Encoding Data

Amplitude Embedding
Encoding the classical data into quantum circuits is an important step as we move toward quantum machine learning applications. Our team is interested in embedding the weather data for quantum computers. There are many ways to encode the data [1,2], we started with the simple amplitude encoding, $|\psi\rangle = \sum_{i=1}^{N} x_i |i\rangle$, where x_i is the classical data, and N is the total number of the data we are interested in encoding. Images can also be mapped into quantum state by taking 2D data into 1D data. There is a proposal to embed the RGB data [1], but for simplicity, we encoded the black and white data into quantum state.

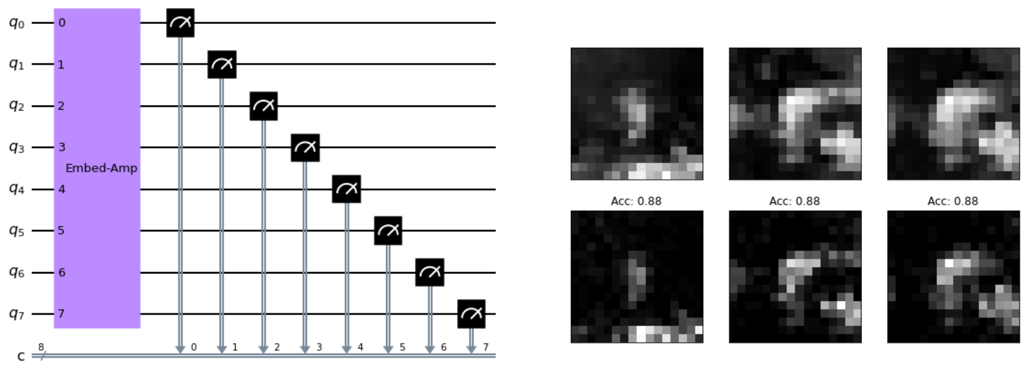

Fig.1 Amplitude Encoding

We used the qiskit *initialize* function to embed the classical dataset. In Fig.1, simple embedding of amplitude is presented. On the right side of the figure, top images are the original data of satellite image of storm [2], and the bottom images are the result of the amplitude encoding. We measure the state and reconstruct the image by looking at the probability distribution. There is overall good accuracy (more than 85%) between original data and the result of the amplitude encoding.

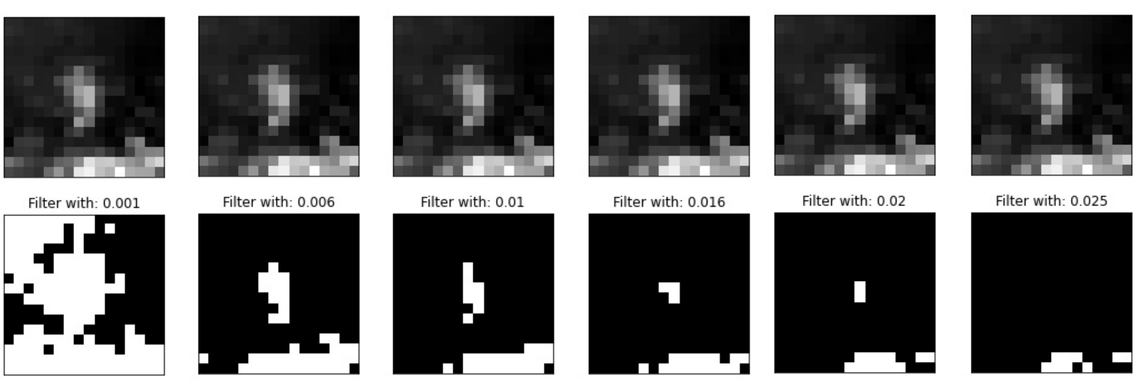

Fig.2 Filtering the image

As we are using the probability distribution, amplitude encoding can be used as an easy implementation of image contrast. By reducing the size of the number of the shots or threshold of pixel value of the image, we can binarize the image. As shown in Figure 2, we increase the threshold from 1 shot to 25 shots out of 1000 shots. This allows us to detect the regions of the clouds.

Phase Embedding

Another interesting way to encode the data is in the phase of the superposition state, $|\psi\rangle = \sum_{i=1}^{N} 1/\sqrt{N}\, exp(i\, x_i)|i\rangle$. In this task, we create the unitary matrix by generating the diagonal matrix, and transform the unitary matrix into a gate by *unitary* function. By phase embedding the classifical information, we provide another interesting application by integrating the grover search algorithm.

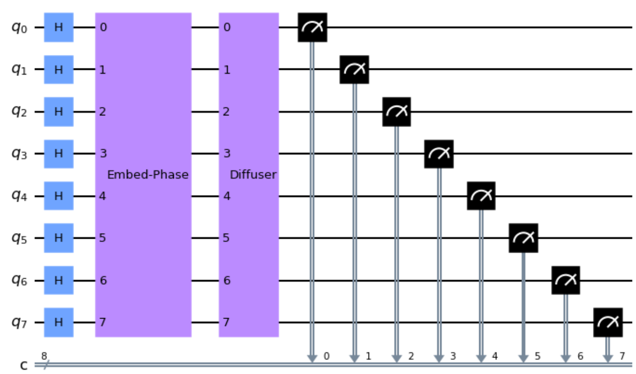

Fig.3 Grover Search

Grover search algorithm is the quantum algorithm which shows quadratic speed up for unstructured searching with high probability of finding particular input value. As we are implementing the phase embedding algorithm, we notice that grover search can be helpful for finding a specific location at the image. For example, Figure 4 shows the satellite image [4] of McMurray wildfire in 2016. As the local fire spreads, we can find the bright spots on a satellite image.

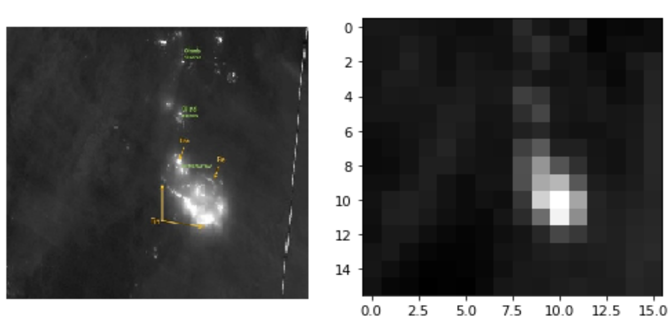

Fig.4 Satellite images show Fort McMurray wildfire from space

On the right side of the figure 4 is the resize the image into 16x16 pixels, this is clear that we have a significantly bright region on the image. If we embed the image in phase of the quantum state, we can map the pixel of the brightness as phase rotation. Then this problem became a grover search problem where we are looking for flipped phase locations in the data. Typically, grover search requires $\pi/(4\sqrt{N})$ iteration, which is in this case ~12.5 iteration. However, as we can see in the original image, we have many bright location more than >7, so iteration is close to $\pi/(4\sqrt{N/k}) = 4.7$where k is the number of the unique data we are interested in.

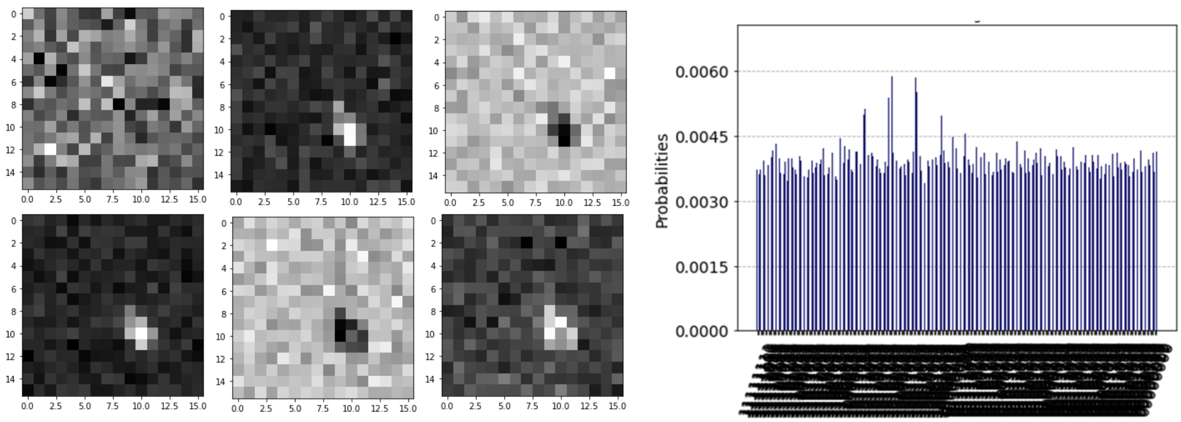

Fig.5 Grover search algorithm for image data

Figure 5 shows how the image changes as the iteration increases. First image (top left) is with no iteration, and the iteration increases to the right. As we approach 5 iterations (bottom right), we can find the bright four spots on the image which correspond to the wild fire location, and we can see a significant probability increase on the right side of the histogram. As we have quadratic speedup for the searching algorithm, this method can be applied to the data acquisition in the space where they have limited storage and resources.

Quantum Neural Network

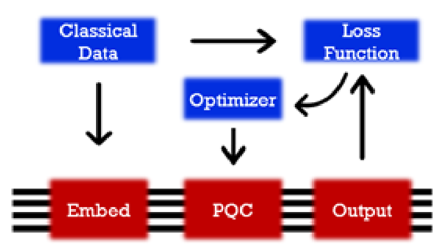

Fig.6 Workflow of classifcal and quantum neural network

Allowing encoding classical data promises the applications of quantum machine learning algorithms. In particular, we applied near-term quantum machine learning called quantum neural network (QNN). Figure 6 (right) shows the typical work flows for classical neural networks. In typical machine learning, data is inserted to the neural network, calculates the loss function, and the hidden layer is optimized. On the other hand, the quantum neural network, parameterized quantum circuit is optimized instead of optimizing the hidden layer.

Parameterized quantum circuit

We embed the data using parameterized quantum circuit (PQC) shown in Ref [5]. In this paper, they define the expressibility of each circuit where expressibility is the measure of how the circuit is expressible in the Hibert space. In particular, we choose circuit 15 where it shows good expressibility and entanglement capability.

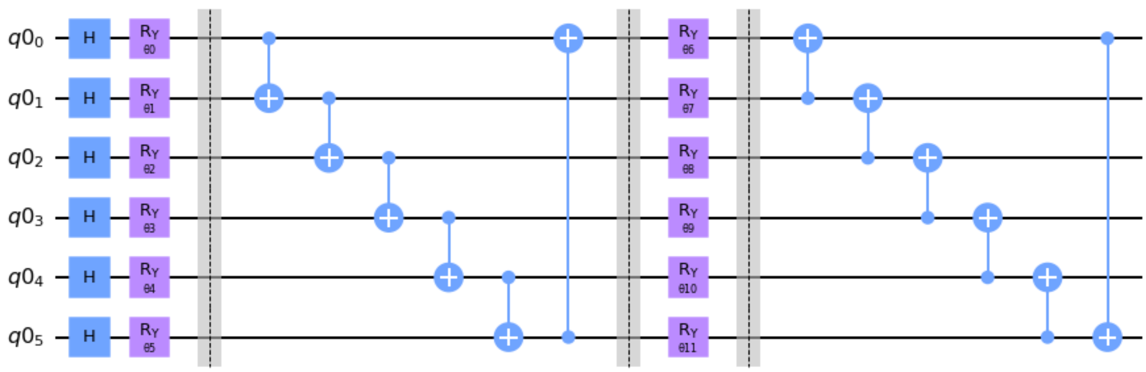

Fig.7 Circuit 15 PQC

We use this PQC for both encoding and optimizing the hidden layer of the parameterized quantum circuit. For encoding the dataset, we had to repeat the PQC over 6 times to have 72 (6*2*7) possible location for encoding the data. Our 8x8 pixel is encoded into the 72 parameters, and the last 6 (72-64) parameters are set to equal to pi. For the training purpose, we load 15 images for encoding the dataset.

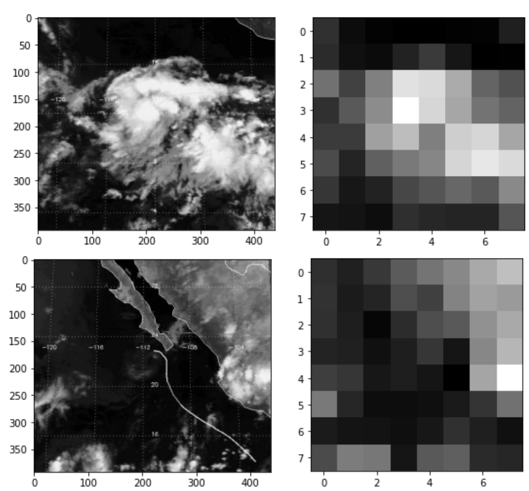

Fig.8 Encoding Image

Figure 8 is the example of the stormy data vs no-storm data. We would like to know by training QNN that given image has “storm” or “no storm.”
As we decrease the size of the image, it is hard to see if there is strom or not, but it is still possible to tell if there are lots of clouds or not. We are not really sure how QNN decides if the image is storm or not, it is possibility that QNN classify the result by overall brightness of the image.

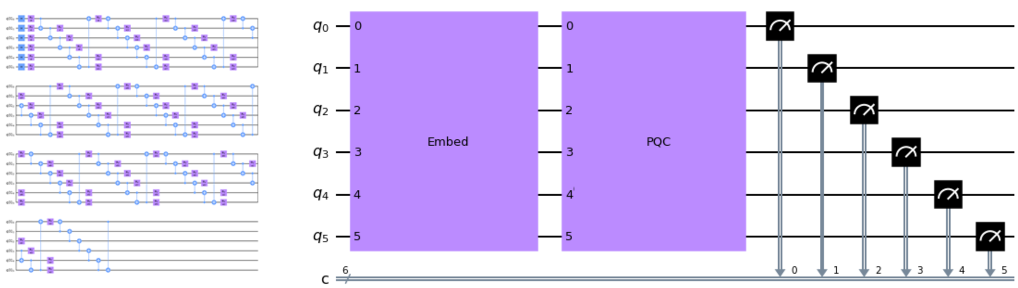

Fig. 8 Encoding circuits and QNN structure

So, first we encode our image into an embedding circuit, pass through the PQC, and measure the bit string. Final bitstring is a map to classify the “storm” or “no storm.” We used the mapping method provided by Ref [6] where the first and last quarter of the bitstring is mapped to 0 ($|000000\rangle$,$|000001\rangle$,$|000010\rangle$….) and the rest of the bitstring is mapped to 1 ($|010000\rangle$,$|010001\rangle$, $|010010\rangle$). By using *CircuitQNN,* we can connect the *Torch* module and optimize the parameterized circuit. *LBFGS* optimizer and *CrossEntropyLoss* is used to optimize the result.

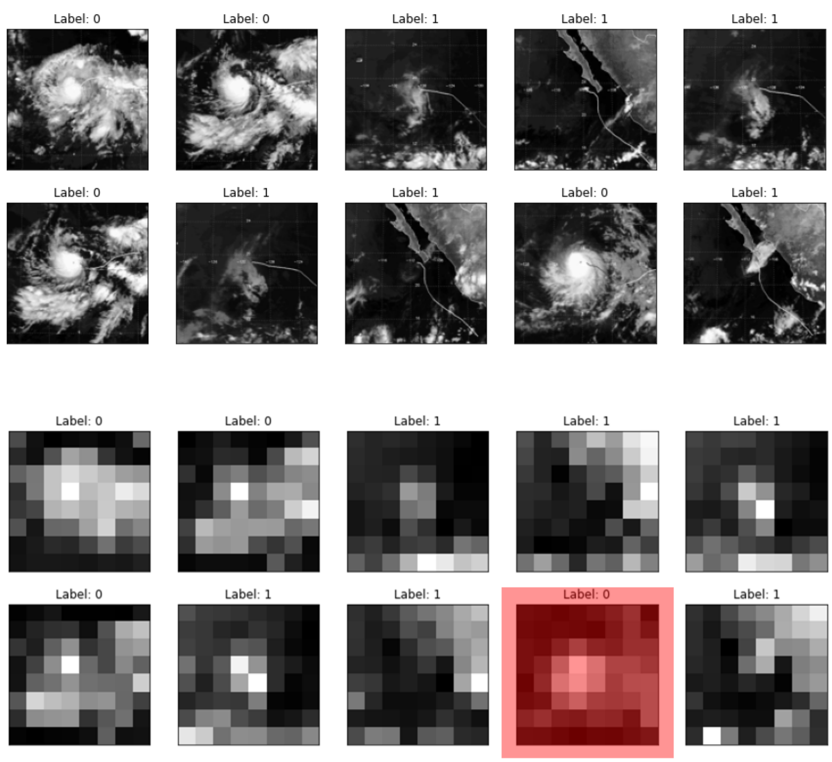

Fig. 9 Classification result

Figure 9 shows our result from verification data. For red marked data, is where we have failed to classify, but the rest of the data is correctly classified!

Training (15 images)	Verifying (10 images)
86%	90%

Results are very promising that we can successfully train the data with high accuracy.

Parameterized quantum pulse?

In the last session, we would like to propose another interesting way of integrating near-term quantum machine learning modules. Current quantum circuits already have amazing capacity to encode and classify the result. For example, we can store 2^n information in qubit, and we have 2^n different ways of mapping our bitstring. However, qudit will provide surprising increased power of parameterized quantum circuits.

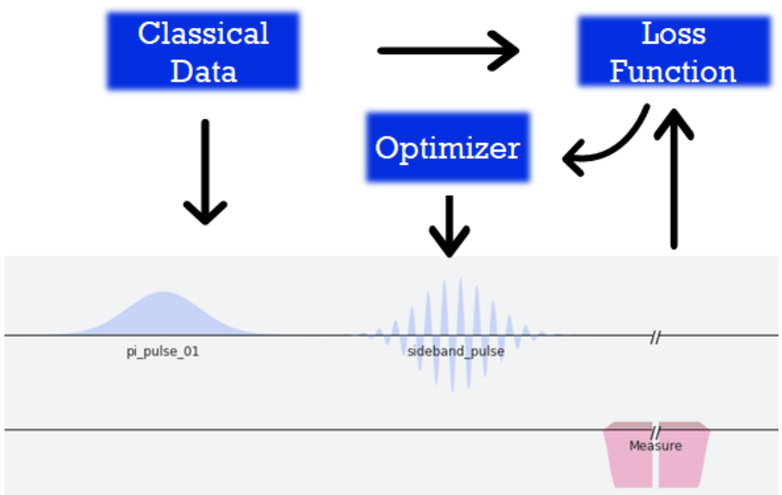

Fig. 10 Possible application of PQC

This will increase the size of mapping space and reduce the required number of circuits, which will help both on encoding, optimizing, and measurement. We can use the length and amplitude of the 0-1 pulse and 1-2 pulses as the parameters for the circuit, so we can embed the data into a more fundamental level. Just with a single pulse, we can start to work with 3 label data (RGB or cat/dog/dogecoin), and with the 9 qudit, 140 x 140 pixels can be mapped where two qubit can only map with 22x22 pixels.

[1] Yu Jing, Yang Yang, Chonghang Wu, Wenbing Fu, Wei Hu, Xiaogang Li, Hua Xu, RGB Image Classification with Quantum Convolutional Ansaetze, https://arxiv.org/abs/2107.11099
[2] Mohd. Hussain Mir, Harkirat Singh,Pixel identification in an image using Grover Search Algorithm, https://arxiv.org/ftp/arxiv/papers/2107/2107.03039.pdf
[3] Storm satellite images https://www.ncdc.noaa.gov/stormevents/
[4] Satellite images show Fort McMurray wildfire from space https://calgaryherald.com/news/local-news/satellite-images-show-fort-mcmurray-wildfire-from-space
[5]Sukin Sim, Peter D. Johnson, Alan Aspuru-Guzik Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms https://arxiv.org/pdf/1905.10876.pdf
[6]Thomas Hubregtsen, Josef Pichlmeier, Patrick Stecher, Koen Bertels Evaluation of Parameterized Quantum Circuits: on the relation between classification accuracy, expressibility and entangling capability https://arxiv.org/pdf/2003.09887.pdf