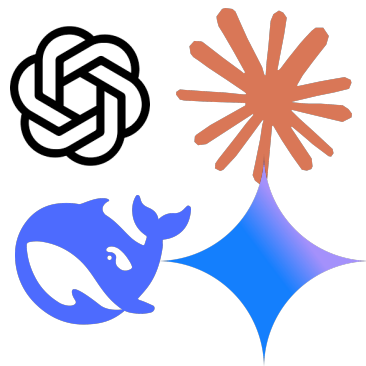


Scalable iPEPS Simulations in the Era of AD and GPUs

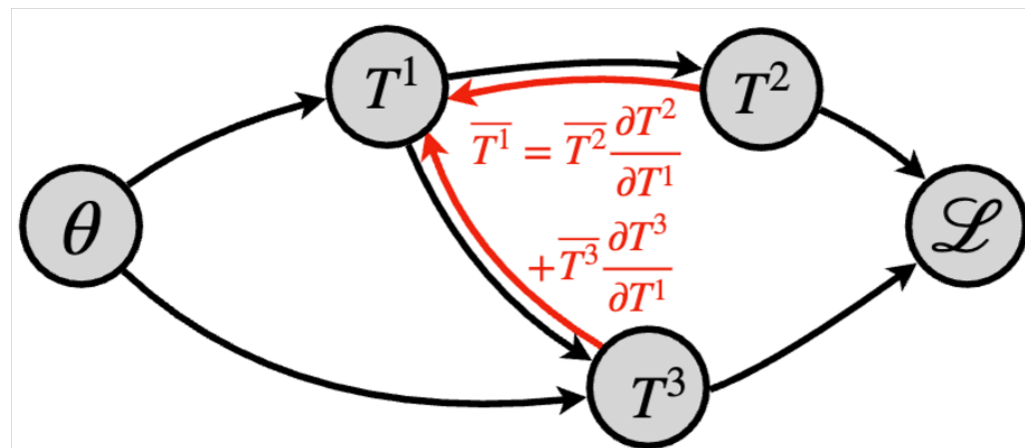
Presenter: Qi Yang @



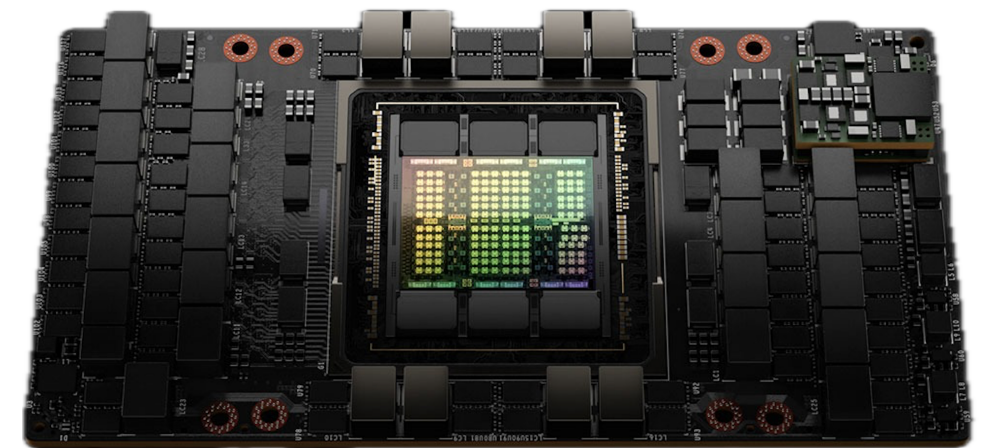
UNIVERSITY
OF AMSTERDAM



We want larger Models !!
We want better PyTorch !!



Automatic Differentiation



Modern GPUs



Can we take a ride?

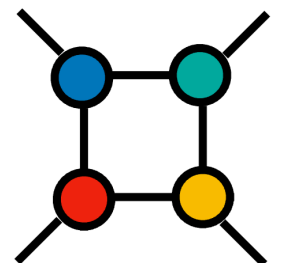
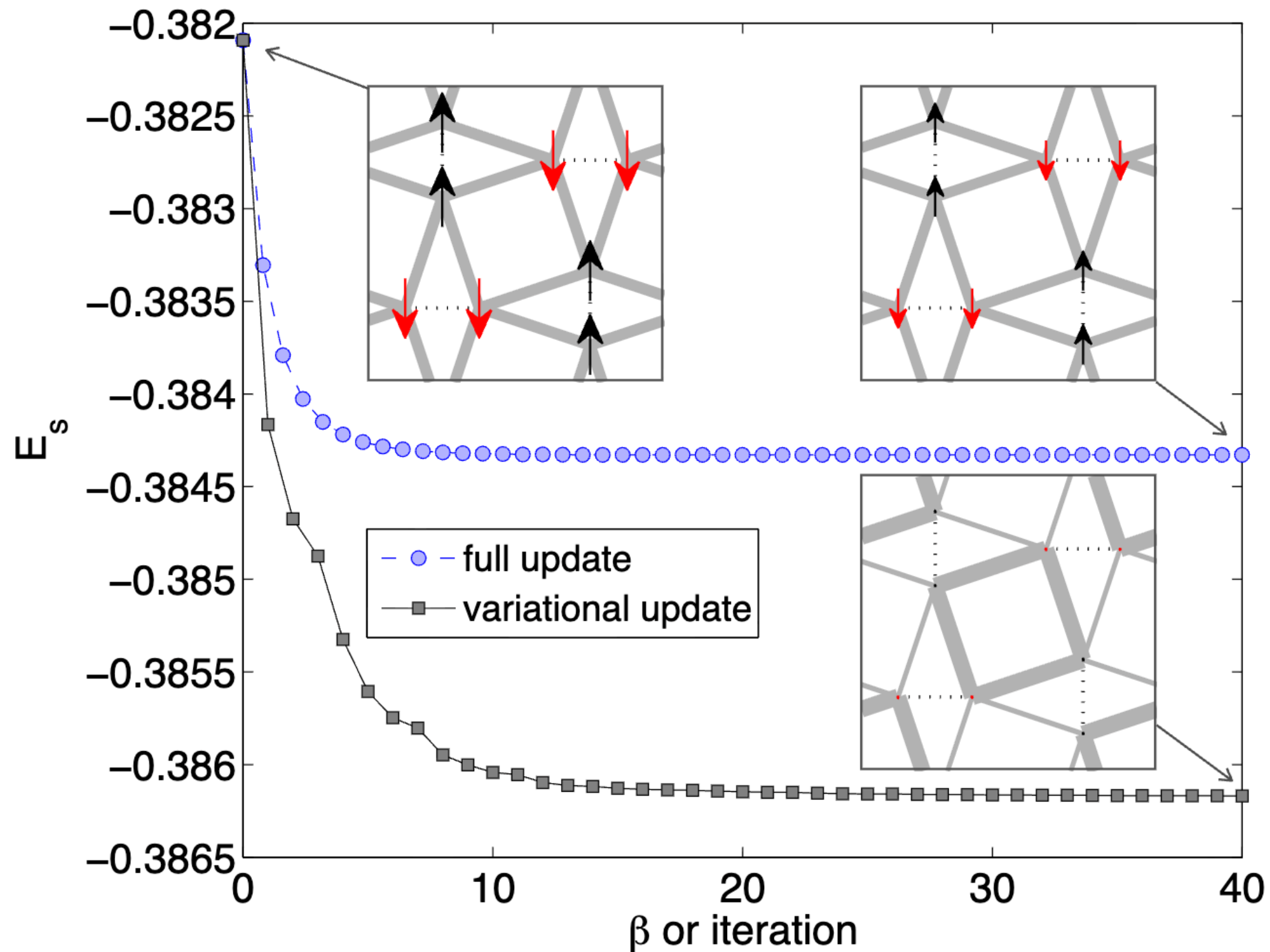


Table of contents

- A brief introduction of AD and iPEPS
- QRCTM: A powerful method hiding in plain sight for 29 years.
- Application: High Spin Kitaev model
- Riemannian optimization for iPEPS
- Technical Tricks

A brief introduction of AD: Why AD?



A brief introduction of AD: Backward

Scalar

$$E = E(\mathbf{x}_N) \quad \mathbf{x}_{n+1} = f_n(\mathbf{x}_n)$$



Jacobian

$$\frac{\partial E}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_3} \frac{\partial \mathbf{x}_3}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \dots = \partial_N E \times \prod_{i=1}^{N-1} \partial_i f_i(x_i)$$

A brief introduction of AD: Backward

Scalar

$$E = E(\mathbf{x}_N) \quad \mathbf{x}_{n+1} = f_n(\mathbf{x}_n)$$



Jacobian

$$\frac{\partial E}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_3} \frac{\partial \mathbf{x}_3}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \dots = \partial_N E \times \prod_{i=1}^{N-1} \partial_i f_i(x_i)$$

$$\text{Step 1: } G_N = \partial_N E, G_i = \partial_i E$$

$$\text{Step i: } G_{i-1} = G_i \times \partial_{i-1} f_{i-1}(x_{i-1})$$

How to know it?

Case 1: Reversible functions, e.g. $f(x) = x^3, \partial_x f = 3x^2 = 3(f(x))^{2/3}$

A brief introduction of AD: Backward

Scalar

$$E = E(\mathbf{x}_N) \quad \mathbf{x}_{n+1} = f_n(\mathbf{x}_n)$$



Jacobian

$$\frac{\partial E}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \frac{\partial E}{\partial \mathbf{x}_3} \frac{\partial \mathbf{x}_3}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \dots = \partial_N E \times \prod_{i=1}^{N-1} \partial_i f_i(x_i)$$

$$\text{Step 1: } G_N = \partial_N E, G_i = \partial_i E$$

$$\text{Step i: } G_{i-1} = G_i \times \partial_{i-1} f_{i-1}(x_{i-1})$$

How to know it?

Case 1: Reversible functions, e.g. $f(x) = x^3, \partial_x f = 3x^2 = 3(f(x))^{2/3}$

Case 2: other functions, e.g. $f(x) = \cos(x) \rightarrow$ **Cache x! Bottleneck!**

D=12, chi=1536, each tensor: 2.7Gb

Variational optimization with AD

One sentence introduction of its application for iPEPS

Once you can calculate: $\langle \psi(A) | H | \psi(A) \rangle$

You automatically get: $\partial_A \langle \psi(A) | H | \psi(A) \rangle$

Liao, Liu, Wang, Xiang, PRX (2019)

Instead of summing over manually:

$$\tilde{C}_1 = \text{blue square} = \text{sum of terms with blue squares in different positions} + \dots$$

$$\tilde{T}_4 = \text{blue horizontal bar} = \text{sum of terms with blue bars in different positions} + \dots$$

$$\tilde{C}_{v1} = \text{blue vertical bar} = \text{sum of terms with blue bars in different positions} + \dots$$

Corboz, PRB.94.035133 (2016)

A brief introduction of AD: Forward

Vector

$$\mathbf{y} = \mathbf{x}_N \quad \mathbf{x}_{n+1} = f_n(\mathbf{x}_n)$$



$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}_1} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}_3} \frac{\partial \mathbf{x}_3}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \dots = \partial_N \mathbf{y} \times \prod_{i=1}^{N-1} \partial_i f_i(x_i)$$

But you only want to know $\Delta \mathbf{y} = \partial_1 \mathbf{y} \times \Delta x_1$

A brief introduction of AD: Forward

Vector

$$\mathbf{y} = \mathbf{x}_N \quad \mathbf{x}_{n+1} = f_n(\mathbf{x}_n)$$



$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}_1} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}_3} \frac{\partial \mathbf{x}_3}{\partial \mathbf{x}_2} \frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1} = \dots = \partial_N \mathbf{y} \times \prod_{i=1}^{N-1} \partial_i f_i(x_i)$$

But you only want to know $\Delta \mathbf{y} = \partial_1 \mathbf{y} \times \Delta x_1$

Step 1: $x_1, \Delta x_1$

Step i: $x_{i+1} = f_i(x_i) \quad \Delta x_{i+1} = \partial_i f_i \times \Delta x_i$

Faster and Cache Free!

A brief introduction of AD: Unified framework

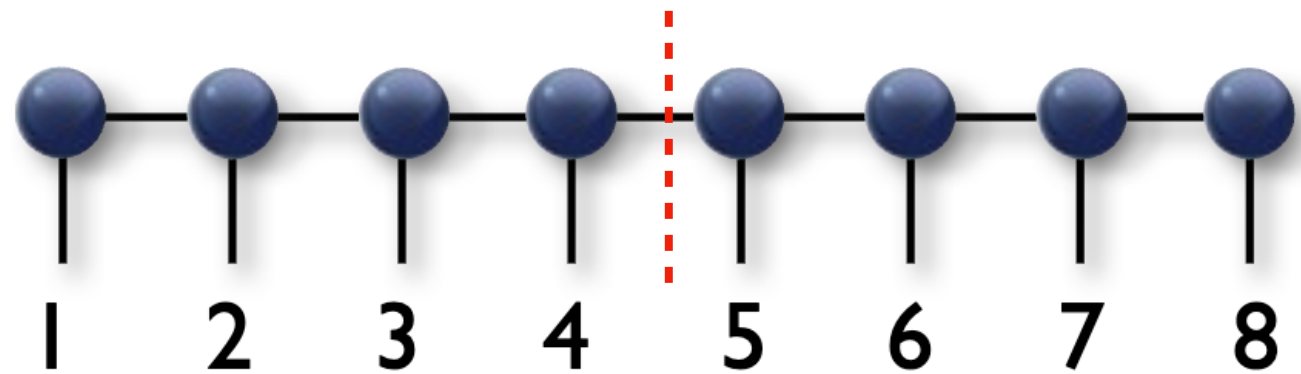
$$\begin{array}{c} \text{Apple} \times \prod_i \frac{\partial x_{i+1}}{\partial x_i} \times \text{Orange} \\ \xrightarrow{\text{Bwd}} \quad \quad \quad \xleftarrow{\text{Fwd}} \end{array}$$

Backward mode:		dim 1	Energy
		dim N	Gradients
Forward mode:		dim N	Tangents
		dim 1	Step size

From MPS to PEPS: entanglement entropy

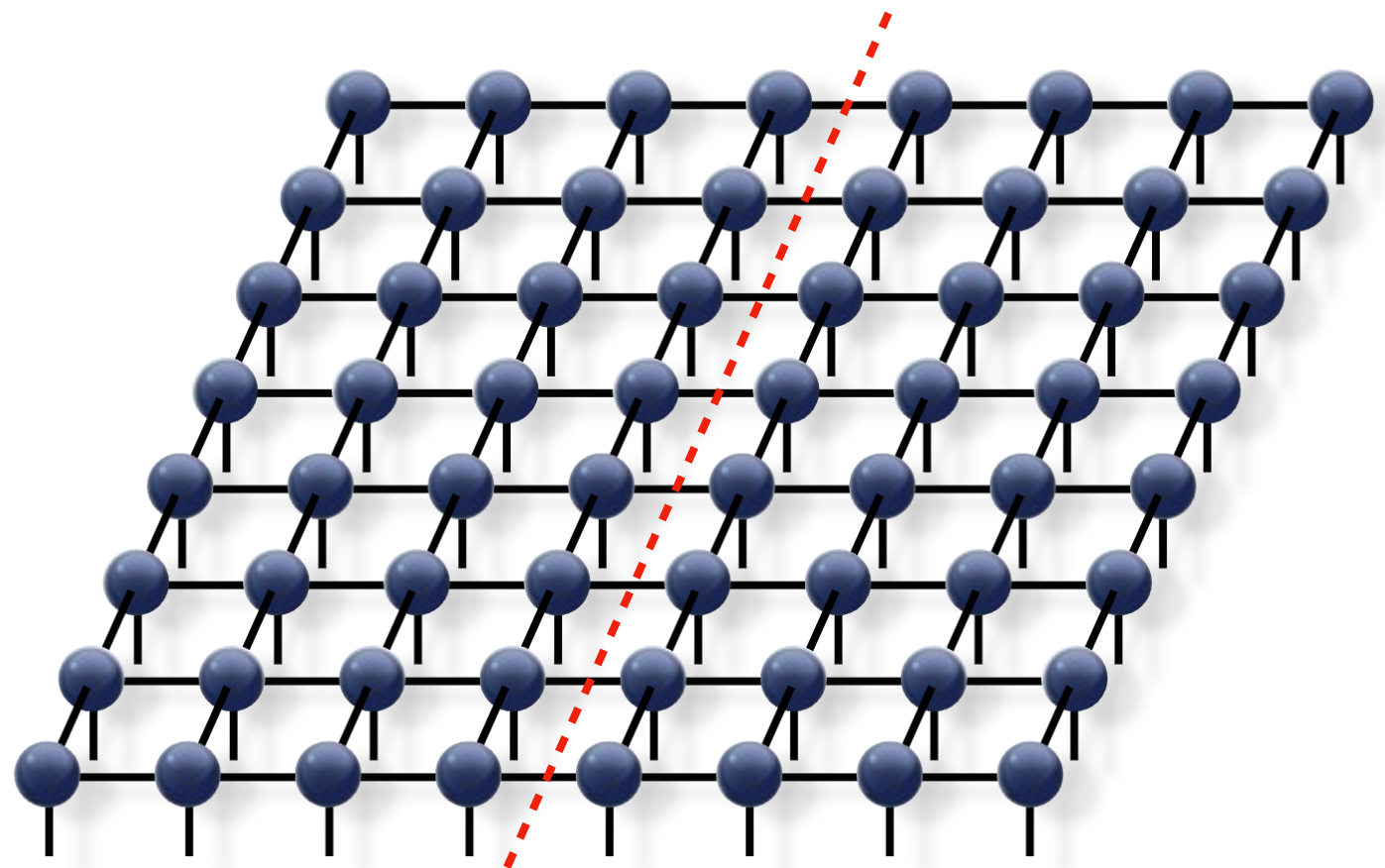
Gapped 2D system Area Law(argued): $S \sim L$

1D MPS $|\psi\rangle =$
 $S < \ln(D)$



Matrix Product states

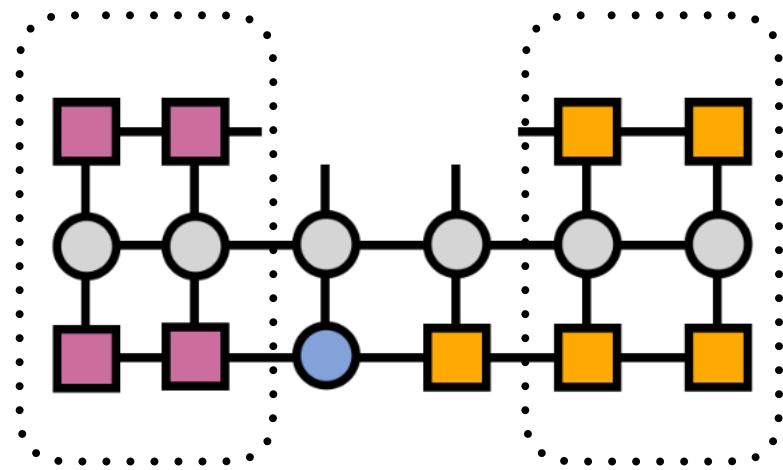
2D PEPS $|\psi\rangle =$
 $S < L \ln(D)$



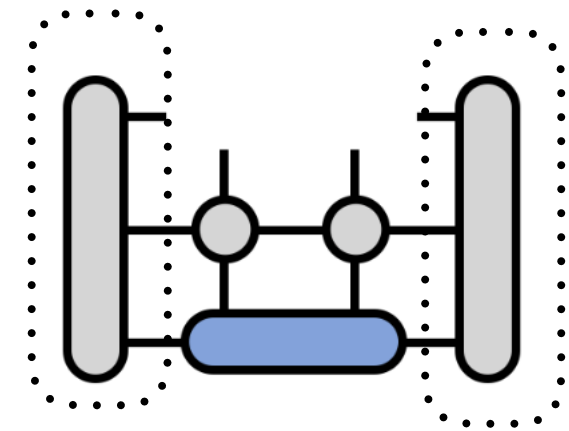
Projected entangled pair states

Environments: Exact vs Approximated.

1D MPS

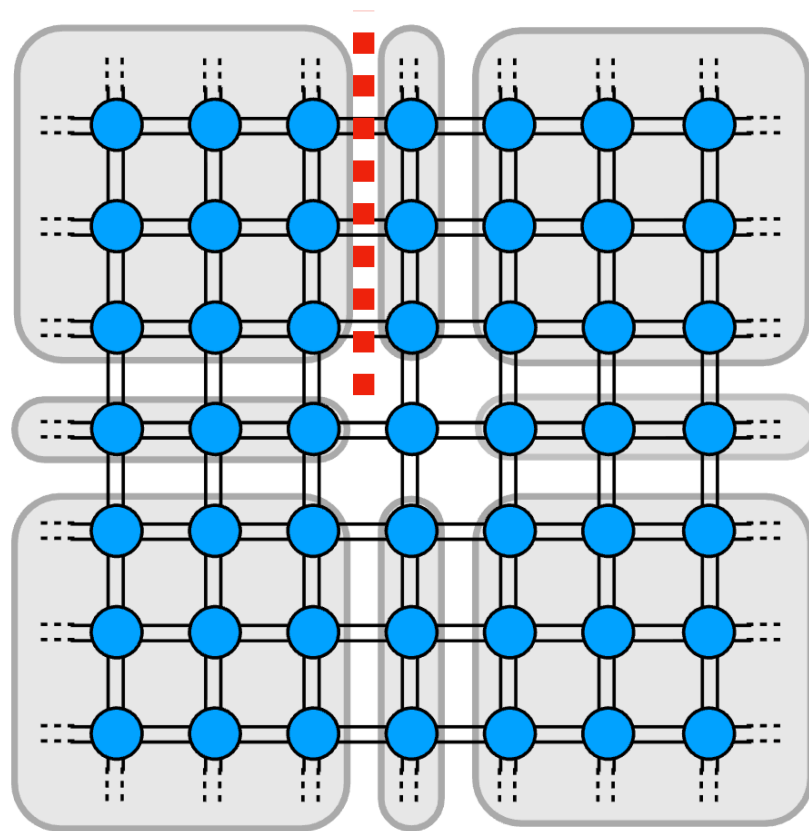
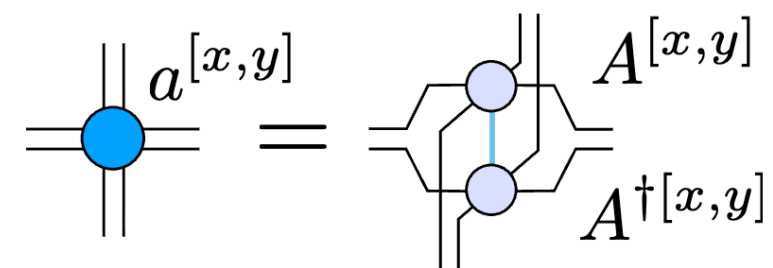


=

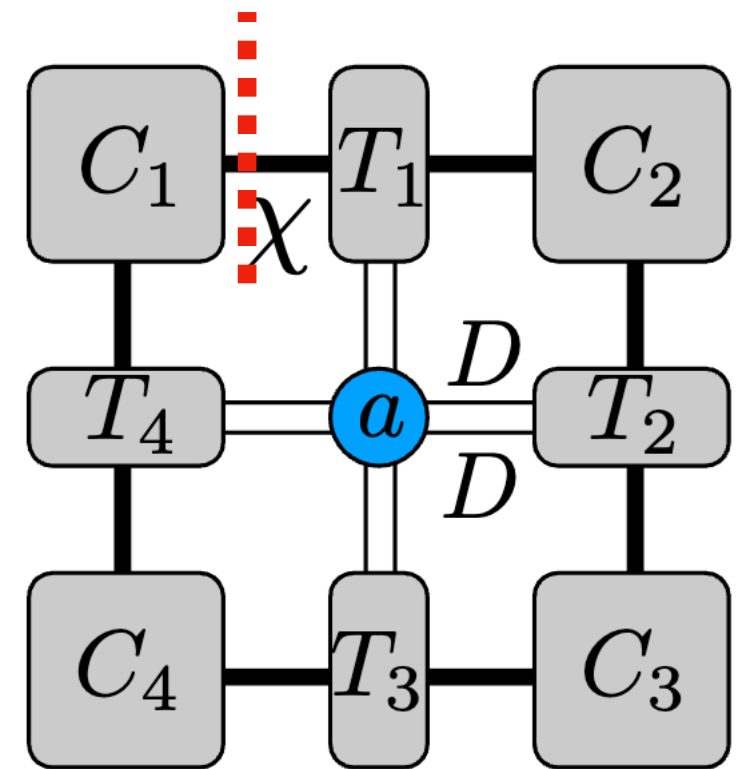


Exact Env

2D PEPS

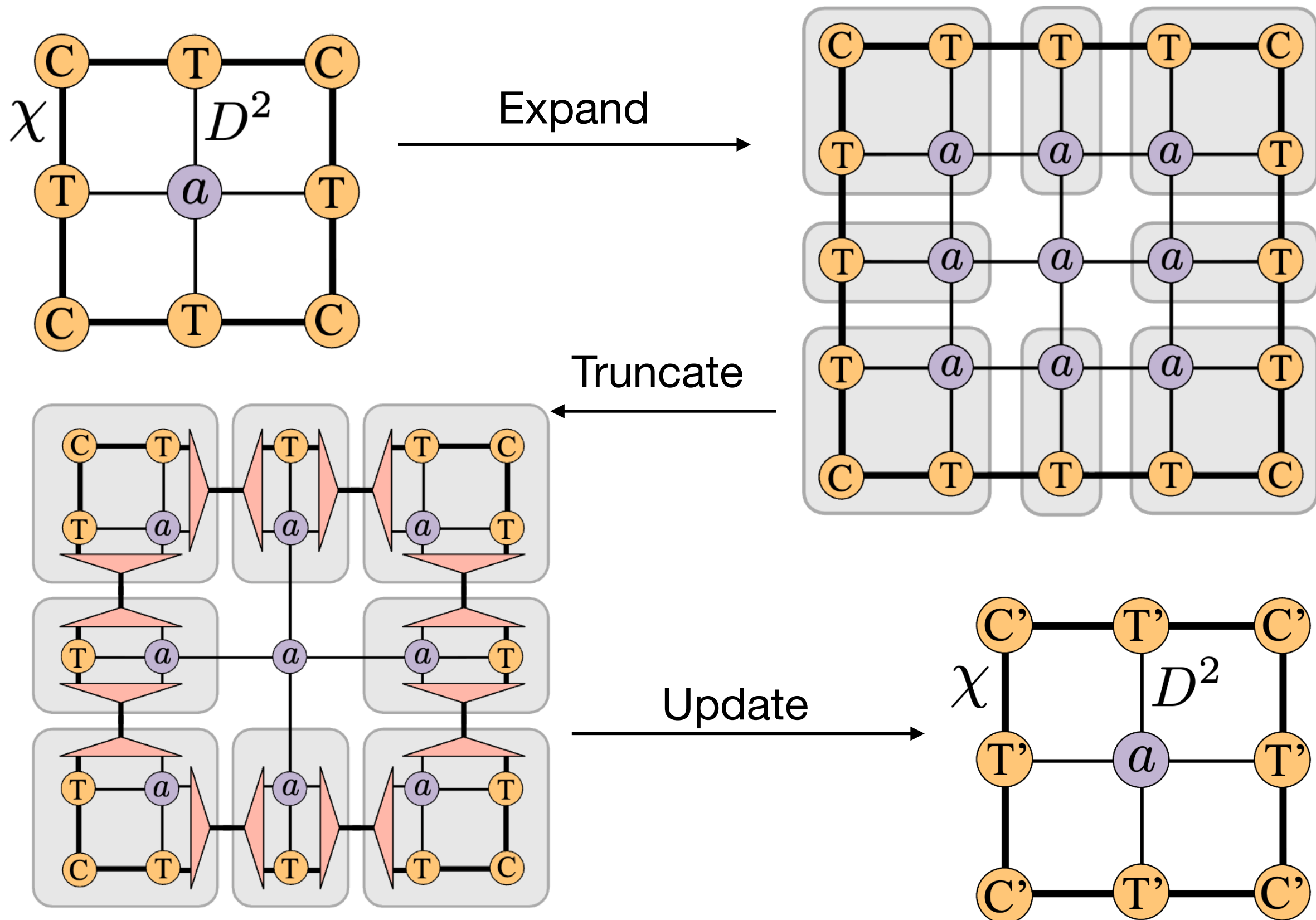


=

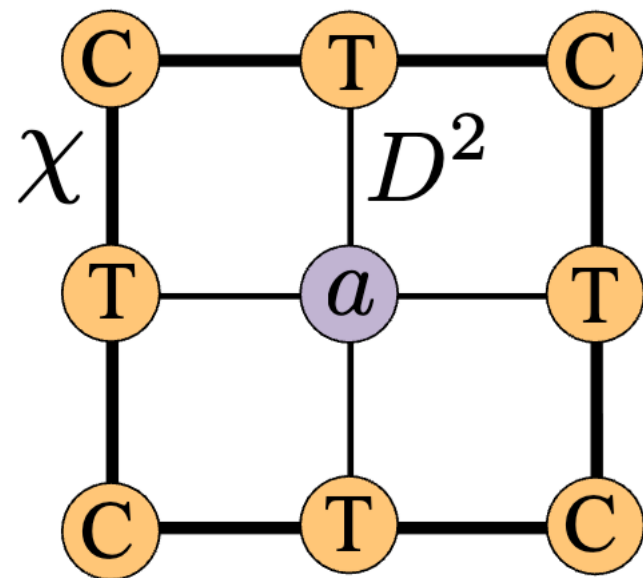


Approximated env

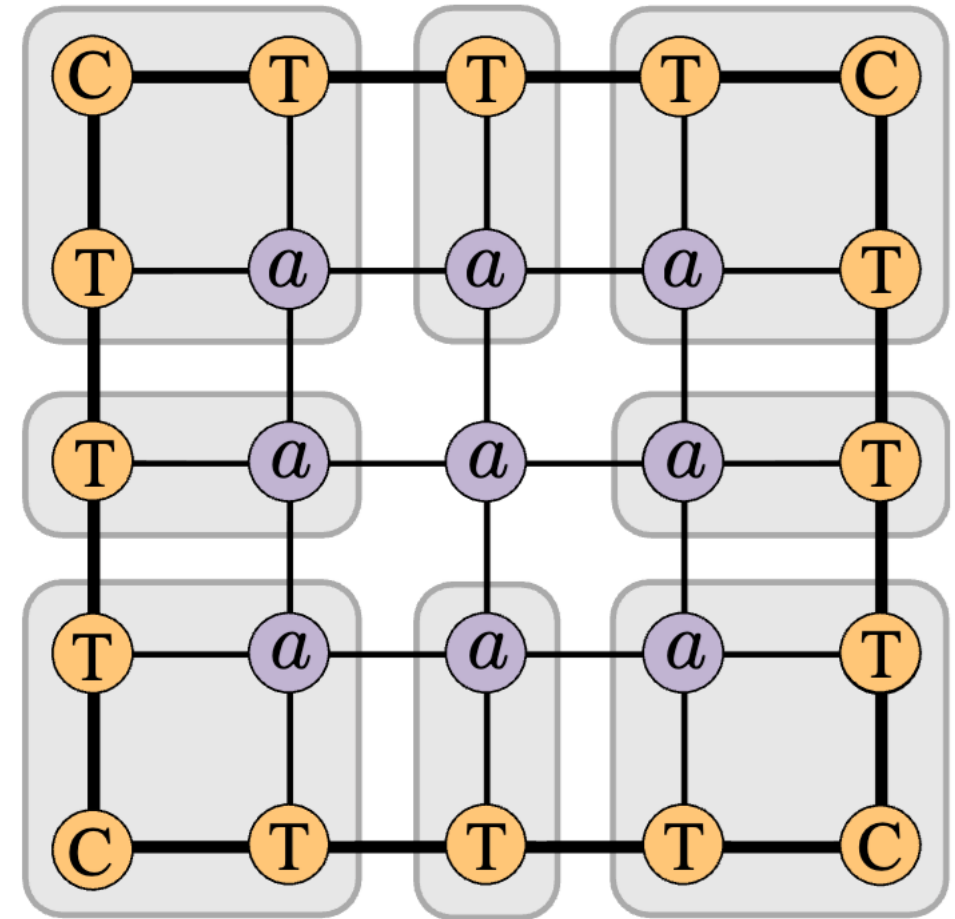
Textbook C4v CTMRG iterations



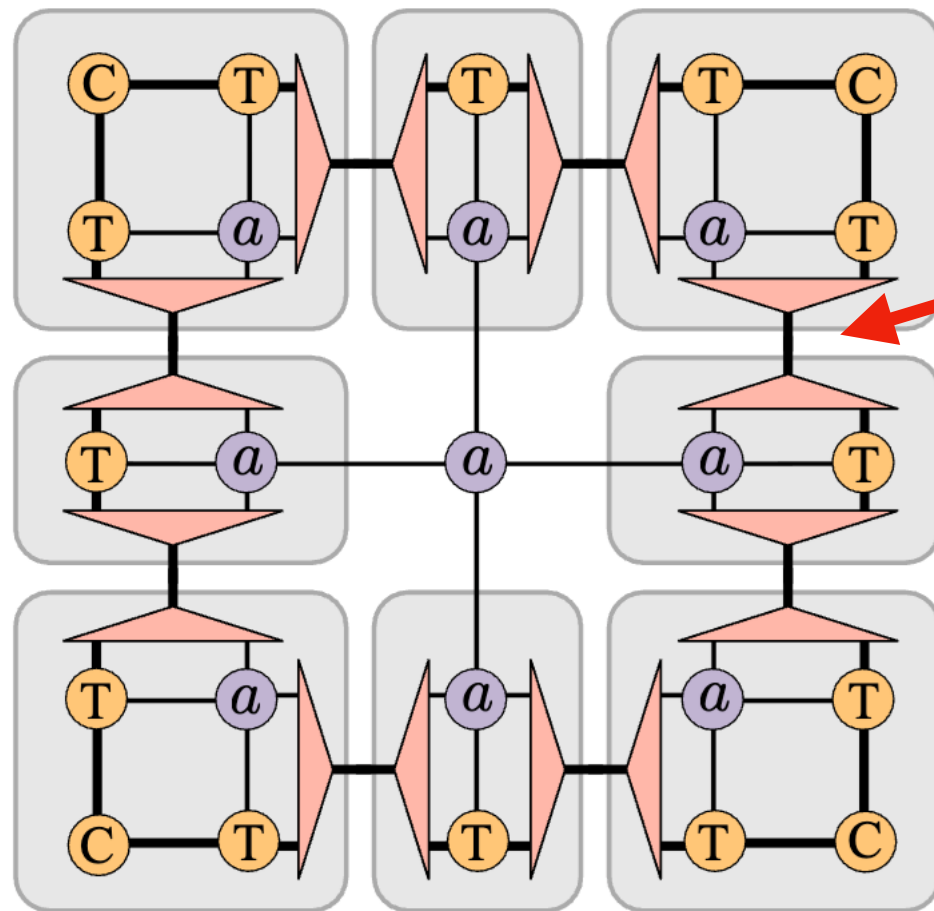
Projectors?



Expand

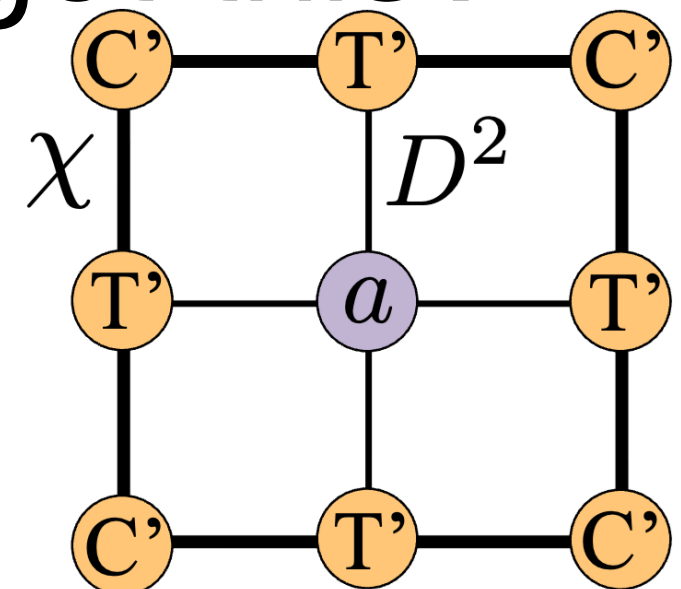


Truncate

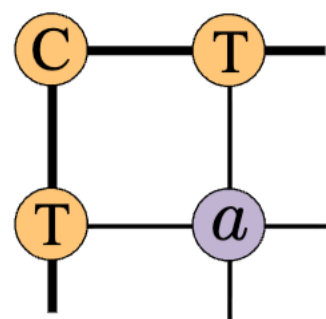
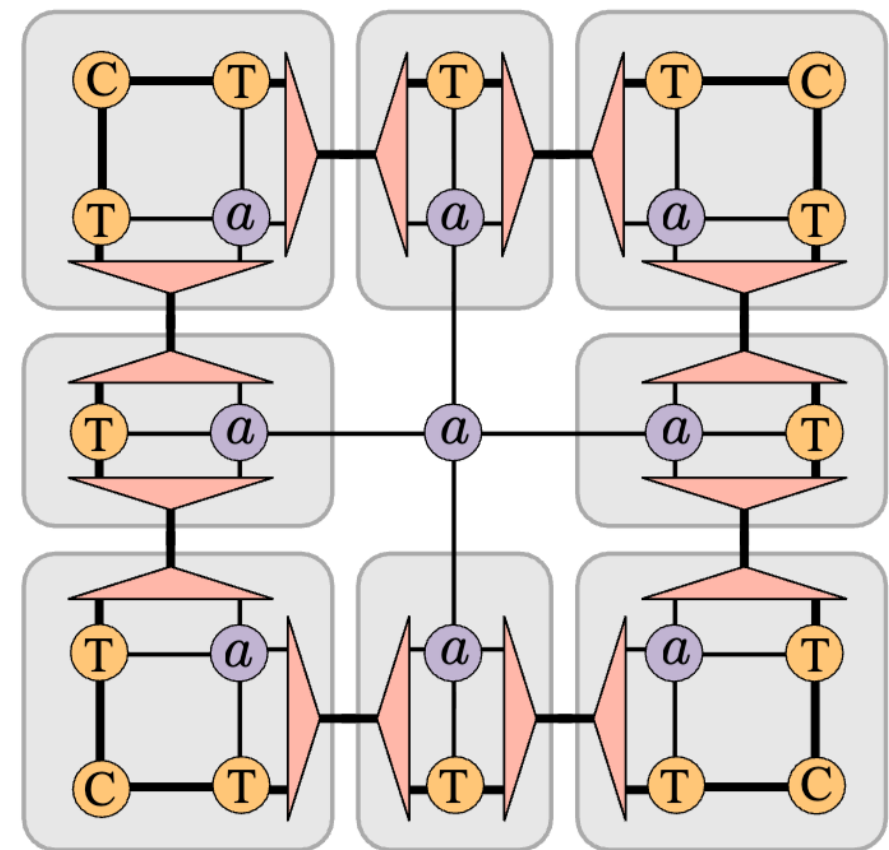
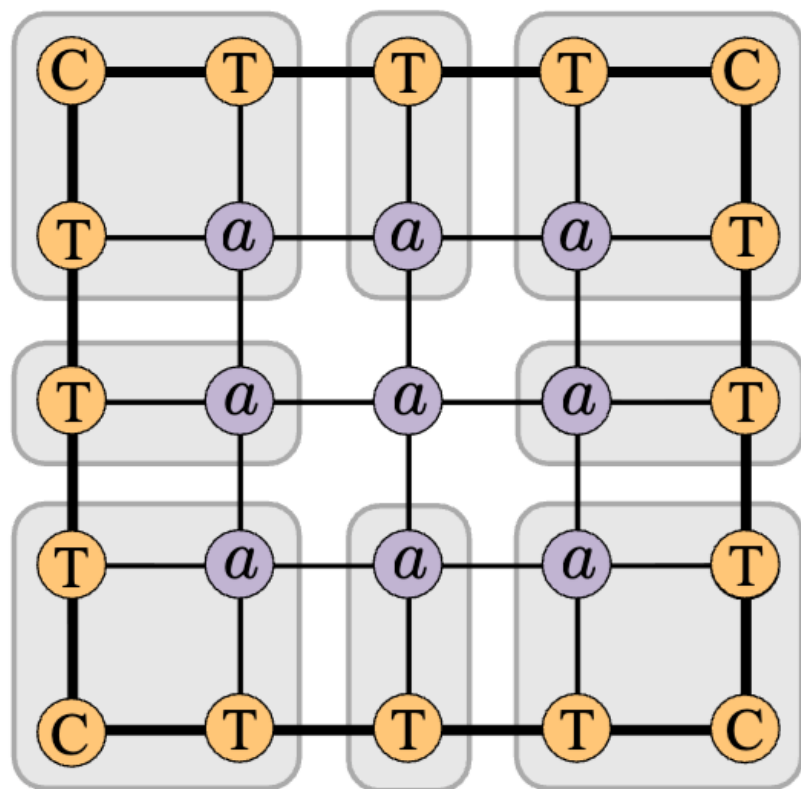


? How to get this?

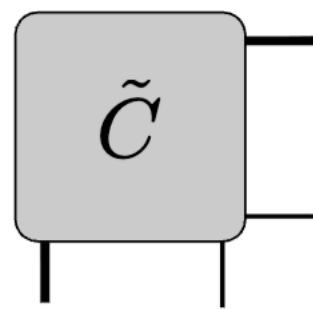
Update



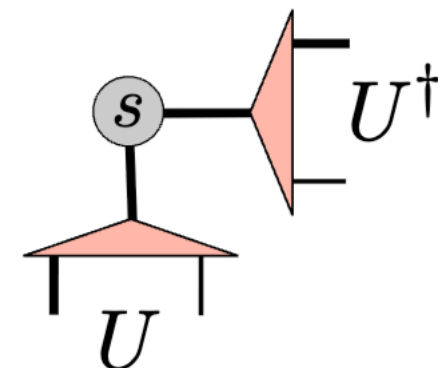
By diagonalizing enlarged corner



$=$

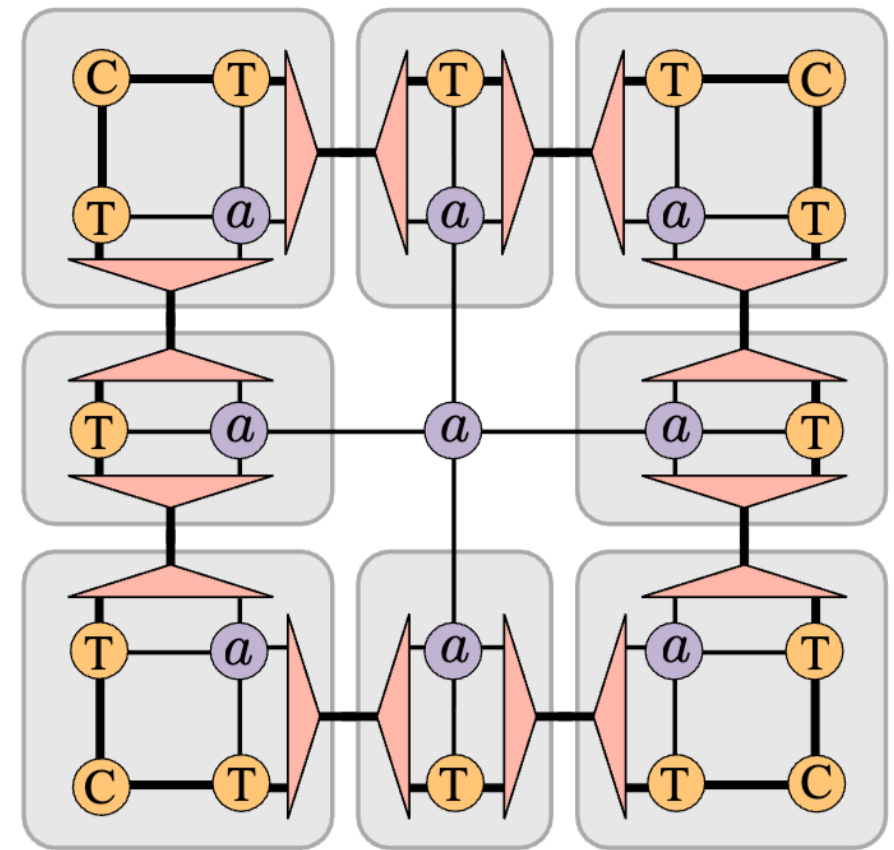
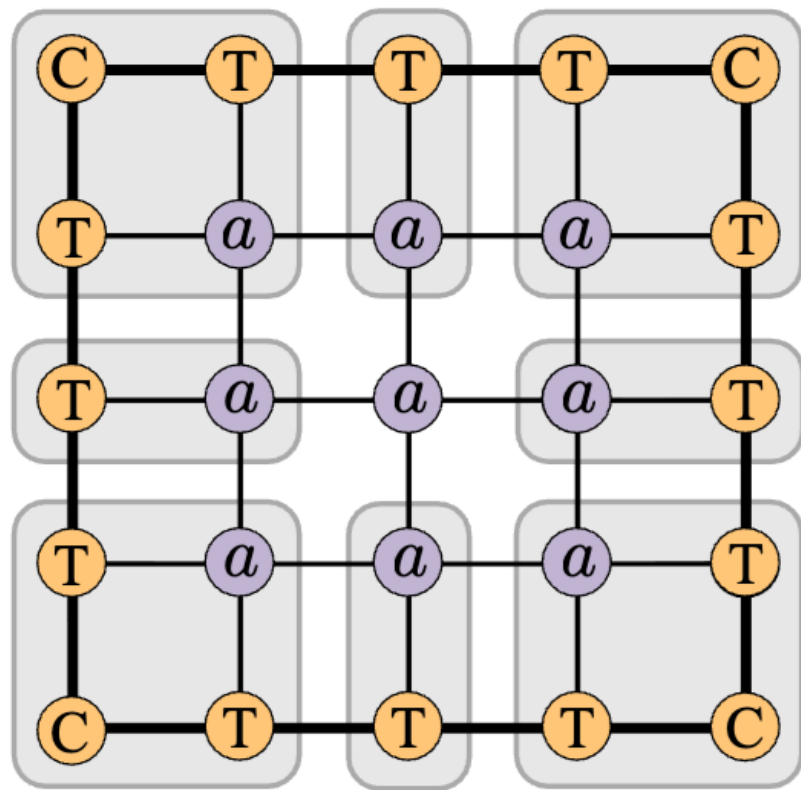


$\approx$



$(\chi D^2) \times (\chi D^2)$ SVD/eigh

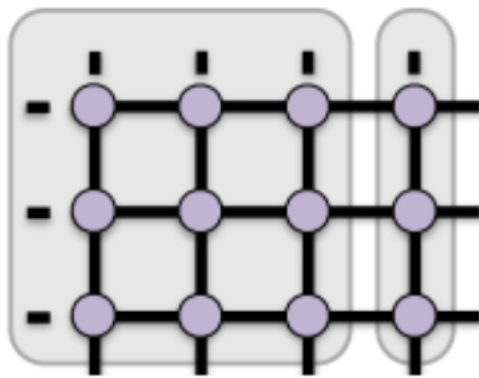
A method hiding in plain sight for 29 years?



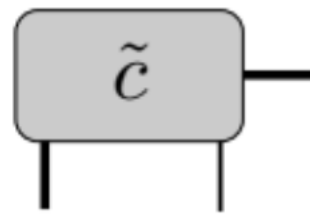
$$\begin{array}{c} \text{C} \\ | \end{array} - \begin{array}{c} \text{T} \\ | \end{array} = \begin{array}{c} \boxed{\tilde{c}} \\ | \quad | \end{array} = \begin{array}{c} \boxed{R} \\ | \\ \text{Q} \end{array}$$

$(\chi D^2) \times (\chi)$
 QR

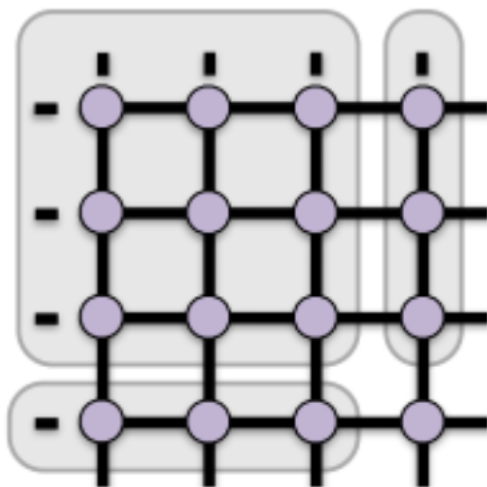
Why this can work?



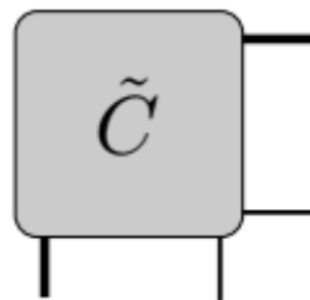
Reduced corner



QR: $(\chi D^2) \times (\chi)$

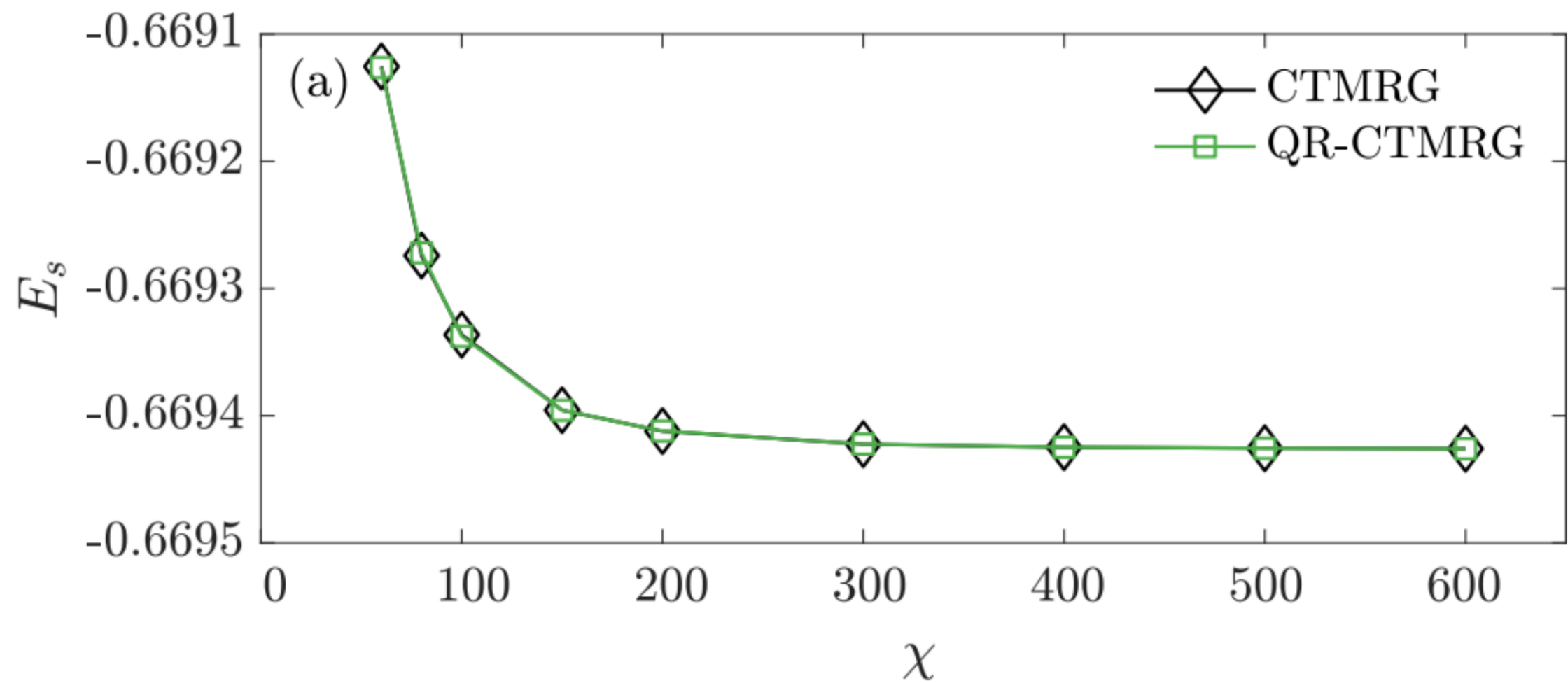


Enlarged corner



SVD: $(\chi D^2) \times (\chi D^2)$

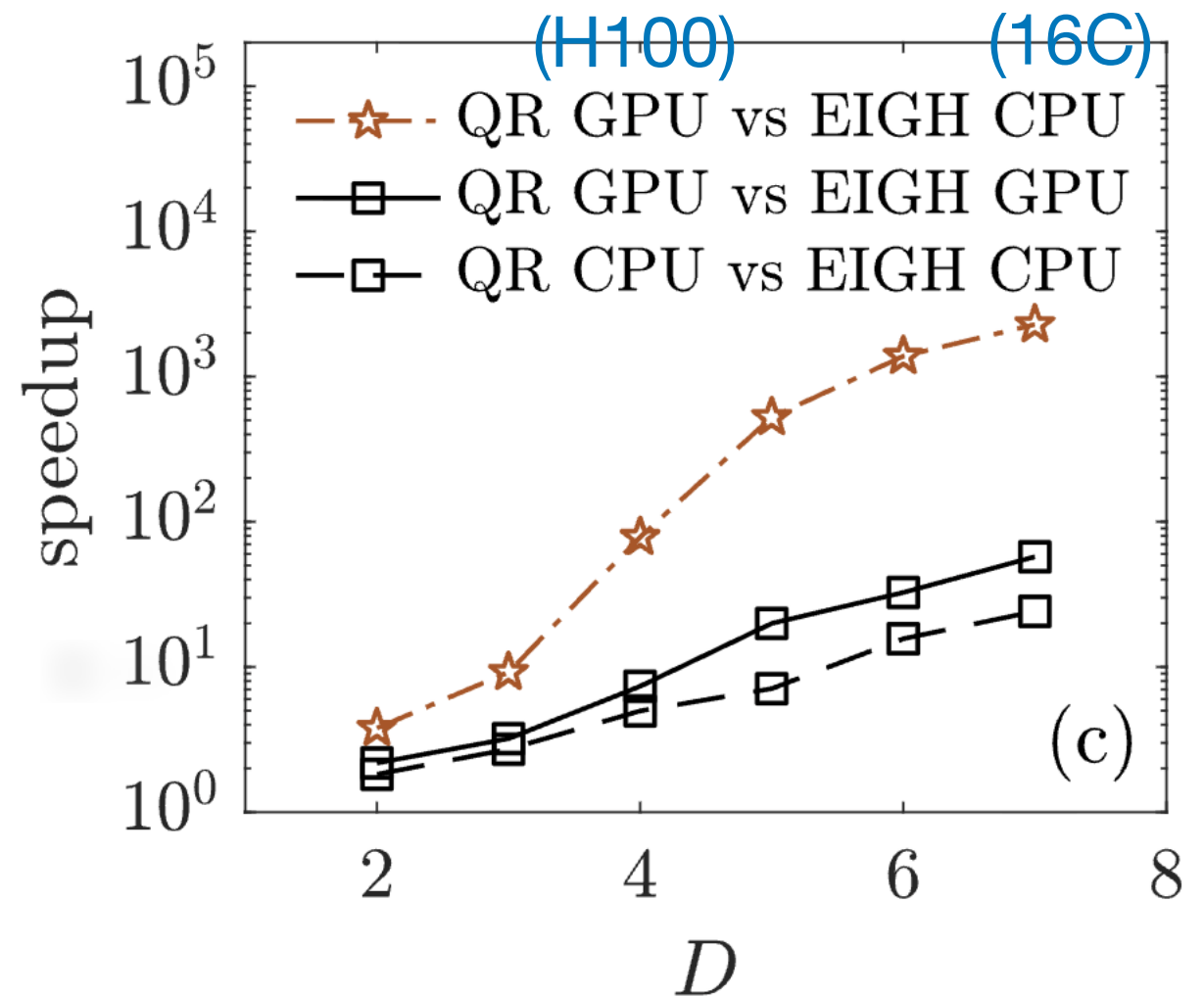
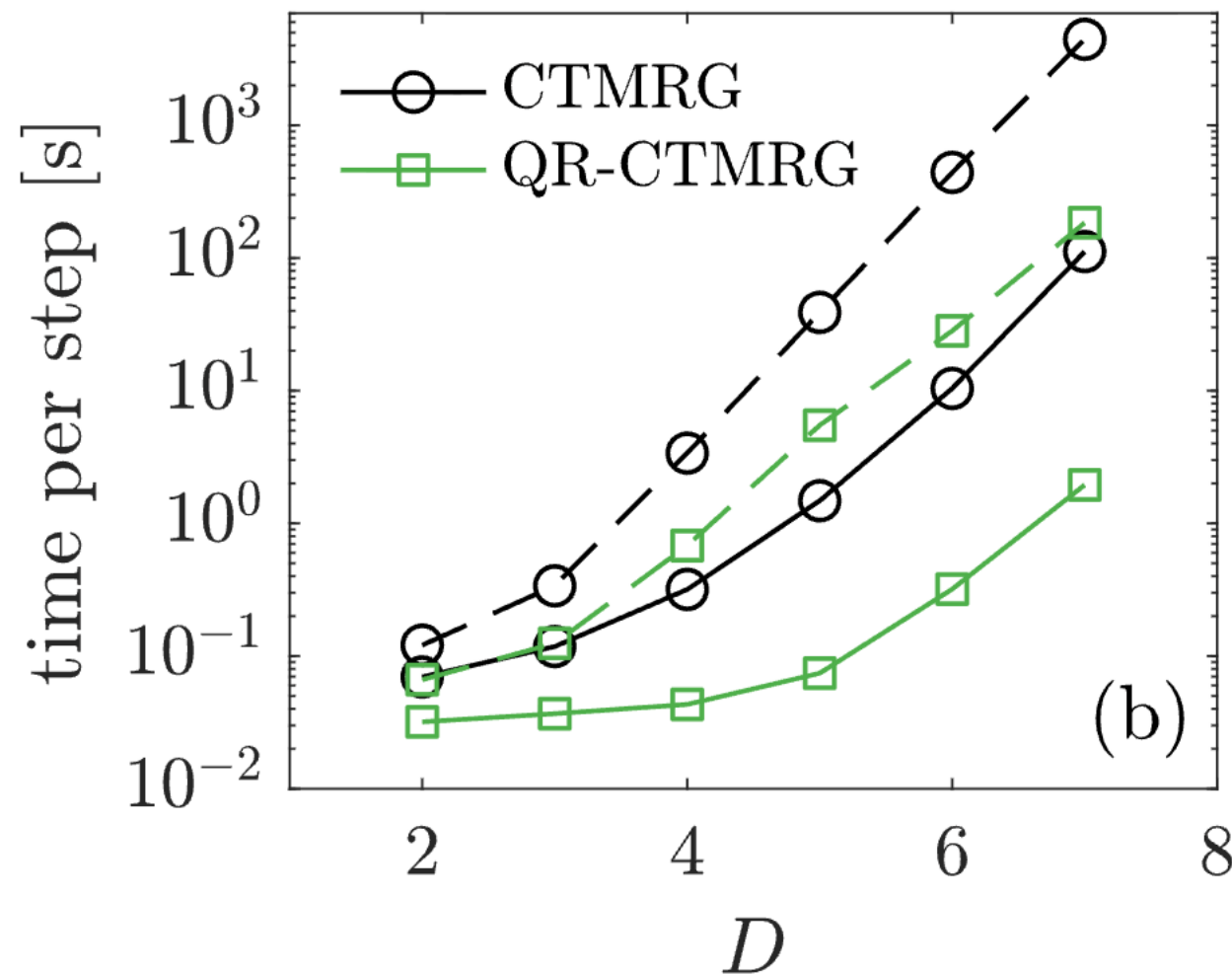
Benchmark with SVD-CTMRG



2D Heisenberg model, $D=6$

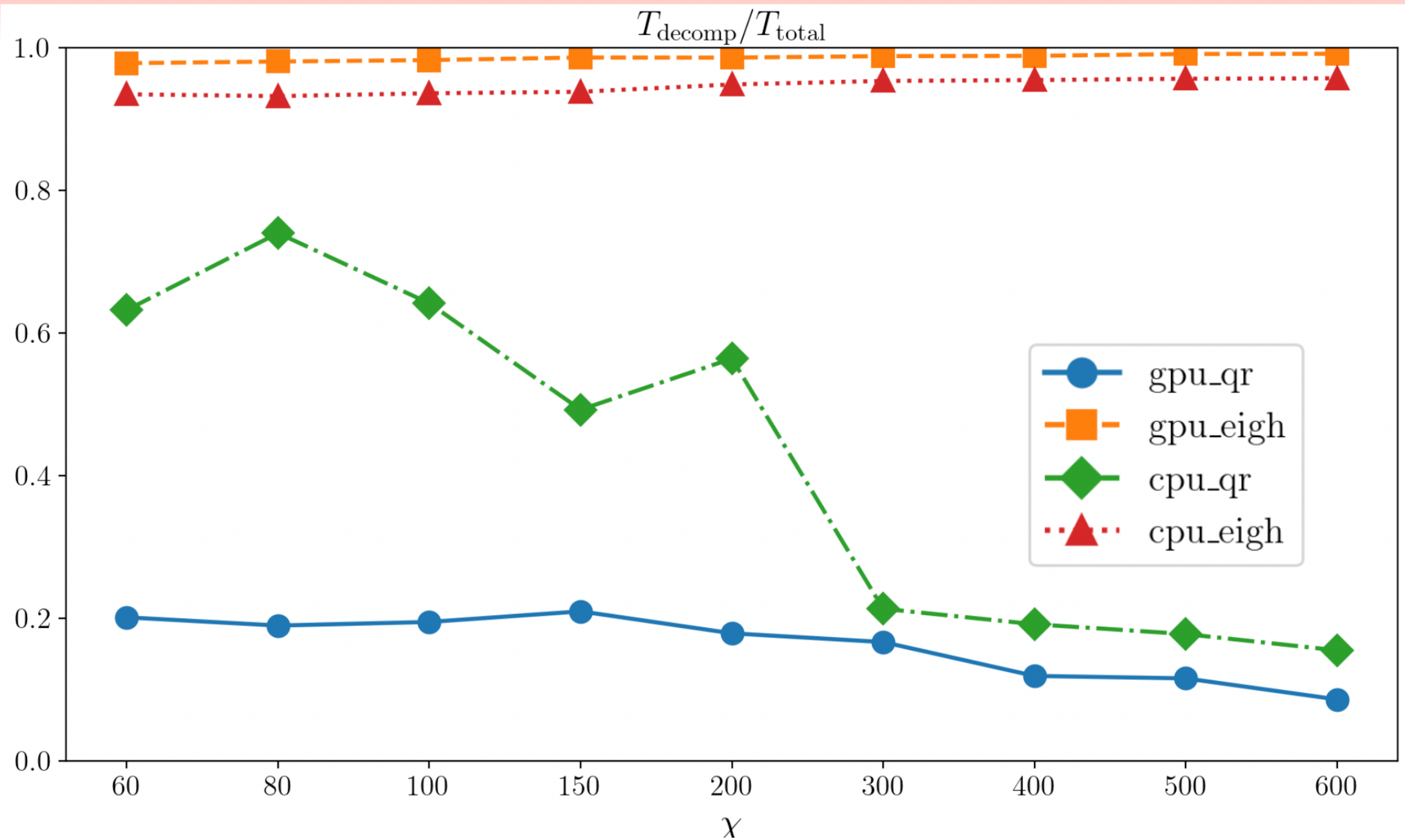
Order of magnitude optimization speed up

2D Heisenberg model, $\chi = 5D^2$



Even complexity are the same, pre-factor of SVD is very large

Reason: Contraction become dominant



GEMM



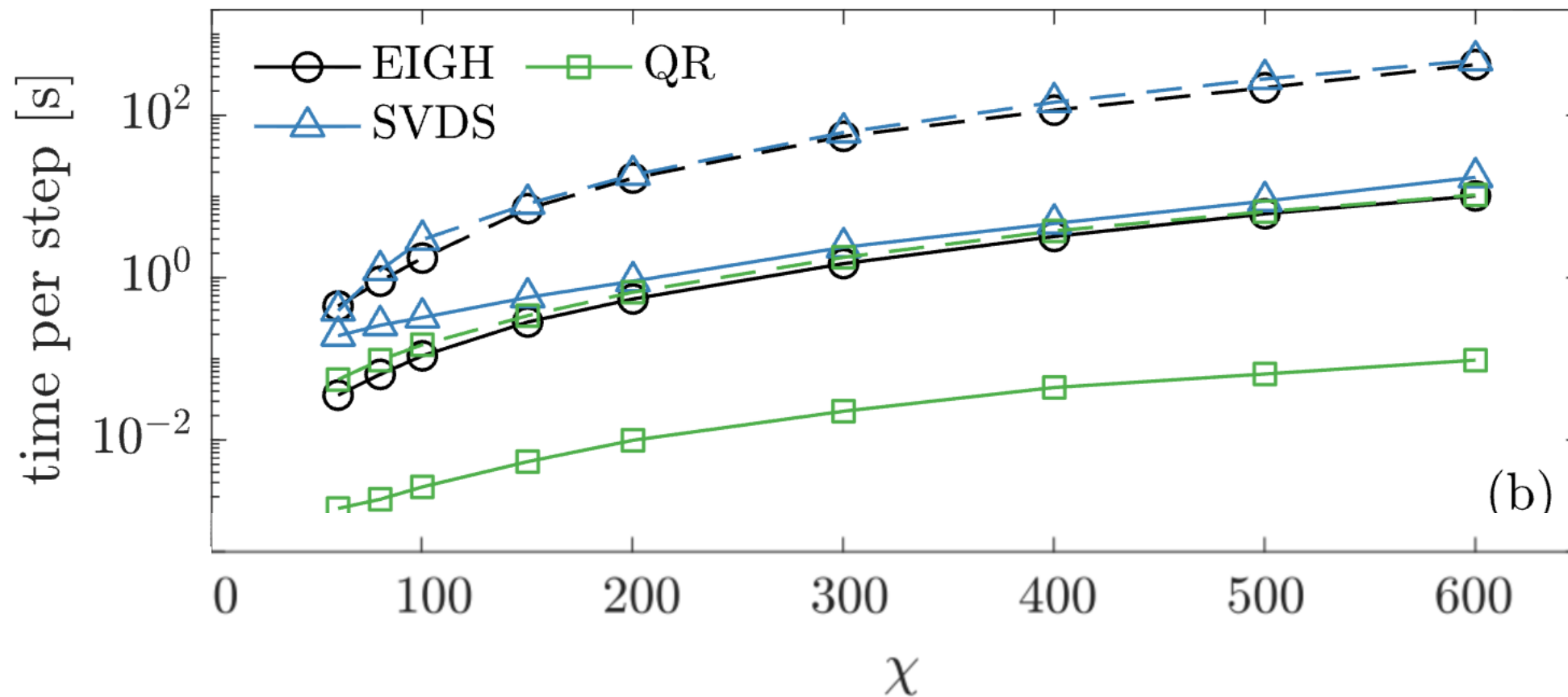
Reshape, QR



SVD, Eigh

D=6, real, H100

How about SVDs?

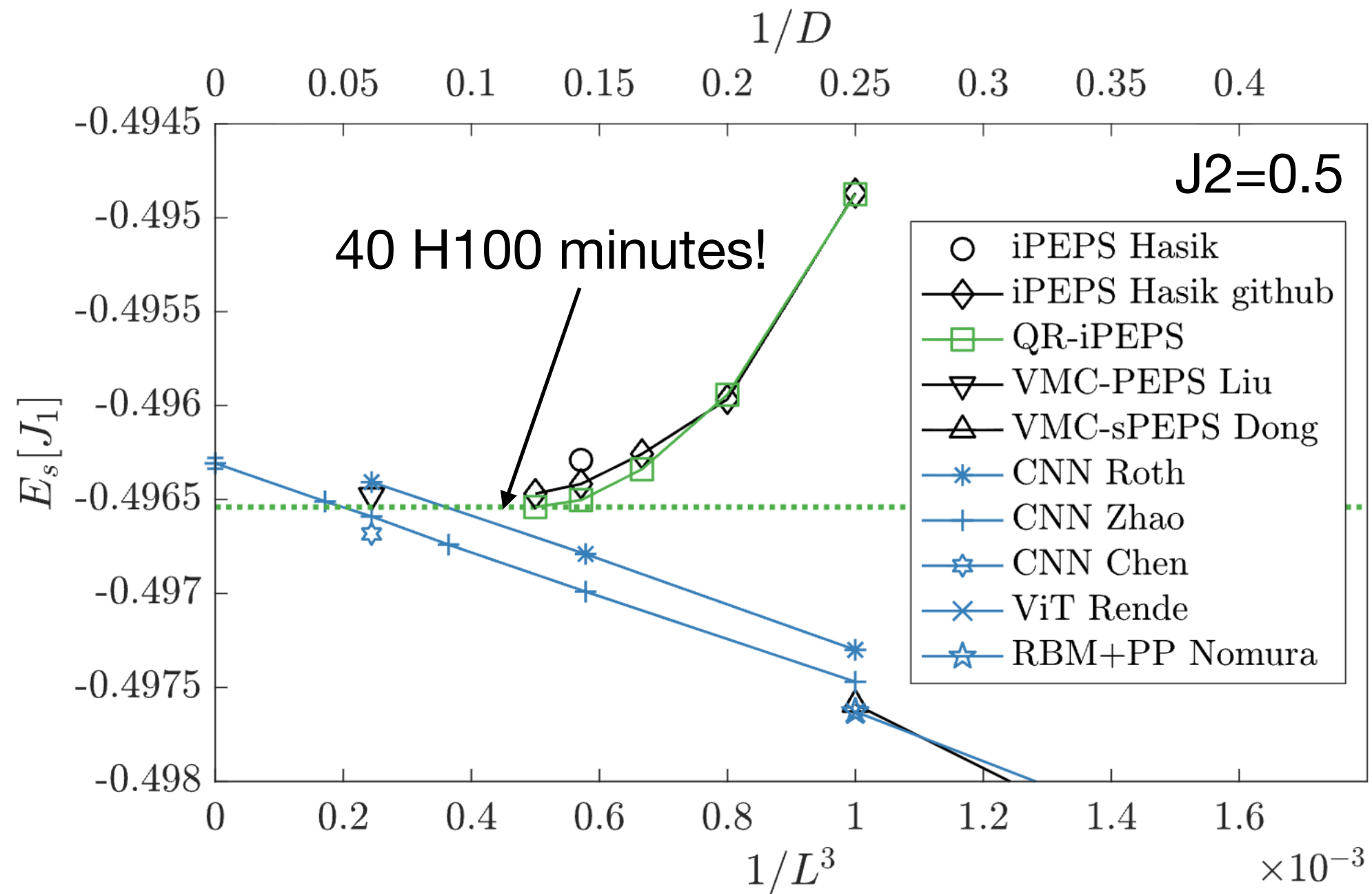


QR : Householder reflection

SVD : Householder reflection + implicit QR iterations to converge

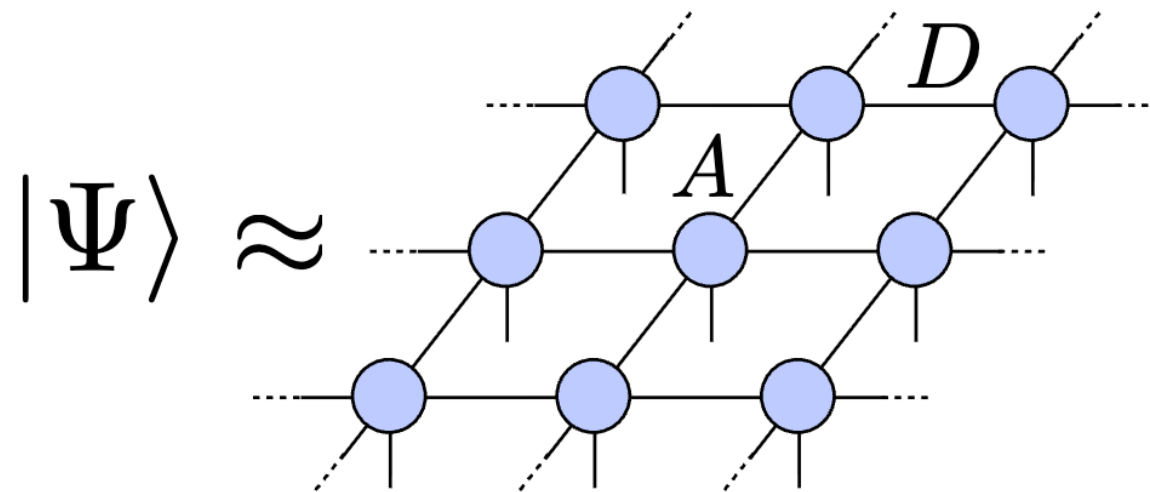
SVDS: A very large Krylov space construction

J1-J2 on Square lattice: SOTA



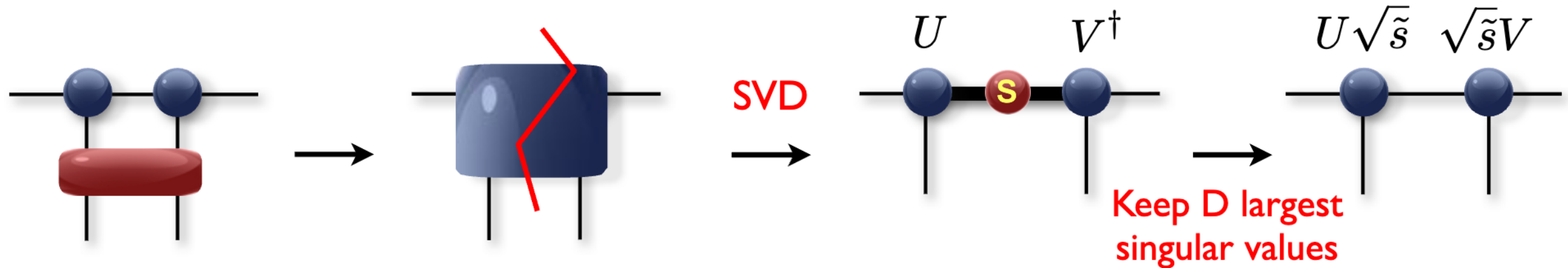
Why wasn't QRCTM invented earlier?

- Classical: Critical.
Preferred: TRG, Fix point approach.
- Quantum:
This ansatz was also overlooked!

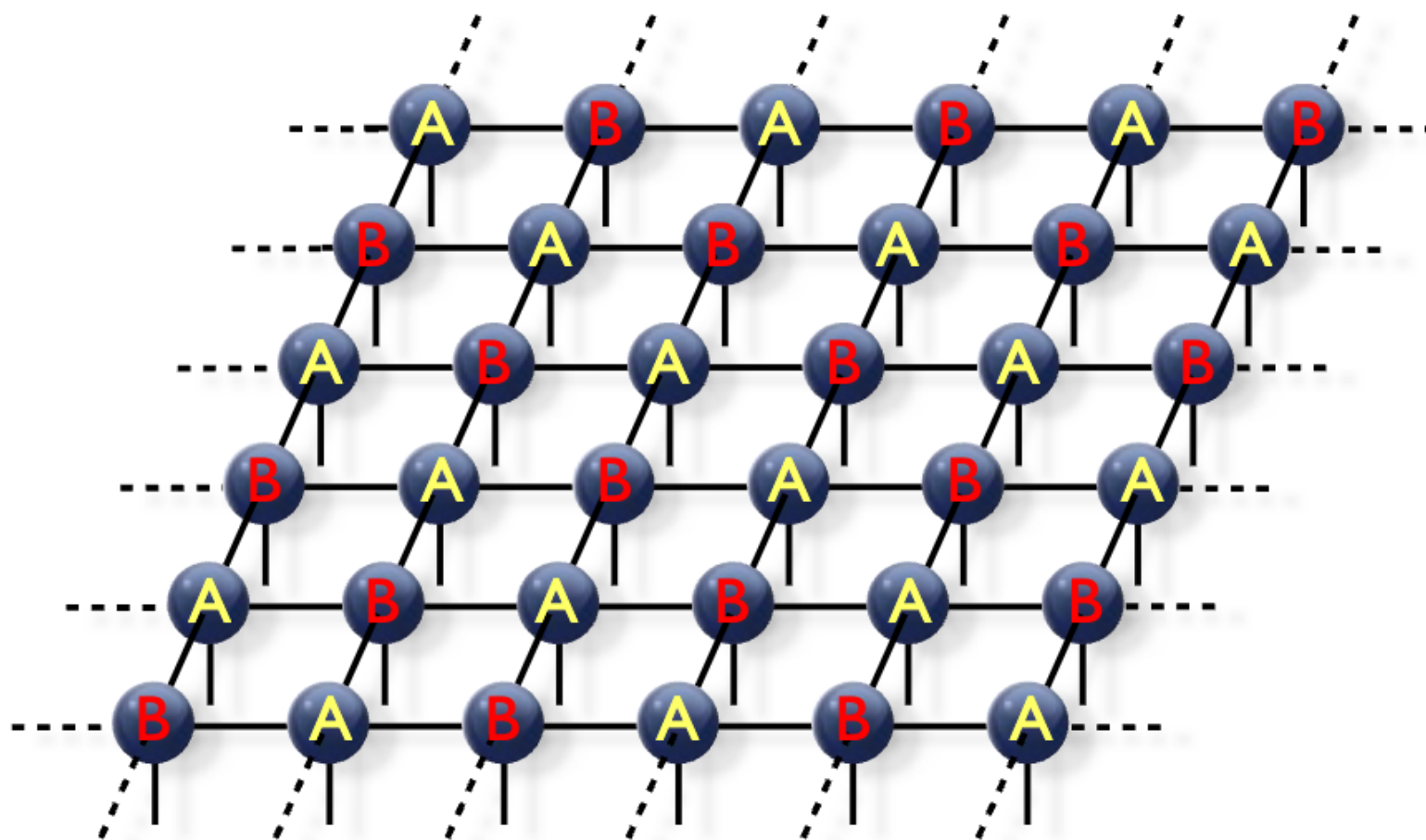
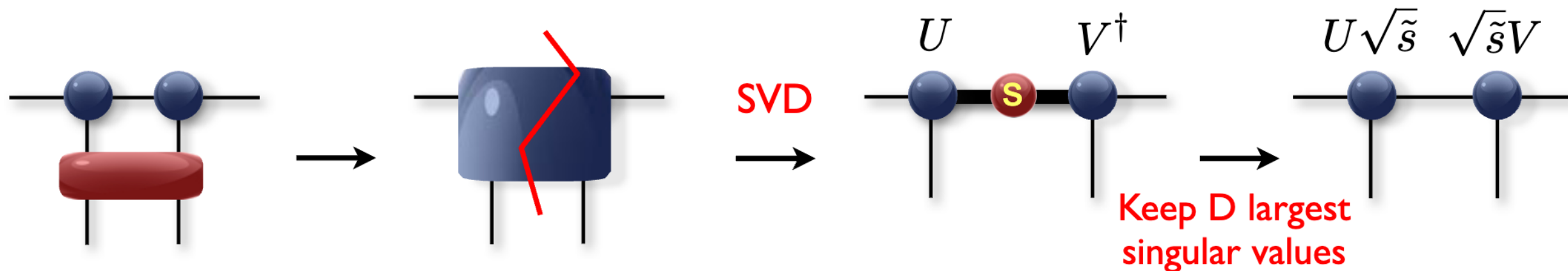


ITE in iPEPS breaks lattice symmetry!

Imaginary time evolution



ITE in iPEPS breaks lattice symmetry!



ITE will not give you
a C_{4v} iPEPS.

But AD enable it!

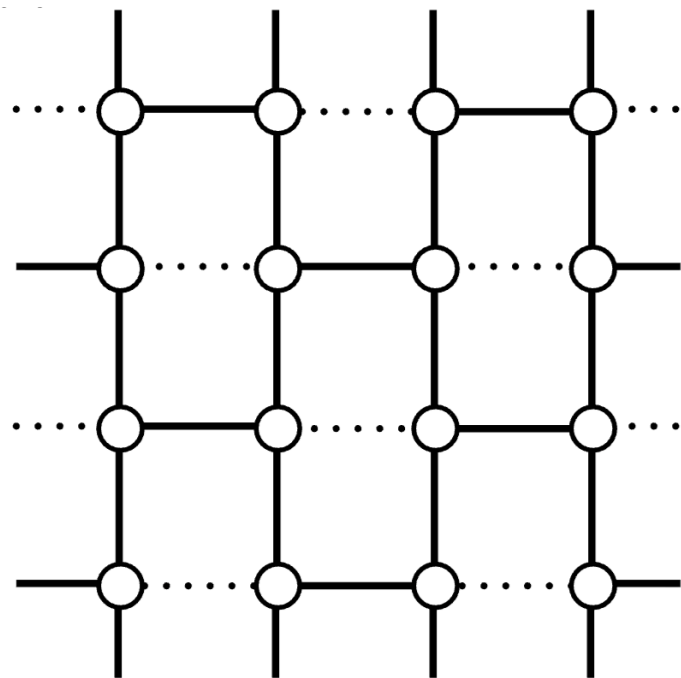
A halfway summary

- **QRCTM** and **GPUs** accelerate the contraction of C4v symmetric iPEPS
- **AD** provides practical algorithms to optimize this iPEPS.
- **SVD Free**: Free from “ $S^{-1/2}$ ” instability.
- Avoid “**large unit-cell**” and “**bi-orthogonalization**”, the origins of instability in iPEPS.
- Everything is fine, but,

where is its killing application?

iPEPS on the Honeycomb Lattice: Brick-Wall Approach

Brick Wall



PhysRevX.2.041013

Large Unit Cell VUMPS

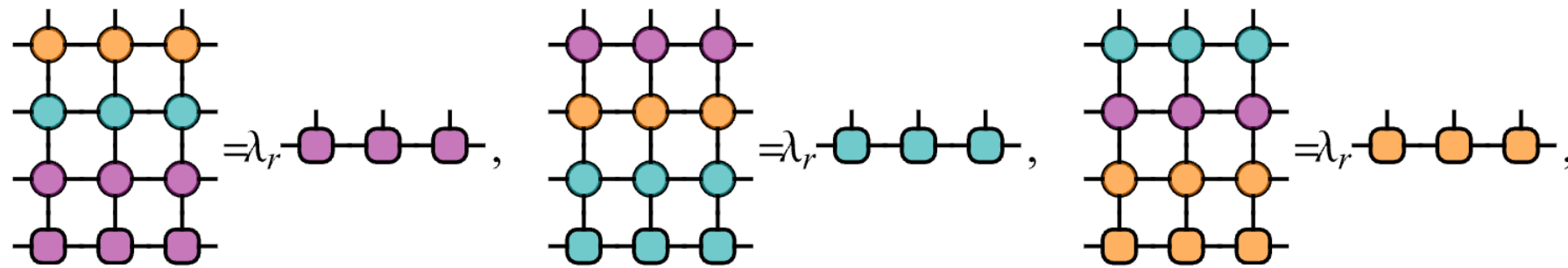


Fig: PhysRevB.108.085103

Large Unit Cell CTMRG

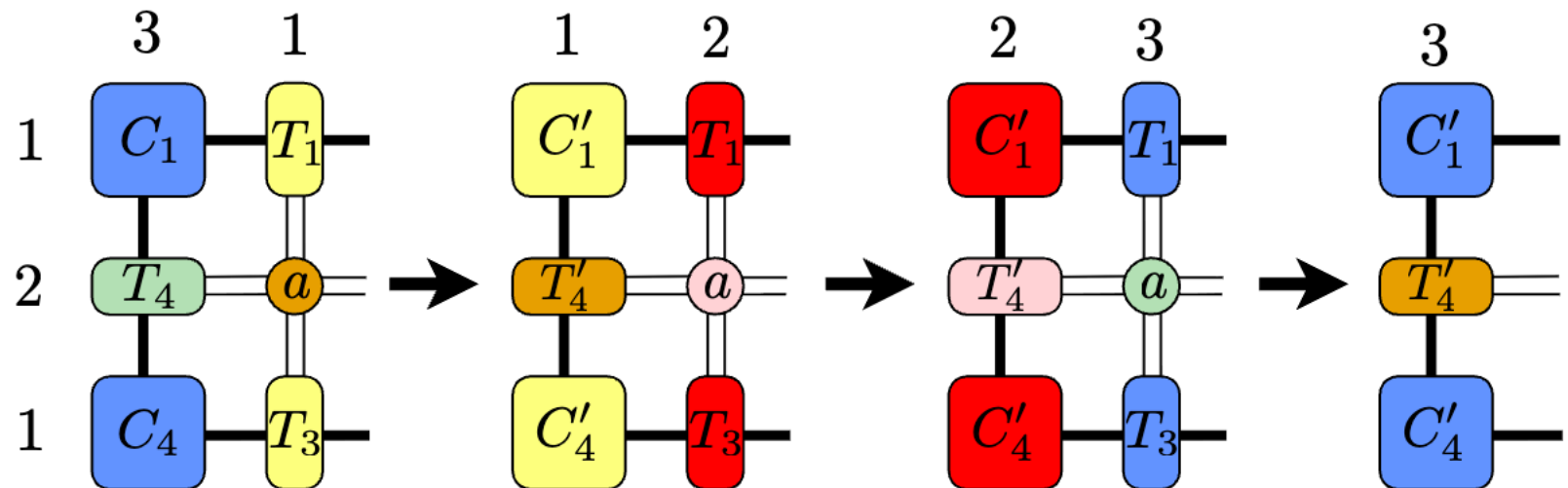
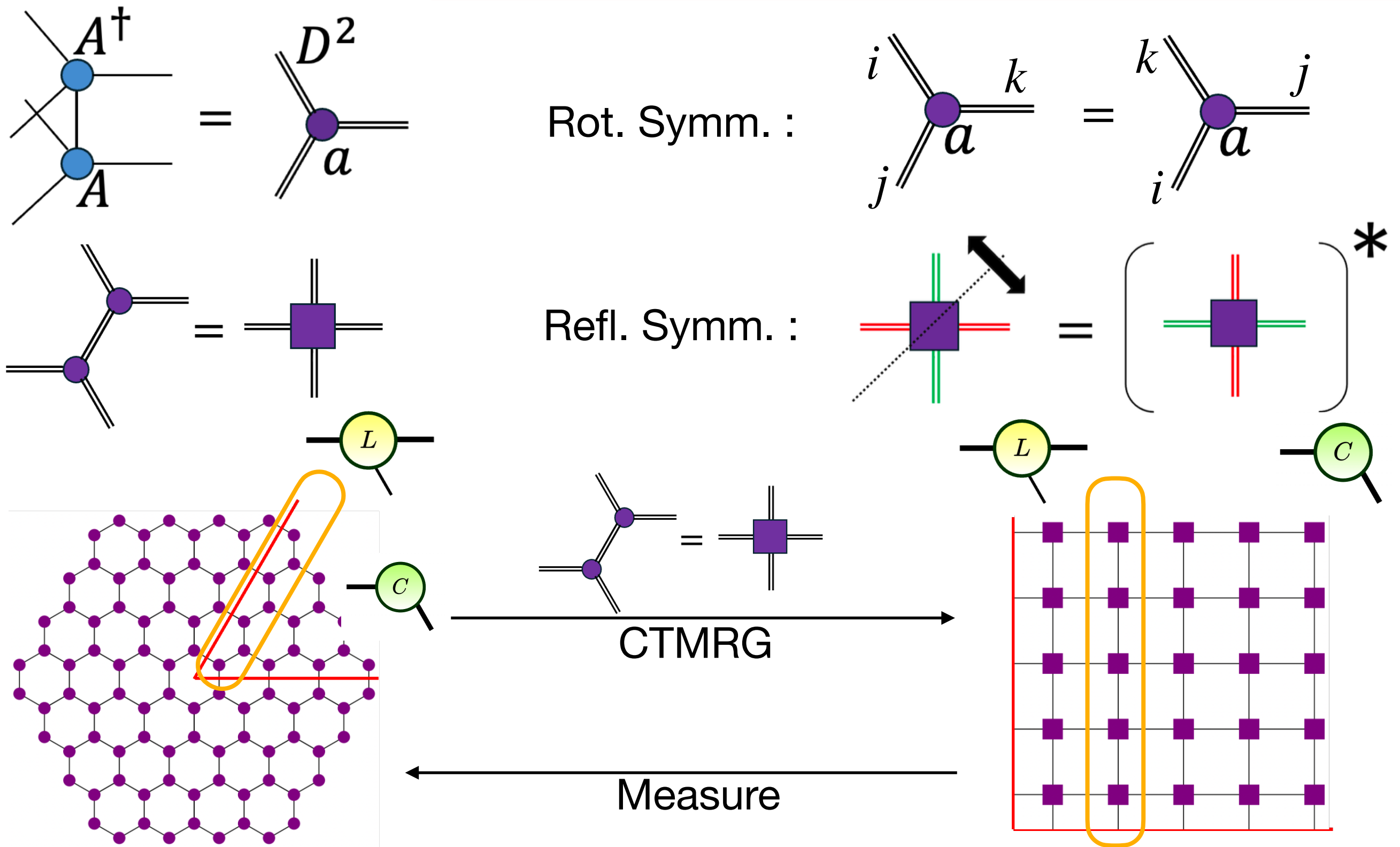


Fig: Philippe Corboz's slides@tnqmp2016

Complex Coding, QR magic is lost.

Figures shown for illustration only; credit for large-unit-cell algorithms goes to the original authors.

Uniform C_{3v} CTMRG on Honeycomb Lattice



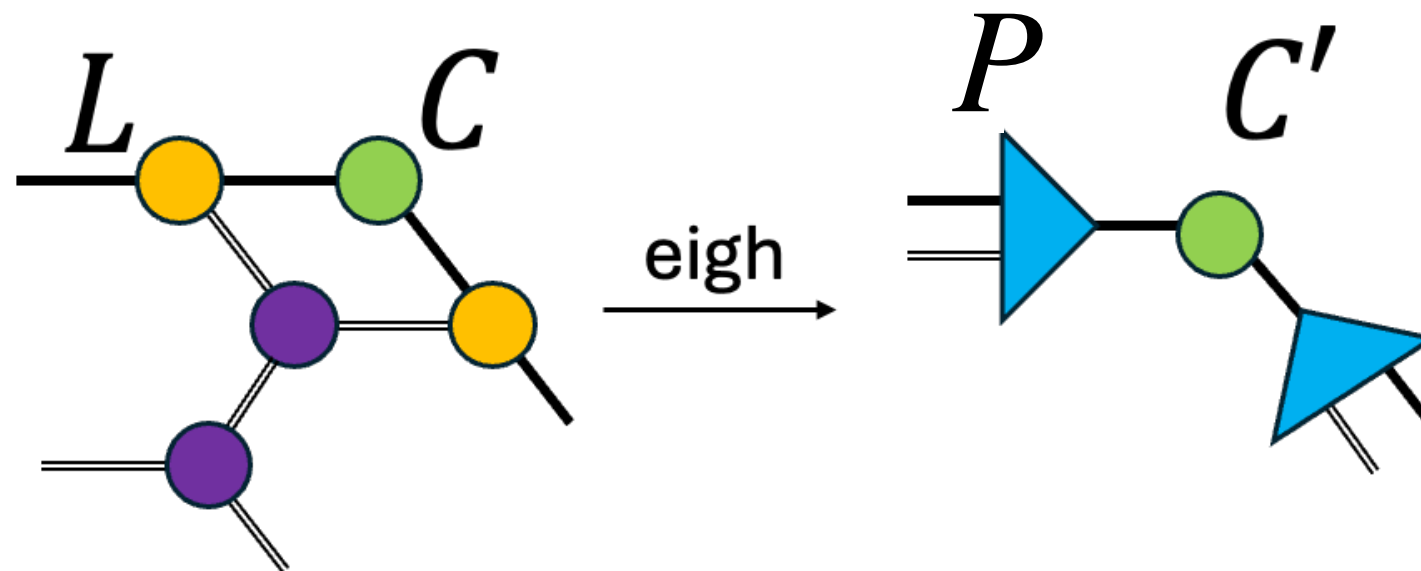
Thanks to our Ukrainian colleagues—their work paved the way

CTMRG for uniform C_{3v} iPEPS

Lukin et al., PhysRevB.107.054424(2023)

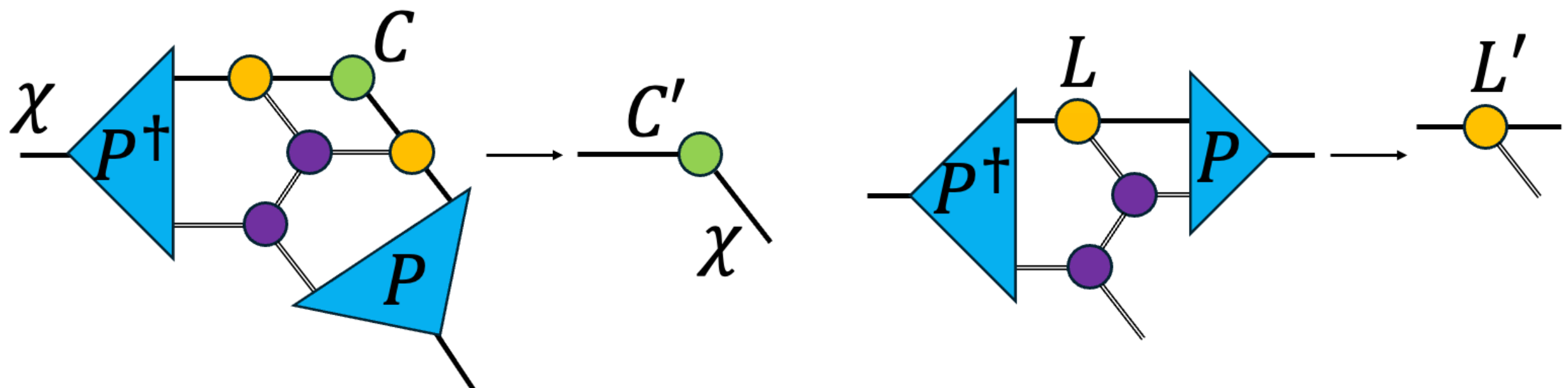
Step 1: Build projector. (expensive EVD)

~95% time



Step 2: Update edge and corner tensors.

~ 5% time



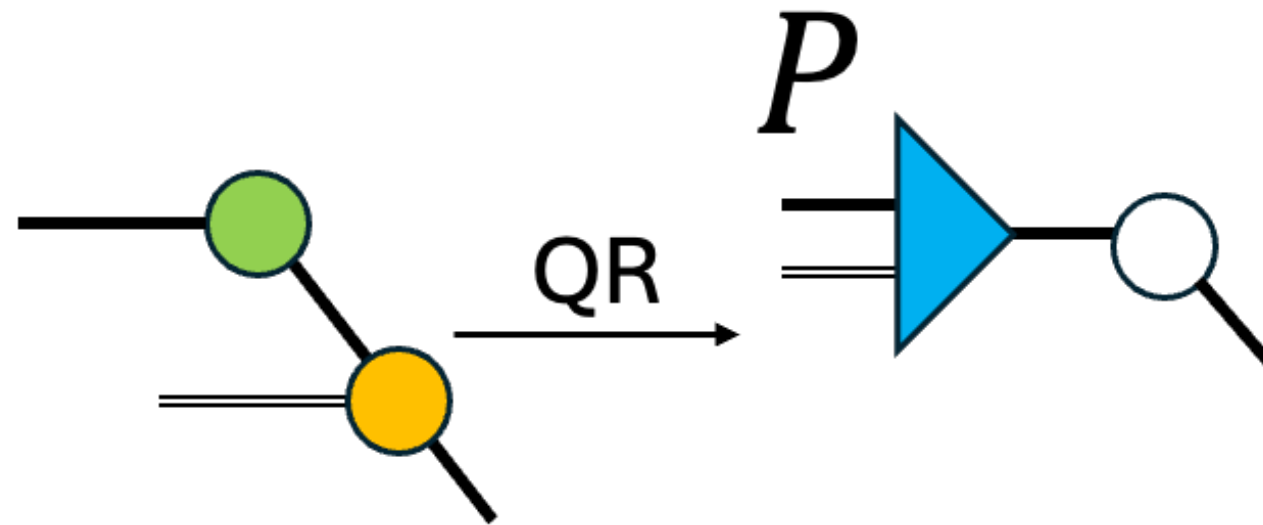
H100, double, very large $D > 6$ and $\chi > 600$

QRCTM for uniform C_{3v} iPEPS

[arXiv:2509.05090](https://arxiv.org/abs/2509.05090)

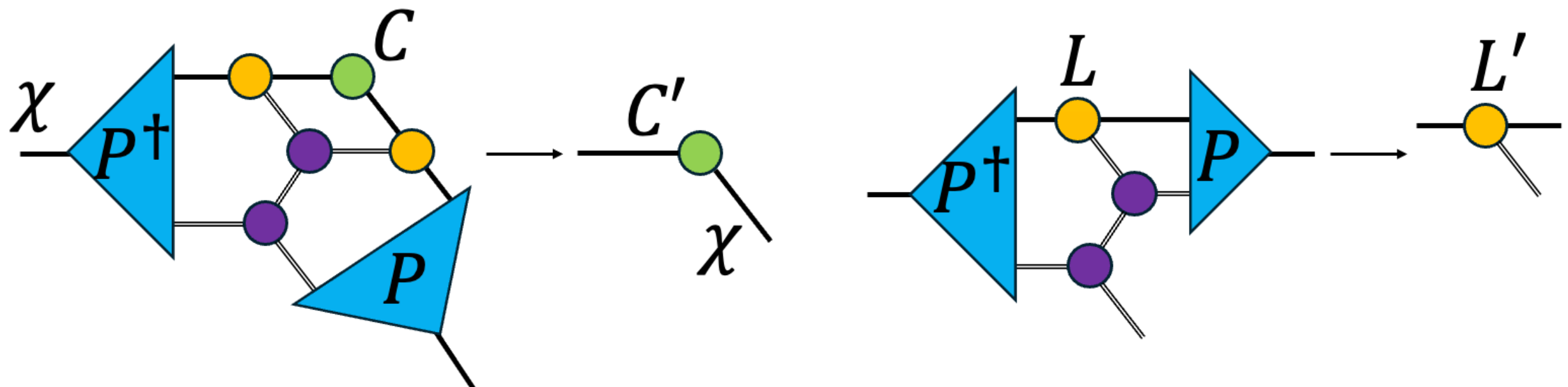
Step 1: Build projector via QR (cheap)

~10% time



Step 2: Update edge and corner Tensors.

~90% time

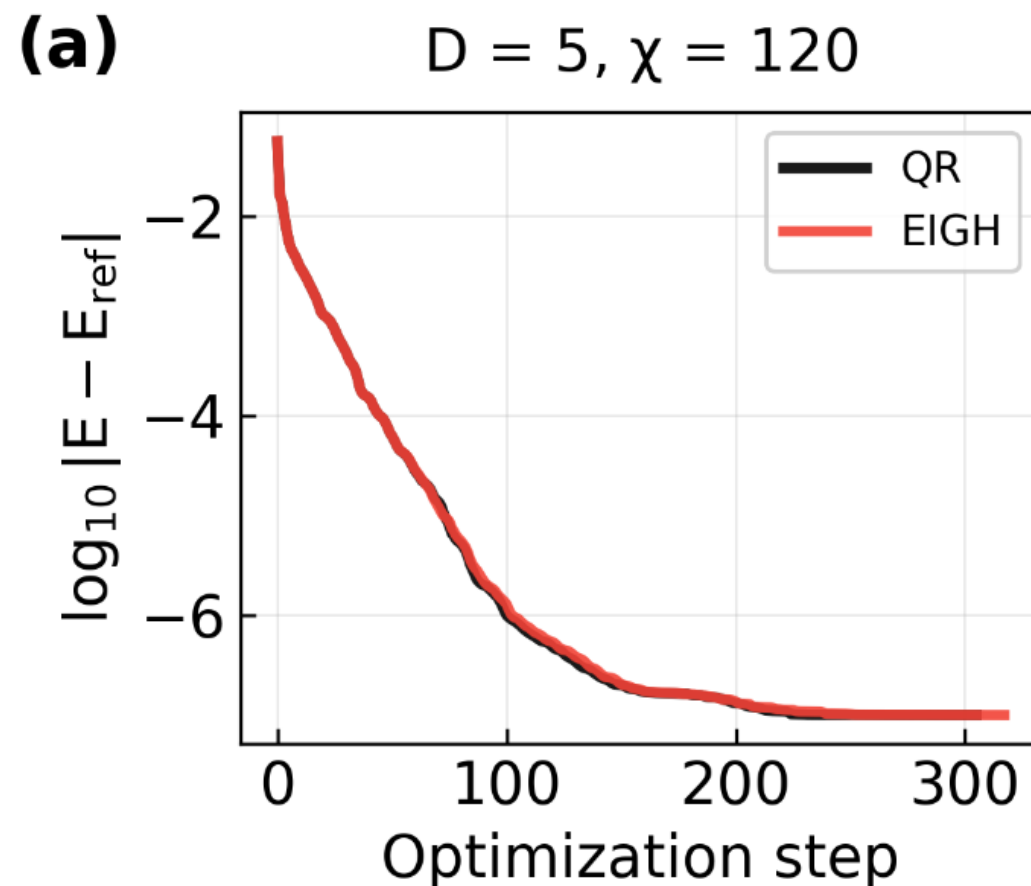


H100, double, D=6 and chi=600

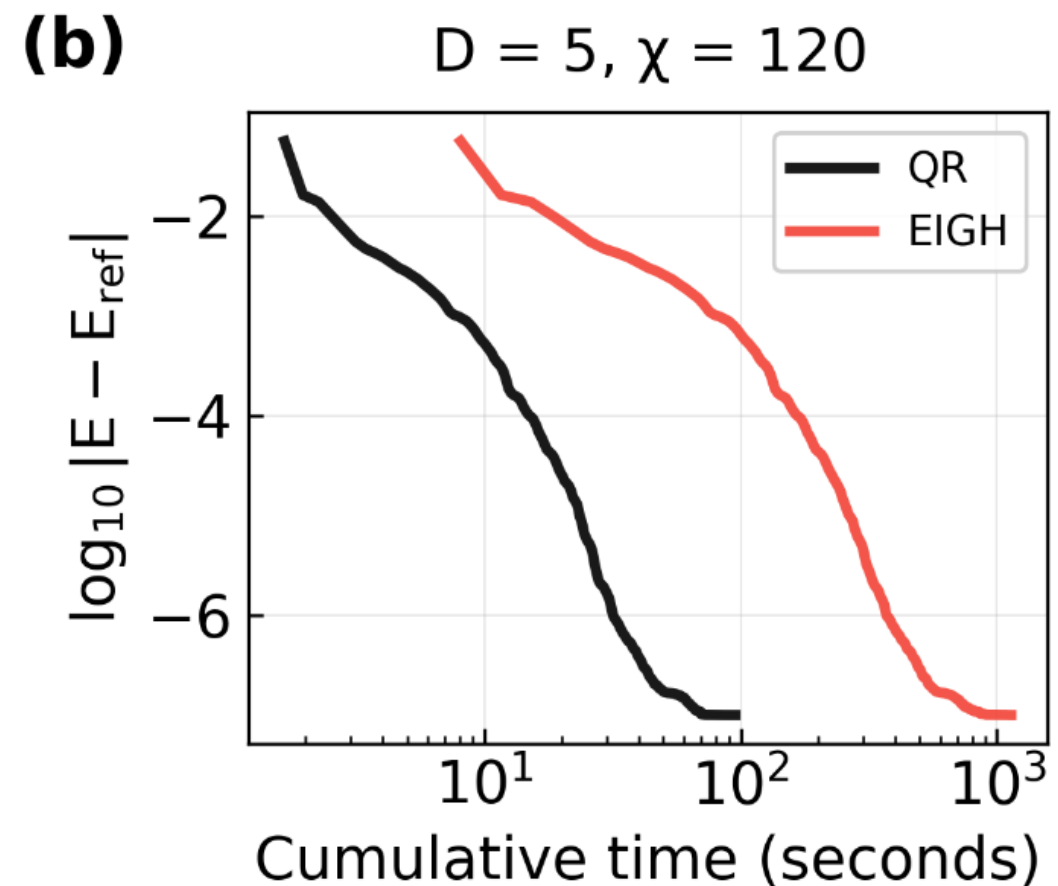
AFM Heisenberg on the Honeycomb Lattice

$$H = \sum_{\langle ij \rangle} \vec{S}_i \cdot \vec{S}_j$$

Training Dynamics



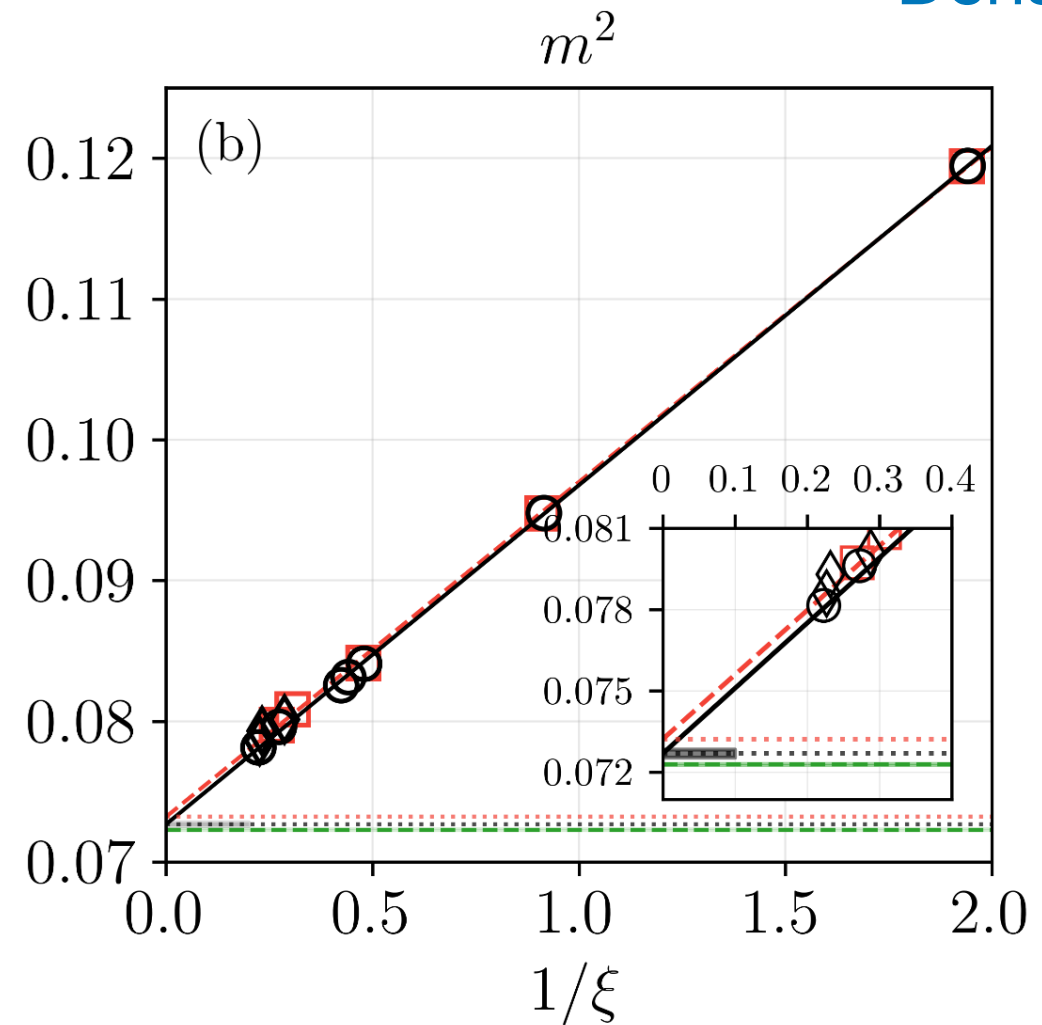
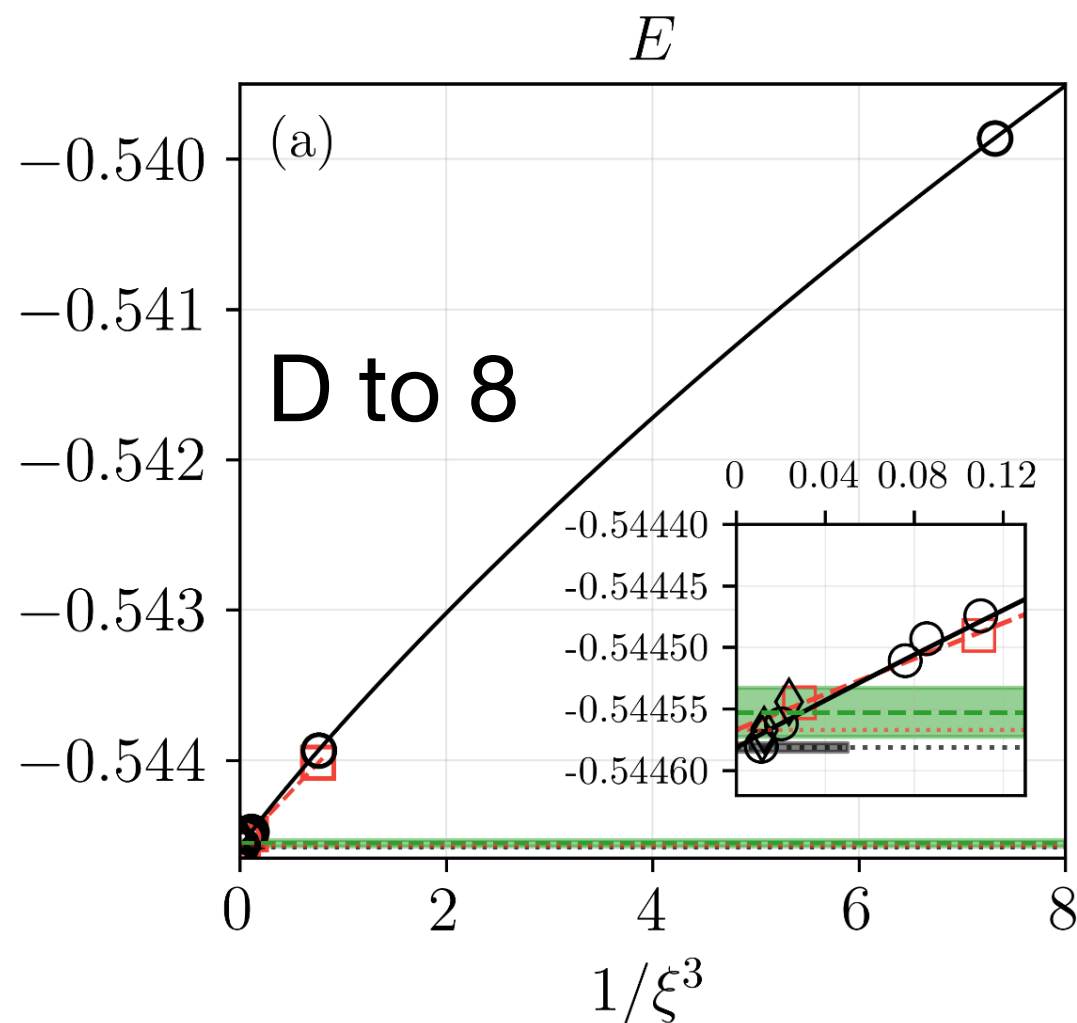
Speed up



Similar training dynamics, SUPER FAST!

AFM Heisenberg on the Honeycomb Lattice

“Dense U1”



“Lower” $\rightarrow E_0 = -0.544582(3)$

$E_{QMC} = -0.544553(20)$

$m_0 = 0.2696(3)$

$m_{QMC} = 0.26885(2)$

D=8, accurate results—consistent with QMC

F. Jiang, Eur. Phys. J. B 85, 1(2012)

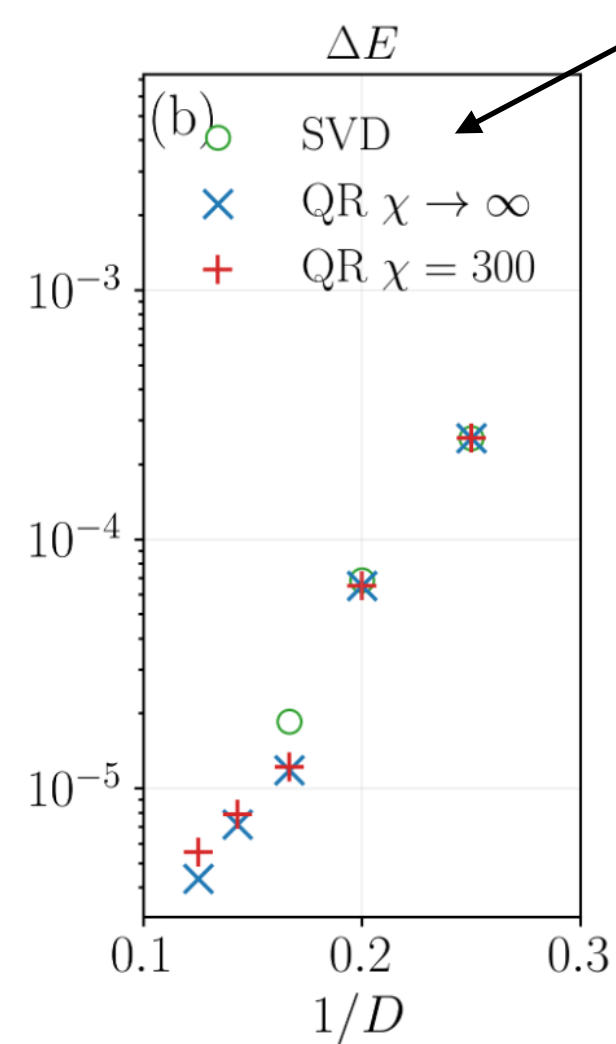
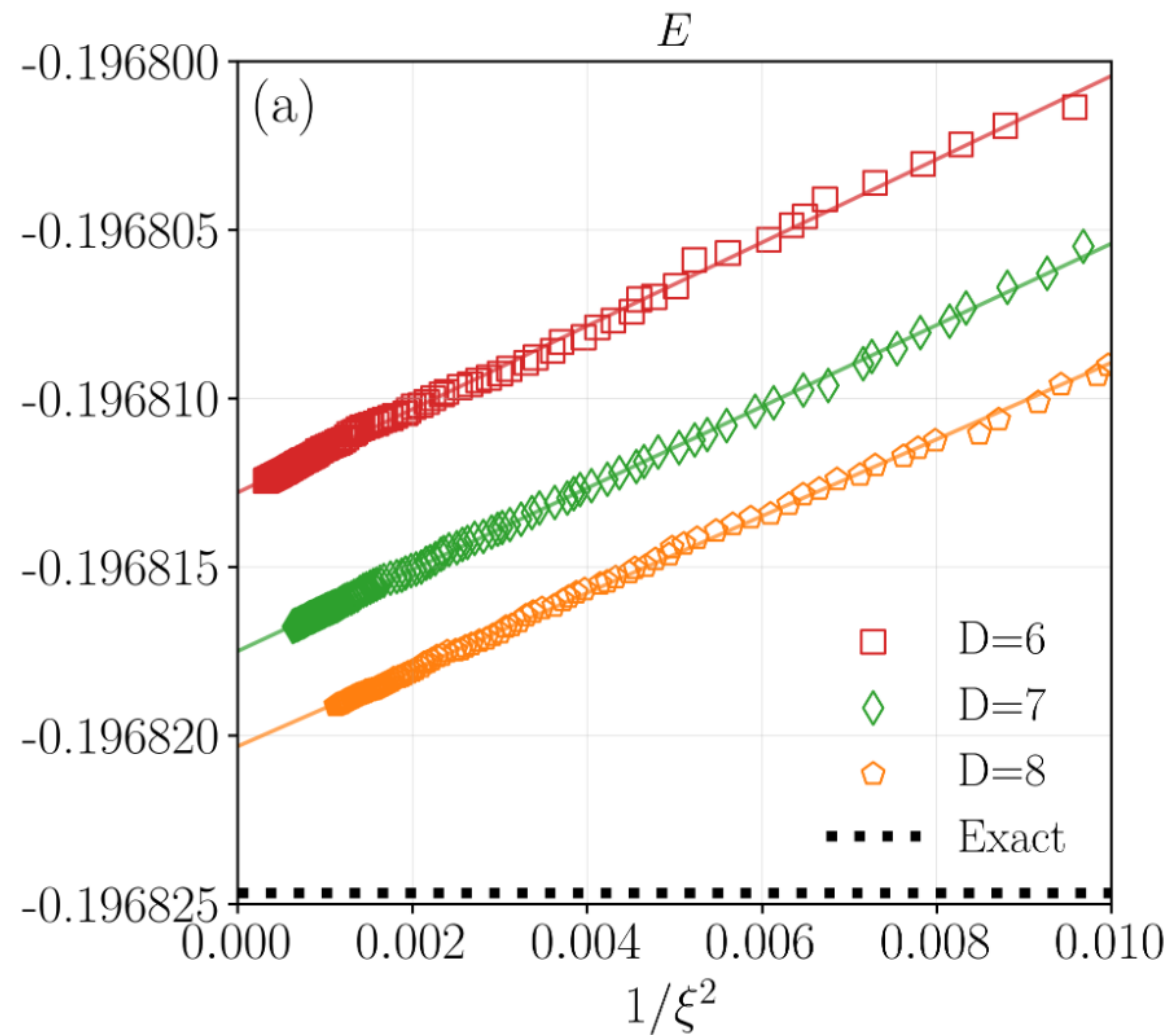
U. Low, Condens. Matter Phys. (2009)

Both QMC and our iPEPS results are extrapolated (FSS, FCLS)

Isotropic Kitaev model (S=1/2) energy

j.aop.2005.10.005

Lukin et al., PhysRevB.107.054424(2023)



Critical SG $D = 8, \|\Delta E/E\| = 7 \times 10^{-5}$

PhysRevLett.123.087203(2019)

AD+CTMRG $D = 6, \|\Delta E/E\| = 9 \times 10^{-5}$

PhysRevB.107.054424(2023)

AD+QRCTM $D = 8, \|\Delta E/E\| = 2 \times 10^{-5}$

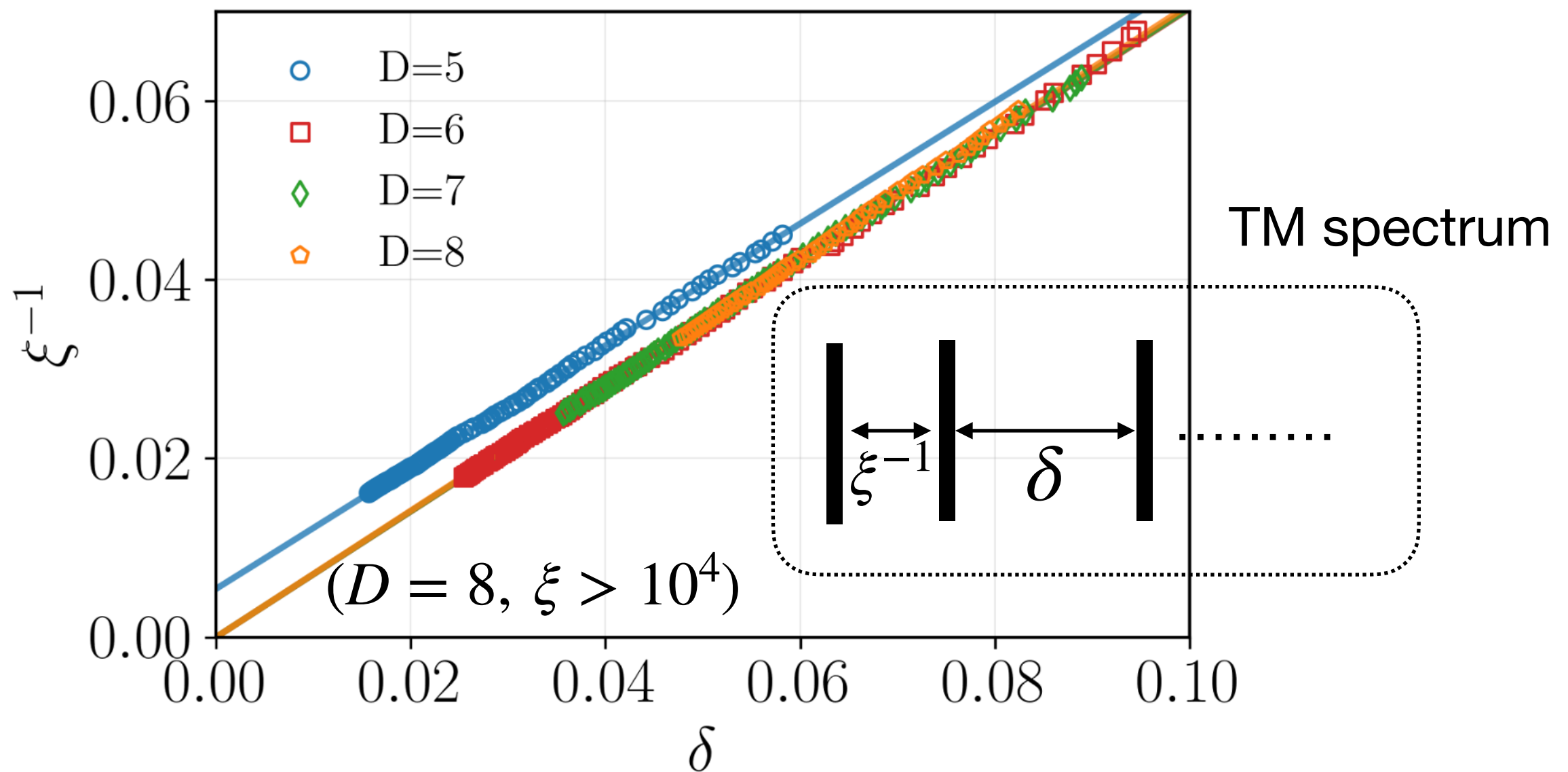
SOTA reported energy with AD+iPEPS

Not extrapolated, energy per site.

Kitaev model: Finite Correlation Length Scaling

Phys. Rev. X 8, 031030 (2018)

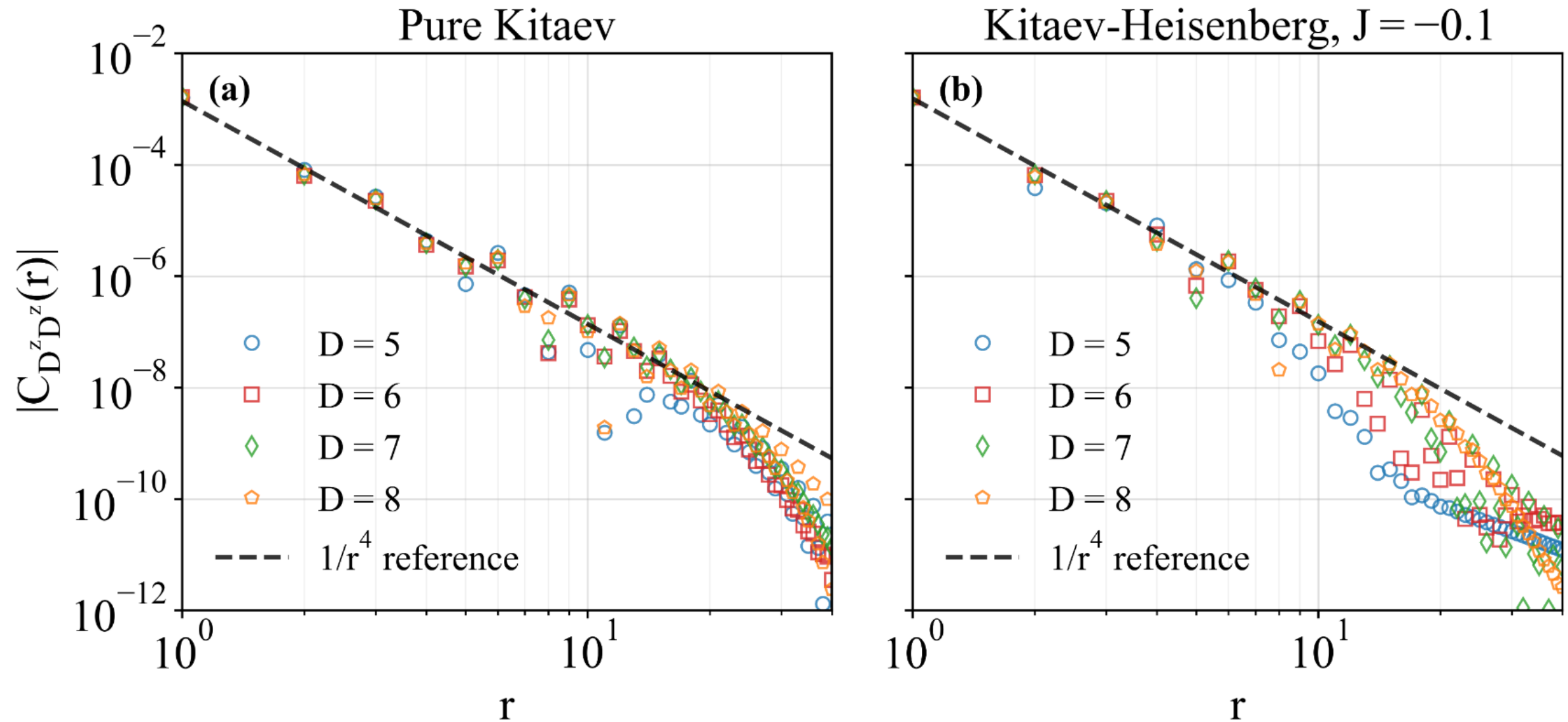
Phys. Rev. X 8, 031031 (2018)



Finite D , infinite ξ !

Finite-correlation-length-scaling reveals gapless nature.

iPEPS evidence for Dimer-Dimer correlation decay



Dimer-Dimer r^{-4} tail persists in Kitaev-Heisenberg model

Phys. Rev. A 78, 012304 (2008)

Phys. Rev. Res. 2, 013005 (2020)

As predicted by field theory; to our knowledge, first confirmed with iPEPS

Higher Spin Kitaev model

$$H = \sum_{\langle i,j \rangle_\gamma} K_\gamma S_i^\gamma S_j^\gamma$$

$$S > 1/2, K_\gamma = -1$$

Is the ground state a **QSL**?
Any **symmetry breaking**?

Semi-classical analysis

PRB 78, 115116 (2008)

Nat. Commun. 9, 1575 (2018)

.....

Results: **Bond order** for Large: $S \geq 2$
 $S=3/2$ (unclear), $S=1$ (no SSB)

Quantum many-body methods

JPSJ 87, 063703 (2018)

PRR 2, 033318 (2020)

PRR 3, 013160 (2021)

PRB 105, L060403 (2022)

Nat. Commun. 13, 3813 (2022)

PRB 106, 174416 (2022)

SciPost Phys. 16, 100 (2024)

PRR 6, 033077 (2024)

PRB 110, 134402 (2024)

PRR 6, 033168 (2024)

arXiv:2503.24246 (2025)

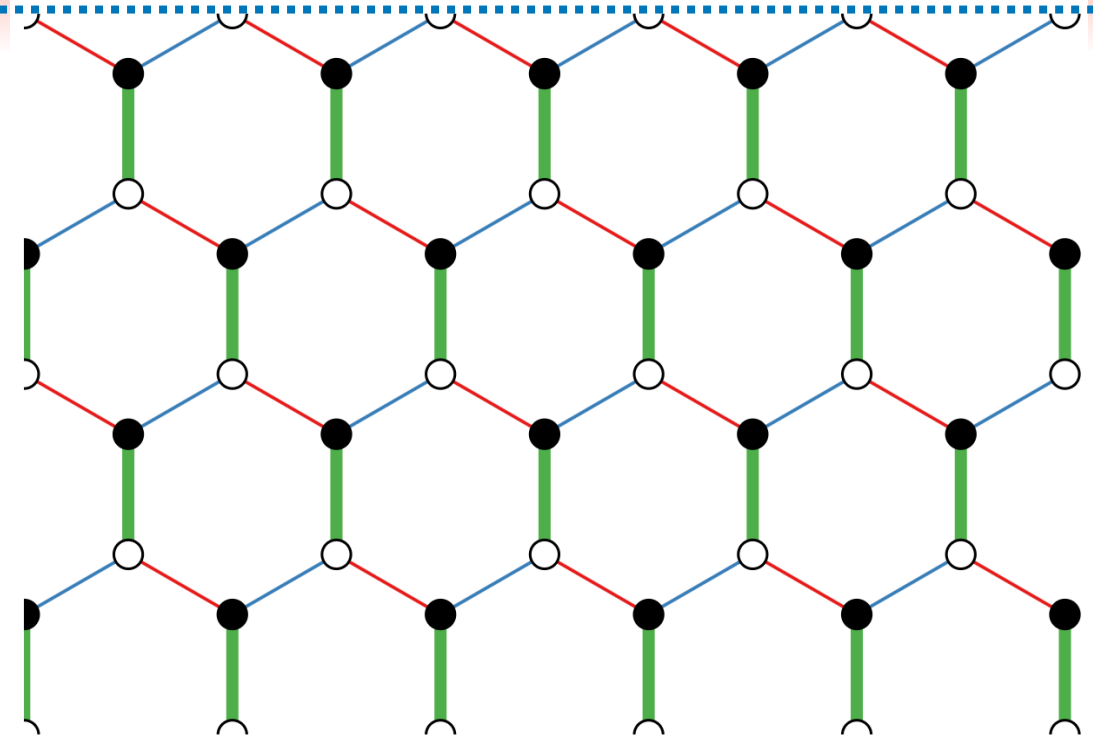
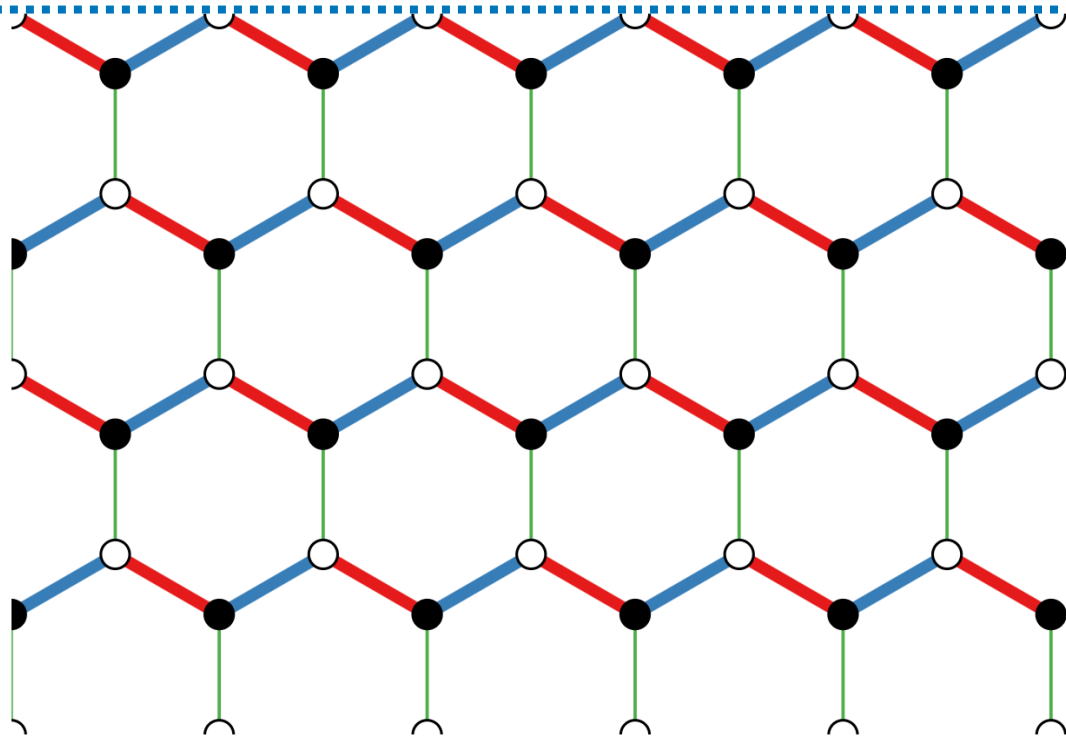
.....

Results: **QSL, no symmetry breaking**

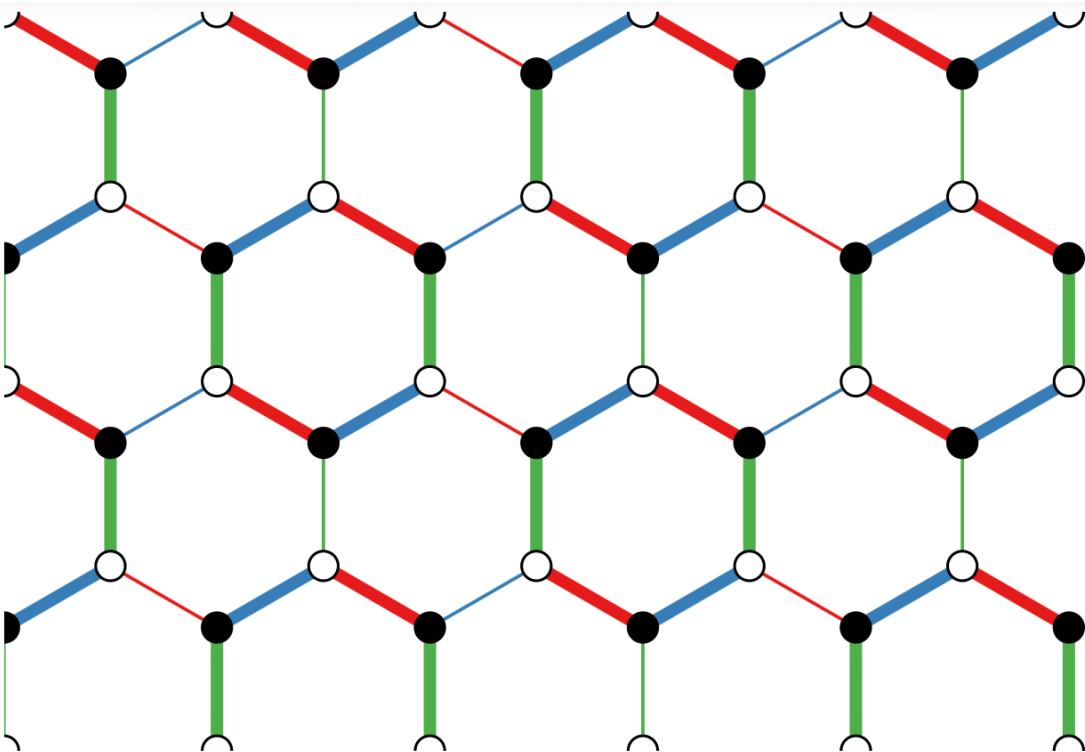
Commun. Phys. 7, 319 (2024)

Result: **(2x2 unit-cell SU), anisotropic**

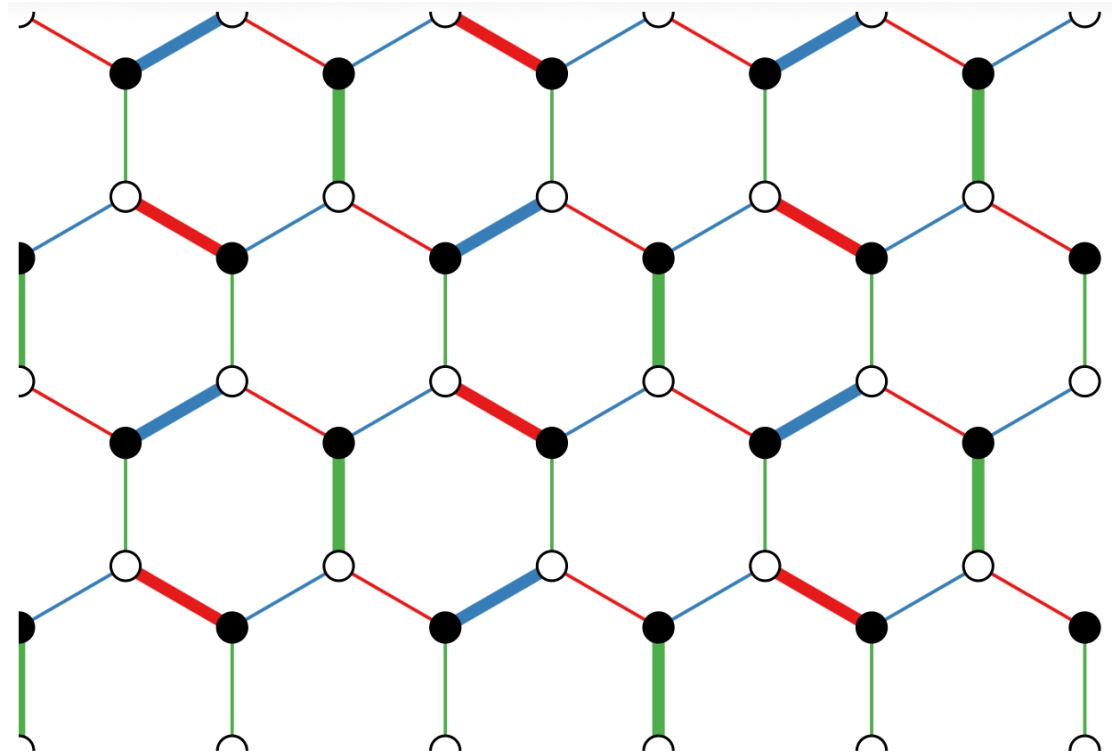
Ground states candidates from SU



Uniform anisotropic, high E, 2x1 unit-cell



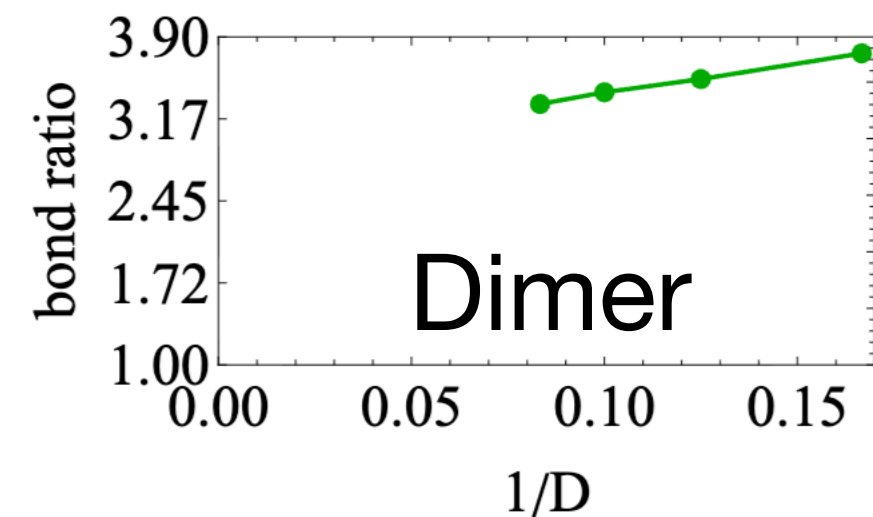
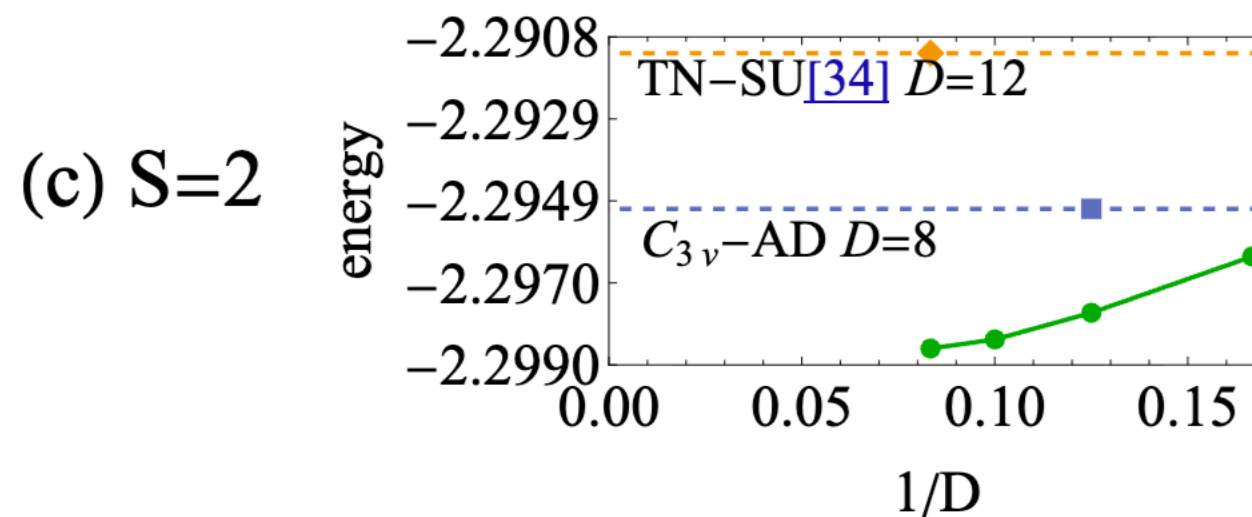
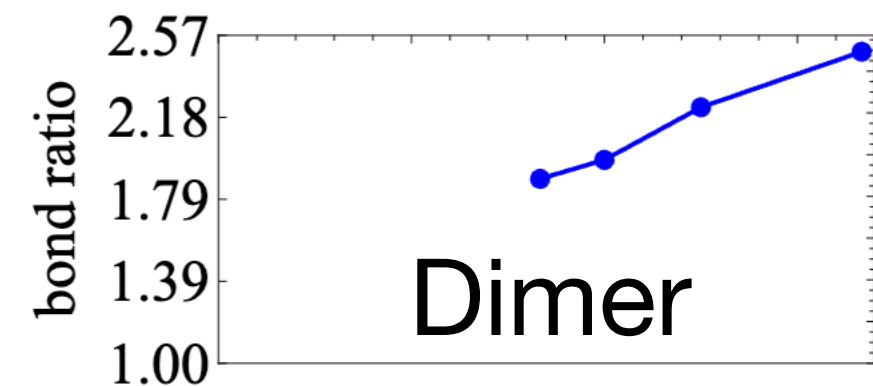
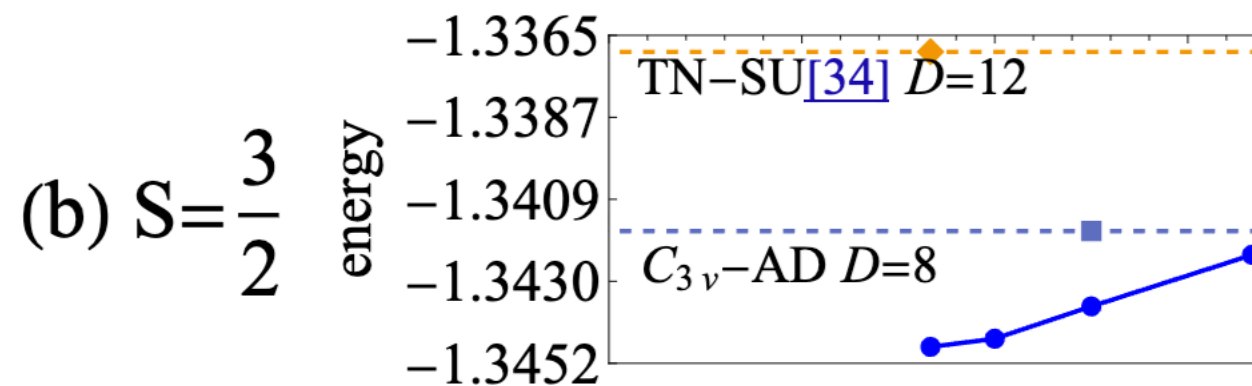
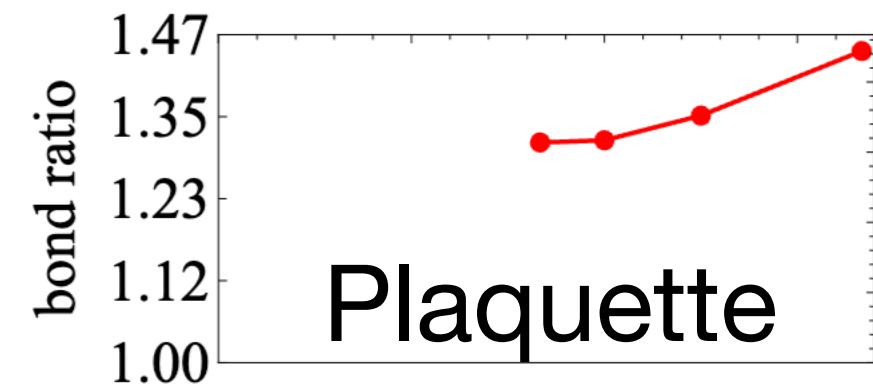
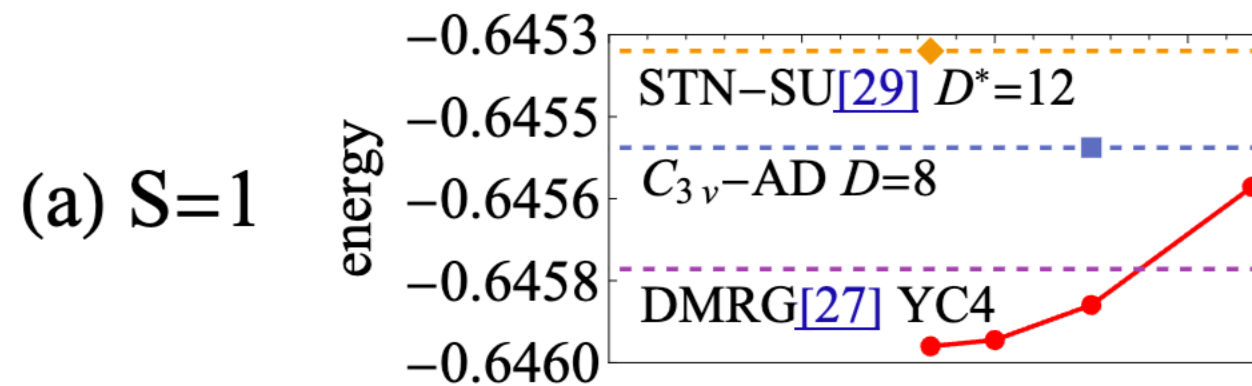
Plaquette



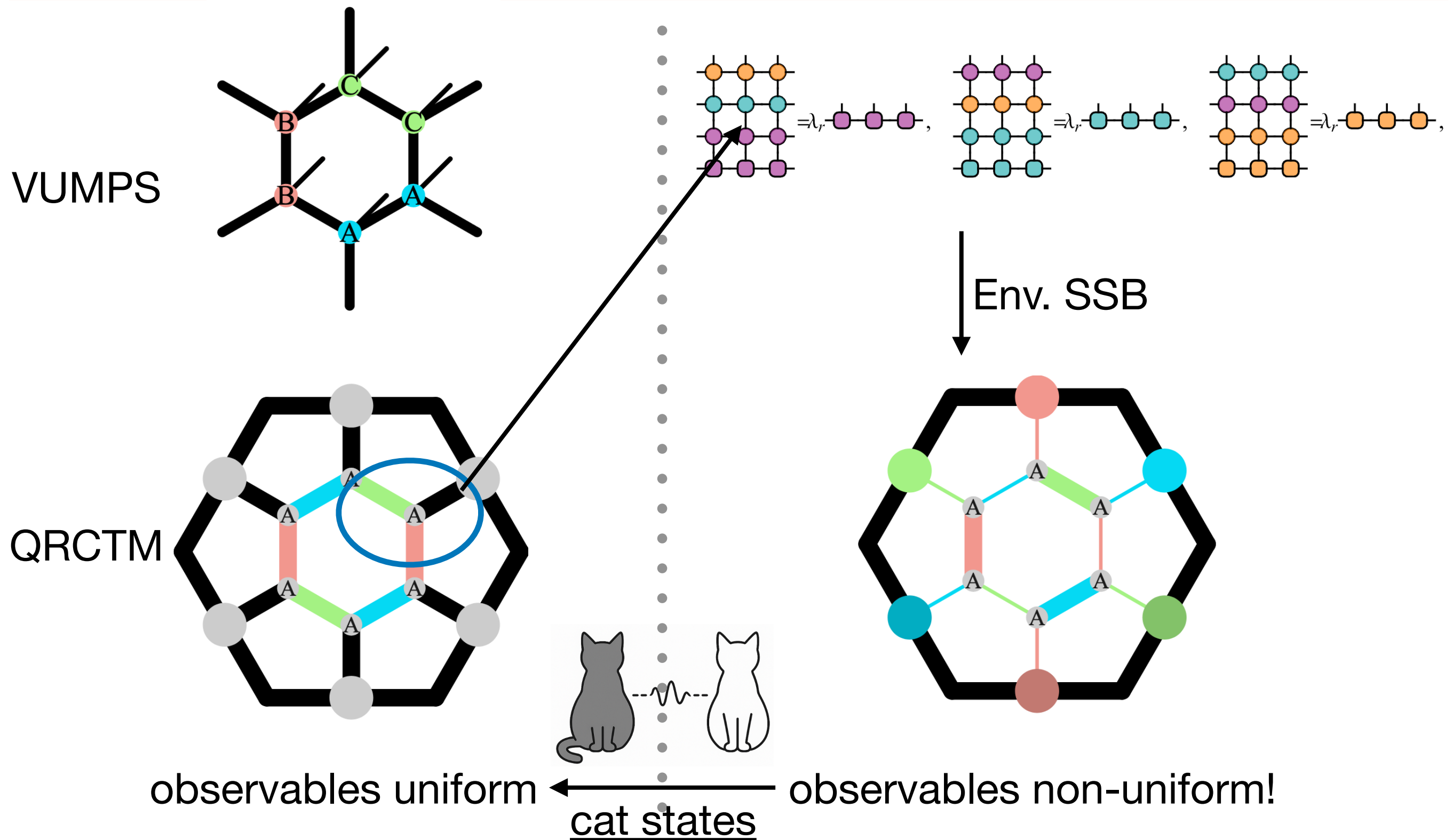
Dimer

Detect SSB: Energy comparison

Comparing with AD+VUMPS, Precondition + multiple GPUs

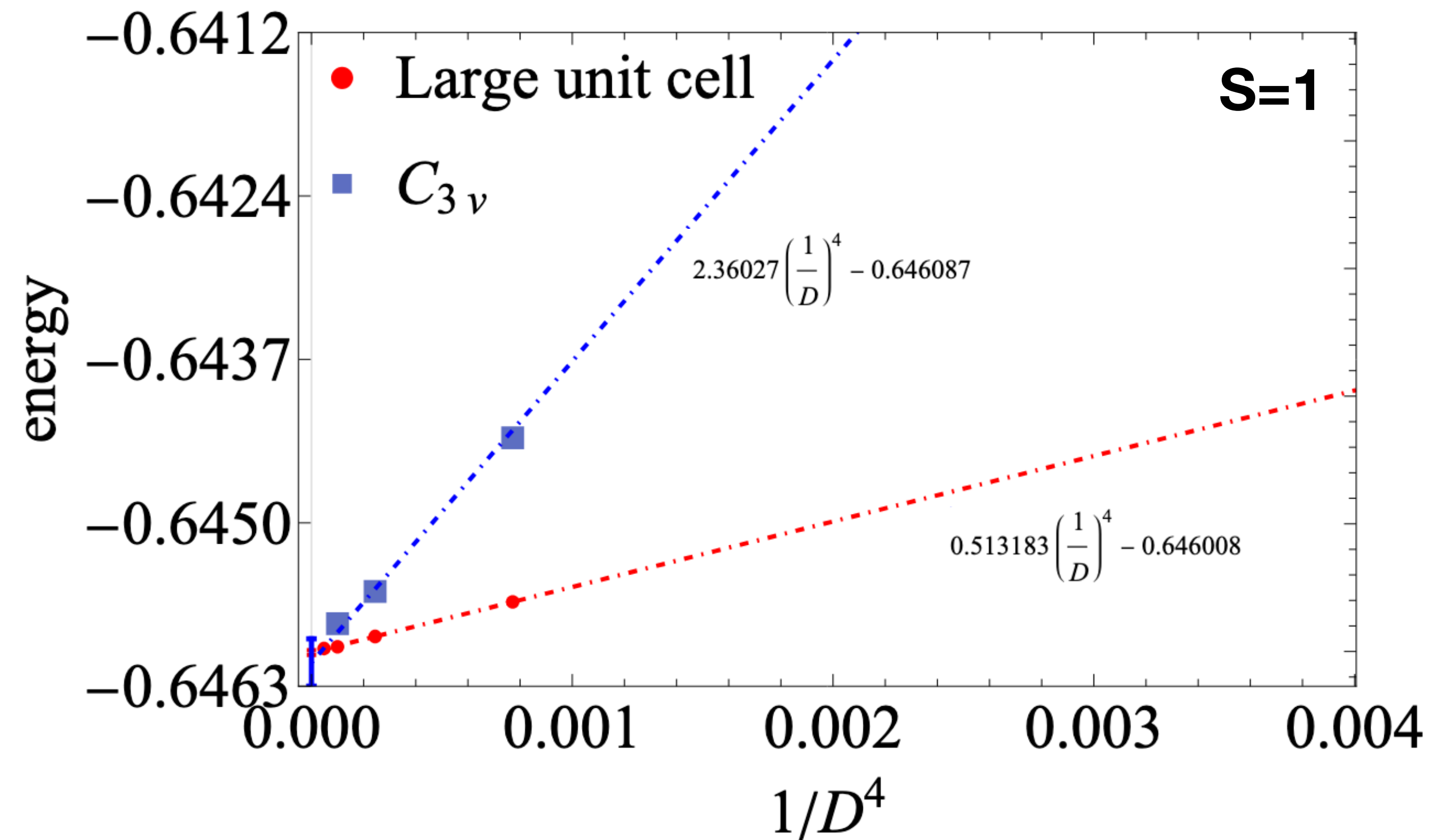


Detect SSB: A New Diagnostic



Another peace of evidence of SSB for $S=1,3/2,2$

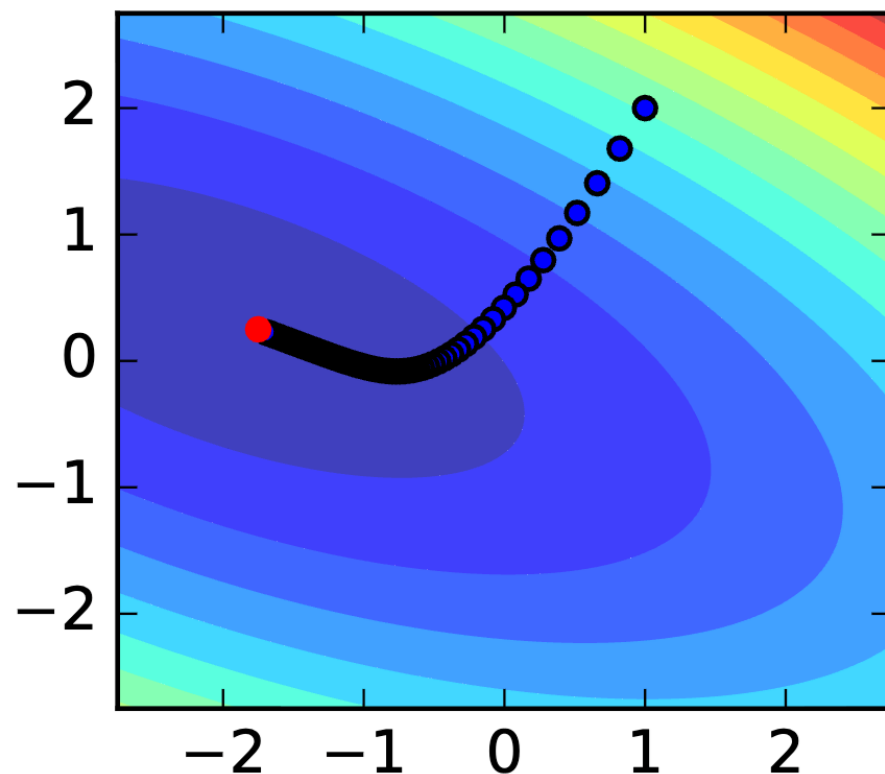
Quantifying SSB: Energy and Scaling?



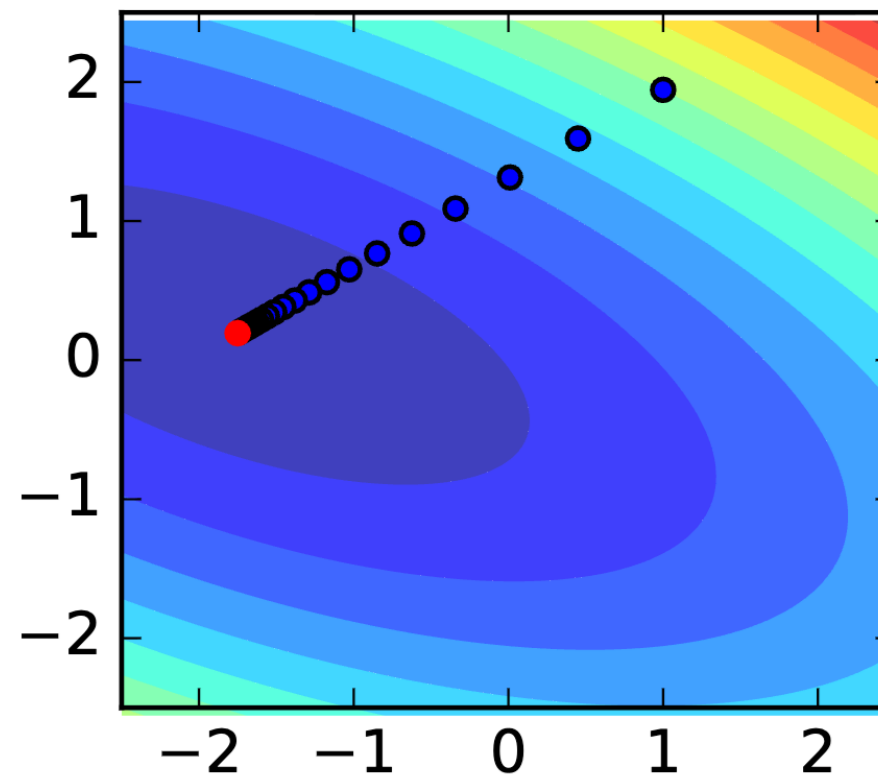
Riemannian optimization

$$f(x_1, x_2) = x_1^2 + ax_2^2 = y_1^2 + y_2^2 \quad g = \begin{pmatrix} 1 & 0 \\ 0 & a \end{pmatrix}$$

gradient descent



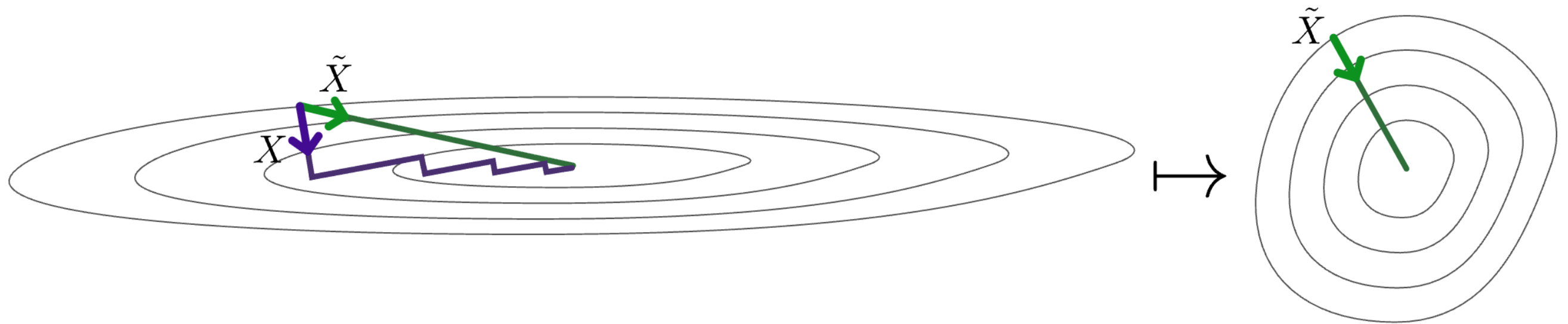
Newton's method



$$\partial_i f = 2x_1 + 2ax_2$$

$$g^{-1} \partial_i f = 2x_1 + 2x_2$$

Riemannian optimization for TNS



$$g_{ij}(A) = \frac{\partial^2 \langle \text{TNS}(A_i) | \text{TNS}(A'_j) \rangle}{\partial A_i \partial A'_j}$$

Gradients G : $G = \partial_A E \rightarrow g^{-1} \partial_A E$

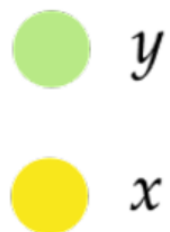
Equivalent: $gF = \partial_A E$

Towards TDVP for 2D?

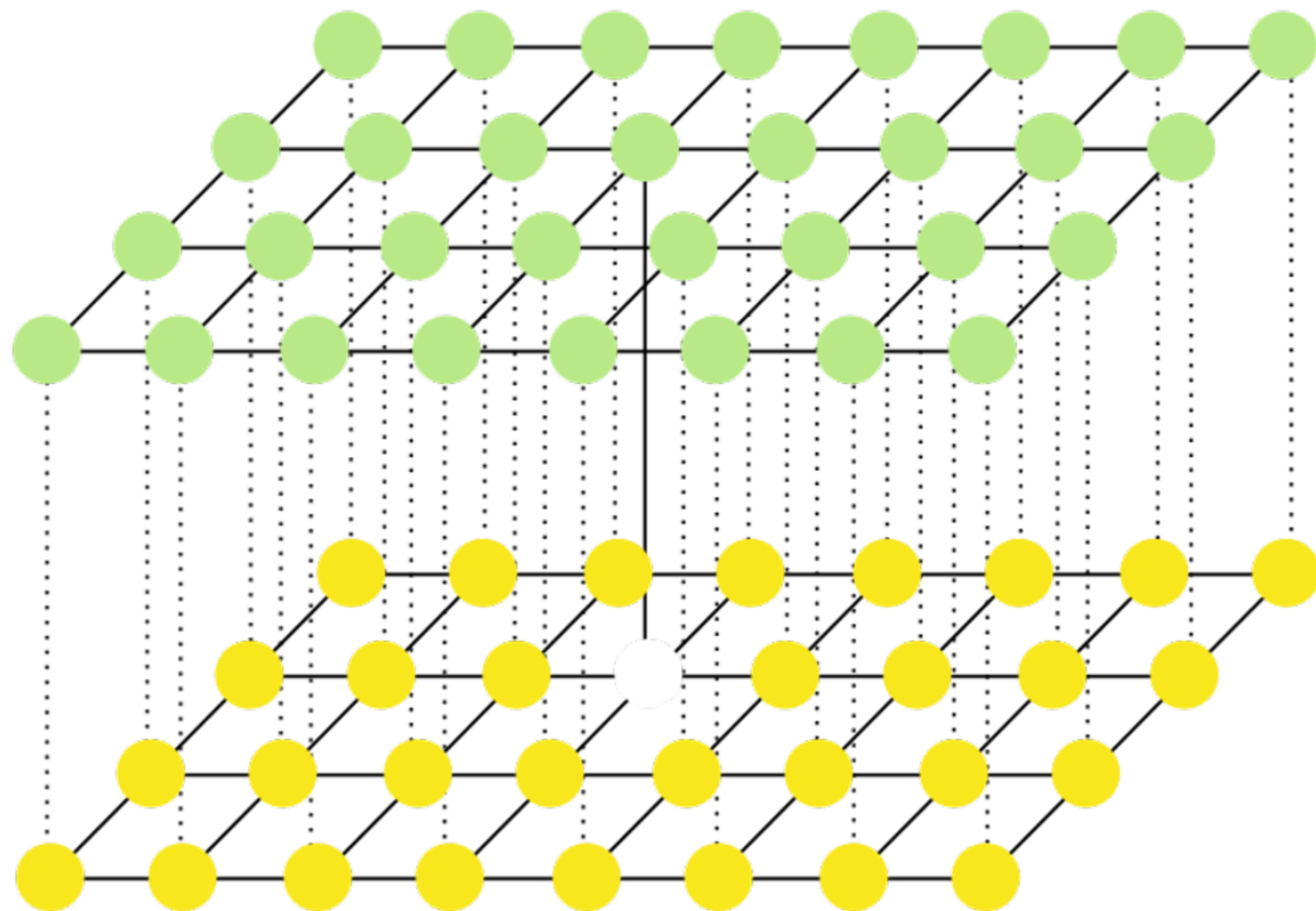
$$G_{xy} = \frac{\partial \langle \psi |}{\partial x} \frac{\partial | \psi \rangle}{\partial y}$$

Towards TDVP for 2D?

$$G_{xy} = \frac{\partial \langle \psi |}{\partial x} \frac{\partial | \psi \rangle}{\partial y}$$



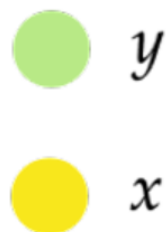
$$\partial_x \langle \psi(y) | \psi(x) \rangle =$$



$$G_{xy} = \partial_y [\partial_x \langle \psi(y) | \psi(x) \rangle]$$

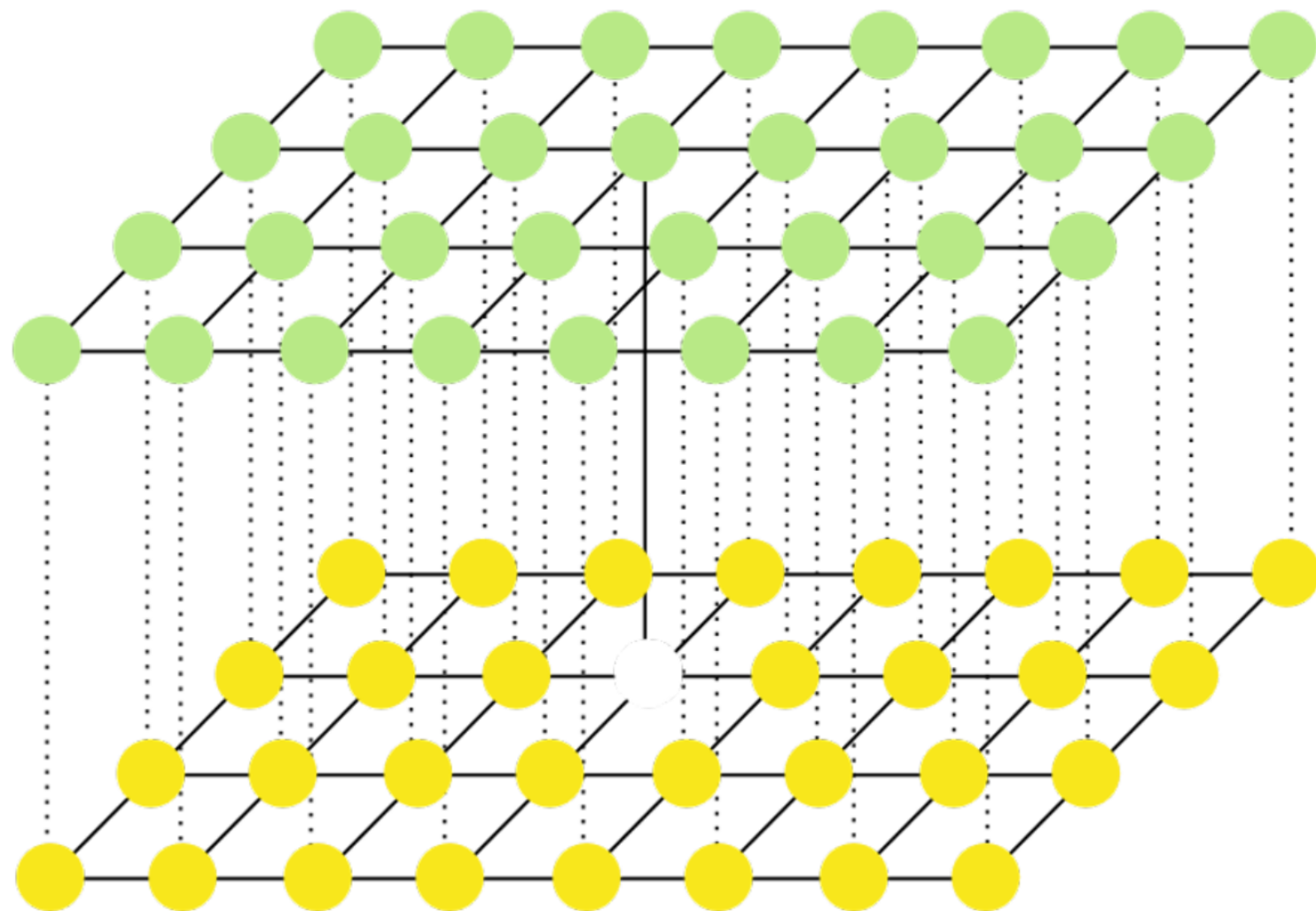
Towards TDVP for 2D?

$$G_{xy} = \frac{\partial \langle \psi |}{\partial x} \frac{\partial | \psi \rangle}{\partial y}$$



$$\partial_x \langle \psi(y) | \psi(x) \rangle =$$

Analytic backward



$$G_{xy} = \partial_y [\partial_x \langle \psi(y) | \psi(x) \rangle]$$

Only forward mode AD! Cheaper and Scalable!

Metric for uniform iPEPS

$$\mathcal{G} = \text{Diagram 1} + \text{Diagram 2} + \text{Diagram 3} + \text{Diagram 4} + \text{Diagram 5} + \dots$$

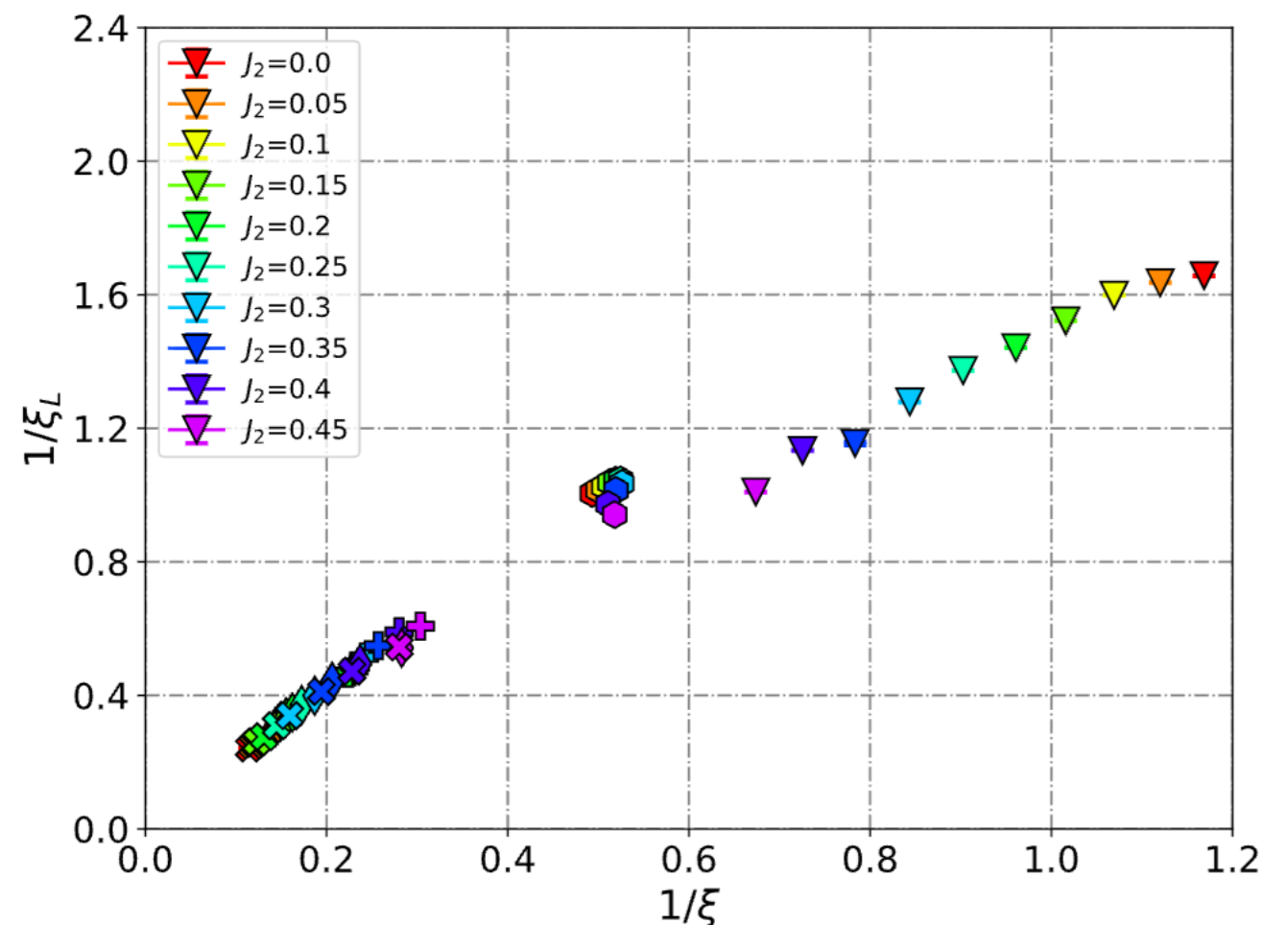
The diagram illustrates the metric $\mathcal{G}$ for uniform iPEPS as a sum of terms. Each term is a 2D lattice diagram with gray and cyan nodes and connecting lines. The first row contains three terms: a single gray node, a 2x2 grid of gray nodes with one cyan node at the bottom-left, and a 3x3 grid of gray nodes with two cyan nodes at the bottom-left and bottom-middle. The second row contains two terms: a 4x4 grid of gray nodes with four cyan nodes at the bottom-left, and a 5x5 grid of gray nodes with five cyan nodes at the bottom-left. The sequence ends with an ellipsis.

Metric for uniform iPEPS

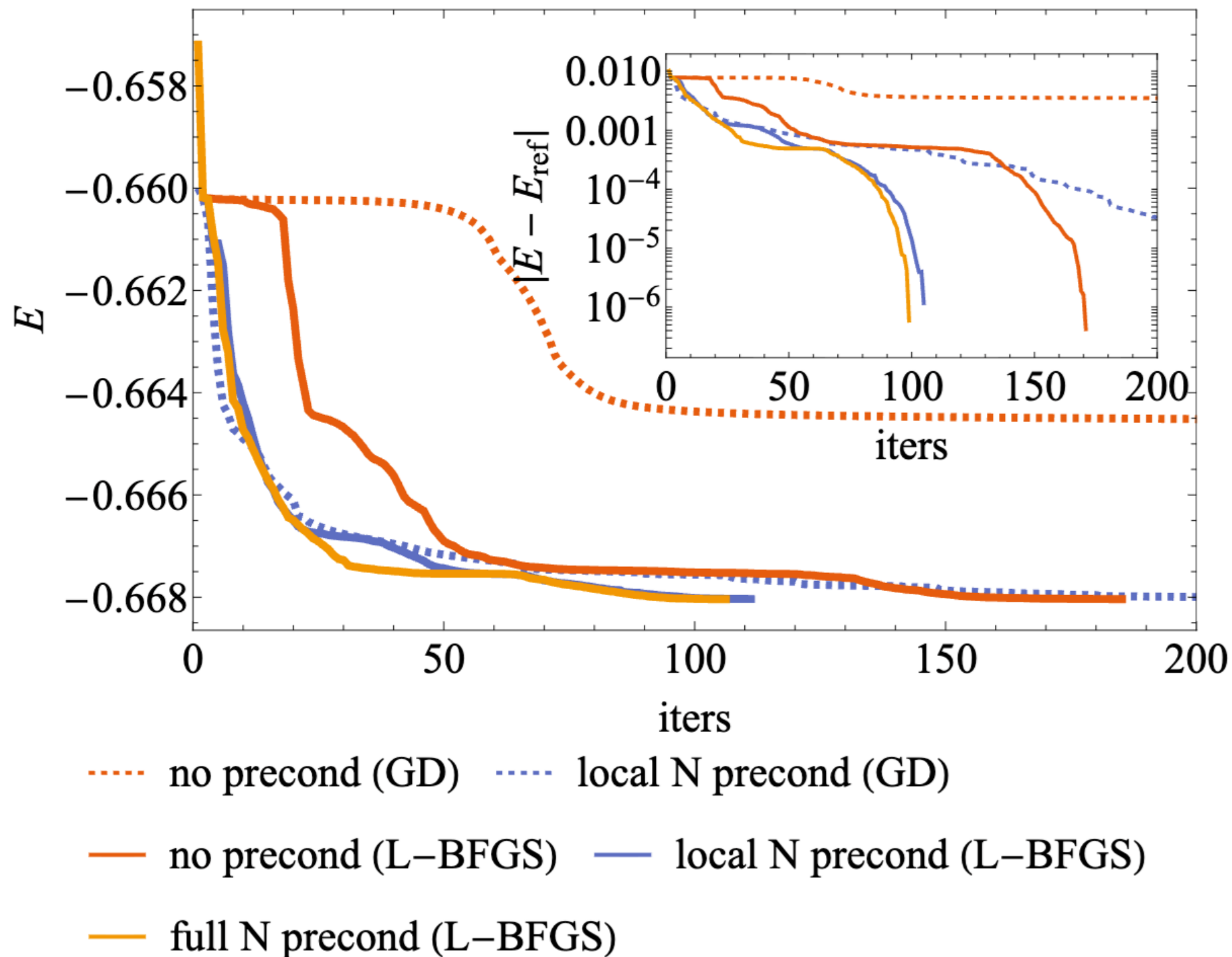
$$\mathcal{G} = \text{[Diagram 1]} + \text{[Diagram 2]} + \text{[Diagram 3]} + \text{[Diagram 4]} + \dots$$

Infinite summation!

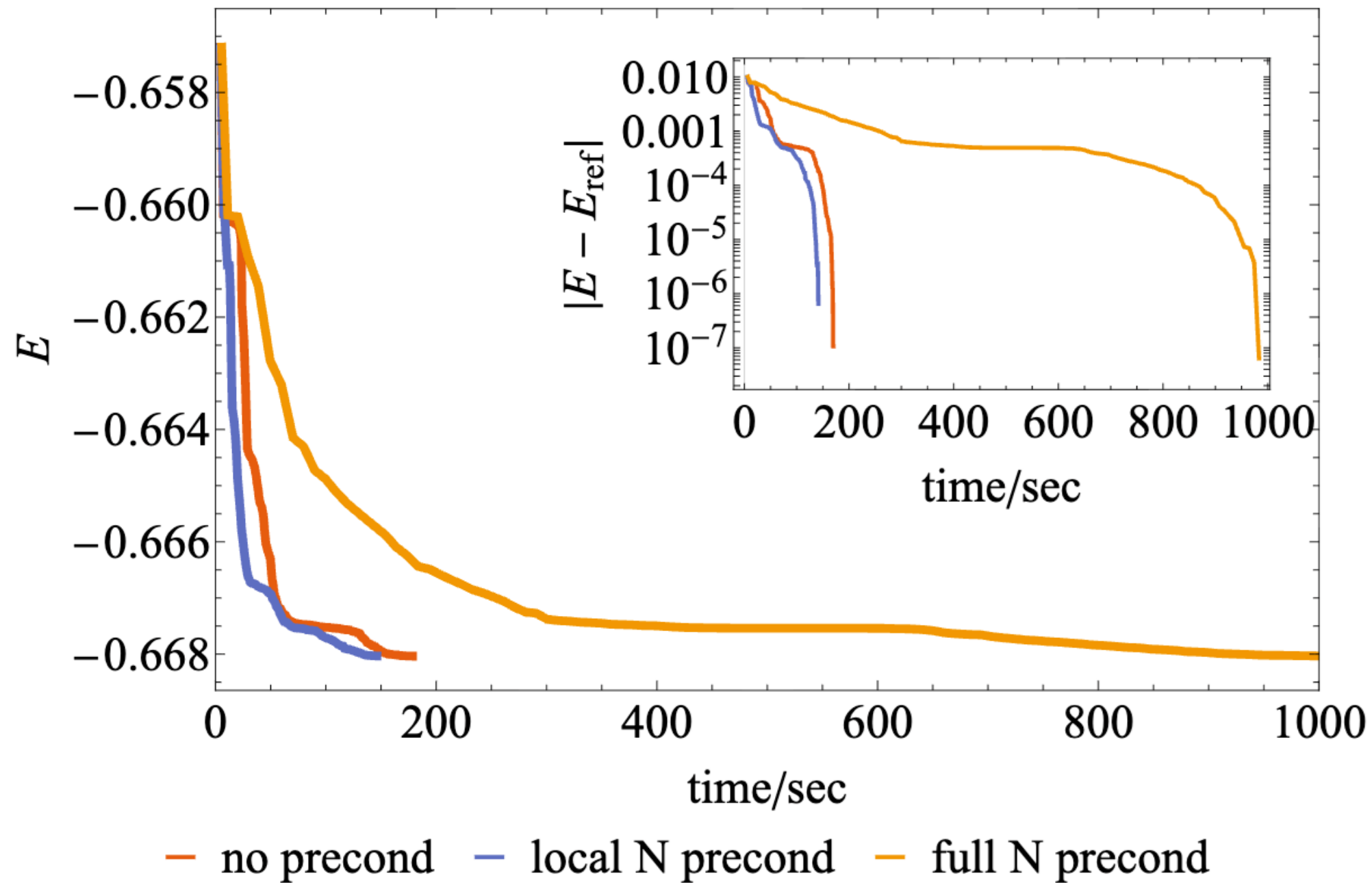
**$O(1)$ “observed”
correlation length**



Benchmark with Heisenberg model ($D=3$)

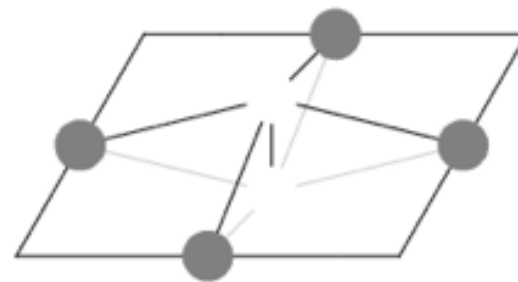


Benchmark with Heisenberg model (D=3)



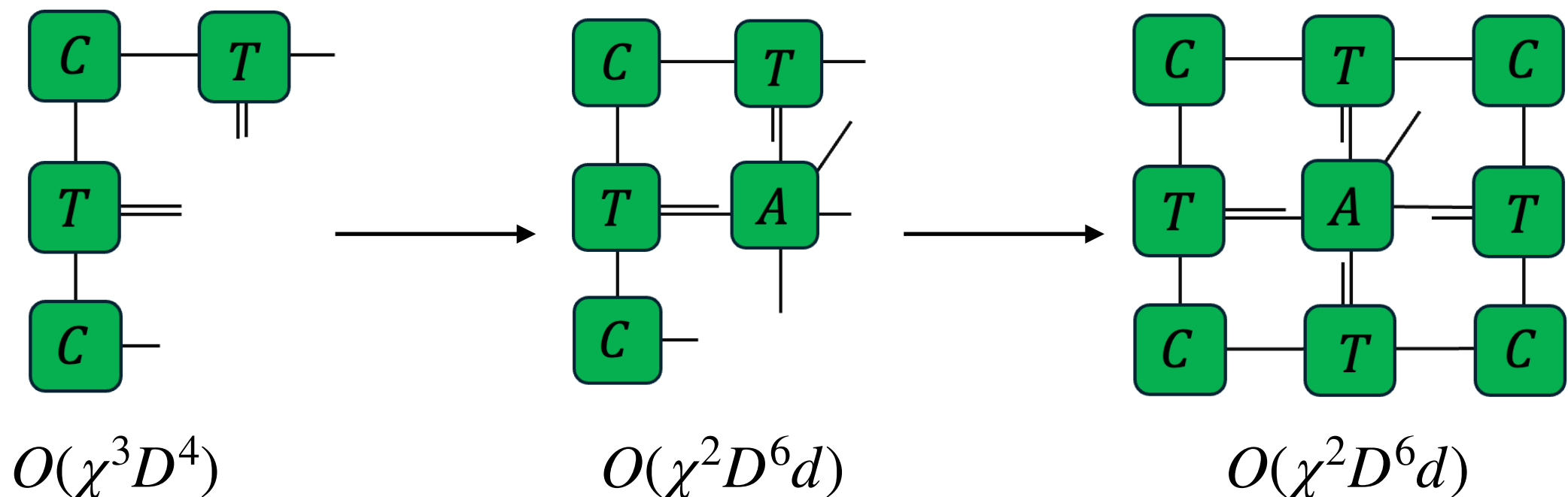
“Matrix-free” Trick

Path A: explicitly construct:



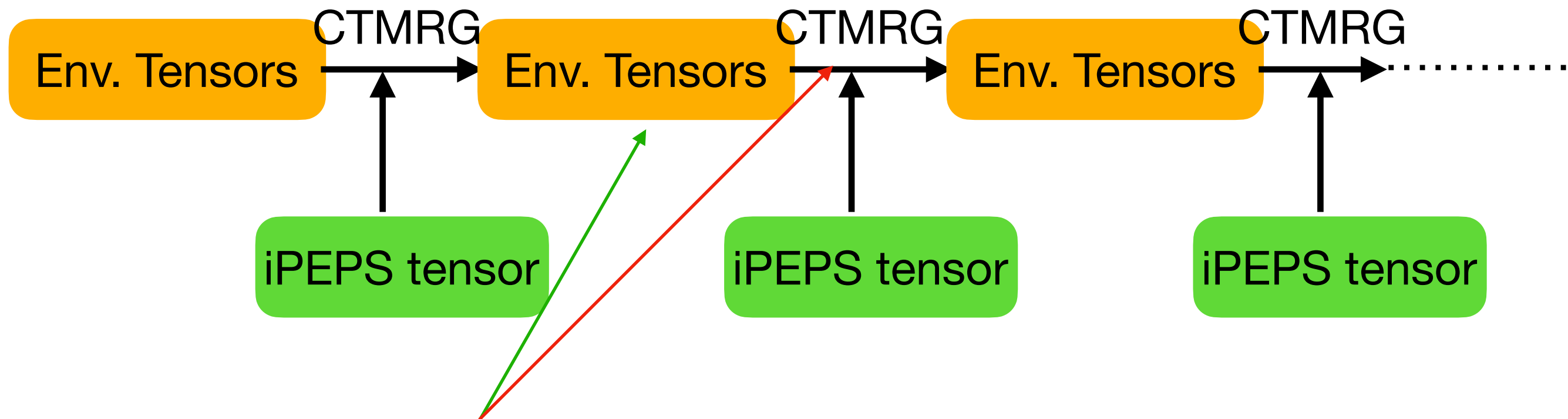
$$O(\chi^3 D^4 + \chi^2 D^8)$$

Path B: implicit construct:



Then use Krylov solver

Scalability Trick 1: CPU-offload + Slicing



1. Using loop to reduce peak
2. Multiple GPU dispatch
3. Cache this on CPU memory!



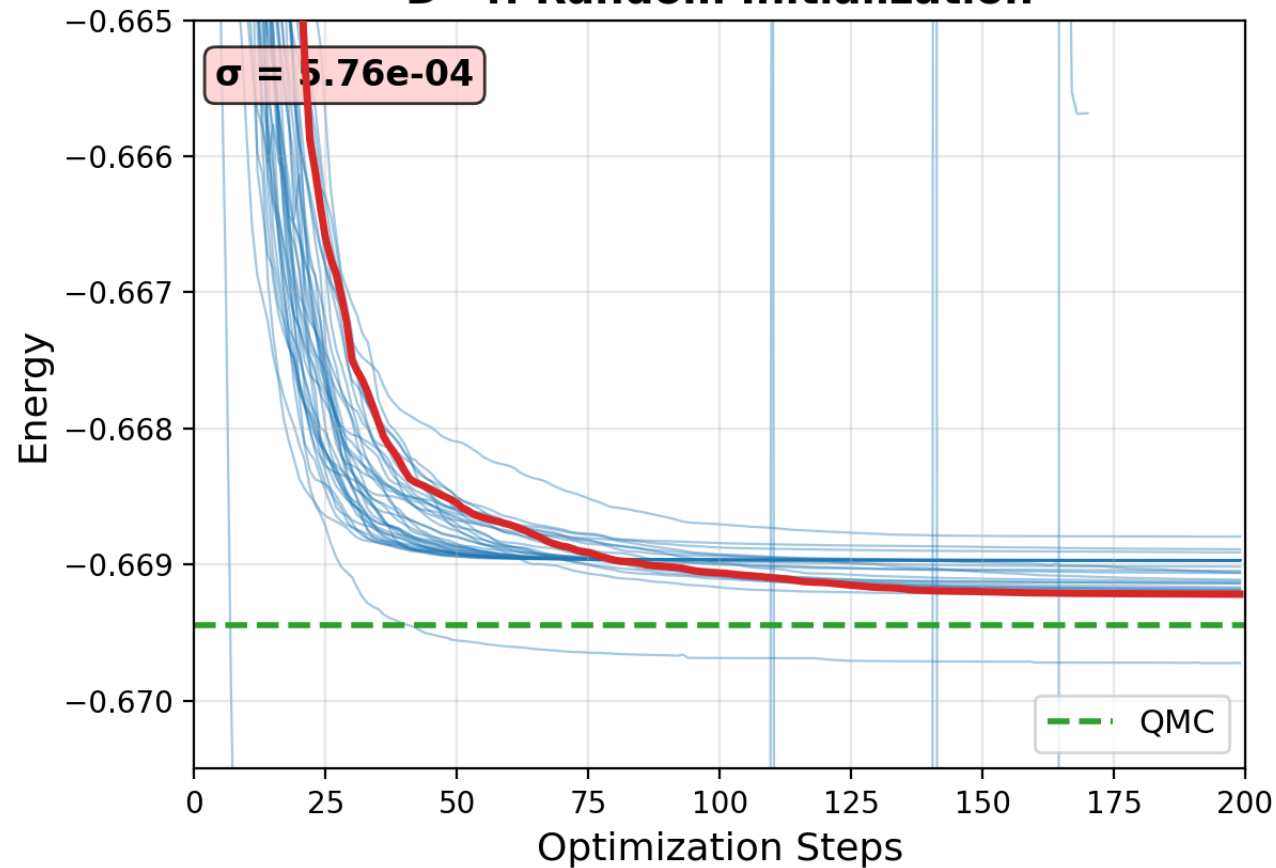
<https://github.com/qiyang-ustc/omeinsum>

One H100 can run AD+iPEPS for Heisenberg model
with $D=12$, $\chi=1536$!

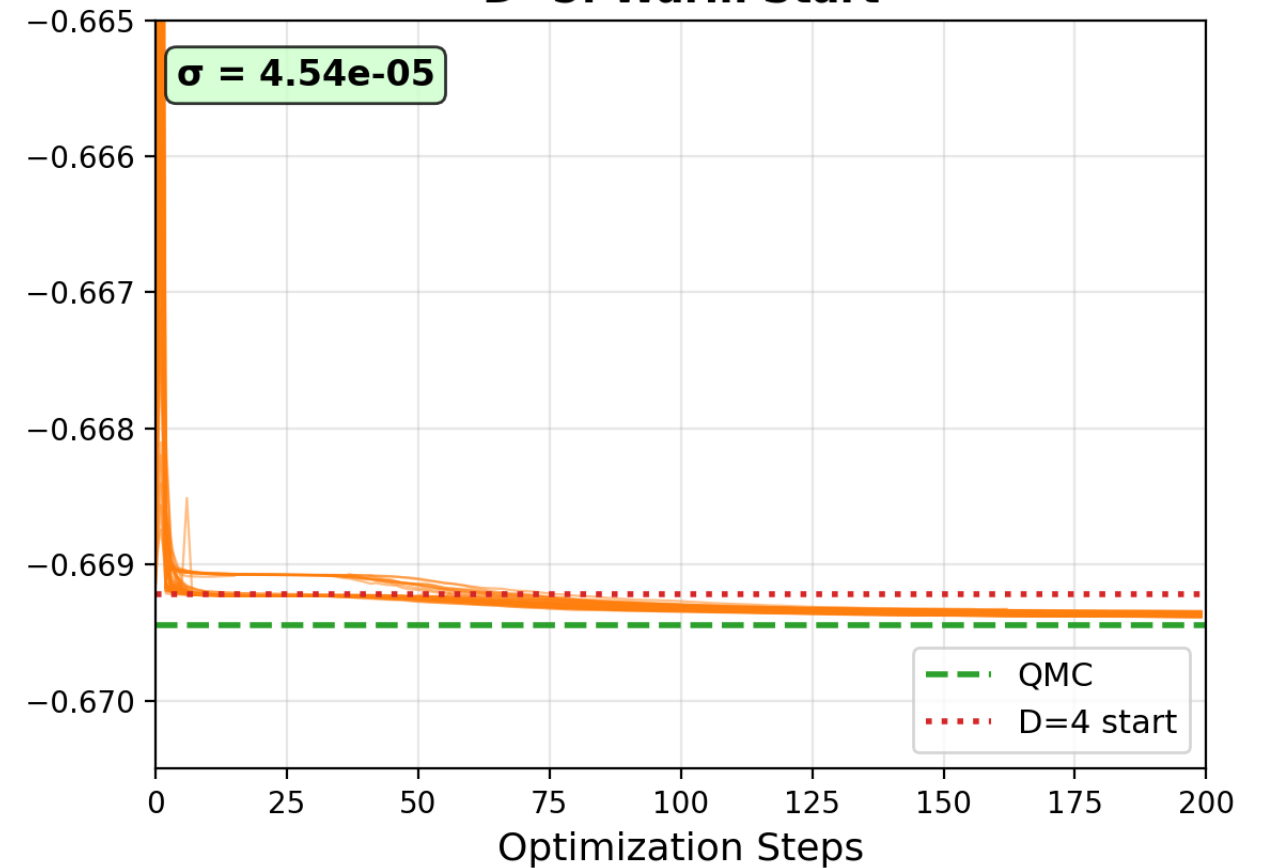
Stability Trick 2: Annealing + Ramping

D ramping

D=4: Random Initialization

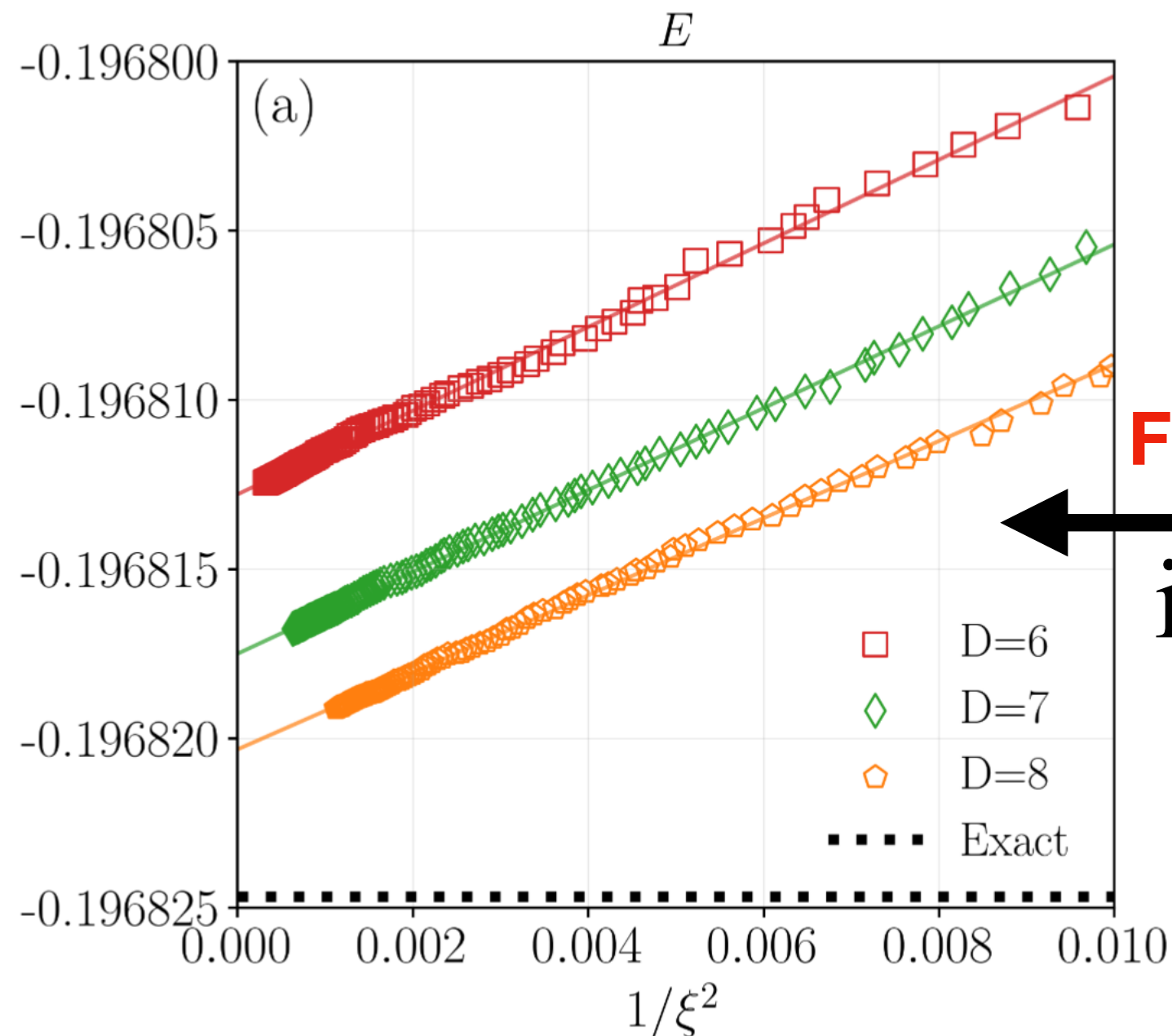


D=5: Warm Start



Sanity check: Variational Principle?

χ ramping



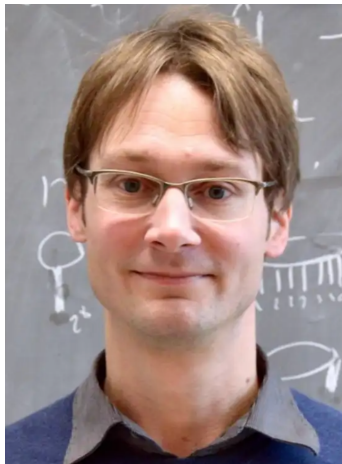
Fix iPEPS tensor

← increase χ

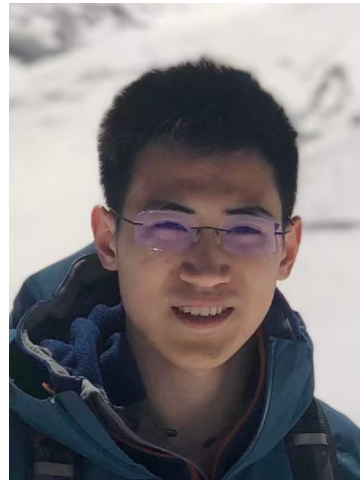
Outlook

- Beyond Spatial symmetry and Fermionic system?
- 2D TDVP?

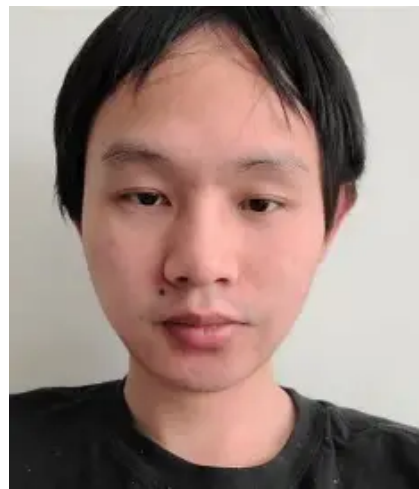
Thanks to my collaborators



P. R. Corboz



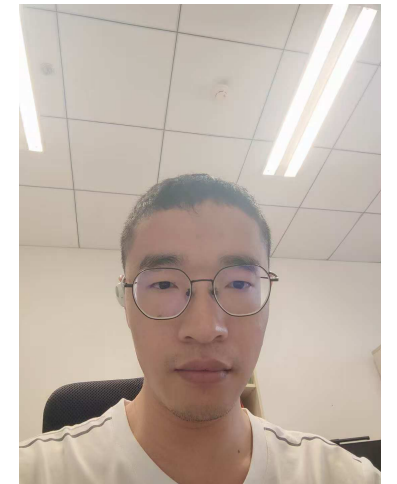
Yining Zhang



Yuchi He



Wei Tang



X.Y. Zhang

Philippe Corboz
Qi Yang †*

Wei Tang

Jutho Haegeman
Xingyu Zhang*

Yuchi He

Yining Zhang†



Jutho Haegeman



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OF AMSTERDAM



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UNIVERSITY

1. QRCTM C4v †

2. QRCTM C3v

3. Higher Spin Kitaev *

4. Precondition *

†*: equal first