Deep learning for quantum error mitigation

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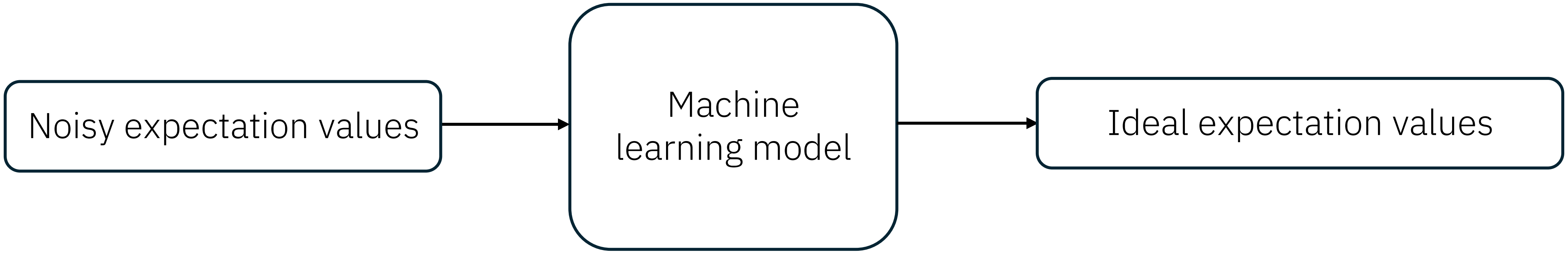
Core idea:


Noisy expectation values
Machine learning model
Ideal expectation values

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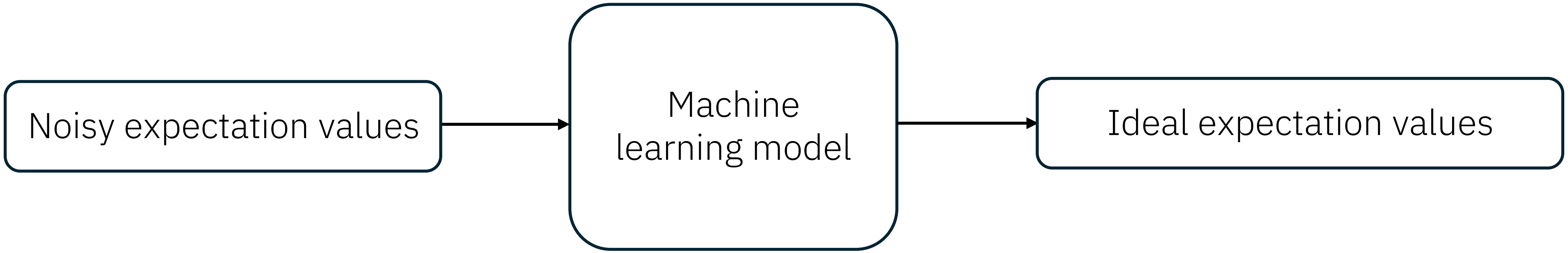

Problem:

- The exact output of a generic large quantum circuit U can't be computed with classical simulation methods.

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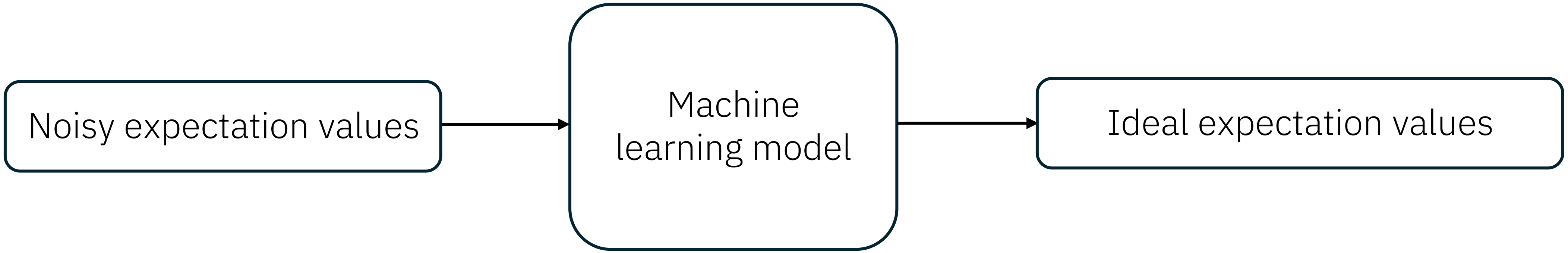


Problem:

- The exact output of a generic large quantum circuit U can't be computed with classical simulation methods.

Solution:

- Train a model using quantum circuits that are both classically simulable and structurally similar to U.
- Use the model to mitigate the errors in the output of U.

Proposed training-sets:

- Near Clifford quantum circuits [1]
- Product states [2]
- Small quantum circuits and scalable neural networks [3]

[1] Piotr Czarnik, Andrew Arrasmith, Patrick J. Coles, and Lukasz Cincio, Error mitigation with Clifford quantum-circuit data, Quantum, **5**, 592 (2021)

[2] Stefan H. Sack, and Daniel J. Egger, Large-scale quantum approximate optimization on nonplanar graphs with machine learning noise mitigation, Phys. Rev. Research **6**, 013223, (2024)

[3] S. Cantori, A. Mari, D. Vitali, and S. Pilati, Synergy between noisy quantum computers and scalable classical deep learning for quantum error mitigation, EPJ Quantum Technol. **11**, 45 (2024)

Our approach:

- Circuit knitting with small sampling overhead O for VQE processes [1]

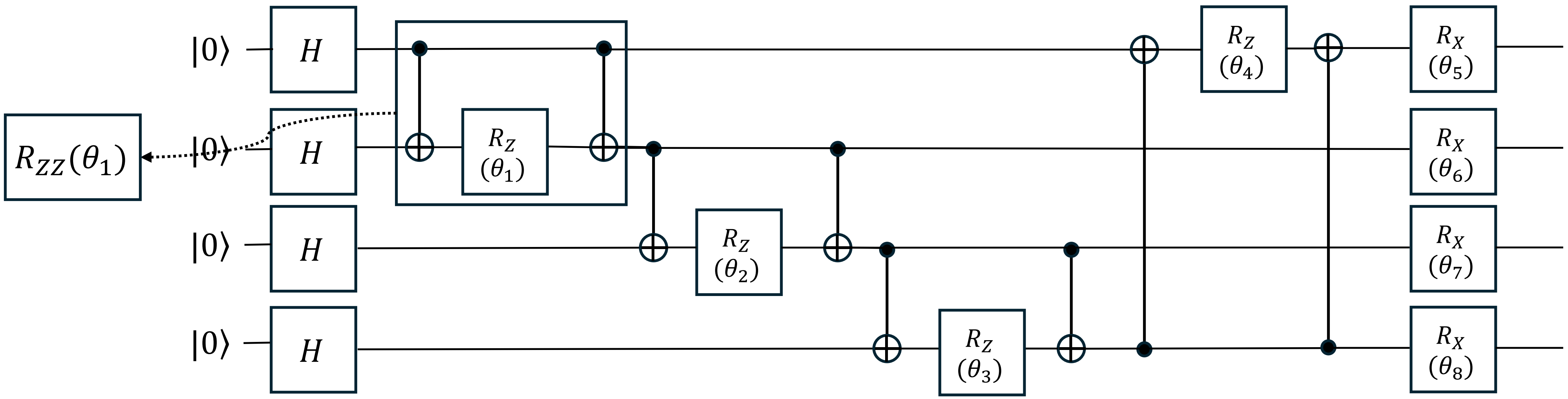
$$O = \prod_{\theta_i \in \mathbb{K}} (1 + 2|\sin\theta_i|)^2 , \qquad \mathbb{K} = \text{set of connecting gates}$$

- We increase the similarity between training circuits and testing circuits

[1] S. Cantori, A. Mari, D. Vitali, and S. Pilati, Deep-learned error mitigation via partially knitted circuits for the variational quantum eigensolver, arXiv:2506.04146 (2025).

Ansatz for the VQE process

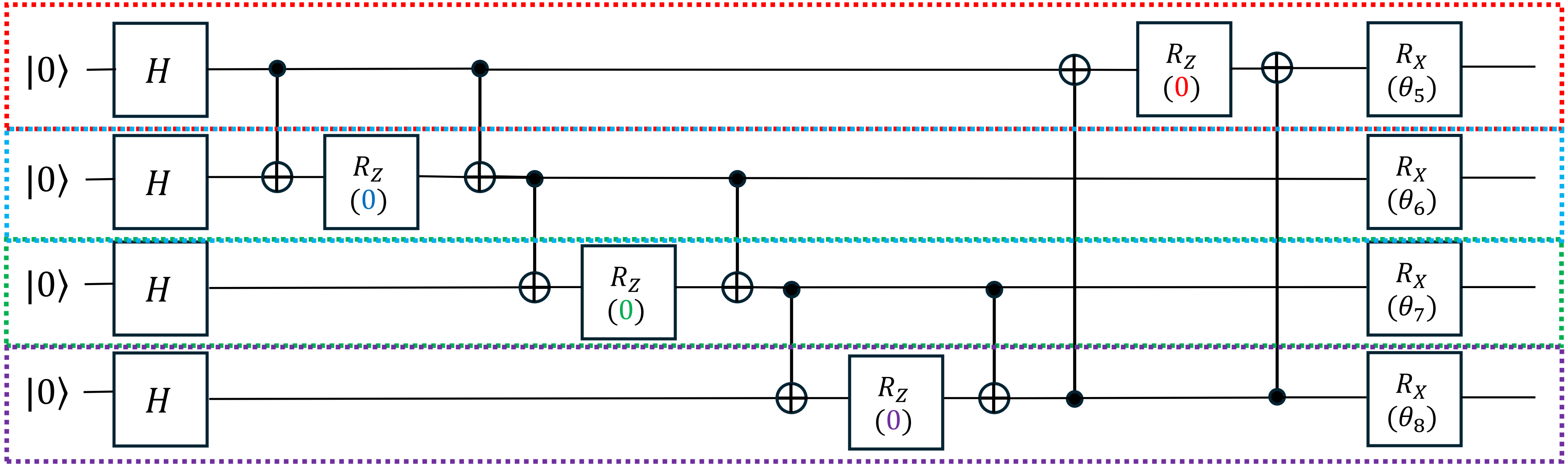
- We use $P = 8$ repetitions of the following block



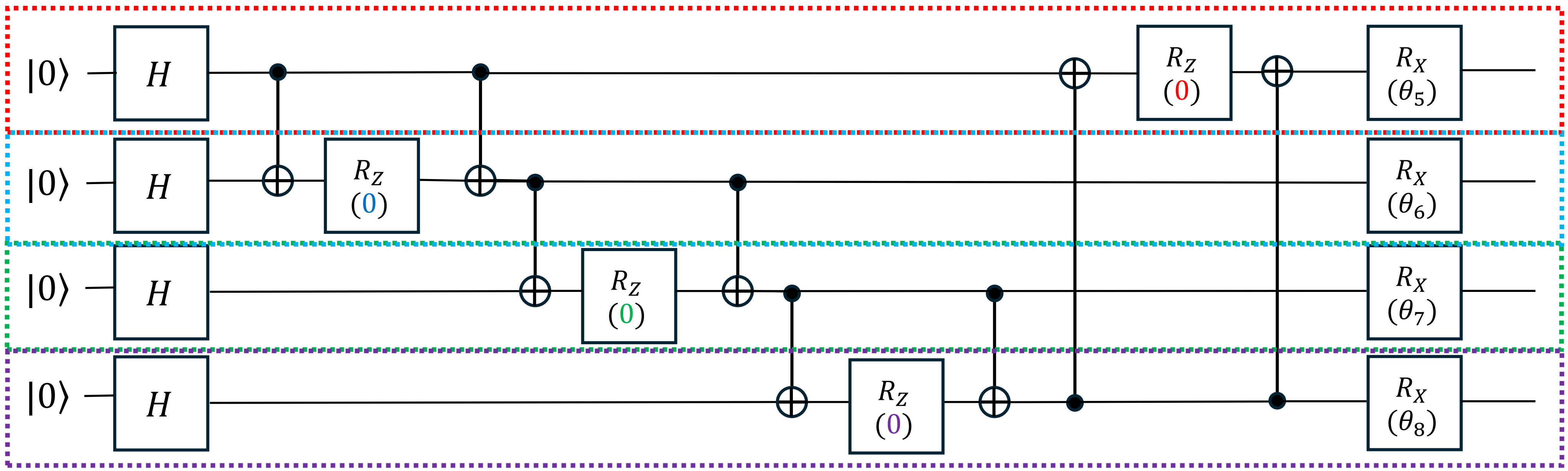
$$H = \sum_i -J_i \, \sigma_i^Z \sigma_{i+1}^Z - h \sum_i \sigma_i^X$$

Wen Wei Ho, Timothy H. Hsieh, Efficient variational simulation of non-trivial quantum states. *SciPost Phys.* 6, 029 (2019)

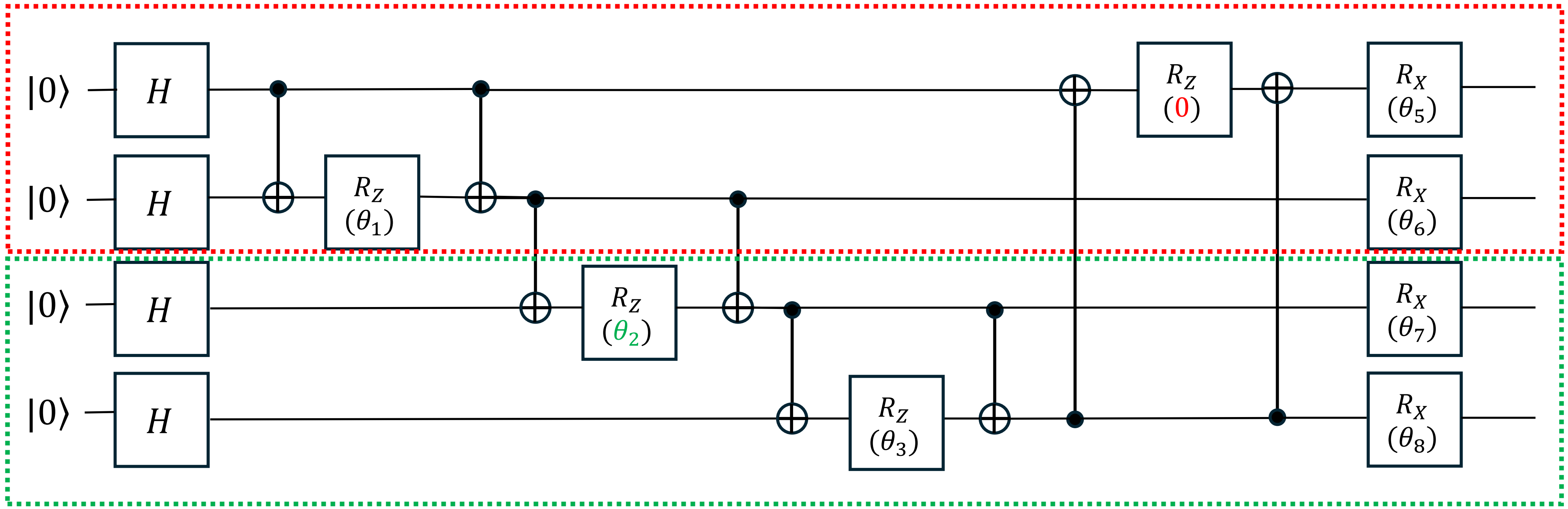
Product states



Product states

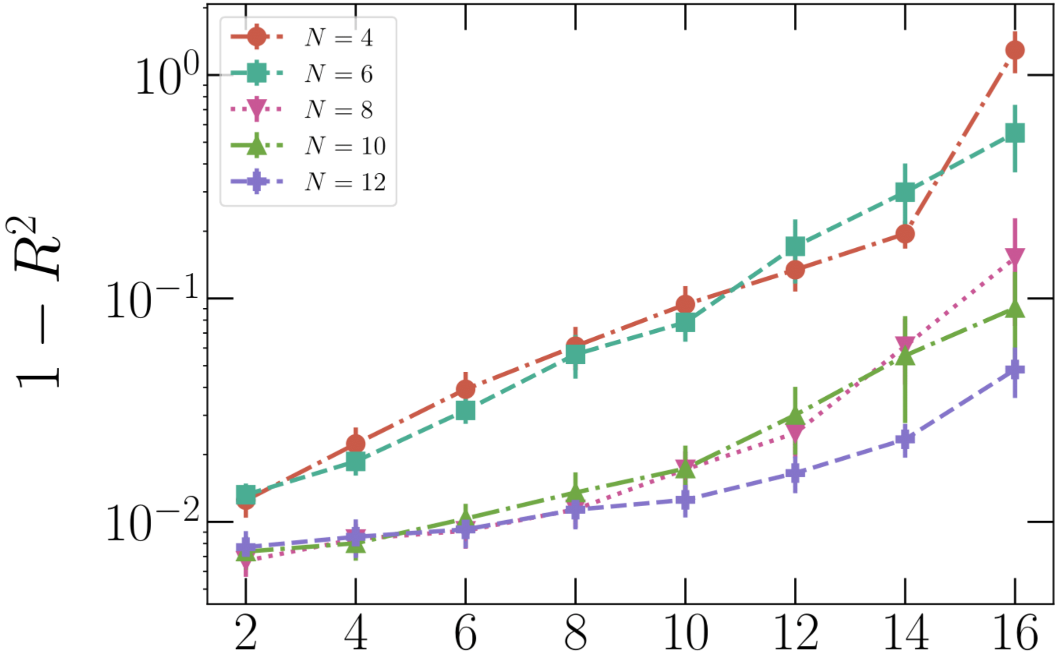


Partially knitted



Importance of similarity between training circuits and testing circuits

$$1 - R^2 = \frac{\sum_{i=1}^{K_{test}} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{K_{test}} (y_i - \bar{y})^2}$$



C ⟶ Number of R_{ZZ} gates that have been cut in the training circuits

Importance of similarity between training circuits and testing circuits

- $C = 2 \times N \times P = 48 \longrightarrow$ product state; $C = 16 \longrightarrow$ near-Clifford circuit with 83% non-Clifford gates.

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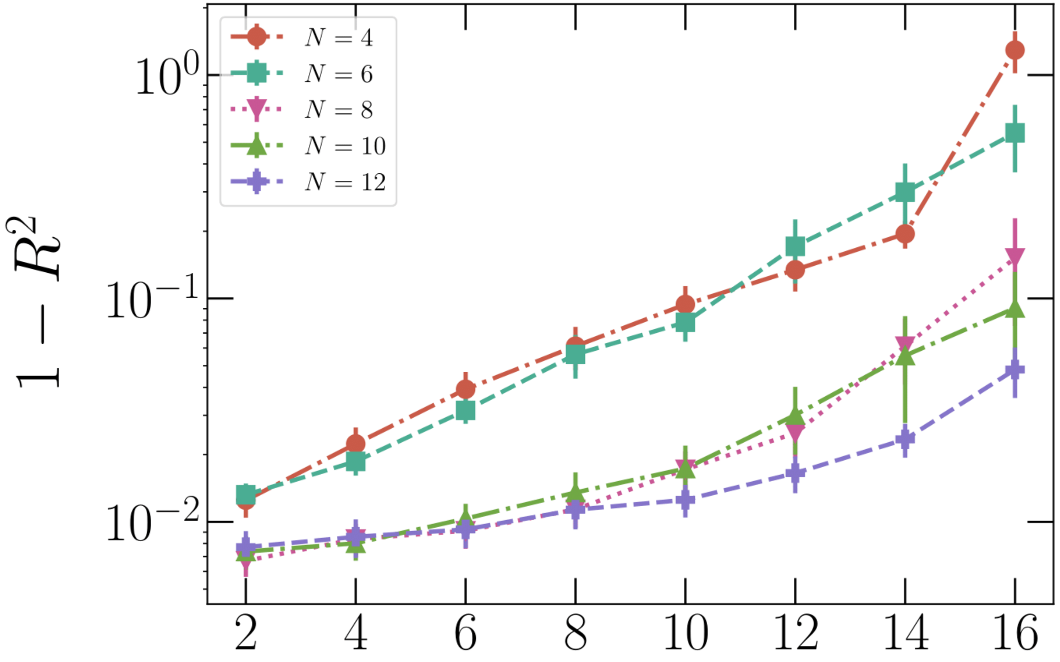

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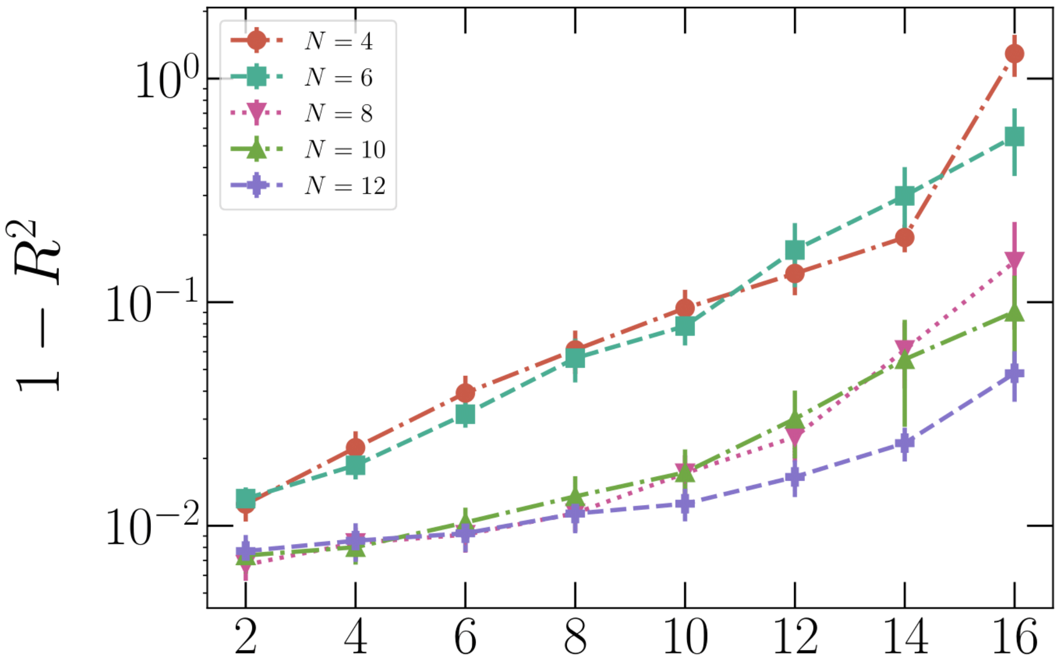

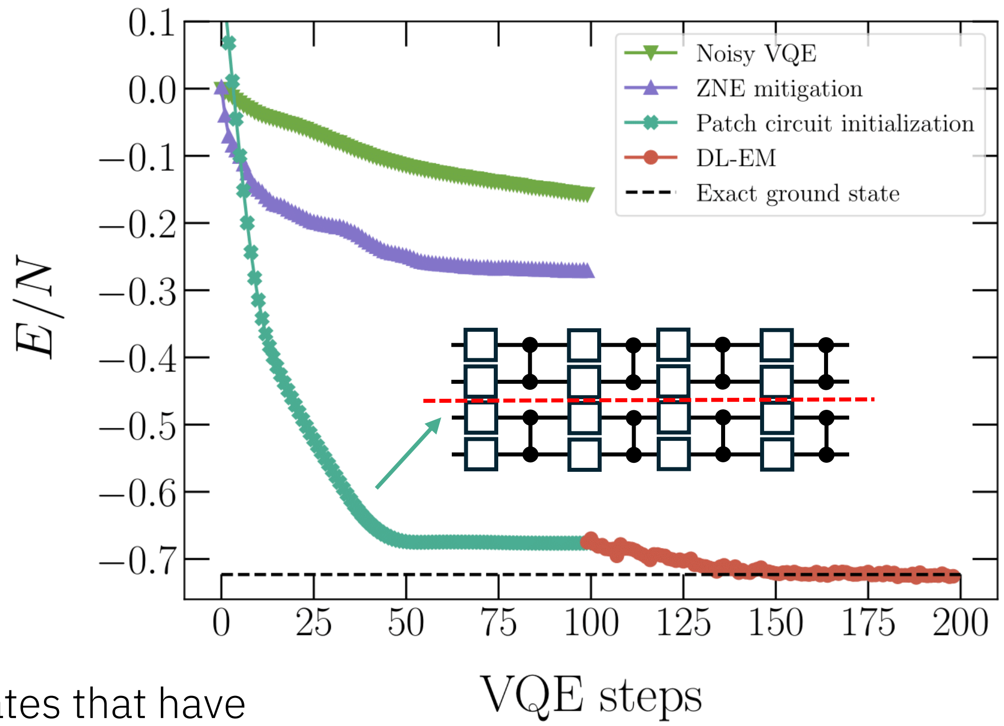

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Future work and open questions:

- Application on real quantum devices.

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- Application on real quantum devices.
- Is there a sweet spot where ML-EM can provide “useful” results “efficiently”?

Acknowledgement

- Co-authors: Dr. Andrea Mari, Prof. David Vitali and Prof. Sebastiano Pilati
- Complex quantum matter group

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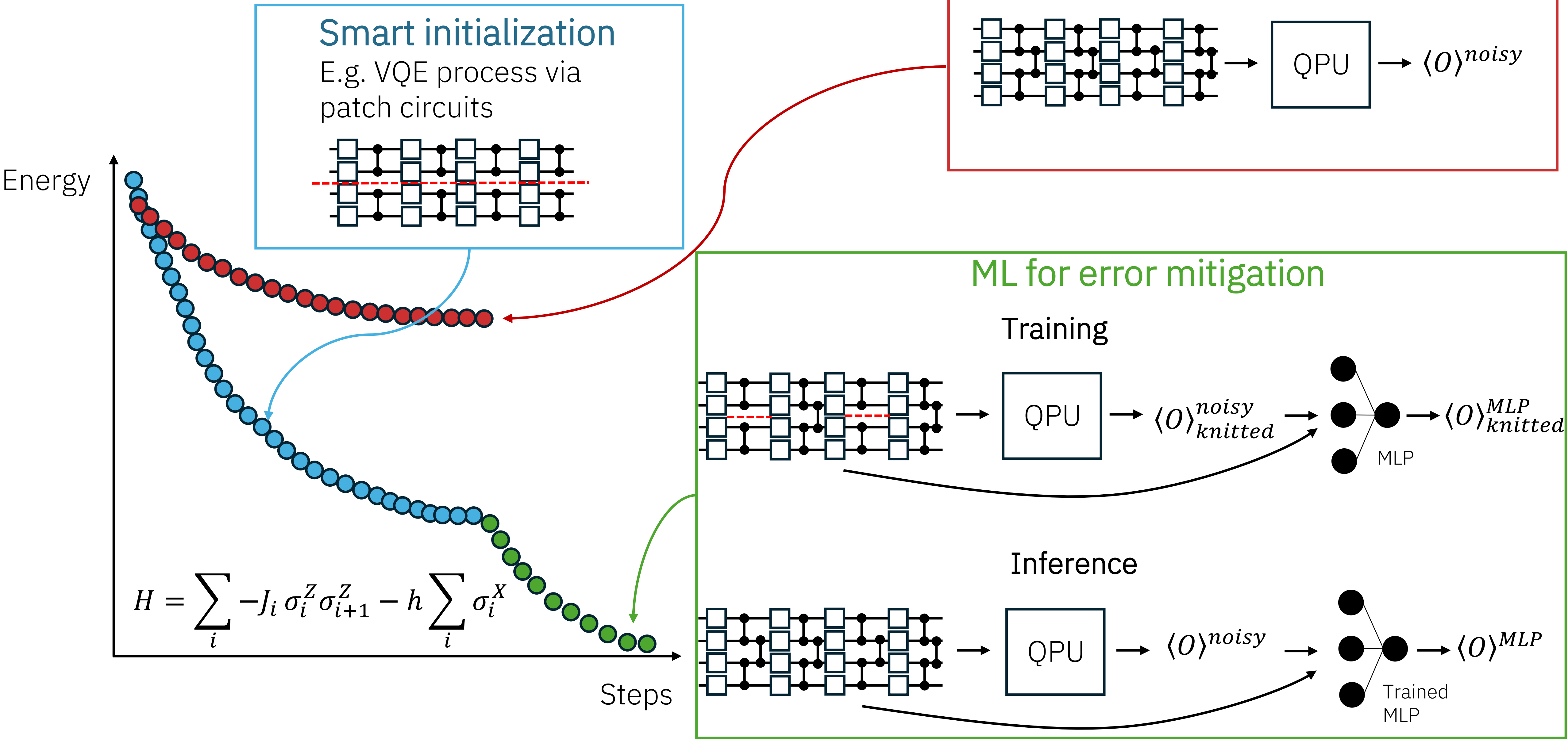
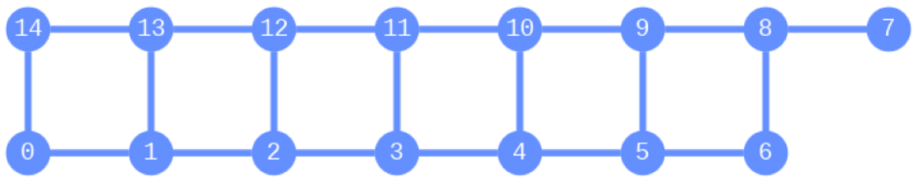
Appendix

Overview (2)


Smart initialization
E.g. VQE process via patch circuits
Noisy VQE
QPU
$\langle O \rangle^{noisy}$
Energy
Steps
$H = \sum_i -J_i \sigma_i^Z \sigma_{i+1}^Z - h \sum_i \sigma_i^X$
ML for error mitigation
Training
QPU
$\langle O \rangle^{noisy}_{knitted}$
MLP
$\langle O \rangle^{MLP}_{knitted}$
Inference
QPU
$\langle O \rangle^{noisy}$
Trained MLP
$\langle O \rangle^{MLP}$

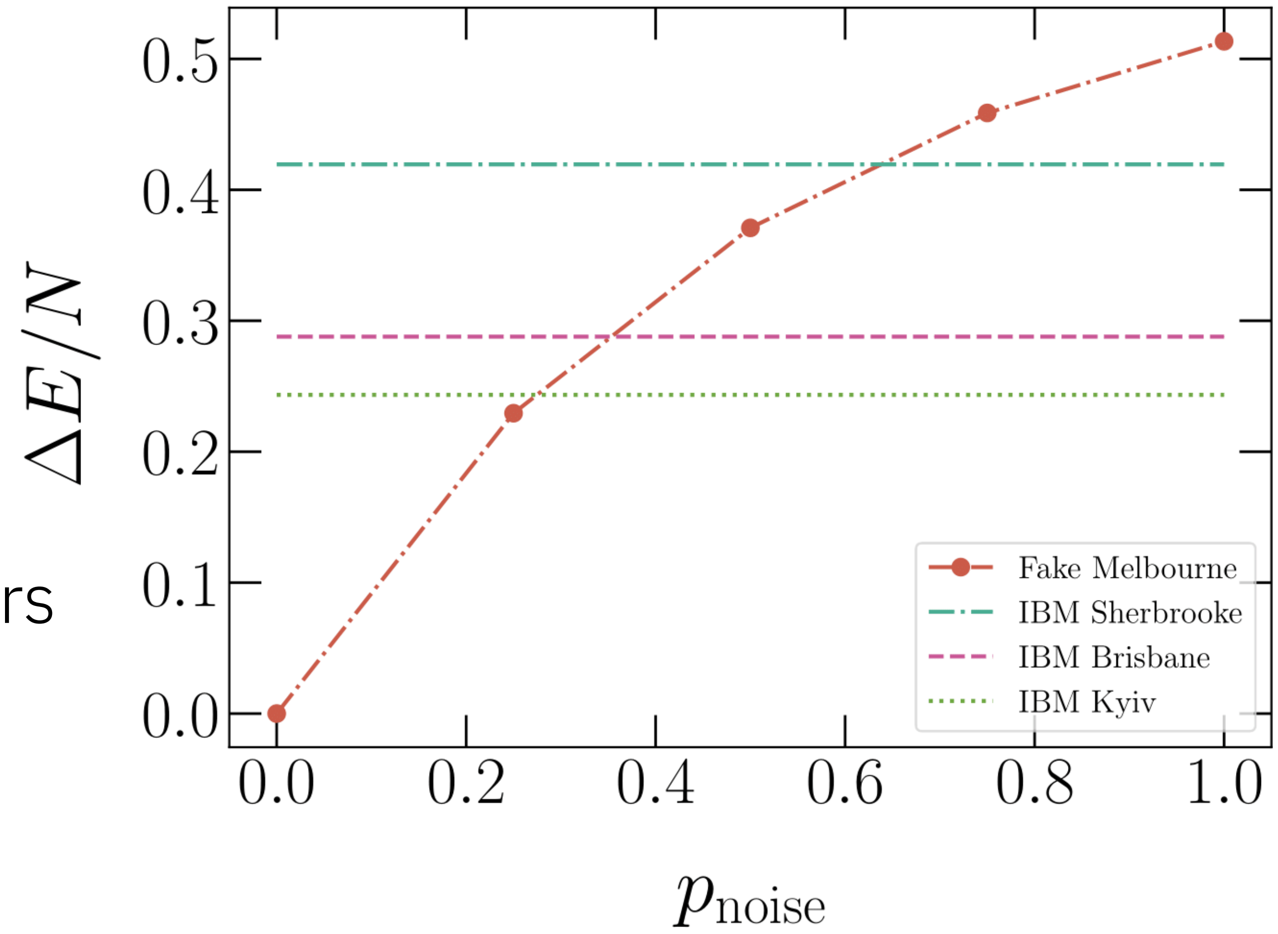
Noise model and comparison with real quantum computers

Fake IBM Melbourne



$p_{\text{noise}} = 0 \implies$ No readout and gate errors

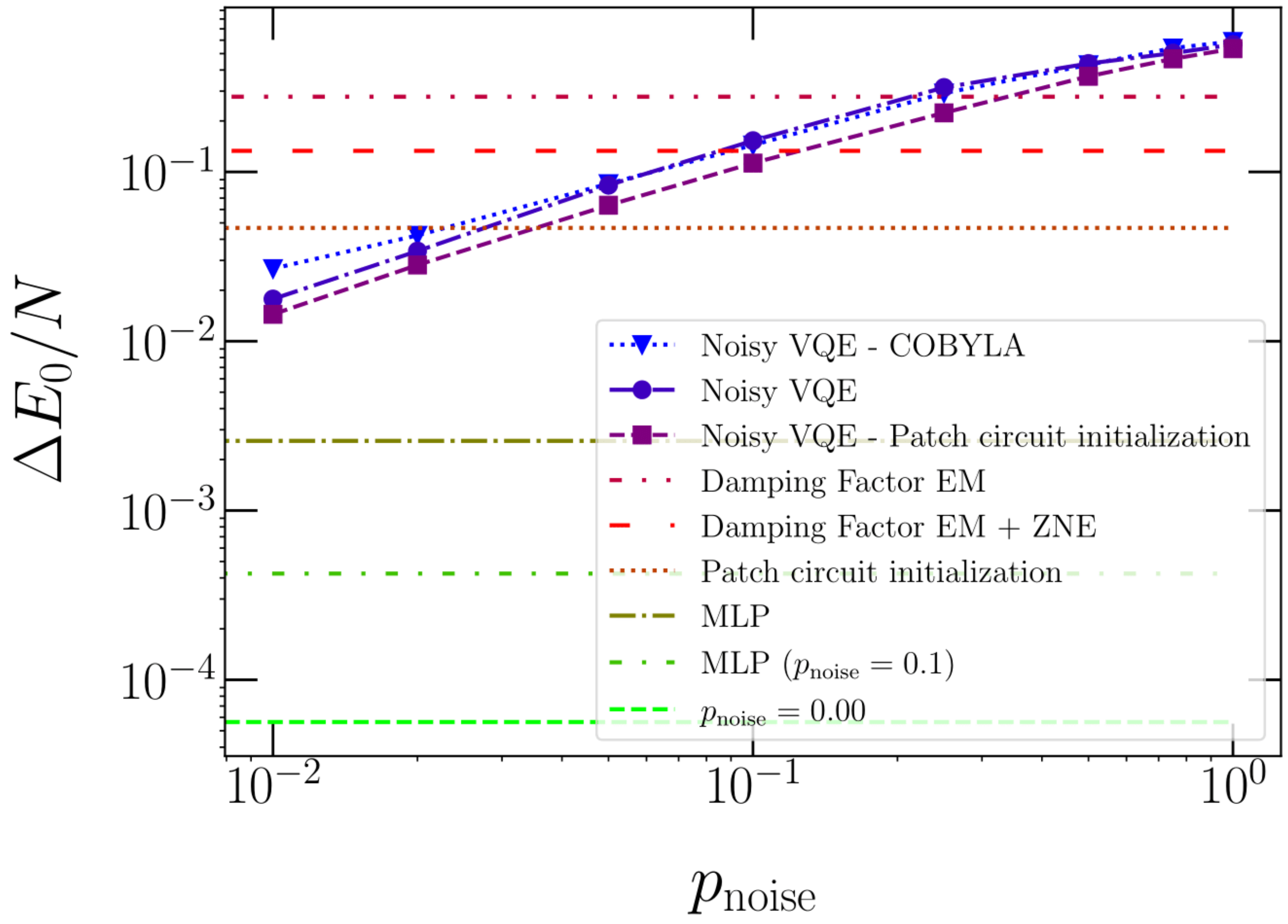
$p_{\text{noise}} = 1 \implies$ Original fake backend

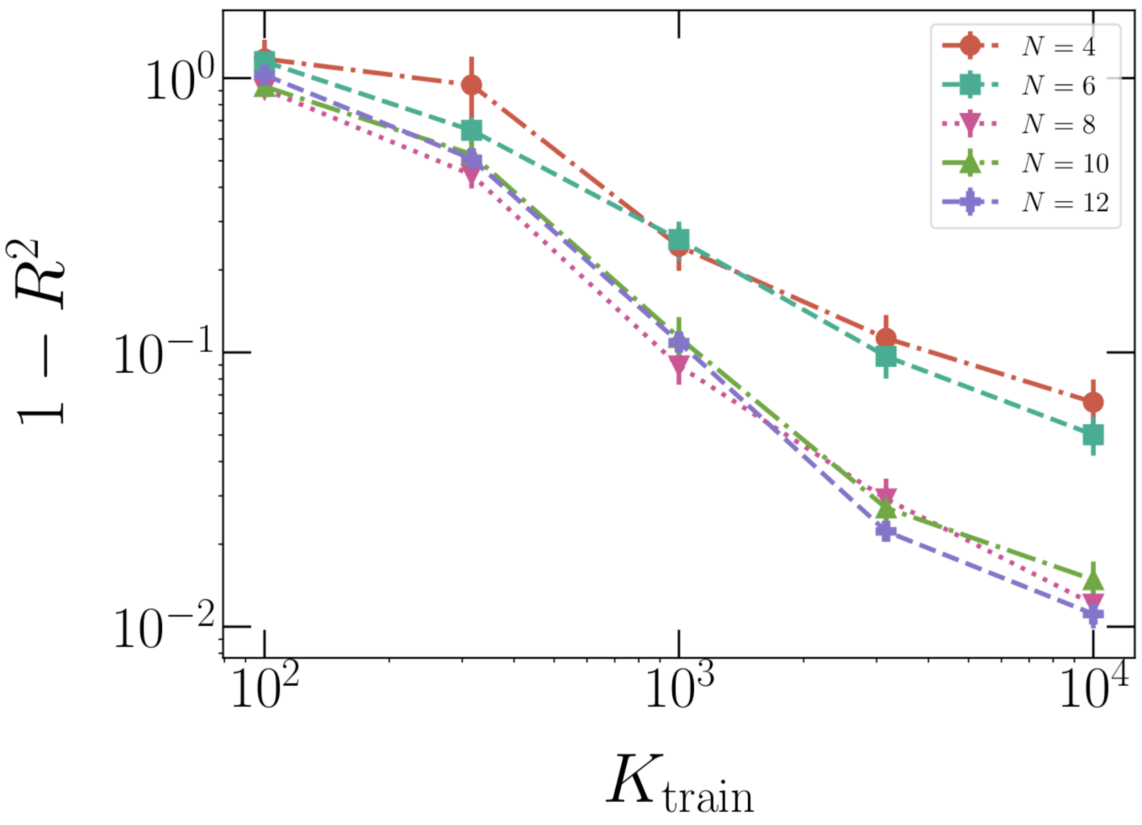


Comparison with other approaches

- Gradient-based (ADAM) and gradient-free (COBYLA) VQE processes;

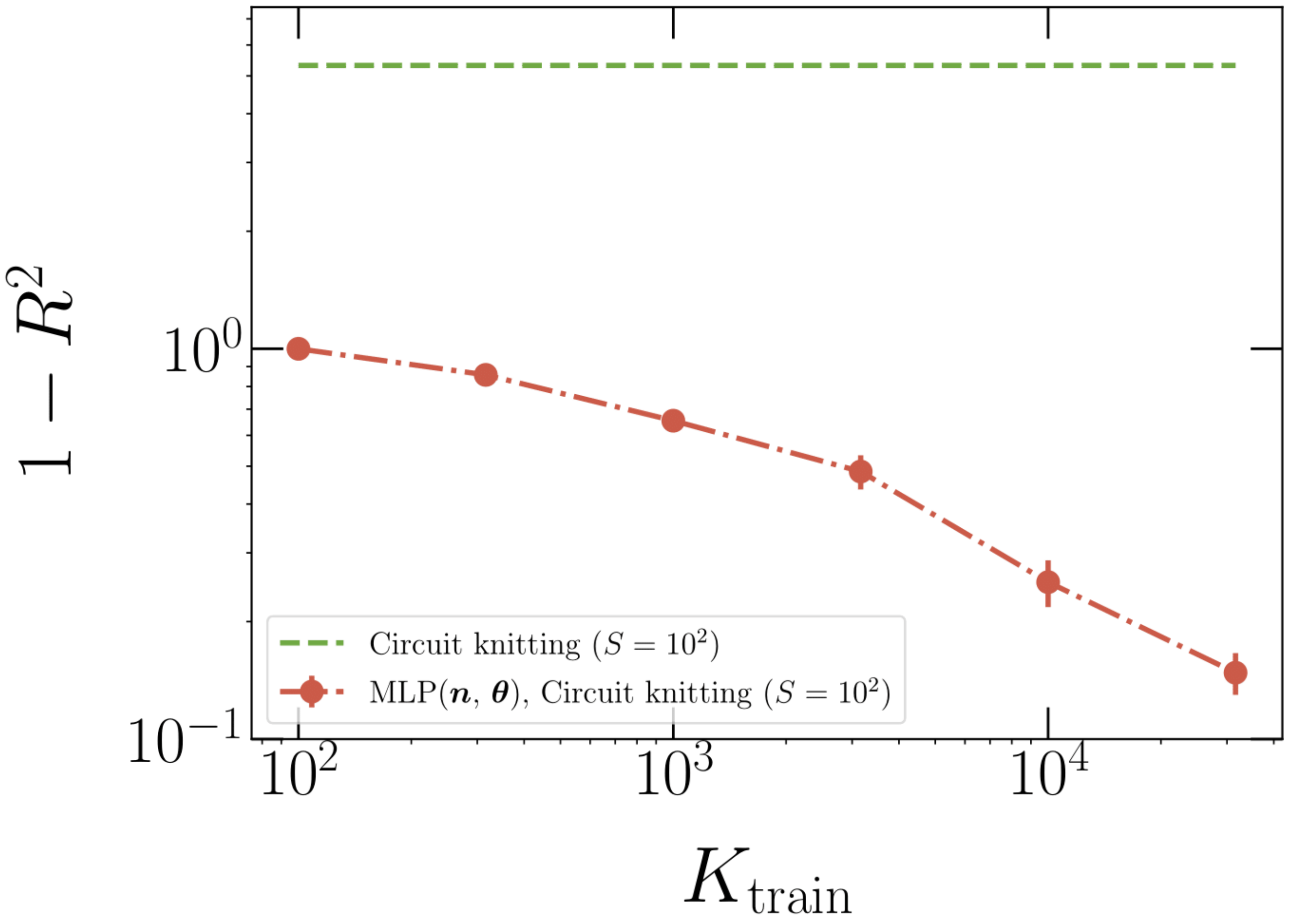
- Damping factor EM: $\langle \mathcal{O} \rangle_{\mathbf{noisy}} = D\langle \mathcal{O} \rangle$, where D can be obtained with reference states;

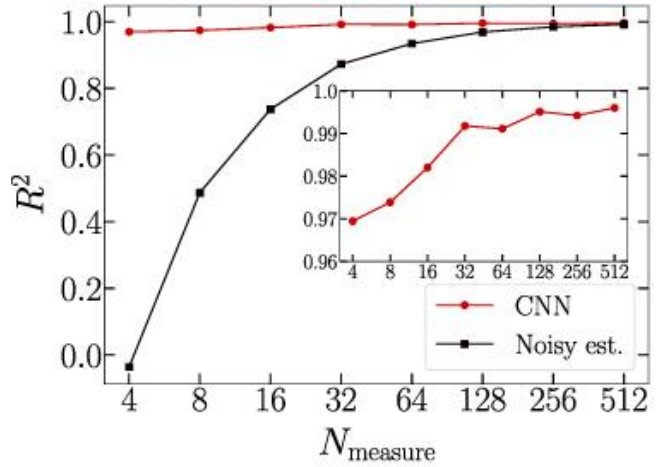




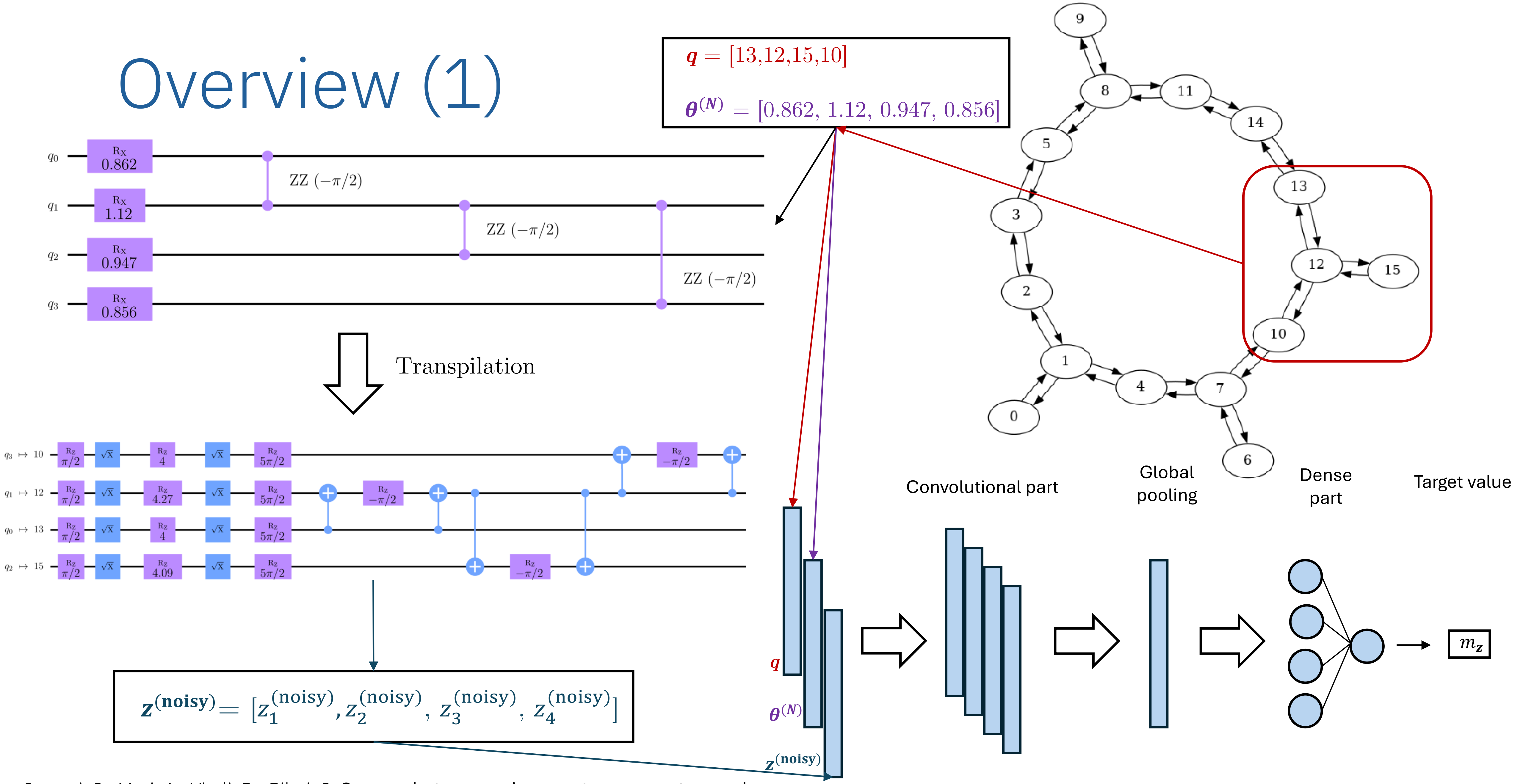
$N = 4$
$N = 6$
$N = 8$
$N = 10$
$N = 12$
$1 - R^2$
10^0
10^{-1}
10^{-2}
10^2
10^3
10^4
K_{train}

Filtering the shot noise of target values





Overview (1)

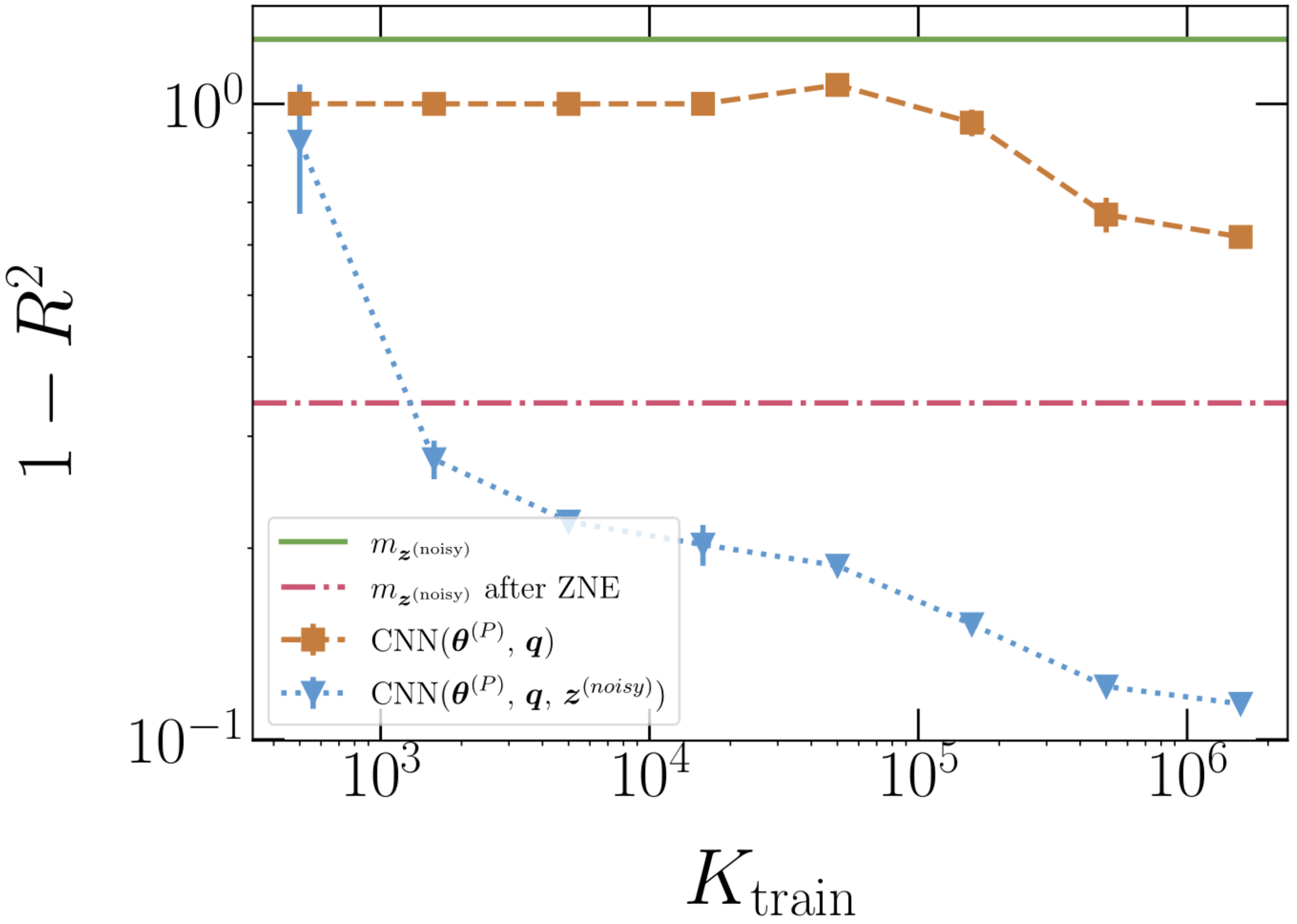


Convolutional neural network (CNN)

Cantori, S., Mari, A., Vitali, D., Pilati, S. **Synergy between noisy quantum computers and scalable classical deep learning for quantum error mitigation.** *EPJ Quantum Technol.* 11, 45 (2024)

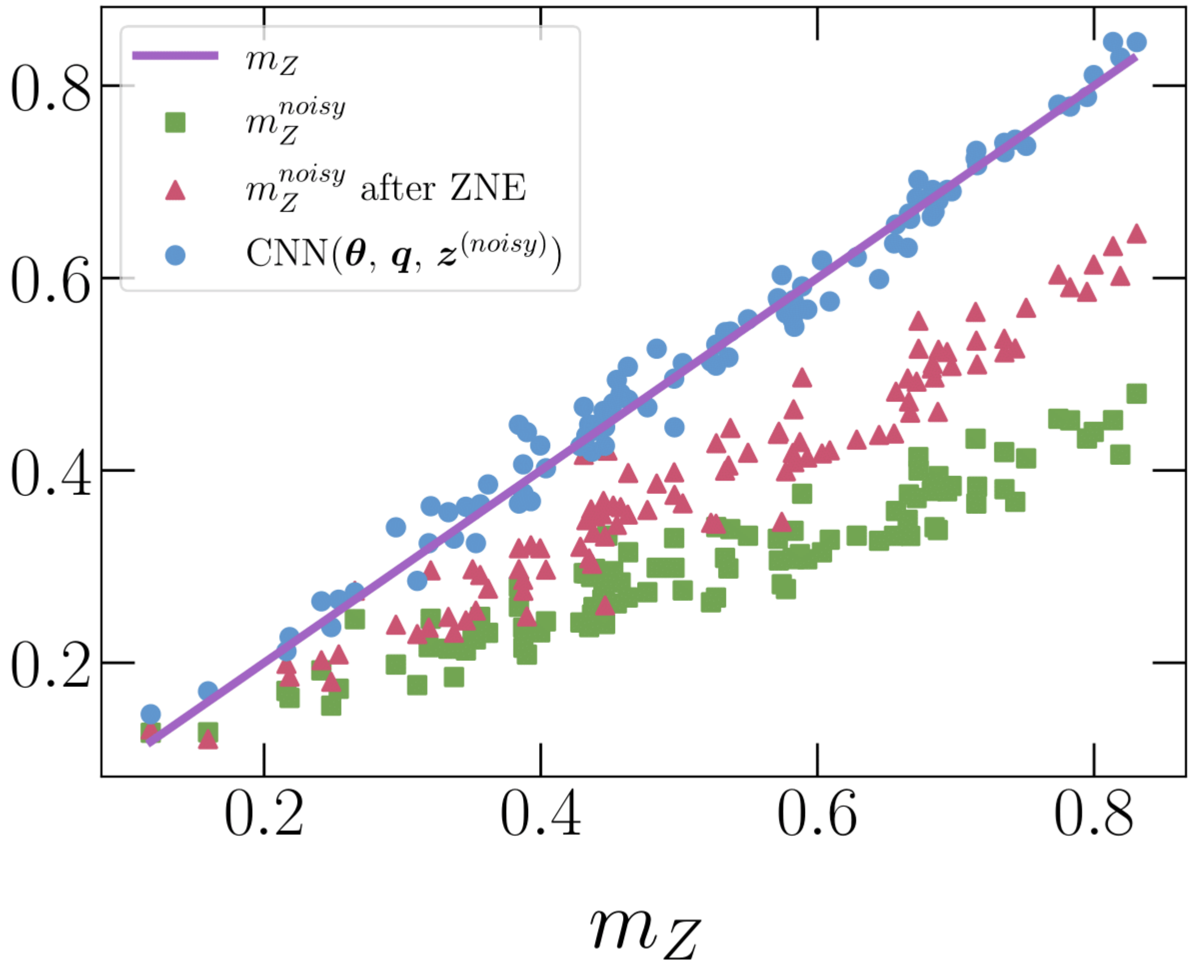
Impact of the training-set size

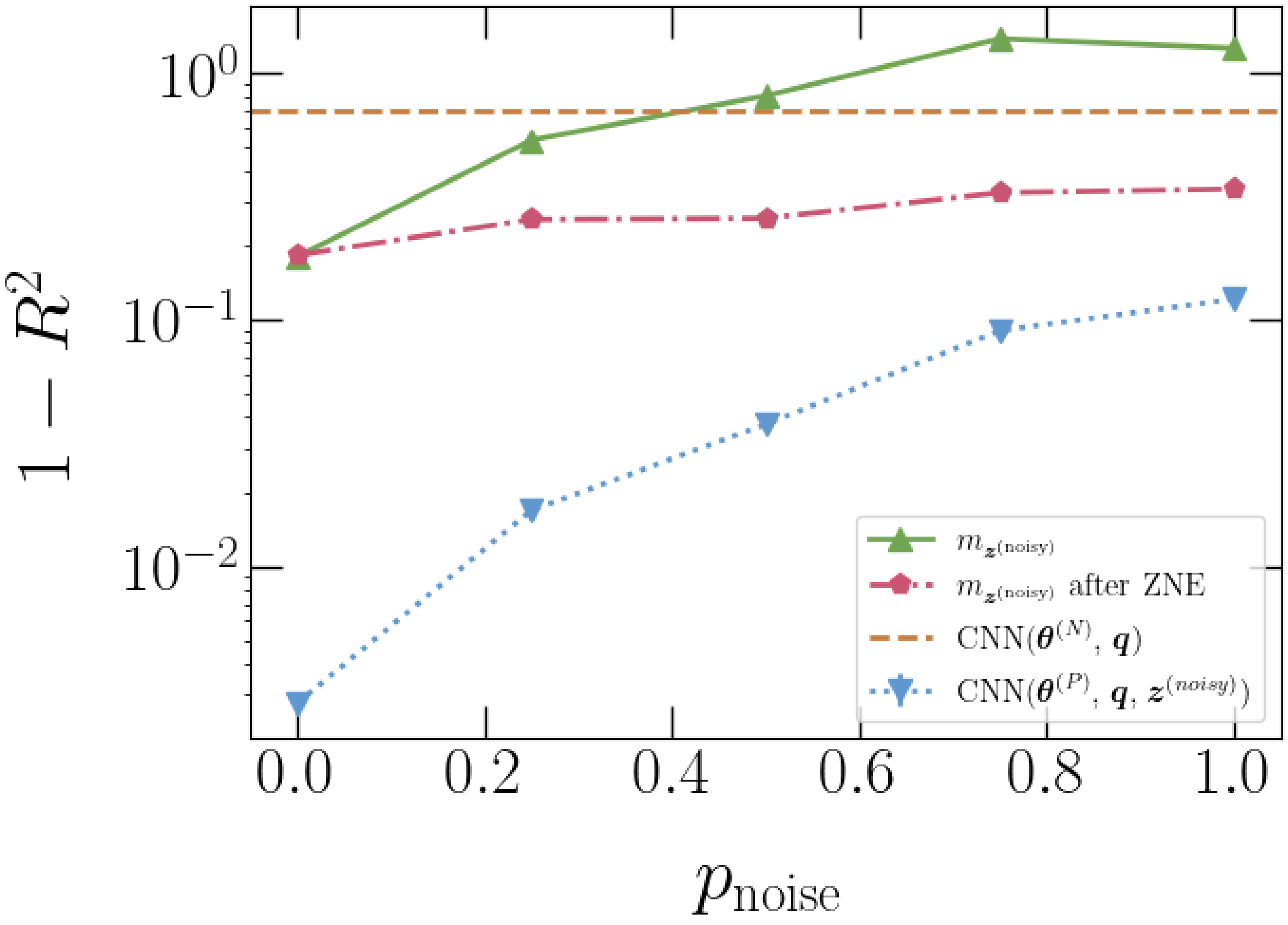
- $1 - R^2 = \frac{\sum_{i=1}^{K_{test}} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{K_{test}} (y_i - \bar{y})^2}$.
- Training on quantum circuits with $N \leq 10$ qubits and testing on quantum circuits with $N = 16$ qubits.
- $P = 20$ layers of gates.



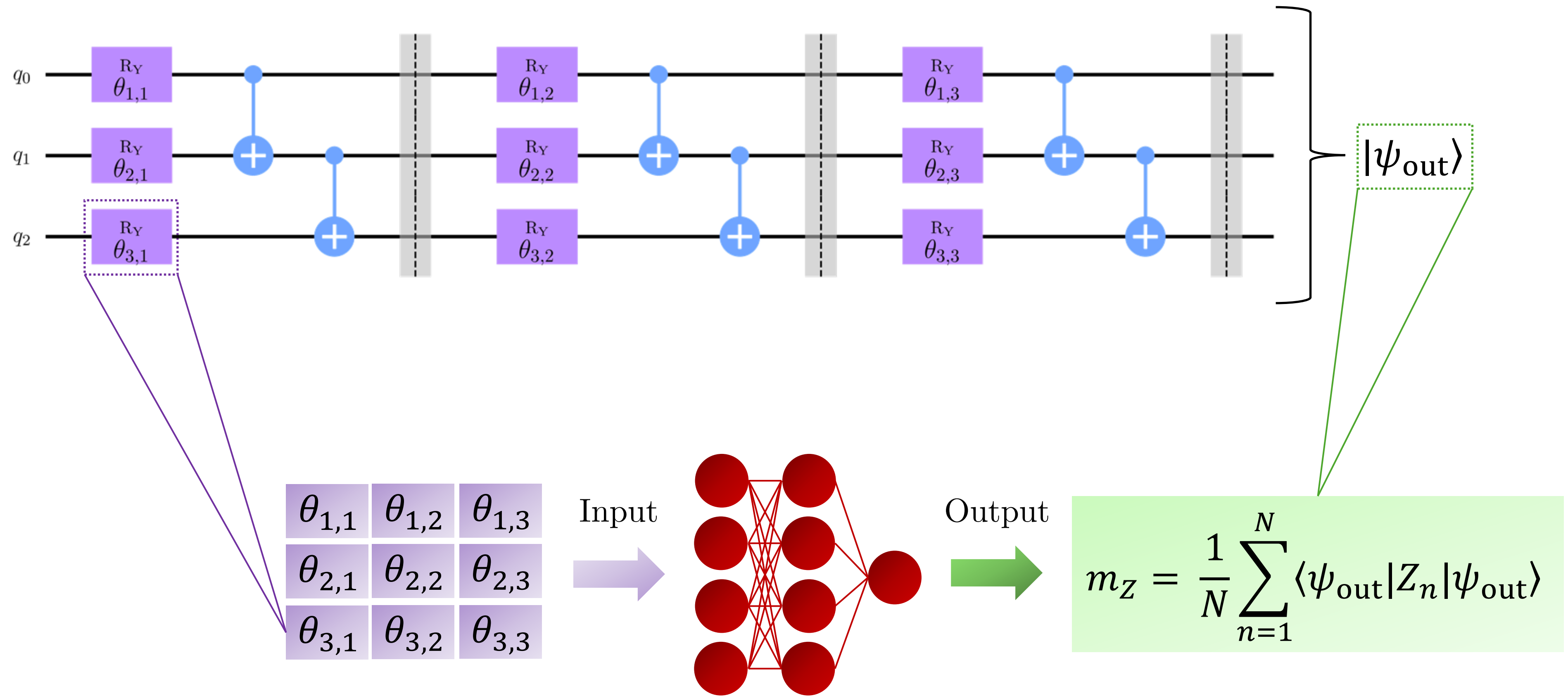
Visualization of the improvement

- Training on quantum circuits with $N \leq 10$ qubits and testing on quantum circuits with $N = 16$ qubits.
- $P = 20$ layers of gates.

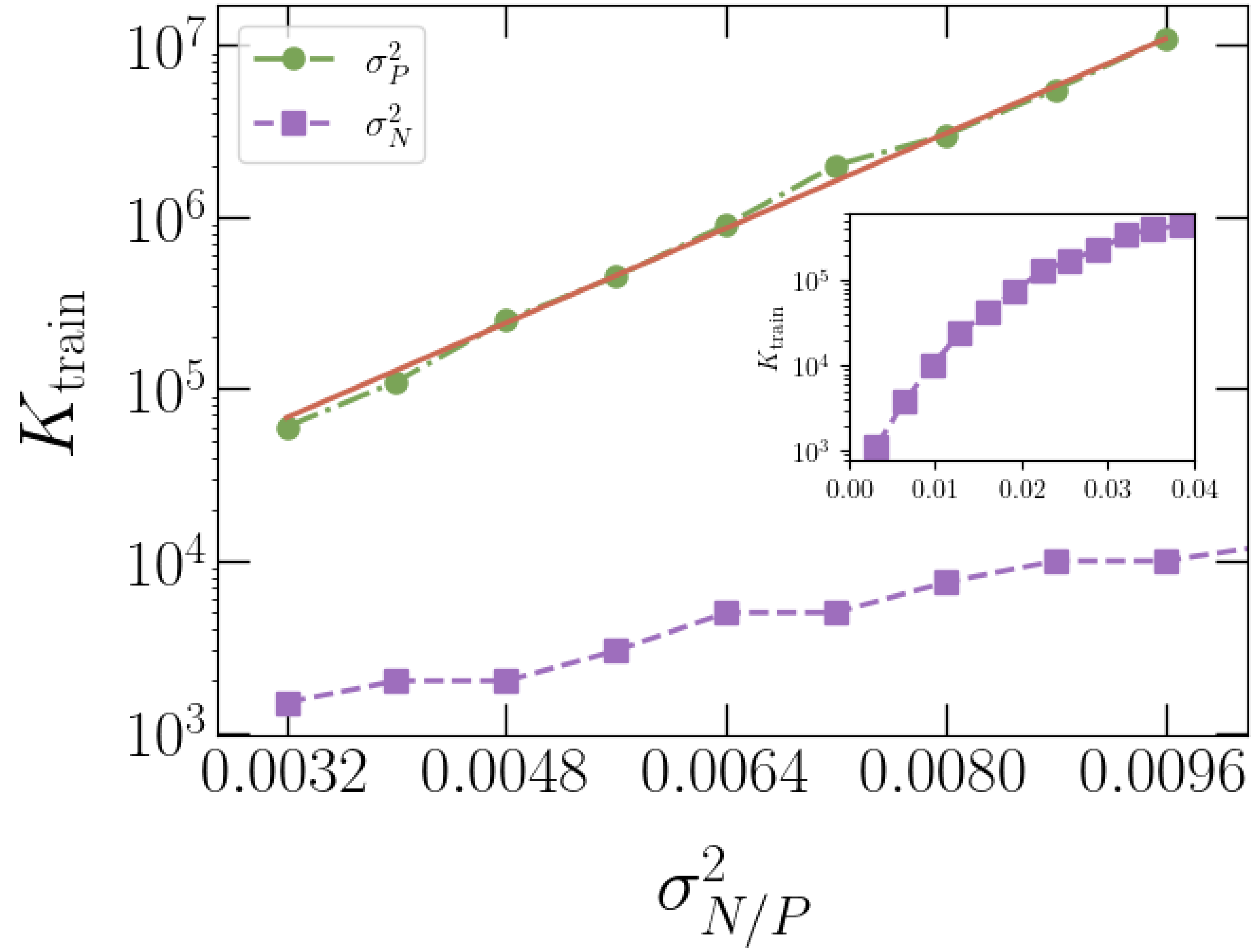




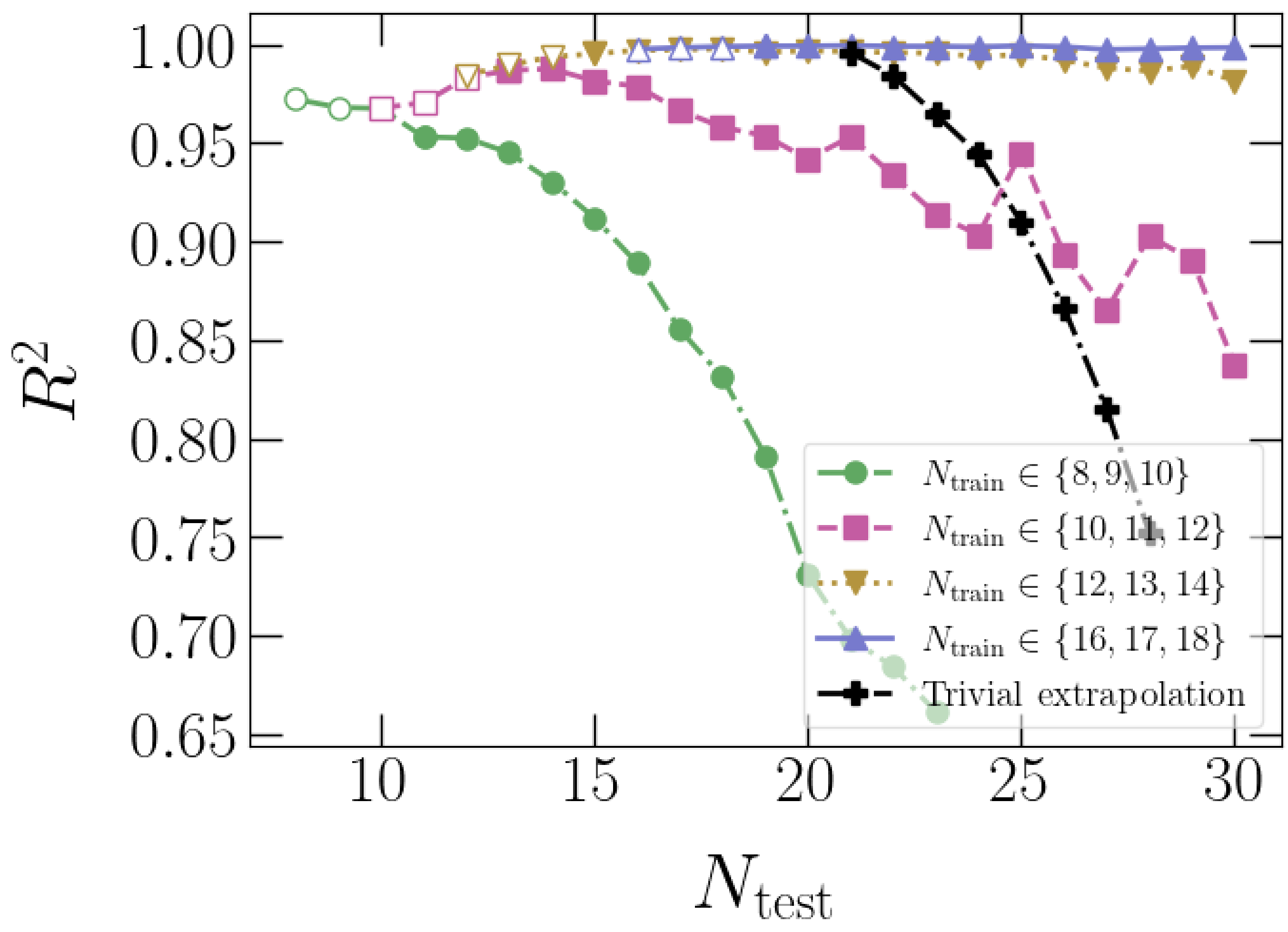
10^{0}
10^{-1}
10^{-2}
$1 - R^2$
0.0
0.2
0.4
0.6
0.8
1.0
p_{noise}
$m_{\boldsymbol{z}^{(\text{noisy})}}$
$m_{\boldsymbol{z}^{(\text{noisy})}}$ after ZNE
CNN($\boldsymbol{\theta}^{(N)}$, $\boldsymbol{q}$)
CNN($\boldsymbol{\theta}^{(P)}$, $\boldsymbol{q}$, $\boldsymbol{z}^{(noisy)}$)



q_0
q_1
q_2
R_Y $\theta_{1,1}$
R_Y $\theta_{2,1}$
R_Y $\theta_{3,1}$
R_Y $\theta_{1,2}$
R_Y $\theta_{2,2}$
R_Y $\theta_{3,2}$
R_Y $\theta_{1,3}$
R_Y $\theta_{2,3}$
R_Y $\theta_{3,3}$
$|\psi_{\text{out}}\rangle$
$\theta_{1,1}$ $\theta_{1,2}$ $\theta_{1,3}$
$\theta_{2,1}$ $\theta_{2,2}$ $\theta_{2,3}$
$\theta_{3,1}$ $\theta_{3,2}$ $\theta_{3,3}$
Input
Output
$m_Z = \frac{1}{N}\sum_{n=1}^{N}\langle\psi_{\text{out}}|Z_n|\psi_{\text{out}}\rangle$



10^7
10^6
10^5
10^4
10^3
K_{train}
σ_P^2
σ_N^2
0.0032
0.0048
0.0064
0.0080
0.0096
$\sigma_{N/P}^2$
0.00
0.01
0.02
0.03
0.04



1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
R^2
10
15
20
25
30
N_{test}
$N_{\text{train}} \in \{8, 9, 10\}$
$N_{\text{train}} \in \{10, 11, 12\}$
$N_{\text{train}} \in \{12, 13, 14\}$
$N_{\text{train}} \in \{16, 17, 18\}$
Trivial extrapolation