Data-driven decoding of quantum error correcting codes using graph neural networks

Moritz Lange[1], Pontus Havström[1], Basudha Srivastava[1, 2], Isak Bengtsson[3], Valdemar Bergentall[1], Karl Hammar[1], Olivia Heuts[1], Evert van Nieuwenburg[4], and Mats Granath[1]

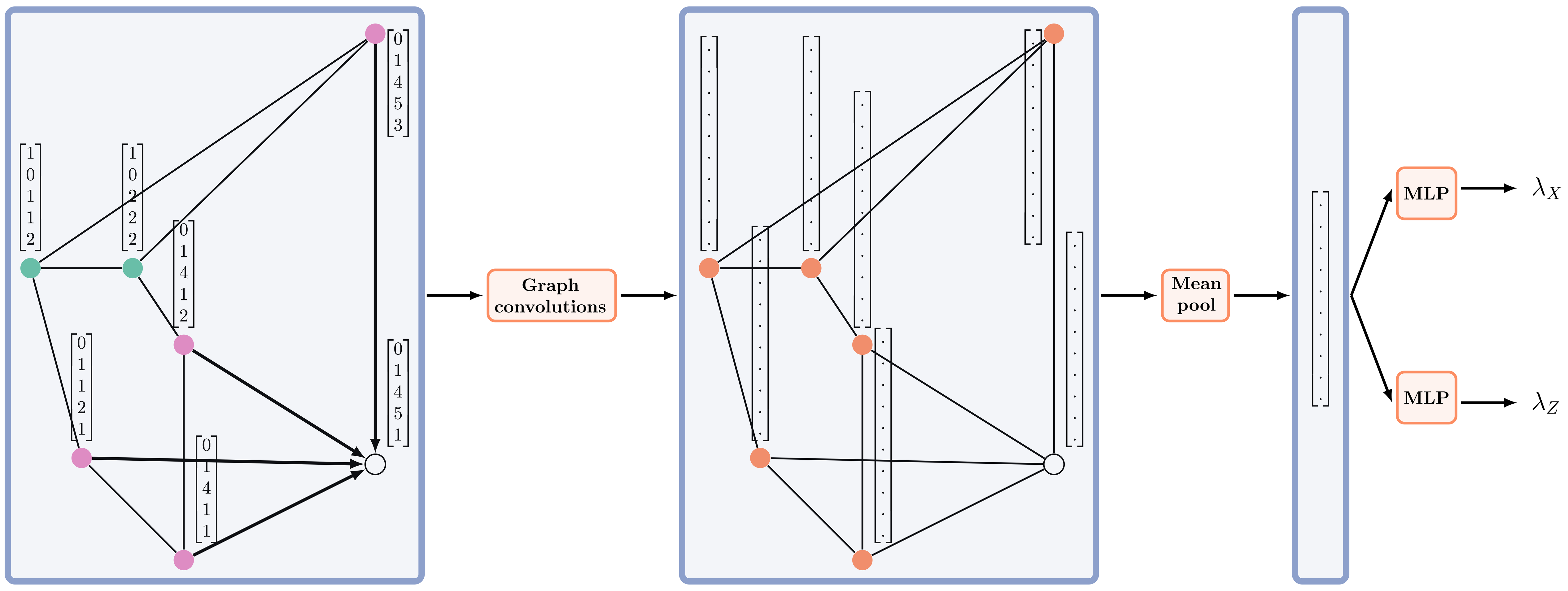
[1]Department of Physics, University of Gothenburg, 41296 Gothenburg, Sweden
[2]Quantinuum, Terrington House, 13-15 Hills Rd, Cambridge, CB2 1NL, UK
[3]Department of Physics, Chalmers University of Technology, 41296 Gothenburg, Sweden
[4]Leiden Inst. of Advanced Computer Science, Leiden University, Leiden, Netherlands

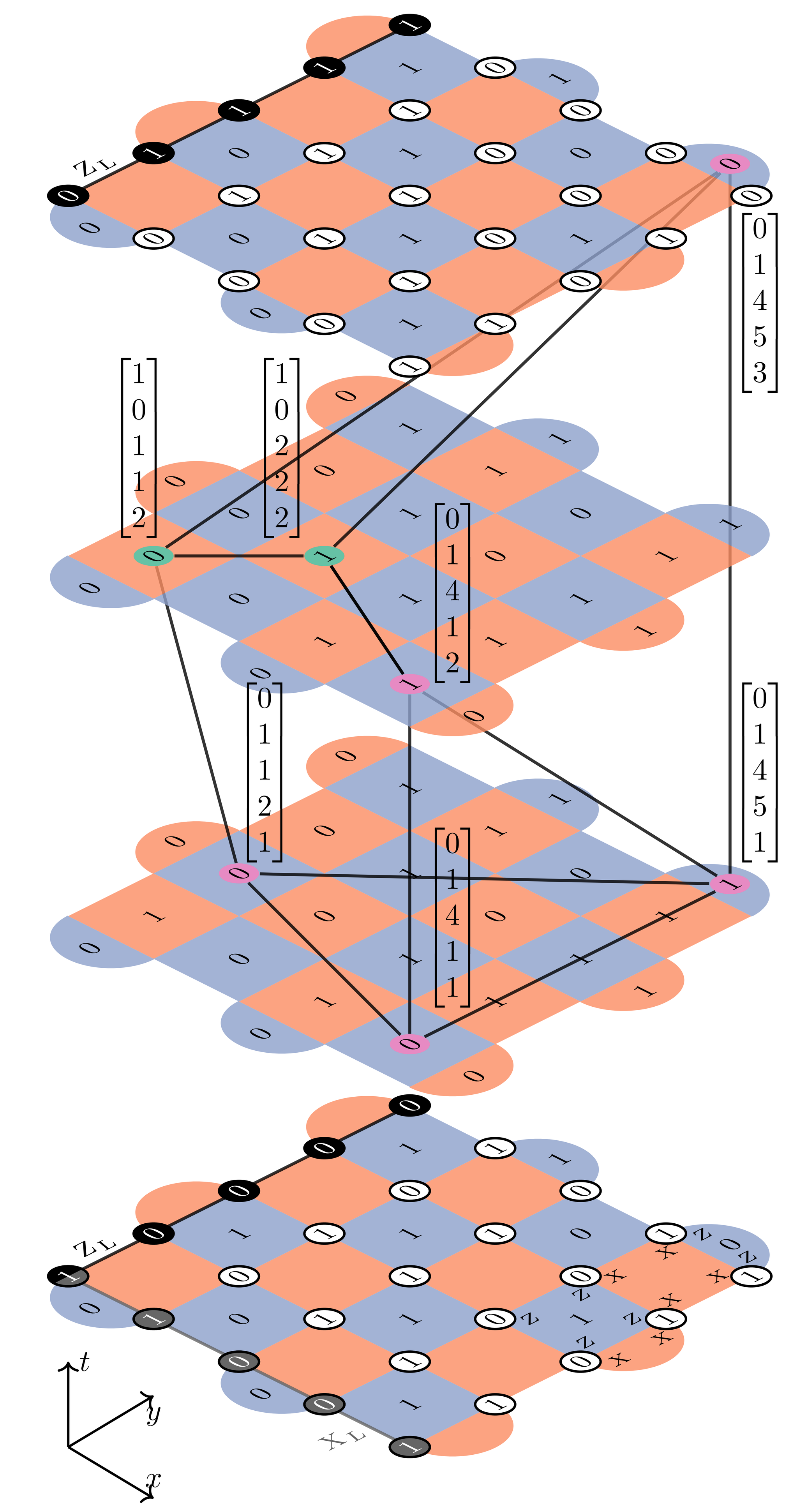
UNIVERSITY OF GOTHENBURG

WACQT | Wallenberg Centre for Quantum Technology

Introduction

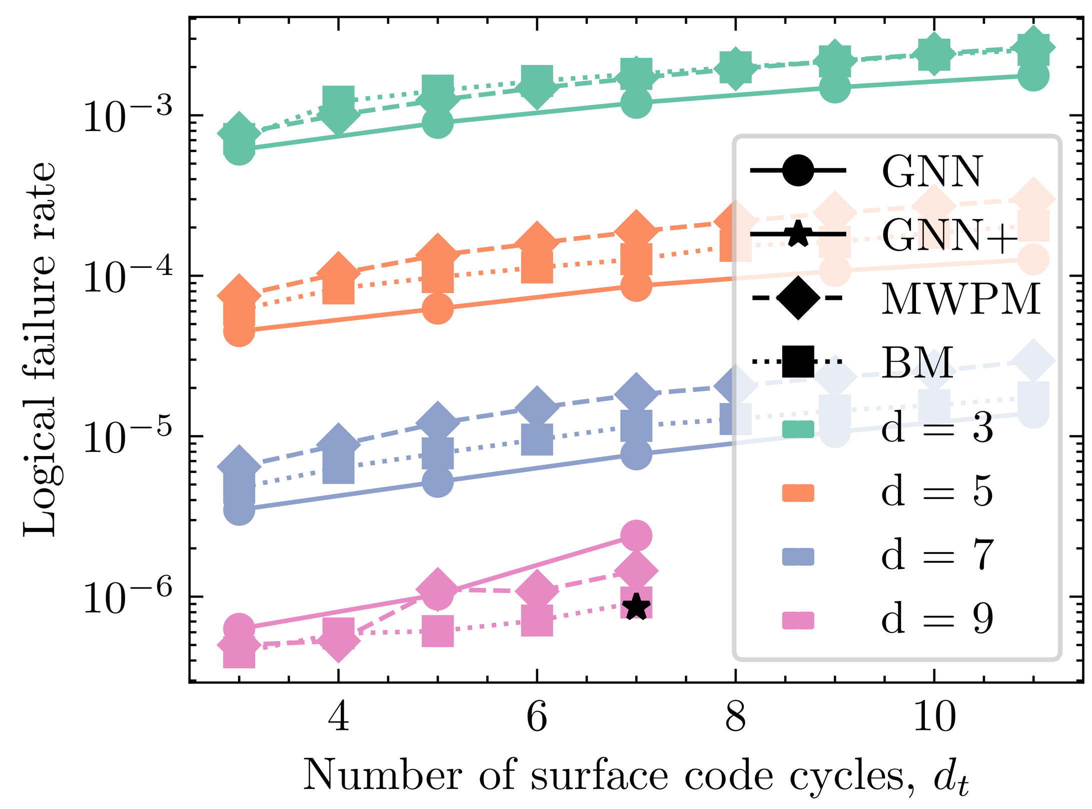
We develop a model-free, data-driven, approach to decoding, using a graph neural network (GNN). The decoding problem is formulated as a graph classification task in which a set of stabilizer measurements is mapped to an annotated detector graph for which the neural network predicts the most likely logical error class. We show that the model can be trained on simulated data with circuit-level noise on the surface code as well as on experimental detector data for the repetition code [2], with performance on par with noise-informed matching decoders. Although training is computationally demanding, inference is fast and scales approximately linearly with the space-time volume of the code.



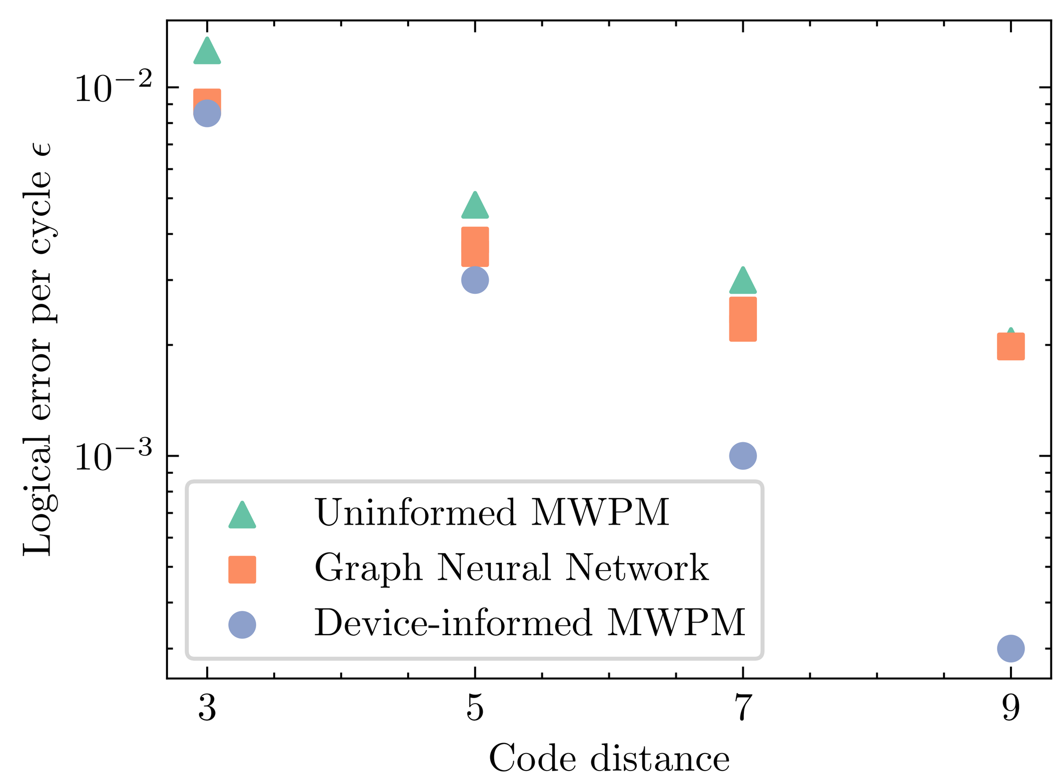


Memory experiment on the distance $d = 5$ surface code.

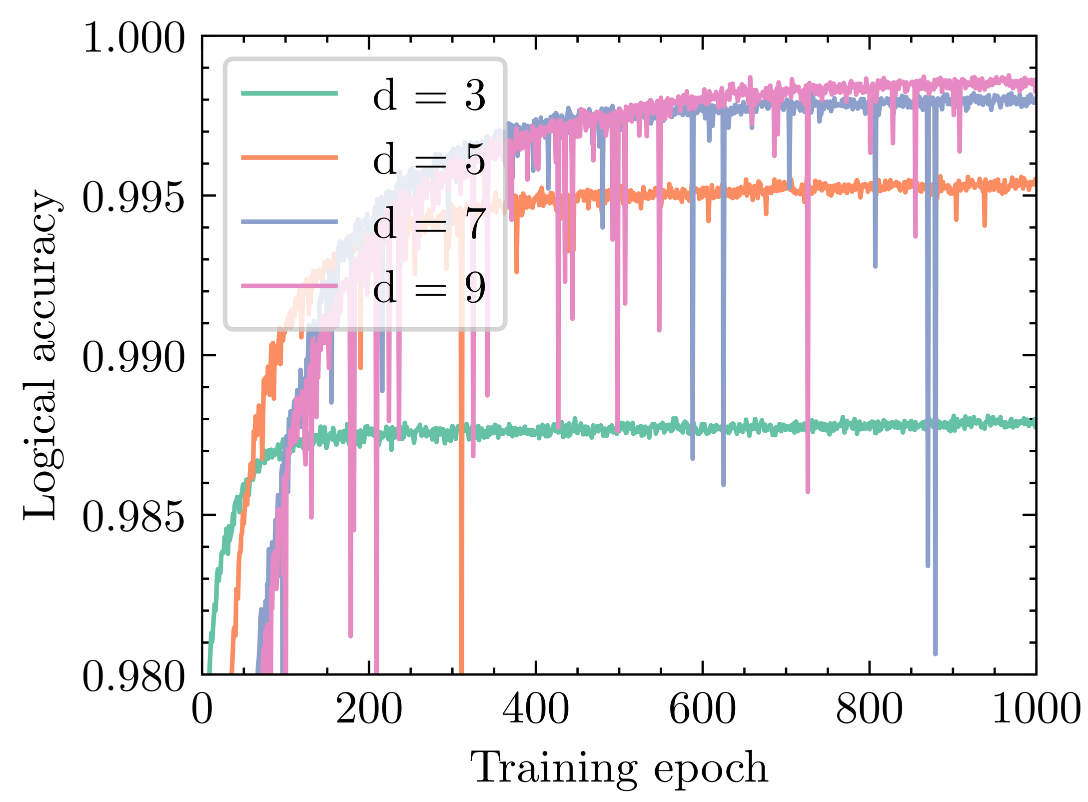
Results



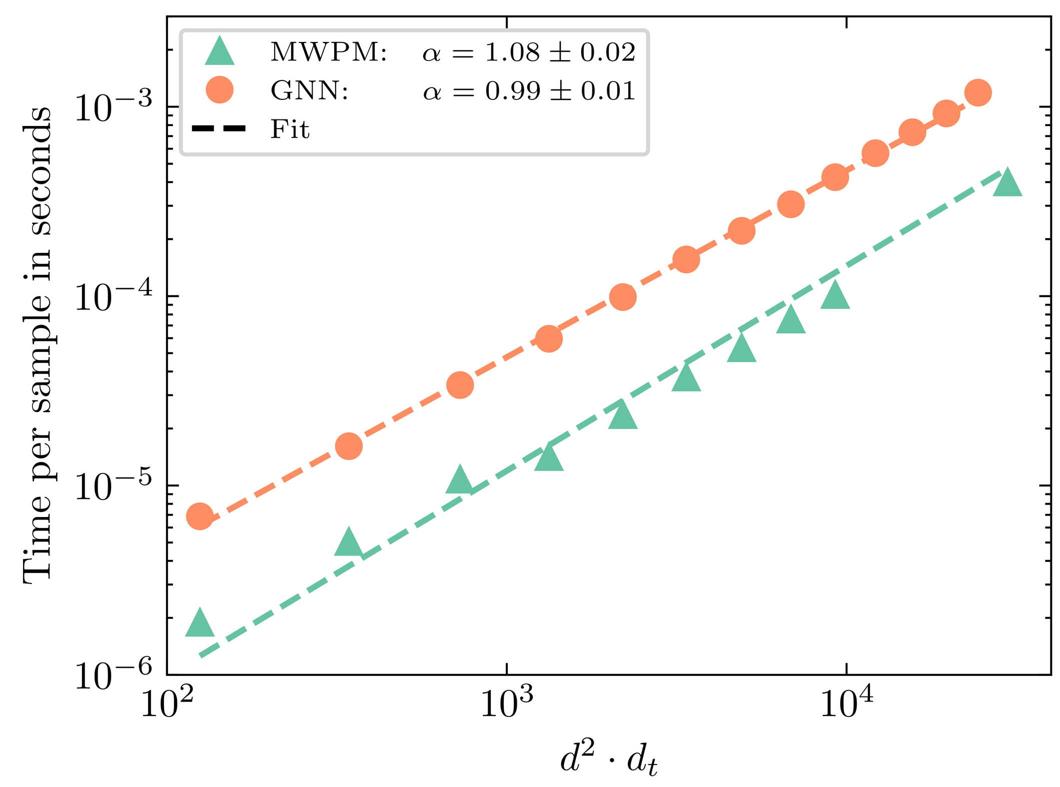
Decoding [3, 4] simulated experimental data [5], with circuit-level noise, on the rotated surface code with code distance d.



Decoding experimental data [2] on the repetition code with code distance d, over 50 rounds of stabilizer measurements.



GNN training and test accuracy versus number of training epochs for circuit-level noise.



Scaling of average decoding time per syndrome versus code volume $d^2 d_t$ for GNN and MWPM.

Acknowledgements

We acknowledge financial support from the Knut and Alice Wallenberg Foundation through the Wallenberg Centre for Quantum Technology (WACQT). Computations were enabled by resources provided by the National Academic Infrastructure for Supercomputing in Sweden (NAISS) and the Swedish National Infrastructure for Computing (SNIC) at Chalmers Centre for Computational Science and Engineering (C3SE), partially funded by the Swedish Research Council through grant agreements no. 2022-06725 and no. 2018-05973. This work was also supported by the Dutch National Growth Fund (NGF), as part of the Quantum Delta NL programme.

References

[1] Moritz Lange, Pontus Havström, Basudha Srivastava, Valdemar Bergentall, Karl Hammar, Olivia Heuts, Evert van Nieuwenburg, and Mats Granath. Data-driven decoding of quantum error correcting codes using graph neural networks, 2023. URL `https://arxiv.org/abs/2307.01241`.

[2] Google Quantum AI. Suppressing quantum errors by scaling a surface code logical qubit. *Nature*, 614(7949):676–681, 2023. URL `https://www.nature.com/articles/s41586-022-05434-1`.

[3] Oscar Higgott and Craig Gidney. Sparse blossom: correcting a million errors per core second with minimum-weight matching. *arXiv preprint arXiv:2303.15933*, 2023.

[4] Oscar Higgott, Thomas C. Bohdanowicz, Aleksander Kubica, Steven T. Flammia, and Earl T. Campbell. Improved decoding of circuit noise and fragile boundaries of tailored surface codes. *Phys. Rev. X*, 13:031007, Jul 2023. doi: 10.1103/PhysRevX.13.031007. URL `https://link.aps.org/doi/10.1103/PhysRevX.13.031007`.

[5] Craig Gidney. Stim: a fast stabilizer circuit simulator. *Quantum*, 5:497, July 2021. ISSN 2521-327X. doi: 10.22331/q-2021-07-06-497. URL `https://doi.org/10.22331/q-2021-07-06-497`.

moritzlange@mailbox.org