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Instituto Galego de Física de Altas Enerxías

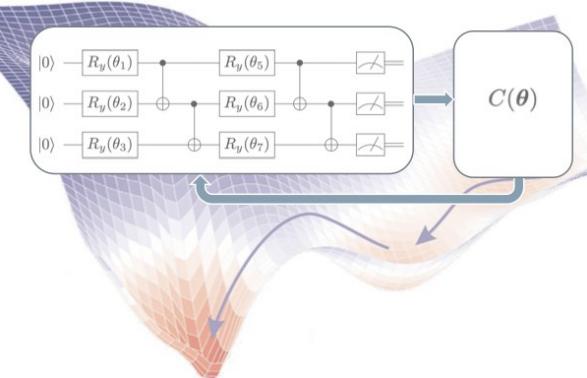
**USC**  
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Funded by the  
European Union

# Variational quantum algorithms: VQE, QAOA



Wenyang Qian

University of Santiago de Compostela

Mar 7, 2025, USC QC Workshop  
<https://indico.cern.ch/event/1480598/>



# Quantum computing

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**The Idea:** “*Nature isn’t classical, dammit, and if you want to make a simulation of nature, you’d better make it quantum mechanical*”

## Simulating Physics with Computers

Richard P. Feynman

*Department of Physics, California Institute of Technology, Pasadena, California 91107*

*Received May 7, 1981*

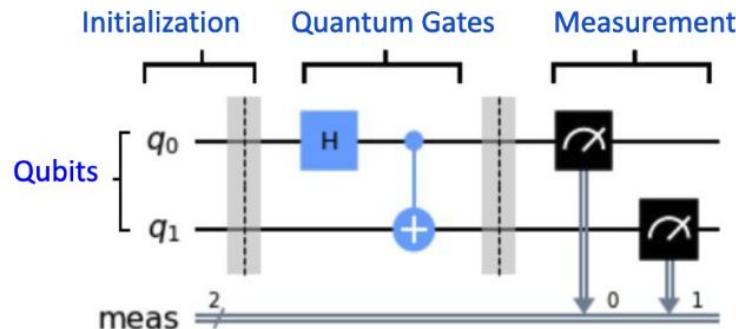


Quantum computing (QC) is a rapidly-emerging technology that harnesses the laws of quantum mechanics to solve problems.

After 40+ years, we are almost there with emerging QC technology...

# Quantum computing

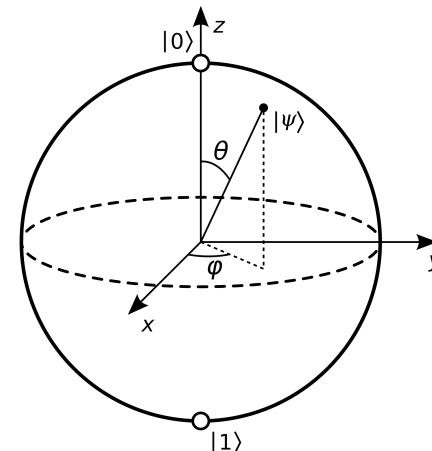
Basic idea: Spin chain = qubits (lines) + unitary gates (operators)



Conceptually clean for universal simulation

Noisy, intermediate-scale (NISQ) era,  $\sim 100$  qubits

Qubits = Digitalization

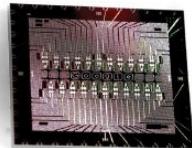


$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

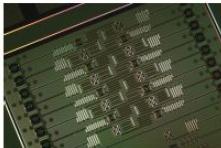
$$|\alpha|^2 + |\beta|^2 = 1$$

# Quantum computing

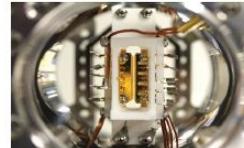
**State-of-the-art:** Noisy intermediate-scale quantum (NISQ) era = substantially imperfect and insufficient qubits. However, this can change fast!



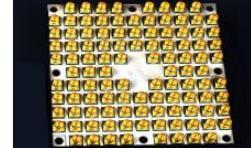
Google



IBM



Rigetti



Intel



USTC



Optimist's prediction:

Neven's law = Double-exponential scaling

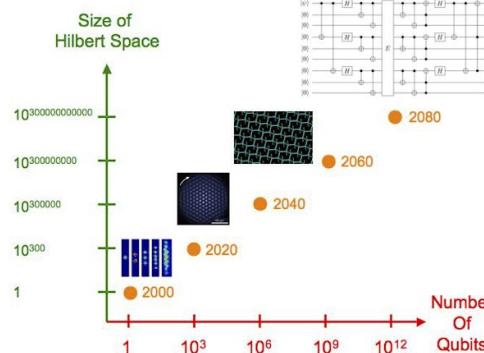


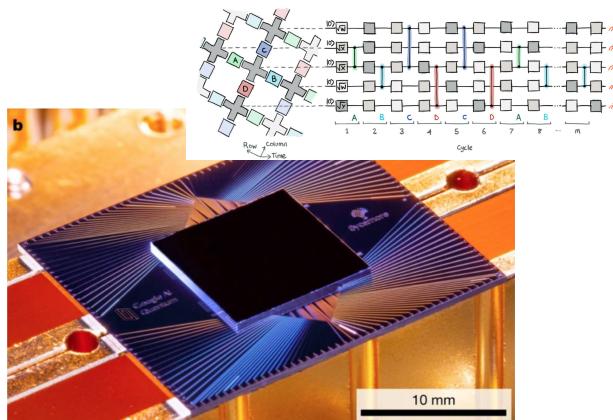
Chart: Quantum Pundit

# Quantum supremacy

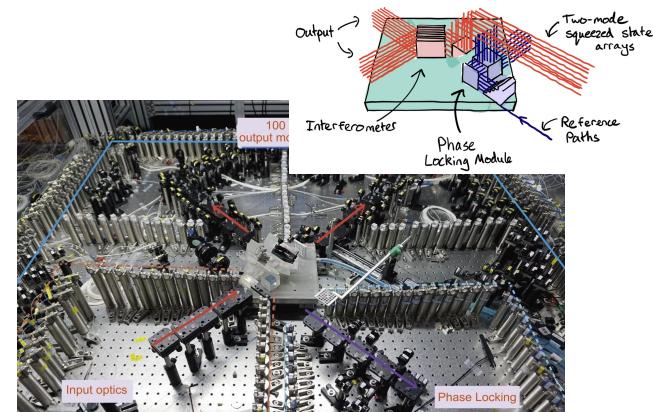
Quantum supremacy = **anything** with a quantum device “cannot” be performed classically



Specific evidence for supremacy are found in sampling distributions!



random circuit 53 qubits, Google Quantum, 1910.11333



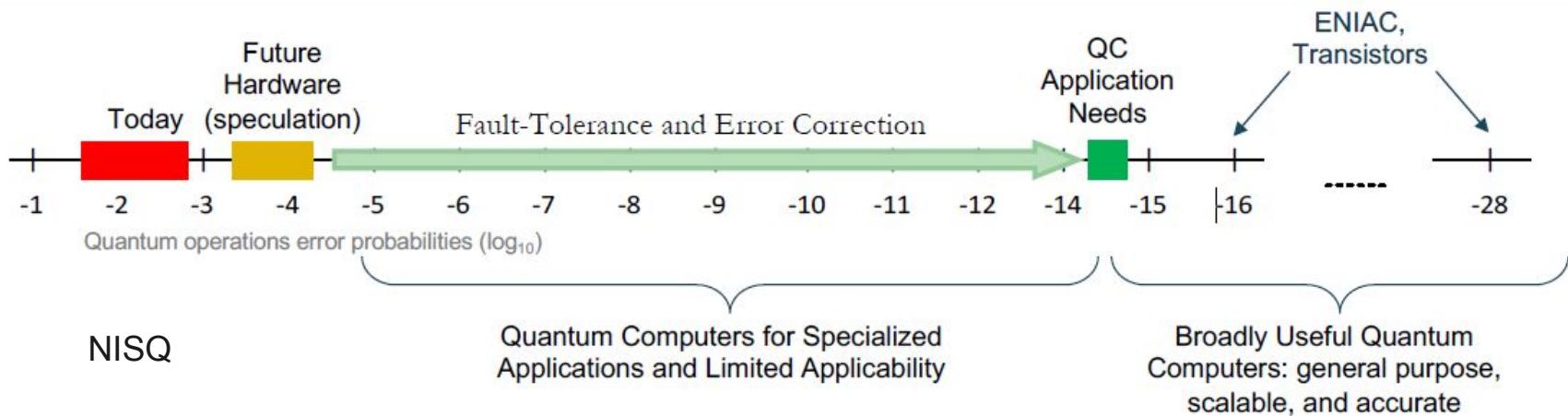
GBS 76 qubits, UTSC, 2012.01625  
Schematic: Pennylane

Quantum advantage = **sth useful** involving a quantum device “cannot” be performed classically



# Quantum supremacy

Simply a matter of time before QC revolutionizes the modern research (**sth useful**)

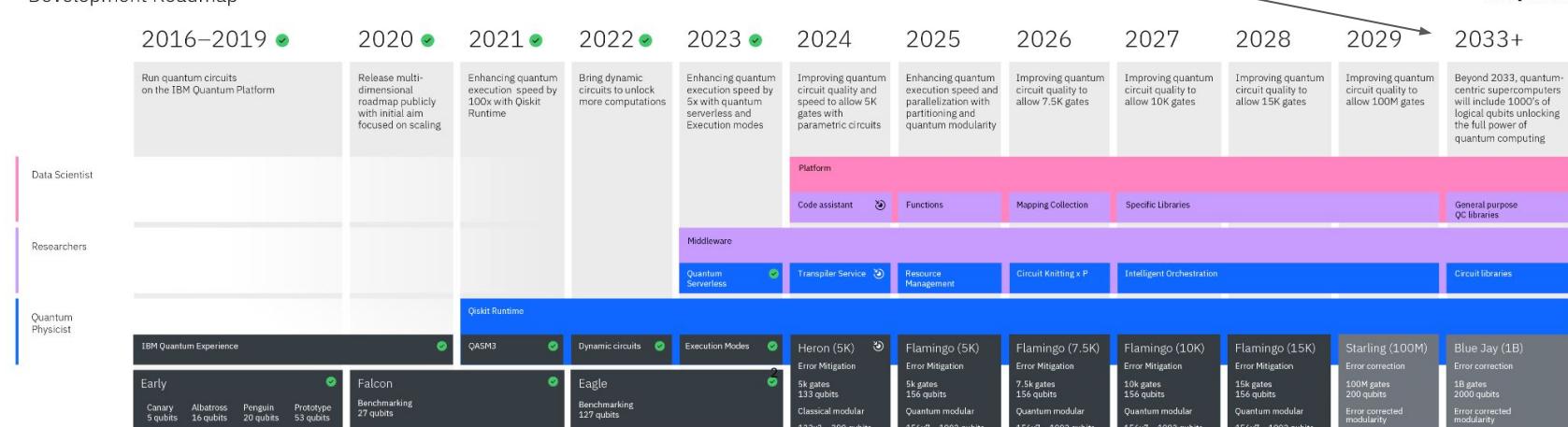


# Quantum technology is growing at fast pace

## Development Roadmap

1 Billion gates + 2000 logic qubits

IBM Quantum



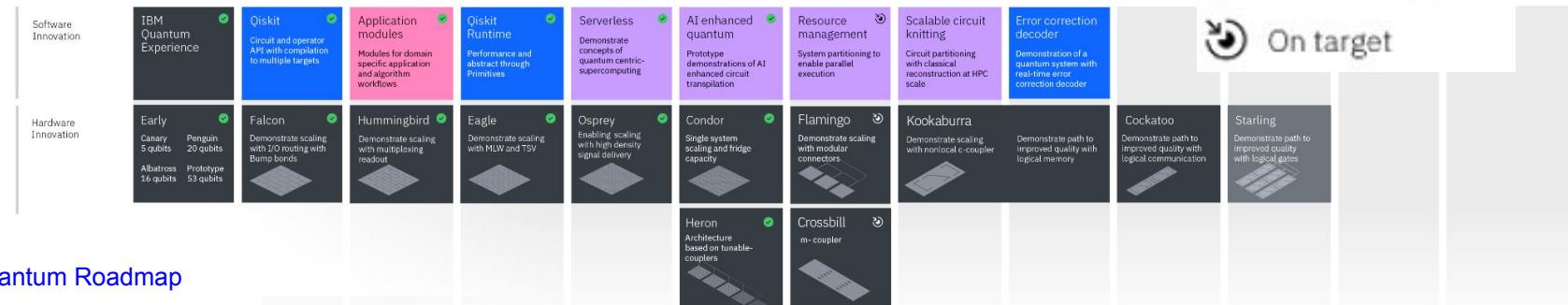
## Innovation Roadmap



Executed by IBM

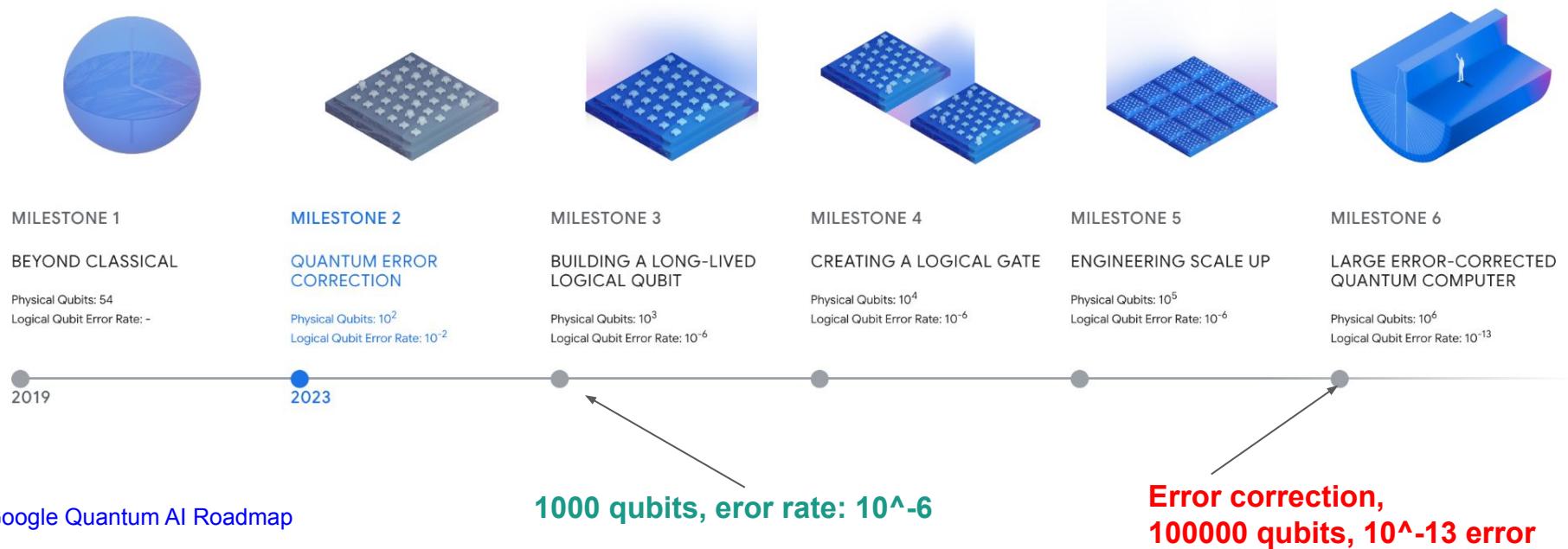


On target

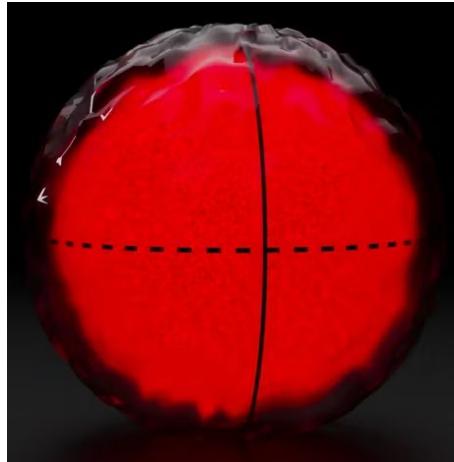


# Quantum technology is growing at fast pace

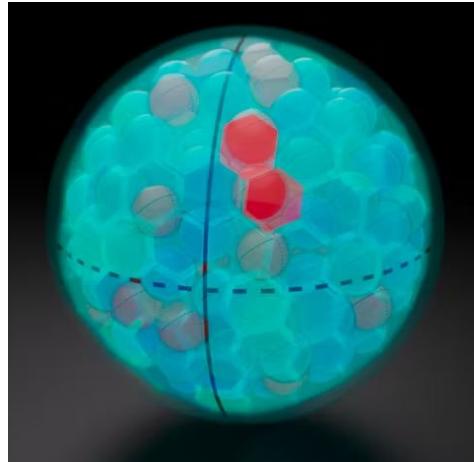
Our focus is to unlock the full potential of quantum computing by developing a large-scale computer capable of complex, error-corrected computations. We're guided by a roadmap featuring six milestones that will lead us toward top-quality quantum computing hardware and software for meaningful applications.



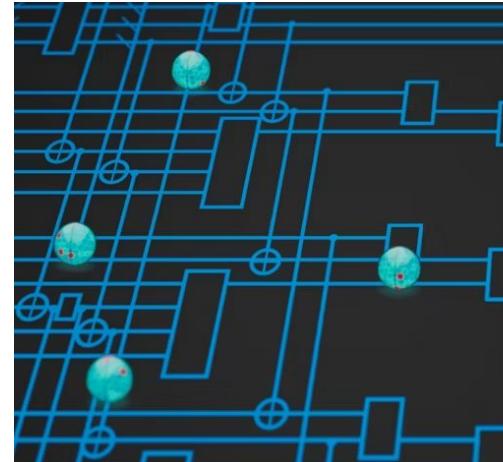
# Quantum technology is growing at fast pace



Noisy physical qubits



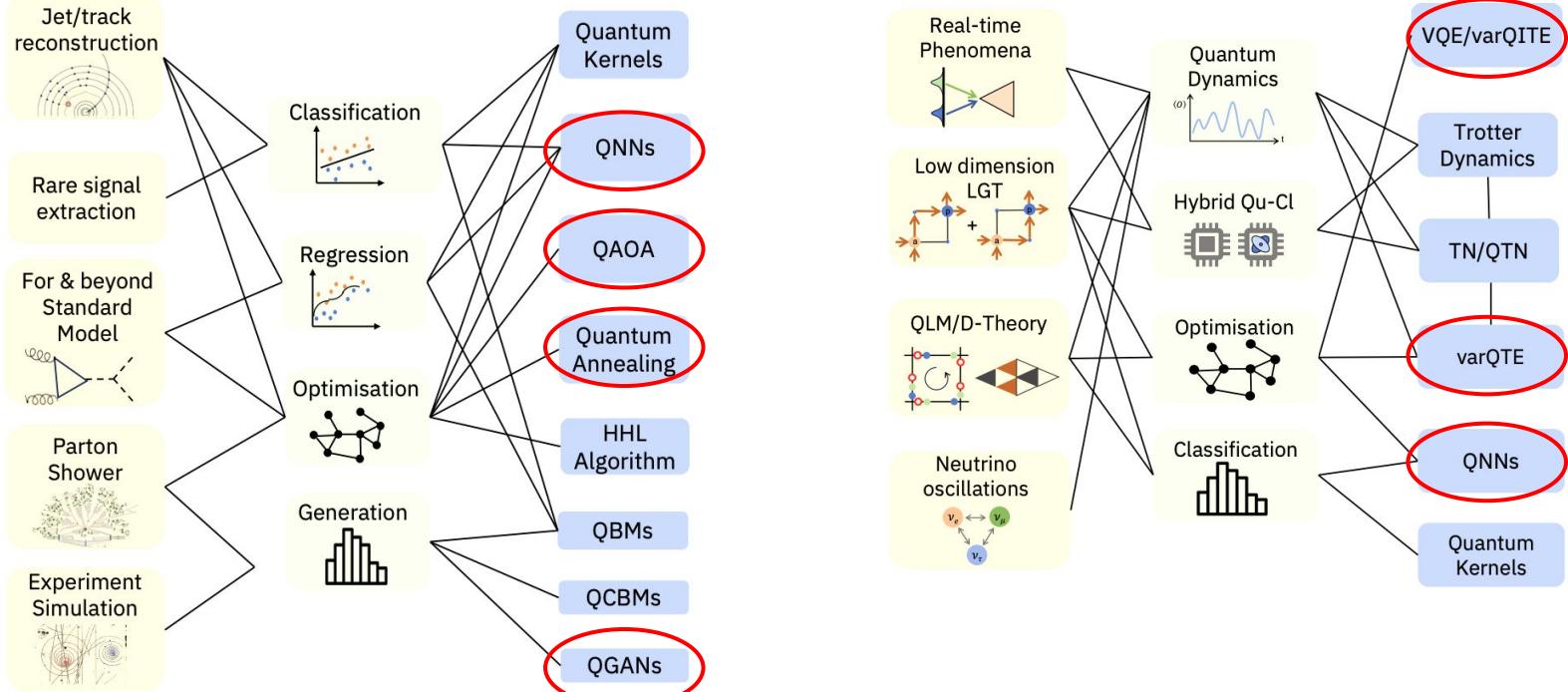
Reliable logical qubits



Quantum supercomputers

# Variational quantum computing

Delgado et al 2203.08805  
 Bauer et al, 2204.03381  
 Di Meglio et al, 2307.03236



Motivations

LHC Physics = large data  
 Quantum search provides theoretical speedup

Classical simulation encounters inherent problems  
 Quantum simulation is an ultimate path to simulate QFT

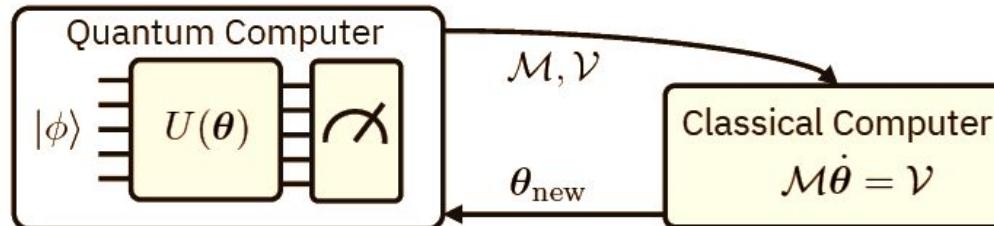
# Variational Quantum Algorithm

Perhaps the most successful applications of QC is the variational quantum algorithm (VQA)

Based on the **Variational Principle**  $\langle \psi_{\text{guess}} | H | \psi_{\text{guess}} \rangle \geq \langle E_0 \rangle = \langle \psi_0 | H | \psi_0 \rangle$

By tweaking the **ansatz (guess wavefunction)**, we can obtain the ground state energy of Hamiltonian

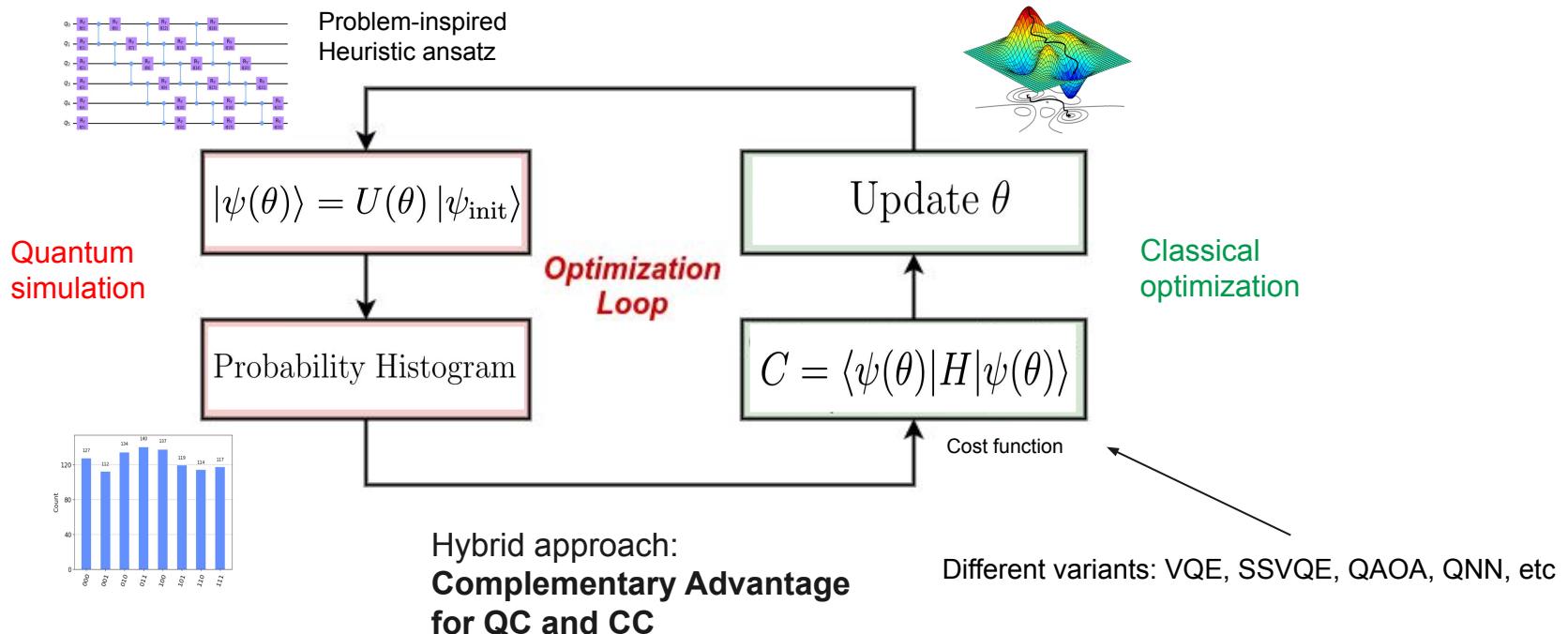
Optimal circuit (i.e. solution) to the chemistry or physics problem is obtained by collaboration between quantum device (QPU) and CPU.



# Variational Quantum Algorithm

Peruzzo, et al, 1304.3061 (2014)  
Nakanishi, Mitarai, Fujii, 1810.09434 (2019)

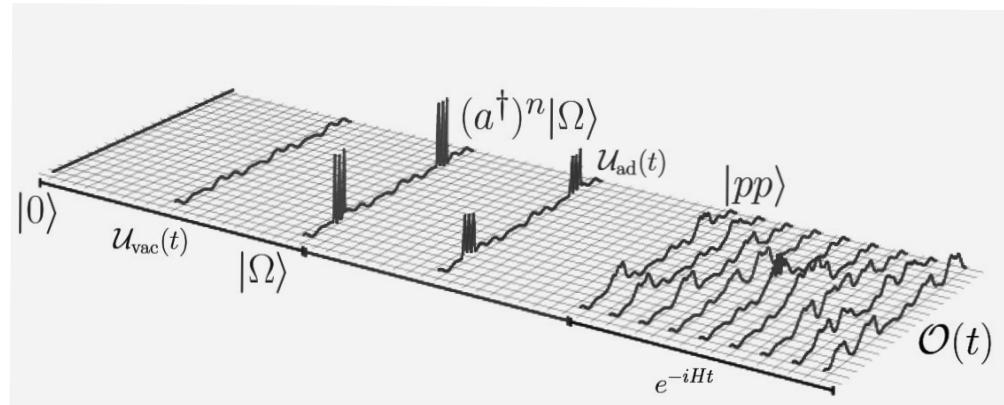
VQA is a collaborative effort between the **quantum simulation** and **classical optimization**



# Quantum simulation I

Wiesner, 9603028 (1996); Zalka, 9603026 (1996)

1. Define problem of interest
2. Encode onto qubits
3. Prepare initial states
4. Variational ansatz
5. Measurement protocol

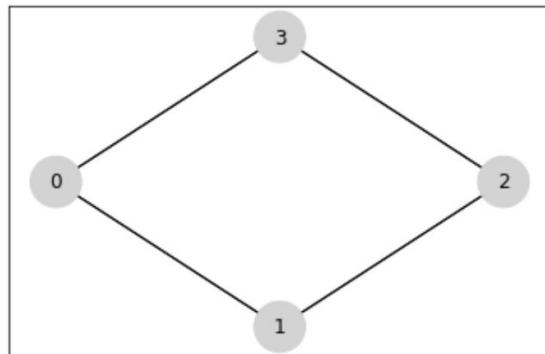


Lamm's talk at Fermilab (2021)

Okay, let us find an interesting problem?

# Maxcut problem (maximum cut)

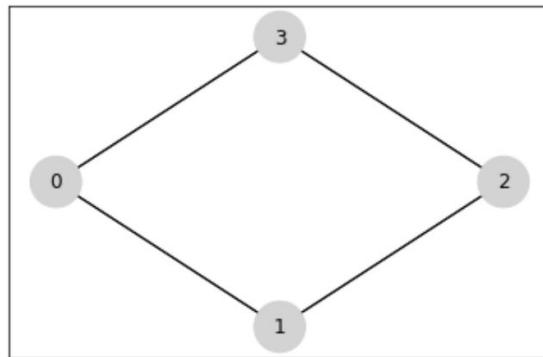
Given a graph of  $n$  nodes, how do we cut the graph into two partitions such that the number of edges between the two partitions are maximized?



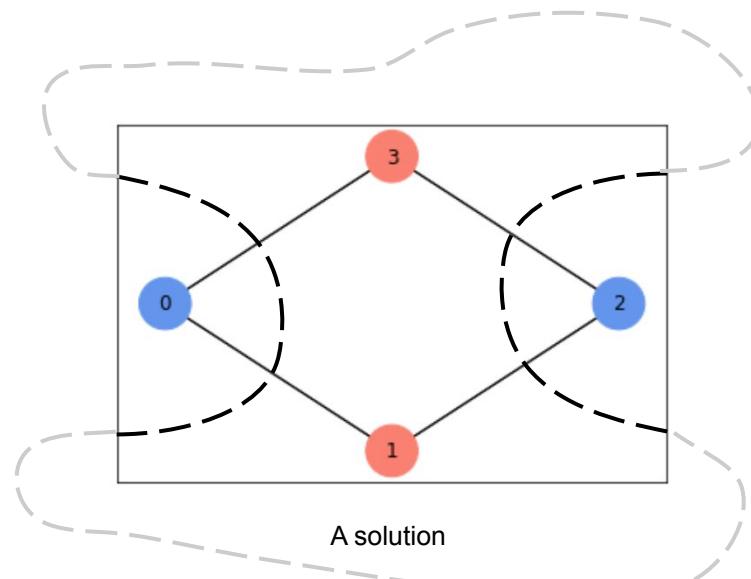
Initial Problem

# Maxcut problem (maximum cut)

Given a graph of  $n$  nodes, how do we cut the graph into two partitions such that the number of edges between the two partitions are maximized?



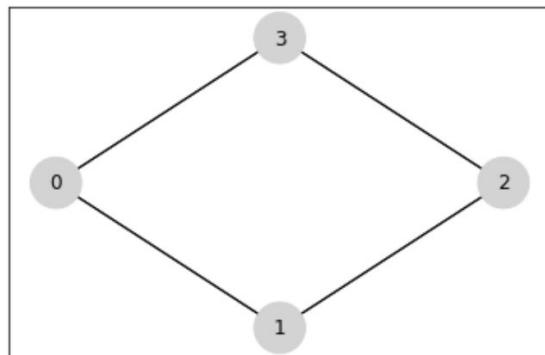
Initial Problem



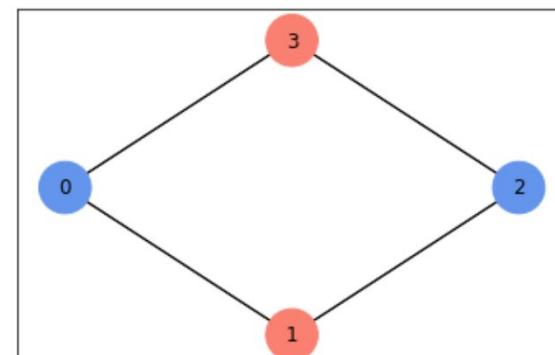
A solution

# Maxcut problem (maximum cut)

Given a graph of  $n$  nodes, how do we cut the graph into two partitions such that the number of edges between the two partitions are maximized?



Initial Problem

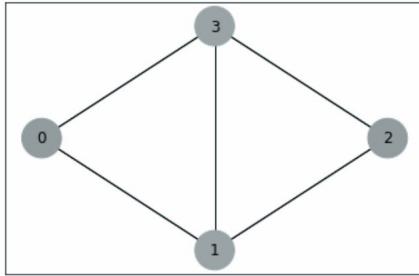


A solution

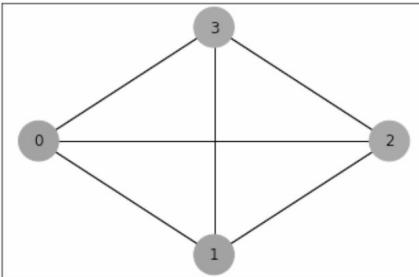
Equivalent to a **coloring problem** to partition the nodes into Red or Blue

# Maxcut problem is **NP-Hard!**

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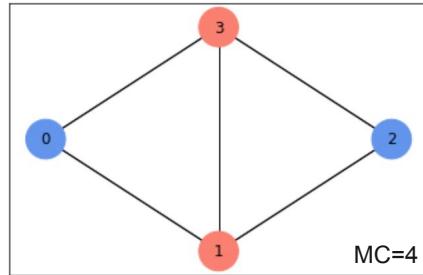


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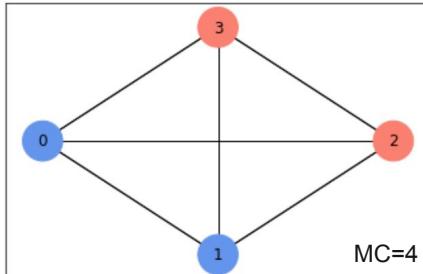
# Maxcut problem is **NP-Hard!**

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MC=4

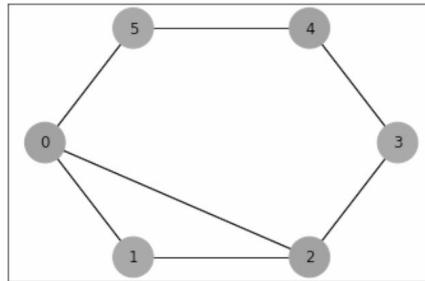
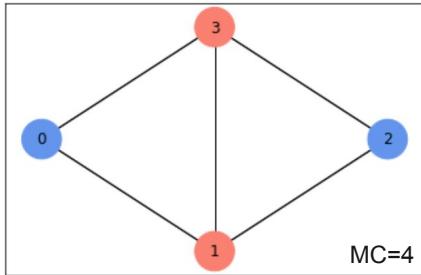
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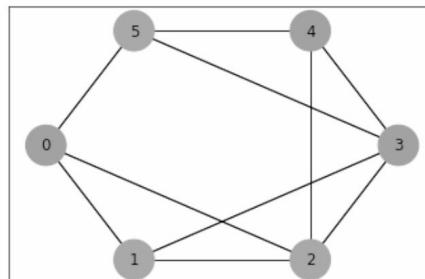
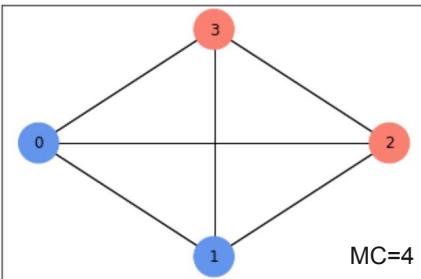
MC=4

# Maxcut problem is NP-Hard!

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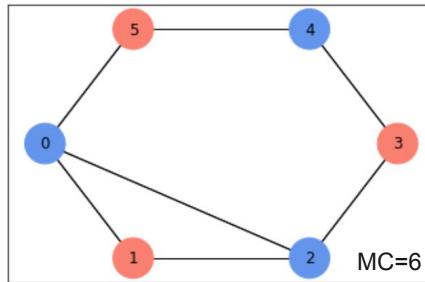
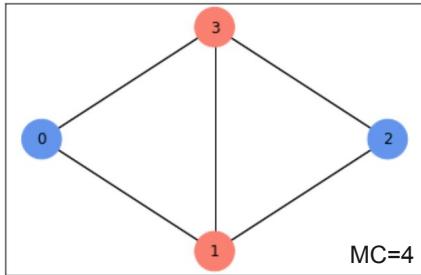


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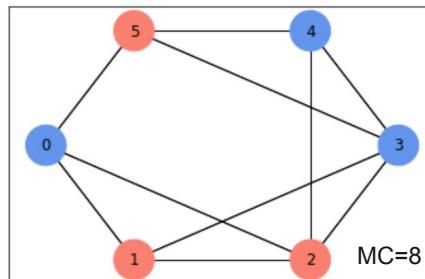
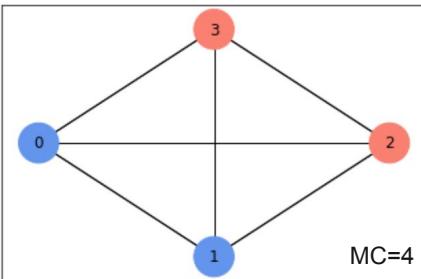


# Maxcut problem is NP-Hard!

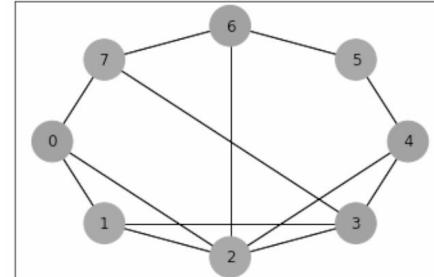
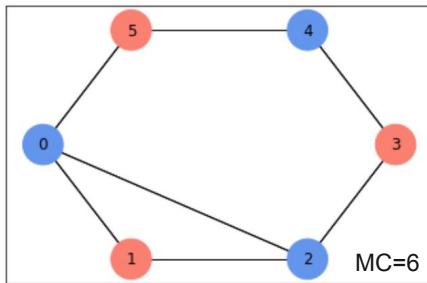
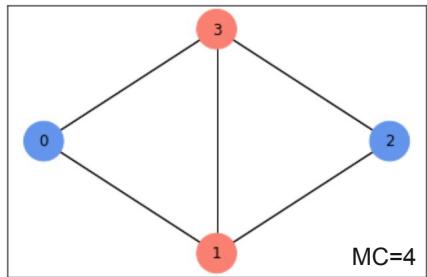
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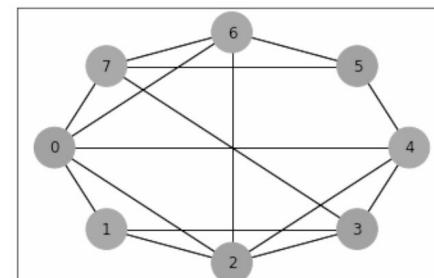
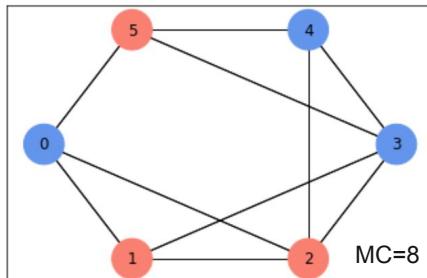
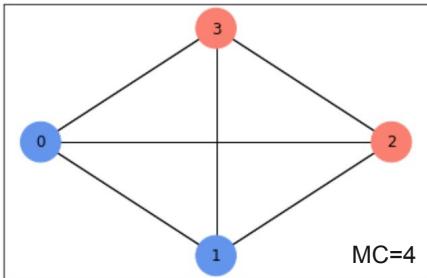
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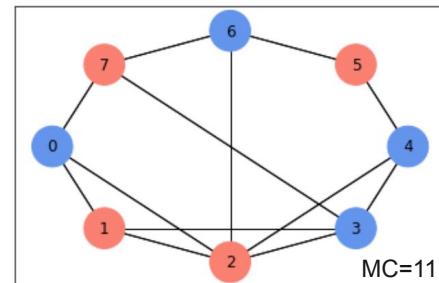
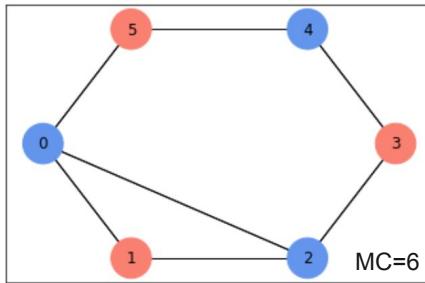
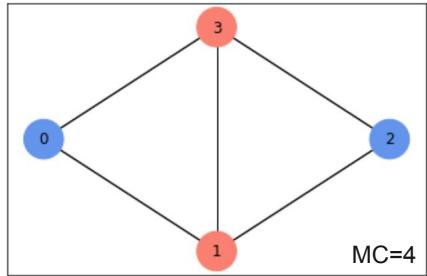
# Maxcut problem is NP-Hard!



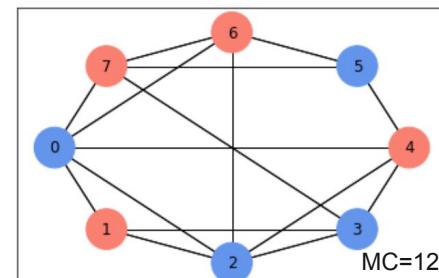
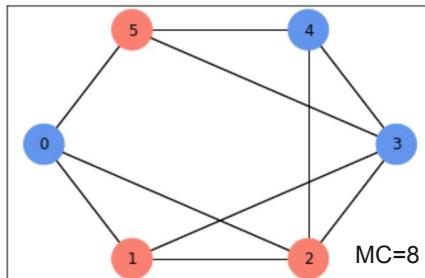
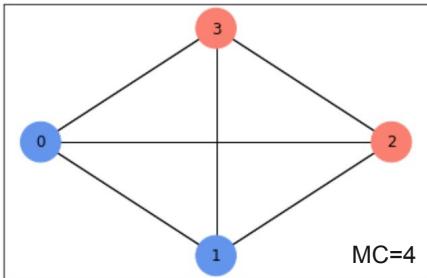
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# Maxcut problem is NP-Hard!

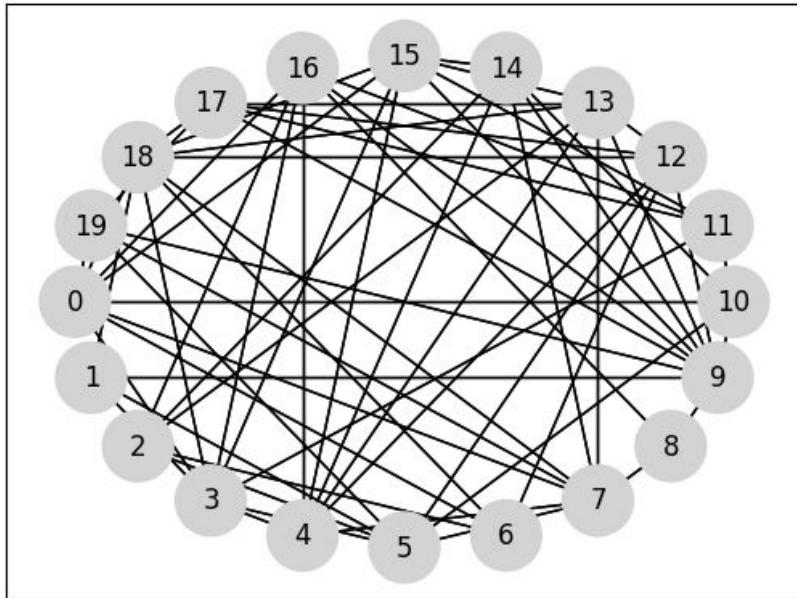


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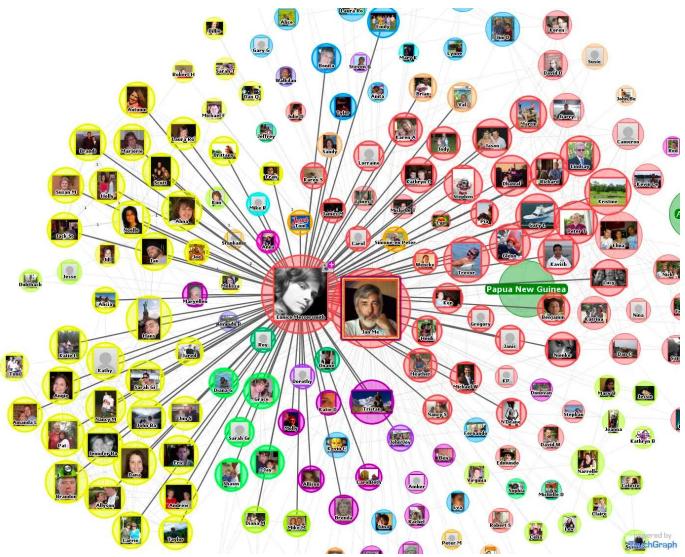
# Maxcut problem is **NP-Hard!**

Eventually, bruteforce solutions  $\mathcal{O}(n!)$  for large graphs becomes impractical...



$n = 20$  is already so slow to compute...

# Maxcut problem is universal & important



Social network:  
recommending new Friends



Vehicle routing:  
finding optimal path

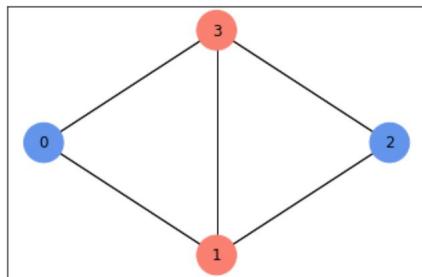
# Maxcut problem state representation

How to leverage quantum computing to solve Maxcut problems?

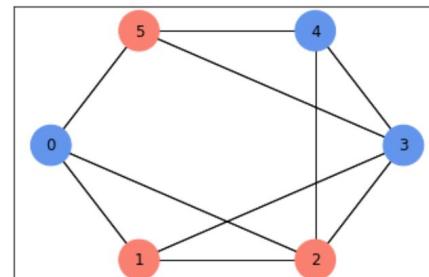
By representing a solution to the  $n$ -node Maxcut using binary sequence!

where  $x_i = 0$  indicates node- $i$  in **Partition 0 (red)**, and  $x_i = 1$  indicates node- $i$  in **Partition 1 (blue)**.

$$\boldsymbol{x} = x_0 x_1 x_2 \cdots x_{n-1} = |x_0\rangle |x_1\rangle |x_2\rangle \cdots |x_{n-1}\rangle$$



$$\boldsymbol{x} = 1010 = |1\rangle_0 |0\rangle_1 |1\rangle_2 |0\rangle_3$$



$$\boldsymbol{x} = 100110 = |100110\rangle$$

# Maxcut problem cost function

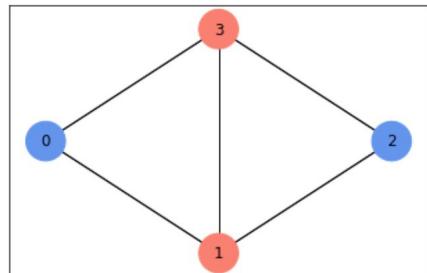
With these binary variables, we can build a cost function for any Maxcut problem

$$H(\mathbf{x}) = \sum_{i,j} w_{ij} x_i (1 - x_j)$$

$$w_{ij} = \begin{cases} 1, & \text{if edge}(i, j) \in G \\ 0, & \text{if edge}(i, j) \notin G \end{cases}$$

connectivity  
(adjacency matrix)

We claim a solution to the maxcut problem must **maximize this Hamiltonian!**



$$\mathbf{x} = 1010 = |1\rangle_0 |0\rangle_1 |1\rangle_2 |0\rangle_3$$

$$w = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

$$w_{01}x_0(1 - x_1) = w_{01} \cdot 1 \cdot (1 - 0) = 1$$

$$w_{03}x_0(1 - x_3) = w_{03} \cdot 1 \cdot (1 - 0) = 1$$

$$w_{10}x_1(1 - x_0) = w_{10} \cdot 0 \cdot (1 - 1) = 0$$

$$w_{12}x_1(1 - x_2) = 0 \qquad \qquad w_{30}x_3(1 - x_0) = 0$$

$$w_{13}x_1(1 - x_3) = 0 \qquad \qquad w_{31}x_3(1 - x_1) = 0$$

$$w_{21}x_2(1 - x_1) = 1 \qquad \qquad w_{32}x_3(1 - x_2) = 0$$

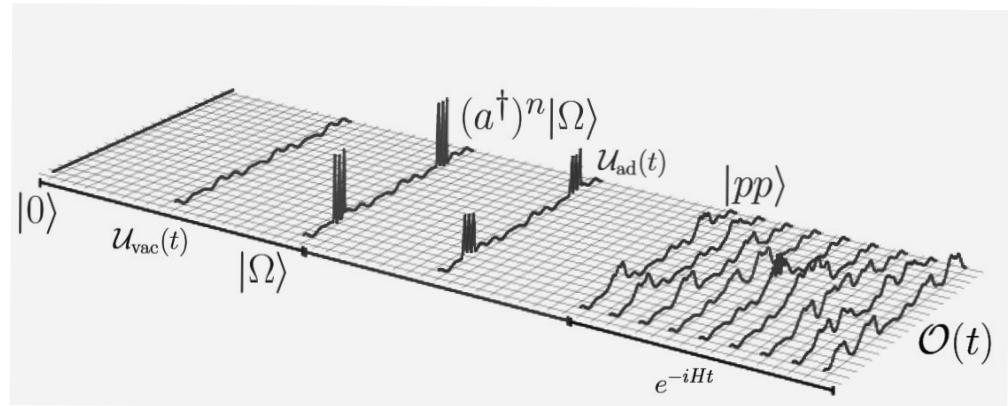
$$w_{23}x_2(1 - x_3) = 1$$

$$H(\mathbf{x}) = 4$$

# Quantum simulation II

Wiesner, 9603028 (1996); Zalka, 9603026 (1996)

1. Define problem of interest
2. **Encode onto qubits**
3. Prepare initial states
4. Variational ansatz
5. Measurement protocol



Lamm's talk at Fermilab (2021)

How do we efficiently encode the problem to qubits?

# Pauli matrices

The problem of interest can be expressed in terms of Pauli matrices, I, X, Y, Z

$$I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad Y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, \quad Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \quad \vec{\sigma} = (\sigma^0, \sigma^1, \sigma^2, \sigma^3) = (I, X, Y, Z)$$

such that we end up with a linear combinations of products of these Pauli matrices

$$H = \sum_i c_i P_i$$

For example:

$$\begin{aligned} H_{ex} &= I_0 I_1 + X_0 X_1 + Y_0 Y_1 + Z_0 Z_1 \\ &= II + XX + YY + ZZ \end{aligned}$$

$$\exp(-iH_{ex}t) = \boxed{\exp(-i[II + XX + YY + ZZ]t)}$$

# Quantum state in Pauli-Z basis

Most quantum devices are in Z-basis or **computational basis**

$$|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, |1\rangle = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

In fact any operations can be represented in this way:

$$\sigma_0 \equiv I \equiv \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = |0\rangle\langle 0| + |1\rangle\langle 1|,$$

$$\sigma_1 \equiv X \equiv \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} = |1\rangle\langle 0| + |0\rangle\langle 1|,$$

$$\sigma_2 \equiv Y \equiv \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix} = i|1\rangle\langle 0| - i|0\rangle\langle 1|,$$

$$\sigma_3 \equiv Z \equiv \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} = |0\rangle\langle 0| - |1\rangle\langle 1|$$

Including the Control-Not gate!

$$\text{CNOT} = (|0\rangle\langle 0|)_0 \otimes I_1 + (|1\rangle\langle 1|)_0 \otimes X_1$$

# Maxcut problem qubit encoding

To map the maxcut problem to quantum circuit, we use

$$x_i \rightarrow \frac{I - Z}{2} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

**Exercise:** Why? check eigenvalue and eigenvector

$$\begin{aligned} Z |0\rangle &= +1 |0\rangle \\ Z |1\rangle &= -1 |1\rangle \end{aligned}$$

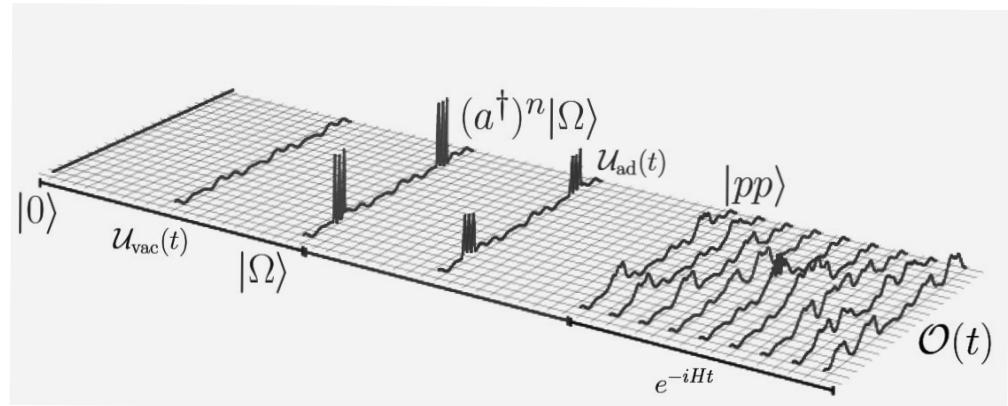
Then, **Maxcut cost function** becomes a sum of Pauli-Z and Pauli-ZZ operators (i.e., Ising Hamiltonian, or sometimes known as the **QUBO** problem)

$$H \rightarrow \sum_{ij} w_{ij} \frac{I_i - Z_i}{2} \left( I - \frac{I_j - Z_j}{2} \right) = \sum_i c_i Z_i + \sum_{ij} d_{ij} Z_i Z_j$$

# Quantum simulation III

Wiesner, 9603028 (1996); Zalka, 9603026 (1996)

1. Define problem of interest
2. Encode onto basis
3. **Prepare initial states**
4. Variational Ansatz
5. Measurement protocol



Lamm's talk at Fermilab (2021)

What initial state should we use?

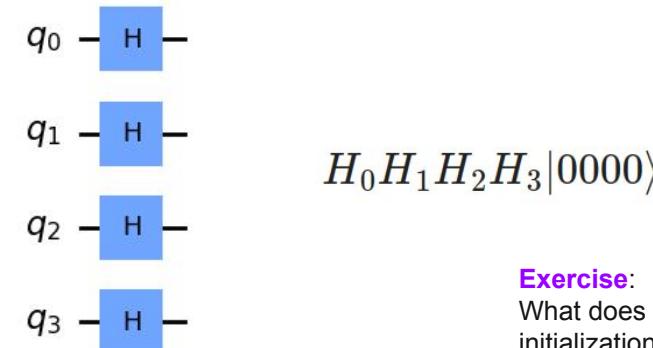
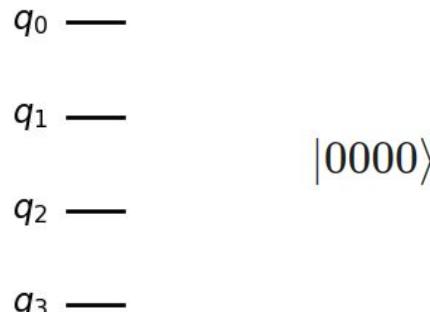
# State preparation

State preparation (initialization) is the First step of quantum computing

Unlike classical computation, one cannot simply prepare an arbitrary state in QC. Often it involves careful analysis of the problem and genius engineering...

Here, we look at two possible initializations

$$\text{Hadamard gate: } H \equiv \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

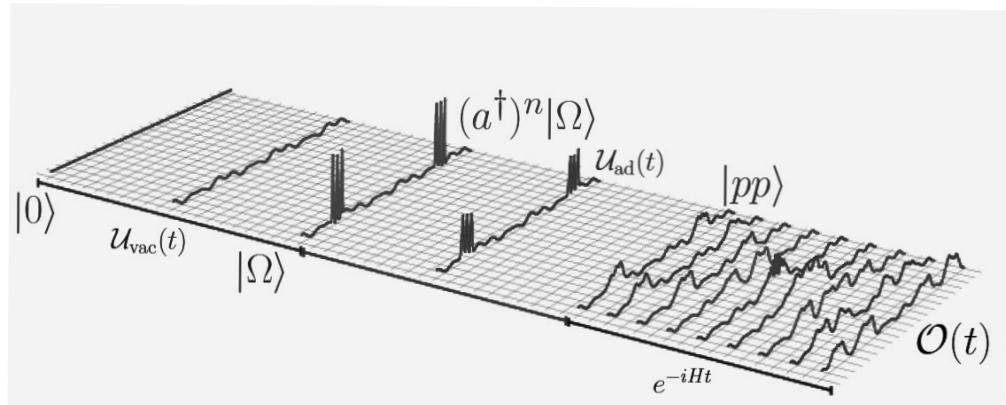


**Exercise:**  
What does Hadamard initialization give you?

# Quantum simulation IV

Wiesner, 9603028 (1996); Zalka, 9603026 (1996)

1. Define problem of interests
2. Encode onto basis
3. Prepare initial states
4. **Variational Ansatz**
5. Measurement protocol

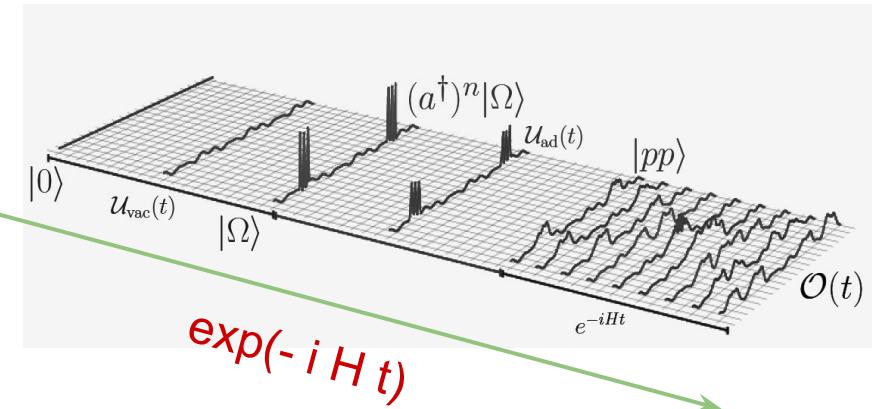
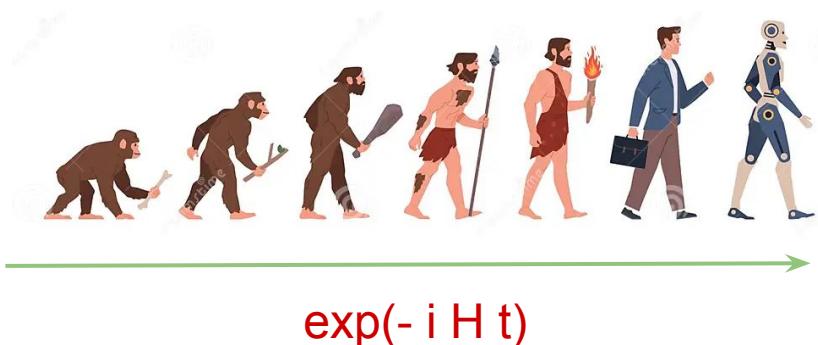


Lamm's talk at Fermilab (2021)

What does variational ansatz (quantum evolution) mean?

# Variational ansatz = Unitary quantum evolution

Literally means evolving some **quantum state** by applying an **operator H** for a **parameter t**.



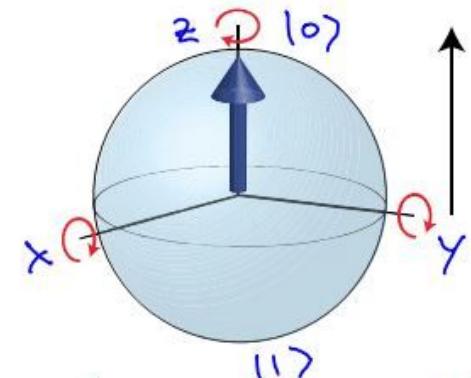
# Single qubit simulation

Rotational gates take care single qubit Pauli terms (Taylor expansion)

$$e^{-iXt} = \cos(t)I - i \sin(t)X = \begin{pmatrix} \cos(t) & -i \sin(t) \\ -i \sin(t) & \cos(t) \end{pmatrix} \quad R_x(2t)$$

$$e^{-iYt} = \cos(t)I - i \sin(t)Y = \begin{pmatrix} \cos(t) & -\sin(t) \\ \sin(t) & \cos(t) \end{pmatrix} \quad R_y(2t)$$

$$e^{-iZt} = \cos(t)I - i \sin(t)Z = \begin{pmatrix} e^{-it/2} & 0 \\ 0 & e^{it/2} \end{pmatrix} \quad R_z(2t)$$



These are just  
**Rotational gates** on Bloch sphere!

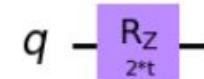
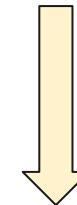
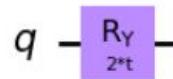
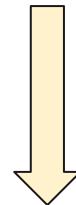
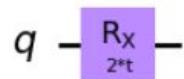
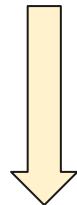
$$|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, |1\rangle = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

# Single qubit simulation

$$e^{-iXt}$$

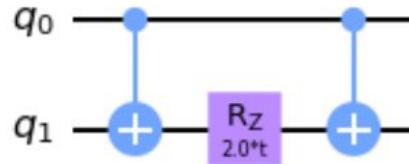
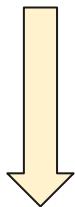
$$e^{-iYt}$$

$$e^{-iZt}$$



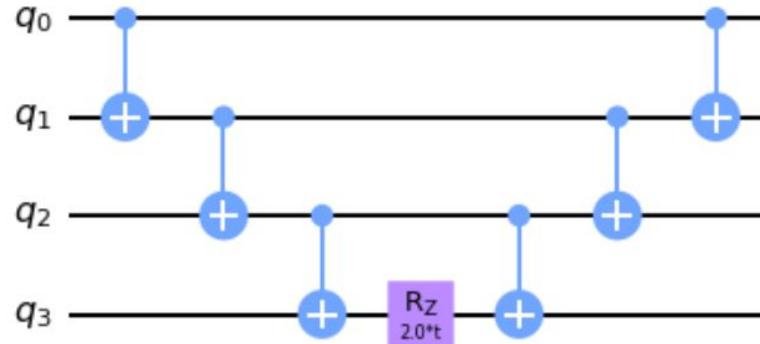
# Multiple qubit simulation

$$\exp(-iZ_0Z_1t) = \text{CNOT}_{0,1} \exp(-iZ_1t) \text{CNOT}_{0,1}$$



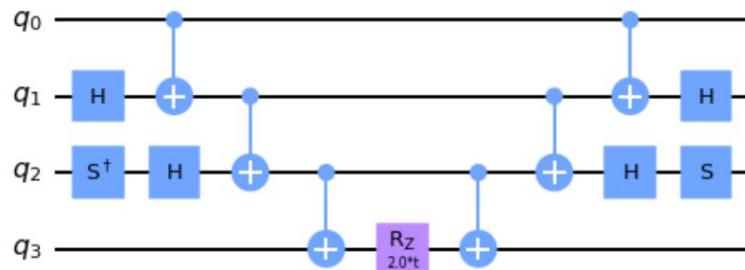
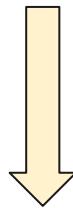
# Multiple qubit simulation

The results can be generalized to  $\exp(-i ZZ\dots Z t)$ , where the circuit is **a tower of control gates**  
For example,  $\exp(-i ZZZZ t)$  becomes

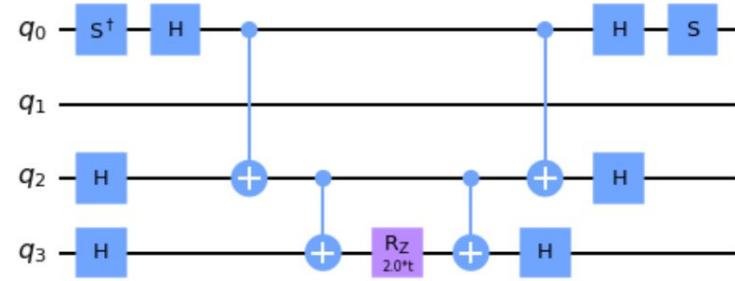
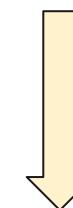


# Multiple qubit simulation

$$\exp(-iZ_3Y_2X_1Z_0t)$$



$$\exp(-iX_3X_2I_1Y_0t)$$



$$X = HZH^\dagger, \quad Y = (SH)Z(SH)^\dagger$$

$$H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

$$S = \sqrt{Z} = \begin{pmatrix} 1 & 0 \\ 0 & i \end{pmatrix}$$

# Two types of VQA

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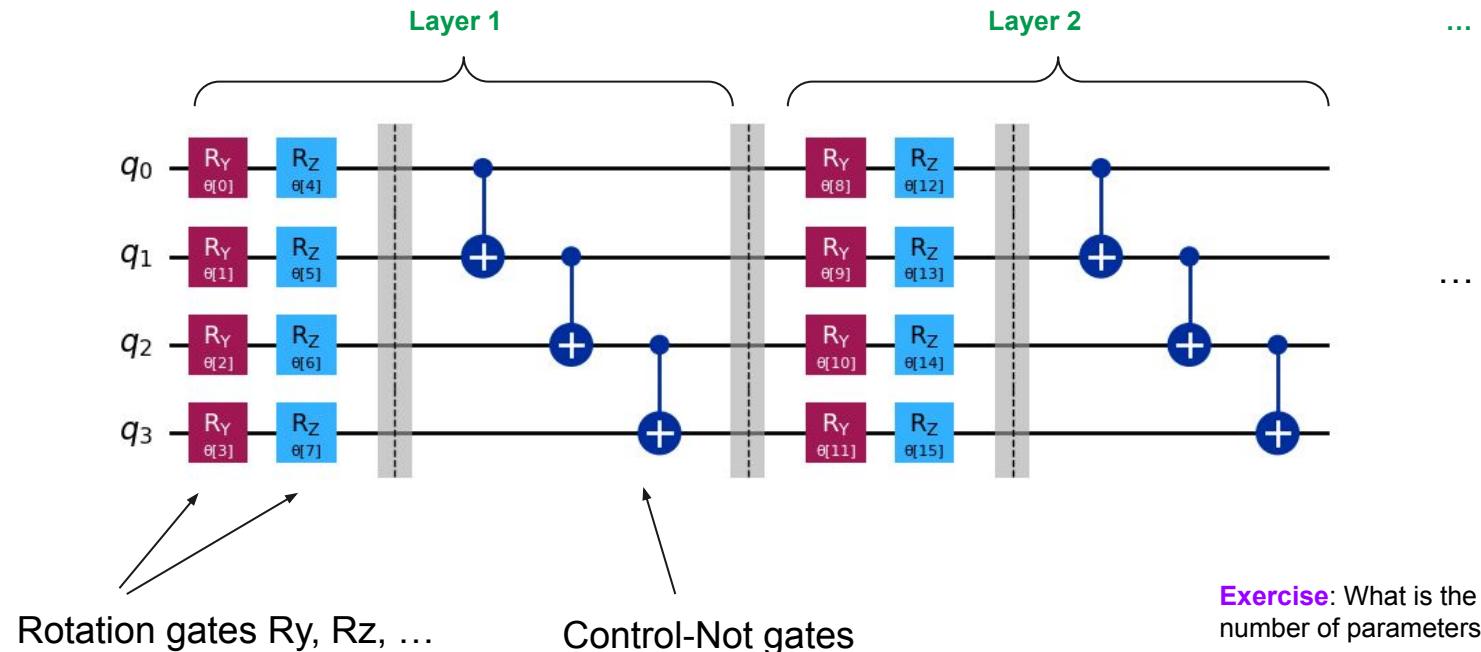
Here we focus on two types of VQAs in this lecture:

- Variational Quantum Eigensolver (VQE)
- Quantum Approximation Optimization Algorithm (QAOA)

Specifically, we use **parameterized** ansatz to perform unitary evolution.

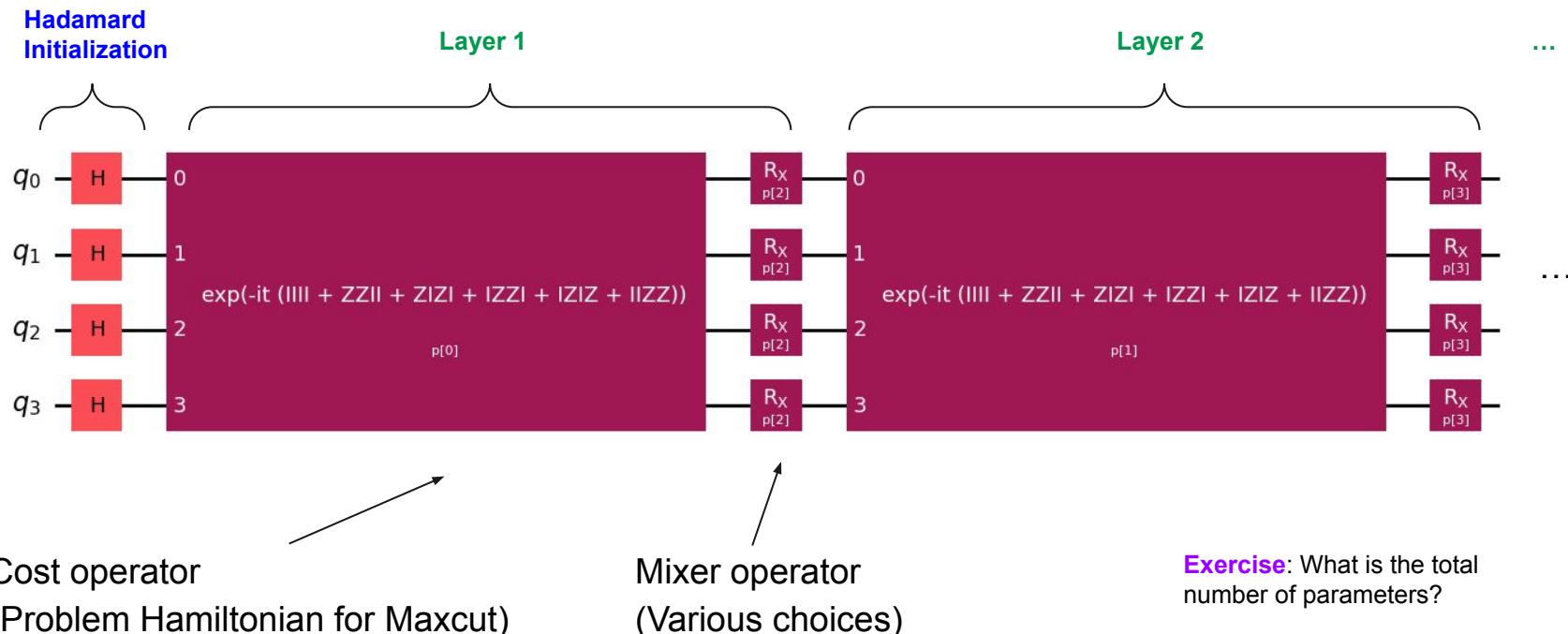
# Variational Quantum Eigensolver

VQE is the simplest variational algorithm that typically uses heuristic, hardware-efficient ansatz that consists of **many layers** of **Rotation gates** and **control-Not gates**.



# Quantum Approximation Optimization Algorithm

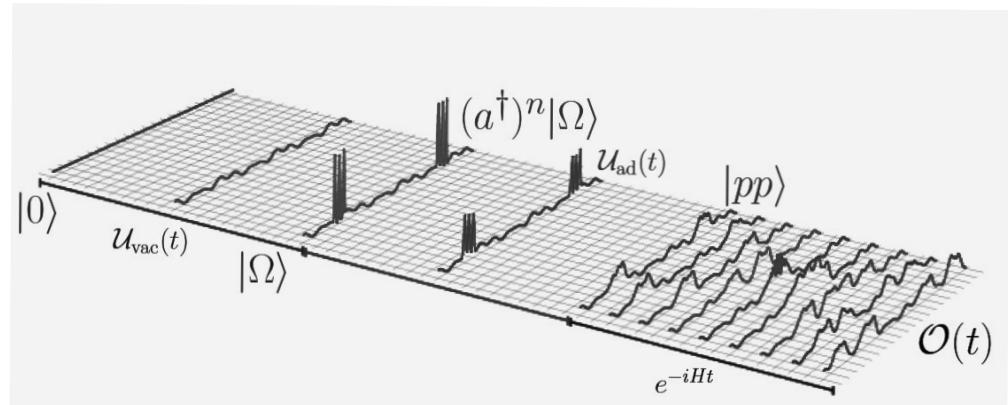
Unlike VQE, QAOA is a **problem-inspired ansatz** that consists of **many layers** of **cost operators** and **mixer operators**. It usually requires a **Hadamard initialization**



# Quantum simulation V

Wiesner, 9603028 (1996); Zalka, 9603026 (1996)

1. Define problem of interest
2. Encode onto basis
3. Prepare initial states
4. Variational ansatz
5. **Measurement protocol**



Lamm's talk at Fermilab (2021)

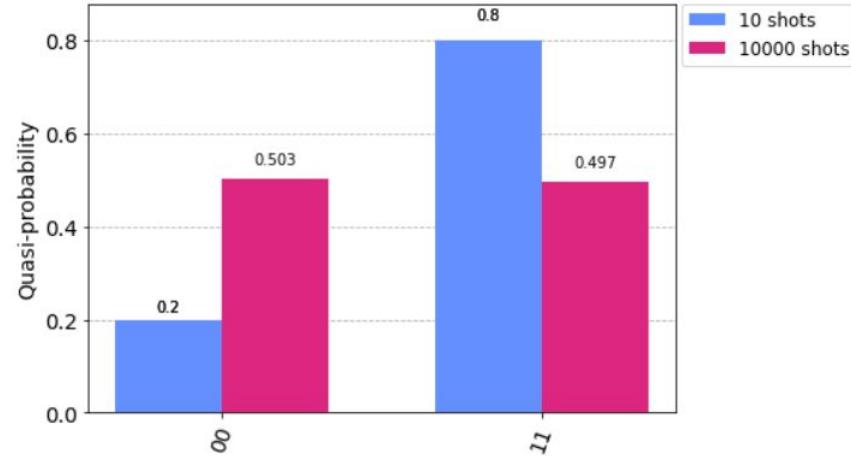
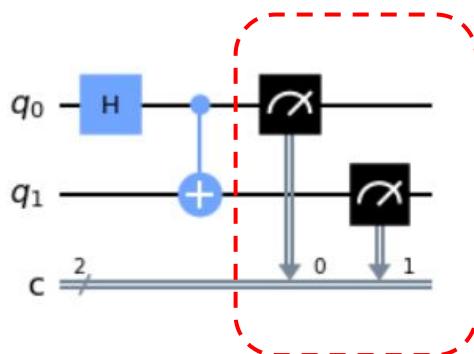
What is measurement and how to compute observable expectation?

# What is measurement?

Measurement is the result of quantum simulation

From quantum mechanics, measurement **collapse** the wavefunction (in a sense, we lost the full information of the state)

Therefore, we must measure/sample the circuit **many times (shots)** to partially reconstruct the state



# Observable

---

- What is observable?

Quantity of interests. For example, energy of the state.

- How are observables constructed?

Formally, it is the expectation value of an operator       $\langle O \rangle = \langle \psi | \hat{O} | \psi \rangle$

On the quantum circuit, it is computed as a **certain weighted sum of probabilities** in the computational basis.

# Expectation of Observable

For example,  $\hat{O}_1 = \frac{1}{2}I_0Z_1$        $|\psi\rangle = \sum_i c_i |i\rangle = c_{00} |00\rangle + c_{01} |01\rangle + c_{10} |10\rangle + c_{11} |11\rangle$

Then      
$$\begin{aligned}\hat{O}_1 |\psi\rangle &= \frac{1}{2} \left( c_{00}IZ|00\rangle + c_{01}IZ|01\rangle + c_{10}IZ|10\rangle + c_{11}IZ|11\rangle \right) \\ &= \frac{1}{2} \left( c_{00}|00\rangle - c_{01}|01\rangle + c_{10}|10\rangle - c_{11}|11\rangle \right)\end{aligned}$$
       $Z|0\rangle = |0\rangle$   
                         $Z|1\rangle = -|1\rangle$

Obviously, this generalizes to any linear combinations of Pauli-Z observables

$$\begin{aligned}\langle\psi|\hat{O}_1|\psi\rangle &= \frac{1}{2}(|c_{00}|^2 - |c_{01}|^2 + |c_{10}|^2 - |c_{11}|^2) \\ &= \frac{1}{2}(P(00) - P(01) + P(10) - P(11))\end{aligned}$$
      linear combo of probabilities

# Expectation of Observable

What about Pauli-X, Pauli-Y based observables?

Just like the simulation problem, the trick is to append quantum gates that move the calculations to computational basis!

$$X = H^\dagger Z H, \quad Y = H_y^\dagger Z H_y \quad H_y = HS^\dagger$$

For example,

$$\begin{aligned} \langle \psi | I_0 X_1 Y_2 Z_3 | \psi \rangle &= \langle \psi | I_0 (H^\dagger Z H)_1 (H_y^\dagger Z H_y)_2 Z_3 | \psi \rangle \\ &= \langle \psi | H_1(H_y)_2 | I_0 Z_1 Z_2 Z_3 | H_1(H_y)_2 | \psi \rangle \\ &= \langle \psi' | I_0 Z_1 Z_2 Z_3 | \psi' \rangle \end{aligned}$$

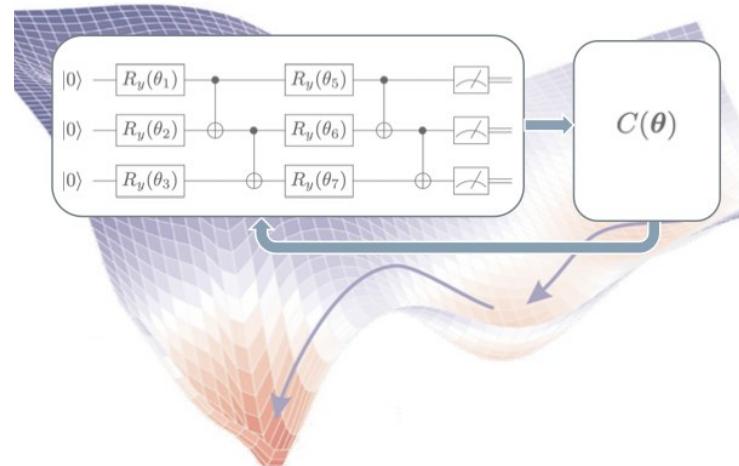
We see that any Pauli observables are just the same as Pauli-Z based observables by **appending basis transformation gates**. Luckily, Qiskit will do the work automatically for you.

# Classical Optimization

Once the quantum simulation is completed, the classical optimization kicks in

The classical tasks are:

1. Evaluate the cost function (in our case is trivially the Hamiltonian expectation)
2. Optimize the parameters with classical optimizer.



# Classical Optimization

In general, optimizers can be divided into two categories depend on whether they use gradients

## 1. Gradient inspired optimizers

examples:

- Limited-memory BFGS Bound optimizer (BFGS)
- Sequential Least Squares Programming optimizer (SLSQP)

Faster Convergence  
Efficient in Noiseless setting  
  
Sensitive to Noise  
Require Gradients

## 2. Gradient-free optimizers

examples:

- Simultaneous Perturbation Stochastic Approximation (SPSA)
- Constrained Optimization BY Linear Approximations (COBYLA)

Easy to Implement  
Robust to Noise  
  
Slower Convergence

Both can be subject to Barren Plateaus with High Dimension. Quantum Optimization is still open question!

# Summary

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- Today we learned about Variational Quantum Algorithm is efficient tool to solve real-world problems
- Specifically we focus on two algorithms: VQE and QAOA
- They are **Hybrid algorithms** that use quantum computer for **unitary evolution** and classical computer for **parameter optimization**.
- In the lab, we will develop these algorithms to solve Maxcut problems!

Thanks for your attention!