

Neural Network Applications in Many-Body Quantum Physics

Moritz Reh, Tobias Schmale, Robert Klassert, Martin Gärtner

Kirchhoff-Institut für Physik, Universität Heidelberg, Im Neuenheimer Feld 227, 69120 Heidelberg



Synthetic Quantum Systems



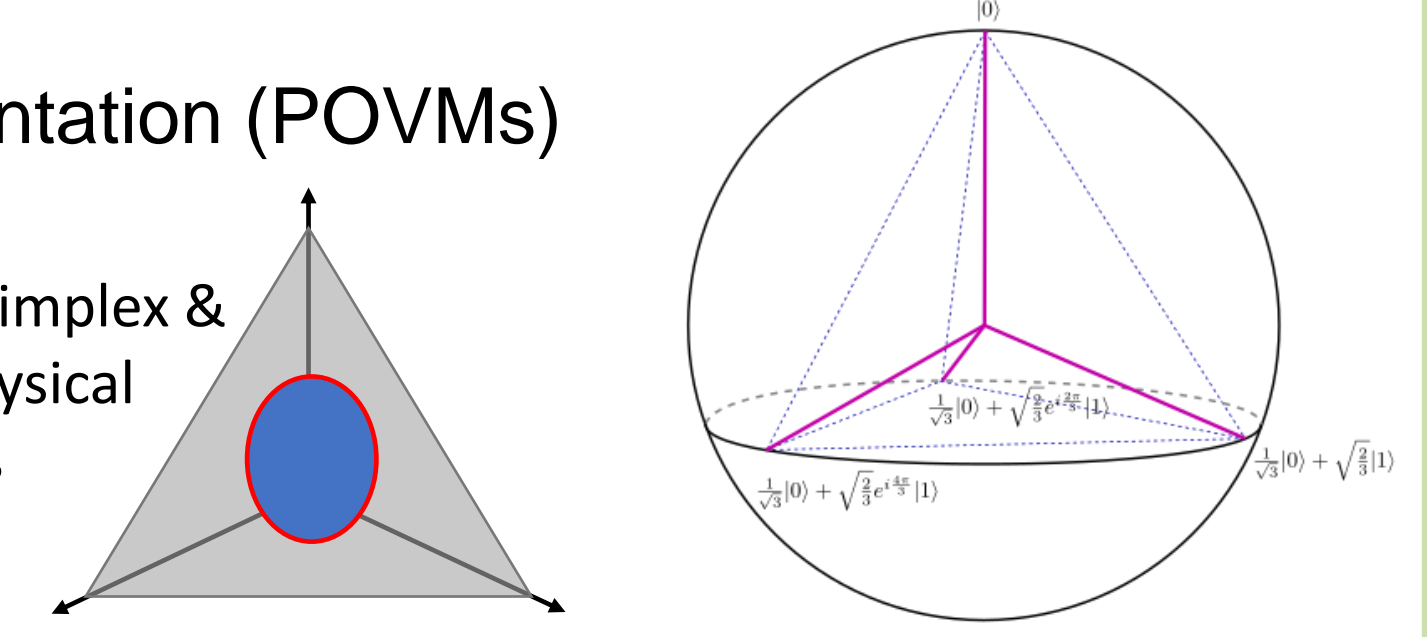
DFG Deutsche Forschungsgemeinschaft

Motivation

- The quantum state ρ of a many-body system is an object whose complexity scales exponentially in the particle number N
- In many cases, the quantum state of interest has a lot of structure and can be described with fewer parameters
- Here, Artificial Neural Networks (ANNs) can be used to parameterize the state. Their generalization properties are well established, e.g. for images (MNIST).

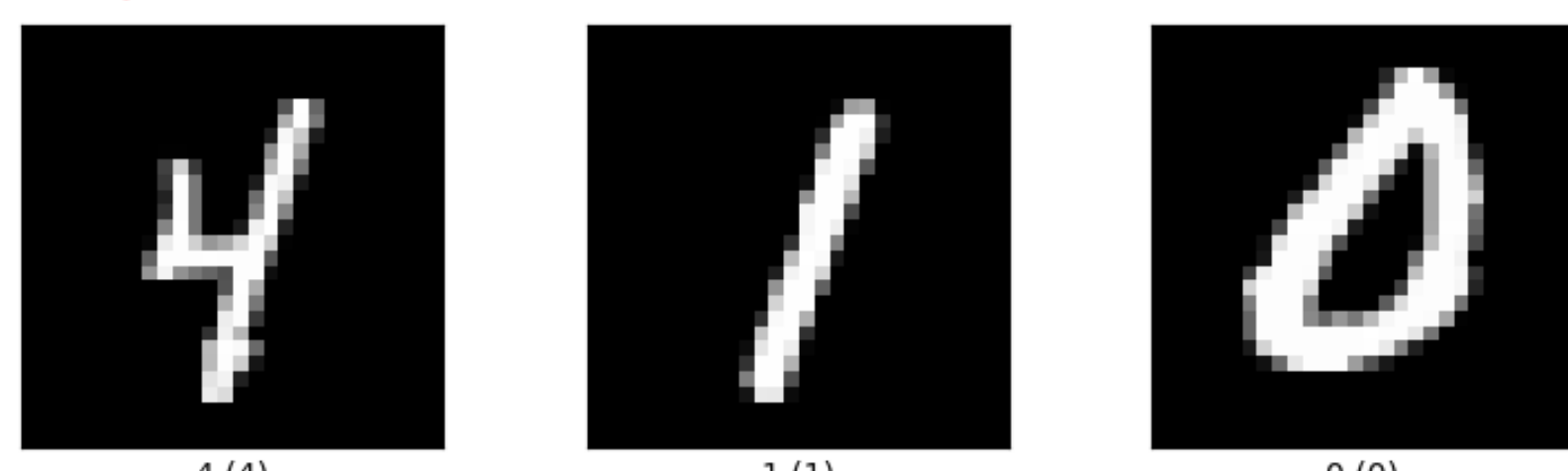
The POVM-formalism

- Directly encoding the density matrix may be challenging for a neural network
- Instead transition to probabilistic representation (POVMs)
- $P^a = \text{tr}(\rho M^a)$, $a \in \{1, \dots, 4^N\}$ Probability simplex & subset of physical distributions
- $\rho = P^a T^{-1} a b M^b$



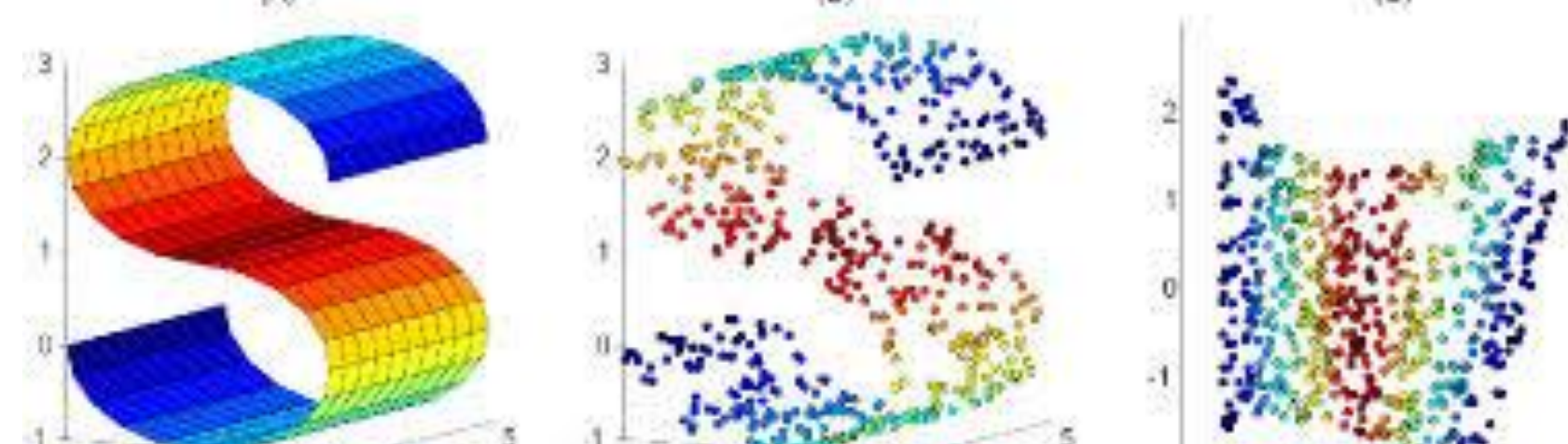
Why neural networks are a suited tool

1 Pattern recognition



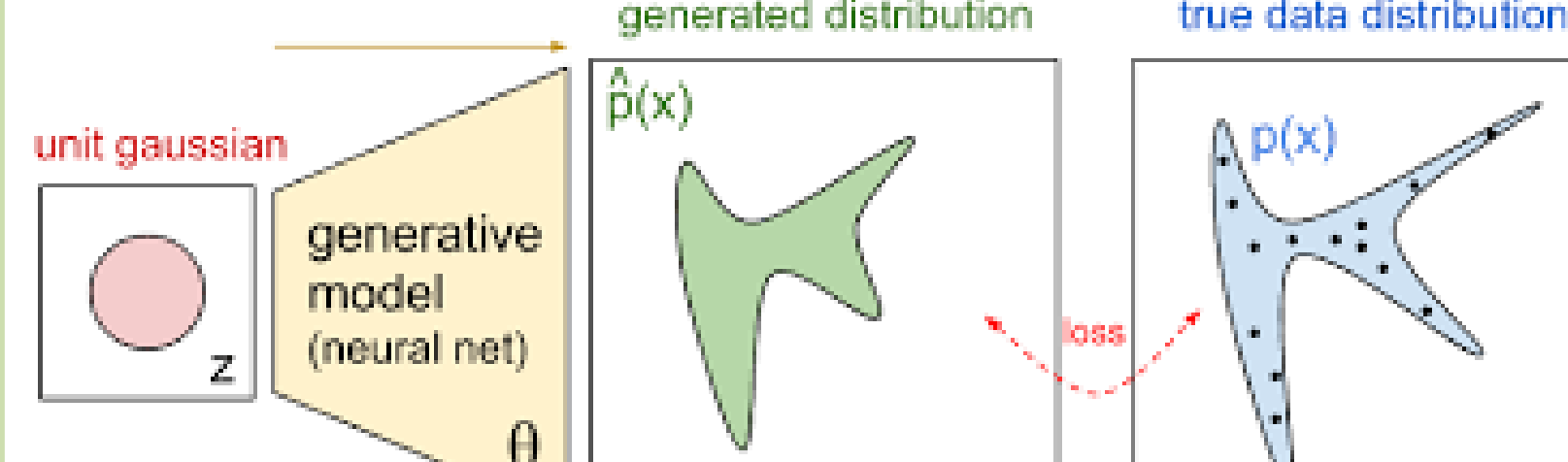
Find features that allow to **generalize on unseen data**

2 Dimensionality reduction



Finding lower dimensional / **compressed representations** of data (e.g. PCA)

3 Generating samples



Obtain samples that are representative of encoded probability distributions

1 **Input:** Sample Configuration $a = a_1 \dots a_N$

2 **Neural Network (Black Box)** Parameters θ

3 **Output:** Approximative P_θ^a

Time-dependent variational principle for open quantum systems with artificial neural networks [1]

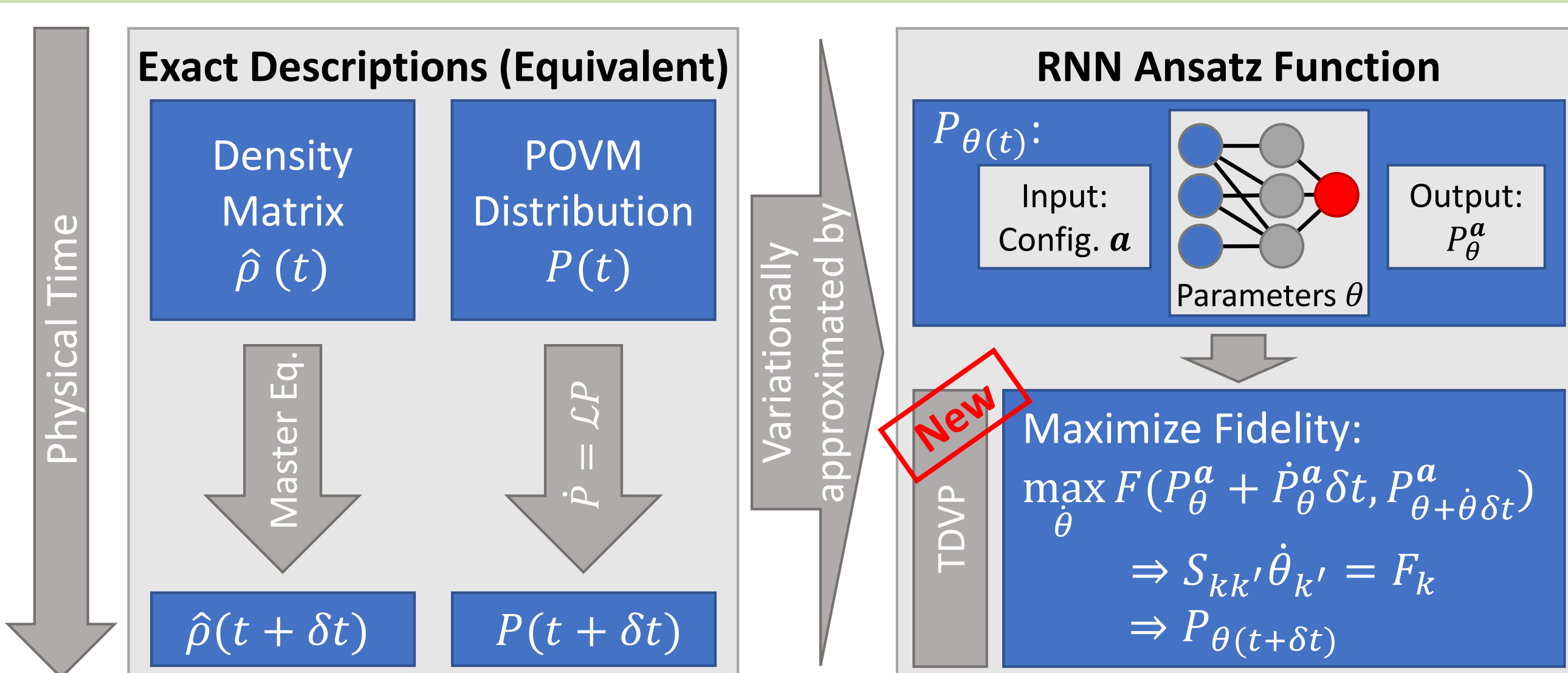
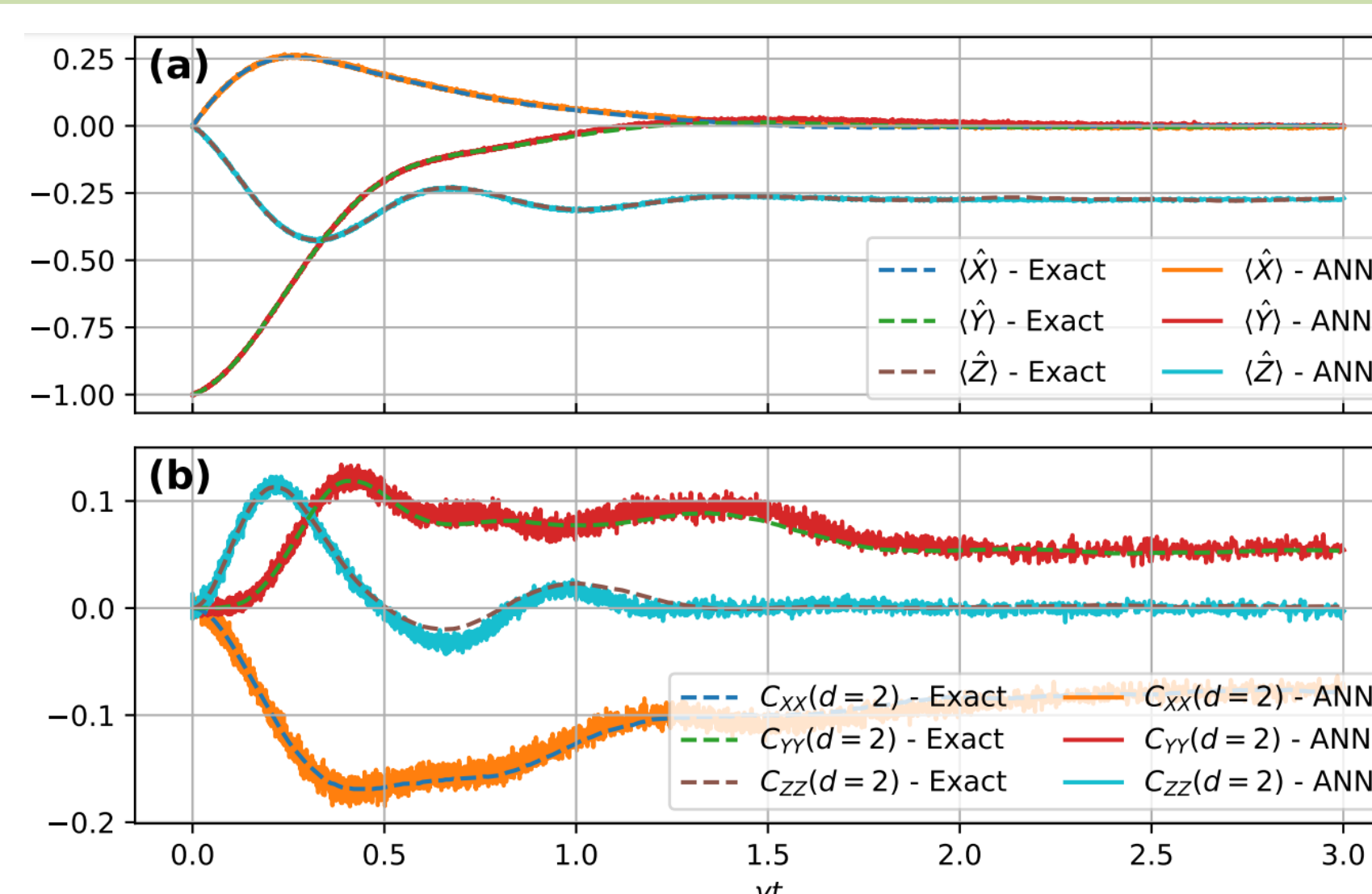
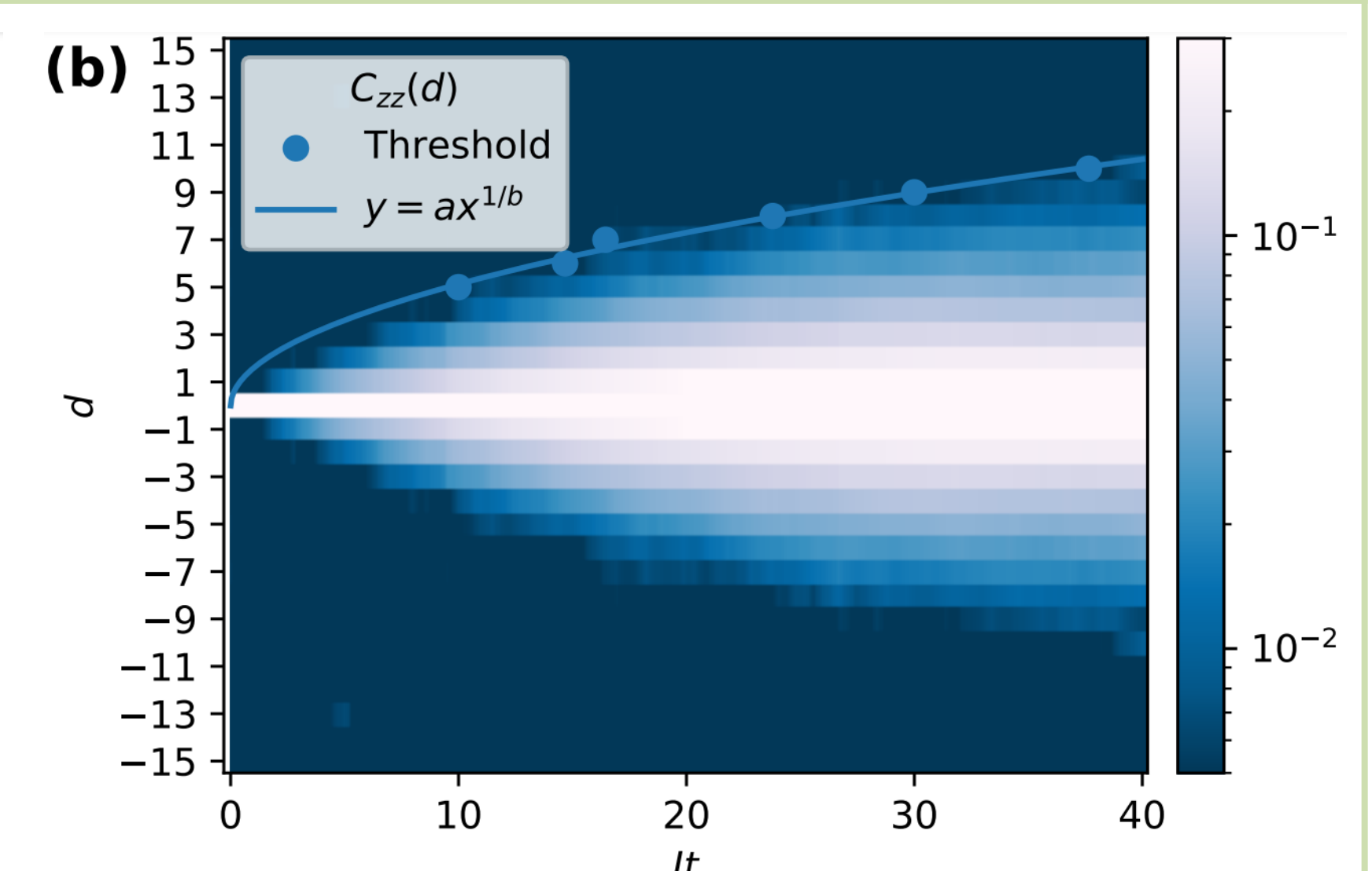


Illustration of the variational approach to OQS dynamics. The righthand side shows the variational approach with the new TDVP equation.

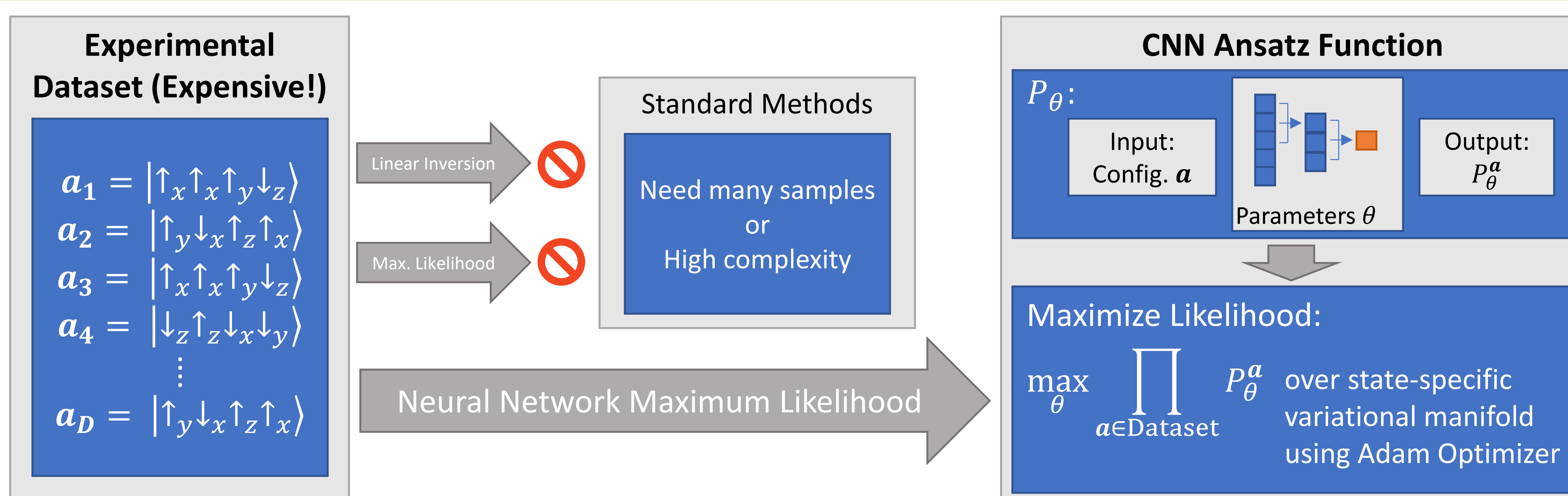


Dissipative dynamics in an anisotropic Heisenberg model with $N = 40$ spins (1D).

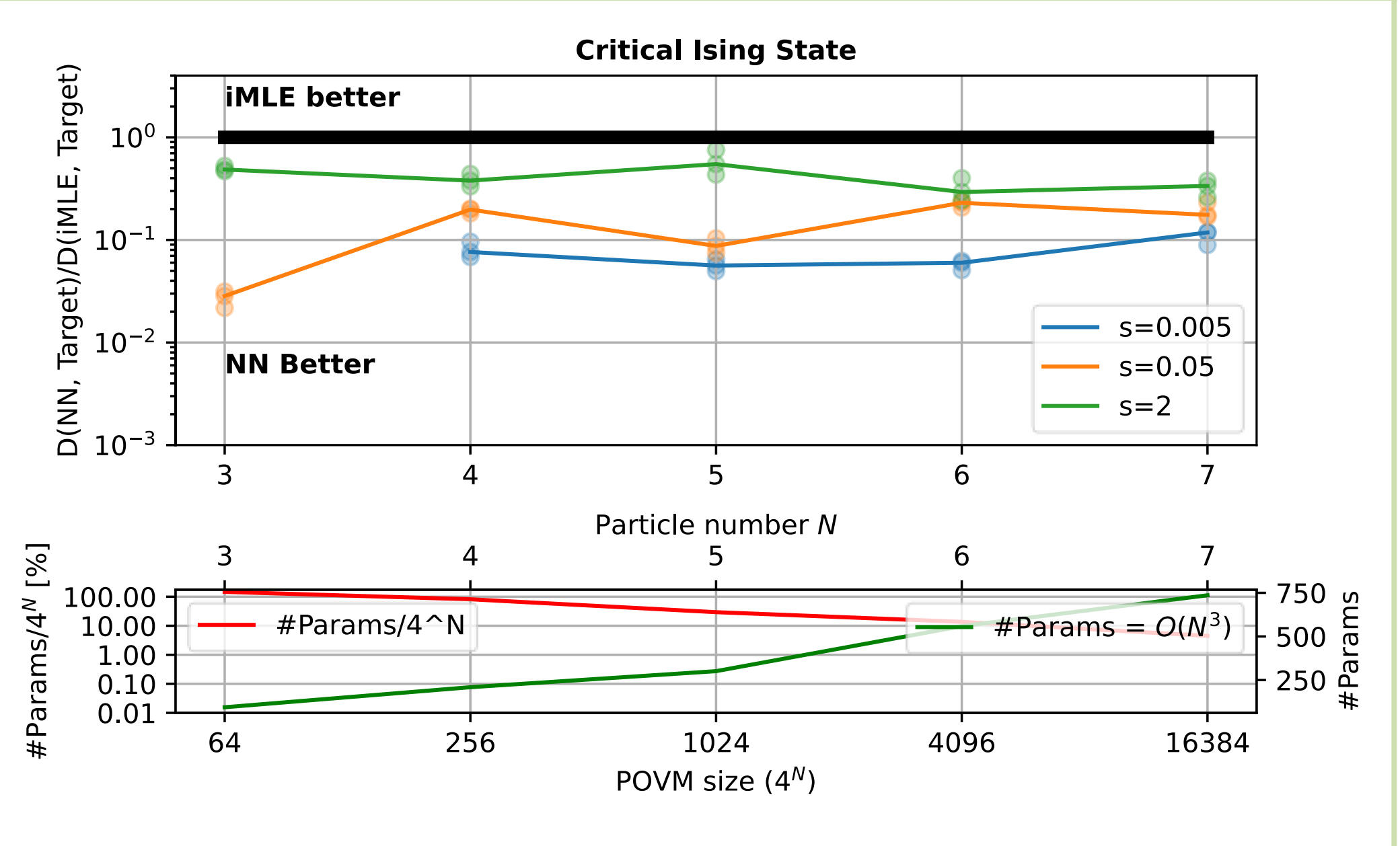


Spreading of correlation in a confinement model with dissipation, $N = 32$ (1D).

Neural Network Quantum State Tomography [2]

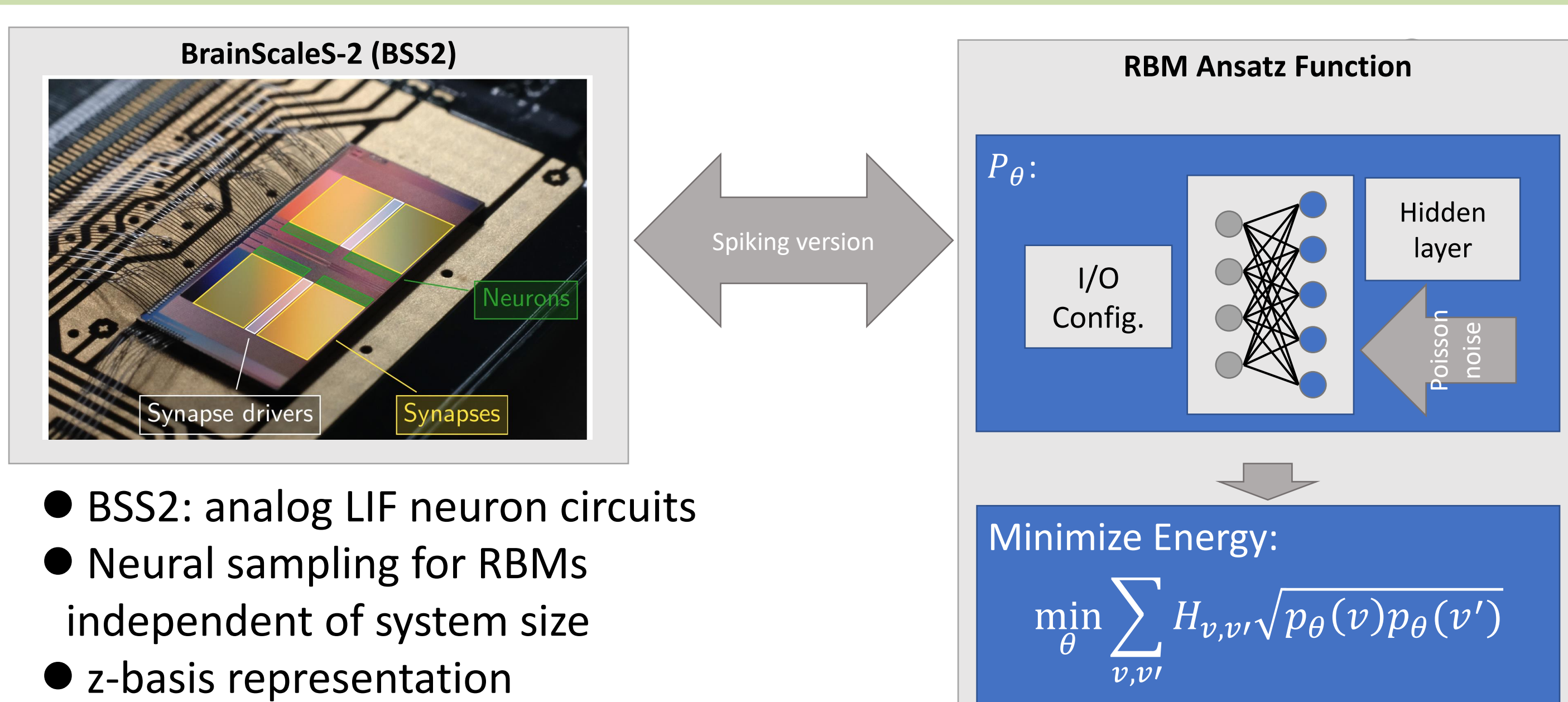


Working principle and advantages of NN-QST

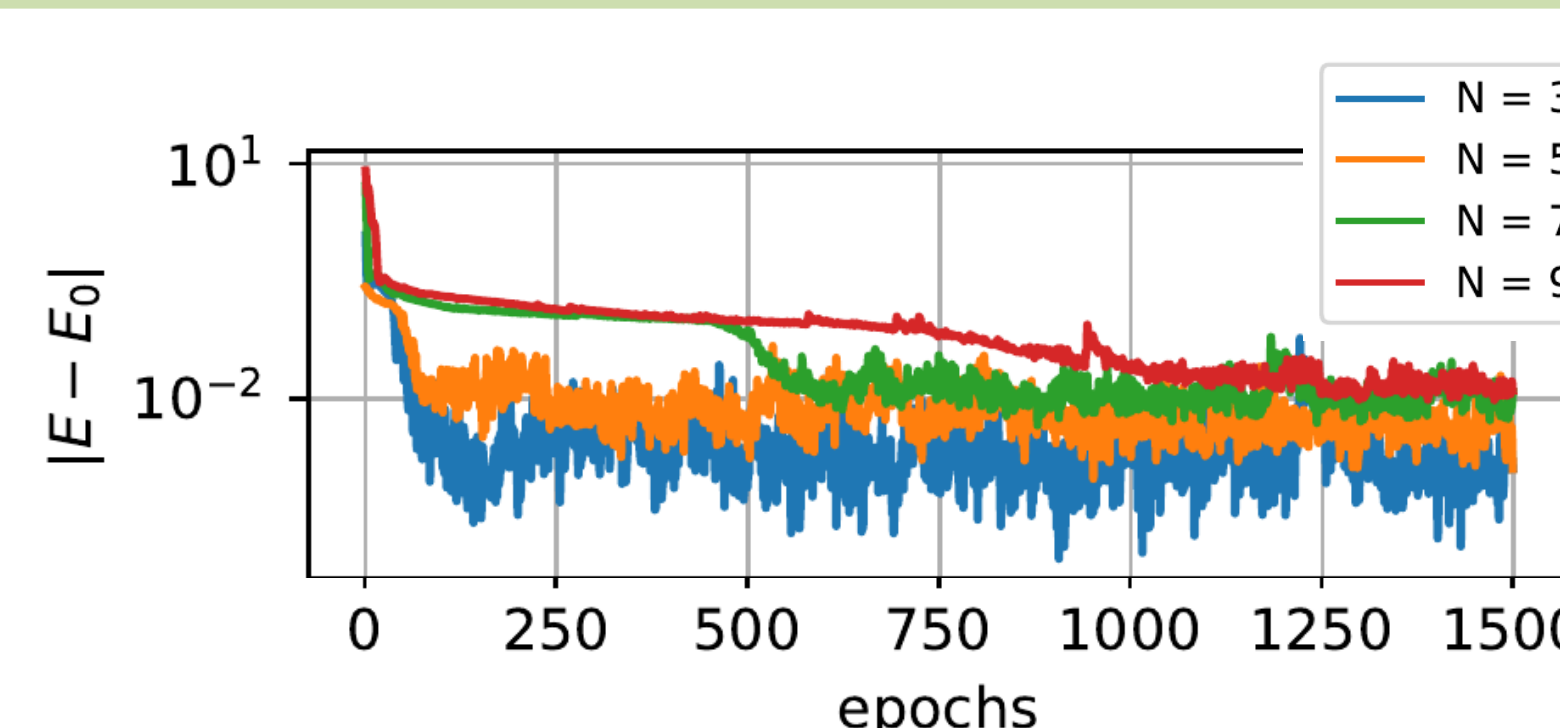


Representing 1D Ising groundstates better than MLE (s=#Samples/4^N)

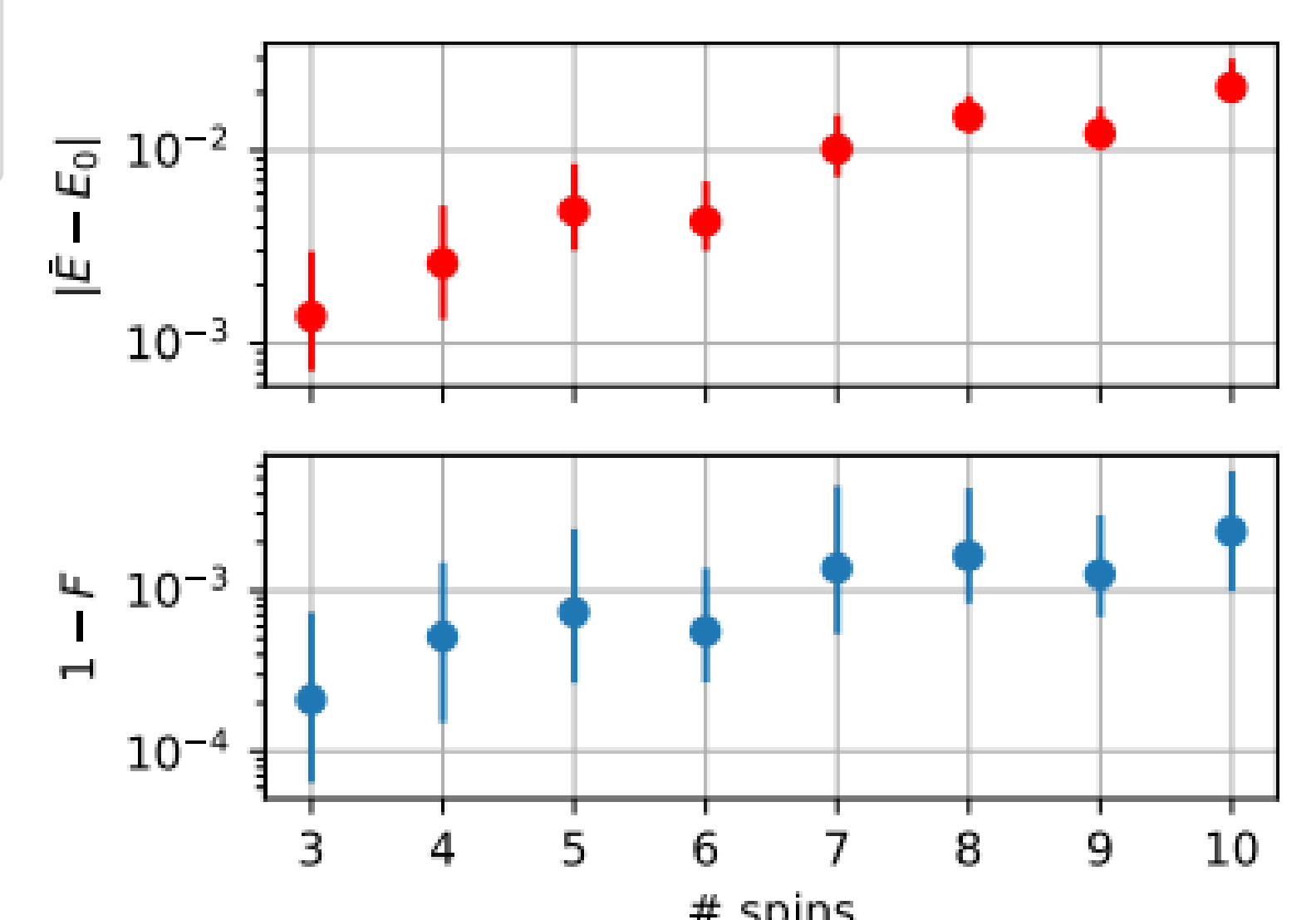
Variational ground state search with spiking neural nets on the BrainScaleS-2 neuromorphic hardware [3]



- BSS2: analog LIF neuron circuits
- Neural sampling for RBMs independent of system size
- z-basis representation



Results for quantum Ising model
Top: learning curves of the energy difference, **Right:** Deviations as function of the system size (fixed network)



References

- [1] Moritz Reh, Markus Schmitt, Martin Gärtner, *arXiv:2104.00013*, 2021
 [2] Marcel Neugebauer, Laurin Fischer, Alexander Jäger, Stefanie Czischek, Selim Jochim, Matthias Weidemüller, and Martin Gärtner, *Phys. Rev. A* 102, 042604, 2020
 [3] Stefanie Czischek, Andreas Baumbach, Sebastian Billaudelle, Benjamin Cramer, Lukas Kades, Jan M. Pawłowski, Markus K. Oberthaler, Johannes Schemmel, Mihai A. Petrovici, Thomas Gasenzer, Martin Gärtner, *arXiv:2008.01039*, 2020