

Quantum Gravity in the Lab

Matrix Quantum Mechanics meets Quantum Computing

Enrico Rinaldi

University of Michigan + (Quantum Computing + Theoretical Quantum Physics Lab. + iTHEMS) @ RIKEN

2021-10-26 NSCL/FRIB Theory Seminar

Short self-intro

who am I?

- I am a **computational physicist**
- Worked on simulations for particle physics and dark matter models using **TOP500 HPC systems**
- *“Interdisciplinary science is all you need”[©]*
- Currently in Tokyo @ **RIKEN Quantum Computing Center**
- Previously @ **AI startup in Tokyo** (better view from the office 😅)



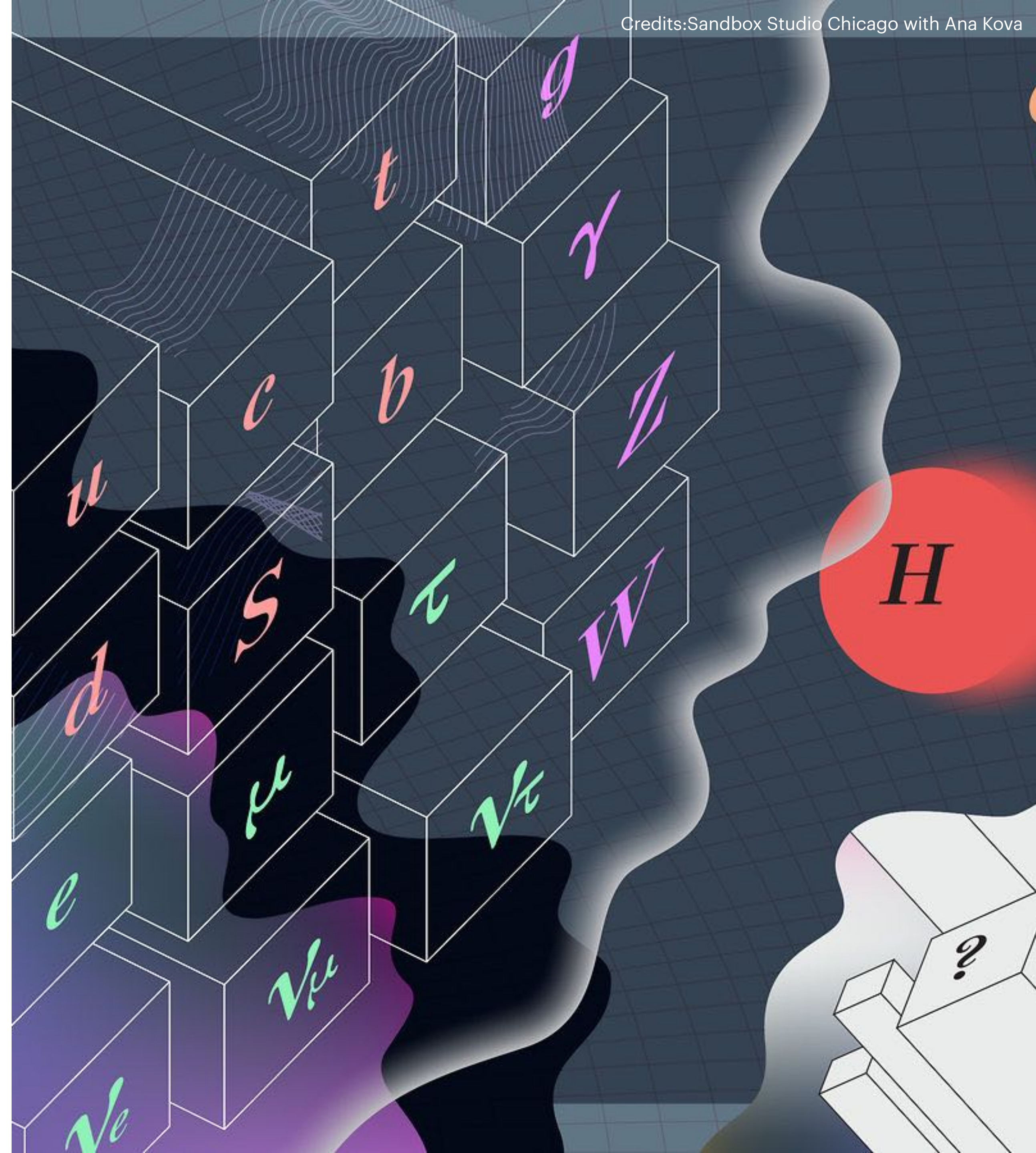


Understanding Gravity

- Einstein's **General Relativity** is at the heart of GPS technology
- In 2017 LIGO won the Nobel Prize for the detection of **gravitational waves** from black hole mergers
- In 2018 the Event Horizon Telescope produced the first "image" of the supermassive **black hole** in the Milky Way

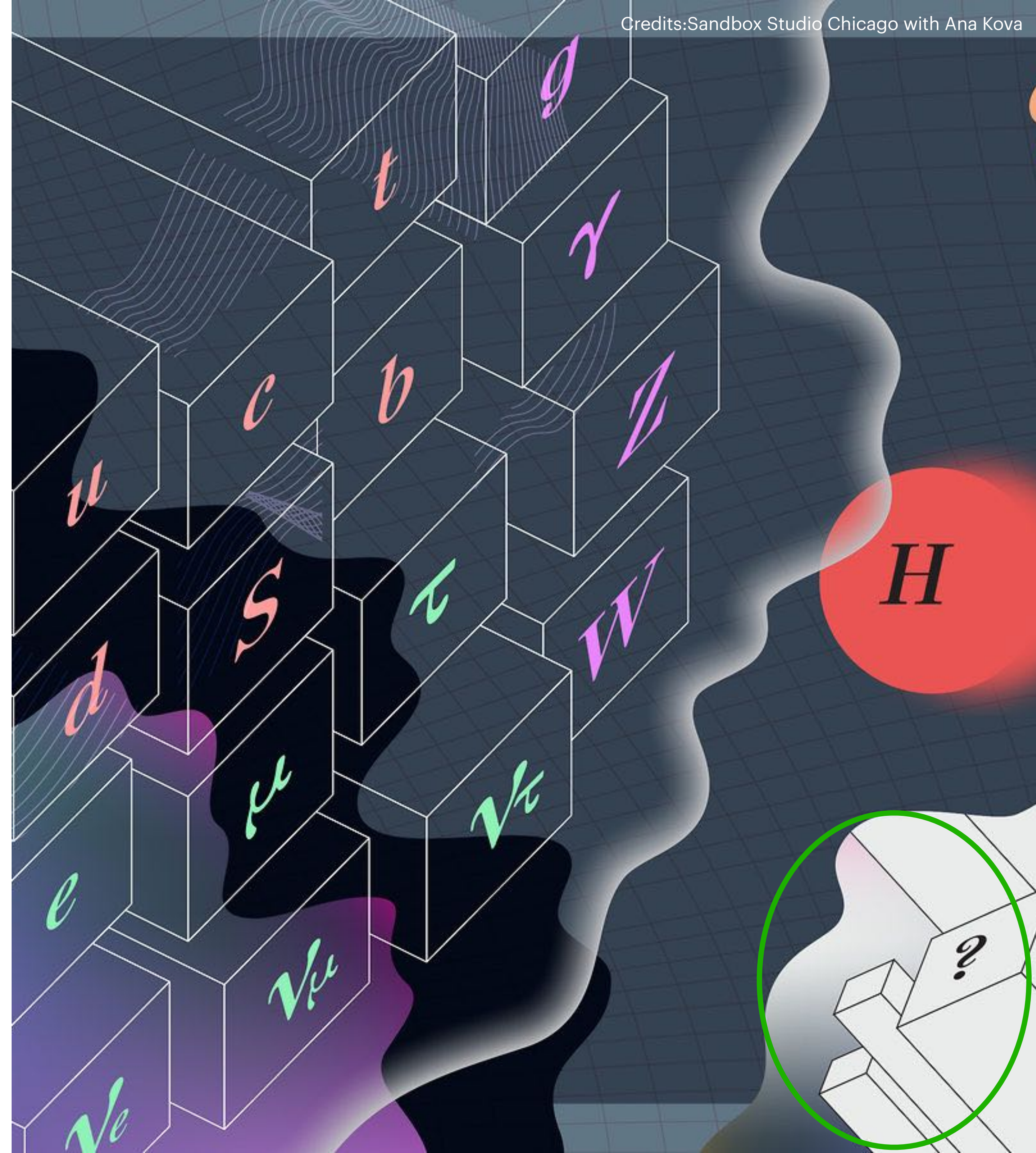
Quantum Field Theory

- The **Standard Model of particle physics** is our most precise description of the subatomic world
- It is a Quantum Field Theory, a very complicated many-body quantum system obeying the rules of **quantum mechanics**



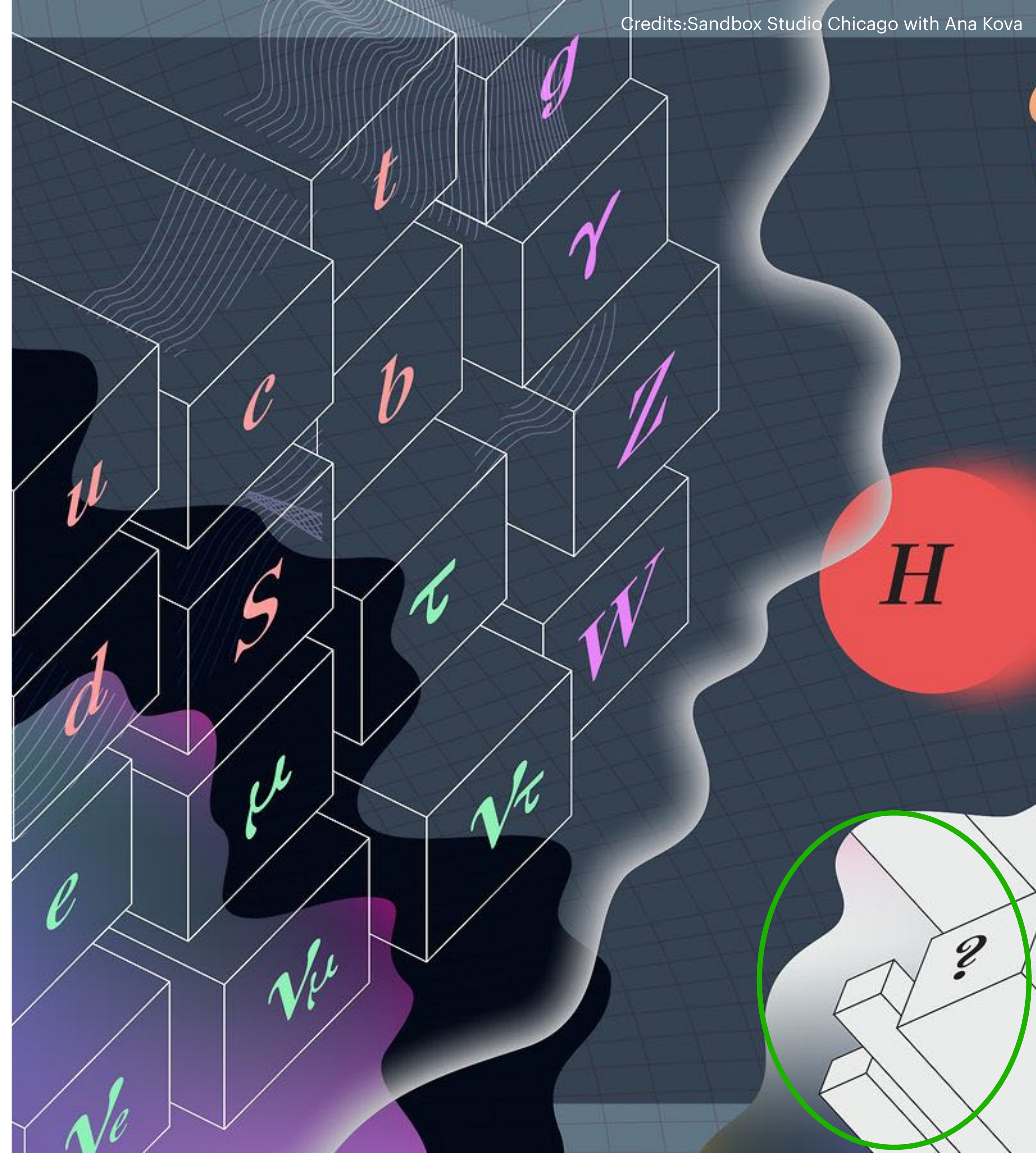
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- Some pieces of this description of the world are still missing:
 - What is the **quantum theory for gravity?**



quantum mechanical process

Schroedinger's Cat

Information going into the black hole

Information Paradox

Hawking's radiation

Black Hole



quantum mechanical process

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Entanglement

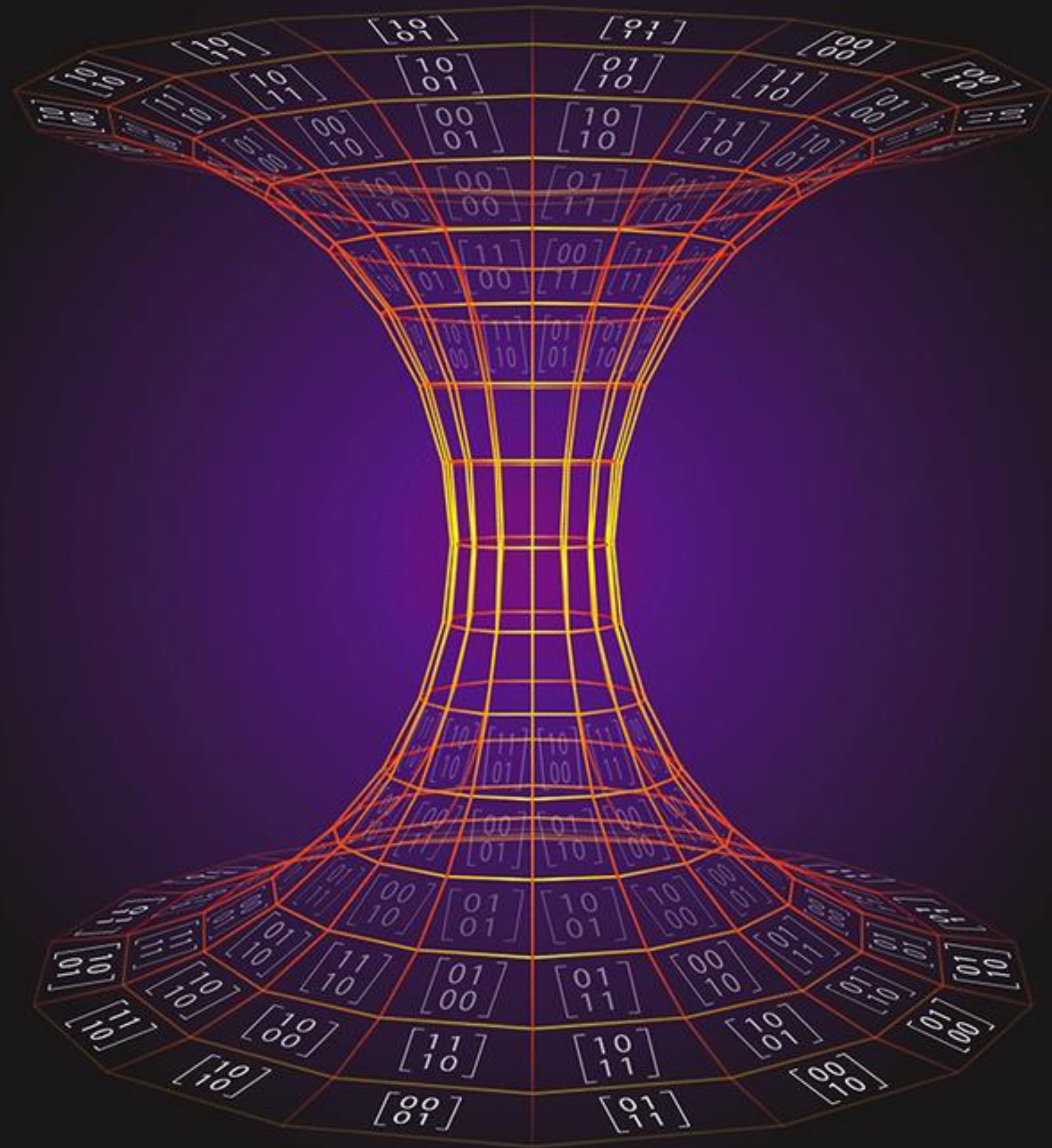
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Outline

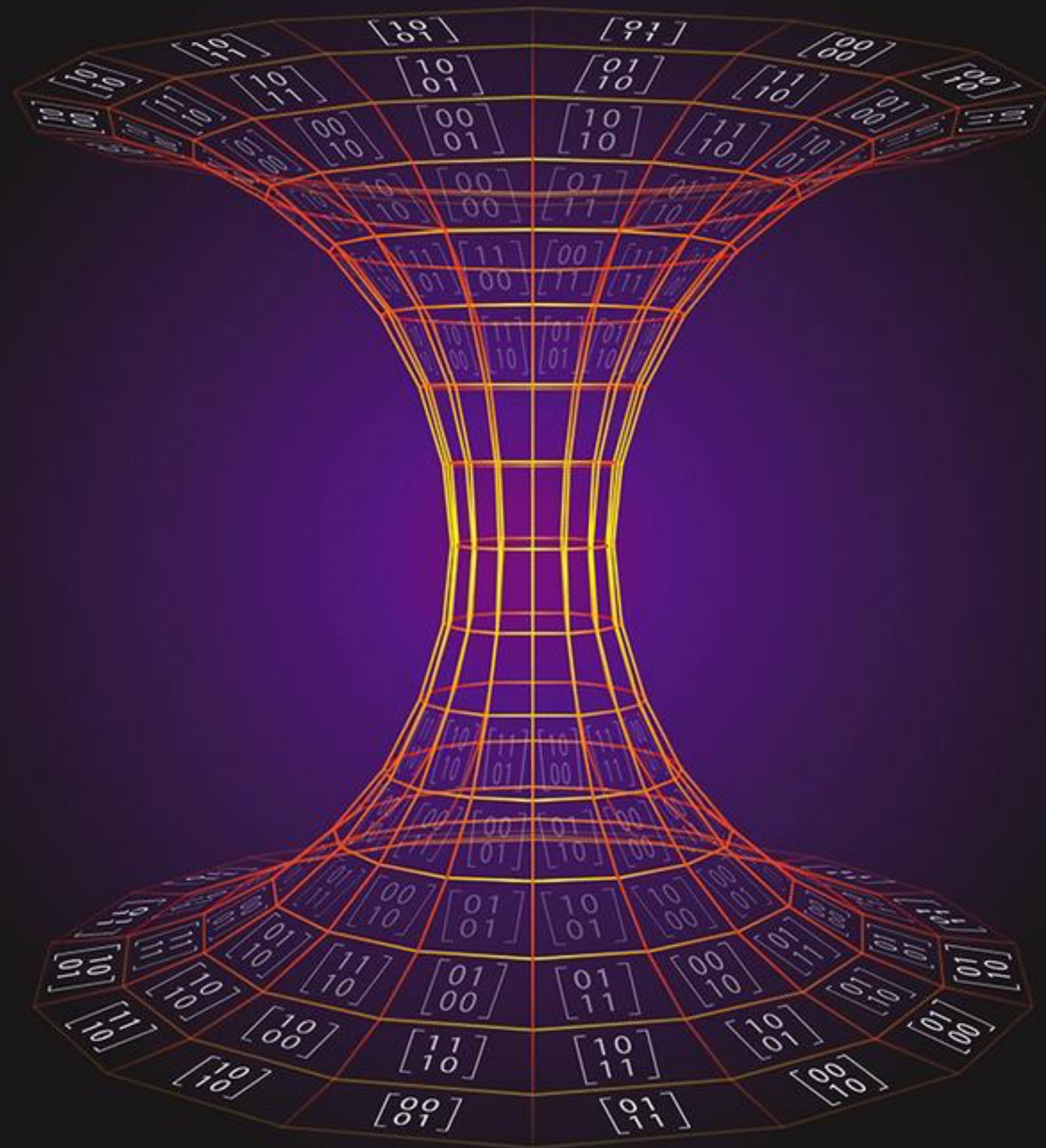
Matrix Models via QC, DL, and MC



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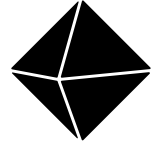
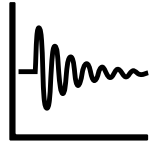
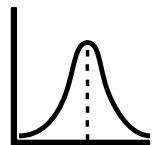
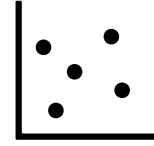
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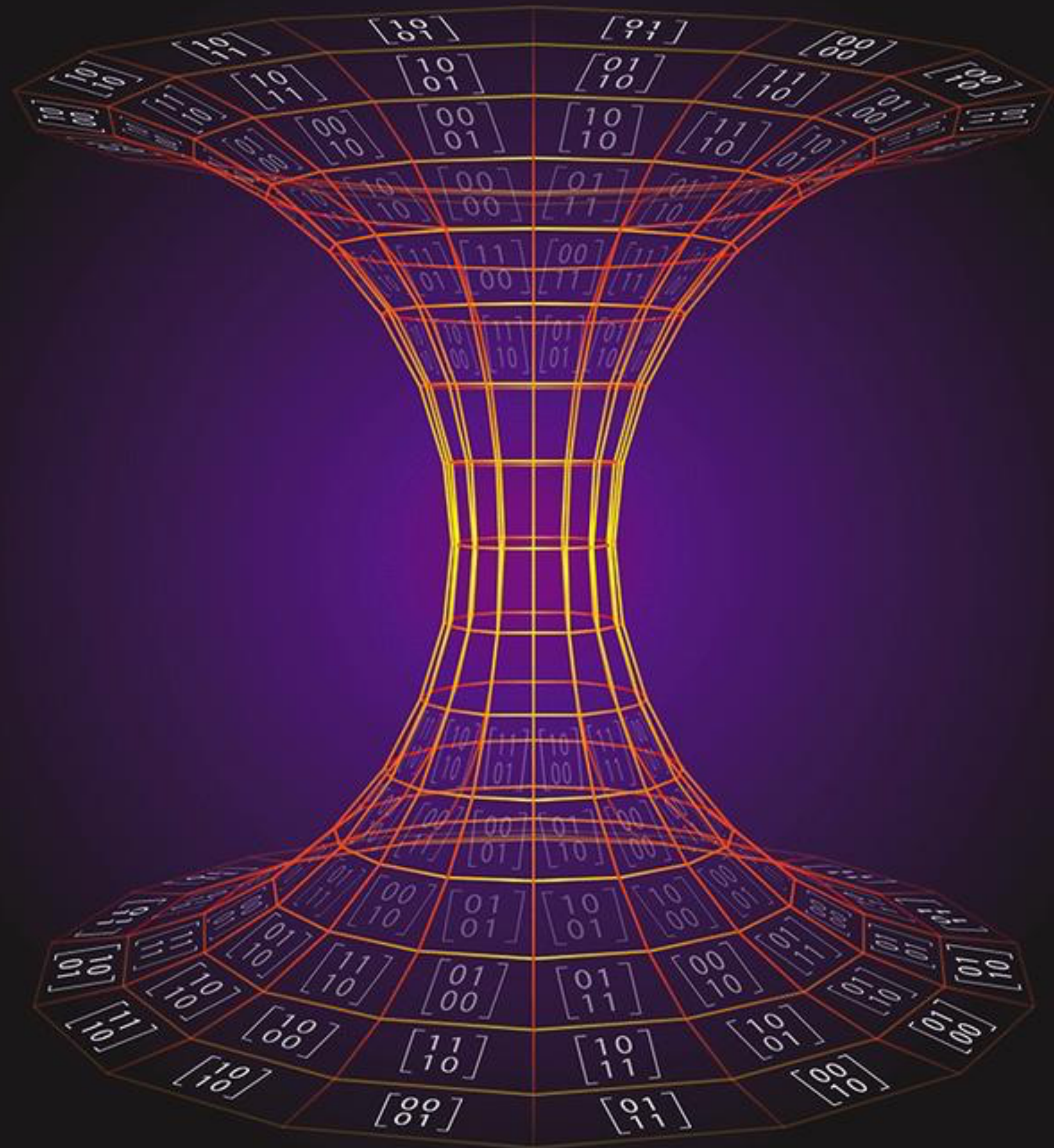
- Introduction to Matrix Models 



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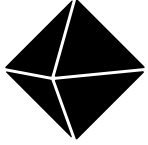
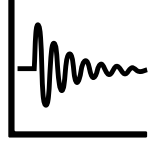
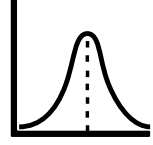
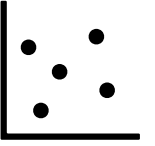
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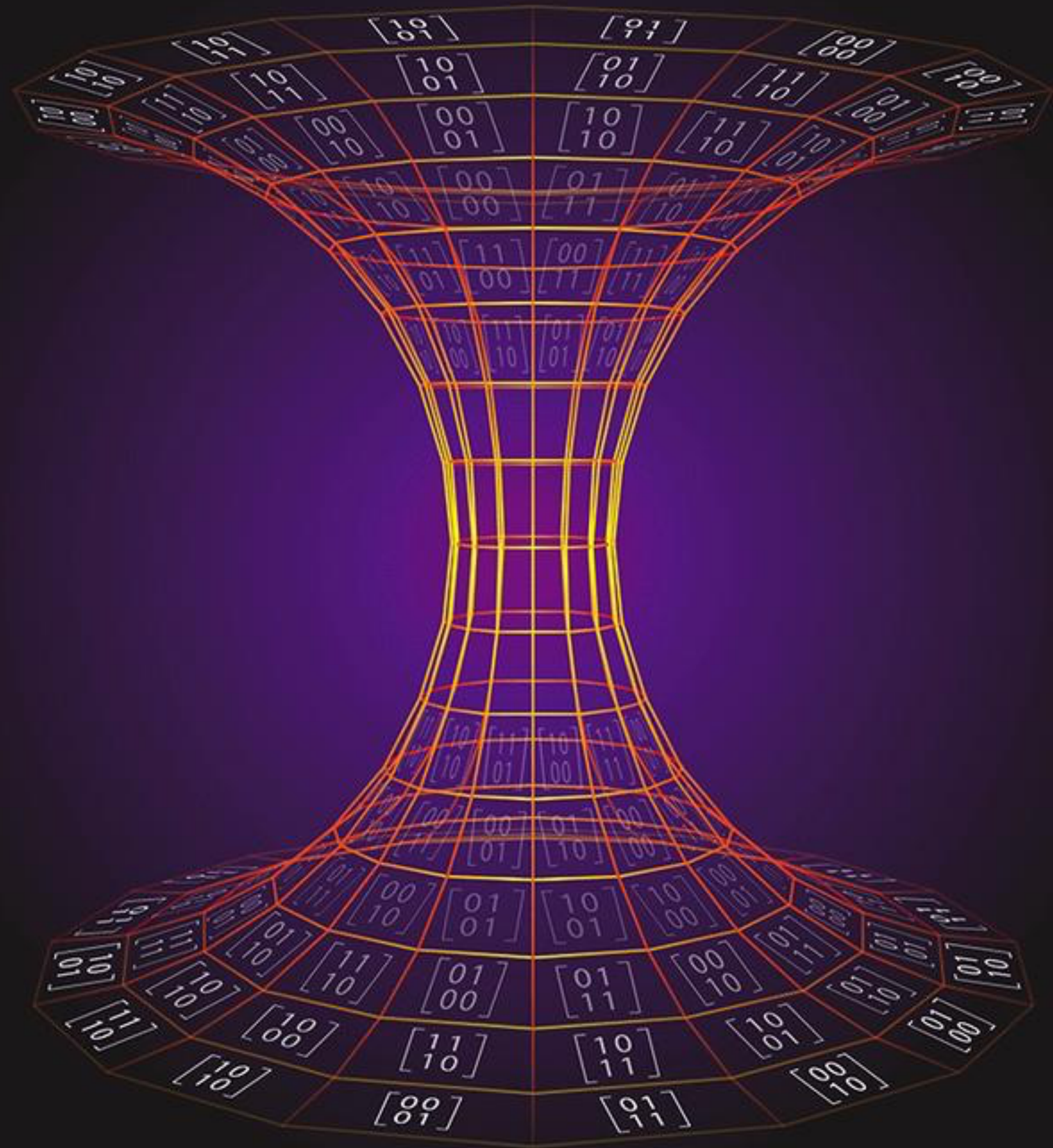
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- **Numerical techniques for matrix quantum mechanics:**
 - Truncated Hamiltonian 
 - Quantum Computing 
 - Deep Learning 
 - Path integral Monte Carlo 



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Matrix Models via QC, DL, and MC

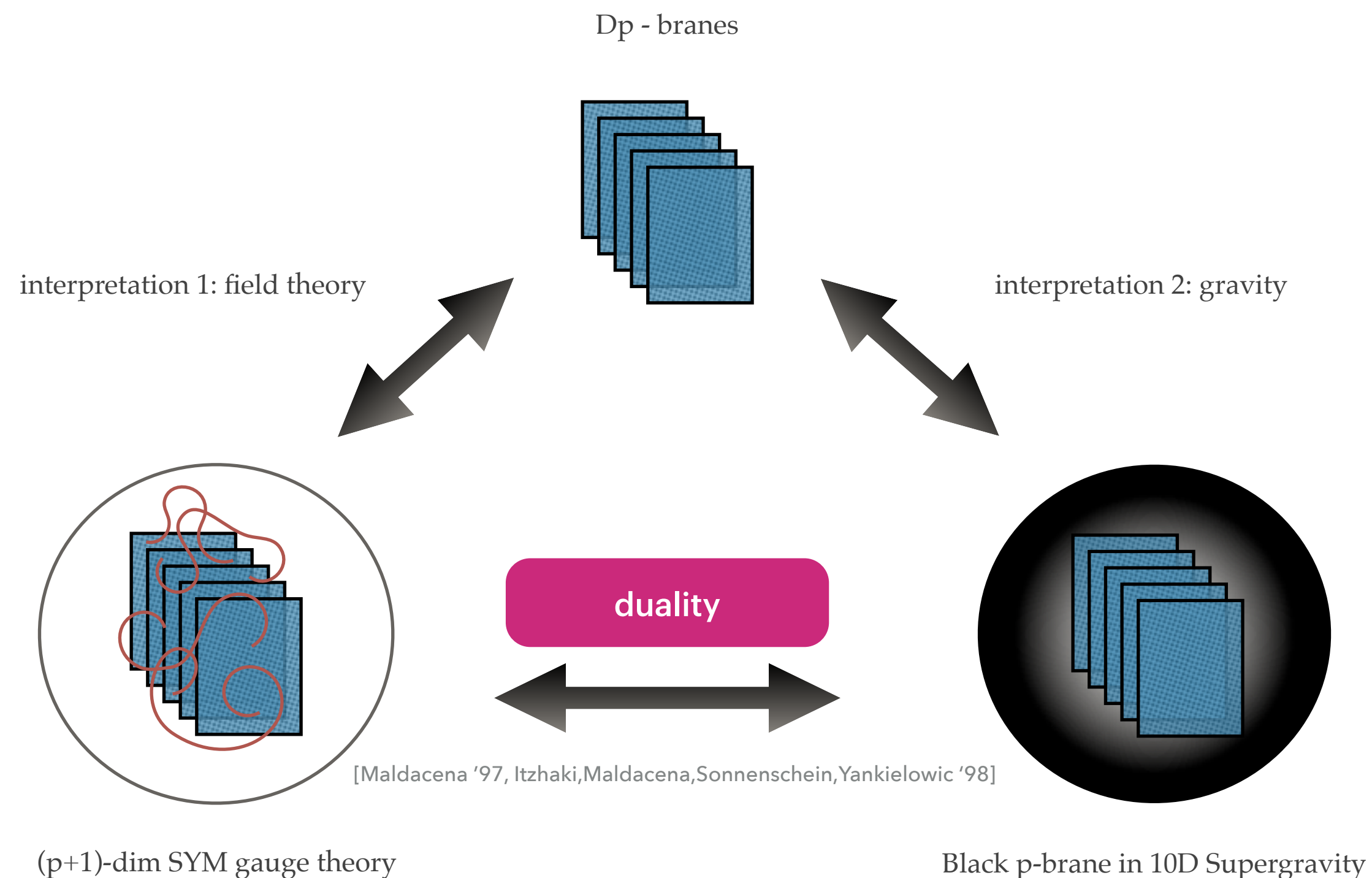
- Introduction to Matrix Models 
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 - Path integral Monte Carlo 
- Conclusions and challenges



Matrix Quantum Mechanics

Motivations

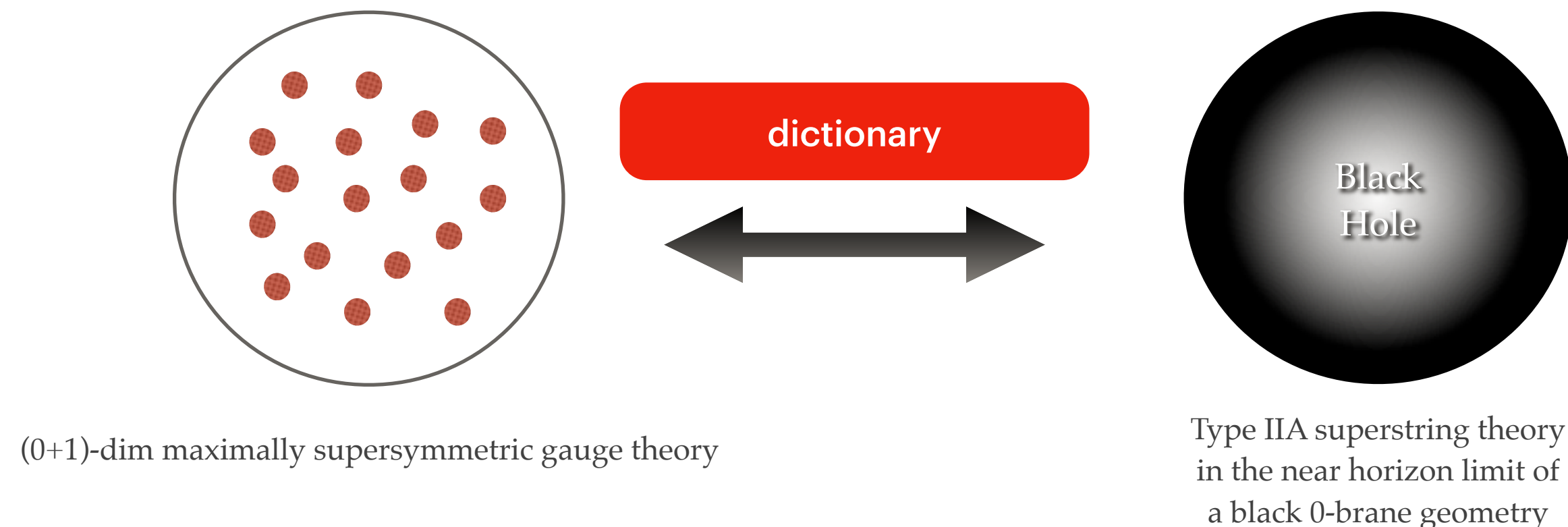
- ★ Holographic duality \rightarrow a quantum field theory **"is"** a gravitational theory
 - D0-branes and open strings \Leftrightarrow Black hole in Type IIA superstring



Matrix Quantum Mechanics

Motivations

- ★ Holographic duality → a quantum field theory “is” a gravitational theory
 - D0-branes and open strings \Leftrightarrow Black hole in Type IIA superstring
- ★ Gauge/gravity duality → use QFT to study QG (*i.e.* emergent geometry)
 - Supersymmetric QFT can be dimensionally reduced to matrix QM



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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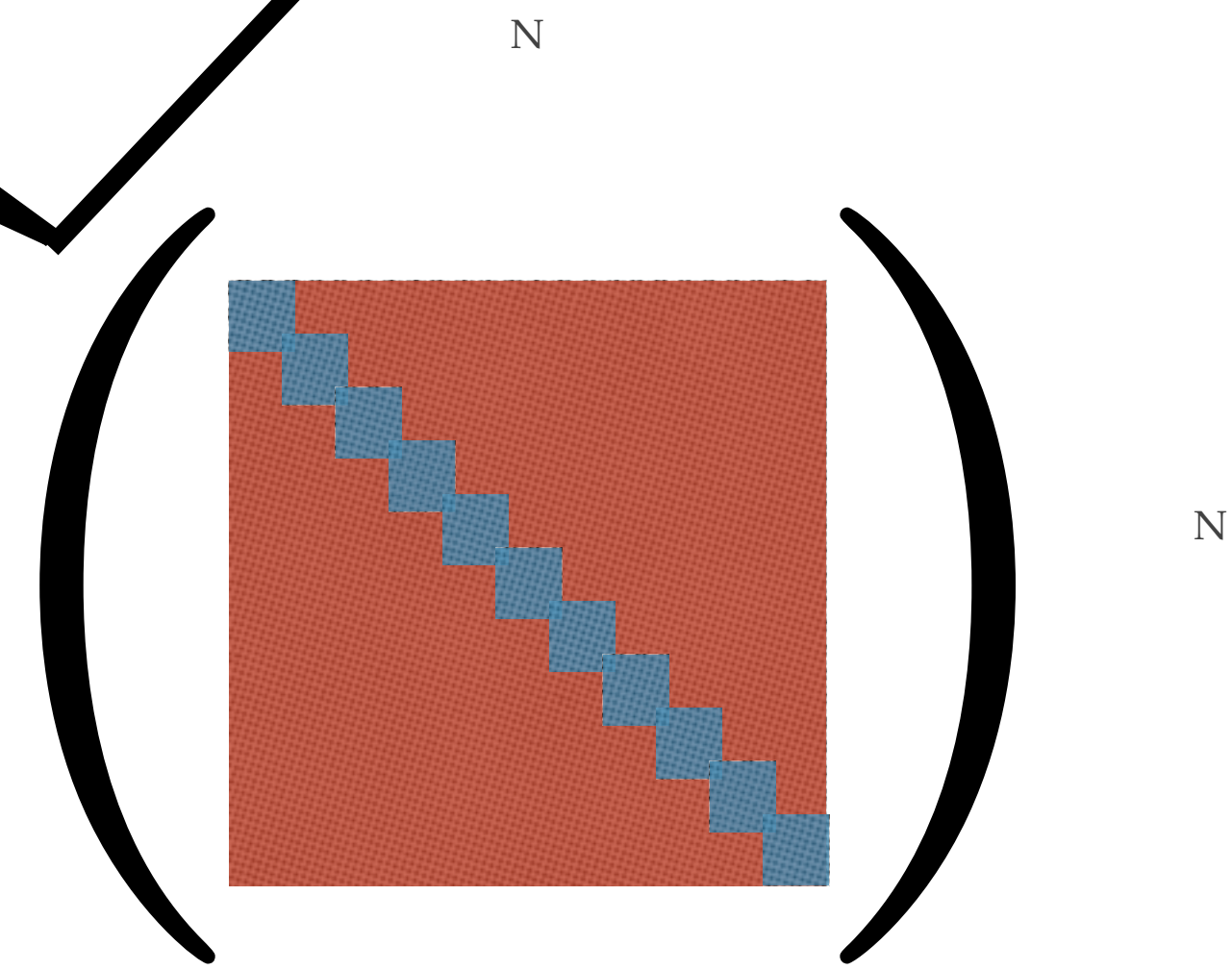
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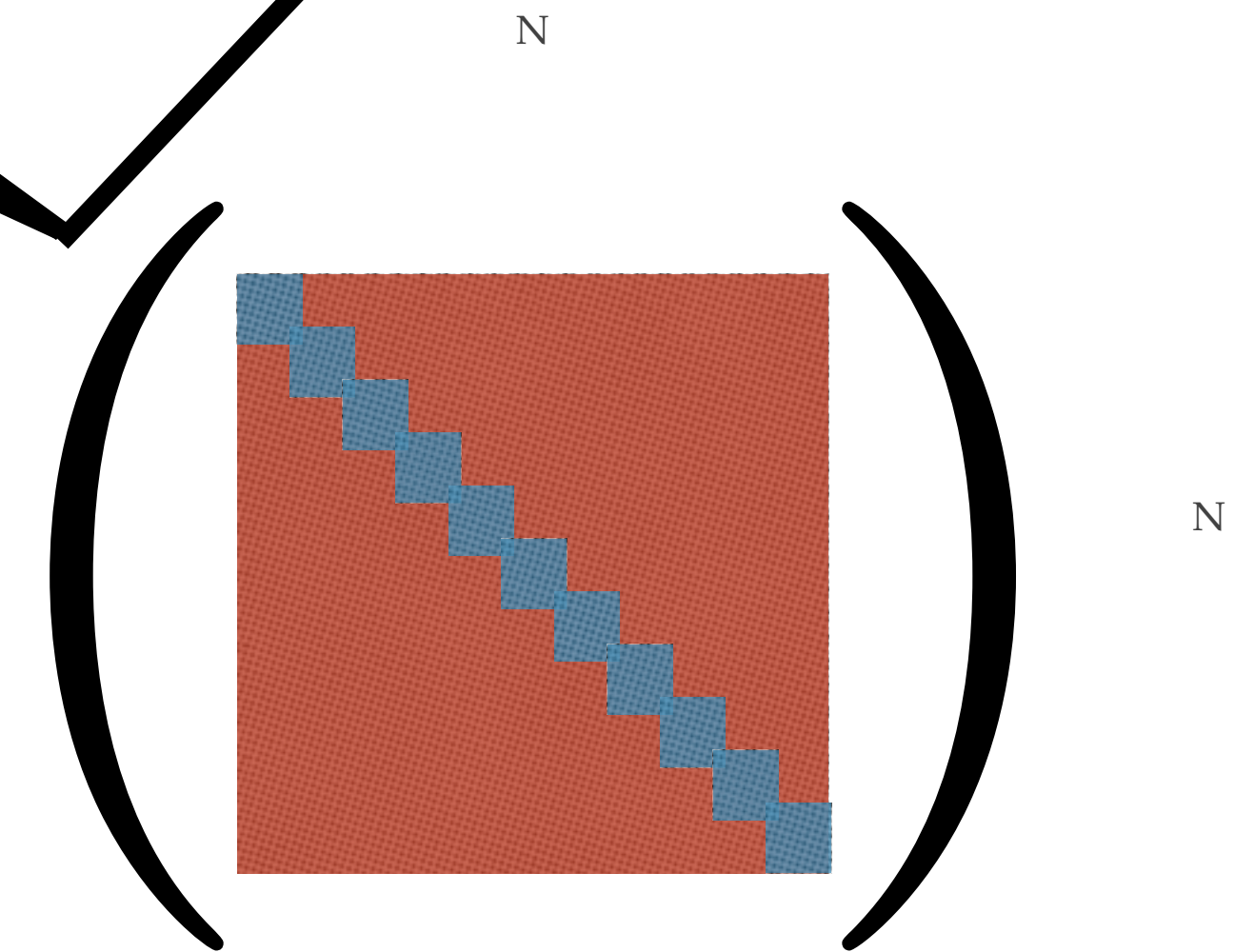
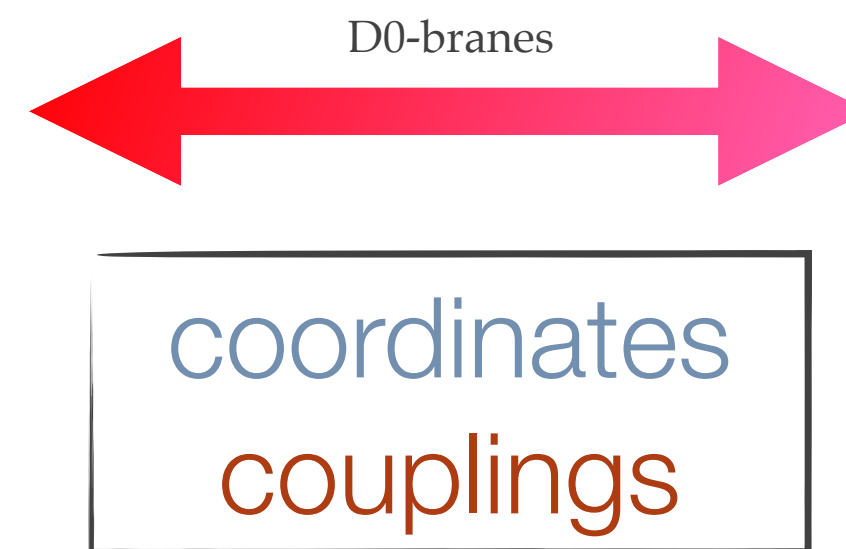
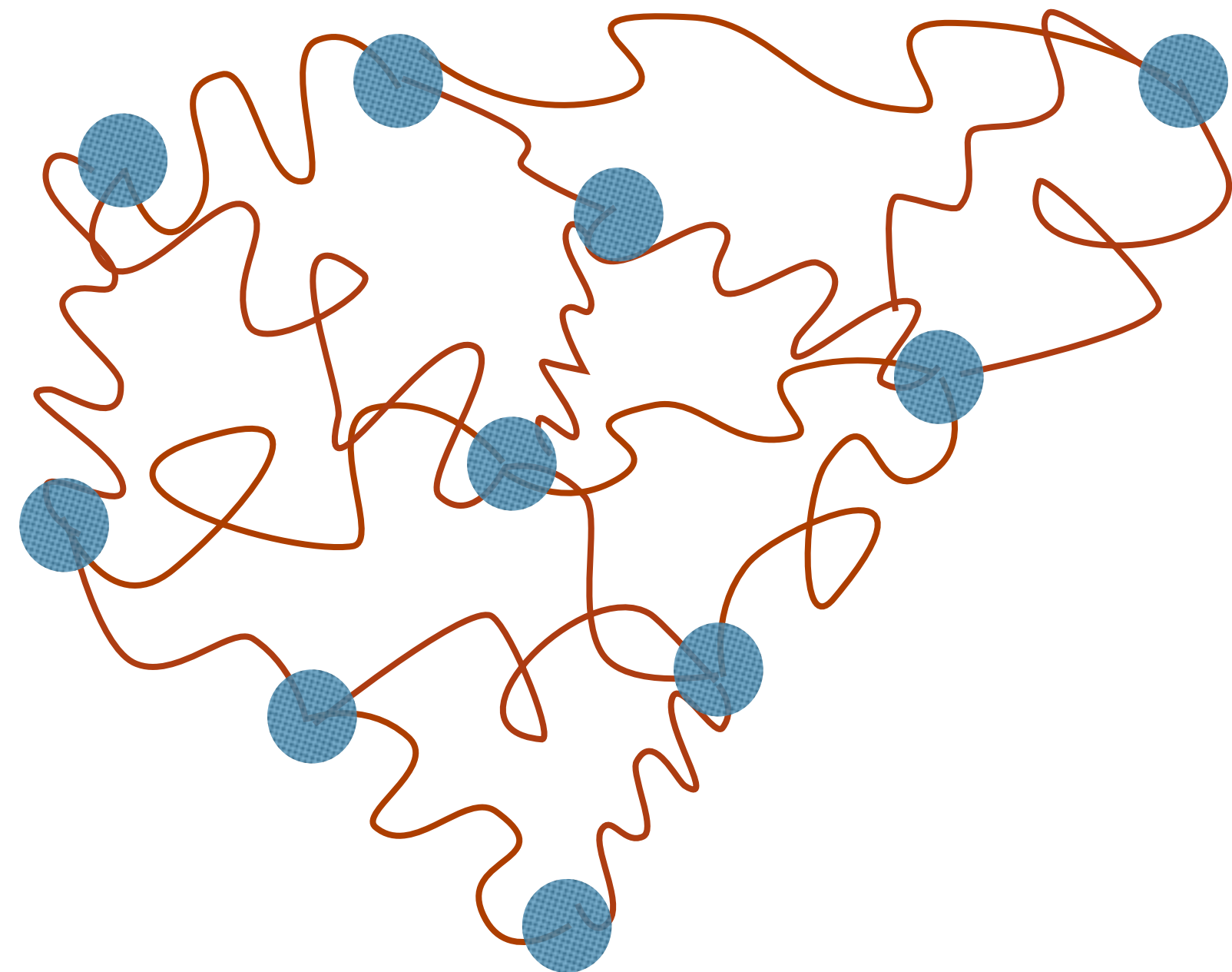
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Numerical Methods

★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)



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Quantum Computers

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

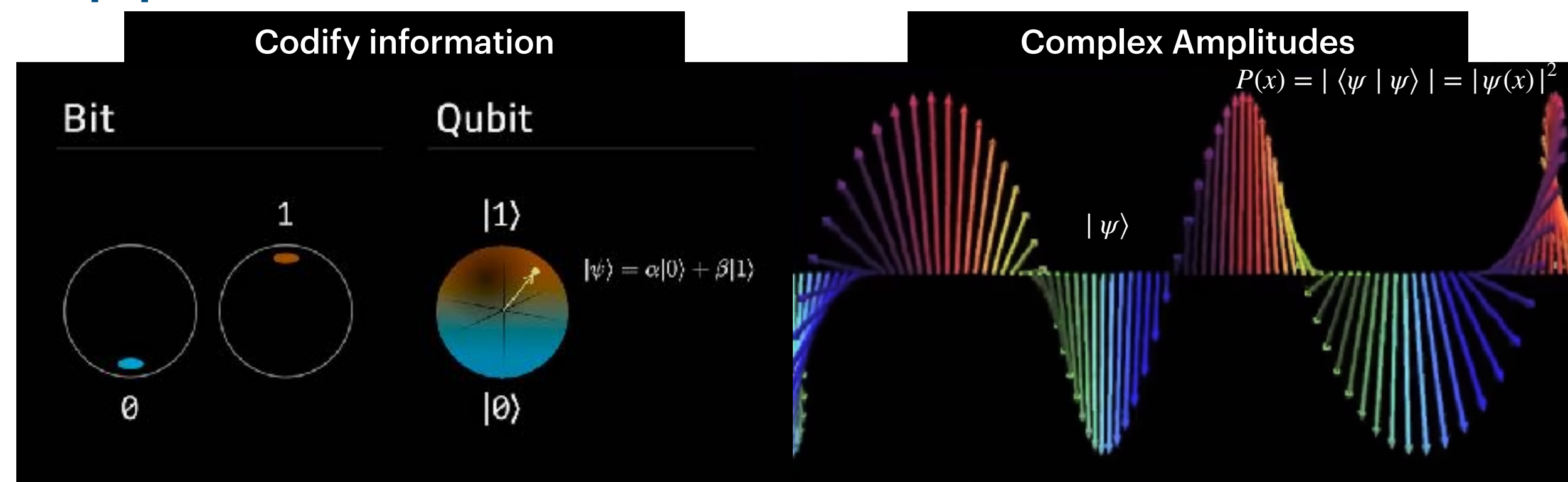
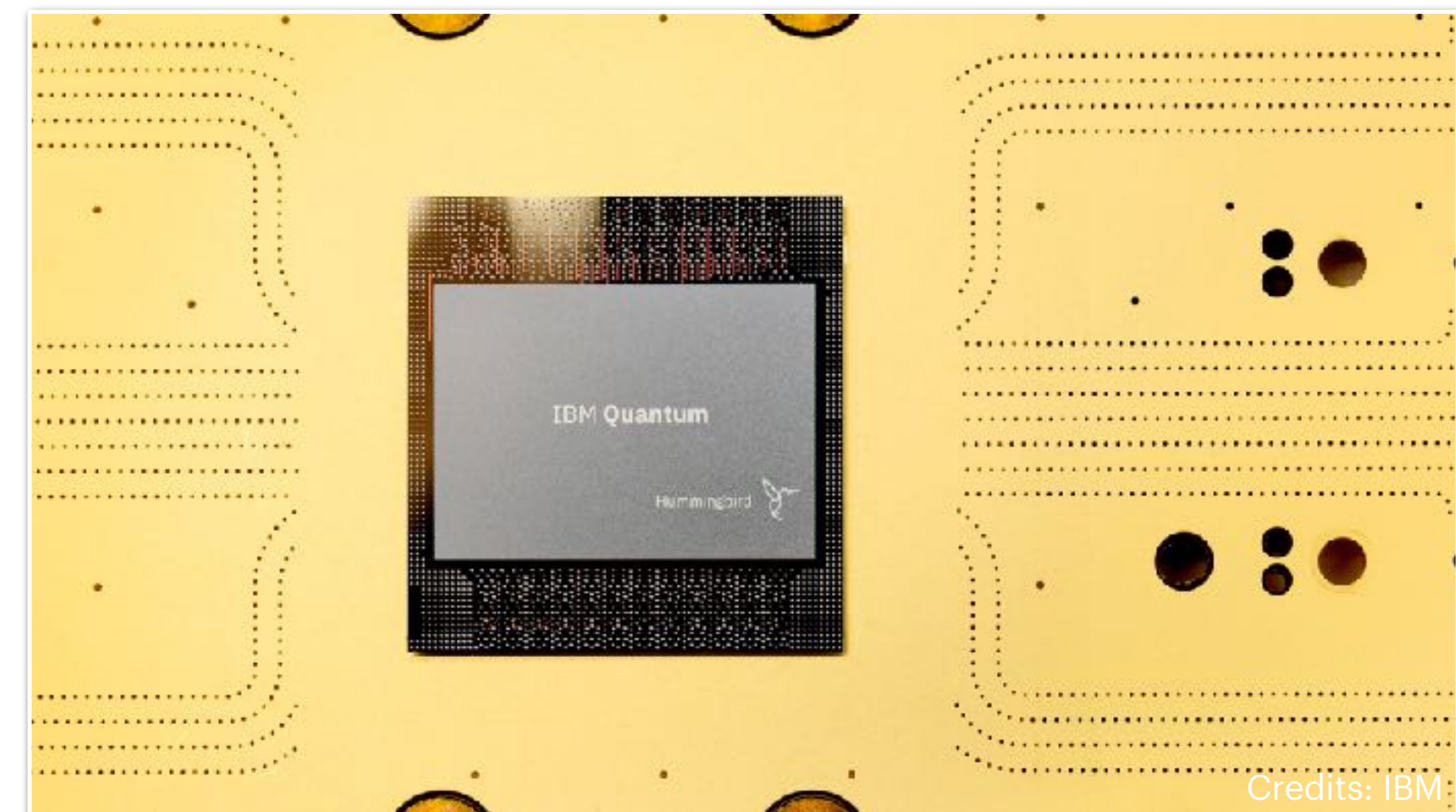
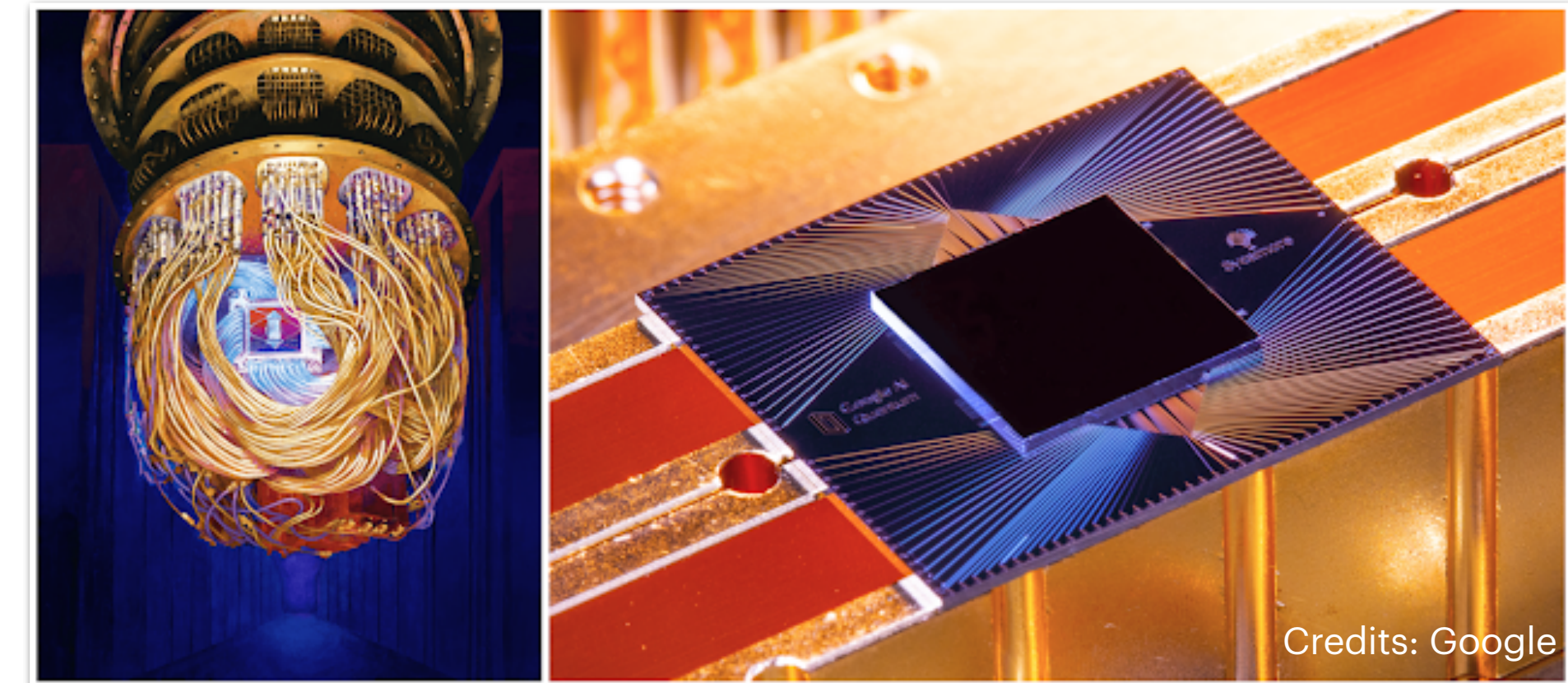
Deep Learning

→ Represent the real and imaginary part of the complex wave function using expressive neural networks

Quantum Technologies

the next computing revolution

- Feynman (1981): *“Nature isn’t classical, dammit, and if you want to make a simulation of Nature, you’d better make it quantum mechanical, and by golly it’s a wonderful problem because it doesn’t look so easy.”*
- Digital QC (~50 qubits → 1000 in 2 yr.) have opened new avenues for both **scientific research** and **industrial applications**



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

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ZERO EN.

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Physical states are invariant under SU(N) Gauge

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

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Numerical Methods for MQM

Prototype: small-scale system

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Bosonic Model

Example: N=2, D=2

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

Physical states are invariant under SU(N) Gauge Symmetry

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

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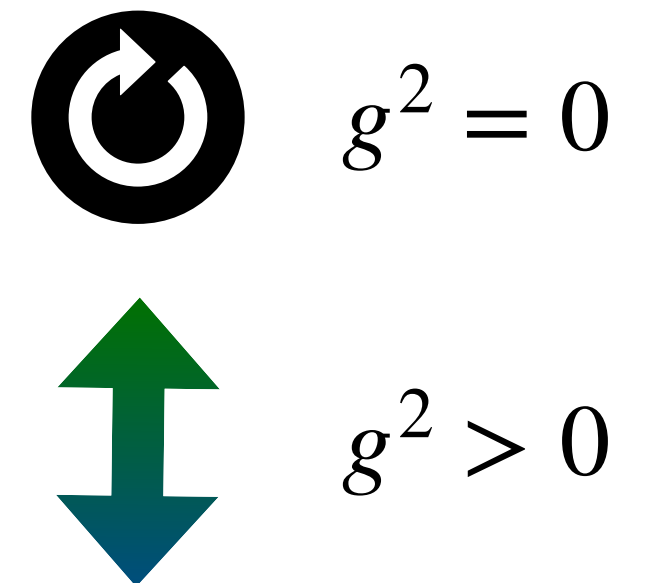
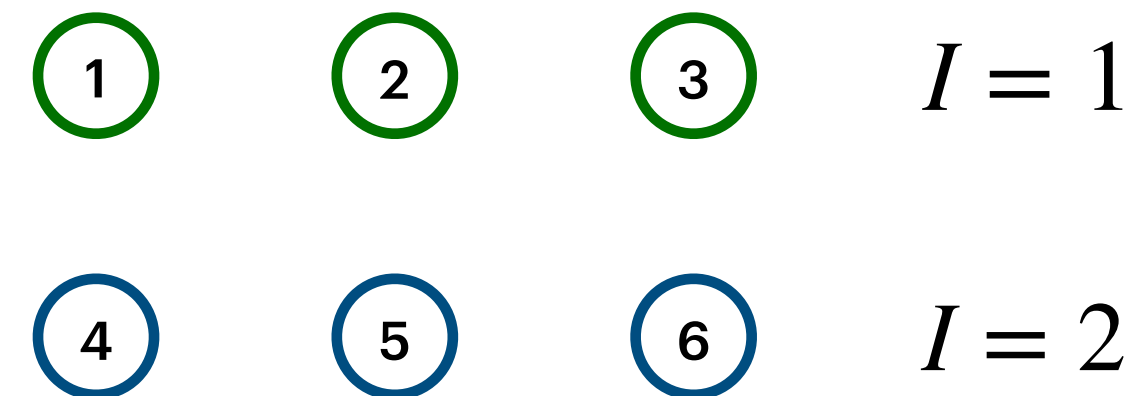
$$\hat{H}_B = \sum_{\alpha, I} \left(\frac{1}{2} \hat{P}_{I\alpha}^2 + \frac{m^2}{2} \hat{X}_{I\alpha}^2 \right) + \frac{g^2}{4} \sum_{\gamma, I, J} \left(\sum_{\alpha, \beta} f_{\alpha\beta\gamma} \hat{X}_I^\alpha \hat{X}_J^\beta \right)^2$$

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

SYMMETRIES

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

Numerical Methods for MQM

Prototype: small-scale system

Bosonic Model

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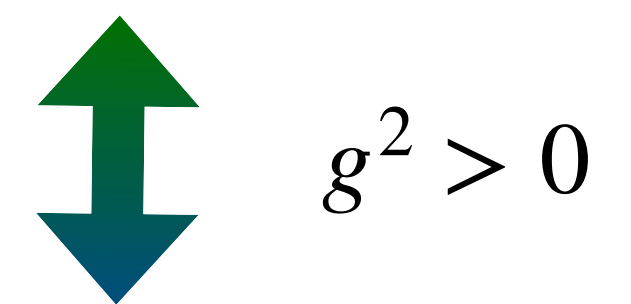
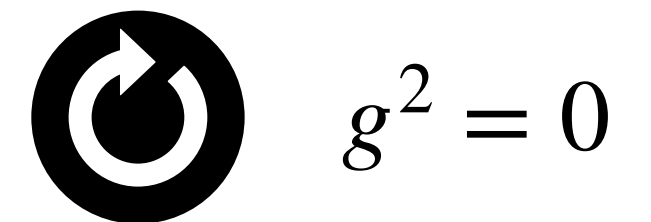
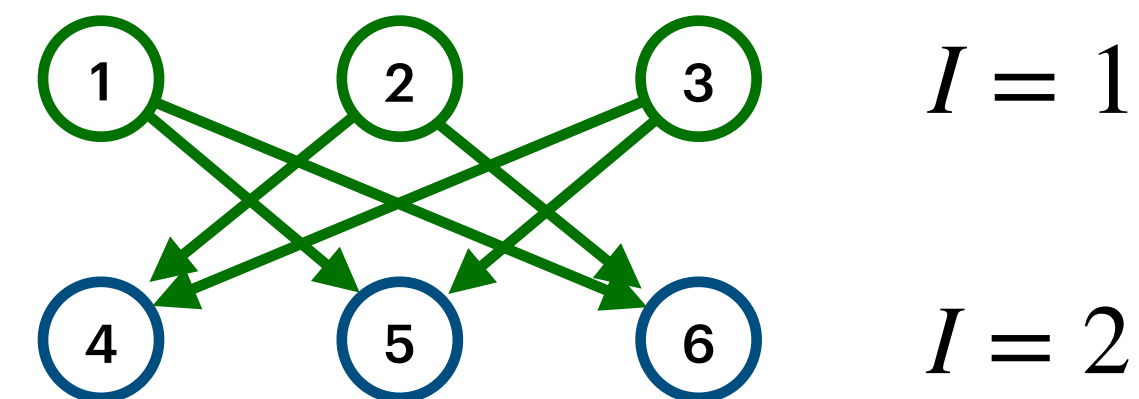
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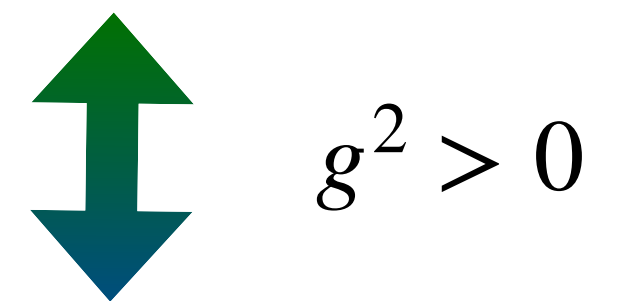
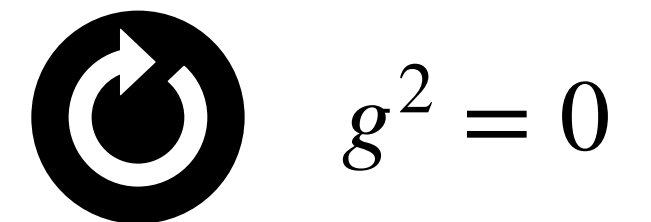
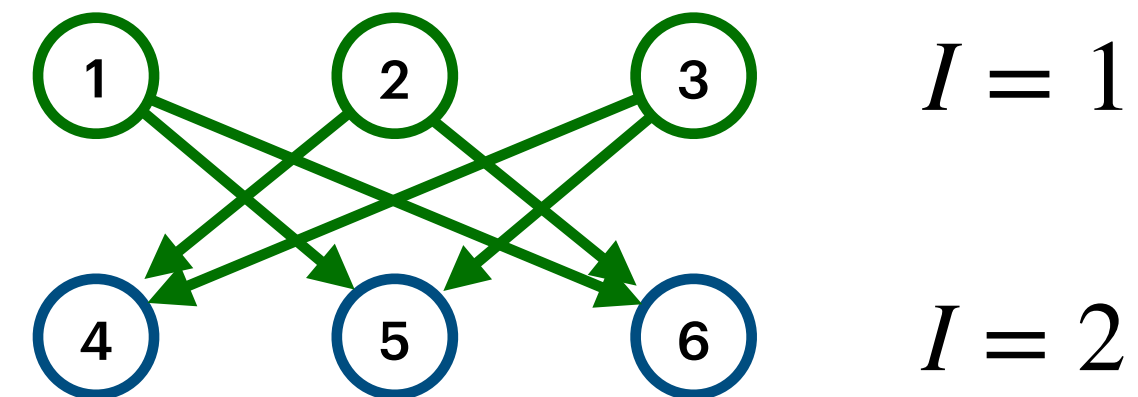
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Numerical Methods for MQM

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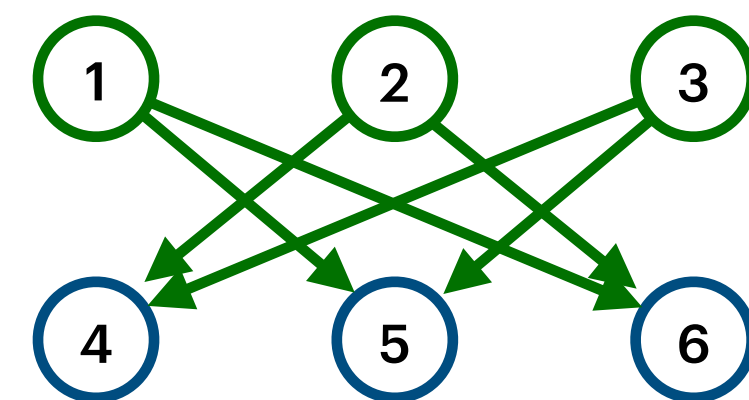
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SYMMETRIES

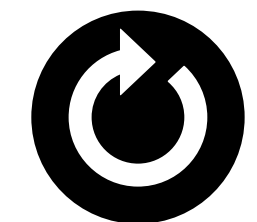
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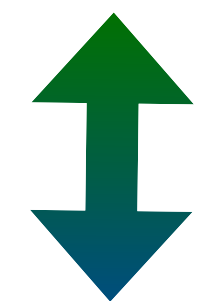


$I = 1$

$I = 2$



$g^2 = 0$

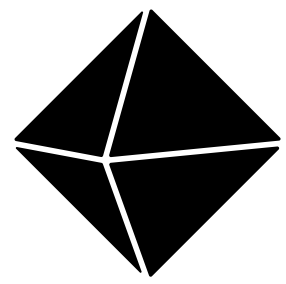


$g^2 > 0$

\hat{X}_I^α → bosonic degrees of freedom
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$| \text{VACUUM} \rangle = \left(\otimes_{I,\alpha} | 0 \rangle_{I\alpha} \right) \rightarrow_{g^2 > 0}$

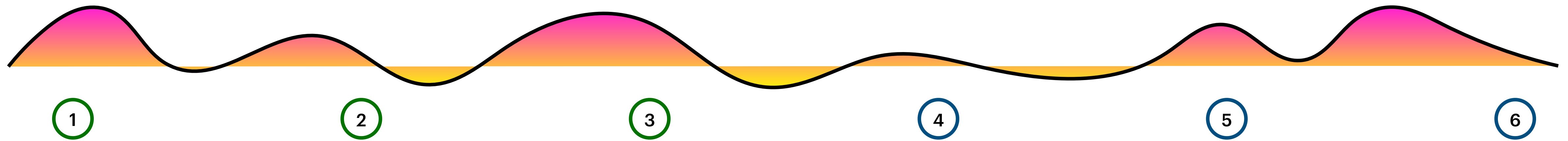
$| \text{Ground State} \rangle = (???)$

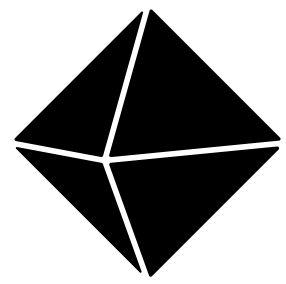


Hilbert space regularization

Truncation

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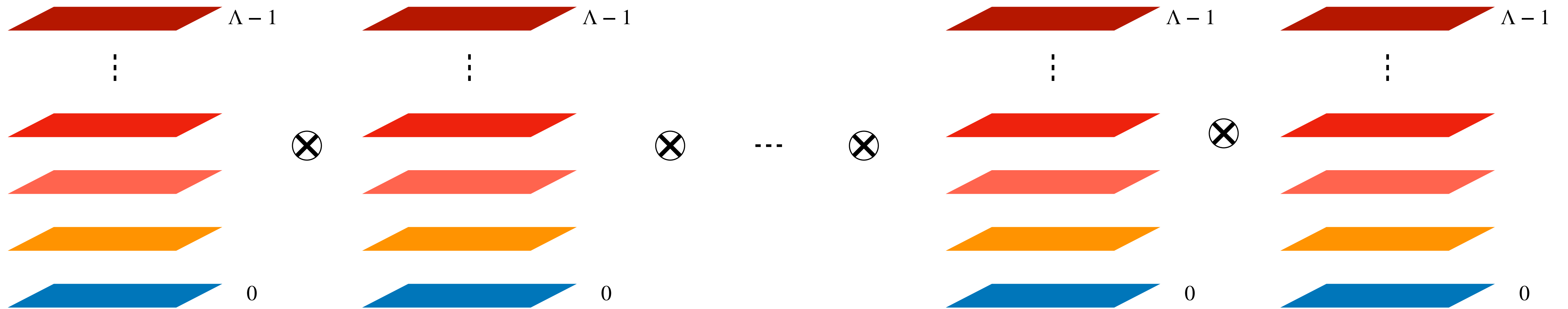
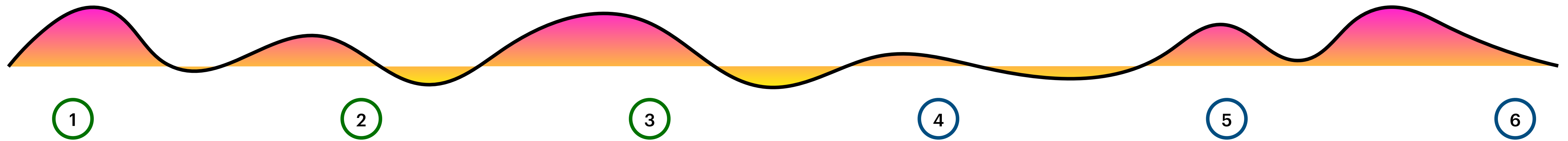


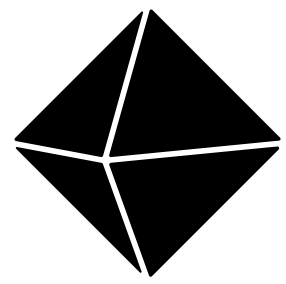


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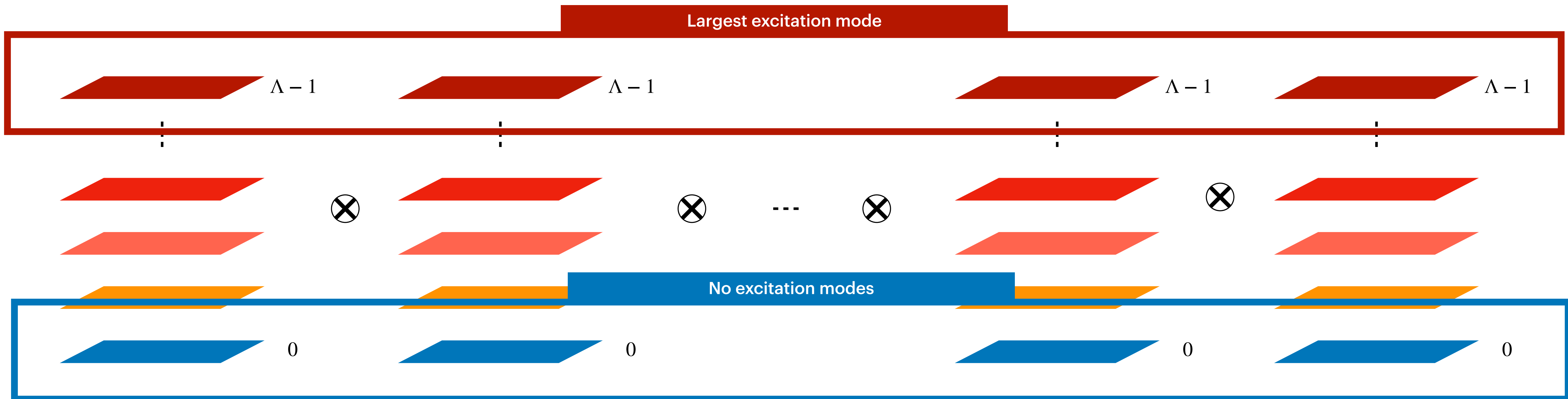
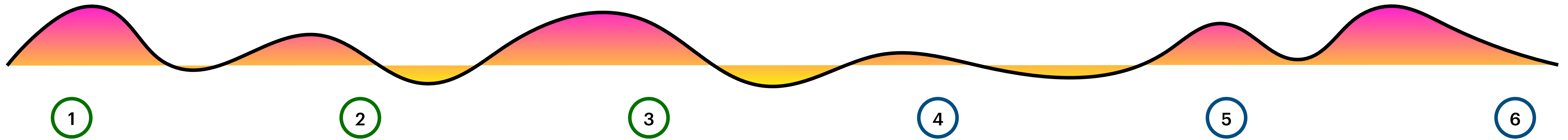


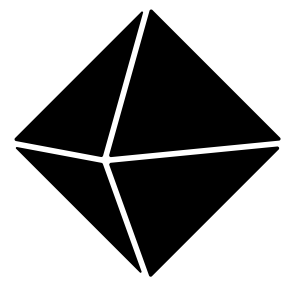


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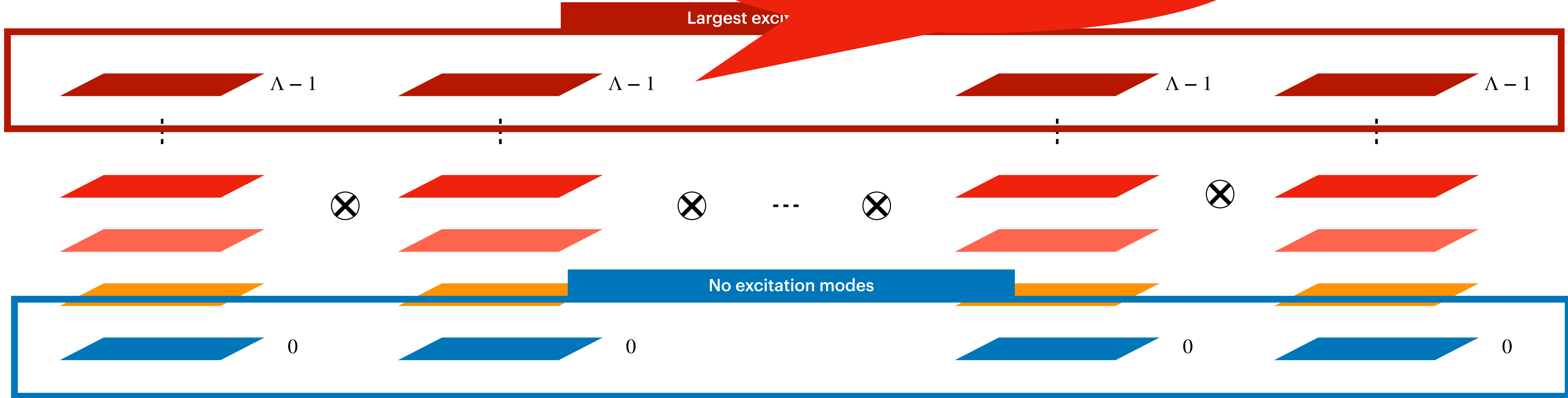
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Challenge: physical results are at $\Lambda = \infty$!





Results

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



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



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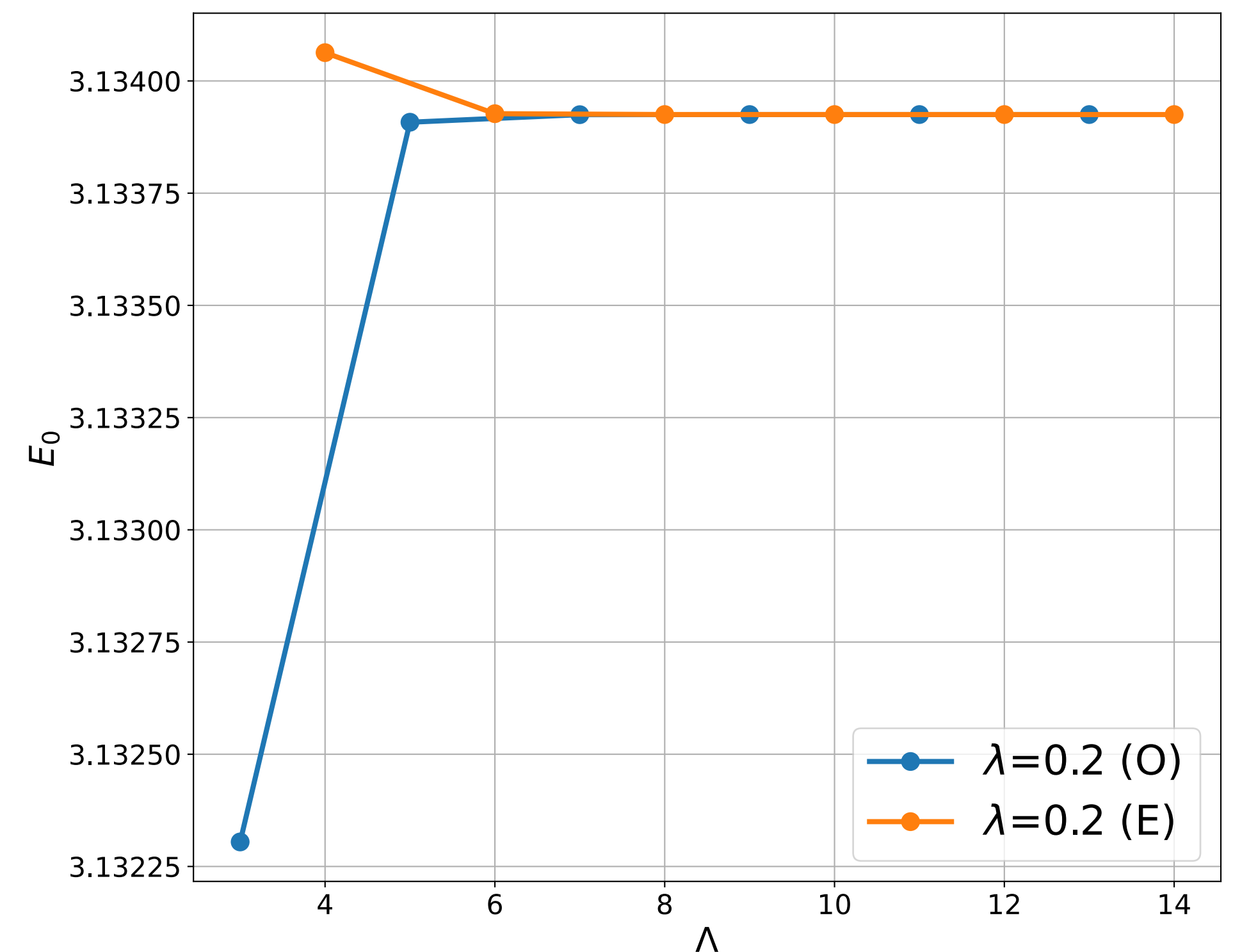


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$$E_0 = \langle E_0 | \hat{H} | E_0 \rangle$$



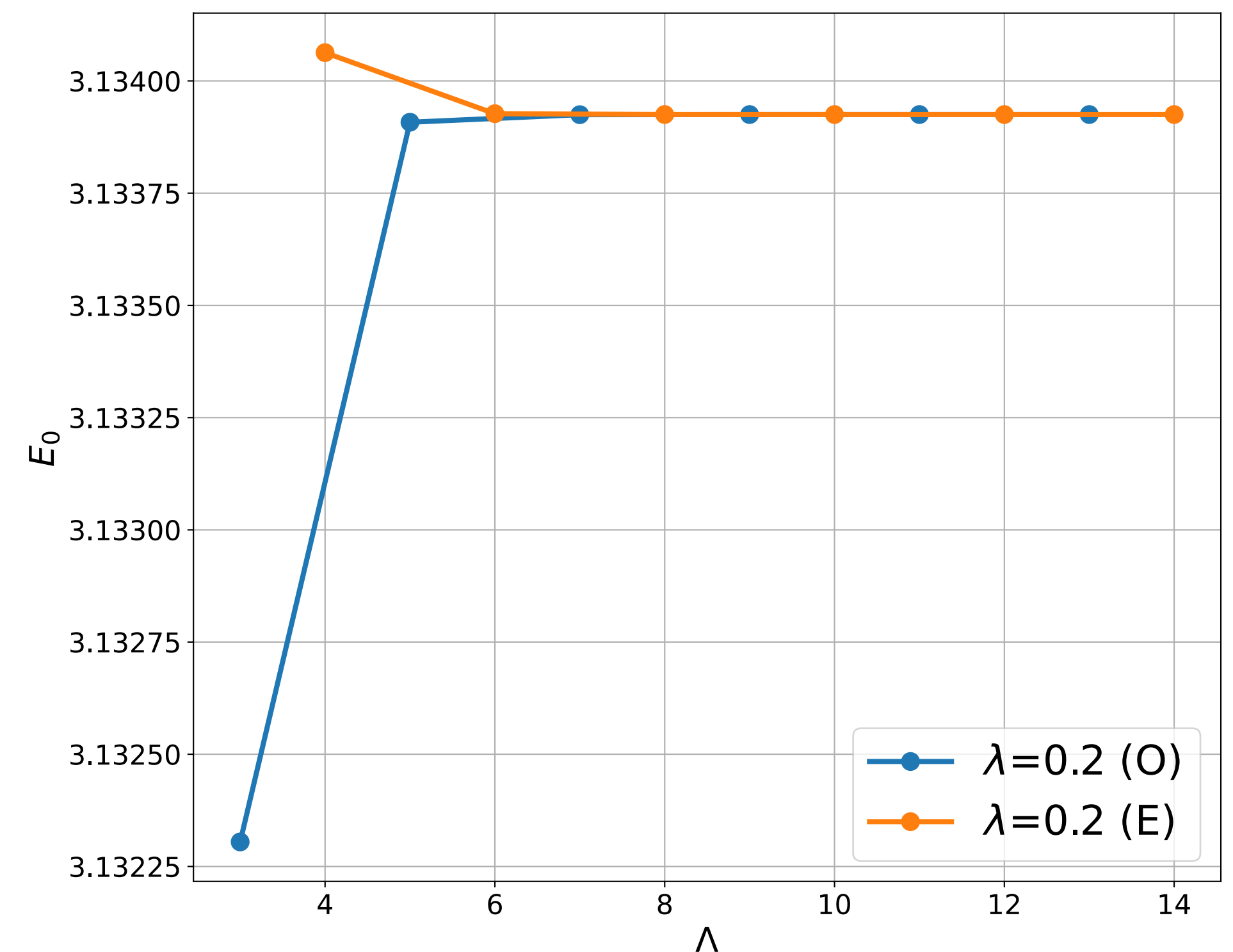


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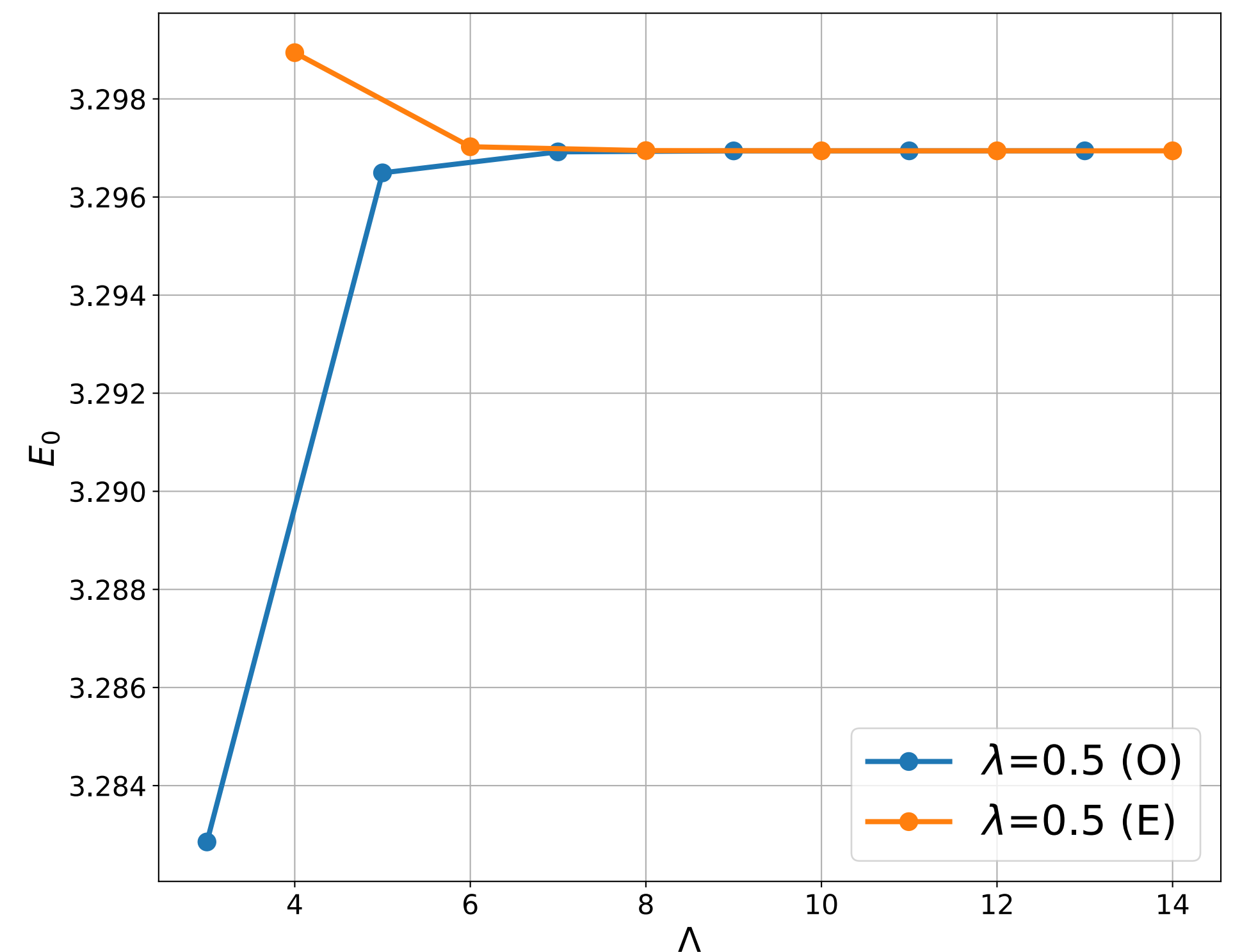


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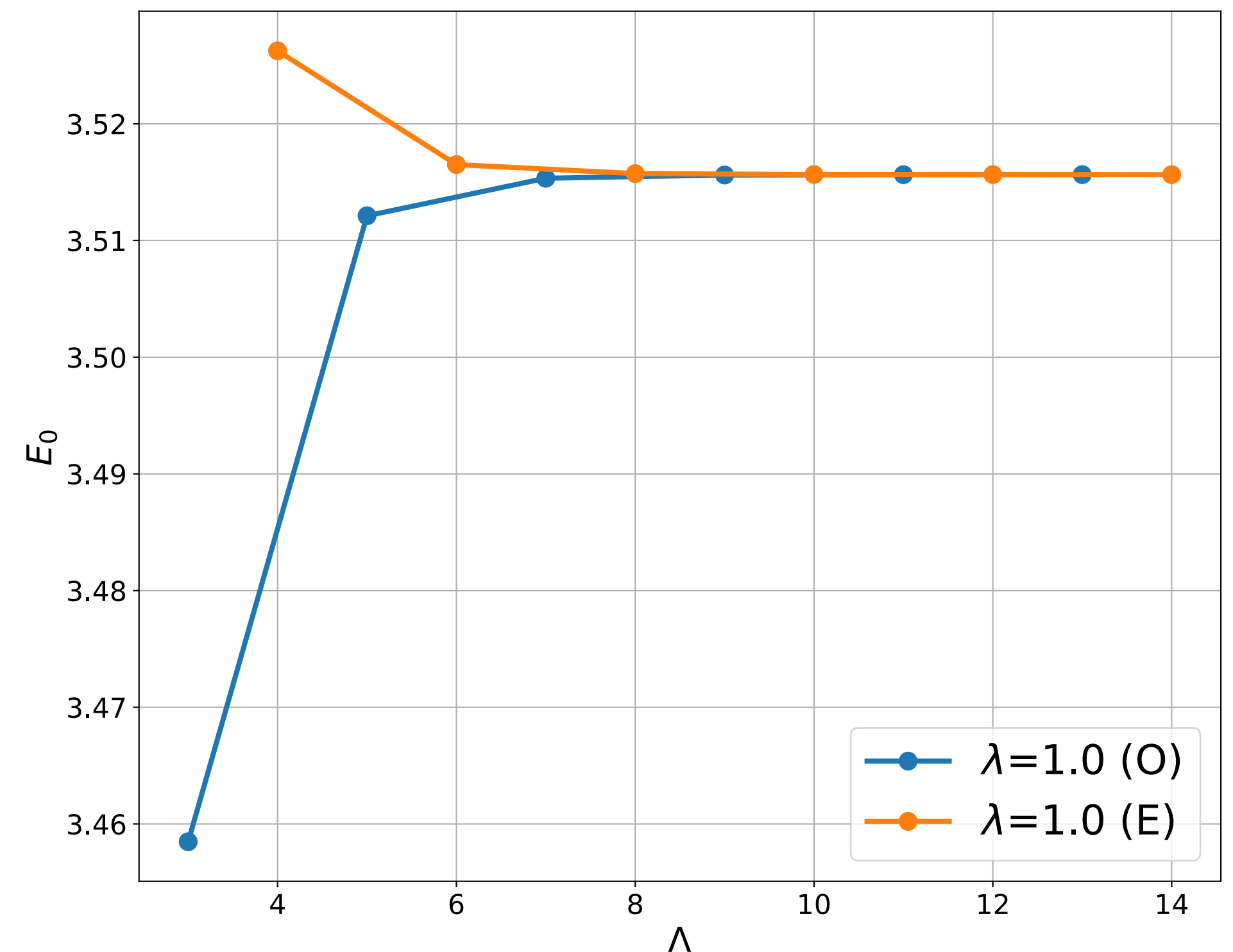


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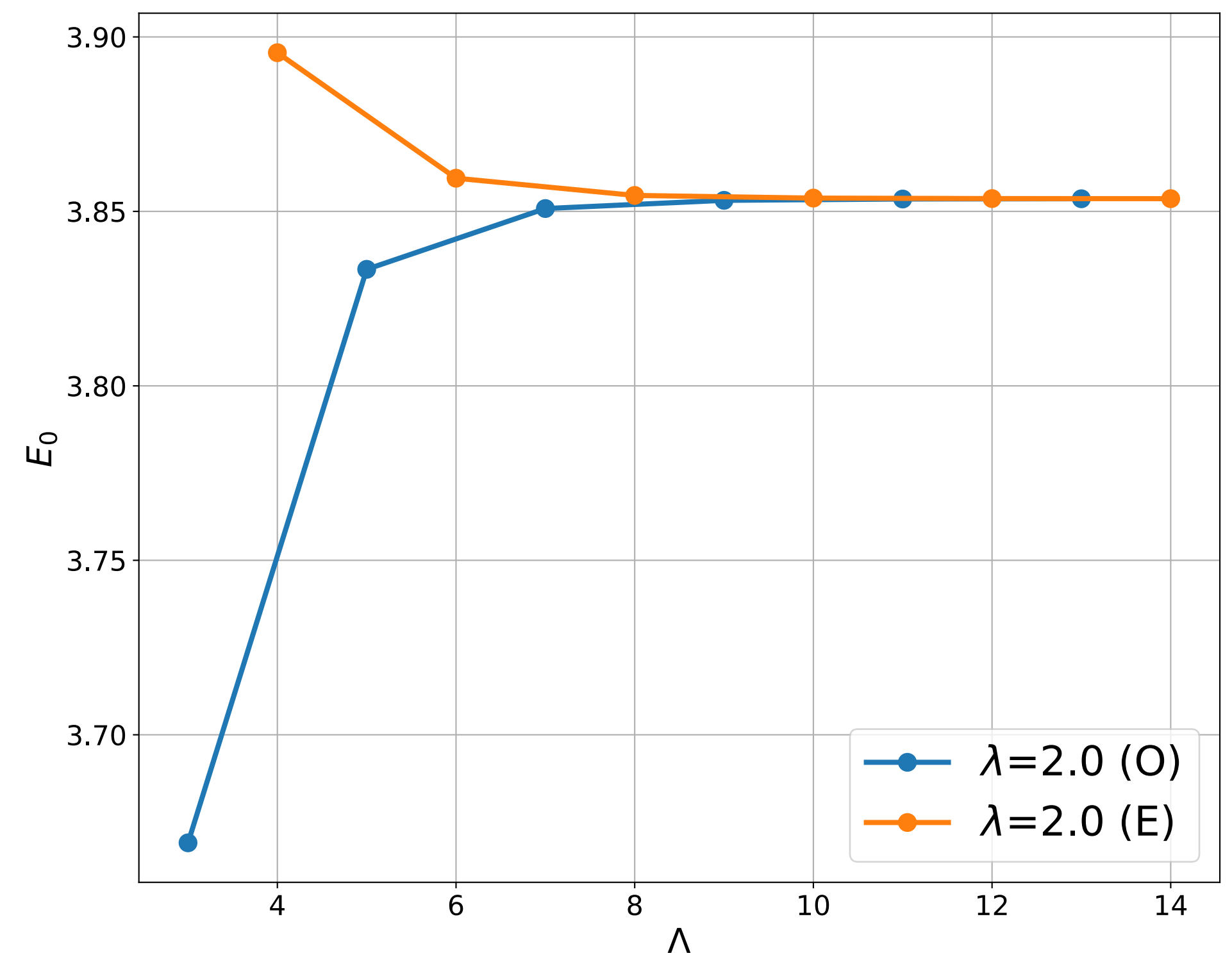


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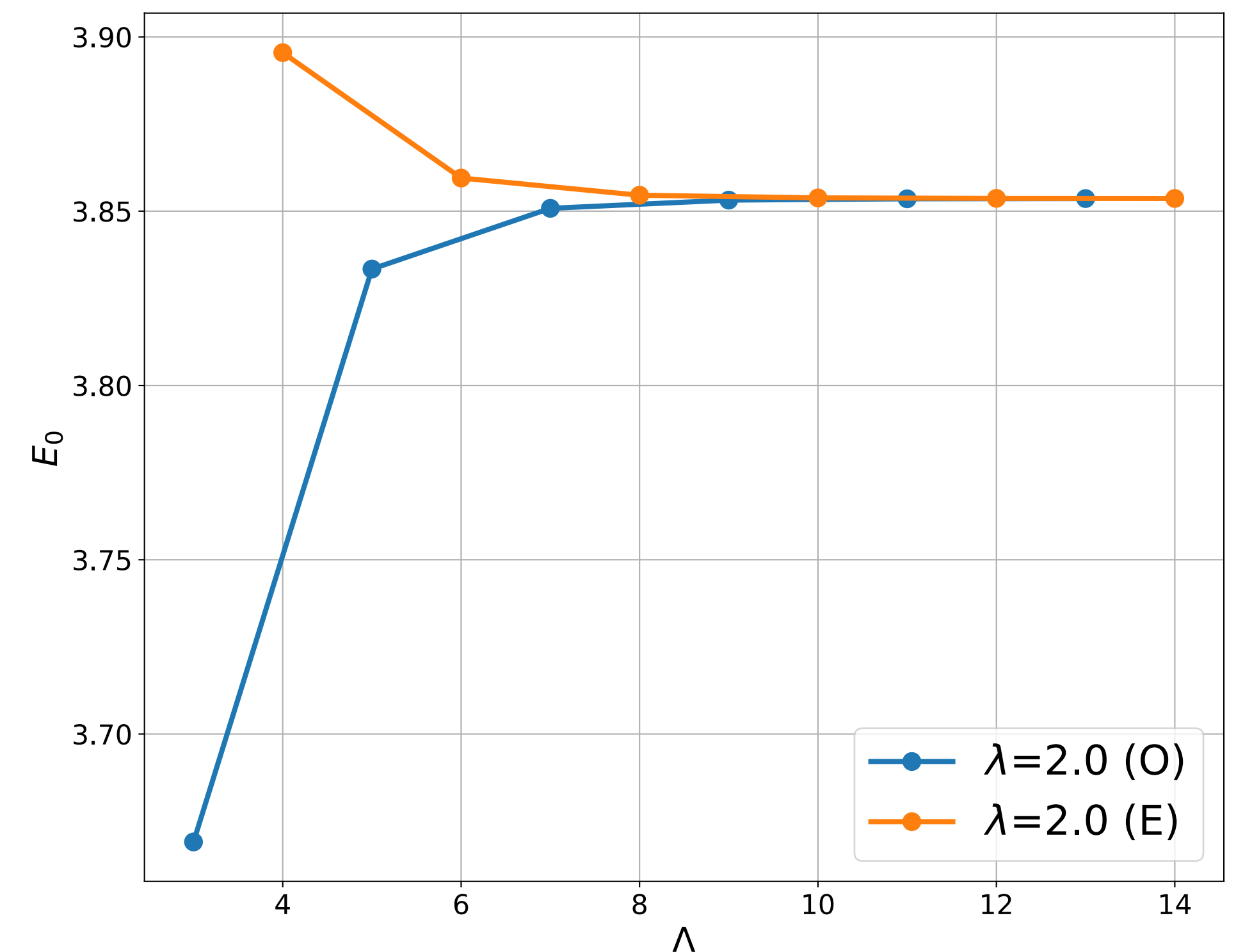
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$$\hat{G}_\alpha = i \sum_{\beta, \gamma, I} f_{\alpha\beta\gamma} \hat{a}_{I\beta}^\dagger \hat{a}_{I\gamma} \longrightarrow \hat{G}_\alpha \left(\bigotimes_{I,\beta} |0\rangle_{I\beta} \right) = 0$$

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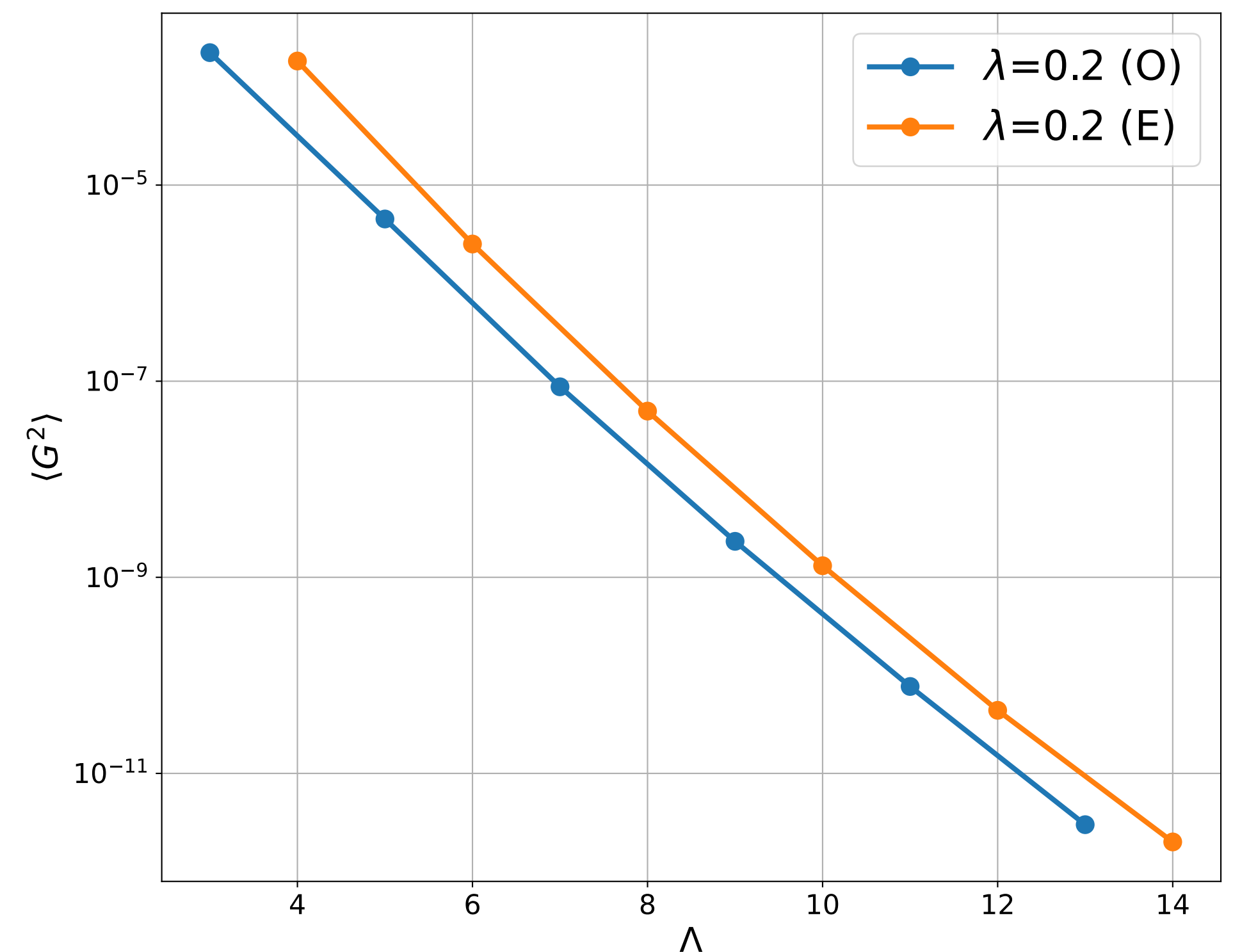
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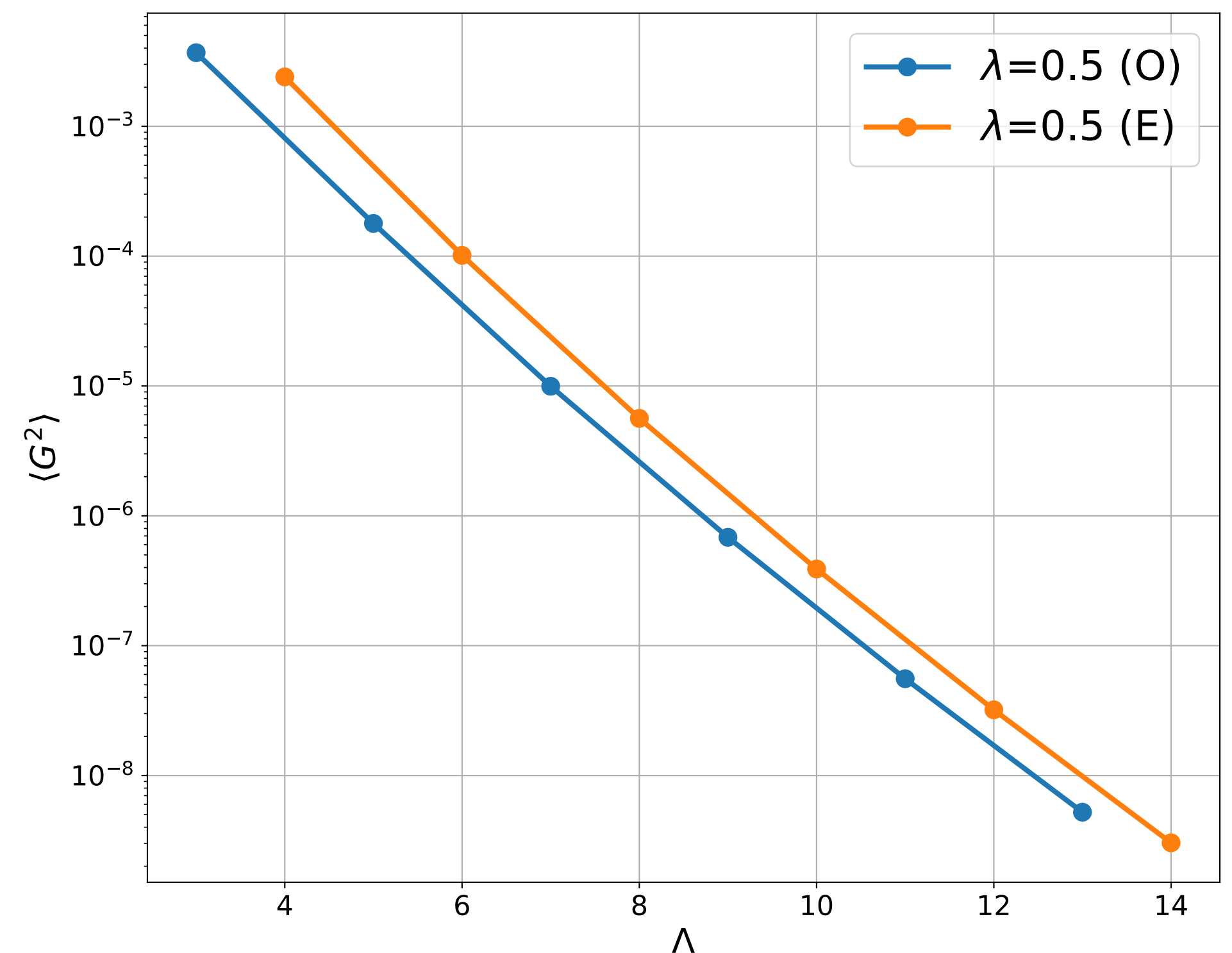
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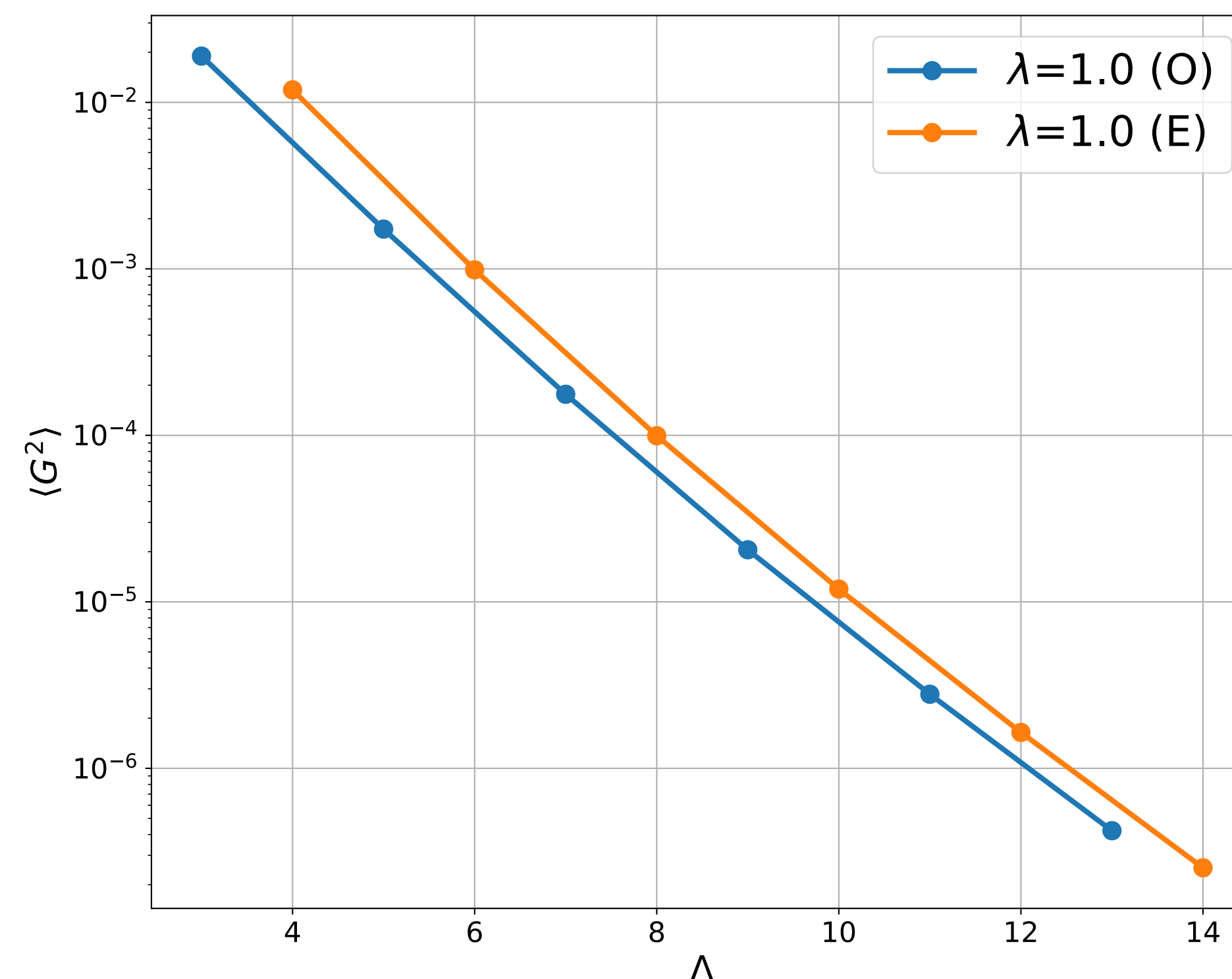
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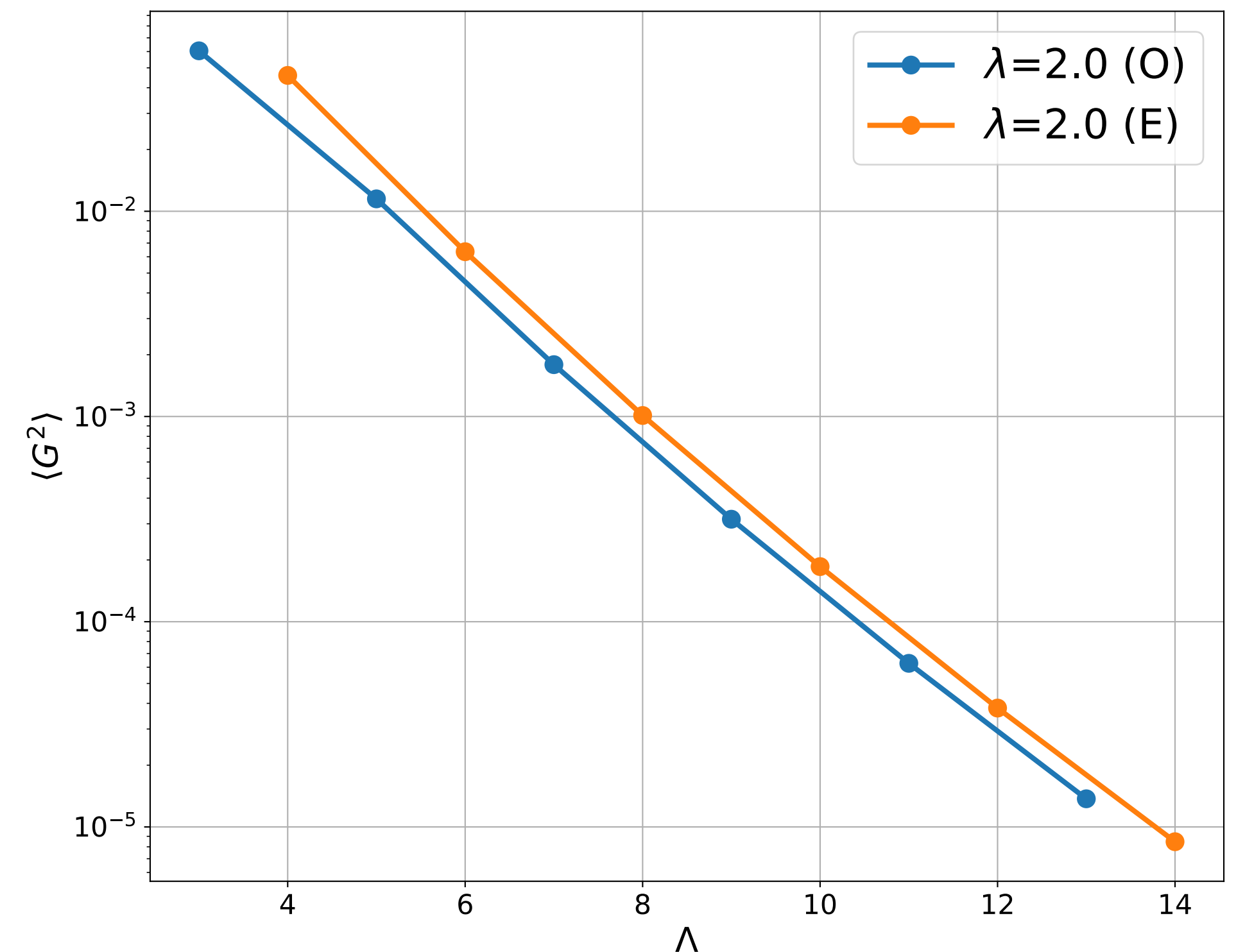
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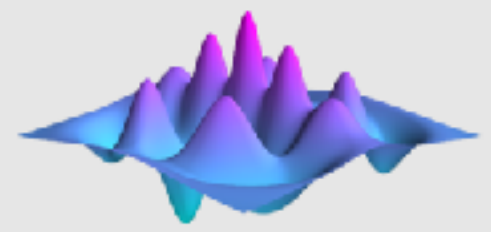
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QuTiP

Quantum Toolbox in Python

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



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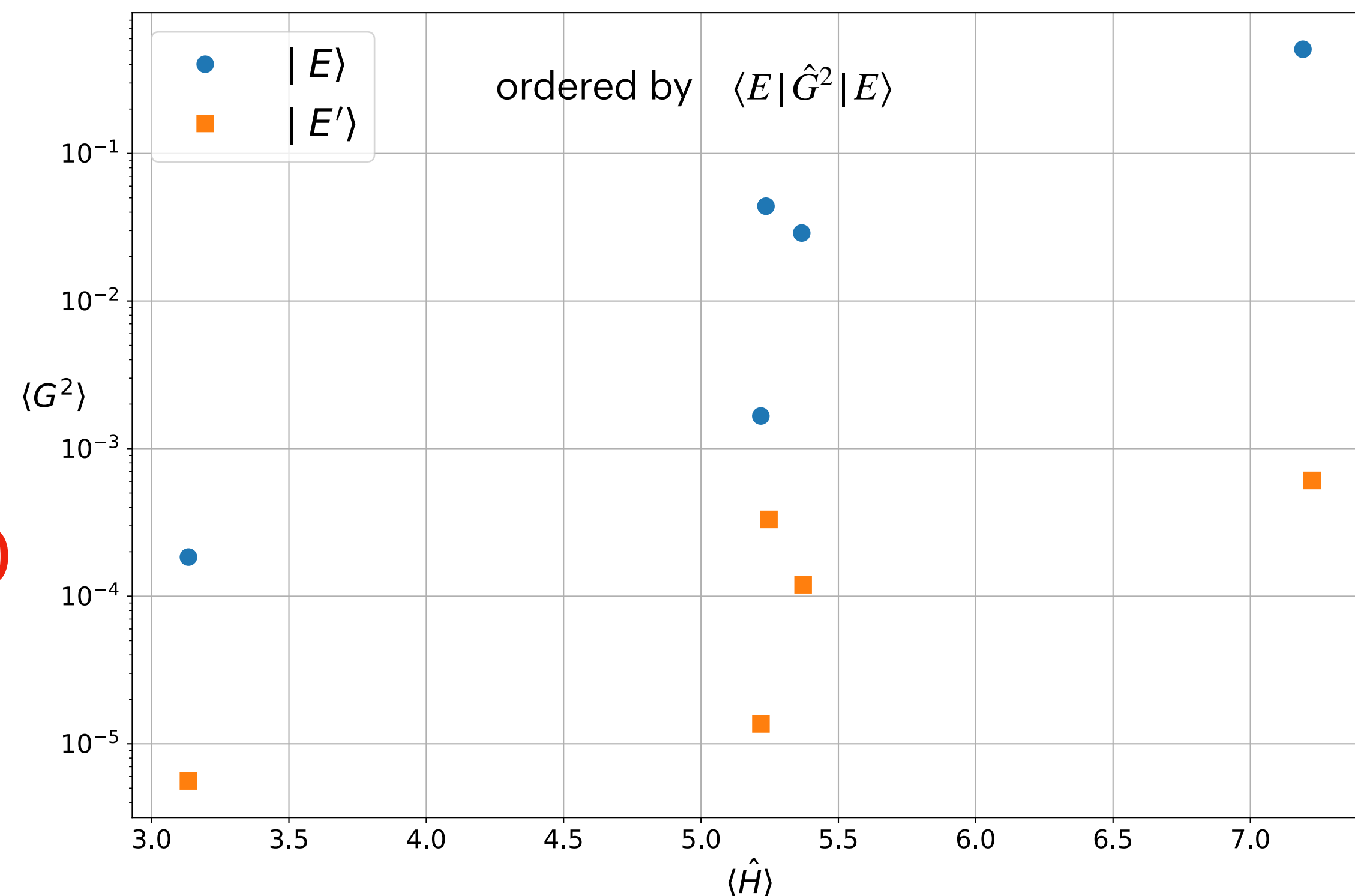
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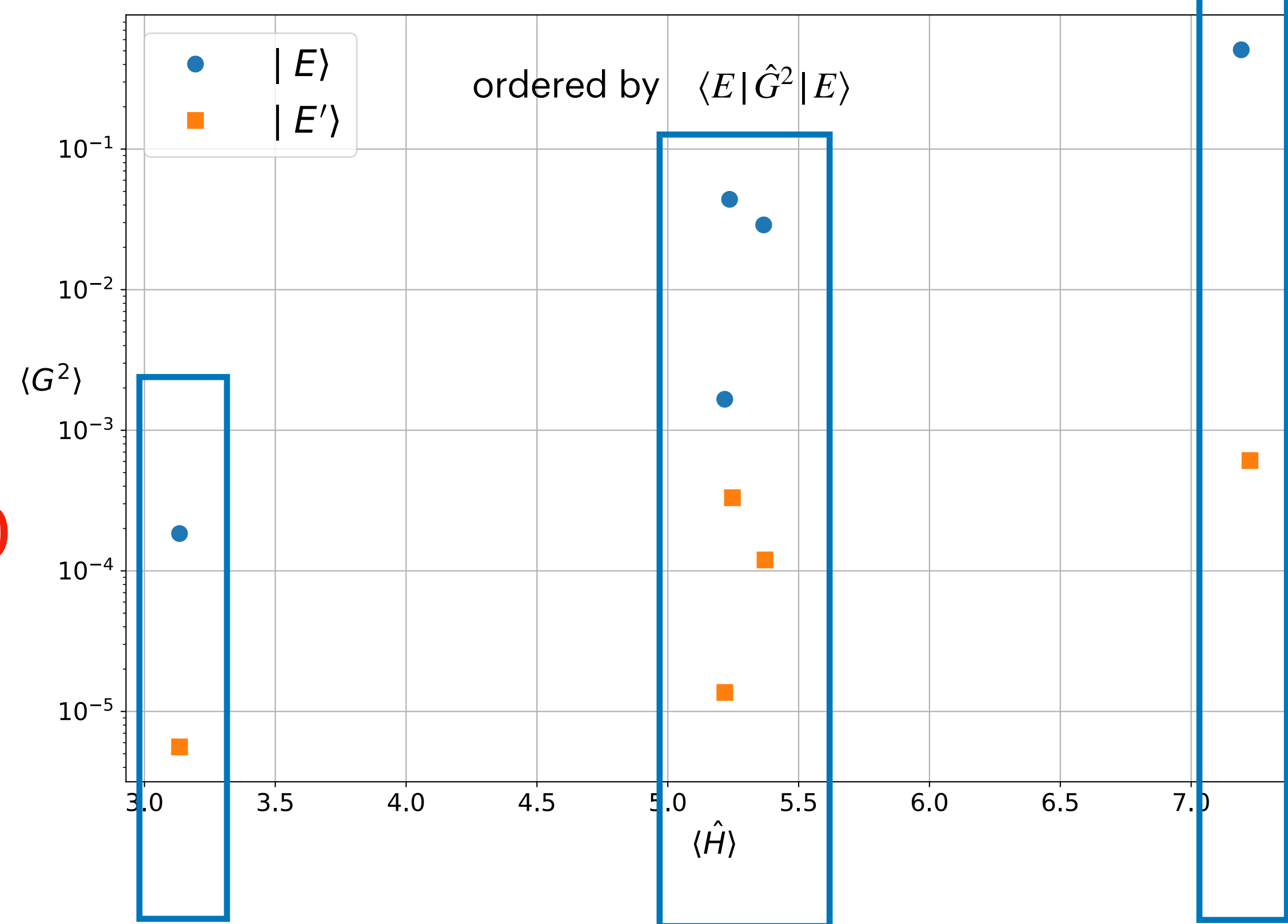
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Qubitization of MQM

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

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Truncation Level

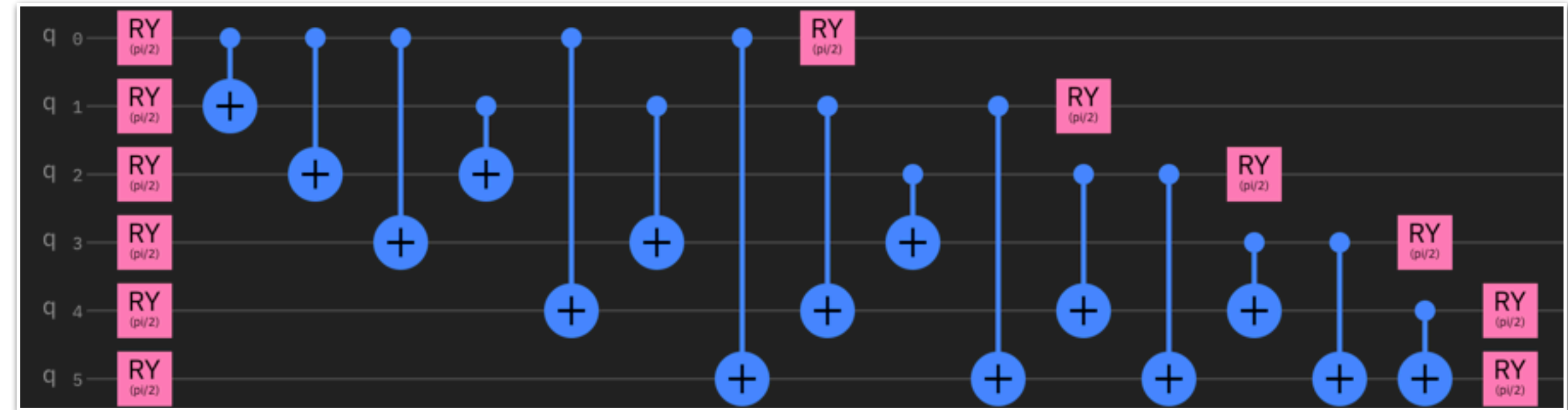
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Truncation Level

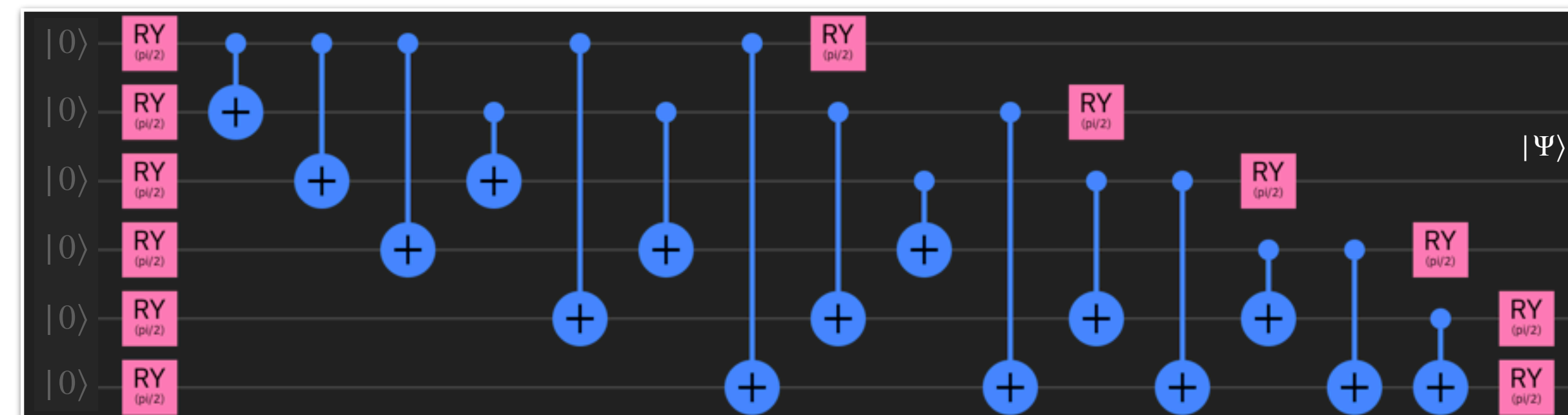
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Qubitization of MQM

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

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$\log_2 \Lambda^6 = 12$ 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

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limited resources





Qubitization of MQM

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

Truncation Level

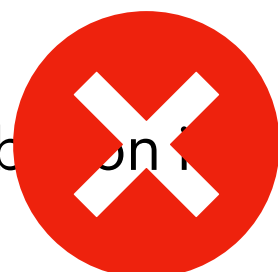
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$\Lambda = 8$

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"

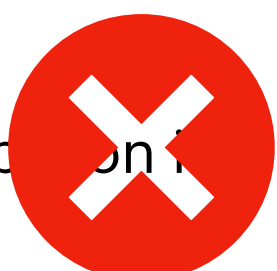
$\Lambda = 2$	Each boson is 1 qubit	$\log_2 \Lambda^6 = 6$ qubits
$\Lambda = 4$	Each boson is 2 qubits	$\log_2 \Lambda^6 = 12$ qubits



$\Lambda = 8$

Each boson is 3 qubits

$\log_2 \Lambda^6 = 18$ qubits



limited resources

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

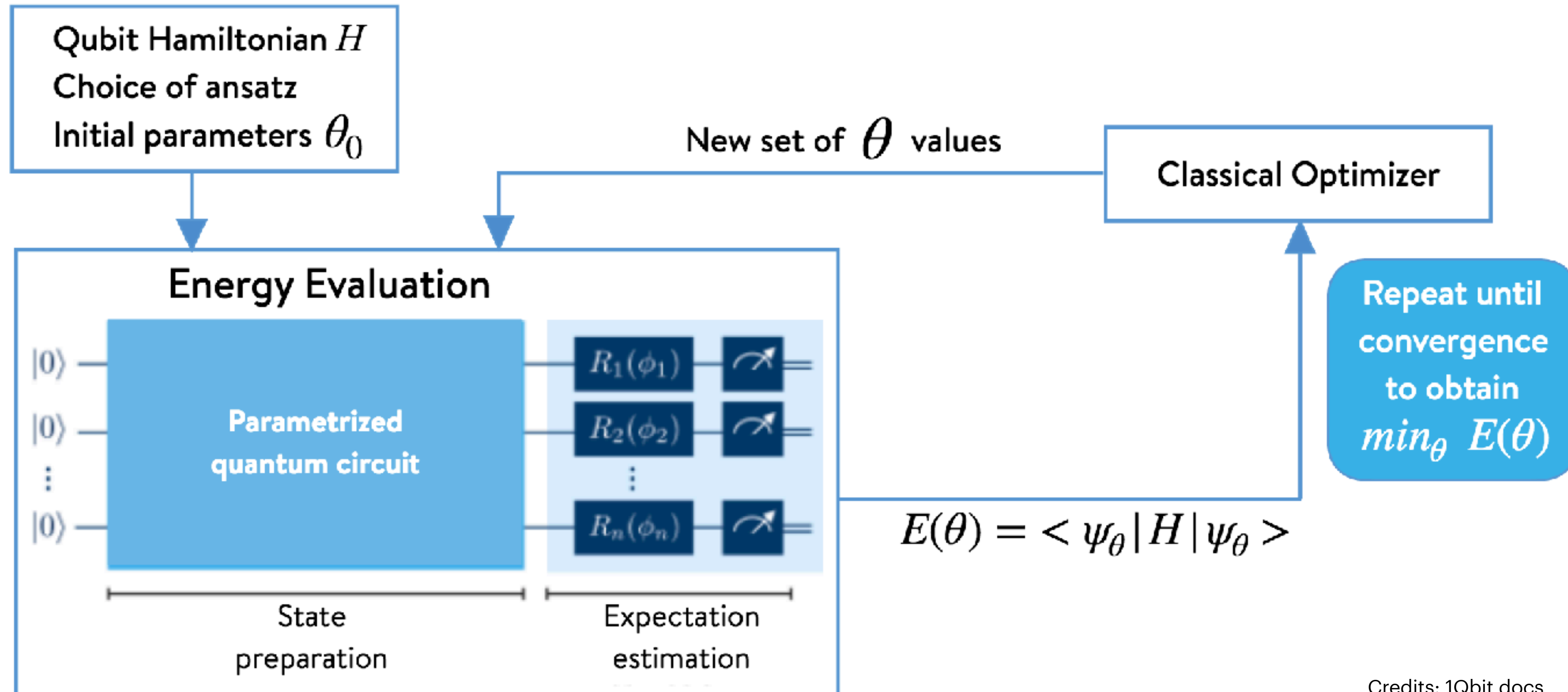
$$\hat{a}_i = \hat{I}_1 \otimes \dots \otimes \hat{I}_{i-1} \otimes \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & \sqrt{2} & 0 \\ 0 & 0 & 0 & \sqrt{3} \\ 0 & 0 & 0 & 0 \end{pmatrix} \otimes \hat{I}_{i+1} \otimes \dots \otimes \hat{I}_6$$

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

Build matrix Hamiltonian which gets mapped to qubits

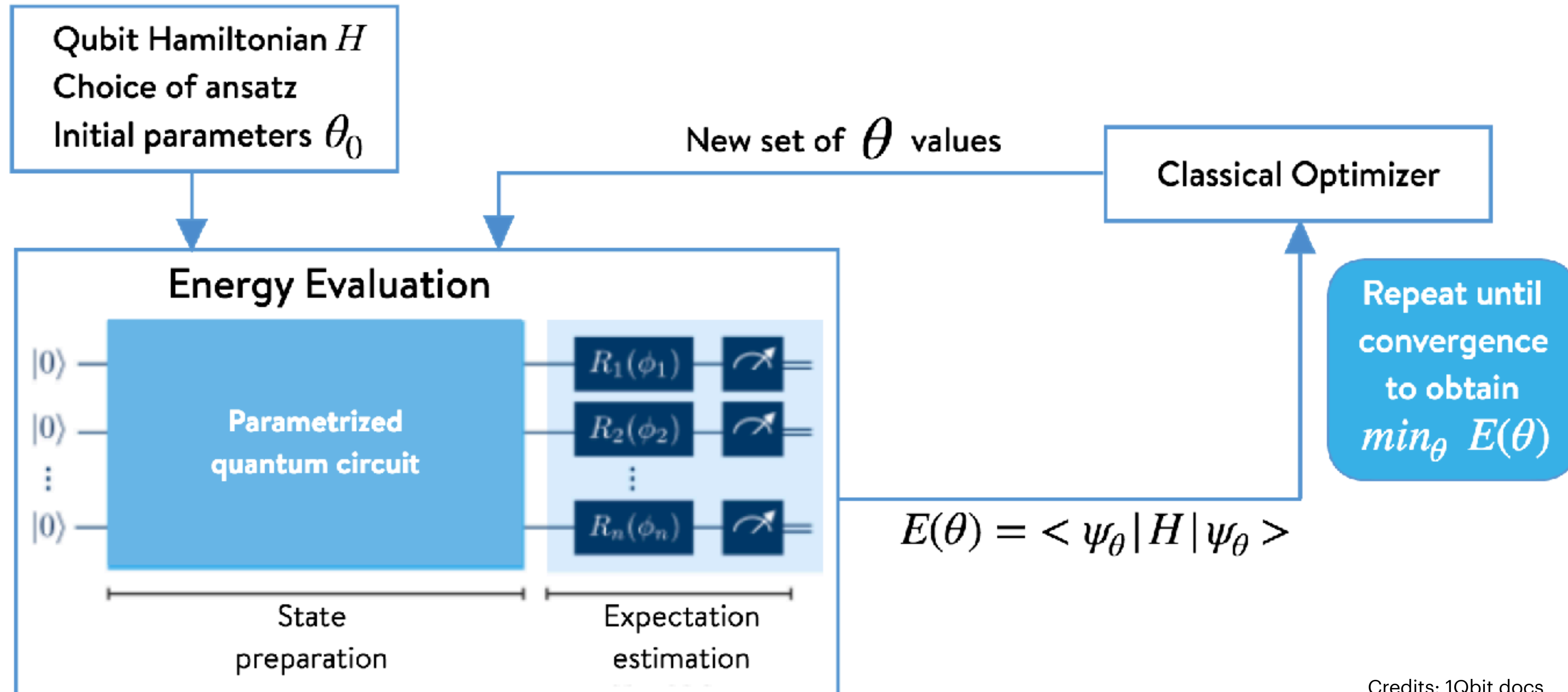
Quantum Computing

Variational Quantum Eigensolver - VQE



Quantum Computing

Variational Quantum Eigensolver - VQE



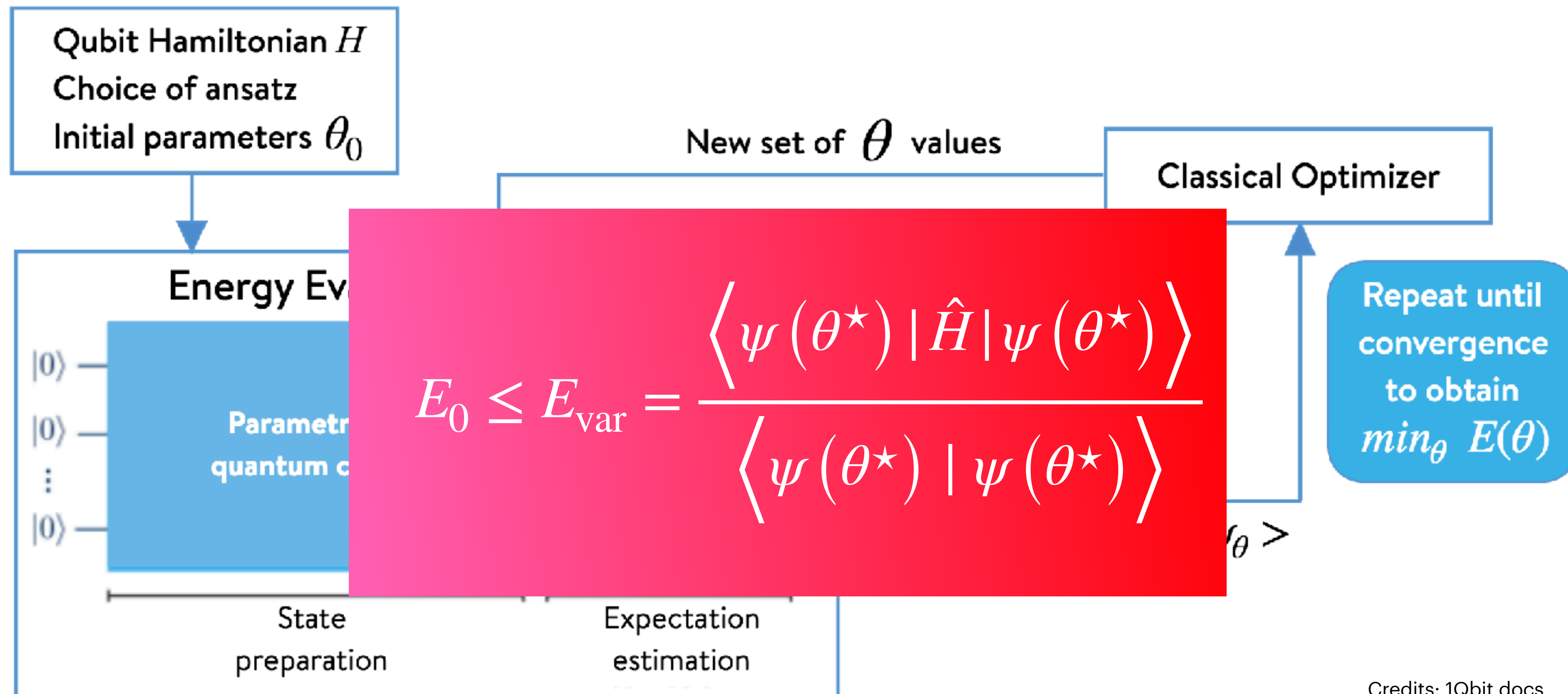
PQC → Variational Ansatz for $|\Phi\rangle$

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

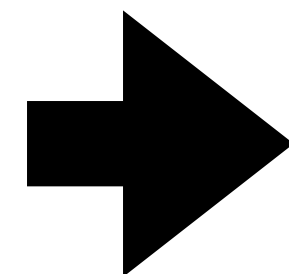
Optimize parameters → θ^*

Quantum Computing

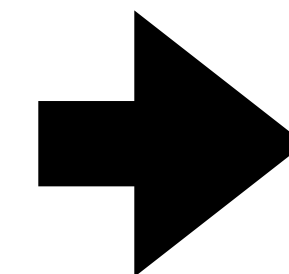
Variational Quantum Eigensolver - VQE



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



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



Optimize parameters → θ^*



VQE details

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

$$\Lambda = 2$$

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



VQE details

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

$\Lambda = 2$

$\log_2 \Lambda^6 = 6$ qubits



Choose Variational Ansatz



VQE details

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

$\Lambda = 2$

$\log_2 \Lambda^6 = 6$ qubits



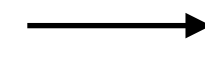
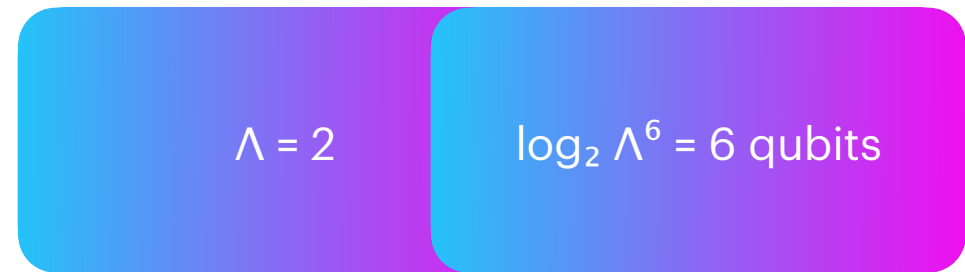
Choose Variational Ansatz

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



VQE details

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

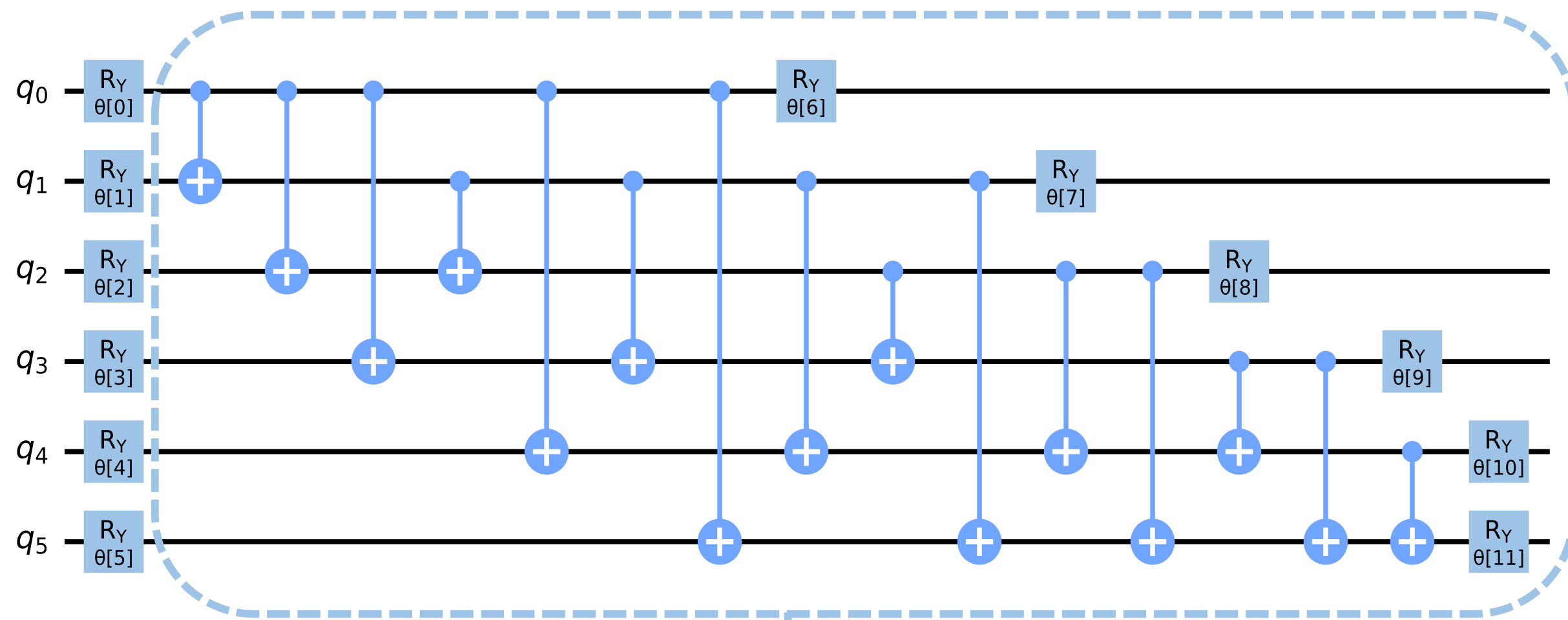


Choose Variational Ansatz

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

depth = 1

parameters = 12

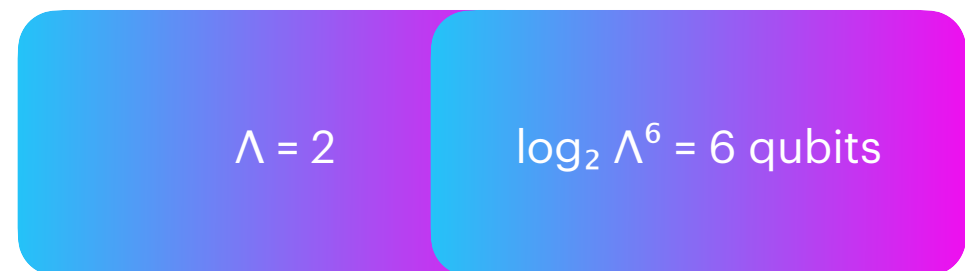


R_y Variational Form



VQE details

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

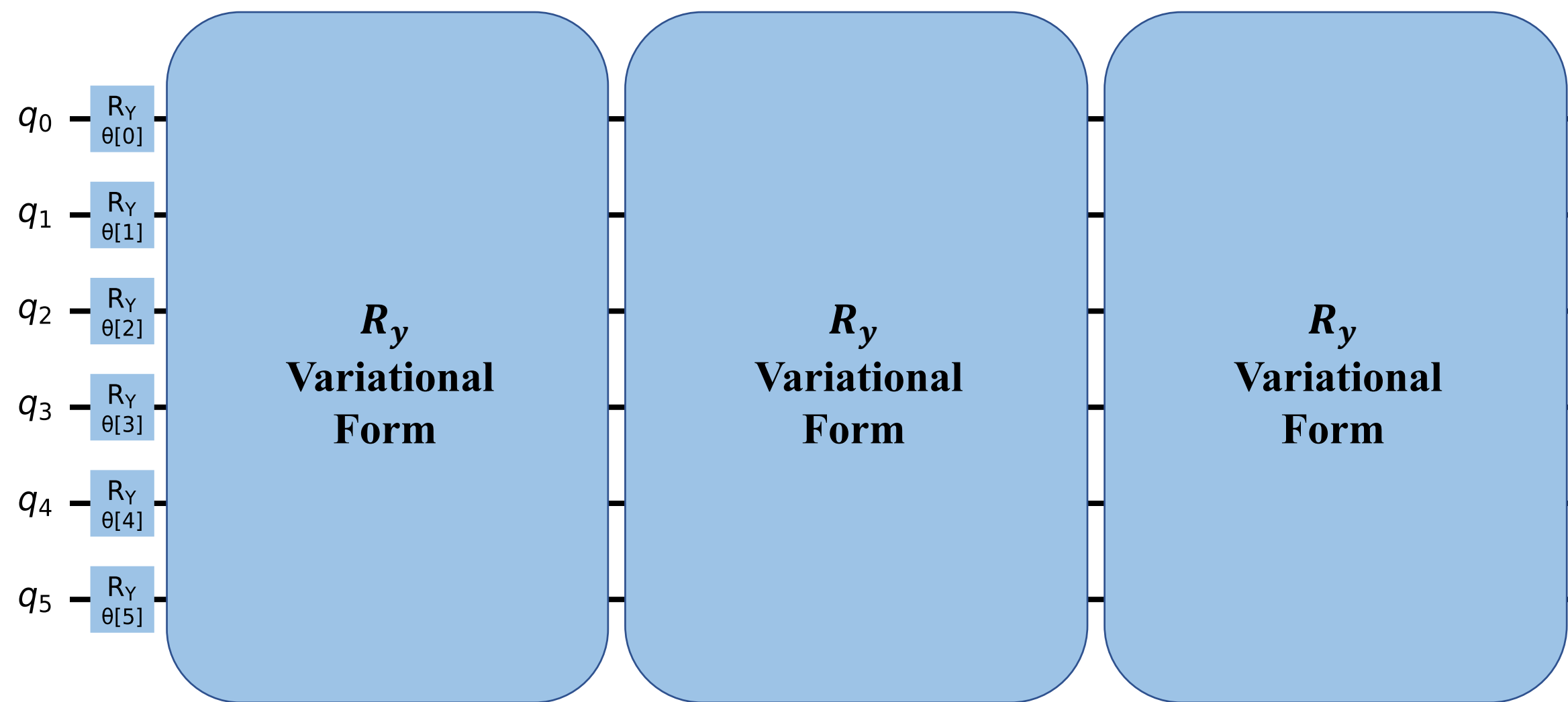


Choose Variational Ansatz

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

depth = 3

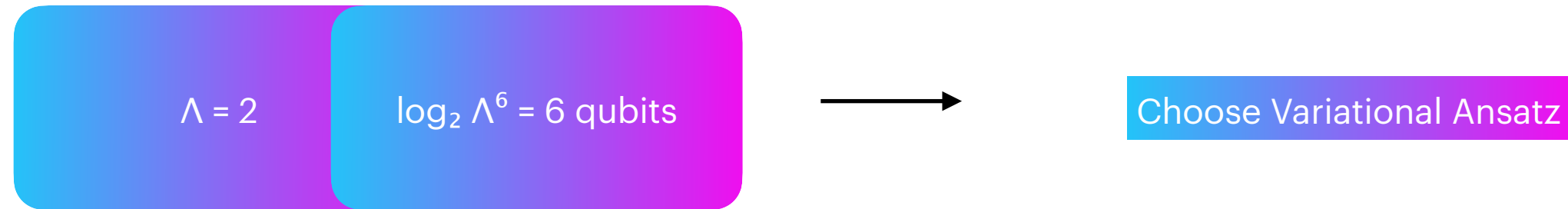
parameters = 24



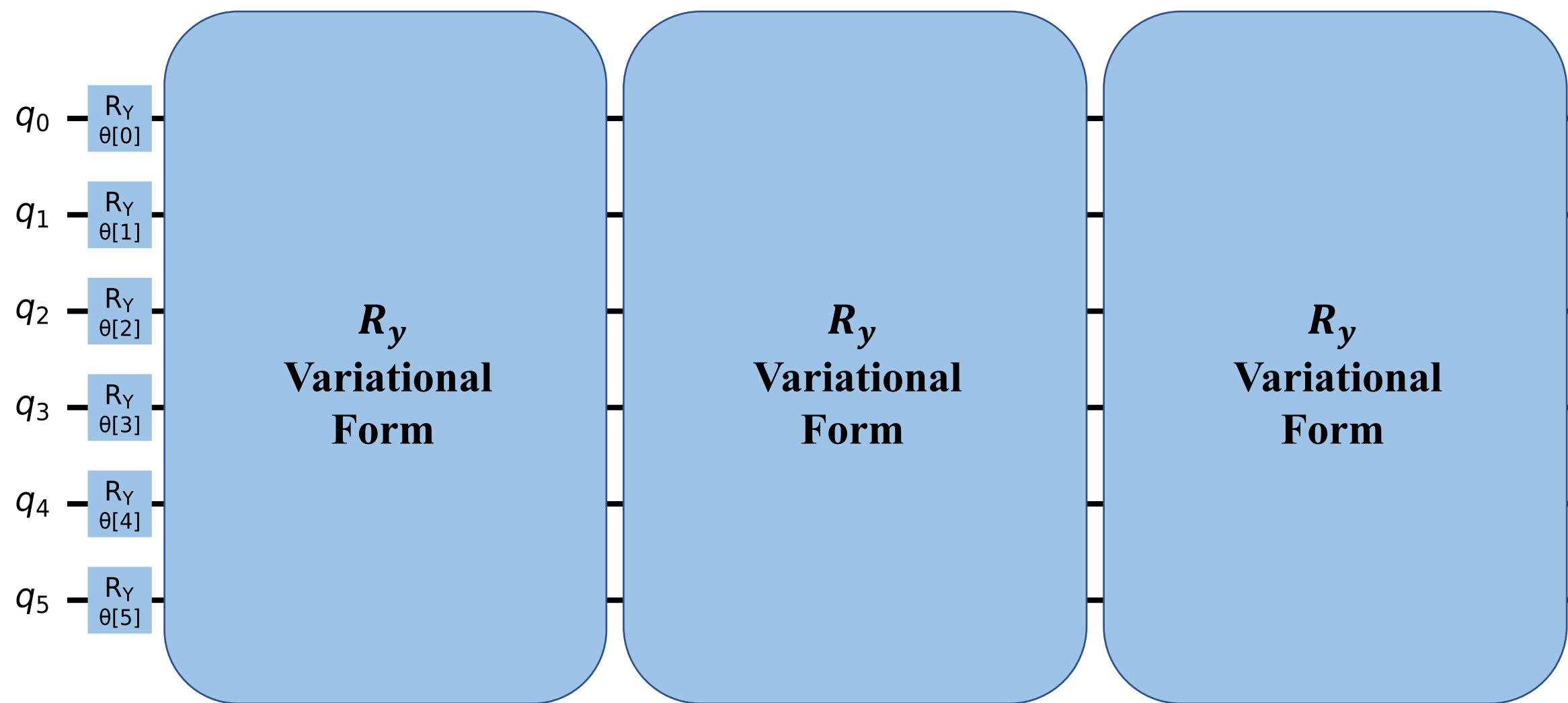


VQE details

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



PQC \rightarrow Variational Ansatz for $|\Phi\rangle$ depth = 3
parameters = 24



Run each multiple instances of PQC from different initial points



VQE details

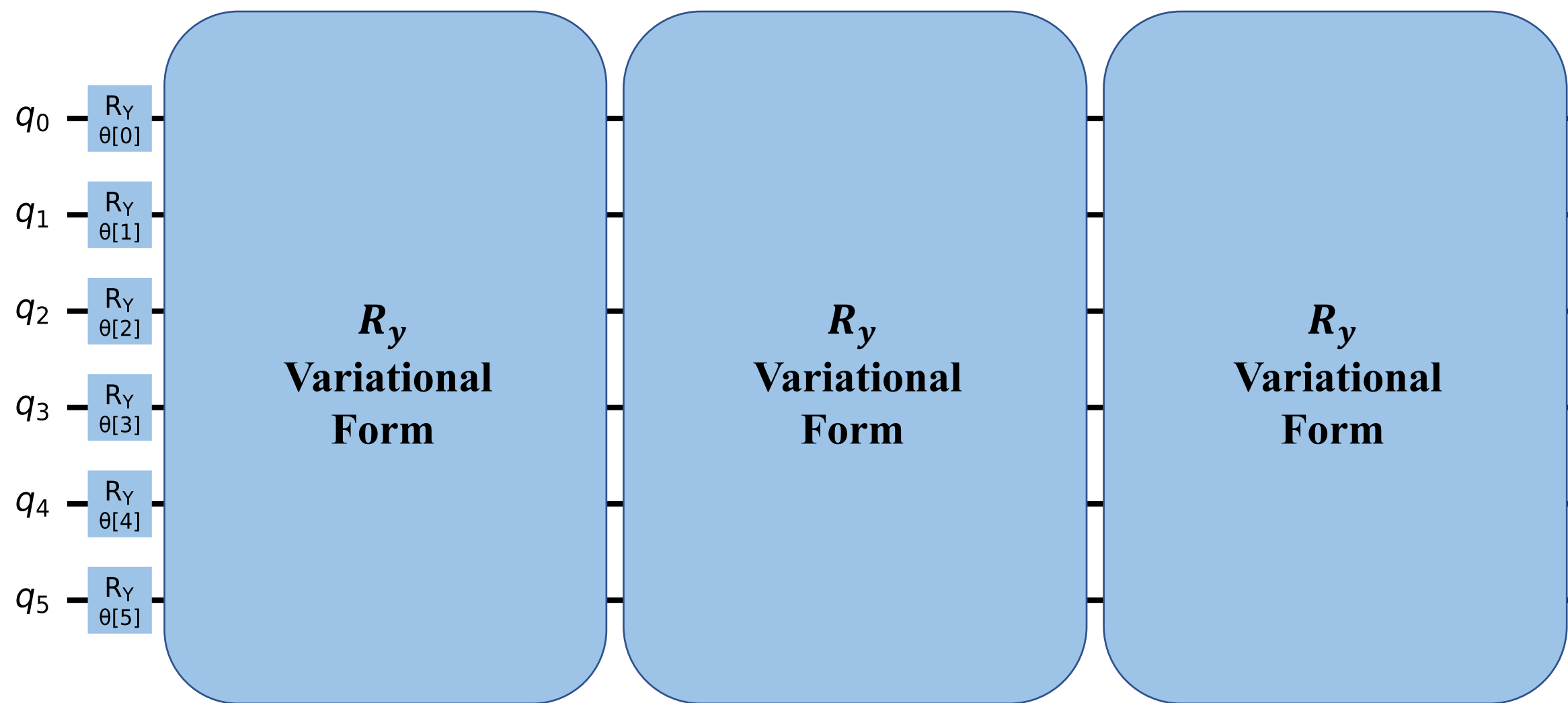
Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$



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

depth = 3

parameters = 24

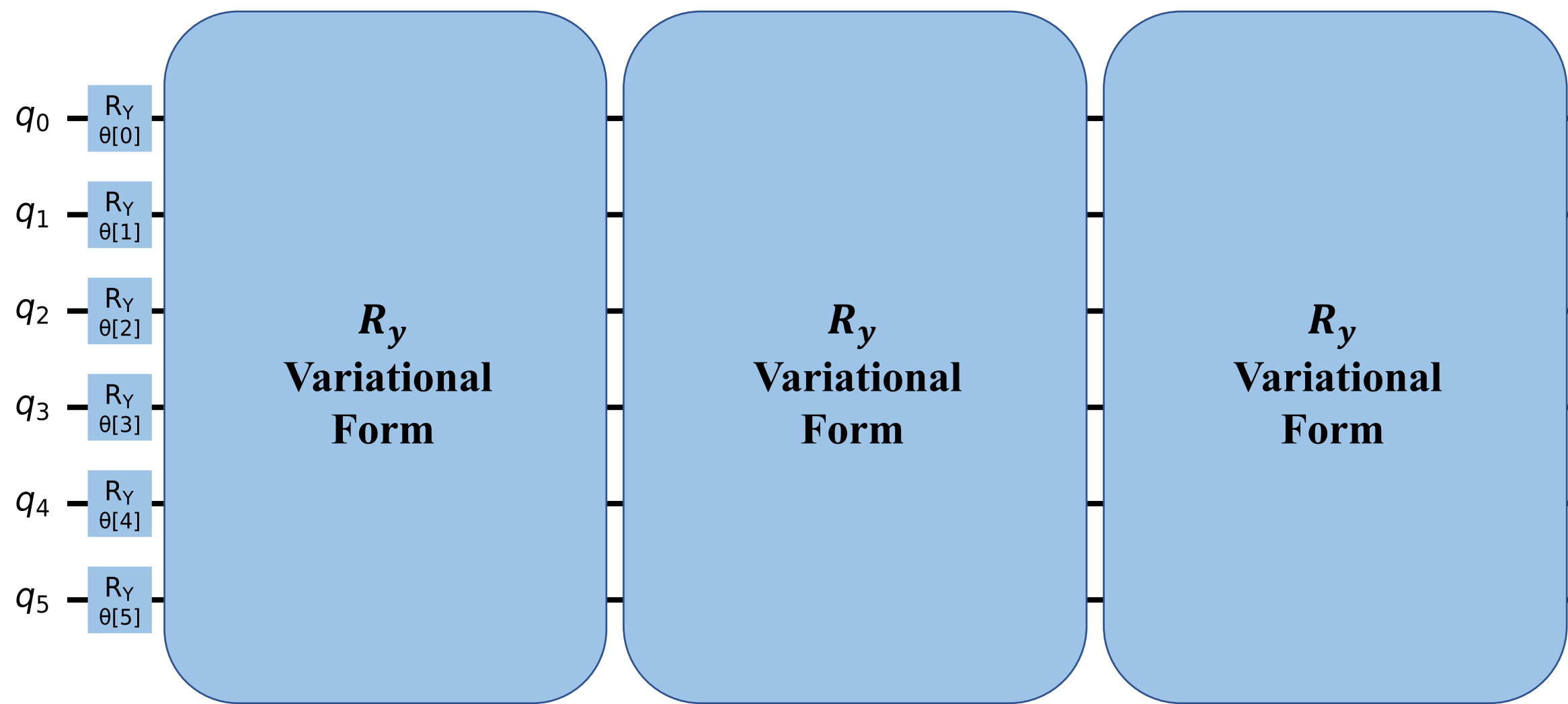
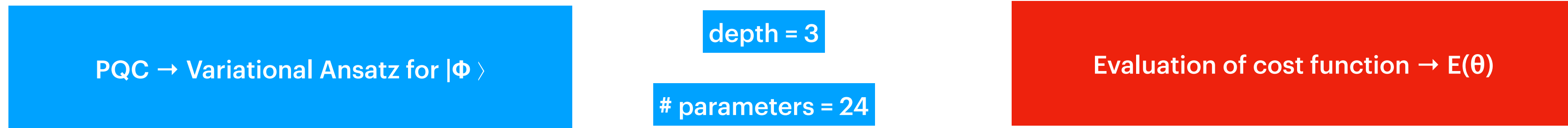


Run each multiple instances of PQC from different initial points



VQE details

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



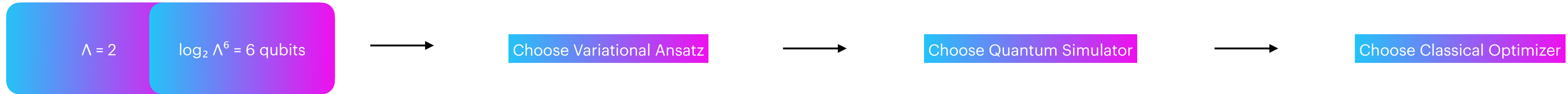
• Statevector simulator

Run each multiple instances of PQC from different initial points



VQE details

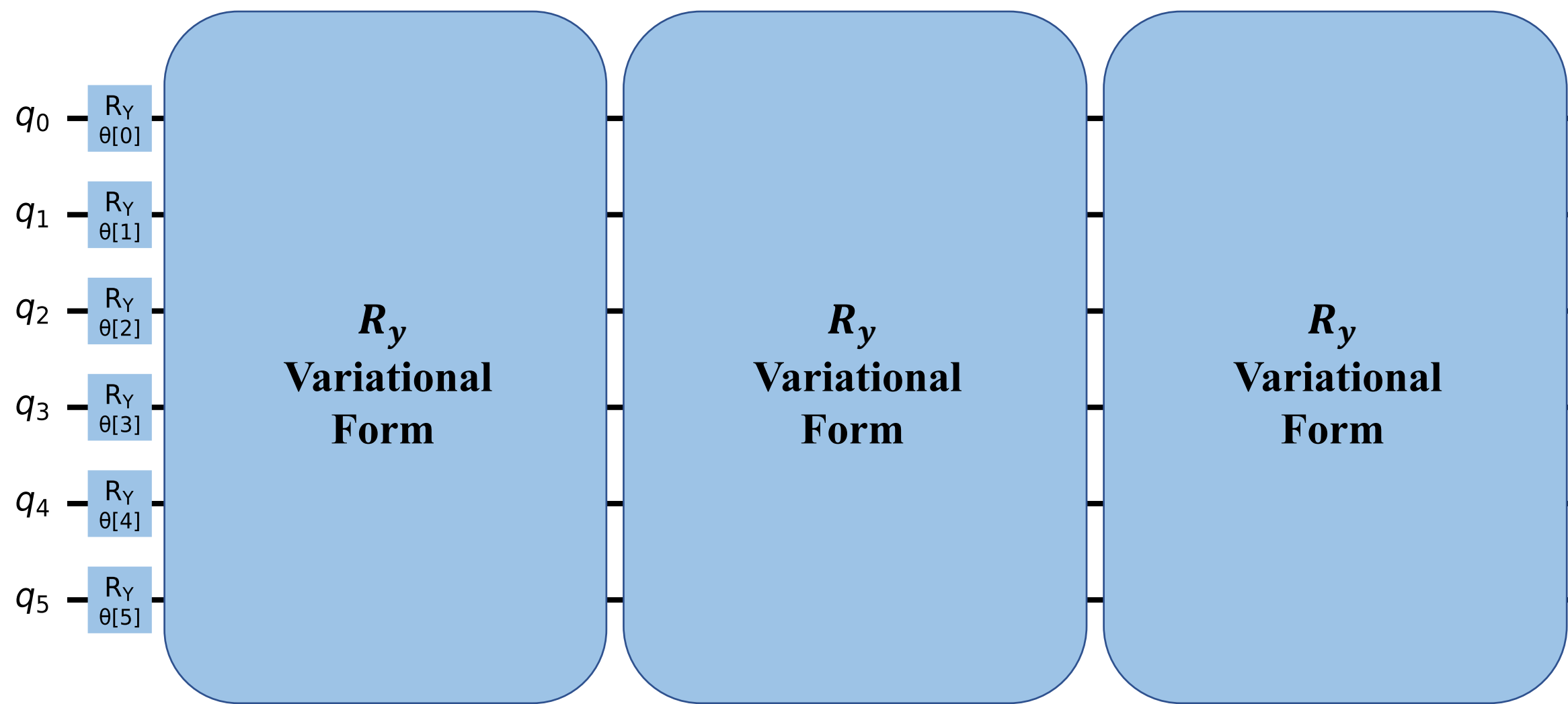
Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$



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

depth = 3
parameters = 24

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



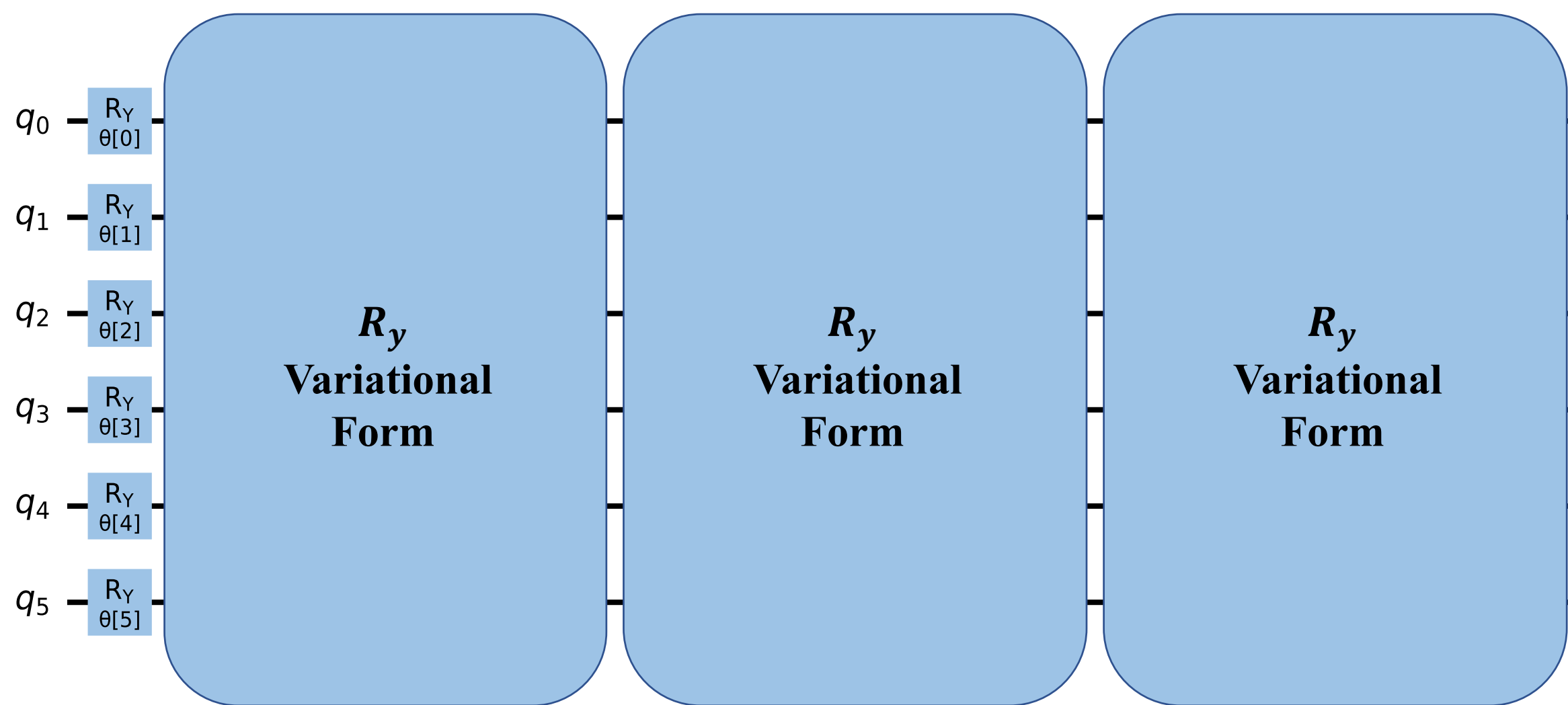
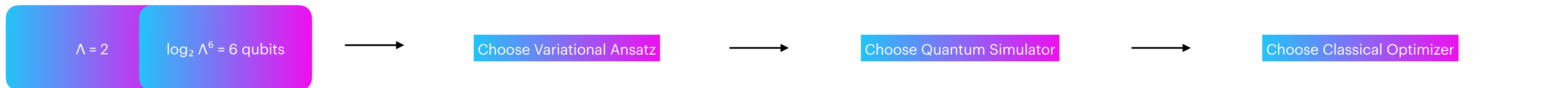
• Statevector simulator

Run each multiple instances of PQC from different initial points



VQE details

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



• 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



Results

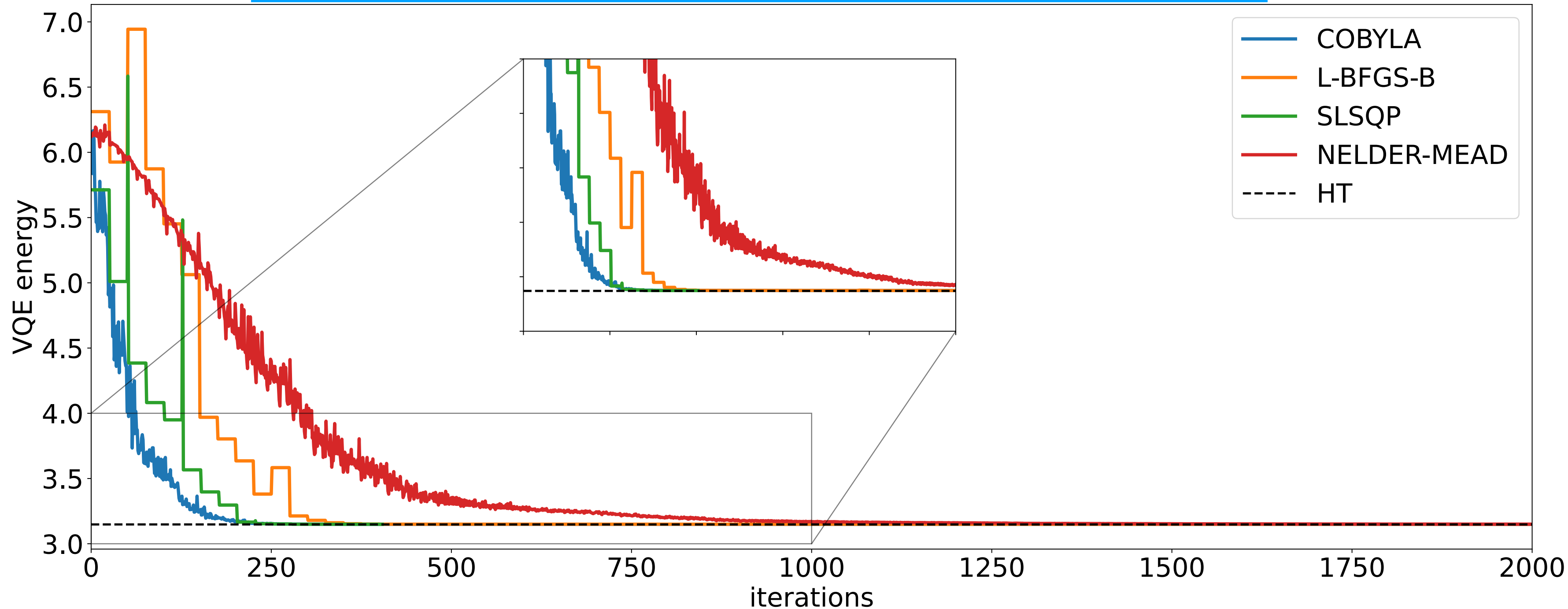
Small-scale: $N=2, D=2, \Lambda \rightarrow \infty$

$\Lambda = 2$

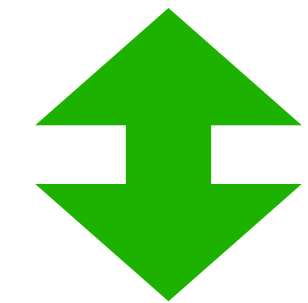
$\log_2 \Lambda^6 = 6$ qubits

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 \rightarrow 24 parameters | Best out of 100 runs



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



Exact Diagonalization: $E_0 = 3.14808$



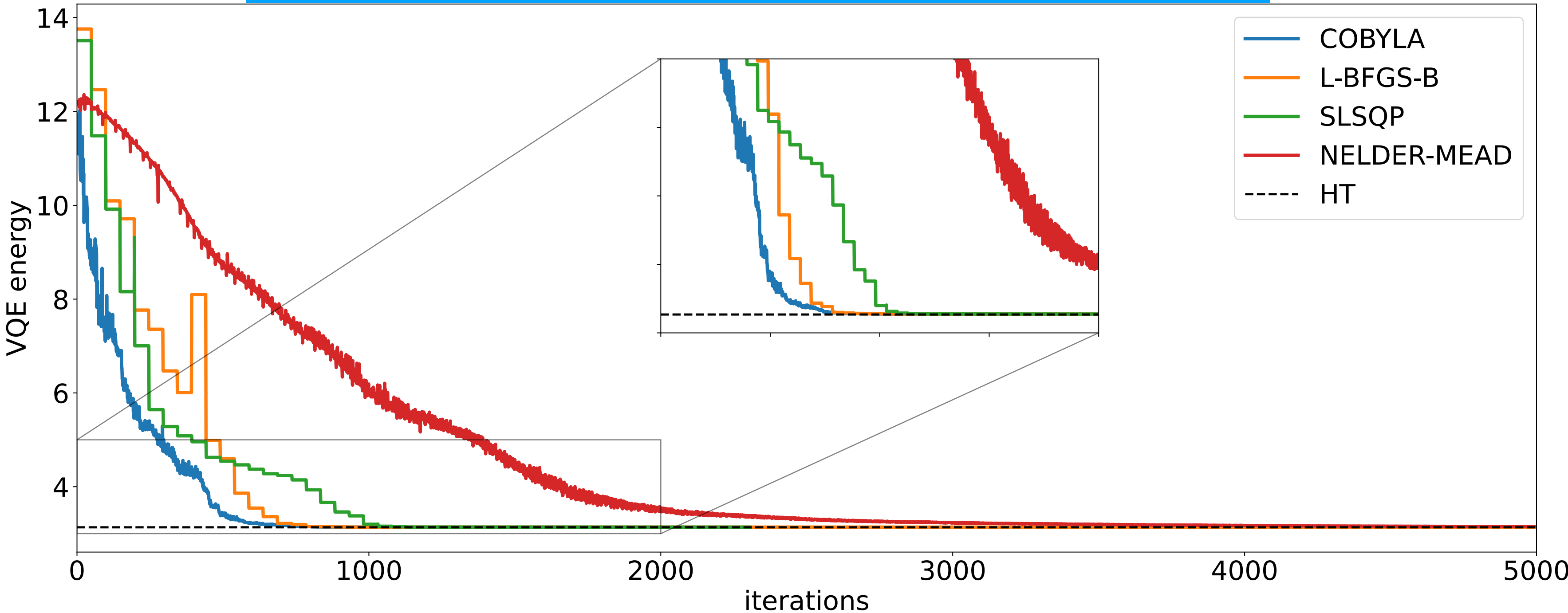
Results

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

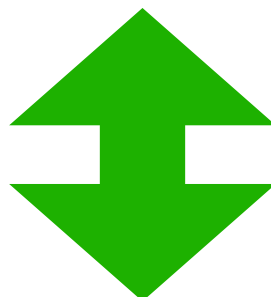
$\Lambda = 4$ $\log_2 \Lambda^6 = 12$ qubits

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 → 24 parameters | Best out of 100 runs



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



Exact Diagonalization: $E_0 = 3.13406$

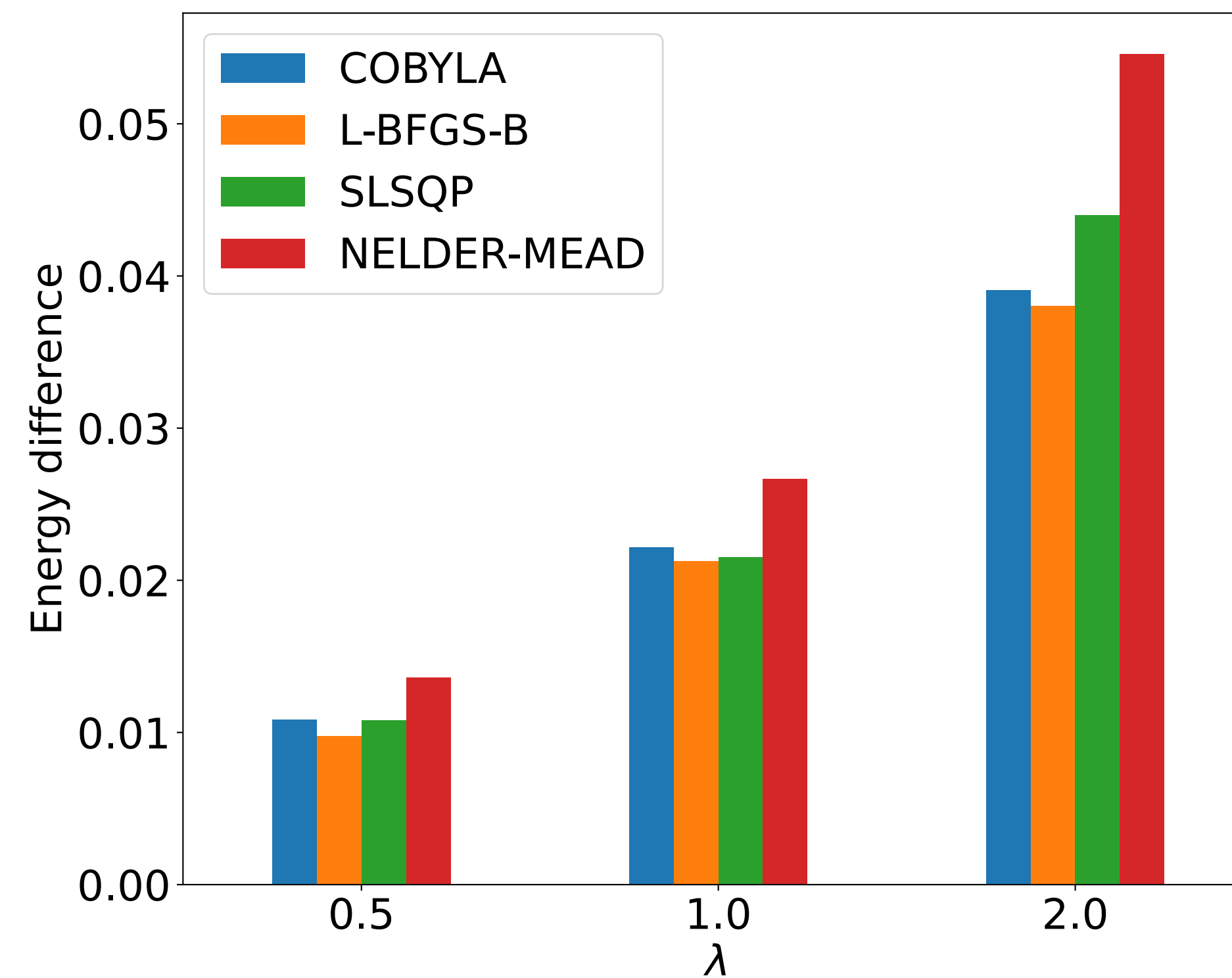
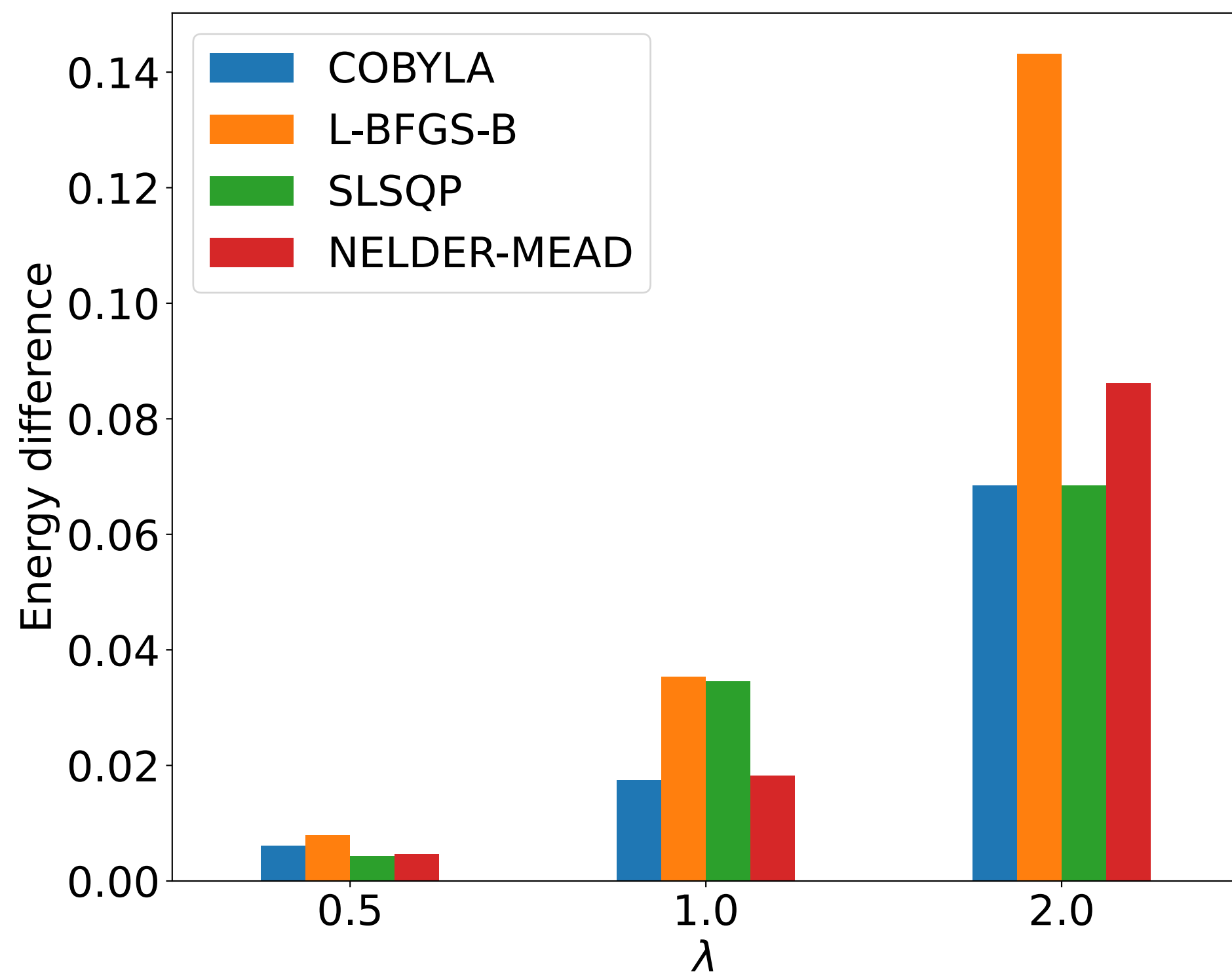


Results

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

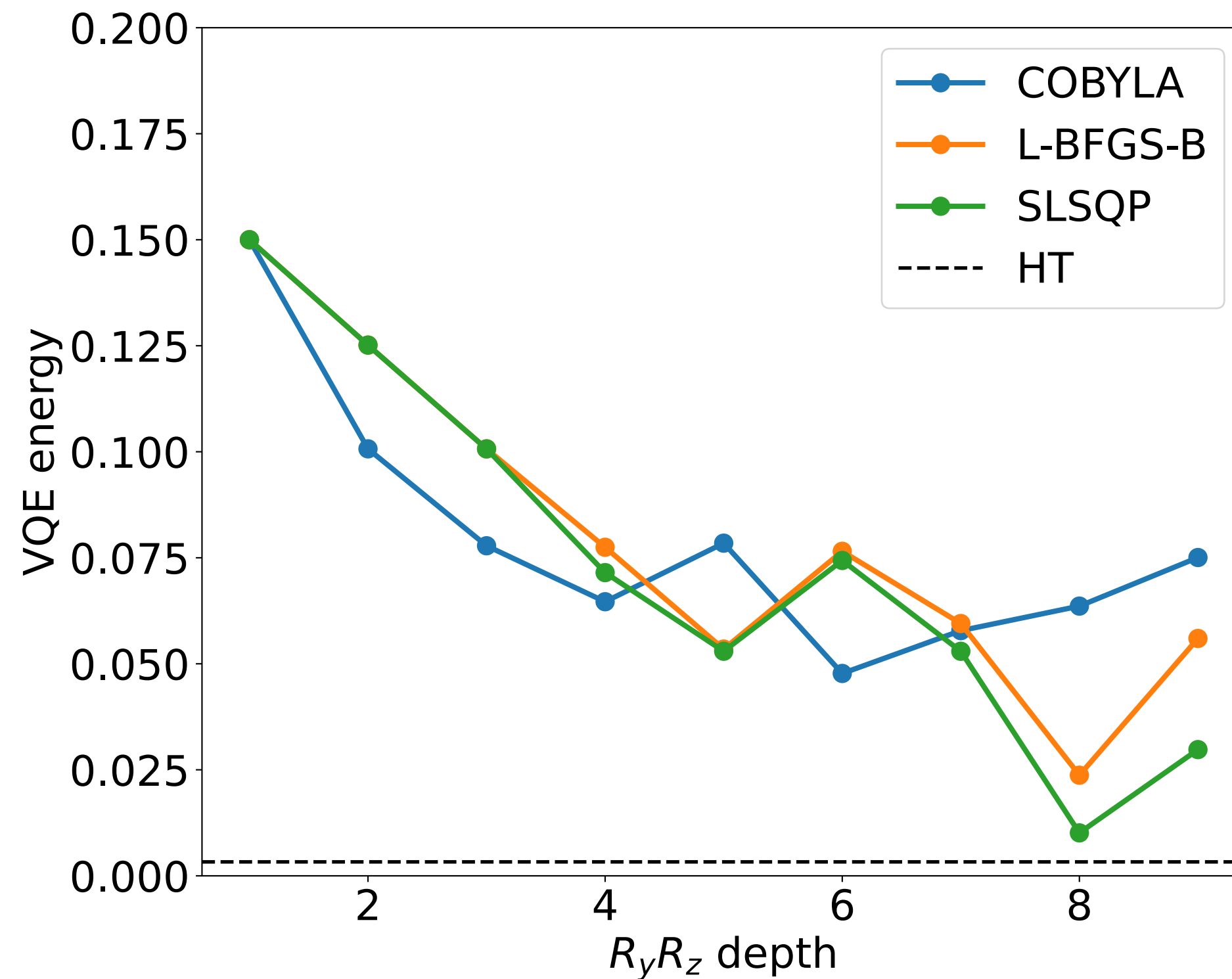




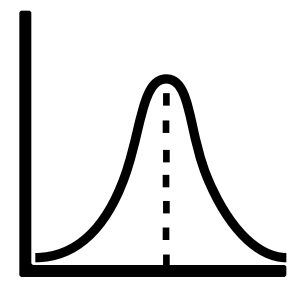
Results

Supersymmetric N=2 D=2 at large coupling

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

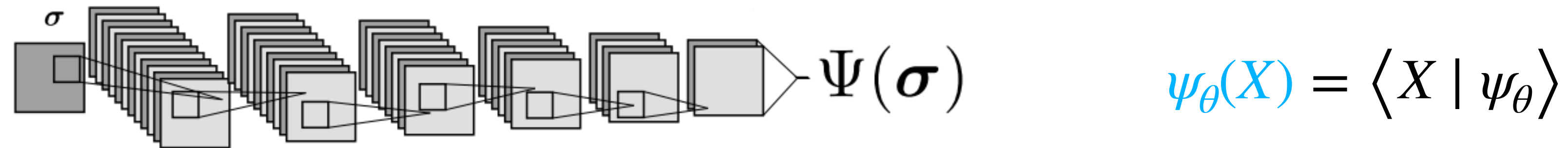


λ	depth = 5				depth = 9	HT (exact)
	COBYLA	L-BFGS-B	SLSQP	NELDER-MEAD	Best	
0.5	0.088492	0.139702	0.134517	0.406003	0.02744	0.01690
1.0	0.135800	0.219268	0.308781	0.752459	0.07900	0.04829
2.0	0.387977	0.622704	0.522396	1.271939	0.17688	0.08385



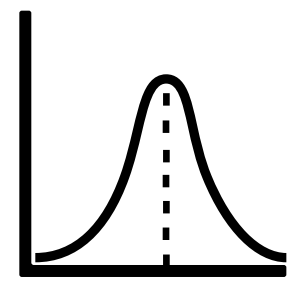
Deep Learning

Variational Quantum Monte Carlo with Neural Quantum States



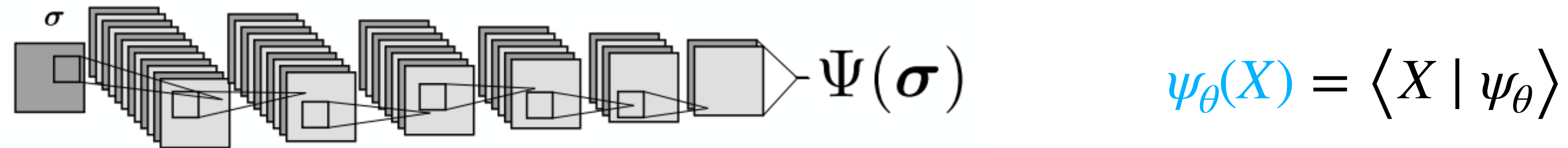
$$E_\theta \equiv \langle \psi_\theta | \hat{H} | \psi_\theta \rangle = \int dX |\psi_\theta(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_\theta \rangle}{\psi_\theta(X)} = \mathbf{E}_{X \sim |\psi_\theta|^2} [\epsilon_\theta(X)]$$

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



Deep Learning

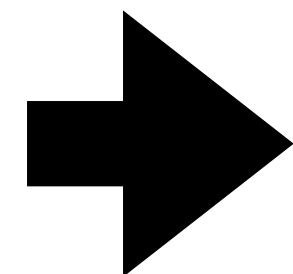
Variational Quantum Monte Carlo with Neural Quantum States



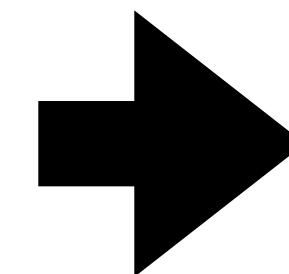
$$E_{\theta} \equiv \langle \psi_{\theta} | \hat{H} | \psi_{\theta} \rangle = \int dX |\psi_{\theta}(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_{\theta} \rangle}{\psi_{\theta}(X)} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\epsilon_{\theta}(X)]$$

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

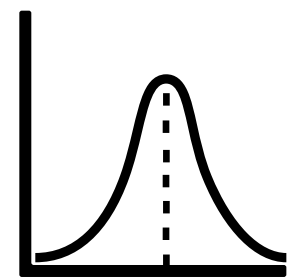
NQS → Variational Ansatz for $|\Phi\rangle$



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

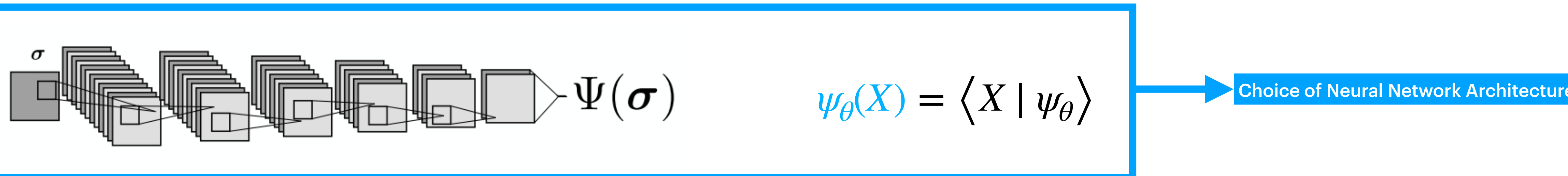


Optimize parameters → θ^*



Deep Learning

Variational Quantum Monte Carlo with Neural Quantum States



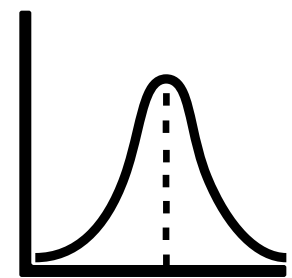
$$E_{\theta} \equiv \langle \psi_{\theta} | \hat{H} | \psi_{\theta} \rangle = \int dX |\psi_{\theta}(X)|^2 \cdot \frac{\langle X | \hat{H} | \psi_{\theta} \rangle}{\psi_{\theta}(X)} = \mathbf{E}_{X \sim |\psi_{\theta}|^2} [\epsilon_{\theta}(X)]$$

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

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

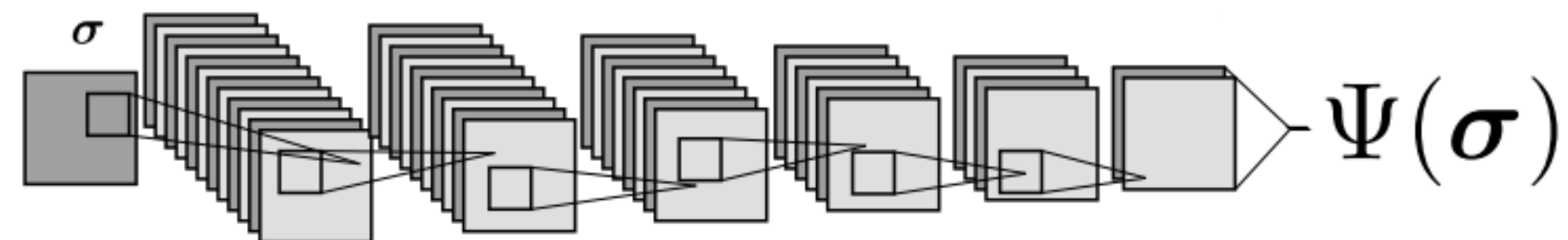
Evaluation of cost function → $E(\theta)$

Optimize parameters → θ^*



Deep Learning

Variational Quantum Monte Carlo with Neural Quantum States



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

Choice of Neural Network Architecture

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

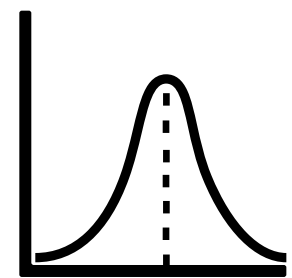
Choice of Monte Carlo Sampling

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

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

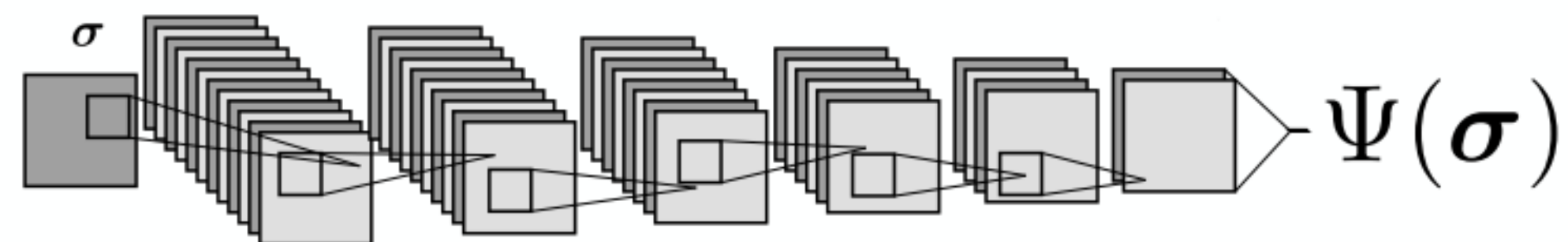
Evaluation of cost function → $E(\theta)$

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

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

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

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



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

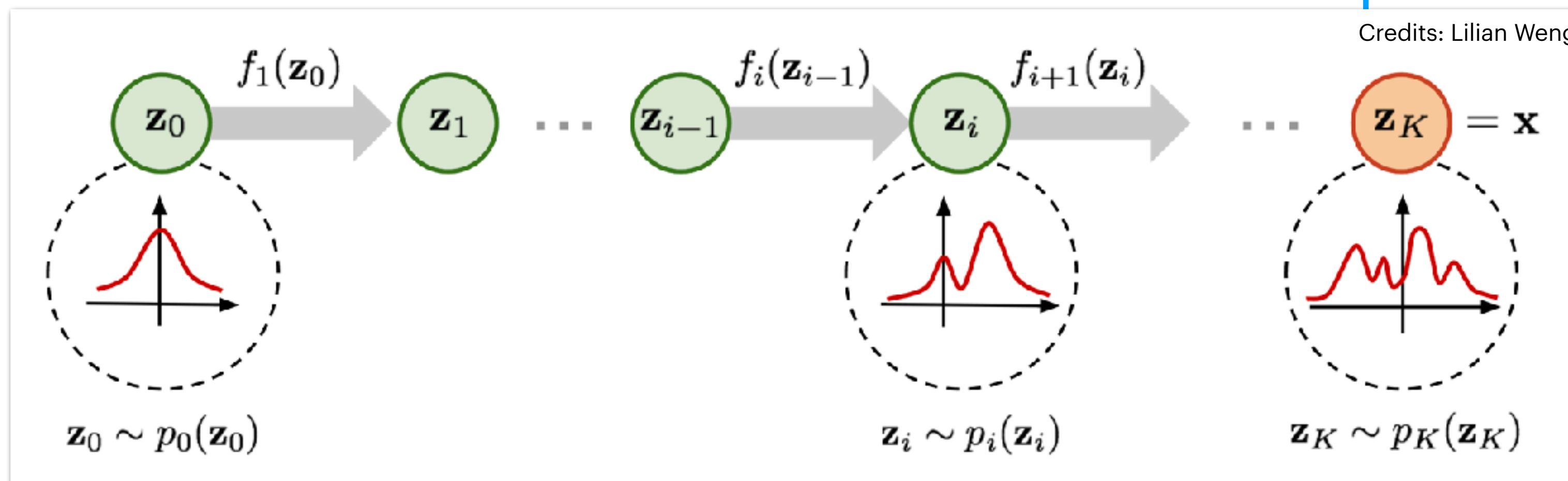
Autoregressive Flow

Neural quantum state

Small-scale: N=2, D=2

Wave function

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



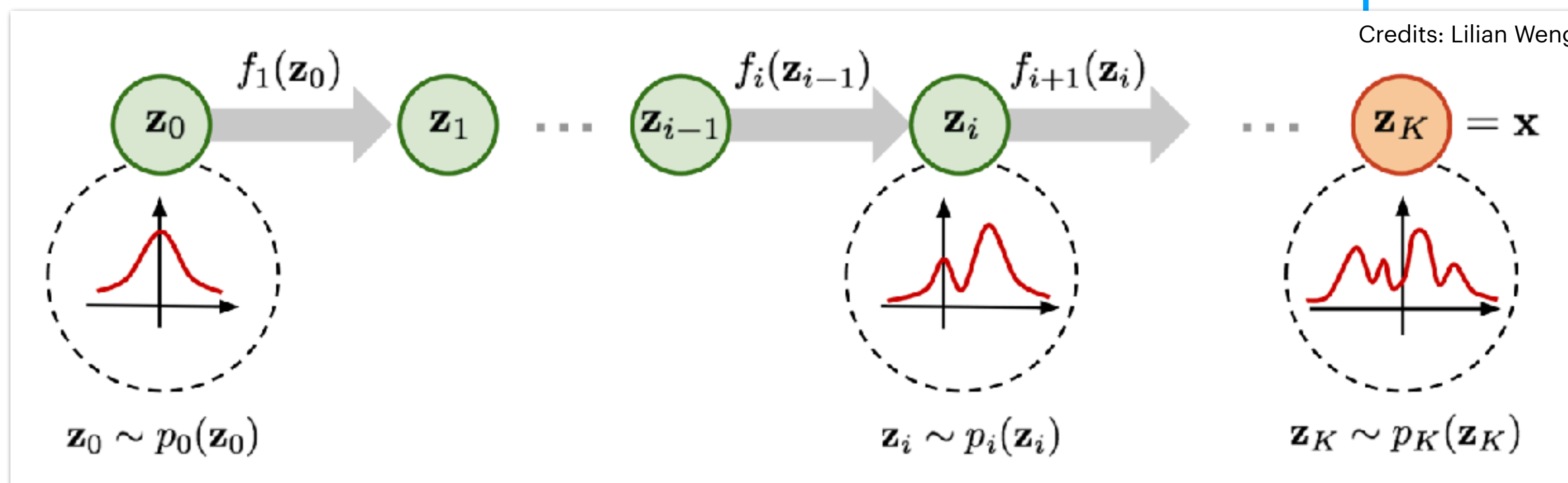
Autoregressive Flow

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

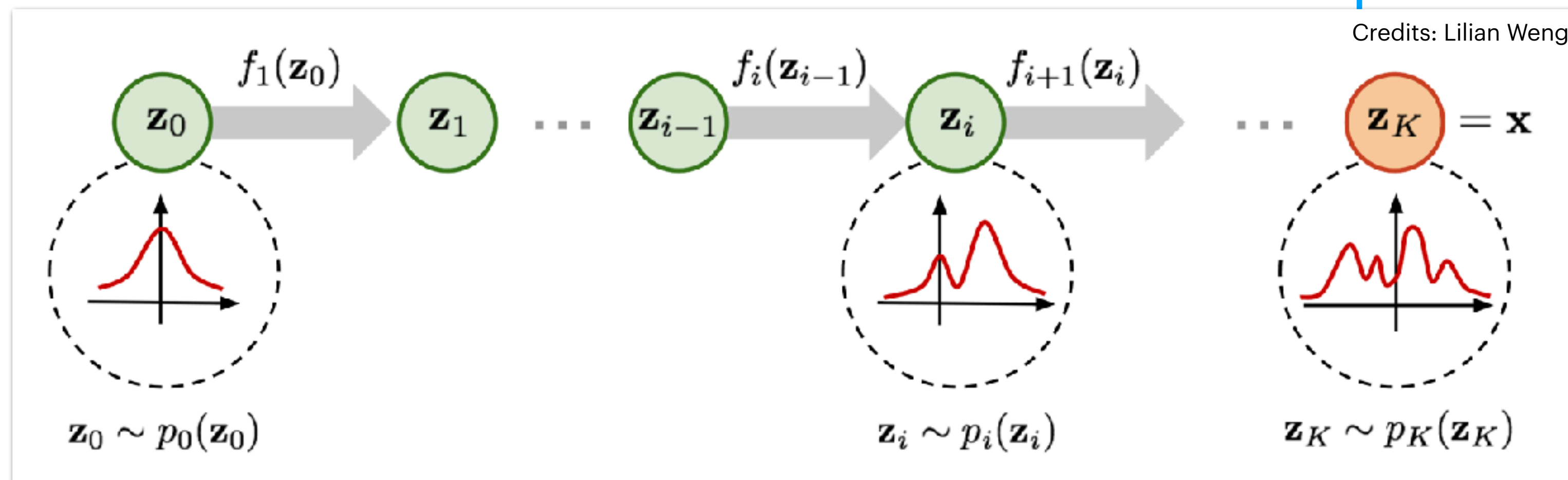
Prob. distribution $p(x_1; F_\theta^0)$

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

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



$$F_\theta^i = A_\theta^{i,m} \circ \tanh \circ A_\theta^{i,m-1} \circ \tanh \circ \dots \circ A_\theta^{i,2} \circ \tanh \circ A_\theta^{i,1}$$

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

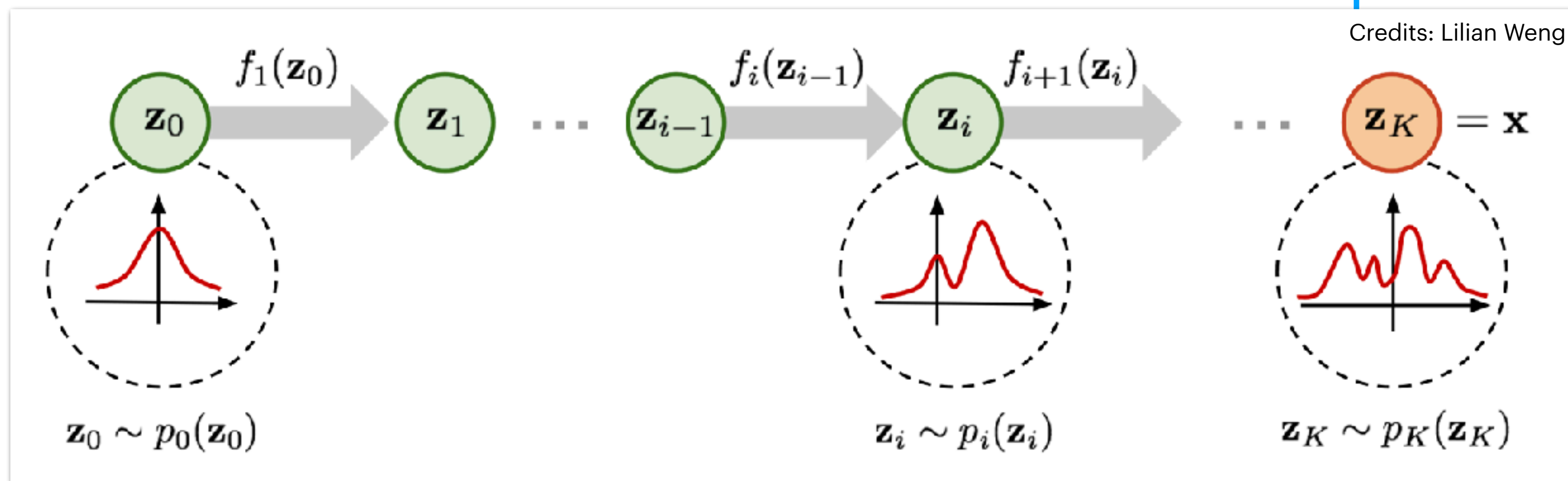
Neural quantum state

Small-scale: N=2, D=2

No truncation Λ

Wave function

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



Autoregressive Flow

Parametrization

Prob. distribution

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



$$F_\theta^i = A_\theta^{i,m} \circ \tanh \circ A_\theta^{i,m-1} \circ \tanh \circ \dots \circ A_\theta^{i,2} \circ \tanh \circ A_\theta^{i,1}$$

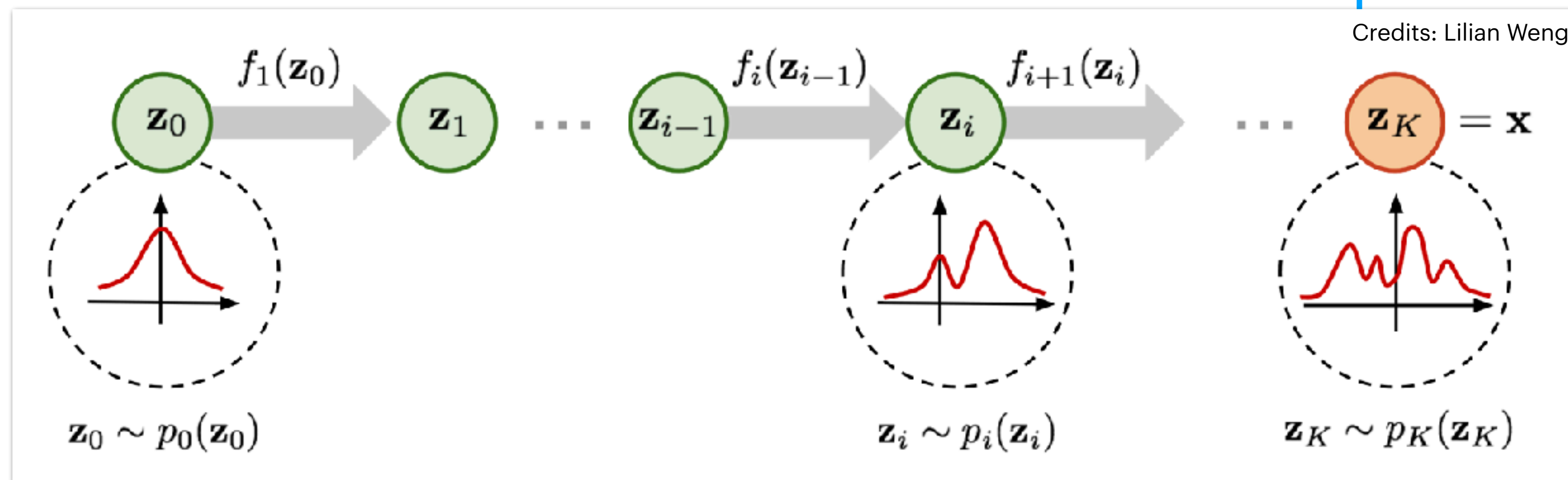
$$A_\theta^{i,a}(\vec{x}) = M_\theta^{i,a} \cdot \vec{x} + \vec{b}_\theta^{i,a}$$

Neural quantum state

Small-scale: N=2, D=2

Wave function

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



Autoregressive Flow

No truncation Λ

Direct Sampling

Parametrization

Prob. distribution

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

$$F_\theta^i = A_\theta^{i,m} \circ \tanh \circ A_\theta^{i,m-1} \circ \tanh \circ \dots \circ A_\theta^{i,2} \circ \tanh \circ A_\theta^{i,1}$$

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Results

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

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

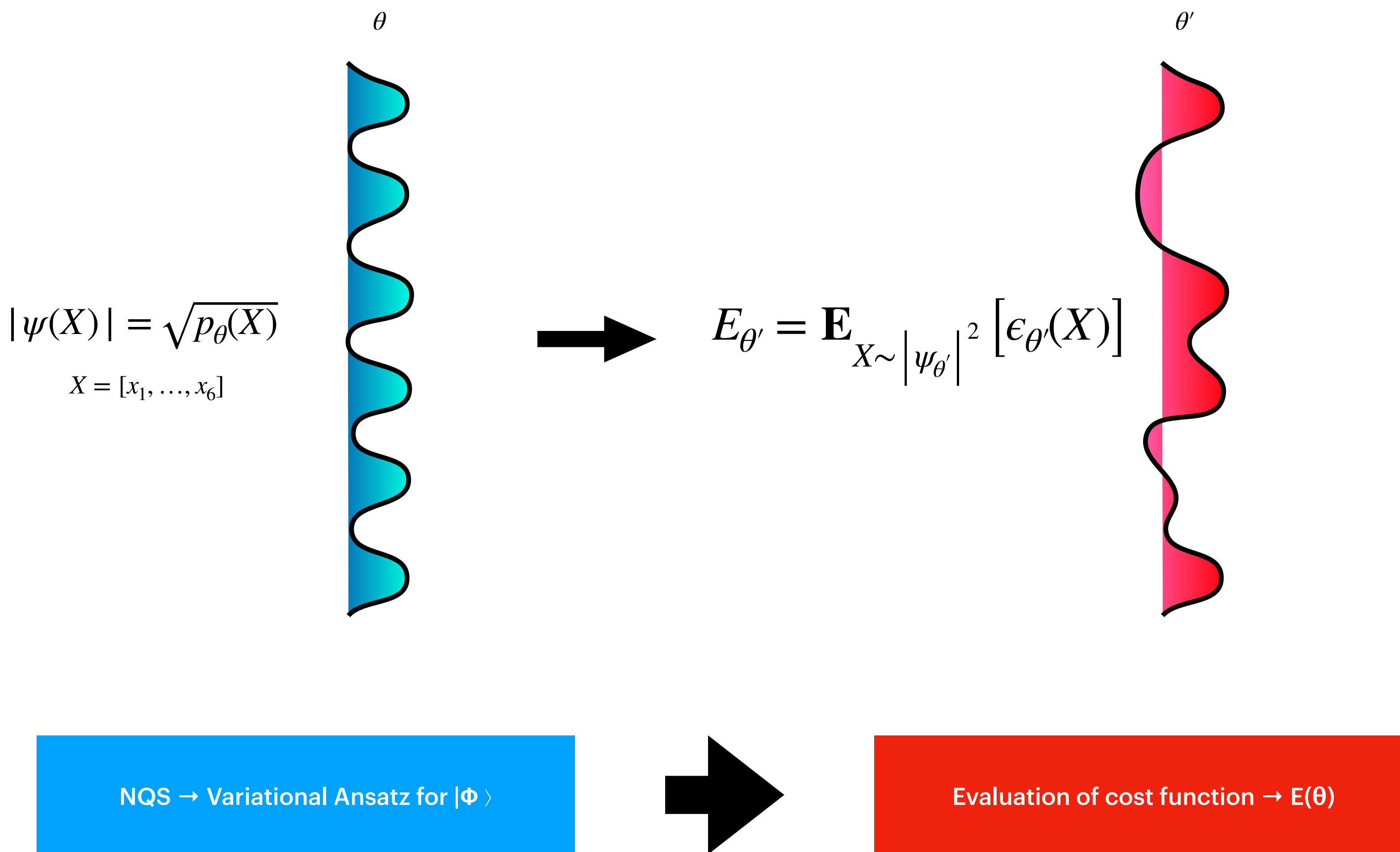
$X = [x_1, \dots, x_6]$



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

Results

Small-scale: N=2, D=2



Results

Small-scale: N=2, D=2

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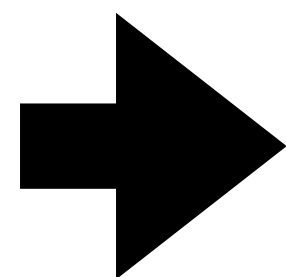
$X = [x_1, \dots, x_6]$



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



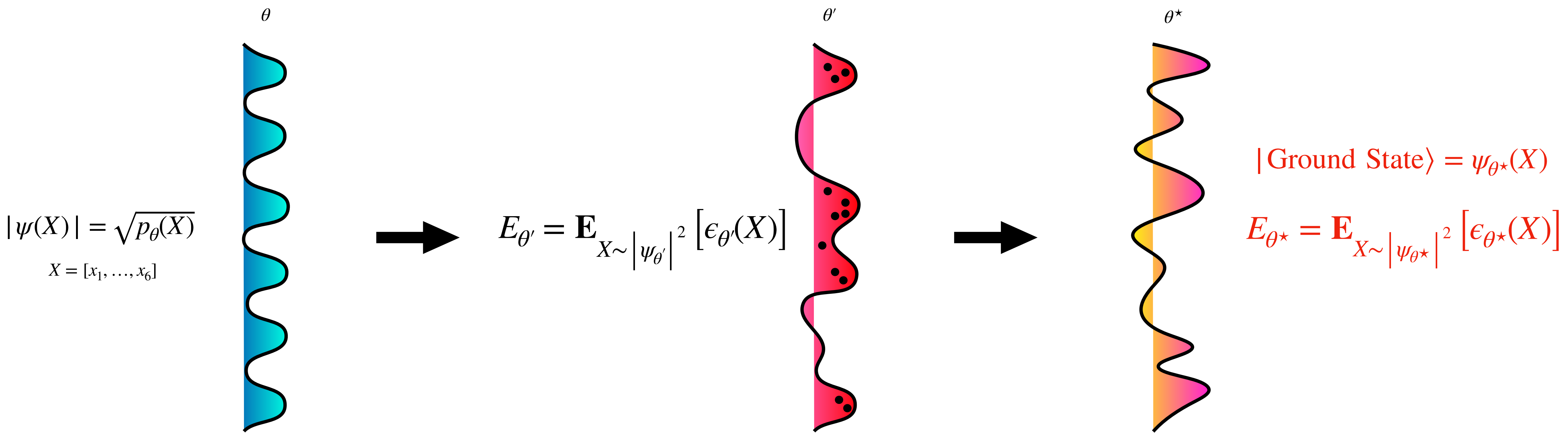
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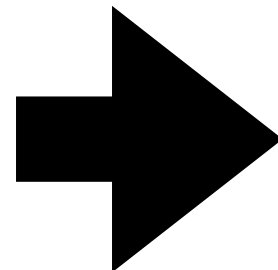
Evaluation of cost function → $E(\theta)$

Results

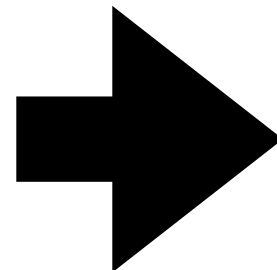
Small-scale: N=2, D=2



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



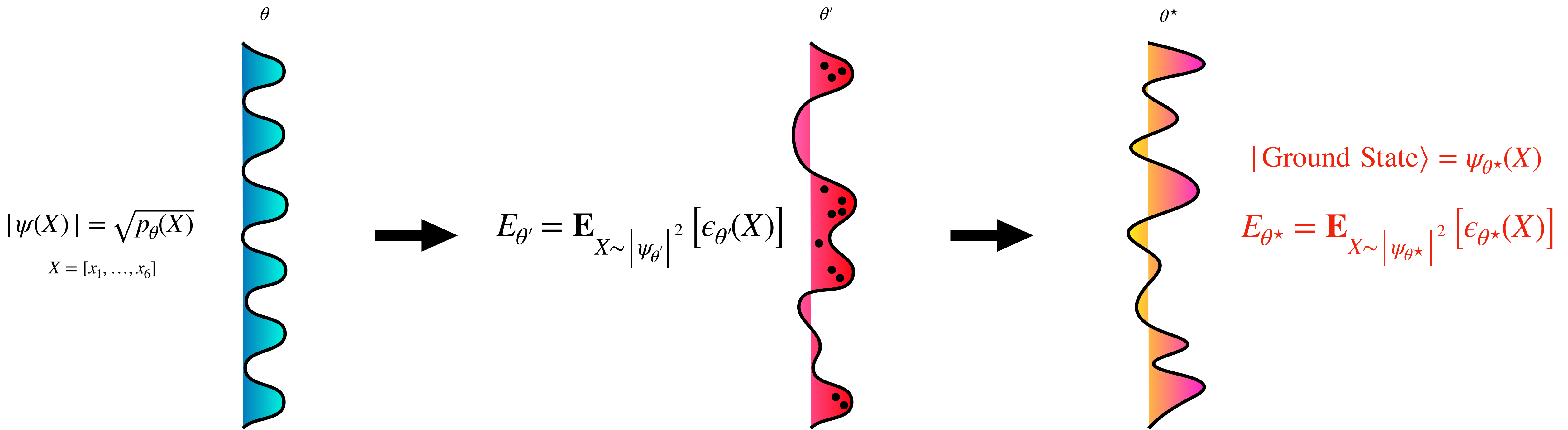
Evaluation of cost function → $E(\theta)$



Optimize parameters → θ^*

Results

Small-scale: N=2, D=2



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

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

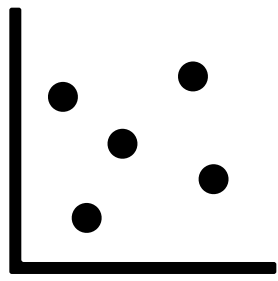
$$E_{\theta'} = \mathbf{E}_{X \sim |\psi_{\theta'}|^2} [\epsilon_{\theta'}(X)]$$

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

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

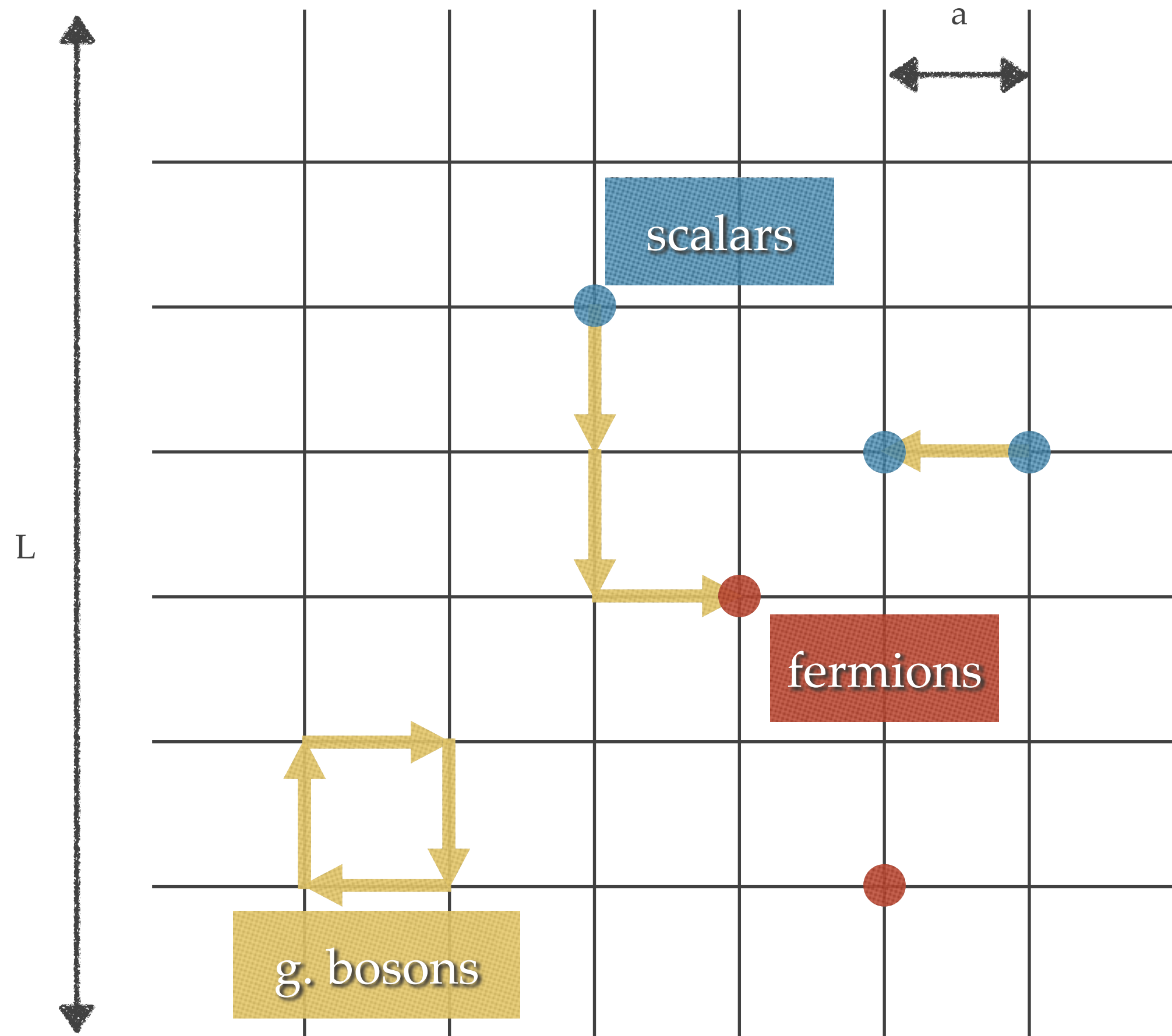
dependence on hidden layer units α

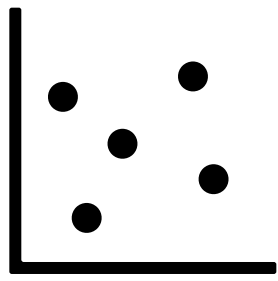
α	1	2	5	10	20	50	HT (exact)
$\lambda = 0.2$	3.137(2)	3.137(2)	3.140(2)	3.138(2)	3.137(2)	3.135(2)	3.134
$\lambda = 0.5$	3.313(2)	3.312(2)	3.308(2)	3.307(2)	3.302(2)	3.305(2)	3.297
$\lambda = 1.0$	3.544(3)	3.544(2)	3.541(3)	3.528(2)	3.519(2)	3.520(2)	3.516
$\lambda = 2.0$	3.914(3)	3.910(3)	3.892(3)	3.872(3)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



Path Integral Monte Carlo

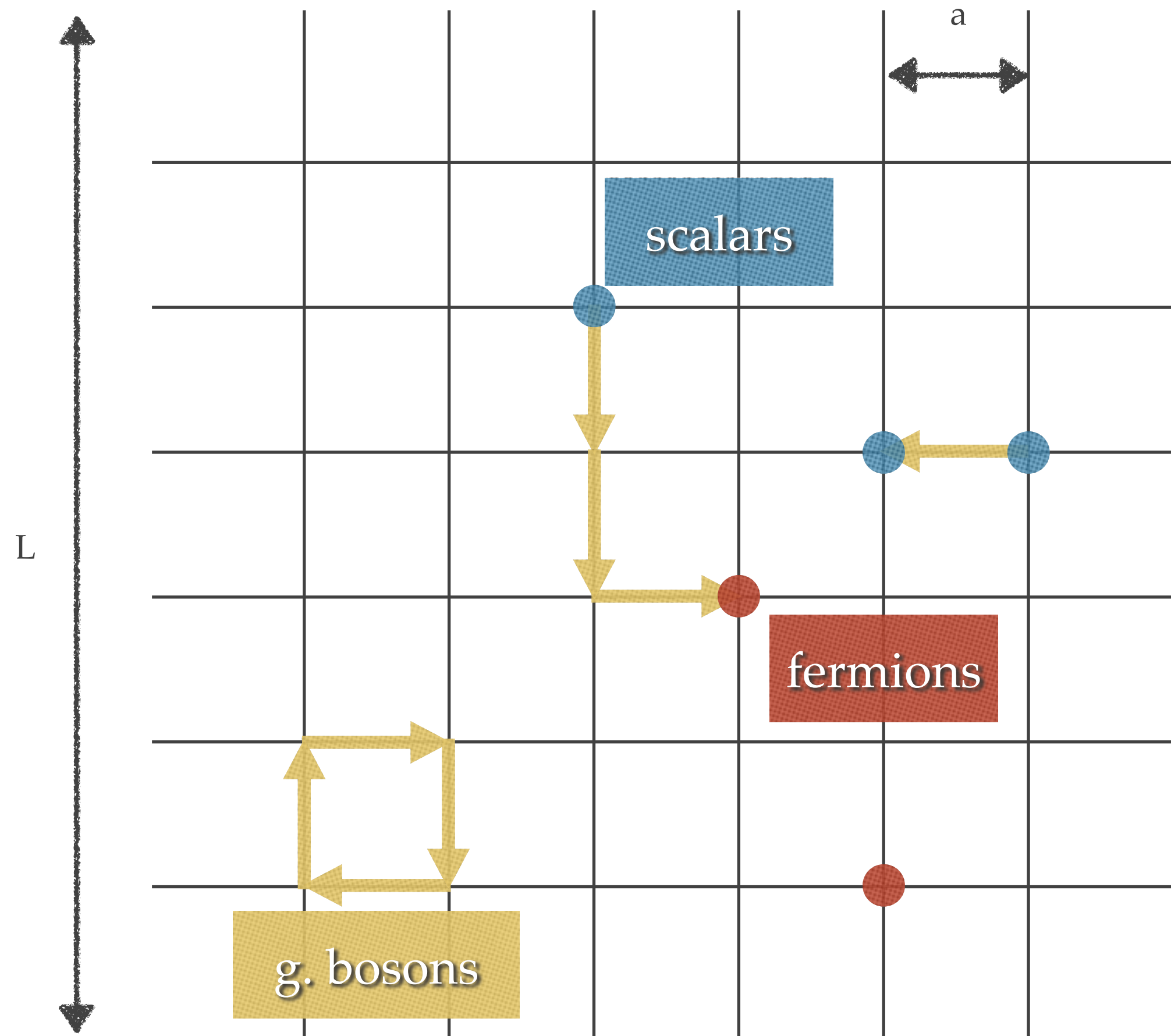
Lattice Gauge Theory Primer



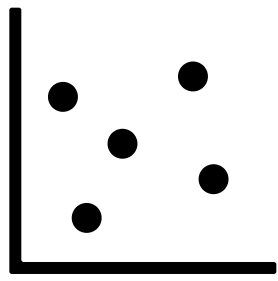


Path Integral Monte Carlo

Lattice Gauge Theory Primer

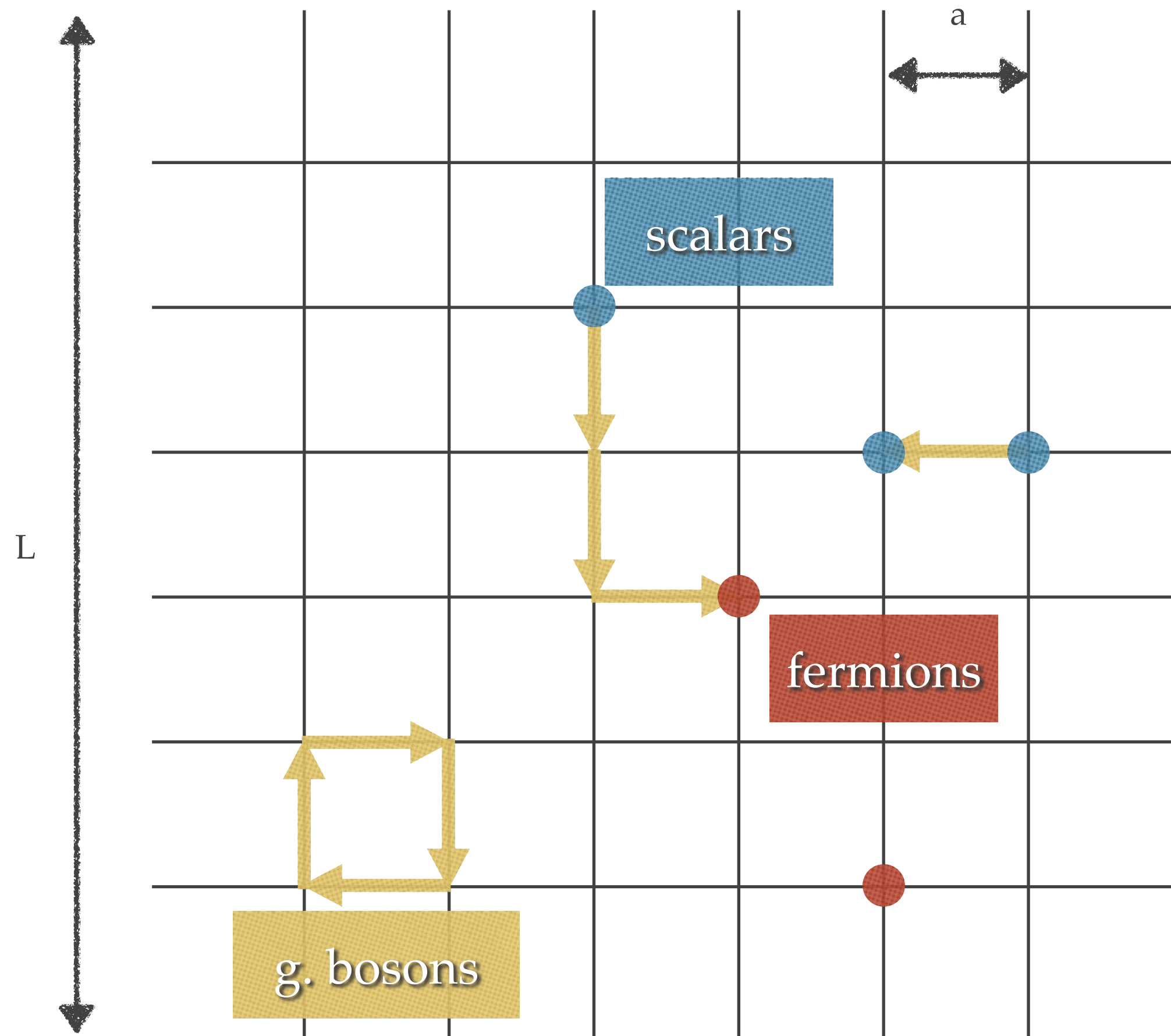


- Discretize space and time
 - lattice spacing “ a ”
 - lattice size “ L ”

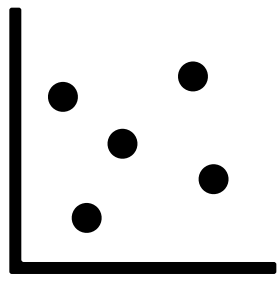


Path Integral Monte Carlo

Lattice Gauge Theory Primer

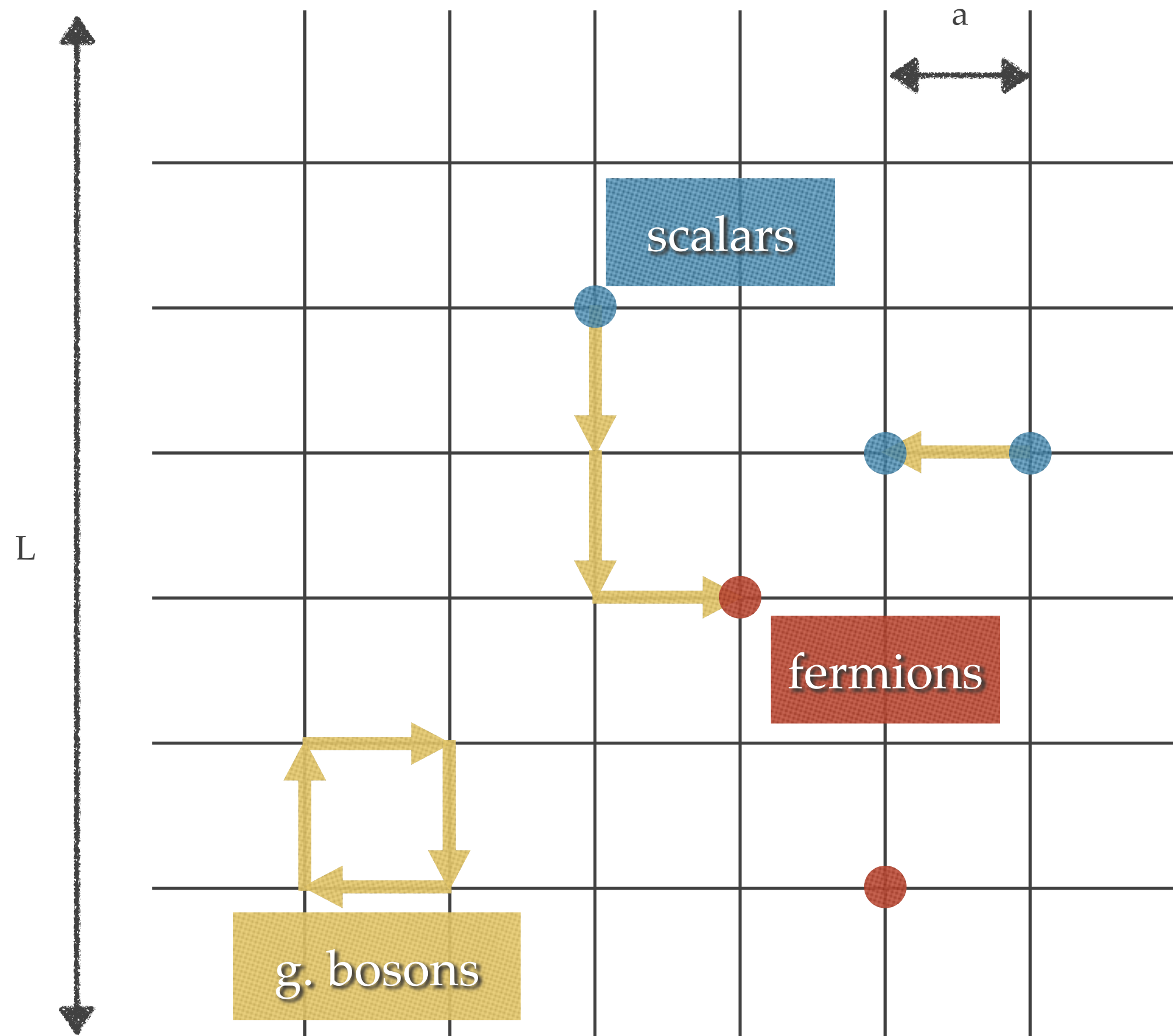


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- Keep all d.o.f. of the theory
 - not a model!
 - no simplifications



Path Integral Monte Carlo

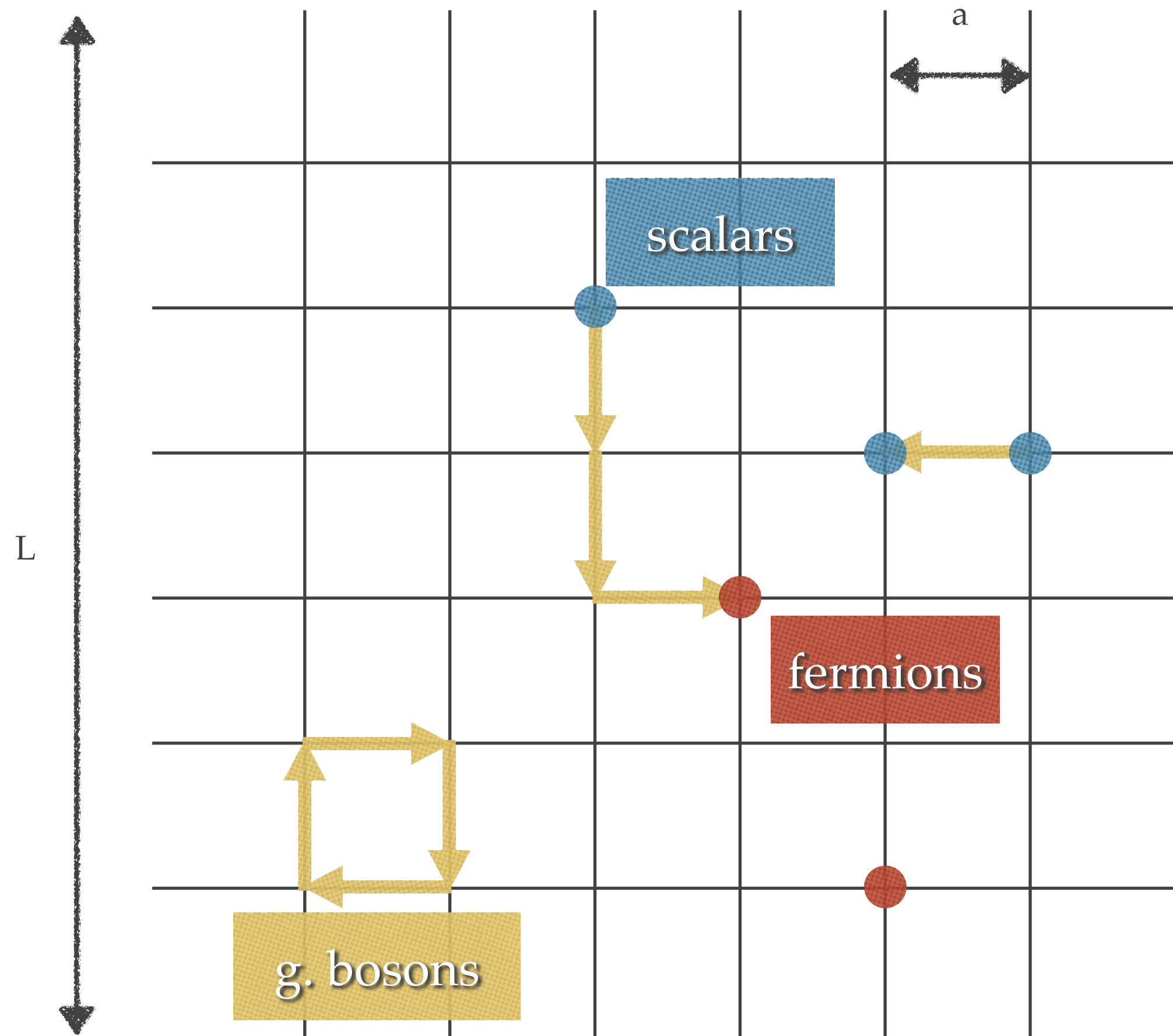
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 - Monte Carlo sampling
 - use **supercomputers**

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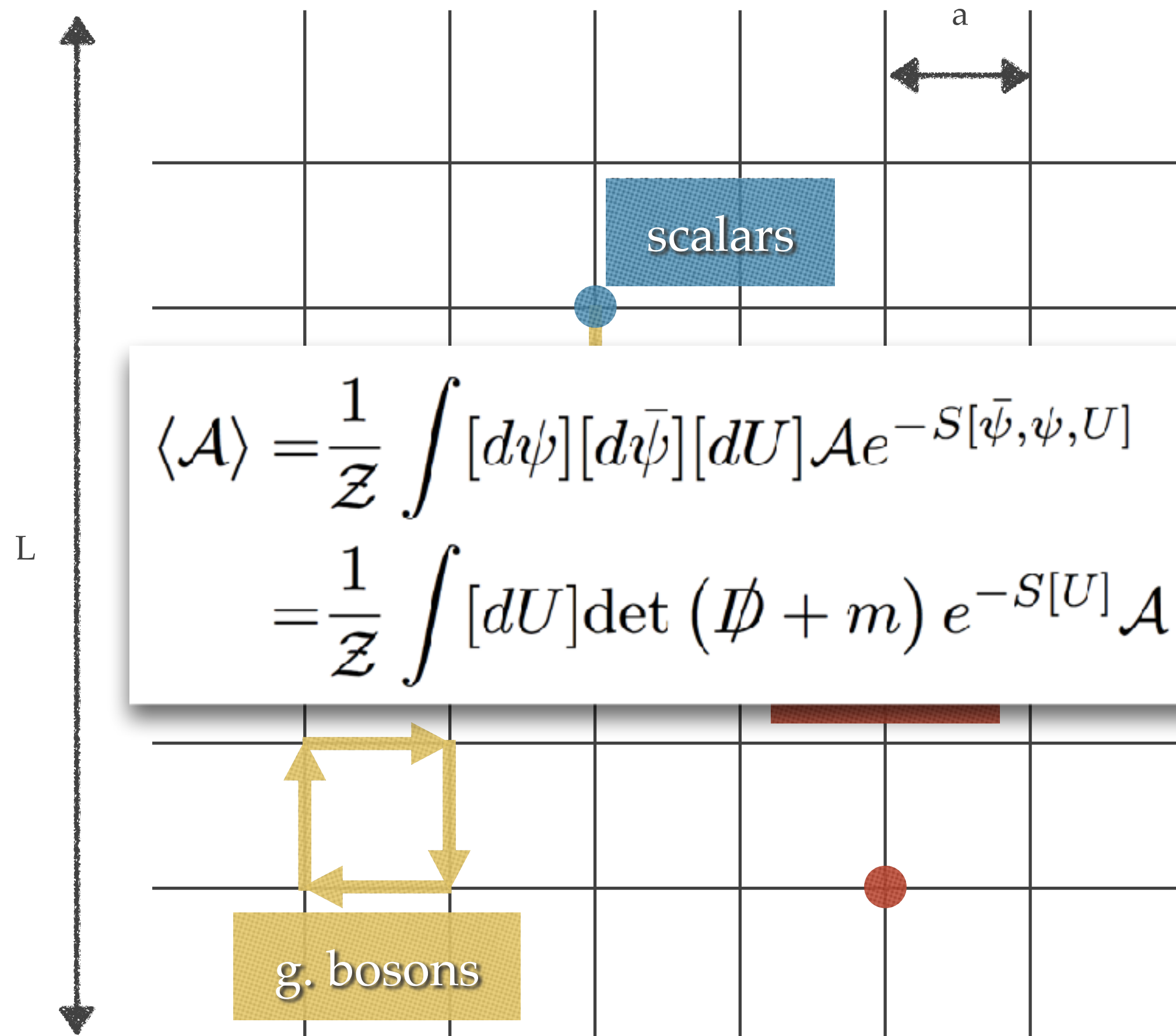
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 - **Statistical**

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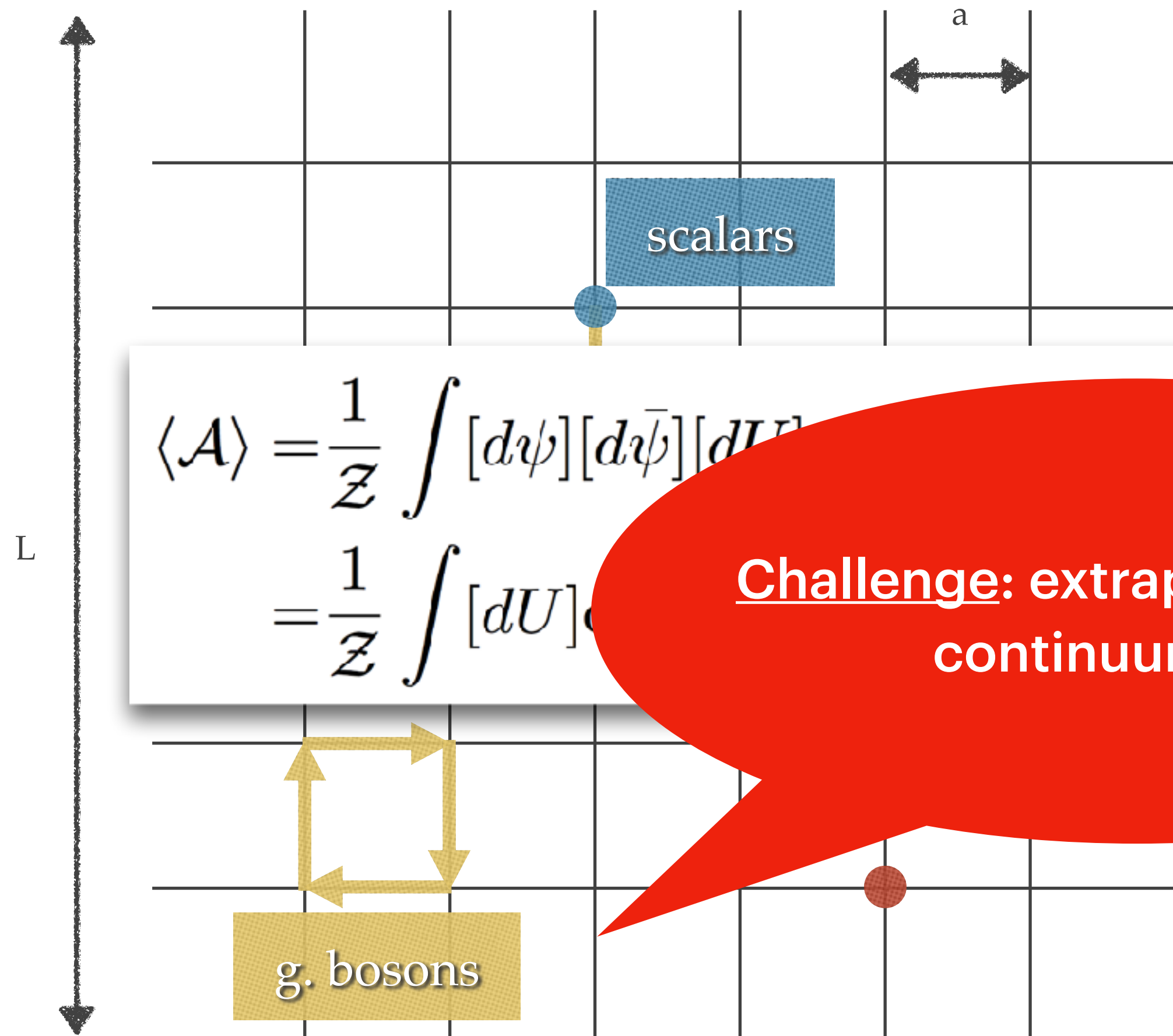
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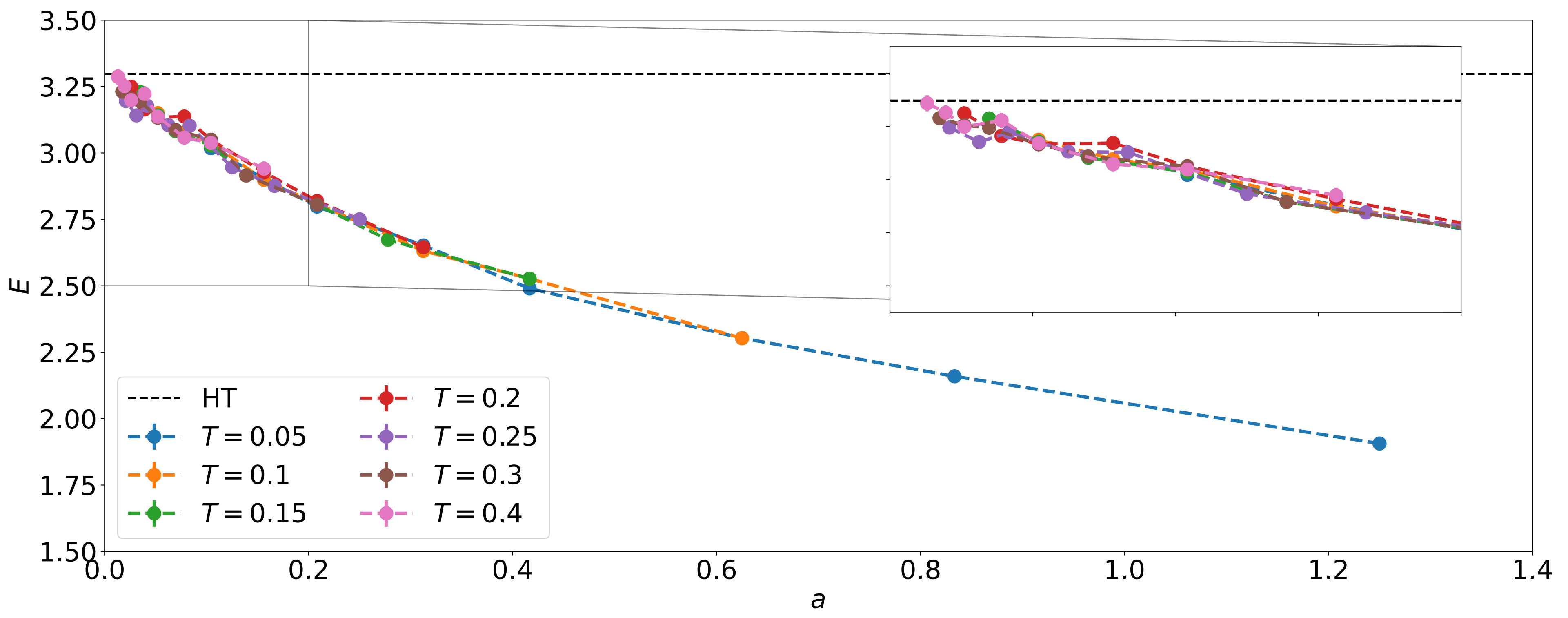
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Results

Small-scale: N=2, D=2

No truncation Λ

- Parameters:**
- Temperature
 - Number of lattice sites
- Observables:**
- Energy



Results

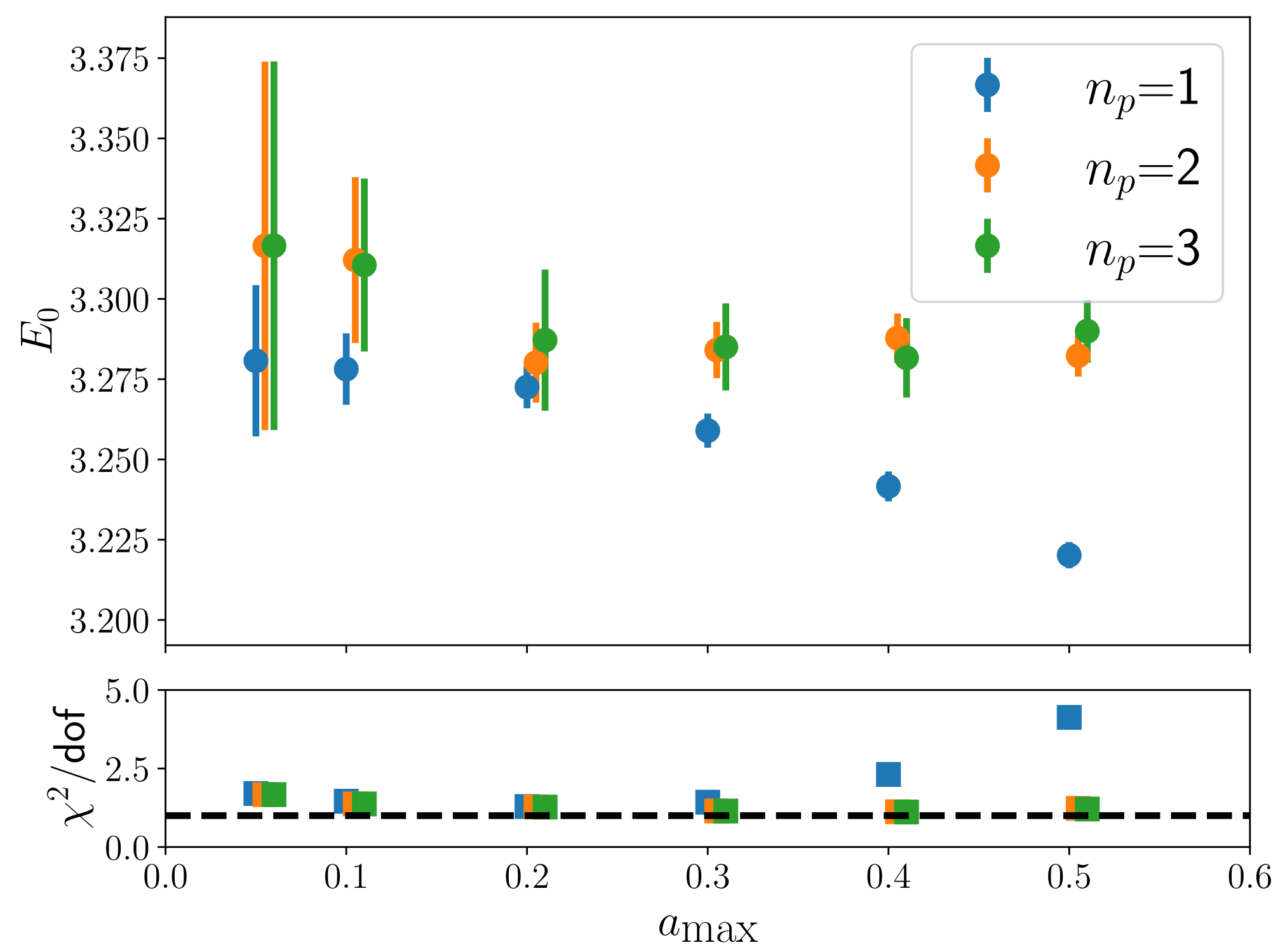
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Global Extrapolation



Results

Small-scale: N=2, D=2

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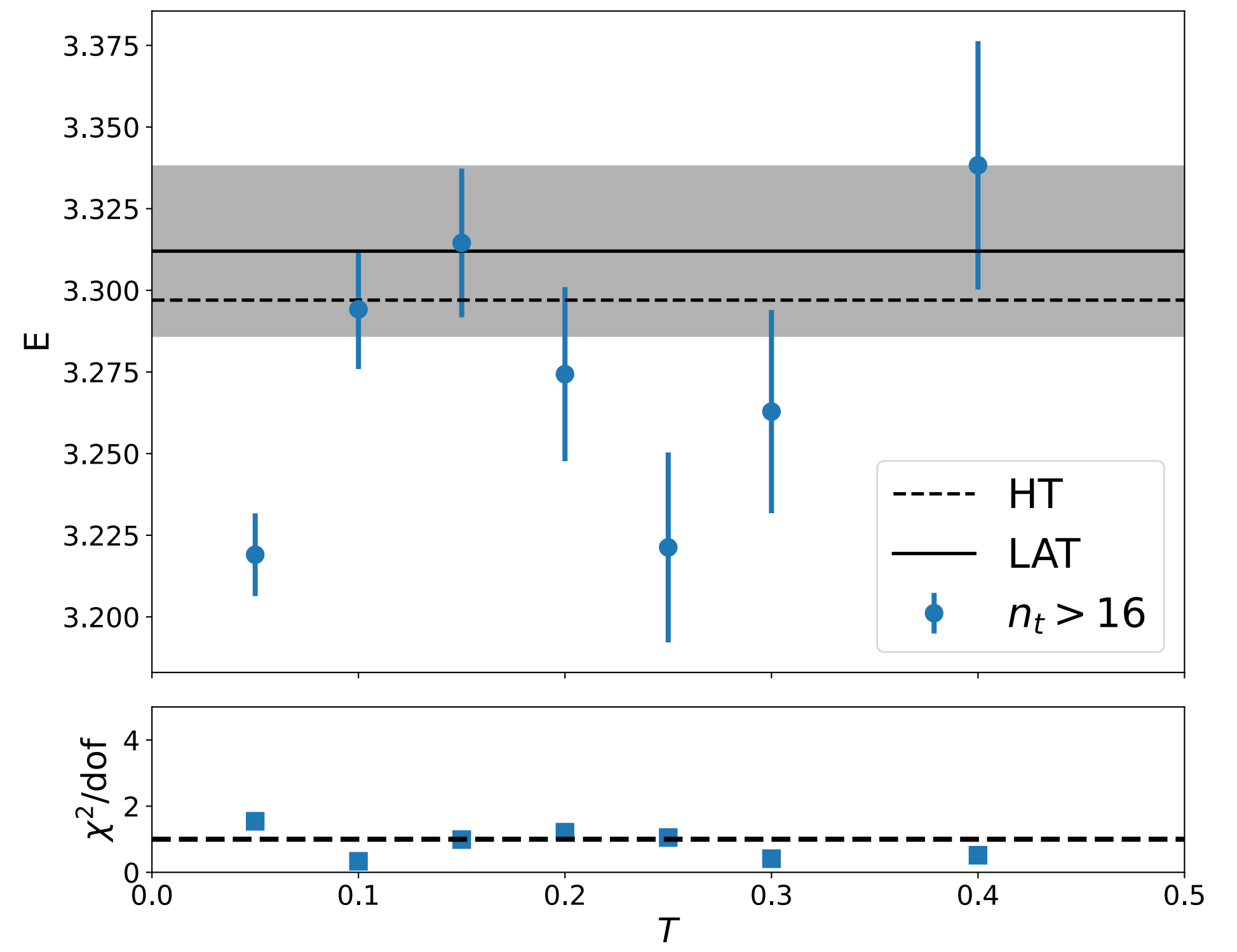
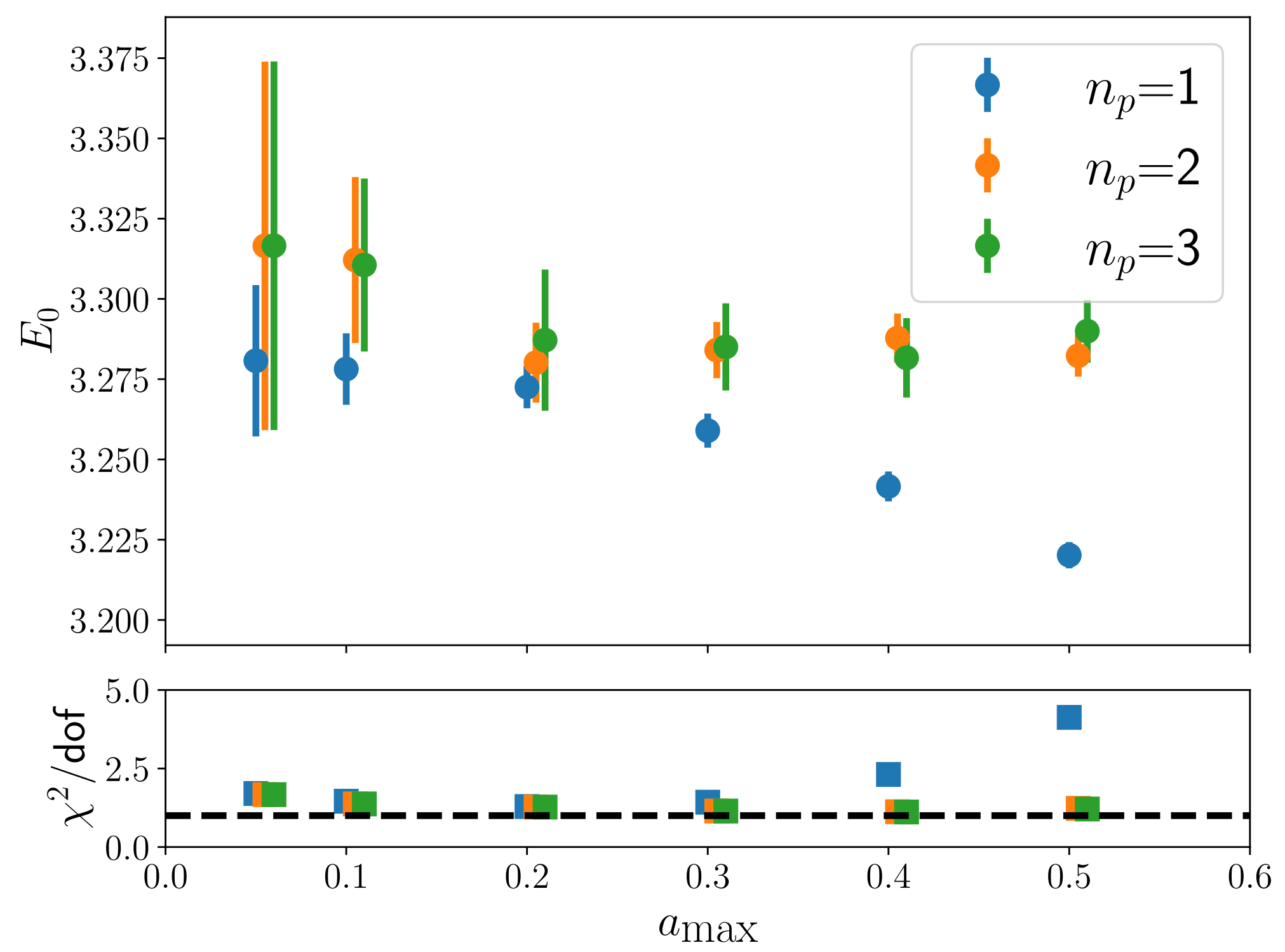
Observables:

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Global Extrapolation

Local Extrapolation

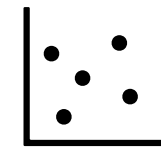
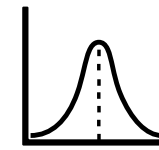
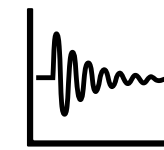
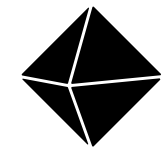
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Comparison

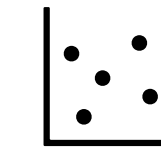
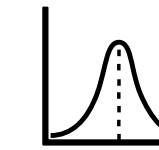
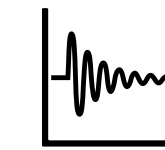
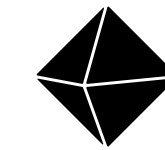
Ground state energy

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	✓	$\Lambda = 4$	✓	✓
N=3	✓	✗	✓	✓
N>3	!!	✗	✓	✓





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)

Conclusions and roadmap

- ✓ Quantum simulations and deep learning can 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. On the road to larger systems!
- ◆ Fast sampling from **generative models** allows an efficient representation of the ground state of matrix models
- ➔ Finding **efficient parametrized quantum circuits** for supersymmetric matrix models is very important: study new PQC construction methods (big industry right now)
- ➔ Using machine learning or tensor network approximations to **simplify quantum simulations** could be crucial with current resources: lead to simpler PQC??
- ➔ **Error-mitigation** will be important on real quantum hardware

LATTICE QUANTUM FIELD THEORY – MATHEMATICS

$$\mathcal{L}_{QCD} = -\frac{1}{4}F^2 + \bar{\psi}(i\not{D} + m)\psi$$

$$\langle \mathcal{O} \rangle = \frac{1}{\mathcal{Z}} \int \mathcal{D}\psi \mathcal{D}\bar{\psi} \mathcal{D}U e^{-S[\bar{\psi}, \psi, U]} \mathcal{O}$$

$$\{U_1, U_2, U_3, \dots, U_N\}$$

$$\approx \frac{1}{N} \sum_{i=1}^N \mathcal{O}[U_i] + O\left(\frac{1}{\sqrt{N}}\right)$$

MICROSCOPIC THEORY OF FIELDS

ψ : quark field

U : gauge field

QUANTUM FEYNMAN PATH INTEGRAL

Physical observable

DISCRETIZE

Makes integral finite dimens.

MARKOV CHAIN MONTE CARLO

Sampling

IMPORTANCE SAMPLING

Estimator

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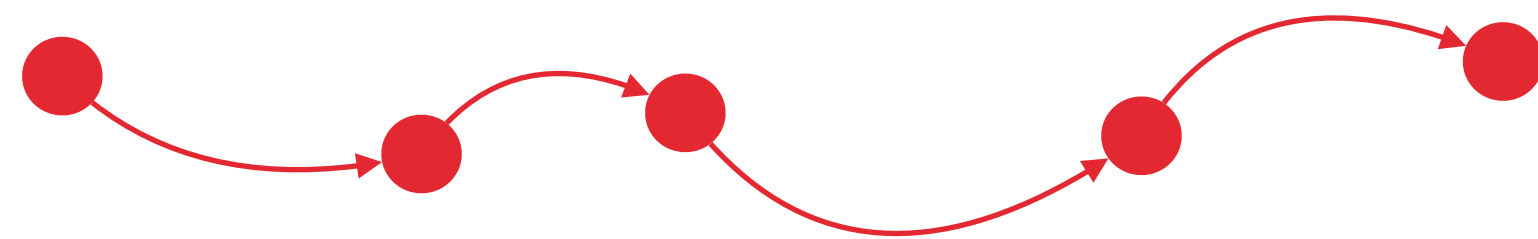
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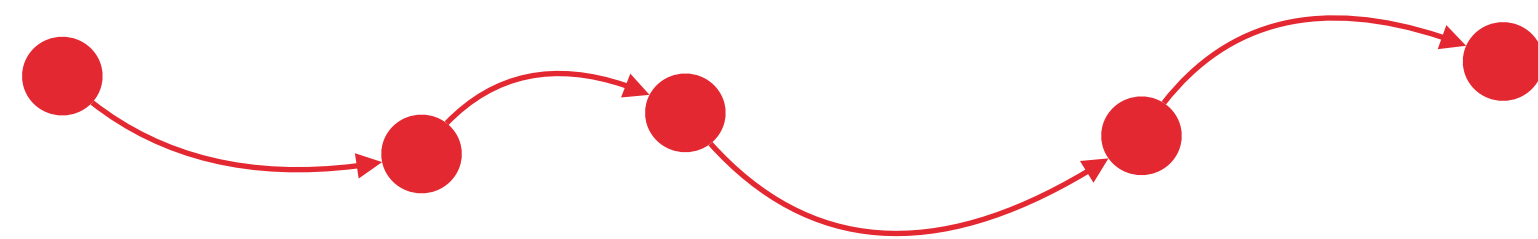
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move in configuration space with prob.

MARKOV CHAIN MONTE CARLO

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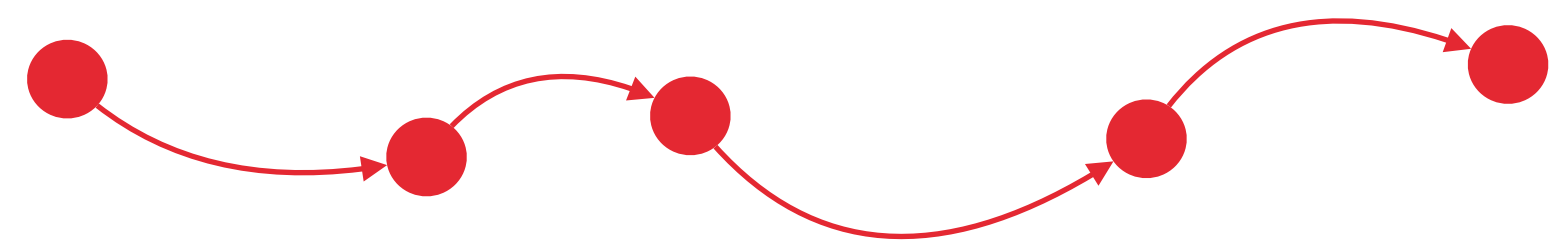
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move in configuration space with prob.

MARKOV CHAIN MONTE CARLO

Sampling

$$\approx \frac{1}{N} \sum_{i=1}^N \mathcal{O}[U_i] + \underbrace{O\left(\frac{1}{\sqrt{N}}\right)}_{\text{statistical error}}$$

statistical error

IMPORTANCE SAMPLING

Estimator