Dynamics of open quantum systems in artificial neural networks

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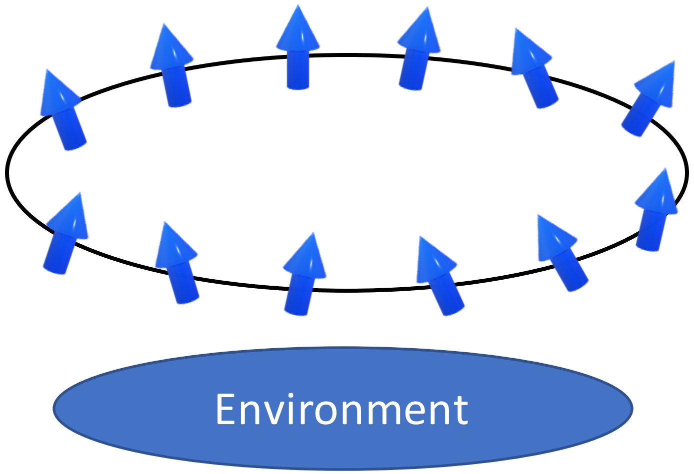
Dynamics of Open Quantum Systems

Why simulate Open Quantum Systems?

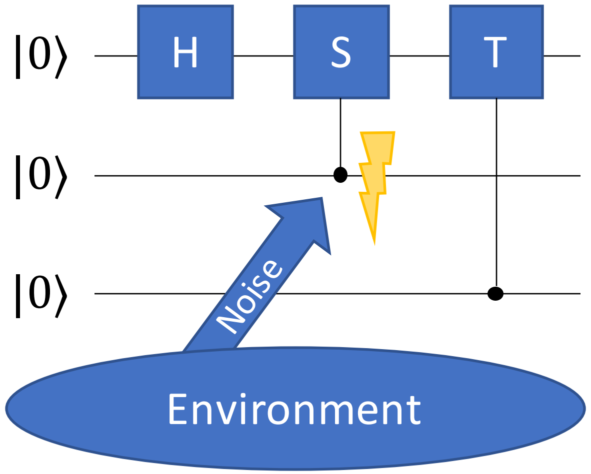
..to discover new physics:

A lack of computational tools prevents the exploration of new interesting physics:



..as a benchmarking tool:

Quantum simulators are sensitive to outside noise – require tools to benchmark these devices:



Evolution equation of the quantum state ρ:

$$\dot{\rho} = -i[H,\rho] + \gamma \sum_i L^i \rho L^{i\dagger} + \{L^{i\dagger} L^i, \rho\}$$

with the spin-Hamiltonian

$$H = \Sigma_{d\in\{x,y,z\}} \Sigma_i J^d \sigma_i^d \sigma_{i+1}^d + h^d \sigma_i^d$$

However: Simulations of these kinds of dynamics (naively) are exponentially hard!

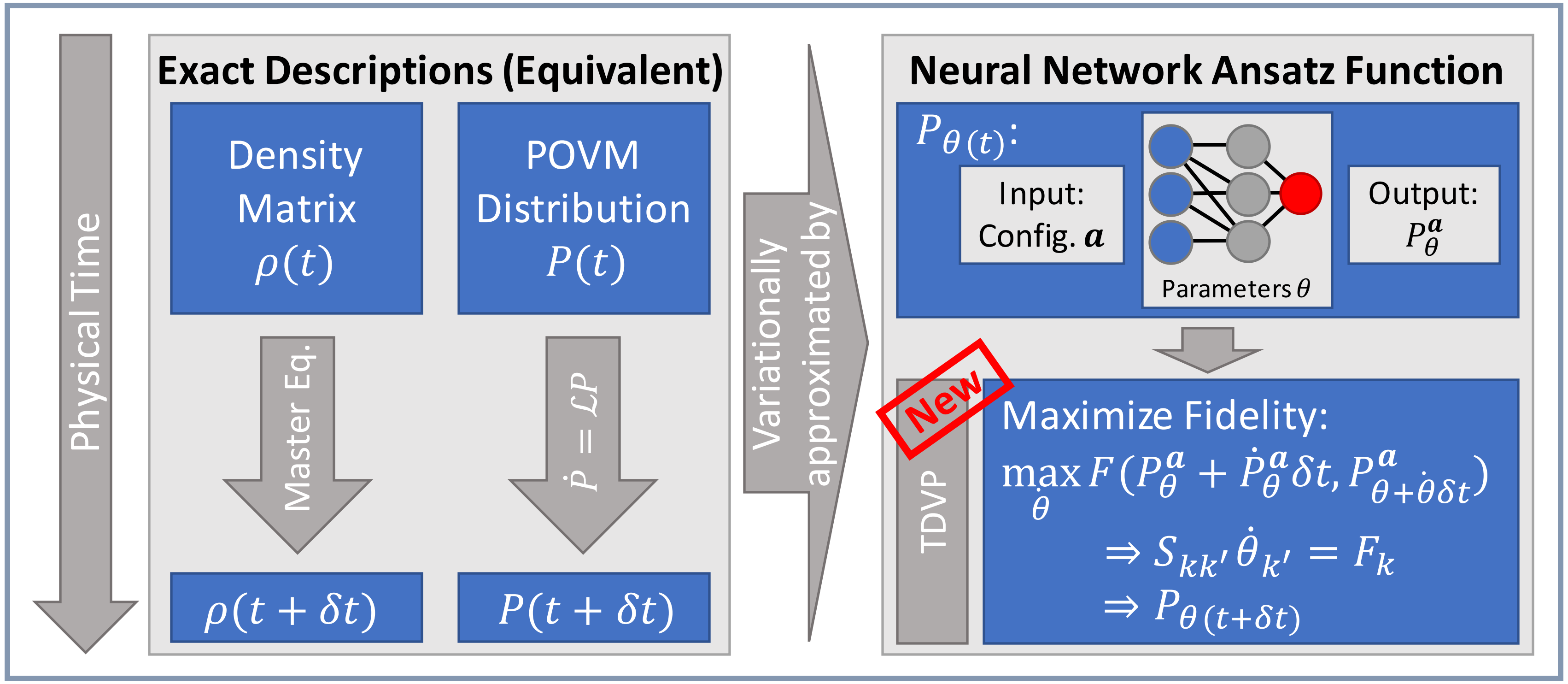
Here: New method to simulate these dynamics based on variational approximation using neural networks.

Outline: 1 theory slide + 2 result slides

Our method in contrast to previous works

What's new?

Our method



Previous Works

Purification-based RBM:

- Hartmann & Carleo (Phys. Rev. Lett. 122)
- Yoshioka & Hamazaki (Phys. Rev. B 99)
- Nagy & Savona (Phys. Rev. Lett. 122)
- Vicentini et. al. (Phys. Rev. Lett. 122)

Advantage: Explicit parameter updates
Disadvantage: Restriction to RBM based architecture

Gradient-descent based:

- Luo et. al. (arXiv:2009.05580)

Advantage: Very general, No limitations in network architecture
Disadvantage: Costly global optimization, potentially run into local minima

Conclusion: "Best of both worlds" – Explicit, second-order accurate parameter updates without fundamental limitations in the network architecture. Efficiency guaranteed by sampling S and F.
Remarks: Identical* to the TDVP for pure states (Carleo & Troyer, $^*\psi \leftrightarrow P, H \leftrightarrow \mathcal{L}$). Number of variational parameters limited by the inversion of S (~ 5000). Results are obtained in 1D and 2D systems using Recurrent Neural Networks.

Results on prototypical spin models

Performance in regimes beyond ED

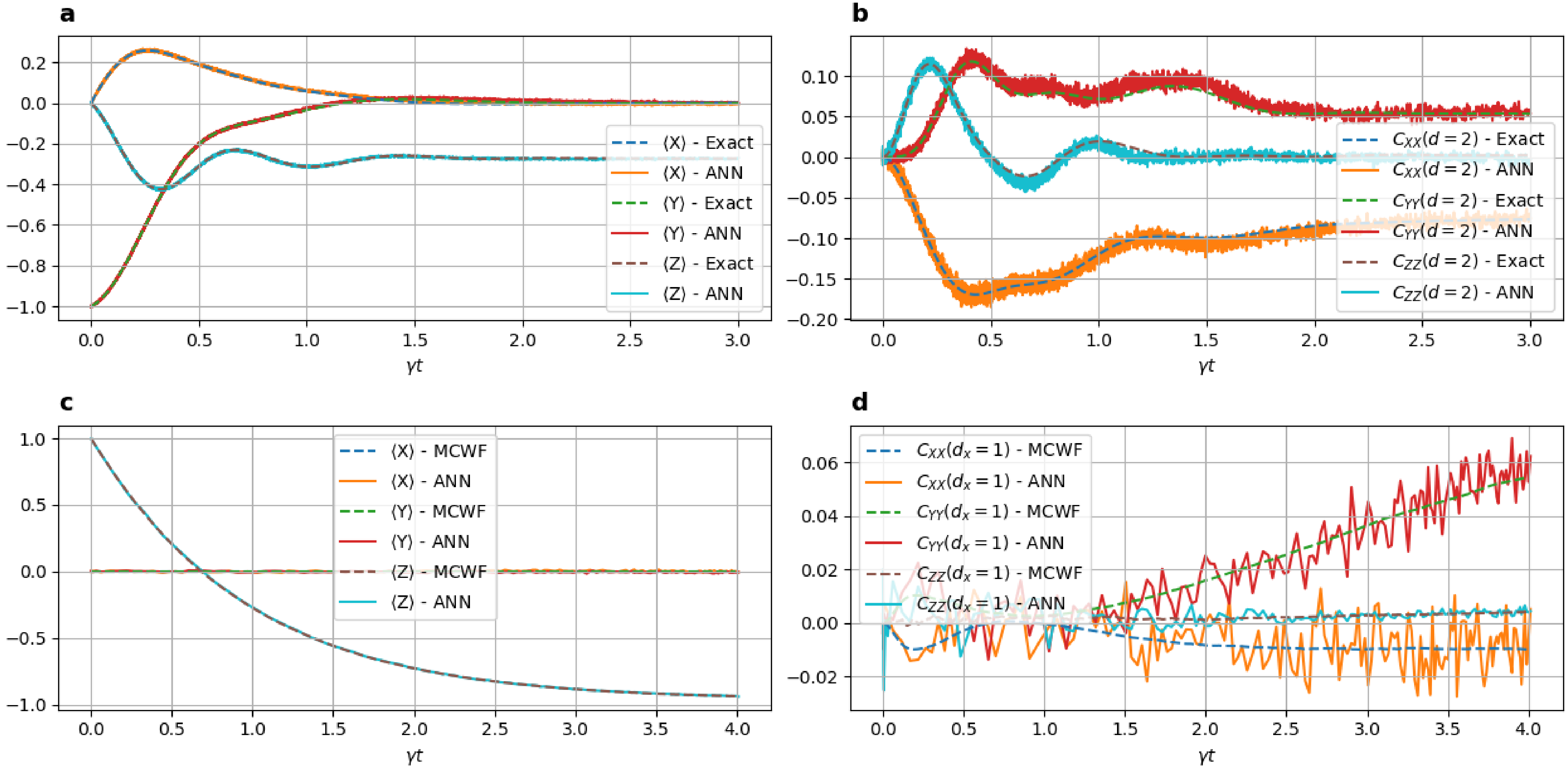
$H = \Sigma_{d\in\{x,y,z\}}\Sigma_i J^d \sigma_i^d \sigma_{i+1}^d + h^d \sigma_i^d$

(a) and (b):
1D,
$N = 40$,
$\langle \sigma_y^{t=0} \rangle = -1$,
$\vec{J}/\gamma = (2.0, 0.0, 1.0)$,
$h_z/\gamma = 1.0$

(c) and (d):
2D,
$N = 4 \times 4$,
$\langle \sigma_z^{t=0} \rangle = 1$,
$\vec{J}/\gamma = (0.9, 1.0, 1.0)$,
$h_z/\gamma = 0.0$

Magnetizations

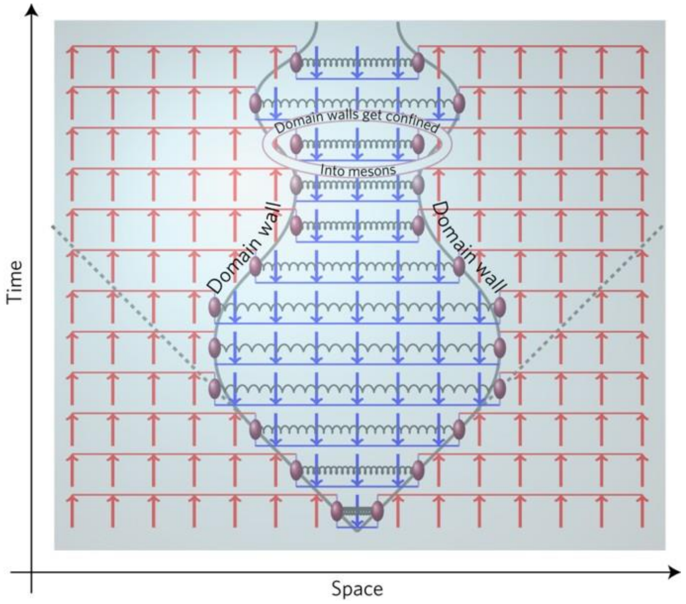
Correlators



Confinement Physics

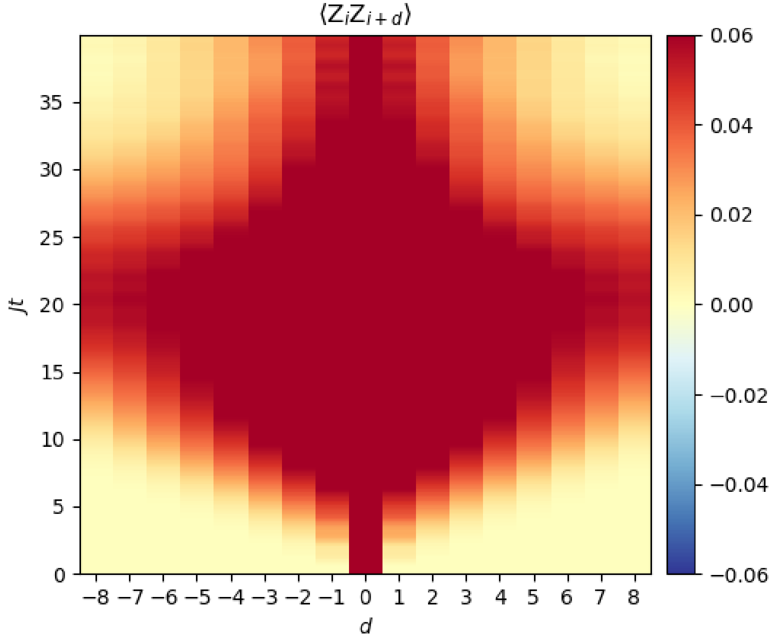
What effect does dissipation have on the confinement dynamics?

Originial work: Real-time confinement following a quantum quench to a non-integrable model, nature physics (2017), Kormos et. al.

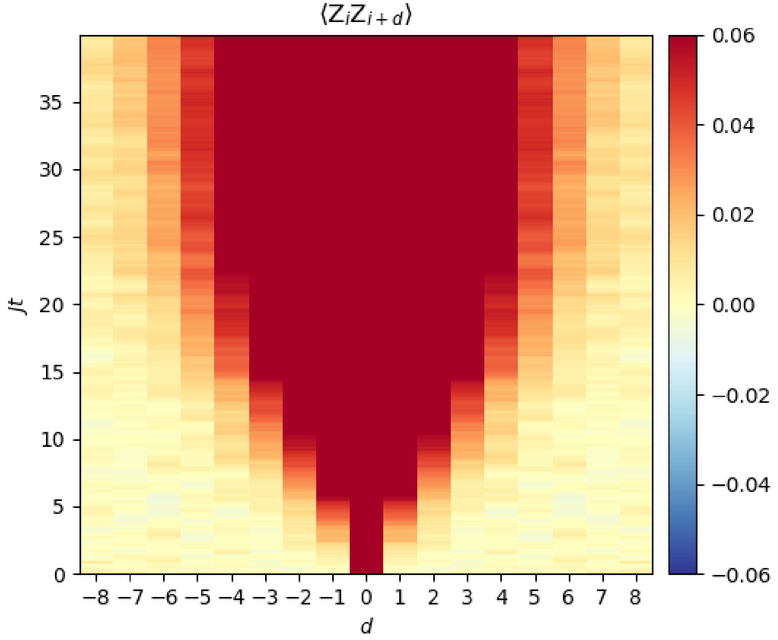


Augmented study: Spin-chain of length $L = 20$ with nearest neighbor couplings $H = \Sigma_i \sigma_i^z \sigma_{i+1}^z + h^z \sigma_i^z + h^x \sigma_i^x$ with $h^z = 0.05$ and $h^x = 0.25$

Pure case (exact data)



w/ Dephasing (ANN, $\gamma = 0.25$)



Conclusion: Novel method to simulate dissipative quantum dynamics with unexplored potentials, which can make full use of GPUs and modern compute clusters. Questions & comments?

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