

Quantum-inspired Generative Models

— Born Machines and Tensor Networks
for Learning Probability Distributions —

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Tensor network = a network of tensor contractions

Ex. Quantum amplitudes of a quantum state

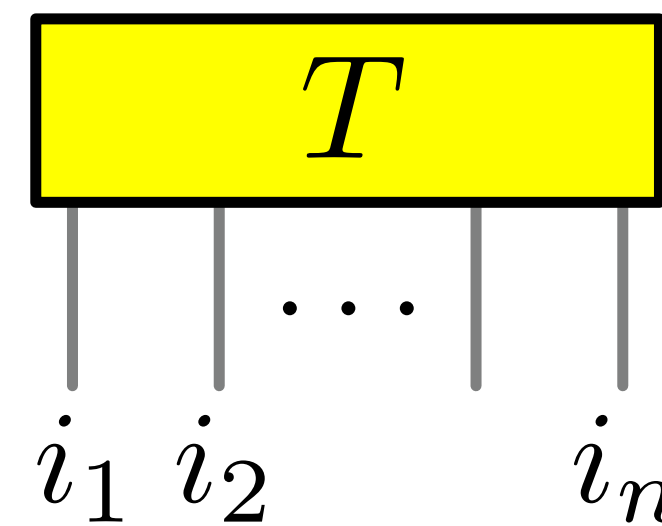
N qubits $|\Psi\rangle = \sum_{i_1=0,1} \cdots \sum_{i_n=0,1} T_{i_1 \cdots i_n} |i_1 \cdots i_n\rangle$

Tensor decomposition

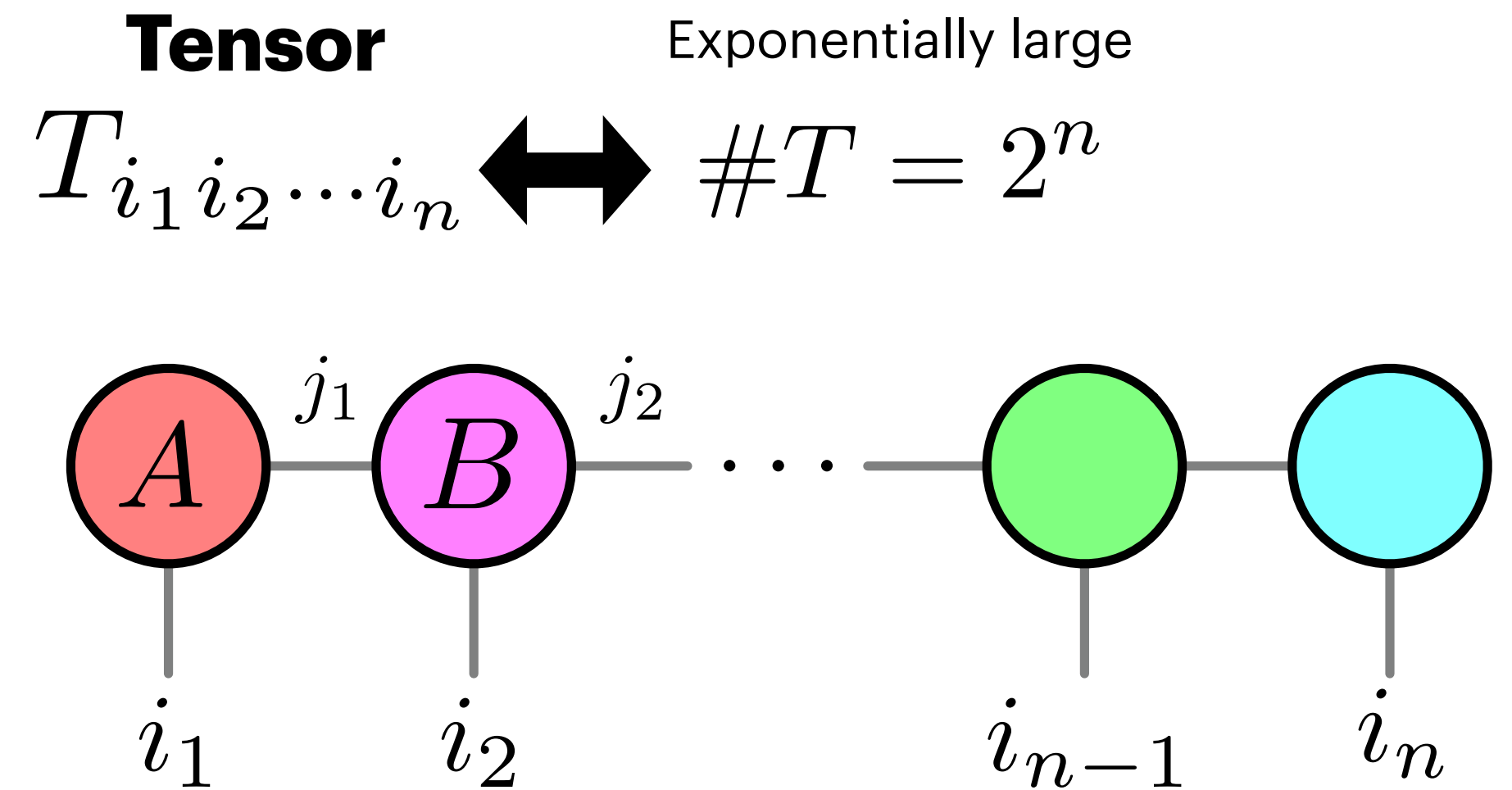
$$T_{i_1 i_2 \cdots i_n} = A_{i_1 j_1} B_{j_1 i_2 j_2} \cdots$$

$$\text{If } D = \#j, \#T \sim O(n \times D^2)$$

Exponential compression
when D remains small



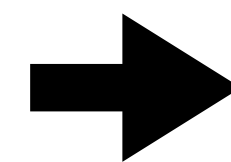
$\approx$



Tensor network : MPS (matrix product state;
also known as tensor train)

Applications to machine learning

Compact representation of
high-dimensional tensors



- ◆ Neural-network parameter compression
- ◆ Data compression

Quantum-inspired algorithms

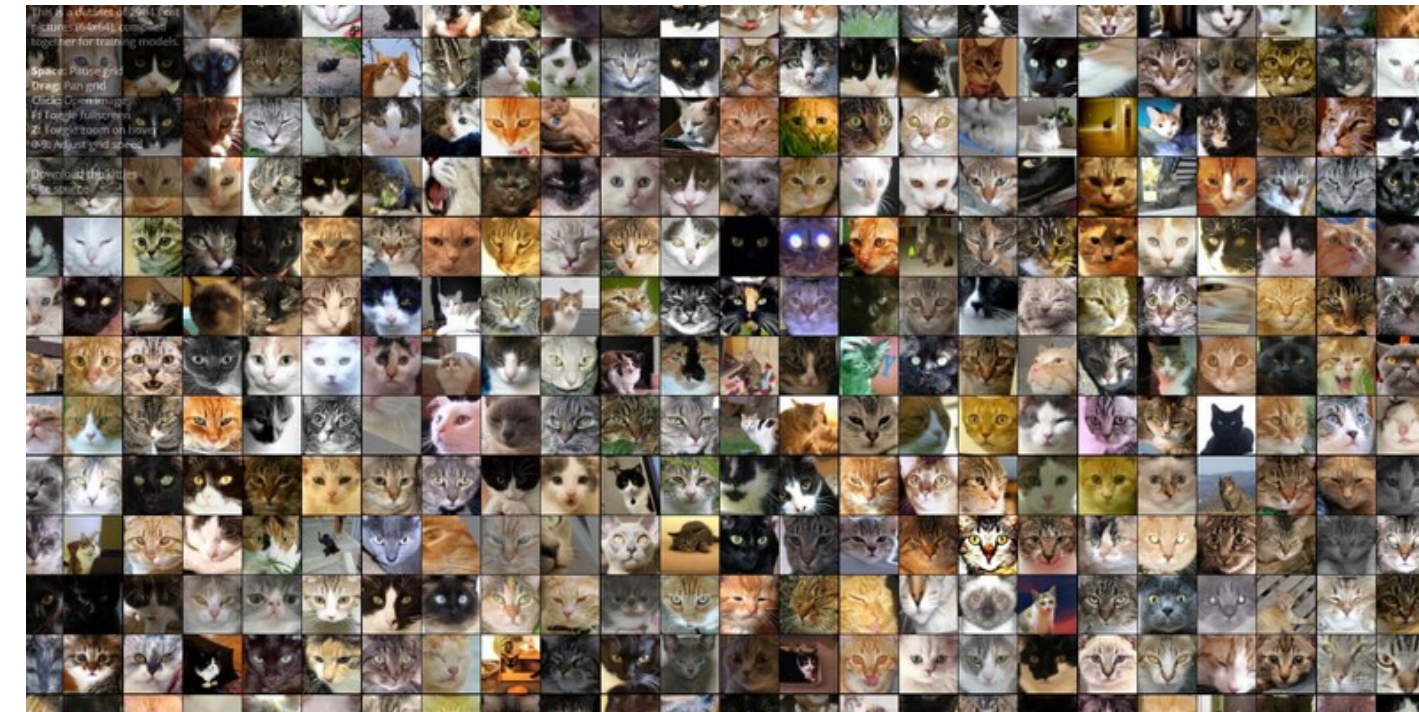
- ◆ Classification (tensor-network kernel)
- ◆ **Generative model**

Born machine: a quantum-inspired generative model

Generative model

$$P_{\theta}(x) \sim$$

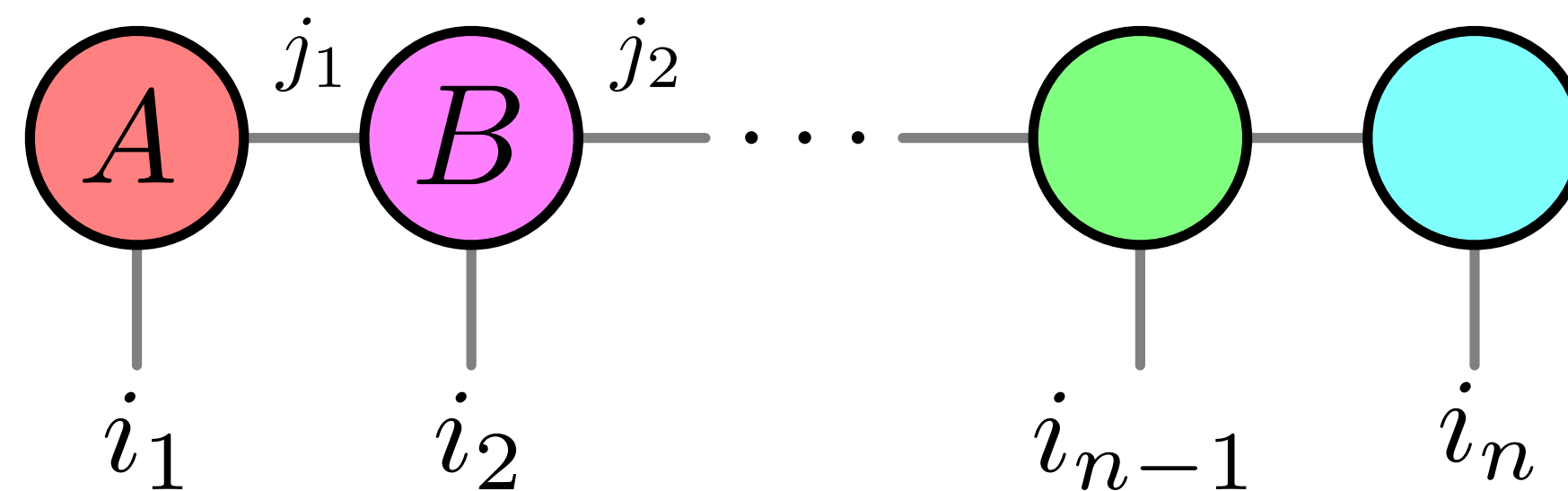
Data distribution



$$= \left\| \begin{array}{c} \Psi_{\theta}(x) \end{array} \right\|_2^2$$

θ : parameters

Wave function

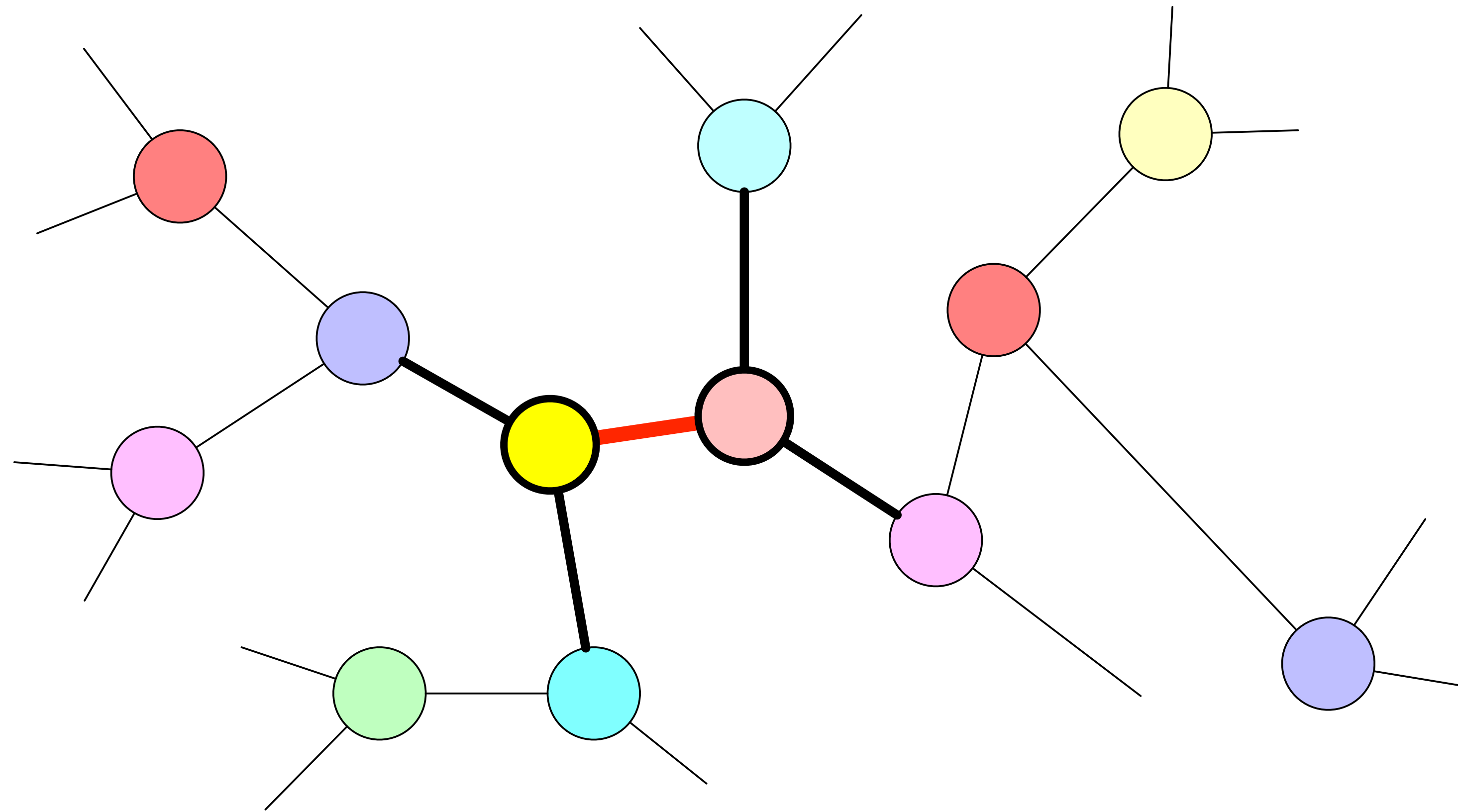


Fixed network structure: MPS

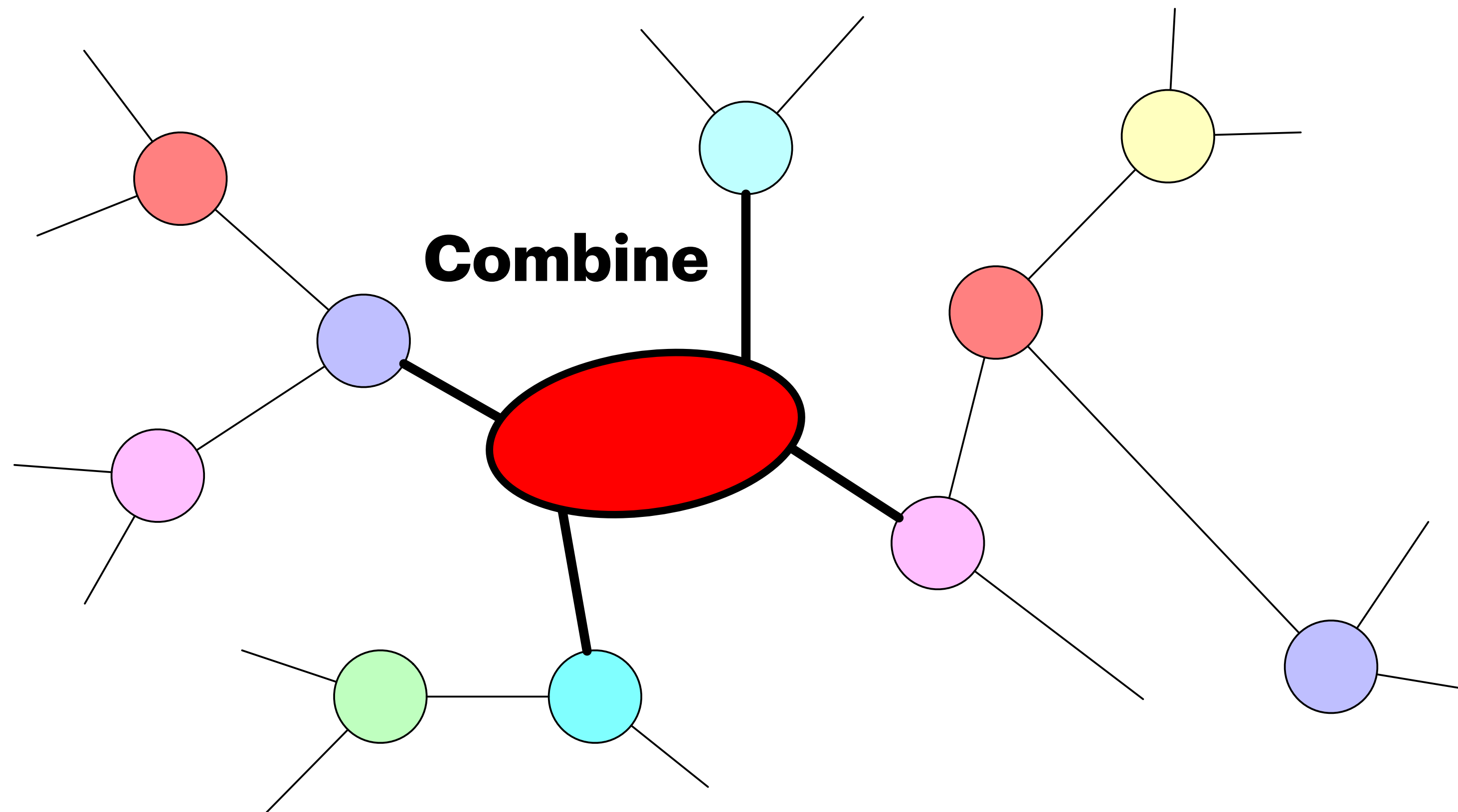
Han, et al. PRX 2018

But performance depends strongly on the network structure.

Adaptive tensor tree algorithm (ATT)

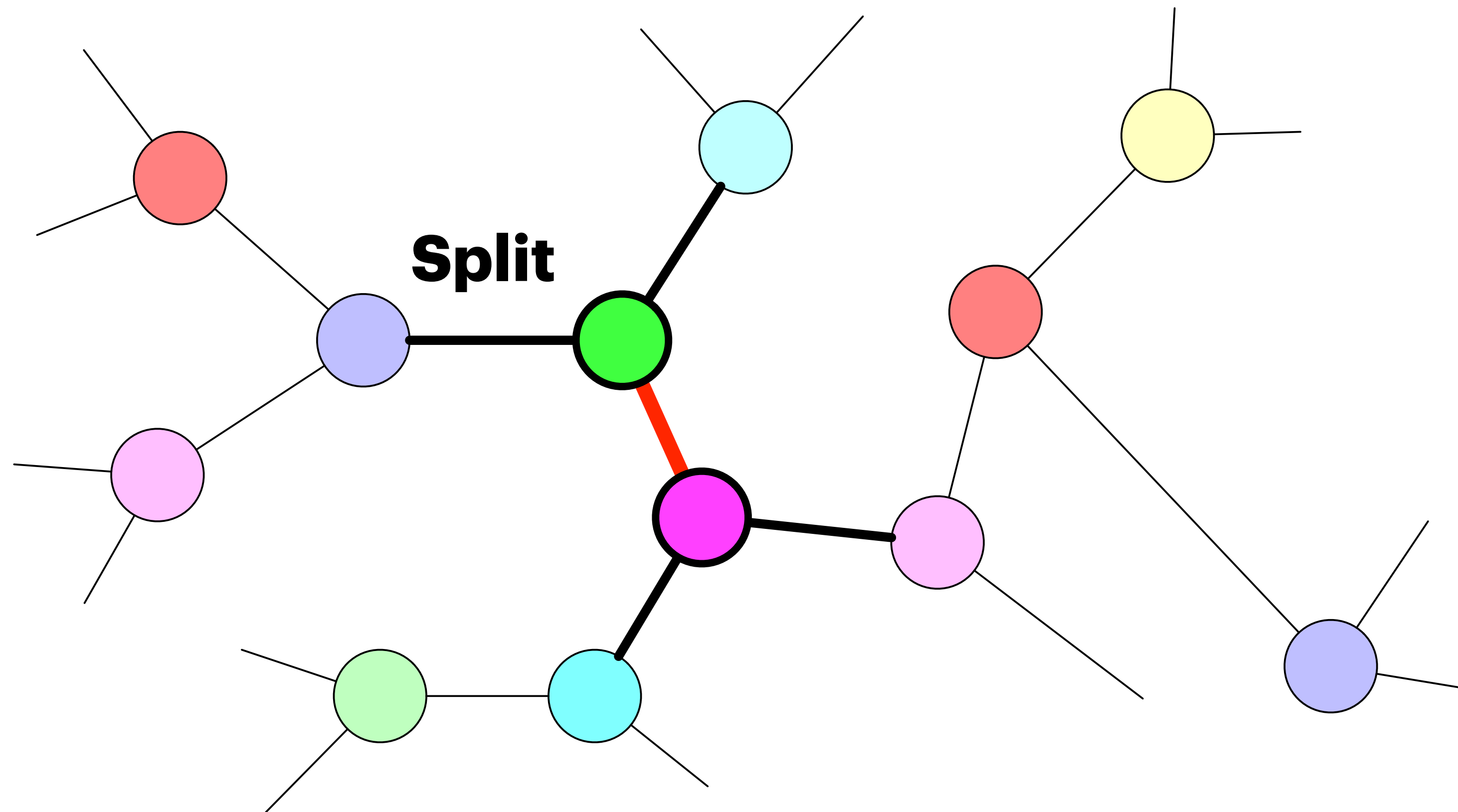


Adaptive tensor tree algorithm (ATT)



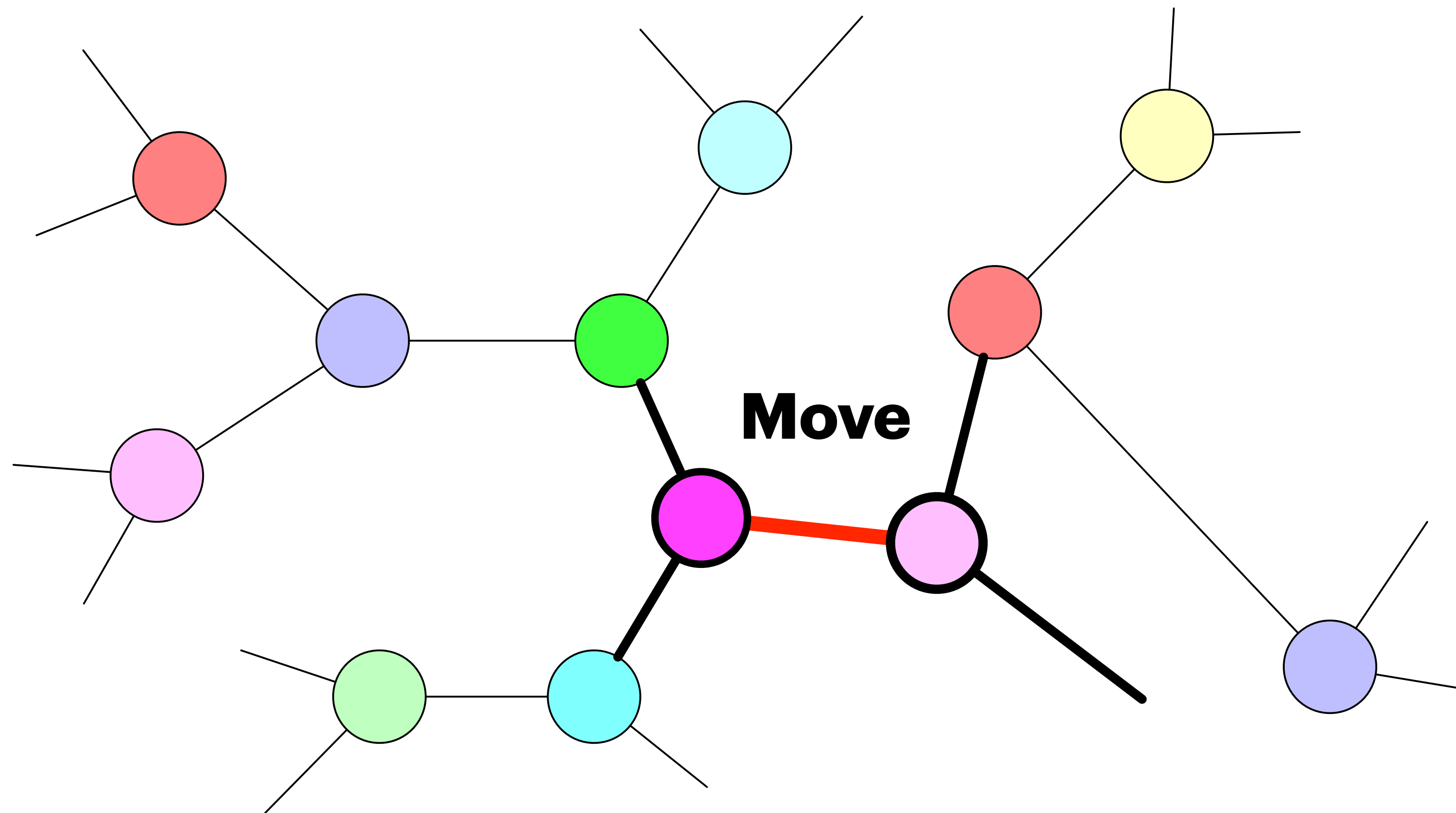
Adaptive tensor tree algorithm (ATT)

Avoid information bottlenecks: $\text{MI}(A : B) \leq \log D$
Choose the split with the smallest bond mutual information



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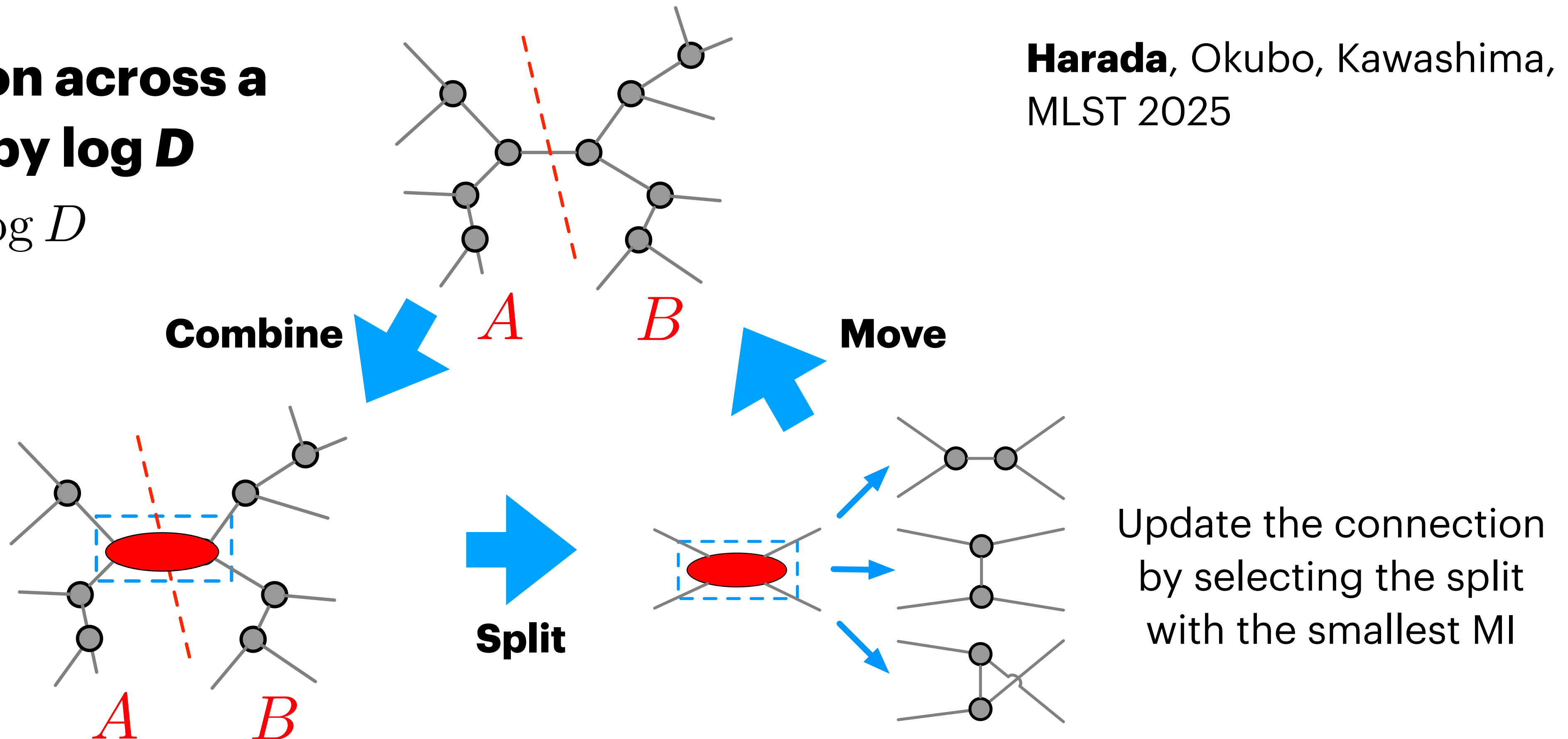
Adaptive tensor tree algorithm (ATT)

Mutual information across a bond is bounded by $\log D$

$$\text{MI}(A : B) \leq \log D$$

Harada, Okubo, Kawashima,
MLST 2025

Optimize the merged tensor by minimizing the negative log-likelihood (NLL)

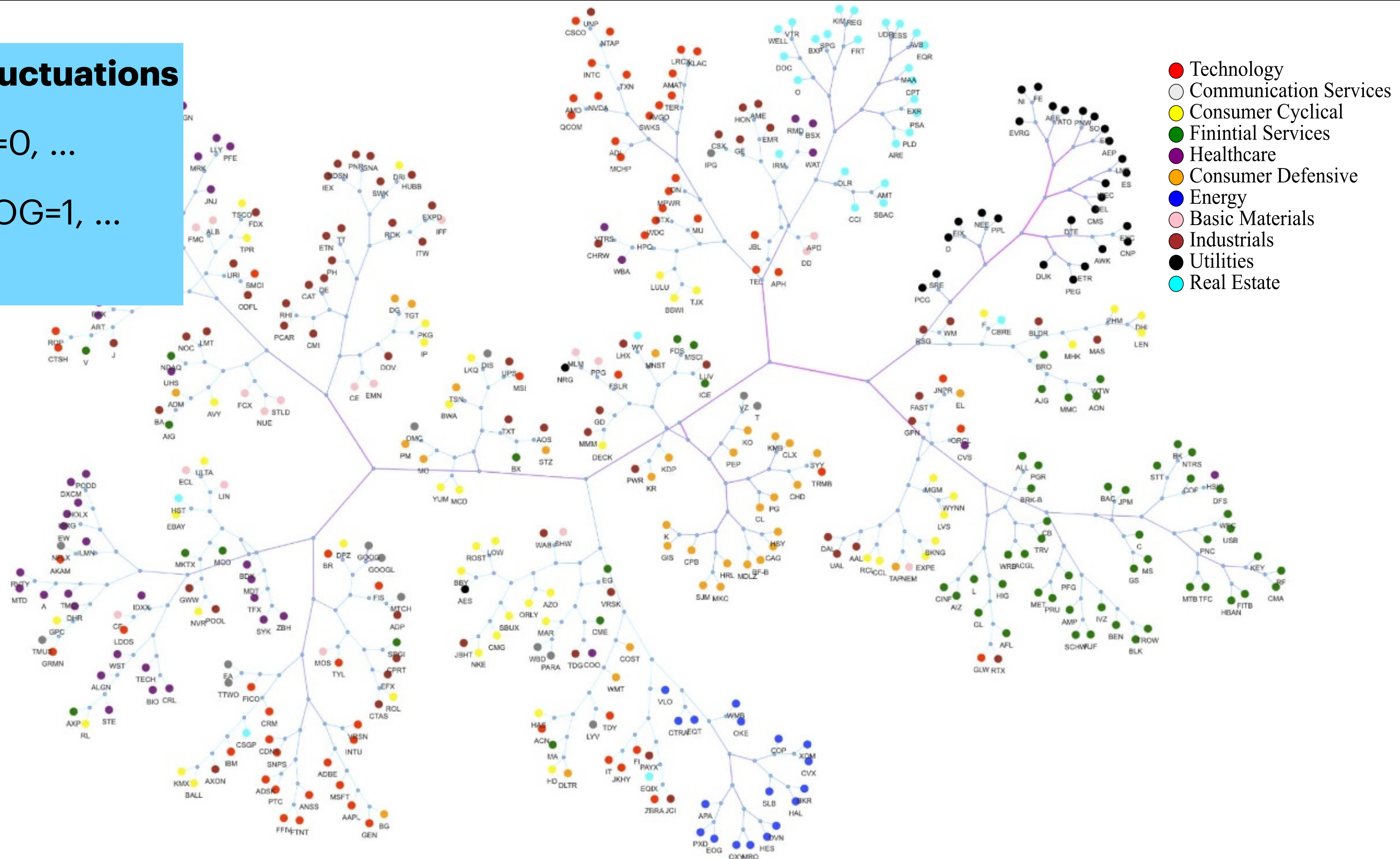


Joint optimization of tensor parameters and network topology

Example: S&P 500

Samples : stock price fluctuations

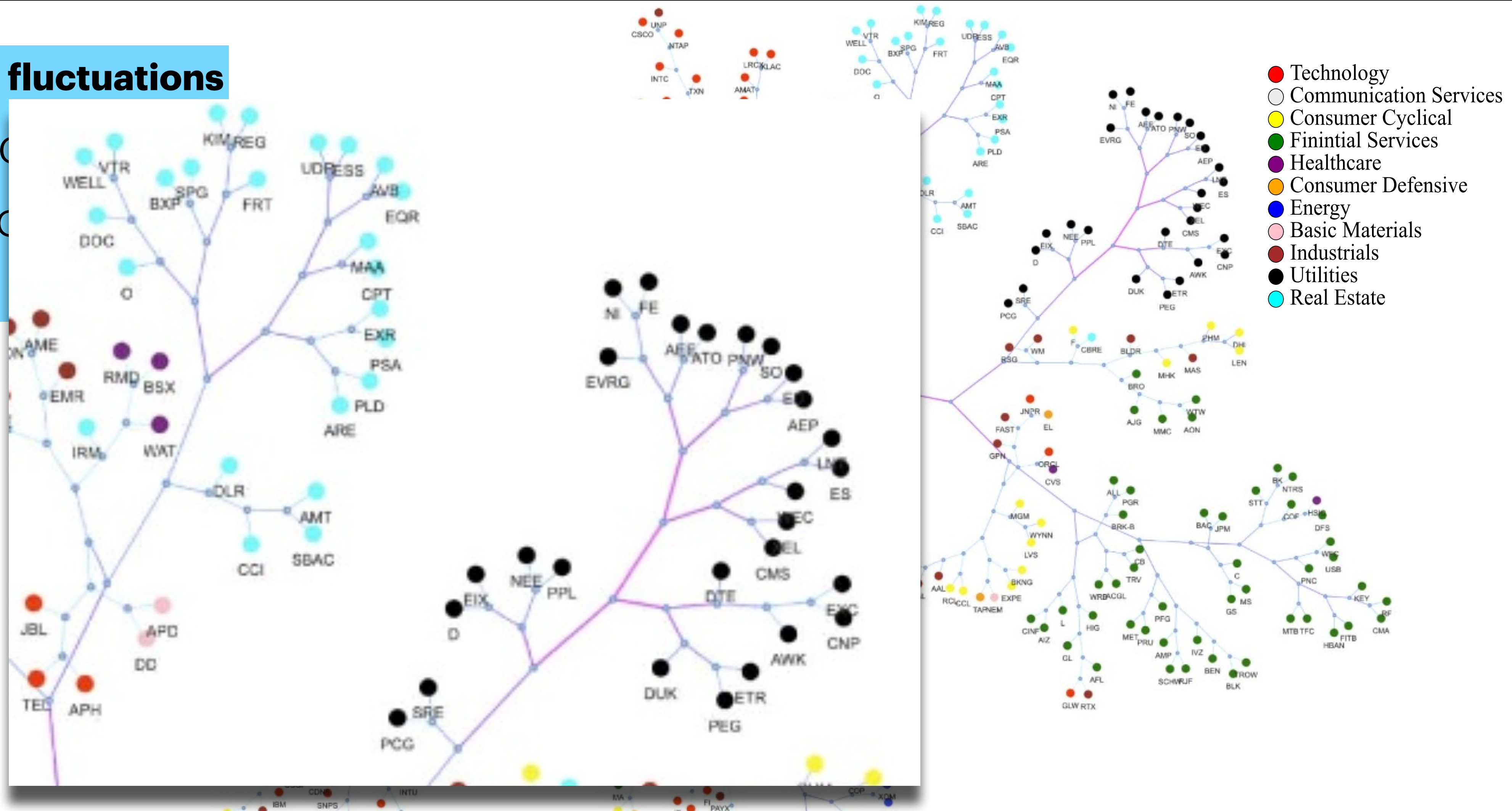
- Day x: AAPL=1, GOOG=0, ...
- Day (x+1): AAPL=1, GOOG=1, ...
- Day (x+2): ...



Example: S&P 500

Samples : stock price fluctuations

- Day x: AAPL=1, GOOG=1
- Day (x+1): AAPL=1, GOOG=1
- Day (x+2): ...



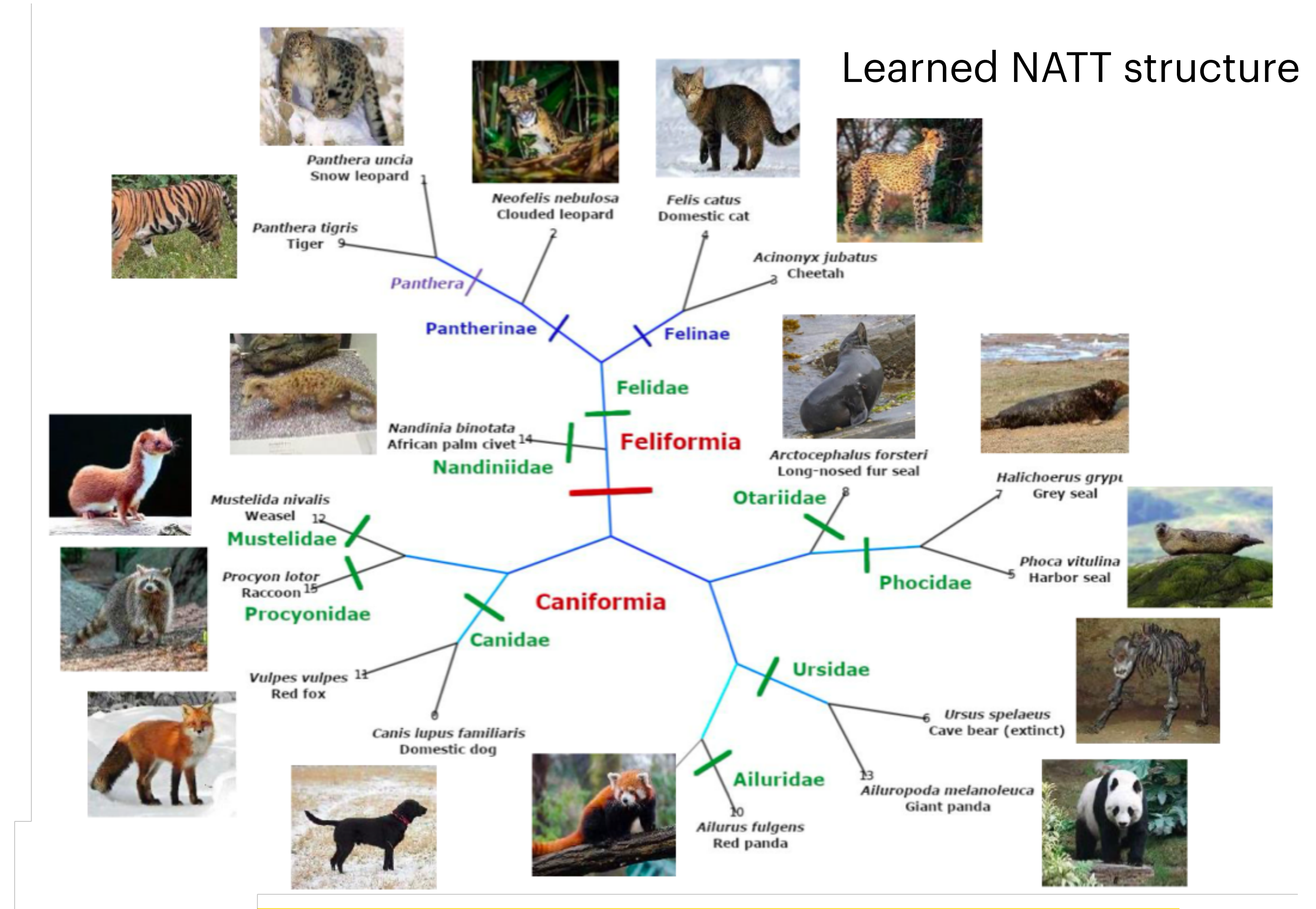
Sector-wise organization emerges in the learned network structure

Non-negative Adaptive Tensor Tree Algorithm (NATT)

Non-negative tensor tree

- Single-layer tensor tree
- All tensor elements are non-negative
- Interpreted as a probabilistic graphical model
- SVD $\rightarrow$ non-negative matrix factorization (NMF)

Akamatsu, **Harada**, Okubo, and
Kawashima, MLST 2026



A phylogeny-like tree emerges
from mitochondrial DNA sequences of 16 species

From Tensor-Network Optimization to Structure Learning

Adaptive tensor trees (ATT / NATT)

mutual information, topology, local reconnection

Graphical models

dependency structure, latent variables

Probabilistic circuits

tractable sum-product computation, structure learning

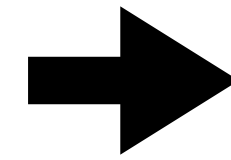
(Yang, et al. AISTATS 2023)

Common question: What network structure best represents the dependencies in data?

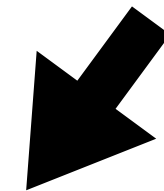
This suggests a connection to structure learning in graphical models and probabilistic circuits.

Summary: From Quantum Many-Body Physics to Machine Learning

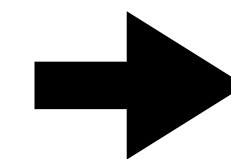
Quantum many-body physics
MPS / tensor networks



Generative modeling
Born machine



Adaptive structure
ATT



Probabilistic structure learning
NATT → graphical models; links to PCs

Network structure itself can be learned from data.

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