Neuromorphic Computing for Science

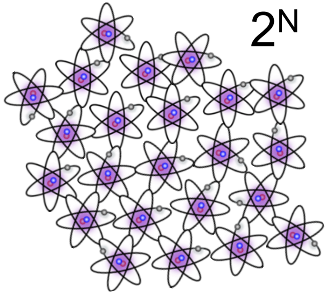
Johan H. Mentink

Radboud University

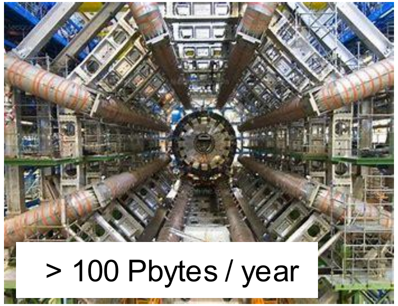
Nijmegen, The Netherlands

Physical Computing workshop – September 3, 2025, Leuven, Belgium

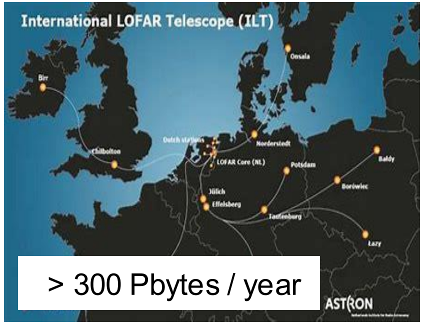
Grand Computational Challenges



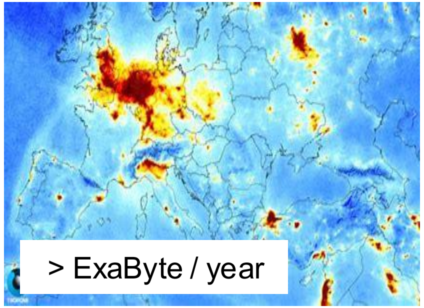
Quantum Many-Body



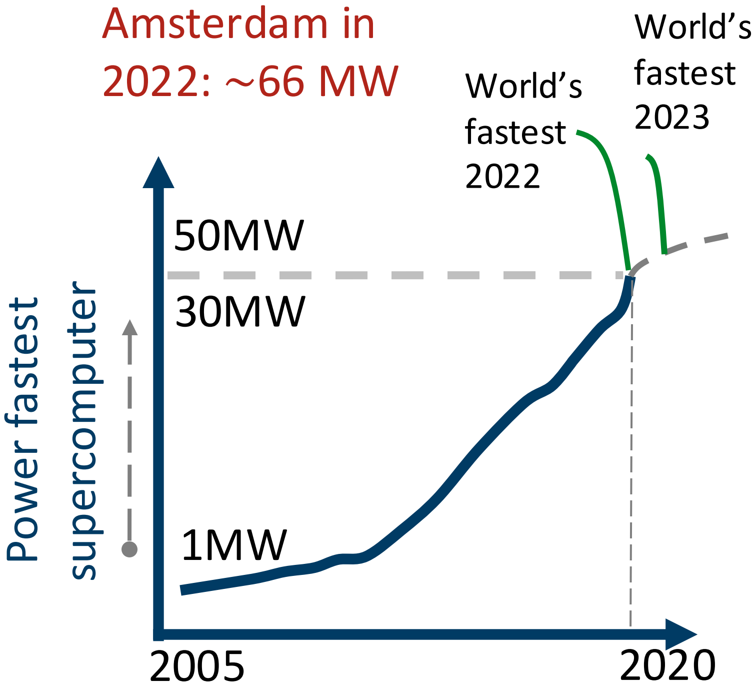
Particle physics



Astronomy

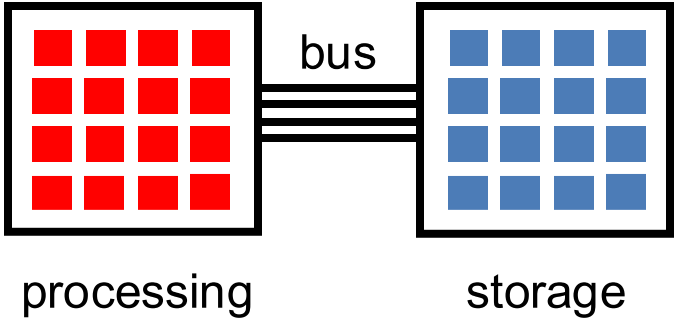


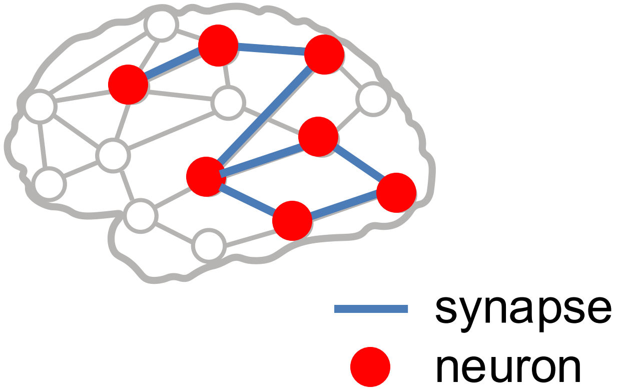
Climate modelling



Courtesy: Sagar Dolas (SURF)

Neuromorphic Computing





50 MW

20 W

Processing and storage separated
Serial, Digital, Deterministic

Processing and storage integrated
Parallel, Analog, Stochastic

Outline

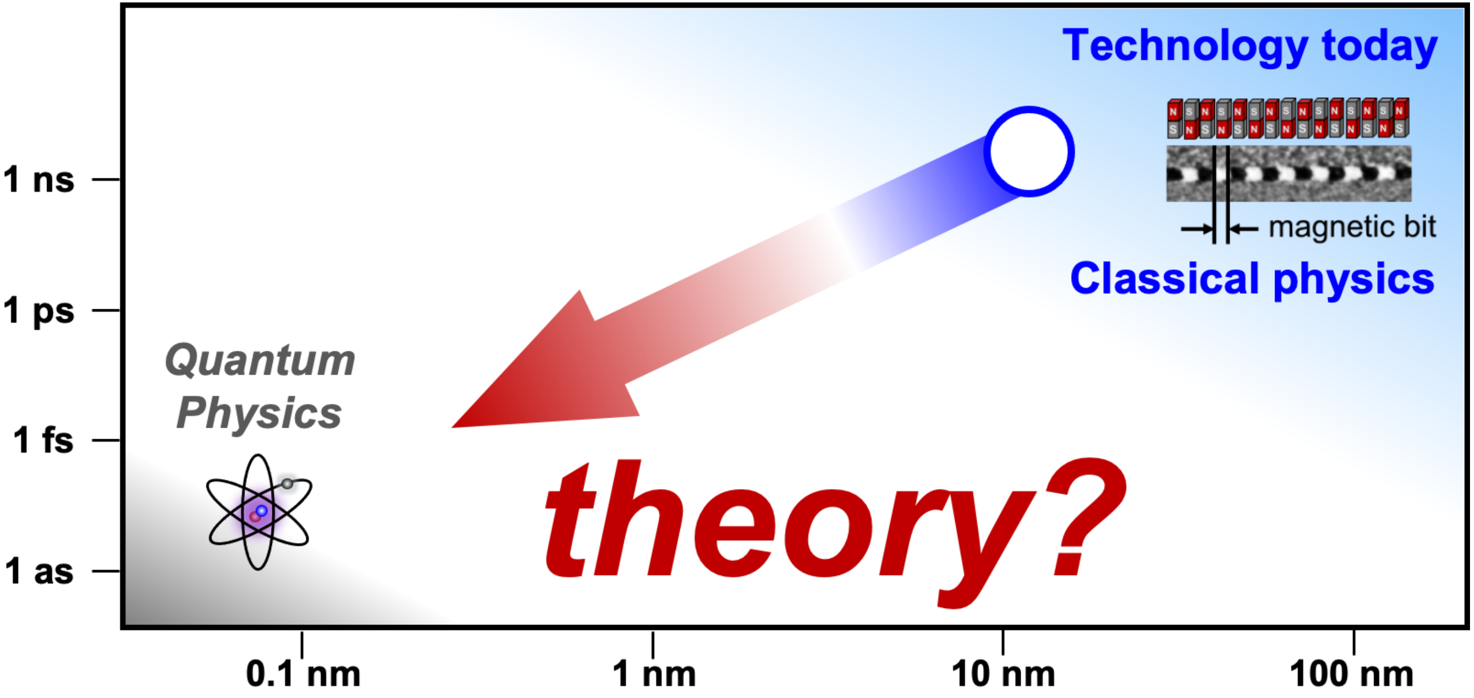
Neural-Network Simulations

Stochastic Ising Machines

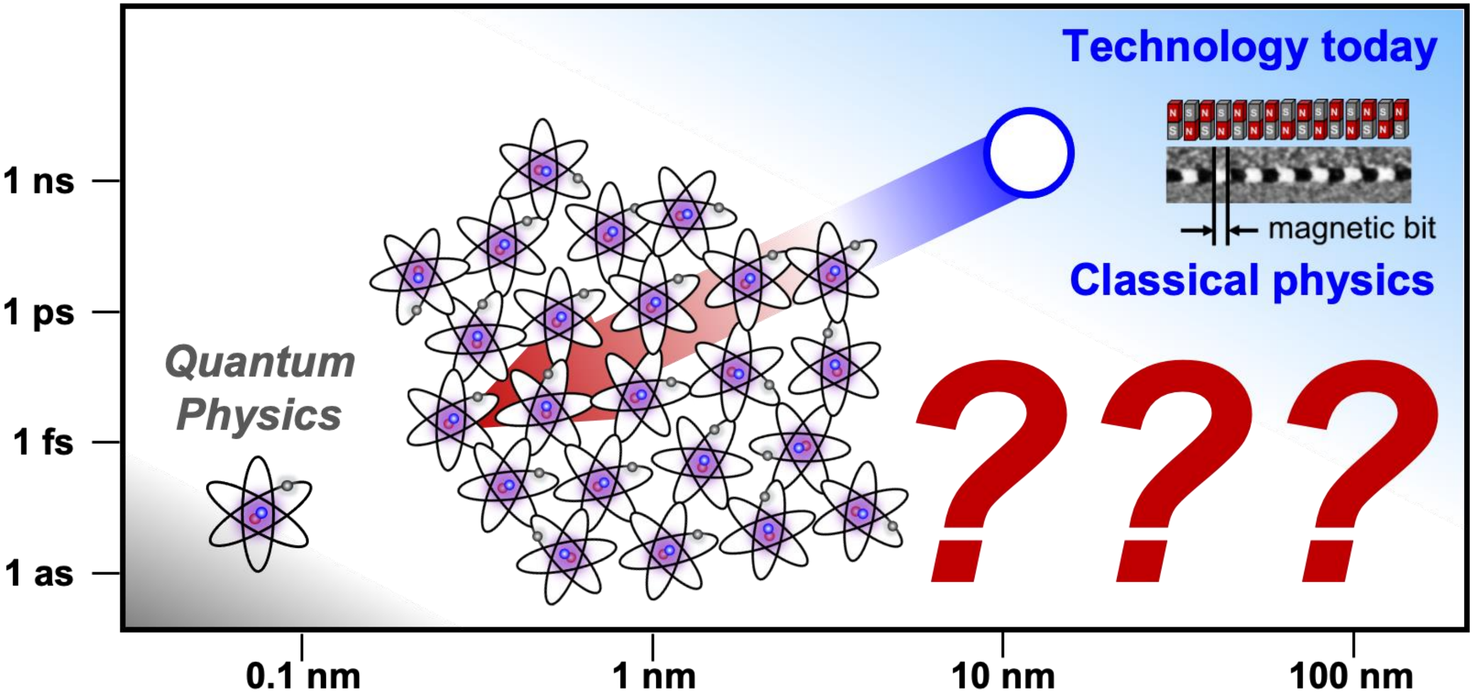
In-memory Computing

Neuromorphic NL Alliance

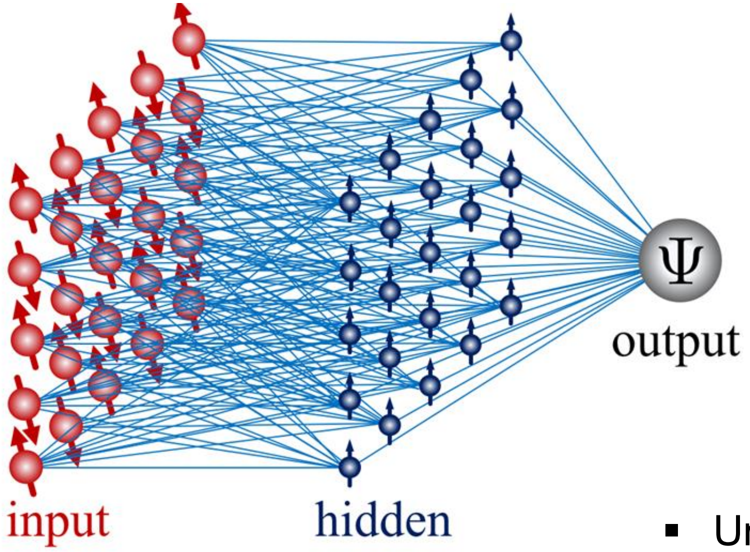
Ultrafast Nanomagnetism



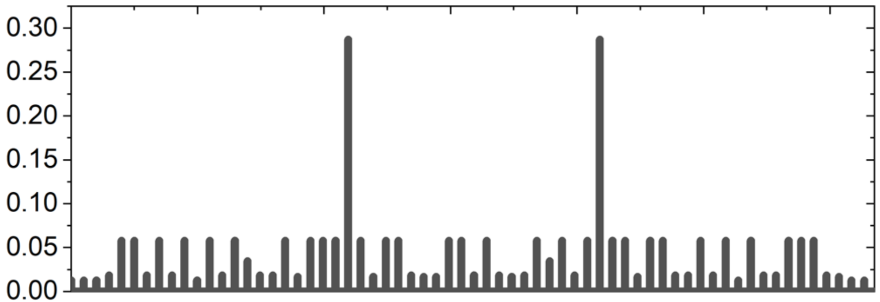
Quantum Many-body Physics



Neural Network Quantum States



$|S\rangle = |\uparrow\downarrow\uparrow \cdots \uparrow\rangle$



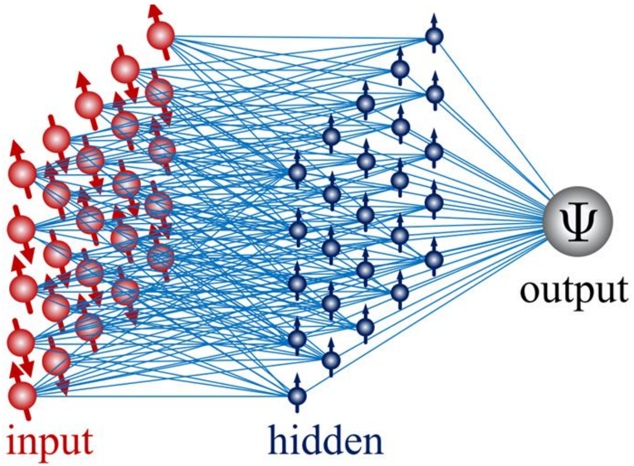
"all" possible quantum states $|S_1\rangle \ldots |S_{2^N}\rangle$

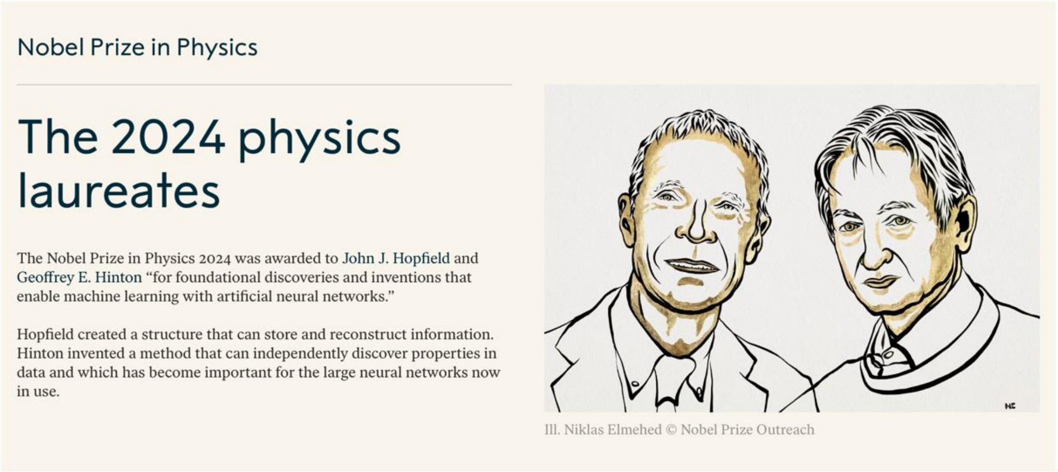
- Universal function approximation theorem
- Computable in polynomial time
- Much reduced limits on simulation time / system size

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

Restricted Boltzmann Machine (RBM)

Neural network quantum states





$$\psi_W(S) = \sum_{\{h_i\}} e^{\sum_j a_j s_j^z + \sum_i b_i h_i + \sum_{ij} w_{ij} h_i s_j^z}$$

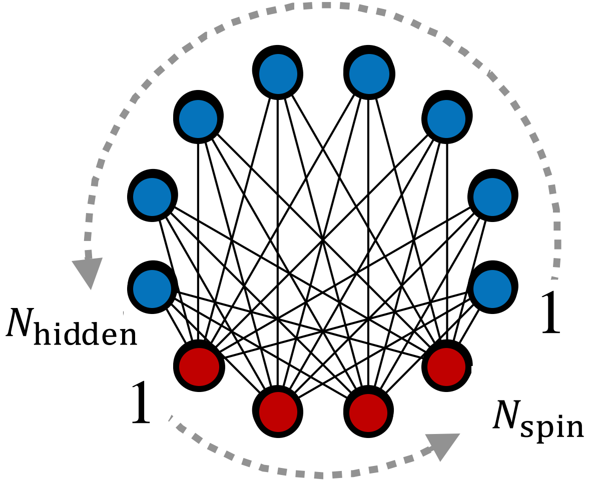
Restricted Boltzmann Machine

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

Hinton et al, 2002, 2006

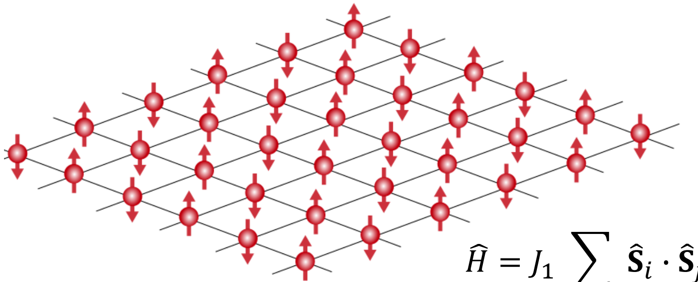
Restricted Boltzmann Machine (RBM)

Neural network quantum states

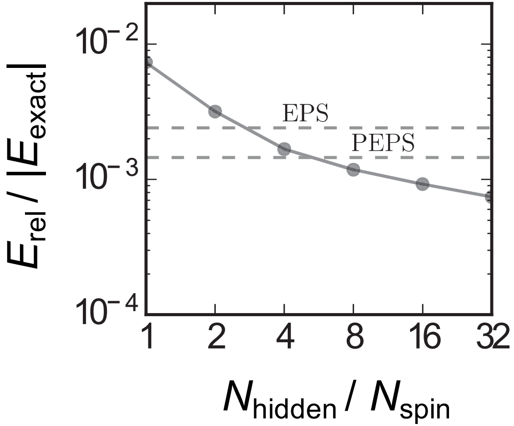


$$\psi_{\mathcal{W}}(S) = e^{\sum_j a_j s_j^z} \prod_{i=1}^{M} 2\cosh\left(b_i + \sum_j w_{ij} s_i^z\right)$$

2D antiferromagnet



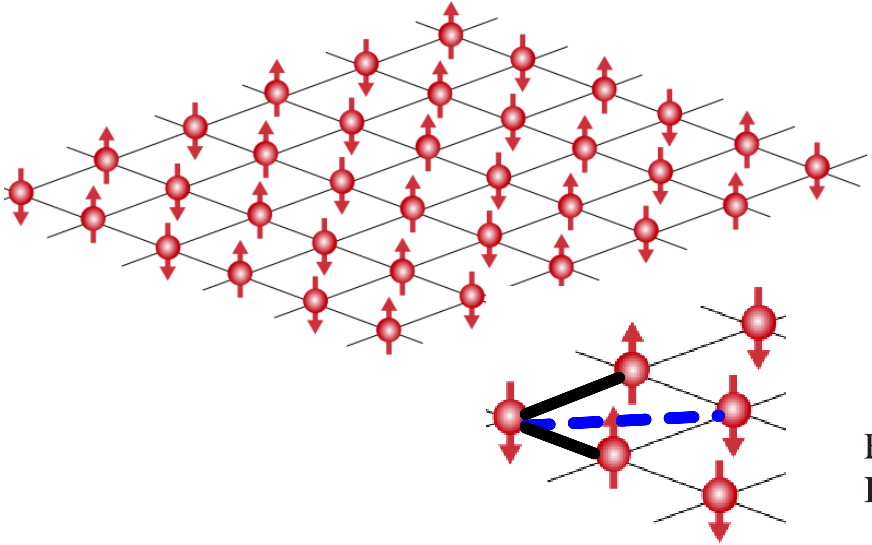
$$\hat{H} = J_1 \sum_{<i,j>} \hat{\mathbf{S}}_i \cdot \hat{\mathbf{S}}_j$$



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

Beyond Benchmarks

2D antiferromagnet



$$\hat{H} = J_1 \sum_{<i,j>} \hat{\mathbf{S}}_i \cdot \hat{\mathbf{S}}_j + J_2 \sum_{\ll i,j \gg} \hat{\mathbf{S}}_i \cdot \hat{\mathbf{S}}_j$$

Dirac-Type Nodal Spin Liquid

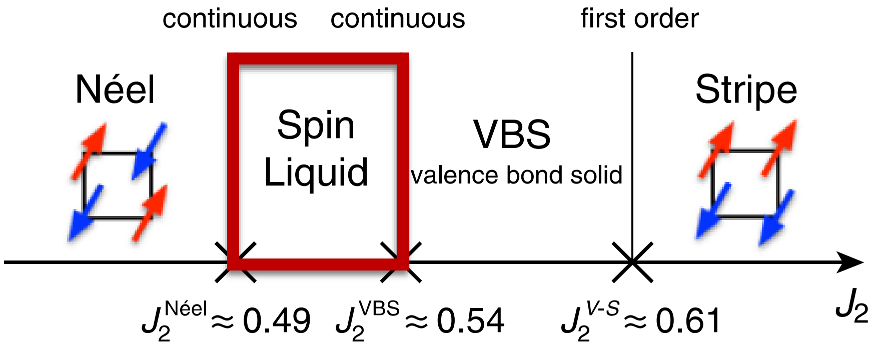
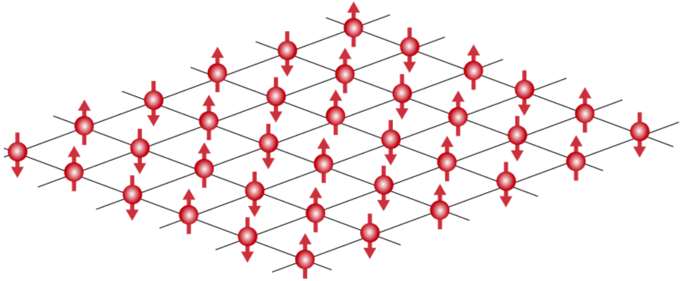


FIG. 1. Ground-state phase diagram of square-lattice J_1-J_2 Heisenberg model ($J_1 = 1$) obtained by the RBM + PP method.

Y Nomura and M Imada, Phys. Rev. X 11, 031034 (2021)

Simulating ultrafast dynamics

2D antiferromagnet

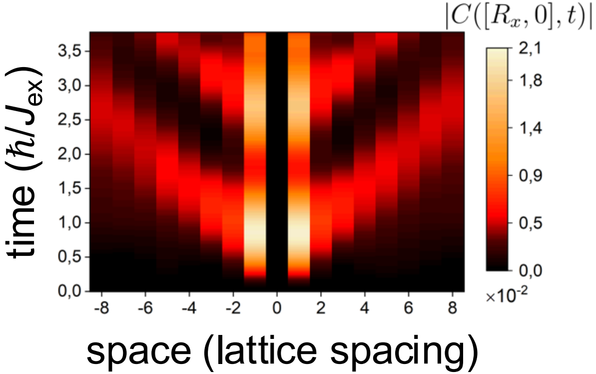


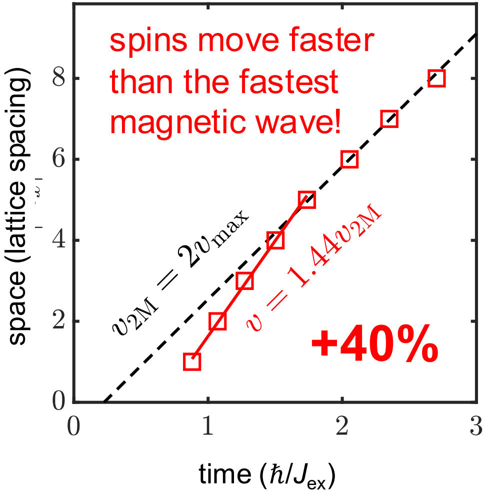
$$\hat{H} = J_1 \sum_{<i,j>} \hat{\mathbf{S}}_i \cdot \hat{\mathbf{S}}_j$$

$$\Delta\hat{H}(t) = \Delta J f(t) \sum_{i,\delta} (\vec{e}\cdot\vec{\delta})^2 \hat{\mathbf{S}}_i \cdot \hat{\mathbf{S}}_{i+\delta}$$

Supermagnonic propagation

Dynamics of correlations $C(R_x,t)$ after perturbation of exchange (ΔJ_{ex})



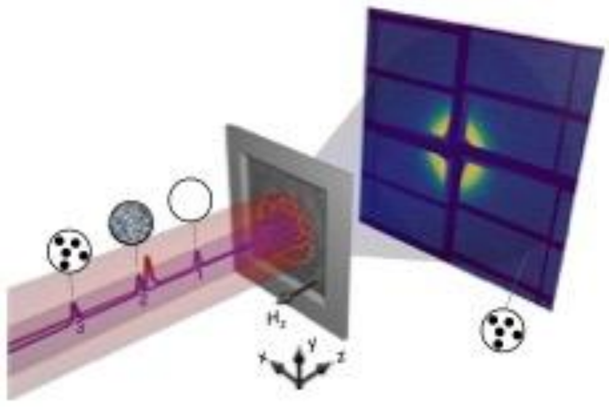


G. Fabiani, M.D. Bouman, J.H. Mentink

SciPost Phys. **7**, 004 (2019), Phys. Rev. Lett. **127**, 097202 (2021), SciPost Phys. 17, 159 (2024).

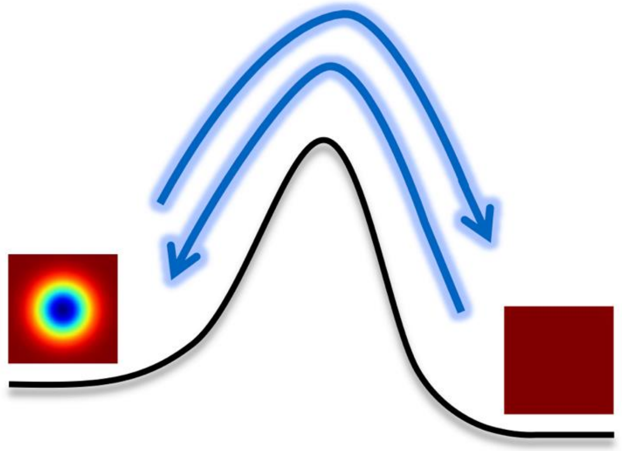
Experimental Frontiers

Picosecond nucleation of magnetic domains



Büttner, Pfau, **JHM**, et al, Nat. Mater. (2021)
Kern et al., Nano Lett (2022)
Gerlinger, Liefferink, …., **JHM**, (arxiv 2022)
Khusyainov, Liefferink, …, **JHM**, Rasing (arxiv 2025)
Chang, .. **JHM**, .. Ropers (arxiv 2025)

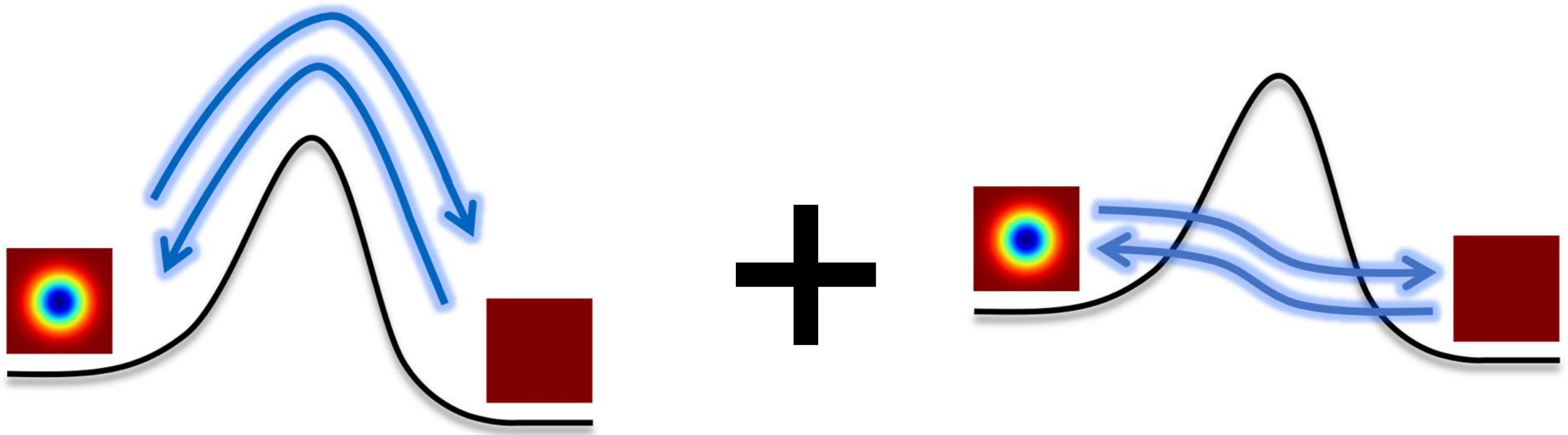
Classical fluctuation states



Key insight from **classical** Heisenberg model on 100x100 lattice

“Killer” applications

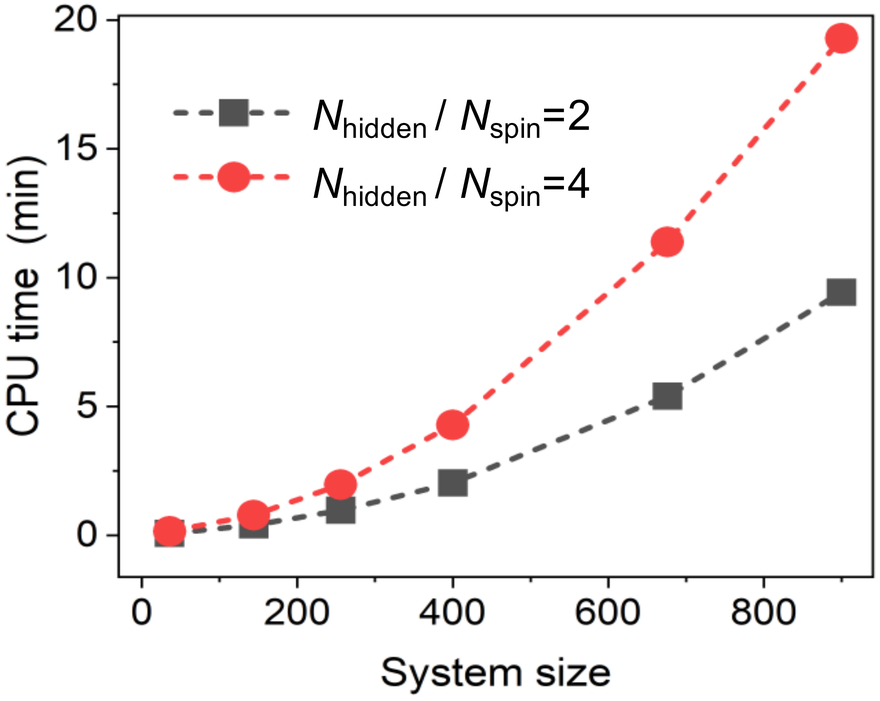
Classical fluctuation states | **Quantum fluctuation states**



Key insight from classical Heisenberg model on 100x100 lattice

Quantum Heisenberg model 100x100 lattice?

Computational challenges



24 x 24	6 hours
100 x 100	> 75 days

G. Fabiani, JHM, SciPost. Phys. **7**, 004 (2019)

Optimization

Variational principles

min $\left\|(\widehat{\mathcal{H}} - E)\psi_{\mathcal{W}}\right\|$

min $\left\|\mathrm{i}\partial_{\mathrm{t}}\psi_{\mathcal{W}}(t) - \widehat{\mathcal{H}}(t)\,\psi_{\mathcal{W}}(t)\right\|$

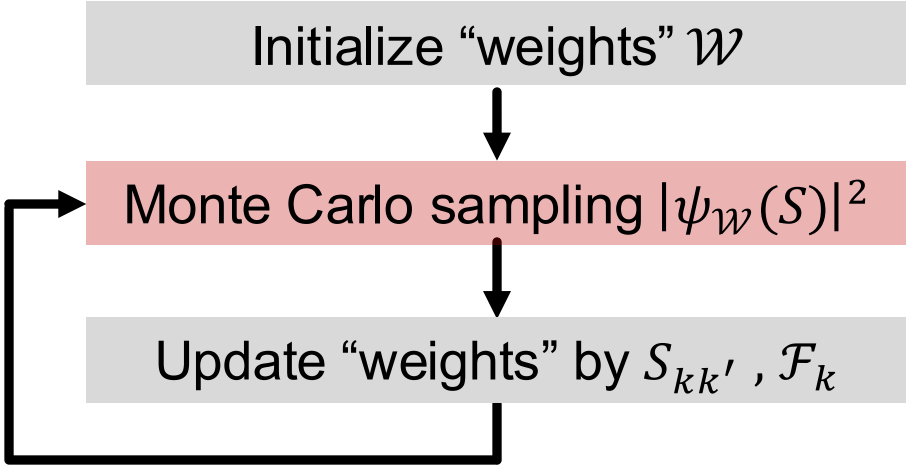
ODE variational parameters

$$S_{kk'}(t)\dot{\mathcal{W}}_{k'}(t) = -i\mathcal{F}_k(\mathcal{W}(t))$$

$$\begin{aligned} S_{kk'} &= \langle O_k^* O_{k'}\rangle - \langle O_k^*\rangle \langle O_{k'}\rangle , \\ \mathcal{F}_k &= \langle E_{\mathrm{loc}} O_k^*\rangle - \langle E_{\mathrm{loc}}\rangle \langle O_k^*\rangle . \end{aligned}$$

Stochastic reconfiguration (Sorella, 1998)

Variational Monte Carlo



Computational Cost

Inference $\psi_{\mathcal{W}}(S)$:
$O\left(N_{\mathrm{spin}} \times N_{\mathrm{hidden}}\right) = O\left(N_{\mathrm{spin}}^2\right)$

Monte Carlo Sampling
N_S states: $O\left(N_{\mathrm{spin}} \times N_S\right)$

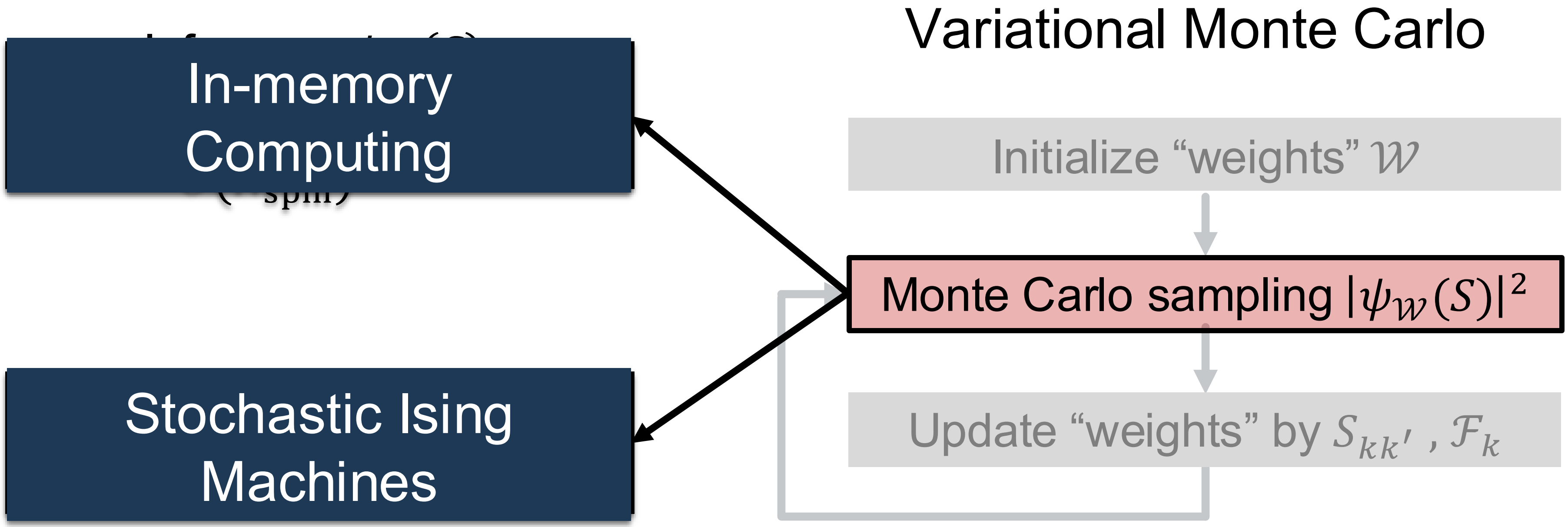
Variational Monte Carlo

Initialize "weights" $\mathcal{W}$

Monte Carlo sampling $|\psi_{\mathcal{W}}(S)|^2$

Update "weights" by $S_{kk'}$, $\mathcal{F}_k$

Computational Cost



Outline

Neural-Network Quantum Simulations

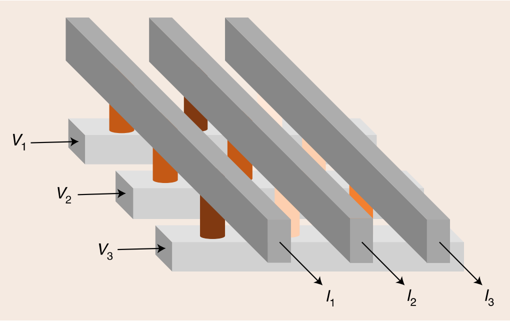
Stochastic Ising Machines

In-memory Computing

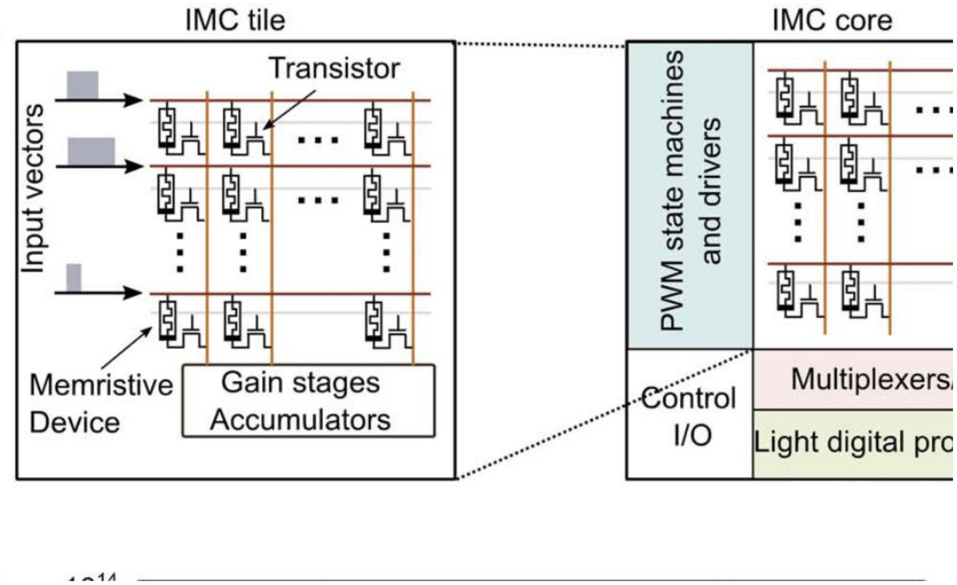
Neuromorphic NL Alliance

Analog in-memory computing (AIMC)

Cross-bar structure



- Memristor elements at crosses
- Matrix-vector multiplication by Ohm and Kirchhoff laws
- Enormous reduction on-chip data-transfer

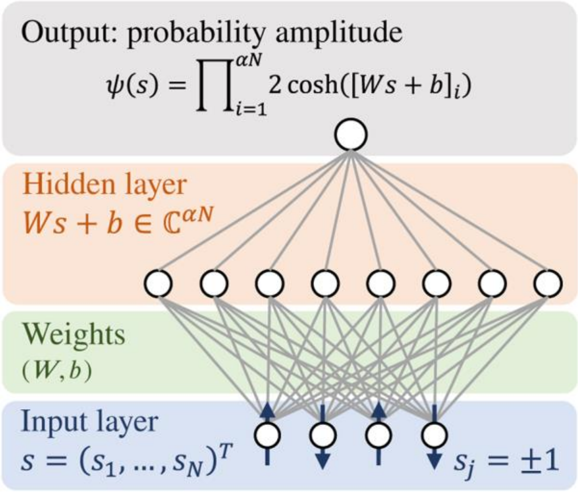


A. Sebastian et al., Nature Nanotech. Rev. 15, 529 (2020)

Lanza et al., Science 376, 1066 (2022)

Science use cases

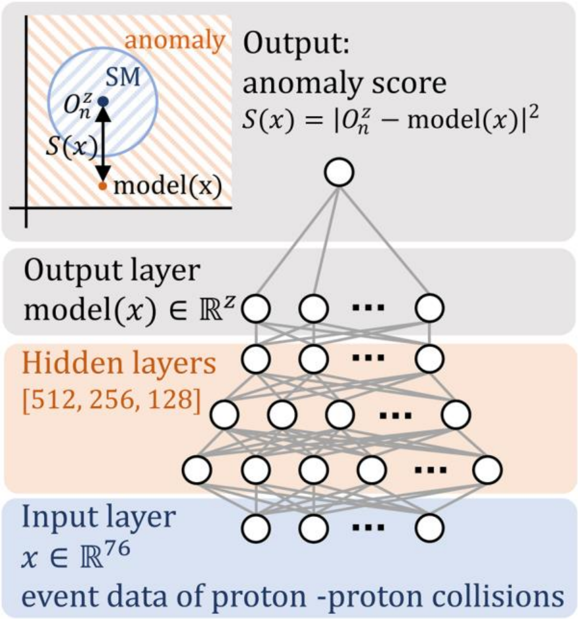
Condensed Matter



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

G. Fabiani, JHM, SciPost. Phys. **7**, 004 (2019)

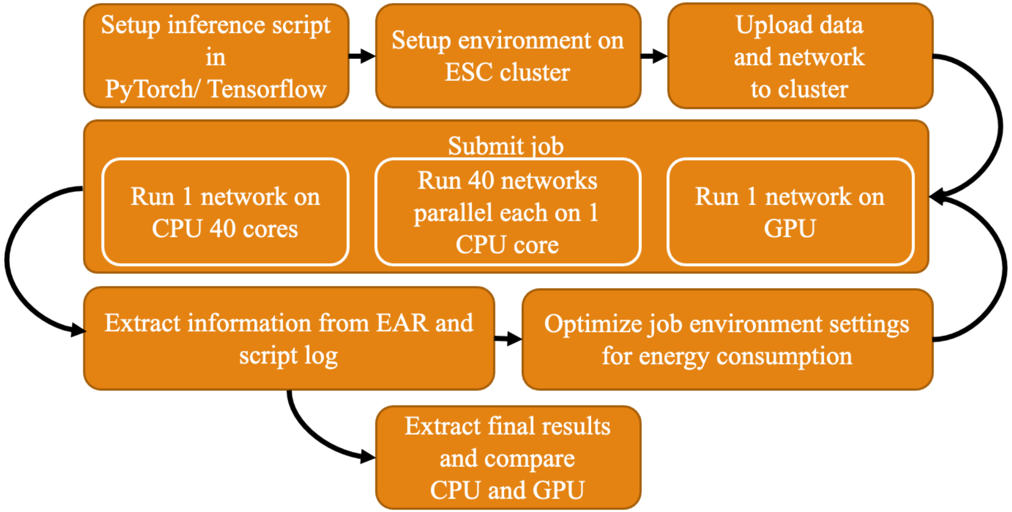
Particle Physics



T. Aarrestad, … S. Caron, … et al., SciPost Phys. 12, 43 (2022)

Energy *measurements*

EAR software: Energy management framework for HPC



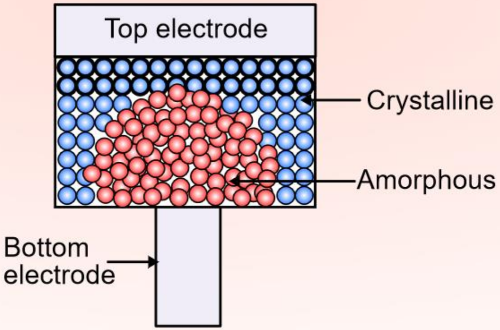
ESC cluster @ SURF

- CPU: Intel Xeon Gold 6248 dual socket (2x20 cores)
- GPU: NVIDIA GPU V100

https://github.com/dkosters/EME

Architecture design for AIMC

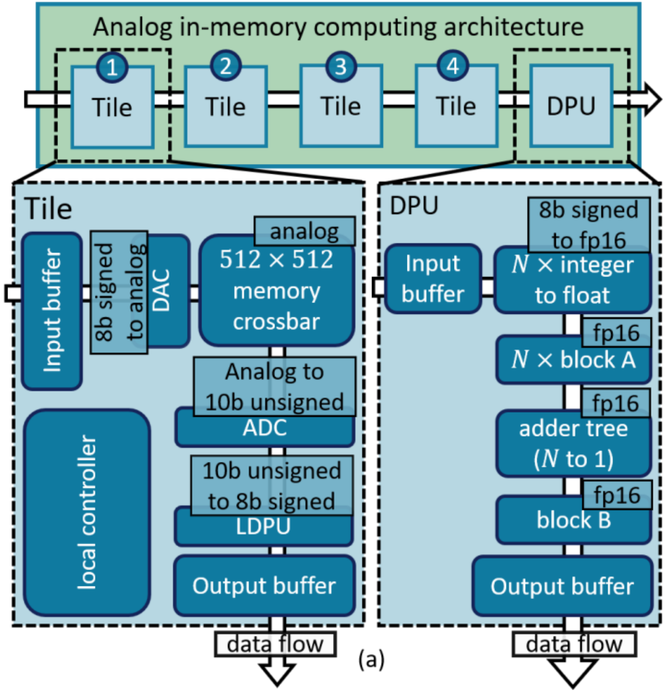
Phase-change memory



Resistance range = 10^4-10^7

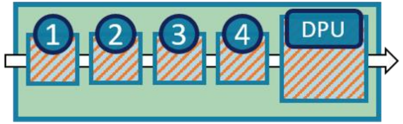
Access time (write) ~ 100ns

Endurance = 10^6-10^9



(a)

Particle Physics



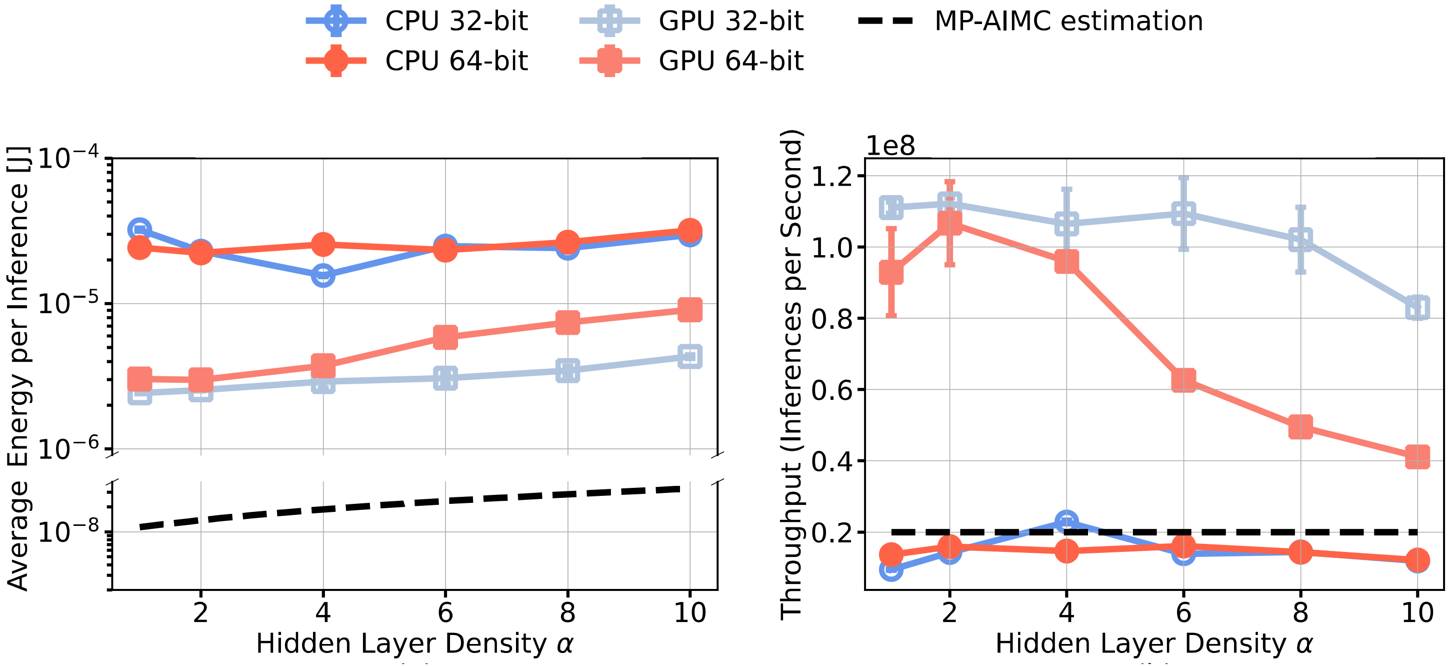
(c)

Condensed Matter

(b)

D.J. Kösters et al., APL Machine Learning 1, 016101 (2023)

Results Neural-Network Quantum states

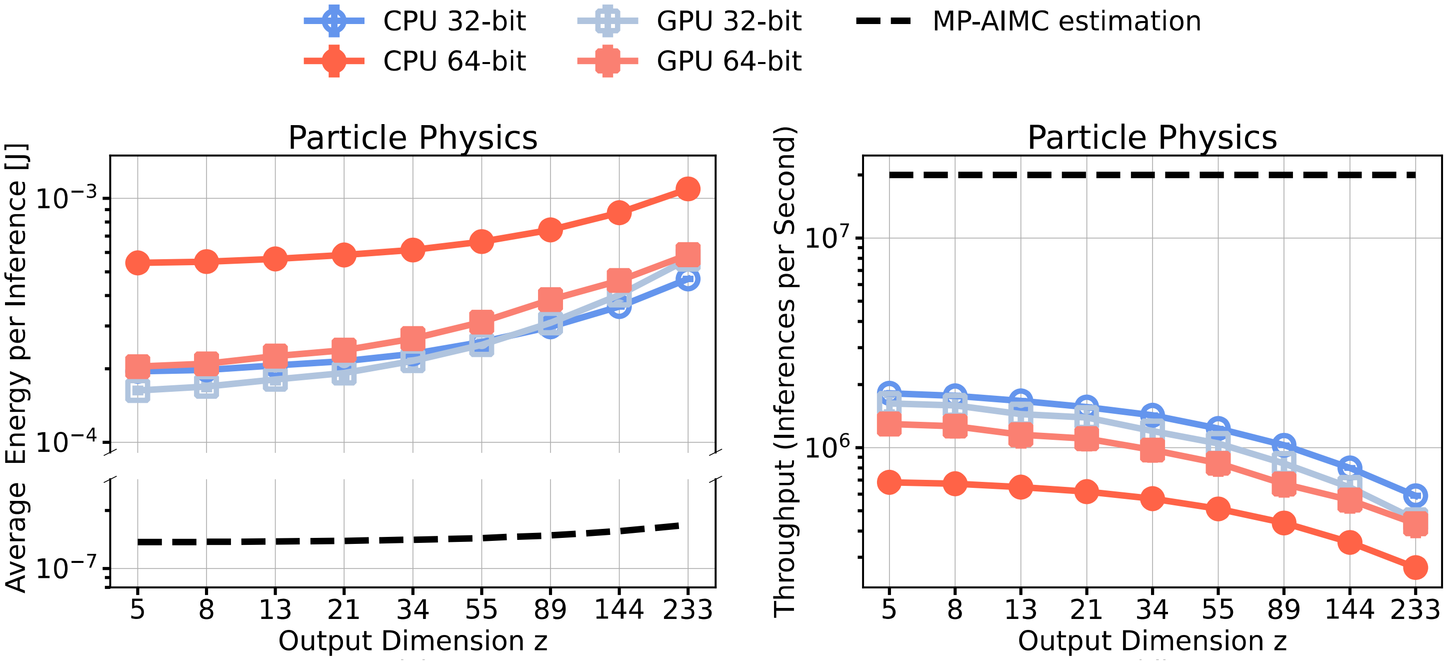


>100x more energy efficient

Flat scaling (by design)

D.J. Kösters et al., APL Machine Learning 1, 016101 (2023)

Results Particle Physics

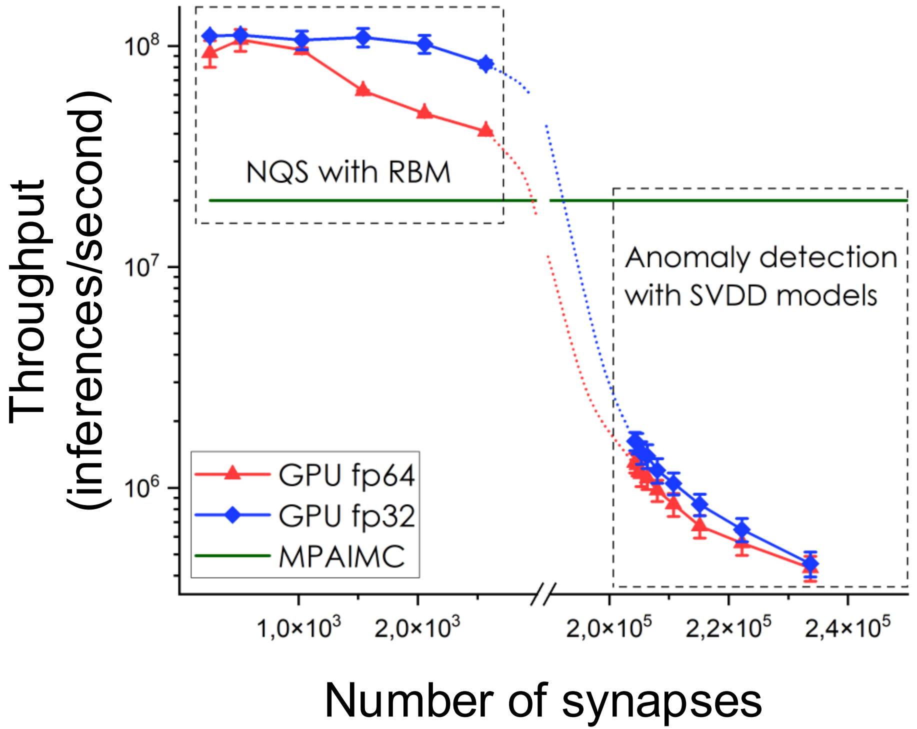


>1000x more energy efficient

Flat scaling (by design)

D.J. Kösters et al., APL Machine Learning 1, 016101 (2023)

Towards neuromorphic advantage



Flat scaling of compute time

$$O(N_{\text{spin}} \times N_{\text{hidden}}) \longrightarrow O(1)$$

Outline

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Optimization

Variational Monte Carlo

Initialize "weights" W

Monte Carlo sampling $|\psi_W(S)|^2$

Update "weights" by $S_{kk'}$, $\mathcal{F}_k$

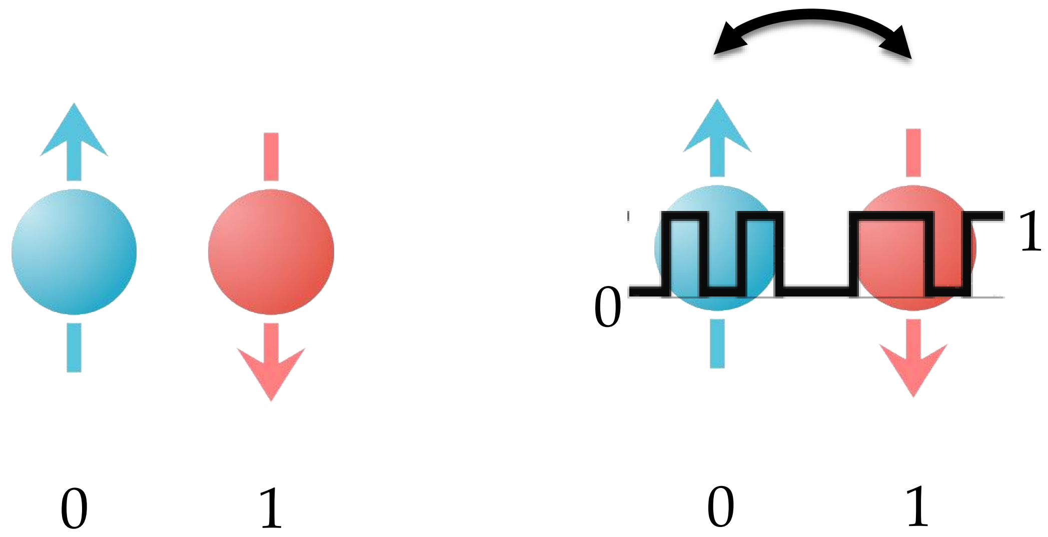
Probabilistic Bits (pbits)

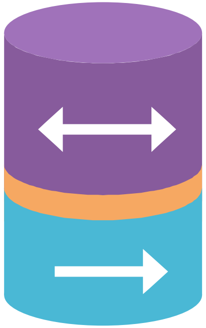
Digital computer

Digital bit

Probabilistic computer

Probabilistic bit





sMTJ

Camsari et al, PRX 7, 031014 (2017) *Stochastic p-Bits for Invertible Logic*

Probabilistic Bits (pbits)

LETTER

https://doi.org/10.1038/s41586-019-1557-9

Integer factorization using stochastic magnetic tunnel junctions

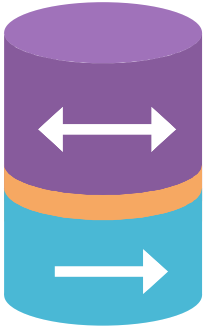
William A. Borders[1,8], Ahmed Z. Pervaiz[2,8], Shunsuke Fukami[1,3,4,5,6,7*], Kerem Y. Camsari[2*], Hideo Ohno[1,3,4,5,6,7] & Supriyo Datta[2]

nature electronics

Massively parallel probabilistic computing with sparse Ising machines

Navid Anjum Aadit, Andrea Grimaldi, Mario Carpentieri, Luke Theogarajan, John M. Martinis, Giovanni Finocchio & Kerem Y. Camsari

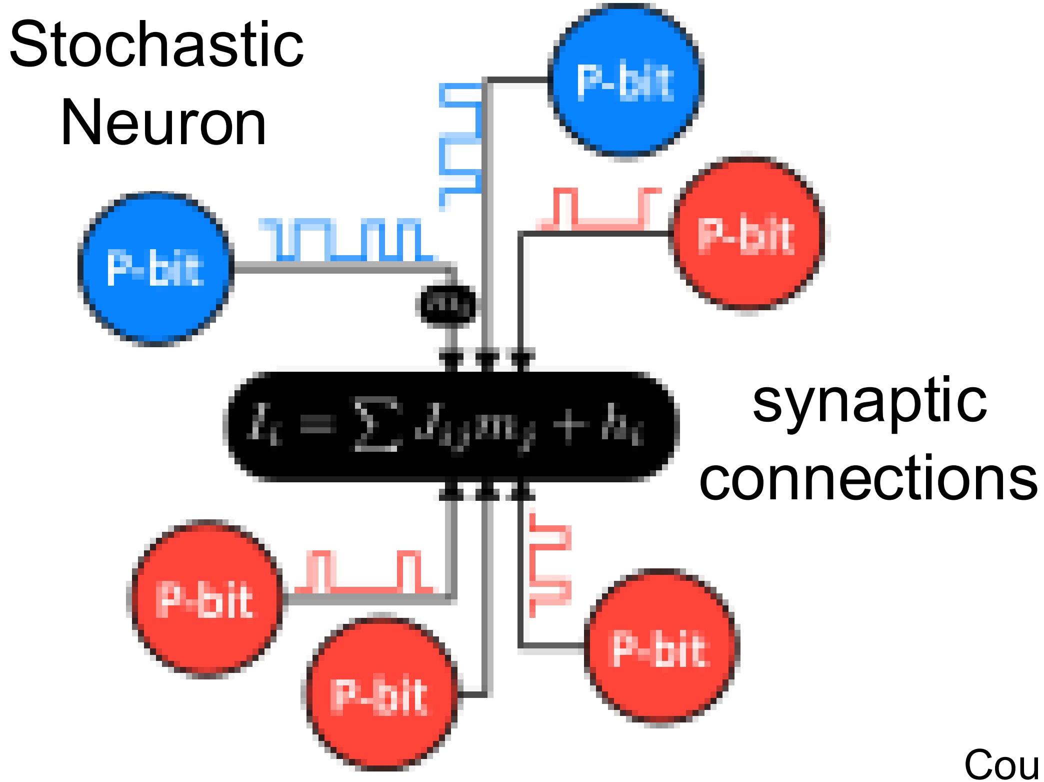
Nature Electronics **5**, 460–468 (2022) | Cite this article



sMTJ

Camsari et al, PRX 7, 031014 (2017) *Stochastic p-Bits for Invertible Logic*

Stochastic Ising Machines



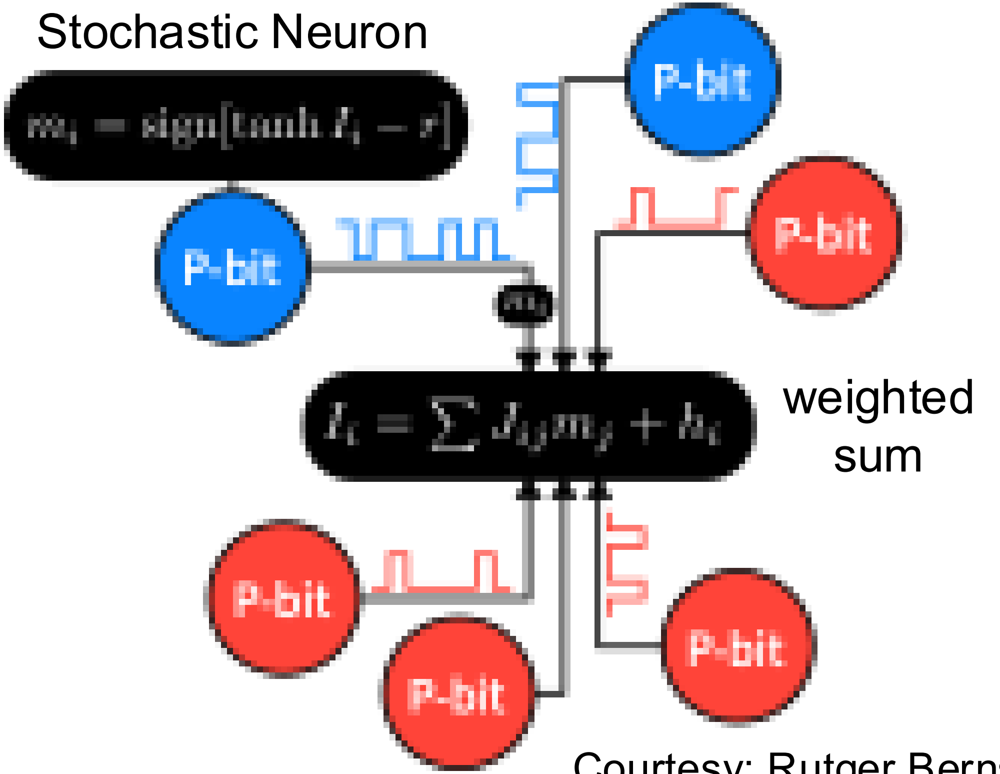
Courtesy: Rutger Berns

Stochastic Ising Machines

Sampling

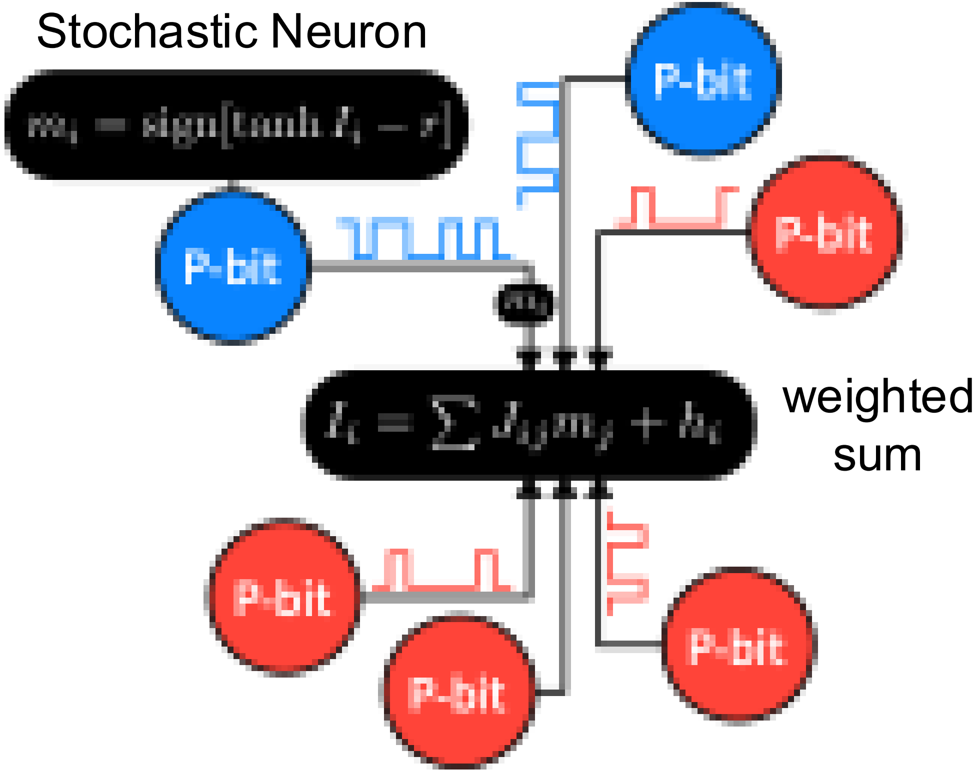
$$p(s) = e^{-H_{\text{ising}}(s)}$$

$$H_{\text{ising}}(s) = \sum_{i<j} J_{ij} s_i s_j + \sum_i h_i s_i$$



Courtesy: Rutger Berns

Stochastic Ising Machines



$$E_{\text{Ising}} = -\sum_{i}^{N_{\text{tot}}} b_i' m_i - \sum_{i}^{N_{\text{tot}}} \sum_{j}^{N_{\text{tot}}} J_{ij} m_i m_j$$

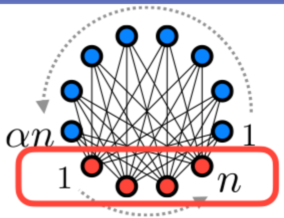
$$I_i = -\frac{\partial E_{\text{Ising}}}{\partial m_i} = \sum_{j}^{N_{\text{tot}}} J_{ij} m_j + h_i$$

$$m_i = \mathrm{sgn}[\tanh I_i - \mathrm{rand}_U(-1,1)]$$

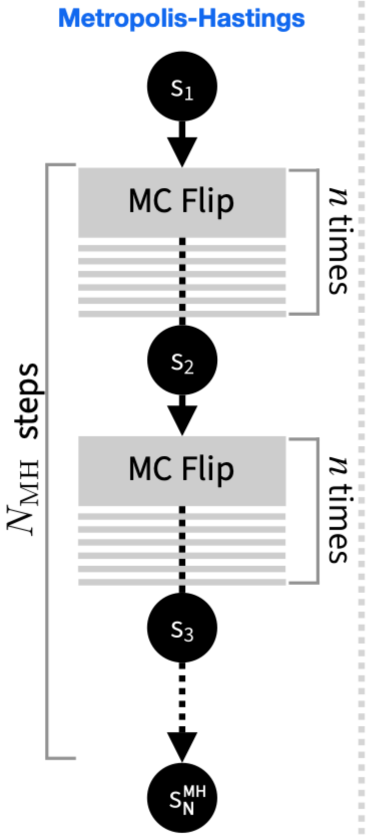
$$p(\{m\}) \propto \exp[-E_{\text{Ising}}(\{m\})]$$

100-1000X less energy

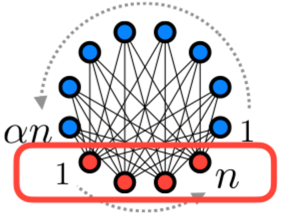
Time complexity



❌ **Sequential** updates

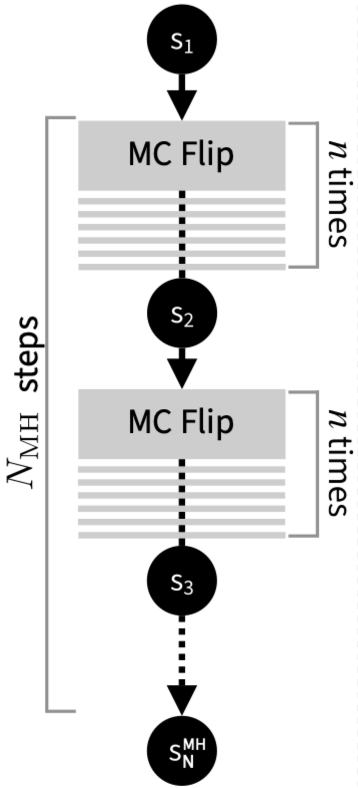


Time complexity

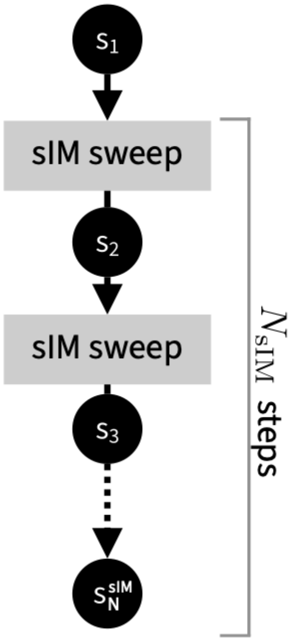


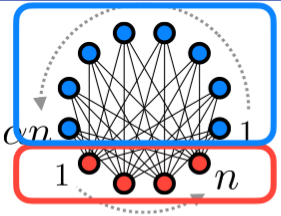
❌ **Sequential** updates

Metropolis-Hastings



stochastic Ising Machine





✅ **Parallel** updates of spins

$$O(N_{\mathrm{pbit}}) \longrightarrow O(1)$$

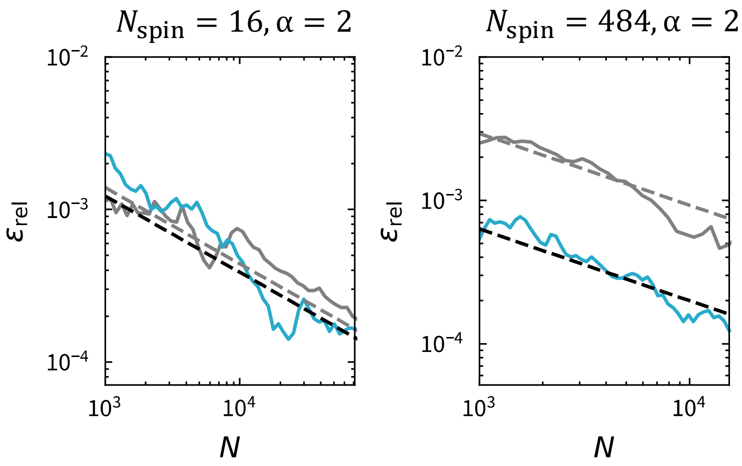
Analysis sampling efficiency

$$\varepsilon_{\mathrm{rel}}(N) = \left|\frac{E_0 - E(N)}{E_0}\right|$$

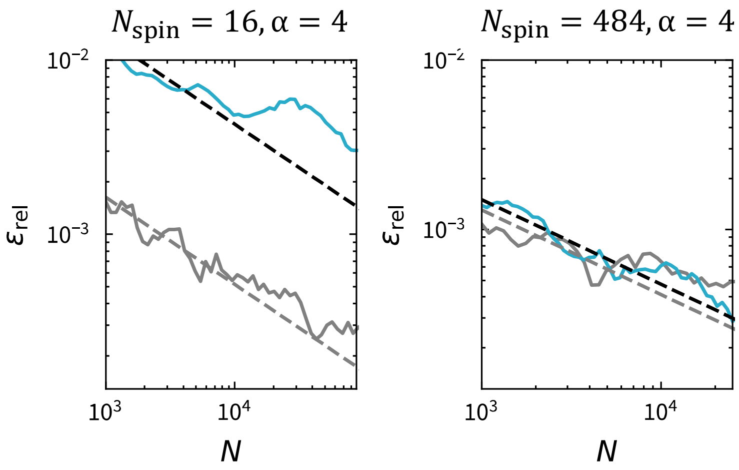
$$E = \langle \psi_{\mathcal{W}} | H | \psi_{\mathcal{W}} \rangle / \langle \psi_{\mathcal{W}} | \psi_{\mathcal{W}} \rangle$$

MC — MC fit
Ising — Ising fit

$$\alpha = \frac{N_{\mathrm{hidden}}}{N_{\mathrm{spin}}}$$



Ising sampling better for large systems



But advantage depends on network width

Predicting Advantage

Provided that distributions the same

$$\varepsilon_{\mathrm{rel}}(N) = \left|\frac{E_0 - E(N)}{E_0}\right| \sim \sigma_{\bar{E}} = \sqrt{\frac{2\tau}{N}\mathrm{var}(E)}$$

$$\frac{\varepsilon_{\mathrm{rel,Ising}}(N)}{\varepsilon_{\mathrm{rel,MC}}(N)} = \sqrt{\frac{\tau_{\mathrm{Ising}}}{\tau_{MC}}}$$

Autocorrelation time τ

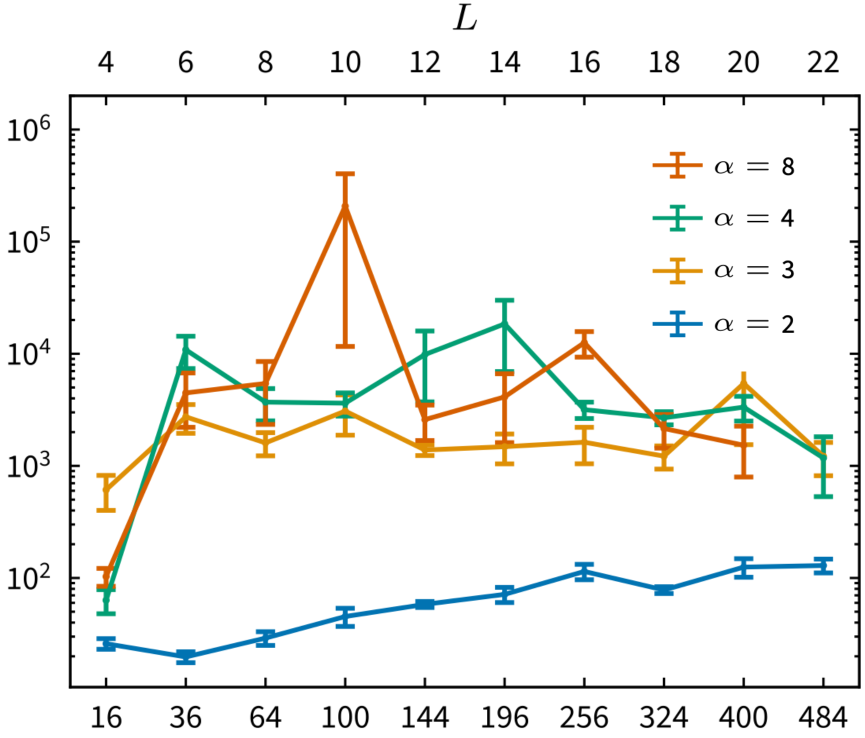
$$\frac{N_{\mathrm{Ising}}}{N_{\mathrm{MC}}} = \frac{\tau_{\mathrm{Ising}}}{\tau_{\mathrm{MC}}}$$

prediction hardware

property model

Exploring many models

$$\frac{N_{\mathrm{Ising}}}{N_{\mathrm{MC}}} = \frac{\tau_{\mathrm{Ising}}}{\tau_{\mathrm{MC}}}$$



Number of quantum spins

orders of magnitude variation

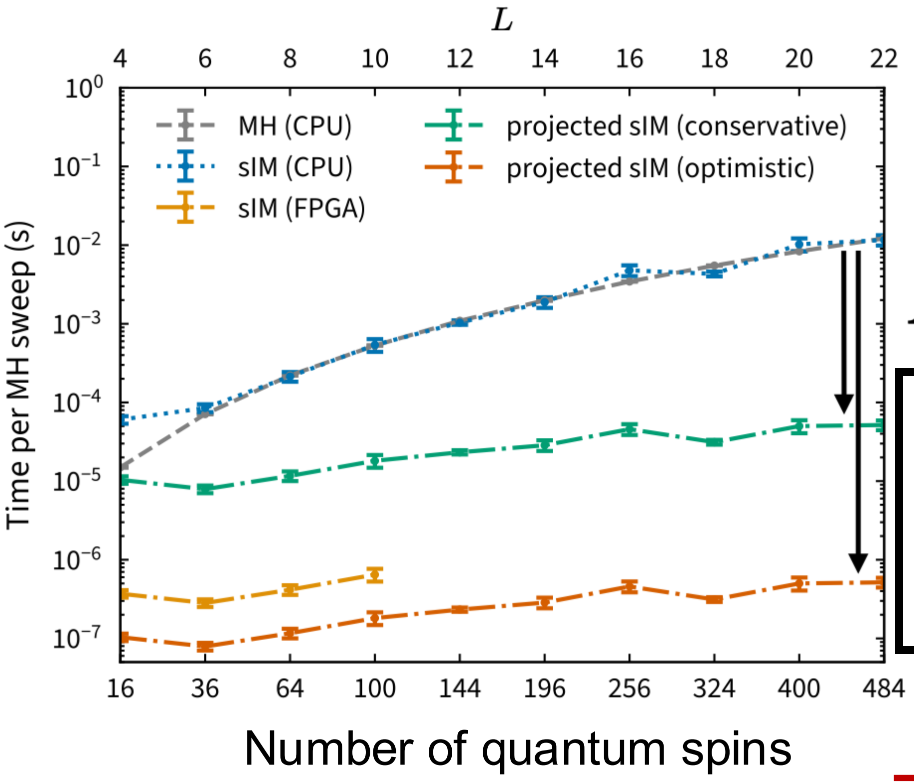
small models seem better

Tune Ising advantage by network choice

R. Berns,.. JHM, arxiv 2504.18359

Projected Speedup

$\alpha = 2$



sMTJ flip ~ 1ns

IMC ~ 4-100 ns

10^2 - 10^4 faster

Energy:

CPU: 200 mJ

IMC+pbits: 2 μJ

10^5 more efficient

N_{spin} large

→ more advantage

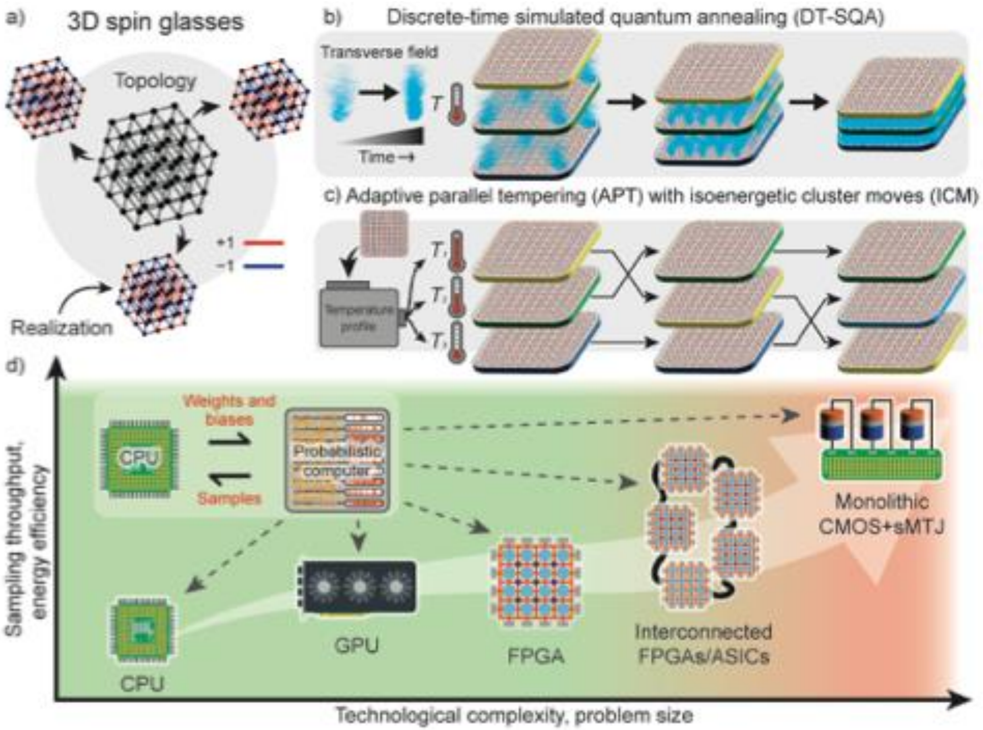
R. Berns,.. JHM, arxiv 2504.18359

Combinatorial Optimization

3D Spin-Glass
Edward-Anderson

$$H = -\sum_{i<j} J_{ij}\sigma_i\sigma_j$$

J_{ij} $\{-1,+1\}$ randomly



Pushing the Boundary of Quantum Advantage in Hard Combinatorial Optimization with Probabilistic Computers

Shuvro Chowdhury,[1] Navid Anjum Aadit,[1] Andrea Grimaldi,[2,3] Eleonora Raimondo,[2,4] Atharva Raut,[5] P. Aaron Lott,[6,7] Johan H. Mentink,[8] Marek M. Rams,[9] Federico Ricci-Tersenghi,[10] Massimo Chiappini,[4] Luke S. Theogarajan,[1] Tathagata Srimani,[5] Giovanni Finocchio,[2] Masoud Mohseni,[11] and Kerem Y. Camsari[1]

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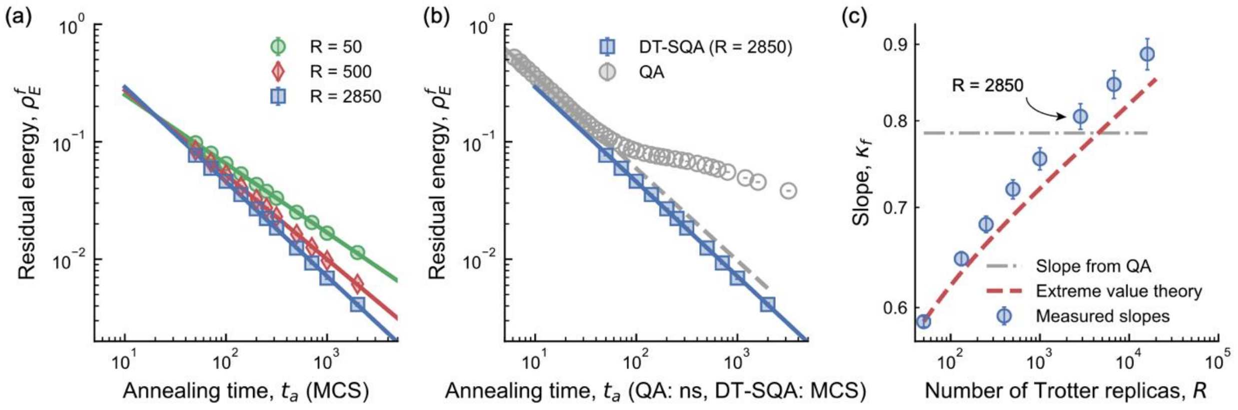

arXiv:2503.10302 Nature Comm. (in press, 2025)

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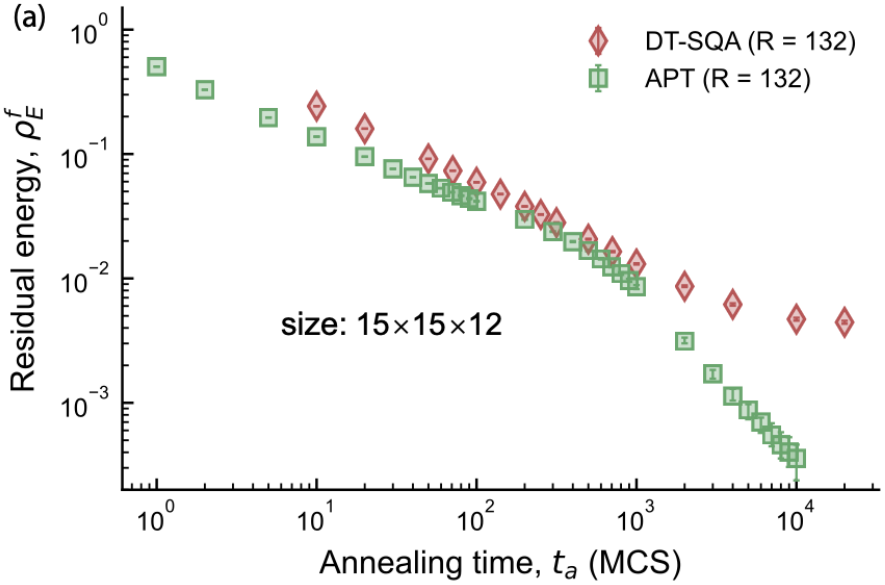

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Summary

- Neuromorphic Computing very promising to break existing computational barriers
- In-memory computing: flat scaling with matrix size

  ~ up to 20X faster, 100-1000X less energy
- Ising Machine: parallel instead of serial sampling

  ~ up to 100-10000X faster, 100-1000X less energy

  NQS: Advantage can be predicted based on network properties
- Even digital emulators / FPGAs can show significant advantage

G. Fabiani, M.D. Bouman, JHM, PRL. 127, 097202 (2021)
D.J. Kösters et al., APL Machine Learning 1, 016101 (2023)
R. Berns et al., arxiv 2504.18359 (2025)
Chowdhury et al., arXiv:2503.10302 (2025)

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erc

3D MAGiC

NIMFEIA

SURF

NWO

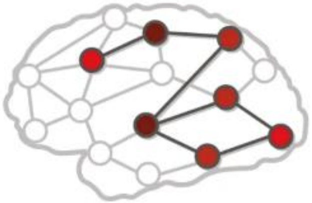
IBM

NL-ECO

Institute for Molecules and Materials
Radboud University

Interdisciplinary Research Platform

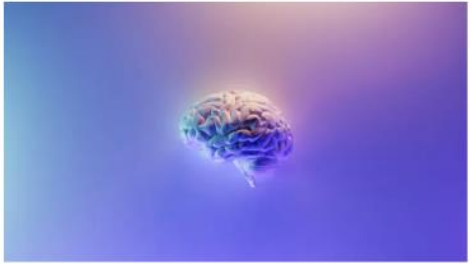
RU Neuromorphic Computing Initiative



Disruptively green neuromorphic scientific computing leveraging stochasticity →

ASMPT Lab →

Research



Neuromorphic Scientific Comput-ing: Towards New Hardware →

Research

Alex Khajetoorians

Marcel van Gerven

Johan Mentink

Outline

Neural-Network Quantum Simulations

Stochastic Ising Machines

In-memory Computing

Neuromorphic NL Alliance

Neuromorphic Computing in the Netherlands

WHITE PAPER

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Contributors

Core team
Johan Mentink (RU, coordinator)
Theo Rasing (RU)
Dominique Kösters (RU)
Isabel Rijk (RU)
Hans Hilgenkamp (UT)
Sander Smink (UT)
Beatriz Noheda (RUG)
Georgi Gaydadjiev (TUD)
Said Hamdioui (TUD)
Sagar Dolas (SURF)
Irene Bonati (SURF)

NL-ECO

Key Aspects

Materials
Wilfred van der Wiel (UT)
Martin Hecke (AMOLF)
Alex Khajetoorians (RU)

Devices
Beatriz Noheda (RUG)
Hans Hilgenkamp (UT)

Circuits
Elisabetta Chicca (RUG)
Federico Corradi (TUE)

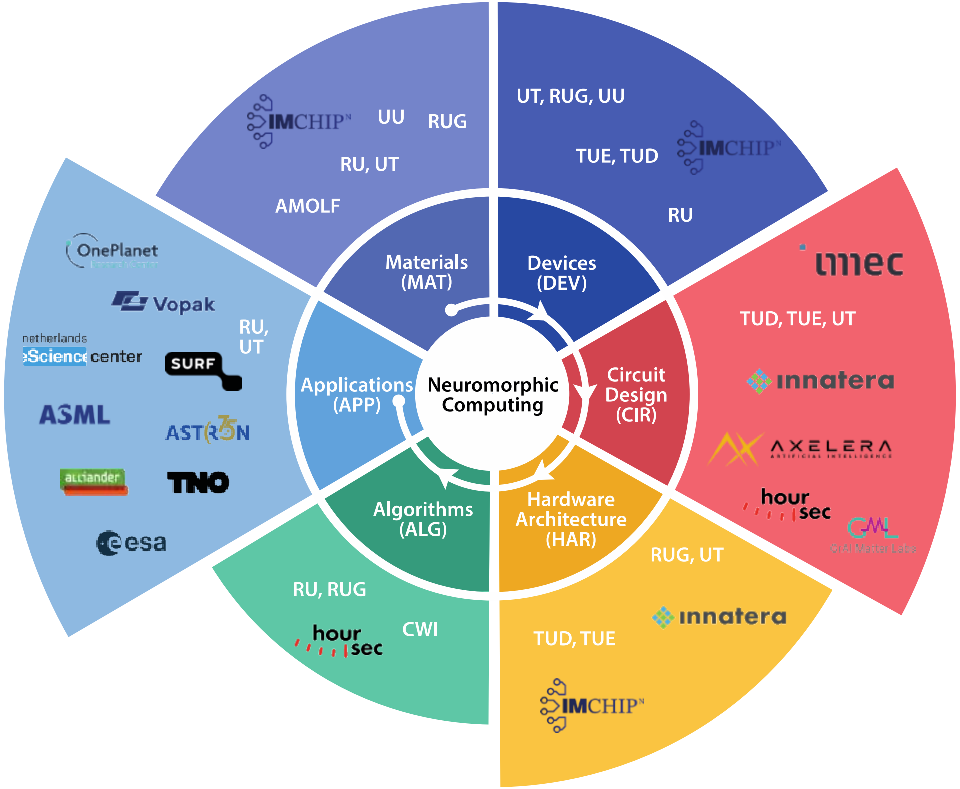
Algorithms
Sander Bothe (CWI)
Herbert Jaeger (RUG)

Architectures
Georgi Gaydadjiev (TUD)
Said Hamdioui (TUD)

Optical neuromorphic computing
Femius Koenderink (AMOLF)
Patty Stabile (TUE)

+ long list of all neuromorphic experts

Current position the Netherlands



Towards Neuromorphic Alliance

- Ecosystem governance
  - Technical roadmap development NL
  - organising the field

- Market-driven Application Lab

- Prototyping facility for Emerging Technology