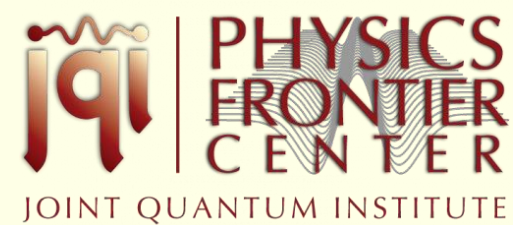
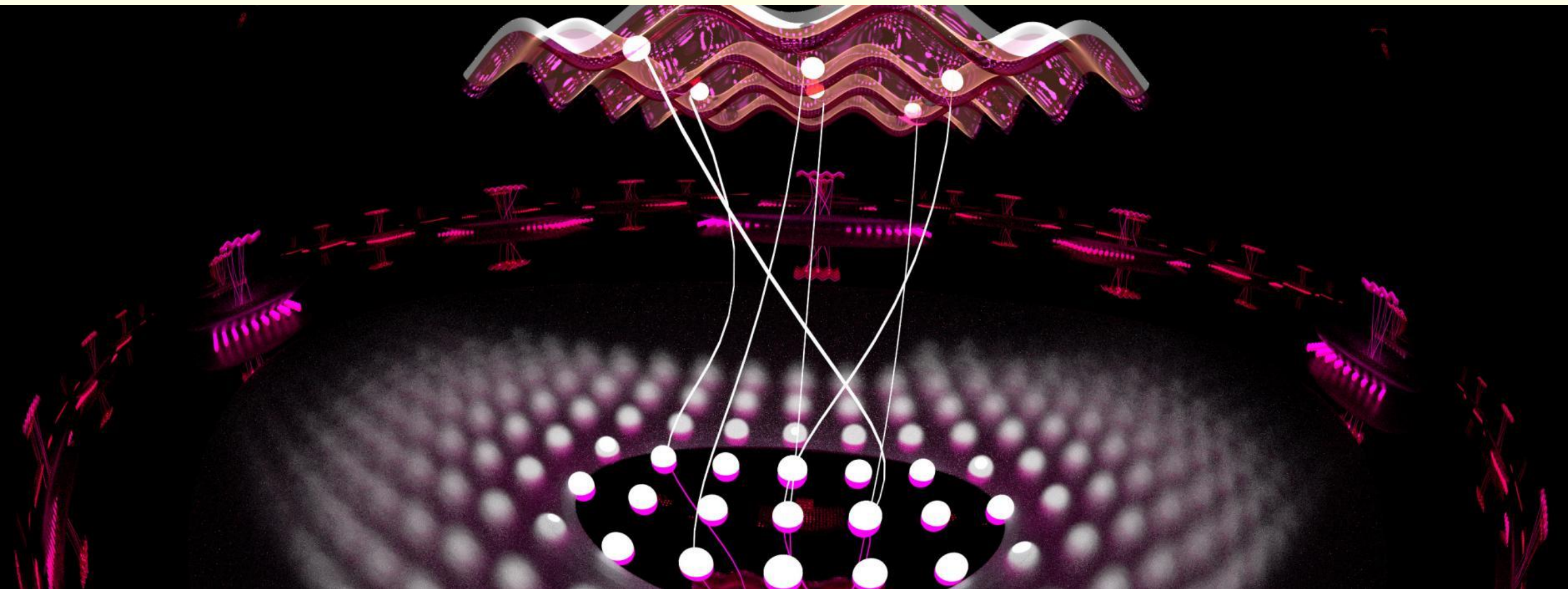


Machine learning quantum states and entanglement



Dong-Ling Deng
University of Maryland



Kavli Institute for Theoretical Sciences, UCAS, Beijing, 07/06/2017

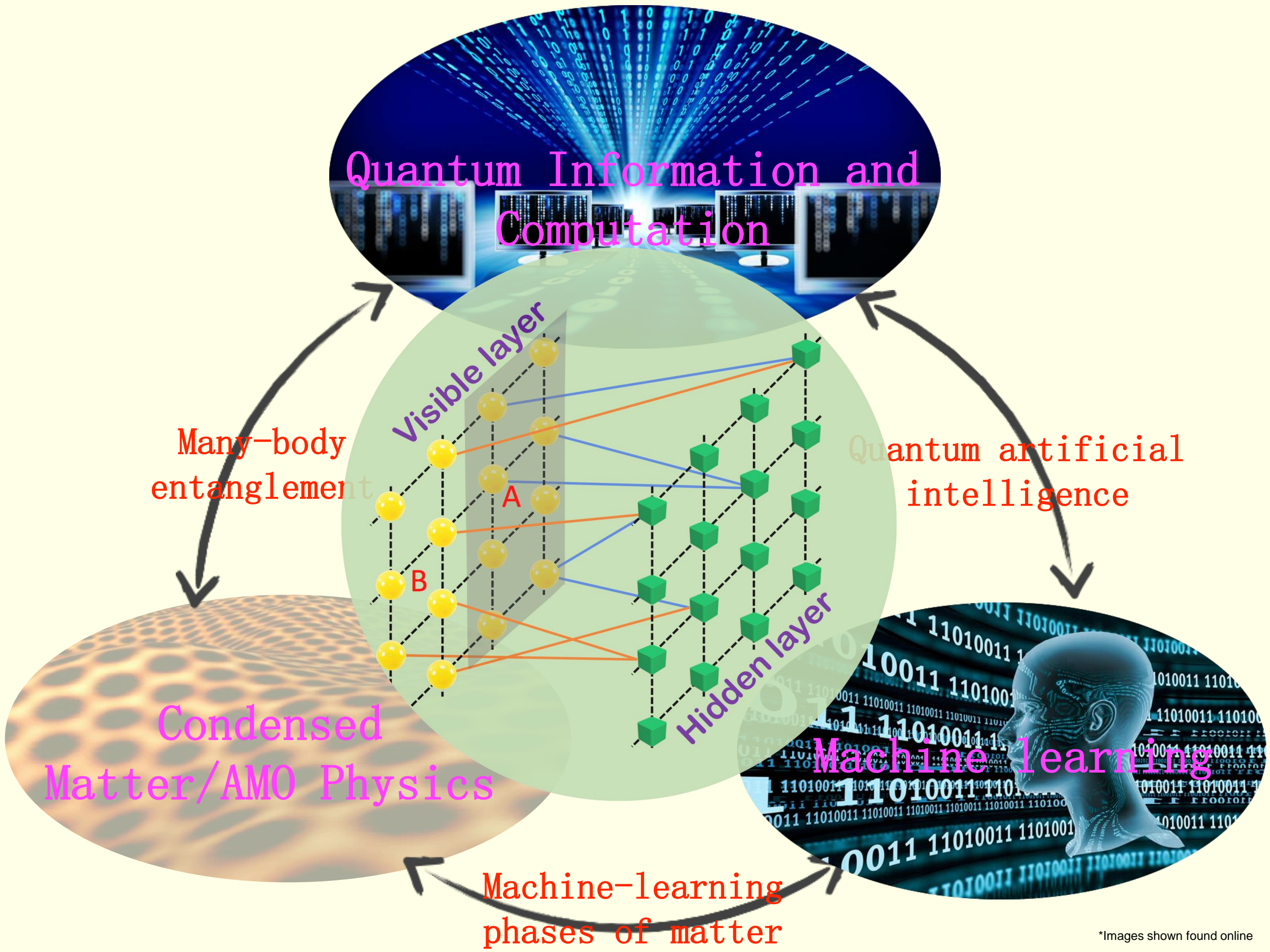
References:

- [1] DLD, Xiaopeng (2016)
- [2] DLD, Xiaopeng (2016)



Outline

- ❑ Background and motivation
- ❑ Restricted Boltzmann machine (RBM)
- ❑ Exact RBM representation of topological states
- ❑ Quantum entanglement in neural network states
- ❑ Summary and outlook



Quantum entanglement and machine-learning phases of matter

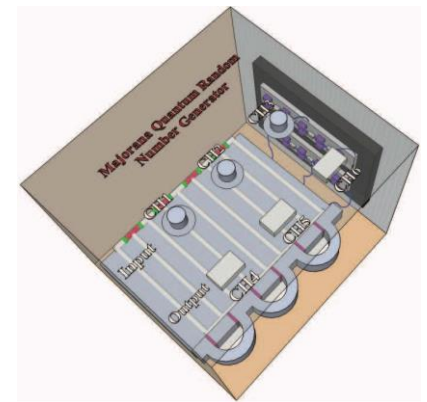
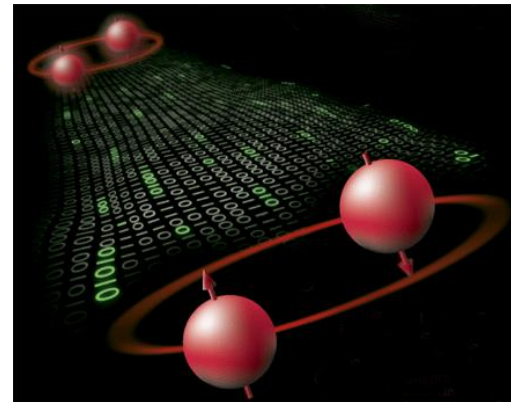
Power of machine learning

Big data, deep learning, symmetry, locality, renormalization group ...



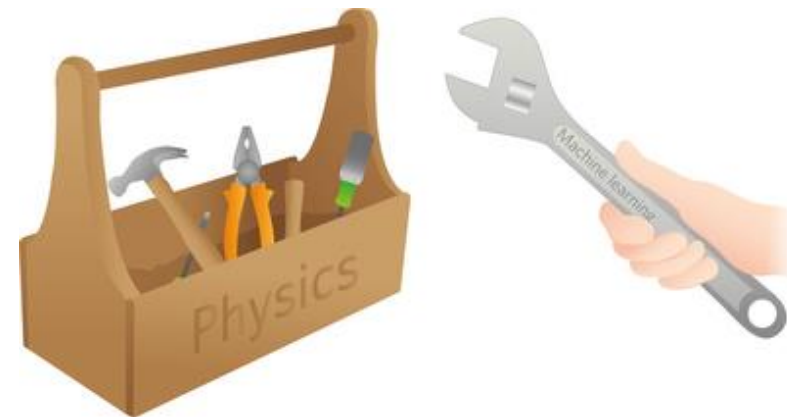
Quantum entanglement

Quantum cryptography, supremacy, simulation, many-body localization, hamiltonian complexity, time crystals, DMRG, MERA ...

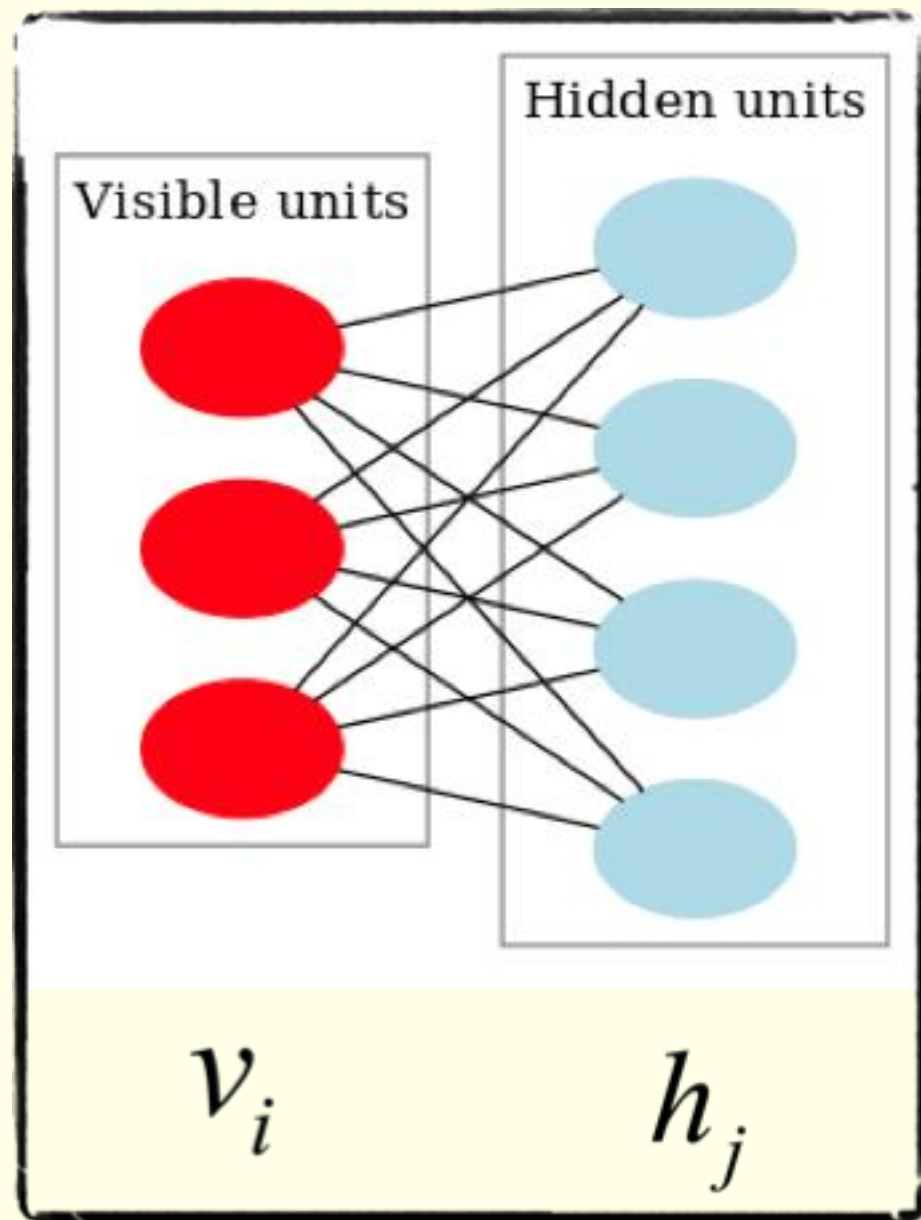


Machine-learning phases of matter

Phase transitions, topological phases, thermalization, many-body problems ...



Restricted Boltzmann machine



Configuration probability:

$$P(v) \propto \sum_h \exp \left[\sum_i a_i v_i + \sum_j b_j h_j + \sum_{ij} W_{ij} v_i h_j \right]$$

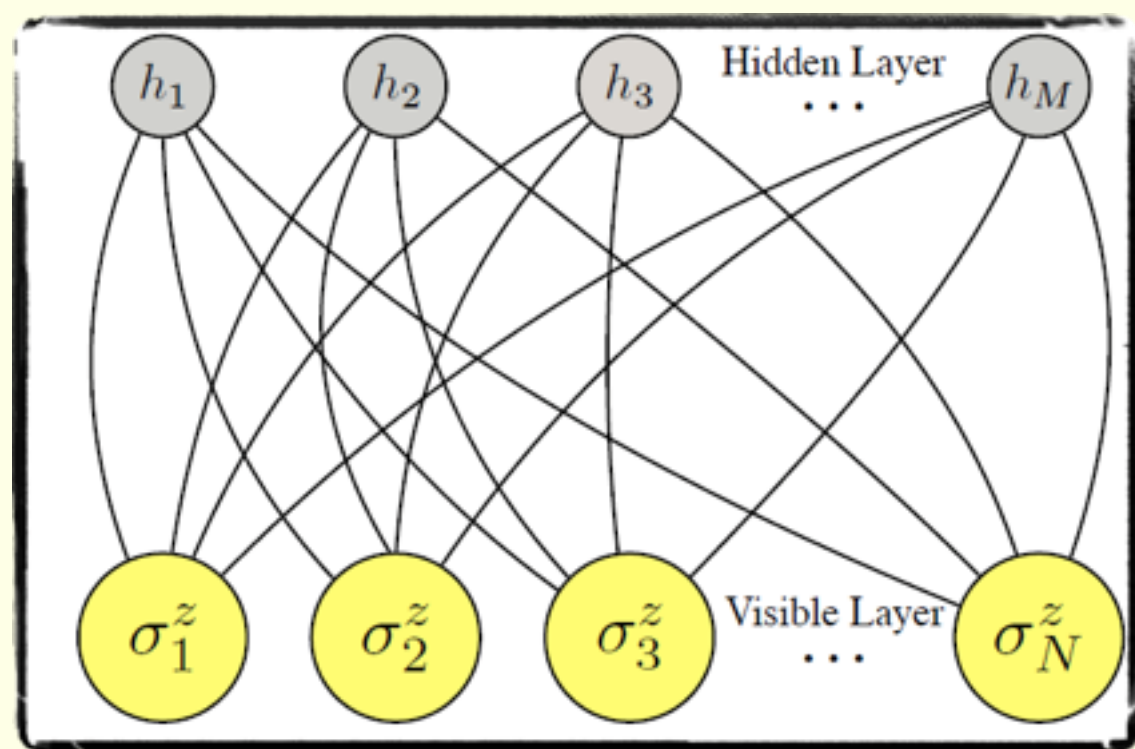
- No intra-layer coupling
- decoupled when h is fixed
- easy to sample

$$P(h) \propto \exp \left(\sum b_j h_j \right)$$

$$P(v|h) \propto \exp \left(\sum a_i v_i + \sum W_{ij} v_i h_j \right)$$



RBM representation of quantum states



Examples for quantum models:

Transverse field Ising:

$$\mathcal{H}_{\text{TFI}} = -h \sum_i \sigma_i^x - \sum_{\langle i,j \rangle} \sigma_i^z \sigma_j^z$$

Anti-Ferro Heisenberg:

$$\mathcal{H}_{\text{AFH}} = \sum_{\langle i,j \rangle} \sigma_i^x \sigma_j^x + \sigma_i^y \sigma_j^y + \sigma_i^z \sigma_j^z$$

Allow complex parameters and regard the probability as the coefficients for spin configurations:

$$\Psi_M(\mathcal{S}; \mathcal{W}) = \sum_{\{h_k\}} e^{\sum_j a_j \sigma_j^z + \sum_k b_k h_k + \sum_{kj} W_{kj} h_k \sigma_j^z}$$

The actual quantum state:

$$|\Phi\rangle = \sum_{\mathcal{S}} \Psi_M(\mathcal{S}, \mathcal{W}) |\mathcal{S}\rangle$$

Question: can RBM represents topological states?



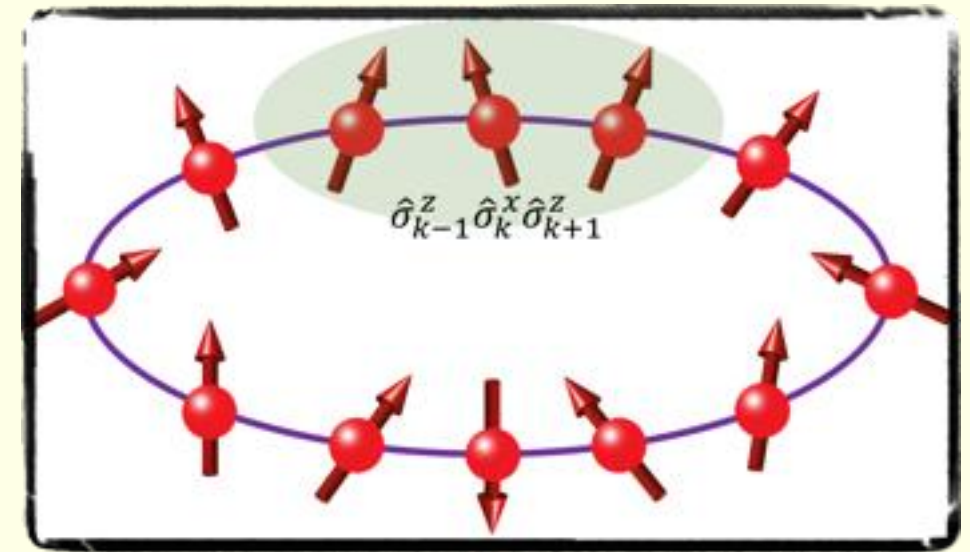
1D symmetry protected topological (SPT) states

Hamiltonian:

$$H_{spt} = - \sum_{k=1}^N \hat{\sigma}_{k-1}^z \hat{\sigma}_k^x \hat{\sigma}_{k+1}^z$$

Symmetry:

$$Z_2 \times Z_2$$



stabilizer ground state: $\hat{\sigma}_{k-1}^z \hat{\sigma}_k^x \hat{\sigma}_{k+1}^z |G\rangle = |G\rangle, \forall k$

Aim: an exact RBM representation

Reminder:

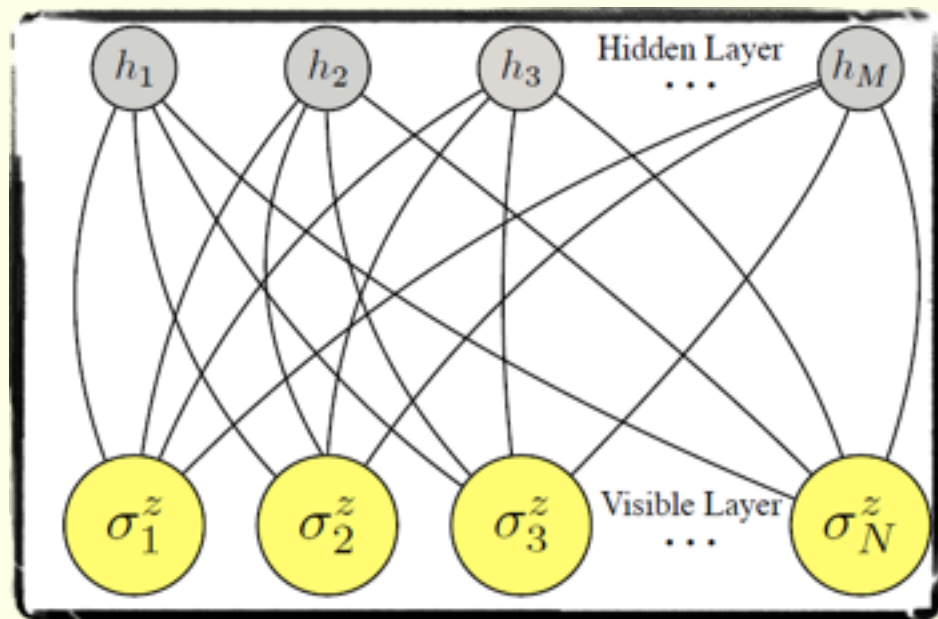
$$\Psi_M(\mathcal{S}; \mathcal{W}) = \sum_{\{h_k\}} e^{\sum_j a_j \sigma_j^z + \sum_k b_k h_k + \sum_{kj} W_{kj} h_k \sigma_j^z}$$
$$|\Phi\rangle = \sum_{\mathcal{S}} \Psi_M(\mathcal{S}, \mathcal{W}) |\mathcal{S}\rangle$$

naively, solve equations: $\hat{\sigma}_{k-1}^z \hat{\sigma}_k^x \hat{\sigma}_{k+1}^z |\Phi\rangle = |\Phi\rangle$

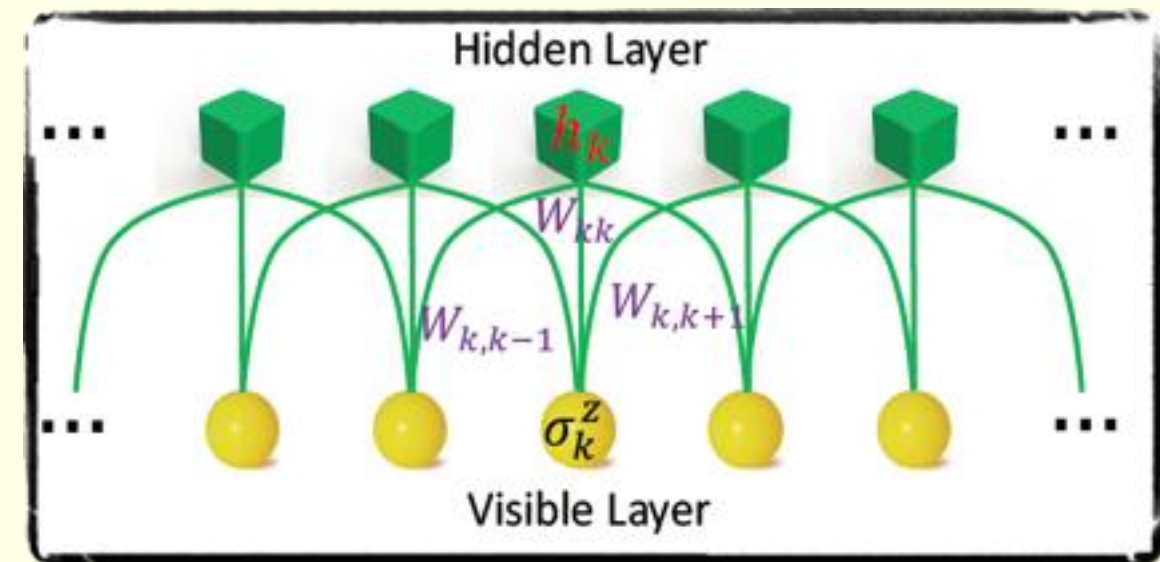
But, with exponentially many highly-nonlinear equations!

Idea: build in locality to RBM to reduce equations

A further-restricted RBM



G. Carleo and M. Troyer, *Science* **355**, 602 (2017)



DLD, X.-P. Li, S. Das Sarma, arXiv: 1609.09060(2016)

Symmetry constraints: $a_k = ia, b_k = ib, W_{kk} = \omega_0, W_{kk\pm 1} = \omega_{\pm 1}$

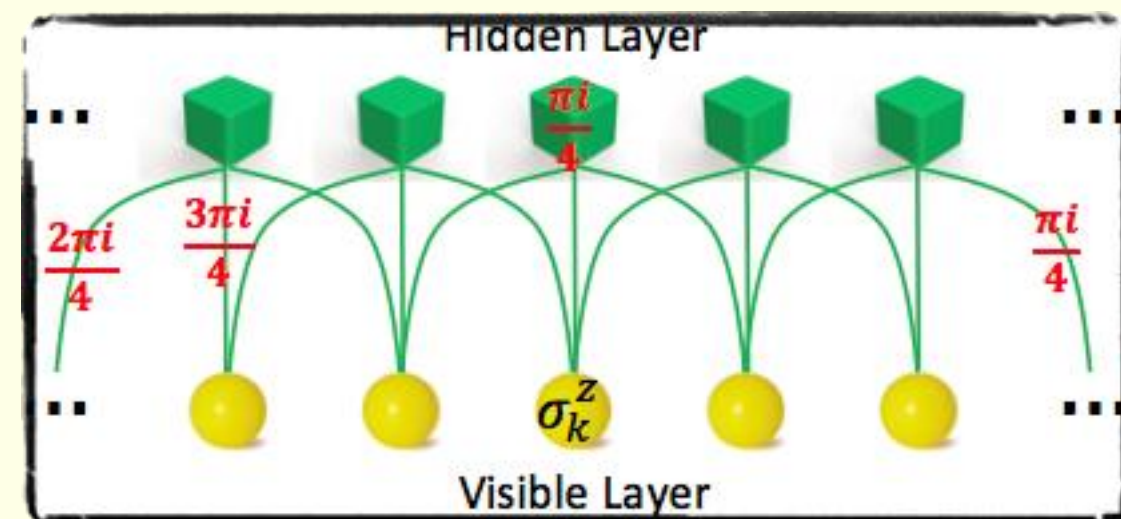
Product form: $\Psi_M = \prod e^{a_j \sigma_j^z} \prod \Gamma_k(\mathcal{S}), \Gamma_k(\mathcal{S}) = 2 \cosh(b_k + \sum_j W_{kj} \sigma_j^z)$

Reduced to 32 equations with 5 variables.

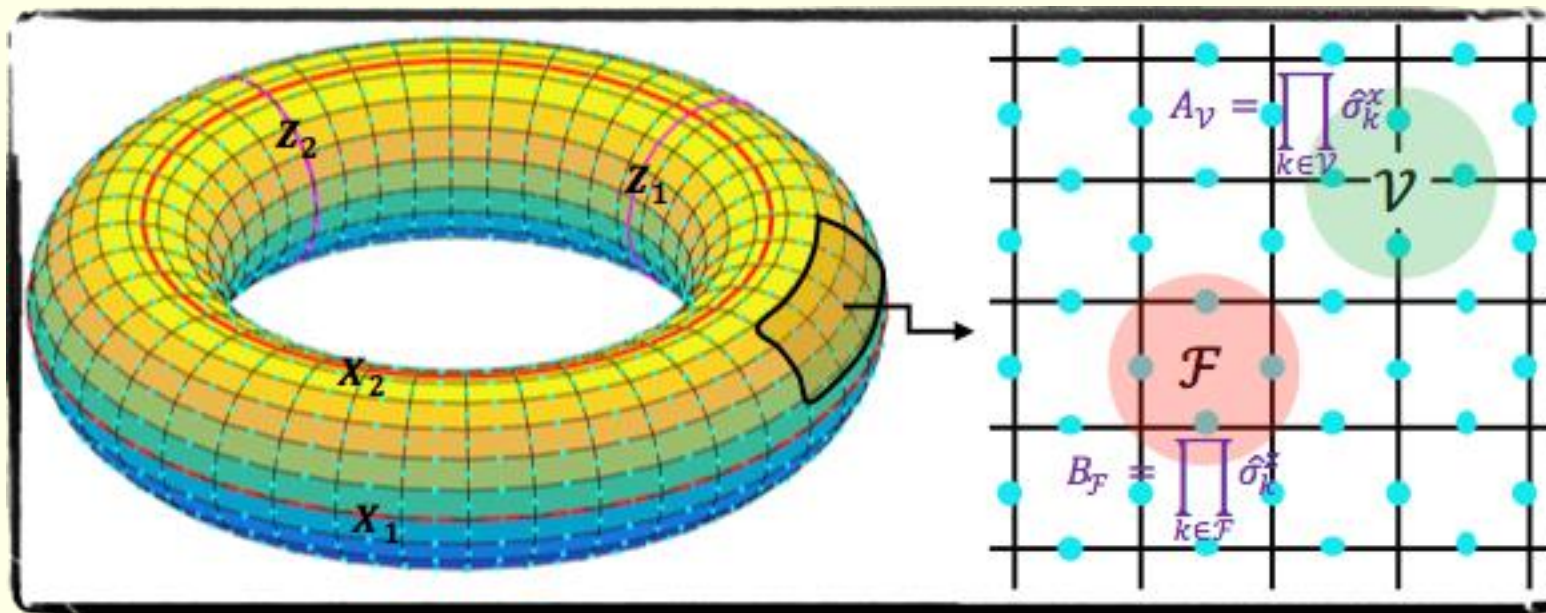
A explicit solution:

$$(a, b, \omega_{-1}, \omega_0, \omega_1) = \frac{\pi}{4}(0, 1, 2, 3, 1)$$

$$\Psi(\mathcal{S}, \mathcal{W}) = \sum_{\{h_k\}} \exp \left\{ \frac{i\pi}{4} \sum_k h_k (1 + 2\sigma_{k-1}^z + 3\sigma_k^z + \sigma_{k+1}^z) \right\}$$



2D Kitaev toric code model



Hamiltonian:

$$H_{tor} = - \sum_{\mathcal{V} \in \mathbb{T}^2} A_{\mathcal{V}} - \sum_{\mathcal{F} \in \mathbb{T}^2} B_{\mathcal{F}}$$

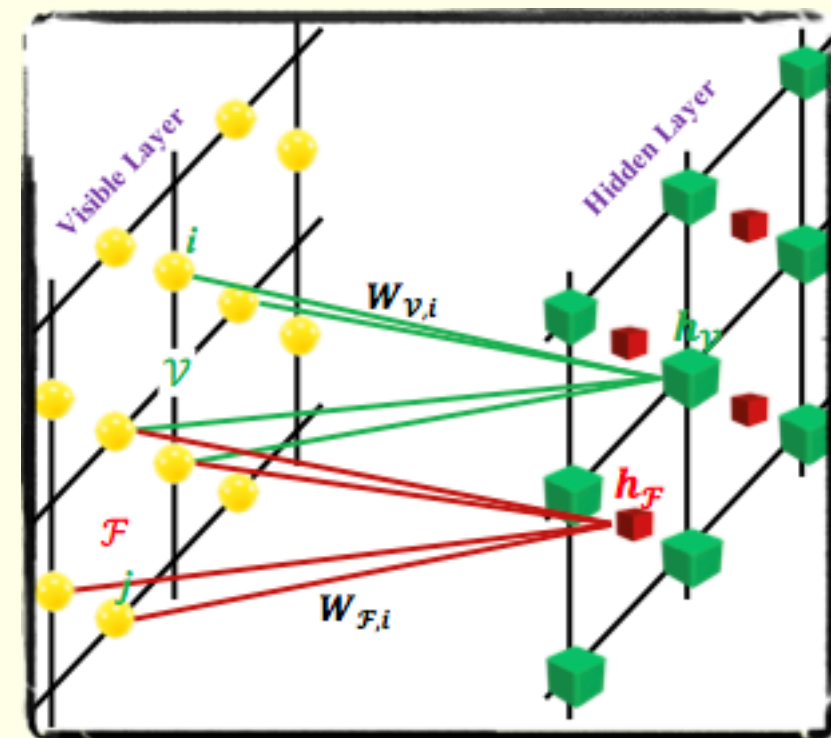
Ground state:

$$\begin{aligned} A_{\mathcal{V}} |G_{tor}\rangle &= |G_{tor}\rangle \\ B_{\mathcal{F}} |G_{tor}\rangle &= |G_{tor}\rangle \end{aligned}$$

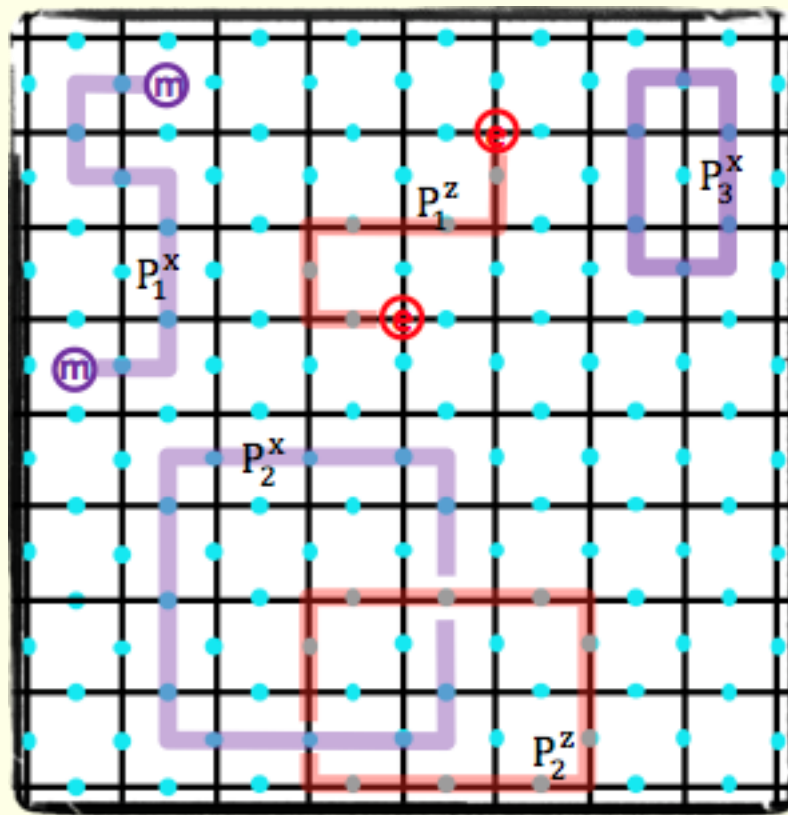
- ★ Intrinsic topological order with long-range entanglement
- ★ Four-fold degeneracy on a torus
- ★ Low-energy excitations are abelian anyons

Solution:

$$\Psi(\mathcal{S}, W) = \sum_{\{h_{\mathcal{V}}, \mathcal{F}\}} \exp \left\{ \frac{i\pi}{2} \sum_{k, \mathcal{V}} h_{\mathcal{V}} \sigma_k^z + \frac{i\pi}{4} \sum_{k, \mathcal{F}} h_{\mathcal{F}} \sigma_k^z \right\}$$



Excited states with abelian anyons



Two types of anyons created by different string operators:

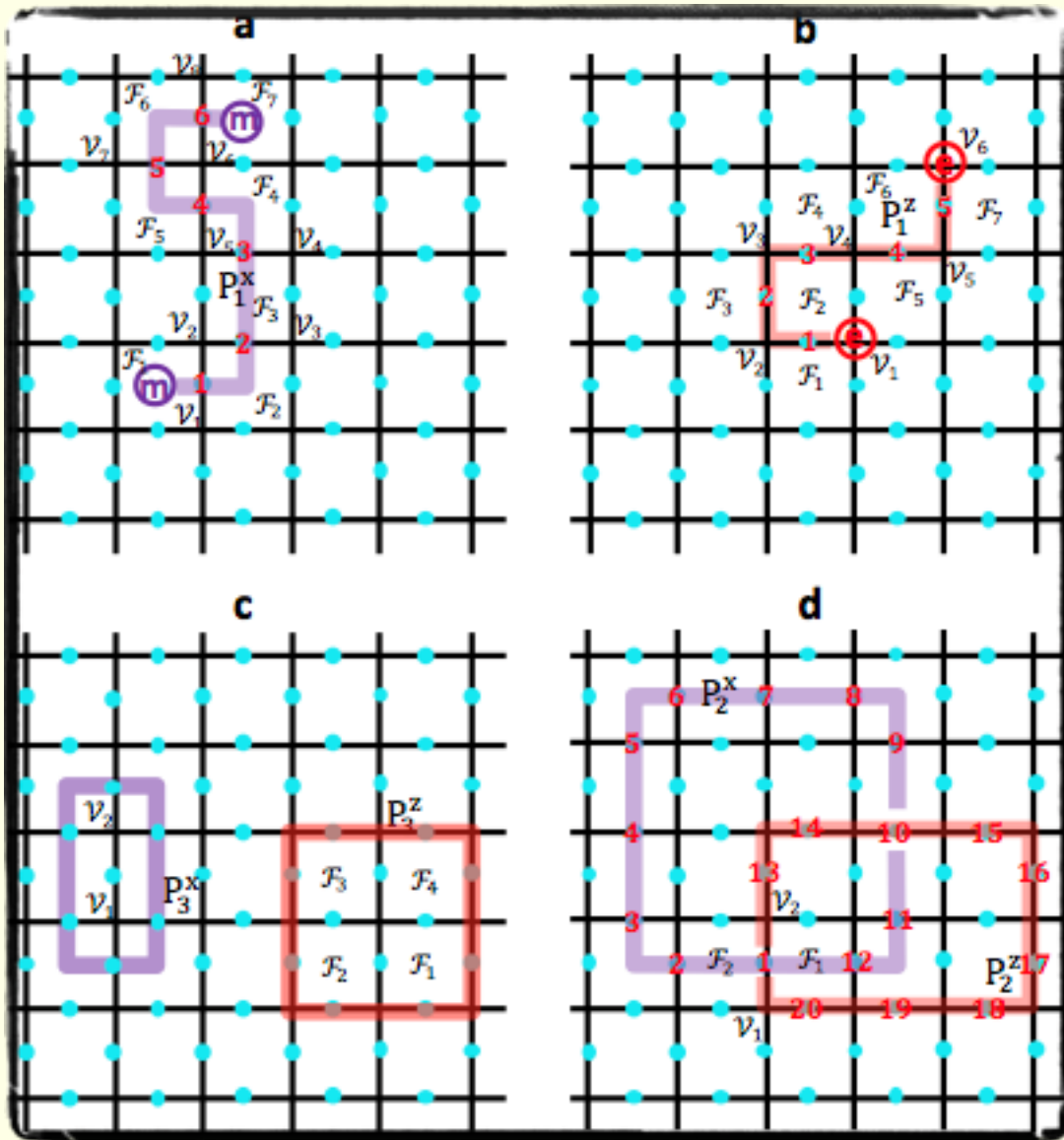
$S_{P^x}^x = \prod_{j \in P^x} \hat{\sigma}_j^x$ creates a pair of x-type quasiparticles (m) at the end of P^x

$S_{P^z}^z = \prod_{j \in P^z} \hat{\sigma}_j^z$ creates a pair of z-type quasiparticles (e) at the end of P^z

Fusion rule: $e \times e = 1; m \times m = 1; e \times m = \psi$

Nontrivial mutual statistics: braiding of e and m yields an overall

An exact neural network description



Two key observations:

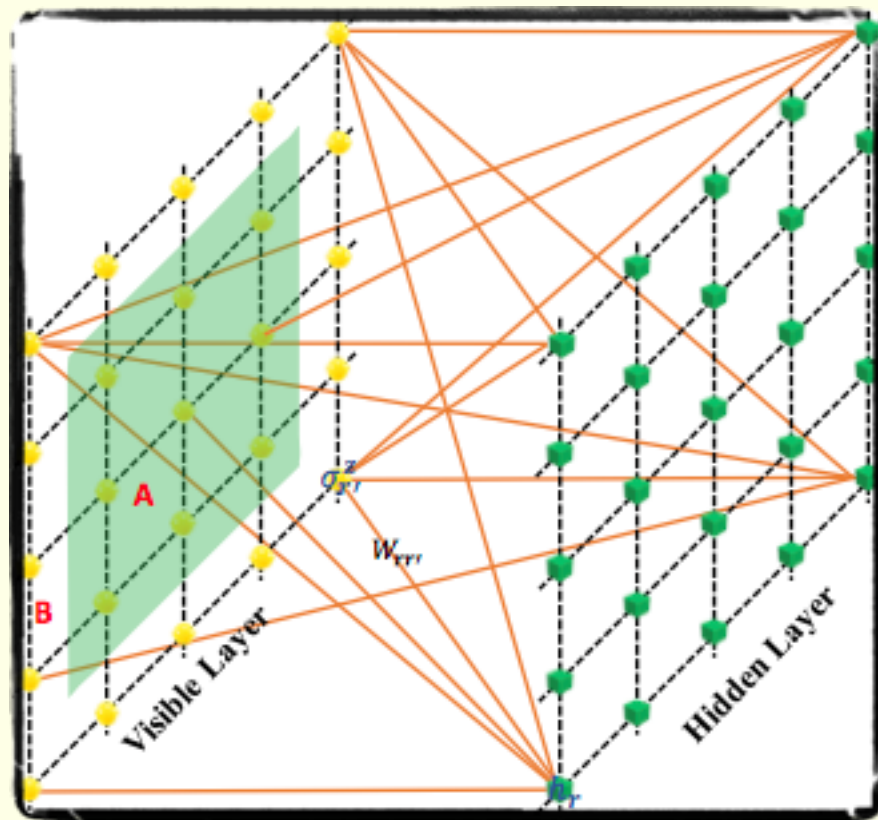
- 1) applying $S_{P^x}^x$ is equivalent to flipping all signs of the weight parameters associated with the visible neurons living on the path P^x
- 2) applying $S_{P^z}^z$ is equivalent to adding hidden neurons along P^z , with each of them connecting only to the corresponding visible neuron.

Two m particles at the ends of P_1^x :

$$\Psi(\mathcal{S}, \mathcal{W}) = \sum_{\{h_{\mathcal{V}}, h_{\mathcal{F}}\}} \exp \left\{ \frac{i\pi}{2} \sum_{\mathcal{V}} h_{\mathcal{V}} \left[\sum_{j \in \mathcal{V}; j \notin P_1^x} \sigma_j^z - \sum_{j \in \mathcal{V}; j \in P_1^x} \sigma_j^z \right] + \frac{i\pi}{4} \sum_{\mathcal{F}} h_{\mathcal{F}} \left[\sum_{k \in \mathcal{F}; k \notin P_1^x} \sigma_k^z - \sum_{k \in \mathcal{F}; k \in P_1^x} \sigma_k^z \right] \right\}$$

Quantum entanglement in neural network states

Entanglement area law for short-range RBMs



The α -th order Renyi entropy:

$$S_{\alpha}^A \equiv \frac{1}{1-\alpha} \log[\text{Tr}(\rho_A^{\alpha})]$$

Theorem 1: All short-range RBM states satisfy an area law:

$$S_{\alpha}^A \leq 2\mathcal{S}(A)\mathcal{R} \log 2, \quad \forall \alpha$$

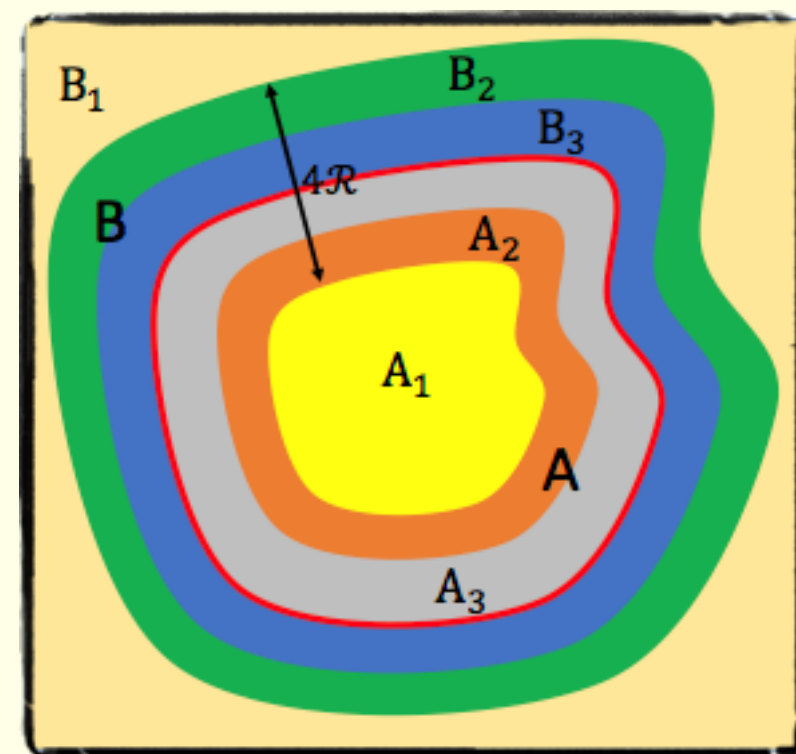
DLD, Xiaopeng Li, S. Das Sarma, *PRX*, 7, 021021 (2017)

Basic idea for the proof:

- Using the product form

$$\Psi_M = \prod e^{a_j \sigma_j^z} \prod \Gamma_k(\mathcal{S})$$

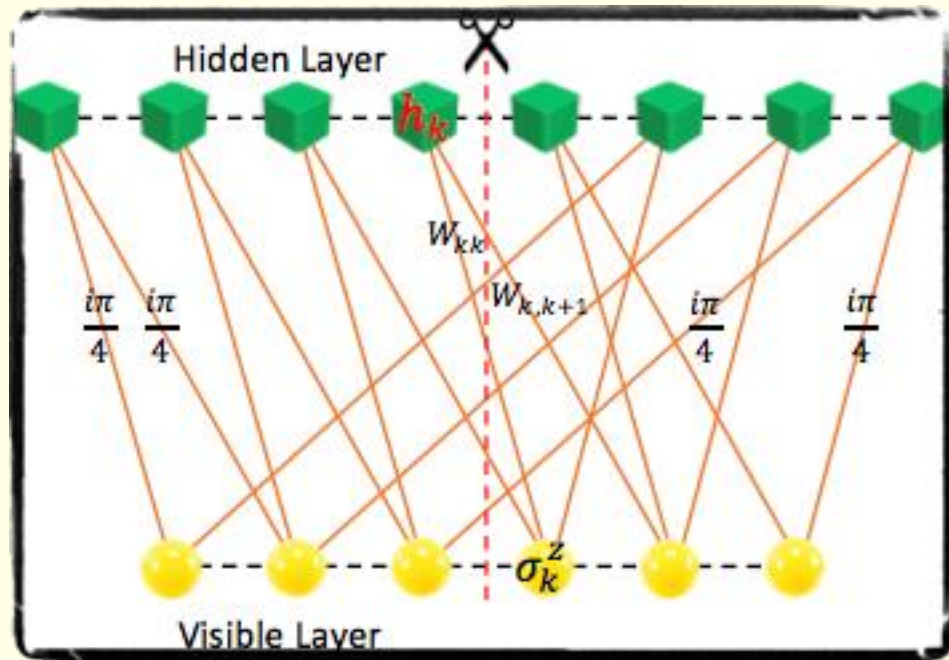
- A deliberate partitions



Remarks:

- The proof is independent of the dimensionality or the geometry of the bipartition
- The 1D SPT cluster states and the toric code states in both 2D and 3D all obey area-law entanglement
- 1D short-range RBM states can be efficiently represented by matrix product states (MPS)
- Speed up reinforcement learning
- New approach to prove entanglement area law for the ground states of local gapped Hamiltonians in higher dimensions?

Exact RBM states with volume-law entanglement



Theorem 2: the right RBM state has a volume law entanglement

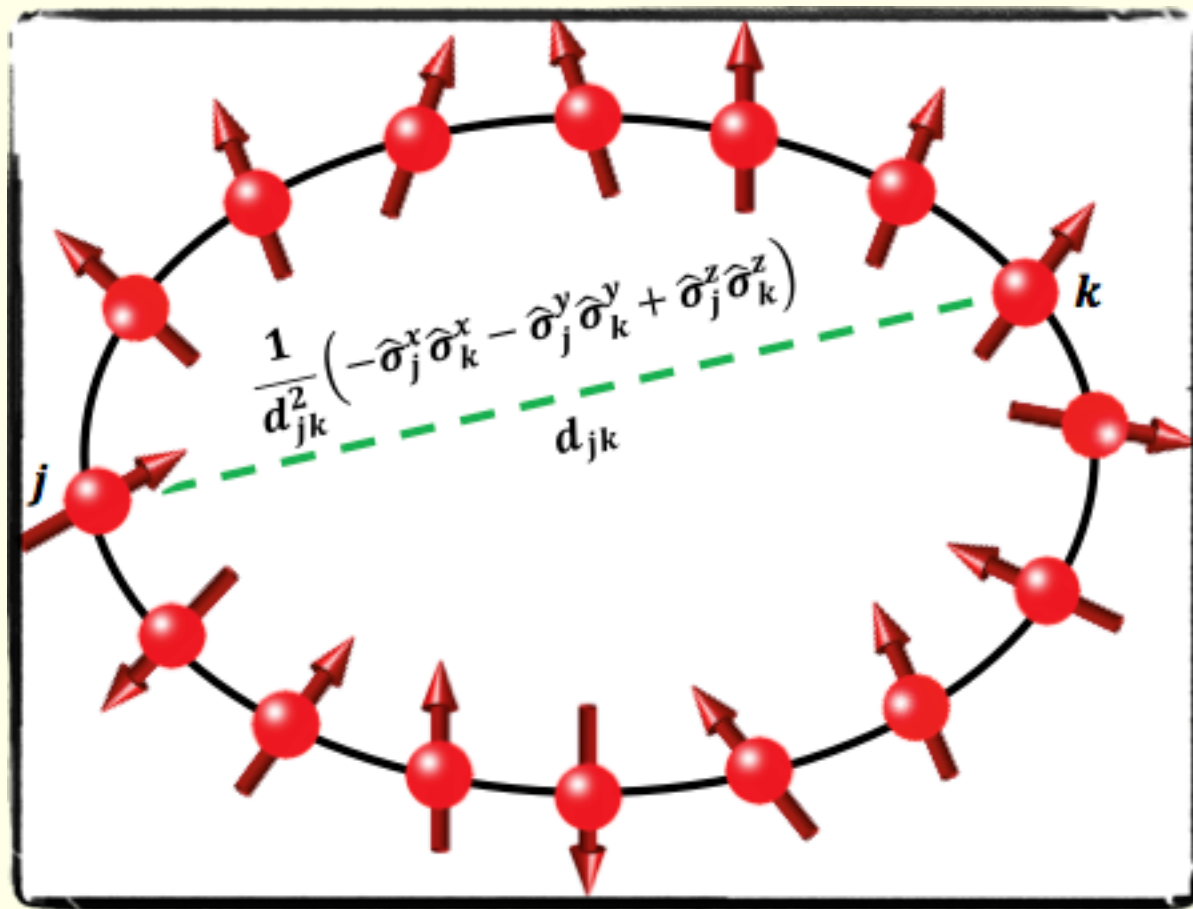
$$S_{\alpha}^A = l \log 2, \quad \alpha$$

Remarks:

- The construction carries over to higher dimensions
- The representation is very efficient
- Unlike MPS/Tensor-network states, entanglement is not the limiting factor for RBMs

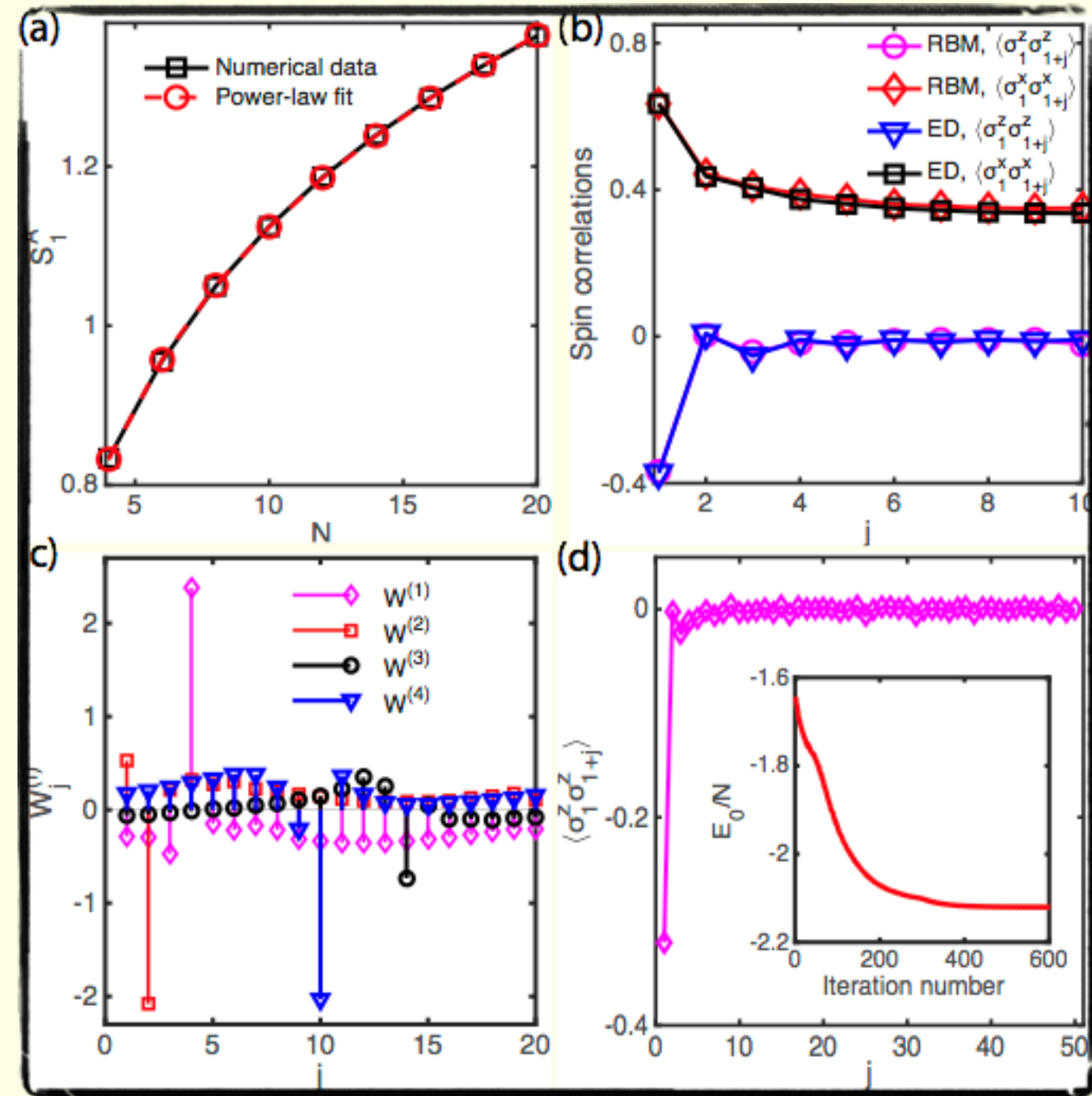
Reinforcement learning of ground states with massive entanglement

Modified Haldane-Shastry model

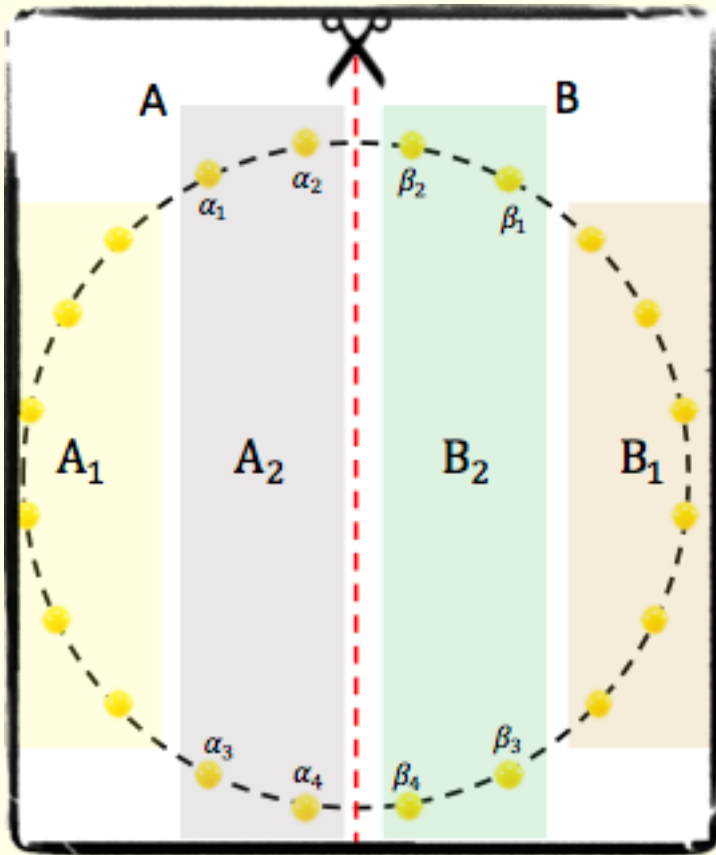


Hamiltonian:

$$H_{\text{MHS}} = \sum_{j < k} \frac{1}{d_{jk}^2} (-\hat{\sigma}_j^x \hat{\sigma}_k^x - \hat{\sigma}_j^y \hat{\sigma}_k^y + \hat{\sigma}_j^z \hat{\sigma}_k^z)$$



An analytical RBM recipe for computing entanglement



Entanglement for the 1D SPT cluster state:

Entanglement entropy:

$$S_{\alpha}^A = 2 \log 2, \forall \alpha$$

Entanglement spectrum:

$$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 1/4, \lambda_{k>4} = 0$$

Remarks:

- Simple, no sophisticated math
- Can deal with *finite* systems with *any* bipartition
- Entanglement spectrum has four-fold degeneracy, a signature of SPT phases
- Carry over to the toric code states straightforwardly
- Only works for certain specific cases
- No systematic way to convert a quantum many body state to RBM

Summary and outlook



Quantum Information and
Computation

A circular graphic featuring a blue background with a perspective view of a server room. In the foreground, several computer monitors display binary code (0s and 1s). The background is filled with a dense, glowing stream of binary digits, creating a sense of depth and data flow.

Refs:

- [1] DLD, Li, & Das Sarma, arXiv: 1609.09060(2016)
- [2] DLD, Li, & Das Sarma, PRX, 7, 021021 (2017)
- [3] Carleo & Troyer, Science 355, 602 (2017)
- [4] Gao & Duan, arXiv: 1701.05039
- [5] Huang & Moore, arXiv: 1701.06246
- [6] Chen, Cheng, Xie, Wang, Xiang, arXiv: 1701.04831

.....



Condensed Matter/AMO
Physics

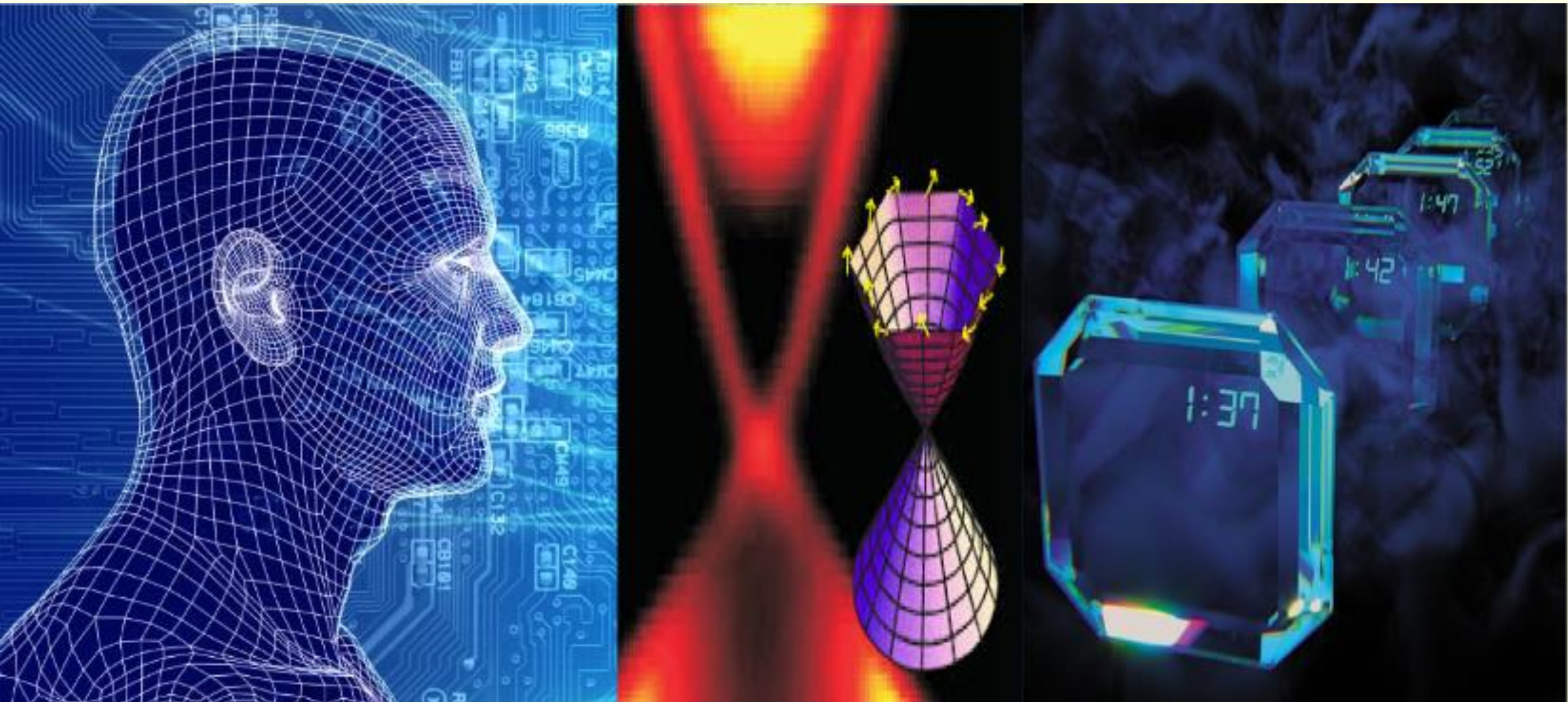
A circular graphic with a textured, orange-brown background. The texture resembles a microscopic view of a material surface or a complex lattice structure, with various shades of brown and orange creating a pattern of peaks and valleys.



Machine learning

A circular graphic featuring a blue background with a dense stream of binary digits (0s and 1s) flowing from left to right. In the foreground, there is a stylized, metallic-looking head of a person, facing right, with a grid-like pattern on its face, suggesting a connection to artificial intelligence or machine learning.

Look forward: a self-learning robot that teaches physicists physics?



.....

Thank you!