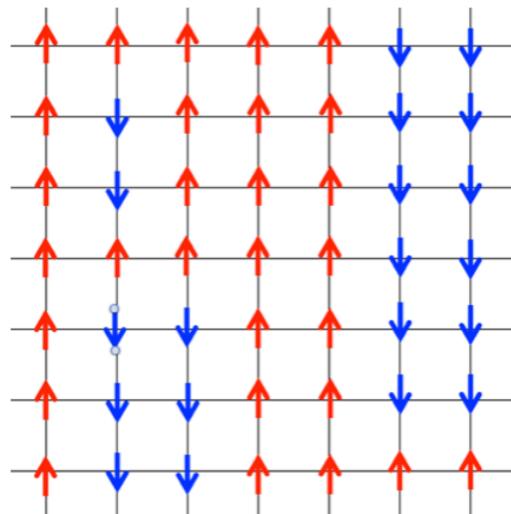
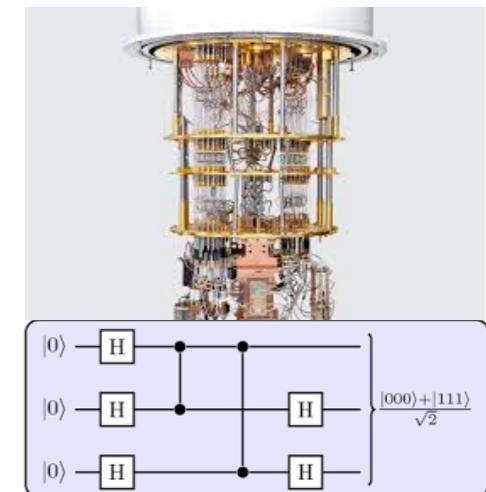


# Computation with Tensor Networks



4	1	9	2	1	3
3	5	3	6	1	7
6	9	4	0	9	1
4	3	2	7	3	8
0	5	6	0	7	6
1	9	3	9	8	5



In collaboration with:  
**Feng Pan, Pengfei Zhou, Sujie Li @ ITP,CAS**  
**Lei Wang @ IOP,CAS**  
**Jinguo Liu @ Harvard**

Pan Zhang  
ITP,CAS

Ellis-ESA Workshop  
2021.05.27



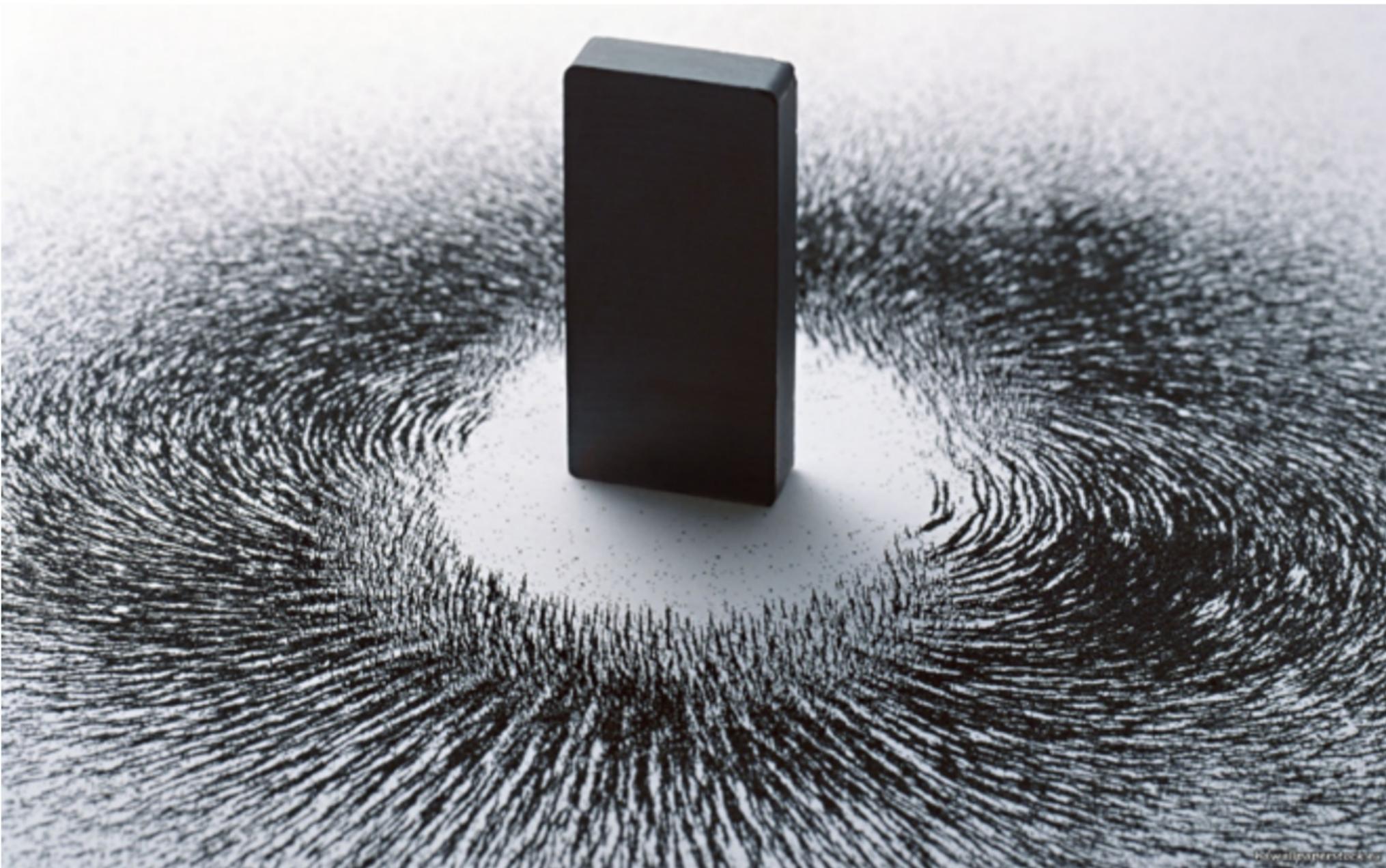
# Statistical Mechanics

$$\mathbf{S} = \{+1, -1\}^n$$

$$\uparrow \uparrow \uparrow \downarrow \uparrow \downarrow \downarrow \downarrow \downarrow \uparrow \uparrow$$

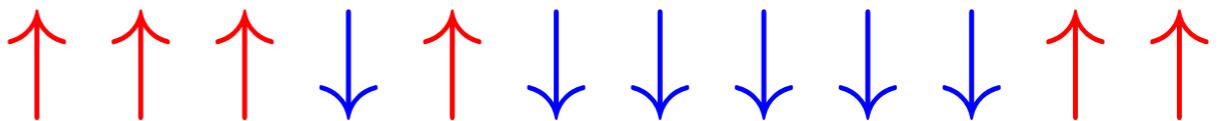
$$P(\mathbf{S}) = \frac{1}{Z} e^{-\beta E(\mathbf{S})}$$

$$Z = \sum_{\mathbf{S}} e^{-\beta E(\mathbf{S})}$$



# Statistical Mechanics

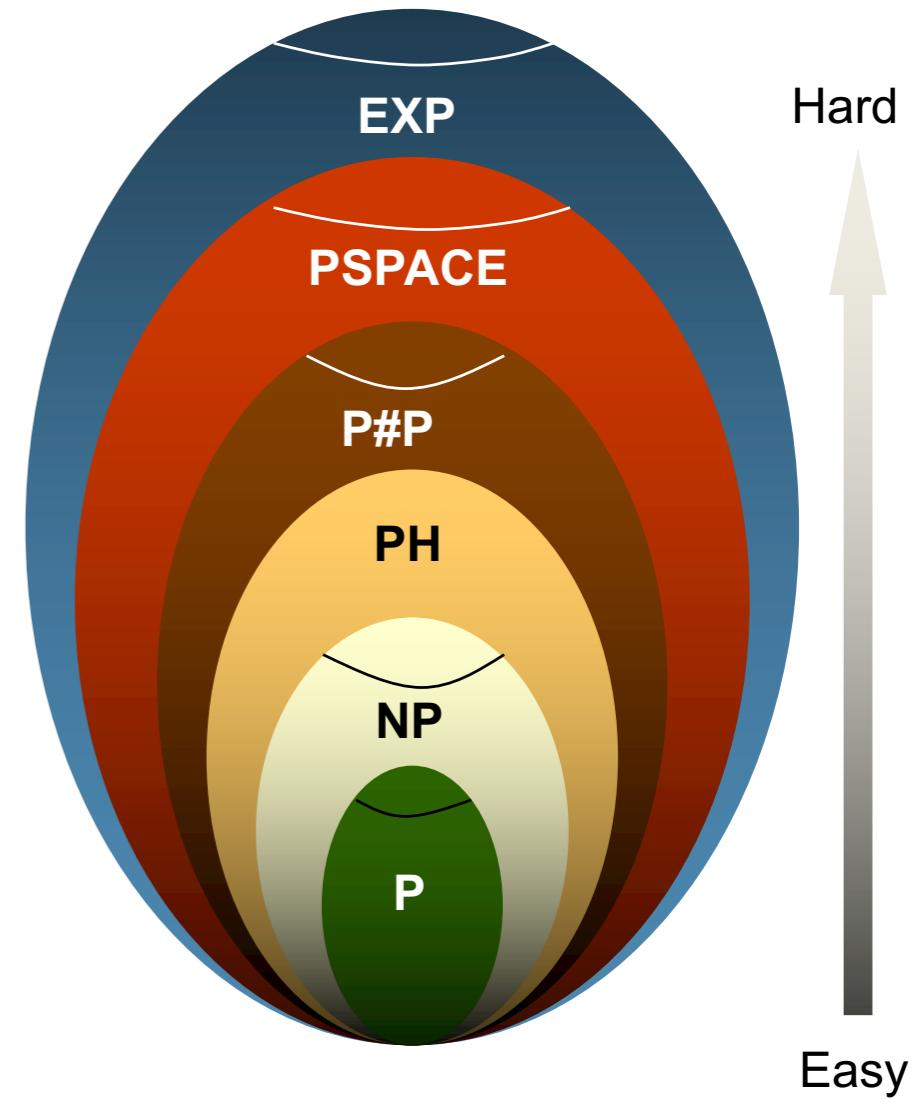
$$\mathbf{S} = \{+1, -1\}^n$$



$$P(\mathbf{S}) = \frac{1}{Z} e^{-\beta E(\mathbf{S})}$$

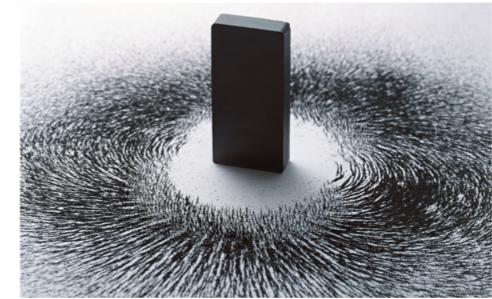
$$Z = \sum_{\mathbf{S}} e^{-\beta E(\mathbf{S})}$$

- Estimating Free Energy
- Computing statistics
- Unbiased sampling



# Applications of Statistical Mechanics

- Physics:  
Thermodynamics,  
Phase transitions ...

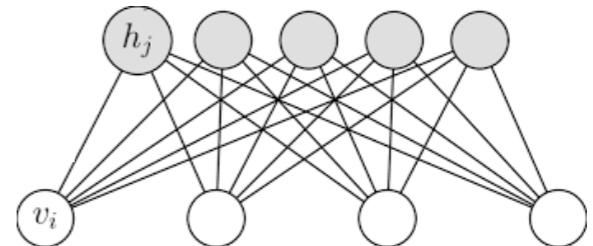


- Combinatorial Optimization

$$P(\mathbf{S}) = \lim_{\beta \rightarrow \infty} \frac{1}{Z} e^{-\beta E(\mathbf{S})}$$



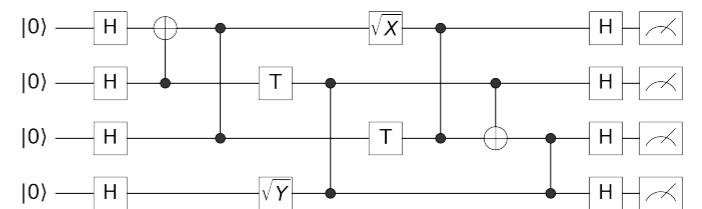
- Machine Learning  
Hopfield model,  
Boltzmann machines



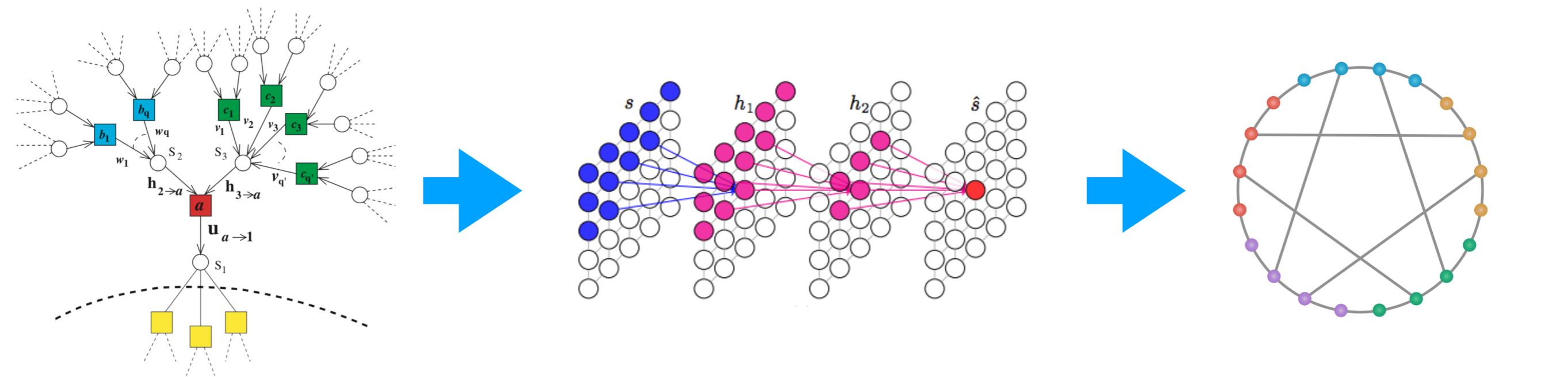
- Statistical Inference  
Bayesian Inference, M.A.P.



- Quantum computation  
Stat. Mech. with complexity interactions



# My research journey on Statistical Mechanics: From Mean-Field to Neural Networks Then to Tensor Networks



## Mean-field

Variational Mean-field  
Belief propagation  
Replica symmetry breaking  
Survey Propagation  
Expectation Propagation

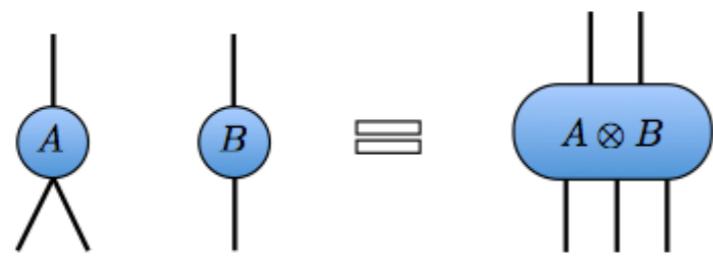
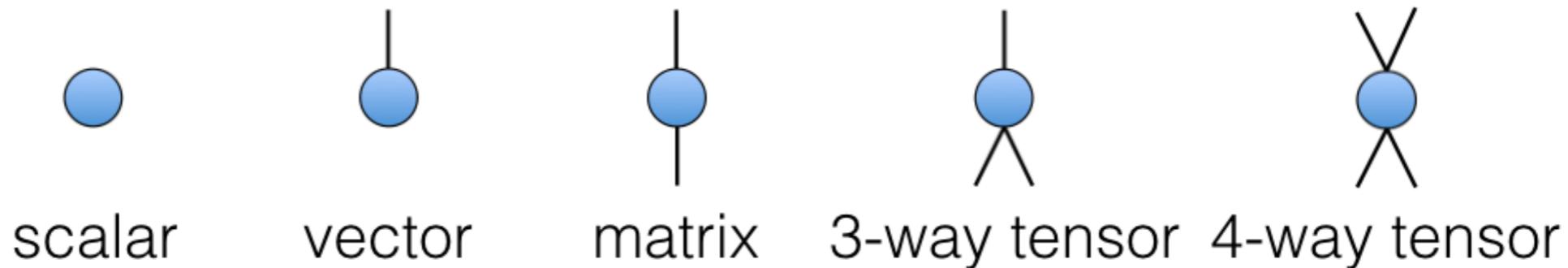
## Neural Networks

Variational Autoregressive Networks  
Feedback-set VAN

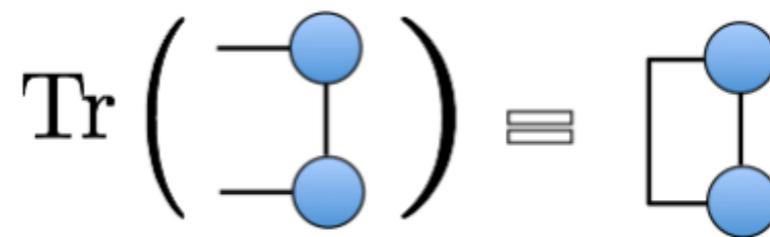
## Tensor Networks

CATN  
Tropical Tensor Networks

# Tensor Network Diagram notations



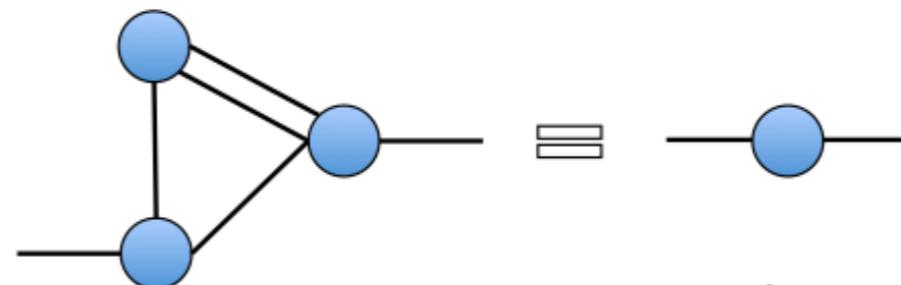
tensor product



Trace



tensor contraction

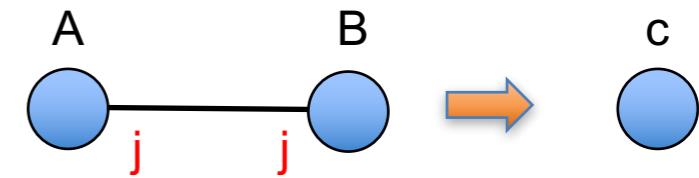


tensor contraction

# Einsum notations of tensor network contractions

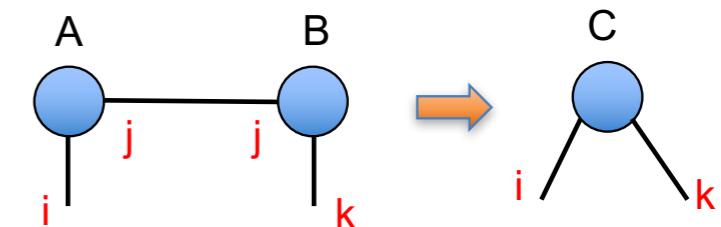
$c = \text{einsum}(A, B, "j, j")$

$$c = A \cdot B$$



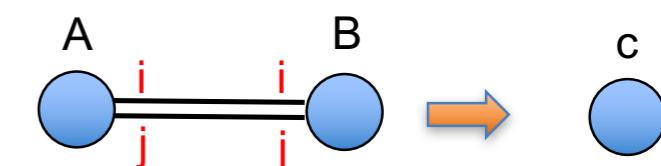
$C = \text{einsum}(A, B, "ij, jk->ik")$

$$C = AB$$



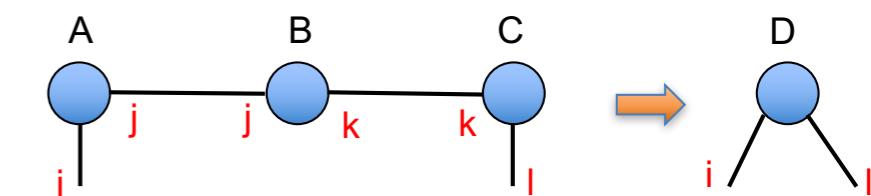
$c = \text{einsum}(A, B, "ij, ij")$

$$C = \text{Trace}(AB)$$



$D = \text{einsum}(A, B, C, "ij, jk, kl")$

$$D = ABC$$

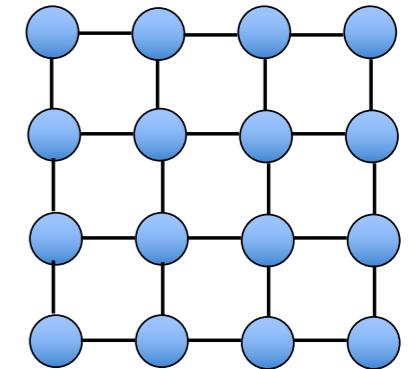
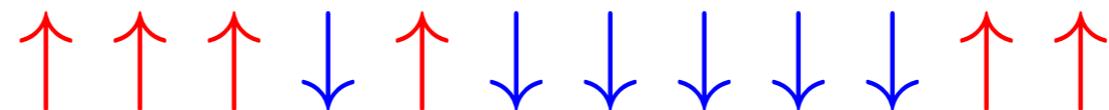


**Space complexity:** the dimension of the largest tensor

**Time complexity:** product of dimensions of all unique indices

# TN contraction for computing the partition function

$$\mathbf{S} = \{+1, -1\}^n$$

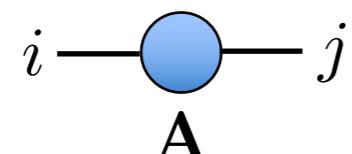
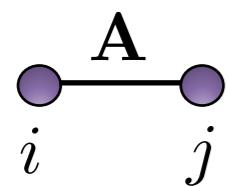


Computing normalization of a **discrete probability distribution**

$$P(\mathbf{S}) = \frac{1}{Z} \tilde{P} = \frac{1}{Z} e^{-\beta E(\mathbf{S})}$$

Any **discrete probability distribution** is a tensor,  
decomposed using tensor networks.

$$Z = \left\| \tilde{P} \right\|_1 = \tilde{P} \cdot \mathbf{1}_{2^n}^\top = \underbrace{\tilde{P} \cdot \left( \begin{array}{c} 1 \\ 1 \end{array} \right) \otimes \left( \begin{array}{c} 1 \\ 1 \end{array} \right) \otimes \cdots \otimes \left( \begin{array}{c} 1 \\ 1 \end{array} \right)}_n,$$

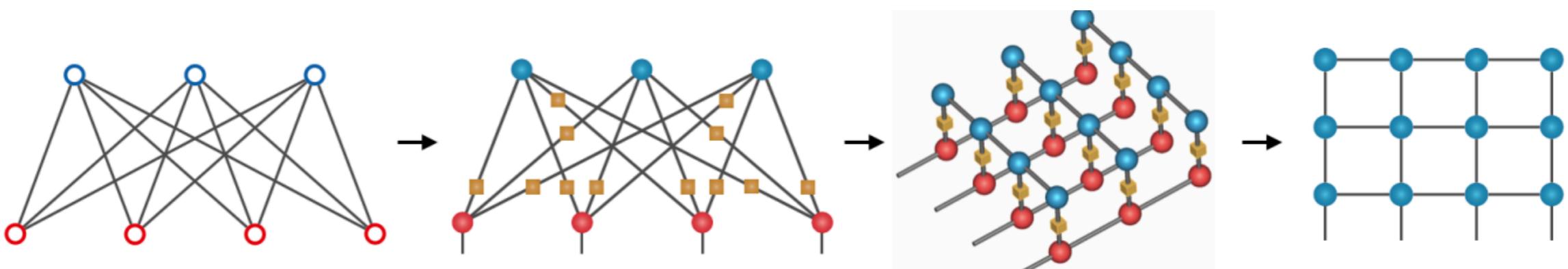
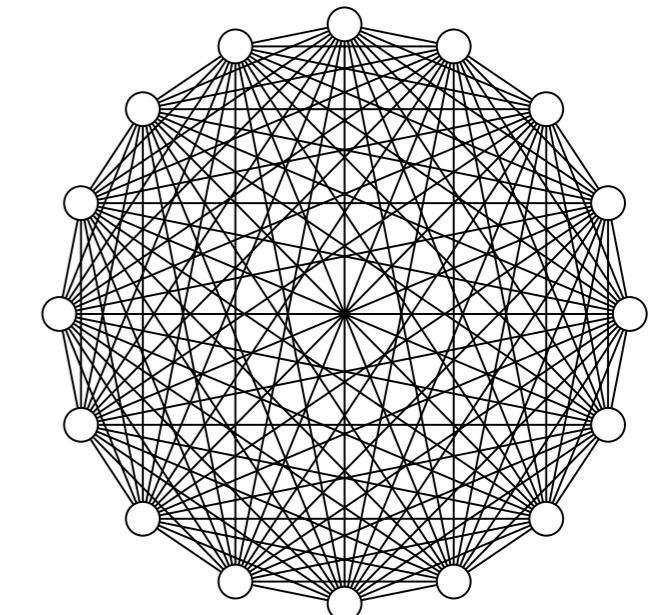
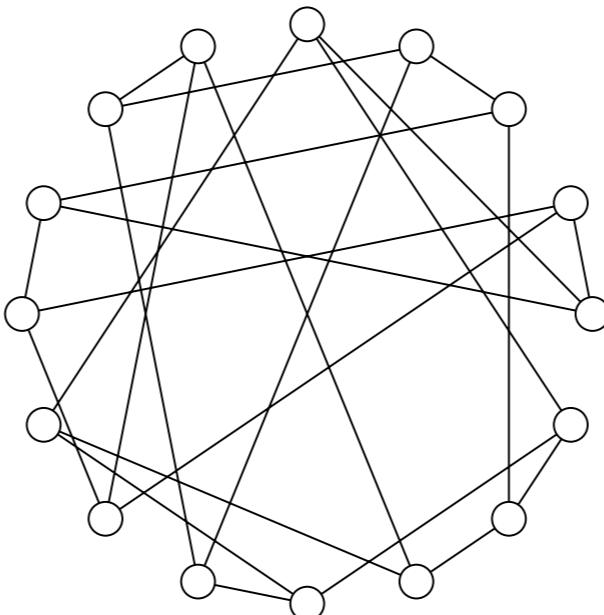
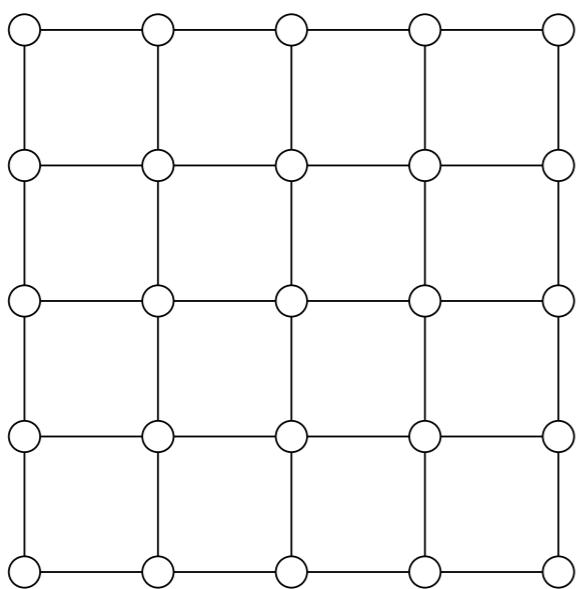


$$Z = \sum_{i,j} A_{ij} = \mathbf{1}^T A \mathbf{1} = [1, 1] \text{---} \begin{matrix} 1 \\ 1 \end{matrix}$$

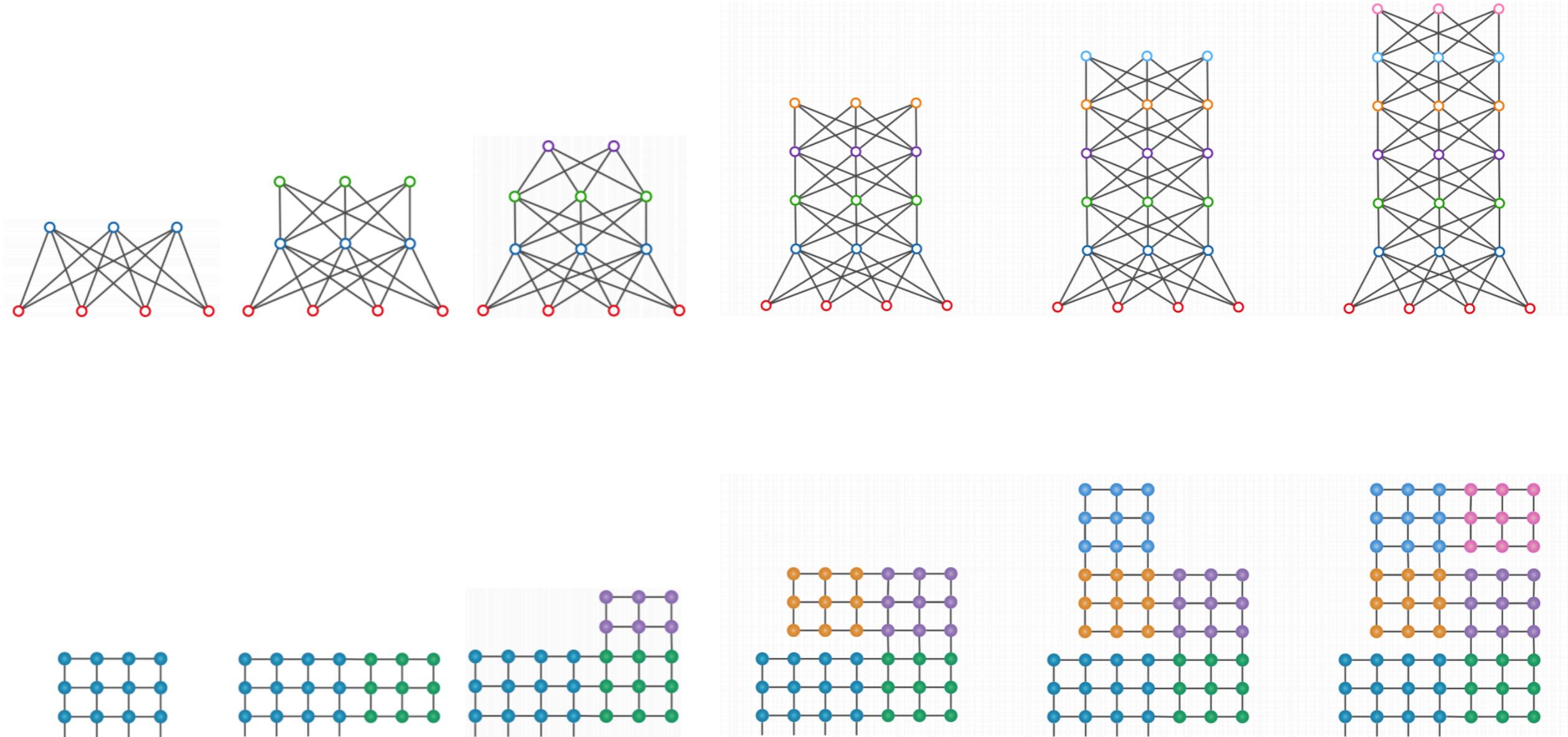
# TN Contraction



$Z(\beta)$



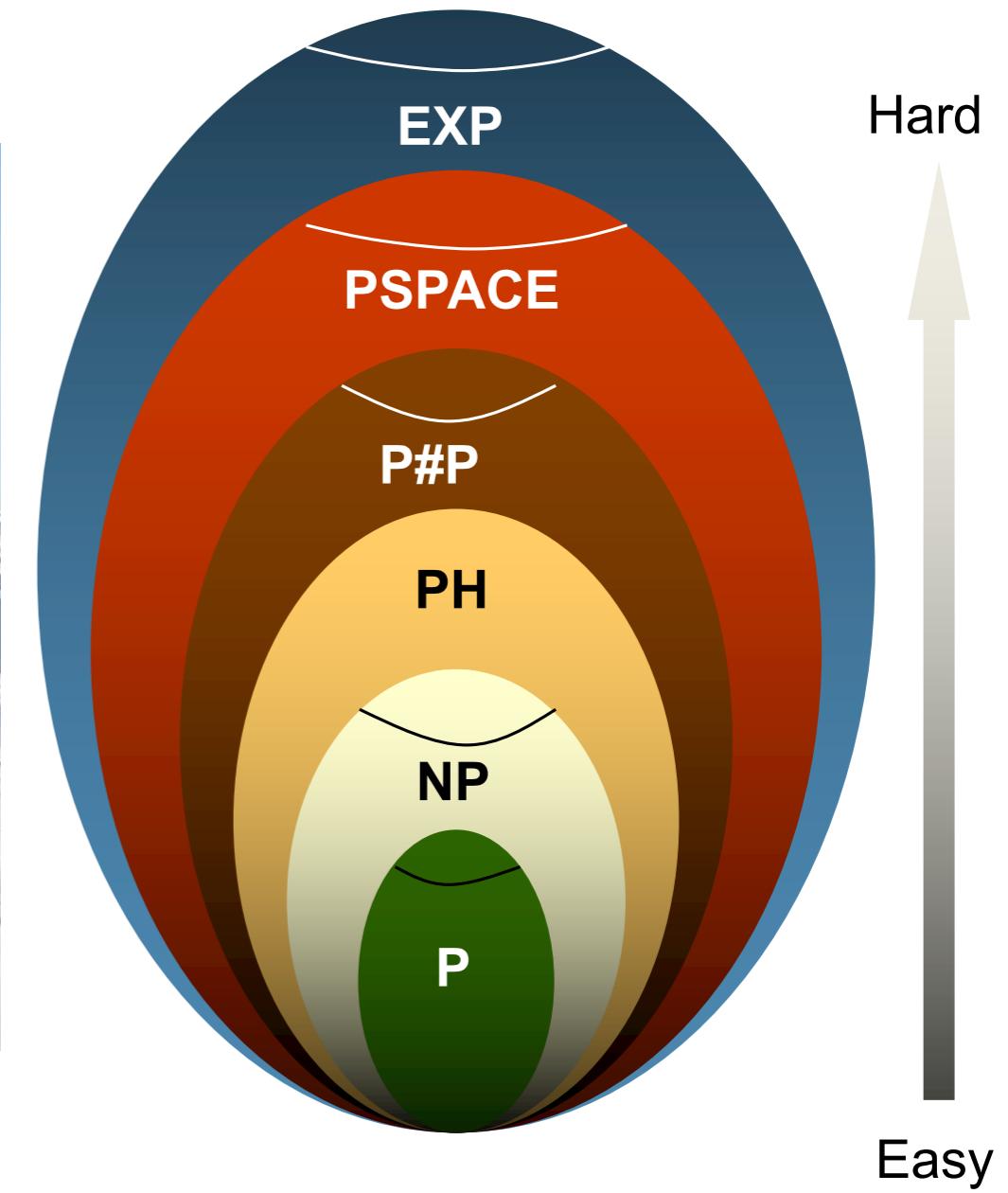
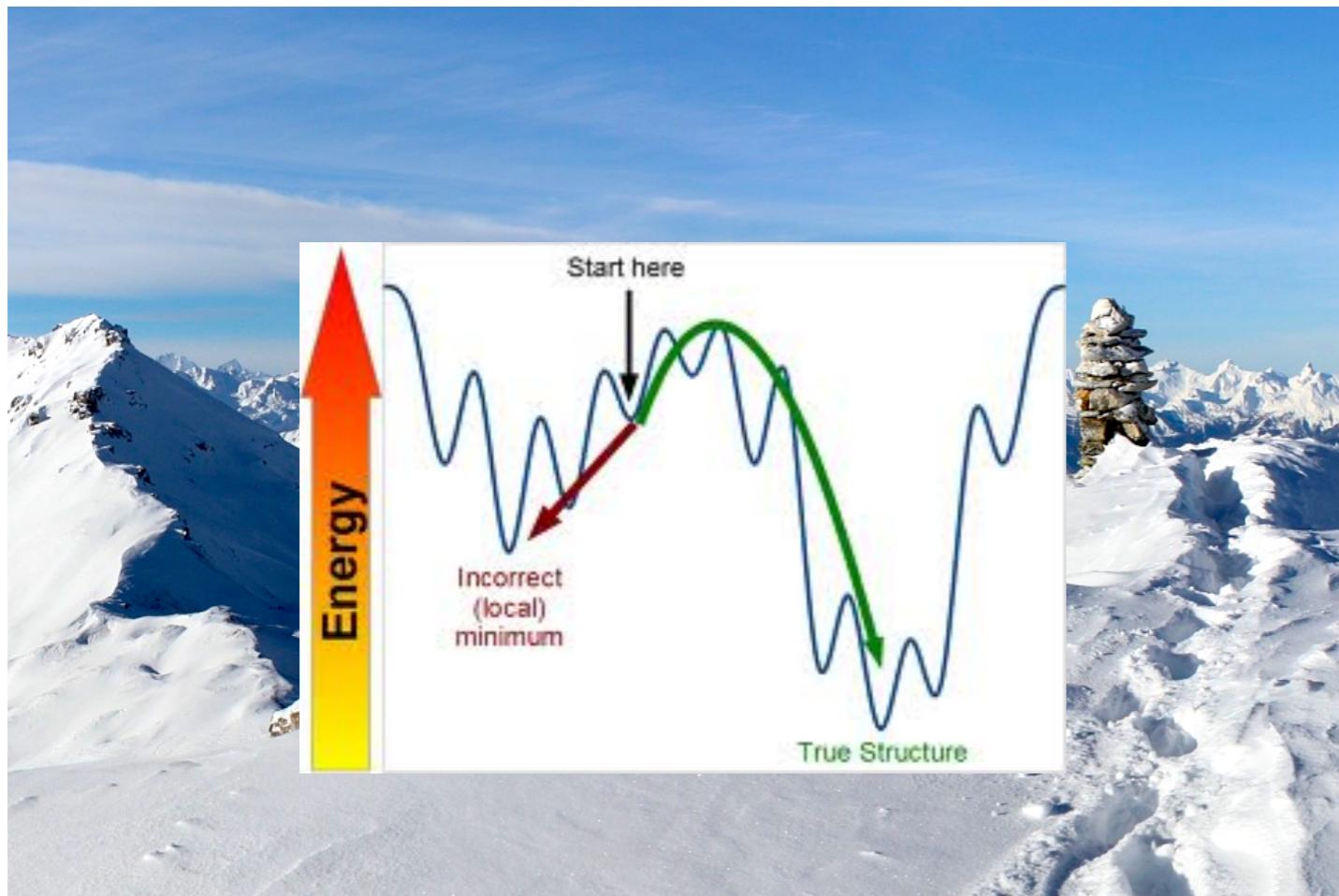
**TN Contraction**  **Z( $\beta$ )**



**Deep Boltzmann Machines**

**2D Tensor Network**

# Towards $T \rightarrow 0$ : Ground States, combinatorial optimization



# Tropical Tensor Network

**Replace  $(\times, +)$  operations in linear algebra with  $(\otimes, \oplus)$**

$$x \otimes y = x + y \quad x \oplus y = \min(x, y)$$

$$F_0 = \lim_{\beta \rightarrow \infty} -\frac{1}{\beta} \ln \sum_{\mathbf{s}} e^{-\beta E(\mathbf{s})}$$

$$= \lim_{\beta \rightarrow \infty} \left[ E_{\min} - \frac{1}{\beta} S(E_{\min}) \right]$$

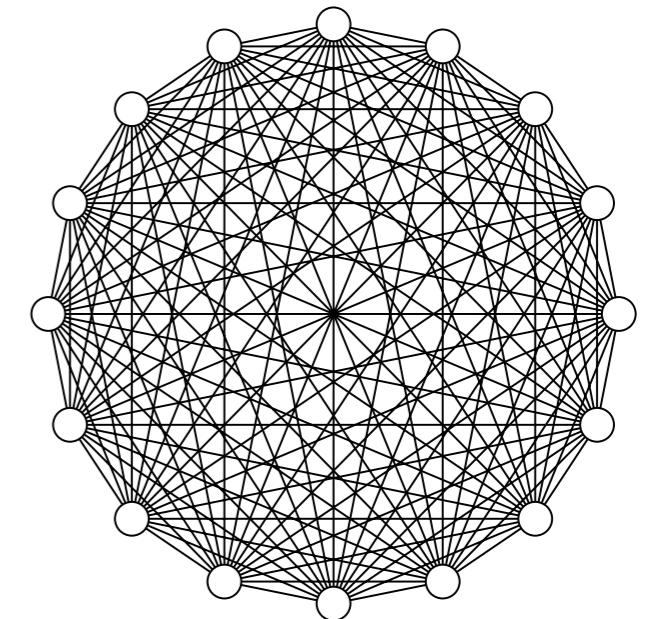
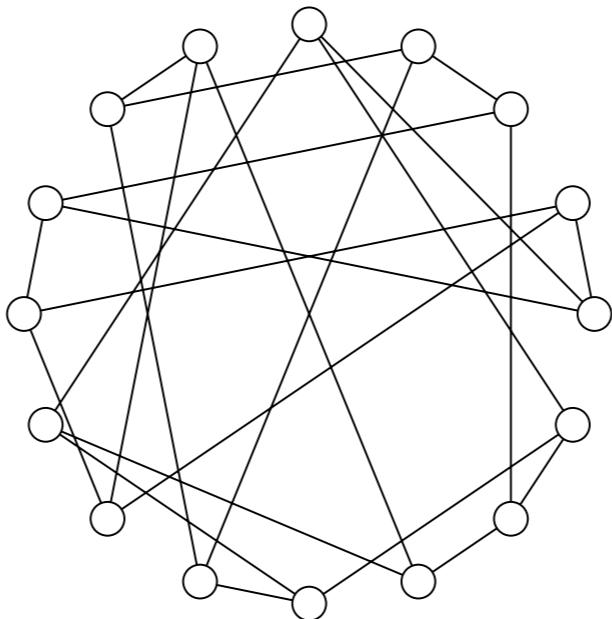
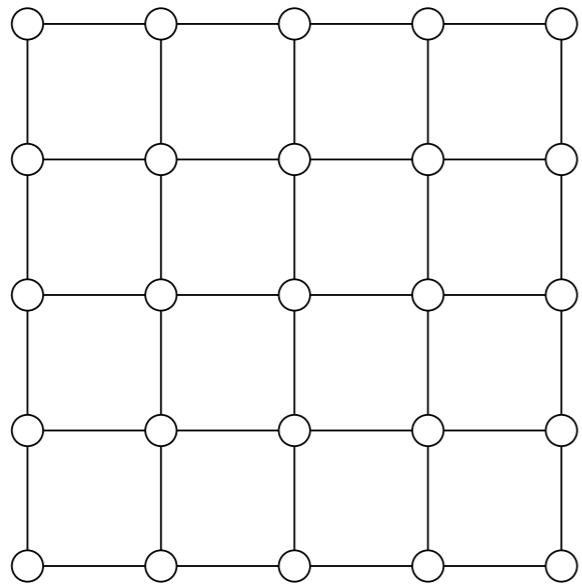
$$\lim_{\beta \rightarrow \infty} -\frac{1}{\beta} \ln(e^{-\beta x} \times e^{-\beta y}) = x \otimes y$$

$$\lim_{\beta \rightarrow \infty} -\frac{1}{\beta} \ln(e^{-\beta x} + e^{-\beta y}) = x \oplus y$$

ground state energy  
→ Tropical tensor network contraction

ground state configuration  
→ Gradient with respect to the field

ground state degeneracy  
→ Mix tropical with ordinary algebra

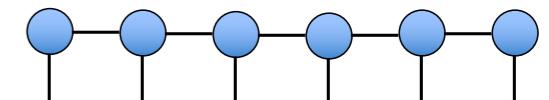


**For large TNs: we need approximate contractions**

# Challenges:

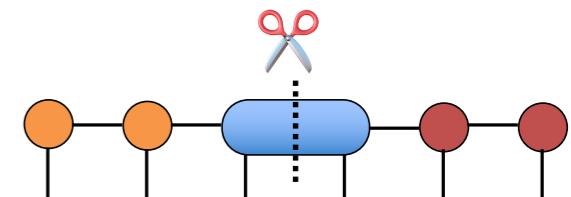
1. Exponential space complexity

**Compressed using MPS**



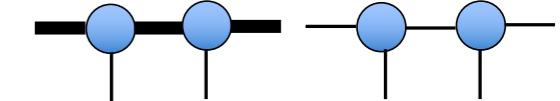
2. Global approximations

**Canonical form, DMRG**



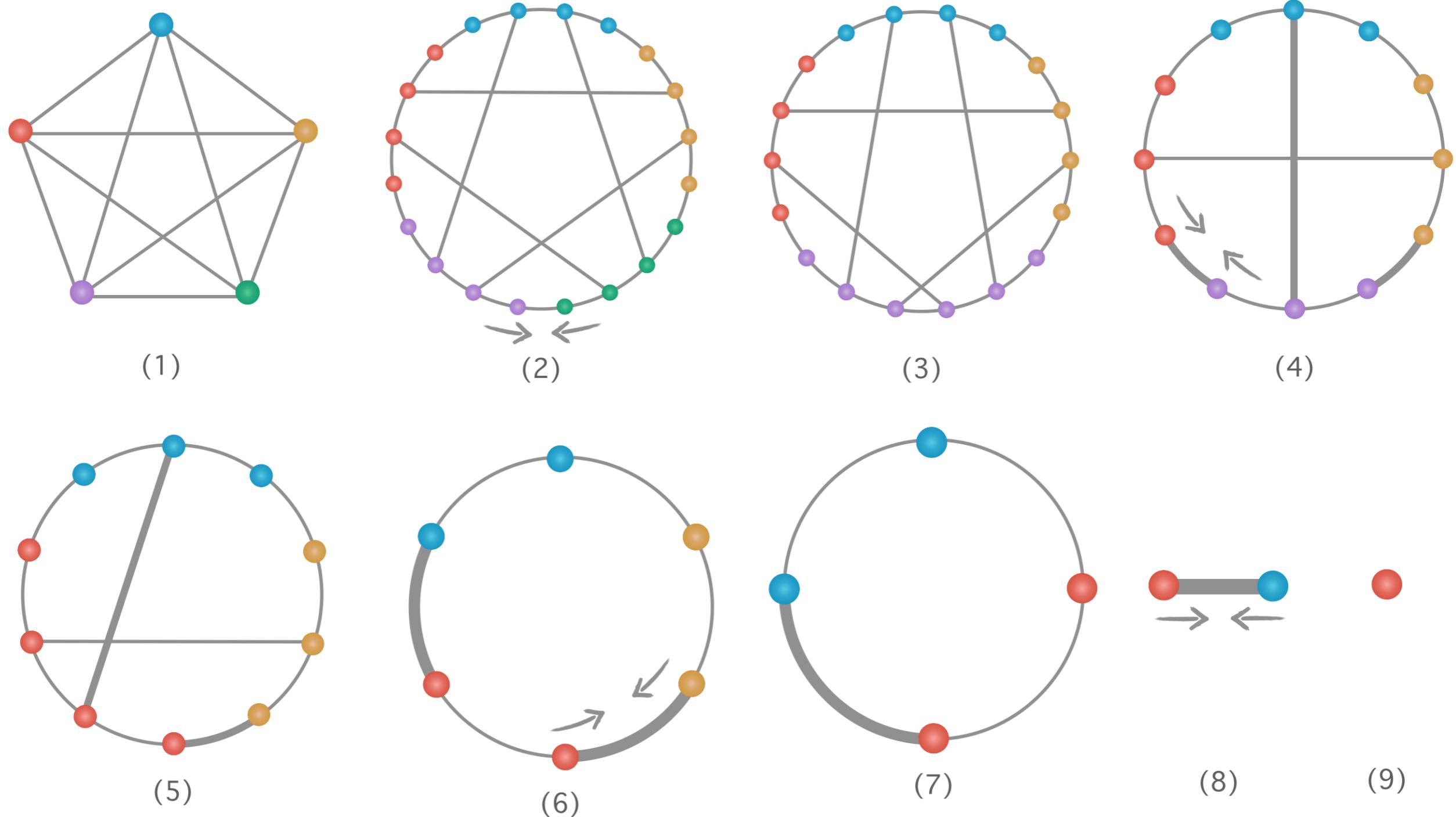
3. Scalability

**Tunable bond dimension**

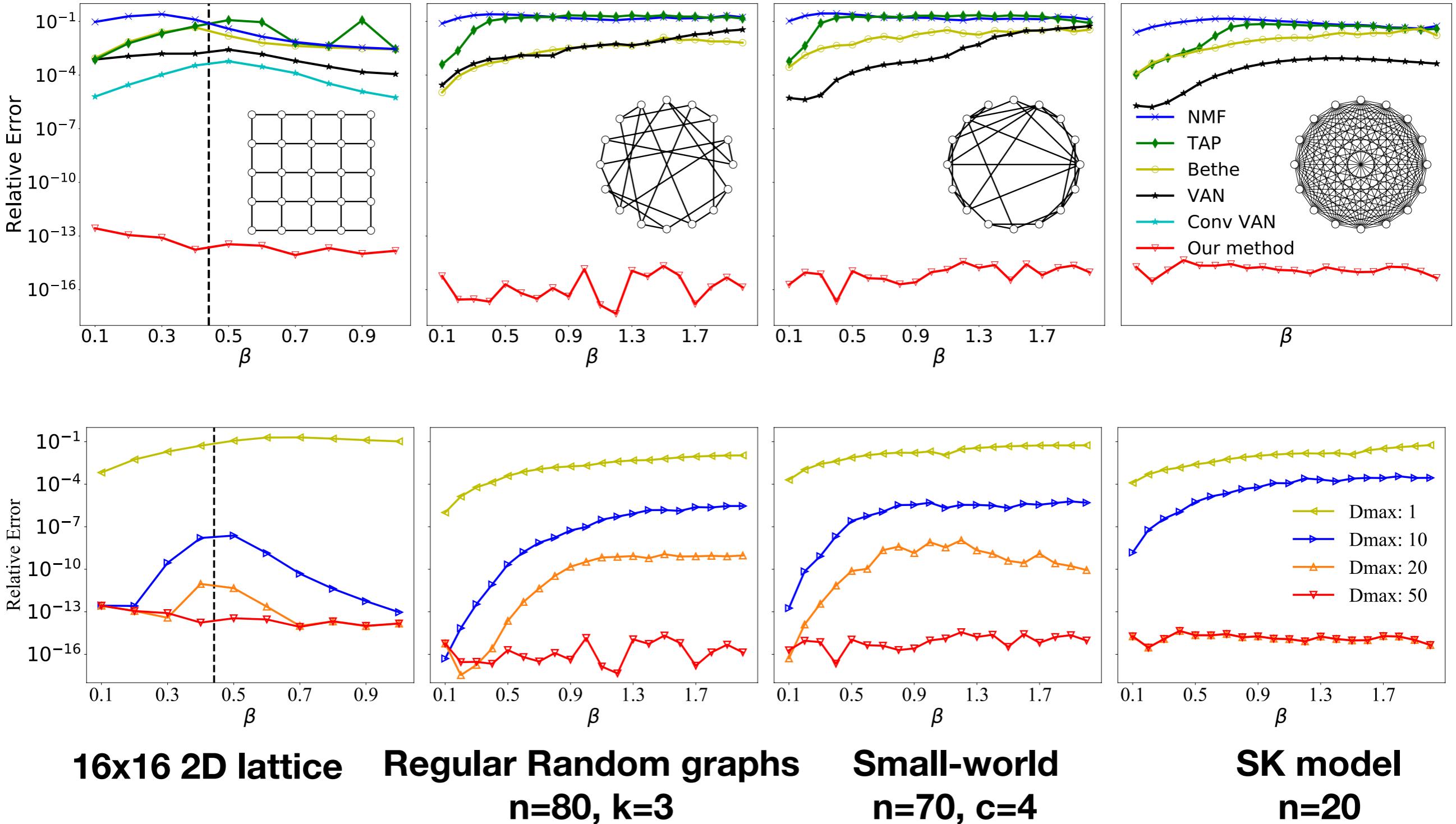


→ **CATN**

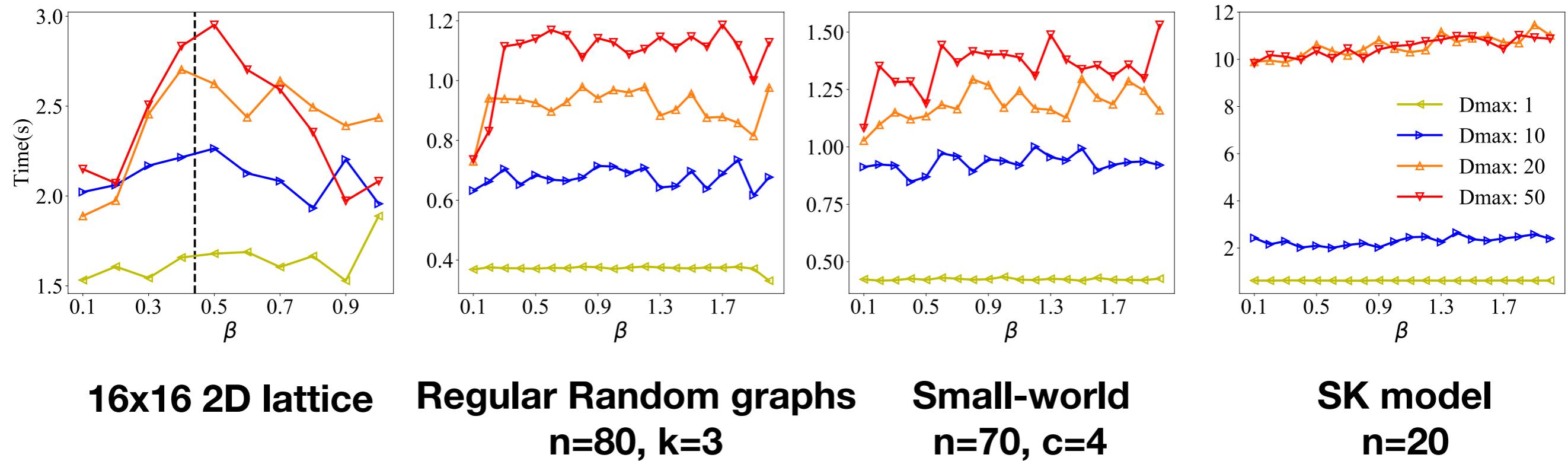
# CATN: Contracting Arbitrary Tensor Networks



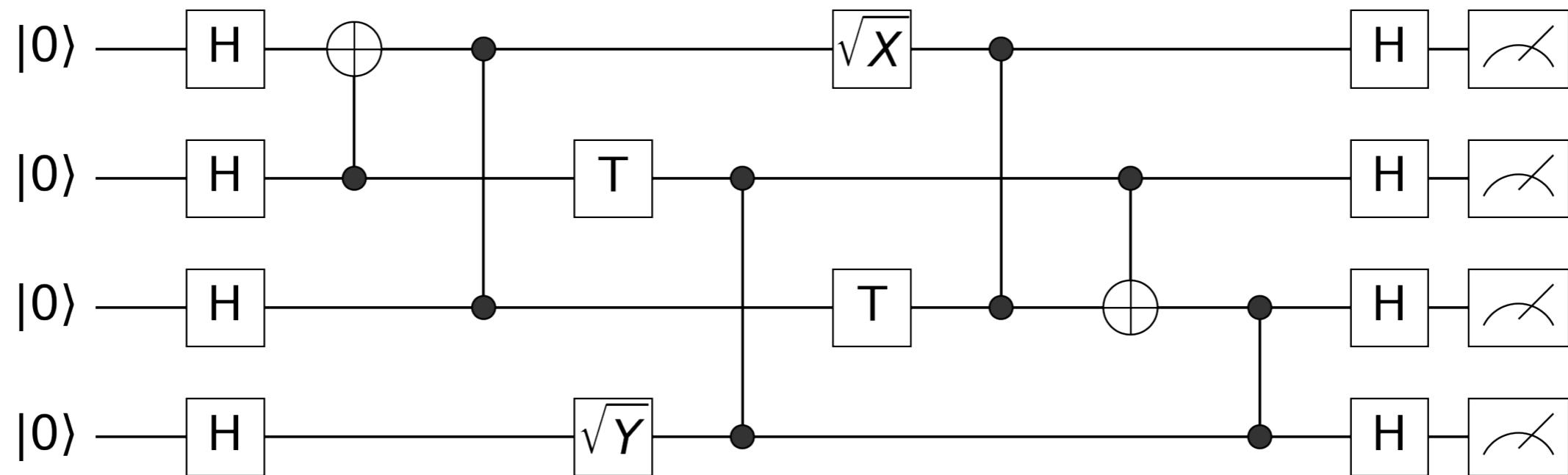
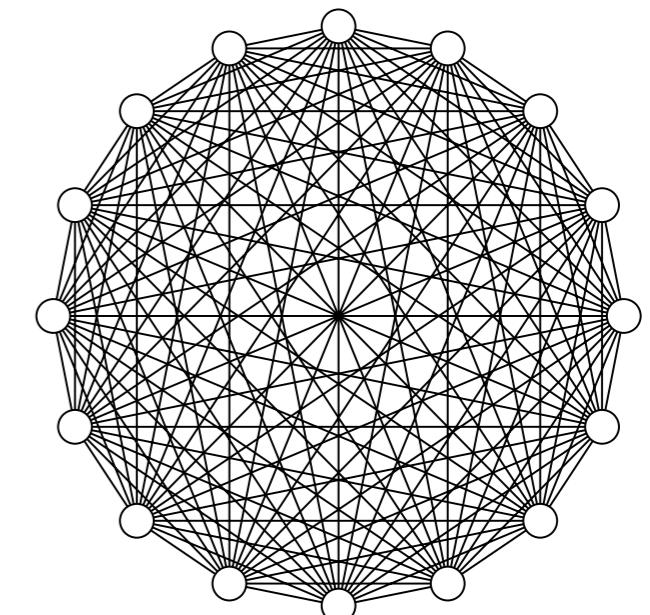
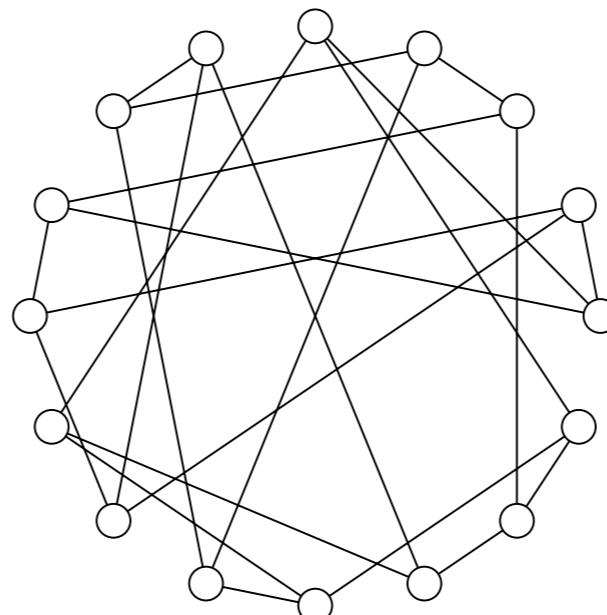
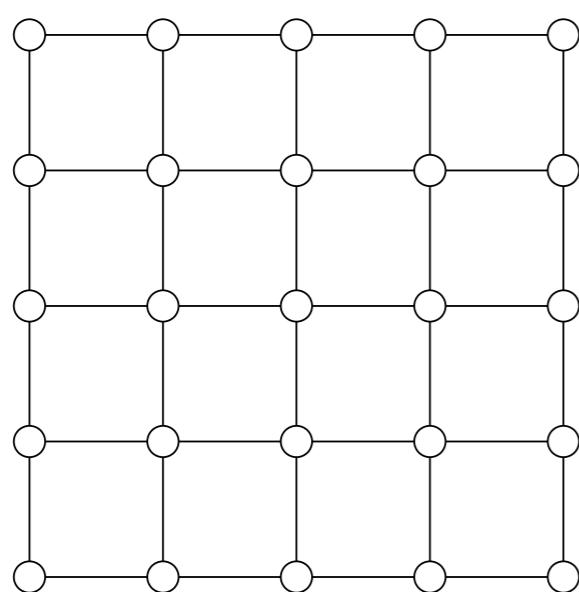
# Computing free energy of spin glasses



# Time used



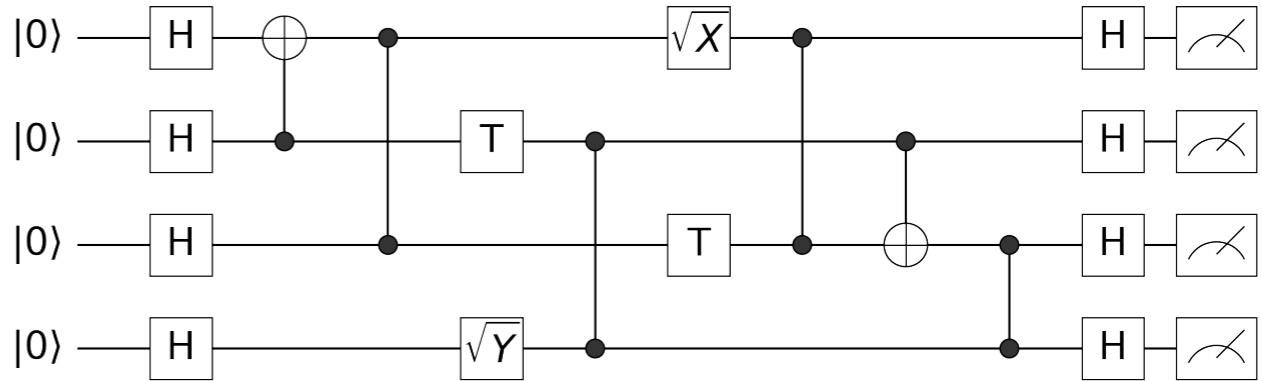
# From partition function to quantum circuit simulation



# Simulation methods

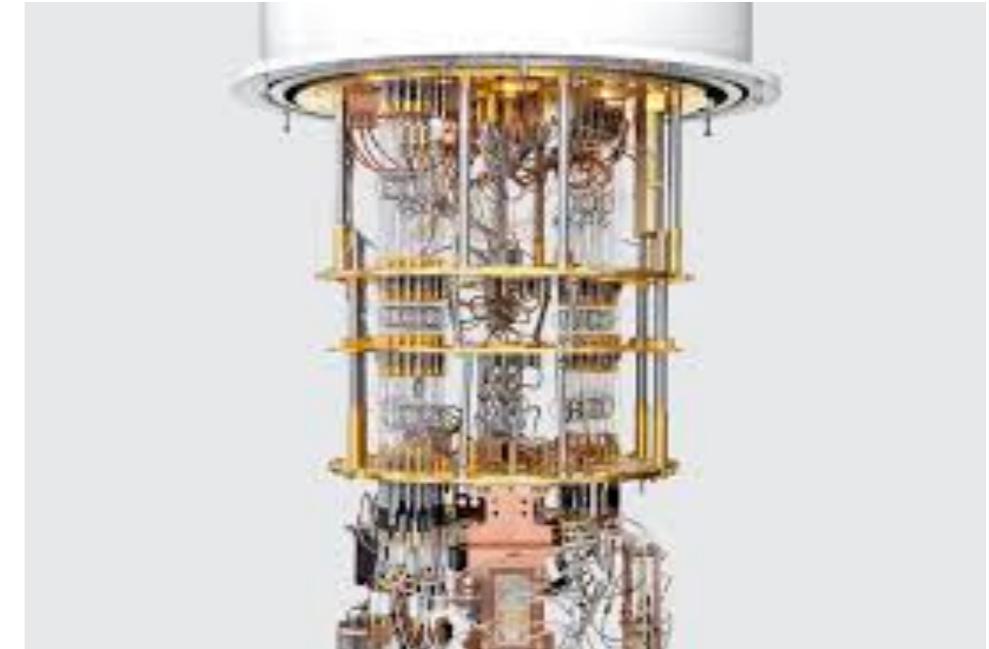
## Full amplitude:

- Storing full state-vector [Yao.jl, Qiskit, Qulacs, Cirq...]
- Schrödinger-Feynmann
- MPS / Group MPS

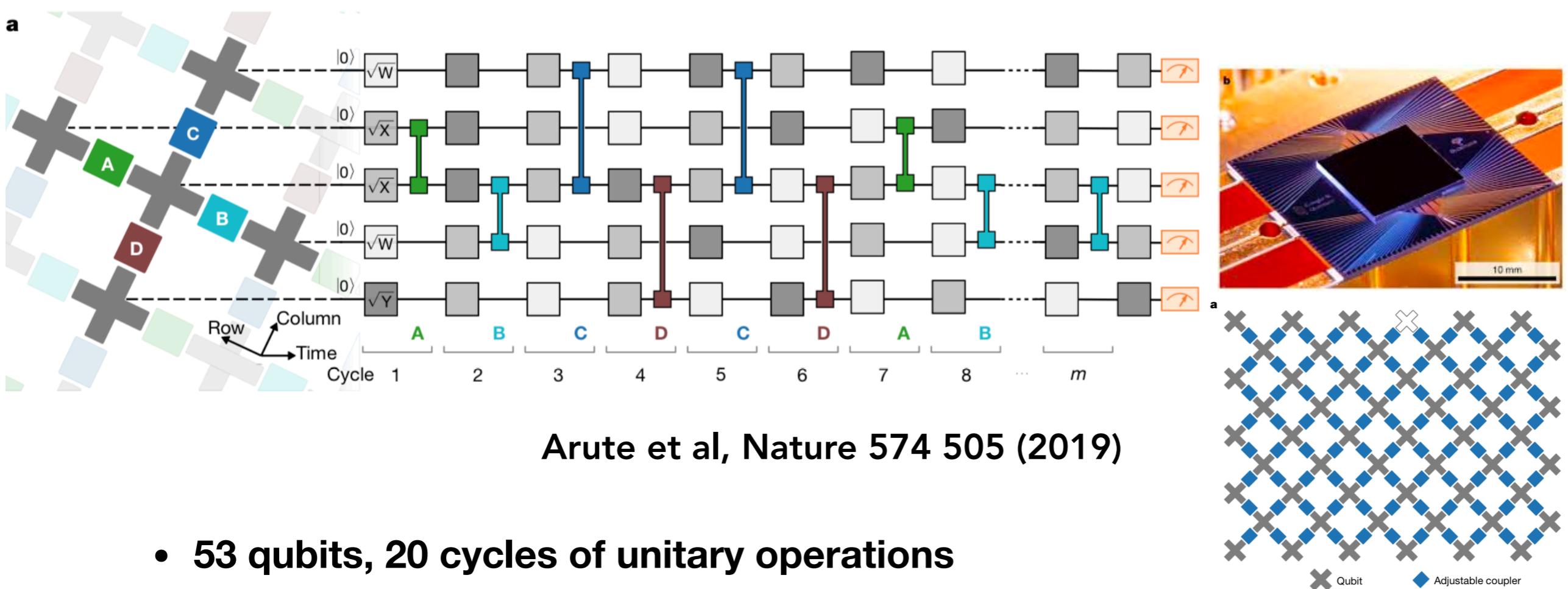


## Single/batch amplitude:

- PEPS based (single amplitude)
- Cotengra (single amplitude)
- Alibaba ACQDP (64-amplitude batch)
- Our method (big-batch)



# Google's Quantum Supremacy experiments



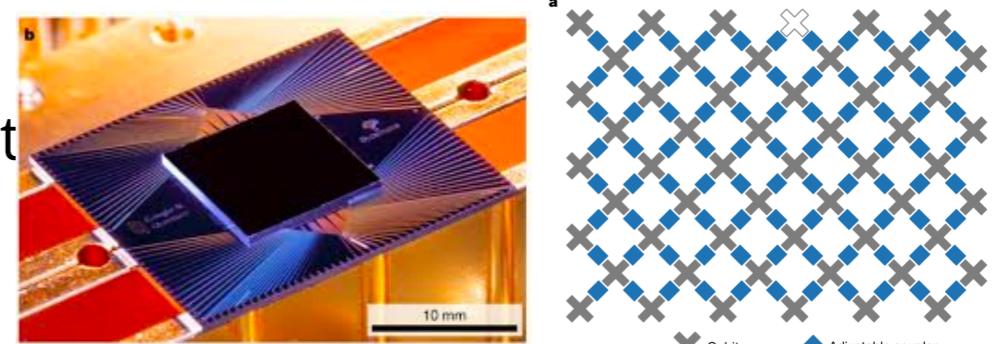
Arute et al, Nature 574 505 (2019)

- **53 qubits, 20 cycles of unitary operations**
- **1 million samples within 200 seconds**
- **Linear Cross Entropy Fidelity (XEB) = 0.002, given by extrapolations**
- **Google's (Shrödinger-Feynmann) classic algorithm requires 10,000 years on Summit**

# Classical simulation of Sycamore

- Google's original estimate [Arute et. al. 2019]

- 10,000 years for simulating the Sycamore circuit with 53 qubits and 20 cycles (using Summit )



Images from Arute et. al. Nature 2019

- IBM's estimate [Pednault et al 2019]:

- 2.5 days (with 250PB memory, all memory and hard disks of Summit)

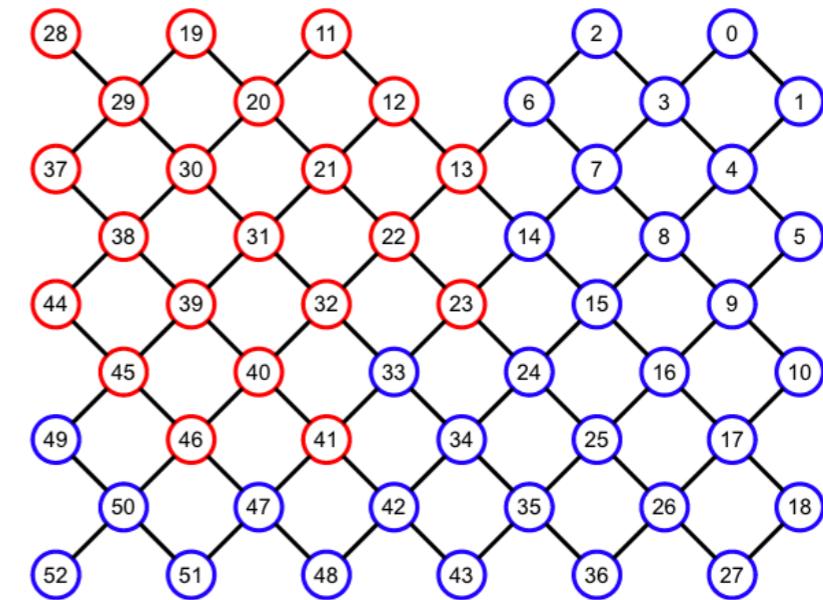
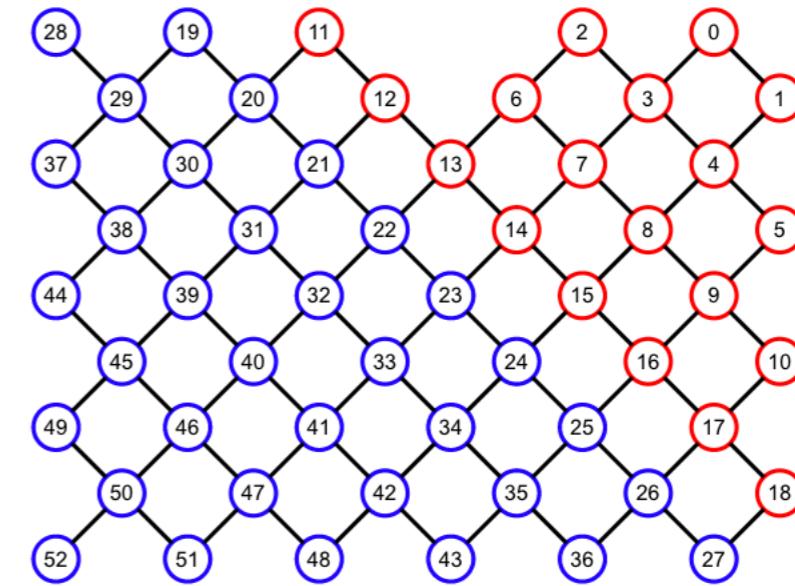
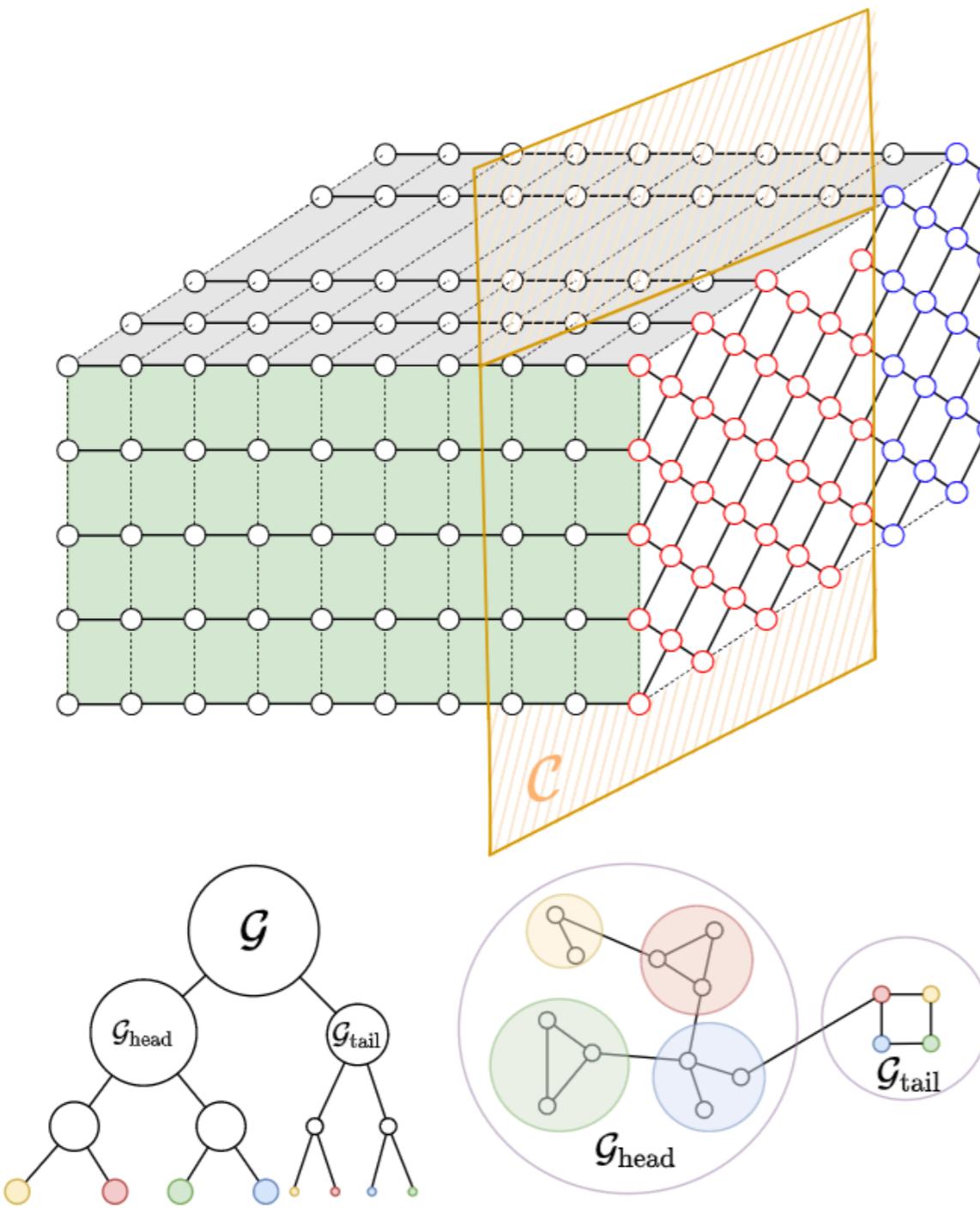
- Cotengra [Gray/Kourtis 2020]

- Balanced Partitioning (Kahypar) + Greedy/optimal + Slicing
  - 3000 years for single amplitude (Single GPU)

- Alibaba's simulator [Huang et. al. 2020]

- Hierarchical partitioning (Kahypar) + Greedy/optimal + Slicing + sampling
  - 20 days for 1 million samples (with Summit-compatible supercomputer)

# Our approach: Big-Head tensor network method

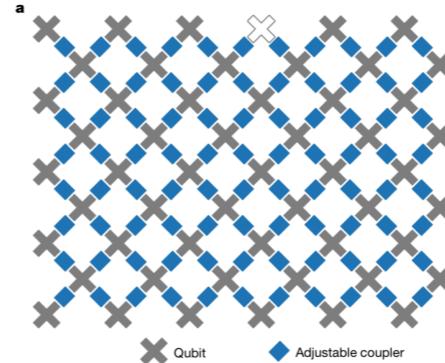
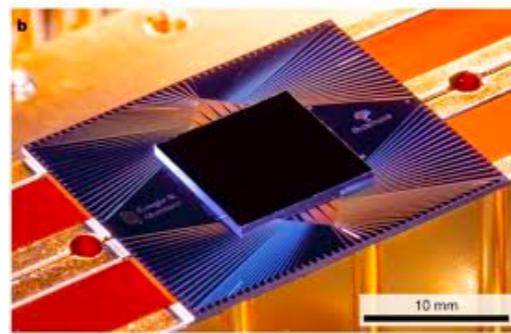


# Computational complexity

	# bitstrings	Time complexity	Space complexity	Computational time	Computational hardware
Google [1]	$10^6$	—	—	10,000 years	Summit supercomputer
Cotengra [12]	1	$3.10 \times 10^{22}$	$2^{27}$	3,088 years	One NVIDIA Quadro P2000
Alibaba [18]	64	$6.66 \times 10^{18}$	$2^{29}$	267 days	One V100 GPU
Ours	<b>2097152</b>	$4.51 \times 10^{18}$	$2^{30}$	149 Days	One A100 GPU

- The computational cost of our algorithm in obtaining **2 million** amplitudes is **smaller** than obtaining **64** amplitudes using Alibaba's method.
- Google, Cotengra, and Alibaba's results are estimations
- We did the computations for the first time.

# Simulating Sycamore with 53 qubits, 20 cycles



	Computation hardware	Time
Google [Arute et. al., 2019] <a href="#">(Estimate)</a>	Summit Super Computer	10,000 Years
IBM [Pednault et. al., 2019] <a href="#">(Estimate)</a>	Summit Super Computer (all disks)	2.5 days
Alibaba [Huang et. al., 2020] <a href="#">(Estimate)</a>	Summit Super Computer (compatible)	20 days
Ours [arXiv:2103.03074] <a href="#">(Computation)</a>	60 GPUs	5 days

# Main results

$$F_{\text{XEB}} = \frac{2^n}{L} \sum_{i=1}^L P_U(\mathbf{s}_i) - 1$$

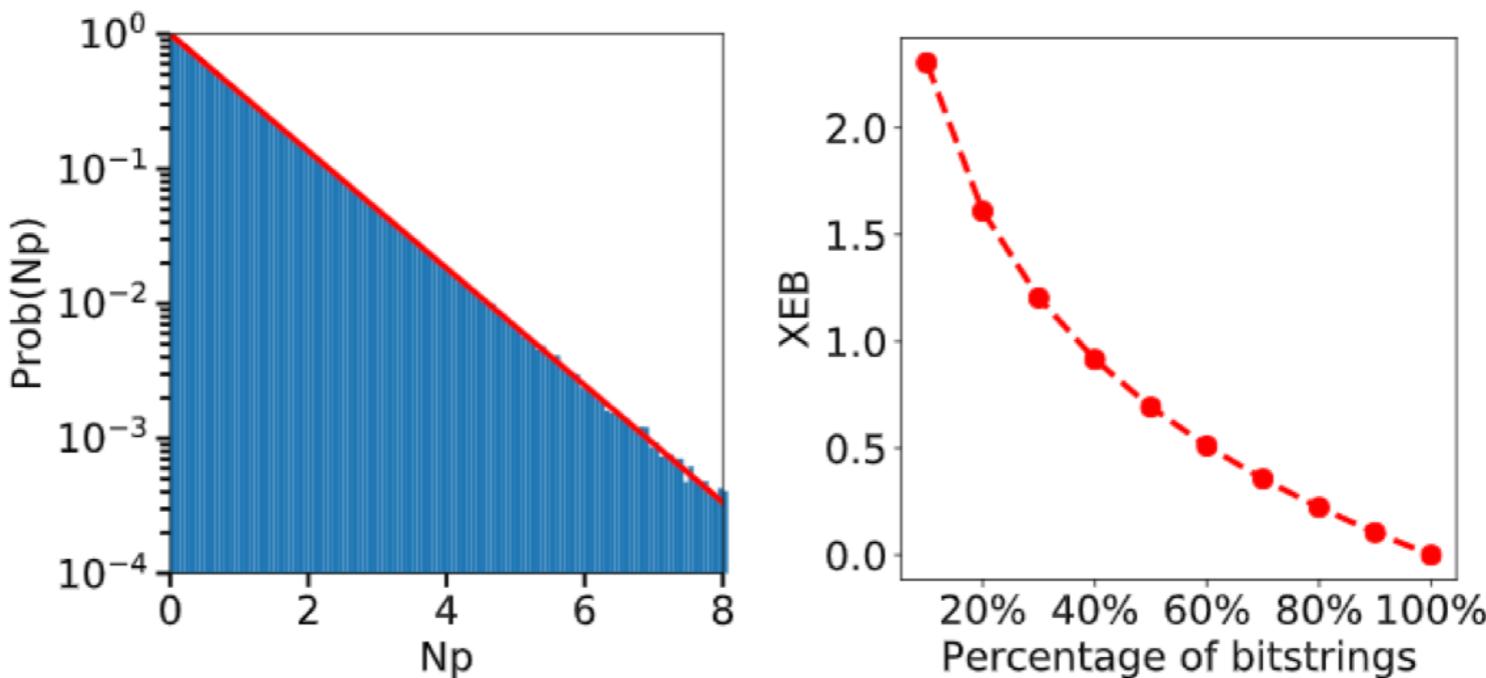


FIG. 2. (Left): Histogram of bitstring probabilities  $P_U(\mathbf{s}) = P_U(\mathbf{s}_1; \mathbf{s}_2)$  for  $l = 2^{21}$  bitstrings obtained from the Sycamore circuit with  $n = 53$  qubits,  $m = 20$  cycles, sequence ABCDCDAB, seed 0, and the assignment of partial bitstring  $\mathbf{s}_1$  are fixed to  $\underbrace{0, 0, 0, \dots, 0}_{32}$ .

32

- Obtained 2 million amplitudes and probabilities, following the Porter-Thomas distribution
- Sampled 1 million bitstrings, XEB fidelity=0.739, larger than Google's XEB

# Discussions

Advantages over Google's hardware:

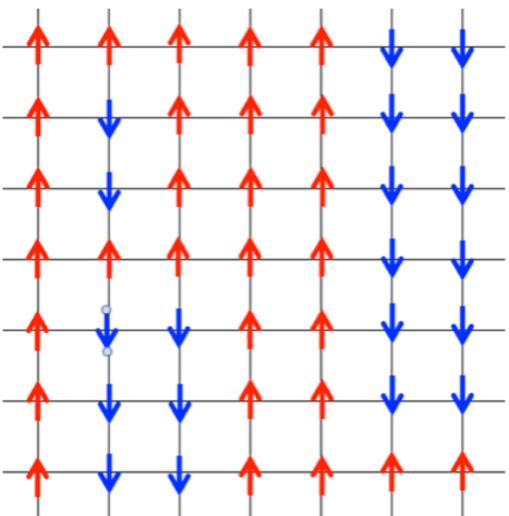
- Exact amplitude computation
- Pass the XEB test with an higher XEB fidelity
- Conditional probability/sampling

Disadvantages over Google's hardware

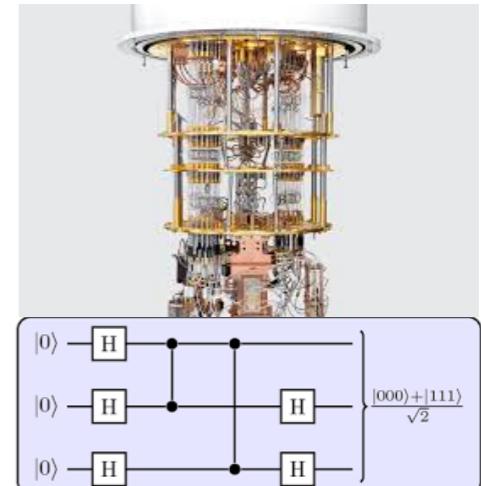
- Exponential algorithm, not scalable
- Bitstring Correlations
- XEB dependence

**Using tensor networks as bridge, combining classical and quantum computations for solving challenge **real-world** problems**

# Computation with tensor networks



4	1	9	2	1	3
3	5	3	6	1	7
6	9	4	0	9	1
4	3	2	7	3	8
0	5	6	0	7	4
1	9	3	9	8	5



Joint probability distribution of microscopic configurations

$$P(\sigma) = \frac{1}{Z} \exp(-\beta E(\sigma))$$

Joint probability distribution of data variables

$$P(\text{Data})$$

Control of quantum states

$$\psi(\sigma)$$

**Exponential space  
Effective models  
Computational power**

**Tensor Network as a bridge !**

Reference:

F. Pan, P. Zhou, S. Li , PZ, PRL 125, 060503 (2020)

J. Liu, L. Wang, PZ, PRL 126, 090506 (2021)

F. Pan, PZ, arXiv:2103.03074 (2021)

S. Li, P. Zhou, F. Pan, PZ, arXiv:2105.04130 (2021)