

# الگوریتم‌های کوانتومی وردشی مروری بر پیشرفت‌ها و چالش‌ها

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مدرسه پاییزه الگوریتم‌های کوانتومی و کاربردهای آن‌ها  
مهر ۱۴۰۳

# Contents

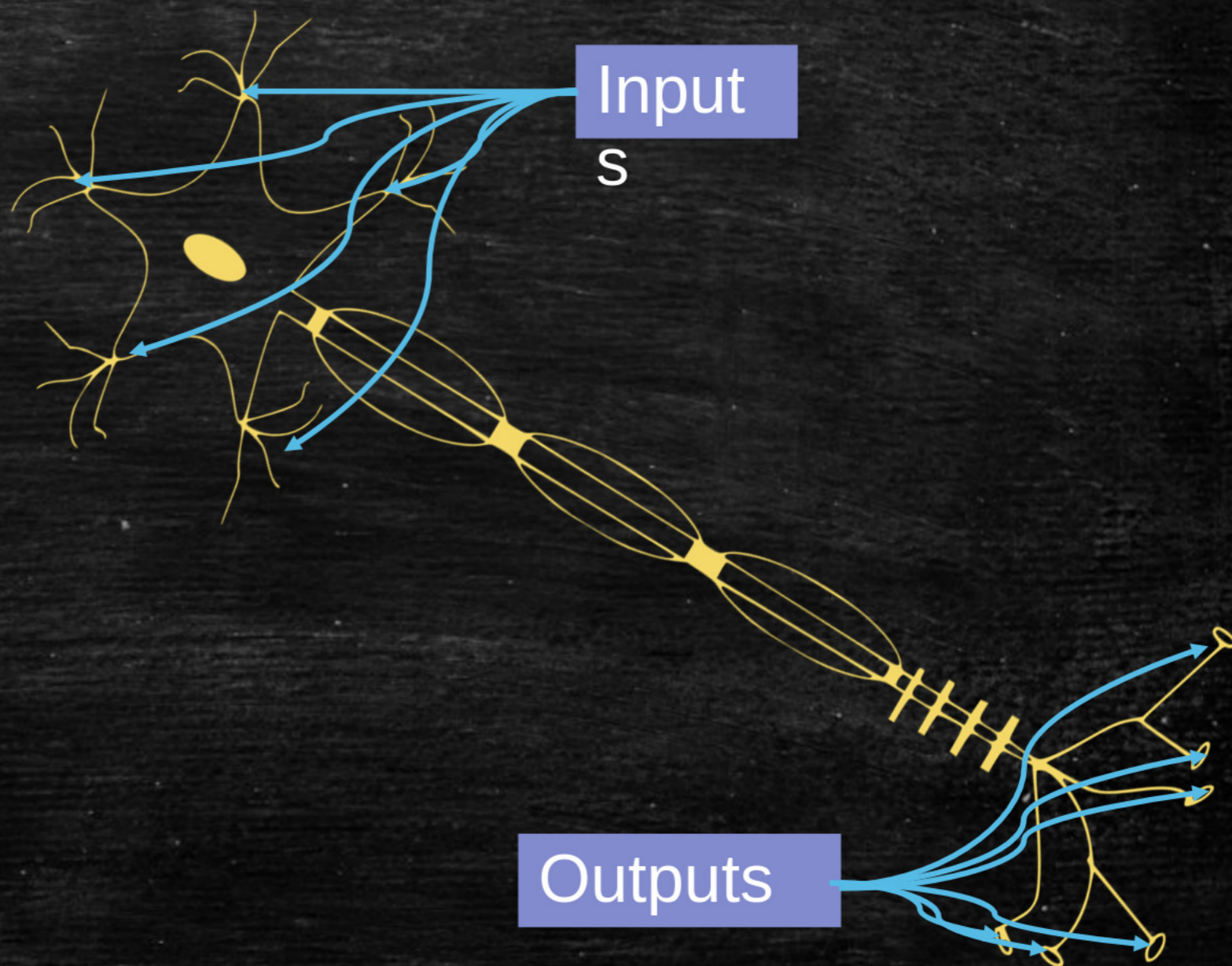
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- What are VQAs?
- Applications
- Challenges
- Solutions

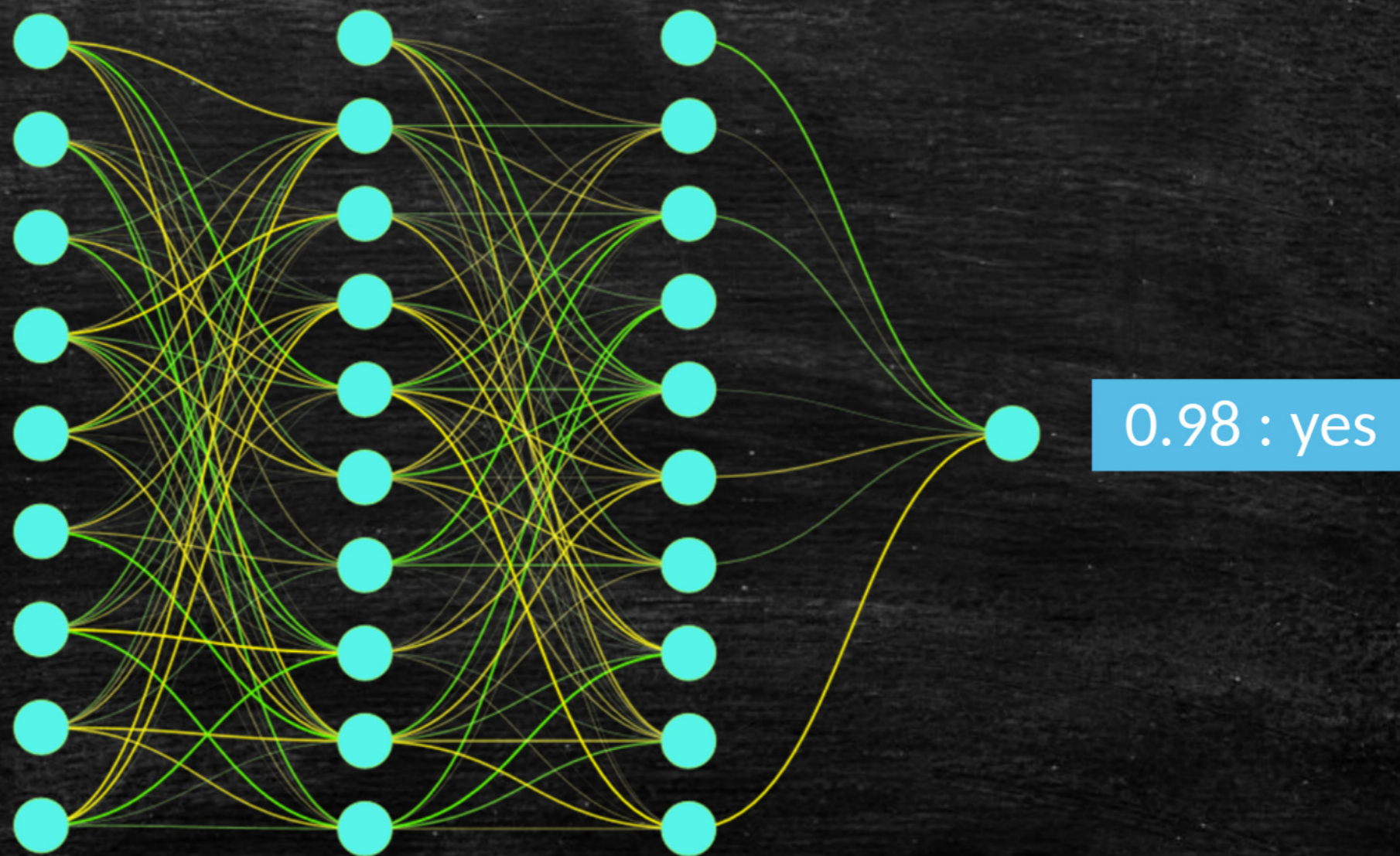
# Machine Learning, a bit of history

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- 1943: Artificial Neuron
- Input Signal  $>$  Threshold
  - -> Output
- Activation function
  - ReLU (Rectified Linear Unit)



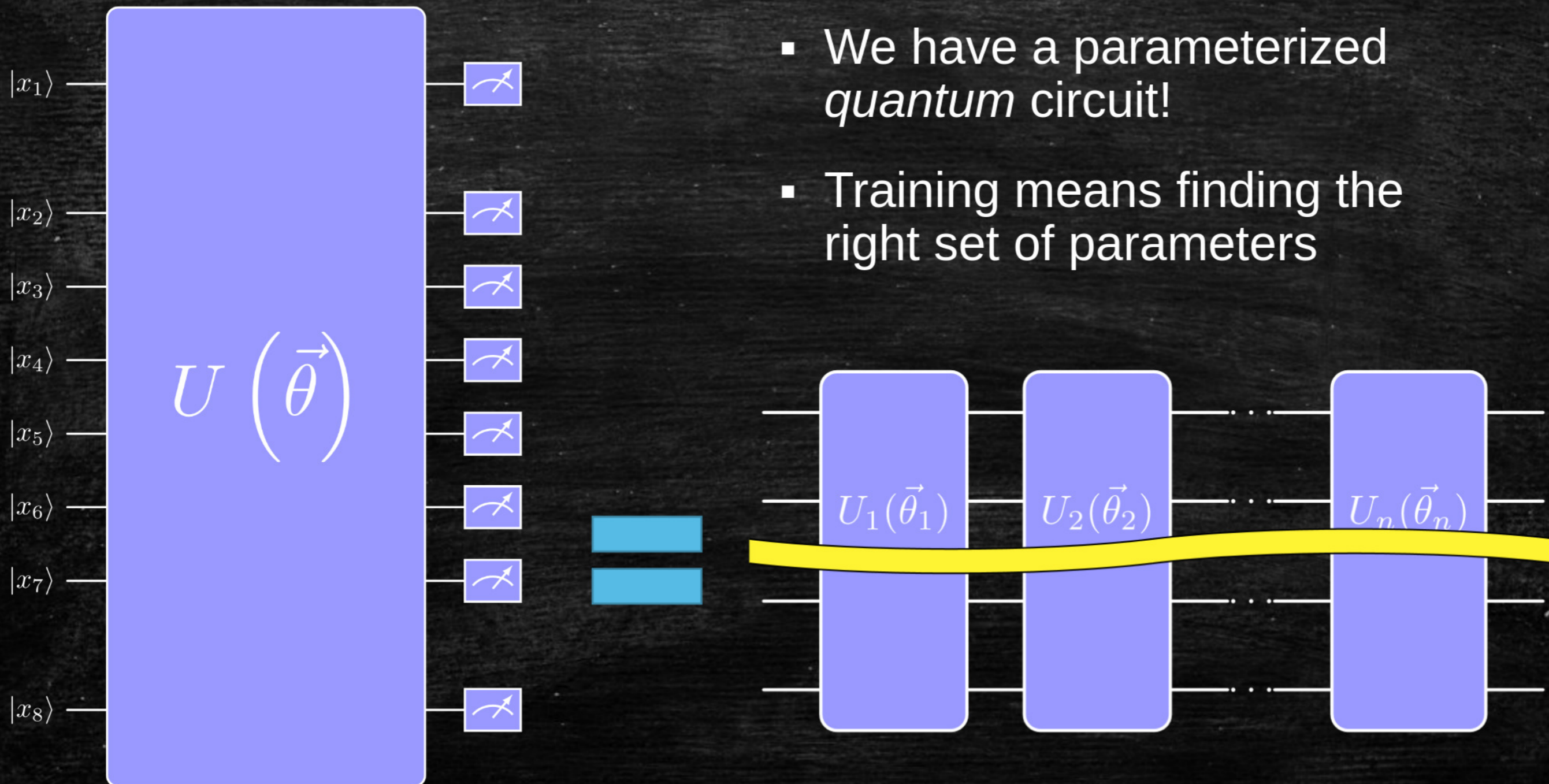
# Machine Learning, neural networks



Is this a Cat?

0.98 : yes

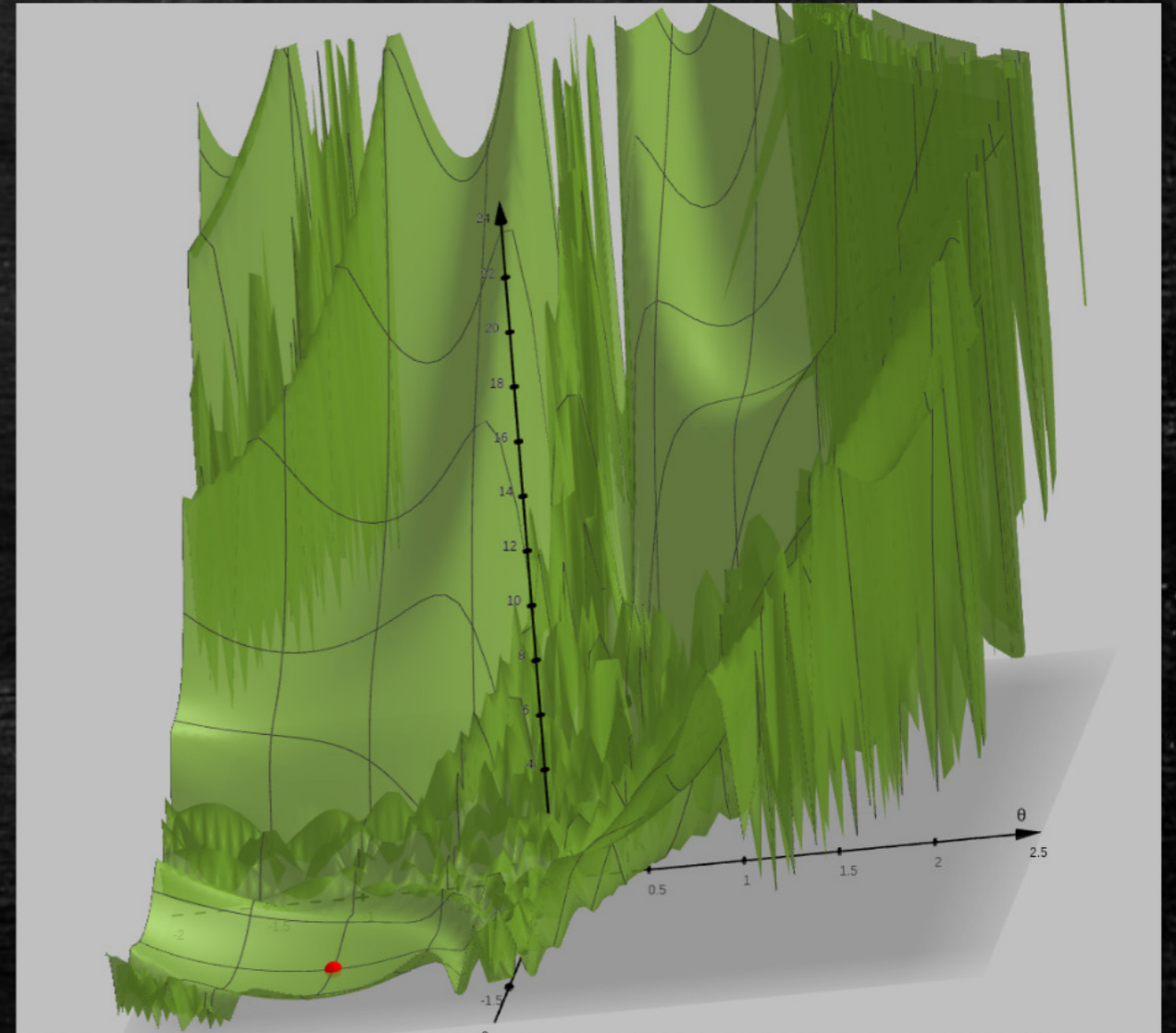
# Variational Quantum Algorithms



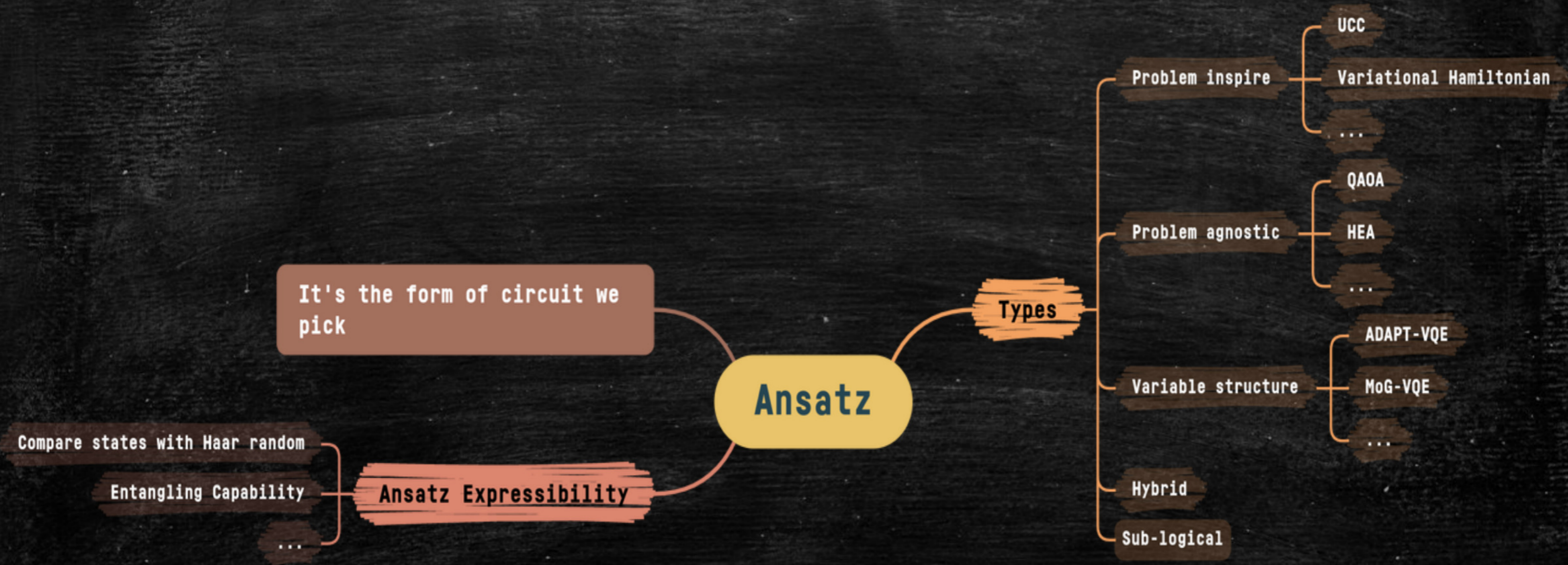
# VQA: Cost function

- Cost function:
  - The circuit  $U(\vec{\theta})$
  - States from a training set  $\{\rho_k\}$
  - A set of Observables  $\{O_k\}$

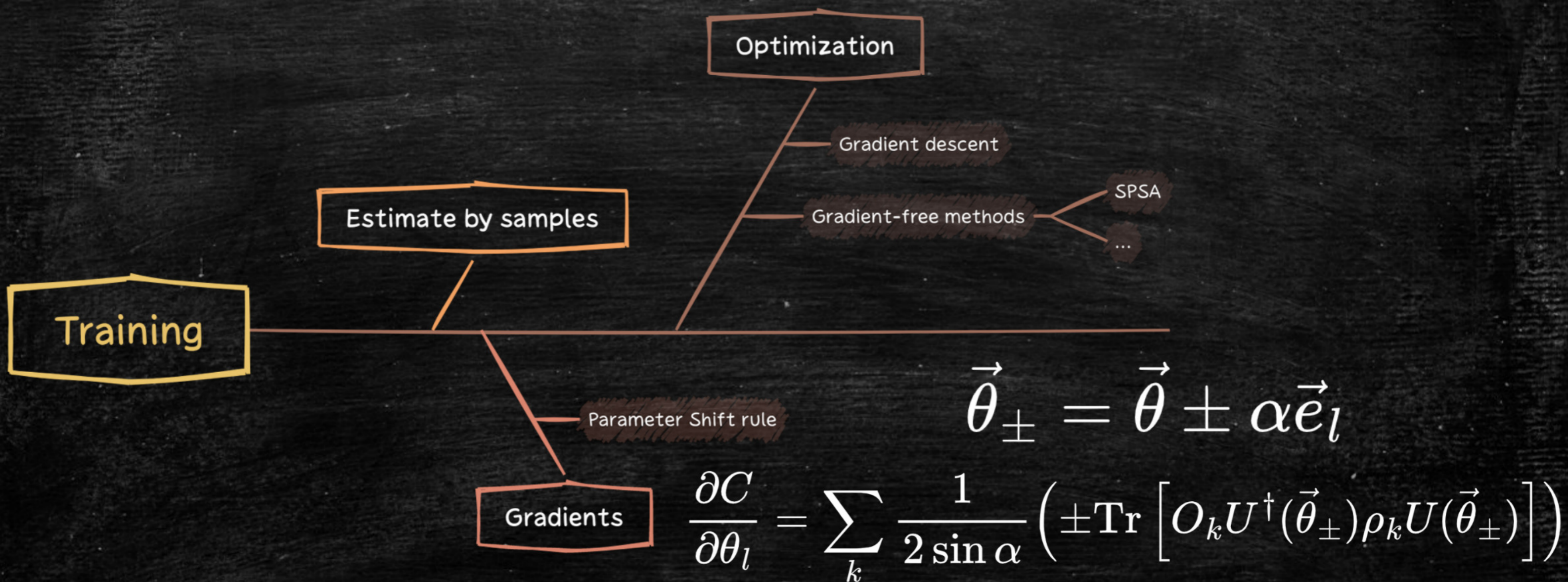
$$C(\vec{\theta}) = \sum_k f_k \left( \text{Tr} \left[ O_k U(\vec{\theta}) \rho_k U^\dagger(\vec{\theta}) \right] \right)$$



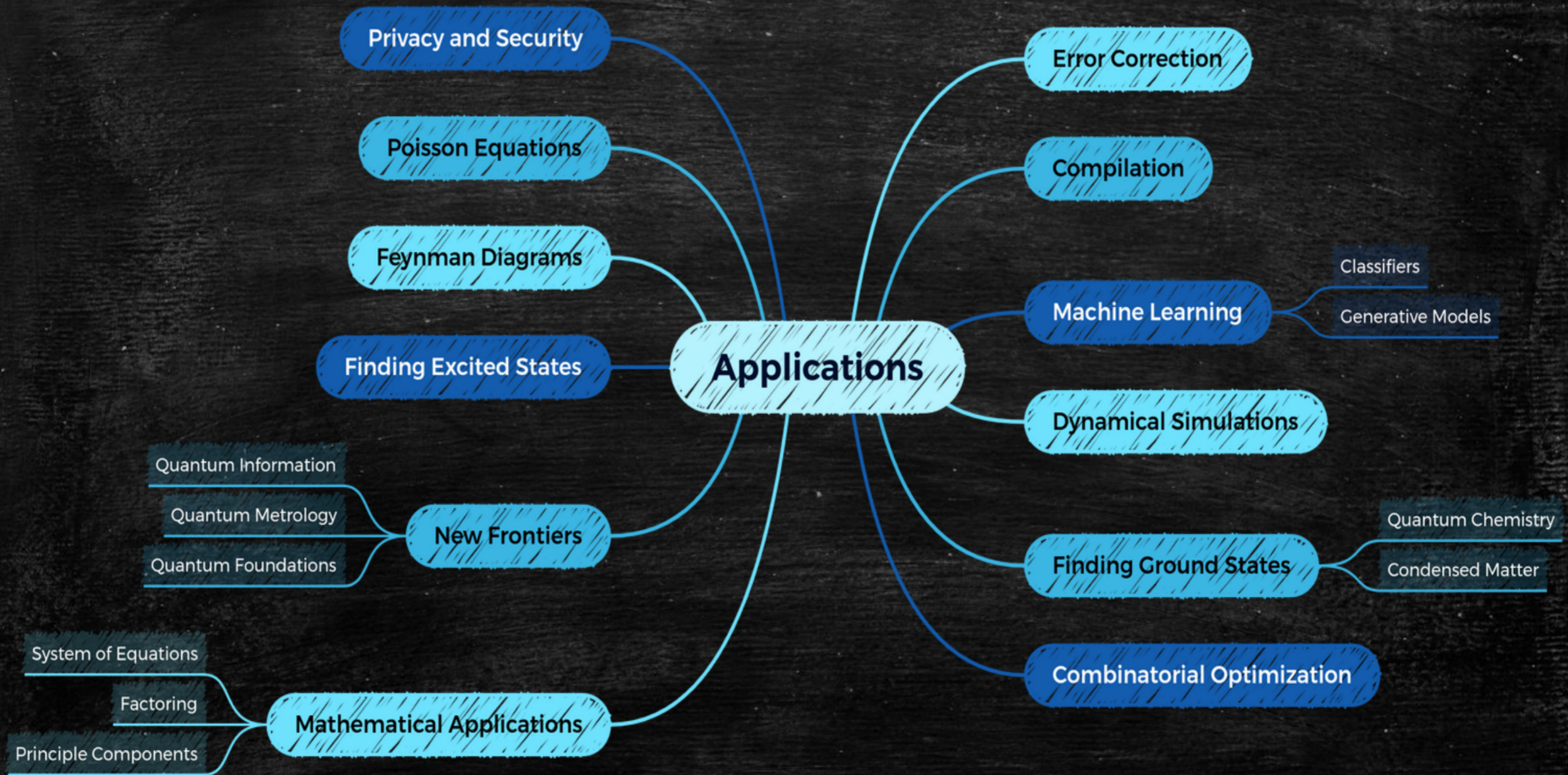
# VQA: Ansatz



# VQA: Training







# Ex. 1: Variational Quantum Eigensolver

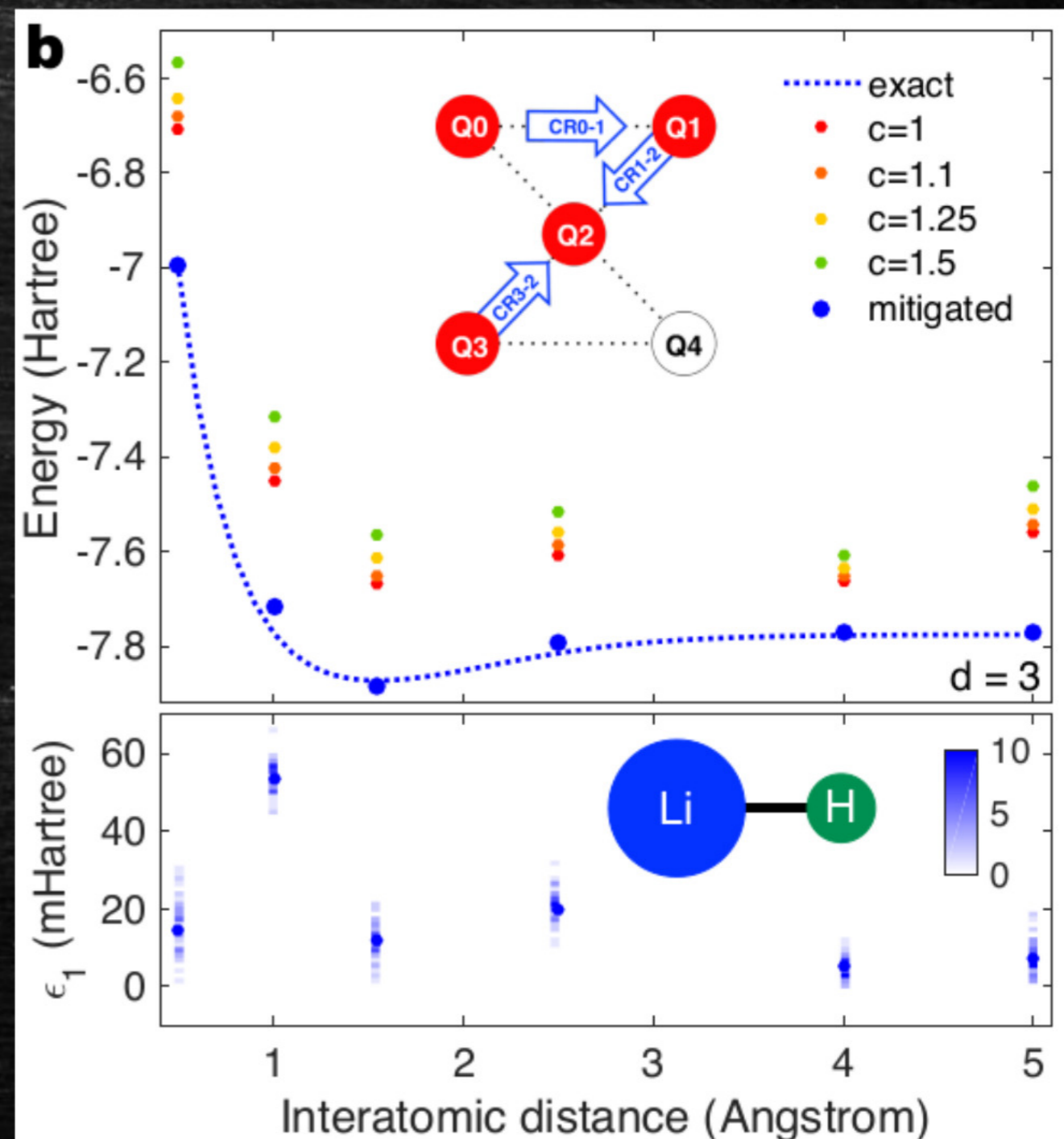
- Cost function

$$C(\vec{\theta}) = \langle \psi(\vec{\theta}) | H | \psi(\vec{\theta}) \rangle,$$

$$|\psi(\vec{\theta})\rangle = U(\vec{\theta})|\psi_0\rangle$$

- The Hamiltonian usually has the form:

$$H = \sum_k c_k \sigma_k$$

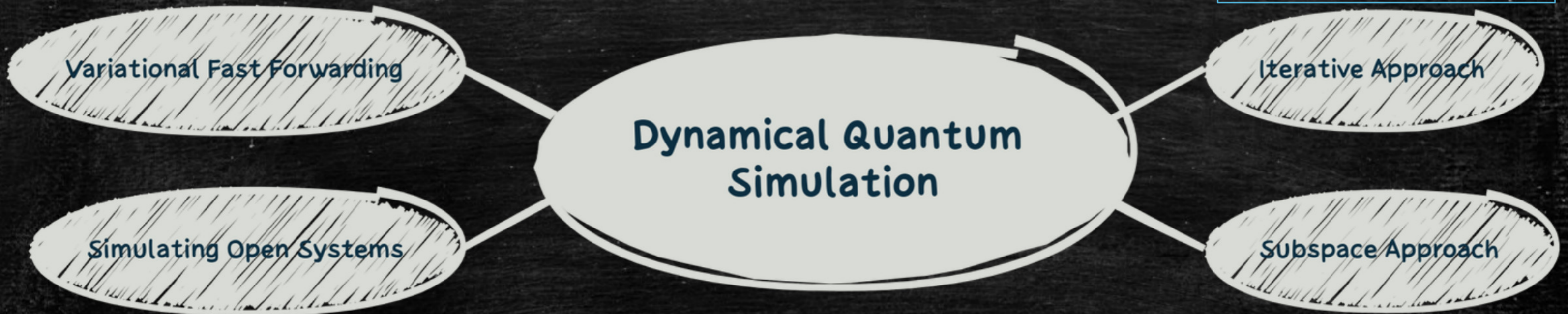


# Ex. 2 Dynamical Quantum Simulation

Increase fidelity between:

$$\exp(-iH\delta t), U(\vec{\theta}^*)\mathcal{T}(E, \delta t)U^\dagger(\vec{\theta}^*)$$

$$\begin{aligned} \min_{\dot{\vec{\theta}}} \delta \left\| \left( \frac{d}{dt} + iH \right) |\psi(\vec{\theta})\rangle \right\| \\ \Rightarrow M(\vec{\theta}) \cdot \dot{\vec{\theta}} = V(\vec{\theta}) \\ \vec{\theta} \rightarrow \vec{\theta} + \dot{\vec{\theta}} \cdot \Delta t \end{aligned}$$



Map the state to comp. basis.

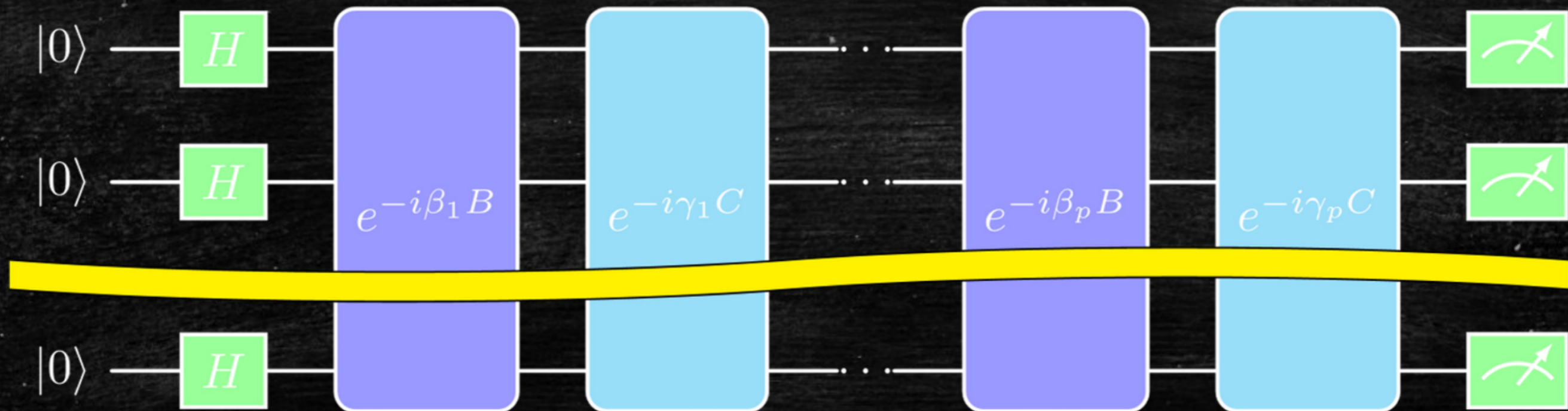
$$\exp(-iHt) \approx U(\vec{\theta}^*)\mathcal{T}(t)U^\dagger(\vec{\theta}^*)$$

# Ex. 3: Optimization, e.g. QAOA

- Map a classical optimization problem to a Hamiltonian:

$$C(z) = \sum_{\alpha=1}^m C_{\alpha}(z)$$

- A mixer operator  $B = \sum_{j=1}^n \sigma_j^X$
- Optimize angles  $\vec{\beta}, \vec{\gamma}$



# Doubts: Overview

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## Challenges

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graph LR; A[Challenges] --- B[Getting stuck in local minima]; A --- C[Barren Plateaus (Vanishing gradients)]; A --- D[Are there any improvements?]
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Getting stuck in local minima

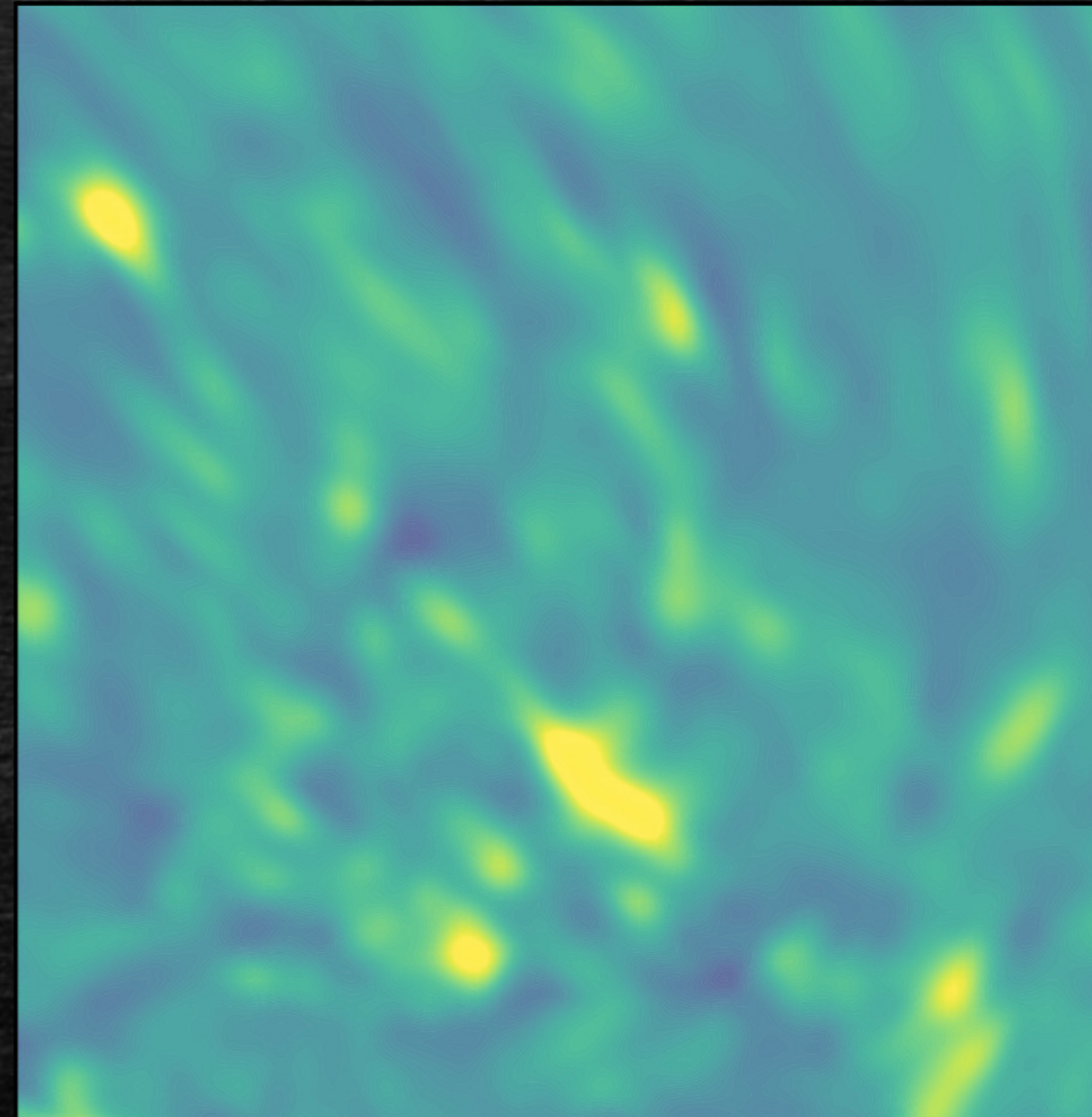
Barren Plateaus (Vanishing gradients)

Are there any improvements?

# Local minima

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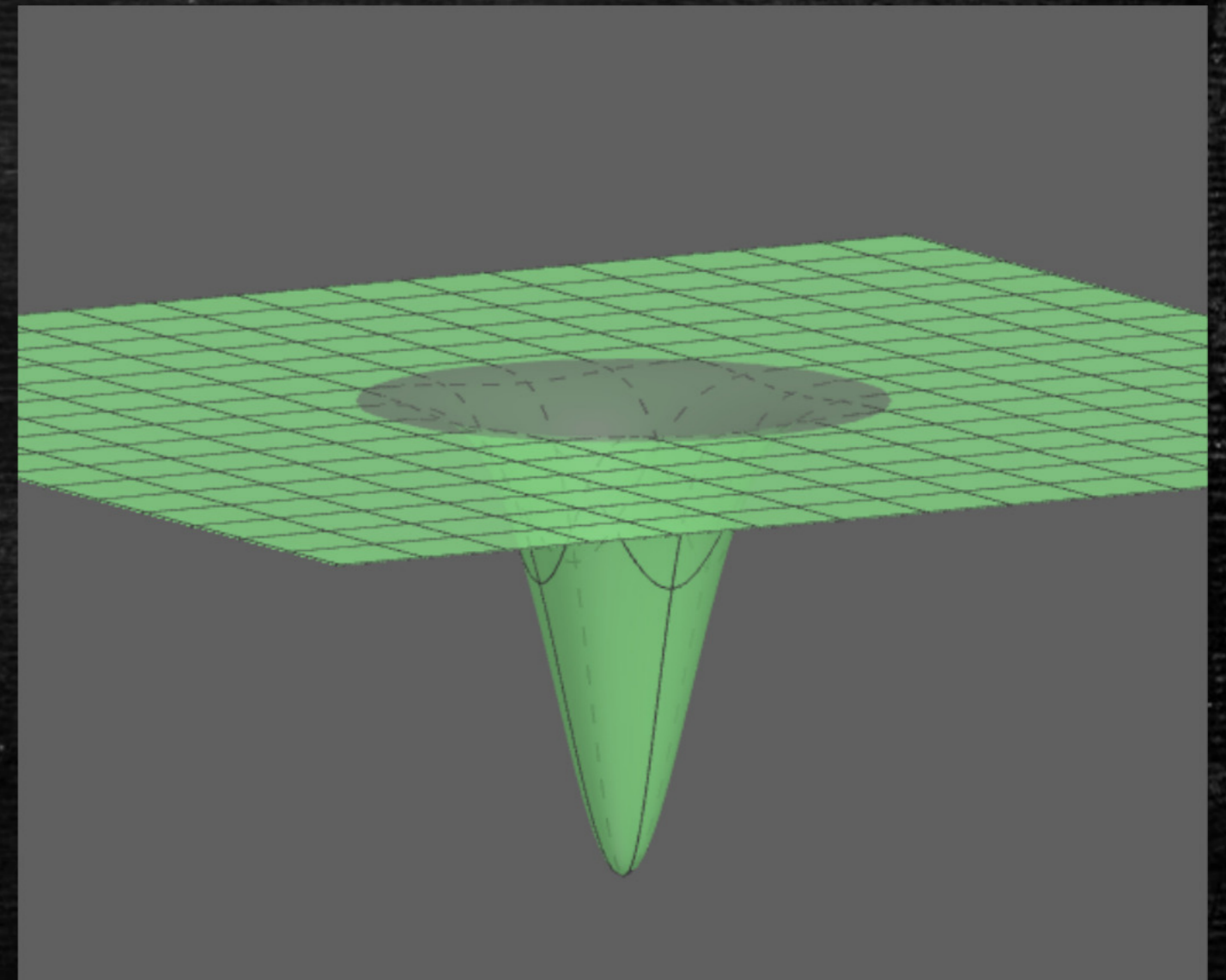
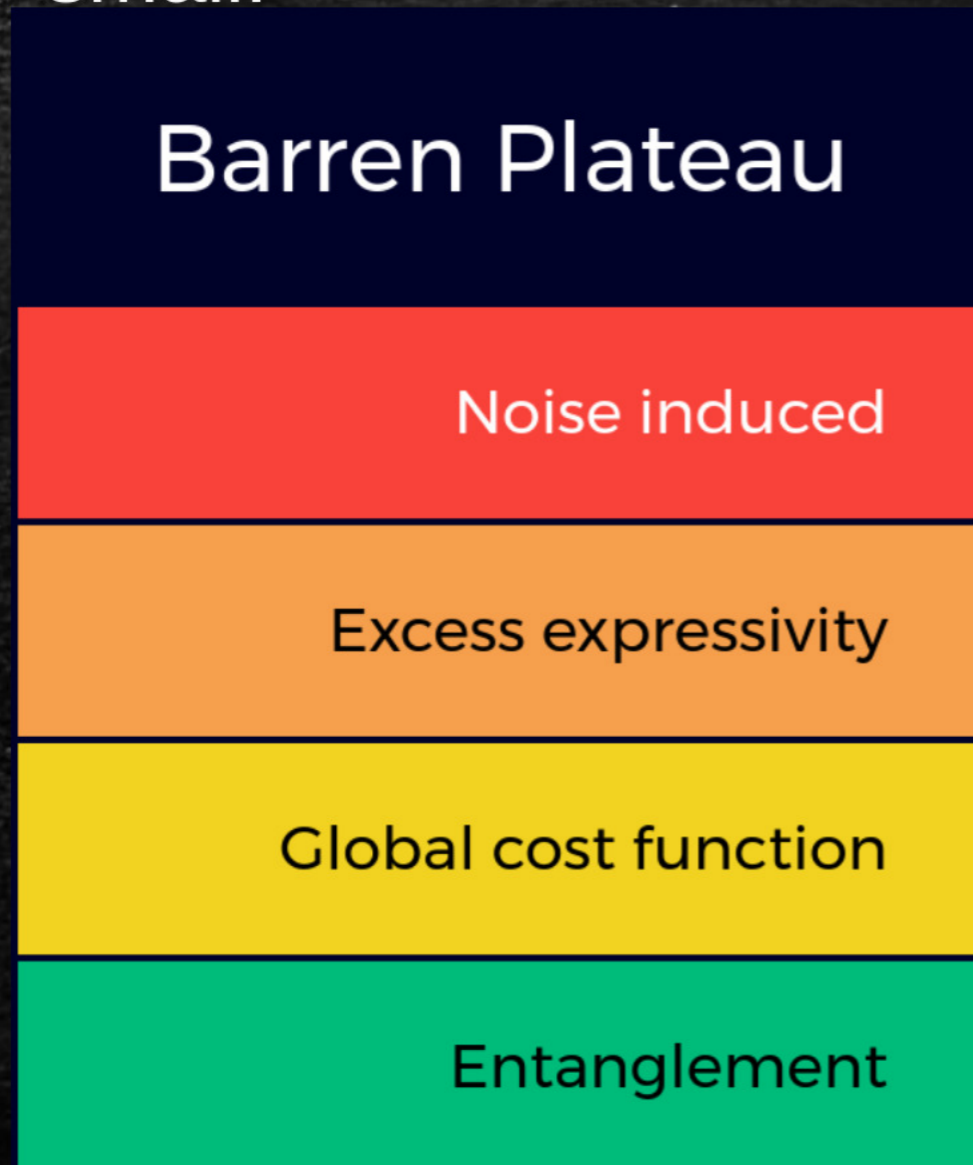
- There is evidence that the parameter hyperspace is not smooth!
  - "Beyond Barren Plateaus: Quantum Variational Algorithms Are Swamped With Traps", 2022
  - "Training Variational Quantum Algorithms Is NP-Hard", 2021



# Barren Plateau

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- In many cases it has been proven that the gradients will be exponentially small.



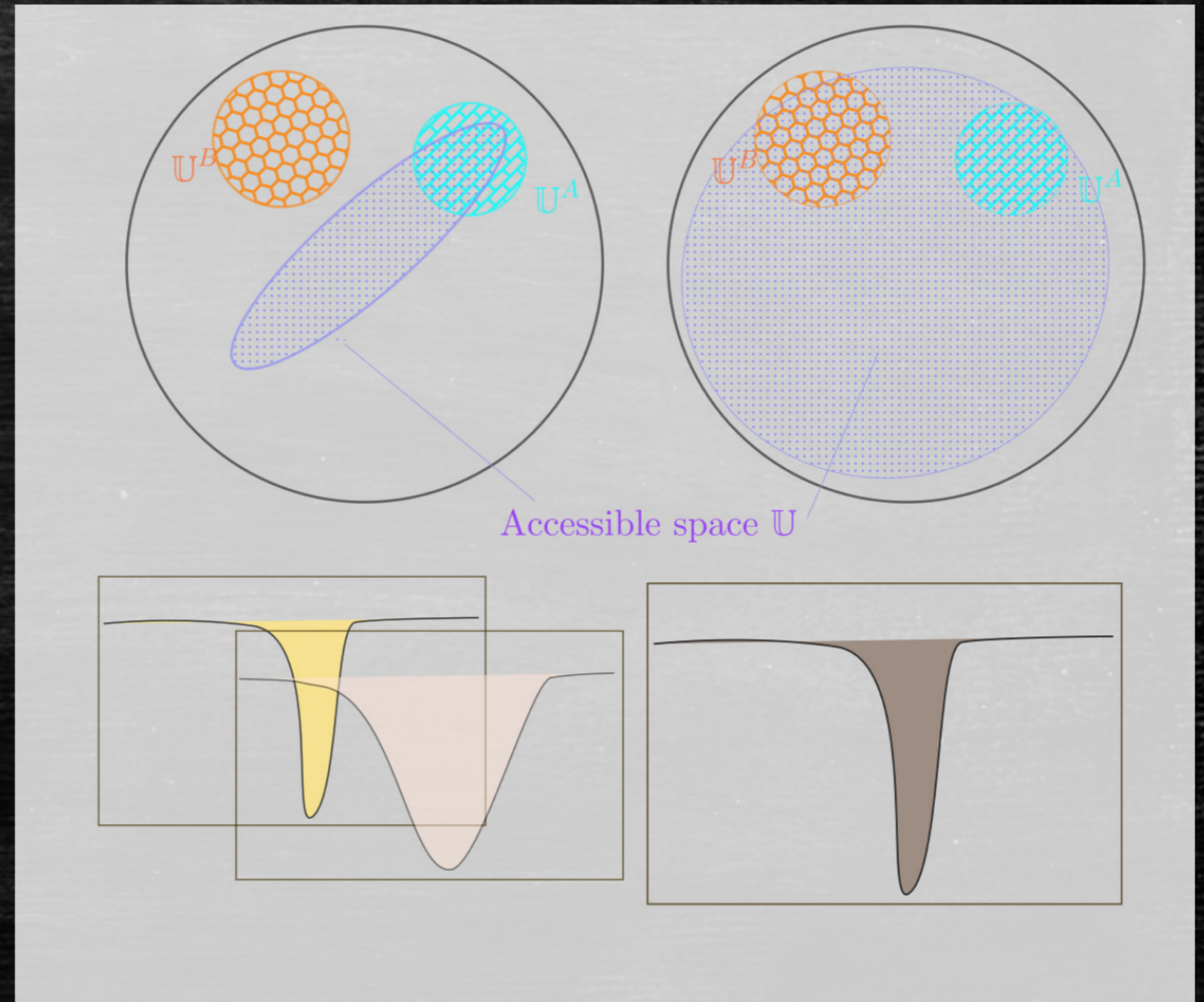
# Barren Plateau: Expressiveness

- We know:

$$C(\vec{\theta}) = \mathbf{Tr} \left[ H U(\vec{\theta}) \rho U(\vec{\theta})^\dagger \right]$$

$$P \left( \frac{\partial C}{\partial \theta_k} \geq \delta \right) \leq \frac{\mathbf{Var}(\partial_k C)}{\delta^2}$$

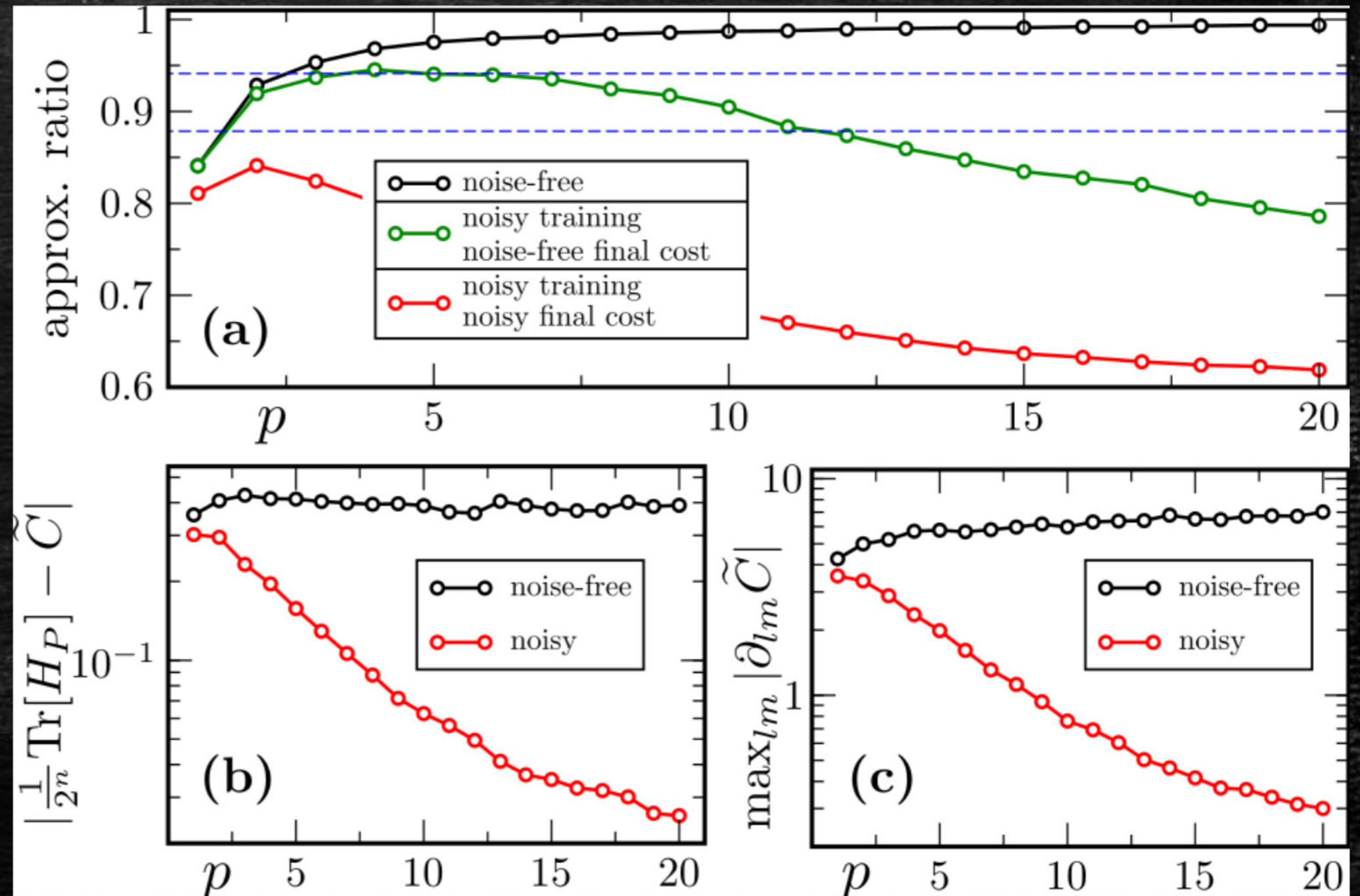
- As the expressibility of the circuit grows, the variance becomes exponentially smaller!





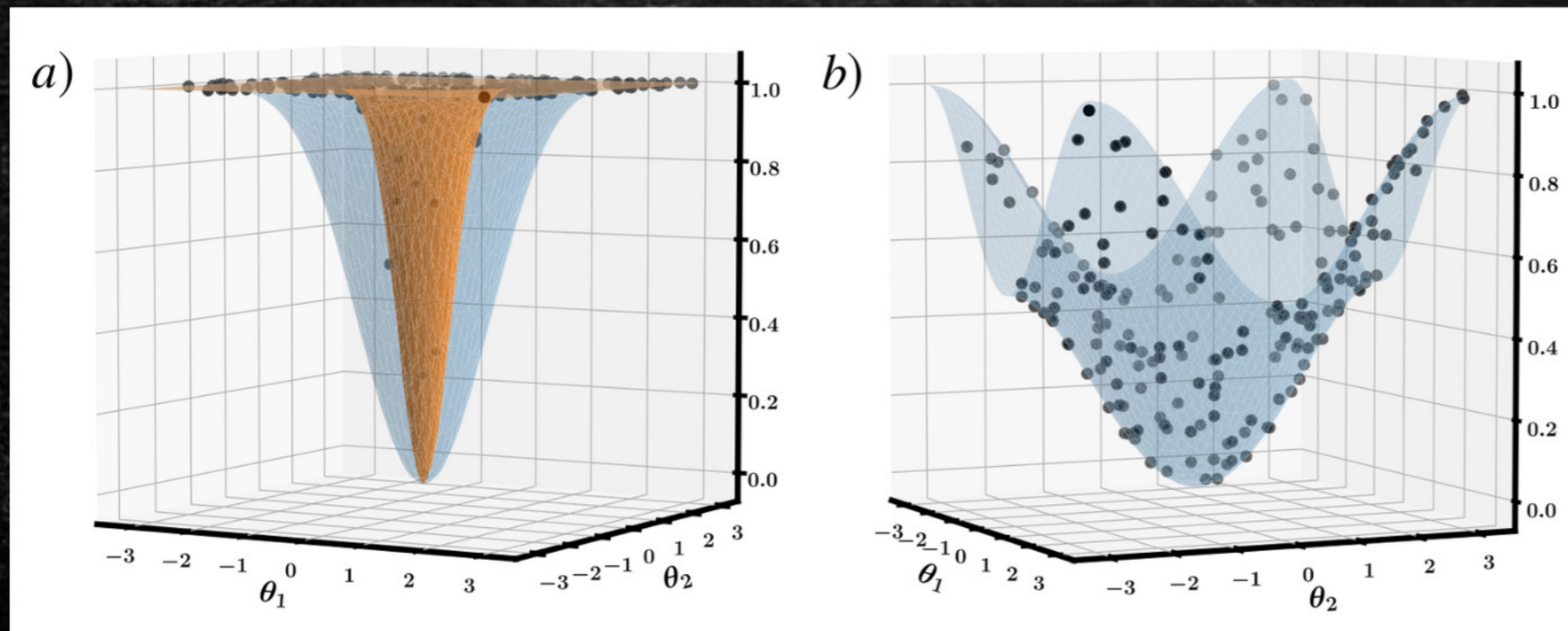
# Barren Plateau: Noise Induced

- Noise: Expectation value of an operators  $\rightarrow$  its average
- Flattens the parameter space
- E.g. QAOA for MaxCut



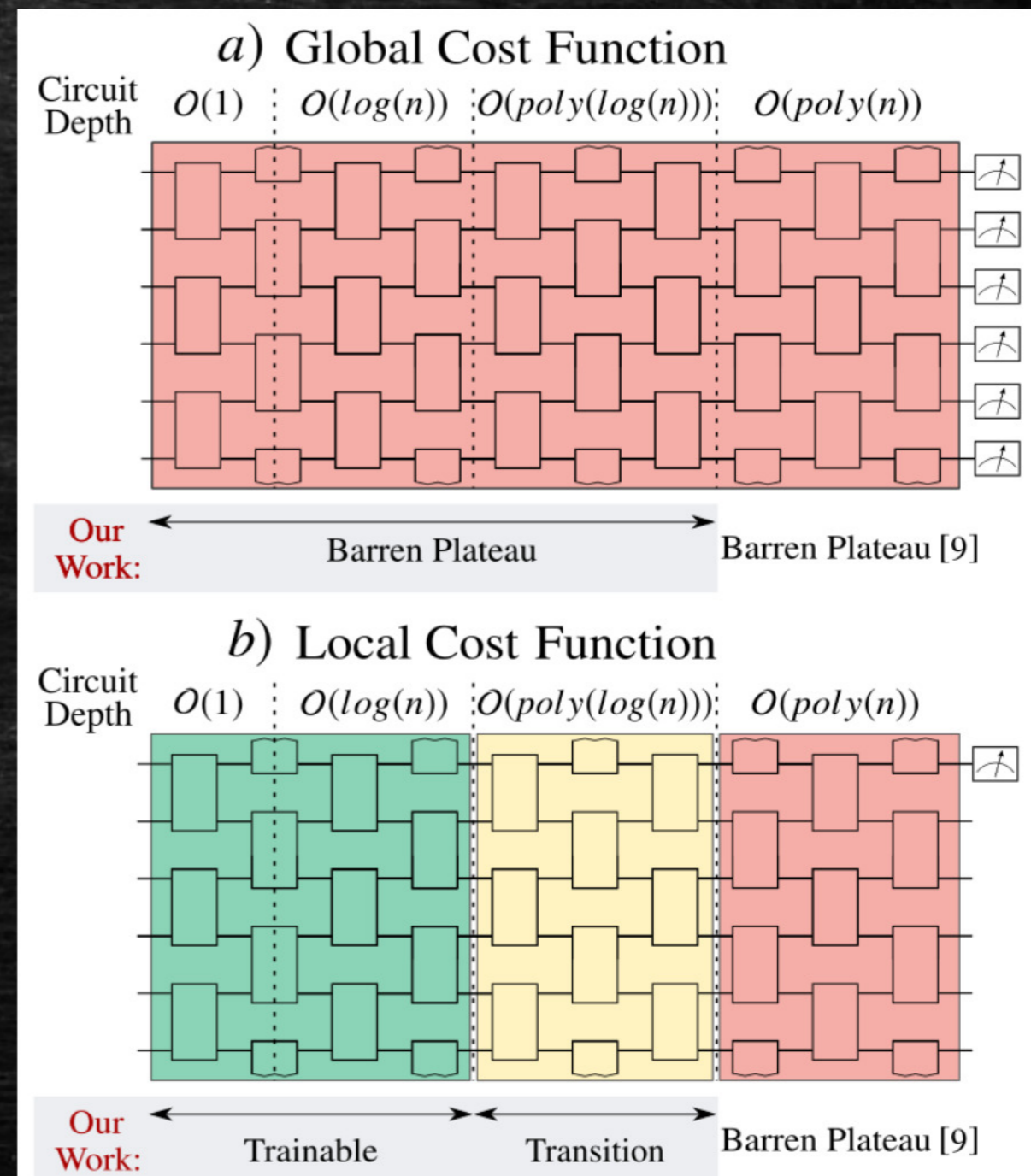
# Barren Plateau: Global cost function

- Circuit depth as well as global cost function can cause BP.

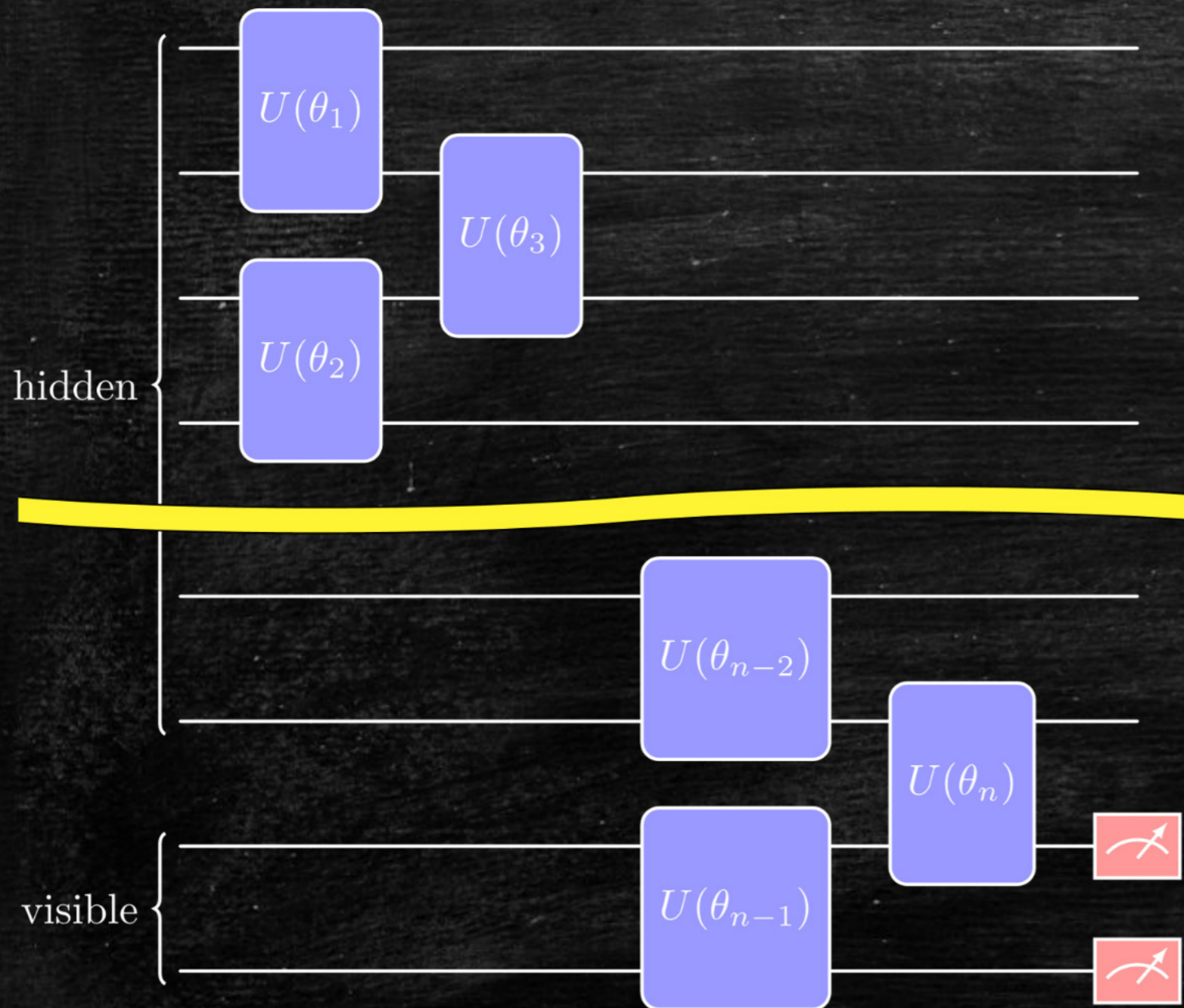


DOI: 10.1038/s41467-018-07090-4

DOI: 10.1038/s41467-021-21728-w



# Barren Plateau: Entanglement



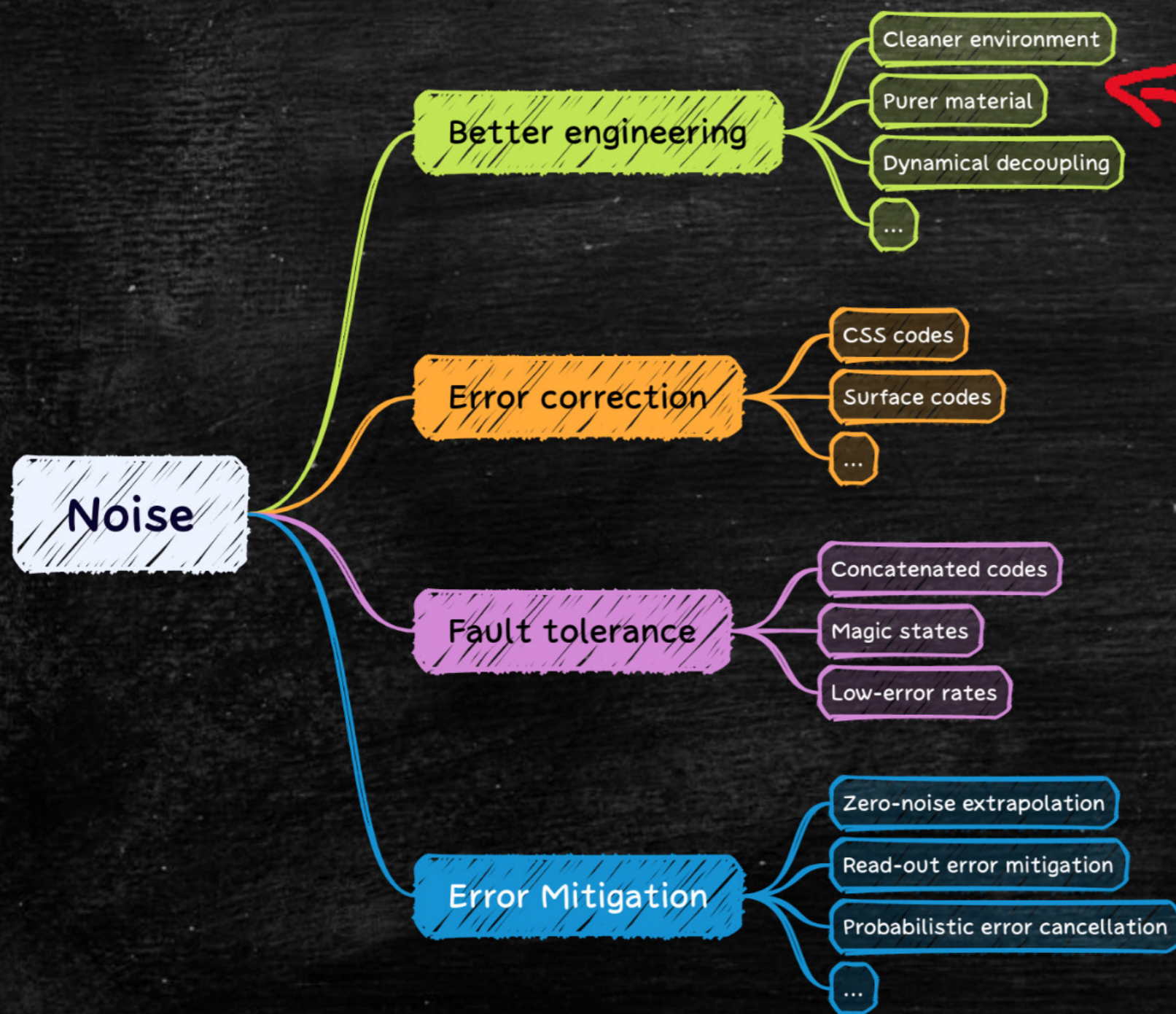
- B/w hidden and visible qubits (volume law)
- Entanglement in the training data
- => Barren Plateau

DOI: 10.1007/s42484-023-00103-6  
DOI: 10.1103/PhysRevLett.128.180505  
DOI: 10.1103/PRXQuantum.2.040316

# Solutions

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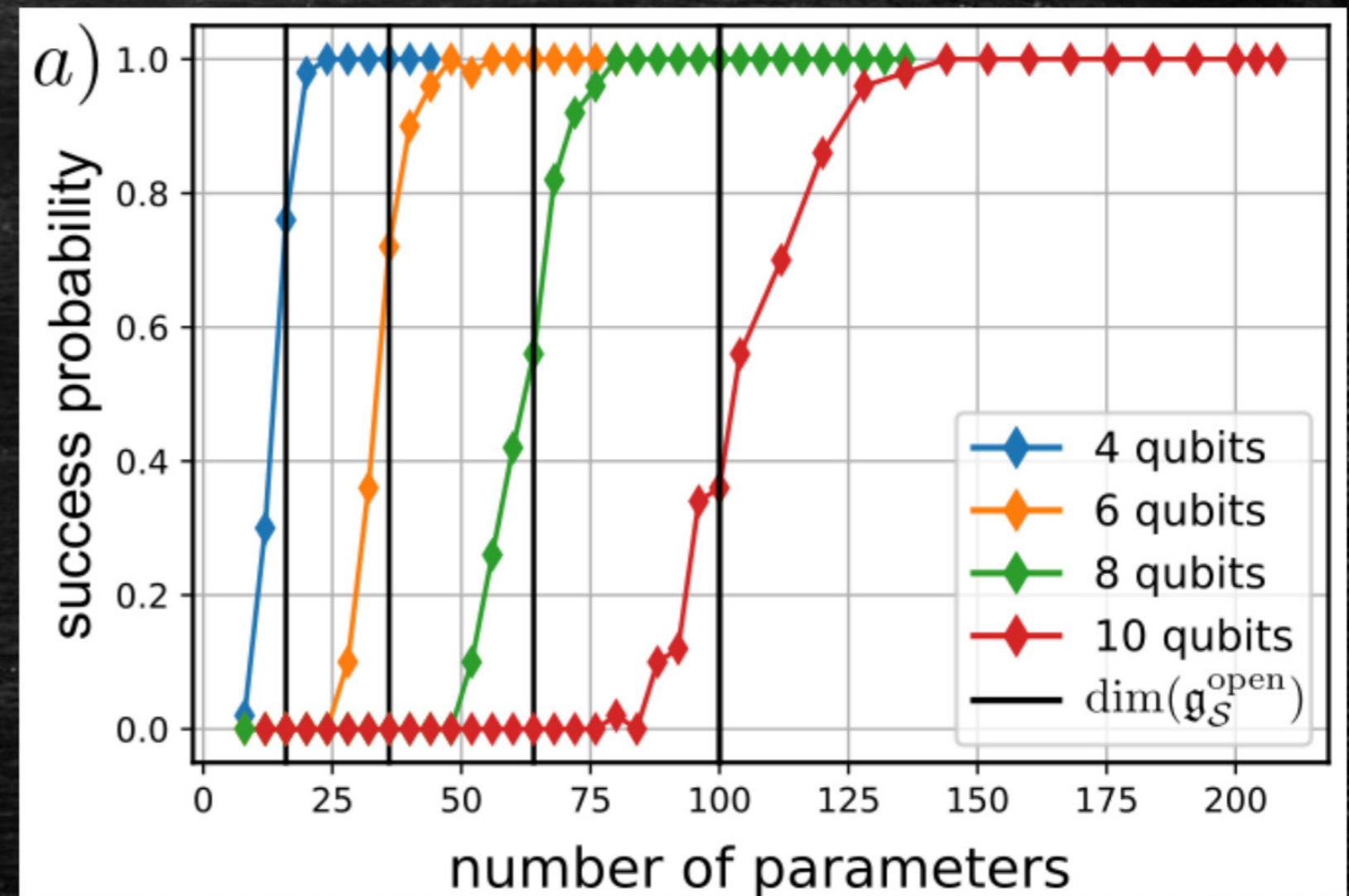
# Solutions: Noise



■ NISQ-era VQA challenges!

# Solutions: LM $\rightarrow$ Overparametrization

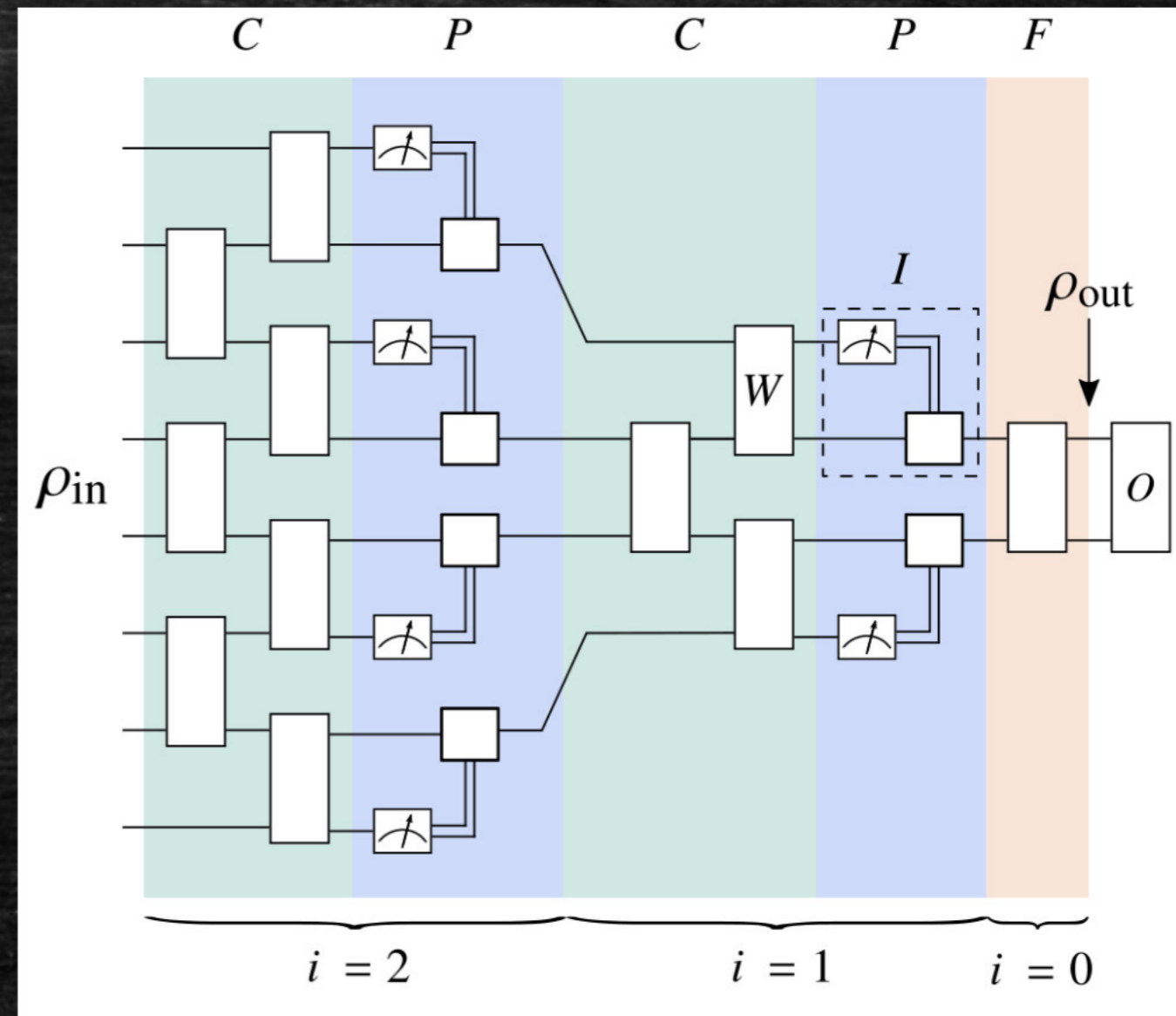
- Overparametrization can increase the success probability.
- The rank of the Quantum Fisher Information Matrix is a good threshold.
- Noise can affect these in a non-intuitive manner.
  - Increases the rank of QFIM
  - Eigs. exponentially small, insensitive to change



DOI: 10.1038/s43588-023-00467-6  
<https://arxiv.org/abs/2302.05059v1>

# Solutions: BP $\rightarrow$ Careful design

- It is very important to choose a good ansatz.
- Some ansatz do not exhibit Barren plateaus.
- There are also techniques one can use in the design of the ansatz to avoid barren plateaus.



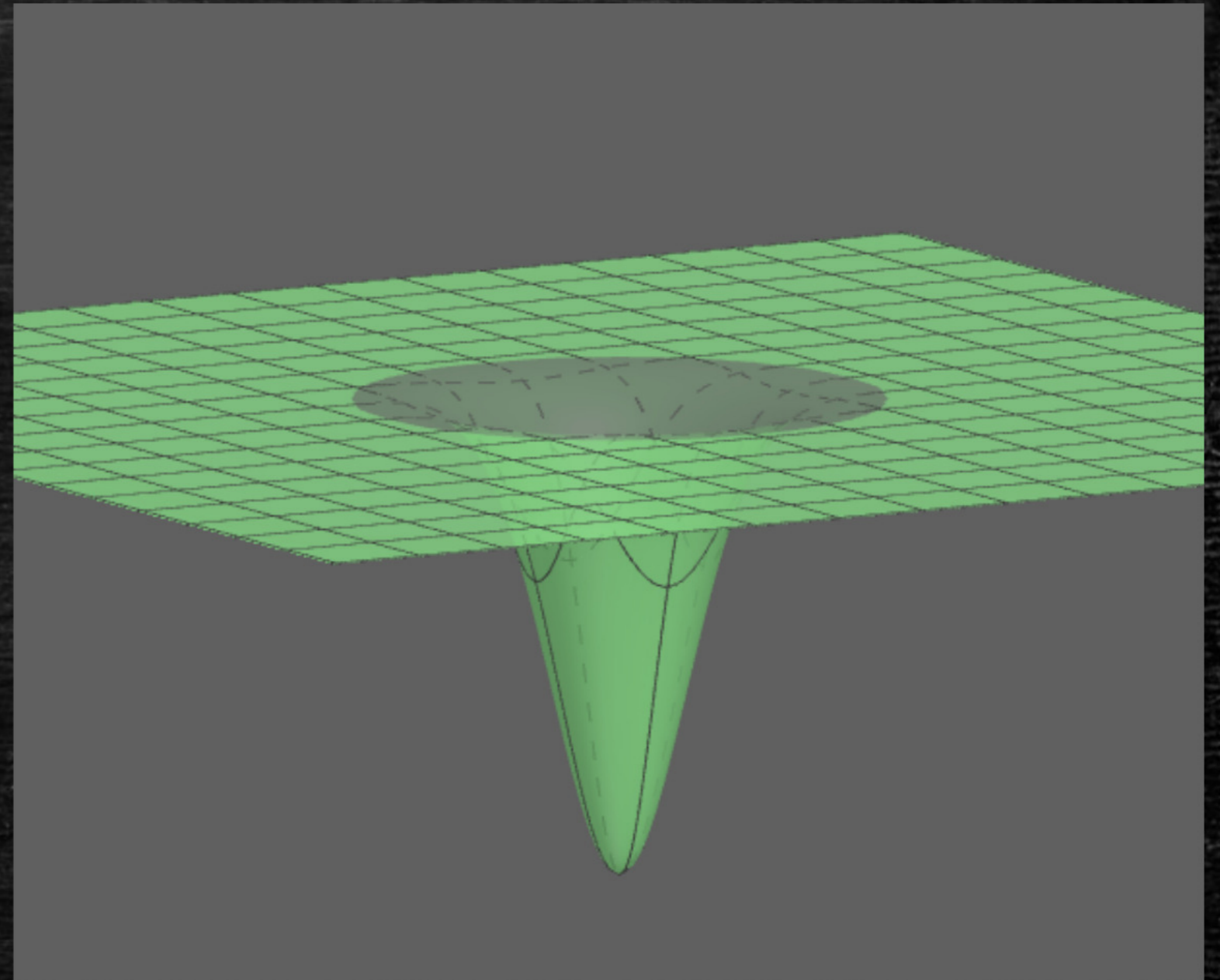
DOI: 10.1103/PhysRevX.11.041011

DOI: 10.1103/PRXQuantum.3.020365

# Solutions: BP -> Hot start

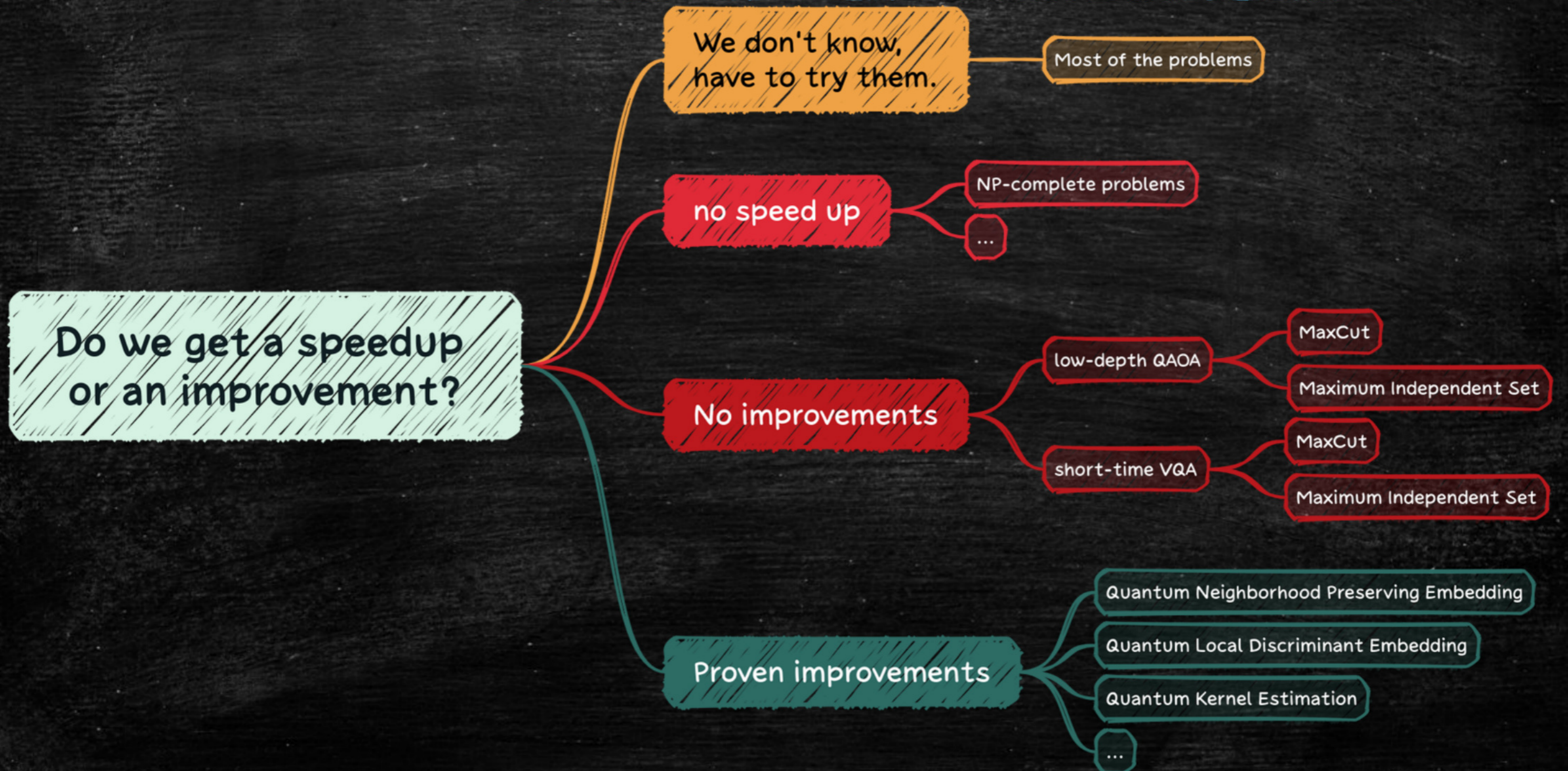
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- There are proposals to use techniques such as:
  - Classical machine learning
  - MPS
  - Classical Shadows
  - ...
- Start from:
  - Good initial states.
  - Good set of parameters
  - ...
- Avoid the BP region.

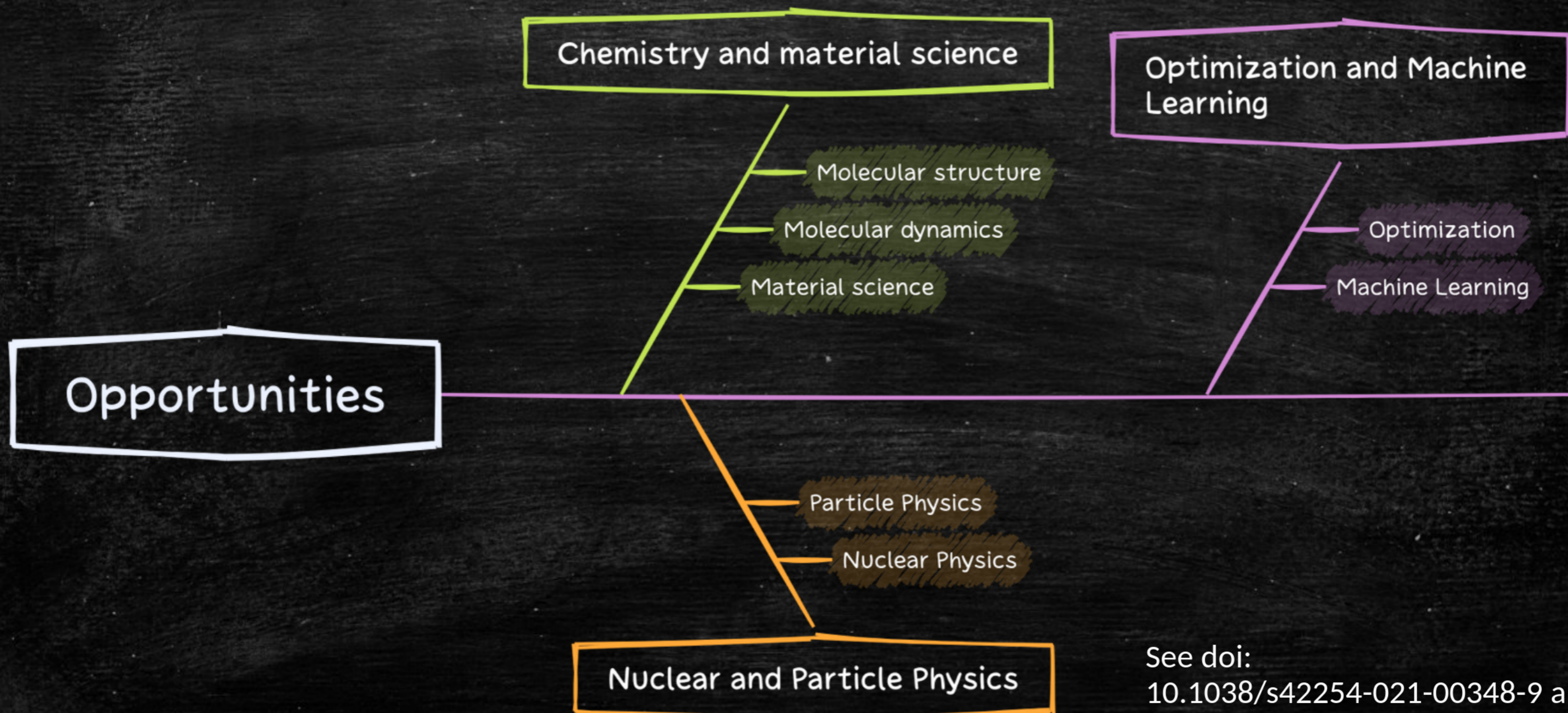




# Speed-up



# Promising Possible Applications



See doi:  
10.1038/s42254-021-00348-9 and  
references therein.

# Summary

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- Variational Quantum Algorithm is a promising approach for getting quantum improvements in NISQ-era.
- There are certain pitfalls one should avoid.
- Its true power is likely to become apparent as more powerful quantum computers emerge.

Thank you!

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