

Quantum Machine Learning and its Applications

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Presented By
SUNIL
24MCM17
MTech-AI.

Agenda



- Quantum Machine learning
- Quantum Model
- Introduction to Variational Circuit
- A Simple Model
- Gradient Descent Methods
- Encoding Classical Data into Quantum Data
- Quantum Neural Network
- Barren Plateaus

Quantum Model



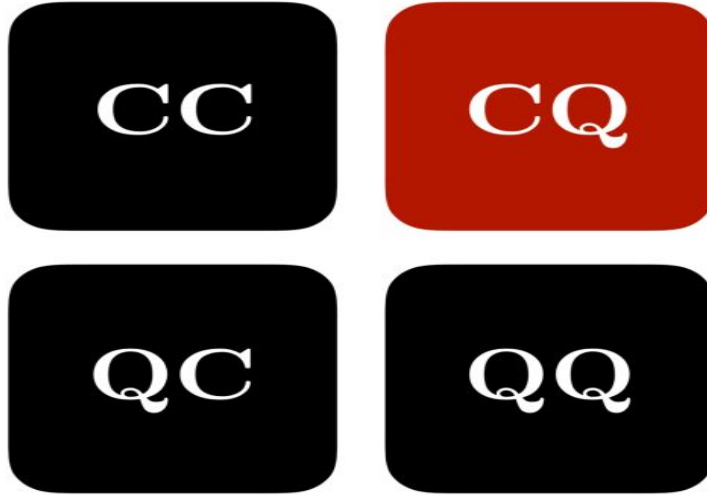
$$f(x; \theta) \rightarrow |f(x; \theta)\rangle$$

Quantum Machine Learning



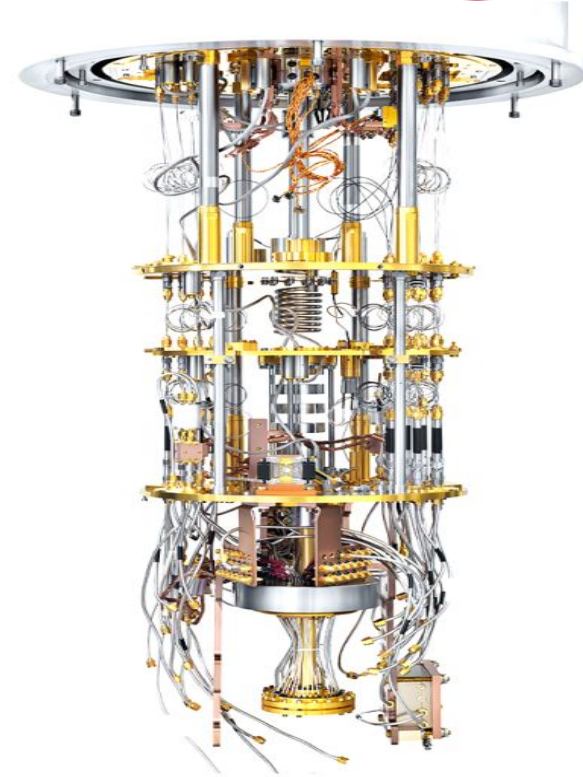
data processing device

data generating system

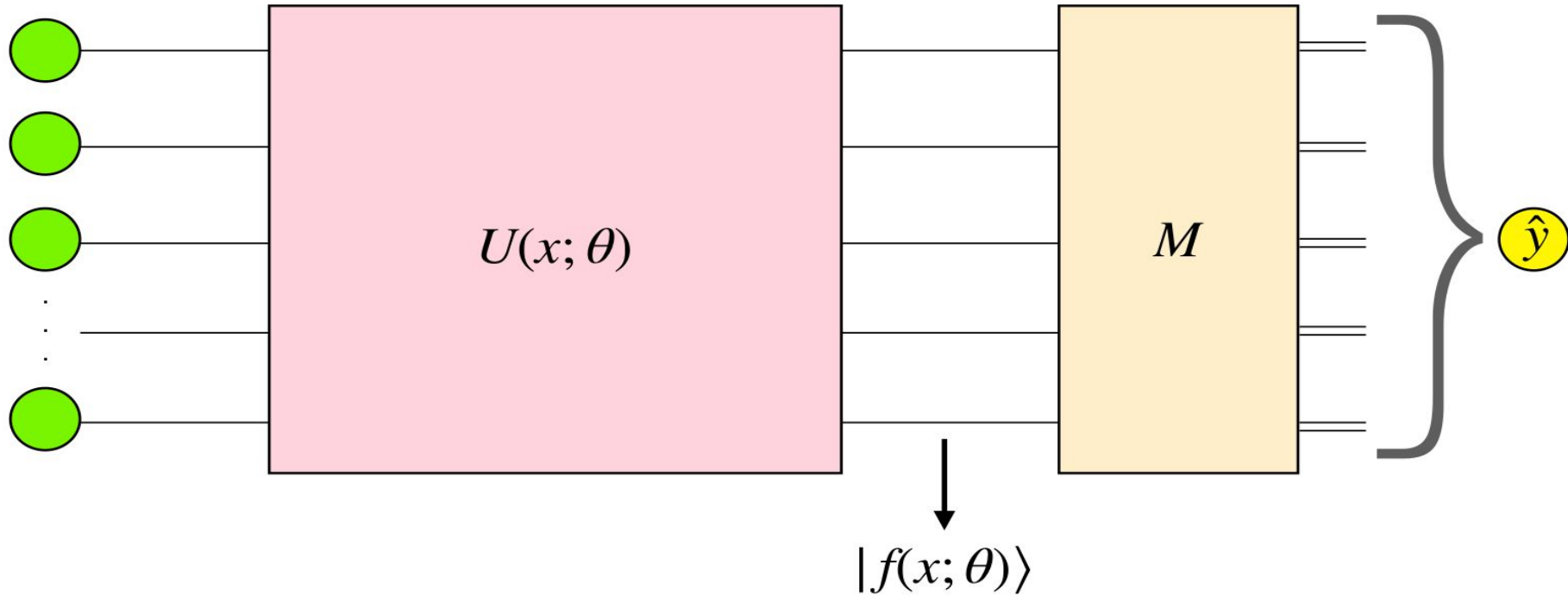


C - classical, Q - quantum

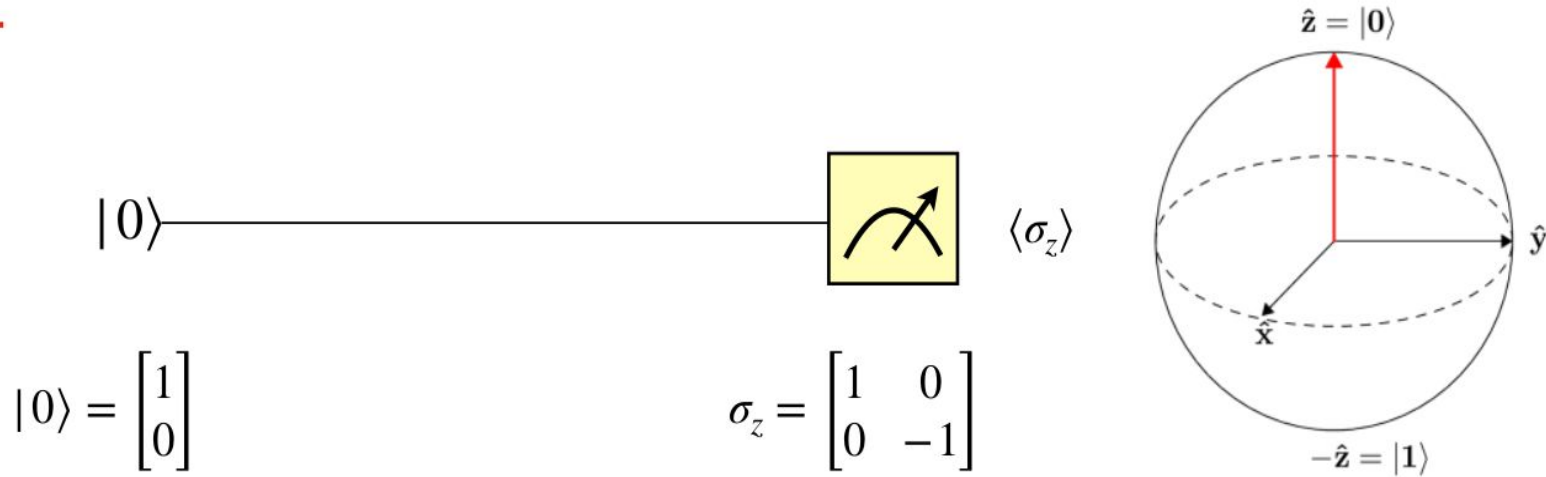
Source: Maria Schuld and Francesco Petruccione. *Supervised learning with quantum computers*. Vol. 17. Springer, 2018.



Quantum Machine Learning

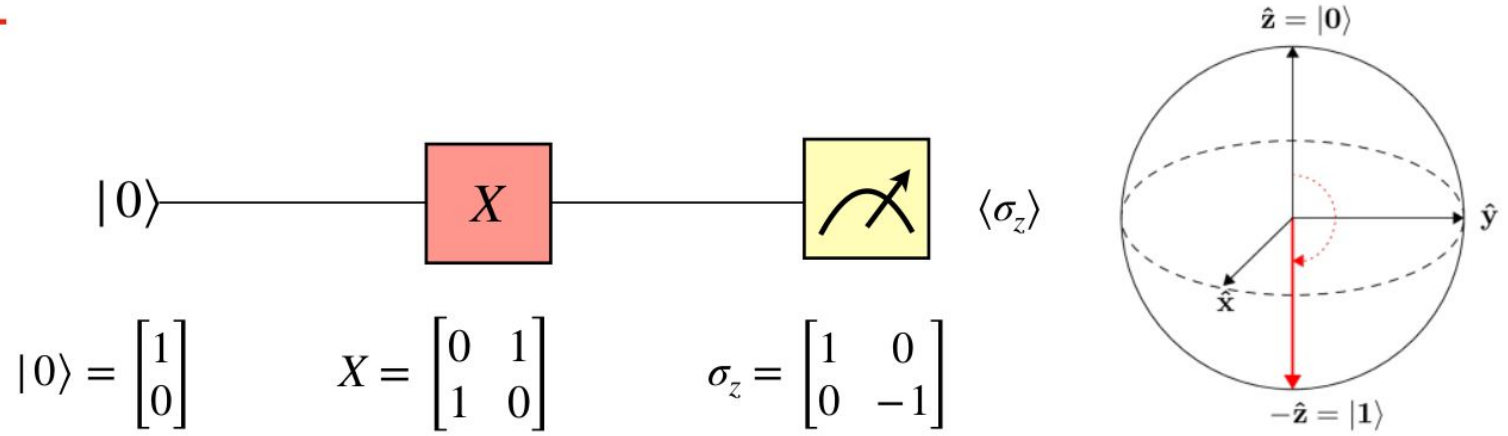


A simple Example



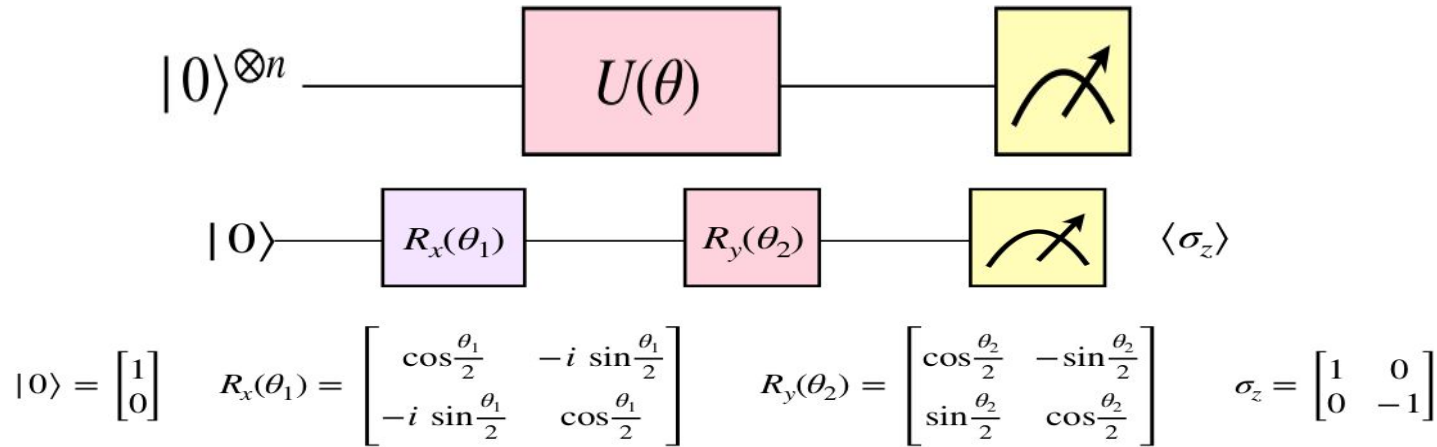
Calculating the expectation value: $\langle 0 | \sigma_z | 0 \rangle = [1 \ 0] \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 1$

A simple Example



Calculating the expectation value: $\langle 1 | \sigma_z | 1 \rangle = [0 \ 1] \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = -1$

A simple Example

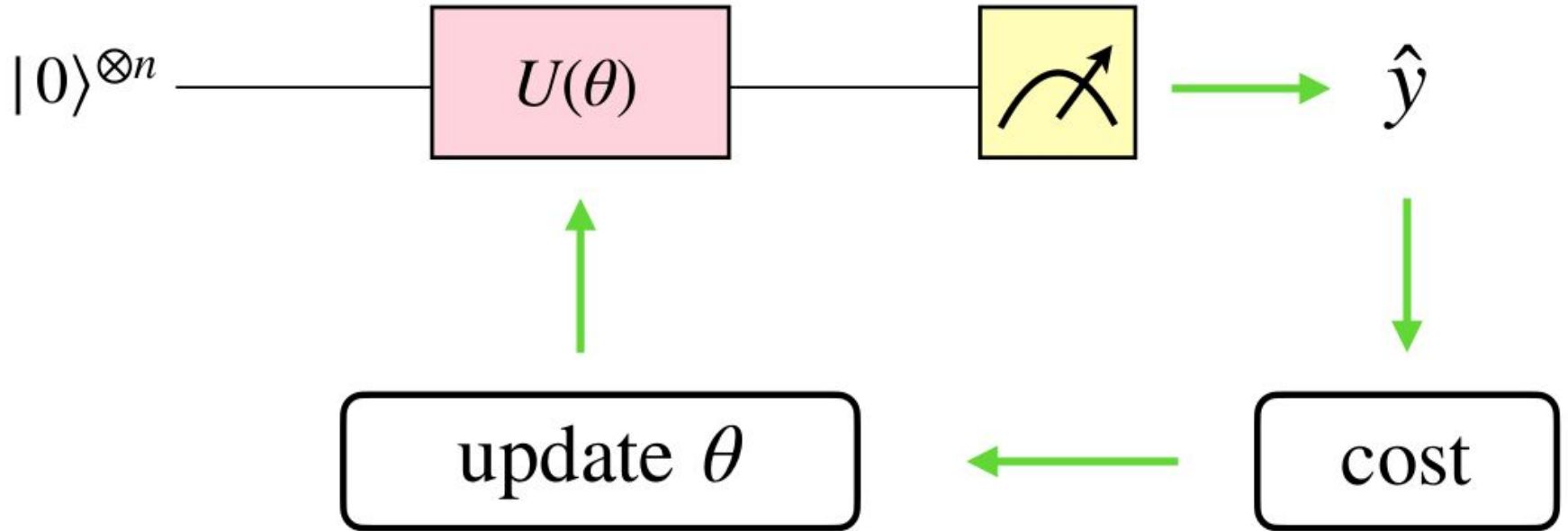


State after operations: $|\psi\rangle = R_y(\theta_2) R_x(\theta_1) |0\rangle$

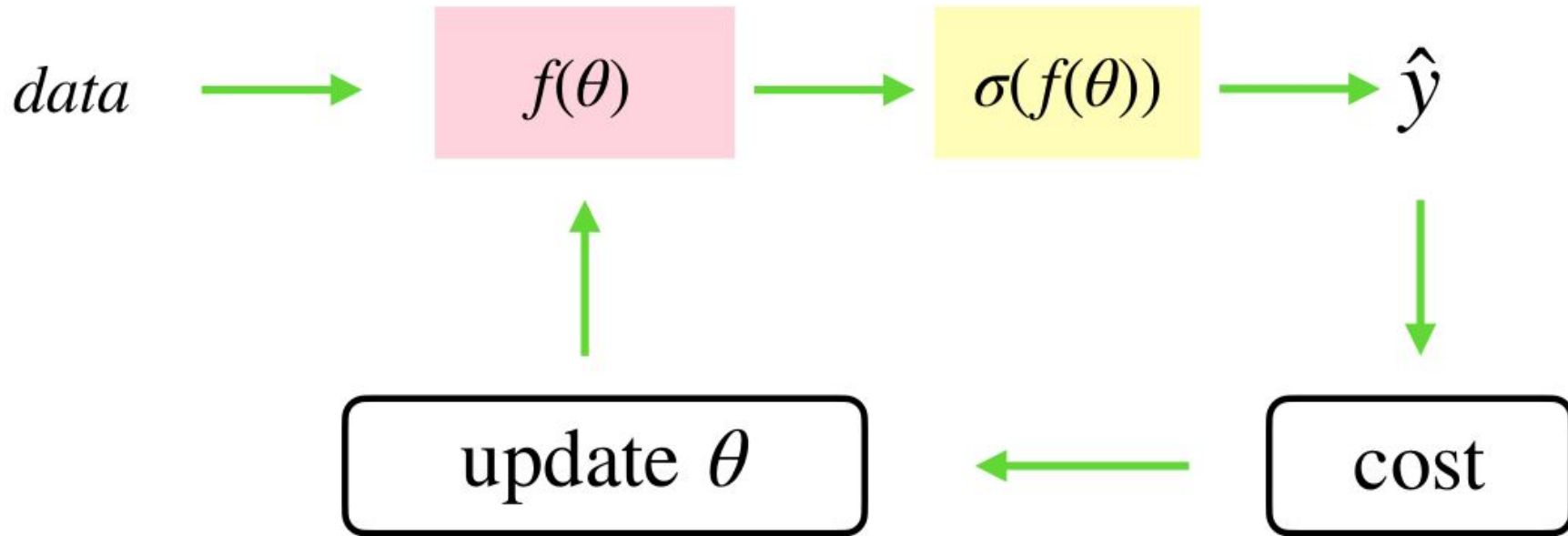
Calculating the expectation value: $\langle \psi | \sigma_z | \psi \rangle = \langle 0 | R_x(\theta_1)^\dagger R_y(\theta_2)^\dagger \sigma_z R_y(\theta_2) R_x(\theta_1) | 0 \rangle = \cos(\theta_1) \cos(\theta_2)$

How do we choose the parameters?

A simple Example



A simple Example



A simple Example

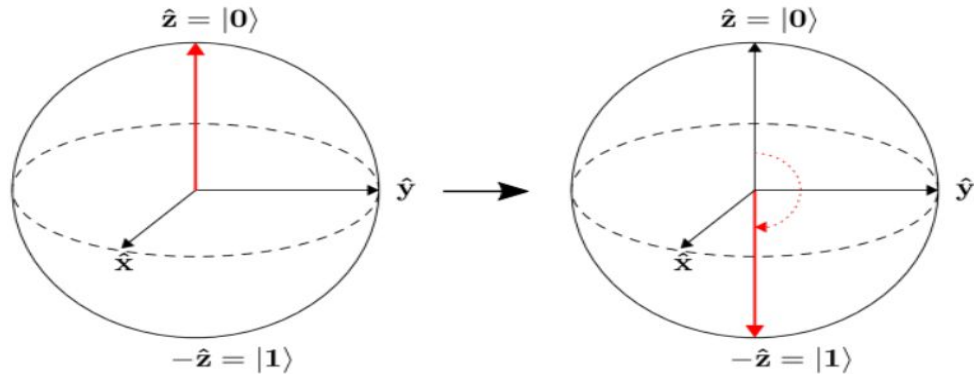


Define a cost function which we want to minimise:

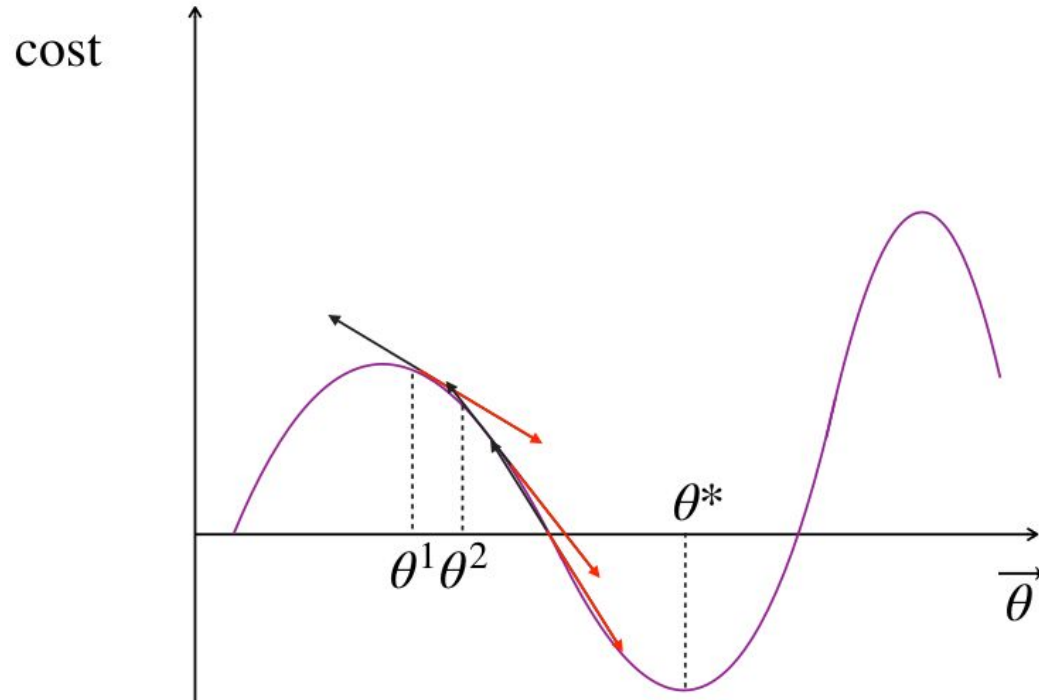
$$\langle \psi | \sigma_z | \psi \rangle = \langle 0 | R_x(\theta_1)^\dagger R_y(\theta_2)^\dagger \sigma_z R_y(\theta_2) R_x(\theta_1) | 0 \rangle = \cos(\theta_1) \cos(\theta_2)$$

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 1$$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = -1$$



Gradient Descent



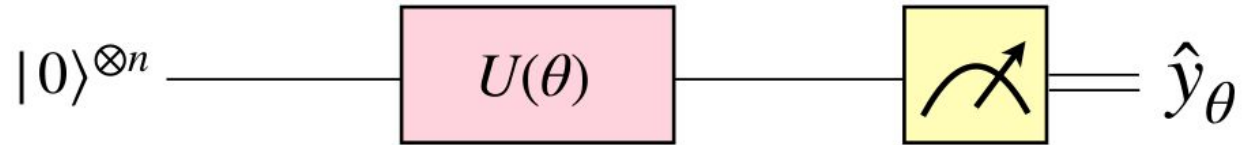
$$\Theta_{n+1} = \Theta_n - \alpha \frac{\partial}{\partial \Theta_n} J(\Theta_n)$$

$\Theta \rightarrow$ Parameter Vector

$J \rightarrow$ Cost Function

$\alpha \rightarrow$ Slope Parameter

Gradient-based methods



Gradient =

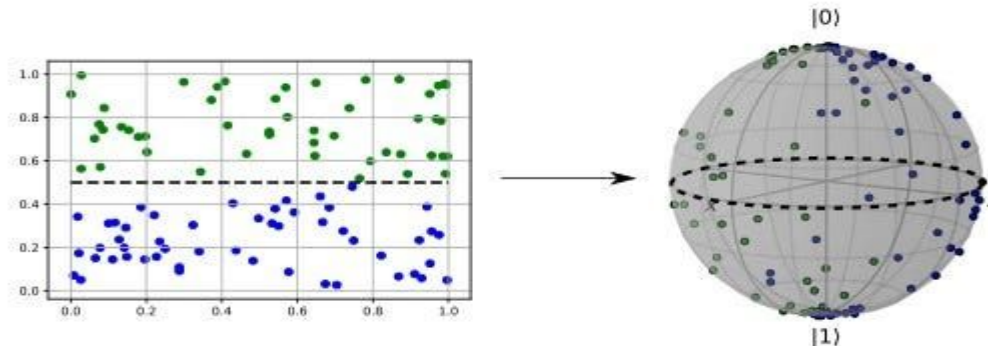


Encoding Classical Data



Types of Encoding classical data into Quantum states

- Basis encoding
- Amplitude encoding
- Angle encoding
- Feature Map



Basic Encoding



For example,

$$x^1 = (0, 1)^T$$

$$x^2 = (1, 1)^T$$

Creating a superposition of states using 2 qubits:

$$\cancel{|00\rangle} + \frac{1}{\sqrt{2}} |01\rangle + \cancel{|10\rangle} + \frac{1}{\sqrt{2}} |11\rangle$$

$$(0, \frac{1}{\sqrt{2}}, 0, \frac{1}{\sqrt{2}})^T$$

Amplitude Encoding



For example,

$$x^1 = (0.888, -1.25)^T$$

$$x^2 = (-0.23, 0.992)^T$$



$$\frac{1}{\sqrt{4}}(0.888, -1.25, -0.23, 0.992)^T$$

$$|00\rangle \quad |01\rangle \quad |10\rangle \quad |11\rangle$$

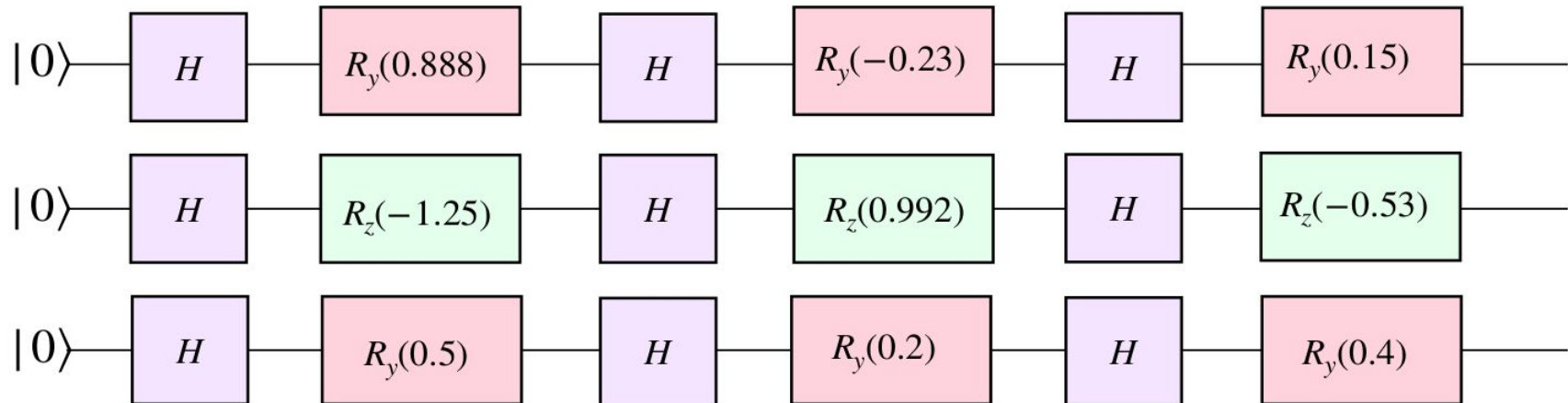
$$|D\rangle = \frac{1}{\sqrt{2^n}} \sum_{i=1}^{2^n} x_i |i\rangle \longrightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0.888 \\ -1.25 \\ -0.23 \\ 0.992 \end{bmatrix} \quad 2^n = 4, n = 2$$

Angle Encoding



For example,

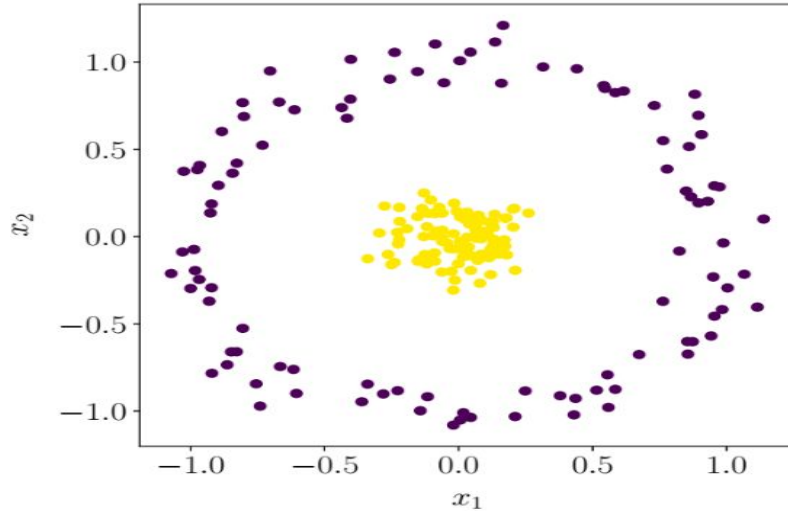
$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \\ 0.5 \end{bmatrix} \quad x^2 = \begin{bmatrix} -0.23 \\ 0.992 \\ 0.2 \end{bmatrix} \quad x^3 = \begin{bmatrix} 0.15 \\ -0.53 \\ 0.4 \end{bmatrix}$$



Higher Order Encoding

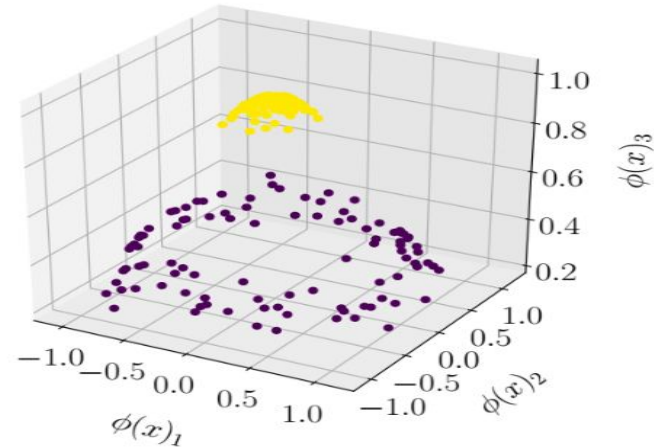


Original dataset



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

Dataset after feature map



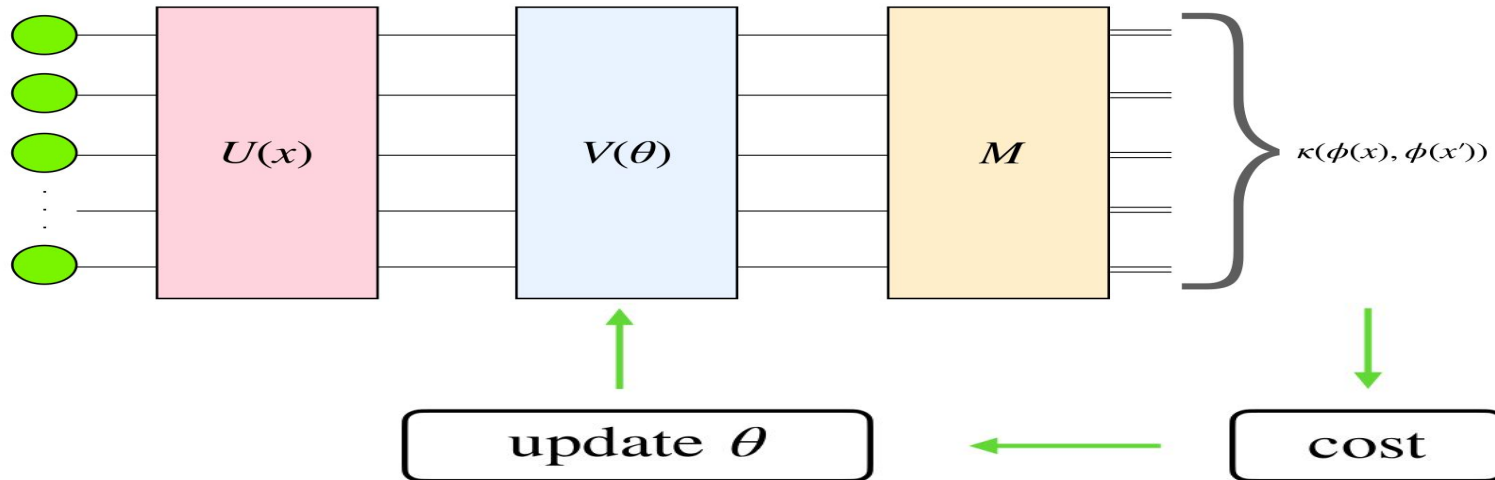
$$\phi(x) = \begin{bmatrix} \phi(x)_1 \\ \phi(x)_2 \\ \phi(x)_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_1 * x_2 \end{bmatrix}$$

Quantum kernels

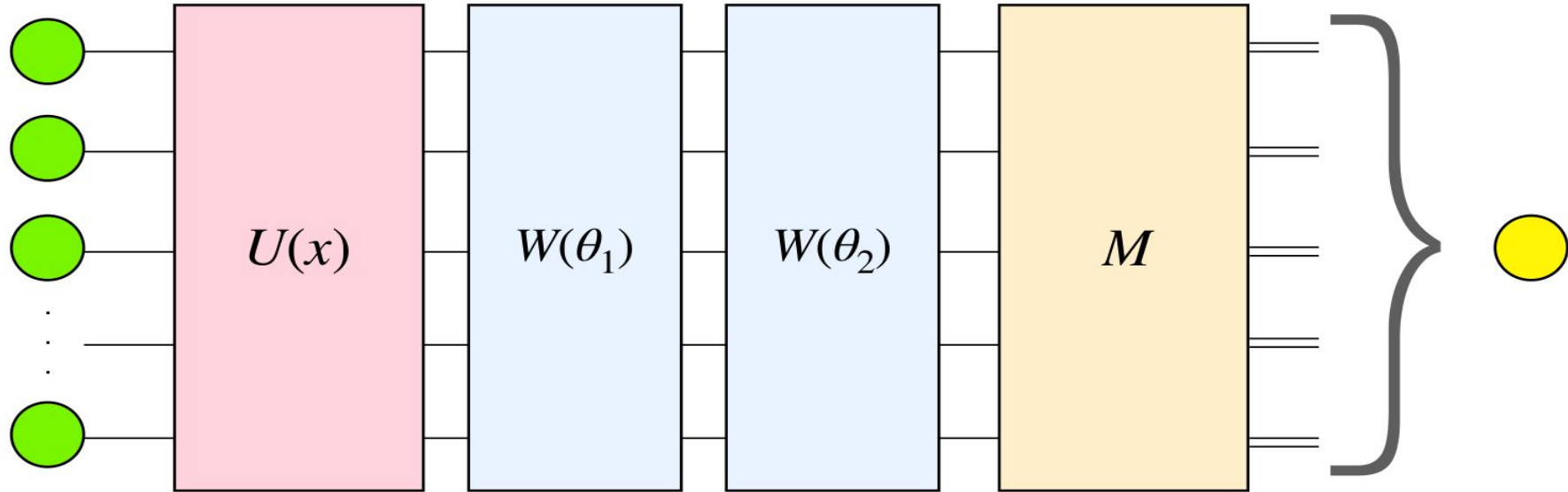


$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \end{bmatrix} \longrightarrow |\phi(x)\rangle = \begin{bmatrix} \phi(x_1) \\ \phi(x_2) \\ \vdots \end{bmatrix}$$

$$\kappa(\phi(x), \phi(x')) = \langle \phi(x) | \phi(x') \rangle$$

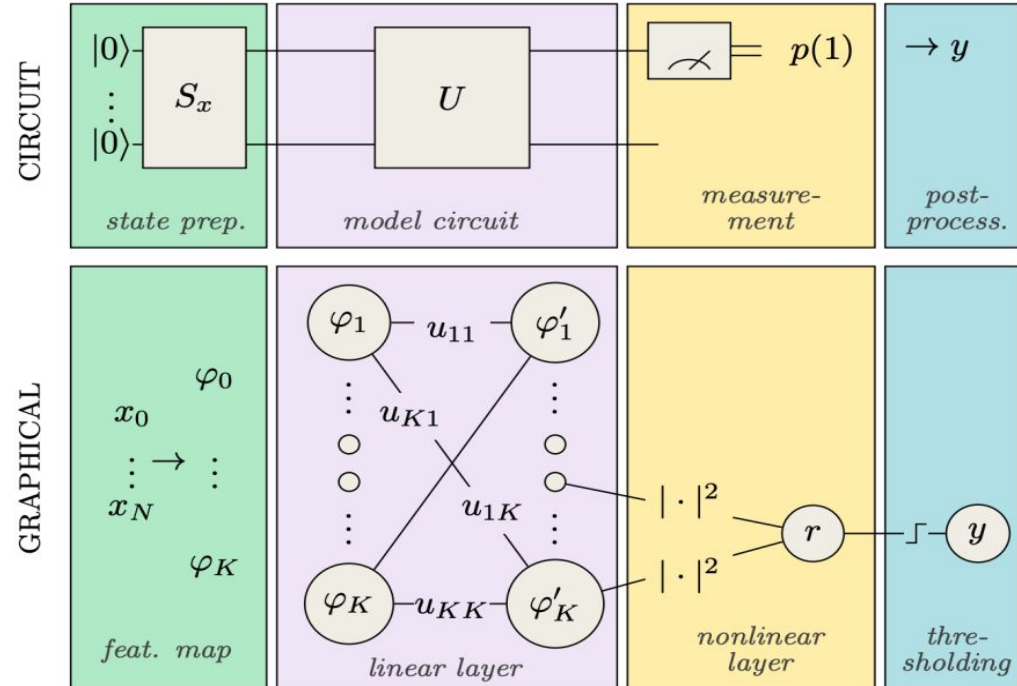
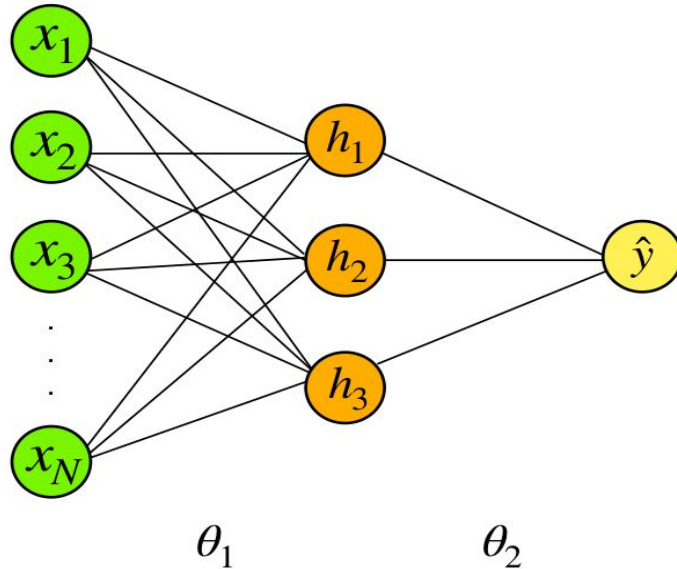


Quantum Neural Network



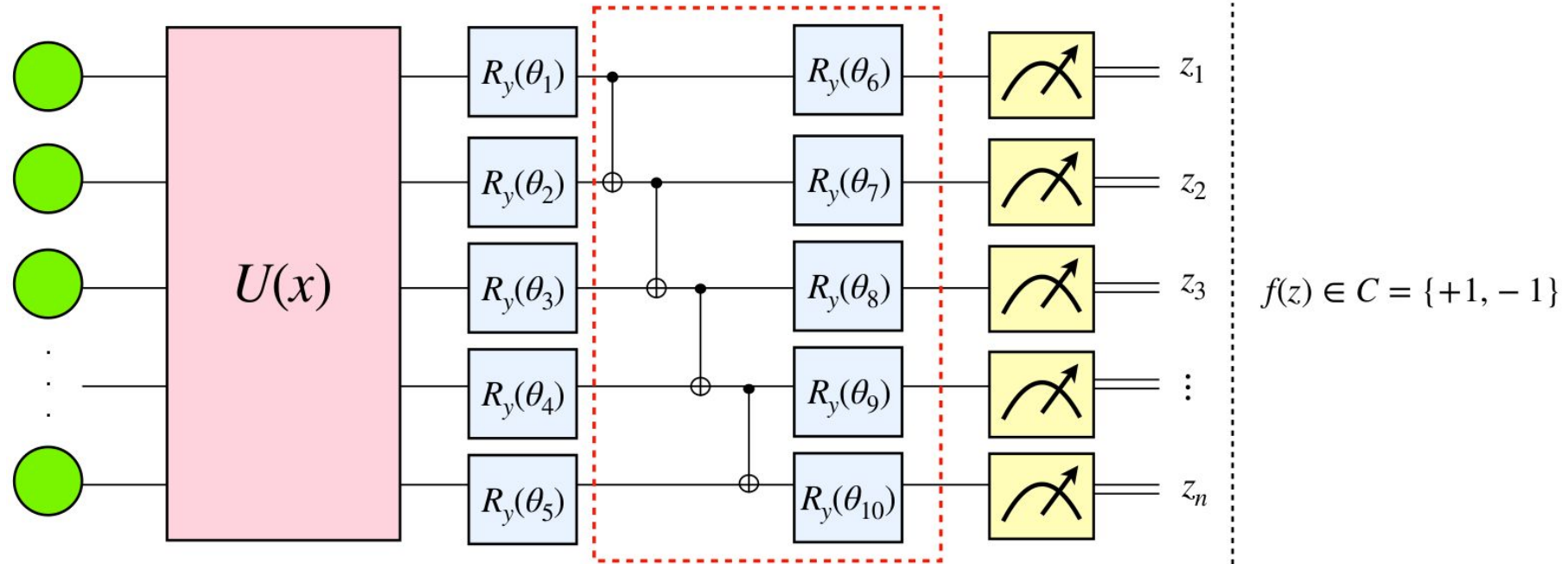
$$\hat{y} = \sigma(\theta_2(\theta_1 x))$$

Quantum Neural Network

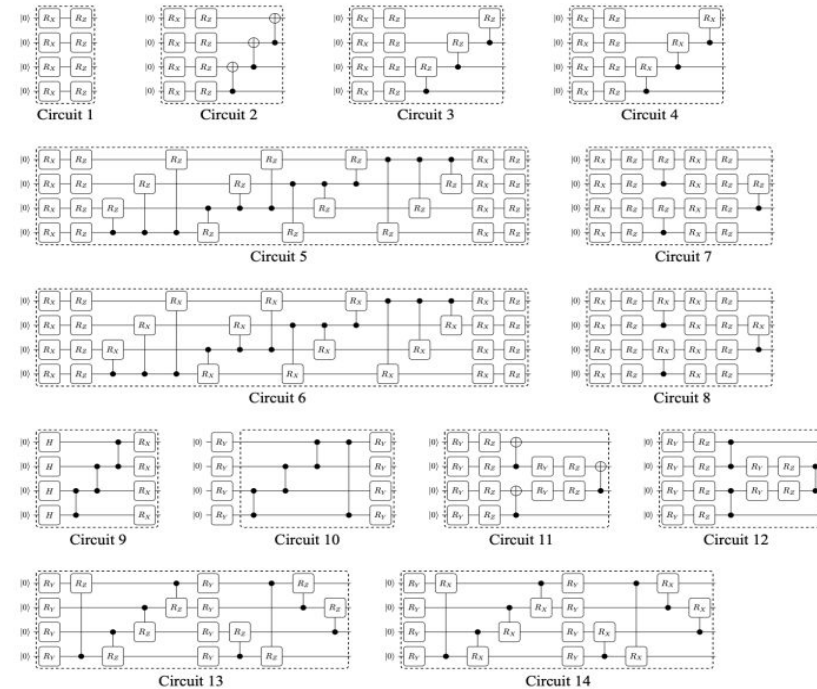
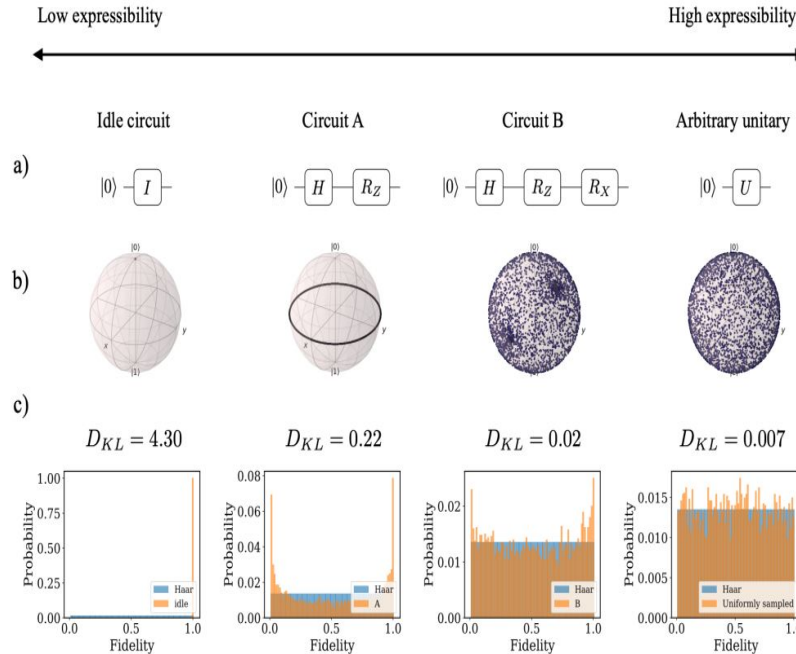


Source: Schuld, Maria, et al. "Circuit-centric quantum classifiers." Physical Review A 101.3 (2020): 032308.

Quantum Variational Classifier



Variational forms



Source: Sim, Sukin, Peter D. Johnson, and Alán Aspuru-Guzik. "Expressibility and Entangling Capability of Parameterized Quantum Circuits for Hybrid Quantum-Classical Algorithms." *Advanced Quantum Technologies* 2.12 (2019): 1900070.

Barren plateaus



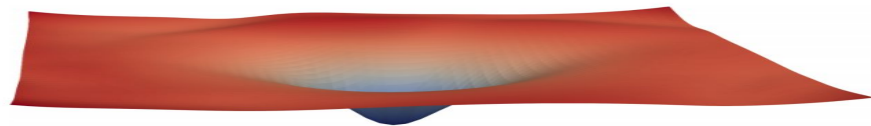
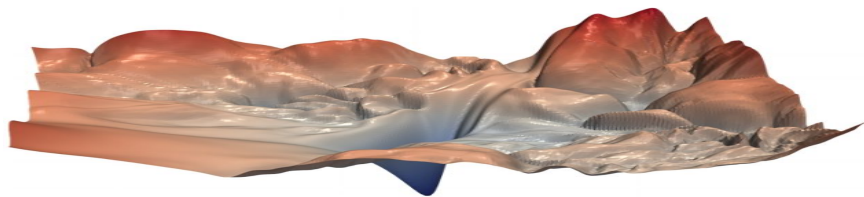
$$\theta_{\text{new}} = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$

Methods to try avoid barren plateaus

- Introduce structure into the circuit
- Use a local cost function
- Higher order optimisation methods
- Loss landscapes

$$\frac{\partial C}{\partial \theta} = \begin{bmatrix} \frac{\partial C}{\partial \theta_1} \\ \frac{\partial C}{\partial \theta_2} \\ \vdots \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} \frac{\partial^2 C}{\partial \theta_1^2} & \frac{\partial^2 C}{\partial \theta_1 \partial \theta_2} & \cdots \\ \frac{\partial^2 C}{\partial \theta_2 \partial \theta_1} & & \\ \vdots & & \end{bmatrix}$$





Thank You