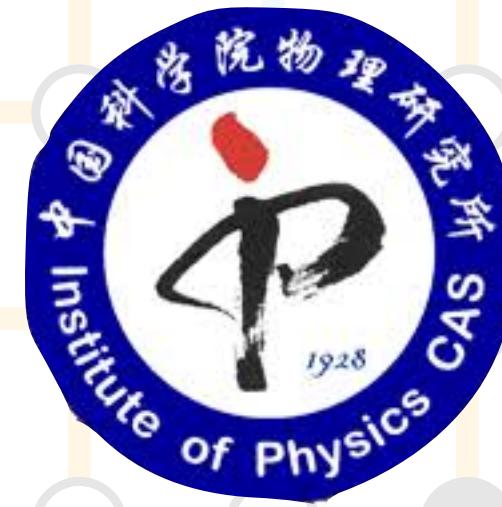


Tropical tensor networks for spin glasses

Lei Wang (王磊)

<https://wangleiphy.github.io>

Institute of Physics, CAS



2008.06888



<https://github.com/TensorBFS/TropicalTensors.jl>

Thanks to my collaborators

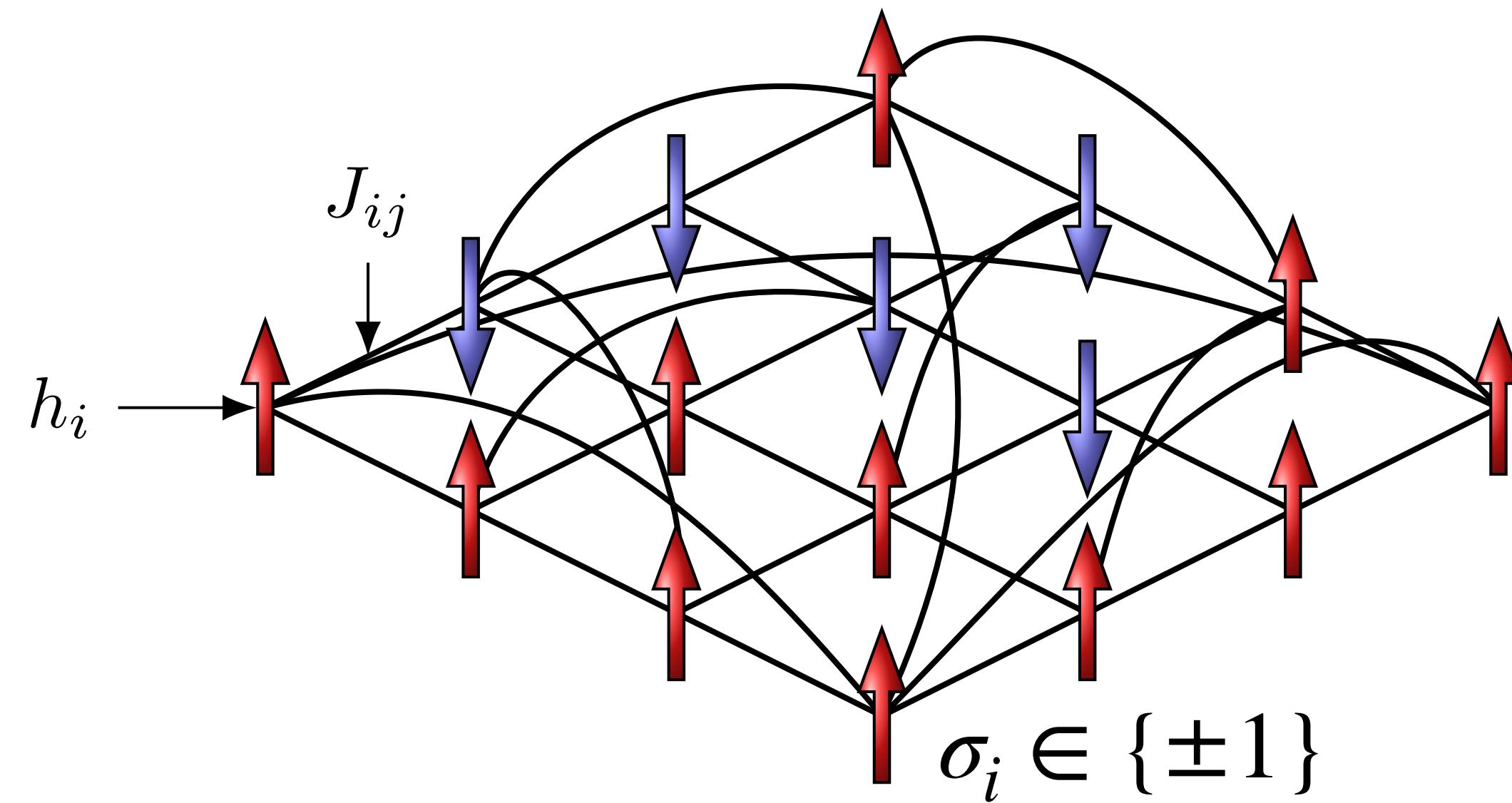


刘金国, QuEra & Harvard



张潘, ITP CAS

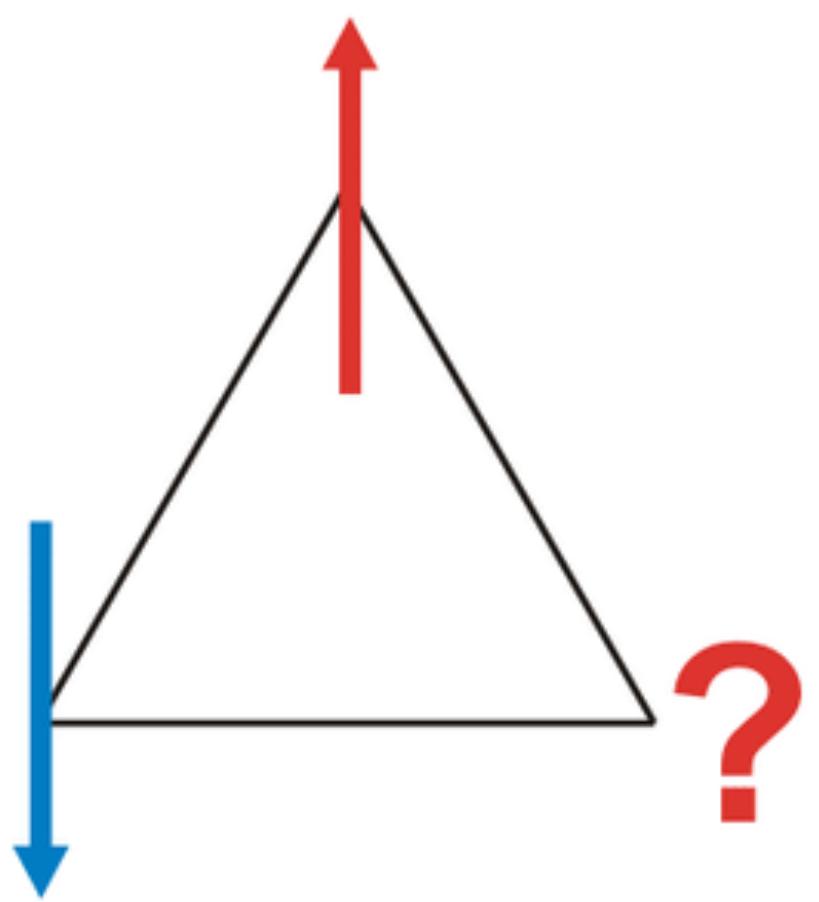
Spin glasses



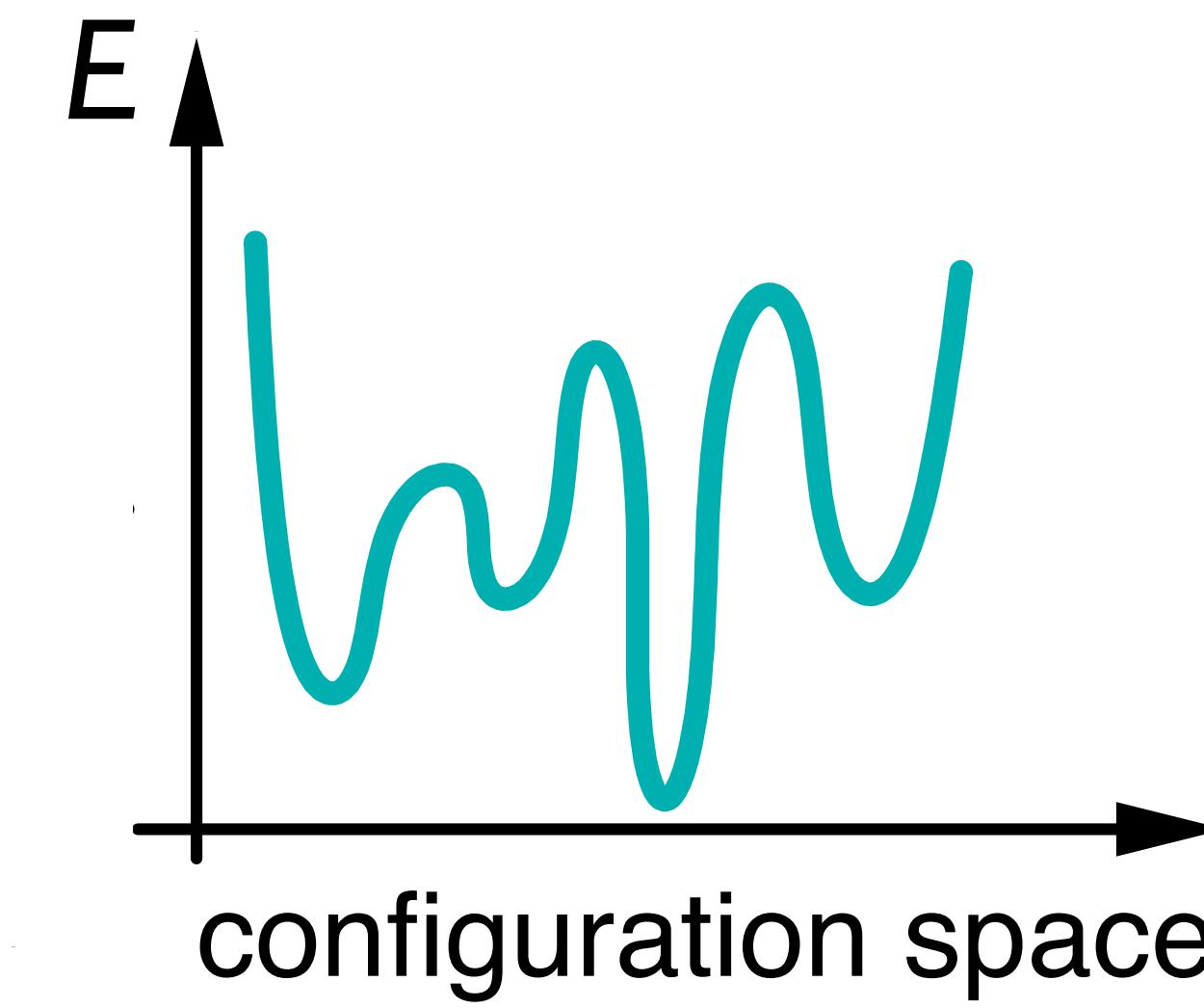
$$E(\{\sigma\}) = \sum_{i < j} J_{ij}\sigma_i\sigma_j + \sum_i h_i\sigma_i$$
$$E^* = \min_{\sigma} E(\{\sigma\}) \quad ???$$

- Same as QUBO, has broad applications in statistical physics, machine learning, coding theory...
- Finding ground state is NP-hard: Barahona 1982
- Ising formulation for many NP problems: Lucas 1302.5834 (including Karp's 21 NP-complete problems)

Difficulties of spin glasses

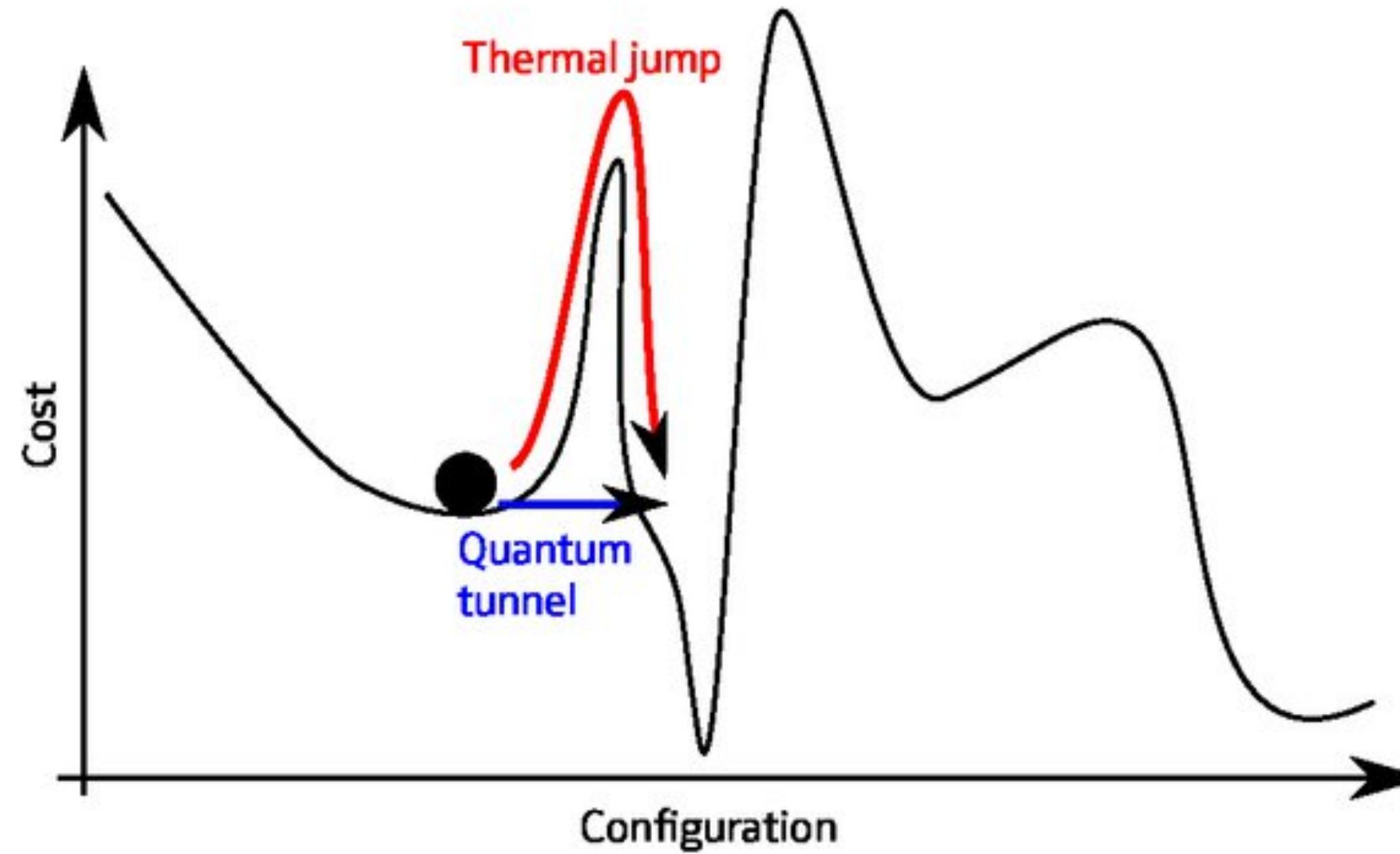


Frustration

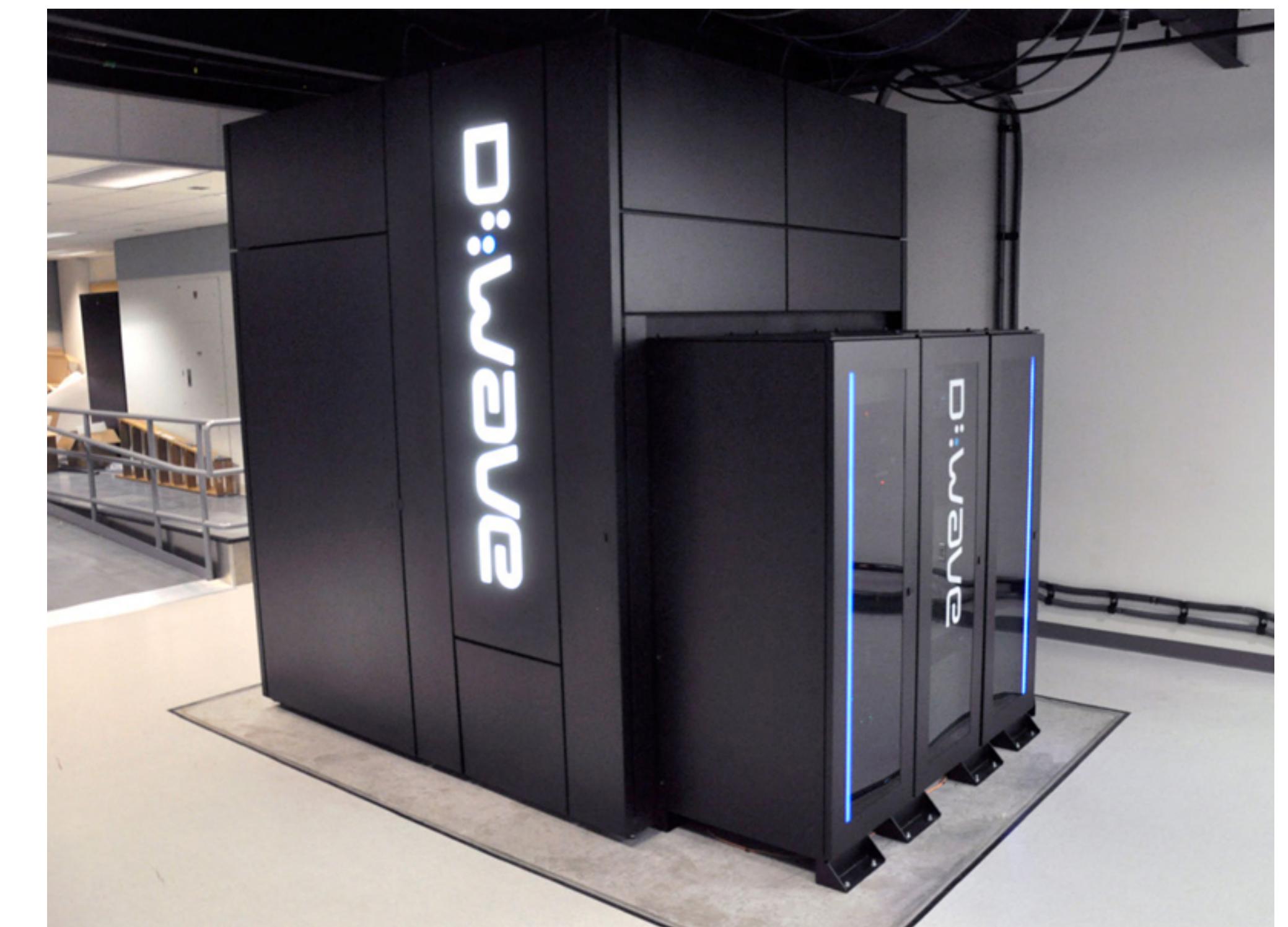


Complex landscape

Approaches to spin glasses



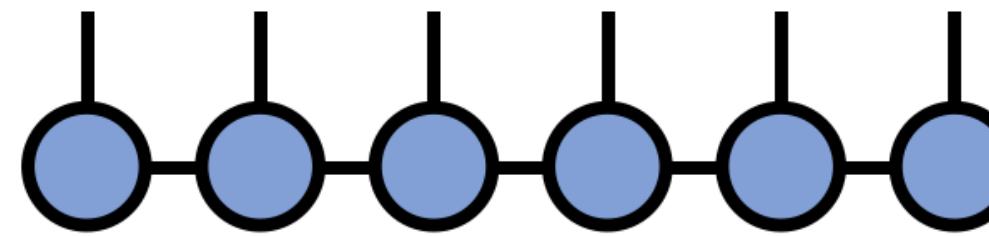
Simulated annealing: thermal fluctuation
Quantum annealing: quantum fluctuation



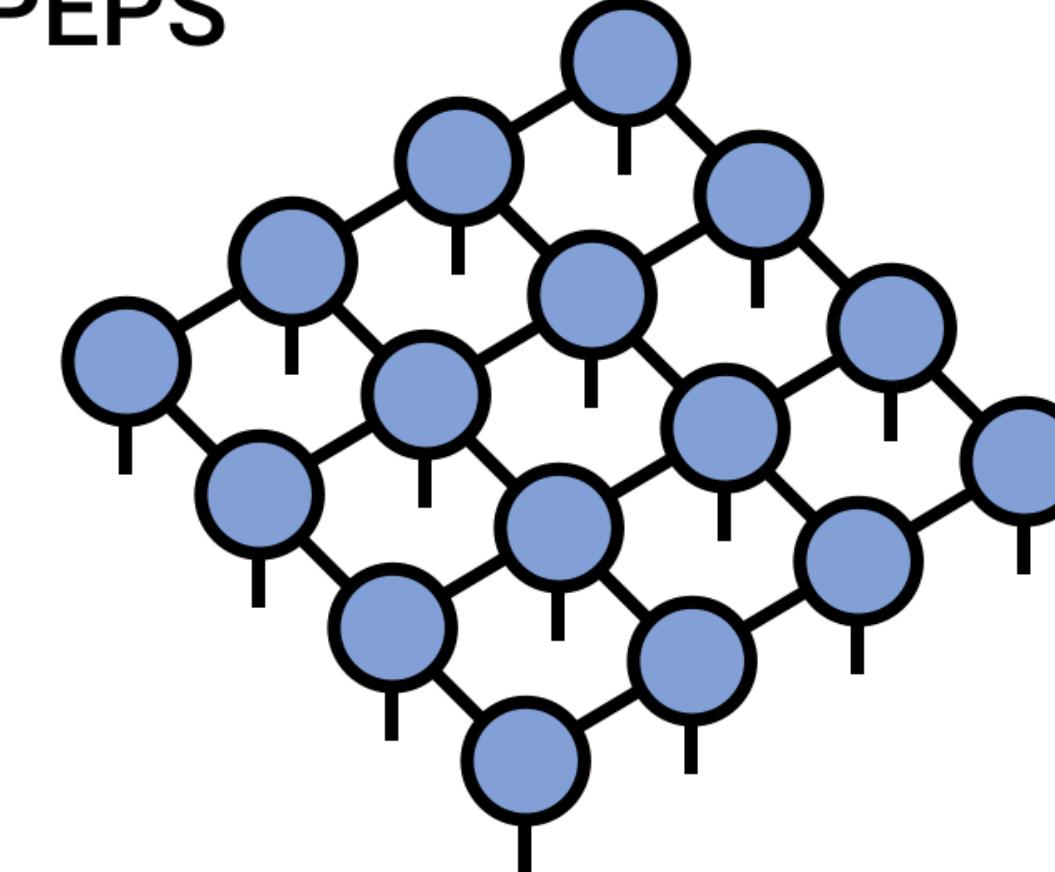
\$15 million “quantum” annealer

Tensor Networks

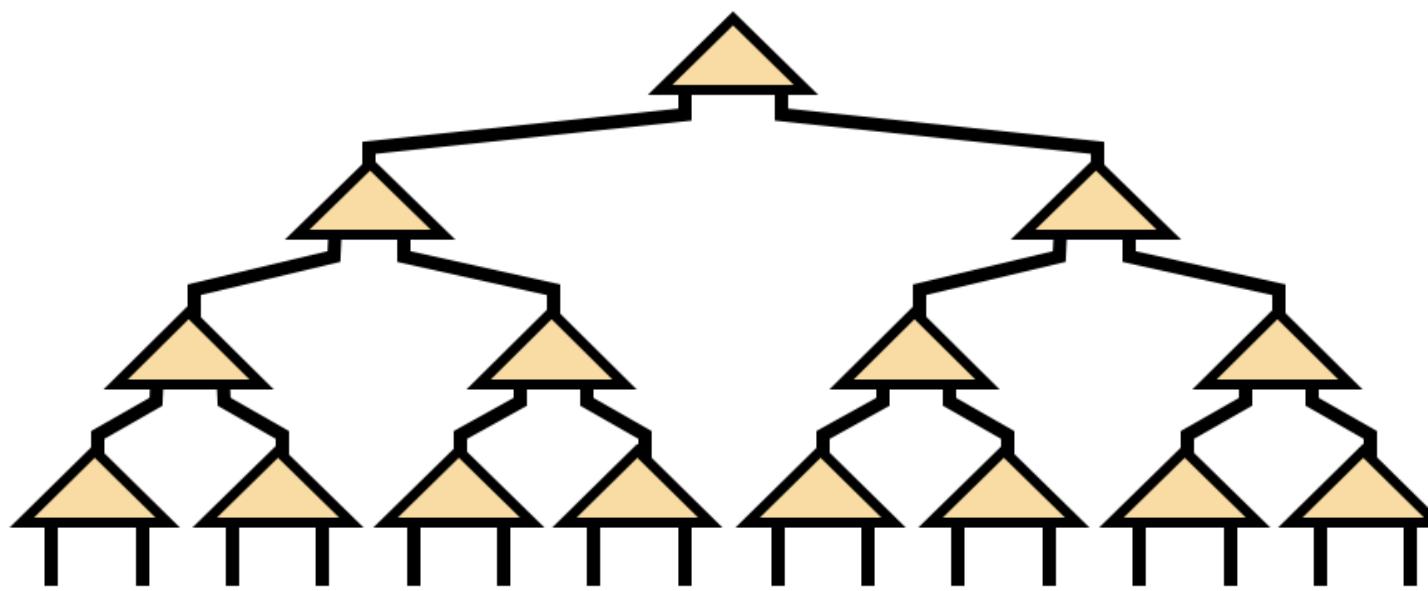
Matrix Product State /
Tensor Train



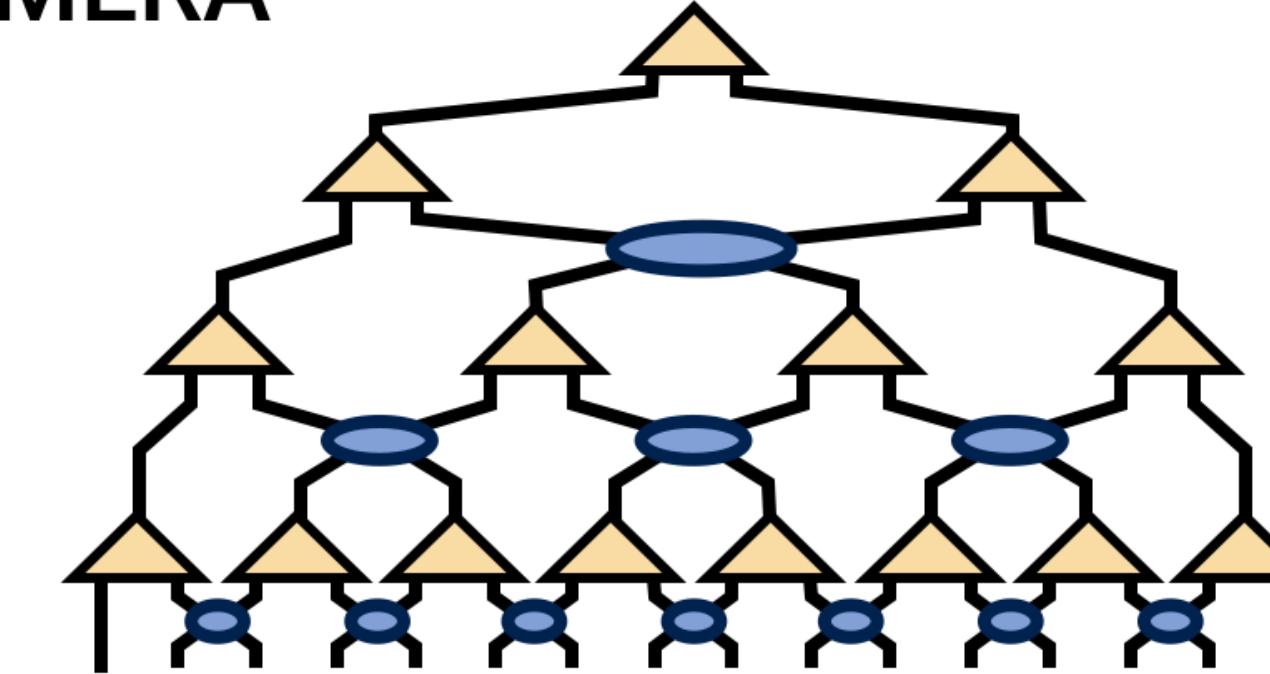
PEPS



Tree Tensor Network /
Hierarchical Tucker

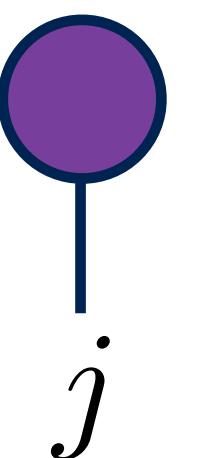


MERA

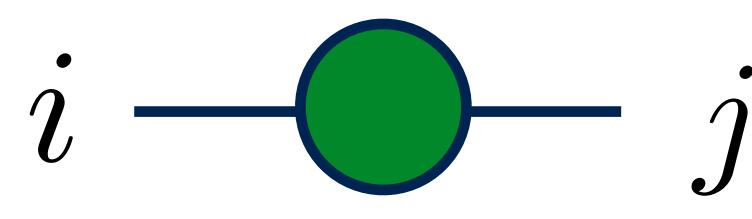


A way to efficiently express multivariable functions

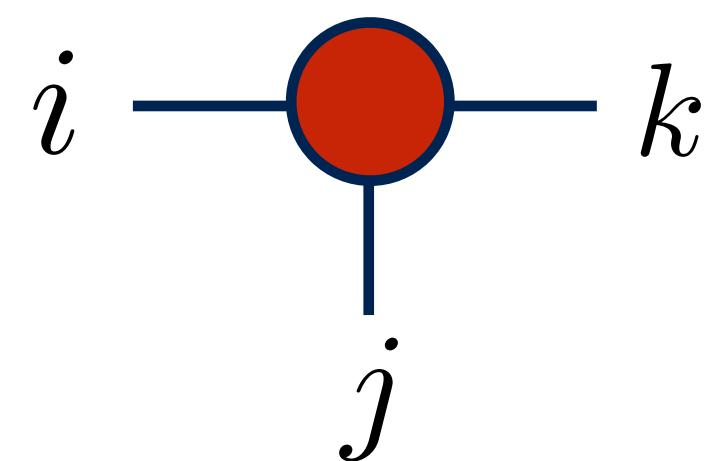
Tensor Notations



v_j



M_{ij}



T_{ijk}

Tensor Contractions

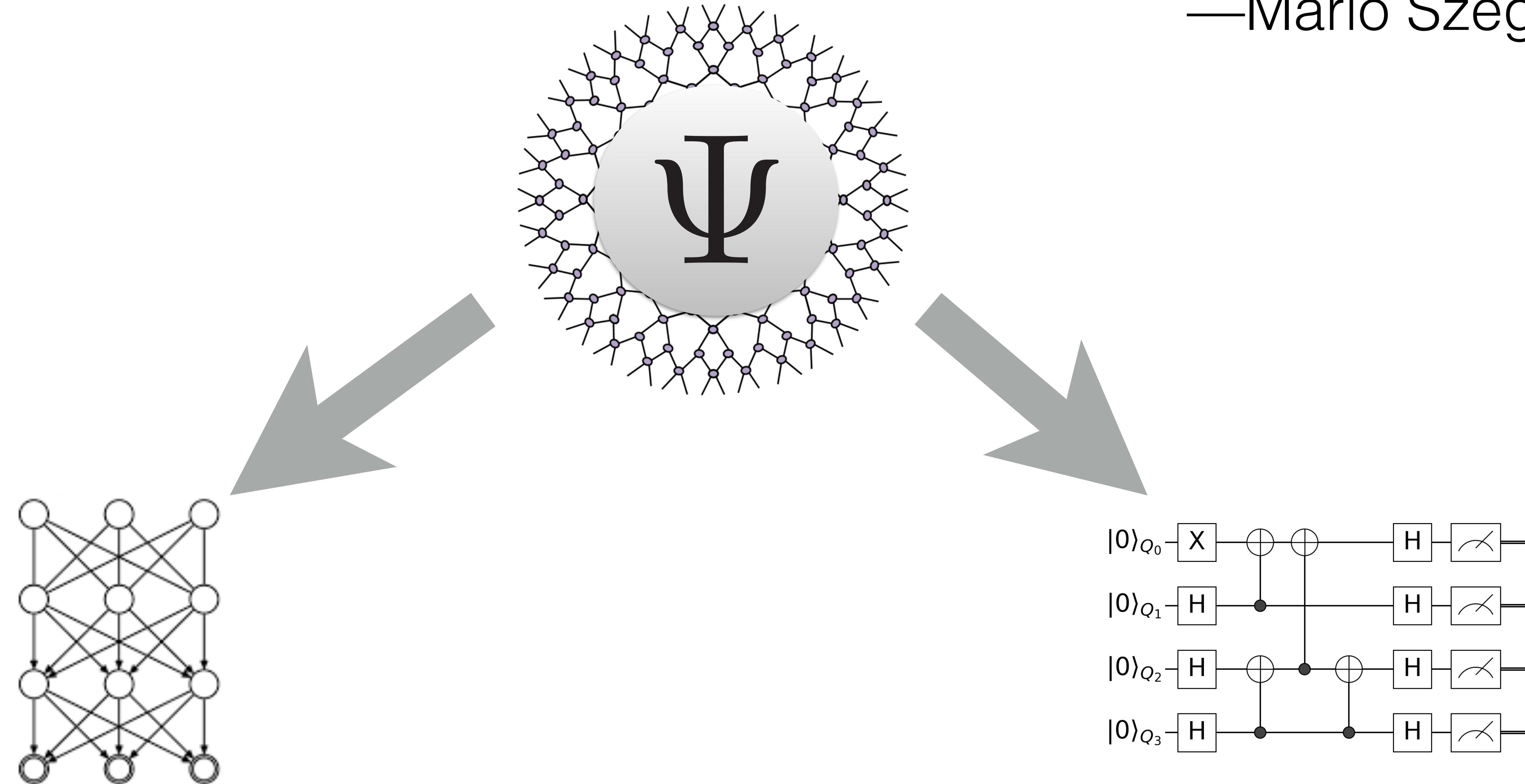
$$\begin{array}{c} \text{---} \\ | \quad | \\ \text{green circle} \quad \text{purple circle} \\ | \quad | \\ \text{i} \quad \text{j} \end{array} \longleftrightarrow M_{ij} v_j$$

$$\begin{array}{c} \text{---} \\ | \quad | \\ \text{green circle} \quad \text{orange circle} \\ | \quad | \end{array} \longleftrightarrow A_{ij} B_{jk}$$

$$\begin{array}{c} | \quad | \\ \text{red circle} \quad \text{blue circle} \\ | \quad | \end{array} \longleftrightarrow A_{ijk} B_{klm}$$

“Tensor network is 21st century’s matrix”

—Mario Szegedy



Neural networks and
Probabilistic graphical models

Quantum circuit architecture,
parametrization, and simulation

Tropical algebra

$$x \oplus y = \min(x, y)$$

$$x \odot y = x + y$$

Tropical algebra

Multiplication table

\odot	1	2	3	4	5	6	7
1	2	3	4	5	6	7	8
2	3	4	5	6	7	8	9
3	4	5	6	7	8	9	10
4	5	6	7	8	9	10	11
5	6	7	8	9	10	11	12
6	7	8	9	10	11	12	13
7	8	9	10	11	12	13	14

Novel Algebras for Advanced Analytics in Julia

2013 IEEE High Performance Extreme Computing Conference

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Abstract—A linear algebraic approach to graph algorithms that exploits the sparse adjacency matrix representation of graphs can provide a variety of benefits. These benefits include syntactic simplicity, easier implementation, and higher performance. One way to employ linear algebra techniques for graph algorithms is to use a broader definition of matrix and vector multiplication. We demonstrate through the use of the Julia language system how easy it is to explore semirings using linear algebraic methodologies.

I. INTRODUCTION

A. Semiring algebra

The duality between the canonical representation of graphs as abstract collections of vertices and edges and a sparse adjacency matrix representation has been a part of graph theory since its inception [5], [6]. Matrix algebra has been recognized as a useful tool in graph theory for nearly as long (see [3] and references therein). A linear algebraic approach to

II. APPLICATION EXAMPLE

A classic example of the utility of the semiring approach is in finding the minimum path between all vertices in graph (see [11] in [4]. Given a weighted adjacency matrix for a graph where $A(i, j) = w_{ij}$ is the weight of a directed edge from vertex i to vertex j . Let $C(i, j)_2$ be the minimum 2-hop cost from vertex i to vertex j . C_2 can be computed via the semiring matrix product:

$$C_2 = A \text{ min.} + A$$

Likewise, C_3 can be computed via

$$C_3 = A \text{ min.} + A \text{ min.} + A$$

and more generally

```
struct Tropical{T} <: Number  
    x::T  
end
```

```
Base.*(a::Tropical, b::Tropical) = Tropical(a.x + b.x)  
Base.+(a::Tropical, b::Tropical) = Tropical(min(a.x, b.x))
```

Tropical tensor networks

$$T = \begin{bmatrix} \cdot & & & \\ \cdot & \cdot & & \\ \cdot & \cdot & \cdot & \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix}$$

Tropical number

(\oplus , \odot) semiring is sufficient
to define tensor network contraction

ALEXANDER A. STEPANOV
DANIEL E. ROSE



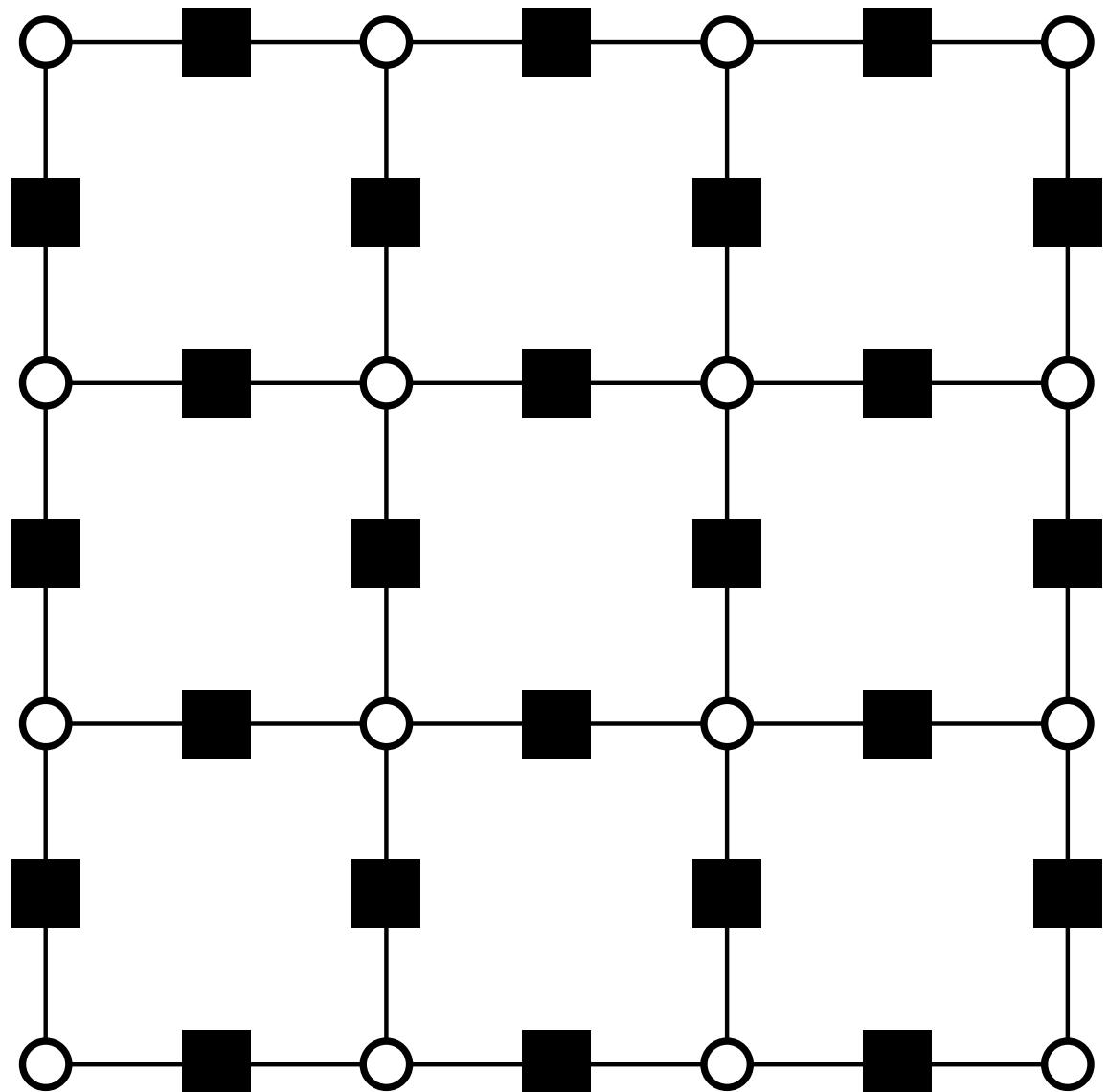
FROM
MATHEMATICS
TO
GENERIC
PROGRAMMING

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**Mathematical abstraction is the key to
efficient and generic programs**

Tropical tensor networks for Ising spin glasses

$$E(\{\sigma\}) = \sum_{i < j} J_{ij} \sigma_i \sigma_j + \sum_i h_i \sigma_i$$



$$\begin{array}{c} \text{---} \\ | \\ \blacksquare \\ | \\ \text{---} \end{array} = \begin{pmatrix} J_{ij} & -J_{ij} \\ -J_{ij} & J_{ij} \end{pmatrix}$$

$$\begin{array}{ccccc} & 1 & & 2 & \\ & \downarrow & & \downarrow & \\ 1 & - & \circ & - & 2 \\ & | & & | & \\ & 1 & & 2 & \end{array} = h_i \quad \begin{array}{ccccc} & 1 & & 2 & \\ & \downarrow & & \downarrow & \\ 2 & - & \circ & - & 2 \\ & | & & | & \\ & 2 & & 2 & \end{array} = -h_i$$

all other elements are ∞

Tropical tensor network contraction
→ ground state energy

$$i \text{---} \underset{\text{yellow}}{\circlearrowleft} \text{---} j = \min_k \left[i \text{---} \underset{\text{red}}{\circlearrowleft} \text{---} k + k \text{---} \underset{\text{blue}}{\circlearrowright} \text{---} j \right]$$

Tropical tensor stores min-marginals of the energy

*also known as algebraic dynamic programming

Physical understanding of the tropical algebra

zero temperature limit of the partition function

$$Z = \sum_{\{\sigma\}} e^{-\beta E}$$

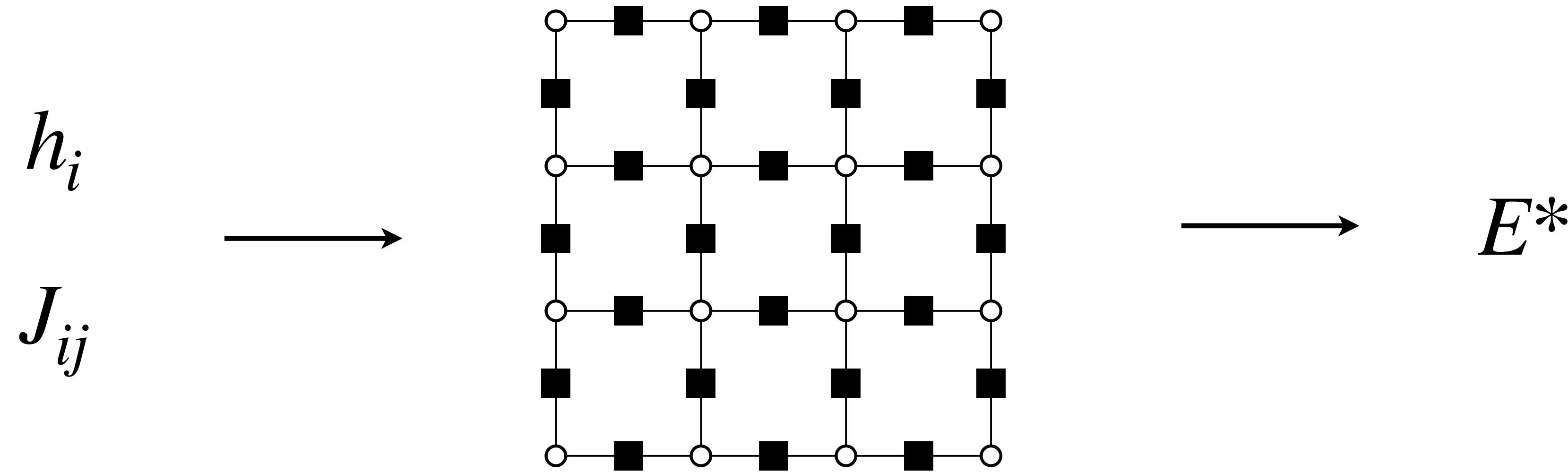
consider $E^* = \lim_{\beta \rightarrow \infty} \frac{-1}{\beta} \ln Z$

a tensor network
with ordinary algebra

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

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

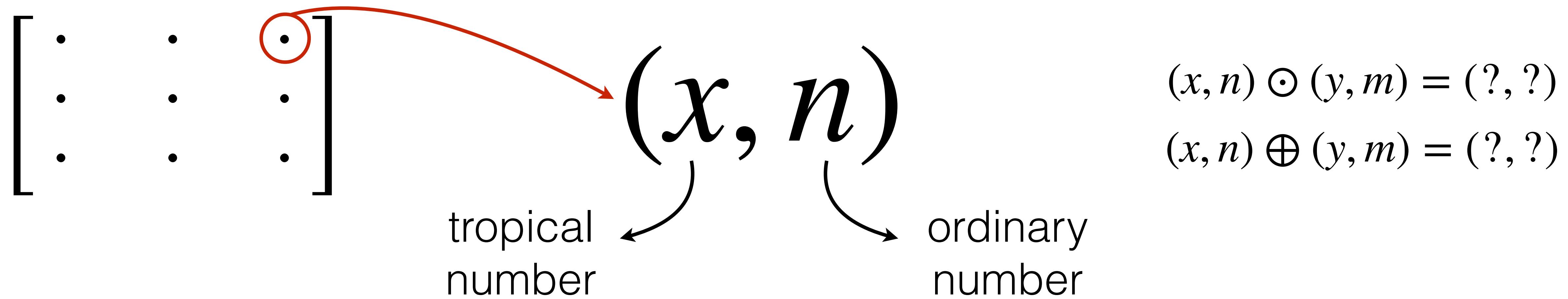
Gradient with respect to the field
→ ground state configuration



$$\sigma_i^* = \frac{\partial E^*}{\partial h_i}$$

Optimal energy is a piecewise linear function of the field

Mix tropical with ordinary algebra
→ ground state degeneracy



The second field counts the minimal energy configuration

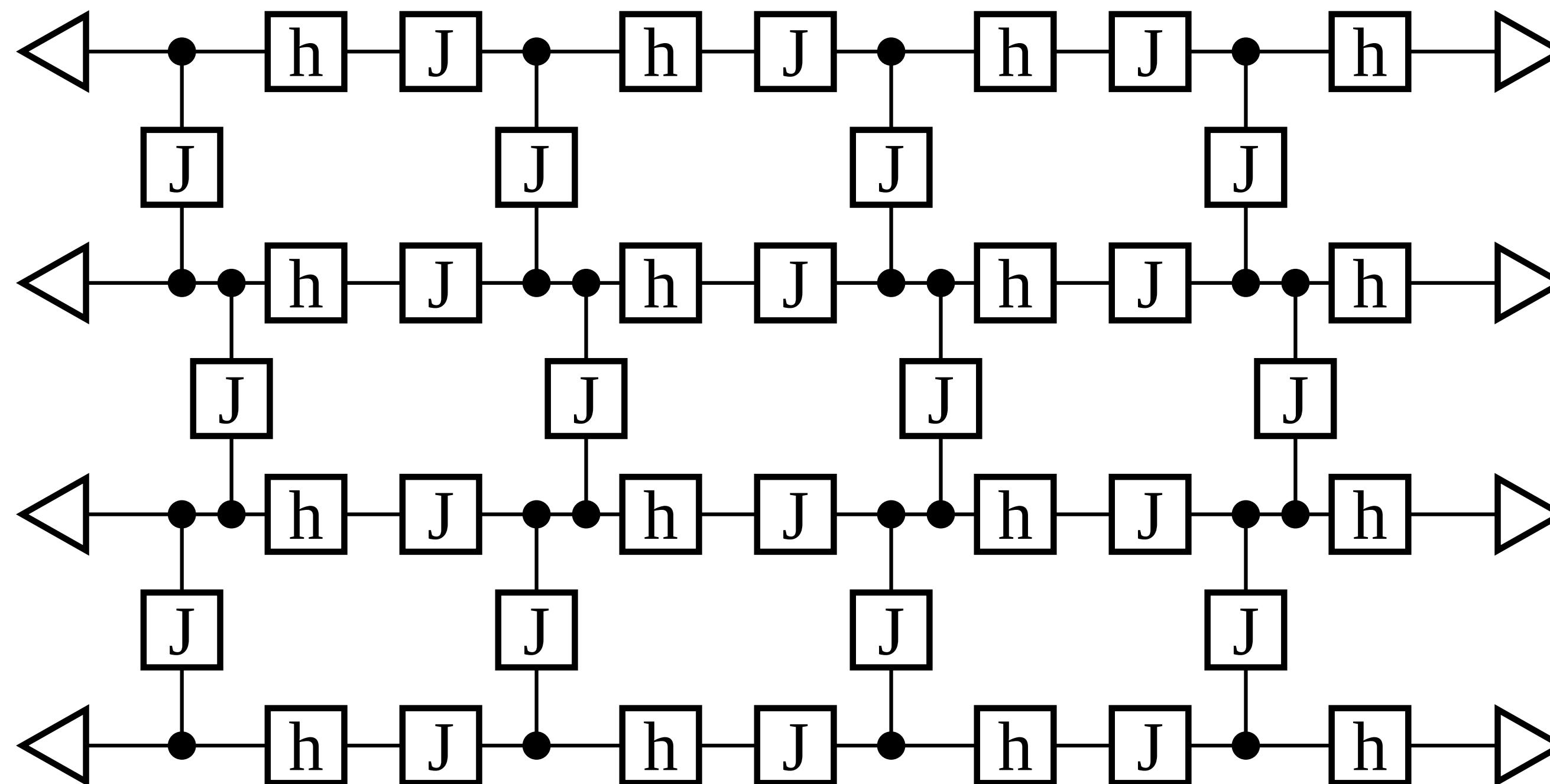
```
struct Tropical{T} <: Number  
    x::T  
    n::T  
end
```

```
Base.*(a::Tropical, b::Tropical) = Tropical(a.x + b.x, a.n * b.n)  
function Base.+(a::Tropical, b::Tropical)  
    x = ...  
    n = ...  
    Tropical(x, n)  
end
```

Let's contract it with Yao.jl!



<https://yaoquantum.org/>



**Yao.jl is general enough to deal with non-unitary gates
with such crazy algebra**

<https://gist.github.com/wangleiphy/ef1f616f26ab37ef7fd3d329f2a5be0e>

```
julia> res = square_solve(L, L, Js, hs)
┌ Warning: Input type of `ArrayReg` is not Complex, got Tropical{Float64}
└ @ YaoArrayRegister ~/.julia/packages/YaoArrayRegister/9wa6b/src/register.jl:92
Layer 1/10
Layer 2/10
Layer 3/10
Layer 4/10
Layer 5/10
Layer 6/10
Layer 7/10
Layer 8/10
Layer 9/10
Layer 10/10
Tropical{Int64}(138, 96)
```

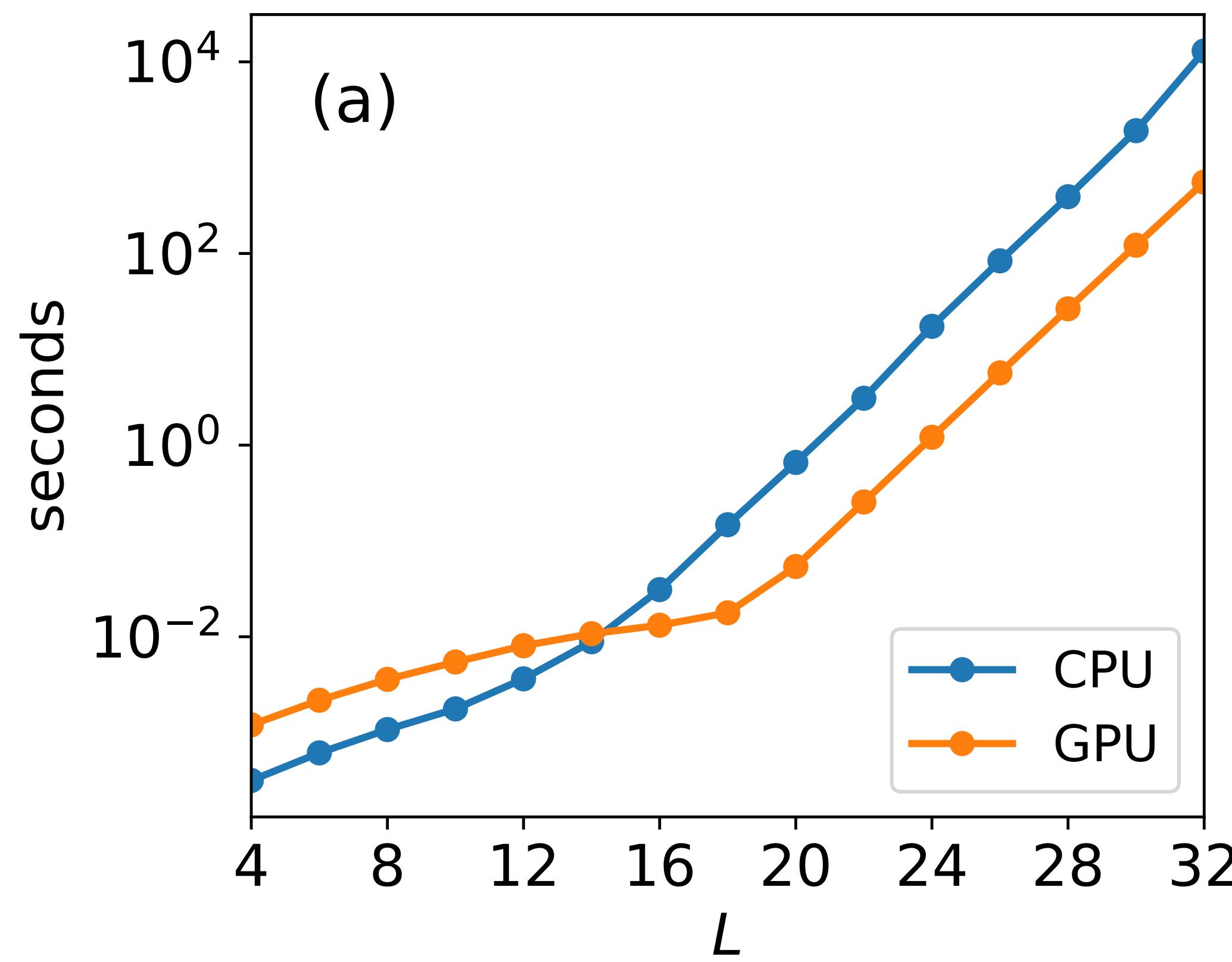
Nevertheless, it works!

One can repurpose quantum circuit simulators for
combinatorial optimization problems

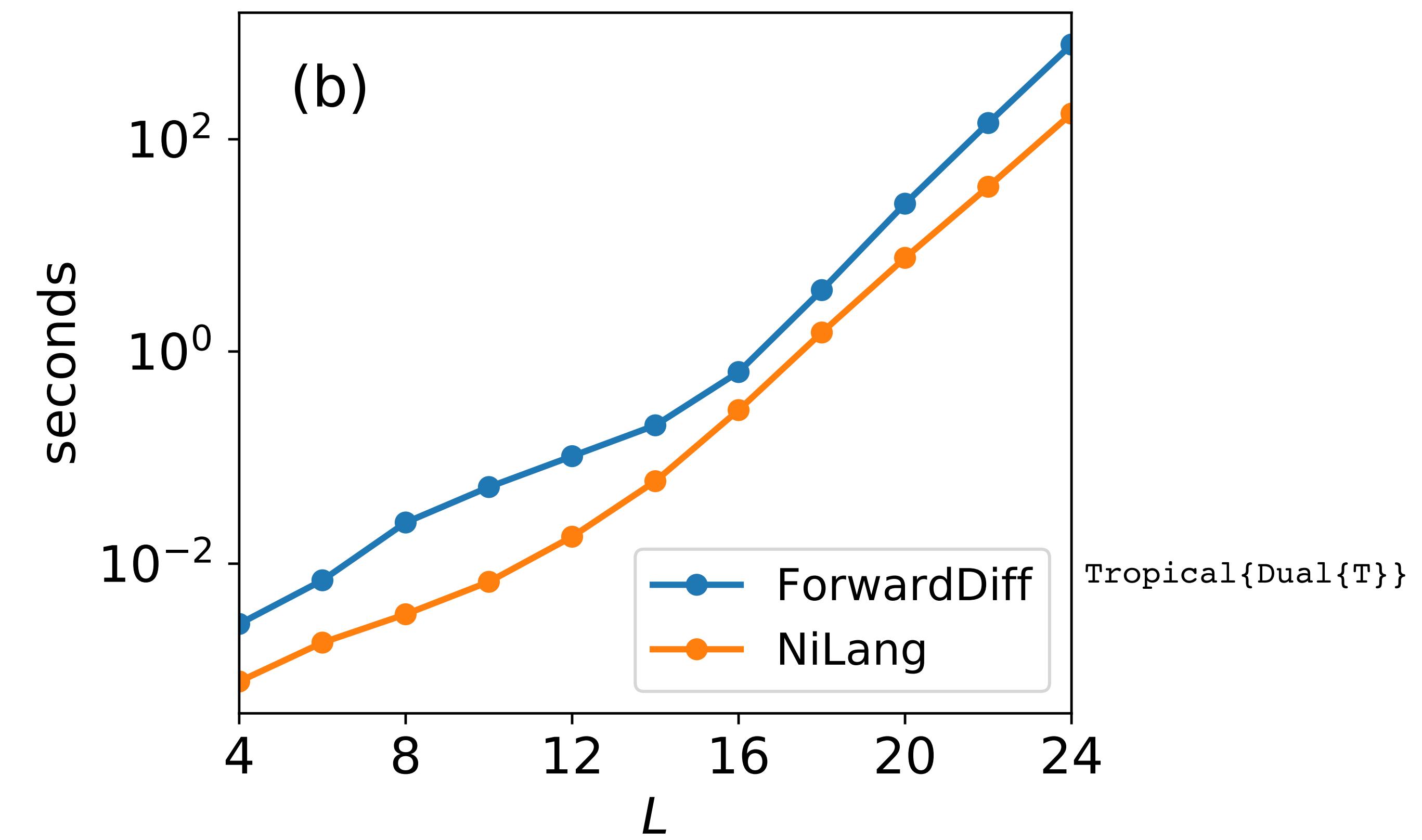
BLAS → “Tropical BLAS”

Square lattice spin glasses

Time for ground state energy

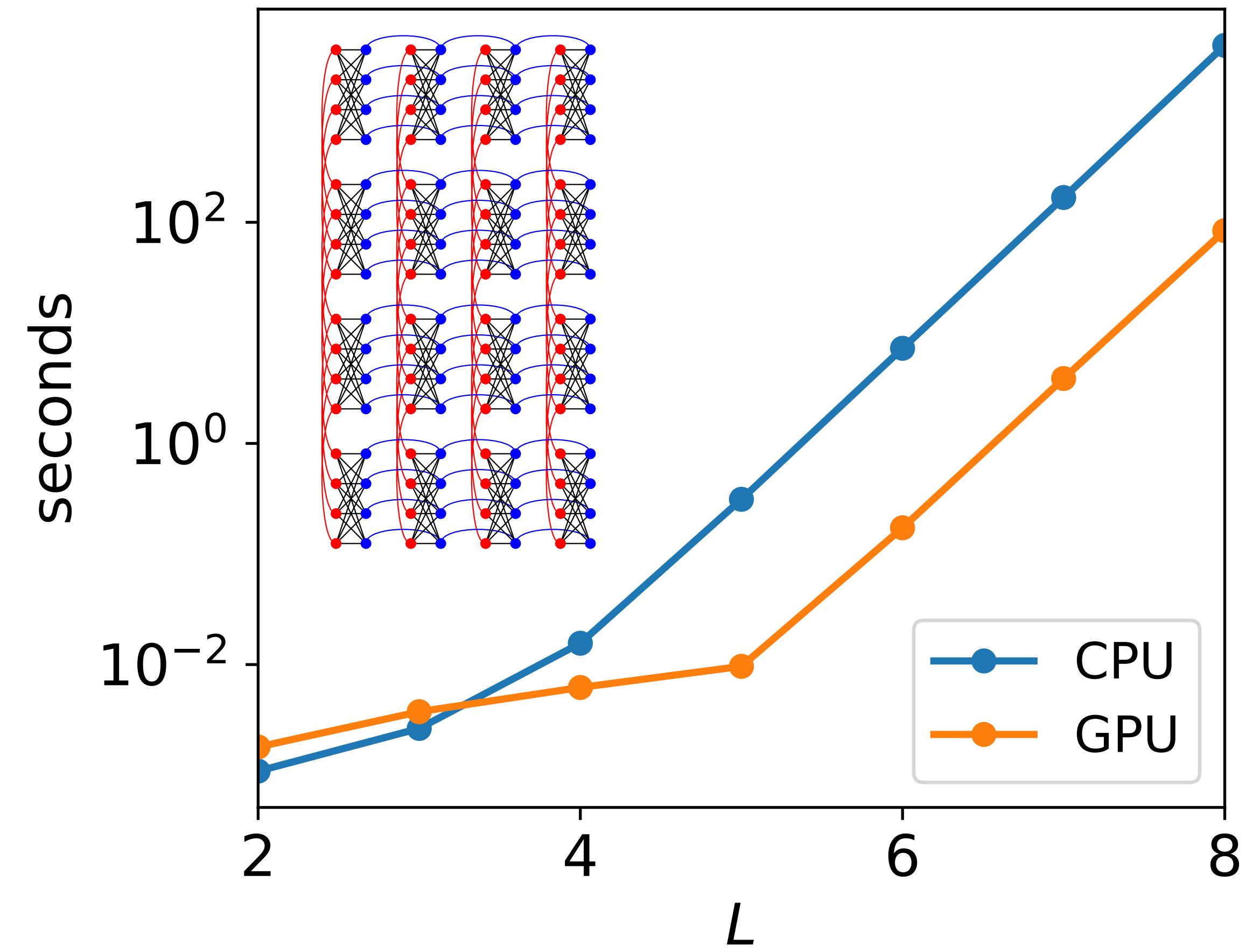


Time for ground state configuration

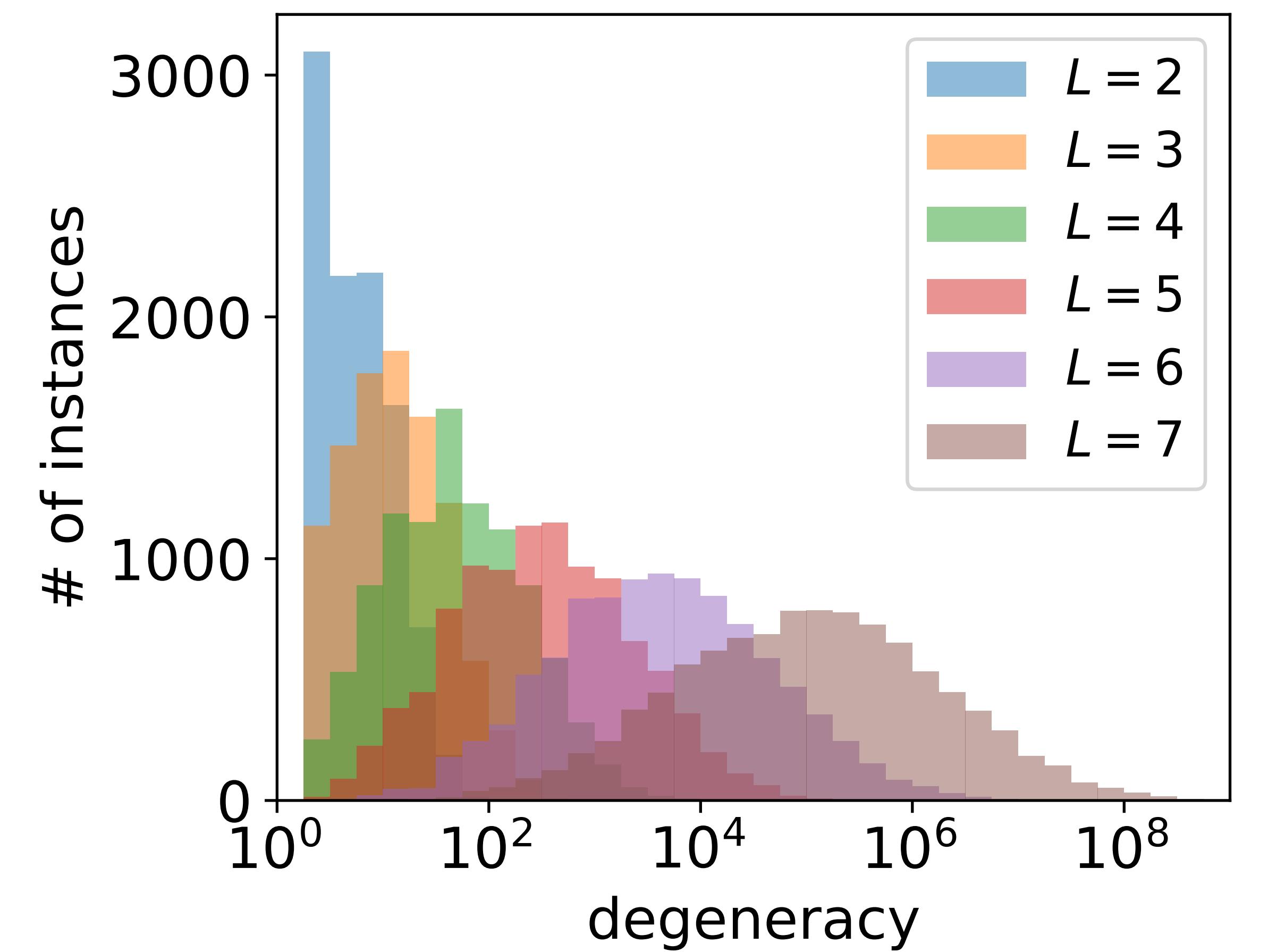


Chimera graph Ising spin glass

Time for ground state energy



Histogram of ground state degeneracy



Summary

Repurpose tensor contractors and quantum simulators for optimization

Differentiable programming as a unified approach to optimal solution

Count # of optimal solutions: application ?

WANTED: Approximated contraction under tropical algebra

谢谢 !