

Classical and Quantum Machine Learning for Error Correction

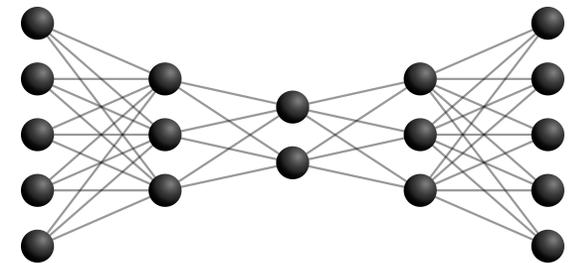
UK-Korea Meeting

17 November 2021

Markus Müller

RWTH Aachen University

Forschungszentrum Jülich, Germany



Since October 2019 with my group in Aachen and Jülich Theoretical Quantum Technology



RWTH AACHEN
UNIVERSITY

JÜLICH
Forschungszentrum



Key Theory and Experimental Areas

- Quantum error correction
- Fault-tolerant quantum computing
- Open quantum systems
- Semiconductor spin qubits
- Majorana qubits
- Superconducting qubits
- QIP with AMO systems



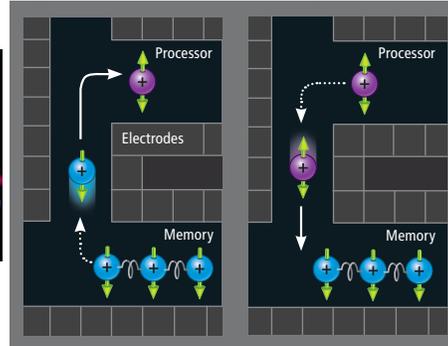
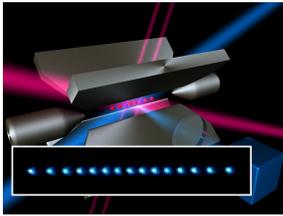
Colleagues at the Institute for Quantum Information (RWTH)
DiVincenzo, Hassler, Bluhm, Catelani, Terhal

www.rwth-aachen.de/mueller-group

www.markus-mueller.website

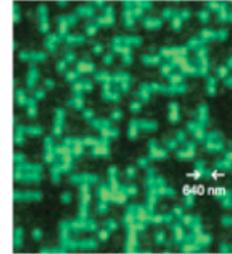
The ongoing race towards scalable quantum computers

► 2D ion-trap quantum computers

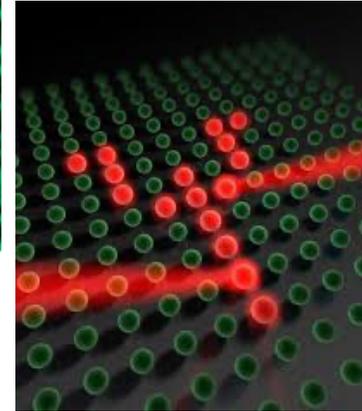


Innsbruck, Mainz, Maryland, Siegen, Zurich, AQT, IONQ ...

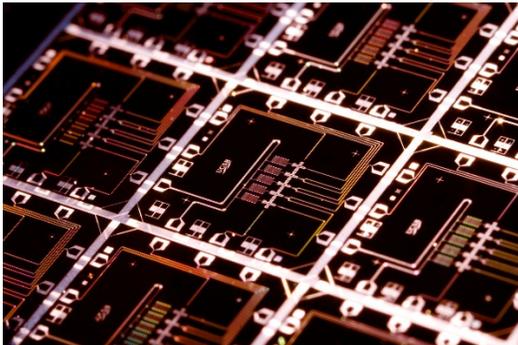
► Cold atoms in optical lattices



Munich,
Harvard
Strathclyde,
PASQAL
(Palaiseau)...

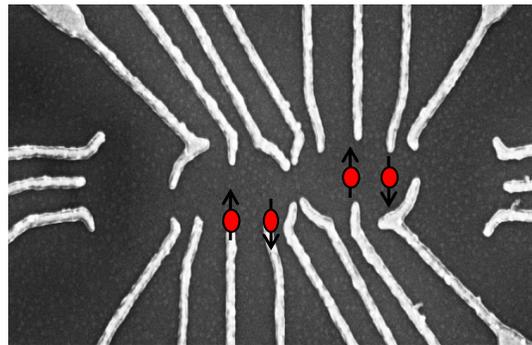


► Super-conducting qubits



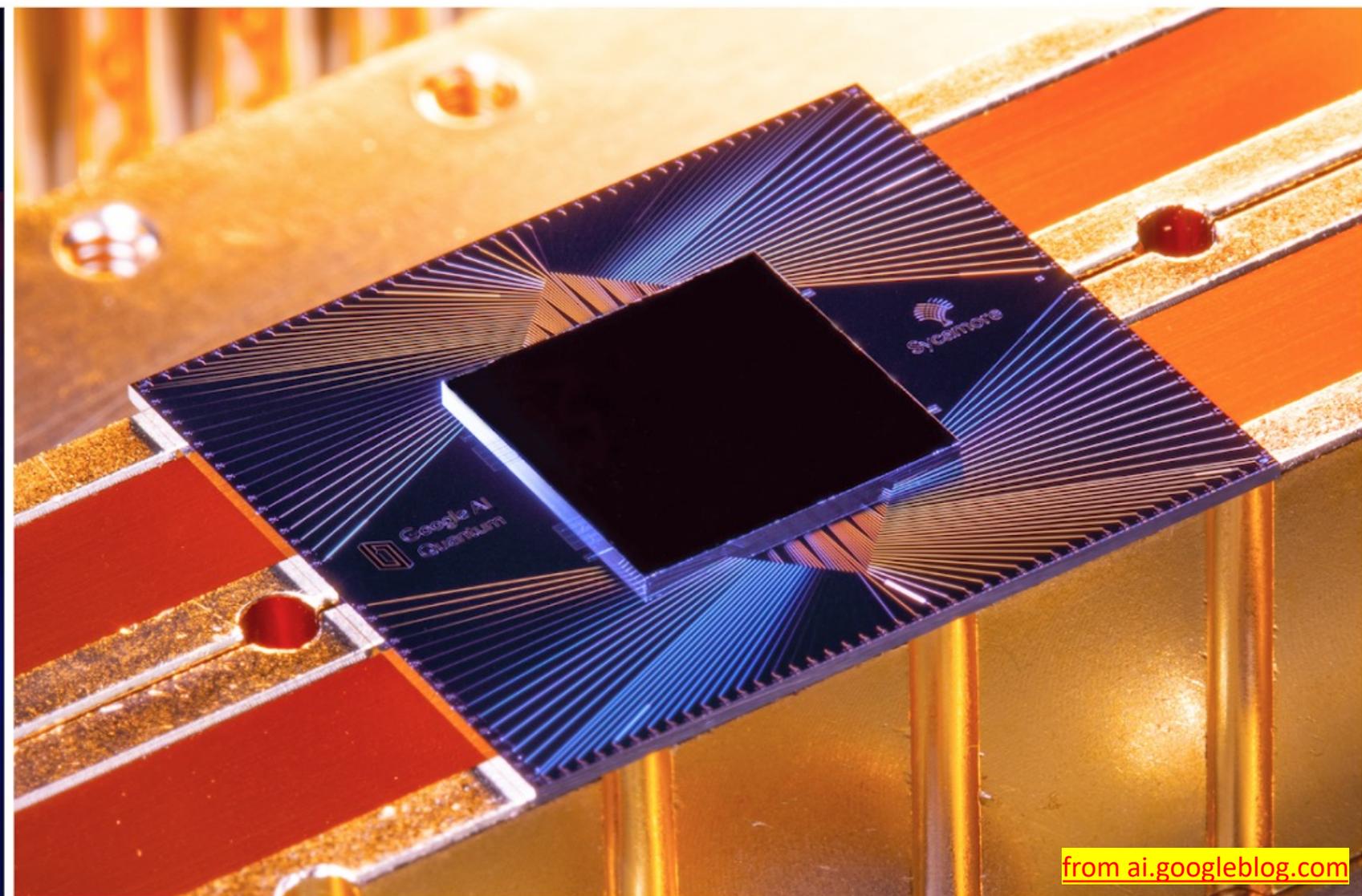
Jülich, Delft, Zurich, IBM, GOOGLE, ...

► Electron spin qubits



Aachen, Jülich, Stuttgart, Cologne ...

- Majorana qubits,
- Photons,
- NV centres, ...



[from ai.googleblog.com](https://ai.googleblog.com)

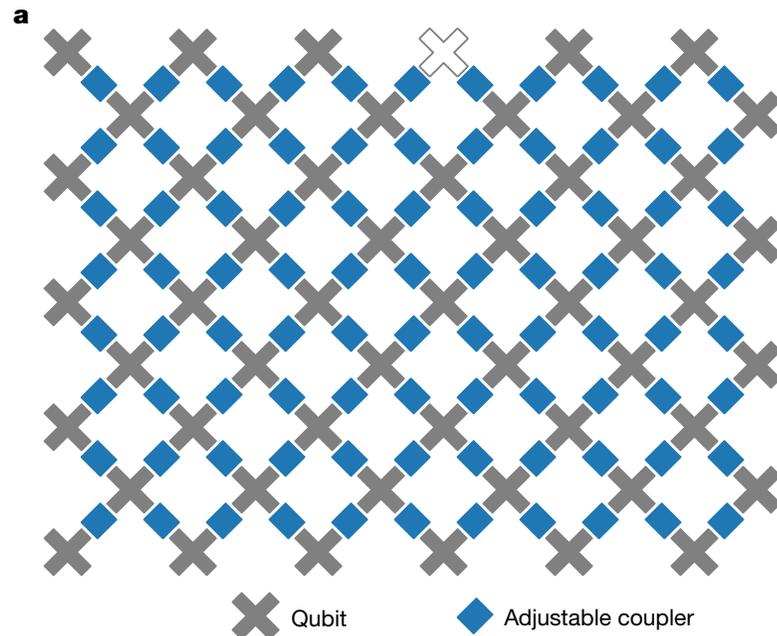
Quantum computers outperforming the best classical computers?

Article | Published: 23 October 2019

Quantum supremacy using a programmable superconducting processor

Frank Arute, Kunal Arya, [...] John M. Martinis ✉

Nature 574, 505–510(2019) | Cite this article



- ▶ First quantum computation a classical computer can't track
- ▶ ... but for a completely useless problem

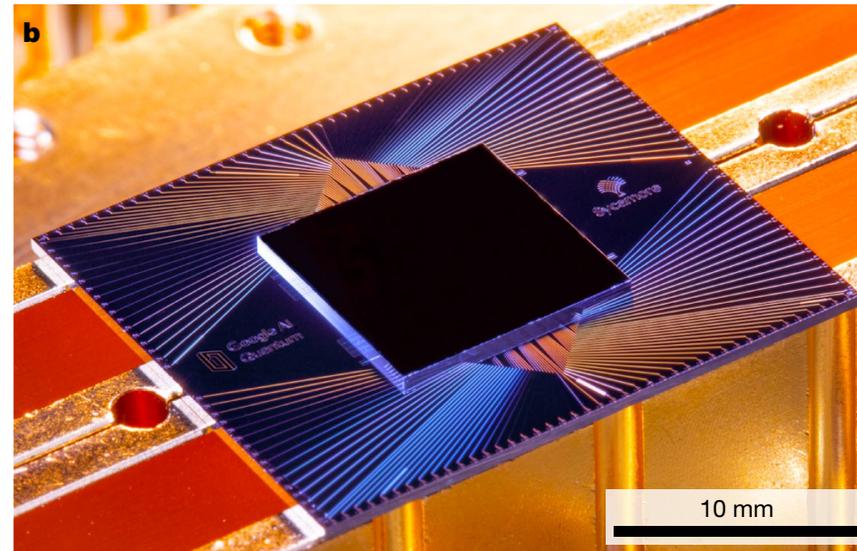
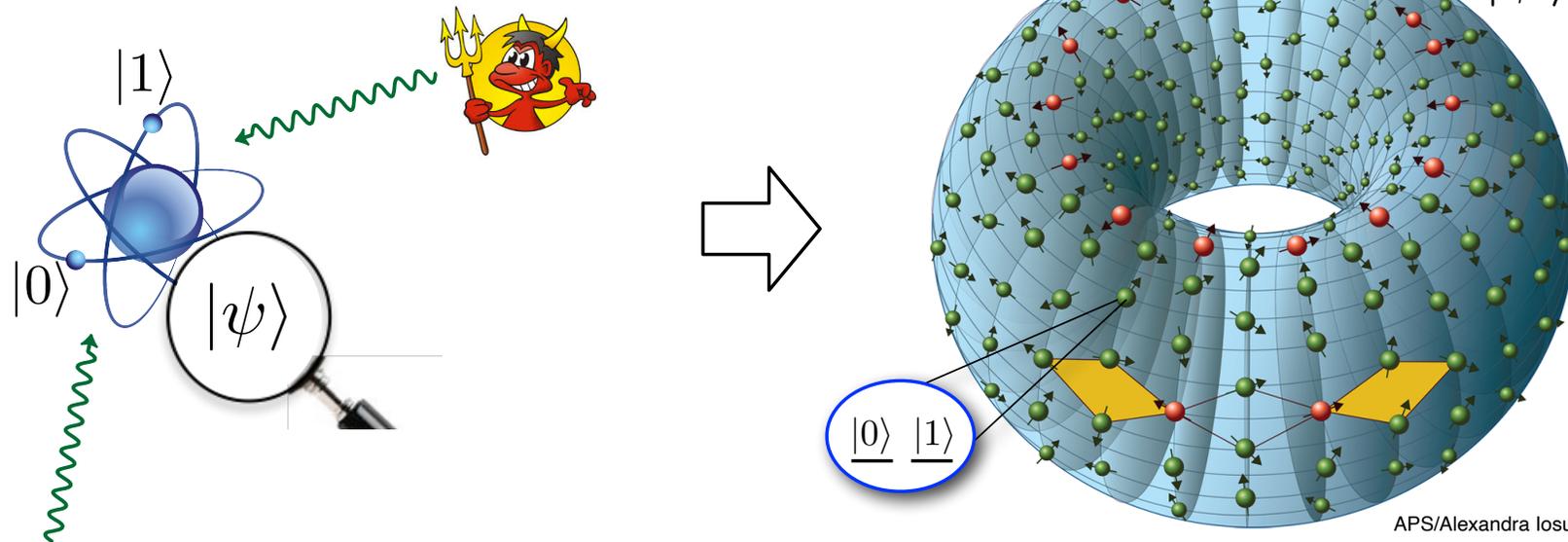


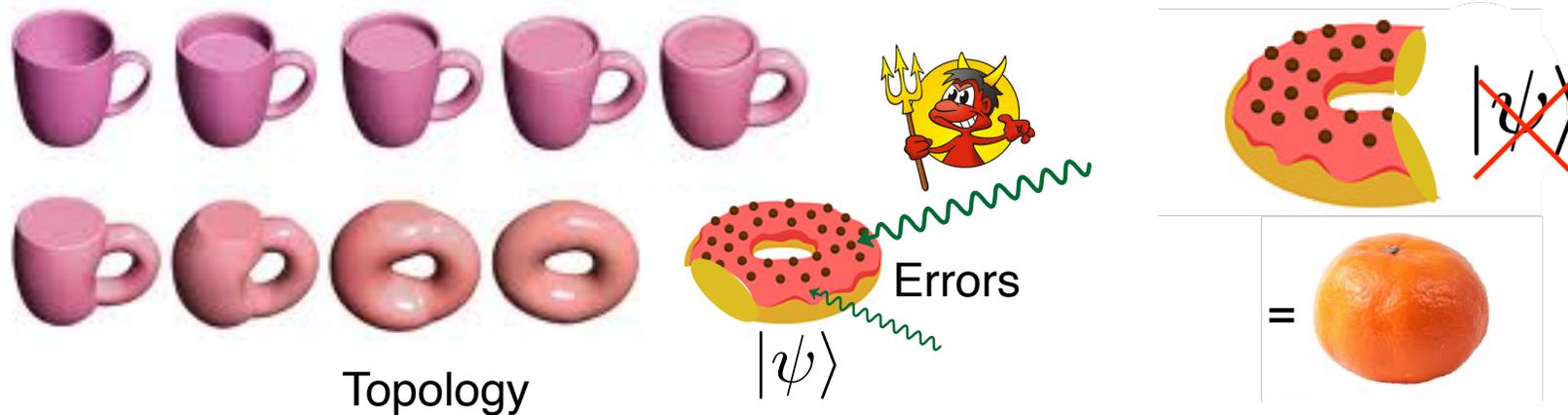
Fig. 1 | The Sycamore processor. **a**, Layout of processor, showing a rectangular array of 54 qubits (grey), each connected to its four nearest neighbours with couplers (blue). The inoperable qubit is outlined. **b**, Photograph of the Sycamore chip.

Topological Quantum Error Correction



APS/Alexandra Iosub

robust encoding of quantum information in **global** properties of many qubits



Topology

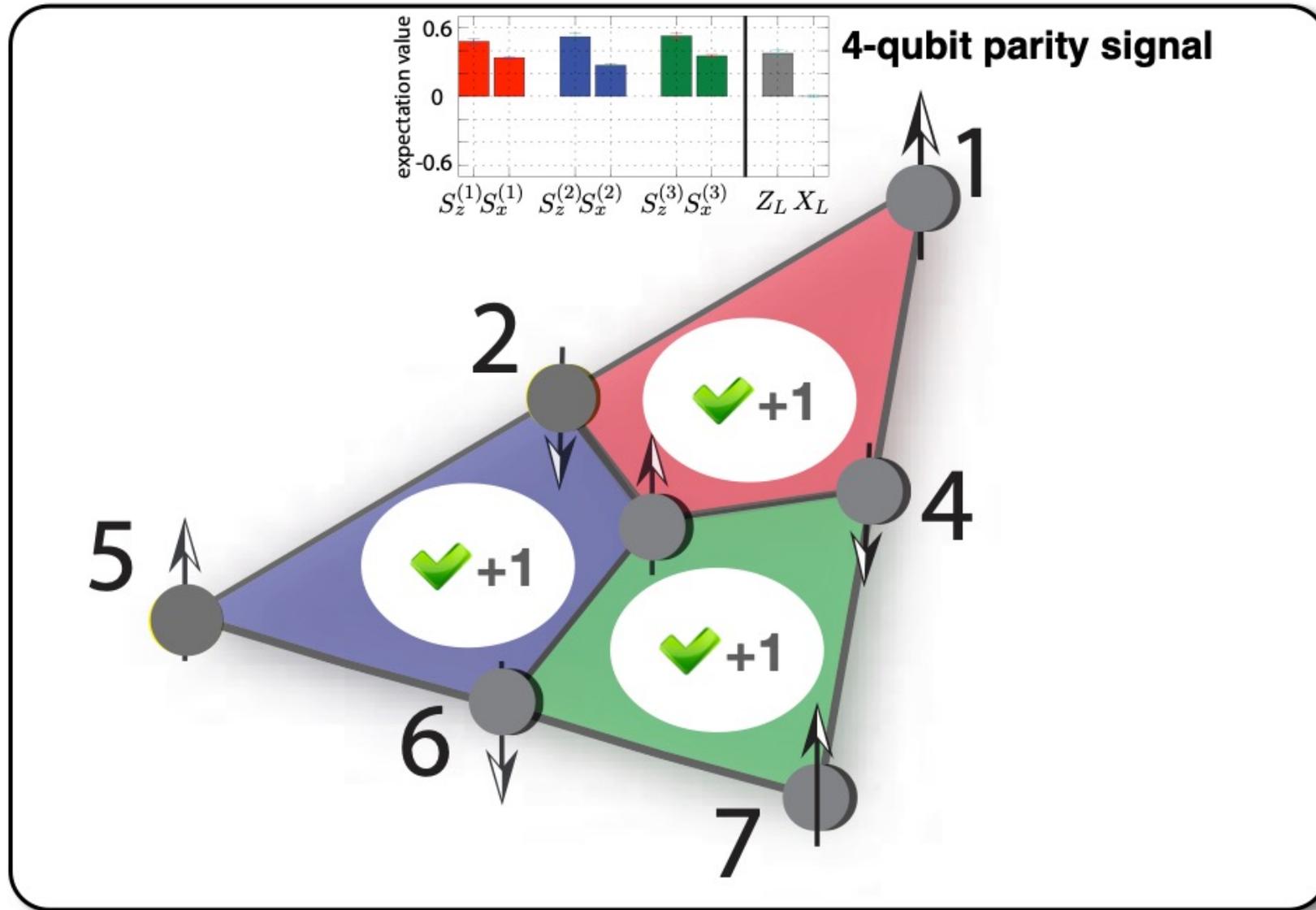
Errors

$|\psi\rangle$

~~$|\psi\rangle$~~

=

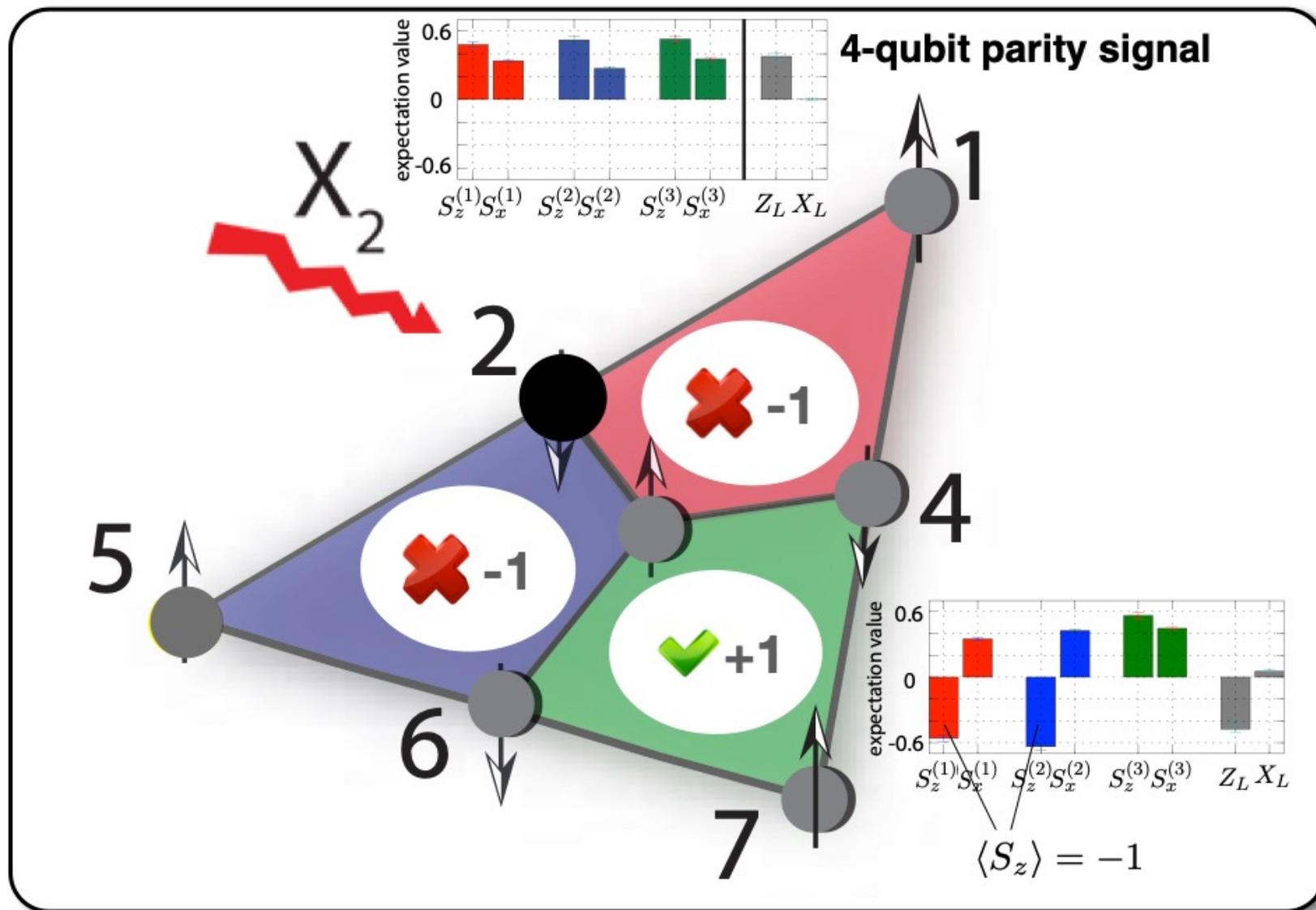
Detection of errors - a pattern recognition problem!



In collaboration with expt. ion-trap group Innsbruck

Science **345**, 302 (2014)

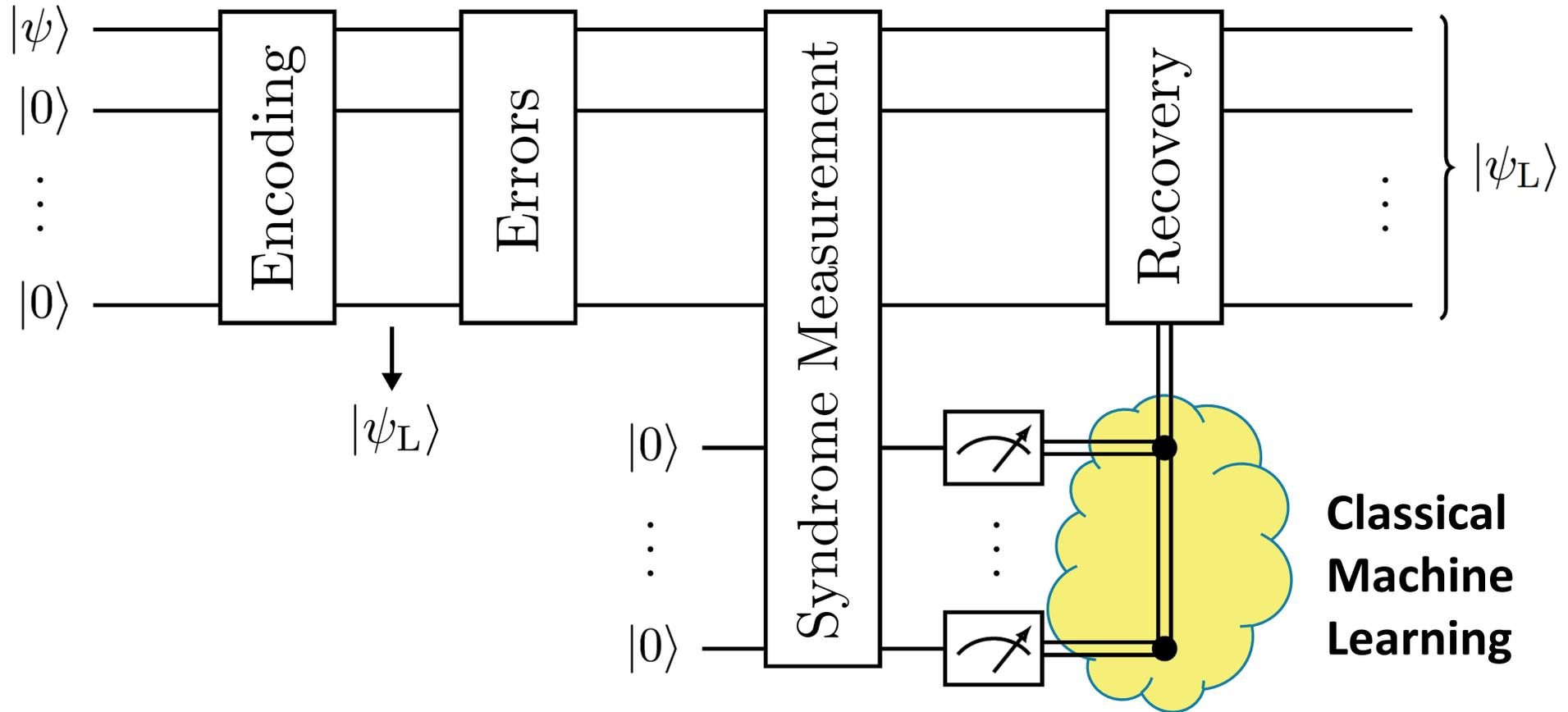
Detection of errors - a pattern recognition problem!



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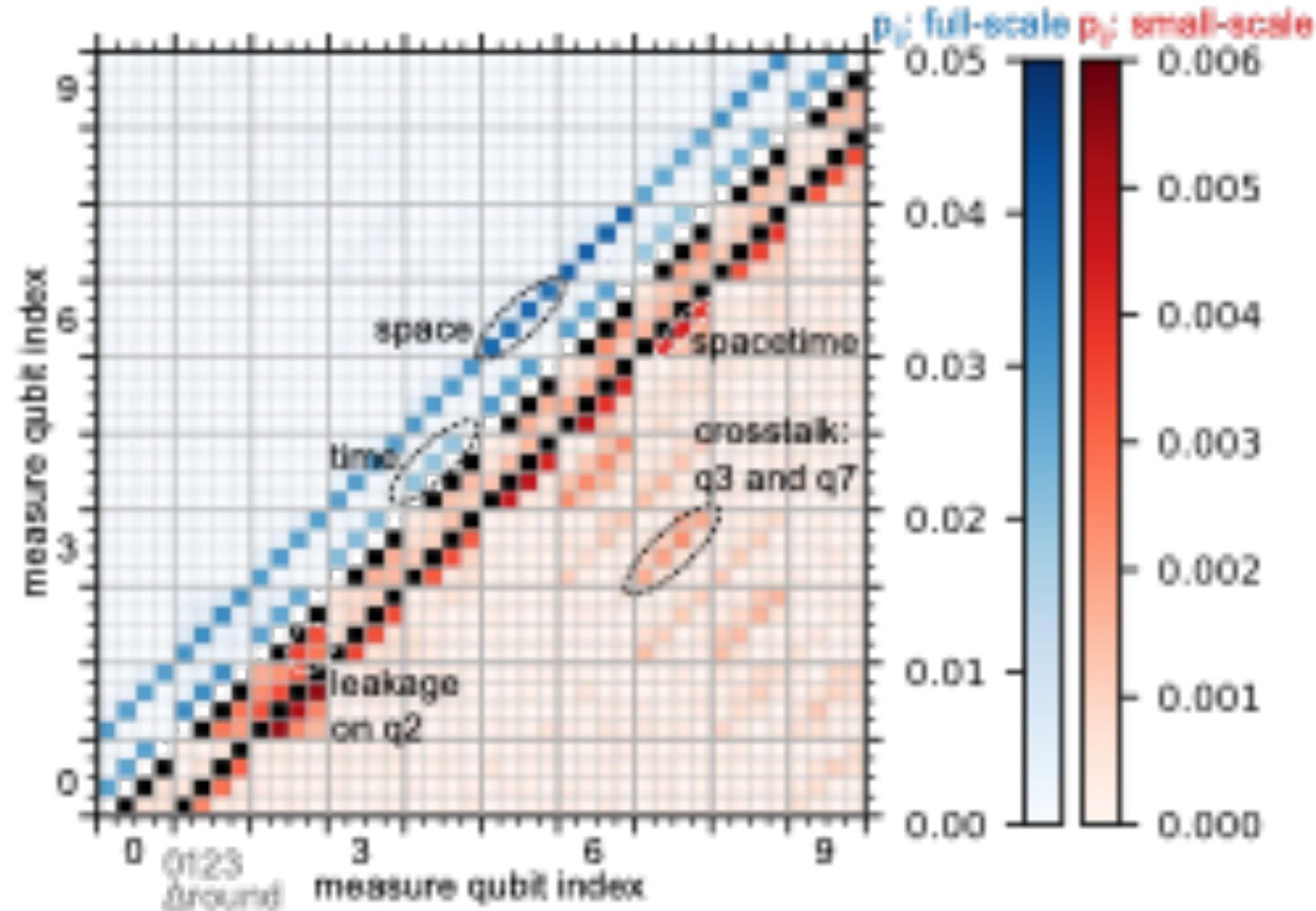
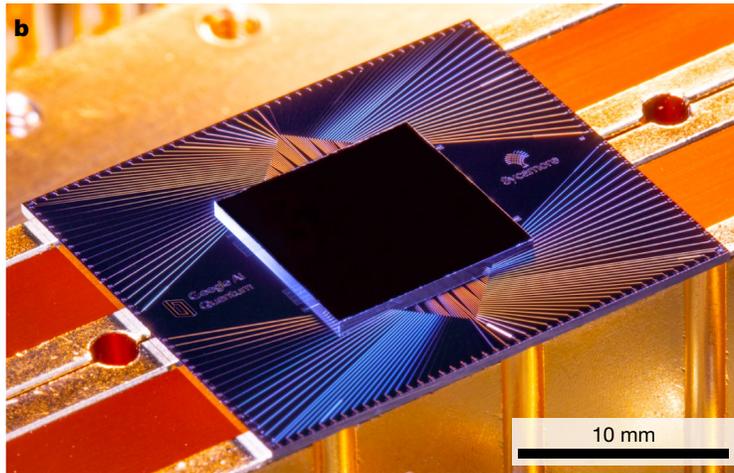
Machine Learning for Quantum Error Correction



B. Terhal *Rev. Mod. Phys.* **87**, 307 (2015)

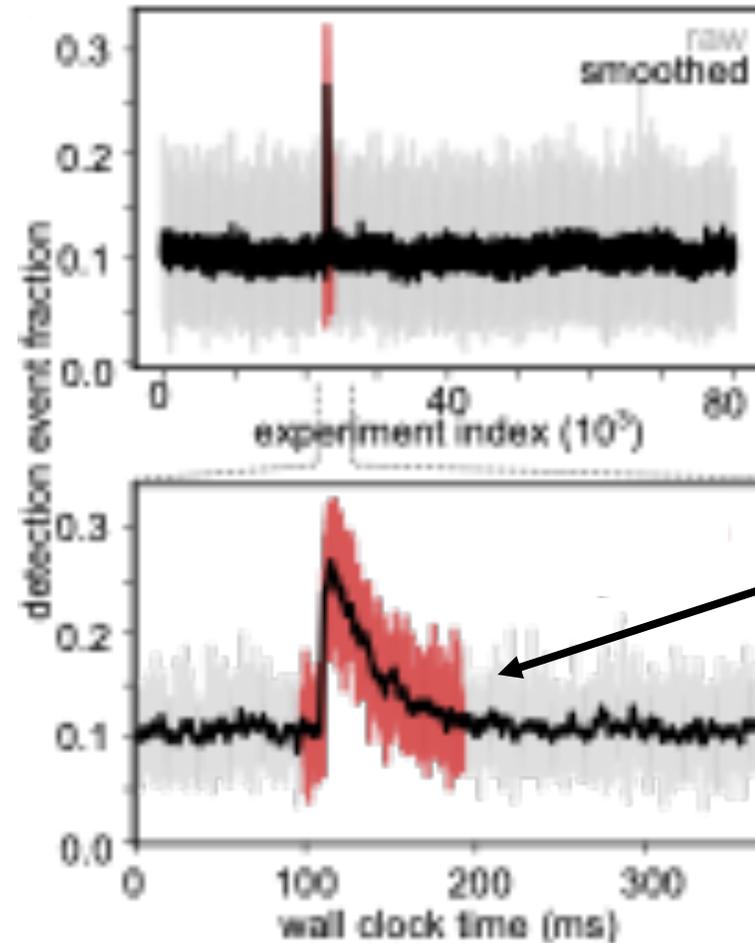
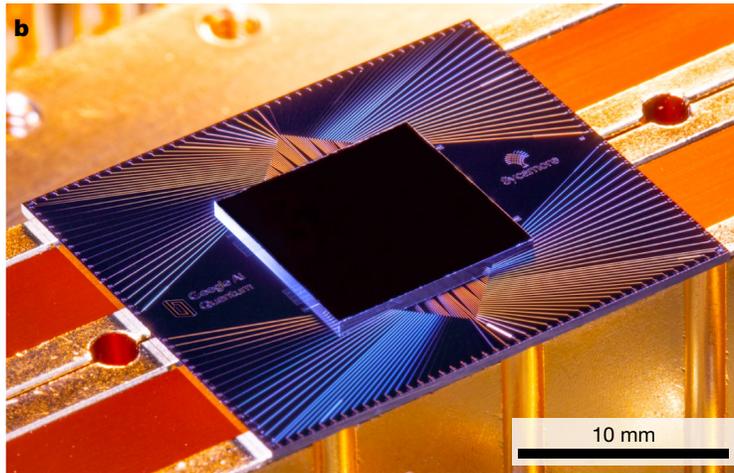
G. Torlai et al. *Phys. Rev. Lett.* **119**, 030501 (2017)

Noise structure of actual quantum devices is complicated, correlated in space and time...



arXiv:2102.06132 (2021) (Google Quantum AI)

Noise structure of actual quantum devices is complicated, correlated in space and time...



Device-wide correlated errors, caused from cosmic rays and nearby radioactive materials

arXiv:2102.06132 (2021) (Google Quantum AI)
See also: Nature 584, 551 (2020)

Neural ensemble decoding for topological quantum error-correcting codes

Milap Sheth,^{1,2,3,*} Sara Zafar Jafarzadeh,^{1,4,†} and Vlad Gheorghiu^{1,2,5,‡}

¹*Institute for Quantum Computing, University of Waterloo, Waterloo, ON, Canada*

Machine learning logical gates for quantum error correction

Hongxiang Chen,^{1,2,*} Michael Vasmer,^{3,†} Nikolas P. Breuckmann,^{4,‡} and Edward Grant^{1,2,§}

¹*Dept. Computer Science, University College London*

Neural Decoder for Topological Codes

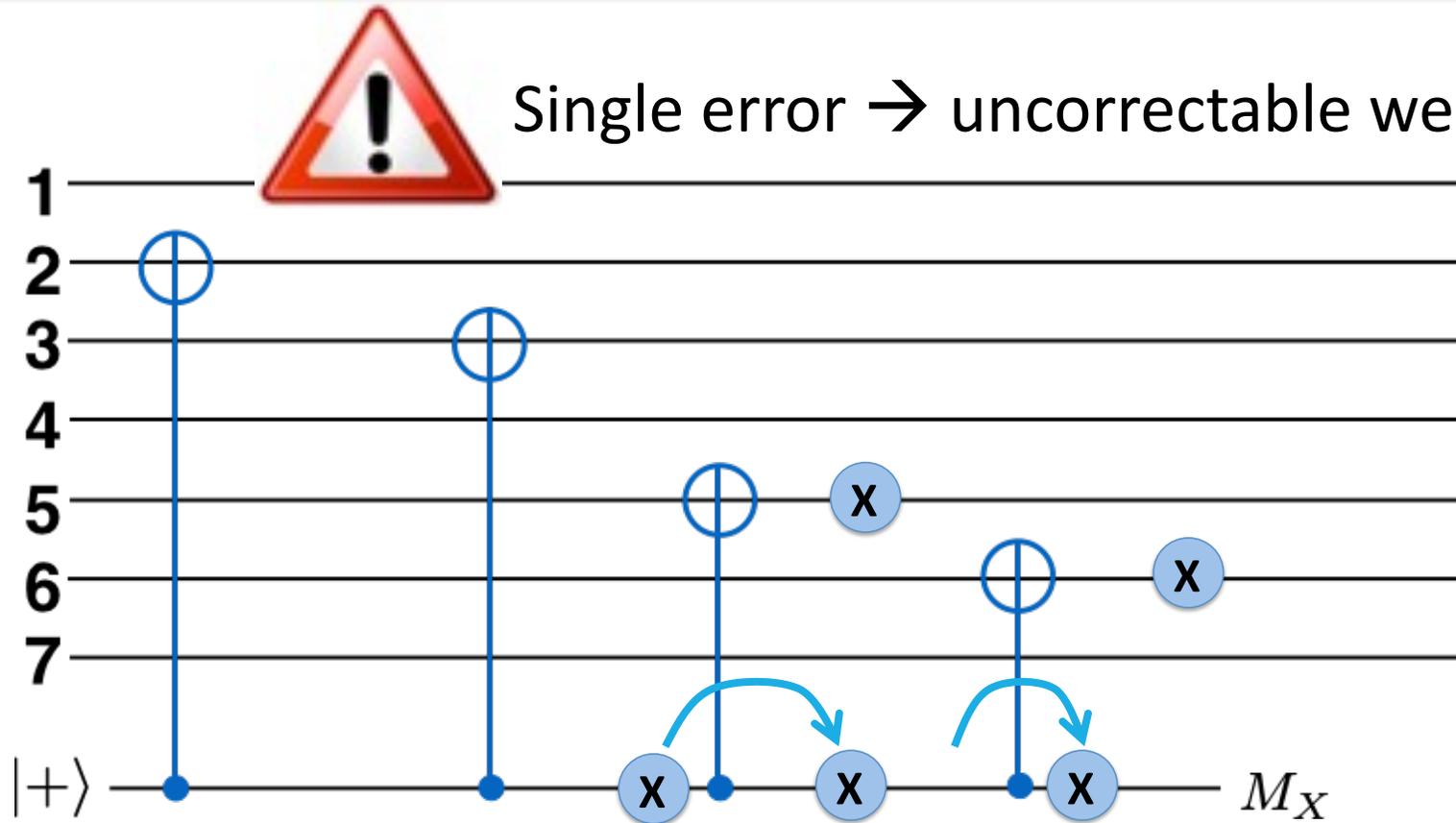
Giacomo Torlai and Roger G. Melko

Phys. Rev. Lett. **119**, 030501 – Published 18 July 2017

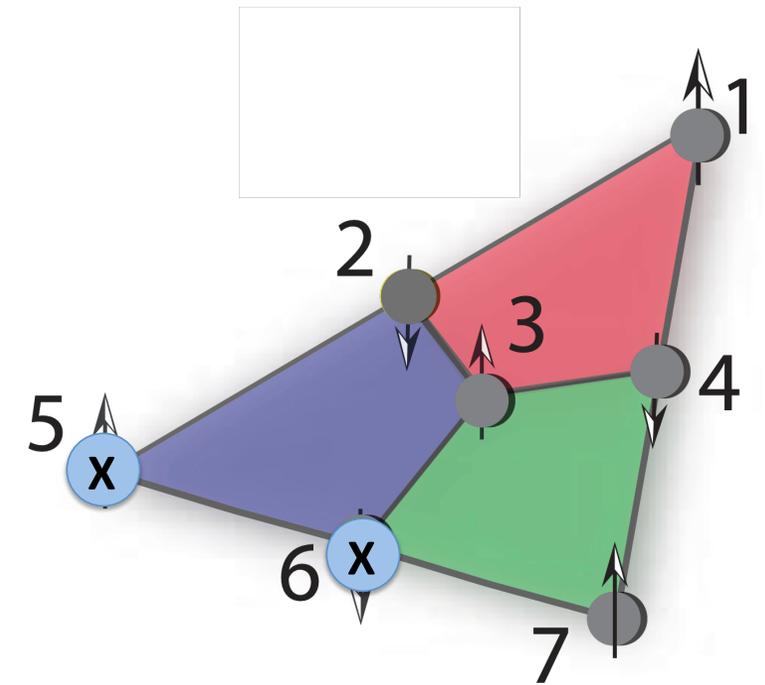
Reinforcement learning decoders for fault-tolerant quantum computation

Ryan Sweke¹ , Markus S Kesselring¹, Evert P L van Nieuwenburg²  and Jens Eisert^{1,3}

Error propagation and the challenge of fault-tolerance

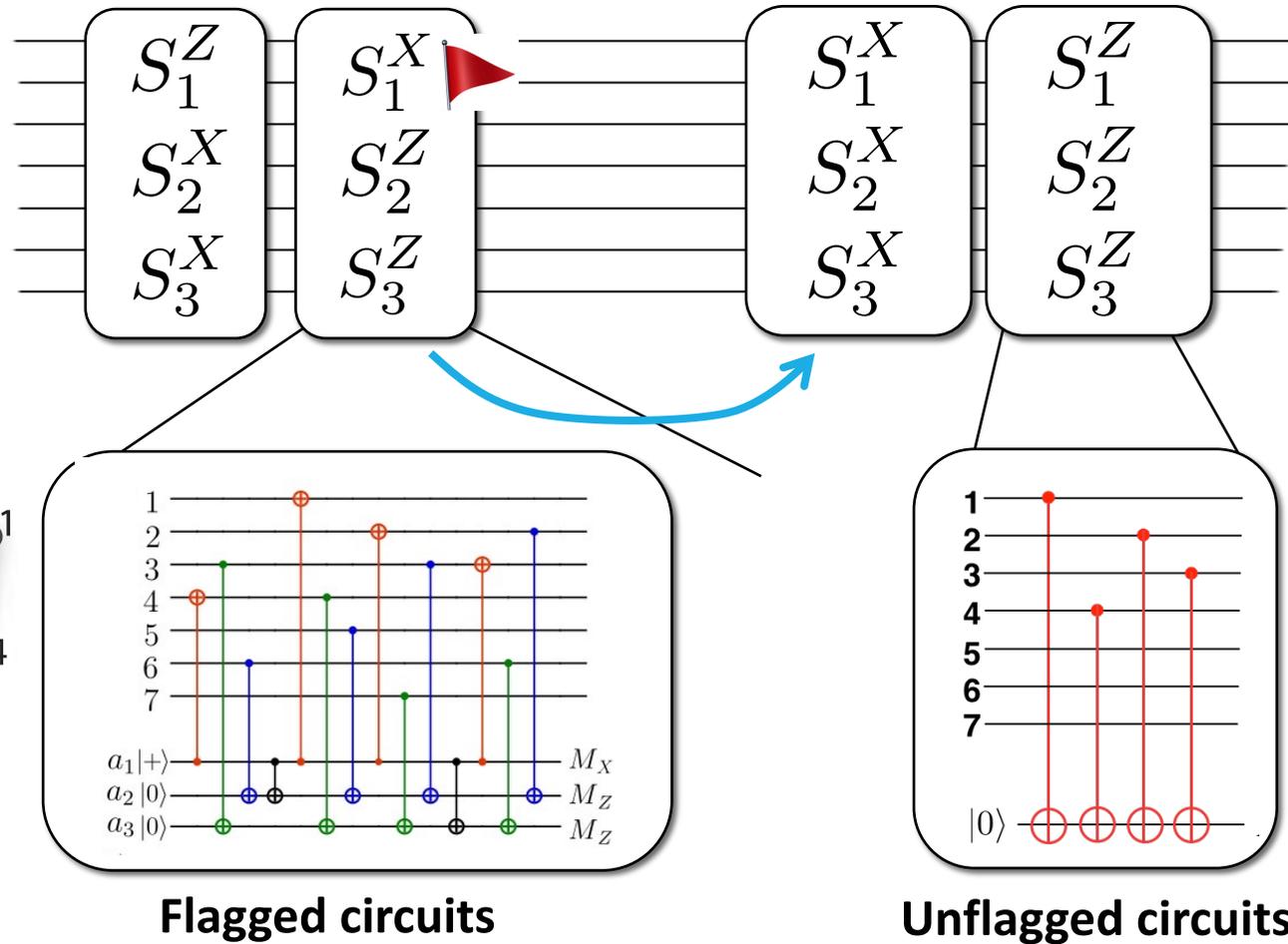


Single error \rightarrow uncorrectable weight-two error \rightarrow failure



Chao and Reichardt, Phys. Rev. Lett. 121, 050502 (2018); Yoder and Kim, Quantum 1, 2 (2017)

Fault-tolerant Quantum Error Correction Cycles



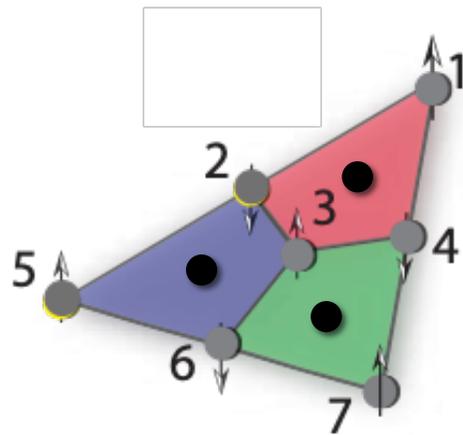
Advantages:

- Low resource overhead
- Gates and measurements in parallel
- Small gate count

Ben W. Reichardt, arXiv:1804.06995

Neural-Network based Quantum Error Correction

- Goal: implement freely extensible (in time) multi-round neural-network-based decoder
- Use recurrent neural network
- First: training and benchmark against hard-coded look-up table for standard depolarising circuit noise
- Later: train for realistic trapped-ion noise model



Input: syndrome increments & flag measurement outputs

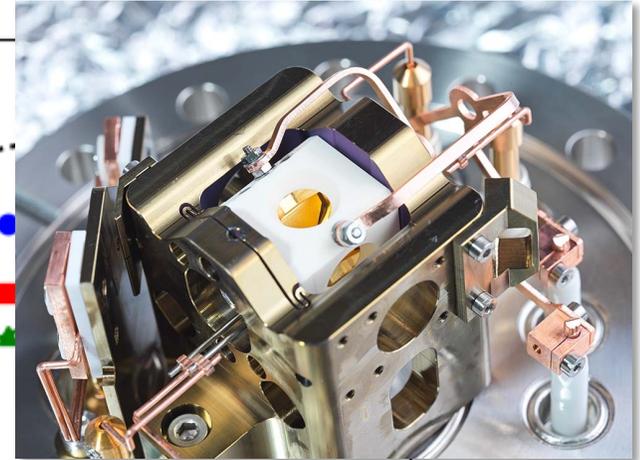
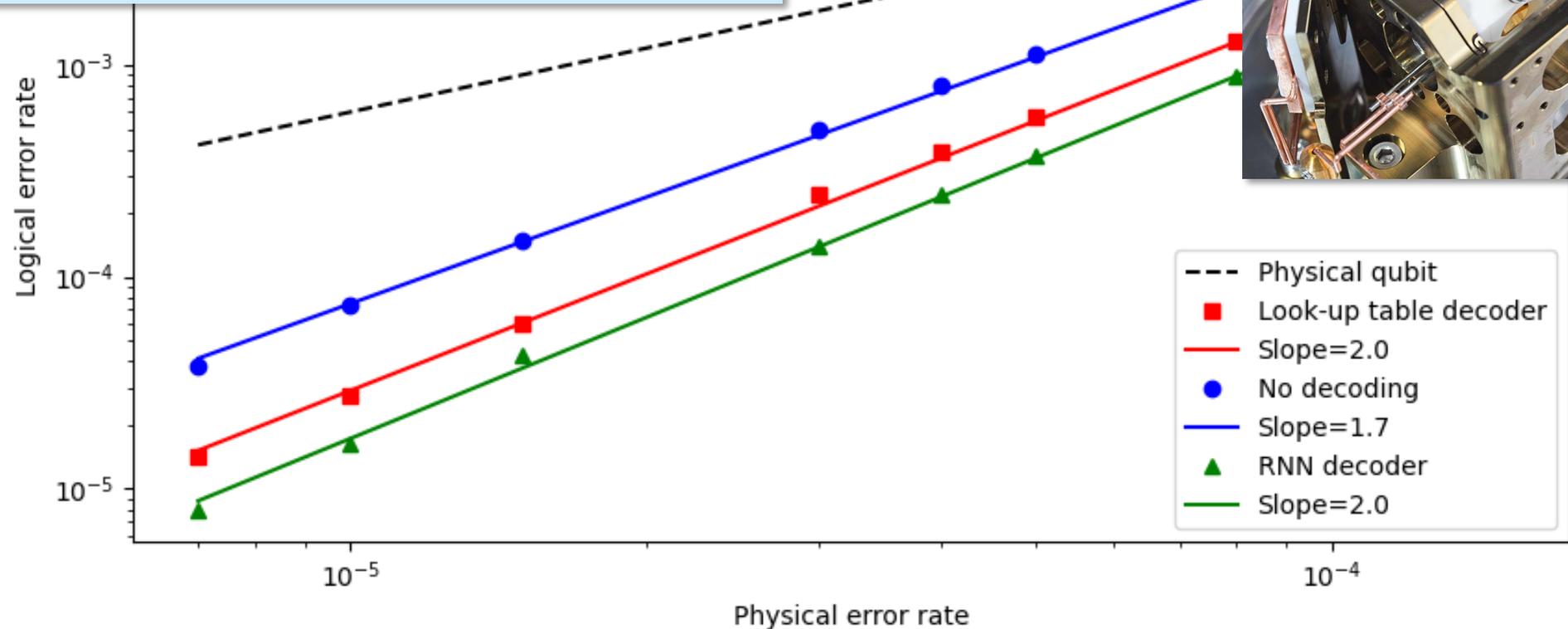


Output: logical bit/phase probability

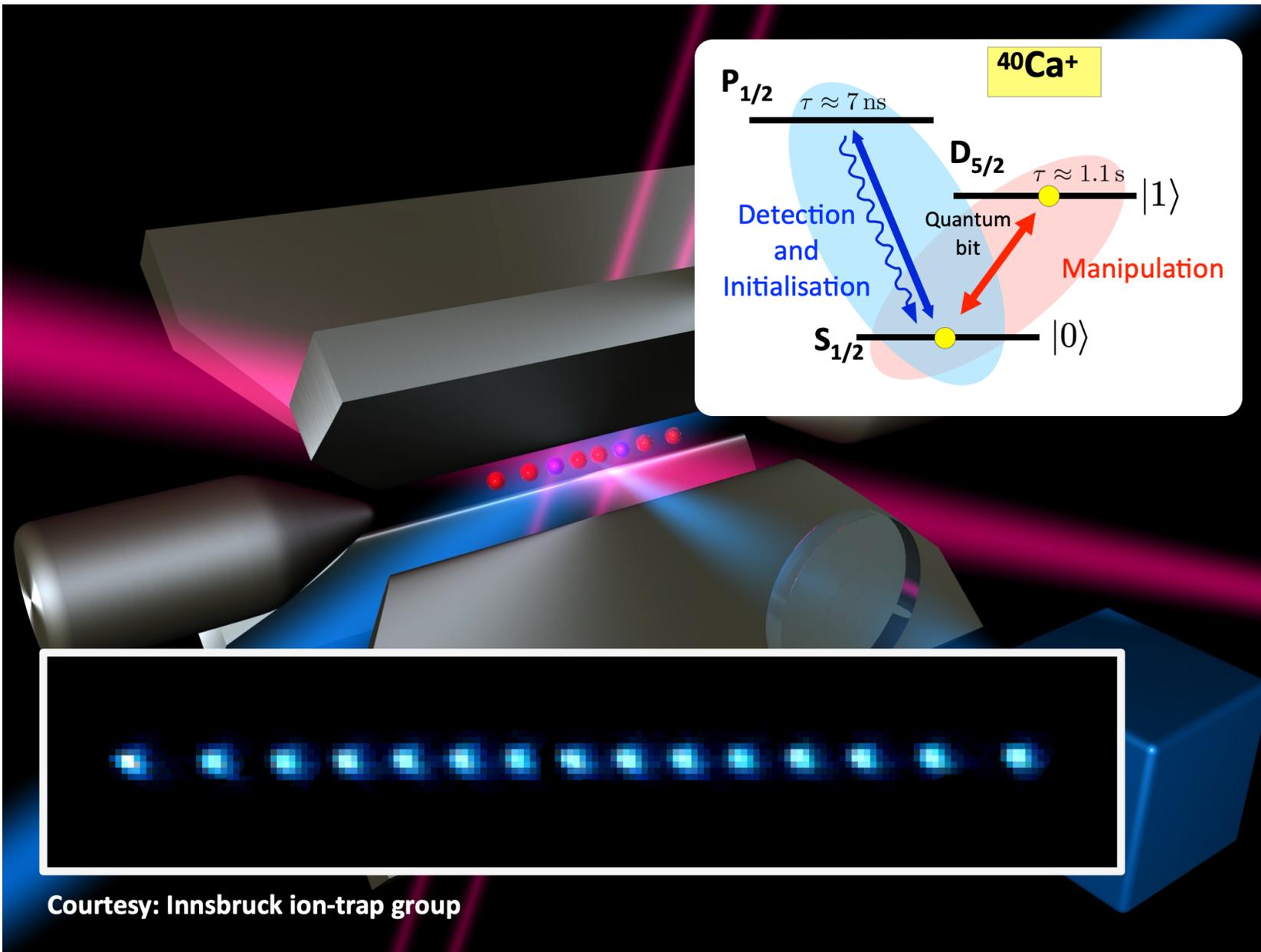
See also e.g. [Baireuther et al., New J. Phys. 21, 013003 \(2019\)](#)

Neural-Network based Quantum Error Correction

- Neural network has ,discovered' fault-tolerant error correction strategy
- Outperforms lookup-table based decoder

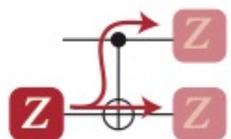


credit: AQT



Courtesy: Innsbruck ion-trap group

Statistical physics mapping for QEC codes with circuit noise

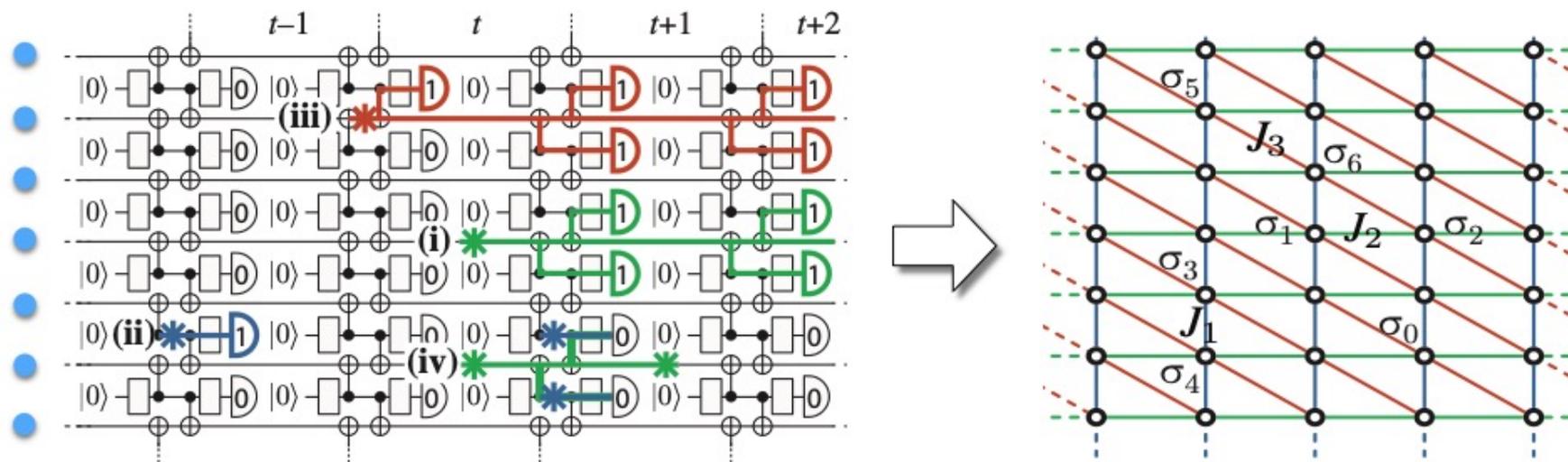


Problem:

Errors propagate through the quantum hardware

Question: How many errors in the quantum circuits can be tolerated?

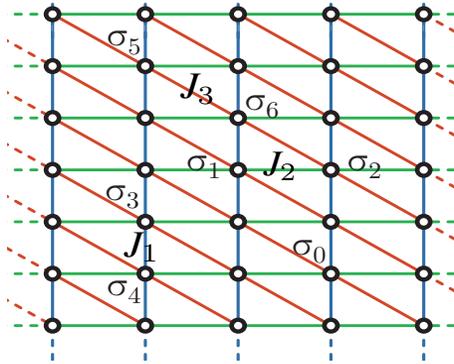
Map topological quantum error correcting codes to classical statistical physics models



D. Vodola, M. Rispler, S. Kim, and M.M., arXiv:2104.04847 (2021):

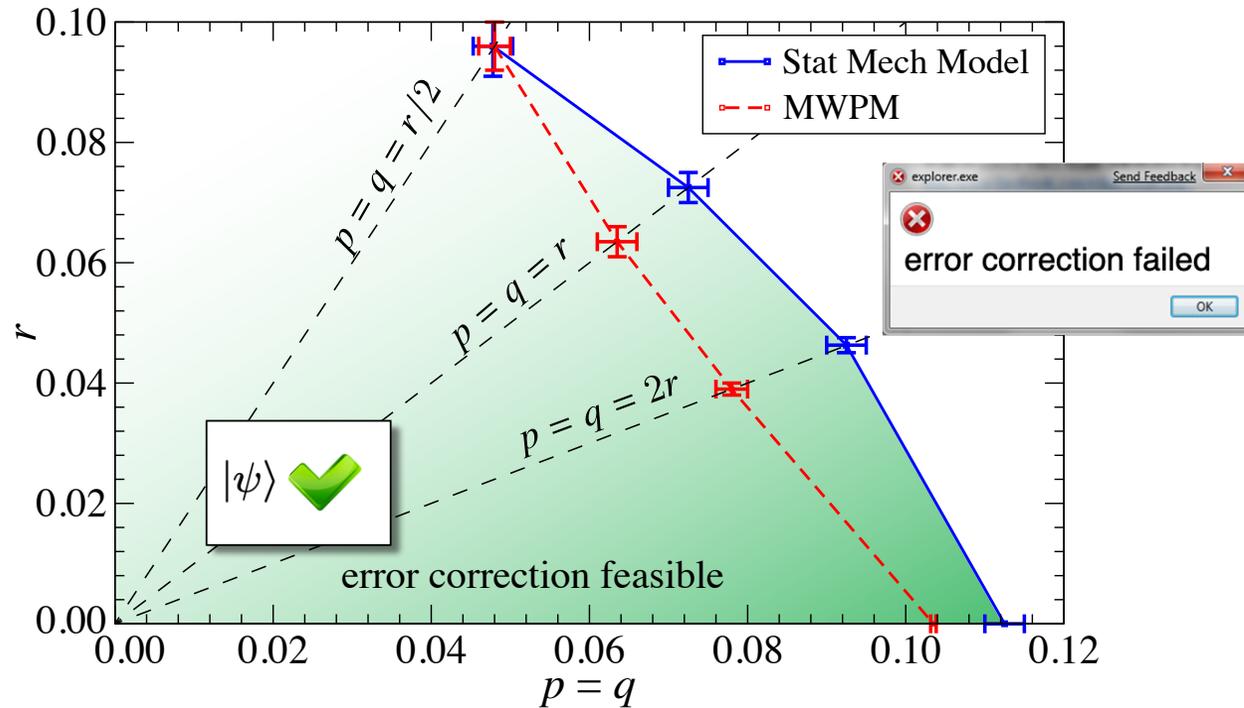
Fundamental thresholds of realistic quantum error correction circuits from classical spin models

Statistical physics mapping for 1D quantum repetition code with circuit noise



- ▶ Identify gap between known error correction strategies and optimal correction capability
- ▶ **fundamental error thresholds** of quantum error correcting codes for realistic noise

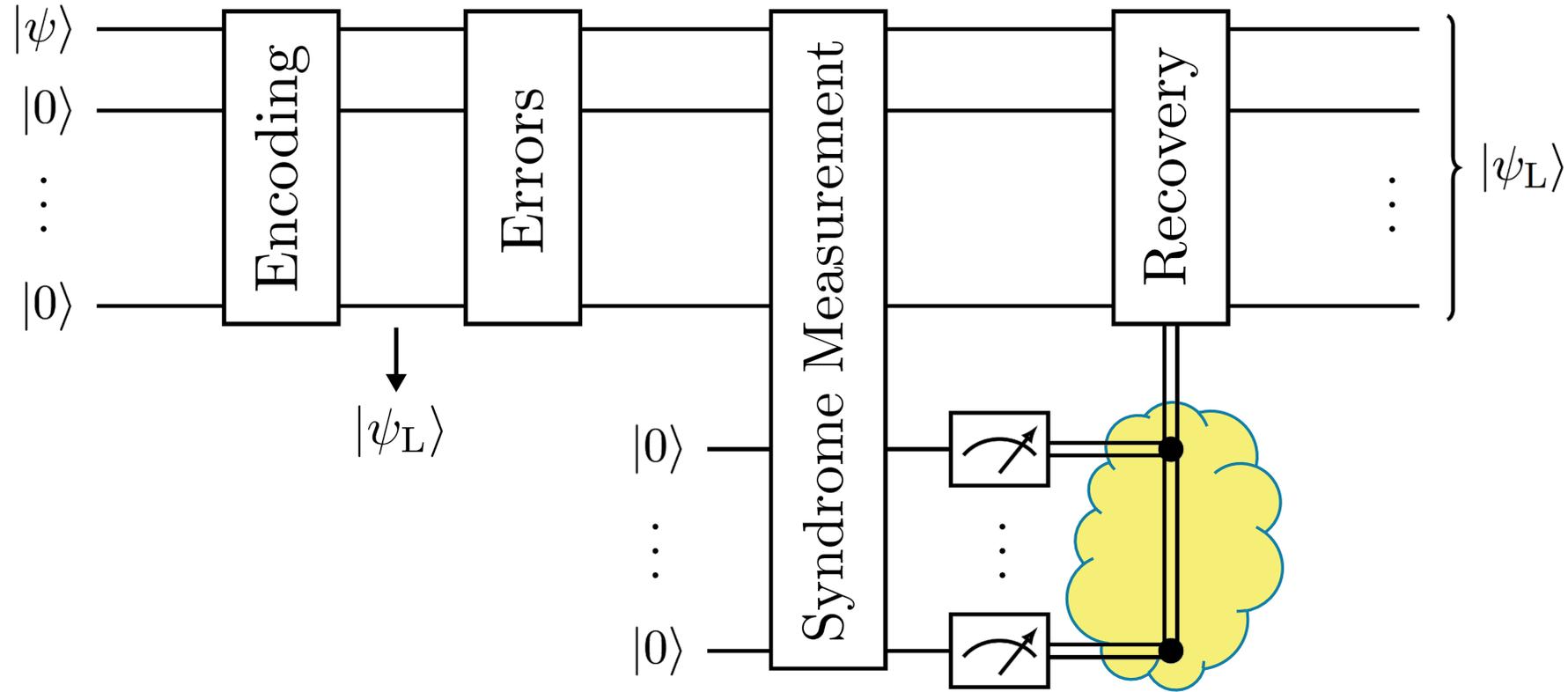
Phase diagram of more general 2D random-bond Ising model



D. Vodola, M. Rispler, S. Kim, and M.M., arXiv:2104.04847 (2021):
 Fundamental thresholds of realistic quantum error correction circuits from classical spin models

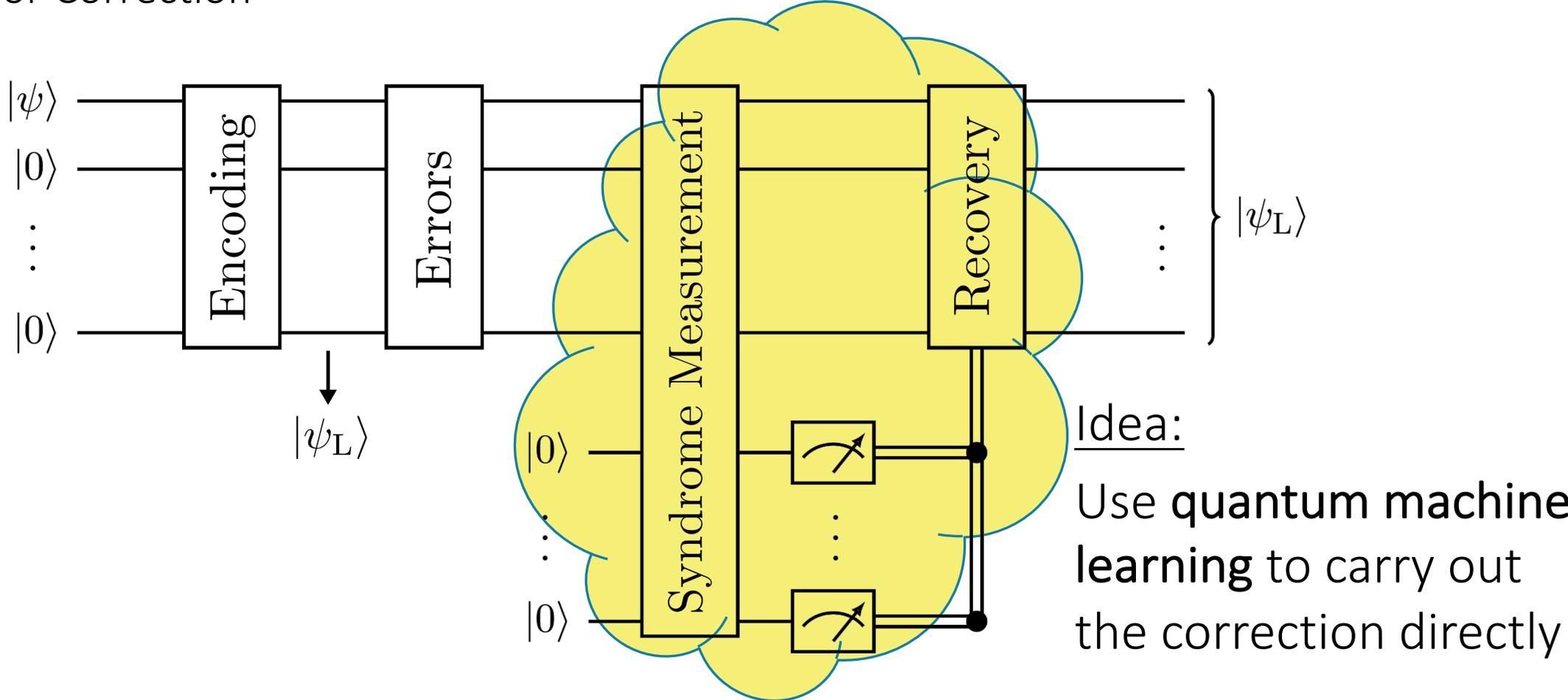
Machine Learning for Error Correction

Quantum Error Correction



Quantum Machine Learning for Error Correction

Quantum Error Correction



Quantum autoencoders for efficient compression of quantum data

Jonathan Romero, Jonathan P Olson and Alan Aspuru-Guzik

Department of Chemistry and Chemical Biology, Harvard University, Cambridge, Massachusetts 02138, United States of America

Quantum Autoencoders to Denoise Quantum Data

Dmytro Bondarenko^{*} and Polina Feldmann[†]

Institut für Theoretische Physik, Leibniz Universität Hannover, Appelstr. 2, DE-30167 Hannover, Germany



(Received 12 November 2019; accepted 24 February 2020; published 31 March 2020)

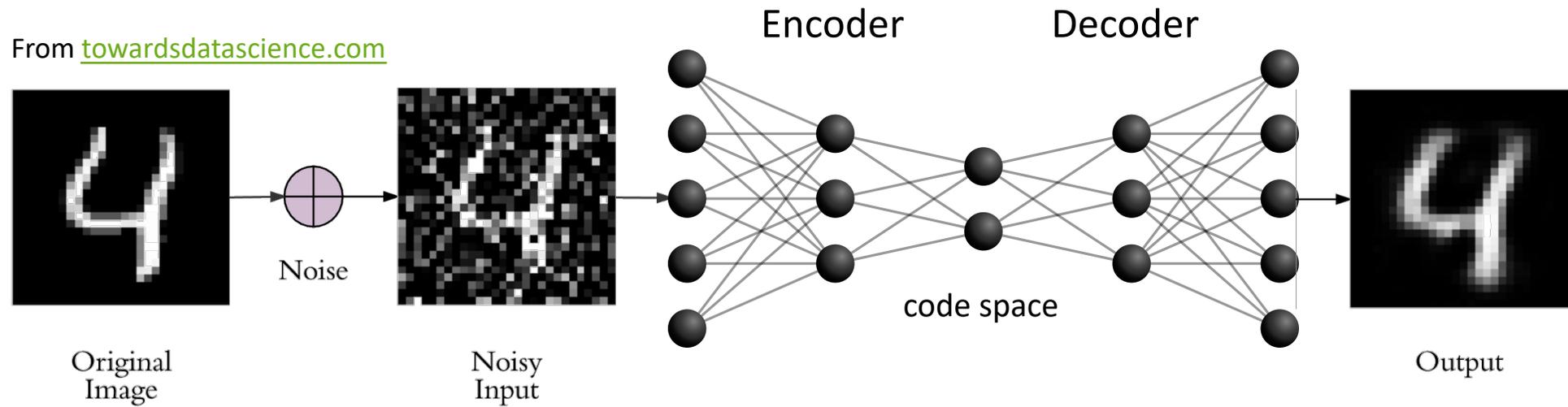
In our work:

1. Use compression principle to perform quantum error correction.
2. Train QNNs to restore *entire code space* - not only specific target states.

Motivation

Autoencoders

From towardsdatascience.com

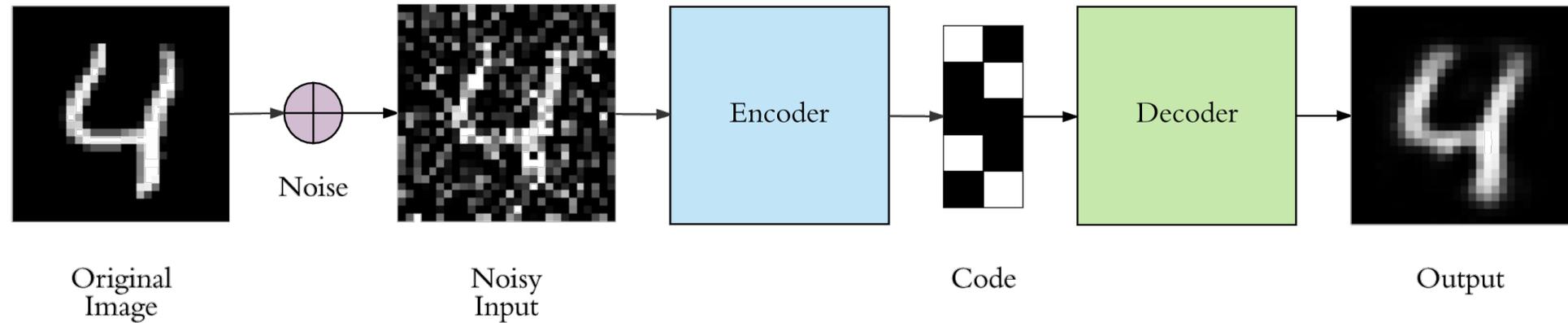


Used e.g. for: – Denoising

Motivation

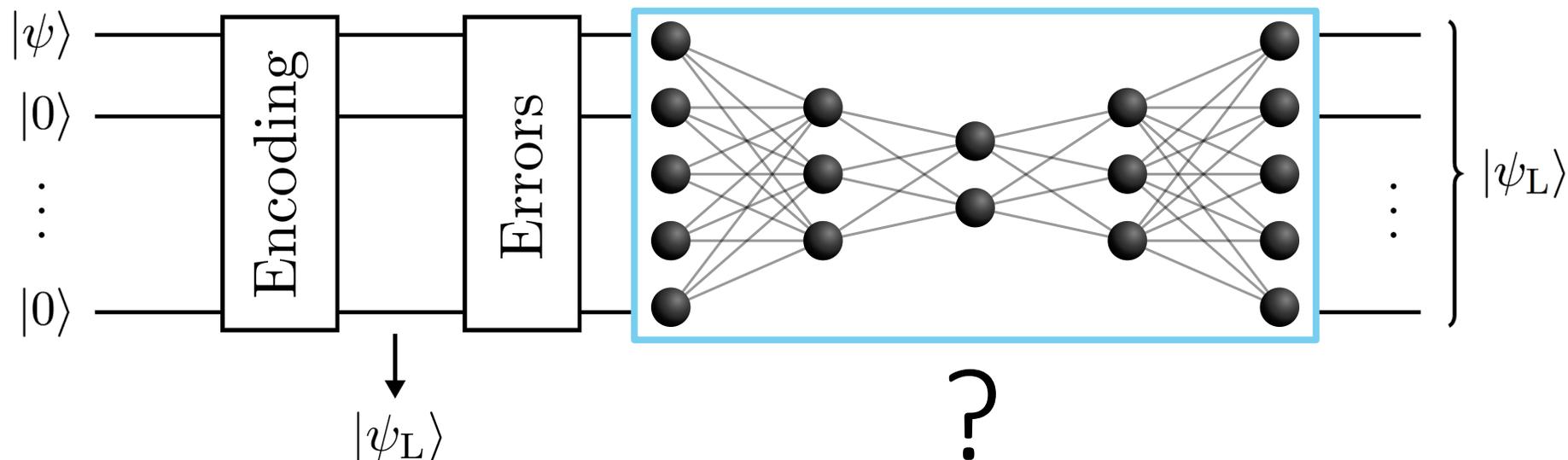
Autoencoders

From towardsdatascience.com



- Used e.g. for:
- **Denoising**
 - Finding efficient data codings
 - Feature learning

Motivation



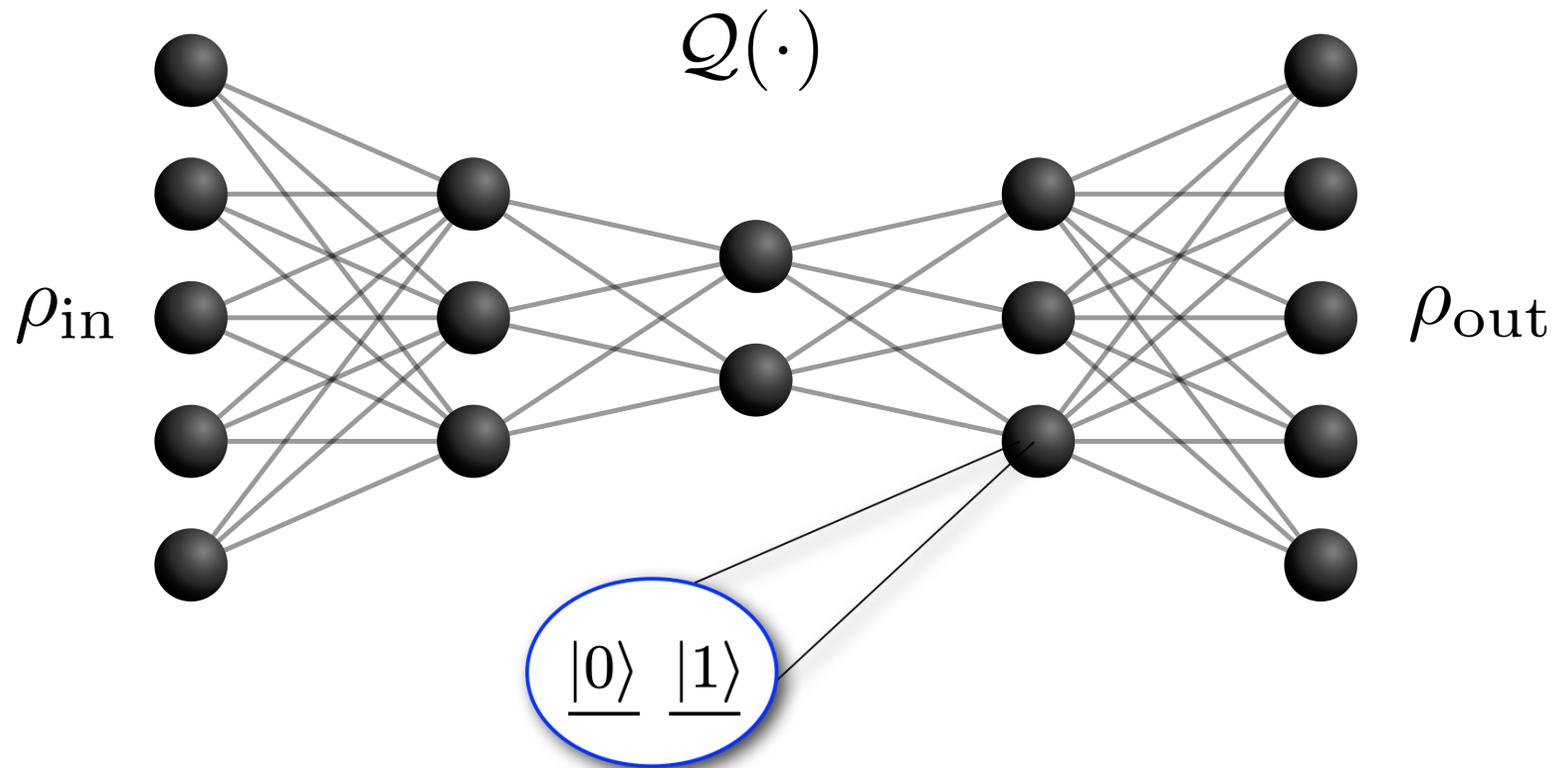
Can quantum error correction be automatized with **Quantum Autoencoders**?

Can QAEs autonomously identify correction strategies optimally suited for specific noise?

J. Romero et al. *Quantum Sci. Technol.* **2**, 045001 (2017)

D. Bondarenko et al. *Phys. Rev. Lett.* **124**, 130502 (2020)

How? Dissipative Quantum Neural Networks



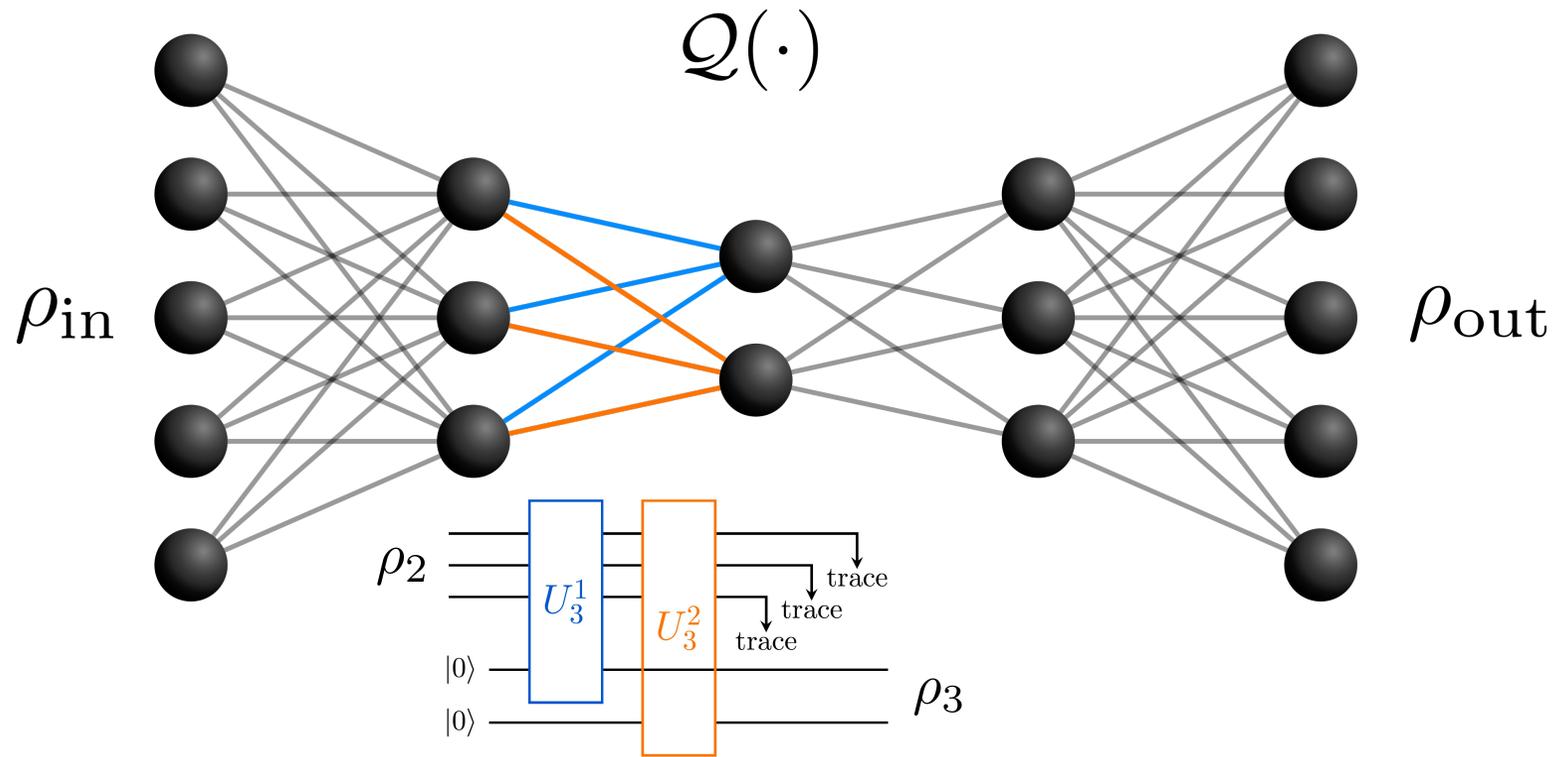
Neurons \rightarrow Qubits

Edges \rightarrow Unitary Operations

A dissipative quantum neural network realizes a quantum channel

$$\rho_{\text{out}} = Q(\rho_{\text{in}})$$

Dissipative Quantum Neural Networks



Neurons \rightarrow Qubits

Edges \rightarrow Unitary Operations

A DQNN realizes a quantum channel

$$\rho_{out} = Q(\rho_{in})$$

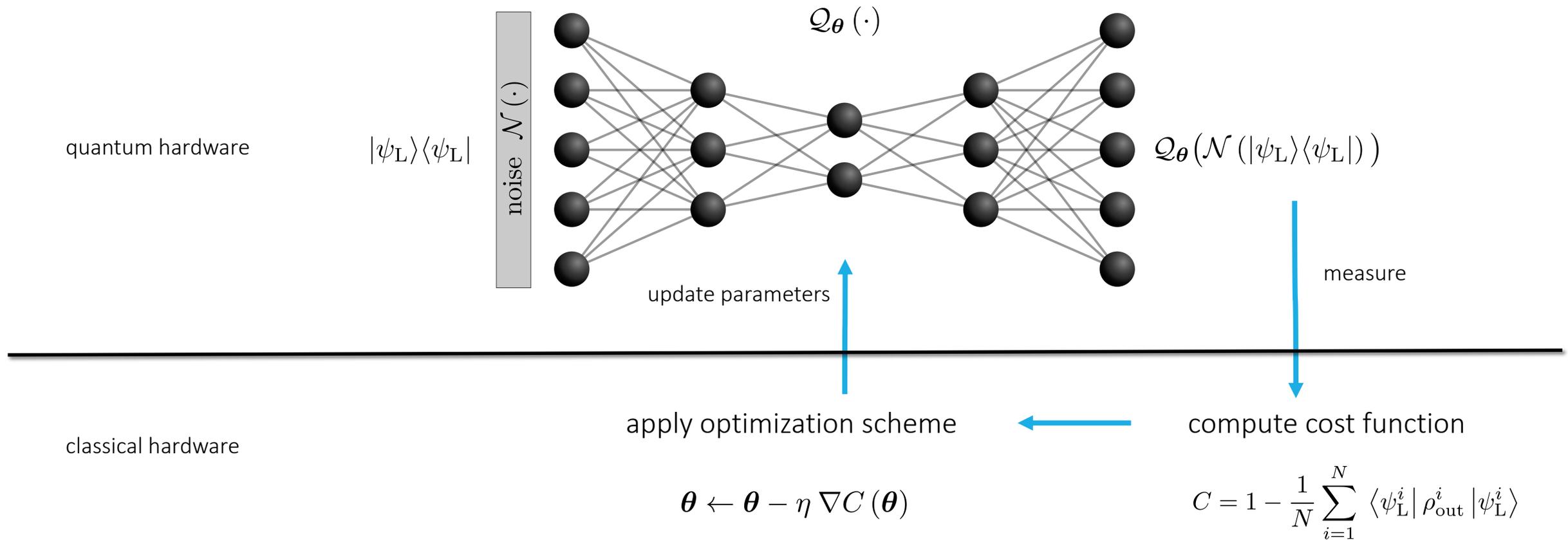
$$\rho_k = \mathcal{E}_k(\rho_{k-1}) = \text{Tr}_{k-1} \left[U_k \left(\rho_{k-1} \otimes |0\rangle\langle 0|^{\otimes m_k} \right) U_k^\dagger \right]$$

$$\rho_{out} = \mathcal{E}_{out}(\dots \mathcal{E}_3(\mathcal{E}_2(\rho_{in})) \dots)$$

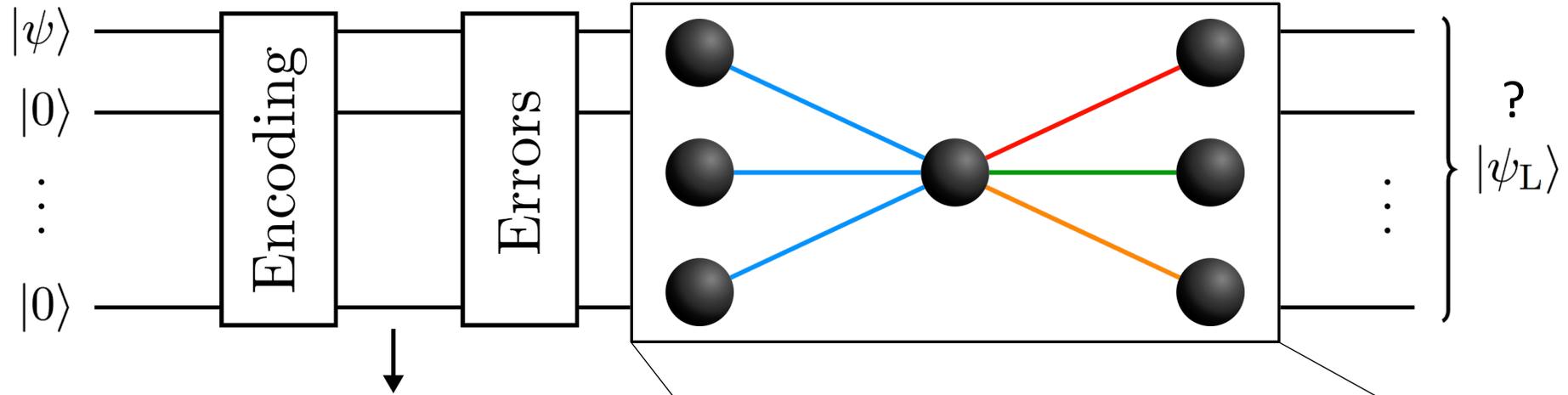
K. Beer et al. *Nat. Commun.* **11**, 808 (2020)

Dissipative Quantum Neural Networks

Training: Quantum-classical hybrid procedure

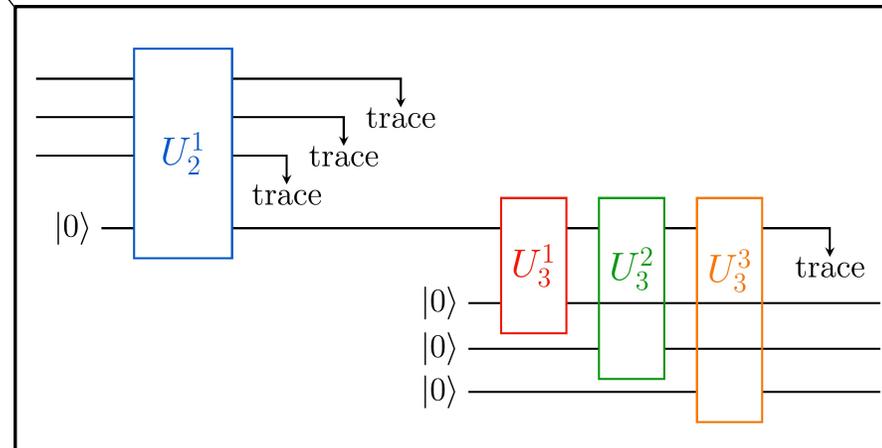


Error Correction with Quantum Autoencoders



$$|\psi_L\rangle = \alpha |000\rangle + \beta |111\rangle$$

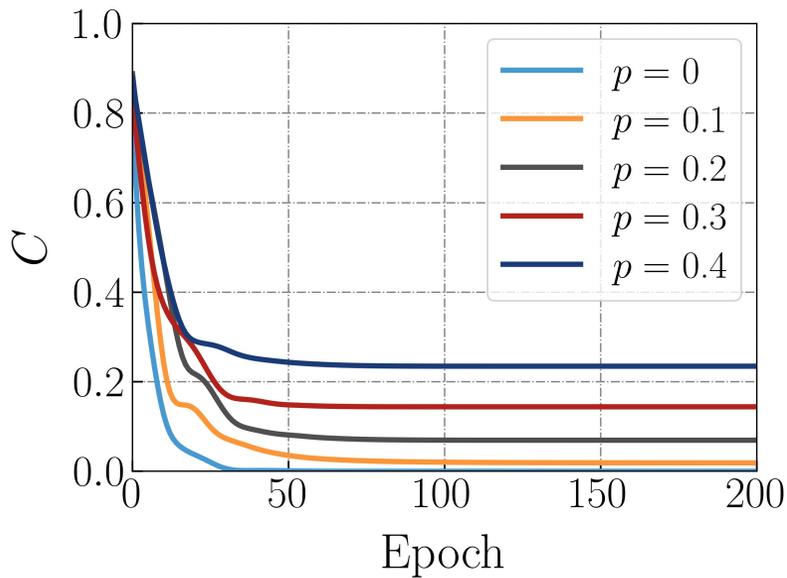
minimal example:
3-qubit repetition code



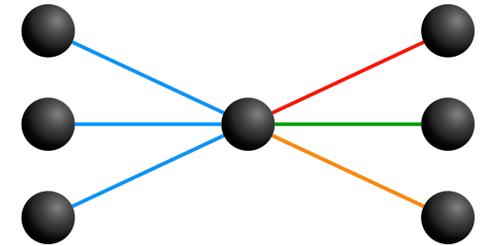
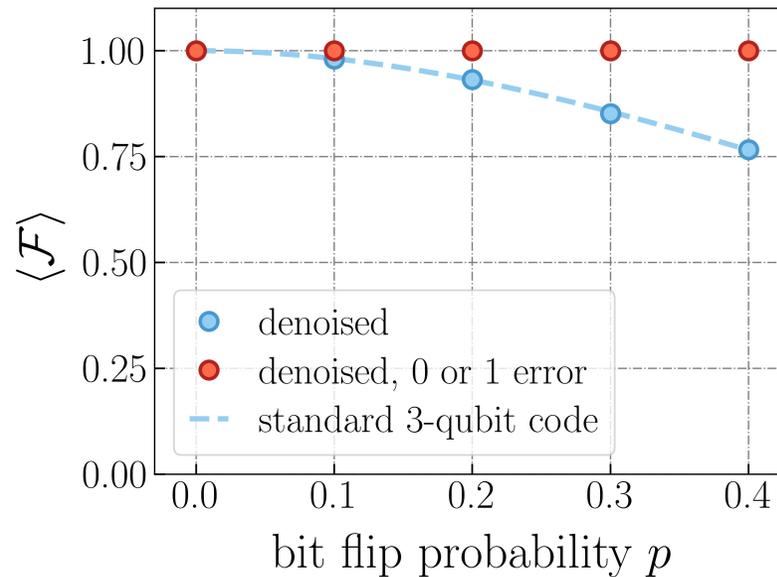
Error Correction with Quantum Autoencoders

Training on states $|000\rangle$, $|111\rangle$ and $\frac{1}{\sqrt{2}}(|000\rangle + |111\rangle)$ subjected to uncorrelated bit flips

Training



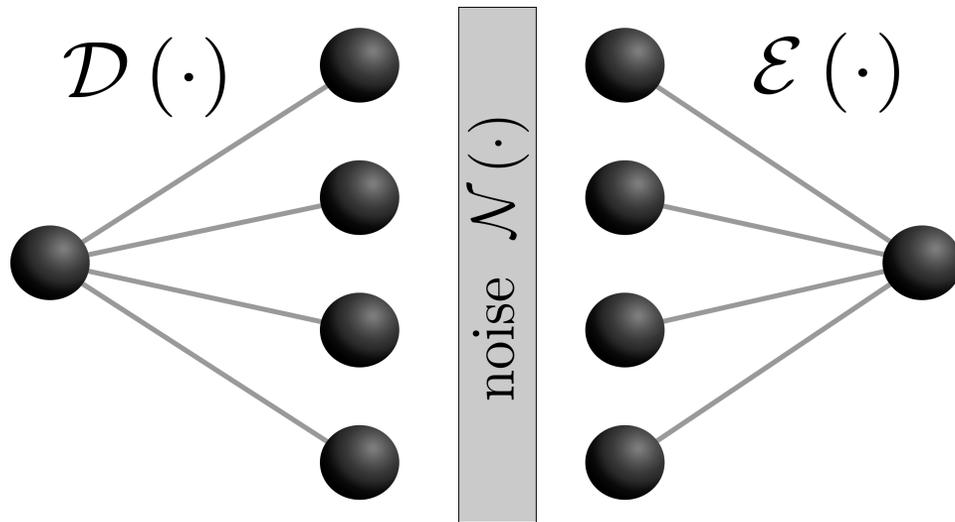
Validation: denoise arbitrary logical states



The QAEs learn precisely the 3-qubit code correction map

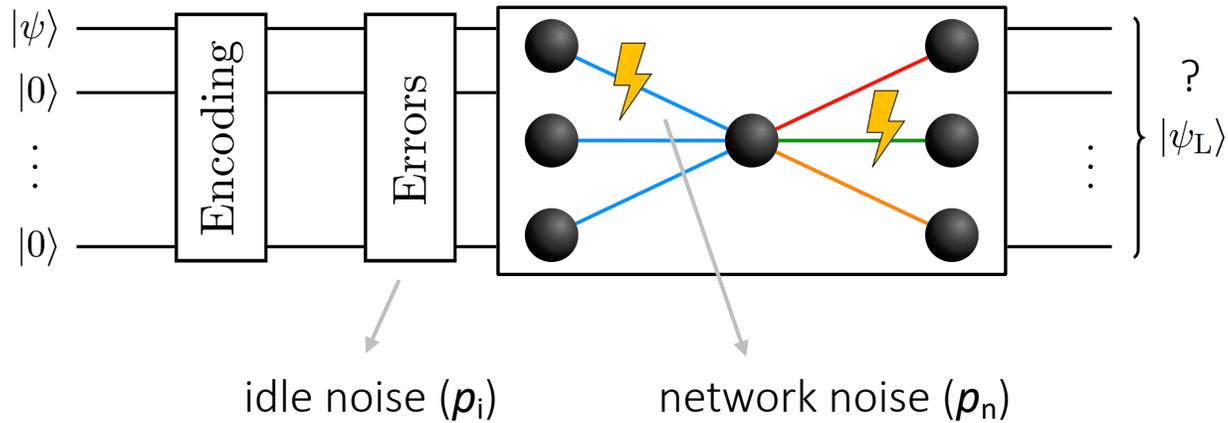
Error Correction with Quantum Autoencoders

Training the network with noise



- ✓ Logical states encoded in a decoherence-free subspace:
robustness against correlated noise
- ✓ Correction of qubit loss possible

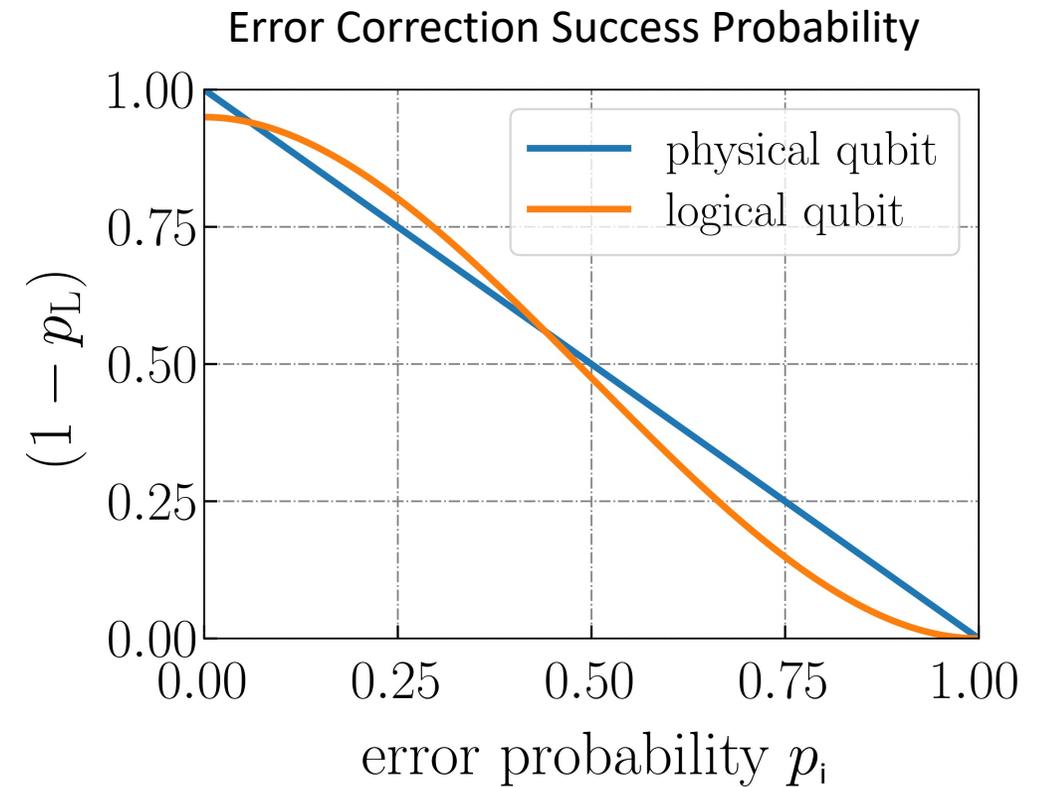
Towards Experimental Realisations



The networks themselves are „quantum“ and can be noisy

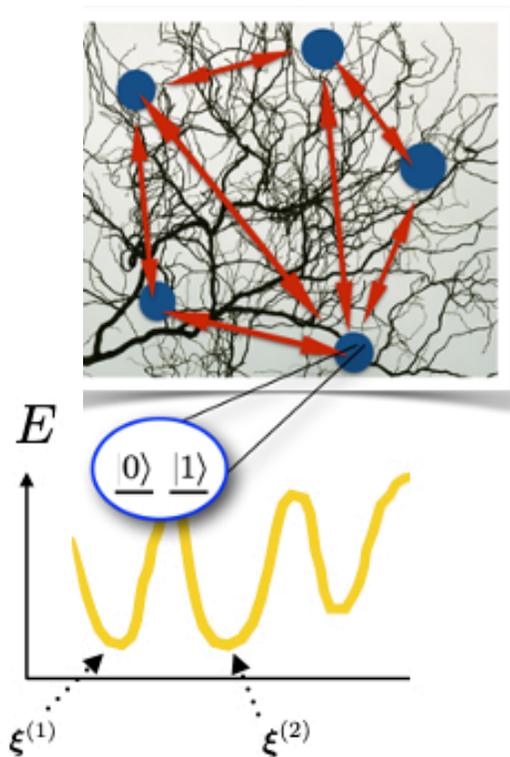


Beneficial error correction still possible

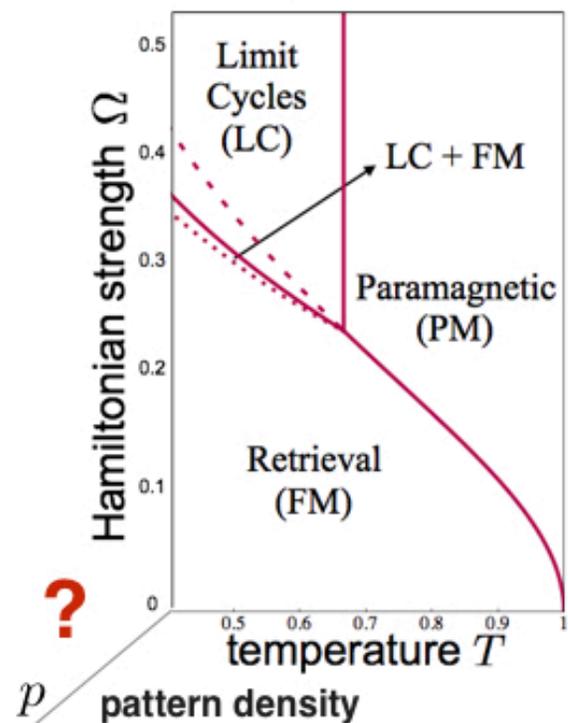


Quantum neural networks as open quantum systems

Classical Neural Network



Quantum Hopfield Network



Storage of quantum patterns? Enhanced storage capacity? Near-term realisations?
 Quantum neural networks for error correction?

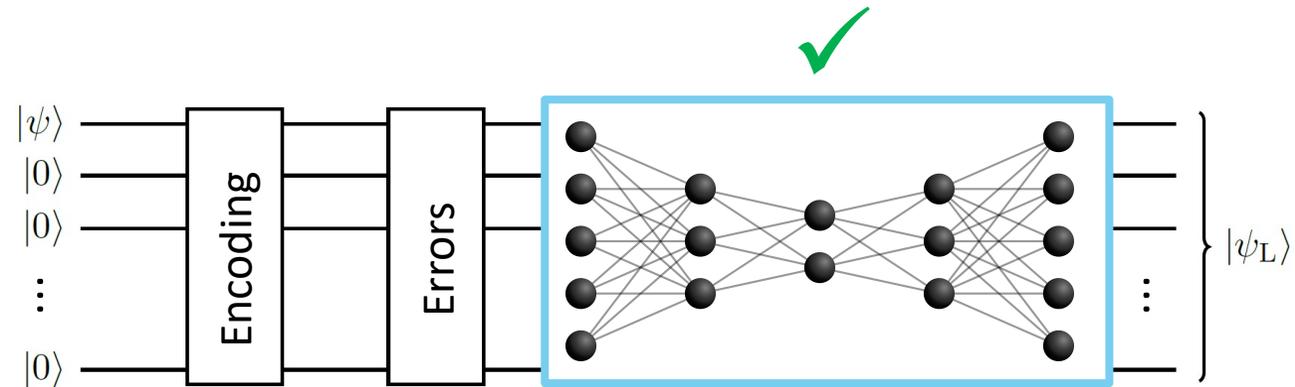
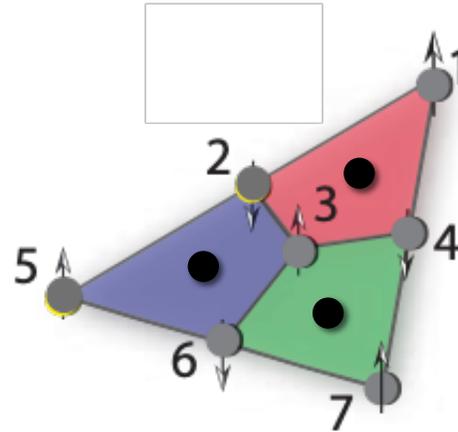
Phase diagram of quantum generalized Potts-Hopfield neural networks

E. Fiorelli, I. Lesanovsky,
 M. Müller

[arXiv:2109.10140 \(2021\)](https://arxiv.org/abs/2109.10140)

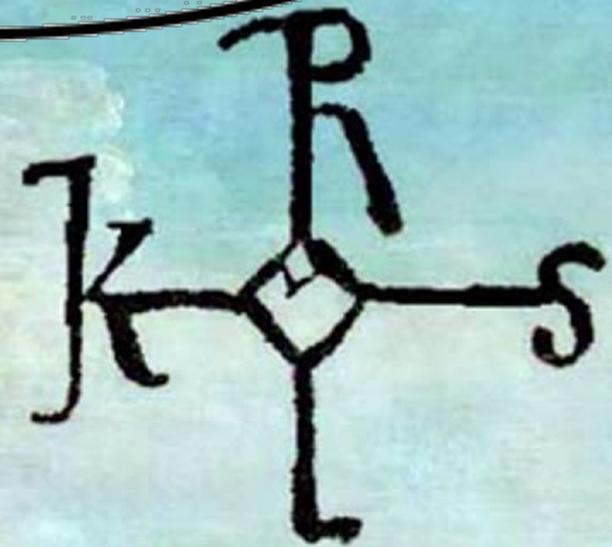
Summary and Outlook

- Classical machine learning for quantum error correction
- New quantum machine learning concepts
- Scalability to larger systems?
- Experimental realisations?





Thanks for
your attention!



K

Karl der Große,
Charlemagne
(did not contribute
to these works)

