

Quantum computing models of artificial neurons

F. Tacchino et al., npj Quantum Information 5, 26 (2019)

S. Mangini et al., Machine Learning: Science and Technology (2020)

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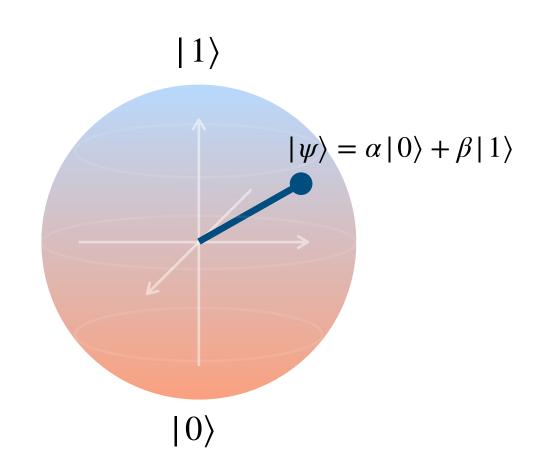
YIQIS 2020

30 September 2020, **Stefano Mangini**

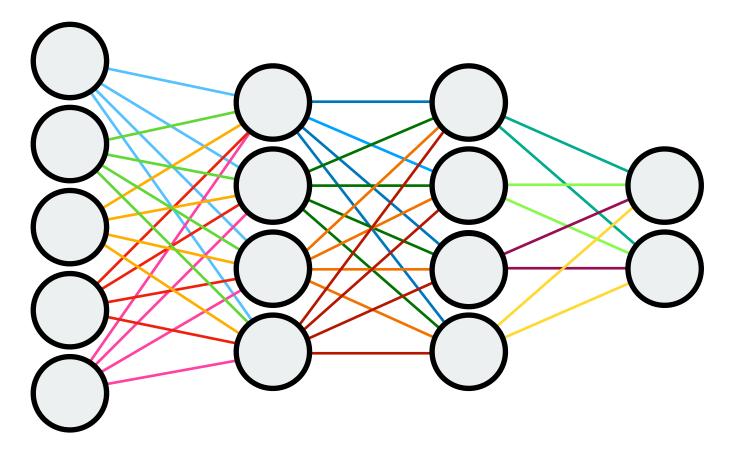
Quantum Machine Learning: what and why?

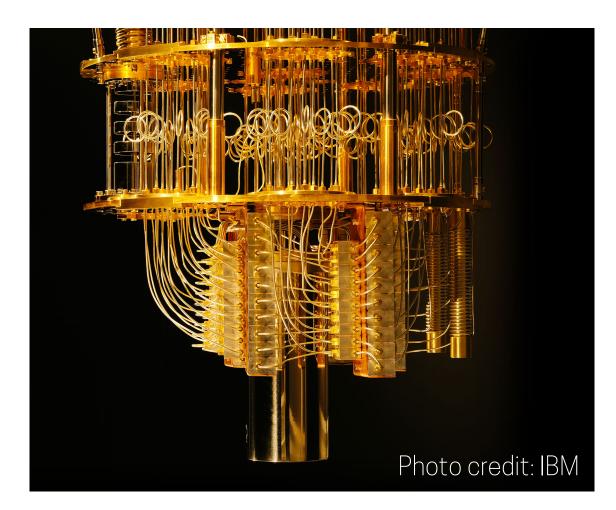


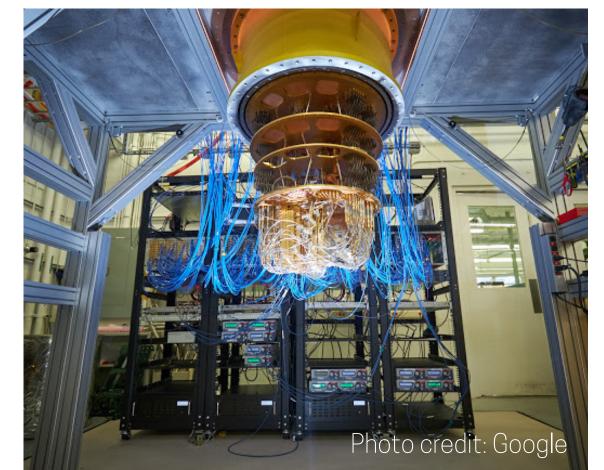
Quantum computing









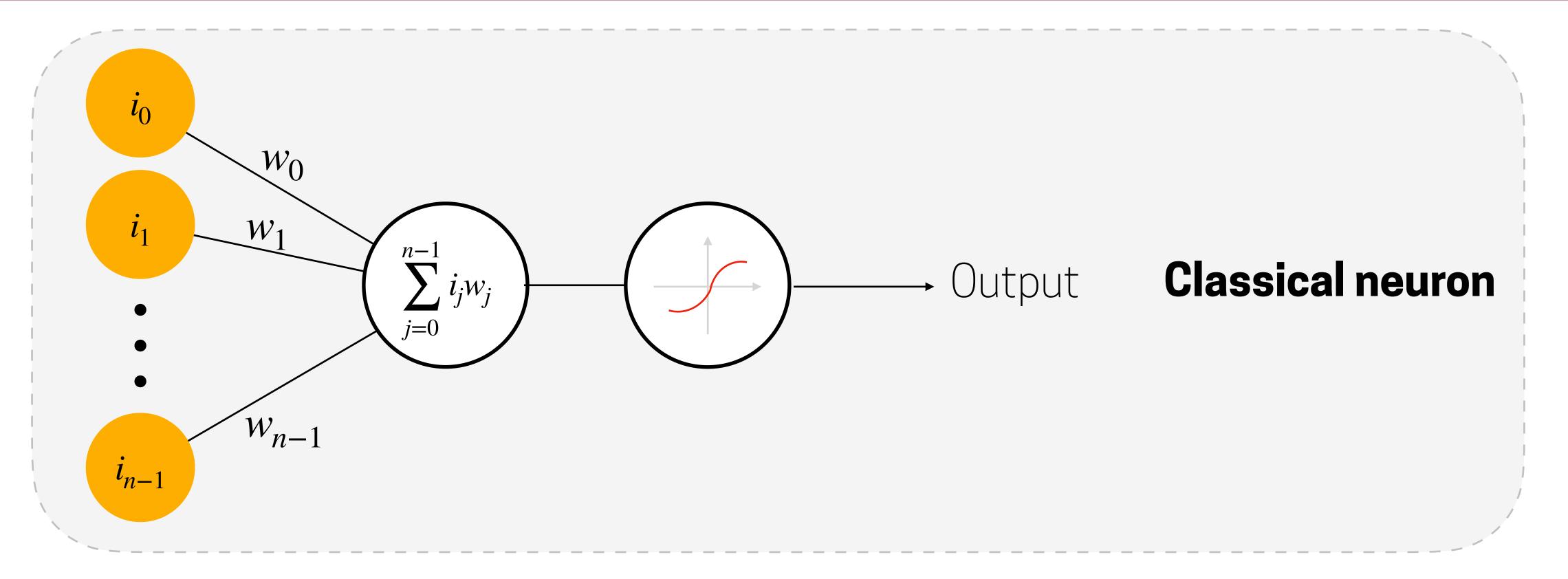






The classical perceptron model





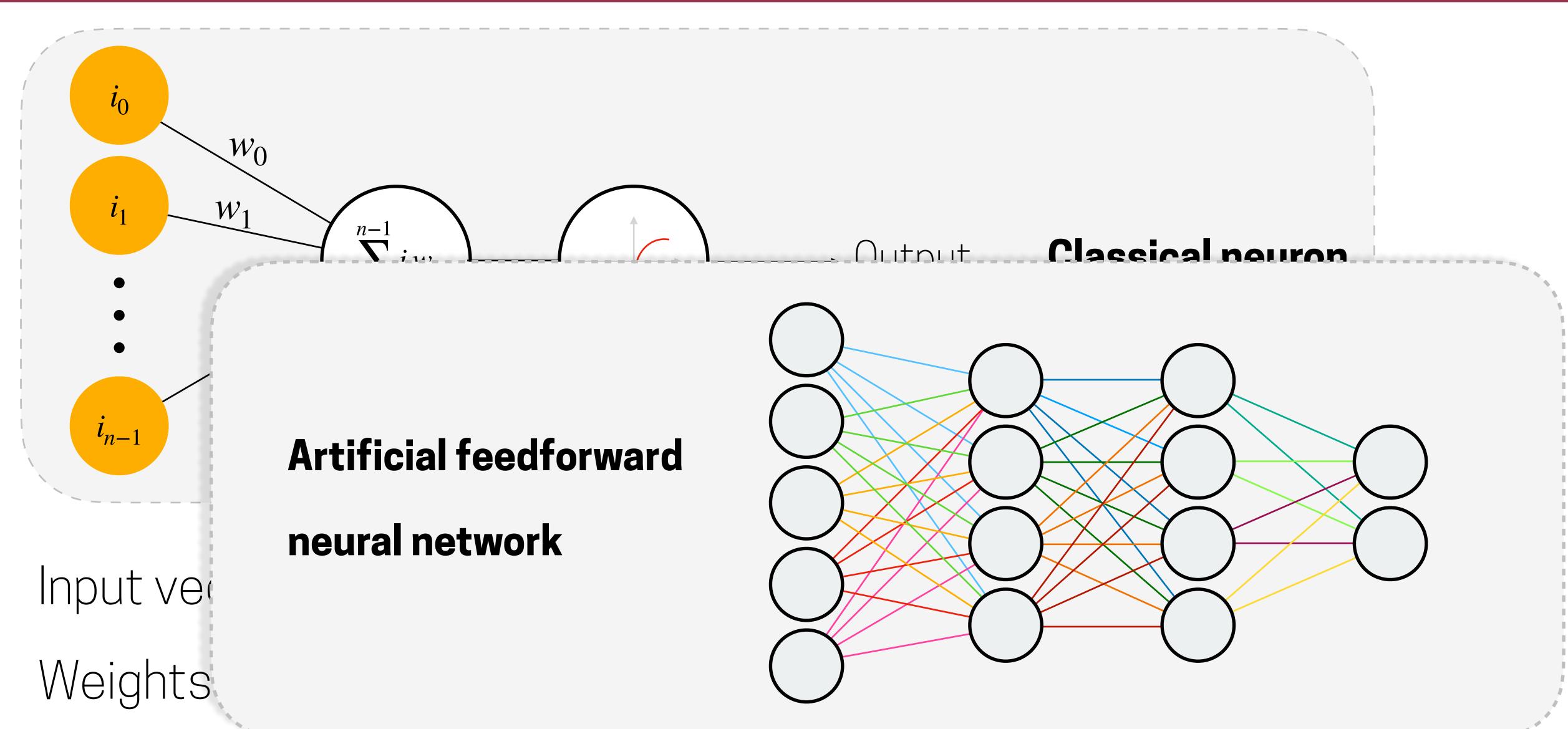
Input vector \vec{i}

Weights (and bias) vector \overrightarrow{w}

Output
$$y = f(\vec{i} \cdot \vec{w})$$

The classical perceptron model





Into the quantum domain



$$\vec{i} = (i_0, i_1, \dots, i_{n-1})$$

$$i_j, w_j \in \{-1, 1\}$$

$$\vec{w} = (w_0, w_1, \dots, w_{n-1})$$

Consider the quantum states

$$|\psi_i\rangle = \frac{1}{\sqrt{2^N}} \sum_{j=0}^{2^N-1} i_j |j\rangle$$

$$|\psi_w\rangle = \frac{1}{\sqrt{2^N}} \sum_{j=0}^{2^N-1} w_j |j\rangle$$

The n-bit long input and weight vector can be encoded in the amplitudes ± 1 of a balanced superposition of the computational basis states of $N = \log_2 n$ qubits

$$\langle \psi_i | \psi_w \rangle = \sum_{j,k=0}^{2^N - 1} i_j w_k \langle j | k \rangle = \sum_{j=0}^{2^N - 1} i_j w_j$$

This class of states are known as Real Equally Weighted (REW) states

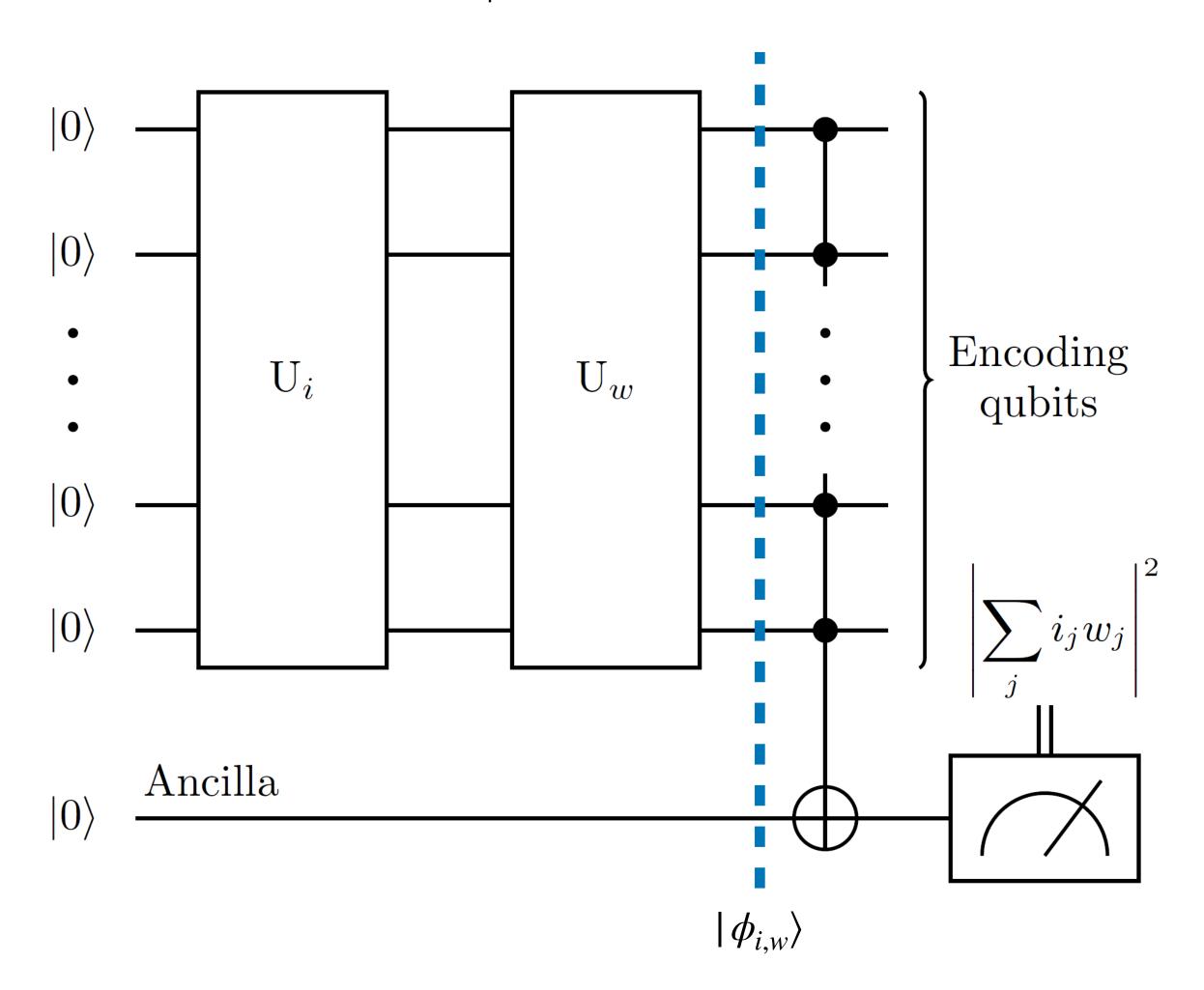
N qubits used to encode 2^N classical bits

F. Tacchino et al., npj Quantum Information 5, 26 (2019)

Quantum artificial neuron



Quantum circuit implementation



Quantum input state preparation

$$U_i | 0 \rangle^{\otimes N} = | \psi_i \rangle$$

Inner product (weighted sum)

$$U_w | \psi_w \rangle = |1\rangle^{\otimes N}$$

because:

$$\langle \psi_{w} | \psi_{i} \rangle = \langle \psi_{w} | U_{w}^{\dagger} U_{w} | \psi_{i} \rangle = \langle \mathbf{1} | U_{w} U_{i} | \mathbf{0} \rangle$$

$$\underbrace{|\phi_{i,w}\rangle}$$

Measurement of ancilla yields $|1\rangle$ with probability $|\sum_{j}i_{j}w_{j}|^{2}$

Activation function!

Classification of checkboard patterns



$$\overrightarrow{w} = \begin{pmatrix} w_0 \\ w_1 \\ \vdots \\ w_{2^{N-1}} \end{pmatrix} \quad \overrightarrow{i} = \begin{pmatrix} i_0 \\ i_1 \\ \vdots \\ i_{2^{N-1}} \end{pmatrix} \qquad N = 2 \qquad \overrightarrow{i} = (i_0, i_1, i_2, i_3) \qquad i_2 \qquad i_3$$

$$N = 2$$
 $\vec{i} = (i_0, i_1, i_2, i_3)$

$$egin{array}{c|c} i_0 & i_1 \ \hline i_2 & i_3 \ \hline \end{array}$$

white if
$$i_j$$
, $w_j = +1$ black if i_j , $w_j = -1$

$$\vec{i} = (1, -1, 1, -1)$$

$$(1, -1, 1, -1)$$

$$(1, -1, 1, -1)$$

$$\overrightarrow{w} = (1, -1, 1, -1)$$

$$\langle \psi_w | \psi_i \rangle = \vec{i} \cdot \vec{w} = 1$$



$$\vec{i} = (1, -1, 1, -1)$$

$$\overrightarrow{w} = (-1,1,1,-1)$$

$$\langle \psi_w | \psi_i \rangle = \vec{i} \cdot \vec{w} = 0$$



From Binary to Continuous values



Binary

$$|\psi_i\rangle=rac{1}{\sqrt{2^N}}\sum_{j=0}^{2^N-1}i_j|j\rangle$$
 with $i_j=\pm 1$

but
$$e^{i\theta} = \begin{cases} 1 & \theta = 0 \\ -1 & \theta = \pi \end{cases}$$

By means of phase encoding we load the data on the quantum states!

input
$$\overrightarrow{\theta}=(\theta_0,\theta_1,...,\theta_{n-1})$$
 weights $\overrightarrow{\phi}=(\phi_0,\phi_1,...,\phi_{n-1})$

$$\theta_j, \phi_j \in [0,\pi]$$
 (not 2π due to

(not 2π due to periodicity)

Quantum states:

$$|\psi_{\theta}\rangle = \frac{1}{\sqrt{2^N}} \sum_{j=0}^{2^N - 1} e^{i\theta_j} |j\rangle$$

$$|\psi_{\phi}\rangle = \frac{1}{\sqrt{2^N}} \sum_{j=0}^{2^N - 1} e^{i\phi_j} |j\rangle$$

$$|\langle \psi_{\phi} | \psi_{\theta} \rangle|^{2} = \left| \sum_{j}^{2^{N}-1} e^{i(\theta_{j} - \phi_{j})} \right|^{2} = \dots =$$

$$= \frac{1}{2^{N}} + \frac{1}{2^{2N-1}} \sum_{i < j}^{2^{N}-1} \cos((\theta_{j} - \phi_{j}) - (\theta_{i} - \phi_{i}))$$

S. Mangini et al., Machine Learning: Science and Technology (2020)

Some useful remarks



The activation function

$$f(\boldsymbol{\theta}, \boldsymbol{\phi}) = \frac{1}{2^N} + \frac{1}{2^{2N-1}} \sum_{i < j}^{2^N - 1} \cos((\theta_j - \phi_j) - (\theta_i - \phi_i))$$

• If
$$\theta = \phi$$

$$f(\theta, \phi) = \frac{1}{2^N} + \frac{1}{2^{2N-1}} \sum_{i < j}^{2^{N}-1} = \frac{1}{2^N} + \frac{1}{2^{2N-1}} \frac{2^N (2^N - 1)}{2} = 1$$

• If
$$\theta = \phi + \Delta$$
, $\Delta_j \sim \text{Unif}(-a/2, a/2)$
$$\langle f(\theta, \phi) \rangle \approx 1 - O(a^2)$$
 Noise resilience!

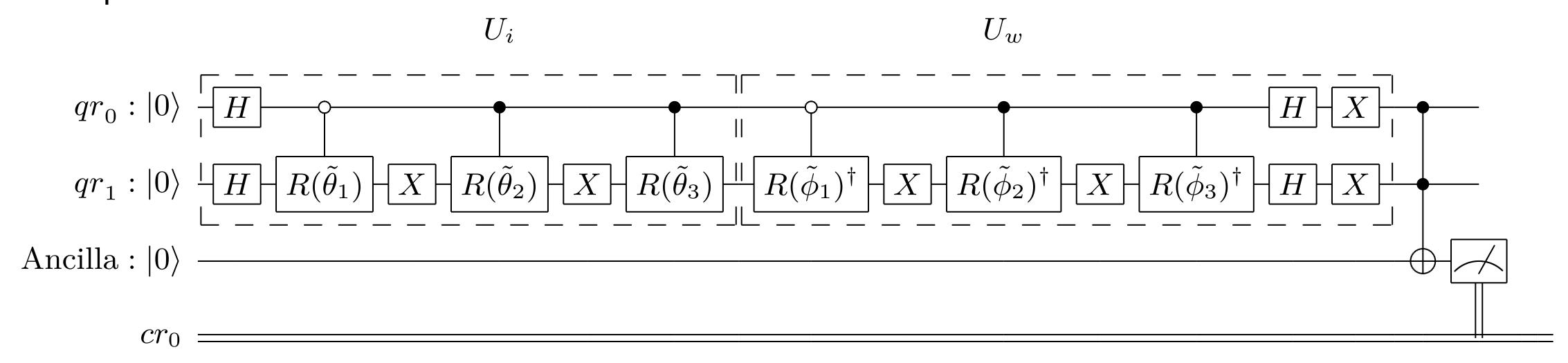
which also holds if

$$\theta = \phi + \Delta$$

Color invariance!



N = 2 qubits



NOT gate

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

Hadamard gate

$$X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \qquad H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \qquad R(\theta) = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\theta} \end{bmatrix}$$

Phase shift gate

$$R(\theta) = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\theta} \end{bmatrix}$$

Controlled gate

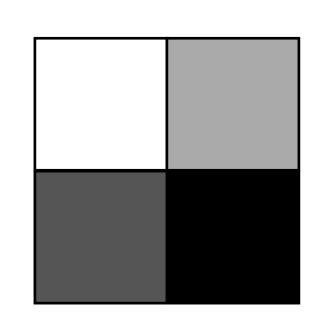
Classification of grayscale patterns



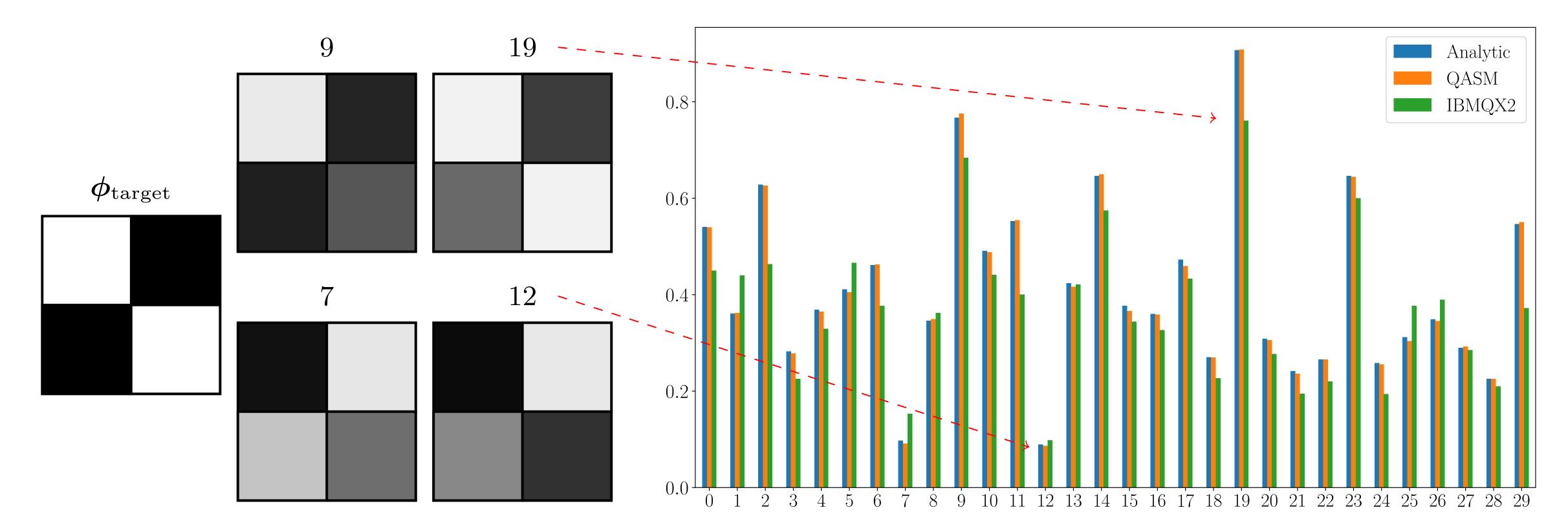
Grayscale images

$$\vec{i} = (255,170,85,0)$$
 $i_j \in [0,255]$

255	170
85	0



Normalization $\vec{i} \rightarrow \frac{\pi/2}{255}\vec{i}$





Key aspect of NN-based algorithm is training, which can now be implemented by means of a classical optimizator based on gradient descent.

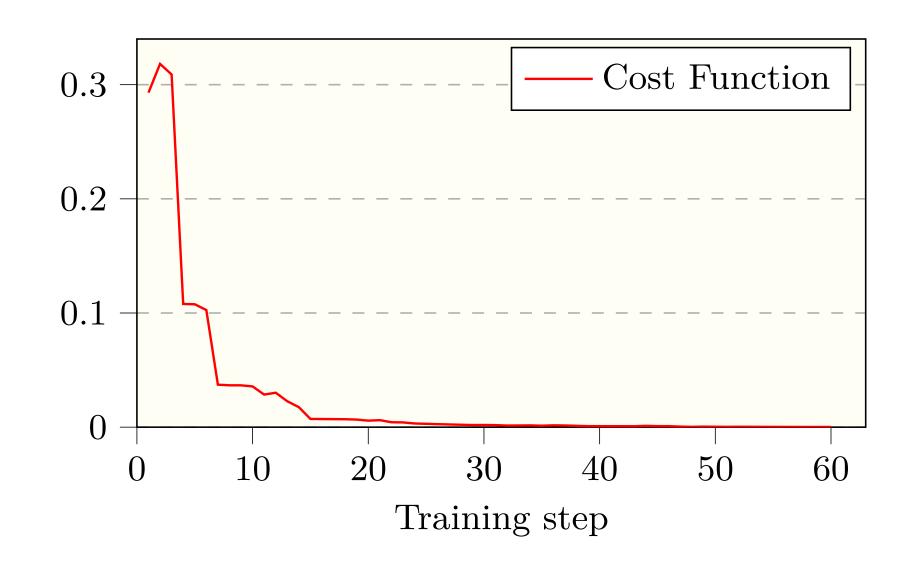
$$\mathscr{L}(\boldsymbol{\phi}) = \sum_{i=0}^{M} (y_i - \tilde{y}_i)^2$$

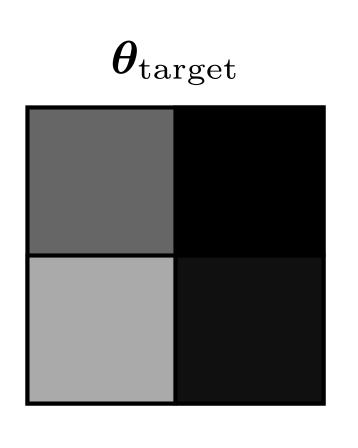
$$y_i = \text{correct label}$$

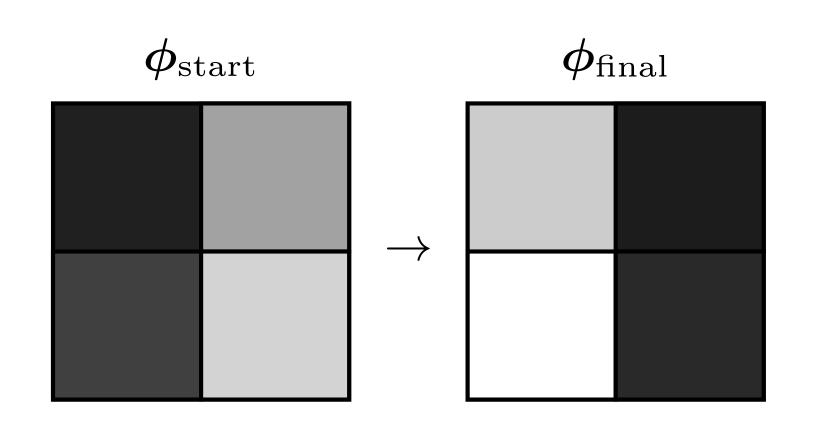
$$M =$$
size of the dataset

$$\tilde{y}_i = \text{predicted label } -----$$

$$\tilde{y}_i = \text{predicted label} \longrightarrow \tilde{y}_i = \begin{cases} 1 & \text{if } f(\theta, \phi) > threshold \\ 0 & \text{otherwise} \end{cases}$$

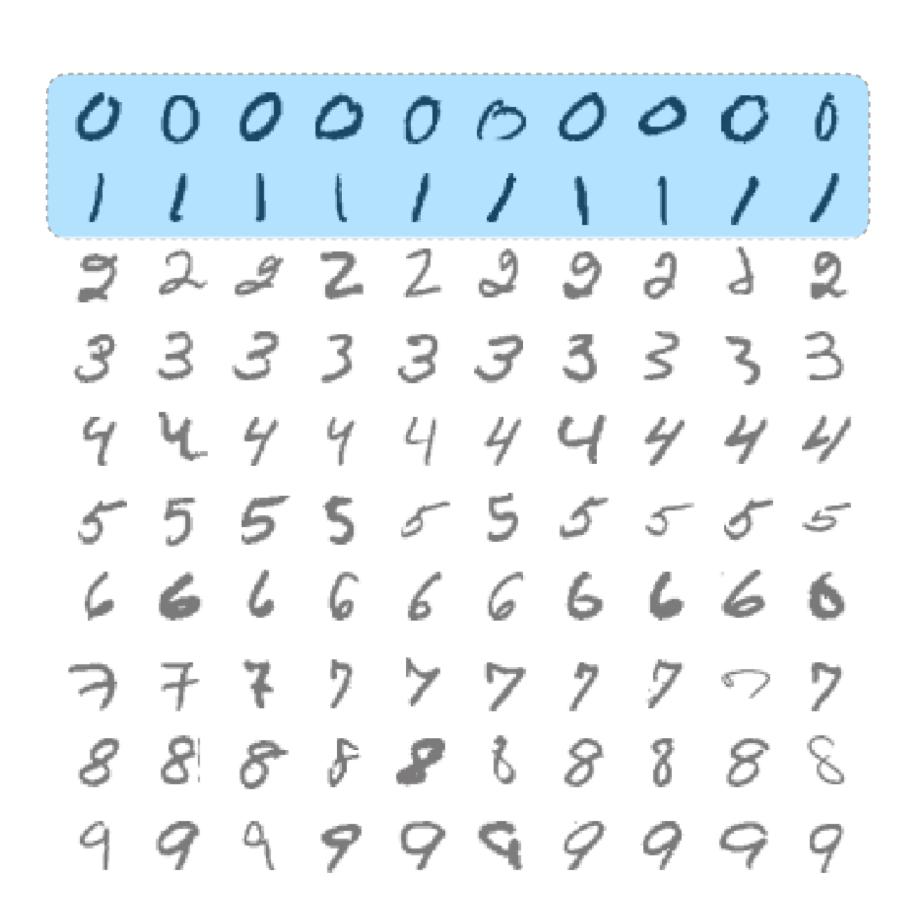


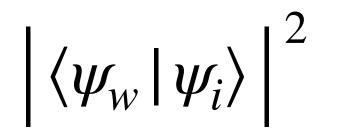


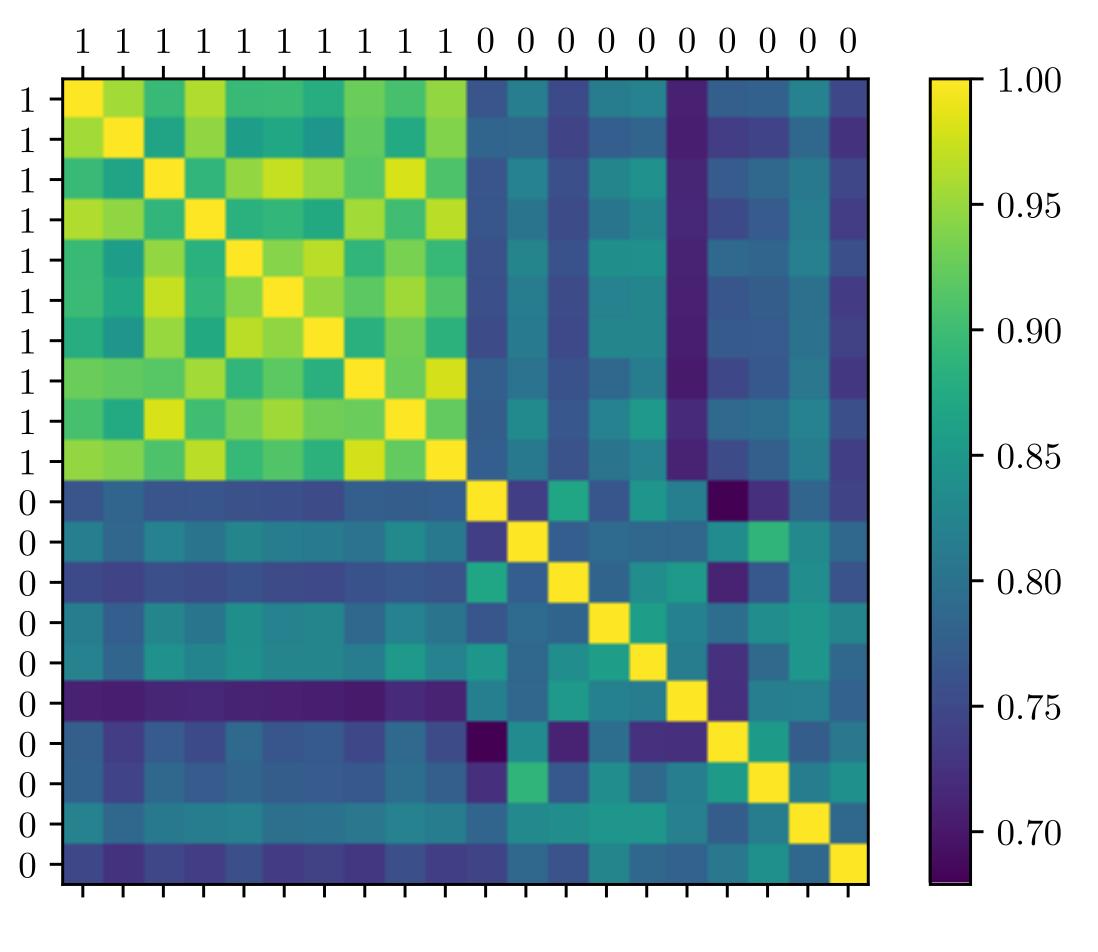


MIST









Accuracy ~ 98 %

Take home message



Key points

- Encode classical data through Phase encoding
- Color invariance and Noise resilience
- Suitable for optimization using gradient descent techniques
- Successfully tested on real quantum hardware (IBMQ)

References

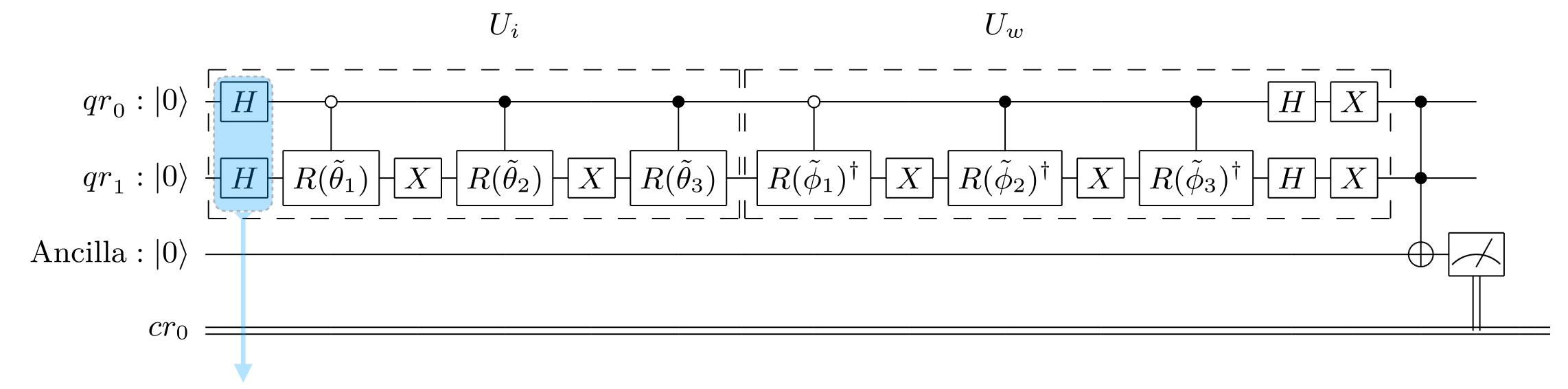
F. Tacchino *et al.*, npj Quantum Information 5, 26 (2019), DOI: https://doi.org/10.1038/s41534-019-0140-4 **S. Mangini** *et al.*, Machine Learning: Science and Technology (2020), DOI: https://doi.org/10.1088/2632-2153/abaf98

Group members: Chiara Macchiavello, Dario Gerace, Daniele Bajoni (UniPv), Francesco Tacchino (IBM Quantum)

Thank you for the attention!



N = 2 qubits

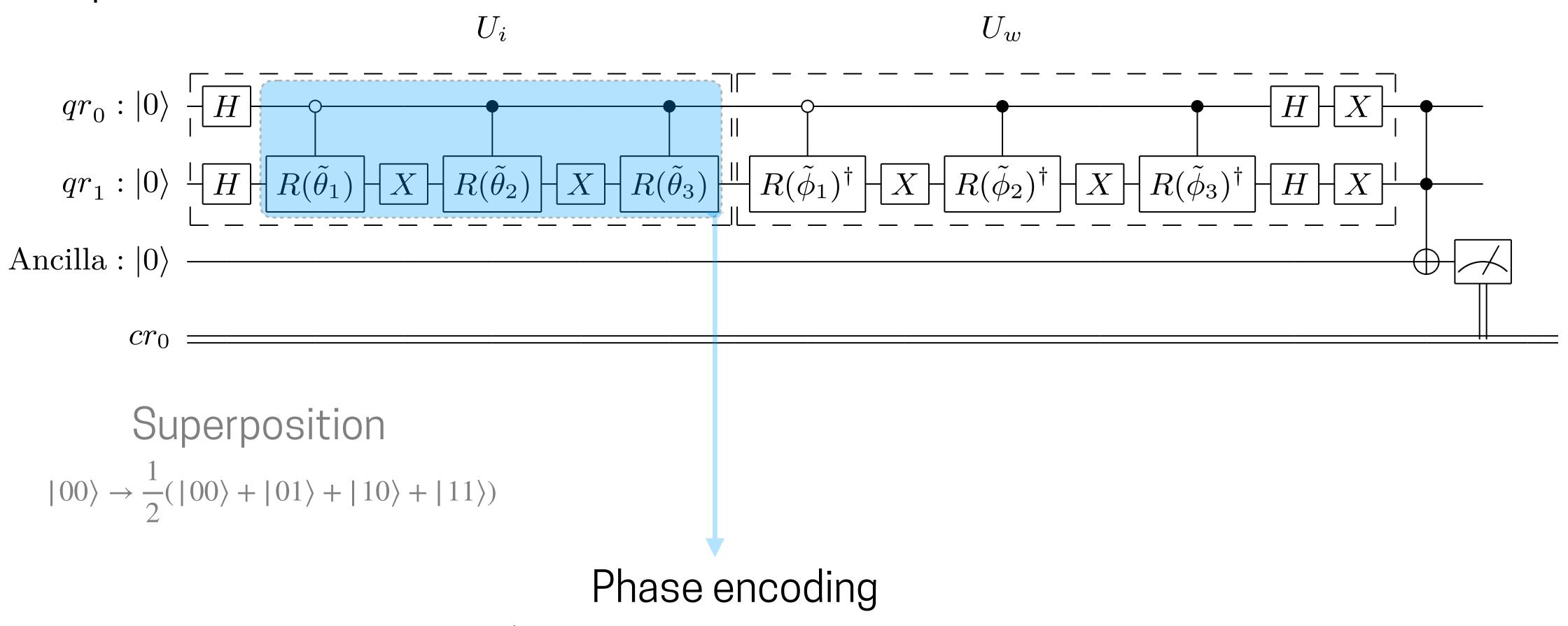


Superposition

$$|00\rangle \rightarrow \frac{1}{2}(|00\rangle + |01\rangle + |10\rangle + |11\rangle)$$



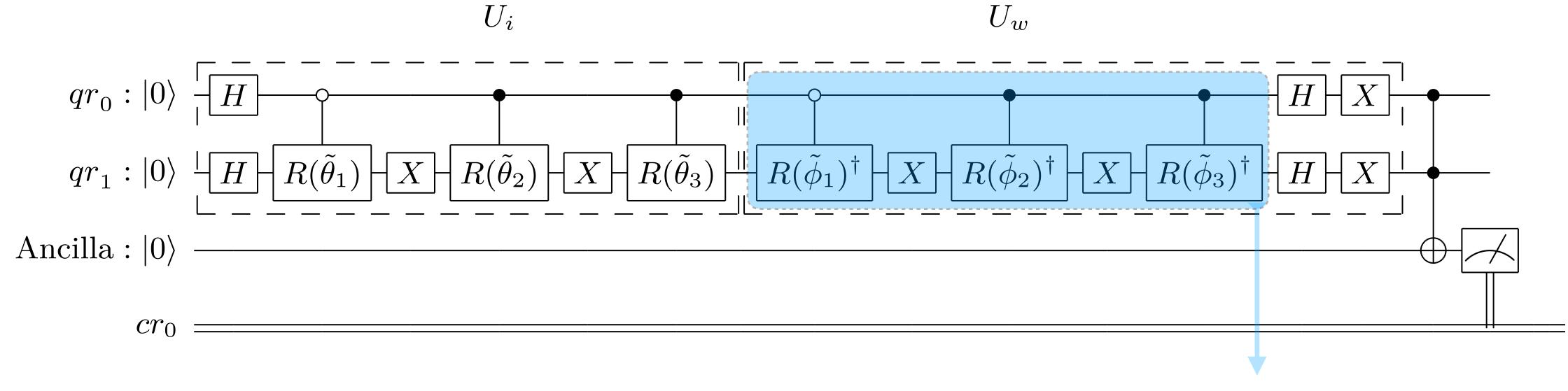
N = 2 qubits



$$\frac{1}{2} \left(00 \right) + e^{i\theta_1} \left| 01 \right\rangle + e^{i\theta_2} \left| 10 \right\rangle + \left| e^{i\theta_3} 11 \right\rangle \right)$$



N = 2 qubits



Superposition

$$|00\rangle \rightarrow \frac{1}{2}(|00\rangle + |01\rangle + |10\rangle + |11\rangle)$$

Weights

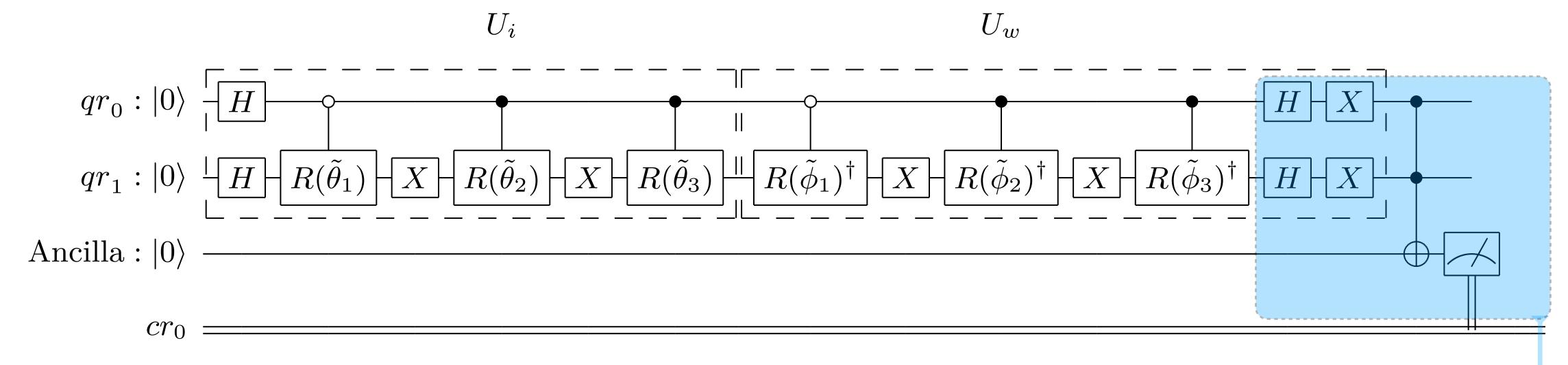
$$\frac{1}{2} \left(|00\rangle + e^{i(\theta_1 - \phi_1)} |01\rangle + e^{i(\theta_2 - \phi_2)} |10\rangle + |e^{i(\theta_3 - \phi_3)} |11\rangle \right)$$

Phase encoding

$$\frac{1}{2} \left(00 \right) + e^{i\theta_1} \left| 01 \right\rangle + e^{i\theta_2} \left| 10 \right\rangle + \left| e^{i\theta_3} 11 \right\rangle \right)$$



N = 2 qubits



Superposition

$$|00\rangle \rightarrow \frac{1}{2}(|00\rangle + |01\rangle + |10\rangle + |11\rangle)$$

Weights

$$\frac{1}{2} \left(|00\rangle + e^{i(\theta_1 - \phi_1)} |01\rangle + e^{i(\theta_2 - \phi_2)} |10\rangle + |e^{i(\theta_3 - \phi_3)} |11\rangle \right)$$

Phase encoding

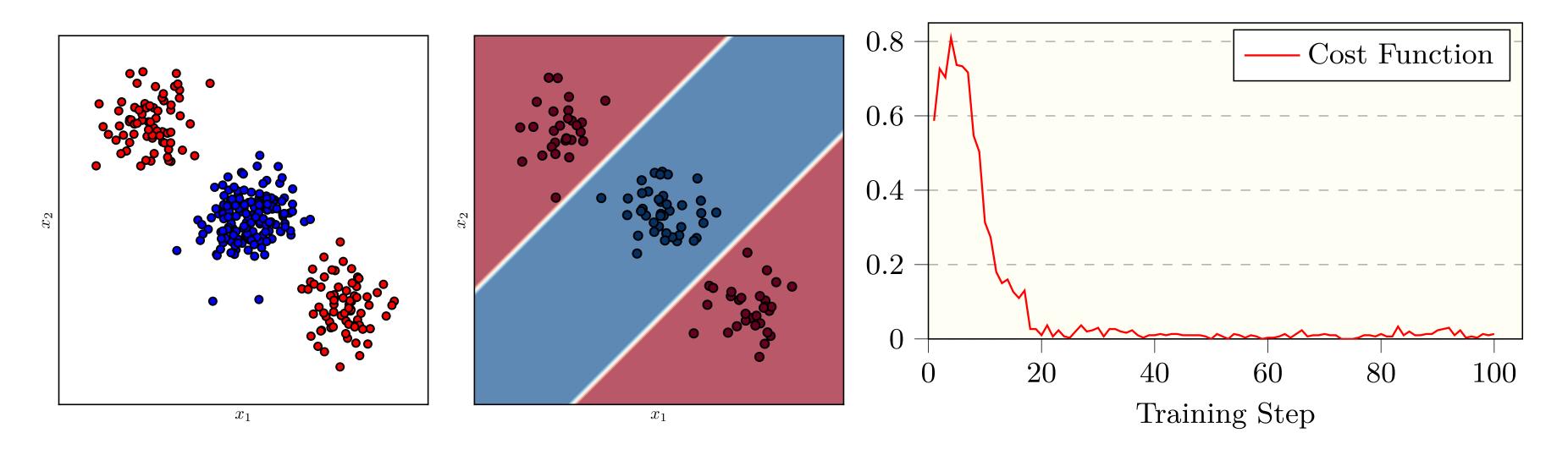
$$\frac{1}{2} \left(00 \right) + e^{i\theta_1} \left| 01 \right\rangle + e^{i\theta_2} \left| 10 \right\rangle + \left| e^{i\theta_3} 11 \right\rangle \right)$$

Result $|\langle \psi_w | \psi_i \rangle|^2$

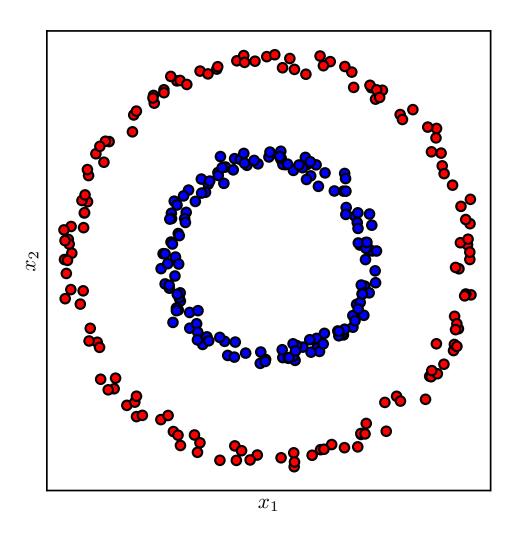
Classification of 2D data

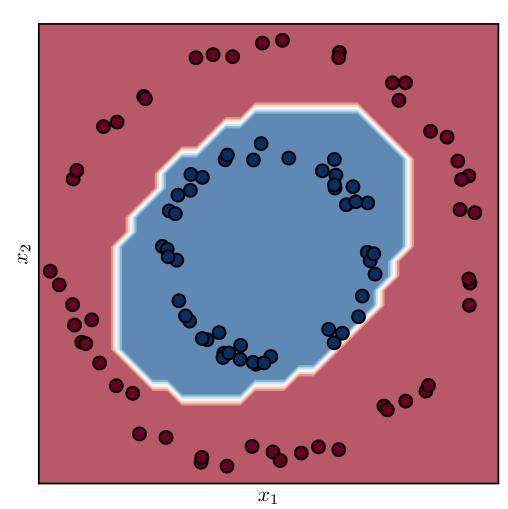


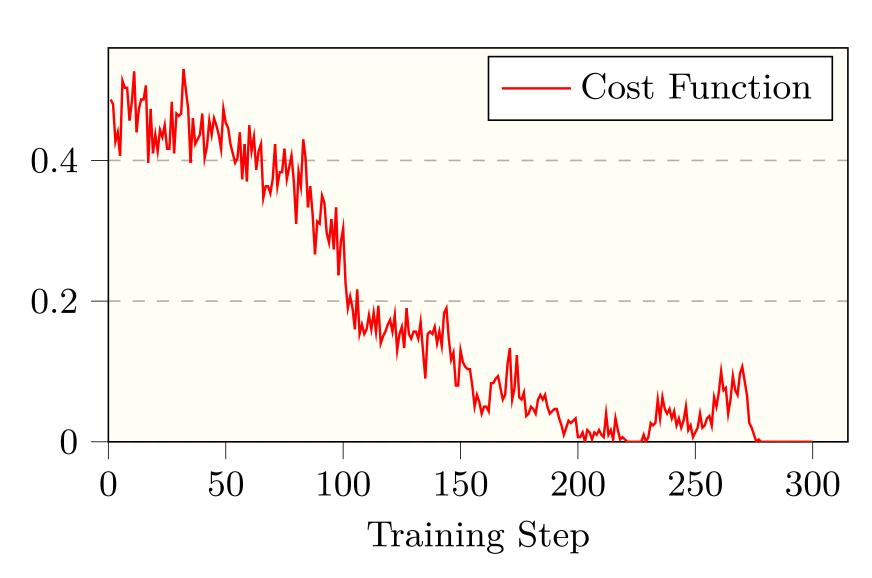
N=1 qubit



N=2 qubit

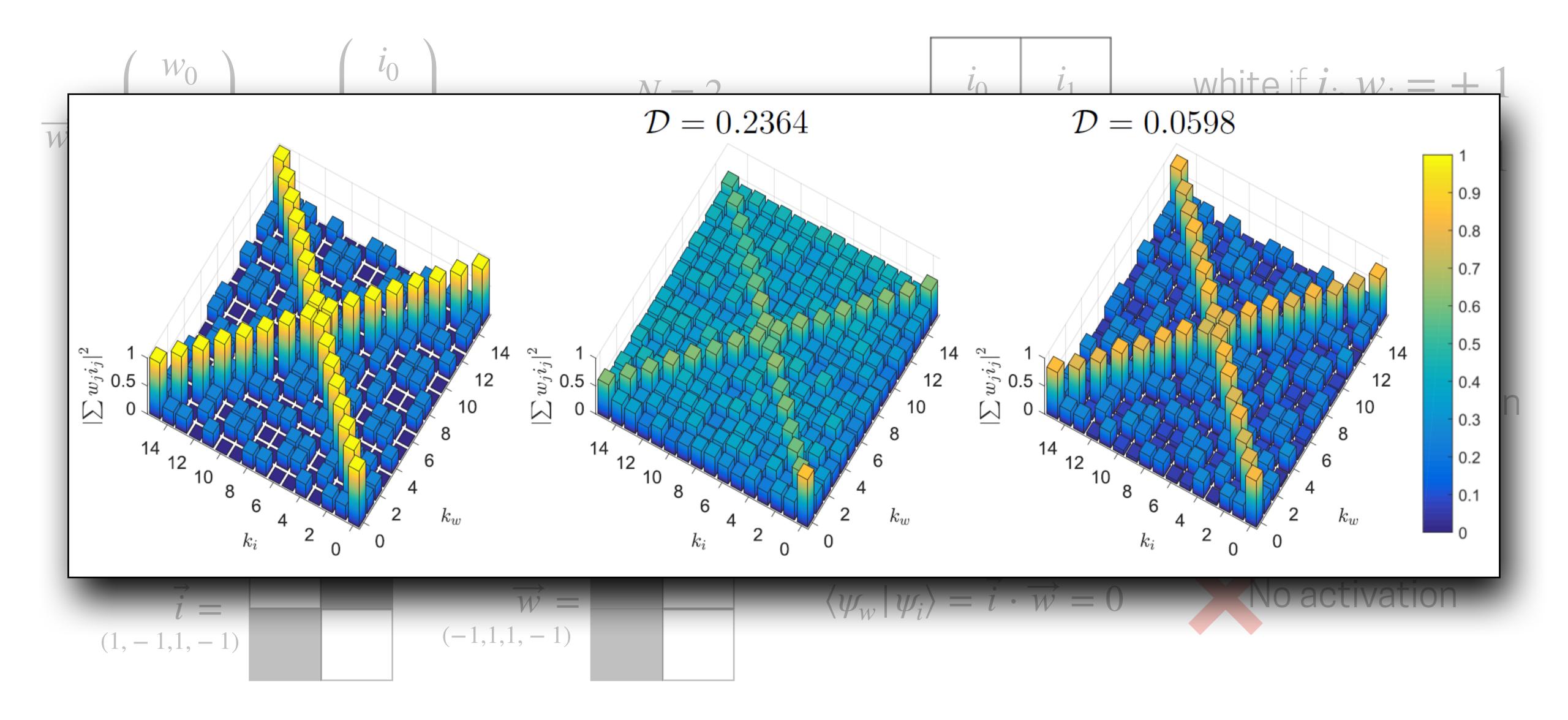






Classification of checkboard patterns





State preparation



For binary encoding of data

Brute-force approach

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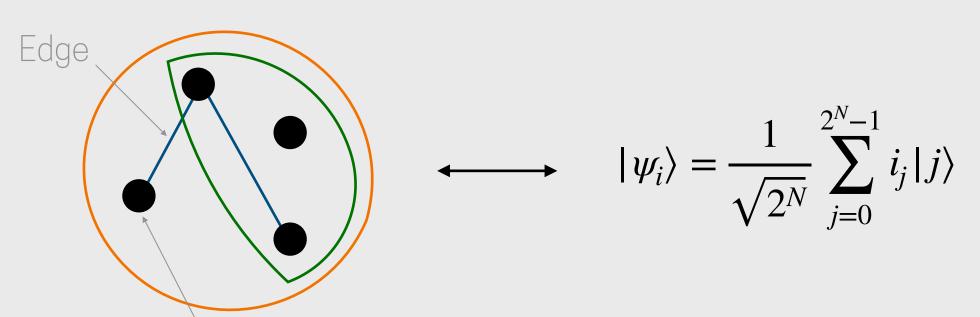
$$|010\rangle \rightarrow i_{010}|010\rangle$$

$$|110\rangle \rightarrow i_{110}|110\rangle$$

•

Requires O(n) operations

Hypergraph states



REW state

Requires O(n) operations but lower multi-qubit operations (at most one N-controlled gate)

Nodes