Introduction to Quantum Machine Learning

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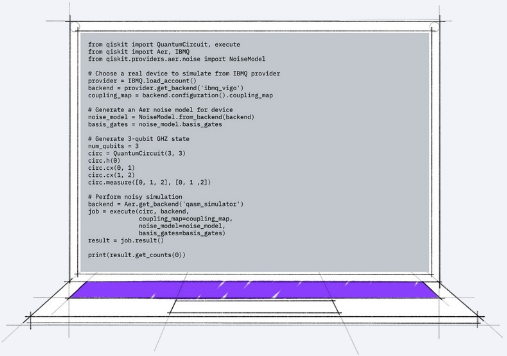
Qiskit

Machine Learning

- Machine learning's primary goal is to train computers to make sense of an ever-expanding pool of data. However, in order to learn from these increasingly complex datasets, the underlying models, such as deep neural networks, also become more sophisticated and expensive to train.

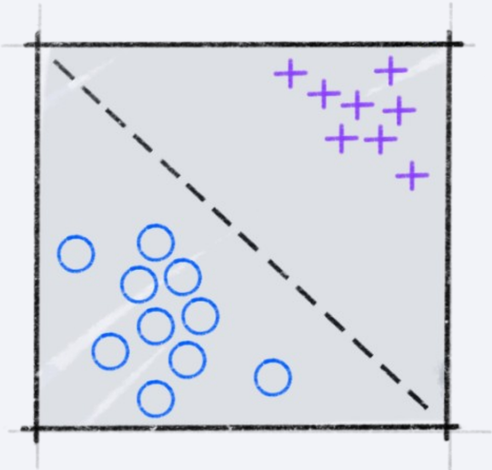
- Machine learning applications touch almost every angle of business, science, and private life, ranging from speech and image recognition to generative models to improve drug design



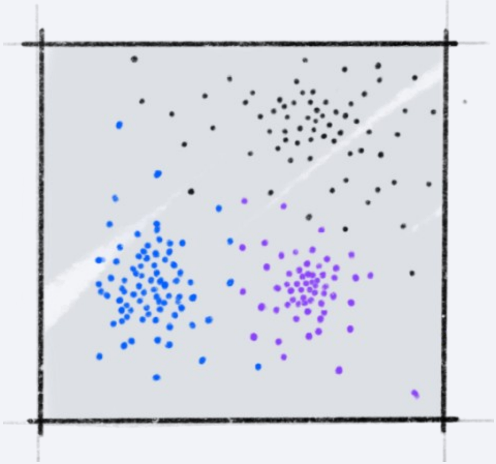
Machine Learning

- Machine learning can be split roughly into three subfields: supervised learning, unsupervised learning, and reinforcement learning.

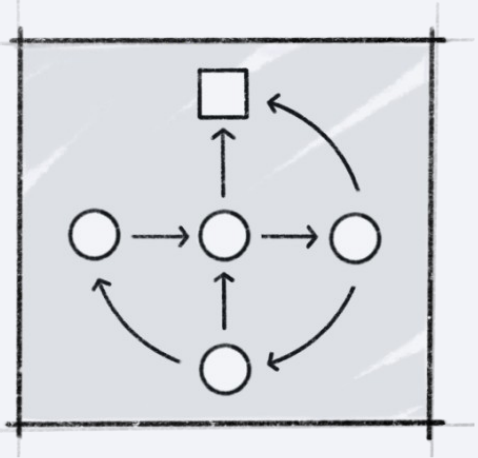
Supervised Learning



Unsupervised Learning



Reinforcement Learning



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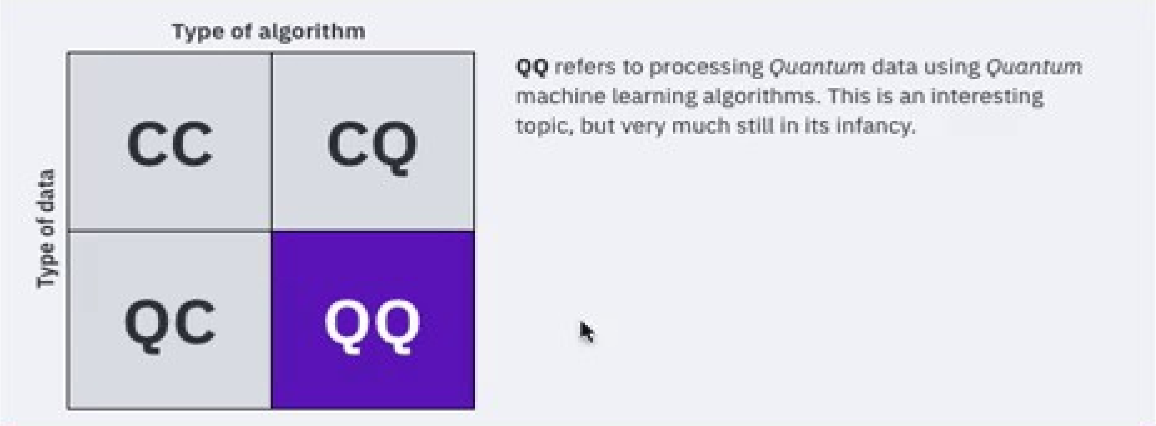
Quantum Machine Learning (QML)

- There are four different approaches for combining quantum computing and machine learning, which are differentiated by whether the data is classical (C) or quantum (Q) in nature, or whether the algorithm is executed on a classical (C) or quantum (Q) computer,



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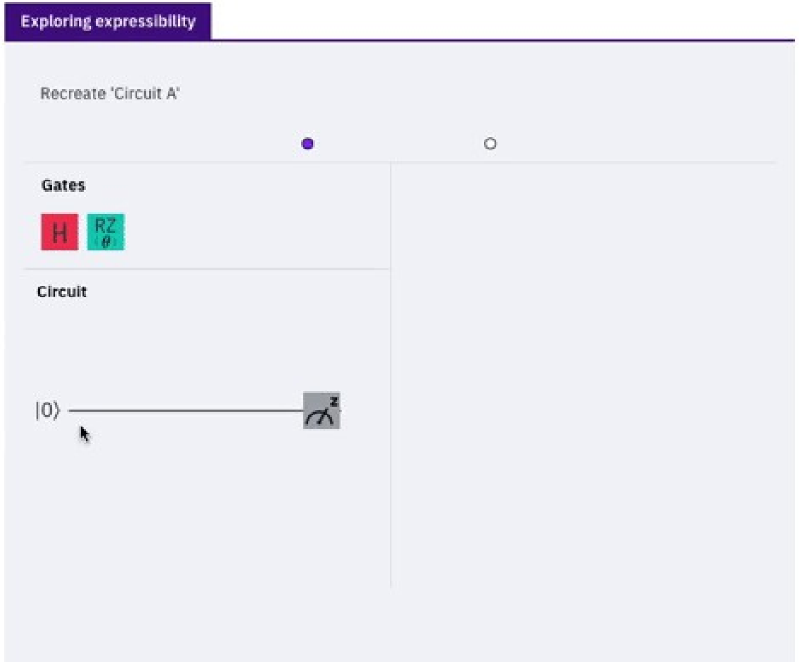
Parameterized quantum circuits

- Parameterized quantum circuits, where the gates are defined through tunable parameters, are a fundamental building block of near-term quantum machine learning algorithms.

Properties

- Expressibility
- Entangling capability
- Hardware efficiency



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Parameterized quantum circuits

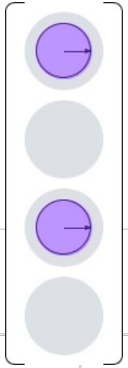
In quantum machine learning, parameterized quantum circuits tend to be used for two things:

- To encode data, where the parameters are determined by the data being encoded.
- As a quantum model, where the parameters are determined by an optimization process.

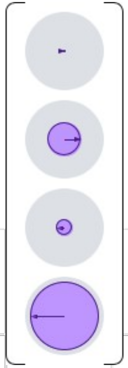
Data Encoding

- It is essential to effectively represent classical data in a quantum system, so that it can be processed by a quantum machine learning algorithm. This is often referred to as data encoding, but it is also called data embedding or data loading.

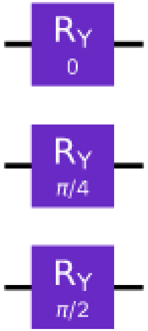
Basis encoding



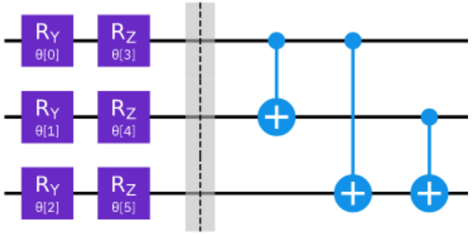
Amplitude encoding



Angle encoding



Arbitrary encoding



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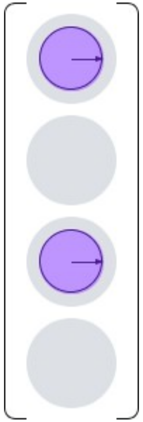
Basis Encoding

- For the classical dataset $\mathscr{X}$ to use basis encoding, each datapoint must be an N-bit string: $x^{(m)} = (b_1, b_2, \ldots, b_N)$ with $b_n \in {0, 1}$ for $n = 1, \ldots, N$ and $m = 1, \ldots, M$, which then can be mapped directly to the quantum state $|x^m\rangle = |b_1, b_2, \ldots, b_N\rangle$.

  We can represent the entire dataset as superposition of computational basis states:

$$|\mathscr{X}\rangle = \frac{1}{\sqrt{M}} \sum_{m=1}^{M} |x^m\rangle$$



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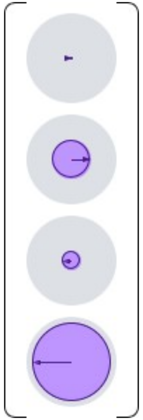
Amplitude Encoding

- The amplitudes of a -qubit quantum state, $$|\psi_x\rangle = \sum_{i=1}^{N} x_i |i\rangle$$

  where $N = 2^n$, x_i is the i^{th} element of x and $|i\rangle$ is the i^{th} computational basis state.

  The dataset $\mathscr{X}$ can be represented in the computational basis as:

$$|\mathscr{X}\rangle = \sum_{i=1}^{N} \alpha_i |i\rangle$$



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Angle Encoding

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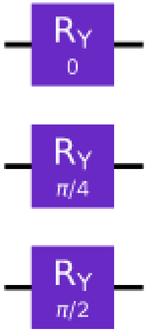
- Angle encoding, encodes N features into the rotation angles of qubits, where $N \leq n$.
  For example, the datapoint $x = (x_1, \ldots, x_N)$ can be encoded as:

$$|x\rangle = \bigotimes_{i=1}^{N} \cos(x_i)|0\rangle + \sin(x_i)|1\rangle$$

The dataset $\mathscr{X}$ can be represented using a unitary

$$S_{x_j} = \bigotimes_{i=1}^{N} U\left(x_j^{(i)}\right) \text{ where } U\left(x_j^{(i)}\right) = \begin{bmatrix} \cos\left(x_j^{(i)}\right) & -\sin\left(x_j^{(i)}\right) \\ \sin\left(x_j^{(i)}\right) & \cos\left(x_j^{(i)}\right) \end{bmatrix}$$



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Arbitrary encoding

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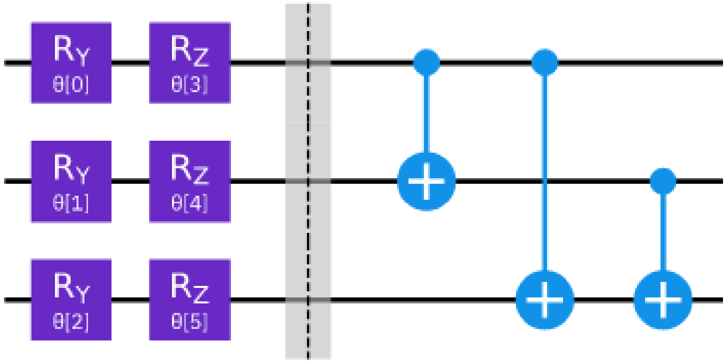
Arbitrary encoding, encodes N features as rotations on N parameterized gates on n qubits, where $N \leq n$. Like angle encoding, it only encodes one datapoint at a time, rather than a whole dataset.



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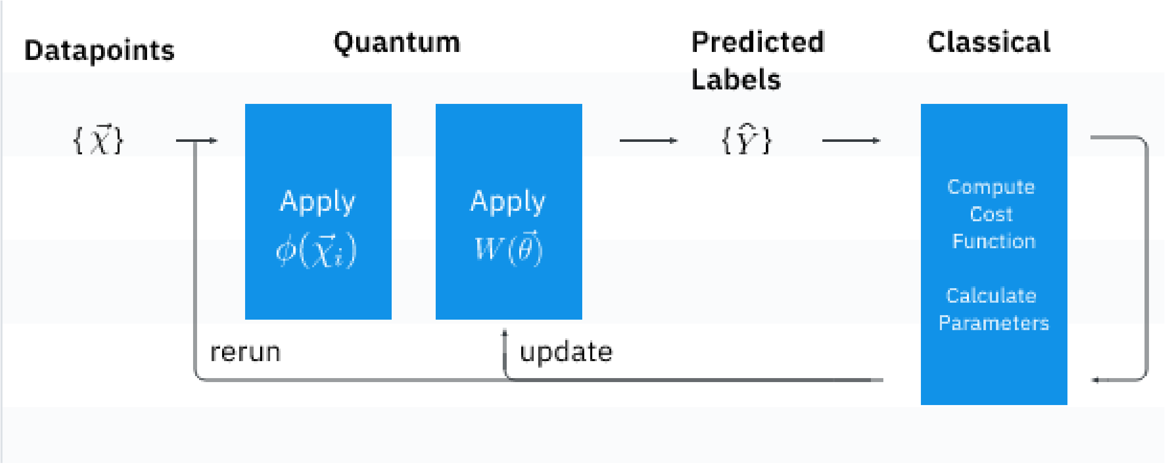
Variational classification

The goal of the algorithm is to find the circuit parameters θ for the parameterized quantum circuit U(θ) that minimizes the cost function C(θ).



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Links

1. Qiskit Quantum machine learning Course: https://qiskit.org/textbook-beta/course/machine-learning-course/
2. Qiskit textbook: https://qiskit.org/textbook/preface.html
3. Qiskit YouTube channel: https://www.youtube.com/c/qiskit
4. Qiskit medium: https://medium.com/qiskit
5. Qiskit slack: qiskit.slack.com

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13. Vojtech Havlicek, Antonio D. Córcoles, Kristan Temme, Aram W. Harrow, Abhinav Kandala, Jerry M. Chow and Jay M. Gambetta, *Supervised learning with quantum enhanced feature spaces*, Nature 567, 209-212 (2019), doi.org:10.1038/s41586-019-0980-2, arXiv:1803.07128.