Supervised Learning & Variational Classification

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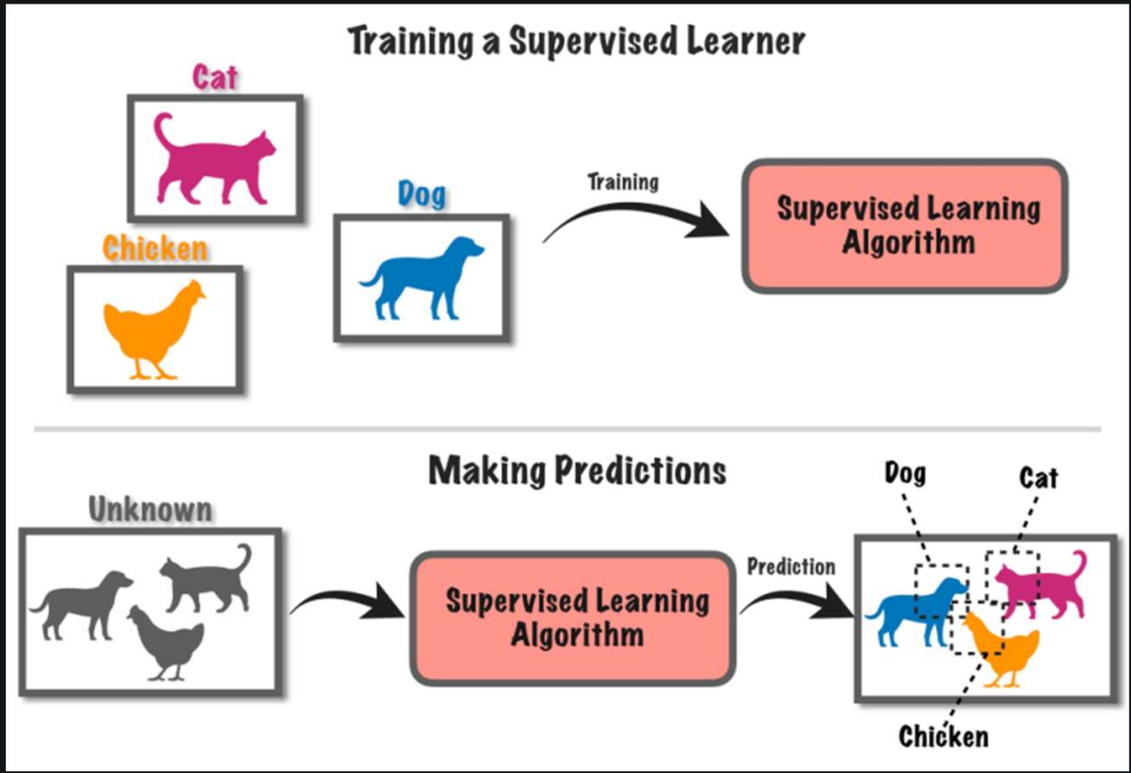
Qiskit

Supervised Learning

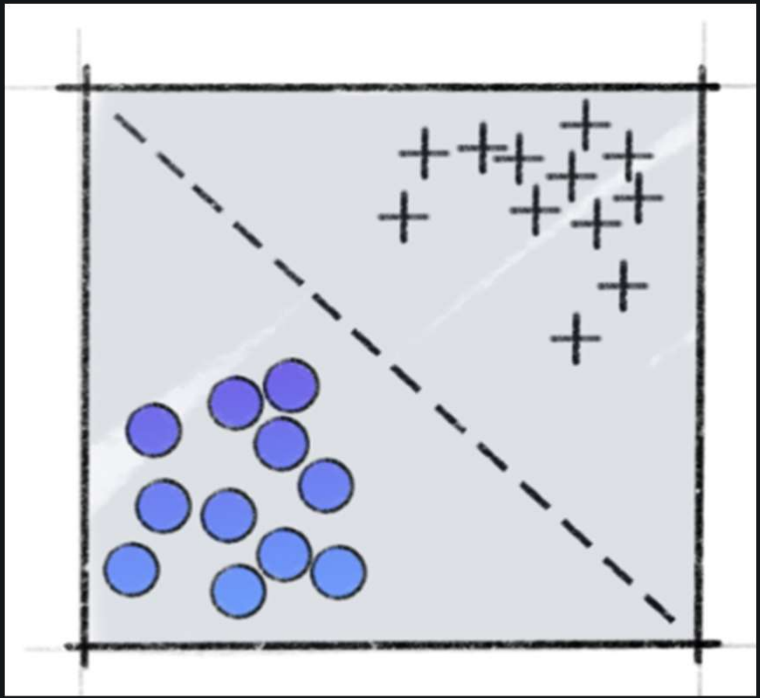
What is supervised learning?

- Machine Learning task
- Learns a function that maps and input to an output
- Need input-output pairs
- Need labeled training data for training the function
- Need non-labeled test data for calculating performance

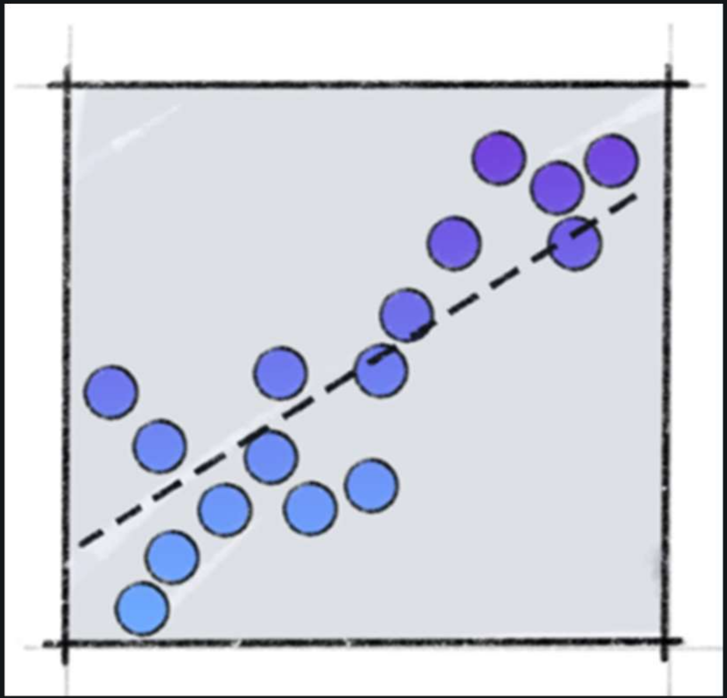


Classification and Regression

- Classification : assign data into specific categories
- -> More focus recently in quantum supervised learning!



- Regression : understand relationship between variables



Quantum variational classification

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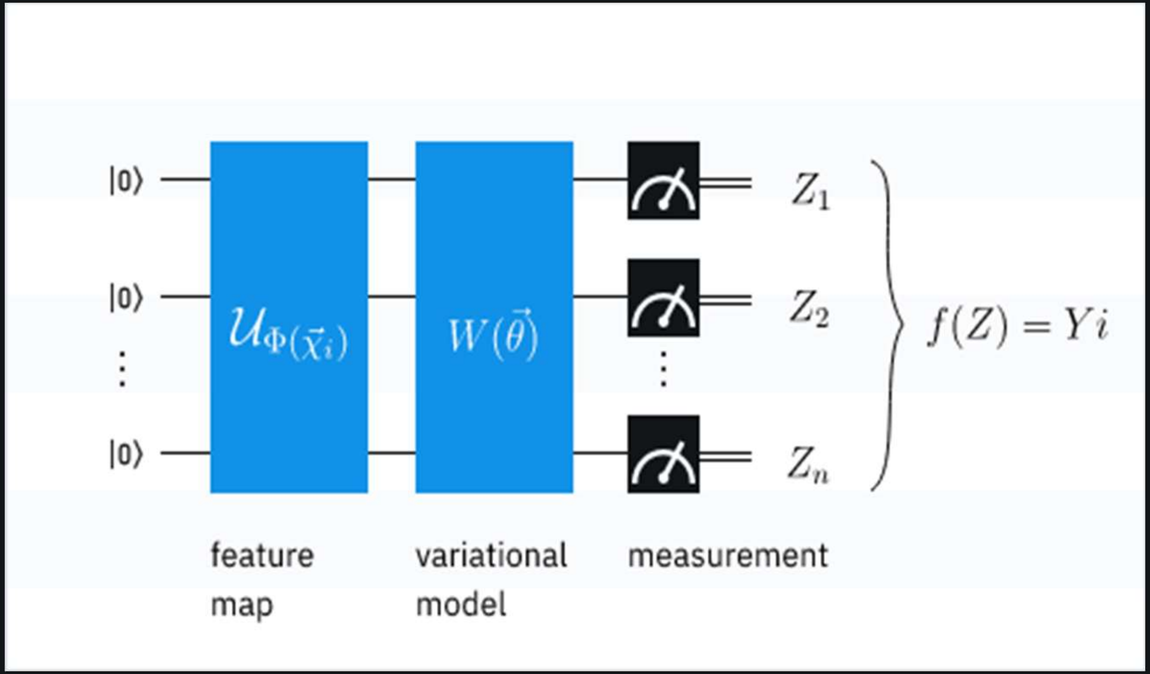
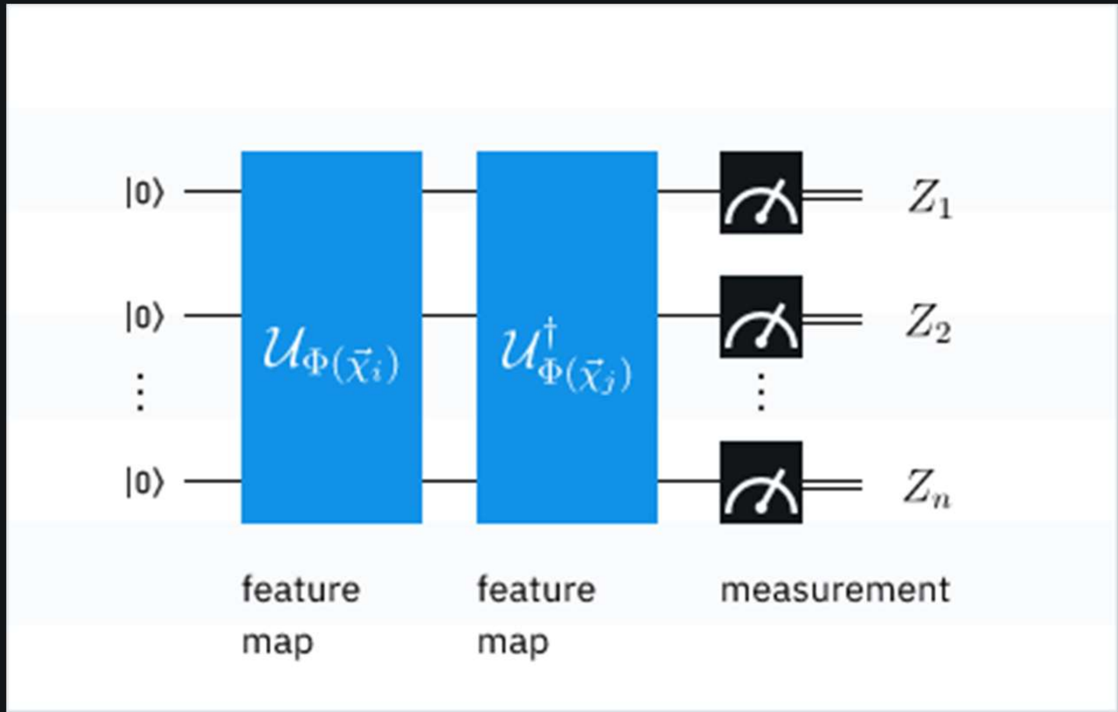
- Encode input data points into quantum states using the quantum feature map
- This feature map is a mapping of input data to the quantum Hilbert space
- Process state with a parameterized quantum circuit W(θ)
- Parameters are estimated by training to match the target states
- More detail later



Quantum kernel estimation

- Same with quantum variational classification with feature map
- Inner product of two quantum encoded quantum states define a kernel (Similar to kernel in classical machine learning)
- More detail next week



Variational Classification

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Variational algorithms

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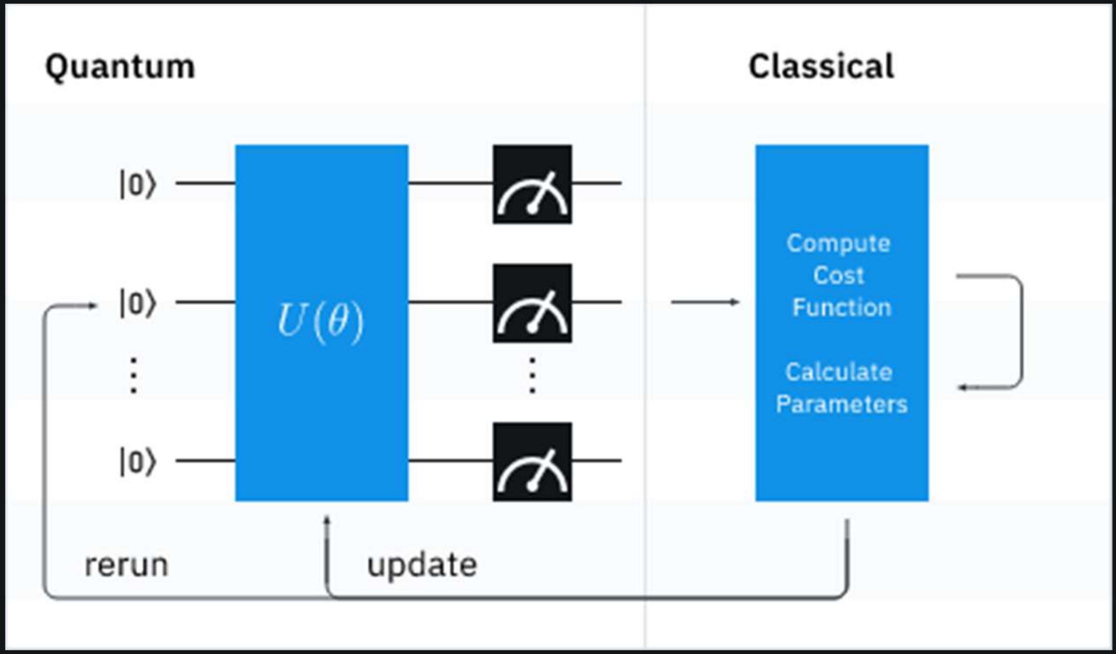
- Introduced in 2014, near-term algorithm (quantum computer + classical computer)
- Using a parameterized quantum circuit U(θ), prepare a state and measure the expectation value (quantum computer)
- Define a cost function C(θ)
- Calculate cost function and provide updated parameters using optimization algorithm (classical computer)
- Goal : find θ for U(θ) that minimize C(θ)



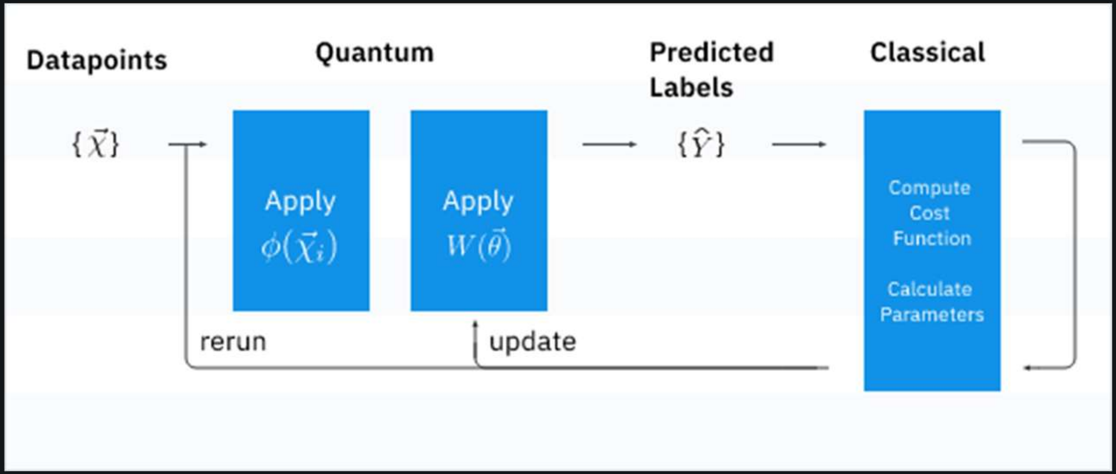
The variational quantum classifier

- A variational algorithm where measured expectation value is interpreted as the output of a classifier

- Binary classification problem :

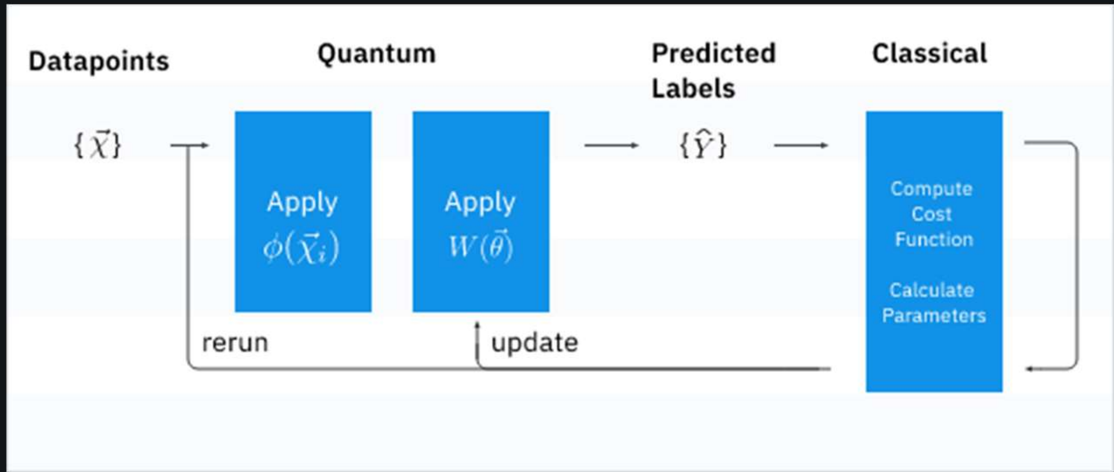
- For each input data vector, build a parameterized quantum circuit that outputs a quantum state : $|\psi(\vec{x}_i;\vec{\theta})\rangle = U_{W(\vec{\theta})}U_{\phi(\vec{x}_i)}|0\rangle$

- Create & measure the circuit of n qubits
- -> left with n length bitstring -> binary output (classification result)



The variational quantum classifier

- Deriving the binary output is done with Boolean function $f:\{0,1\}^n \rightarrow \{0,1\}$
- Parity function : Returns True if the input bit string has an odd number of 1s, and returns False otherwise
- In the training phase, find values for θ(vector) that gives the best prediction
- Classical computer compare predicted labels with real labels, and compute cost function
- Using a classical optimization algorithm, chooses another θ



Implementation with qiskit

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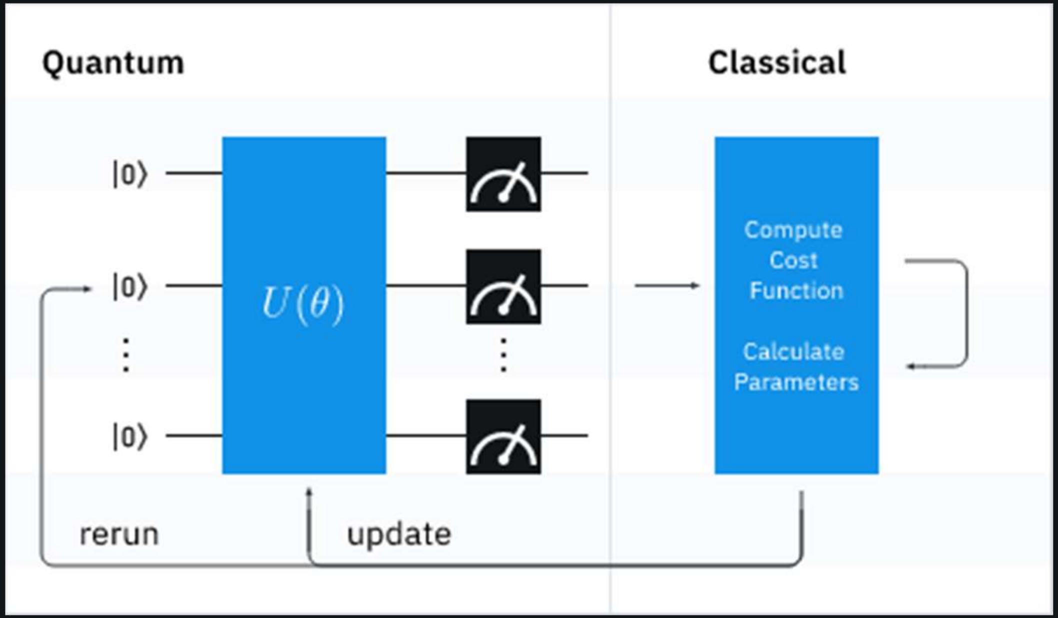
https://colab.research.google.com/drive/1H7EZys4dEqL3JXrZV7_dJGVzplQsnhS6?hl=ko#scrollTo=yEPlQRnlFp26

https://learn.qiskit.org/course/machine-learning/variational-classification#variational-23-0

Variational training

- Finding the optimal parameters of the variational circuit takes most of the processing time, and depends on the optimization method

- Optimal circuit parameters are found if the minimum of the loss function is found
- -> Relationship between the loss function and the circuit parameters isn’t simple



Variational training

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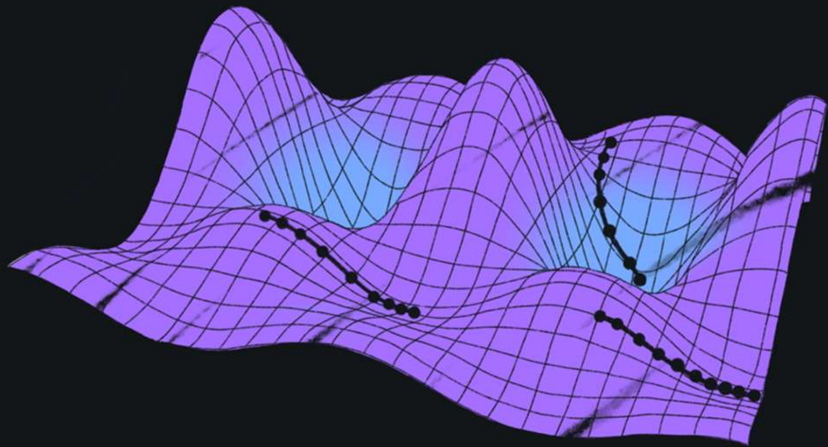
- Loss landscape can be complicated

- When the optimization method search for the minimum, there can be several searched that end up in the local minimum
- -> Hard to find global minimum

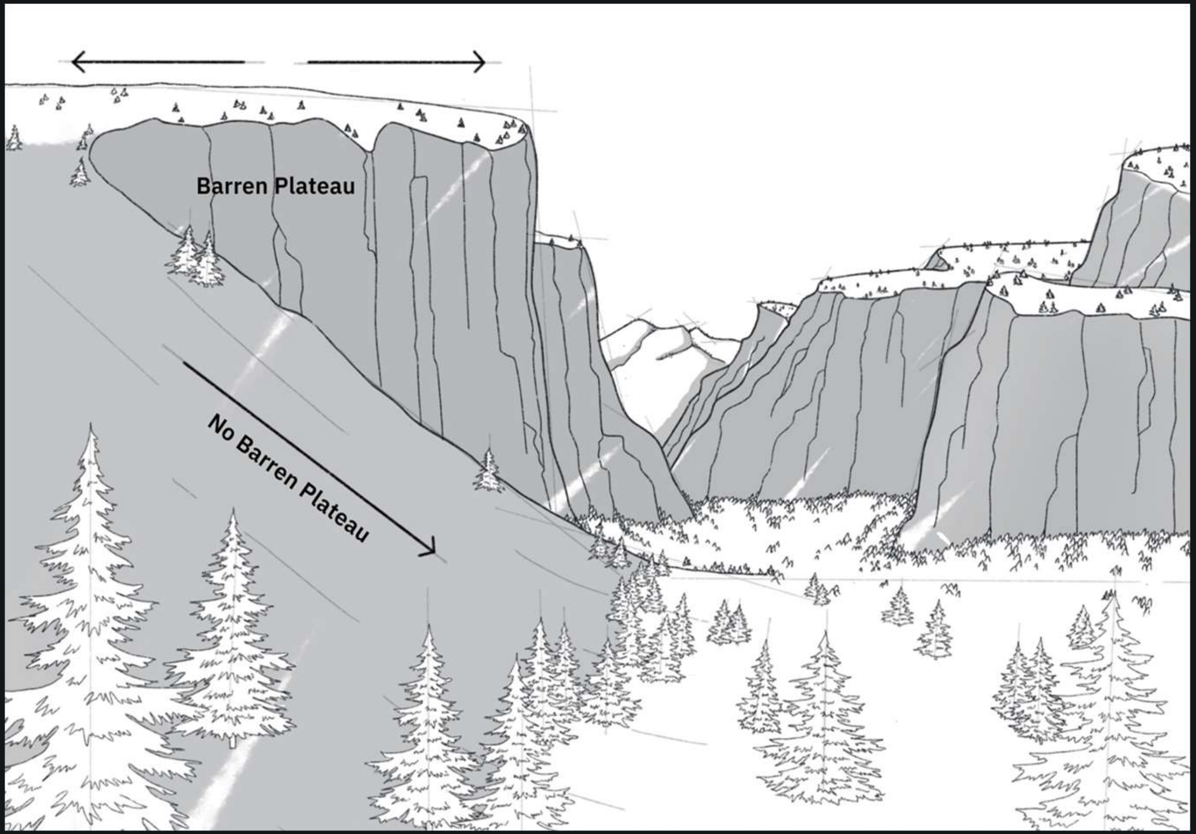
- Optimization methods :
- 1. Gradient - based
- Slow convergence speed, no guarantee to find optimal solution
- 2. Gradient - free
- Robust to find global minima
- In high-dimensional problems, require higher computational capacities



Variational training

- If the loss landscape is flat, it can be difficult to determine the direction to search
- ->Barren Plateau

- Some ways to overcome barren plateau
- 1. Structured initial guesses
- 2. Consider full quantum circuit as a sequence of shallow blocks, selecting some parameters randomly and choosing the rest of the parameters such that all shallow blocks implement the identity to restrict the effective depth
- Currently in research!



Thank You
감사합니다!