**Deep Learning Project Proposal**

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**What is the problem that you will be investigating? Why is it interesting?**

In the field of quantum computing, the study of highly complex quantum states is a promising avenue towards quantum advantage (showing that quantum computers can solve classically intractable problems). These states are very hard to simulate with traditional computing methods. Recently, Harvard physicists proposed a *quantum convolutional neural network (QCNN)*, which was able to identify whether unknown quantum states exhibited certain kinds of interesting topological properties [1] more efficiently than traditional methods. When we refer to a state being ‘topological,’ what we mean is that it “exhibit[s] non-trivial quantum evolutions that are described by topology, i.e. they are abstracted from local geometrical details” [2].

As a simple example, we can consider a system of two particles in 2D where we swap the positions of the particles by moving them around each other. For a nontopological state such as a system of two electrons, the action of swapping the two particles does not meaningfully change the state. However, for a topological state such as a system of two Majorana fermions, the action of swapping the two particles nontrivially changes the state. The basic idea of topological quantum computing involves encoding information in the ‘braids’ that are formed when these particles are moved around each other (see Fig. 1).

Diagram

Description automatically generated

We propose to extend this approach to a different topological state and test its performance as a starting point. The topological states we propose to test are Floquet Majorana modes. (which Nikhil has studied previously).

**What dataset are you using?**

We will make our own dataset of custom quantum circuits, using IBM’s Qiskit software. Nikhil has access to IBM’s quantum devices through Qiskit as an ex-IBM intern, and there is publicly available code to generate Floquet Majorana modes in [3].

**What Deep learning approach will you use/develop?**

We will use a modified version of the QCNN approach developed in [1]. The fundamental architecture of the QCNN will not have to be changed to accommodate this new state. \_\_\_\_\_\_\_\_

**What are anticipated challenges of this project?**

Some of the anticipated challenges of this project would be:

* the lack of available quantum computers and computational strength (few qubits)
* it would be time consuming to run a QCNN in a quantum computer
* copying values would be difficult and state collapse would be necessary for the pooling layer
* quantum devices are very noisy and can often become scrambled, however there are methods to mitigate this noise
* coherence time – similar to environmental noise, training a quantum neural network would be challenging due to the time required and limited coherence time during which quantum states can be preserved
* qubit connectivity – in order to perform convolution operations we would need to have specific connections between qubits which can be difficult in current hardware
* limited training data – apart from coming up with the data to use, it would be difficult to use complex and large training data

**How will you evaluate your results?**

**Qualitatively, what kind of results do you expect (e.g. plots or figures)?**

In addition to the regular training/test loss plots, we could have a phase diagram which shows the transition between topological and non-topological states, and overlay it with the QCNN classification output. This will show us the regimes in which our QCNN performs well and not-so-well. We will also have a figure comparing the QCNN sample complexity to the traditional quantum tomography sample complexity. Also, we can plot the generalization gap, we can observe if our model is overfitting or underfitting. We can try to come up with a visualization of feature maps to better understand and visualize the internal workings of the QCNN. We will also try to visualize the network in some way such as the parameters to gain insight into how the network is making predictions.

**Quantitatively, what kind of analysis will you use to evaluate and/or compare your results (e.g. what performance metrics or statistical tests)?**

We will use MSE as our loss function, following the methodology described in the following resource [1]. We are also aware of some specifically designed loss functions for quantum neural networks that we can potentially try out such as fidelity loss (i.e. distance between two quantum states) or the variational quantum classifier (VQC) loss (i.e. hybrid loss function containing classical and quantum components). Some other more general quantitative analysis to encompass performance/accuracy would be confusion matrices, a receiver operating characteristic (ROC) curve (curve that shows trade-off between true positive rate and false positive rate of the QCNN for different threshold values), simple cross-validation, general statistical significance tests (such as t-test or Wilcoxon signed-rank test), and precision recall curves.

**Bibliography**

[1] [I. Cong *et al*. “Quantum Convolutional Neural Networks,” *Nature Physics* ***15*** (2019).](https://www.nature.com/articles/s41567-019-0648-8)

[2] V. Lahtinen *et al.* A Short Introduction to Topological Quantum Computation (*SciPost Physics*, 2017).

[3] [N. Harle *et al.* “Observing and braiding topological Majorana modes on programmable quantum simulators,” *arXiv* (2022).](https://arxiv.org/pdf/2203.15083.pdf)