EUROPYTHON

2021   Jul 26–Aug 1   Online

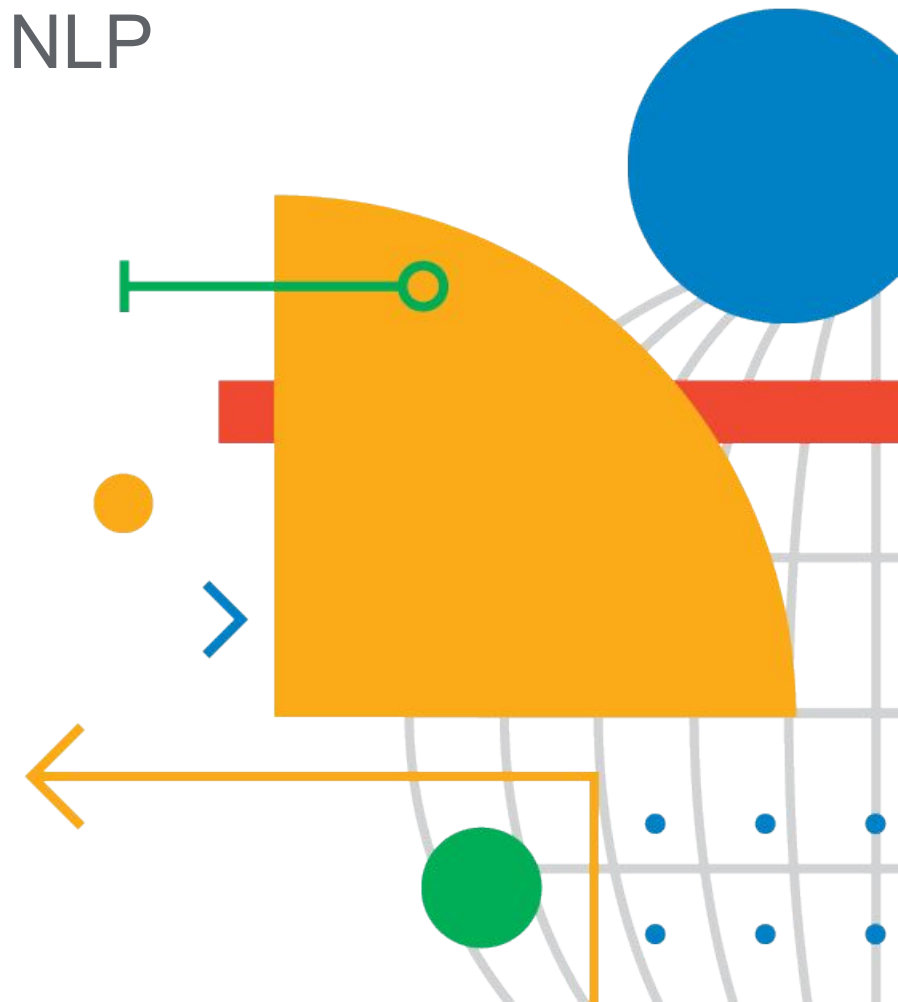# Introduction to Quantum Deep Learning

**Abhilash Majumder**

MSCI
Github-abhilash1910

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- Realizing the performance of Hybrid Circuits
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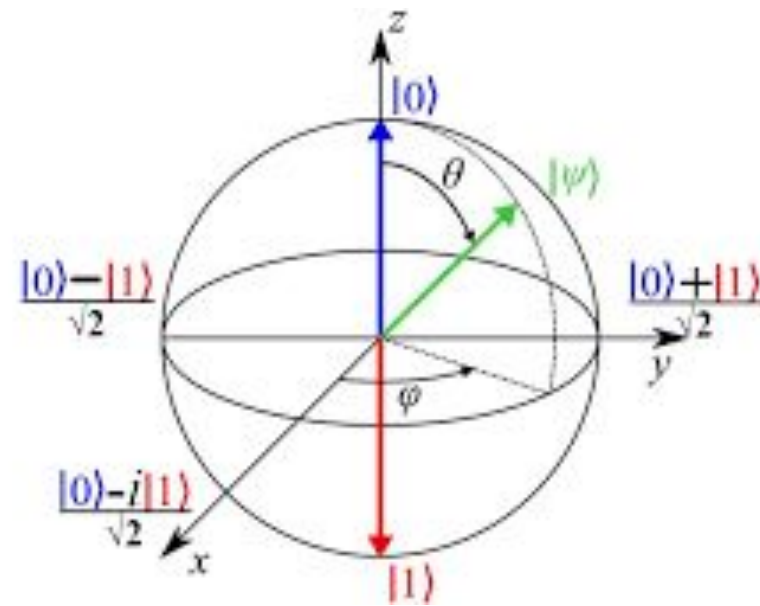
Introduction to Quantum Computing and Qubit Systems:

- Quantum computing is a branch which relies on the probability of Qubit states.

- Unlike Classical bits, Qubits rely on 0s and 1s. All the probabilistic states of a Qubit can be represented as an additive form of these 0s and 1s.

- A Qubit is represented by a summation of orthogonal vectors denoted as |0> (=[1 0]) and |1> (=[0 1])) .

- A simple Qubit state can be thought of as Q= 1/sqrt(2) |0> + i/sqrt(2) |1> .Since these |0> and |1> represents an orthornormal basis, we can plot any 2D vector with the help of these.

- These vectors can be rotated along x,y,z axes to generate certain other variations of the qubit state. Though only the final states can be extracted, intermediate states of Qubit rotations cannot be preserved.

- Qubits can be normalized, an $p(|x\rangle) = |\langle x|\psi\rangle|^2$ g a state in the state |x> is given as :
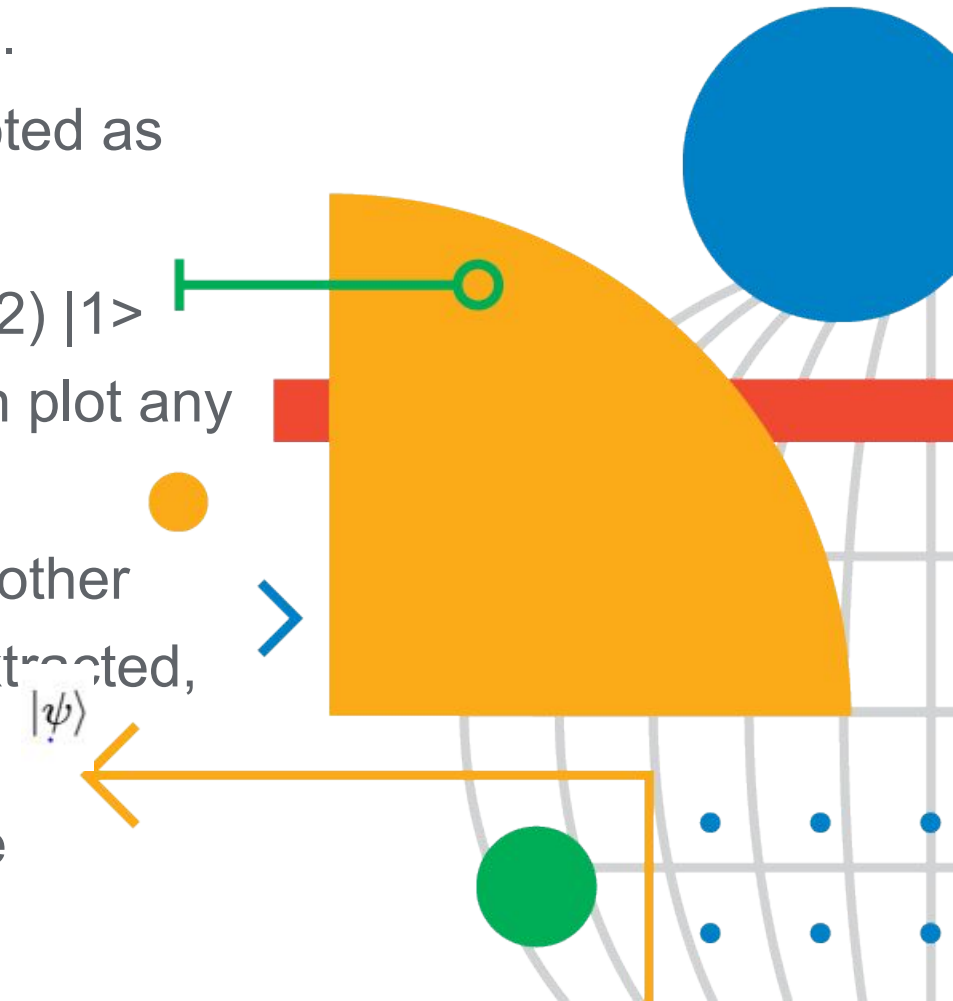
Introduction to Quantum Computing and Qubit Systems:

- Qubits are generally represented by Bloch sphere, which holds relation between the angles of the qubit components (phases).

- Essentially a Qubit can be represented as :

$$|q\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\phi}\sin\frac{\theta}{2}|1\rangle$$

Introduction to Quantum Computing and Qubit Systems:

- Quantum circuits(ansatz) can be created simply by rotating the qubits along certain axes. There are some gates which are applied to Qubits during the process.

- X gate(switching gate) is represented as the Pauli matrix:

$$X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = |0\rangle\langle 1| + |1\rangle\langle 0|$$

- Y and Z gates perform rotation of 180 degrees along the axes :

$$Y = \begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix} \qquad Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

$$Y = -i|0\rangle\langle 1| + i|1\rangle\langle 0| \qquad Z = |0\rangle\langle 0| - |1\rangle\langle 1|$$

- The Hadamard gate is used to create a superposition of Quantum states and can be shown in the

$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

Introduction to Quantum Computing and Qubit Systems:

- Rz gate is used for applying a rotation along Z axes:

$$R_\phi = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\phi} \end{bmatrix}$$

- The I gate is used to apply identity transform to the Qubit, and the S gate is a special form of Rz gate with $|\psi\rangle$ = 90 degrees.

$$S = \begin{bmatrix} 1 & 0 \\ 0 & e^{\frac{i\pi}{2}} \end{bmatrix}, \quad S^\dagger = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{i\pi}{2}} \end{bmatrix}$$

- The T gate is represented as Rz with $|\psi\rangle$ = 45 degrees

$$T = \begin{bmatrix} 1 & 0 \\ 0 & e^{\frac{i\pi}{4}} \end{bmatrix}, \quad T^\dagger = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{i\pi}{4}} \end{bmatrix}$$

Introduction to Quantum Computing and Qubit Systems:

- Generally the I,S,T,Z gates can be represented as U gates:

$$U_3(\theta, \phi, \lambda) = \begin{bmatrix} \cos(\theta/2) & -e^{i\lambda}\sin(\theta/2) \\ e^{i\phi}\sin(\theta/2) & e^{i\lambda+i\phi}\cos(\theta/2) \end{bmatrix}$$

- These rotations of the qubits form the crux of quantum circuits .

Quantum Variational Circuits:

- Quantum variational circuits (ansatz) are created by converting the classical data bits into quantum states in Hilbert space via quantum feature mapping. This process is generally known as Quantum Embeddings.

- A feature map can be thought of as a mapping of X (input vector) to F (Hilbert space) , where x-> |φ (x)> by Unitary transformation (U gates).
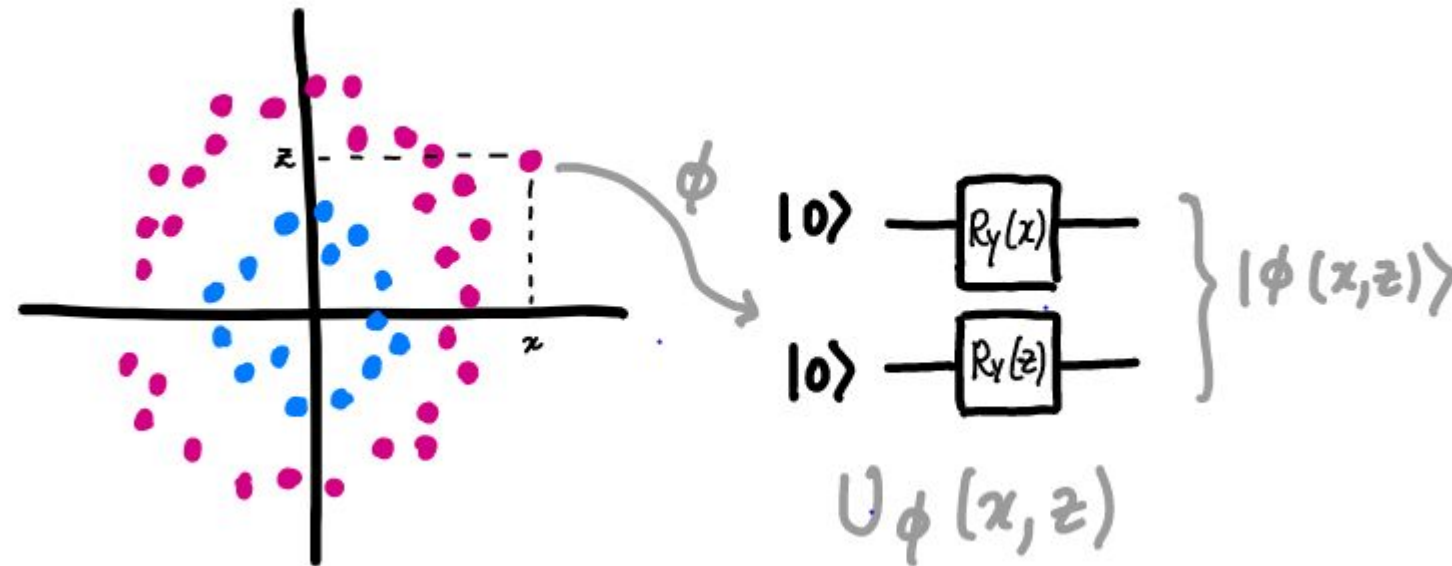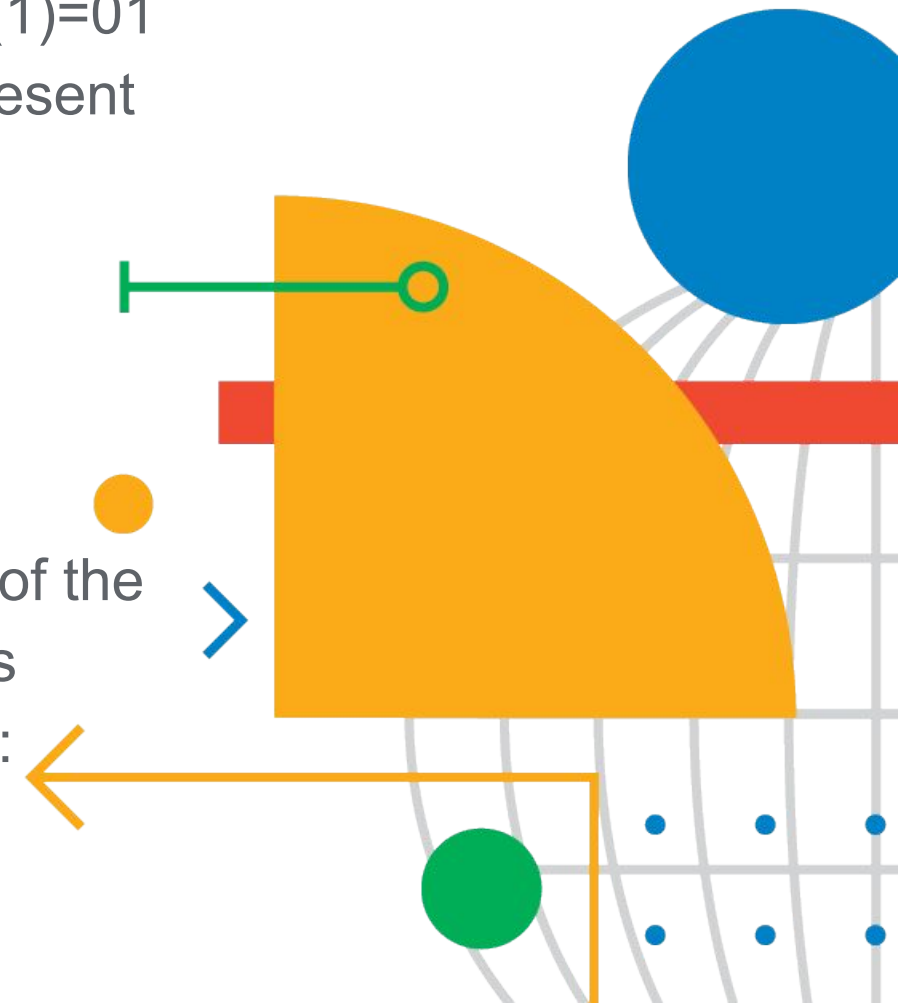
Quantum Variational Circuits:

- Quantum embeddings in Hilbert space can be categorized as Basis Embeddings and Amplitude Embeddings.
- Basis Embeddings associates each input with the computational basis of a qubit system.Classical data is converted to binary strings and then embedded to quantum subsystems. For a classical system having x(1)=01 and x(2)=11 as inputs, the corresponding basis uses 2 qubits to represent |x(1)>=|01> and |x(2)>=|11> as:

$$|\mathcal{D}\rangle = \frac{1}{\sqrt{2}}|01\rangle + \frac{1}{\sqrt{2}}|11\rangle.$$

- Amplitude Embeddings classical data is embedded in the amplitude of the quantum system..A normalized classical N dimensional datapoint y is represented by the amplitudes of a n bit qubit quantum state $|\psi\rangle$ as:

$$|\psi_x\rangle = \sum_{i=1}^{N} x_i |i\rangle,$$

Quantum Variational Circuits:

- Once the Quantum states are created (by quantum feature maps) , they are passed through the ansatz and undergo a sequence of multi-qubit Unitary operations (rotations). An example of a pure quantum variational circuit is as follows:
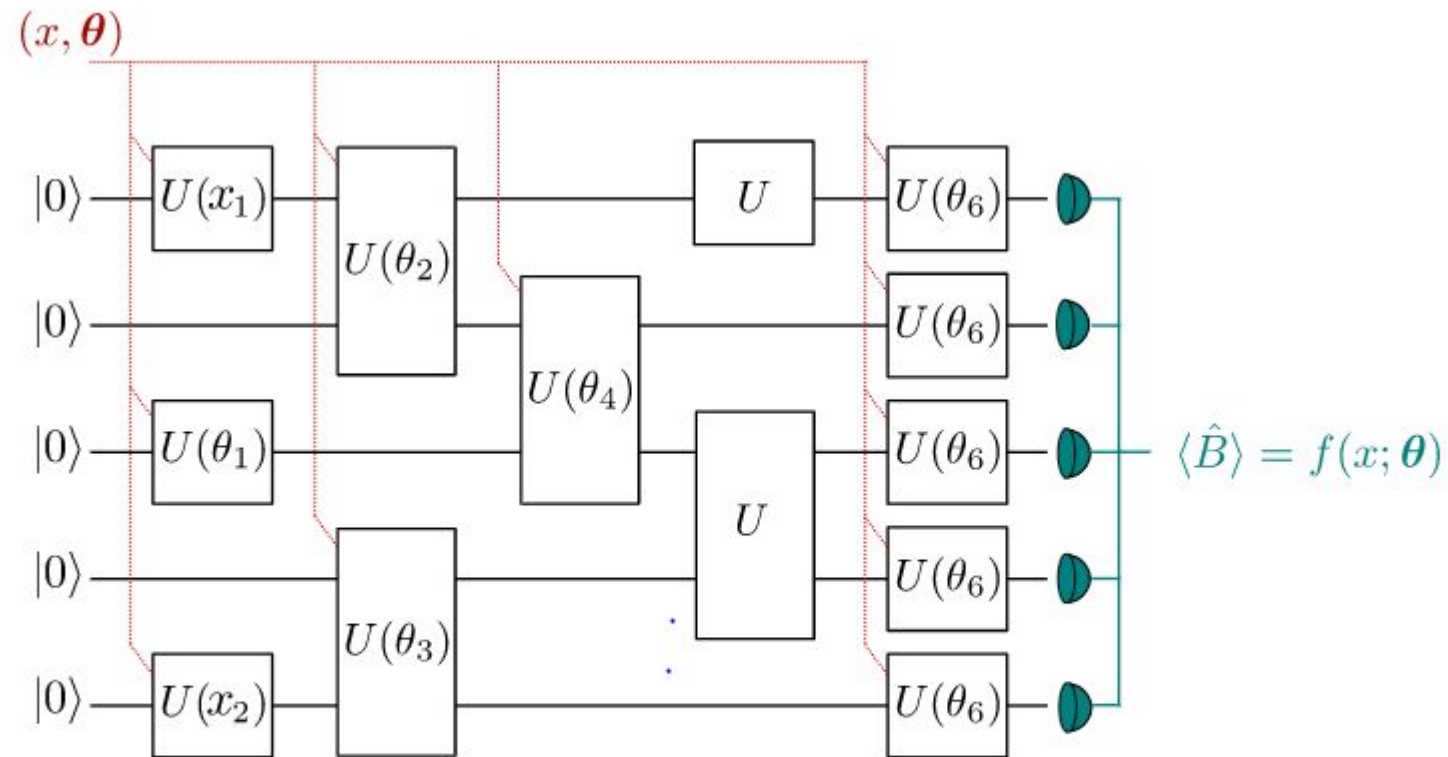

Example circuit showing how the argument x and the variational parameters $\boldsymbol{\theta}$ enter the quantum circuit. Circuits can also contain gates which have no free parameters (e.g., a CNOT).

Quantum Variational Circuits:

- There are different architectures of Quantum Variational Circuits such as : Layered,Parameterised , Tensor Network architectures,Alternating Operator architectures.
- In layered architectures a sequence of gates is repeated in the variational circuit where the repetition count form the hyperparameters of the circuit.

$$A(\alpha) \quad B(\beta)$$
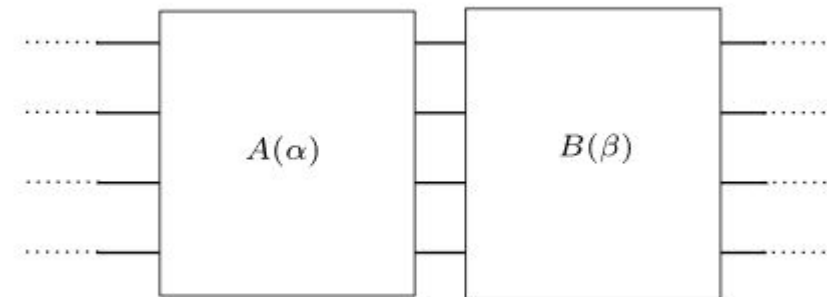
- Parameterised Circuits:Based on the number of intermediate Unitary operations in the ansatz , layer circuits can be sub classified as A parameterized or B as parameterized. An example of A being fixed (Hadamard) and B being parameterized (single qubit and Rz gates) are called Instantaneous Quantum Polynomial Circuits
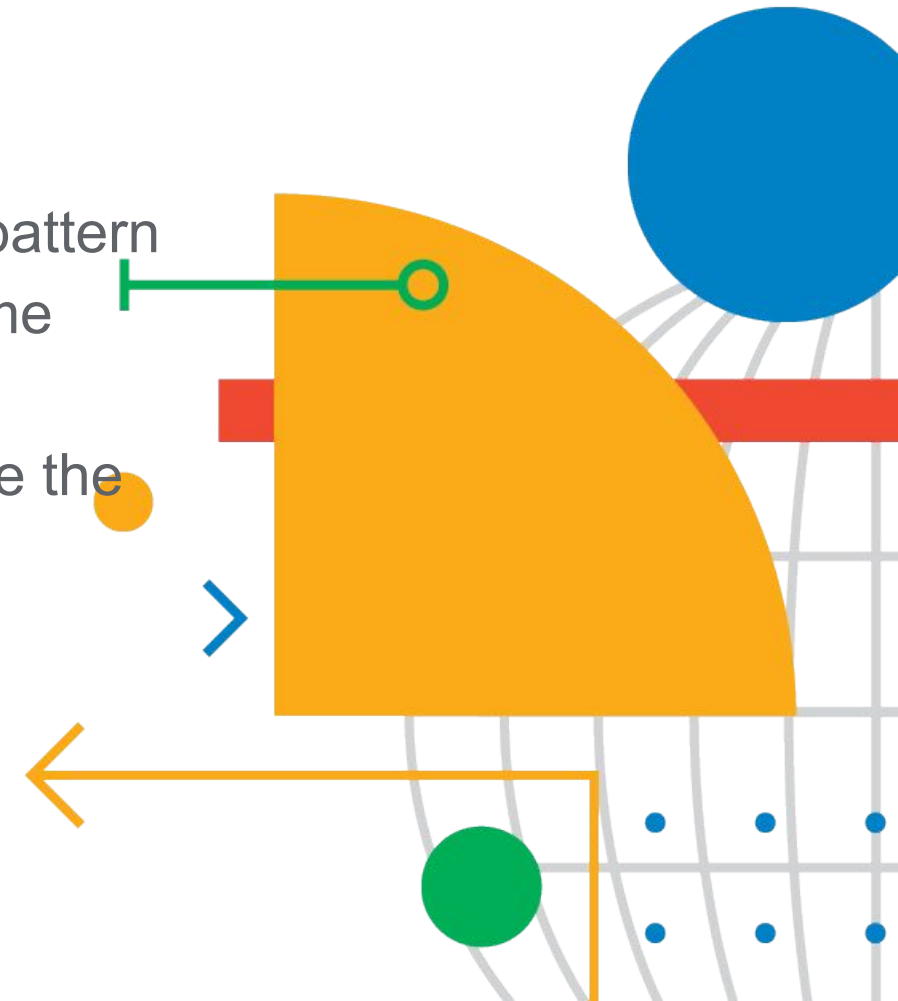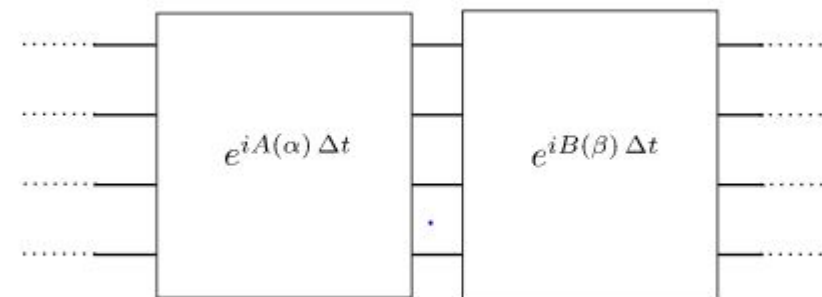
Quantum Variational Circuits:

- IQP Parameterized circuits is as follows:
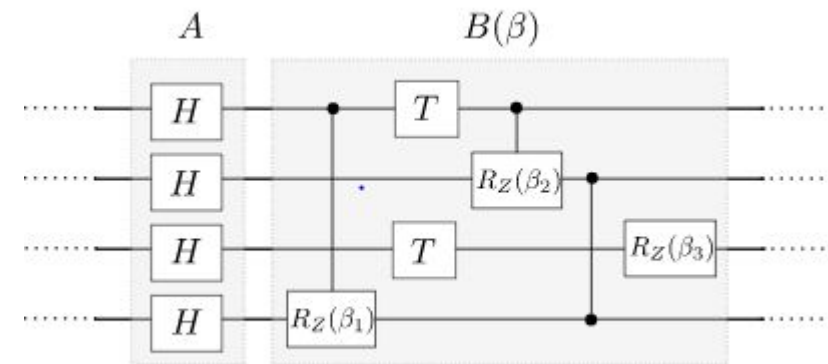
- Alternating operator Ansatz: In these architectures, there is layered pattern similar to Parameterised architectures, but unitary operations are time evolving Hamiltonians , which are used in Quantum Approximate Optimization Algorithms. The ansatz uses phase shift rule to compute the output.

Quantum Variational Circuits:

- Tensor network Ansatz follows for generic tensor networks , have single fix structure without parameterized layers .These ansatz are suitable for studying quantum subsystem entanglements.
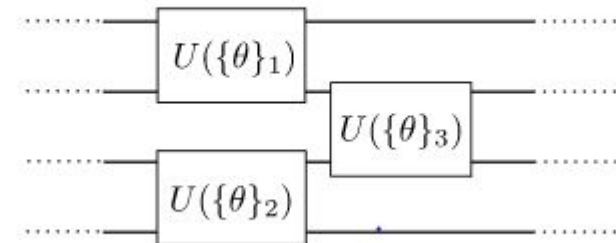

- These ansatz of pure quantum circuits employ automatic differentiation modules (computation graphs) for getting the output. Alternately,since most of the Unitary operations are phase changes, Phase shift in variational circuits are employed to compute autogradients.

$$\nabla_\theta f = f(\theta_1) - f(\theta_2)$$
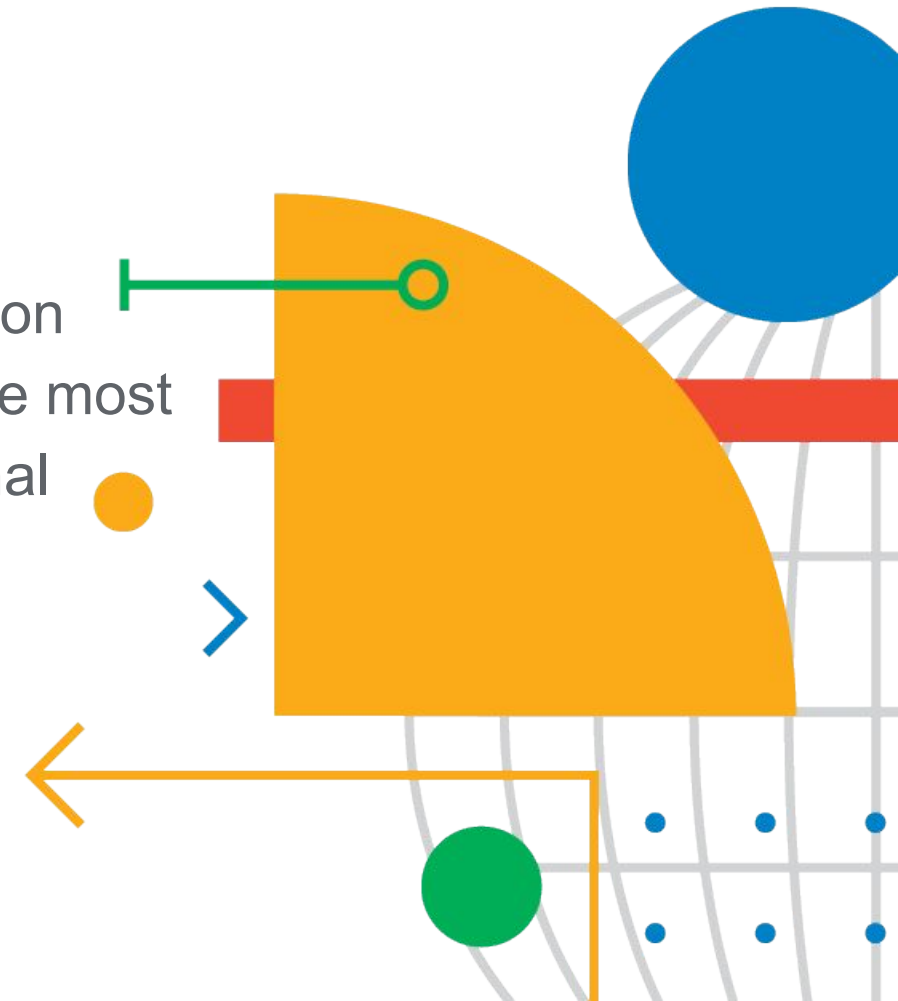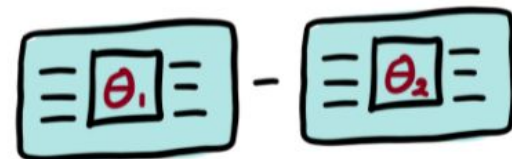
Creating Hybrid Quantum Circuits:

- The real importance of Quantum circuits lie in merging with traditional neural networks (sequential modules). These can be Quantum-Classical/Classical-Quantum/Classical-Quantum-Classical ansatz.
- A typical Quantum Convolution Network can be represented as follows:
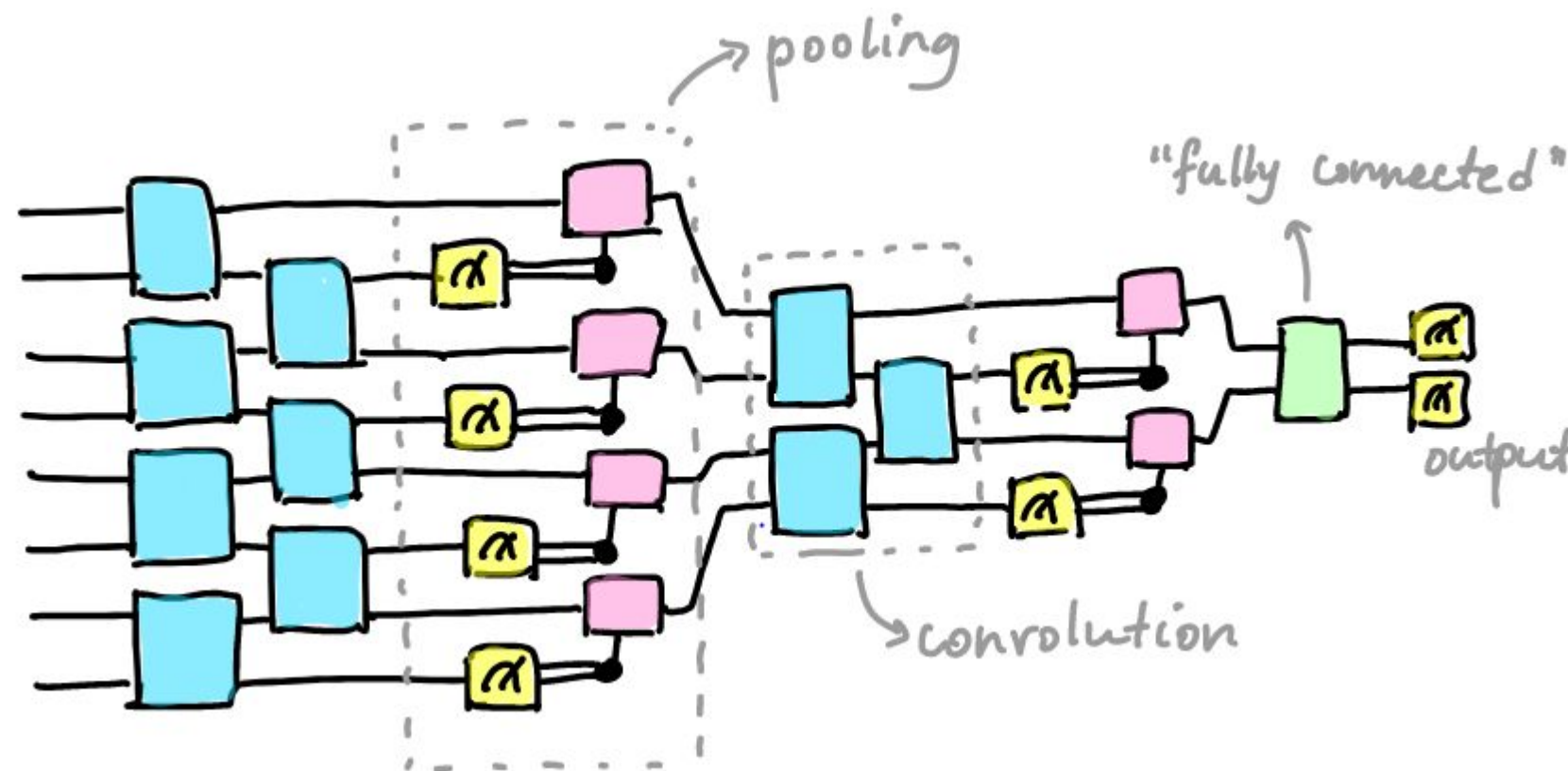
Creating Hybrid Quantum Circuits:

- In Quantum CNN, hyperparameters of the parameterized layered ansatz perform convolution and then a subset of the qubits are chosen for pooling.The outputs are phase changed qubits in static state.
- A merge of Classical -Quantum-Classical Circuit where the front and terminal classical circuit represents a 2 neuron based simple dense layer, can be represented as follows:
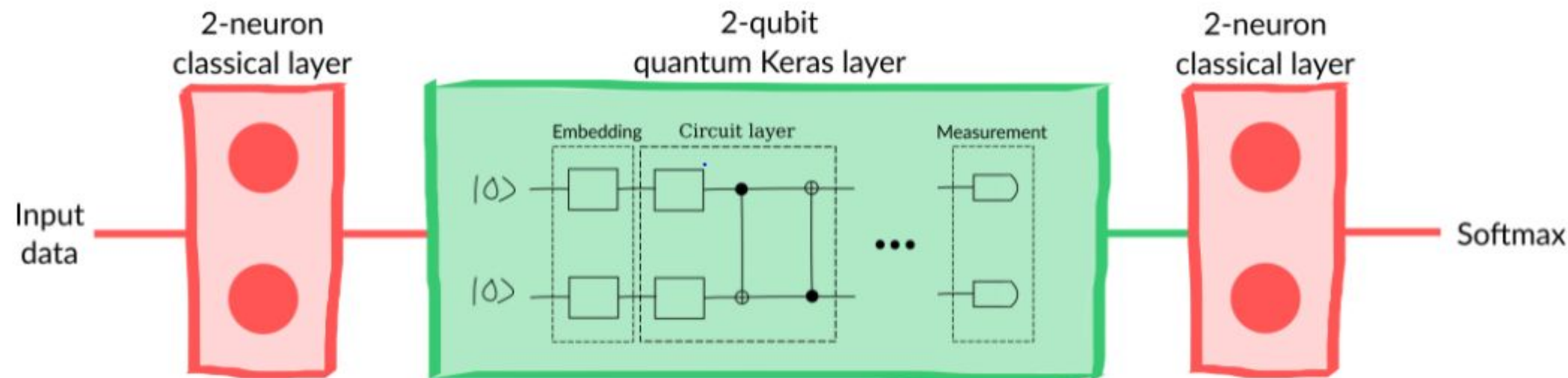

- Since classical->quantum conversion is a compression of higher features to (amplitude)embeddings, the greater the number of trainable parameters in the dense layer, the greater amount of time will be consumed in the operation of the quantum circuit.

Realizing the performance of QHC:

- Quantum Hybrid Circuits have a good performance as the loss landscape in which it operates, generally tend to avoid barren plateaus (though not all times). It tries to overcome through Natural Gradient Descent or Fischer Approximation methods.
- Training of a classical-quantum hybrid circuit such as Quanvolution Network yields higher levels of accuracy. This is because quantum circuits can produce highly complex intermediate kernels which are unsolvable by classical systems. Since we cannot abstract the intermediate phase values of the qubits during the Unitary operations , those intermediate kernel states are always lost. However the final quantum qubit state is preserved from those complex kernels.A simple Quantum embedding with 180 degrees phase shift followed by a random circuit of some layers can provide greater accuracy and better loss statistics than traditional CNNs.
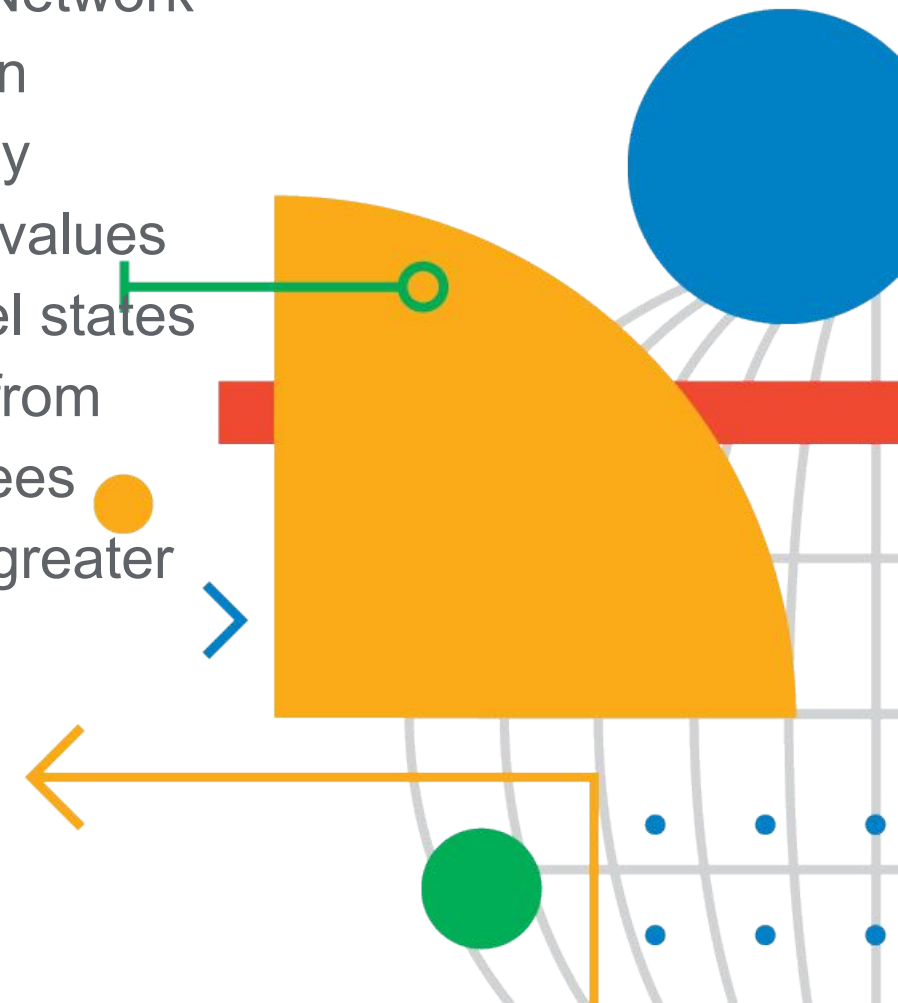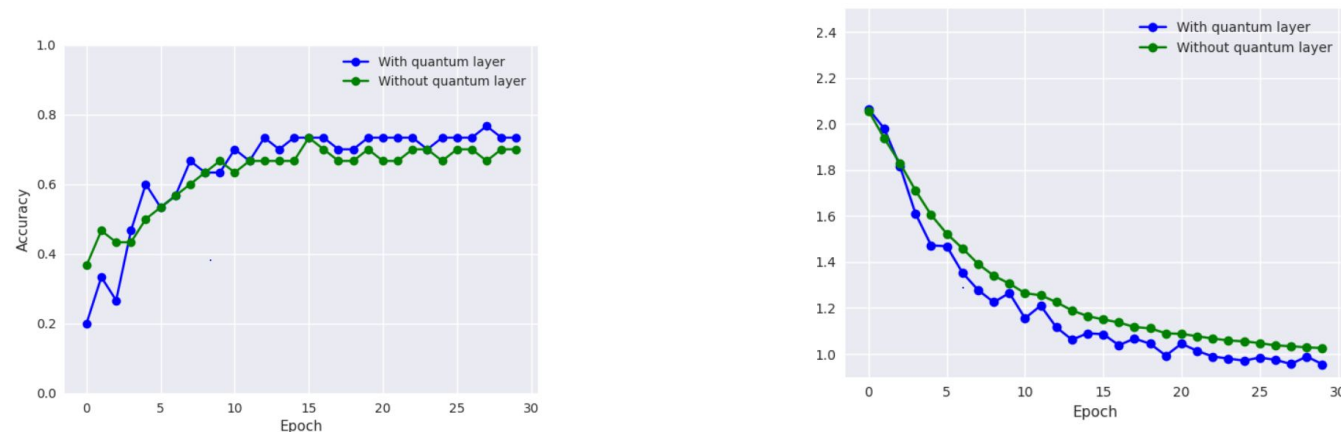
Realizing the performance of QHC:

- QNNs (quanvolution NNs) can be represented as :
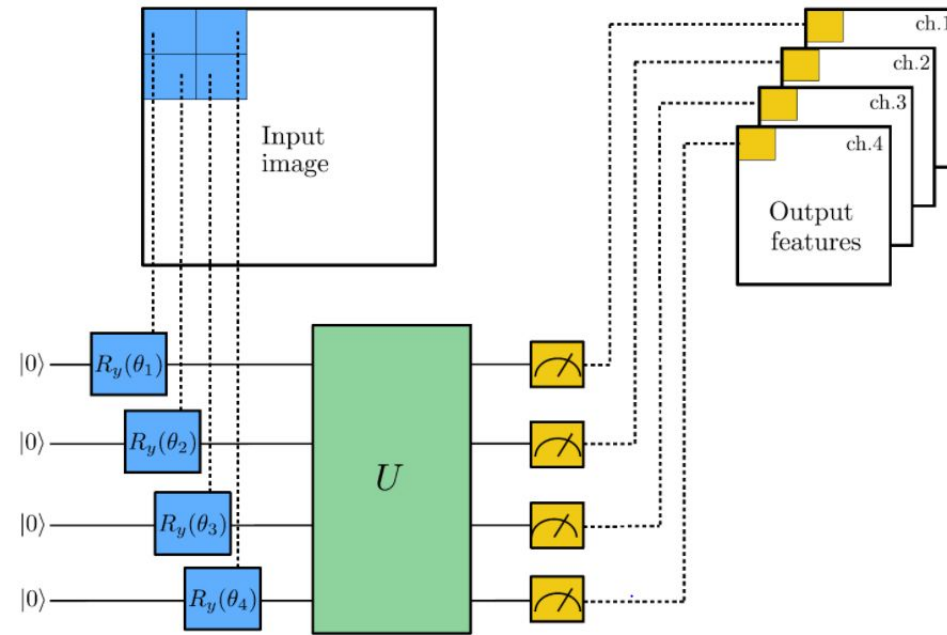
- The corresponding accuracy and loss of MNIST classification:

Applications in the field of Quantum RL and NLP:

- QHC s have become important from a Reinforcement Learning perspective owing to the infinite number of computation states (quantum) in which the qubit can exist.Since there are a family of on policy RL algorithms which use policy gradient variations to estimate the most probable and rewarding states.Grover's algorithm has been used extensively in this field of research.

- In the field of Quantum search, Grover's algorithm performs really well computationally over an oracle to verify the correct solution of the search. This happens through the process of phase shift and reflection (amplitude amplification). Quantum search in QHC is used in researches spanning NLP search.

- In the field of GCN/GNNs , quantum graph neural networks are being employed which applied a time evolved hamiltonian to a graph kernel feature space. These are some of the advancements in the fields of NLP /RL.
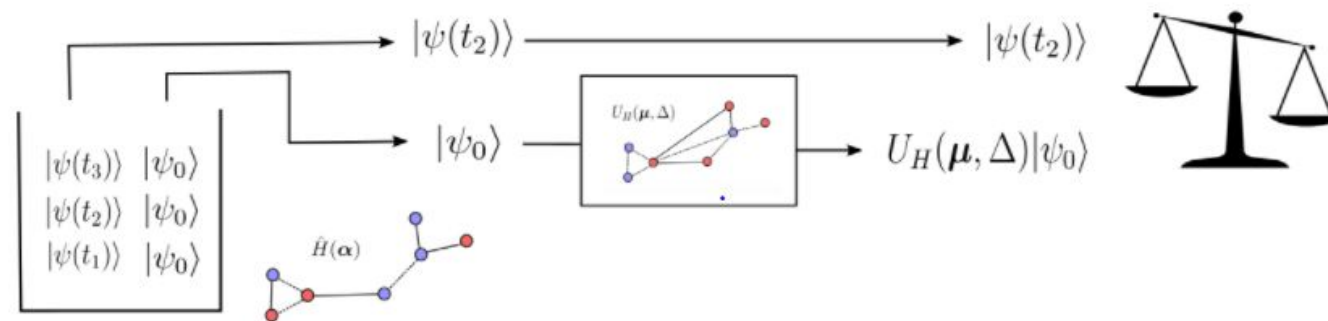
Applications in the field of Quantum RL and NLP:

- QHC s are also used in the field of GANs to provide adversarial learning.
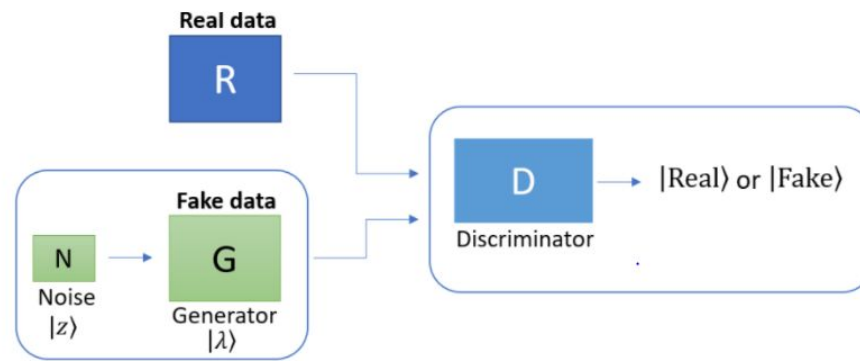
- QGRNN (Quantum Graph Recurrent Networks) is another variation of Quantum Graph Models:

Democratizing adoption of QHCs:

- QHCs or variational circuits are thus an entirely new paradigm of deep learning. With the superposition of merged traditional networks and quantum ansatz, these are very powerful owing to the infinite number of states which they can be present in.
- Due to the high intermediate sample spaces (due to a lot of Unitary rotations), QHCs are time-consuming however provide a better loss statistic than traditional ones.
- There have been significant growth of open source Quantum ML with libraries such as Pennylane(Xanadu), tensorflow-quantum(Tensorflow Google), Qiskit(IBM) which have further enhanced democratization of these circuits.
- The field of research in quantum variations of traditional learning is deepening due to easy accessibility of quantum hardware in local systems,simplified platforms and shorter codebases.
- Quantum Deep Learning will be a game changer in the years to come.

Repository and Links:

- https://github.com/abhilash1910/EuroPython-21-QuantumDeepLearning
- https://pennylane.ai/qml/
- https://qiskit.org/textbook/preface.html
- https://pennylane.ai/qml/demos/tutorial_quanvolution.html
- https://github.com/XanaduAI/quantum-transfer-learning
- https://github.com/XanaduAI/quantum-neural-networks
- https://github.com/tensorflow/quantum
- https://qiskit.org/documentation/machine-learning/tutorials/index.html
  .

Thank You!

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Q&A

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