nature physics

SUPPLEMENTARY INFORMATION
https://doi.org/10.1038/s41567-019-0648-8

In the format provided by the authors and unedited.

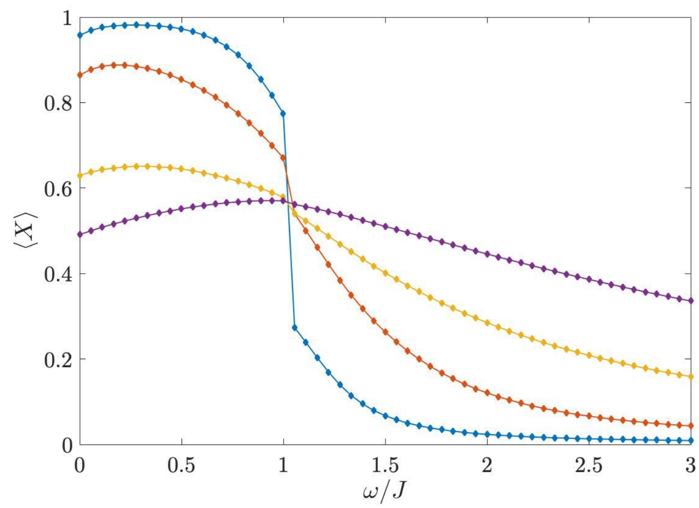
Quantum convolutional neural networks

Iris Cong[1], Soonwon Choi[1,2*] and Mikhail D. Lukin[1]

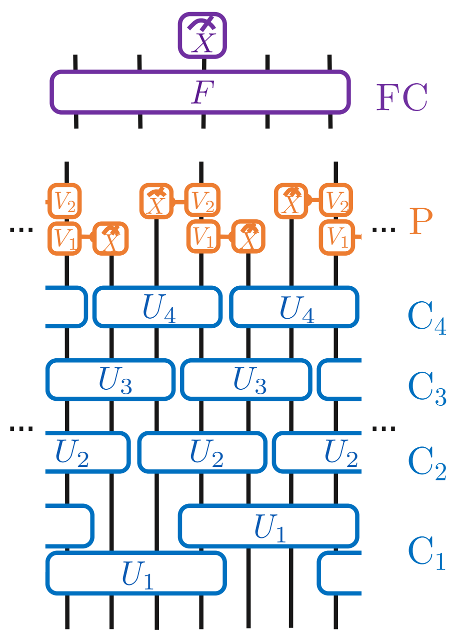
[1]Department of Physics, Harvard University, Cambridge, MA, USA. [2]Department of Physics, University of California, Berkeley, Berkeley, CA, USA.
*e-mail: soonwon@berkeley.edu

Supplementary Figures: Quantum Convolutional Neural Networks

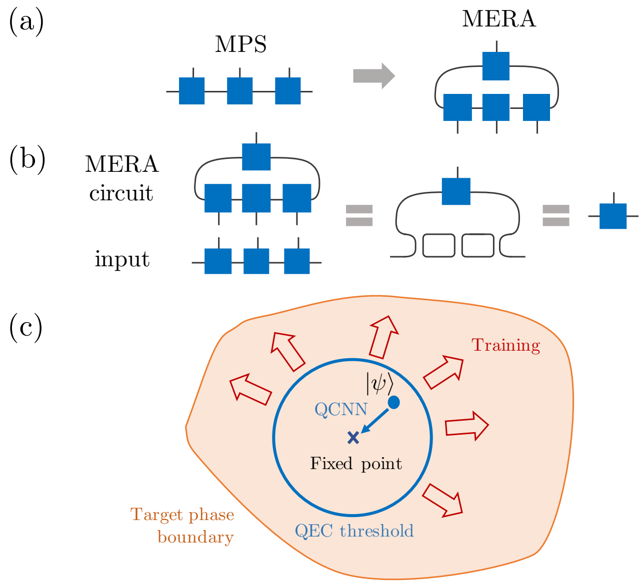
Iris Cong,[1] Soonwon Choi,[1,2] and Mikhail D. Lukin[1]
[1]Department of Physics, Harvard University, Cambridge, Massachusetts 02138, USA
[2]Department of Physics, University of California, Berkeley, CA 94720, USA



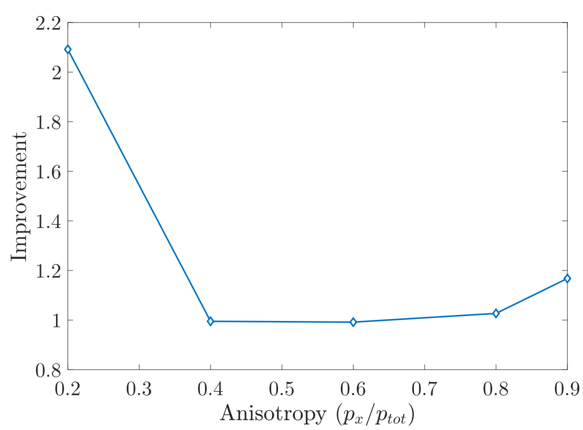
Supplementary Figure 1: Exact QCNN output (at depth $d = 1, ...4$) for the Haldane chain Hamiltonian with $N = 54$ spins.



Supplementary Figure 2: Circuit parameterization for training a QCNN to solve QPR. Our circuit involves 4 different convolution layers ($C_1 - C_4$), a pooling layer, and a fully connected layer. The unitaries are initialized to random values, and learned via gradient descent.



Supplementary Figure 3: (a) Given a state with a translationally invariant, isometric matrix product state representation (e.g. a fixed point state for a 1D SPT phase), we explicitly construct an isometry for the MERA representation of this state. Blue squares are the matrix product state tensors, while black lines are the legs of the tensor. While we have illustrated a 3-to-1 isometry, the generalization to arbitrary n-to-1 isometries is straightforward. (b) Diagrammatic proof showing that a MERA constructed from the above tensor maps the fixed-point state back to a shorter version of itself. The first equality uses the definition of isometric tensor, and loops in the middle diagram simplify to a constant number unity. The generalization of this isometry to higher dimensions is discussed in Ref. 48. (c) One helpful initial parameterization for QPR problems consists of a MERA for the fixed point state $|\psi_0(\mathcal{P})\rangle$ and a choice of nested QEC, so that states within the QEC threshold flow toward $|\psi_0(\mathcal{P})\rangle$. Training procedures then expand this threshold boundary to the phase boundary.



Supplementary Figure 4: Ratio between the logical error rate of the Shor code and that of the QCNN code for the anisotropic depolarization error model. We fix the total input error rate $p_{\text{tot}} = p_x + p_y + p_z = 0.001$ and $p_y = p_z$, while varying the ratio p_x/p_{tot}.