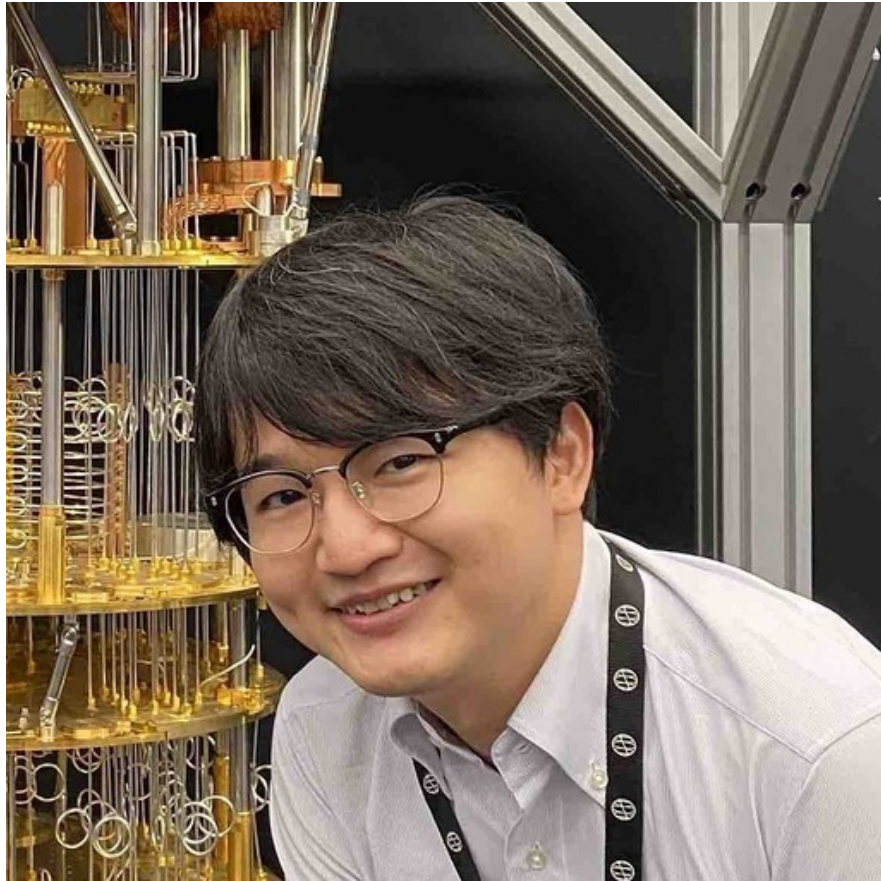




Qiskit Advocate Mentorship Program, Spring'23



Project : *Implement Date-reuploading classifier in Qiskit Machine Learning #3*



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Project Description

Data re-uploading is a recently proposed idea of quantum neural network, which uses a quantum circuit with a series of data re-uploading and processing layers. Unlike the conventional quantum circuit of quantum neural network, it has multiple layers of re-uploading input data. In this project, we will implement the data re-uploading quantum neural network in Qiskit Machine Learning. The goal of this project is to write code and create a pull request.

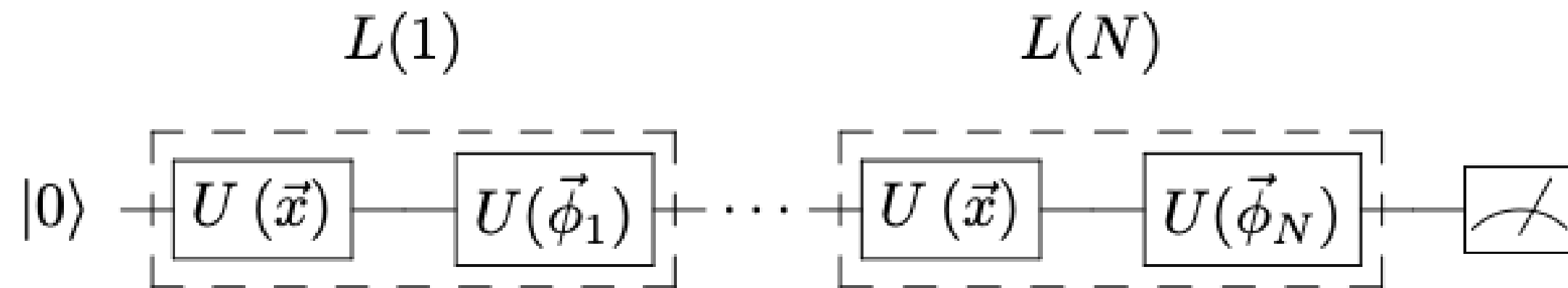


Figure from Pérez-Salinas et al. (2019)

Step 1 - Prepared Data-reuploading class

a) For Single Qubits: Only Rotational Gate layer (L)

$$U(\varphi, \mathbf{x}) = L(N) L(N-1) \dots L(2)L(1)$$

$$L(i) = U \left(\vec{\theta}_i + \vec{w}_i \circ \vec{x} \right)$$

$$L(i) = U \left(\vec{\theta}_i^{(k)} + \vec{w}_i^{(k)} \circ \vec{x}^{(k)} \right) \dots U \left(\vec{\theta}_i^{(1)} + \vec{w}_i^{(1)} \circ \vec{x}^{(1)} \right),$$

$$U(\vec{\theta}) = Rx(\theta_x)Ry(\theta_y)Rz(\theta_z) \quad \vec{\theta} = (\theta_x, \theta_y, \theta_z) \quad \vec{w} = (w_x, w_y, w_z) \quad \vec{x} = \text{input data} \quad (N) = \text{no of layers}$$

b) Multi qubits without entanglement : Stacking the same ansatz(U)for multiple qubits.

c) Multi qubits with entanglement (CZ gates). Alternating between (L) Rotational Layer and and (E)entanglement layer.

$$U(\varphi, \mathbf{x}) = L(N) E L(N-1) E \dots E L(2)EL(1)$$

[Note : followed Linear entanglement]

Step2: Integration with QNN implementation of Qiskit Machine Learning (EstimatorQNN and SamplerQNN) and used PyTorch with TorchConnector feature of Qiskit.

Step3: Optimization

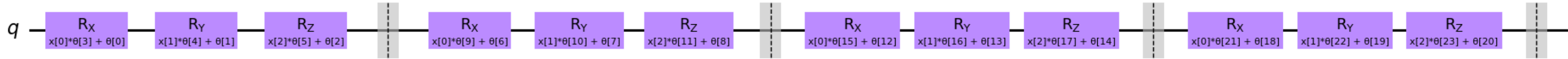
The optimization process is initiated using the optimizer and loss function.

Step4: After optimization, the trained model (**model1**) is used to make predictions on the input data (**X₁**), and the accuracy of the predictions is calculated by comparing them to the ground truth labels (**y₁**)

Progress



DRC = DataReuploading(num_qubits=1, num_features=2, num_layers=4)

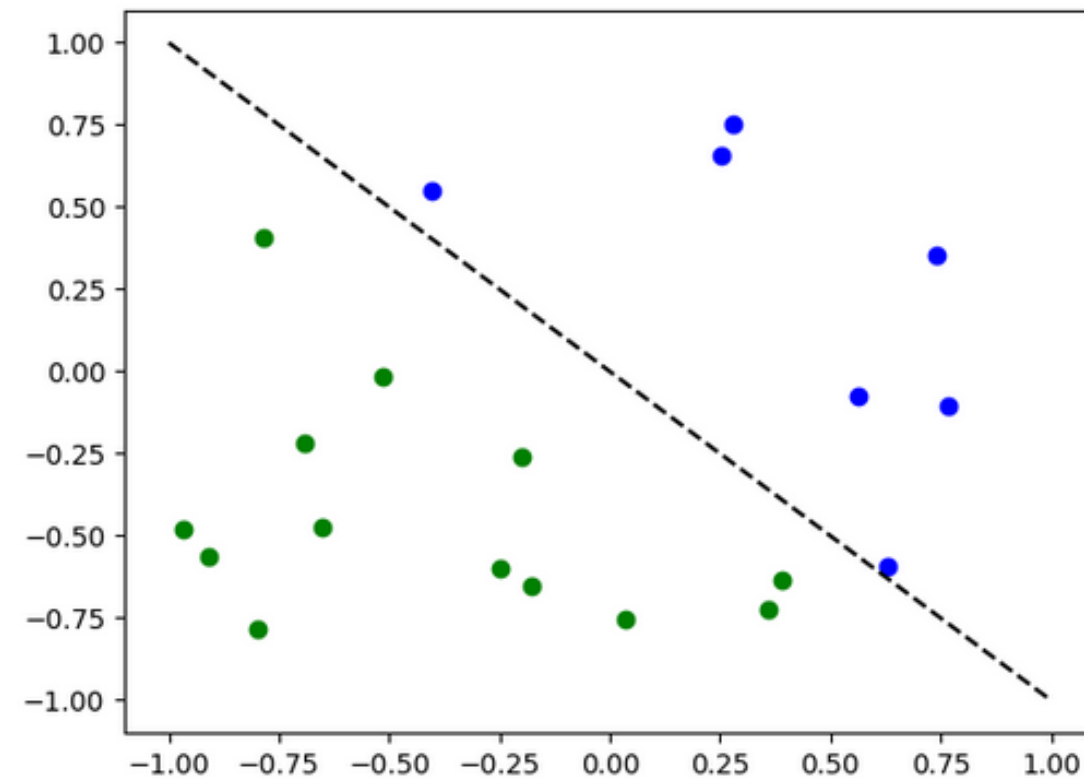


```
# Evaluate model and compute accuracy
y_predict = []
for x, y_target in zip(X, y):
    output = model1(Tensor(x))
    y_predict += [np.sign(output.detach().numpy())[0]]

print("Accuracy:", sum(y_predict == y) / len(y))

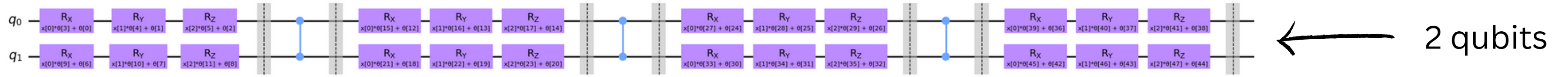
# Plot results
# red == wrongly classified
for x, y_target, y_p in zip(X, y, y_predict):
    if y_target == 1:
        plt.plot(x[0], x[1], "bo")
    else:
        plt.plot(x[0], x[1], "go")
    if y_target != y_p:
        plt.scatter(x[0], x[1], s=200, facecolors="none", edgecolors="r", linewidths=2)
plt.plot([-1, 1], [1, -1], "--", color="black")
plt.show()
```

Accuracy: 1.0

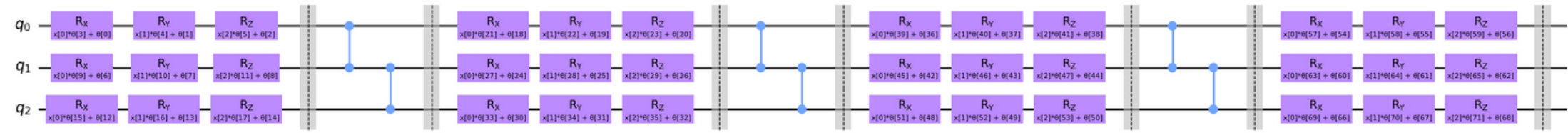


Result: accuracy 100%

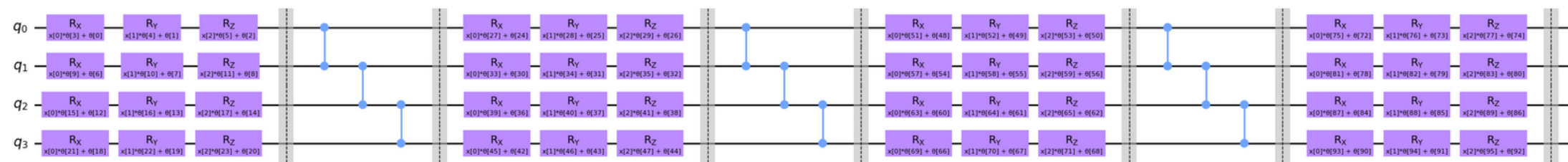
Example Circuits



3 qubits



4 qubits



Work to be done..

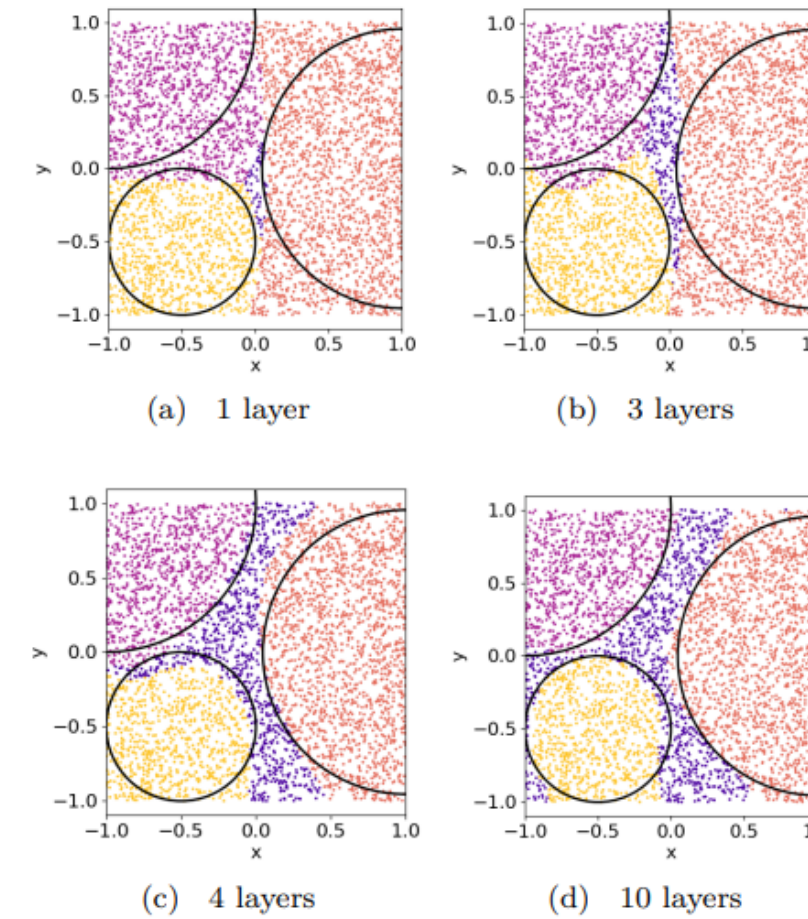
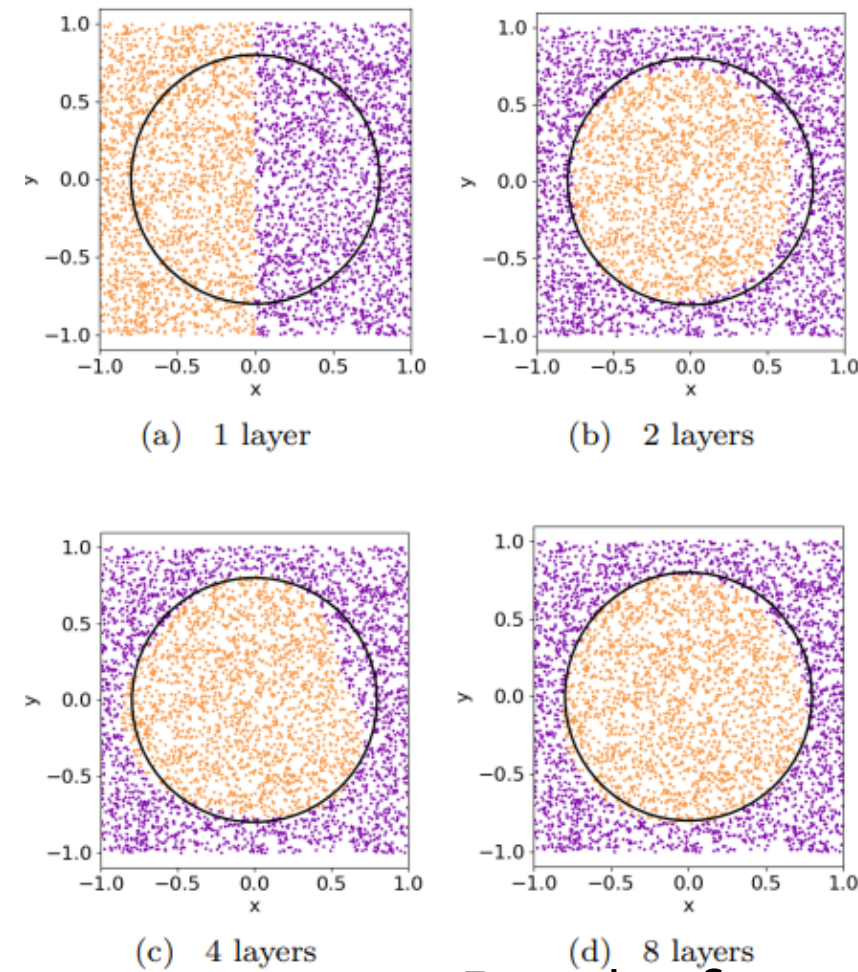


- We will implement the prepared class inside the Qiskit Machine Learning.
- We will write some tutorials with different datasets and configurations.

For ex: Training the ansatz with single qubits and multi qubits with different number of features and layers

Work to be done..

- Circle Classification



Results from the original paper : <https://quantum-journal.org/papers/q-2020-02-06-226/pdf/>

Results of the circle classification obtained with a single-qubit classifier with different number of layers using the L-BFGS-B minimizer and the weighted fidelity cost function.

Results of the 3-circles problem classification obtained with a single-qubit classifier with different number of layers using the L-BFGS-B minimizer and the weighted fidelity cost function.

To do- WE WILL TRY TO DO THE SAME CLASSIFICATION USING OUR PREPARED CLASS AND WE WILL BE USING REGULAR FIDELITY

THANK YOU!