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Variational Quantum Algorithms as Machine Learning Models

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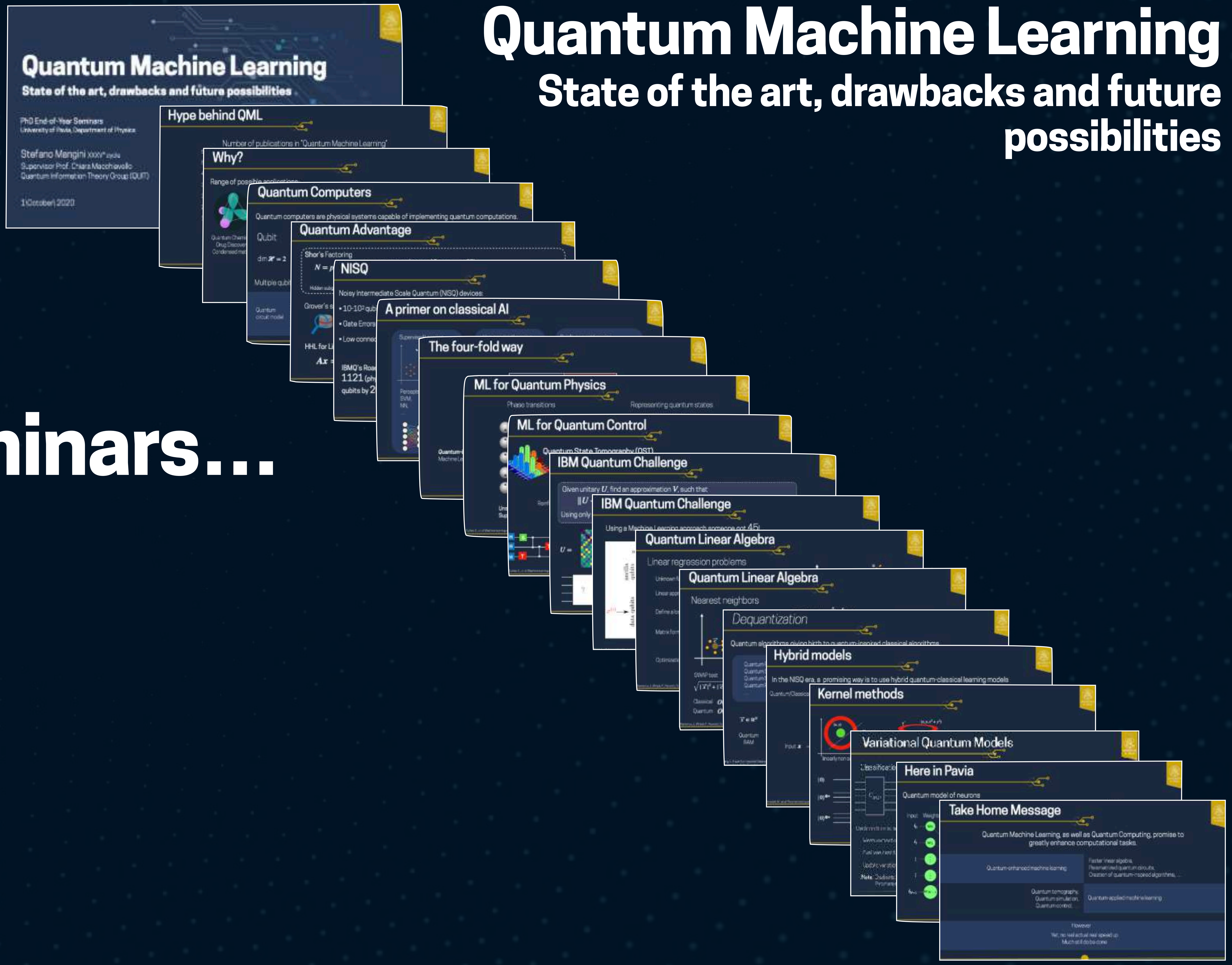
End-of-Year PhD Seminars, Department of Physics, University of Pavia
1\October\2021

Quantum Machine Learning

State of the art, drawbacks and future possibilities

Previously on End-of-Year Seminars…



Quantum Machine Learning
State of the art, drawbacks and future possibilities

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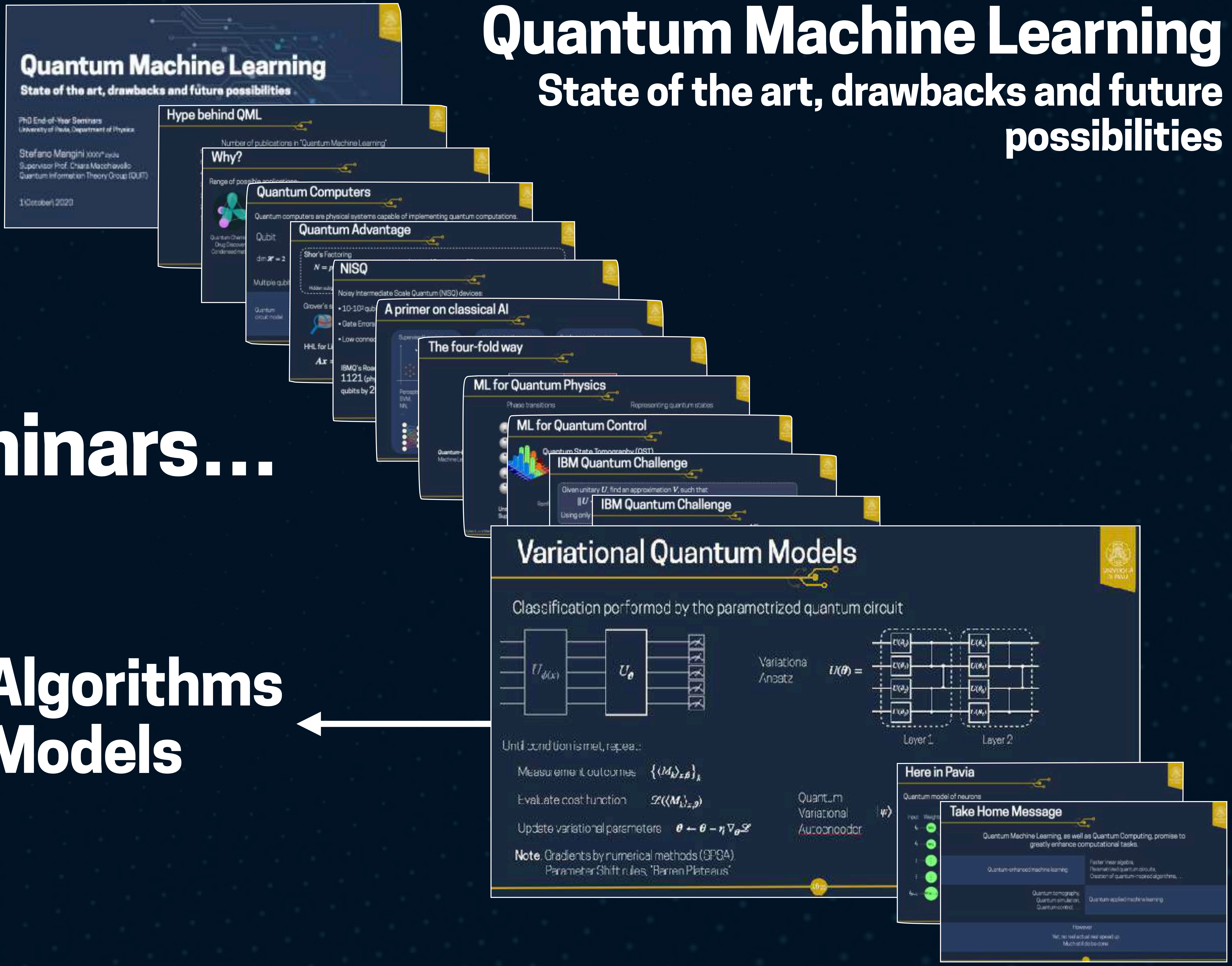


Variational Quantum Algorithms as Machine Learning Models

Introduction

1. Quantum Neuron

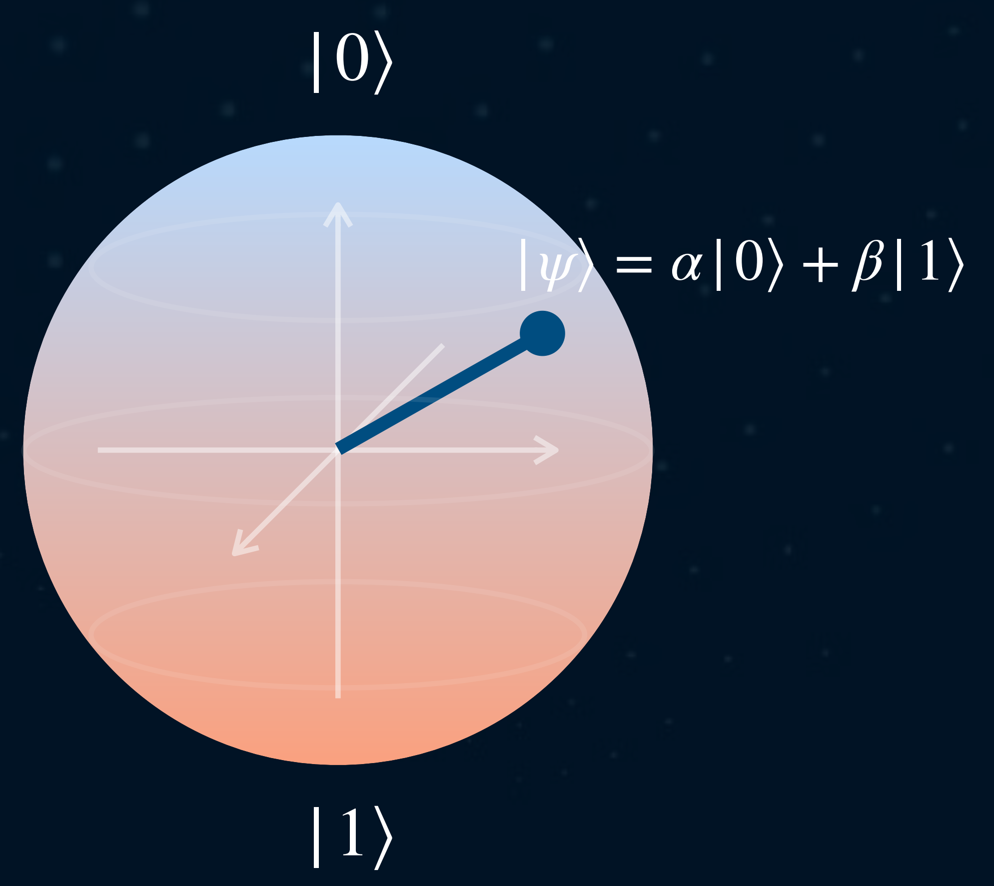
2. Variational Learning

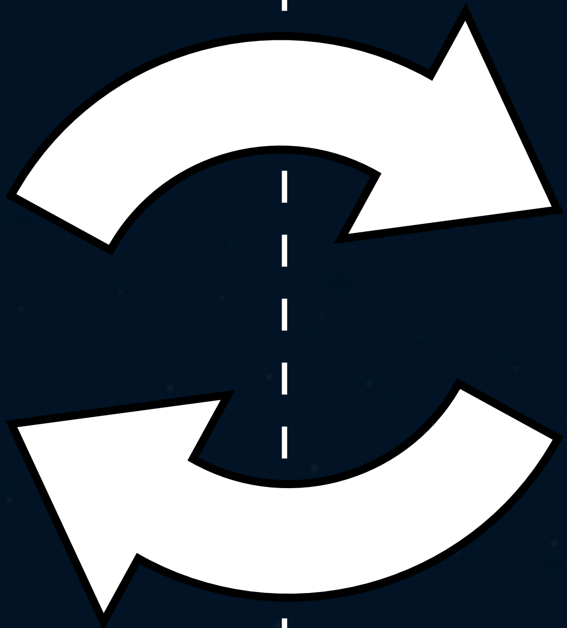
3. A concrete application

Outlooks

Quantum Machine Learning

Quantum computing





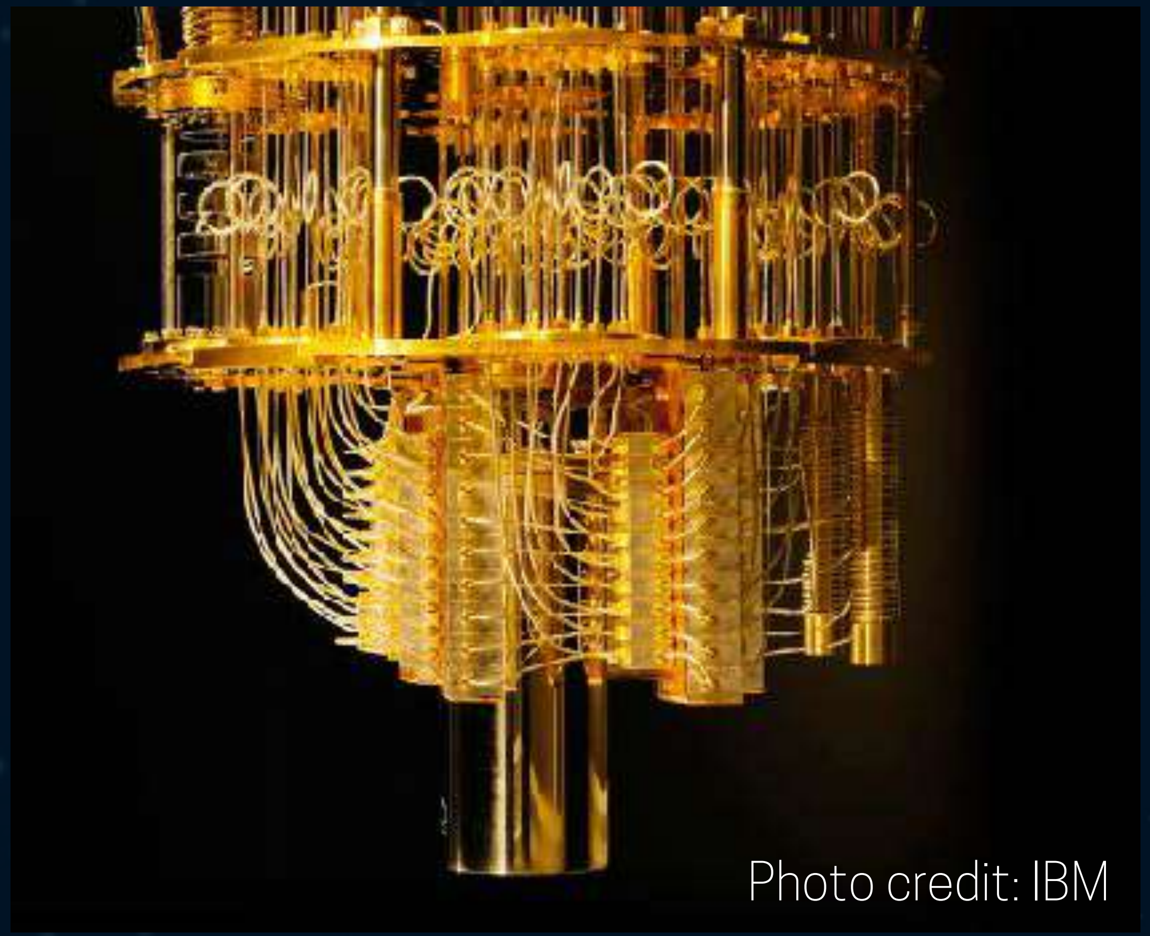


Photo credit: IBM

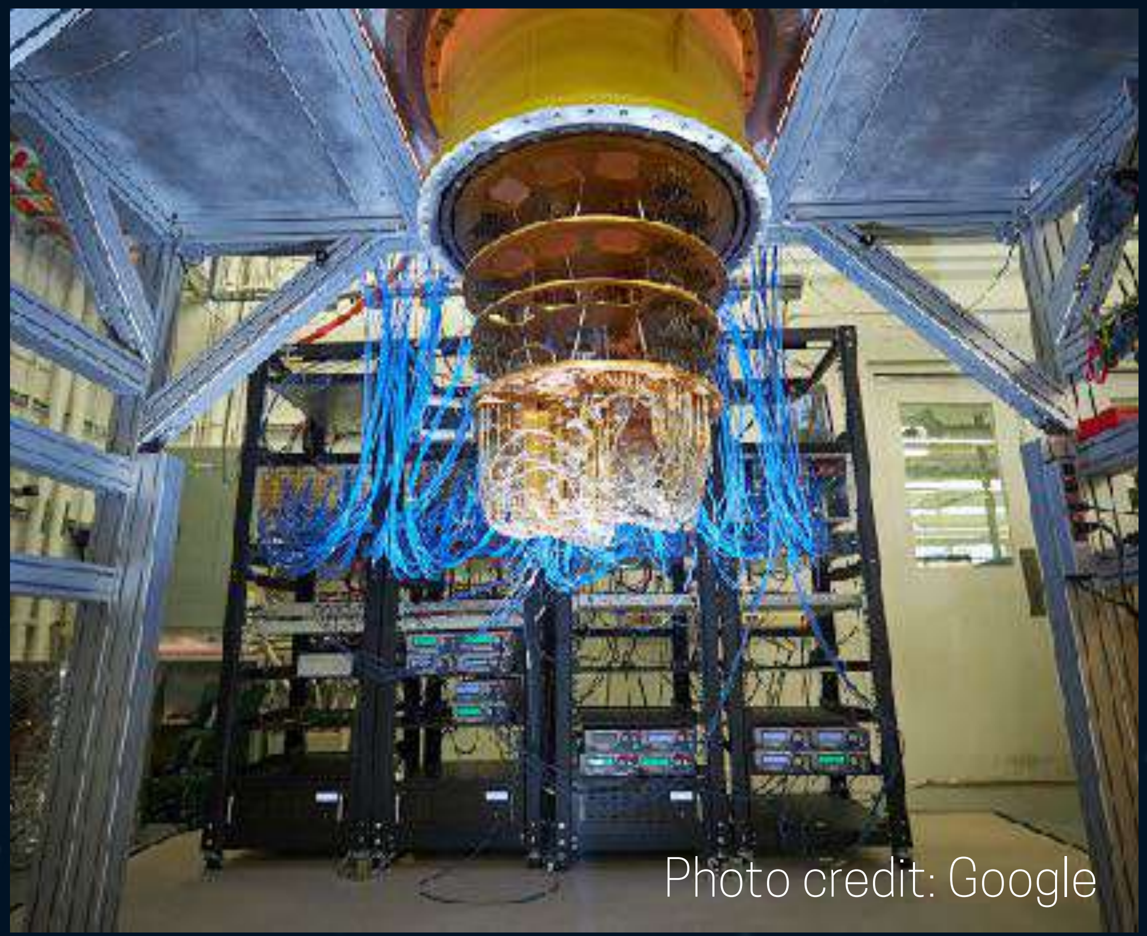
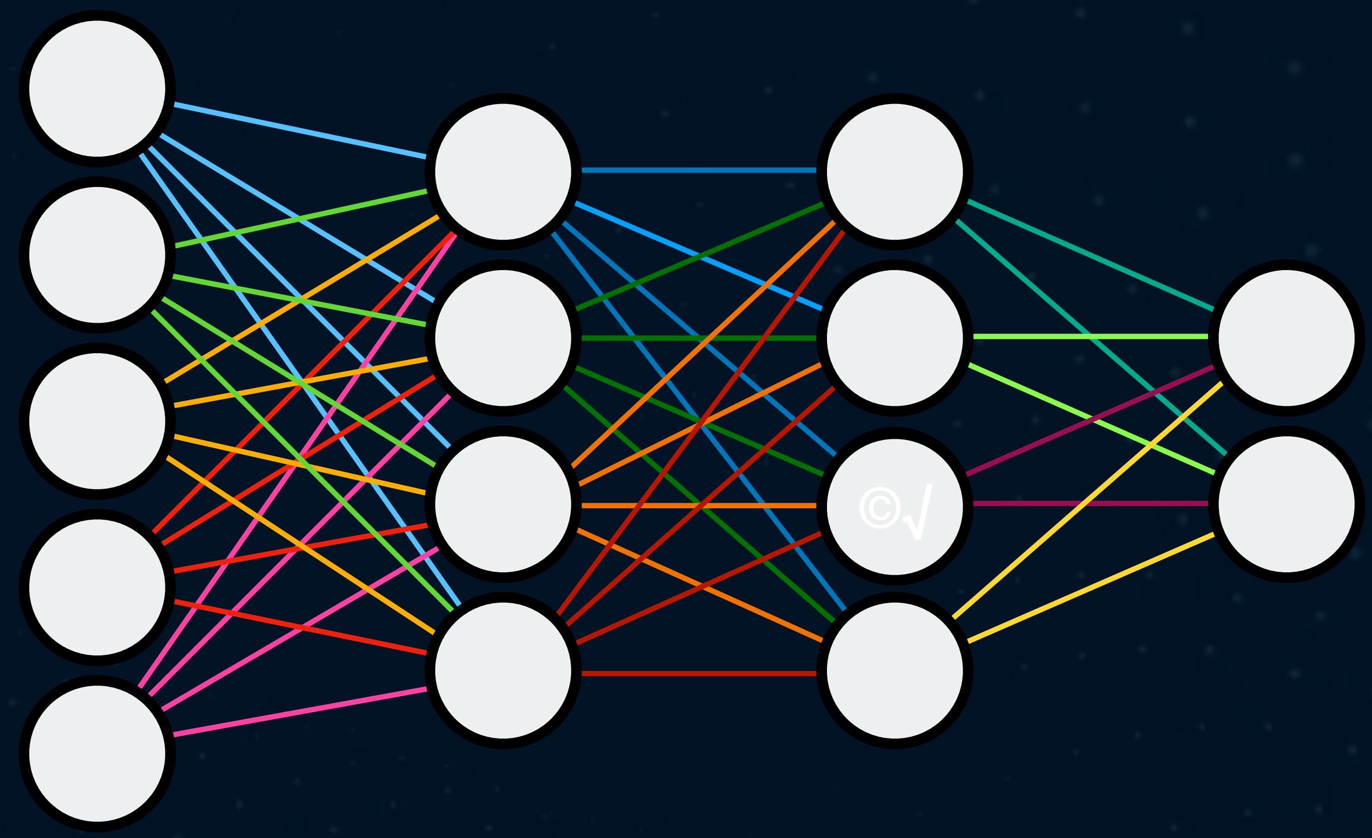
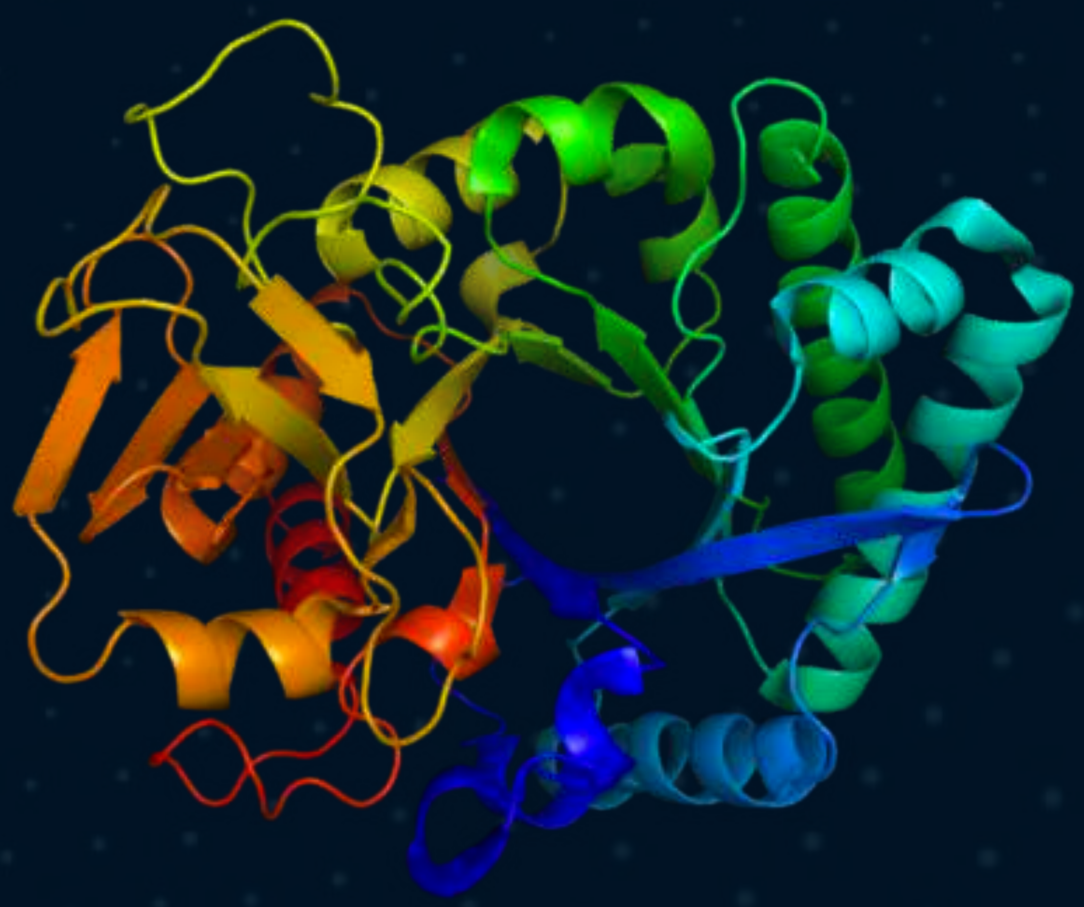


Photo credit: Google

Machine Learning

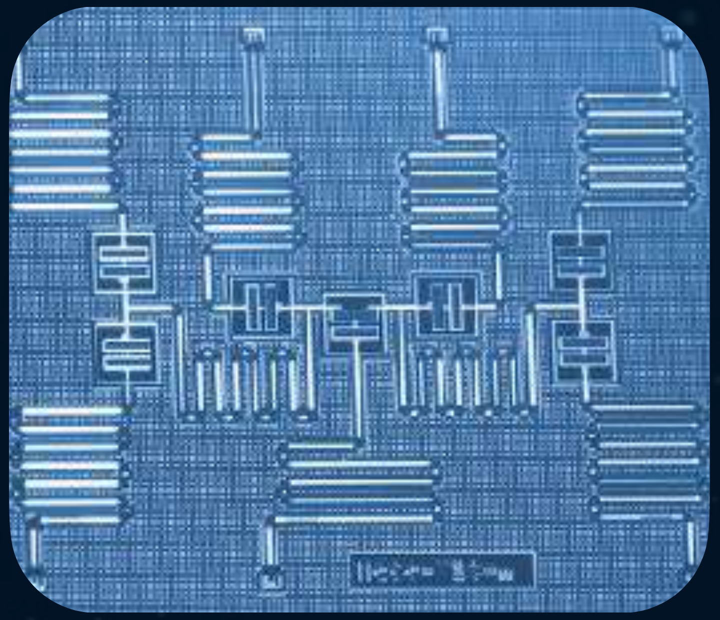




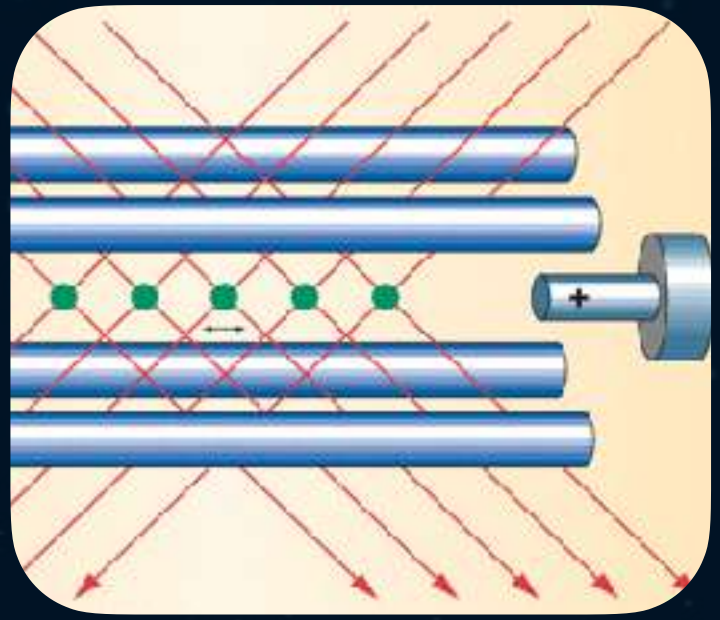
…do we have Quantum Computers?

Yes! sort of…

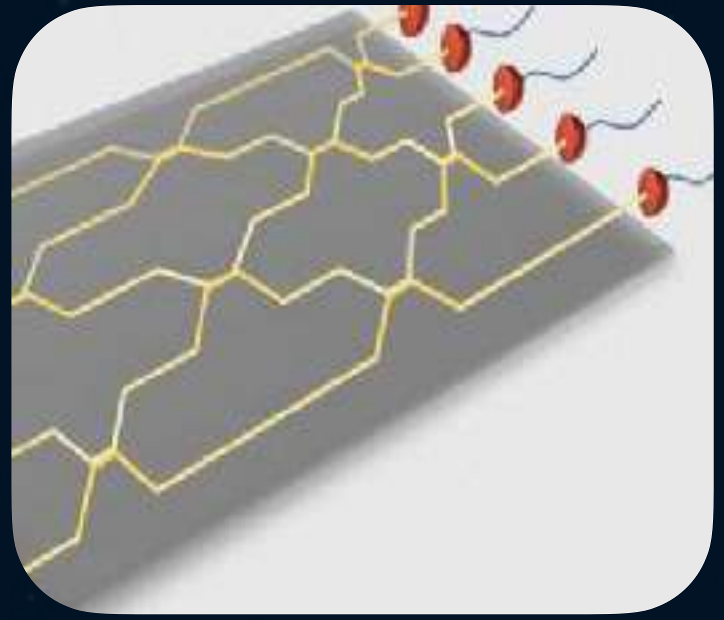
Different technologies



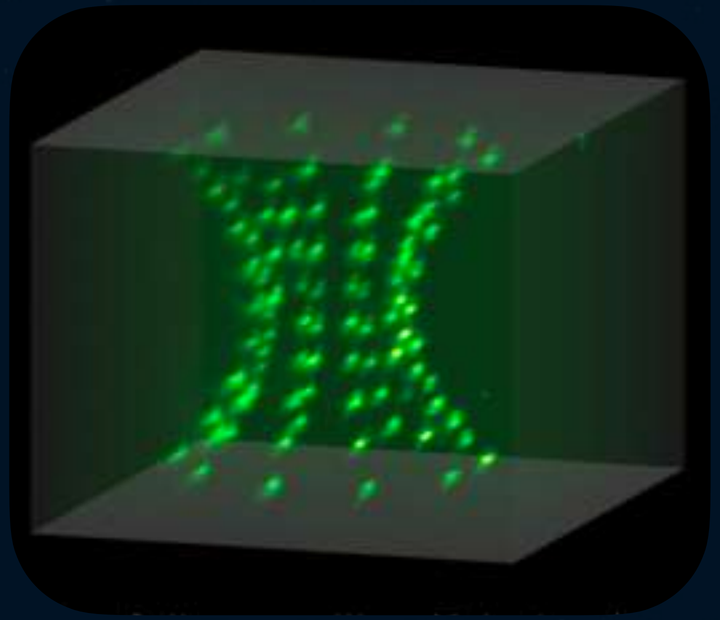
Superconducting circuits
(IBM, Google)



Ion Traps
(IonQ, Honeywell)

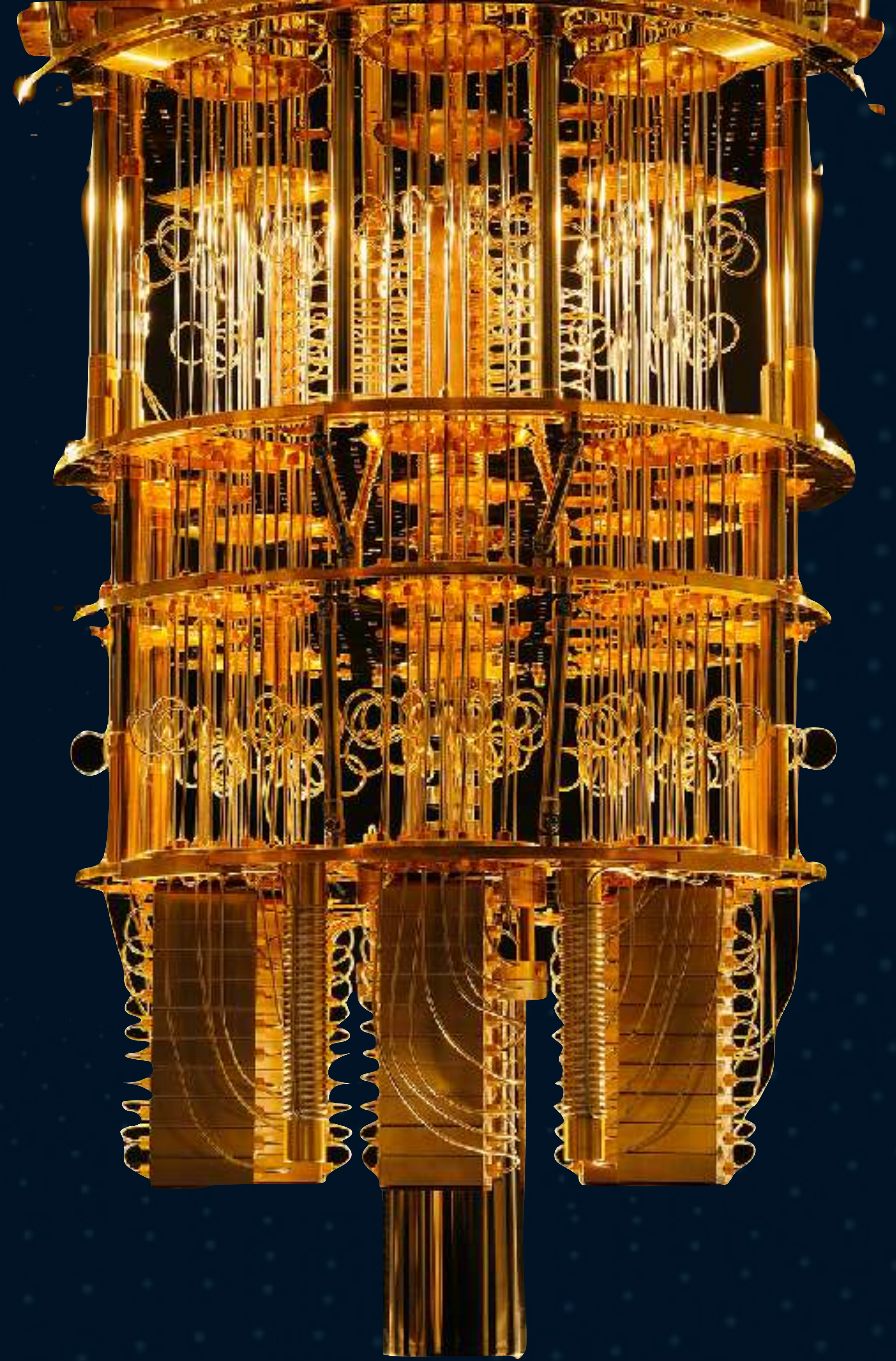


Photonics
(Xanadu, PsiQuantum)



Neutral Atoms
(Pasqal)

…



Noisy — qubits are subject to error rates $\sim 98\,\%$

Intermediate — current best quantum hardware $\sim 50/100$ qubits

Scale

Quantum

Implementation Shor's algorithm requires $\sim 20M$ qubits
won't be around for $?$ years and need Error Correction…

Variational (NISQ-friendly) Paradigm

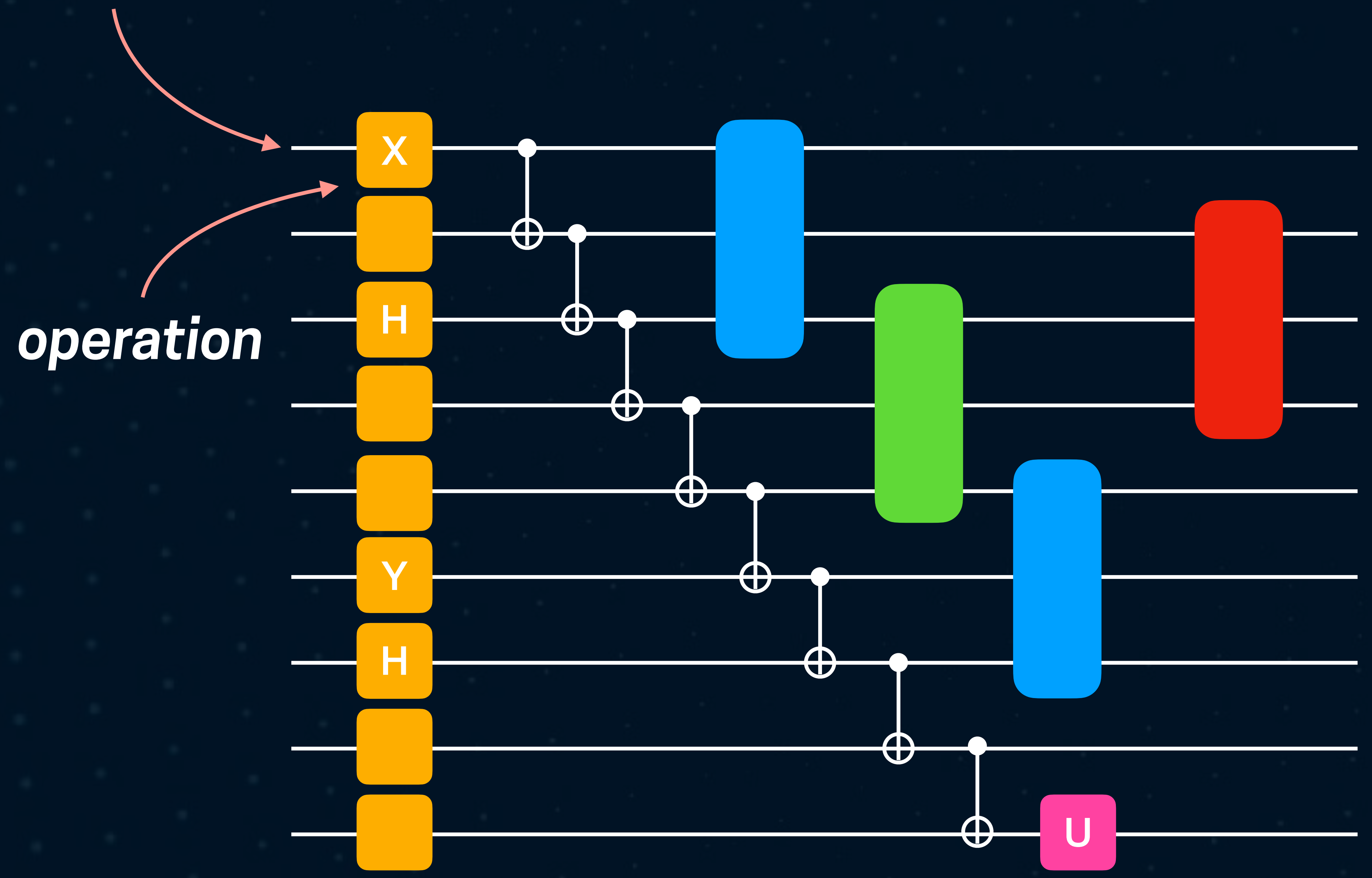
“Usual” quantum algorithms (Shor)

requires many qubits

uses lots of gates (operations)

assumes ideal execution (noise free)

qubit



theoretical success guarantees

Parametrized gates

$R_y(\theta) = e^{i\theta\sigma_y/2}$

Repeat until convergence

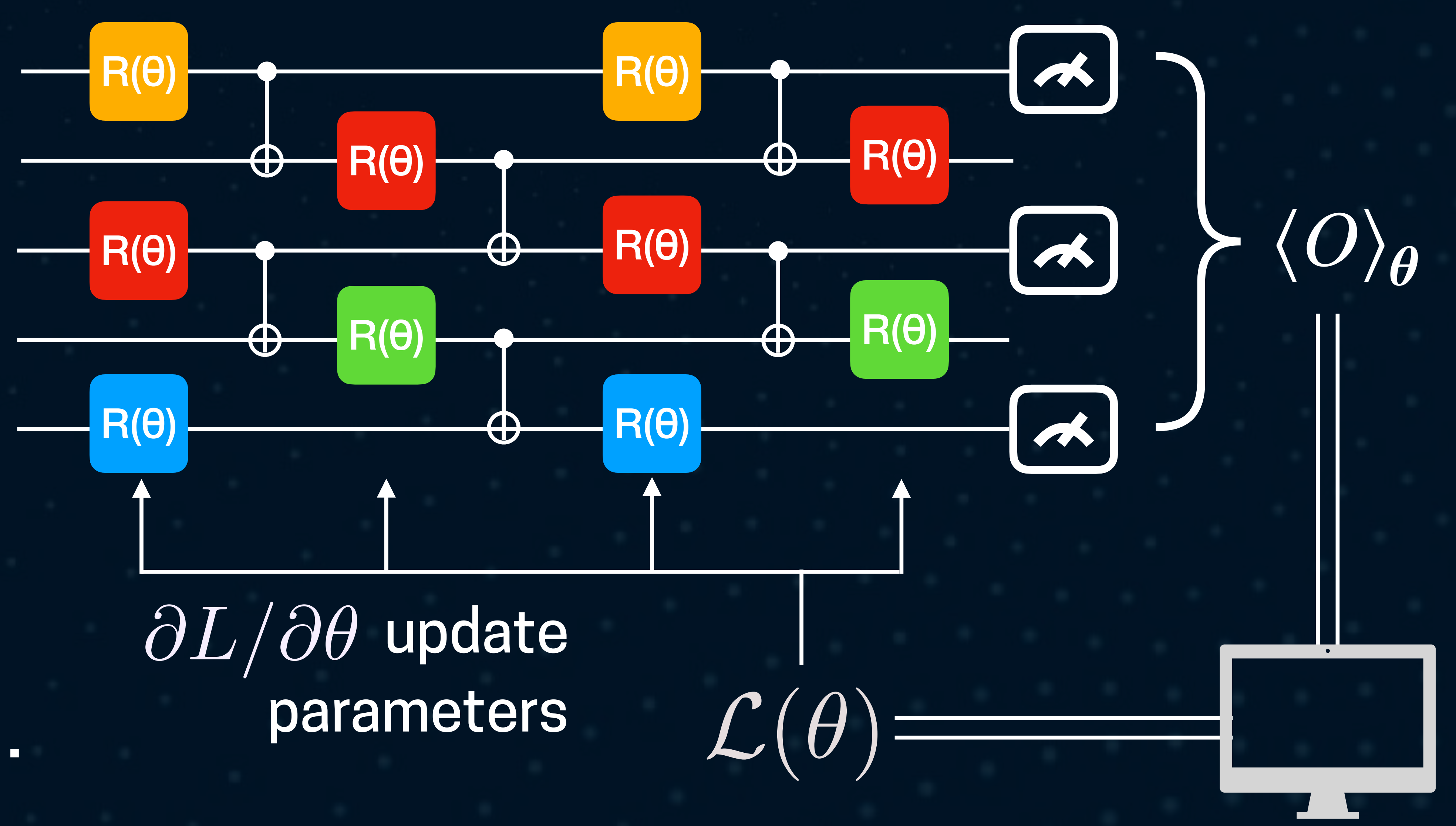
too good to be true... usually no provable guarantees, but heuristic results

Variational quantum algorithms

requires few qubits

uses few gates (operations)

somewhat resilient to noise



Loss function embedding the task to be solved (e.g. minimize energy of a variational state)

Variational (NISQ-friendly) Paradigm

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requires many qubits

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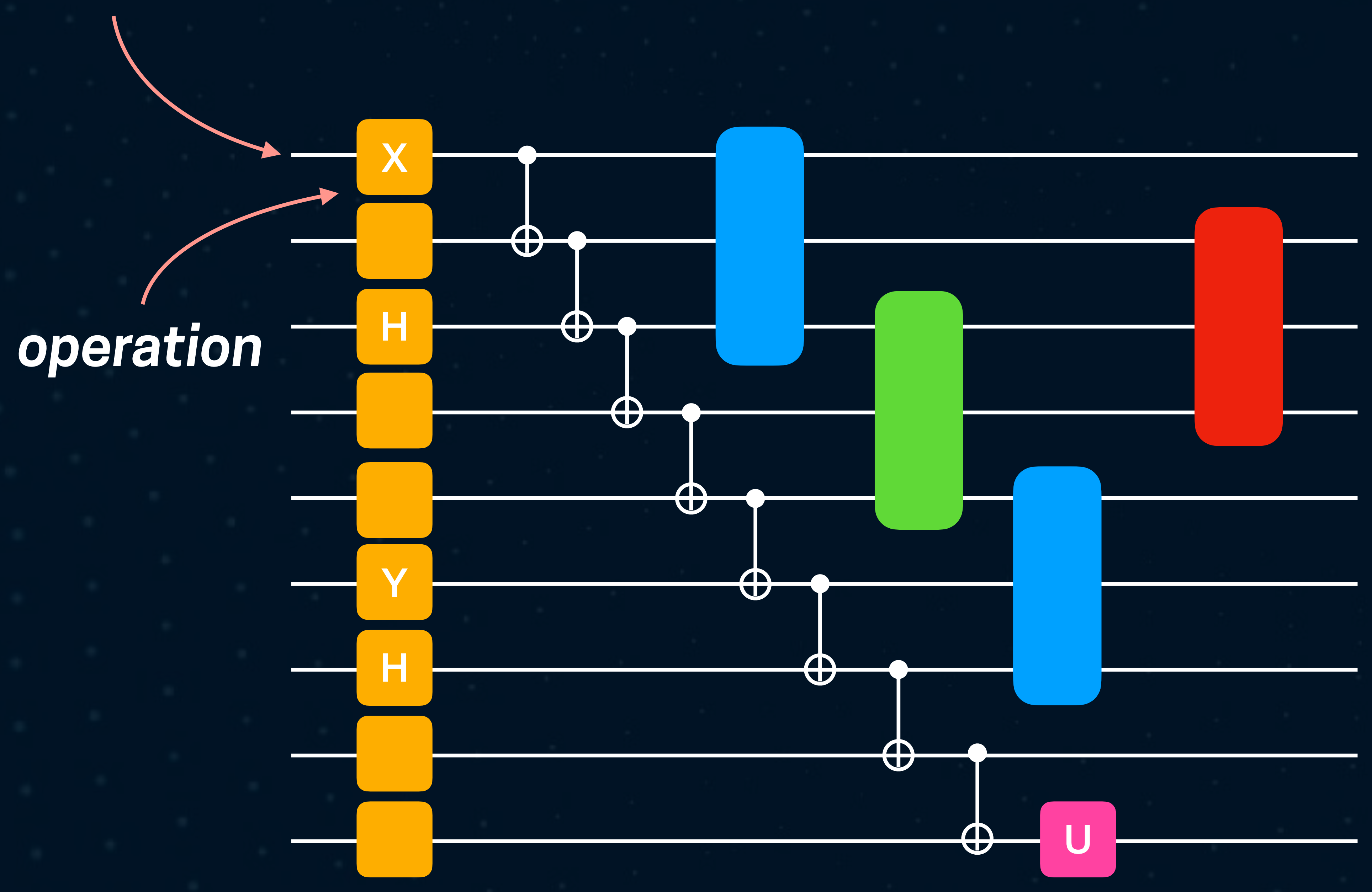


theoretical success guarantees

Variational ~~Quantum~~ algorithms

Quantum Neural Networks

requires few qubits

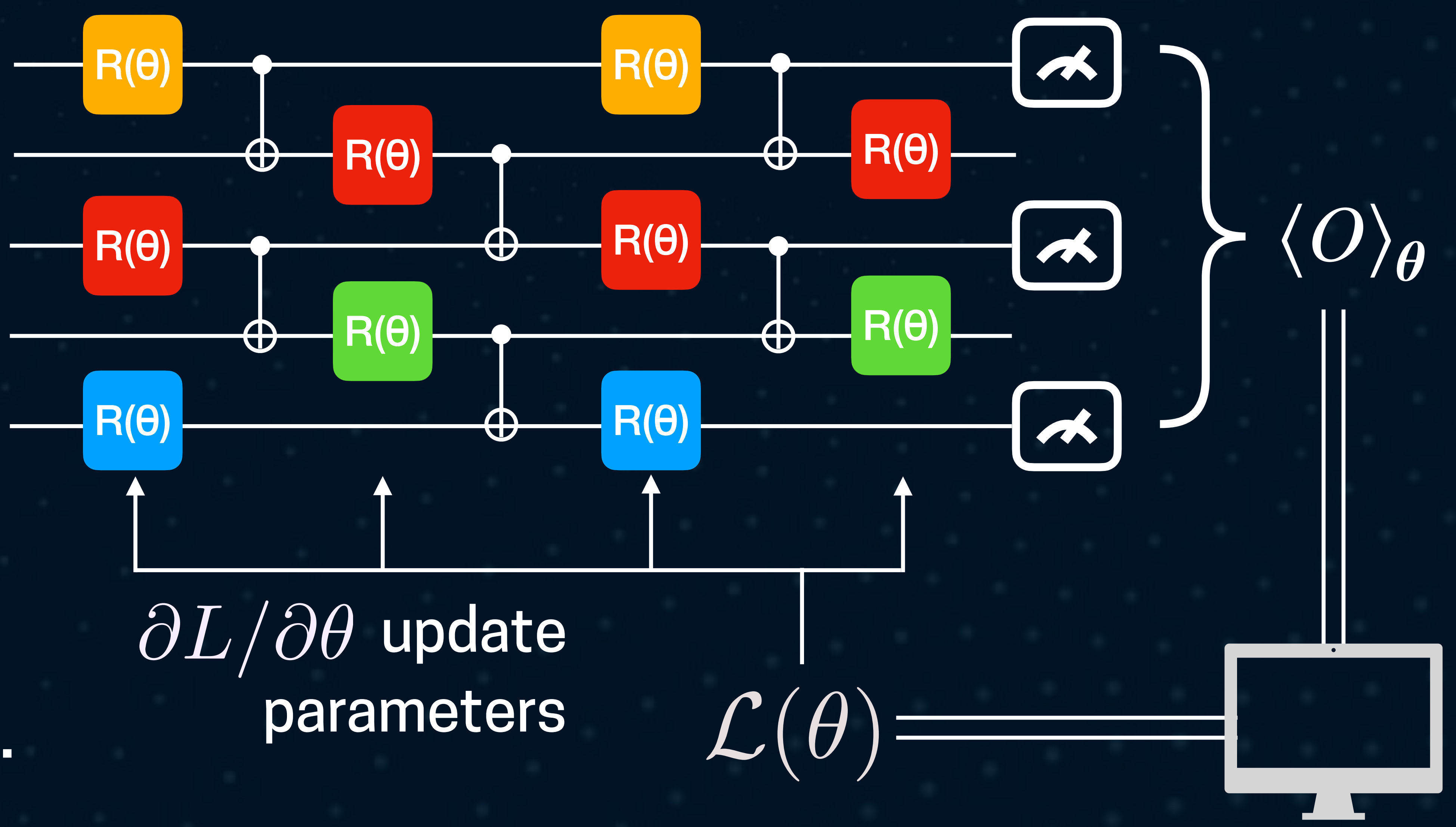
uses few gates (operations)

somewhat resilient to noise

Parametrized gates

$R_y(\theta) = e^{i\theta\sigma_y/2}$

Repeat until convergence

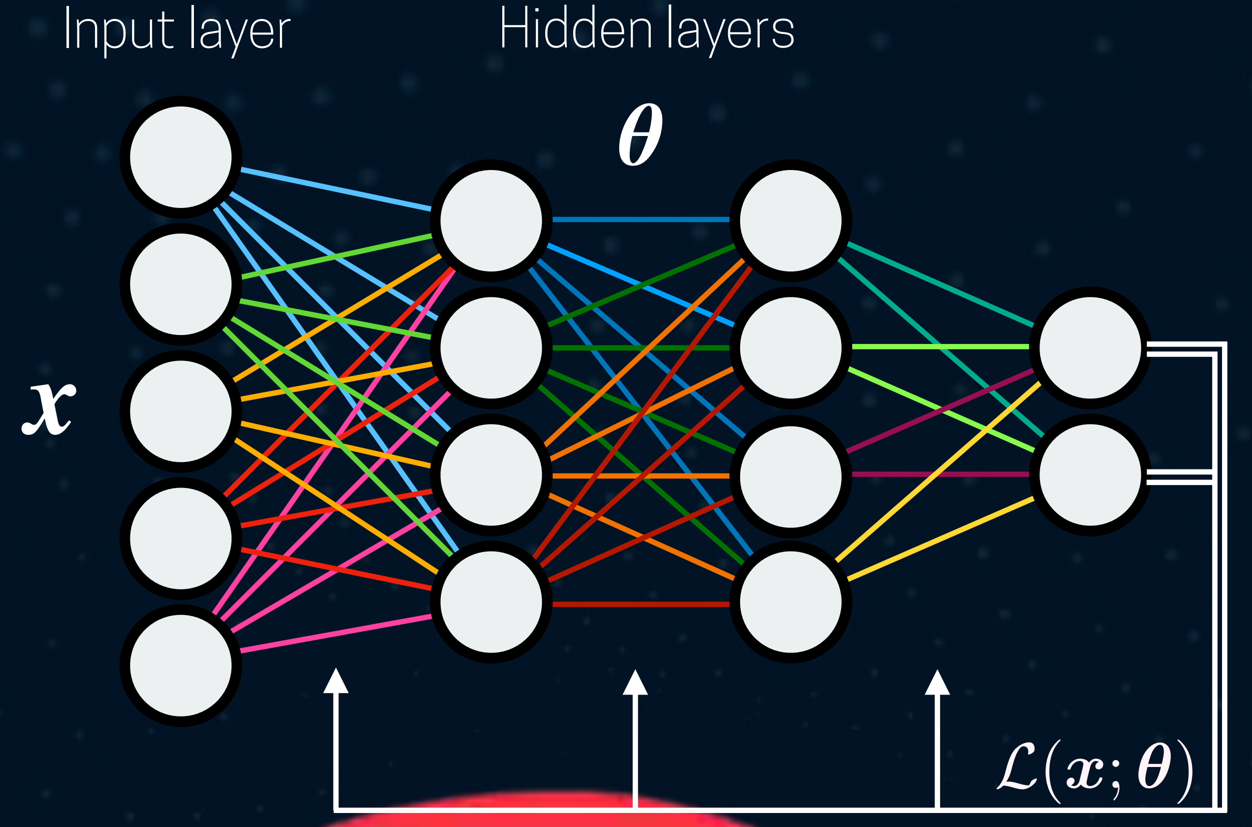


too good to be true... usually no provable guarantees, but heuristic results

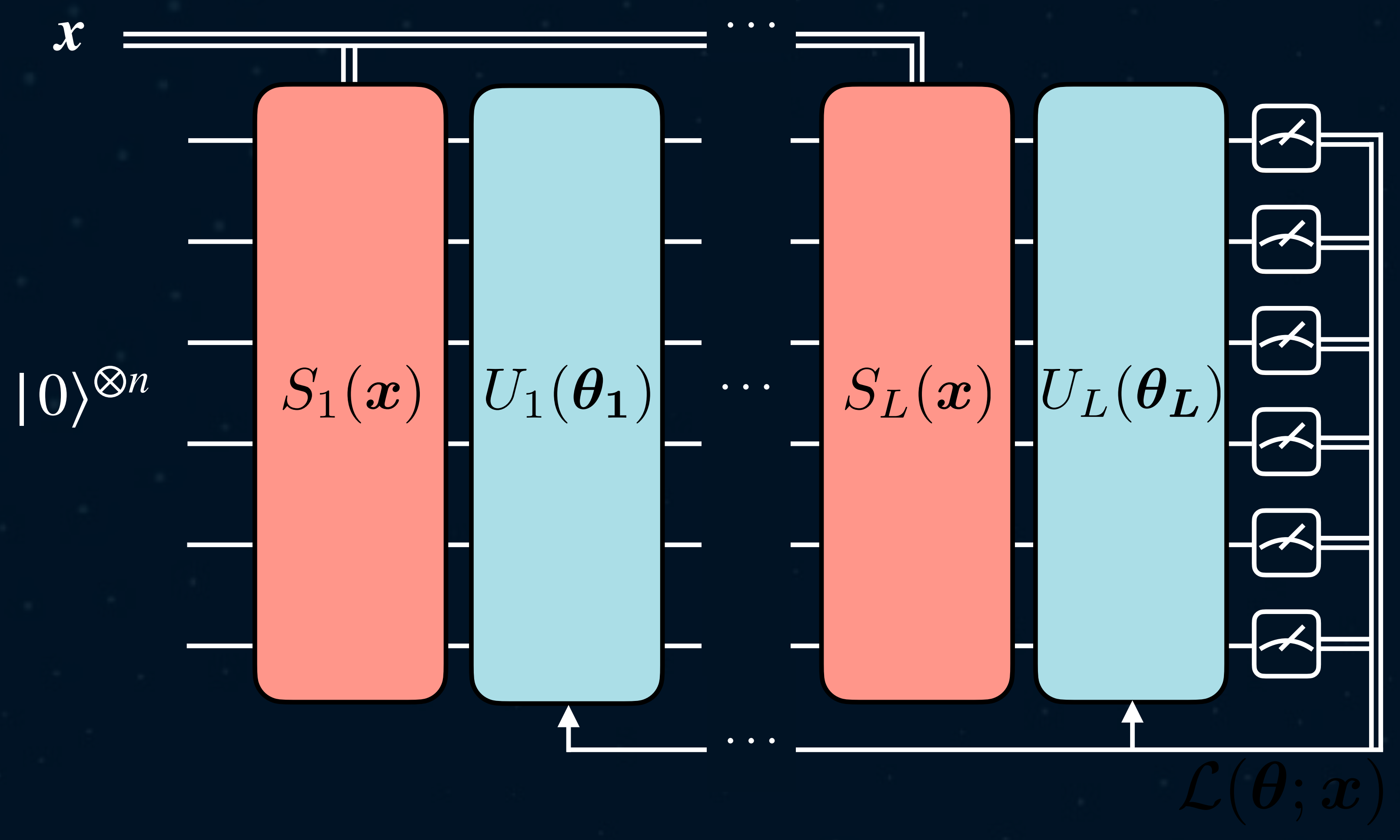
Loss function embedding the task to be solved
(e.g. minimize energy of a variational state)

Various QNN/QML models [0]

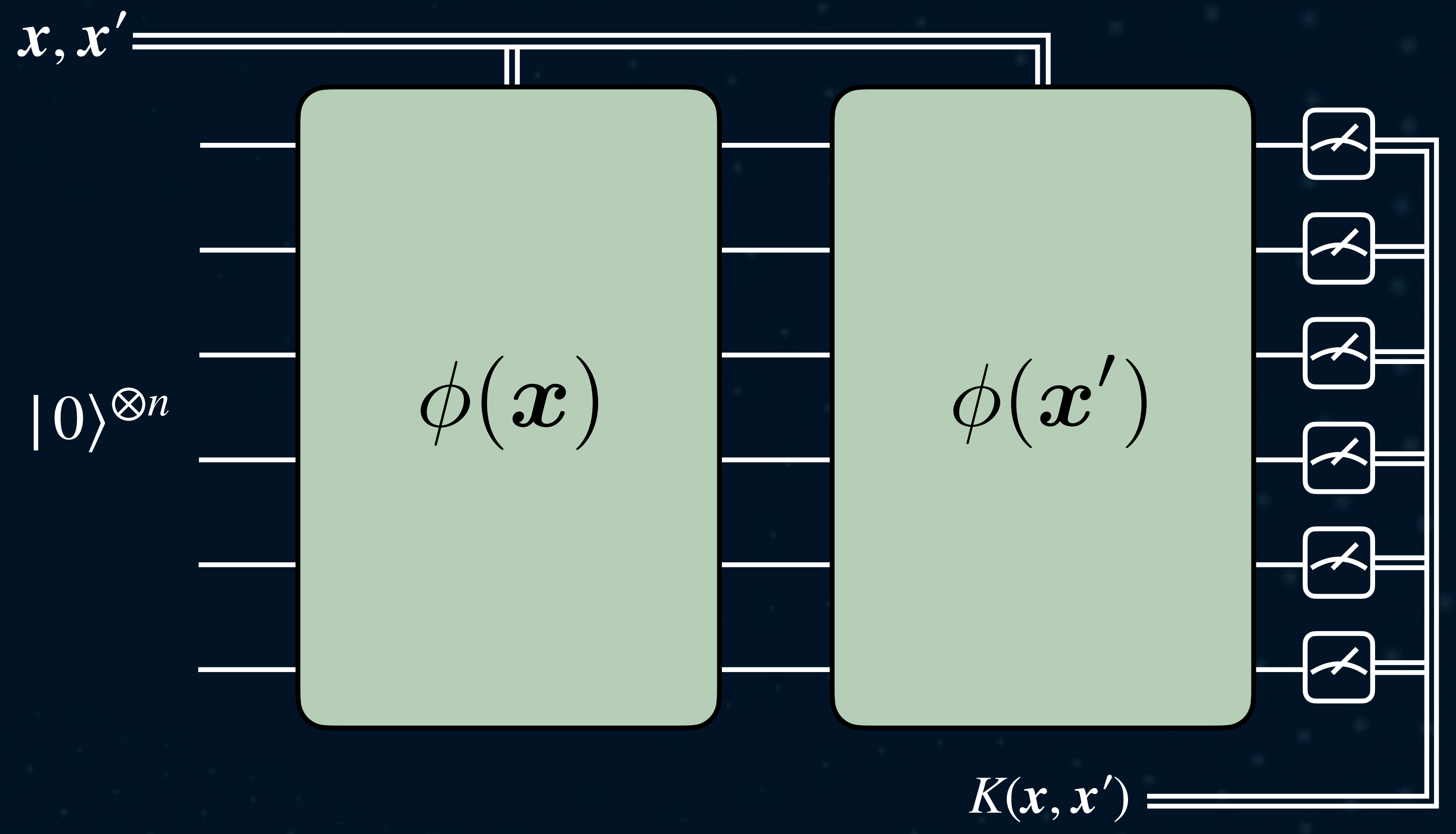
Classical Neural Networks



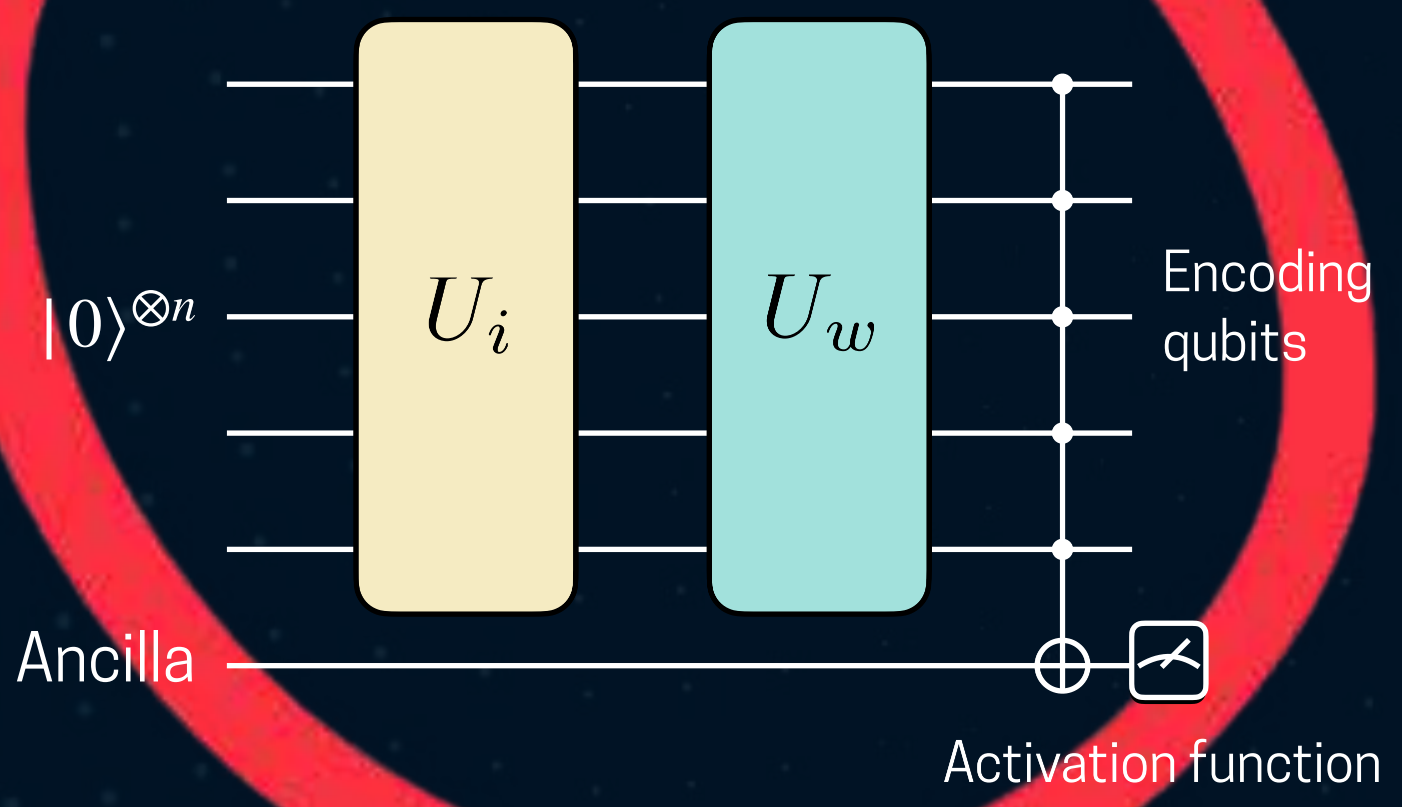
Quantum Neural Networks



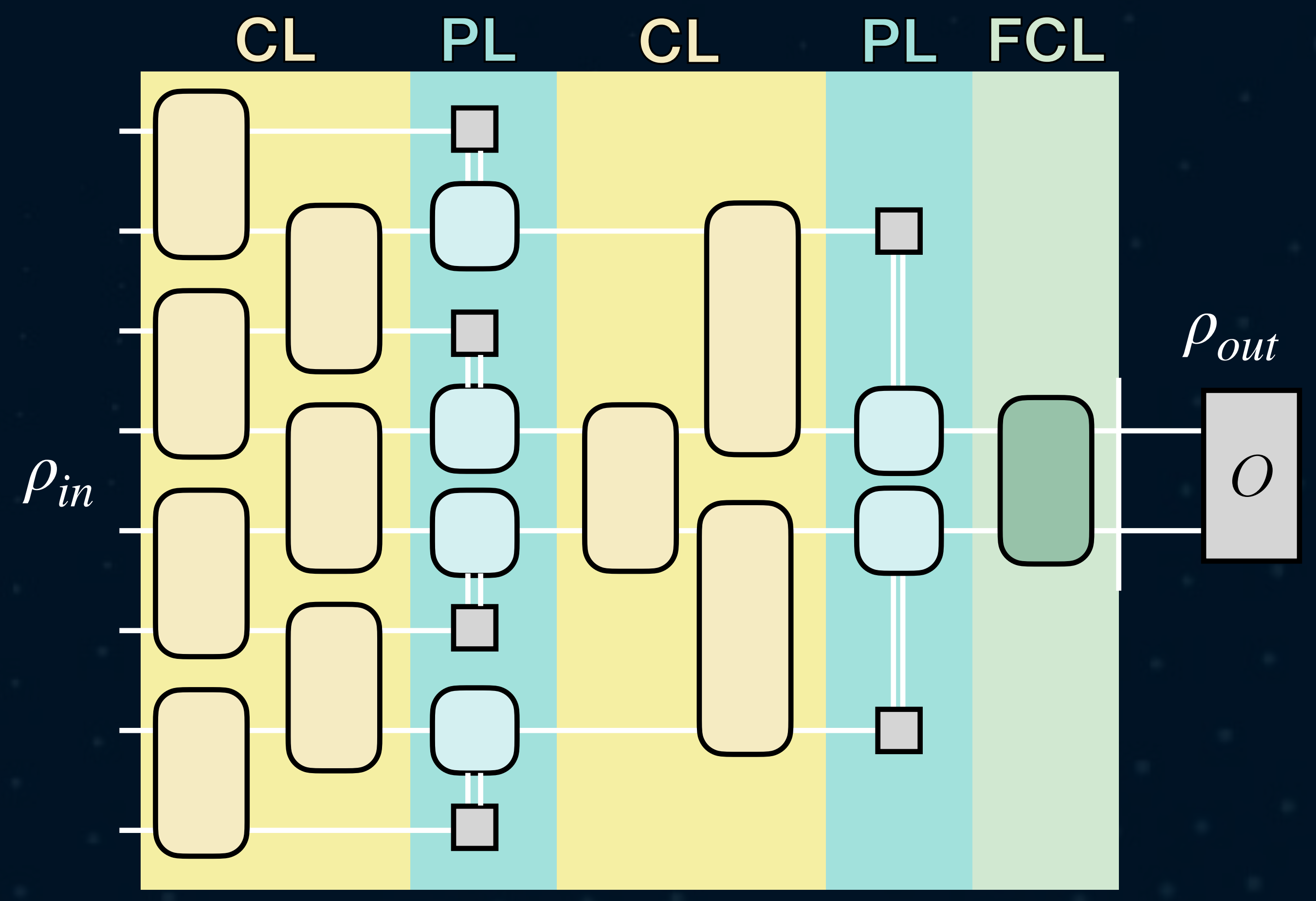
Quantum Kernel Methods



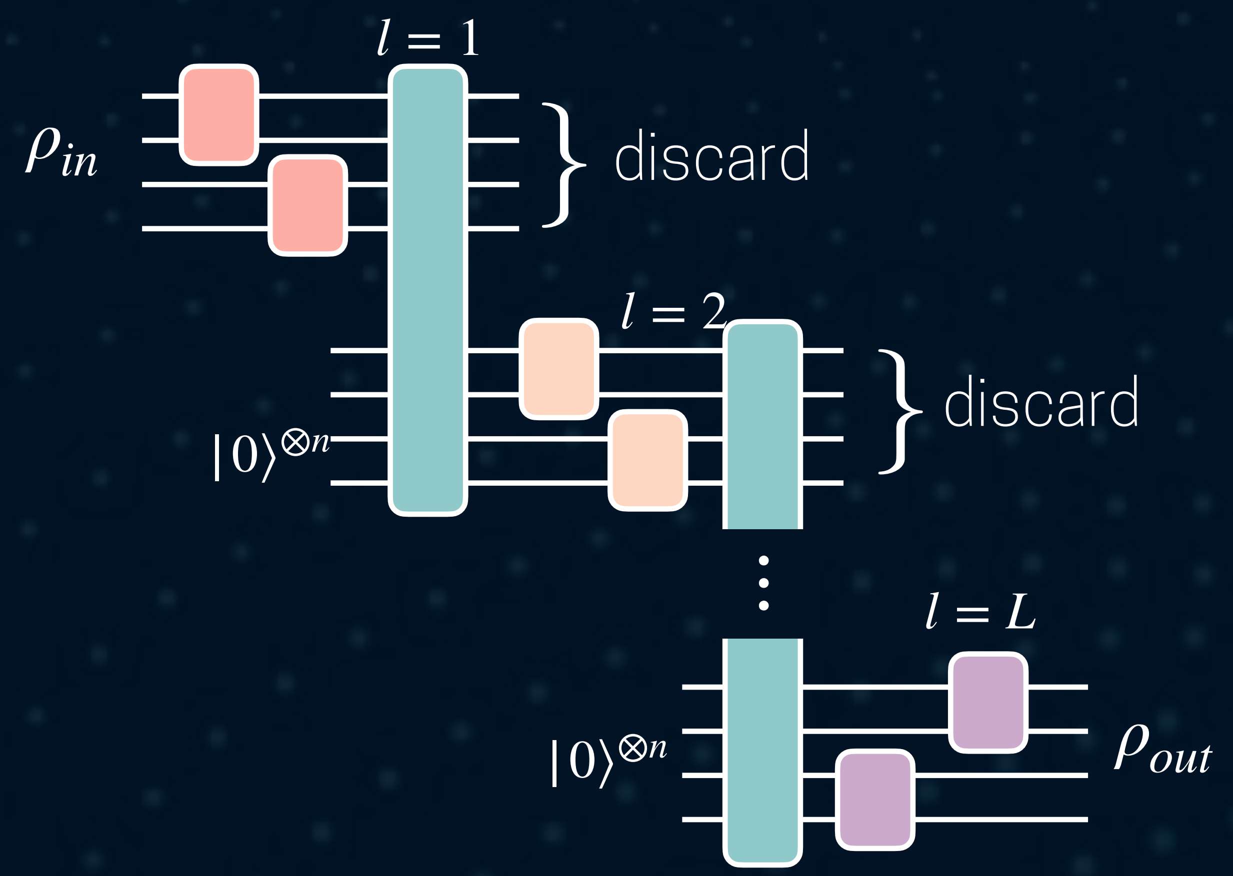
Quantum Perceptrons



Quantum Convolutional Neural Networks



Quantum Dissipative Neural Networks



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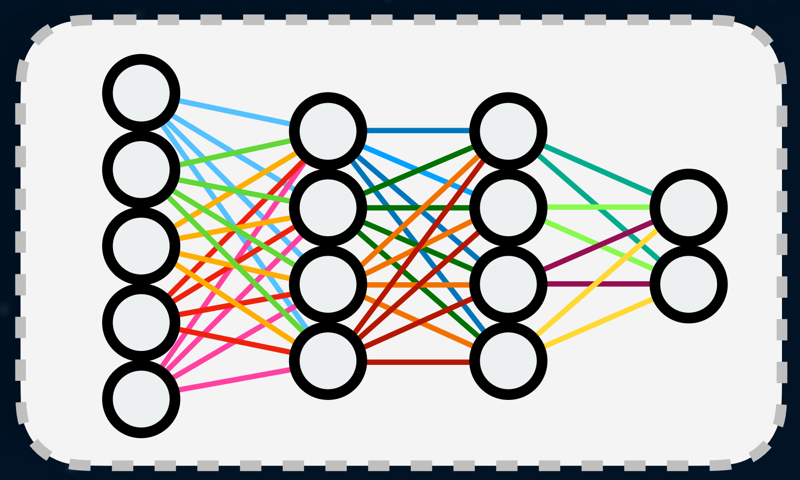
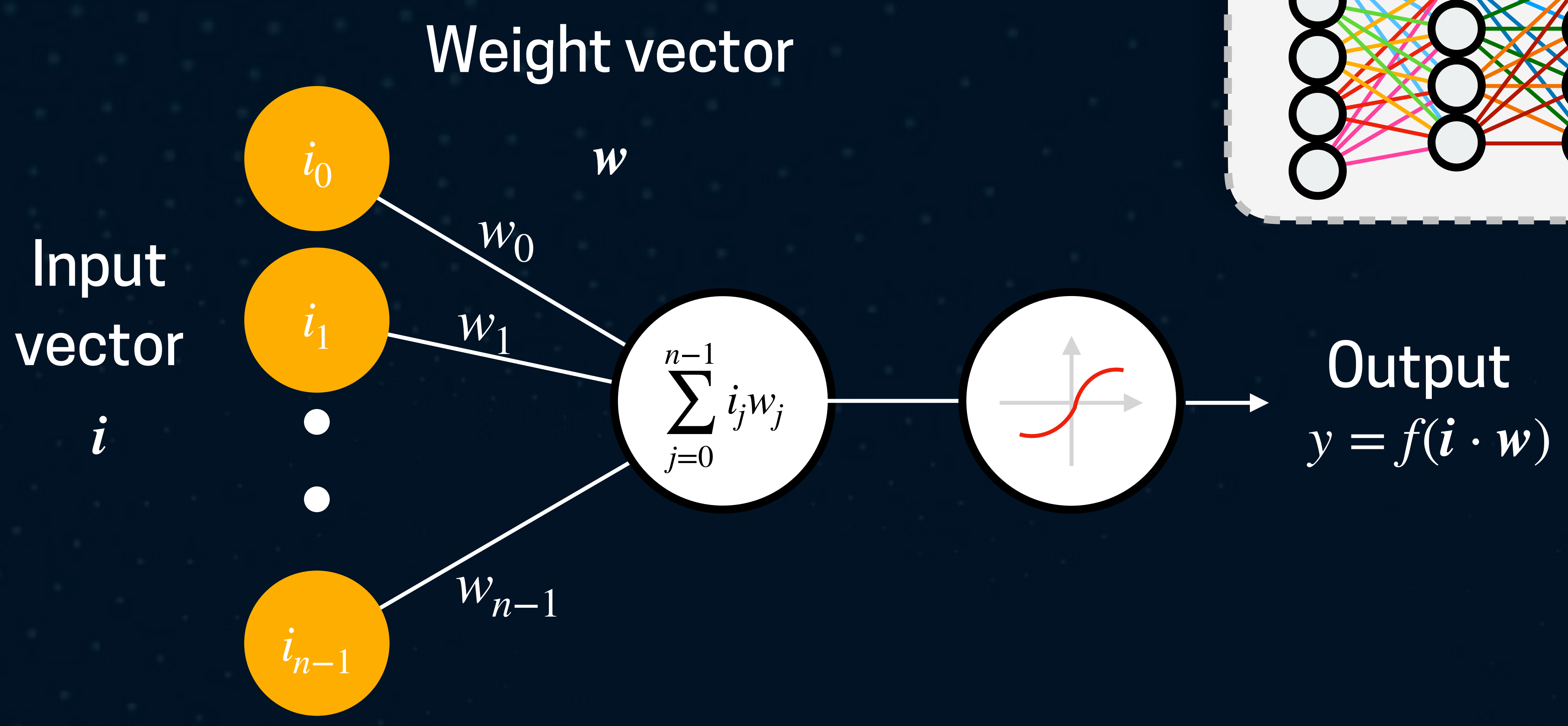
A Quantum Perceptron

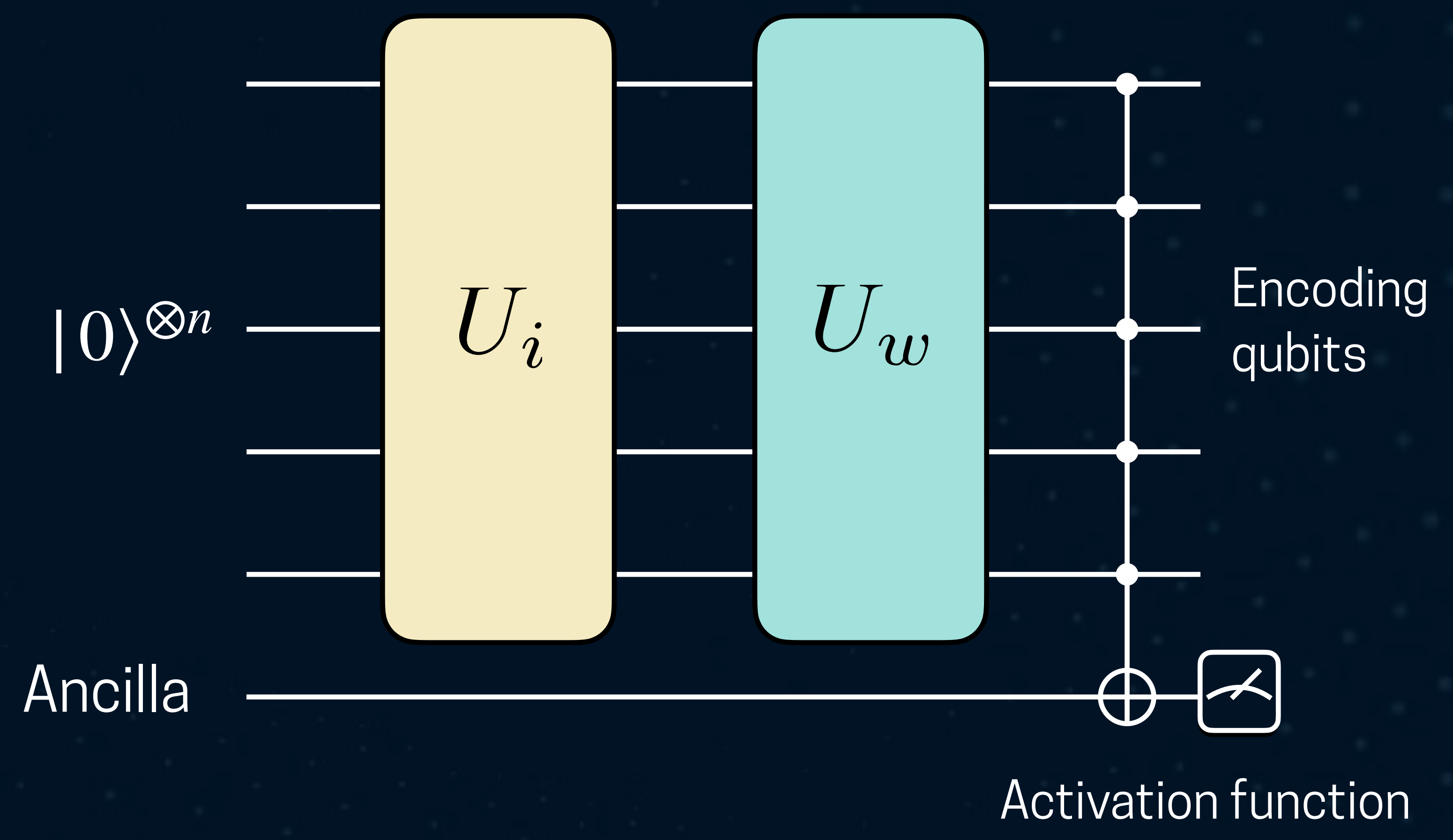
Classical





- Takes inputs, has weights (i.e. *trainable parameters*)
- Scalar product of inputs and weights
- Nonlinear activation function

Quantum



$$\vec{i}\,,\vec{w} \longrightarrow |\psi_i\rangle\,,|\psi_w\rangle$$

promoted to quantum states

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

inner product in Hilbert space

$$f(x) \longrightarrow \left|\langle\psi_w|\psi_i\rangle\right|^2$$

nonlinearity induced by measurement

[1] S. Mangini *et al.*, "Quantum computing model of an artificial neuron with continuously valued input data", *Mach. Learn.: Sci. Technol.* **1** 045008 (2020).

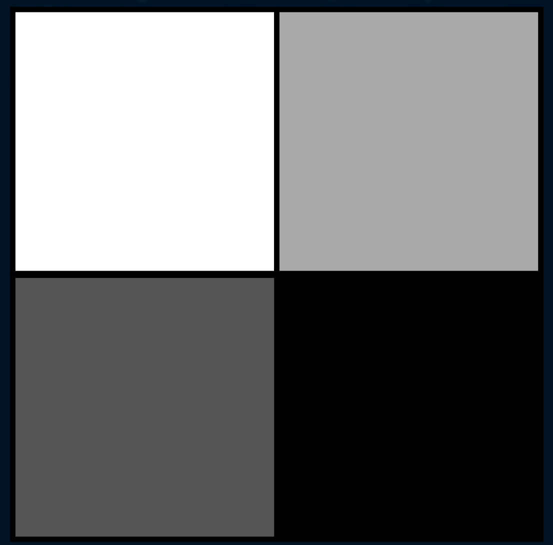
Pattern classification

Grayscale images

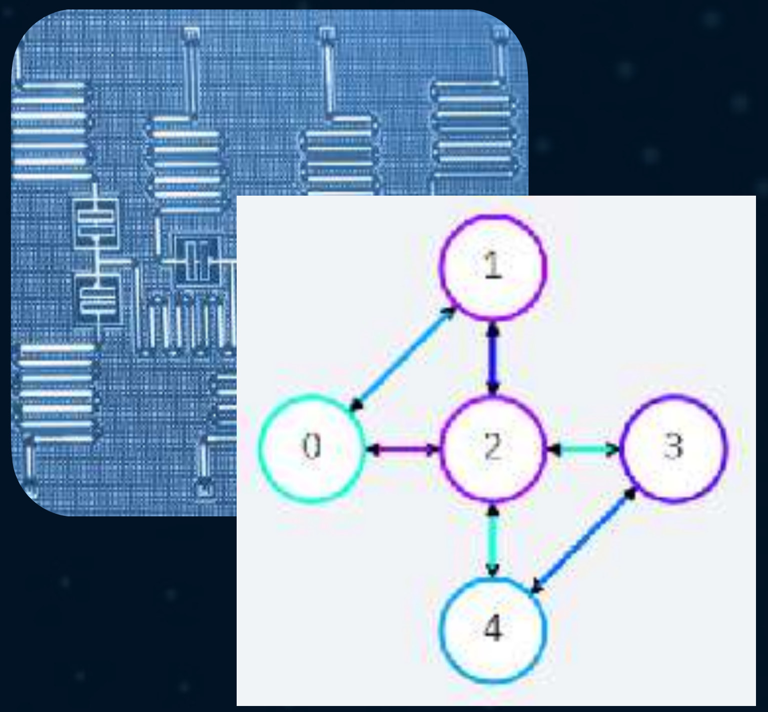
$\boldsymbol{i} = (255,170,85,0)$

$i_j \in [0,255]$

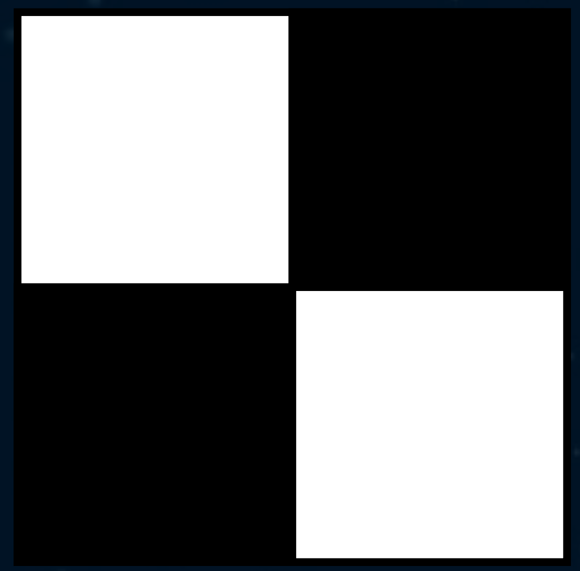
255	170
85	0



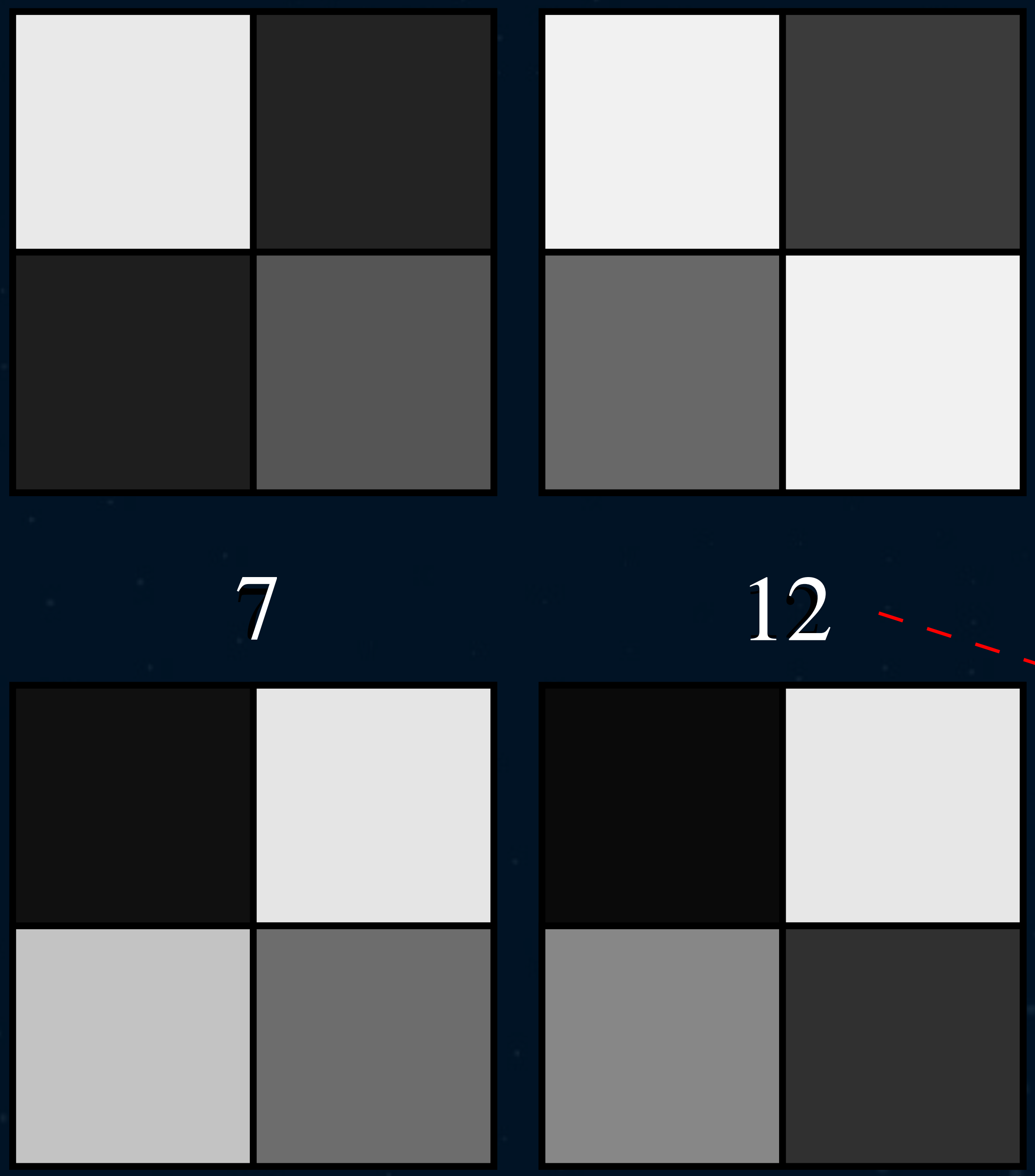
Normalization $\boldsymbol{i} \to \dfrac{\pi/2}{255}\boldsymbol{i}$

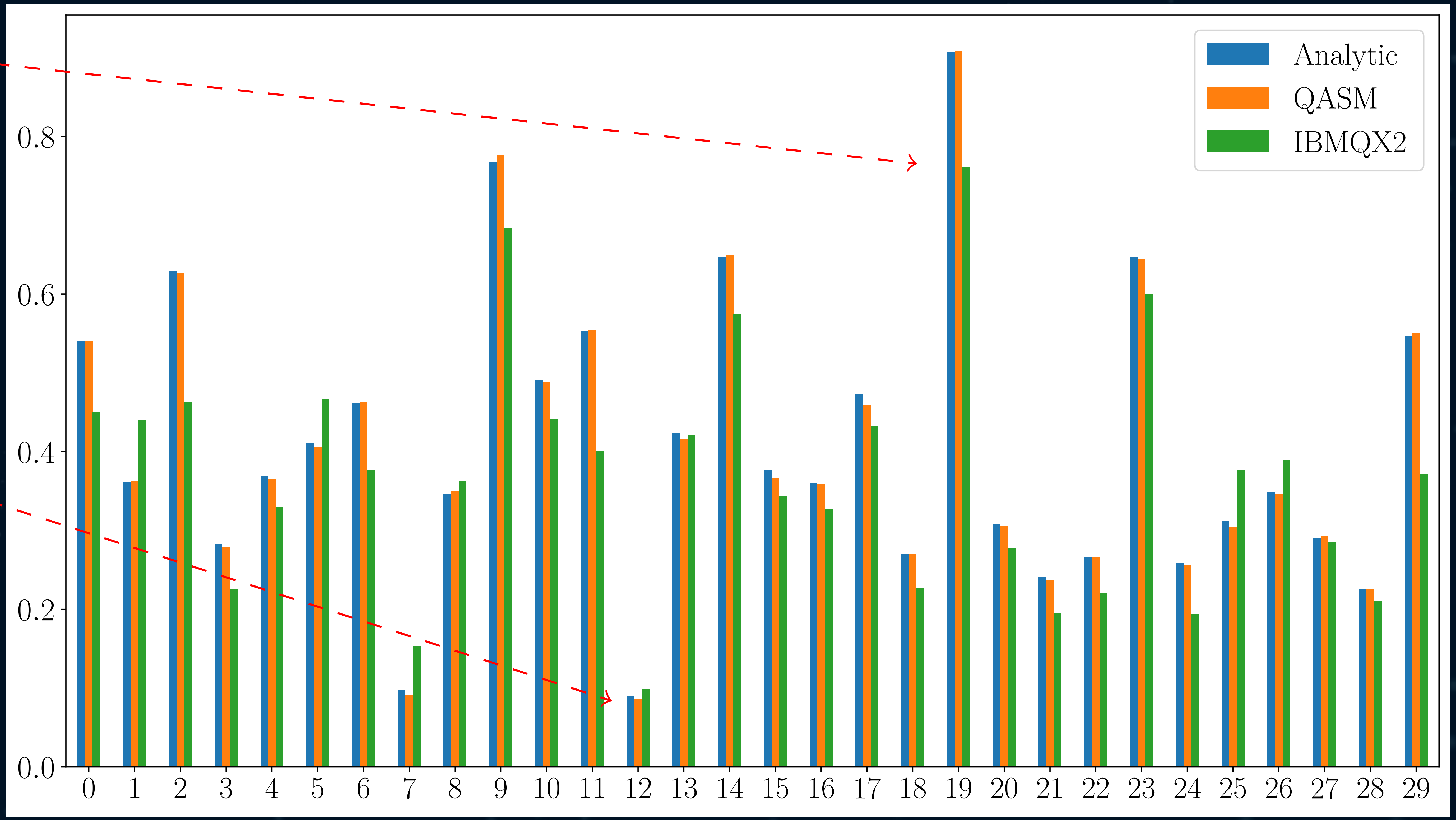


ϕ_{target}



9 19 7 12





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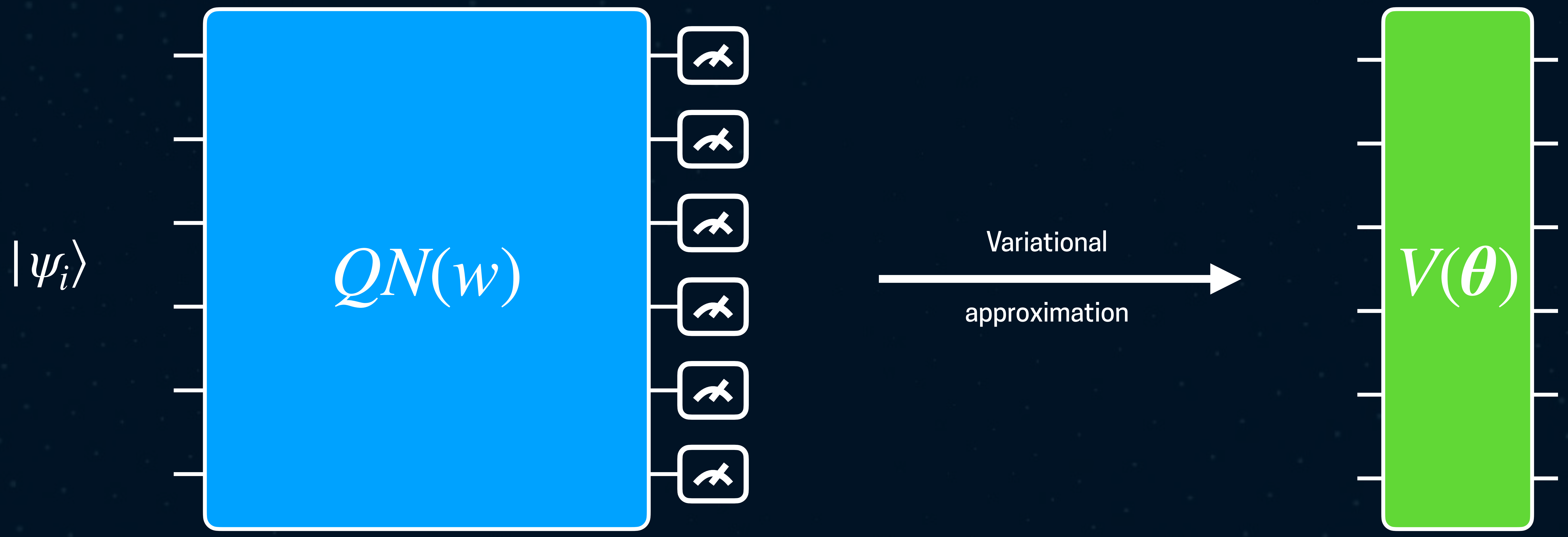
Size matters [2]

Circuit implementation is *inefficient* (too big). Instead of using the exact circuit for the quantum neuron, let's try to implement a *variational approximation* of it!



Variational *"ansatz"*

$$V(\boldsymbol{\theta}^*) \approx QN(\boldsymbol{w})$$

$\boldsymbol{\theta}^*$ optimal angles

Note: optimal values are specific to a $\boldsymbol{w}$

Exact implementation

$$|\psi_i\rangle \quad \longrightarrow \quad \langle \psi_i | \psi_w \rangle \longrightarrow |\langle \psi_i | \psi_w \rangle|^2$$

Optimization problem:

measures the distance between V and QN are

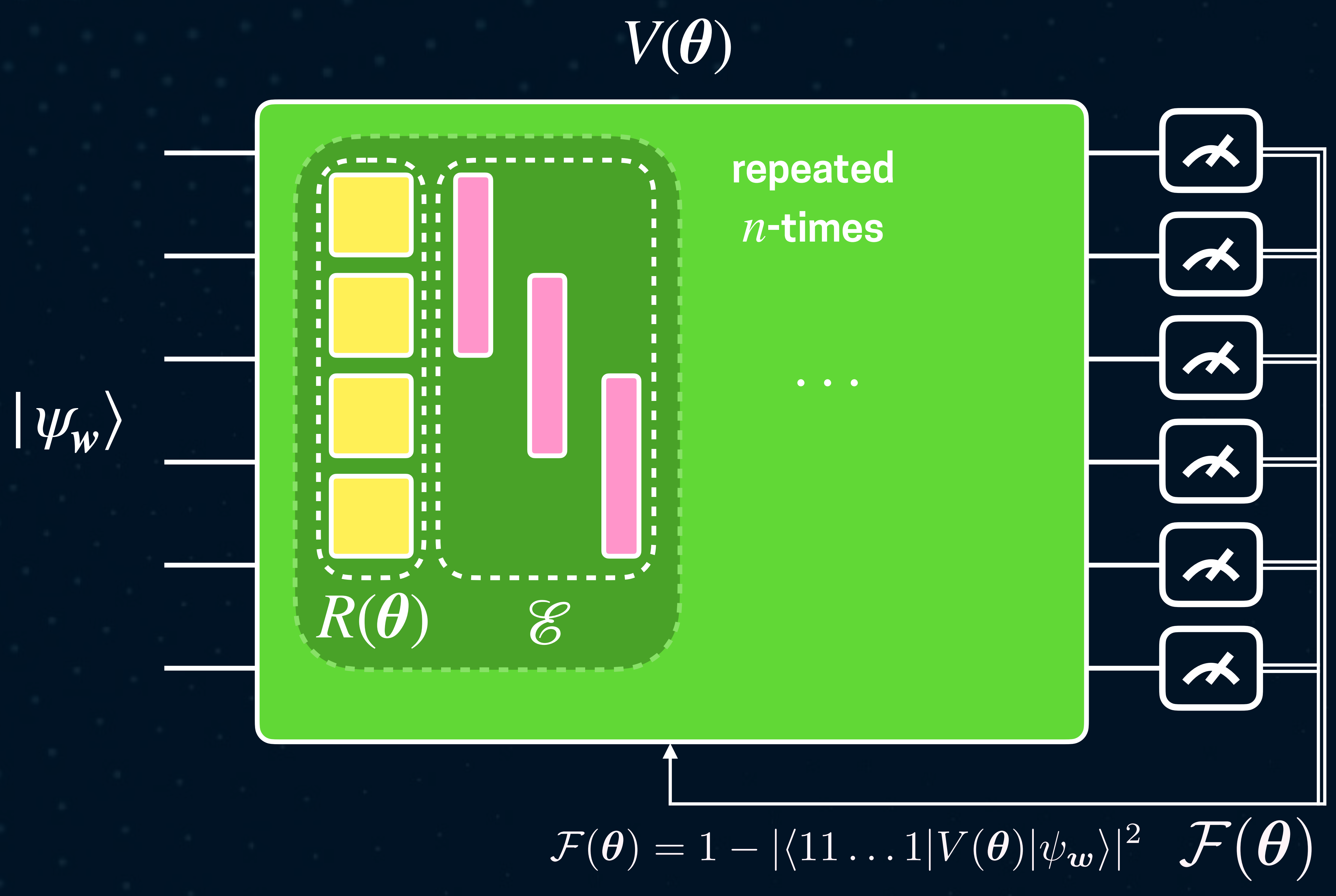
$$\mathcal{F}(\boldsymbol{\theta}) = 1 - |\langle 11\ldots1|V(\boldsymbol{\theta})|\psi_{\boldsymbol{w}}\rangle|^2$$

$$\boldsymbol{\theta}^* = \text{arg min}_{\boldsymbol{\theta}} \ \mathcal{F}(\boldsymbol{\theta})$$

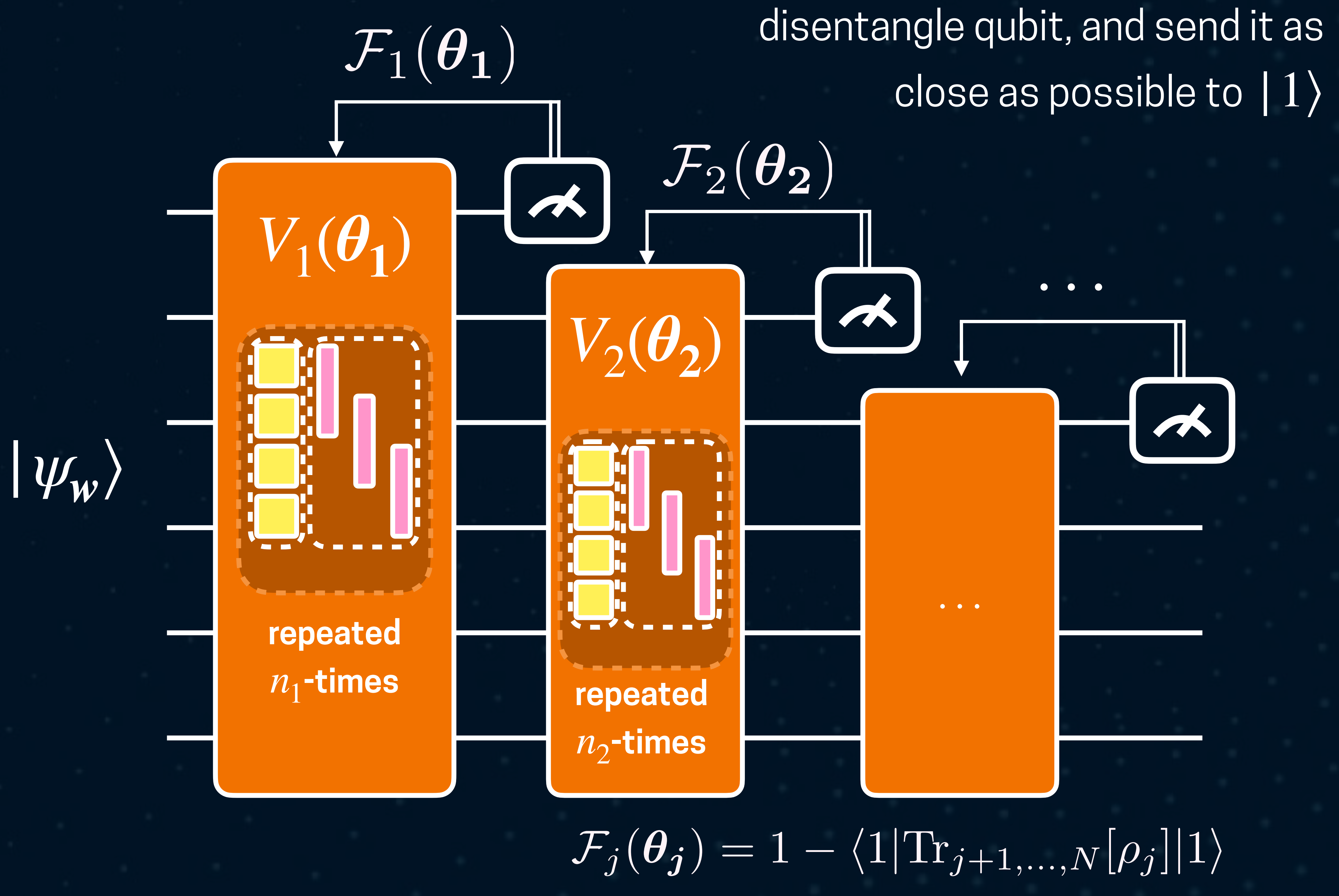
[2] F. Tacchino, **S. Mangini** *et al.*, "Variational Learning for Quantum Artificial Neural Networks", *IEEE Transactions on Quantum Engineering*, vol. 2, pp. 1-10 (2021)

Global and Local cost functions

Global strategy



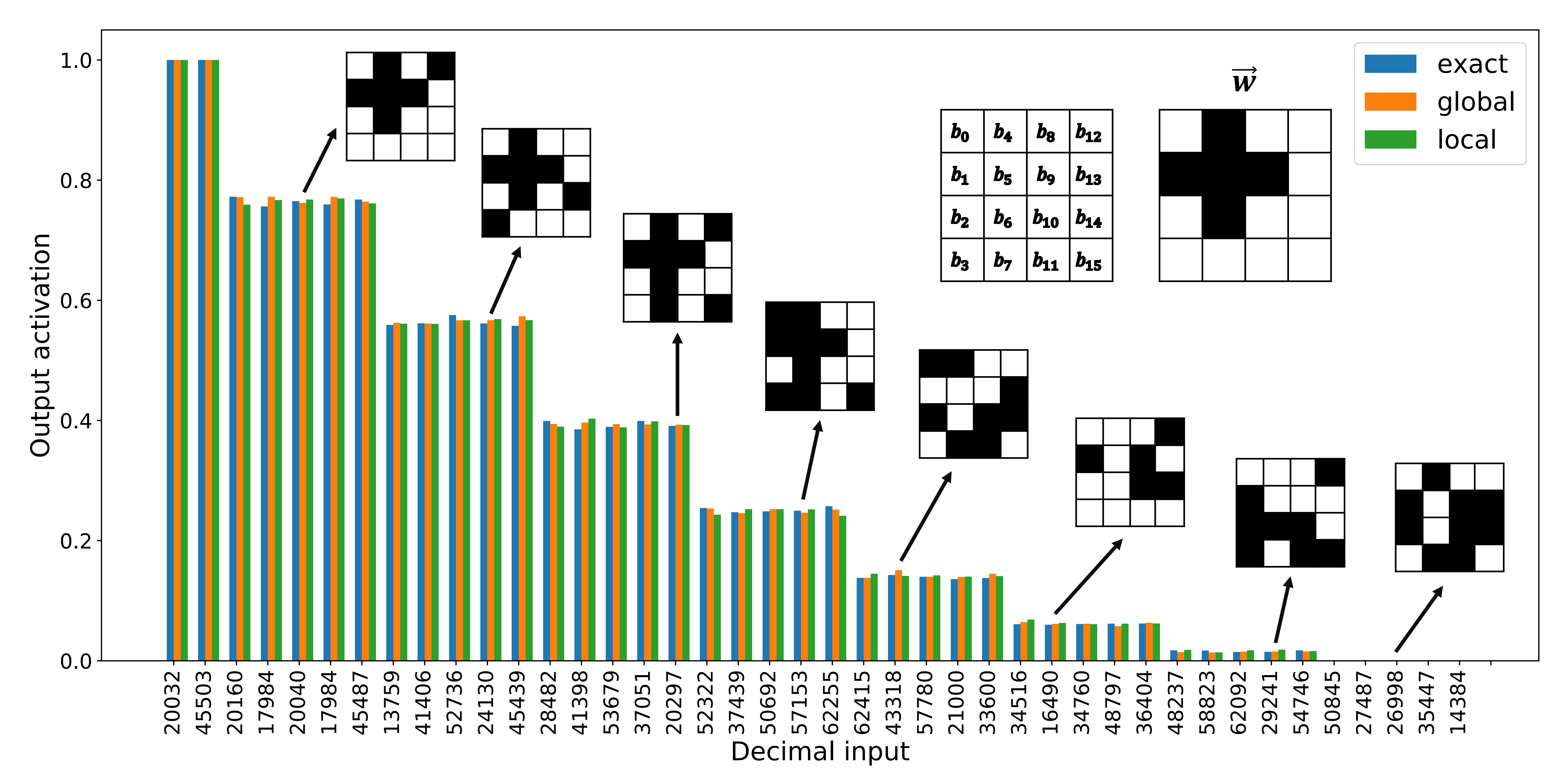
Local strategy



Minimize *single* but *difficult* cost function $\overset{?}{\leq}$ **Minimize *multiple* but *easy* cost functions**

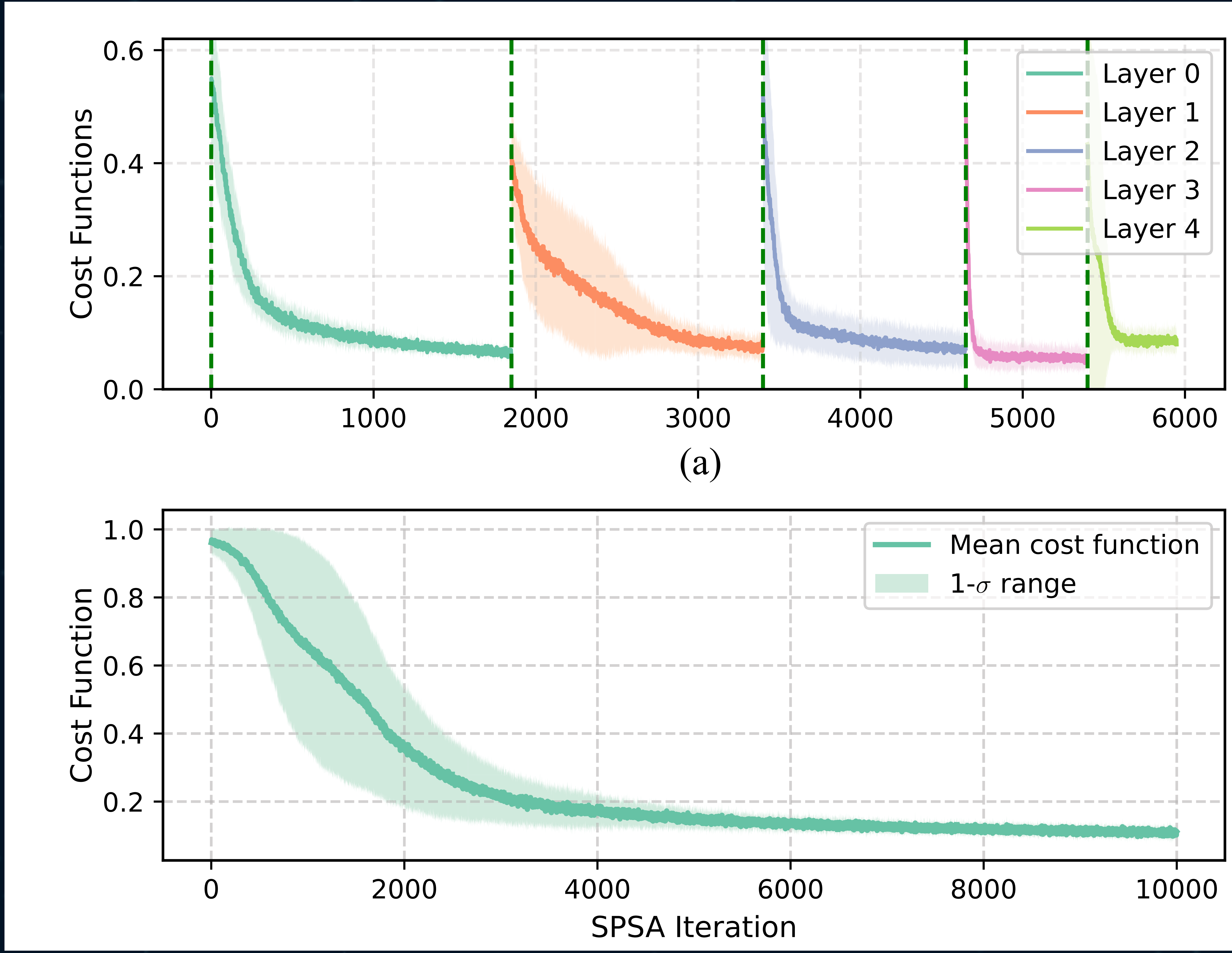
[2] F. Tacchino, **S. Mangini** *et al.*, "Variational Learning for Quantum Artificial Neural Networks", *IEEE Transactions on Quantum Engineering*, vol. 2, pp. 1-10 (2021)

Noise free: everything works out



[2] F. Tacchino, **S. Mangini** *et al.*, "Variational Learning for Quantum Artificial Neural Networks", *IEEE Transactions on Quantum Engineering*, vol. 2, pp. 1-10 (2021)

Global vs. Local: noise plays major role



$\mathcal{F}_{\text{local}}$
0.87 ± 0.02

$\mathcal{F}_{\text{global}}$
0.89 ± 0.02

Number of optimization steps to reach target fidelity in presence of measurement noise.

In presence of noise… buy Local.

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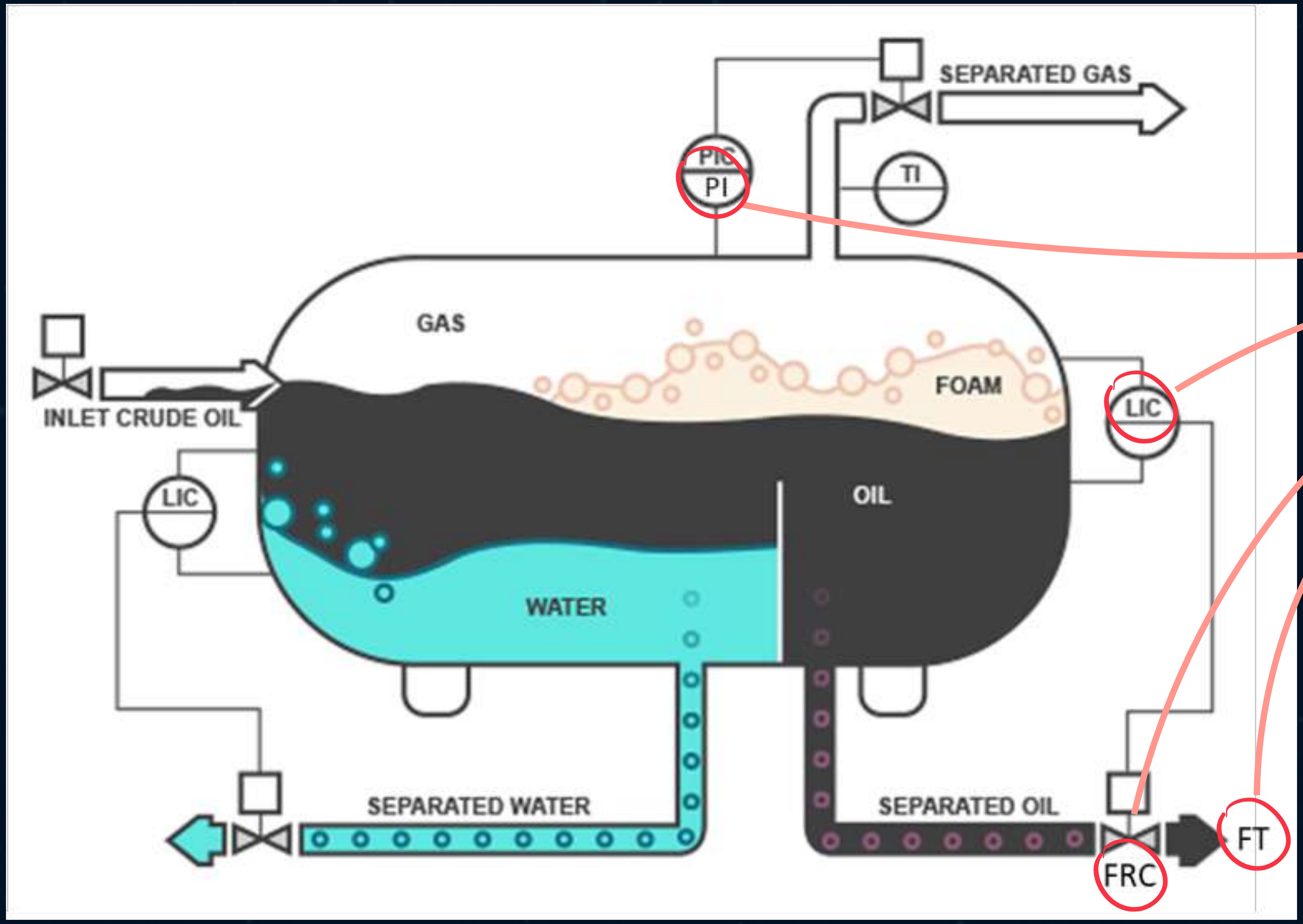
Quantum computing feat. Eni

Use of quantum computers for an industrial case study. In particular, build a quantum autoencoder and classifier to analyze data from a separator.

A separator



1. Data compression

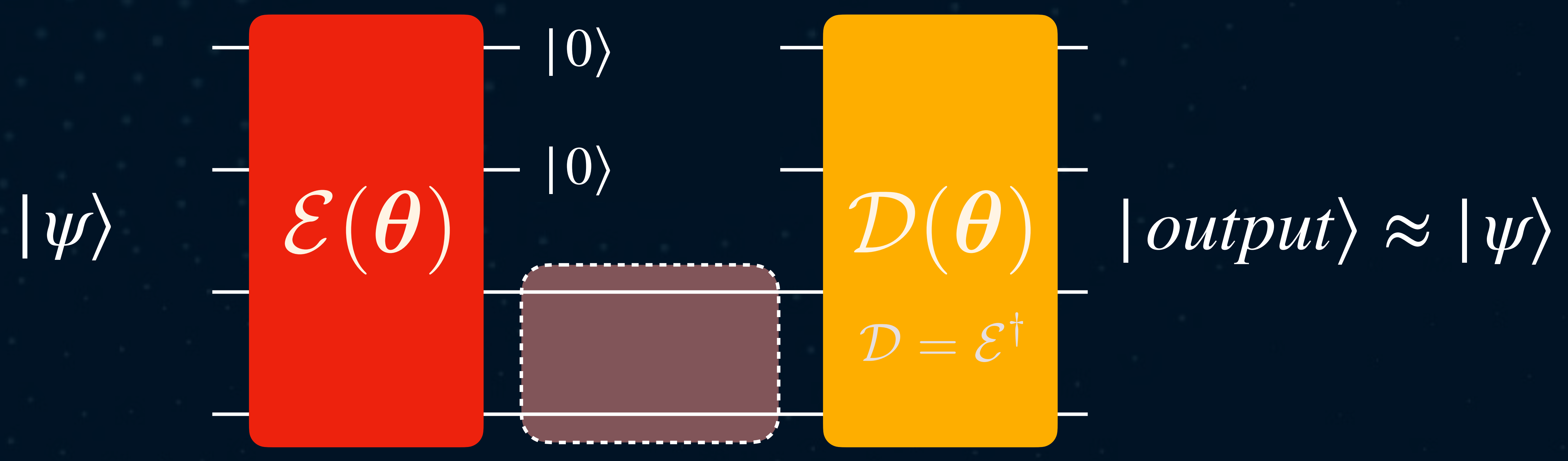
$\boldsymbol{x} \in \mathbb{R}^4$ $(x_{FRC}, x_{FT}, x_{LIC}, x_{PI})$ → → $\boldsymbol{y} \in \mathbb{R}^2$

2. Classification

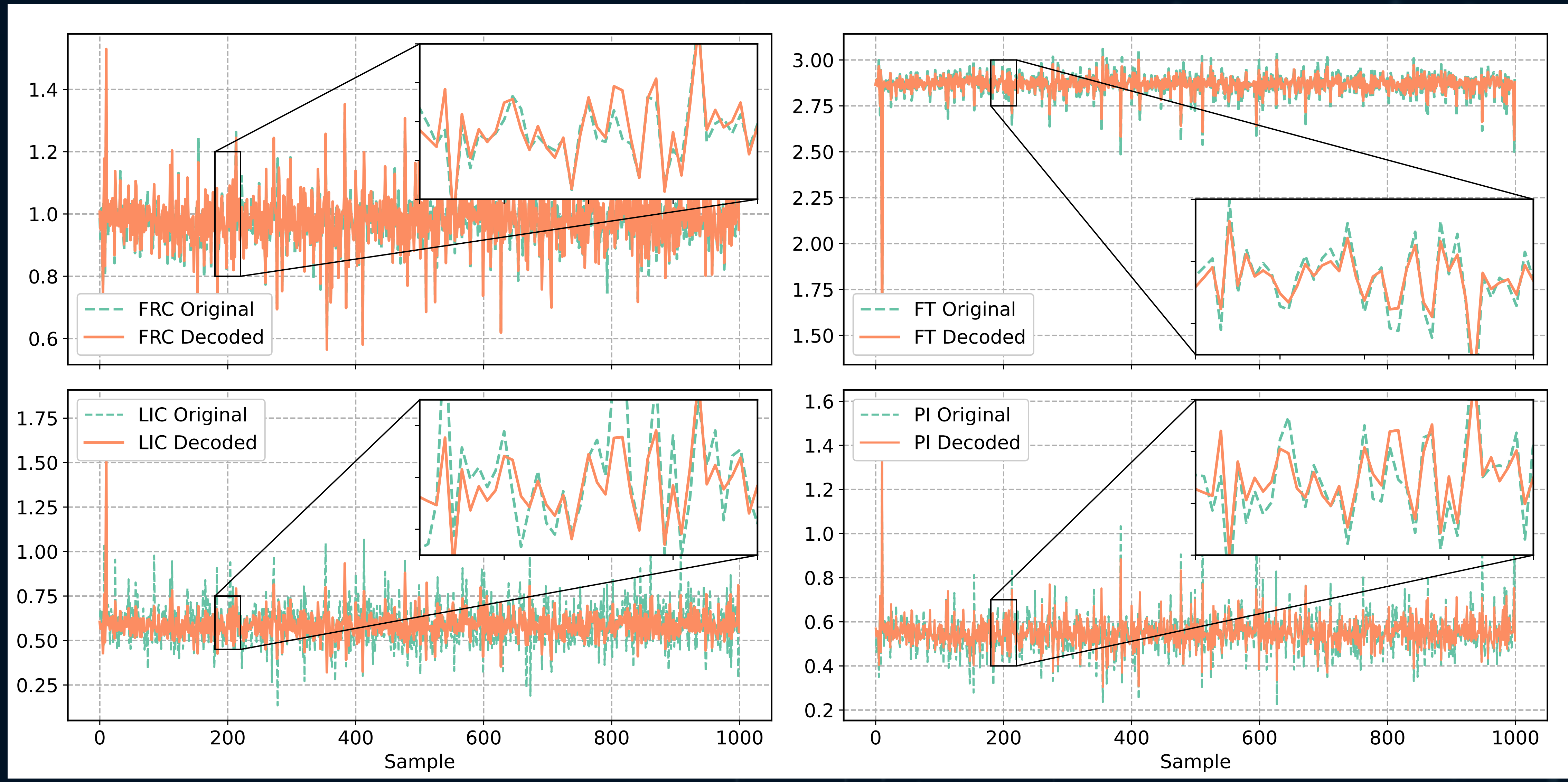
$\boldsymbol{y} \in \mathbb{R}^2$ → Class A / Class B

Quantum Autoencoder and Classifier

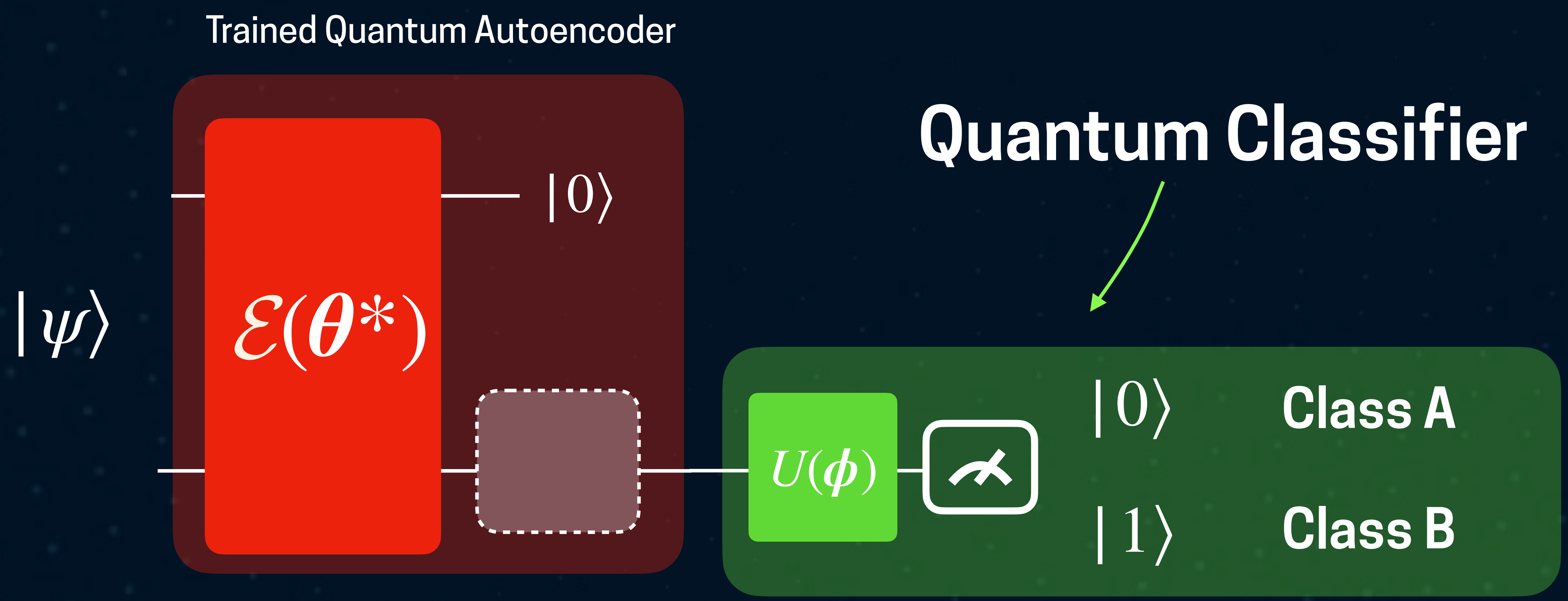
1. Quantum Autoencoder

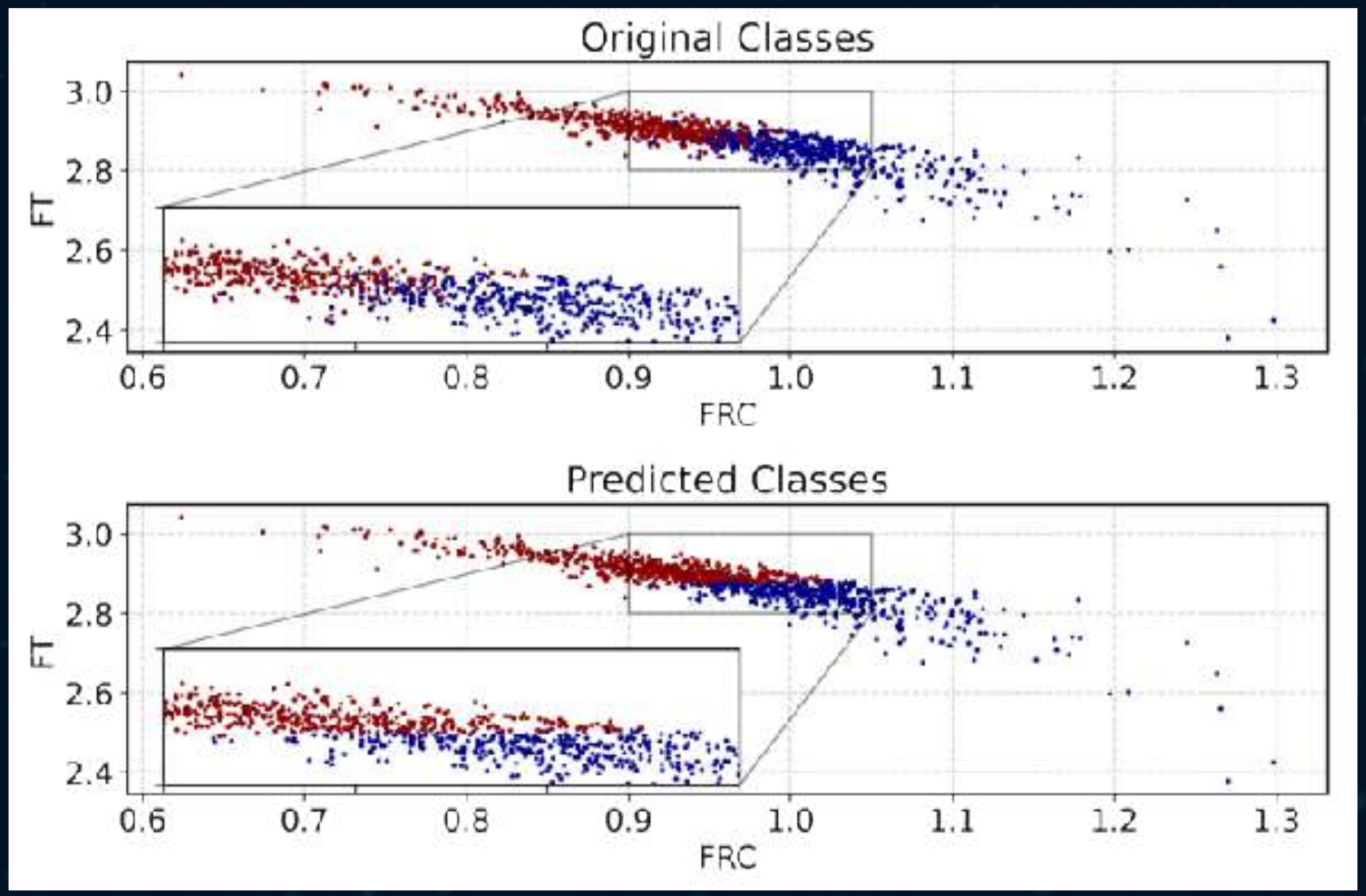


Compressed quantum state



2. Quantum Classifier





Accuracy $\sim 85\,\%$

Real device: $\sim 83\,\%$

[3] **S. Mangini** *et al.*, "Quantum neural network encoder and classifier applied to an industrial case study ", under review (2021)

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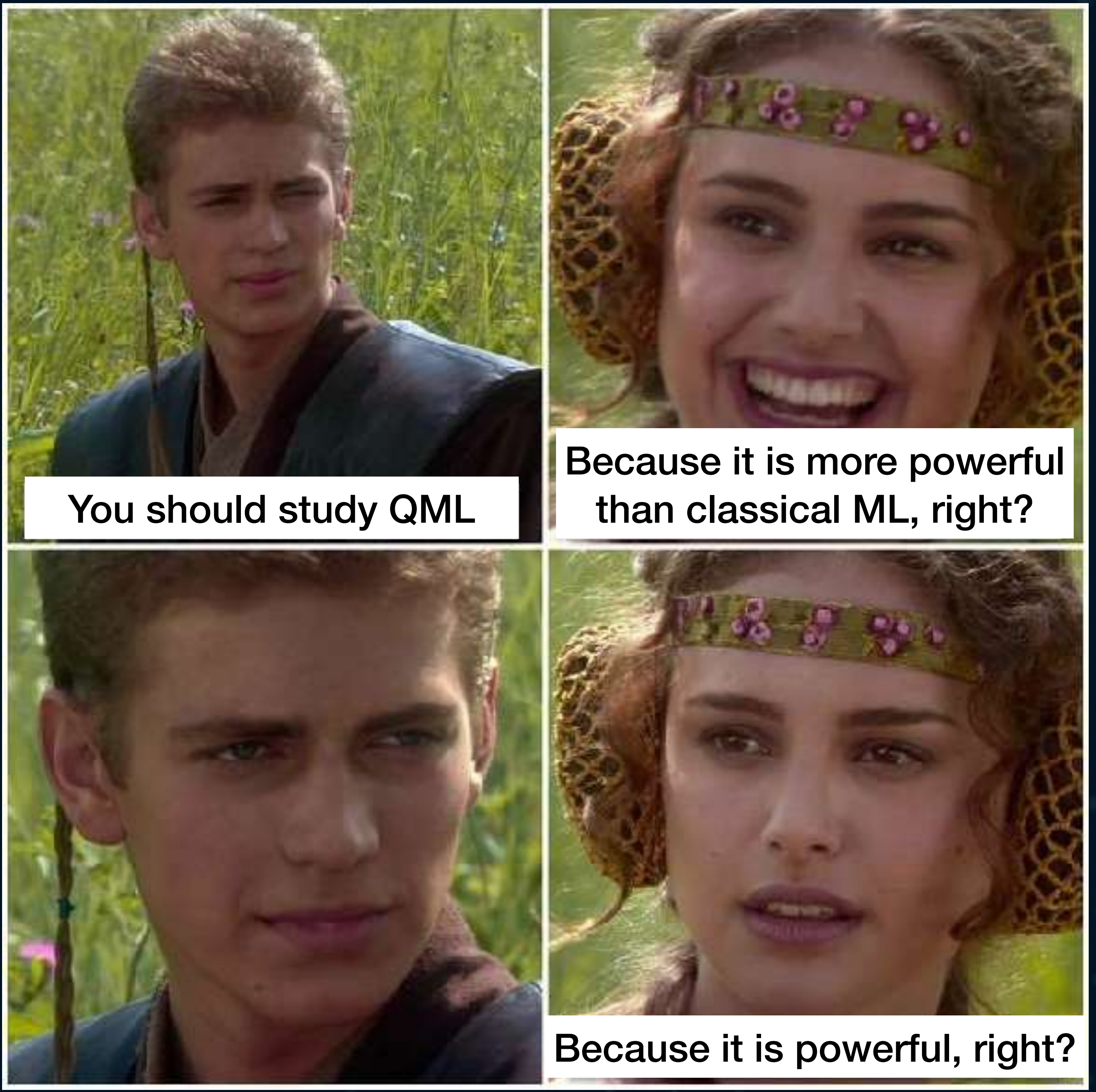
Plans for the future year...

Q1

Is QML actually useful?

Preliminary sobering results in the literature (classical ML is too good)
New analysis and algorithms
Study different use cases



Q2

Broaden research in Quantum Information and Computing

Quantum Noise
Quantum Thermodynamics
Classical ML to analyze Quantum Processes

the end.

References

[0] S. Mangini *et al.*, “Quantum computing models for artificial neural networks”, *EPL (Europhysics Letters)* **2**, 1 (2021).

[1] S. Mangini *et al.*, “Quantum computing model of an artificial neuron with continuously valued input data”, *Mach. Learn.: Sci. Technol.* **1** 045008 (2020).

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[0] [1] [2]

Group members: Chiara Macchiavello, Dario Gerace, Daniele Bajoni (Univ. of Pavia), Francesco Tacchino (IBM Quantum)

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