Applying Variational Circuits in Deep Learning Architectures for Improving Discriminative Power of Speaker Identification Embeddings

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Overview

Intro

Background Of Study

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

Background of Study

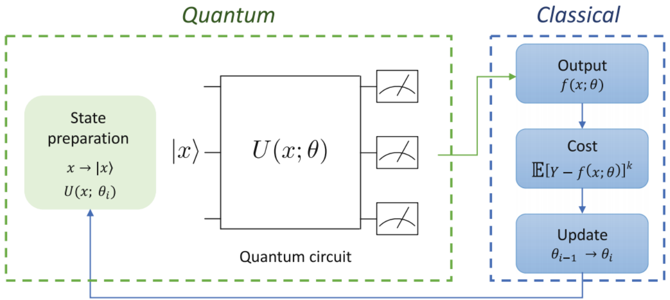


Fig. 1. Scheme of a hybrid quantum-classical algorithm for supervised learning. The quantum variational circuit is depicted in green, while the classical component is represented in blue. (Color figure online)

Problem Statement

- Modern dataset is constantly increasing and classical Machine learning algorithms in the near the near future will suffer computational bottlenecks, thus the pressure to innovate machine learning is fast increasing everyday [2].
- At the time of writing, there's no quantum application to audio data.
- The purpose of this research is to apply variational circuit to deep learning architectures (RESNET) to speaker audio data and investigate how quantum algorithms can improve the embeddings.
- We investigate using photonic quantum circuits.

Limitation of Study

- Limited number of qumodes.
- No perfect quantum hardware available, thus we have to make use of Near term quantum computers that have limited qumodes.
- The current photonic quantum computer available in the world is not yet ready for machine learning tasks.
- The overhead of simulating quantum algorithms on classical devices is very high and slow.
- Coming up with quantum algorithms that outperform classical computers is very difficult since the laws of physics restricts our access to information stored in quantum systems [4].

Definition of Terms

- Qubits or Qumodes or Wires
- Gates
- Circuits
- Fourier transform
- FFT - Fast Fourier Transform
- MFCC - Mel Frequency Cepstral Coefficients
- STFT - Short Time Fourier Transform
- Spectogram

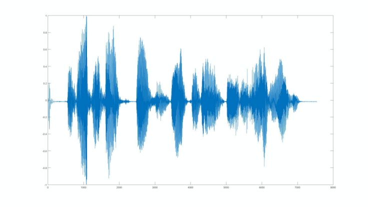


Figure 1: Raw audio waveform

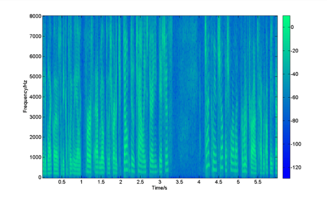


Figure 2: Spectogram

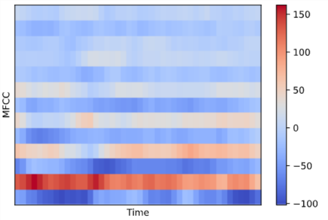


Figure 3: MFCC

Review

Transfer Learning Hybrid Neural Network [6]

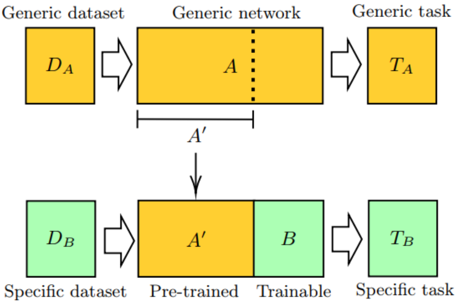


FIG. 1. General representation of the *transfer learning* method, where each of the neural networks A and B can be either classical or quantum. Network A is pre-trained on a dataset D_A and for a task T_A. A reduced network A', obtained by removing some of the final layers of A, is used as a fixed feature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

Continuous Variable Neural Networks [3]

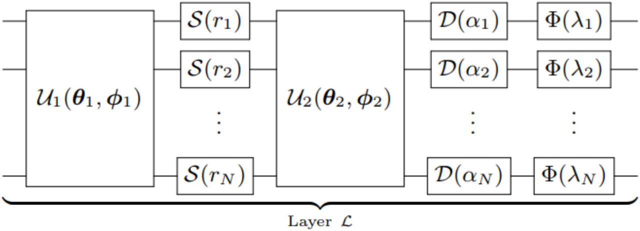
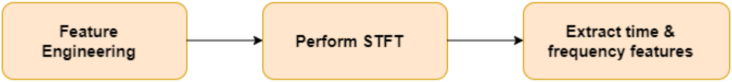


FIG. 1. The circuit structure for a single layer of a CV quantum neural network: an interferometer, local squeeze gates, a second interferometer, local displacements, and finally local non-Gaussian gates. The first four components carry out an affine transformation, followed by a final nonlinear transformation.

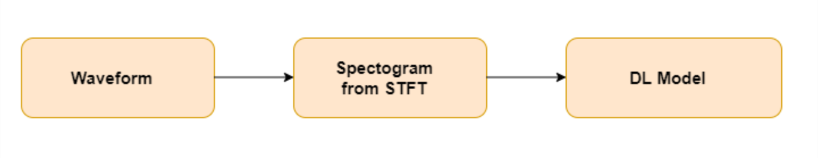
Deep Learning for Audio Signal Signal Processing [5]

- Deep learning has enabled practical applications in signal processing often outperforming traditional signal processing techniques on a large scale.
- Raw audio samples form a one-dimensional time series signal, which is different from images (2-D).
- Unlike images, audio signals have to be studied sequentially and in chronological order (audio-specific solutions).

Traditional ML Preprocessing pipeline for Audio data



Deep Learning pipeline for Audio data

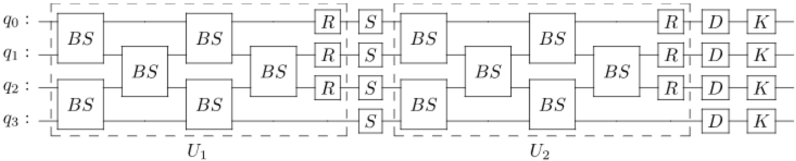


Methodology

Architectural Design

- **`Base Model(RESNET18):`**
    - Up-Sample the audio to required input of the RESNET (3, 224, 224).
    - Replace the output to the required number of classes of the speaker dataset.

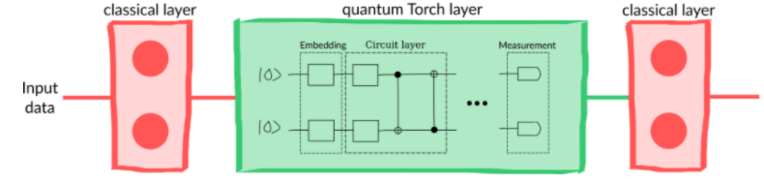
- CV quantum layer



Four mode layer

Architectural Design

- **Hybrid Model**
  - Replace the final layer of the base model with the quantum model.



Experiment and Results

Experimental Environment

- Librosa was used to preprocess audio data.
- Experiments were conducted using Pytorch-Lightning.
- The quantum experiments were run using pennylane on the strawberryfields simulator.
- Future experiments could include running on actual strawberryfields hardware.

Encoding Methodology

- The best method to encode data into a Quantum circuit is still an open research question.
- Data was encoded using the `Displacement` encoding.

Datasets

- **Initial Experiment with Images**
  - The hymenoptera dataset (ants and bees) was used.
  - Dataset contains **120** training images each for ants and bees. There are **75** validation images for each class.
- **Research Experiment(Audio) Data**
  - The original data for the experiment is the Russian University students speech digits dataset.
  - Dataset contains **1775** samples of approximately **3 seconds** audio from **81** different speakers(**54** males and **27** females).
  - Mock experiment with kaggle dataset containing **5** speakers with duration **1** second and sample rate **16000** |<->| (**0.25%** of data for test and **0.2%** of remaining for validation)

Results

Table 1: Results so far

qubit(Img)	init CV(Img)	Curr CV(Img)	Base (2 spkr)
96%	54%	[79%]	99%

Further Works

Further Works

- Apply baseline model (RESNET18) to the Russian Spoken Digits dataset (when available).
- Apply the hybrid model to the Russian Spoken Digits dataset.
- Modify the hybrid model to improve performance.
- Analyze the results and submit paper for publication.

Conclusion

Conclusion

- Eventhough there is still a lot of work to do, quantum machine learning remains a very promising emerging field of research.

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Thanks

Questions?