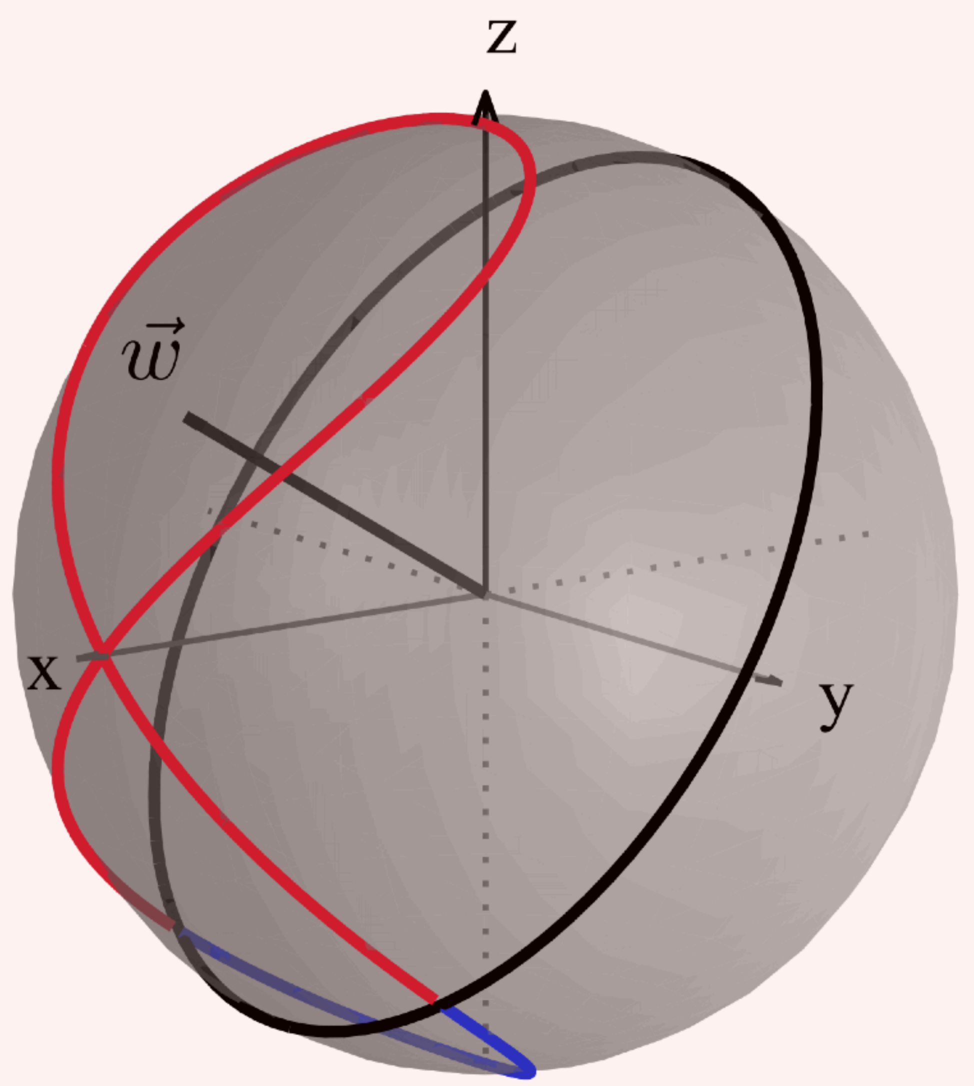


Basic programming for quantum machine learning with Qiskit and PennyLane

NITheP Mini-school

Amira Abbas

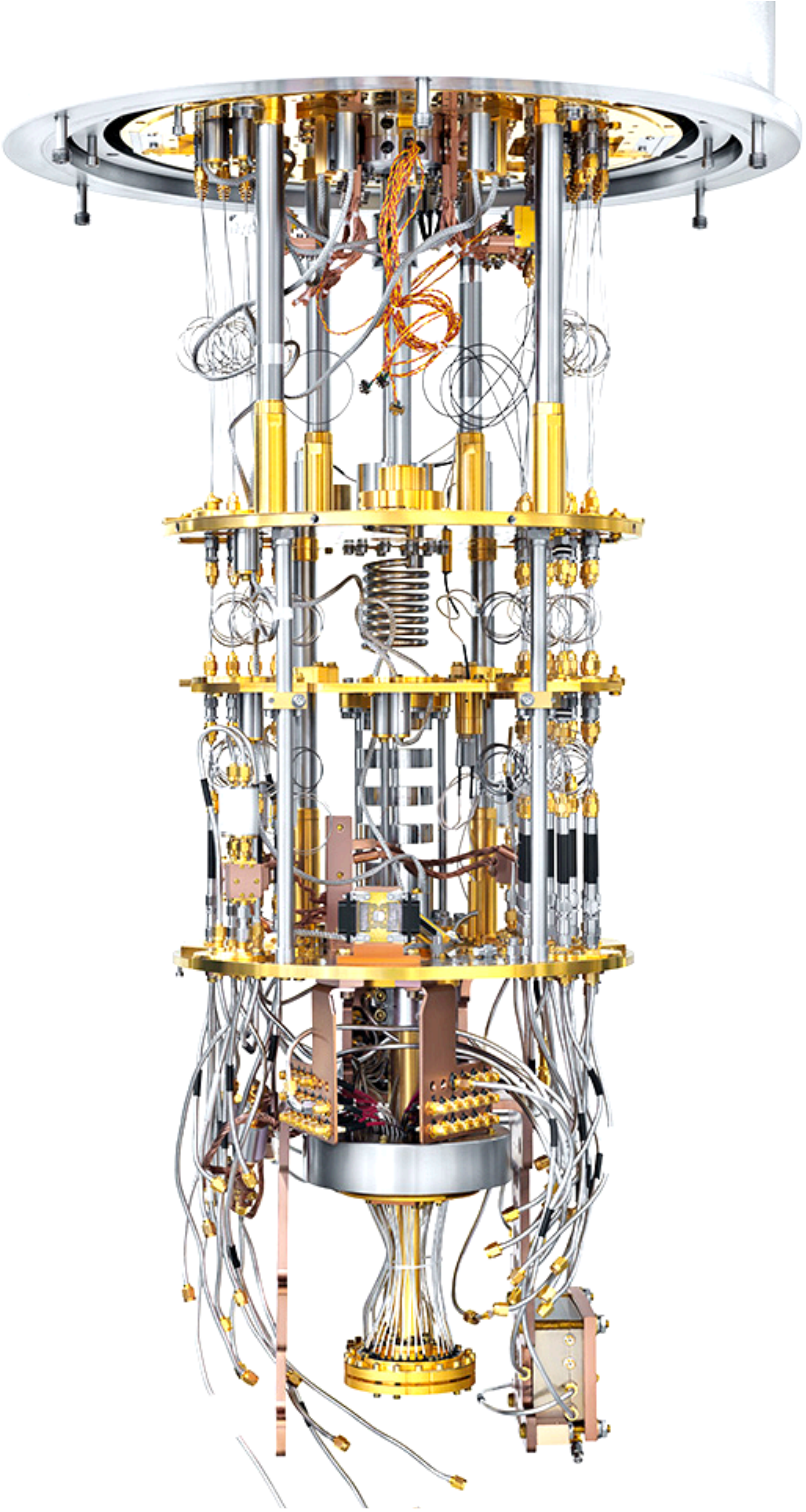
22/09/2020

UNIVERSITY OF KWAZULU-NATAL ™
INYUVESI YAKWAZULU-NATALI

NITheP
National Institute for Theoretical Physics

Previously

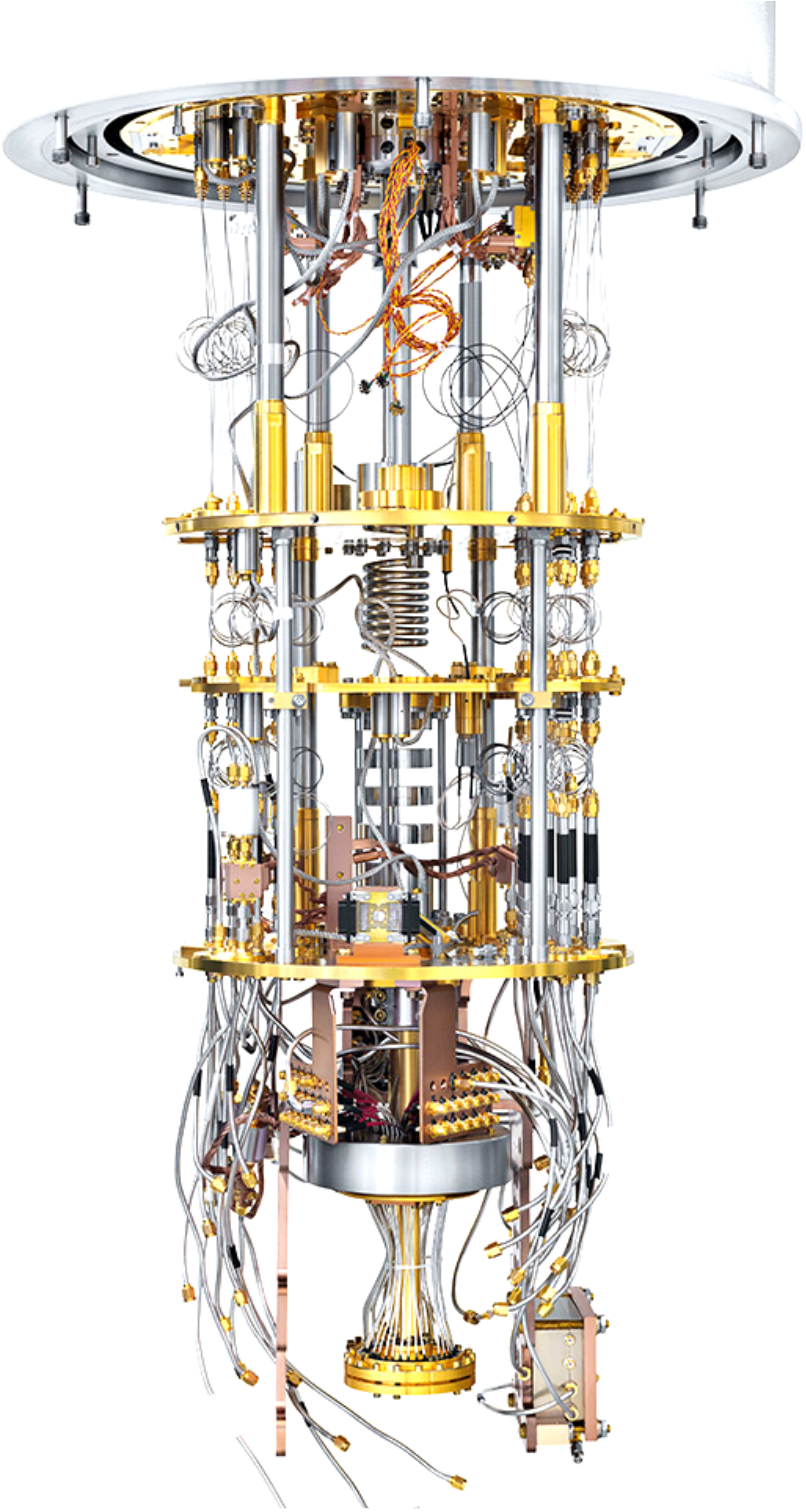
Variational circuits



Previously

Variational circuits

Data encoding

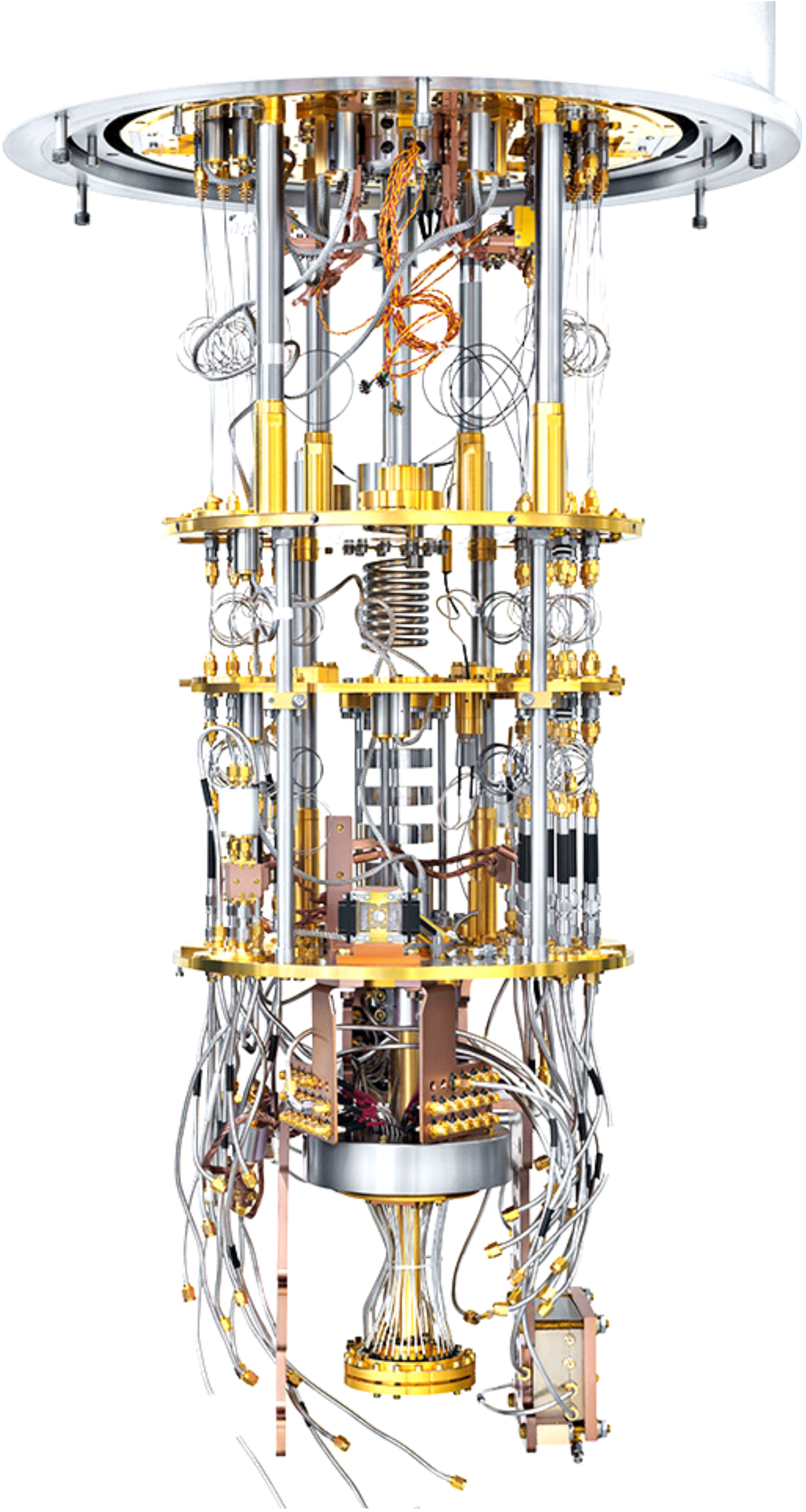


Agenda

Variational circuits

Data encoding

Combine the two to create QML models

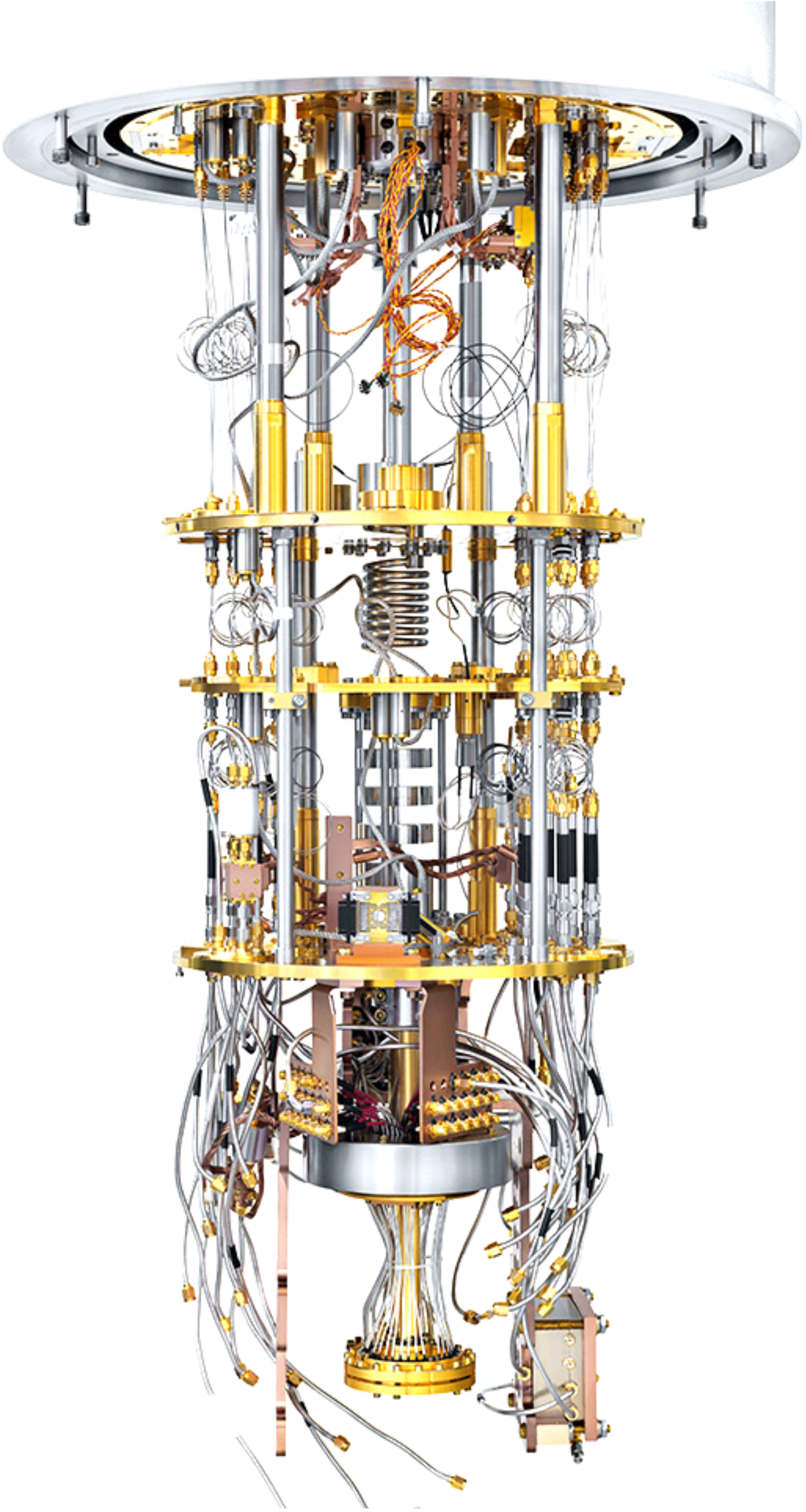


Agenda

Variational circuits

Data encoding

Kernel functions



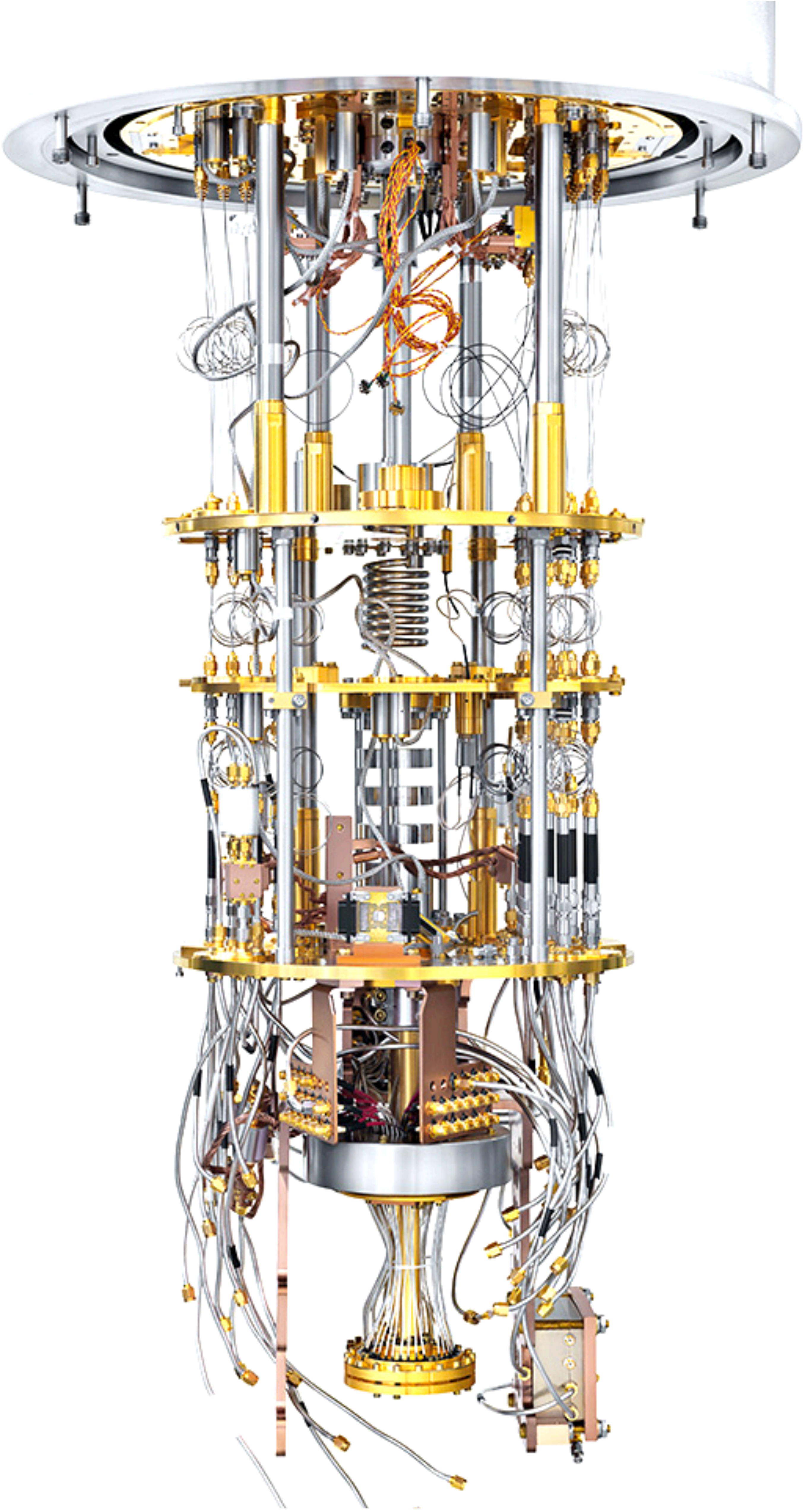
Agenda

Variational circuits

Data encoding

Kernel functions

Neural networks



Agenda

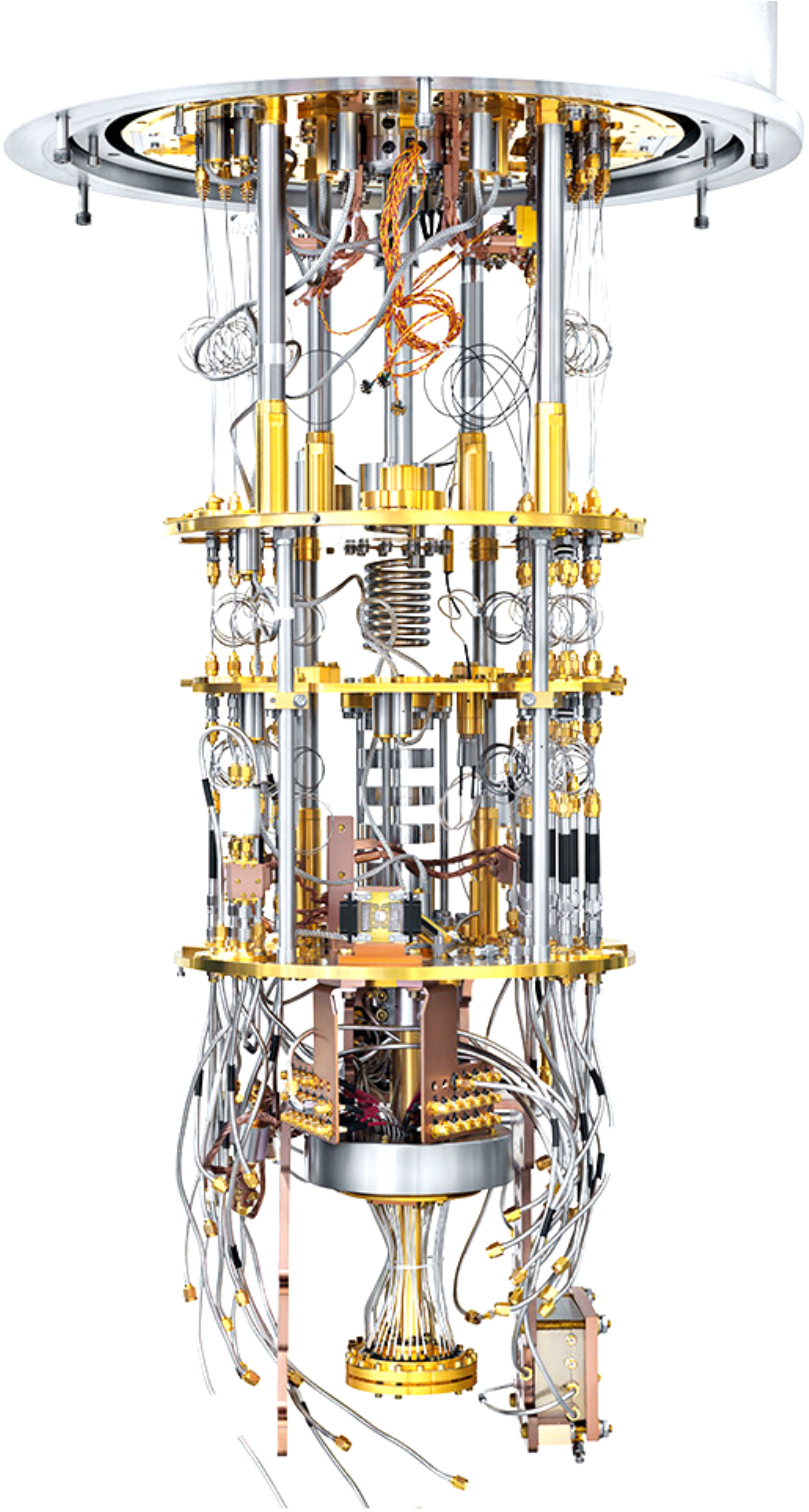
Variational circuits

Data encoding

Kernel functions

Neural networks

Variational classifier



Agenda

Variational circuits

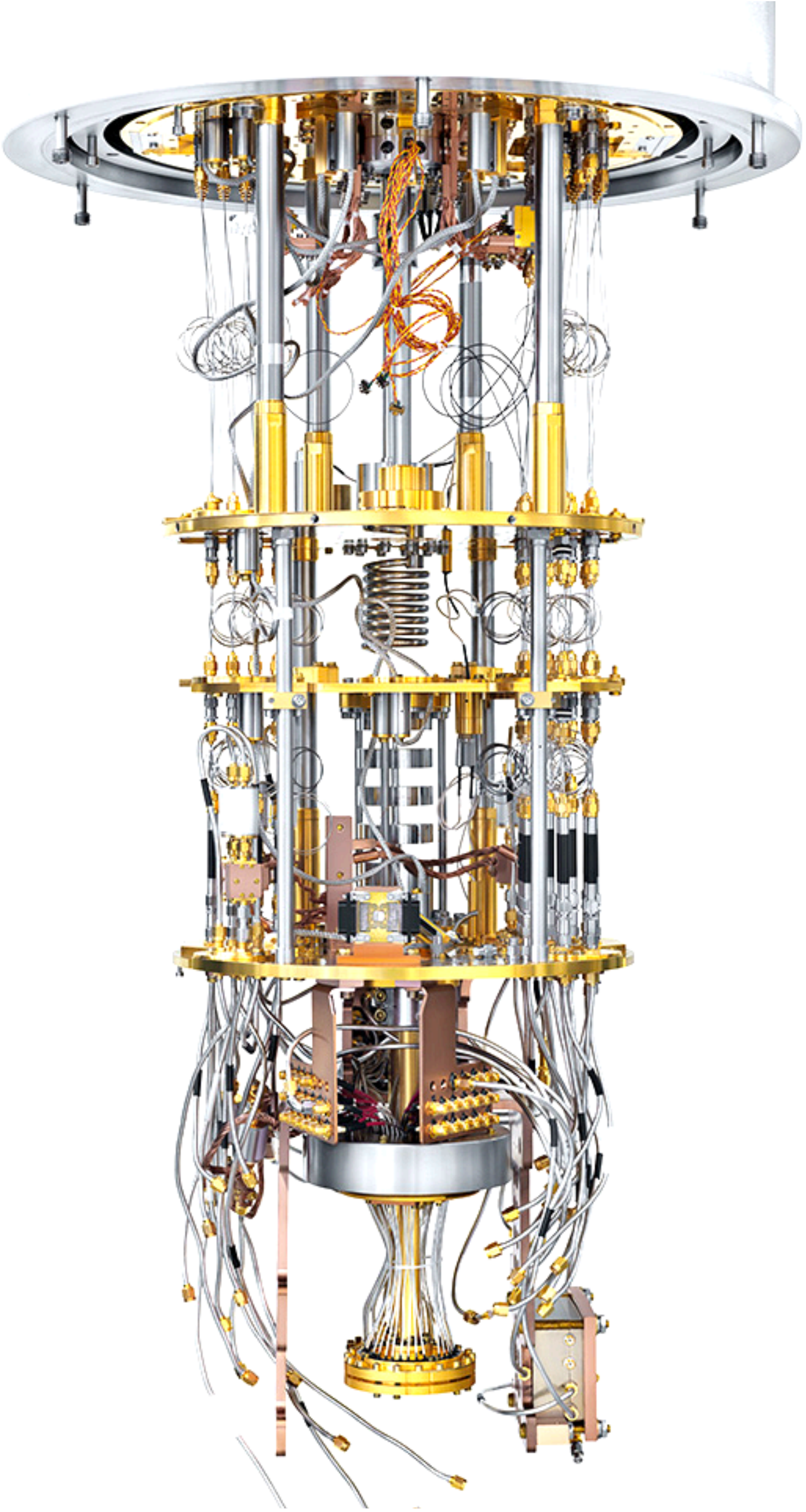
Data encoding

Kernel functions

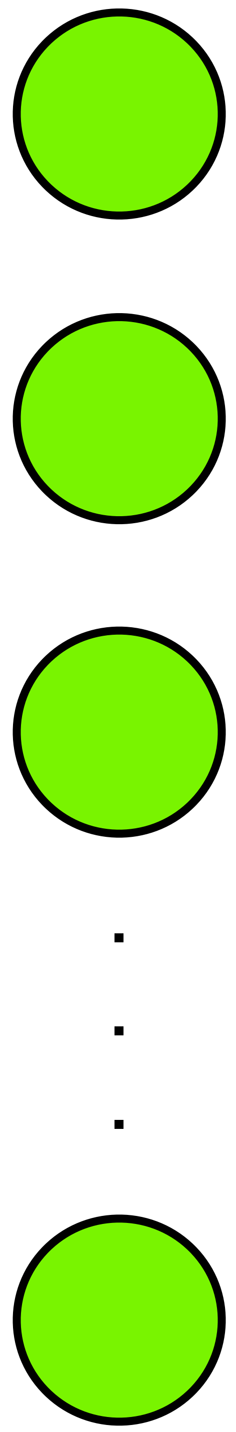
Neural networks

Variational classifier

Code a variational quantum classifier using Qiskit

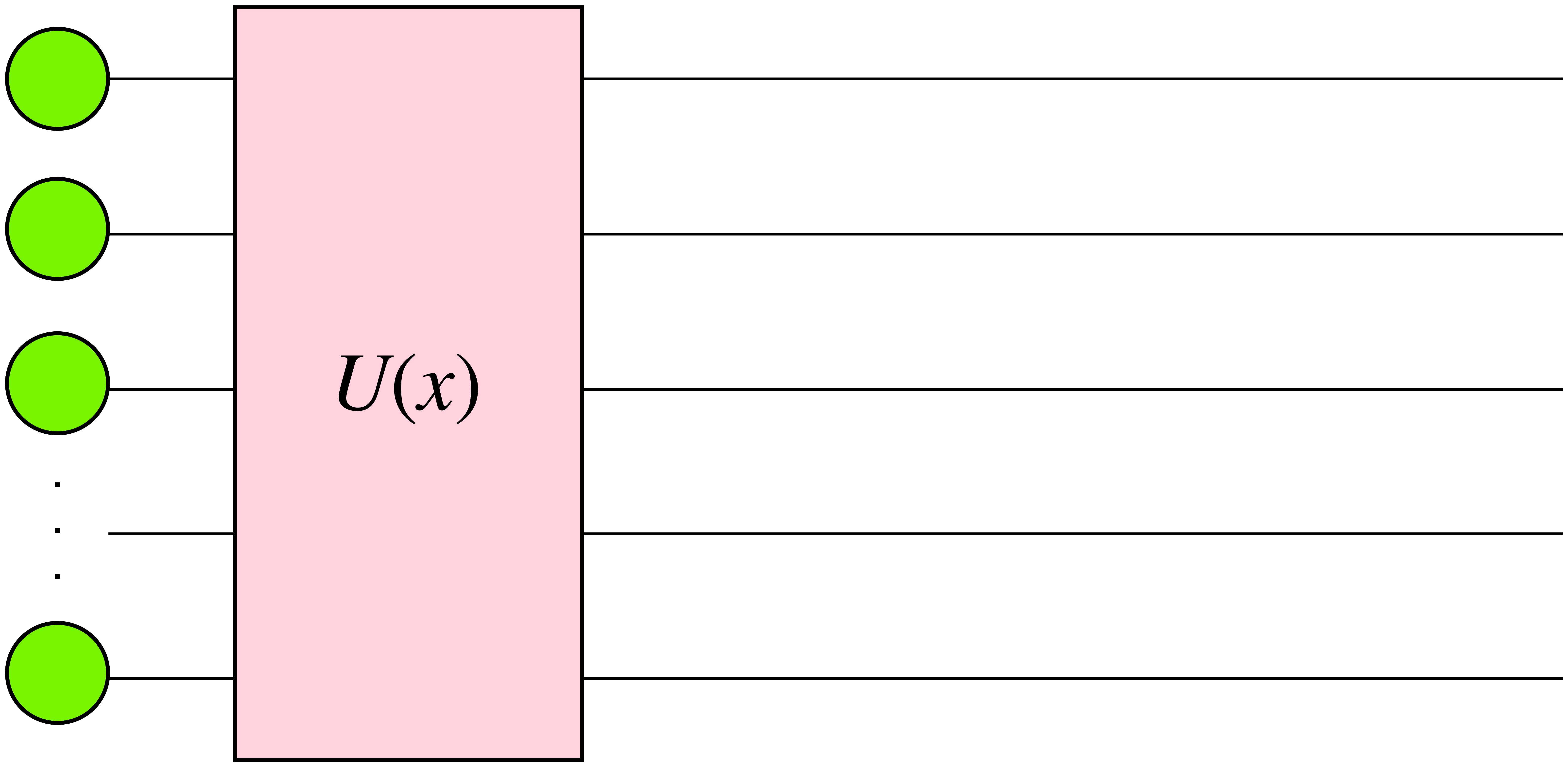


Quantum machine learning

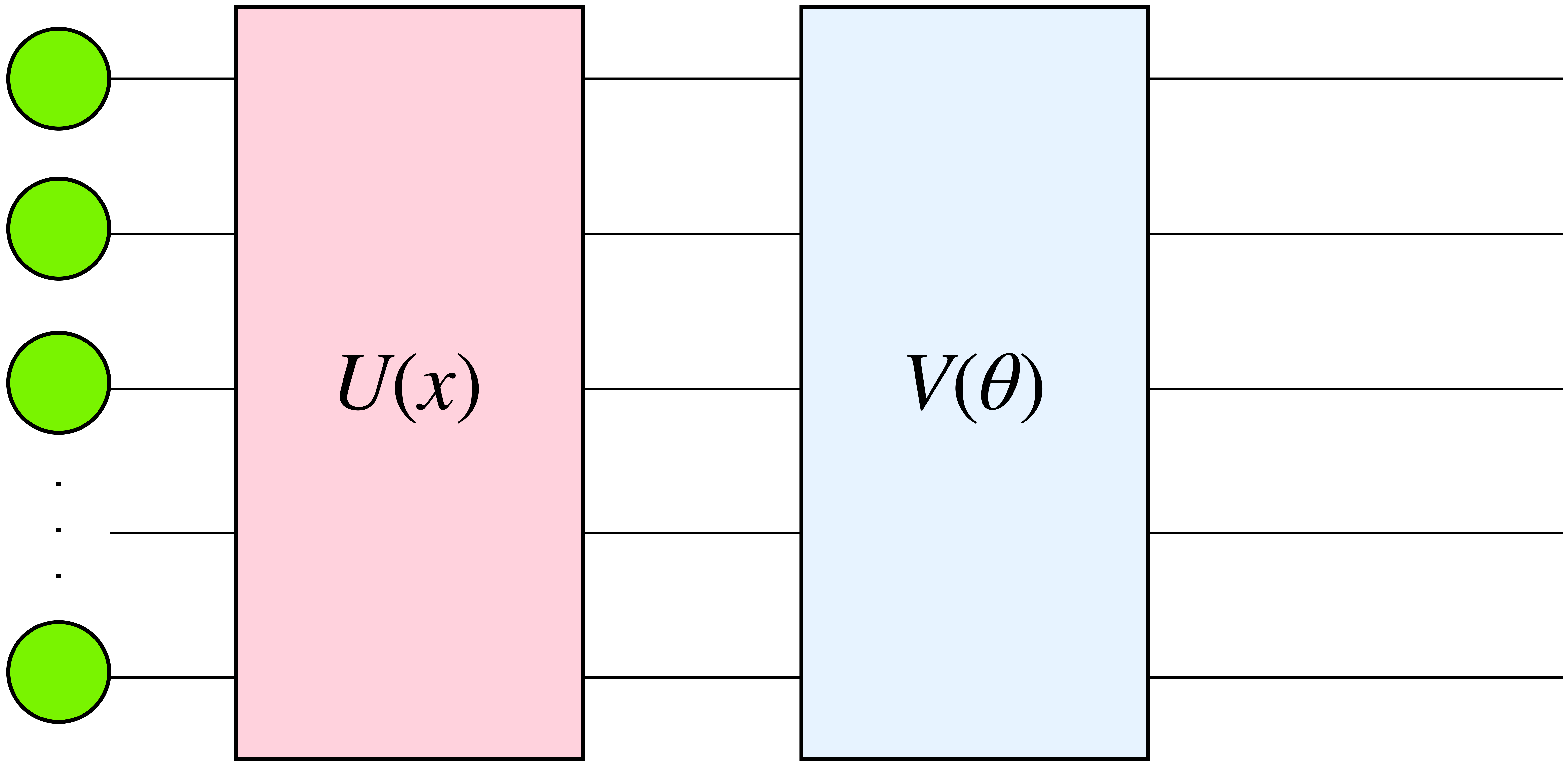


Quantum machine learning

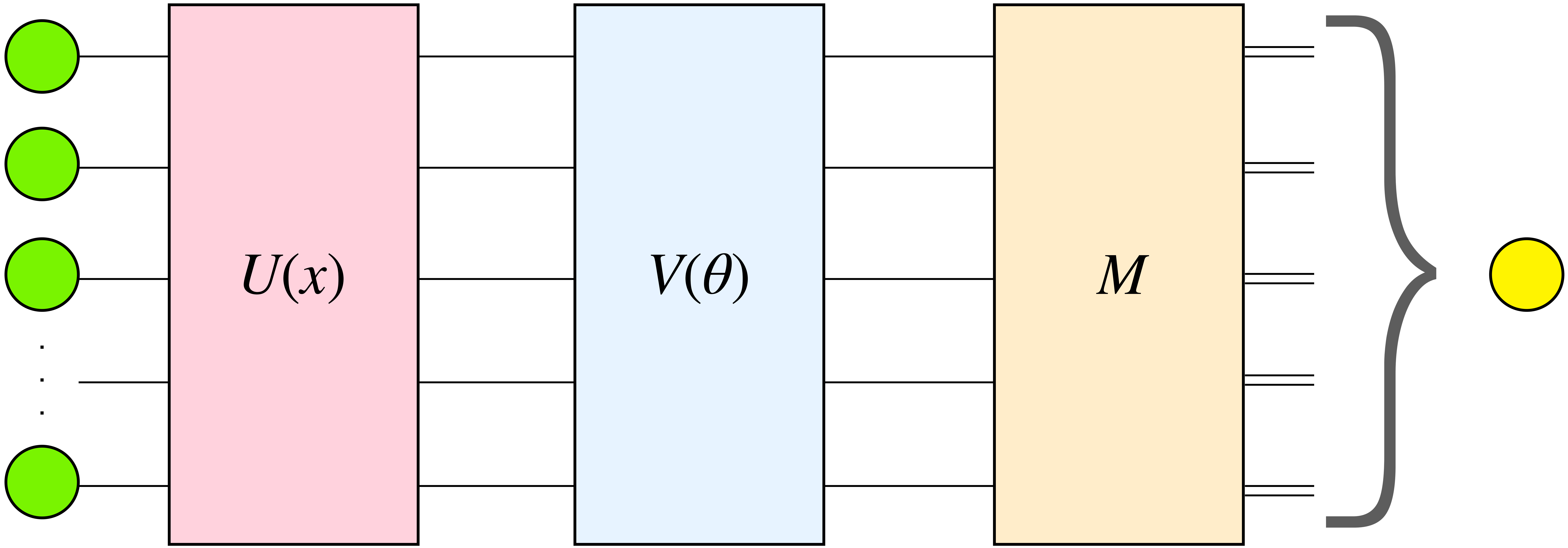
Quantum machine learning



Quantum machine learning

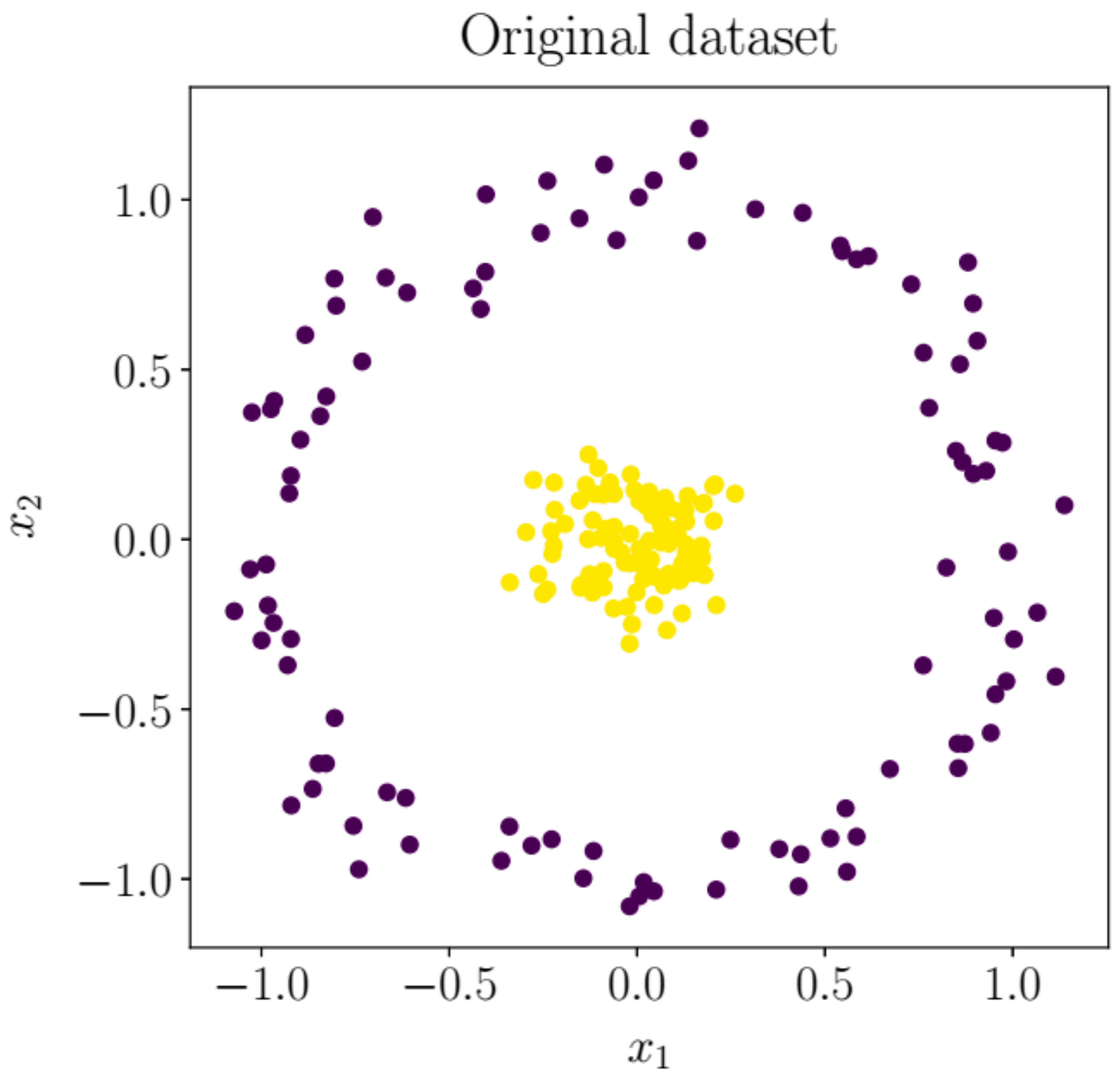


Quantum machine learning

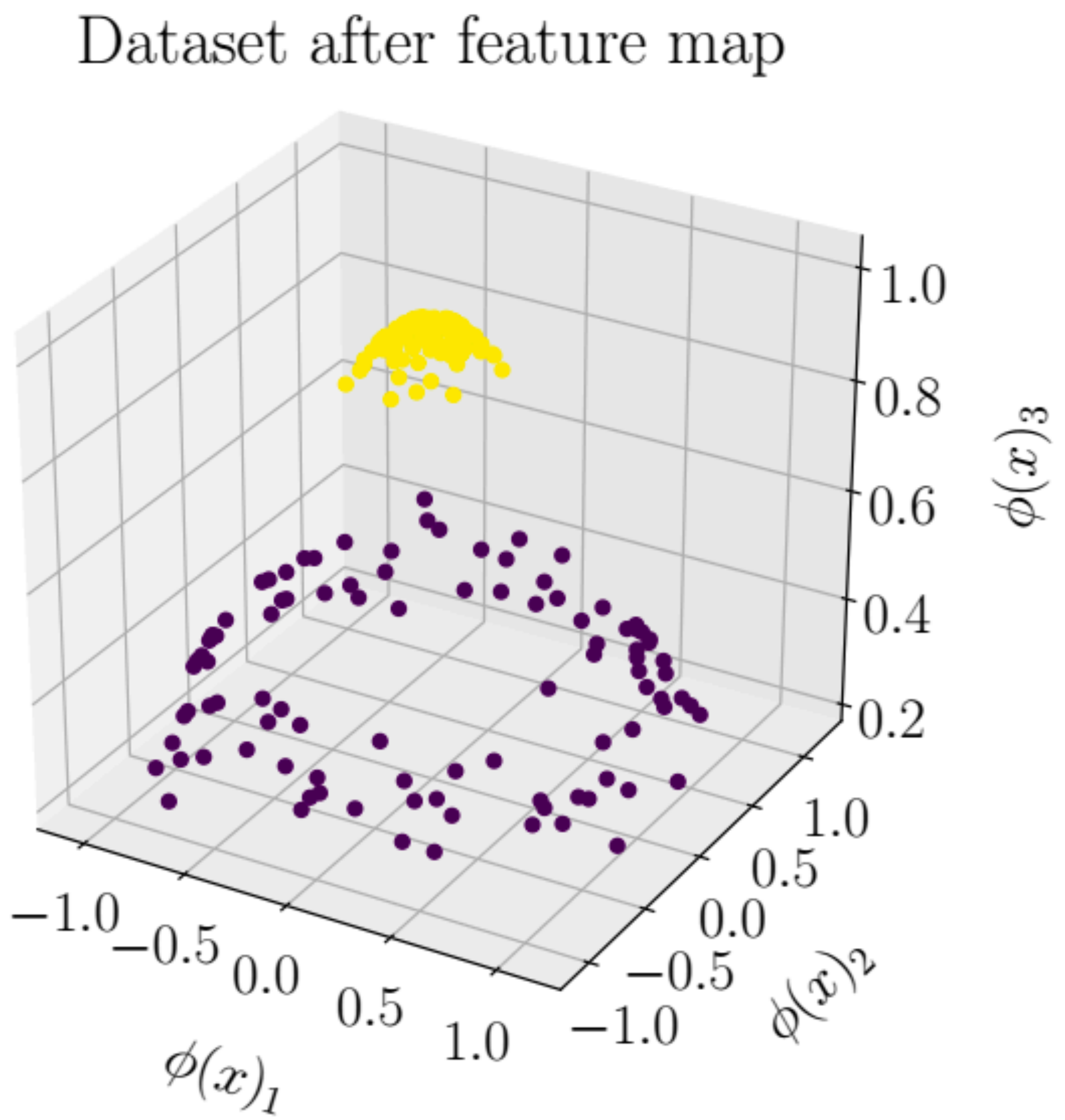


Support vector machine

Feature maps



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



$$\phi(x) = \begin{bmatrix} \phi(x_1) \\ \phi(x_2) \\ \phi(x_3) \end{bmatrix}$$

Kernel functions

$\kappa(x, x')$

Kernel functions

$$\kappa(x, x') = \text{similarity}$$

Kernel functions

$$\kappa(\phi(x), \phi(x')) = \text{similarity}$$

Kernel functions

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

Quantum feature maps

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

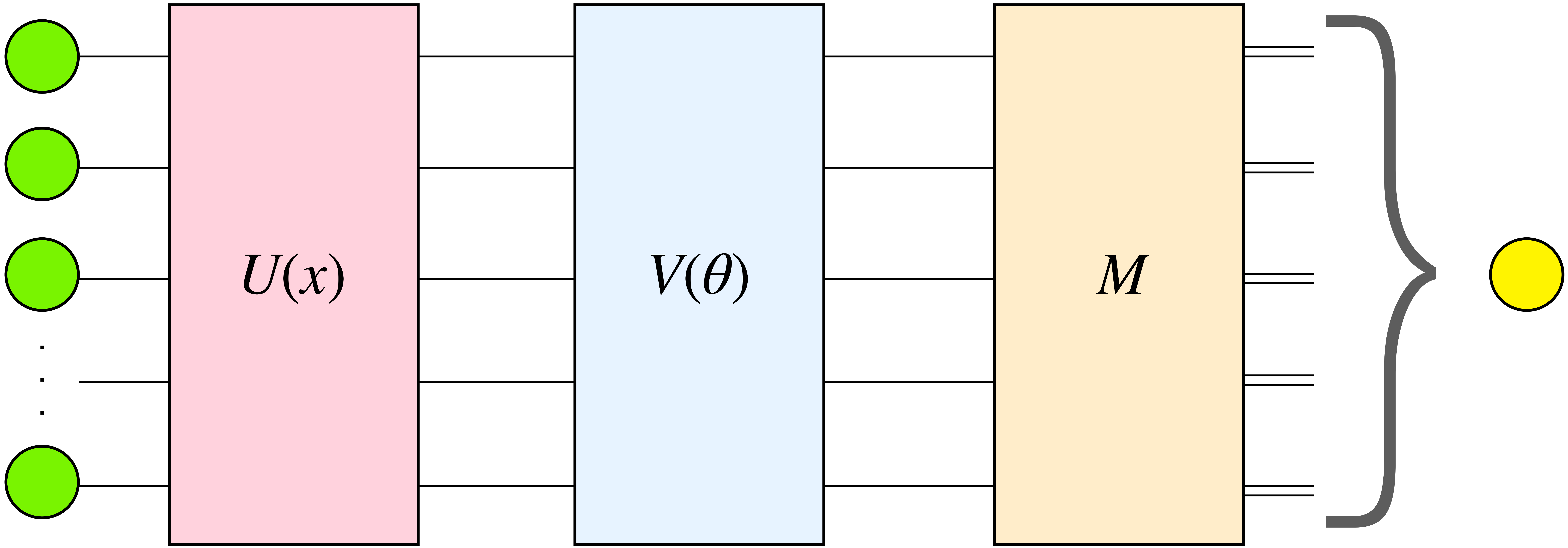
Quantum kernel functions

$$\kappa(\phi(x), \phi(x')) =$$

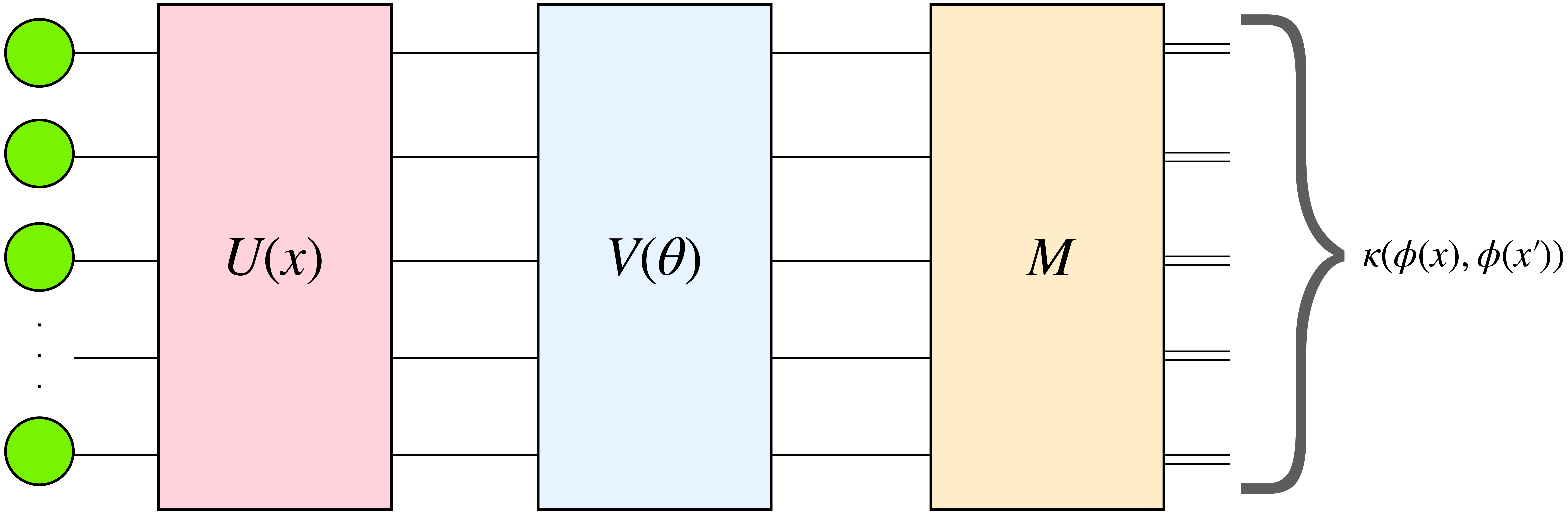
Quantum kernel functions

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

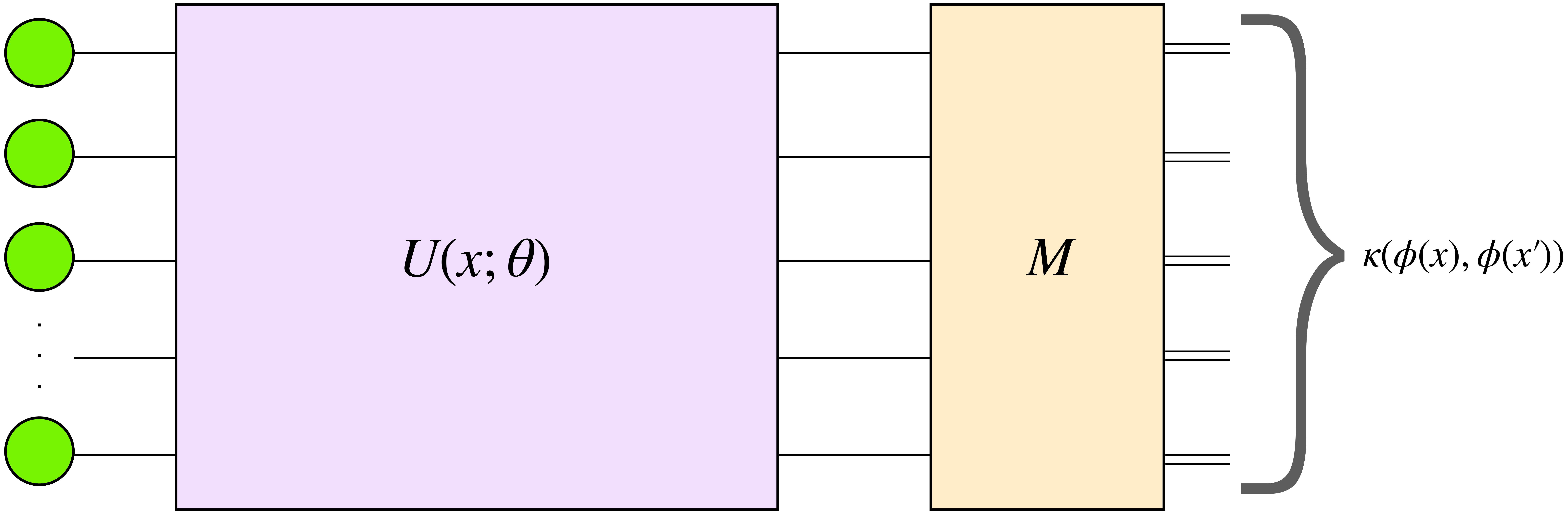
Quantum kernel functions



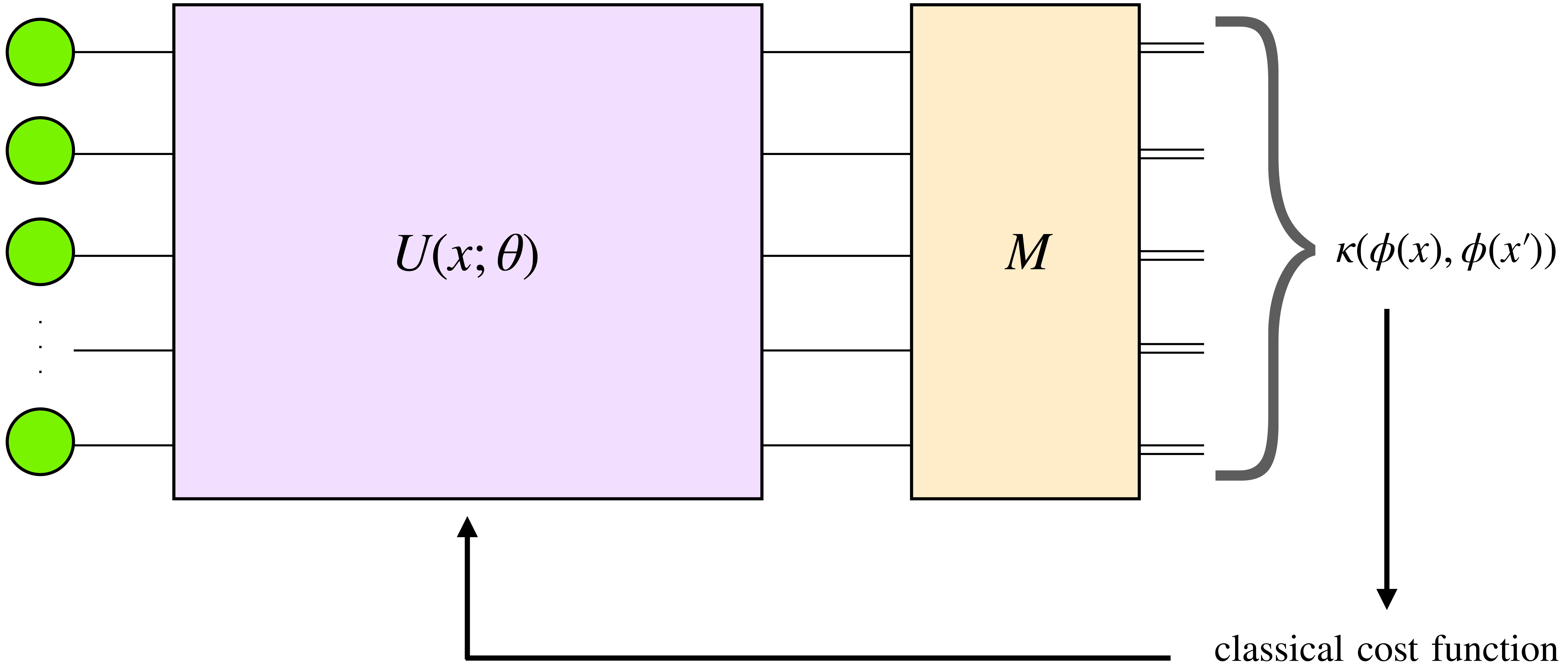
Quantum kernel functions



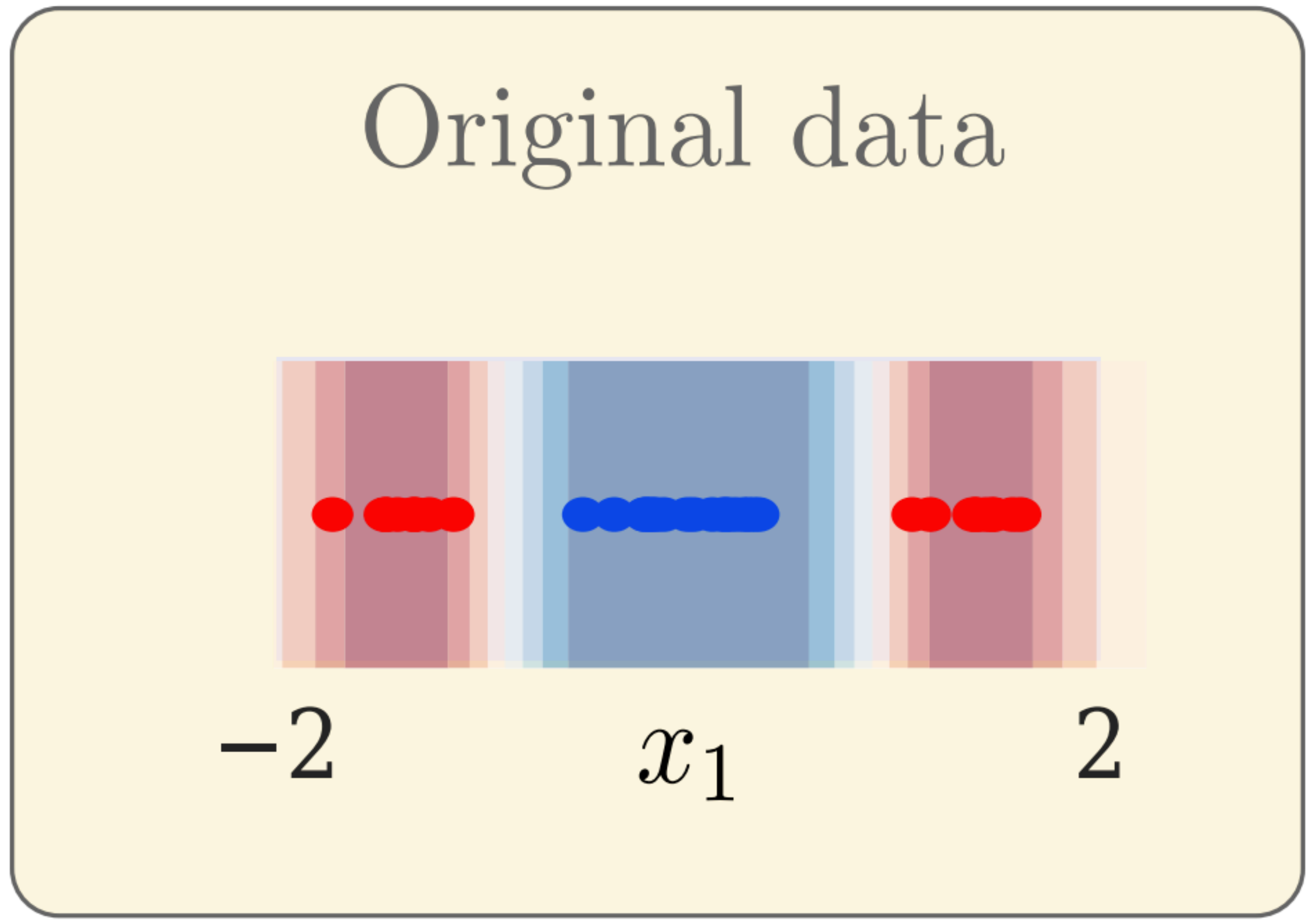
Quantum kernel functions

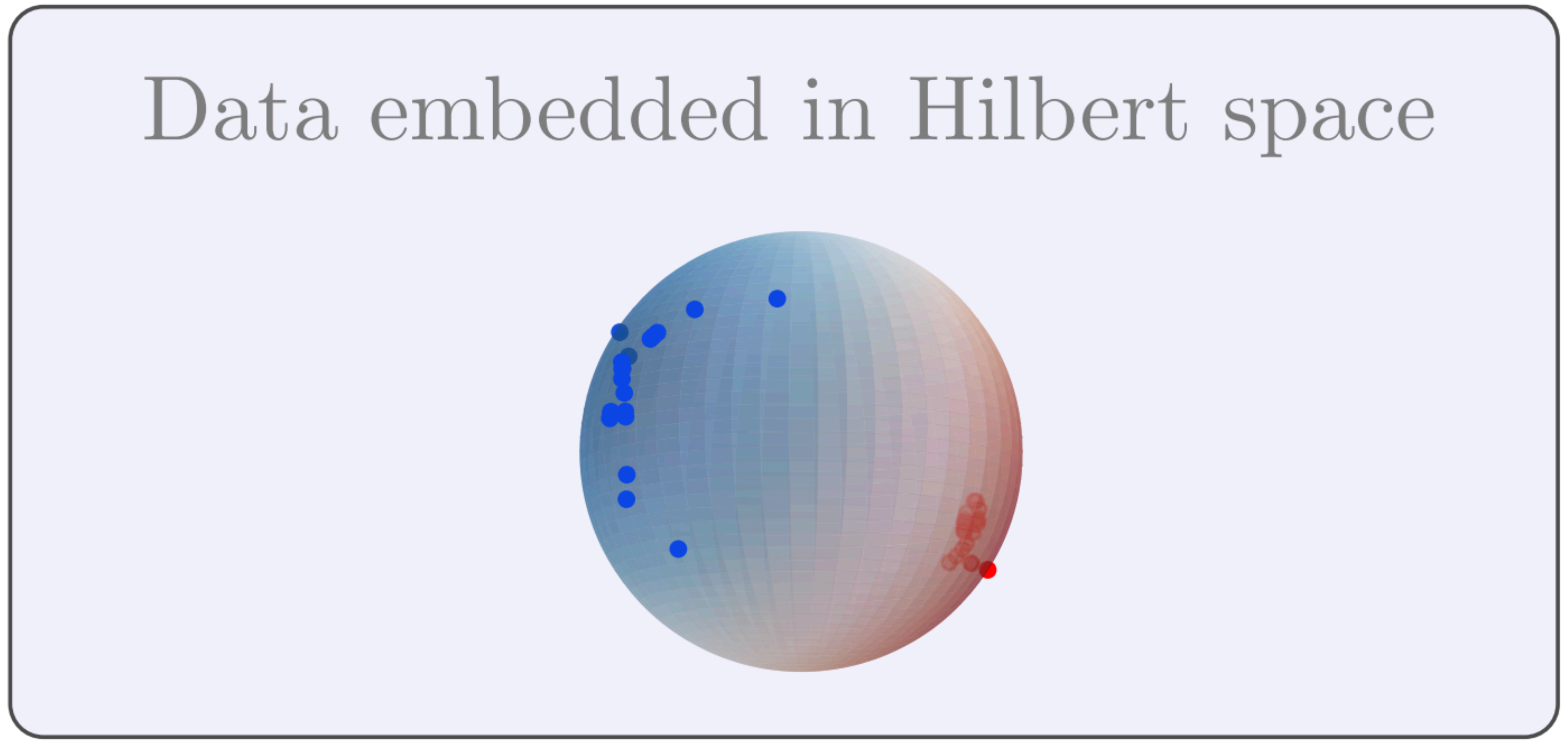


Quantum-enhanced support vector machine



Quantum kernel functions





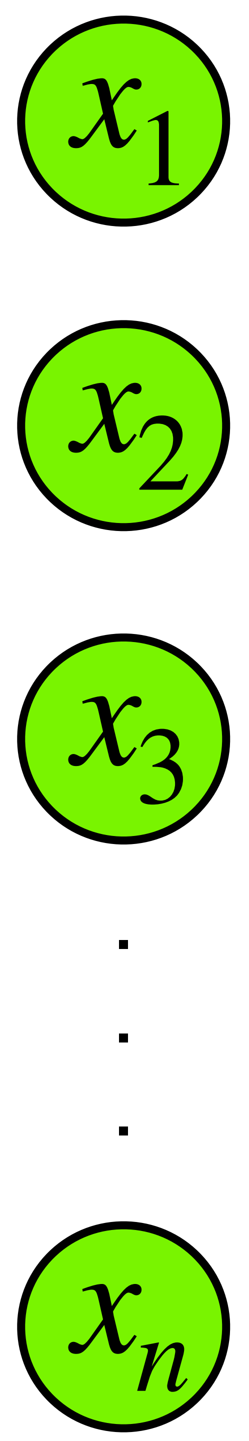
Source: Lloyd, Seth, et al. "Quantum embeddings for machine learning." arXiv preprint arXiv:2001.03622 (2020).

Quantum-enhanced kernels

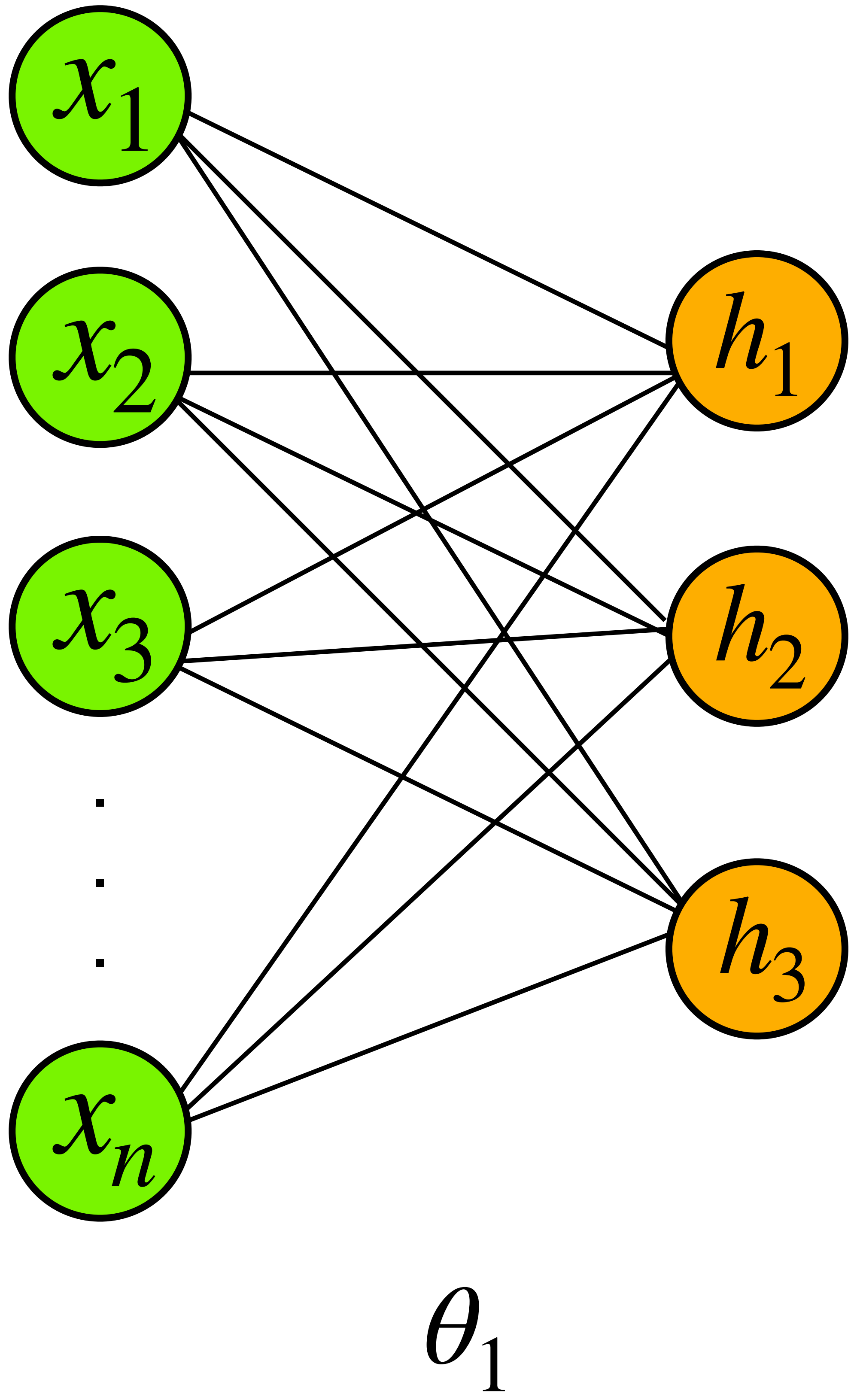
- Schuld, Maria, Mark Fingerhuth, and Francesco Petruccione. "Implementing a distance-based classifier with a quantum interference circuit." EPL (Europhysics Letters) 119.6 (2017): 60002.
- Schuld, Maria, and Nathan Killoran. "Quantum machine learning in feature Hilbert spaces." Physical review letters 122.4 (2019): 040504.
- Havlíček, Vojtěch, et al. "Supervised learning with quantum-enhanced feature spaces." Nature 567.7747 (2019): 209-212.
- Blank, Carsten, et al. "Quantum classifier with tailored quantum kernel." npj Quantum Information 6.1 (2020): 1-7.

Neural network

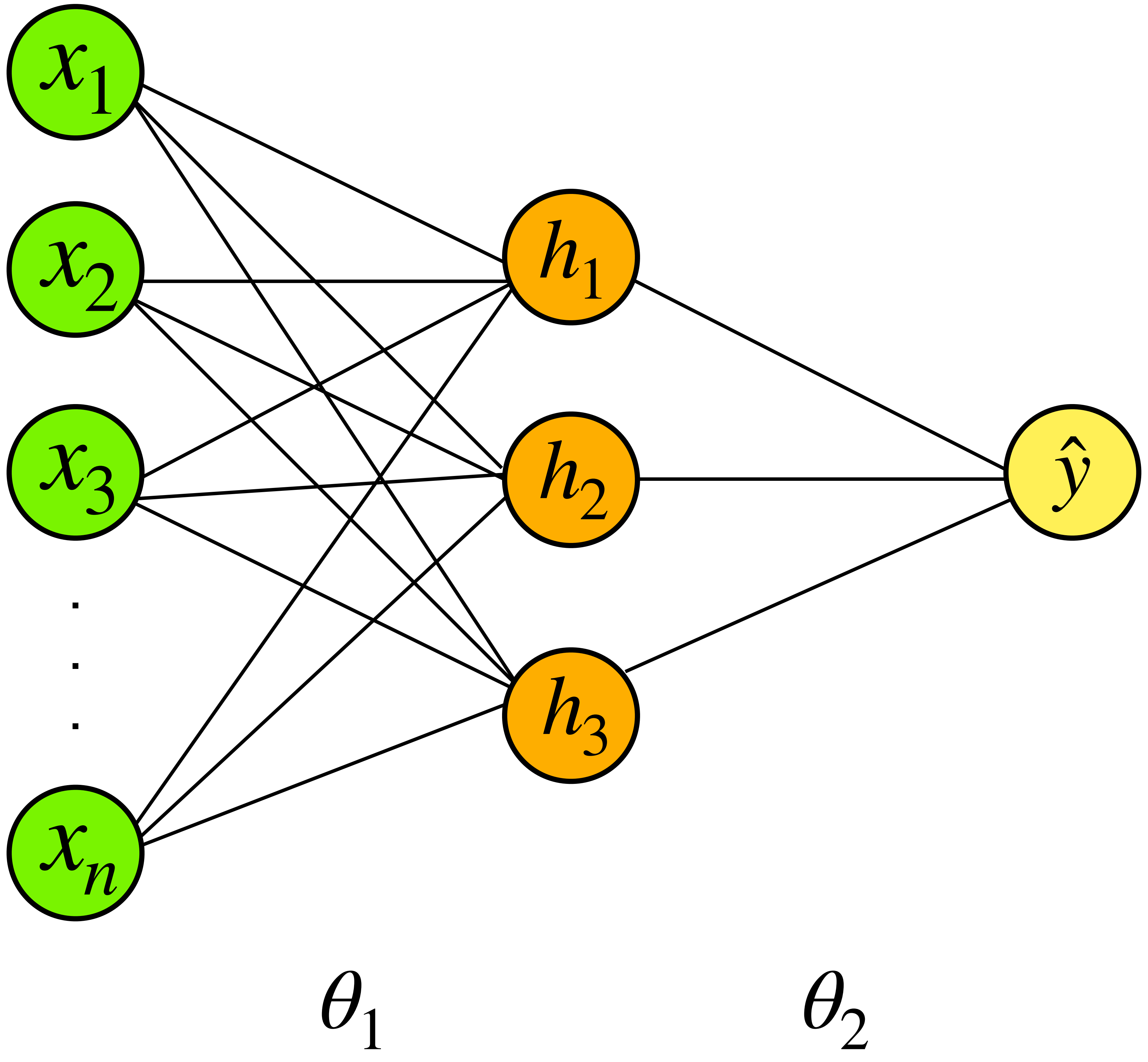
Neural network



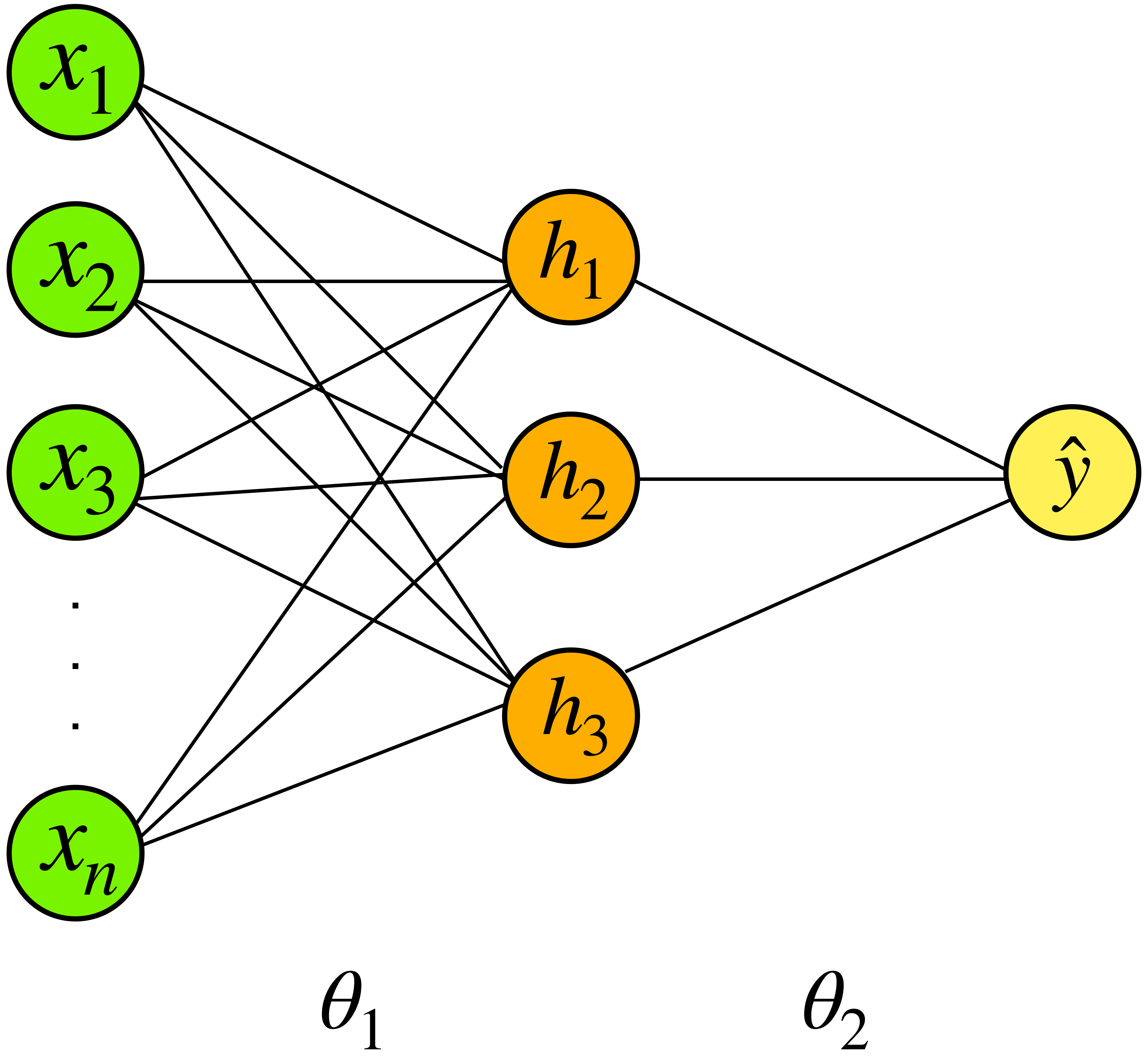
Neural network



Neural network

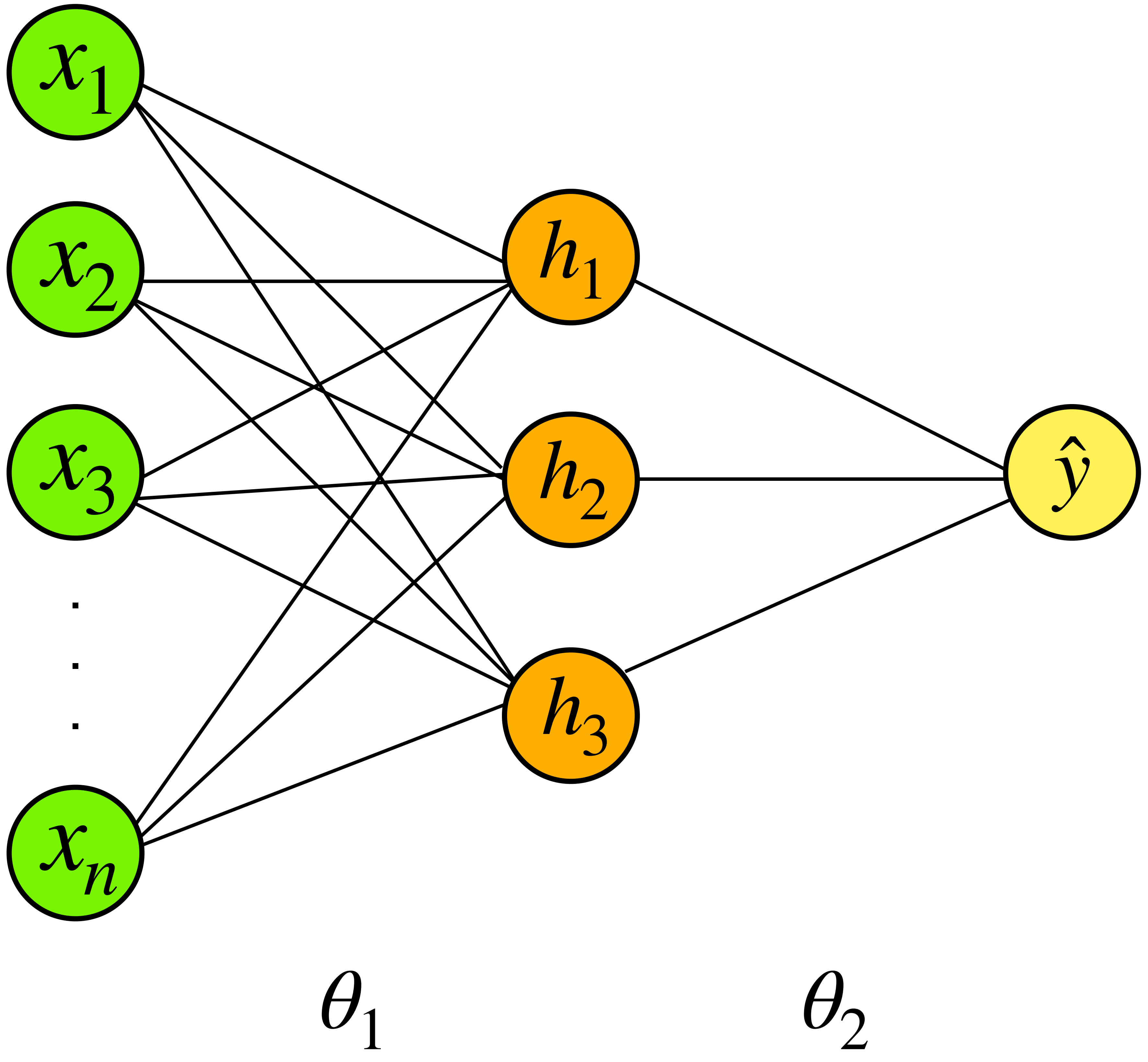


Neural network



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

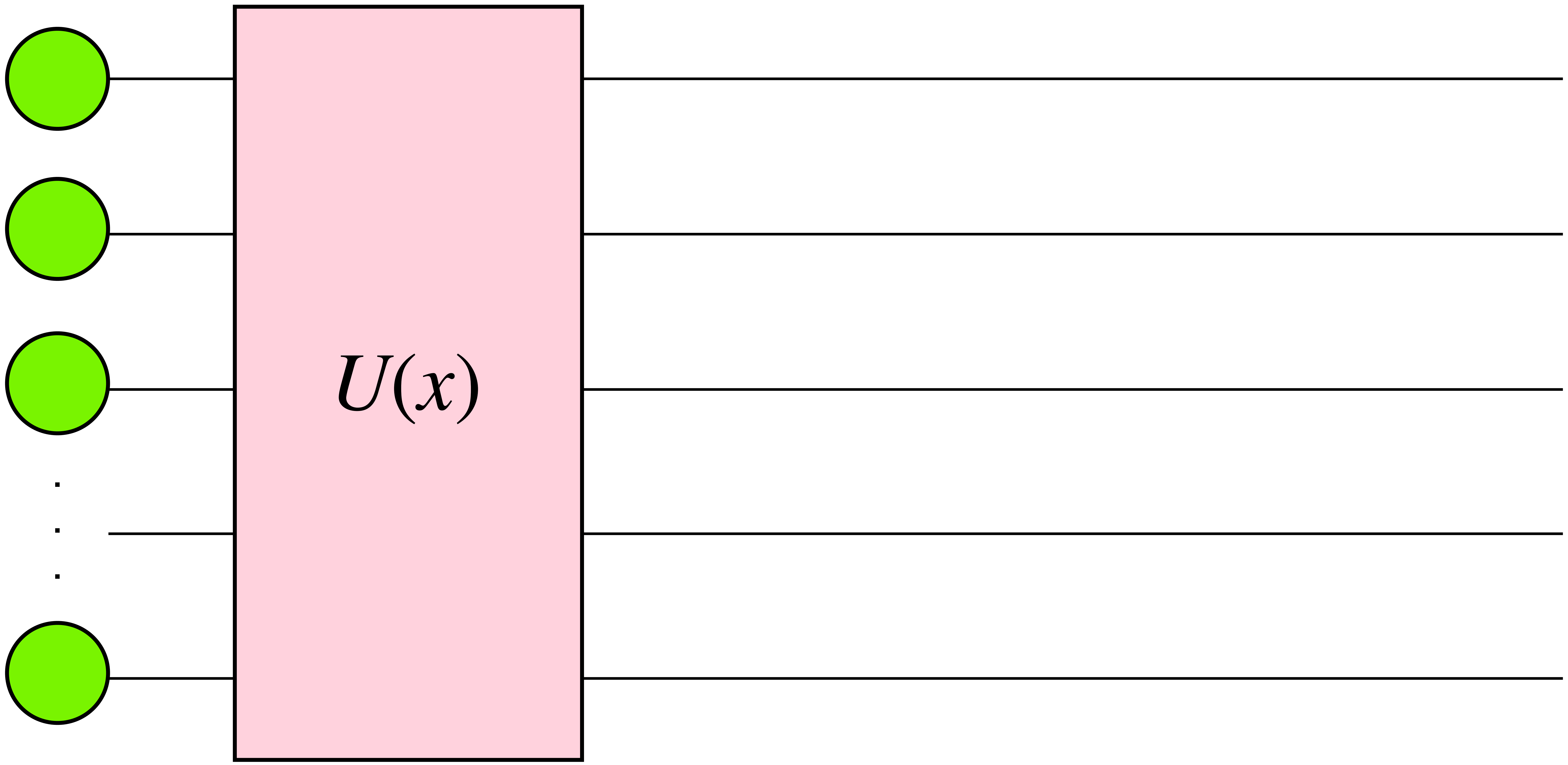
Linear neural network



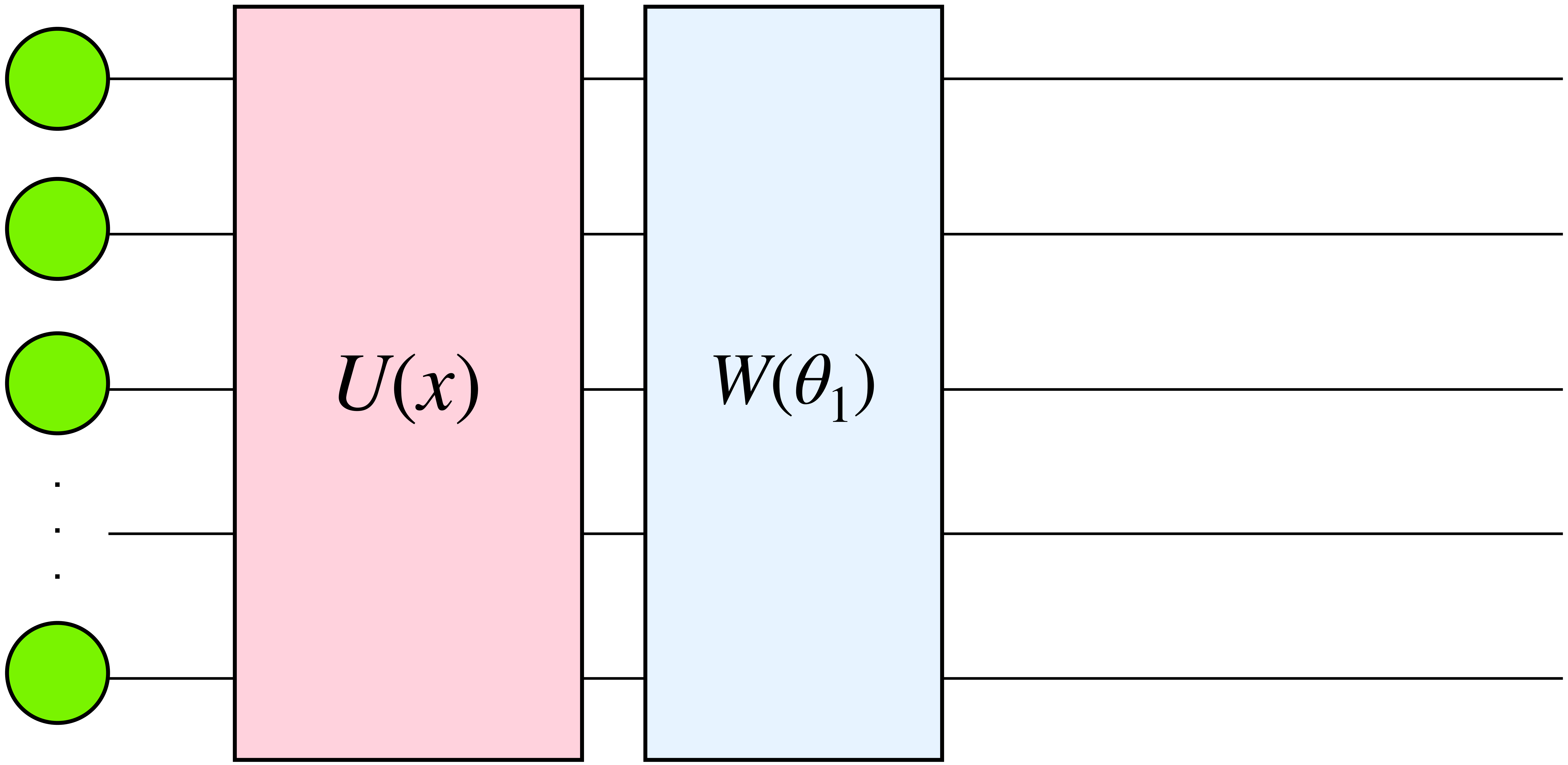
$$\hat{y} = \theta_2(\theta_1 x)$$

Quantum neural network

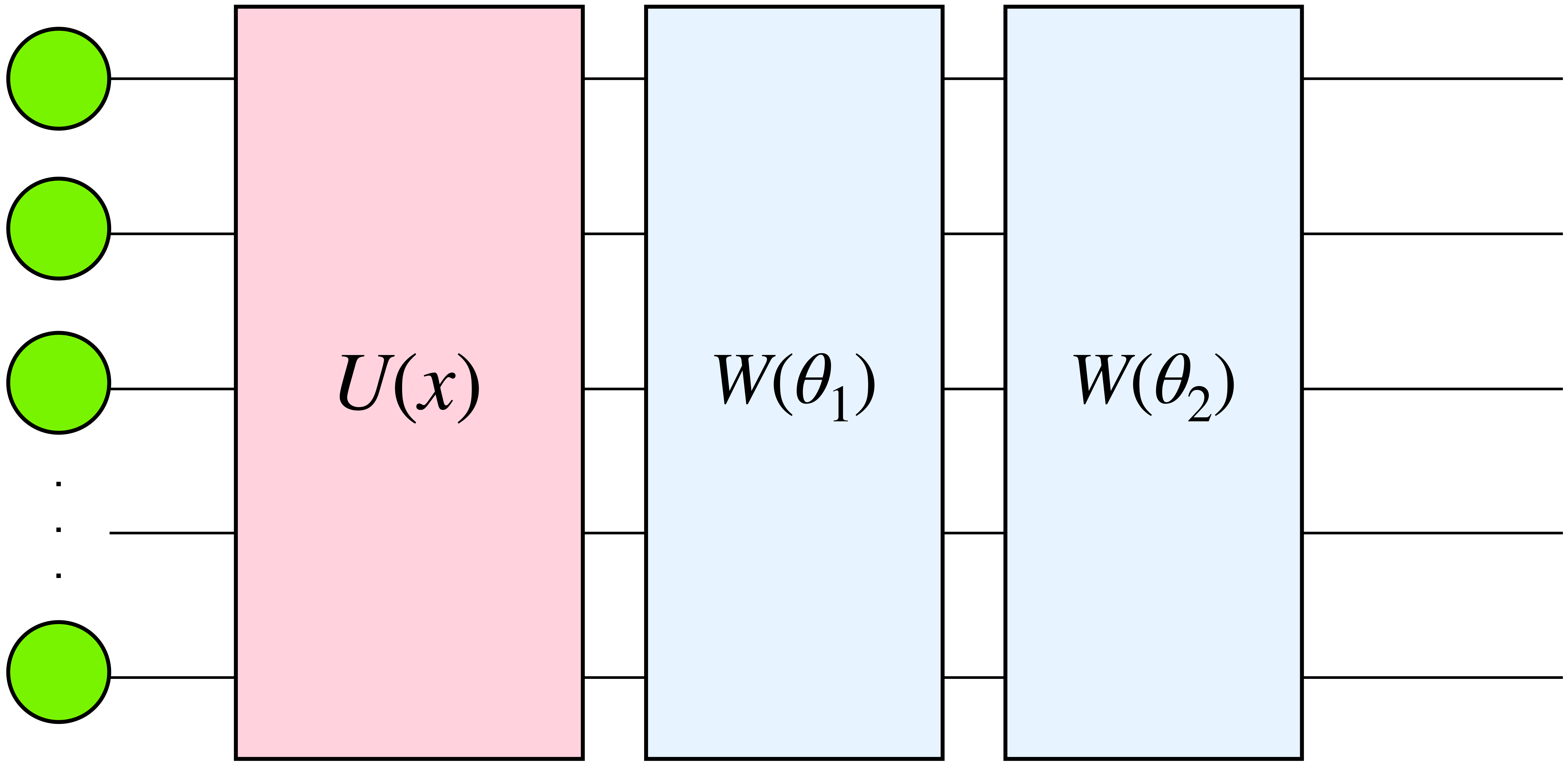
Quantum neural network



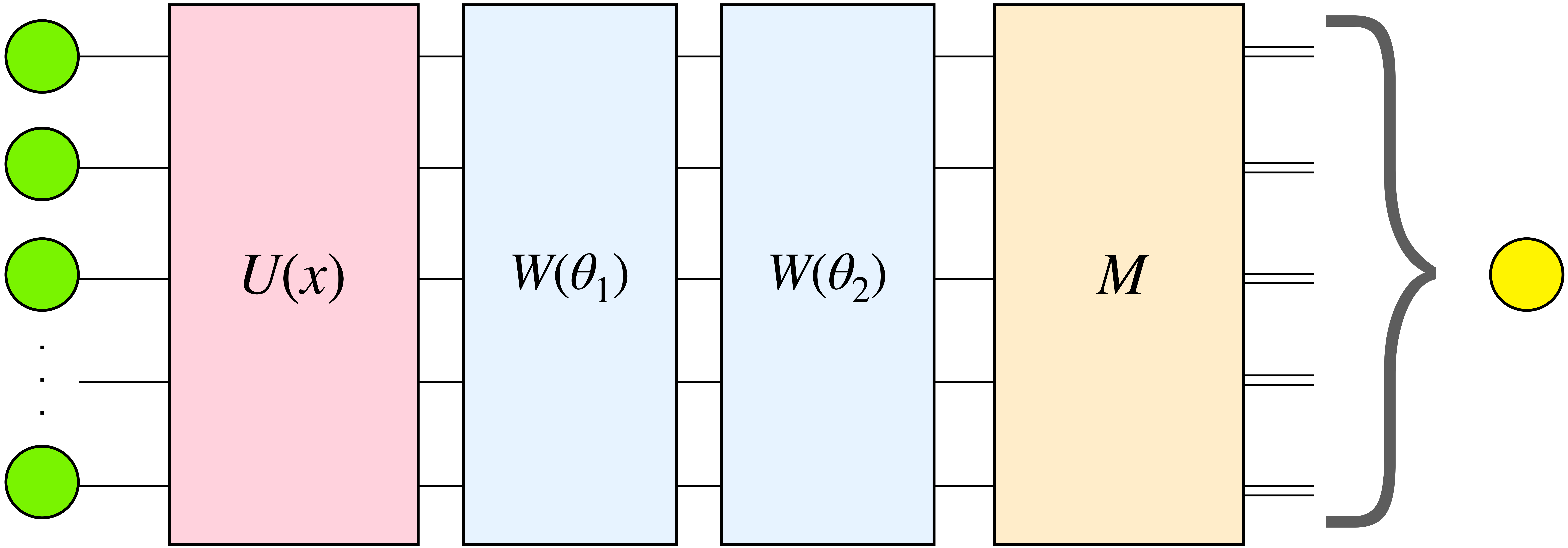
Quantum neural network



Quantum neural network



Quantum neural network



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

Quantum neural network

- DQNNs
  Beer, Kerstin, et al. "Training deep quantum neural networks." Nature communications 11.1 (2020): 1-6.

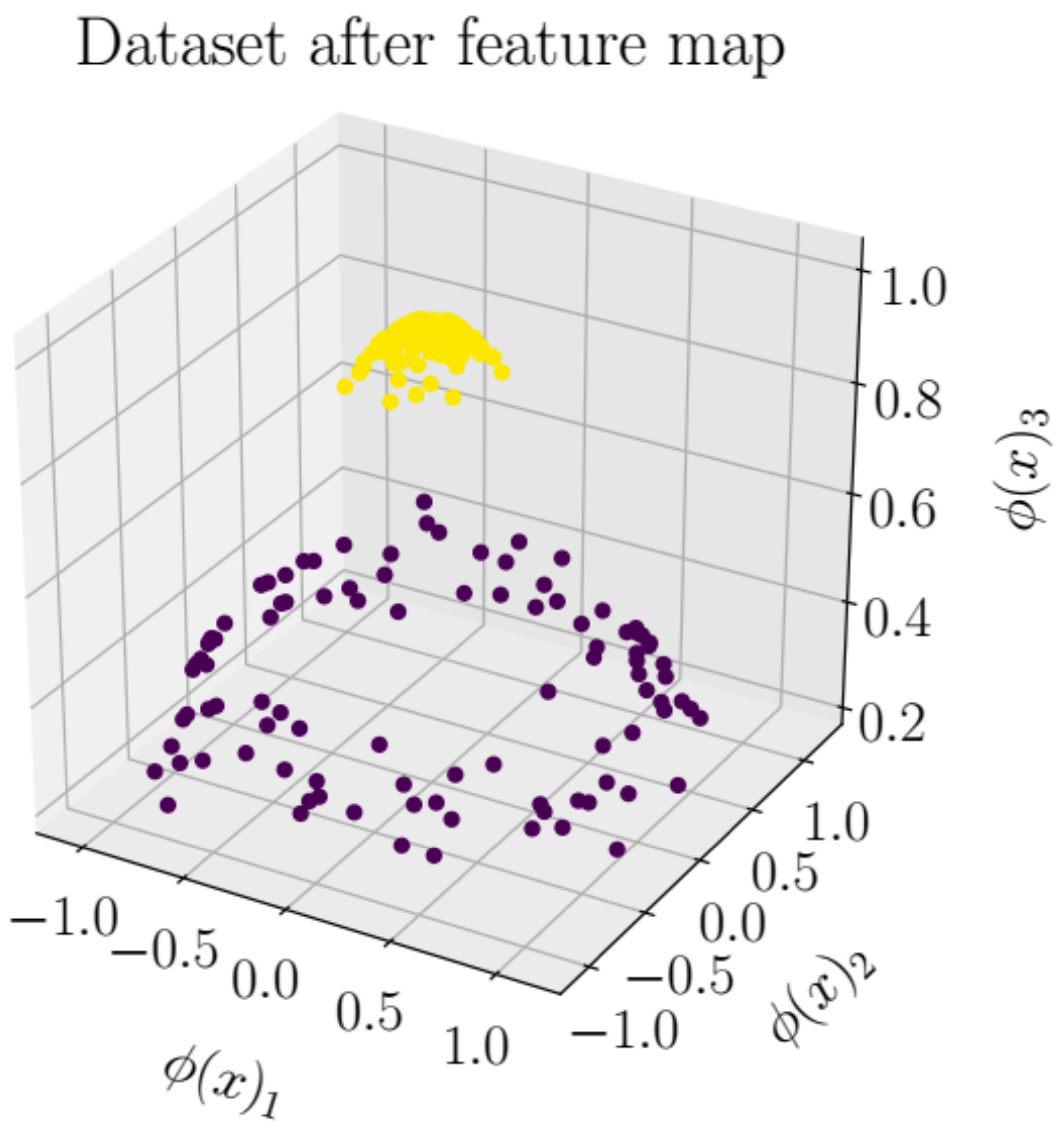
- Variational quantum auto encoder
  Romero, Jonathan, Jonathan P. Olson, and Alan Aspuru-Guzik. "Quantum autoencoders for efficient compression of quantum data." Quantum Science and Technology 2.4 (2017): 045001. APA

- QGAN
  Zoufal, Christa, Aurélien Lucchi, and Stefan Woerner. "Quantum generative adversarial networks for learning and loading random distributions." npj Quantum Information 5.1 (2019): 1-9.

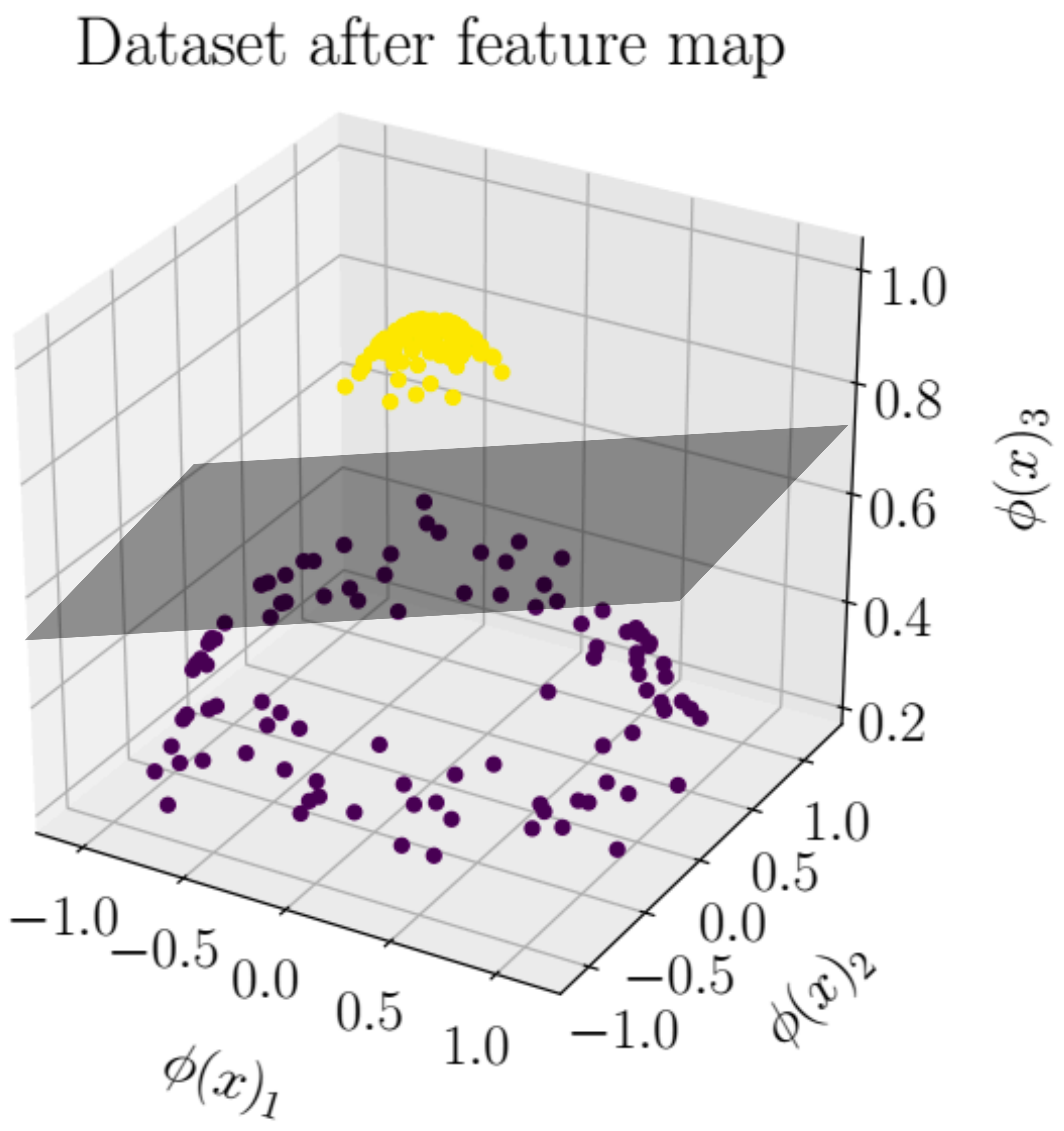
- Quantum convolutional neural networks
  Cong, Iris, Soonwon Choi, and Mikhail D. Lukin. "Quantum convolutional neural networks." Nature Physics 15.12 (2019): 1273-1278.

Quantum variational classifier

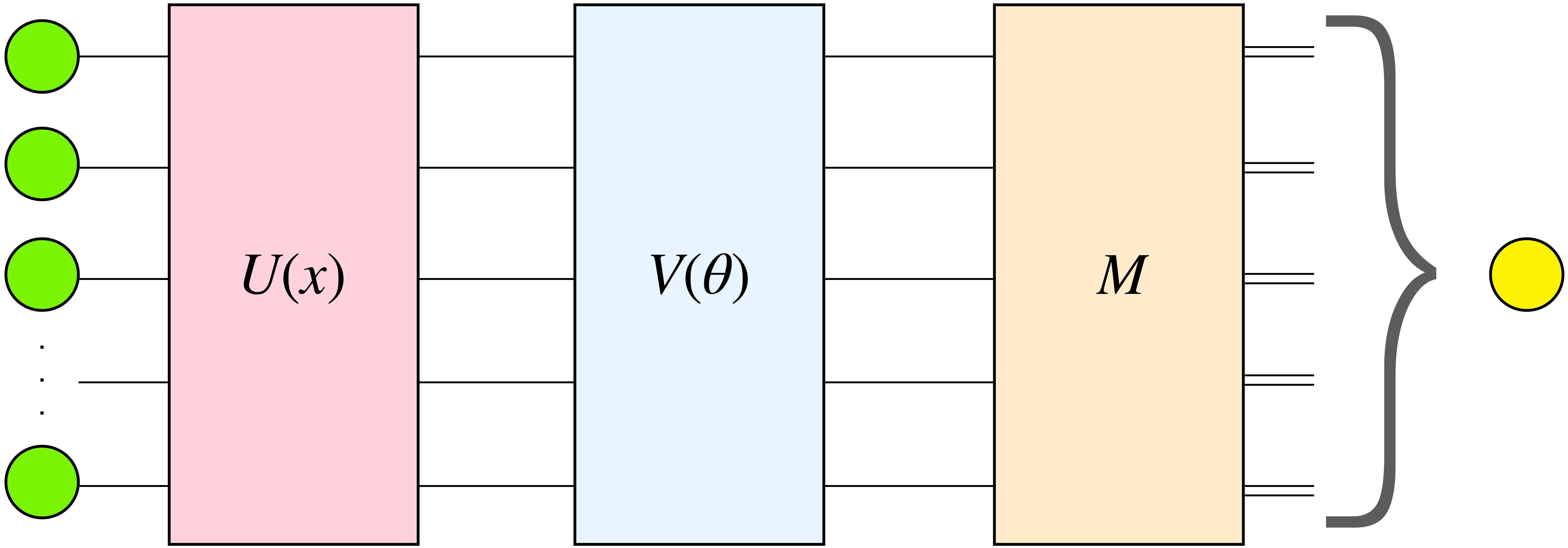
Quantum variational classifier



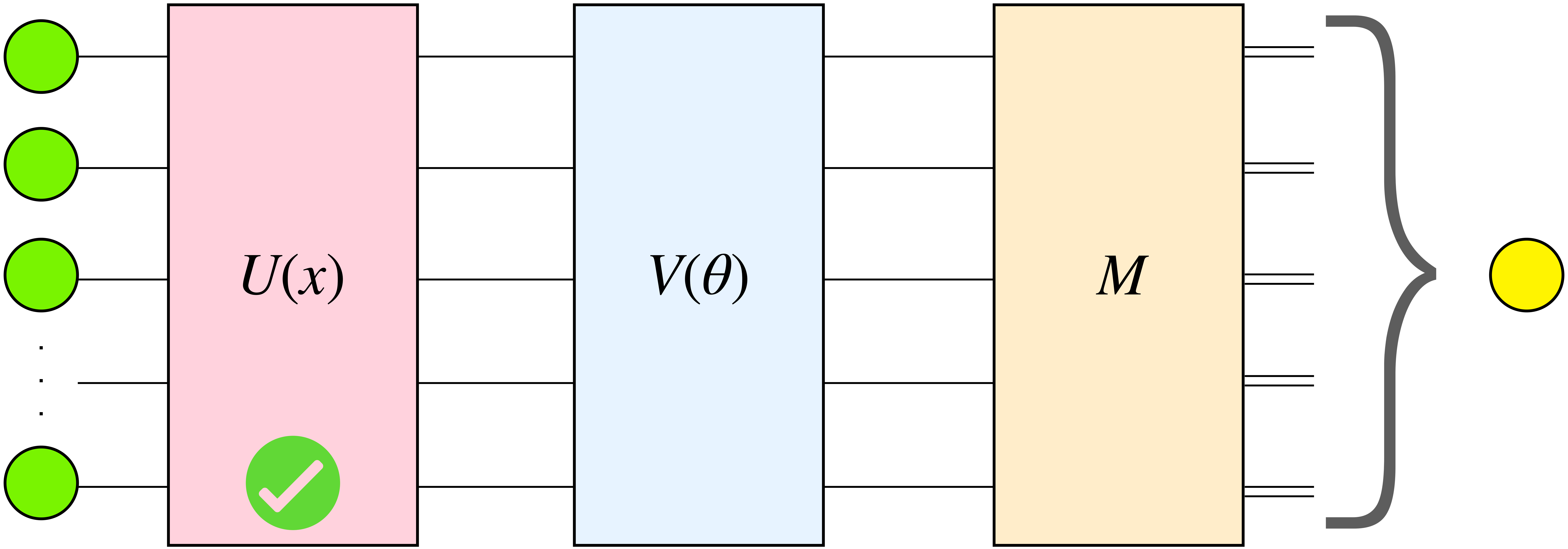
Quantum variational classifier



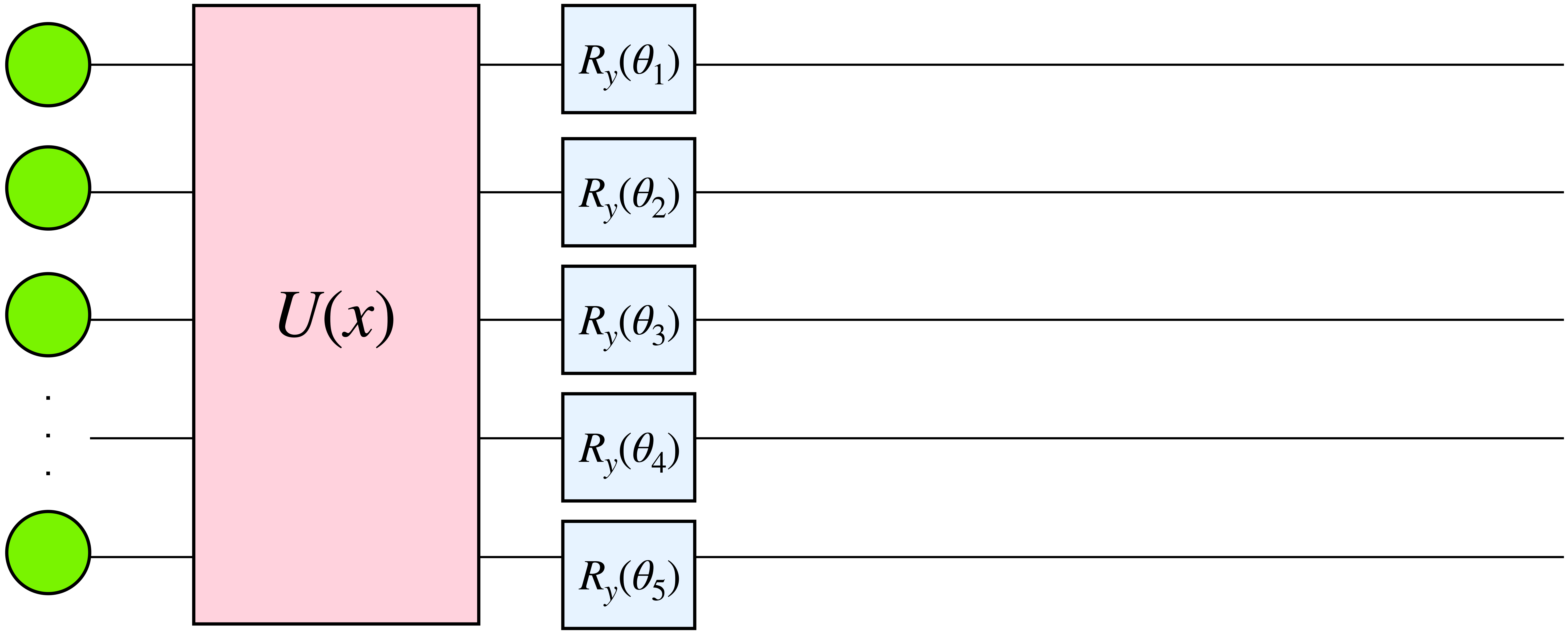
Quantum variational classifier



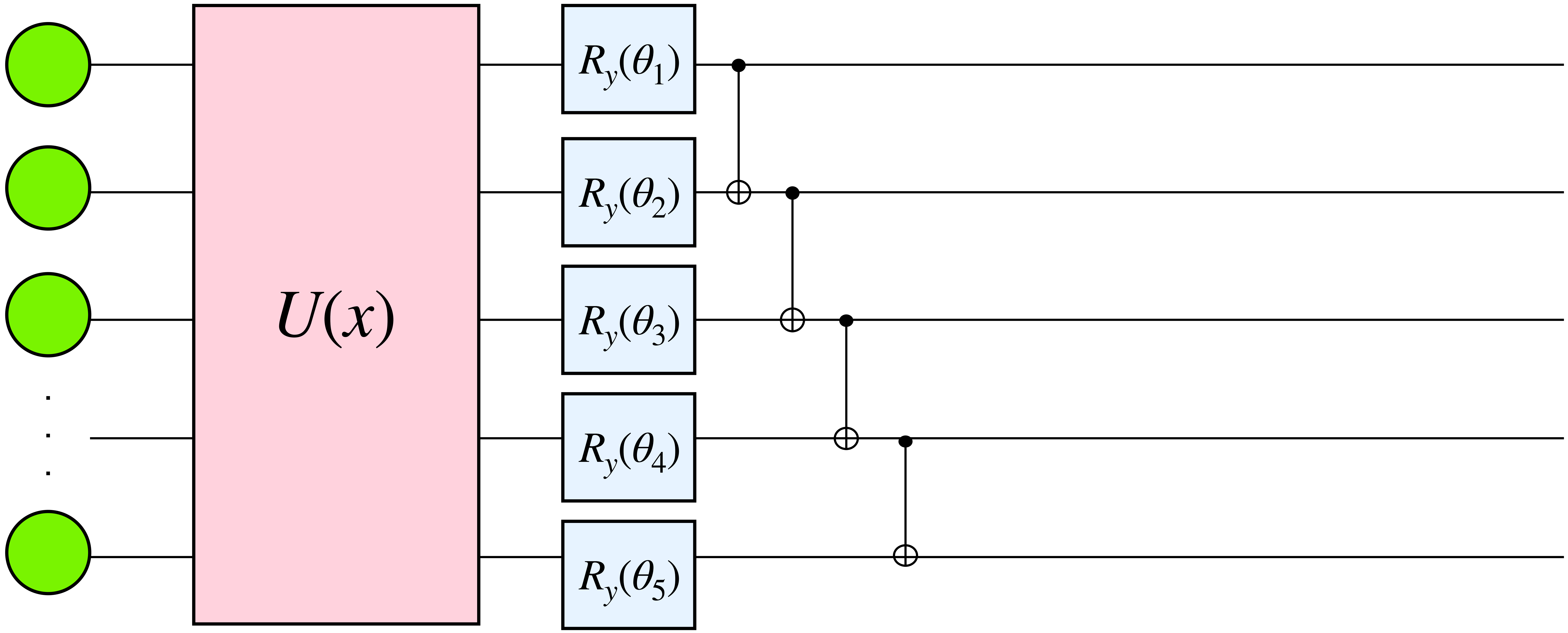
Quantum variational classifier



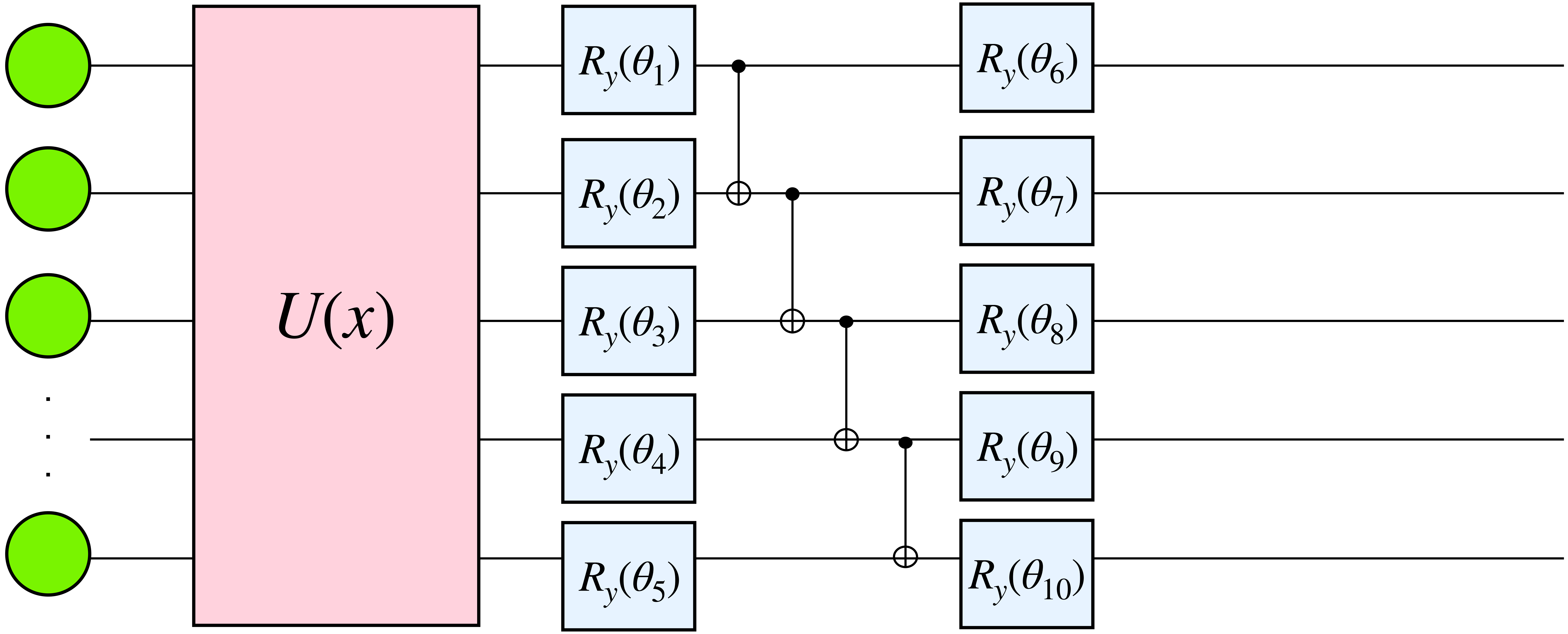
Quantum variational classifier



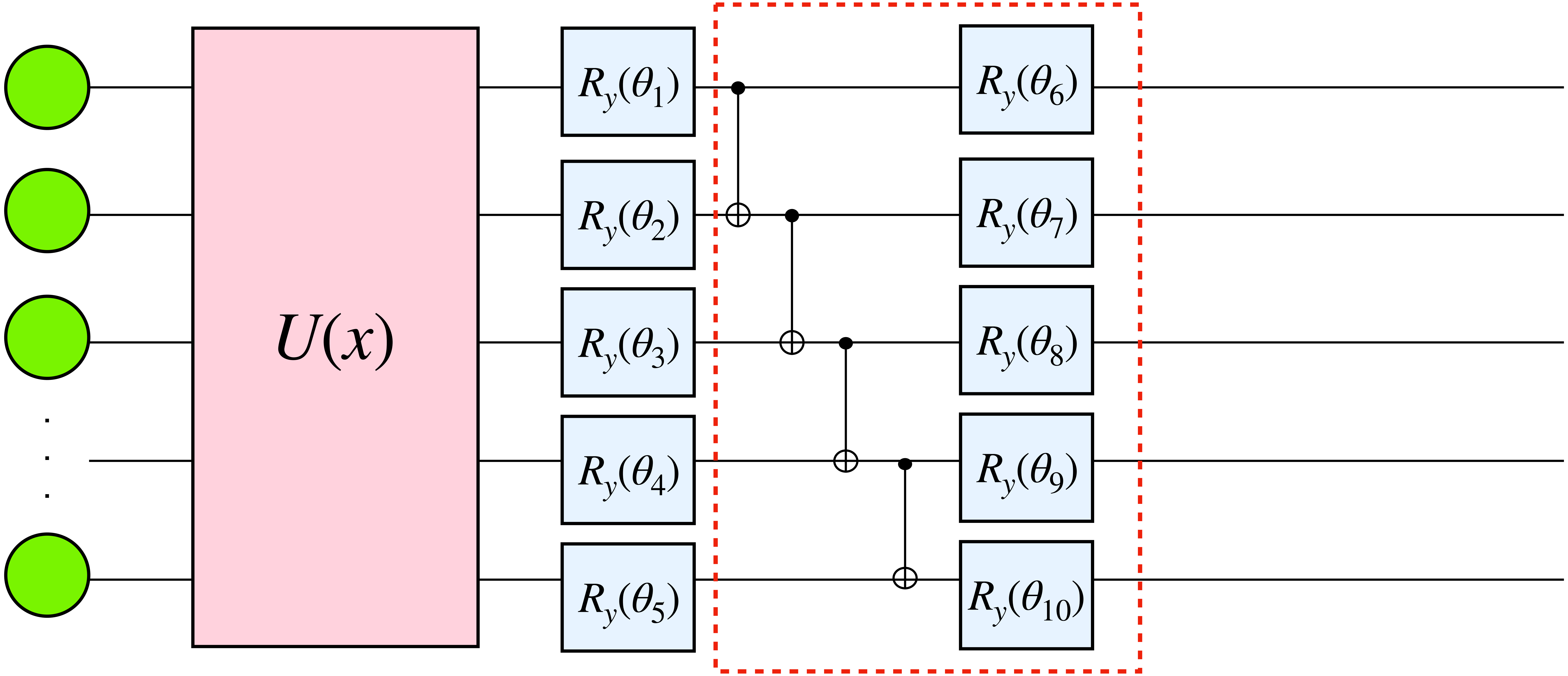
Quantum variational classifier



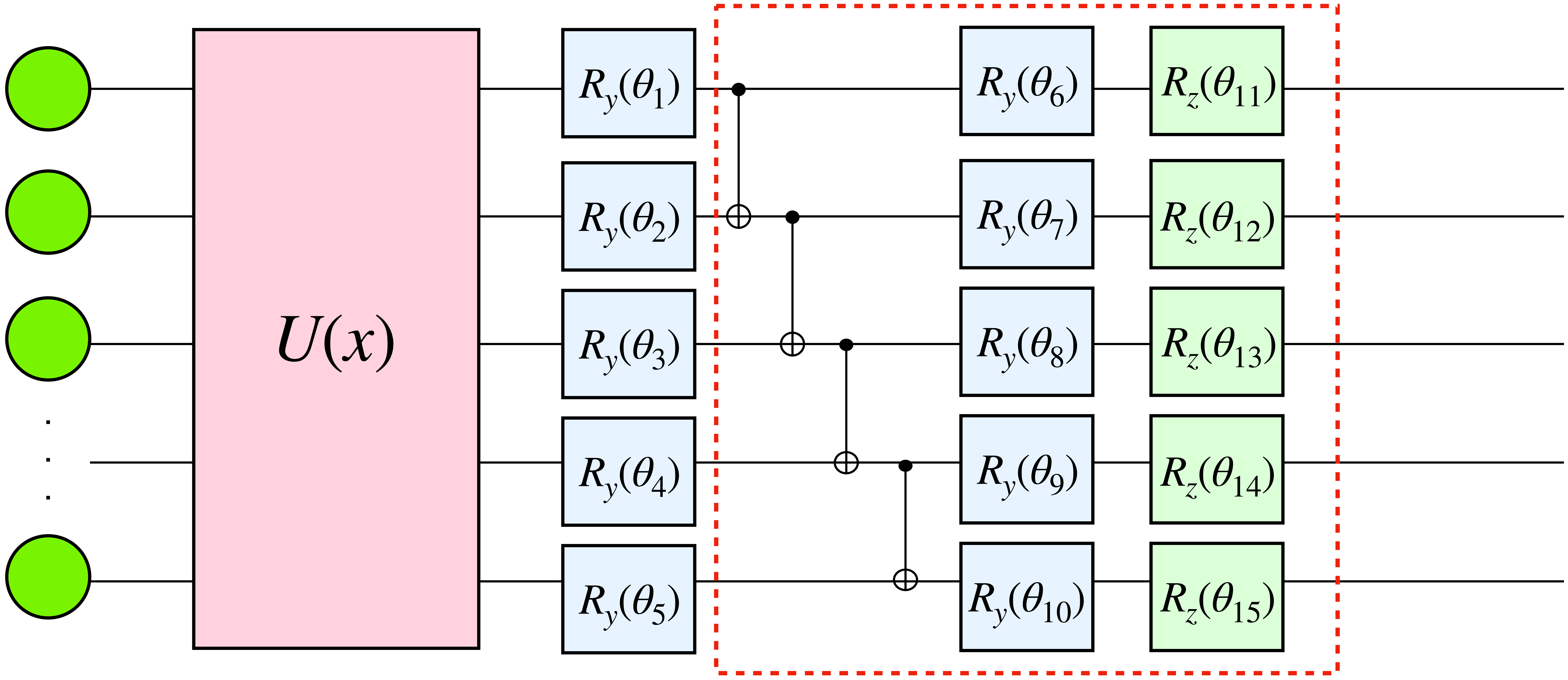
Quantum variational classifier



Quantum variational classifier

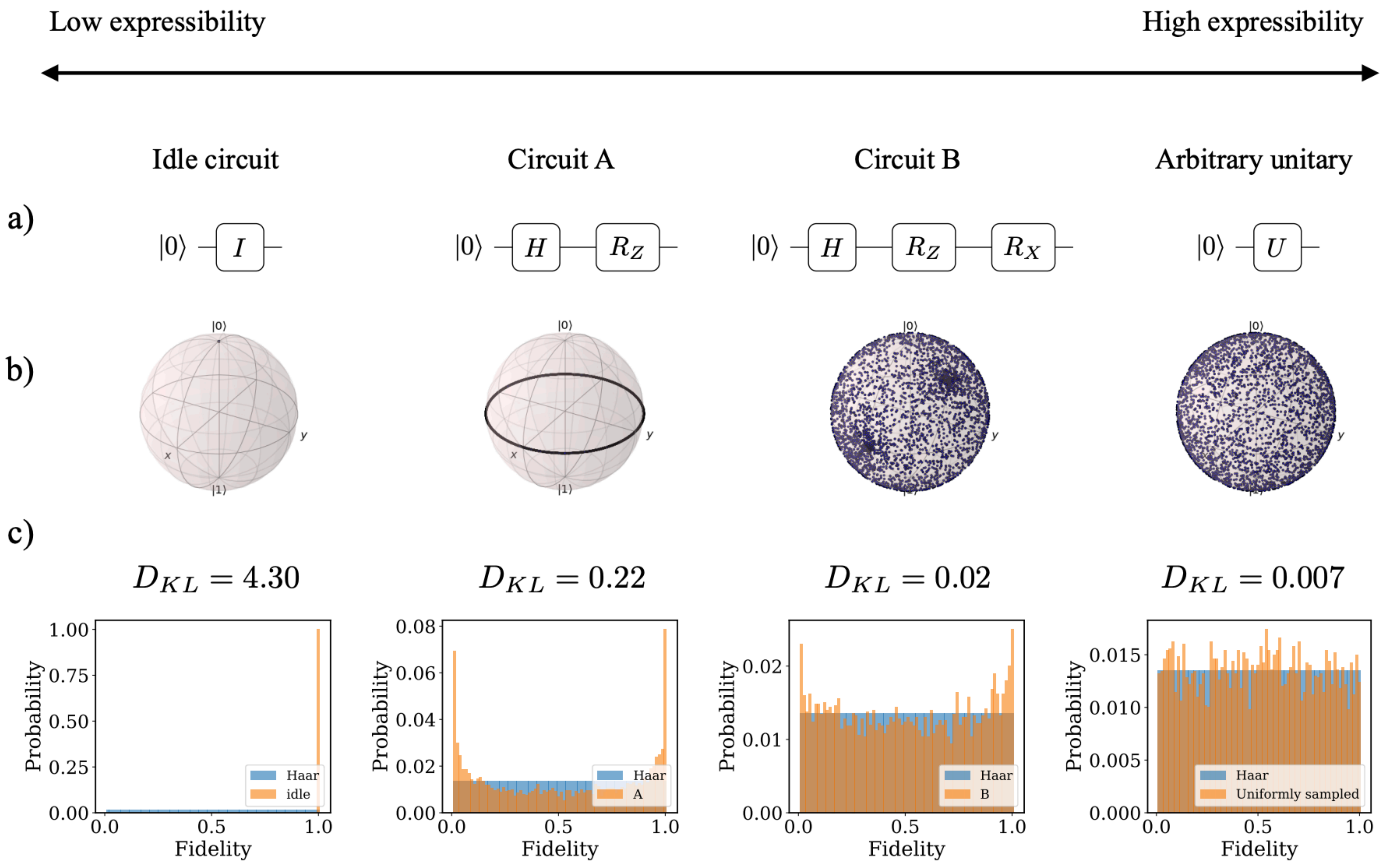


Quantum variational classifier



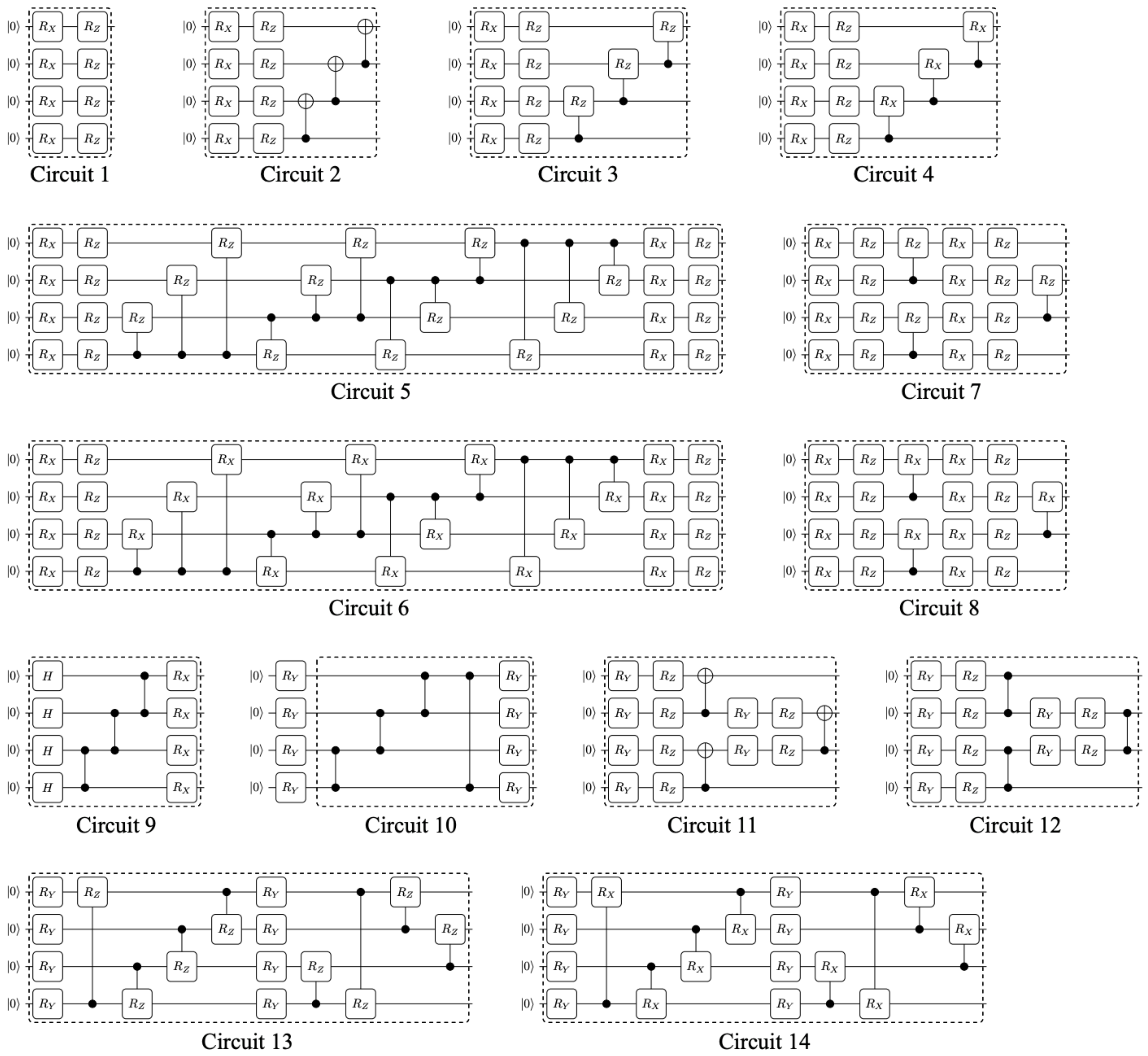
Source: Havlíček, Vojtěch, et al. "Supervised learning with quantum-enhanced feature spaces." *Nature* 567.7747 (2019): 209-212.

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.

Variational forms



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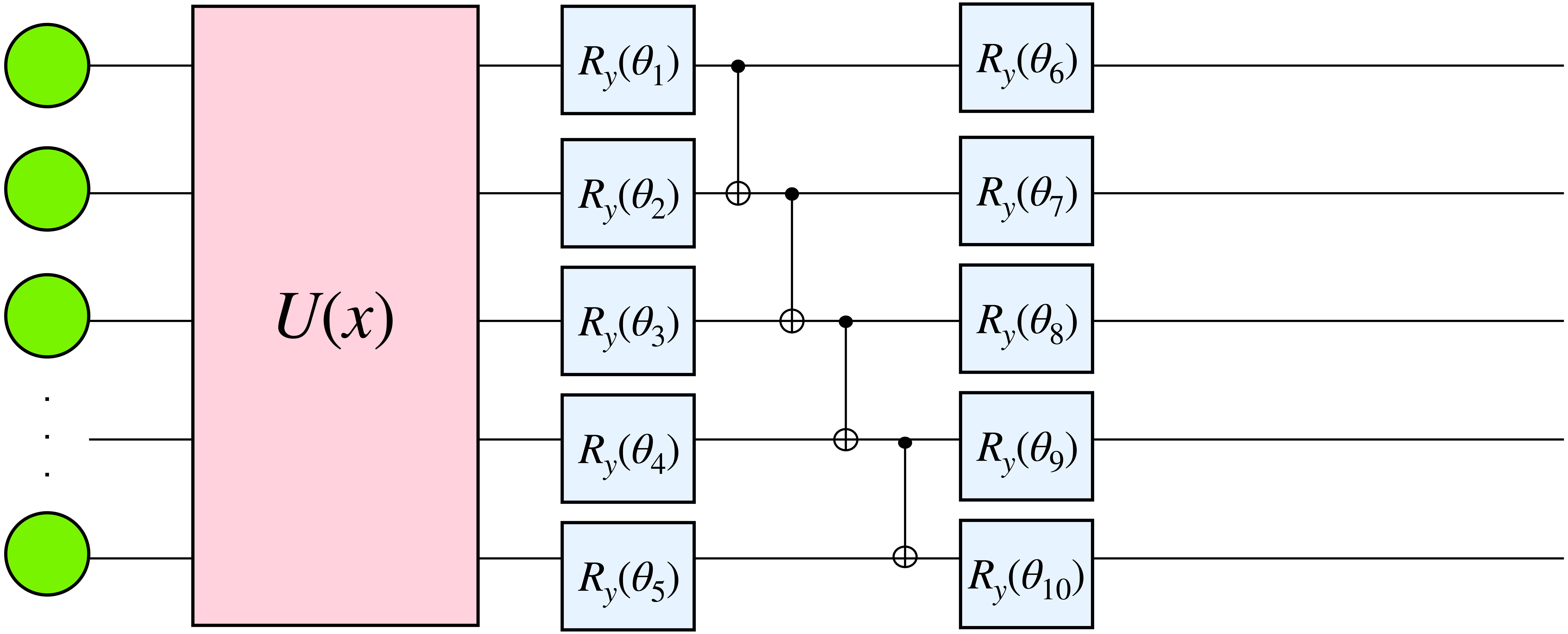
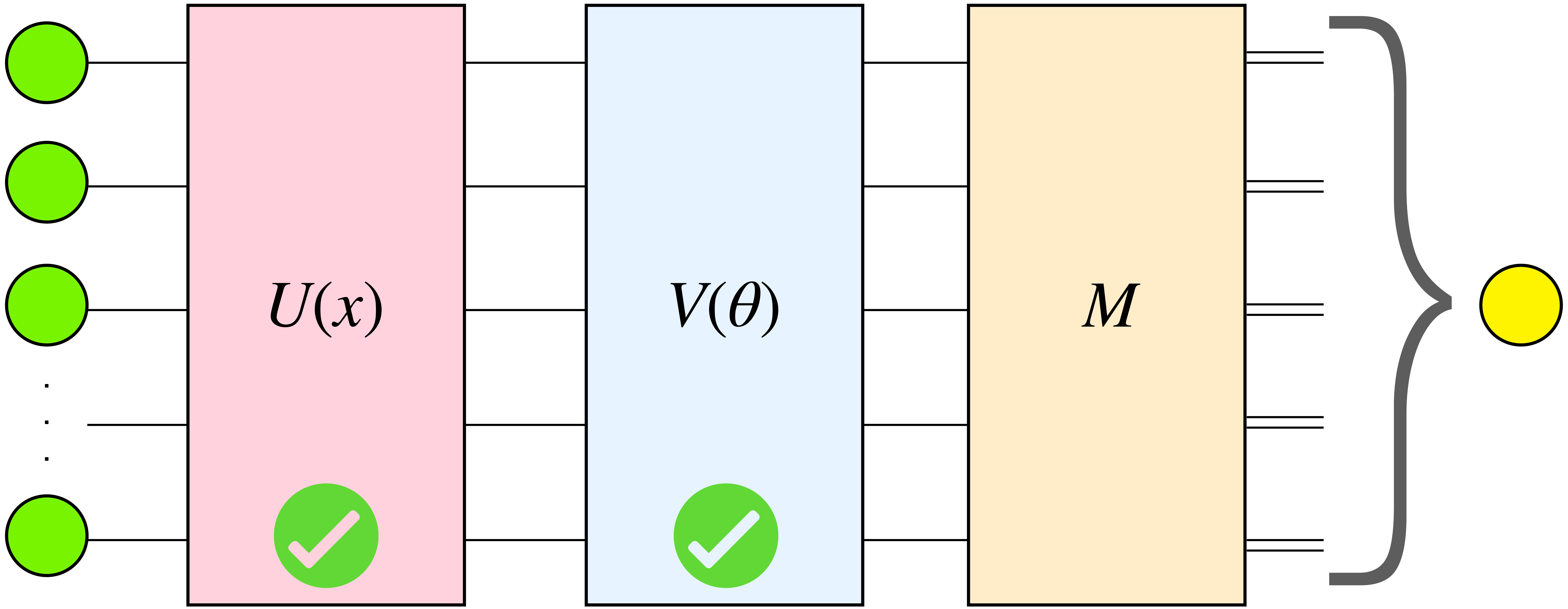
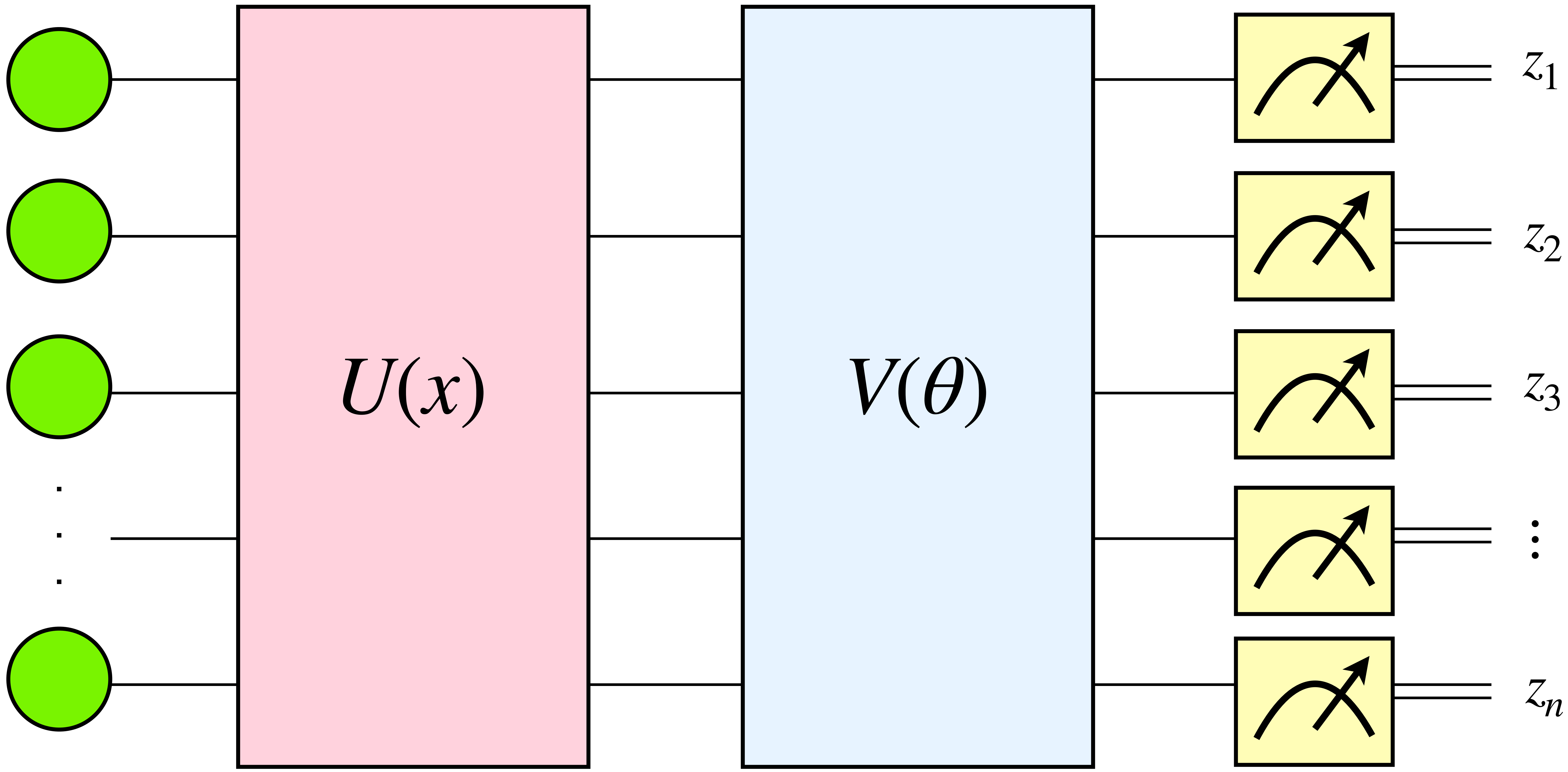
Quantum variational classifier



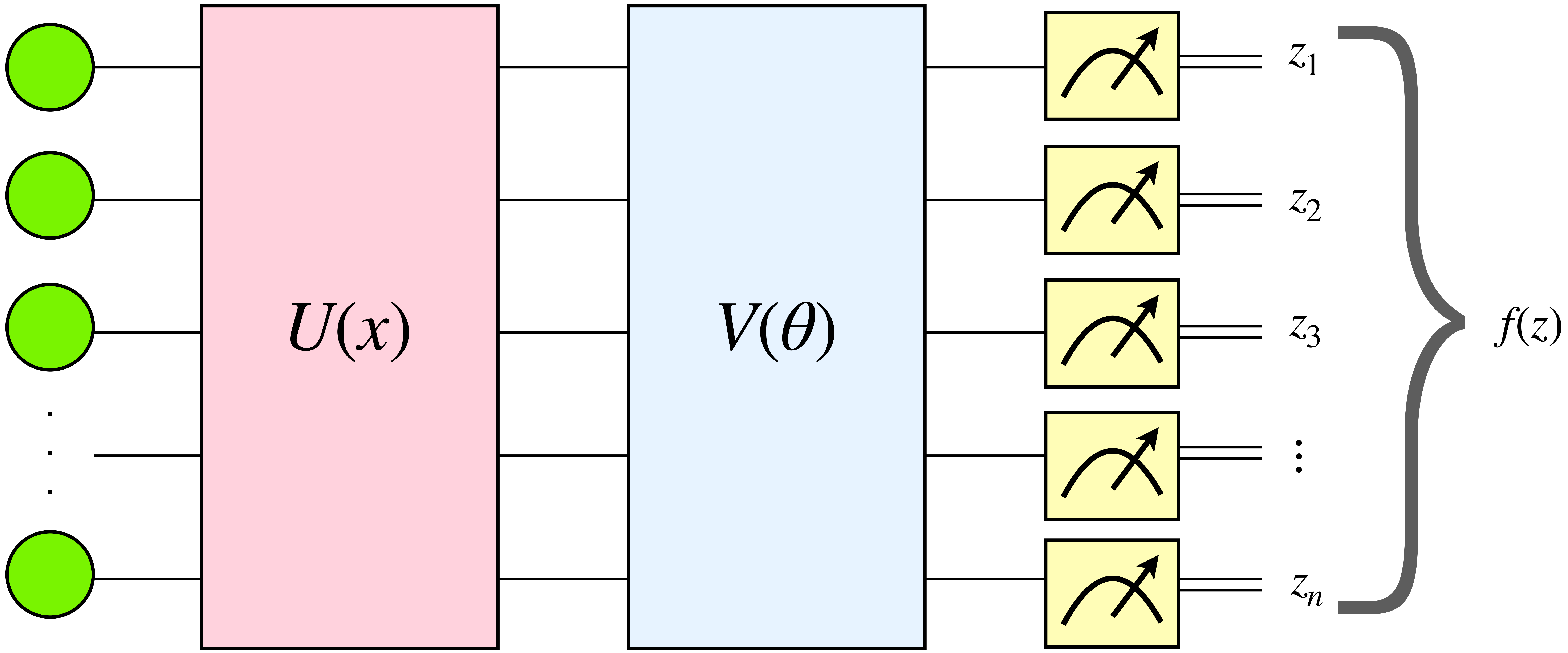
Quantum variational classifier



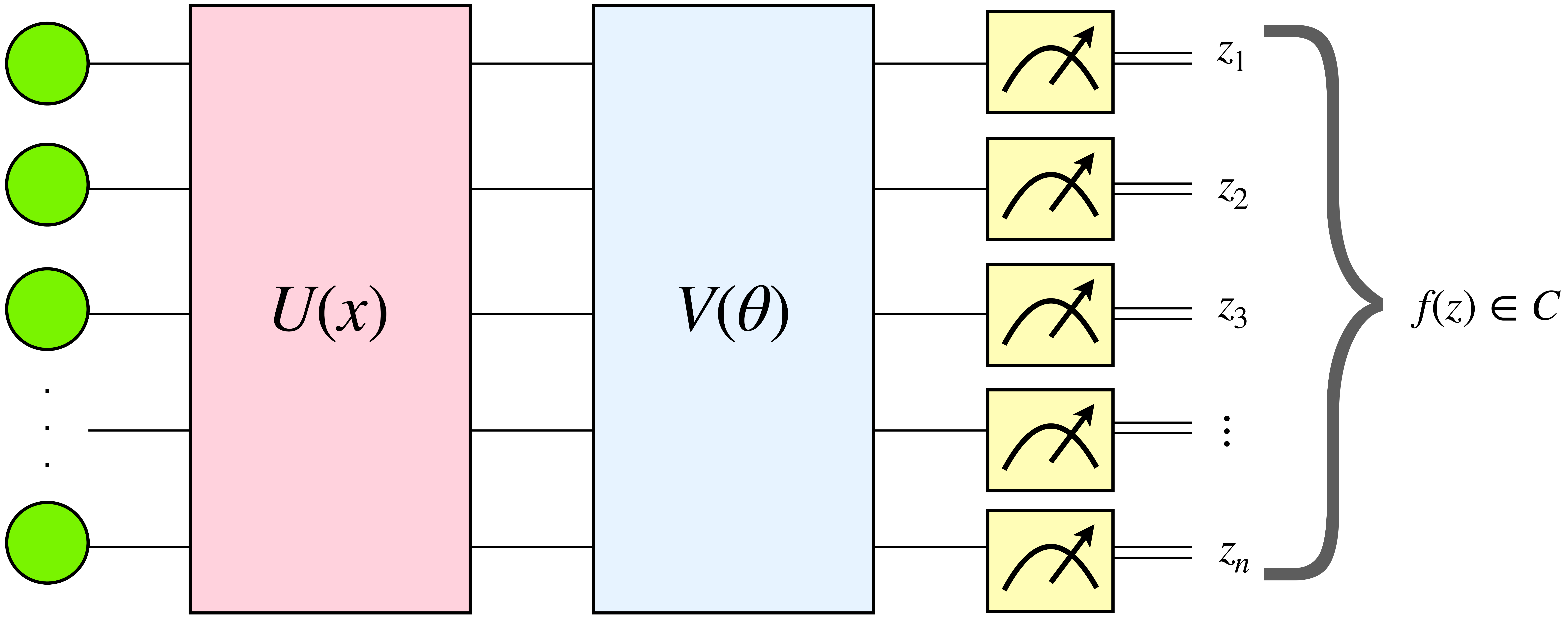
Quantum variational classifier



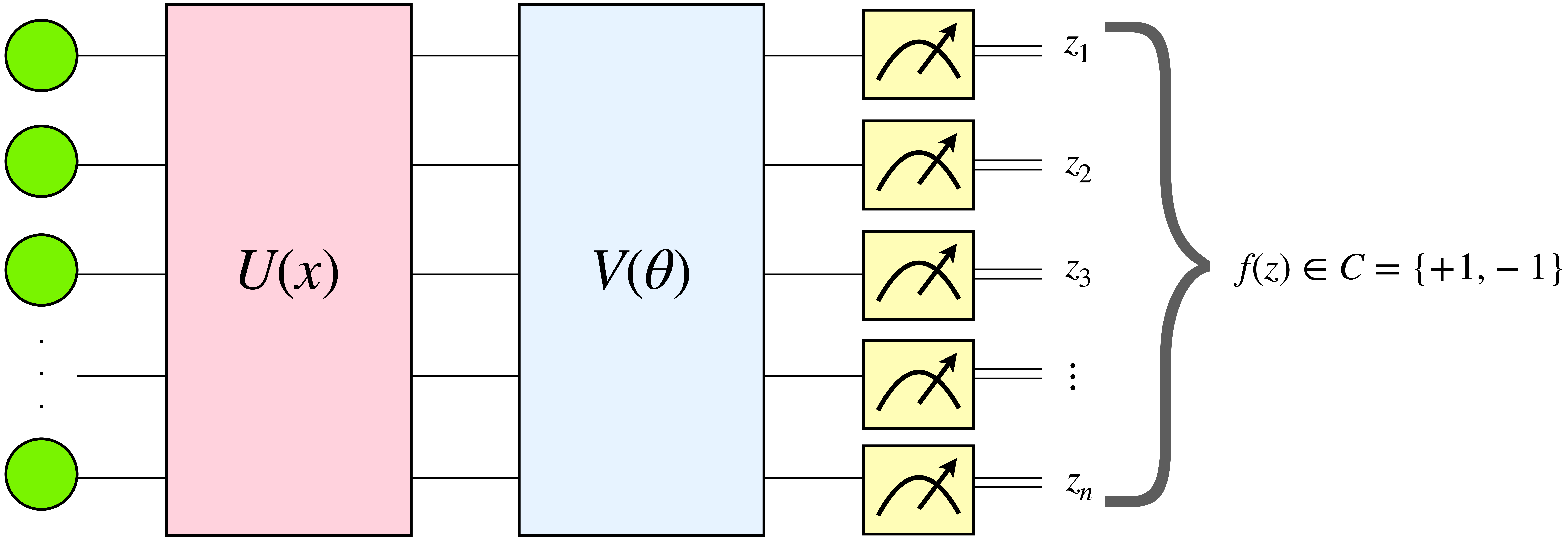
Quantum variational classifier



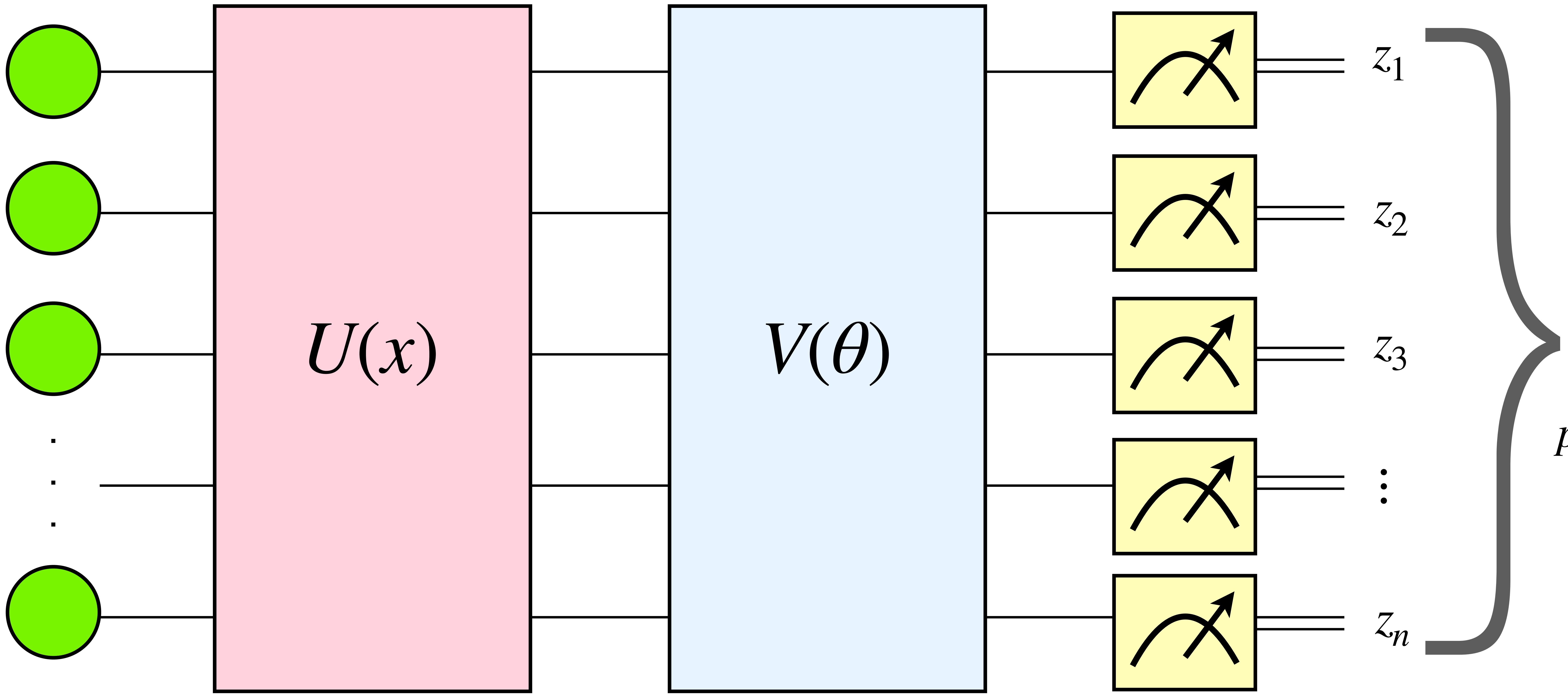
Quantum variational classifier



Quantum variational classifier



Quantum variational classifier



$$f(z) \in C = \{+1, -1\}$$

$$p_y = \langle U(x) \,|\, V^{\dagger}(\theta) M_y V(\theta \,|\, U(x) \rangle$$

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$
\begin{array}{lll}
00000 & 00001 & 00010 \\
\vdots & & \\
11101 & 11110 & 11111
\end{array}
$$

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$
\begin{array}{ccc}
00000 & 00001 & 00010 \\
\vdots & & \\
11101 & 11110 & 11111
\end{array}
$$

There will be an expectation value associated with all possible states

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$
\begin{array}{ccc}
00000 & 00001 & 00010 \\
\vdots & & \\
11101 & 11110 & 11111
\end{array}
$$

There will be an expectation value associated with all possible states

We can calculate probabilities over labels

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$\begin{array}{ccc} 00000 & 00001 & 00010 \\ \vdots & & \\ 11101 & 11110 & 11111 \end{array}$$

Compute the parity of the basis states and sum the expectation value based on the result

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

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$
\begin{array}{ccc}
00000 & 00001 & 00010 \\
\vdots & & \\
11101 & 11110 & 11111
\end{array}
$$

Compute the parity of the basis states and sum the expectation value based on the result

$$f(00000) = 0$$
$$f(00001) = 1$$

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

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$
\begin{array}{ccc}
00000 & 00001 & 00010 \\
\vdots & & \\
11101 & 11110 & 11111
\end{array}
$$

Compute the parity of the basis states and sum the expectation value based on the result

$$f(00000) = 0 \rightarrow 0.2$$
$$f(00001) = 1 \rightarrow 0.1$$

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

Quantum variational classifier

In the case of 5 qubits, there are $2^5 = 32$ possible basis states

$$\begin{array}{ccc} 00000 & 00001 & 00010 \\ \vdots & & \\ 11101 & 11110 & 11111 \end{array}$$

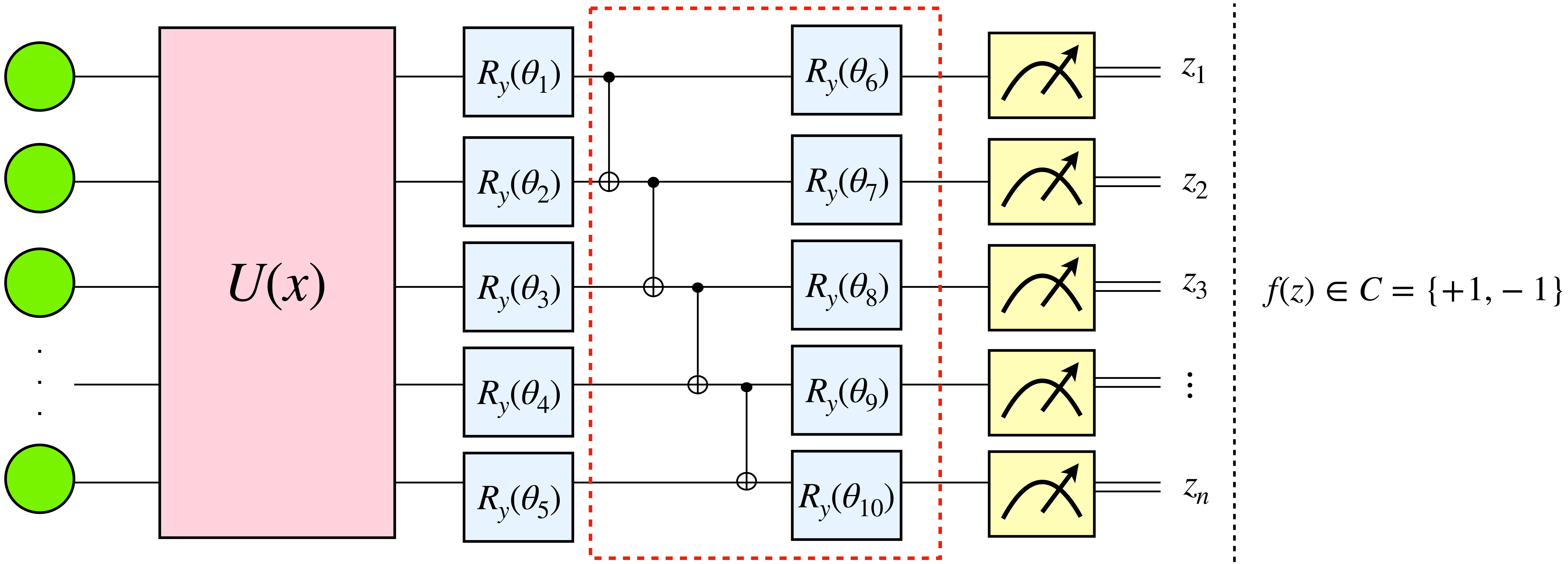
Compute the parity of the basis states and sum the expectation value based on the result

$$f(00000) = 0 \rightarrow 0.2$$
$$f(00001) = 1 \rightarrow 0.1$$

$\sum_i \langle z_i \rangle$ for basis states with even parity and map to $P(C = 1)$

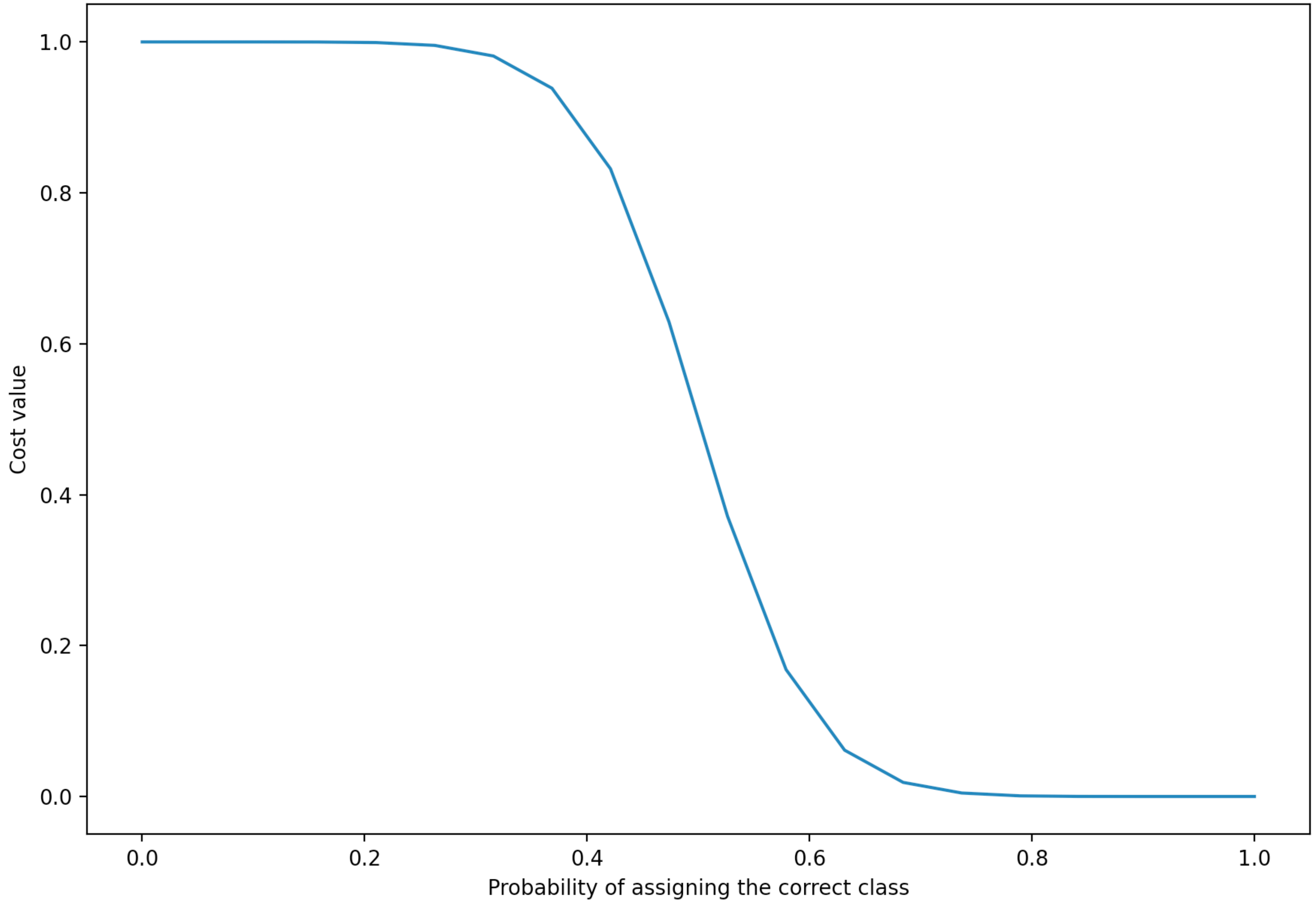
Source: Havlíček, Vojtěch, et al. "Supervised learning with quantum-enhanced feature spaces." *Nature* 567.7747 (2019): 209-212.

Quantum variational classifier



Quantum variational classifier

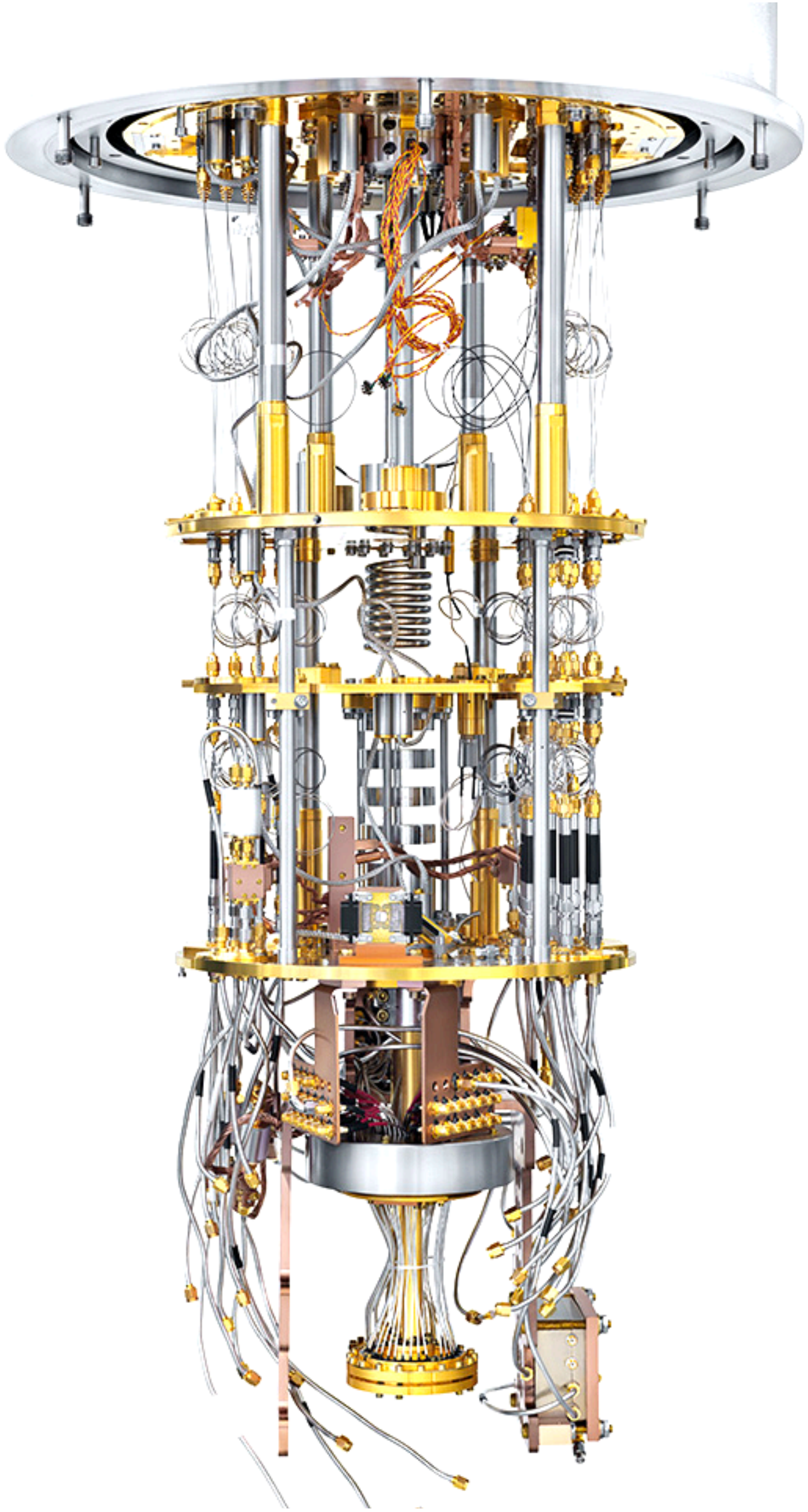
Now we can use classical cost functions



Jump to the code

Next up

Barren plateaus



Thank you!

NITheP Mini-school

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INYUVESI YAKWAZULU-NATALI

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National Institute for Theoretical Physics