Applying Variational Circuit In Deep Learning Architectures For Improving Discriminative Power Of Embedding

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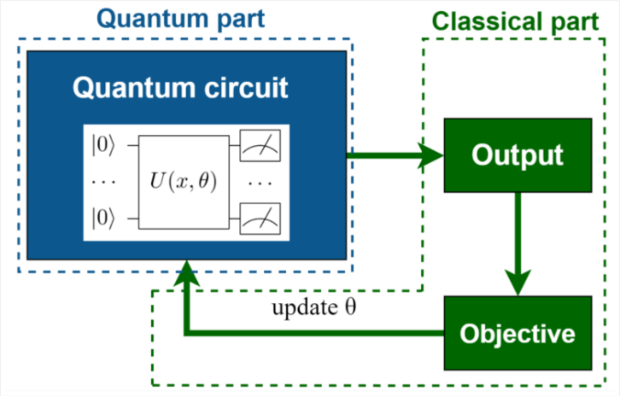
Overview

- Variational Circuit
  - VC are parameter-dependent quantum circuits that can be optimized by a classical computer with regard to a given objective [1]
- Embedding
  - Embeddings are functions that maps classical data into quantum states that can be acted upon by quantum operations for quantum information processing

Introduction
Background Of Study



Learning of variational quantum circuit involves iterative execution of quantum and classical parts of the algorithm.

- Modern datasets is constantly increasing and classical Machine learning algorithms in the near future will suffer computational bottlenecks.
- The purpose of this research is to apply quantum algorithms to deep learning architectures to provide exponential speedups in training and prediction and also to increase the accuracy of machine learning models.

Limitation of Study

- Limited number of qubits or qumodes.
- No perfect quantum hardware so we have to make use of Near term quantum computers that have limited number of qubits or qumodes.
- The current photonic quantum computer available is not yet ready for machine learning tasks.
- The overhead of simulation quantum algorithms on classical devices is high and very slow

Definition of Terms

- Qubits, Qumodes, Wires
- Variational Circuit
- Embeddings
- Gates
- Circuits

Review

Transfer Learning in Hybrid Neural Networks

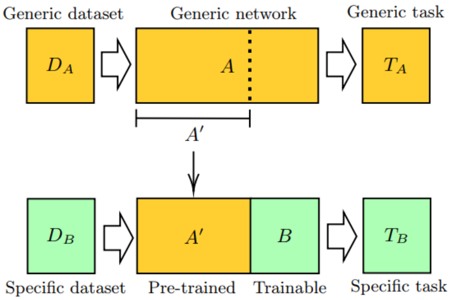


FIG. 1. General representation of the *transfer learning* method, where each of the neural networks A and B can be either classical or quantum. Network A is pre-trained on a dataset D_A and for a task T_A. A reduced network A', obtained by removing some of the final layers of A, is used as a fixed feature extractor. The second network B, usually much smaller than A', is optimized on the specific dataset D_B and for the specific task T_B.

Review

Continuous Variable quantum Neural networks

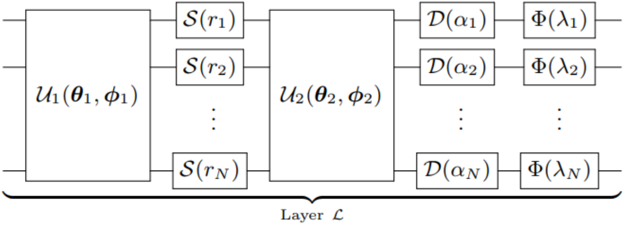


FIG. 1. The circuit structure for a single layer of a CV quantum neural network: an interferometer, local squeeze gates, a second interferometer, local displacements, and finally local non-Gaussian gates. The first four components carry out an affine transformation, followed by a final nonlinear transformation.

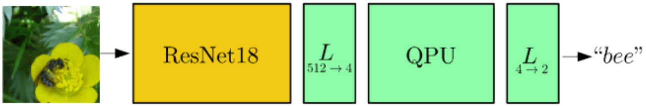
Experiment And Results

Dataset

- Data was obtained from the Pytorch official website
- Train a model to classify ants and bees.
- Training Images: 120 images each for ants and bees.
- Validation Images: 75 images for each class.

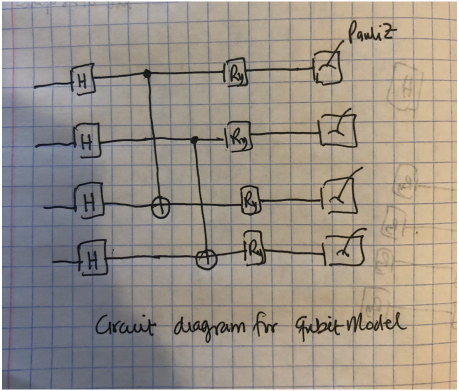
$$B = L_{4\to 2} \circ Q \circ L_{512\to 4}$$

A graphical representation of the full data processing pipeline is given in the figure below.



Experiment And Results

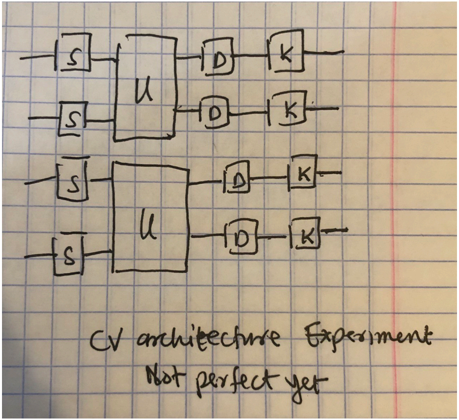
Qubit Model



Experiment And Results

CV Model - (Qumode)

Still in trial phase to get circuit that gives best results



Experimental Results		
Parameters	Qubit Circuit	CV Circuit
Quantum depth	6	6
Num Epochs	25	5
Batch size	4	4
Learning rate	0.001	0.001
Optimizer	Adam	Adam
Accuracy	0.96	0.54

The classical neural network has accuracy of 0.93 after 30 epochs

Further Work

- Better Implementation of the Continuous Variable (Qumode) Circuit to achieve Higher results
- Apply both Qubit based Circuit and continuous variable circuit to complex tasks
- Apply both circuits to other deep learning architectures
- Try different versions -Pre-train a quantum model and attach classical network as FC

References

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