

An Introduction to Quantum Computing and Quantum Machine Learning with Quantum Parametric Circuits



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National Institute for **Theoretical and Computational Sciences**



South African Quantum Technology Initiative



- History of Quantum Computing
- Basic of Quantum Computations
- QPC examples VQE/VQLS/QAOA/QCNN
- Application of architectural search to Ansatz design

Outline

• Universal error correcting fault -tolerant quantum computers vs NISQ devices

Quantum Computers

Quantum Mechanics: early 1900





Richard P. Feynman



Yuri I. Manin (Юрий Манин)

Computer Science: 1930



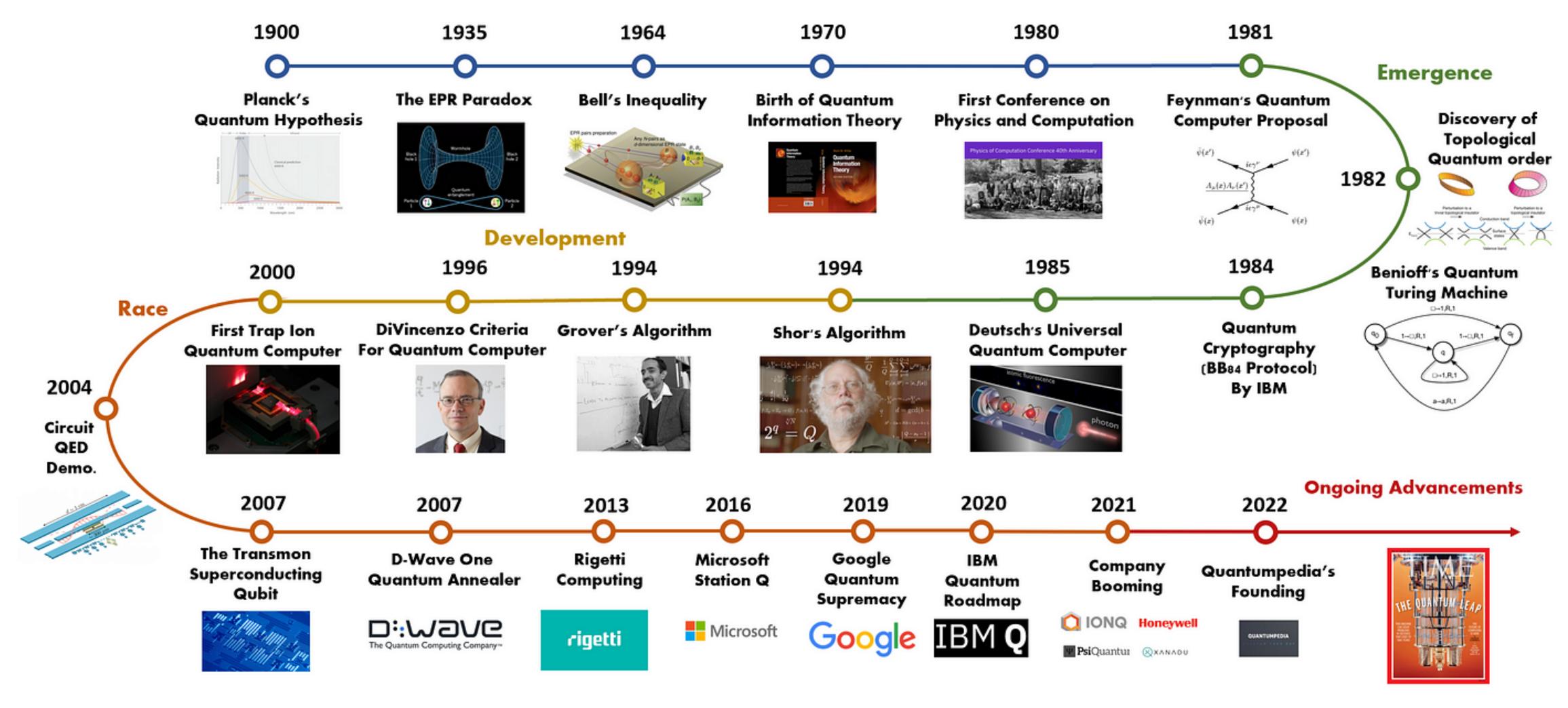
Yu. I. Manin, "Computable and Non-Computable," Sovetskoe Radio, Moscow, 1980, 128 p.

R.P. Feynman, Simulating physics with computers, Internat. J. Theoret. Phys. 21 (6-7) (1982) 467–488, http://dx.doi.org/ 10.1007/bf02650179.



Quantum Computers

Theoretical Foundations



https://quantumpedia.uk/a-brief-history-of-quantum-computing-e0bbd05893d0



Shor's Algorithm

Shor, P.W. (1994). "Algorithms for quantum computation: Discrete logarithms and factoring". Proceedings 35th Annual Symposium on Foundations of Computer Science. pp. 124–134. doi:10.1109/ <u>sfcs.1994.365700</u>.

Shor, Peter W. (October 1997). "Polynomial-Time Algorithms for Prime Factorization and Discrete Logarithms on a Quantum Computer". SIAM Journal on Computing. 26 (5): 1484–1509. arXiv:quant-ph/9508027. doi:10.1137/S0097539795293172. 2337707.

Shor's Code - QEC

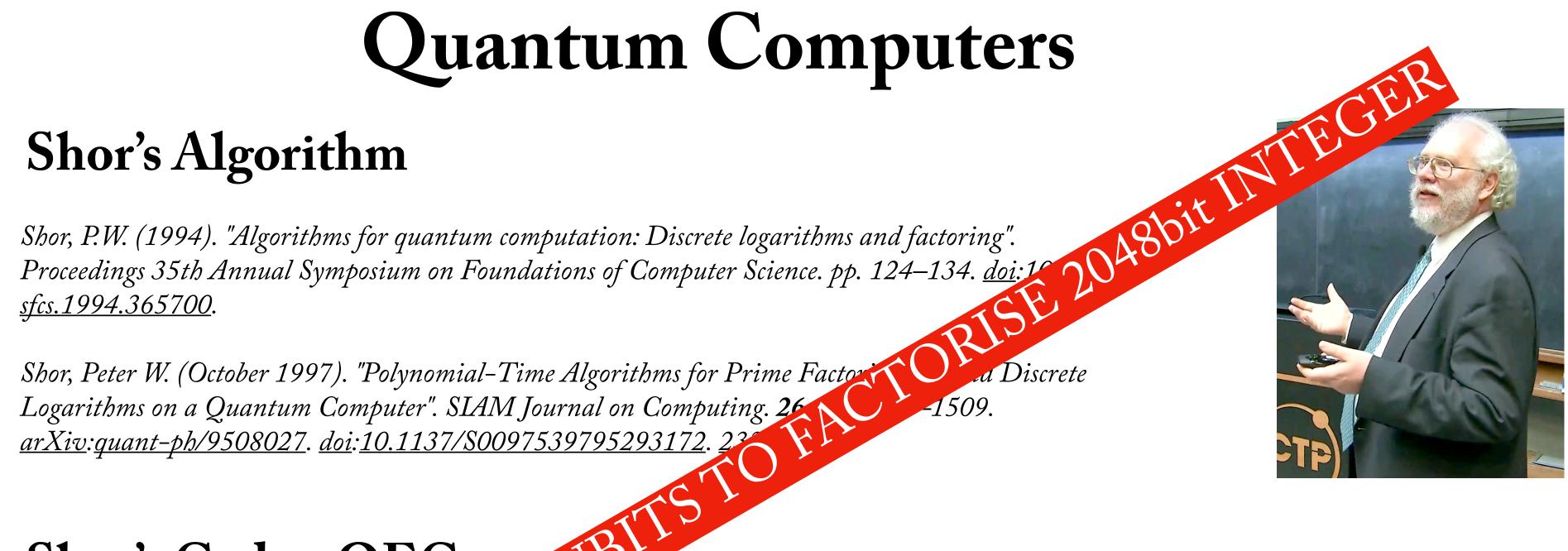
Shor, Peter W. (1995). "Scheme for reducing decoherence in quantum computer memory". Physical Review A. 52 (4): R2493 – R2496

Fault-tolerant quantum computation

Shor, Peter W. (1997). "Fault-tolerant quantum computation" quant-ph/9605011; 37th Symposium on Foundations of Computing, IEEE Computer Society Press, 1996, pp. 56-65

Quantum Computers





Shor's Algorithm

Shor, Peter W. (October 1997). "Polynomial-Time Algorithms for Prime Factor" Logarithms on a Quantum Computer". SIAM Journal on Computing. 26 arXiv:quant-ph/9508027. doi:10.1137/S0097539795293172. 27

Shor's Code - QEC

Shor, Peter W. (1995). "Scheme f

Shor



997). "Fault-tolerant quantum computation" quant-ph/9605011; posium on Foundations of Computing, IEEE Computer Society Press, 1996, pp. 56–65

decoherence in quantum computer memory". Physical Review A. 52 (4): R2493 – R2496

Quantum Computers - Current Status (NISQ)

Google - Willow Chip (2024)



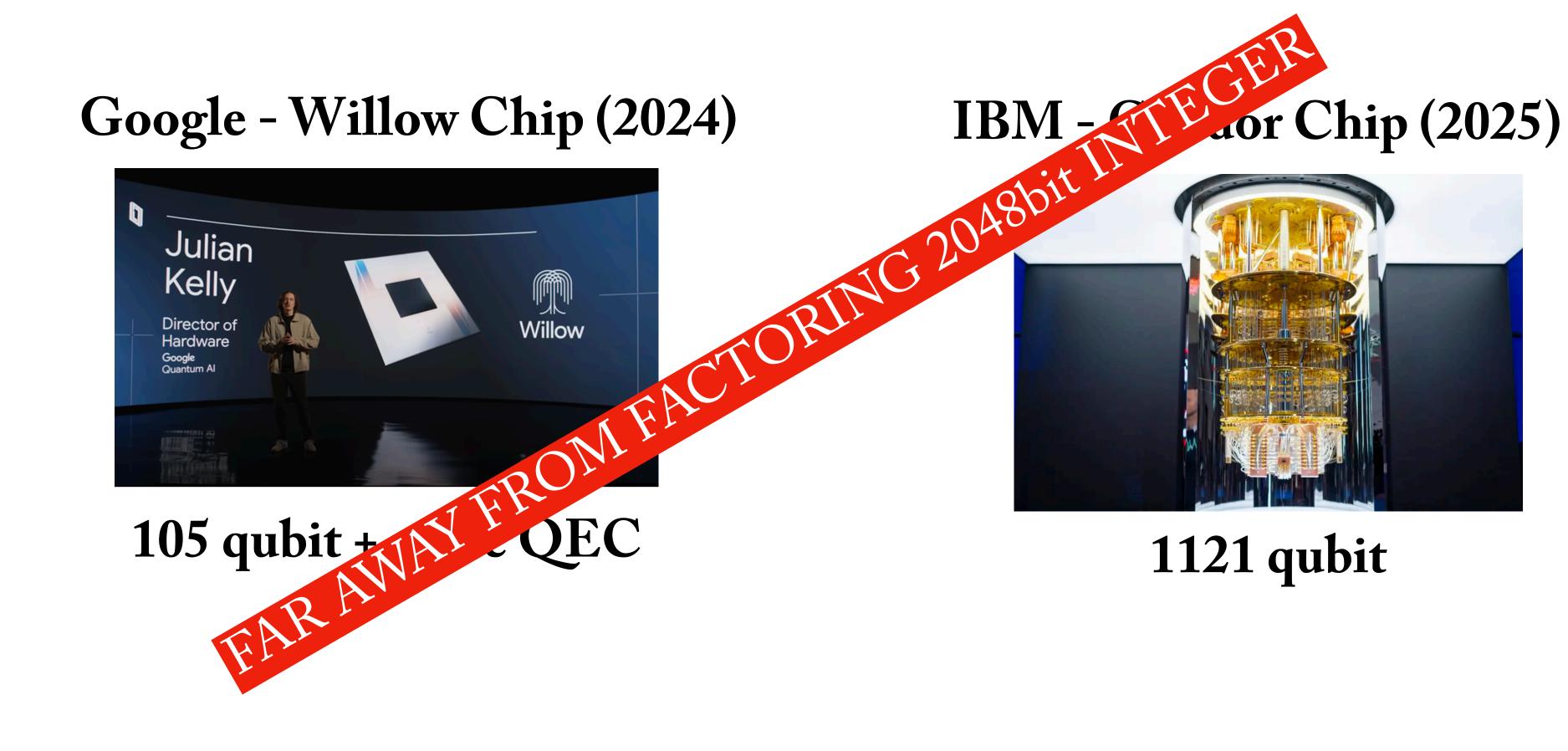
105 qubit + some QEC

IBM - Condor Chip (2025)



1121 qubit

Quantum Computers - Current Status



Math of Quantum Computing on a single page

- *n*-qubit system: superposition of all *n*-bit strings:

- of amplitudes. Gates: unitaries on 1 qubit

$$X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}, \quad T = \begin{pmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{pmatrix}, \quad H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

or on 2 qubits, CNOT: $|a, b\rangle \mapsto |a, a \oplus b\rangle$ $CNOT = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}$

- gates via matrix product

• Qubit is superposition of 0 and 1: $\alpha_0 |0\rangle + \alpha_1 |1\rangle \in \mathbb{C}^2$

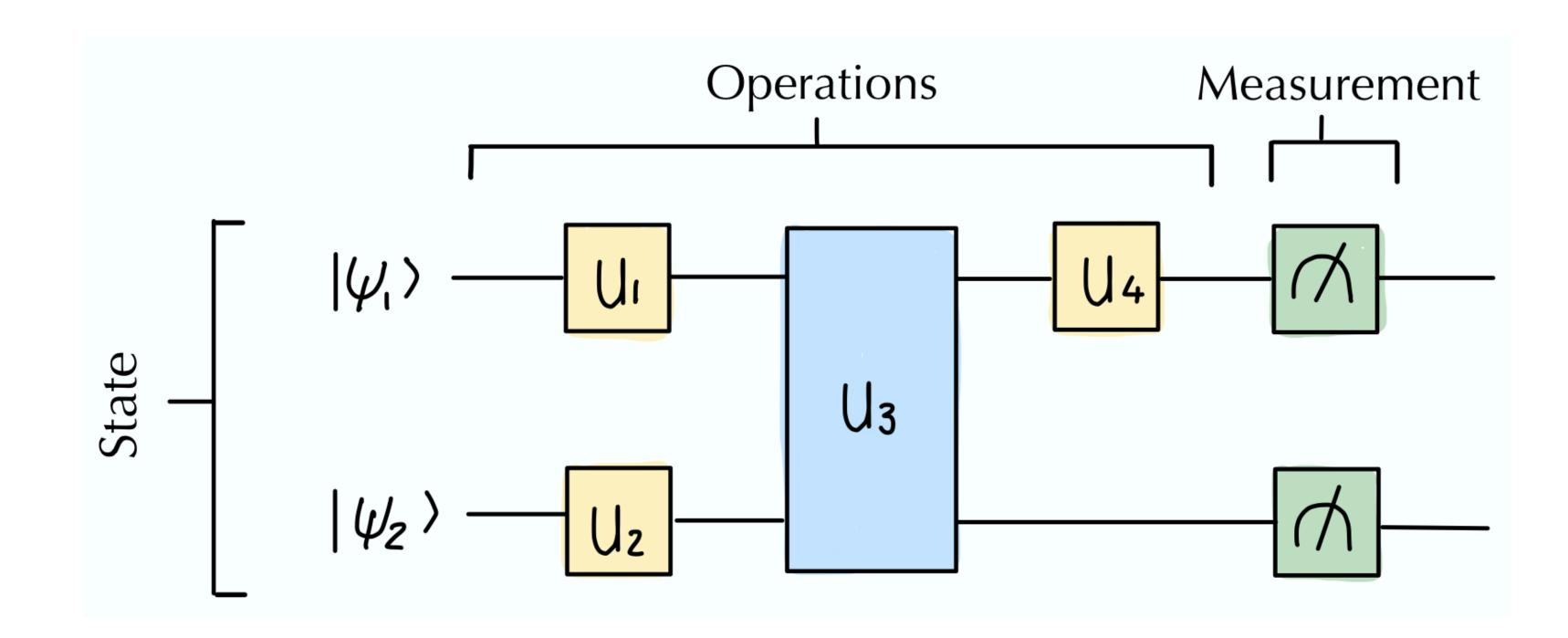
$$\sum_{x \in \{0,1\}^n} \alpha_x \left| x \right\rangle \in \mathbb{C}^{2^n}$$

• Measurement: see outcome $x \in \{0,1\}^n$ with probability $|\alpha_x|^2$

• Unitary transformation: matrix that preserves the length of the vector

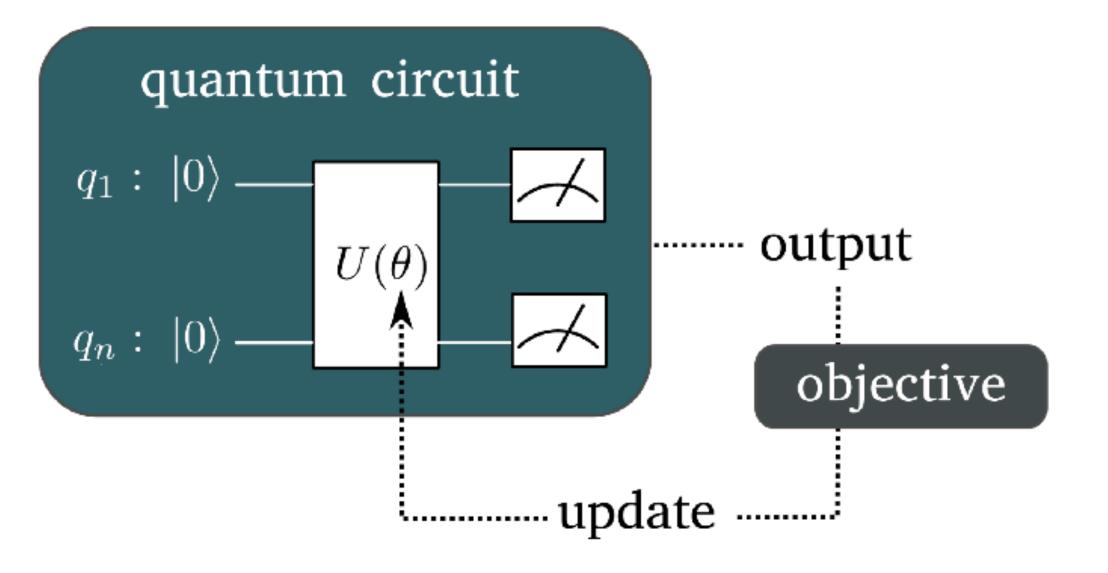
• Combine simultaneous gates via tensor product, combine sequential

Circuit Model of Quantum Computations



Circuit for Quantum Computer

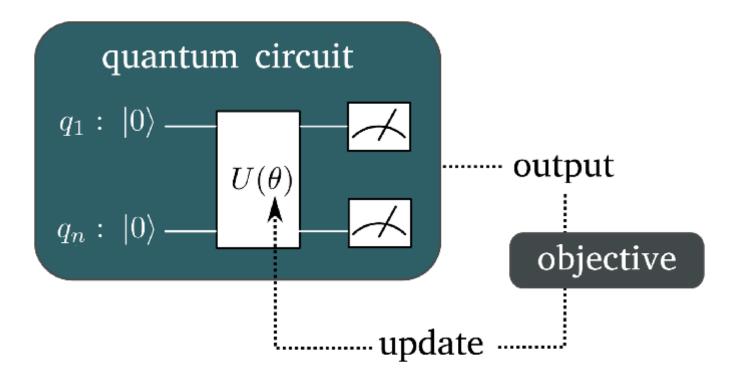
Quantum Computing with NISQ devices

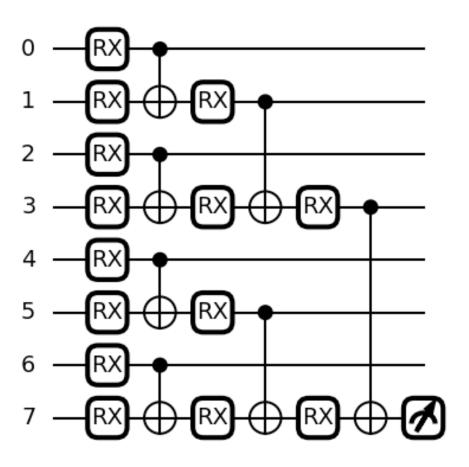


Quantum Parametric Circuit

Quantum Computing with NISQ devices Quantum Parametric Circuit



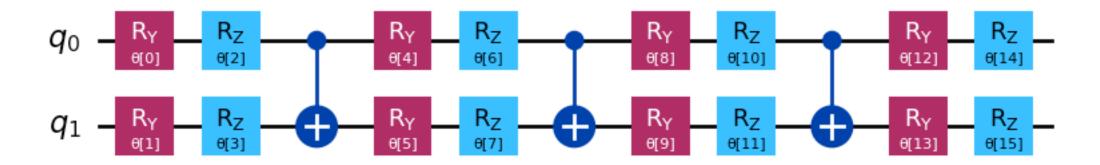




$$RX(heta) = \exp\left(-irac{ heta}{2}X
ight) = egin{pmatrix} \cos\left(rac{ heta}{2}
ight) & -i\sin\left(rac{ heta}{2}
ight) \ -i\sin\left(rac{ heta}{2}
ight) & \cos\left(rac{ heta}{2}
ight) \end{pmatrix}$$

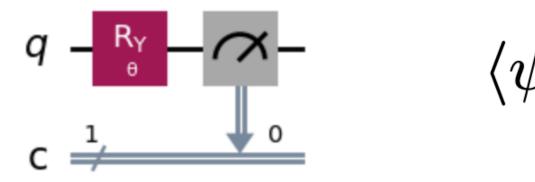
$$RZ(\phi) = \exp\left(-irac{\phi}{2}Z
ight) = egin{pmatrix} e^{-irac{\phi}{2}} & 0 \ 0 & e^{irac{\phi}{2}} \end{pmatrix}$$

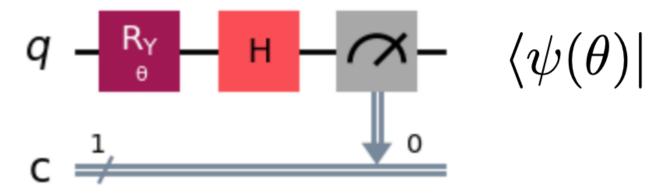
$$RY(heta) = \exp\left(-irac{ heta}{2}Y
ight) = egin{pmatrix} \cos\left(rac{ heta}{2}
ight) & -\sin\left(rac{ heta}{2}
ight) \ \sin\left(rac{ heta}{2}
ight) & \cos\left(rac{ heta}{2}
ight) \end{pmatrix}$$



QPC for Ground State of a Two Level System

 $\hat{H}_{\rm TLS} = \omega \hat{Z} + \lambda \hat{X}$





 $\langle \psi(\theta) | \hat{H}_{\mathrm{TLS}} | \psi|$

 $\min_{\theta} (\langle \psi(\theta) | \hat{H}_{\mathrm{T}}$

Ansatz
$$|\psi(\theta)\rangle = \hat{R}_y(\theta)|0\rangle$$

 $\langle \psi(\theta) | \hat{Z} | \psi(\theta) \rangle = \cos \theta$

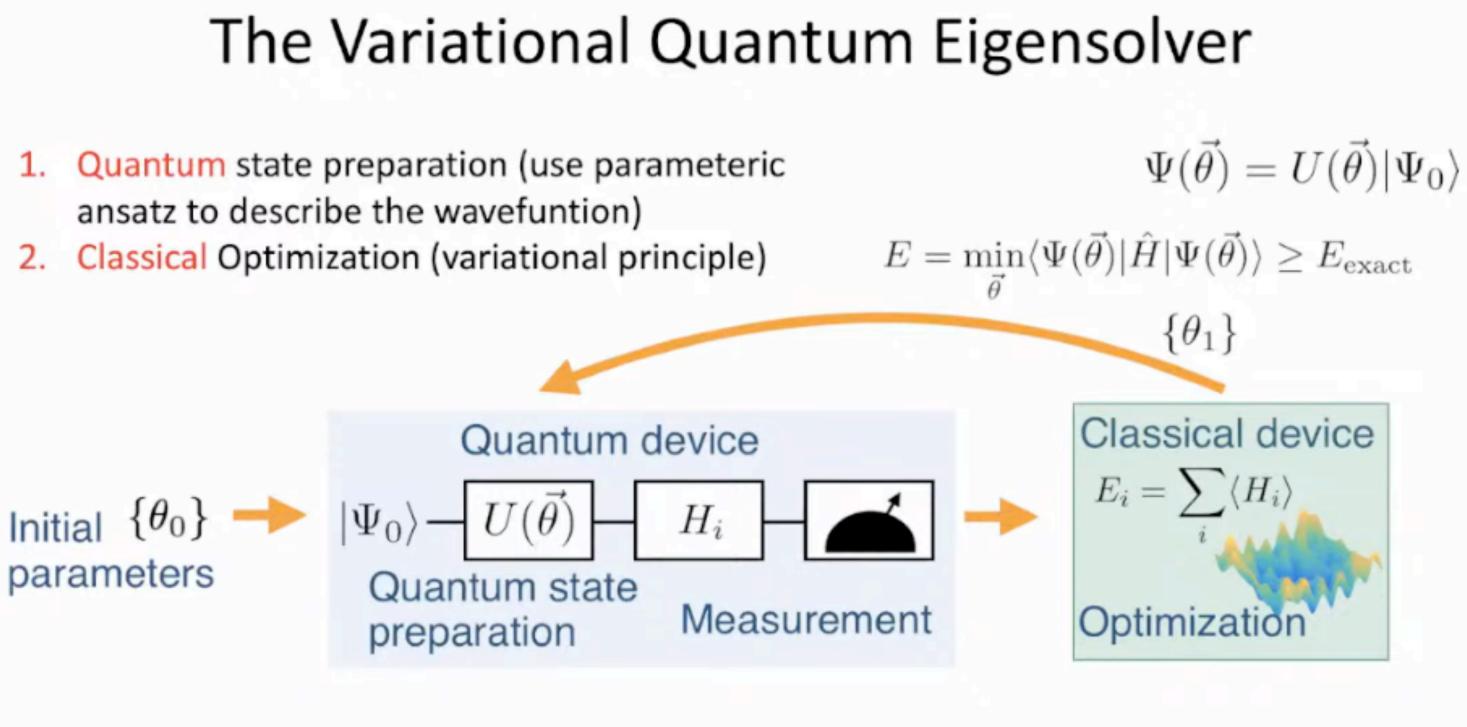
$$|\hat{H}\hat{Z}\hat{H}|\psi(\theta)\rangle = \langle\psi(\theta)|\hat{X}|\psi(\theta)\rangle = \sin\theta$$

$$\langle (heta)
angle = \omega \cos \theta + \lambda \sin \theta$$

 $\langle \sigma_{\rm LS} | \psi(\theta)
angle) = -\sqrt{\omega^2 + \lambda^2}$

General case: QPC for Ground State Estimation

- 1. ansatz to describe the wavefuntion)



Solving Systems of Linear Equations with QPC

PRL 103, 150502 (2009)

Ş **Quantum Algorithm for Linear Systems of Equations**

Aram W. Harrow,¹ Avinatan Hassidim,² and Seth Lloyd³ ¹Department of Mathematics, University of Bristol, Bristol, BS8 1TW, United Kingdom ²Research Laboratory for Electronics, MIT, Cambridge, Massachusetts 02139, USA ³Research Laboratory for Electronics and Department of Mechanical Engineering, MIT, Cambridge, Massachusetts 02139, USA (Received 5 July 2009; published 7 October 2009)

Solving linear systems of equations is a common problem that arises both on its own and as a subroutine in more complex problems: given a matrix A and a vector \vec{b} , find a vector \vec{x} such that $A\vec{x} = \vec{b}$. We consider

HHL scales as poly(log(N), k)

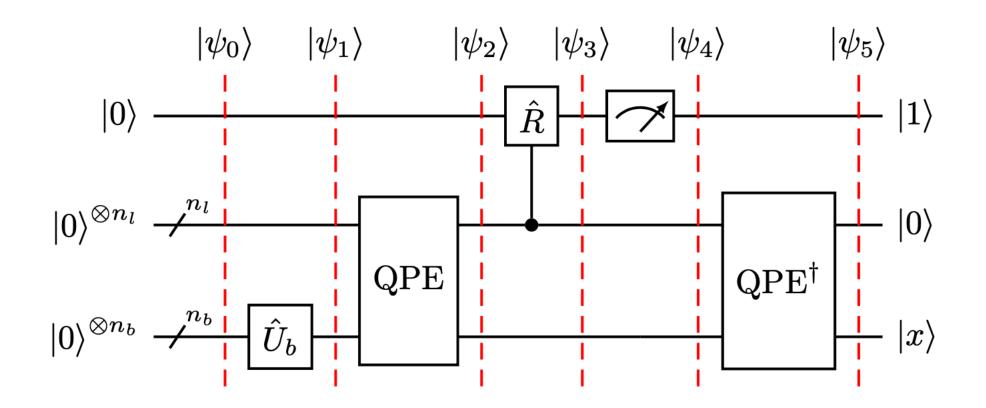
 $A\vec{x} = \vec{b}$. $\longrightarrow A|x\rangle = |b\rangle$, $\xrightarrow{U = e^{iAt}} |x\rangle = A^{-1}|b\rangle$.

HHL works in fault-tolerant settings only!

PHYSICAL REVIEW LETTERS

week ending 9 OCTOBER 2009

Classical algorithms scales as $N\sqrt{\kappa}$.



Solving Systems of Linear Equations with QPC

$$|x\rangle := \frac{\sum_{i} x_{i} |i\rangle}{||\sum_{i} x_{i} |i\rangle||_{2}}, \qquad \mathbf{A} = \sum_{i=1}^{m} c_{i} A$$
$$|b\rangle := \frac{\sum_{i} b_{i} |i\rangle}{||\sum_{i} b_{i} |i\rangle||_{2}}, \qquad \tilde{\mathbf{A}} = \begin{pmatrix} 0 & \mathbf{A} \\ \mathbf{A}^{\dagger} & 0 \end{pmatrix}$$

$$C_G = \frac{\langle x | H_G | x \rangle}{\langle \psi | \psi \rangle},$$

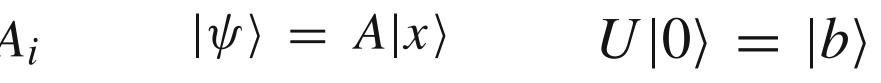
$$H_G = A^{\dagger} \left(\mathbb{1} - |b\rangle \langle b| \right) A.$$

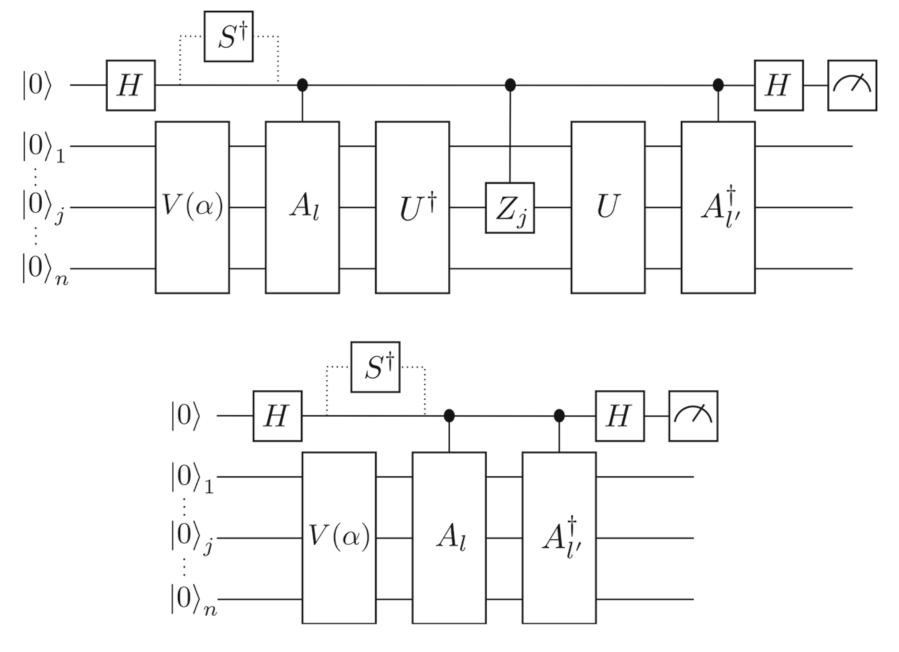
Global CF is susceptible to BP!

$$H_{L} = A^{\dagger} U \left(\mathbb{1} - \frac{1}{n} \sum_{j=1}^{n} |0_{j}\rangle \langle 0_{j}| \otimes \mathbb{1}_{\bar{j}} \right) U^{\dagger} A,$$
 Find the definition of the set of the s

$$C_L = \frac{\langle x | H_L | x \rangle}{\langle \psi | \psi \rangle}.$$

Carlos Bravo-Prieto, Ryan LaRose, M. Cerezo, Yigit Subasi, Lukasz Cincio, and Patrick J. Coles, Variational Quantum Linear Solver, Quantum 7, 1188 (2023). Pellow-Jarman, A., Sinayskiy, I., Pillay, A. et al. Near term algorithms for linear systems of equations. Quantum Inf Process 22, 258 (2023). https://doi.org/10.1007/s11128-023-04020-2





ig. 2 Hadamard Test Circuits for cost function C_L Eq. (9). The top circuit is employed when calculating he value of the numerator $\langle x | H_L | x \rangle$, while the bottom circuit is employed when calculating the value of the denominator, $\langle \psi | \psi$. The S[†] gate is included when calculating imaginary-valued parts of the cost function nd excluded when calculating the real-valued parts, and therefore, drawn in as a dotted line. $V(\alpha)$ denotes The ansatz, A_l the *l*-th unitary from the linear sum $A = \sum_i c_i A_i$ and U the unitary such that $U|0\rangle = |b\rangle$. $_{i}$ denotes a standard Z gate on the j-th qubit, and H being a standard Hadamard gate



Quantum Approximate Optimization Algorithm (QAOA)

Many problems in Optimization theory/Graph Theory/Computer Science can be formulated as a minimum energy state of classical spin glass.

> frontiers in PHYSICS

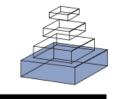
Ising formulations of many NP problems

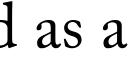
Andrew Lucas *

Lyman Laboratory of Physics, Department of Physics, Harvard University, Cambridge, MA, USA

Partitioning problems (number partitioning, graph partitioning) Cliques, covering and packing problems (exact cover, set packing, vertex cover) Satisfiability, minimal maximal matching, knapsack with integer weights, coloring problems Hamiltonian cycles and paths, traveling salesman, tree problems...

REVIEW ARTICLE published: 12 February 2014 doi: 10.3389/fphy.2014.00005



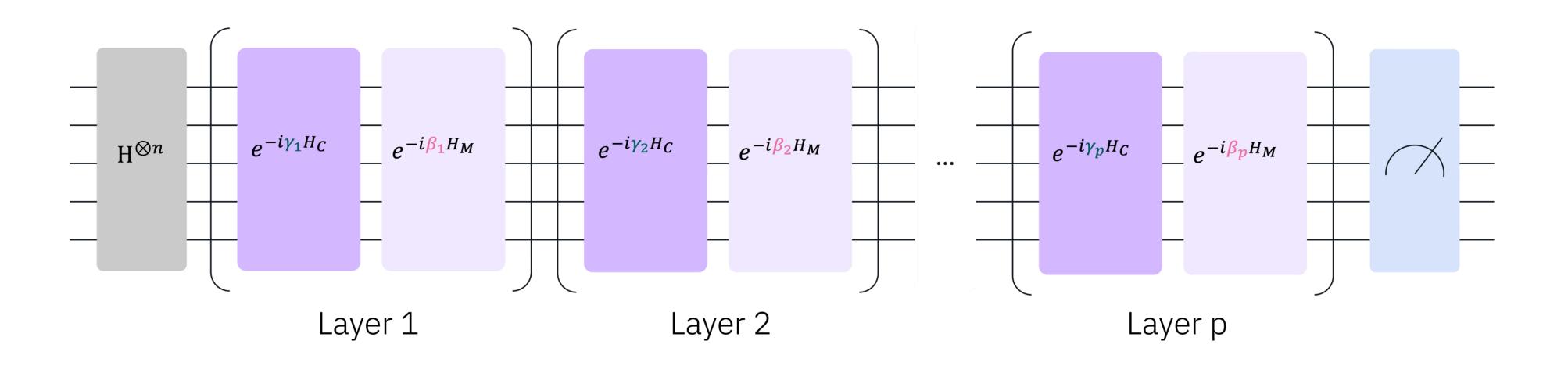




Quantum Approximate Optimization Algorithm (QAOA)

$$H_0 = -h_0 \sum_{i=1}^N \sigma_i^x,$$

We go from the ground state of the driver's Hamiltonian



 $H(t) = \left(1 - \frac{t}{T}\right)H_0 + \frac{t}{T}H_P,$

$$H(s_1, \ldots, s_N) = -\sum_{i < j} J_{ij} s_i s_j - \sum_{i=1}^N h_i s_i.$$

To the ground state of the problem Hamiltonian

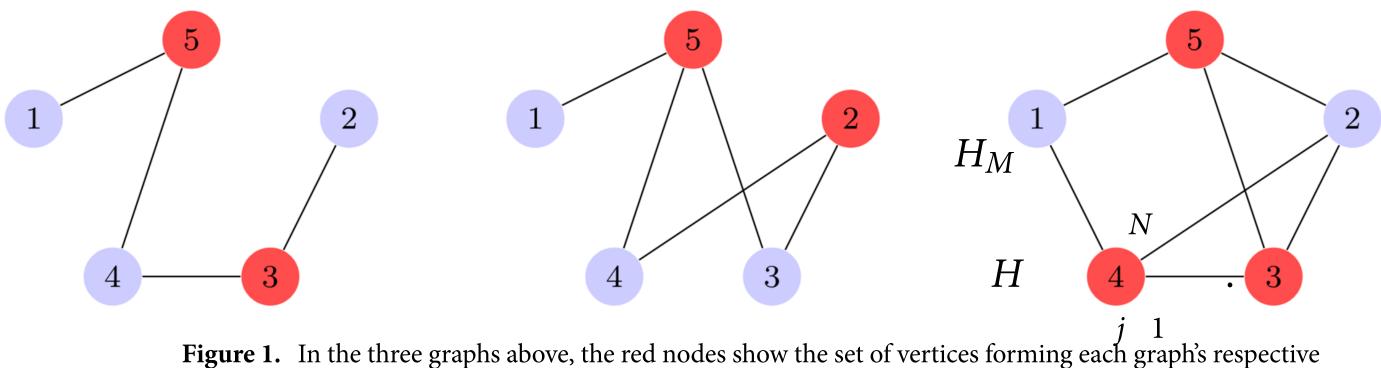
G = (V, E)



Minimize:
$$\sum_{i \in V} x_i$$

Subject to: $x_i + x_j \ge 1$, $\forall (i,j) \in E$

and:
$$x_i \in \{0, 1\}, \quad \forall i \in V^{C_{\alpha}(z) = 1}$$
 α



each edge is still incident to at least one.

 $z=z_1z_2\ldots z_N,$

С

A Pellow-Jarman, S McFarthing, IS, DK Bark, A Pillay, F Petruc poine, The effect of classical optimizers and Ansatz depth on QAOA performance in provide best depth of the part of the effect of classical optimizers and Ansatz depth on QAOA performance in provide the part of the part of the effect of the part of th

QAOA example: Minimum Vertex Cover

$$z = z_1 z_2 \dots z_N,$$

$$H_C^m = A \sum_{\substack{i \in V \\ \alpha = 1}} (1 - x_u)(1 - x_v) + B \sum_{v \in V} x_v$$

$$\sigma_i^z \qquad z_i$$

$$H_C$$

 $H_C = C \quad \stackrel{z}{_1}, \quad \stackrel{z}{_2}, \quad , \quad \stackrel{z}{_N}.$

minimum vertex cover. Each edge in the graph under consideration must have, at least one vertex in the cover. The cover forms the minimum cover of a graph, when it contains the fewest number of vertices, whilst ensuring

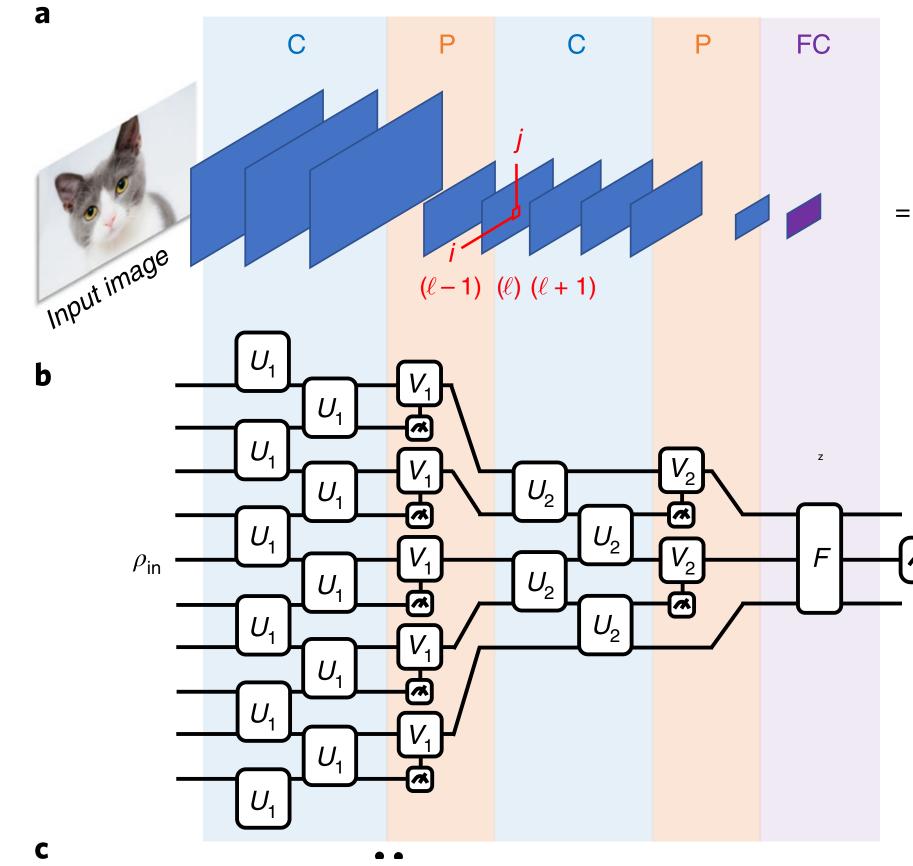
nature portfolio



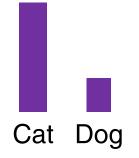
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Quantum Convolutional Neural Networks



Cong, I., Choi, S. & Lukin, M.D. Quantum convolutional neural networks. Nat. Phys. 15, 1273–1278 (2019).



The concept of QCNNs. (a) Simplified illustration of classical CNNs. A sequence of image-processing layers transforms an input image into a series of feature maps (blue rectangles) and finally into an output probability distribution (purple bars). C, convolution; P, pooling; FC, fully connected. (b) QCNNs inherit a similar layered structure. Boxes represent unitary gates or measurement with feed-forwarding.



Quantum Convolutional Neural Networks

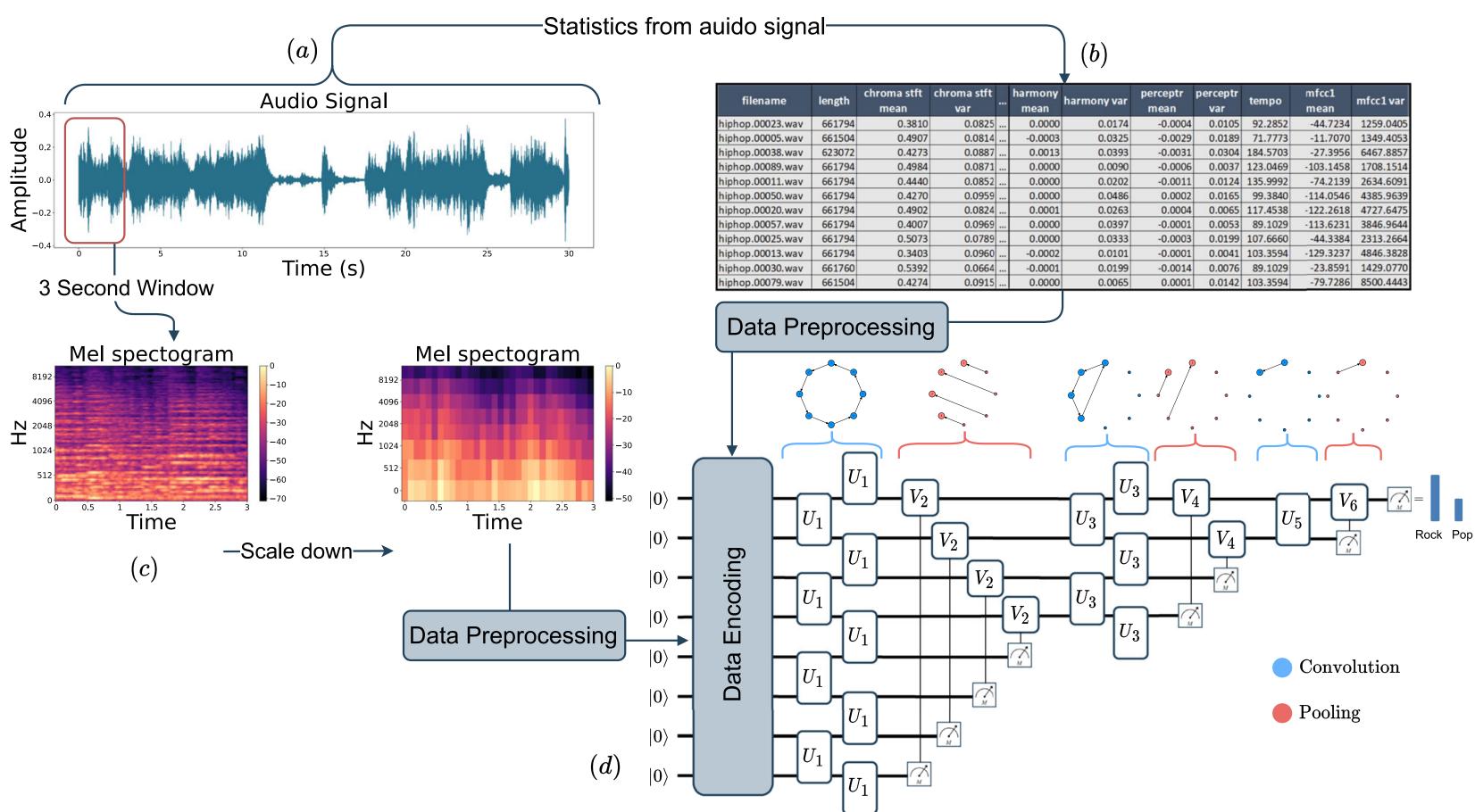
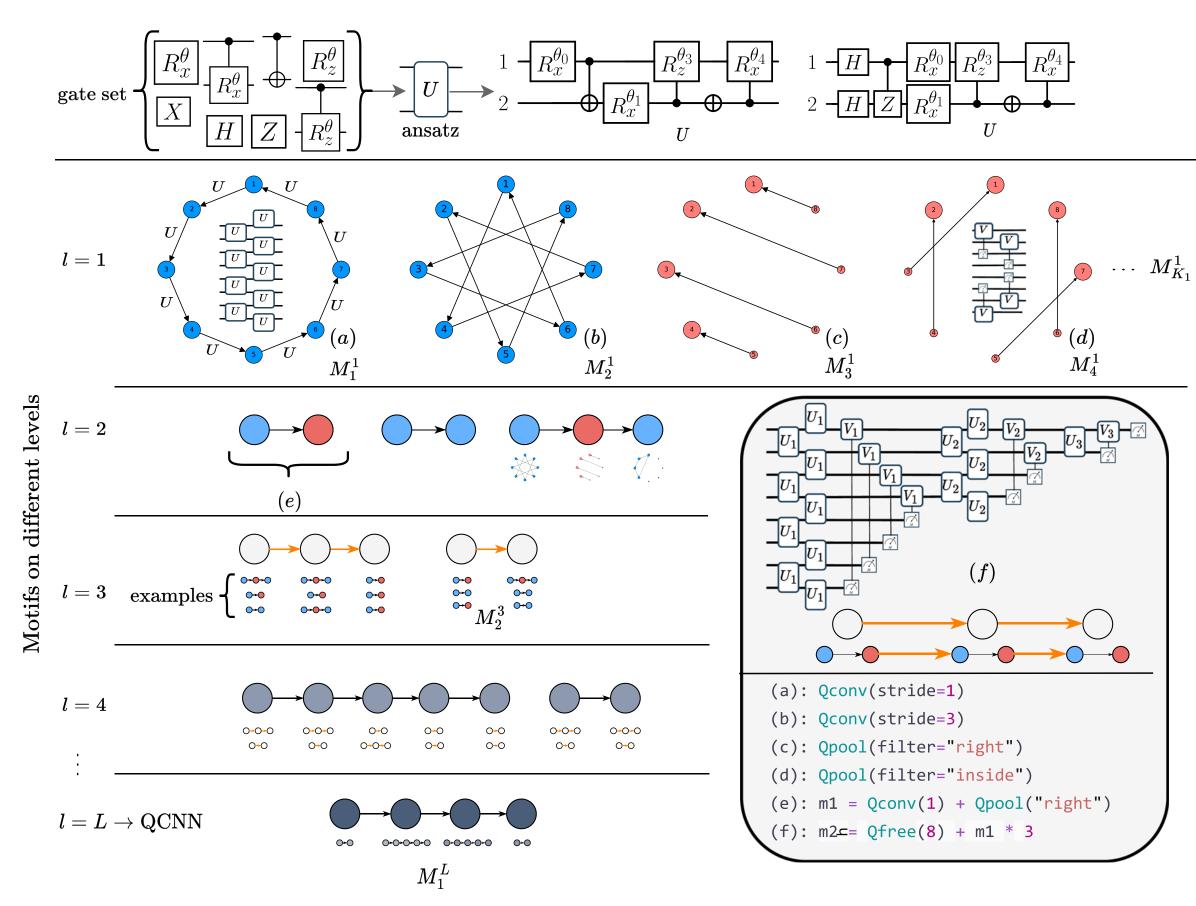


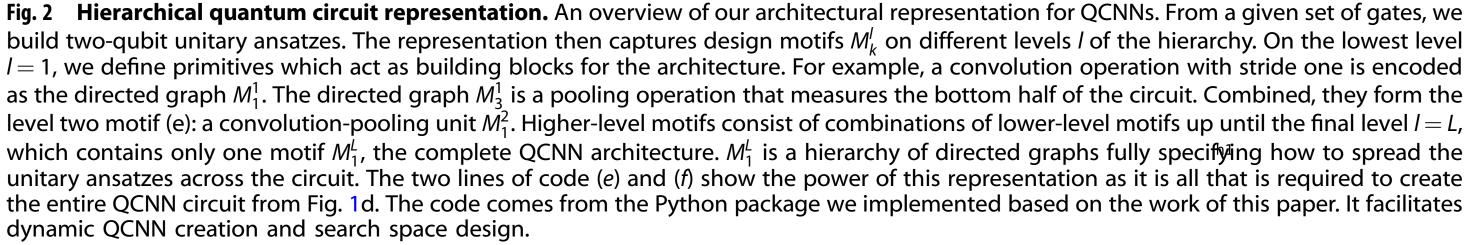
Fig. 1 Machine-learning pipeline for music genre classification. The machine-learning pipeline we implemented for music genre classification. Given an audio signal of a song (a), we generate two forms of data: tabular (b) and image (c). Each form has data preprocessing applied before being encoded into a quantum state (d). The QCNN circuit shown in (d) favours Principal Component Analysis (PCA) because qubits are pooled from bottom to top, and principal components are encoded from top to bottom. This architecture is an instance of the reverse binary tree family that we generated with our framework.

M Lourens, IS, DK Park, C Blank and F Petruccione. "Hierarchical quantum circuit representations for neural architecture search", npj Quantum Inf 9, 79 (2023)

length	chroma stft mean	chroma stft var	:	harmony mean	harmony var	perceptr mean	perceptr var	tempo	mfcc1 mean	mfcc1 var
661794	0.3810	0.0825		0.0000	0.0174	-0.0004	0.0105	92.2852	-44.7234	1259.0405
661504	0.4907	0.0814		-0.0003	0.0325	-0.0029	0.0189	71.7773	-11.7070	1349.4053
623072	0.4273	0.0887		0.0013	0.0393	-0.0031	0.0304	184.5703	-27.3956	6467.8857
661794	0.4984	0.0871		0.0000	0.0090	-0.0006	0.0037	123.0469	-103.1458	1708.1514
661794	0.4440	0.0852		0.0000	0.0202	-0.0011	0.0124	135.9992	-74.2139	2634.6091
661794	0.4270	0.0959		0.0000	0.0486	0.0002	0.0165	99.3840	-114.0546	4385.9639
661794	0.4902	0.0824		0.0001	0.0263	0.0004	0.0065	117.4538	-122.2618	4727.6475
661794	0.4007	0.0969		0.0000	0.0397	-0.0001	0.0053	89.1029	-113.6231	3846.9644
661794	0.5073	0.0789		0.0000	0.0333	-0.0003	0.0199	107.6660	-44.3384	2313.2664
661794	0.3403	0.0960		-0.0002	0.0101	-0.0001	0.0041	103.3594	-129.3237	4846.3828
661760	0.5392	0.0664		-0.0001	0.0199	-0.0014	0.0076	89.1029	-23.8591	1429.0770
661504	0.4274	0.0915		0.0000	0.0065	0.0001	0.0142	103.3594	-79.7286	8500.4443
	661794 661504 623072 661794 661794 661794 661794 661794 661794 661794 661760	length mean 661794 0.3810 661504 0.4907 623072 0.4273 661794 0.4984 661794 0.4984 661794 0.4270 661794 0.4270 661794 0.4270 661794 0.4902 661794 0.4902 661794 0.4007 661794 0.5073 661794 0.3403 661760 0.5392	length mean var 661794 0.3810 0.0825 661504 0.4907 0.0814 623072 0.4273 0.0887 661794 0.4984 0.0871 661794 0.4440 0.0852 661794 0.4270 0.0959 661794 0.4902 0.0824 661794 0.4007 0.0969 661794 0.5073 0.0789 661794 0.3403 0.0960 661760 0.5392 0.0664	length mean var "" 661794 0.3810 0.0825 661504 0.4907 0.0814 623072 0.4273 0.0887 661794 0.4904 0.0852 661794 0.4984 0.0871 661794 0.4440 0.0852 661794 0.4270 0.0959 661794 0.4007 0.0069 661794 0.4007 0.0969 661794 0.3403 0.0789 661794 0.3403 0.0960 661794 0.3403 0.0960 661760 0.5392 0.0664	length mean var mean 661794 0.3810 0.0825 0.0000 661504 0.4907 0.0814 -0.0003 623072 0.4273 0.0887 0.0013 661794 0.4907 0.0887 0.0003 661794 0.4984 0.0871 0.0000 661794 0.4440 0.0852 0.0000 661794 0.4270 0.0959 0.0000 661794 0.4902 0.0824 0.0001 661794 0.4007 0.0969 0.0000 661794 0.3403 0.0789 0.0000 661794 0.3403 0.0960 -0.0002 661760 0.5392 0.0664 -0.0001	length mean var mean harmony var 661794 0.3810 0.0825 0.0000 0.0174 661504 0.4907 0.0814 -0.0003 0.0325 623072 0.4273 0.0887 0.0013 0.0393 661794 0.4984 0.0871 0.0000 0.0090 661794 0.4440 0.0852 0.0000 0.0202 661794 0.4440 0.0852 0.0000 0.0202 661794 0.4270 0.0959 0.0000 0.0486 661794 0.4902 0.0824 0.0000 0.0397 661794 0.4007 0.0969 0.0000 0.0333 661794 0.5073 0.0789 0.0000 0.0333 661794 0.3403 0.0960 -0.0002 0.0101 661760 0.5392 0.0664 -0.0001 0.0199	length mean var mean harmony var mean 661794 0.3810 0.0825 0.0000 0.0174 -0.0004 661504 0.4907 0.0814 -0.0003 0.0325 -0.0029 623072 0.4273 0.0887 0.0013 0.0393 -0.0031 661794 0.4984 0.0871 0.0000 0.0090 -0.0006 661794 0.4440 0.0852 0.0000 0.0202 -0.0011 661794 0.4440 0.0852 0.0000 0.0202 -0.0011 661794 0.4270 0.0959 0.0000 0.0486 0.0002 661794 0.4902 0.0824 0.0000 0.0397 -0.0001 661794 0.4007 0.0969 0.0000 0.0333 -0.0003 661794 0.3403 0.0960 0.0000 0.0333 -0.0003 661794	length mean var mean harmony var mean mean var 661794 0.3810 0.0825 0.0000 0.0174 -0.0004 0.0105 661504 0.4907 0.0814 -0.0003 0.0325 -0.0029 0.0189 623072 0.4273 0.0887 0.0013 0.0393 -0.0031 0.0304 661794 0.4984 0.0871 0.0000 0.0090 -0.0006 0.0037 661794 0.4440 0.0852 0.0000 0.0202 -0.0011 0.0124 661794 0.4270 0.0959 0.0000 0.0486 0.0002 0.0165 661794 0.4902 0.0824 0.0001 0.0263 0.0004 0.0055 661794 0.4007 0.0969 0.0000 0.0337 -0.001 0.0053 661794 0.5073 0.0789 0.0000 0.0333 -0.0001 <td>length meanmeanwarmeanharmony var meanmeanvartempo6617940.38100.08250.00000.0174-0.00040.010592.28526615040.49070.08140.00030.0325-0.00290.018971.77736230720.42730.08870.00130.0393-0.00310.0304184.57036617940.49840.08710.00000.0090-0.00060.0037123.04696617940.44400.08520.00000.0202-0.00110.0124135.99926617940.42700.09590.00000.04860.00020.016599.38406617940.40070.09690.00000.0397-0.0010.0053117.45386617940.50730.07890.00000.0333-0.0030.0199107.66606617940.34030.09600.00020.0101-0.0014103.35946617600.53920.06640.00010.0199-0.00140.007689.1029</td> <td>length meanmeanwarmeanharmony varmeanwartempomean6617940.38100.08250.00000.0174-0.00040.010592.2852-44.72346615040.49070.08140.00030.0325-0.00290.018971.7773-11.70706230720.42730.08870.00130.0393-0.00310.0304184.5703-27.39566617940.49840.08710.00000.0090-0.00160.0037123.0469-103.14586617940.44400.08520.00000.0202-0.00110.0124135.9992-74.21396617940.442700.09590.00000.02630.00040.0065117.4538-122.26186617940.40070.09690.00000.0333-0.00010.005389.1029-113.62316617940.34030.09600.00020.0101-0.0011103.3594-129.32376617600.53920.06640.00010.0199-0.00140.007689.1029-23.8591</td>	length meanmeanwarmeanharmony var meanmeanvartempo6617940.38100.08250.00000.0174-0.00040.010592.28526615040.49070.08140.00030.0325-0.00290.018971.77736230720.42730.08870.00130.0393-0.00310.0304184.57036617940.49840.08710.00000.0090-0.00060.0037123.04696617940.44400.08520.00000.0202-0.00110.0124135.99926617940.42700.09590.00000.04860.00020.016599.38406617940.40070.09690.00000.0397-0.0010.0053117.45386617940.50730.07890.00000.0333-0.0030.0199107.66606617940.34030.09600.00020.0101-0.0014103.35946617600.53920.06640.00010.0199-0.00140.007689.1029	length meanmeanwarmeanharmony varmeanwartempomean6617940.38100.08250.00000.0174-0.00040.010592.2852-44.72346615040.49070.08140.00030.0325-0.00290.018971.7773-11.70706230720.42730.08870.00130.0393-0.00310.0304184.5703-27.39566617940.49840.08710.00000.0090-0.00160.0037123.0469-103.14586617940.44400.08520.00000.0202-0.00110.0124135.9992-74.21396617940.442700.09590.00000.02630.00040.0065117.4538-122.26186617940.40070.09690.00000.0333-0.00010.005389.1029-113.62316617940.34030.09600.00020.0101-0.0011103.3594-129.32376617600.53920.06640.00010.0199-0.00140.007689.1029-23.8591

Quantum Convolutional Neural Networks





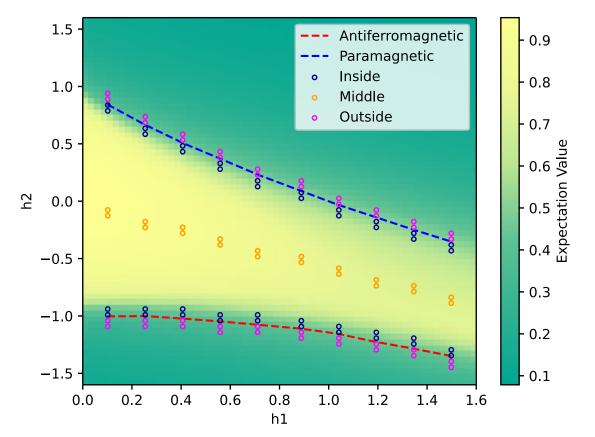


Fig. 5 Quantum phase recognition result. Expectation values for the circuit found via evolutionary search for a system of N = 15 spins. Points represent a test set of 64×64 ground states for various h_1 and h_2 values of the Hamiltonian, J = 1. The inside, middle and outside points were used to evaluate an architecture's fitness during search. The same colour scale as in⁵ is used to facilitate comparison.

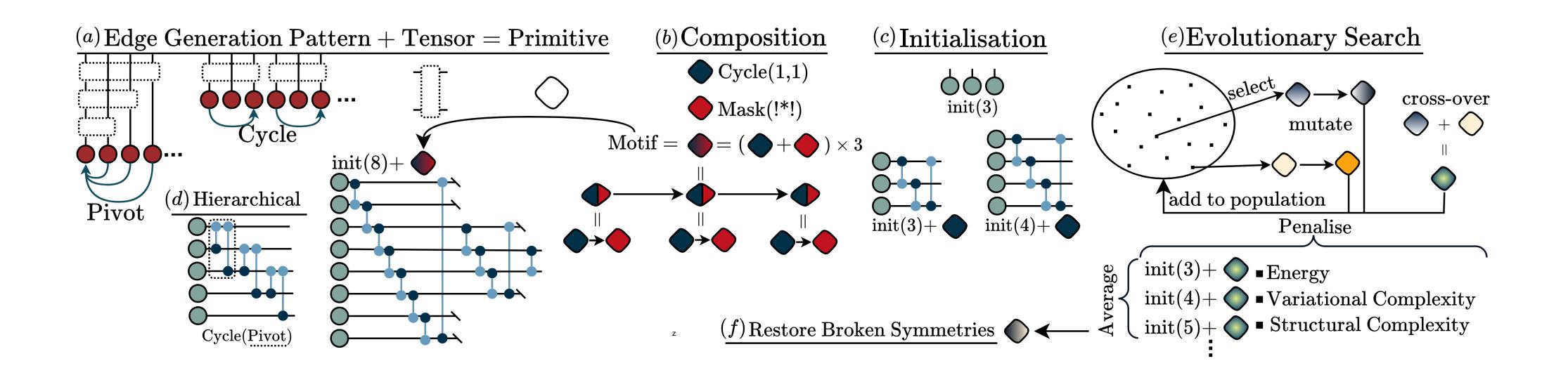
Table 3. Performance of architecture found with an evolutionary
 search.

Metric	Reference	Found
Number of parameters	1308	11
Sample complexity (inside)	61.523	36.079
Sample complexity (middle)	10.992	13.253
MSE (outside)	0.164	0.167

Different performance metrics (lower is better) for the 15-qubit QCNN from ref. ⁵ and the architecture found via evolutionary search. The best performing architecture for each metric is highlighted in bold. Sample complexity represents the expected number of measurements required to be 95% confident that the ground state is in the SPT phase (non-zero expectation value). Metrics are calculated on a set of points in the test set, where inside refers to SPT points near the phase boundary, outside to non-SPT points near the phase boundary and middle to points in between, as shown in Fig. 5.

d

Surprising Application: Ansatz Search



motifs each generation. (f) Once the ansatz is found, broken symmetries are restored.

Matt Lourens, IS, Johannes N. Kriel, and Francesco Petruccione, Generating Generalised Ground-State Ansatzes from Few-Body Examples, arXiv:2503.00497 (2025)

FIG. 1. Overview of our method, a domain-specific-language (DSL) enables ansatz generation via an evolutionary algorithm. (a) A primitive is an edge generation pattern associated with a tensor. (b) Composition: Sequences of primitives form motifs; sequences of motifs form higher-level motifs. (c) Specifying the number of nodes generates edges, and the associated tensor is repeated and connected to each edge, forming a tensor network. (d) A specified network, being itself a tensor, can again be associated with an edge generation pattern to form a new primitive. (e) The evolutionary algorithm mutates and crosses over



Surprising Application: Ansatz Search

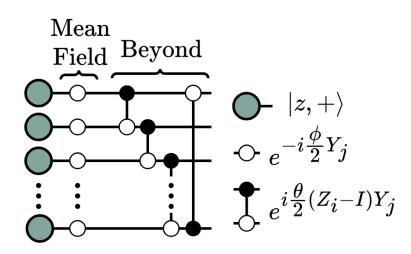


FIG. 2. The ansatz generated by our method for the LMG and TFIM models.

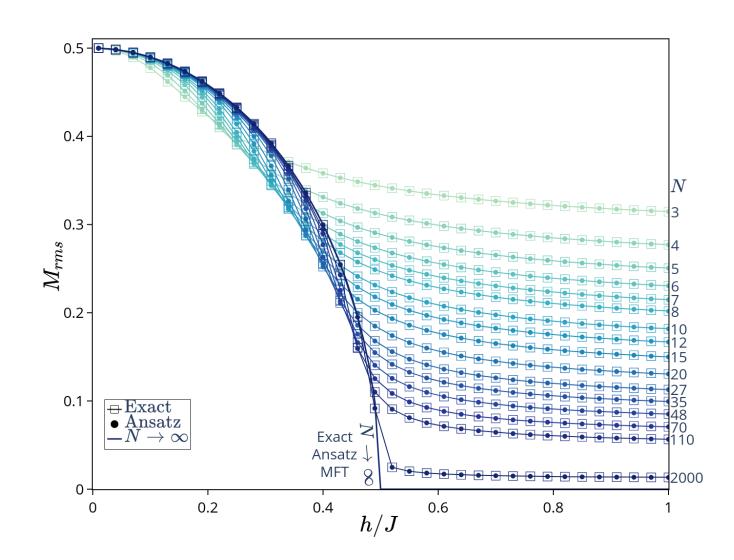


FIG. 3. RMS magnetisation of Eq. (20) vs h/J for the LMG model. Exact results compared to the symmetrised ansatz.

Matt Lourens, IS, Johannes N. Kriel, and Francesco Petruccione, Generating Generalised Ground-State Ansatzes from Few-Body Examples, arXiv:2503.00497 (2025)

$$\begin{aligned} |\theta,\phi\rangle &= \left(\prod_{k=0}^{N-1} C_{k,k+1}^{\theta} R_{k+1}^{\theta}\right) \left(\prod_{j=0}^{N-1} R_{j}^{\phi}\right) |z,+\rangle^{\otimes N} \\ C_{ij}^{\theta} &= e^{i\frac{\theta}{2}Z_{i}Y_{j}} \quad \text{and} \quad R_{j}^{\theta} = e^{-i\frac{\theta}{2}Y_{j}}. \end{aligned}$$

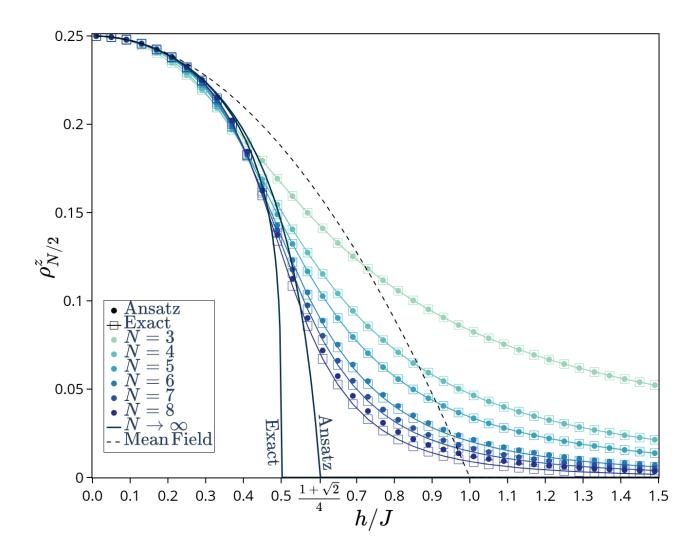
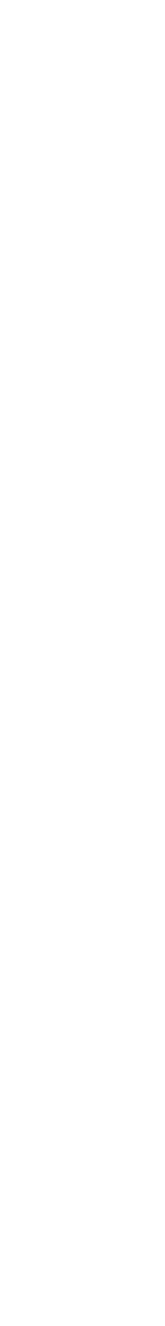


FIG. 5. TFIM long-range correlation $\rho_{N/2}^z$ vs h/J. Shows results from the symmetrised ansatz (finite $N, N \to \infty$), exact values, and the mean-field prediction.

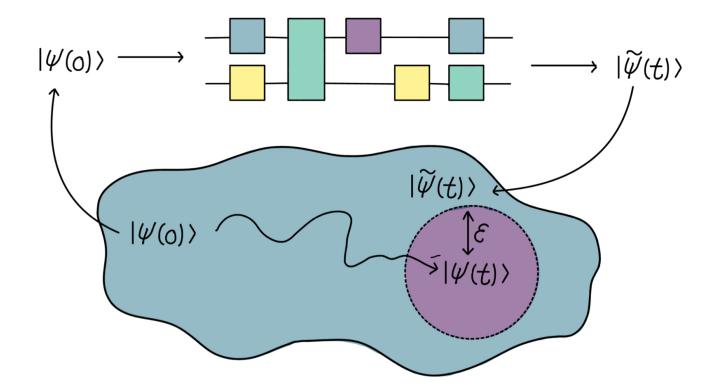






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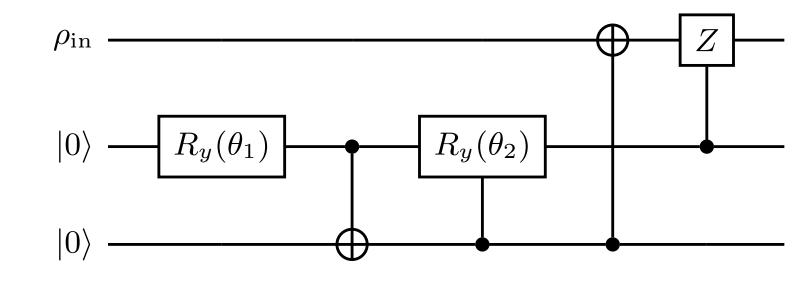


South African Quantum Technology Initiative



National Institute for **Theoretical and Computational Sciences**

Thank you!



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