Through the lens of Quantum Neural Network

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In recent times, Quantum Neural Network (QNN) is projected as an important application for near-term noisy intermediate-scale quantum computers performing Quantum Learning tasks [1]. The achievements of artificial neural networks (ANN) is often projected onto the success of QNN, backing with the power of quantum computing. But rather than just providing a quantum supremacy over ANN, it is also important to understand the statistical learning theory of QNN. Though the learning theory of ANN is yet to address the puzzle of generalization completely [2, 3, 9], a QNN perspective of generalization will lead us to understand the quantum learning systems from a statistical viewpoint. The statistical learning theory of QNN will not only act as a bridge to the world of statistical mechanics and quantum computation but also to the general theory of relativity by optimizing loss function on a Riemannian manifold like Diffusion metric in parameter space as proposed by Fioresi *et. al.* [4]. On the other hand, evolution of unitaries in parameterized QNN measures quantum complexity in unitary space [7] and scrambling of information [6]. Correlating the trajectory of parameters in parameter space with the evolution of unitary in unitary space opens up a new lens to look into Quantum Gravity. A phase transition phenomenon in ANN has already been reported from an information perspective [8], the phase transition in QNN becomes important to analyse discontinuities in quantum learning systems. Moreover, as neuroscience holds the fundamental architecture of neural networks, despite the proposal of quantum processing in neurons by Fisher [5] not much progress has been made to understand learning systems like human cognition from the perspective of quantum chaos and learning manifolds. Thus it not only becomes important to appreciate the application capability of QNN but also to see the quantum learning systems through the lens of QNN.

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