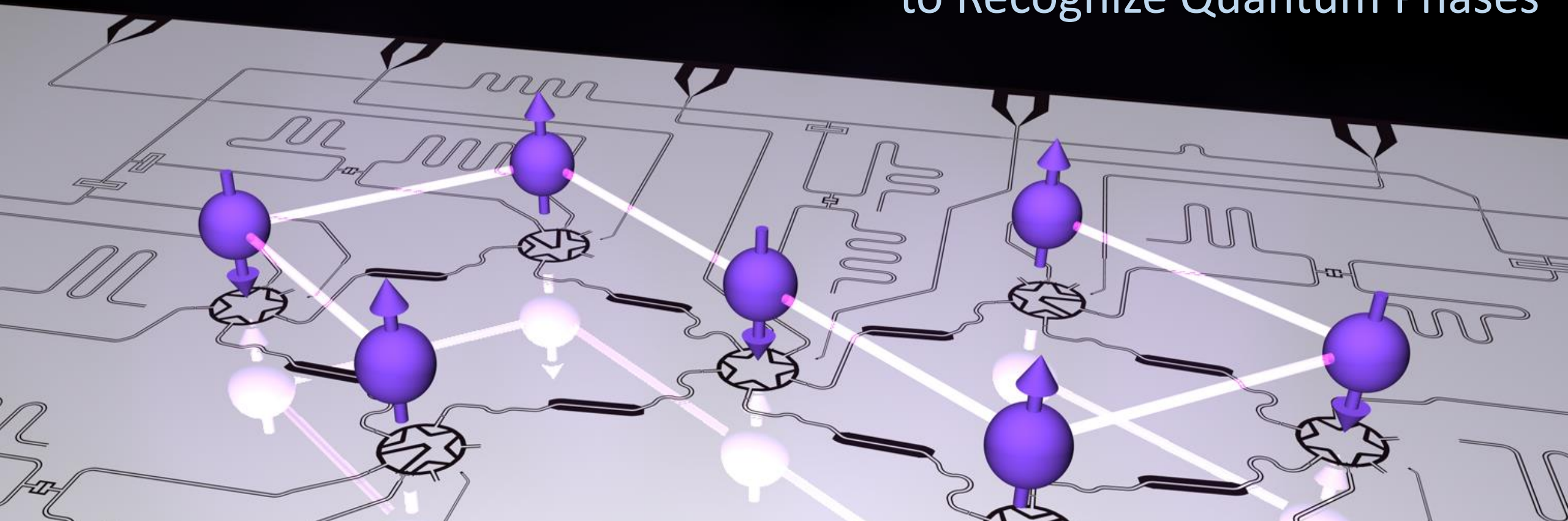


Sergi Masot Llima,  
BSC-Quantic,  
Benasque, 23/02/2022

# Realizing Quantum Convolutional Neural Networks on a Superconducting Quantum Processor to Recognize Quantum Phases



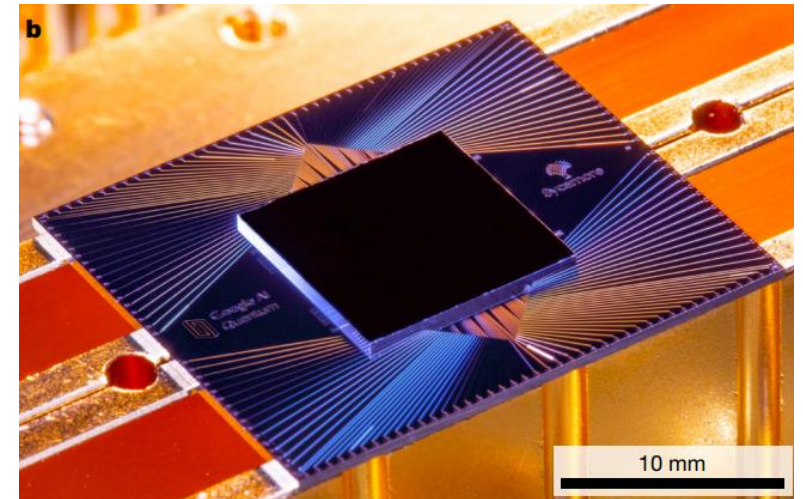
J. Herrmann,<sup>1</sup> S. M. Llima,<sup>1,4</sup> A. Remm,<sup>1</sup> P. Zapletal,<sup>2</sup> N. A. McMahon,<sup>2</sup> C. Scarato,<sup>1</sup> F. Swiadek,<sup>1</sup> C. K. Andersen,<sup>1</sup> C. Hellings,<sup>1</sup> S. Krinner,<sup>1</sup> N. Lacroix,<sup>1</sup> S. Lazar,<sup>1</sup> M. Kerschbaum,<sup>1</sup> D. Zanuz,<sup>1</sup> G. J. Norris,<sup>1</sup> M. J. Hartmann,<sup>2</sup> A. Wallraff,<sup>1,3</sup> and C. Eichler<sup>1</sup>

<sup>1</sup> Department of Physics, ETH Zurich, CH-8093 Zurich, Switzerland  
<sup>2</sup> Friedrich-Alexander University Erlangen-Nürnberg (FAU), Institute for Theoretical Physics, Germany  
<sup>3</sup> Quantum Center, ETH Zurich, CH-8093 Zurich, Switzerland  
<sup>4</sup> Quantic-CASE, Barcelona Supercomputing Center, Barcelona, Spain

# Motivation: Quantum Phase Recognition

- Experimentally study applications and performance of quantum neural network.
- In particular:* Scenarios in which processed data is intrinsically quantum (no classical analogue, circumvents data loading bottleneck)

	Classical Algorithm	Quantum Algorithm
Classical Data	<b>CC</b> Image or Speech Recognition	<b>CQ</b> Quantum speedup for classifying classical data [1]
Quantum Data	<b>QC</b> Using NN for qubit readout [2]	<b>QQ</b> This experiment



States output by quantum hardware are becoming too complex to be analyzed by classical means [3]

- Possible use in:*
  - Quantum auto-encoding [5]
  - Certification of Hamiltonian dynamics [6]
  - Quantum error correction [4]
  - Quantum phase recognition [4]

[1] Havlicek et al., *Nature* **567** (2019), [2] Lienhard et al. *APS Phys.* (2020)  
 [3] Arute et al., *Nature* 574 (2019), [4] Cong et al., *Nat. Phys* (2019),  
 [5] Romero et al., *QST* (2017) [6] Wiebe et al., *PRL* (2017)

# Overview

- Quantum Phase Recognition
  - Hamiltonian with a symmetry protected topological phase
  - Identifying quantum states: direct measurement vs QCNN
- Quantum Convolutional Neural Networks
  - Inspiration behind the algorithm: classical CNN
  - Advantages and physical interpretation
- Superconducting Quantum Processor
- Experimental results
  - Characterization of the prepared ground state
  - Performance of the QCNN
- Conclusions and outlook

# The problem

## Quantum Phase Recognition



**Barcelona  
Supercomputing  
Center**

*Centro Nacional de Supercomputación*

# Quantum Phase Recognition with a QCNN

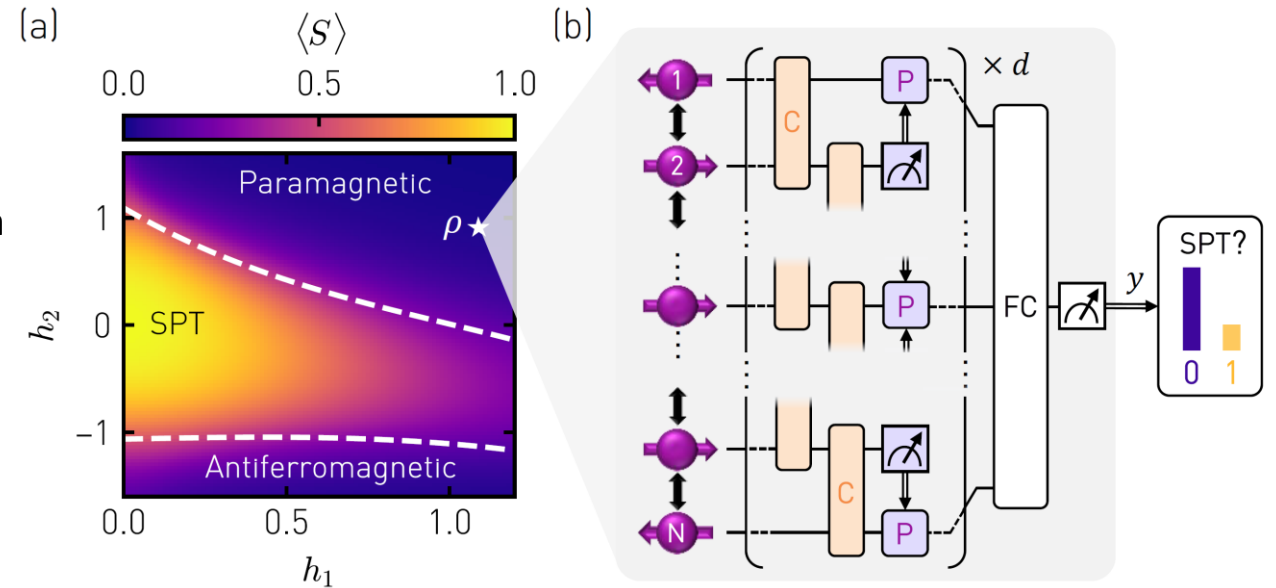
## Quantum Face Recognition

- Task: Decide for a prepared quantum state  $\rho_0$  if it exhibits symmetry-protected topological (SPT) order [1, 2].
- Model system: Ground states of the Cluster-Ising Hamiltonian

$$H = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$

- Signature of SPT phase: Finite string order parameter [3]

$$\langle S \rangle = \langle Z_1 X_2 X_4 \dots X_{N-3} X_{N-1} Z_N \rangle$$



# Theoretical background – Hamiltonian

$$\mathcal{H} = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$

- Has an symmetry protected topological phase under  $\mathbb{Z}_2 \times \mathbb{Z}_2$  symmetry
  - $\prod_{i \text{ odd}} X_i$
  - $\prod_{i \text{ even}} X_i$
- Characterized by String Order Parameter [1]:  $\langle S \rangle = \langle Z_1 X_2 X_4 \dots X_{N-3} X_{N-1} Z_N \rangle$

# Theoretical background – Hamiltonian

$$\mathcal{H} = -X_1 Z_2 - Z_1 X_2 Z_3 - Z_2 X_3 - \frac{h_1}{J} (X_1 + X_2 + X_3) - \frac{h_2}{J} (X_1 X_2 + X_2 X_3)$$

- Has an SPT phase under  $\mathbb{Z}_2 \times \mathbb{Z}_2$  symmetry
  - $X_1 X_3$
  - $X_2$  - Not exact due to **boundary terms!**
- Characterized by String Order Parameter
  - $\langle S \rangle = Z_1 X_2 Z_3$

Limits:

- $h_1 \rightarrow \infty$ :  $\mathcal{H} = -h_1 \sum_{i=1}^N X_i$

$$|\psi_g\rangle = |+++ \rangle$$

- $h_1 = 0, h_2 = 0$ :  $\mathcal{H} = -\sum_{i=2}^{N-1} Z_{i-1} X_i Z_{i+1}$

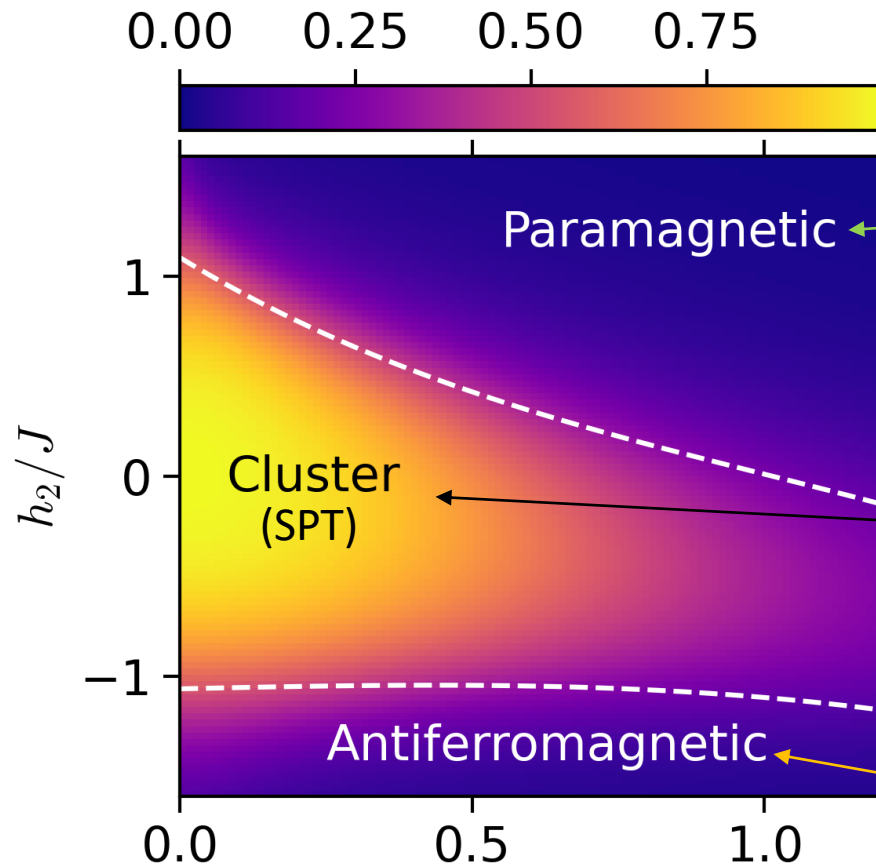
$$|\psi_g\rangle = \frac{1}{\sqrt{2}} (|+ 0 + \rangle + |- 1 - \rangle)$$

(cluster state)

- $h_2 \rightarrow -\infty$ :  $\mathcal{H} = -h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$

$$|\psi_g\rangle = |+ - + \rangle$$

# Theoretical background – SPT phase



Limits:

- $h_1 \rightarrow \infty$ :  $\mathcal{H} = -h_1 \sum_{i=1}^N X_i$

$|\psi_g\rangle = |+++ \rangle$

- $h_1 = 0, h_2 = 0$ :  $\mathcal{H} = -\sum_{i=2}^{N-1} Z_{i-1} X_i Z_{i+1}$

$|\psi_g\rangle = \frac{1}{\sqrt{2}} (|+ 0 + \rangle + |- 1 - \rangle)$   
(cluster state)

- $h_2 \rightarrow -\infty$ :  $\mathcal{H} = -h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$

$|\psi_g\rangle = |+ - + \rangle$



# Quantum Phase Recognition with a QCNN

## Quantum Face Recognition

- Task: Decide for a prepared quantum state  $\rho_0$  if it exhibits symmetry-protected topological (SPT) order [1, 2].
- Model system: Ground states of the Cluster-Ising Hamiltonian

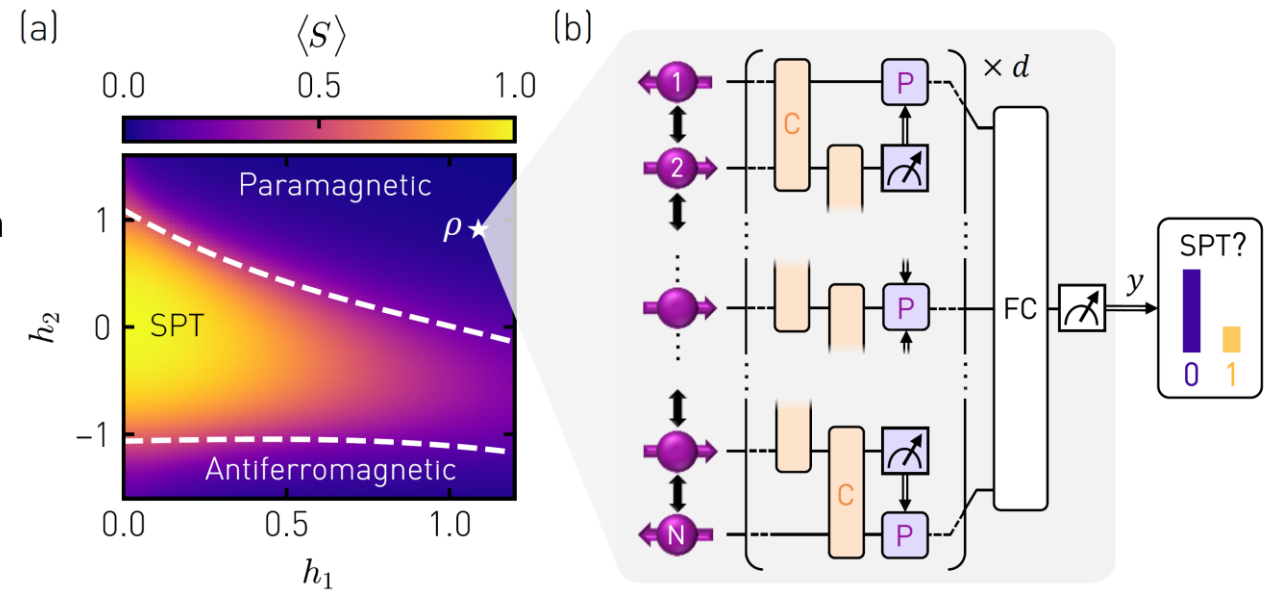
$$H = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$

- Signature of SPT phase: Finite string order parameter [3]

$$\langle S \rangle = \langle Z_1 X_2 X_4 \dots X_{N-3} X_{N-1} Z_N \rangle$$

## Questions

- Can we detect SPT phase by processing  $\rho_0$  with a quantum algorithm rather than by averaging  $\langle S \rangle$ ?
- Possible advantages: Improve sampling efficiency close to phase boundary and error tolerance capability [4]



# The algorithm

## Quantum Convolutional Neural Networks



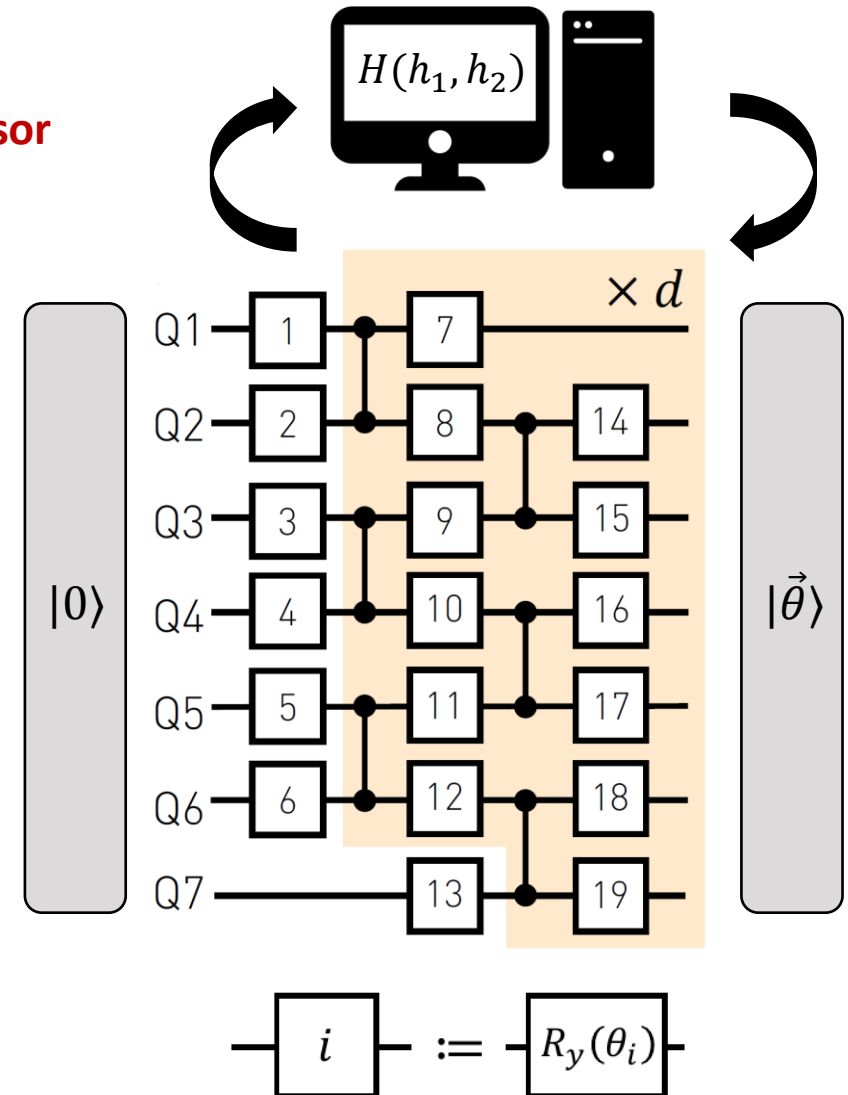
**Barcelona  
Supercomputing  
Center**  
*Centro Nacional de Supercomputación*

# Variational state preparation circuit

Step 1: Prepare (approximate) ground states of  $H$  on quantum processor

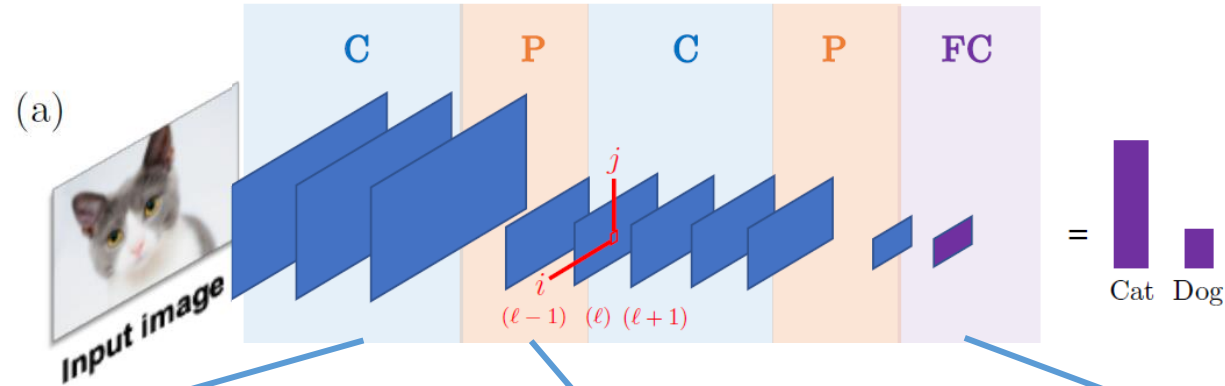
## Ansatz

- Hardware-efficient ansatz alternating between layers of CZ gates and single qubit rotations
- Use single layer  $d=1$  in experiment
- 19 variational parameters
- Optimize variational parameters offline on classical computer by minimizing energy  $\langle \vec{\theta} | H | \vec{\theta} \rangle$  with L-BFGS B
- Fidelity w.r.t. exact GS exceeds 82% for all states

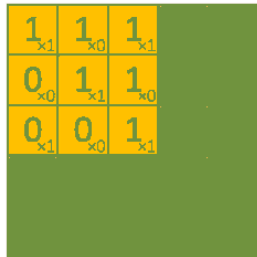


# Classical convolutional neural networks

Example: Image recognition



Convolutional layer

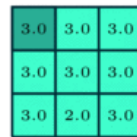


Image

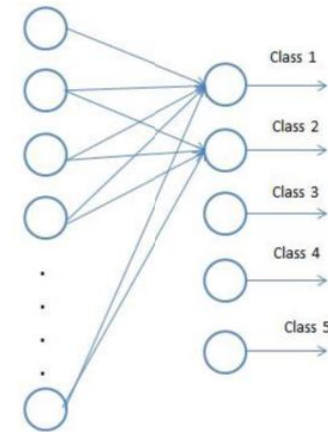


Convolved Feature

Pooling layer



Fully connected

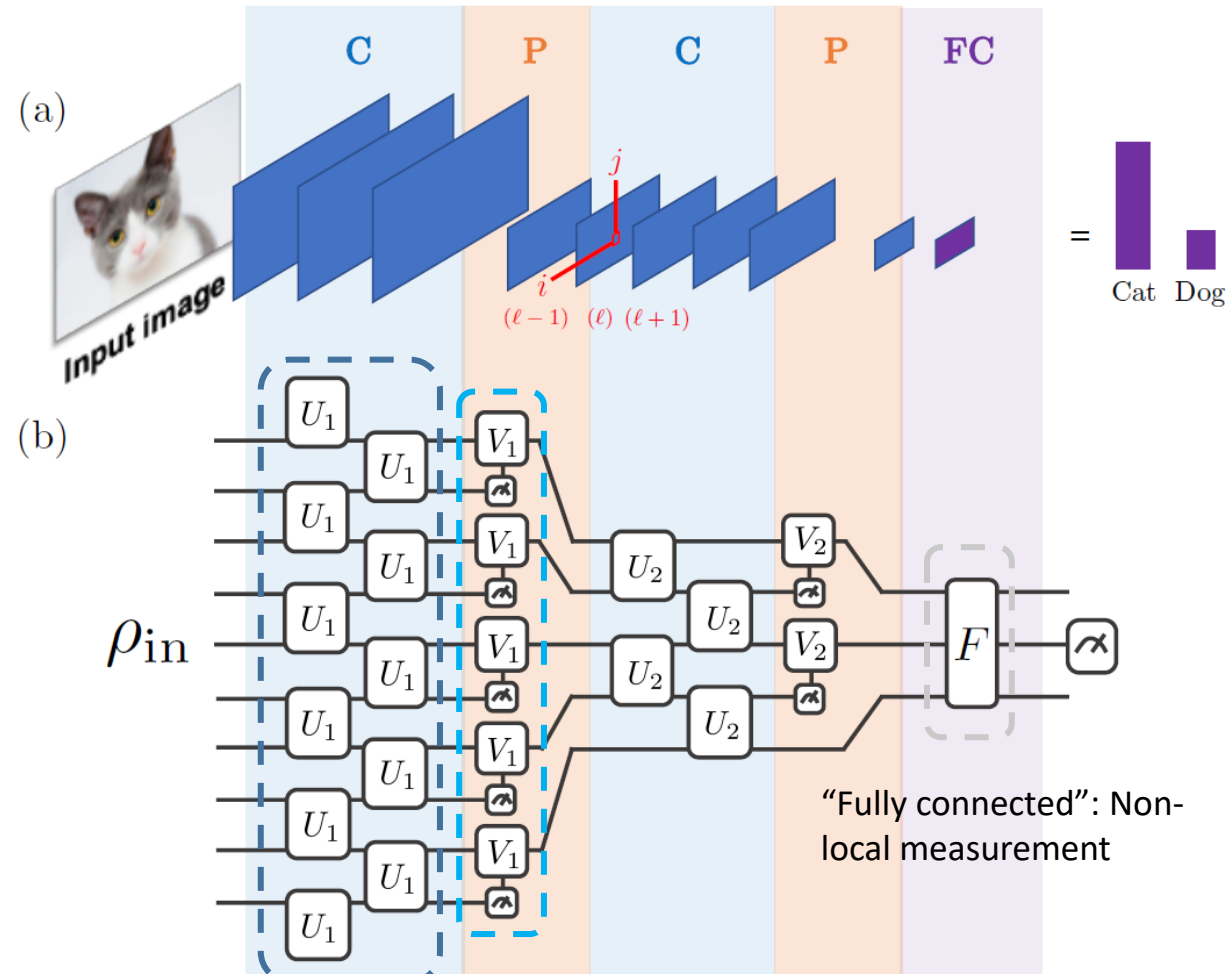


Data is processed using trainable weights  $w$  on the input data. At data size of data to the most relevant features

$$y_{i,j} = w_0x_{i,j} + w_1x_{i+1,j} + \dots + w_8x_{i+2,j+2} \text{ (maximum, averaging,...)}$$

All remaining data points are processed simultaneously with trainable weights

# Quantum CNN structure

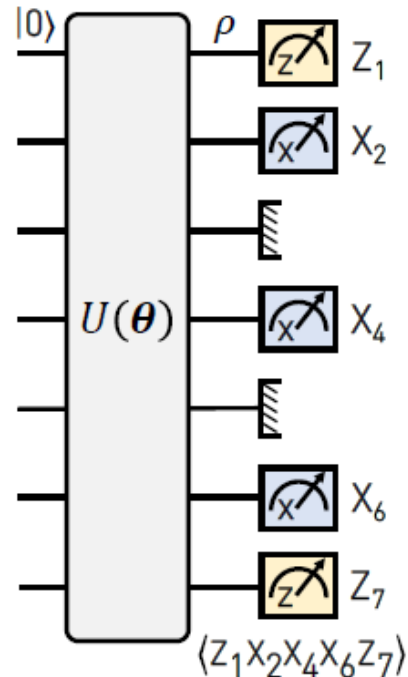


“Convolution” with  
quasilocally controlled unitaries  
and measurements

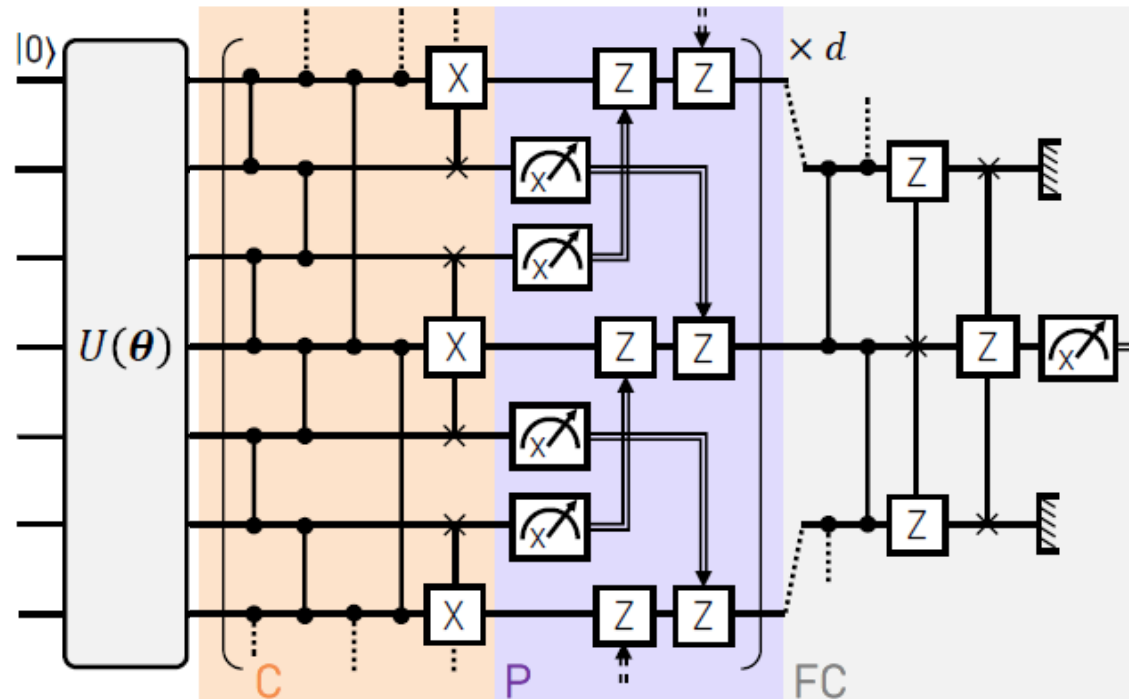
# Quantum Phase Recognition with a QCNN

Step 2: Measure  $\langle S \rangle$  or QCNN output from state preparation circuit

(a) Direct Sampling



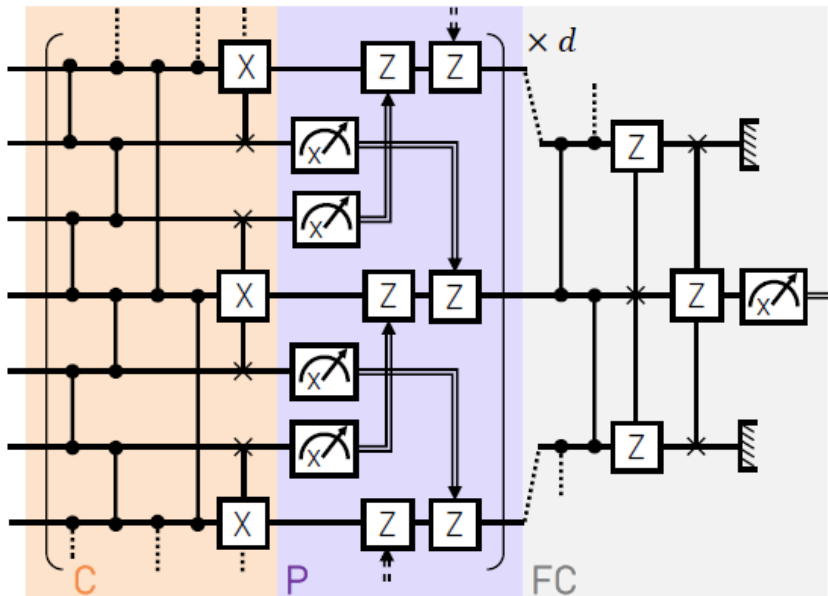
(b) QCNN Sampling



## Quantum Convolutional Neural Network

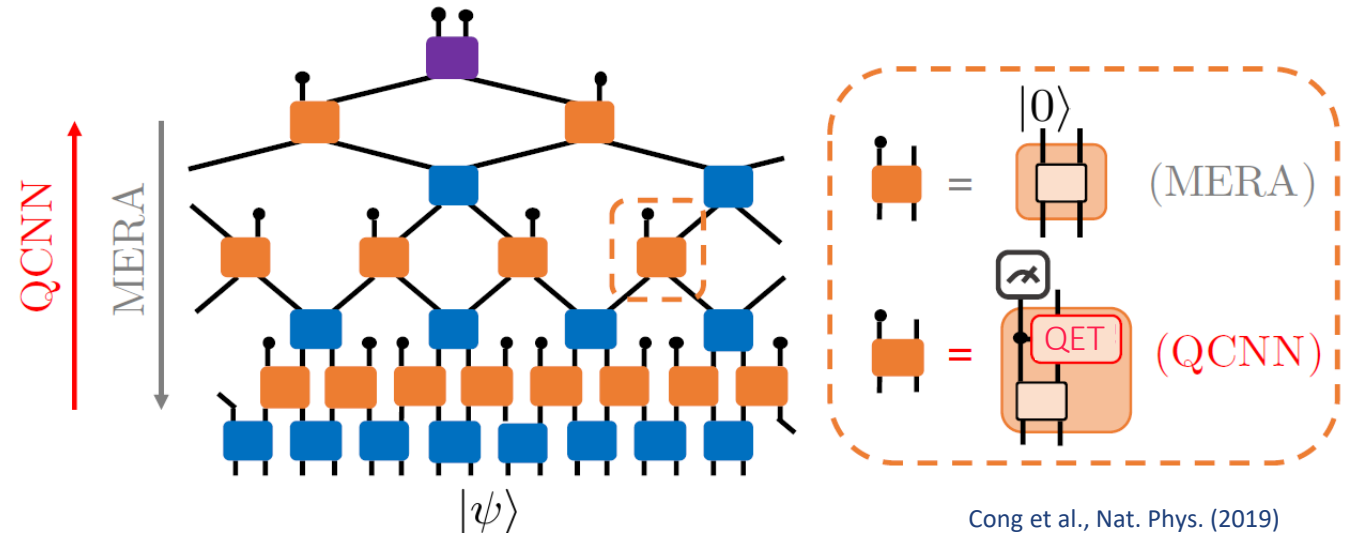
- Convolutional layer ideally maps cluster state onto ground state  $|00000\rangle$
- Inspired by the multiscale entanglement renormalization ansatz (MERA)

# Theoretical understanding



Herrmann, Masot-Llima et al. (2021)

QCNN = Multiscale Entanglement Renormalization Ansatz (MERA)  
+ Quantum Error Tolerance (QET)



Cong et al., Nat. Phys. (2019)

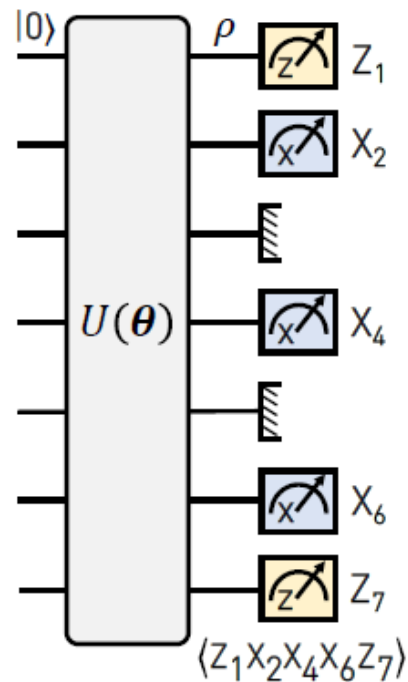
The QCNN output corresponds to measuring a multi-scale string order parameter of the form

$$S_M = \sum_{jk} \eta_{jk}^{(1)} S_{jk} + \sum_{jklm} \eta_{jklm}^{(2)} S_{jk} S_{lm} + \dots$$

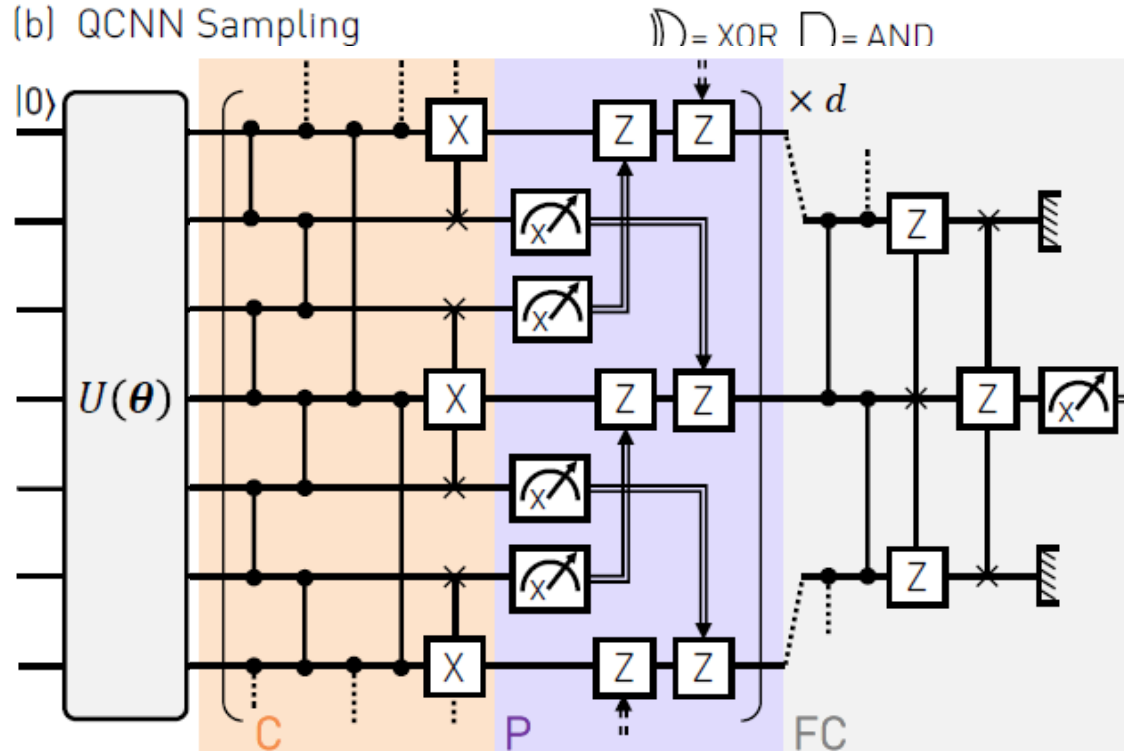
- The number of terms grows double exponentially with the depth of the circuit
- For our experiment with  $N = 7$  and  $d = 1$  the QCNN measures a sum of 10 different string order parameters
- All terms are measured simultaneously and cannot be constructed from a direct measurement of all qubits in a single local basis (X, Y or Z basis)

# Quantum Phase Recognition with a QCNN

(a) Direct Sampling



(b) QCNN Sampling



## Quantum Convolutional Neural Network

Quantum Convolutional and Pooling layers, followed by a classical sector (AND & XOR gates) to map the sampled multibit string  $\vec{x}$  onto a single output bit  $y$  described by Boolean function  $f(x)$ .

Ability to tolerate errors (depicted for 1 and Z errors)



# Quantum Phase Recognition with a QCNN

## Quantum Phase Recognition

- Task: Decide for a prepared quantum state  $\rho_0$  if it exhibits symmetry-protected topological (SPT) order [1, 2].
- Model system: Ground states of the Cluster-Ising Hamiltonian

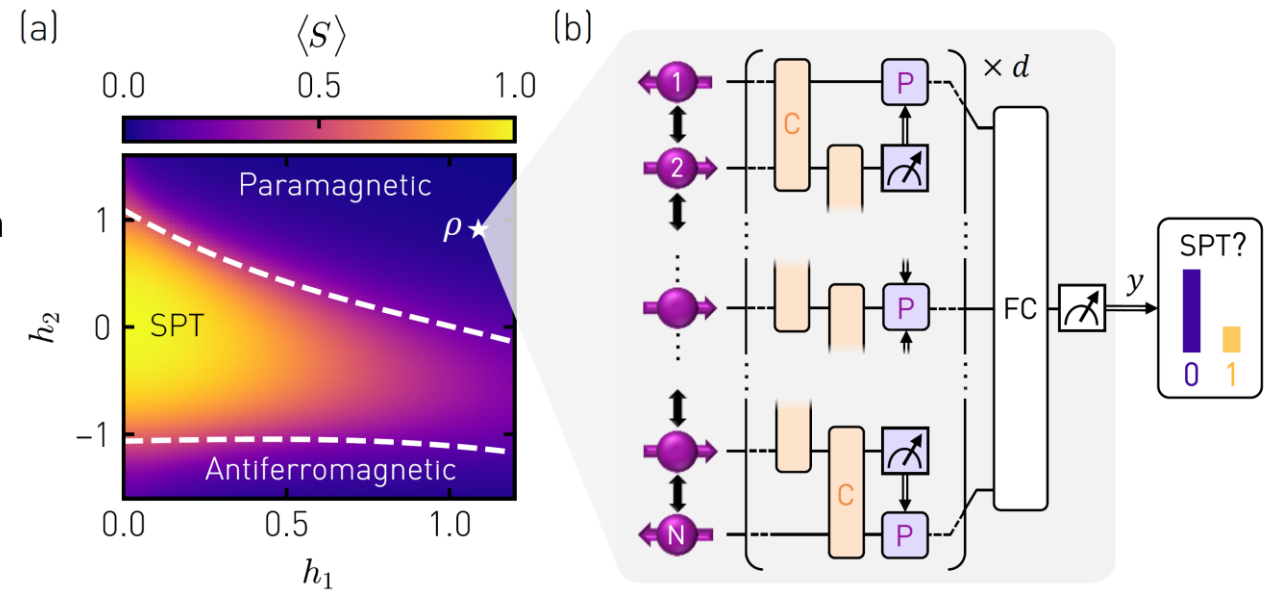
$$H = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$

- Signature of SPT phase: Finite string order parameter [3]

$$\langle S \rangle = \langle Z_1 X_2 X_4 \dots X_{N-3} X_{N-1} Z_N \rangle$$

## Questions

- Can we detect SPT phase by processing  $\rho_0$  with a quantum algorithm rather than by averaging  $\langle S \rangle$ ?
- Possible advantages: Improve sampling efficiency close to phase boundary and error tolerance capability [4]



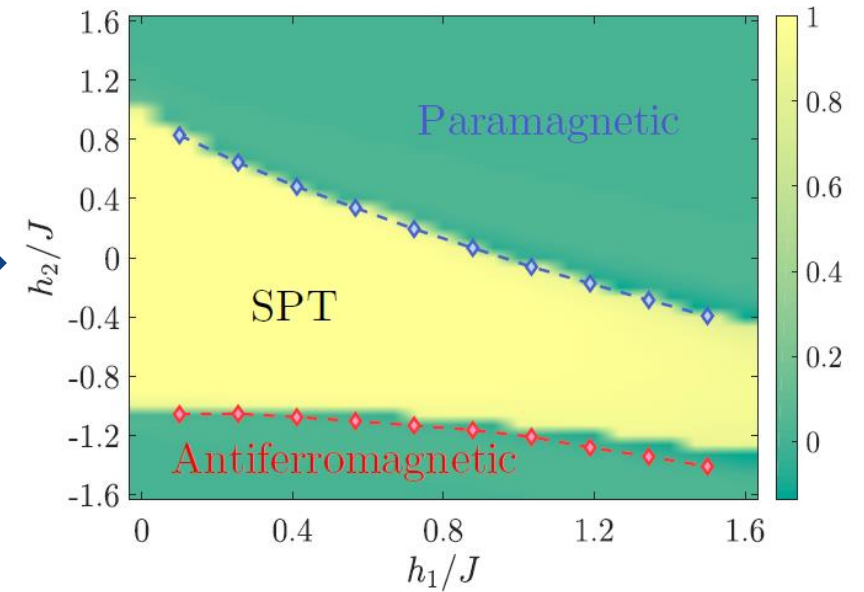
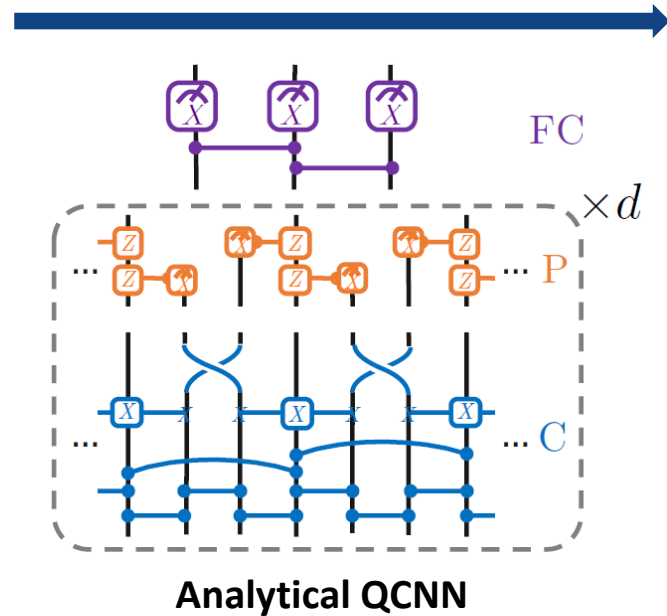
## The algorithm

- Variant of Quantum Convolutional Neural Network [4]
- Entangling gates in **convolutional layer**
- Pooling** reduces the number of qubits while retaining characteristic features
- Fully-connected** layer to map decision onto a single output qubit

# Advantage: Sample complexity

Theoretical proposal with a long chain:

$$H = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$

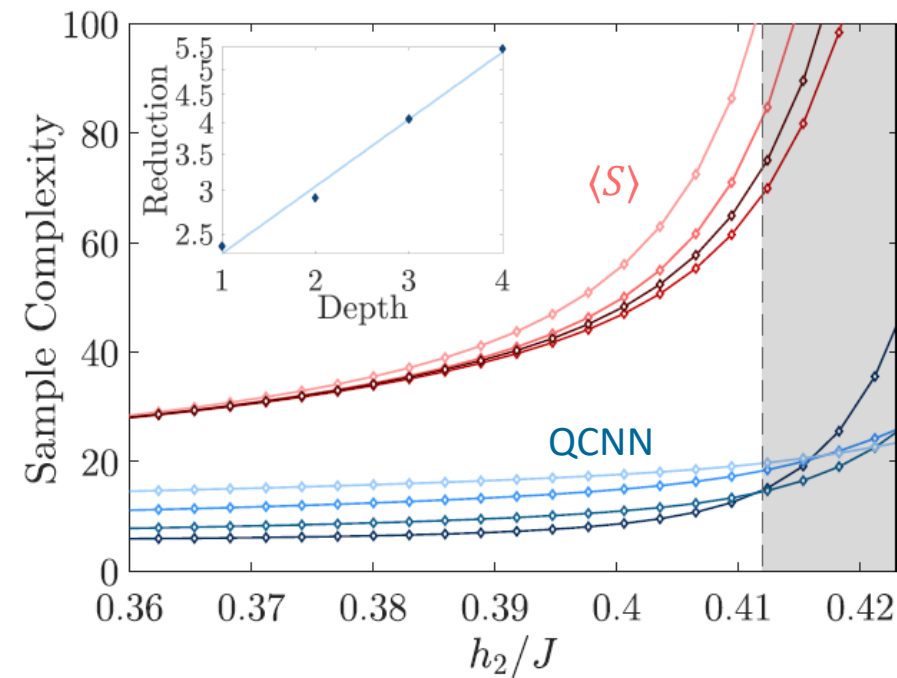
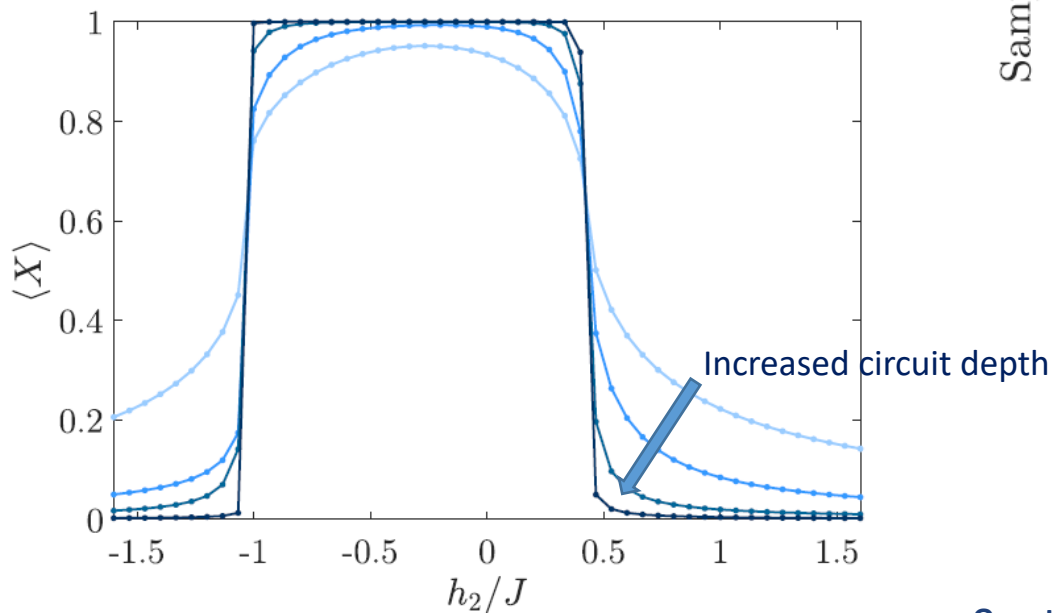
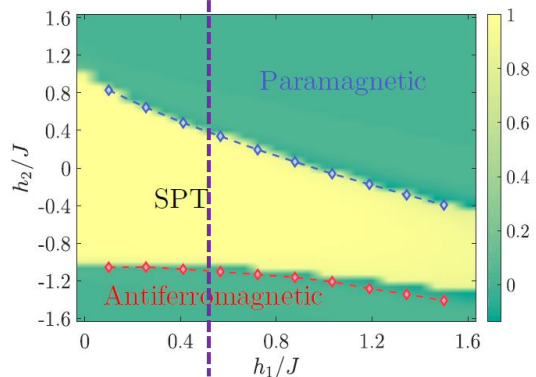


**N=45 chain**

- Boundaries calculated with iDMRG simulation
- Color indicates phases according to analytical QCNN

# Advantage: Sample complexity

$$H = - \sum_{i=1}^{N-2} Z_i X_{i+1} Z_{i+2} - h_1 \sum_{i=1}^N X_i - h_2 \sum_{i=1}^{N-1} X_i X_{i+1}$$



# The device

## Superconducting Quantum Processor



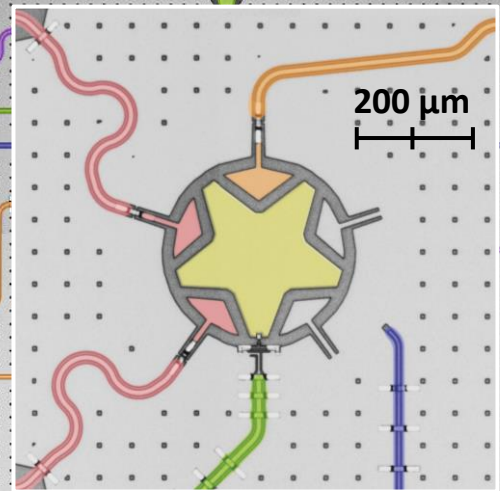
**Barcelona  
Supercomputing  
Center**

*Centro Nacional de Supercomputación*

# The 7-Qubit Device

QUDEV

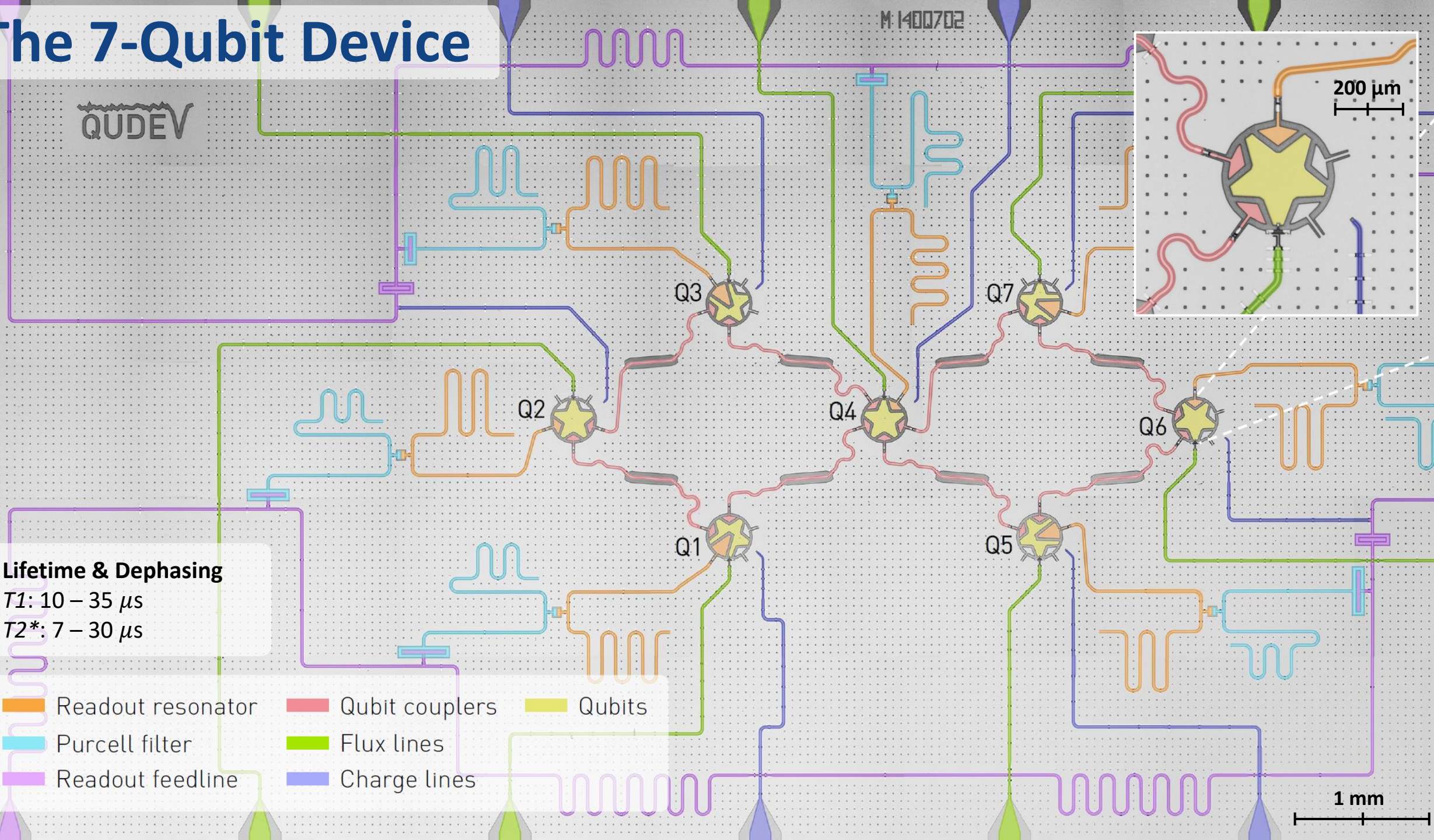
M 1400702



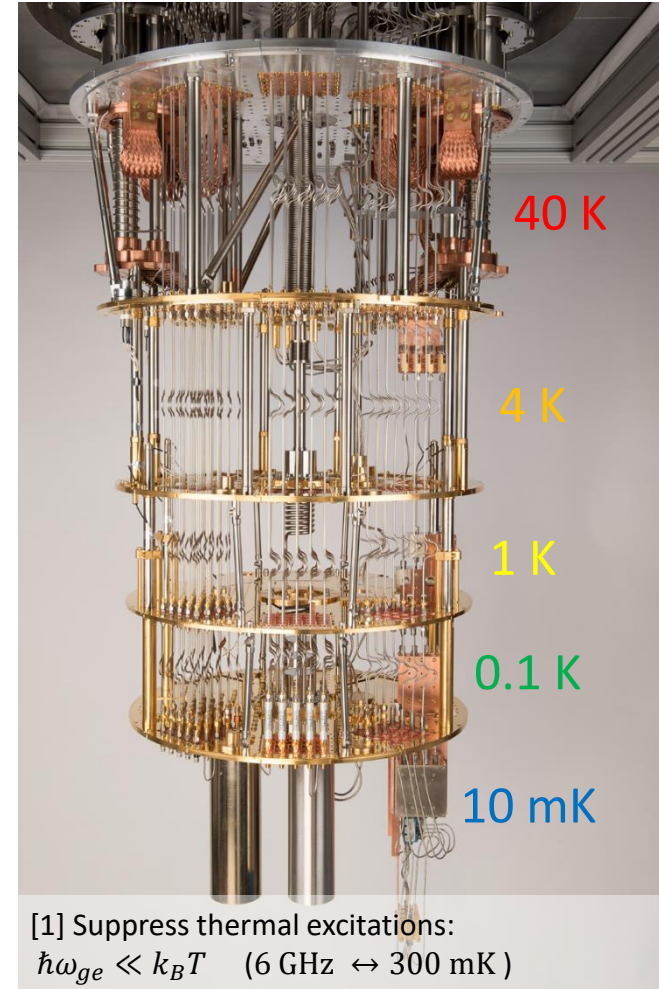
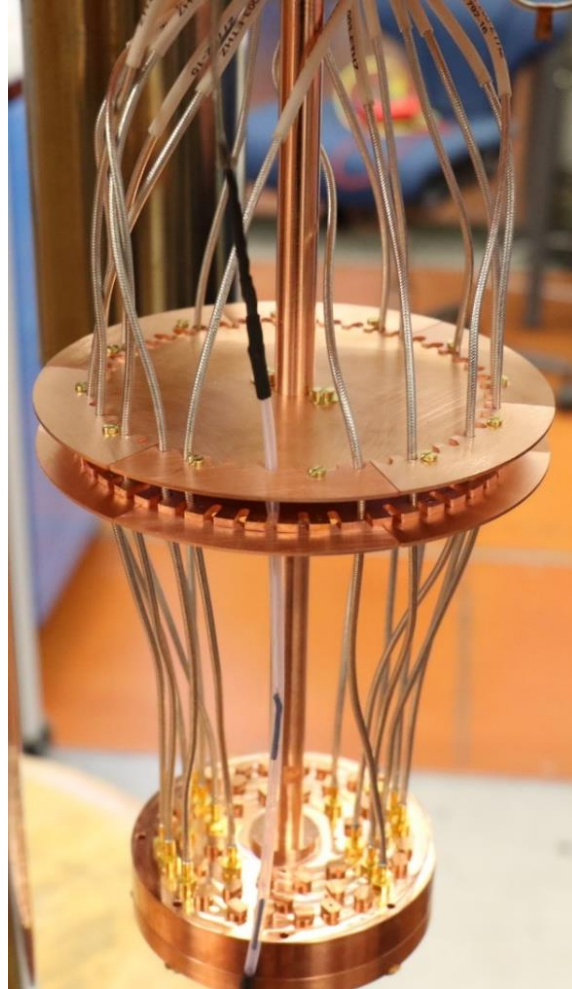
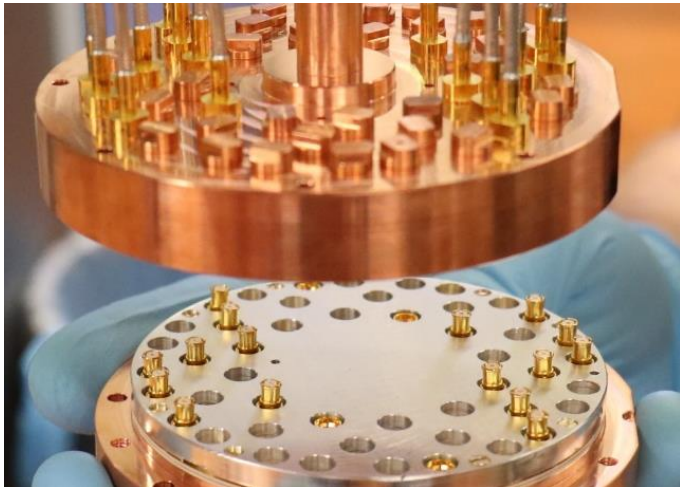
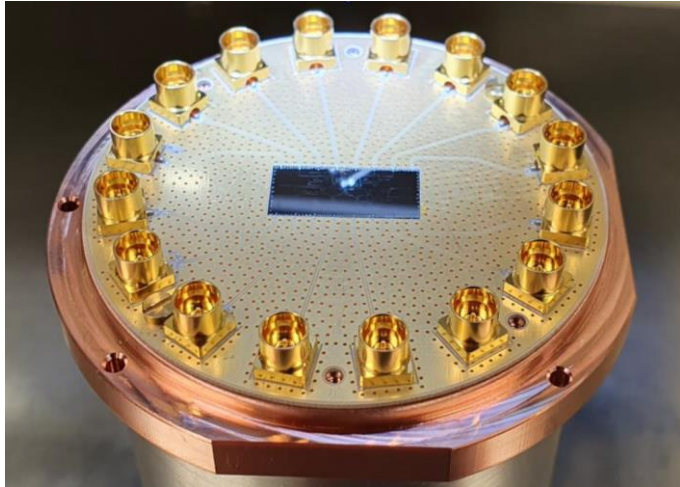
**Lifetime & Dephasing**  
 $T_1$ : 10 – 35  $\mu$ s  
 $T_2^*$ : 7 – 30  $\mu$ s

- Readout resonator
- Purcell filter
- Readout feedline
- Qubit couplers
- Flux lines
- Charge lines
- Qubits

1 mm

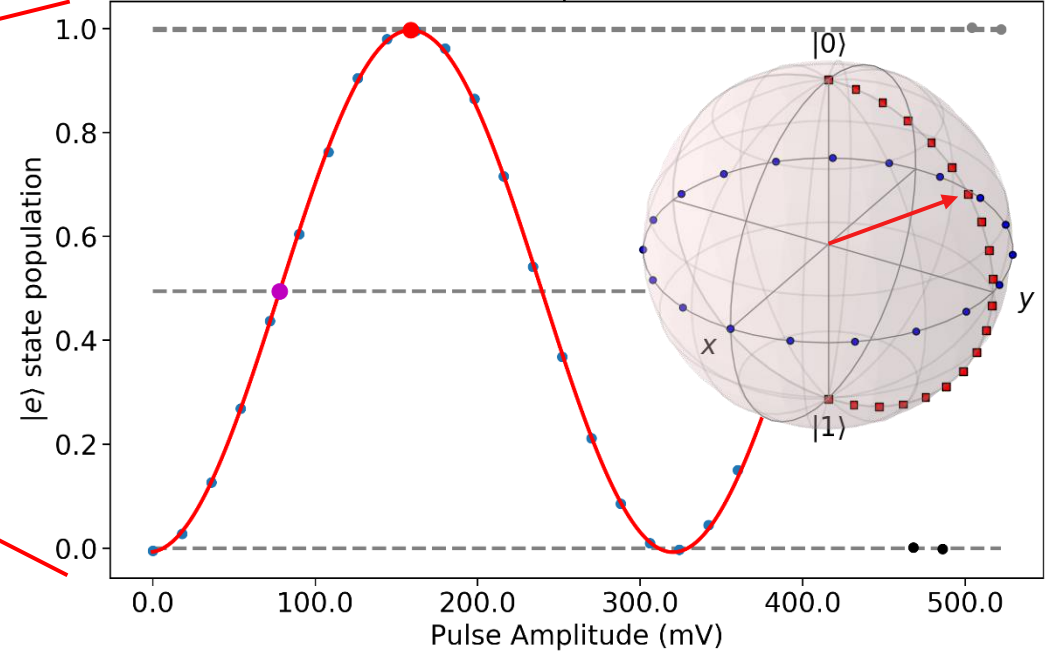


# Cryogenic setup for superconducting qubits



[1] Suppress thermal excitations:  
 $\hbar\omega_{ge} \ll k_B T$  (6 GHz  $\leftrightarrow$  300 mK)

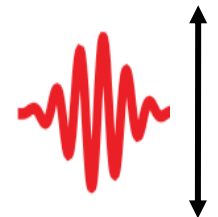
# Single & Two Qubit Gate Control



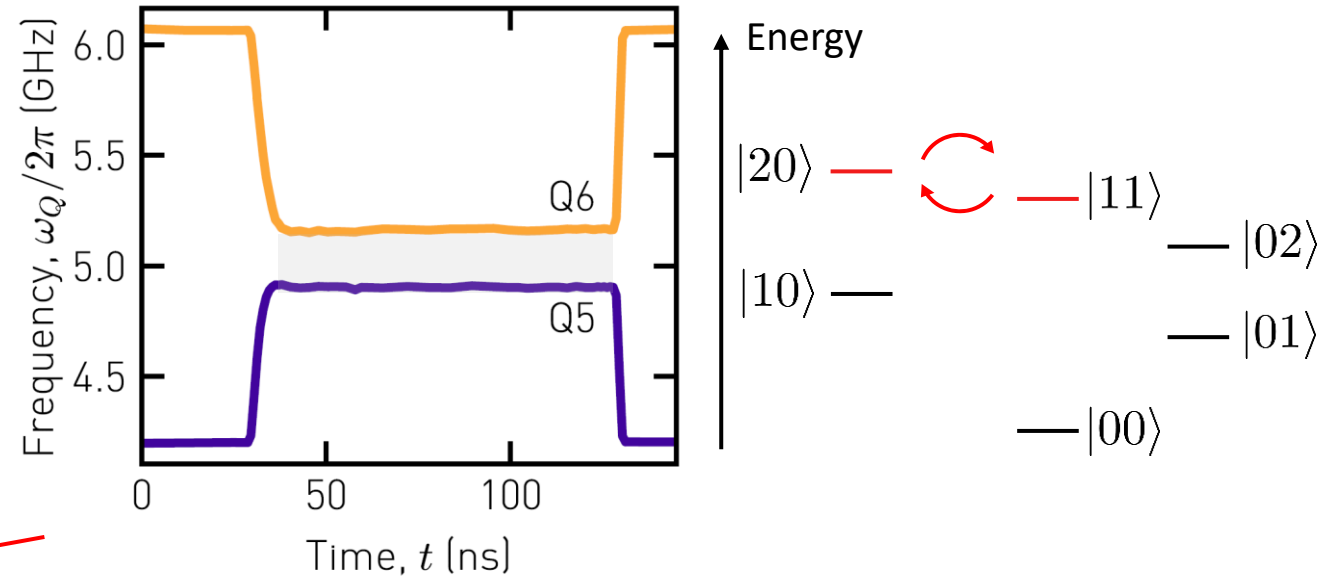
- Required qubit connectivity is 1D linear chain
- **Single qubit** error from randomized benchmarking

## Single Qubit Control:

- Via microwave pulses (50 ns length) [1]
- Scale pulse amplitude linearly to implement arbitrary  $R_y(\theta_i)$  rotation



# Single & Two Qubit Gate Control



## Two Qubit CZ Gate:

- Required qubit connectivity is 1D linear chain
- **Single qubit** error from randomized benchmarking
- **Two qubit CZ** error, from quantum process tomography
  - Measured Chi-Matrices reused for simulation

- Implemented via dc-flux pulses bringing  $|11\rangle \leftrightarrow |20\rangle$  [1, 2]
- Both qubits are fluxed to reach interaction frequency
  - Flexible choice of interaction frequency



# The outcome

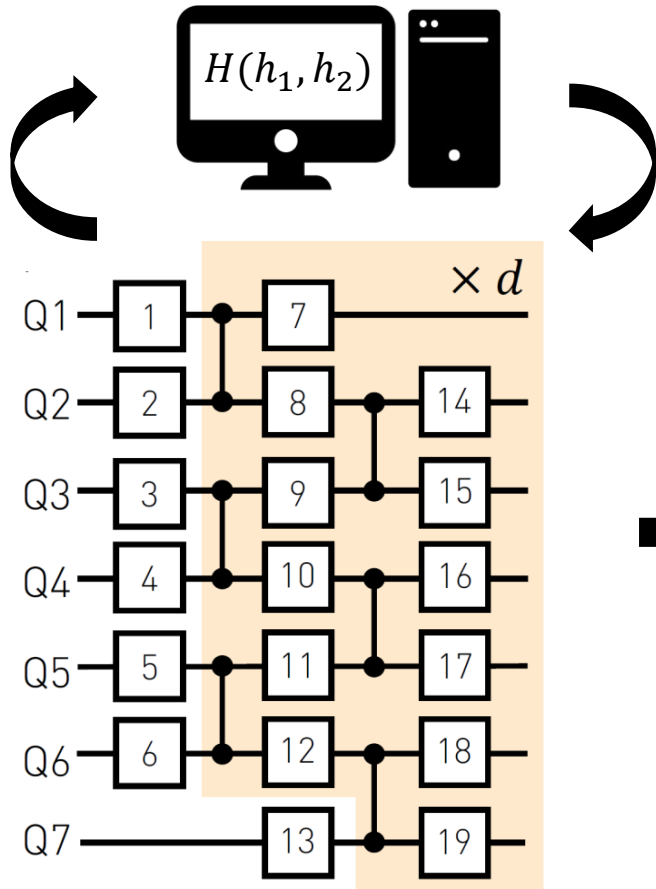
## Experimental results



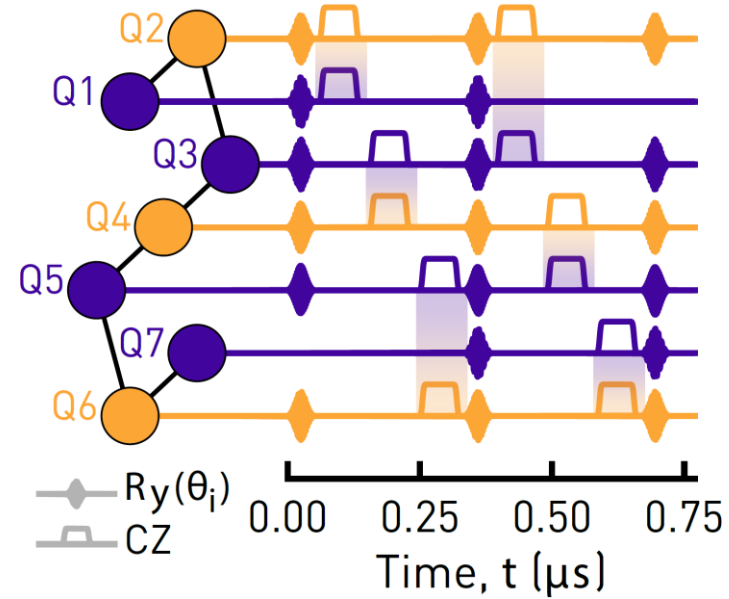
**Barcelona  
Supercomputing  
Center**

*Centro Nacional de Supercomputación*

# Variational ground state preparation

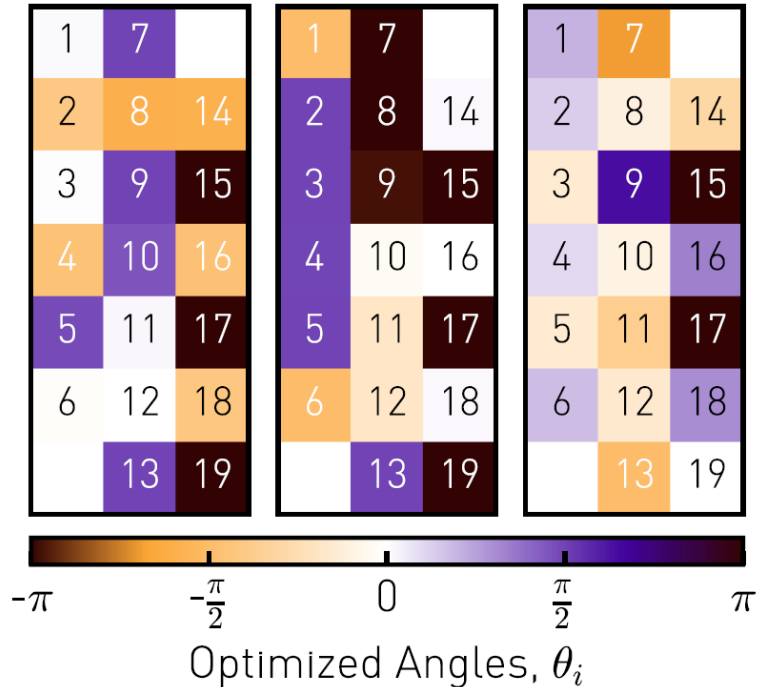


Compile pulse sequence and run on quantum device

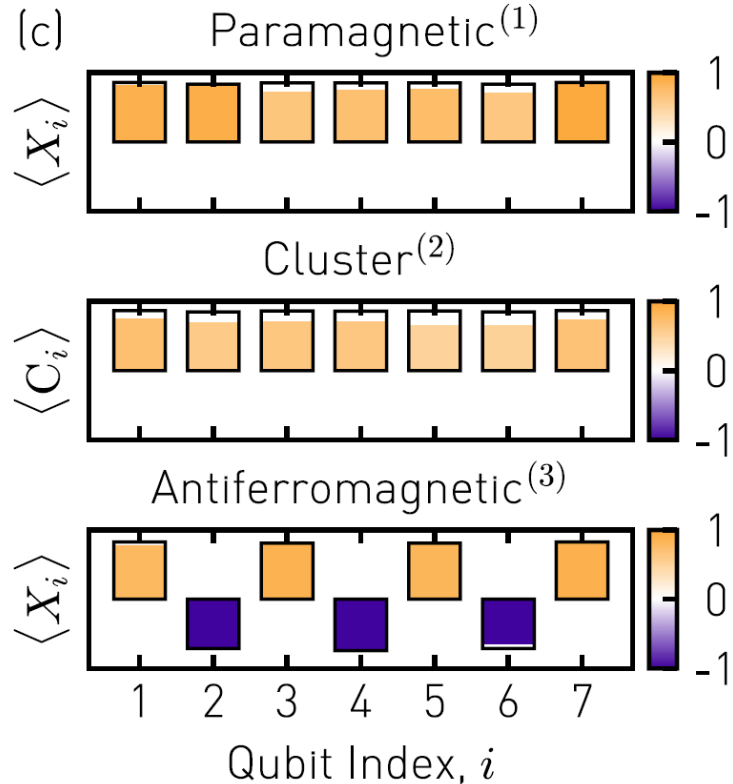


# Characterization of exp. prepared Variational Ground

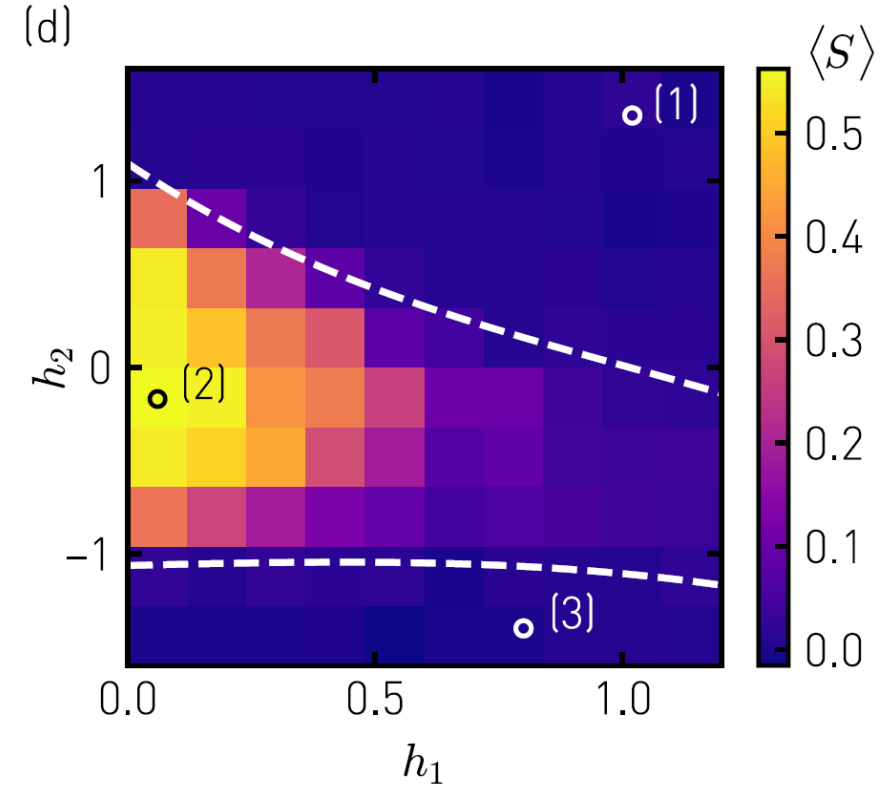
(b) Paramag.<sup>(1)</sup> Cluster<sup>(2)</sup> Antiferro.<sup>(3)</sup>



- Examples for optimized set of rotation angles
- Exploit symmetries in state preparation circuit to mitigate effect of T1 decay [1]

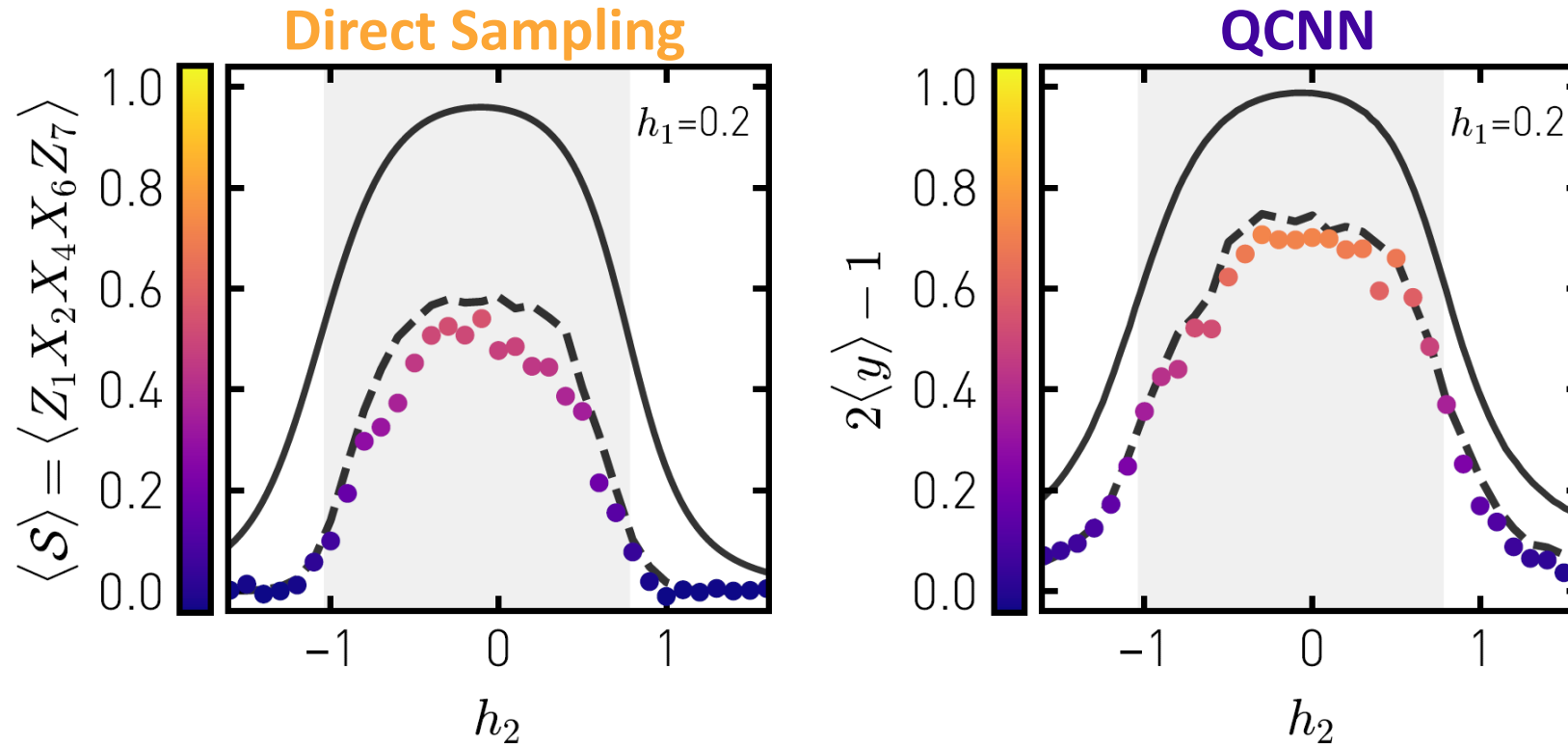


- Paramagnetic (antiferromagnetic) phases exhibit finite local  $\langle X_i \rangle$  with identical (toggling) sign
- Cluster phase characterized by finite  $\langle C_i \rangle = \langle Z_{i-1} X_i Z_{i+1} \rangle$  correlations



- Measured phase diagram showing the measured  $\langle S \rangle$  in good agreement with theoretically expected one
- Reduced contrast due to finite state preparation fidelity

# Comparison between Direct Sampling and QCNN



## Measure S across phase boundaries

- Output of QCNN and directly sampled SOP both follow the simulation (dashed line).
- Reduced contrast compared to ideal value (solid line) due to finite error probability
- QCNN achieves higher contrast due to error correcting capability

# Conclusions and outlook



**Barcelona  
Supercomputing  
Center**

*Centro Nacional de Supercomputación*

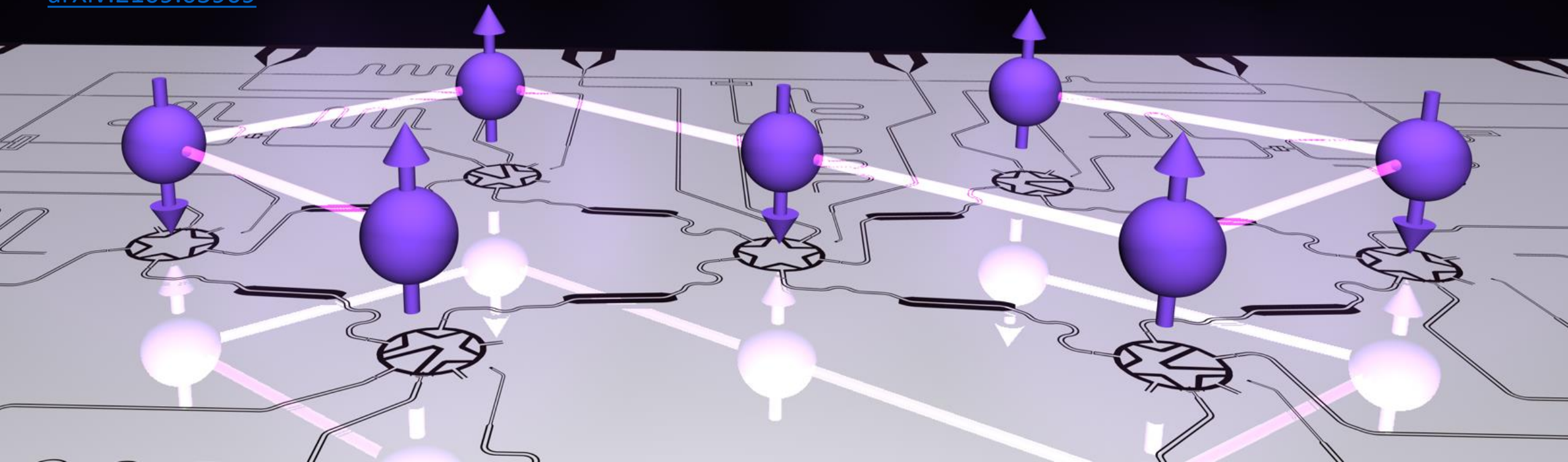
## Achieved

- Built and operated a programmable 7Q quantum processor to demonstrate ...
  - ... the preparation of a topological quantum phase
  - ... a Quantum Convolutional Neural Network to recognize topological order

[arXiv:2109.05909](https://arxiv.org/abs/2109.05909)

## Next steps Quantum Neural Networks

- Use larger system size to study sampling efficiency near phase boundary in dependence on depth of QCNN
- Explore trainability of parametrized QCNN
- Applications beyond quantum phase recognition (eg. in Quantum Error Correction)



**Thank you for your attention!**

[arXiv:2109.05909](https://arxiv.org/abs/2109.05909)

