Quantum Computing Hackathon 2022

Team 2

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Contents

Problem Background

- Iris Flower Dataset: 150 samples that fall into one of **3 classes** (Species), *Iris Setosa, Iris Versicolor* and *Iris Virginica*
- Each data sample defined by **4 features**: Sepal length, sepal width, petal length, petal width
- **Objective:** train model that implements quantum computation to identify the corresponding class of each sample.

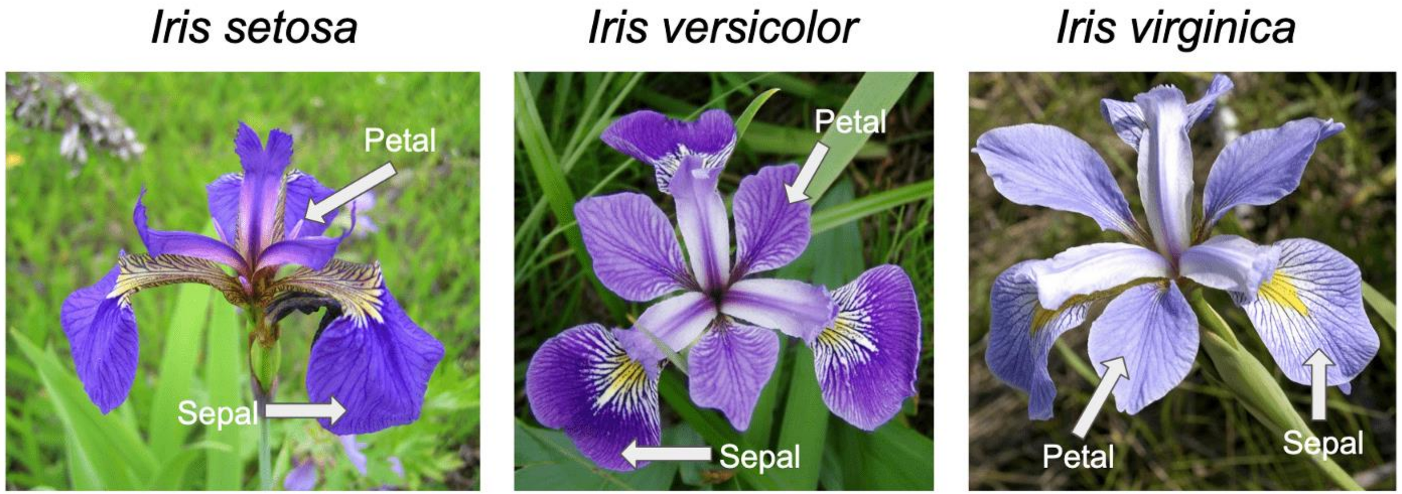


Image source: https://www.embedded-robotics.com/iris-dataset-classification/

Dataset Characteristics

- *Iris Setosa* is easily distinguishable, but *Iris Versicolor* and *Iris Virginica* do not form distinct clusters.

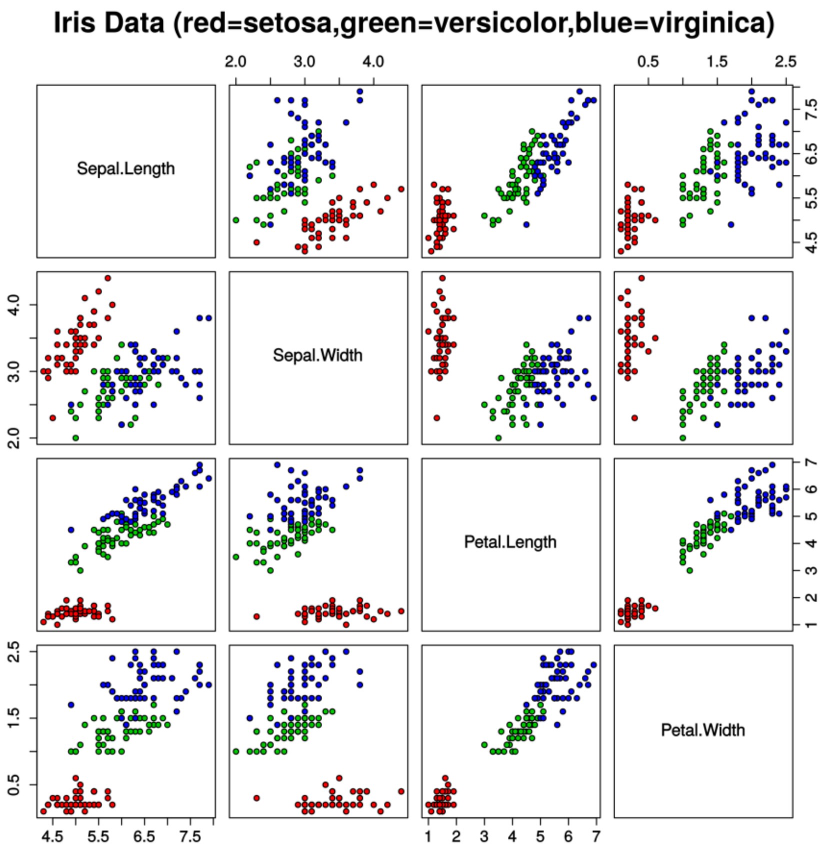


Image source: https://en.wikipedia.org/wiki/Iris_flower_data_set

*Very little overlapping in univariate histograms generated from **Petal Width** and **Petal Length**.*

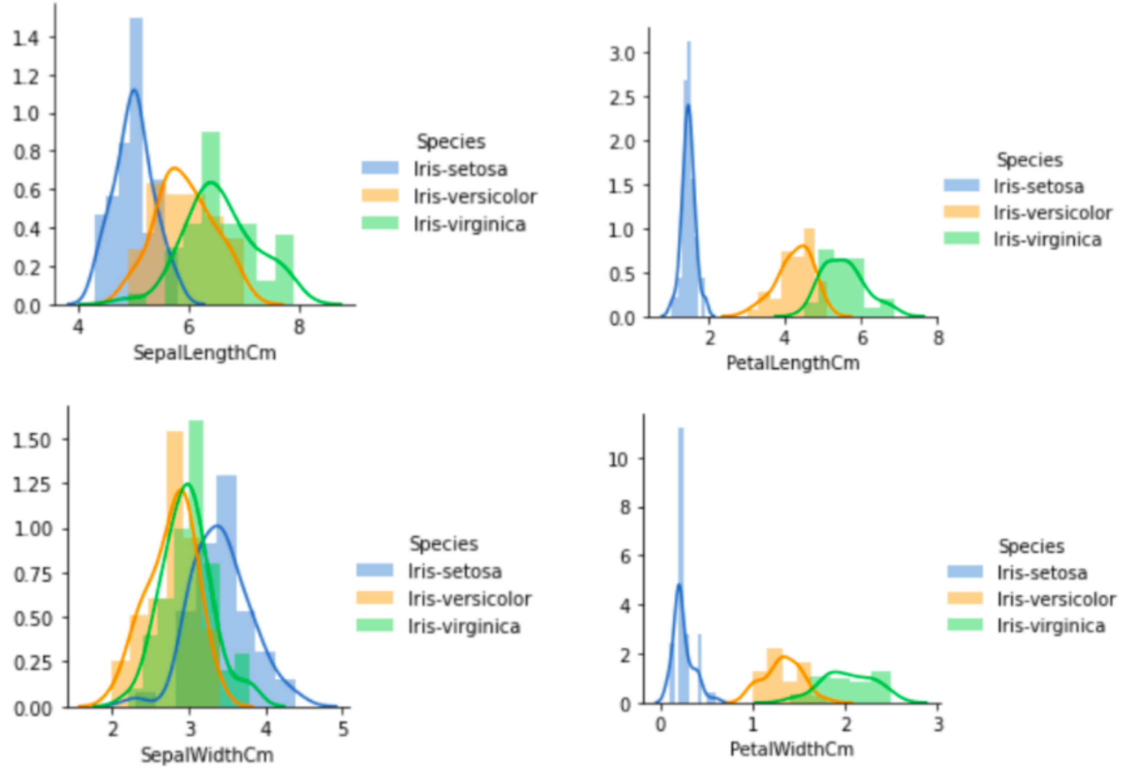


Image source: https://www.geeksforgeeks.org/exploratory-data-analysis-on-iris-dataset/

Data Pre-Processing

*Implemented using workflow outlined in *Polyadic Quantum Classifier* (2020) by Cappelletti et al.*

- Data split: 60% Training (90 data samples) and 40% Testing (60 data samples)
- Data Standardization (**x** --> **z**) : $$\boldsymbol{z}_{\boldsymbol{X}}(\boldsymbol{x}) = \frac{\boldsymbol{x} - \overline{\boldsymbol{X}}}{\sigma_{\boldsymbol{X}}}$$
- Data Encoding (z **-->** f(**x**)) : $$f(\boldsymbol{x}) = \left(1 - \frac{\alpha}{2}\right)\frac{\pi}{q}\,\boldsymbol{z}_{\boldsymbol{X}(\boldsymbol{x})}$$
- Where

$$q = \Phi^{-1}(1 - \epsilon^{\frac{1}{d}}/2),$$

d is the dimension of $\boldsymbol{X}$ and Φ^{-1} the quantile function

General Methodology

- Start with 2 qubits → Entangle based on features of flower → Read out entangled state to determine flower species
- Learning: finds set of θ which has the highest accuracy of correctly predicting the species
  - Characteristics are fed in with the ω_i
  - Loss function – Evaluates error, want to minimize

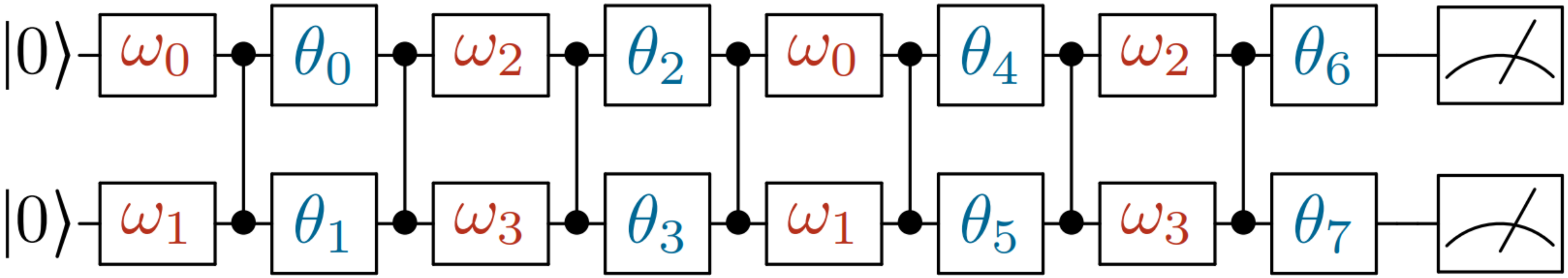
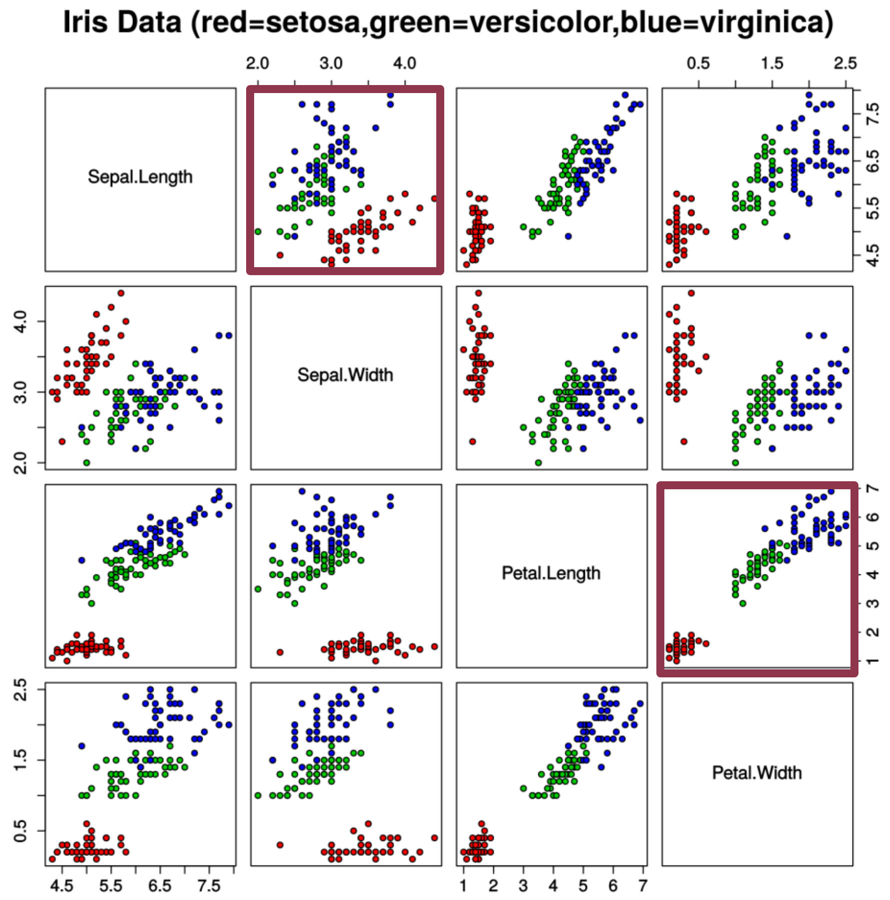


Image source: Cappelletti *et al.* (2020)

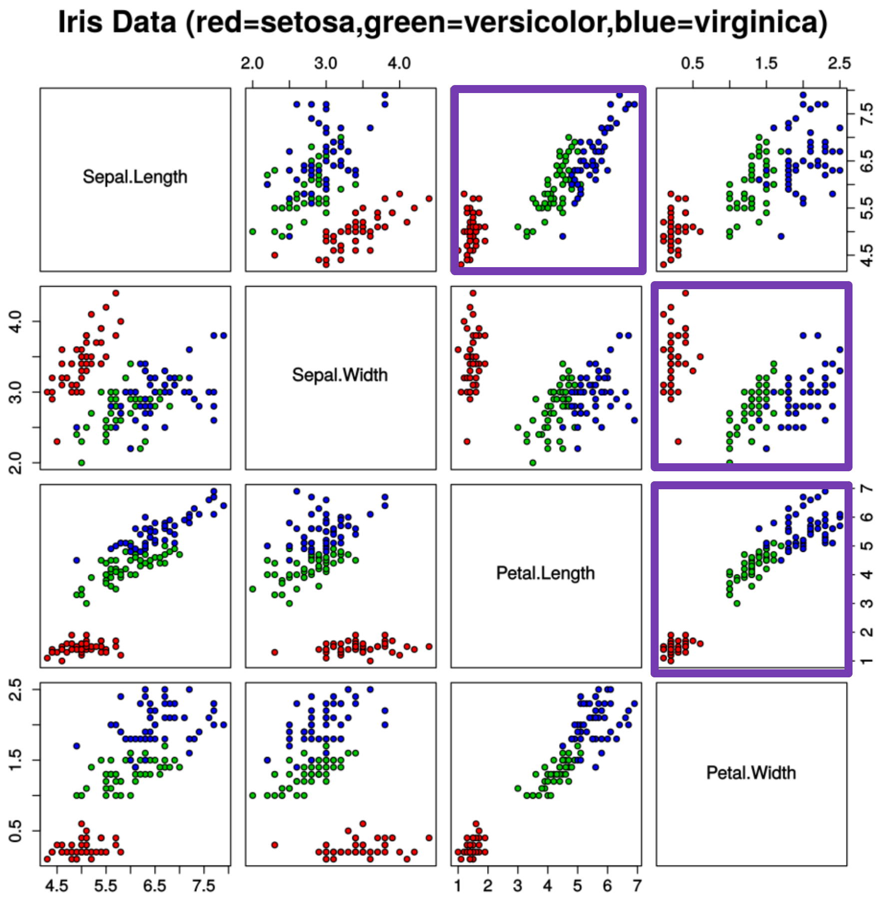
Attempt 1: Feature Selection

Pairings	# of Layers	Average Accuracy	Iterations
sl & sw x2 pl & pw x2	8	0.803	111



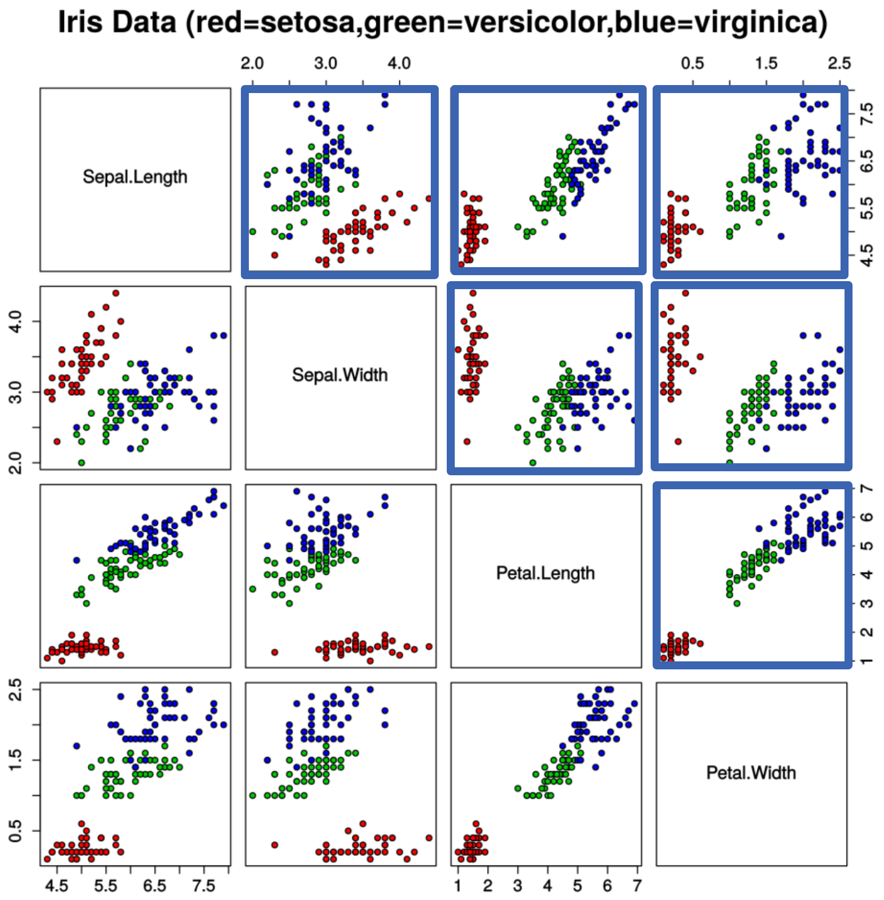
Attempt 1: Feature Selection

Pairings	# of Layers	Average Accuracy	Iterations
sl & sw x2 pl & pw x2	8	0.803	111
sl & pl sw & pw pl & pw x2	8	0.843	118



Attempt 1: Feature Selection

Pairings	# of Layers	Average Accuracy	Iterations
sl & sw x2 pl & pw x2	8	0.803	111
sl & pl sw & pw pl & pw x2	8	0.843	118
sl & sw x3 pl & pw x3	12	0.707	153
All	12	0.966	158



Attempt 2: Prediction & Loss Function

Since the data is encoded in three of the four available states, one of the states is extraneous. The state space is span(00,01,10) and the extra state is the 11 state.

We can avoid any support of the predictions on this extra state by including a term in the loss function which increases monotonically with the weight on the extra state, as follows:

$$\mathrm{L2Loss}(predict, target) = \sum_{i=0}^{N_{\mathrm{elements}}} (predict_i - target_i)^2. + \alpha \ N_{predict=11}$$

This extra term encourages predictions in the code space and inhibits a prediction in the extra state.

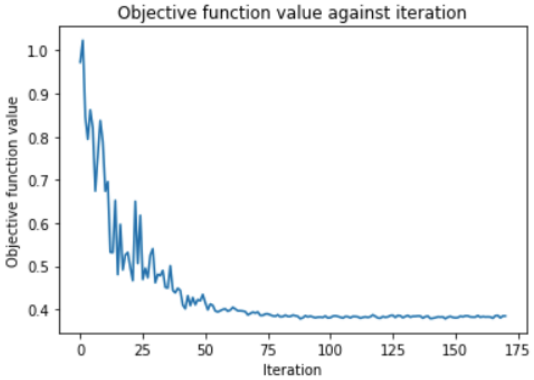
Attempt 3: A Single-Layer Ansatz

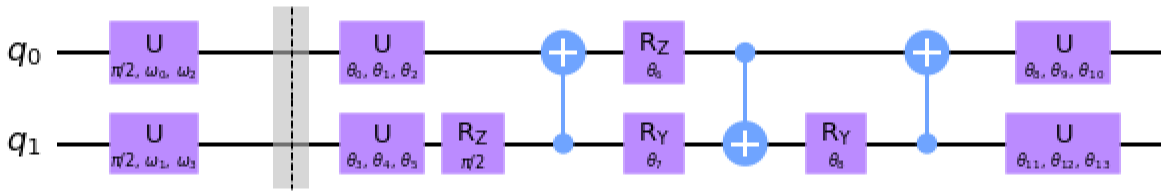
Multiple simple layers VS A single complex layer?

- Encode the data into qubit rotations

$$U2(\phi, \lambda) = RZ(\phi).RY(\frac{\pi}{2}).RZ(\lambda)$$

- Apply a generic two-qubit gate parameterized by 14 parameters*





Accuracy: ~83.67%

Lessons:
- Limited representation power
- More parameters -> harder to optimize

*: Vatan, Colin Williams (2003). "Optimal Quantum Circuits for General Two-Qubit Gates"

Conclusion

<u>Avg. Test result is 0.97 after avg. 138.6 iterations</u>

- 12-layer scheme with all 6 characteristic pairs used
- Weighted Loss function with $\alpha = 0.01$

$$\mathrm{L2Loss}(predict, target) = \sum_{i=0}^{N_{\text{elements}}} (predict_i - target_i)^2 + \alpha \ N_{predict=11}$$