Semiquanduqtol

Semi - QUantum Algorithm for Neuromorphic Design
Using QuanTum Optimization and Learning

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Content

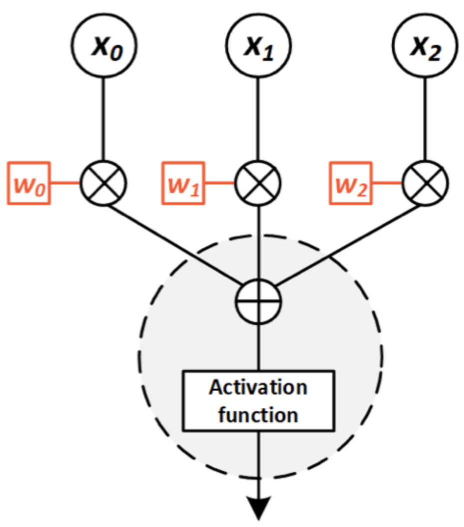
Motivation

Those pictures are from https://snntorch.readthedocs.io/en/latest/tutorials/tutorial_2.html

Artificial Intelligence has been very successful in the fields such as computer vision.
Its success relies on the idea of imitating neurons, a powerful computing mechanism.
Can we make neural networks even more powerful by building models that have a better resemblance to neurons?
Spiking Neural Network (SNN) is a novel approach to building neural networks. It closely resembles how our brain cells work.
While conventional neural networks represent data in matrices of numbers, SNN represents data in a time sequence of pulses.
It is anticipated to be more energy-efficient than conventional neural networks.

References: (we recommend reading the "Introduction" paragraph on this page)
[*https://snntorch.readthedocs.io/en/latest/*](https://snntorch.readthedocs.io/en/latest/)

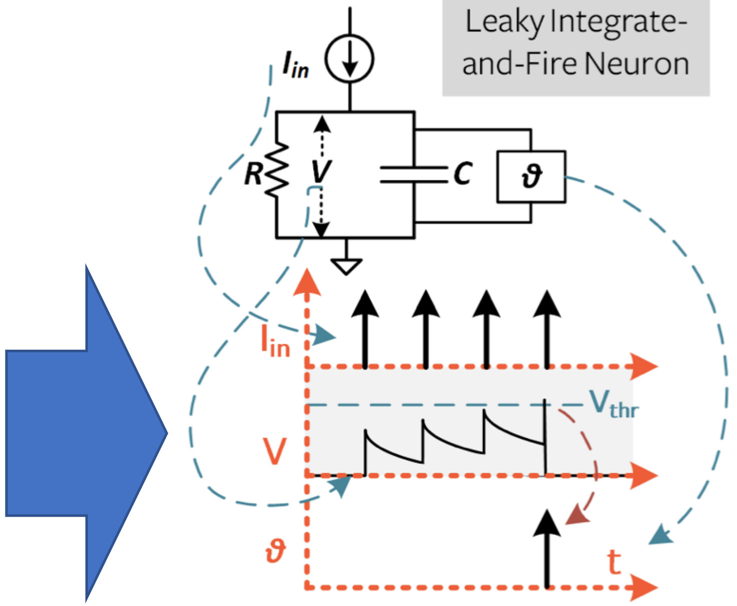
Artificial Neuron



Takes the weighted sum of inputs to produce an output (or activation). No time-varying dynamics or spiking.

Conventional neural networks

Leaky Integrate-and-Fire Neuron



When an input current is applied, the membrane voltage increases with time until it reaches a constant threhsold V_{th} at which point a delta function spike occurs, and the membrane is reset. ϑ is used as the output signal; membrane potential is an internal state.

SNN

Project Goal

End to end Neuromorphic (AI semiconductor) designing using quantum Optimization algorithm and hybrid quantum machine learning

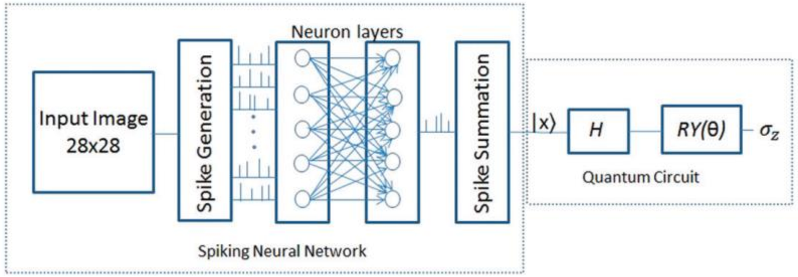
- Part 1 : Training Hybird Quantum Spiking Neural Network

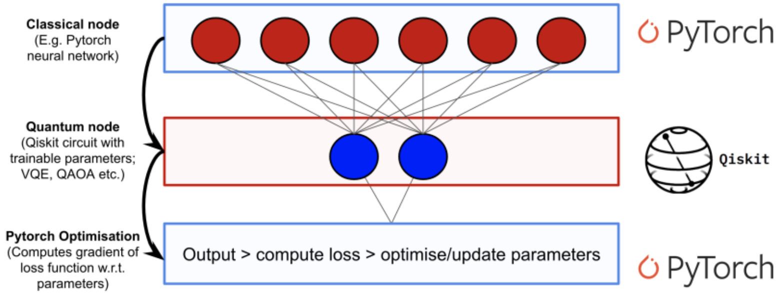
- Part 2 : Mapping SNN to Neuromorphic Hardware
    - Part 2a : Cluster SNN to smaller graph
    - Part 2b : Map Cluster to Neromrophic Crossbar

Part 1 [Ref #1]

Training Hybird Quantum Spiking Neural Network

- The overall structure basically follows the qiskit's Hybrid QCNN network (https://qiskit.org/textbook/ch-machine-learning/machine-learning-qiskit-pytorch.html) & the structure proposed in the reference [2] (They are very similar)
- The main difference is actually the classical model part (CNN vs SNN)
- SNN samples data from image (Data with time information)
- We feed-forwards the spike data to SNN
- The output of SNN is also spike data
  ➔ (T, 2) tensor where T is the number of time steps
- We sum up these spike data ((T,2) -> (1,2) by summing up)
- Use the output as a single qubit rotation angle (Ry)
- Use Z expectation value to classify MNIST digits
- Data : MNIST with 2 classes(3 & 6)





- We want to properly train this QSNN network
  & Plan to use IBM's real quantum device with QEC(e.g. CSS code)
- Possible advantage of QSNN : SNN also has probabilistic nature (Sampled data / Can treat sequence data
  ➔ Can generate sequence like RNN / …). Therefore, we expect that there combination is somewhat natural and quantum computer will handle such property of SNN well.

Part 2a [Ref #2]

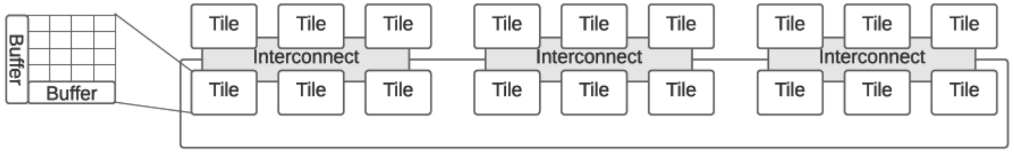
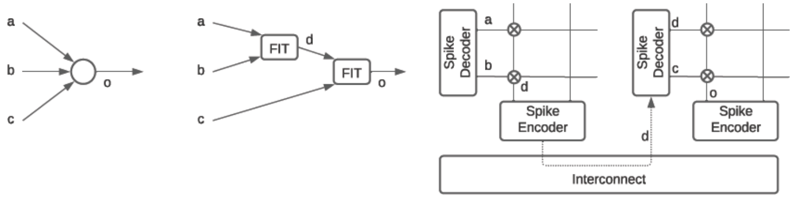


Figure 1

Cluster Spiking Neural Network graph to smaller graphs

- Cross bar based neromorphic is consist of crossbar and interconnect like upper figure 1
- Crossbar based neromrophic has limited amount of hardware, full SNN graph have to be divided(clustered) to several small graph like figure 2(a) to (b) which works like (c)
- Problem is divide graph to smaller graph like figure 3



(a) Original Neuron (b) Decomposed Neuron (c) Mapping the decomposed neuron to two crossbars

Figure 2

Problem formulation

objective

$$x^T L_G x = \sum_{(i,j)\in G} w(i,j)(x_i - x_j)^2$$

$$\begin{aligned}
\text{subject to} \quad & \sum_{i=1}^{n} x_{i,j} = \frac{n}{k} && j = 1,\ldots,k \\
& \sum_{j=1}^{k} x_{i,j} = 1 && i = 1,\ldots,n \\
\text{with} \quad & x_{i,j} \in \{0,1\}, && i = 1,\ldots,n.\ j = 1,\ldots,k
\end{aligned}$$

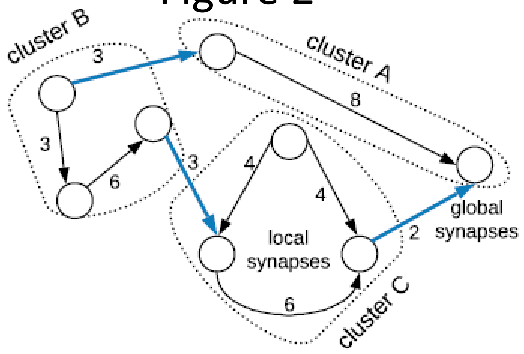


Figure 3

Optimization Method : Quantum Approximate Optimization Algorithm (QAOA)

- Express constraint binary quadratic optimization problem to quadratic unconstraint binary optimization
- Use Qiskit to express QAOA circuit
- Find Optimize value using that circuit

Part 2b [Ref #2]

Map Cluster to Crossbar based Neuromorphic hardware
- minimize spike congestion on shared interconnected
- to minimize energy consumption and spike latency

Problem formulation

Objective : minimize (total spike #) x (Spike moving distance)

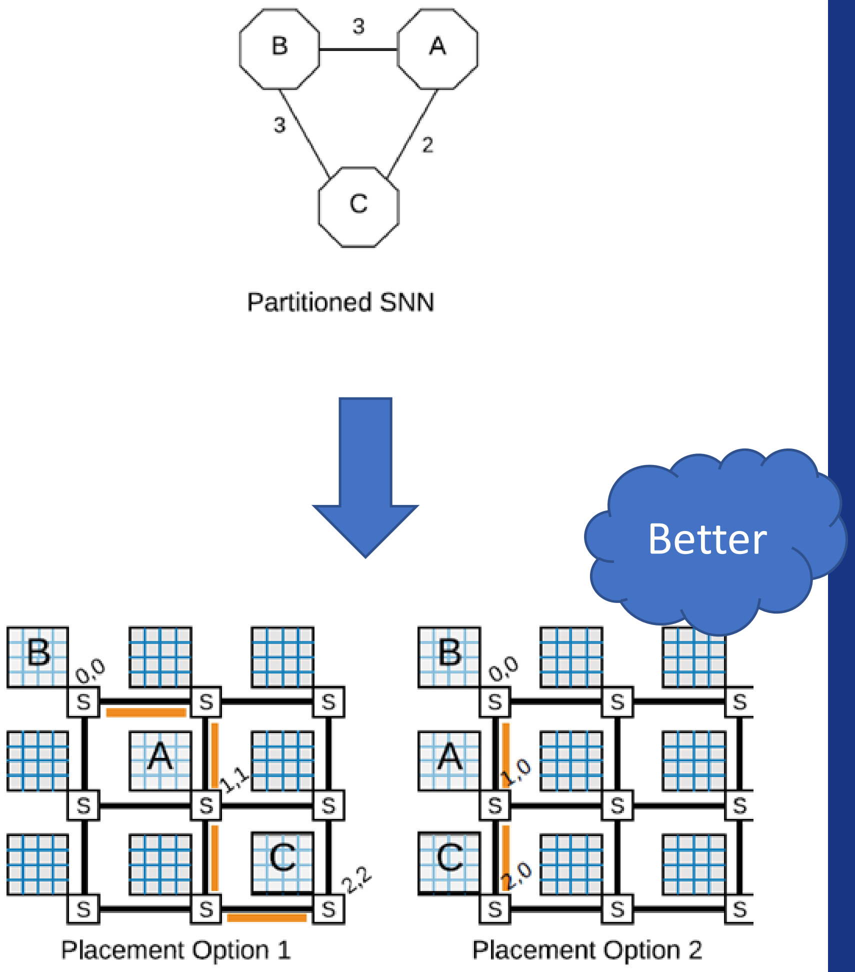
Subject to

$$\sum_i m_{ij} \leq 1 \quad \forall j$$

$$\sum_j m_{ij} = 1 \quad \forall i$$

$$m_{ij} = \begin{cases} 1 & \text{if cluster } c_i \in \mathcal{C} \text{ is mapped to crossbar } v_j \in \mathcal{V} \\ 0 & \text{otherwise} \end{cases}$$

Optimization Method : Durr –Hoyer algorithm [ref #3]
- Build quantum circuit that can execute Durr Hoyer using Qiskit
  - Build oracle that can express unconstraint objective function
  - Build Grover algorithm in Qiskit



Result and Conclusion

Simulation Result
- show Hybrid Quantum SNN can propose classification of MNIST
- show Quantum optimization algorithm can design neuromorphic of given SNN

Conclusion

- Quantum algorithm can design neuromorphic

Future work

In this Project : Topic is to design Classical Neuromorphic helped by quantum

Future : Quantum Neuromorphic

- Hybrid quantum network -> Fully quantum network

- Quantum Scale graph mapping using quantum algorithm

References

[1] A Ajayan and A P James, "Edge to quantum : hybrid quantum-spiking neural network image classifier"

[2] Adarsha Balaji et al, "Mapping Spiking Neural Networks to Neuromorphic Hardware"

[3] Christoph Durr and Peter Hoyer, "A quantum algorithm for finding the minimum"

Thank You