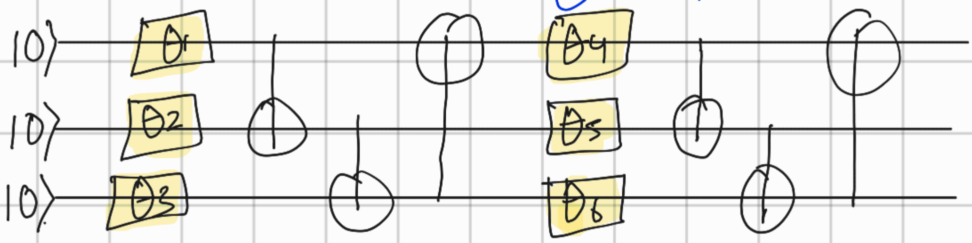
The Adjoint is all you need!

Variational Quantum Circuits have a low circuit cost, can be trained in Hybrid manner, but are very expensive to train.



We need exponential parameters to assure convergence, but exponential many samples being required to estimate gradients known as Barren Plateaus.

This obstacle can be mitigated, if we make use of specific parameterized Quantum circuit, that obeys symmetry.

The symmetries of Ansatz cause its action to break into invariant subspaces and in each invariant subspace the quantities controlling trainability and convergence only depends on characteristics of the subspace i.e its dimension.

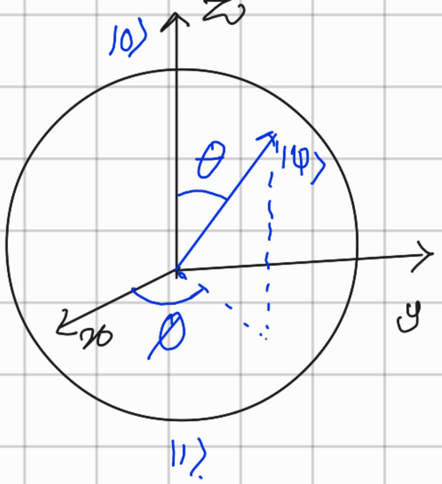
Existing Theoretical Results
(Trainability and Barren Plateaus in QNN)

It is important to analyze the trainability of a QNN in order to avoid winters and guarantee that QNNs will outperform NNs.

trainability = are we able to train a QNN efficiently

We quantify how well a QNN is performing by defining the Cost (loss) function. Each value of the parameter leads to a cost function value, i.e the hyper parameter space defines the cost function landscape.

Precision and Barren Plateaus



How do we estimate it's probability of being in the $|0\rangle$ state?

$$P(0) = Tr\left[|0\rangle\langle 0|\rho\right]$$

$P(0) = \frac{N_0}{N}$ with a precision of order $\frac{1}{\sqrt{N}}$

Barren Plateaus - In average, the cost function partial derivates become exponentially flat with the system size.

$$\frac{\partial C}{\partial \theta} = \partial C = \frac{1}{2}\left(C\left(\theta + \frac{\pi}{2}\right) - C\left(\theta - \frac{\pi}{2}\right)\right) \quad \text{(Parameter shift rule)}$$