Building a quantum classifier

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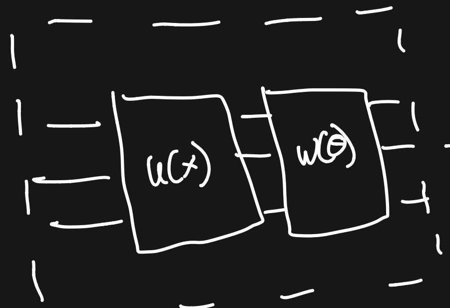
NISQ era

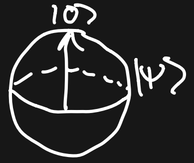
$X \rightarrow$



$\rightarrow \hat{y}$

Barren plateaus

$\hat{H}$



$\cos\frac{\theta}{2} + i\sin\frac{\theta}{2}$

$|\psi\rangle \otimes |\phi\rangle$

QML vs ML

$\langle 0|M|0\rangle$

Qiskit

Hilbert space is a big place!

- Carlton Caves

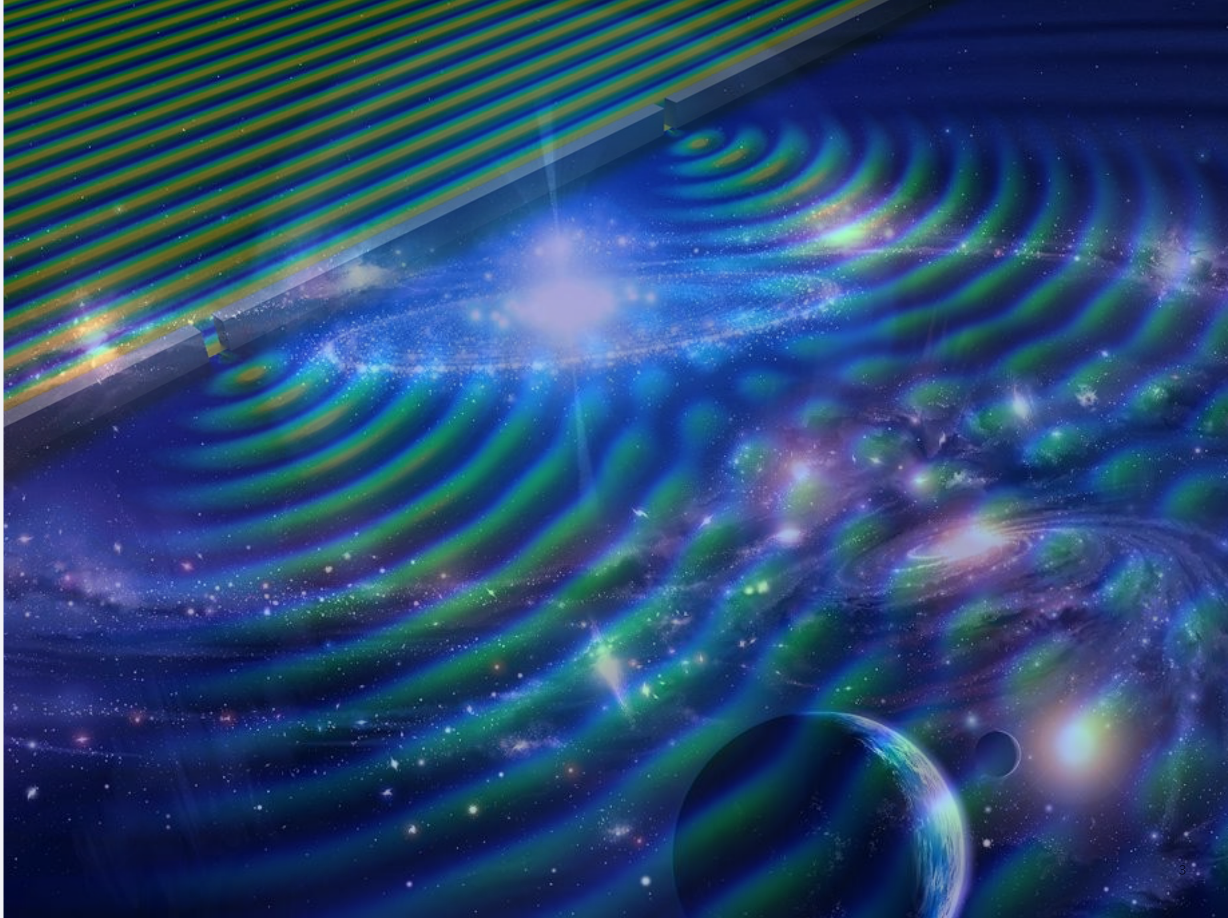
With just 275 qubits, we can represent more states than the number of atoms in the observable universe

$$2^{275}$$

Hilbert space is a big place!

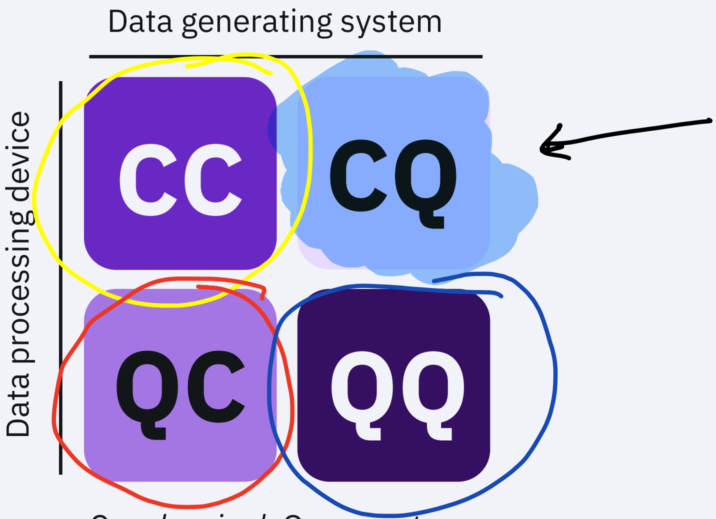
- *Carlton Caves*

Interference



Quantum machine learning

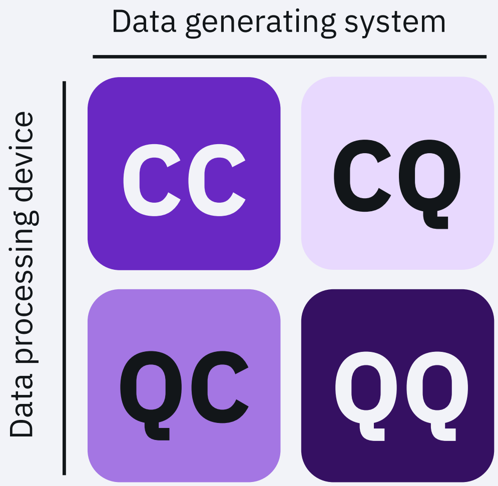
Qiskit



C – *classical*, Q – *quantum*

Image credit: *Maria Schuld and Francesco Petruccione. Supervised learning with quantum computers. Vol. 17. Springer, 2018.*

Quantum machine learning



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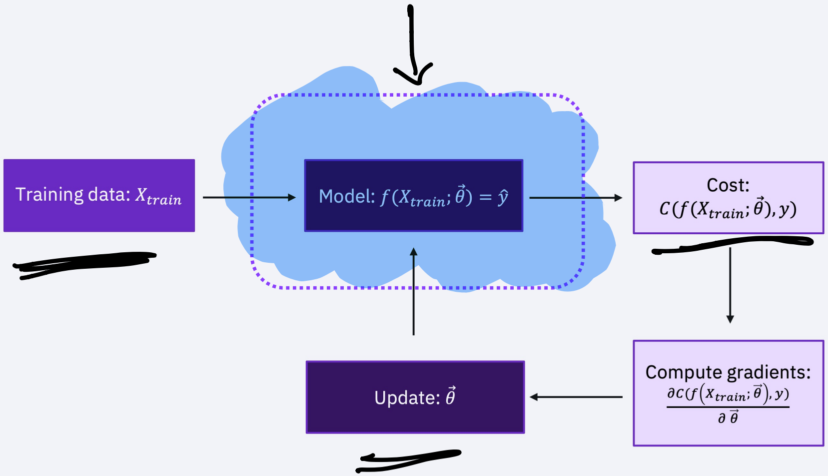


Image credit: *Maria Schuld and Francesco Petruccione. Supervised learning with quantum computers. Vol. 17. Springer, 2018.*

Near-term
vs
fault-tolerant

Noisy, error-prone, small devices

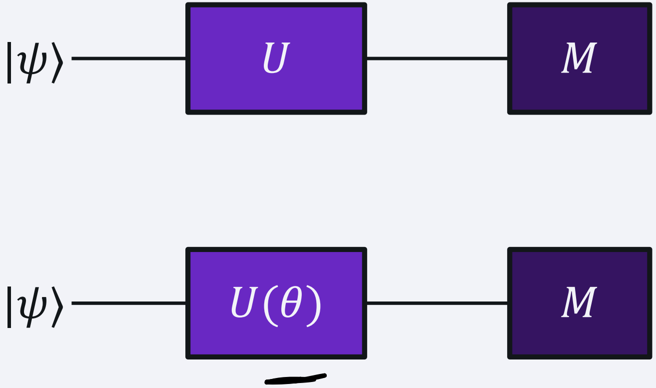
What can we do now?

Variational models

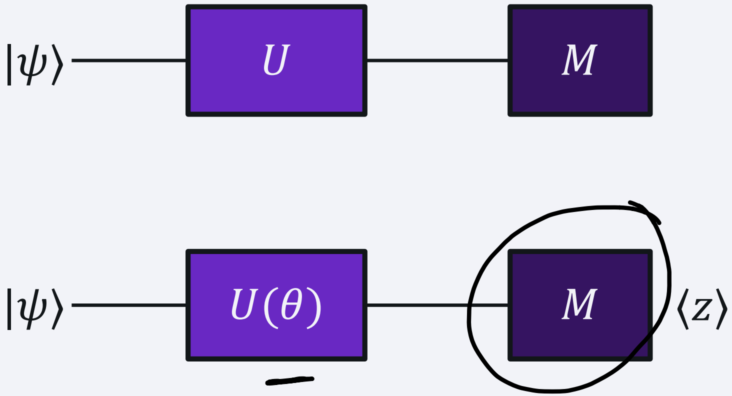
Variational models

Variational models

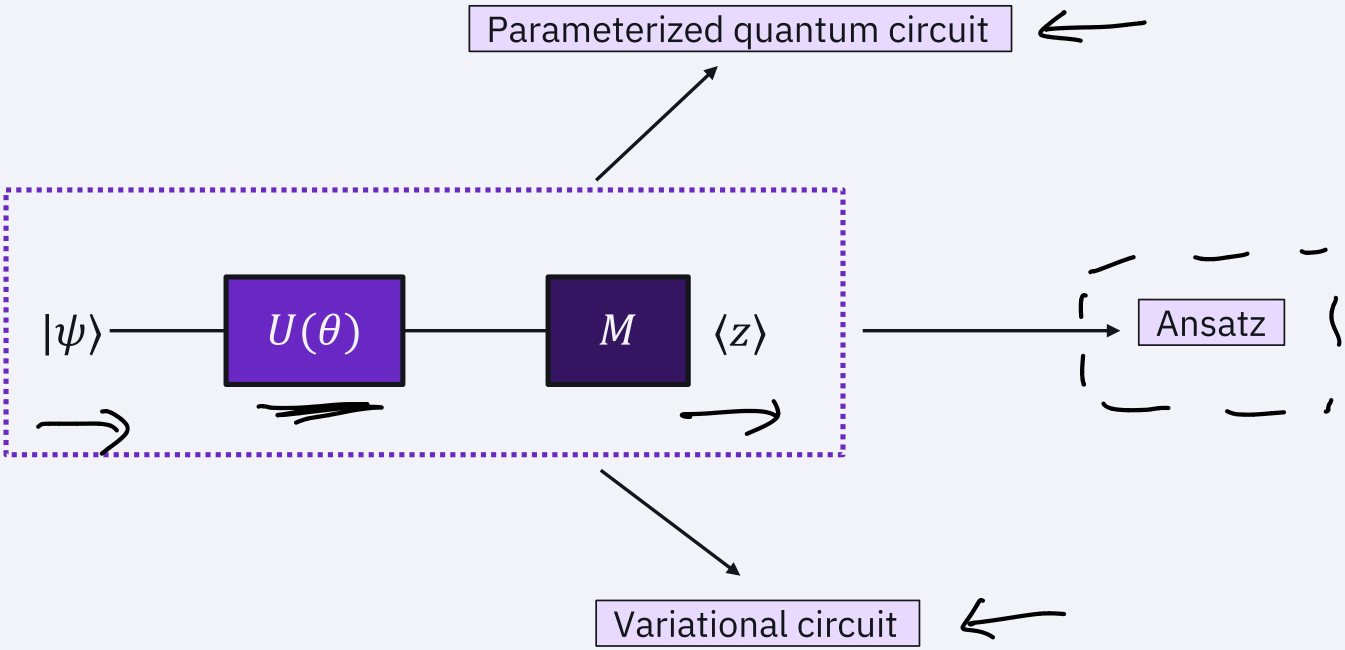
Variational models



Variational models



Variational models



A first attempt

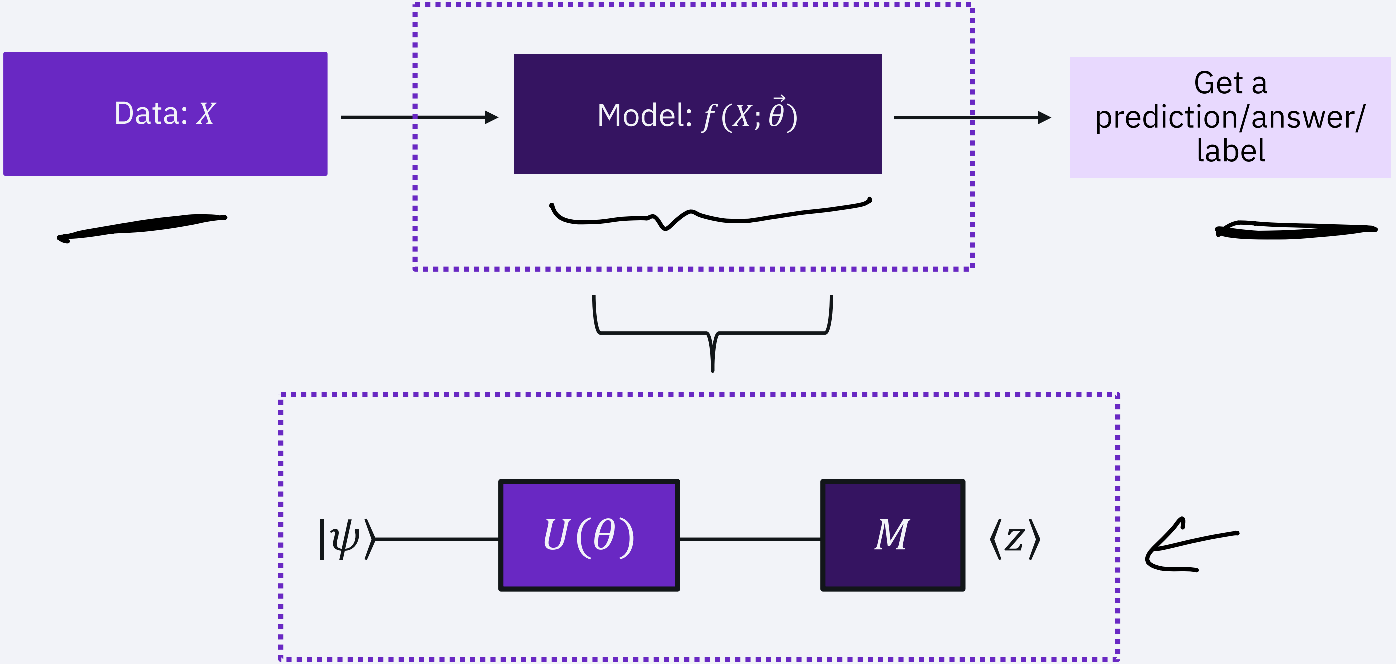
Variational circuit as a classifier

Variational circuit as a classifier

Data: X → Model: $f(X; \vec{\theta})$ → Get a prediction/answer/label

Variational circuit as a classifier

Qiskit



Variational circuit as a classifier

Task: Train a quantum circuit on labelled samples in order to predict labels for new data

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Step 1: Encode the classical data into a quantum state

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Variational circuit as a classifier

Qiskit

Task: Train a quantum circuit on labelled samples in order to predict labels for new data

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Step 2: Apply a parameterized model

Step 3: Measure the circuit to extract labels

Variational circuit as a classifier

Qiskit

Task: Train a quantum circuit on labelled samples in order to predict labels for new data

Step 1: Encode the classical data into a quantum state x

Step 2: Apply a parameterized model

Step 3: Measure the circuit to extract labels

Step 4: Use optimization techniques (like gradient descent) to update model parameters

Data encoding

Basis encoding ← Basis states

2 qubits

$|00\rangle$ 0

$|01\rangle$ x_1

$|10\rangle$ 0

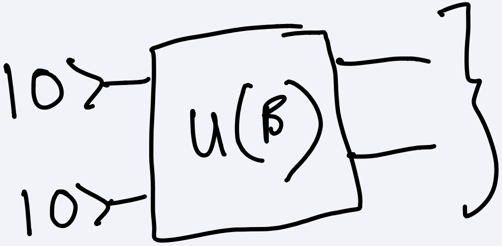
$|11\rangle$ x_2

$x_1 \rightarrow 01$

$x_2 \rightarrow 11$

Data encoding

Amplitude encoding



$$|\psi\rangle = \begin{bmatrix} 0.8 \\ 0.1 \\ 0 \\ 0.1 \end{bmatrix}$$

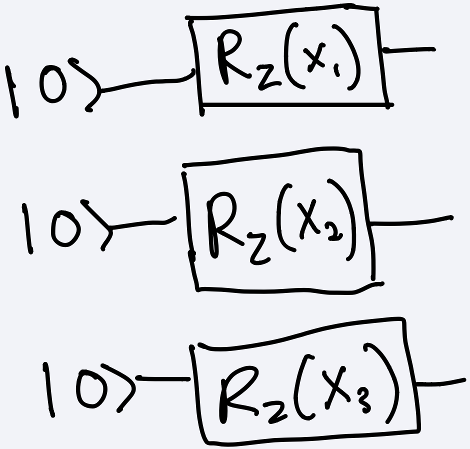
$$|0\rangle \otimes |0\rangle = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$x_1 = \begin{bmatrix} 0.8 \\ 0.1 \\ 0 \\ 0.1 \end{bmatrix}$$

Data encoding

Angle encoding

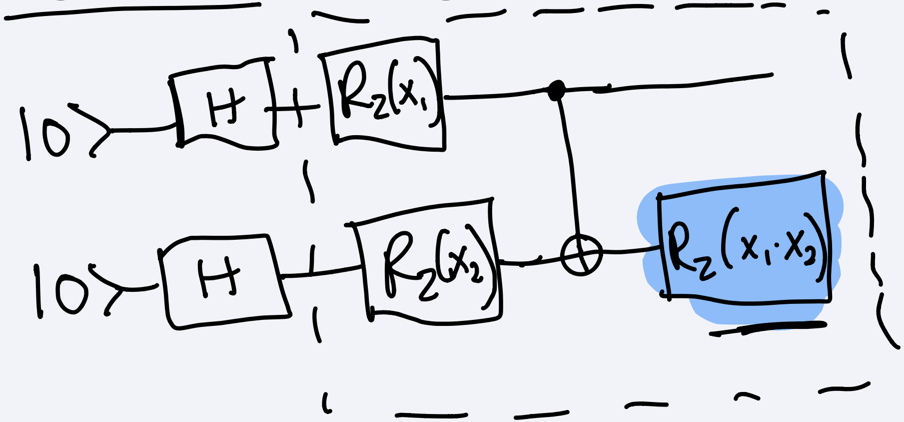
$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$



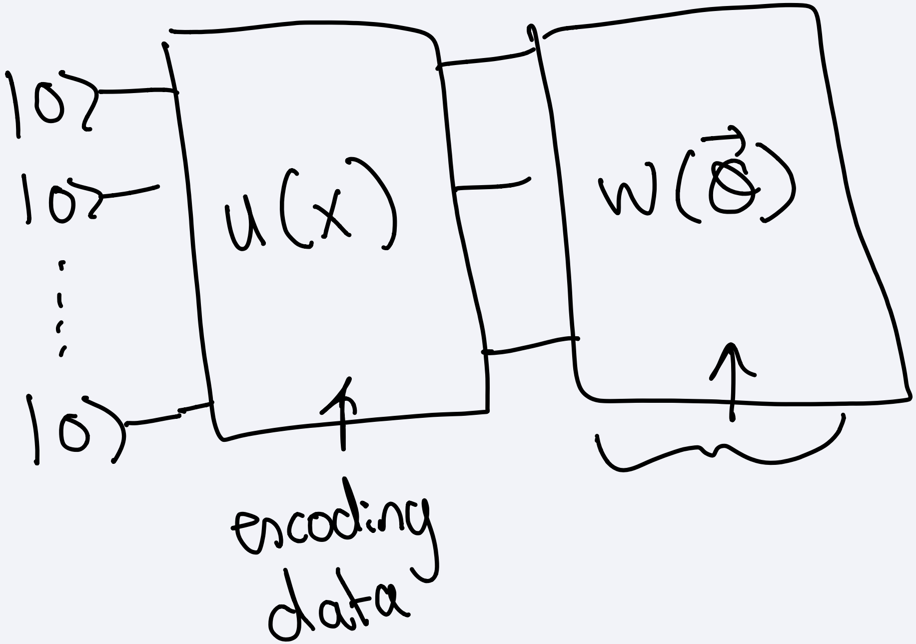
Data encoding

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Higher order encoding

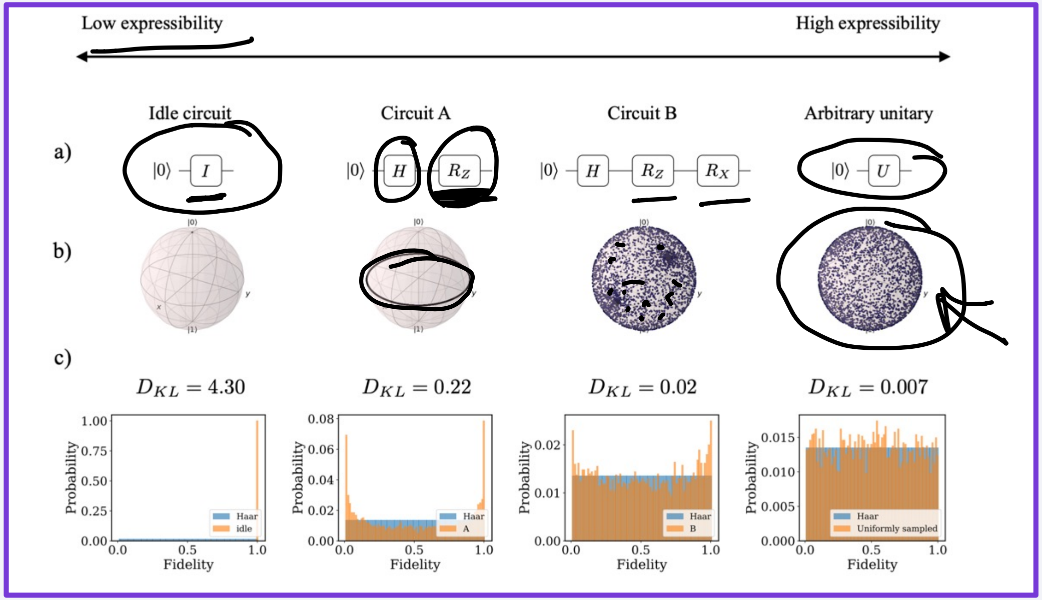


Applying a variational model



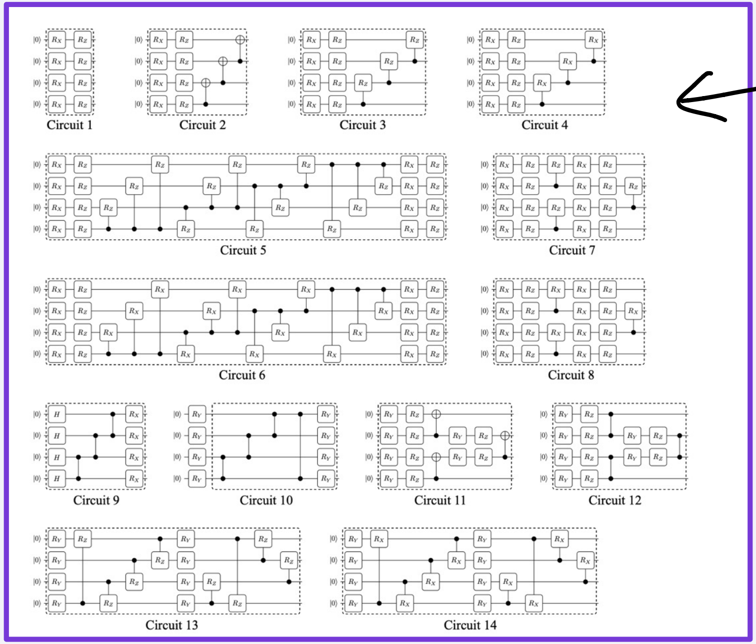
Applying a variational model

Qiskit



Sim et al. "Expressibility and Entangling Capability of Parameterized Quantum Circuits for Hybrid Quantum-Classical Algorithms." Advanced Quantum Technologies 2.12 (2019): 1900070.

Applying a variational model



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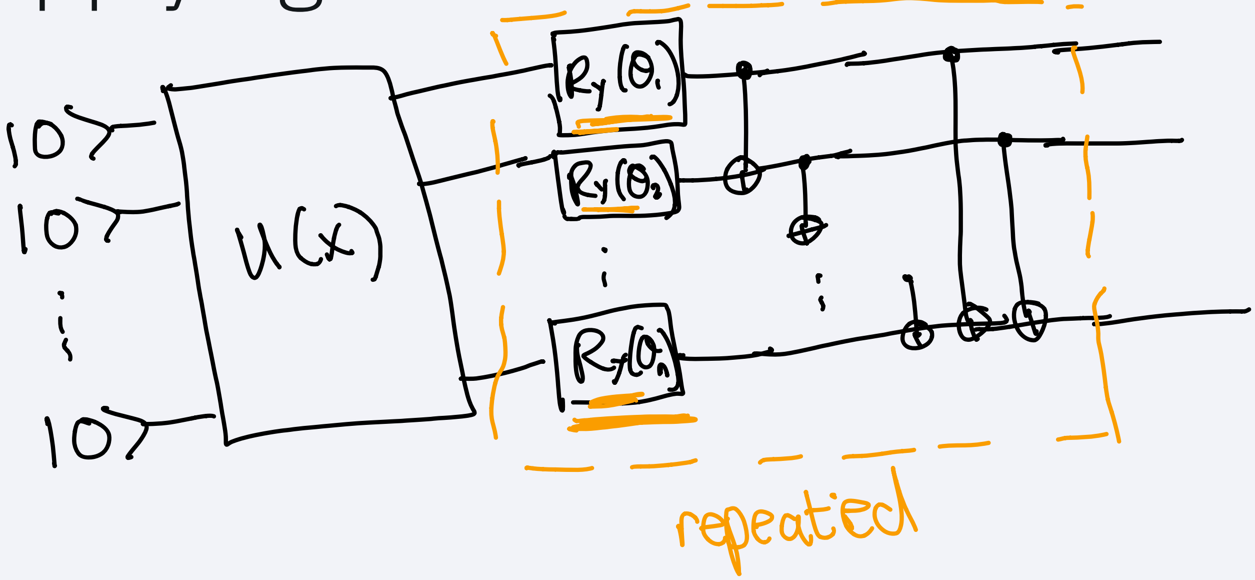
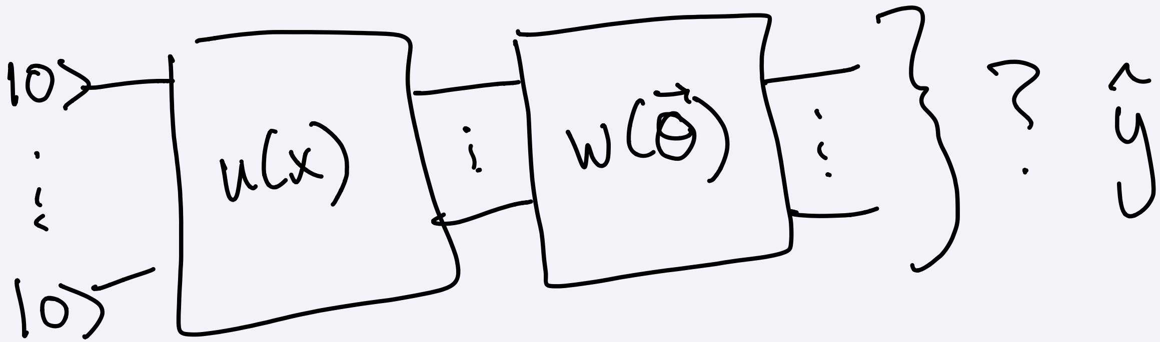
Applying a variational model

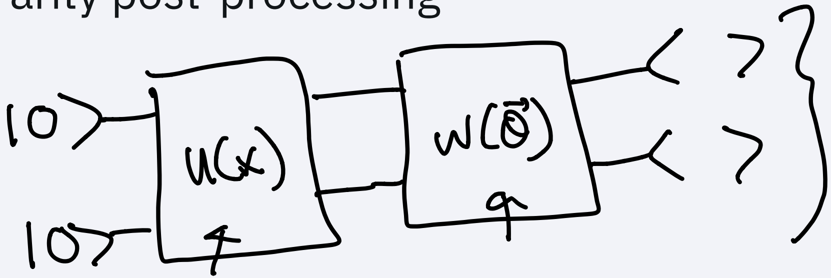


Extracting labels



Extracting labels

Parity post-processing



2 qubits

$00 \to 0.8$

$01 \to 0.1$

$10 \to 0$

$11 \to 0.1$

even $\to +1$

odd $\to -1$

$00 \to$ even

$01 \to$ odd

$10 \to$ odd

$11 \to$ even

$$Pr(\hat{y} = 1) = 0.9$$

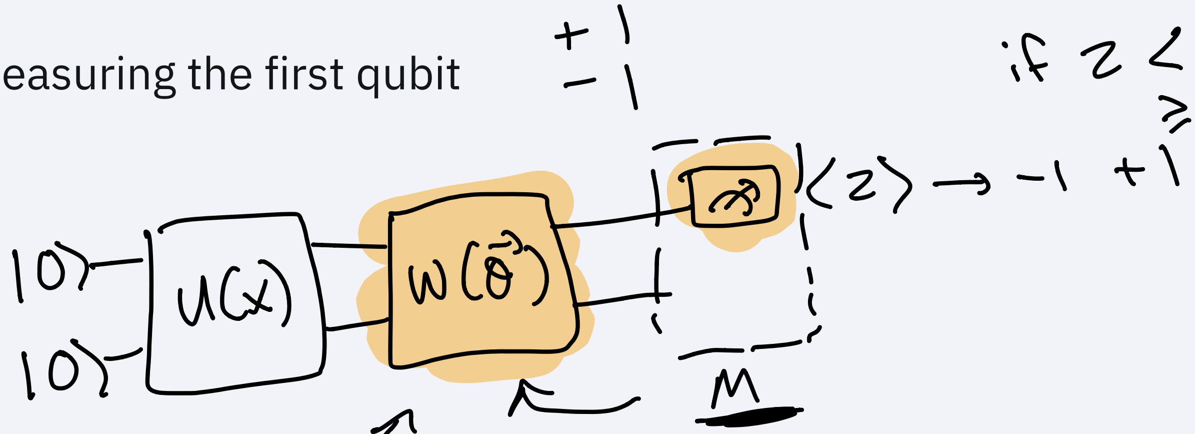
$$Pr(\hat{y} = -1) = 0.1$$

$$\text{even} = 0.8 + 0.1 = \boxed{0.9}$$

Source: Havlíček, Vojtěch, et al. "Supervised learning with quantum-enhanced feature spaces." *Nature* 567.7747 (2019): 209-212.

Extracting labels

Measuring the first qubit



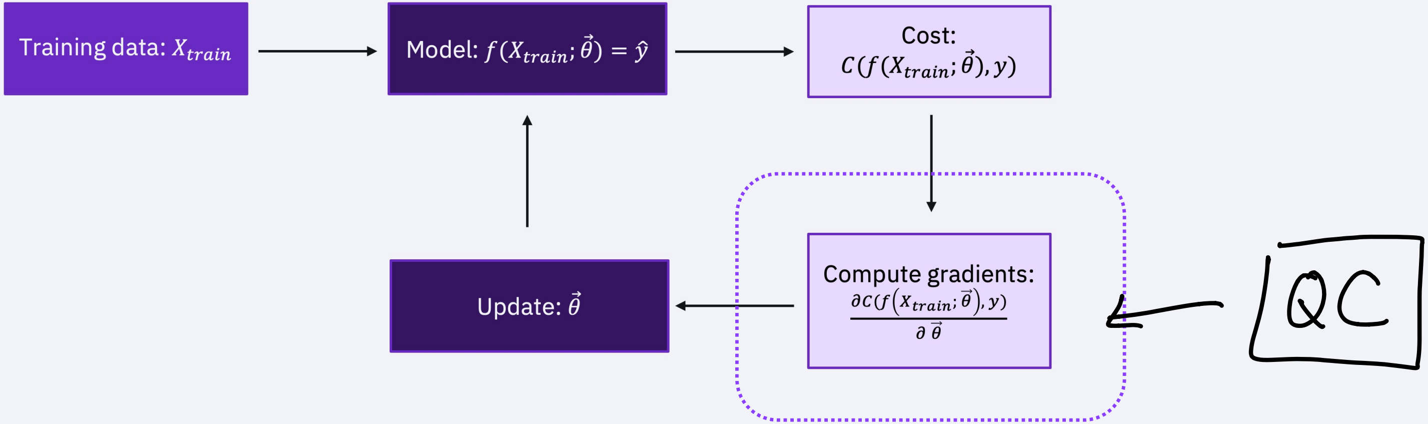
$$\text{if } z < 0 \rightarrow -1$$
$$\geq 0 \rightarrow +1$$

$\underline{M^c}$ = $\underline{\text{rotations}}$ before $\underline{M}$

Optimization

Optimization

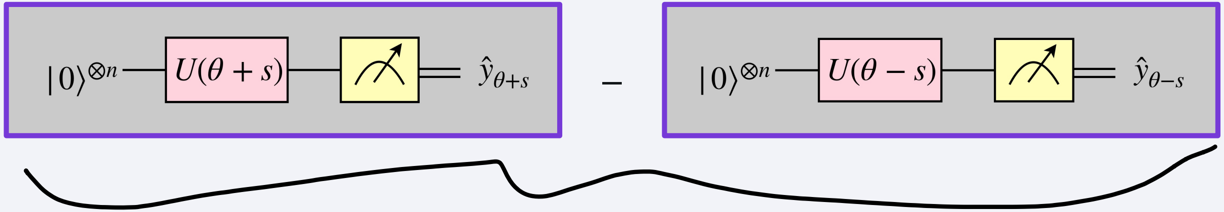
Qiskit



Optimization

Gradient descent?

Gradient =



Source: Schuld, Maria, et al. "Circuit-centric quantum classifiers." Physical Review A 101.3 (2020): 032308.

Is this advantageous?

Data encoding

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

n qubits $\rightarrow$ $|\phi_x\rangle = \begin{bmatrix} \\ \\ \\ \end{bmatrix} \begin{matrix} 1 \\ \vdots \\ \vdots \\ 2^n \end{matrix}$

2 qubits

$$|\phi_x\rangle = \begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \\ x'_4 \end{bmatrix}$$

This attempt does not provide any known advantage

They are linear classifiers in a feature space (recall support vector machines and their linear decision function)

Recap

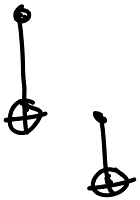
Qiskit

Data encoding

Basis
Amplitude
Angle
Higher order

Variational models

R_Y
R_Y
⋮



Optimization

✓

gradients of circuits

So what next?

Coming up

- QAOA
- Looking at the right feature space
- Quantum support vector machines
- Quantum kernels
- Quantum advantages for machine learning?