Quantum Machine Learning

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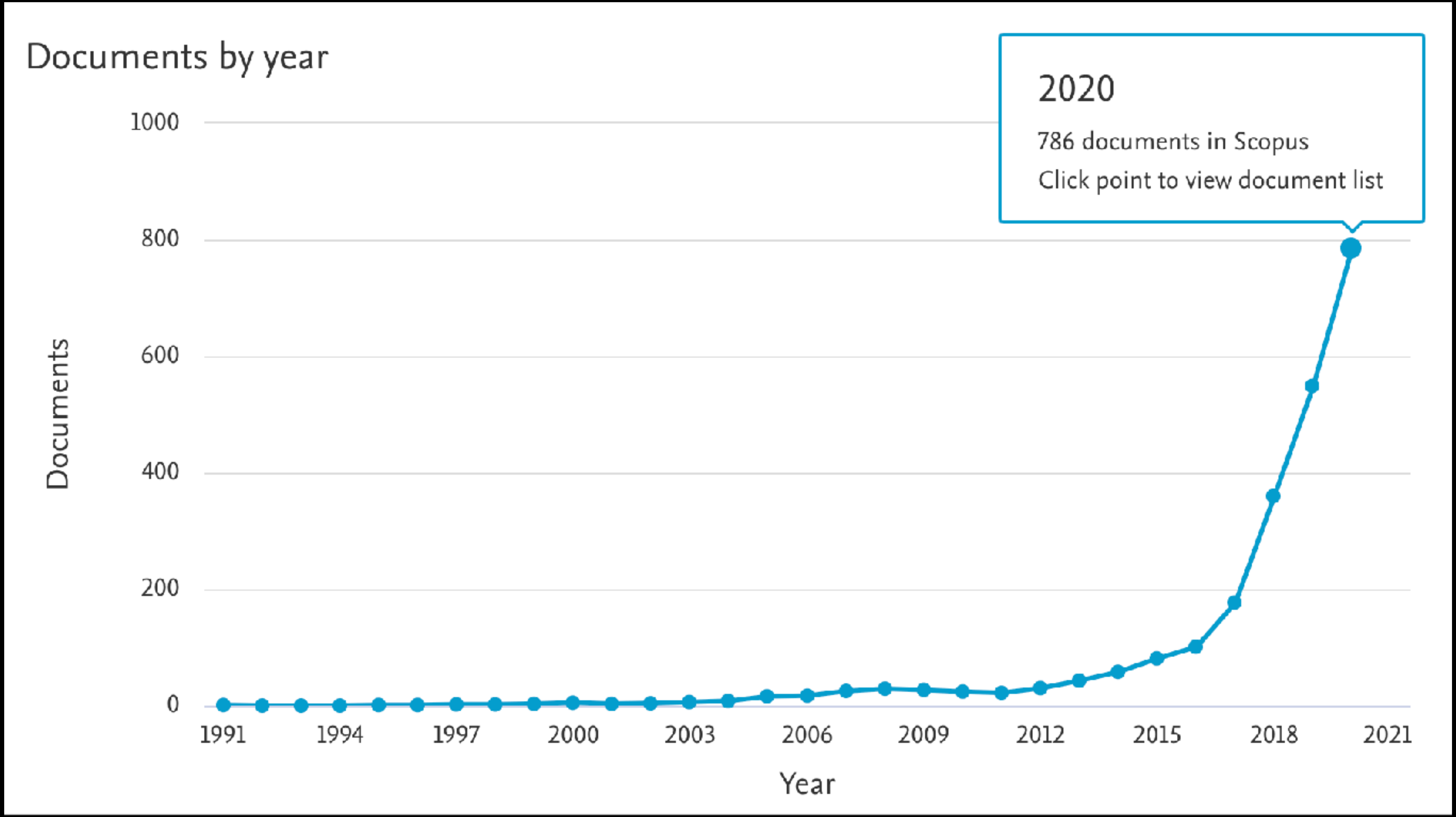
Quantum Computer Programming 2022-2

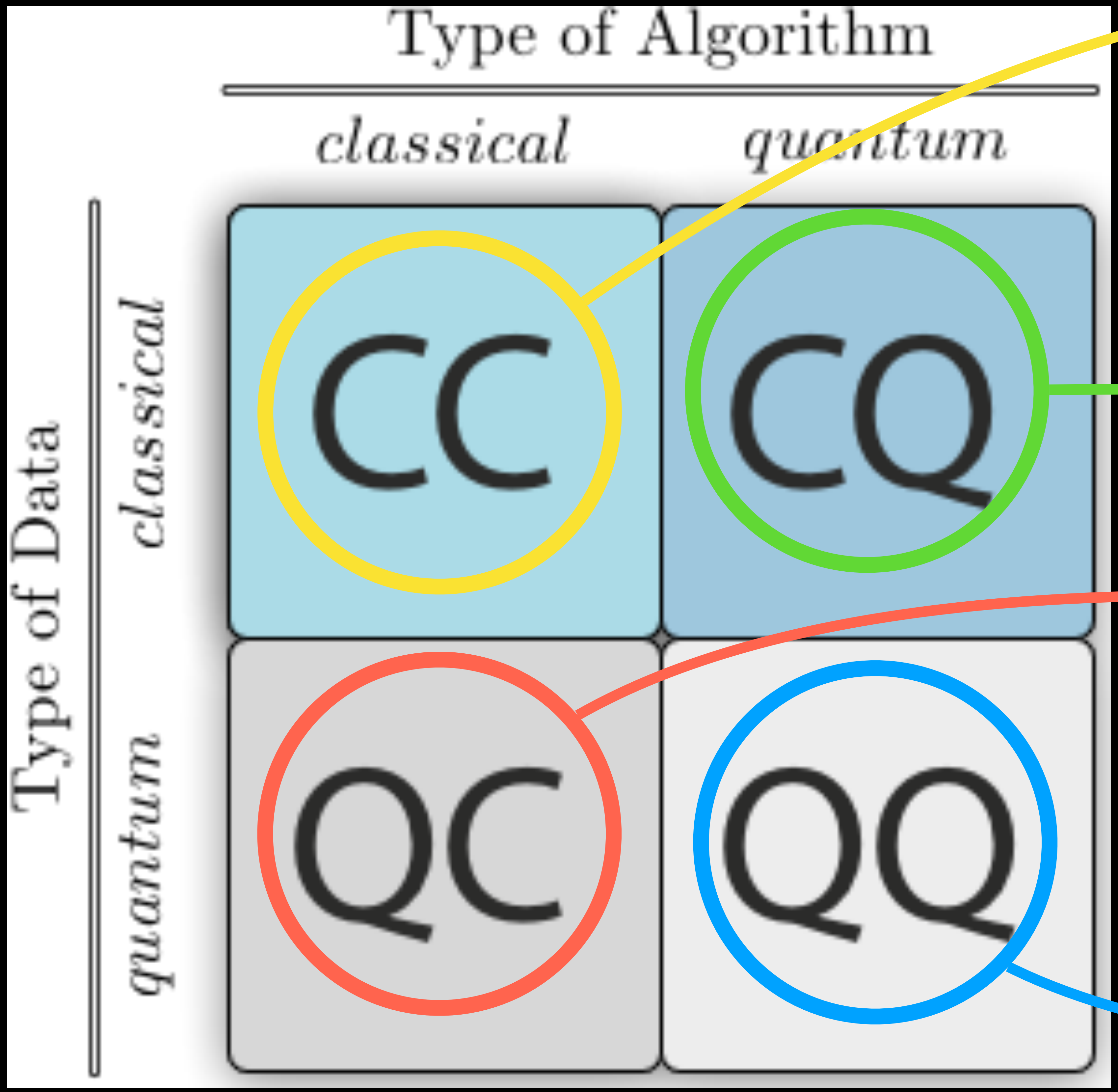
Quantum machine learning

Number of papers per year



Quantum machine learning

Approaches



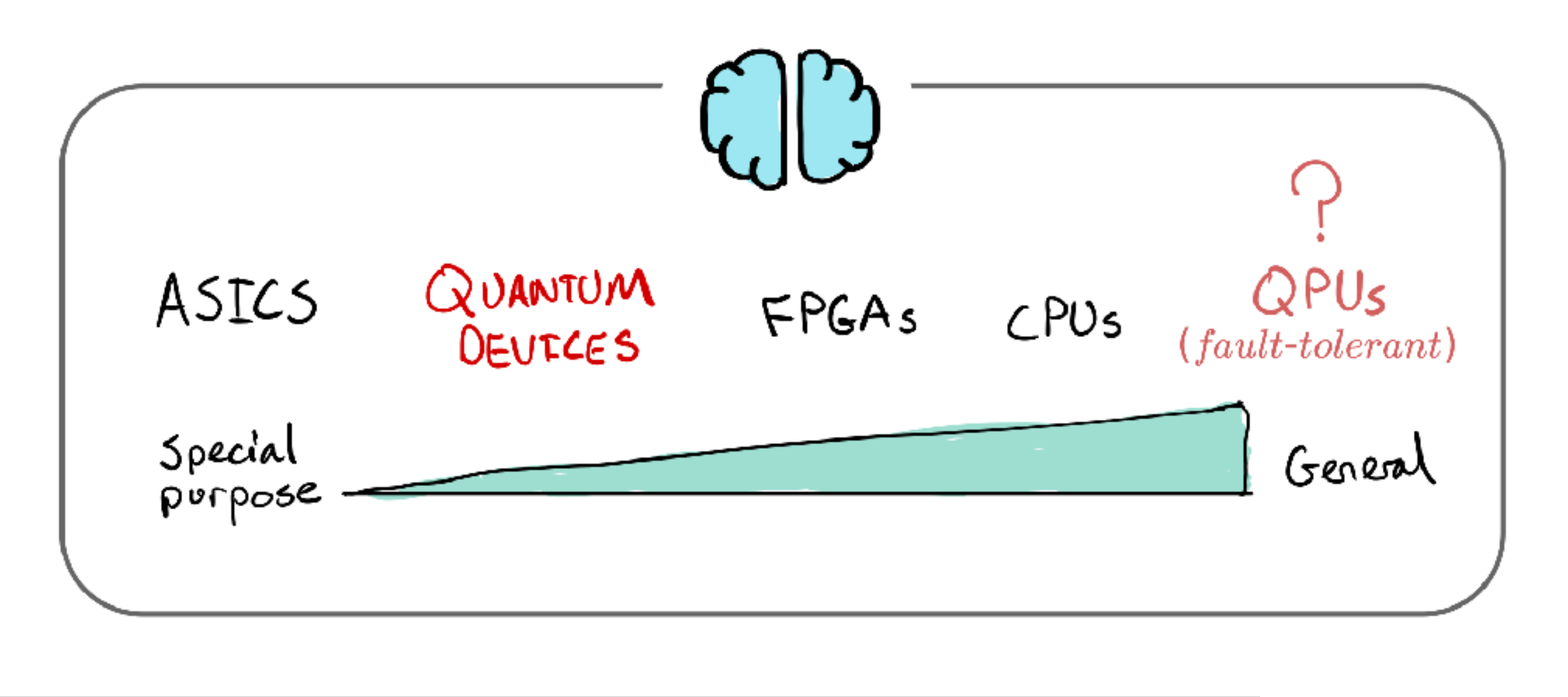
Classical ML

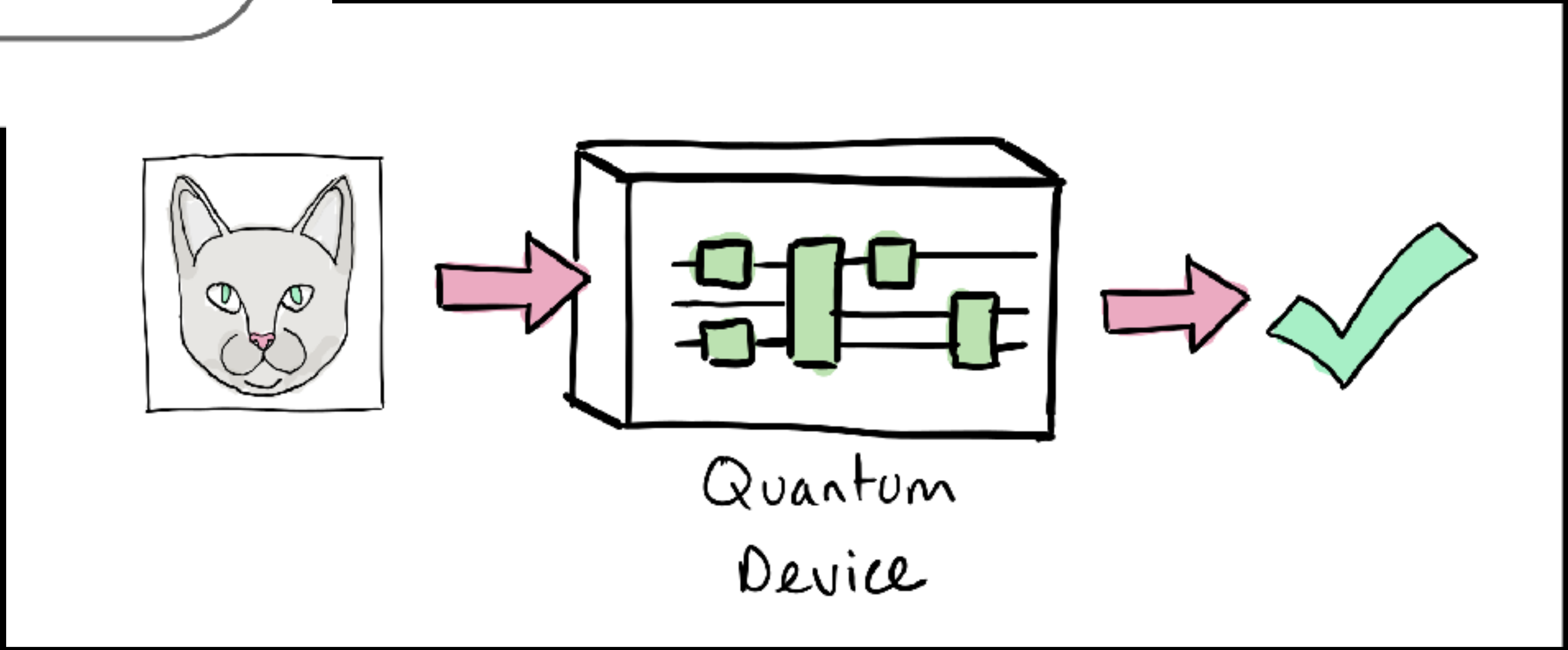
Quantum “accelerated” ML

Quantum “inspired” ML
ML applied to quantum systems

Quantum simulation of quantum systems

Quantum “accelerated” ML



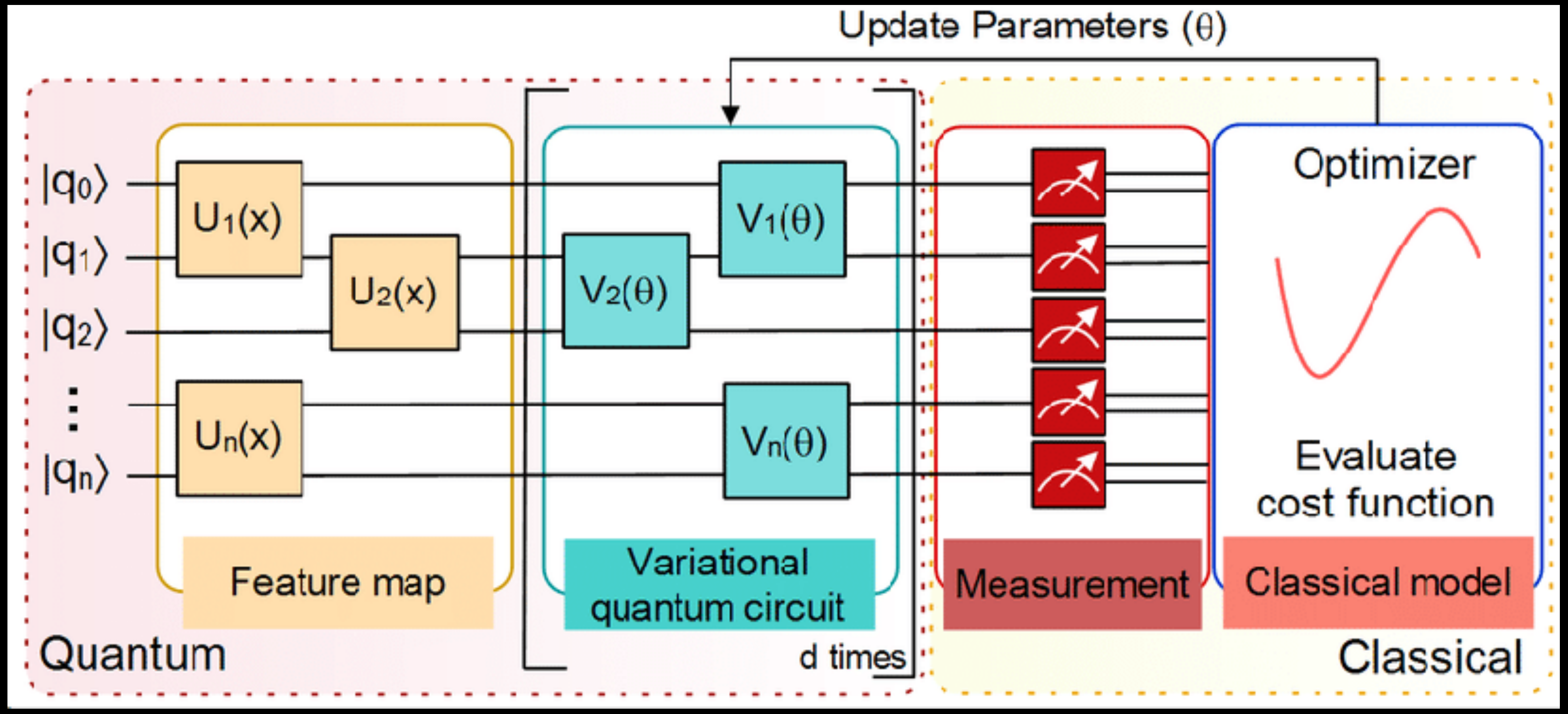


From: https://pennylane.ai/qml/whatisqml.html

Quantum “accelerated” ML

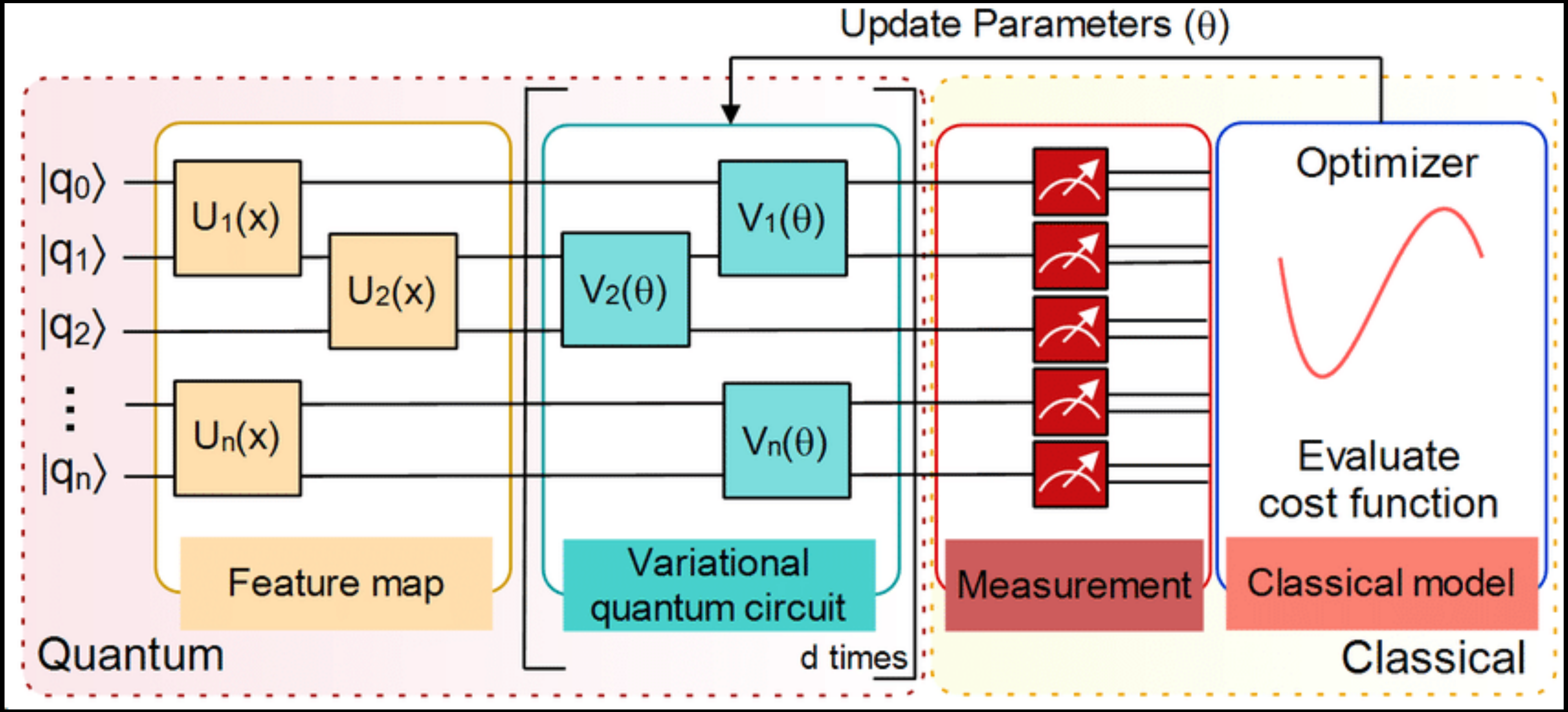
Algorithms

- Variational classifiers
- Quantum kernels
- Quantum SVMs
- Quantum neural networks
- Quanvolutional neural networks
- Quantum GANs
- Etc.



Quantum "accelerated" ML

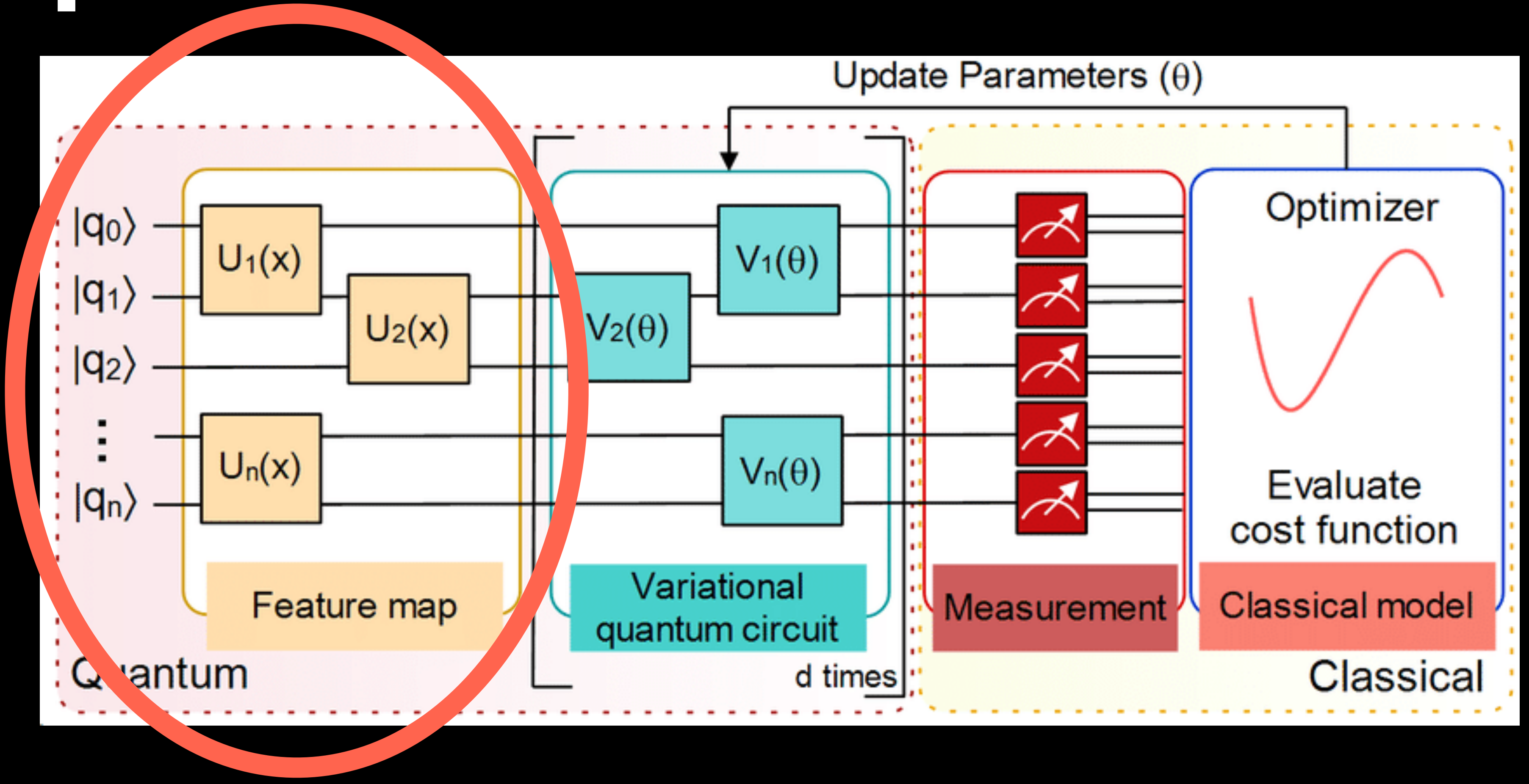
Variational Classifier

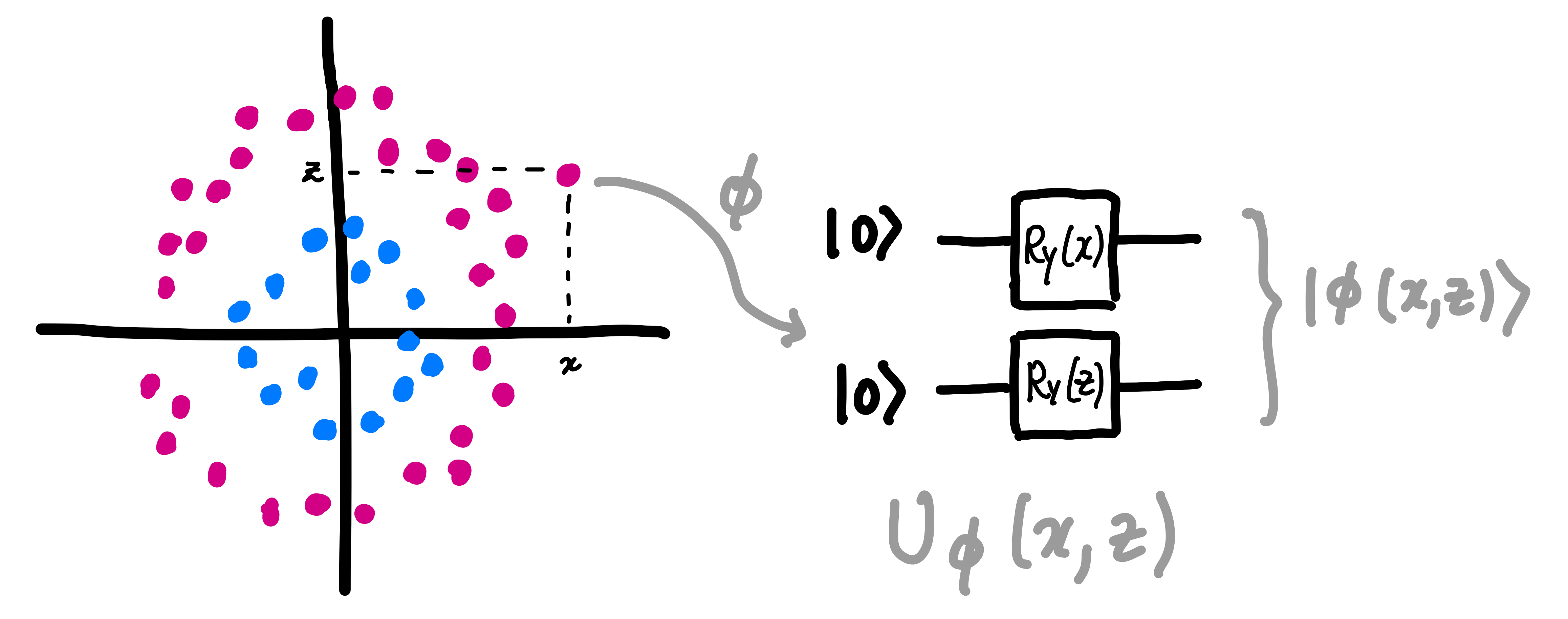


Sen, P., & Bhatia, A. S. (2021). Variational Quantum Classifiers Through the Lens of the Hessian. *arXiv preprint arXiv:2105.10162*.

Quantum “accelerated” ML

Quantum feature map





- Basis encoding
- Amplitude encoding
- Angle encoding
- Hamiltonian encoding

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Quantum “accelerated” ML

Basis embedding

- Input dataset:

$$\mathscr{D} = \{x^{(1)}, \ldots, x^{(m)}, \ldots, x^{(M)}\},\ x^{(i)} \in X^N$$

- Dataset is represented as superpositions of computational basis states:

$$|\mathscr{D}\rangle = \frac{1}{\sqrt{M}} \sum_{m=1}^{M} |x^{(m)}\rangle$$

- For binary variables requires *N* qubits

Quantum "accelerated" ML

Amplitude embedding

- A normalized classical *N*-dimensional datapoint is represented by the amplitudes of an *n*-qubit quantum state with $N = 2^n$

$$|\psi_x\rangle = \sum_{i=1}^{N} x_i |i\rangle,$$

- The input examples are concatenated together

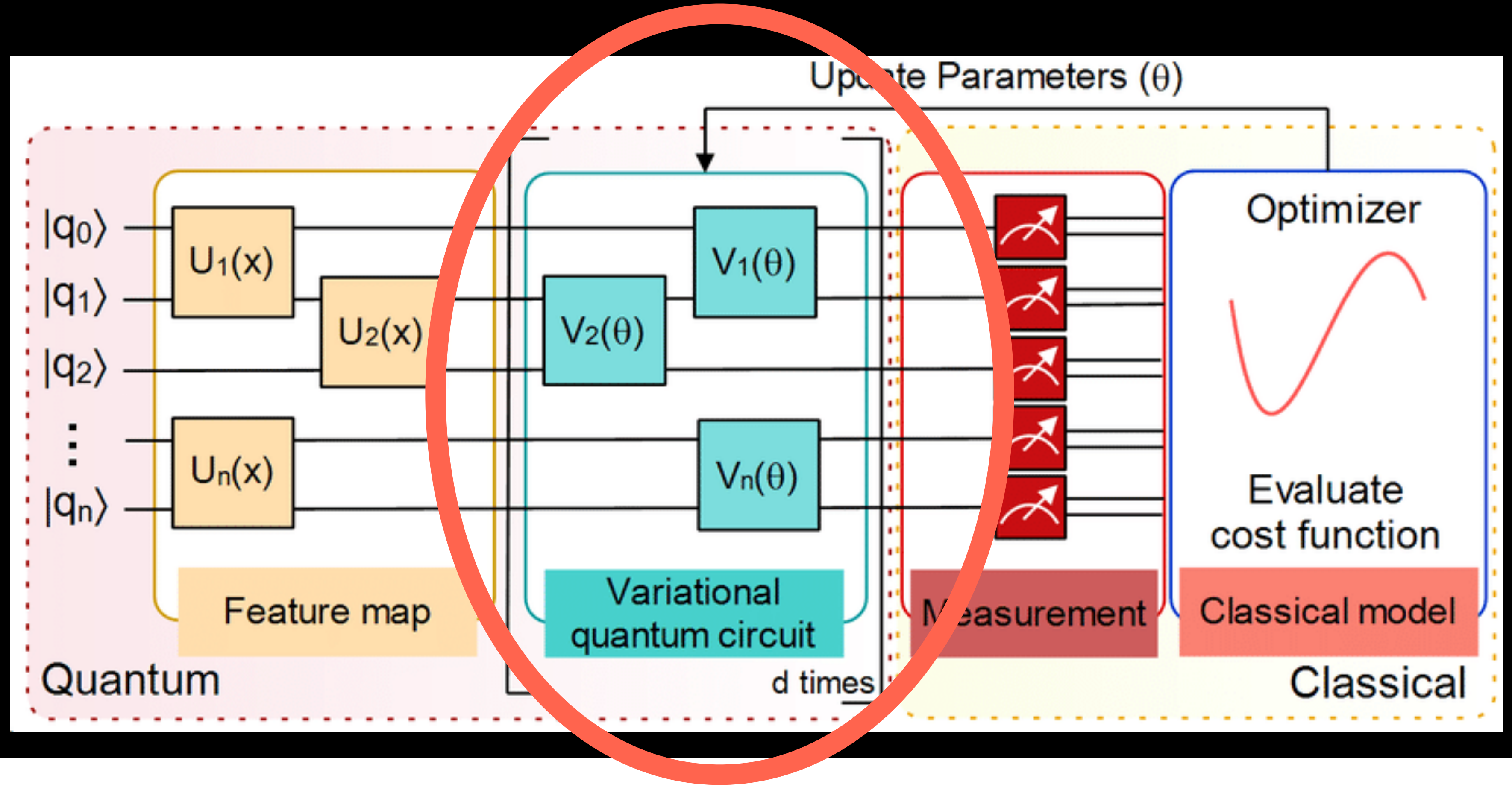
$$\alpha = C_{norm}\{x_1^{(1)}, \ldots, x_N^{(1)}, x_1^{(2)}, \ldots, x_N^{(2)}, \ldots, x_1^{(M)}, \ldots, x_N^{(M)}\},$$

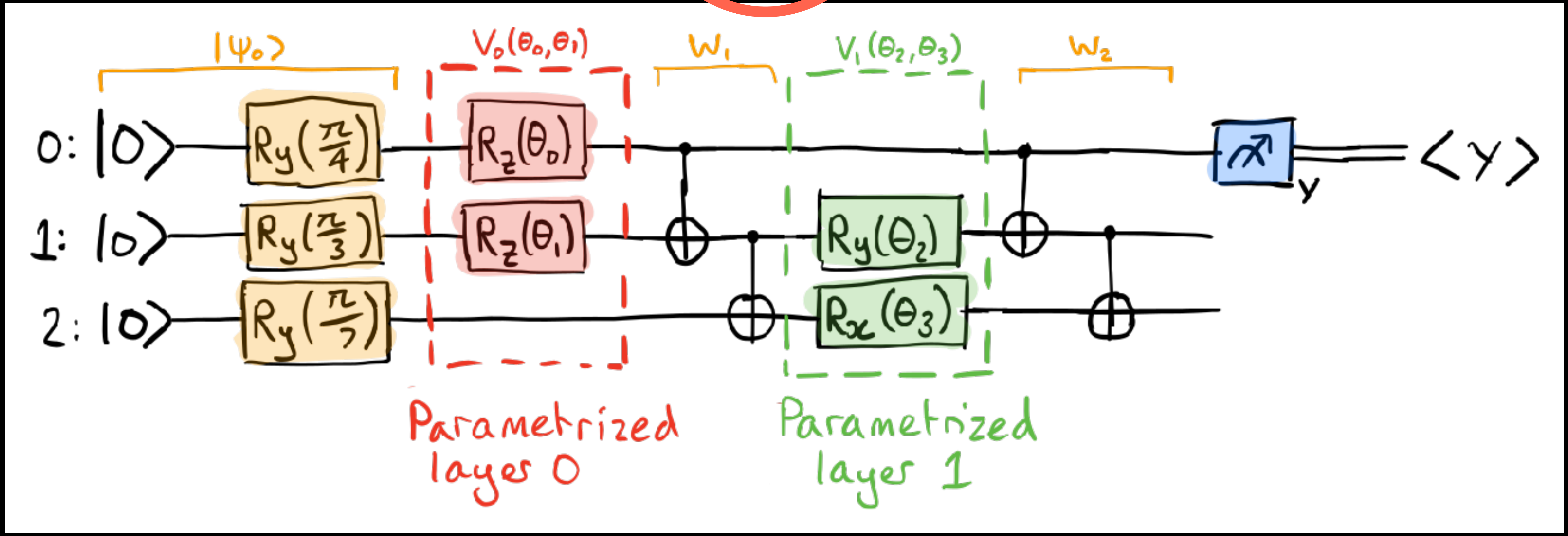
- The dataset is represented as:

$$|\mathscr{D}\rangle = \sum_{i=1}^{2^n} \alpha_i |i\rangle,$$

Quantum “accelerated” ML

Quantum circuit





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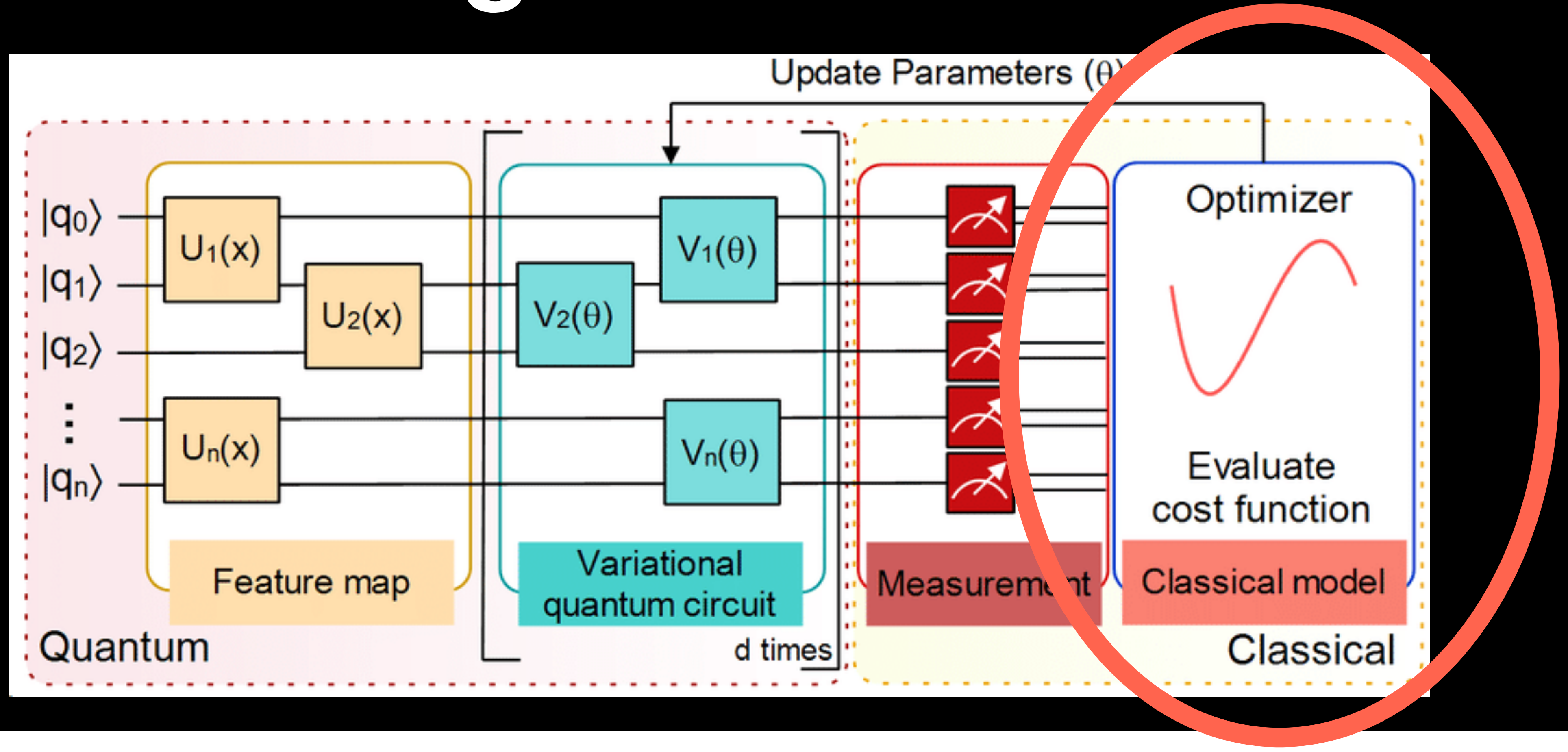
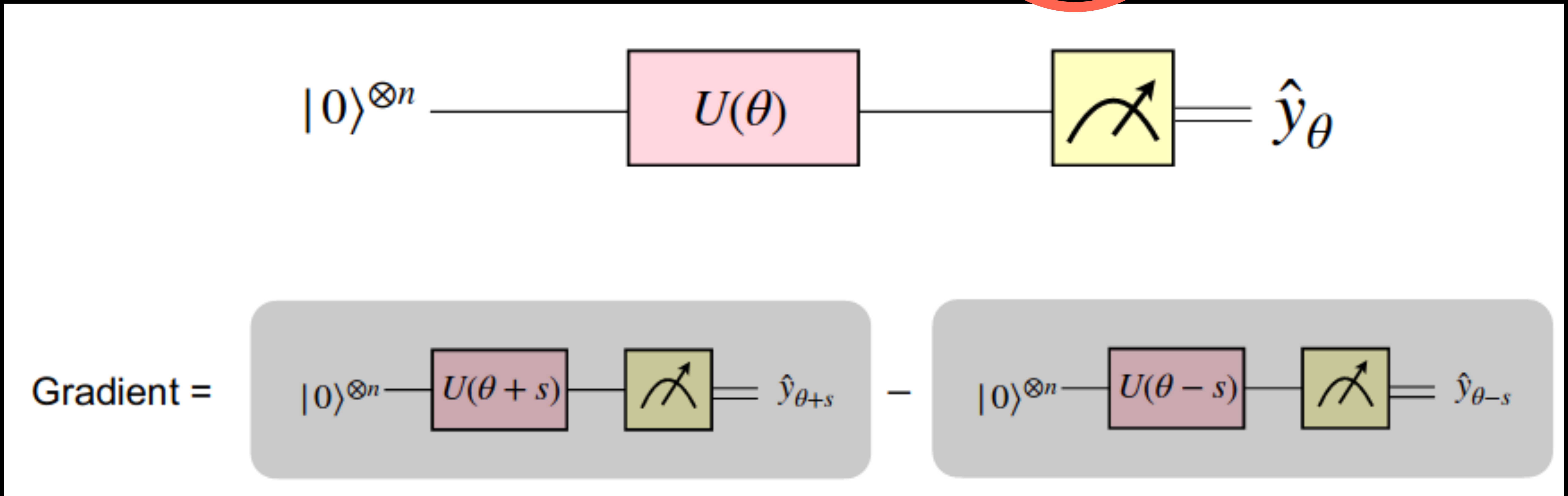
Quantum "accelerated" ML

Parameter shift to calculate gradients





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Quantum “accelerated” ML

Parameter shift

- Objective function:

$$f(\theta) = \langle\psi|\ U_G^\dagger(\theta)\ A\ \ U_G(\theta)\ |\psi\rangle$$

- Parameterized gate with generator *G* (Hermitian):

$$U_G(\theta) = e^{-i\theta G} = I\cos(\theta) - iG\sin(\theta)$$

- If G has only two eigenvalues e_0 and e_1, we have:

$$\frac{d}{d\theta}f(\theta) = r\Big[f(\theta + \frac{\pi}{4r}) - f(\theta - \frac{\pi}{4r})\Big] \qquad r = \frac{a}{2}(e_1 - e_0)$$

Quantum "accelerated" ML

Parameter shift for Pauli gates

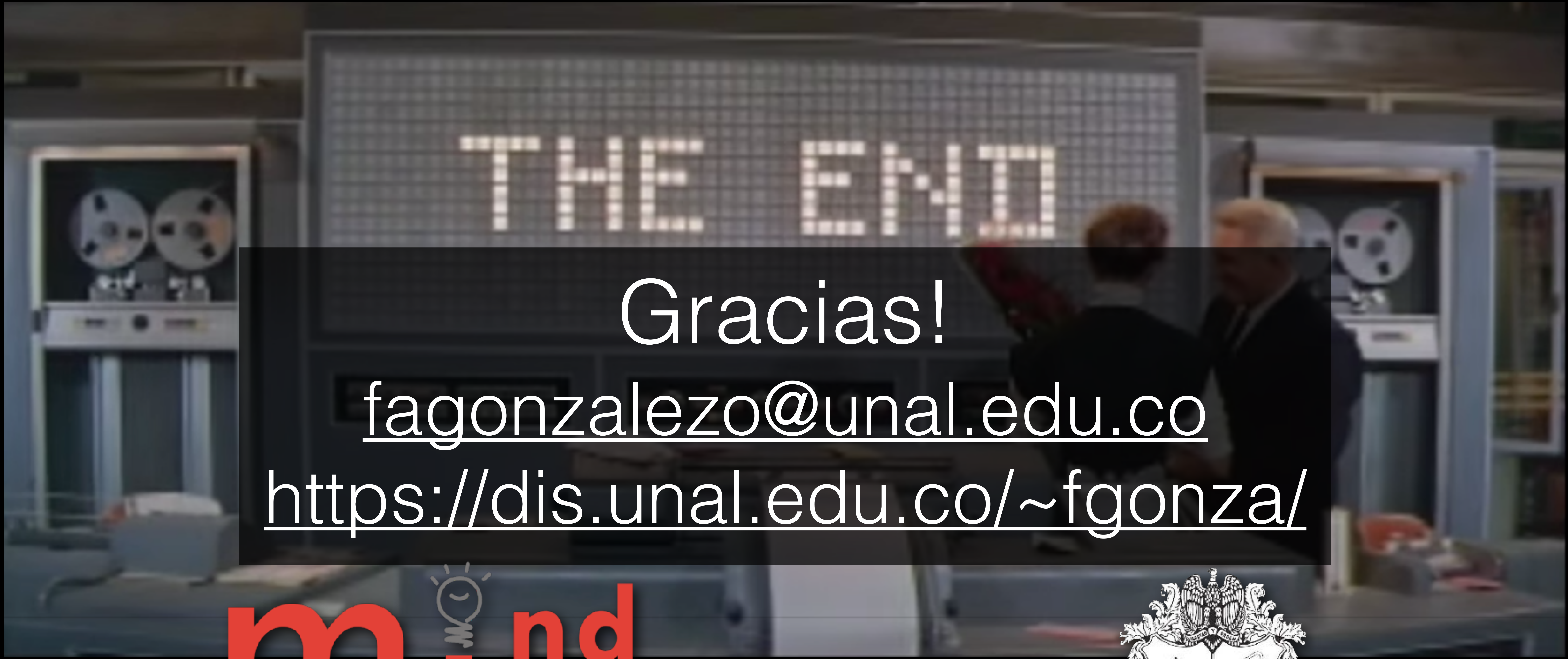
$$R_X(\theta) = e^{-i\frac{1}{2}\theta X} \qquad r = \frac{1}{2}$$

$$R_Y(\theta) = e^{-i\frac{1}{2}\theta Y} \qquad r = \frac{1}{2}$$

$$R_Z(\theta) = e^{-i\frac{1}{2}\theta Z} \qquad r = \frac{1}{2}$$

$$\frac{d}{d\theta} f(\theta) = \frac{1}{2}\left[f(\theta + \frac{\pi}{2}) - f(\theta - \frac{\pi}{2})\right]$$

Crooks, G. E. (2019). *Gradients of parameterized quantum gates using the parameter-shift rule and gate decomposition.* arXiv preprint arXiv:1905.13311



Gracias!

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https://dis.unal.edu.co/~fgonza/

mind LAB
machine learning perception and discovery