

# *Tensor Networks & Entanglement*

I S U R O L I A S I M O L K Y & E V I L A N D I S W I C H I L

*Andrej Gendiar*

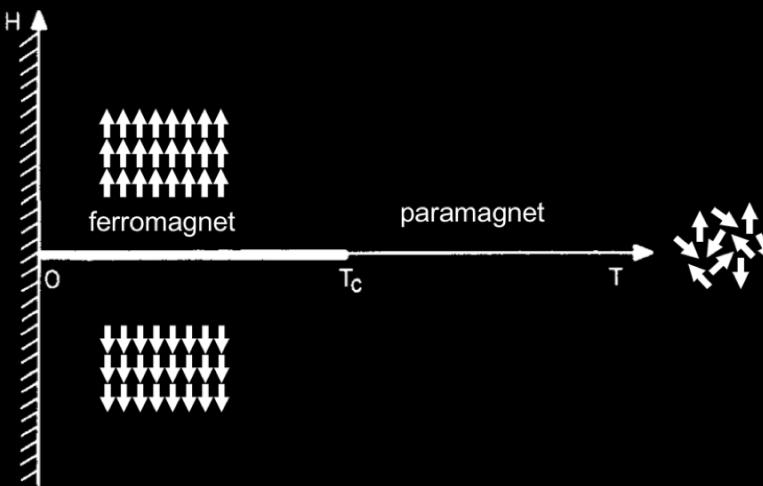
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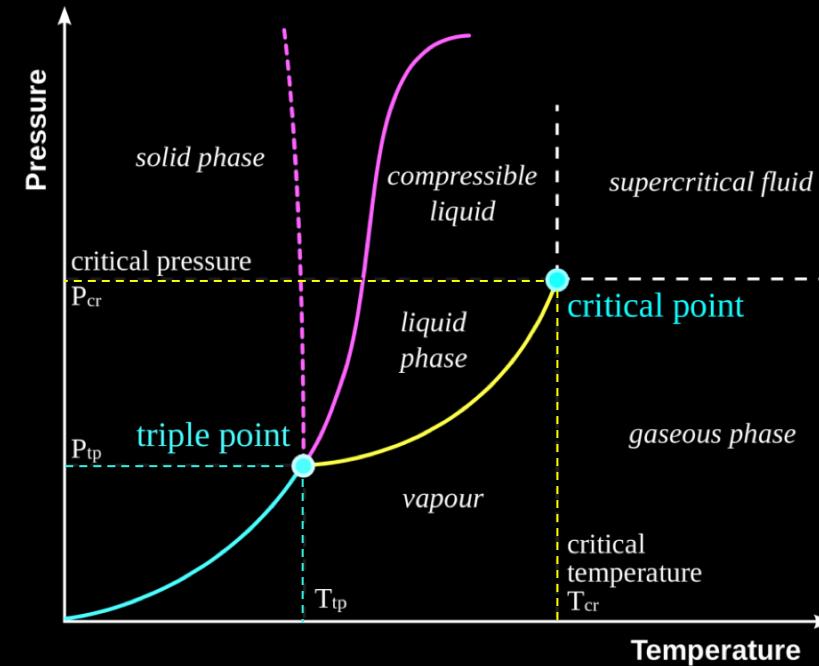
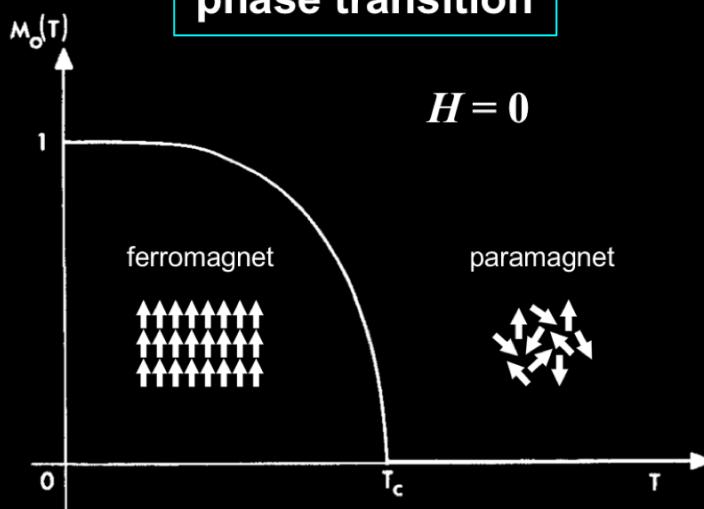
*1<sup>st</sup> eduQUTE in Bratislava, Feb 19<sup>th</sup> - 22<sup>nd</sup>, 2018*

*Motivation remarks*  
*Part 1*

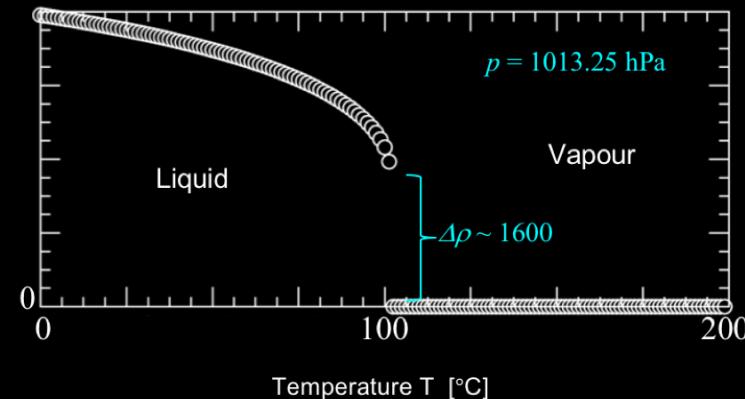
# Phase transitions

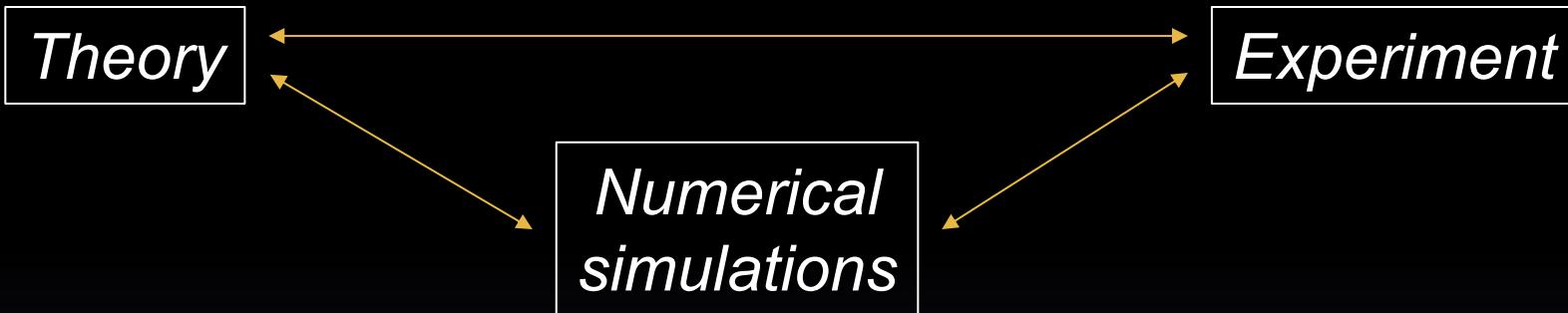


The 2<sup>nd</sup> order  
phase transition



The 1<sup>st</sup> order  
phase transition





### ***Numerical methods (in terms of Tensor Networks)***

- ❖ **DMRG** *Density Matrix Renormalization Group*
- ❖ **CTMRG** *Corner Transfer Matrix Renormalization Group*
- ❖ **MPS** *Matrix Product States*
- ❖ **TEBD** *Time Evolving Block Decimation*
- ❖ **HOTRG** *Higher-Order Tensor Renormalization Group*
- ❖ **TPVF** *Tensor Product Variational Formulation*
- ❖ **MERA** *Multi-scale Entanglement Renormalization Ansatz*

# Entanglement Entropy

(What else is it good for?)

$$H|\psi_n\rangle = E_n|\psi_n\rangle, \quad n = 0, 1, 2, \dots$$

$$\rho'_A = \text{Tr}_B \{ |\psi_0(A, B)\rangle\langle\psi_0(A, B)|\}$$

$$S = -\text{Tr}(\rho'_A \log_2(\rho'_A)) \geq 0$$



*Motivation remarks*  
*Part 2*

*A quantum state of Hamiltonian  
is like*

*"a state of mind in brain"*

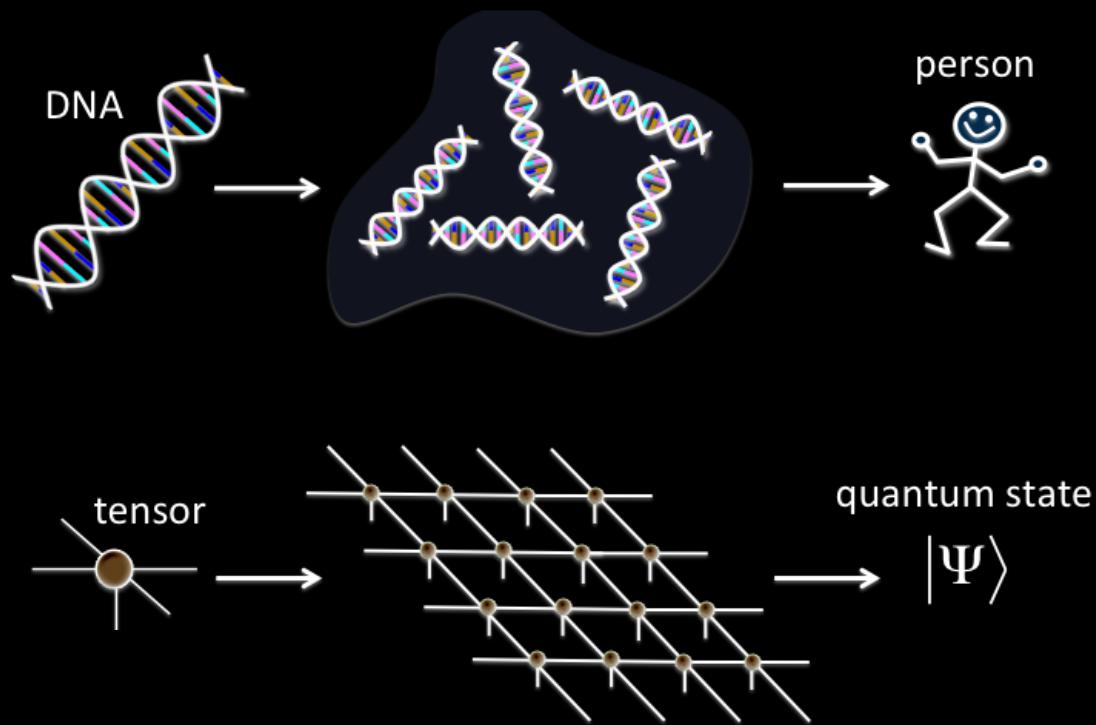
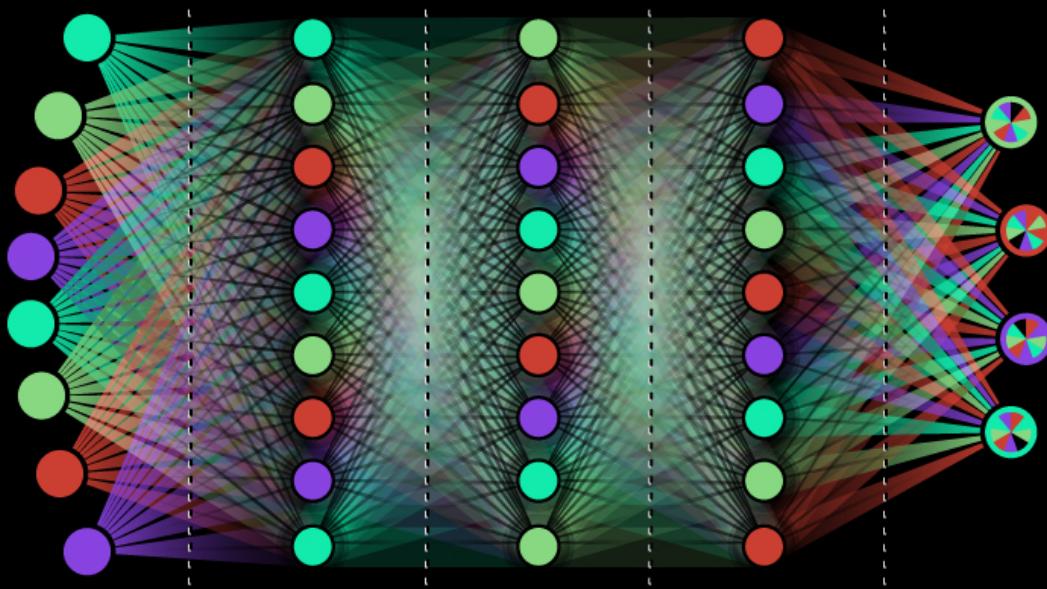




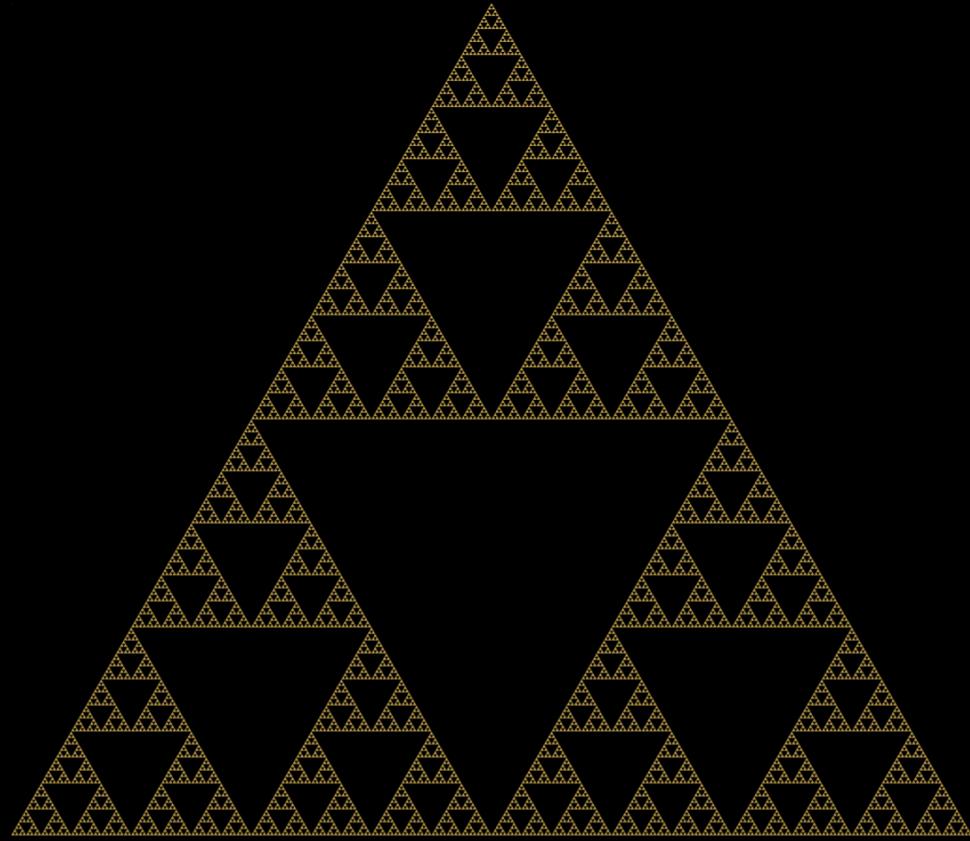
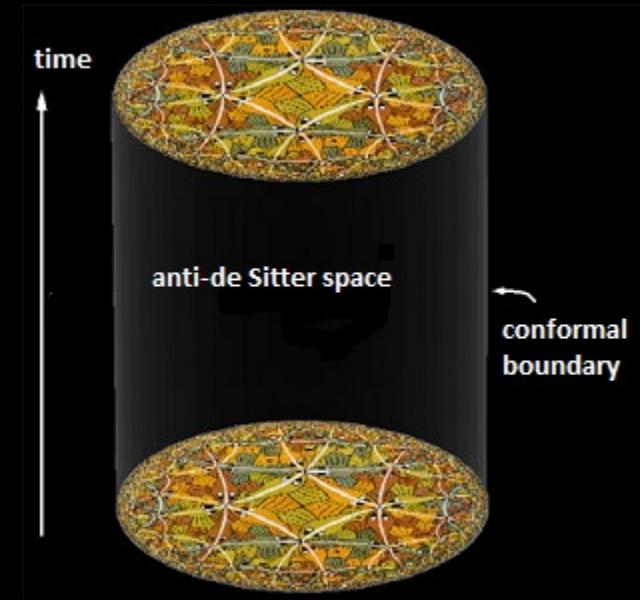
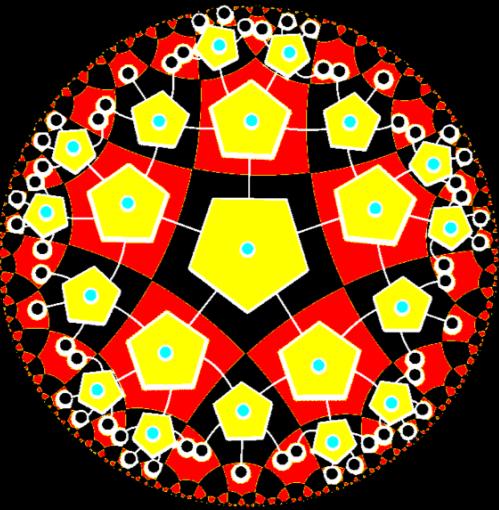
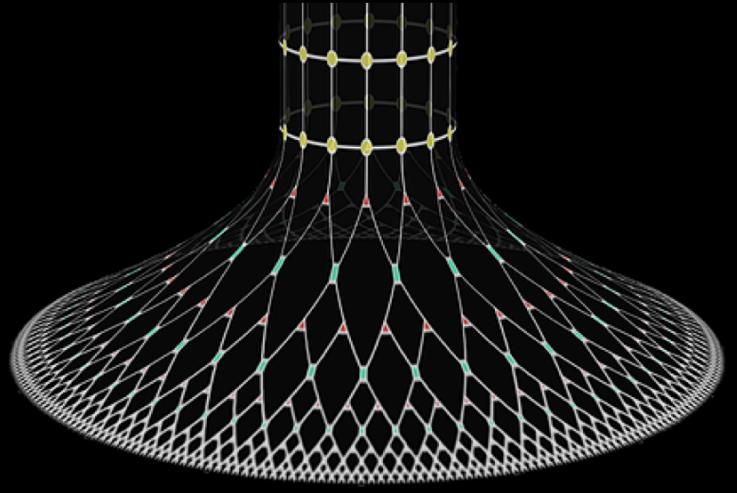


### DEEP NEURAL NETWORK

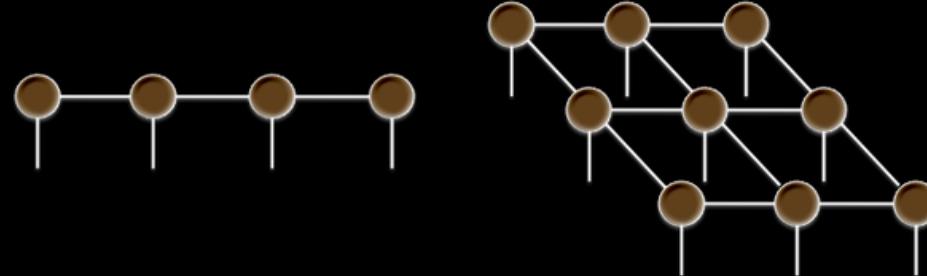
Input layer → Hidden layer 1 → Hidden layer 2 → Hidden layer 3 → Output layer



$$\frac{1}{\sqrt{2}}| \text{cat sitting} \rangle + \frac{1}{\sqrt{2}}| \text{cat lying down} \rangle$$



Matrix Product State → Tensor Product State



*Quantum mechanics*  
*Introduction to numerics*

# Introduction to solving quantum-mechanical problems

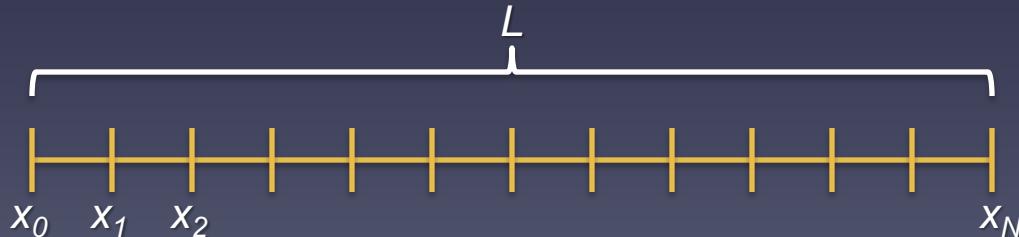
- Only a few simple systems are exactly (analytically) solvable!
- The aim is to find out efficient approximations
  - either analytically (by pen and heaps of paper and time)
  - or numerically (by computers and much shorter time)
- If exact solutions exist, they may serve as benchmarks
- Two examples: Let us study two simplest quantum systems numerically  
At first, continuous variables has to be discretized.

Discretization:

$$0 \leq x \leq L \rightarrow x_i = \frac{iL}{N} \quad \text{and} \quad i = 0, 1, 2, \dots, N$$

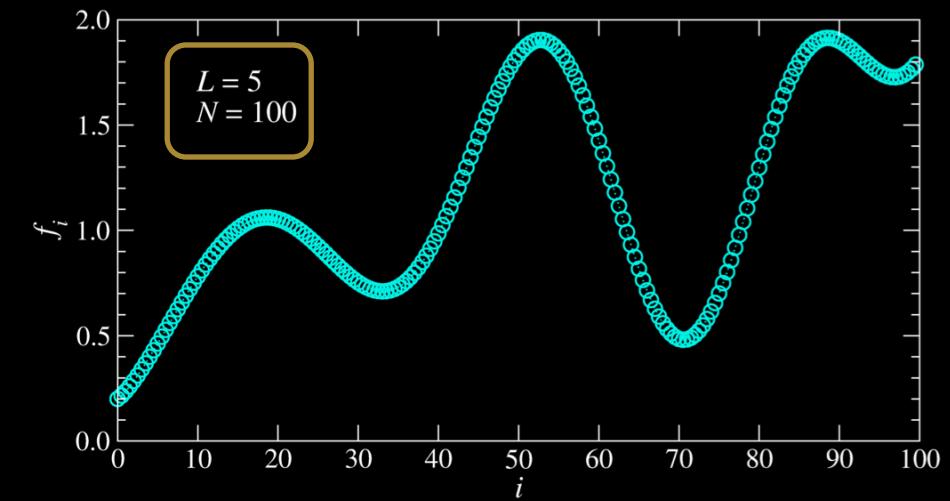
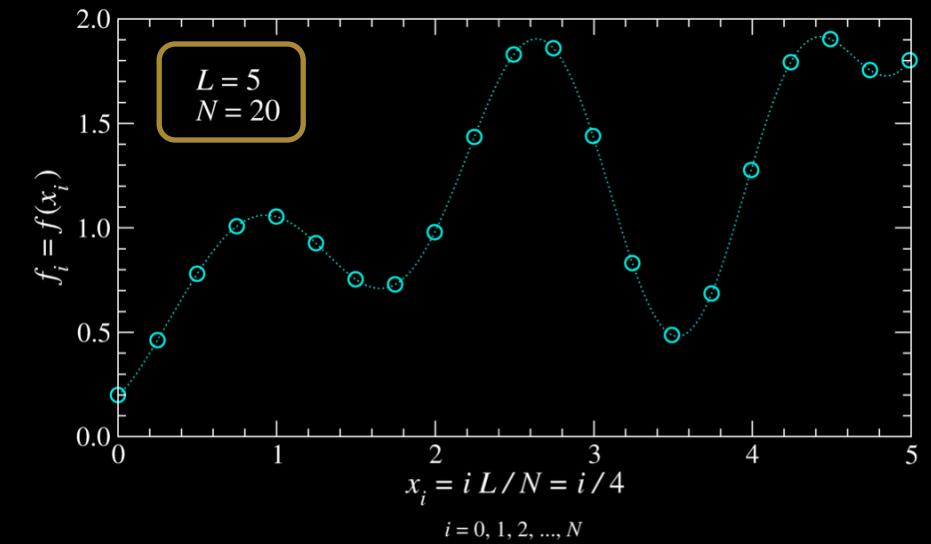
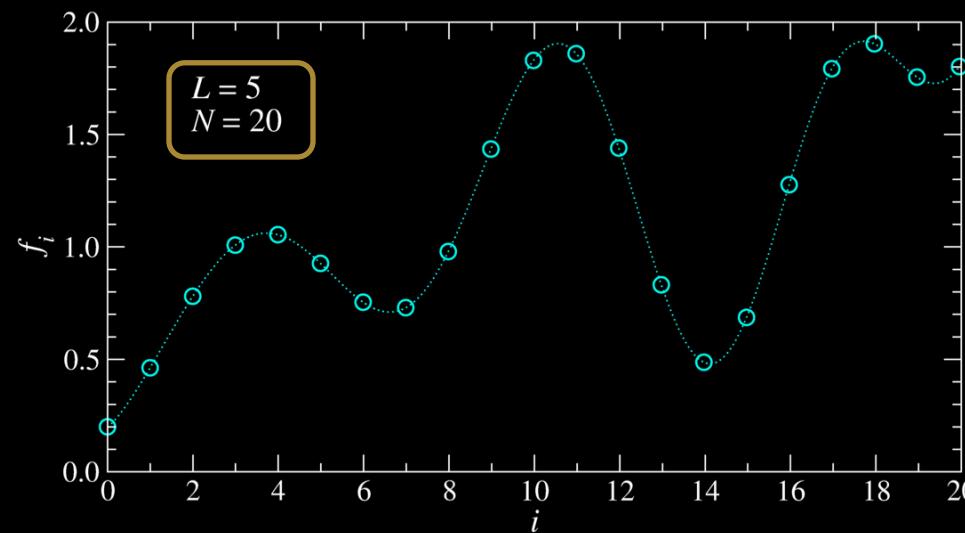
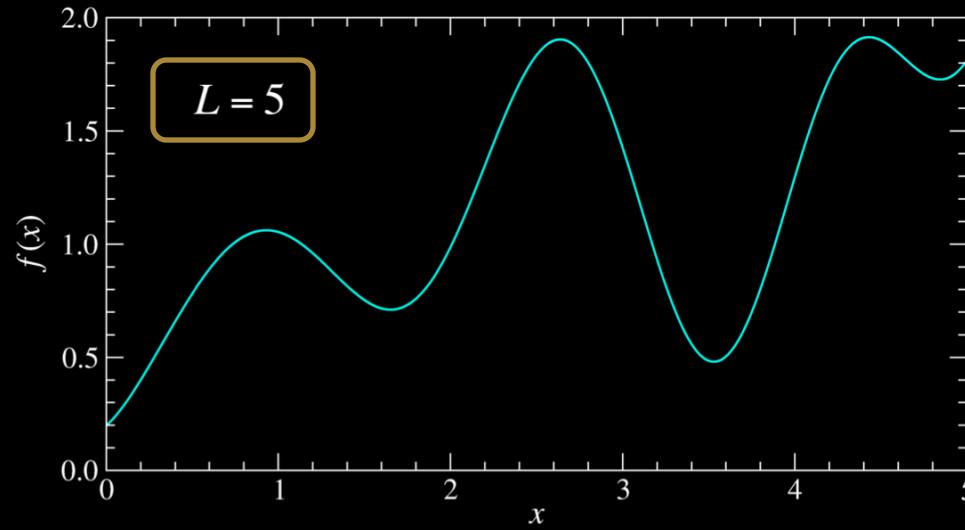
$$x \rightarrow x_i \rightarrow i$$

$$f(x) \rightarrow f(x_i) \rightarrow f_i$$



**Discretization:**

$$\begin{aligned}x &\rightarrow x_i \rightarrow i \\ f(x) &\rightarrow f(x_i) \rightarrow f_i\end{aligned}\quad 0 \leq x \leq L \rightarrow x_i = \frac{iL}{N} \quad \text{and} \quad i = 0, 1, 2, \dots, N$$



## A simple example: 1D particle in a box (infinite potential well)

$$\left[ -\frac{\hbar^2}{2m} \Delta + V(x) \right] \Psi(x) = E \Psi(x), \quad V(x) = \begin{cases} 0, & 0 \leq x \leq L \\ \infty, & \text{otherwise} \end{cases}$$

$$-\Delta \Psi(x) = \frac{2m}{\hbar^2} E \Psi(x) \quad \text{let} \quad \hbar^2 / 2m = 1$$

$$\downarrow \quad -\Delta \Psi(x_i) = E' \Psi(x_i), \quad x_i = \frac{iL}{N} \quad \text{and} \quad i = 0, 1, 2, \dots, N \quad \downarrow \text{discretized}$$

$$-\frac{\Psi\left(\frac{(i-1)L}{N}\right) - 2\Psi\left(\frac{iL}{N}\right) + \Psi\left(\frac{(i+1)L}{N}\right)}{\left(\frac{L}{N}\right)^2} = E' \Psi\left(\frac{iL}{N}\right)$$

$$-\Psi_{i-1} + 2\Psi_i - \Psi_{i+1} = \tilde{E} \Psi_i$$

fixed boundary conditions:

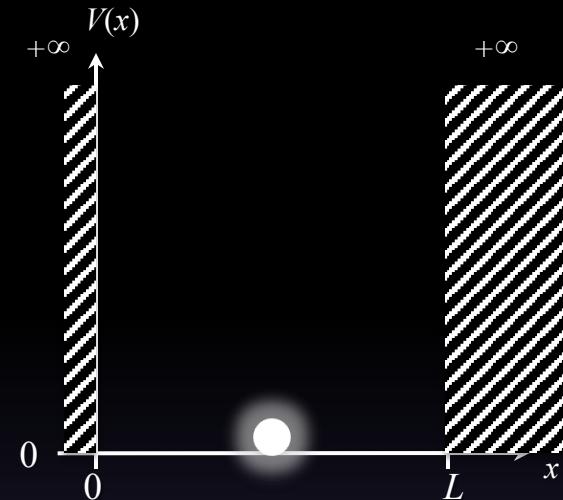
$$\Psi_{-1} = \Psi_{N+1} = 0$$

periodic boundary conditions:

$$\Psi_{-1} = \Psi_{N+1} = -1$$

Matrix to be diagonalized to get  $E_0$ :

$$\begin{pmatrix} 2 & -1 & 0 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & 0 & \dots & 0 \\ 0 & 0 & -1 & 2 & -1 & 0 \\ 0 & 0 & 0 & -1 & 2 & 0 \\ \vdots & & & & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & 2 \end{pmatrix} \begin{pmatrix} \Psi_0 \\ \Psi_1 \\ \Psi_2 \\ \Psi_3 \\ \vdots \\ \Psi_N \end{pmatrix} = \tilde{E}_0 \begin{pmatrix} \Psi_0 \\ \Psi_1 \\ \Psi_2 \\ \Psi_3 \\ \vdots \\ \Psi_N \end{pmatrix}$$



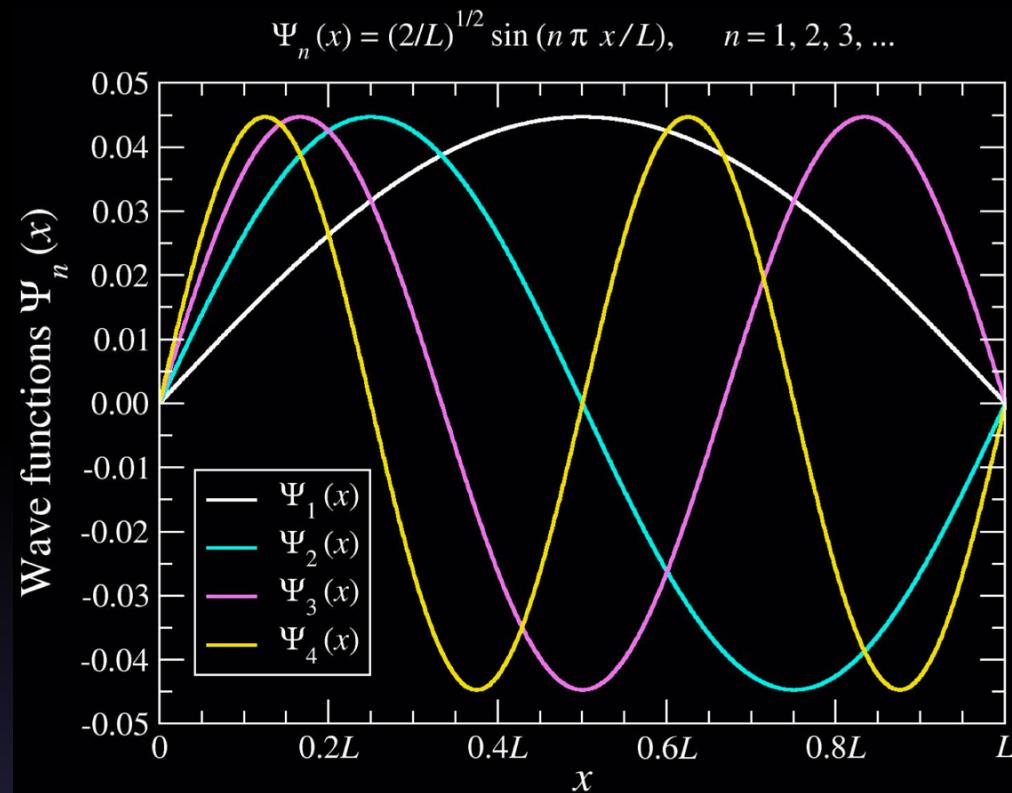
$$\hat{H} = -\frac{\partial^2}{\partial x^2} \approx -\sum_{j=1}^{N=1} (\hat{c}_j^\dagger \hat{c}_{j+1} + \hat{c}_{j+1}^\dagger \hat{c}_j) + 2 \sum_{j=1}^{N=1} \hat{c}_j^\dagger \hat{c}_j$$

**Exact solution exists!**

For the 1D particle  
in the box we get:

$$E_n = \frac{\pi^2}{L^2} n^2, \quad n = 1, 2, \dots$$

$$\Psi_n(x) = \sqrt{\frac{2}{L}} \sin\left(\frac{\pi n}{L} x\right)$$



$N$	Relative error $\varepsilon = (E_n^{\text{num}} - E_n^{\text{exact}}) / E_n^{\text{exact}} \times 100\%$			
	$\varepsilon_0$ [%]	$\varepsilon_1$ [%]	$\varepsilon_2$ [%]	$\varepsilon_3$ [%]
100	1.978	2.002	2.042	2.098
500	0.399	0.400	0.402	0.404
1 000	0.200	0.200	0.200	0.201
5 000	0.040	0.040	0.040	0.040
10 000	0.020	0.020	0.020	0.020
50 000	0.004	0.004	0.004	0.004

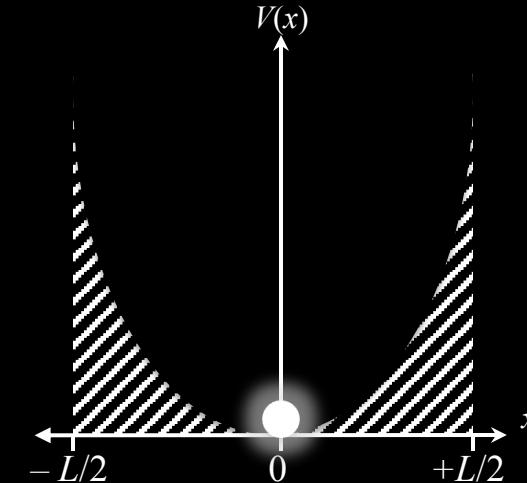
## Another simple example: Linear Harmonic Oscillator in 1D

$$\left[ -\frac{\hbar^2}{2m}\Delta + \frac{1}{2}m\omega^2x^2 \right] \Psi(x) = E \Psi(x)$$

$$-\Delta\Psi(x) + x^2\Psi(x) = 2E' \Psi(x)$$

$$-\Delta\Psi(x_i) + (x_i)^2\Psi(x_i) = 2E' \Psi(x_i),$$

$$-\frac{\Psi\left(\frac{(i-1)L}{N}\right) - 2\Psi\left(\frac{iL}{N}\right) + \Psi\left(\frac{(i+1)L}{N}\right)}{\left(\frac{L}{N}\right)^2} + \left(\frac{iL}{N}\right)^2\Psi\left(\frac{iL}{N}\right) = 2E' \Psi\left(\frac{iL}{N}\right)$$



$$\left( \begin{array}{cccccc} 2 & -1 & 0 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & 0 & \cdots 0 \\ 0 & 0 & -1 & 2 & -1 & 0 \\ 0 & 0 & 0 & -1 & 2 & 0 \\ \vdots & & & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots 2 \end{array} \right) + \left( \begin{array}{cccccc} \ddots & & & \vdots & & . . . \\ & 2^2 & 0 & 0 & 0 & 0 \\ & 0 & 1^2 & 0 & 0 & 0 \\ \cdots & 0 & 0 & 0 & 0 & 0 \\ & 0 & 0 & 0 & 1^2 & 0 \\ & 0 & 0 & 0 & 0 & 2^2 \\ \vdots & & & \vdots & & \ddots \end{array} \right) \left( \begin{array}{c} \Psi_{-\frac{N}{2}} \\ \vdots \\ \Psi_{-1} \\ \Psi_0 \\ \Psi_1 \\ \vdots \\ \Psi_{\frac{N}{2}} \end{array} \right) = \tilde{E}_0 \left( \begin{array}{c} \Psi_{-\frac{N}{2}} \\ \vdots \\ \Psi_{-1} \\ \Psi_0 \\ \Psi_1 \\ \vdots \\ \Psi_{\frac{N}{2}} \end{array} \right)$$

$$\hat{H} = - \sum_{i=-N/2}^{N/2} \left( \hat{c}_i^+ \hat{c}_{i+1} + \hat{c}_{i+1}^+ \hat{c}_i \right) + \sum_{i=-N/2}^{N/2} \left[ 2\hat{c}_i^+ \hat{c}_i + \left( i - \frac{L}{2} \right)^2 \right] = \sum_{i=0}^N \left( \hat{a}_i^+ \hat{a}_i + \frac{1}{2} \right) \approx -\frac{\partial^2}{\partial x^2} + x^2$$

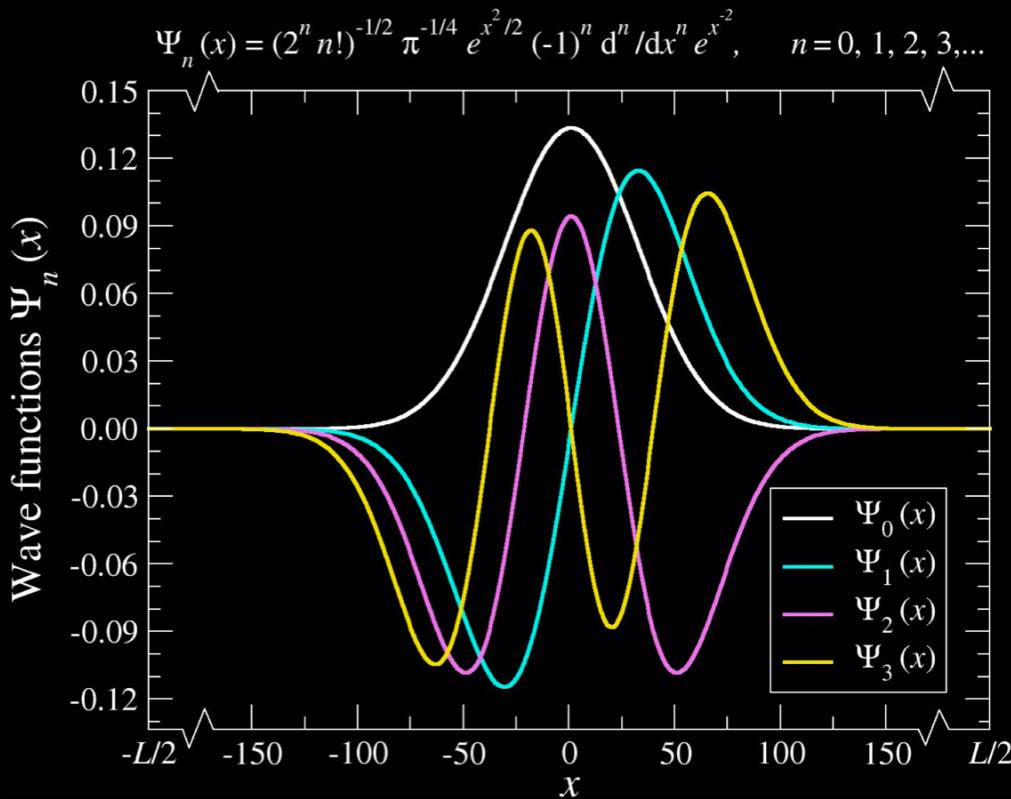
Exact solution exists:  
**Hermite polynomials**

$$E_n = \left(n + \frac{1}{2}\right), \quad n = 0, 1, 2, \dots$$

$$\Psi_n(x) = \frac{1}{\sqrt{2^n n!}} \sqrt{\frac{1}{\sqrt{\pi}}} \exp\left(-\frac{x^2}{2}\right) \underbrace{(-1)^n \exp(x^2) \frac{d^n}{dx^n} [\exp(-x^2)]}_{H_n(x)}$$

Recall that  $\hbar = \omega = m = 1$

$N$	Relative error				
	$\varepsilon_0$	$\varepsilon_1$	$\varepsilon_2$	$\varepsilon_3$	$\varepsilon_4$
5 000	0.006	0.010	0.016	0.022	



## Numerical efficiency when diagonalizing matrices

DMRG: developed to reach a controlled accuracy of exact diagonalization

### ➤ Single-particle problem

Size $N$	Matrix dimension of Hamiltonian	
	Exact diagonalization	DMRG
10	10	4
100	100	4
1000	1000	4
10 000	10 000	4

### ➤ Many-body problem

Lattice size	Estimated memory consumption in a computer		The model
	Exact diagonalization	DMRG	
10	1 MB	$\approx 1$ MB	Heisenberg model
	$10^{50}$ GB	$\approx 100$ MB	
	$10^{600}$ GB	$\approx 1$ GB	
100	1 GB	< 8 MB	Hubbard model
	$10^{100}$ GB	$\approx 1$ GB	
	$10^{1200}$ GB	$\approx 10$ GB	

*Schrödinger equation  
(for a single particle in 3D)*

$$i\hbar \frac{\partial}{\partial t} |\Psi(\vec{r}, t)\rangle = \left[ -\frac{\hbar^2}{2m} \nabla^2 + V(\vec{r}, t) \right] |\Psi(\vec{r}, t)\rangle$$

*Time-independent Schrödinger equation  
(for  $N$  particles in one-dimension)*

$$\sum_{j=1}^N \left[ -\frac{\hbar^2}{2m_j} \frac{\partial^2}{\partial x_j^2} + V(x_1, x_2, \dots, x_N) \right] |\Psi_n(x_1, x_2, \dots, x_N)\rangle = E_n |\Psi_n(x_1, x_2, \dots, x_N)\rangle$$

*Time-independent Schrödinger equation in second quantization  
(for  $N$  interacting particles in one-dimension)*

$$\underbrace{\left[ -t \sum_{j=1}^{N-1} (c_j^+ c_{j+1} + c_{j+1}^+ c_j) - \sum_{j=1}^N V_j c_j^+ c_j - U \sum_{j=1}^{N-1} c_j^+ c_j c_{j+1}^+ c_{j+1} \right]}_H |\phi_n\rangle = E_n |\phi_n\rangle$$

$$[H|\phi_n\rangle = E_n |\phi_n\rangle]$$

*Solving the Schrödinger equation means to find  $E_n$  and  $|\phi_n\rangle$   
(e.g. by diagonalizing the Hamiltonian).*

*Can we prepare an entangled state(?!)*

$$H = -J(S_1^x \otimes S_2^x + S_1^y \otimes S_2^y + S_1^z \otimes S_2^z) = \begin{pmatrix} -J & 0 & 0 & 0 \\ 0 & J & -2J & 0 \\ 0 & -2J & J & 0 \\ 0 & 0 & 0 & -J \end{pmatrix}$$

*Diagonalize the  $4 \times 4$  Hamiltonian matrix*       $H|\phi_n\rangle = E_n|\phi_n\rangle, \quad n = 0,1,2,3$

**Result:**       $E = \begin{pmatrix} -J & 0 & 0 & 0 \\ 0 & -J & 0 & 0 \\ 0 & 0 & -J & 0 \\ 0 & 0 & 0 & 3J \end{pmatrix}$

$$|\phi_0\rangle = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \quad |\phi_1\rangle = \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \end{pmatrix},$$

$$|\phi_2\rangle = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}, \quad |\phi_3\rangle = \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ -1 \\ 1 \\ 0 \end{pmatrix}$$

$$|\phi_n\rangle = \sum_{i=\uparrow}^{\downarrow} \sum_{j=\uparrow}^{\downarrow} \phi_{ij} |ij\rangle = \phi_{\uparrow\uparrow}^{(n)} |\uparrow\uparrow\rangle + \phi_{\uparrow\downarrow}^{(n)} |\uparrow\downarrow\rangle + \phi_{\downarrow\uparrow}^{(n)} |\downarrow\uparrow\rangle + \phi_{\downarrow\downarrow}^{(n)} |\downarrow\downarrow\rangle = \phi_{\uparrow\uparrow}^{(n)} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \phi_{\uparrow\downarrow}^{(n)} \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix} + \phi_{\downarrow\uparrow}^{(n)} \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \end{pmatrix} + \phi_{\downarrow\downarrow}^{(n)} \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$$

## Reduced density matrix

Let us start by finding spectrum of energies  $E_n$  and the corresponding eigenstates  $|\psi_n\rangle$  of a given Hamiltonian (that is how the QM works)

$$H|\psi_n\rangle = E_n|\psi_n\rangle$$

- ❖ Reduced density matrix in a pure state  $\rho' = \text{Tr}_{\text{env}}(|\psi_0\rangle\langle\psi_0|)$
- ❖ Reduced density matrix in a mixed state  $\rho'' = \text{Tr}_{\text{env}}(\sum_j c_j |\psi_j\rangle\langle\psi_j|)$
- What is the reduced density matrix typically good for?
  - ✓ To obtain expectation (mean) values of operators  $\langle A_s \rangle = \text{Tr}_s(A_s \rho')$
  - ✓ Quantum entanglement von Neumann entropy  $S = -\text{Tr}(\rho' \log_2(\rho'))$
- Reduced density matrix (detail):  $\rho'_s = \text{Tr}'_e |\psi_0(s, e)\rangle\langle\psi_0(s, e)|$ 
  - ✓ System interacts with environment
  - ✓ Entanglement entropy  $S_s = S_e = -\text{Tr}_e(\rho'_e \log_2(\rho'_e))$



## Information inside the reduced density matrix

The reduced density matrix completely describes a subsystem (in contact with environment).

Properties of the entanglement entropy:

$$S = -Tr_s(\rho'_s \log_2 \rho'_s) \geq 0$$

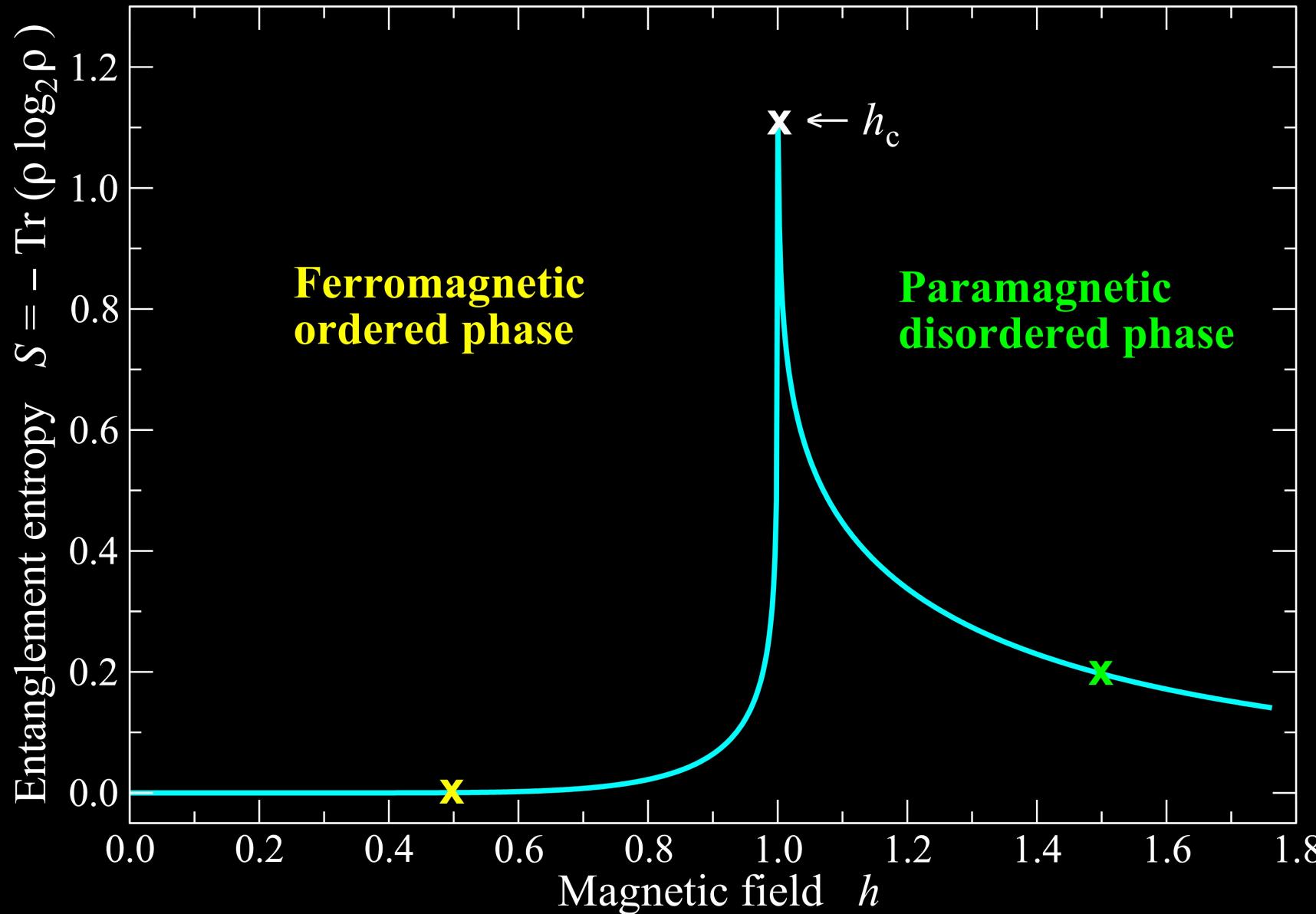
If the reduced density matrix is diagonalized  $U^\dagger \rho'_s U = \Omega$ ,

the eigenvalues sorted in descending order are:  $\omega_1 \geq \omega_2 \geq \omega_3 \geq \dots \geq \omega_N$

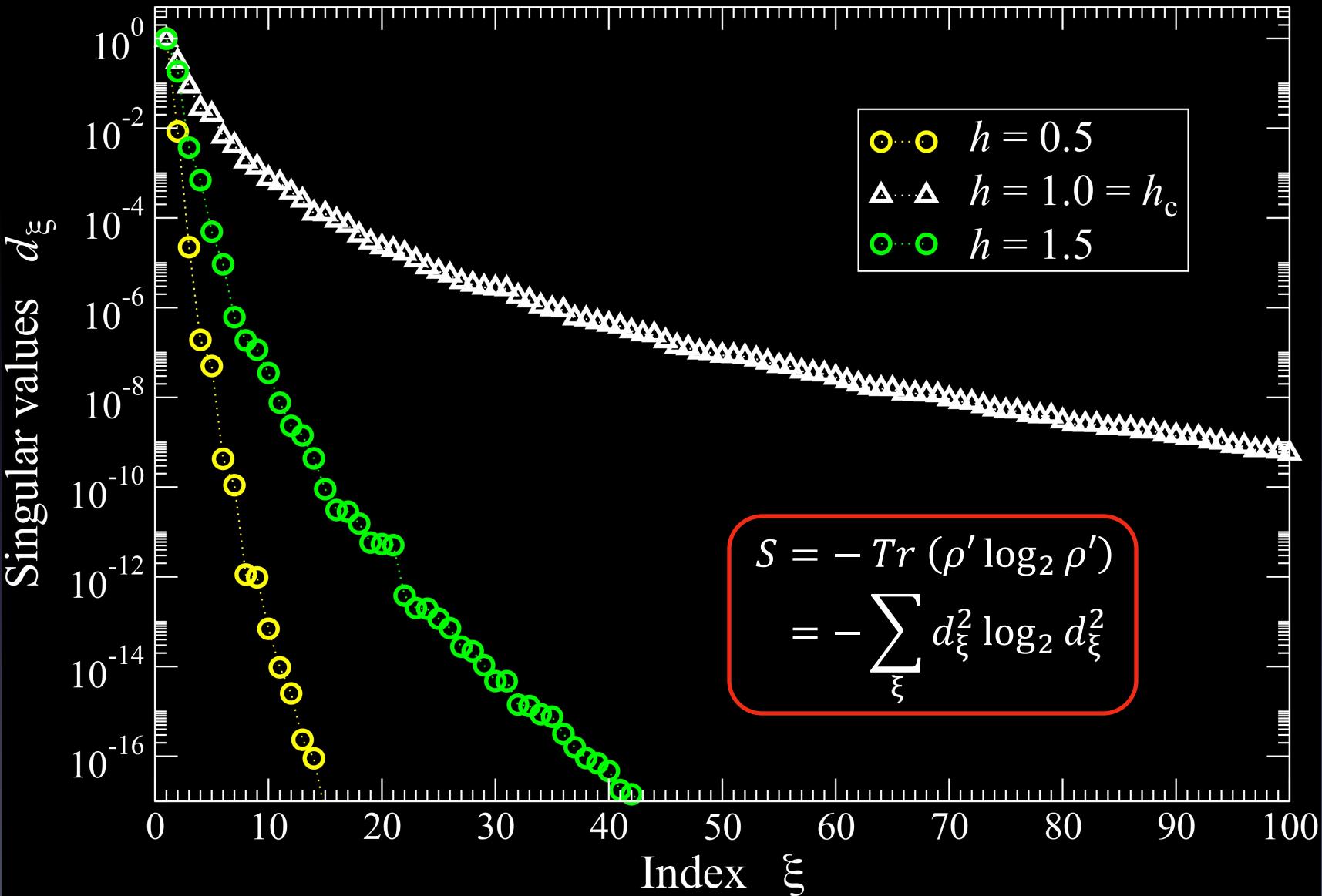
- ✓ No entanglement:  $\omega_1 = 1, \omega_j = 0, \forall j > 1$
- ✓ Weak entanglement:  $\omega_j \propto \exp(-\beta j)$
- ✓ Strong entanglement:  $\omega_j \propto j^{-\alpha}$

$$U^\dagger \rho'_s U = \Omega = \begin{pmatrix} \omega_1 & 0 & 0 \\ 0 & \omega_2 & 0 & \dots \\ 0 & 0 & \omega_3 & & \\ & \vdots & & \ddots & \\ & & & & \omega_N \end{pmatrix}$$

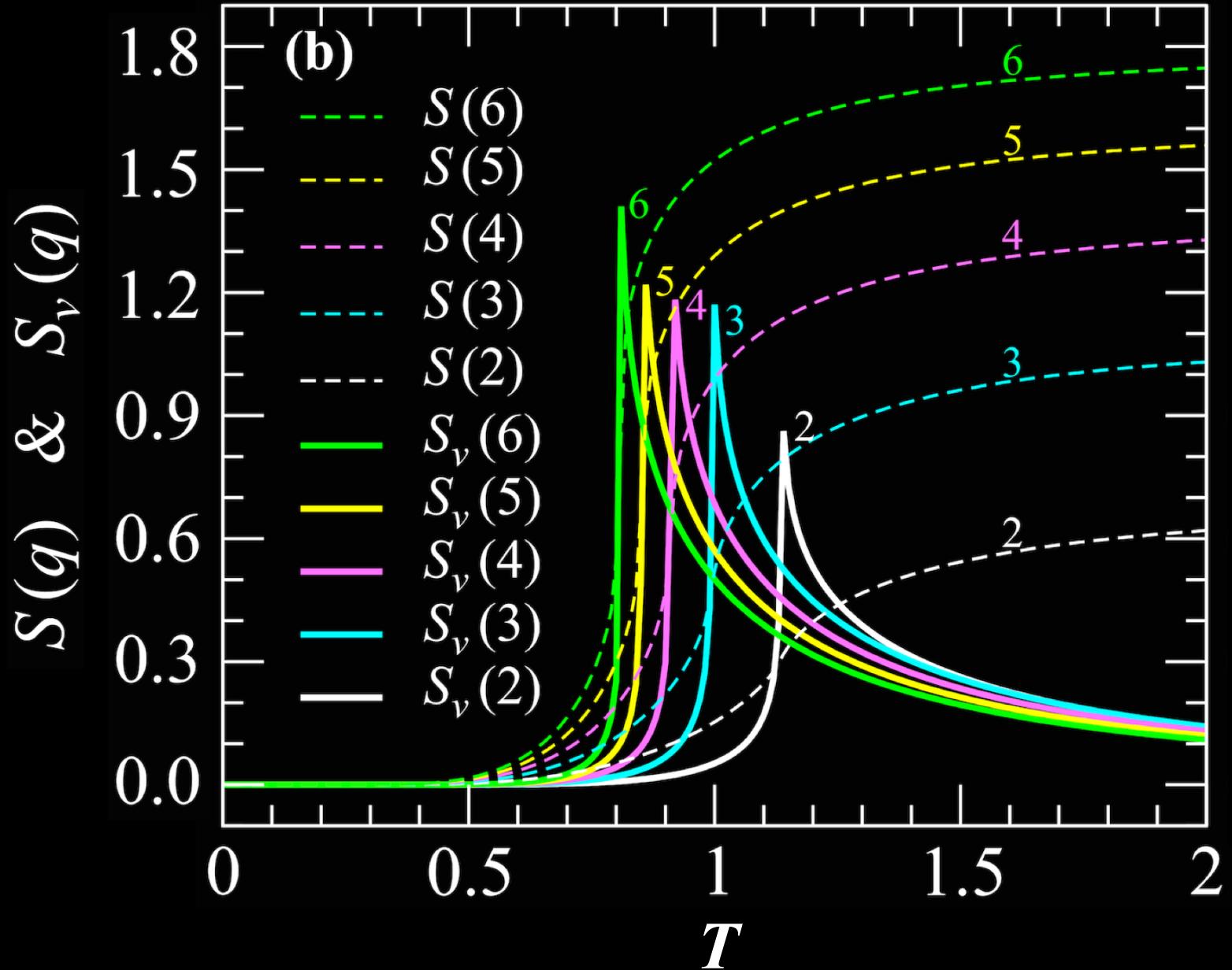
*Entanglement entropy for quantum spin system*  $S = -\text{Tr}(\rho' \log_2 \rho')$



## *Decay of the singular values (Schmidt coefficients) $d_\xi$*



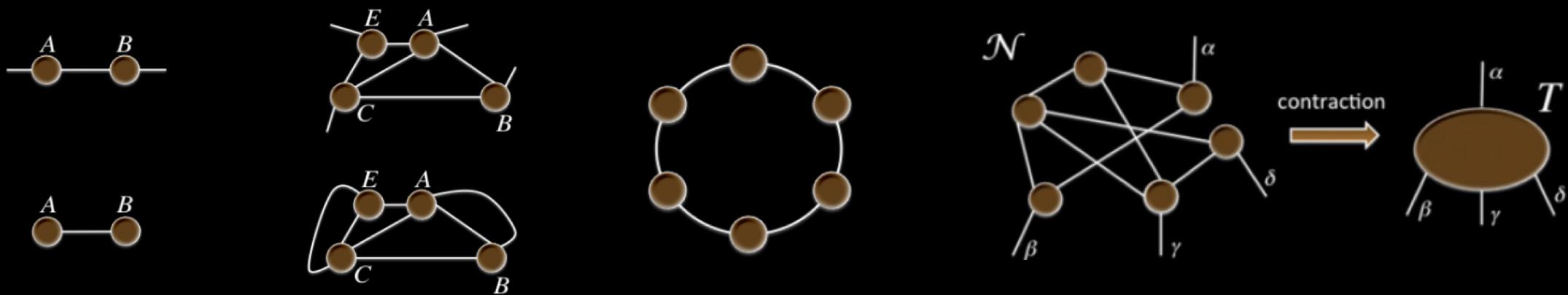
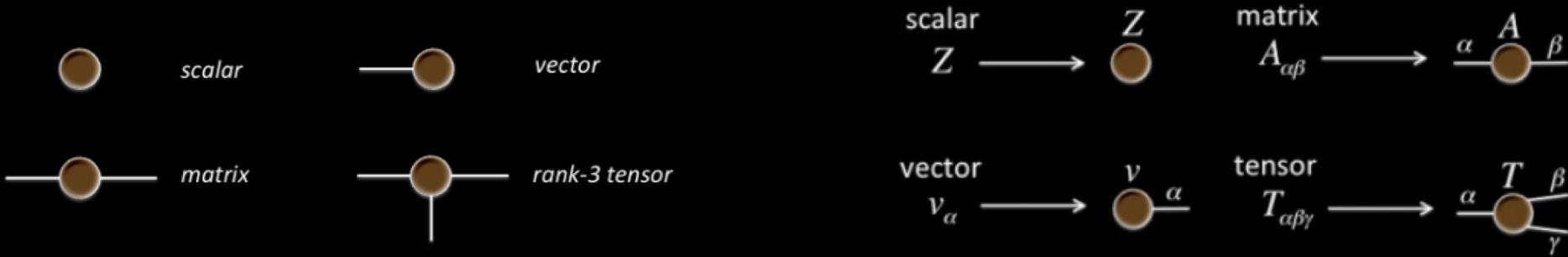
*Comparison between the thermodynamic entropy and entanglement entropy*



*Matrix Product State  
SVD and Entanglement*

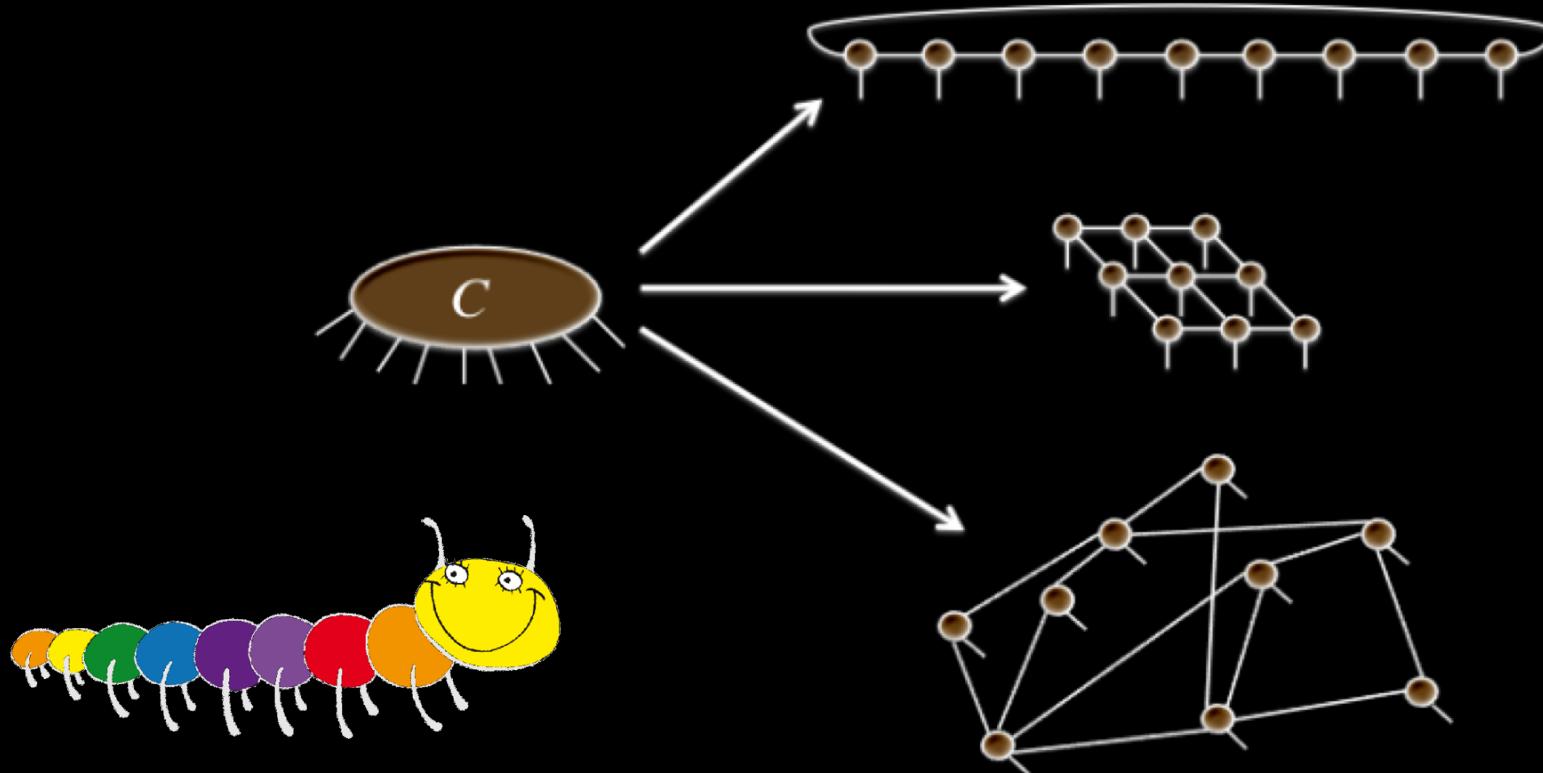
# **Tensor Network is a Tensor Product State**

(and it's like playing a Tetris game...)



## ***Tensor Network is a Tensor Product State***

(and it's like playing a Tetris game...)

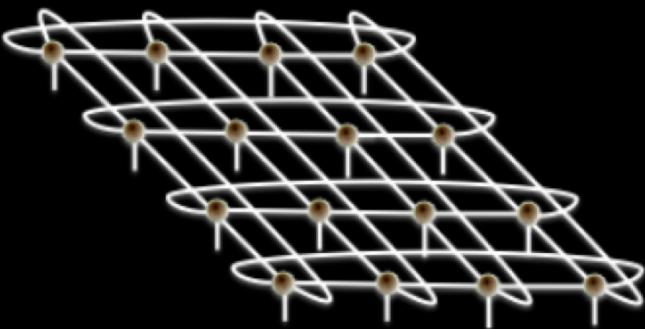
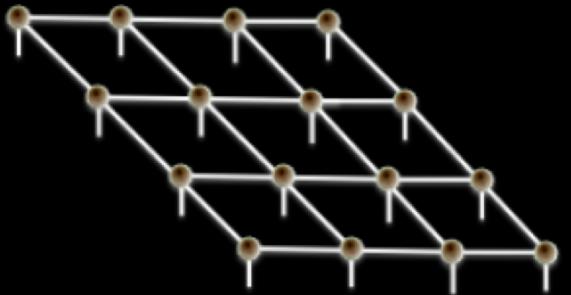


## **Tensor Network is a Tensor Product State**

(and it's like playing a Tetris game...)



1D state  $|\phi\rangle$



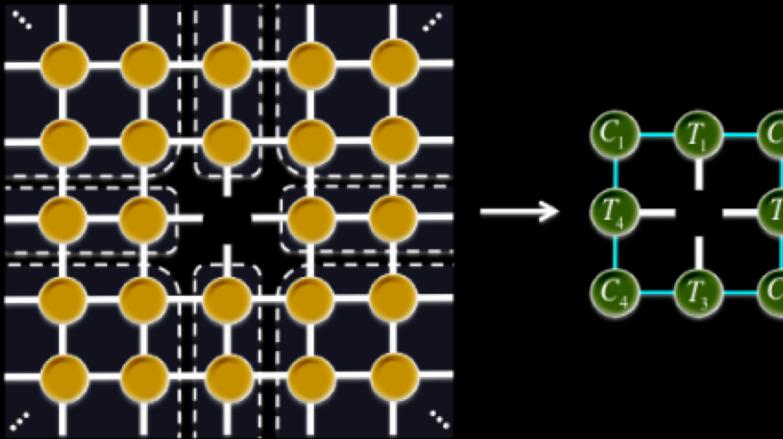
2D state  $|\phi\rangle$

*For open/fixed  
boundary conditions*

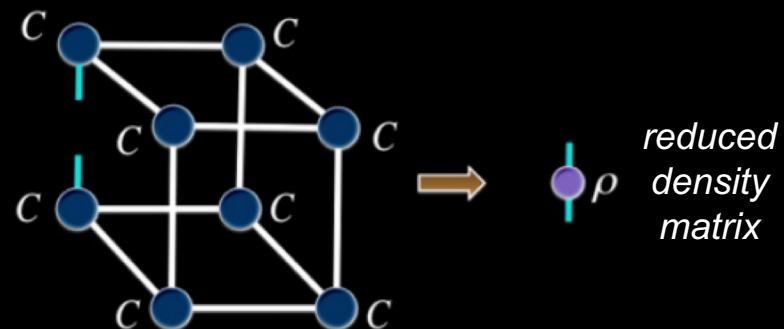
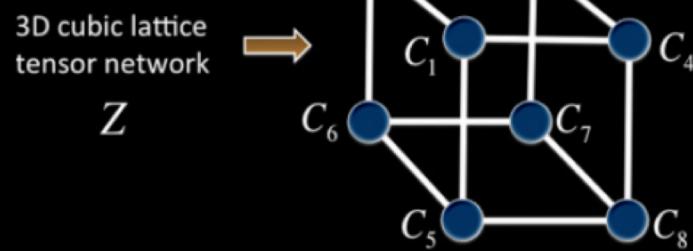
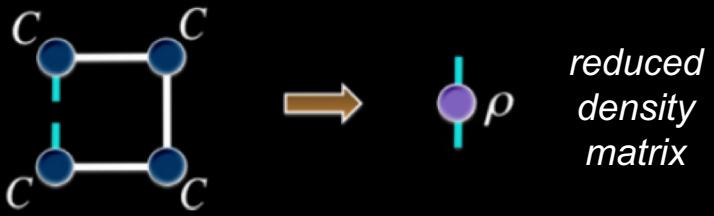
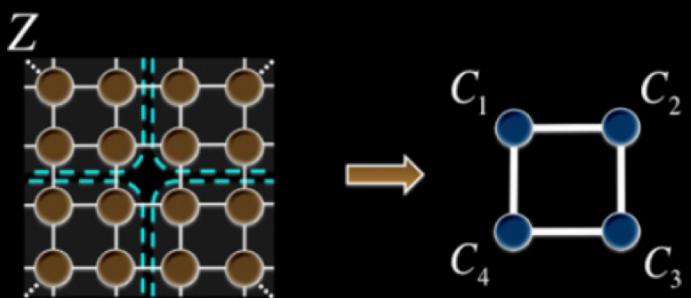
*For periodic  
boundary conditions  
(it is a torus!)*

# **Tensor Network is a Tensor Product State**

(and it's like playing a Tetris game...)

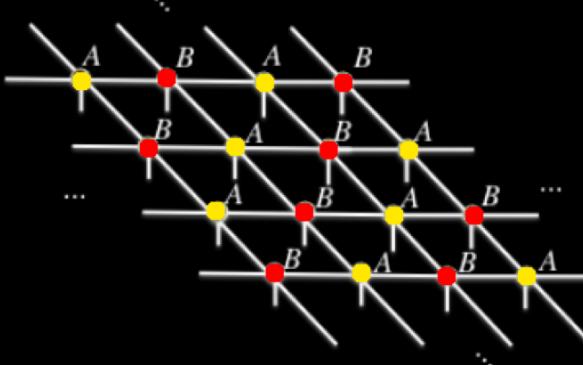
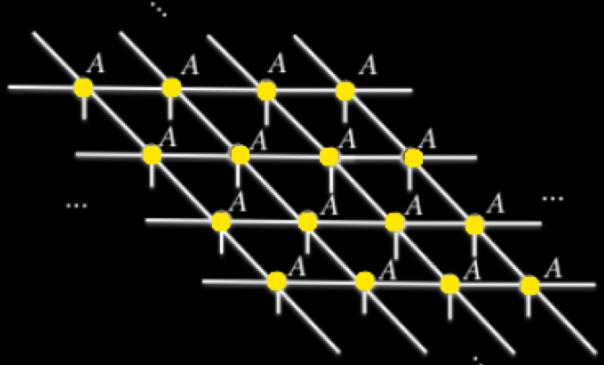


*2D Tensor Network  
for  
Corner Transfer Matrix  
Renormalization Group*

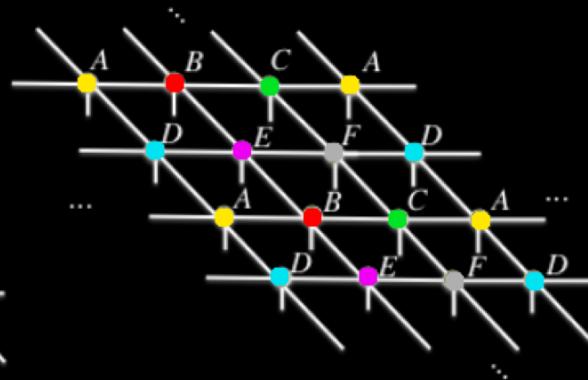
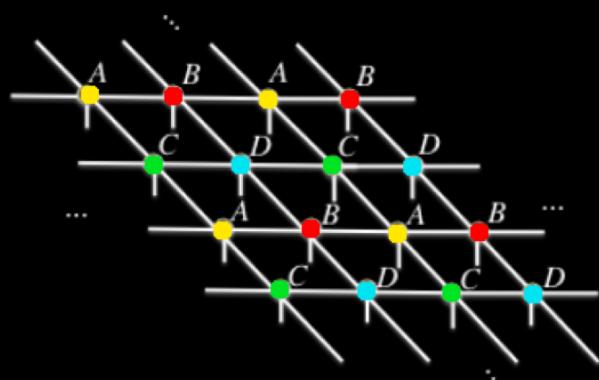


## **Tensor Network is a Tensor Product State**

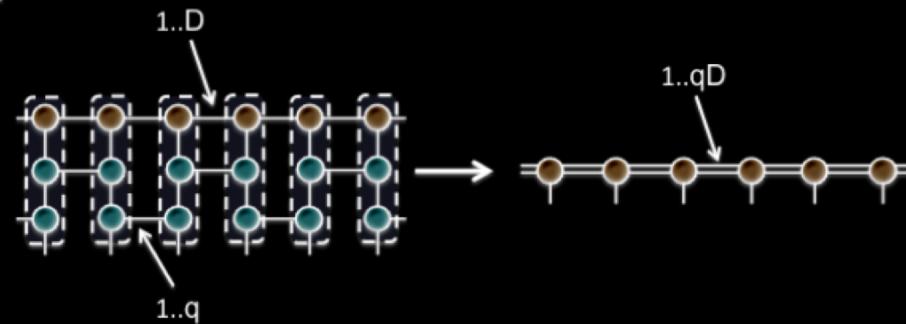
(and it's like playing a Tetris game...)



If studying quantum  
(topological) phases



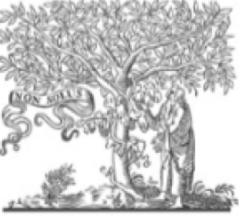
(imaginary) time evolution



*For more details, read the outstanding review  
by Román Orús*

Annals of Physics 349 (2014) 117–158

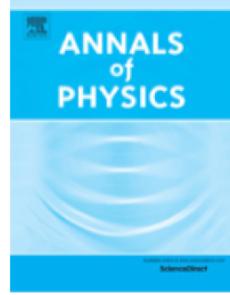
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A practical introduction to tensor networks:  
Matrix product states and projected entangled  
pair states

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 CrossMark

**Matrix diagonalization**

$M$  a square matrix ( $n \times n$ )

$$M = UDU^{-1}$$

$$M = UDU^+ \text{ (if Hermitian)}$$

$$U^+U = \mathbb{I}$$

**Singular value decomposition**

(Schmidt decomposition)

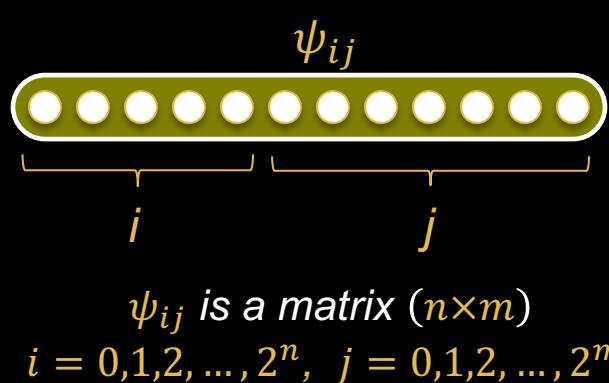
$M$  is a rectangular matrix ( $n \times m$ )

$$M = UDV^+$$

$$U^+U = V^+V = \mathbb{I}$$

*Decomposing a vector  $|\psi\rangle$  into the product of two matrices  $A$  and  $B$*

$$|\psi\rangle = \sum_{ij} \psi_{ij} |ij\rangle = \sum_{ij} \sum_{\xi} A_{i\xi} B_{\xi j} |ij\rangle \stackrel{SVD}{=} \sum_{ij} \sum_{\xi\xi'} U_{i\xi} D_{\xi\xi'} V_{\xi'j}^+ |ij\rangle$$



$$A_{i\xi} = U_{i\xi} \sqrt{D_{\xi\xi}} \quad B_{\xi j} = \sqrt{D_{\xi\xi}} V_{\xi'j}^+$$

$A_{i\xi}$  is a matrix ( $n \times k$ )  
 $B_{\xi j}$  is a matrix ( $k \times m$ )  
 $k = \min(n, m)$

The case of  $L=6$   $|\Psi\rangle = \underbrace{\circlearrowleft a_1 \circlearrowleft a_2 \circlearrowleft a_3 \circlearrowleft a_4 \circlearrowleft a_5 \circlearrowleft a_6}_{a_1 a_2 \cdots a_6} = \sum_{\xi} \underbrace{\circlearrowleft a_1 \circlearrowleft a_2 \circlearrowleft a_3 \circlearrowleft a_4 \circlearrowleft a_5 \circlearrowleft a_6}_{\xi_0 \xi_1 \xi_2 \xi_3 \xi_4 \xi_5 \xi_6}$  where  $(A_i)_{\xi_{i-1} \xi_i}^{a_i} = \underbrace{\circlearrowleft a_i}_{\xi_{i-1} \xi_i}$

$$|\Psi\rangle = \sum_{a_1 a_2 \cdots a_6} \underbrace{\Psi_{a_1 a_2 a_3 a_4 a_5 a_6}}_{vector(1 \times 2^6)} |a_1 a_2 a_3 a_4 a_5 a_6\rangle \stackrel{MPS (SVD) decomposition}{\equiv} \sum_{a_1 a_2 \cdots a_6} \sum_{\xi_0 \cdots \xi_6} (A_1)_{\xi_0 \xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_2 \xi_3}^{a_3} (A_4)_{\xi_3 \xi_4}^{a_4} (A_5)_{\xi_4 \xi_5}^{a_5} (A_6)_{\xi_5 \xi_6}^{a_6} |a_1 a_2 a_3 a_4 a_5 a_6\rangle$$

$$\underbrace{\Psi_{a_1 a_2 a_3 a_4 a_5 a_6}}_{vector(1 \times 2^6)} = \underbrace{\Psi_{a_1 a_2 a_3 a_4 a_5 a_6}^{a_1}}_{matrix(2 \times 2^5)} = \sum_{\xi_1=1}^{\min(\dim a_1, \dim a_2 a_3 \cdots a_6) = 2^1} \underbrace{U_{\xi_1}^{a_1} S_{\xi_1}^{\xi_1} (V^T)_{a_2 a_3 a_4 a_5 a_6}^{\xi_1}}_{(A_1)_{\xi_1}^{a_1} \underbrace{\Psi_{a_2 a_3 a_4 a_5 a_6}^{\xi_1}}_{(reshaped)}} = \sum_{\xi_1=1}^{2^1} (A_1)_{\xi_1}^{a_1} \underbrace{\Psi_{a_3 a_4 a_5 a_6}^{a_2 \xi_1}}_{\Psi_{a_2 a_3 a_4 a_5 a_6}^{\xi_1}} \stackrel{SVD}{=} \sum_{\xi_1=1}^{2^1} (A_1)_{\xi_1}^{a_1} \sum_{\xi_2=1}^{\min(\dim a_2 \xi_1, \dim a_3 \cdots a_6) = 2^2} \underbrace{U_{\xi_2}^{a_2 \xi_1} S_{\xi_2}^{\xi_2} (V^T)_{a_3 a_4 a_5 a_6}^{\xi_2}}_{(A_2)_{\xi_1 \xi_2}^{a_2} \underbrace{\Psi_{a_3 a_4 a_5 a_6}^{\xi_2}}_{(reshaped)}} =$$

## Singular Value Decomposition (Schmidt decomposition)

of a  $m \times n$  rectangular matrix  $M$  is the following decomposition:

$$M = USV^+$$

$U$  is a unitary  $m \times m$  square matrix

$S$  is a diagonal  $m \times n$  rectangular matrix (with non-negative real numbers)

$V$  is a unitary  $n \times n$  square matrix ( $V^+$  is conjugate transpose of  $V$ )

and  $U^+U = V^+V = 1$ . Let  $k = \min(m, n)$

$$M = \begin{bmatrix} U & S & V^+ \end{bmatrix}$$

$$M = \begin{bmatrix} M \\ U & S & V^+ \end{bmatrix}$$

The decomposition of an eigenstate  $\Psi_0$  (Schmidt decomposition) onto the product of two matrices  $A_s$  and  $A_e$ :

$$|\Psi_0\rangle = \sum_{ij} \Psi_{ij} |i\rangle_s |j\rangle_e$$



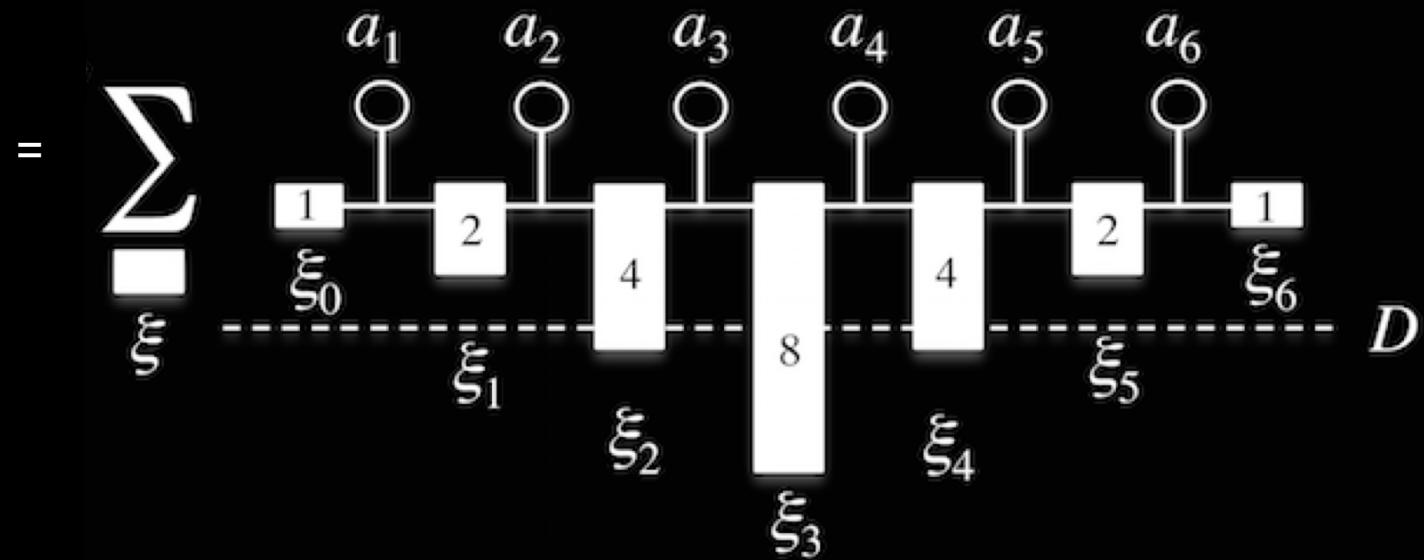
system  $A_s$  environment  $A_e$



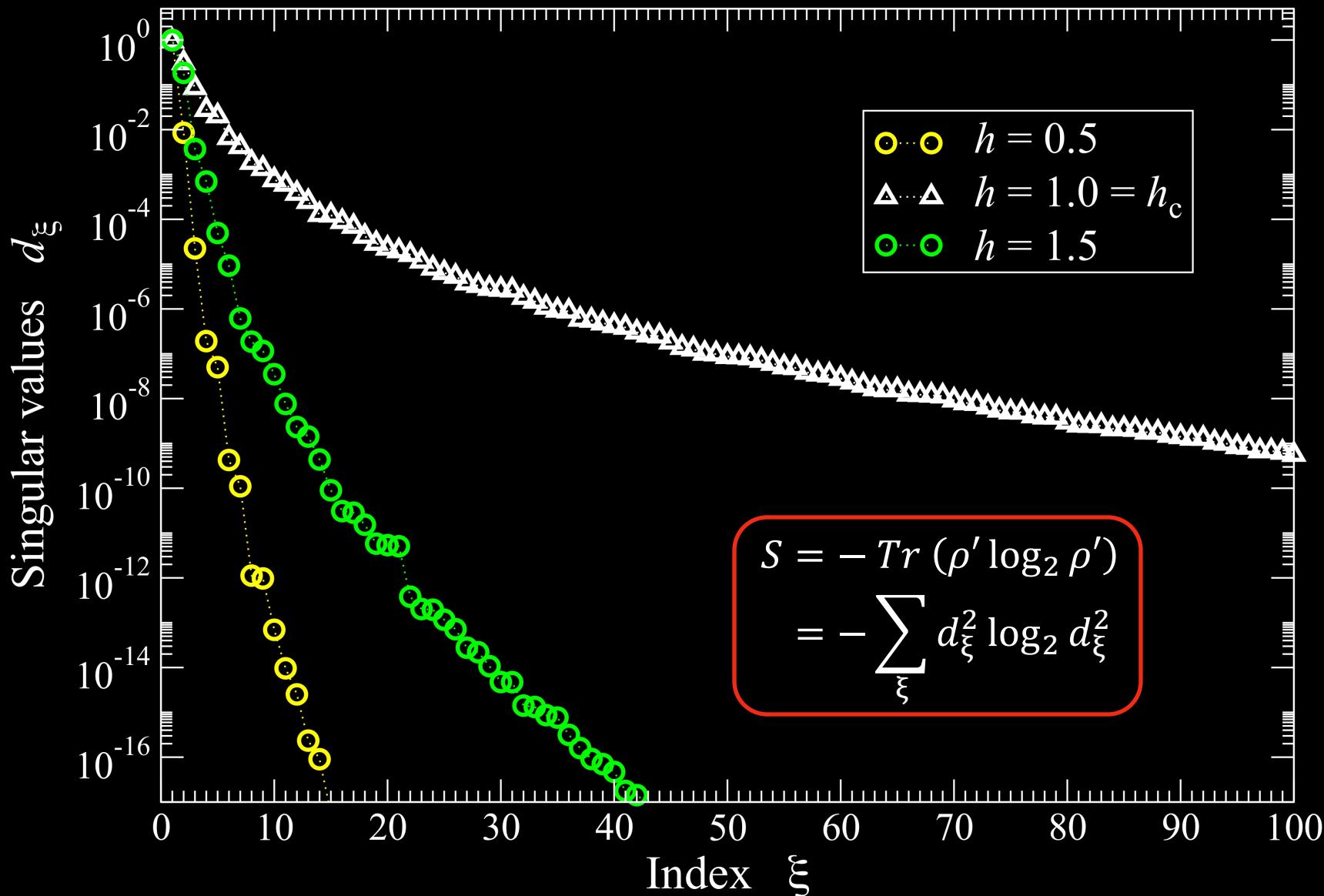
Analytically:

$$\Psi_0(a_1, a_2, \dots, a_{L/2}, a_{L/2+1}, \dots, a_L) = \Psi_{a_{L/2+1}, \dots, a_L}^{a_1, a_2, \dots, a_{L/2}} = \sum_m^D \underbrace{U_m^{a_1, a_2, \dots, a_{L/2}}}_{A_s} \underbrace{D_m^m V_{a_{L/2+1}, \dots, a_L}^{+ m}}_{A_e}$$

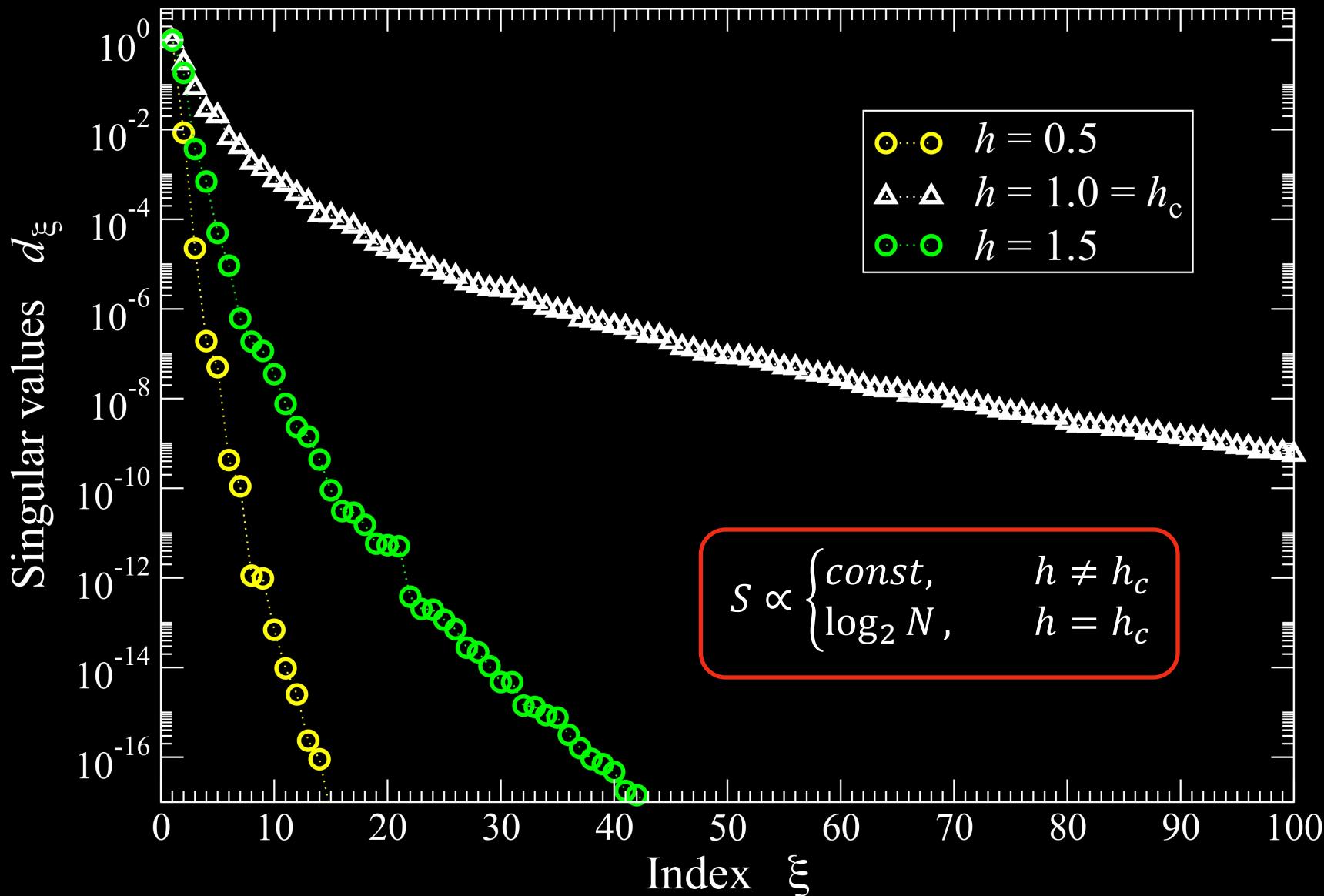
$$|\Psi\rangle = \sum_{a_1 a_2 \cdots a_6} \underbrace{\Psi_{a_1 a_2 a_3 a_4 a_5 a_6}}_{\substack{MPS \text{ (SVD)} \\ decomposition}} |a_1 a_2 a_3 a_4 a_5 a_6\rangle \equiv \sum_{a_1 a_2 \cdots a_6} \sum_{\xi_0 \cdots \xi_6} (A_1)_{\xi_0 \xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_2 \xi_3}^{a_3} (A_4)_{\xi_3 \xi_4}^{a_4} (A_5)_{\xi_4 \xi_5}^{a_5} (A_6)_{\xi_5 \xi_6}^{a_6} |a_1 a_2 a_3 a_4 a_5 a_6\rangle$$

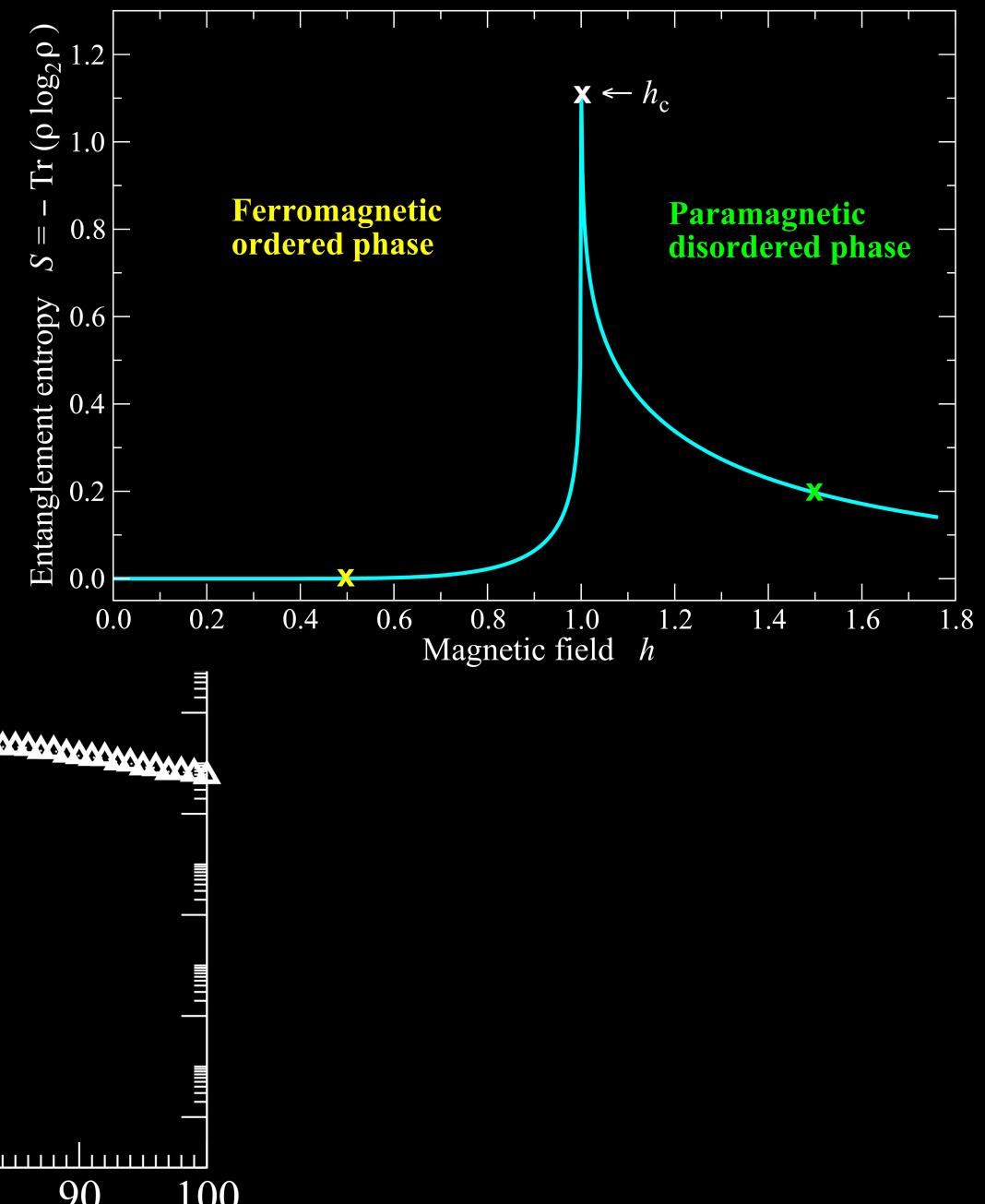
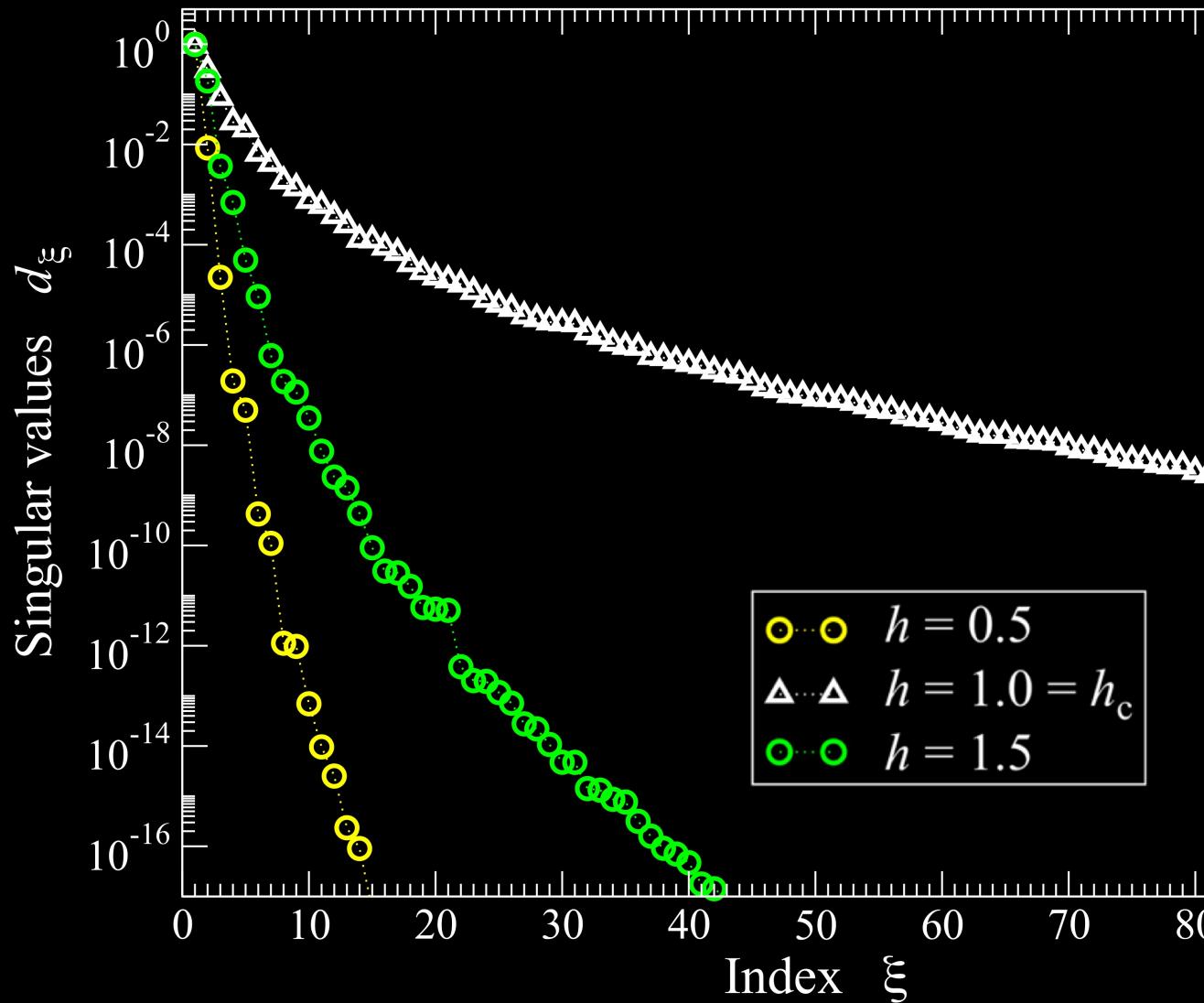


## *Decay of the singular values (Schmidt coefficients) $d_\xi$*



## *Decay of the singular values (Schmidt coefficients) $d_\xi$*

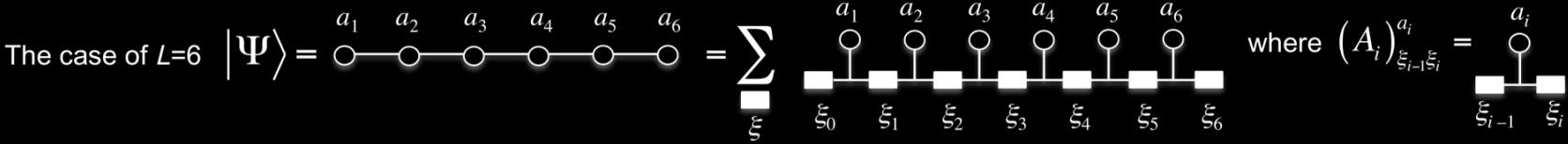




*Thank you*

[andrej.gendiar@savba.sk](mailto:andrej.gendiar@savba.sk)

*More details on singular value decomposition in 1D chain of 6 spins*



$$|\Psi\rangle = \sum_{a_1 a_2 \cdots a_6} \underbrace{\Psi_{a_1 a_2 a_3 a_4 a_5 a_6}}_{\text{decomposition}} |a_1 a_2 a_3 a_4 a_5 a_6\rangle \equiv \sum_{a_1 a_2 \cdots a_6} \sum_{\xi_0 \cdots \xi_6} (A_1)_{\xi_0 \xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_2 \xi_3}^{a_3} (A_4)_{\xi_3 \xi_4}^{a_4} (A_5)_{\xi_4 \xi_5}^{a_5} (A_6)_{\xi_5 \xi_6}^{a_6} |a_1 a_2 a_3 a_4 a_5 a_6\rangle$$

$$\Psi_{a_1 a_2 a_3 a_4 a_5 a_6} \xrightarrow{\text{reshape}} \begin{array}{l} \text{vector } (1 \times 2^6) \\ \text{matrix } (2 \times 2^5) \end{array} \xrightarrow{\text{SVD}} \sum_{\xi_1=1}^{\min(\dim a_1, \dim a_2 a_3 \cdots a_6) = 2^1} \underbrace{(A_1)_{\xi_1}^{a_1}}_{\Psi_{a_2 a_3 a_4 a_5 a_6}^{\xi_1}} \underbrace{S_{\xi_1}^{\xi_1} (V^T)^{\xi_1}_{a_2 a_3 a_4 a_5 a_6}}_{(A_1)_{\xi_1}^{a_1}} = \sum_{\xi_1=1}^{2^1} (A_1)_{\xi_1}^{a_1} \underbrace{\Psi_{a_2 a_3 a_4 a_5 a_6}^{a_2 \xi_1}}_{\Psi_{a_2 a_3 a_4 a_5 a_6}^{\xi_1} (\text{reshaped})} \xrightarrow{\text{SVD}} \sum_{\xi_1=1}^{2^1} (A_1)_{\xi_1}^{a_1} \sum_{\xi_2=1}^{\min(\dim a_2 \xi_1, \dim a_3 \cdots a_6) = 2^2} \underbrace{(A_2)_{\xi_1 \xi_2}^{\xi_2}}_{(A_2)_{\xi_1 \xi_2}^{a_2 \xi_1}} \underbrace{S_{\xi_2}^{\xi_2} (V^T)^{\xi_2}_{a_3 a_4 a_5 a_6}}_{(A_2)_{\xi_1 \xi_2}^{a_2 \xi_1}} =$$

$$= \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} (A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} \underbrace{\Psi_{a_3 a_4 a_5 a_6}^{a_3 \xi_2}}_{\Psi_{a_3 a_4 a_5 a_6}^{\xi_2} (\text{reshaped})} \xrightarrow{\text{SVD}} \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} (A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} \sum_{\xi_3=1}^{\min(\dim a_3 \xi_2, \dim a_4 a_5 a_6) = 2^3} \underbrace{(A_3)_{\xi_1 \xi_2 \xi_3}^{\xi_3}}_{(A_3)_{\xi_1 \xi_2 \xi_3}^{a_3 \xi_2}} \underbrace{S_{\xi_3}^{\xi_3} (V^T)^{\xi_3}_{a_4 a_5 a_6}}_{(A_3)_{\xi_1 \xi_2 \xi_3}^{a_3 \xi_2}} = \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} \sum_{\xi_3=1}^{2^3} (A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_1 \xi_2 \xi_3}^{a_3} \underbrace{(A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4}}_{\Psi_{a_4 a_5 a_6}^{a_4 \xi_4} (\text{reshaped})} \underbrace{S_{\xi_4}^{\xi_4} (V^T)^{\xi_4}_{a_5 a_6}}_{(A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4}} =$$

$$= \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} \sum_{\xi_3=1}^{2^3} \sum_{\xi_4=1}^{\min(\dim a_4 \xi_3, \dim a_5 a_6) = 2^2} \underbrace{(A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_1 \xi_2 \xi_3}^{a_3} (A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4}}_{(A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4}} \underbrace{S_{\xi_4}^{\xi_4} (V^T)^{\xi_4}_{a_5 a_6}}_{(A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4}} = \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} \sum_{\xi_3=1}^{2^3} \sum_{\xi_4=1}^{2^2} \sum_{\xi_5=1}^{\min(\dim a_5 \xi_4, \dim a_6) = 2^1} \underbrace{(A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_1 \xi_2 \xi_3}^{a_3} (A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4} (A_5)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5}^{a_5}}_{(A_5)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5}^{a_5}} \underbrace{S_{\xi_5}^{\xi_5} (V^T)^{\xi_5}_{a_6}}_{(A_5)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5}^{a_5}} =$$

$$= \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} \sum_{\xi_3=1}^{2^3} \sum_{\xi_4=1}^{2^2} \sum_{\xi_5=1}^{\min(\dim a_6 \xi_4, \dim a_6) = 2^1} \underbrace{(A_1)_{\xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_1 \xi_2 \xi_3}^{a_3} (A_4)_{\xi_1 \xi_2 \xi_3 \xi_4}^{a_4} (A_5)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5}^{a_5} (A_6)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5 \xi_6}^{a_6}}_{(A_6)_{\xi_1 \xi_2 \xi_3 \xi_4 \xi_5 \xi_6}^{a_6}} =$$

$$\text{in general } \sum_{\xi_0=1}^{2^0} \sum_{\xi_1=1}^{2^1} \sum_{\xi_2=1}^{2^2} \sum_{\xi_3=1}^{2^3} \sum_{\xi_4=1}^{2^2} \sum_{\xi_5=1}^{2^0} (A_1)_{\xi_0 \xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_2 \xi_3}^{a_3} (A_4)_{\xi_3 \xi_4}^{a_4} (A_5)_{\xi_4 \xi_5}^{a_5} (A_6)_{\xi_5 \xi_6}^{a_6} \xrightarrow{\text{graphically}} \sum_{\xi} \langle \xi_0 | \xi_1 | \xi_2 | \xi_3 | \xi_4 | \xi_5 | \xi_6 | D$$

$$\approx \sum_{\xi_0=1}^D \sum_{\xi_1=1}^D \sum_{\xi_2=1}^D \sum_{\xi_3=1}^D \sum_{\xi_4=1}^D \sum_{\xi_5=1}^D (A_1)_{\xi_0 \xi_1}^{a_1} (A_2)_{\xi_1 \xi_2}^{a_2} (A_3)_{\xi_2 \xi_3}^{a_3} (A_4)_{\xi_3 \xi_4}^{a_4} (A_5)_{\xi_4 \xi_5}^{a_5} (A_6)_{\xi_5 \xi_6}^{a_6}$$

For any finite  $L$

$$\begin{aligned}
 |\Psi\rangle &= \sum_{a_1 a_2 \cdots a_L} \Psi_{a_1 a_2 \cdots a_L} |a_1 a_2 \cdots a_L\rangle \stackrel{\substack{\text{decomposition} \\ \text{MPS (SVD)}}}{=} \sum_{a_1 a_2 \cdots a_L} \sum_{\xi_0 \cdots \xi_L} \prod_{i=1}^L (A_i)_{\xi_{i-1} \xi_i}^{a_i} |a_1 a_2 \cdots a_L\rangle \\
 &= \sum_{a_1 a_2 \cdots a_L} \sum_{\xi_0=1}^{2^0} \sum_{\xi_1=1}^{2^1} \cdots \sum_{\xi_{L/2-1}=1}^{2^{L/2-1}} \sum_{\xi_{L/2}=1}^{2^{L/2}} \sum_{\xi_{L/2+1}=1}^{2^{L/2-1}} \cdots \sum_{\xi_L=1}^{2^0} \prod_{i=1}^L (A_i)_{\xi_{i-1} \xi_i}^{a_i} |a_1 a_2 \cdots a_L\rangle \stackrel{(D < 2^{L/2})}{\approx} \sum_{a_1 a_2 \cdots a_L} \sum_{\xi_0 \cdots \xi_L}^D \prod_{i=1}^L (A_i)_{\xi_{i-1} \xi_i}^{a_i} |a_1 a_2 \cdots a_L\rangle
 \end{aligned}$$

Note that  $\dim \left\{ (A_i)_{\xi_{i-1} \xi_i}^{a_i} \right\} = q D^2$ , where, e.g.,  $q = \begin{cases} 2 & \text{Heisenberg,} \\ 4 & \text{Hubbard.} \end{cases}$

Consider spinless electrons on a linear chain with a finite length  $L$  divided into two parts with sizes  $k$  and  $L - k$ , where  $(1 \leq k \leq L-1)$ . We show that von Neumann entanglement entropies  $S_{\text{sys}}$  and  $S_{\text{env}}$  for both of the chains are identical for a fixed  $k$ .

$$S_{\text{sys}} = -\text{Tr}_{\text{env}} \left( \rho_{\text{sys}} \log_2 \rho_{\text{sys}} \right) \quad \rho_{\text{sys}} = \text{Tr}_{\text{env}} |\Psi\rangle\langle\Psi| = \sum_j \Psi_{ij} \Psi_{ji}^*$$

$$\rho_{\text{env}} = \text{Tr}_{\text{sys}} |\Psi\rangle\langle\Psi| = \sum_i \Psi_{ji}^* \Psi_{ij}$$

$$|\Psi\rangle = \sum_{i=1}^{2^k} \sum_{j=1}^{2^{L-k}} \Psi_j^i |i\rangle_{\text{sys}} |j\rangle_{\text{env}} \stackrel{\text{SVD}}{=} \sum_{i=1}^{2^k} \sum_{j=1}^{2^{L-k}} \sum_{\xi=1}^{m=\min(2^k, 2^{L-k})} U_{\xi}^i \underbrace{S_{\xi}^{\xi}}_{\substack{\equiv s_{\xi} \\ \text{diag.} \\ \text{matrix}}} \left( V^T \right)_j^{\xi} |i\rangle_{\text{sys}} |j\rangle_{\text{env}} = \sum_{\xi=1}^m \underbrace{s_{\xi}}_{\substack{= |\xi\rangle_{\text{sys}} \\ = |\xi\rangle_{\text{env}}}} \underbrace{\sum_{i=1}^{2^k} U_{\xi}^i |i\rangle_s}_{\substack{= |\xi\rangle_{\text{sys}} \\ = |\xi\rangle_{\text{env}}}} \underbrace{\sum_{j=1}^{2^{L-k}} \left( V^T \right)_j^{\xi} |j\rangle_e}_{\substack{= |\xi\rangle_{\text{sys}} \\ = |\xi\rangle_{\text{env}}}} = \sum_{\xi=1}^m s_{\xi} |\xi\rangle_{\text{sys}} |\xi\rangle_{\text{env}}$$

$$\rho_{\text{sys}} = \text{Tr}_{\text{env}} |\Psi\rangle\langle\Psi| = \sum_{j=1}^{2^{L-k}} \sum_{\xi=1}^m s_{\xi} |\xi\rangle_{\text{sys}} |\xi\rangle_{\text{env}} \sum_{\eta=1}^m [s_{\eta} |\eta\rangle_{\text{sys}} |\eta\rangle_{\text{env}}]^* = \sum_{\xi=1}^m \sum_{\eta=1}^m \underbrace{s_{\xi} s_{\eta}^*}_{\substack{s_{\eta}^* = s_{\eta} \\ = \delta_{\xi, \eta}}} |\xi\rangle_{\text{sys}} \langle \eta |_{\text{env}} \langle \eta |_{\text{sys}} = \sum_{\xi=1}^m s_{\xi}^2 |\xi\rangle_{\text{sys}} \langle \xi |_{\text{sys}}$$

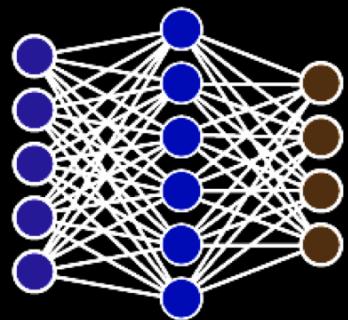
$$\rho_{\text{env}} = \text{Tr}_{\text{sys}} |\Psi\rangle\langle\Psi| = \sum_{i=1}^{2^k} \sum_{\xi=1}^m [s_{\xi} |\xi\rangle_{\text{sys}} |\xi\rangle_{\text{env}}]^* \sum_{\eta=1}^m s_{\eta} |\eta\rangle_{\text{sys}} \langle \eta |_{\text{env}} = \sum_{\xi=1}^m \sum_{\eta=1}^m \underbrace{s_{\xi}^* s_{\eta}}_{\substack{s_{\xi}^* = s_{\xi} \\ = \delta_{\xi, \eta}}} |\xi\rangle_{\text{sys}} \langle \eta |_{\text{env}} \langle \eta |_{\text{sys}} = \sum_{\xi=1}^m s_{\xi}^2 |\xi\rangle_{\text{env}} \langle \xi |_{\text{env}}$$

For any fixed  $k$ , even if  $k \neq L/2$ , we get

$$\left\{
 \begin{array}{l}
 S_{\text{sys}} = -\text{Tr}_{\text{sys}} (\rho_{\text{sys}} \log_2 \rho_{\text{sys}}) = \sum_{\xi=1}^m s_{\xi}^2 \log_2 (s_{\xi}^2) \\
 S_{\text{env}} = -\text{Tr}_{\text{env}} (\rho_{\text{env}} \log_2 \rho_{\text{env}}) = \sum_{\xi=1}^m s_{\xi}^2 \log_2 (s_{\xi}^2)
 \end{array}
 \right\} \Rightarrow \boxed{S_{\text{sys}} \equiv S_{\text{env}}}.$$

Neural network

Input      Hidden      Output



Deep neural network

Input      Hidden      Hidden      Hidden      Output

