

Introduction to DMRG

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References:

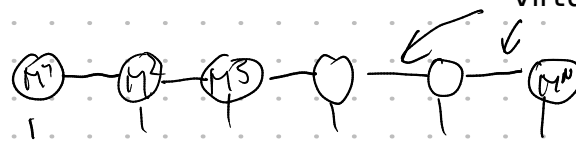
White PRL 69, 2863 (1992)
JH, Pollmann arXiv:1805.0055 (follow here)
Schollwoeck arXiv:1008.3477

Recap

$$|\psi\rangle = \sum_{\{j_n\}} \text{[Diagram: A cloud labeled } \psi \text{ with legs labeled } j_1, \dots, j_N \text{]}$$

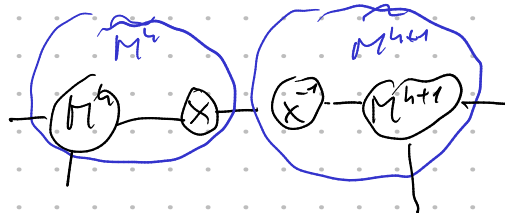
e.g. Spin $\frac{1}{2}$: $j_n = |\uparrow\rangle, |\downarrow\rangle$
 \downarrow
 $|j_1 \dots j_N\rangle$

MPS ansatz



virtual bonds, bond dimension χ

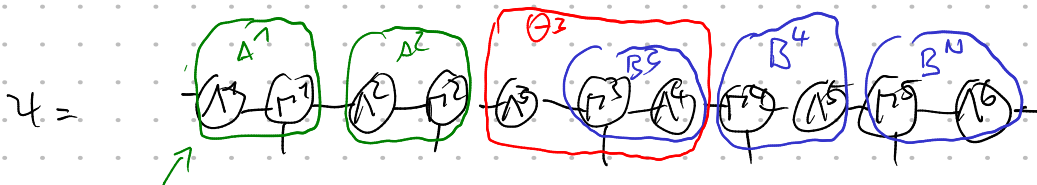
Gauge freedom



yields same MPS

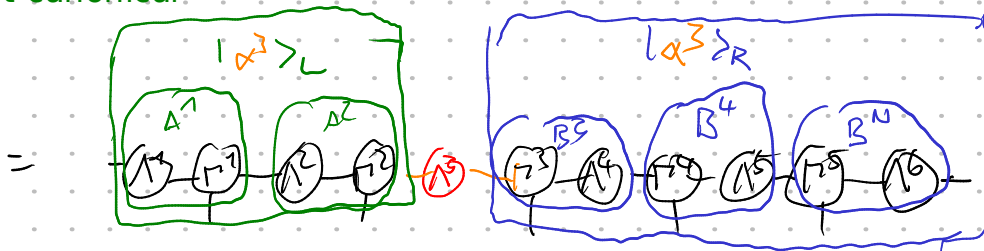
$$\text{for } X X^{-1} = \mathbb{1}$$

can be used to bring the MPS in canonical form defined by the Schmidt decomposition



left canonical

right canonical



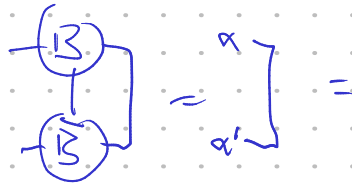
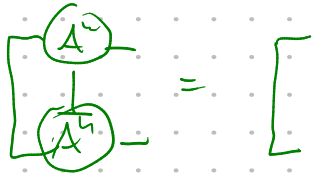
$$= \sum_{\alpha^3} |\alpha^3\rangle_L \lambda^3_{\alpha^3} |\alpha^3\rangle_R$$

Schmidt states form an orthonormal basis on left/right part!

→ identify virtual bond indices with Schmidt states

$$|\alpha^n\rangle_R = \text{[Diagram: A cloud with legs labeled } |j^n\rangle, |j^N\rangle \text{]}$$

Orthonormality conditions



Matrix product operators

= generalization of MPS to operators

convenient for Hamiltonians beyond nearest neighbors

$$H = \sum_{\vec{j}^1, \vec{j}^N} \left(\bigcirc^V \right) - \left(\bigcirc^{\vec{j}^1} \right) - \left(\bigcirc^{\vec{j}^2} \right) - \left(\bigcirc^{\vec{j}^3} \right) - \dots - \left(\bigcirc^{\vec{j}^N} \right) - \left(\bigcirc^U \right) \quad | \vec{j}^1, \dots, \vec{j}^N \rangle \langle \vec{j}^1, \dots, \vec{j}^N |$$

for translation invariant Hamiltonians often $\left(\bigcirc^{\vec{j}^n} \right) = \left(\bigcirc^{\vec{j}^{n+1}} \right)$

entries = local operators on site n

$$\left(\bigcirc^{\vec{j}^n} \right) = \begin{pmatrix} \mathbb{1}_n & z_n & -g x_n \\ 0 & 0 & z_n \\ 0 & 0 & \mathbb{1}_n \end{pmatrix} \quad \left(\bigcirc^L \right) = (1 \ 0 \ 0) \quad , \quad \left(\bigcirc^R \right) = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$\begin{aligned} \rightarrow \quad v_L W W v_R &= (\mathbb{1}_n \ z_n \ -g x_n) \begin{pmatrix} -g x_n \\ -z_n \\ \mathbb{1}_n \end{pmatrix} \\ &= -g \mathbb{1}_n x_n - z_n z_n - g x_n \mathbb{1}_n \end{aligned}$$

$$\Rightarrow H = -J \sum_n z_n z_{n+1} - g \sum_n x_n \quad = \text{transverse field ising model}$$

General block structure for the MPO

$$W = \begin{pmatrix} \mathbb{1} & C & D \\ & A & B \\ & & \mathbb{1} \end{pmatrix} \quad v_L = (1, 0, \dots, 0, 0) \quad , \quad v_R = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}$$

yields

$$H = \sum_n D_n + C_n B_{n+1} + C_n A_{n+1} B_{n+2} + C_n A_{n+2} A_{n+2} B_{n+3} + \dots$$

$$W = \begin{pmatrix} \mathbb{1} & x^n & y^n & -h z^n \\ & \downarrow x^n & & \\ & & \downarrow y^n & \\ & & & \mathbb{1} \end{pmatrix} \quad \leadsto \quad H = J \sum_n (x^n x^{n+1} + y^n y^{n+1}) - h \sum_n z^n$$

$$W = \begin{pmatrix} \mathbb{1} & P^n & 0 & 0 \\ & x^n & 0 & 0 \\ & & P^n & \\ & & & \mathbb{1} \end{pmatrix} \quad \leadsto \quad H = \sum_n P_n X_{n+1} P_{n+2}$$

One can formalize this with the finite state machine picture to autogenerate MPOs given the terms of H

Side note: W is not diagonalizable, it Jordan block structure:

$$W \cong \begin{pmatrix} 1 & \varepsilon \\ & 1 \end{pmatrix} \quad \begin{pmatrix} 1 & \varepsilon \\ & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} + \varepsilon \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

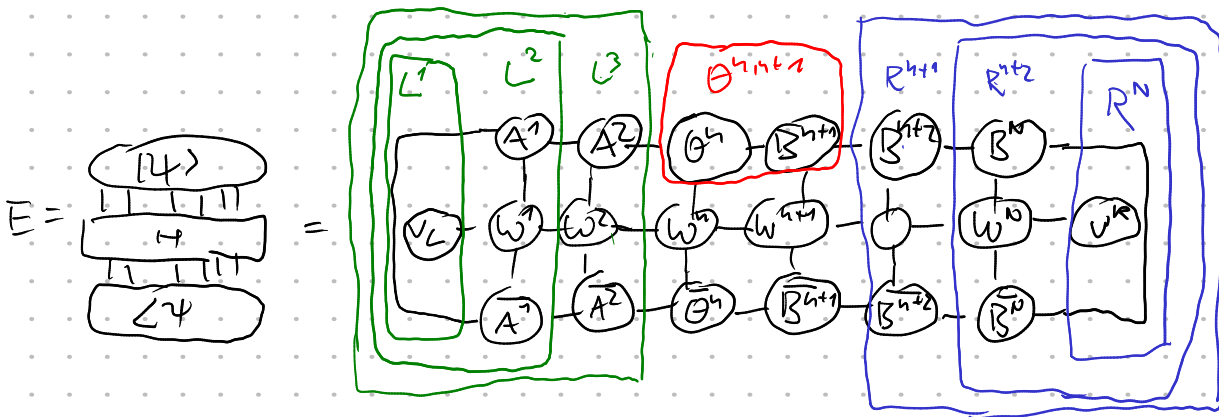
$$\begin{pmatrix} 1 & \varepsilon \\ & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

H is extensive, applying the transfer matrix adds energy density!

Density Matrix Renormalization Group (DMRG) algorithm

goal: variational minimization of the energy

$$E = \langle \psi | H | \psi \rangle$$



left/right environments contain only left/right-canonical MPS tensors!

Finite DMRG

Start with an MPS in right canonical form

for n in $\{1, 2, \dots, N-1\}$:

right sweep

find the optimal $\Theta^{n,n+1}$ keeping other tensors fix

split $\Theta^{n,n+1} = \text{SVD} = A^n - \Lambda^{n+1} - B^{n+1}$ and truncate

use Λ^n to calculate updated L^{n+1}

for n in $\{N-2, \dots, 1\}$:

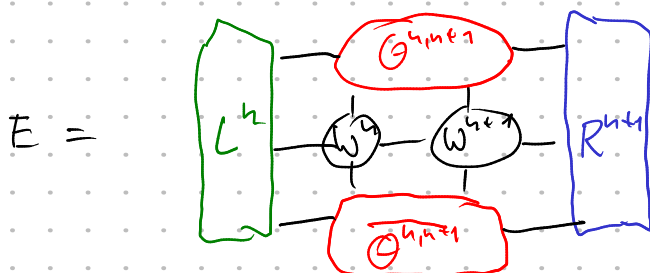
left sweep

find optimal $\Theta^{n,n+1}$

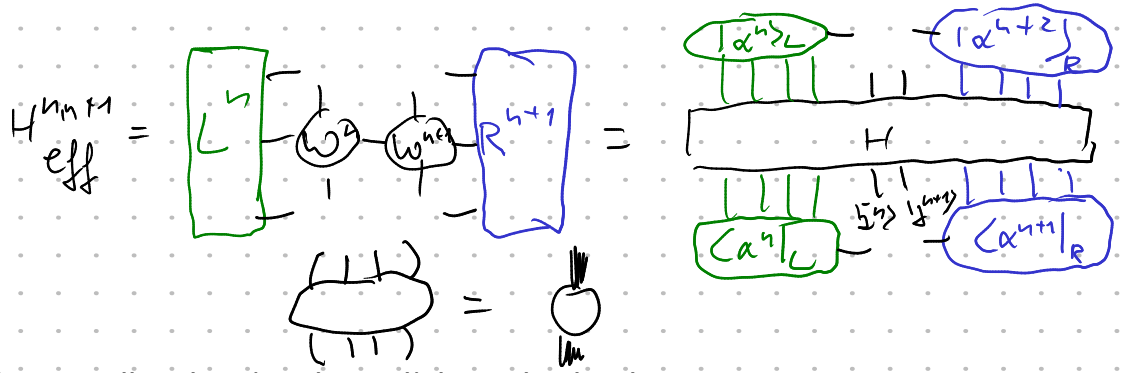
split $\Theta^{n,n+1} = A^n - \Lambda^{n+1} - B^{n+1}$ and truncate

use B^{n+1} to calculate the updated R^n

How to find optimal $\Theta^{n,n+1}$?



define



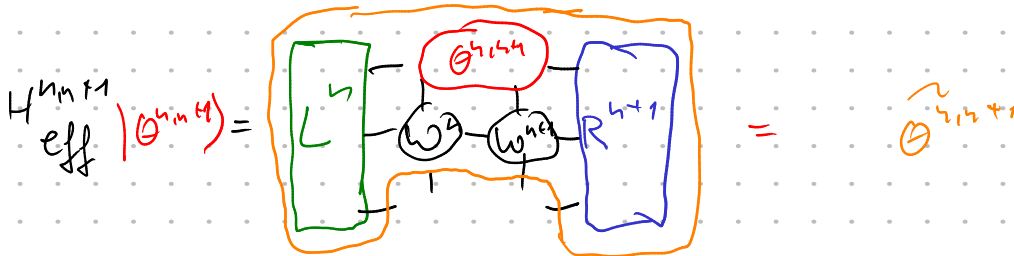
This is the Hamiltonian (projected) into the basis

$$|\alpha^n\rangle_L \otimes |\beta^n\rangle \otimes |\beta^{n+1}\rangle \otimes |\alpha^{n+2}\rangle_R$$

This is an orthonormal basis!

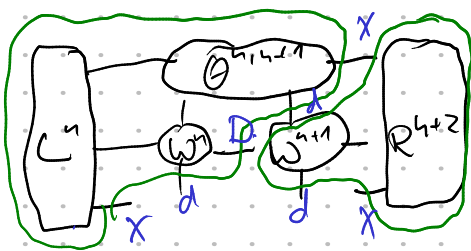
Hence, the optimal $|\Theta^{n,n+1}\rangle$ is simply given by diagonalizing $H_{\text{eff}}^{n,n+1}$

viewed as a matrix acting on the top indices



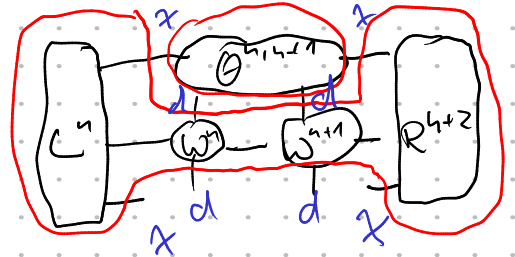
The ground state of $H_{\text{eff}}^{n,n+1}$ can be found with Lanczos algorithm (or similar)

Note: contraction order matters!



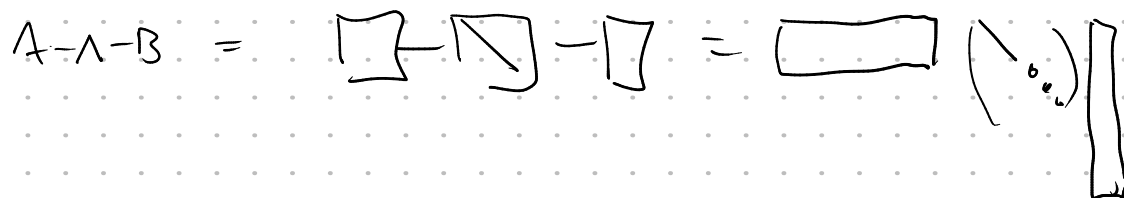
$$O(x^3 D d^2)$$

vs



$$O(x^4 d^4)$$

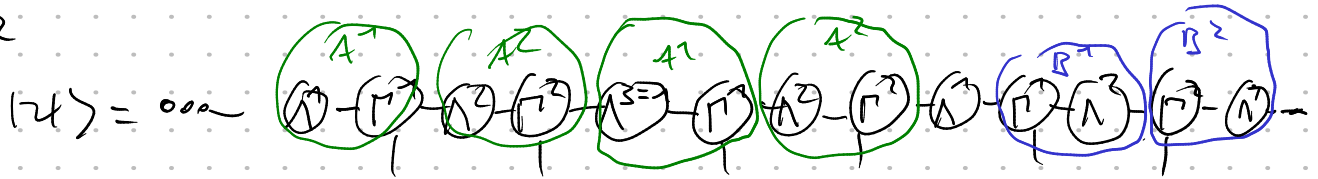
One can also do this optimizing a single site at once



Infinite DMRG

consider a system which is translation invariant with unit cells with N sites

Say $N=2$



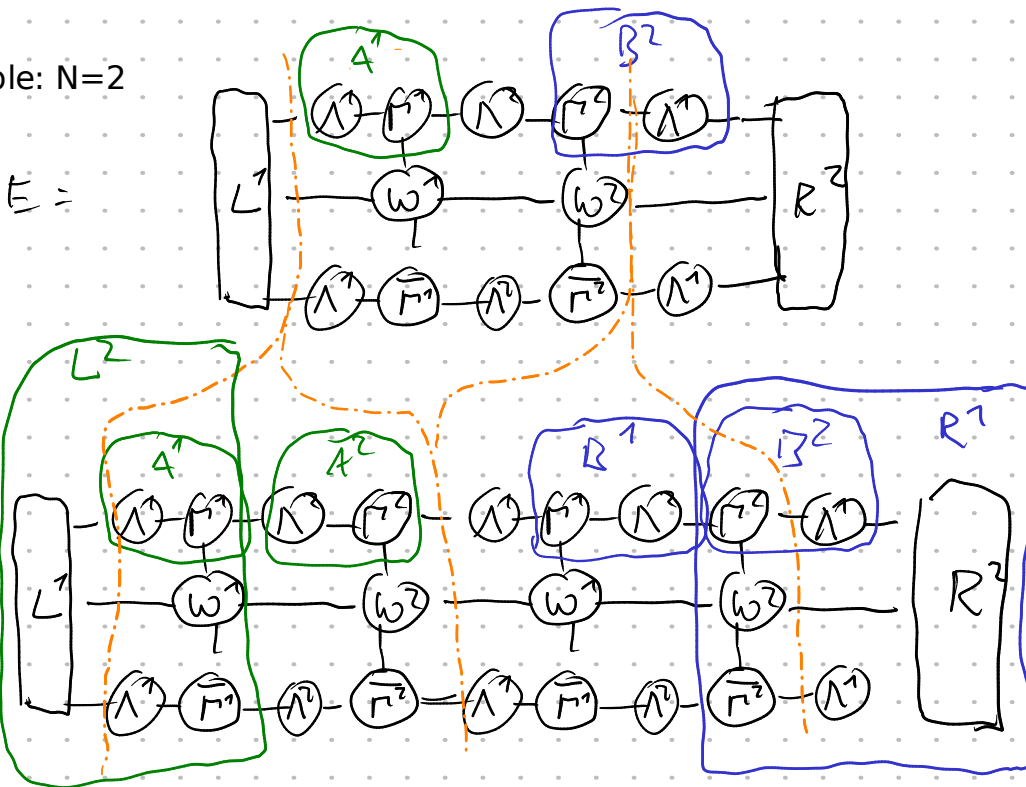
Start with a small system of just one unit cell

sweep left-right left in a single unit cell (as in finite DMRG)
but include the bond between unit cells (which is trivial for finite DMRG)

During each sweep, grow the left/right environets by one unit cell, assuming translation invariance

Repeat until actual translation invariance is reached

Example: $N=2$



Note: total energy increases by energy density!