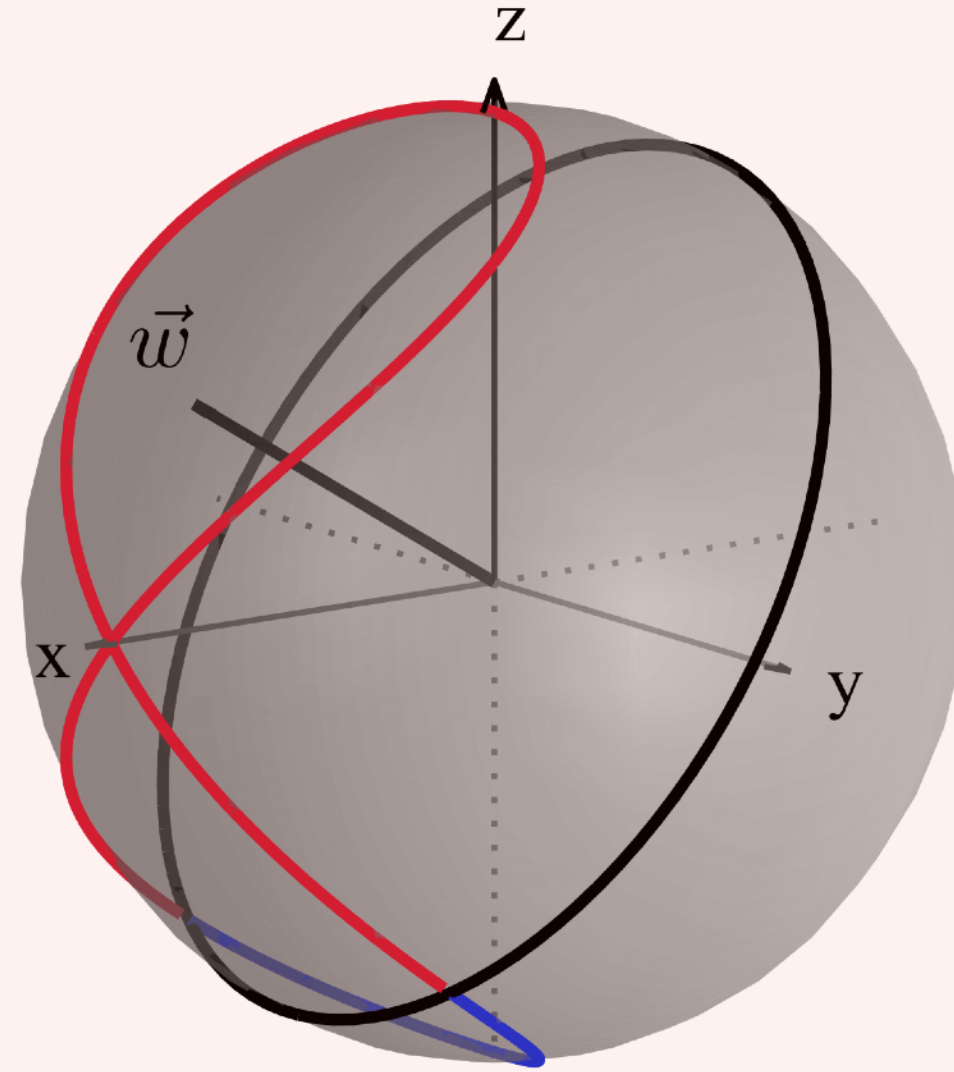




Basic programming for quantum machine learning with Qiskit and PennyLane

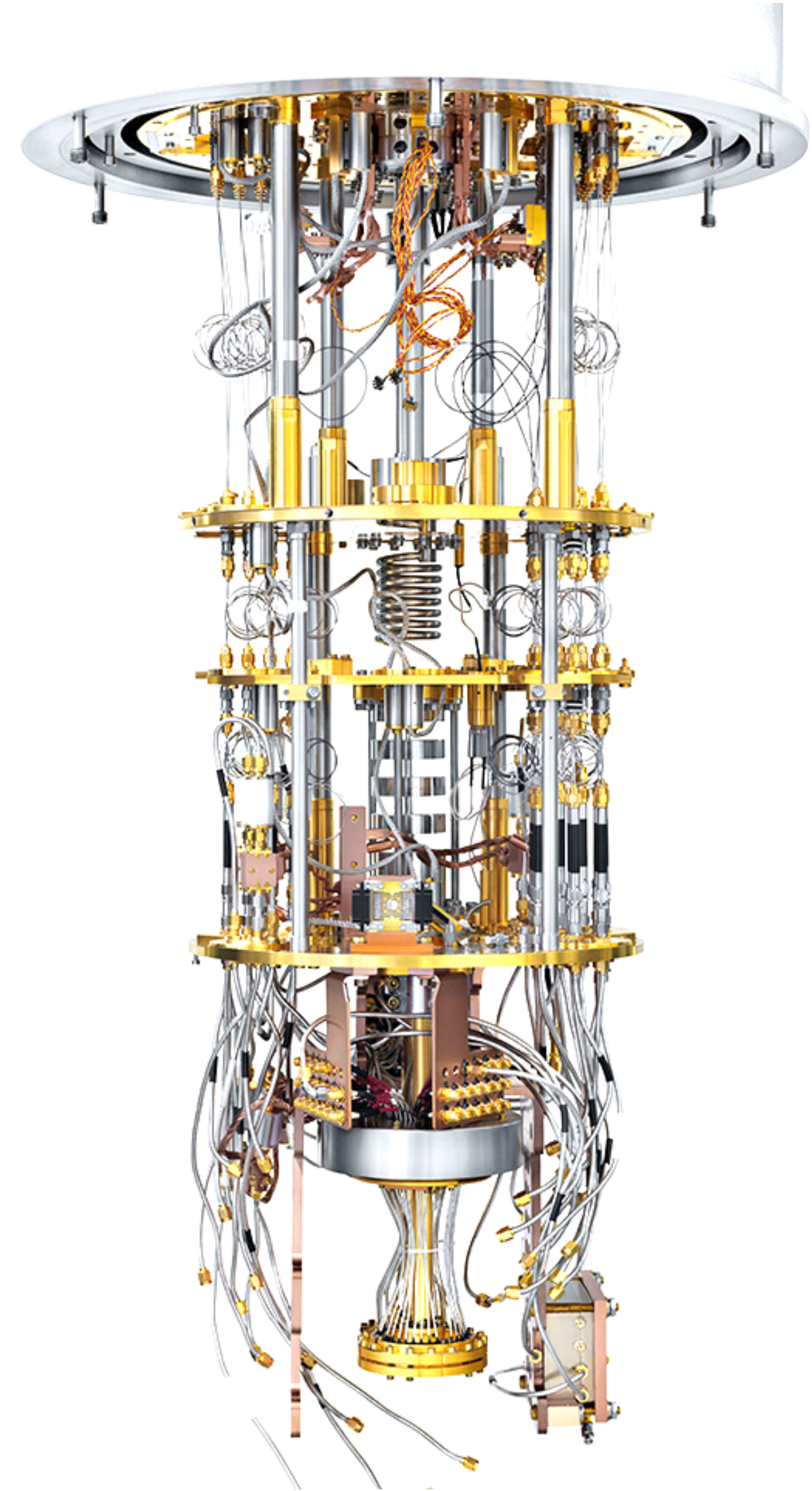
NITheP Mini-school

Amira Abbas
29/09/2020

Thank you!

Previously

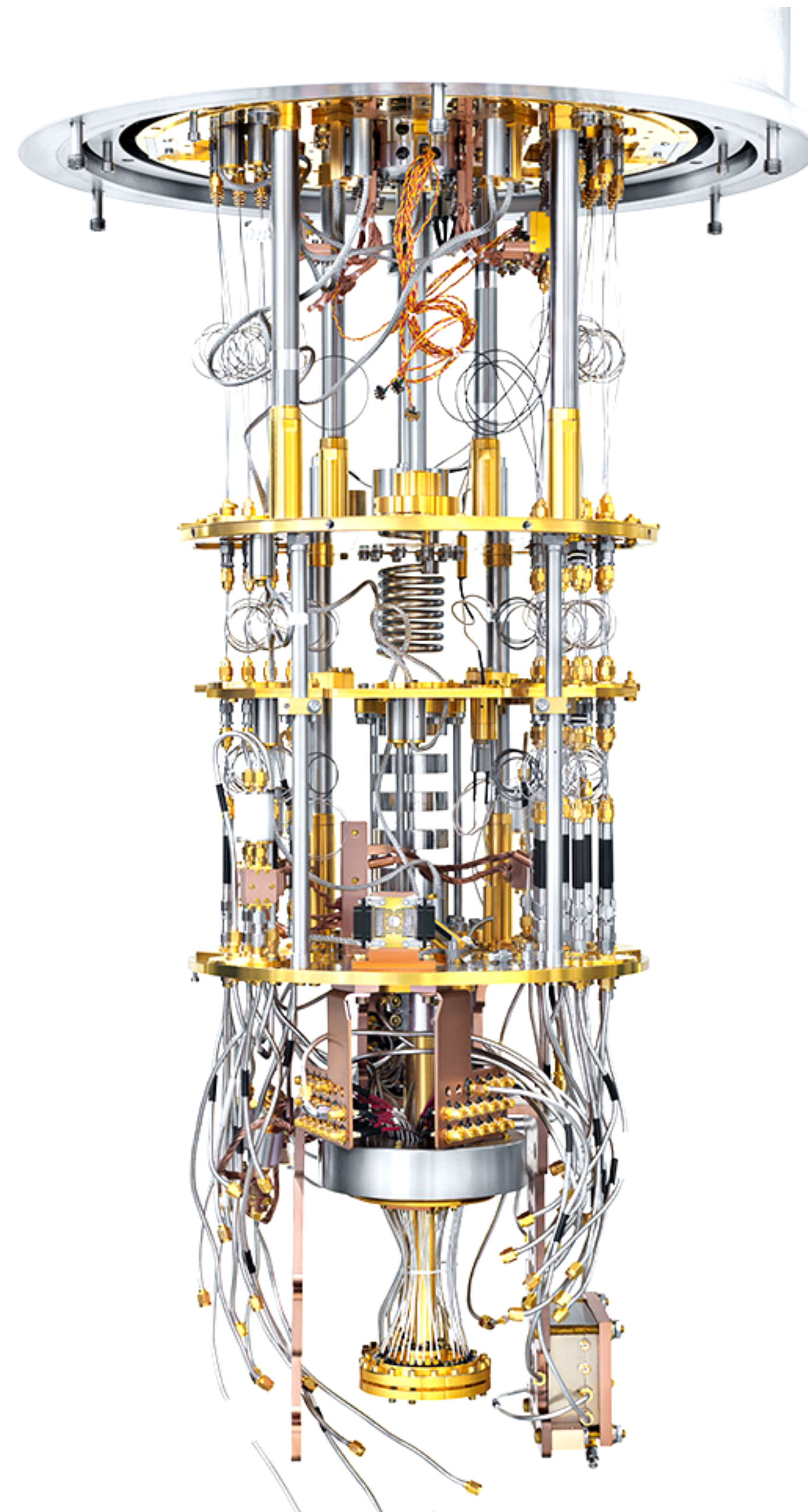
Quantum models



Previously

Quantum models

Coded a variational quantum classifier

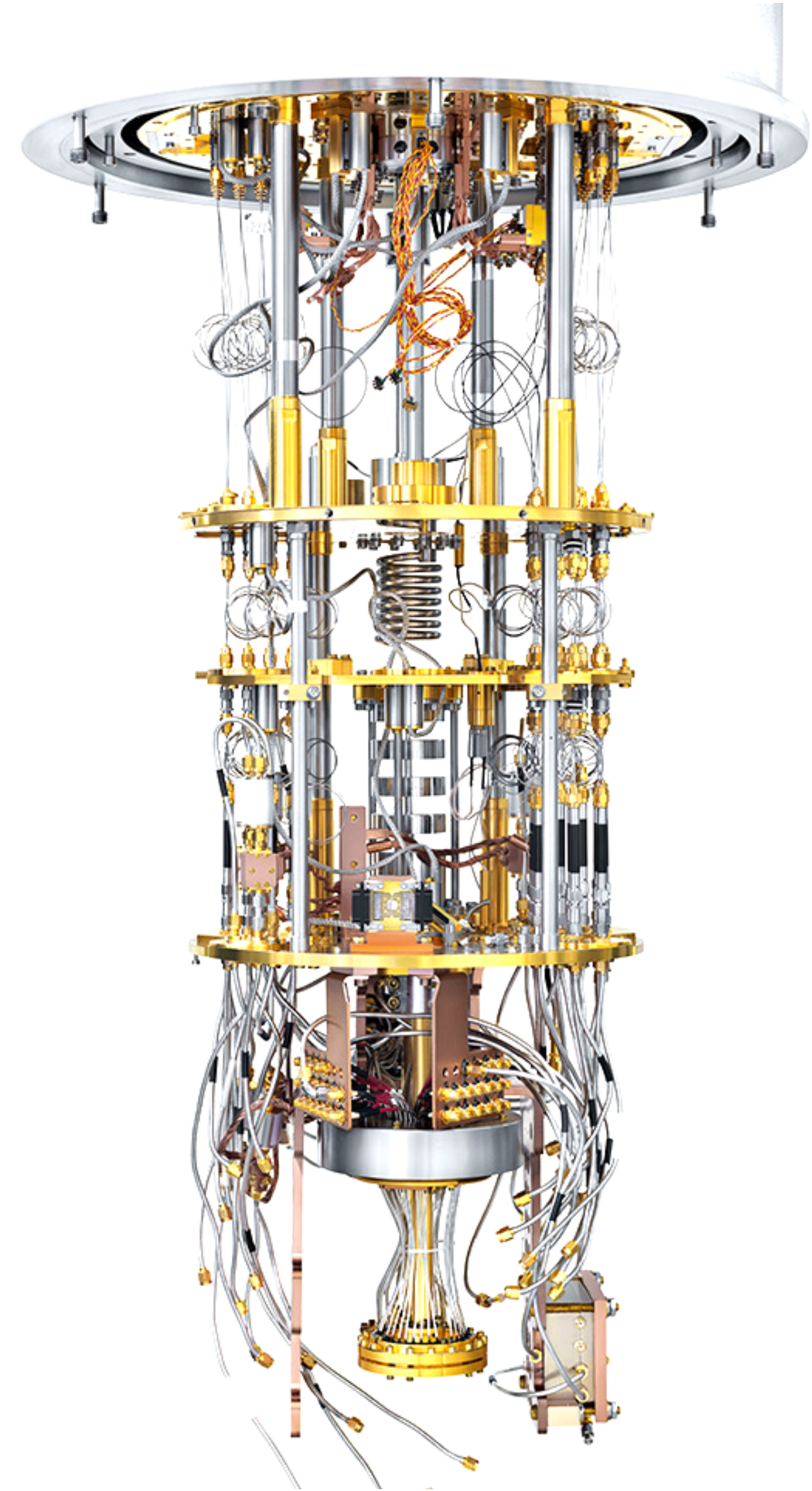


Agenda

Quantum models

Coded a variational quantum classifier

Barren plateaus



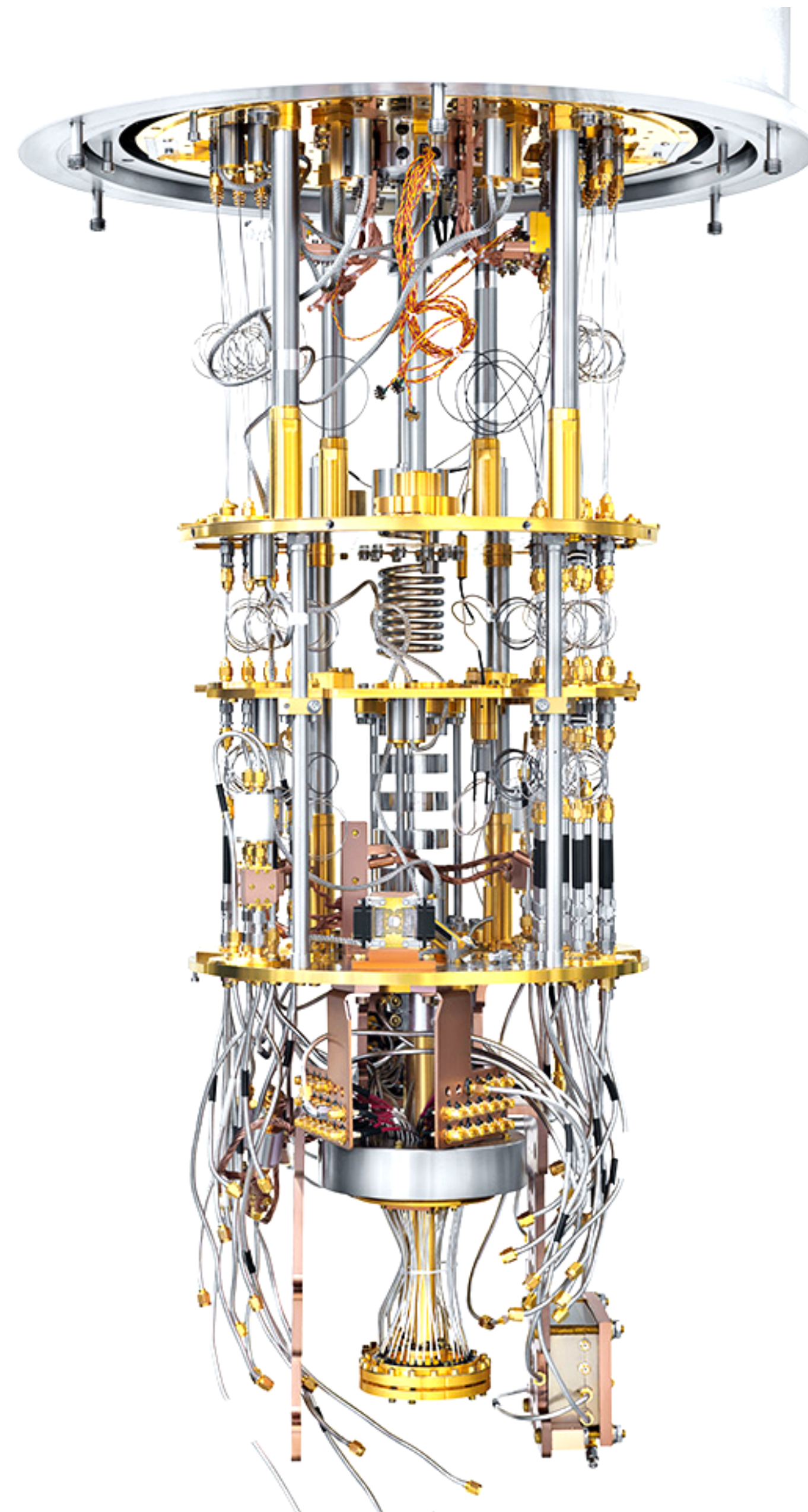
Agenda

Quantum models

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Agenda

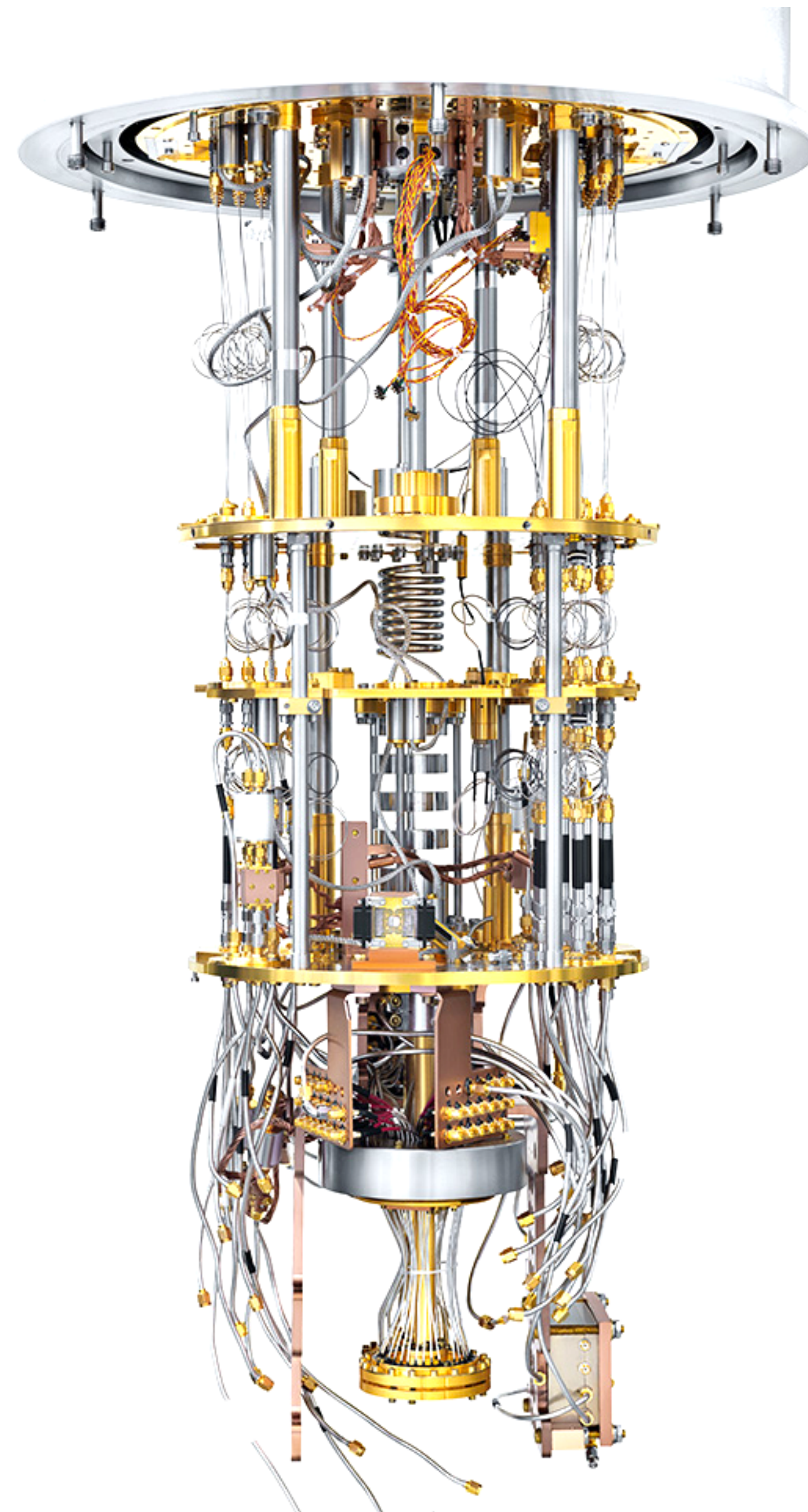
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Loss landscapes



Agenda

Quantum models

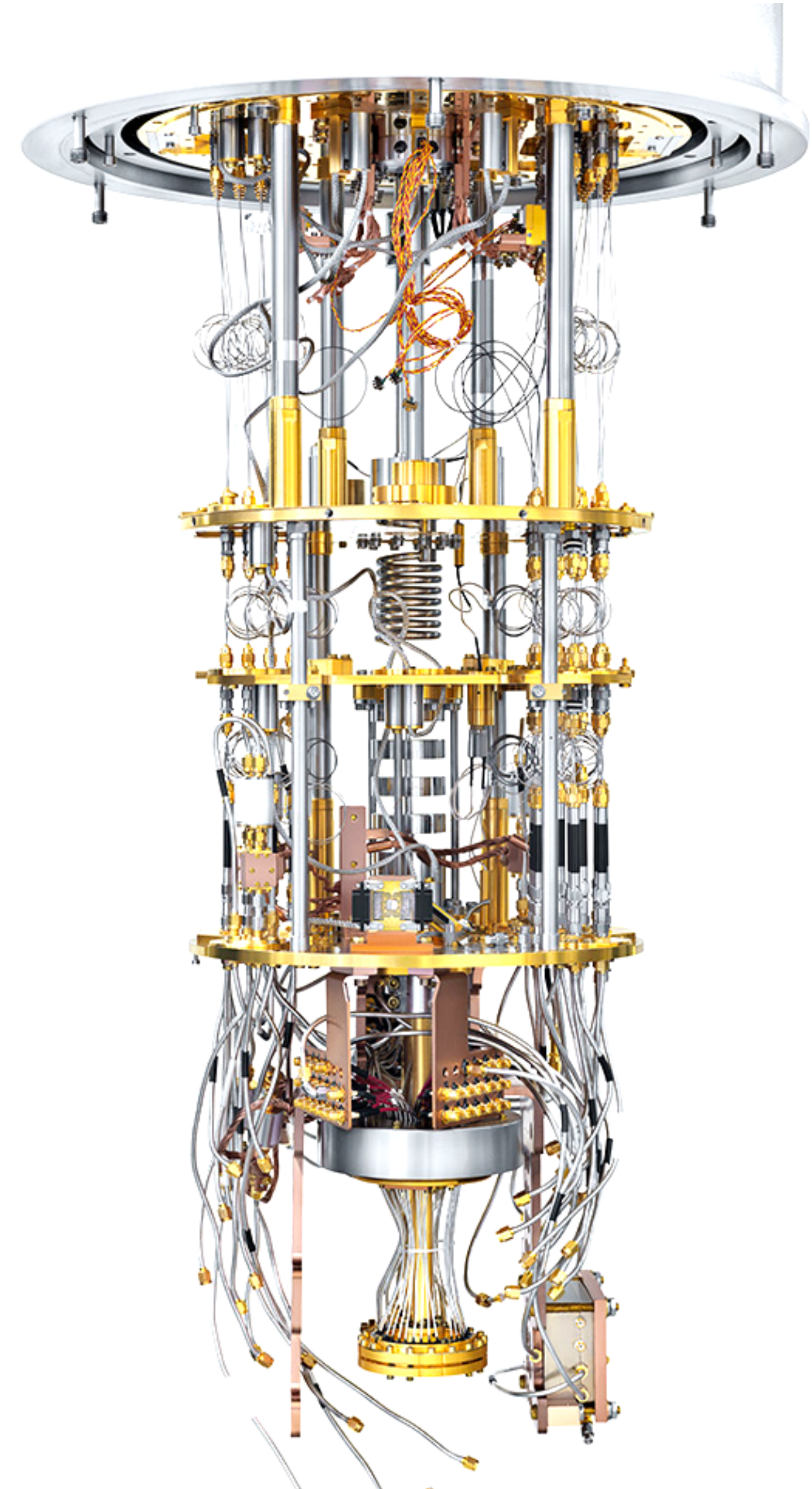
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Barren plateaus

Quantum neural networks

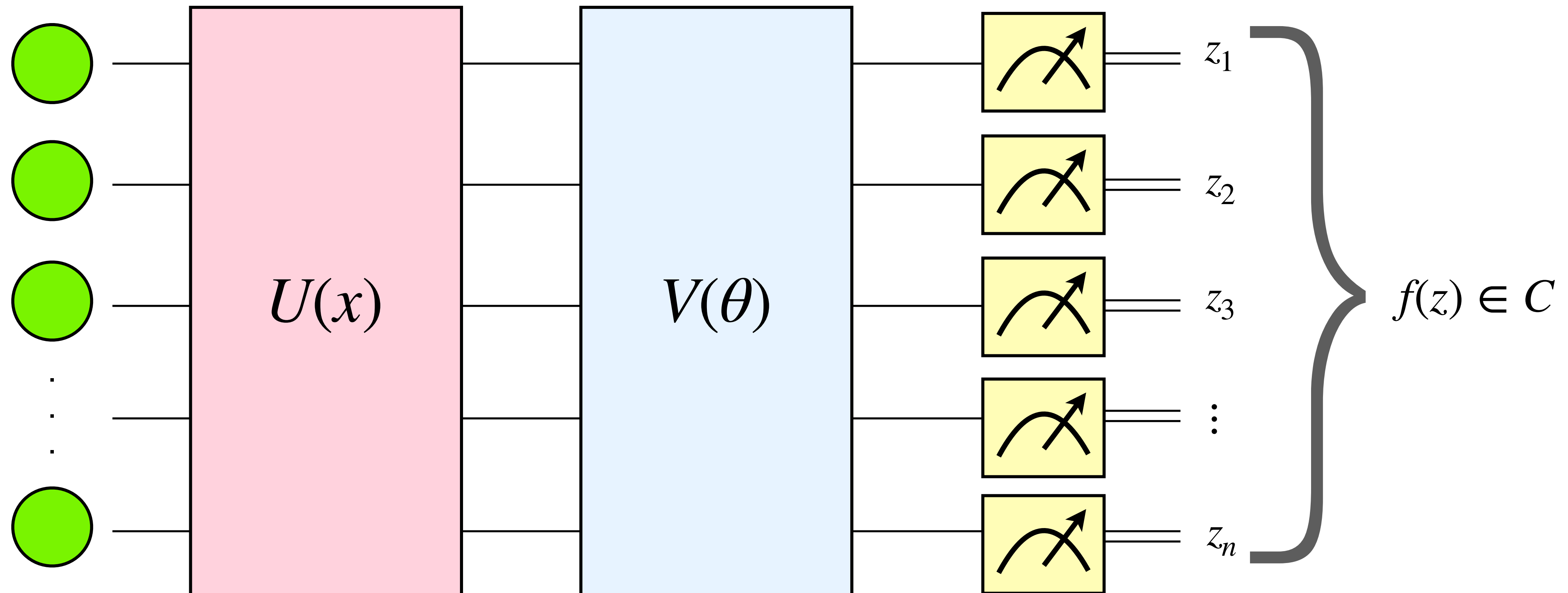
Loss landscapes

Demonstrate barren plateaus using PennyLane

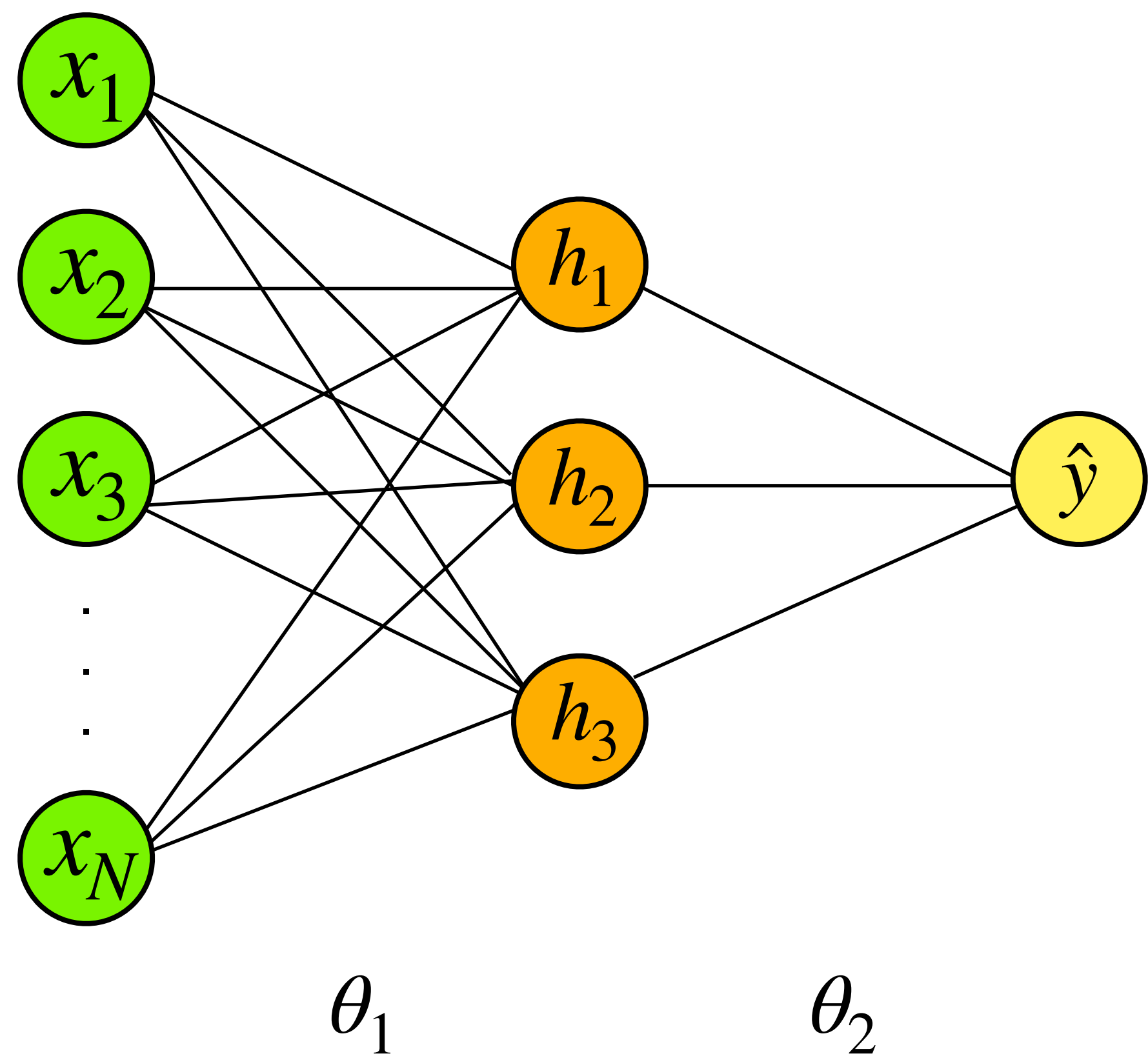


Quantum neural network

Quantum variational classifier

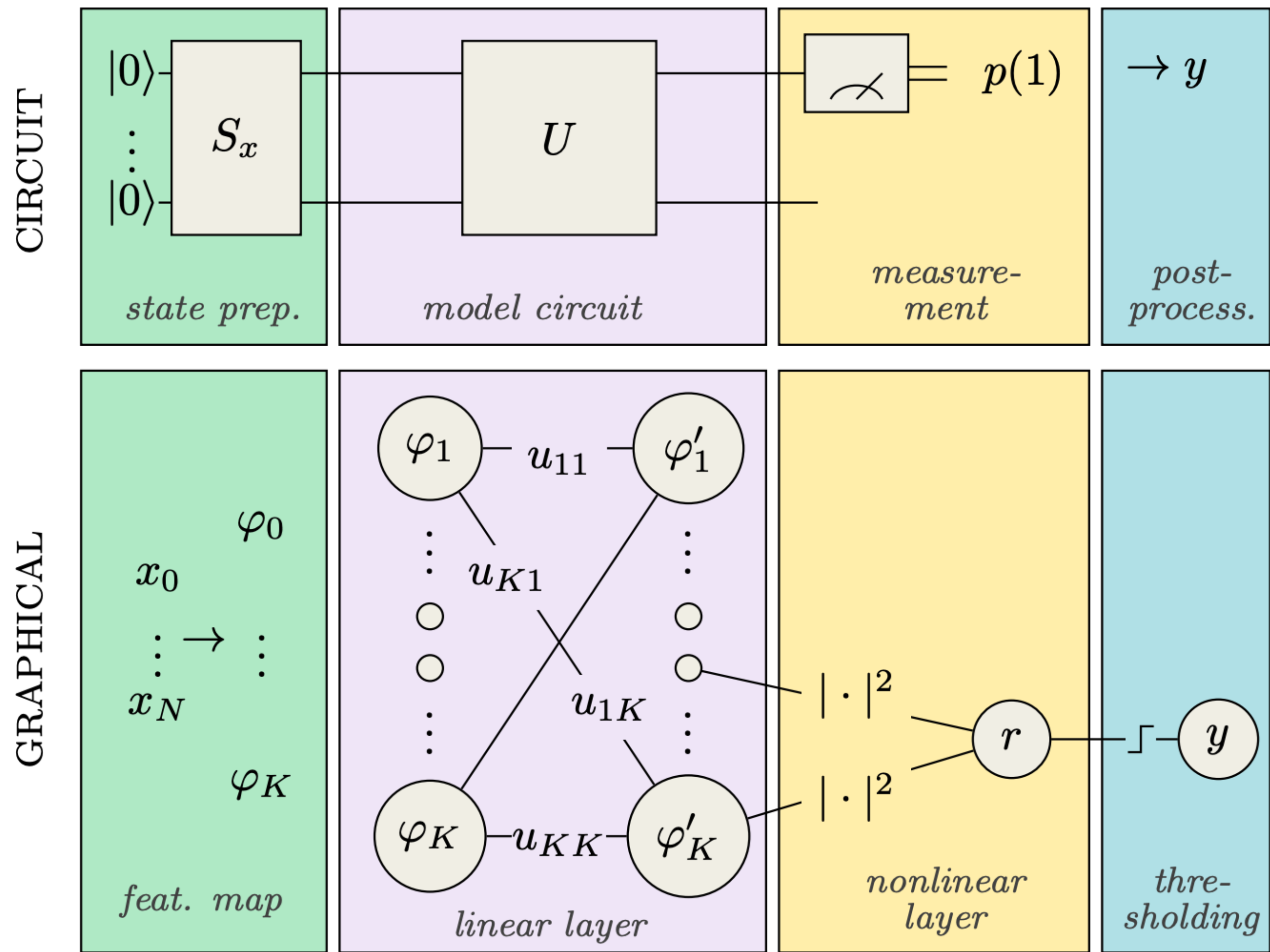
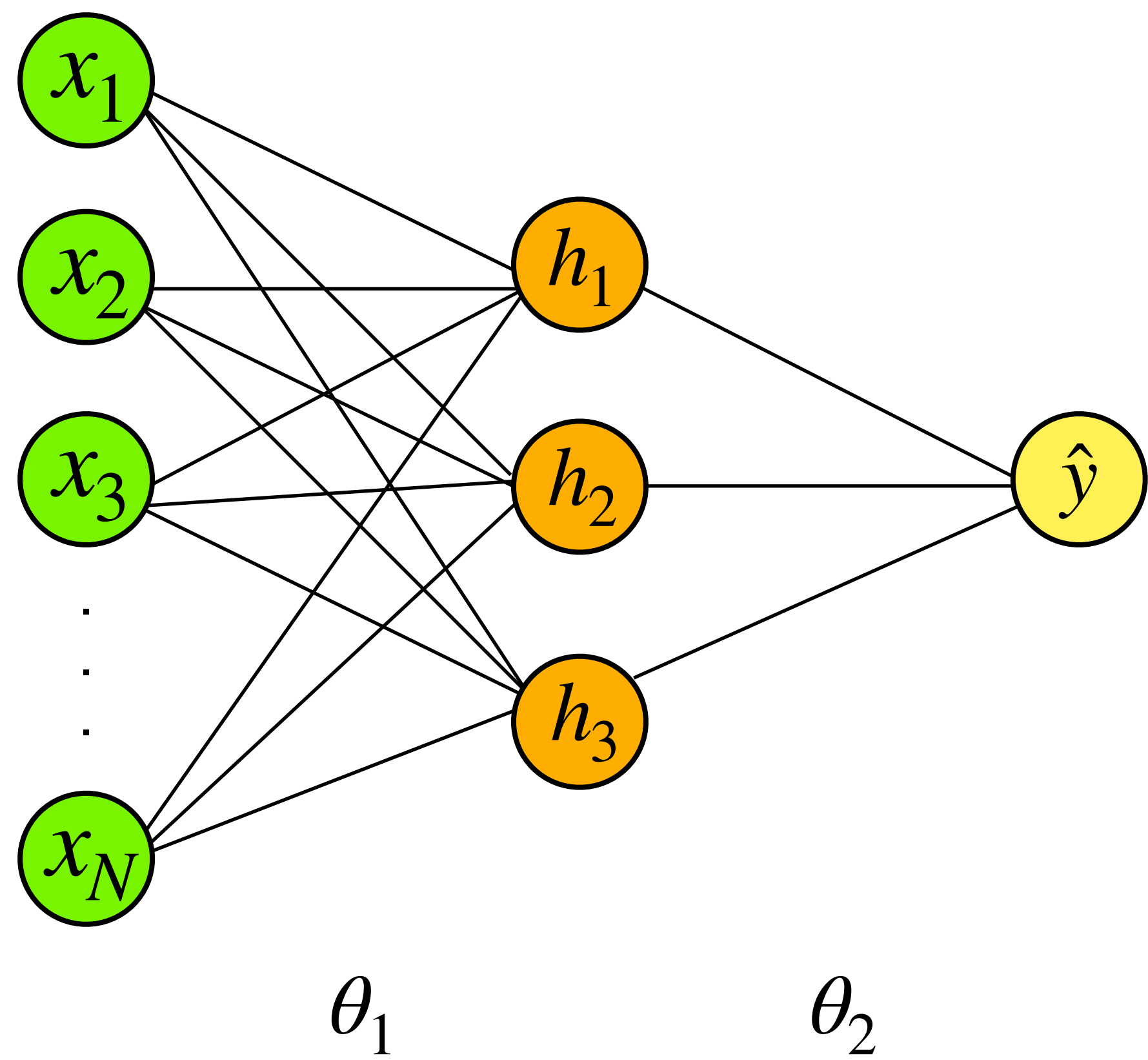


Linear neural network



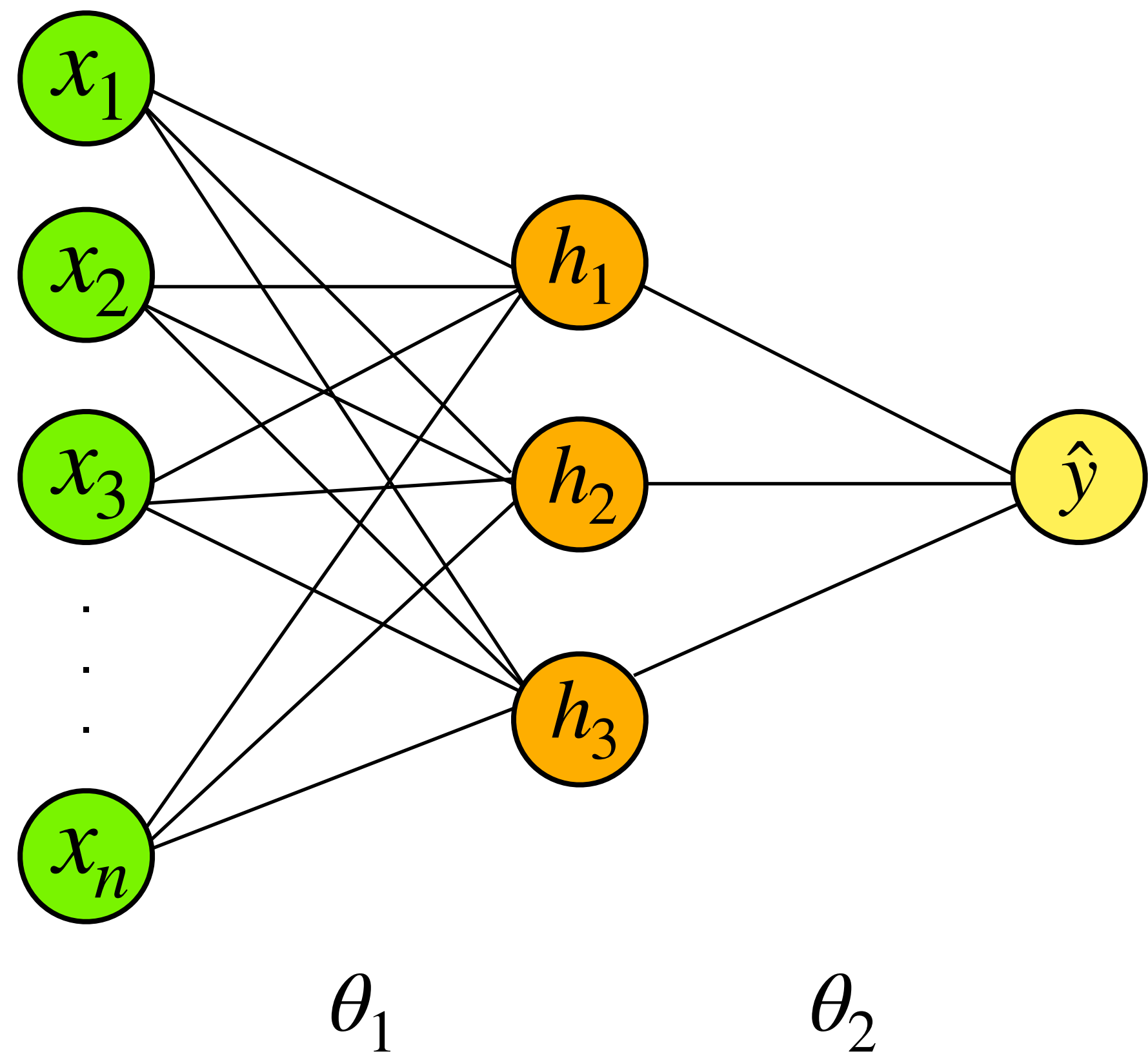
$$\hat{y} = \theta_2(\theta_1 x)$$

Quantum neural networks

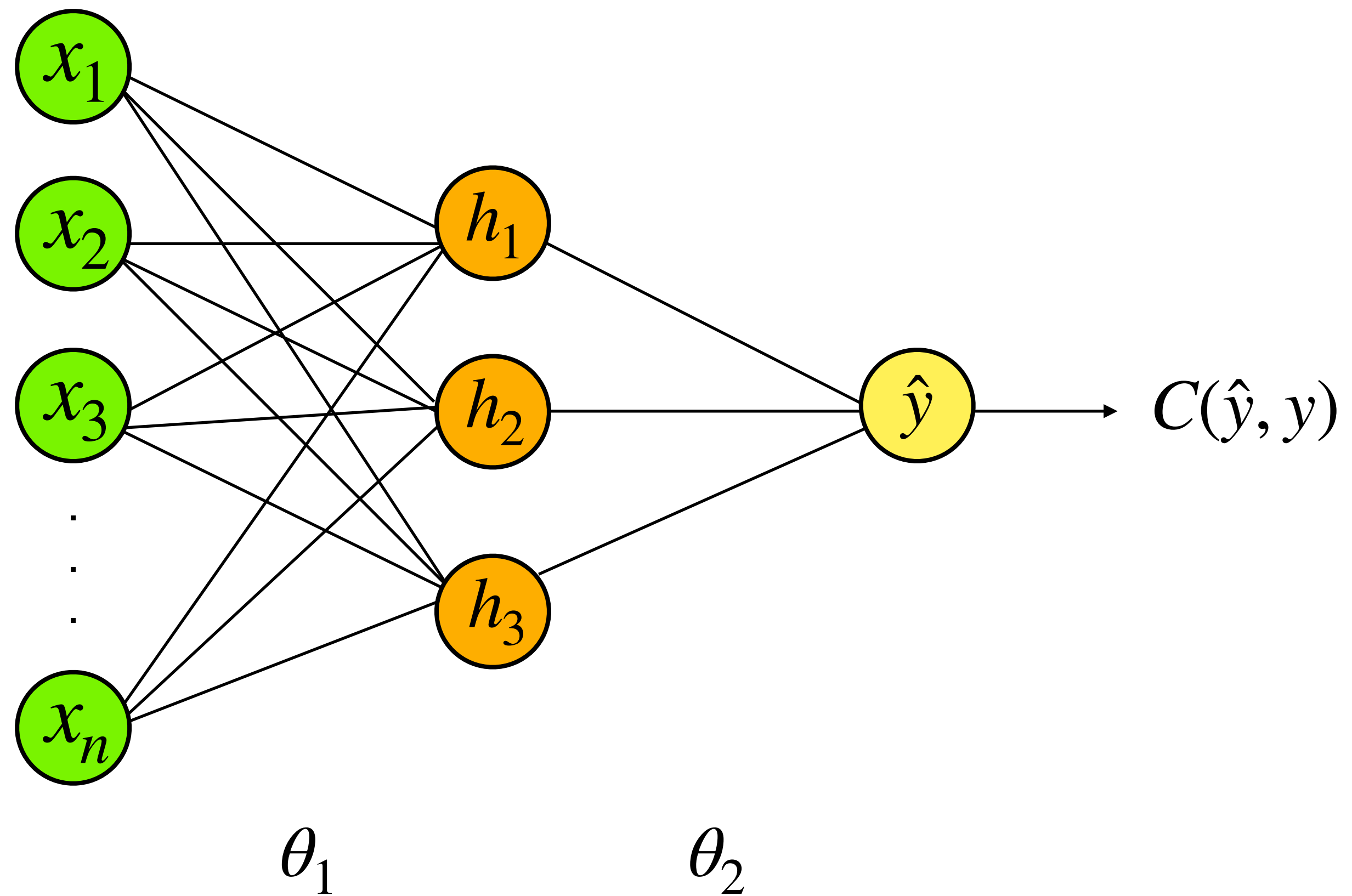


Classical optimisation

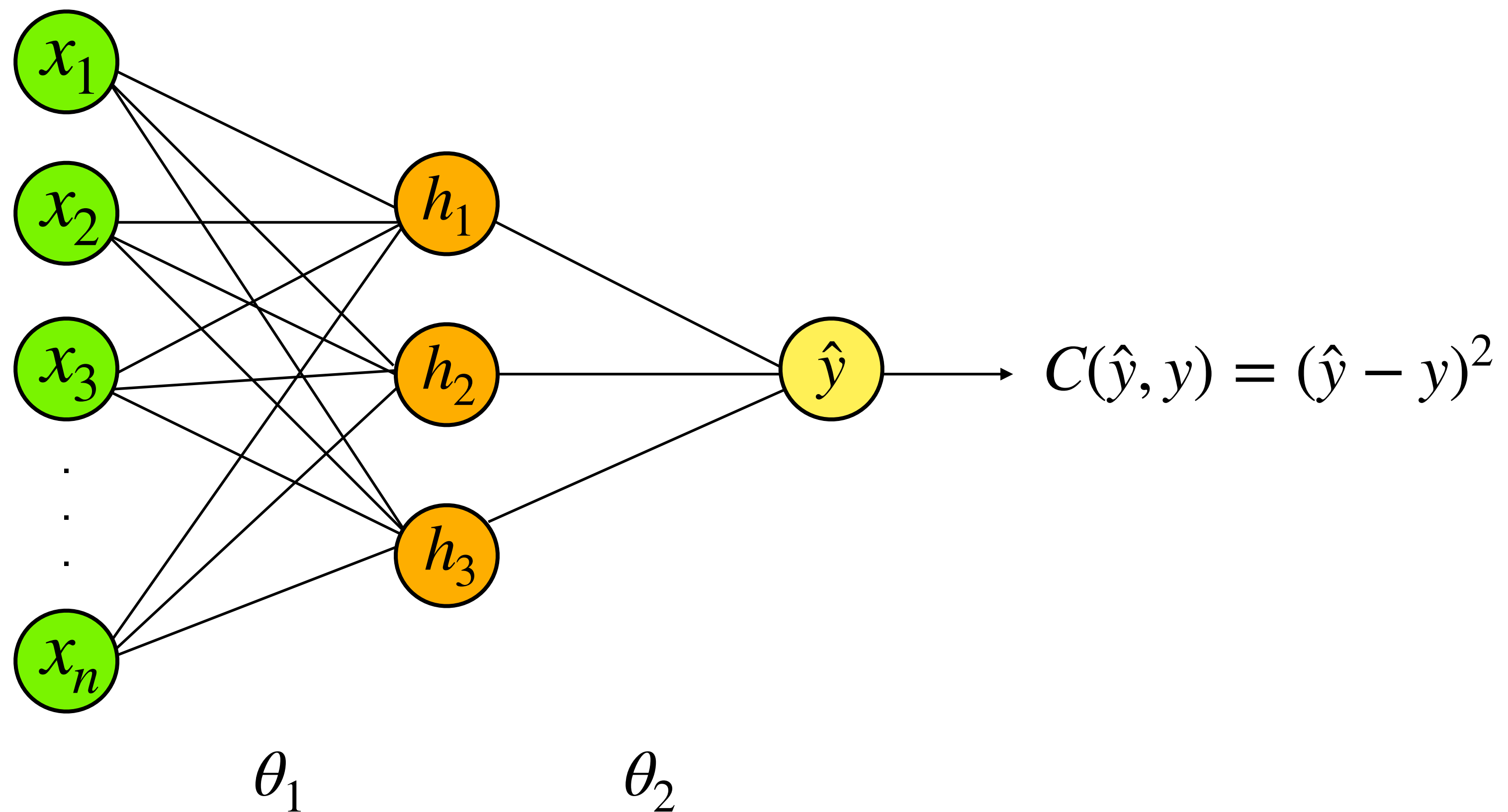
Classical neural networks



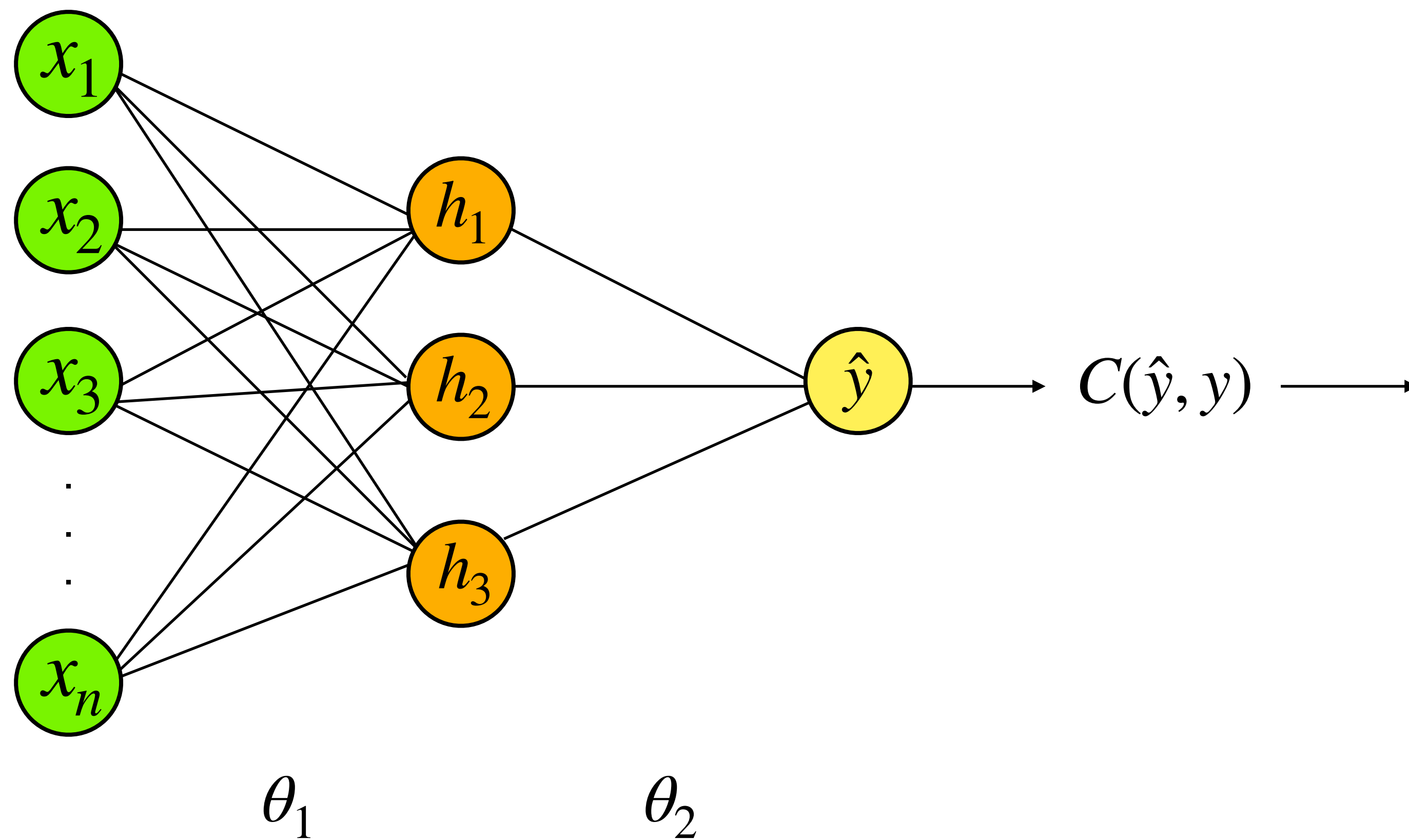
Classical neural networks



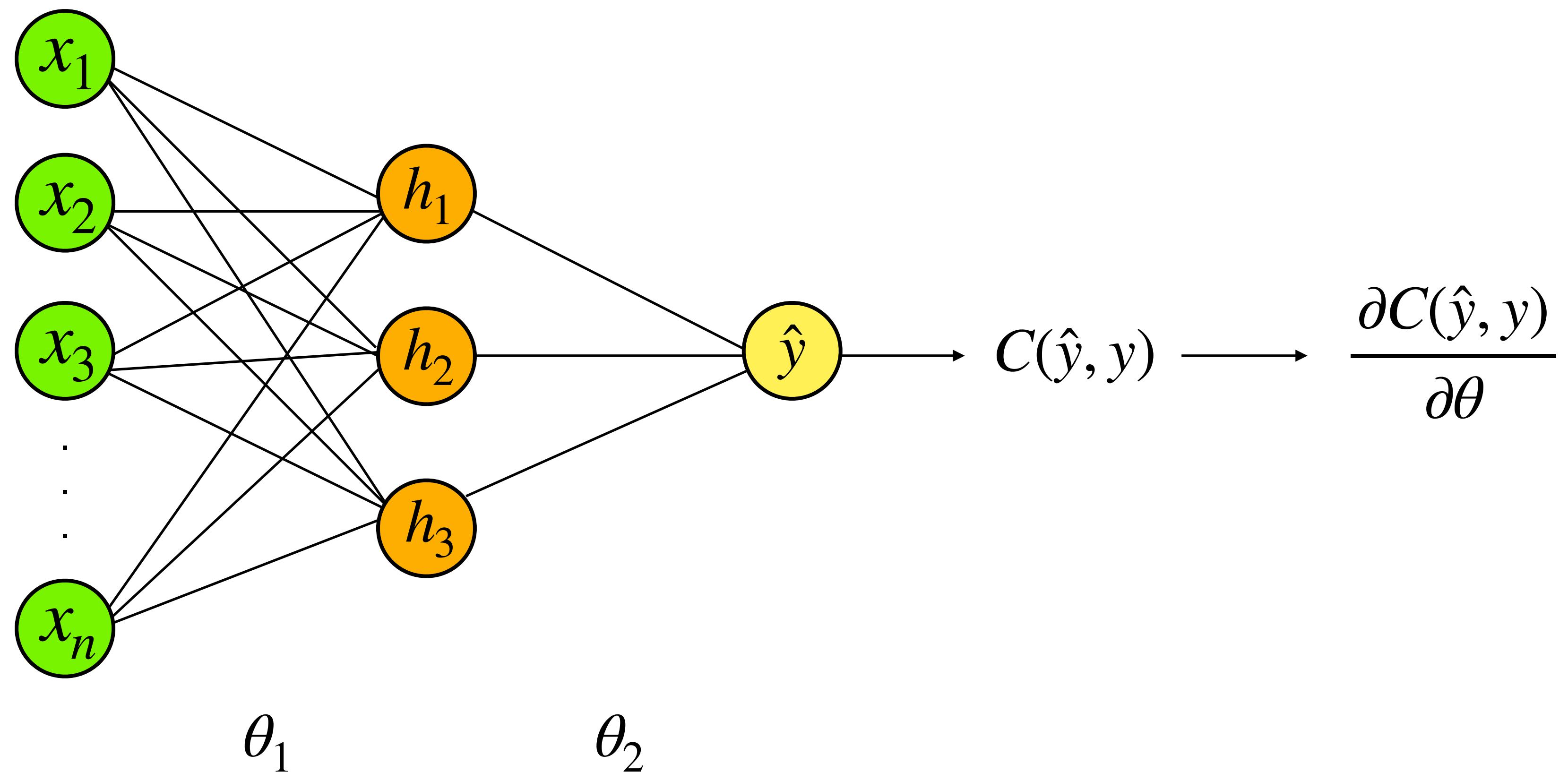
Classical neural networks



Classical neural networks



Classical neural networks



Gradient descent

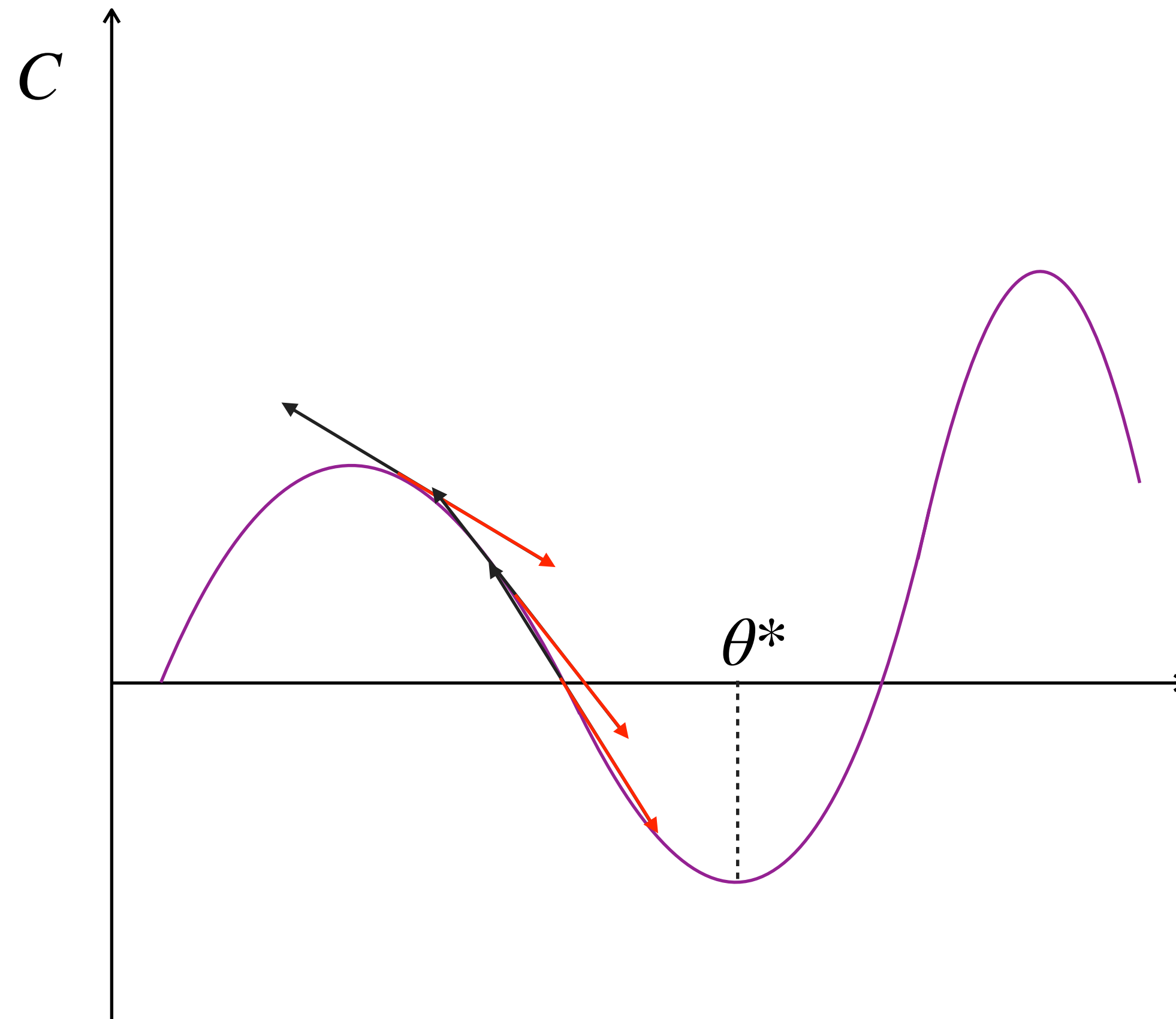
$$\theta_{\text{new}} = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$

Gradient descent

$$\theta^* = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$

Gradient descent

$$\theta^* = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$



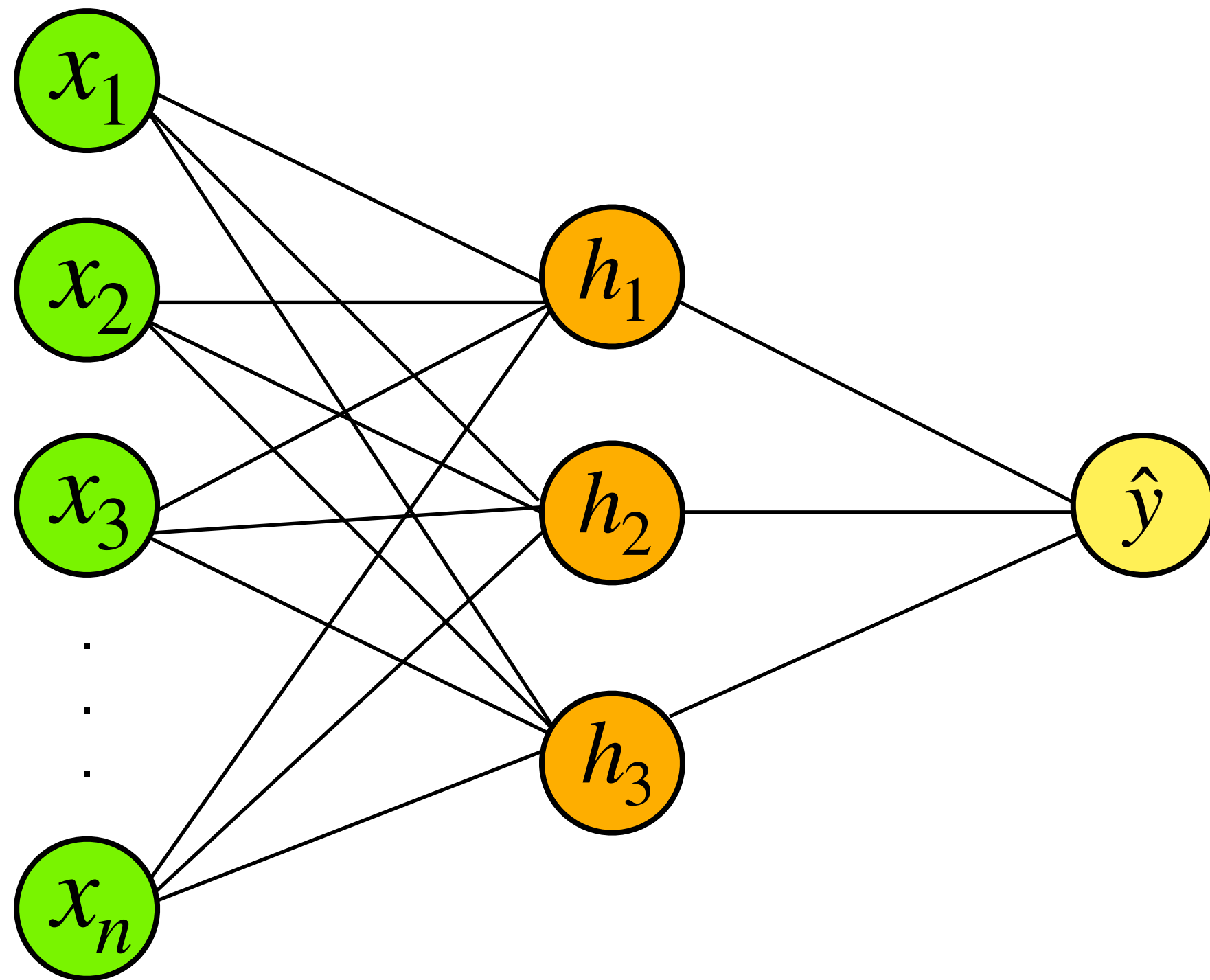
Vanishing and exploding gradients

Classical neural networks

$$\theta^* = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$

Classical neural networks

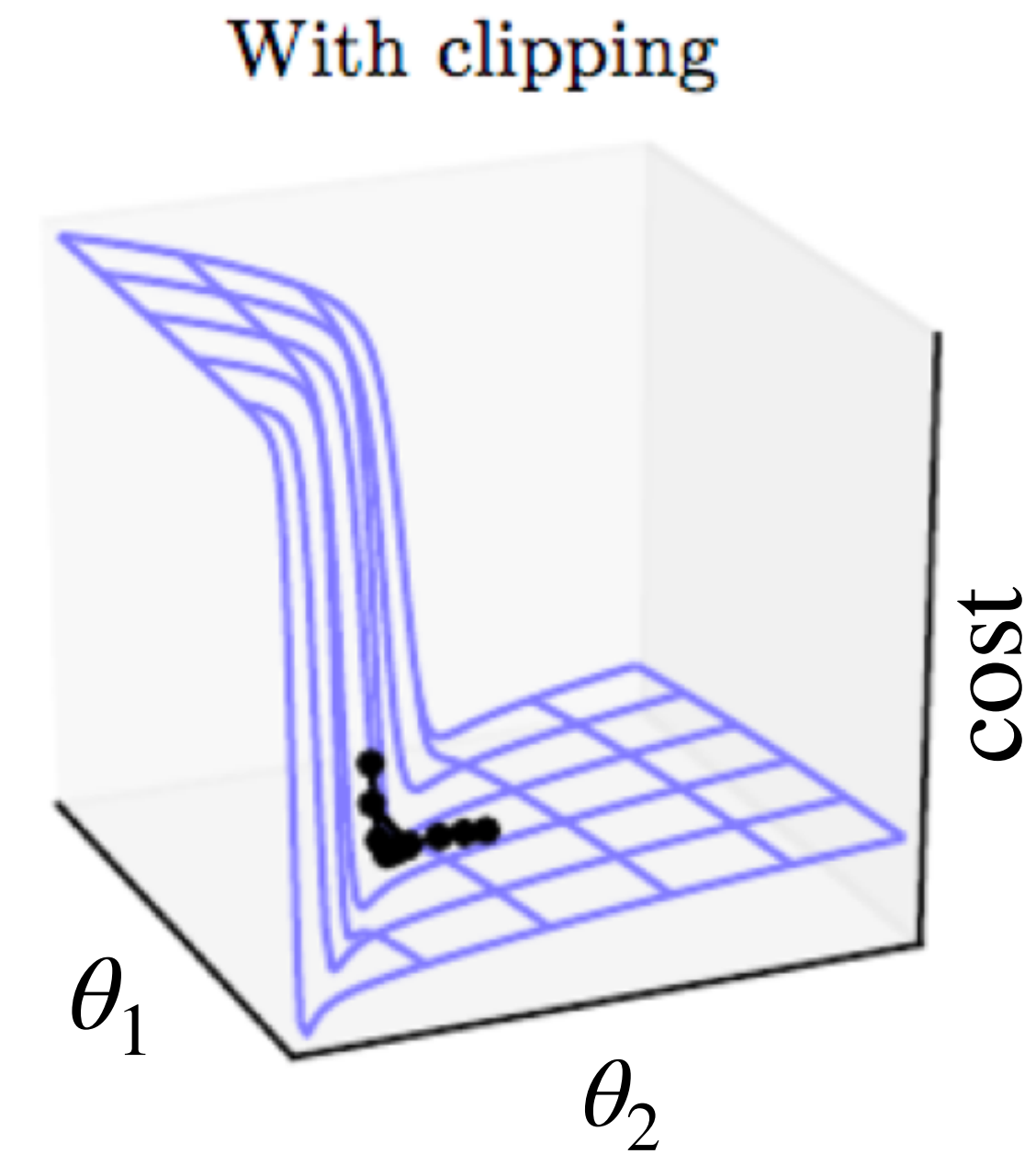
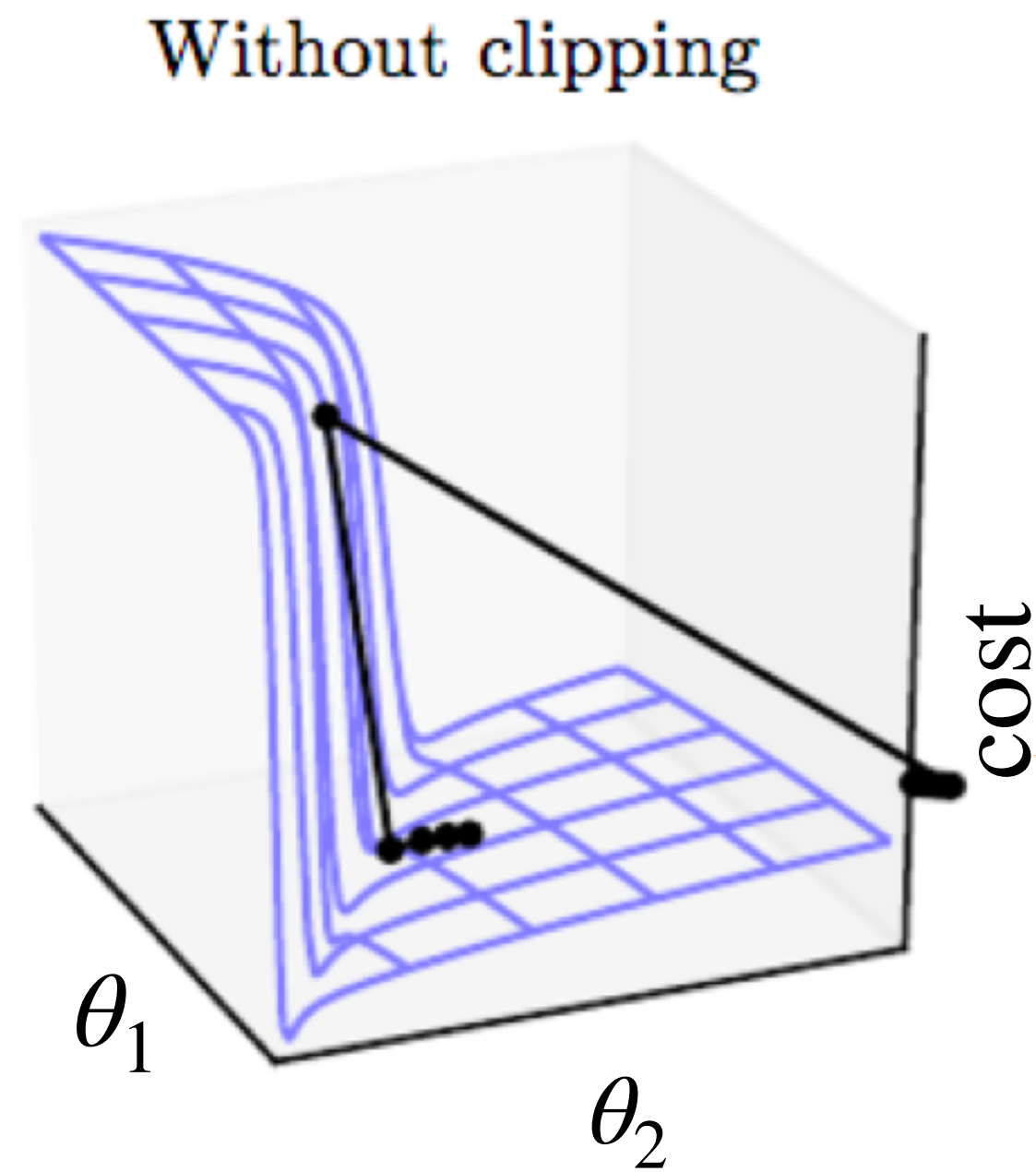
$$\theta^* = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$



Using the chain rule can cause gradients to vanish/explode

Classical neural networks

- Gradient clipping



Classical neural networks

- Gradient clipping
- Weight regularisation

L1 regularization on least squares:

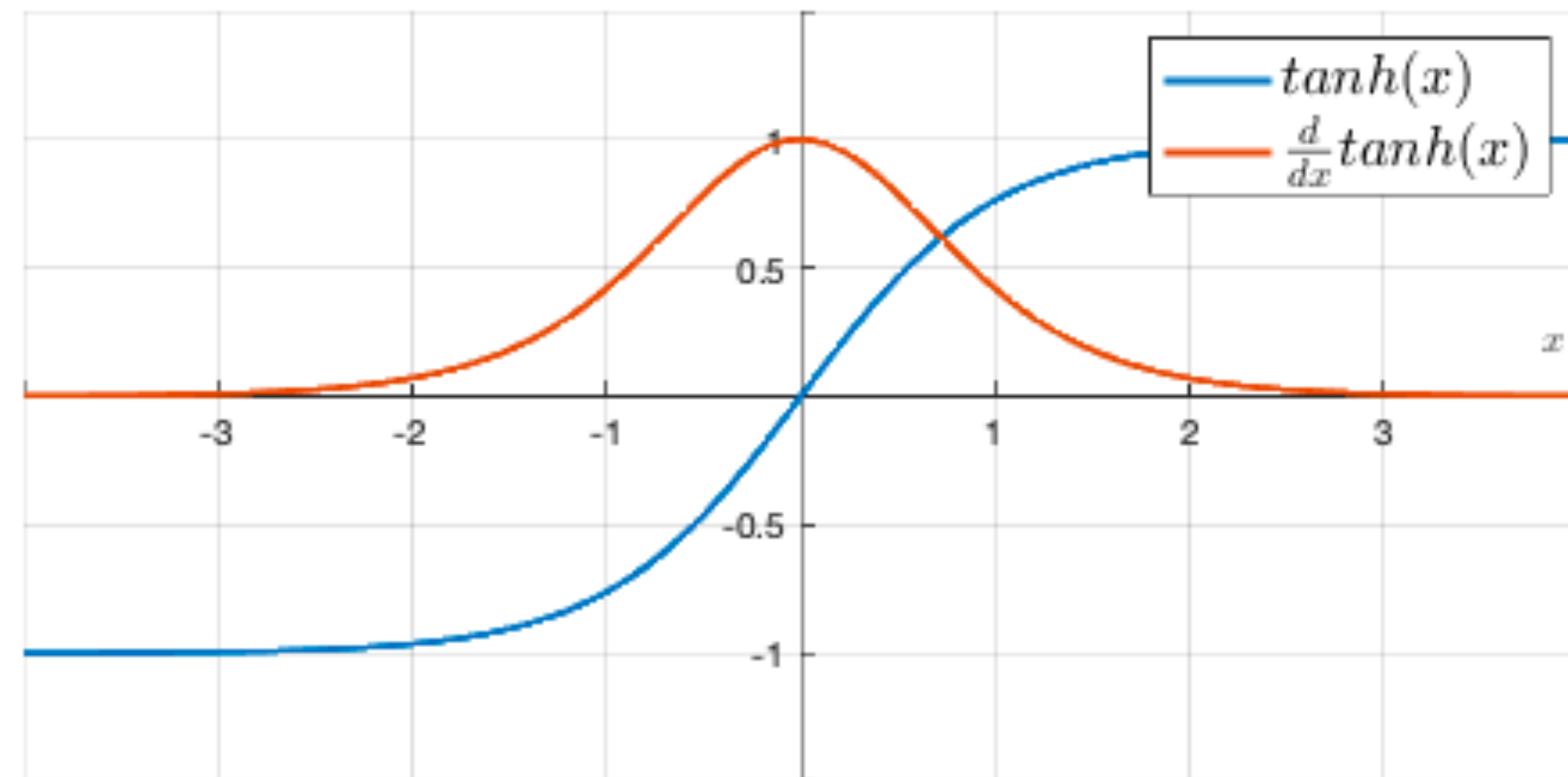
$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \sum_j \left(t(\mathbf{x}_j) - \sum_i w_i h_i(\mathbf{x}_j) \right)^2 + \lambda \sum_{i=1}^k |w_i|$$

L2 regularization on least squares:

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \sum_j \left(t(\mathbf{x}_j) - \sum_i w_i h_i(\mathbf{x}_j) \right)^2 + \lambda \sum_{i=1}^k w_i^2$$

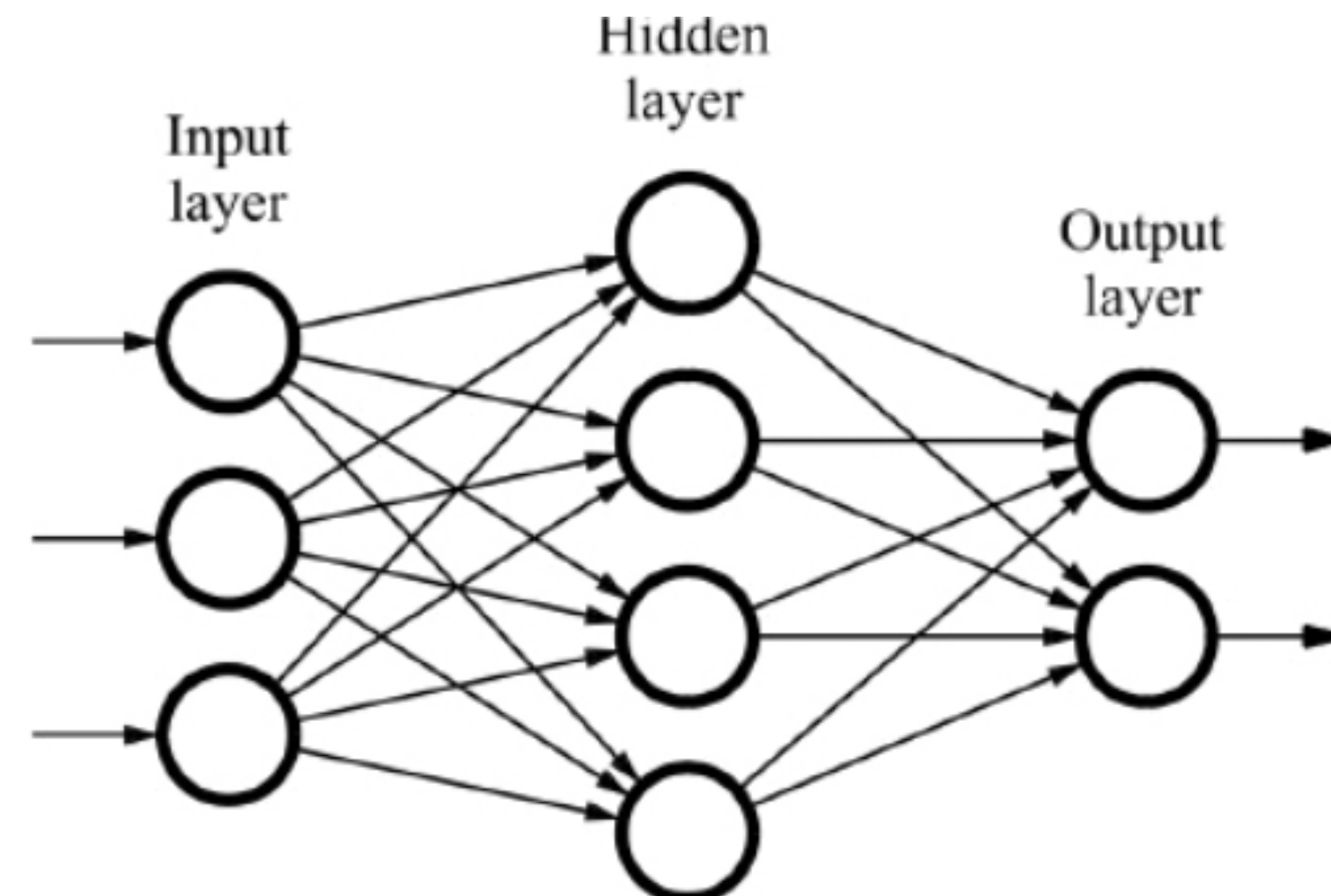
Classical neural networks

- Gradient clipping
- Weight regularisation
- Avoiding certain activation functions



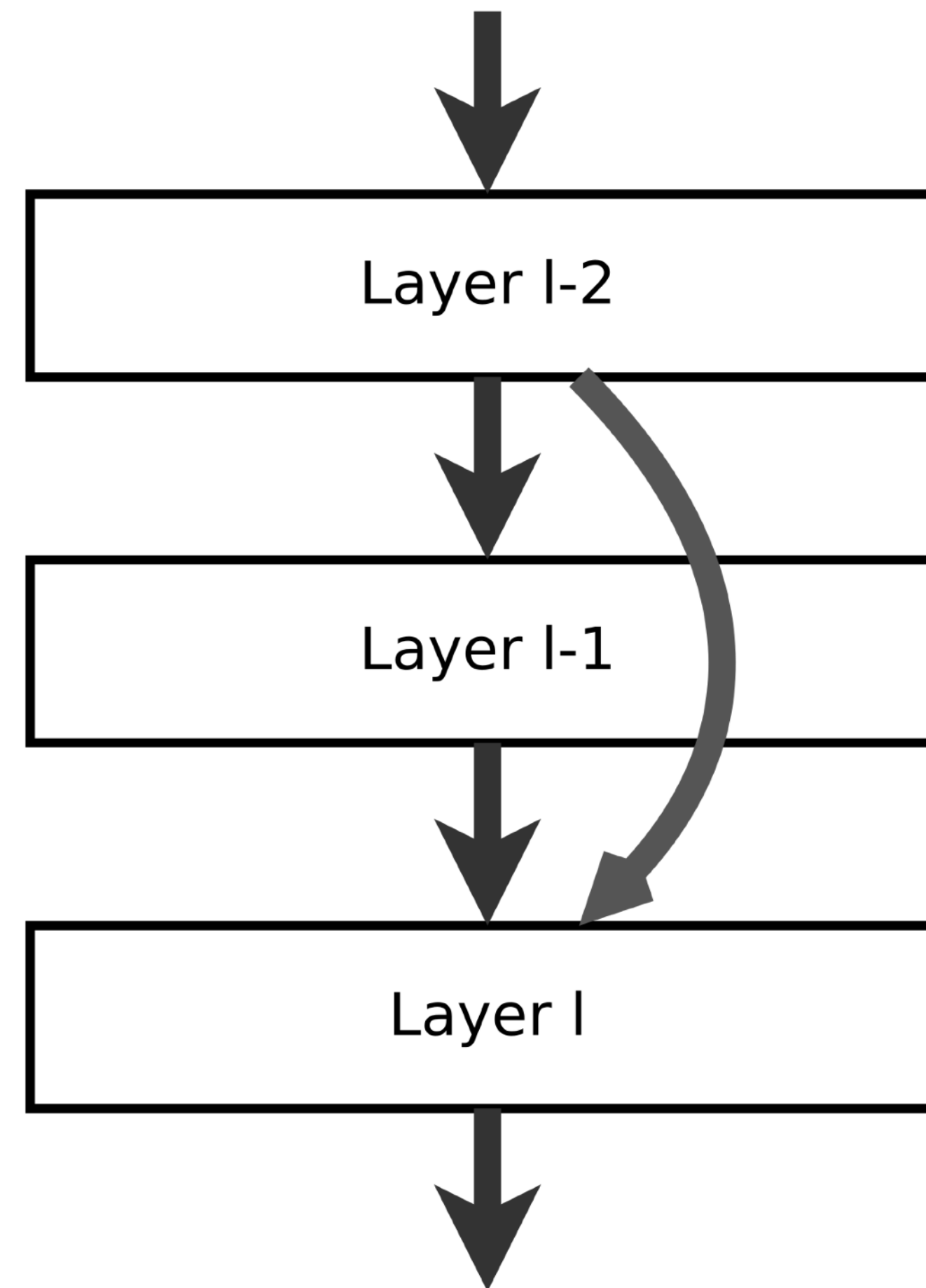
Classical neural networks

- Gradient clipping
- Weight regularisation
- Avoiding certain activation functions
- Redesigning the network

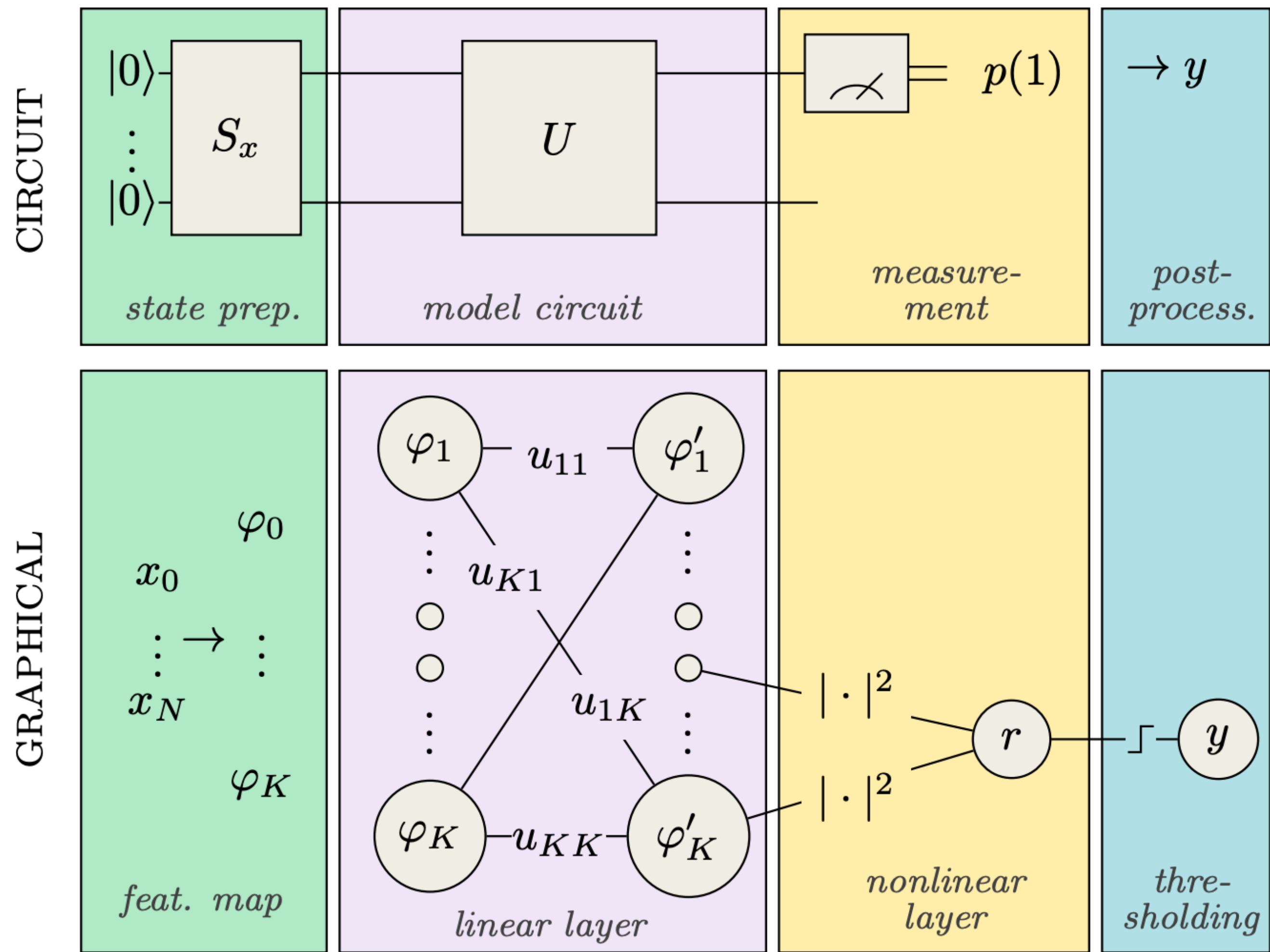
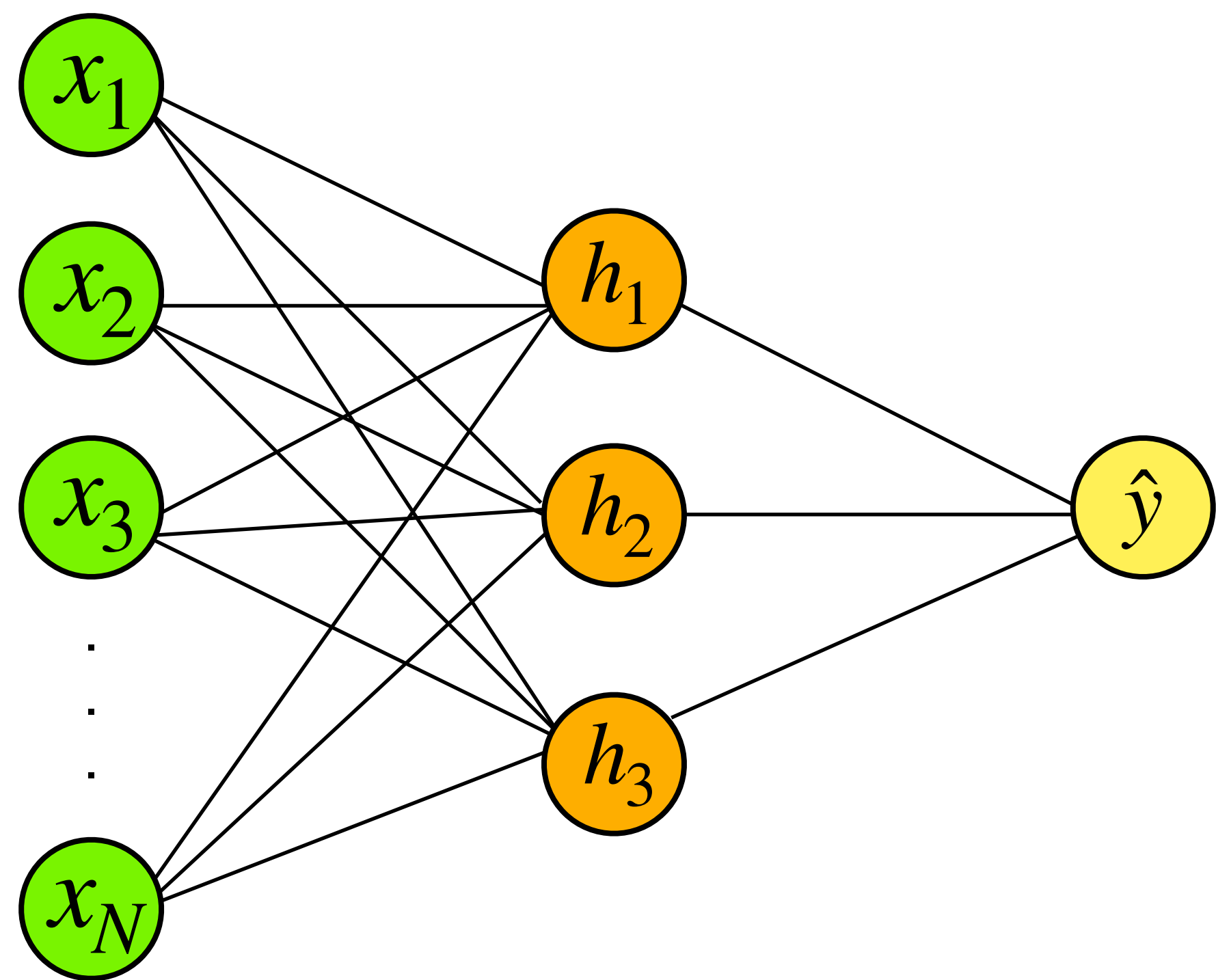


Classical neural networks

- Gradient clipping
- Weight regularisation
- Avoiding certain activation functions
- Redesigning the network
- Residual networks

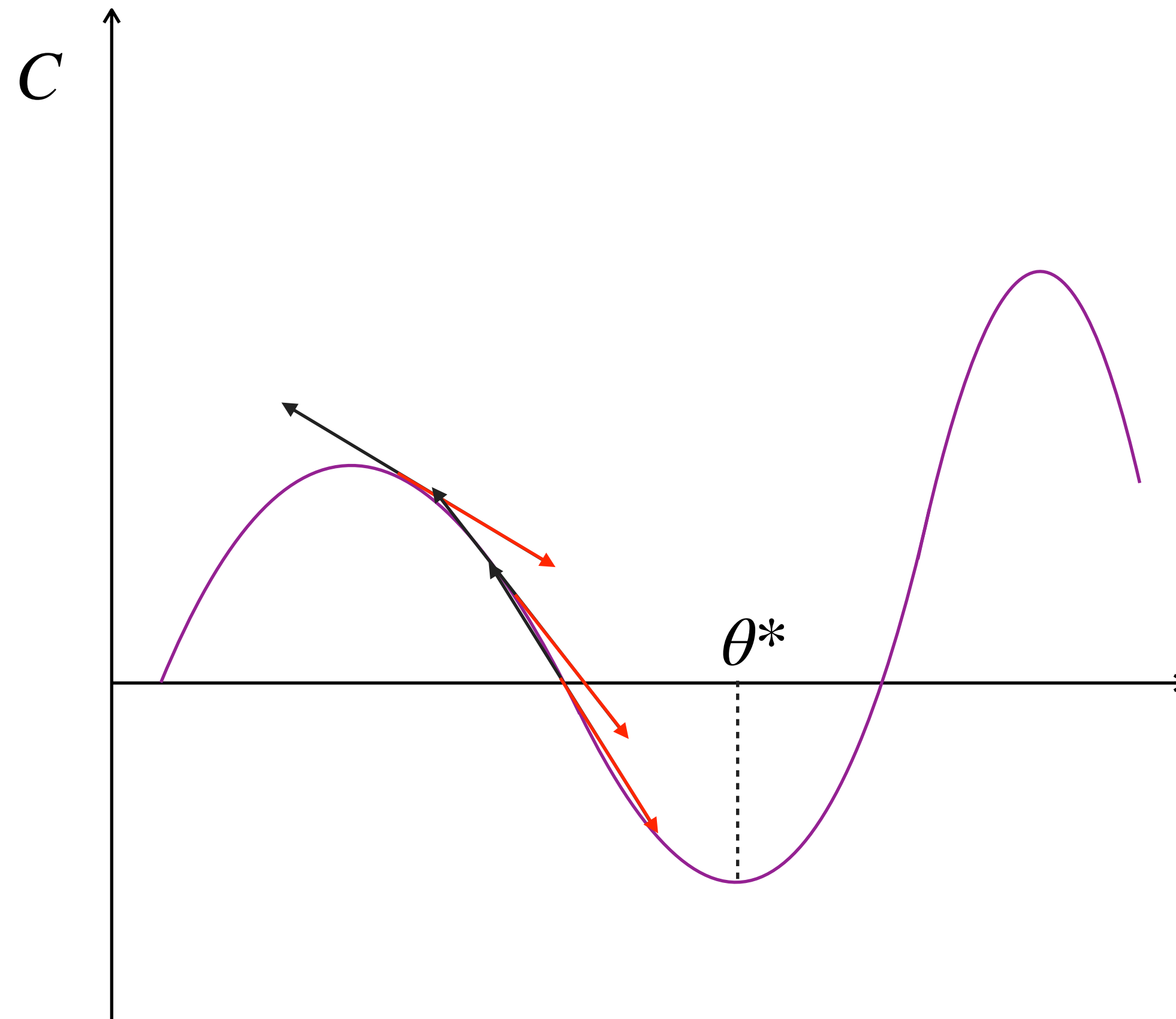


Quantum neural networks



Gradient descent

$$\theta^* = \theta - \eta \frac{\partial C(\hat{y}, y)}{\partial \theta}$$



Barren plateaus

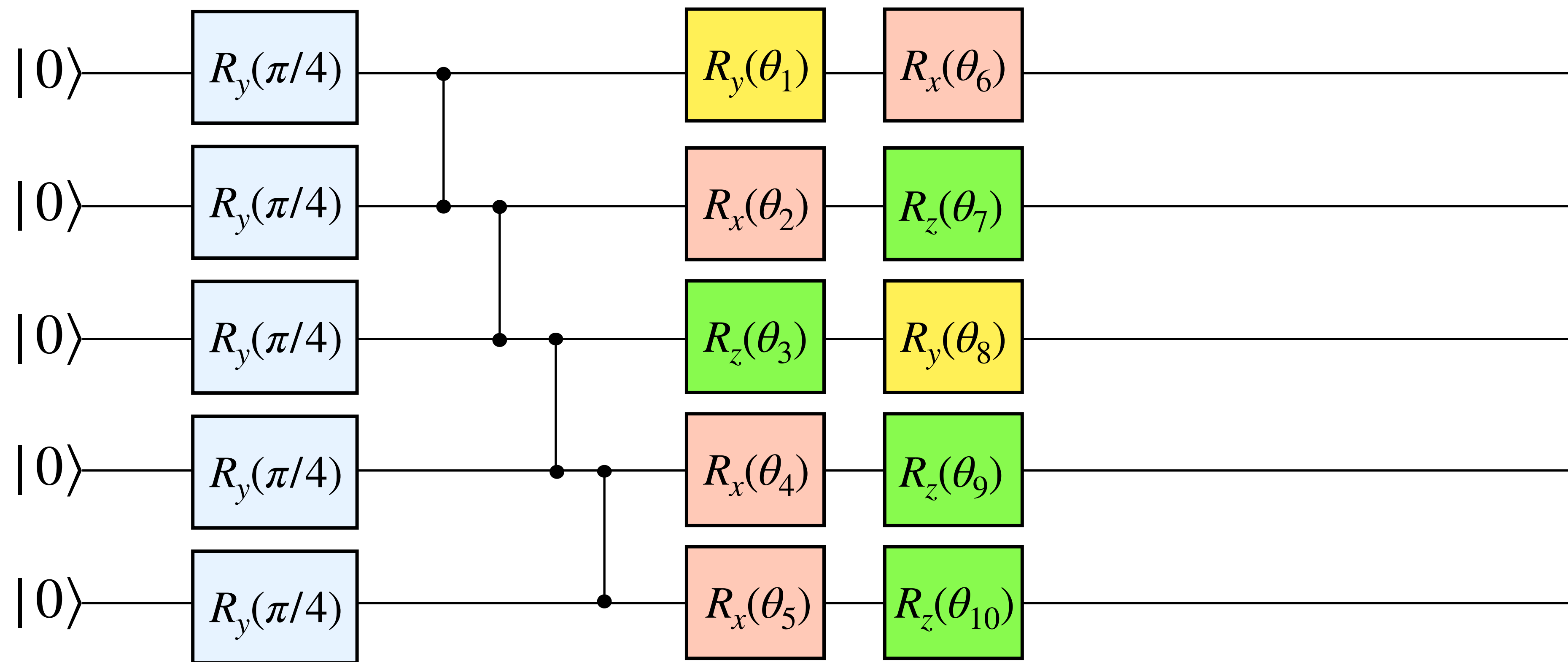
Random initialisation

If θ is initialised randomly, gates are drawn randomly



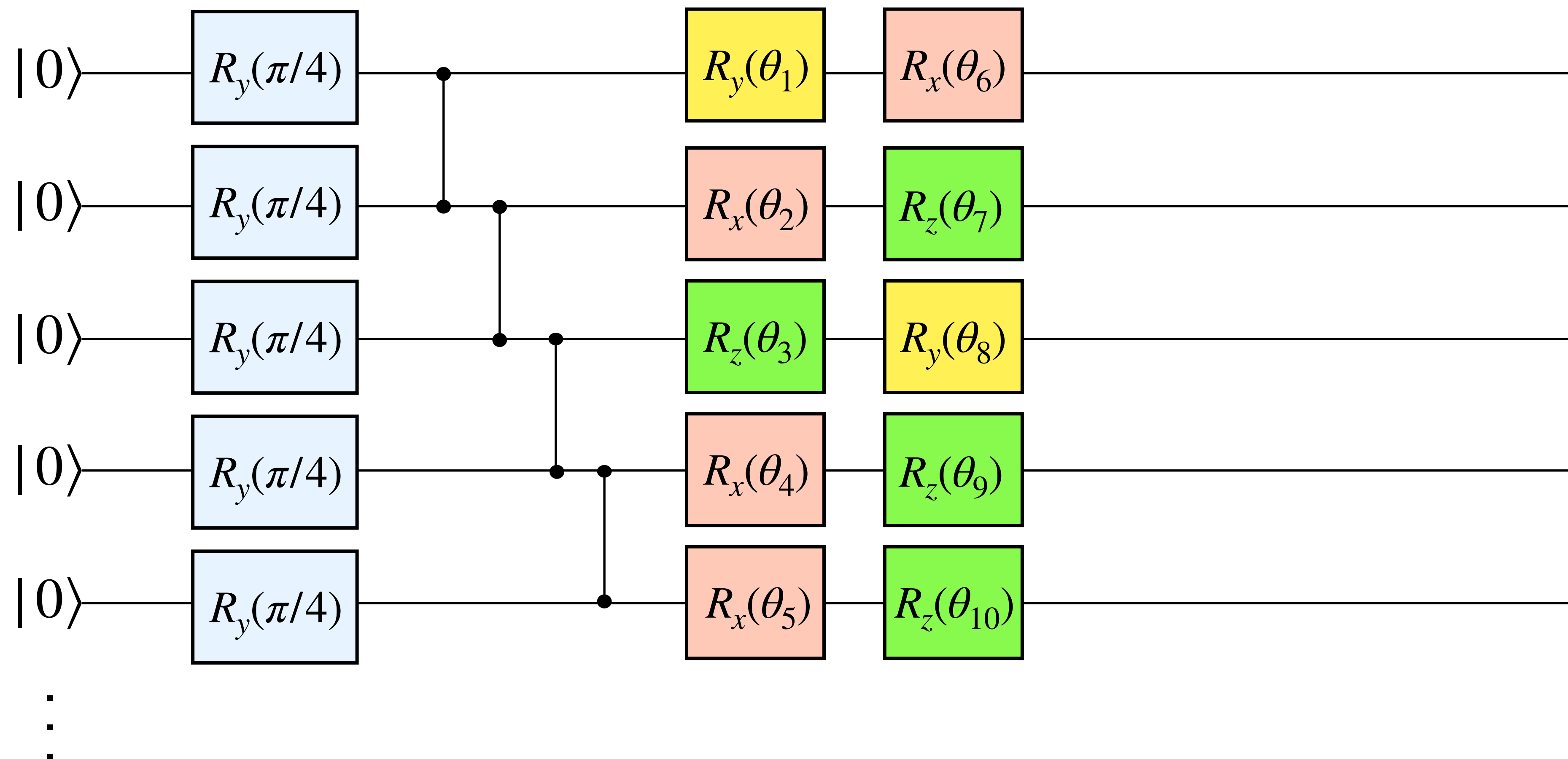
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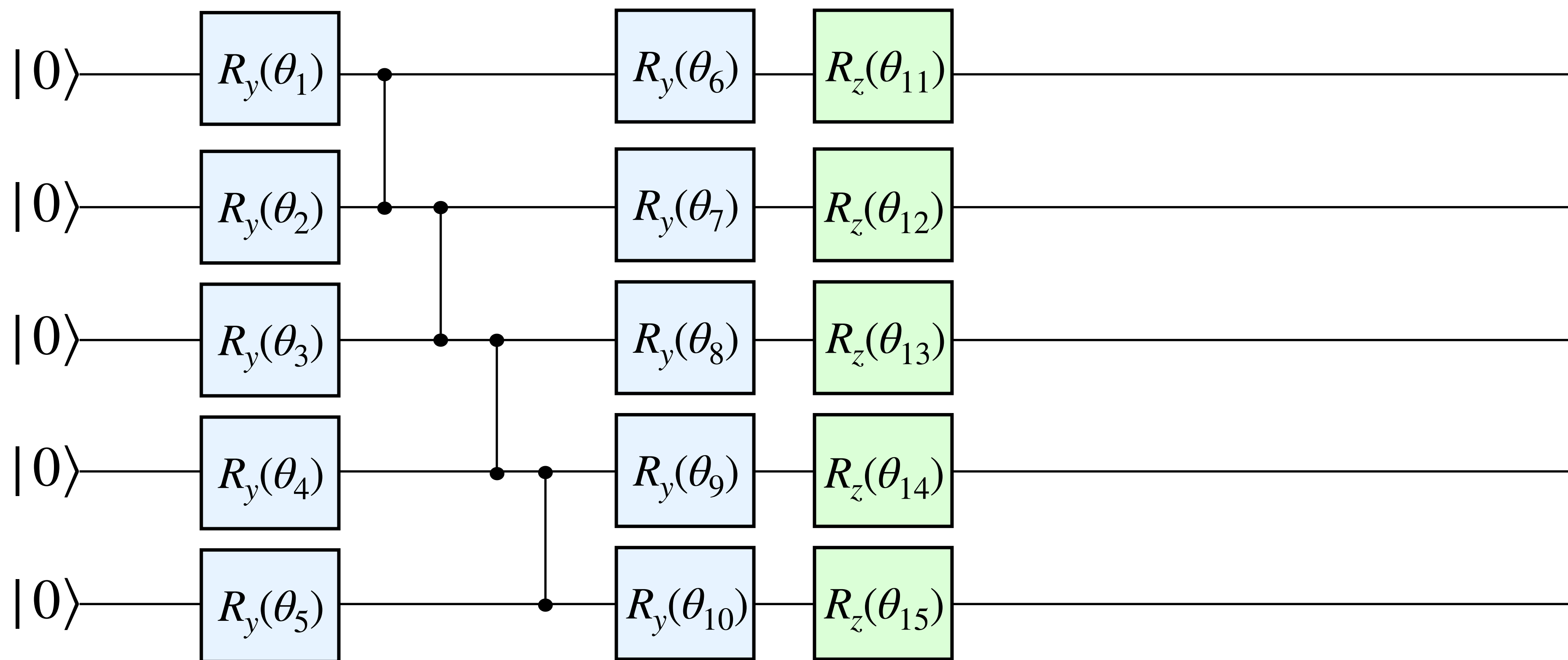


Random initialisation

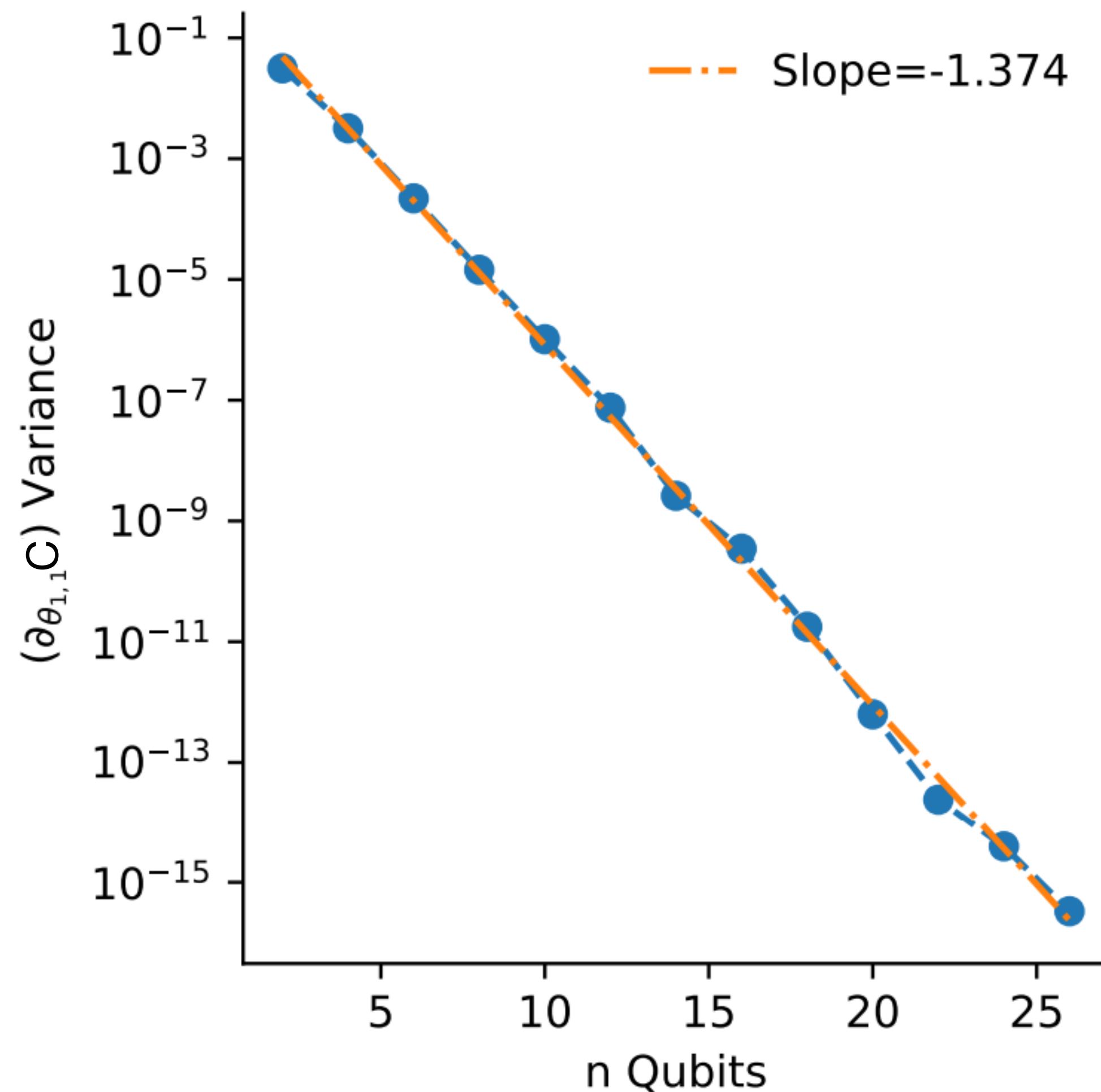
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Random initialisation

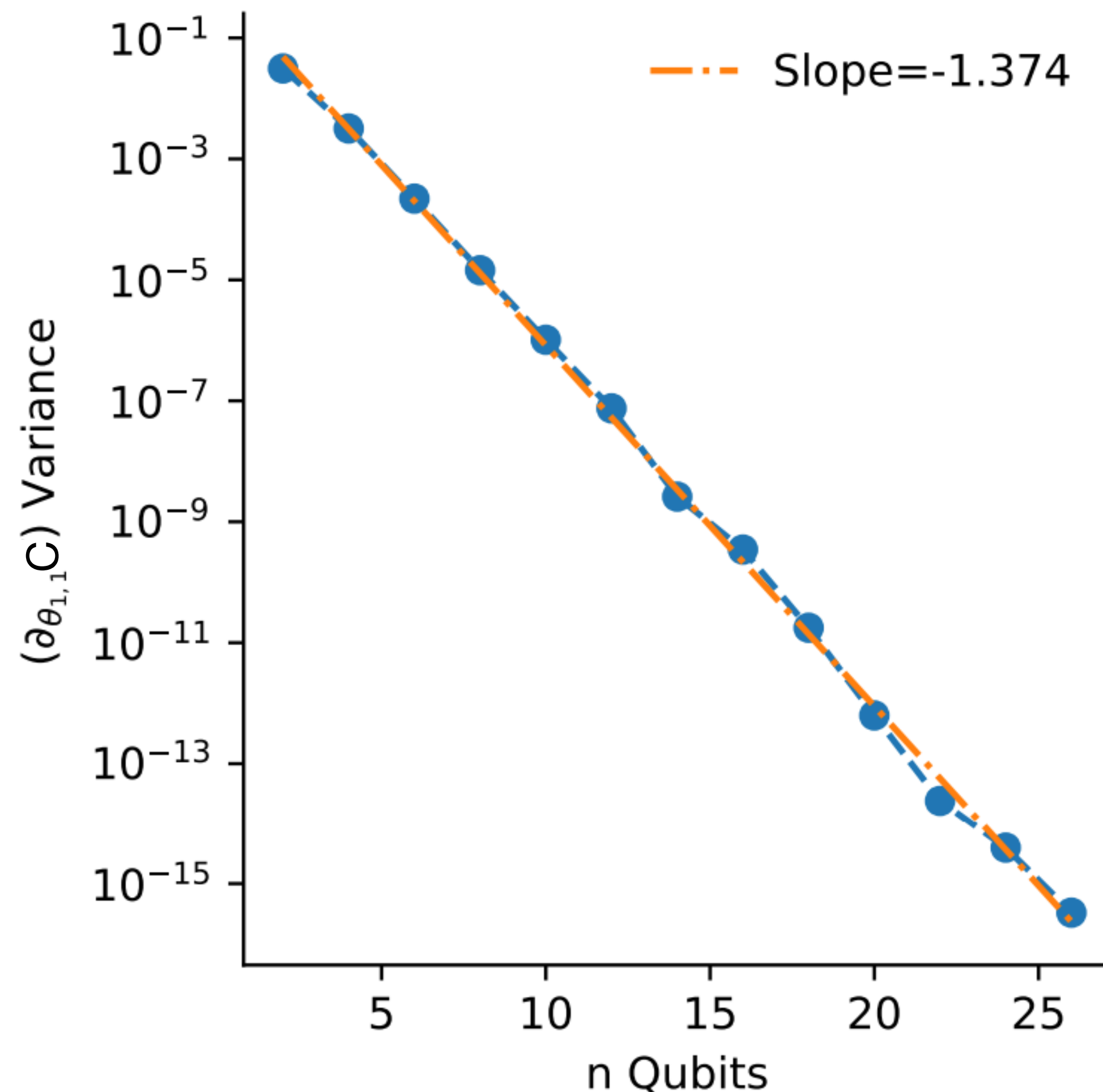


Random initialisation

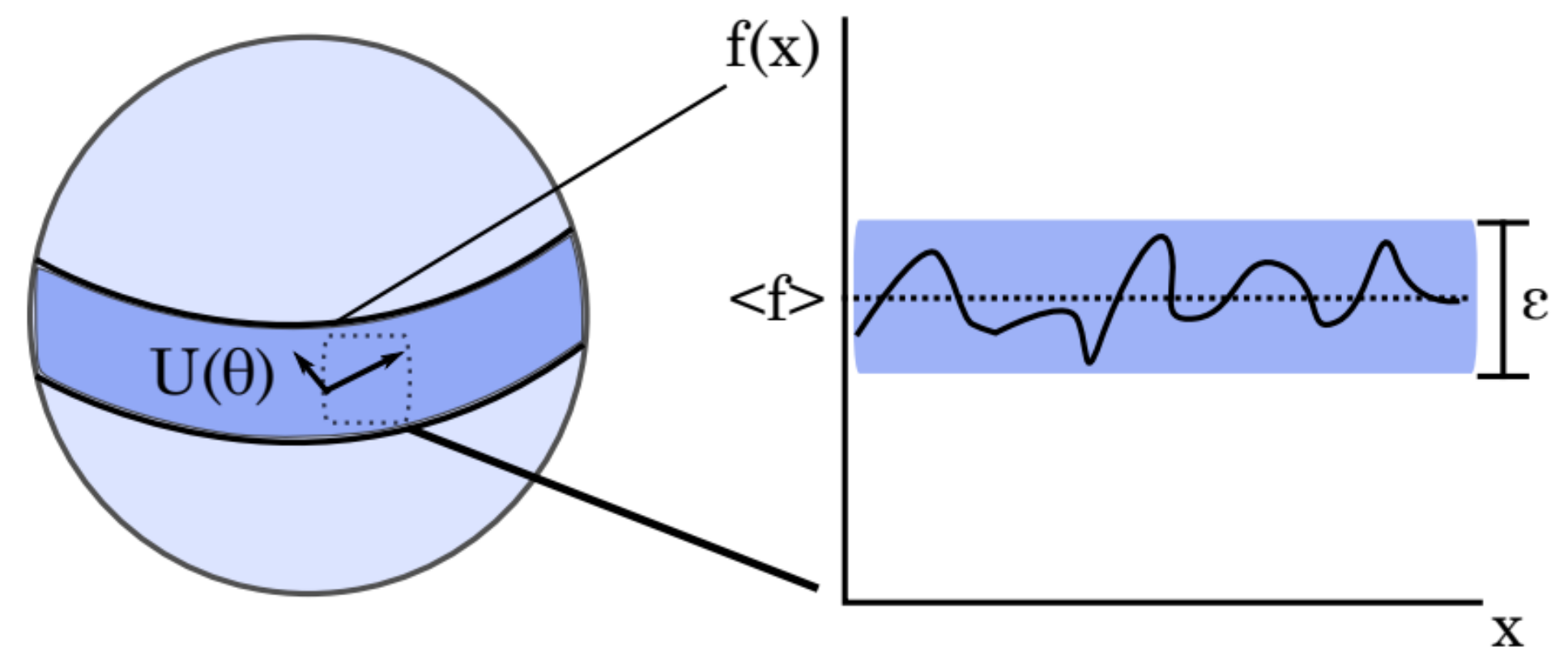


- If θ is initialised randomly, this can cause problems in variational circuits
- The variance of the gradient of the loss function vanishes

Random initialisation



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- The variance of the gradient of the loss function vanishes
- Gradients become concentrated around zero
- Require greater precision to estimate the gradients which removes quantum advantages



Barren plateaus

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Methods to try avoid barren plateaus

Methods to try avoid barren plateaus

- Introduce structure into the circuit (encoding with data) or initialising layers to the identity
Grant, Edward, et al. "An initialization strategy for addressing barren plateaus in parametrized quantum circuits." Quantum 3 (2019): 214.

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<https://www.eventbrite.ca/e/quantum-research-seminars-toronto-tickets-122394389915>

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Methods to try avoid barren plateaus

The Hessian matrix

$$\frac{\partial C}{\partial \theta} = \begin{bmatrix} \frac{\partial C}{\partial \theta_1} \\ \frac{\partial C}{\partial \theta_2} \\ \vdots \end{bmatrix}$$

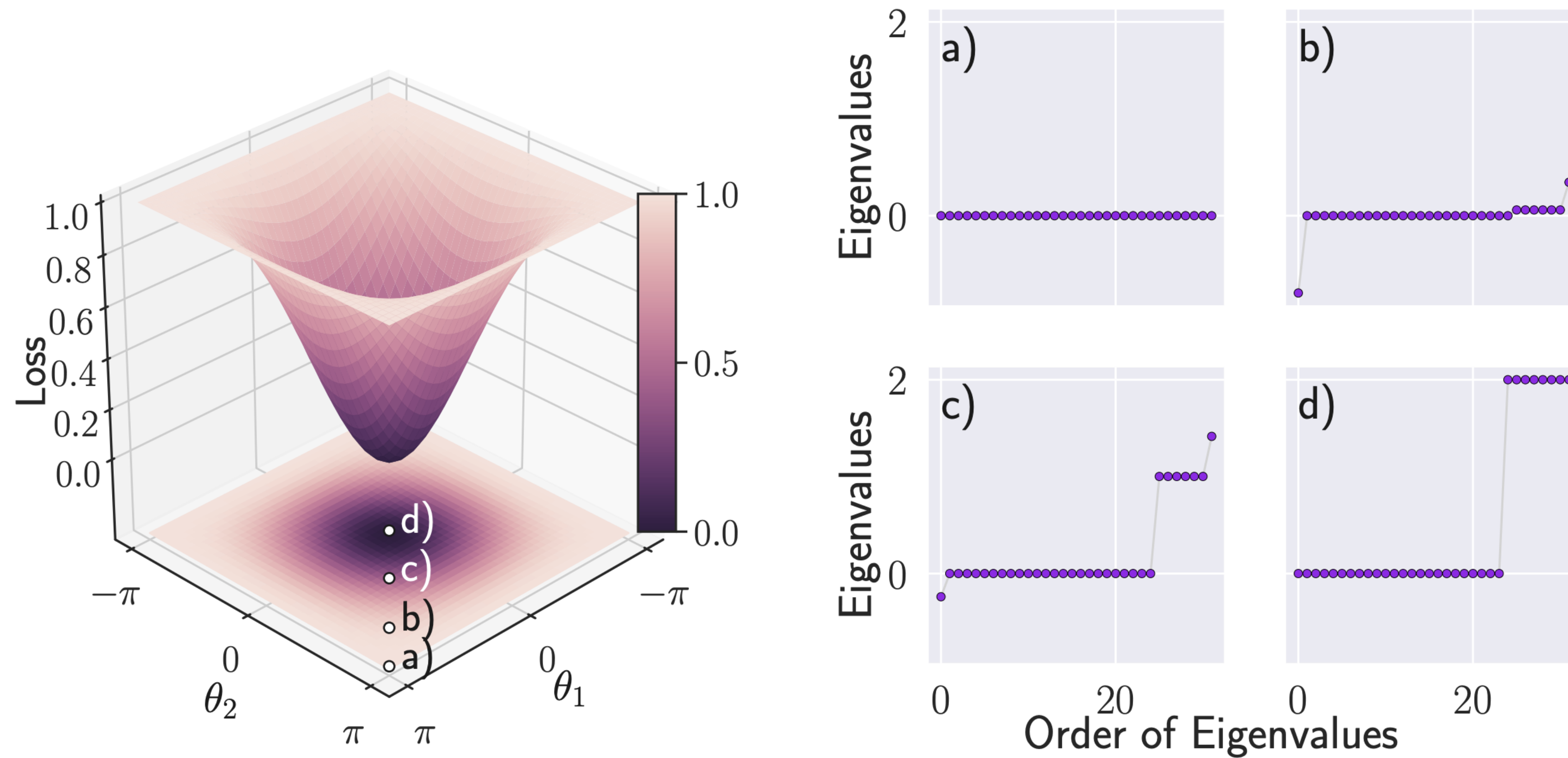
Methods to try avoid barren plateaus

The Hessian matrix

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$$\mathbf{H} = \begin{bmatrix} \frac{\partial^2 C}{\partial \theta_1^2} & \frac{\partial^2 C}{\partial \theta_1 \theta_2} & \cdots \\ \frac{\partial^2 C}{\partial \theta_2 \theta_1} & & \\ \vdots & & \end{bmatrix}$$

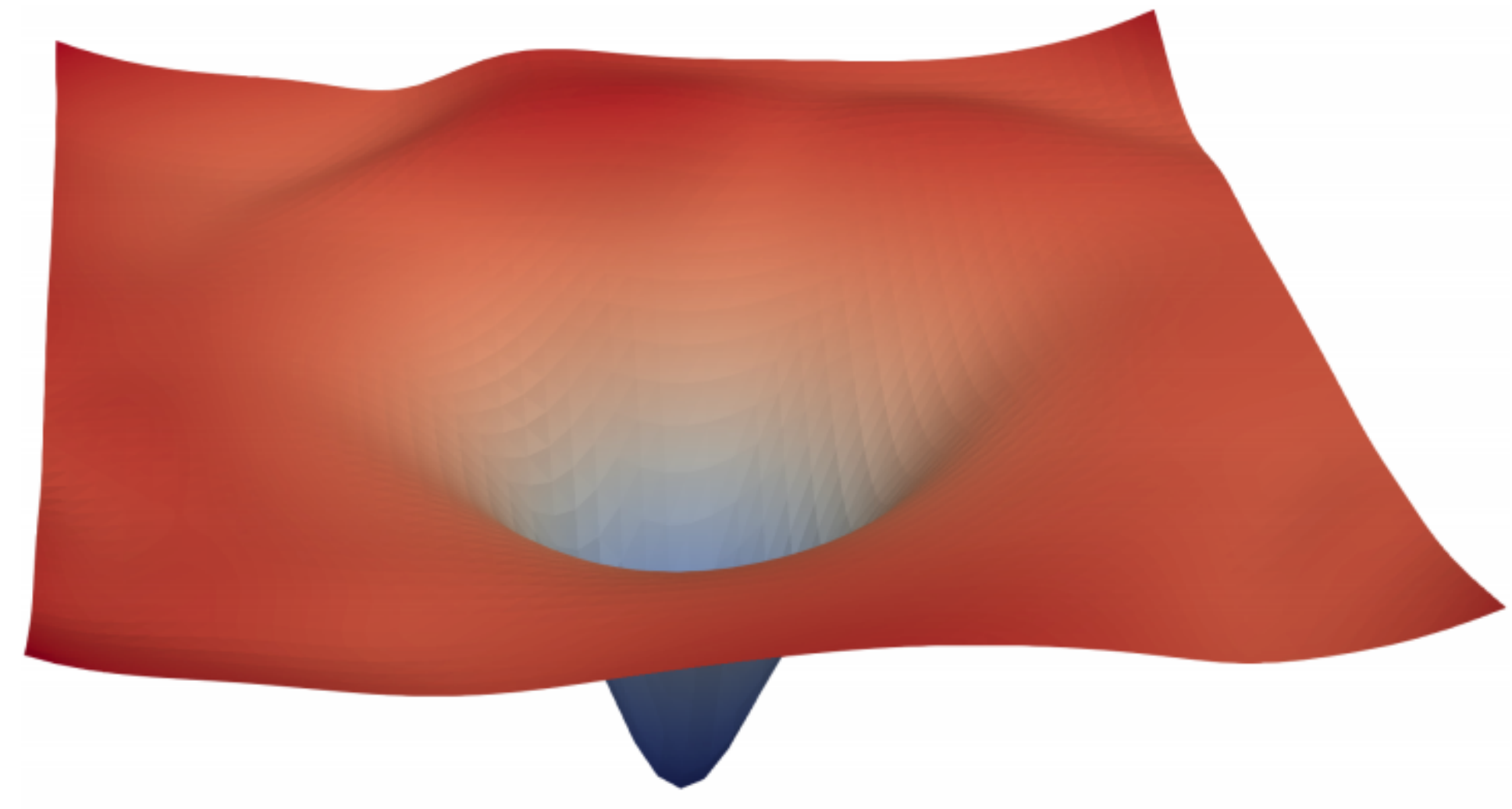
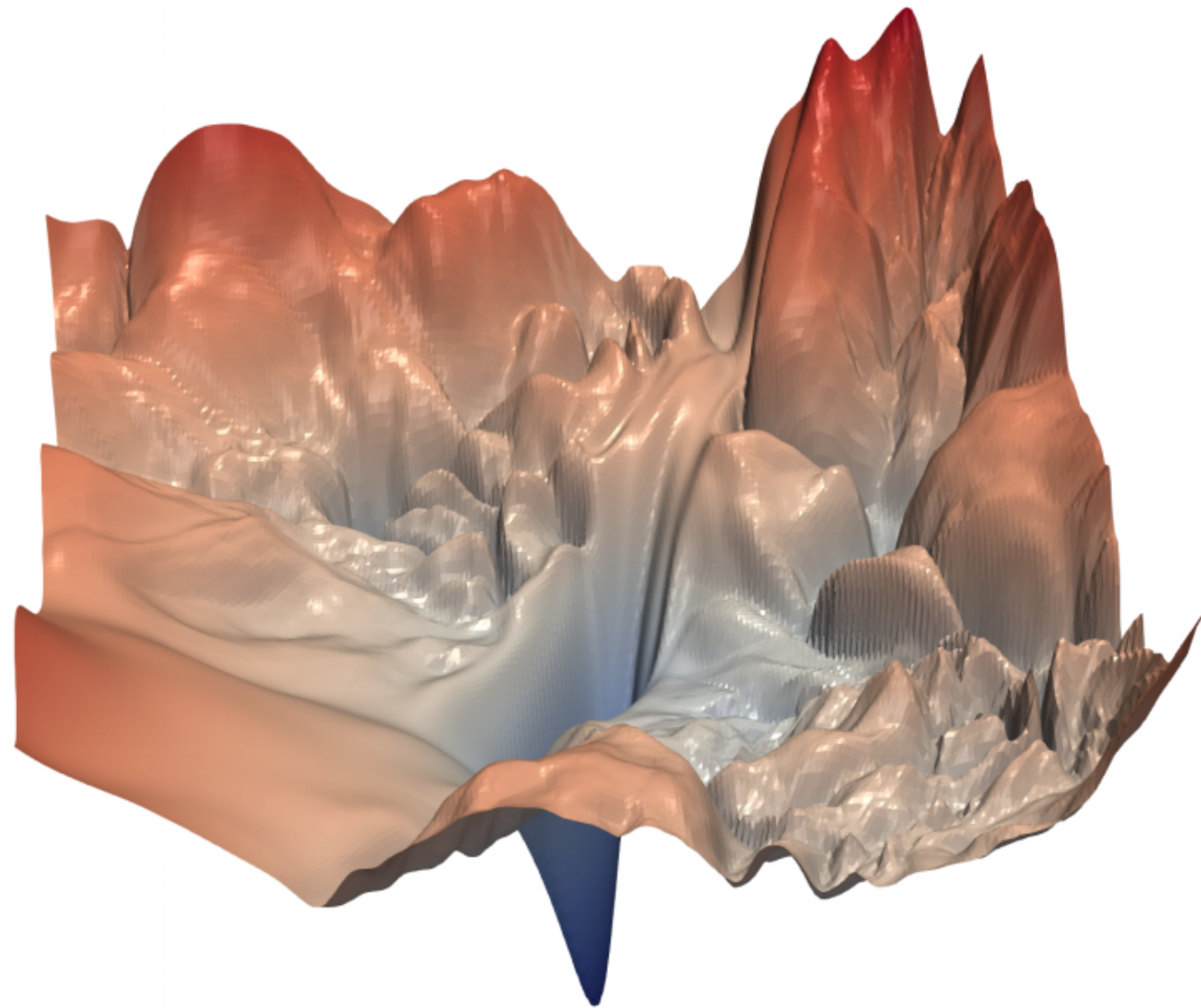
Loss landscape of quantum models



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Cerezo, M., and Patrick J. Coles. "Impact of Barren Plateaus on the Hessian and Higher Order Derivatives." *arXiv preprint arXiv:2008.07454* (2020).

Loss landscapes



Jump to the code

Thank you!

NITheP Mini-school

Amira Abbas
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amyami187@gmail.com

