer



$$\langle \mathcal{A} \rangle = \frac{1}{\mathcal{Z}} \int [d\psi][d\bar{\psi}][dU]$$
$$= \frac{1}{\mathcal{Z}} \int [dU]$$

Challenge: extrapolation to the continuum limit

- Discretize space and time
 - lattice spacing “a”
 - lattice size “L”
- Keep all d.o.f. of the theory
 - not a model!
 - no simplifications
- amenable to numerical methods
 - Monte Carlo sampling
 - use supercomputers
- Precisely quantifiable and improvable errors
 - Systematic
 - Statistical

Results

Small-scale: $N=2, D=2$

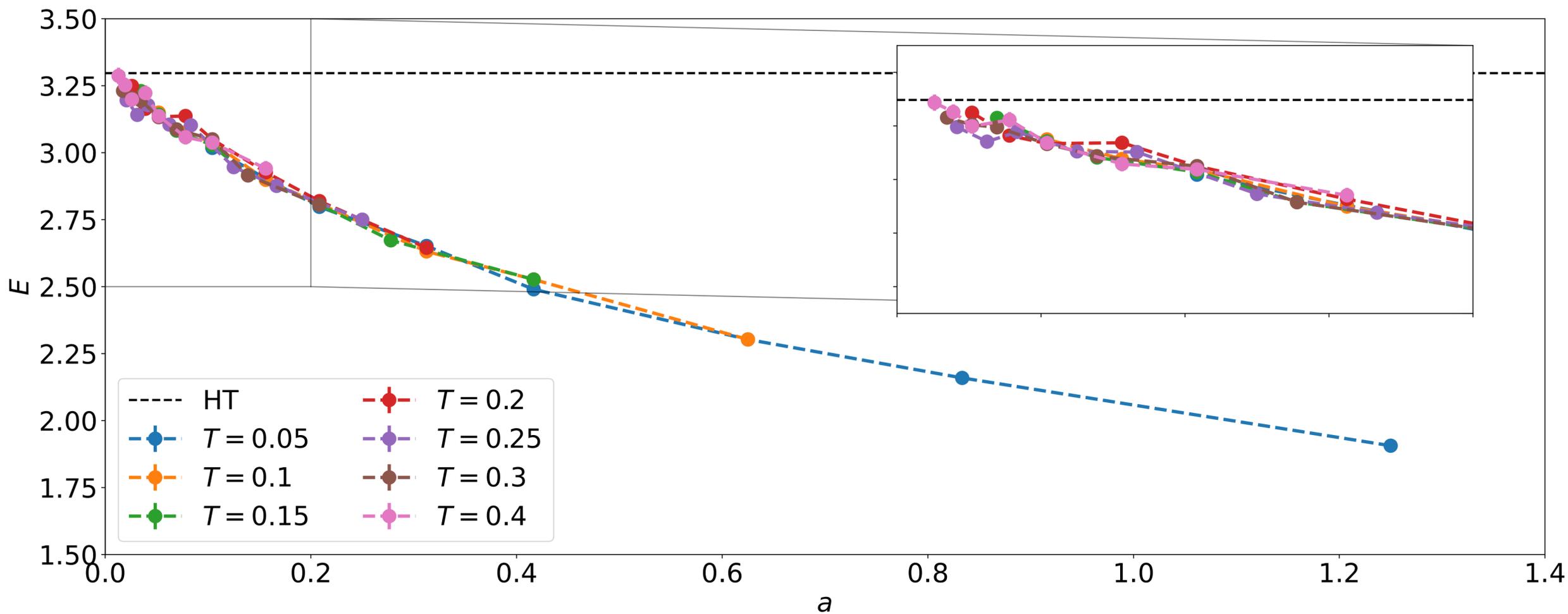
No truncation Λ

Parameters:

- Temperature: T
- Number of lattice sites: N_t

Observables:

- Energy



Results

Small-scale: N=2, D=2

No truncation Λ

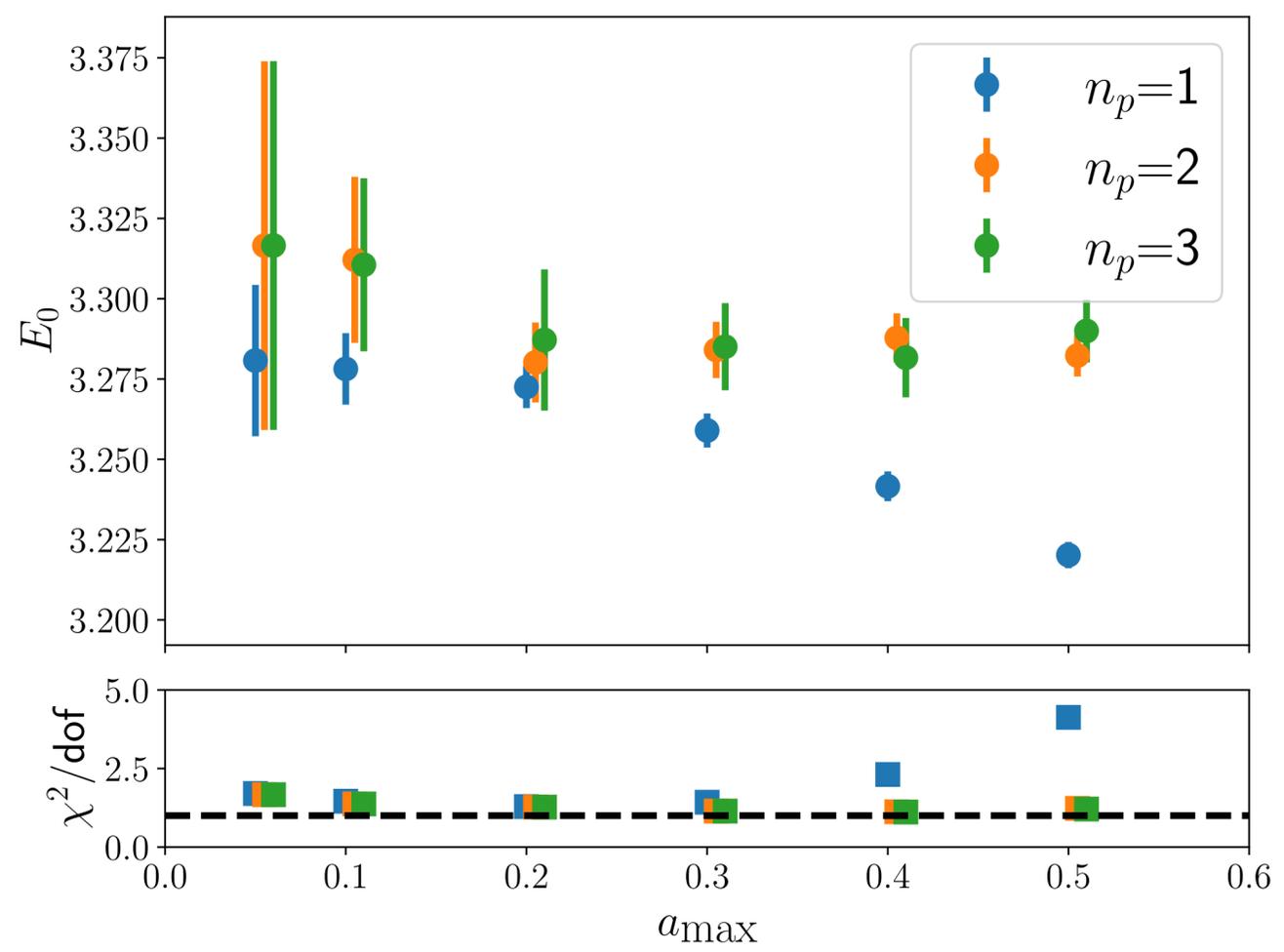
Parameters:

- Temperature: T
- Number of lattice sites: N_t

Observables:

- Energy

Global Extrapolation



Results

Small-scale: N=2, D=2

No truncation Λ

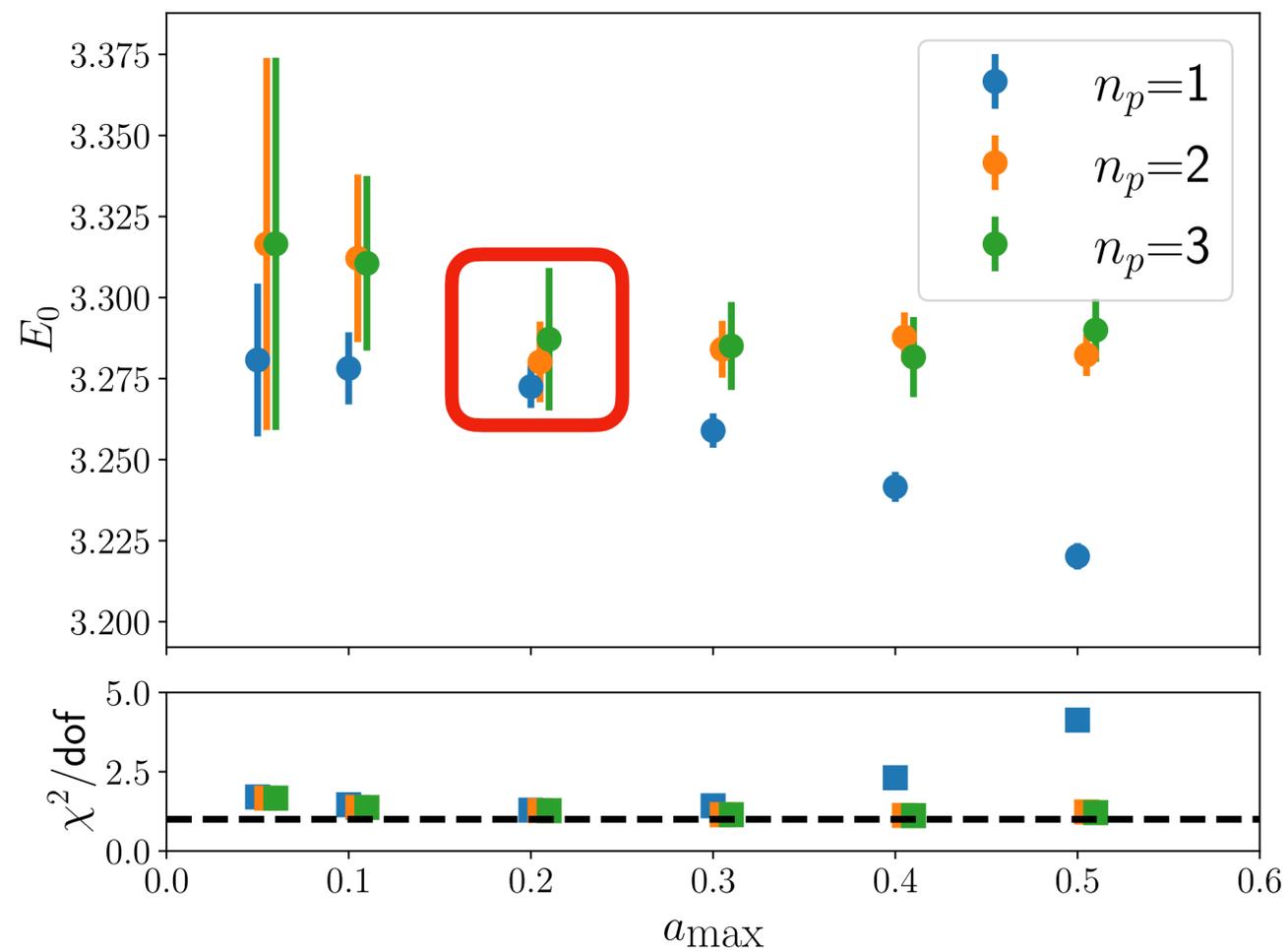
Parameters:

- Temperature: T
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Observables:

- Energy

Global Extrapolation



Results

Small-scale: N=2, D=2

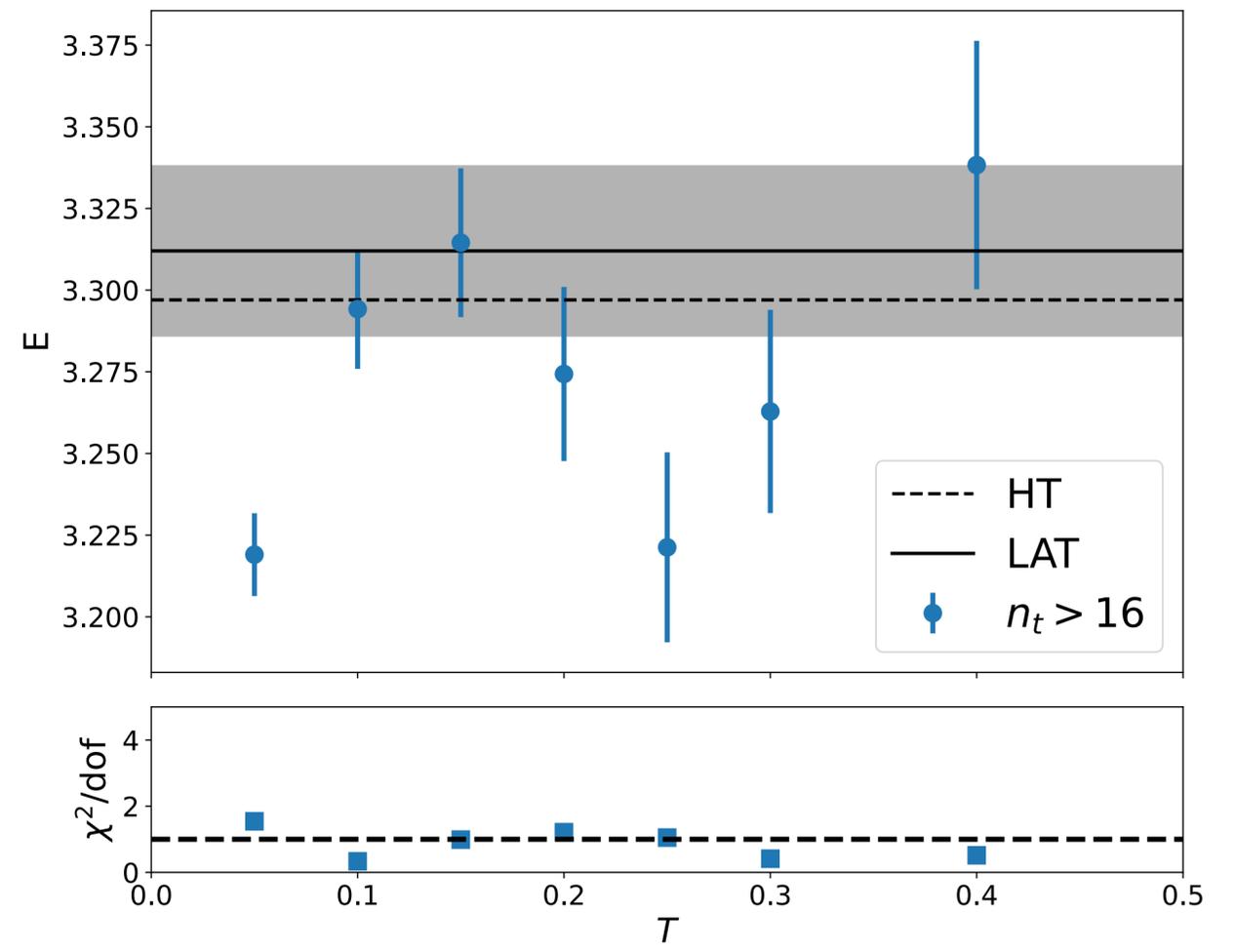
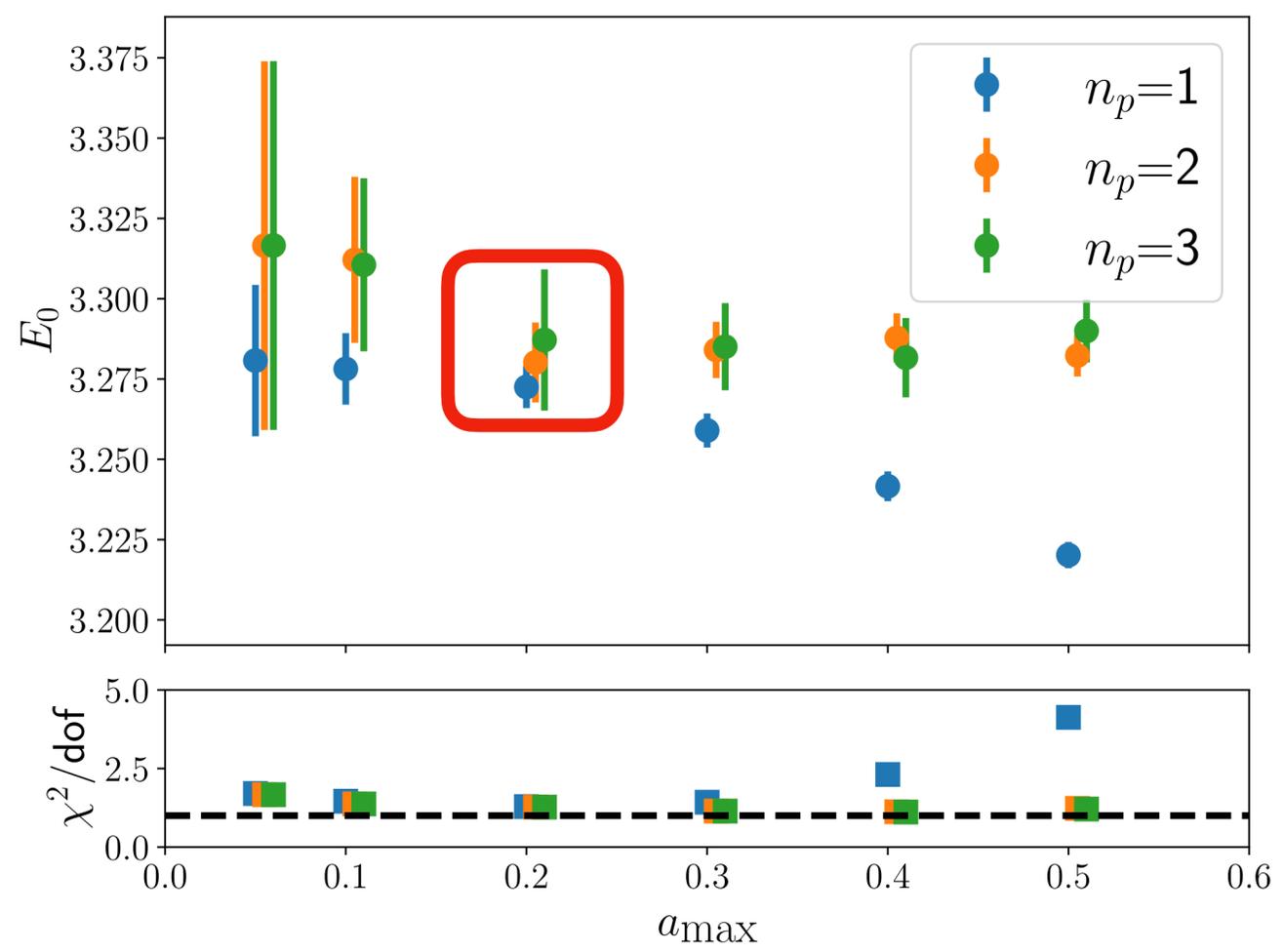
- Parameters:**
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- Observables:**
- Energy

No truncation Λ

Global Extrapolation

Local Extrapolation



Results

Small-scale: N=2, D=2

Parameters:

- Temperature: T
- Number of lattice sites: N_t

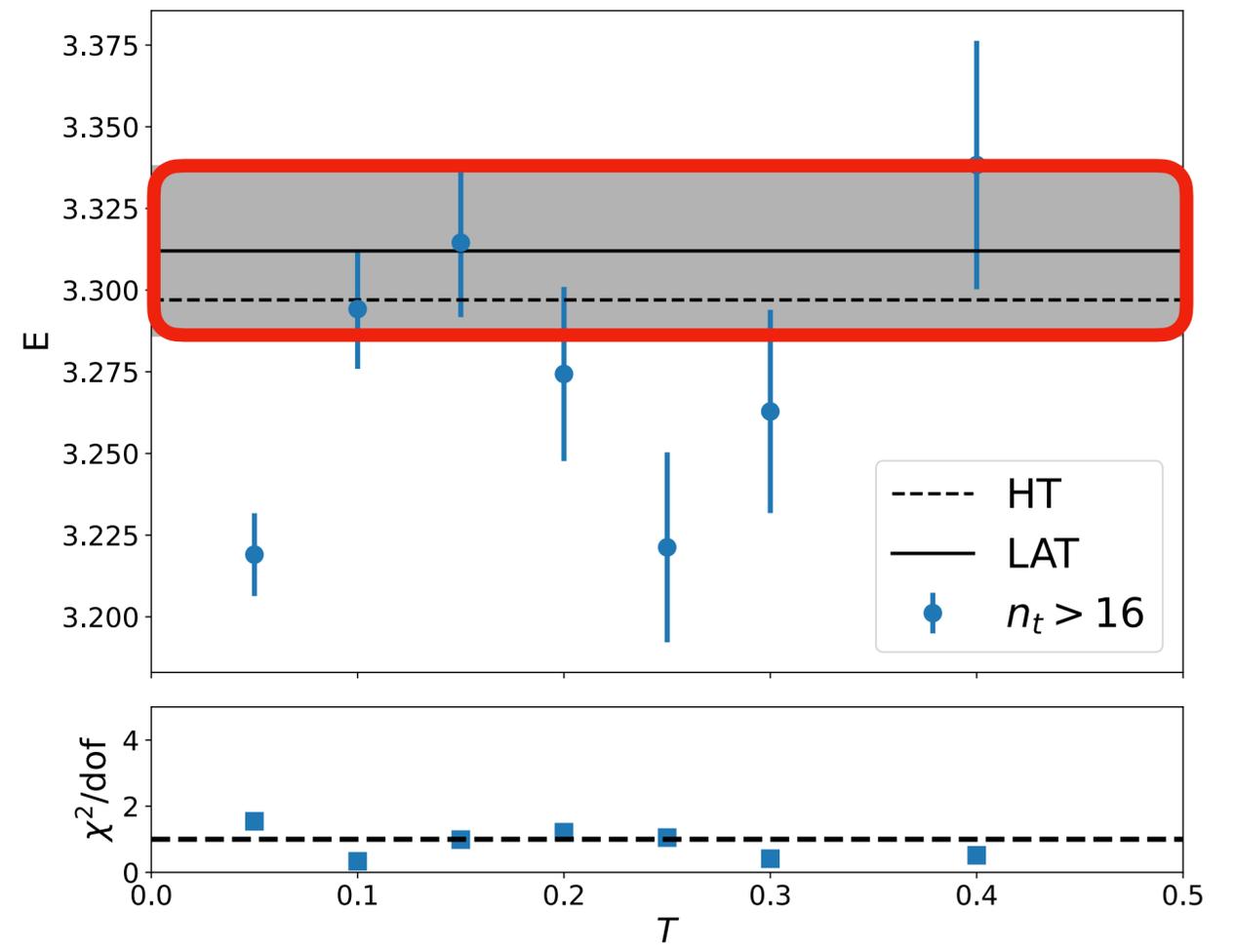
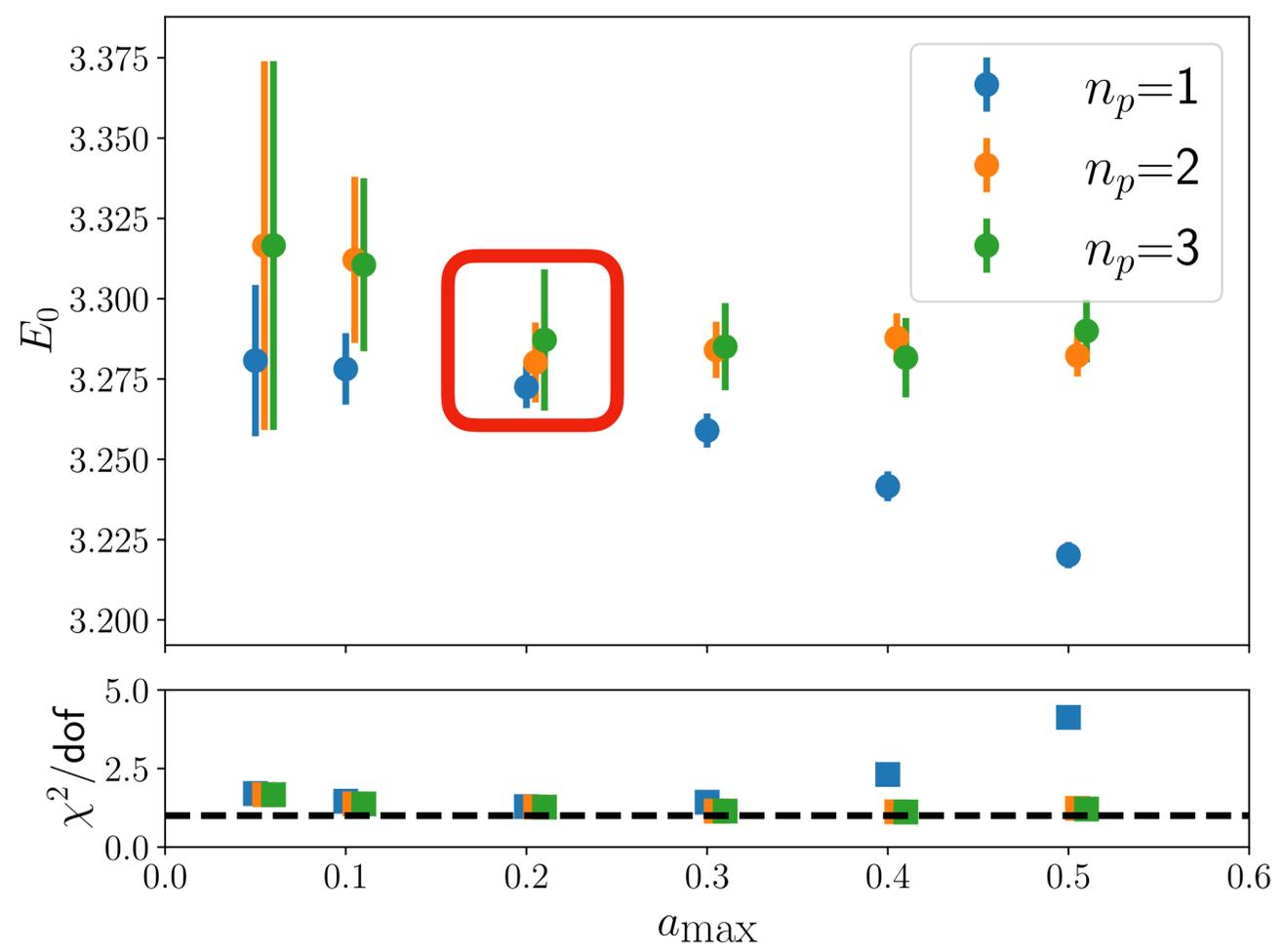
Observables:

- Energy

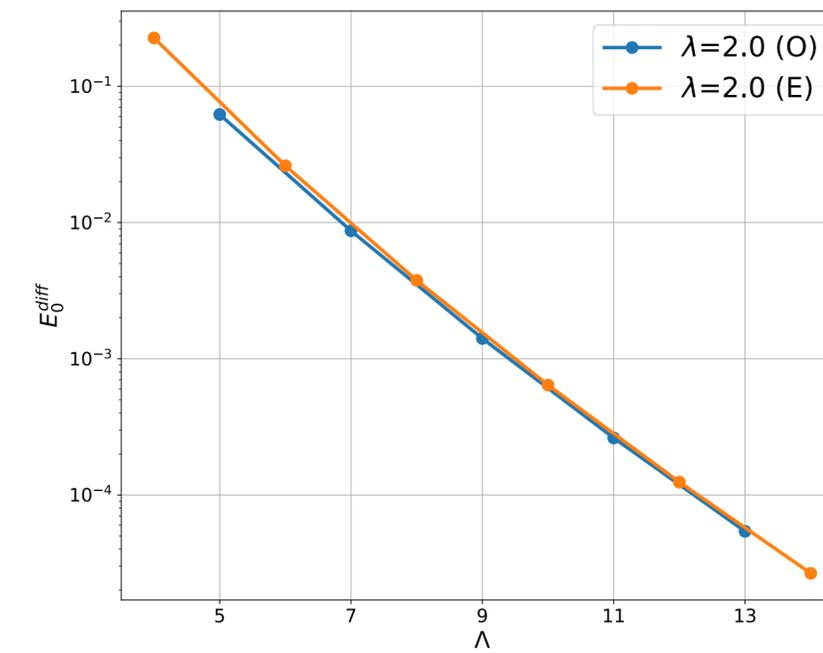
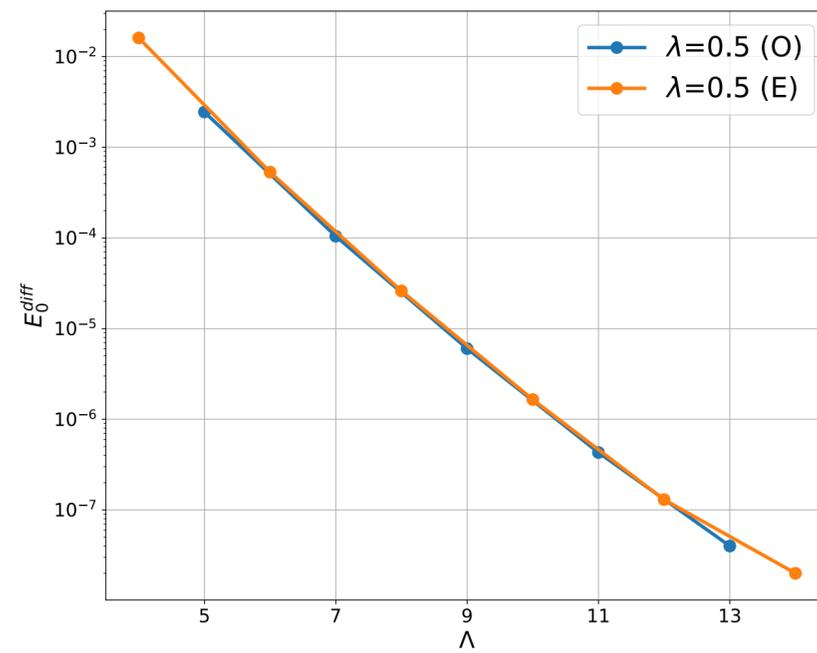
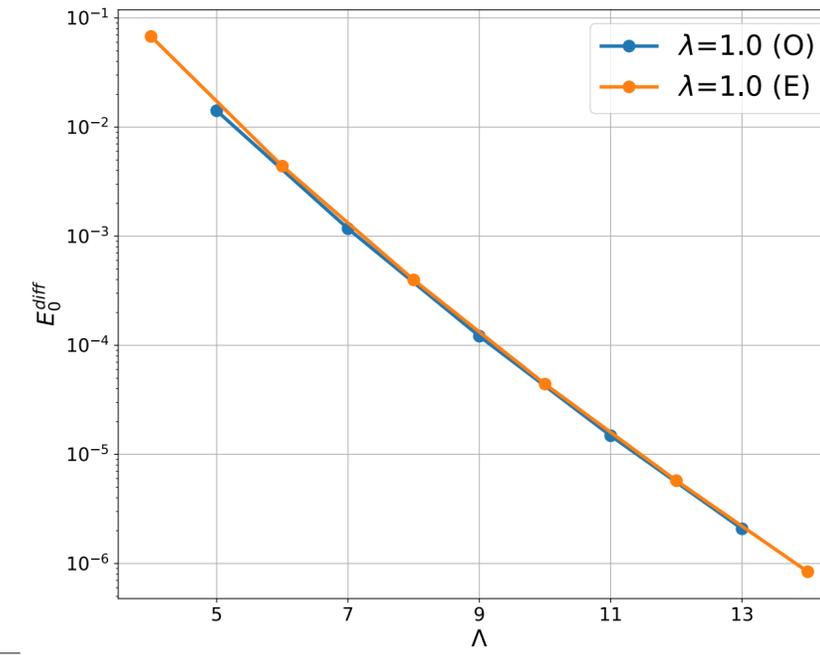
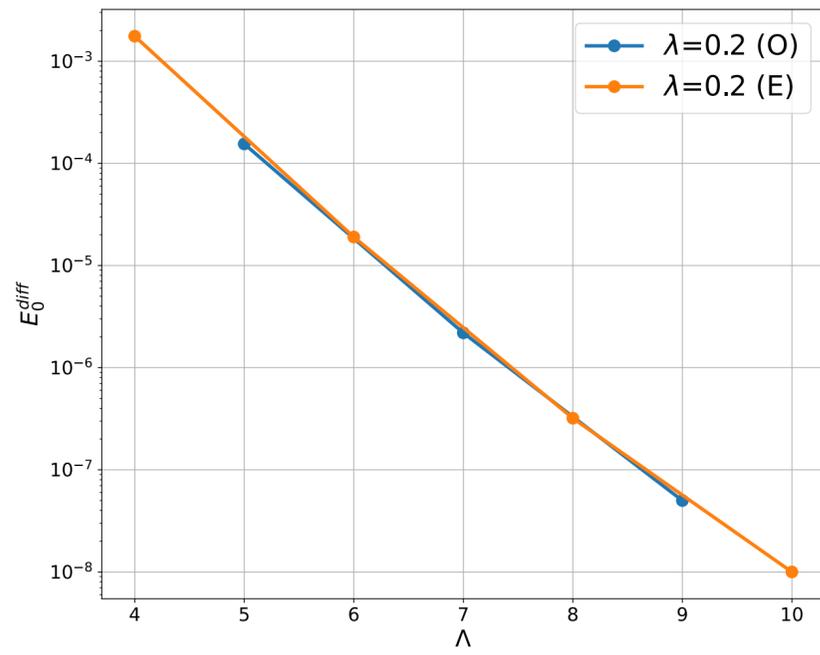
No truncation Λ

Global Extrapolation

Local Extrapolation



Energy difference Dependence on Λ



Comparison

Benchmarking different methods

Bosonic Model

Supersymmetric Model

SU(2)

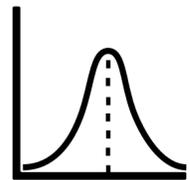
	$\lambda = 0.5$	$\lambda = 1.0$	$\lambda = 2.0$
 $E_{0,HT}$	3.297	3.516	3.855
 $E_{0,DL}$	3.302(2)	3.519(2)	3.857(3)
 $E_{0,MC}$	3.312(26)	3.497(33)	3.847(30)
 $E_{0,VQE}$	3.309	3.547	3.933

SU(2)

	$\lambda = 0.5$	$\lambda = 1.0$	$\lambda = 2.0$
 $E_{0,HT}$	0.000	0.000	0.000
 $E_{0,DL}$	0.009(5)	0.014(6)	0.034(7)
 $E_{0,VQE}$	0.027	0.079	0.177

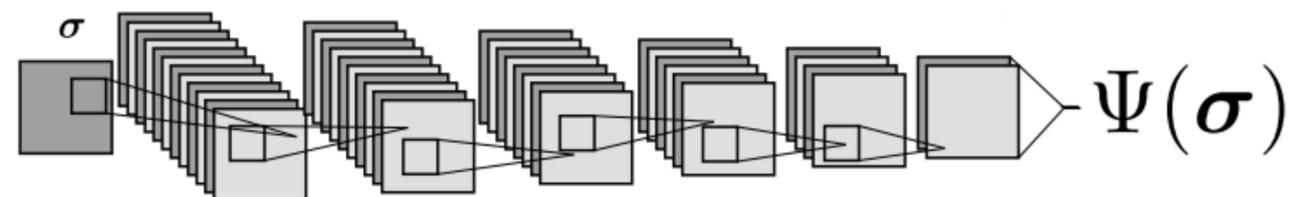
SU(3)

	$\lambda = 0.5$	$\lambda = 1.0$	$\lambda = 2.0$
 $E_{0,DL}$	8.824(7)	9.432(7)	10.426(8)
 $E_{0,MC}$	8.836(38)	9.381(38)	10.236(41)



Deep Learning

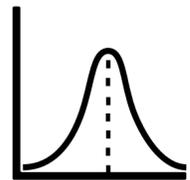
Variational Quantum Monte Carlo with Neural Quantum States



$$\psi_{\theta}(X) = \langle X | \psi_{\theta} \rangle$$

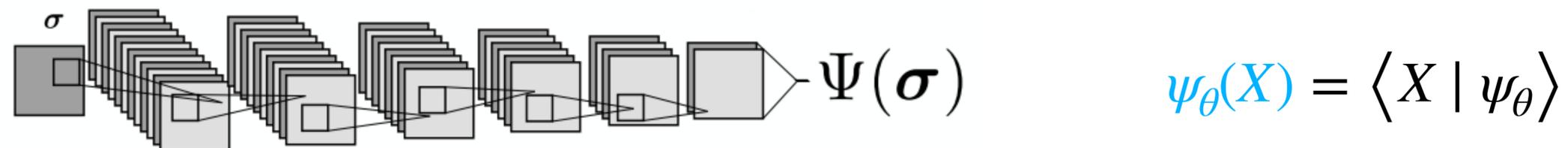
$$E_{\theta} \equiv \langle \psi_{\theta} | \hat{H} | \psi_{\theta} \rangle = \int dX |\psi_{\theta}(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_{\theta} \rangle}{\psi_{\theta}(X)} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\epsilon_{\theta}(X)]$$

$$\nabla_{\theta} E_{\theta} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\nabla_{\theta} \epsilon_{\theta}(X)] + \mathbf{E}_{X \sim |\psi_{\theta}|^2} \left[\epsilon_{\theta}(X) \nabla_{\theta} \ln |\psi_{\theta}|^2 \right] \quad \theta' = \theta - \beta \nabla_{\theta} E_{\theta}$$



Deep Learning

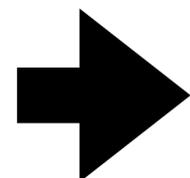
Variational Quantum Monte Carlo with Neural Quantum States



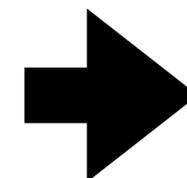
$$E_\theta \equiv \langle \psi_\theta | \hat{H} | \psi_\theta \rangle = \int dX |\psi_\theta(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_\theta \rangle}{\psi_\theta(X)} = \mathbf{E}_{X \sim |\psi_\theta|^2} [\epsilon_\theta(X)]$$

$$\nabla_\theta E_\theta = \mathbf{E}_{X \sim |\psi_\theta|^2} [\nabla_\theta \epsilon_\theta(X)] + \mathbf{E}_{X \sim |\psi_\theta|^2} \left[\epsilon_\theta(X) \nabla_\theta \ln |\psi_\theta|^2 \right] \quad \theta' = \theta - \beta \nabla_\theta E_\theta$$

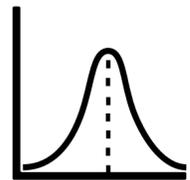
NQS → Variational Ansatz for $|\Phi\rangle$



Evaluation of cost function → $E(\theta)$



Optimize parameters → θ^*



Deep Learning

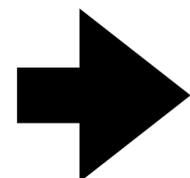
Variational Quantum Monte Carlo with Neural Quantum States



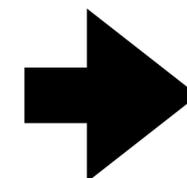
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$$\nabla_\theta E_\theta = \mathbf{E}_{X \sim |\psi_\theta|^2} [\nabla_\theta \epsilon_\theta(X)] + \mathbf{E}_{X \sim |\psi_\theta|^2} \left[\epsilon_\theta(X) \nabla_\theta \ln |\psi_\theta|^2 \right] \quad \theta' = \theta - \beta \nabla_\theta E_\theta$$

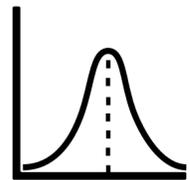
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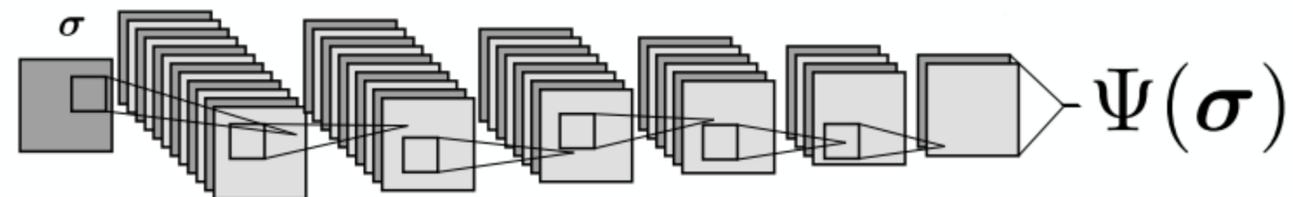


Optimize parameters → θ^*



Deep Learning

Variational Quantum Monte Carlo with Neural Quantum States



$$\psi_{\theta}(X) = \langle X | \psi_{\theta} \rangle$$

Choice of Neural Network Architecture

$$E_{\theta} \equiv \langle \psi_{\theta} | \hat{H} | \psi_{\theta} \rangle = \int dX |\psi_{\theta}(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_{\theta} \rangle}{\psi_{\theta}(X)} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\epsilon_{\theta}(X)]$$

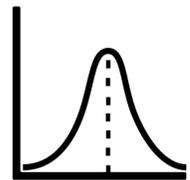
Choice of Monte Carlo Sampling

$$\nabla_{\theta} E_{\theta} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\nabla_{\theta} \epsilon_{\theta}(X)] + \mathbf{E}_{X \sim |\psi_{\theta}|^2} \left[\epsilon_{\theta}(X) \nabla_{\theta} \ln |\psi_{\theta}|^2 \right] \quad \theta' = \theta - \beta \nabla_{\theta} E_{\theta}$$

NQS → Variational Ansatz for $|\Phi\rangle$

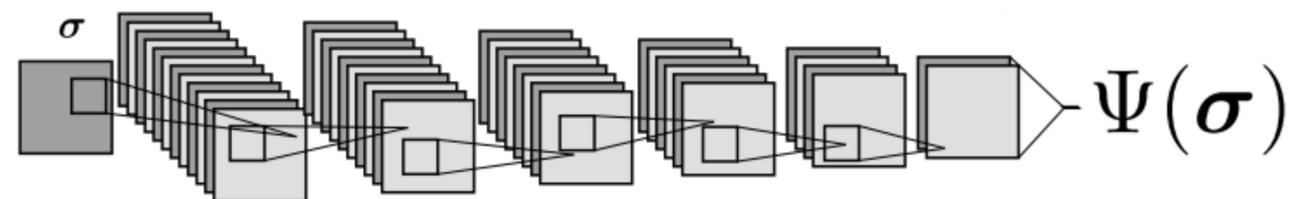
Evaluation of cost function → $E(\theta)$

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Deep Learning

Variational Quantum Monte Carlo with Neural Quantum States



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Choice of learning algorithm

NQS → Variational Ansatz for $|\Phi\rangle$

Evaluation of cost function → $E(\theta)$

Optimize parameters → θ^*

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)}$$

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$



$$p_\theta(X) = p(x_1; F_\theta^0) p(x_2; F_\theta^1(x_1)) p(x_3; F_\theta^2(x_1, x_2)) \dots$$

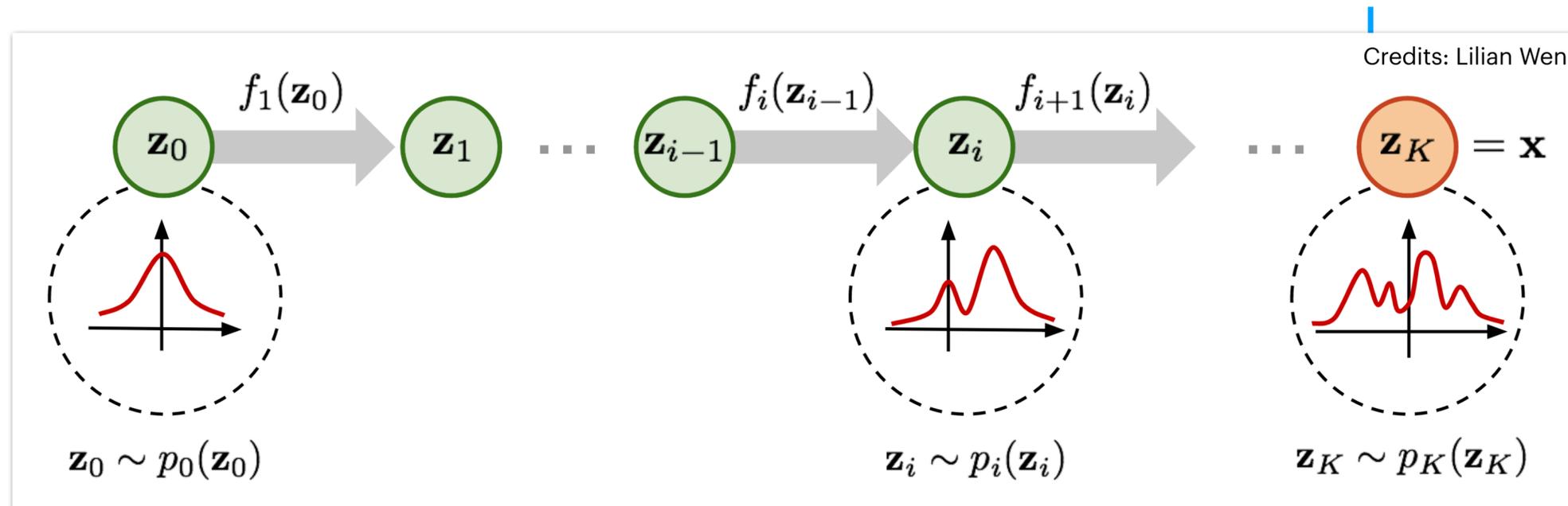
Autoregressive Flow

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$



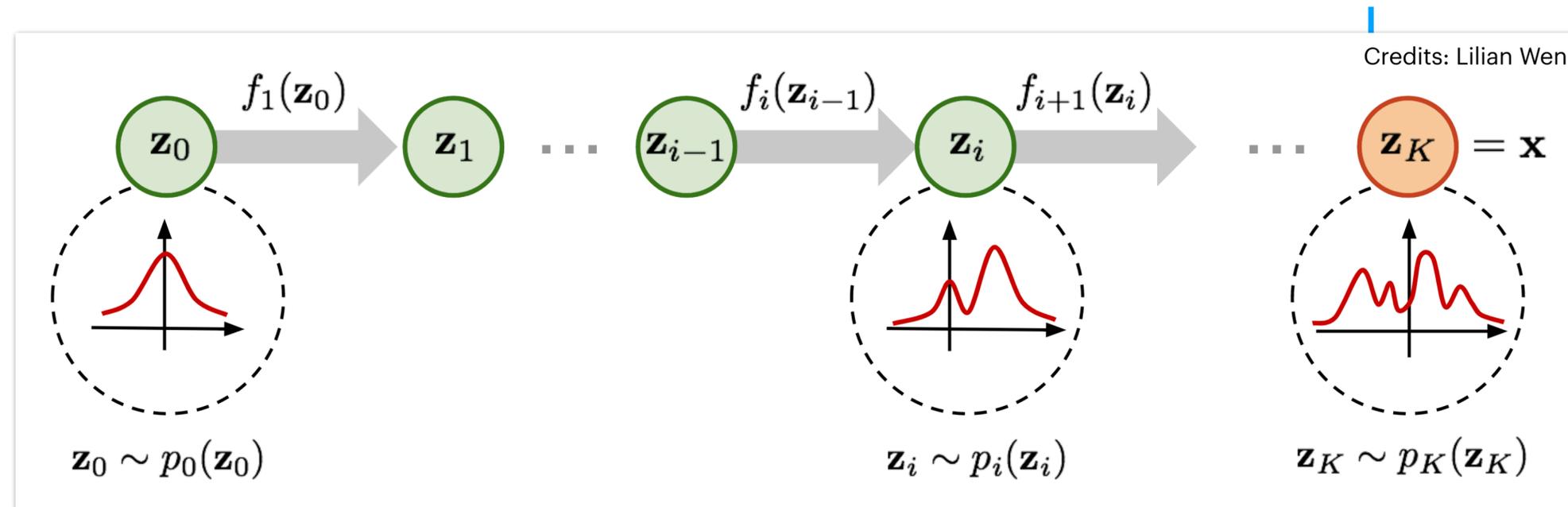
Autoregressive Flow

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$



Autoregressive Flow

Prob. distribution

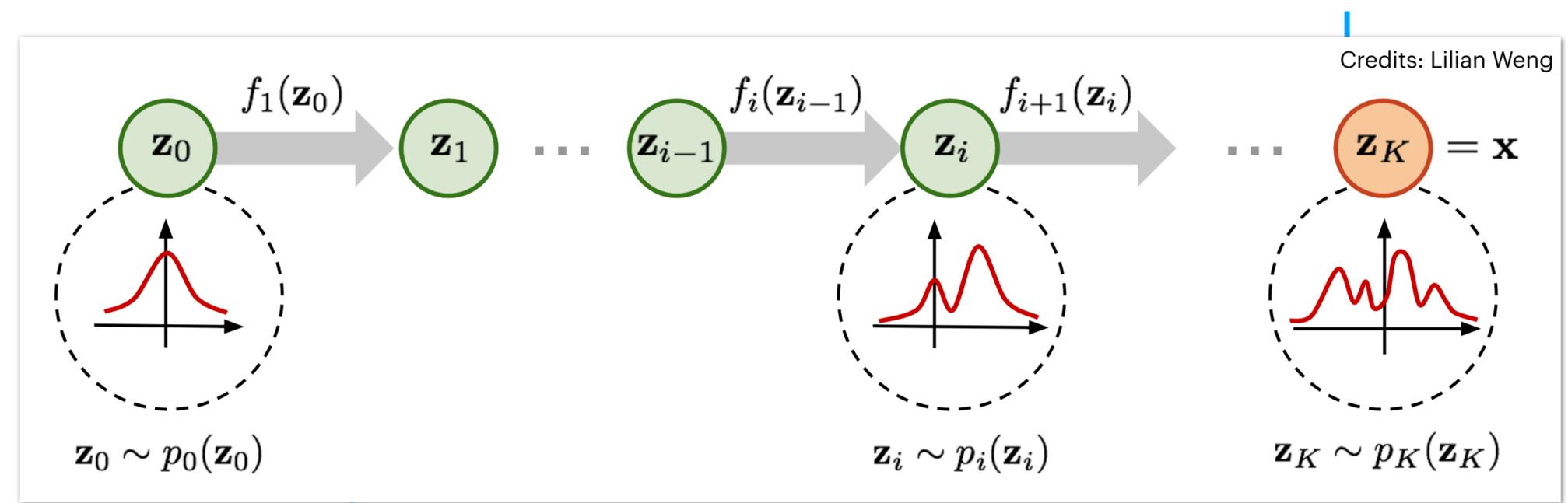
$$p(x_1; F_\theta^0)$$

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$



Autoregressive Flow

Parametrization

Prob. distribution

$$p(x_1; F_\theta^0) \longrightarrow F_\theta^i = A_\theta^{i,m} \circ \tanh \circ A_\theta^{i,m-1} \circ \tanh \circ \dots \circ A_\theta^{i,2} \circ \tanh \circ A_\theta^{i,1}$$

$$A_\theta^{i,a}(\vec{x}) = M_\theta^{i,a} \cdot \vec{x} + \vec{b}_\theta^{i,a}$$

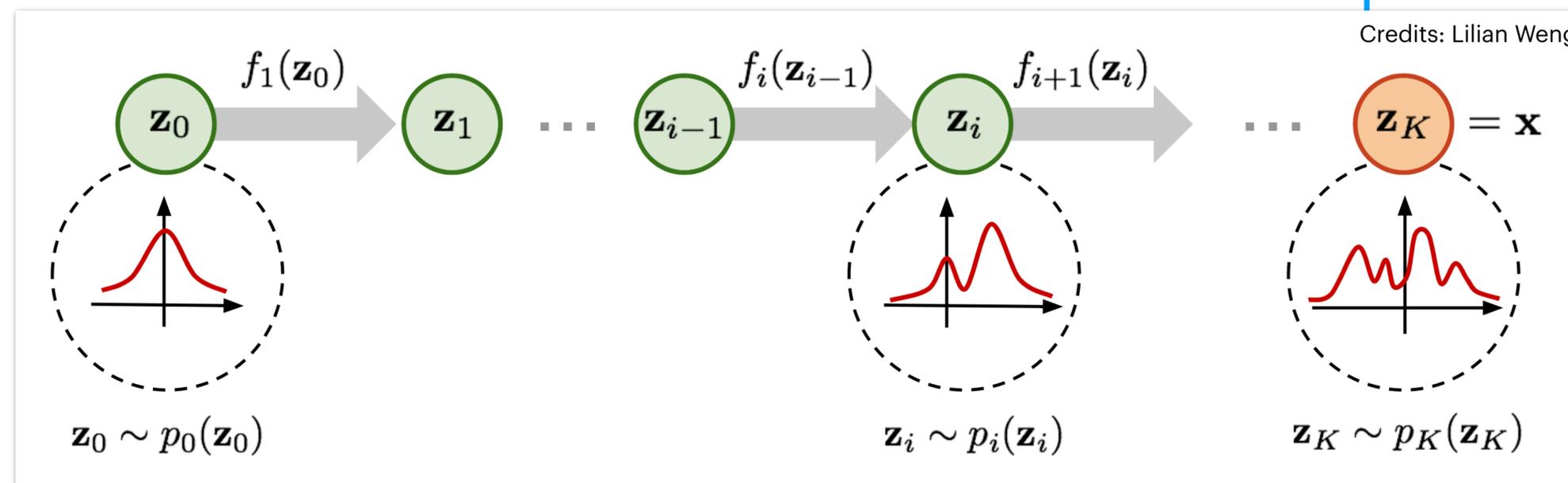
Neural quantum state

Small-scale: N=2, D=2

No truncation Λ

Wave function

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Autoregressive Flow

Parametrization

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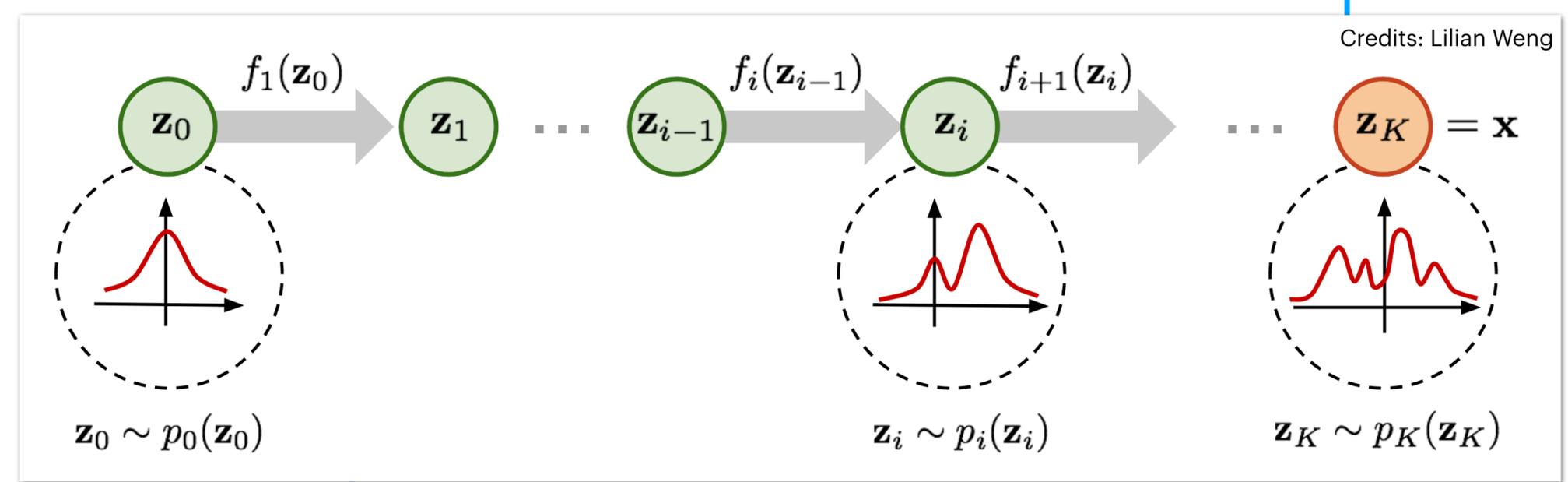
$$A_\theta^{i,a}(\vec{x}) = M_\theta^{i,a} \cdot \vec{x} + \vec{b}_\theta^{i,a}$$

Neural quantum state

Small-scale: N=2, D=2

Wave function

$$\psi(X) = |\psi(X)| e^{i\theta(X)} \longrightarrow |\psi(X)| = \sqrt{p_\theta(X)}$$



- No truncation Λ
- Direct Sampling

Autoregressive Flow

Parametrization

Prob. distribution

$$p(x_1; F_\theta^0) \longrightarrow F_\theta^i = A_\theta^{i,m} \circ \tanh \circ A_\theta^{i,m-1} \circ \tanh \circ \dots \circ A_\theta^{i,2} \circ \tanh \circ A_\theta^{i,1}$$

$$A_\theta^{i,a}(\vec{x}) = M_\theta^{i,a} \cdot \vec{x} + \vec{b}_\theta^{i,a}$$

Optimization

Small-scale: N=2, D=2

$$|\psi(X)\rangle = \sqrt{p_\theta(X)}$$

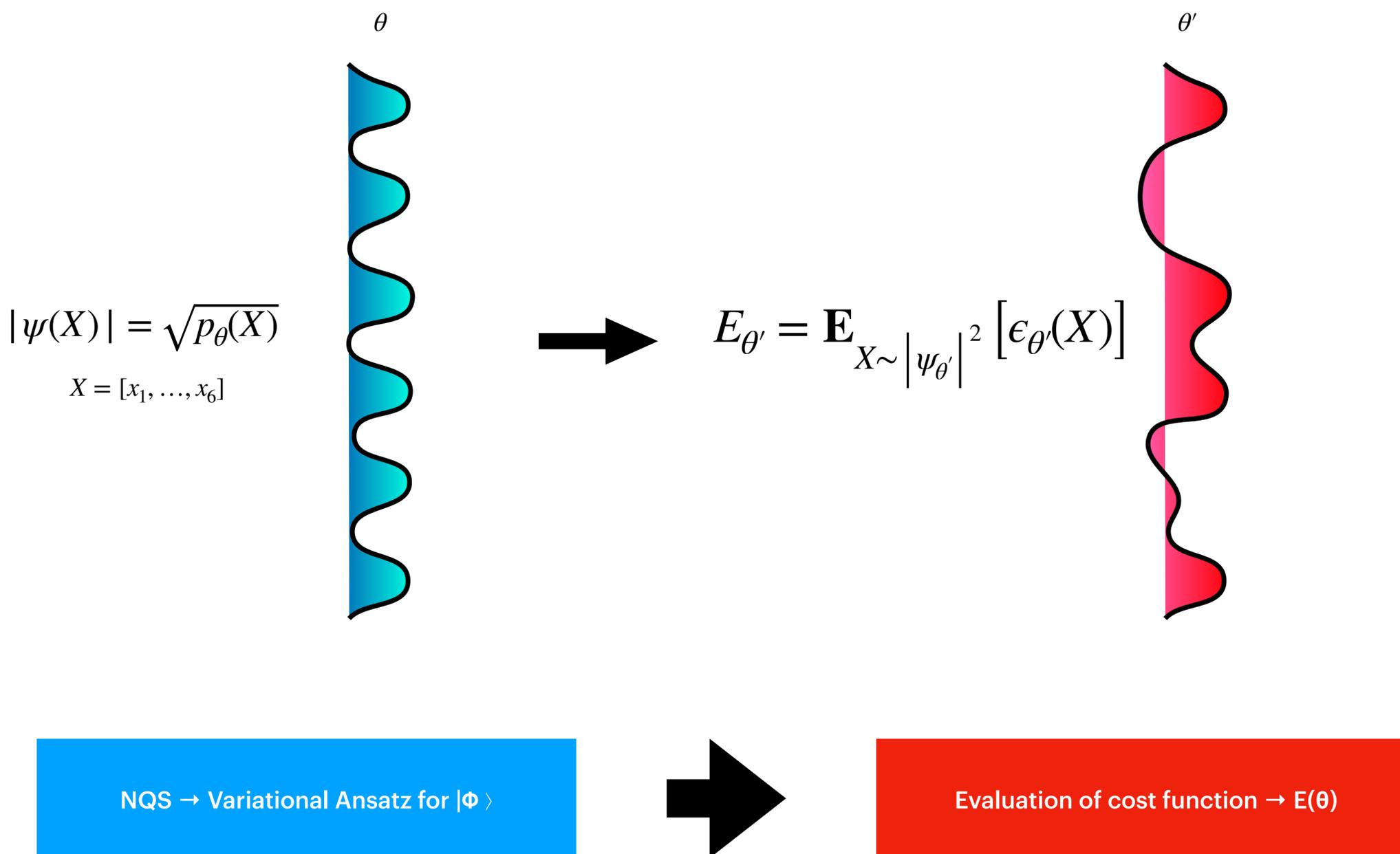
$X = [x_1, \dots, x_6]$



NQS → Variational Ansatz for $|\Phi\rangle$

Optimization

Small-scale: N=2, D=2



Optimization

Small-scale: N=2, D=2

$$|\psi(X)| = \sqrt{p_\theta(X)}$$

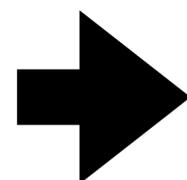
$X = [x_1, \dots, x_6]$



$$E_{\theta'} = \mathbf{E}_{X \sim |\psi_{\theta'}|^2} [\epsilon_{\theta'}(X)]$$



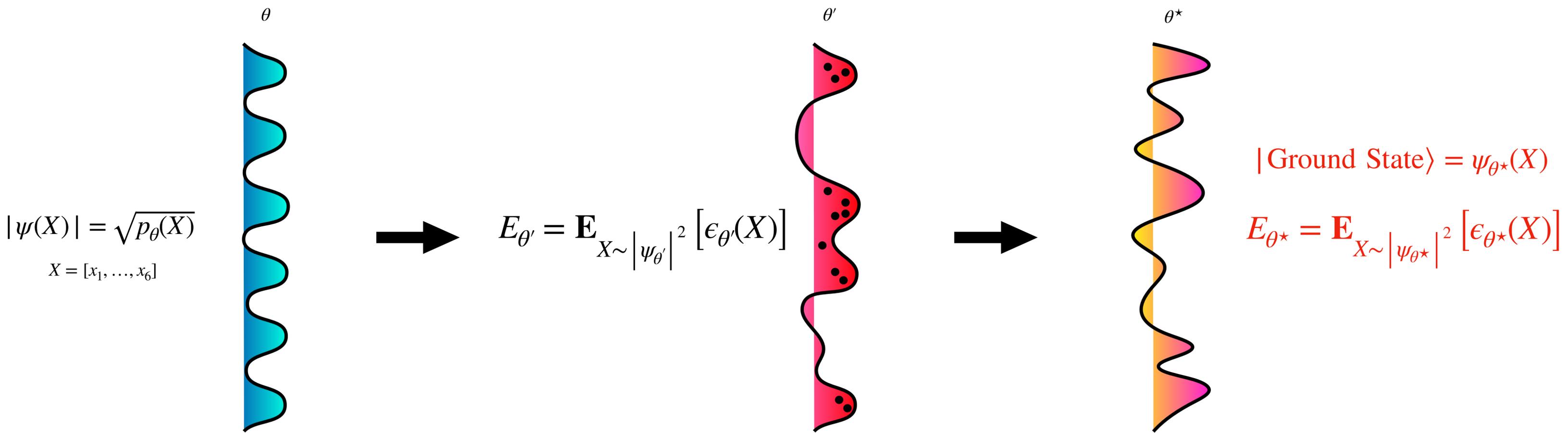
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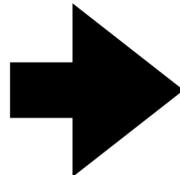
Evaluation of cost function → $E(\theta)$

Optimization

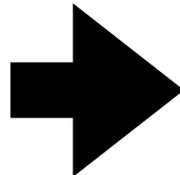
Small-scale: N=2, D=2



NQS → Variational Ansatz for $|\Phi\rangle$



Evaluation of cost function → $E(\theta)$



Optimize parameters → θ^*

Optimization

Small-scale: N=2, D=2

$$|\psi(X)| = \sqrt{p_\theta(X)}$$

$X = [x_1, \dots, x_6]$



$$E_{\theta'} = \mathbf{E}_{X \sim |\psi_{\theta'}|^2} [\epsilon_{\theta'}(X)]$$



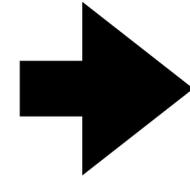
$$|\text{Ground State}\rangle = \psi_{\theta^*}(X)$$

$$E_{\theta^*} = \mathbf{E}_{X \sim |\psi_{\theta^*}|^2} [\epsilon_{\theta^*}(X)]$$

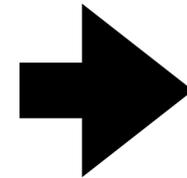
Results

Small-scale: N=2, D=2

$$\hat{H}' = \hat{H} + c \sum \hat{G}_\alpha^2$$



	c = 0			
λ	0.2	0.5	1.0	2.0
$E_{0,\text{var}}$	3.137(2)	3.299(2)	3.518(2)	3.856(3)
G_{var}^2	0.0028(4)	0.0059(6)	0.0062(7)	0.0122(9)
$E_{0,\text{singlet}}$	3.135(2)	3.297(2)	3.520(2)	3.859(3)

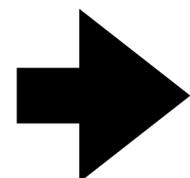


	c = 10			
λ	0.2	0.5	1.0	2.0
$E_{0,\text{var}}$	3.137(2)	3.309(2)	3.545(3)	3.912(3)
G_{var}^2	0.00011(8)	0.00019(7)	0.00022(11)	0.00021(8)
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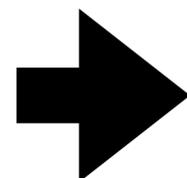
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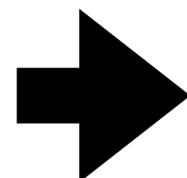
α	1	2	5	10	20	50	HT (exact)
λ = 0.2	3.137(2)	3.137(2)	3.140(2)	3.138(2)	3.137(2)	3.135(2)	3.134
λ = 0.5	3.313(2)	3.312(2)	3.308(2)	3.307(2)	3.302(2)	3.305(2)	3.297
λ = 1.0	3.544(3)	3.544(2)	3.541(3)	3.528(2)	3.519(2)	3.520(2)	3.516
λ = 2.0	3.914(3)	3.910(3)	3.892(3)	3.872(3)	3.857(3)	3.859(3)	3.854

dependence on hidden layer units α

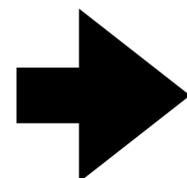
Results

Small-scale: N=2, D=2

$$\hat{H}' = \hat{H} + c \sum \hat{G}_\alpha^2$$



	c = 0			
λ	0.2	0.5	1.0	2.0
$E_{0,var}$	3.137(2)	3.299(2)	3.518(2)	3.856(3)
G_{var}^2	0.0028(4)	0.0059(6)	0.0062(7)	0.0122(9)
$E_{0,singlet}$	3.135(2)	3.297(2)	3.520(2)	3.859(3)



	c = 10			
λ	0.2	0.5	1.0	2.0
$E_{0,var}$	3.137(2)	3.309(2)	3.545(3)	3.912(3)
G_{var}^2	0.00011(8)	0.00019(7)	0.00022(11)	0.00021(8)
$E_{0,singlet}$	3.139(2)	3.307(2)	3.544(3)	3.908(3)

α	1	2	5	10	20	50	HT (exact)
λ = 0.2	3.137(2)	3.137(2)	3.140(2)	3.138(2)	3.137(2)	3.135(2)	3.134
λ = 0.5	3.313(2)	3.312(2)	3.308(2)	3.307(2)	3.302(2)	3.305(2)	3.297
λ = 1.0	3.544(3)	3.544(2)	3.541(3)	3.528(2)	3.519(2)	3.520(2)	3.516
λ = 2.0	3.914(3)	3.910(3)	3.892(3)	3.872(3)	3.857(3)	3.859(3)	3.854

dependence on hidden layer units α

Results

Supersymmetric: N=2, D=2

dependence on hidden layer units α

$$\lambda = 1.0$$

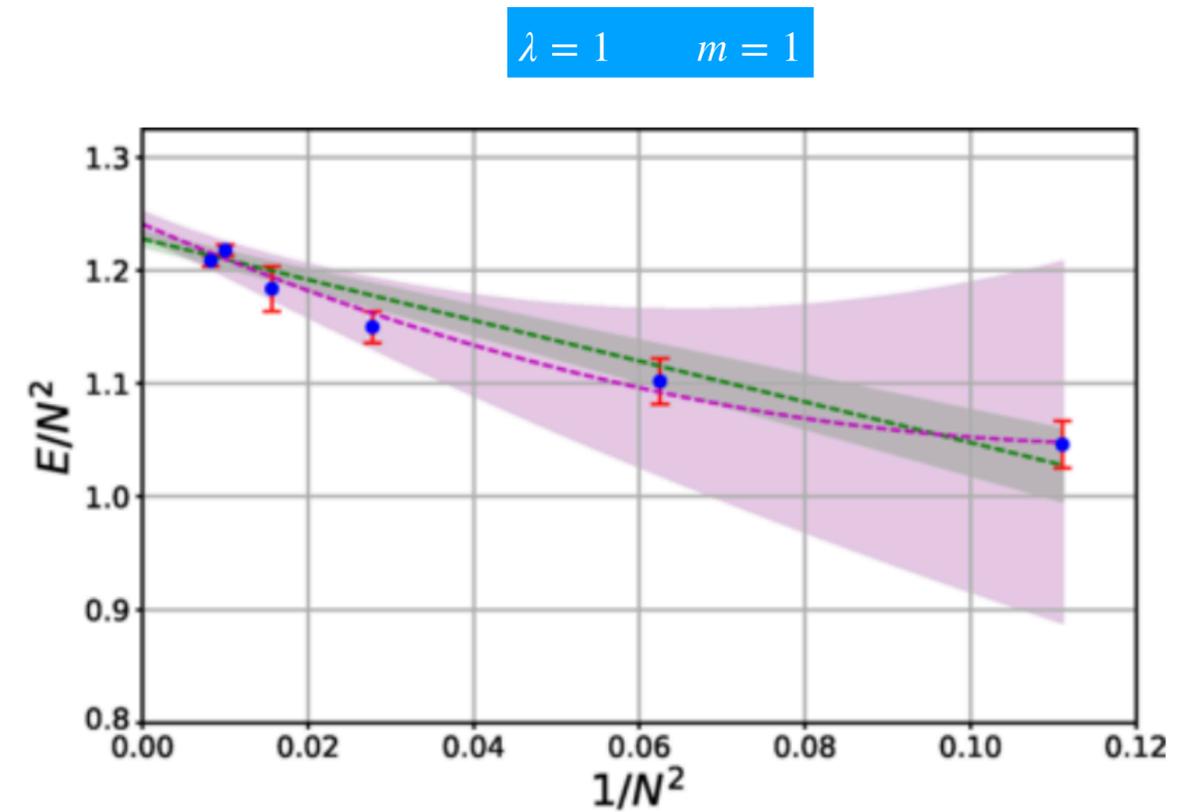
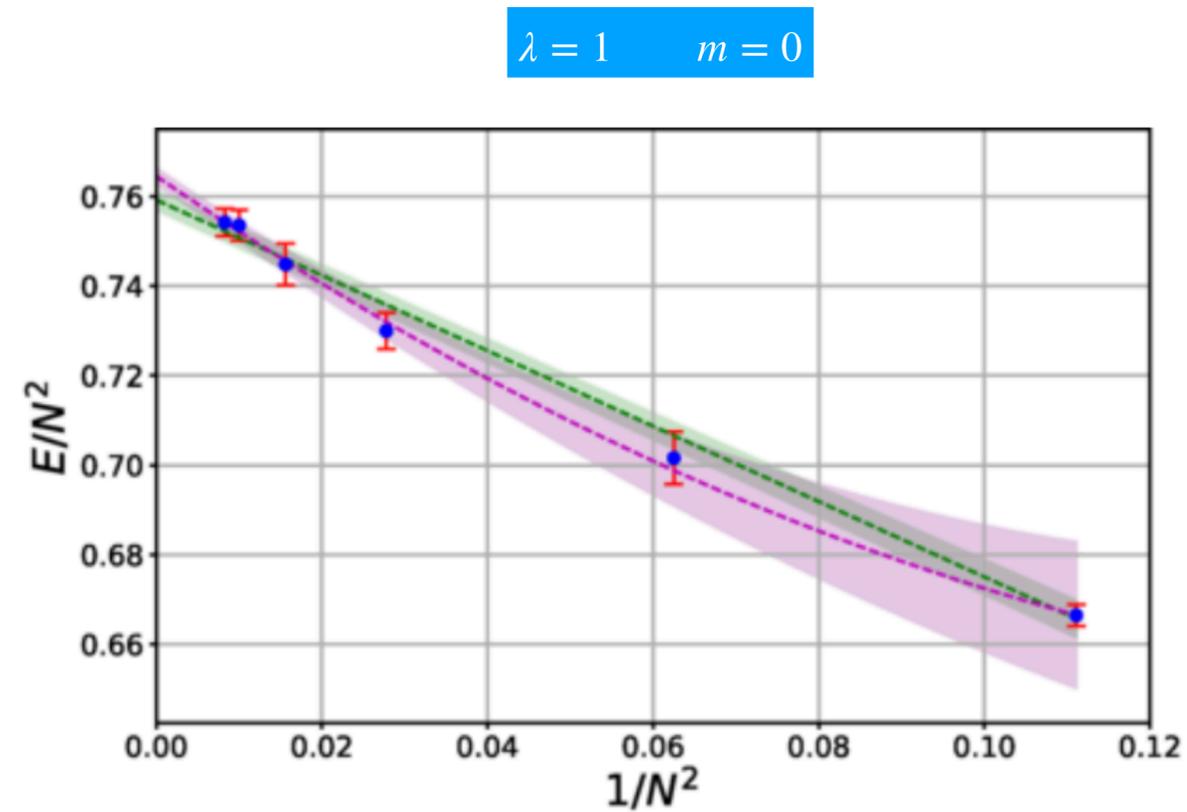
α	1	2	5	10	20	50	HT (exact)
H	0.058(6)	0.053(6)	0.041(6)	0.031(6)	0.014(6)	0.005(6)	0.000
G^2	0.007(8)	-0.008(8)	0.014(8)	0.007(9)	0.022(9)	0.012(9)	0.000
M	-0.0003(3)	-0.0004(3)	-0.0001(4)	0.0001(4)	-0.0003(5)	-0.0001(4)	0.0000
F	0.1844(6)	0.1833(6)	0.1895(6)	0.1922(6)	0.1946(7)	0.1935(7)	0.2034

Strong coupling

	$\lambda = 0.5$	$\lambda = 1.0$	$\lambda = 2.0$
H	0.009(5)	0.014(6)	0.034(7)
G^2	0.010(6)	0.022(9)	0.038(14)
M	-0.0002(3)	-0.0003(5)	0.0006(7)
F	0.1224(4)	0.1946(7)	0.2729(9)

Results

Large N limit: $N=3,4,6,8,10,11$ with $D=2$



Extrapolated results are not compatible with the Path Integral Monte Carlo ones