# On Unsupervised Reconstruction with Dressed Multilayered Variational Quantum Circuits

Pablo Rivas, *Senior, IEEE*
School of Eng. and Computer Science
Dept. of Computer Science, Baylor University
Email: Pablo_Rivas@Baylor.edu

Liang Zhao
Marketing Department
St. Ambrose University
Email: ZhaoLiang@sau.edu

***Abstract*—The advantages of unsupervised quantum machine learning are still under study and appear to be very promising. Trainable variational quantum circuits are one example of successful approaches to combining classic machine learning and quantum. However, there is no clear path toward a quantum advantage for different types of variational circuits. This paper furthers the research efforts in understanding the potential and applications of hybrid quantum circuits. We study different circuits and see how similar they perform in an unsupervised learning task in an autoencoder configuration over a large multimodal dataset.**

***Index Terms*—autoencoders, learning representations, quantum machine learning, quantum variational circuits**

## I. Introduction

Unsupervised machine learning algorithms have received growing attention in recent years. The idea that traditional supervised models can be improved through pre-training with unsupervised tasks for better generalization and efficiency has shown effective [1]. One of such disciplines studies the possibility of using quantum theory to make improvements and achieve *quantum advantage* [2]. A way to reach quantum advantage is by learning from massive amounts of data in parallel by embedding data through quantum techniques [3], [4]. Quantum advantage can also be achieved by using recent advances in quantum numerical optimization that may be usable in gradient descent-like calculations [5], and trainable variational quantum circuits [6], [7]. This paper focuses on the latter by studying the architecture shown in Fig. 1.

Variational quantum circuits [6], can be defined in terms of a unitary operation, $U$, implemented as a variational circuit on an input state $|\mathbf{x}\rangle$, that produces the the output state $|y\rangle$ as follows: $|\mathbf{x}\rangle \rightarrow |y\rangle = U(\mathbf{w})|\mathbf{x}\rangle$, where $\mathbf{w}$ denotes the parameters of the variational circuit. The unitary operation can be decomposed into parts and implemented in combination with a classic neural network. We take advantage of this to explore the reconstruction abilities of variational quantum circuits across two different configurations: one that explores a multilayered approach in contrast to a second one that uses fewer layers and more qbits. We use a large multimodal dataset to learn representations of a variety of features.

We discuss background material and methodology in Sec. 2. Results and conclusions are in Sec. 3.

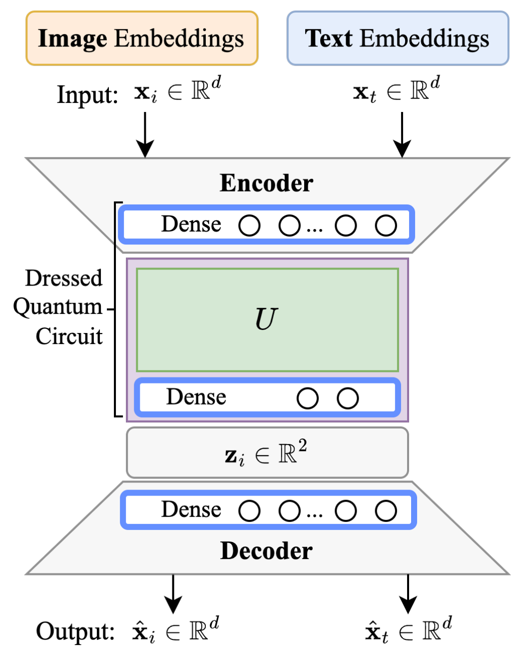



Fig. 1. Hybrid variational quantum neural architecture.

## II. Background

Some of the most exciting work in the quantum machine learning area has occurred in recent years. Many works already discuss the classical models in machine learning in an appropriate length, e.g., deep learning, supervised or unsupervised, and even adversarial learning [8]–[11]; some of the particular algorithms they normally expose include $k$-means, $k$-nearest neighbors, support vector machines, and random forests. Some of the most important work in variational approaches can be found in [12]–[14]. These works have widely influenced quantum machine learning research, and our investigation continues the work of trainable variational quantum circuits. Mari *et al.* [6] is closely related to our work because both approaches combine classic and quantum methods. However, the authors focus on ResNet-based transfer learning.

In order to appropriately discuss the experiments conducted with variational circuits, depicted as $U$ in Fig. 1, we will briefly introduce the elements used to construct $U$ next.

### A. Variational quantum circuits

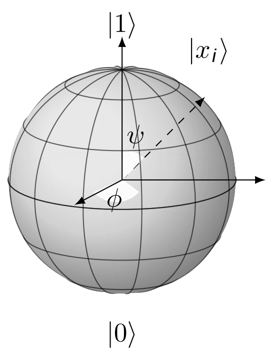
The unitary operation, $U$, can be expressed as the following quantum layers.

*1) Hadamard operators layer:* The Hadamard operator on a qbit facilitates superposition:

$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}.$$

*2) Single qbit $Y$ rotation layer:* The *trainable* rotation of a qbit makes it change the spin angle, $\phi$, as follows (see Bloch sphere on the bottom as reference):

$$R_Y(\phi) = e^{-i \quad Y=2} = \begin{bmatrix} \cos(\phi/2) & -\sin(\phi/2) \\ \sin(\phi/2) & \cos(\phi/2) \end{bmatrix}$$




*3) CNOT qbit entangling layer:* The CNOT operation links qbits and propagates superposition:

$$\text{CNOT} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}.$$

*4) Expectation layer over Pauli $Z$ operators:* Finally, the output of the circuit is based on the expected value of several measurements. The measurements are applied after the Pauli Z operator defined as follows:

$$\sigma_z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}.$$

### B. Dressing a variational quantum circuit

Dressing a quantum circuit is the process of preparing the circuit to connect $U$ to a neural network. In our case, this looks like adding dense layers before and after the quantum circuit, as shown in Fig. 1 in the middle [6], [7]. The number of neurons in the encoder layer matches the number of qbits.

Finally, the variational circuits we are studying are shown in Fig. 2. The difference between the two circuits is that one has twice as many layers that entangle and rotate qbits (left), and the other has twice as many qbits (right). The main premise of having two different circuits is to study whether two circuits seemingly equally powerful perform differently in the task of learning representations.

The next thing we define as part of the learning model is a loss function.

### C. Model loss function

For the proposed autoencoder architecture, shown in Fig. 1, we use a multimodal dataset of text-image embeddings of size $\mathbf{x} \in \mathbb{R}^{512}$ each. Considering these inputs our loss is defined as:

**image-text quantum autoencoder parameters**

$$\mathcal{L}(\theta; \mathbf{x}_i, \mathbf{x}_t) = \alpha_i ||\mathbf{x}_i - \hat{\mathbf{x}}_i||_1 + \alpha_t ||\mathbf{x}_t - \hat{\mathbf{x}}_t||_1$$

**CLIP image-text embeddings**

where $\hat{\mathbf{x}}$ is the reconstruction. Minimizing this loss yields a new latent space that minimizes embedding reconstruction loss. Note that for $\alpha_i = \alpha_t = \frac{1}{2}$, the loss is an average of the two components.

## III. Experimental Results

After training the cirquits in Fig 2 using the configuration in Fig 1 using text-image embeddings from an unlabeled 83Gb dataset, we obtain the results shown in Fig. 3.

From the figure, we can observe that the structure of the learning spaces differs slightly across different configurations. Notably, the architecture that seems problematic is in (d), as it appears that the data becomes noisy. The problems in (d) can be attributed to a large number of qbits and a large number of layers and, perhaps, increasing interference that could potentially be managed by performing an ablation study on the configuration that facilitates entanglement.

From Fig. 3 we can also observe that the model can preserve the structure of the data and its distribution. The data comes from the Contrastive Language-Image Pre-training (CLIP) model, which has gained popularity in text-image pairs research, and it has motivated many applications [15]. From the original CLIP embeddings dataset, we know that the embeddings of text and images are similar in their distribution; however, there are some cases that are considered outliers to the larger distribution. This is consistent in (a)-(d) as there are two clusters that are visually verifiable.

One major point of discussion is that from Fig. 3 (b) and (d) we see very few differences, even across multiple runs. This comparison is analog to comparing wide and deep dense neural networks, i.e., models with many layers of few neurons, and models with few layers with many neurons [16]. Based on the observations, there seems to be a similar effect in quantum hybrid approaches that use multilayered variational circuits. The implications of this are important as this could suggest that variational quantum circuits at scale can improve the quality of hybrid quantum machine learning models. This can be relevant as quantum computers become more accessible.

## IV. Conclusions

In this paper, we have presented a hybrid quantum machine learning architecture to study different variational circuit configurations in an autoencoder model configuration. We trained the models and monitored the responses, as shown in Fig. 3. As it can be observed, When the elements of the loss $\mathcal{L}(\theta; \mathbf{x}_i, \mathbf{x}_t)$ are treated as a classic average, i.e.,

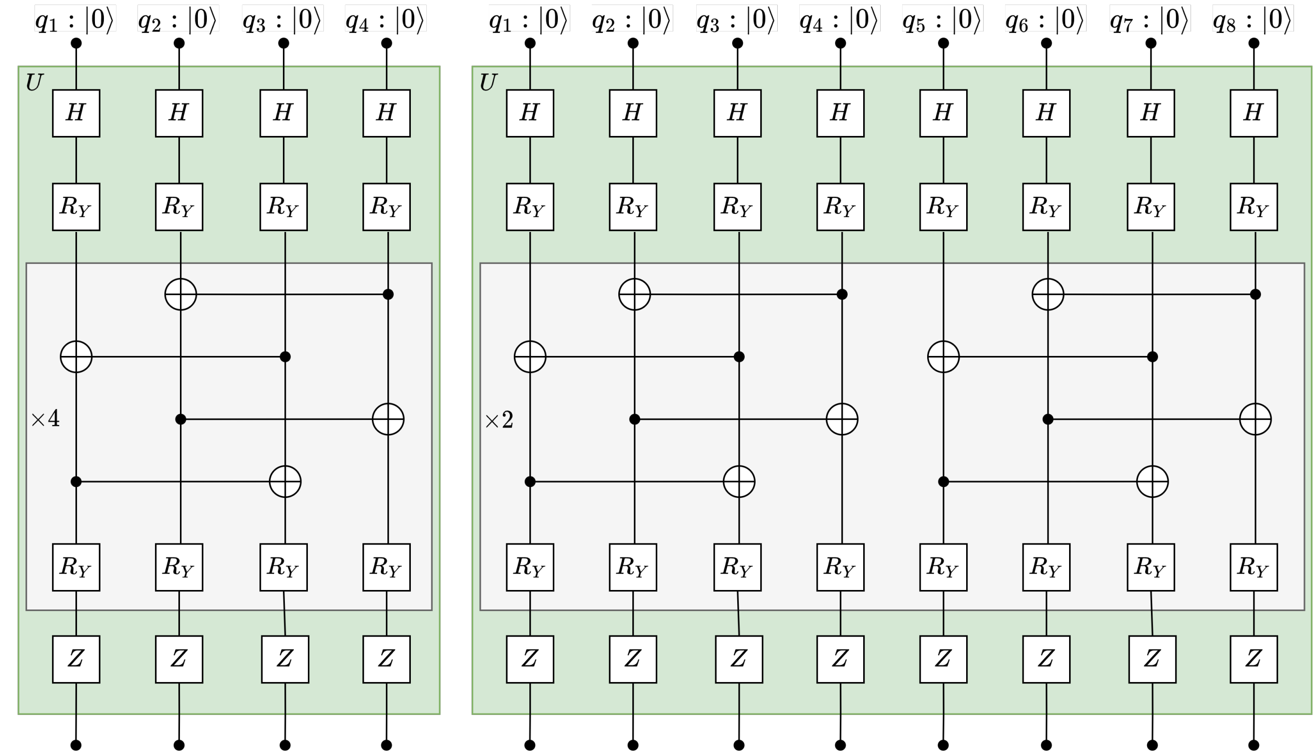



Fig. 2. Variational quantum circuits. On the left is a circuit with four qbits and four layers. On the right is a circuit with eight qbuts and two layers.

$\alpha_i = \alpha_t = \frac{1}{2}$, we have immediate reconstruction gains and clustering abilities while preserving the distribution of the dataset in a low-dimensional space induced by the quantum dressed circuit.

We observed that the models perform similarly for configurations in which the circuit has more layers vs. more qbits. This can not only be useful in designing circuits at scale, but it can provide a quantum advantage in the near future. Further, this could aid in better understanding the inductive bias of quantum machine learning models.

Finally, after the models are trained, they can be used to produce lower-dimensional CLIP-based embeddings for specific applications or datasets. For the models discussed here, quantum advantage occurs upon deployment for real-time applications, having a broader impact as quantum technology becomes more accessible.

## ACKNOWLEDGMENT

Part of this work was funded by the National Science Foundation under grants CNS-2136961 and CNS-2210091.

## REFERENCES


[1] M.-H. Wang, "Artificial intelligence and subfields," *Santa Clara University, Department of Computer Engineering*, 2017. 1

[2] D. Ristè, M. P. Da Silva, C. A. Ryan, A. W. Cross, A. D. Córcoles, J. A. Smolin, J. M. Gambetta, J. M. Chow, and B. R. Johnson, "Demonstration of quantum advantage in machine learning," *npj Quantum Information*, vol. 3, no. 1, pp. 1–5, 2017. 1

[3] H. J. Kappen, "Learning quantum models from quantum or classical data," *Journal of Physics A: Mathematical and Theoretical*, vol. 53, no. 21, p. 214001, 2020. 1

[4] M. Schuld, I. Sinayskiy, and F. Petruccione, "Simulating a perceptron on a quantum computer," *Physics Letters A*, vol. 379, no. 7, pp. 660–663, 2015. 1

[5] F. G. Brandão, A. Kalev, T. Li, C. Y.-Y. Lin, K. M. Svore, and X. Wu, "Quantum sdp solvers: Large speed-ups, optimality, and applications to quantum learning," *arXiv preprint arXiv:1710.02581*, 2017. 1

[6] A. Mari, T. R. Bromley, J. Izaac, M. Schuld, and N. Killoran, "Transfer learning in hybrid classical-quantum neural networks," *Quantum*, vol. 4, p. 340, 2020. 1, 2

[7] P. Rivas, L. Zhao, and J. Orduz, "Hybrid quantum variational autoencoders for representation learning," in *2021 International Conference on Computational Science and Computational Intelligence (CSCI)*, 2021, pp. 52–57. 1, 2

[8] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006. 1

[9] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org. 1

[10] P. Wittek, *Quantum machine learning: what quantum computing means to data mining*. Academic Press, 2014. 1

[11] P. Rivas, *Deep Learning for Beginners: A beginner's guide to getting up and running with deep learning from scratch using Python*. Packt Publishing Ltd, 2020. 1

[12] M. Cerezo, A. Arrasmith, R. Babbush, S. C. Benjamin, S. Endo, K. Fujii, J. R. McClean, K. Mitarai, X. Yuan, L. Cincio *et al.*, "Variational quantum algorithms," *Nature Reviews Physics*, pp. 1–20, 2021. 1

[13] A. Khoshaman, W. Vinci, B. Denis, E. Andriyash, H. Sadeghi, and M. H. Amin, "Quantum variational autoencoder," *Quantum Science and Technology*, vol. 4, no. 1, p. 014001, 2018. 1

[14] X. Yuan, S. Endo, Q. Zhao, Y. Li, and S. C. Benjamin, "Theory of variational quantum simulation," *Quantum*, vol. 3, p. 191, 2019. 1

[15] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark *et al.*, "Learning transferable