



Vamos a comenzar en breve, a las 1 CDT / 2 EDT

Cómputo Cuántico para Química



El cómputo cuántico es una de las áreas de expansión prometedora para la química teórica. Las computadoras cuánticas usan efectos cuánticos para realizar procesos de cómputo. Este nuevo tipo de computadora puede simular a los átomos y a las moléculas, así como a los materiales de manera exacta.

En esta presentación, el Dr. Alán Aspuru-Guzik Profesor de Química y de Ciencias de Computación en la Universidad de Toronto describirá qué es el cómputo cuántico, cuál es el estado actual del campo y algoritmos y experimentos que recientemente se han realizado en estas computadoras.

Lo Que El Público Aprenderá

- Qué son las computadoras cuánticas
- Por qué las computadoras cuánticas prometen ser una herramienta valiosa para las ciencias químicas
- El estado actual del cómputo cuántico para la química

Ponente y Moderadora



Alán Aspuru-Guzik
Universidad de
Toronto



Ingrid Montes
Universidad de
Puerto Rico, Recinto
de Rio

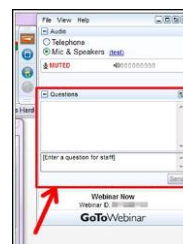
El Vigésimo Webinar en Español auspiciado por ACS y SQM

<http://bit.ly/ComputoCuantico>

1



¿Tiene preguntas para el ponente?



“¿Por qué he sido “silenciado”?”

No se preocupe. Todo el mundo ha sido silenciado, excepto el ponente y la moderadora. Gracias, y disfruten de la presentación.

Escriba y someta sus preguntas durante la presentación

2



¿Está en un grupo hoy viendo el webinar en vivo?



Díganos de dónde son ustedes y cuántas personas están en su grupo!

3



La Diversidad de la Audiencia



Hoy tenemos representantes de 24 países

4



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¡C&EN en Español!

C&EN pone a su disposición traducciones al español de sus artículos más populares.

August 14, 2018

La FDA aprueba la primera terapia con ARN interferente

El Dr. a Cingolotto pone fin a dos décadas de trabajo académico e industrial para llevar los ARN interferentes al mercado farmacéutico.



FDA approves first-ever RNAi therapeutic

Novel for Cingolotto caps two decades of academic and industry work to translate RNA interference from idea to drug.

July 31, 2018

El óxido nítrico del permafrost tibetano esconde malas noticias para el calentamiento global

Los científicos estiman que el deshielo podría liberar grandes cantidades de este gas de efecto invernadero.



Nitrous oxide from Tibetan permafrost packs global warming punch

Scientists estimate that thawing ground could be a major source of the greenhouse gas.

July 25, 2018

Peces sin olfato en los océanos acidificados

Los crecientes niveles de CO₂ podrían impedir que los peces encuentren comida o detecten sus depredadores.



Fish struggle to smell in acidic oceans

Rising CO₂ levels could stop fish finding food and detecting predators.

Gracias a una colaboración con la organización española Divúlgame.org, C&EN ahora es capaz de ofrecer traducciones al español de algunos de nuestros mejores contenidos. Queremos hacer de la ciencia de vanguardia más accesible a la comunidad química de habla española, y esta es nuestra contribución. Le da a los nacidos en España, América Latina, o los EE.UU., pero cuyo primer idioma es el español la oportunidad de leer este contenido en su lengua materna. Esperamos que les guste y sea de su utilidad.



Dr. Bibiana Campos Seijo
Editora en Jefe, C&EN

<http://bit.ly/CENespanol>

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Sociedad Química de México



Desde sus comienzos de la Sociedad Química de México, se buscaba un emblema sencillo, no demostrar partidismo alguno y significar al gremio, debería representar un símbolo no sólo para los químicos, sino también para ingenieros, farmacéuticos, metalurgistas, en fin que englobe e identifique por igual a los científicos en todas sus áreas de la ciencia química.

www.sqm.org.mx

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¡El Próximo Webinar de 2018!

Miércoles, el 17 de Octubre

“El Reto de la Terapia Antioxidante”



Alberto Nuñez Sellés,
Universidad Nacional Evangélica

<http://bit.ly/ACS-SQMwebinars>

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“Cómputo Cuántico para Química”



Dr. Alán Aspuru-Guzik
Profesor de Química y de Ciencias de
Computación, Universidad de Toronto



Dra. Ingrid Montes
La Junta de Directores, ACS
Profesora de Química Orgánica, Universidad de
Puerto Rico, Recinto de Río Piedras

Las imágenes de la presentación están disponibles para descargar ahora desde el panel de GoToWebinar

<http://bit.ly/ComputoCuantico>

El Webinar de hoy esta auspiciado por la Sociedad Química de México y the American Chemical Society

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The Age of Variational Quantum Algorithms

Alán Aspuru-Guzik

Professor of Chemistry
 Professor of Computer Science
 University of Toronto
 Vector Institute for Artificial Intelligence



Chief Scientific Officer
 Zapata Computing

Chief Vision Officer
 Kebotix





Early classical mechanical simulators

Antikythera Mechanism
circa 200 BC



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Digital Computer Simulation



Without the computer-based simulation, the material culture of late-twentieth-century microphysics is not merely inconvenienced - It does not exist. [...] Machines [...] are inseparable from their virtual counterparts - all are bound to simulations.

-Peter Galison

From *Image and Logic: A material culture of microphysics* (1997)

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Simulating Matter



Flow batteries

e.g. Huskinson, et al., Nature 505 195 2014

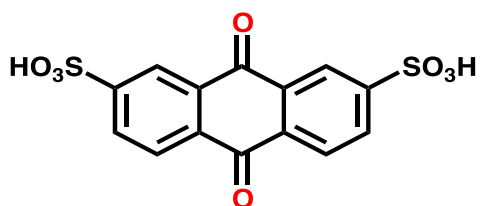


Organic light-emitting diode displays

e.g. R. Gomez-Bombarelli, Nature Materials 15, 1120 2016

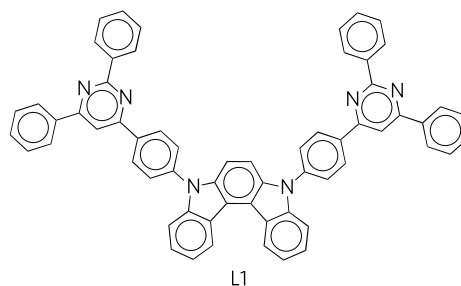
15

Simulating Matter



Flow batteries

e.g. Huskinson, et al., Nature 505 195 2014



Organic light-emitting diode displays

e.g. R. Gomez-Bombarelli, Nature Materials 15, 1120 2016

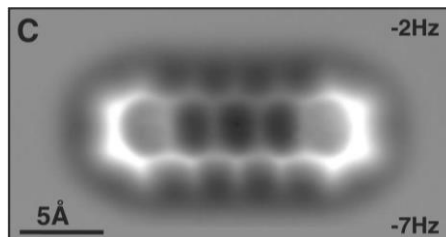
16

Simulating Matter



Flow batteries

e.g. Huskinson, et al., Nature 505 195 2014

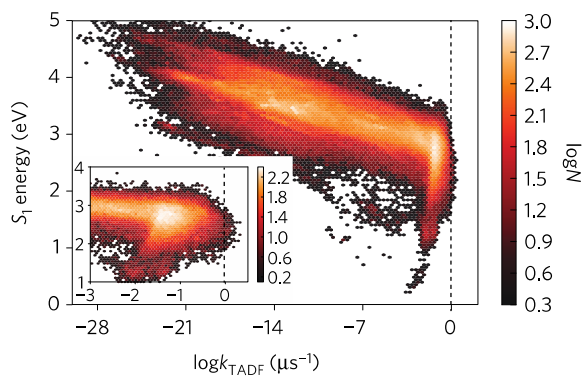
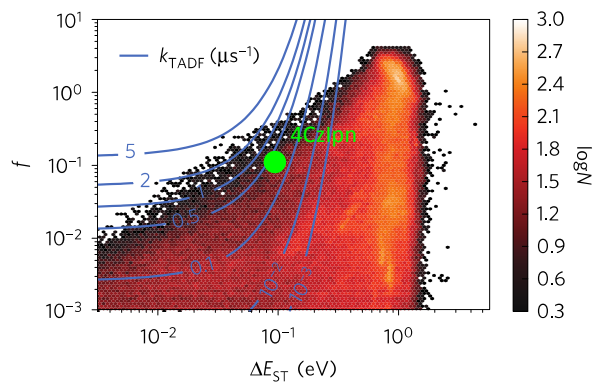


Pentacene on a surface

Gross et. al., Science 325 1110 2009

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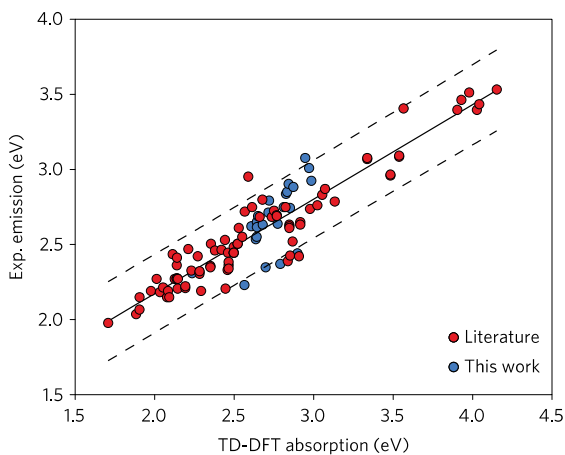
Data Mining 500,000 Quantum Calculations



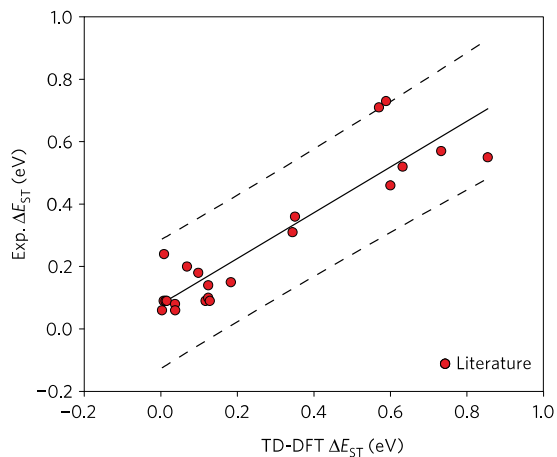
R. Gomez-Bombarelli, et al. Nature Materials 15, 1120 2016

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Calibration of TDDFT with Experiment

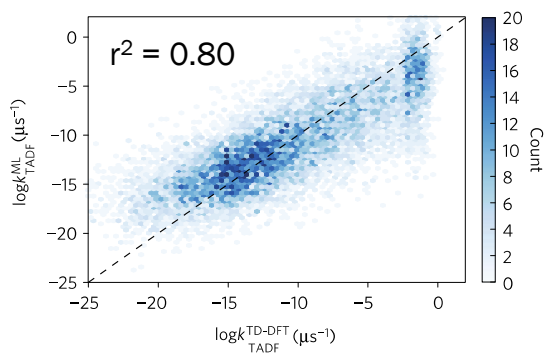


TD-DFT/B3LYP/6-31G(d) vertical absorption against PL emission maximum in **toluene**

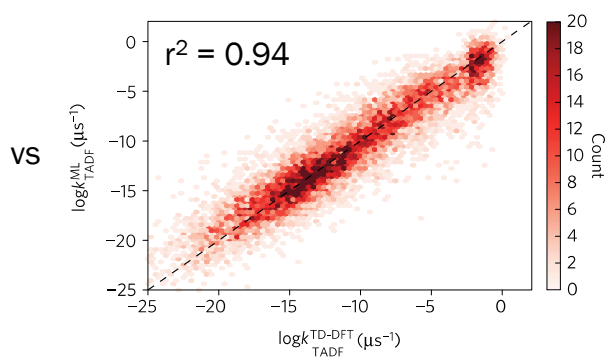


TD-DFT/B3LYP/6-31G(d) ST-Gap vs thermal activation in frozen **toluene**

Machine Learning



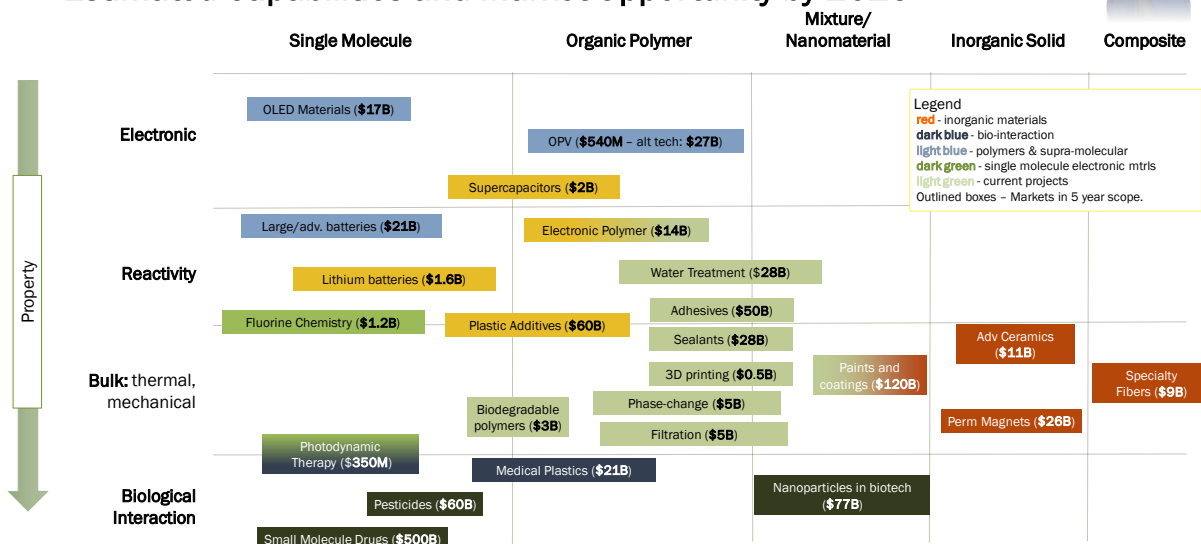
Linear regression model (c.f. QSAR)



Convolutional neural network
(modern machine learning)



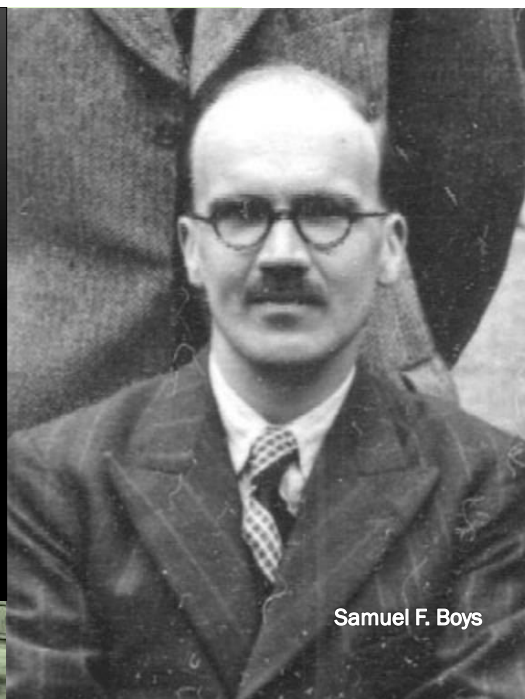
Estimated Capabilities and Market Opportunity by 2025



*market info source: BCC Research Inc, multiple research reports (2012-2015) 21

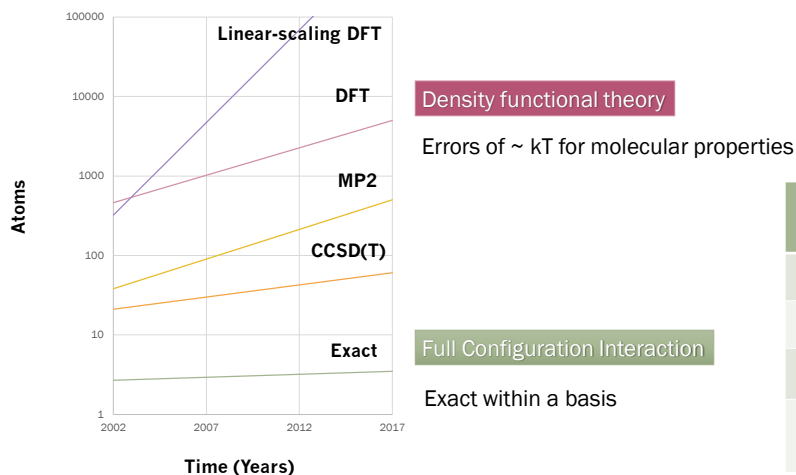
“[H]e produced a paper tape of his whole computer program and unrolled it along the length of the chemical lecture bench. There, in one roll, was something, of which one could ask a chemical question at one end and it would produce an answer at the other! . . . most of the audience probably thought the demonstration bizarre. But it was prescient”

Handy, Pople, Shavitt, JPCA (1996)



Samuel F. Boys

Classical Computer Algorithms

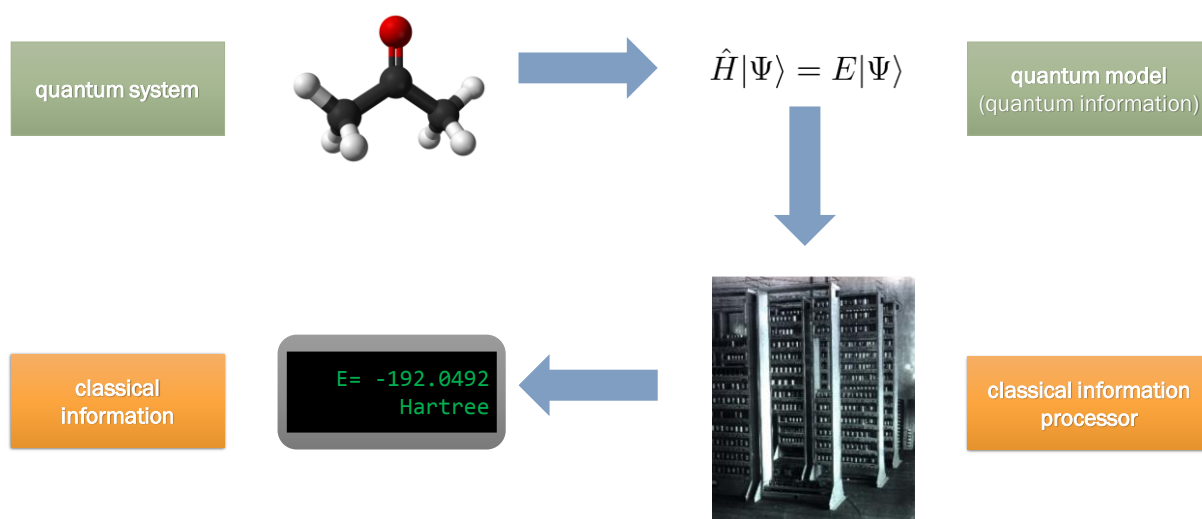


Method	Formal Scaling ^{1,2}
Hartree-Fock	$O(N^4)$
MP2	$O(N^5)$
CCSD(T)	$O(N^7)$
DMRG	$O(N^3M^3)$

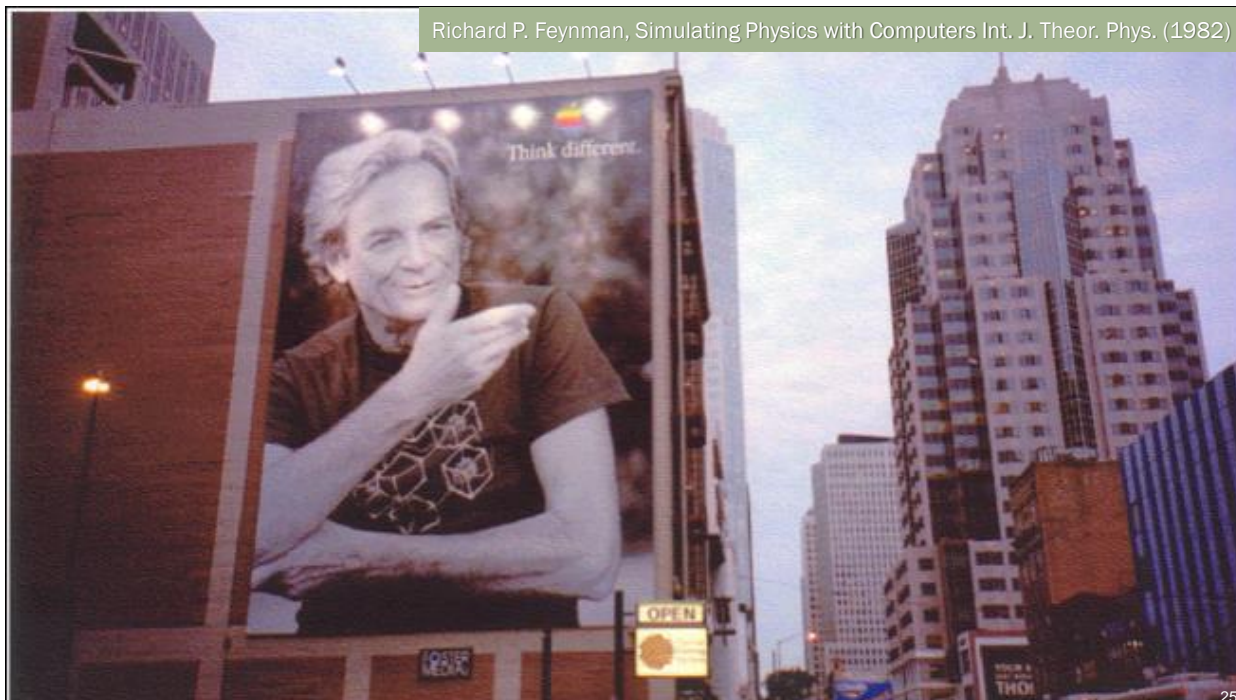
Figure adapted from M. Head-Gordon, M. Artacho, *Physics Today* 4 (2008)

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The Current Paradigm



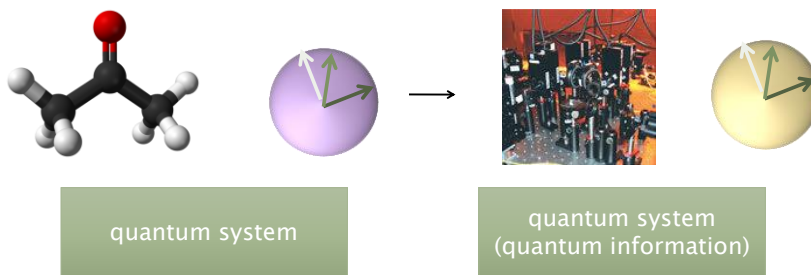
24



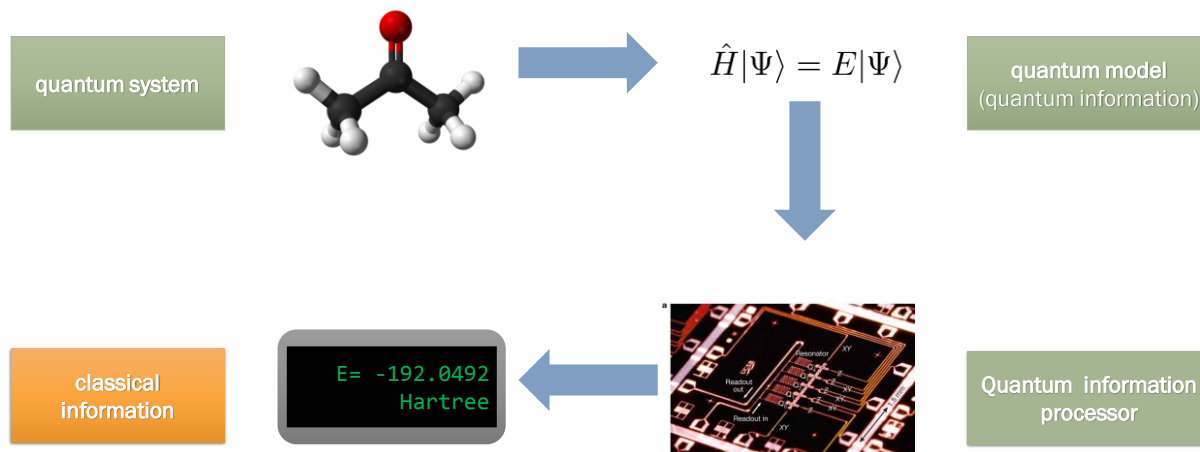
Quantum Computer Simulation



$$\begin{aligned}
 |\psi^{mol}\rangle &\rightarrow |\psi^{QC}\rangle \\
 \hat{U}^{mol}(t) = e^{-i\hat{H}^{mol}t} &\rightarrow \hat{U}^{QC}(t) = e^{-i\hat{H}^{QC}t}
 \end{aligned}$$



The Quantum Simulation Way



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Disruption and Quantum Supremacy

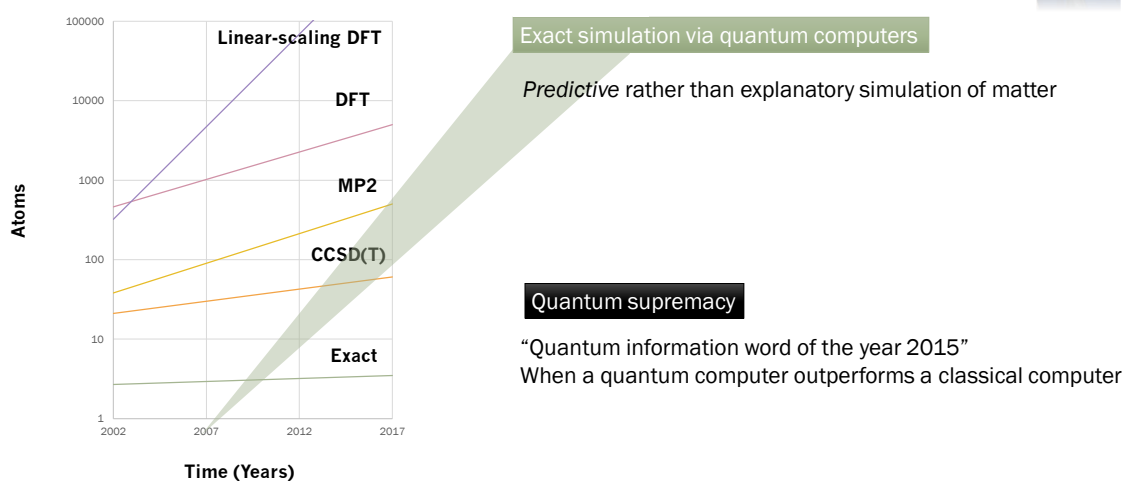
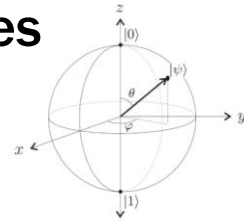
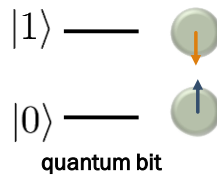
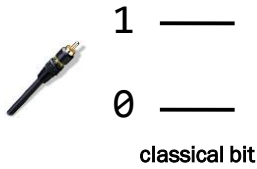


Figure adapted from M. Head-Gordon, M. Artacho, *Physics Today* 4 (2008)

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Quantum Computers in 3 slides



$$|\psi\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\phi}\sin\frac{\theta}{2}|1\rangle$$

Bloch sphere

quantum bit

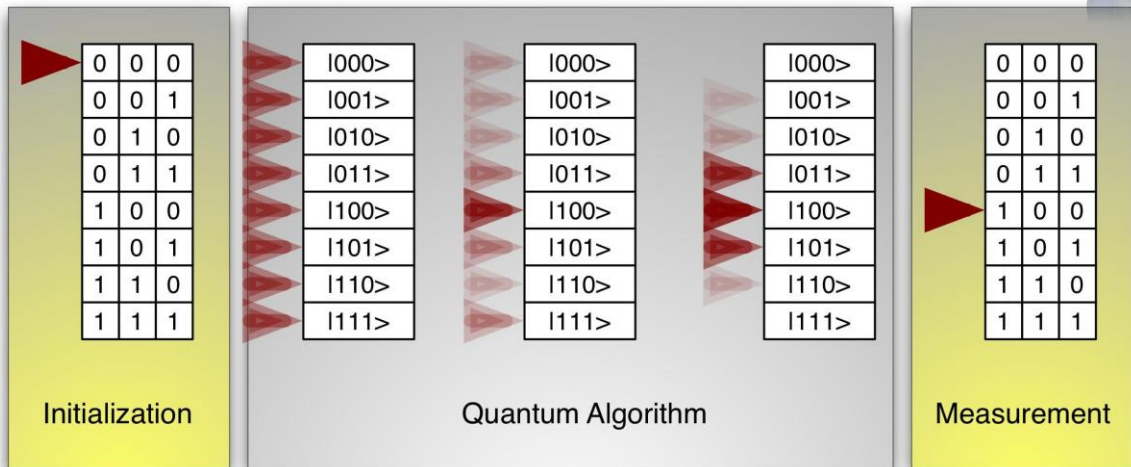
- Superposition
- Entanglement
- Collapse upon measurement

quantum computer

- Collection of controllable qubits
- Subject to decoherence
- Ability for quantum error correction

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Quantum Computation



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Quantum Gates and Circuits



Single qubit gates

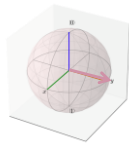
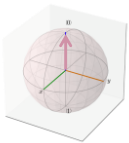
Rotations

$$R_{\hat{n}} = \exp[-i(\vec{\sigma} \cdot \hat{n})\theta/2]$$

$$\vec{\sigma} \equiv [\sigma_x, \sigma_y, \sigma_z]$$

Hadamard gate

$$H = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$



Two qubit gates

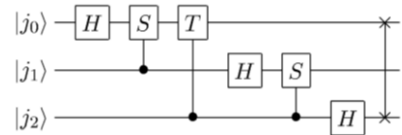
Controlled-not (CNOT) gate

$$\text{CNOT} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\begin{aligned} |00\rangle &\rightarrow |00\rangle \\ |01\rangle &\rightarrow |01\rangle \\ |10\rangle &\rightarrow |11\rangle \\ |11\rangle &\rightarrow |10\rangle \end{aligned}$$

Subroutines

Quantum Fourier Transform



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The Power of Quantum Computers



Myth

Quantum algorithms are always faster and more efficient than classical ones

Quantum algorithm hall of fame

Search	quadratic speedup
Factoring	exponential speedup
Quantum simulation	exponential speedup*

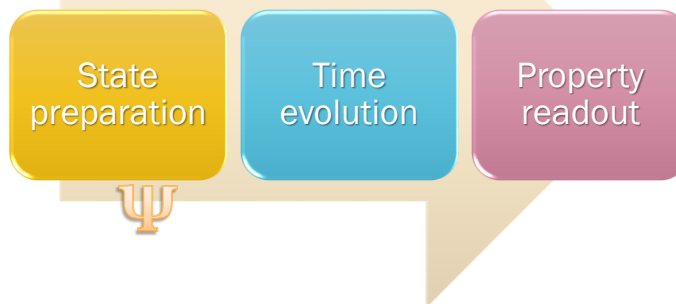
* Restrictions may apply. Read your owner's manual.

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Quantum Computer Simulation



Merlin



Arthur

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Complexity Classes



- Quantum Merlin Arthur
(**Complete:** two-body Hamiltonian problem)

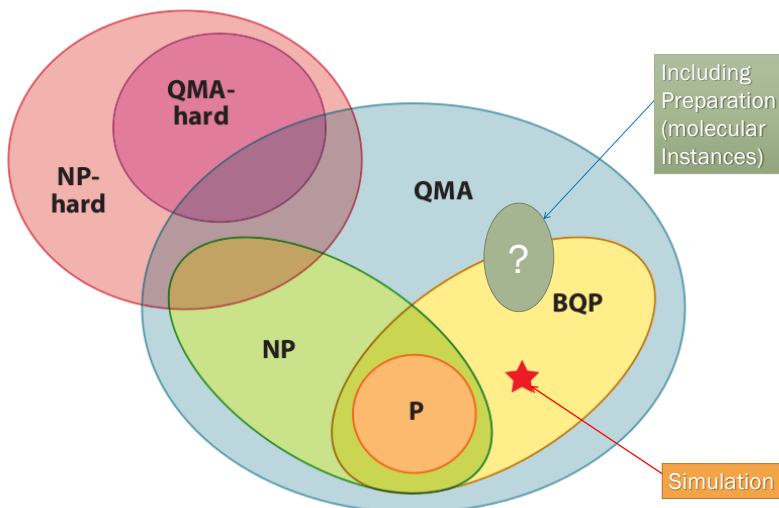
Decision problems that have a proof that can be verified by a quantum computer

- Bounded Quantum Polynomial (BQP)

The class of decision problems **solvable in polynomial time** by a quantum computer

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Quantum Complexity of Chemical Simulation

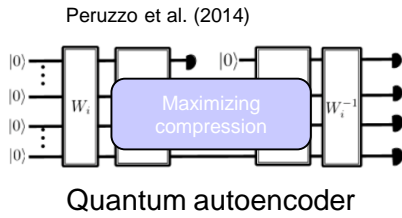
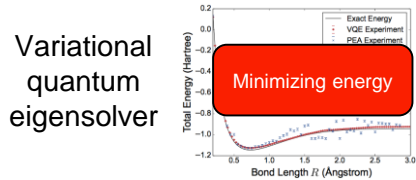


<http://www.youtube.com/watch?v=6ybd5rbQ5rU>

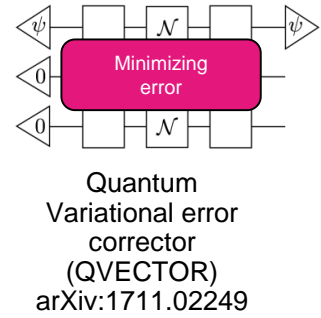
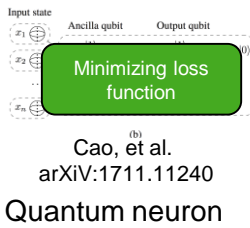
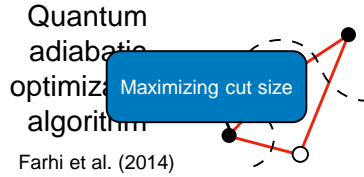
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The age of variational quantum algorithms ... training quantum circuits.



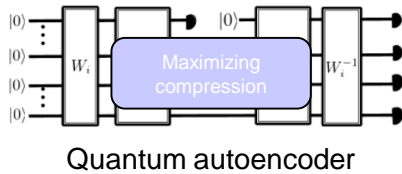
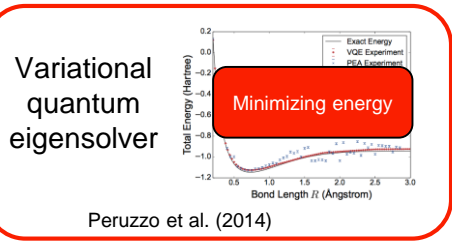
Romero, et al.
Quantum Sci. Technol. 2 (2017): 045001



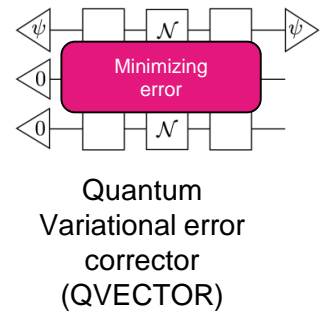
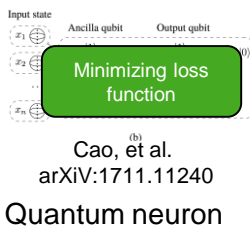
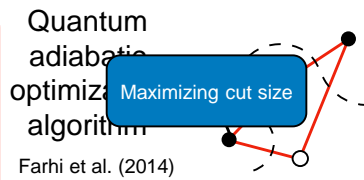
... and many other algorithms, e.g. Machine Learning

37

The age of variational quantum algorithms ... training quantum circuits.



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



... and many other algorithms, e.g. Machine Learning

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Requires fault-tolerance

Hybrid Quantum-Classical Algorithms

Iterative phase
estimation
algorithm

*Aspuru-Guzik et al.,
Science (2005)*

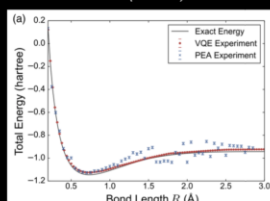
Variational
quantum
eigsolver

*Peruzzo et al., Nat.
Comm. (2014)*

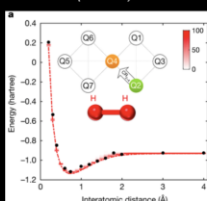
Imaginary-time
variational
quantum simulator

*McArdle et al., arXiv
(2018)*

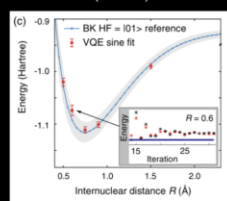
PRX Google
(2016)



Nature IBM
(2017)

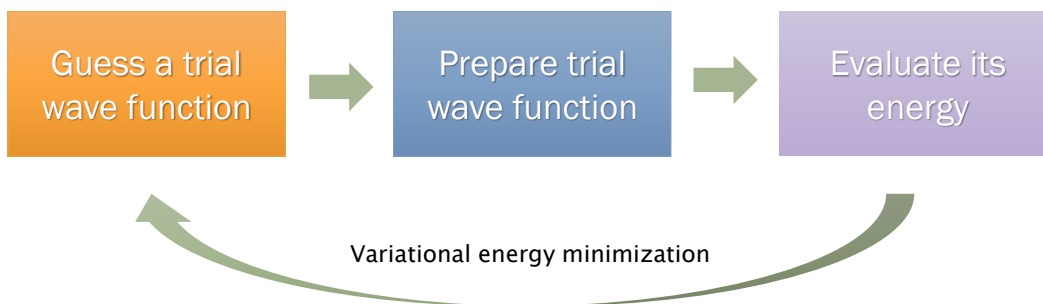


PRX Innsbruck
(2018)



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The Variational Quantum Eigensolver (VQE)



Peruzzo, McClean, Shadbolt, Yung, Zhou, Love, Aspuru-Guzik, O'Brien. Nature Communications 5 4213 2014

Romero, et al arXiv:1701.02691. Quantum Science and Technology (2018) In Press

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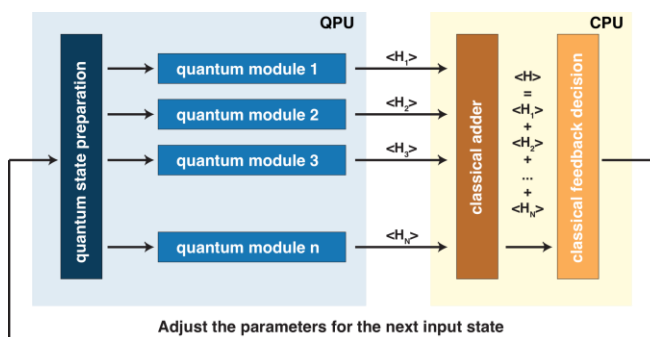
The Variational Quantum Eigensolver (VQE)



Minimize energy: $\operatorname{argmin}_{|\psi\rangle} \frac{\langle \psi | \mathcal{H} | \psi \rangle}{\langle \psi | \psi \rangle}$.

$$\mathcal{H} = h_{\alpha}^i \sigma_{\alpha}^i + h_{\alpha\beta}^{ij} \sigma_{\alpha}^i \sigma_{\beta}^j + h_{\alpha\beta\gamma}^{ijk} \sigma_{\alpha}^i \sigma_{\beta}^j \sigma_{\gamma}^k + \dots$$

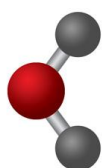
$$\langle \psi | \mathcal{H} | \psi \rangle \equiv \langle \mathcal{H} \rangle = \mathcal{H} = h_{\alpha}^i \langle \sigma_{\alpha}^i \rangle + h_{\alpha\beta}^{ij} \langle \sigma_{\alpha}^i \sigma_{\beta}^j \rangle + h_{\alpha\beta\gamma}^{ijk} \langle \sigma_{\alpha}^i \sigma_{\beta}^j \sigma_{\gamma}^k \rangle + \dots$$



Peruzzo, McClean, Shadbolt, Yung, Zhou, Love, Aspuru-Guzik, O'Brien. Nature Communications 5 4213 2014

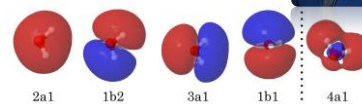
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Quantum Chemistry in 1 Slide



Self-consistent solution in local basis

Molecular orbitals and "integrals"



Molecular Hamiltonian

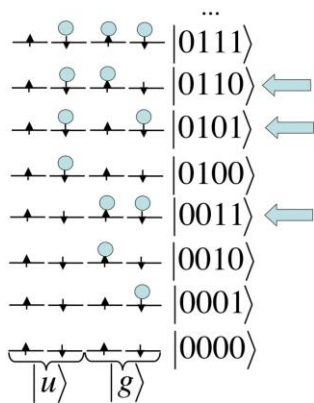
$$\hat{H} = \sum_X \hat{h}_X = \sum_{p,q} \langle p | \hat{T} + \hat{V}_N | q \rangle \hat{a}_p^\dagger \hat{a}_q + \frac{1}{2} \sum_{p,q,r,s} \langle p | \langle q | \hat{V}_e | r | s \rangle \hat{a}_p^\dagger \hat{a}_q^\dagger \hat{a}_r \hat{a}_s$$

One electron integrals

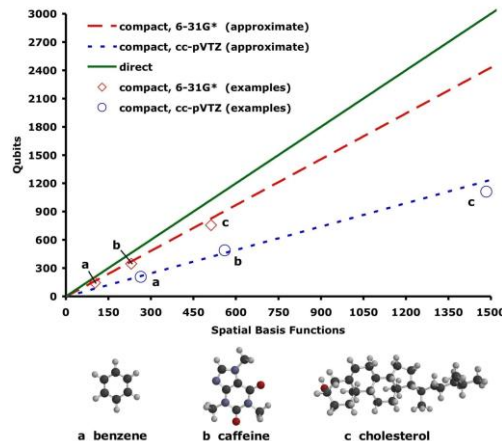
Two-electron integrals

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Mapping and Baseline Resource Requirements



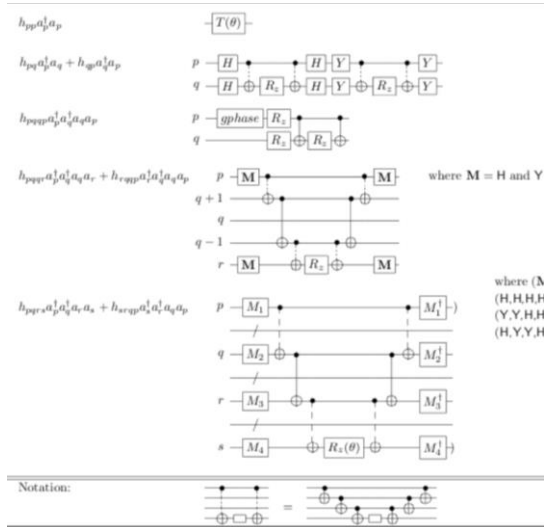
Direct mapping



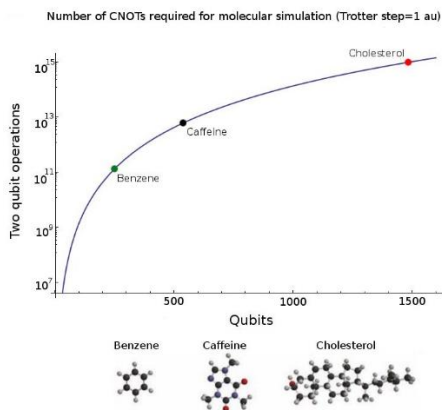
A. Aspuru-Guzik, A. D. Dutoi, P. J. Love, M. Head-Gordon, Science (2005) **Full quantum circuit:** J. D. Whitfield, et. al., Mol. Phys. (2011) **Error correction:** N. Cody Jones, J. D. Whitfield, et al. New. J. Phys.(2012)

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Steep Scaling for Baseline Algorithm



where $(M_1, M_2, M_3, M_4) = (H,H,H,H), (H,Y,H,Y), (Y,H,Y,H), (Y,Y,H,H), (H,H,Y,Y), (Y,H,H,Y), (H,Y,Y,H)$ and (Y,Y,Y,Y)



44

Experimental Implementations



Quantum optics

Hydrogen molecule	2 qubits	Lanyon, et al.,	Nat Chem 2 106	2010
HeH ⁺	2 qubits	Peruzzo, et al.,	Nat Comms 5 4213	2014

Nuclear Magnetic Resonance

Hydrogen molecule	2 qubits	Du, et al,	Phys Rev Lett 104 030502	2010
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Nitrogen vacancy centers

HeH ⁺	2 qubits	Wang, et al.,	ACS Nano 9 7769	2015
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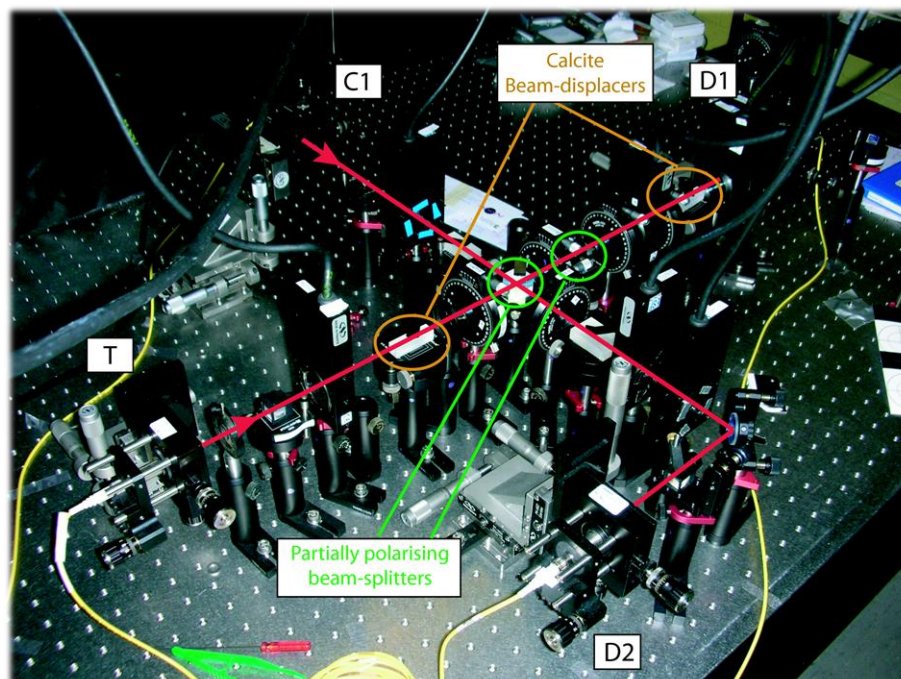
Superconducting qubits

Hydrogen molecule	3 qubits	O'Malley, et al,	Phys Rev X 6 031007	2016
BeH ₂	6 qubits	Kandala, et al.	Nature 548 242	2017

Ion traps

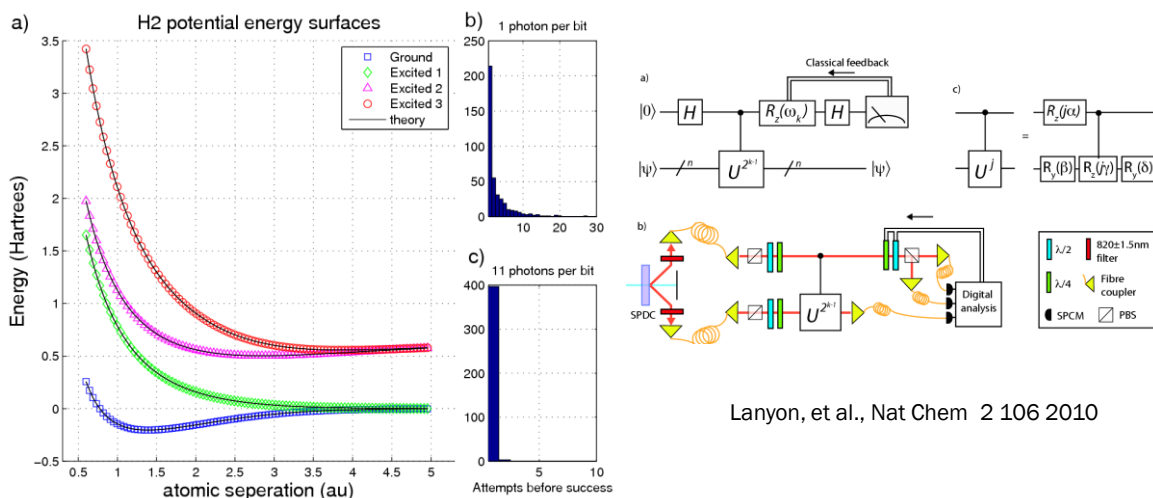
HeH ⁺	3 qubits	Shen, et al,	arXiv:1506.00443	2015
LiH	3 qubits	Hempel, et al.	To be submitted	2016

45



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First Quantum Simulation of Hydrogen Molecule Potential Energy Surface



47

Hierarchy of Post-HF Methods

We can recover the **electron correlation** by expanding the wavefunction in the configurational space.



$$|\Phi_0\rangle + \dots + |\Phi_i^a\rangle + \dots + |\Phi_{ij}^{ab}\rangle + \dots$$

$$\Phi_i^a = a_a^\dagger a_i |\Phi_0\rangle$$

$$\Phi_{ij}^{ab} = a_a^\dagger a_b^\dagger a_i a_j |\Phi_0\rangle$$

$$\binom{N}{\eta} \text{ determinants}$$

$$|FCI\rangle = \left(c_0 + \sum_{i,a} c_i^a a_a^\dagger a_i + \sum_{i>j, a>b} c_{ij}^{ab} a_a^\dagger a_b^\dagger a_i a_j + \dots \right) |\Phi_0\rangle$$

Configuration interaction (CI)

$$|CC\rangle = \exp \left(\sum_{i,a} t_i^a a_a^\dagger a_i + \sum_{i>j, a>b} t_{ij}^{ab} a_a^\dagger a_b^\dagger a_i a_j + \dots \right) |\Phi_0\rangle$$

Coupled cluster (CC)

Helgaker, T., Jorgensen, P. and Olsen, J., 2014. Molecular electronic-structure theory.

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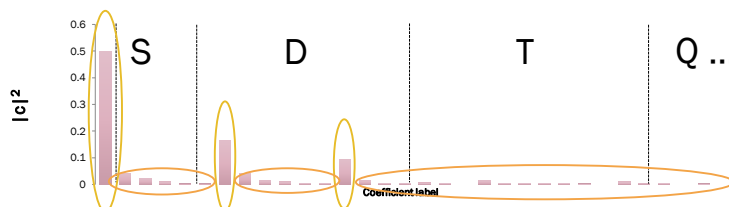
Dynamic and Static Correlation

Single reference



Chemical Accuracy
($<1\text{kcal/mol}$)
43.3 meV
1.6 mHartree

Strongly correlated = "Multireference"

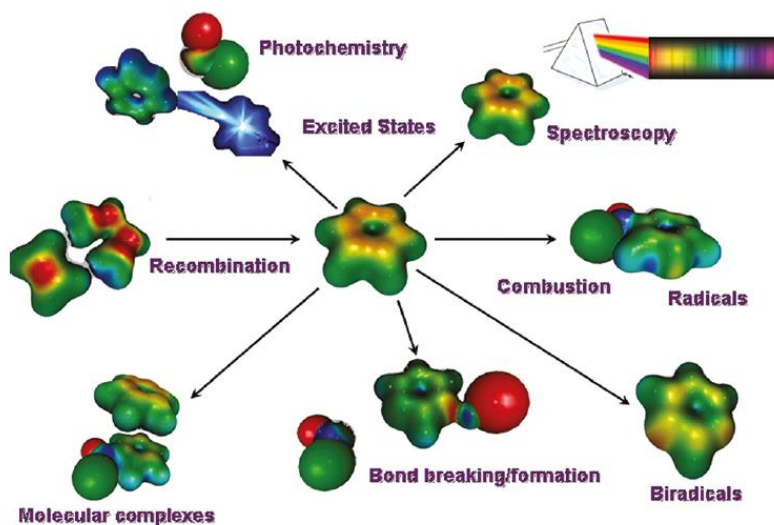


Dynamic Correlation

Static Correlation

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"Multireference" World of Chemistry



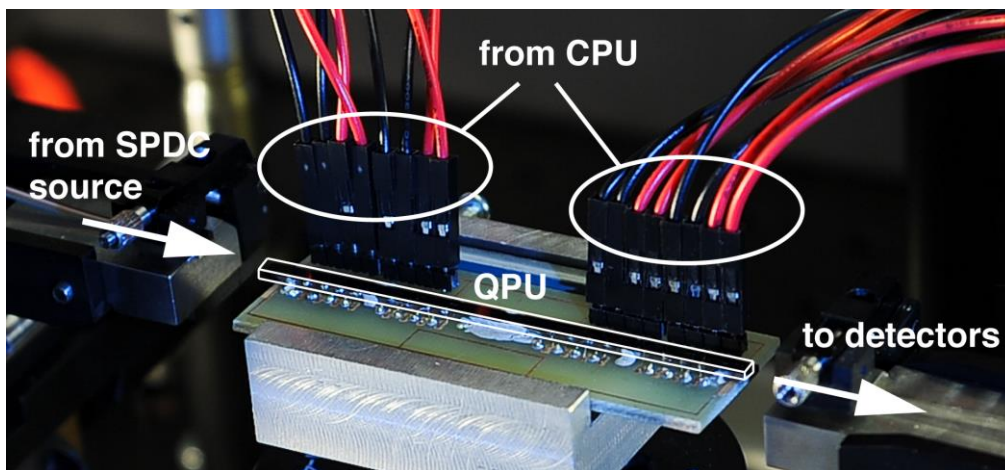
From: Lyakh et al. *Chem. Rev.* **102**, 182, (2012).

The accurate modeling of multireference phenomena is perhaps the biggest challenge for quantum chemistry.



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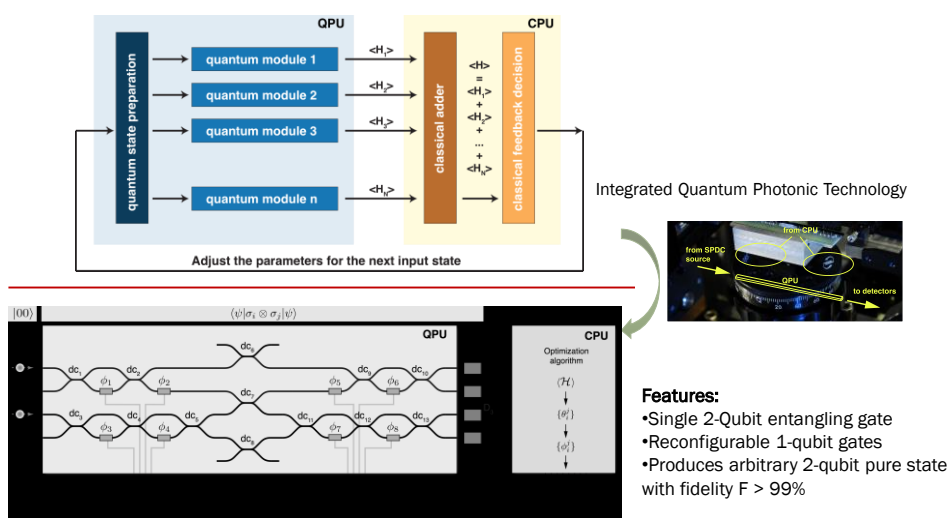
The Variational Quantum Eigensolver (VQE)



Peruzzo, McClean, Shadbolt, Yung, Zhou, Love, Aspuru-Guzik, O'Brien. Nature Communications 5 4213 2014

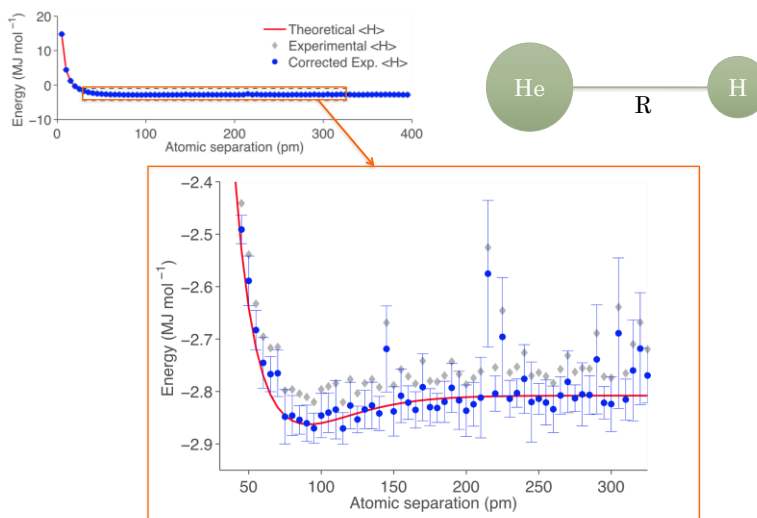
51

Physical Implementation



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Experimental Electronic Curve for HeH⁺



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Unitary Coupled Cluster Ansatz



$$U(\vec{t}) = \exp[-i(T - T^\dagger)] \quad \tau_a : \text{excitation operator}$$

$$= \exp\left[-i \sum_a t_a (\tau_a - \tau_a^\dagger)\right]$$

In a quantum computer we can implement an approximated unitary:

$$U(\vec{t}) \approx U_{Trot}(\vec{t}) = \left(\prod_i e^{\frac{t_i}{\rho} (\tau_i - \tau_i^\dagger)} \right)^\rho$$

Parameter scaling
O(n_e² N²)

The BCH expansion for UCC is **infinite**.¹

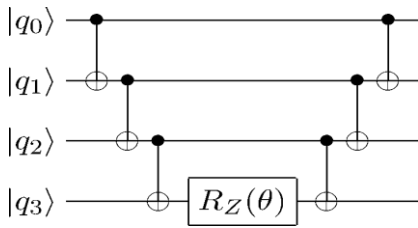
1. Taube, A.G. and Bartlett, R.J., 2006. Int. J. Quantum Chem. **106**(15), pp.3393-3401.

54

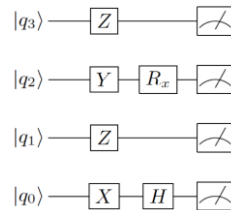


VQE for UCC: How it all fits together

- 1 Second-quantized excitation operator
 - 2 Pauli operators
- Jordan-Wigner transformation
 or Bravyi-Kitaev transformation
- 3 Exponentiation
 - 4 Measurement



... for all terms ...



... for all terms ...

This circuit implements $e^{-i\frac{\theta}{2}\sigma_3^z\sigma_2^z\sigma_1^z\sigma_0^z}$

H and R_x are used to change from Z to X and Y basis.

Measuring the term

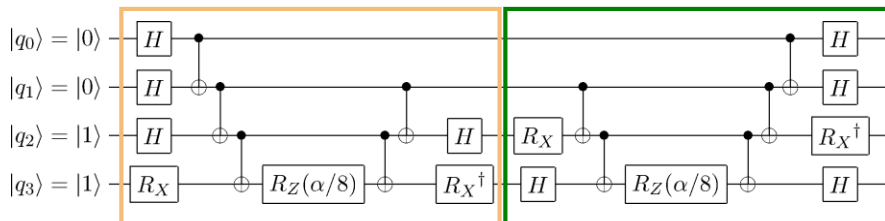
$$\sigma_z^3 \sigma_y^2 \sigma_z^1 \sigma_x^0$$

Example: Minimal-basis H_2 Jordan-Wigner



$$\begin{aligned} \hat{H}_{JW} = & f_1 \mathbf{1} + f_2(\sigma_0^z + \sigma_1^z) + f_3(\sigma_2^z + \sigma_3^z) + f_4 \sigma_3^z \sigma_2^z \\ & + f_5 \sigma_1^z \sigma_0^z + f_6(\sigma_2^z \sigma_0^z + \sigma_3^z \sigma_1^z) + f_7(\sigma_2^z \sigma_1^z + \sigma_3^z \sigma_0^z) \\ & + f_8(\sigma_3^x \sigma_2^y \sigma_1^y \sigma_0^z - \sigma_3^x \sigma_2^x \sigma_1^y \sigma_0^y + \sigma_3^y \sigma_2^x \sigma_1^x \sigma_0^y - \sigma_3^y \sigma_2^y \sigma_1^x \sigma_0^x) \end{aligned}$$

$$\hat{U}(\alpha) = \exp[i\alpha/8(-\sigma_3^y \sigma_2^x \sigma_1^x \sigma_0^x + \sigma_3^x \sigma_2^y \sigma_1^x \sigma_0^x + \sigma_3^x \sigma_2^x \sigma_1^y \sigma_0^x + \sigma_3^x \sigma_2^x \sigma_1^x \sigma_0^y + \sigma_3^x \sigma_2^y \sigma_1^y \sigma_0^y + \sigma_3^y \sigma_2^x \sigma_1^y \sigma_0^y - \sigma_3^y \sigma_2^y \sigma_1^x \sigma_0^y - \sigma_3^y \sigma_2^y \sigma_1^y \sigma_0^x)]$$

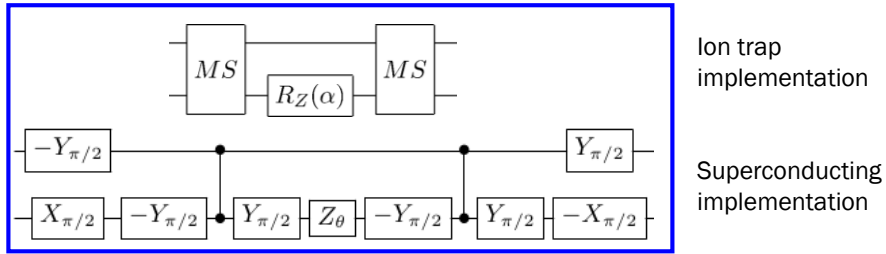
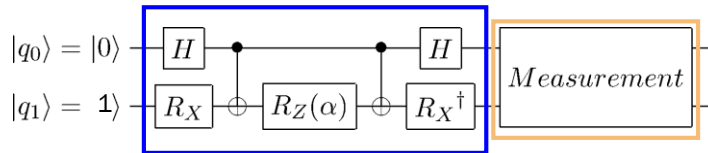


$$|0011\rangle \rightarrow (1 - c)|0011\rangle + c|1100\rangle$$

Example: Minimal-basis H₂ Bravyi-Kitaev



$$H_2^{BK} = c_0 \mathbf{1} + c_1 \sigma_0^z + c_2 \sigma_1^z + c_3 \sigma_0^z \sigma_1^z + c_4 \sigma_0^x \sigma_1^x + c_5 \sigma_0^y \sigma_1^y$$



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Romero, et al arXiv:1701.02691

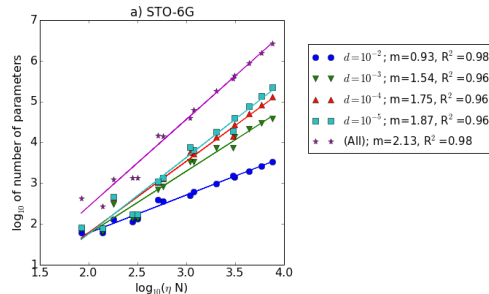
Optimization of the Cost of UCC



Use classical approximations of the amplitudes to reduce circuit size

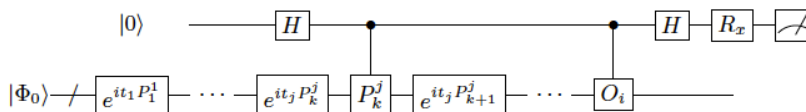
Select terms using MP2

$$t_i^a = 0; \quad t_{ia}^{ab} = \frac{h_{ijba} - h_{ijab}}{\epsilon_i + \epsilon_j - \epsilon_a - \epsilon_b}$$



Gradients for UCC

$$\frac{\partial E(\vec{t})}{\partial t_j} = 2 \sum_i^M \sum_k^{N_S^j} h_i \text{Im}(\langle \Phi_0 | V_k^{j\dagger}(\vec{t}) O_i U(\vec{t}) | \Phi_0 \rangle)$$

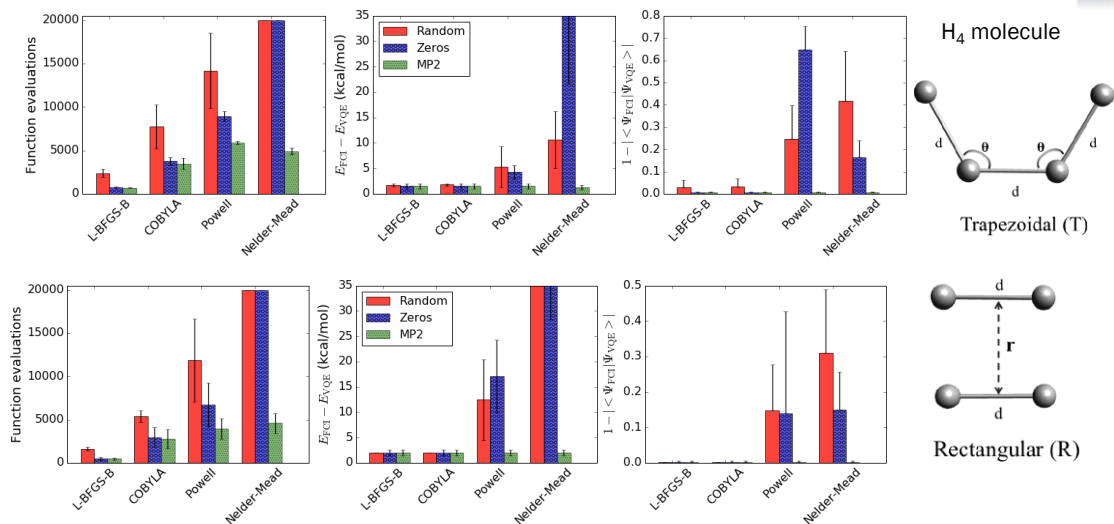


Romero et al. arXiv: 1701.02691 (2017).

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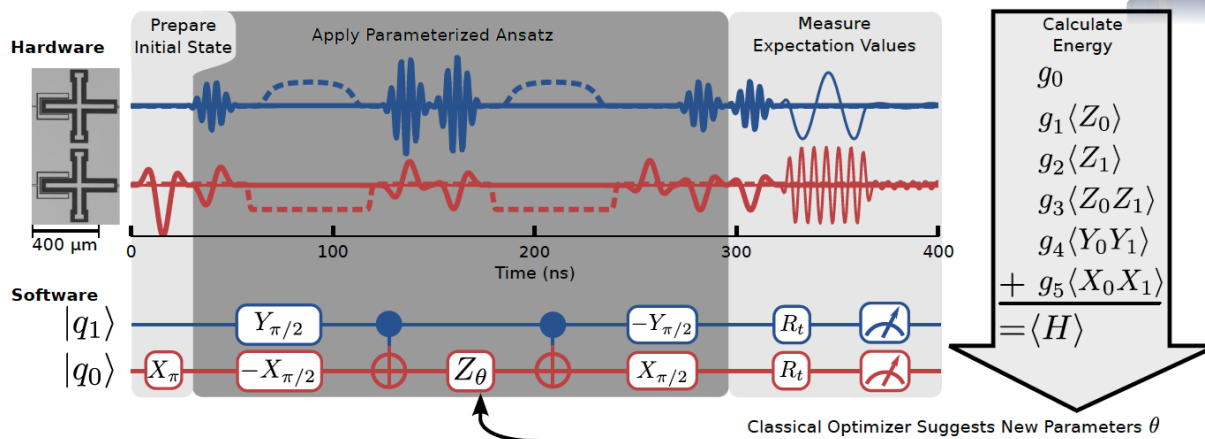
Strategies for UCC Calculations



Romero et al. arXiv: 1701.02691 (2017).

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Superconducting VQE for H₂

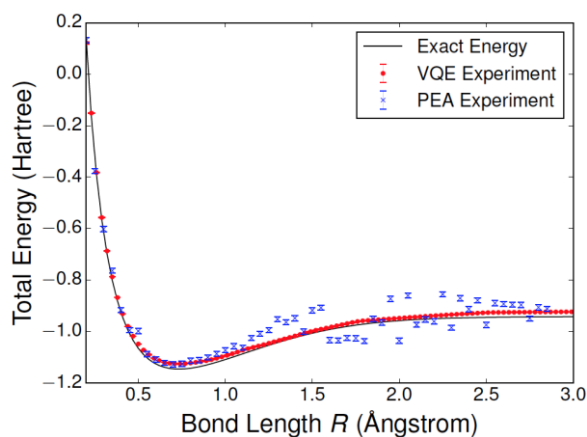


Used Xmon qubits to compute energy surface of molecular hydrogen
 Started in Hartree-Fock state, used unitary coupled cluster, got chemical accuracy

P. O'Malley, et al. Physical Review X 6 031007 2016

60

Superconducting VQE vs Phase Estimation



Predicted dissociation energy without exponentially costly compilation for first time
Substantial robustness to systematic errors seen

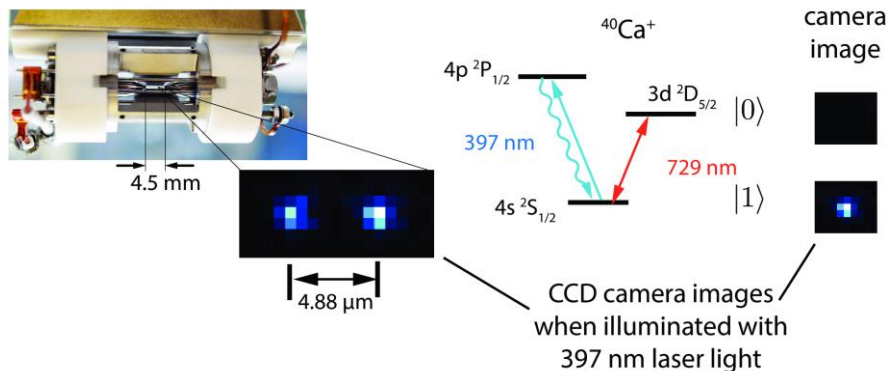
P. O'Malley, et al. Physical Review X 6 031007 2016

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Ion Trap Implementation



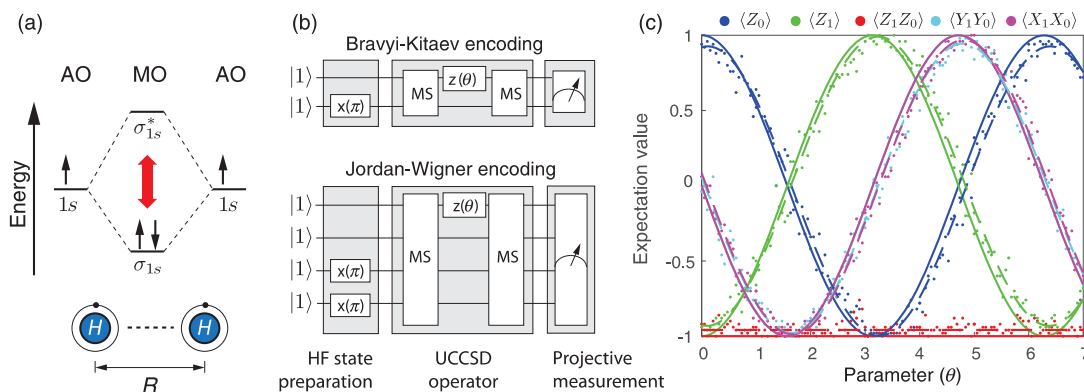
Collaboration with Rainer Blatt (Innsbruck)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen, Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
Phys. Rev. X **8**, 031022

62

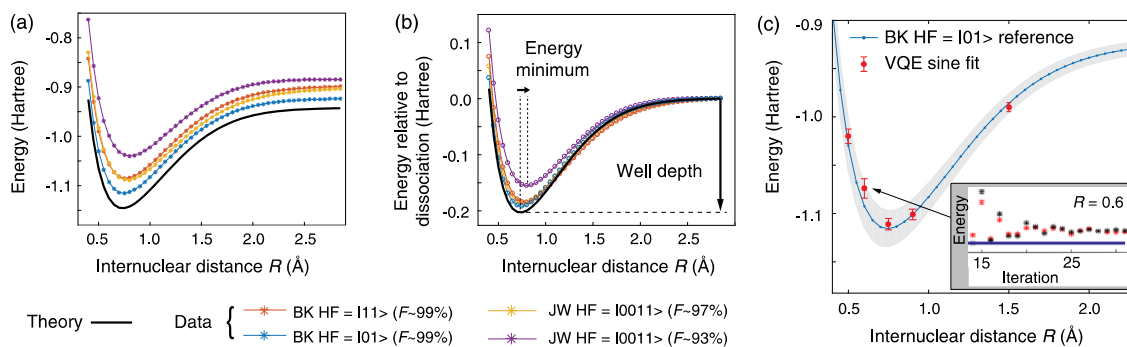
Ion Trap Implementation (H_2)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen, Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
 Phys. Rev. X **8**, 031022

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Ion Trap Implementation (H_2)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen, Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
 Phys. Rev. X **8**, 031022

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Ion Trap Implementation (H_2)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen,

Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
 Phys. Rev. X **8**, 031022

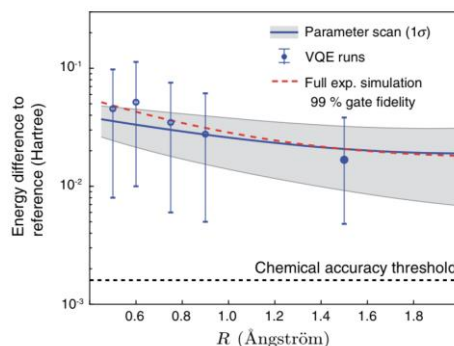
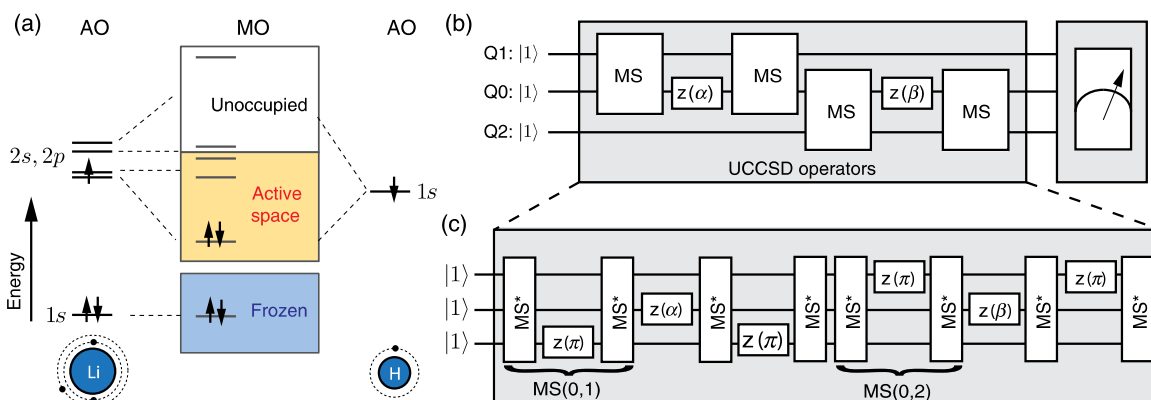


FIG. 7. Energy errors of the reconstructed H_2 potential energy surface and the influence of decoherence. Differences are given with respect to the full configuration interaction (FCI) calculation performed in the chosen molecular basis. The red line corresponds to a full simulation of the quantum circuit, including multiple decoherence channels and the experimentally determined gate fidelity (see Appendix B 6 for details).

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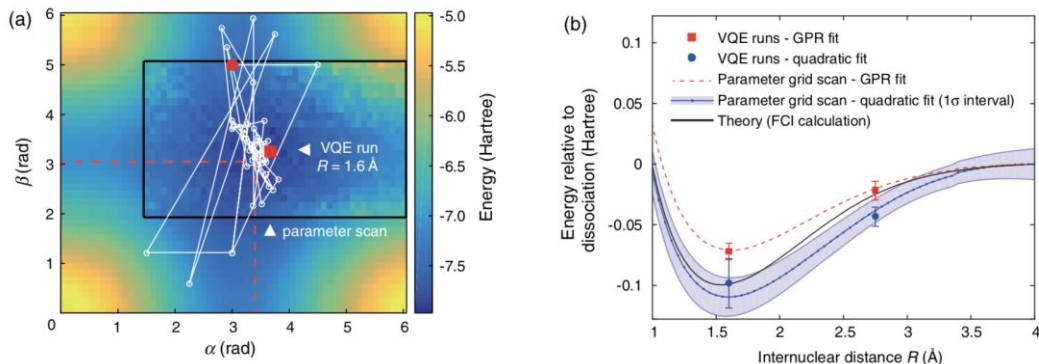
Ion Trap Implementation (LiH)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen, Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
 Phys. Rev. X **8**, 031022

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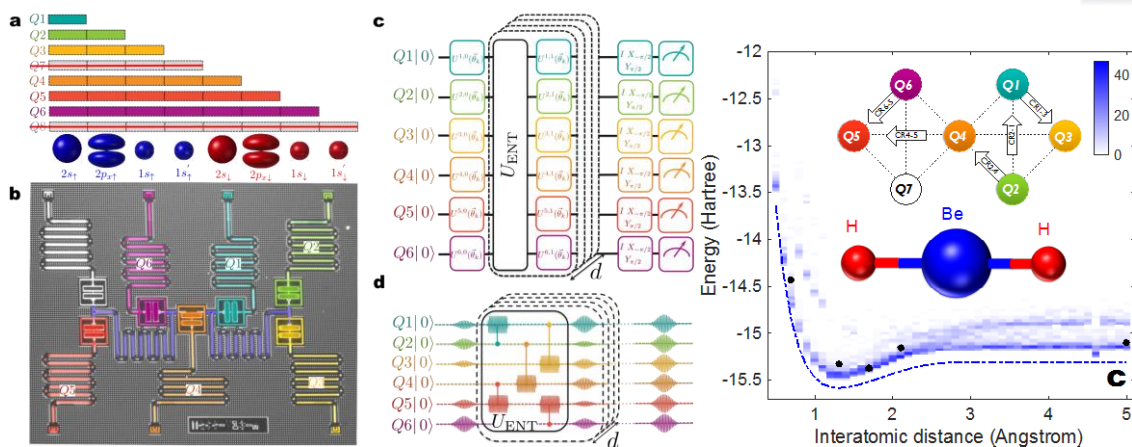
Ion Trap Implementation (LiH)



Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Heng Shen, Petar Jurcevic, Ben P. Lanyon, Peter Love, Ryan Babbush, Alán Aspuru-Guzik, Rainer Blatt, and Christian F. Roos
 Phys. Rev. X **8**, 031022

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Variational Eigensolver by IBM Team!



Hardware-efficient Quantum Optimizer for Small Molecules and Quantum Magnets

Abhinav Kandala,* Antonio Mezzacapo,* Kristan Temme, Maika Takita, Jerry M. Chow, and Jay M. Gambetta
 IBM T.J. Watson Research Center, Yorktown Heights, NY 10598, USA
 (Dated: April 18, 2017)

H-Be-H, 6 qubit simulations.

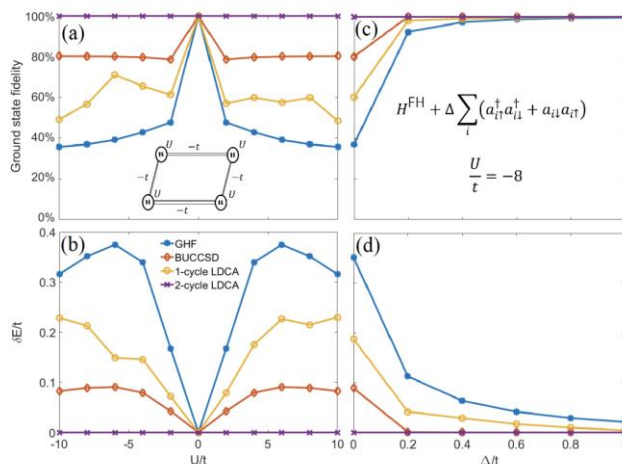
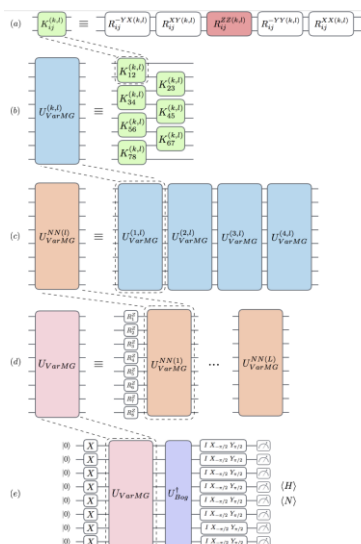
Kandala, et al Nature 549 242 (2017)

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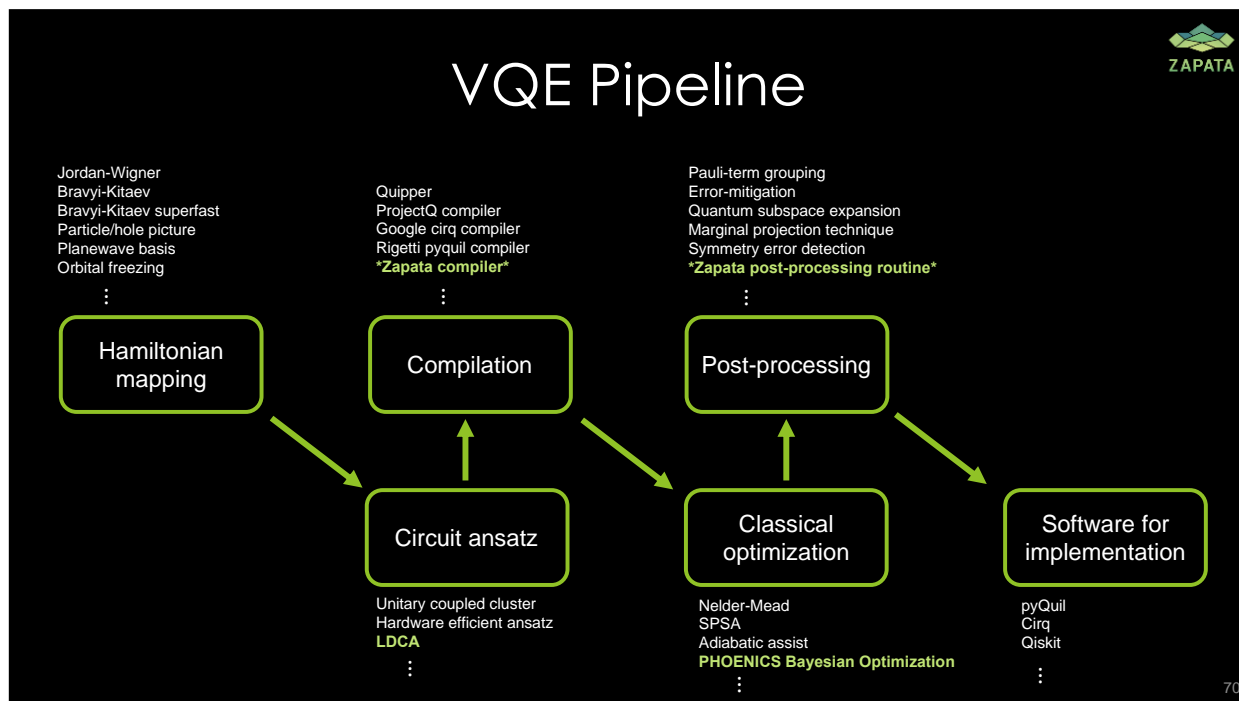
Low-depth Correlated Ansatz (LDCA)

Approach motivated by Bogoliubov coupled cluster theory



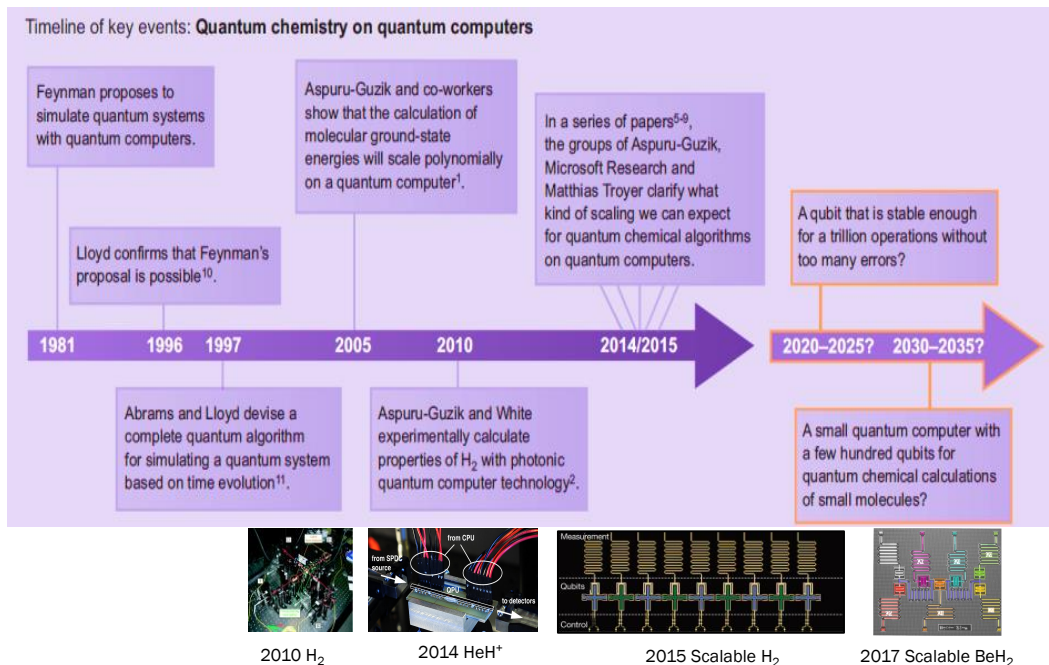
Dallaire-De Mers, J. Romero, L. Veis, S. Sim, A. Aspuru-Guzik arXiv:1801.01053 (2018)

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Quantum Chemical Advantage?



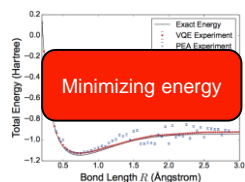
Leonie Mueck, Nature Chemistry 7 361 2015

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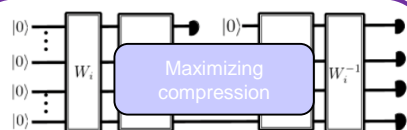
The age of variational quantum algorithms ... training quantum circuits.



Variational quantum eigensolver



Peruzzo et al. (2014)



Quantum autoencoder

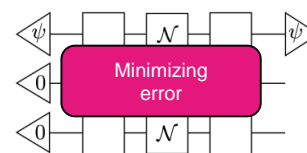
Romero, et al.
Quantum Sci. Technol. 2 (2017): 045001

Quantum adiabatic optimization algorithm

Farhi et al. (2014)



Cao, et al.
arXiv:1711.11240
Quantum neuron



Quantum Variational error corrector (QVECTOR)

... and many other algorithms, e.g. Machine Learning

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Machine Learning



The goal of *machine learning* is to design algorithms that can learn from and make predictions on data.

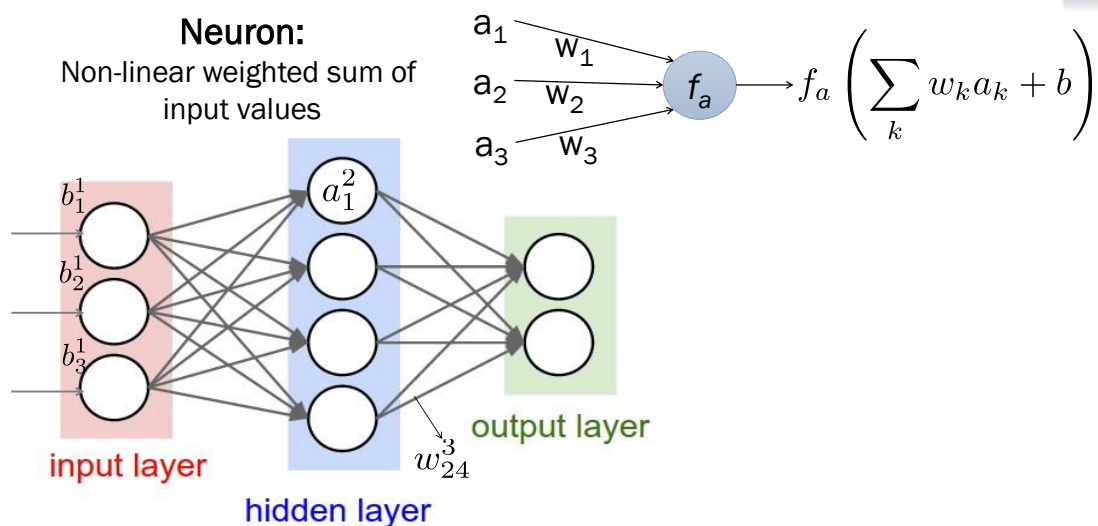


“A computer program is said to learn from experience E with respect to a class of tasks T and performance measure P , if its performance at tasks T , as measured by P , improves with experience E ”

-Tom Mitchell (CMU)

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Feedforward Neural Networks



Michael A. Nielsen "Neural networks and deep learning", Determination press. 2015.

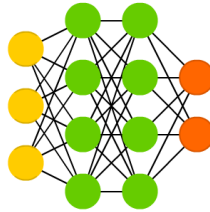
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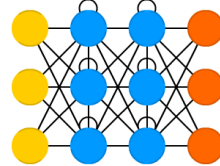
Diversity of Neural Networks

- Input Cell
- Hidden Cell
- Output Cell
- Match Input Output Cell
- △ Noisy Input Cell

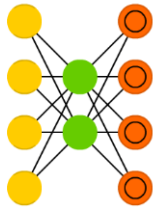
Deep Feed Forward (DFF)



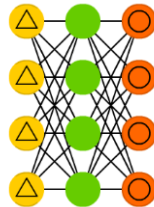
Recurrent Neural Network (RNN)



Auto Encoder (AE)



Denosing AE (DAE)



Sparse AE (SAE)



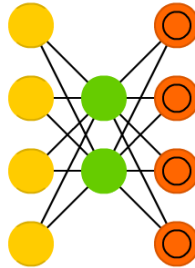
Reproduced from: <http://www.coolinfoographics.com/blog/2016/9/20/the-mostly-complete-chart-of-neural-networks.html>. May28 th, 2017.

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Autoencoders



Image



Image



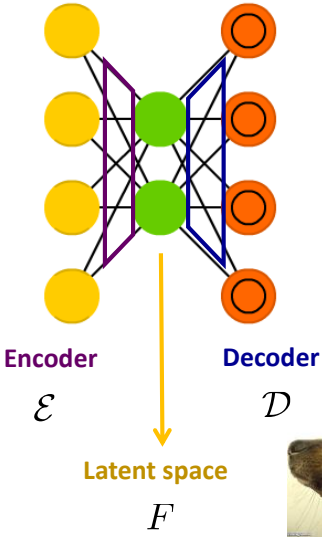
- Input Cell
- Hidden Cell
- Match Input Output Cell

Input Hidden layers Output

Image: asimovinstitute.org



Autoencoders

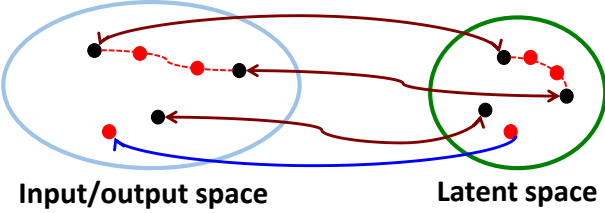


$$\mathcal{E} : X \rightarrow F \quad \underset{\mathcal{E}, \mathcal{D}}{\operatorname{argmin}} \quad \|X - (\mathcal{D} \circ \mathcal{E})X\|^2$$

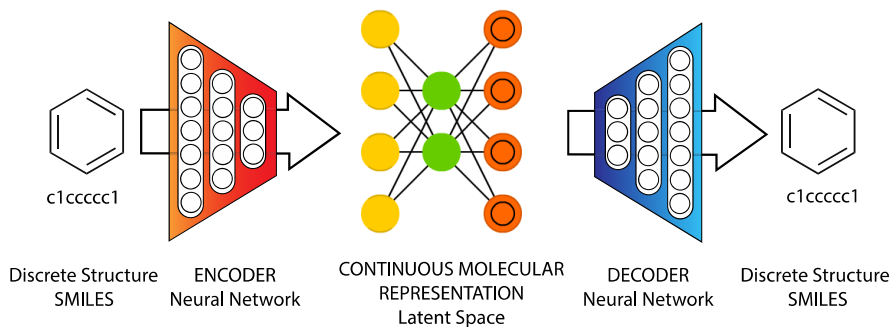
$$\mathcal{D} : F \rightarrow X'$$

The encoding network can be used for dimensionality reduction and feature extraction

The decoding network can be used as a *generative model*.



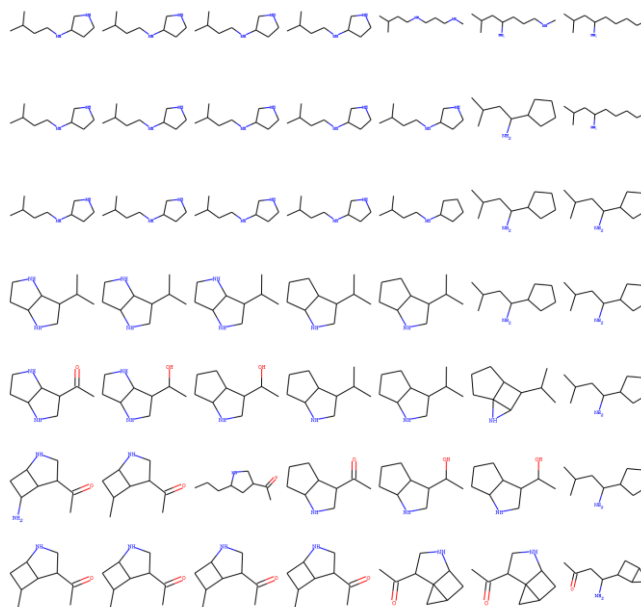
Autoencoders for Chemical Space



- Input Cell
- Hidden Cell
- Match Input Output Cell

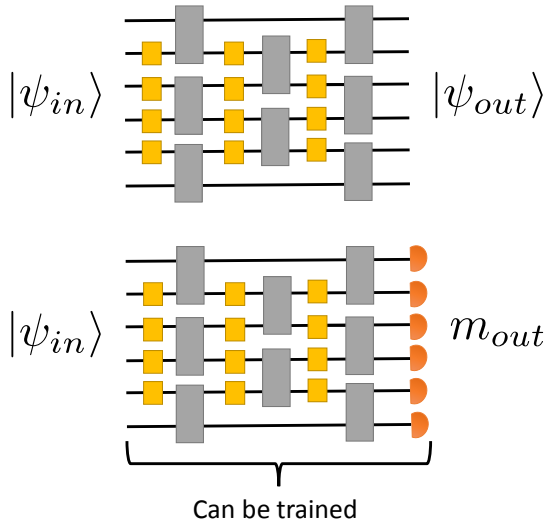
R. Gomez-Bombarelli, et al ACS Central Science 10.1021/acscentsci.7b00572 (2018)

Exploring latent space



Training Quantum Circuits

An analogy to machine learning



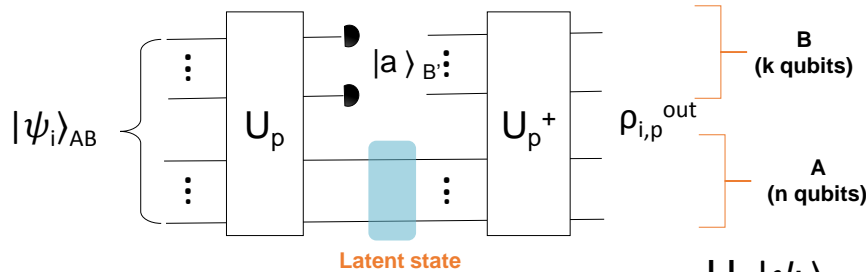
Define suitable cost functions as expectation values of observables

Optimize them to train quantum circuits for performing quantum tasks

Near-term quantum computers, without error correction and short-depth, are excellent candidates for these *task-driven* applications.

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Quantum Autoencoder Model



$$U_p |\psi_i\rangle_{AB} = |\psi_i^c\rangle_A |a\rangle_B$$

Given:

- An ensemble of pure states $\{q_i, |\psi_i\rangle_{AB}\}$ and a pure reference state $|a\rangle_B$ on k qubits.
- A family of unitary operators $\{U^p\}$ acting on $n+k$ qubits, parameterized according to a parameter vector $\mathbf{p} = (p_1, p_2, \dots)$.

Task:

- Find the unitary U^p which maximizes:

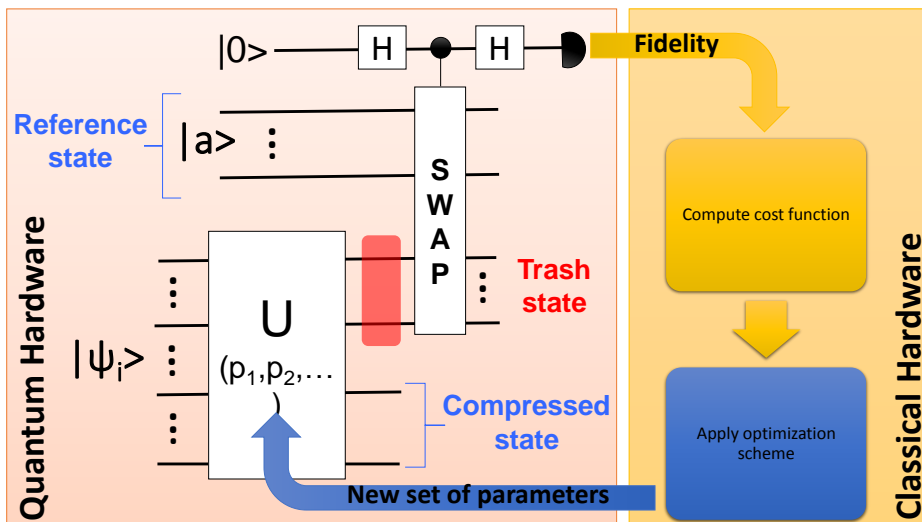
$$C(p) = \sum_i q_i F(|\psi_i\rangle_{AB}, \rho_{i,p}^{out})$$

Romero, J., Olson, J. and Aspuru-Guzik, A., . Quantum autoencoders for efficient compression of quantum data. *Quantum Sci. Technol.* 2 (2017): 045001.

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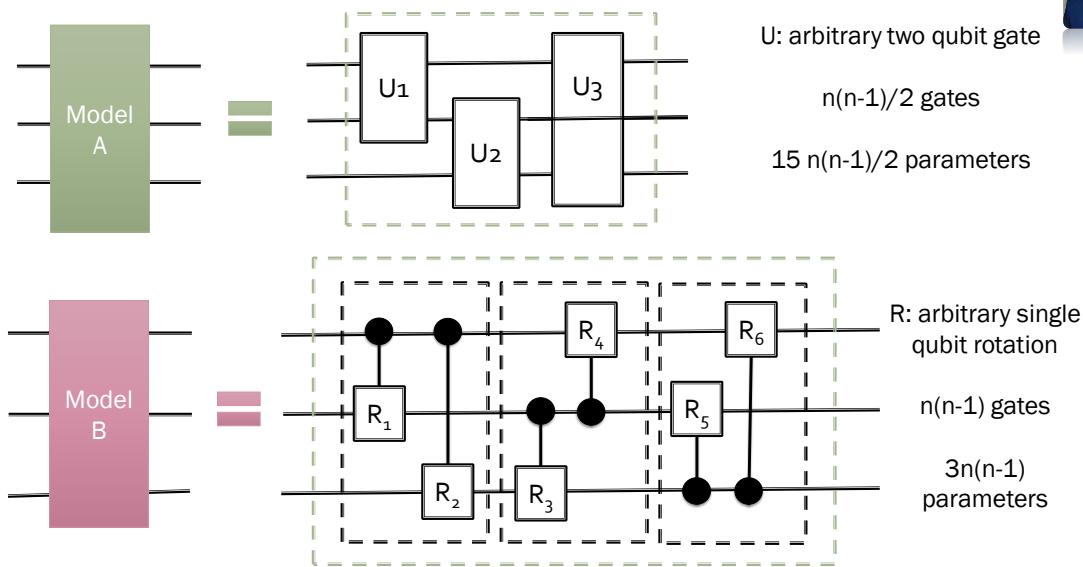
Hybrid Approach for Circuit Training



Romero, J., Olson, J. and Aspuru-Guzik, A., 2016. Quantum autoencoders for efficient compression of quantum data. *Quant Sci Tech* 2 045011 (2017)

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Heuristics for Autoencoder Unitaries



Romero, J., Olson, J. and Aspuru-Guzik, A., 2016. Quantum autoencoders for efficient compression of quantum data. *Quant Sci Tech* 2 045011 (2017)

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Application: Wave Function Compression

Romero, et al *Quant Sci Tech* 2 045011 (2017)



For many Hamiltonians, eigenstates are generally sparse and obey certain symmetries.

Example: In many body systems there are

Restriction in the number of particles: with m particles within a second quantized representation, wavefunctions are spanned by a subspace of size $\binom{N}{m}$, compared to 2^N .

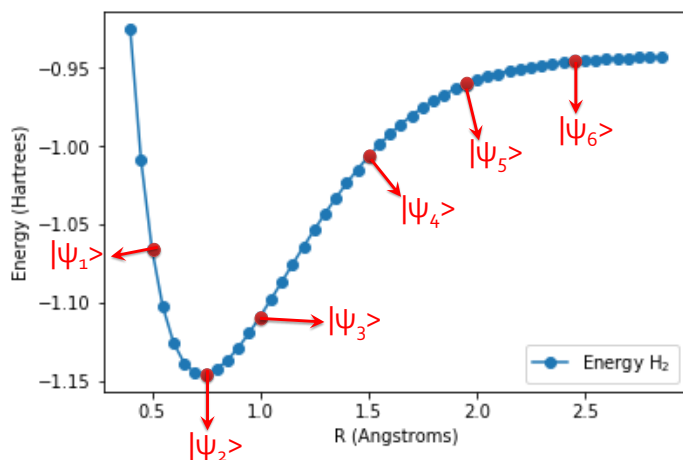
Restriction in spin projection: The total wavefunction is spanned by determinants with the correct spin projection:

$$S_z |k\rangle = M |k\rangle; \quad M = \frac{n_\alpha - n_\beta}{2}$$

85

Example: H₂ molecule (4-2-4 autoencoder)

Romero, et al *Quant Sci Tech* 2 045011 (2017)



- We selected some points in the PES for which we have the wavefunction (Use VQE as oracle).
- Use these states as training set for the autoencoder. (6)
- Use other points in the PES as test set. (44)

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H₂ Results

Romero, et al arXiv:1612.02806



Circuit	Final size (# qubits)	Set	$-\log_{10}(1 - \mathcal{F})$ MAE	$-\log_{10}$ Energy MAE (Hartrees)
Model A	2	Training	6.96(6.82-7.17)	6.64(6.27-7.06)
	2	Testing	6.99(6.81-7.21)	6.76(6.18-7.10)
	1	Training	6.92(6.80-7.07)	6.60(6.23-7.05)
	1	Testing	6.96(6.77-7.08)	6.72(6.15-7.05)
Model B	2	Training	6.11(5.94-6.21)	6.00(5.78-6.21)
	2	Testing	6.07(5.91-6.21)	6.03(5.70-6.21)
	1	Training	3.95(3.53-5.24)	3.74(3.38-4.57)
	1	Testing	3.81(3.50-5.38)	3.62(3.35-4.65)

* MAE: Mean Absolute Error. Log chemical accuracy in Hartrees ≈ -2.80

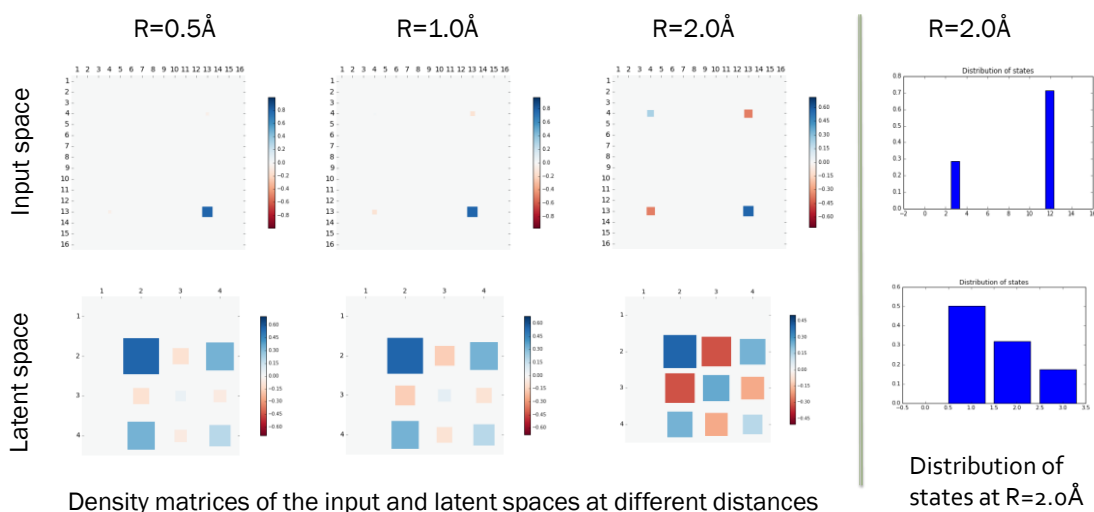
Average error in the fidelity after one cycle of compression and decompression using the quantum autoencoder trained from ground states of the Hydrogen molecule

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Compressed H₂

Romero, et al *Quant Sci Tech* 2 045011 (2017)

- Average fidelity in training set: 0.9895 - Average fidelity in testing set: 0.9873



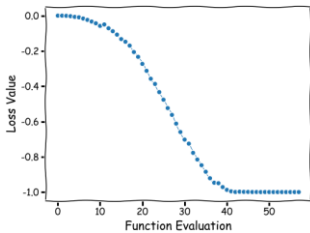
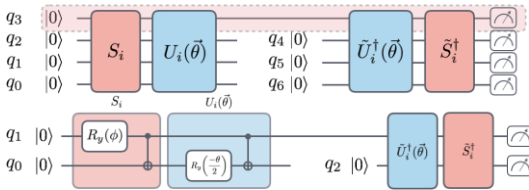
88

Twitter alert at 9:28 AM!

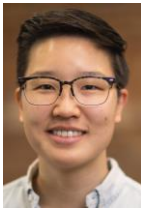


<https://medium.com/rigetti/qcompress-implementation-of-the-quantum-autoencoder-using-forest-and-openfermion-7f99f7e45ff8>

Experiment!: H₂ molecule (4-1-4, 2-1-2 autoencoder)



Run in Noiseless QVM

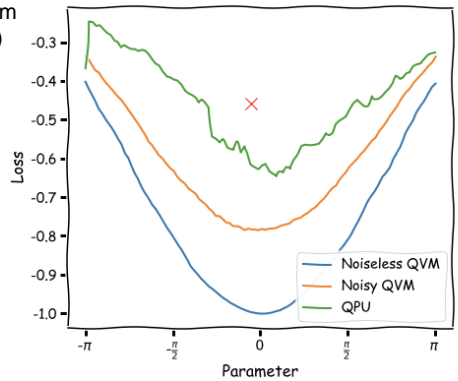


Hannah Sim (Harvard)



QCompress: Implementation of the Quantum Autoencoder using Forest and OpenFermion

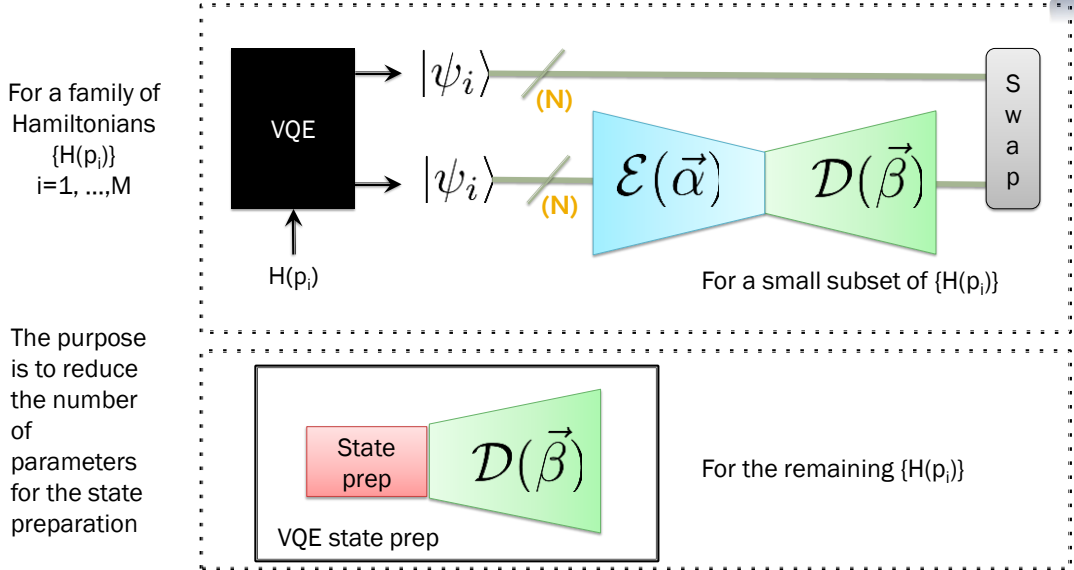
By Sukin (Hannah) Sim



<https://medium.com/rigetti/qcompress-implementation-of-the-quantum-autoencoder-using-forest-and-openfermion-7f99f7e45ff8>

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CUSP (Zapata Computing + Google) Autoencoder + Variational eigensolver

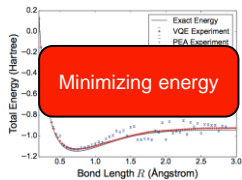


91

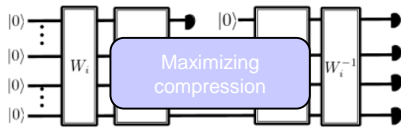
The age of variational quantum algorithms ... training quantum circuits.



Variational quantum eigensolver



Peruzzo et al. (2014)



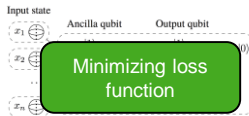
Quantum autoencoder

Romero, et al.

Quantum Sci. Technol. 2 (2017): 045001

Quantum adiabatic optimization algorithm

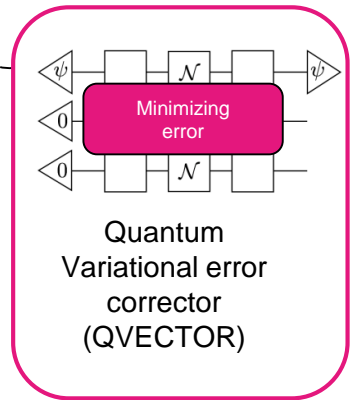
Farhi et al. (2014)



Cao, et al.

arXiv:1711.11240

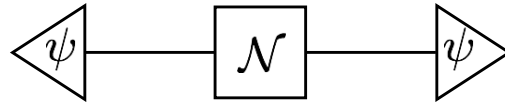
Quantum neuron



... and many other algorithms, e.g. Machine Learning

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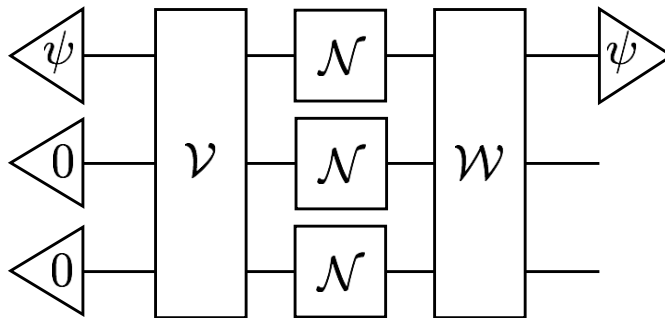
Quantum Error Correction in a Nutshell



$$\mathcal{F}_{\text{avg}} = \int d\psi \sum_i \langle \psi | N_i | \psi \rangle \langle \psi | N_i^\dagger | \psi \rangle$$

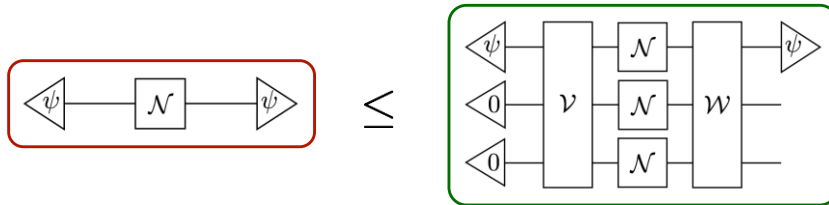
93

Quantum Error Correction in a Nutshell



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Quantum Error Correction in a Nutshell



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Quantum Error Correction in a Nutshell

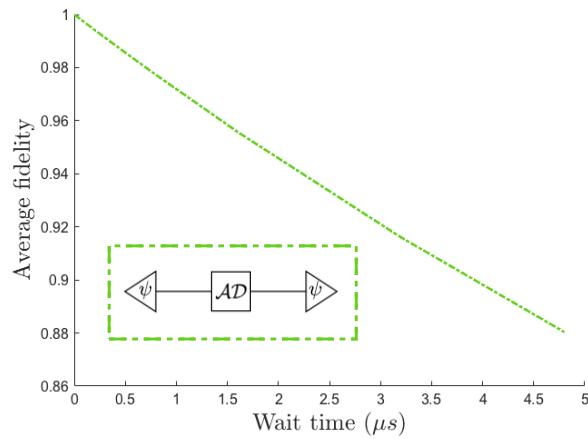


What is the quality of error correction for this process?

96



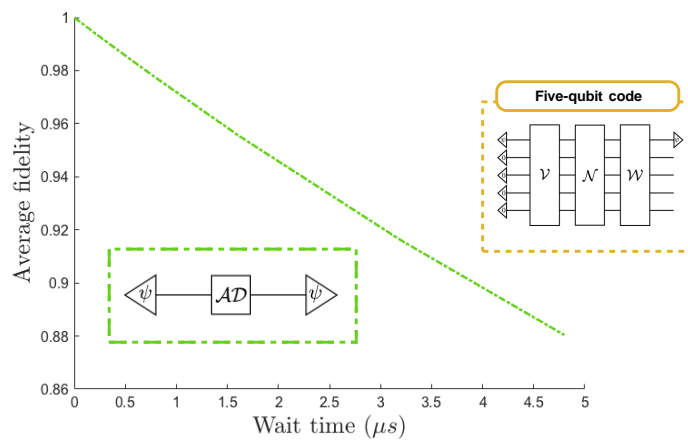
Single Qubit Decoherence



$$T_2 = 60\mu s = T_1/3$$

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Single Qubit Decoherence

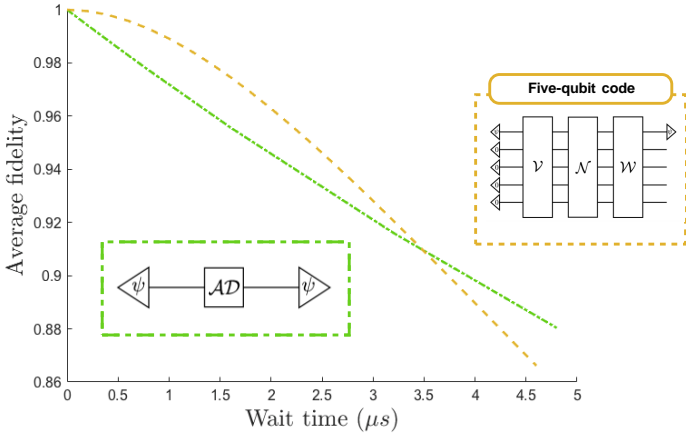


$$T_2 = 60\mu s = T_1/3$$

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Encode-Wait-Decode for 5-Qubit Stabilizer Code



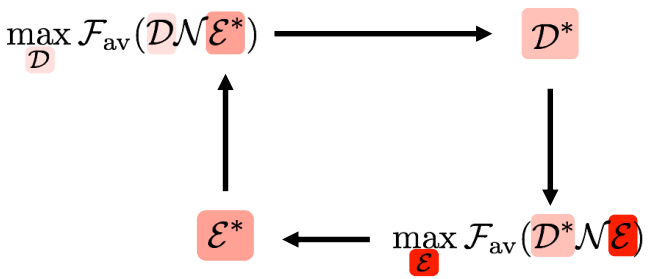
$$T_2 = 60\mu s = T_1/3$$

99

Bi-convex Optimization of Average Fidelity

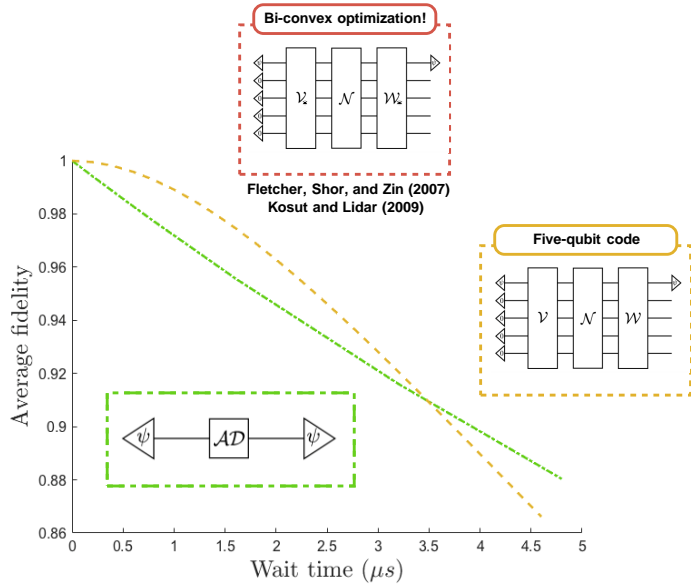


- 1) Solve SDP for optimal decoding
- 2) Plug in optimized decoding
- 3) Solve SDP for optimal encoding
- 4) Plug in optimized encoding
- 5) Repeat 1-4 until sufficient convergence of average fidelity



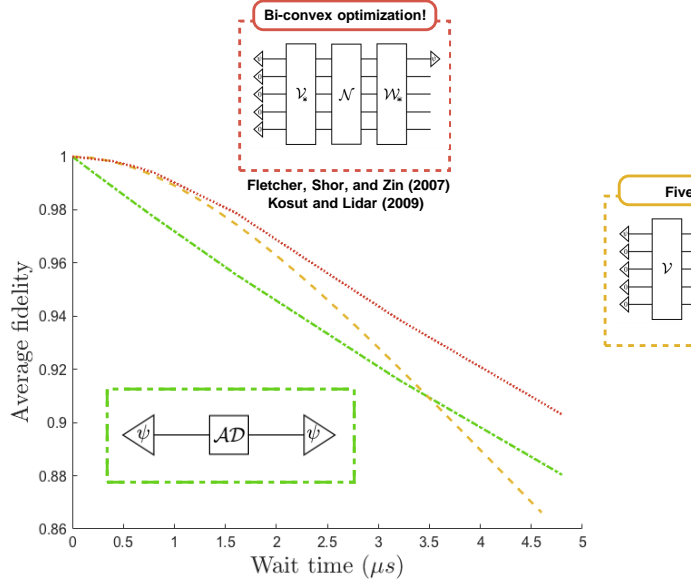
Fletcher, Shor, and Zin (2007) Kosut and Lidar (2009)

100



$$T_2 = 60\mu s = T_1/3$$

101



$$T_2 = 60\mu s = T_1/3$$

102





Previous Approaches

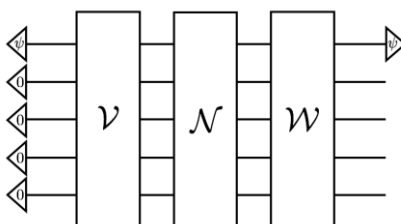
1. Require noise model
2. Optimization unscalable
3. Gate compilation needed

Our Algorithm (QVECTOR)

- Model Free
- Efficient Evaluation
- Built-in Gate Decomposition

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Quantum Variational Error CorrectOR

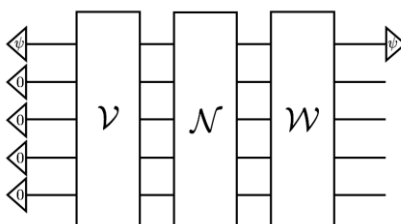


Variational quantum optimization algorithm for designing quantum error correcting schemes...

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QVECTOR



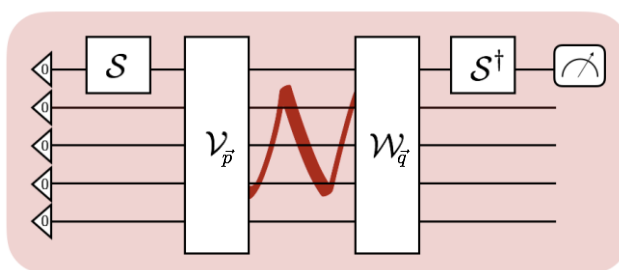
Variational quantum optimization algorithm for designing quantum error correcting schemes...

Objective: maximize average fidelity

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Model Free



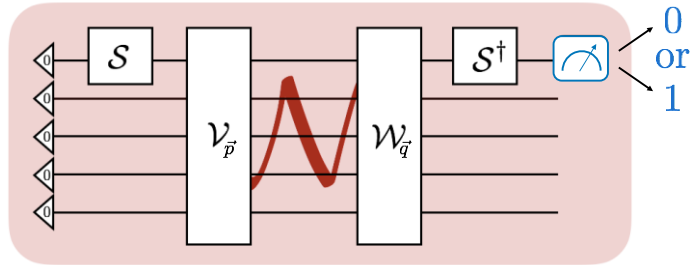
In situ optimization...

... noise “perfectly” simulates itself.

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Efficient Evaluation



N random samples S (from 2-design)

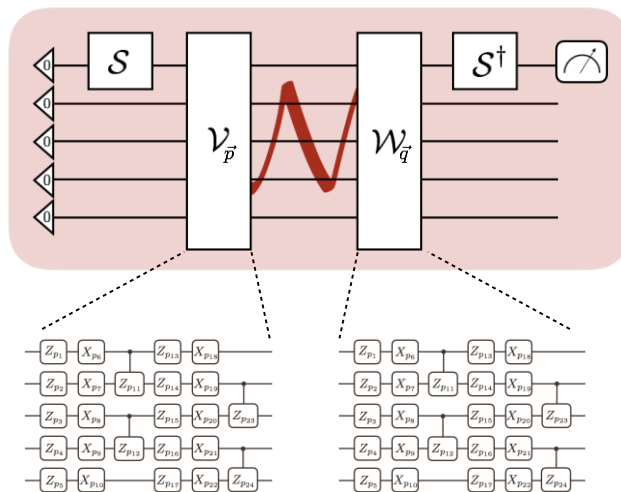
Fraction of 0-outcomes estimates average fidelity to $\mathcal{O}(1/\sqrt{N})$.

2-design samples from Clifford group instead of Haar-random unitaries

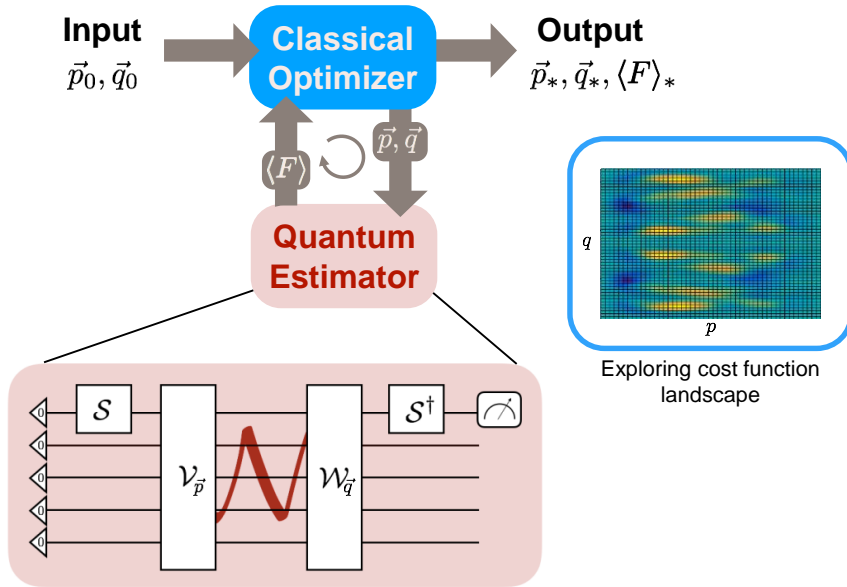
Dankert et al. (2009)

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Built-in gate decomposition

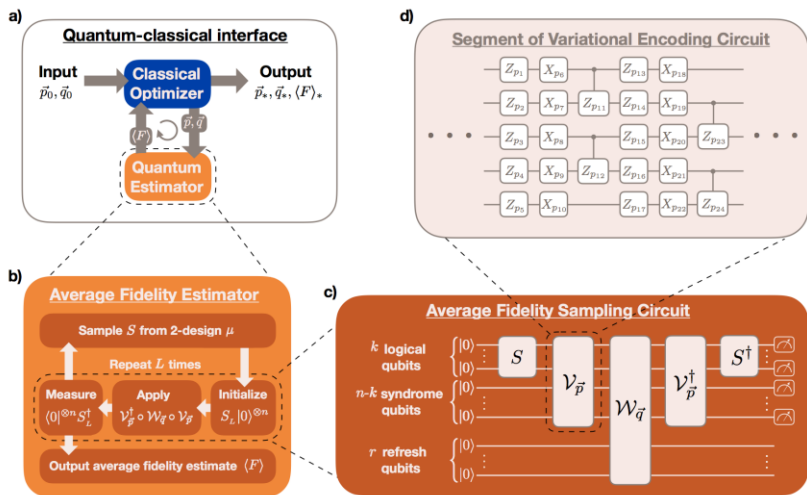


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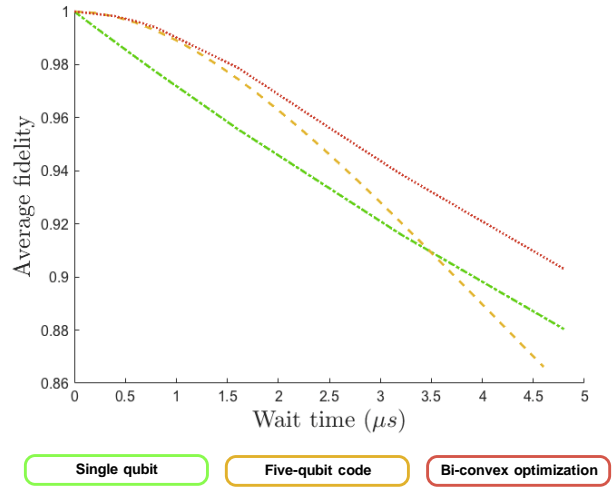


109

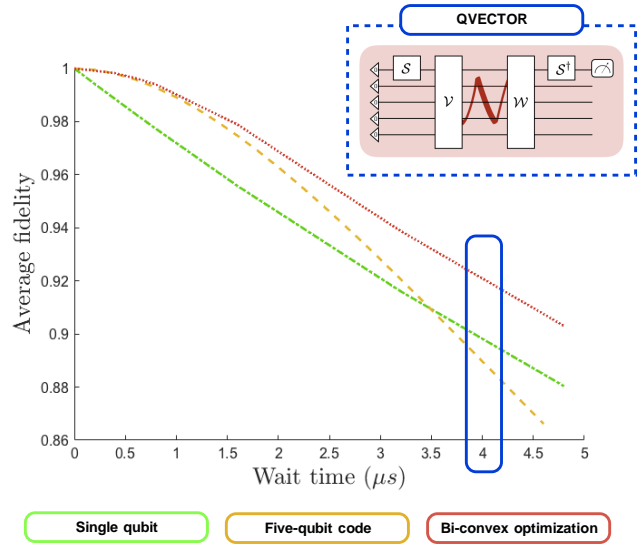
QVECTOR Schematic



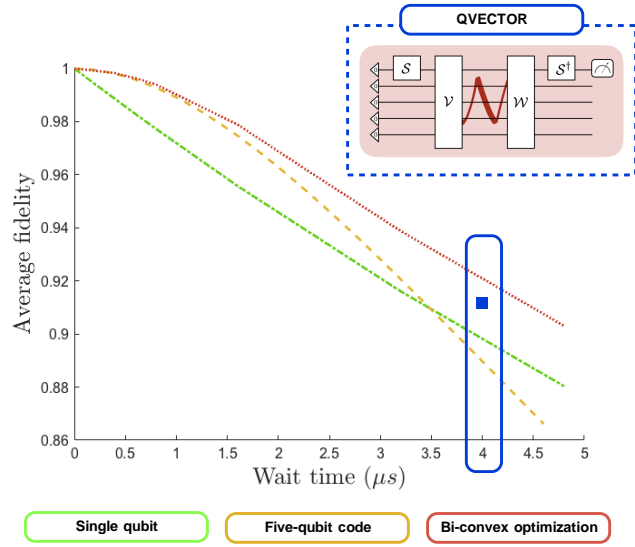
110



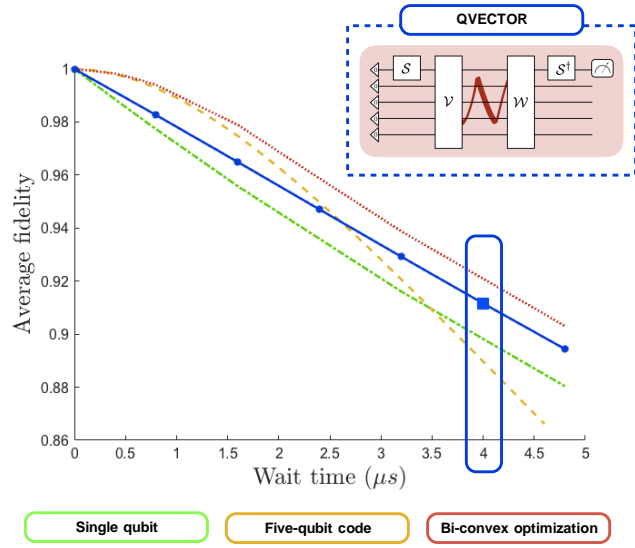
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The age of variational quantum algorithms ... training quantum circuits.



Variational quantum eigensolver

Minimizing energy

Peruzzo et al. (2014)

Maximizing compression

Quantum autoencoder

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

Quantum adiabatic optimization algorithm

Maximizing cut size

Farhi et al. (2014)

Minimizing error

Quantum Variational error corrector (QVECTOR)

Quantum neuron

Minimizing loss function

Cao, et al.
arXiv:1711.11240

... and many other algorithms, e.g. Machine Learning

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Basic requirements for quantum NN



1. Initial state encodes any N -bit binary string



2. Reflects one or more basic neural computing mechanisms

e.g. attractor dynamics, synaptic connections, integrate & fire, training rules, structure of a NN

3. The evolution is based on quantum effects

Superposition and entanglement

Schuld, M., Sinayskiy, I. & Petruccione, F. *Quantum Inf Process* (2014) 13: 2567

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QM + NN: an unlikely match ?

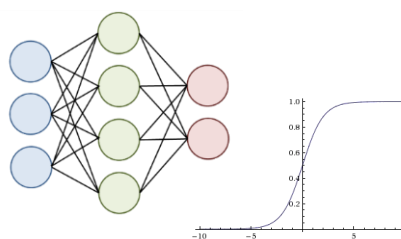
Quantum Mechanics (QM)

- Unitary evolution
- Rotation in Hilbert space



Neural Networks (NN)

- Lossy transformations
- Clustering, classification, compression etc



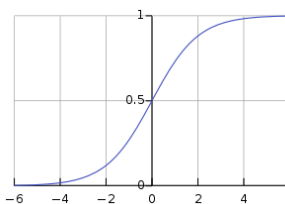
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Challenges



- Sigmoid / step function activation

How to realize on quantum computers, whose dynamics is **linear**?



Reversible circuits
Dissipative dynamics



Cost scaling?

- Measurement? Open system?

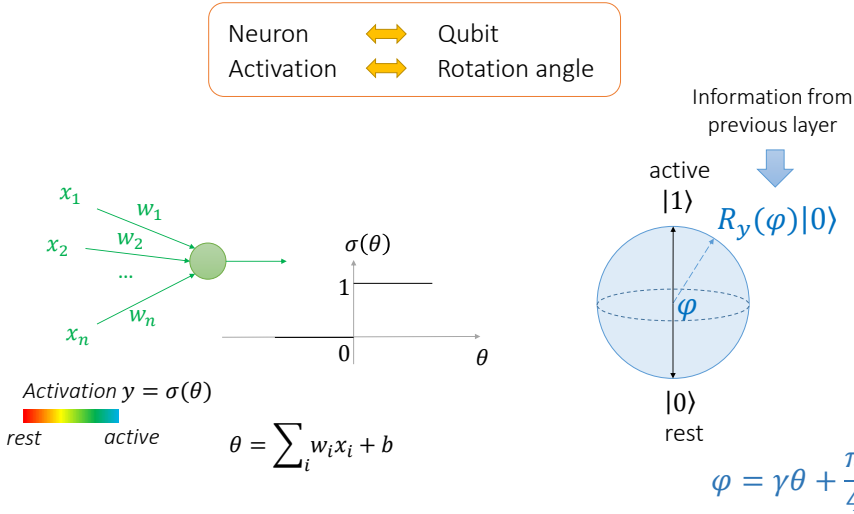
May collapse the state / reduce to classical probabilistic algorithms

Story of quantum error correction

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Our Proposal



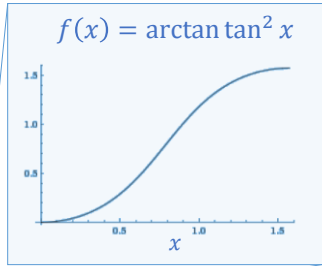
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Introduce Nonlinearity

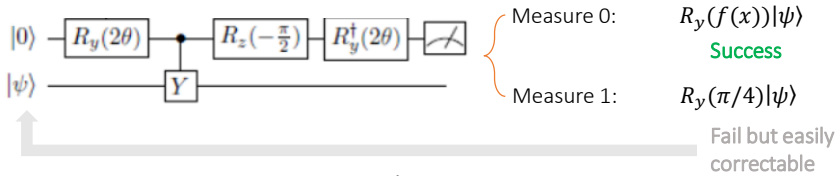
Repeat-until-success (RUS) circuits:

Given ability to realize $R_y(2x)$

One could use RUS to realize $R_y(2f(x))$



Nonlinear!



$$R_y(\theta) = \begin{pmatrix} \cos \frac{\theta}{2} & -\sin \frac{\theta}{2} \\ \sin \frac{\theta}{2} & \cos \frac{\theta}{2} \end{pmatrix}$$

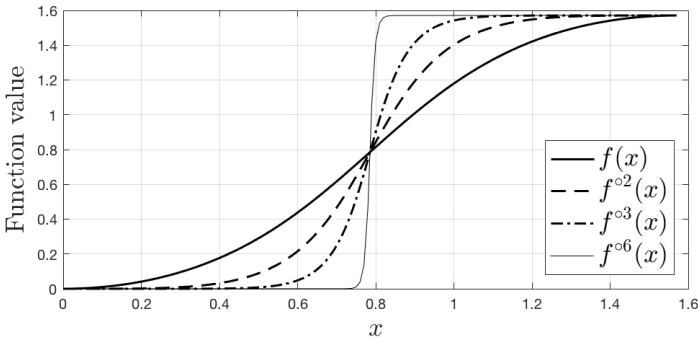
120



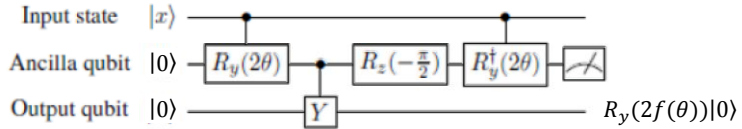
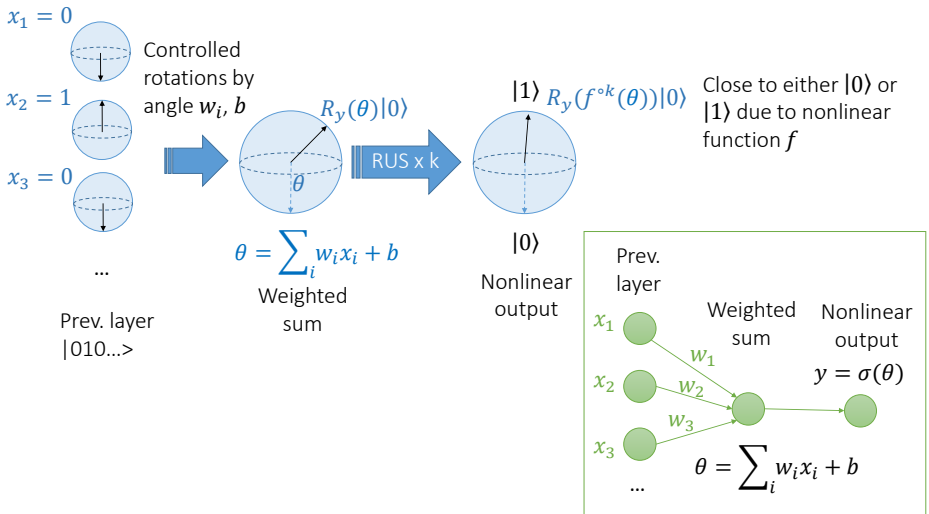


$$R_y(x) \rightarrow R_y(f(x)) \rightarrow \dots \rightarrow R_y(f^{\circ k}(x))$$

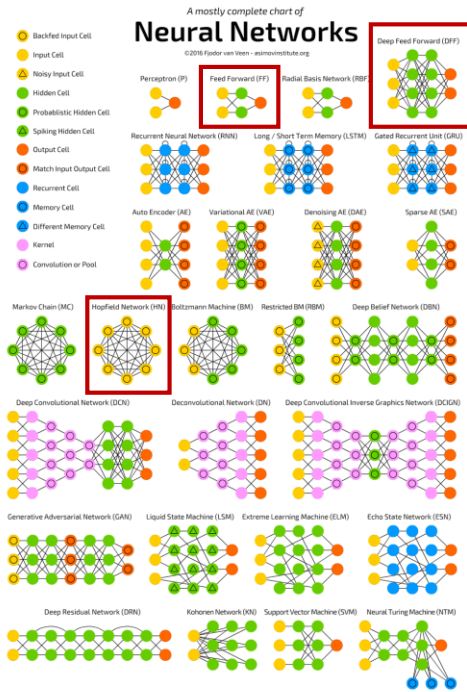
$$\underbrace{f(f(\dots f(x) \dots))}_{k \text{ times}} = f^{\circ k}(x)$$



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- Size
- Neuron type
- Connectivity
- Activation function
- Weight/bias setting
- Training method
- ...

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Feed Forward (FF)



Hopfield Network (HN)

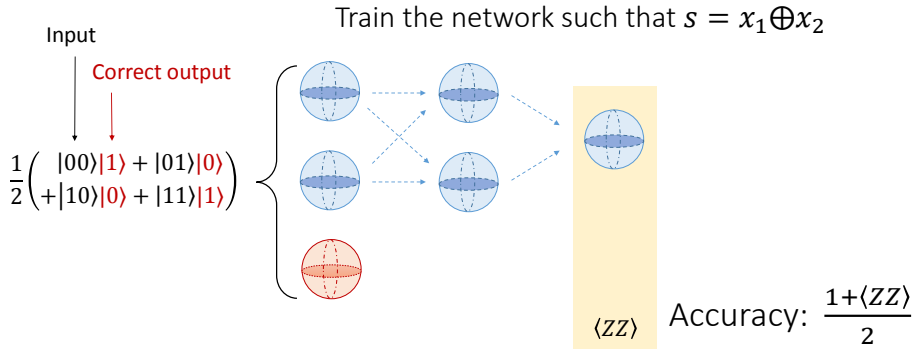
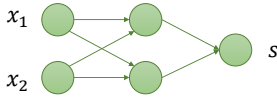


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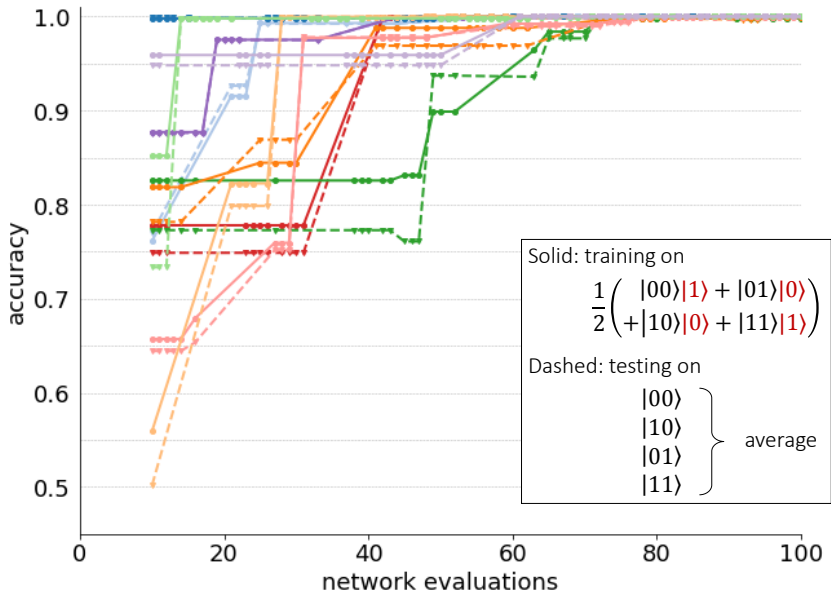


XOR Network

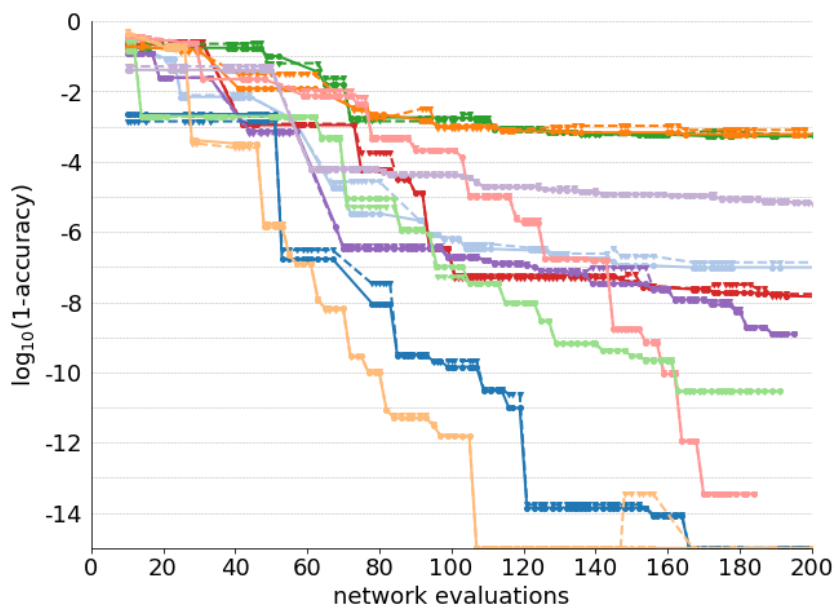
x_1	x_2	s
0	0	1
0	1	0
1	0	0
1	1	1



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Summary



- Building block for quantum neural network satisfying
 - Initial state encoding n -bit strings
Neuron \leftrightarrow Qubit
 - One or more neural computing mechanisms
Sigmoid/step function, attractor
 - Evolution based on quantum effects
Train with superposition of examples
- Application and extensions
 - Superposition of weights (networks) ?
 - Different forms of networks
 - Different activation functions

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Enter the quantum *software* era.

How about a *platform neutral*, near-term focused quantum software startup?

Look no further!

Z is the new Q



Zapata Computing

Email: info@zapatacomputing.com

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Collaborators



Jonathan Romero



Jonathan Olson



Hanna Sim



Peter Johnson



Yudong Cao



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Ville Bergholm (ISI)
Dominic Berry (McQuarrie)
Sergio Boixo (Google)
Jacob Biamonte (Skolkovo)
Rainer Blatt (Innsbruck)
P.-L. Dallaire Demers (Xanadu)
Jianfeng Du (USTC)
Gian-Giacomo Guerresci (Intel)
Stephen Jordan (NIST)
Cornelius Hempel (Sydney)
Joonsuk Huh (Pohang)
Ivan Kassal (Sydney)
N. Cody Jones (HRL)
Lucas Lamata (UPV)
Peter Love (Tufts)

Salvatore Mandrà (NASA)
John Martinis (Google)
Sarah Mostame (Intel)
Jarrod McClean (Google)
Masoud Mohseni (Google)
Hartmut Neven (Google)
Alejandro Perdomo-Ortiz (NASA)
Alberto Peruzzo (Sydney)
Enrique Solano (UPV)

Jeremy O'Brien (Bristol)
Bryan O'Gorman (NASA)
Peter O'Malley (Google)
Borja Peropadre (BBN)
Nicolas Sawaya (Intel)
Mikhail Smelyanskiy (Facebook)
Dave Wecker (Microsoft)
Annie Wei (MIT)
Jonathan Welch
James Whitfield (Dartmouth)
Andrew White (Queensland)
Nathan Wiebe (Microsoft)
Jörg Wrachtrup (Stuttgart)
Man-Hong Yung (Tsinghua)
Yoshi Yamamoto (Stanford)

Current quantum subgroup members

Yudong Cao
Peter Johnson
Ian Kivilchan
Mattias DeGroot
Jonny Olson
Tim Menke
Jonathan Romero
Hannah Sim

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Aspuru-Guzik Group

<http://matter.toronto.edu>

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 Profesor de Química y de Ciencias de
 Computación, Universidad de Toronto



Dra. Ingrid Montes
 La Junta de Directores, ACS
 Profesora de Química Orgánica, Universidad de
 Puerto Rico, Recinto de Río Piedras

Las imágenes de la presentación están disponibles para descargar ahora desde el panel de GoToWebinar
<http://bit.ly/ComputoCuantico>

El Webinar de hoy esta auspiciado por la Sociedad Química de México y the American Chemical Society

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C&EN pone a su disposición traducciones al español de sus artículos más populares.

August 14, 2018

La FDA aprueba la primera terapia con ARN interferente

El si a Onpattro pone fin a dos décadas de trabajo académico e industrial para llevar los ARN interferentes al mercado farmacéutico.

FDA approves first-ever RNAi therapeutic

Now for Onpattro caps two decades of academic and industry work to translate RNA interference from idea to drug.



July 31, 2018

El óxido nítrico del permafrost tibetano esconde malas noticias para el calentamiento global

Los científicos estiman que el deshielo podría liberar grandes cantidades de este gas de efecto invernadero.



Nitrous oxide from Tibetan permafrost packs global warming punch

Scientists estimate that thawing ground could be a major source of the greenhouse gas.

July 25, 2018

Peces sin olfato en los océanos acidificados

Los crecientes niveles de CO₂ podrían impedir que los peces encuentren comida o detecten sus depredadores.



Fish struggle to smell in acidic oceans

Rising CO₂ levels could stop fish finding food and detecting predators.

Gracias a una colaboración con la organización española Divúlgame.org, C&EN ahora es capaz de ofrecer traducciones al español de algunos de nuestros mejores contenidos. Queremos hacer de la ciencia de vanguardia más accesible a la comunidad química de habla española, y esta es nuestra contribución. Le da a los nacidos en España, América Latina, o los EE.UU., pero cuyo primer idioma es el español la oportunidad de leer este contenido en su lengua materna. Esperamos que les guste y sea de su utilidad.



Dr. Bibiana Campos Seijo
Editora en Jefe, C&EN

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