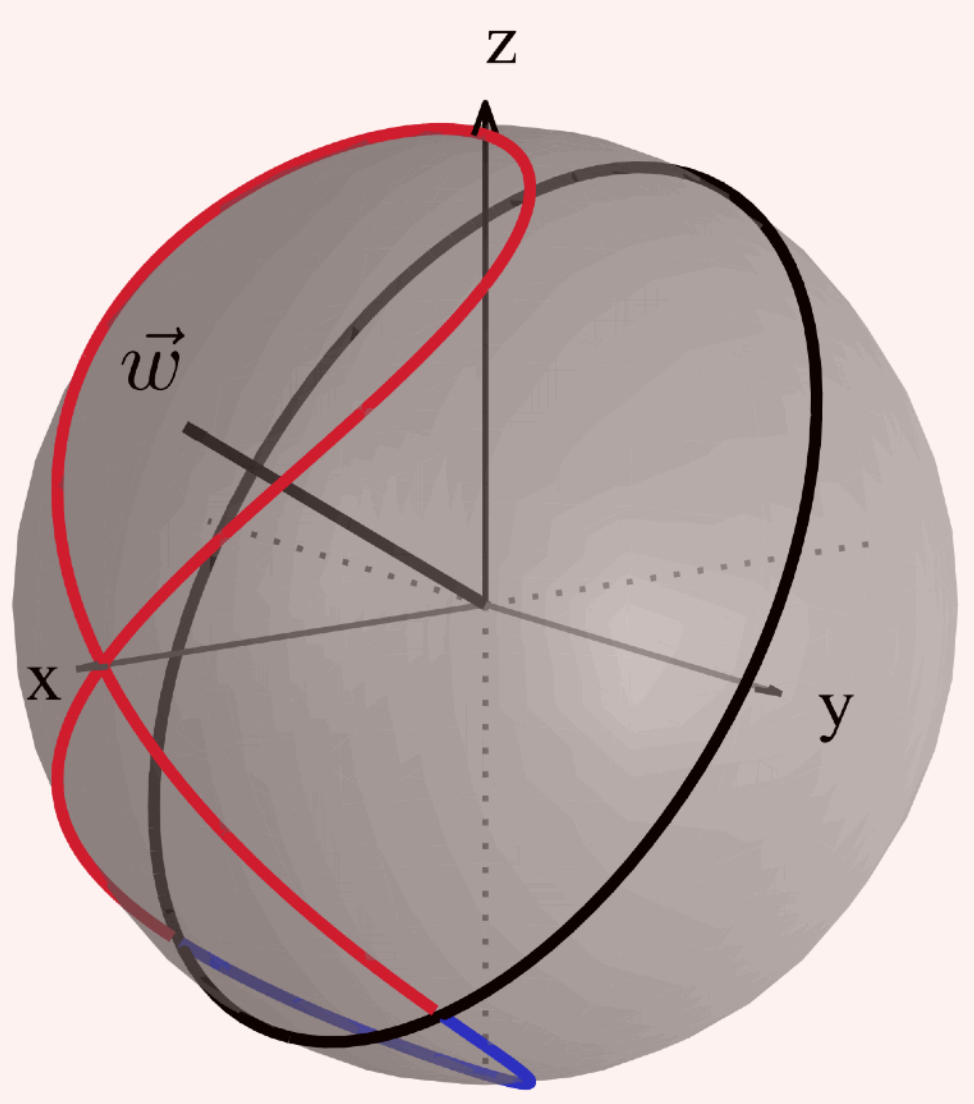


Basic programming for quantum machine learning with Qiskit and PennyLane

NITheP Mini-school

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

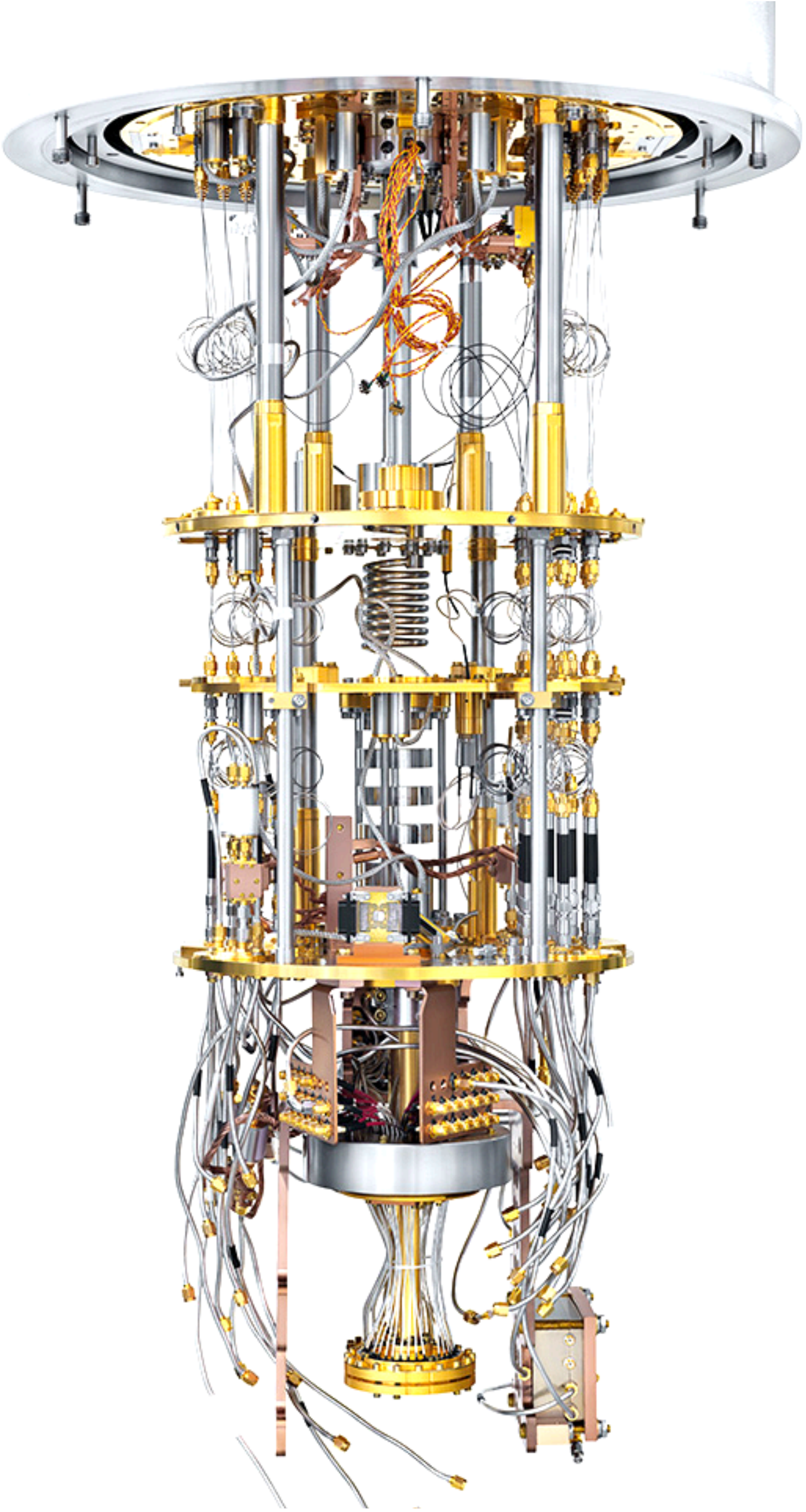
Amira Abbas

15/09/2020

NITheP
National Institute for Theoretical Physics

Previously

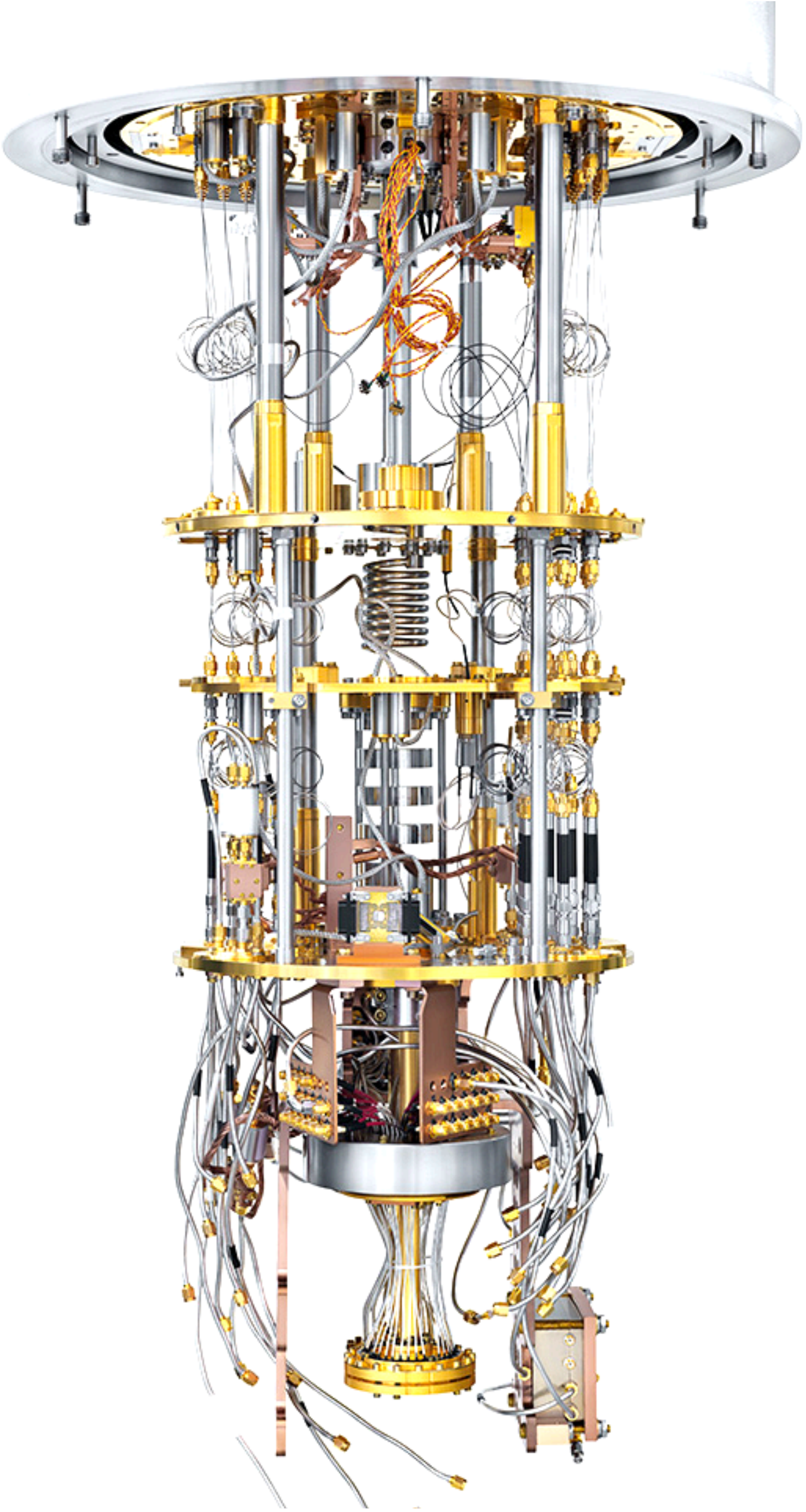
An introduction to variational circuits



Previously

An introduction to variational circuits

A simple model

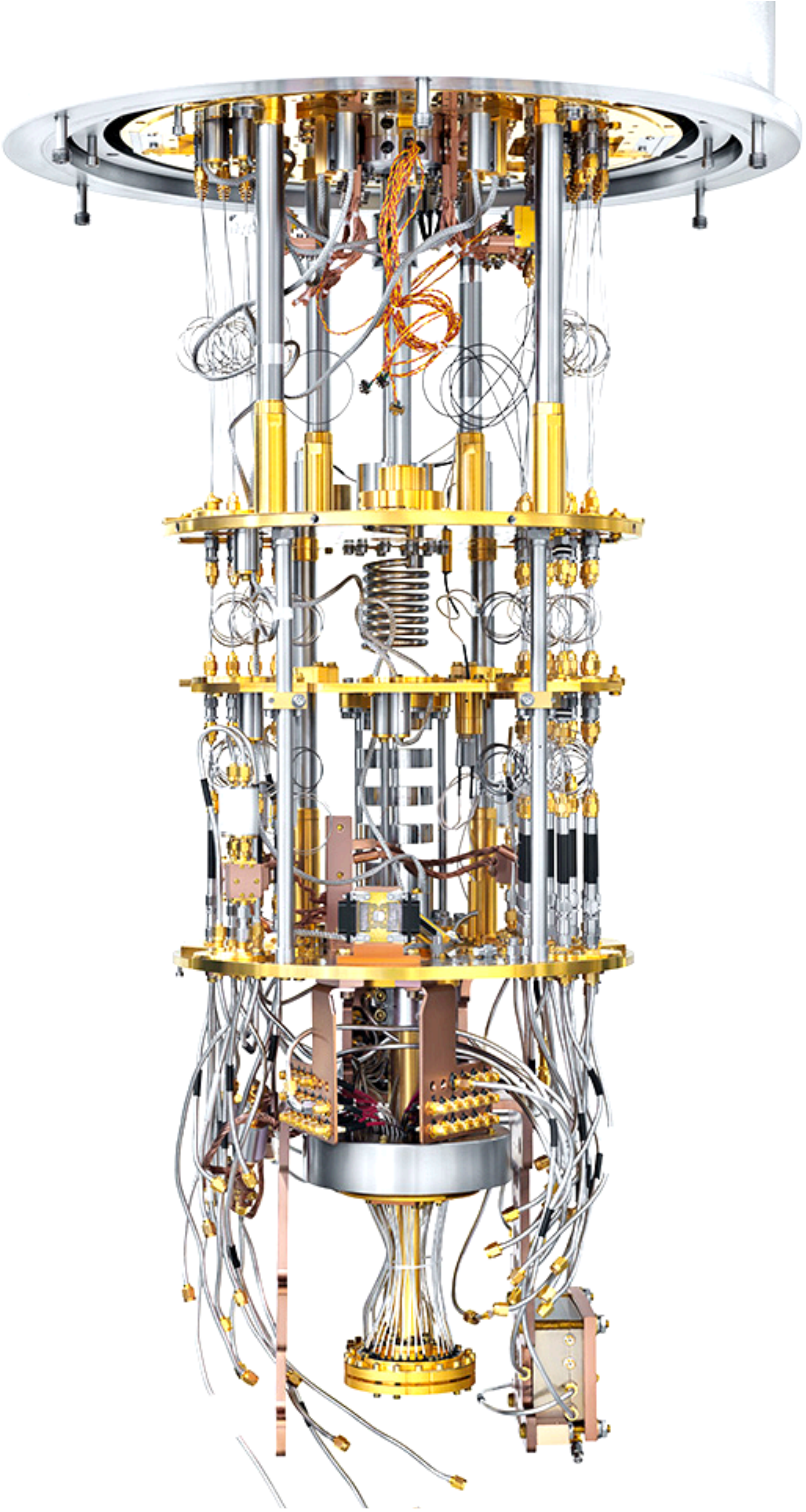


Previously

An introduction to variational circuits

A simple model

Circuit optimisation



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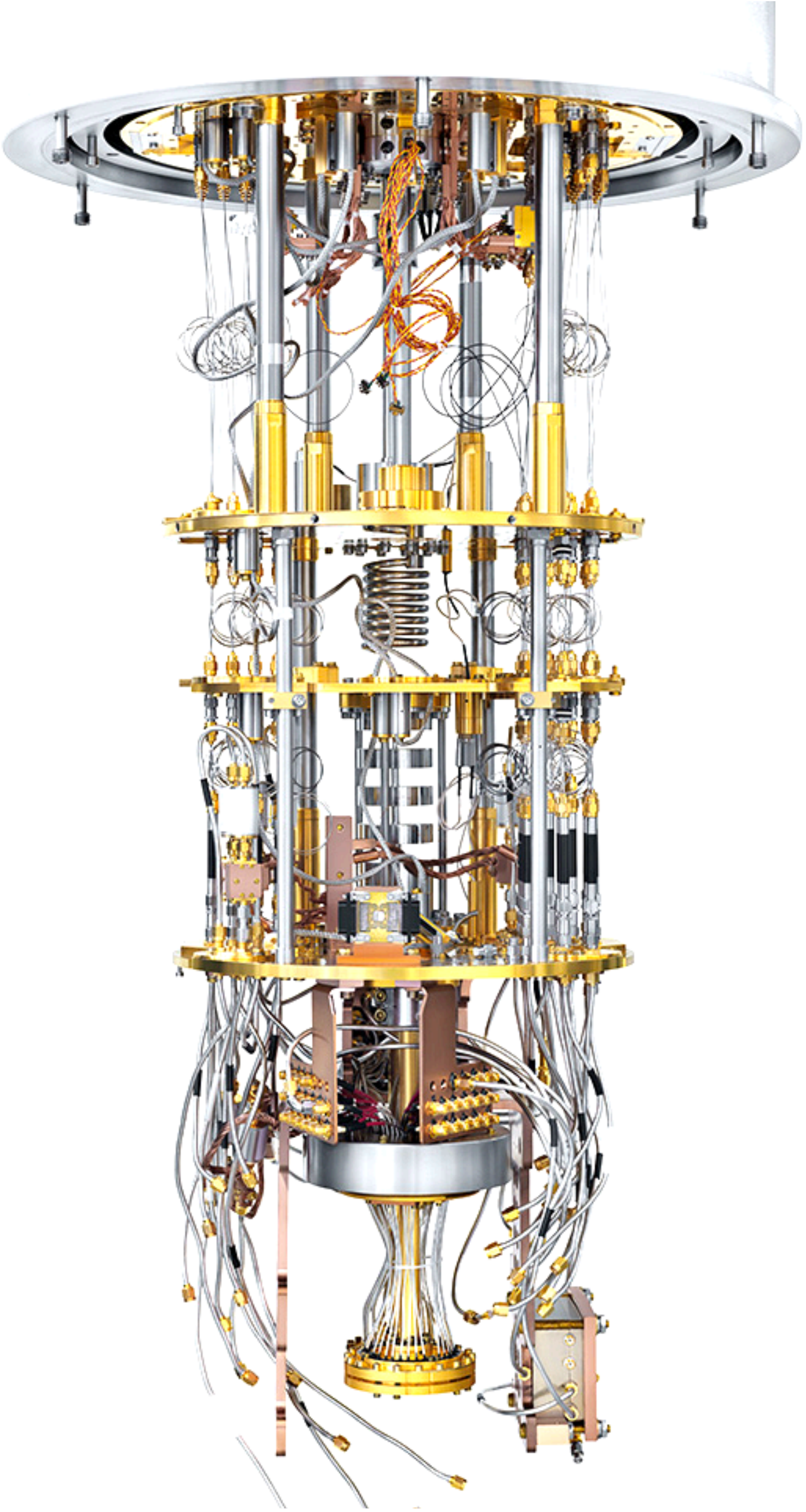
Build the model with PennyLane



Agenda

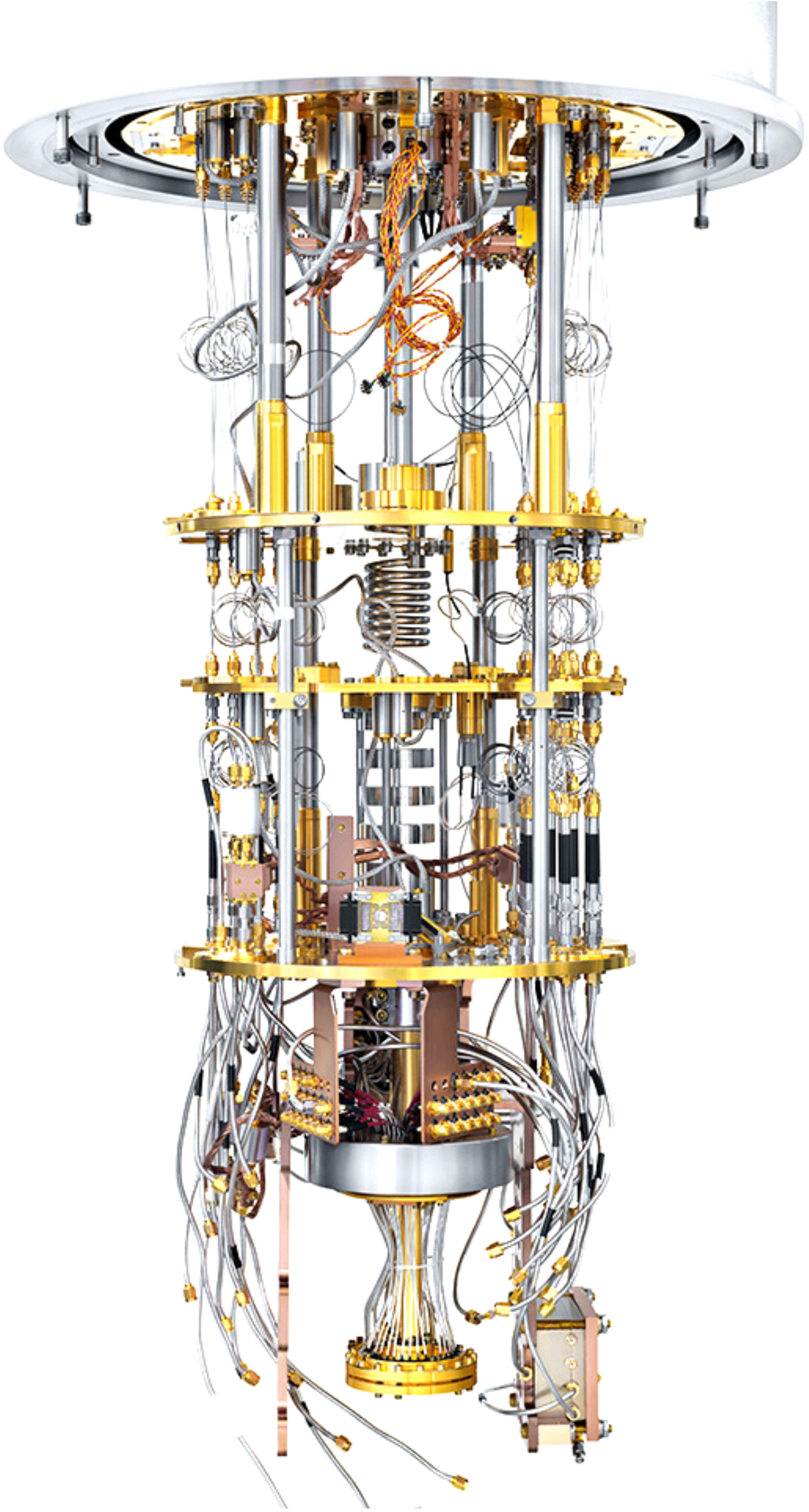
An introduction to variational circuits

A simple model

Circuit optimisation

Build the model with PennyLane

Data encoding techniques



Agenda

An introduction to variational circuits

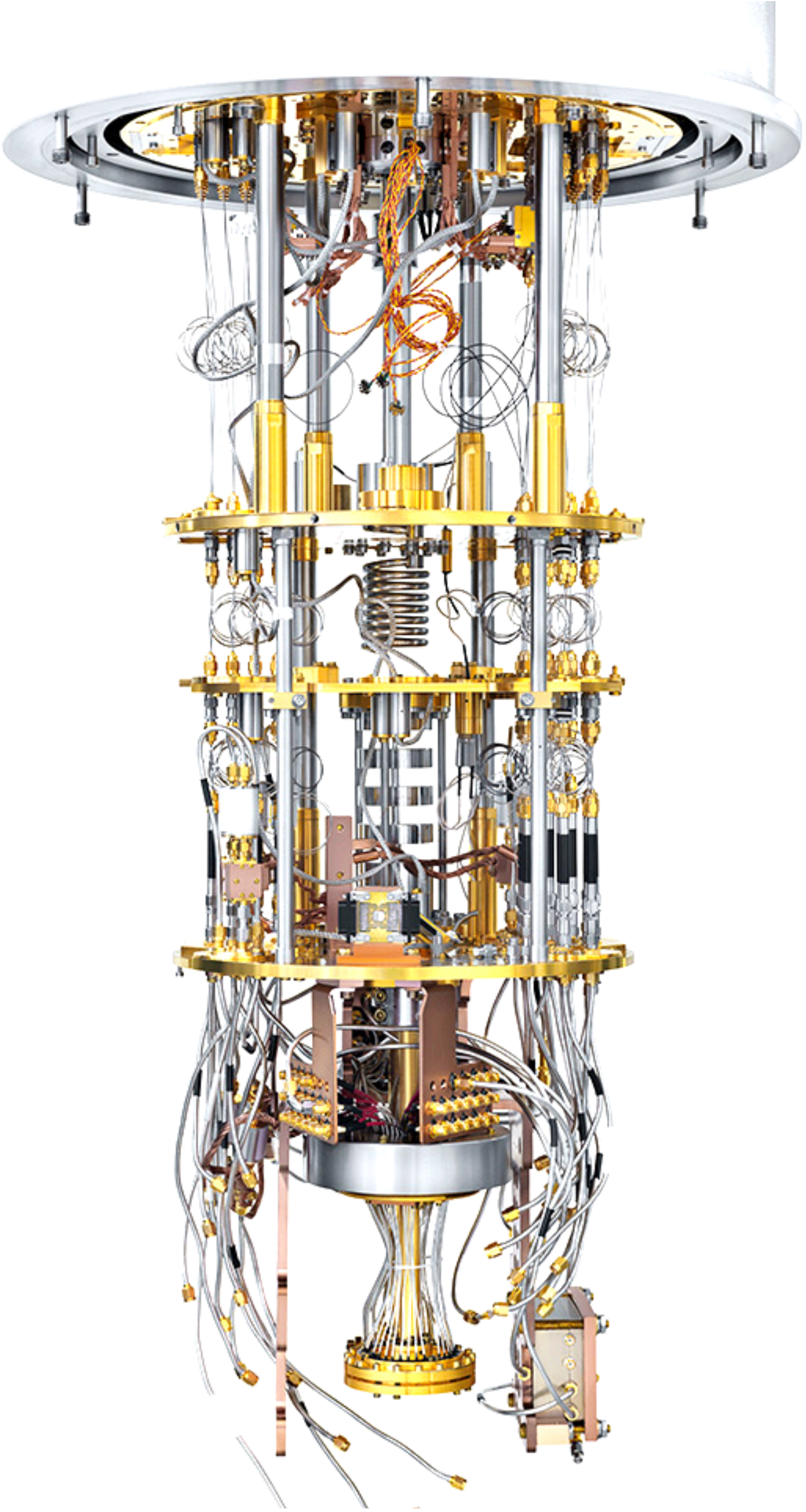
A simple model

Circuit optimisation

Build the model with PennyLane

Data encoding techniques

Create circuits and encode data with PennyLane and Qiskit



Getting data into a quantum computer

Data encoding

- State preparation routines
  - Quantum circuits for general multi-qubit gates: https://arxiv.org/pdf/quant-ph/0404089.pdf
  - Quantum-state preparation with universal gate decompositions: https://arxiv.org/pdf/1003.5760.pdf
  - Quantum Networks for generating arbitrary quantum states: https://arxiv.org/pdf/quant-ph/0407102.pdf

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  - Amplitude encoding - https://arxiv.org/pdf/1703.10793.pdf
  - Angle encoding - https://arxiv.org/pdf/1711.11240.pdf
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- Open research question

Basis encoding

Basis encoding

Binary dataset D where each $x^m \in D$ is a binary string of the form $x^m = (b_1^m, \ldots, b_N^m)$ with $b_i^m \in \{0,1\}$ for $i = 1, \ldots, N$.

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

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

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

Basis encoding

For example,

$$x^1 = (0,\ 1)^{\mathrm{T}}$$
$$x^2 = (1,\ 1)^{\mathrm{T}}$$

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

Basis encoding

For example,

$$x^1 = (0,\ 1)^{\mathrm{T}} \ \rightarrow |01\rangle$$
$$x^2 = (1,\ 1)^{\mathrm{T}} \ \rightarrow |11\rangle$$

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

Basis encoding

For example,

$$x^1 = (0,\ 1)^{\mathrm{T}}$$
$$x^2 = (1,\ 1)^{\mathrm{T}}$$

Creating a superposition of states using 2 qubits:

$$\frac{1}{\sqrt{4}}\big(\,|00\rangle \ + \ |01\rangle + \ |10\rangle \ + \ |11\rangle\big)$$

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

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$$\frac{1}{\sqrt{4}}\big(|00\rangle + |01\rangle + |10\rangle + |11\rangle\big)$$

$$\left(\frac{1}{\sqrt{4}}, \quad \frac{1}{\sqrt{4}}, \quad \frac{1}{\sqrt{4}}, \quad \frac{1}{\sqrt{4}}\right)^{\mathrm{T}}$$

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

Basis encoding

For example,

$$x^1 = (0,\ 1)^{\mathrm{T}}$$
$$x^2 = (1,\ 1)^{\mathrm{T}}$$

Creating a superposition of states using 2 qubits:

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

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

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

Basis encoding

For example,

$$x^1 = (0,\ 1)^{\mathrm{T}}$$
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Creating a superposition of states using 2 qubits:

$$|D\rangle = \frac{1}{\sqrt{2}}|01\rangle + \frac{1}{\sqrt{2}}|11\rangle$$

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Basis encoding

For example,

$$x^1 = (01,\ 01)^{\mathrm{T}}$$
$$x^2 = (11,\ 10)^{\mathrm{T}}$$

Creating a superposition of states using 4 qubits:

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

Basis encoding

For example,

$$x^1 = (01,\ 01)^{\mathrm{T}}$$
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Creating a superposition of states using 4 qubits:

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Basis encoding

For example,

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Creating a superposition of states using 4 qubits:

$$|D\rangle = \frac{1}{\sqrt{2}}|0101\rangle \ + \ \frac{1}{\sqrt{2}}|1110\rangle$$

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

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

Basis encoding

- Amplitude vector becomes very sparse in higher dimensions
- Most freedom to do computation
- Schemes are not always efficient
- Ventura, Dan, and Tony Martinez. "Quantum associative memory." Information Sciences 124.1-4 (2000): 273-296.

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

Amplitude encoding

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For example,

$$x^1 = (0.888,\ -1.25)^{\mathrm{T}}$$
$$x^2 = (-0.23,\ 0.992)^{\mathrm{T}}$$

Amplitude encoding

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$$x^1 = (0.888,\ -1.25)^{\mathrm{T}}$$
$$x^2 = (-0.23,\ 0.992)^{\mathrm{T}}$$

$$\downarrow$$

$$(0.888,\ -1.25,\ -0.23,\ 0.992)^{\mathrm{T}}$$

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

Amplitude encoding

For example,

$$x^1 = (0.888,\ -1.25)^{\mathrm{T}}$$
$$x^2 = (-0.23,\ 0.992)^{\mathrm{T}}$$

$$\downarrow$$

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

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

Amplitude encoding

$$|D\rangle = \frac{1}{\sqrt{2^n}} \sum_{i=1}^{2^n} x_i |i\rangle$$

Amplitude encoding

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

Amplitude encoding

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

Amplitude encoding

$$|D\rangle = \frac{1}{\sqrt{2^n}} \sum_{i=1}^{2^n} x_i |i\rangle \longrightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x^{1024} \end{bmatrix}$$

$$2^n = 1024$$

Amplitude encoding

$$|D\rangle = \frac{1}{\sqrt{2^n}} \sum_{i=1}^{2^n} x_i |i\rangle \longrightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x^{1024} \end{bmatrix}$$

$$2^n = 1024,\ n = 10$$

Angle encoding

Angle encoding

For example,

$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \end{bmatrix} \qquad x^2 = \begin{bmatrix} -0.23 \\ 0.992 \end{bmatrix}$$

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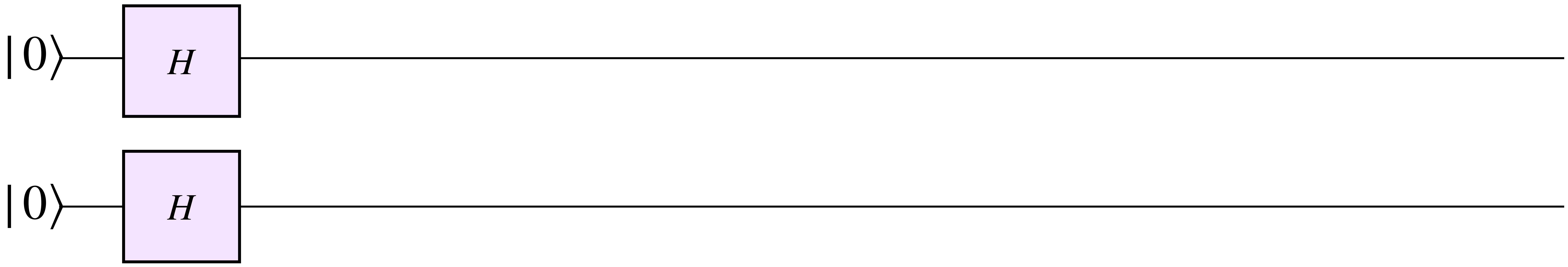

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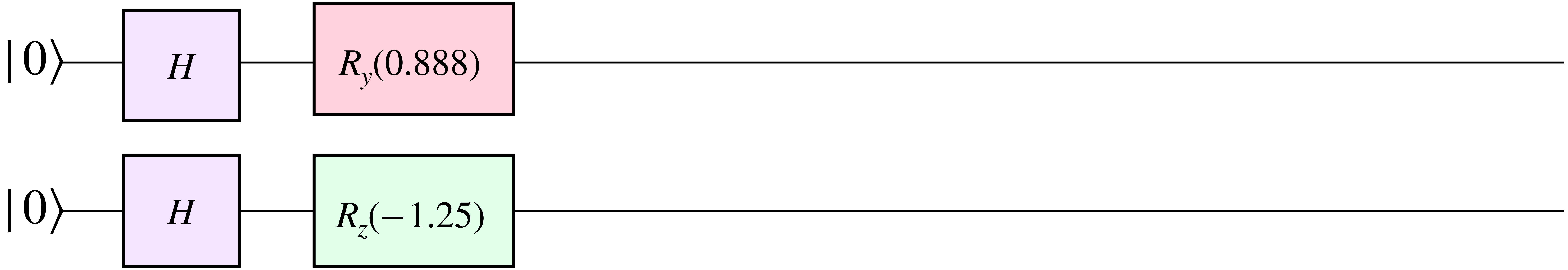

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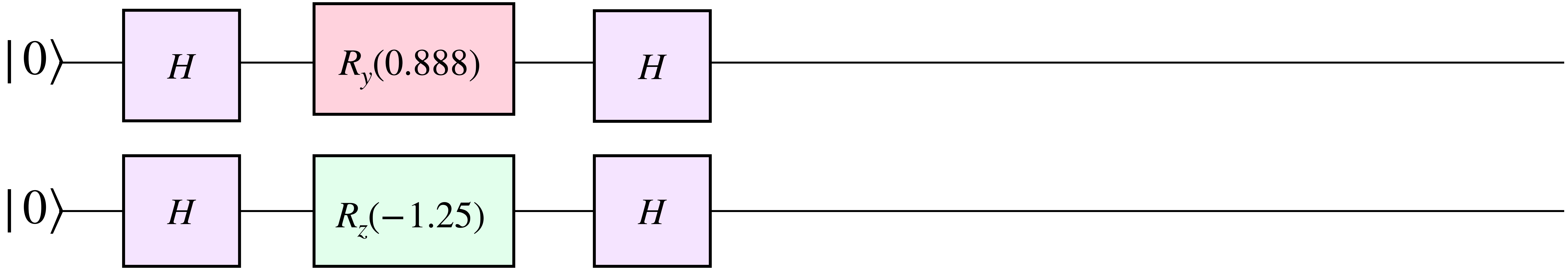

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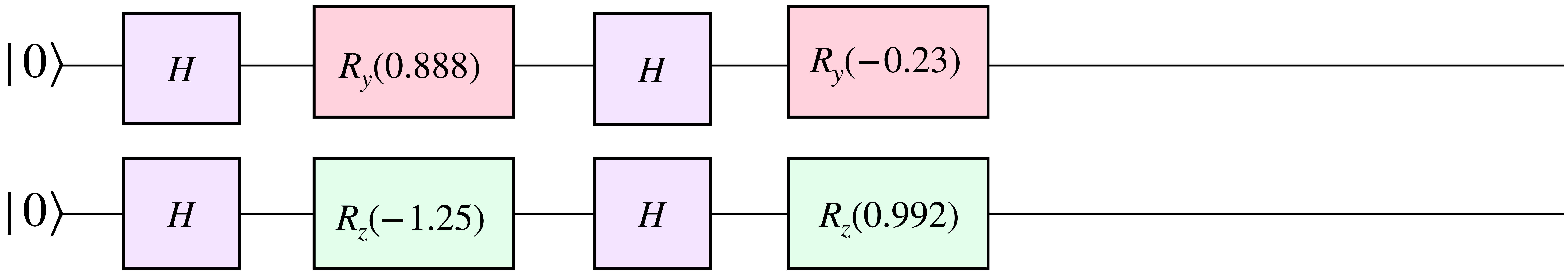
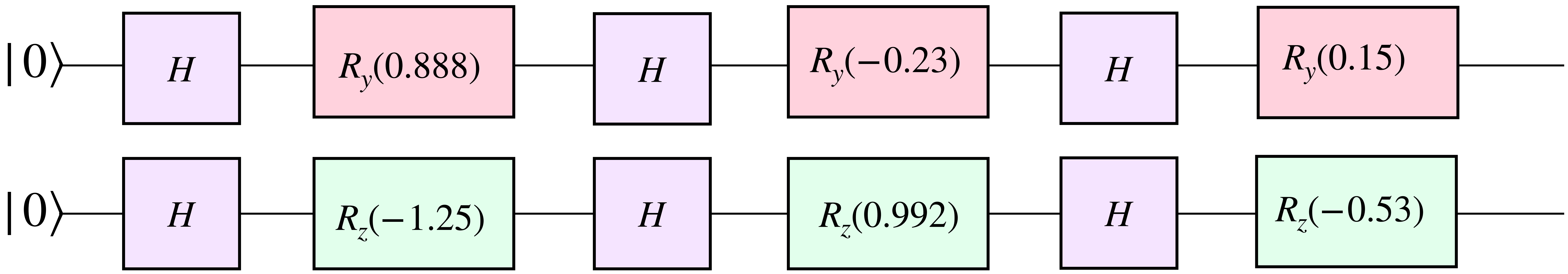


Angle encoding

For example,

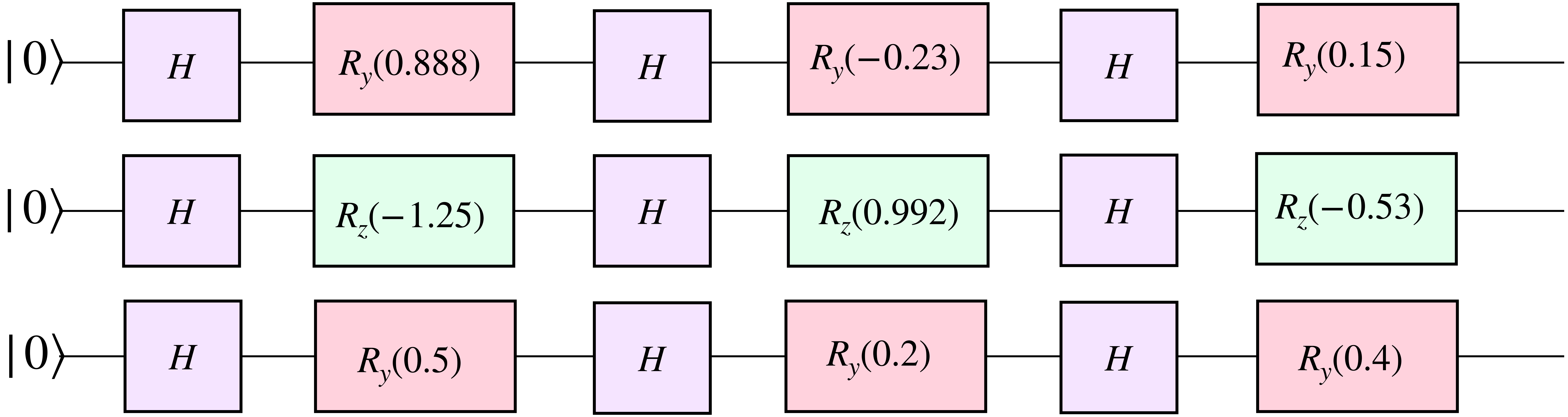
$$x^1 = \begin{bmatrix} 0.888 \\ -1.25 \end{bmatrix} \qquad x^2 = \begin{bmatrix} -0.23 \\ 0.992 \end{bmatrix} \qquad x^3 = \begin{bmatrix} 0.15 \\ -0.53 \end{bmatrix}$$



Angle encoding

For example,

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



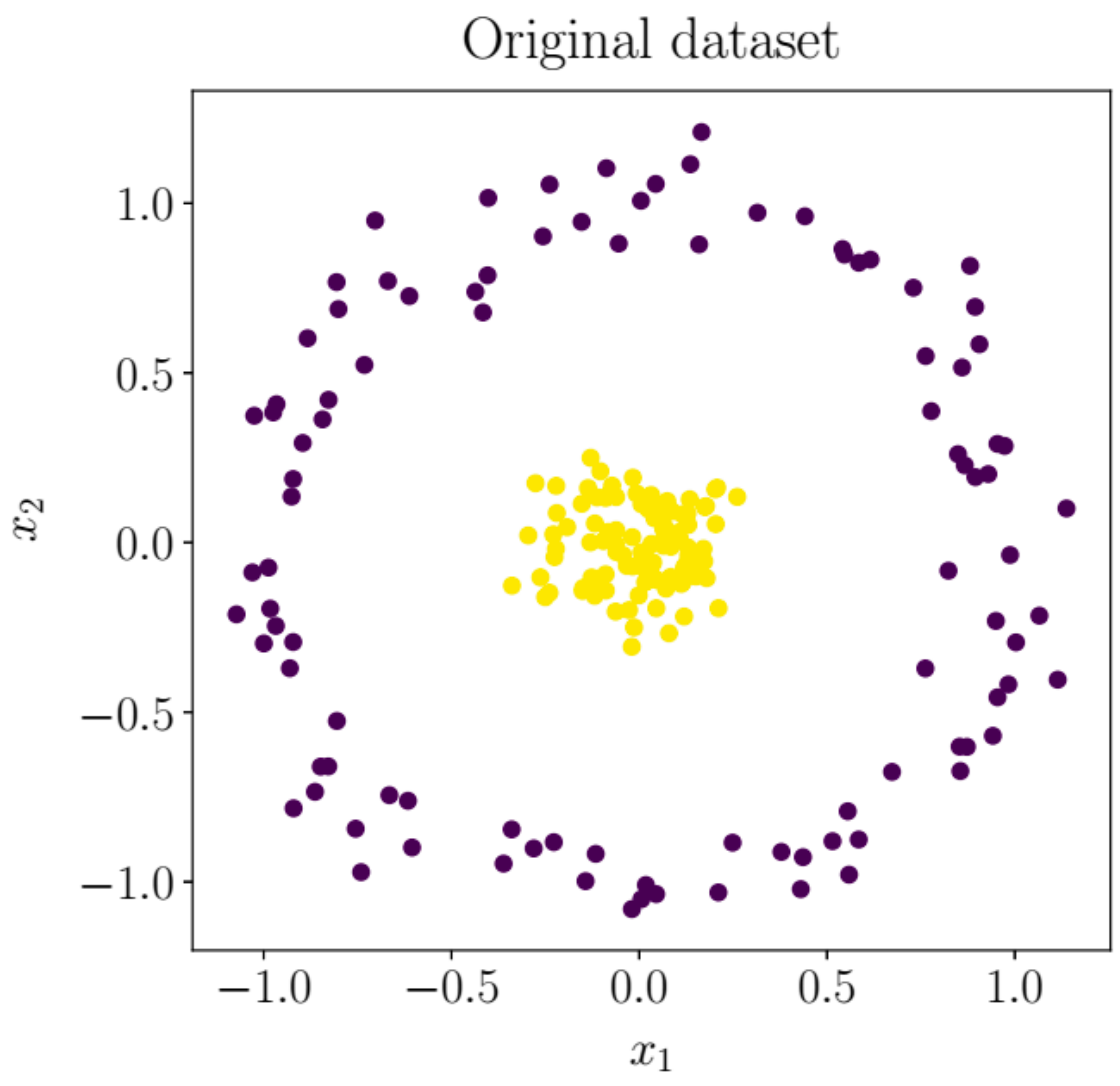
Angle encoding

- Simple, intuitive
- Inexpensive
- Schuld, Maria, Ryan Sweke, and Johannes Jakob Meyer. "The effect of data encoding on the expressive power of variational quantum machine learning models." arXiv preprint arXiv:2008.08605 (2020).

Quantum feature maps

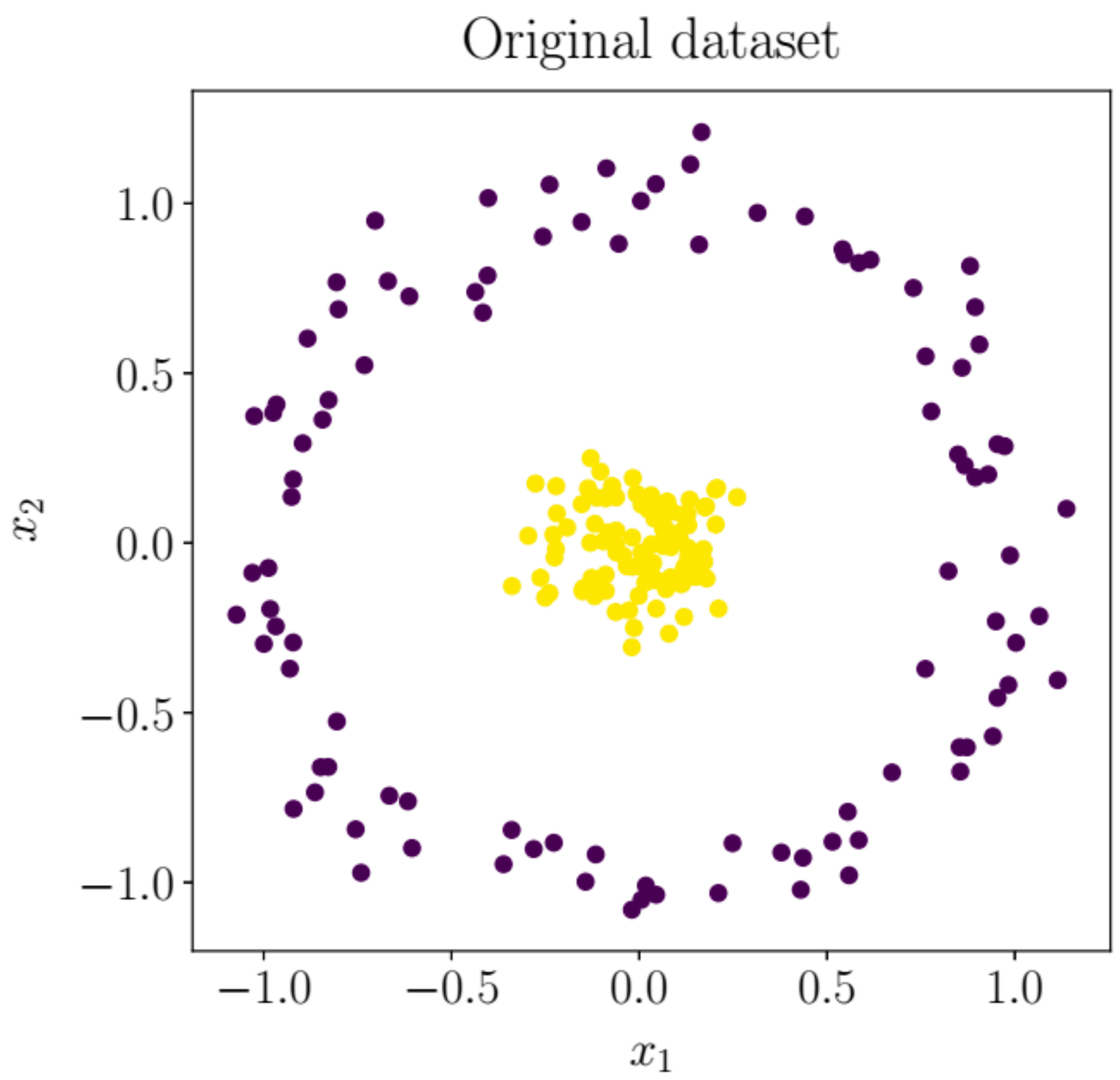
Feature maps

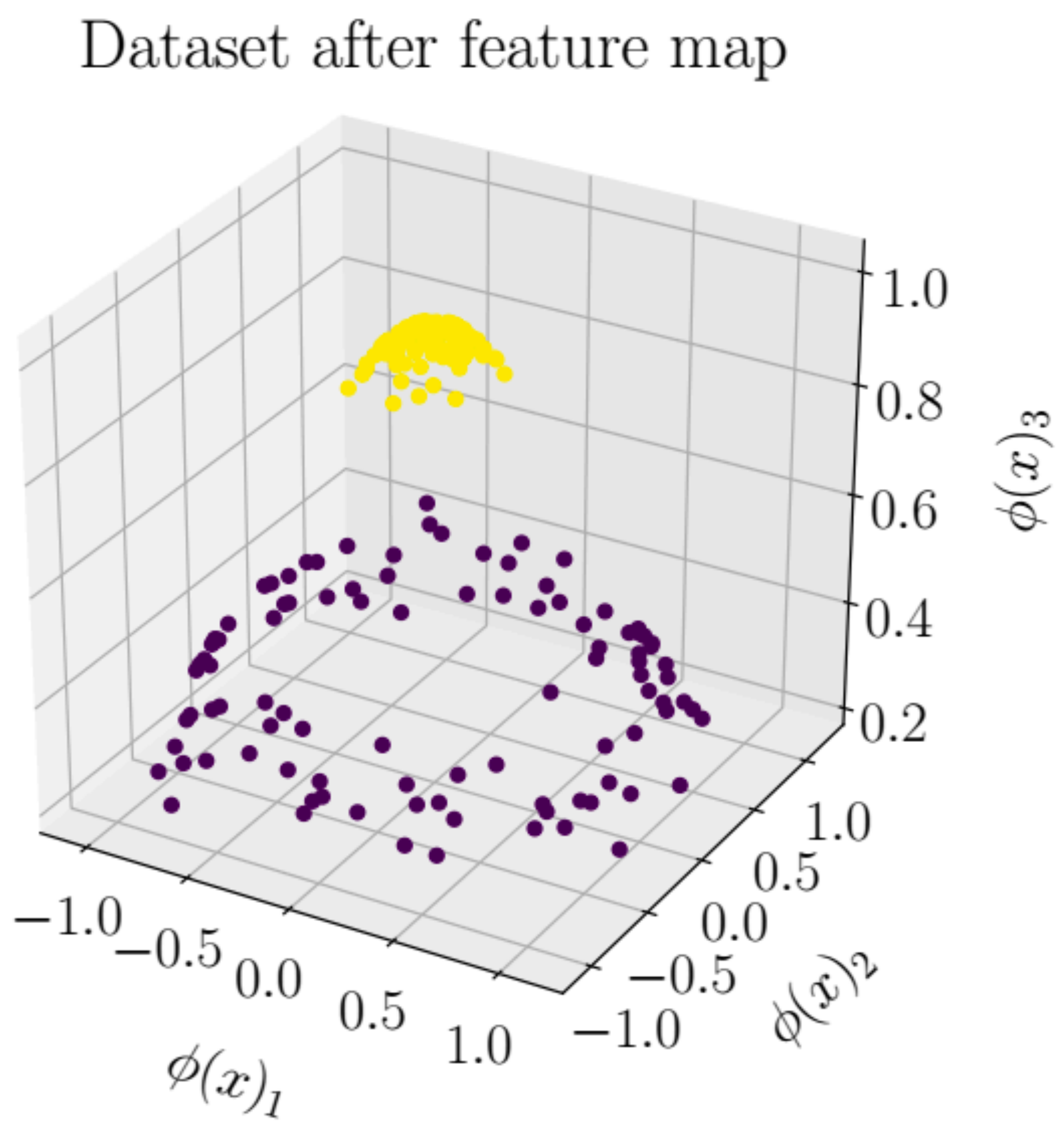
Feature maps



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

Feature maps





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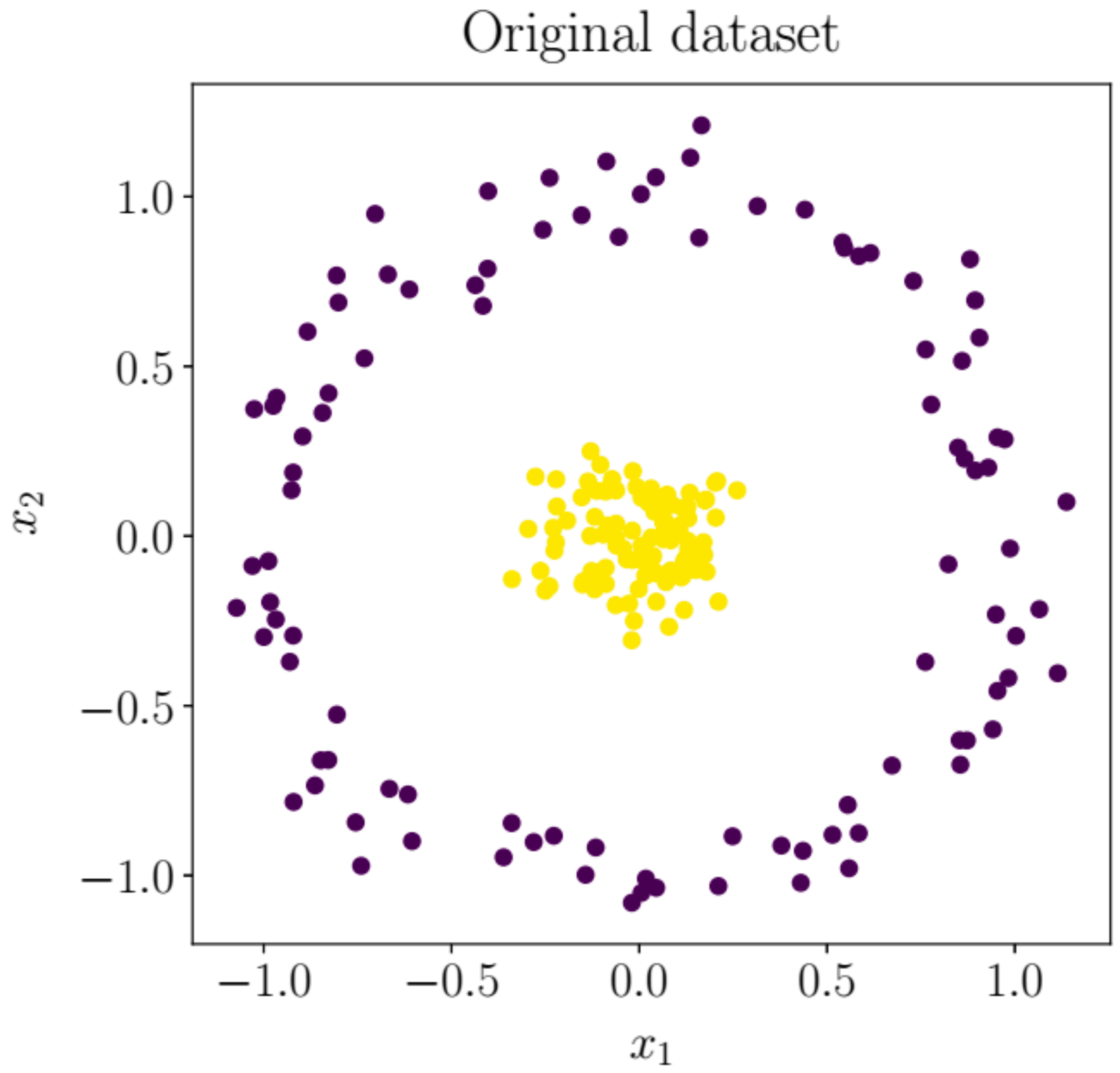
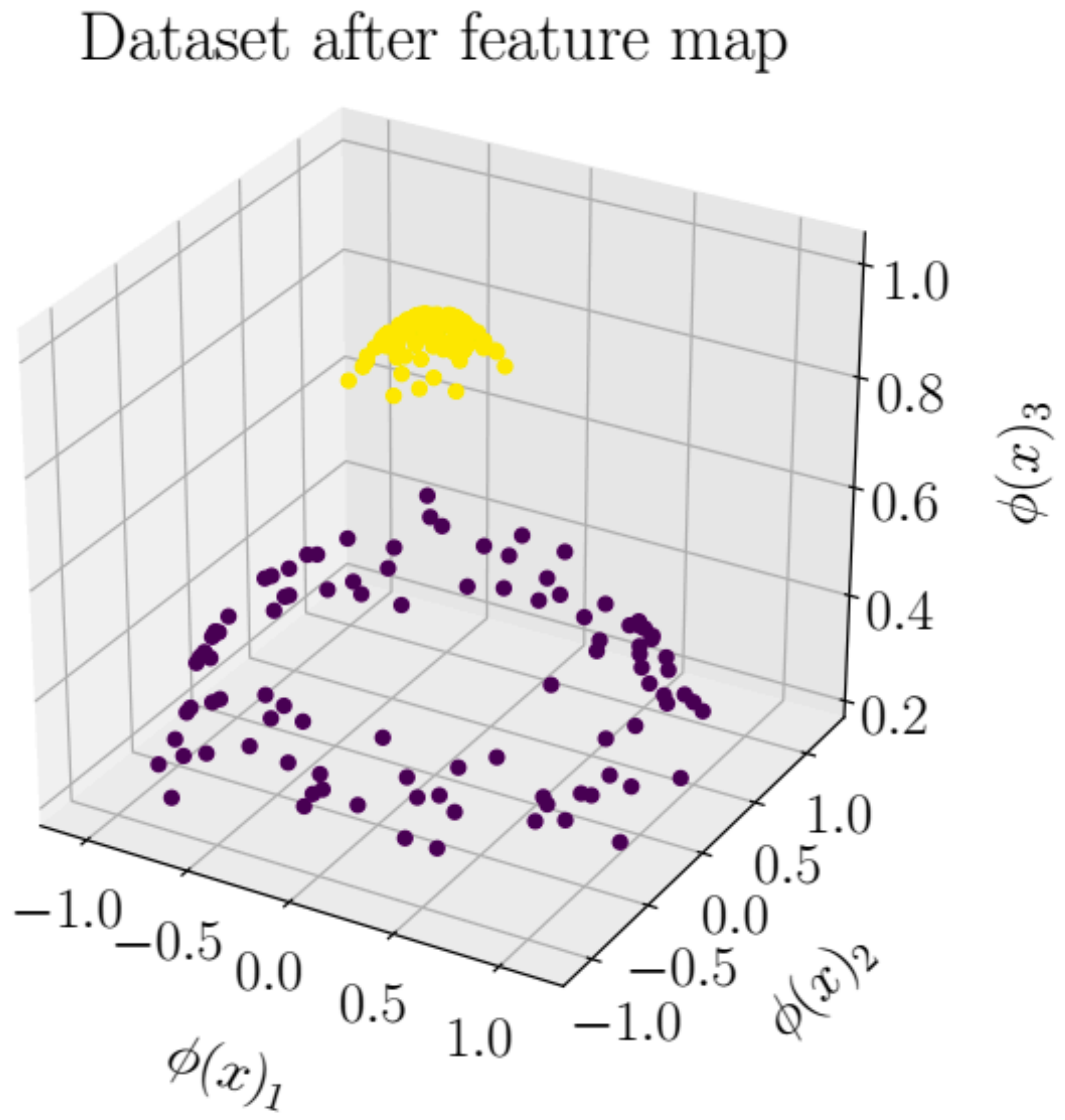
Feature maps

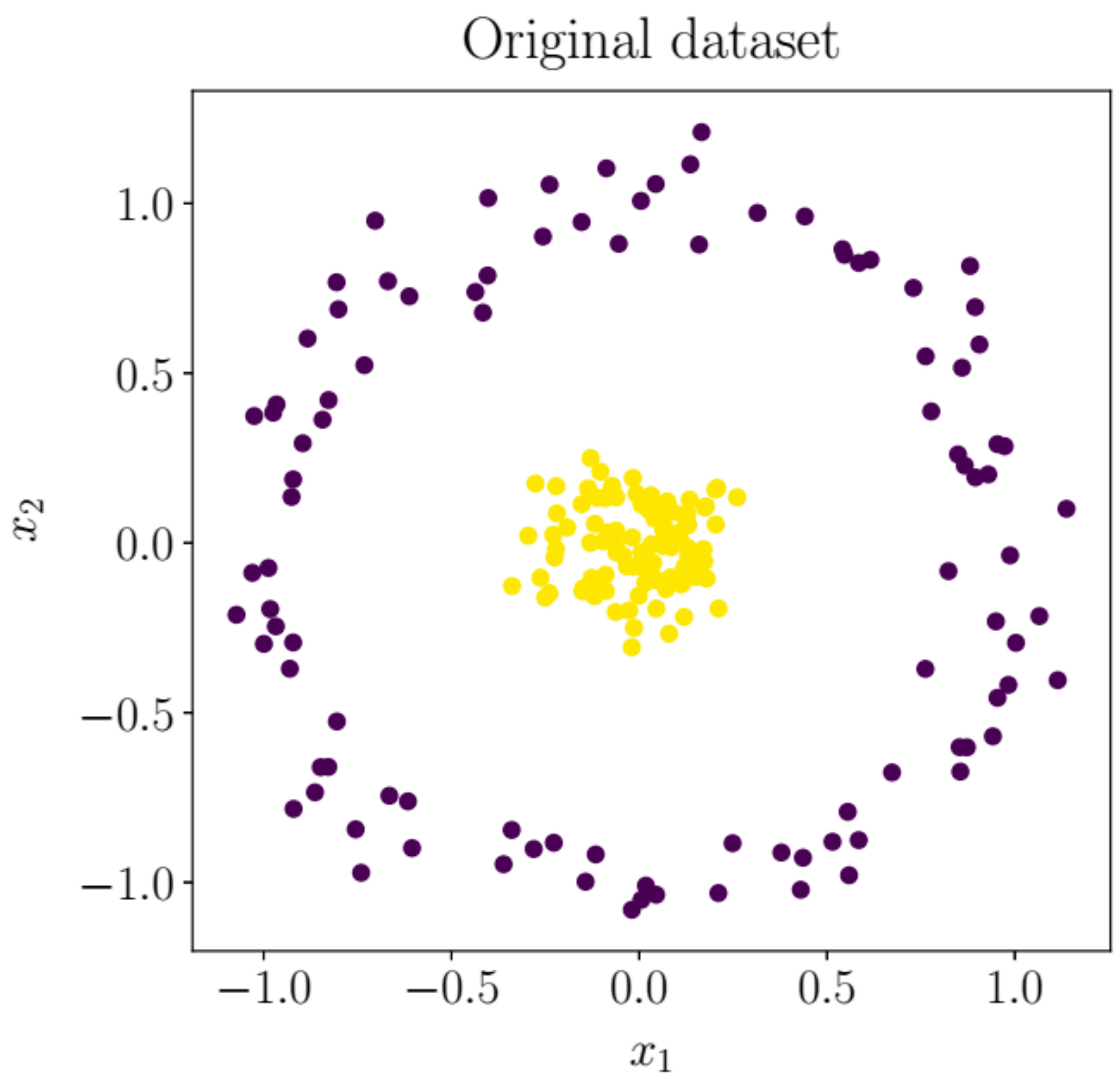


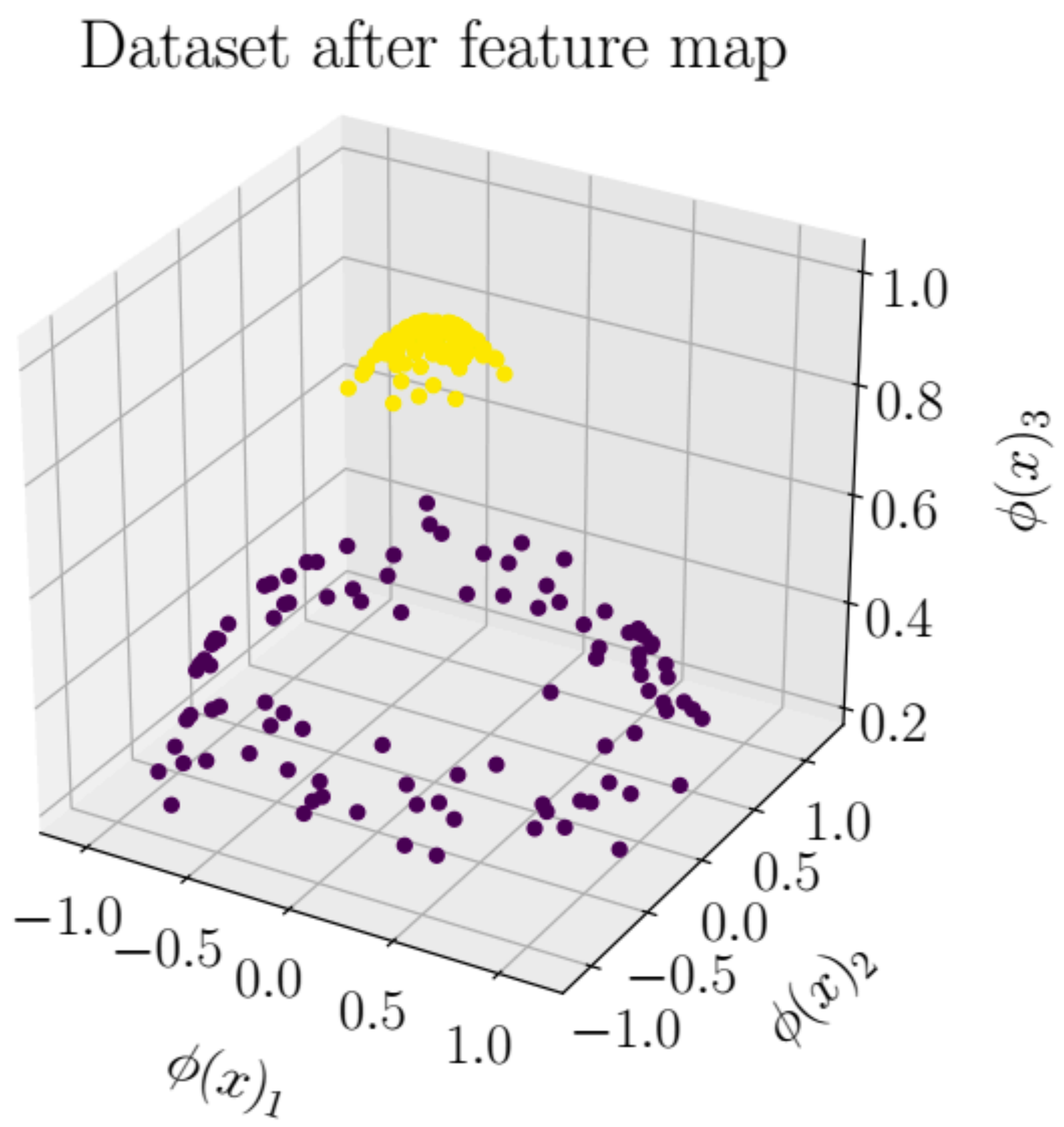


$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

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

Feature maps





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

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

Quantum feature maps

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

Quantum feature maps

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

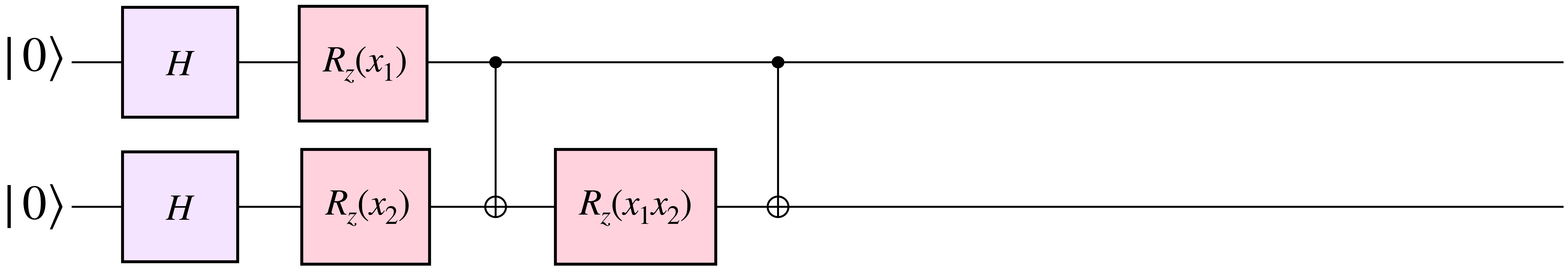
Higher order embedding

Higher order embedding

For $x^1 = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$:

Higher order embedding

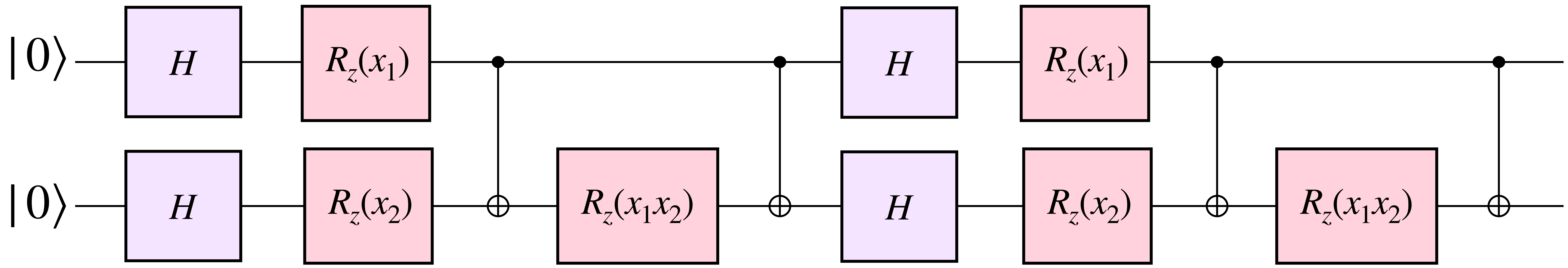
For $x^1 = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$:



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

Higher order embedding

For $x^1 = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$:



Conjectured to be difficult to simulate classically

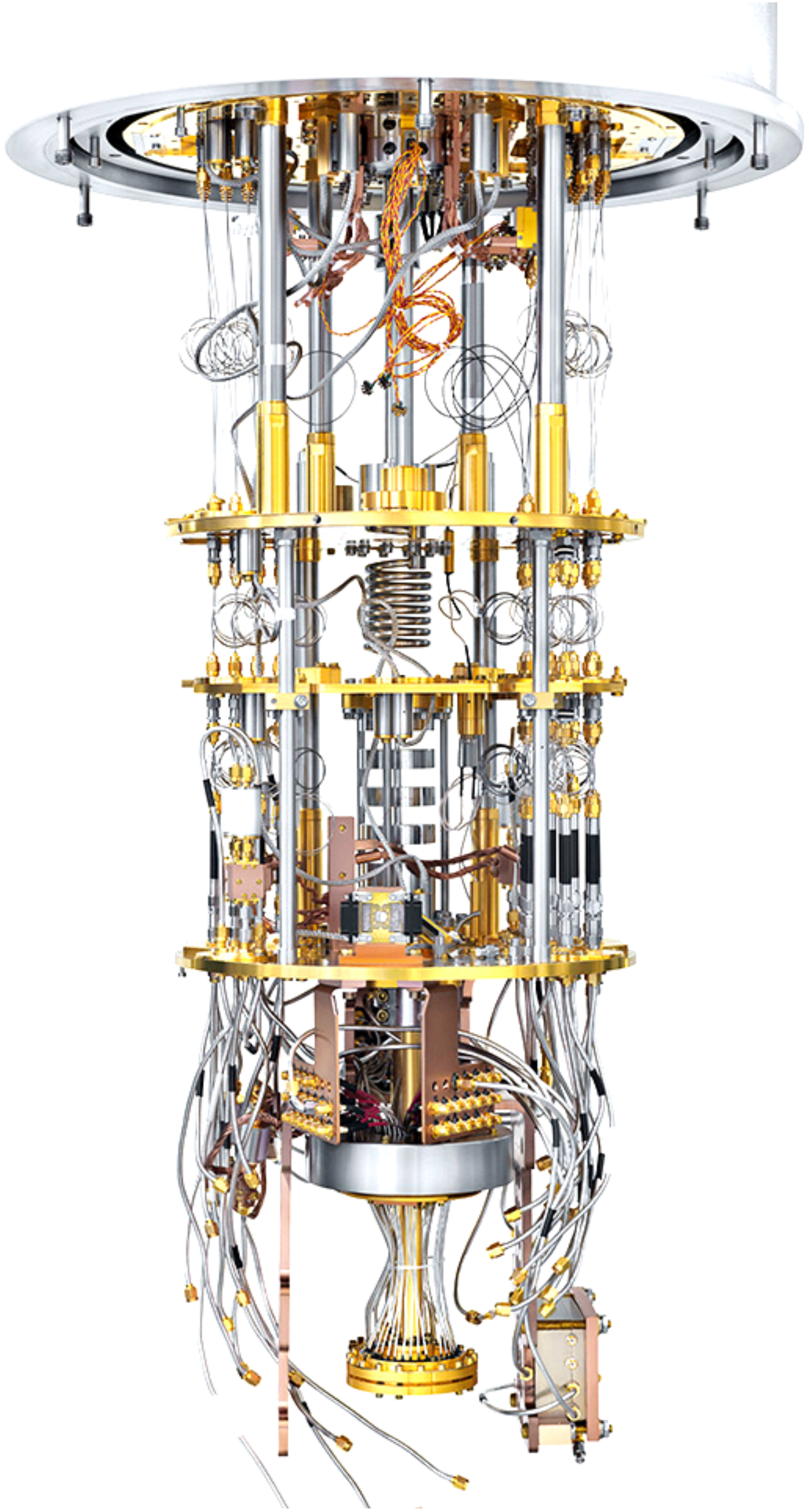
Source: Havlíček, Vojtěch, et al. "Supervised learning with quantum-enhanced feature spaces." Nature 567.7747 (2019): 209-212.

Jump to the code

Next up

More sophisticated models

Barren plateaus



Thank you!

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amyami187@gmail.com