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Modeling neuronal activity with Quantum Generative Adversarial Networks

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***Abstract*—Understanding the information processing in neuronal networks relies on the development of computational models that accurately reproduce their activity data. Machine learning techniques have shown promising results in generating synthetic neuronal data, but interpretability remains an issue due to a large number of parameters requiring fitting. Quantum machine learning models, particularly quantum generative learning, are emerging as more compact alternatives that offer similar outcomes. This study presents an efficient framework for generating synthetic neuronal data using a Quantum Generative Adversarial Network (QGAN), with a quantum generator and a classical discriminator. We tested the proposed framework for the minimal case of two neurons, considering the case of single time-steps. Preliminary results demonstrate the QGAN's capability to achieve reliable outcomes with a reduced number of trainable parameters, scaling efficiently for increasing neuronal network sizes. The model effectively captures spiking frequencies of real data, although further refinement is required to incorporate temporal correlations for more extended time-steps. Despite certain limitations, this study lays the foundation for future advancements in using quantum adversarial generative networks to model neuronal activity. The promising potential of QGANs in this domain highlights the possibility of gaining valuable insights into the functioning of complex biological systems through quantum-inspired computational methods.**

***Index Terms*—quantum machine learning, neuronal activity, generative models**

I. Introduction

The development of computational models that reproduce neuronal activity data is an important step towards a better understanding of how information is processed in neuronal networks. Several models for neuronal activity achieve outstanding results in capturing neuronal network correlations [1]. Recently, General Adversarial Networks have been applied to produce synthetic neuronal data indistinguishable from real measurements [2], however, they lack interpretability. Quantum machine learning models are arising as a more compact alternative to classical methods, with the possibility of achieving similar results with a reduced number of parameters. Specifically, the field of quantum generative learning is receiving much attention [3]. Since their conception, quantum generative adversarial networks (QGANs) are being quickly improved, with higher-dimensional data being produced with a more stable training routine. Inspired on previous works in which QGANs are used to produce discrete distributions [4], and other quantum generative models being tested on neuronal data [5], we show an efficient framework which enables the generation of synthetic neuronal data for large neuronal networks, considering spatial and temporal correlations. We apply a hybrid QGAN, with a quantum generator that produces synthetic activity data, and a classical discriminator that tries to distinguish real from fake data. The outcome is a generator that can faithfully reproduce neuronal activity data. Compared to classical alternatives, the quantum generator has the advantage of achieving reliable outcomes with a reduced number of trainable parameters, that scale efficiently for increasing systems' sizes.

II. Methods

The discriminator is a fully-connected neural network, with an input size equal to the samples taken from the generator or from the real data, one hidden layer with 16 units, with a ReLU activation function, and one output layer with $\mathrm{sigmoid}$ activation, representing the probability of classifying a coming from the real dataset.

Following the work proposed by [3], the generator is composed by a series of sub-generators, each one using a parametrized quantum circuit, with n qubits, of which a ancilla and f feature qubits, with different sets of trainable parameters. The output of the individual sub-generators is concatenated to build the full generator's output. This setting allows for a reduced number of resources, since the same quantum circuit can be used for the different sub-generators. In order to capture time correlations, in this work, each sub-generator is used to produce the spiking state of all the neurons for one specific time-step, and following sub-generators produce the states for the subsequent times. For each sub-generator, first, a random state is obtained by encoding a noise vector to an initial state, so that $|\boldsymbol{z}\rangle = U_{\boldsymbol{z}} |0\rangle^{\otimes n}$. This is achieved by applying $R_Y(\gamma)$ gates to all qubits, with γ being a random angle uniformly sampled from the interval $[0, \pi]$. Then, a final state is retrieved by applying a parametrized unitary to the random state, $|g\rangle = U_{\boldsymbol{\theta}} |\boldsymbol{z}\rangle$; this unitary consists of a series of layers (in this work, 5), each one applying $R_Y(\boldsymbol{\theta}_i^k)$ and $R_Z(\boldsymbol{\theta}_i^l)$ gates to every qubit, and CNOT gates between each pair of nearest-neighboring qubits. The final state of the circuit is in the form $|g\rangle = \sum_j^{2^n-1} p_j |j\rangle$, where j runs over all the

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possible basis states. In order to obtain a non-linear output, partial measurements are performed to the ancilla qubits at the end of the circuit, and only the amplitudes correspondent to the feature qubits are saved and used as the output of the circuit. A constant that depends on the system size, 2^N for N neurons, is subtracted from the feature amplitudes, and the new values are passed through a $\mathrm{sigmoid}$ activation function. This process clusters the amplitudes close to 0.5, facilitating training convergence. Fake samples are considered to be equal to 1 if the final post-processed amplitude is greater than 0.5, and 0 otherwise. This post-processing step is done to effectively produce binary outputs for different network sizes.

The dataset used is the recorded spiking activity coming from the retinal ganglion cells of the salamander retina [**?**]. Training is performed for 1000 steps, with a batch-size equal to 8, using Adam optimizer with learning rates set to 7×10^{-4} for the generator and 4×10^{-4} for the discriminator. During training, the Jensen-Shannon (JS) divergence is calculated as a metric of the distance between the estimated and the real data distributions. In this work we show the preliminary results where we tested the framework for two neurons sampled from the dataset, considering a single time-step, thus only using one sub-generator.

III. Results

In Fig. 1(a) we show the JS divergence as a function of training steps. The three red lines present in the figure are specific training steps for which the generated data distribution and a sample of synthetic spikes (insets) are shown, from left to right, in figures 1(b), 1(c), and 1(d), respectively. The untrained generator, Fig. 1(b), produces all states with similar probabilities, whereas at the optimal training step (minimum of the JS divergence), Fig. 1(c), the spiking states probabilities are very similar to the real data distribution. However, for prolonged training steps the model diverges from the optimal point, and a typical mode-collapse behavior is observed, with the generator producing a single state (00 state, Fig. 1(d)). The inset of Fig. 1(a) shows the activity of 500 training steps sampled from the real dataset. Comparing this with the three training steps highlighted, using the generator to produce 500 sequential data points for each, we see that the untrained model, inset of Fig. 1(b), yields a very dense signal, with an overestimate of the activity, while the final generator, inset of Fig. 1(d), shows no activity, since it is always producing the same silent state. The optimal generator, inset of Fig. 1(c), produces data with a similar spiking frequency to the real data, however, it lacks temporal correlations, not showing a characteristic behavior with prolonged periods of spiking activity, and other periods with no activity at all. This result is expected, given that we trained the model with single time-step samples.

IV. Conclusion

In this work, we used a QGAN to produce neuronal activity data. The quantum generator enables the modeling of neuronal activity using a constrained number of trainable parameters. In

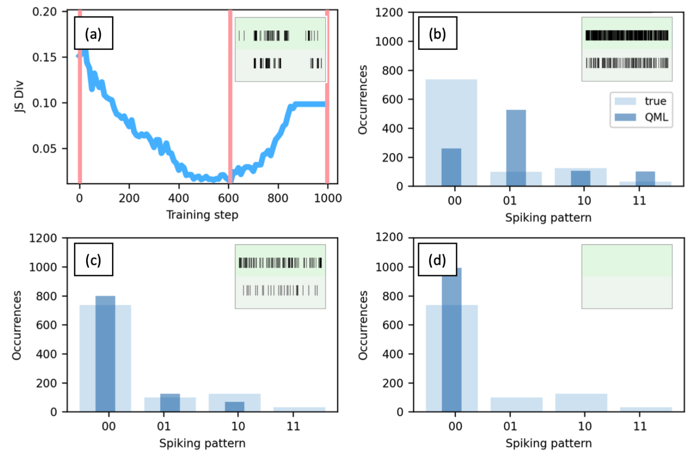

Fig. 1. (a) Jensen-Shannon divergence as a function of training steps. The inset shows a sample of activity from the real data, for 500 steps. The three red lines represent highlighted training steps, for which, from left to right, the model output distributions, and insets showing a sample of 500-steps activity obtained using the correspondent model, are shown in (b), (c), and (d), respectively.

the setting built in this work, the number of qubits necessary scales with the logarithm of the number of biological neurons, while the number of parameters is estimated to increasing linearly with the number of neurons, with a direct relation to the number of sub-generator used.

The preliminary results evidence a promising potential in using quantum generative adversarial networks to model neuronal activity in an efficient and concise manner. As next steps, we aim to train models for increasing number of neurons and time-steps. This is equivalent to increase the number of qubits, and the number of sub-generators. We expect the training instability to play a role in modeling larger models, however, more sophisticated techniques can be adapted to the QGAN framework, like using the Wasserstein distance to define the networks' loss functions.

V. Acknowledgment

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