Approximate Quantum Random Access Memory Architectures

Koustubh Phalak, Student Member, IEEE, Junde Li, Student Member, IEEE, Swaroop Ghosh, Senior Member, IEEE

Abstract—Quantum supremacy in many applications using well-known quantum algorithms rely on availability of data in quantum format. Quantum Random Access Memory (QRAM), an equivalent of classical Random Access Memory (RAM), fulfills this requirement. However, the existing QRAM proposals either require qutrit technology and/or incur access challenges. We propose an approximate Parametric Quantum Circuit (PQC) based QRAM which takes address lines as input and gives out the corresponding data in these address lines as the output. We present two applications of the proposed PQC-based QRAM namely, storage of binary data and storage of machine learning (ML) dataset for classification. For the machine learning task, we perform binary classification using three different setups, (a) QNN with QRAM (QRAM + QNN), (b) QNN with normal data embedding and (c) Fully Connected Neural Network (FCNN). We show that QRAM + QNN converges (with 100% classification accuracy) faster i.e., by 6th epoch, compared to the other two setups which converge at around 10th and 15th epochs. The loss for QRAM + QNN (0.53) is less than FCNN setup (0.89) and comparable to QNN with normal embedding (0.48). For the storage of binary data, we evaluate Hamming Distance (HD) and percentage correct prediction metrics to quantify the performance. We observe an increase in HD from 0 to 3.97 and decrease in percentage of correct predictions from 100% to 0.58% as we increase the number of address and data lines from 2 to 9. We propose agglomerative clustering of data as a pre-processing step before training the QRAM to improve the HD i.e., from 3.97 to 2.17 and increase the percentage correct predictions to 10.1% from 0.58% till 9 address lines.

Index Terms—Quantum Random Access Memory, classification, binary data, storage.

1 INTRODUCTION

R ECENT advances of quantum computing in various fields such as, machine learning (ML) have shown great potential. Machine learning methods augmented with quantum computing like quantum clustering, quantum decision trees, quantum support vector machines, and quantum neural networks (QNNs) [1] are able to provide quantum speedup using quantum algorithms compared to their classical counterparts [2]. An important aspect for such augmented quantum algorithms is the conversion of classical data into quantum domain. Encoding methods like basis embedding, amplitude embedding, angle embedding [3] (Chapters 5 and 6) use various mathematical formulae to embed classical data onto qubits. Basis embedding encodes binary data of n bits onto n qubits. Amplitude embedding normalizes 2^n data and embeds them onto n qubits. Angle embedding performs rotation operation on qubits, either using RX, RY or RZ gates and embeds n classical datapoints onto n qubits. While these methods are useful for small and simple datasets, they are not efficient for more complex datasets. Quantum Random Access Memory (QRAM) to store and load quantum data could be much more effective for quantum machine learning problems. The user should be able to store new classical data or update it onto the QRAM and load the stored quantum data as needed.

In this paper, we propose a Parametric Quantum Circuit (PQC)-based trainable approximate QRAM which takes address as input and gives output as the data for that address. We say that the QRAM is approximate because the predicted output of QRAM will not be exactly same as the input. This happens because data loading methods for NISQ era quantum computers are not perfect and there are different errors in execution of quantum circuits. We introduce relevant background on quantum computing and quantum machine learning and previously published related works on QRAM in Section 2 and the architectures for the proposed QRAM in Section 3. We then show two applications for the proposed QRAM architecture: one for storage of digit images for performing binary classification and other for storage of binary data, in Sections 4 and 5 respectively. We give concluding remarks in Section 6. To the best of knowledge, this is the first approximate QRAM architecture which can be used to load arbitrary data in quantum form to any quantum circuit.

2 BACKGROUND AND RELATED WORKS

2.1 Background

Qubits: Qubits are the fundamental units of a quantum computer (analogous to classical bits for a classical computer). Unlike classical bits, qubits store information in the form of states represented using ket notation $|\psi\rangle = \begin{pmatrix} a \\ b \end{pmatrix}$ where $a^2$ denotes the probability of the qubit being measured to 0 and $b^2$ denotes the probability of the qubit being measured to 1. Each qubit has two basis states, one with $a = 1, b = 0$ (defined as $|0\rangle$) and one with $a = 0, b = 1$ (defined as $|1\rangle$). There are different types of qubits like superconducting qubits, ion trap qubits, photonic qubits, neutral atom qubits, etc.

Quantum Gates: A quantum gate is a unitary operation performed on a qubit that changes the state of the said qubit. Every quantum gate can be represented as a unitary matrix, and can work on either a single qubit or more than one qubits. The most common ones are single qubit gates like hadamard gate (H), bit-flip gate (X), Pauli Y and Z gates, and two qubit gates like CNOT gate, SWAP gate, and controlled Pauli gates. There are also special gates like reset gate and measurement gate.

Quantum Circuit: A quantum circuit is a program that contains an ordered sequence of various quantum gates that act on specified number of qubits and may contain intermediate reset and measurement operations. A user typically builds a quantum circuit, and obtains classical measurement output back. Based on the gates used and their placement, various quantum circuits can be used for targeted applications.

Parametric Quantum Circuit: A Parametric Quantum Circuit (PQC) is a special type of quantum circuit where user can feed...
custom tunable parameters to change the output of the circuit according to the value of the parameters fed (typically encoded as rotation angle of a single qubit gate). It is a trainable quantum circuit which can be trained like a normal ML model. 

**QNN:** Quantum Neural Network (QNN) is a trainable PQC that has hidden layers similar to a classical neural network. All the layers have trainable parameters that are updated every epoch.

### 2.2 Related Works

Various implementations of QRAM have been proposed in literature previously like bucket brigade QRAM [4], circuit-based QRAM [5] and entangling quantum generative adversarial network [6]. These implementations, however, pose a few problems with respect to applicability of QRAM for quantum machine learning tasks. [4], [5], [6] all use QRAM that write and read data into superposition. The work presented in [4] relies on qutrit technology. However, so far such technology is not realizable easily. [5] is easy to replicate since they used a quantum circuit-based QRAM, however the read operation they use is not well-defined, and moreover the data that can be stored can only be integer. The authors show an application of the stored superposition QRAM values for quantum forking. However the extent of its utility is limited [7]. The authors in [6] preprocess data in quantum using EQGAN (Entangling Quantum Generative Adversarial Network) which is a circuit-based quantum GAN that is used as a QRAM to store data. They show better results with EQGAN for quantum classification application. However, EQGAN does not have addressable data like a classical RAM. The above challenges make it difficult to realize a practical QRAM which can be used for various applications.

Other works have also been proposed that discuss QRAM for optimization of quantum machine learning (QML) tasks ([5]). Modification and efficient implementations to overcome challenges of the original QRAMs are also proposed. For example, [6] present efficient implementation of the bucket-brigade QRAM [4] whereas [10] and [7] are extensions of the circuit-based QRAM [5]. A comparison of various quantum memories is shown in Table I.

### 3 Proposed QRAM architecture

#### 3.1 Basic architecture

The proposed QRAM (Fig. 2) is a trainable PQC, which has $n$ address lines for less than $2^n$ datapoints. For each individual datapoint, a unique address is provided, and an address-data pair is formed. We use the convolution ansatz 1 and pooling layer from [11] as the basic layer for the proposed QRAM although other circuits are also possible. The reason for choosing this particular ansatz is that it has the lowest circuit depth and gate count. This will reduce the overall depth of the QRAM circuit which in turn can provide better fidelity of computation on real quantum hardware. We combine the ansatz in a circular fashion by strongly entangling layers to provide strong entanglement between qubits. According to [12], having strongly entangled qubits can provide exponential speedup for classification problems. We first load the address into qubits using any $n$ bits to $n$ qubits embedding like either angle embedding or basis embedding, and then pass the embedded quantum data through a sequence of the layers defined in Fig. 2. These layers are placed in circular fashion. Finally, three strongly entangling layers [13], which is inspired from [14], are placed at the end before taking measurement on all qubits. We note that the proposed QRAM is an application of PQC that can be used to load data. This PQC is called a QRAM since it provides addressability to data like classical RAMs and stores data in quantum form.

#### 3.2 Training architecture of QRAM

We use the basic QRAM architecture defined above to design QRAMs for each application. For the ML task, we use an auxiliary QRAM which takes digit image and generates ground truth probabilities for the qubits and the main QRAM which takes address of the digit image and outputs predicted probabilities (Fig. 2a). Training of QRAM is done in two steps; in the first step both the auxiliary QRAM and main QRAM parameters are trained so that the ground truth probabilities and the predicted probabilities are as close to each other as possible, and in the second step the parameters of the auxiliary QRAM are fixed and only the main QRAM parameters are trained to further reduce the loss. Both steps involve training the QRAM for 100 epochs each. After training, the auxiliary QRAM is discarded and the output of the main QRAM for each address is provided to a QNN in quantum format for classification (Fig. 2b)). For the binary data QRAM, a single basic architecture PQC is used which outputs Pauli-Z expectation value measurement to output individual data bits on all qubits. For both the scenarios, the proposed QRAM is approximate since it predicts the output in each address approximately rather than accurately. For ML QRAM, the approximation error is difference between the predicted probabilities and ground truth probabilities for every image, and for binary data QRAM, the approximation error arises from the Hamming distance between predicted data bits and actual data bits. Note that the proposed QRAM architecture can handle only sequential access of data and does not scale for datasets of larger sizes for which we can use multiple parallel banks of QRAMs.

### 4 QRAM for Machine Learning Tasks

#### 4.1 Experimental Setup

We augment a QRAM with a QNN to perform binary classification of 0 and 1 digits in digits dataset provided by UCI Machine Learning Repository. We train the QRAM to load the digit images, and compare the performance with quantum classifier with embedding and classical Fully Connected Neural Network (FCNN). We report the training and testing losses, training and
testing accuracies for the three cases. For all the setups, we maintain a batch size of 16 and learning rate of 0.001. Since the number of images of both classes combined are 360, we use 9 address lines to fit all images. Both the QRAM and the QNN use the same basic architecture as described above. We also performed noisy simulations and experimental inferencing on a shorter dataset of 0 and 1 classes of 64 images with noise characteristics of IBM Jakarta. We train this dataset on ideal simulator for 100 epochs and noisy simulator for 100 epochs.

### 4.2 Classification Results

For each case, the training and testing loss curves (Fig. 3(a)) are nearly identical. This is because the logarithmic factor in binary cross entropy brings the training and testing loss values very close to each other. Fig. 3(b) and (c) reports the training and testing accuracies respectively. We observe 100% classification accuracy for all the three setups. We note that the QRAM + QNN and QNN with embedding only setups outperform FCNN in terms of loss and convergence. QRAM + QNN converges the fastest at around $6^{th}$ epoch, QNN with embedding converges around $10^{th}$ epoch, and FCNN converges at around $15^{th}$ epoch. The final loss for QRAM + QNN is around 0.53, for QNN with embedding is 0.48 and for FCNN only is 0.89. The proposed QRAM + QNN setup also outperforms the EQGAN performance (6) which achieves around 65% classification accuracy on a dataset of two classes of normal distributions. From the noisy simulation results, we observe 100% testing accuracy on PennyLane and IBM QASM simulators and roughly 63% testing accuracy for IBM Jakarta and IBM Oslo hardware.

From the results, it can be noted that, (i) the higher classification accuracy relative to EQGAN indicates that quantum `read` operation performed by generatively learning a general data distribution is less accurate than mapping an address value to a digit image through training an extra auxiliary PQC network, (ii) the faster convergence relative to QNN with embedding indicates that QRAM storage realized by pre-training both QRAMs (main and auxiliary) together could pre-process the `write` operation, thereby accelerating the classification task where fine-tuning is required. The pre-training phase relates more to `write` to QRAM, whereas fine-tuning more to `read` operation and, (iii) the faster convergence of two quantum algorithms relative to FCNN indicates potential quantum computing advantages with stronger representation powers of QNNs, as extensively demonstrated in the QNN community.

## 5 QRAM for Storage of Binary Data

### 5.1 Experimental setup

For storage of binary data, we feed address value as input and get data value as the output from the QRAM. The QRAM structure is defined based on the number of address lines and

| Quantum memory | Requirements | Pros | Cons | Complexity |
|----------------|--------------|------|------|-------------|
| Fanout QRAM    | Less decoherence error, Trapped ion qubits | Less interactions ($O(1)$) with quantum bus to load data | Susceptible to decoherence error | Depth: $O(2^n)$ # Interactions: $O(n)$ |
| Bucket-Brigade QRAM | Qutrits | Solves decoherence problem of fanout QRAM by using polynomial ($O(n)$) controls per qubit | Qutrits are not easily realizable | Depth: $O(2^n)$ # Interactions: $O(n^2)$ |
| Circuit-based QRAM | Superconducting/Trapped ion qubits | Easy to realize, uses separate qubits to store addresses and data in superposition states | Limited applications (e.g., quantum forking) | Depth: $O(2^n)$ Interactions: $O(n)$ |
| QROM | Superconducting/Trapped ion qubits | Easy to realize. data cannot be modified and can only be read | Stores only integer data | Depth: $O(2^n)$ # Interactions: $O(n)$ |
| EQGAN QRAM | Superconducting/Trapped ion qubits | Provides 20% increase in classification accuracy with QNN | Data is not addressable | Depth: $O(1)$ # Interactions: $O(n)$ |
| Proposed QRAM | Superconducting/Trapped ion qubits | Addressable data stored in quantum Hilbert space | Cannot be scaled directly for large datasets | Depth: $O(1)$ # Interactions: $O(n)$ |

**TABLE 1**

Comparison of various quantum memories.

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Fig. 2. Basic QRAM Architecture. Strongly entangling layers are replicated from [13] which in turn are inspired from [14].
data lines used. For each setup, we keep the number of address lines and data lines equal. We send the binary address into quantum format and the QRAM gives approximate classical data as the output. In order to embed each address into a single qubit, we keep the number of qubits same as the number of address and data lines. For an $n$-address QRAM, the number of address-data pairs will be $2^n$, and for each address, the data is chosen randomly in the range of $\{0,1,2,...,2^n-1\}$. $2^n$ address-data pairs are too low to train the QRAM when $n$ is low. In order to compensate for the low number of datapoints, we replicate the entire dataset of $2^n$ datapoints repeatedly till the dataset becomes large enough to train the QRAM parameters correctly. We call this dataset expansion. For example in a 2-address QRAM, if the address-data pairs are $\{00-01,01-11,10-00,11-01\}$, these 4 pairs are repeated continuously $\{00-01,01-11,10-00,11-01,00-01,01-11,10-00,11-01,...\}$ until the overall dataset size is large enough. Next, we train the QRAM PQC for 100 epochs and evaluate the average HD per epoch and calculate the percentage correct predictions per epoch. For any particular datapoint if the Hamming Distance (HD) between the predicted data output and actual data is zero we assume that the prediction is correct. If the HD is non-zero we assume that the prediction is incorrect. These metrics are evaluated for 100 epochs from 2 address lines to 9 address lines.

5.2 Experimental results

From Fig. 4, we note a general trend of increase in Hamming distance and decrease in percentage correct predictions with increase in number of address lines. This is expected since presence of more datapoints makes it harder for the QRAM to predict individual bits of these datapoints correctly. We get average Hamming distance of 0 and 100% correct predictions only for a 2-address QRAM. After that, we start observing non-zero Hamming distance (HD = 0.25 for 3-address QRAM). There is also a drop in percentage correct predictions which varies from 75% (3-address QRAM) to 0.58% (9-address QRAM). The HD in this range is approximately 8% (0.25, 3-address QRAM)-45% (3.97, 9-address QRAM) of the total number of data lines meaning that on an average 8-45% of the data bits are being mispredicted. We also show the loss curves in Fig. 4(c). For every epoch mean squared error is calculated which increases with address lines.

5.3 Clustering based pre-processing and results

We also propose an agglomerative clustering pre-processing step prior to storing the data in QRAM to improve the performance of the QRAM at higher number of address lines. The idea is to cluster the data and allocate one QRAM per cluster for better training. The clustering is performed in such a way that the average HD within each cluster is minimized. Since the data is divided into clusters, the number of individual datapoints per QRAM are lower, making the mapping from address to data easier. With clustering, we observe zero HD and 100% correct predictions up to 4-address QRAM and from 5-address QRAM to 9-address QRAM the HD increases from 0.18 to 2.17 and percentage correct predictions reduces from 87.5% to 10.1% (Fig 4). We also observe that the loss for each address line is lower with clustering as compared to the case without clustering.

6 CONCLUSION

We presented QRAM models for ML task and binary data storage. For ML, we showed that QRAM + QNN provides faster convergence compared to FCNN and QNN with embedding, and the overall loss is less than FCNN, and slightly higher than QNN with embedding. For storage of binary data, we calculated HD and percentage correct predictions from 2 to 9 address lines and improved the results via an agglomerative clustering based pre-processing. In all the experiments performed, the PQC structure of the QRAM is kept fixed, and also the QRAM does not support storage of incremental data. A detailed analysis of the impact of the choice of PQC ansatz and task-incremental learning [15] of the QRAM PQC can be explored in the future.

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