Noisy Intermediate-Scale Quantum algorithms

Alba Cervera-Lierta

Perspectives on Quantum Computation for Particle Physics (CERN)

July 15, 2021

the matter lab

UNIVERSITY OF TORONTO

Outlook

1. Quantum computing in the NISQ era
2. Variational Quantum Algorithms
3. Squeezing the NISQ lemon
4. Applications
5. Example: QML applied to quantum simulation
6. NISQ horizon

Quantum computing in the NISQ era

Quantum Computing in the NISQ era and beyond

John Preskill

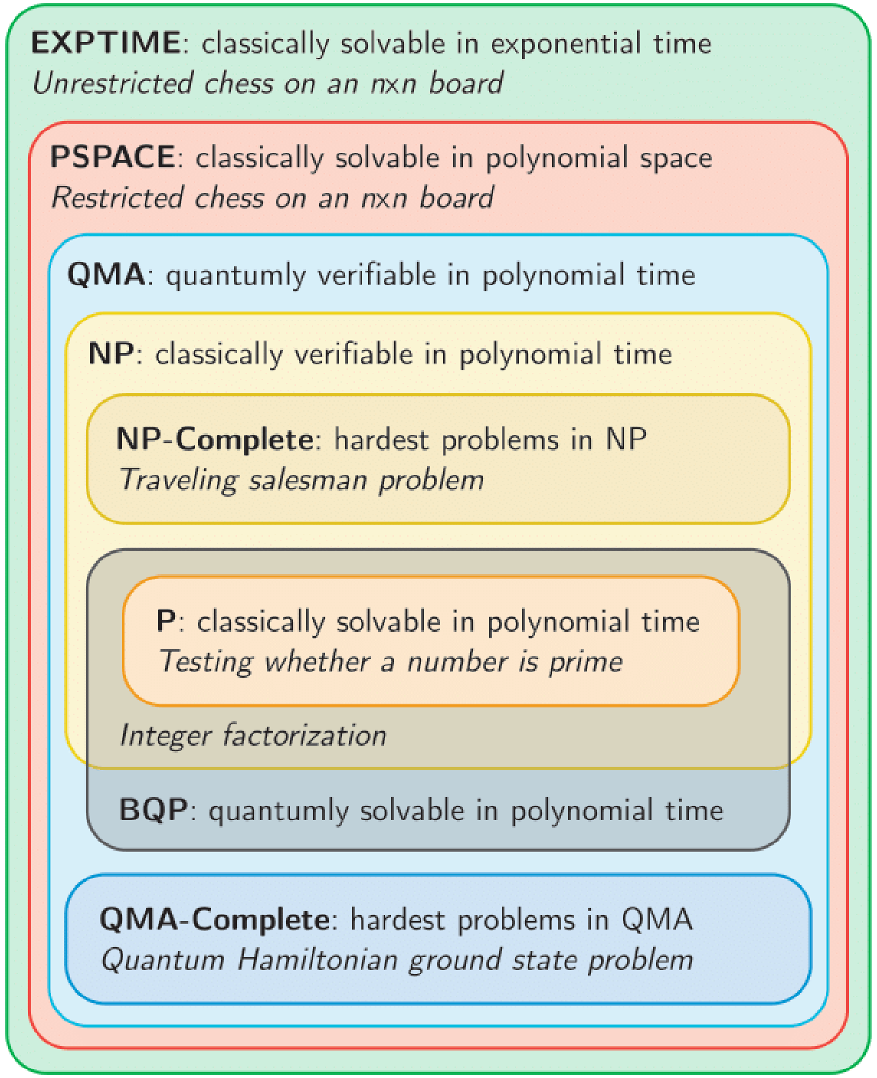
Quantum 2, 79 (2018)

Noisy intermediate-scale quantum (NISQ) algorithms

Kishor Bharti,[1,*] Alba Cervera-Lierta,[2,3,*] Thi Ha Kyaw,[2,3,*] Tobias Haug,[4] Sumner Alperin-Lea,[3] Abhinav Anand,[3] Matthias Degroote,[2,3,5] Hermanni Heimonen,[1] Jakob S. Kottmann,[2,3] Tim Menke,[6,7,8] Wai-Keong Mok,[1] Sukin Sim,[9] Leong-Chuan Kwek,[1,10,11,†] and Alán Aspuru-Guzik[2,3,12,13,‡]

arXiv:2101.08448

The power of quantum



Why do we need a quantum computer?

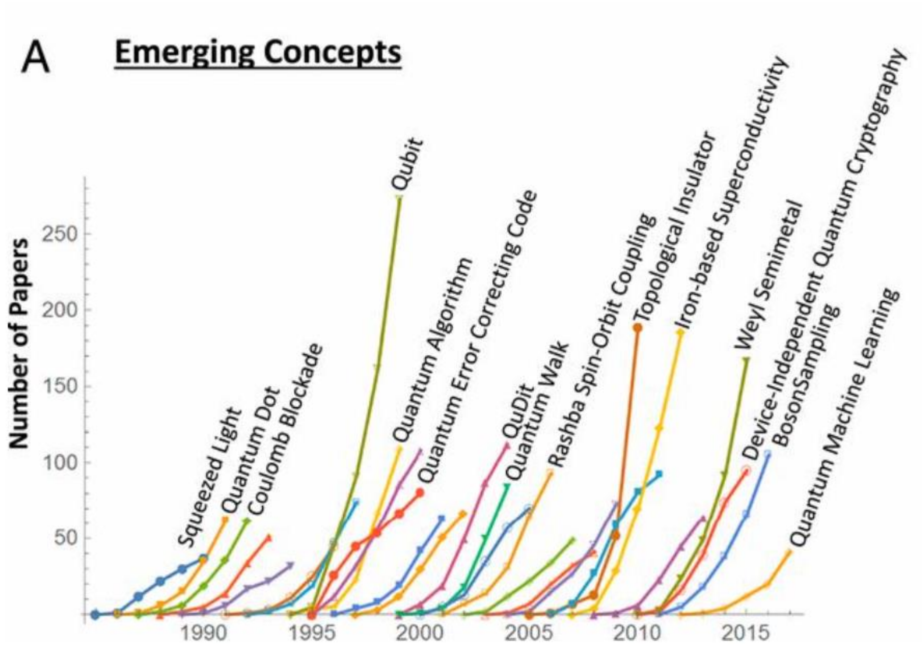
- Quantum simulation
- Solve problems beyond P and BPP

Quantum computers are powerful but not limitless

Which problems are BQP?

Approximate solutions to NP problems?

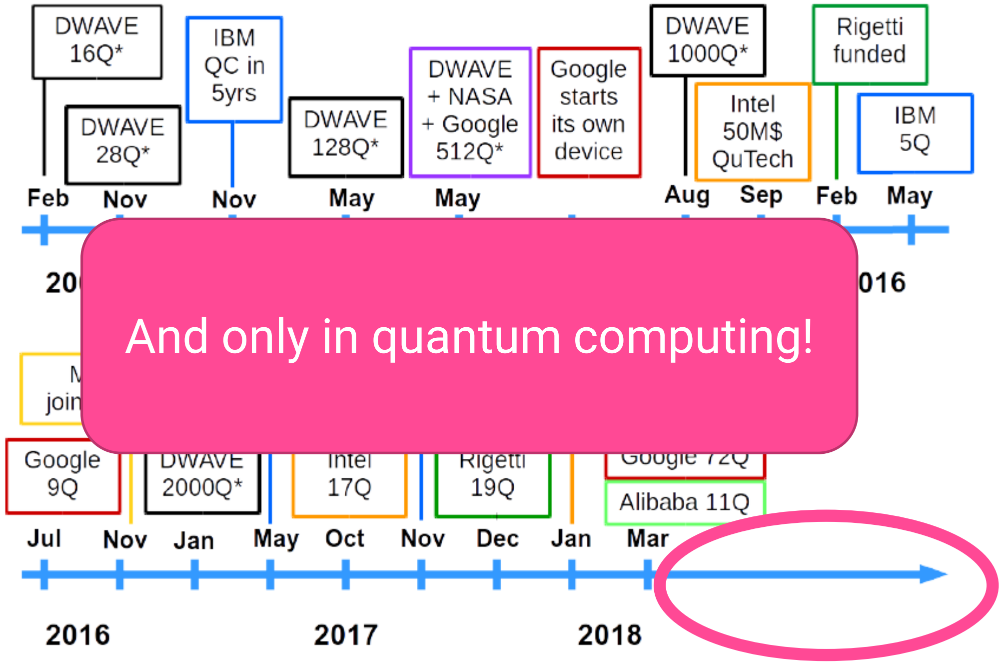
The power of quantum



qubit, April ’95, Schumacher, *Quantum coding*. PRA 51, 2738–2747

Predicting research trends with semantic and neural networks with an application in quantum physics, M. Krenn, A. Zeilinger, PNAS 117 (4) 1910-1916 (2020)

From a popular science talk in 2018:



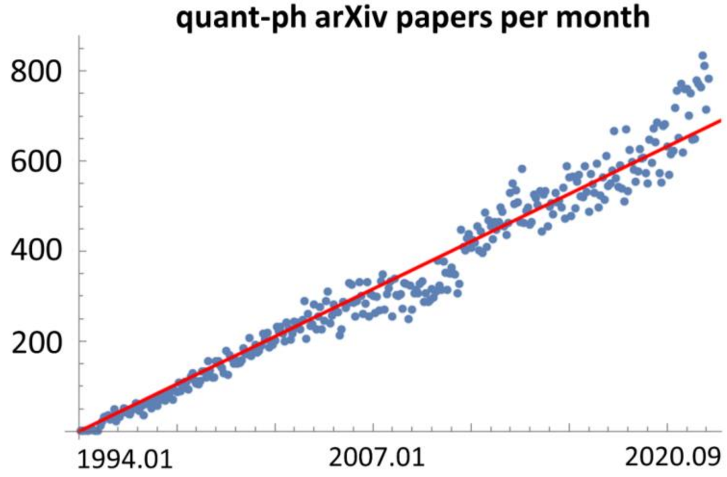
Trapped ions companies: IonQ, Honeywell, Alpine QT

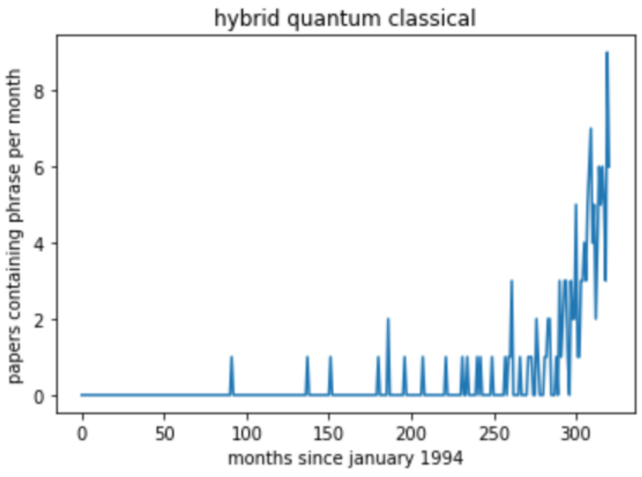
Quantum supremacy using a programmable superconducting processor, Google AI, Nature 574, 505(2019).

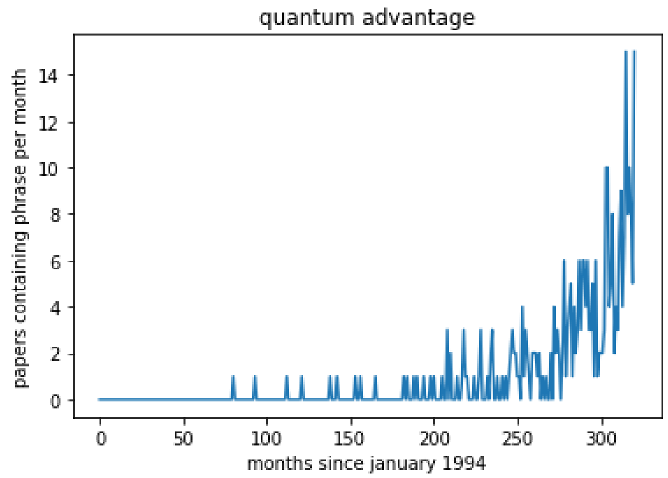
Quantum computational advantage using photons, USTC (Chao-Yang Lu, Jian-Wei Pan’s group), Science 370, 1460 (2020).

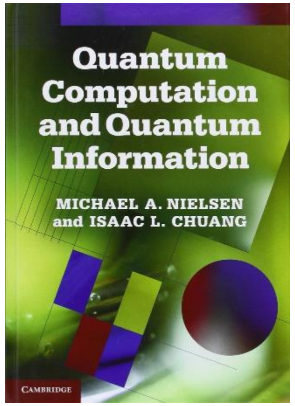
Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

Quantum is trendy





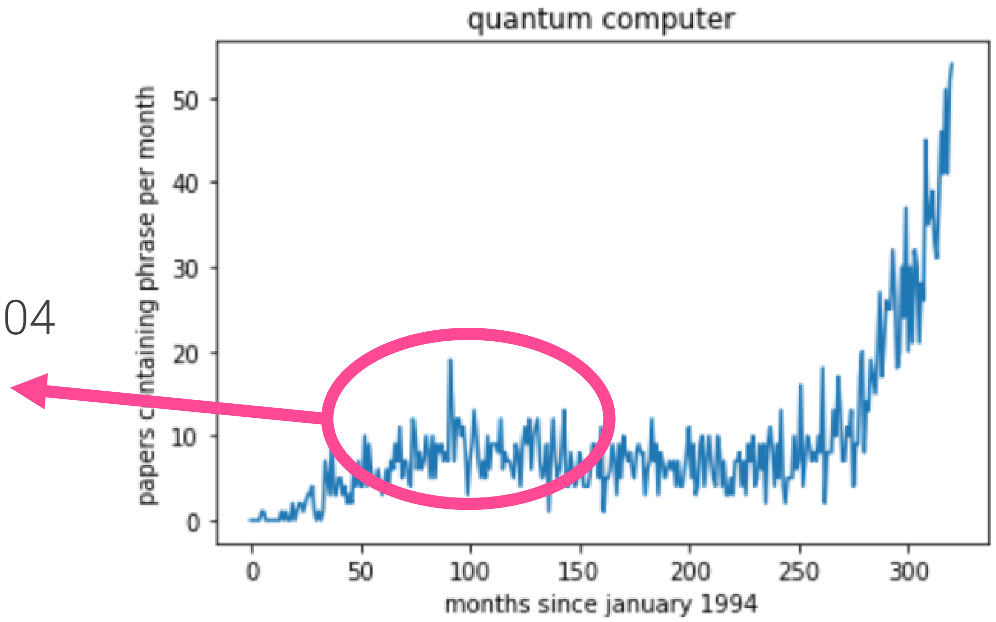




1st ed 2000
?

April 2000 – June 2004

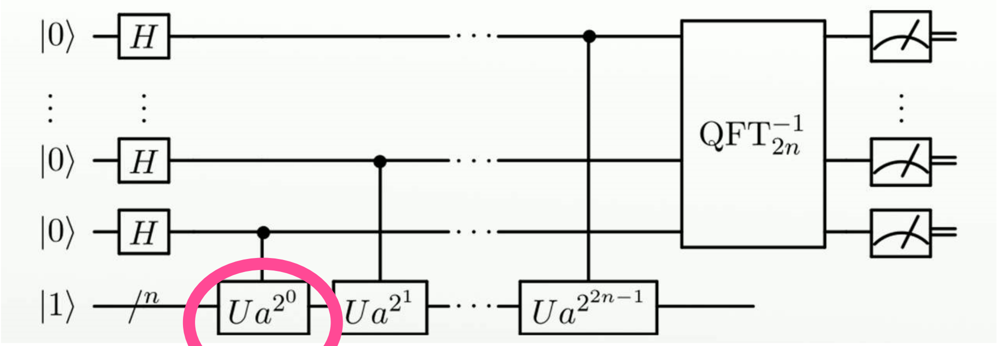
What happened?

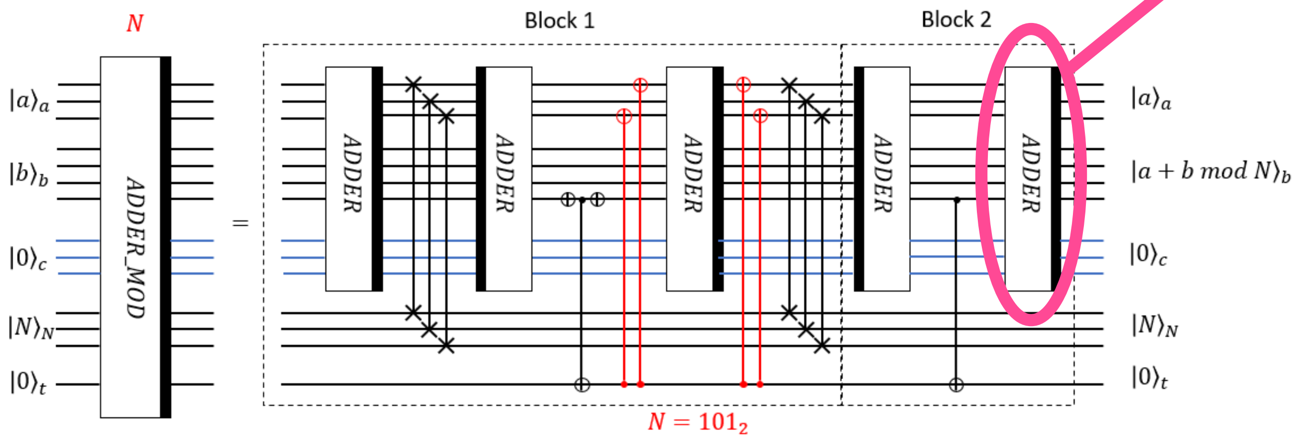


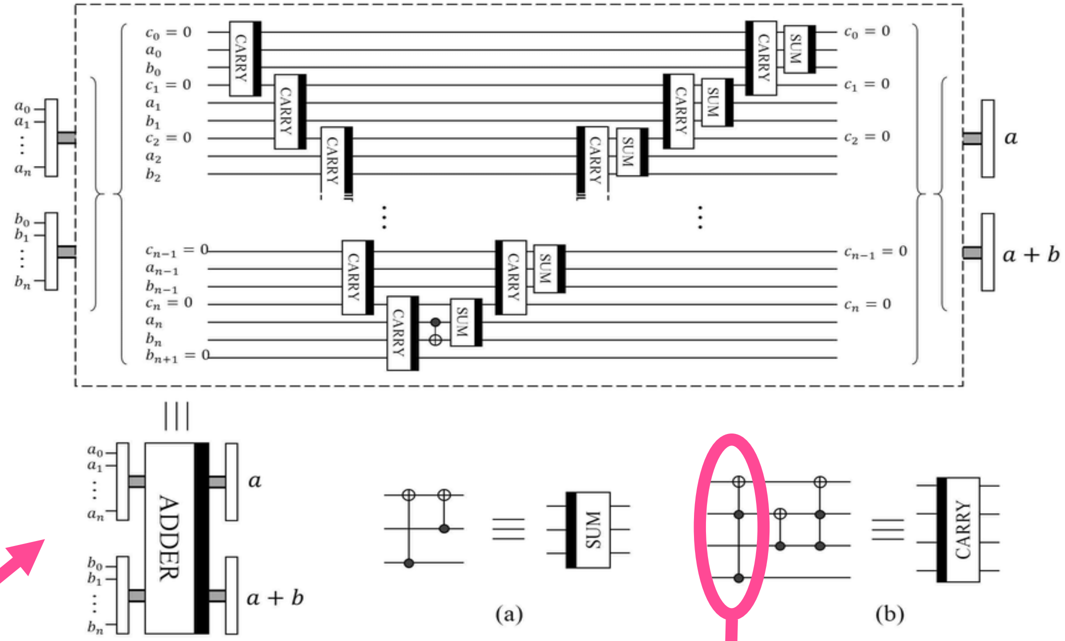
Credit: Mario Krenn @MarioKrenn6240

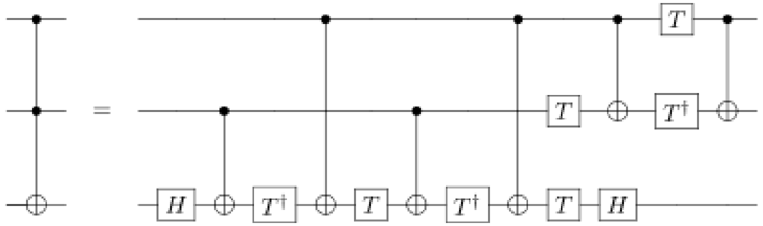
From theory to experiment

Integer factorization (Shor's) algorithm





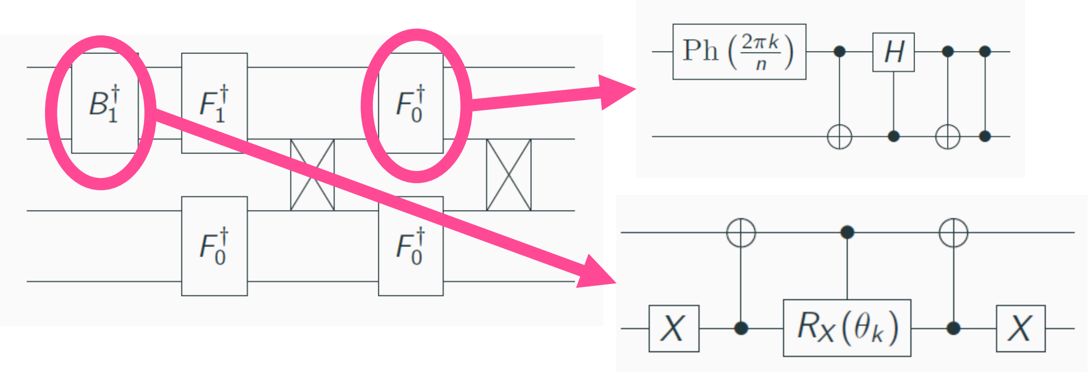


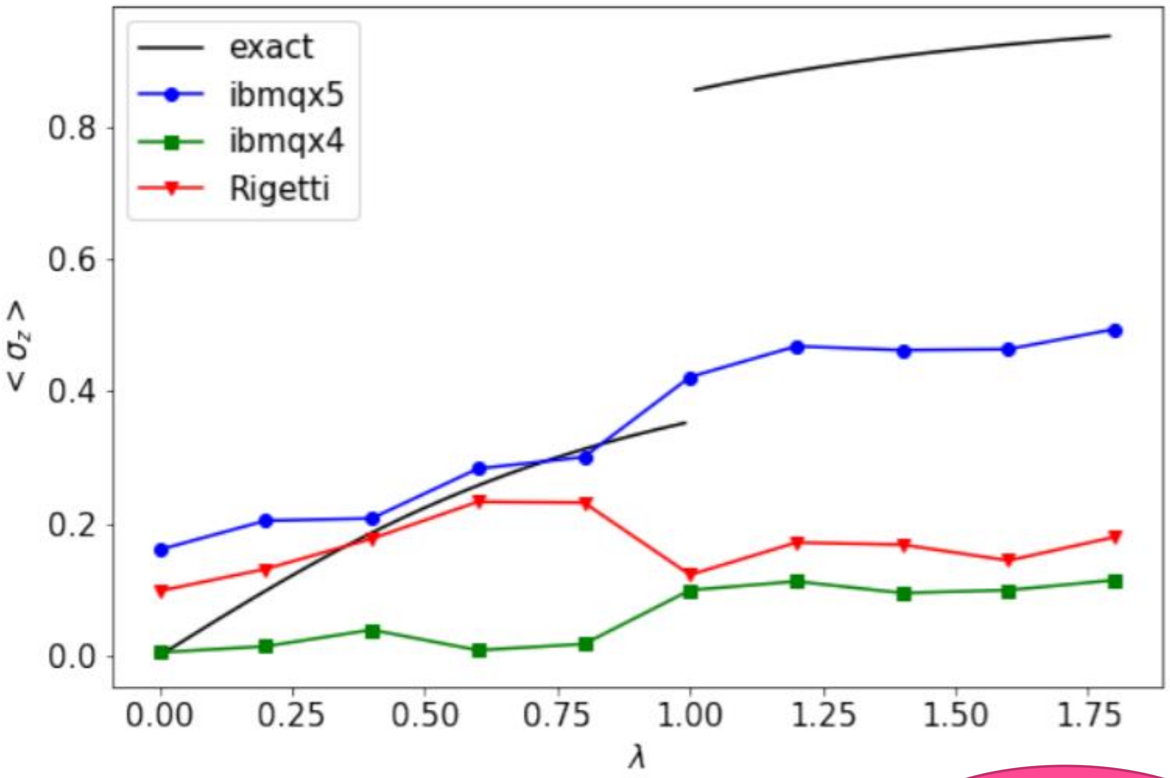


Shor, P.W. , IEEE Comput. Soc. Press: 124 (1994), A. Ekert, R. Jozsa, Rev. Mod. Phys. 68, 733 (1996)

From theory to experiment

Example: $n = 4$ Ising model simulation.





~35 gates circuit depth
~500 ns entangling gates
~100 ns single-qubit

<17500 ns = 17.5 μs

Qubits coherence time → ~50 μs

March-May 2018

Errors coming from readout, cross-talk, relaxation, … are relevant and difficult to track

F. Verstraete, J. I. Cirac, J. I. Latorre, Phys. Rev. A 79 032316 (2009), ACL, Quantum 2 114 (2018)

Noisy Intermediate-Scale Quantum

Why is QC hard experimentally?

- Qubits have to interact strongly (by means of the quantum logic gates)…
- …but not with the environment…
- …except if we want to measure them.

What is the state-of-the-art in digital quantum computing?

- ~50 qubit devices
- Error rates of ~10^-3
- No Quantum Error Correction (QEC)

Noisy Intermediate-Scale Quantum (NISQ) computing

- 50-100 qubits
- Low error rates
- No QEC

What can we do in NISQ?

- Good trial field to study physics
- Possible applications?
- A step in the path towards Fault Tolerant QC

Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

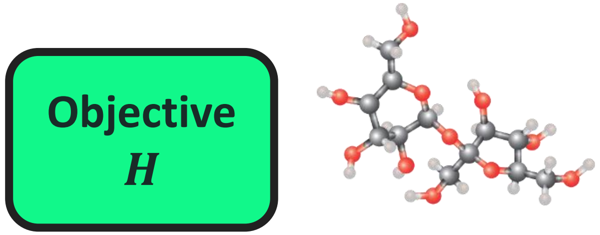
Variational Quantum Algorithms

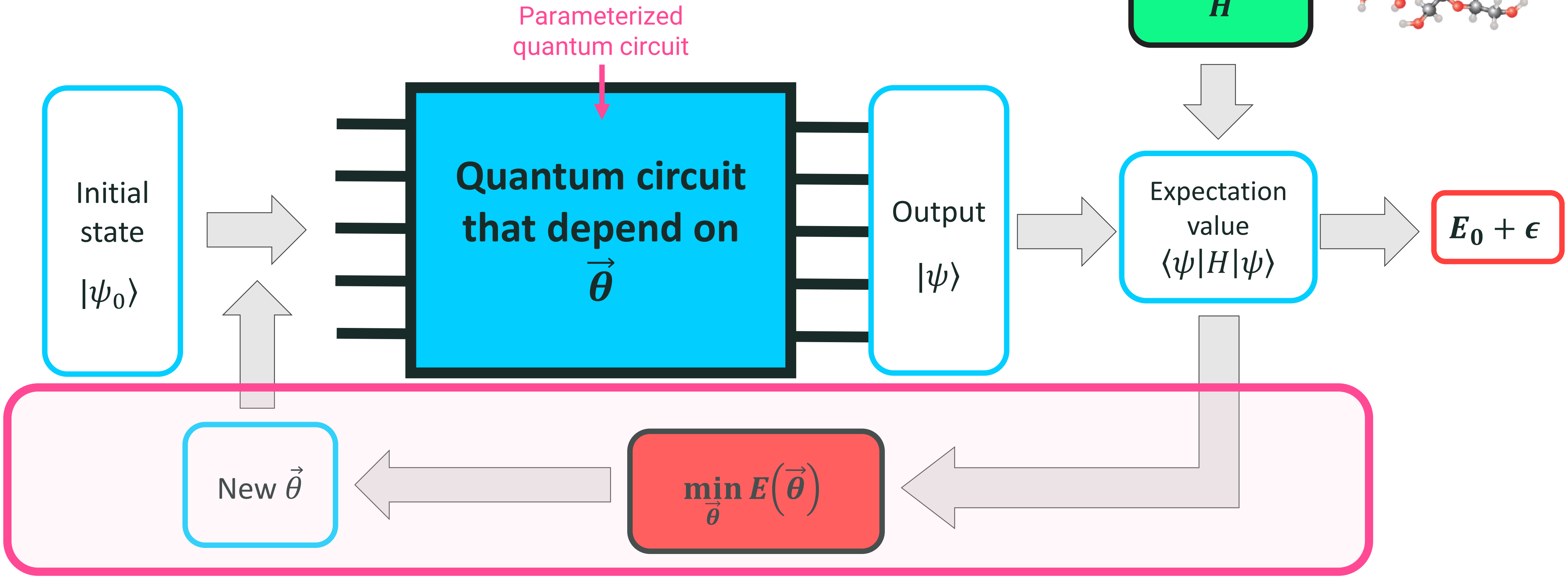
Variational Quantum Algorithms is one of the most used NISQ paradigms, but it is not the only one

The parents of VQA are the Variational Quantum Eigensolver (VQE) and the Quantum Approximate Optimization Algorithm (QAOA).

Variational Quantum Algorithms

e.g. Variational Quantum Eigensolver, Classifier, Autoencoder, QAOA…

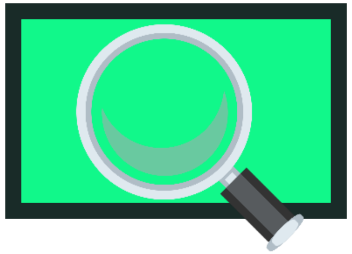




Classical optimization

Variational principle: $\mathrm{E} = \langle\psi|H|\psi\rangle \geq E_0$

Objective function



It encodes the problem in a form of a quantum operator, e.g. a Hamiltonian

$$\langle H \rangle_{\mathcal{U}(\boldsymbol{\theta})} \equiv \langle 0 | \mathcal{U}^{\dagger}(\boldsymbol{\theta}) H \mathcal{U}(\boldsymbol{\theta}) | 0 \rangle$$

The objective is decomposed into Pauli strings which expectation value can be measured with the quantum computer.

$$H = \sum_{k=1}^{M} c_k \hat{P}_k \longrightarrow \langle H \rangle_{\mathcal{U}} = \sum_{k=1}^{M} c_k \langle \hat{P}_k \rangle_{\mathcal{U}}$$

An objective can also be the fidelity w.r.t. a particular target state that we are trying to match.

$$F\left(\Psi, \Psi_{\mathcal{U}(\boldsymbol{\theta})}\right) \equiv |\langle \Psi | \Psi_{\mathcal{U}(\boldsymbol{\theta})} \rangle|^2$$

We can use projectors or SWAP test to obtain the value of that fidelity

$$\max_{\boldsymbol{\theta}} F\left(\Psi, \Psi_{U(\boldsymbol{\theta})}\right) = \min_{\boldsymbol{\theta}} \left(-\langle \hat{\Pi}_{\Psi} \rangle_{\mathcal{U}(\boldsymbol{\theta})}\right)$$

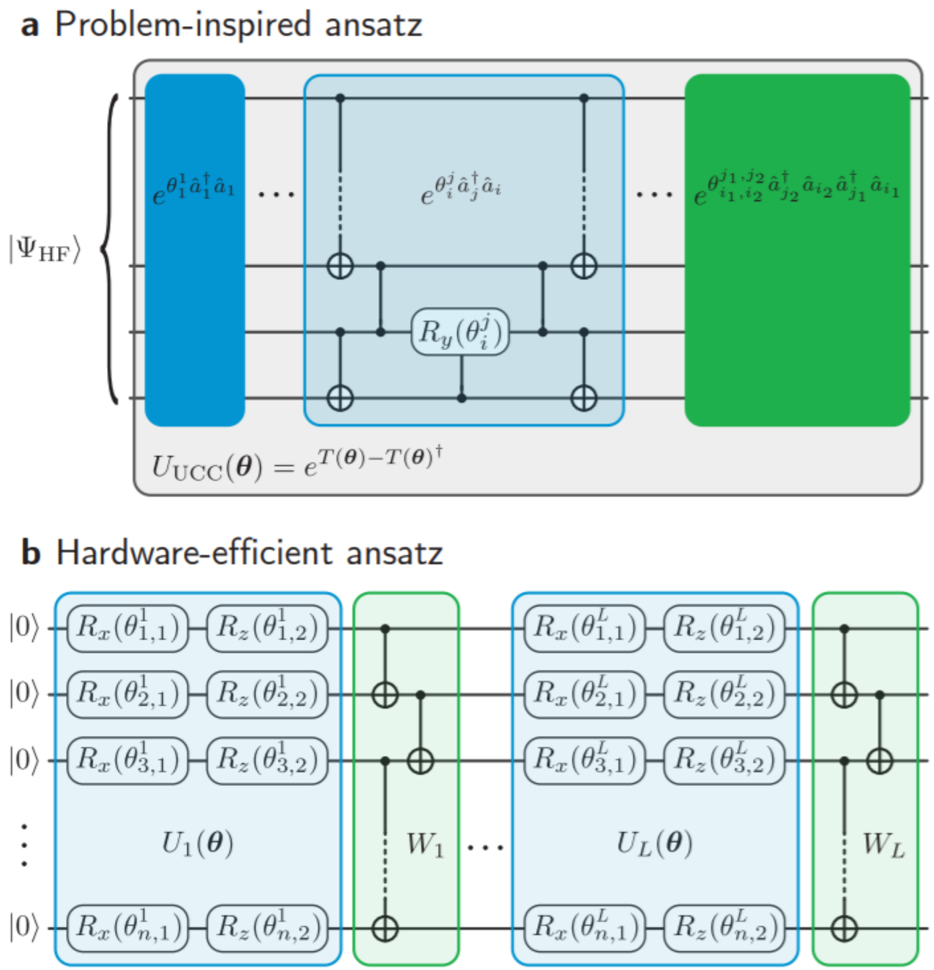
Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

Parameterized quantum circuits

It prepares what will eventually be the approximation of the g.s. of our Objective function.

It depends on a series of parameters that have to be finetunned to minimize the objective

They can be designed from a physical point of view (e.g. UCC, QAOA,...) or from a practical point of view (using a limited set of gates and circuit topology).



Classical optimization

We need to navigate the quantum circuit parameter space, e.g. by using gradiend based methods

$$\theta_i^{(t+1)} = \theta_i^{(t)} - \eta \, \partial_i f(\boldsymbol{\theta})$$

The gradients are expectation values of the quantum circuit derivatives w.r.t. a parameter.

Example: parameter-shift rule

$$\mathcal{U}(\boldsymbol{\theta}) = V(\boldsymbol{\theta}_{\neg i}) G(\theta_i) W(\boldsymbol{\theta}_{\neg i}) \qquad G = e^{-i\theta_i g}$$

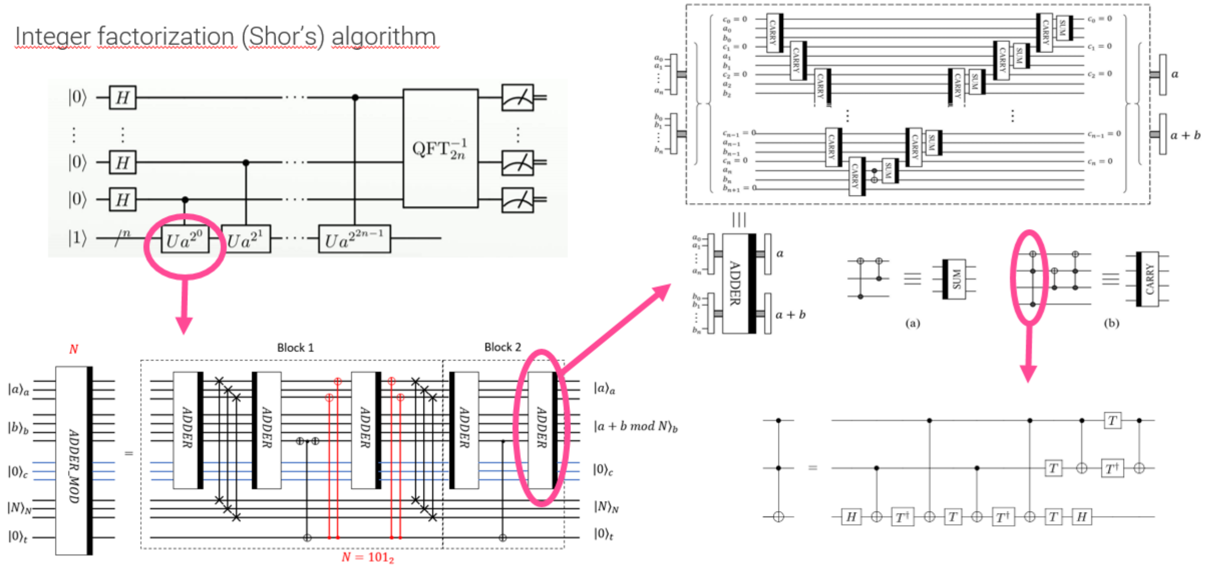
Eigenvalues of g are $\pm\lambda$

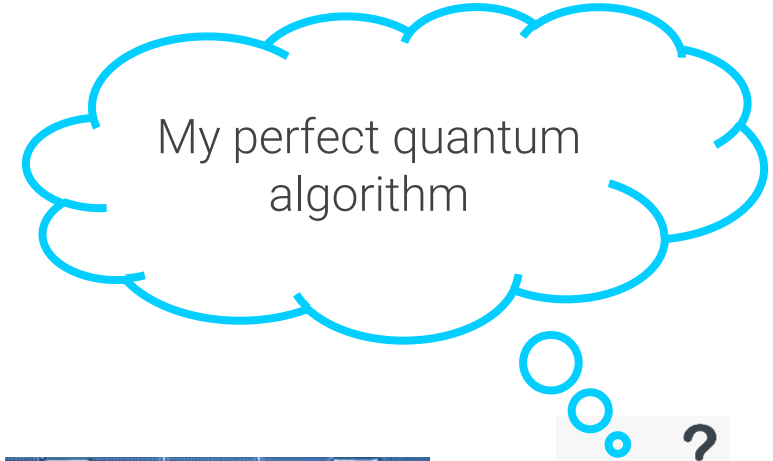
$$\partial_i \langle f(\boldsymbol{\theta}) \rangle = \lambda \left(\langle f(\boldsymbol{\theta}_+) \rangle - \langle f(\boldsymbol{\theta}_-) \rangle \right) \qquad \boldsymbol{\theta}_\pm = \boldsymbol{\theta} \pm (\pi/4\lambda) \boldsymbol{e}_i$$

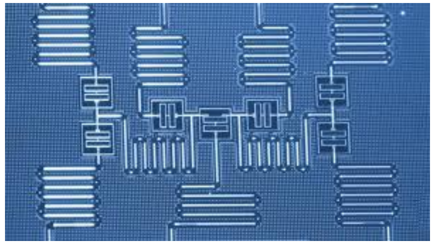
Gradient-free: genetic algorithms, reinforcement learning, …

Squeezing the NISQ lemon

Integer factorization (Shor's) algorithm







Quantum Error Mitigation

A set of classical post-processing techniques and active operations on hardware that allow to correct or compensate the errors from a noisy quantum computer.

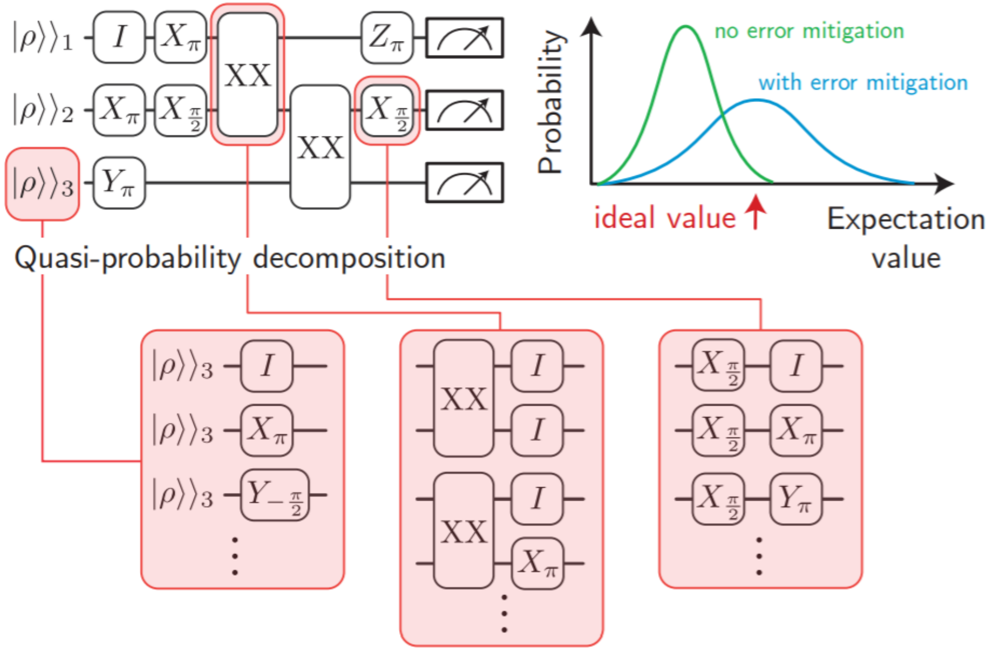
Zero-noise extrapolation

Instead of running our circuit unitary U, we run different circuits $U(UU^{\dagger})^{n}$ (increasingly noisy). Extrapolate the result for zero-noise U

Stabilizer based approach

relies on the information associated with conserved quantities such as spin and particle number conserving ansatz. If any change in such quantities is detected, one can pinpoint an error in the circuit.

Probabilistic error cancellation



Quantum Error Mitigation

Quantum Optimal Control strategies

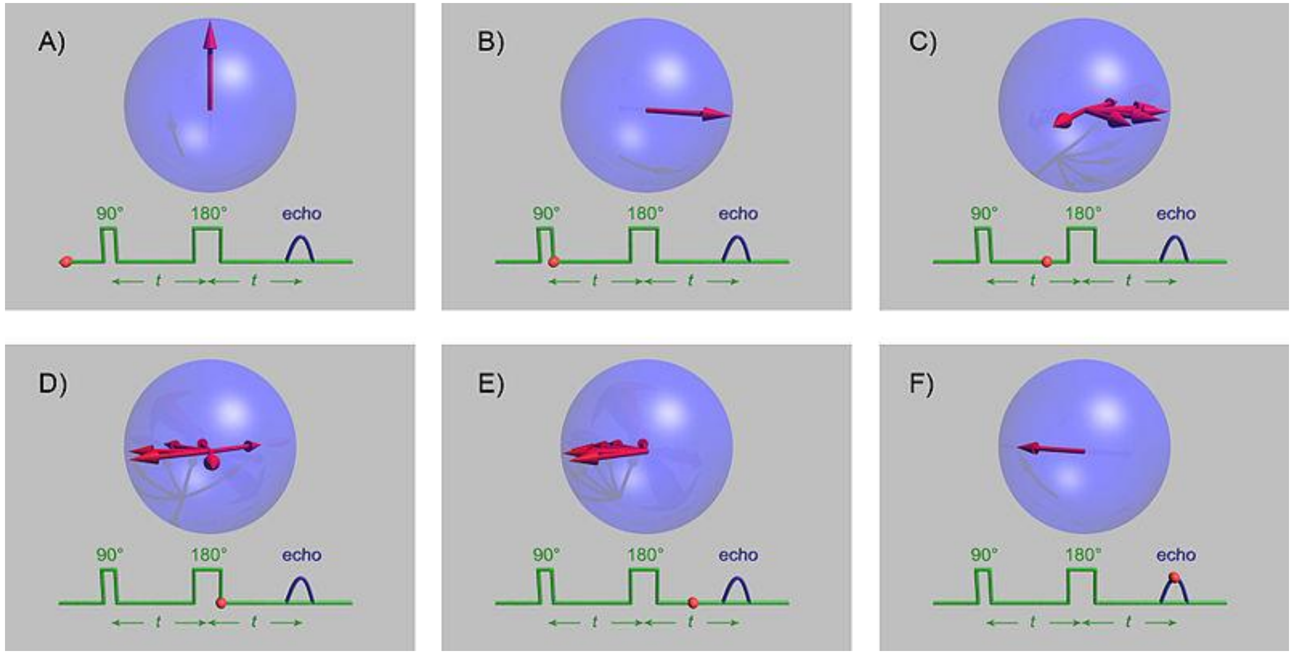
Dynamical Decoupling:

Designed to suppress decoherence via fancy pulses to the system so that it cancels the system-bath interaction to a given order in time dependent perturbation theory

Pulse shaping technique:

passive cancellation of system-bath interaction.

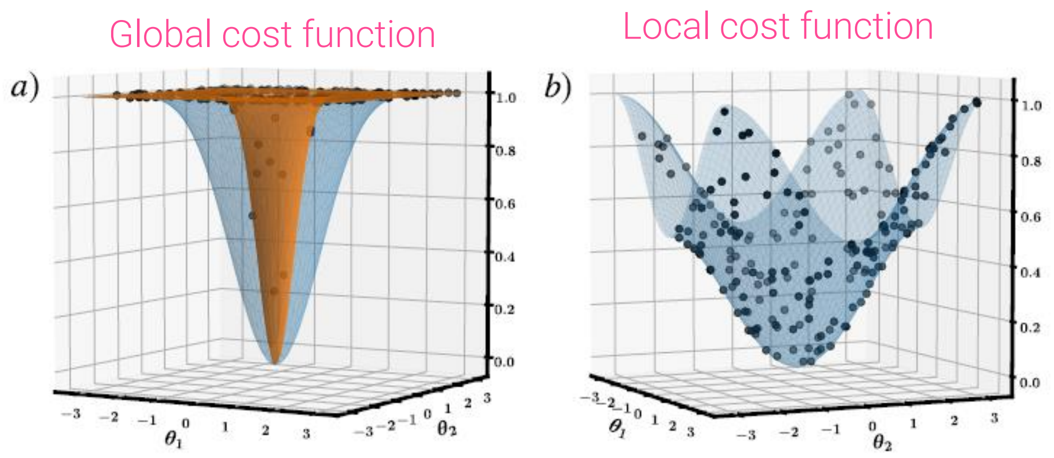
Among many others…



The *barren-plateaux* problem

Compute the gradients with the quantum circuit and use these values to run a classical minimizer, e.g. Nelder-Mead, Adam, …

With no prior knowledge about the solution, $\vec{\theta}$ parameters are initialized at random.



Consequence: *barren-plateaux*

The expected value of the gradient is zero!
The expected value of the variance is also zero!

Solutions

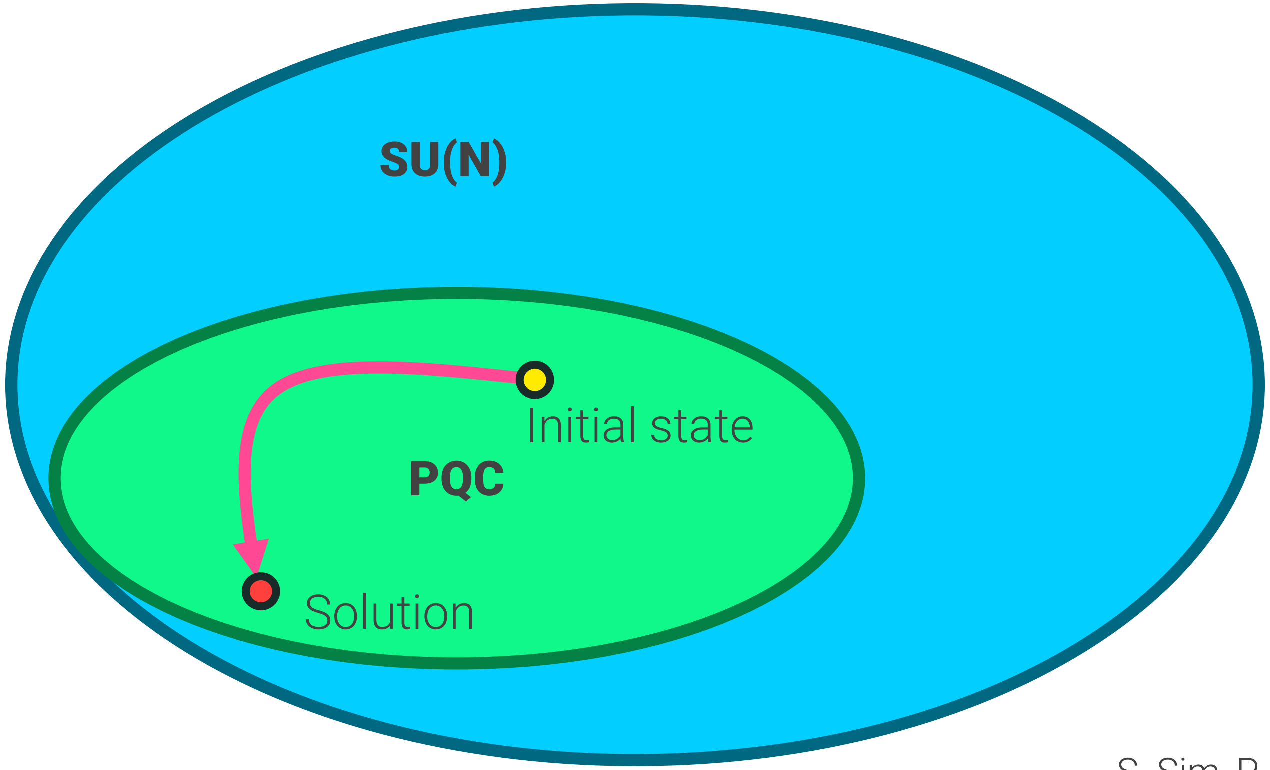
- Use parameters close to the solution.
- Use local cost functions instead of global ones.
- Introduce correlations between parameters.

Ref.: M. Cerezo *et. al.* arXiv:2001.00550v2 [quant-ph]

- McClean, J.R., Boixo, S., Smelyanskiy, V.N. et al. Nat Commun 9, 4812 (2018)

Expressibility

When setting a PQC ansatz we have to be careful to not narrow the Hilbert space accesible by the PQC so we can reach a good approximation of the solution state.

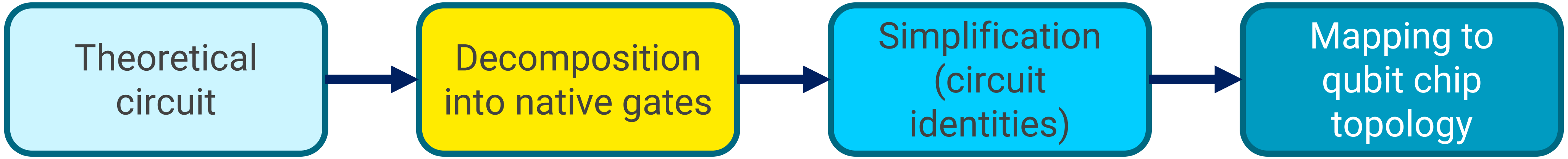


We can quantify the expressibility of a PQC by computing the distance between a Haar distribution of the states and states generated by the PQC.

$$A_U^{(t)} = \left\| \int_{\text{Haar}} (|\psi\rangle\langle\psi|)^{\otimes t} d\psi - \int_{\boldsymbol{\theta}} (|\psi_{\boldsymbol{\theta}}\rangle(\langle\psi_{\boldsymbol{\theta}}|)^{\otimes t} d\psi_{\boldsymbol{\theta}} \right\|$$

S. Sim, P. D. Johnson, A. Aspuru-Guzik, Adv. Quantum Technol. 2 1900070 (2019)

Circuit compilation



Native and universal gate sets:

Solovay-Kitaev theorem: With a universal gate set we can approximate with epsilon accuracy any SU(N) with a circuit of polynomial depth.

Gottesman–Knill theorem: Circuits composed by gates from the Clifford group (Clifford circuits) can be simulated efficiently with a classical computer.

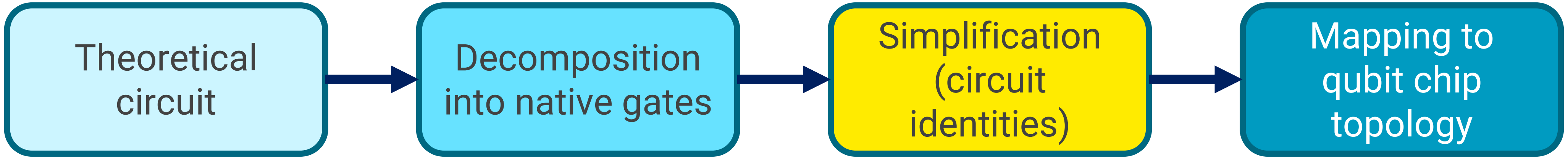
Gate sets are usually composed by Clifford gates + one non-clifford gate, e.g. {H, S, CNOT} + T

However, depending on the hardware implementation, some gates are easier to control.
e.g. CZ gates for superconducting circuits, XX gates for trapped ions.

The more native gates, the shorter and simpler the circuit

Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

Circuit compilation



Circuit simplification: use identities or tools like the ZX calculus (graph representation of quantum circuits)

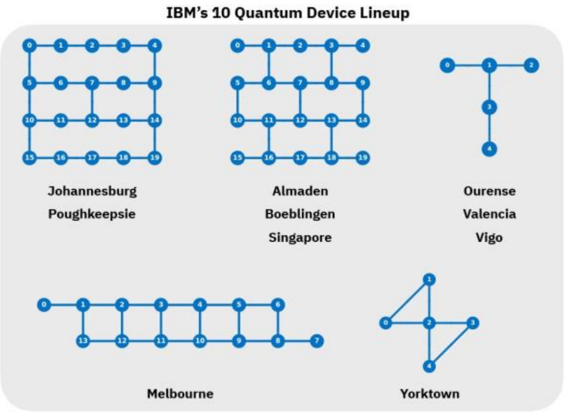
"Interacting quantum observables: categorical algebra and diagrammatics",
B. Coecke, R. Duncan, NJP 13 (4): 043016 (2011).

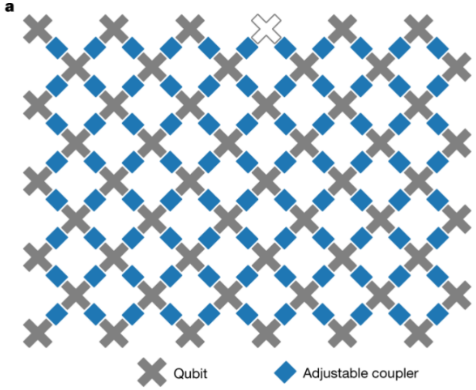
Circuit compilation

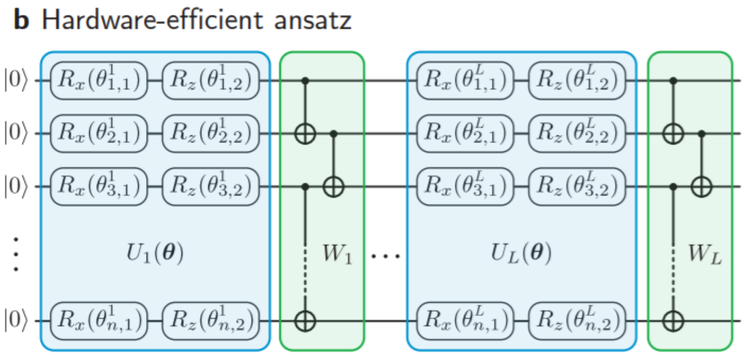
Theoretical circuit → Decomposition into native gates → Simplification (circuit identities) → Mapping to qubit chip topology

Circuit simplification: use identities or tools like the ZX calculi (graph representation of quantum circuits)

Qubits connectivity problem: not all qubits are physically connected, so we have to map our quantum circuits to the real devices.



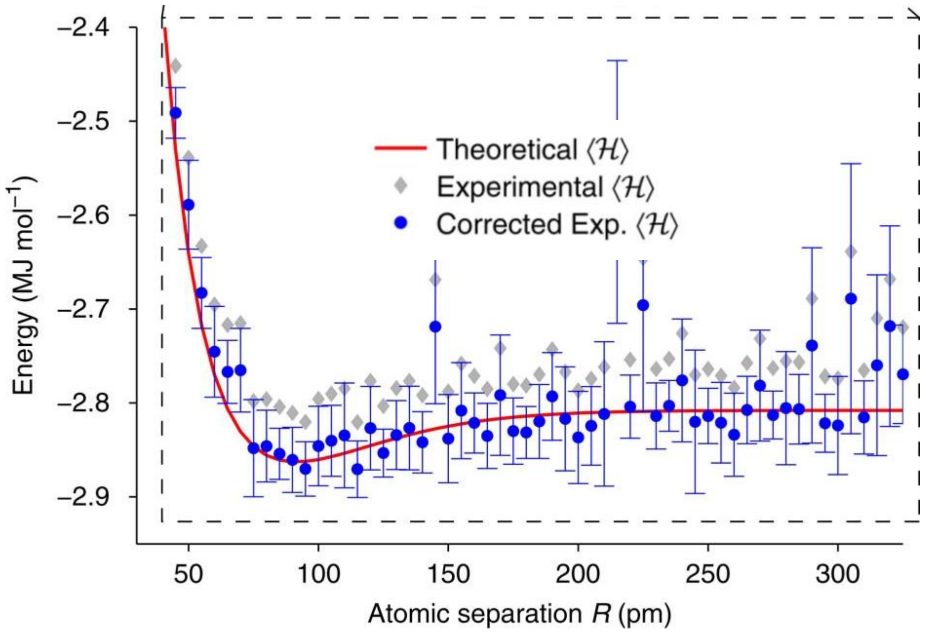




Applications

Chemistry: the Variational Quantum Eigensolver

Bond dissociation curve of the He–H⁺ molecule.



GOAL: find $|\psi\rangle$ that minimizes $\frac{\langle\psi|\mathcal{H}|\psi\rangle}{\langle\psi|\psi\rangle}$.

Electronic structure Hamiltonian decomposed into Pauli strings

$$\langle\mathcal{H}\rangle = \sum_{i\alpha} h^i_\alpha \langle\sigma^i_\alpha\rangle + \sum_{ij\alpha\beta} h^{ij}_{\alpha\beta}\langle\sigma^i_\alpha\sigma^j_\beta\rangle + \ \ldots$$

Quantum circuit that generates the ground state of that Hamiltonian (Unitary Couple-Cluster ansatz)

Unitary operation (Cluster operator)

Hartree-Fock

Excitations Hartree-Fock orbitals

$$|\Psi(\boldsymbol{\theta})\rangle = e^{T(\boldsymbol{\theta})-T(\boldsymbol{\theta})^\dagger}|\Psi_{\mathrm{HF}}\rangle$$

$$T(\boldsymbol{\theta}) = T_1(\boldsymbol{\theta}) + T_2(\boldsymbol{\theta}) + \cdots$$

$$T_1(\boldsymbol{\theta}) = \sum_{\substack{i\in\mathrm{occ}\\ j\in\mathrm{virt}}} \theta_i^j \hat{a}_j^\dagger \hat{a}_i$$

$$T_2(\boldsymbol{\theta}) = \sum_{\substack{i_1,i_2\in\mathrm{occ}\\ j_1,j_2\in\mathrm{virt}}} \theta_{i_1,i_2}^{j_1,j_2} \hat{a}_{j_2}^\dagger \hat{a}_{i_2} \hat{a}_{j_1}^\dagger \hat{a}_{i_1}$$

Transform the fermionic operators to Pauli strings (e.g. Jordan Wigner) and they become the generators of the quantum gates.

A. Peruzzo, J. McClean, P. Shadbolt, M.-H.Yung, X.-Q. Zhou, P. J. Love, A. Aspuru-Guzik , J. L. O'Brien, Nature Comm. 5, 4213 (2014)

Quantum Approximate Optimization Algorithm

Can be understood as an approximation of the Trotter decompositiong of adiabatic evolution.

Mixing Hamiltonian

$$H_M \equiv \sum_{i=1}^{n} \hat{\sigma}_x^i$$

Problem Hamiltonian

$$H_P \equiv \sum_{i=1}^{n} C(e_i)|e_i\rangle$$

Combinatorial optimization problem encoded in Pauli strings

$$C_\alpha(z) = \begin{cases} 1 & \text{if } z \text{ satisfies } C_\alpha(z) \\ 0 & \text{if } z \text{ does not satisfy} \end{cases}$$

$$H_P = \sum_{(i,j)\in E} \frac{1}{2}\left(I - \hat{\sigma}_z^i \otimes \hat{\sigma}_z^j\right) \equiv \sum_{(i,j)\in E} C_{ij}$$

Construct the circuit ansatz by alternating the problem and mixing Hamiltonians where β and γ are the variational parameters to be optimized classically.

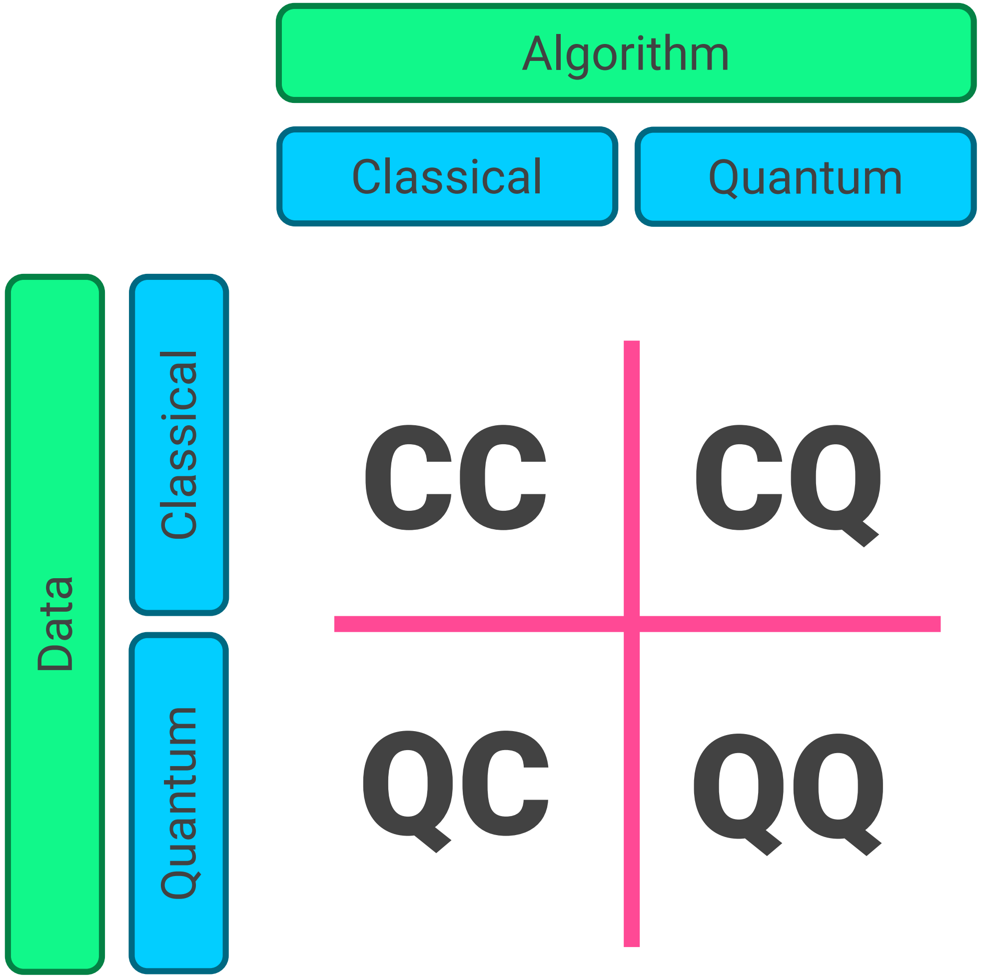
full superposition state

$$|\Psi(\gamma,\beta)\rangle \equiv e^{-i\beta_p H_M} e^{-i\gamma_p H_P} \cdots e^{-i\beta_1 H_M} e^{-i\gamma_1 H_P} |D\rangle$$

Objective function: $\langle \Psi(\gamma,\beta)| H_P(\gamma,\beta) |\Psi(\gamma,\beta)\rangle$

E. Farhi, J. Goldstone, S. Gutmann, arXiv:1411.4028 (2014)

Machine Learning



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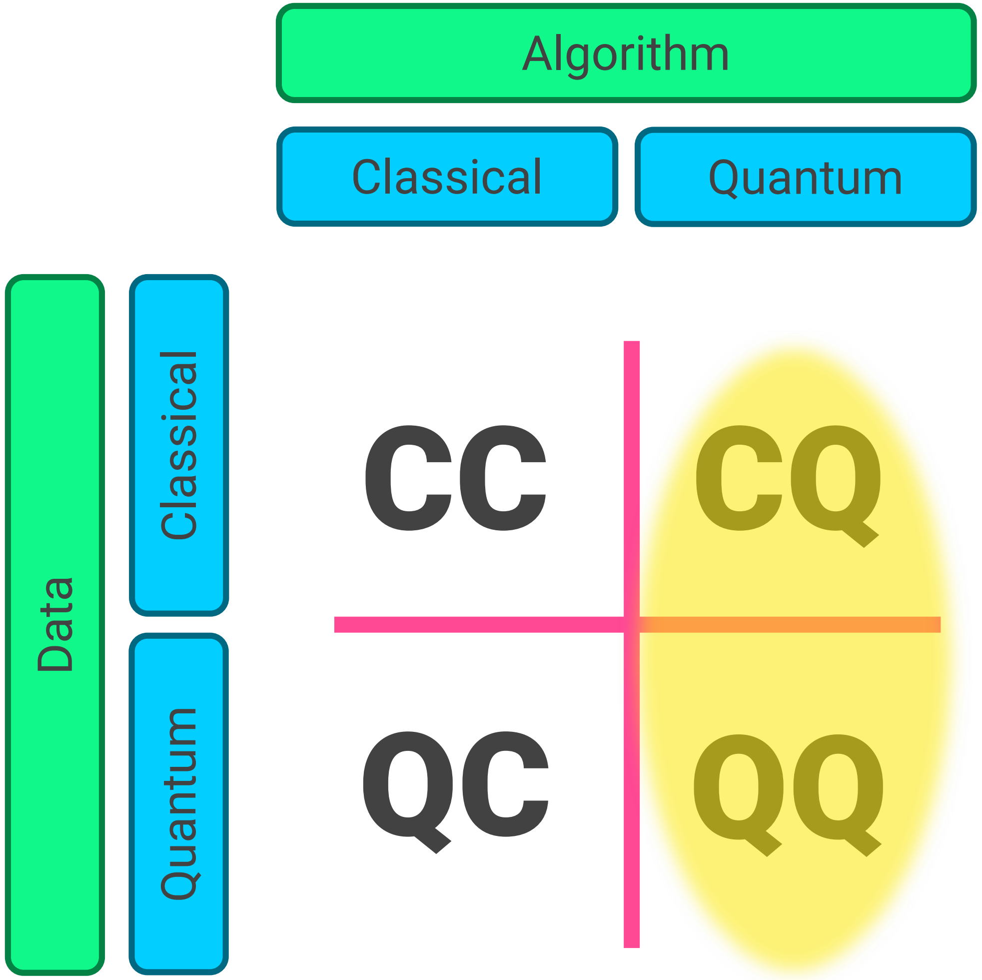
Machine Learning

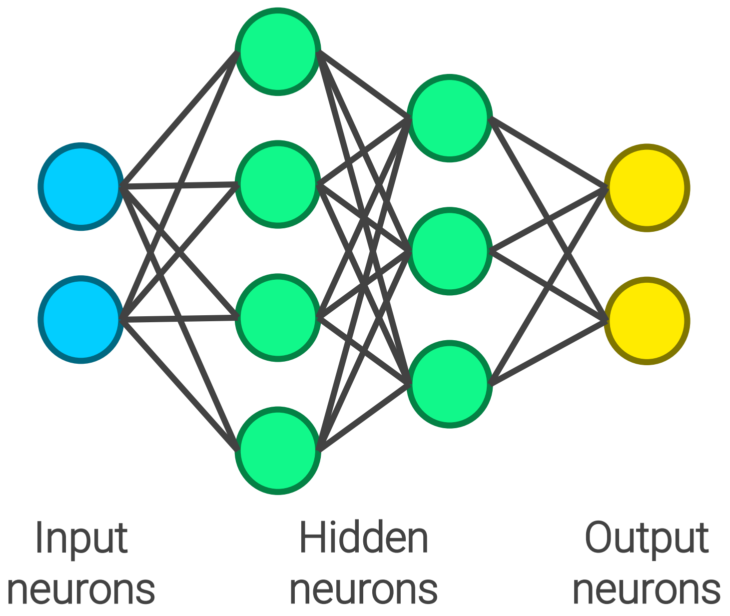


QML
Quantum algorithms feed with classical or quantum data

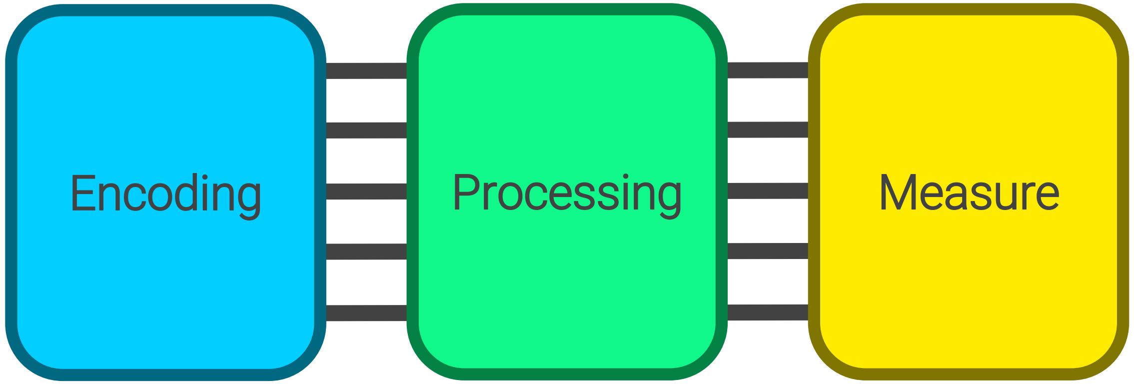
- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

From classical to quantum NN

Classical



Quantum
(circuit centric)



K Mitarai, M Negoro, M Kitagawa, K Fujii Phys. Revs A 98 (3), 032309 (2018)

E. Farhi and H.Neven, arXiv:1802.06002 (2018)

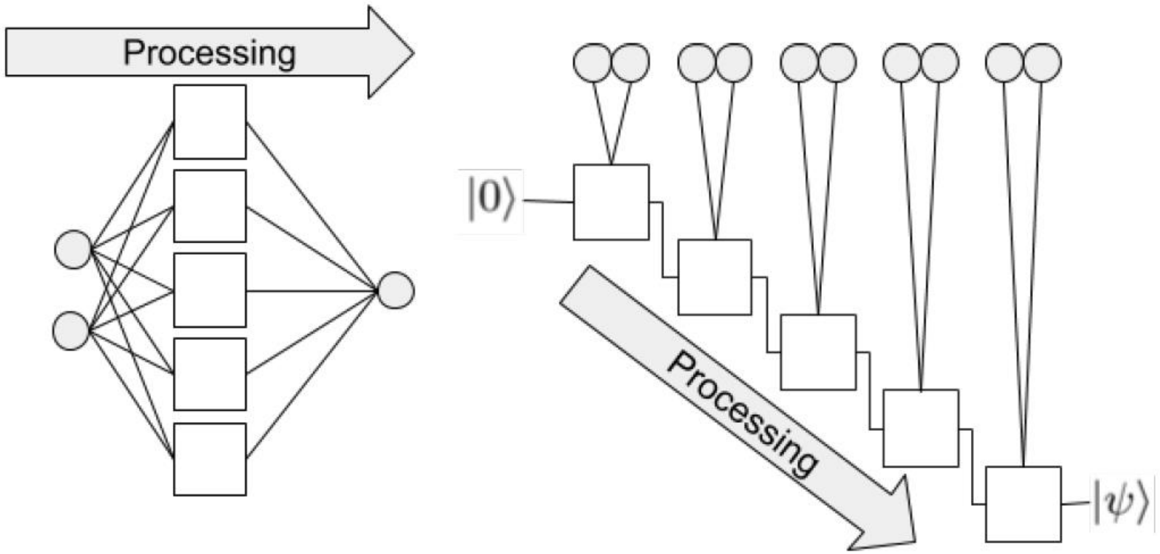
M. Schuld and N. Killoran, Phys. Rev. Lett. 122, 040504 (2019)

M. Schuld, A. Bocharov, K. M. Svore, and N. Wiebe, Phys. Rev. A 101, 032308 (2020)

The minimal QNN

What is the most simple (but universal) NN? → Single hidden layer NN

What is the most simple (but universal) QNN? → Single-qubit QNN



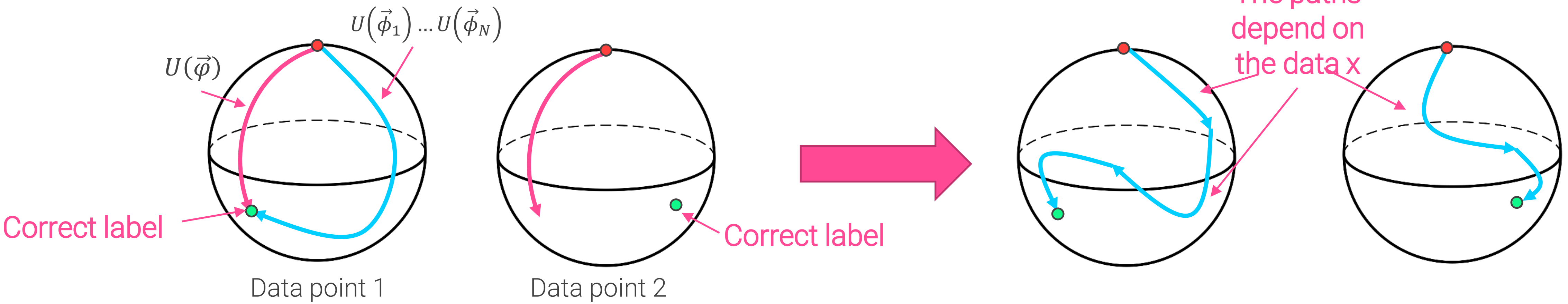
(a) Neural network (b) Quantum classifier

Encoding the data

A product of unitaries can be written with a single unitary → $U(\vec{\phi}_1) \ldots U(\vec{\phi}_N) \equiv U(\vec{\varphi})$

Data re-uploading

If we add some fixed parameter dependency (the data), the operation becomes flexible and data-depedent. → $\mathcal{U}(\vec{\phi}, \vec{x}) \equiv U(\vec{\phi}_N)U(\vec{x}) \ldots U(\vec{\phi}_1)U(\vec{x})$



A. Pérez-Salinas, ACL, E. Gil-Fuster and J. I. Latorre, Quantum 4, 226 (2020)

Data re-uploading hands-on

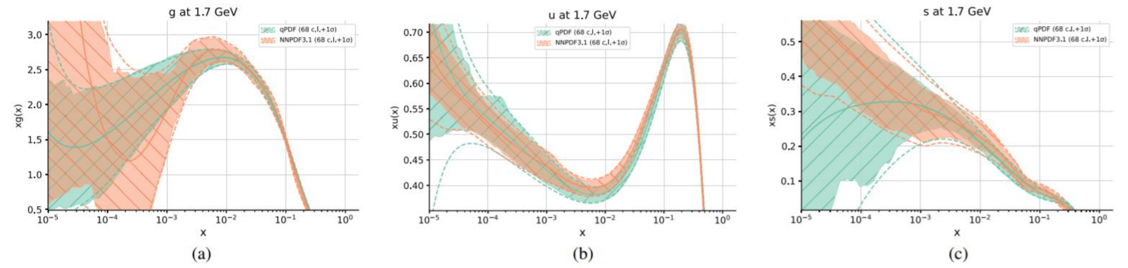
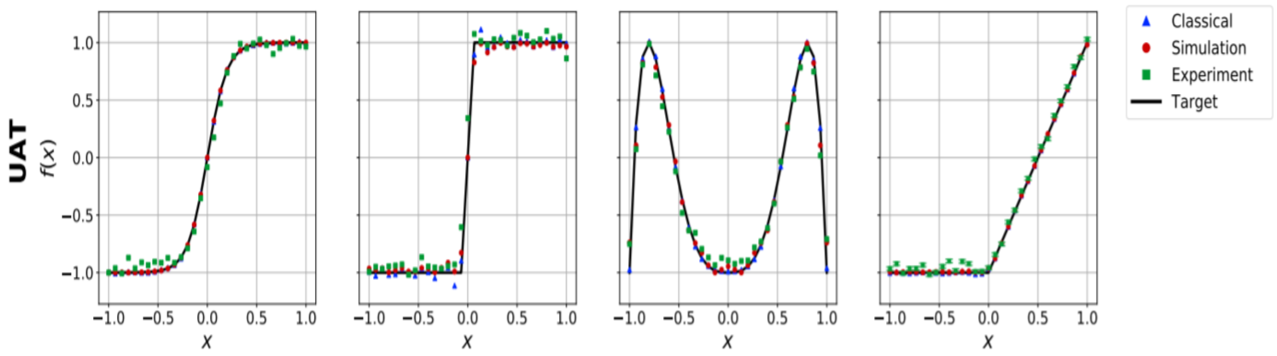
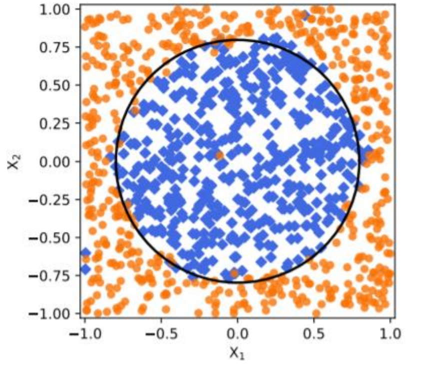


FIG. 12. Fit results for the gluon and the u and s quarks. As previously seen in Fig. 4, qPDF is able to reproduce the features of NNPDF3.1. We now see this is also true when the fit performed by comparing to data and not by comparing directly to the goal function. The differences seen at low-x can be attributed to the lack of data in that region.





(d) QPU, 4 layers; $\mathcal{A}_q = 93 \pm 2\%$

PDF

Determining the proton content with a quantum computer
A. Pérez-Salinas, J. Cruz-Martinez, A. A. Alhajri and S. Carrazza
Phys. Rev. D 103 (3), 034027, (2021)

Superconducting circuits

One qubit as a universal approximant
A. Pérez-Salinas, D. López-Núñez, A. García-Sáez, P. Forn-Díaz, and J. I. Latorre
Phys. Rev. A 104, 012405 (2021)

Trapped-ions

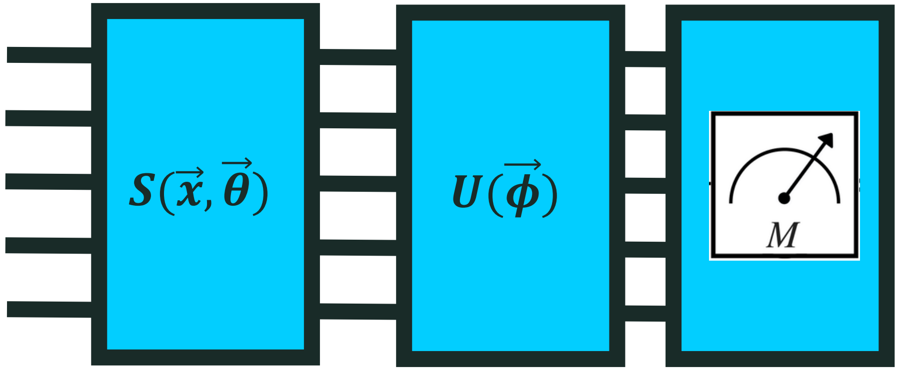
Realization of an ion trap quantum classifier
T. Dutta, A. Pérez-Salinas, J. P. S. Cheng, J. I. Latorre and M. Mukherjee
arXiv:2106.14059

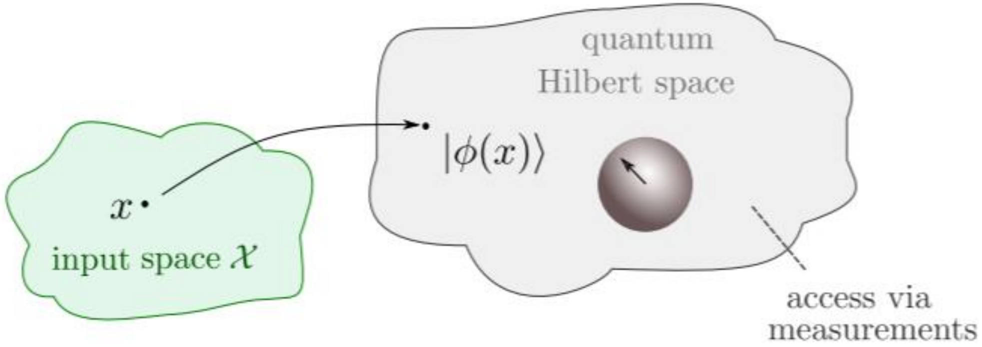
Supervised Learning

$$|\psi_0\rangle \rightarrow |\psi(\vec{x},\vec{\theta})\rangle \rightarrow |\psi(\vec{x},\vec{\theta},\vec{\phi})\rangle$$

Encode the data (quantum feature space)

Rotate to the correct measurement basis





We can then compute the Kernel

$$\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j) \equiv \langle \Phi(\boldsymbol{x}_i) | \Phi(\boldsymbol{x}_j) \rangle$$

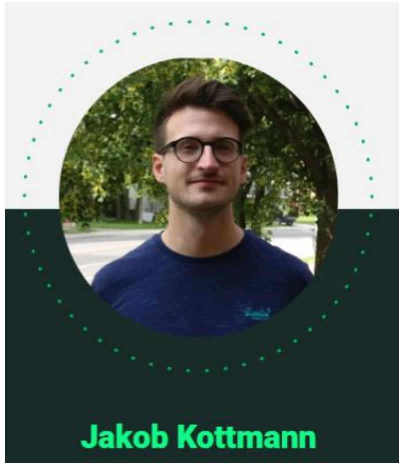
Or minimize the fidelity w.r.t. target states

$$C(\boldsymbol{\theta}) = \sum_{i=1}^{\mathcal{D}} \left(1 - |\langle y_i | \Psi(\boldsymbol{x}_i, \boldsymbol{\theta}) \rangle|^2\right)$$

Example: QML applied to quantum simulation

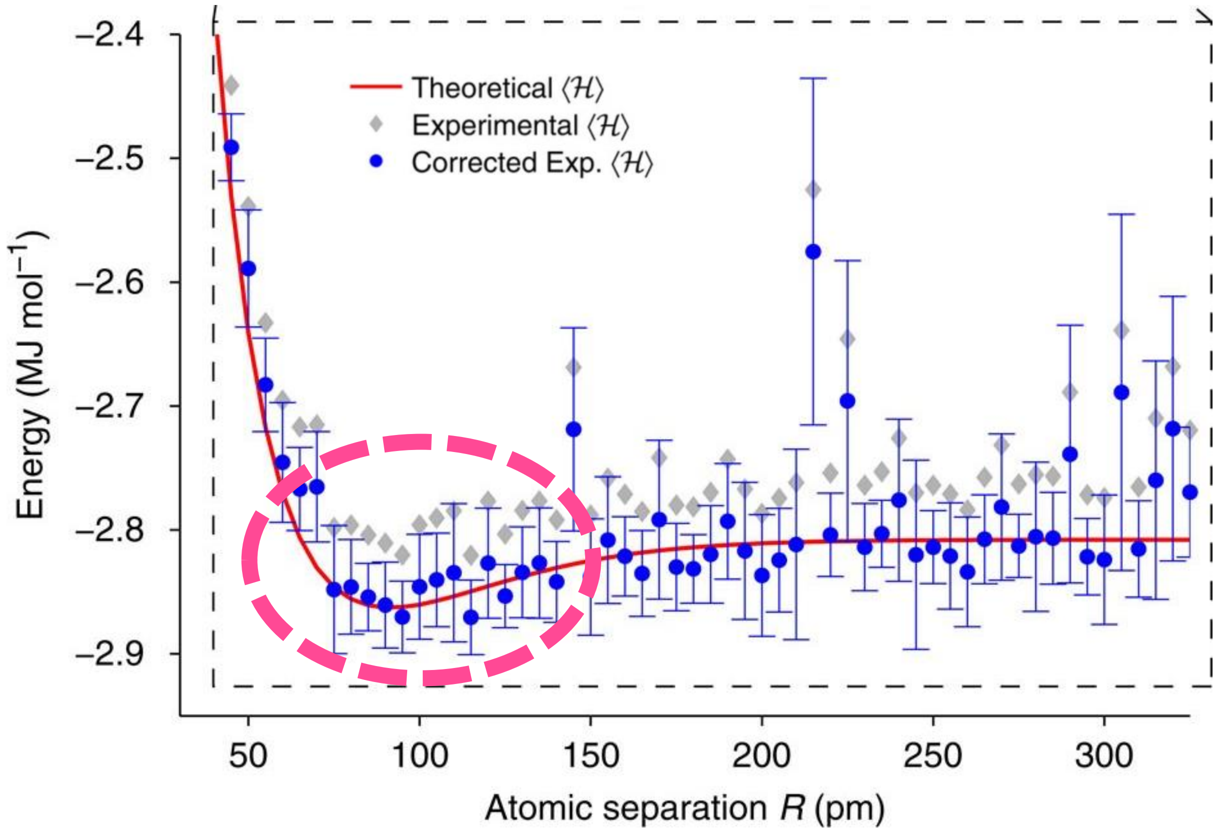
Meta-Variational Quantum Eigensolver: Learning Energy Profiles of Parameterized Hamiltonians for Quantum Simulation

Alba Cervera-Lierta, Jakob S. Kottmann, and Alán Aspuru-Guzik
PRX Quantum **2**, 020329 – Published 28 May 2021



What's the true goal of VQE?

Bond dissociation curve of the He–H⁺ molecule.



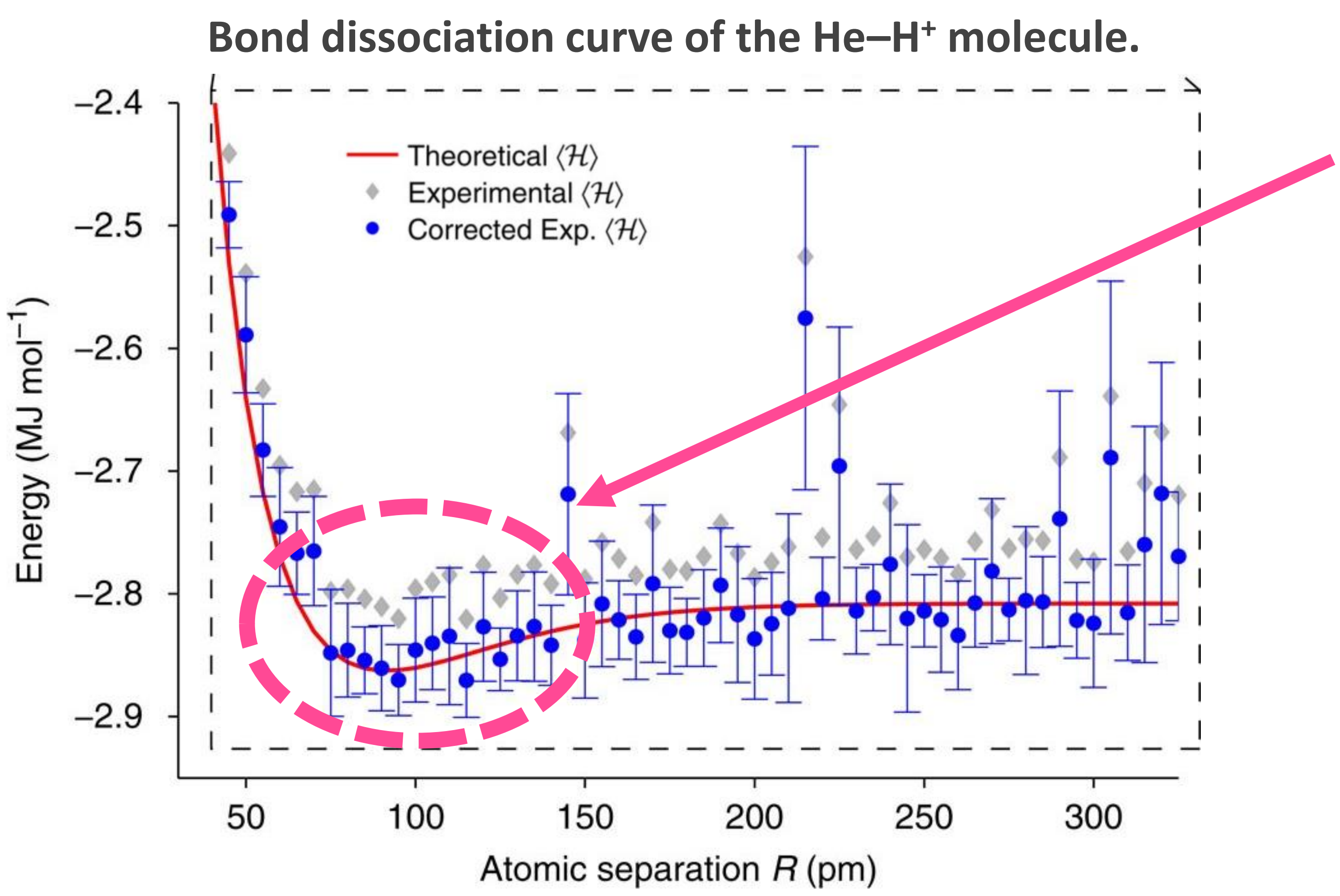
GOAL: find $|\psi\rangle$ that minimizes $\frac{\langle\psi|\mathcal{H}|\psi\rangle}{\langle\psi|\psi\rangle}$.

Find the atomic separation that minimizes the energy

$$\min\langle H(R)\rangle$$

A. Peruzzo, J. McClean, P. Shadbolt, M.-H.Yung, X.-Q. Zhou, P. J. Love, A. Aspuru-Guzik , J. L. O'Brien, Nature Comm. **5**, 4213 (2014)

What's the true goal of VQE?



To obtain this you need to scan from 0 to 300.

Each blue point is a VQE, that is, you have to **prepare, run and optimize** the quantum circuit.

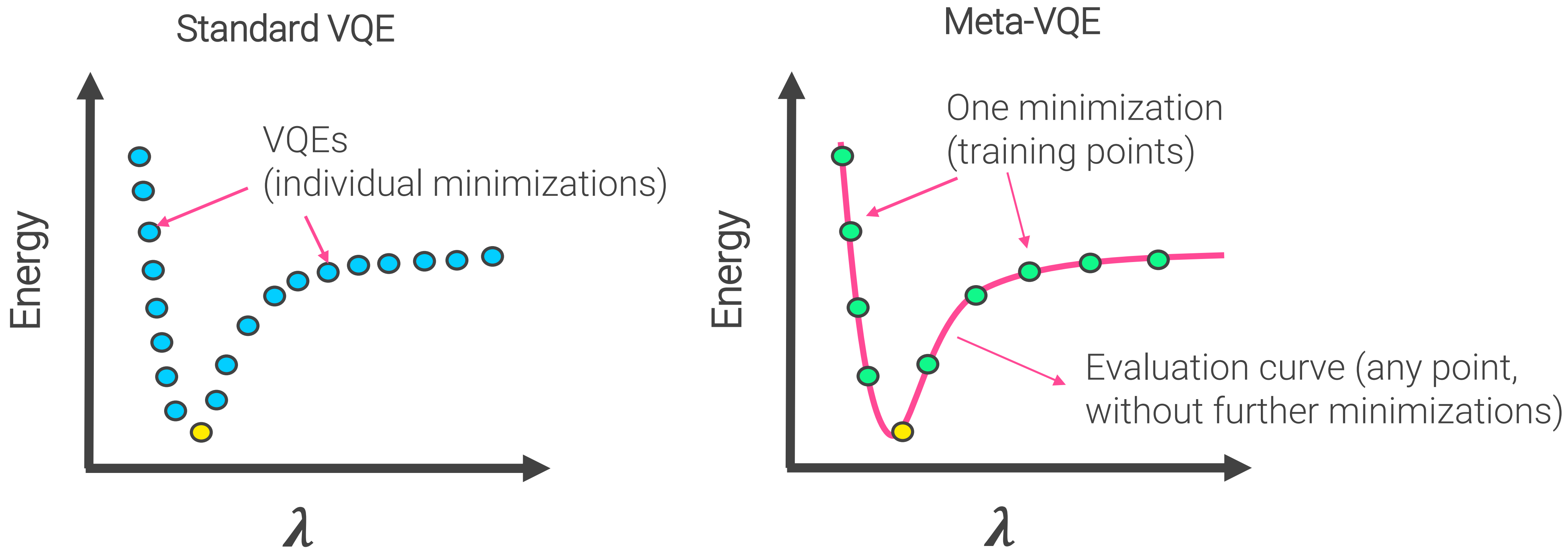
Can we avoid to compute the uninteresting points?

A. Peruzzo, J. McClean, P. Shadbolt, M.-H.Yung, X.-Q. Zhou, P. J. Love, A. Aspuru-Guzik , J. L. O'Brien, Nature Comm. 5, 4213 (2014)

Meta-VQE outlook

Parameterized Hamiltonian $H\left(\vec{\lambda}\right)$

Goal: to find the quantum circut that **encodes** the ground state of the Hamiltonian for any value of $\vec{\lambda}$



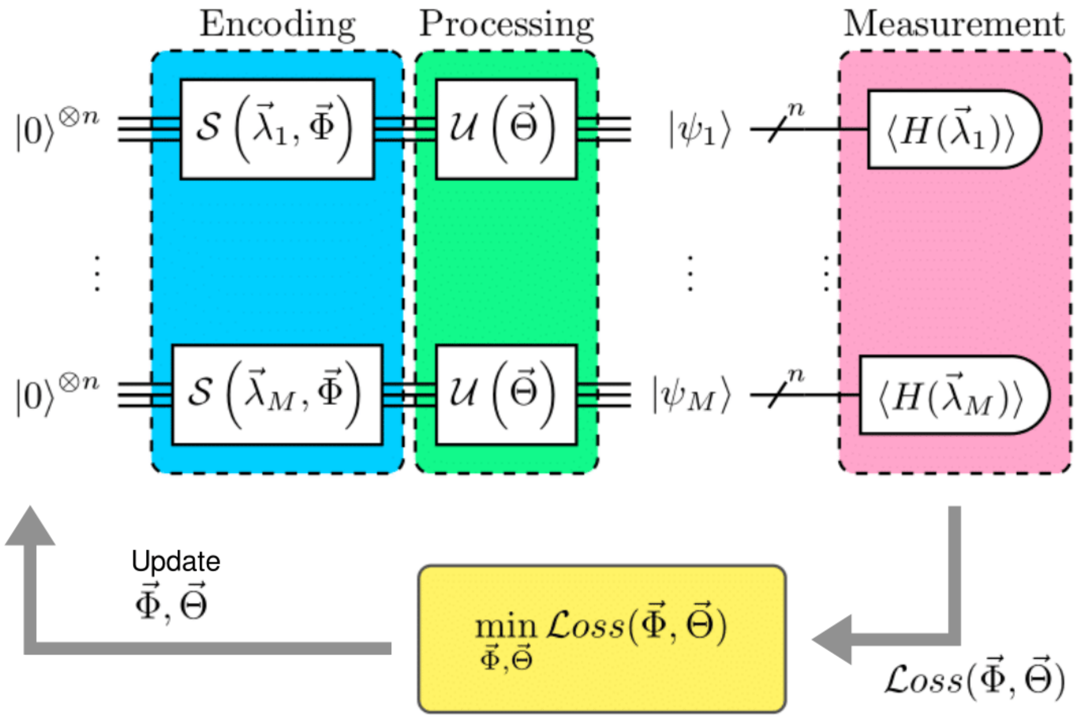
See also: K. Mitarai, T. Yan, K. Fujii, Phys. Rev. Applied **11**, 044087 (2019)

The Meta-VQE

Parameterized Hamiltonian $H\left(\vec{\lambda}\right)$

Training points: $\vec{\lambda}_i$ for $i = 1, \ldots, M$

Loss function with all $\left\langle H(\vec{\lambda}_i)\right\rangle$



<u>Goal:</u> to find the quantum circut that **encodes** the ground state of the Hamiltonian for any value of $\vec{\lambda}$

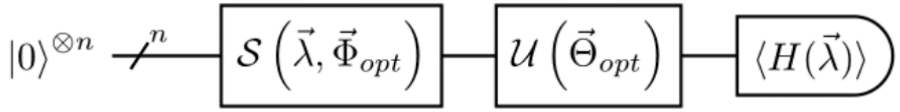
Output: $\vec{\Phi}_{opt}$ and $\vec{\Theta}_{opt}$

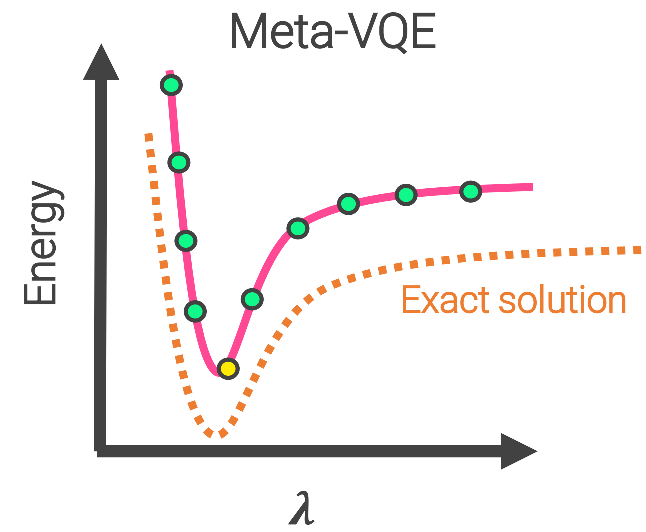
See also: K. Mitarai, T. Yan, K. Fujii, Phys. Rev. Applied **11**, 044087 (2019)

The Meta-VQE output

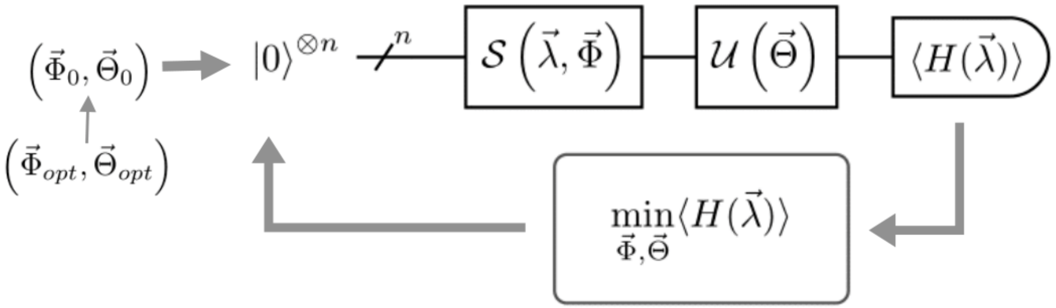
Output: $\vec{\Phi}_{opt}$ and $\vec{\Theta}_{opt}$

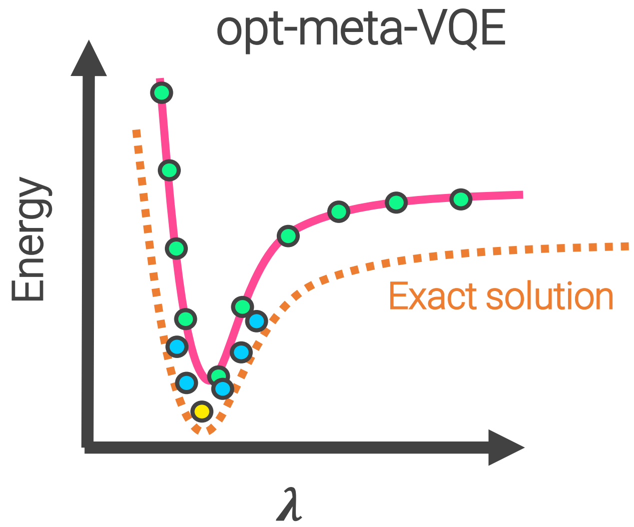
Option 1: run the circuit with test $\vec{\lambda}$ and obtain the g.s. energy profile.





Option 2: use $\vec{\Phi}_{opt}$ and $\vec{\Theta}_{opt}$ as starting point of a standard VQE optimization (*opt-meta-VQE*)





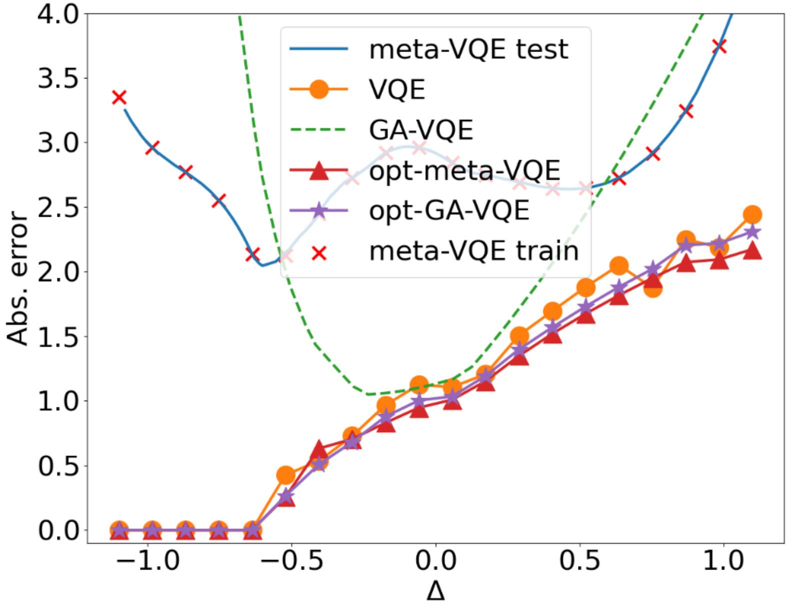
Benchmarks

1D XXZ spin chain (14 qubits)

Ansatz: $R_z(\theta)R_y(\vartheta)\otimes$alternating CNOTs

Linear encoding: $\theta = w_1 \boldsymbol{\Delta} + \phi_1$

$$H = \sum_{i=1}^{n} \sigma_i^x \sigma_{i+1}^x + \sigma_i^y \sigma_{i+1}^y + \Delta \sigma_i^z \sigma_{i+1}^z + \lambda \sigma_i^z$$

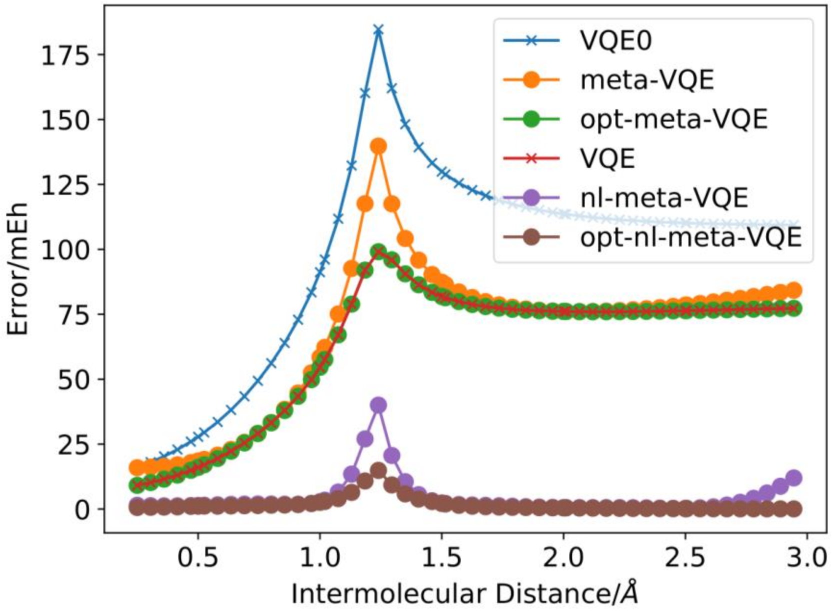


H_4 molecule 8 spin-orbitals (STO-3G)

Ansatz: k-UpCCGSD (k=2 for these results)

Linear encoding: $\theta = \alpha + d\beta$

Non-linear encoding: $\theta = \alpha e^{\beta(\gamma - d)} + \delta$

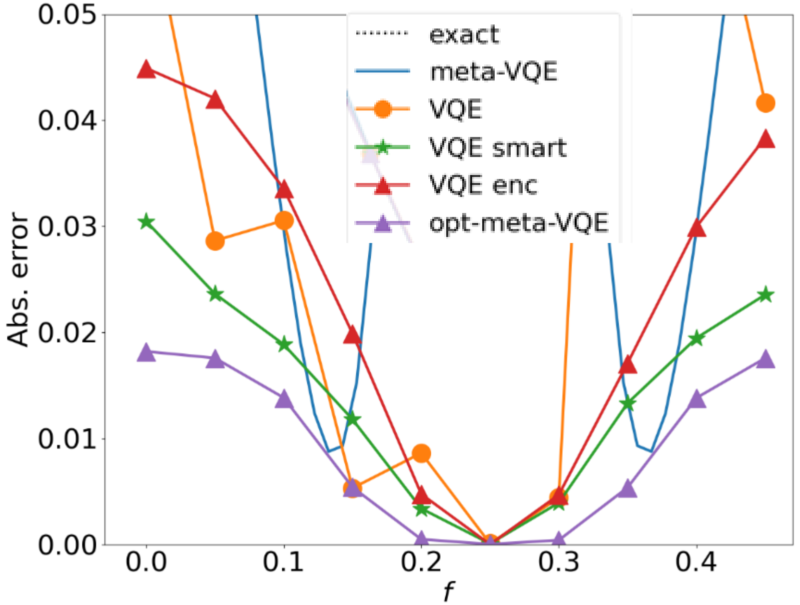


Single-transmon simulation*

Ansatz: $R_x R_z$+ all connected XX gates

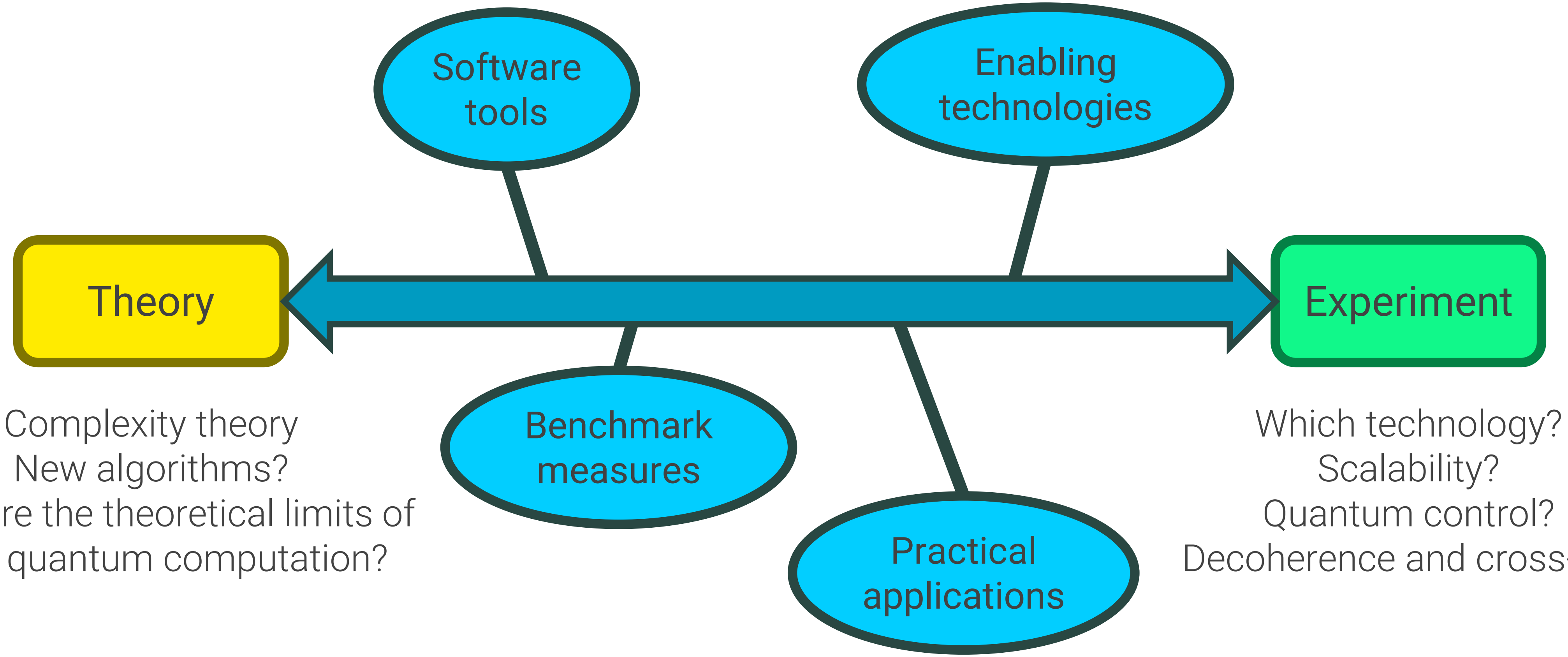
Linear encoding: $\theta = w_1 \boldsymbol{f} + \phi_1$

*Kyaw, Menke, Sim, Sawaya, Oliver, Guerreschi, Aspuru-Guzik, arXiV:2006.03070 (2020)



NISQ horizon

NISQ road

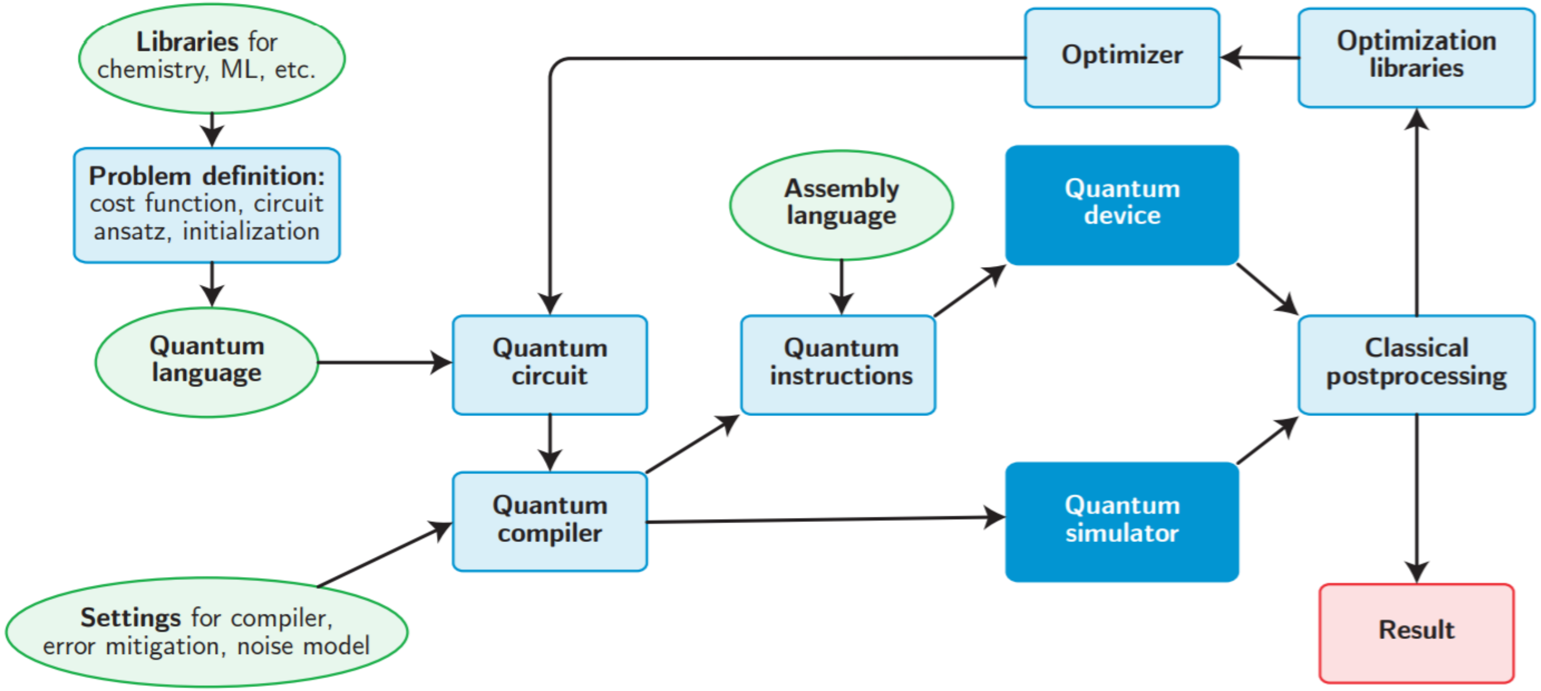


Complexity theory
New algorithms?
What are the theoretical limits of NISQ quantum computation?

Which technology?
Scalability?
Quantum control?
Decoherence and cross-talk

Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

How to program a NISQ algorithm



Qiskit
Cirq
<Q#>
PENNYLANE
PYQUIL
Qibo
|Q⟩
TEQUILA
JAX
SciPy
GPyOpt
Phoenics
Mitiq
Orquestra
Psi4
OpenFermion

J. Kottmann, S. Alperin-Lea, T. Tamayo-Mendoza, et. al.,
arXiv:2011.03057 (accepted in Quantum Science and Technology)

Next goal: fault-tolerant quantum computing

Quantum Error Correction: protect the quantum information in a highly entangled state.

QEC comes with a big qubit overhead: thousands (posible milions) of qubits to implement a quantum advantage experiment.

That's why we have NISQ… but most of the NISQ algorithms can also be implemented in the **Fault-Tolerant era.**

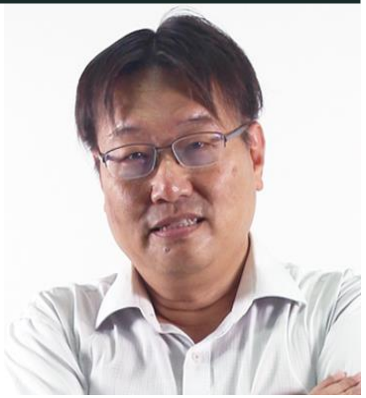
Noise limits NISQ algorithms such as VQAs.

Next goal in quantum computing is Fault-tolerant quantum computation. We don't know how much will it take, but so much physics to explore along the way!

Acknowledgements

Alán Aspuru-Guzik

Leong-Chuan Kwek



Kishor Bharti

Thi Ha Kyaw

Tobias Haug

Sumner Alperin

Abhinav Anand

Matthias Degroote

Hermanni Heimonen

Jakob Kottmann

Tim Menke

Wai-Keong Mok

Sukin (Hannah) Sim

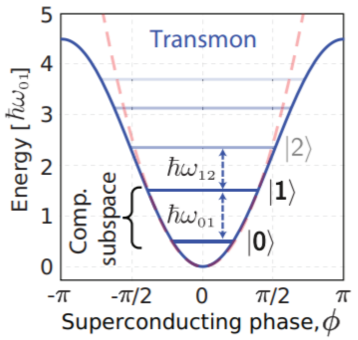
the matter lab

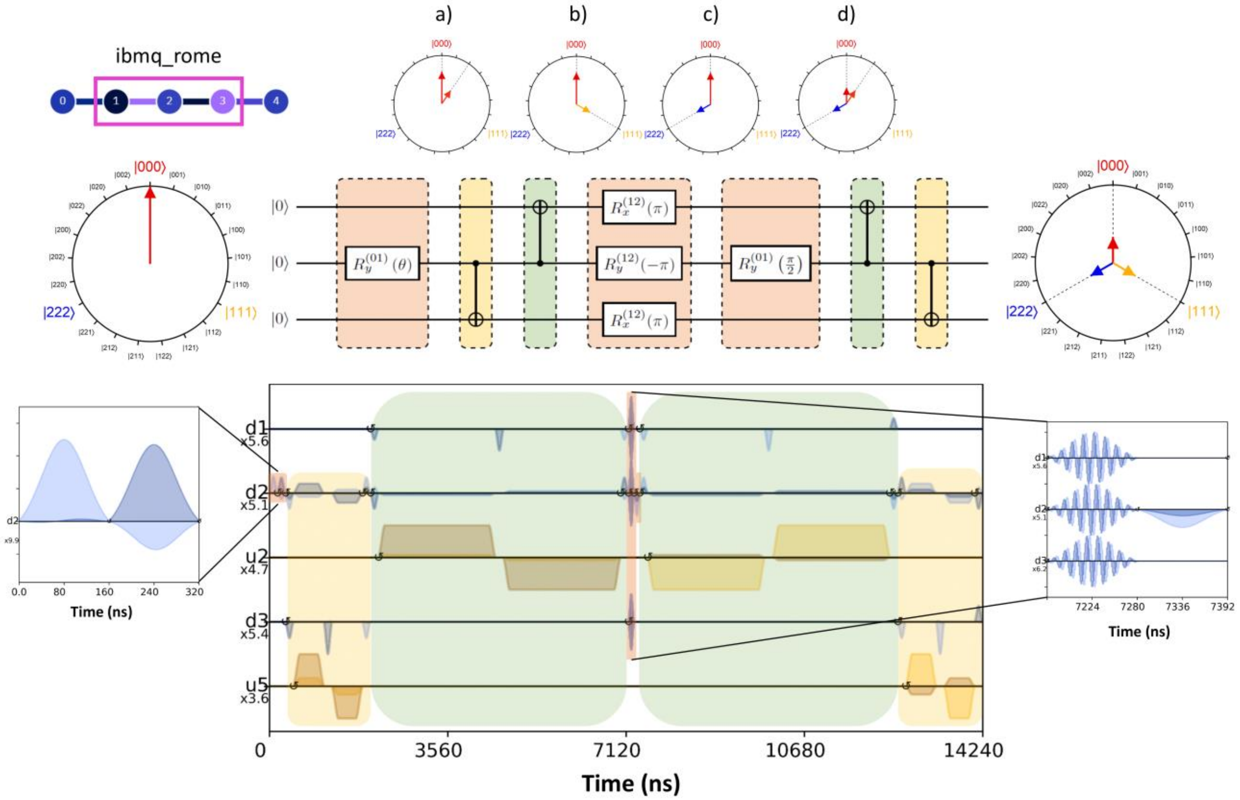
Centre for Quantum Technologies

Noisy Intermediate-Scale Quantum (NISQ) algorithms, K. Bharti, ACL, T.H. Kyaw, et. al., arXiv:2101.08448 (2021)

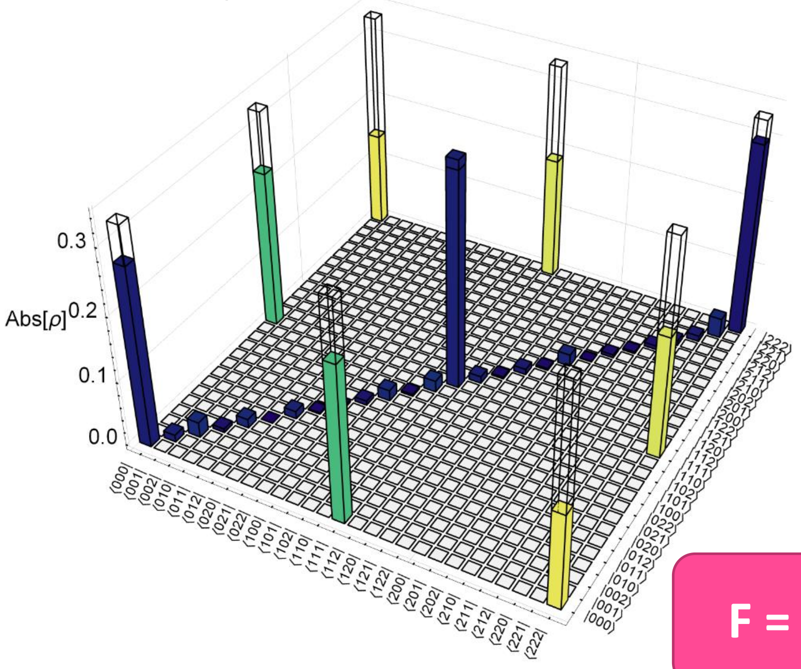
Bonus: beyond qubits

Physical systems used for qubits contain more dimensions that we can technically access and control!





$$|GHZ\rangle = \frac{1}{\sqrt{3}}(|000\rangle + |111\rangle + |222\rangle)$$



F = 76 ± 1%