

Quantum State Reconstruction with Artificial and Spiking Neural Networks

Stefanie Czischek

AMLD 2022

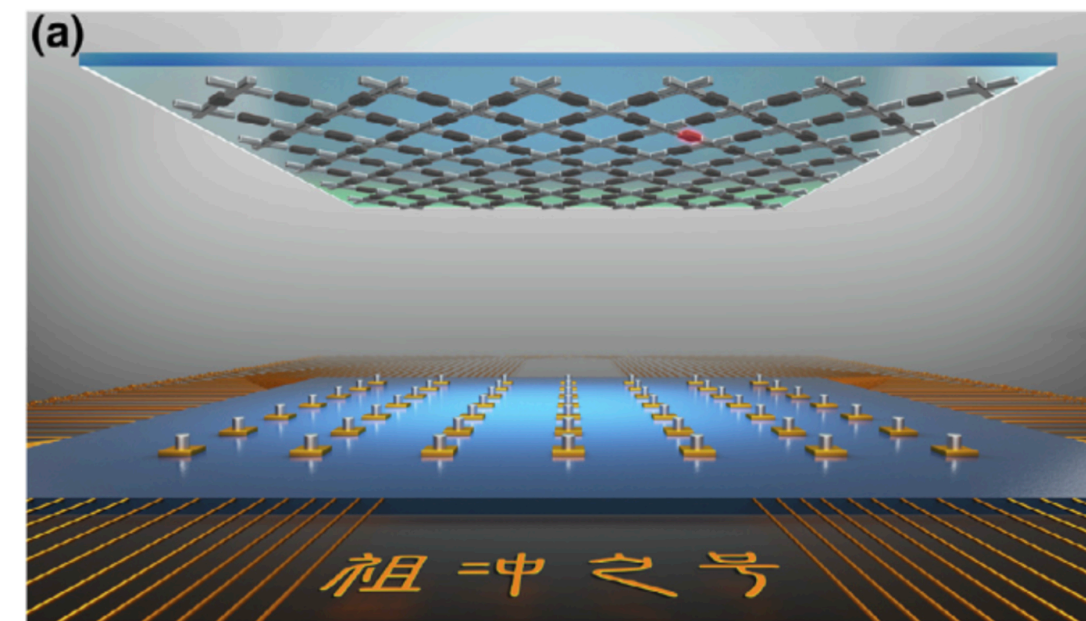
March 29, 2022



Quantum Computation and Simulation

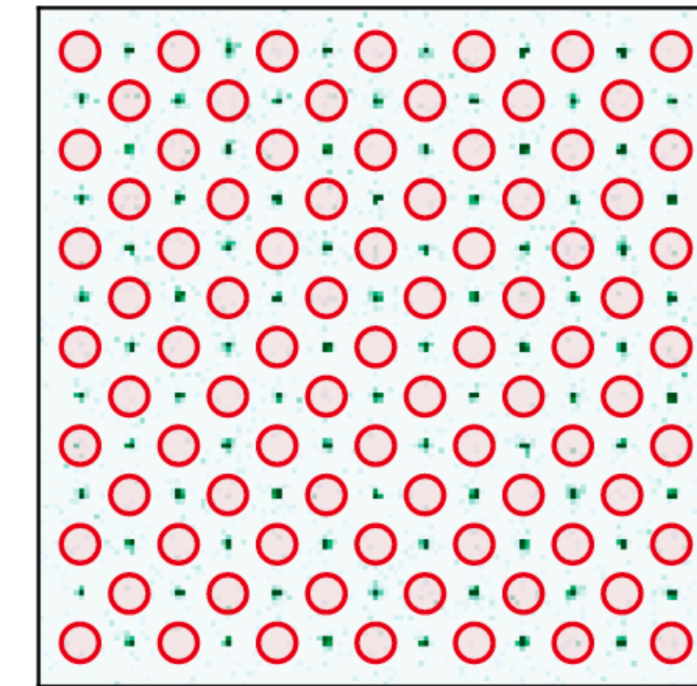
- Growing number of qubits
- Precise control
- Individual addressing
- High-quality preparation of target quantum states

Superconductors



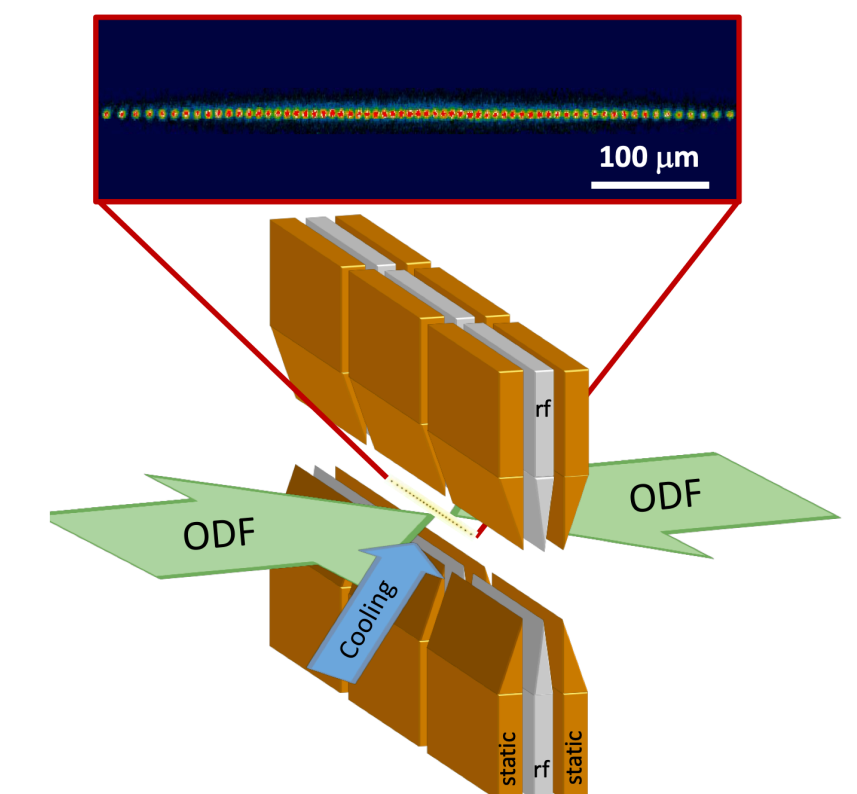
[Q. Zhu et al., Science Bulletin 67 (2022)]

Rydberg atoms



[S. Ebadi et al., Nature 595 (2021)]

Trapped ions



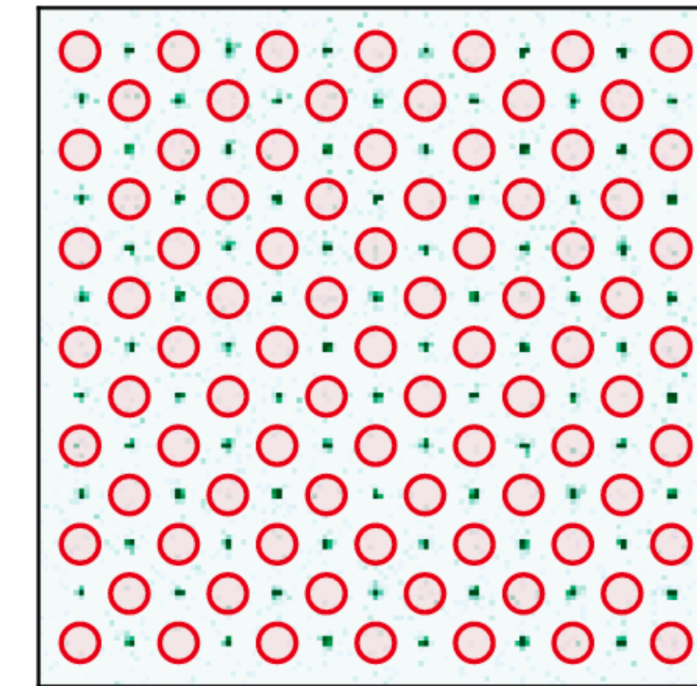
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Quantum Computation and Simulation

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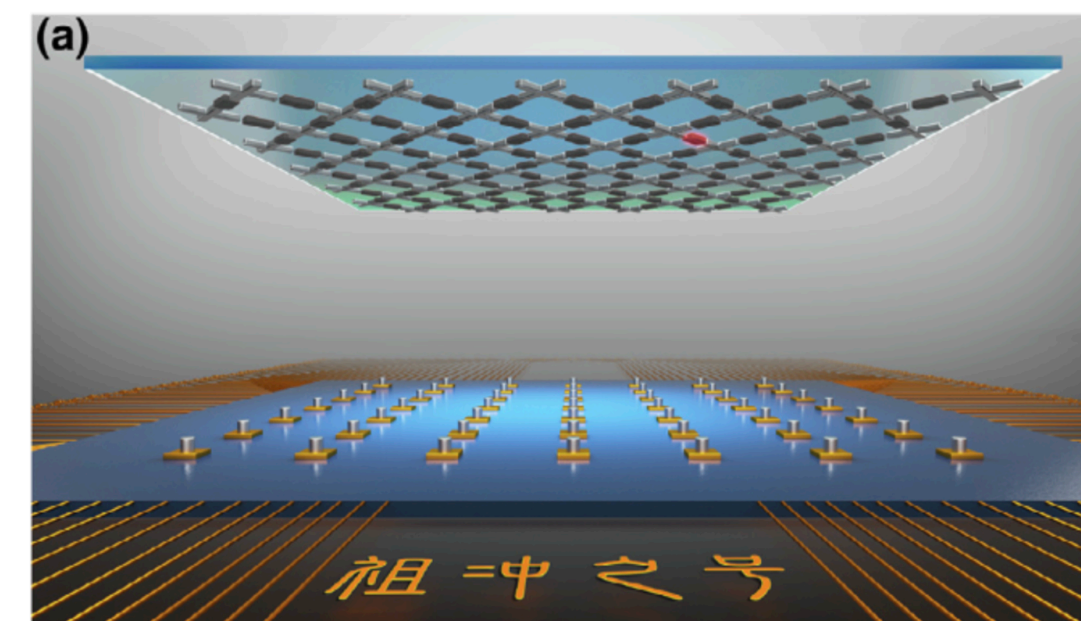
What can we do with those prepared states?

Rydberg atoms



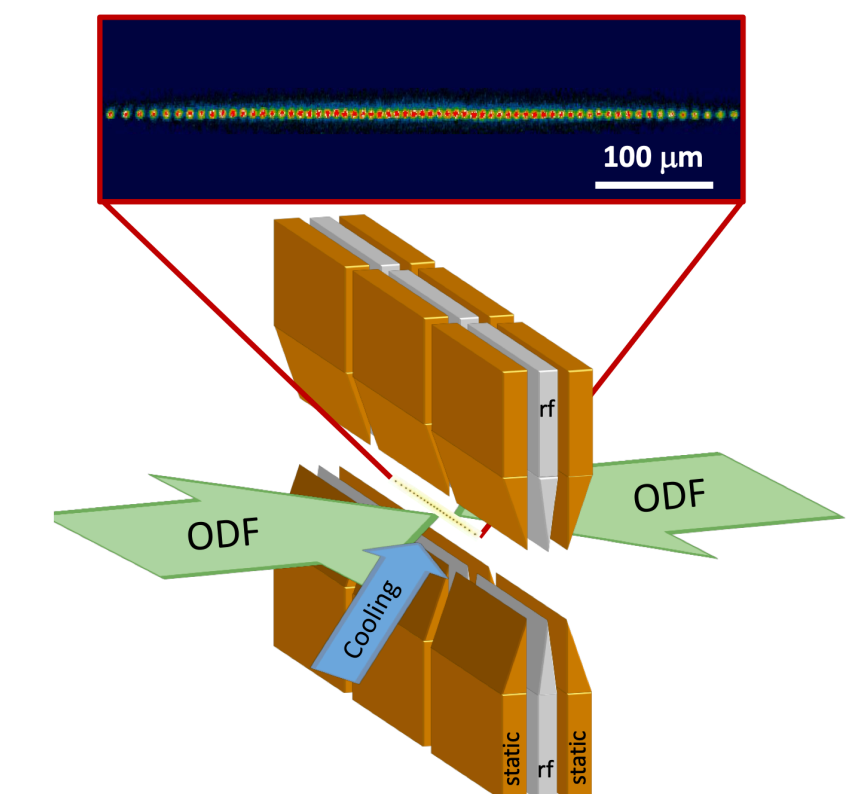
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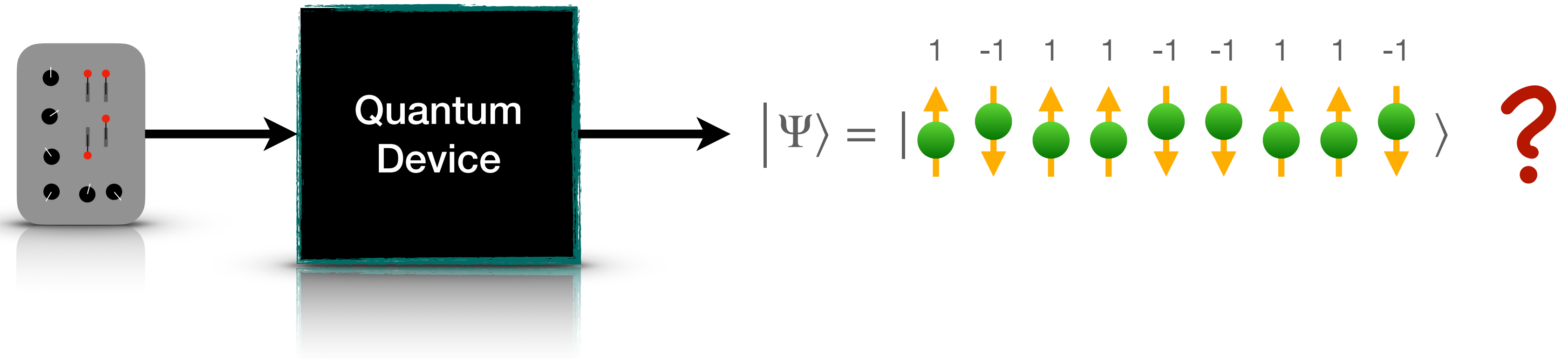
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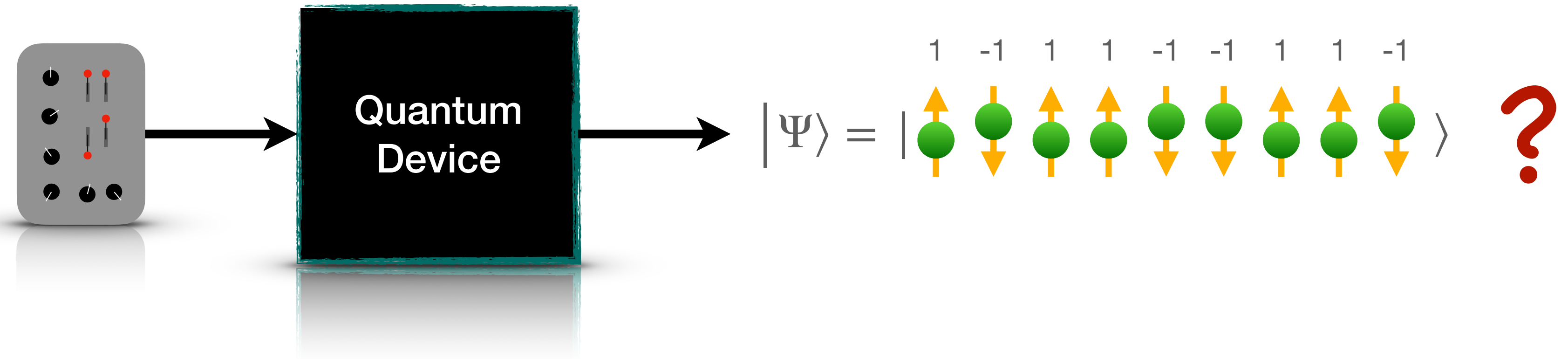
Quantum State Reconstruction



- Perform limited amount of measurements
- Tomographically reconstruct quantum state
 - Generate more measurement data

[G. Torlai et al., PRR 2 (2020)]

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Generally:

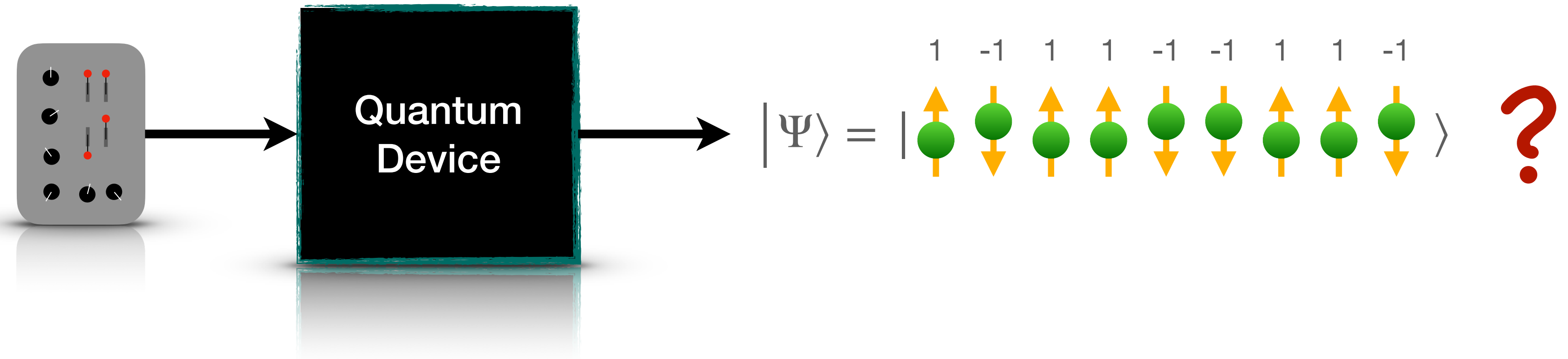
$$|\Psi\rangle = \sum_{\{\varphi\}} \Psi(\varphi) |\varphi\rangle \in \mathbb{C}^{2^N} \quad \Psi(\varphi) \in \mathbb{C}$$

(wavefunction) (amplitude)

$$\varphi \in \{(-1, -1, \dots, -1), (-1, -1, \dots, -1, 1), \dots, (1, 1, \dots, 1)\}$$

(basis states)

Quantum State Reconstruction



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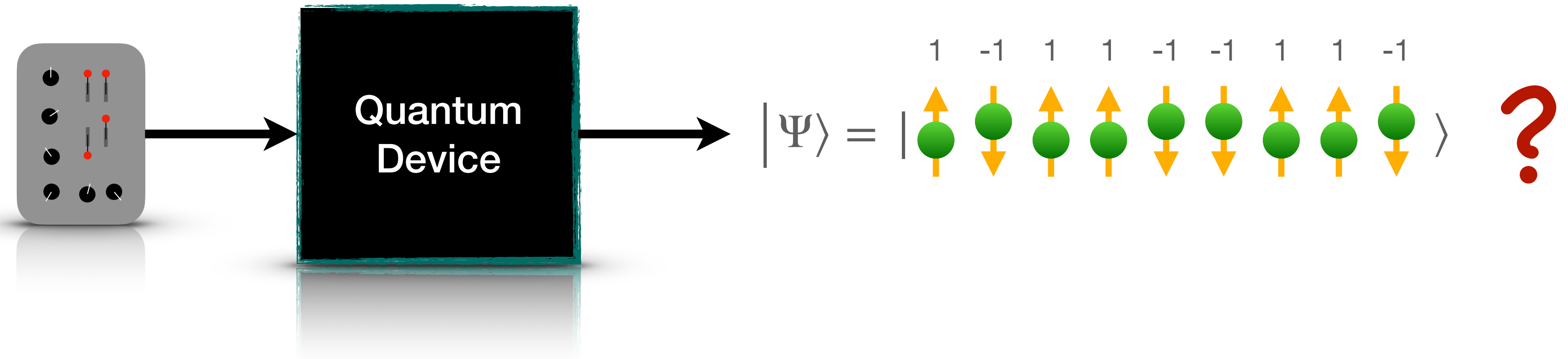
(basis states)

Measurements:

$$\langle \mathcal{O} \rangle = \langle \Psi | \mathcal{O} | \Psi \rangle \quad \langle \mathcal{O} \rangle = \sum_{\{\varphi, \tilde{\varphi}\}} \langle \varphi | \mathcal{O} | \tilde{\varphi} \rangle \Psi(\tilde{\varphi}) \Psi(\varphi)^*$$

$$\langle \mathcal{O}_{\text{diag}} \rangle = \sum_{\{\varphi\}} \mathcal{O}_{\text{diag}}(\varphi) \Psi(\varphi) \Psi(\varphi)^*$$

Quantum State Reconstruction



- Perform limited amount of measurements
- Tomographically reconstruct quantum state
 - Generate more measurement data
- Find efficient expression for $\Psi(\varphi)$

[G. Torlai et al., PRR 2 (2020)]

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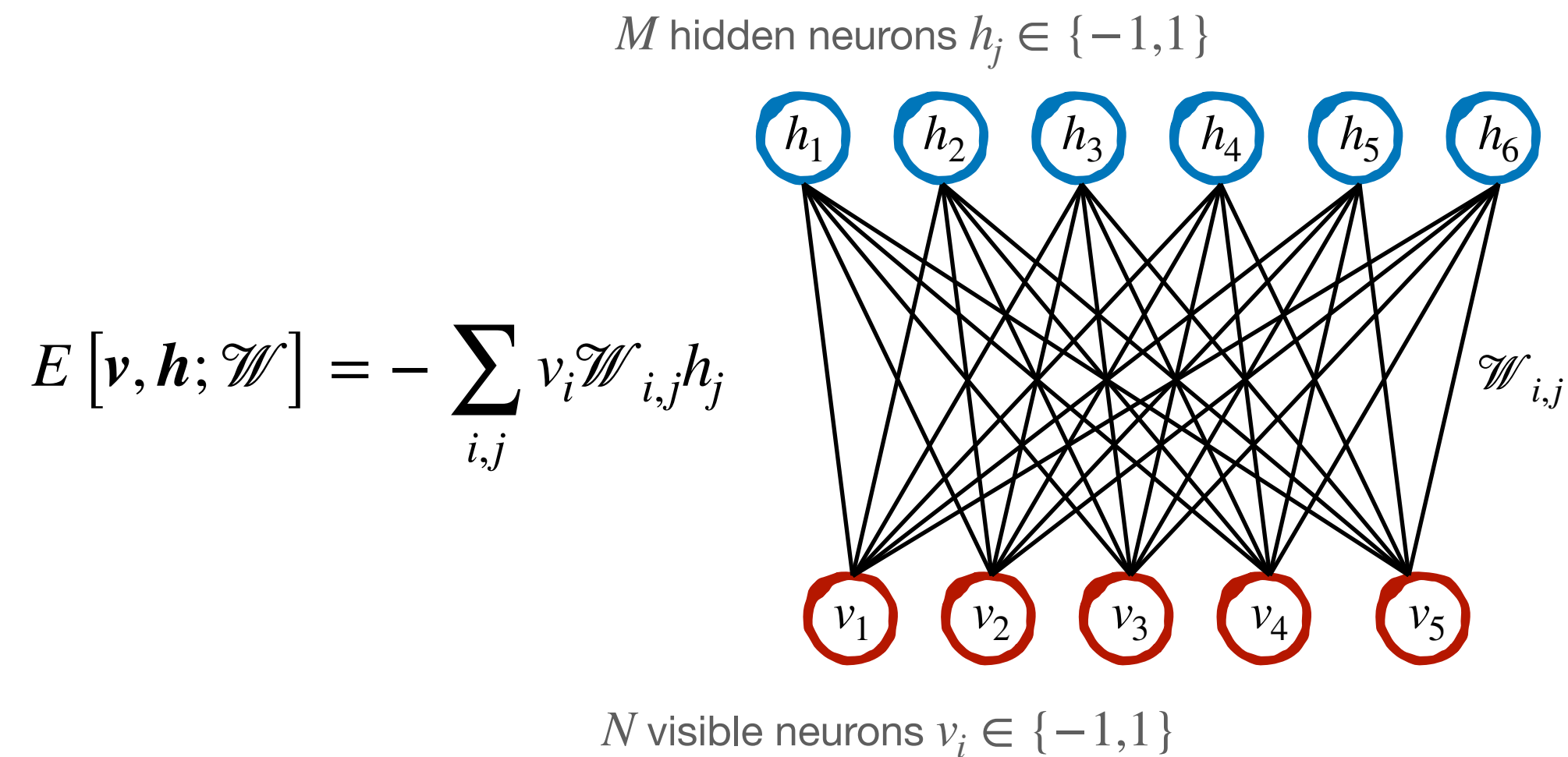
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Quantum State Reconstruction with ANNs

Restricted Boltzmann machine 🐙

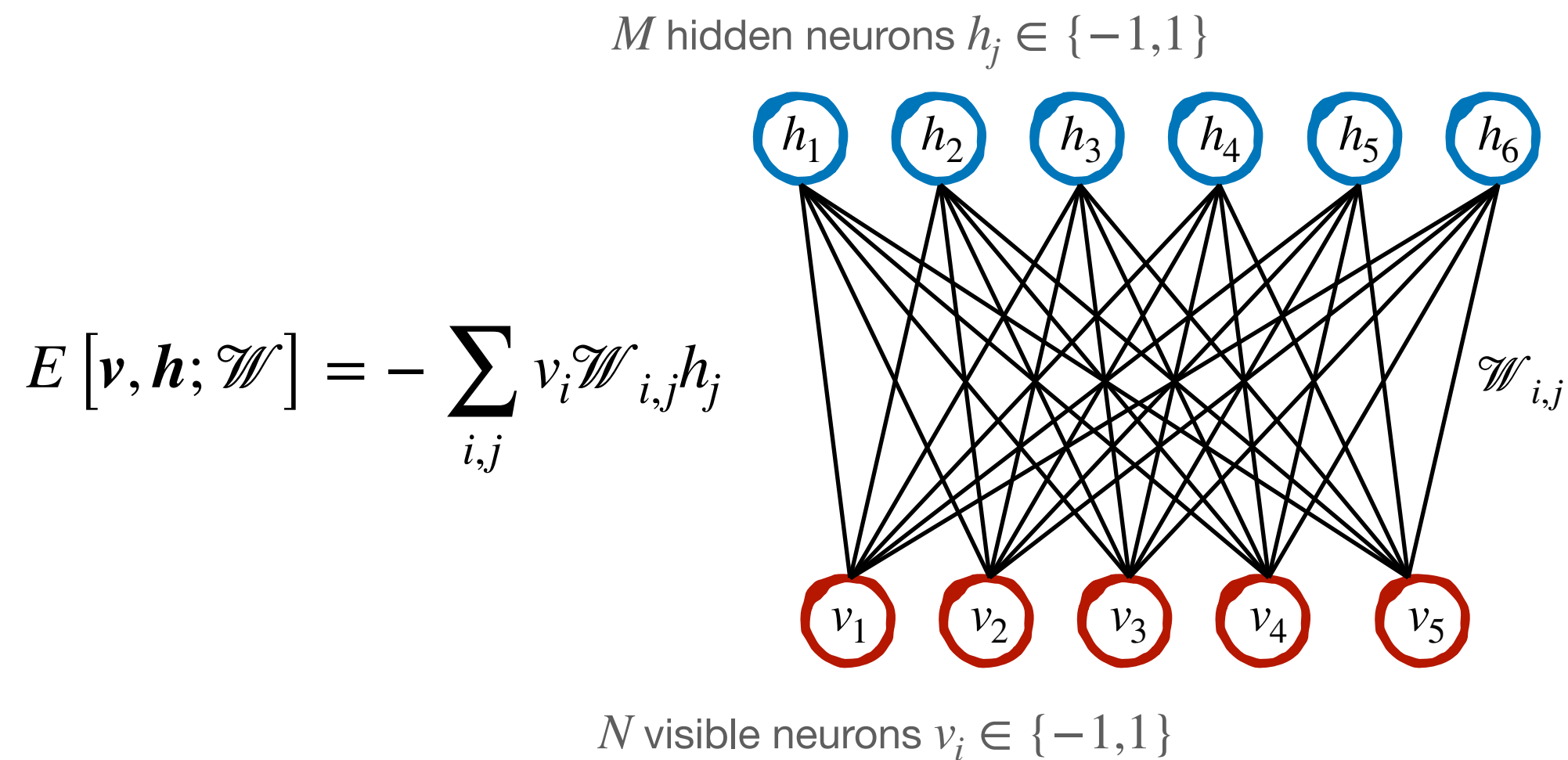


$$P_{\mathcal{W}}[\mathbf{v}, \mathbf{h}] = \frac{1}{Z(\mathcal{W})} e^{-E[\mathbf{v}, \mathbf{h}; \mathcal{W}]}$$

$$Z(\mathcal{W}) = \sum_{\{\mathbf{v}\}, \{\mathbf{h}\}} e^{-E[\mathbf{v}, \mathbf{h}; \mathcal{W}]} \quad P_{\mathcal{W}}[\mathbf{v}] = \sum_{\{\mathbf{h}\}} P_{\mathcal{W}}[\mathbf{v}, \mathbf{h}]$$

Quantum State Reconstruction with ANNs

Restricted Boltzmann machine 🐙



$$E[\mathbf{v}, \mathbf{h}; \mathcal{W}] = - \sum_{i,j} v_i \mathcal{W}_{i,j} h_j$$

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Quantum state

$$|\Psi\rangle = | \uparrow \downarrow \uparrow \uparrow \downarrow \downarrow \uparrow \uparrow \downarrow \rangle$$

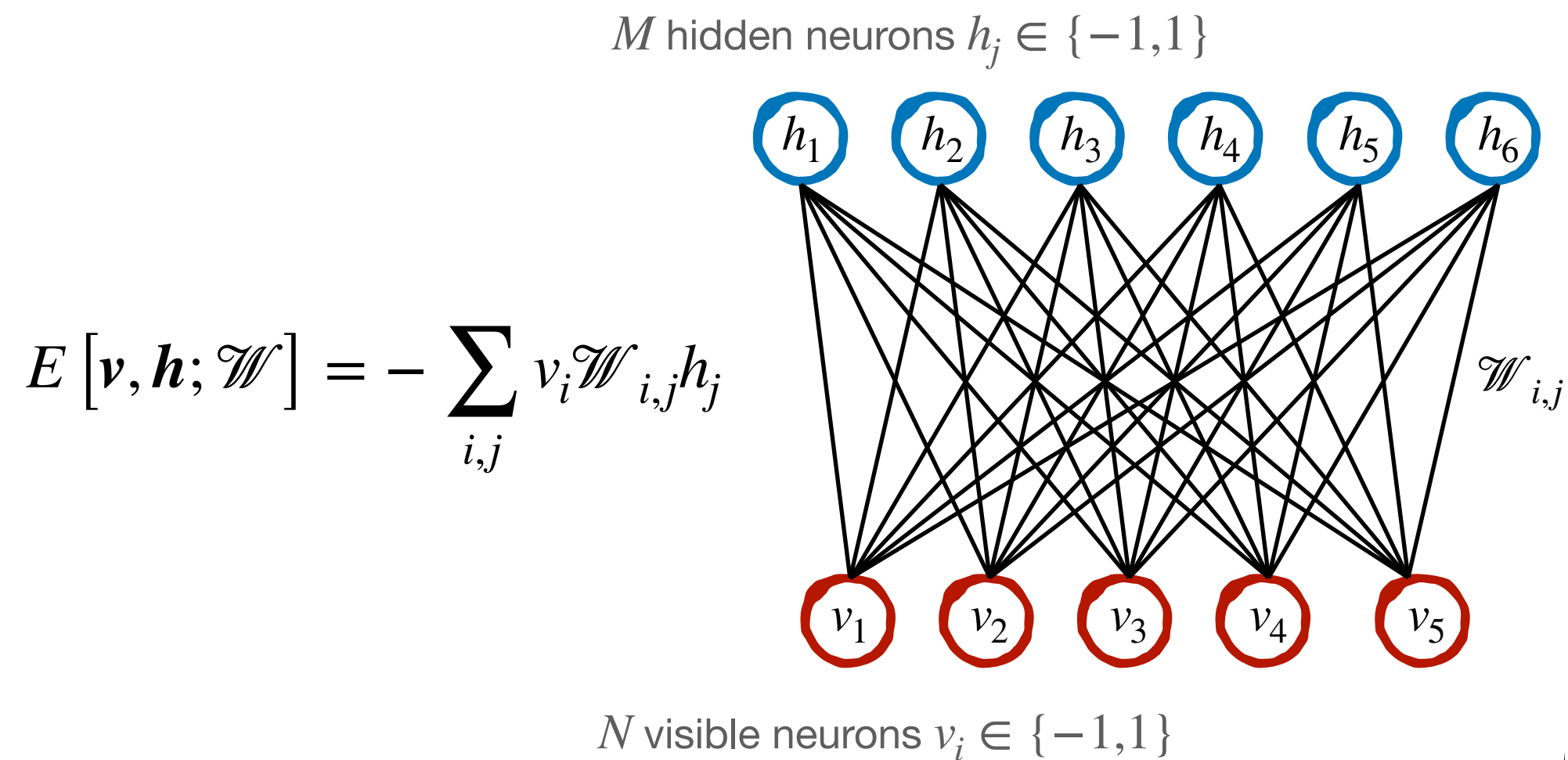
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$$\langle \mathcal{O}_{\text{diag}} \rangle = \sum_{\{\varphi\}} \mathcal{O}_{\text{diag}}(\varphi) \Psi(\varphi) \Psi(\varphi)^* = \sum_{\{\varphi\}} \mathcal{O}_{\text{diag}}(\varphi) |\Psi(\varphi)|^2$$

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Train the restricted Boltzmann machine such that

$$P_{\mathcal{W}}[\mathbf{v}] \approx \Psi(\mathbf{v}) \Psi(\mathbf{v})^*$$

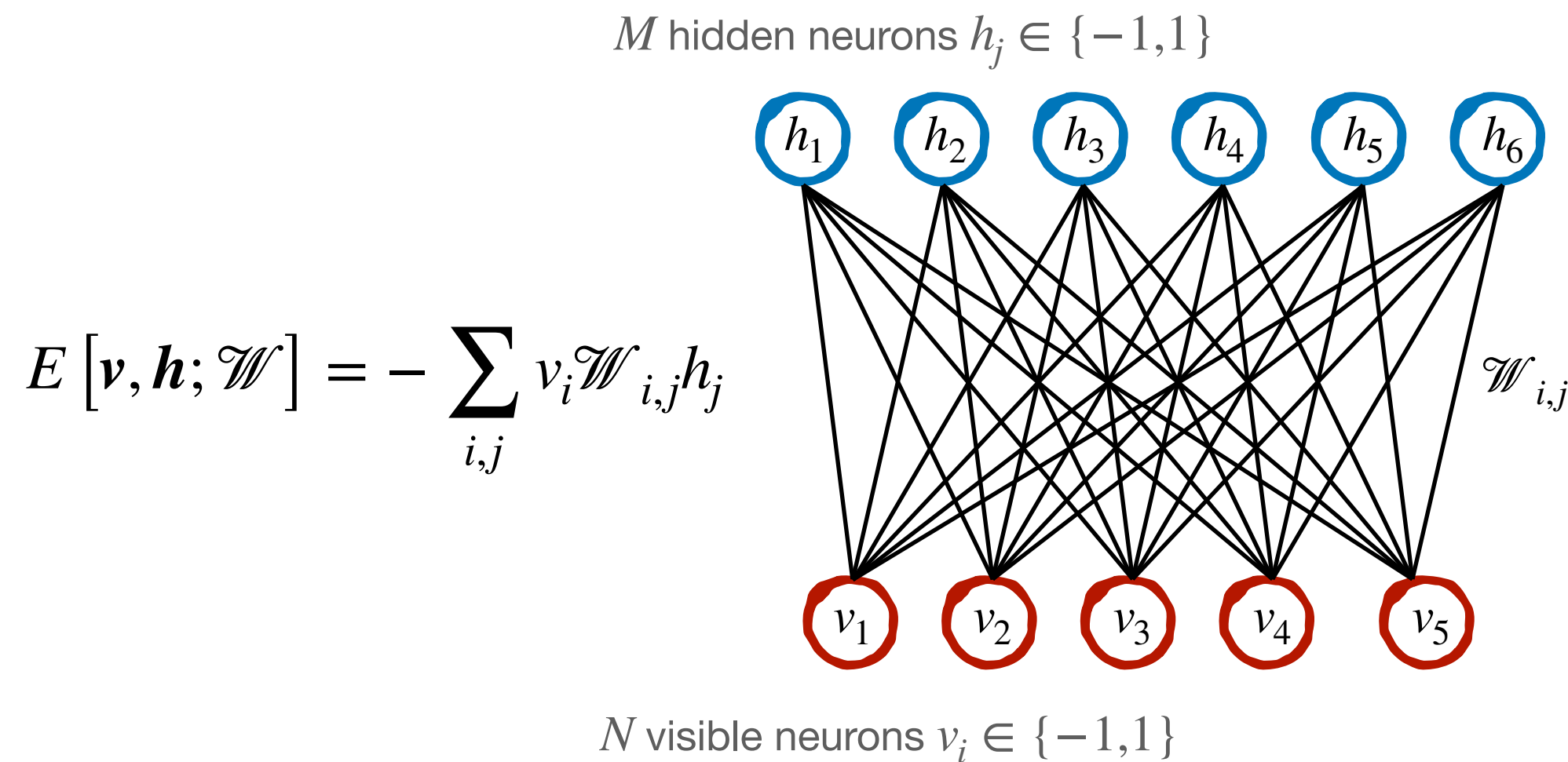
Full information only if

$$\text{Im}[\Psi(\mathbf{v})] = 0 \quad \forall \mathbf{v}$$

Quantum State Reconstruction with ANNs

Restricted Boltzmann machine 🐙

Quantum state



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True for stoquastic Hamiltonians
(e.g. Rydberg atoms)

[SC et al., arXiv:2203.04988 (2022)]

[J. Carrasquilla and G. Torlai, PRX Quantum 2 (2021)]

$$\hat{H} = \begin{pmatrix} d & -|o\rangle & -|o\rangle & -|o\rangle \\ -|o\rangle & d & -|o\rangle & -|o\rangle \\ -|o\rangle & -|o\rangle & d & -|o\rangle \\ -|o\rangle & -|o\rangle & -|o\rangle & d \end{pmatrix}$$

Otherwise modify the network architecture

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[G. Torlai, R.G. Melko, PRL 120 (2018)] [G. Carleo, M. Troyer, Science 355 (2017)]

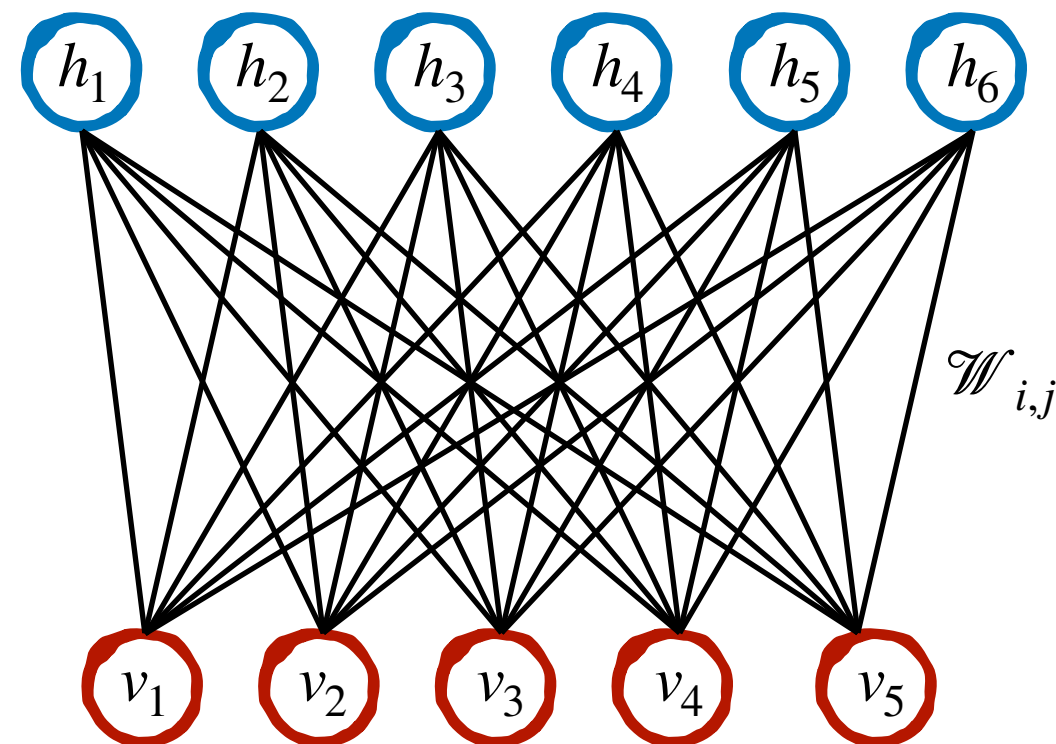
Quantum State Reconstruction with ANNs

Restricted Boltzmann machine 

Efficient approximation on spiking neuromorphic hardware!

[M. Petrovici et al., BMC Neurosci 16 (2015)]

M hidden neurons $h_j \in \{-1, 1\}$



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Quantum state

$$|\Psi\rangle = | \begin{array}{ccccccccc} \uparrow & \downarrow & \uparrow & \uparrow & \downarrow & \downarrow & \uparrow & \uparrow & \downarrow \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \end{array} \rangle$$

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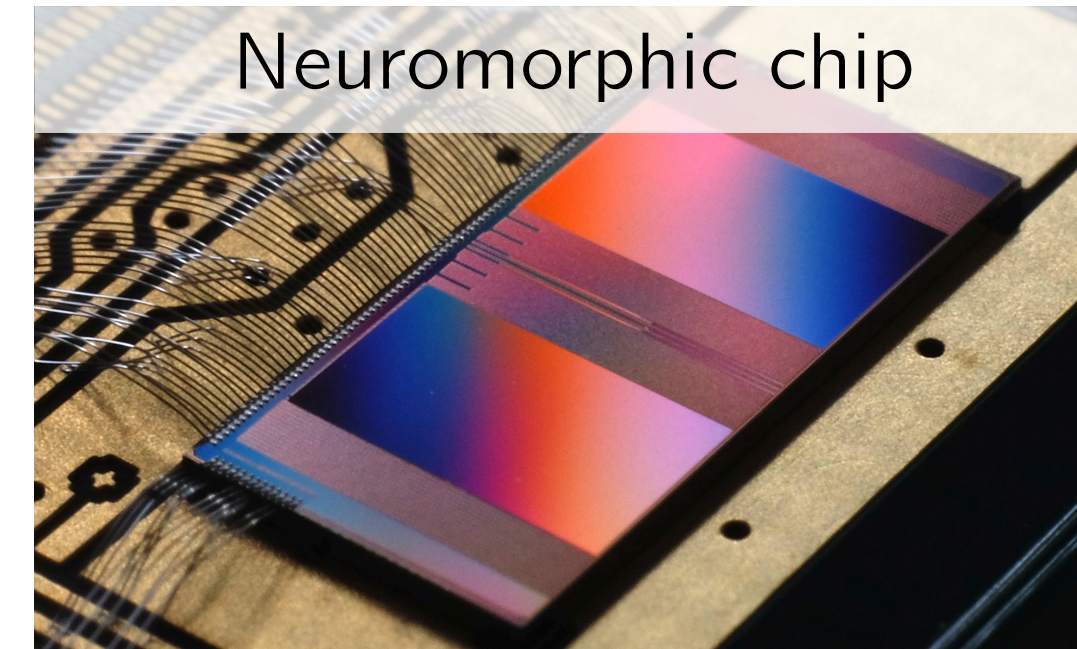
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Spiking Neuromorphic Hardware

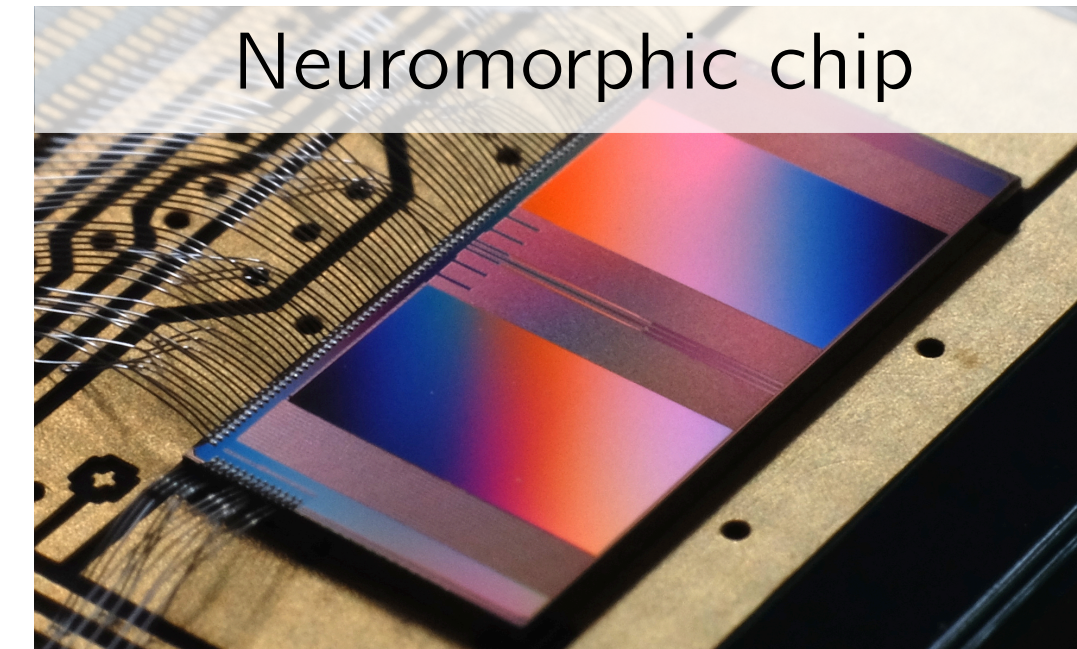


BrainScaleS
ScaleS

- Biological neural networks:
Fast and energy-efficient
- Dynamical behaviour

- Capture biological properties
- Analog electronic circuits for
efficient emulation
- BrainScaleS (Heidelberg University)
- SpiNNaker (University of Manchester)
- Loihi (Intel)

Spiking Neuromorphic Hardware



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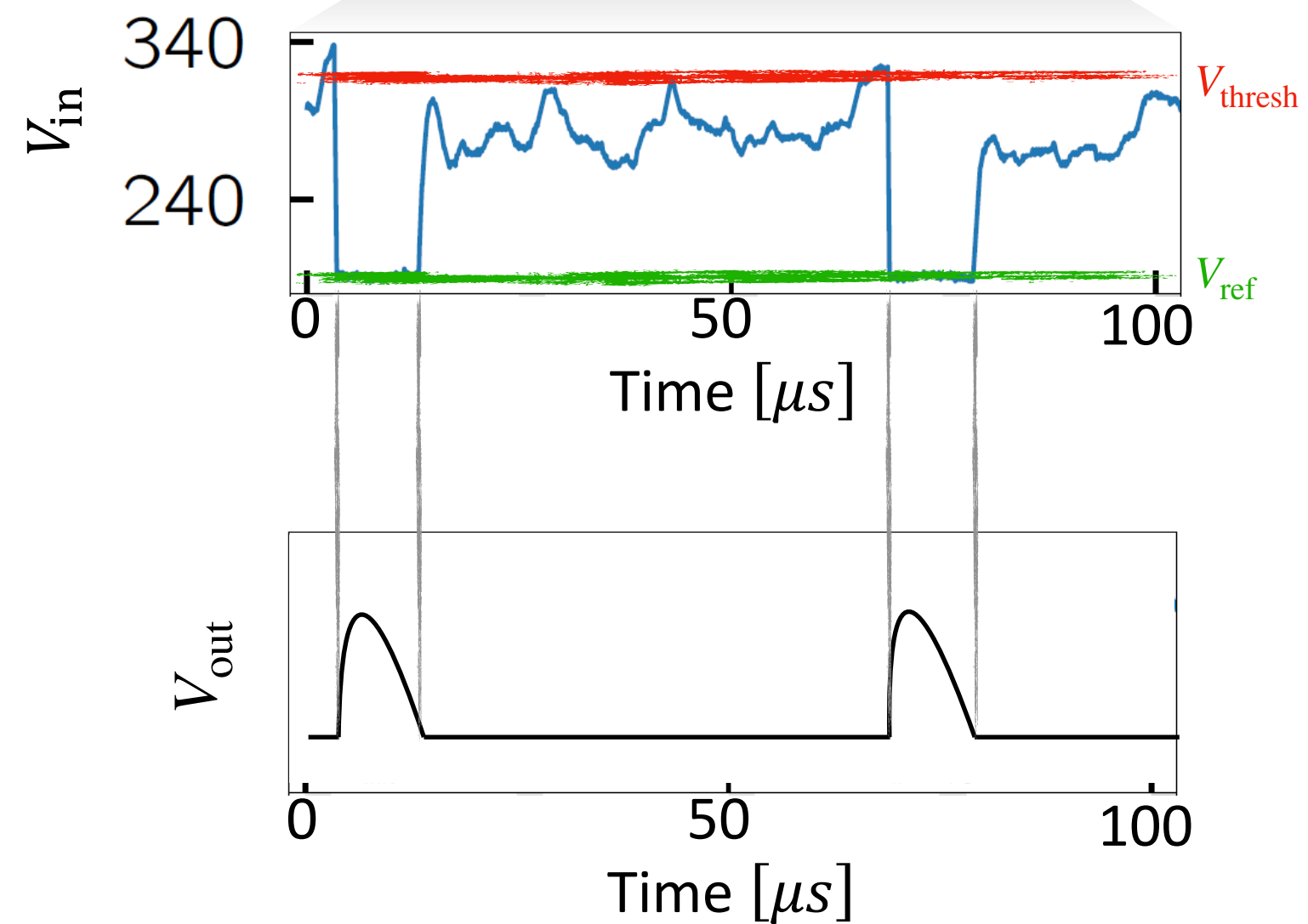
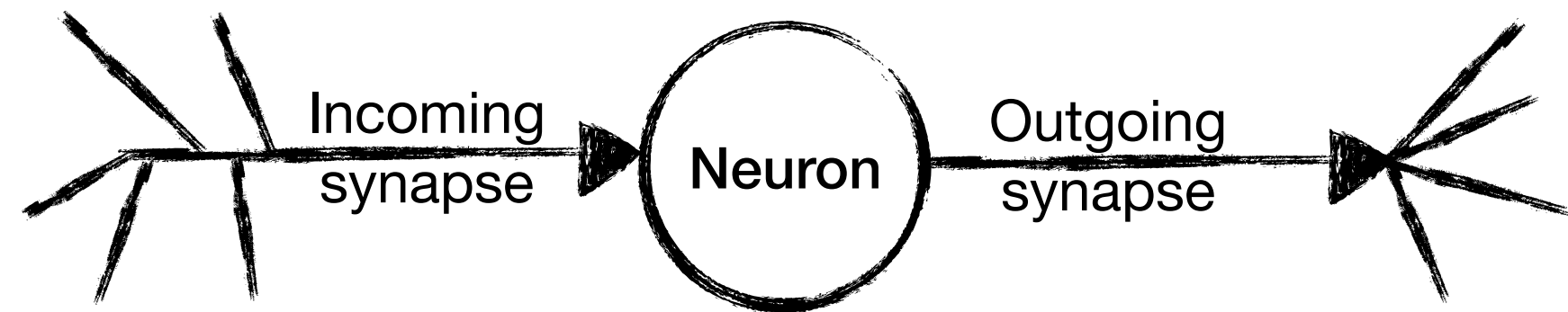
- Biological neural networks:
Fast and energy-efficient
- Dynamical behaviour

Quantum state reconstruction with
neuromorphic hardware:

- Generate a huge amount of data
- Integrate small chips in experimental setup

- Capture biological properties
- Analog electronic circuits for
efficient emulation
- BrainScaleS (Heidelberg University)
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Spiking Neurons



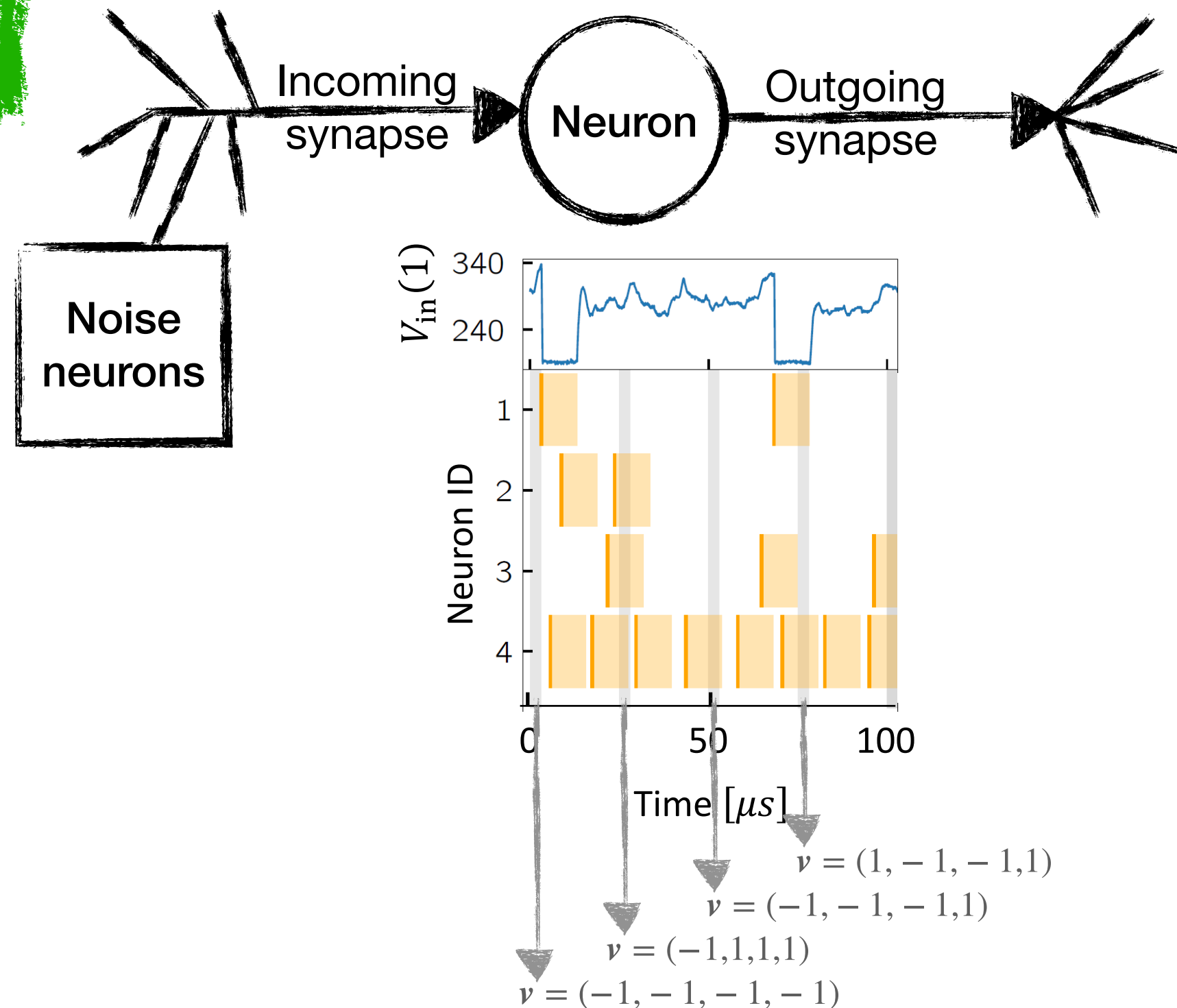
$$V_{in}(i) \propto \sum_j V_{out}(j) W_{i,j}$$

- Leaky Integrate-and-Fire (LIF) neurons mimic biological neurons
- Potential V_{in} evolves in time
- V_{thresh} : neuron sends out spike V_{out} and becomes refractory
- Neuron connections are weighted and trained

Sampling with Spiking Neurons

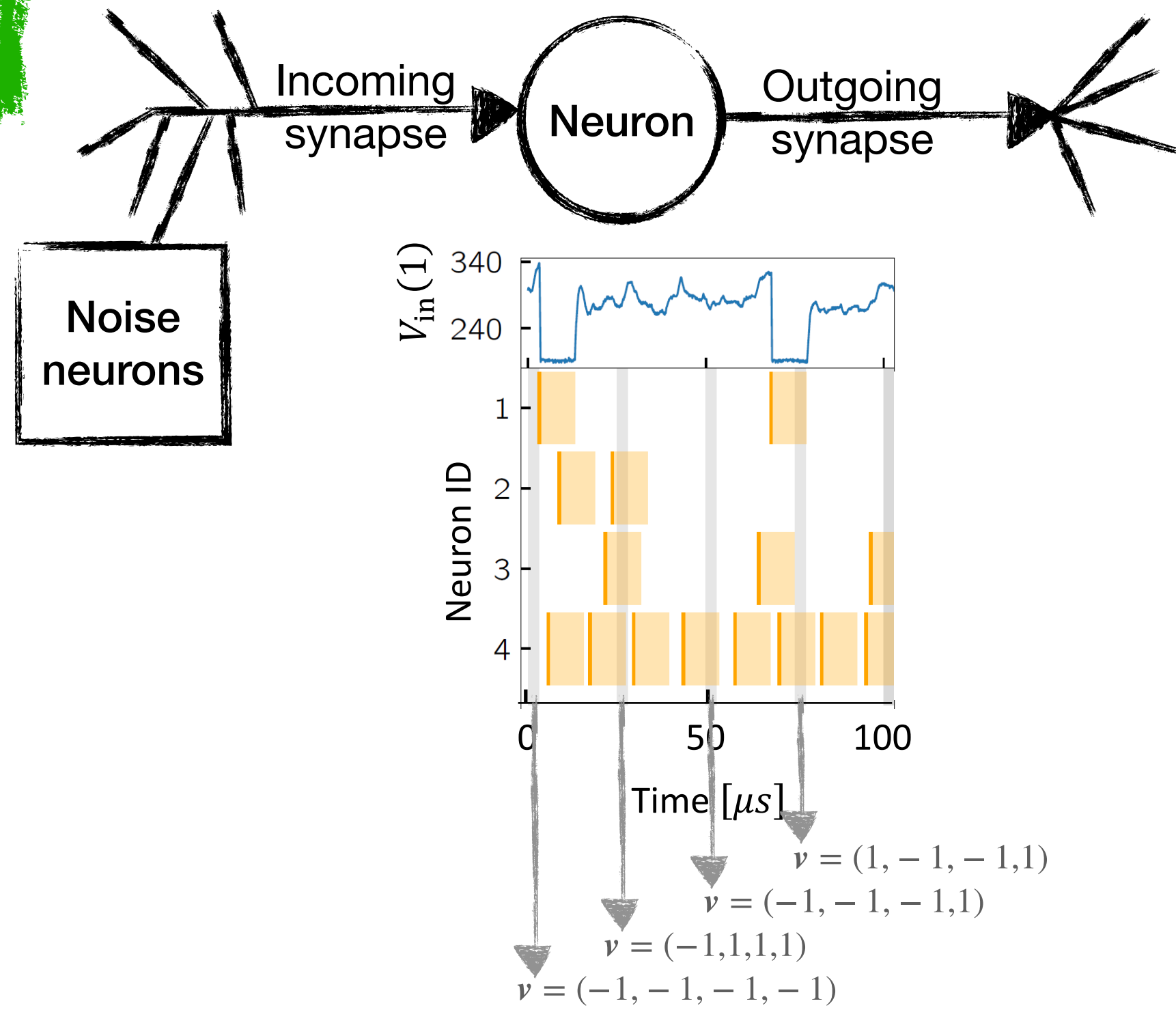
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[SC et al., SciPost Physics **12** (2022)]

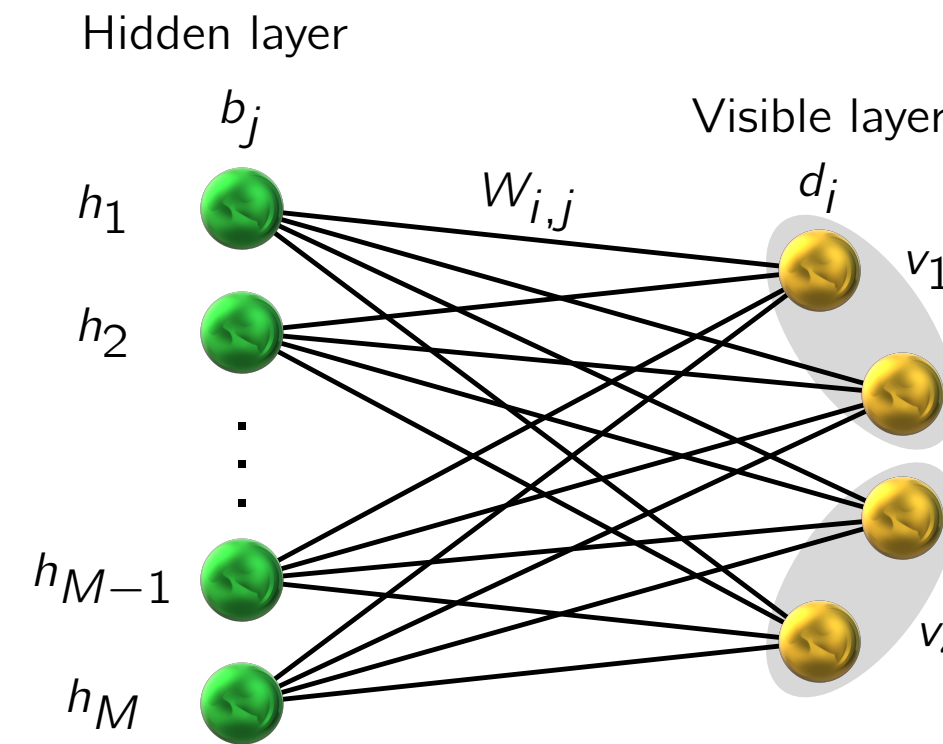


- Two neuron states: refractory or not
- Add noise neurons for stochasticity
- Read neuron states as samples

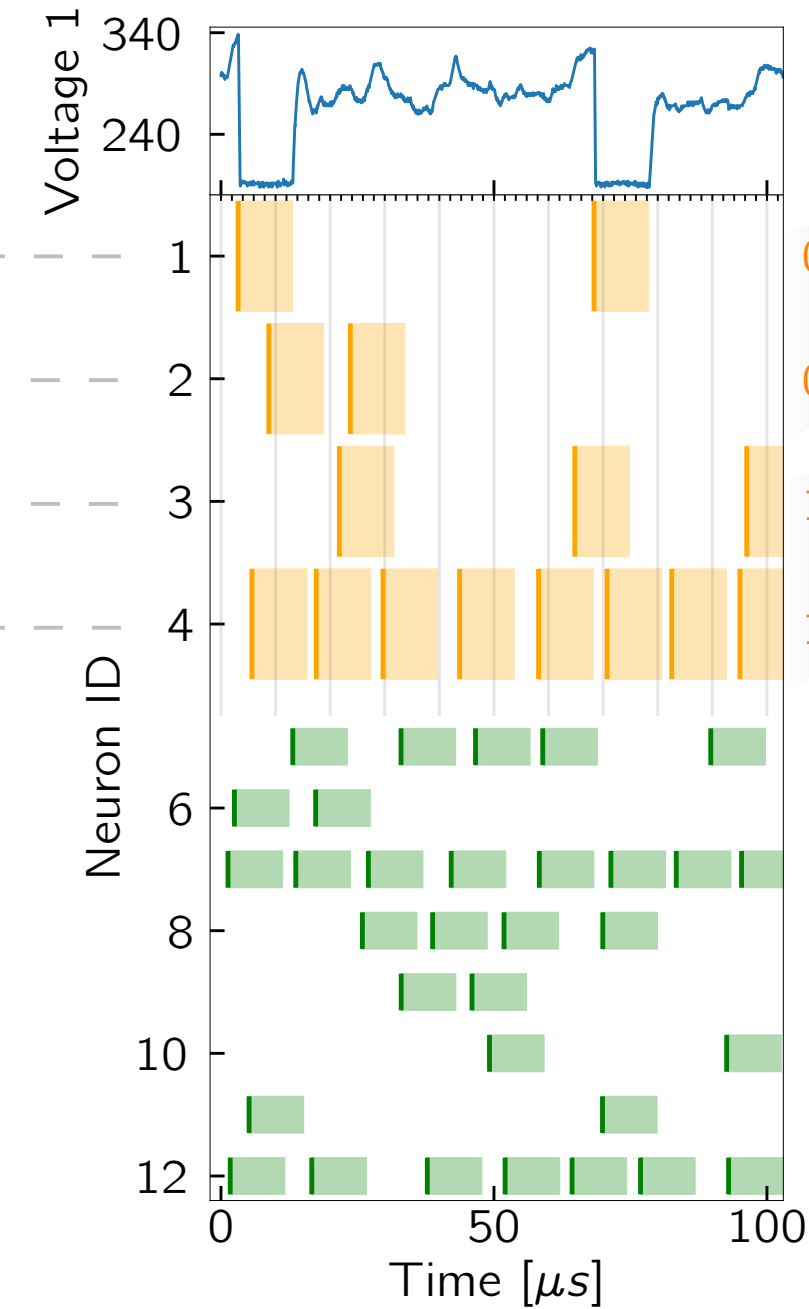
Sampling with Spiking Neurons



Network structure

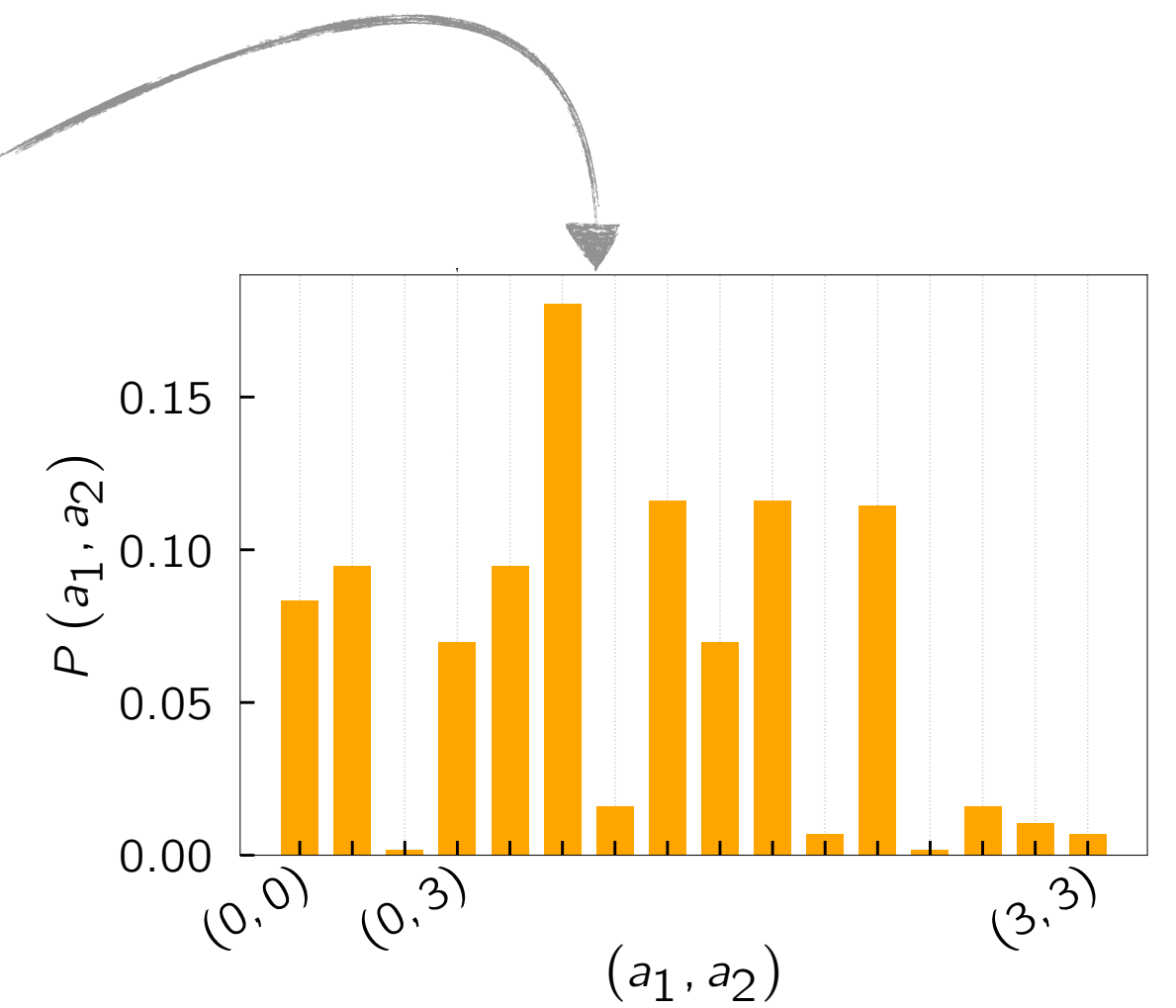


Spiking neurons



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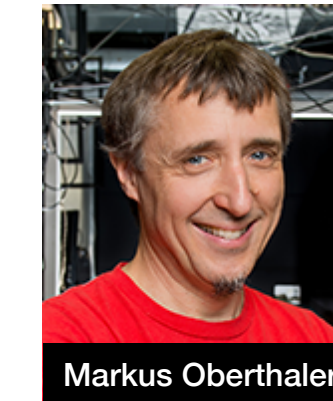
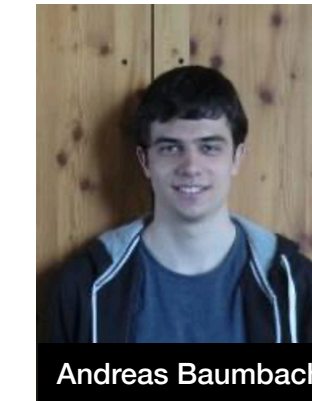
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- Neuron configurations approximate Boltzmann distribution
 - Simulate an RBM

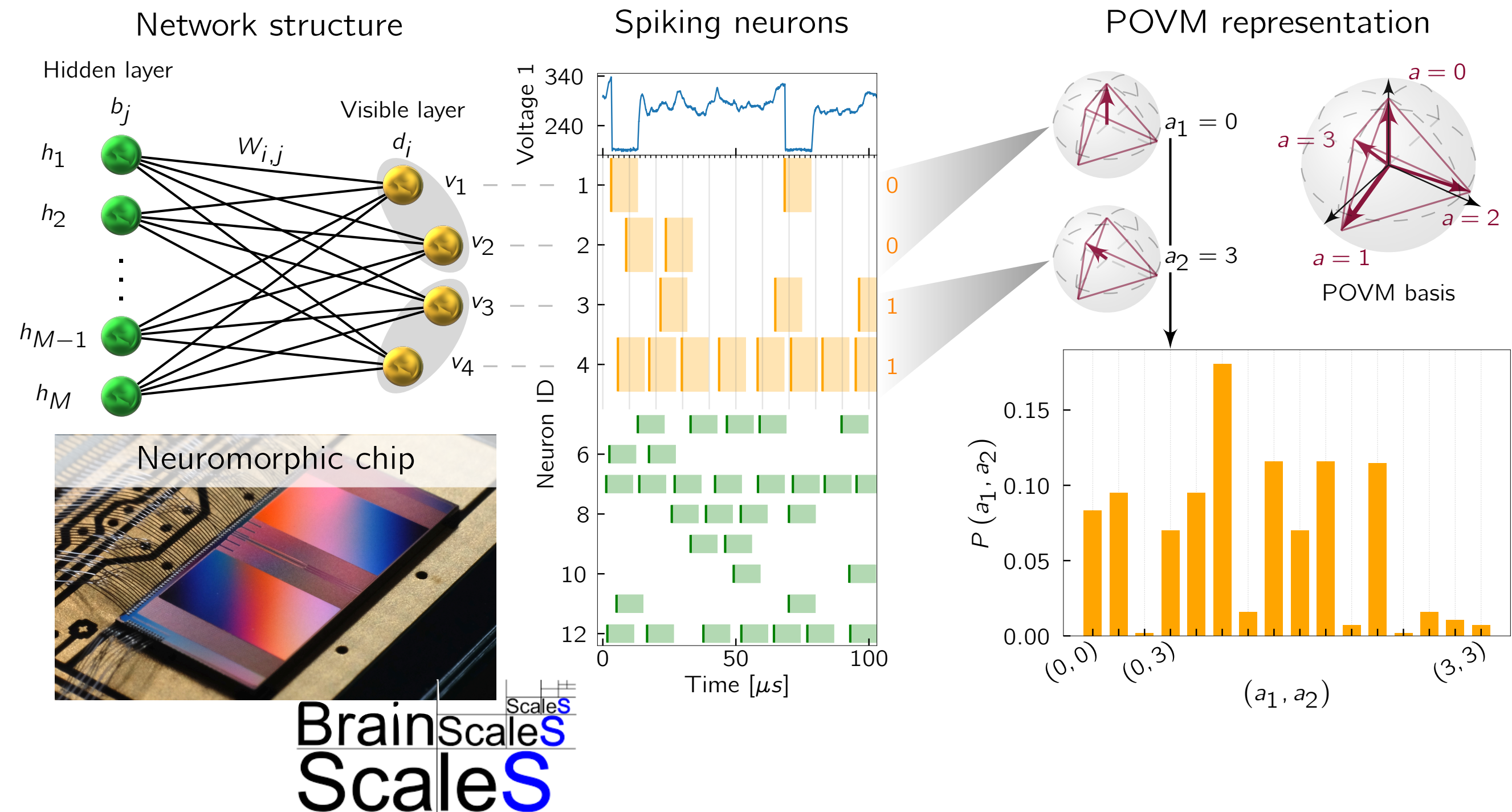
Bell State Reconstruction



[SC et al., SciPost Physics 12 (2022)]

- Train BrainScaleS-2 chip to reconstruct Bell state
- Sample every $2\mu\text{s}$

$$|\Psi\rangle = \frac{1}{\sqrt{2}} \left[| \uparrow \uparrow \rangle + | \downarrow \downarrow \rangle \right]$$



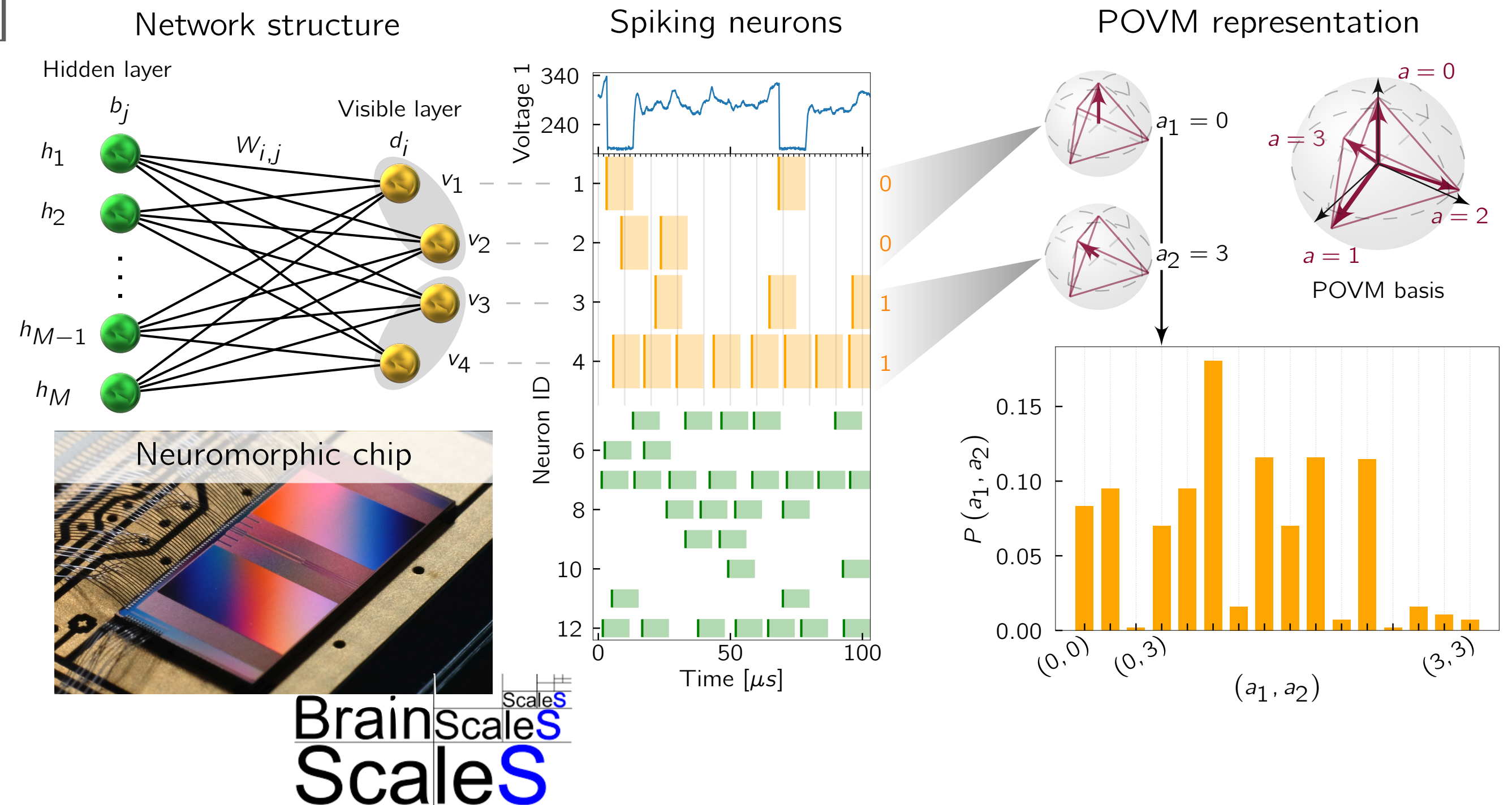
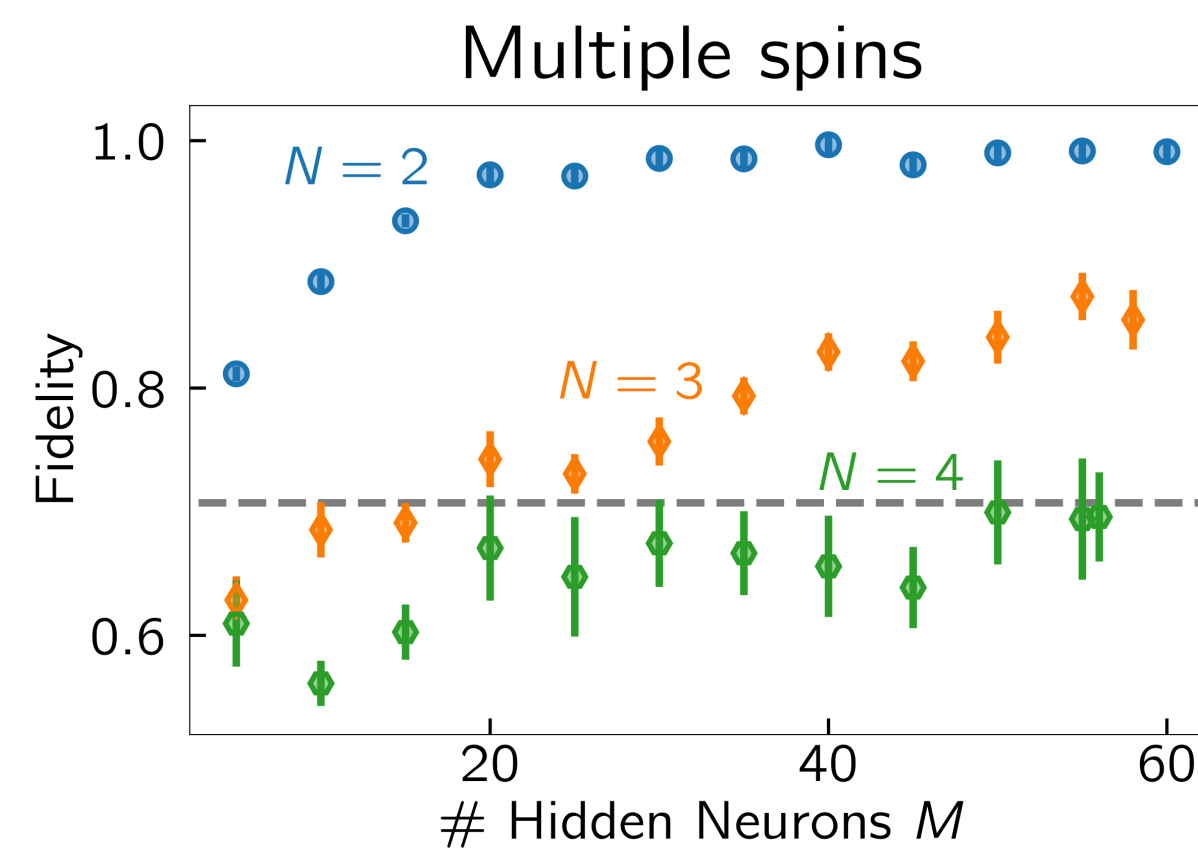
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[SC et al., SciPost Physics 12 (2022)]

- Train BrainScaleS-2 chip to reconstruct Bell state
- Sample every $2\mu\text{s}$
- High fidelities $\mathcal{F}(\rho_T, \rho_R) = \text{Tr} \left[\sqrt{\sqrt{\rho_T} \rho_R \sqrt{\rho_T}} \right]$
- Limited for larger system sizes

$$|\Psi\rangle = \frac{1}{\sqrt{2}} \left[| \uparrow \uparrow \rangle + | \downarrow \downarrow \rangle \right]$$



Summary

- Quantum state reconstruction
 - Based on measurement data
- Spiking neuromorphic hardware
 - Accelerate sampling
 - Requires many neurons
- Develop more suitable approach

